Data-driven and Machine Learning based Design Creativity

By

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A thesis submitted for the degree of Doctor of Philosophy

July 2019
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List of Publications

The following journal and conference papers were published during this PhD research.

**Journal Publications:**


Peer-reviewed Conference Publications:


Abstract

The power of “big data” and artificial intelligence has advanced not only computer science but also other research fields. In this thesis, patterns, novel insights and knowledge of design creativity are explored and uncovered by exploiting huge, versatile and highly contextualized design data and advanced machine learning algorithms.

Bisociation is applied to creative knowledge discovery along with network-based data mining and visualization techniques for exploring useful relationships and patterns between cross-domain concepts. In order to evaluate the proposed model, a web tool called B-Link has been developed in a longitudinal case study which shows its capability of augmenting creativity in idea generation tasks. In addition to the study of semantic creativity, a visual conceptual blending model is also developed for blending two semantically distinct concepts into image data, taking advantage of generative adversarial networks. This model is implemented in a design case study demonstrating its capability in generating images of a synthesized spoon and leaf for creative design.

Taking combinational creativity as an example of design creativity, a novel approach for interpreting design creativity is introduced, in which image recognition and natural language processing technologies are investigated for key information extraction (e.g. combination pairs). A framework of reusing creative knowledge in a design creativity system is proposed, in which the functionality and relations of each module are fully illustrated. By integrating data, algorithms and creativity theories systematically, the framework shows the potential for recycling creative knowledge in a creative system for design.
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Acknowledgements

It would not have been possible to accomplish this Ph.D. thesis without the support and help from my supervisor, family, colleagues and friends. First of all, I would like to thank my supervisor Peter R.N. Childs who encouraged and supported my work throughout my Ph.D. study. Many thanks for providing me with sufficient resources, freedom and a joyful environment to explore new ideas. His continuous enthusiasm, patient guidance, and promotion have made my way of pursuing academic achievements easier and happier.

I would like to thank all my friends and colleagues in the Dyson School of Design Engineering and the Data Science Institute at Imperial College London. A special thanks to Feng Shi, Ji Han, and Pan Wang for their support and collaboration on my research. Many thanks to Hao Dong for his help with coding and Shiyi Liang’s suggestions on my thesis.

Thank you to all those who participated in my case studies.

I would like to express my deepest gratitude to my parents, who are always standing behind me. Liuchun, thank you for being my brother and helping me.
Chapter 1. Introduction

The principal focus of this chapter is to present an overview of the thesis, including background introduction, research questions and objectives, and the thesis structure. Specifically, it starts with the introduction of three essential concepts, which are the foundation of this thesis: design creativity, data-driven design, and machine learning in design. Research questions and objectives on how data and machine learning algorithms can contribute to design creativity are then proposed considering the support of creativity theories, data, and algorithms. The thesis structure is presented at the end of this chapter.

1.1 Background

1.1.1 Design creativity

Creativity has been widely considered as an integral part of the engineering design process (Thompson and Lordan, 1999; Howard et al., 2007; Toh and Miller, 2015). The creative person, process and product are regarded as the core elements of achieving creativity (Rhodes, 1961; Couger et al., 1993; Warr, 2007). Without some elements of creativity in design there is little potential for innovation where novel ideas are implemented and transformed into commercial value (Howard et al., 2007). Design creativity has become a popular research topic which involves some basic questions, such as the definition of design creativity, the assessment of design creativity, and the augmentation of creativity.

There exist many definitions of creativity. Webster’s dictionary (Merriam-Webster, 2019) defines creativity as the ability or power to create—to bring into existence, to invest with a new form, to produce through imaginative skill, to make or bring into existence something new. When this concept is related to a human being, namely personal creativity, according to psychologist Stemberg (Sternberg and Lubart, 1995), it is related to a person’s intelligence, knowledge, thinking styles, personality, motivation,
and environmental context. In a comprehensive survey conducted by Sarkar and Chakrabarti (2008), over 160 definitions of creativity are analyzed. Two different types of methods are summarized: majority analysis and relationship analysis, and a general definition of creativity is proposed: *creativity occurs through a process by which an agent uses its ability to generate ideas, solutions or products that are novel and valuable.* As the definitions of creativity from different researchers are various, Demirkan and Afacan (2012) indicated that the nature of creativity is so complex that no single definition of creativity can be applied to encompass and identify this concept. An overview of creativity is presented in Chapter 2 where fundamental creativity theories are reviewed.

Creativity is a broad and general concept and can be defined for different purposes. The creativity for creative design has some specific features. A classic study conducted by Getzels and Jackson revealed that individual creativity and IQ value went together until up to an IQ of 120 (Gibson, 1993). Generally, an individual designer usually has a required intelligence, which can either be obtained by nature or from education, so that there appears to be a correlation between personal intelligence and creativity.

According to Li et al. (2007), design creativity has several key attributes. As shown in Figure 1.1, knowledge and creative thinking are two critical attributes of design creativity and lay a solid foundation for it. Knowledge is the source from which new ideas are generated, but it alone will not make a person creative. If a designer relies only on his own knowledge and experiences, his design creativity will be restrained. Hence knowledge needs to be combined with creative thinking. Li et al. (2007) further indicated that creativity is likely to rise with the increase of knowledge. Creative thinking helps overcome thinking inertia so that it enables designers to make full use of their entire knowledge and previous innovation experiences flexibly. In the design creativity model, information is taken into account as another key attribute. It answers fundamental questions such as “who”, “what”, “where” and “when” while knowledge extends existing information to provide answers for “how” and “why” questions. When information technology (IT) and related computer support tools are applied, knowledge database (such as Szykman et al. (2000)’s NIST project mentioned in Section 3.2) and
information retrieval can be the critical attributes to further affect design creativity. Knowledge base and network information search tools, such as a scientific-effects base, a multi-level network information search assistant and patent base linkage, which are the external modules of creative design process, can be used at any time during the course of designing, and enable designers to stimulate their creative inspiration effectively. Research in cognitive science, computer science, and design theory provides a substantial foundation for the development of human-based, computer-assisted creative design methods (Colton and Wiggins, 2012). This thesis aims to further advance research on this direction by investigating data-driven methods for enhancing design creativity in different aspects: a long-term creativity by forming a data-driven cycle in Chapter 3, semantic network inspired creativity in Chapter 4, visual blended creativity in Chapter 5.

---

**Figure 1.1 Design creativity model (Li et al., 2007)**

By classifying design into three categories: drawing, problem-solving and the pursuit of an ideal, Taura and Nagai (2010) re-defined design as the process of “composing a desirable figure toward the future”, and proposed a new definition of design creativity: the degree to which a desirable figure is realized. A ‘desirable figure’ is regarded as an ideal image in the case of the pursuit of an ideal design, originated from human’s mind. In a problem-solving process, a problem is defined as the difference between the current
state and the desired goal. Thus, the process of developing a solution to achieve the goal is synonymous with the design process. In the model of design process proposed by Taura and Nagai, shown in Figure 1.2, the push-type process composes a design image or concept that represents a desirable figure while the pull-type process is a problem-solving process that is pulled forward from a predetermined goal.

![Diagram of design process](image)

**Figure 1.2 Extended model of the design process (Taura and Nagai, 2010)**

### 1.1.2 Data-driven design

With the arrival of “Internet of Things” or the cyber-physical systems era, a large amount of human-generated and machine-generated data are creating unprecedented opportunities and challenges across various research areas, such as computer science and electronic engineering. In the field of design, there is a vast amount of versatile and highly contextualized data generated in various ways, such as the design process. By exploiting such massive data with data-driven design methodologies, novel patterns, and new knowledge can be uncovered (Kim et al., 2017).

Data-driven design is a general and abstract concept. As the words suggest, it covers three aspects: data, driven, and design. **Data** refers to the digital format of information which can be largely stored in different places, such as a data center, and read or processed in multiple types of digital devices from anywhere via Internet or Ethernet. Its excellent characteristics have triggered a revolution of the information era. **Driven** means the state-of-the-art algorithms and methodologies that are developed for analyzing, interpreting, visualizing data, and extracting novel insights and useful information from data. **Design** represents the ways in which data and related methods are used. As design is a broad and multi-disciplinary field where several subjects are involved, such as mechanical engineering, civil engineering, and the arts, the
applications of design can be various, including conceptual design, design process, and user experience (Shi, 2018).

Data-driven design is a methodology rather than a simple concept. It is centered on data, powered by computational algorithms, and applied to the design area. In a data center where design data are all gathered, a data-driven platform can advance the design process. In Chapter 2, data-driven design is reviewed from the perspective of design creativity tools, showing how tools are developed to achieve design creativity. It is then further developed regarding different aspects in following chapters, including idea generation, concept blending, design interpretation and a conceptual data-driven cycle. Especially in Chapter 4, a large network-based database is established from scratch along with algorithms mining hidden associations between conceptual data.

Song et al. (2018, 2019) propose a data-driven method for platform design by drawing the boundary of a platform-system, complementing other platform design approaches and assisting designers in the architecting process. Based on patent data, their method was applied to identify functions for spherical rolling robots. A network is an important data structure which is not only flexible and capable of storing and retrieving rich information but also convenient to be visualized. Due to these advantages, network data and related analysis methods have become popular in data-driven design. Sarica et al. (2019) presented a data-driven network visualization methodology to locate knowledge positions of a firm as a subspace of technologies for innovative design. Based on a large quantity of patent data, Luo et al. (2018) proposed the total technology space map (TSM) which is comprised of various knowledge domains according to knowledge proximity. The map is used as a visual ideation aid for fast high-level design opportunity conception. To retrieve design precedents in a patent database, Song and Luo (2017) proposed an iterative and heuristic methodology for data-driven design. It integrates the mining of patent texts, citation relationships and inventor information to identify relevant patents.

There are many design problems that can be solved using data-driven approaches. Ranscombe et al. (2017) use the Holistic Styling Analysis (HSA) to improve the
comparison of 3D geometry shape of products. As a data-driven styling method, HSA provides an objective assessment of appearance difference for designers to form the basis of styling in the design process. Zhang et al. (2017) showcase the identification of performance requirements for smartphone design based on the analysis of collected operating data for CPU utilization.

1.1.3 Machine learning in design

A wealth of knowledge that designers can re-use to design better products in a shorter-to-market period can be extracted from the design process. To acquire knowledge in design, many methods have contributed to the field of machine learning in design (MLinD). As a foundation for MLinD, Sim and Duffy (1998) provide answers to basic questions on MLinD systems, such as “what types of design knowledge can be learned?” and “how is learning taking place?”. Prior to the definition of MLinD, five main elements of MLinD are presented: input knowledge, knowledge transformers, output knowledge, goals/reasons for learning, and learning triggers, as shown in Table 1.1. To validate the proposed foundation of MLinD, existing MLinD systems were selected and reviewed.

<table>
<thead>
<tr>
<th>Basic elements of learning</th>
<th>Persidis and Duffy</th>
<th>Grecu and Brown</th>
</tr>
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<tr>
<td>Iₖ (input knowledge)</td>
<td>• Not explicitly addressed</td>
<td>• What are the elements supporting learning?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Availability of knowledge for learning</td>
</tr>
<tr>
<td>Kₖ (knowledge transformer)</td>
<td>• How is learning carried out?</td>
<td>• Methods of learning</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Local vs. global learning</td>
</tr>
<tr>
<td>Oₖ (output knowledge)</td>
<td>• What knowledge is learned?</td>
<td>• What might be learned?</td>
</tr>
<tr>
<td>Tₖ (trigger)</td>
<td>• What can trigger learning?</td>
<td>• What can trigger learning?</td>
</tr>
<tr>
<td></td>
<td>• When is learning triggered?</td>
<td></td>
</tr>
<tr>
<td>Gₖ (goal/reason)</td>
<td>• Not explicitly addressed</td>
<td>• Consequences of learning</td>
</tr>
</tbody>
</table>
To present the dimensions of MLinD and identify the main points of focus within each dimension, Grecu and Brown (1998) introduced the triggers of learning, the elements supporting learning, what gets learned, the availability of knowledge for learning and methods of learning. As consequences of learning, the performance of the design system and the success of the learning mechanism can be measured by the design improvements and the design process improvements.

Table 1.2 Stages in the evolution of design automation (Tong and Sriram, 2012)

<table>
<thead>
<tr>
<th>DESIGN AUTOMATION GOAL</th>
<th>PROBLEM</th>
<th>AI ISSUE</th>
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<tbody>
<tr>
<td>Permit design capture</td>
<td>What functions does the user interface provide?</td>
<td>Deductive or object-oriented databases</td>
</tr>
<tr>
<td>Build tools for specific tasks</td>
<td>How to automate specialized types of reasoning</td>
<td>Inference; Expert systems</td>
</tr>
<tr>
<td>Integrate tools</td>
<td>How to communicate between tools?</td>
<td>Representation; Architectures</td>
</tr>
<tr>
<td>Manage versions</td>
<td>Which task, tool, parameters?</td>
<td>Search space</td>
</tr>
<tr>
<td>Model design process</td>
<td>Which model is right for the task?</td>
<td>Taxonomy of tasks and corresponding methods</td>
</tr>
<tr>
<td>Find good design fast</td>
<td>How to guide choices?</td>
<td>Control</td>
</tr>
<tr>
<td>Improve design system</td>
<td>Where and how to improve?</td>
<td>Machine learning</td>
</tr>
<tr>
<td>Reuse design knowledge</td>
<td>How to acquire? How to re-use?</td>
<td>Machine learning, case-based reasoning</td>
</tr>
</tbody>
</table>

Engineering design involves mapping a specific function onto a (description of a) realizable physical structure (the designed artifact). The desired function is what it is supposed to have, while the artifact’s structure is the actual physical parts out of which it is made (Tong and Sriram, 2012). There is a sequence of somewhat predictable stages for automating such a mapping process for engineering design, as shown in Table 1.2. As can be seen from the table, design tools can be developed through the following process: permitting design capture; automating specific expert tasks; constructing unified representations and system architectures; modeling and automating the complete design process; automatically controlling the design process; automatically
re-using design knowledge; automatically optimizing design tool performance. With the revolution of AI design tools, they can be expected to play an increasingly more active role in the whole design process.

For instance, symbolic design reformulation is an enduring challenge in design automation. Existing design tools for symbolic design reformulation either require high levels of knowledge processing or large training databases of design cases. To address these limitations, Sarkar et al. (2010) presented a singular value decomposition and unsupervised clustering-based method which is able to learn semantic knowledge from the syntax of design representations and then perform reformulation. Similarly, for configuration design problems, which are common in engineering design, McComb et al. (2018) used hidden Markov models to automatically extract helpful design heuristics from a cognitive study of configuration design in order to observe how humans naturally attempt to solve those configuration design problems.

Case-based reasoning (CBR) is another interesting research topic in artificial intelligence community, which has shown its impact on design creativity. CBR assumes the existence of a collection of selected cases, represented in a complete and discrete form. It serves as the memory for reflecting similar problems and solutions in order to solve new problems. The process involved in CBR can be represented by a schematic cycle, described by Aamodt and Plaza (1994), consisting of four “Res”: Retrieve the most similar cases; Reuse the cases; Revise the proposed solution; Retain the new solution. In design domain, design tasks are appropriate for applying, integrating, exploring, and pushing the boundaries of CBR. For instance, Geol et al. (1997) developed a case-based design system where a structure-behavior-function (SBF) model was utilized for indexing design cases for retrieving, adapting, verifying and storing purposes. Combining with computer science, case-based design (CBD) can take the advantage of artificial intelligence to implement systems for CBR. Schmitt (2012) indicated that CBD systems have four major processes: case definition, case retrieval, case adaption, and case combination. With regard to the question of creativity raised by CBD, Schmitt also outlined five criteria formalizing the measurement of the degree of creativity of the artifacts produced by CBD systems, including:
Creativity requires knowledge of a set of precedents. This corresponds to an intelligent database of existing designs, organized by index.

Creativity is a function of the designer’s ability to explain the precedents and the reasons for being in the database, which refers to the capacity of programs to perform inference or explanation.

Creativity relies on heuristics to find applicable solutions of the past and to adapt them to new design problem, which corresponds to heuristic search and inductive reasoning.

Creativity builds on the capacity of external critic to ask challenging questions. This demands computer software to be able to reason with common sense knowledge.

Creativity is a function of the idiosyncratic experiences of individual designers. It requires the programming of individual case bases and the access to different case bases.

The first three criteria show the CBD systems should be creative to have the capacity to learn, remember, and apply knowledge, while the last two criteria indicate the necessity of questioning the individual discovery. These criteria are in line with the discussion in computational creativity community, which is further illustrated in Chapter 2. CBR can be also combined with a variety of theories to assist product concept design. In the model Hu et al. (2019) proposed, Quality Function Deployment, Case-based Decision Theory (CBDT), the Theory of Inventive Problem Solving (TRIZ), Image-Scale, and solid-modelling are integrated together to support general decision-making and innovative solution generation. The feasibility and effectiveness of this model was examined by a “cordless hand-tool design” case study.

Since Alexnet won the ImageNet competition by more than 10.8 percentage lower of top-5 error than the runner-up in 2012 (Krizhevsky et al., 2012), deep neural networks based machine learning technologies have demonstrated their capability and scalability of learning in computer science. As a new frontier for design, machine learning techniques have been increasingly applied to design science research (Kazakci, 2015). Fuge et al. (2014) explored different machine learning algorithms for recommending
design methods, given a particular problem. They demonstrated that automatically grouping frequently co-occurring methods using spectral clustering replicates human-provided groupings to 92% accuracy. McComb (2018) applied deep neural networks to the rapid design of engineered systems, such as oil platforms. The results have shown deep learning can be used to accurately and rapidly synthesize and analyze offshore structures including buoys, oil rigs, and cruise ships.

Design creativity is an important component of intelligent design systems which are able to generate creative artifacts or exhibit creative behaviors. As a part of the field of computational creativity, the combination of design creativity and computer science, state-of-the-art intelligent design systems are usually developed with machine learning techniques. Karimi et al. (2018) introduce a computational model of concept shifts for a co-creative design system. Given a source sketch, the proposed CNN-LSTM model finds a target sketch of a different category so that it shares the same visual information. In Chapter 5 and 6, advanced machine learning approaches and algorithms are proposed in order to generate visual creativity and interpret creativity respectively. A state of the art generative adversarial networks (GANs) model is proposed to blend images falling in two semantically distinct domains in Chapter 5, so that designers can be inspired by visual blending in early stage of conceptual design. Chapter 6 exploits advanced deep learning models for image recognition and relation recognition (for textual data) together to extract meta-data containing combinational creativity.

1.2 Research gaps and motivation

Along with emerging advanced digital technologies, design engineering has involved use of a variety of digital tools and methods, such as computer-aided design and sketch tools. With these tools and methods, a large amount of data is generated during a design process. Data represents design knowledge in a digital design process, and it makes the whole process more efficient to manage, iterate and finalize. In conceptual design phase, idea generation is a common step to initialize possible solutions to a design problem. Ideation tools help augment designers’ creativity by deploying various creative thinking methods. Recently, data-driven ideation tools have been pursued by researchers, and
are reviewed in the second chapter. The format of data involved in ideation tools can either be semantic (textual data) or visual (imagery data).

In the research of data-driven idea generation, data-driven design methodologies and machine learning techniques are mainly the focus of investigation. Data-driven design methodologies aim to gain insights from database by exploiting data analysis techniques, such as data mining and visualization. Machine learning, as a useful method for mimicking patterns in data of high dimension, is explored in the design field to produce creative solutions based on existing design patterns. However, from the perspective of data, the existing research focuses on how to use data in order to augment creativity, while the flow of design data is overlooked. Starting from ideation, a conceptual design solution is initialized by an idea, followed by modeling and prototyping in several iterations, the design is completed and then finalized. However, if the creative knowledge hidden in innovative designs can be identified and reused to inspire designers in the ideation stage, a closed loop of data flow can be formed. In previous research, there is no clear data flow which can be tracked in idea generation, design conceptualization and design concept interpretation.

This thesis aims to investigate such a data-driven cycle for design creativity. In the early stage of conceptual design, it is necessary to explore various source of data and mine insights for design creativity, as well as the data-driven method of how to make full use of data to produce creativity. In this thesis, semantic data is first investigated for ideation using data-driven method, the conceptual design is then continued with imagery data. To close the data-driven cycle, a methodology concerning how to extract meta-data from existing innovative design solutions by exploiting machine learning techniques. While a variety of data analysis and machine learning techniques are investigated throughout this thesis, fundamental computational creativity theories are discussed and developed along with studies as well.
1.3 Research questions and objectives

1.3.1 Research questions

The main research question in this thesis is to clearly present and justify the data-driven cycle for design creativity described in the previous section. The discussion on this data-driven cycle is limited to conceptual design, in which it is interesting to investigate the relation among raw data, ideas and conceptual design when they are involved in the data-driven cycle for design creativity.

At the very early stage of conceptual design, designers usually need to generate ideas via various methods, such as brainstorming, so that either their design solutions can be creative or their design problems can be solved in a better way. Generally, ideas can be expressed in various forms, and the most common ways are: semantically and visually. Expressing ideas in a semantic way is quick, simple, natural and easy for documentation. Semantic data is the most abundant data source as well, and it can be stored as documentation in a variety of electronic devices, such as on a PC, server, and data center.

To obtain insights from semantic data, we need to collect a large amount of data from sources, then process data to make sure that it is in the appropriate structure. The next step is data mining, and it is an essential step of data-driven design, in which sophisticated algorithms can be designed and applied. When mining algorithms produce results, these raw results might need to be converted to different forms for presentation as a postprocessing step. Therefore, it is necessary to understand the possible impact of semantic data sources on creativity and how to mine insights from data using computational techniques.

When designers have semantic ideas available, as a further step of conceptual design or a supplementary of design, visualization of an idea is necessary. Similar to a sketch, which is common and sometimes an essential part of design for designers, how can we visualize a semantic idea? It is necessary to explore the advanced techniques in computer vision in order to investigate the second challenging research question. In recent years, deep learning has contributed much to the advance of computer vision.
problems, such as image recognition. With machine learning in design methodologies, the proposed research question is expected to be solved by investigating the possible method for generating visual solutions based on given a semantic idea.

After iterations of modifications and improvements, conceptual design solutions are finalized and can be then developed into products as the outcome of a design process. A conceptual design is rich in design knowledge. To reuse the knowledge from creative designs, it is crucial to explore the extraction of creativity from existing solutions. From the point of view of data-driven design, creative designs are expected to be interpreted by machines and then decomposed into metadata for further utilization.

![Figure 1.3 A data-driven design creativity cycle](image)

By summarizing all the steps involved in the data-driven cycle for design creativity, the flowchart in Figure 1.3 shows the flow of data representing design knowledge. Specifically, the whole loop starts from a collection of metadata. After necessary preprocessing for either semantic data or image data, creativity theories are combined with data mining and machine learning algorithms to model design creativity, which results in creative idea generation. The following step needs the involvement of design...
expertise, where the generated creativity is examined and then qualified if the creativity is perceived as appropriate. Then design creativity interpretation module plays a vital role to transform creative design solutions to metadata containing creativity. The interpreted metadata becomes the internal source to database, which forms a cycle of data-driven design. In addition to internal supply of metadata, external data source is also necessary especially when the cycle is launched.

1.3.2 Research objectives

As described in Section 1.2.1, this research involves methodologies for mining creativity from semantic data, generating visual creativity from image data with machine learning techniques, and interpreting creativity by transforming matured creativity from products into metadata for knowledge reuse. Eventually, based on data science and existing study of creativity, an integrated data-driven framework for recycling creative knowledge is expected to be discussed and justified.

In the field of deep learning, there are three pillars for its advance: data, algorithm, and computing power (Graphics Processing Units, GPU). Similarly, this research is supported by the following three pillars: data, data-driven algorithms, and creativity theories. To be specific, the research objectives of this thesis, which are related to these three pillars, are as follows:

- To process data (including semantic and visual data) from a variety of sources, including design data, and restructure them for further processing with data mining and machine learning algorithms.
- To develop appropriate data mining algorithms for analyzing semantic data and provide design insights; To develop appropriate machine learning algorithms for generating visual design solutions and provide design creativity.
- To investigate and justify how each theoretical part works in the proposed data-driven design creativity cycle.
1.4 Thesis overview

1.4.1 Key contribution

This thesis aims to study design creativity by exploiting data-driven and machine learning methods. Different aspects of the proposed data-driven cycle are studied throughout the main chapters, including research methodology, idea generation with semantic data, design conceptualization by conceptual blending, and design creativity interpretation. Meanwhile, a variety of computational methods are presented as well, such as the network-based data mining and visualization method, the GANs-based image generation model, and an integrated approach combining image recognition and natural language processing techniques. Details of key contribution can be summarized as follows:

- The initial contribution is the proposal of a conceptual data-driven cycle for design creativity, which seeks to present how a data-driven cycle can be formed in a creative system where creativity can be generated and reused. Studies in following chapters are brought in to justify this cycle while demonstrating the feasibility of its implementation.

- A data-driven method is proposed in Chapter 4 in order to augment creativity in design ideation. It introduces two novel data mining algorithms for retrieving implicit associations between concepts, as well as the corresponding data exploration method where visualization and interaction assist users to explore data during the whole idea generation process.

- A machine learning model based on GANs is proposed in Chapter 5 for conceptual blending. Different from models in traditional style transfer and image-to-image translation tasks, it is capable of blending two semantically distinct images rather than either simply superposing images or applying one image’s style into another one.
• Chapter 6 focuses on combinational creativity interpretation with computing methods, which is an early research in this direction. It proposes an integrated approach for extracting combinational creativity from images and texts, by exploiting advanced image recognition and natural language processing techniques.

1.4.2 Thesis structure

The primary motivation of this thesis is to explore design creativity in the context of data science and propose an integrated framework so that design creativity can be augmented in a closed cycle. As an overview of this thesis, a brief description of each chapter is provided below.

Chapter 1 introduces three main concepts which are studied throughout this thesis: design creativity, data-driven design, and machine learning in design. A brief definition of the main concepts is presented along with some research from past to present, which may not be complete and broad enough but the primary purpose is to give an overview of the main topics in this thesis. This chapter also describes the research questions and objectives.

Chapter 2 provides a general but fundamental review of creativity theories, computational creativity, and creativity tools. Creativity theories are investigated towards their integration with artificial intelligence. The exploration of computational creativity attempts to answer fundamental questions related to machine creativity evaluation and creativity modeling. The review of existing creativity tools present the practical gaps in data-driven design creativity. Within the review of state-of-the-art research and applications, opportunities and challenges are identified as well.

Chapter 3 proposes a data-driven cycle for design creativity, presenting the corresponding research methodology. Before introducing the cycle, it reviews existing creative systems and identifies the gap between conceptual design and meta-data. In the proposed cycle, key steps are articulated from the perspective of data and creativity. Then it justifies the relations between each step and explains how the whole cycle
supports the reuse of creative design knowledge. Eventually, this chapter discusses the cycle’s implementation and limitations.

**Chapter 4** introduces a data-driven creativity tool for semantic idea generation. Based on the review and challenges observed in real-world creative tasks, guidelines are proposed for designing an interactive tool to support creativity in idea generation: data-driven creativity model, discovery process, visualization, and interaction. As an implementation of the proposed guidelines, the interactive data-driven semantic idea generation tool B-Link is presented. B-Link extracts critical information from academic publications and combines exploratory creativity and bisociation as the computational creativity model to guide users’ idea generation. A network data visualization interface is provided to assist users to interact with data and think beyond their expertise knowledge.

**Chapter 5** investigates a visual concept blending model for creativity generation based on computational creativity. With the state-of-the-art technique in machine learning, generative adversarial networks, the proposed model is able to synthesize two semantically distinct concepts, such as spoon and leaf in the case study, by generating concepts-blended images. The model is implemented in a design case study and shows its advance in creative design in terms of variety and novelty.

**Chapter 6** explores the interpretation and extraction of combinational creativity. An approach consisting of deep learning models for detecting and extracting creativity from textual and visual materials is proposed, on the basis of three driving forces behind combinational creativity, namely: problem-, similarity-, inspiration-driven creativity. In the evaluation of this approach, a combinational creativity dataset is used for testing proposed image recognition and NLP approaches where basic components of combinational designs are identified according to their textual descriptions and images. The results show that the base is more comfortable to be extracted than additive in a combinational relation, while the NLP module performed better than the image recognition module.
Chapter 7 provides the conclusions of this thesis. It summarizes the key contributions of this research on how data science and computational creativity theories are applied to solve creativity related research questions. The chapter also discusses the limitations within this research and the future directions for advancing this research.

A flow diagram of this thesis showing the principal findings of each chapter is given in Figure 1.4.

Figure 1.4 Flow chart of the thesis
Chapter 2. A General Review of Computational Design Creativity

This chapter provides a general but fundamental review of creativity theories, including bisociation which is applied in Chapter 4, the systems model and Boden’s taxonomies which are the foundation of Chapter 3 and 6, triangular creativity, and creativity in design where the relationship between design and creativity is discussed. The definition and state-of-the-art research of computational creativity are then explored with the attempt of investigating how creativity theories have an impact on computational creativity and what the recent research is. Eventually, to review creativity from a data-driven application point of view, recent creativity tools are classified into three categories: traditional, program-based, and data-driven. By comparing these creativity tools, a new research direction on computational creativity is concluded.

2.1 Creativity theories

Creativity has been the motivation for many lines of study throughout human history, arising from its tremendous contribution to our world and its seemingly mysterious nature. Before the study with consideration of computer science, most of the works on creativity came from the areas of psychology, philosophy and cognitive science. Instead of introducing these creativity research from a historical perspective, some works which have a direct influence on computational creativity are introduced in this section. Bisociation is an important concept for the study in Chapter 4 in which it is developed in a data-driven approach for creative knowledge discovery. The creativity theories introduced in section 2.1.2 are the foundation of what is developed in Chapter 3 and 6. They help explain from where creativity originates, how creativity patterns can be explored, and how they are related to artificial intelligence and the research in this thesis. Section 2.1.3 introduces three aspects of creativity and explores their relations, which contributes a clearer understanding of creativity. The relationship between design and
creativity is discussed in section 2.1.4 in order to show the importance of design creativity studies.

2.1.1 Bisociation

The concept *bisociation* was initially presented as a methodology for creative thinking by Arthur Koestler in the book *The Act of Creation* in 1964. In his model of bisociation, creativity can be obtained by bridging knowledge in two otherwise not – or only very sparsely – connected domains whereas knowledge in a given domain is associated (Koestler, 1964; Berthold, 2012). Three essential components can be identified within the model: matrices of thought, codes of rules and strategies. According to Koestler, a matrix of thought refers to any ability, habit, skill, or any pattern of ordered behavior governed by a ‘code’ of fixed rules. Matrices shape our perceptions, thoughts, and activities and they can be considered as the condensation of learning into “habit” (Dubitzky et al., 2012). The code which defines the matrix can be put into mechanical equations which contain the essence of the pattern in a compressed ‘coded’ form. The code could be innate or acquired. In his example of chess, the rules of the game are fixed, but the patterns of knowledge that relate to the performance of play vary across players. In another example, in mathematics, operations such as addition, multiplication and integration constitute fixed rules that govern mathematical reasoning. A strategy corresponds to the perception of elements in the matrix in order to achieve a goal or pattern of behavior. In a chess game, this would be the decision of the “next move” (Pereira, 2007).

Koestler’s basic model of bisociation can be illustrated as shown in Figure 2.1, in which the two orthogonal planes represent two matrices of thought $M_1$ and $M_2$ which can be regarded as two knowledge domains or bases from the view of data science. Note that the knowledge in $M_1$ and $M_2$ are self-contained and “habitually incompatible”. The dots $c_1, c_2, \ldots, c_6$ denote six concepts in $M_1$ or $M_2$ where $c_1, c_2, c_3, c_6$ are perceivable in $M_2$ and $c_1, c_2, c_3, c_4$ and $c_5$ are perceivable in $M_2$. $\pi$, the red line representing an event, idea, situation, method or problem, can be perceived simultaneously in both matrices. The line $\pi$ cuts across $M_1$ and $M_2$ as the concepts $c_1, c_2, c_3$ are associated with the problem $\pi$. 
and they are perceived simultaneously (Dubitzky et al., 2012). The bisociation cannot form if concepts are merely linked in one associative context ($M_1$ or $M_2$).

Figure 2.1 Illustration of Koestler’s concept of bisociation (Koestler, 1964; Dubitzky, et al., 2012)

The Archimedes’ “Eureka act” can be an example of perceiving a problem solution. To measure the volume of the King’s crown, Archimedes came up with a novel solution when he was taking a bath. If the existing geometry knowledge that Archimedes already has is in matrix $M_1$, and the common knowledge that the water level raises when his body slides into the basin is in matrix $M_2$, Archimedes found the solution to his problem when both matrices were simultaneously active. Prior to that, he failed to find the solution as he only focused reasoning on $M_1$ in his habitual way.

Koestler’s bisociation concept is distinguished from the type of analogical or metaphoric thinking which originates from daily life and results in the creativity from a specific associative style of mind (Cunha et al., 2010; Dubitzky et al., 2012). The distinguishing characteristics of bisociation, analogy and metaphor are summarized in Table 2.1. No similarities are shared between bisociations when different thinking routines are simultaneously activated and combined together to solve existing problems, while these routines could be easily understood separately in two independent domains. However, both analogy and metaphor share properties when mapping from sources to
targets, and sometimes they are difficult to understand for readers when the mappings are implicit.

Table 2.1 Comparison of characteristics of bisociation, analogy and metaphor

<table>
<thead>
<tr>
<th></th>
<th>Domain</th>
<th>Similarity</th>
<th>Literalness</th>
<th>Novelty</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bisociation</td>
<td>Independent combination</td>
<td>None</td>
<td>easily understood</td>
<td>novel</td>
<td>creative and problem solving</td>
</tr>
<tr>
<td></td>
<td>Source-to-target mapping</td>
<td>rational match</td>
<td>easily understood</td>
<td>repetitive</td>
<td>explanatory-predictive</td>
</tr>
<tr>
<td>Metaphor</td>
<td>Source-to-target mapping</td>
<td>attributes match or relation match</td>
<td>hard to understand</td>
<td>repetitive</td>
<td>expressive-affective and explanatory-predictive</td>
</tr>
</tbody>
</table>

From the perspective of artificial intelligence, bisociation and association are defined differently by Dubitzky et al. (2012) as follow:

“**Bisociation**: Let $\pi$ denote a concrete problem, situation or event and let $X \subset U$ denote the concepts associated with $\pi$. Further, let $K_i^R$ and $K_j^R$ denote two habitually incompatible agent-specific knowledge bases ($i \neq j$). Bisociation occurs when elements of $X$ are active or perceived simultaneously in both $K_i^R$ and $K_j^R$ at a given point in time $t$.

**Association**: Let $\pi$ denote a concrete problem, situation or event and let $X \subset U$ denote the concepts associated with $\pi$. Further, let $K_i^R$ denote an agent-specific knowledge base. Association occurs when elements of $X$ are active or perceived in $K_i^R$ at time $t$ only.”

Where the *habitually incompatible knowledge base* is defined as:

“Two agent-specific knowledge bases $K_i^R$ and $K_j^R$ ($i \neq j$) are said to be habitually incompatible if, at a given point in time $t$, there is no concept $c$: $c \in K_i^R \cap c \in K_j^R$ that is active or perceived simultaneously in $K_i^R$ and $K_j^R$. ”

31
As can be seen from the definitions, association functions are only in one knowledge base or not habitually incompatible knowledge bases, while bisociation has more strict constraints.

The characteristics of bisociation has correlation with artificial intelligence problem solving: a matrix corresponds to a knowledge base which can be established by a certain amount of data; the code of rules refers to a set of constraints that define the problem and even a solution; the strategy is then the algorithms which are implemented for searching for the bisociations (Pereira, 2007). In terms of constructing a matrix, an information network is a common data structure for bisociation, namely bisociative information networks (Kötter and Berthold, 2012a). It is flexible to integrate relations from semantically meaningful information as well as loosely paired information fragments with an arbitrary number of elements by applying a weighted k-partite graph structure, as shown in Figure 2.2. Vertices in the graph represent arbitrary units of information, e.g., a gene, specific molecule, index term, or abstract concepts. Vertices of the same type are grouped into vertex partitions such as documents and genes. Connections between vertices are called edges. An edge only exists between vertices in diverse partitions. Bisociative information networks model the main characteristics of integrated information repositories without storing all the details (Kötter and Berthold, 2012a).

![Figure 2.2 Example of a 5-partite bisociative information network](image)

The study of bisociation has been expanded from cognitive creativity to computational creativity in which a strong correlation between bisociation and artificial intelligence is
discussed. However, bisociative information network has been mainly used as a data structure for representing and retrieving information. The author is highly motivated to extend the study of bisociative information network for bisociative knowledge discovery by integrating data mining and exploration seamlessly, in which users’ involvement is added so that the discovery can be taken in a recurrent way.

2.1.2 The systems model and Boden’s taxonomies

In a study which took several years to interview and analyze 91 people who are widely deemed creative, Csikszentmihalyi (1996) proposes a systems model of creativity which describes how creativity works and how culture is transformed by the curiosity and dedication of creative individuals. In that model, three elements are taken into account: the domain, the person, and the field. The domain is comprised of a set of symbolic rules and procedures. For example, mathematics is a domain, even its branches such as algebra and statistics can be seen as domains. In a broader view, domains are nested in culture, or the symbolic knowledge shared by a particular society or humanity as a whole (Csikszentmihalyi, 1996). The creative person is defined by Csikszentmihalyi as the individuals who have changed our culture in some important respect from a historical perspective, such as Edison, Einstein and Mozart. The field refers to all the individuals and institutions who act as the gatekeepers to the domain, the peers who are responsible for judging the person and the idea. It is the field that recognizes and preserves new works of art, products or theories.

From the qualitative analysis of noble individuals who create or drastically change a domain including art, science, politics, and economy, Csikszentmihalyi concludes creativity with a strong definition: creativity is any act, idea, or product that changes an existing domain, or that transform an existing domain into a new one (Csikszentmihalyi, 1996). Followed by the definition, Csikszentmihalyi explores the creative process with five steps: preparation, incubation, insight, evaluation and elaboration. Preparation refers to the process of becoming a master of a domain which is full of information and knowledge. This process depends on many external factors (e.g. education, family, socioeconomic environment, political issues within a field) as well as internal factors
(e.g. talent, persistence, curiosity). Incubation is described by Csikszentmihalyi as the process of thinking a problem "below the threshold of consciousness", when the creative person feels their mind has been blocked. The incubation process tends to combine, more or less randomly, seemingly irrelevant associations between ideas to find the solution to a problem in unpredictable or consciously unprepared situations. This process corresponds to Koestler’s bisociative process (Koestler, 1964), as Csikszentmihalyi points out that creativity generally involves crossing the boundaries of domains. The insight appears only when the person is prepared to identify it, which means the ripeness of the incubation. This is confirmed by the interviewed individuals, according to Csikszentmihalyi, that the insight happens with a significant amount of confidence, knowledge and luck. Evaluation and elaboration are steps for embodying the captured insight, which are more dependent on the whole system rather than the individual as the creativity evaluation process interacts more with the domain and the field. To examine whether the insight is valuable and worth pursuing, a thorough understanding of its paradigm is necessary. This requires the domain for developing the idea, conducting the research, and testing related hypotheses. Eventually, it is the field that judges its creativity. For example, the acceptation of an academic paper by a well-known journal can be regarded as the elaboration of creativity.

Csikszentmihalyi also raises the question of distinguishing creativity from two other concepts: personal creativity and talent. He argues that children can be talented but never really creative as creativity demands the change of domain as well as being mastered the old ways in that domain. For instance, Mozart demonstrated talent in playing a piano but not creative enough to produce a masterpiece in his childhood. These three concepts (true creativity, personal creativity and talent) provides interesting challenges to computational modeling, such as the measurement of computational creativity, which draws our attention to Boden’s taxonomies about creativity (2004): h-creativity and p-creativity.

To clarify whether it is novel for a single person or for the whole of human history, Boden defines psychological creativity (p-creativity) as the new and useful idea or discovery is deemed creative by its producer, while historical creativity (h-creativity)
refers to a creative idea from the view of human history (Boden, 2004). This is in line with other research by Csikszentmihalyi (1996) and Lubart (1999) that true creativity (as opposed to mere novelty) cannot exist without external evaluation. However, as argued by Pereira (2007), one can never determine h-creativity in the absolute verdict as an idea may be deemed as h-creative for a while but may not for a long period. Although this argument testifies the complexity of this clarification, p-creativity is the main focus in Boden’s analysis as h-creativity can be considered as a special case of p-creativity (Simonton, 2017).

To identify the process for producing novel ideas or discovery, Boden presents three types of creativity (2004): combinational creativity, exploratory creativity and transformational creativity. Combinational creativity results from an unusual combination of, or association between, familiar ideas. Exploratory and transformational creativity are concerned with how a subject deals with a conceptual space. According to Boden, a conceptual space is an accepted style of thinking in a particular domain, which is similar to the definition of Koestler’s matrix as well as the definition of the domain in Csikszentmihalyi’s systems model. Exploratory creativity focuses on the exploration of the conceptual space without jumping beyond its boundaries. It is capable of achieving p-creative or even h-creative outcomes, but no changes are made to the well-defined conceptual space. Transformational creativity involves a transformation process in which one or more dimensions define the conceptual space concerned. It demands changes in the conceptual space, such as structural mapping, formulated catalyzation.

In Boden’s illustration of exploratory creativity and transformational creativity, there is a clear opposition between them in terms of conceptual space. However, some argue that transformational creativity is also exploratory at a meta-level (Wiggins, 2001; Colton, 2001; Ram et al., 1995). In particular, transformational creativity starts from a conceptual space, with a transformation mechanism (a set of mapping rules), it ends with meta-level reasoning in which creativity could be identified from a new concept as a result of transforming an existing concept. For example, given the mapping rule “profession : a famous professional”, the transformation can be achieved from
“scientist : Einstein” to “musician : Mozart”. By considering such a meta-level rule mapping, the transform process could necessarily be exploratory. This argument has been formalized in Wiggin’s framework of creative systems (Wiggins, 2006) which is reviewed in Chapter 3.

Csikszentmihalyi’s systems model (the domain, the person and the judge) provides the theoretical intuition of forming a data-driven cycle for design creativity in Chapter 3 where three elements are taken into account: data, algorithm, and expert. Data provides information or meta-knowledge with algorithms, which corresponds to the domain for nurturing creative individuals; algorithm is analytical to the person who is responsible for the generation and discovery; expert acts as the field who evaluates the raw creativity, and catalyzes the raw creativity to mature creativity. Boden’s three types of creativity motivate the implementation of computational creativity in the proposed cycle where creativity can be modelled in an exploratory way and then interpreted on a combinational basis, as illustrated in Chapter 3.

2.1.3 Creative process, person and product

Creativity exists along with its embodiment, when researchers are trying to define it. Formal theoretical research on creativity, principally originating from Guilford’s (1959) empirical study of creativity, mainly measure creativity in three ways: creative process, creative person and creative products (Wang, 2013). The creative process is regarded as an individual’s internal cognitive process, which could be either sub-conscious or conscious. Boden (2004) describes the creative process as the exploration and transformation of conceptual spaces. As extended by Gabora (2002), knowledge is bundled and connected to each other by associations in a conceptual space. Similarly, Koestler (1964) describes the creative process as a bisociative process where an individual obtains bisociation by connecting knowledge in two perpendicular matrices. In line with Boden’s three types of creative processes, Santanen et al. (2002) elaborate on explorational and transformational creativity processes from their ignition (by some stimulus) to the termination. They also claim that the more mutually remote the bundles of knowledge forming new combinations, the more creative the resultant process; the
further the mutual distance, the more unrelated the combination and therefore the greater the novelty, which is also demonstrated in Han et al.’s case study (Han et al, 2018b).

**Figure 2.3 Triangular creativity**

It is the creative person who conducts some internal cognitive process which results in creativity. The research interest of creativity from the perspective of the creative person was galvanized due to Guilford’s (1950) presidential address to the American Psychological Association, in which Guilford defines the creative personality as a matter of those patterns of traits which are the characteristics of creative persons. Although the traits of creative people were not revealed in that address, the ongoing research by Guilford (1959) attempts to identify the unique abilities of the creative person:

- The fluency of thinking: the ability to produce a large number of ideas for a problem
- The flexibility of thinking: the ability to produce varied solutions
- Originality: the ability to generate uncommon and acceptable solutions
- Sensitivity to problems: the ability to find problems
- Redefinition: the ability to think about problems from different perspectives
- Elaboration: the ability to think of details of problems and solutions.

Based on these findings, Guilford (1964) concludes that creative production is a general ability that humans have and it depends on many different intelligent factors represented
by a triple operation/product/content (as shown in Figure 2.4), which is referred to as the operation of divergent production in his Structure of Intellect (SOI).

![Figure 2.4 The structure of intellect (Guilford, 1967; Pereira, 2007)](image)

Following on from Guilford’s research, Gough (1979) identifies the traits and patterns dominant in creative persons and describes them in an Adjective Check List with 300 descriptor words. This list was then used in devising a test for identifying creative persons: The Creative Personality Scale, in which creative individuals tend to score more than less creative ones. Similarly, Csikszentmihalyi (1996) conducted a longitudinal investigation, including interviews, of socially acknowledged creative individuals and found three key elements of creativity: domain, person, and field.

A creative product is described by Jackson and Mersick (1965) with distinguishing signs in terms of aesthetic responses from an observer: surprise, satisfaction, stimulation and savoring. It is then defined in the context of creativity as the result of the ideas produced by some creative process and undergone by a creative person (Amabile, 1983). Generally, a creative product is viewed as a tangible product, such as a piece of art, a music composition or an architectural structure. Since a creative product is tangible, the appreciation of its creativity raises many questions (Gilchrist, 1972; Jackson and Mersick, 1965): how many of the requirements does a creative product satisfy (if we
can answer it logically)? To what degree does the creative product satisfy the observer? To answer these questions, researchers propose concepts such as “novelty” and “appropriateness” to evaluate creative products (Gilchrist, 1972; Amabile, 1983). Boden (1994) extends the notion of novelty with two categories: psychological novelty (p-novel) and historical novelty (h-novel), which corresponds to her classification of creativity as introduced in section 2.1.2. Appropriateness differentiates between novelty and creativity as it reflects the characteristics of the desired solution when structuring a problem (Simon, 1973).

As an extension of “3P”, press (or environment) is recognized as the fourth “P” by researchers (Rhodes, 1961; Jordanous, 2016). Press refers to the environment in which the creativity is situated. It is the press that receives the creative work and gives the feedback to the person/producer thus influence the person/producer. Rhodes (1961) concentrated on the creative person’s behaviors during the creative process, rather than how the creative product is judged by the external world after being created. Of the Four Ps, press is often neglected when one takes an individualistic view of creativity (Jordanous, 2016). For instance, Boden’s (2004) creativity mainly focuses on different cognitive processes rather than a detailed examination of social or environmental influences.

2.1.4 Creativity in design

There is no single and universally accepted definition of design. Based on the review of views of design by Atwood et al. (2002), definitions of design commonly focus on designers engaging in some process to produce a solution for people, physical items or more abstract systems to address a need or a problem. In his review, design involves: process of inventing; creating/making; democratic and participatory process; structuring argumentation; initiating change; courses of action. The design process is described by researchers with three essential phases (Alexander, 1964; Johnes, 1970; Warr, 2007): analyzing a problem; synthesizing a solution; and evaluating the outcome. Furthermore, the design process is highly iterative in which requirements and solutions might change over time.
When comparing design with creativity, the design product is the result of the design process while the creative product results in the implementation of creative ideas from the creative process. The creative product needs novelty and appropriateness, while the design product requires the creation of new solutions and needs to meet design criteria (Guindon, 1990; Warr, 2007). By threading design and creativity together, Warr (2007) defines creativity in design as the generation of ideas, in which a combination of two or more existing bundles of knowledge is facilitated to produce a new knowledge structure. Novelty and appropriateness are considered as the metrics for evaluating creativity in design. Warr (2007) also claims that creative ideas may then be implemented or embodied in a creative product.

![Diagram of the creative process of design](image)

**Figure 2.5 The creative process of design (Warr, 2007)**

As reviewed by Warr (2007), there is a parallel between the creative process and the design process. Specifically, the creative process involves problem framing, idea generation, and idea evaluation (Amabile, 1983), as shown in Figure 2.5; while the design process has three phases: analyzing a problem, synthesizing a solution, and evaluating the outcome (Alexander, 1964). The phases are considered descriptive rather
than prescriptive, which underlines the iterative nature of creativity and design (Warr, 2007). An evidence of the relation between creativity and design is Shneiderman’s (2000) categorization of creative process models which can be mapped to Fallman’s (2003) illustration of design: inspirationalists, structuralists, and situationalists. Inspirationalists emphasize on the way in which an individual generates ideas like the “eureka” moment, which maps to the romantic account of creatives and inventors. Structuralists prefer systematic approaches for exploring and transforming conceptual spaces which aligns to the conservative account of design. Situationalists focus on social perspective, including interaction and collaboration with other individuals and the surrounding environment, which can be mapped to the pragmatic fact of design.

Creativity in design is a multi-faceted phenomenon, and cannot be measured by a single metric. Warr (2007) measures creativity by the quantity, divergence, and quality of ideas, which means the core facets of creativity are the ability to produce large numbers of creative ideas, produce many different categories of creative ideas, and produce high-quality creative ideas. In line with the triangular creativity, Oman et al. (2013) propose the evaluation methods by assessing the creativity of process, personality and product, which refers to the assessment of idea generation methods (the creative process) and the assessment of produced ideas (the creative product). The evaluation of creativity demands the involvement of expertise. Amabile (1983) developed the Consensual Assessment Technique (CAT) for creativity evaluation by involving a consensual judgement of creativity from experts. The CAT technique is considered as the “gold standard” in creativity research and is testified in various research and case studies (Kaufman et al., 2009). It is also applied in the research of this thesis, with details described in Chapter 4 and 5.

2.2 Computational Creativity

2.2.1 Defining computational creativity

In order to distinguish computational creativity from other creativity (e.g. human creativity), a prevalent definition of computational creativity is that it refers to the study
and support of computational systems which exhibit behaviours that would be deemed to be creative by unbiased observers (Wiggins, 2006; Colton, 2008; Colton and Wiggins, 2012). This definition is intuitively simple and tends to give a general measurement of computational creativity. However, it reveals little about what creativity really is, which nullifies the aim of computational creativity research, according to Widmer et al. (2009). From a complementary perspective for defining computational creativity, Peinado and Gervas (2006) claim that computational creativity should also involve how to create something new and useful at the same time. It borrows the characteristics of creativity from psychological research into the computational field: novelty and value. Alongside the definition of computational creativity, researchers also attempt to account for creativity from a perspective of artificial intelligence (AI). Boden’s (2004) descriptive hierarchy of creativity leaves a legacy for the community of creativity in AI, and continues to have philosophical impact in computational creativity.

As a popular and promising field in creativity research, computational creativity aims to model or simulate creativity, or to enhance human creativity using computational methods. Not only has computational creativity been demonstrated to be capable of automatically producing art and poetry, but also it is able to discover creative knowledge and tackle technical problems with creative problem solving (CPS) processes (as asserted by Besold et al., 2015). The definition of computational creativity depends on the different motivations and goals of computational creativity research. According to Boden (2009), computer models aim mainly for psychological creativity (P-creativity), which means there is no need for computers to match all previous achievements of human beings throughout history, even though the ultimate goal of artificial intelligence is historical creativity (H-creativity).

To formally develop computational creativity theory (CCT), Colton et al. (2011) proposed two descriptive models: FACE and IDEA. The FACE model (Frame, Aesthetic, Concept, Expression of concept) describes creative acts performed by programs in terms of tuples of generative acts. The IDEA (Interactive Development Execution Appreciation cycle) shows how creative acts can have an impact. In FACE, each letter of the name represents measures on context, aesthetics, concepts of interest
and how they are expressed, respectively. And a creative act is defined as a non-empty tuple of generative acts in which the above four letters are applied. The IDEA model assesses computational creativity by measuring the effects of one creative act on an ideal audience, such as changes in well-being or the cognitive effort for appreciation. In the comparative studies of applying these two models, Colton et al. (2011) argue that the entire creative acts should be evaluated rather than focusing on the output of systems only, and instead of assessing the value of artefacts produced with respect to given aesthetic measures, it is more important to assess the impact of creative acts.

The assessment of progress in building creative systems is further developed by Colton et al. (2014), by introducing a diagrammatic formalism which depicts creative acts in timelines and allows comparison to audience evaluation of process and product. It involves several aspects: quality of artefacts; quantity, level and variety of creative acts; and audience perception of software behaviour. Though the audience evaluation model is far from complete, a case study was carried out, which shown the mapping and justification in the building of eight versions of evolutionary art software.

2.2.2 Computational creativity methods

In order to simulate creative processes and capture creativity, many models and systematic methods have been proposed in the field of computational creativity. Martin and Majidjan (2013) developed the fuzzy formal concept analysis method to find embedded structure in data and extract novel concepts. Garcia et al. (2006) proposed a computational framework based on the Engagement and Reflection model of creative process which abstracted the way in which the human brain tackles creative compositions in the field of storytelling, and demonstrated this with three instantiation examples related to storytelling, image interpretation and graph generation.

Analogy and metaphor are important approaches for nurturing and enhancing creativity. In their review on computational models of analogy, Gentner and Forbus (2011) presented models aimed at capturing the range of analogical phenomena at cognitive level, such as analogical mapping, retrieval, and generalisation, while others focused on modeling interactions between analogy and other processes, and modeling analogy as a
part of larger cognitive systems. Schwering et al. (2009) proposed the Heuristic-Driven Theory Projection (HDTP) model which computed an interpretation via a mapping based on common facts describing the visual appearance. It then transferred and applied conceptual properties to the metaphorical target.

Having observed a large number of examples of human creativity, Boden (2004) distinguishes three processes of creativity for modeling in artificial intelligence: combinatorial creativity, exploratory creativity, and transformational creativity. In exploratory creativity, Boden views the exploration of conceptual spaces as a territory map exploration, in which all possibilities could be encompassed such as serendipity and creativity. Wiggins (2006) summarised Boden’s descriptive hierarchy of creativity, and proposed a framework for characterizing exploratory creativity. Toivonen and Gross (2015) define exploratory creativity as looking for patterns, rules, or models of a fixed type in given data from the view of data mining. Based on Boden’s exploratory creativity, Liapis et al. (2013) developed a system called DeLeNoX, which autonomously creates artifacts in constrained spaces.

Recently bisociation has sparked researchers’ interest as a computational creativity model (Dubitzky et al., 2012). In the bisociation model, technical problems are solved by bridging knowledge in two otherwise not – or only very sparsely – connected domains whereas knowledge in a given domain is associated (Koestler, 1964). Transferring bisociation to a data analysis scenario places the discovery question on patterns across domains whereas the research question of pattern discovery in individual domains has already been tackled (Berthold, 2012). Segond and Borgelt (2012) suggest a new measure known as “bisociation index” for the relationship strength, which is calculated by selecting the favored edges whose similarity of the terms weights is no less than the magnitude of these weights. This index is applied to determine whether a link (or edge) between two nodes should be generated when constructing a BisoNet. Of interest Dubitzky et al. compare bisociation with Boden’s definition of combinational creativity and regard them as aligned with each other, and they proposed a framework for bisociation from the view of computational creativity based on their observations (Dubitzky et al., 2012).
2.3 Design creativity tools

Kaufman and Sternberg (2010) summarised ten categories of traditional creativity theories, such as psychometric creativity, cognitive creativity and problem-solving creativity. However, with the advance of computing technologies, researchers into artificial intelligence have started to challenge the question of how computers can be creative. Regarding this question, there have been many creativity tools developed based on specific theories and algorithms, arising from both traditional and computational creativity research. The tools are divided into three categories for further evaluation here. In each class, an example tool is highlighted to illustrate techniques and for comparing corresponding methodologies.

2.3.1 Traditional ideation creativity tools

A creativity tool needs to effectively influence the thinker during idea generation. There are many traditional creativity tools, such as Brainstorming, Checklists, Lateral Thinking, Mind Mapping, Morphological Analysis, TRIZ, and SCAMPER (Childs, 2018; Hernandez et al., 2013). Linsey et al. (2011) systematically examined four common and well-documented concept generation techniques, and concluded with some insights guiding those techniques’ implementation. Daly et al. (2016) focused on novice designers’ use of ideation techniques, by investigating the qualities of generated concepts with one of three different ideation techniques, and pointed out specific strengths in them.

Here SCAMPER is highlighted as a well-known example. SCAMPER was developed by Bob Eberle (1996), and the acronym stands for “Substitute – Combine – Adapt – Magnify/ Minify/ Modify – Put to other uses – Eliminate – Reverse/ Rearrange”. Each letter helps remind the users of related words or phrases and provoke related ideas. SCAMPER can be particularly useful when users get stuck or feel uninspired and are required to have multiple ideas or to provoke thinking from another perspective (Childs, 2018).
<table>
<thead>
<tr>
<th>Method</th>
<th>Key feature</th>
<th>shortcomings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brainstorming</td>
<td>Explore new ideas in an open environment via group</td>
<td>No control on idea judgement; highly restricted by individual’s knowledge</td>
</tr>
<tr>
<td></td>
<td>discussions.</td>
<td>and creativity;</td>
</tr>
<tr>
<td>SCAMPER</td>
<td>A list of questions is used for developing or</td>
<td>Difficult to apply all aspects of SCAMPER; difficult to produce new ideas</td>
</tr>
<tr>
<td></td>
<td>modifying existing ideas.</td>
<td>from scratch;</td>
</tr>
<tr>
<td>TRIZ</td>
<td>Solve problems based on provided 39 generic parameters</td>
<td>Complicated to apply; difficult and time-consuming to master it; parameters</td>
</tr>
<tr>
<td></td>
<td>and 40 inventive principles.</td>
<td>and principles are antiquated;</td>
</tr>
<tr>
<td>Six Thinking Hats</td>
<td>Six thinking styles helping users to be productive,</td>
<td>Restricted by individual’s knowledge, experience and traits; can be</td>
</tr>
<tr>
<td></td>
<td>focused and involved.</td>
<td>time-consuming;</td>
</tr>
<tr>
<td>Morphological Analysis</td>
<td>Break down problem into sub-functions in a form of</td>
<td>May need Additional knowledge base; evaluation and selection of solutions</td>
</tr>
<tr>
<td></td>
<td>matrix, then combine one means from each sub-function.</td>
<td>are problematic and time-consuming;</td>
</tr>
<tr>
<td>Design-by-Analogy</td>
<td>Generate ideas based on related scenarios and</td>
<td>Requires analogous items; less feasible for novice designers due to</td>
</tr>
<tr>
<td></td>
<td>connected experiences (analogies).</td>
<td>limited knowledge;</td>
</tr>
<tr>
<td>WordTree</td>
<td>Structured approach for re-representing design</td>
<td>Difficult to use due to the limit of users’ knowledge and skill of</td>
</tr>
<tr>
<td></td>
<td>problems and identifying potential analogies in</td>
<td>domain transfer;</td>
</tr>
<tr>
<td></td>
<td>ideation.</td>
<td></td>
</tr>
<tr>
<td>Bio-inspired Design</td>
<td>Design-by-analogy based method using biological</td>
<td>Difficult to search and evaluate biological analogies, map knowledge;</td>
</tr>
<tr>
<td></td>
<td>system to generate ideas.</td>
<td>difficult to communicate between design and biology domain;</td>
</tr>
<tr>
<td>77 Design Heuristics</td>
<td>A set of patterns providing “cognitive shortcuts”</td>
<td>Overwhelming to select appropriate heuristics; tend to be</td>
</tr>
<tr>
<td></td>
<td>to produce ideas and innovative solutions for</td>
<td>antiquated and need to be kept updated;</td>
</tr>
<tr>
<td></td>
<td>designers.</td>
<td></td>
</tr>
<tr>
<td>Concept Synthesis</td>
<td>Produce new ideas by interpreting novel noun-noun</td>
<td>Depend on users’ capability of interpretation, associative thinking and</td>
</tr>
<tr>
<td></td>
<td>phrases via property mapping/ concept blending/</td>
<td>level of expertise.</td>
</tr>
<tr>
<td></td>
<td>concept integration.</td>
<td></td>
</tr>
</tbody>
</table>
Traditional creativity tools are either intuitive-based or logical-based methods for supporting creativity, according to Shah et al. (2003). Intuitive methods focus on mechanisms for removing mental blocks, such as brainstorming and morphological analysis, while logical methods rely heavily on decomposition and analysis of the problem, such as TRIZ. Han (2018) categorised traditional creativity tools as non-computational based methods, among which ten common methods were reviewed. Their key features and shortcomings are summarised in Table 2.2. Two types of shortcomings can be concluded from that table: 1) those methods that are simple to understand and implement are limited by individual’s knowledge, personality and experience, such as brainstorming; 2) other methods are difficult to master and time-consuming to apply, due to their high complexity and overwhelming availability of selection.

2.3.2 Program-based creativity tools

It is difficult for novice designers to master those principle-based creativity methods, such as TRIZ, as discussed in last section. Researchers have attempted to implement complicated methods into computational programmes where expertise is less demanded and the overwhelming of selection is mitigated. Vattam et al. (2011) developed DANE (also known as Design-by-Analogy to Nature Engine) as a knowledge-based computer-aided design system for supporting bio-inspired design. DANE is based on a database with a SBF (structure-behaviour-function) model, by which data are hierarchically linked for representing biological and engineering information. Its outcome, in various forms such as text and image, can be used as biological stimuli for supporting idea generation. Garvey et al. (2018) developed software for morphological analysis and indicated that it can be applied to support creativity and technology forecasting, scenario planning and system uncertainty analysis.

Taking Combinator as an example, this is a simple-to-learn and easy-to-use computer program tool based on combinational creativity theory (Han et al., 2016). The Combinator aims to help novice designers as well as experienced designers generate valuable ideas through presenting combined associated images, thereby tackling
challenges in fast-moving product design markets. In the software, users are free to provide a keyword, then choose how many nouns and in which way they would like to combine images. Combined images can be automatically generated to inspire designers according to their settings.

The program-based creativity tools add lower barriers to entry to users by mitigating the complexity of applying existing methods while being efficient to retrieve information from knowledge base. However, there are several shortcomings in these tools: 1) idea evaluation and selection methods are missing, even though implemented methods manage to produce new ideas, such as concept synthesis and morphological analysis; 2) methods using information retrieval mainly focus on function-based information, such as SBF-based models, which are feasible for engineering design, but their capability is limited by other areas, such as industrial design and product design; 3) though the program-based tools are efficient to support ideation, the methods embedded are from cognitive creativity research, which means programs are rule-based and lack of the intelligence of machine to discover creative patterns.

2.3.3 Data-driven creativity tools

In order to simulate the creativity process and capture creativity, computational models and systematic methodologies have been proposed in the field of computational creativity. Wiggins and Bhattacharya (2014) proposed a computational framework based on Baars’ Global Theory enhanced with mechanisms based on information theory from the view of neuroscience. Wang et al. (2015) proposed a context-awareness systematic approach for idea cultivation, construction, integration and evaluation in a dynamic discovery process. Sosa classified and revealed computational creativity by illustrating multi-dimensional approaches to the study of creativity with sample simulation scenarios (Sosa and Gero, 2016).

Data-driven creativity is an emerging branch of computational creativity which places data in the center of creativity tool design. Two separate lines of research were compared and discussed by Shneiderman (2002): information visualization, and data mining. The former emphasises the importance of giving users an overview and insight
to data distribution, while the latter focuses on interesting patterns based on statistical algorithms and machine learning. His study shown that a combined approach is better for novelty discovery, which supports the study in Chapter 4. Varshney et al. (2013) proposed a big data approach for a computational creativity system with a case study on the generation of culinary recipes and menus (Pinel et al., 2015). Lin et al. developed a Personalized Creativity Learning System (PCLS) to provide personalized learning paths for optimizing the performance of creativity with data mining techniques (Lin et al., 2013). Ojha et al. developed a creativity tool called I-get to generate perceptual pictorial metaphors and novel ideas with its FISH (Fast Image Search in Huge database) data mining algorithm (Ojha et al., 2015).

Associative browsing is a type of exploratory information-seeking, which encompasses a common and intuitive set of exploratory strategies in which users step iteratively from familiar to novel pieces of information. Taking the associative browser Refinery as an example, Refinery users are allowed to specify the ‘frontier’ of their knowledge from literature by interacting with results (Kairam et al., 2015). Specifically, by voting on results to express their degree-of-interest, users are able to identify desired documents from literature datasets with the support of bottom-up exploration of large and heterogeneous network data. Benefitting from its random-walk algorithm, the system computes the degree-of-interest scores for associated content, and visualizes the heterogeneous query nodes, facilitating serendipitous discovery and stimulating continued creativity.

Data-driven creativity tools are able to find more accurate information from the knowledge base, and discover patterns from large datasets using data mining and machine learning. Research from computational creativity have also advanced data-driven approaches, transforming creativity theories from cognition to systems. Patterns are useful for solving technical and functional problems, but less capable in the context of product design and novelty. Besides, the data employed by most of the tools is antiquated, such as patents and past inventions (Han, 2018), while the data structure cannot support the update of new data or external data. Two data types are commonly
used in data-driven approaches: text and imagery, but most of existing methods just focus on one of both due to their heterogeneous characteristics.

To conclude, traditional tools require expertise in order to use them effectively (such as TRIZ) and a physical environment to proceed (such as gathering people in a meeting room), even though they are simple and easy to conduct. With the benefit of computing, program-based tools are able to deal with complex creativity problems without high levels of subject-specific expertise, and the program interface can help visualize results and stimulate creativity. Compared with program-based tools, data-driven tools are able to dig into creativity more deeply with the support from big data and machine learning algorithms. However, most data-driven creativity tools simply focus on data mining at the back-end and overlook the modeling of creativity. With a model which is capable of mimicking a creative process and stimulating users’ creativity, users are enabled to explore creative knowledge and obtain embodied creativity. A comparison between traditional, program and data-driven creativity tools is given in Table 2.3.
2.4 Conclusions

Although most creativity theories originate from psychology, philosophy and cognitive science, they provide fundamental understanding for modeling creativity with computational methods. Bisociation can be applied to creative knowledge discovery, which is demonstrated in Chapter 4. Csikszentmihalyi’s systems model shares similarities with the integrated data-driven creative system proposed in chapter 3. Boden’s combinational creativity provides intuition for machine learning algorithms to understand and interpret design creativity, as illustrated in Chapter 6.

Creativity is embodied by the creative process, product and person. A creative system can be built by modeling a creative process and stimulating users’ creativity via human-computer interaction, which is presented in the work of Chapter 4. A creative product represents creativity in a tangible manner, thus interpreting it means the acquisition of meta-knowledge about creativity, as implemented in Chapter 6. In a creative system, the creative process is responsible for modeling and generating creativity, while it is a person that applies its expertise to mature the generated creativity, and eventually transforms it into the creative product.

In spite of the increasing research on computational creativity, the large majority is exploratory. In order to have a powerful computational creative system, the capability of modeling and interpreting creativity computationally should be emphasized, which means the value of data should be sophisticatedly mined at a high-level and the advanced machine learning algorithms of modeling and understanding creativity should be developed. On the other hand, existing research on creativity, especially in the design field, has not systematically considered a data-driven and creativity theories based approach for creativity, including the modeling of creativity with various data formats, the interpretation of creativity, and the reuse of creative knowledge. Hence the following chapters aim to address these issues along with the proposed research questions in Chapter 1.
Chapter 3. Research Methodology

This chapter presents the research methodology by investigating how a data-driven cycle can be possibly formed for design creativity. It first examines existing creative systems and the reuse of design knowledge, which opens up research opportunities for creative system. In the proposed data-driven cycle, key steps are explained and justified as well as their relations. This chapter also describes how this cycle is sustainable to support design creativity generation and creative knowledge reuse. Implementation and limitations of the proposed cycle are discussed, in addition to a systemic analysis of this cycle from perspectives of data-driven, machine learning, and knowledge recycle.

3.1 A creative system

Generally, the study of a creative system is considered alongside computational creativity. It can be defined as “a collection of processes, natural or automatic, which are capable of achieving or simulating behavior which in humans would be deemed creative”, according to Wiggins (2006), and this definition is widely accepted in the computational creativity community. This is in line with the definition of computational creativity by Colton and Wiggins (2012): “The philosophy, science and engineering of computational systems which, by taking on particular responsibilities, exhibit behaviors that unbiased observers would deem to be creative.” Inspired by Boden’s (2004) descriptive hierarchy of computational creativity, Wiggins (2006) proposes a framework for characterizing creative systems and indicates that Boden’s transformational creativity is actually exploratory creativity at the meta-level. In his framework, septuple symbols \(< \mathcal{U}, \mathcal{L}, [\mathcal{.}], \ll \ldots \gg, \mathcal{R}, \mathcal{J}, \mathcal{E} >\) are defined for describing creative systems. The function of each is briefly explained in Table 3.1, more details are given in Wiggins (2006). Among them, \(\mathcal{R}, \mathcal{J}, \mathcal{E}\) are three essential components in the framework describing systems’ functioning. With \(\mathcal{R}\) which is generated by \([\mathcal{.}]\) and a suitable comparator (a real number between 0 and 1, e.g., 0.5), Boden’s conceptual space can be formalized as follows (Dean et al., 2018):
\[ \{ c \mid c \in \mathcal{U} \cap \mathcal{L}(c) \geq 0.5 \} \]  

(3.1)

Similar to the standard AI search framework, \( T \) is to describe the behavior of a creative agent as it traverses the conceptual space from known artifacts to unknown ones, and back again possibly. \( \mathcal{E} \) expresses the notion of value proposed by Boden (1998), by evaluating which value is attributed to a created artifact. Given \( \mathcal{R}, T, \text{and } \mathcal{E} \), a new concept \( c_{\text{out}} \) can be obtained through the creative system by exploratory creativity (Wiggins, 2006):

\[ c_{\text{out}} = \ll \mathcal{R}, T, \mathcal{E} \gg (c_{\text{in}}) \]  

(3.2)

**Table 3.1 Symbols for describing Wiggins’ (2006) creative systems**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mathcal{U} )</td>
<td>a universe of possible concepts or artifacts</td>
</tr>
<tr>
<td>( \mathcal{L} )</td>
<td>a language expressing concepts (artifacts) and rules</td>
</tr>
<tr>
<td>( \ll \cdot \gg )</td>
<td>a function generator mapping a subset of ( \mathcal{L} ) to a function</td>
</tr>
<tr>
<td>( \ll \cdot, \cdot, \cdot \gg )</td>
<td>a function generator mapping three subsets of ( \mathcal{L} ) to a function</td>
</tr>
<tr>
<td>( \mathcal{R} )</td>
<td>a subset of ( \mathcal{L} ), which defines what it is to be creative</td>
</tr>
<tr>
<td>( T )</td>
<td>a subset of ( \mathcal{L} ), which describes creative behaviors in a traversal</td>
</tr>
<tr>
<td>( \mathcal{E} )</td>
<td>a subset of ( \mathcal{L} ), which defines the evaluation of creative outputs</td>
</tr>
</tbody>
</table>

Prior to Wiggins’s framework, there are few formalisms of creative systems. Ritchie proposed a set of formal empirical criteria for computational creativity. These criteria were originally introduced in Ritchie (2001) then revised and updated in Ritchie (2007). The criteria collectively describe the output of the creative system from aspects of the typicality and value. According to Ritchie, Typicality is a rating of how typical the output is in the intended domain, while the value is a rating of how valuable the output is (Jordanous, 2012). However, many argued that there are contradictions and inconsistencies between individual criteria, such as in Pereira (2007) and in Jordanous (2013). For instance, the value would demand a compromise from typicality which is explicitly made in everyday observation of creativity, according to the criteria 5 and 6.

53
Although a set of features were named as “criteria” by Ritchie, they cannot be applied to formalize a creative system.

Despite Wiggins and Ritchie’s description of creative systems, surprisingly high proliferation of such systems was proposed, spreading a variety of areas and approaches. Pereira (2007) provided an overview of them based on their implementation, published data and the basic definition of creative systems. Based on his analysis of existing systems, taxonomies for computational creativity models were abstracted, including a systems model, evolutionary model, domain-centered model, and cognition-centered model. According to Pereira (2007), existing systems only achieved transformational creativity at an elementary level, such as HR (Colton et al., 1999) and Metacat (Marshall, 2002).

Table 3.2 Comparison of requirements for creative behaviors

<table>
<thead>
<tr>
<th>Rabinow</th>
<th>Colton</th>
<th>Cohen</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge</td>
<td>Skill</td>
<td>Knowledge</td>
</tr>
<tr>
<td>Motivation to explore</td>
<td>Imagination</td>
<td>Emergence</td>
</tr>
<tr>
<td>Evaluation</td>
<td>Appreciation</td>
<td>Awareness, motivation to act</td>
</tr>
</tbody>
</table>

Consistent with Ritchie (2001) from a product-focused standpoint, Colton (2008a) emphasizes the importance of considering the creative process rather than the output when assessing a creative system. He proposes a creative tripod framework for creative systems, in which three qualities are considered: skill, imagination, and appreciation. Colton emphasizes that a creative system should only be perceived to possess these qualities rather than positing these qualities as necessary and sufficient conditions. Specifically, to make a system appear to be creative to its users is more important than to develop a system which produces creativity of some level independently of users’ perception. Jordanous (2013) compared Colton’s three tripod qualities with the abilities outlined by Rabinow (reported by Csikszentmihalyi (1996)) as a creative thinker and Cohen’s requirements for a creative “behavior X” (Cohen, 1999). As shown in Table 3.2, parallels can be drawn between them and shows similarities to some extent.
In addition, Colton demonstrates how his framework can be applied to creative systems with two examples. One is a mathematical concept discovery program called HR (Colton et al., 1999), another is an artistic image generator The Painting Fool (Colton, 2008b). However, Colton does not discuss how the three qualities in the tripod relate to and interact with each other nor how much each quality contributes to the overall creativity of the system.

A literature survey was conducted by Jordanous (2011) to examine the progress in computational creativity research. With the retrieval of various combination of keywords such as “computational creativity” and “creative system”, there are 75 out of the 132 retrieved papers, accounting for only 57%, presenting details of creative systems while the remaining papers discuss theoretical aspects of creativity or related issues. The survey also shows the domains covered by creative systems, in which language (31%), music (25%) and art/image (23%) are the popular domains. This result is consistent with Pereira’s survey (2007) which mentioned the absence of the ability to do a cross-domain transfer of ideas in the majority of creative systems. Even worse, the majority is tailored to work with its own single domain. For instance, the HR proposed by Colton et al. (1999) makes use of the data derived from mathematical fields and is claimed to be able to do the cross-domain transfer (Colton et al., 2000), but it is applied to other domains in an isolated manner. Recently, this was largely mitigated by its latest upgraded version HR3 in which a further variety of artefact types within a theory can be produced as well as be independent of any logical formalism (Colton et al., 2014).

Charnley et al (2014) presented the FloWr framework for implementing creative systems as scripts and manipulated visually as flowcharts innovating at process level. In FloWr, nodes can be re-used for retrieving, categorizing, sorting, combining and analyzing text, resulting the production of poems, fictional ideas, tongue twisters. Experimentation was taken to help users construct and optimize flowcharts with the aim of automatically constructing novel processes. It was believed that software which writes software should be a major focus in computational creativity research. In another interesting research study by Cook and Colton (2018), the notion of continuous creativity was proposed for describing how an automated game designer (a creative
system called ANGELINA) was rebuilt to be “always-on”. Presence is introduced to describe the impact on its environment in addition to product and process, which is in line with “4P” as introduced in Chapter 2.1.3. The concept of continuous creativity focuses on the long-term growth of a creative system, which raises an essential question of how a data-driven cycle can be possibly formed for design creativity so that a creative system can benefit from up-to-date historical data to achieve long-term growth.

Therefore, this chapter attempts to explore the opportunities for research on continuous creativity for design by investigating the following aspects:

- The gap of creative knowledge reuse in the domain of design;
- A conceptual data-driven cycle for design creativity;
- A possible approach for implementing the proposed data-driven cycle.

### 3.2 Design knowledge reuse

Knowledge management in conceptual design is centered on information gathering, and the capture and use of design knowledge, according to Lang et al. (2002). The reuse of design expertise helps accelerate future designs. Shahin et al. (1999) propose a design reuse system which is primarily based on structuring product information. Within design function deployment, their approach suggests structuring design information into a product concept, solution concept, embodiment design and detailed design for efficient reuse. However, this form of structured information incorporates heterogeneous data which cannot be applied for integral reuse. Dani and Harding (2004) suggest addressing the interdependent factors affecting knowledge reuse simultaneously. They implement a value net to the reuse process, which provides multiple viewpoints for users to identify appropriate reuse activities through interaction with a reuse agent. The activities are represented by process models in a detailed, prescriptive and structured manner.

In terms of shared understanding and knowledge representation, the development of ontologies and their application to engineering design is providing a means to represent domain knowledge (Kerr et al., 2004). Lim et al. (2010) classified the ontological
applications into three categories: design information annotation, sharing and retrieval; interoperability and interchange protocol between systems; product design configuration. For the purpose of information retrieval, Li and Ramani (2007) showed the competitiveness of ontology-based information retrieval systems over traditional keyword-based search techniques. Witherell et al. (2007) emphasize the potential value of ontologies in representing application-specific knowledge, and show the facilitation of knowledge sharing and exchanging in engineering design.

A large design repository project led by NIST (the National Institute of Standards and Technology) attempted to provide a complete, fully integrated representation of design artifacts for design knowledge reuse. According to Szykman et al. (2000), a design repository is defined as an intelligent, knowledge-based design artifact modeling system which is used to facilitate the representation, capture, sharing, and reuse of corporate design knowledge. To achieve that, geometry representation uses STEP AP203\(^1\) (an international standard for the exchange of product model data) and VRML (Virtual Reality Modeling Language) for web-based access, while a function is represented by a generic schema for structuring function related information. In addition, XML based representations are applied to facilitate interoperability and knowledge exchange among designers. Even though the design repository supports a range of design knowledge types, design rationale or methodologies are missing in its integration (Baxter, 2007).

Knowledge reuse, the idea of reusing previously created artifacts consisting of formalized pieces, has attracted a lot of research. Dusink and van Katwijk (1995) indicate in a broad survey of the research topic that knowledge reuse speeds up the development process by reducing the amount of time and effort which was taken in previously solved issues. There are a variety of proposals and analysis of design knowledge reuse methodologies and systems in the research literature, from design science to computer aided design/ computer aided manufacture (CAD/ CAM) and from knowledge management to artificial intelligence (Baxter, 2007). From the perspective of data-driven design, information is comprised of a number of data parts and their

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\(^1\) STEP AP203, also called ISO 10303, as introduced at: [https://en.wikipedia.org/wiki/ISO_10303](https://en.wikipedia.org/wiki/ISO_10303)
description while knowledge is the ability of the individual to understand information and describes the manner in which they handle, apply and use it in a given situation (Court, 1995). Hicks et al. (2002) discussed the definitions and relations between data, information and knowledge for a better understanding of the capture and reuse of information and knowledge in engineering design. In the framework proposed by them, as shown in Figure 3.1, a bi-directional inference facilitates the continuous conversion of knowledge to information and information to knowledge. As knowledge may not be structured and specific, the reuse of knowledge requires the individual to dynamically step from knowledge back to information and then generate knowledge from another perspective.

![Figure 3.1 Bi-directional information and knowledge transformation processes for decision making (Hicks et al., 2002)](image)

Zhang et al. (2012) propose a framework for design knowledge reuse from a perspective of product life-cycle. There are four layers in the framework, namely the application layer, process-task layer, knowledge representation layer and shared layer. The shared layer is ontology-based, which provides definitions of domain concepts, attributes and
relationships. The knowledge representation layer structures various types of knowledge source to meta-knowledge. A life-cycle based design process is fully covered in the process-task, which contributes to the application layer in terms of keyword retrieval, design map and tree browse.

3.3 A conceptual data-driven cycle for design creativity

Benefiting from the active community of computational creativity (Colton, et al., 2015), the research on creative systems has achieved much in different aspects, such as framework (Wiggins, 2006), computational creativity models (Colton, 2009; Colton and Wiggins, 2012), and related applications (Jordanous, 2013; Charnley et al., 20014; Cook and Colton, 2018). However, current research mainly focuses on the evaluation of computational creativity, and methodologies of generating creativity, which means these studies only focus on how to correctly transform data into creativity but neglect the reverse transformation from creativity to data. The bi-directional transform between data and creativity can form a closed creative knowledge reuse loop so that creativity is not only produced from existing mechanisms in creative systems but also benefits from produced creative knowledge with creativity interpretation mechanisms. From a long-term perspective, this bi-directional transform enables a creative system to evolve from such a data-driven cycle, thus achieve continuous creativity.

In this chapter, a such conceptual data-driven cycle for a creative system applied to the design engineering field is proposed. Within the cycle, various aspects are discussed including data, creativity generation mechanisms, creativity interpretation mechanisms and design creativity knowledge reuse. Furthermore, the relationships between different modules are explored so that their contribution to the entire cycle is clear, while the integration of these modules is explained in detail as well.

3.3.1 From data to design creativity

Data gives raw information and it is the meta-information to be processed with computational techniques. Most human and machine generated data are often highly unstructured and heterogeneous and need to be further cleaned or transformed into
structured representations within specific contexts. Generally, the purpose of processing data is to obtain knowledge and transform knowledge for different utilization, such as decision making, and retrieval. Data exists in a variety of formats, of which textual and image data are the two widely used formats within the context of design creativity. Some (Hicks et al., 2002) may argue that verbal data is also widely used, but verbal data can be converted to textual data easily with speech recognition technologies.

Textual data is easy to create, store, transfer and update in various ways, and it is full of information and knowledge. In the big-data era, a large amount of textual data is available in digital forms and stored in electronic devices. According to a study (Yu et al., 2005), approximately 80% of a company’s information is contained in textual format, including technical documents, progress service reports, legal terms and customer-side note. In design engineering, textual data are analyzed for various purposes. Chaklader and Parkinson (2017) attempt to analyze a large number of consumer reviews to quickly and economically provide information for the establishment of design specifications related to human-artifact interaction. Textual data is not just limited to internal design information, external resources are also useful for data-driven design. Cheong et al. (2017) use Wikipedia data as the corpus to automatically extract design function knowledge by means of functional basis taxonomy, WordNet, and word2vec. Song and Luo (2017) applied patent mining techniques to search for precedents of a product design in patent databases in order to learn about relevant prior arts, seek design inspiration, or for benchmark purposes.

Image data, including sketches, drawings, product sample images, and CAD designs, are widely used in design engineering. They are full of knowledge, some of them are even creative. From the perspective of engineering, image data mainly expresses product’s functionality and behavior, and manufacturing procedure. On the other hand, image data from the design perspective tends to illustrate product shape, appearance, and visual feelings. Thus much data-driven design research applies image data to assist the design process or support innovative design. Dering and Tucker (2017) propose a deep learning approach based on 3D convolutions to predict functional quantities (such as sitting, storing liquid and emitting sound) of digital design concepts, which is much
more efficient than traditional methods such as computational fluid dynamics. The rapid advance of sensor technologies contributes to the massive accumulation of population-based shape data. By analyzing these image data with mining algorithms, design knowledge of shape variability of the population can be obtained while faithful 3D shape models can be constructed for various applications, such as mass customization, part-specific failure prediction and just-in-time part maintenance (Wang and Qian, 2017). Image data is also demonstrated to be helpful for augmenting creativity (Han et al., 2016). By computationally blending two distinct concepts with generative adversarial networks, a novel approach is proposed in Chapter 6 to generate creative images for innovative design.

Both textual data and image data have been successfully utilized for design creativity. According to existing applications, these data can either from external resources or internal resources. Here the origin of data resources is distinguished by public access, which means the data available for the public is external while authority required data belongs to internal. The most significant external resource in the world for textual data and image data is the Internet. According to the Web Index\(^2\), there are more than 50 billion webpages indexed by search engines such as Google and Bing until 2019. Among such a large number of webpages, there are tremendous useful data which can be retrieved and analyzed. For example, Wikipedia is the world’s largest online encyclopedia which provides information or even knowledge about concepts, celebrities, events and so on. Wikidata\(^3\) is one of the well-known knowledge bases in which data is collected and structured from Wikipedia. In design engineering, design data can be obtained from various online websites, such as the design magazine Dezeen and the award-winning product website RedDot. For internal resources, it depends on the main activities within the internal organizations. Usually, the internal data needs extra processing compared to external data as organizational sensitive and confidential information have to be removed. After the desensitization, the procedure of internal data pre-processing is the same as external data.

\(^2\) The Web Index: [https://thewebindex.org/](https://thewebindex.org/)

\(^3\) Wikidata: [http://wikidata.org/](http://wikidata.org/)
Once data (either from internal or external) is collected and well pre-processed, a transformation mechanism from data to creativity needs to be established. To achieve that, two studies concerning two kinds of data format, i.e. semantic and imagery data, are conducted, as introduced in Chapter 5 and 6 respectively, in which two design creativity methods are proposed: bisociative knowledge discovery (BKD) and visual conceptual blending (VCB). Bisociative knowledge discovery is based on Koestler’s concept ‘bisociation’ (Koestler, 1964) in which creativity can be obtained by bridging knowledge in multiple domains. In the research conducted in Chapter 4, a network-based BKD model is proposed for semantic data analysis and visualization. As shown in Figure 3.2, the multi-domain knowledge base is established with the integration of internal and external textual data. Data in the knowledge base are structured into a network with different edges and weights, according to their co-occurrence or degree of correlation (Shi et al., 2017a).

![Figure 3.2 Bisociative knowledge discovery](image_url)

In the BKD model, two key modules are proposed to support the discovery process: exploration and search path. The exploration module starts from a given concept which can be the subject of a design project or a design problem, then it calculates the correlation between the given concept and the knowledge base network graph. Since it
has been indicated in previous research (Han et al., 2018b) that ‘far distance’ between two concepts tends to generate higher levels of creativity than close distance, the retrieval process of exploration module ends by outputting those relatively far concepts which construct a network graph. As “far” and “close” are relative for evaluating the distance between concepts, here flexibility of adjusting the correlation degree is implemented in the algorithm design in which users can select a distance they think is appropriate. On the other hand, the search path module starts from two given concepts, and calculates optimal paths between them. The optimal paths are determined by the accumulated correlation degree between connected concepts in paths. The experiments in Shi et al. (2017a) show that a relatively short path contains implicit knowledge while avoids excessive computation workload and irrelevant information. Different types of path distance can be used for calculating shorter distance which corresponds to higher correlation degree of the path, such as the six types proposed in (Shi et al., 2017b).

The involvement of human evaluation is essential for a creative system (Colton, 2008a; Wiggins, 2006). In the human-computer interaction (HCI) module, users are responsible for providing the exploration and search path module with input (e.g. keywords for retrieval) and evaluating the outcome’s creativity when observing network-based knowledge graphs. More manipulations will need to be performed within the exploration and search path modules in order to extend the retrieval scope if the user is not satisfied with the current results. This process repeats recurrently between HCI and the BKD model until a satisfying outcome is found as shown in Figure 3.2.

The VCB model proposed in Chapter 5 generates novel and creative images by learning key features from two image sets representing two distinct concepts. With the powerful synthesis capability of proposed generative adversarial networks architecture, features from two concepts can be well represented in the generated images. As shown in Figure 3.3, image data needs to be collected and processed at the beginning, and then is fed into the VCB model for training. Once the model is fully trained, it is able to generate unlimited new images without conditions. Human’s involvement focuses on selecting the images deemed creative. Particularly, a user needs to observe a generated image and evaluates its creativity according to the user’s own judgment. A new image will be
generated from the VCB model if the previous one is not satisfied with the user. This process iterates until the generated images are satisfying.

![Diagram of Visual Conceptual Blending (VCB) model](image)

**Figure 3.3 Visual conceptual blending**

With bisociative knowledge discovery and visual conceptual blending mechanisms, design creativity is expected to be obtained from textual data and image data respectively. From the above discussion of transforming data to design creativity, it can be observed that there are three pillars supporting a design creativity system: data, algorithm, and design creativity theories. Data is fundamental in a data-driven design methodology, its amount, property and characteristics determine where creativity is originated. Design creativity theories provide a theoretical foundation for creativity generation and augmentation, they lead to what creativity can be obtained. Algorithms execute the transformation process from data to design creativity, and their implementation determines the performance (level of creativity) the system can achieve.

### 3.3.2 From design creativity to data

Previous research on creative systems pay much attention to creativity generation and augmentation, but little effort has been made to interpret existing creativity for creative knowledge reuse. Interpreting existing creativity computationally is challenging due to the complexity of creativity and its various forms. The definition and discussion of computational creativity have been continuing for decades, which is not the intent of this thesis. However, according to previous research including Boden and Wiggin’s development of computational creativity, there are two conceptual spaces. One is
known and another is unknown, and the mapping from known to unknown embodies creative knowledge. Taking Boden (2004)’s three types of computational creativity as an example, exploratory creativity, combinational creativity and transformational creativity are achieved by three different mapping methods from known conceptual space to unknown conceptual space. Based on that assumption, given known creativity, interpreting the creativity is a process of interpreting the creative knowledge behind its mapping mechanism. For example, interpreting combinational creativity, as introduced in Chapter 6, is a process of identifying its combination pair (base and additive).

Figure 3.4 Interpretation of creative designs

Creativity exists in the real world in various forms, either physical or digital, even descriptive. In design engineering, it widely exists in those innovative product designs. To facilitate the transformation from design creativity to data, these innovation designs should be in digital forms. Specifically, for those physical or non-digital designs, they should be converted into digital forms with various digitalization methods. For example, provided with an innovative design of chair, photos can be taken and documents can be created for describing this chair. In addition, the Internet is full of creativity resources. As claimed by Han et al. (2019), some digital resources from international design competitions, such as the Red Dot Award and the iF Award, are creativity-oriented and thereby encourage creative design. Although the award-winning designs in these competitions might lack creativity assessment, they are arguably considered more
creative than the conventional products in the market. Furthermore, novelty and usefulness, which are commonly used for creativity assessment (Chulvi et al., 2012), are the top assessment criteria of award-winning designs in these competitions (Hasdoğan, 2012).

Consistent with section 3.3.1, only textual and image data are considered here for demonstration purposes. As shown in Figure 3.4, two separate modules are applied to process textual and image data respectively. In the natural language processing (NLP) module, named entity recognition (NER) and relation extraction (RE) are two main techniques for extracting key information. NER is responsible for recognizing those entities in pre-defined categories, while RE attempts to detect all possible pre-defined relation types based on extracted entities. In some algorithms design, the two modules may be integrated to function together and extract a pre-defined relation along with corresponding entities (Miwa and Bansal, 2016). On the other hand, with object detection techniques, the image recognition module aims to detect all elements within an image. Here the “element” may have different definitions according to the level of involved ontologies in the image set. For example, the “element” refers to a household product (object) in Chapter 6, while it may refer to a part in machinery.

The output of the NLP module and image recognition module can either be used independently for creative knowledge extraction in case that related data is provided exclusively, or fed into the reasoning unit in which NER extractions and image recognition results are analyzed together for a more accurate interpretation of creative knowledge. The relations extracted from textual data can be directly considered as creative knowledge representations; the elements detected from image data contains creative knowledge as well, but due to the complexity of image data, some elements may be noises data rather than creative knowledge representations. In order to achieve more accurate interpretation outcome, a reasoning unit is applied on top of NLP and image recognition modules to provide an integrated analysis of textual and image data.
3.3.3 The formation of a data-driven cycle for design creativity

To conclude the transformation between data and design creativity, with computational models such as BKD and VCB, textual data and image data can be processed for generating creativity; with NLP and image recognition techniques, creative design or solutions can be interpreted for creative knowledge reuse. These two processes manipulate data and creativity in two opposite ways, but they can form a cycle in a design creativity system if they can be integrated to work together. As shown in Figure 3.5, it is the data-driven cycle of a system where textual data and image data are collected and pre-processed for its establishment of a multi-domain knowledge base, these two types of data are then fed into two computational creativity models, BKD and VCB, for creativity augmentation and generation.

Figure 3.5 A data-driven cycle for design creativity
As discussed in previous sections, BKD is a semantic network-based model which attempts to construct a network database for semantic network analysis and network graph visualization. VCB is designed for blending two distinct concepts and generating graphic creativity by means of generative adversarial networks. It is argued that either the textual creativity provided by BKD or the graphic creativity generated by VCB, the obtained creativity is raw creativity which has not been finalized and integrated into other activities, such as a design process. There is a gap between raw creativity and mature creativity, which is called post-processing for creativity. In fact, mature creativity refers to the creativity existing in those conceptual creative designs or solutions which have been adopted by experts or have been examined by products. Considering the current level of computational creativity research, post-processing for creativity is a necessary step to achieve mature creativity. Generally, human being’s expertise plays an essential role in the post-processing for creativity, in which professional knowledge is applied to the integration of raw creativity with design requirements.

The mature creativity existing in conceptual designs or solutions is highly qualified, thus it is worth interpreting these designs or solutions for creative knowledge reuse. As a solution to creativity interpretation, NLP and image recognition technologies are applied to interpret the textual and image data respectively. The textual and image data utilized here are not the raw data as fed in the BKD or VCB but the representations of mature creative designs or solutions in various digital forms. Some may argue that this process is similar to creative knowledge discovery (CKD) as both processes result in creative knowledge. In fact, the resources and the outcome are quite different. The resources for CKD are knowledge bases in which creativity is not guaranteed, while the resources for creativity interpretation are full of creative knowledge and exists in real-world applications or markets. The outcome of CKD involves users’ requests while the outcome of creativity interpretation is the meta-data representing creativity in the simplest form. It is the extracted meta-data that is valuable for reuse purposes. At the end of the process, the meta-data is integrated into the previous established multi-
domain knowledge base, which recurrently contributes to the improvement of the capability of the design creativity system in term of creativity generation.

In the proposed data-driven cycle, mature creative designs or solutions are not limited to be generated within the system (by either BKD or VCB), they can be from external resources as well. If they originate from the internal system, post-processing for creativity is mandatory; if they are from external resources, their quality of creativity should be well evaluated before being interpreted. When interpreted meta-data is reused in the system, the system can be improved from two levels: the existing multi-domain knowledge base is strengthened by its level of creative knowledge; the systematic capability of generating creativity can be improved iteratively by learning from the meta-data, and this positive feedback boosts the system’s sustainability.

From a systematic perspective, the proposed cycle of a design creativity system embodies the philosophy of computational creativity: data-driven, machine learning-based, and recycled. Machine learning algorithms work as an engine, they produce creativity with human being’s involvement and then feed human beings. The input of such an engine is meta-data stored and updated in database, while the corresponding output is creativity support for designers. When design decision is made by designers, the design solutions will go into markets where creativity is embodied. They are then processed by the system and transformed into meta-data for recycling. In line with Cook and Colton’s (2018) notion of continuous creativity, three key features help distinguish the proposed cycle for design creativity:

- Data-driven – data flows throughout the whole cycle of a creative system with different forms, such as meta-data in database and explicit creativity in design product or solutions.
- Continuous – the cycle has no beginning or end, and keeps running within the system to support creativity, while the system updates itself seamlessly.
- Modular – as introduced in Figure 3.5, the cycle is supported by different modules which are responsible for a variety of functionality.
• Long-term - since the transformation from meta-data to creativity (embodied by products or solutions) involves designers, it takes some time to proceed with the next step (creativity interpretation) even complete the cycle.

3.4 Research originality and significance

There are several aspects showing the key difference between the research of a data-driven cycle for design creativity and previous research on design creativity. The research questions presented in this research are fundamentally proposed from the perspective of data. By tracing the data flow in conceptual design process, it is significant to investigate how creativity can be mined from data and how to reuse existing creative designs. In the studies of this thesis, it is well explained how the three fundamental topics, i.e. data source, algorithm and design theories, work in a data flow to support the data-driven cycle.

Since the scope of this research is limited to conceptual design, the main concern is to improve the creativity level of conceptualization. Idea generation, as a common way adopted in conceptualization, can help transform data to creativity (embodied in ideas). Semantic and imagery data are the key data formats to be studied in idea generation due to their capability of representing rich information. Similarly, given the fact that conceptual designs or solutions are widely existing in the design field, and some of them are regarded as innovative and creative, it is necessary to collect these designs and identify the elements representing creativity from them. These elements can be stored in knowledge base as meta-data and further support idea generation. Given the proposed data-driven cycle, the following three chapters introduce the methods for generating ideas from two different data source and extracting meta-data from creative conceptual designs respectively.

3.5 Conclusion

In this chapter, by reviewing existing creative systems and design knowledge reuse, it is found that the transformation between data and creativity lacks discussion and study.
In the proposed conceptual data-driven cycle, a bi-directional transformation mechanism between data and creativity is established, which forms a creative knowledge cycle so that a creative system is not only able to generate creativity but also able to interpret creativity. Textual and imagery data are considered for demonstration purposes in such a transformation process, as they are the most common digital formats. These transformations are facilitated in idea generation and design conceptualization. To obtain meta-data from creative conceptual designs, the NLP module is applied for semantic creativity interpretation while the image recognition module interprets graphic creativity. The interpreted meta-data containing creativity is fed into the system’s existing knowledge base recurrently, which boosts the whole systems’ creativity performance and achieves continuous creativity.
Chapter 4. Semantic Network Analysis for Bisociative Knowledge Discovery

This chapter investigates the state-of-the-art research on creative knowledge discovery, especially that related to bisociation. An information network, as an important data structure for data mining, has shown significant potential in bisociative knowledge discovery (BKD) research. However, there is still a gap in integrating data mining algorithms and data visualization in a single tool so that users are able to not only obtain bisociations from the machine side but also spark creative ideas from the human being. In order to solve such an integration issue, a network-based computational model bridging human-computer interaction and data mining is presented in this chapter. The model is implemented as an ideation tool B-Link for creative design, and further applied in a case study for model evaluation along with a multi-dimensional in-depth long-term case study.

Some of the work described in this chapter has been previously published as:


4.1 Creative knowledge discovery

Creative Knowledge Discovery (CKD) is a general term, but in this chapter its consideration is limited to the field of computational creativity. According to Martin et al. (2013), CKD is a method aimed at searching for valuable, previously unknown (or ignored) relationships between concepts, and creating new patterns either by taking advantage of existing patterns or by analogy to patterns in other domains (Chan and Schunn, 2015). CKD is viewed as an important branch of computational creativity (Dubitzky et al., 2012), which is an active novel multidisciplinary subject aiming to simulate, model or produce creativity using computing techniques. Compared to the topics reviewed in Chapter 2, CKD practically focuses on the discovery process which falls into the category of data-driven creativity tools as data mining techniques are massively exploited.

As reviewed in Chapter 2, computational creativity is a broad research topic studied in many areas, such as musical creativity, linguistic creativity, visual creativity, creative problem solving and educational creativity. CKD deals specially with available information using mining methods in the context of knowledge discovery, and its goal is to produce creative knowledge by finding gaps between concepts which are from different domains (Sosa and Gero, 2016). CKD is also referred to as creative information exploration by Dubitzky et al. (2012) where domains are highlighted and not limited to design, engineering, the arts and other scientific discovery disciplines. CKD is distinguished from knowledge discovery in databases (KDD) by Martin and Majidian (2013), as the latter searches for explanatory and/or predictive patterns and explores rules from large volumes of data within a specific domain, while creative knowledge discovery is concerned more with serendipity via cross domain exploration, which has previously not been recognized as associated with usual thinking processes, and looks for new links or new perspectives. For example, a biological study would pre-select scientific papers from relevant life science journals or resources before applying a particular text mining task. The pre-selected information already introduces certain limits on what can be explored.
As an essential analysis technique for creative knowledge discovery, data mining has largely been relied on for extracting information from datasets and transferring it into understandable patterns by various data analysis algorithms, such as topological data mining, graph-based data mining and entropy-based data mining. For instance, decision tree is a common method building classification or regression models in the form of a tree structure, its core algorithm is called ID3 (Iterative Dichotomiser 3) which uses entropy and information gain to construct a decision tree. When constructing such ontology based knowledge datasets for data mining, natural language processing is a necessary step to recognize the syntactic structure and understand the semantic meaning from its context. Recently, visual analytics as a new discipline has been applied to make sense of large amounts of data by analytical reasoning facilitated by visual interfaces (Yan et al., 2012). This integrates traditional information visualization with fast computational methods, such as data mining, to reduce overwhelming information quantities so that creative patterns become more prominent in a limited visual configuration (Bang and Selva, 2016).

Generally, research methods for CKD can be summarized into three categories: data mining algorithm based case studies, software development with an interface, and creativity experimentation. In a case study, the preliminary learning about disciplines and knowledge should be conducted, then typical information on creativity in various kinds of fields is collected, finally deep analysis for creative knowledge discovery is implemented (Shabalina, 2015). When establishing a problem-solving space, this methodology depends much more on data mining and analysis algorithms which tend to find close associated patterns rather than far associated patterns (Martin and Majidian, 2013). Han et al. (2018b) indicate that ‘far distance’ between two concepts tends to generate higher levels of creativity than close distance. Software development with interfaces involves development activities such as software design, and software quality such as trustworthiness (Haun et al., 2012). For instance, the Combinator developed by Han et al (Han, 2016) aims to stimulate creative ideas for engineering design based on combinational creativity. Software integration releases a human’s potential of producing creativity with human’s involvement compared to implementing the
corresponding method without software, as illustrated in Chapter 2 where program-based creativity tools outperform traditional tools, but it relies on users’ individual creativity personality largely and has less computer autonomy (Holzinger, 2013). The emphasis on experimentation for CKD is to solve the critical paradoxes on creativity. For instance, can it be referred to as ‘creative’ according to the nature of creativity if the exact method for creativity is known? Therefore, the rational and logical solutions should be the ones that not only enhance creativity without a structured method of simulating the process, but also depend on the creative feelings which are originated from the overall comprehension of various kinds of knowledge (Teng et al., 2015). For example, when several creative solutions are generated with a CKD mechanism, the experimentation will allow users or experts to play with a different solution so that a decision of choice can be made based on their overall comprehension of each solution.

In summary, there are two problems across above three methods for CKD: 1) existing data mining algorithms for CKD focus on close associated patterns rather than far associations, while their underlying assumption has always been that the data originates from one domain (Berthold, 2012); 2) software with interface translates theoretical creativity methods into program, which is more practical and straightforward, but neglects the potential contribution from data exploration. For example, when users look at a sub set of information from a specific viewpoint, it might change during the investigation process. Benefiting from the personal and dynamic view of exploration, users can learn, investigate, understand even conceptualize their initial discovery need by building up a personal mental map or model (Gossen et al., 2012). The study conducted by Shneiderman (2002) showed that a combined approach of information visualization and data mining is better for novelty discovery. Thus a synergistic combination approach of creativity method, data mining, and data exploration needs to be considered (Holzinger et al., 2014a).

The study in this chapter is inspired by the BISON project (Berthold 2012; Dubitzky et al. 2012), but with three main differences. First, we agree with their descriptive definitions related to bisociation from the perspective of computational creativity, such as bisociation types, domain, bisociation information network, bisociative information
exploration, but we proposed our own guidelines framing the steps for creative knowledge discovery based on bisociation and gaps in existing research. Second, the implementation is built upon a large and domain-distinguishing database, novel algorithms for data mining, and integrated data exploration, instead of very limited domains numbers (such as only two in Jursic et al. (2012)), mining typical bisociation types (such as b-terms), and static network data visualization. Finally, the developed tool is validated through a combined evaluation method of qualitative and quantitative analysis, and further evaluated in a design study.

4.2 Bisociative knowledge discovery

Recently, modern knowledge discovery research, especially creative knowledge discovery, has started focusing on establishing a framework supporting the discovery of domain-crossing connections (Berthold et al., 2008). As introduced in Chapter 2, bisociation is an important method for creativity and has been widely developed in various research topics. Applying bisociation in creative knowledge discovery, namely bisociative knowledge discovery (BKD), represents an important challenge in the quest to build truly creative discovery support systems which trigger new ideas and uncover new insights to support much deeper discoveries (Berthold, 2012).

In order to formalize the types of bisociations (e.g. transforming unstructured data into structured data) and develop methods for exploring them, a more sophisticated model of the knowledge space is necessary. In bisociative knowledge discovery, a network graph is widely used for modeling complex bisociations with various types of information and performing data mining tasks, due to its inherent flexibility. Generally, there are three types of bisociation represented by network graphs: bridging concepts, bridging graphs, and bridging by structural similarity (Kötter and Berthold, 2012a).

Bridging concepts is the most natural type of bisociation which links concepts from two or more domains, such as the one shown in Figure 4.1. Bridging concepts are highly used in humor and riddles by employing ambiguous concepts or metaphors. For example, the riddle “I have a pet which is also a car” refers to an ambiguous word
“jaguar” since it may refer to either an animal or a car. A concept graph is always necessary for detecting bridging concepts in an integrated database as it can be used to identify potential bisociative concepts in a network by searching for densely connected quasi k-partite sub-graphs and associated vertices (Kötter and Berthold, 2012b).

![Concept Graph](image)

**Figure 4.1 Bridging concept (Kötter and Berthold, 2012a)**

In bridging graphs, two (or multiple) domains are connected by a subset of concepts that share some relations between two domains. In a network-based representation, the subset can be a relatively dense subgraph, while it may be a chain of concepts in other representations. One possible bridging graph can connect seemingly unrelated domains, as shown in Figure 4.2(a). The Eureka act of the Archimedes example introduced in Chapter 2 belongs to this type of bridging graph. Another bridging graph can be a linking of two disconnected concepts from the same domain via a network routine through another unrelated domain (Figure 4.2(b)). An example of this type of bridge graph is shown in Figure 4.3, which is presented by Nagel et al. (2012) with Schools-Wikipedia\(^4\) (2008/09) dataset. The graph connects a domain of movies and actors with a mathematical domain by direct links (highlighted in Figure 4.3), which demonstrates how the two bridging concepts “probability space” and “arithmetic mean” existing in the domain of movies are explained in more details in the domain of statistics. *Schwarzenegger* is used in a voting example in the article about *Probability theory*, while the link from the article *The Golden Compass* film is explanatory in the report about different ratings of the movie.

Bridging by graph similarity is the most abstract pattern of bisociation among the three. It does not contain straight-forward types of a link connecting two domains but is represented by sub-graphs which are structurally similar in two distinct domains. As shown in Figure 4.4, the two distinct domains may not even be connected, but potential bisociations can be discovered by calculating a vertex similarity on the basis of the structural properties of vertices. Thiel and Berthold (2010) proposed spatial similarity and structural similarity, which are based on spreading activation, as the metrics to identify bisociations that are structurally similar but in disconnected sub-graphs.
CrossBee (on-line Cross-Context Bisociation Explorer) is a bisociative knowledge discovery system which aims to support the search of hidden links connecting two different domains (Jursic et al., 2012). It is based on a set of specially tailored heuristics for text mining to evaluate a term’s quality by assigning it with a *bisociation score* (b-score) which measures the potential to be a bridging concept (called B-term). By identification and score ranking, the user of the system is able to explore the most promising concepts primarily. Its methodology is evaluated by the standard migraine-magnesium problem, which is well-known in literature mining, and the autism-calcineurin problem. However, CrossBee has several limitations: 1) it only handles two pre-identified domains at once, such as the autism-calcineurin datasets; 2) the results are generated merely by ranking scores instead of network-based data mining, which may be ambiguous as the same word or phrase may have different meanings depending on the context; 3) the datasets used for evaluation are small, e.g. only 60 pairs of articles connecting the migraine and magnesium domain in the migraine-magnesium datasets (Swanson, 1988).

Ahmed and Fuge (2018) attempt to solve these issues by introducing bridging topics (called b-topics) to capture richer representations for bisociations across domains. By constructing bisociative information networks (BisoNets), the proposed model uses the Latent Dirichlet Allocation (LDA) based topic modelling method to obtain b-topics from OpenIDEO, a dataset containing thousands of ideas from its online collaborative community (Fuge and Agogino, 2014). With such a large dataset, Ahmed and Fuge extend the application of bisociative knowledge discovery from two domains to fourteen domains. However, in unknown domains, it is difficult to know how many...
topics exist with the standard LDA method, even in a situation where many more domains are requested to be analyzed. Besides, the generated b-topics still require some creative imagination from the designer to connect the b-topics with the challenge at hand, even though they are accurate. Novel exploration or intervention method is missing to help spark users’ inspiration.

To enable bisociative knowledge discovery in large, heterogeneous information networks, Haun et al. (2012) present the Creative Exploration Toolkit (CET) which allows exploration in dynamic graph structures and integrates advanced graph mining methods in an interactive visualization framework. The interface of CET, as shown in Figure 4.5, uses the Stress Minimization Layout to determine the initial graph layout which is followed by an overlap removal. The nodes in the graph are free to be moved for a certain arrangement, to be selected for further action and expanded by double-clicking them. Even though CET is designed for graph visualization and presentation, domain-specific semantics are not supported. The CET provides powerful extensibility for external tools and resources, e.g. its graph data sources and data analysis algorithms.

**Figure 4.5 The interface of CET (Haun et al., 2012)**
rely on KNIME (an information mining platform), but those external tools may constrain its capability of finding bisociations.

4.3 Network analysis and information visualization

A network is a useful tool that is able to integrate a large amount of information from various domains with varying quality in a flexible way. The network structure provides a quantitative and/or graphical representation of the ‘interconnectedness’ between the elements, while the network composition describes the characteristics of the network’s elements and quantifies the diversity of those attributes. The network’s elements are commonly referred to as nodes, vertices, or points, and the relationship between two nodes are usually represented as a line and referred to as edges, links, ties, or arcs.

According to the information attached to vertices, a vertex can have multiple properties (Kötter and Berthold, 2012a):

- **Attribute**: an attribute can be assigned to a vertex to represent the original data or the translated information which is user-readable. These attributes may either contribute to network analysis or carry specific semantic information.

- **Type**: type can be utilized for distinguishing different semantic vertices by categories, especially in k-partite graphs. These types are often organized in a hierarchy or an ontology.

- **Hierarchy**: vertices in a network can be condensed as a sub-graph of the network, and even to represent a more complicated concept, e.g. in a cellular process.

Similarly, an edge can have multiple properties as well:

- **Attribute**: an attribute can be assigned to an edge to represent the relation between two vertices. An attribute might be a link directing to the original data or a translation of a user-readable label, and it can be applied in a reasoning process but may not carry semantic information.
• **Type:** this is used to distinguish different semantics of edges such as activations or neurons. Similarly, types are often organized in a hierarchy or an ontology.

• **Weight:** this denotes the strength of an edge, such as the probability or tightness of two connected vertices. It is widely used in the network analysis process.

• **Direct:** this explicitly expresses the edge with a relation in only one direction, such as the dependency between child and parent.

• **Multi-relation:** this term represents relations as multi edges supporting any number of members, such as the occurrences in topic maps. This allows a more flexible expression of relationships among multiple vertices, such as the co-authors of a paper.

According to the properties of knowledge units that networks support, the common prominent types of information networks are ontology based, semantic, topic maps, and weighted (Newman, 2003; Kötter and Berthold, 2012b). **Ontologies** provide a framework for facilitating effective and efficient knowledge-sharing by modeling a domain network. They are based on typed and directed relations using a curated vocabulary for vertices and edges dedicated to a certain domain. The construction of an ontology is usually manual or semi-automatic and requires a comprehensive knowledge of the domain to be described. Ontology based network analysis has been widely used in areas involved with high-dimensional space, such as engineering design, organization modeling, and knowledge browsing. For example, the Open Biomedical Ontologies (OBO) consortium has created a file exchange format and over 60 ontologies for different domains (Smith et al., 2007).

A **semantic network** is a type of network using typed relations to interpret the semantics of integrated vertices and their edges. In contrast to ontologies, the vertices in a semantic network do not represent a controlled vocabulary but rather an information unit defined by attributes and associated edges. Typical standardized semantic networks are expressed in semantic triples which are the atomic entity in the Resource Description
Framework (RDF) data model (Lassila and Swick, 1998). A semantic triple consists of a subject, predicate and object, such as the statement “The sky has the color blue” is transformed as a triple of “the sky” (subject), “has the color” (predicate) and “blue” (object). ConceptNet (Speer and Havasi, 2013) is a semantic network constructed through a pattern recognition process by data mining technique. This extracts the predetermined patterns in text mining and then represents the knowledge information as a network including edges and vertices.

**Topic maps** represent information with three main components: topics, associations and occurrences. A topic can be any concept, from people, organizations to ideas, events and files. Relations between any number of topics are represented by associations. Associations are assigned a type that describes connected topics. Generally, occurrences are not stored in a topic map but are referenced using mechanisms supported by the system such as the Uniform Resource Identifiers (URI). Occurrences can have many different types that describe their semantics. Topic maps are popular in social network analysis (Chan and Liebowitz, 2005). They can be applied to build knowledge maps for better understanding the knowledge flow in organizations and analyzing the strengths and weaknesses of the networks effectively.

A **weighted network** is a network where the edges among vertices have weights assigned to them. The edge weight represents the strength of a relation such as reliability or probability. Probabilistic networks model the probability of the existence of a relationship and are mainly used in biology, such as the gene-gene networks. Heuristic weights are another type of weights widely applied to modeling the reliability or relevance of a given relation. It is convenient for the integration of well-controlled sources such as ontologies. It is used widely in analysis rather than visualization (Shi et al., 2016). Wang et al. proposed a data-driven network analysis based approach to assist prediction and decision making by data mining (Wang and Chen, 2015).

Generally, a network can be used in two forms as a computing technique: data structure and visualization graph. In data mining many types of network structure are used (Cash et al., 2014). Some of them are specific for particular areas such as chemistry and
biology, and others are different in terms of properties of knowledge units and relations. Recognizing the effective characteristics of a network approach in knowledge representation, researchers have tried to use various information networks for bisociative knowledge discovery. Kötter and Bethold (2012a) propose BisoNets with a weighted k-partite graph structure for bisociative knowledge discovery and compare it with the above four types of networks (Table 4.1).

Table 4.1 Property conjunction matrix of information networks (Kötter and Bethold, 2012a)

<table>
<thead>
<tr>
<th>Information Units</th>
<th>Relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>A T H</td>
<td>A T W D M</td>
</tr>
<tr>
<td>Ontologies</td>
<td>×</td>
</tr>
<tr>
<td>Semantic Networks</td>
<td>×</td>
</tr>
<tr>
<td>Topic Maps</td>
<td>× ×</td>
</tr>
<tr>
<td>Weighted Networks</td>
<td>×</td>
</tr>
<tr>
<td>BisoNets</td>
<td>× × ×</td>
</tr>
</tbody>
</table>

Note: A=Attributed, T=Typed, H=Hierarchical, W=Weighted, D=Directed, and M=Multi-relation. “A” and “T” share the same meaning across both “Information Units” and “Relation” column.

As can be seen, BisoNets support all the primary properties introduced above, which allows it to integrate data from diverse sources and flexible to process heterogeneous data in an easier way. Doboli et al. (2015) presented a model for semantic network representation aimed at assisting the correct and quick understanding of the features and structure in creative problem-solving. Elements forming the model include features, concepts, categories, associations between concepts, associations to expected goals, objectives and rewards, association sequences, and distinguishing features. The study showed that divergent elements and universal connectors are important for flexibility, which is a main requirement in divergent thinking. Interestingly, the universal connector, which refers to the element connecting categories with few common features, shares
some similarities with the definition of bridging concepts. In addition, it showed that divergent elements, which refer to the concepts falling into the same category but not associated to each other, are more likely to be the vertices connecting two domains, which is intuitive to the algorithm design for mining bisociations.

A network, as a rich form of a graph, provides an efficient way to visualize information and solve visual analytic problems. Komarek et al. (2015) compared and presented modern approaches of drawing complex graphical data creating compelling network visualizations, including force-directed graphs, hive plots, arc diagrams, Sankey flow diagrams and chord diagrams, some of which are shown in Figure 4.6. For instance, the force-directed graph (Figure 4.6a) is a weighted network with direct edges. Its edges are assigned forces based on their relative weights. These forces are used either to simulate the motion of edges and nodes in the network or to minimize their energy. The Sankey diagram (Figure 4.6b) is a specific flow diagram in which the width of arrows is proportional to the flow rate, it is commonly used in workflow analysis. In various knowledge discovery fields, network based visual analytics tools are designed to relieve information overload and assist browsing knowledge, such as Refinery (Kairam et al., 2015). Furthermore, there is a new trend that network insights have been identified to understand and analyze products in engineering design (Wang et al., 2016).

(a) Force-directed graph
Network visualization can concisely capture richer information from the data compared with the textual description, especially when a large amount of information is required to be integrated. Network visualization also provides a structural manner to view a diverse type of data and rich information. Most importantly, network visualization can spark intuitive insights and knowledge. Human beings can leverage their visual system to intuitively discover patterns and identify new knowledge (Keim, 2002). Due to the above benefits, it is essential to perform creative data exploration in the context of human-computer interaction, visual data analysis and bisociative knowledge discovery, which is defined as Bisociative information exploration (Gossen et al., 2012). Its overall requirements are suggested as follows:

- Supporting dynamic exploration within information presentation spaces;
- Supporting bisociation (cross-domain knowledge) discovery functions for users;
- Supporting human creative thinking for users;
- Supporting real-time data mining for user’s queries at the user interface.

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5 [https://github.com/d3/d3-sankey](https://github.com/d3/d3-sankey)
By comparing the three most common solutions for data exploration, which are lists, item sets and graphs, it is argued that graphs are the most promising approach for bisociative information exploration. *Enronic* is a tool developed for visualizing applied natural language processing (Heer, 2004). This provides an exploratory data environment for efficient exploration and direct analysis of complex graph structure, such as a graph based email corpora in Enronic’s case. CET is another data exploration tool which integrates graph exploration and data mining for real-time utilization, as introduced in section 4.2. Though the network visualization in this study is inspired by those tools, the main differences can be summarized as follows: 1) the network visualization is exploratory as well as multi-domain supported, which shown results containing cross-domain vertices; 2) data exploratory works in parallel with mining functionalities so that users can understand and conceptualize their discovery in a dynamic and iterative way.

### 4.4 Guidelines for bisociative knowledge discovery

As discussed above, bisociation shows significant potential for modeling computational creativity. With the exploration of the state-of-the-art bisociative knowledge discovery research, networks have many advantages for not only data mining but also data visualization in order to capture bisociative terms (such as bridging concepts) and spark user’s inspiration. However, there is a gap in integrating data mining algorithms and data visualization in a single tool so that users are able to obtain bisociations and creative ideas from not only the machine side but also the human being side. When exploring the possibility of such integration, there should be a solid foundation for applying the characteristics of networks to BKD. Therefore, the following guidelines are proposed to support bisociative knowledge discovery from different aspects.

**G1. A computational model of data-driven creativity**

In the proposed model, it is fundamental to have a large and domain-distinguishing database, on top of which novel algorithms for far-associations mining and integrated data exploration interface will be then considered: taking datasets as a multi-domain
knowledge repository which can be explored like a territory map, the data can be seen as different locations distributed in the map. According to the bisociation theories, the data in the knowledge repository should be collected from different domains, and any implicit or explicit relationships between data should be recorded in the datasets.

In order to facilitate such a map-like creativity exploration, the information network can be chosen as an appropriate data structure (Cash et al., 2014). The information network is flexible to allow integration of a large amount of information from various domains with varying quality in a flexible way (Hao et al., 2014; Doboli et al., 2015; Wang and Chen, 2015). The network structure provides a quantitative representation of the ‘interconnectedness’ between elements, while the network composition describes the characteristics of the network’s constituent elements and quantifies the diversity of those attributes (Scott, 2012).

G2. The data-driven discovery process

The basis of discovery is searching by association. This helps users discover those concepts which are either familiar but may not easily be recalled by users or not familiar but may be desired by users. However, presenting the associative search results, no matter if the association is close or far, is not enough to inspire users and capture creativity. Users need to be conducted into deeper discovery, which means the interaction between mining results and users in creativity exploration interface should be provided (Yamamoto and Nakakoji, 2005). Based on the proposed data-driven creativity model in G1, it is also worthwhile for users to search possible pathways linking two elements (representing two different concepts possibly) in the network datasets which are the start and end of the pathways respectively. According to Koestler’s definition of bisociation, these two elements should derive from different domains (Tucker and Kang, 2012). Therefore, the creativity tool should have the capacity for clustering data by domains, thus users would be allowed to search latent linkages between domains in order to facilitate discovery.
G3. Visualization and interaction

Traditional data search results are usually shown as lists. This is useful when users are very clear about the target content. However, it is a less appropriate option for creative searches as latent useful information is unlikely to be shown in dominant places in result lists, and users may not find a target result beyond the first few pages of result lists (Keefe and Isenberg, 2013). In general, for a big data repository, it is difficult for users to interact with data and discover valuable information from datasets (Haun et al., 2012). To address these issues, interactive visualization should be provided in data-driven creativity tools (Holzinger et al., 2014a).

A network provides an effective data structure to facilitate data mining on creativity discovery as reviewed in the first guideline (G1), and is also an efficient graph type to visualize data and interact with data. As a graphical representation of relationships between data, a network not only aids visualization of data in the datasets known as a knowledge repository, but also has the capacity for users to interact with data, offering possibilities for users to discover serendipities (Herman et al., 2000).

4.5 An interactive network-based computational creativity model

By integrating network analysis and network visualization in bisociative knowledge discovery, a network-based computational creativity model is proposed to integrate data exploration and data mining. Compared to existing BKD research, the novelty of proposed model comes from: 1) constructing a large and domain-distinguishing database; 2) novel algorithms for mining far-associations rather than close-associations; 3) supporting dynamic data exploration which works in parallel with data mining. The model originates from bisociative thinking and is developed as a computational creativity model which takes advantage of a network’s capability for knowledge representation, analysis and visualization. As shown in Figure 4.7, this HCI-BKD model consists of four layers where information is exchanged in between. Data is collected and pre-processed in the first layer for data construction in the network layer where
structured data is used to support mining algorithms implemented in the BKD layer. The BKD and HCI layer work as the front end supporting the application of discovering far associations.

![Figure 4.7 The network-based HCI-BKD model](image)

In the data layer, key information is extracted from digital texts as raw data and is transformed into structured data. It is worth noting that collected information should originate from diverse domains as the theoretical basis of computational creativity requires cross-domain bisociation in order to produce creativity, the exact approach of collecting domain-distinguishing data is introduced in the tool development (Section 4.6.1). There are many ways to collect raw data, such as using a web crawler or directly from a server end database. Usually, raw data is not able to be stored in a database as an appropriate data structure is required for indexing and retrieving. To simplify the construction of the proposed model, keywords extracted from documents are considered as the exclusive structure to be stored in datasets. There are many sophisticated methods performing keywords extraction from textual documents, including statistics-based (TF-IDF), machine learning approaches (e.g. Support Vector Machine), and vector space models etc. (Beliga, 2014). In our implementation, a combined approach of
statistical and linguistic techniques is applied in order to capture various kinds of relations and adapt to large-scale data environment. Specifically, with syntactic analysis at linguistic level, textual data is segmented into separate and complete sentences, of which every single word is further extracted by tokenization and tagged by part-of-speech tagger respectively. Among those extracted words and associated tags, noun phrases can be identified using phrase chunking and constituency tree, and then are processed with frequent itemset and association rule mining (Zaki and Hsiao, 2002) at statistical level in the second layer. When stop-words are removed from extracted noun phrases, the noun phrases are refined to be the concepts used as the vertices in our constructed ontology network. The concepts which appear within the same sentence or clause are assigned with edges in the ontology network to represent association relations.

In the second layer, data is constructed in the structure of a network and stored as a database for further network analysis in which data mining algorithms are developed. In the construction of a network database, association rules need to be applied when determining connections of vertices and accumulated weights. In the case of the proposed model, a keyword-based network is constructed on the basis of Shi et al.’s method (Shi et al., 2017a). It is assumed that all the keywords extracted from the same sentence have close association relation between each other, and the keywords in the same clause would be more relevant to each other than those in different clauses of the same sentence, thus one unit of weight is added to the association between keywords in the same clause while a reduced weight (0 < r < 1) is added to the association between keywords in the same sentence but different clauses. In our implementation, r is set to the median value 0.5.

In order to help capture far associations (bisociation) rather than close relationships between vertices in a constructed network, the raw weights need to be normalized with practical statistical meanings for retrieval. The weight normalization process, including global scaling and local fluctuation, tunes the weight of each edge throughout the whole network in order to add the significance of associations. As shown in Equation 4.1 and 4.2, \( w_{\text{min}} \) and \( w_{\text{max}} \) are the minimum and maximum value of the raw weights throughout the whole network, \( w_{ij} \) refers to the raw weight of the edge between vertex \( i \) and \( j \), and
$s_i$ denotes the sum of raw weight at vertex $i$. The calculation of $\bar{w}_{ij}^g$ shows that the significance of an edge is normalized across the whole network, while $\bar{w}_{ij}^l$ is tuned by local fluctuation expressing the relative importance for vertex $i$ (Serrano et al., 2009).

$$\bar{w}_{ij}^g = (w_{ij} - w_{min})/(w_{max} - w_{min}) \quad (4.1)$$
$$\bar{w}_{ij}^l = w_{ij}/s_i \quad (4.2)$$

The next step is network analysis when the data network is well normalized using the Equations in 4.1 and 4.2, including receiving requests from an upper layer and analyzing the algorithms-driven network. In proposed retrieval algorithms, rules are established to determine the retrieval results ranking based on the degree of association between knowledge concepts in the constructed semantic network. Basically, three categories of rules need to be established corresponding to three corresponding types of requests for the following layer: exploration, search path and cluster.

The third layer represents the process of bisociative knowledge discovery in which three sequential steps are followed. These three steps originate from the proposed discovery process in G2. The discovery initiates when search actions are taken by users, and is followed by automatic retrieval which is driven by algorithms in the BKD layer. The ‘Exploration’ step generates a certain number of concepts associated with the concept given in the search. The retrieval can be achieved by calculating the probability of the path from one vertex representing keyword $K_1$ given by an end-user to another vertex with edge connection in n-1 steps:
\[ P(K_1, K_n) = P(K_1 \rightarrow K_2 \rightarrow \cdots \rightarrow K_n) \]
\[ = \frac{w_{12}w_{23} \cdots w_{(n-1)n}}{s_1s_1 \cdots s_{n-1}} \]
\[ = \prod_{k=1}^{n-1} \frac{w_{k(k+1)}}{s_k} \]
\[ = \prod_{k=1}^{n-1} \overline{w}_{k(k+1)} \]  

(4.3)

As can be seen, step n-1 and the edge weight of two vertices \( w_{k(k+1)} \) are the two key variables determining the retrieval results returned to an end-user. It is reasonable that the association between two vertices connected by only one edge can be potentially closer than the same vertices indirectly connected by multiple edges, thus it is assumed that far association is essentially the concatenation of a series of edges. Therefore, it can be deducted that the association degree of any two concepts (represented by vertices in the network database) can be determined by the number of steps n and the overall weight of the association \((K_1 \rightarrow K_2 \rightarrow \cdots \rightarrow K_n)\). The approach of retrieving the best associations will be illustrated below along with the “Search Path” algorithm.

When the meaning of generated concepts is understood by end-users, new search actions may be taken to explore more associated concepts until switching to the second step ‘Search Path’ which helps identify the possible paths connecting two concepts. Given two concepts, one of which could be unfamiliar to end-users as it might be chosen from the results in previous operations of ‘Exploration’, ‘Search Path’ returns all possible pathways connecting the two concepts. In each pathway, the intermediate concepts from the constructed ontology network are retrieved. This path retrieval is implemented by calculating the weighted distance between the two vertices \( K_I \) and \( K_I \) representing the two keywords given by an end-user within t-1 steps:
\[ D(K_1, K_t) = D(K_1 \rightarrow K_2 \rightarrow \cdots \rightarrow K_t) \]
\[ = \frac{1}{w_{12}^g} + \frac{1}{w_{23}^g} + \cdots + \frac{1}{w_{(t-1)t}^g} \]
\[ = \sum_{k=1}^{t-1} \frac{1}{w_{k(k+1)}^g} \]

This equation retrieves the concepts from a global perspective using weight normalization Equation 4.1, thus it prefers the information flow on the most significant edges with regard to the whole network (which is domain-distinguishing) and therefore may cross different domains. Similarly, the number of steps \( t \) and the overall weight of associations are the variables for retrieving the best vertices.

It is reasonable that a longer path could potentially cross more different knowledge domains and link more irrelevant information at two ends. Therefore, without constraining the maximum number of edges in a path, it may result into a very long path which costs tremendous computing workload and is overwhelming for end-users to consume the associations along the path. According to Shi et al. (2017b)’s experiment and case studies, harmonic means (HM) for normalizing the overall weights can help retrieve domain-specific concepts in terms of “exploration” and longer paths in terms of “Search Path”, while geometric mean (GM) helps retrieve concepts that contain various general meanings falling into multiple domains in terms of “exploration” and shorter paths in terms of “Search Path”. Therefore, the equations of calculating the normalized overall weights for different purposes can be written as follows:

\[ GM(K_1, K_t) = GM(K_1 \rightarrow K_2 \rightarrow \cdots \rightarrow K_t) \]
\[ = \sum_{k=1}^{t-1} (-\log \bar{w}_{k,k+1}) \]
\[ HM(K_1, K_t) = HM(K_1 \rightarrow K_2 \rightarrow \cdots \rightarrow K_t) \]
\[ = \sum_{k=1}^{t-1} \frac{1}{\bar{w}_{k,k+1}} \]
With the two equations above and Dijkstra's shortest path algorithm (Dijkstra, 1959), the number of edges and the overall weights can be balanced for different usage scenarios:

- **Exploration – General**: vertices retrieved tend to have general semantic meanings which are highly possible to bridge more domains; this is implemented by applying global weight $\overline{w}_{ij}^g$ to HM.
- **Exploration – Specific**: vertices retrieved tend to have more specific semantic meanings which might go across less domains; this is implemented by applying local weight $\overline{w}_{ij}^l$ to GM.
- **Search Path – Basic**: paths retrieved tend to be shorter where the vertices are more likely to have general semantic meanings; this is implemented by applying $\overline{w}_{ij}^g$ to GM.
- **Search Path – Professional**: paths retrieved tend to be longer where the vertices are more likely to have specific semantic meanings; this is implemented by applying $\overline{w}_{ij}^l$ to HM.

The above four scenarios are applied to the tool development, and will be introduced in the section on tool design (Section 4.6.1).

At this stage, bisociations are expected to be generated when end-users are trying to understand connections in the generated paths. If confusion occurs due to the emergence of those cross-domain unfamiliar concepts, end-users can be relieved in the next step ‘Cluster’. ‘Cluster’ provides an option to cluster the concepts, which are generated as the outcome of the previous two steps, into groups (or clusters). A certain number of groups are highlighted in the network graph in which concepts are represented by vertices, while a group represents the knowledge of a specific domain. Furthermore, paths between two groups can also be identified at this stage, which contributes to the formation of bisociation knowledge. By following the three steps for discovering potential bisociation knowledge, a comprehensive map of associated concepts is obtained in users’ mind, while bisociative knowledge can be discovered by identifying far associated concepts from an unfamiliar domain which has connections with existing known domain concepts and thus forming a bisociation idea.
During the discovery process facilitated in the third layer, interactions always happen between the third layer and the fourth layer as a network graph is generated at the beginning of a retrieval task. Generally, in the visualization of a network graph, concepts are represented by nodes whose size indicates the importance of corresponding concepts, whilst relationships are represented by edges whose length shows the tightness of corresponding associations. In the HCI layer, whenever the network graph is updated due to actions taken in any of the three steps in the third layer, new insights can be obtained by looking up knowledge concepts in the graph. New search ideas may be generated during such an interaction period, which results in further actions in the third layer, thereby pushing the discovery process forward until bisociative knowledge is captured.

4.6 Usability study

Two of the main innovations of this research are the novel algorithms for BKD and the dynamic data exploration method, which are validated in a developed tool implementing the proposed algorithms and data exploration method. Two studies are conducted to evaluate the two innovations with different focus. In this section, a usability study is undertaken in order to examine: 1) how usable this tool is to make discoveries effectively, efficiently and with positive attitude from the perspective of human-computer interaction; 2) how useful this tool is to stimulate users’ creativity. Specifically, three aspects are concerned in this study which are related to the proposed data exploration method: presentation of the data, interaction with the data, and the usability of the data itself.

4.6.1 Ideation tool development

Based on the proposed interactive network-based computational model, a prototype tool called B-Link has been developed. B-Link is designed as an idea generation tool for two main reasons: 1) idea generation is deemed to be the foundation of innovation (Cash and Štorga, 2015) and is commonly demanded at the early stage of design; 2) the data

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6 URL: [http://www.imperial.ac.uk/design-engineering/research/engineering-design/creativity/b-link/](http://www.imperial.ac.uk/design-engineering/research/engineering-design/creativity/b-link/)
in constructed database is noun phrases based, which is suitable for inspiration related tasks rather than problem-solving tasks. When constructing the database, academic publications were chosen as original data sources due to the convenience of data access and cross-domain knowledge collection. Academic publications are generally a rich source of knowledge in terms of data quantity and quality, having wide coverage of research fields, and are thereby potential sources for opportunities for creativity discovery (Jagmohan et al., 2014). Initially, with natural language processing, more than three million keywords with around 30 million relationships in between were extracted from over 3.7 million online academic publications. By indexing and tailoring the network dataset where those keywords and relations with extremely low frequency are abandoned, nearly 0.5 million keywords and 3.7 million relations were left and well reconstructed.

B-Link is presented as a web platform for users’ bisociative knowledge discovery. Its interface is implemented with HTML/CSS/JavaScript, using D3’s force-directed network layout (Bostock et al., 2011) and jQuery libraries for visualization and human-computer interaction. In the constructed force-directed graph, each vertex is labelled with a concept (a refined noun-phrase from the first layer of proposed model) while each edge representing the relation between two vertices is assigned three kinds of forces for simulating the dynamic placement and movement of vertices and edges in the network graph. The first force is a many-body force which can simulate the attraction effect among the vertices if the strength of the edges in between is positive, or a repulsion effect if the strength is negative. These two effects help clearly display the graph rather than mess up for data exploration. Furthermore, spring force is applied to recover the graph from users’ manipulation. Similar to a physical spring, its strength is proportional to the difference between the actual distance of an edge and the desired distance. The third force works globally rather than locally compared to the other two forces. It is a center force that translates the graph to the center of the viewport in the tool interface by calculating the center of mass of all vertices from the graph. Figure 4.8 shows an example of the layout of the network graph in B-Link, where the distance between vertices is well calculated and displayed without overlay.
There are other graphic features which are shown in Figure 4.8 and provide rich information for data exploration:

- **Size of vertex**: the size of vertex indicates the importance of the corresponding concept as it is determined by the sum of raw weights of all edges connecting to that vertex in the network graph.

- **Edge distance**: the distance of each edge is calculated based on Equation 4.5, and then normalized to the whole network graph. The length of an edge indicates the association degree of the edge, which means a shorter edge represents closer association between the vertices connected by that edge.
• Edge strength: the strength of each edge is proportional to the length of edge, according to Hooke’s law. Therefore, a shorter edge has stronger strength and more stable connection than a longer edge.

• Edge width: similar to edge distance, the width of edge is used as an additional feature to represent the association degree of two concepts. Likewise, a thicker edge means higher association than a thinner edge.

• Color: the color of vertices and edges changes to red in some specific scenarios, including the selection of a specific vertex, and the focus on a specific path. When a path is highlighted, the width of edges is increased as well, as shown in Figure 4.8.

The above graphic features facilitate an animated and dynamic visualization and interaction for users. Dynamic movements include position, velocity and accelerated velocity, which are calculated based on applied forces and automatically take effect during use. When browsing the graph, available operations include translate, zoom, click and highlight. Specifically, users can move and zoom in and out the graph to adjust the viewport. Dragging on vertices is also allowed for users to scrutinize each vertex of interest, while clicking on vertices can highlight and select them. All these conveniences can enable the visualization more realistic and much easier to gain inspiration from idea generation activity. Dynamic interaction is supported as well when users are querying and retrieving a semantic network graph, which is unique compared to other creativity tools. This is achieved in two ways: 1) the guidelines for BKD are implemented via HCI design in the tool so that users can follow steps to complete their idea generation while exploring data, which is further illustrated below; 2) by integrating new retrieval results into existing network graph, users’ data exploration consequences are kept and updated in the tool interface, which helps users form a unique and individual knowledge map.

The query and mining engine is implemented in Python, while the NetworkX library (Schult and Swart, 2008) is used to construct and analyze network data. The main interface of B-Link is the Action panel. As shown in Figure 4.9, the Action panel (top-left) which includes Explore (bottom-left), Search Path (bottom-right) and Cluster (top-right) is designed as an implementation of the third layer of the proposed model.
Whenever an action is taken from the *Action* panel, the results will be shown in two ways simultaneously, a list and a network graph. In the list (refer to the left side of the interface shown in Figure 4.9), results are shown in sequence according to the ranking of calculated value based on Equation 4.5 or 4.6 (ascending order), which helps users examine results in order. When a user selects one item in a results list, the corresponding result in the network graph will be highlighted as well. This interaction provides users with the freedom to explore associated knowledge of interest. As discussed, a network graph structure can intuitively present the relations between concepts and the information of concepts at specific levels, which cannot be readily achieved by a list structure. Therefore, a network graph and a list are complementary, and the combination of these can maximize users’ data exploration experience.

The *Explore* function in the *Action* panel corresponds to the implementation of “Exploration” algorithm. It is used to retrieve related concepts given a concept in the panel, such as the concept “creativity” example in Figure 4.9. There are two types of knowledge concepts retrieval available: *General* and *Specific*, as introduced in Section 4.5. *General* is used for retrieving general concepts, while *Specific* tends to return specific concepts. In addition, a minimum step function is provided to restrict the minimum number of steps in retrieved results, where the steps mean the edges between the given concept and retrieved results (excluding intermediate concepts). The range of allowed minimum steps is from 1 to 5. Therefore, the larger minimum steps, the retrieved concepts tend to be further associated. This can be useful when close associations need to be filtered.

*Search Path* returns the paths connecting two knowledge concepts given the query. It provides two kinds of paths: *Professional* and *Basic*. The former tends to show longer paths where the concepts are involved in less domain, while the latter option returns shorter paths where the concepts tend to have general meaning and more domains are crossed, as introduced in Section 4.5.
Figure 4.9 The interface of the action panel and each specific action.
The third function is Cluster, providing clustering analysis on existing network concepts within the interface by grouping them into different clusters. K-means clustering algorithm is implemented for this functionality. As shown in Figure 4.9, the graph is divided into two groups automatically denoted by two different colors. Similar to Search Path, two options are provided to explore the connectivity at cluster level. In the example shown in Figure 4.9, the path between the cluster “creativity” and “design” is bridged by “innovation” and “prototyping”.

During B-Link’s development iterations, it was recognized that devices which are smaller than laptops or desktop computers but have touch screens such as mobiles and tablets, are more efficient and interesting for users to interact with visualized networks rather than normal LCD/LED screens (Holzinger et al., 2014b). Therefore, B-Link was redesigned to be compatible with smaller devices with good user experience. This compatibility is also beneficial for the following longitudinal study as participants are flexible to use different devices. Both desktop and mobile interface designs are shown in Figure 4.10.

![Figure 4.10 Desktop interface design (left) and mobile interface design (right)](image_url)
4.6.2 Evaluation methodology

Evaluation methodology for usability of BKD has been a challenge for researchers due to multiple factors such as the quantity of data and the difficulty of defining creativity (Jordanous, 2012). Recently, an emerging evaluation methodology called Multi-dimensional In-depth Long-term Case studies (MILCs) has been embraced by the growing community of researchers studying information exploration based creativity tools (Shneiderman and Plaisant, 2006; Valiati et al., 2008). In the term ‘Multi-dimensional In-depth Long-term Case studies’, the multi-dimensional refers to the use of multiple methods for performance evaluation, such as observations, interviews, surveys, and automated logging information; the in-depth indicates intensive engagement of researchers with expert users in the role of an assessment assistant; the long-term means the longitudinal studies which track expert users’ strategy changes due to proficient usage of a specific tool after necessary initial training; the case studies are detailed reports about a small group of individuals working on their own tasks in a normal environment (Shneiderman and Plaisant, 2006).

Seo and Shneiderman (2006) conducted three longitudinal case studies and an email user survey (57 samples collected) to focus on knowledge discovery in high-dimensional data, and the Hierarchical Clustering Explorer (HCE) tool was used during 6 weeks of user experience observation and interviews. Perer et al. (2008) used four long-term case studies with domain experts to investigate the performance of a social network analysis tool, SocialAction, which integrates statistics and visual exploratory features. To practically evaluate the application of ten information visualization heuristics from prior research, Vaataja et al. applied the MILCs method to the visualization tool development process and field study (Vaataja et al., 2016a).

To validate the proposed interactive network-based data exploration method, MILCs is modified to be used as the evaluation methodology. Specifically, case studies are conducted from two different points of view: quantitative and qualitative. A long-term in-depth case study is used as a qualitative way to assess the efficacy of the creativity model in detail, and expert users from diverse domains should be involved and provide feedback on user experience. It is also worthwhile to conduct quantitative user studies.
in order to obtain an overall evaluation, such as surveys. A questionnaire is designed and deployed in this study as the quantitative evaluation approach, which will be illustrated in Section 4.6.3. Additionally, logged usage data based on end-user interactions can provide information to verify end-user behaviors and usage (Vaataja et al., 2016b). Logged usage data means the data logged from a computational tool when users are interacting with the tool, such as time, data input, and operations. As a supplementary method, logged usage data assists design survey questions, and helps verify end-users’ feedback of the survey. In this study, the logged usage data includes users’ id reference (email address), logged-in date and time, users’ operations (all functionalities provided in the interface, such as the search button in “Exploration”), corresponding input (such as the input in the search box of “Exploration” table) and retrieved output (including retrieved concepts and paths).

4.6.3 Interviews and a questionnaire survey

The proposed MILCs methodology was applied to validate the usability of B-Link with two studies: an in-depth long-term interview, and a questionnaire. Specifically, the in-depth long-term interview study was conducted by recruiting eight academic researchers as expert users. All the expert users either held PhD degrees or were on the progress of PhD study, and they all had expertise in the areas covered by our dataset. The interview consisted of four sessions which lasted for 4 weeks. The interview in the first week was longer than those in the following three weeks.

The first session started with a brief introduction and explanation of the study procedure. Participants were told that data in the tool were from academic publications, and they were suggested to explore the data at their leisure for academic purposes. The primary study task required participants to freely use the tool for up to 10 minutes on the desktop website of B-Link, and then up to 5 minutes on the mobile version of B-Link with their smartphones. At the end of the session, each participant completed a brief questionnaire about the tool (for quantitative data collection) and engaged in a 10-minute interview about their experience after the questionnaire. During the exploration task, the participants were encouraged to report any observations about the tool, including errors,
surprising discoveries during exploration, or any inconvenience in use. The devices used for browsing both the desktop website and mobile version website were all from the participants themselves, and there was no restriction on browser brand and version.

After the first session, expert users were familiar with B-Link, and were able to use B-Link in their daily work environment. Therefore, in the following three sessions, expert users were not required to show up in a face-to-face interview, and they could choose to give feedback in phone calls. They were just required to use B-Link in their research work every week, and report their usage weekly, such as frequency, problems encountered, and insights generated.

As an alternative quantitative way to validate B-Link, the questionnaire survey was distributed to users from different backgrounds, and data was collected in terms of HCI and functionality. The questionnaire survey was designed as webpages and a hyperlink was embedded in the tool so that it could be easily accessed when users were trying B-Link. Questionnaires were circulated by group emails to undergraduates, postgraduates, PhD students and university researchers. Each questionnaire consisted of three parts (18 questions in total): basic information (5/18), human-computer interaction (5/18) and functionality evaluation (8/18). It is worth mentioning that partial questions in functionality evaluation were designed on-the-fly, which means part of logged usage data were collected including some keywords from users’ queries and corresponding retrieved results were randomly quoted in the designed on-the-fly questions, including the questions No. 11, No.12 and No.14 in Table 4.2. This on-the-fly design is useful for evaluating how good a specific functionality (and associated algorithm) is, as questions become specific rather than abstract.

In question No.11, each user was asked to evaluate the relevance and interestingness of three chosen pairs of phrases according to the user’s Explore results. The purpose is to measure the semantic difference of given two phrases in user’s generated network graph. Relevance is a common measurement in natural language processing to determine semantic relatedness between two lexically expressed concepts, which is also called semantic relatedness, similarity, and semantic distance in other literature (Budanitsky
and Hirst, 2006). Specifically, the large semantic distance of two phrases means their relevance is low, and vice versa. Interestingness measure is a widely used method in association rule mining (Paul et al., 2014) in order to discover implicit relationships between concepts. Though it is subjective for users to rate interestingness as a qualitative measure in the survey, here a basic criterion is proposed based on implicit association: the association can be too weak to be observed if the semantic distance between two concepts is too far, thus the interestingness is not strong; similarly, the association can be too strong to spark interest if the semantic distance is too close, thus the interestingness is not strong as well; the association can be implicit and interesting only if the semantic distance is median. Since the range of semantic distance cannot be quantified in the survey, ‘median’ is subject to the user’s estimation. Three pairs of concepts, which were randomly chosen from a user’s exploration results in Explore, were presented to each user for rating relevance and interestingness respectively. The two measures relevance and interestingness are complementary to evaluate the semantic distance between each pair of concepts, since too high or low relevance can lead to low interestingness.

The twelfth question aims to evaluate the functionality of Search Path from the perspective of novelty and usefulness. Since “Search Path” is a crucial step to find bisociations during the discovery process, it is designed to be evaluated by users from the perspective of creativity. Plucker et al. (2004) define creativity from the perspective of novelty and usefulness, which are then employed to evaluate creativity by using the FBS (Function-Behavior-Structure) model and the SAPhIRE model by Sarkar and Chakrabarti (2011). All the words describing novelty and usefulness in the question are selected from O’Quin and Besemer (1989)’s revised version of the Creative Product Semantic Scale (CPSS) for creativity evaluation in survey, which helps users understand how to evaluate the novelty and usefulness of a specific path. Two paths, which were randomly chosen from a user’s retrieval results, were presented to each user for rating their novelty and usefulness respectively. The combination of the two measurements evaluates the creativity of retrieval paths.
<table>
<thead>
<tr>
<th>No.</th>
<th>Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Your email address</td>
</tr>
<tr>
<td>2</td>
<td>Your social role (in a drop-down list): Academic professional/ Student/ Industrial technician/ Service industry worker/ Others</td>
</tr>
<tr>
<td>3</td>
<td>Your current education level: Bachelor/ Master/ Doctor</td>
</tr>
<tr>
<td>4</td>
<td>Your academic background: Art/ Business/ Engineering-Design/ Engineering-others/ Medicine/ Natural Science/ Social Science/ Others</td>
</tr>
<tr>
<td>5</td>
<td>Tick the tools you have used: Google Map/ WikiLinks/ Others</td>
</tr>
<tr>
<td>6</td>
<td>Is it easy for you to understand how to use our website service?</td>
</tr>
<tr>
<td>7</td>
<td>Do you have difficulty in finding the right button to proceed?</td>
</tr>
<tr>
<td>8</td>
<td>Is our website service fully compatible with your device and browser?</td>
</tr>
<tr>
<td>9</td>
<td>Did you try clicking nodes in the network map instead of typing in the search-box?</td>
</tr>
<tr>
<td>10</td>
<td>Compared with a traditional search with a results list, do you think the network search with network graph is better? [rate in a 5-point Likert scale]</td>
</tr>
<tr>
<td>11</td>
<td>According to your Explore results, please evaluate the following three pairs of phrases in term of their relevance and interestingness. Note: ‘relevance’ examines the semantic meaning distance (the larger the more relevant); the criteria for interestingness is: semantic far or close is less of interest, while the median distance is more of interest.</td>
</tr>
<tr>
<td>12</td>
<td>Please evaluate the following two paths in term of their novelty and usefulness. Note: a path of high ‘novelty’ tends to be fresh/ original/ revolutionary versus overused/ common/ customary; high ‘usefulness’ refers to feasible/ appropriate/ effective.</td>
</tr>
<tr>
<td>13</td>
<td>Do you think your network map is properly divided into groups ?</td>
</tr>
<tr>
<td>14</td>
<td>Are you inspired by the following path between clusters?</td>
</tr>
<tr>
<td>15</td>
<td>Did you try the feature “Minimum Steps”? If yes, please rate it.</td>
</tr>
<tr>
<td>16</td>
<td>Did you try to change the features “General – Specific” or “Professional – Basic”? If yes, please rate it.</td>
</tr>
<tr>
<td>17</td>
<td>Did you try all these features: Explore, Search path, Cluster and Search Path between clusters ?</td>
</tr>
<tr>
<td>18</td>
<td>Please comment if you have any opinion on B-Link (Optional)</td>
</tr>
</tbody>
</table>
As the last step of discovery, Cluster explicitly helps users find the possible bisociations by presenting the bridging concepts between clusters. Users then can use these bisociation graphs to generate ideas. Since users’ idea generation finalizes here, the evaluation measurement question is straight forward to ask whether they are inspired from paths between clusters. One path selected from a user’s Cluster retrieval results was presented in the question No.14.

In these three questions (No.11, No.12 and No.14), users were asked to rate the corresponding measurements using a 5-point Likert scale regarding each data (a pair of concepts/ path/ path of clusters) presented in the question. The other questions in functionality evaluation are designed to check users’ involvement in the tool and other minor functionalities such as minimum step and clustering.

4.6.4 Results and discussion

A. Interviews

In the first session of the interview study, all eight expert participants used the tool actively, including a substantial number of unique queries in their professional research fields. No participant expressed frustration over unintended queries, indicating that B-Link’s design supports rapid and expressive query formulation. Based on verbal feedback and observations from the first session, they all appeared to find satisfaction in using the tool, and all of them explored its use for the full 15 minutes. Despite the high level of domain familiarity, every participant found novel items of interest, based on their own self-reports. Participants were inspired by the serendipitous experience of encountering novel information along with associations to the content which was familiar and meaningful to them.

Taking one expert participant’s case as an example, this expert has an academic background of computing, so he typed the phrase “deep learning” in the search box and started trying “Explore” in both options of “General” (concepts generated are more
general as introduced in section 4.5) and “Specific” (concepts generated are more specific as introduced in section 4.5), each of which gave him the top ten results in the first page as shown in Table 4.3. According to his judgment, 2 out of 10 concepts (highlighted in yellow) generated with the “General” option were largely related to deep learning in the domain of computing science, and the others were much more related to human learning in the domain of social science. 6 out of 10 concepts (highlighted in yellow) generated with the “Specific” option were directly related to deep learning in the domain of computer science. Although the other two (highlighted in blue) were indirectly related, the results make sense as deep learning techniques have been widely used in image processing research, such as image recognition. This coincides with the design of our algorithms “Exploration – General” and “Exploration – Specific” as described in section 4.5, since “General” tends to retrieve concepts containing general meaning while “Specific” returns specific concepts, and cross-domain concepts are retrieved from both algorithms as well. As “deep learning” has multiple cross-domain meanings, most of the results from “General” fall into education domain rather than computer science and their lexical meanings are relatively general, such as education and online learning. On the other hand, most concepts from “Specific” have specific meaning in computer science (only one out of ten, “adult student”, belongs to education), such as convolutional neural network and image annotation. Furthermore, “deep learning” itself is a general concept which is commonly used in media but less used in machine learning papers which rather like to use deep neural network instead”, as quoted from the expert participant, which further verifies the functionality of “Specific” as deep neural network appears in the results. The expert participant summarized that “Exploration” assisted him in creating a knowledge set about “deep learning” with various degree of association. He mentioned as well that the network graph helped him recognize that “semantic gap” (highlighted in orange) was a concept belonging to the domain of computing as it is connected with “image feature” and “image annotation” (see Figure 4.11), which was interesting and surprising to him as he had not known much about “semantic gap” before in his research. As a result, he further explored “semantic gap” and reported that “Explore” helped him quickly understand this concept.
from a macro perspective which motivated him to come up with research ideas of integrating “semantic gap” into his research.

**Table 4.3 Results of “Exploration” of “deep learning”**

<table>
<thead>
<tr>
<th>List</th>
<th>General</th>
<th>Specific</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>convolutional neural network</td>
<td>convolutional neural network</td>
</tr>
<tr>
<td>2</td>
<td>restricted Boltzmann machine</td>
<td>restricted Boltzmann machine</td>
</tr>
<tr>
<td>3</td>
<td>online learning</td>
<td>unsupervised feature learning</td>
</tr>
<tr>
<td>4</td>
<td>distance education</td>
<td>contrastive divergence</td>
</tr>
<tr>
<td>5</td>
<td>e-learning</td>
<td>adult student</td>
</tr>
<tr>
<td>6</td>
<td>distance learning</td>
<td>deep belief network</td>
</tr>
<tr>
<td>7</td>
<td>community of inquiry</td>
<td>deep neural network</td>
</tr>
<tr>
<td>8</td>
<td>blended learning</td>
<td>image feature</td>
</tr>
<tr>
<td>9</td>
<td>social presence</td>
<td>image annotation</td>
</tr>
<tr>
<td>10</td>
<td>education</td>
<td>semantic gap</td>
</tr>
</tbody>
</table>

**Figure 4.11** “semantic gap” is connected with “image feature” and “image annotation”
After trying “Explore” different concepts, this expert switched to “Search Path” starting to search the path between “deep learning” and “design” as he was wondering about the potential applications of deep learning techniques in the design field, while keeping the previous retrieved results in the network graph. With the default option (“Professional”) provided, he found “optimization” was a significant joint connecting “design” and “deep learning” as shown in Figure 4.12, which inspired him with the idea that deep learning could be potentially used for the optimization of a design. A consultation is made in order to validate the creativity of this idea. According to the consultation result with experts in design optimization field, this idea could be novel as deep learning techniques had not been used in design optimization (at the time of this study), and could be useful as well since there is a direct connection between deep learning and optimization. As another example of bisociative knowledge discovery, he came up with another idea that deep learning may also be used for design education, when noticing “education” in the network graph had both connections with “design” and “deep learning”. Both examples indicate that ideas were largely sparked in “Search Path” by comprehending retrieved paths and combining two concepts in the graph. The expert participant concluded that “Search Path” enabled him to break cross-domain barriers and generate new multidisciplinary ideas which could be creative.

![Figure 4.12 The links between “design” and “deep learning”](image-url)
He also reported that the option “Basic” was less useful than “Professional” due to the shorter length of paths and more general concepts retrieved from “Basic”. Eventually the expert participant tried “Cluster” dividing all generated concepts in the network into three groups, which delivered a knowledge map of three domains including “deep learning”, “design” and “human learning”, according to the participant’s comprehension. He reported the satisfaction on the clustering results as concepts from the network graph were correctly clustered and links between clusters were clearly shown up when retrieving their paths.

In the following three sessions, despite reporting occasional technical issues and giving suggestions, most of them (7/8) reported that they were inspired by using the tool especially when they were getting stuck in generating ideas or solving problems, which was different from the situation they had in the first session. They thought B-Link was more effective when getting stuck than used in an open-ended experiment environment in which participants could hardly go deep with a specific topic. B-Link could be a useful tool for engineering design projects, according to the feedback from one of the expert participants who is a course leader of a module called Engineering Design Project. He tried several concepts related to “spirometer”, which was one design task from his module. He mentioned that the results showed a map of knowledge about spirometry and flow rate measurement methods when exploring keywords “spirometer” and “flow meter”, and then gave inspiration for designing a spirometer when searching the path between “spirometry” and “airflow rate”.

B. Questionnaire survey

Forty-eight questionnaires were successfully submitted by the users of B-Link tool in this experiment. Users’ basic information, including social role, current education level and academic background, are collected from the first five questions and shown in Figure 4.13. In our survey of HCI, 82% of participants thought it was easy to understand how to use B-Link, 96% of participants reported the website of B-Link was fully compatible with their devices and browsers. Nearly 46% participants did not try or did not know that they could click nodes in the network graph instead of typing in the text-
free search box, which indicates the space to improve. Since question No.10 involves rating on a 5-point Likert scale, the mean value ($\mu$) and standard deviation ($\sigma$) of its results were calculated. The results indicated that the network search method in B-Link was rated more interesting ($\mu=4.8$, $\sigma=0.42$) compared with a traditional search method such as Google Search.

![Pie charts showing social role, education level, and academic background of participants in B-Link.]

Figure 4.13 (a) Social role of participants; (b) Current education level of participants; (c) Academic background of participants.

In our survey of functionality validation, partial questions were designed on-the-fly. They would not be shown in users’ questionnaires if users did not try corresponding actions in B-Link’s Action panel. Therefore, the logged usage data was used to verify if users had followed the whole bisociative knowledge discovery process by trying all the three actions. Once those end users who submitted questionnaires but had not tried all the three actions were detected, their questionnaire results were excluded for further analysis. This will not introduce bias into the result analysis toward positive feedback,
because survey participants were told to try all three actions in the panel before giving feedback. Eventually, participants’ rating data of evaluating the bisociative knowledge discovery from five aspects were processed by calculating the mean value (μ) and standard deviation (σ) of the ratings of three key questions (No. 11, 12, and 14). The results are presented in Table 4.4, and are illustrated in Figure 4.14.

Table 4.4 Rating results summarization

<table>
<thead>
<tr>
<th>Metrics</th>
<th>μ</th>
<th>σ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relevance</td>
<td>4.3</td>
<td>0.46</td>
</tr>
<tr>
<td>Interestingness</td>
<td>3.55</td>
<td>0.87</td>
</tr>
<tr>
<td>Novelty</td>
<td>3.1</td>
<td>1.1</td>
</tr>
<tr>
<td>Usefulness</td>
<td>4.2</td>
<td>0.59</td>
</tr>
<tr>
<td>Inspiration</td>
<td>3.8</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Figure 4.14 Rating results visualization

Relevance and interestingness are rated on the basis of retrieved results from “Explore”. As can be seen, the mean value (μ=4.3) of relevance is high, which means the semantic
distance of retrieved concepts is relatively shorter. It indicates that the tool is capable of retrieving associations and the amount of far associations seems lower than close associations. However, the backend logging data from survey participants shows that the frequency of “minimum step = 1” (the default setting) appeared in queries is much higher than other options (minimum step = 2/3/4/5), accounting for 42% of the all options. The percentage of other options appeared in queries decreases as steps increases. As introduced in section 4.6.1, the larger minimum step the further associations can be retrieved. Therefore, it is reasonable to believe that the high usage of one step association contributes to the high relevance value, and the amount of far associations could be higher if larger steps were used in queries. As its complementary measure, interestingness has a lower mean score ($\mu=3.55$) than relevance, which is reasonable since relevance is proportional to semantic distance while interestingness is more related to median semantic distance. Nevertheless, the mean value of interestingness is larger than 3, indicating that the associations (no matter whether they are far or close) retrieved by “Exploration” algorithm is able to spark users’ interests.

Novelty and usefulness are the measurements on creativity of retrieved results from “Search Path”. The mean value of novelty ($\mu=3.1$) is slightly above 3 with high standard deviation ($\sigma=1.1$), which means the retrieved paths tend to be novel but the degree of novelty may vary a lot. The high standard deviation could also be interpreted as the high variation of participants’ criteria on novelty, which needs to be mitigated in future research. On the other hand, the mean rating of usefulness is much higher than novelty, indicating that the retrieved paths are very useful to participants’ creative thinking. The overall mean rating for creativity is 3.65 by averaging the mean value of novelty and usefulness, suggesting that B-Link is capable of discovering creative knowledge by presenting associative paths. Since there is a big difference between the mean value of novelty and usefulness (22% difference), a possible explanation could be that it is difficult to recognize the novelty of a path consisting of concepts without placing the path into a specific application scenario, such as problem solving or idea generation. This speculation is further examined in the case study illustrated in Chapter 4.7.
The survey also showed that participants were inspired by the paths connecting clusters, according to the positive mean value ($\mu=3.8$) of inspiration. Since “Cluster” is the last step in the action panel and according to the five metrics evaluation results, it can be concluded that B-Link tool is effective to inspire participants by retrieving interesting concepts and useful paths along with its interactive data exploration approach.

Based on the positive interview records and questionnaire data, users felt inspired and perceived a certain level of creativity attainment, which indicates that the proposed model can be considered as effective. However, some limitations are observed from the usability study as well. As a new tool with uncommon exploration methodology, some participants spent more time getting used to the tool but were still slightly confused on the usability of this tool. They subconsciously compared B-Link to existing search tools supported by more extensive resources such as Google Scholar, which has a negative effect on a direct creativity tool validation as the available data for retrieval in B-Link is much limited compared to search engine. Another reason for users’ confusion could be the lack of target tasks as this user study was open-ended for participants, sometimes they might not know what to explore and cannot go deep with their exploration. This concern is eliminated in the design case study introduced in the next section.

Challenges are identified in this usability study as well. Even though the usability of three main functionalities are investigated in the interview and survey, the effectivity of each algorithm is not quantified for examination. For instance, it would be good to do a benchmark with other association retrieval algorithms or tools by measuring the semantic distance of retrieved pairs of associations. Despite above, it is noticed that users’ exploration is limited by the homogeneous data in B-Link. It would be interesting and useful if a variety of media types including both textual and non-textual data are included and mixed in the database, and if the database is flexible to dynamically update multi-type collections (Kairam et al., 2015). Chapter 5 discussed the “bisociation” of images in order to mitigate part of this concern.
4.7 Evaluation in a design case study

This research further evaluated the effectiveness of the proposed model in a design case study which requires bisociative knowledge discovery. Even though the constructed database covers a variety of domain knowledge concepts, design related domain knowledge concepts are added to the database. This is achieved by capturing the raw texts from well-known design websites such as Yanko Design\textsuperscript{7}, Red Dot Design Award\textsuperscript{8} and iF World Design Guide\textsuperscript{9}. These websites contain the latest design related information such as news, innovative products and reports of design trend. These text resources potentially strengthen the knowledge domain of design by introducing novel design concepts and relations into the database, which eliminates the bias in the design case study.

The task was to design a spoon with a variety of ideas conceptually. Five minutes were given for explaining the use of the provided ideation tool, and an additional ten minutes were then given for recording generated ideas on white sheets including simple sketch and description. Participants were required to meet two requirements: the spoon can be at least used to assist in eating soup; the more ideas, the better. The participants were told that this was an open-minded design task, their idea could break through the classic shape of a spoon.

In the case study, there were two groups of participants completing the ideation task. One is the treatment group, participants in this group used our developed semantic ideation network B-Link to augment their capability of ideation. Another control group had no access to the developed ideation tool but was allowed to use other tools to help with natural brainstorming, including Google Search, Wordnet, and ConceptNet, which are the common tools for information retrieval benchmark (Han et al., 2016). Each group consisted of twelve participants who were engineering students specializing in

\textsuperscript{7} Yanko Design website: https://www.yankodesign.com/
\textsuperscript{8} Red Dot Design Award website: https://www.red-dot.org/
\textsuperscript{9} iF World Design Guide website: https://ifworlddesignguide.com/
different disciplines, and only two in each group had a background of design engineering. Each group is balanced with participants’ education background.

For participants of the treatment group, inspirations can be obtained by retrieving the network graph with two main functions: “Exploration” and “Search Path”. “Exploration” provides far associations from multiple domains when given a keyword or phrase. “Search Path” shows association paths between two keywords or phrases given by a participant. All results can be shown in a semantic network graph which is convenient for users to understand causality between keywords, which stimulates inspirations.

At the beginning of the task, a brief introduction and explanation were given. The participants in the treatment group were taught about how to use our developed B-Link tool even though it was already user-friendly to use. Similarly, the participants in the control group were instructed on how to use ConceptNet and WordNet. The participants in the control group were independent of choosing a tool for the task or even without a tool, as this allows participants to achieve their best performance in their most comfortable way. All participants were given white sheets to document their ideas, which prompted participants to both sketch and describe their ideas. Ideation sheets were collected and de-identified for data analysis.

4.7.1 Idea evaluation

A standard set of metrics, which are accepted and employed in design science literature for the purpose of evaluating ideation outcome, were utilized for the analysis of collected data, which include: novelty, quality, variety and quantity. They were first introduced by Shah et al. (2003) and then adapted by Chan et al. (2011). Novelty is a measure of the uniqueness of a design solution, and is defined as the degree to which a particular solution type is unusual within a space of possible solutions. Quality is a measure of the feasibility of a developed design or system in question to satisfy design requirements. For example, the assessment of quality might be to estimate how reasonable and convenient the spoon can be used to eat soup. Variety measures the degree of diversity of the explored solution space during ideation. The generation of similar ideas indicates a lower variety, which means a lower probability of finding better
ideas among the total possible solution space. Quantity is a direct and basic measure of the number of ideas produced. Specifically, the quantity was calculated based on the total number of ideas generated by each individual in each group. These four metrics are usually measured independently, for example, if two ideas from the same participant are very similar to each other, they are accounted as two in terms of quantity, but the variety of the group of ideas is relative low.

Consensual Assessment Technique (CAT) was utilized for the measurement of novelty, quality and variety. This technique is widely used for assessing the performance of creative work samples based on knowledgeable raters’ intuitions about what the metrics mean in a field (Amabile, 1983), and it gives the advantage of capturing aspects of creative work that are difficult to judge or define objectively. In this technique, two raters independently perform subjective ratings of every solution and then evaluate the levels of the consensus reached across judges. The two raters for our case study were experts in the product design field, having completed at least three years of design engineering product design coursework. The level of rater expertise in our study is comparable to other research using CAT (Daly et al., 2016).

After all ideation sheets were collected from both groups, they were presented in front of the two raters. With CAT, the two raters evaluated all ideas in terms of novelty, quality, variety and quantity independently. During the evaluation, the raters did not know the ideas were created in two groups with different ideation approaches. 75 ideas generated were presented on papers in a different order for each rater. Consistent with CAT, the raters were asked to score each concept using a scale from 1 to 7 (where 1 is the “lowest” of a category – lowest novelty, lowest quality, and 7 is the “highest”) based on their understanding of the design field and the estimation of ideas relative to one another. The raters completed several rounds of scoring when considering exclusively one of the two metrics (novelty and quality). In each rating task, the raters were given the full range of ideas placed in a random order in the first round of rating, and were instructed to place these ideas into piles labeled from 1 to 7. From the second round, as raters already had a clearer mind of the scale and all ideas, they rearranged all ideas again by moving ideas into different piles as needed until there were no more changes.
Each rating task ended when the rater thought all ideas had been well placed into appropriate piles. Overall, each rater scored the 75 ideas generated by all participants in two groups, in terms of novelty and quality.

**Table 4.5 Calculated adjacent agreement percentage and Cronbach’s coefficient**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Adjacent agreement</th>
<th>Cohen’ Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Novelty</td>
<td>80.0%</td>
<td>0.534</td>
</tr>
<tr>
<td>Quality</td>
<td>85.3%</td>
<td>0.519</td>
</tr>
<tr>
<td>Variety</td>
<td>91.7%</td>
<td>0.893</td>
</tr>
</tbody>
</table>

The variety scores were completed in a similar way with the CAT approach. The raters evaluated the variety of the whole set of ideas generated by a single participant on a seven-point scale. The piles in this rating task shown the variety of each individual’s set of ideas on a scale from 1 (not varied) to 7 (most varied). The set size of ideas could be different as each participant generated a different number of ideas. The raters scored 24 idea sets from two groups in total, in term of variety.

In the final rating round, each individual’s idea set was assessed based on the number of ideas generated in order to evaluate quantity (also known as fluency). The rating work was conducted in a separate time period for each round. The consensus between raters on each independent measure was evaluated based on a computed percent of adjacent agreement, which is proposed by Stemler (2004). For each scale with seven levels, a consensus was considered to be reached for one same rating task where a score was given if the score given by one rater did not differ by more than one point above or below the score given by another rater. As a result, the percentage of adjacent agreement between raters for novelty was 80%; for quality, the percentage was 85.3%; and the percentage of variety was 91.7%. All the adjacent agreements are all larger than 75% (fall in the fourth quarter), which show high robustness of the evaluation scores. To estimate consistency between raters, Cohen’s Kappa value was calculated for each metric as well, which are listed in Table 4.5. When calculating Cohen’s Kappa, the scale
was transformed from the original seven scales to three scales. Specifically, a score of 1 or 2 falls into the category “Low”, a score of 3, 4 or 5 falls into category “Normal”, and a score of 6 or 7 falls into category “High”. As can be seen from Table 4.5, all values are greater than 0.50, which is typically considered as acceptable and reliable for the scoring results based on the CAT approach.

4.7.2 Results

The average of two raters’ scores for each rating was used in the statistical analysis. A normality check was undertaken first using the Shapiro-Wilk’s W test across both groups in two sessions, and all the p values obtained were bigger than 0.05, which meant that our data did not fall into normal distributions. Then the independent Mann-Whitney U-test was chosen to interpret the coded data. Examples of high and low scores in terms of the metrics of novelty and quality are introduced in Table 4.6. The average CAT scores of ratings for each experimental group in terms of novelty, quality and variety are shown in Figure 4.15. For novelty and quality of generated ideas, there is no significant difference between the treatment group and control group (p=0.147 and p=0.433, respectively). However, the treatment group performed significantly better than the control group in terms of idea variety (p=0.023). The average number of ideas generated for each group in each session is shown in Figure 4.16, it indicates that the treatment group generated more ideas than the control group significantly (p=0.046).
Table 4.6 Examples of low and high scoring ideas

<table>
<thead>
<tr>
<th>Metric</th>
<th>Low score example</th>
<th>High score example</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Novelty</strong></td>
<td>- This is a utensil used to eat liquid foods</td>
<td>It is a straw-spoon inspired by B-Link (explained in the example). With normal functionality of spoon, it can also be used as a straw for drinking.</td>
</tr>
<tr>
<td></td>
<td>- You grab it by the handle and pick up food up with the bowl</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- It can be made of different materials: wood, metal, plastic, etc.</td>
<td></td>
</tr>
<tr>
<td><strong>Quality</strong></td>
<td>The color of the spoon can change according to its temperature:</td>
<td>- Depth: 5 – 30 mm (based on human’s mouth size)</td>
</tr>
<tr>
<td></td>
<td>- Low temperature: blue</td>
<td>- The ergonomically designed handle which is easy to grasp and heat resistant.</td>
</tr>
<tr>
<td></td>
<td>- Normal temperature: green</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- High temperature: red</td>
<td></td>
</tr>
</tbody>
</table>
Figure 4.15 Results of CAT scores for ideas generated in two groups

Figure 4.16 The average number of ideas generated for a single participant

4.7.3 Discussion

As it can be seen from the evaluation results in Figure 4.15 and Figure 4.16, the treatment group outperformed control group with greater variety and quantity, which means the proposed bisociative knowledge discovery model shown better performance by producing more ideas (by 48% higher quantity) with high diversity (by 75% wider variety). To further verify the contribution of algorithms in the model, the expert raters
reviewed the treatment group’s ideas written down in ideation sheets, they found most of the ideas were the results of combining concepts which appeared in their search results using the B-Link’s “Exploration” and “Search Path” functions. This means within the limited time, our approach provided more effective inspirations for the participants quickly compared to other tools used by the control group.

Figure 4.17 “straw” was found in the network (left) and the idea was illustrated (right)

For example, when searching “spoon” with two steps opted in “Exploration”, the “spoon -> coffee -> drink -> straw” was retrieved as one of the results appeared in the semantic graph. Then an idea came up by combining “spoon” and “straw” and was illustrated by a participant as shown in Figure 4.17. This example additionally indicated that the proposed algorithm has the capacity of retrieving useful far associated concepts for users. In contrast, from the observation of participants’ ideation sheets, it is found that it happened more frequently in the control group that participants tended to stick on similar ideas which fell into the same thinking direction. For instance, there was one participant in the control group came up with four ideas of designing a spoon which looked like banana, palm, carrot and cat’s claw respectively. In the treatment group, benefiting from our weight normalization algorithms (localization and globalization), our model is able to retrieve concepts from multiple domains upon a single request, and
then the variety of generated ideas would be wide if the participants utilized these retrieved results.

However, the results revealed that the BKD model did not contribute much more in terms of idea novelty and quality compared to the approach in the control group. Several possible factors may explain the similar performance of novelty between two groups. Among all the ideas generated in the study, only a few ideas which were evaluated as high novelty appeared in both groups were found, which means that few participants in the control group were able to reach the same level of creativity as well as the treatment group did. Daly et al. (2016) also indicated that alternative idea generation methods might work to promote creativity to the same degree but in different ways. Another interesting finding was that even though the participants in the treatment group had the high possibility to find the node “leaf” (as it appears in top-10 results when retrieving with the option “General” and “Minimum Steps = 2 & 3”) when using our developed model, only one participant wrote down the idea of combining “leaf” into the spoon design. It indicates that there is still a gap between receiving inspiration and comprehending inspiration, which remains for further studies. It is also explored about the reason for the treatment group’s similar results in term of ideation quality compared with the control group. As quality means how an idea meets requirements and how the idea can be implemented in a realistic way, it is found that those ideas which fell into low quality either did not completely comply with requirements or were unspecific to implement them. Taking one participant’s idea as an example, the idea was “To have a spoon that can clean itself to avoid wetting our hands” which was not clear enough for a spoon design.

It is of interest to notice that “Exploration” is able to expand a knowledge graph from a given concept to other domains, which is beneficial for “Search Path” to select a more interesting pair of concepts. The results of “Search Path” contribute to idea generation, which is the initial step in the proposed data-driven cycle, as well as visual conceptual blending in the second step. As discussed in Chapter 5, visual conceptual blending concerns about two semantically distinct concepts, which can be easily retrieved from
“Search Path”. In this way, “Search Path” algorithm bridges the data-driven cycle from idea generation to visual design conceptualization smoothly.

4.7.4 Contribution to the data-driven cycle

The study presented in this chapter aims to explore creative knowledge from various data sources, and demonstrates the effectiveness of proposed methods in idea generation, which corresponds to the transformation from meta-data to creativity. As indicated in this chapter, cross-domain knowledge is essential for improving creativity in conceptual design. Data mining and visualization techniques are effective ways to achieve such a transformation when dealing with semantic data. The main contribution of this chapter is to show how semantic data is able to produce creativity and inspire designers in idea generation. It serves as the initial steps of the data-driven cycle, by covering semantic data collection and pre-processing, data exploration and idea generation.

4.8 Conclusion

In this chapter, creativity knowledge discovery is discussed within the field of computational creativity by differentiating it from traditional knowledge discovery in databases. By applying bisociation to creative knowledge discovery, bisociative knowledge discovery (BKD) is becoming a popular research topic. This research investigates the state-of-the-art research of BKD, and by taking advantage of network’s data structure and visualization capability, a novel model is proposed for integrating data mining and dynamic data exploration as a single tool in BKD so that users are able to not only obtain bisociations from the machine side but also provoke or ‘spark’ creative ideas from the human being side. In this proposed model, real-time BKD algorithms and network graph based human-computer interaction (HCI) are two layers working together to guide discovery during the discovery process.

To demonstrate the network-based computational creativity model, B-Link has been developed as a prototype tool which is driven by constructed network data and shown as a network knowledge graph for users’ interaction. Furthermore, an applicable validation methodology, the Multi-dimensional In-depth Long-term Case studies
(MILCs), is introduced and applied in order to validate the capability of the proposed model. The longitudinal interviews and online questionnaire surveys are conducted in MILCs while logged usage data is analyzed to understand users’ behaviors and verify submitted questionnaires. The case study interview results indicated that all expert users are satisfied with the usability of B-Link, and the survey verified the effectiveness of the tool from five metrics. This suggests that B-Link is able to effectively guide and prompt users’ inspiration and aid bisociative knowledge discovery.

To further evaluate how the model performs in a real-world design activity, a design case study is conducted. In the design task, B-Link is employed as a design ideation tool for augmenting the participants’ creativity so that the participants are expected to produce more creative ideas in terms of novelty, variety, quality and quantity. Results of the design study demonstrate again that our model effectively improved the overall creativity of participants’ design within a limited time.

In summary, the two studies indicate that the network-based BKD model is capable of discovering bisociative knowledge and improving users’ creativity when interacting with network graphs, which is the main contribution of this chapter. Even though it has been demonstrated that the proposed model is effective to find creative associations between concepts, namely bisociations, the scope of bisociative knowledge discovery discussed in this research is mainly limited within concepts representing knowledge. For future work, a heterogeneous network should be discussed for BKD in a wider scope in which knowledge can be represented by different media types including both textual and non-textual data.
Chapter 5. A Generative Model for Visual Conceptual Blending

This chapter investigates a theoretical creativity model called conceptual blending, from the perspective of artificial intelligence. Considering the limited research on blending concepts in a visual way due to the difficulty of image manipulation, this research proposes a visual concept blending model for creative design based on computational creativity. With the state-of-the-art technique in machine learning, generative adversarial networks, the proposed generative model is able to synthesize two semantically distinct concepts, such as spoon and leaf as demonstrated in a case study, by generating concept-blended images. The case study shows the capabilities of the model in terms of variety and novelty.

Some of the work described in this chapter has been previously published as:


5.1 Conceptual blending

5.1.1 Introduction

The theory of conceptual blending, also known as conceptual integration, was initially developed by Gilles Fauconnier and Mark Turner (1998), and motivated as a specific cognitive phenomenon, such as metaphor, analogy, and reasoning. In the original theory, conceptual blending takes two knowledge structures (the mental spaces) as inputs, and generates a new one (called blend space) according to a given mapping. Mental spaces are dynamically constructed during a discourse, e.g. conversation, to involve relevant concepts. From a symbolic perspective of artificial intelligence, a mental space could be represented as a semantic network for data analysis, in which nodes denote identifying concepts corresponding to the elements of a mental space (Pereira, 2007).

The mappings between two mental spaces are called cross-space (or cross-domain) mappings. They connect elements of one mental space to others in another mental space. It should be noted that a mapping does not have to be one to one. One element may have more than one counterpart or no counterparts. A mapping may be established by different mapping rules, such as identity and analogy. According to Pereira (2007), it takes three steps to generate a blend:

- **Composition**: This is a selective projection process in which some elements from the inputs are “fused” and “made” as new elements which did not exist in the separate inputs. “The paired inputs are projected onto the blend as well as other surrounding elements and relations (Pereira, 2007).”

- **Completion**: This is a process of filling out of a pattern which stems from the matches of structure projections in the long-term memory of mental spaces (Grady et al., 1999). According to the background knowledge of frames, cognitive and cultural models, this kind of composite structure projection can be viewed as a part of a larger self-contained structure in a blend space.
• **Elaboration**: The structure in the blend may continue to be elaborated. According to its own emergent logic, the cognitive work within the blend can keep running and simulate the event forward.

Take the “surgeon-as-butcher” as an example, which is discussed as a metaphor by Grady et al. (1999). The input space of the surgeon contains the concepts “surgeon”, his “scalpel”, “patient” and so on. Another input space of the butcher has the concepts “butcher”, and relevant “cleaver” and “animal”. Therefore, mappings can be “surgeon - butcher”, “cleaver - scalpel” and “patient - animal” between two input spaces. Correspondingly, the shared generic space may have concepts “professionals”, “cutter” and “target”, while the blend space could emerge new knowledge structure, such as “professional - cutting tool - target object”.

The Blend maintains partial structure from inputs, which is defined as *generic space*, and has an emergent structure of its own. As shown in Figure 5.1, the circles represent mental spaces; black dots denote elements in the spaces; solid lines are the mappings between inputs; and dashed lines indicate the correspondences among elements in the four spaces. In the blend space, hollow dots are drawn to represent emergent structures.

![Figure 5.1 The four-space model of conceptual blending (Fauconnier & Turner, 2002; Li et al., 2012)](image-url)
Fauconnier (2001) emphasizes that conceptual blending cannot be replaced by analogy. Instead, the cross-space mappings in the four-space model are most often analogical, and the projections between mental spaces in a network (e.g. input to blend, or generic to input) are also an analogical type of structure-mapping. Furthermore, much of the power of analogy and metaphor originates from the fact that the source and target mental spaces may belong to superficially different conceptual domains. However, such cross-mappings are not restricted to analogy in the usual sense. In addition to structure and inference transfer, conceptual integration networks provide a coherent, integrated constitution of novel forms of thought and action. To further illustrate the hidden complexity of such integrations, Fauconnier provides successive examples of blends of using a computer mouse, including object blend, arrow, and mouse blend, grasping and moving blend, and containment blend. As shown in Figure 5.2, given the mappings from the physical world in terms of objective properties, mouse manipulations and screen illumination are connected to the grasping and moving of three-dimensional objects.

![Figure 5.2 Connections in the containment blend (Fauconnier, 2001)](image-url)
5.1.2 Theoretical development

It is agreed by Pereira (2007) that conceptual blending as a framework can be considered for use in artificial intelligence, and more specifically for computational creativity. However, there is no proposed method for distinguishing whether a blend is or is not creative, although eight optimality principles – human scale, topology, pattern completion, integration, vital relations, unpacking, web, and relevance – were proposed as quality measures (Fauconnier and Turner, 2002); no clue is confirmed for how or why a pair of inputs should be chosen to potentiate creativity during the selective projection. This evokes a computational approach where all possible blends have to be generated and evaluated individually, namely the neo-Darwinian algorithm by Johnson-Laird (2002). However, this algorithm could result in an explosion of blends and is infeasible for large input spaces. In contrast, the neo-Lamarckian approach, put forward by Johnson-Laird, provides only useful products by applying quality constraints on the search space. To do it computationally, a mechanism for selecting elements from input spaces effectively during the generation process is required (Li et al., 2012).

Brandt and Brandt (2002) indicated that conceptual blending could only be analyzed in the context of the discourse during which they were uttered, and there are no fixed meanings for blends in communication. As argued by Brandt and Brandt, the metaphor “this surgeon is a butcher” may mean different things under different circumstance. To clarify this plurality of meanings, a blending construction process should not solely depend on the attributes of the input space, but also on the context. In their proposed new model, the context-free generic space is substituted by a context-driven semiotic space.

As shown in Figure 5.3, which takes the surgeon-as-butcher as an example again, the semiotic space retrieves situational relevance from the input spaces in order. When we are talking about a particular surgery, the input space of the surgeon, which is the reference space, becomes available. As communication continues, the goal may be revealed. For instance, it suggests that the surgeon is irresponsible. A presentative space, including the relevant entities (a butcher in our example), is then retrieved and mapped to the reference space. Eventually, what elements from the two input spaces should be
projected into the blend is still determined by the communication, which is captured through the situational relevance. If the accusation of the irresponsibility of the surgeon is learned from the communication, then we should project the careless attitude of the butcher into the blend. An elaboration loop of blends is in the process until sufficient details are retrieved for the goal of the communication. As can be seen, the retrieval of input spaces, the projection elements, and stopping conditions are all driven by contexts and goals.

Figure 5.3 The context-dependent blending, adapted from Brandt and Brandt (2005)

Li et al. (2012) extended Brandt and Brandt’s contextualized blending theory to the construction of novel concepts. Blends generated from the communication are usually meant to emphasize certain aspects of, even to attach new properties to the inputs. In addition, the blends that are standalone concepts may not convey the meaning related to their input spaces. As an example, the concept lightsaber in Star Wars is a blend of a sword and a laser emitter, but the word does not tell us anything about swords or laser. Nevertheless, as pointed out by Li et al. (2012), the meaning of a novel concept can still vary depending on the context. The saying “my new kitchen knife is a lightsaber” is to emphasize the sharpness of a knife rather than the original meaning of lightsaber.
5.1.3 Applications for creativity

Conceptual blending is a promising methodology for modeling creativity due to its nature of the generation of new concepts from the integration of input knowledge. It is a domain-independent and evaluative methodology, and consistent with the processes which are often associated with creativity, such as metaphor and conceptual combination (Pereira, 2007). Moreover, conceptual blending is a contextual process which may interact and produce a variety of equally valid solution spaces given a set of constraints “in parallel”.

As a powerful mechanism for computational creativity, conceptual blending is capable of synthesizing known concepts into creative yields. Although it is a challenging task to apply artificial intelligence to conceptual blending, there are a few computational models which try to blend concepts in an automatic way. Goguen (1999) proposed a formal theory of complex signs, called algebraic semiotics, trying to address interface issues including user interface design, natural language and art. Veale and O’Donoghue (2000) presented a computational model Sapper to establish a dynamic blending between two domains. The blend is built according to a unifying set of correspondences of concepts from input domains. It relies on the metaphor interpretation system instead of having an independent domain. Therefore, their work lacks the creation of the actual blend space.

Divago, as described by Pereira and Cardoso (2006), is a system that aims to implement a set of principles suggested by a computational blending model, and to be able to generate novel and valuable concepts out of its knowledge base. Complied with the conceptual blending theories, these newly generated concepts have an emergent structure of their own instead of simply consisting of the composition of previous concepts. As shown in Figure 5.4 about the architecture of Divago, it mainly consists of the multi-domain knowledge base, the Mapper, the Blender, the Factory, the Constraints and the Elaboration (Pereira, 2007). Given a pair of concepts which is selected from the knowledge base by divergence and bisociation, the Mapper builds a structural alignment between them. Then the Blender produces a set of projections based on the implicitly defined set of all possible blends.
To effectively search from a combinatorial explosion of possible blends, the Factory has a parallel search engine which is implemented by a genetic algorithm (GA). From a population of projections, the GA first selects those with high scores as computed by the Constraints module which sums the weights of eight optimality principles. These principles also take into account the information extracted from the knowledge base module as well as the Goal module in which external queries are received and processed. After the evaluation of GA, highly ranked blends are randomly modified to create the next population. In such an evolution process, the GA also interacts with the Elaboration module, making sure that the blends are subject to the application of context-dependent knowledge. The GA stops and returns the best solution until reaching a satisfactory solution or a specified number of iterations.

Figure 5.4 The architecture of Divago (Pereira, 2007)

However, there are several notable limitations of the Divago system. The input spaces are either given by a user or randomly generated from the knowledge base, instead of being selected by algorithms. As the Goal and Elaboration modules do not directly participate in the projections generation by the Blender, an explosion of possible blends may happen, which could lead to the difficulty of the convergence of the GA. Moreover, given enough rules and frames by the Elaboration module, rule firing and pattern
matching can potentially go on indefinitely as no explicit stopping criteria are specified (Li et al., 2012). To address some of these issues, Li et al. (2012) present two computational mechanisms for the selective projections of input space attribute into the blend space: the gadget generation algorithm, and the pretend play algorithm. They utilize goals and context respectively to guide the generation of standalone conceptual blends. Two case studies are conducted in the domains of story generation and virtual characters engaged in pretend play correspondingly. The results show that goals can be used to prune the search space and improve average-case performance.

In the design creativity field, inspired by the finding that objects with high dissimilarity tend to lead to more creative outcomes when they are blended (Taura et al., 2005), Karimi et al. (2018) present a deep learning model for generating visual conceptual blends in the domain of sketching. It starts with a conceptual shift: when a sketch recognized as belonging to one category is visually similar to another sketch which is from a semantically distinct category, visual conceptual blending can be achieved by identifying a potential conceptual shift. To achieve that, three steps of algorithms are implemented: learning, clustering, and identification. The learning step extracts features from each sketch using a CNN-LSTM model; the clustering groups sketches of a category into different subcategories with the k-means method; the last step finds the most visually similar sketch to the user’s input which comes from a different category by computing the distances between the sketch and each cluster.

Karimi et al. propose two user scenarios for creativity: conceptual shifts and conceptual shift chain. The former presents a sketch from a user and a corresponding identified sketch, while the latter shows a series of concepts that are linked by structural similarity. The results of the conceptual shift are then used for sketch blending, which is achieved in two different ways: superposition and adjacency. However, the two methods are not implemented in algorithms. Instead, they require users to position conceptual shifts on the canvas, which is similar to the methods applied in the Combinator by Han et al. (2018a).
5.2 Generative Adversarial Networks

With the growing advances in artificial intelligence, the ability of machines to mimic the real world has increased significantly, including image recognition, object detection and segmentation, speech and natural language processing. In the last few years, a type of generative model known as Generative Adversarial Networks (GANs) has achieved tremendous success primarily in the context of computer vision. They are able to transform vectors of generated noise into synthetic samples resembling data gathered in the training datasets. The basic principle of GANs is inspired by the two-player zero-sum game, in which the total gains of two players are expected to be balanced. Each player’s gain or loss of capability is exactly the cost of the corresponding loss or gain of the capability of another player.

Figure 5.5 Training process of a GAN (Silva T., 2018)

GANs comprise two modules, a generator G and a discriminator D, which are two neural networks trained simultaneously to compete with each other (Goodfellow, 2014). As shown in Figure 5.5, the generator G is modeled to transform a random vector z into an image given $x_G = G(z)$ where the noise vector z is sampled from a distribution $p_z$ such as a uniform or Gaussian distribution. This transformation can be achieved through various up-sampling methods, such as nearest-neighbour algorithm, max un-pooling, and transposed convolution (also called de-convolution originally in Zeiler et al., 2010). For instance, transposed convolution, which is the method used in this research, works
similar to a convolution operation in a neural network layer, where the number and size of kernel (the weights for a matrix multiplication on the input array) and the number of strides (the movement along a specific dimension of the input array) are required. Typically, the output is the same size as the input if padding is allowed and the stride of the convolution operation is a unit, such as (1x1) for a 2D convolution; the output size is the half of the input size if the stride is 2 for each dimension, such as (2x2) for a 2D convolution. However, the output size is the double of the input size in transposed convolution if the stride is 2. This is due to the inversed convolution operation: the multiplication of the kernel and the array projected by the kernel in the input is a value falling into the corresponding location of the output, thus its inverse operation is the multiplication of the kernel and a value from the input resulting into an array with the identical size as the kernel. In this way, image array can be obtained by up-sampling a vector in multiple iterations. There are various ways to construct convolutional neural networks in a generator to generate images. Typical and state of the art architectures of generator are introduced in the next section including their applications.

G is trained to reproduce the true data distribution $p_{data}$ by generating images from the data distribution $p_g$ that are difficult for the discriminator D to differentiate from real images, as shown in Equation 5.1. According to Bayes’s law, the data distribution of generated images can be obtained by the integration of the product of two probabilities: the probability of generated image conditioned on a random vector, and the probability of that vector withdrew from a distribution. The $p_g(x_G|z)$ needs to be learned during the training on G so that it can represent the distribution of true data where $p_g = p_{data}$.

$$p_g(x_G) = \int_z p_g(x_G|z)p_z(z)dz \quad (5.1)$$

Meanwhile, the discriminator D takes an image (either from true datasets or the generator G) as input and outputs the probability of an image to be real. D aims to be trained to output a low probability when fed a “fake” image, and estimate a high probability for the sample from the true data distribution. During the training process, the generated images from G try to cheat the discriminator D, while D tries to avoid
being cheated. Thus the discriminator D and generator G are trained adversarially to
improve their capability by optimizing the following objective function (Goodfellow,
2014):

\[
\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log (1 - D(G(z)))]
\] (5.2)

Where \( x \) is sampled from the real data distribution \( p_{\text{data}}(x) \), \( z \) is sampled from a prior distribution \( p_z(z) \), and \( E \) is the expectation of corresponding distribution. D and G represent the discriminator and generator respectively. The objective of this function is to minimize \( \log(1-D(G(z))) \) by training G so that D can be cheated to output a high probability \( D(G(z)) \), and to maximize \( D(G(x)) \) which represents the probability of correctly recognizing the true data \( x \), which explains the minimax game between G and D.

However, in the early steps of learning procedures, G might generate poor samples. In such a case, D is expected to recognize the majority of samples generated by G, which might result in the saturation of the term of \( \log(1 - D(G(z))) \). When \( 1 - D(G(z)) \) converges to 1, the working mechanism then suffers a gradient vanishing problem of the generator. To overcome this issue, the objective function is rewritten as follows (Goodfellow, 2014):

\[
\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log D(G(z))] \] (5.3)

Where the only difference to Equation 5.2 is to maximize \( \log D(G(z)) \) instead of \( \log(1 - D(G(z))) \). This new value function provides much stronger gradients in the early stage of learning for G, without changing the optimization point.

It was theoretically shown by Goodfellow et al. (2014) that this minimax game has a
global optimum for \( p_g(x) = p_{\text{data}}(x) \). Given that G and D have enough capacity and
D is allowed to reach its optimum at each step of training, \( p_g \) can converge to \( p_{\text{data}} \) by
keeping updated using the proposed mini-batch stochastic gradient descent training algorithm. It is also mentioned that the GAN model can be improved or extended in several different ways: 1) its efficiency of training can be improved by devising better methods, which is introduced in part-A of next section; 2) a conditional generative model \( p(x \mid c) \) can be applicable by adding \( c \) as input to both \( G \) and \( D \), which is introduced in part-B of next section.

5.2.1 Types of GANs

A. Convolutional GAN (DCGAN)

It has been demonstrated that Convolutional Neural Networks (CNNs) are extremely well suited for image data processing. However, the early experiments conducted on CIFAR-10 suggested that CNNs are more difficult for training GANs until the employment of the Laplacian pyramid of adversarial networks (LAP-GAN) (Denton et al., 2015). This decomposes the generation process into multiple scales where multiple generators were cascaded: a noise vector \( z \) was taken as the initial input for a convolutional generator to generate a low resolution (8x8) image, which was then up-sampled (16x16) and taken as a conditioned input of another generator to obtain a sharper image (with the same resolution). This process repeats across two subsequent levels to yield an image with higher resolution (64x64). Additionally, Radford et al. (2016) proposed deep convolutional GAN (DCGAN) which is capable of generating images in high resolution with a single generator. It has been widely used in the design of new GAN architectures for various image generation tasks. As shown in Figure 5.6, DCGANs make use of convolution layers in \( D \) with stride of 2 and transposed convolution layers with stride of 2 to learn the spatial down-sampling and up-sampling operations respectively, which are the key requirements in the mapping from image space to noise vectors \( z \) (the input vector at left side of Figure 5.6). In addition, the constraints and tricks introduced by Radford et al. significantly stabilize the training procedure of GANs in most settings, resulting in the high quality of generated images.
As the extension to the synthesis of images in 2D, Wu et al. (2016) trained volumetric generative convolutional neural networks to generate 3D chairs, tables and cars when given information such as object type, viewpoint, and color. In addition, they also presented a method mapping from 2D images to 3D versions of objects.

B. Conditional GANs

The vanilla GANs can be further extended to conditional GANs, in which the generator \( G \) and the discriminator \( D \) are conditioned on additional constraints such as class labels, texts and images. Conditional GANs have the advantage of being able to provide better representations for multi-modal data generation, such as the tasks of generating images from class labels and texts. For example, InfoGAN (Chen et al., 2016), as a variant of conditional GANs, is capable of learning semantic representations when dealing with complex intertangled factors in image appearance, including variations in pose, lighting and emotional content of facial images. This decomposes the noise source into an incompressible noise \( z \) and a “latent code” (as an extra condition), attempting to discover latent factors of variation by maximizing the mutual information between the latent code and the output from the generator.

AC-GAN is another variant of the conditional GANs which is capable of generating class-conditioned images of high solution (Odena et al., 2017). By employing an auxiliary classifier in the discriminator \( D \), the AC-GAN performs classification on
given images and effectively produces sharp images of all 1000 classes of the complicated ImageNet dataset (Russakovsky, et al., 2015).

5.2.2 Applications of GANs

With the popularity of GANs in the context of machine learning, discovering new applications for GANs is an active area of research. Due to the advance of GANs in computer vision, this research examines several popular associated applications that have appeared in the state-of-the-art literature using GAN-based models for image-manipulation, analysis or characterization, which may not fully reflect the potential breadth of application of GANs. These applications are relevant to this research from several aspects: 1) image synthesis aims to generate realistic images using noise vectors z, which can be regarded as a method for visual concepts synthesis in the context of this research; 2) image-to-image translation is similar to the purpose of visual concepts blending as it tries to translate images from one style to another; 3) super-resolution can be useful when higher resolution is demanded, which can be critical for generative models.

A. Classification and regression

When the G and D of a GAN are fully trained, they can be reused for other downstream tasks. For instance, the convolutional layers of the discriminator in a DCGAN can be used as a feature extractor for assessing the quality of the unsupervised representations in the DCGAN (Radford et al., 2016), which helps achieve good classification scores on both supervised and semi-supervised datasets. When jointly learning an inference mechanism with the adversarial training, the quality of data representation can be improved, such as the encoder of ALI (Dumoulin et al., 2017), which achieved a misclassification rate significantly lower than the DCGAN.

GANs can be used for synthesizing more training samples when labeled training data is in limited supply. Shrivastava et al. (2017) successfully used GANs to refine synthetic images without destroying their annotation information for training models (no real training data), they achieved state-of-the-art performance on the pose and gaze
estimation tasks. Due to the difficulty of assessing the quality of generated samples for models that need quantitative verification, classification tasks are likely to remain as quantitative tools for judging the performance of GANs.

B. Image synthesis

Much of the recent GAN research focuses on improving the capability of image generation tasks in terms of quality and utility. To generate realistic images in high resolution, Brock et al. (2019) trained large-scale GANs, called BigGAN, by applying orthogonal regularization which is first introduced by Brock et al. (2017) to the generator which allows fine control over the trade-off between sample fidelity and variety. As shown in Figure 5.7, their impressive results have high fidelity and low variety gap, which demonstrates that GANs can benefit significantly from scaling and improve state-of-the-art by a large margin.

![Samples generated by BigGAN at 512x512 resolution (Brock et al., 2019)](image)

**Figure 5.7 Samples generated by BigGAN at 512x512 resolution (Brock et al., 2019)**

PGGAN is the state-of-the-art GAN model which is capable of synthesizing realistic images at an unprecedented high resolution of 1024x1024 (Karras et al., 2018). Similar to LAPGAN, it generates images in multiple stages, but the PGGAN only has one generator instead of having multiple cascaded generators (as introduced in section 5.2.1-A). During its training, layers are progressively added to the networks along with the process of generating images of increasing resolutions. With such a training scheme,
PGGAN is able to generate the underlying structure and then add fine details gradually, which makes the training process stable and fast as well.

C. Image-to-image translation

Compared to ordinary unconditional image synthesis, image-to-image translation is more challenging as constraints are conditioned on the input images. The conditional GAN architecture and its variants have been successfully applied in many image-to-image translation tasks. These GANs can be divided into two categories according to their requirements on the learning pair of images: 1) supervised learning, in which the input and output images are paired; 2) unsupervised learning, in which the input and output images are not paired but from two different domains.

Pix2Pix is a popular but effective conditional GAN framework for supervised image-to-image translation (Isola et al., 2017), which offers a general-purpose solution for learning the mapping from an input image to output image. It demonstrates the effectiveness of GANs for the problems in computer vision which previously required separate machinery, including semantic segmentation, generating maps for aerial photos, and colorization of sketches. Its variant Pix2PixHD improves the resolution of generated realistic images as high as 2048x1024, with proposing a novel adversarial loss function for training as well as new multi-scale generator and discriminator architectures (Wang et al., 2018).

CycleGAN attempts to address the unsupervised image-to-image translation problem by introducing a cycle consistency loss which helps preserve the essential information from an input image after a cycle of translation and a reverse translation (Zhu et al., 2017). This kind of unsupervised learning makes data preparation much simpler and applications broader. For instance, artistic style transfer renders natural images in the style of artists, such as Van Gogh or Picasso, by simply training on unpaired images of paintings and natural images (Li and Wand, 2016). However, as two generators are required for each pair of image domains, CycleGAN has limited scalability in multi-domain image-to-image translation tasks. StarGAN successfully addresses this issue with only one single generator, as shown in Figure 5.8 (Choi, et al., 2018). Its unified
model architecture allows simultaneous training of multiple datasets with different domains within a single network. Choi et al. (2018) empirically demonstrate how the model is trained with both the *CelebA* dataset which contains attributes such as hair color, gender, and age, and the *RaFD* dataset which includes labels corresponding to facial expressions, as shown in Figure 5.9.

**Figure 5.8 Comparison between cross-domain models and StarGAN (Choi et al., 2018)**

**Figure 5.9 Multi-domain image-to-image translation results on the CelebA and RaFD dataset by StarGAN with a single generator (Choi et al., 2018)**

**D. Super-resolution**

Super-resolution aims to improve the resolution of an image from low to high. Compared with traditional models, GANs have been proved to be more powerful for recovering the finer texture details when super-resolving at large upscaling factors. The SRGAN model extends earlier effort by adding an adversarial loss which constraint
images to reside on the manifold of natural images, and a content loss function which focuses on perceptual similarity instead of pixel similarity (Ledig et al., 2017). SRGAN is the first framework capable of inferring photo-realistic natural images for 4x upscaling factors. Furthermore, the perceptual quality using SRGAN gains significantly in the extensive mean-opinion-score (MOS) test benefiting from its content loss from a pre-trained classifier.

5.3 A generative model for visual conceptual blending

5.3.1 The conceptual blending GAN model

Assuming two semantically distinct concepts are found interesting to be combined as a novel idea when exploring a multi-domain database, e.g. the implementation in Chapter 4, then this idea could be sparked by blending two nodes representing two different concepts (far association) in a network. Even though the person who comes up with this idea may have a basic idea of how to blend these two concepts, which is referred as a conceptual blending, it could stimulate the person further if this conceptual blending idea is shown in a visualized way. As an implementation of this visual conceptual blending, provided with two concepts from two semantically distinct domains, the visual concept blending model aims to produce blended images which synthesize both concepts. In this research, the theoretical four-space model is accepted for blending concepts. Different from the methods applied in previous research as introduced in section 5.1 and 5.2, this study contributes to the following aspects:

- A novel computational method for blending concepts instead of using non-computational method or genetic algorithms, which requires much less effort for human involvement.

- The existing GANs architectures are not suitable for this task. Image synthesis focus on the variety and realism of images within one domain, while image-to-image translation or style transfer targets one domain based on another domain such as the two architectures introduced in Figure 5.8.
The generation of photo-realistic images which synthesize two semantically distinct concepts with computational methods is a really challenging problem. Recently, GANs have shown their capability in many image generation tasks, as described in section 5.2. Apparently, distinguished from conceptual blending, CycleGAN (Zhu et al., 2017) or StarGAN translate an image from domain A to domain B (or multiple domains), but they are not able to blend the features from two domains and generate new images falling into a third domain. The purpose of our model is similar to CycleGAN, but the CycleGAN model is to generate images in target domain Y from source domain X, then reconstruct the image in source domain X from target domain Y. However, the model expected here generates an image containing the features not only from the concept A but also from concept B by two different discriminators to blend these two concepts. This chapter investigates how to produce images which synthesize important features from two concepts which fall into two distinguishing categories using GAN formulations.

As a supervised learning method, two datasets are established first by collecting images representing two known concepts. No pre-processing is required to train images except to keep all images at the same resolution. The inputs are the training images representing their corresponding concepts, and the Gaussian distribution is used as the noise distribution Z. The input image pair consists of one image from the concept-A domain and another image from the concept-B domain, and the noise vector z from Gaussian distribution are concatenated together along the channel dimension (i.e. W x H x \([C_A + C_B + C_z]\)) for the input of the single generator. The input image pair works as the conditions for the generator so that it can learn what features need to be blended rather than learning only general information from concept-A and B domains. This can be really useful in real world when designers wish to blend two existing images representing two concepts, and helpful as well for having a more stable generator training. Two discriminators are created to distinguish the domain-specific images from fake images generated by the generator. In summary, the model has two discriminators and one generator, as shown in Figure 5.10. This architecture design is unique to other existing methods, as the generated images need to cheat two discriminators.
simultaneously which are in charge of two domains. For instance, the generator will be punished for the failure of cheating discriminator B even though the output is good enough to cheat discriminator A, which keeps G trained to learn features from concept A and B in a balanced way. As blending is challenging, the two discriminators can be very strong at the beginning of training, which may result into vanishing gradient for G. However, the input pair of A and B can help mitigate this issue since they are the conditioned input for G.

Figure 5.10 The conceptual blending GAN model

For the architecture of the designed generator, an encoder-decoder architecture is employed. As shown in Figure 5.11, a concatenation of an image from concept-A datasets, an image from concept-B datasets, and the latent vector $z$ from Gaussian distribution, is fed into the encoder, which is the first part of the generator (the left side of dash line arrow in Figure 5.11). The encoder consists of three convolutional layers, each of which is followed by a layer of batch normalization (Ioffe and Szegedy, 2015) and Rectified Linear Units (ReLU) (Nair and Hinton, 2010). Then six residual blocks (He et al., 2016) are applied, each of which is made up of two groups of a convolutional layer, batch normalization and ReLU. These residual blocks work to obtain better representations of the input in a deeper encoding process. The decoder is composed of two transposed convolutional layers and a convolutional layer for the generation of blending images.
Each discriminator consists of five convolutional layers, as shown in Figure 5.12. The second, third and the fourth layer are followed by a layer of batch normalization and leaky-ReLU (Mass et al., 2013). The last convolution layer is flattened and fed into a single sigmoid output. The same architecture is employed for the two discriminators. During the period of model training, the model does not extract the specific features from the two different datasets, e.g. the shape from one dataset and the color from another dataset. In particular, the output of the last residual block in the generator is directly used as an input for the transposed convolutional networks, so no specific rule is set for choosing the feature from images. Meanwhile, the choices of generator and discriminator design, such as the number of residual blocks and layers of convolution, are made by several factors: the size of input and output, empirical choices demonstrated by other GANs. Furthermore, this generator is used to do creative work. The visual blending will be not creative enough if specific features, which can be imagined by a human, are set to extract.
5.3.2 Implementation

Given two domains of images $x_A$ and $x_B$, and two discriminators for each of the domain, we optimize the following full objective function:

$$
\min_G \max_{D_A D_B} V(D_A, D_B, G)
= \mathbb{E}_{x \sim p_{data}(x)} \left[ \log D_A(x) \right] + \mathbb{E}_{x \sim p_{data}(x)} \left[ \log D_B(x) \right]
+ \mathbb{E}_{A \sim p_A(A), z \sim p_z(z)} \left[ \log (1 - D_A(G(A, z))) \right]
+ \mathbb{E}_{B \sim p_B(B), z \sim p_z(z)} \left[ \log (1 - D_B(G(B, z))) \right]
$$

(5.4)

where $x_i$ is the true image from dataset, and $z$ is the noise vector as input for the generator $G$ along with a pair of images from concept-A and concept-B; $D_i$ is the discriminator. Assuming that $x_A$ is a target image which is similar to the product which is expected to be designed (e.g. a spoon), $x_B$ is the style image which $x_A$ is expected to have these types of features (e.g. a leaf). As these two types of images belong to different distributions, which makes it challenging to train the generator, so the
discriminators are more likely to converge quickly and lead to failure on the generator. To solve this problem, two tricks are applied:

- As mentioned previously, batch normalization is used on the generator to stabilize the training process.
- Soft and noisy labels on discriminators are used when inputting real images into them by setting a random number between 0.7 and 1.2 instead of 1. This method is also well known as label smoothing (Salimans et al, 2016). It can be regarded as a regularizer to reduce confidence of the discriminator (in the correct class), which in return gives strong gradients to update the generator.

The proposed conceptual blending GAN model is implemented with TensorFlow (Abadi et al., 2016). In the training phase, the Adam optimization approach is used with a momentum of 0.5. The learning rate is set to 0.0001 with a batch size of 64 and the model is trained for more than 100 epochs. The learning rate is decayed to zero linearly over the last half number of epochs. The model was trained on Nvidia Titan Xp for around eight hours.

5.4 Case study

5.4.1 Design tasks

A design case study is conducted in order to verify the proposed GAN model. Two factors were considered before choosing a design task. As this case study targets not only professional designers but also non-specialists, background knowledge for understanding the design task should be at a low level so that participants are able to focus on the illustration of their design solutions exclusively. Another factor considered is the incoherence between the selection of two semantically distinct concepts and the training of visual concepts blending model. As the visual concepts blending model needs time to collect training data and train the time-consuming GAN model (usually lasts from hours to days depending on several factors, such as the resolution of input and output image), it is impractical in a case study for the GAN model to generate
corresponding blended images given two arbitrary concepts. As a solution to this issue in our case study, the two concepts are directly given to experiment participants in the design task, and the GAN model is well trained to be able to generate images prior to the experiment.

With consideration of the above factors, the design task in our case study was to design a spoon which should be inspired by a natural leaf. The inspiration could be various, such as borrowing elements or features from a leaf, or provoked by observing an image containing a leaf. Ten minutes were given for illustrating generated ideas on white sheets including sketches and description. Similar to the case study in Chapter 4, participants were required to meet two requirements: the spoon can be at least used to assist in eating soup; the more sketches, the better. Additionally, the participants were reminded that this was an open-minded design task.

Figure 5.13 Samples of training datasets (left: spoons; right: leaves)

Similar to the arrangement in Chapter 4, in this case study, two groups of participants were involved. One is the treatment group, participants in this group were provided with more than one hundred images generated by developed visual concepts blending GAN model for design idea generation purpose. Another control group had no access to the developed GAN model tool but was allowed to use Google Image search engine to help idea generation, as Google Image is efficient to search images for idea generation and is commonly accepted in design studies (Han et al., 2016). The images searched from
Google are based on the keywords “spoon” and “leaf”. Each group consisted of twelve participants who were engineering students specializing in different disciplines, and only two in each group had a background of design engineering. The participants in this case study are the same as the study in Chapter 4 as a continuation of previous investigation.

Before training the developed visual concepts blending GAN model, 3772 images of spoons and 7408 images of leaves were collected as training data, samples of which are shown as in Figure 5.13. All images are kept in the resolution of $256 \times 256$ without additional pre-processing, and they are directly fed into the GAN model for training and validation. When the training is completed, then the well-trained model was used to inference blending images for the treatment group. Note that the input of the model is from the Gaussian distribution, after being well trained, the model is able to generate an unlimited number of images automatically. For example, Figure 5.14 shows the images randomly generated by our model without any filtering intervention, although the objects in these images do not look natural, features such as color, shape, texture, and functioning from spoon and leaf are blended. One of the most observable blended features can be the colour from leaf and the shape from spoon. Since the resolution of output images is $64x64$, the details of blended feature is blurred to some extent. However, that can be improved with super resolution techniques as introduced in section 5.2.2 or a more sophisticated model for higher resolution in future research. By observing images produced by the proposed GAN model, potential inspirations of how to blend spoon and leaf might be obtained by participants from the treatment group.
Before the beginning of the design task, a brief introduction and explanation of the design task were given. All participants were given white sheets to document their design ideas, which prompted participants to sketch and describe their ideas. Ideation sheets were collected and de-identified when the design session ended and was used in data analysis.

5.4.2 Model validation

Before applying the trained GAN model to the case study, it is necessary to validate the performance of the proposed GAN model. The validation criteria of computational creativity model are difficult to set, and the estimation depends on the perception of human beings heavily. There is no mathematic formula for calculating the performance of creativity, so the quality of generated images was evaluated based on the following criteria which are followed by human judges:

1) Whether the generated images keep the feature from source image A.

2) Whether the generated images keep the feature from source image B.
3) Whether the generated images blend the features from source image A and B.

4) Whether the generated images are diverse.

A benchmark was conducted among our model, CycleGAN, and neural style transfer (Gatys et al., 2016), both of which are un-supervised learning methods. Neural style transfer (NST) is one of the popular and very successful models using deep neural network for image stylization, especially before the advance of GANs. As introduced in section 5.2.2 of this chapter, CycleGAN is another popular and powerful model due to its sophisticated model architecture and unsupervised learning method, and it was widely used in image-to-image translation tasks. With the same training datasets, the proposed GAN model, NST model and CycleGAN were trained until they were fully converged. The best training strategies and hyper-parameters for each model were chosen after multiple rounds of training experiments in order to have fair benchmark.

Twenty pairs of images of leaf and spoon were selected separately from the dataset for benchmark. The selection criterion is to balance randomness and variety for each type of image (spoon and leaf), which means we firstly randomly chose images from datasets, then manually checked whether a certain variety is maintained. They are then used to generate images using three different models. A human evaluation on Amazon Mechanical Turk (AMT) was performed by presenting these twenty selected sets of images. Each set consists of five images: one image of spoon and one image of leaf from datasets, along with one generated image from the conceptual blending GAN model, one image generated by CycleGAN, and one image generated by the NST model. As shown in Table 5.1, three sets (rows) of samples are given showcasing how the results are generated (last three columns) by three different models on condition of a spoon image and a leaf image. Due to the restriction of model architecture, the generated images from CycleGAN can only take one type of images as input (either spoon or leaf) for model inference, thus the generated images used in the evaluation were based on images of spoon as the input.
Ten people from AMT were recruited to perform the evaluation. Before the evaluation, the identity of the generated images in each set were encoded, and then the order of images was mixed to be presented. Each judge was given all the twenty sets of images, and were told to judge three “fake” (generated) images based on two reference images (spoon and leaf), with proposed four criteria above. The first three criteria were judged by comparing each other among three “fake” images, while the last criterion (“diversity”) was judged by comparing the variation of all the twenty images generated by one model to another. Human judges scored 0 for the worst and 2 for the best regarding each criterion. Then all the ranking scores were averaged to calculate the quality scores for model comparison, as shown in Table 5.2. The result shows that the proposed GAN model outperformed CycleGAN and NST in the following aspects:

- Blending the features: The results show that our model is capable of generating images blending features that captured from the two source images in distinct domains to some extent. While CycleGAN can only transform the images from
domain A to domain B or vice versa, which is more likely to fail in the transformation, such as the second and the third samples in Table 5.1. Neural style transfer model, which is good at stylization, treated leaf images as the style target but failed to blend it into spoon images in a meaningful way.

- Maintaining the source features: Our model is also able to maintain the features of the raw images. In particular, it not only blends the features from two concepts which are in semantically distinct domains, but also synthesizes them on the condition that the source features are learned to some extent. This include features such as shape, colour, and texture. CycleGAN can synthesize leaf and spoon occasionally by maintaining their key features, which looks more like a superposition operation. NST model can only maintain spoon features, and very few leaf features where only colour is well maintained.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Our model</th>
<th>CycleGAN</th>
<th>NST</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Spoon</td>
<td>1.34</td>
<td>1.53</td>
<td>1.78</td>
</tr>
<tr>
<td>2) Leaf</td>
<td>1.54</td>
<td>1.22</td>
<td>0.71</td>
</tr>
<tr>
<td>3) Spoon &amp; Leaf</td>
<td>1.4</td>
<td>0.95</td>
<td>0.88</td>
</tr>
<tr>
<td>4) Diversity</td>
<td>1.63</td>
<td>1.27</td>
<td>0.82</td>
</tr>
</tbody>
</table>

When the model is validated to be capable of generating useful blends, the architecture for the design task was slightly modified in order to make sure both groups have no external inputs. The input of the generator in the proposed GAN model should only be from the Gaussian distribution instead of a triple of images which are from concept-A, concept-B and Gaussian distribution respectively. Therefore, the encoder part of the generator is removed so that only the decoder is used to take the random vector from Gaussian distribution as input. With the same hyperparameter used in the benchmark with CycleGAN, the modified GAN model is trained for 150 epochs until it is fully converged. The objective function is updated as follows:
\[
\min \max_G V(D_A, D_B, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D_A(x)] + \mathbb{E}_{x \sim p_{data}(x)}[\log D_B(x)]
\]

\[
+ \mathbb{E}_{z \sim p_{z}(z)}[\log (1 - D_A(G(z)))]
\]

\[
+ \mathbb{E}_{z \sim p_{z}(z)}[\log (1 - D_B(G(z)))]
\]  

5.4.3 Design evaluation

The same creativity evaluation criteria used in the design case study of Chapter 4 were employed for this study, which include: novelty, quality, variety and quantity. The assessment of quality in this design task is to examine if designed spoon contains elements from leaf and how reasonable and convenient the spoon can be used to eat soup. Quantity is calculated based on the total number of sketches illustrated by each individual in each group. These four metrics are measured independently, even though they were considered by each expert.

When all design illustration sheets were collected from both groups, they were presented in front of the two raters. The same Consensual Assessment Technique (Daly et al., 2016) methodology was employed in the evaluation process. The two raters who are experienced designers evaluated all sketches, based on their understanding of novelty, quality, variety and quantity independently. During the evaluation, the raters did not know the illustrations were created in two groups with different experiment setting. Sixty design solutions were collected and presented on papers in a different order for each rater. Consistent with CAT, a ranking scheme of score range from 1 to 7 was performed with several rounds until both raters confirmed that all illustrations had been thoroughly evaluated. Overall, each rater scored the sixty valid sketches illustrated by participants in two groups, in terms of novelty and quality. Variety was evaluated in a similar way with the same ranking scheme. The raters examined the whole set of sketches illustrated by a single participant on a seven-point scale. In total, the raters scored twelve sketch sets from each group, in which the set size of sketches for each participant could be different as one might record the different number of sketches. The rating ended when the ranking of piles did not change anymore.
Quantity was evaluated in the final rating round, in which each individual’s design set was assessed based on the number of sketches. All these above coding work was conducted on a separate time period for each round. To validate the consensus achieved between raters, the adjacent agreement (Stemler, 2004) and Cohen’s Kappa value were calculated. As a result, the percentage of adjacent agreement between raters was 81%, 71.7%, 79.2%, in term of novelty, quality, variety respectively. The adjacent agreements for novelty and variety are higher than 75% showing high adjacency between raters, while the agreement for quality shows moderate adjacency (higher than 50%). By transforming the 7-score ranking into three categories (“low”, “normal” and “high”), the Cohen’s Kappa was calculated as listed in Table 5.3. All values are greater than 0.50, which is typically considered as acceptable and reliable for the scoring results based on the CAT approach.

### 5.4.4 Results

The same strategy employed in the last chapter was applied for the statistical analysis of coded results. As the Shapiro-Wilk’s W test across both groups indicated that our data did not fall into normal distributions, the independent Mann-Whitney U-test was chosen to interpret the coded data. Examples of high and low scores in terms of the metrics of novelty and quality are introduced in Table 5.4 where ideas were randomly selected from experts’ evaluation without group identity. The average CAT scores of ratings for each experimental group in terms of novelty, quality and variety are shown in Figure 5.15. There is no difference for idea quality between treatment group and control group (p=0.516) which demonstrated that the participants from both groups have similar averaged basic design illustration skill, and for variety, the difference was
observed between two experimental groups (p=0.295). For novelty, the treatment group scored significantly higher than the control group (p=0.027). The average number of ideas generated for each group in each session is shown in Figure 5.16. In term of quantity, the treatment group generated more ideas than the control group significantly with the p value equal to 0.043.

**Table 5.4 Examples of low and high scoring ideas**

<table>
<thead>
<tr>
<th>High Quality &amp; Low Novelty</th>
<th>High quality &amp; High Novelty</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
</tr>
</tbody>
</table>
| - This is a utensil used to eat liquid foods.  
- You grab it by the handle and pick up food up with the bowl.  
- It can be made of different materials: wood, metal, plastic, etc. | One end of the spoon (bowl part) looks like a leaf while the other end (handle) has many branches and the end of each branch has a “seed” which contains a kind of flavor, such as sugar or salt. |
By comparing the scores rated by two expert raters with CAT, the designs produced by two groups are evaluated in terms of novelty, quality, variety and quantity. As seen from the results, treatment group performed better than the control group in terms of quantity and novelty, which means that the proposed visual concepts blending model shown better performance by producing more idea (by 41% higher quantity) with high
originality (by 34% higher novelty). Similarly, the contribution of algorithms in the GAN model was verified by reviewing the ideas illustrated by participants in the treatment group and their associated images generated by our model, which was measured by the matching degree between an idea and its associated generated images and determined by the experts. As the example shown in Figure 5.17, when one participant in treatment group observed the image generated by our model (the left one in Figure 5.17) where 20 leaf-inspired spoons are presented in four rows and five columns, the novel idea of designing a leaf-like spoon with an animal (looks like a squirrel) standing on the top was provoked. When reviewing the matching degree between the left and right image in Figure 5.17, the experts concluded that they were well match since the key novelty of an animal (even though too blurred to identify) standing on a leaf was captured by the participant. However, the rated variety of both groups did not achieve a high level. This can be explained from the generated ideas in which the majority are aesthetically novel while functional novelty is rarely involved, which means the design task tend to be shape-dominant rather than function-dominant.

![Figure 5.17 leaf-inspired spoons generated by the model (left) and the idea illustrated (right)](image)

Comparing generated blending to images from Google Image is a common setting in ideation experiments, such as in Han et al. (2016), but the images retrieved from search engine are not blended stimuli which might be less convincing regarding the performance of proposed model. Therefore, a better alternative could be to use another
blending tool for control group ideation so that the performance can be measured in a benchmark. However, the limitation of this approach could be the implementation of compared blending tools. Usually, blending methods and tools are usually revealed in published papers but rarely available for readers to test in a benchmark. This is hopefully to be addressed in future research.

Even though the conceptual blending system Divago developed by Pereira (2007) is able to generate blended images as well, the proposed GAN model has several competitive advantages:

- In Divago, the mappings cannot automatically be made by the Mapper. Instead, they were hand-coded due to the representation simplicity of Mapper and no structural alignment. However, our model learns the mappings automatically from training datasets, even the structural features can be captured by the GAN architecture.

- The projections are too restrictive to have multiple projections for the same concept map element in Divago. In our GAN model, with different values from the Gaussian distribution as the inputs, projections can be generated as many as needed.

- Divago is extremely slow in generating the blended images compared to our GAN model. In Divago, it can take at most four to five hours to find a solution. It first needs to search possible concepts maps to produce a “wavefront obj” file defining the image content. Then several parts of the image should be coded separately and placed together. In our model, though the model training may take hours, generating one image takes far less than one second during the inference phase. Furthermore, no extra processing needs to be done on the output of the GAN model, as the whole process is quite straight forward.

Imagery data can be regarded as a common format representing conceptual design, and widely exists in digital world. Therefore, it is an essential data format in the proposed data-driven cycle with two folds. It first represents as the outcome of visual conceptual...
blending, which is regarded as conceptual design when dealing with design issues. On the other hand, those innovative conceptual designs, which usually are rich of creativity, are commonly used in imagery data, making it fairly available and accessible in digital space. This is important for the next step in the proposed data-driven cycle to interpret design creativity, as the meta-data representing creativity in design solutions (imagery data) can be possibly identified and further contribute to creativity augmentation.

5.4.5 Contribution to the data-driven cycle

The study presented in this chapter aims to blend two semantically distinct concepts visually with computational approach, and demonstrates the effectiveness of proposed method in benchmark experiments and a design case study, which corresponds to the transformation from visual data to creativity in the proposed data-driven cycle. This study builds on the outcome of previous study in the last chapter as the two concepts for blending can be selected from discovery outcome using B-Link where explicit connections between concepts are provided. This study shows that the visual conceptual blending approach is capable of producing innovative conceptual designs based on semantic inspirations. Together with the study of bisociative knowledge discovery, this study achieves a transformation from data to design conceptualization with a certain level of creativity, thus completing a conceptual design process.

5.5 Conclusion and future work

In this chapter, the theoretical four-space model of conceptual blending and its development are introduced, such as the context-dependent blending model. As a creativity model, conceptual blending shows its great potential in augmenting creativity in various applications. With the power of machine learning, especially the Generative Adversarial Networks, this research explores how the GAN techniques can be applied to conceptual blending in a computational way.

The proposed GAN model has a novel encoder-decoder architecture for capturing key features in images representing two semantically distinct domains, and two discriminators for pushing the generator to blend key features from two concepts. The
model is validated in a benchmark with CycleGAN, which shows the strength of our model in blending concepts. To further test the model in the application of design creativity, a design case study is conducted. According to the results evaluated by expert raters with the CAT approach, the GAN model is able to generate a variety of images in which “spoon” and “leaf” are synthesized for a creative design task, which directly contributes to participants’ idea generation process.

The proposed GAN model for conceptual blending has its limitations compared to other computational creativity models. For instance, function-based analysis is missing in the theoretical conceptual blending model. For a complex engineering design problem with multiple functions, the proposed conceptual blending model might be not sufficient compared with function analysis based models, such as the function-behaviour-structure (FBS) model (Gero and Kannengiesser, 2004). This issue is expected to be addressed by bringing in a systematic functional analysis model, in which concepts will be retrieved based on functionality and other key features, and blending is then performed based on characteristics of functional components and aesthetic features. But such a complicated blending of multiple concepts could be extremely challenging as it requires a much more powerful generator in a GAN related models.

Although the proposed computational model has been examined for design creativity in the case study, it could potentially be used for other general purposes in which conceptual blending activities are needed, such as advertising and commercial innovation for strategy. There are no specific limitations when applying the GAN model into production except the relatively time-consuming data collection and model training process, and the model can be used to generate blending images directly once it is well trained on a task-specific dataset.
Chapter 6. Interpretation of Combinational Design Creativity

This chapter explores the interpretation and extraction of creative designs. Based on three driving forces behind combinational creativity, namely problem-, similarity-, inspiration-driven creativity, an integrated approach is proposed for extracting creativity from textual and visual materials. In this approach, an image recognition module is developed to interpret objects in images, while the natural language processing module is introduced to extract a combination relation pair. The approach is evaluated on a dataset by identifying the bases and additives in combinational designs according to their descriptions and images. The results demonstrate that the base is easier to be extracted than the additive in a combinational relation, while the relation extraction module performed better than the image recognition module. Further analysis and observations are provided in this research for future study.

Some of the introductory content described only in section 6.1 and 6.2 in this chapter has been previously published as:


6.1 Combinational creativity

According to Boden (2004), combinational creativity is the easiest form of creativity for human beings, which is achieved through associating ideas that were previously unlinked or indirectly linked. A number of people have explained creativity by using the term ‘combinational creativity.’ For example, Frigotto and Riccaboni (2011) described that the nature of creativity is to combine; Henriksen et al. (2014) indicated that creativity is the process of producing new combinations and alterations with existing ideas to create something new; Childs (2018) suggested that creativity arises from the combination of essential mental capabilities. Combinational creativity has been applied widely in design, and in various forms. For instance, bisociation is a form of combinational creativity connecting unrelated and often conflicting ideas in new ways (Koestler, 1964); another form is analogy that involves exploring shared conceptual structure (Boden, 2009); and the three types of concept synthesis: property mapping, concept blending and concept integration (Nagi et al., 2009).

Conceptual combinations involve merging previously separate concepts into units for presenting new thoughts and provoking new ideas (Wilkenfeld and Ward, 2001), which is considered as the cognitive aspect of combinational creativity. Conceptual combination is a basic creative cognition supporting a range of generative outcomes (Ward, 2001). Wilkenfeld and Ward (2001) illustrated that conceptual combinations could produce emergent properties which are not from either of the constituents. Secondly, multiple forms of interpretation can be yielded from the same combination. Kohn et al. (2011) revealed that conceptual combinations could benefit creative problem solving (convergent thinking) rather than divergent thinking. Scott et al. (2005) indicated two approaches for generating new conceptual combinations, the analogical approach (feature search and mapping) and the case-based approach (integration and elaboration of event models). Mumford et al. (1997) showed that conceptual combinations are positively related to the quality and originality of creative problem solutions.
A combinational creative idea can be composed by elements such as ideas, concepts, words, images and sounds, as well as abstract ones such as music styles and artistic genres (Ward and Kolomyts, 2010). Noun–noun combination, which is the conventional form of combinational creativity, is mainly considered in this study. In noun–noun combinations, a noun is not restricted to single noun words (such as ‘pen’, ‘robot’) and it can be noun phrases (such as ‘vacuum cleaner’, ‘coffee machine’). A number of research projects have studied noun–noun compound phrases and how people interpret them, for example the studies by Costello and Keane (2000) and Ward et al. (2013). Noun–noun compound phrases are often interpreted by three methods, which are property mapping, hybrid and relational thinking (Nagai et al., 2009; Toshiharu et al., 2007). Based on the three interpretation methods, Nagai et al. (2009) revealed that combined concepts or ideas can be interpreted through using property-mapping, concept blending and concept integration. Property-mapping includes transferring some features from an existing idea to another idea, and it is regarded as the most effective method. For example, a combined concept ‘snow-chocolate’ can be interpreted as a ‘white-chocolate’, as ‘white’ is a feature of ‘snow.’ Concept blending involves blending two basic ideas at the abstract level to produce a new idea that inherits partial structural features from the basic ideas as well as possessing its own structural features. For instance, a ‘powdered chocolate,’ which is a chocolate in the form of snow, can be derived from the ‘snow-chocolate’ idea. Concept integration includes combining two basic ideas by applying thematic relations. For example, according to the ‘snow-chocolate’ concept, an ‘iced chocolate drink’ can be generated from the scene of the situation that chocolates and snow are melted together.

Recently, a number of computational design tools have employed the concept of ‘combine’ to support designers in idea generation at early design phases. For example, Bacciotti et al. (2016) developed a method combining concepts from two different dimensions to identify scenarios for stimulating the users’ creative mind. However, this method requires the users to confront a protracted series of questions and stimuli which might create boredom. Georgiev et al. (2017) indicated a method for creating new scenes to produce new product ideas by combining or synthesizing existing scenes from
different contexts. New scenes are produced based on keywords, thereby the new scenes generated might not be related to the existing scenes of keywords. Han et al. (2016) developed a tool, called the Combinator, which can produce combinational ideas in text and image forms by combining unrelated ideas. Nevertheless, the idea combination process is performed in a random manner. All these tools have been indicated to be useful for supporting creative idea generation, but there is potential to improve their capabilities by exploring approaches that can produce combinational creativity.

This section has described some aspects of combinational creativity and approaches for generating noun–noun combinational ideas in design. Various ideas can be generated from the same noun–noun compound idea by applying different generation approaches. However, few studies have investigated what drives the combination of the basic ideas, and how to interpret the combination from real-world examples computationally. For instance, the motivations and reasons for why ‘snow’ and ‘chocolate’ can be combined to prompt creativity are uncharted, which prompts another question of how to find the combination pair ‘snow’ and ‘chocolate’ from the combinational idea “snow chocolate” with a computational method. Before proposing the method for interpreting such combinational ideas, the driven approaches or motivations that generate combinational creativity are reviewed.

### 6.2 Three driven approaches

In this chapter, the term 'idea' is regarded as an object or the concept of an object. To be more precise, an idea can be considered as the representations, such as features, functions and attributes, of an object as well as the aesthetics of the object. Here, an 'object' is not limited to a physical object, but also involves abstract objects, such as artistic genres. 'Aesthetics' involves both the physical shape of the object as well as the notion of the figure. The definition of ‘idea’ is based on Taura and Nagai's study (2013) and in line with the research in design study (Hatchuel and Weil, 2009). As illustrated in the previous section, the study is focused on noun-noun combinations. Here, the two nouns are considered as two ideas which constitute a combinational idea. The following paragraphs illustrate how designs are promoted during the design process. Three
hypotheses are made on how combinational creativity is driven with corresponding practical instances. The three driving forces, which are problems, similarity representations, and inspirations, are proposed based on previous studies on design process, design strategy, and design cognition.

6.2.1 The problem-driven approach

A problem can be considered as a recognition of an incomplete pattern requiring resolutions (Coccia, 2016). In order to solve a problem, related data are assimilated to discover a solution by means of mental acts. In design, a problem is defined as a gap between a target and its existing situation, and problem-driven is an approach to produce ideas based on the problem (Taura and Nagai, 2013). In addition, problem-driven is the dominant strategy employed by designers, which often leads to quality solutions (Kruger and Cross, 2006). This indicates that solving a problem in design can be regarded as exploring ideas to bridge the gap between the target of an object and its current situation.

For example, designing a parasol that can be used all day is considered as the target of the object. A parasol (the object) is generally used to protect from the sunshine during daytime, which is the existing situation of the object. Thus, the problem or the gap between the object and the target is to use the parasol during the night. A torch is often used outdoors during the night, and this can be understood as an idea that can bridge the gap and solve the problem. Thus, the target can be achieved through implementing a torch on a parasol. In terms of combinational creativity, this example can be interpreted as combining a parasol (the object) and a torch (the problem-solving idea) to achieve an all-day parasol (the target). A practical design solution of an all-day parasol, which combines a parasol and a garden torch, is the NI Parasol 350 Sunbrella (Foxcat Design, 2014), as shown in Figure 6.1(a). In combinational creativity, the problem-driven approach can be considered as combining a primary idea and a problem-solving idea to achieve a target idea. In the problem-driven approach, a problem is a driving force of combinational creativity in idea generation.
a. NI Parasol 350 Sunbrella
(The problem-driven approach)

b. GoBites
(The similarity-driven approach)

c. Juicy Salif
(The inspiration-driven approach)

d. Eggboard light
(The problem-driven approach and the inspiration-driven approach)

Figure 6.1 Examples of the three driven approaches

6.2.2 The similarity-driven approach

Two designs can be similar when sharing a set of common representations, such as features, functions, and purposes (Earl and Eckert, 2002). For example, a candle and a light bulb are both used for illumination. Here, a candle and a light bulb are similar for sharing a common representation which is the function or purpose of illumination. The perception of the similarity between two ideas involves recognizing surface similarity, which refers to the attributional resemblance, and structural similarity, which refers to the underlying relational resemblance (Eckert et al., 2003; Ozkan and Dogan, 2013). Chan (2015) illustrates that artworks that possess similar critical common features, should have a similar appearance and can be categorized as the same style. This suggests
that two ideas sharing a similar representation or a set of common representations can be classified into the same idea category. The two ideas belonging to the same category are associated via similar representations. Suzuki (2005) indicates that, in human memory, an idea can be recalled with its associated idea due to the capability of associative memory. For example, a pencil is generally recalled when a pen is mentioned. Similar ideas are associated within the human brain through learning and experience (Suzuki, 2005). Similar ideas are associated via common representations, which can be regarded as ideas that are subconsciously pre-combined by humans. Although two ideas are already associated due to similar representations, the combination of the ideas may still be novel. From cognition perspective, the combination stems from the similarity between two ideas, but the novelty can result from the reasoning process of combination. Examples are given below to explain this in a concrete way.

The similar representations of different ideas are considered as a driving force for producing combinational creativity, which is classified as the similarity-driven approach. For instance, a spoon and a fork are both used for serving food which is a common representation that classifies spoon and fork into the cutlery product category. Thereby, a spoon and a fork can be integrated into a separate piece of cutlery. With regard to combinational creativity, this instance can be considered as combining a spoon and a fork, which were associated via a similar representation, for producing a piece of combinational cutlery. GoBites (Humangear, 2015) is a practical design which combines a spoon and a fork, as shown in Figure 6.1(b). In terms of combinational creativity, the similarity-driven approach can be understood as combining a primary idea and an associated similar-representation idea to produce combinational creativity. As illustrated above, similar representations are considered as one of the drivers of combinational creativity in idea generation.

6.2.3 The inspiration-driven approach

Inspiration is widely recognized in daily life, which often leads to creative design ideas (Oleynick et al., 2014). It is defined as the process of being mentally stimulated to do
or feel something, especially to do something creative. In design, inspiration is described as a process integrating the use of any entities in any forms that produce creative solutions for existing problems (Goncalves et al., 2014). The descriptions are in line with the inner sense-driven process proposed by Taura and Nagai (2013) which generates new ideas based on 'inner criteria' and 'intrinsic motivation' by referring to existing ideas. Taura and Nagai (2013) explained that 'inner criteria' are constructs which underlie the mind that guide the process of idea generation. 'Intrinsic motivation' stimulates people to perform an activity with no expectations of external reward. Enjoyment and satisfaction are typically experienced when people are intrinsically motivated. In design, an idea can be produced by referring to an existing idea with a source of inspiration (Goncalves et al., 2014), which is referred to as the inspiration-approach in this study.

Prior experiences, knowledge and examples, as well as previous designs, are often presented as sources of inspiration (Sio et al., 2015; Chan et al., 2018; Eckert et al., 2000; Eckert and Stacey, 2000). Sources of inspiration significantly contribute to design defining the contexts for new designs and provoking idea generation (Chan et al., 2018; Eckert and Stacey, 2000). Here, the sources of inspiration are considered as inspirational ideas that are explored by designers based on 'inner criteria' and 'intrinsic motivation'. A practical inspiration-driven combinational design example is the Juicy Salif designed by Philippe Starck, which is a combination of a lemon squeezer and a squid, as shown in Figure 6.1 (c). The Juicy Salif was inspired by a dish of squids which Philippe Starck was having at a waterfront restaurant (Watson-Smyth, 2010). With regards to combinational creativity, the inspiration-driven approach can be interpreted as combining an existing idea and an inspirational idea to form a combinational idea. In this approach, combinational creativity is driven by inspirations or inspirational ideas.

6.2.4 Summary

As illustrated in the previous section, this study is focused on conventional noun–noun compound ideas, where the two nouns are considered as two ideas for composing the combinational idea. One of the nouns is the primary idea or the basic idea, which is
called the base. The other noun, which is the additional idea for forming the combination, is called as the additive. As discussed above, the three driven approaches to combinational creativity are indicated as follows:

1) **The problem-driven approach**: combinational creativity is driven by design problems. A target combinational idea is achieved by combining a basic idea (the base) and a problem-solving idea (the additive).

2) **The similarity-driven approach**: combinational creativity is driven by similar representations between two ideas. A combinational idea is generated by combining a primary idea (the base) and a similar representation idea (the additive).

3) **The inspiration-driven approach**: combinational creativity is driven by inspiration or a source of inspiration. A combinational idea is produced by combining a basic idea (the base) and an inspirational idea (the additive).

From the illustrations above, the three approaches are driven by three different forces which result in three different additives. In the problem-driven approach, the additive is a problem-solving idea which can bridge the gap between the base (object) and the target. In the similarity-driven approach, the additive is an idea that shares a common representation or a set of common representations with the base. In the inspirational-driven approach, the additive is an inspirational idea that can stimulate designers to produce solutions by referring to the base. However, in actual design idea generation, these approaches can complement each other instead of performing independently. For example, a combinational idea can be achieved by combining a base and an additive which is a problem-solving idea as well as an inspirational idea. A practical instance is the Eggboard light (Eggboard, 2016), which was designed to absorb sound, is composed of light and an egg carton, as shown in Figure 6.1(d). The egg carton is the additive idea which solved the sound-absorbing problem as well as delivered inspirations. This type of integrative driven approach is in line with the design process indicated by Taura and Nagai (2013), in which the inner sense-driven phase and problem-driven phase realize the design process complementarily.
In this chapter, the study of combinational creativity is extended to data-driven domain. Based on the previous research that combinational creativity is formed by base and additive with different driven approaches, this study would like to investigate how computing algorithms can identify base and additive from a combinational creative design solution. This study can be significant for data-driven design and creativity since base and additive are the meta-data for forming combinational creativity. With these meta-data captured from raw data such as online design articles, a data-driven creative system can be implemented to support creativity, which will be further illustrated in the next chapter.

6.3 Techniques for interpreting combinational design creativity

It can be concluded from all the three driven approaches that base and additive are the two essential elements of combinational creativity. In a complicated design solution, there may be more than one base or additive. To simplify the modeling of combinational creativity, only a single pair of base and additive is considered in this research. Hence, the research challenge is, given a combinational design containing a pair of base and additive, how we can extract the base and additive respectively in a computational way. As far as we know from the literature, this has not been studied from a perspective of combinational design creativity.

A combinational design can be presented or expressed in different digital formats, such as image, text, or 3D model. The most common formats among them are images and textual description, as they are highly used on the Internet and digital systems. Therefore, the challenge can be understood as the extraction of a pair of base and additive from the source of images and texts. Taking Figure 6.1(d) as an example, given that image and its textual description below:

“The design of the Eggboard pendant luminaire picks up this principle, translating it into a high-quality lighting option. Surfaces of simple egg cartons
possess outstanding sound absorption qualities thanks to the specific surface structure.” (Eggboard, 2016)

It is expected to extract the word “pendent luminaire” as the base, and the word “egg cartons” as the additive of that combinational design.

In summary, the purpose of this research is to apply exclusively machine learning techniques to interpreting the base and additive from a combinational design without human intervention, which is an extremely challenging task and has not been investigated yet. The contribution of this study is concluded as follows:

- Framing this combinational creativity interpretation problem as an integrated problem of image classification and natural language processing (NLP);
- The possible technical solutions for image classification and NLP are explored and investigated;
- An integrated approach is proposed for detecting the bases and additives from combinational designs (images and textual descriptions provided);
- The difficulties and failures cases are analyzed and discussion is given for guiding future work.

6.3.1 Image interpretation

To computationally interpret an image containing the combinational creativity, the most common techniques in computer vision are image classification and object detection. Image classification aims to determine the subject in an image, and the number of subjects is usually limited to one in classic competitions, such as the ImageNet challenge ILSVRC (2015), which is a benchmark in object classification and detection with millions of images and hundreds of object classes. Object detection deals with detecting instances of semantic objects of a particular class, such as humans, buildings or cars (Wikipedia, 2019), which means all subjects with known labels (classes) should be determined from an image. As shown in Figure 6.2, the left image is labeled as “cat” while the right image is detected with two cats, one duck, and one dog.
Image classification is a sub-task of object detection as the latter needs to detect all possible known classes (labels), but it is easier to undertake object detection. Even though many images in real-world scenarios contain multiple object classes, research on computational design creativity is primarily limited to product design, in which the only subject is the product designed (or to be designed) in most cases, such as the images presented in Figure 6.1. Thus the challenge of interpreting the combinational design image is to perform image classification on design images.

Image classification was traditionally tackled by image analysis algorithms such as SIFT (Scale-Invariant Feature Transform) (Lowe, 1999) with mitigated results until the late 90s. For instance, SIFT first extracts from a set of reference images and stored in database, then objects are recognized in a new image by individually comparing each feature from that image to the database and find matches based on Euclidean distance of feature vectors. Good matches are finally filtered out by identifying agreements on features such as object, scale, and orientation. However, a significant gap in performance was brought by using deep neural networks. Inspired by Convolutional Neural Networks (CNN) (LeCun et al., 1998), the first well-known deep learning model AlexNet published by Krizhevsky et al. (2012) drew significant attention by obtaining a top-5 error rate of 15.3% outperforming the second-best one with an accuracy of 26.2% using a SIFT model. The AlexNet, which has 60 million parameters, is composed of five convolutional layers, three max-pooling layers and three fully connected layers.
followed by a final layer with a Softmax function\(^\text{10}\) (also called normalized exponential function) which is responsible for classifying an object into one of the 1000 classes., as shown in Figure 6.3.

![Figure 6.3 AlexNet architecture (Krizhevsky et al., 2012)](image_url)

In a convolutional layer, convolution operation (mathematically called cross-correlation) is performed over the precedent input (an array with multiple dimensions) with a filter. Usually, there are multiple filters with the same size performing this convolution operation. The resultant is a new array representing condensed features from the input, which is commonly called feature map. In a max-pooling layer, there are some filters as well. Instead of doing matrix multiplication in convolution operation, maximum value is extracted, which helps reduce information from precedent feature map. For instance, the spatial dimension is reduced from 55x55 to 27x27 as shown in Figure 6.3 after the first max-pooling layer. Fully connected layer, which is also called dense layer, compresses the data from precedent layer into a vector.

Since the milestone achieved in 2012, CNNs have become the dominant approach in image classification competitions, and their model layers have reached greater depths in order to achieve higher performance. In 2014, Simonyan and Zisserman (2014) released the VGG-16 model, which reached 7.3% top-5 error rate in ILSVRC-2014. The VGG-16 model consists of sixteen convolutional layers, multiple max-pooling layers and three final fully-connected layers. By introducing ReLU activation functions

\(^{10}\) The equation of Softmax can be found at: [https://en.wikipedia.org/wiki/Softmax_function](https://en.wikipedia.org/wiki/Softmax_function)
for chaining multiple convolutional layers, the model is able to learn more complicated patterns.

In the same year, the winner model GoogLeNet, proposed by Szegedy et al. (2015), outperformed VGG-16 with 6.7% error by exploiting an efficient deep neural network architecture called Inception. The main idea of the Inception module is to learn local sparse structure by small CNNs. As shown in Figure 6.4, each module is composed of 1x1, 3x3, 5x5 convolution layers and a 3x3 max-pooling layers. The feature maps produced by a module are then concatenated by the next Inception module. Due to the use of the Inception module instead of fully connected layers, the GoogLNet is much smaller than VGG-16.

![Inception module](image)

**Figure 6.4 Inception module (Szegedy et al., 2015)**

It has been noticed by researchers that there is a trend of increasing error rate along with the increasing depth of CNNs not due to overfitting problem but to the difficulty of training and optimizing extremely deep modules (He et al., 2015). The introduction of “Residual Learning” by He et al. (2015) attempts to solve this issue by creating a connection between the output of multiple convolutional layers and their original input with an identity mapping, as shown in Figure 6.5. Their model “ResNet-152”, composed of 152 convolutional layers with 3x3 filters using residual learning by a block of two layers, achieved the best by a top-5 error rate of 3.57% in ILSVRC-2015.
Distinct from the ResNet in which identity mapping is proposed to merge a previous layer into a subsequent layer, DenseNet (Huang et al., 2017) has been proposed where each layer has additional inputs from all preceding layers and passes its own feature-maps to all subsequent layers, as illustrated in Figure 6.6. DenseNets have several compelling advantages over the previous models (Tsang, 2018):

- Strong gradient flow: the vanishing-gradient problem is alleviated as the error signal can be easily propagated to earlier layers more directly.

- Parameter and computational efficiency: due to the channel-wise concatenation, the number of model parameters is substantially reduced.

- More diversified features: as each layer in DenseNet receives all preceding layers as input, more diversified features can be captured which result in richer pattern.

- Low complexity features: in a standard CNN model, high dimensional features are extracted for the classifier; instead, the classifier of DenseNet is provided with features in a variety of complexity level, which tends to have smoother decision boundaries.
6.3.2 Natural language processing

Natural language processing (NLP) is a subfield of computer science with a collection of computational techniques for learning, understanding, and producing human language content (Hirschberg and Manning, 2015). NLP enables computers to perform a wide range of natural language related tasks at all levels, ranging from parsing and part-of-speech (POS) tagging, to machine translation and dialogue systems. In the challenge of interpreting combinational design creativity with NLP, particularly extracting a pair of base and additive from the textual description of creative design, Information Extraction (IE) is the NLP technique pursued to achieve the extraction. Generally, IE involves extracting structured information that can be interpreted easily by computational algorithms from plain unstructured text. IE systems are extremely important, and they are widely used for applications such as search and QA. IE is a challenging task which consists of several sub-tasks including named entity recognition (NER), relation classification and extraction, and event extraction.

In order to detect potential entities such as the bases and additives in combinational designs, named entity recognition (NER) could be exploited for this task. NER aims to detect, locate and categorize targeted nouns from textual data. In a classic task of NER, entities of person (PER), organization (ORG) and location (LOC) are expected to be extracted from news stories with NER. In the following example, the bold italic named entities are the targeted entities for NER (Mohit, 2014):
Before joining <ORG>UCB</ORG>, <PER>Lisa North</PER> worked for <ORG>Pegasus Books</ORG> in <LOC>North Berkeley</LOC>.

The approaches for building a NER system can be classified into three main streams: rule-based approaches, statistical and hybrid. Early approaches for NER are primarily rule-based, which involve three principal components (Mohit, 2014): (1) a set of named entity extraction rules; (2) gazetteers\footnote{Gazetteer is a term which is commonly used to refer to a domain specific lexicon, such as gazetteer for geographic location names.} for different types of named entity classes; (3) the extraction algorithms which apply the rules and gazetteers to textual data. Rule-based systems are relatively precise but with the cost of lower recall due to the low coverage of domain knowledge. In addition, the gazetteers take a long period of work to construct even when undertaken by experienced computational linguists.

Statistical models for NER have become popular along with the expansion of available data resources and computational power. With a large amount of training data and sophisticated algorithms, they can outperform the state-of-the-art rule-based systems, such as the work reported by Mikheev et al. (1999). Usually, two key components are needed for statistical models: well annotated (for supervised methods) or partially annotated (for semi-supervised methods) training datasets and a statistical model. The statistical algorithm is essential for the performance of NER, and various statistical models have been studied for decades, such as Hidden Markov Model (HMM) based (Wang et al.), Support Vector Machine (SVM) based (Saha et al.), Conditional Random Field (CRF) based systems (Majumder et al.). Recently, with the advance in machine learning especially deep neural networks, deep learning models taking word embeddings and character-level representation of words as input, in combination with a classical machine learning (e.g., CRF or SVM) as the final layer, is the state-of-the-art approach to NER (Chiu and Nichols, 2016).

There are many tools that have been developed for NER. Natural Language Tool Kit (NLTK) is the most used platform for NLP including NER (Loper and Bird, 2002). It provides more than 50 corpora and lexical resources with functions for tokenization,
part-of-speech (POS), NER and so on. Stanford NER is a Java implementation for NER. It is built on a linear chain CRF sequence model (Finkel et al.). SpaCy (2019) is a well-known python library for industrial-strength NLP. It applies deep neural networks models for NER, in which convolutional layers with residual connections, layer normalization and max-out non-linearity are used. However, currently available NER tools support a very limited set of types, such as only four types (person, location, organization and MISC) are in NLTK and Stanford NER. SpaCy supports much more than the previous two tools, but is still limited to 18 categories\textsuperscript{12}. A fine-grained entity recognition (FGER) for extracting entities of a broad set of types (e.g. actor, director, doctor, food, product, furniture, animal etc.) is in demand for a broader range of applications (Nguyen and Nguyen, 2018).

NER helps to extract the combinational pair of base and additive which is the first half of the extraction. The second half is the extraction of a combinational relation. With supervised methods, relation extraction (RE) refers to the classification from a set of known relations given the entity pair in the contextual data. Traditional supervised methods for RE typically work in either feature-based methods or kernel-based methods. Both types of methods use pre-existing NLP systems to extract feature and elaborately-designed kernels, which result in the accumulating errors for downstream modules (Kumar, 2017). In addition, the manually constructed features may not be able to capture all information needed. Recently, neural networks based deep learning attempts to tackle these issues with supervised learning.

Training datasets is essential for deep learning based RE. Early works using deep learning employed the same supervised training datasets that were previously used by non deep learning models. The ACE (Automatic Content Extraction) 2005 dataset (Walker et al., 2006) contains 599 documents related to news and Weblogs in which relations are annotated into seven major categories. Six major relation types have enough annotated instances (700 instances per relation type on average) for training and testing. Another popular dataset is SemEval-2010 Task 8 in which 10,717 samples are

\textsuperscript{12} The list of supported types can be obtained from: https://spacy.io/api/annotation#named-entities
annotated and divided into 9 major ordered relation types, such as Cause-Effect (CE), Product-Producer (PP), and Instrument-Agency (IA). Since each relation can be in reversed order, $9 \times 2$ types of relations are included plus one more “other” type (Hendrickx et al., 2009). For example, provided with two named entities (underlined) of interest in the following sentence, it falls into the “Cause-Effect” category:

Those cancers were caused by radiation exposure.

However, the annotation of these datasets requires intensive human effort to make sure of their high quality. To avoid the laborious task of manual construction of datasets for RE, Mintz et al. (2009) proposed a distant supervision approach for automatically collecting large amounts of data for supervised learning. Aligning with known knowledge bases (KBs), such as Freebase (Bollacker et al., 2008), a relation can be discovered in a given textual data on the assumption that the textual data containing the mention of an entity pair would express the relation if that relation exists between an entity pair in the known KB, as shown in Figure 6.7. Sorokin and Gurevych (2017) constructed a Wikipedia-Wikidata sentence-level relation dataset with distant supervision approach, in which 353 different relation types were featured (out of approximately 1700 non-meta relation types in the Wikidata scheme). In the dataset, 284,295 relation triples are constructed for training, which is far larger than previous supervised datasets.

Figure 6.7 Pipeline for generating training data with distant supervision (Smirnova and Cudré-Mauroux, 2018)

In deep learning based approaches for RE, word embeddings (Mikolov et al., 2013) are used to encode sentences and then are fed into neural network layers, such as
convolutional neural networks (CNNs) or Recurrent neural networks (RNNs). Zeng et al. (2015) proposed a piecewise CNN model with a multi-instance learning paradigm, in which a piecewise max-pooling layer is employed for learning richer representations from different segments based on the positions of two entities in a relation, instead of using a normal max-pooling layer which reduces the size of a hidden layer. To focus on the most-relevant information in given textual data and capture richer representations, Lin et al. (2016) applied an attention mechanism over all the instances from the bag for the multi-instance problem, and showed significant improvements on the prediction of correct relations with higher confidence. Sorokin and Gurevych (2017) proposed an LSTM-based encoder to jointly learn context-aware representations for multi-relations in a single sentence and made predictions with an attention mechanism on contextual relations.

6.4 Extraction of combinational design creativity

6.4.1 The extraction approach

To extract the combinational pair from the context of the corresponding image and textual description exclusively with computational techniques, an integrated interpretation approach is proposed. As shown in Figure 6.8, a state-of-the-art deep learning model is employed for interpreting images, namely image classification, and filter the results with a preset threshold. For textual data, NLP techniques NER and RE are applied. Due to the limited types of named entities which may not be covered for provided textual data, such as only 18 categories are supported in spaCy, all existing entities in a sentence-level are expected to be extracted. Then all extracted entities are fed into the RE model in which context-aware sentence-level representations are captured. Since combination is a high-level represented relation, and can be a mixture of different relations as explained in the three driven approaches, such as analogical relation, cause-effect relation, even technological relation, the extraction of combination relation is so complicated that all possible relations from textual data should be extracted for further examination. With all possible results from a provided
image, and all possible entities and relations from given semantic data, the reasoning unit analyzes their correlations and determines the base and additive respectively.

The reasoning unit plays an essential role in determining the base and additive, since there are errors accumulated from previous processes including image classification, entity recognition, and relation extraction. Taking image classification as an example, due to the complexity and intrinsic innovation of a product, which is reflected in an image, the object in the image may be failed to be detected or detected with a low probability. To alleviate these negative effects, several reasoning strategies are applied in the approach, as shown in Figure 6.9. In the reasoning unit, it is verified first that all previous modules should have produced an appropriate amount of results (more than zero). Then similarity check and relation check are performed respectively. In similarity check, those entities which share similar semantic meanings between image recognized entities and sentence-level recognized entities, are identified, as there is a high probability that base and additive exist among them. On the other hand, the target combination relation and the corresponding pair of entities are identified in the relation check, by comparing the similarity between the image recognized entities and the entities in recognized relations.
In the verification process where the base and additive are determined, the top five most similar entities from the similarity check and all matched entities from relation check are collected. Then it is checked whether any of the five entities from similarity check matches to the entities in the relation check. The relation whose entities have a higher ranking of similarity, is the identified combination relation if the check passes. Otherwise, the top two similar entities from the similarity check are taken as the base and the additive respectively.
Figure 6.9 Algorithmic flowchart of the reasoning unit

Since the categories for image classification are really limited compared to the vocabulary of English corpora (English is the only language applied to this research), similarity check and relation check play important roles in the reasoning unit. The similarity between two entities is checked on the semantic meaning and is calculated relatively with a range restriction of the whole vocabulary, so the results are obtained by comparing with others. The implementation of the similarity calculation method will be illustrated in the next section.

6.4.2 Implementation

A. Dataset

In order to verify the proposed approach for interpreting combinational design creativity, this research uses the dataset established by Han et al. (2019) for investigating the three
driven approaches of combinational creativity. In that dataset, information of 200 combinational creativity originated products were collected from the winners of top international design competitions, such as Red Dot Design Award and iF Award (International Forum Design Award). The 200 samples are checked and confirmed to have combinational creativity with their corresponding bases and additives. In Han et al.’s study, that dataset was used to determine which approach(s) is taken from the three driven approaches by means of expert evaluation given the information shown in Table 6.1. Since this dataset had been evaluated by experts, it is convincing to use it as the gold standard to measure the performance of proposed approach.

**Table 6.1 An overview of combinational design creativity dataset**

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Image</th>
<th>Description</th>
<th>Base</th>
<th>Additive</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Baby Bottle</td>
<td><img src="image1.png" alt="Image" /></td>
<td>The form is inspired by a natural tree shape and eliminates water pooling and prevents minerals and bacteria from building up.</td>
<td>Drying Rack</td>
<td>Tree</td>
</tr>
<tr>
<td></td>
<td>Drying Rack</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Sharp 1</td>
<td><img src="image2.png" alt="Image" /></td>
<td>This knife block set and its integrated knife sharpener are a space-saving combination of different functions. It saves users from having to search for a knife sharpener when needed.</td>
<td>Knife Block</td>
<td>Knife Sharpener</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Origami</td>
<td><img src="image3.png" alt="Image" /></td>
<td>Inspired by the origami paper folding technique, the surface of this teaware features an inventive structure. It lends the two-piece tea set a unique feel while also adopting the round shape of classic tea ware.</td>
<td>Tea set</td>
<td>Origami Paper Folding</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>...</td>
</tr>
</tbody>
</table>

As shown in Table 6.1, the dataset has full information about each product regarding its combinational creativity, including its name, image, description, and the combination
pair (base and additive). The information of name, image and description are collected directly from the official websites of design competitions. The number of images for each product is limited to one, while the description is limited to up to five sentences. Based on the above information, the combination pair of each product is manually extracted and validated by two design experts. For example, for the no.2 product “Sharp 1” in Table 6.1, its base and additive are “knife block” and “knife sharpener” respectively according to its image and description “This knife block set and its integrated knife sharpener is a space-saving combination of …”. The dataset has been verified to make sure that the words of all bases and additives are originated from the corresponding products’ description and/or names. For instance, the base “drying rack” (from the product No.1 in Table 6.1) does not appear in the product’s description, but only appears in its name.

B. Image interpretation module

As introduced in section 6.3.1, DenseNet is one of the state-of-the-art models for image classification and is more efficient and more accurate than previous models, such as ResNet. This study employs the same architecture of DenseNet-121 for interpreting the images in the combinational design creativity dataset. As shown in Figure 6.10, the model starts with a convolutional layer (including a convolutional neural network, a batch normalization and a ReLU) and a max-pooling layer, followed by four dense blocks and three transition blocks. Each dense block has a certain number (e.g. 6 for 1x1 and 3x3 in block 1) of convolutional layers densely connected sequentially as shown in Figure 6.6(b), specifically, following the way of BN-ReLU-Conv(1x1)-BN-ReLU-Conv(3x3) which is computationally efficient. Each transition block facilitates the down-sampling by locating between two dense blocks. It consists of a 1x1 convolutional layer and a 2x2 average pooling layer. At the end of the last dense block, a global average pooling is performed and then a softmax classifier is attached.

The ILSVRC 2012 classification dataset\(^\text{13}\) (Deng et al., 2009) is employed for training the DenseNet-121 model, and the trained model was directly used for image interpretation.

\(^{13}\) The details can be found at: http://image-net.org/challenges/LSVRC/2012/index#introduction
classification without being trained on the combinational creativity dataset which is only used for evaluation. The ILSVRC 2012 dataset consists of 1.2 million images for training, and 50,000 for validation, from 1,000 classes. The same data augmentation scheme is adopted for training images as by Huang et al. (2017). The model is trained until its validation error rate achieved the original paper’s performance, which is 25.05% top-1 error and 7.71% top-5 error respectively. Addressing the concern of missing classes in the ImageNet-1000 dataset respecting to the classes in the combinational design creativity dataset, a commercial image prediction API provided by clarifai is used as an alternative, which is a leading artificial intelligence company specialized in image analysis, in order to make sure all bases are predictable. There are several reasons to use clarifai: 1) the purpose of this research is not to evaluate an image classification model, but instead to evaluate whether the base and additive from a combinational design (images and texts involved) can be detected, which is far challenging than image classification; 2) existing academic datasets cannot cover all the object involved in the combinational creativity dataset, which makes the experiment difficult to proceed; 3) it was found that few additives were not detected by neither DenseNet nor clarifai due to their visual complexity, even though all bases could be recognized; 4) only 12% objects need to be recognized using clarifai, which occupies only a small portion of total recognized objects.

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14 The official website of clarifai: [https://www.clarifai.com/](https://www.clarifai.com/)
To extract entities and relations from textual descriptions (including product names), two different models performing these two tasks are developed respectively. As we extract all possible entities at sentence-level instead of named entity recognition, a general-purpose NLP tool is sufficient for this extraction. spaCy is chosen for its popularity and excellent performance. With tokenization and POS tagging, all recognized nouns as extracted entities are collected.
Figure 6.11 The architecture of the RE model (modified from Sorokin and Gurevych, 2017)

Provided with all recognized entities in a single sentence, more than one relation may appear in a single sentence, thus a context-aware architecture for extracting the target relation (Sorokin and Gurevych, 2017) is adopted in this study. As shown in Figure 6.11, the model first tokenizes a sentence into $x = \{x_1, x_2, \ldots, x_n\}$, and marks each token as either belonging to an entity or to not an entity. It then maps the token sentence to a $k$-dimensional embedding vector using a matrix $W \in \mathbb{R}^{|V| \times k}$, where $|V|$ is the size of the vocabulary. Here it employs the pre-trained Word2Vec model from Google by Mikolov.
et al. (2013) where three million 300-dimensional embeddings of words or phrases are trained. Similarly, the entity markers are converted into a marker embedding matrix \( P \in \mathbb{R}^{3 \times d} \) by randomly initializing each entity, in which \( d \) is the dimension of the embedding and there are three marker types. Each marker embedding is concatenated with word embedding \((W_n, P_n)\) and fed into the LSTM layer.

Since multiple relations (including target relation and contextual relations) may exist in a single sentence, the model has multiple output vectors for corresponding relations within the same LSTM layer, which are denoted as \( O_t \in \mathbb{R}^O \) for target relation and \( O_i \in \mathbb{R}^O \) for contextual relation. An attention mechanism is applied in the model by computing a score for a contextual relation with respect to the target relation: \( g(o_i, o_t) = o_i A o_t \), where \( A \) is a weight matrix learned in the LSTM layer. Then a weight can be obtained by following the equation:

\[
a_i = \frac{\exp(g(o_i, o_t))}{\sum_{j=0}^{m} \exp(g(o_j, o_t))} \tag{6.1}
\]

We sum the contextual relation representations with the following equation:

\[
o_c = \sum_{i=0}^{m} a_i o_{i} \tag{6.2}
\]

The resulting context representation \( O_c \) is concatenated with the target relation: \( O = [O_t, O_c] \). Finally, the concatenated vector is fed into the softmax layer to predict the target relation type.

The context-aware RE model was trained with the Wikidata dataset constructed by Sorokin and Gurevych (2017). The dataset has 284,295 relation triples, and 578,99 relation instances for training (there are multiple relation triples in one instance), while 353 different relation types are supported. The model was trained with the Adam optimizer and categorical cross-entropy as the loss function. The learning rate is fixed to 0.01 with an early stopping strategy for the validation process. The model achieved
the performance reported in Sorokin and Gurevych (2017) before it was used in the following experiment.

6.4.3 Interpretation experiment

Before performing the experiment of extracting combination pairs, this study first makes sure that the image interpretation module and the ER&RE module are well trained and ready for inference use. It then uses the two modules to analyze the images and textual descriptions in the combinational design creativity dataset. For image classification, since the results for each image interpretation are presented in an order of probability, only the top 10 highest probability results are collected. For entity recognition and relation extraction, all interpreted results are collected. Then all the results from the image interpretation and ER&RE modules are fed into the reasoning unit.

In the similarity check, spaCy is employed for calculating the words’ or phrases’ semantic similarity. In particular, the similarity is determined by comparing word vectors or word embeddings which are multi-dimensional representations capturing the syntactic and semantic information about words or phrases. Word vectors can be generated using an algorithm such as word2vec (Mikolov et al., 2013). The comparison results are normalized into the range between zero and one. For example, the similarity between “bulb” and “lamp” calculated by spaCy is around 0.781, while the similarity between “bulb” and “fire” is about 0.243. It means “bulb” has a more similar meaning to “lamp” than “fire”. The same similarity calculation method is applied to the relation check as well.

When bases and additives are determined by the proposed approach, the criteria for checking whether the predicted bases and additives are correct are that: 1) it should be identical if the base or additive consists of only one word; 2) at least one keyword must be identical if the base or additive consists of a phrase. For instance, the predicted additive from No.1 product in Table 6.1 must contain the word “tree”, while the predicted base at least has to contain the word “rack” as it is the keyword in “drying rack”.
6.5 Results and observations

6.5.1 Overall results analysis and observations

Table 6.2 Results of combinational creativity interpretation

<table>
<thead>
<tr>
<th></th>
<th>Correct number</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base &amp; Additive</td>
<td>136 / 200</td>
<td>68 %</td>
</tr>
<tr>
<td>Base or Additive</td>
<td>50 / 200</td>
<td>25 %</td>
</tr>
<tr>
<td>None</td>
<td>14 / 200</td>
<td>7 %</td>
</tr>
<tr>
<td>Base</td>
<td>178 / 200</td>
<td>89 %</td>
</tr>
<tr>
<td>Additive</td>
<td>144 / 200</td>
<td>72 %</td>
</tr>
<tr>
<td>Image interpretation</td>
<td>248 / 400</td>
<td>62 %</td>
</tr>
<tr>
<td>Entity extraction</td>
<td>400 / 400</td>
<td>100 %</td>
</tr>
<tr>
<td>Relation extraction</td>
<td>152 / 200</td>
<td>76 %</td>
</tr>
</tbody>
</table>

In the extraction of combinational design pairs of each product from the dataset, 136 of 200 pairs were correctly extracted, which accounts for a successful interpretation rate of 68%, as shown in Table 6.2. However, there are 50 out of 200 (25%) products whose bases or additives are correctly extracted but their counterparts were mistakenly extracted. Only 7% of products are totally extracted incorrectly. To figure out whether base or additive is more difficult to be extracted, we reported the total number of bases and additives correctly extracted in Table 6.2 as well. It shows 89% bases are correctly extracted while additives account for only 72%, which means additive extraction has a higher error rate. This reveals the fact that combinational designs inherit primary features from corresponding bases, and that the mixture of features from bases and additives make additives difficult to be detected.

A benchmark with ResNet model was conducted in order to verify whether the applied image recognition model is performing decently. As introduced in section 6.3.1, ResNet
is a popular and powerful model in image recognition due to its identity mapping design so that the neural networks can be as deep as more than hundreds of layers without performance drop. Here ResNet-50 was chosen for a fair comparison, as it has more parameters (more than 20 million) than DenseNet-121 (less than 10 million). Similarly, a trained ResNet-50 model on ILSVRC 2012 dataset was utilized in the benchmark experiment. With the same setting for image interpretation, 240 labels were correctly recognized by the ResNet model, resulting in the accuracy being 60% compared to 62% by DenseNet-121. This indicates that the model applied in the creativity interpretation experiment is reliable.

![Figure 6.12 Portion of base and additive examples](image)

Through the exact portion of the additive in a combinational design is difficult to measure from both images and textual descriptions, which is beyond the scope of this research, what can be deduced is that the features from additives are less than the features from bases in those combinational designs whose additives cannot be correctly extracted. In Figure 6.12(a), the portion of base and additive can be perceived as half and half, and both fork and spoon can be detected by our DenseNet model successfully with a relatively high probability. However, only the base in Figure 6.12(b), which is “chair”, is detected with a high probability (which means the top 10 of prediction results for that image). As can be observed, the features of “table” have a small portion in the whole image which results in the failure of image prediction. In fact, due to the complexity of product design, here only a rough qualitative estimation is made to analyze the portion of base and additive, and a further quantitative study needs to be
conducted in future. In addition, the degree of a combination may also have an essential effect on the detection in terms of image prediction.

6.5.2 Modular analysis and observations

To further analyze the 25% partial correct extraction rate, a modular analysis of the proposed approach is conducted. As shown in Table 6.2, the image interpretation module only achieves an accuracy of 62% which is calculated based on the correctly predicted bases and additives from the top-10 results through all 200 images. Specifically, as can be calculated, 78% of total bases are correctly predicted, while only 46% of total additives are predicted. This further explains the lower overall additive extraction accuracy compared to the base extraction accuracy. In addition, it supports the fact that combinational design contains more elements from the base and fewer elements from the additive. As there is less feature about the additive in a combinational design, it is more challenging to detect additives by the image interpretation module, as demonstrated in the examples of Figure 6.12.

There are other factors which limit the accuracy of image prediction, as listed below:

- The number of images for each design: in the combinational design creativity dataset, only one image is assigned to each product. Since every image reflects an angle of observing a design, more images tend to increase the angles of showing a product, which results in a higher probability of correct image prediction, especially for the combinational design. In Figure 6.13 (a), due to the angle of the photo taken, it is difficult to recognize the features of “LED”.

- The complexity of product design: even though the products selected in the datasets belong to ordinary products for daily use, such as chair and kitchenware, the combinational creativity in these products increases the difficulty of recognition by computational algorithms. In Figure 6.13(b), this fresh combination of grater and drum makes our model difficult to detect neither “grater” nor “drum”.

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• The visibility of base and additive: generally, the functional combination tends to be invisible in designs which makes it nearly impossible for the image interpretation module to detect such a combination. In instance, in Figure 6.13(c), due to the invisibility of “Bluetooth” which is the additive of the “LED lamp – Bluetooth” combination, our DenseNet model is not able to detect “Bluetooth”.

![Image](image1.jpg)

(a) LED – moss

(b) grater – drum

(c) LED lamp – Bluetooth

(d) pouffe – pig

Figure 6.13 Examples of failure cases

• The mixture degree of combinational design: the degree of combination also plays a vital role in image interpretation. The deeper (higher degree) the combination is, the more difficult to predict the base or additive. In the combination of “pouffe - pig”, as shown in Figure 6.13(d), the pouffe is designed analogical to the appearance of a pig. However, since it is a “fake” pig and even it is disassembled as two components, our model is not capable of interpreting it as a “pig”. This kind of design can be rather easier for human to recognize what it may look like as human being is good at making analogies and imagining. With
some level of reasoning, a human can readily give the right answer by digesting the information from both images and textual description. However, it is difficult for machine to do that using either reasoning or imagination.

As all entities need to be extracted in every sentence, bases and additives are contained in the extraction results with an accuracy of 100%. Even though this approach brings noises (the extracted entities other than bases and additives), it is guaranteed that all bases and additives can be captured without missing extractions for the following processes. Future research can be conducted to filter those noise entities so that the downstream processes can achieve higher accuracy. A possible approach can be topic extraction which aims to extract topics from contextual data using a method such as TF-IDF or TF*PDF (Bun and Ishizuka, 2002).

The module of RE contributed 76% to the combination pair extraction, which is higher than the image interpretation module. Benefiting from its context-aware architecture, the RE module is capable of extracting multiple relations at sentence-level. For example, given the following description about the design of a product called “Bionic”:

*The design idea for this vase series was inspired by tree trunks and their branches, and aims to increase awareness of the great importance of preserving the environment.*

The results of extracting all possible entities and relations, are visualized in Figure 6.14(b). Specifically, two relations are extracted: “tree trunks – vase series” and “tree trunks – design idea”. The former one is the target combination pair that needs to be identified by the following step relation check and verification. However, there are some difficult scenarios and failure cases as well:

- The target base or additive does not appear in the description but in the product name only. For example, in Table 6.1, part of the name of No. 1 design is the base, but it does not appear in the description. Even though the design name and its description are fed into the RE module together, it is difficult for the module
to capture the relation between the base and the additive due to low connection and appearance frequency.

- The target base or additive appears in different sentences. Even though the maximum number of sentences is limited for describing each design, there are chances that base and additive may not appear in the same sentence. This results in missing extractions or a situation in which the base and additive are connected indirectly by an intermediary entity. The first situation is fatal to the final identification, while the second one is solvable in further study.

- The target base or additive is extracted in a relation but the another is not. In some cases, the name of the design and its base are mixed to be used for describing the design, which makes the RE module confused to extract the relation. In other cases, the additives are mentioned together with other nouns (entities), which disturbs the extraction. However, even though this case is handled in the verification step, the ranking of entities may not be able to guarantee accurate extractions.

![Image of the sample](image1.png)  
![Visualization of relation extraction results](image2.png)

**Figure 6.14 A relation extraction example**
6.5.3 Bottleneck of the integrated approach

From the perspective of module performance, the image interpretation module is the bottleneck of the whole functioning model, as observed in Table 6.2. Even though DenseNet-121 is one of the state-of-the-art models for image prediction, it is trained on the ImageNet-1000 dataset only where most of the images are from online and the content of images tends to be ordinary rather than creative. Even though clarifai is powerful commercial image recognition engine, it contributed very little to this problem with two facts: 1) only 12% objects in the dataset were detected by clarifai which could not recognized by DenseNet; 2) clarifai is trained on natural objects and ordinary images which are similar to the data in ImageNet-1000. A better solution could be training the model on an intensive product image dataset on top of the pre-trained model by transfer learning (Shin et al., 2016). On the other hand, based on the analysis of factors affecting the accuracy which are discussed in section 6.5.2, solutions can be provided to alleviate their negative impact. For example, increasing the number of images for each product design; handing the invisible issue over to the RE module with extra attention; using a novel method for interpreting images, such as dissembling an image into several parts for analysis.

From the perspective of combination pair extraction, additive extraction is the bottleneck of overall performance. As analyzed above, generally, features from additive tend to be less absorbed than from base in a combinational design, which is the leading cause for lower accuracy in combination pair extraction. By comparing the performance between the image interpretation module and RE module, RE module performs better at interpreting additives. In addition, the factors affecting the performance of image interpretation module do not apply to the RE module. Therefore, improving the performance of the RE module is the solution to the bottleneck of overall performance. Based on the analysis of failure cases in the RE module (in section 6.5.2), there are several ways to be considered for improvements:
• More attention can be paid to the name of product design. If the name is not a new word or phrase which is out of vocabulary, the entities in it have a high potential to be the base or additive.

• The proposed context-aware architecture can be extended to cross-sentence level. In case that base and additive appear not in the same sentence, intermediary entities should be analyzed to search for connected base and additive.

• The RE module can be improved for combination relation extraction. There are some patterns when describing the combination relation, such as “... is inspired by ...” (an example is provided in No.1 of Table 6.1), “... is a combination of ...”, and “... is ... as well as ...”. These patterns can be learned exclusively by training the machine learning based RE module with a dataset full of combination relations.

6.5.4 Contribution to the data-driven cycle

The study of this chapter aims to extract combination elements (base and additive) from conceptual designs, and analyzes the difficulties of this task from a technical perspective. Due to the complexity in combinational creativity, challenges still remain for future exploration. In contrast with bisociative knowledge discovery and visual conceptual blending which transform data to design creativity, this study focuses on the interpretation of one common design creativity using machine learning techniques, transforming design creativity to data, thus closing the cycle loop. The extracted metadata can be added into the database for bisociative knowledge discovery, supporting the data-driven cycle to generate design creativity as internal data source. As can be seen, the three studies form the data-driven cycle and lead to continuous creativity in conceptual design.

6.6 Conclusion

In this chapter, combinational creativity is introduced with three driven approaches in which how combinational relations are established is explored. As it is understood that
combinational creativity is formed by base and additive in three driven ways, this study further explores how to extract the base and additive as a combination pair from visual and textual materials with computational methods. In the challenge of interpreting combinational design creativity, the main contribution is the proposal of an integrated computational approach for extracting a combination pair from images and texts jointly. To validate this approach, the image interpretation module and the ER&RE module are implemented with state-of-the-art deep learning architectures.

In an experiment with the combinational design creativity dataset, the results have shown that the proposed approach is able to extract combination pairs from real-world creative designs, especially the bases. However, due to the complexity of the combination in creative designs and other factors discussed in this chapter, additives tend to be more challenging to be interpreted than bases. The performance of the image interpretation module and NLP modules were compared, and it was concluded that NLP modules are more powerful than the image module for extracting additives. Observations and possible improvements for the proposed approach are discussed in this chapter as well, which would be helpful for future studies.
Chapter 7. Conclusions

This chapter provides the conclusions of this thesis. It summarizes the work by answering the research questions proposed at the beginning of the thesis. Then the key findings and contributions of the conducted research are introduced, focusing on how data, machine learning algorithms, and creativity theories support the generation and interpretation of design creativity. This chapter also discusses the limitations within this research and the future directions for studying design creativity with data-driven and machine learning based approaches.

7.1 Discussion of the data-driven cycle

There can be many ways to implement the proposed data-driven cycle. As demonstrated in this thesis, one possible implementation could be developing the same functioning models including BKD, VCB, NLP and image recognition which has been validated in previous chapters. Although this is not enough to fully study the proposed cycle for design creativity, it opens up opportunities for future research with further discussion and evaluation on its working mechanism. Instead of repeating implementation of those modules, here data collection and processing are mainly discussed. Internal resources are managed by its owners and can be obtained easily with assistance from internal technicians. For external resources, data collection is mainly facilitated by web crawling unless existing datasets or knowledge bases can be used. A web crawler is a robot which visits webpages and fetches specific content reclusively by following hyperlink rules along with seed URLs. Web crawling is widely used in search engines such as Google and Baidu, and also used to collect data by analysts. For example, Mukhopadhyay et al. (2007) designed a domain-specific web crawler which identifies relevant web pages based on ontological knowledge. As the knowledge base in the proposed cycle should contain multi-domain knowledge, despite the academic data collection method presented in Chapter 3, Wikipedia can be another rich resource.
Generally, textual data is easier to be cleaned compared to image data as there are many NLP techniques available for processing textual data. For image data to be used by VCB, image recognition technologies can help find the required images, but sometimes further cleaning may be required. For example, when collecting images about “cat”, an image containing “cat” and “dog” could bring noise into the learning process. In order to alleviate this issue, image segmentation is an alternative technique to be explored. Image segmentation is the process of partitioning an image into multiple segments according to objects’ boundaries (Haralick and Shapiro, 1992). As shown in Figure 6.6, the left image containing “cat” and “dog” is segmented as the right image in which the boundaries of “cat” and “dog” are drawn. With image segmentation, the target object(s) in an image can be extracted solely without being contaminated by other objects, this technique makes sure that target object(s) can be learned by the VCB model exclusively.

Figure 7.1 Image segmentation example (DeepLab, 2019)

Some models in the proposed implementation are deep neural networks, including VCB, NLP and image recognition. Among them, VCB consumes the most computing resources due to data collection and model training. Usually, in order to train a generative adversarial network model such as VCB, a large amount of data is required for each concept. Although there is no standard amount of data for training, the empirical number is more than 1,000 for each category and the more the better. Furthermore, the cleaning of image data needs a powerful image segmentation model, such as the DeepLab model proposed by Chen et al. (2018), which means further efforts are demanded. Model training is another time-consuming factor. Due to the complexity of a GAN model and the required data amount, training the proposed VCB model can
take from hours to days. Although NLP and image recognition models consume less computing resources, they need to be trained with new datasets which are suitable for specific tasks rather than using pre-trained models as did in Chapter 5, if they are expected to achieve better performance. Different from VCB, the training of NLP and image recognition models can be one-off once the creative system is made.

Another limitation is the incoherence between the BKD and VCB models. As data collection and considerable training time are demanded in VCB, when provided with two concepts (a pair of bisociation) obtained from the BKD model, VCB is not able to immediately generate blended graphs unless VCB is well trained for the two concepts in advance. Due to this issue, the BKD and VCB model work independently from each other in the proposed cycle. The solution to this issue could be to abandon the proposed GAN architecture in VCB, and use a parametric model which does not require model training instead. However, a parametric model may be criticized for its weakened capability of generating creativity. This solution and the corresponding argument are required for future investigation.

Due to the time and effort limitation, the research presented here has limitations. It lacks of an overall case study validating the overall functionality of the data-driven cycle and testing the described limitations above. The relation between different stages in the cycle needs to be examined in addition to justifications. At the end of a cycle, extracted meta-data from design creativity are added to the database for BKD. Further investigation can be conducted to study the effect of added data on BKD’s performance.

### 7.2 Research summary

In this thesis, computational design creativity is studied along with data mining and machine learning based methodologies, but from a systematic view, it is studied by threading design creativity theories, data, and computing algorithms. By introducing the background of design creativity, data-driven design, and machine learning in design, the principal research question is proposed for this thesis: With the support of data, algorithms and design creativity theories, how to build up a creative system which is
able to generate, interpret and recycle design creativity knowledge? This is then substituted by three research questions:

- How can design creativity from semantic data be effectively captured and augmented?
- How to produce creative (graphic) designs by learning from image data with machine learning algorithms?
- How to interpret creative designs effectively from semantic and image data with machine learning methods, and transform them into metadata for creative knowledge reuse?

Before answering the above four questions, an exploration of creativity theories is provided, including those methodologies related to the research in this thesis. To further explore creativity in the context of computer science, the definition and state-of-the-art research of computational creativity are then reviewed with the attempt of investigating how computational creativity research was conducted on top of creativity. As computational creativity tends to be implemented and applicable rather than theoretical and descriptive, design creativity tools are investigated and classified into three categories according to properties such as program-based or data-driven. The investigation confirms the significance of the proposed research questions.

A creative system, as defined by Wiggins (2006), aims to achieve or simulate behaviors which humans deem creative. Existing research on creative systems has discussed much about what a creative system is, how to model a creative system, and how to evaluate a creative system, but there is little discussion about the reuse of creative knowledge from a systemic point of view. By reviewing design knowledge reuse, a data-driven cycle for reusing creative knowledge in a design creativity system is proposed in Chapter 3. In that cycle, a bi-directional transformation between data and creativity, which forms a closed creative knowledge reuse loop, is expected to support continuous creativity. Specifically, built on top of a multi-domain knowledge base, two models, namely the BKD and VCB, are responsible for transforming semantic data and image data into raw creativity. Then the involvement of human experts’ knowledge helps mature the raw creativity into creative designs or solutions. Followed by a creativity interpretation
module, in which the NLP and image recognition techniques are applied to process semantic and image data respectively, the creative designs or solutions are transformed to meta-data again, which facilitates the recycling of creativity. To summarize, the cycle is data-driven, creativity theories supported, and it works by applying a variety of machine learning algorithms. Most importantly, it supports continuous creativity within the system.

To implement the proposed data-driven cycle, research is conducted and illustrated correspondingly in three chapters. Within the field of creative knowledge discovery, existing methods for semantic data analysis are data mining based which tend to find close associated patterns and also lack the involvement of user’s interaction. Bisociative knowledge discovery (BKD), as an application of bisociation theory in creative knowledge discovery, is explored in Chapter 4 in order to provide a foundation for capturing and augmenting creativity. Instead of exclusively employing existing data mining techniques to process semantic data, network is highlighted in this study not only as a data structure but also as a visualization interface to support human-computer interaction (HCI). Integrating BKD with network based data mining and visualization techniques, guidelines are proposed for creativity generation and augmentation from three perspectives: creativity modeling, discovery, and HCI. As an implementation of these guidelines, an HCI-BKD model is proposed in Chapter 4 containing three essential functions along with a network visualization interface. The implementation of “Exploration” provides implicit associations given a concept, which is similar to the exploratory creativity proposed by Boden (2004) but focuses on cross-domain bisociation exploration. Another function “Search Path” retrieves possible paths from one concept to another aimed to capture the implicit knowledge hidden in the pathway from a departure node to a destination node within the structured network database. Although this process is similar to Boden’s (2004) combinational creativity, the difference between BKD and combinational creativity is that the two concepts should be from two knowledge matrices represented by two distinct domains (“perpendicular”, according to Koestler (1964) and Dubitzky, et al. (2012)). “Cluster”, as the third function, provides an overview of the current network graph by clusters with the attempt
of distinguishing graph data by domains. This function assists users with the awareness of picking up cross-domain knowledge concepts. The BKD-HCI model facilitates users’ interaction with these three functions in the interface of network visualization, which results in creative ideas (bisociations) after users’ iterative operations within this model. The whole process of creative knowledge discovery was validated in Multi-dimensional In-depth Long-term Case studies (MILCs), and then followed by a design case study which further confirms the capability of the proposed BKD-HCI model.

Although semantic data is one of the most popular and essential formats of data, it has less capability of expressing visual information than image data, especially when dealing with design creativity. Hence Chapter 5 investigates how to make use of image data to obtain design creativity. Conceptual blending is regarded as a validated methodology for generating creativity by taking two mental spaces as inputs and generating a new blend space via a given mapping. Existing methods of conceptual blending either are not computationally capable or have weak capability of generating visual creative blends due to the limitation of algorithms. Generative adversarial network (GAN), a growing and promising technique for generating image data, has been widely applied for image synthesis, image-to-image translation, and super-resolution. In the proposed conceptual blending GAN model, an encoder-decoder architecture is adopted as its generator which is responsible for generating blended images, while another encoder architecture is employed as discriminators for distinguishing real and fake images. This model is trained with a supervised method, in which two datasets representing two distinct concepts desired to be blended. Before testing the model’s efficacy in a design study, the model was implemented and then validated in a benchmark with CycleGAN. In the experiment of blending “spoon” and “leaf”, the validated GAN model demonstrated its capability of generating a variety of images which synthesize “spoon” and “leaf” for a creative design task, with evaluation metrics including quality, quantity, variety and novelty.

Chapter 4 and 5 explore how to augment and generate creativity with computational methods in terms of different data formats, Chapter 6 deals with design creativity in the opposite way. With existing creative products, how to interpret their creativity is an
interesting research topic as the interpreted creative knowledge can be reused in the design process. However, interpreting creativity is different as it can exist in different formats, some of which are so complicated that modeling the interpretation process computationally can be really difficult. In Chapter 6, combinational creativity is investigated from the perspective of three-driven approach. With a fuller understanding of combinational creativity, the existing technologies, including start-of-the-art models for image prediction and natural language processing (NLP), are explored with the attempt to interpret graphic and semantic data respectively. An integrated approach is proposed to extract the base and additive from combinational design creativity. In the approach, images and semantic data are processed by corresponding modules respectively, and the processing results are then fed into the reasoning unit for final identification of base and additive. To validate the approach, the image prediction module was implemented with the DenseNet-121 architecture pre-trained on ILSVRC 2012 datasets, while the entity recognition and relation extraction modules were implemented with spaCy and an attention-based LSTM model. The approach was tested on a combinational design creativity database which consists of related information about 200 creative products. The results show that the proposed approach is able to extract combination pairs from the real-world creative designs, although with some failure cases which were thoroughly analyzed from multiple aspects.

7.3 Key findings and contributions

This thesis explores computational creativity in the field of design from a practical perspective. Data is the meta element for a creative system, which can either represent creativity in various forms or provide insights for creativity generation and augmentation in computational ways. To computationally model design creativity, theoretical creativity methodologies provide fundamental support, such as Koestler’s (1964) bisociation theory, conceptual blending and Wiggin’s (2006) framework of creative systems. Eventually, it is data mining and machine learning algorithms that embody the transformation between data and creativity. To conclude, in the context of
data, creativity theories, and artificial intelligence techniques, a list of key findings and contributions are made, as illustrated below:

- The review of creativity theories provides foundations for the studies conducted in this thesis; gaps and opportunities are identified from the review of computational creativity and existing design creativity tools.

- In order to facilitate the bi-directional transformation process between data and creativity, a collection of data manipulation steps is covered throughout this thesis. Specifically, for semantic data, it includes data collection, data cleaning with NLP techniques, structuring data with network, and NLP related high-level processing (e.g. relation extraction); for image data, the processing is straightforward, including data collection and image prediction.

- By reviewing existing creative systems and design knowledge reuse, a novel cycle for reusing creative knowledge in a design creativity system is proposed. Creativity theories involved in this cycle are successfully developed for modeling computational creativity in design:
  - Bisociation is applied to creative knowledge discovery along with network-based data mining and data visualization, which is further developed as guidelines for creativity modeling, discovery, and HCI.
  - Conceptual blending is an essential method for modeling creativity, but previous research focuses on semantic rather than graphic processing. In this thesis, the method of visual conceptual blending is extended to a generative model, which is much more powerful than traditional computational methods such as genetic algorithms.
  - Combinational creativity is studied from the perspective of three driven approaches in order to understand its composition, which leads to the proposal of design creativity interpretation approach.

- It is necessary to apply advanced artificial intelligence techniques to modeling design creativity, if computational creativity is discussed and evaluated from a
practical perspective. Hence a variety of novel models have proposed along with powerful algorithms:

- In the model of BKD, three key network-based data mining algorithms are implemented for discovering bisociations: exploration, search path, and clustering. Furthermore, HCI is implemented in network visualization providing an efficient way to boost user’s discovery.

- As a promising technique for generating image data, especially images, GAN shows its high potential for creativity generation. In this thesis, a novel GAN architecture is developed and implemented for visual conceptual blending.

- In order to extract the base and additive from combinational creativity, a novel approach of integrating state-of-the-art image recognition and NLP techniques is explored, implemented and tested, which shows more space for investigating creativity interpretation in future research.

Back to the overall research aim of this thesis, studying computational design creativity in a data-driven cycle with the support of three pillars, namely design data, design creativity modeling algorithms, and design creativity theories, has been achieved through answering the research questions and fulfilling the research objectives as illustrated above. To summarize, this thesis has provided a practical understanding of how data can be mined, visualized, blended and interpreted for design creativity. It also has demonstrated how creativity theories could be developed and applied to model design creativity computationally.

### 7.4 Future Research

Even though data-driven and machine learning based methodologies are proposed and successfully applied for modeling design creativity in this thesis, each proposed model is not perfect. Hence future research is planned to explore improved approaches and algorithms. For the BKD model proposed in Chapter 4, especially for the HCI interface, some suggestions are received from users including design experts. It was suggested
that more functions could be provided in the network interaction when exploring the graph. For example, when right-clicking a node, related Wikipedia information popping up may be of interest. Other functions suggested including node manipulation, such as grouping nodes, function integration and so on. Despite the advice from users, it is noticed that users’ exploration is limited by the homogeneous data in the BKD model. A variety of media types including both textual and non-textual data could be included and integrated into the database, and the database could be flexible to dynamically update multi-type collections (Chau et al., 2011; Kairam et al., 2015).

As discussed in Chapter 3, the VCB model requires a lot of efforts for data collection, cleaning and model training, due to the complexity and depth of proposed GAN architecture. Despite that, there is another issue that may be of concern. It is widely aware in the deep learning community that how the deep neural networks work is still a black box, the working mechanism within a deep learning model is unknown (Zhang et al., 2016). This leads to performance control problems as current models are trained based on the tuning of hyperparameters which are experimental and empirical (Shwartz-Ziv and Tishby, 2017). In the case of proposed GAN model, the generated images are not controllable as there are few hyperparameters which are responsible for controlling the outcome. Although this may contribute to the serendipity of generated images in terms of creativity, it is not beneficial for the study of understanding and modeling creativity. Recently, Variational Autoencoders (VAE) has shown its advantage of controlling the output with the latent spaces which allows continuous easy sampling and interpolation (Sønderby et al., 2016). Razavi et al. (2019) proposed a VQ-VAE-2 model for large scale image generation, which is able to generate samples with quality that rivals that of state of the art GANs, such as the BigGAN (Brock et al., 2019) introduced in Chapter 5, while not suffering from GAN’s known shortcomings. Future research could explore how to control the generation of images for visual conceptual blending with VAE models.

The limitations of the proposed approach for interpreting combinational creativity has been discussed in Chapter 6, along with possible solutions for improvements in future studies. There is other research may of interest for creativity interpretation. The pair of
combination represents creative knowledge in combinational creativity, thus it would be interesting to explore the computational distance between a pair of base and additive. Although Han et al. (2018b) have shown that far-related ideas are used more often in practical combinational designs, the computational distance has not been studied yet. Despite combinational creativity, other creativity forms could be of interest as well, such as the exploratory and transformational creativity proposed by Boden (2004). Compared with combinational creativity, exploratory and transformational creativity are more difficult to interpret as their mapping rules varies in many different ways. To interpret them, a better understanding and investigation from computational modeling perspective is necessary. In addition, related datasets cannot be found within the research community, which should be solved in future work in order to validate and evaluate relevant interpretation models.

As mentioned in the proposed framework for reusing creative knowledge in a creative system, there is a consistency problem between the BKD and VCB model. Specifically, there is no communication between the semantic data and image data as they are utilized in two different models for different purposes. However, creativity can be presented in various forms. For instance, a creative product can be presented in images but also can be described in a textual way. Thus the communication between different data formats can further contribute to the generation and augmentation of design creativity. Future research could be conducted on the integration of the two models at a higher level. For instance, image data can be allowed to represent concepts in the network graph, and algorithms for generating novel images can be implemented in the network as well. On the other hand, the details of how to reuse interpreted creative knowledge is less discussed in the framework, which leaves more space for future study.
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- A Data-Driven Text Mining and Semantic Network Analysis for Design Information Retrieval, by Feng Shi; Liuqing Chen; Ji Han; Peter Childs, J. Mech. Des. 2017; 139(11)

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