Analyzing replacement policies in list-based caches with non-uniform access costs

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***Abstract*—List-based caches can offer lower miss rates than single-list caches, but their analysis is challenging due to state-space explosion. Building upon recent theoretical results, we analyze in this setting randomized replacement policies subject to non-uniform access costs. In our model, costs can depend on the stream a request originated from, the target item, and the list that contains it.**

We first show that, similarly to the uniform-cost case, the random replacement (RR) and first-in first-out (FIFO) policies can be exactly analyzed using a product-form expression for the equilibrium state probabilities of the cache. We then tackle the state space explosion by means of partial differential equations, deriving limiting expressions for the equilibrium performance measures as the number of items and the cache capacity grow in a fixed ratio. Simulation experiments indicate that our asymptotic formulas rapidly converge to the equilibrium distribution of the cache.

I. Introduction

Replacement policies provide a strategy to select items to replace in a cache and are an important performance factor influencing the design of web systems [26], content delivery networks [2], and peer-to-peer traffic [30]. We here focus on the theoretical analysis of randomized policies operating within a single cache, a problem that has attracted much attention over the years [3], [5], [10], [11], [16], [24], [27], [33]. We consider in particular *list-based* caches, which are known to deliver lower miss rates than single-list caches [14], but due to state-space explosion issues are still not fully understood. We ask in particular the question on how we can model access costs to items and lists in this setting.

Costs are useful in cache modeling to abstract factors such as item importance, item size, fetch latency, optional eviction, or access price [4], [26], [32]. Models that ignore these factors are said to assume uniform costs. In the literature, [32] is among the first works to analyze the least-recently used (LRU) and CLIMB policies when an item has an access cost. Later, [4] studies optimal policies for a single-list with non-uniform costs. Other cost-based algorithms are surveyed in [26]. The goal of this work is to generalize the theory of list-based caches to account for access costs.

This extension is motivated by the recent development in [14] of the first general framework to analyze list-based caches with the random replacement (RR), FIFO, or CLIMB policies, under the independent reference model (IRM) [1], [20]. Within that study it is observed that list-based caches can deliver substantially lower miss rates than single-list caches, even when the latter are equipped with a LRU policy. The present work is to our knowledge the first one to expand the scope of the theory to non-uniform access costs. Our model is fairly general, as costs can be differentiated across multiple request streams and depend on the requested item and the list that contains it. We also slightly generalize the IRM model by allowing arrival rates to depend on the cache state.

Our main technical contributions are as follows. First, we define a Markov process for the list-based RR and FIFO policies with non-uniform costs and show that, similarly to the uniform case, this process admits a product-form solution. Although the resulting expression of the equilibrium distribution is different from the one in [14], it includes it as a special case, when costs are chosen to be uniform.

Next, we systematically investigate the equilibrium performance metrics of RR and FIFO under this generalized model. In particular, we develop an asymptotic expression of the normalizing constant of state probabilities that allows us to derive the limiting values of the miss rates as the scale of the system grows. Our approach applies for the first time in cache theory the singular perturbation method used in geometric optics [21]. We are not aware of similar approximations having been applied before in caching theory, despite their importance in other areas (e.g., queueing theory [29]).

In addition to asymptotic analysis, we derive exact recurrence relations for the performance measures, which provide novel theoretical formulas exploited in the proofs. We also propose a set of analytical bounds that may be used to inexpensively approximate a cache performance in situations where speed is critical, such as in numerical optimization programs. We use examples and simulations to illustrate the validity and accuracy of our approximations.

The paper is organized as follows. The reference model is introduced in Section II and its equilibrium behavior analyzed in Section III. An exact analysis framework is developed in Section IV. Section V develops the normalizing constant asymptotics. Iterative analysis and bounds are introduced in Section VI. Numerical results are reported in Section VII. Section VIII overviews related work and it is followed by conclusions. Proofs and background material are given in the Appendix.

II. Preliminaries

Throughout, we use i, k as item indexes, l, j as list indexes, and v as stream index. Our reference model consists of a cache partitioned into h lists arranged in a serial topology, each having a capacity of m_l items, $l = 1, \dots, h$. We use the convention that $l = 0$ indexes items outside the cache. We denote the

capacity vector by $\boldsymbol{m} = (m_1, \dots, m_h)$ and set $m = \sum_{l=1}^{h} m_l$. The total number of items is n and we require it to exceed the cache capacity ($n > m$). We take the usual assumption that items have identical sizes. The time required to replace an item is assumed negligible compared to inter-request time, and thus treated as instantaneous. The cache serves u independent streams, each issuing requests for an item k residing in list l according to a Poisson process with rate $\lambda_{vkl} > 0$, $v = 1, \dots, u$, $k = 1, \dots, n$, $l = 0, \dots, h$.

A. List-based replacement policies

The challenge in designing effective replacement policies is that item popularity is not known a-priori, otherwise one could minimize miss rates by keeping the most frequently accessed objects in the cache [32]. The focus is therefore on policies that self-organize item storage so to optimize miss rates. List-based replacement policies under uniform access costs include RR($\boldsymbol{m}$), FIFO($\boldsymbol{m}$), CLIMB($\boldsymbol{m}$), and LRU($\boldsymbol{m}$) [14], [15]. In these policies, when an item i residing in list l is requested, it is promoted to list $l+1$, demoting an item chosen according to a policy-dependent criterion. A detailed description of the policies can be found in Appendix A. To simplify notation, in the following we omit the dependence on $\boldsymbol{m}$.

Our goal is in particular to investigate RR and FIFO in the context of non-uniform access costs. Since CLIMB can be reduced to a special case of these policies, it is implicitly covered by our analysis. Contrary to RR and FIFO, the Markov process of LRU is not known to admit an explicit solution in list-based caches and can only be analyzed using time-to-live (TTL) approximations [15]. For this reason, and similarly to prior work on randomized policies [14], [18], [33], LRU falls beyond the scope of our investigation, which stems from an exact product-form result valid only for RR and FIFO.

The variants of the previous policies that allow for non-uniform costs are denoted by RR-c, FIFO-c, LRU-c, and CLIMB-c. The last two variants are developed in [32] for single-list caches under non-uniform costs. The authors use a randomization approach to model the impact of costs on the cache dynamics. Compared to [32], we also adopt randomization, but we consider list-based caches.

B. Cost model

Let a_{vkl}, $l = 1, \dots, h-1$, denote the cost for item k to access list $l+1$ after a hit from stream v. Similarly, let a_{vk0} be the cost of loading item k into the cache after a cache miss from stream v. Following [32], we define the *normalized access cost* $c_{vkl} = a_{vkl}/\max_k a_{vkl}$, which may be interpreted as the probability that, after stream v hits item k in list l, item k is allowed to move to list $l+1$. This randomization ensures that items are promoted in proportion to their cost. Indeed, it is best to retain in the cache high-cost items, unless low-cost items are requested at a frequency that balances the gap in cost [4], [32]. As we see in the next section, we introduce a notion of *cost factor* that encompasses both access costs and request rates.

III. Analytical model

A. Markov process

Define the state vector $\boldsymbol{s} = [s(i,j)]$, such that $s(i,j) \in [1,n]$ is the index of the item in position i of list j, and let $\mathcal{S}$ be the space of all feasible cache states. We take the convention that $m_0 = n - m$ and that $s(i,0)$ indexes the item with the ith largest index among those outside the cache. Let $\pi(\boldsymbol{s})$ be the equilibrium probability of the continuous-time Markov chain modeling the replacement policy. We take the usual assumption that the cache is initially full. We now give a product-form result for $\pi(\boldsymbol{s})$.

Theorem 1. *In list-based caches, the RR-c and FIFO-c replacement policies admit the equilibrium distribution*

$$\pi(\boldsymbol{s}) = \frac{\prod_{j=0}^{h} \prod_{i=1}^{m_j} \gamma_{s(i,j)j}}{E(\boldsymbol{m})} \tag{1}$$

for all $\boldsymbol{s} \in \mathcal{S}$, where $E(\boldsymbol{m})$ is a normalizing constant and we define

$$\gamma_{ij} = \begin{cases} \prod_{l=0}^{j-1} \sum_{v=1}^{u} \lambda_{vil} c_{vil} & \text{if } j > 0 \\ 1 & \text{if } j = 0 \end{cases}$$

for all $i = 1, \dots, n$ and $j = 0, \dots, h$.

The proof is given in Appendix B. We refer to γ_{kl} as the *cost factor* for item k to access list l. The cost factor differs from the access cost c_{vkl} in that it accounts for both the costs and the item request rate involved in item k movement from outside the cache into list l. Note that in uniform cost models with level-independent arrivals, the cost factor reduces to $\gamma_{kl} = \lambda_k^l$ in continuous-time, where $\lambda_k = \sum_{v=1}^{u} \lambda_{vk0}$ is the request rate for item k, and to $\gamma_{kl} = p_k^l$ in discrete-time, where p_k is the popularity of item k and which is the case studied in [14].

B. Performance measures

Let $\pi_{kl}(\boldsymbol{m})$ be the (marginal) probability that item k is in list l, and let $\pi_{k0}(\boldsymbol{m})$ denotes the miss ratio for item k. By definition we have $\sum_{l=0}^{h} \pi_{kl}(\boldsymbol{m}) = 1$ and since at all times list l contains exactly m_l items we have $\sum_{k=1}^{n} \pi_{kl}(\boldsymbol{m}) = m_l$. Using the product-form result (1), we can write

$$\pi_{kl}(\boldsymbol{m}) = m_l \gamma_{kl} \frac{E_k(\boldsymbol{m} - 1_l)}{E(\boldsymbol{m})} \tag{2}$$

where 1_l is the unit vector in direction l, m_l counts the possible positions of k within list l, and by (1) the rest is the probability of states in which item k is in list l.

Define now $\pi_k(\boldsymbol{m}) = \sum_{l=1}^{h} \pi_{kl}(\boldsymbol{m})$ as the probability that item k is in the cache. Noting that $E_k(\boldsymbol{m})$ encompasses all and only the states where k is outside the cache, we can write the miss ratio for item k as

$$\pi_{k0}(\boldsymbol{m}) = \frac{E_k(\boldsymbol{m})}{E(\boldsymbol{m})} = 1 - \pi_k(\boldsymbol{m}) \tag{3}$$

From the definitions, the miss rate for stream v and item k is

$$M_{vk}(\boldsymbol{m}) = \pi_{k0}(\boldsymbol{m}) \lambda_{vk0} c_{vk0} \tag{4}$$

The miss rate of item k is then $M_k(\boldsymbol{m}) = \sum_v M_{vk}(\boldsymbol{m})$ and the cache miss rate is $M(\boldsymbol{m}) = \sum_{v,k} M_{vk}(\boldsymbol{m})$.

IV. Exact analysis

In this section, we derive recurrence relation to calculate the performance measures. The algorithms we derive are exact and require polynomial time and space in n and m. Thus, they alleviate the problem that the state space $\mathcal{S}$ grows exponentially in size with n and m, preventing direct numerical analysis of RR-c and FIFO-c using the product-form result (1). Note that all expressions reported in this section have been numerically verified against examples where the Markov process could be solved exactly.

A. Recurrence relation for the normalizing constant

We begin by conditioning on the list containing item k, so that we can recursively express the normalizing constant as

$$E(\boldsymbol{m}) = E_k(\boldsymbol{m}) + \sum_{j=1}^{h} m_j \gamma_{kj} E_k(\boldsymbol{m} - 1_j) \tag{5}$$

for an arbitrary $k = 1, \dots, n$. Here, $E_k(\boldsymbol{m})$ is the normalizing constant of a model without item k and each m_j term recursively unfolds into a factorial that counts the permutations of the positions of item k within list j. A similar expression is obtained in [14] for uniform cost models. The recurrence relation requires the boundary conditions $E(\mathbf{0}) = 1$, and $E(\boldsymbol{m}) = 0$ if either $\sum_i m_i > n$ or $m_j < 0$ for any j.

Using (5), $E(\boldsymbol{m})$ can be computed in $\mathcal{O}(n \prod_{i=1}^{h}(m_i + 1))$ time and space. Note that (5) can incur floating-point range exceptions due to the rapid growth of $E(\boldsymbol{m})$. Such exceptions can be addressed either by exact arithmetic or by dynamic scaling of the normalizing constant value [23]. The latter leverages that if we scale the cost factors as $\gamma'_{kj} = S\gamma_{kj}$, $E(\boldsymbol{m})$ is scaled by a factor S^m due to (1). The factor S can then be dynamically chosen so to scale $E(\boldsymbol{m})$ and avoid range exceptions [23].

B. Exact analysis of miss rates

We now consider the problem of computing the miss rate $M(\boldsymbol{m})$. Let us define

$$\xi_l(\boldsymbol{m}) = m_l \frac{E(\boldsymbol{m} - 1_l)}{E(\boldsymbol{m})} \tag{6}$$

and denote $F_l(\boldsymbol{m}) = m_l/\xi_l(\boldsymbol{m})$. Note that by (5) and by the definition of miss rate, we may write

$$M(\boldsymbol{m}) = \frac{E(\boldsymbol{m} + 1_1)}{E(\boldsymbol{m})} = F_1(\boldsymbol{m} + 1_1) = \frac{m_1 + 1}{\xi_1(\boldsymbol{m} + 1_1)} \tag{7}$$

Thus, computational methods for $\xi_l(\boldsymbol{m})$ are sufficient to determine the miss ratio $M(\boldsymbol{m})$. To this end, we observe that $\xi_l(\boldsymbol{m})$ admits the exact recurrence relation

$$\xi_l(\boldsymbol{m}) = \frac{1 + \sum_{\substack{j=1 \\ j \neq l}}^{h} \gamma_{kj} \xi_j^{-k}(\boldsymbol{m} - 1_l) + \gamma_{kl} \xi_l^{-k}(\boldsymbol{m} - 1_l)}{\frac{I\{n>m\}}{\xi_l^{-k}(\boldsymbol{m})} + \sum_{\substack{j=1 \\ j \neq l}}^{h} \gamma_{kj} \frac{\xi_j^{-k}(\boldsymbol{m}-1_l)}{\xi_l^{-k}(\boldsymbol{m}-1_j)} + \gamma_{kl}} \tag{8}$$

for arbitrary $k = 1, \dots, n$, where I is the indicator function. Relation (8) is a non-uniform cost extension of known results for $F_l(\boldsymbol{m})$ [11, Eq. 2.7] and [14, Thm. 2] in uniform cost models. We omit the details of the proof of (8) as this follows similarly to earlier work by applying (5) to (6), and then dividing numerator and denominator by $E_k(\boldsymbol{m} - 1_l)$. Using (8), we can compute the miss rate in $\mathcal{O}(hn \prod_{j=1}^{h}(m_h + 1))$. The recursion has boundary conditions: i) $\xi_l(\boldsymbol{m}) = +\infty$ if $m > n$ or $\min_l m_l < 0$; ii) $\xi_l(\mathbf{0}) = 0$; iii) $\xi_l(1_l) = \gamma_{k,l}$ if $m_k = 1$ and $n = 1$; iv) $\xi_l(\boldsymbol{m}) = 0$ if $m_l = 0$.

C. Exact analysis of marginal probabilities

Note that (8) provides miss rates, but neither marginal state probabilities nor item miss rates. In small and medium-sized models such quantities may be recursively computed using the following result.

Theorem 2. *The probability of finding item k in list l is*

$$\pi_{kl}(\boldsymbol{m}) = \gamma_{kl} \xi_l(\boldsymbol{m})(1 - \pi_k(\boldsymbol{m} - 1_l)) \tag{9}$$

for all items $k = 1, \dots, n$ and lists $l = 1, \dots, j$.

The proof is given in Appendix C. The form of (9) bears some resemblance to the celebrated arrival theorem for queueing networks [28], [31]. It may be seen as relating the equilibrium distribution of the cache with the conditional distribution of states seen by item k while residing in list l. We are not aware of earlier work noting this connection. A similar argument holds also for the arrival theorem, which is sometimes seen as the distribution of states in a queueing network conditional on a job residing at a specific station [35].

We are now ready to obtain a recurrence relation for the marginal probabilities. Since $\sum_{k=1}^{n} \pi_{kl}(\boldsymbol{m}) = m_l$ and due to (9), solving for $\xi_l(\boldsymbol{m})$ we find

$$\xi_l(\boldsymbol{m}) = \frac{m_l}{\sum_{k=1}^{n} \gamma_{kl}(1 - \pi_k(\boldsymbol{m} - 1_l))} \tag{10}$$

Finally, plugging (10) into (9), and using that $\pi_k(\boldsymbol{m}) = \sum_{l=1}^{h} \pi_{kl}(\boldsymbol{m})$, we get the exact recurrence relation

$$\pi_{il}(\boldsymbol{m}) = \frac{m_l \gamma_{il}(1 - \sum_{j=1}^{h} \pi_{ij}(\boldsymbol{m} - 1_l))}{\sum_{k=1}^{n} \gamma_{kl}(1 - \sum_{j=1}^{h} \pi_{kj}(\boldsymbol{m} - 1_l))} \tag{11}$$

for all $i = 1, \dots, n$ and $l = 1, \dots, h$. The recursion has termination conditions $\pi_{il}(\boldsymbol{m}) = 0$ if either $\boldsymbol{m} = \mathbf{0}$ or $\min_j m_j < 0$. Solving (11) recursively requires $\mathcal{O}(nh \prod_{i=1}^{h}(m_i + 1))$ time and $\mathcal{O}(n \prod_{i=1}^{h}(m_i + 1))$ space. From the knowledge of the marginal probabilities it is straightforward to compute item miss rates using the expressions given in Section III-B.

V. Normalizing constant asymptotics

Exact recurrence relation have time and space requirements that grow polynomially with m and n and exponentially with the number of lists h. In practice, this means that they are applicable only to small caches. This issue can be effectively addressed through asymptotic expansion methods, as we show in this section.

We prove an asymptotic limit for $E(\boldsymbol{m})$ that can be used to approximate performance measures under non-uniform costs. The main contribution is to develop an asymptotic expansion for $E(\boldsymbol{m})$ in the limit $n \to \infty$ and $m \to \infty$, with $n/m \sim O(1)$.

Fixing a constant ratio of n to m avoids degenerate models where cache misses, or cache hits, occur with probability one.

A. Singular perturbation method

We develop an asymptotic expansion of $E(\boldsymbol{m})$ using the singular perturbation method [21], which reformulates multivariate recurrence relations as partial differential equations (PDEs) that can be explicitly solved. We first set $k = n$ and $H(\boldsymbol{m}) = E(\boldsymbol{m})/\prod_{j=1}^{h} m_j!$, so that (5) becomes $H(\boldsymbol{m}) = H_n(\boldsymbol{m}) + \sum_j \gamma_{nj} H_n(\boldsymbol{m} - 1_j)$, and after scaling variables we have the recurrence relation

$$h(\boldsymbol{x}, y) = h(\boldsymbol{x}, y - \epsilon) + \sum_{j=1}^{h} g_j(y) h(\boldsymbol{x} - \epsilon 1_j, y - \epsilon) \tag{12}$$

where $\epsilon = 1/S$, S is a scale parameter, $y = n\epsilon$, $x_j = m_j\epsilon$, $\boldsymbol{x} = \boldsymbol{m}\epsilon$, $x = \sum_j x_j$, and we assume that $g_j(y)$ is a smooth function such that $g_j(k\epsilon) = \gamma_{kj}$. Without loss of generality, we take the convention $g_j(0\epsilon) = g_j(n\epsilon)$, $\forall j$.

The recurrence relation (12) can be solved asymptotically using the singular perturbation method [21], which is based on a real-domain variant of the WKB approximation popular in physics, we point to [22] for a tutorial. In what follows, we study in particular the limit $S \to \infty$, i.e., $\epsilon \to 0$, and assume an asymptotic expansion in WKB form

$$h(\boldsymbol{x}, y) \sim D(\epsilon) B(\boldsymbol{x}, y) e^{\phi(\boldsymbol{x}, y)/\epsilon} \tag{13}$$

The formal derivation to obtain $\phi(\boldsymbol{x}, y)$, $B(\boldsymbol{x}, y)$, and $D(\epsilon)$ is given in Appendix D, and leads to

$$\phi(\boldsymbol{x}, y) = \int_0^y \log\left(1 + \sum_{j=1}^{h} g_j(v)\xi_j\right) dv - \sum_{j=1}^{h} x_j \log \xi_j \tag{14}$$

where the terms ξ_j, $j = 1, \ldots, h$ satisfy

$$x_j = \int_0^y \frac{g_j(v)\xi_j}{1 + \sum_{l=1}^{h} g_l(v)\xi_l} dv \tag{15}$$

We show later in Section VI-A that the terms ξ_l may be seen as the asymptotic limits of the values $\xi_l(\boldsymbol{m})$ defined in (10). The remaining coefficients are $D(\epsilon) = \epsilon^{h/2}$ and

$$B(\boldsymbol{x}, y) = \frac{(2\pi)^{-h/2}}{\sqrt{\det \boldsymbol{J}}\sqrt{\xi_1 \cdots \xi_h}} \tag{16}$$

where the matrix $\boldsymbol{J} = [J_{jl}]$, $j, l = 1, \ldots, h$, is given by

$$J_{jl} = \int_0^y \frac{\delta_{jl} g_j(v)}{1 + \sum_r g_r(v)\xi_r} dv - \int_0^y \frac{\xi_j g_j(v) g_l(v)}{(1 + \sum_r g_r(v)\xi_r)^2} dv \tag{17}$$

with $\delta_{jl} = 1$ if $j = l$, and $\delta_{jl} = 0$ otherwise.

B. Approximating a finite system

Having determined the asymptotics of $h(\boldsymbol{x}, y)$, we can now use the Euler-Maclaurin formula [34] to rewrite (13) in terms of the variables $\boldsymbol{m}$ and n. For an arbitrary function $f(x)$, the formula may be written as

$$\sum_{k=1}^{n} f(k) = \int_0^n f(x)dx + \frac{f(n) - f(0)}{2} + O(n^{-1})$$

Scaling variables in (15) so that the integral ranges in $[0, n]$, the error of the Euler-Maclaurin formula is $O(\epsilon)$, and thus the resulting finite formula is asymptotically exact. Since we have chosen $g_j(0\epsilon) \equiv g_j(n\epsilon)$, this is given by

$$m_j = \sum_{k=1}^{n} \frac{\gamma_{kj}\xi_j}{1 + \sum_{l=1}^{h} \gamma_{kl}\xi_l} \tag{18}$$

for $j = 1, \ldots, h$. Under uniform costs, [14] obtains an expression similar to (18) as the steady-state limit of fluid differential equations. Our derivation shows that the result holds under non-uniform costs, and does not require fluid modeling. Using an argument similar to [14, Thm. 7] it follows that (18) has a unique positive solution.

Using Euler-Maclaurin we can also write

$$\phi(\boldsymbol{m}) = \sum_{k=1}^{n} \log\left(1 + \sum_{j=1}^{h} \gamma_{kj}\xi_j\right) - \sum_{j=1}^{h} m_j \log \xi_j$$

and replace $\boldsymbol{J}$ with matrix $\boldsymbol{C} = [C_{jl}]$ where

$$C_{jl} = \sum_{k=1}^{n} \frac{\delta_{jl}\gamma_{kj}}{1 + \sum_{r=1}^{h} \gamma_{kr}\xi_r} - \sum_{k=1}^{n} \frac{\xi_j \gamma_{kj}\gamma_{kl}}{(1 + \sum_{r=1}^{h} \gamma_{kr}\xi_r)^2}$$

The above expressions provide by (13) the asymptotic expansion of $H(\boldsymbol{m})$, which finally gives

$$E(\boldsymbol{m}) \sim (2\pi)^{-h/2} \frac{\prod_{k=1}^{n}\left(1 + \sum_{j=1}^{h} \gamma_{kj}\xi_j\right)}{\prod_{j=1}^{h} \xi_j^{m_j + 1/2}} \frac{\prod_{j=1}^{h} m_j!}{\sqrt{\det \boldsymbol{C}}} \tag{19}$$

where the ξ_j's are the unique solutions of (18).

C. Performance measures

For large $\boldsymbol{m}$, we can expand $E_k(\boldsymbol{m} - 1_l)$ in a neighborhood of $\boldsymbol{m}$ to obtain by (19) the leading terms

$$\pi_{kl}(\boldsymbol{m}) \sim \begin{cases} \left(1 + \sum_{j=1}^{h} \gamma_{kj}\xi_j\right)^{-1} & \text{if } l = 0 \\ \gamma_{kl}\xi_l\left(1 + \sum_{j=1}^{h} \gamma_{kj}\xi_j\right)^{-1} & \text{if } l \geq 1 \end{cases} \tag{20}$$

for all $k = 1, \ldots, n$ and $l = 0, \ldots, j$. Additional terms in the expansions may also be used to generate higher-order approximations, which involve the derivatives of $\sqrt{\det \boldsymbol{C}}$. However, these are seldom needed since the cost of computing these terms is comparable to computing performance measures directly applying (19) to the definitions given in Section III-B. We shall indicate the latter approach as the *singular perturbation approximation* (SPA), to distinguish it from the approach that numerically solves (18) for the ξ_l's and then calculates performance measures by (20). For the reasons explained in the next section, we shall refer to the latter approach as the *fixed-point iteration* (FPI).

1) Example: Table I illustrates the singular perturbation method. We consider small-scale models where $E(\boldsymbol{m})$ can be computed numerically using (5). The model has $u = 2$ users, $\lambda_{1kl} = k^{-0.6}$, $\lambda_{2kl} = k^{-1.4}$. We set access costs to $a_{vkl} = 1$. We fix $n = 2S$ and $m = S$ and use a scaling $S = 2, 4, 8, 10$. As shown in the table, (19) converges to the exact value $E(\boldsymbol{m})$.

TABLE I
EXAMPLE: NORMALIZING CONSTANT ASYMPTOTICS

n	m_1	m_2	$E(\boldsymbol{m})$	SPA - eq. (19)	rel. err.
4	2	0	$1.2969 \cdot 10^1$	$1.3691 \cdot 10^1$	0.056
8	4	0	$3.5950 \cdot 10^2$	$3.6940 \cdot 10^2$	0.028
16	8	0	$6.7136 \cdot 10^5$	$6.8063 \cdot 10^5$	0.014
20	10	0	$3.8500 \cdot 10^7$	$3.8926 \cdot 10^7$	0.011
4	1	1	$1.6173 \cdot 10^1$	$1.8919 \cdot 10^1$	0.170
8	2	2	$2.5697 \cdot 10^2$	$2.7810 \cdot 10^2$	0.082
16	4	4	$6.2439 \cdot 10^4$	$6.4990 \cdot 10^4$	0.041
20	5	5	$9.7236 \cdot 10^5$	$1.0042 \cdot 10^6$	0.033

VI. FURTHER APPROXIMATIONS

A. Fixed-point iteration (FPI)

We now introduce a fixed-point method to obtain the ξ_l variables. Let us first consider a regular perturbation expansion [22] of (11), which for large m and n, with $m/n \sim O(1)$, assumes the form $\pi_{il}(\boldsymbol{m}) \sim \hat{\pi}^0_{il} + \epsilon\hat{\pi}^1_{il} + ...$, for small $\epsilon > 0$. Plugging the last expression in (11), we get at the lowest order

$$\hat{\pi}^0_{il} = \frac{m_l\gamma_{il}(1-\sum_{j=1}^{h}\hat{\pi}^0_{ij})}{\sum_{k=1}^{n}\gamma_{kl}(1-\sum_{j=1}^{h}\hat{\pi}^0_{kj})} \tag{21}$$

for $i = 1, \dots, n$, $l = 1, \dots, h$. This is a non-linear system of equations with nh equations and nh unknowns. It is possible to verify that the system is solved by setting

$$\hat{\pi}^0_{il} = \frac{\gamma_{il}\xi^0_l}{1+\sum_{j=1}^{h}\gamma_{ij}\xi^0_j} \tag{22}$$

where $\xi^0_l = m_l(\sum_{k=1}^{n}\gamma_{kl}(1+\sum_{l=1}^{h}\hat{\pi}^0_{il}))^{-1}$. This can be checked for instance by fixing the terms corresponding to ξ^0_l in (21), and treating the result as a system of linear equations. Solving for $\hat{\pi}^0_{il}$ and rearranging terms, one can verify that (22) holds after plugging the expression of ξ^0_l. By comparing (22) with (18), we conclude that asymptotically it must be $\xi^0_l = \xi_l$. The same conclusion follows by calculating the leading term of (6) as in Section V-C. This provides support to our earlier statement that the variables ξ_l appearing in the expansion of $E(\boldsymbol{m})$ are simply the asymptotic limits of $\xi_l(\boldsymbol{m})$.

The explicit expression of ξ^0_l enables us to solve (18) by introducing a fixed point iteration over the marginal probabilities. This is given by

$$\xi_l^{(t+1)} = \frac{m_l}{\sum_{k=1}^{n}\gamma_{kl}(1+\sum_{l=1}^{h}\pi_{il}^{(t)})} \tag{23a}$$

$$\pi_{il}^{(t+1)} = \frac{\gamma_{il}\xi_l^{(t+1)}}{1+\sum_{j=1}^{h}\gamma_{ij}\xi_j^{(t+1)}} \tag{23b}$$

for all $i = 1, \dots, n$ and $l = 1, \dots, 0$ and iterations $t \geq 0$. As mentioned before, the FPI method solves (18), which can be done by (23), and then plugs the obtained ξ_l values into (20) to obtain performance measures. The iteration can be initialized with a guess of the marginal probabilities, e.g., $\pi_{il}^{(0)} = 1/(h+1)$. We stop it when the maximum relative change of the miss ratios $\pi_{i0}^{(t)} = 1 - \sum_l \pi_{il}^{(t)}$ across iterations does not exceed a user-specified tolerance (e.g., $\tau = 10^{-6}$). We did not observe situations in which the iteration does not converge or it is sensitive to the initial conditions, which is expected since (18) has a unique solution.

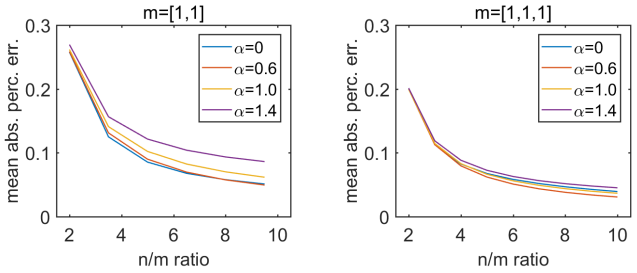


Fig. 1. Approximation error in $[0, 1]$ of (23) for the miss ratio $M(\boldsymbol{m})$ in two-stream caches with $h = 2$ and $h = 3$ lists, with convergence tolerance $\tau = 10^{-6}$. The cache has two users with request rates $\lambda_{1kl} = p_k$, $p_k = k^{-\alpha}$, $k = 1, \dots, n/3$, $\lambda_{2kl} = q_k$, $q_k = k^{-\alpha}$, $k = (n/3+1), \dots, n$, and $\lambda_{1kl} = \lambda_{2kl} = 0$ otherwise. Costs are set to $a_{vkl} = 1$.

1) Example: Figure 1 illustrates the miss ratio computed by fixed-point iteration against the exact solution obtained using (8) for two caches with $h = 2$ and $h = 3$ lists and $u = 2$ streams. The streams request two independent sets of objects, both according to a Zipf-like popularity distribution with parameter α.

As the ratio n/m grows, we see that the cache approaches the asymptotic behavior and the error visibly decreases. It is clear from the example that considering models with larger number of lists h also reduces error, for fixed ratio n/m, and makes the results less sensitive to the exponent α. The maximum number of iterations of (23a)-(23b) is observed to be $t_{max} = 23$ for $\alpha = 0$, and $t_{max} = 36$ for $\alpha = 1.4$. This means in practice that the iteration converges within the tolerance in just a few milliseconds. We also observe the number of iterations to slightly decrease as n/m grows. We remark that the results are representative also of other parameterizations. Experiments with larger models are reported in Section VII.

B. Bound analysis

Here we determine some simple analytical bounds on $\xi_l(\boldsymbol{m})$ and π_{i0}. The quantities $\xi_l(\boldsymbol{m})$ allow us by (7) to bound the miss rate $M(\boldsymbol{m})$, whereas the probabilities π_{i0} can be used to bound the miss rates using (4). Bounds may help to quickly assess performance measures in settings where speed can be more important than high-accuracy, as in the numerical solution of NP-hard optimization programs.

1) Bounds on $\xi_l(\boldsymbol{m})$: It is possible to verify that

$$m_l\left(\gamma_l^+(n-m+1)\right)^{-1} \leq \xi_l(\boldsymbol{m}) \leq m_l\left(\gamma_l^-(n-m+1)\right)^{-1} \tag{24}$$

where $\gamma_l^+ = \max_k \gamma_{kl}$ and $\gamma_l^- = \min_k \gamma_{kl}$. These follow from (10) by bounding γ_{kl} with γ_l^+ or γ_l^- and noting that $\sum_k(1-\pi_k(\boldsymbol{m}-1_l)) = n-m+1$. For an important class of models, we then state a tighter lower bound. Lower bounds are the most important in practice, as they lead to worst-case estimates of the miss rates. The bound assumptions are satisfied by a rather broad class of models including, but not limited to, all models with uniform costs.

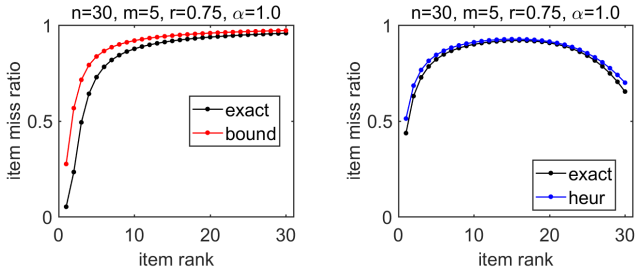


Fig. 2. Single-stream cache with capacity $\boldsymbol{m} = (3, 2)$ and request rates $\lambda_{vkl} = p_k\lambda$, with $\lambda = 1$ and Zipf-like popularity $p_k = k^{-\alpha}$. Items are ranked according to p_k. The left figure shows a monotone cache with $a_{vkl} = (1-r)r^k$, the right cache is non-monotone with costs c_{vkl}^{-1}.

Theorem 3. *Consider a cache where for each pair of items i and $k > i$, we have $\gamma_{il} \geq \gamma_{kl}$, $\forall l$. Then*

$$m_l \left(\bar{\gamma}_l(n - m + 1)\right)^{-1} \leq \xi_l(\boldsymbol{m}) \tag{25}$$

where $\bar{\gamma}_l = \sum_k \gamma_{kl}/n$ is the average cost factor for list l.

The proof is given in Appendix E and shows that the argument generalizes for any list where $\gamma_{kl} \geq \gamma_{il}$ implies $\pi_k(\boldsymbol{m} - 1_l) \geq \pi_i(\boldsymbol{m} - 1_l)$. If the property holds for all lists, we say that the model is *monotone*.

2) Bounds on $\pi_{i0}(\boldsymbol{m})$: Using (9) and the results of the previous section, we now develop upper bounds on the miss rate $\pi_{i0}(\boldsymbol{m})$. We first need to establish two monotonicity properties.

Lemma 1. $\xi_j(\boldsymbol{m} - 1_l) \leq \xi_j(\boldsymbol{m}) \leq \xi_j^{-i}(\boldsymbol{m})$, $\forall j, l, i$.

Lemma 2. $\pi_{i0}(\boldsymbol{m}) \leq \pi_{i0}(\boldsymbol{m} - 1_l)$, $\forall i, l$.

The proofs are rather technical and given in Appendix F and G. Note that since the bounds hold for all i and l, one could choose them to maximize the lower bounds and minimize the upper bound. We are now ready to bound the miss rates.

Theorem 4. *The item miss ratios satisfy the bound*

$$\pi_{i0}(\boldsymbol{m}) \leq \left(1 + \sum_{j=1}^{h} \gamma_{ij}\xi_j(\boldsymbol{m})\right)^{-1} \tag{26}$$

for all items $i = 1, \dots, n$ and lists $l = 1, \dots, h$.

The proof is given in Appendix H. Note that bound is asymptotically exact, as it converges to (20) as n and m increase in a fixed ratio. A closed-form upper bound can be readily obtained by replacing the expression of $\xi_l(\boldsymbol{m})$ with the lower bound in either (24) or (25). Although (25) is not guaranteed to be a bound in non-monotone models, combining it with (26) still provides a non-iterative heuristic approximation of π_{i0}, as illustrated in the next example.

3) Example: Figure 2 illustrates (26) for a monotone and a non-monotone cache. Estimates are computed by replacing $\xi_j(\boldsymbol{m})$ in (26) with (25). As shown in the figure, the heuristic can return values that are very close to the exact.

VII. Numerical results

A. Simulation-based validation

Since exact theory applies only to small models, we have performed a simulation study to assess the accuracy of the proposed approximations. The set of parameters used in the study is given in Table II. Whenever $n = m$, we set $n = m+2$ to avoid degeneracies.

TABLE II
Simulation parameters for RR-c, FIFO-c, LRU-c

n	Number of items	10, 1000
n/m	Items-to-capacity ratio	2, 4, 10
h	Number of lists	1, 2, 5
u	Number of streams	1, 2, 4
α	Zipf parameter	0.6, 1.0, 1.4
c	Access cost to next list	0.1, 0.5, 1.0

TABLE III
Summary of simulation results

		mean abs. perc. err	
u	n	FPI	SPA
1	10	0.095 ± 0.099	0.010 ± 0.020
2	10	0.069 ± 0.071	0.009 ± 0.012
4	10	0.041 ± 0.044	0.009 ± 0.012
1	1000	0.026 ± 0.027	0.026 ± 0.027
2	1000	0.029 ± 0.025	0.029 ± 0.025
4	1000	0.025 ± 0.017	0.025 ± 0.017

Access costs are set identically for each list and equal to c. Each stream sends Poisson requests at rate $\lambda = 1$, scaled by a Zipf-like distribution with parameter α, with the object ranks assigned uniformly at random within each stream. Each simulation collects $2 \cdot 10^7$ state samples from the cache. We study both RR-c and FIFO-c, for a total of 972 simulations. As expected, the results for RR-c and FIFO-c are nearly identical, thus we discuss only RR-c.

We compare the FPI and SPA methods of Section V-C, based on the mean absolute percentage error on the item miss ratios $\pi_{i0}(\boldsymbol{m})$. The results are given in Table III with 95% confidence intervals. In small models with $n = 10$ items, SPA incurs significantly lower error than FPI, 1.0% instead of 9.5%. For such instances, we have observed the maximum error of FPI to reach 50.7%, whereas for SPA it is just 15.5%. However, with $n = 1000$ items the two methods return nearly identical accuracy, less than 3% error. Note that the slightly higher error of SPA compared to the case $n = 10$ is not statistically significant, and it may be explained by the increased variance in the simulation results going from $n = 10$ to $n = 1000$.

We have noticed the results to be nearly insensitive to changes in the access cost c. Table III also shows that the results are weakly sensitive to the number of streams u. Figure 3 illustrates the dependence of the error on the ratio n/m and α. Both approximations tend to be more accurate in caches with a higher n/m ratio, confirming the trend shown in the example given in Figure 1. SPA appears instead slightly better than FPI under increasing values of α.

Overall, the results indicate that FPI often suffices in practice, but SPA can provide more robust estimates in models with a small capacity or under large values of the Zipf parameter α.

B. Youtube trace

Lastly, we use a trace-driven simulation to illustrate the applicability of the proposed methods to real datasets. We have

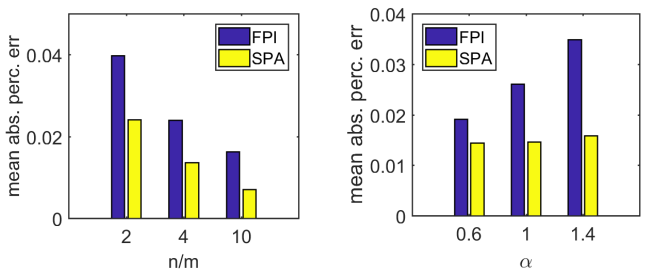


Fig. 3. Sensitivity of FPI and SPA to changes in the item-to-capacity ratio n/m and the Zipf-like distribution parameter α in the simulations.

simulated the 2008 Youtube trace collected in [36] and also used to validate the list-based cache models in [14], [18]. The trace consists of $611,968$ requests, spanning $n = 303,332$ items and originating from $u = 16,337$ client IPs. Each client IP is mapped to a single stream v, which is then associated to a Poisson process with rate $\lambda_{vk} = n_{vk}/T$, where n_{vk} is the total number of occurrences of item k requested from stream v and T is the timespan of the trace.

We run trace-driven simulations, using caches with capacity $m = 5000$, $m_1 = 2900$, and $m_2 = \cdots = m_h = (m - m_1)/(h-1)$ and varying the number of lists $h = 2, 3, 5$, the replacement policy (FIFO-c, RR-c), and the access costs to the next list $c = 0.1, 0.5, 1.0$. For each experiment, we then compute the item-miss rate M_k, $k = 1 \dots, 303332$, and compare it with the theoretical value obtained by FPI.

Despite the large number of items, FPI produces an estimate of all $303,332$ item miss rates in just 8.2 seconds on a Intel Core i5 laptop. Even though the Youtube trace is temporally-correlated, thus departing from IRM and Poisson assumptions, and about half of the items are accessed just a single time each, the mean percentage error of FPI on the M_k values is only 1.74%, with a maximum error of just 4.68%. Both values are compatible with the uncertainties of the simulation, since the trace is simulated only once. Overall, the experiments indicate that our model can reliably reproduce simulation results in the presence of access costs and multiple request streams.

VIII. Related work

Recently, most of the research literature has focused on time-to-live (TTL) caches, which can be analyzed either by Che's approximation [7] or by exact methods [6]. Che's approximation has also been shown to be valid for randomized policies [12]. However, there is still a limited body of work on using this method to study list-based caches [15].

This paper is mostly related to earlier work under the independent reference model (IRM), which includes [20], [16], [10], [11], [9], and references therein. Although real systems deviate from the IRM assumptions, IRM theoretical results provide useful insights, such as the characterization of the miss ratio of LRU [5], and formulas for the approximate analysis of cache networks [13] and hybrid memory systems [18].

Recently, some frameworks that simplify the mathematical analysis of caches have been investigated [25], [14]. This work builds in particular upon the proposal in [14], which provides a general framework to study list-based caches. [18] offers another example of generalization of [14], but to list-based caches with flat and layered list topologies. It seems in principle possible to extend our results to this case.

IX. Conclusion

We have generalized models for list-based caches to include non-uniform access costs. After solving the Markov process for the RR and FIFO policies, we have developed exact and approximate formulas to efficiently analyze performance measures such as miss rates. We have then applied singular perturbation methods to determine the asymptotic behavior of the cache. Simulation results indicate that our approximations typically incur less than 3% error on large models.

In the future, it would be interesting to apply our results to approximate the behavior of cache networks and to develop dynamic policies for cost optimization.

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APPENDIX

A. List-based replacement policies

• *RR*($\boldsymbol{m}$): a cache miss for item i is handled by evicting a random item from list 1 and replacing it with item i. Conversely, a cache hit swaps the positions of item i in list l and of an item k chosen at random in list $l+1$, if $l<h$, or otherwise if $l=h$ item i does not move.
• *FIFO*($\boldsymbol{m}$): this policy is similar to RR($\boldsymbol{m}$), but the demoted item k is picked from the end of list $l+1$ and moved into the former position of i in list l. Following this, for $l<h$, all other items in list $l+1$ move back by one position, and i is placed at the front of list $l+1$. For $l=h$, item i does not move.
• *LRU*($\boldsymbol{m}$): this policy is similar to FIFO($\boldsymbol{m}$), but the victim item k is moved to the front of list l, shifting items in l back by one position up to filling the position held by the requested item i. A hit on item i in list h moves i to the list front, shifting back by one position all items in between.
• *CLIMB*($\boldsymbol{m}$) [3]: this is simply the limiting case of FIFO($\boldsymbol{m}$) and RR($\boldsymbol{m}$) when $\boldsymbol{m}=(1,\dots,1)$ and $h=m$.

B. Proof of product-form solution

Under RR-c, consider a state $\boldsymbol{s}_t\in\mathcal{S}$, and let $\boldsymbol{s}_{t+1}\in\mathcal{S}$ be obtained from $\boldsymbol{s}_t$ after a request to item k promotes it from list j to list $j+1$, demoting i from list $j+1$ to list j. The transition rates are

$$q(\boldsymbol{s}_t,\boldsymbol{s}_{t+1})=\frac{\sum_{v=1}^{u}\lambda_{vkj}c_{vkj}}{m_{j+1}}, q(\boldsymbol{s}_{t+1},\boldsymbol{s}_t)=\frac{\sum_{v=1}^{u}\lambda_{vij}c_{vij}}{m_{j+1}}, \tag{27}$$

This holds also for cache misses, if we see items outside the cache as residing in list $j=0$.

Using (27), it is possible to check that (1) satisfies for any path $\boldsymbol{s}_0\to\boldsymbol{s}_1\to\cdots\to\boldsymbol{s}_S$ Kolmogorov's criterion [19]

$$\pi(\boldsymbol{s}_0)\textstyle\prod_{t=1}^{S}q(\boldsymbol{s}_{t-1},\boldsymbol{s}_t)=\pi(\boldsymbol{s}_S)\prod_{t=1}^{S}q(\boldsymbol{s}_t,\boldsymbol{s}_{t-1})$$

The latter is necessary and sufficient for the Markov process to be reversible and for (1) to be its equilibrium distribution [19].

In the case of FIFO-c, the process is not reversible. However, it is sufficient to plug (1) in the global balance equations to verify the statement. The global balance equations are

$$\left(\sum_{j=0}^{h-1}\sum_{k=1}^{m_j}\sum_{v=1}^{u}\lambda_{vs(k,j)j}c_{vs(k,j)j}\right)\pi(\boldsymbol{s}) = \left(\sum_{j=0}^{h-1}\sum_{k=1}^{m_j}\sum_{v=1}^{u}\lambda_{vs(1,j+1)j}c_{vs(1,j+1)j}\right)\pi(\boldsymbol{z}_{kj}) \tag{28}$$

where $s\equiv s(i,j)$ and $\boldsymbol{s}$ is obtained from $\boldsymbol{z}_{kj}\in\mathcal{S}$ by promoting item $s(1,j+1)$ at position k of list j to the front of list $j+1$. From the definitions, according to (1)

$$\frac{\pi(\boldsymbol{z}_{kj})}{\pi(\boldsymbol{s})}=\frac{\gamma_{s(1,j+1)j}\gamma_{s(k,j)(j+1)}}{\gamma_{s(1,j+1)(j+1)}\gamma_{s(k,j)j}} \tag{29}$$

Noting that (28) may be rewritten as

$$\sum_{j=0}^{h-1}\sum_{k=1}^{m_j}\frac{\gamma_{s(k,j)(j+1)}\pi(\boldsymbol{s})}{\gamma_{s(k,j)j}}=\sum_{j=0}^{h-1}\sum_{k=1}^{m_j}\frac{\gamma_{s(1,j+1)(j+1)}\pi(\boldsymbol{z}_{kj})}{\gamma_{s(1,j+1)j}}$$

the result follows after plugging (29).

C. Proof of normalizing constant asymptotic expansion

It is possible to verify with a little algebra that

$$\frac{\partial E(\boldsymbol{m})}{\partial\gamma_{kl}}=m_lE_k(\boldsymbol{m}-1_l)=\frac{\pi_{kl}(\boldsymbol{m})}{\gamma_{kl}}E(\boldsymbol{m}). \tag{30}$$

Applying this relationship to (5) and using (6) we find

$$\pi_{kl}(\boldsymbol{m})=m_l\gamma_{kl}\frac{E_k(\boldsymbol{m}-1_l)}{E(\boldsymbol{m})}=\gamma_{kl}\xi_l(\boldsymbol{m})\frac{E_k(\boldsymbol{m}-1_l)}{E(\boldsymbol{m}-1_l)}$$

and the result follows by (3).

D. Proof of normalizing constant asymptotic expansion

1) Derivation of $\phi(\boldsymbol{x},y)$: Plugging (13) into (12) we get

$$B(\boldsymbol{x},y)e^{\phi(\boldsymbol{x},y)/\epsilon}=B(\boldsymbol{x},y-\epsilon)e^{\phi(\boldsymbol{x},y-\epsilon)/\epsilon} + \textstyle\sum_{j=1}^{h}g_j(y)B(\boldsymbol{x}-\epsilon 1_j,y-\epsilon)e^{\phi(\boldsymbol{x}-\epsilon 1_j,y-\epsilon)/\epsilon} \tag{31}$$

Expanding (31) in powers of ϵ, we obtain at the lowest order $1=e^{-\phi_y}+\sum_j g_j(y)e^{-\phi_y-\phi_j}$, where ϕ_j (resp. ϕ_y) denotes

partial differentiation with respect to x_j (resp. y). Multiplying both sides by e^{ϕ_y} and simplifying yields

$$1 - e^{\phi_y} + \sum_{j=1}^{h} g_j(y) e^{-\phi_j} = 0 \tag{32}$$

We now apply the method of characteristics for non-linear PDEs [8]. Let t be the integration variable over the characteristic curves of the PDE and let $\boldsymbol{\xi} = (\xi_1, \dots, \xi_h)$ parameterize the family of curves. We need to solve

$$dy = -e^{\phi_y} dt \tag{33a}$$
$$dx_j = -g_j(y) e^{-\phi_j} dt \tag{33b}$$
$$d\phi = \phi_y dy + \sum_j \phi_j dx_j \tag{33c}$$
$$d\phi_y = -\sum_j g'(y) e^{-\phi_j} dt \tag{33d}$$
$$d\phi_j = 0 \tag{33e}$$

where all variables are intended as functions of $(t, \boldsymbol{\xi})$. We first solve (33e) as $\phi_j = \log \xi_j$, where we have set the unknown integration constant to $\log \xi_j$, $j = 1, \dots, h$. Multiplying (33d) by (33a), and integrating we find under the initial conditions $\phi = 0$, $\boldsymbol{x} = 0$, and $y = 0$ if $t = 0$, that $\phi_y = \log\left(1 + \sum_j g_j(y)\xi_j\right)$, where intermediate integration constants need to be set to unity for consistency with (32). Plugging the last result in (33a) and integrating we obtain t, after which (33b) yields (15). Using the above results, (33c) integrates to (14).

2) Derivation of $B(\boldsymbol{x}, y)$: Expanding (12) and matching first-order terms, we write after simplifications

$$\frac{dB}{dt} = \frac{B}{2}(\phi_{yy} e^{\phi_y} + \textstyle\sum_j g_j(y)(\phi_{jj} + 2\phi_{jy}) e^{-\phi_j})$$

Plugging (14), this becomes similar to the transport equation studied in [21]. Similar passages as in [21] yield the solution

$$B(\boldsymbol{x}, y) = \frac{b(\xi_1, \dots, \xi_h)}{\sqrt{\det \boldsymbol{J}} \sqrt{1 + \sum_j g_j(y)\xi_j}} \tag{34}$$

where $b(\xi_1, \dots, \xi_h)$ is an arbitrary function, the matrix $\boldsymbol{J}$ is given in (17), and the ξ_j's depend on $\boldsymbol{x}$ and y via (15).

3) Boundary condition: We now match arbitrary function $b(\xi_1, \dots, \xi_h)$ to the value of $H(\boldsymbol{m})$ for the special case $\gamma_{kj} = g_j(k) = \gamma$, $\forall k, j$, for arbitrary γ. The normalizing constant in this case is

$$H_0(\boldsymbol{m}, n) = \frac{n!}{(n-m)! m_1! \cdots m_h!} e^{\log \gamma \sum_j j m_j}$$

Using Stirling approximation $n! \sim \sqrt{2\pi n}\left(\frac{n}{e}\right)^n$ and scaling the variables in $H_0(\boldsymbol{m}, n)$ to obtain a scaled constant $h_0(\boldsymbol{x}, y)$, we get after simple manipulations

$$h_0(\boldsymbol{x}, y) \sim \frac{(2\pi)^{-h/2}}{\sqrt{\prod_j x_j}} \sqrt{\frac{y}{y-x}} e^{\gamma/\epsilon}$$

where $\gamma = y \log y - (y - x)\log(y - x) - \sum_j x_j \log x_j + \log \gamma \sum_j j x_j$. For small $\boldsymbol{x}$ and y, we note that (15) gives $x_j = \xi_j \gamma^j y (1 + \sum_{l=1}^{h} \gamma^l \xi_l)^{-1}$, implying $\xi_j = x_j (y - x)^{-1} \gamma^{-j}$ by summing over j. Substituting the expression of ξ_j in (14) it is possible to verify that ϕ matches γ. We are thus left with requiring that

$$\frac{b(\xi_1, \dots, \xi_h)}{\sqrt{\det \boldsymbol{J}} \sqrt{1 + \sum_j \gamma^j \xi_j}} = \frac{(2\pi)^{-h/2}}{\sqrt{\prod_j x_j}} \sqrt{\frac{y}{y-x}}$$

From the definition of J_{ik}, we find $J_{ik} = (y - x)(\delta_{ik}\gamma^i - \frac{x_i}{y}\gamma^k)$. Using this result we compute $\det \boldsymbol{J}$ and determine with a little algebra the required value of $b(\xi_1, \dots, \xi_h)$, which yields (16). Lastly, to match $H_0(\boldsymbol{m})$, we need to set $D(\epsilon) = \epsilon^{h/2}$.

E. Proof of Theorem 3

To prove the lower bound, we show that the assumption implies $\pi_i(\boldsymbol{m}) \geq \pi_k(\boldsymbol{m})$, $\forall \boldsymbol{m}$, so that the statement follows by Chebyshev's sum inequality [17]. Using (3), we need to show that $E_k(\boldsymbol{m}) \geq E_i(\boldsymbol{m})$ for all i, $k > i$. Note that $E_k(\boldsymbol{m})$ is obtained from $E_i(\boldsymbol{m})$ by replacing γ_{kl} in $E_i(\boldsymbol{m})$ with $\gamma_{il} \geq \gamma_{kl}$. The statement then holds since the normalizing constant is by (30) non-decreasing with the cost factors.

F. Proof of Lemma 1

The proof is by induction on the number of items n.
Case $n = m + 1$. The case holds since by (6) it is $\xi_j^{-k}(\boldsymbol{m} - 1_l) = 0$, being $E(\boldsymbol{m} - 1_l - 1_j) = 0$.
Induction step. If the model with $n - 1$ items does not include item k, the hypothesis is $\xi_j^{-k}(\boldsymbol{m} - 1_l) \leq \xi_j^{-k}(\boldsymbol{m})$, $\forall j, l$. Using (8) and scaling numerator and denominator by $\xi_l^{-k}(\boldsymbol{m})$ yields

$$\frac{\xi_l(\boldsymbol{m})}{\xi_l^{-k}(\boldsymbol{m})} = \frac{1 + \sum_{\substack{j=1 \\ j \neq l}}^{h} \gamma_{kj} \xi_j^{-k}(\boldsymbol{m} - 1_l) + \gamma_{kl} \xi_l^{-k}(\boldsymbol{m} - 1_l)}{1 + \sum_{\substack{j=1 \\ j \neq l}}^{h} \gamma_{kj} \xi_j^{-k}(\boldsymbol{m}) + \gamma_{kl} \xi_l^{-k}(\boldsymbol{m})} \tag{35}$$

since $I\{n > m\} = 1$ and by (6) it is $\xi_j^{-k}(\boldsymbol{m})/\xi_l^{-k}(\boldsymbol{m}) = E_j(\boldsymbol{m} - 1_l)/E_k(\boldsymbol{m} - 1_l) = \xi_j^{-k}(\boldsymbol{m} - 1_l)/\xi_l^{-k}(\boldsymbol{m} - 1_j)$. If we compare term-by-term numerator and denominator in (35), by the induction hypothesis it follows that $\xi_l(\boldsymbol{m}) \leq \xi_l^{-k}(\boldsymbol{m})$. Plugging (6) in the last inequality, we get $E(\boldsymbol{m} - 1_l)E_k(\boldsymbol{m}) \leq E_k(\boldsymbol{m} - 1_l)E(\boldsymbol{m})$. Diving both sides by $E(\boldsymbol{m})E(\boldsymbol{m} - 1_l)$, by (3) we get $\pi_k(\boldsymbol{m}) \geq \pi_k(\boldsymbol{m} - 1_l)$. The last relationship implies in particular $\pi_k(\boldsymbol{m} - 1_j) \geq \pi_k(\boldsymbol{m} - 1_l - 1_j)$, thus by (10) we can write $\xi_j(\boldsymbol{m} - 1_l) \leq m_j\left(\sum_{i=1}^{n} \gamma_{il}(1 - \pi_k(\boldsymbol{m} - 1_j))\right)^{-1} = \xi_j(\boldsymbol{m})$ since $\delta_{jl} = 1$ and $\delta_{jl} = 0$, if $j \neq l$.

G. Proof of Lemma 2

We give the proof for $\pi_i(\boldsymbol{m}) = 1 - \pi_{i0}(\boldsymbol{m})$ by showing that $\pi_i(\boldsymbol{m}) \geq \pi_i(\boldsymbol{m} - 1_l)$, for any l. By (3), we need show that $E(\boldsymbol{m} - 1_l)E_i(\boldsymbol{m}) \leq E_i(\boldsymbol{m} - 1_l)E(\boldsymbol{m})$. Plugging (5) in $E(\boldsymbol{m} - 1_l)$ and $E(\boldsymbol{m})$, with the choice $k = i$, after simplifications it is sufficient to show that $E_i(\boldsymbol{m} - 1_l - 1_j)E_i(\boldsymbol{m}) \leq E_i(\boldsymbol{m} - 1_l)E_i(\boldsymbol{m} - 1_j)$, for all $j \neq l$. Dividing by $E_i(\boldsymbol{m})E_i(\boldsymbol{m} - 1_j)$ this may be seen as stating $\xi_j^{-i}(\boldsymbol{m} - 1_l) \leq \xi_j^{-i}(\boldsymbol{m})$, which holds after applying Lemma 1 to a model without item i.

H. Proof of Theorem 4

We obtain the bound by summing (11) over all l, and then by Lemma 2 replacing $\pi_i(\boldsymbol{m} - 1_l)$ with its upper bound $\pi_i(\boldsymbol{m})$. This yields $\pi_i(\boldsymbol{m}) \geq \sum_{l=1}^{h} \gamma_{il} \xi_l(\boldsymbol{m})(1 - \pi_i(\boldsymbol{m}))$. The proof follows solving for $\pi_i(\boldsymbol{m})$ and using this to compute $\pi_{i0}(\boldsymbol{m})$.