Request Patterns and Caching for VoD Services with Recommendation Systems

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Abstract—Video on Demand (VoD) services like Netflix and YouTube account for ever increasing fractions of Internet traffic. It is estimated that this fraction will cross 80% in the next three years. Most popular VoD services have recommendation engines which recommend videos to users based on their viewing history, thus introducing time-correlation in user requests. Understanding and modeling this time-correlation in user requests is critical for network traffic engineering. The primary goal of this work is to use empirically observed properties of user requests to model the effect of recommendation engines on request patterns in VoD services. We propose a Markovian model to capture the time-correlation in user requests and show that our model is consistent with the observations of existing empirical studies.

Most large-scale VoD services deliver content to users via a distributed network of servers as serving users requests via geographically co-located servers reduces latency and network bandwidth consumption. The content replication policy, i.e., determining which contents to cache on the servers is a key resource allocation problem for VoD services. Recent studies show that low start-up delay is a key Quality of Service (QoS) requirement of users of VoD services. This motivates the need to pre-fetch (fetch before contents are requested) and cache content likely to be requested in the near future. Since pre-fetching leads to an increase in the network bandwidth usage, we use our Markovian model to explore the trade-offs and feasibility of implementing recommendation based pre-fetching.

I. INTRODUCTION

Internet usage patterns are shifting towards content distribution and sharing with Video-on-demand (VoD) services like Netflix [1] and YouTube [2] accounting for over 50% of all Internet traffic. This fraction is expected to cross 80% by 2019 [3]. Most popular VoD services provide recommendations to users which heavily influence their viewing patterns. More specifically, recommendations lead to correlation in the videos requested by a user across time. The primary goal of this work is to model the viewing patterns of users of VoD services with recommendation engines. An accurate model of usage patterns is a crucial ingredient in the design of resource allocation algorithms which effectively manage Internet traffic and ensure high Quality of Service (QoS) to the users.

Meeting the QoS demands of users is critical for a VoD service to retain and expand its customer base. A recent study by Akamai [4] found that users start leaving if a video takes more than two seconds to start streaming. Moreover, for each additional second of start-up delay, the rate of abandonments increases by approximately 5.8%. The probability of a user returning to the VoD service within one day after watching a failed video is 8% versus 11% after watching a normal one. Evidently, frequent start-up delays can lead to a loss of customers, thus reducing the revenue of the VoD service.

Most large-scale VoD services serve their users via Content Delivery Networks (CDNs) which have multiple servers/caches with storage and service capabilities spread across the world. Efficient use of the available storage resources, e.g., serving user requests via geographically co-located servers can enhance the QoS for the user. More specifically, a frequent cause of start-up delay is that videos requested by users are not available on geographically co-located servers, and have to be fetched from other servers after they are requested. The delay in start-up is caused by the large geographical/network distance between the users and servers which cache the requested content.

The goal of reducing start-up delay motivates caching policies that are aggressive in adapting the content stored on the local servers in order to minimize the probability of delayed start-up. One possible solution is to pre-fetch (fetch before videos are requested) and cache videos that are likely to be requested in the near future [5]–[9]. Since pre-fetching leads to an increase in the bandwidth consumption of the CDN, there is a trade-off between bandwidth usage of the network and the quality of service provided to the users. We explore this trade-off in this work.

A. Contributions

The contributions of this work can be summarized as follows.

Modeling the request process: We propose a Markovian model which captures the time-correlation in user requests in VoD services due to the presence of recommendation systems. We show that our model is consistent with empirically observed properties of request patterns in such VoD services [10]–[13].

Performance evaluation of caching policies: We study a caching policy which pre-fetches videos likely to be requested in the future in order to minimize the chance of delayed start-up. More specifically, while a user is watching a video, our policy pre-fetches a pre-determined number of the corresponding recommended videos to the local cache, thus reducing the probability that the next request from this user experiences any start-up delay.

As discussed above, pre-fetching content reduces start-up delay, but, leads to increased bandwidth consumption. Via simulations, we explore this trade-off as a function of the
relative costs of bandwidth consumption and delayed start-up. Our results characterize when pre-fetching content can lead to a reduction in the overall cost of service, even with the increased bandwidth usage.

B. Organization

The rest of the paper is organized as follows. In Section II, we discuss existing literature on empirical studies of viewing patterns in VoDs with recommendation systems. In Section III, we define our Markovian request model and discuss its properties. We describe our CDN setting in Section IV and discuss the proposed caching scheme in Section V. In Section VI, we evaluate the performance of the proposed policy via simulations. We present our conclusions in Section VII.

II. LITERATURE REVIEW

A. Request Patterns in VoDs with Recommendations

We first summarize the observations of empirical studies which study the effect of recommendation systems on the users’ viewing patterns [10]–[13]. These studies have been conducted either by crawling the YouTube webpage [12], or via the YouTube API [12], or by collecting browsing data from university networks [12], [13]. The studies represent the relationship between videos using a directed graph, where nodes represent videos and each node has a directed edge to all the corresponding recommended videos. They focus on the properties of the graph [10], the effect of the placement/rank of a video in the recommendation list of another video [12], [13], and the effect of recommendations on the overall video popularity profile [11].

1) Small-World Recommendation Graph: The key insight obtained in [10] is that the graph representing the YouTube recommendation network is small-world. We use the following definitions to formally define small-world networks.

(i) Characteristic Path Length: The characteristic path length of a network is defined as the mean distance between two nodes, averaged over all pairs of nodes.

(ii) Clustering Coefficient: The clustering coefficient of a network is defined as the average fraction of pairs of neighbors of a node that are also neighbors of each other. Small-world networks are a class of networks that are highly clustered (high clustering coefficient), like regular lattices, yet have small characteristic path lengths, like random graphs [14]. Compared to random graphs with the same average degree, small-world networks are characterized by high clustering coefficients and similar path lengths. In [10], the authors use these two characteristics to conclude that the YouTube recommendation graph is small-world.

2) Content Popularity Profiles: It has been observed that content popularity for VoD services without recommendation systems is heavy-tailed and can often be well-fitted with the Zipf distribution defined as follows: the popularity of the $i^{th}$ most popular video is proportional to $i^{-\beta}$, where $\beta$ is a positive constant called the Zipf’s parameter. Typical values of $\beta$ for VoD services lie between 0.6 and 2 [7], [15].

Empirical studies have concluded that content popularity for VoD services with recommendation systems, e.g., YouTube, can be well-fitted with the Zipf distribution for the popular videos and popularity for the less popular videos decreases faster than the rate predicted by the Zipf distribution [11].

3) Click Through Rate: The Click Through Rate (CTR) for position $r$ in the recommendation list of Video $i$ is defined as the fraction of times a user requests the video in position $r$ in the recommendation list of Video $i$. In [12], the authors found that the mean of the CTR follows the Zipf distribution as a function of $r$. In addition, Figure 3 in [13] shows that the CDF of the CTR is concave.

4) Chain Count: Chain count is defined as the average number of consecutive videos a user requests by clicking on videos in the recommendation list before requesting a video which is not the list of recommended videos for the video currently being watched. For YouTube, the chain count is estimated to be between 1.3 and 2.4 in [13].

5) Degree Distribution: The degree distribution of the recommendation graph has been found to follow the power law. More specifically, the number of nodes with degree $k$ is approximately proportional to $k^{-3}$ [16].

B. Pre-fetching based caching schemes

Caching schemes which use pre-fetching have been shown to be beneficial for TV-on-demand and VoD services [5]–[9]. To the best of our knowledge, none of the existing works have attempted to model the request arrival process for VoD services with recommendation systems, and instead, use trace data to evaluate the performance of the proposed policies. In addition, another key difference between the existing literature and this work is that we study the trade-off between bandwidth usage and quality of service, while most of the existing works (except [7]) focus only on the improvement in quality of service (cache hit-ratio) by pre-fetching content.

In [5], the authors use trace data from a campus network gateway to analyze the performance of pre-fetching content to serve YouTube requests. A key observation in [5] that it is not necessary to pre-fetch complete videos to avoid start-up delays. Fetching a fraction of the video is often sufficient as the rest of the video can be fetched while the users’ watch the initial part of the video. In [6], the authors compare the performance of pre-fetching+caching and the Least Recent Used (LRU) caching scheme which does not pre-fetch content, for Hulu (a VoD service) on a university network. In [7], trace data from a Swedish TV service provider is used to evaluate the benefits of pre-fetching episodes of shows that a specific user is watching in order to reduce latency. In [8], the authors study the setting where the requests arrive according to a known Markov process. They propose an MDP based pre-fetching scheme and prove its optimality. Although our work also assumes that the underlying request process is Markovian, unlike [8], our caching policy works without the knowledge of the transition probabilities. This is an important distinction, since for VoD services like YouTube with massive content catalogs, content popularity is often time-varying and
unknown [17]. In [9], the authors study a pre-fetching and caching scheme for HTTP-based adaptive video streaming. They propose a pre-fetching and caching scheme to maximize the cache hit-ratio assuming the bandwidth between the local cache and the central server is limited.

III. OUR REQUEST MODEL

In this section, we discuss our model for the request process for VoD services with recommendation systems.

A. Model Definition

We construct a directed graph $G(V, E)$, where the set $V$ consists of all the videos offered by the VoD service and an edge $e = \{i, j\} \in E$ implies that Video $j$ is one of the recommended videos for Video $i$. We then assign weights to edges. Each user’s request process is a random walk on this weighted graph and therefore, the request arrival process is Markovian and can be completely described by a transition probability matrix.

We use a subset of the properties discussed in Section II-A to construct this matrix and verify that the remaining properties discussed in Section II-A are satisfied by our Markovian model.

Motivated by the fact the empirical studies like [10] have found that this graph is small-world, and the degree distribution follows the power law [16] we use the Barabasi-Albert model [13] to generate a random small-world graph. Refer to Figure 1 for a formal definition of the Barabasi-Albert model.

1: Initialize: Generate a connected graph of $m$ nodes ($v_1$, $v_2$, ..., $v_m$). Let $v = m + 1$.
2: Introduce a new node $n_v$ which connects to $m$ existing nodes. These $m$ edges from $n_v$ are added in a sequential manner as follows. The probability that each of the $m$ edges from the new node go to an existing node $n_i$ is given by $p_i$ such that

$$ p_i = \frac{K_i}{\sum_j K_j}, $$

where $K_i$ is the current degree of node $n_i$.
3: $v = v + 1$. If $v < n$, goto Step 2.

Fig. 1. Barabasi-Albert Model – An algorithm to generate a random small-world graph with a degree distribution following the power law.

Since the Barabasi-Albert model generates a undirected graph, we replace each edge by two directed edges to obtain a directed graph on the set of videos. This means that if $v_i$ recommends $v_j$, our model assumes that $v_j$ also recommends $v_i$. This is motivated by the fact that YouTube uses the relatedness score [19] for each pair of videos to determine homepage recommendations. The relatedness score of two videos is proportional to the number of times two videos are co-watched in a session. Therefore, by definition, if $v_i$ is closely related to $v_j$, $v_j$ is closely related to $v_i$.

Users can request videos via multiple sources. We divide them into two categories:

- The first set of requests come via the recommendations made by VoD service when the user is watching a video. We introduce a quantity $P_{cont}$, defined as the probability that a user requests a recommended video after he/she finishes watching the current video. Formally, after watching a video, each user requests one of the recommended videos with probability $P_{cont}$ independent of all previous requests. By definition, the expected chain count (defined in Section II-A) is given by $1/(1 - P_{cont})$. The value of $P_{cont}$ should be between 0.2 and 0.7 to be consistent with the chain count values observed in [13].
- The second set of requests come from all other sources on the Internet including the VoD homepage, the user’s social networking page, etc. To model the second type of requests, we add a dummy node $n_0$ to the graph $G$. This dummy node represents all other sources of requests and is connected to all other nodes in the $G$ via two directed edges.

The next step is to assign transition probabilities corresponding to each edge in this directed graph $G(V, E)$. Let $P_{i,j}$ be the probability a node makes the transition from node $n_i$ to node $n_j$.

- By definition, $P_{i,j} = 0$ if $\{i, j\} \notin E$.
- Recall that $P_{cont}$ is the probability that a user requests one of the recommended videos after watching the current video. If not, we assume that the user goes to node $n_0$ which represents all other sources of video requests. Therefore, by definition, $P_{i,0} = 1 - P_{cont}$, $\forall i > 0$.
- Motivated by the fact that for VoD services without recommendations, content popularity follows the Zipf distribution (as discussed in Section II-A), we set the value of $P_{0,j} \propto j^{-\beta}$ for a positive constant $\beta$ called the Zipf parameter. Typical values of $\beta$ for VoD services lie between 0.6 and 2 [?], [15].
- To assign transition probabilities to edges between a video and its recommended videos, we use the distance between two videos as a measure of similarity in the content of the two videos. For each $i, j \in E$, $P_{i,j} \propto P_{cont} \cdot (D(i,j))^{-\kappa}$, where $D(i,j) = |i - j|$ and $\kappa$ is a positive constant. We use the $P_{i,j}$'s to determine the order in which the recommended videos are presented to the user. For Video $i$, we assume that the recommended videos are ordered in decreasing order $P_{i,j}$.

Remark 1: Our model is characterized by five parameters, namely, the total number of videos $n$, the size of the graph used in the first step of the Albert-Barabasi model (Figure 1), $m$, the Zipf parameter $\beta$, the probability that a user requests one of the recommended videos after watching the current video $P_{cont}$, and $\kappa$.

B. Properties

Our model uses the empirically observed properties that the recommendation graph is small-world, its degree distribution
follows the power law, content popularity in the absence of recommendations follows the Zipf distribution, and the chain count is between 1.3 and 2.4. In this section, we verify that our Markovian model satisfies the remaining properties discussed in Section II-A.

1) Content Popularity Profile: The popularity of a video is the fraction of total requests for the video. Since the requests are generated by a finite state irreducible Discrete Time Markov Chain (DTMC), this is equal to the steady state probability of requesting the video. We therefore compute the content popularity profile of our model by calculating the stationary distribution of the Markov Chain. Figure 2 illustrates the content popularity profile for a system consisting of 2000 videos as a function of the Zipf Parameter $\beta$. Figure 3 shows how final distribution varies with $P_{cont}$.

We see that, as desired, the content popularity profile follows the Zipf distribution for the popular videos and decreases faster than as predicted by the Zipf distribution for the unpopular videos. We thus conclude that the content popularity profile for our model is consistent with the observations in [11].

2) Click Through Rate: As discussed in Section II-A, the median Click Through Rate (CTR) follows the Zipf distribution. To verify this for our model, we compute the probability of requesting the $r^{th}$ ranked recommended video for each video. We plot the median of this quantity across all videos as a function of $r$ in Figure 4. We see that the median CTR can be approximated by the Zipf distribution. Our model is therefore consistent with the observations in [12]. Varying $\kappa$ allows us to change the slope of median CTR.

3) CDF of Click Through Rate: As mentioned in Section II-A in [13], the authors compute the Cumulative Distribution Function (CDF) of the Click Through Rate (CTR). To evaluate the CDF, we compute the CTR for the $r^{th}$ ranked video in the recommendation list as follows:

$$CTR(r) = \sum_{i=1}^{n} \pi(i) \times P_{cont}$$

We plot the CDF of the CTR as a function of the position $r$ in Figure 5. Qualitatively, Figure 5 shows the same trend as observed in Figure 3 in [13].

IV. CDN SETTING

We consider a Content Delivery Network (CDN) consisting of a central server which stores the entire catalog of contents offered by the VoD service, assisted by a local cache with limited storage capacity (Figure 6). Content can be fetched from the central server and replicated on the local cache to serve user requests. The motivation behind such a network architecture is to serve most of the user requests via the local cache, thus reducing the load on the network backbone, and...
We divide the cost of serving requests into two parts:

A. Request Model

We assume that the local cache serves $u$ users concurrently and the arrival requests from each user are generated i.i.d. according to the Markovian process described in Section III. We assume that the service time of each request is an Exponential random variable with mean 1.

B. Cost Model

We divide the cost of serving requests into two parts:

(i) Cost of Bandwidth Usage: Each time a video is fetched from the central server and replicated on the local cache, the CDN pays a fetching cost denoted by $C_{\text{Fetch}}$. Without loss of generality, we normalize $C_{\text{Fetch}} = 1$ and let $C_{\text{Delay}} = \gamma \times C_{\text{Fetch}}$, where $\gamma$ is the start-up delay penalty.

Let $\text{Cost}(t)$ denote the total cost of serving requests that arrive before time $t$, $F(t)$ be the number of fetches from the central server to the local cache made before time $t$ and $D(t)$ be the number of delayed start-ups by time $t$. Then we have that

$$\text{Cost}(t) = F(t) + \gamma \times D(t).$$

The goal is to design content caching policies to minimize the total cost of serving user requests.

V. CACHING POLICIES

We propose a caching policy which uses the fact that user requests are being generated according to a Markov process to determine which contents to cache. We refer to this policy as the PreFetch policy. The key idea of the PreFetch policy is to pre-fetch the top $r$ recommended videos as soon as a user requests a specific video, thus reducing the chance that the next request from this user will have to face any start-up delay. The policy uses the Least Recently Used (LRU) metric to purge stored content in order to make space to store the fetched content.

We use the following definitions in the formal definition of the PreFetch policy:

**Definition 1:**
- A video is said to be *in use* if it is being used to serve an active request.
- A video is referred to as a *tagged video* if it is one of the top $r$ (where $r$ is a pre-determined integer $\geq 1$) recommendations for any one of the videos currently in use.

Refer to Figure 7 for a formal definition of the PreFetch policy.

1. **Input:** An integer $r \geq 1$.
2. **Initialize:** Set of cached videos, $C = \emptyset$, set of tagged videos, $T = \emptyset$, set of videos in use, $U = \emptyset$, set of cached videos currently not in use or tagged, $V = C \setminus (T \cup U)$.
3. On arrival (request for Video $i$) do,
4. if Video $i \notin C$, then
5. if $|C| < \text{cache size}$, then
6. fetch Video $i$; $C = C \cup \text{Video} i$
7. else if $V \neq \emptyset$, then
8. fetch Video $i$; replace the Least Recently Used (LRU) video in $V$ with Video $i$.
9. else
10. remove a video $\in T$, chosen uniformly at random, and replace it with Video $i$.
11. end if
12. Update $C$, $V$, $T$ and $U$.
13. end if
14. if top $r$ recommendations of Video $i$ not in cache, then
15. pre-fetch missing recommended videos,
16. for each pre-fetched video do
17. if $|C| < \text{cache size}$, then
18. add video to the cache, update $C$,
19. else if $V \neq \emptyset$, then
20. replace LRU video in $V$ with fetched video,
21. else
22. remove a video $\in T$, chosen uniformly at random, and replace it with fetched video.
23. end if
24. Update $C$, $V$, $T$ and $U$.
25. end for
26. end if

**Remark 2:** We assume that the storage capacity of the local cache is large enough to store more videos than the number of users it serves simultaneously.

**Remark 3:** The PreFetch caching policy can be implemented without the knowledge of the relative popularity of various videos. The only information required to implement the PreFetch policy is the list of recommended videos corresponding to each video in the catalog, which is always known to the VoD service.

As discussed in [5], a possible generalization of the PreFetch policy is to pre-fetch only a fraction of the recommended videos instead of pre-fetching entire videos, and fetching the remaining part of the video only after the request is made. If there exists an $\alpha < 1$ such that while the user watches the first $\alpha$ fraction of the video, the remaining $(1-\alpha)$ fraction of the video can be pre-fetched, the CDN can provide uninterrupted service to the user without any start-up delay by pre-fetching only the first $\alpha$ fraction of the video.

In the next section, we compare the performance of our
PreFetch policy with the popular Least Recently Used (LRU) caching policy. The LRU policy has been traditionally used for caching and has been widely studied for decades. Refer to Figure 8 for a formal definition of the LRU policy.

1: On arrival (request for Video $i$) do,
2: if Video $i$ not present in the cache, then
3: fetch Video $i$; replace the Least Recently Used (LRU) cached video with Video $i$.
4: end if

Fig. 8. Least Recently Used (LRU) – A caching policy.

VI. SIMULATION RESULTS

In this section, we compare the performance of the LRU policy and the PreFetch policy. Our goal is to understand if exploiting the time correlation between requests from a user by pre-fetching recommended videos can lead to better performance. In addition, we also study how the performance of the two caching policies depends on the request arrival process and various system parameters like number of users using a local server ($u$), size of cache, fraction of video pre-fetched ($\alpha$).

Requests arrive according to the request model discussed in Section III. We assume that the VoD service has a content catalog consisting of 1000 videos. We use the Albert-Barabasi model (Figure 1) to generate the recommendation graph with $m = 20$. We fix $\kappa = 0.8$ (defined in Section III) for all the results presented in this section. We assume that the service time of each request is an Exponential random variable with mean of one time unit. We assume all videos are of unit size. For each set of system parameters, we simulate the system for $10^5$ time units.

A. Cost v/s Startup delay penalty ($\gamma$)

In Figure 9 we compare the performance of the PreFetch policy and the LRU policy as a function of the Start-up delay penalty ($\gamma$). Recall that $P_{cont}$ is the probability that the next video requested by the user is one of the recommended videos. The PreFetch policy pre-fetches the top $r$ ($\geq 1$) recommendations of a video from the central server to the cache the moment a video is requested, thus ensuring that there is no start-up delay if the user requests one the top $r$ recommended videos. In addition, the total cost of service is the sum of the cost of bandwidth usage and cost due to startup delay. In Figure 2, for each value of Start-up delay penalty ($\gamma$), we use the empirically optimized value of $r$ which leads to the lowest cost of service. The optimal value of the number of recommendations to pre-fetch ($r$) increases with increase in Start-up delay penalty ($\gamma$) as shown in Figure 10.

We observe that for low values of Start-up delay penalty ($\gamma$), LRU outperforms the PreFetch policy. As the Start-up delay penalty ($\gamma$) increases, PreFetch outperforms the LRU policy. This illustrates the tradeoff between bandwidth usage, i.e., number of pre-fetches and quality of service, i.e., reducing startup delay.

B. Cost v/s Number of users ($u$)

In Figures 11 and 12 we compare the performance of the two policies where the value of $r$ used by the PreFetch policy is empirically optimized for each value of $u$ and $\gamma$. We see that as the number of users increases from 1 to 5, there is a sharp drop in the cost for both LRU and PreFetch policy. Since all the users access videos according to the same Markov process, when there are multiple users accessing the cache, the probability that the popular videos and their top recommendations are always present in the cache increases. This reduces the number of cache misses and the number of pre-fetches for the most popular videos, thus reducing the overall cost of service.
As seen in Figure 11 when the Startup delay cost $\gamma$ is low, the LRU caching policy outperforms the (optimized) PreFetch policy for all values of $u$. For $\gamma = 63$ (Figure 12), the PreFetch policy outperforms the LRU caching policy. Our simulations shows that for $\gamma \leq 11$, the optimal number of recommendations ($r$) to cache is 1. The optimal value of $r$ is between 4 - 6 for $\gamma = 63$.

Figure 13 illustrates that cache hit rates are higher for the PreFetch policy as compared to that of the LRU policy for all values of $u$ and $\gamma$.

C. Cost vs $P_{cont}$

Recall that $P_{cont}$ denotes the probability that the next video is accessed via the recommendation list. We vary the value of $P_{cont}$ between 0.2 and 0.6 (to be consistent with the observations in [13]) and evaluate the performance of LRU and optimal PreFetch policy for $\gamma = 11$ and $\gamma = 63$.

In Figure 14 we see that LRU outperforms the (optimized) PreFetch policy for low values of $P_{cont}$ and PreFetch outperforms LRU as $P_{cont}$ increases. Since increasing the value of $P_{cont}$ increases the probability that the next video is accessed via the recommendation list, we conclude that if the Startup delay cost is not very high ($\gamma = 11$), for low values of $P_{cont}$, the excess bandwidth usage due to pre-fetching outweighs the benefits of reducing startup delay.

Figure 15 illustrates that the PreFetch policy outperforms LRU for $\gamma = 63$ for all values of $P_{cont}$ considered. In addition, the relative performance of PreFetch policy improves with respect to LRU policy with increase in $P_{cont}$.

Fig. 12. Cost vs Number of users for a system with Number of videos = 1000, Startup delay penalty ($\gamma$) = 63, Zipf parameter ($\beta$) = 0.8, $P_{cont}$ = 0.4 and Cache size = 200. The PreFetch policy outperforms the LRU policy.

Fig. 13. Hit rate vs Number of users for a system with Number of videos = 1000, Zipf parameter ($\beta$) = 0.8, $P_{cont}$ = 0.4 and Cache size = 200. Cache hit rates are significantly improved by using PreFetch scheme for all values of $u$ and $\gamma$.

Fig. 14. Cost vs $P_{cont}$ for a system with Number of videos = 1000, Startup delay penalty ($\gamma$) = 11, Zipf parameter ($\beta$) = 0.8 and Cache size = 200. For low values of $P_{cont}$, the excess bandwidth usage due to pre-fetching outweighs the benefits of reducing startup delay, and for higher values of $P_{cont}$, pre-fetching leads to reduced cost of service.

Fig. 15. Cost vs $P_{cont}$ for a system with Number of videos = 1000, Startup delay cost ($\gamma$) = 63, Zipf parameter ($\beta$) = 0.8 and Cache size = 200. The PreFetch policy outperforms LRU for all values of $P_{cont}$ considered.

Fig. 16. Optimal number of recommendations to pre-fetch ($r$) vs $P_{cont}$ for a system with Number of videos = 1000, Startup delay penalty ($\gamma$) = 63, Zipf parameter ($\beta$) = 0.8 and Cache size = 200. The optimal number of recommendations to pre-fetch increases with $P_{cont}$.

Fig. 17. Hit rate vs $P_{cont}$ for a system with Number of videos = 1000, Startup delay penalty ($\gamma$) = 11, Zipf parameter ($\beta$) = 0.8 and Cache size = 200. The PreFetch policy has higher hit rate and the difference between the hit rates of the PreFetch policy and the LRU policy increases with increasing $P_{cont}$.
Startup delay penalty \( \gamma \) = 63, Zipf parameter \( \beta \) = 0.8 and Cache size = 200. The PreFetch policy has higher hit rate and the difference between the hit rates of the PreFetch policy and the LRU policy increases with increasing \( P_{\text{cont}} \).

In Figure 16 we plot the optimal value of \( r \) as a function of \( P_{\text{cont}} \). We conclude that with increasing \( P_{\text{cont}} \), it is beneficial to pre-fetch more videos from the recommendation list.

Figures 17 and 18 corresponding to \( \gamma = 11 \) and \( \gamma = 63 \) respectively, illustrate that cache hit rate is higher for the PreFetch policy as compared to the LRU policy.

D. Cost v/s Zipf parameter \( (\beta) \)

Fig. 19. Cost vs Zip parameter \( (\beta) \) for a system with Number of videos \( = \) 1000, Startup delay penalty \( (\gamma) \) = 63, \( P_{\text{cont}} \) = 0.4 and Cache size \( = \) 200. The performance of both the LRU policy and the PreFetch policy improve with increasing \( \beta \).

Fig. 20. Hit rate vs Zipf parameter \( (\beta) \) for a system with Number of videos \( = \) 1000, Startup delay penalty \( (\gamma) \) = 63, \( P_{\text{cont}} \) = 0.4 and Cache size \( = \) 200. The hit rates for both the LRU policy and the PreFetch policy improve with increasing \( \beta \).

As discussed in Figure 2, increasing the value of the Zipf parameter \( \beta \) makes the overall content popularity more lopsided, i.e., a smaller fraction of the videos account for the same fraction of the total requests. Therefore, the performance for both the LRU policy and the PreFetch policy improves with increasing \( \beta \) (Figure 19). as the small pool of popular videos are available in the local cache more often for both policies. We focus on \( \beta \) values between 0.6 and 2 since typical values of \( \beta \) lie in that range for most VoD services \([21]–[27]\). For Startup delay penalty \( \gamma > 11 \), the PreFetch policy outperforms the LRU policy for all \( \beta \) between 0.6–2. Optimal \( r \) for \( \gamma = 63 \) falls between 4 – 6 for these values of \( \beta \). Figure 20 illustrates that cache hit rates increase with increasing \( \beta \).

E. Cost v/s Cache size

Fig. 21. Cost vs Cache size for a system with Number of videos = 1000, Startup delay penalty \( (\gamma) \) = 63, \( P_{\text{cont}} \) = 0.4 and Zipf parameter \( (\beta) \) = 0.8. The performance of both policies improves with increasing cache size.

Fig. 22. Hit rate vs Cache size for a system with Number of videos = 1000, Startup delay cost \( (\gamma) \) = 63, \( P_{\text{cont}} \) = 0.4 and Zip parameter \( (\beta) \) = 0.8. The hit rates for both policies improve with increasing cache size.

We expect the performance of all policies to improve with the increase in cache size. In Figures 21 and 22 we see that the PreFetch policy performs considerably better than the LRU policy for all cache sizes considered.

F. Cost v/s Fraction to prefetch \( (\alpha) \)

In the simulation results discussed so far, we pre-fetch complete videos. We now explore the possibility of pre-fetching only a fraction of the video and fetching the remaining part of the video only after the request is made. If there exists an \( \alpha < 1 \) such that while the user watches the first \( \alpha \) fraction of the video, the remaining \( (1 - \alpha) \) fraction of the video can be pre-fetched, the CDN can provide uninterrupted service to the user without any startup delay by pre-fetching only the first \( \alpha \) fraction of the video.

Pre-fetching only a fraction of video reduces the bandwidth usage, thus reducing the overall cost of service as shown in Figures 23 and 24. Since the bandwidth usage per pre-fetch is reduced, this allows the CDN to pre-fetch more
recommendations at the same cost (Figure 25) which leads to improved cache hit rates (Figure 26).

VII. CONCLUSIONS

In this work, we propose a Markovian model for request arrivals in VoD services with recommendation engines which captures the time-correlation in user requests and is consistent with empirically observed properties.

Low start-up delay is a key QoS requirement of users of VoD services. In addition, minimizing the bandwidth consumption of the network is key to reduce the cost of service. Given the trade-off between these two goals, we show that the time-correlation in user requests can be used to design caching policies which outperform popular policies like LRU which do not exploit this time-correlation. More specifically, we show that our caching policy PreFetch which employs recommendation based pre-fetching outperforms the LRU policy in terms of the joint cost of start-up delay and bandwidth consumption when the relative is cost of start-up delay is high.

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