

Predictive Edge Caching through Deep Mining of Sequential Patterns in User Content Retrievals

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ABSTRACT

Edge caching plays an increasingly important role in boosting user content retrieval performance while reducing redundant network traffic. The effectiveness of caching ultimately hinges on the accuracy of predicting content popularity in the near future. However, at the network edge, content popularity can be extremely dynamic due to diverse user content retrieval behaviors and the low-degree of user multiplexing. It's challenging for the traditional reactive caching systems to keep up with the dynamic content popularity patterns. In this paper, we propose a novel Predictive Edge Caching (PEC) system that predicts the future content popularity using fine-grained learning models that mine sequential patterns in user content retrieval behaviors, and opportunistically prefetches contents predicted to be popular in the near future using idle network bandwidth. Through extensive experiments driven by real content retrieval traces, we demonstrate that PEC can adapt to highly dynamic content popularity at network edge, and significantly improve cache hit ratio and reduce user content retrieval latency over the state-of-art caching policies. More broadly, our study demonstrates that edge caching performance can be boosted by deep mining of user content retrieval behaviors.

KEYWORDS

edge caching, proactive caching, deep mining, sequential prediction, content retrievals

1 INTRODUCTION

Emerging applications, such as Virtual/Augmented/Mixed Reality, require high-throughput and low-latency content delivery. Edge caching is a promising solution to simultaneously reduce user content retrieval latency and mitigate traffic congestion in core networks. The key to achieve high caching gain is to accurately predict the content popularity in the near future. The classic caching policies, such as

LFU, LRU and their variants, assume contents that are popular in the past will continue to be popular in the near future. Caching replacement is therefore guided by simple statistics of the past content requests, such as time elapsed since the last request (LRU) and the frequency of past requests (LFU). Compared with the traditional CDN servers, each edge cache node is equipped with smaller storage and serves a smaller user group. As a result, the aggregate content popularity of users served by an edge cache node is less stationary, and more difficult to be accurately estimated by simple aggregate statistics of the past requests.

Lots of efforts have been made recently to address the edge caching challenge. Some methods, e.g. CRFP [22] and SG-LRU [13], have been proposed to improve or combine LFU and LRU policies. Recently, machine learning methods have been applied to improve caching performance by explicitly or implicitly learning the future content popularity, e.g. LHR[42], Learning Relaxed Belady (LRB) [33], and CEC [54]. But all of these methods are still reactive caching, in which cache replacements are only triggered by cache misses. Meanwhile, proactive caching, e.g. [4], enjoys the freedom of prefetching any content at any time with additional bandwidth cost. As discussed in [6], content popularity estimation is critical for efficient proactive caching. [34] gives the theoretically upper bound for proactive caching when content popularity is stationary. Periodical proactive cache updates, e.g. [26], can cope with non-stationary content popularity. However, it cannot adapt to the content popularity variations between two updates.

In this paper, we propose a novel Predictive Edge Caching (PEC) system that predicts the future content popularity using fine-grained learning models that mine sequential patterns in user content retrieval behaviors, and opportunistically pre-fetches contents predicted to be popular in the near future to improve cache hit ratio and reduce content retrieval latency. To address the diverse user content interests and

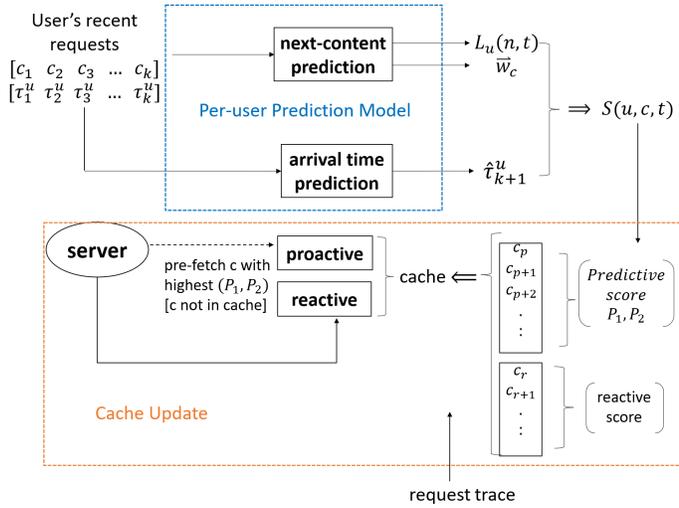


Figure 1: Overview of PEC System. The upper part is per-user next-content prediction model. Given user’s recent requests with timestamps, the predicted contents $L_u(n, t)$ and their weights \vec{w}_c can be obtained. With the estimated arrival time $\hat{\tau}_{k+1}^u$, a real time predictive score $S(u, c, t)$ will be generated. The lower part is realtime caching policy with caching scores. The cache is partitioned into proactive portion and reactive portion, which are updated according to the predictive and reactive caching scores respectively.

content consumption behaviors, instead of using the aggregate content request statistics of all users, we mine each individual user’s content request history and predict when and which content each user is likely to request the next using sequential machine learning models. We then aggregate the next-content predictions of all users to generate predictive caching scores reflecting the future content popularity. Contents predicted to be popular will be proactively prefetched into cache in the background using spare network bandwidth. To closely keep track of dynamic content popularity, per-user next-content predictions, predictive caching score updates, and proactive content prefetches are all conducted in realtime. The high-level structure of PEC is illustrated in Figure 1. Within this novel predictive edge caching framework, we make the following contributions:

- We develop machine learning models to mine the user sequential viewing patterns. We show that n-gram and self-attention sequential models have complementary performance, and can be easily combined to generate accurate fusion prediction. We use simple, yet robust, statistical methods to predict the arrival time of the next request.

- To guide online prefetching, we develop models to aggregate per-user content request predictions into per-content predictive caching scores, and update them continuously as posterior probabilities over time.
- We design a hybrid caching system that prefetches contents with high predictive scores into the proactive portion and caches popular contents missed by the predictions into the reactive portion. The sizes of the two portions are dynamically adjusted, and the content replacements in the two portions are orchestrated to maximize the caching gain.
- We develop a three-level strategy that controls the bandwidth consumption of proactive downloading to minimize its negative impact on the regular traffic.
- Through extensive edge caching simulations driven by real-world data traces, we demonstrate that, compared with the state-of-art reactive and the traditional periodical proactive caching policies, PEC can significantly improve the cache hit ratio and reduce user content retrieval latency with controlled bandwidth overhead.

The rest of the paper is organized as the following. In Section 2, we introduce the related work. Sequential models for the next-content prediction are developed in Section 3.1, and Section 3.2 presents the statistical model for the next request arrival time prediction. Section 4 presents the design for using per-user predictions in hybrid caching. We perform comprehensive evaluation using real world data in Section 5. And the final Section 6 delivers the conclusion.

2 RELATED WORK

To meet the new challenges of content delivery, more and more researchers are focusing on edge caching in different ways. Caching methods can be roughly classified into two types: reactive caching and proactive caching. Reactive caching approaches, such as LRU, LFU, First-In First-Out (FIFO) and Greedy-Dual-Size-Frequency (GDSF) [10, 24, 5, 7], replace the cached content having the lowest score with the requested content upon each cache miss, while proactive caching approaches update the whole cache periodically [8, 25, 43, 11]. In [12], authors investigated LRU, LFU and Belady’s algorithms, and concluded caching for video streaming can benefit from look-ahead technique. AViC in [2] estimates chunk request time and evicts the furthest chunk when updating cache. In [47], contents are prefetched to edge cache nodes based on the aggregated content consumption statistics, instead of per-user content prediction. Our work develops an adaptive real-time proactive caching approach which prefetches contents to become popular using idle bandwidth to adapt to dynamic popularity at edge.

Machine learning (ML), as a modern powerful tool, has also been well introduced into the caching field. Some efforts have been made on estimating dynamic content popularity [46, 40, 1, 33, 20, 42], while other efforts have applied deep reinforcement learning (DRL) to directly generate content placement strategy given various evolving state features [39, 31, 48, 18, 9, 28, 30, 16, 27, 52, 41, 36, 49, 44, 29, 54]. In [26], LEAP, a machine learning model is trained to prefetch video segments to improve user's QoE in adaptive video streaming. Most of the proposed machine learning models are trained to learn the aggregated content consumption patterns of a group of users served by the same cache. LRB [32] is a machine learning model to estimate the arrival time of the next request for a content (from any user in the group) within or out of the Belady boundary. Our machine models are designed to mine the sequential patterns of how each individual user consumes contents and predict for each user which content she will consume the next. Nearly Optimal Cache (NOC) in [51] aims to minimize the dynamic regret, which is the performance gap between an online learning algorithm and the best dynamic policy in hindsight. NOC has provably good worst-case performance for dynamic environments with no prior distribution assumptions, but it potentially degrades the performance when working with friendly request patterns. Sequential prediction model is a hot topic in both industry and academia, ranging from the traditional Markov chain model [14], to the recent machine learning models, such as recurrent neural network (RNN) [15], long short-term memory (LSTM) [37], convolutional neural network (CNN) [38], and transformer [35] with self-attention mechanism. Self-attention model [17] outperforms some state-of-art sequential prediction models. In [21], temporal-aware self-attention model delivers a promising prediction accuracy.

3 PER-USER NEXT CONTENT REQUEST PREDICTION

The key for achieving high caching gain is to accurately predict which contents will be popular in the near future. We estimate the short-term content popularity on an edge cache node by predicting the next content that will be requested by each user served by the edge cache. Given the past content requests generated by user u , our model predicts 1) which content user u will request next 2) when the next request will be generated. More specifically, given the content request history of user u ,

$$\mathcal{R}^{(u)}(t) \triangleq \{\langle \tau_1^{(u)}, c_1^{(u)} \rangle \cdots \langle \tau_i^{(u)}, c_i^{(u)} \rangle, \cdots \langle \tau_k^{(u)}, c_k^{(u)} \rangle\},$$

where $\tau_i^{(u)}$ and $c_i^{(u)}$ are the arrival time and content of the i -th request respectively, we want to predict $\tau_{k+1}^{(u)}$ and $c_{k+1}^{(u)}$ for the next request from user u .

3.1 Sequential Models for Next-content Prediction

How a user sequentially consumes contents is highly dependent on the type of contents. For example, after u finishes episode m of a TV series A , there is a good chance that u will move on to the $(m+1)$ -th episode of A the next. We can use a simple heuristic model to predict the next content for users watching TV series:

$$P(c_{k+1}^{(u)} = A_{m+1} | c_k^{(u)} = A_m) = 1,$$

where A_m denotes episode m of TV series A . We applied the simple heuristic to our datasets¹, the prediction accuracy is 45.31%. However, there is no such strong sequential patterns for the other types of contents, such as movies, shows, short videos, etc. We now develop learning-based sequential models for the next-content prediction.

3.1.1 n -gram model. Sequential models are widely used in Natural Language Processing. We adopt the simple, yet powerful, n -gram model to solve our problem. More specifically, by assuming the next content only depends on the previous $n-1$ contents, the probability of the next content can be estimated by the conditional probability of

$$P(c_{k+1}^{(u)} = c | c_k^{(u)}, c_{k-1}^{(u)}, \cdots, c_{k-n+2}^{(u)}). \quad (1)$$

Empirical conditional probability is derived from the history data. An illustration of 3-gram is shown in Fig.2.

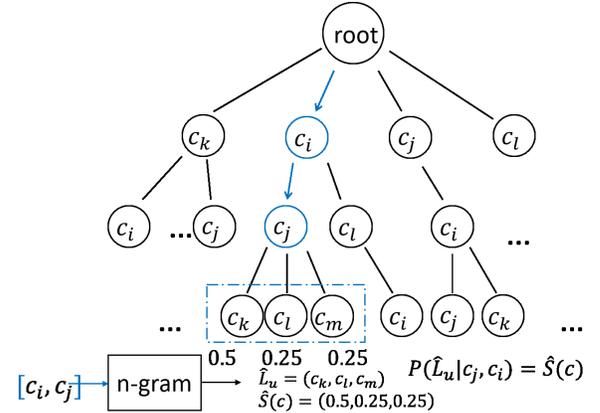


Figure 2: 3-gram Model: after building the 3-gram tree, given input sequence $[c_i, c_j]$, model predicts the next-content candidates \hat{L}_u with their probabilities.

¹The datasets will be described in detail in Section 5.1

3.1.2 Time-aware Self-attention Sequential (TSAS) Model. The n -gram Markovian model can capture short-range content transition patterns, but falls short to model complex transition patterns in longer ranges. Meanwhile, Deep neural networks, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), can be used to mine long-range patterns, but they perform well only with dense data. More recently, self-attention based sequence-to-sequence models, such as Transformer [35], have achieved state-of-the-art performance in various NLP tasks. The main idea is to learn the “self-attention weights” that quantify the pairwise impacts of words in the same sentence and predict the future words based on the previous words. The self-attention mechanism has been extended for sequential recommendation by additionally incorporating positional information and time information [21] [17] in user-item interaction sequence.

Caching is highly time-sensitive. We not only need to place popular contents in the cache, but also should do it at the ‘right’ time. Contents to become popular the next day don’t have to be cached now. Meanwhile, other than the watched contents, the time a user spent on each content also tells a lot about the user’s content preference and watching habit. For example, if a user often skips to another video within 10 minutes, it makes more sense to predict she will watch a short video instead of a long movie next. As a result, to accurately predict the next content $c_{k+1}^{(u)}$, we should not only consider the user’s past content sequence, $\{c_1^{(u)}, \dots, c_k^{(u)}\}$, but also the timestamps of those contents $\{\tau_1^{(u)}, \dots, \tau_k^{(u)}\}$.

Motivated by the work in [21], we develop a customized time-aware self-attention model for next-content prediction. We convert each user’s content request history into sequences of length n . For the clarity of presentation, we now denote one sequence from any user as $\{\langle \tau_1, c_1 \rangle \dots \langle \tau_n, c_n \rangle\}$. We train a self-attention model using length- n sequences from all users². We assume that the impact of the j -th request of the sequence on the i -th request (We only consider $j < i$ for the causality consideration) depends on: 1) the requested content c_j , 2) $\tau_i - \tau_j$, the time elapsed from the j -th request to the i -th request.

As illustrated in Figure 3, to learn the self-attention weights, we embed contents using an embedding matrix $E^{(c)} \in \mathbb{R}^{|C| \times d}$, where d is the dimension of the latent embedding space. A content embedding vector is projected to the corresponding Key, Query and Value vectors using learnable projection matrices $W^k, W^q, W^v \in \mathbb{R}^{d \times d}$ respectively. All the time intervals are quantized and capped to be integers within $[0, k]$, and then embedded using two matrices $E^{(t,k)}, E^{(t,v)} \in \mathbb{R}^{k \times d}$, one for Key, the other for Value. We summarize the context

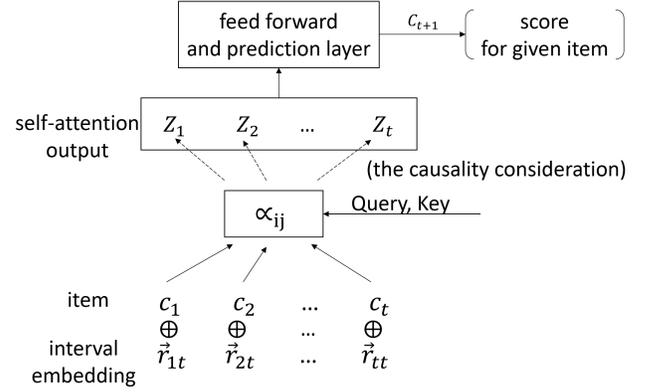


Figure 3: TSAS Model Structure.

of the first $i - 1$ requests as a weighted sum of the embedding value vectors of the requested contents and the time-intervals between requests:

$$z_i = \sum_{j=1}^{i-1} \alpha_{ij} (E_{c_j}^{(c)} W^v + E_{\tau_i - \tau_j}^{(t,v)}), \quad (2)$$

where $E_l^{(*)}$ represents the l -th row vector of the embedding matrix $E^{(*)}$, and the self-attention weight coefficient α_{ij} between request i and j is calculated by the softmax function:

$$\alpha_{ij} = \frac{\exp(m_{ij})}{\sum_{k=1}^n \exp(m_{ik})}$$

$$m_{ij} = \frac{E_{c_i}^{(c)} W^q (E_{c_j}^{(c)} W^k + E_{\tau_i - \tau_j}^{(t,k)})^T}{\sqrt{d}}.$$

We add non-linearity by feeding the output of the self-attention layer to a point-wise Feed-Forward Network (FFN) with dropout and layer normalization. Finally, the probability of content c for the i -th request is predicted as:

$$P(c_i = c | \langle \tau_1, c_1 \rangle \dots \langle \tau_{i-1}, c_{i-1} \rangle) \sim \mathbf{Z}_i \cdot E_c^{(c)}, \quad (3)$$

where \mathbf{Z}_i is the latent context vector outputted by the self-attention layer and FFN, and $E_c^{(c)}$ is the content embedding vector for candidate c .

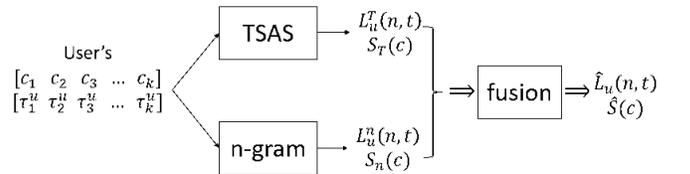


Figure 4: Fusion Prediction System.

²Padding will be applied if a user has requested less than n contents.

3.1.3 Fusion Prediction Model. To combine the short-range and long-range sequential patterns captured by the n-gram and TSAS models, we generate final prediction using model fusion. We tried different fusion methods, including CombSum, combMNZ and Reciprocal Rank Fusion(RRF) [23]. Among them, combSum fusion achieved the best performance and it has ranking scores for the final output, which can be used as content caching scores.

The diagram of the fusion prediction system is shown in Fig. 4. Specifically, we generate two top-n lists from the n-gram and TSAS models. The two lists are merged, and for each candidate content c in the merged list, we normalize its n-gram and TSAS scores $S_n(c)$ and $S_T(c)$ from (1) and (3) using max-min normalization, respectively. We then rank all the contents based on their combined normalized scores, and put the top n contents into the fused top-n list. The weight for each content is simply its combined normalized score:

$$w_c = \frac{S_n(c) + S_T(c)}{2}. \quad (4)$$

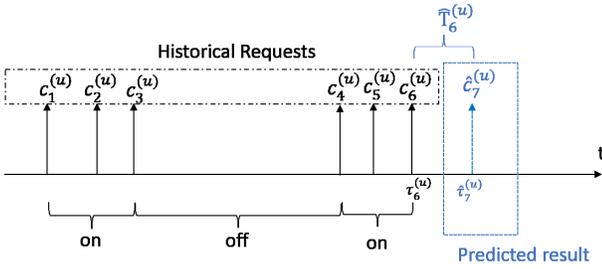


Figure 5: Predict Content and Arrival Time of Next Request for Each User with On-Off View Pattern

3.2 Next-request Arrival Time Prediction

For the purpose of caching, other than predicting the next content $c_{k+1}^{(u)}$, it is also important to predict when u will request the next content, i.e., $\tau_{k+1}^{(u)}$. A user's activities follow *on-off* pattern. When a user is actively watching videos, after finishing content c_k , she will generate the next content request. So the next-request arrival time is simply $\tau_{k+1}^{(u)} = \tau_k^{(u)} + T^{(u)}(c_k)$, where $T^{(u)}(c_k)$ is the random variable of the time duration that u will watch the current content c_k . Meanwhile, if the user leaves the video watching session after finishing c_k , the next request will be generated when she becomes active again, then $\tau_{k+1}^{(u)} > \tau_k^{(u)} + T^{(u)}(c_k)$, and the gap is the length of the user's off-period. The off-periods are very random, depending on lots of other factors outside of video watching. The length of an off-period can be easily hours or even days, much longer than the time-scale of

edge caching. Meanwhile, a user typically watches multiple videos within each on-period, so the inter-arrivals between adjacent requests in the complete trace are dominated by the inter-arrivals between two adjacent requests within the same on-period. In this section, we will focus on predicting the interval till the next request within the same on-period. If the next request does not arrive beyond the predicted arrival range, we will cancel our prediction and wait for the user to become active again. The next content and arrival time prediction with on-off pattern is illustrated in Fig.5.

The key is to predict $T^{(u)}(c_k)$. One way is to use the statistics of the watching time of other users for c_k . However, we don't have the actual watching time in our trace. As a work-around, we use the interval till the next request after c_k to approximate the watching time for c_k . To mitigate the approximation error when c_k is the last request of an on-period, we first cap the watching time for each video type with a reasonable upper bound, e.g. three hours for movies. Then we use the sample median, instead of sample mean, to estimate $\mu(T(c_k))$, to limit the impact of the outliers. Similarly, we also obtain the sample variance of the watching time $\sigma^2(T(c_k))$. Then we assume that user u will finish the current content c_k and generate the next content request at a uniformly random time in a future window of $[a(\tau_{k+1}^{(u)}), b(\tau_{k+1}^{(u)})]$, where $a(\tau_{k+1}^{(u)}) = \tau_k^{(u)} + \mu T(c_k) - \sigma(L(c_k))/2$, and $b(\tau_{k+1}^{(u)}) = \tau_k^{(u)} + \mu(T(c_k)) + \sigma(L(c_k))/2$.

It is also possible to generate more "personalized" watching time prediction by treating $T^{(u)}(c_k)$ as u 's personal preference/rating for content c_k . We applied Matrix Factorization to estimate $T^{(u)}(c_k)$, but the estimation errors are higher than the simple sample median estimation. We will further study personalized watching time prediction in future.

4 CACHING WITH PER-USER CONTENT PREDICTION

Given the per-user next content request prediction from all users, we now aggregate them into time-sensitive predictive cache scores for hybrid proactive-reactive caching.

4.1 Time-sensitive Predictive Caching Score

As soon as we predicted the next content $c_{k+1}^{(u)}$ and its arrival range $[a(\tau_{k+1}^{(u)}), b(\tau_{k+1}^{(u)})]$, we assign predictive caching scores to quantify its potential caching gain. This score should be time-sensitive. If the predicted arrival range is still ahead, i.e., $t < a(\tau_{k+1}^{(u)})$, it is not immediately urgent to cache the content. If $a(\tau_{k+1}^{(u)}) \leq t < mid$, where $mid = \frac{a(\tau_{k+1}^{(u)}) + b(\tau_{k+1}^{(u)})}{2}$, i.e., the estimated lower bound for arrival has passed, but the midpoint of the range is still ahead, it becomes urgent

to cache the content, we update our uniform prior distribution and assign a predictive caching score proportional to the posterior density function $p(\tau_{k+1}^{(u)} = t | \tau_{k+1}^{(u)} \geq t)$. If the time has passed the midpoint of the estimate range, we gradually reduce our confidence about the predicted arrival. We don't update the posterior density any more, and use a fixed predictive score of 2, which is the posterior density when t reaches the midpoint, until the predicted arrival upper bound $b(\tau_{k+1}^{(u)})$, beyond which the prediction is concluded wrong, and the predictive caching score for the predicted content is set back to zero. The user u 's contribution to the predictive caching score of $c_{k+1}^{(u)}$ is updated as:

$$S(u, c_{k+1}^{(u)}, t) = \begin{cases} 0 & t < a(\tau_{k+1}^{(u)}) \\ \frac{b(\tau_{k+1}^{(u)}) - a(\tau_{k+1}^{(u)})}{b(\tau_{k+1}^{(u)}) - t} & a(\tau_{k+1}^{(u)}) \leq t < \text{mid} \\ 2 & \text{mid} \leq t \leq b(\tau_{k+1}^{(u)}) \\ 0 & t > b(\tau_{k+1}^{(u)}) \end{cases} \quad (5)$$

An example of score update is illustrated in Fig. 6. Meanwhile, whenever u requests a new content, we will generate a new prediction based on the newly requested content, the predictive caching score for the previously predicted content from u will be reset, and caching score for the newly predicted content will be calculated according to (5).

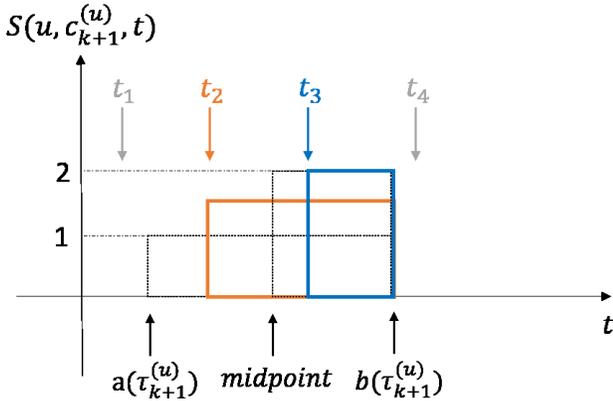


Figure 6: An example of updating predictive score as posterior probability over time.

At any given time t , let $\mathcal{A}(t)$ be the set of the active users. For each $u \in \mathcal{A}(t)$, based on her most recent content request sequence, we can generate the top- n list $\mathcal{L}_u(n, t)$ of contents that u is mostly likely to request the next using the fusion model in Sec. 3.1.3. Each content c in the top- n list has a prediction weight w_c from (4). The total weighted predictive caching score for any content in the combined top- n list of

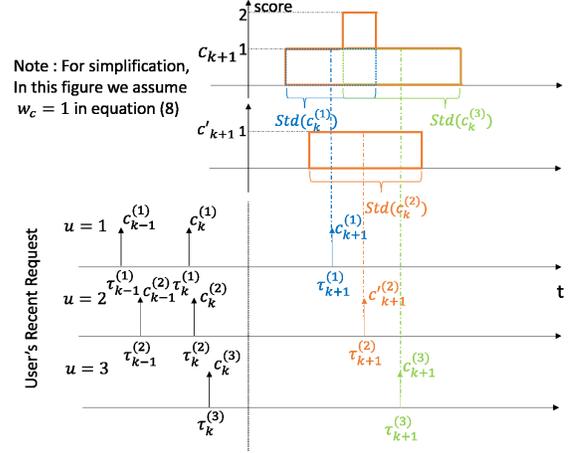


Figure 7: An example of aggregating user-content scores $S(u, c, t)$ into content predictive score $\mathcal{P}_1(c)$. There are 3 users and two content (c_{k+1} and c'_{k+1}) in this example. To simplify the figure, each user only has one predicted content. User1 and user3 are predicted to request c_{k+1} , and user2 is predicted to request c'_{k+1} . $\mathcal{P}_1(c_{k+1})$ is the envelope of the orange distribution.

all the active users can be calculated as:

$$\mathcal{P}_1(c, t) = \sum_{u: c \in \mathcal{L}_u(n, t)} w_c S(u, c, t), \quad \forall c \in \cup_{u \in \mathcal{A}(t)} \mathcal{L}_u(n, t), \quad (6)$$

where $S(u, c, t)$ is calculated using (5). For TV-series data, we only predict one candidate (the next episode), i.e., $n=1$, and $w_c = 1$. An user-content scores aggregation example is shown in Fig. 7. If a content shows up in multiple users' top- n lists, but the expected arrival range has not arrived yet, according to (5), the content still get zero predictive score. To distinguish such a content from a content not showing up in any user's top- n list, we give them the second class caching priority, and use its nearest predicted arrival time as the secondary predictive caching score:

$$\mathcal{P}_2(c, t) = \frac{1}{\min_{u: c \in \mathcal{L}_u(n, t)} a(\tau_{k+1}^{(u)}) - t}. \quad (7)$$

The secondary caching score decreases with the shortest time interval till the expected arrival of any active user, following the Farthest-In-Future (FIF) caching replacement policy. For comparison, $\mathcal{P}_1(c, t)$ has higher priority over $\mathcal{P}_2(c, t)$ if $\mathcal{P}_1(c, t) > 0$.

4.2 Hybrid Proactive-Reactive Caching

4.2.1 Partitioning Cache into Proactive and Reactive Portions.

If the contents that are in the top- n next-content lists are not currently in the cache, one can proactively download them into the cache so that they can be directly served from the

cache if they are indeed requested by a user. So the predictive caching scores are the most suited for proactive caching to achieve high hit ratio and low latency. Meanwhile, we cannot solely depend on predictive scores to manage the whole cache. First, our prediction models are designed for active users and active items, and the predictive scores are time-varying. As a result, at any time, only a portion of contents that are recently active have predictive scores. Sometimes they cannot even fill up the cache, such as during early morning. Secondly, our sequential prediction models work on the per-user basis, and are not designed to capture the content interest similarity cross users. For example, after user A watched c , the sequential model is unlikely to predict A will immediately watch c again. But if c is indeed a popular content, other users will likely to watch it in the near future. We need to resort to the conventional reactive caching algorithms to take advantage of the homogeneity of content interests of a user group. To verify this, we con-

Table 1: Prediction Accuracy Comparison between Proactive and Reactive Caching Scores

Recall	Predictive score	LRU2
Top 10	0.4750	0.5417
Top 10-50	0.3781	0.3448
Top 50-100	0.3350	0.2321
Top 100-200	0.3186	0.1746
Top 200-500	0.2548	0.1200

ducted a case study using two days of user content requests in our *datasetA₁*. At the beginning of every 30 minutes, we generate a list of 2,000 contents with the highest predictive caching scores, and another list of 2,000 contents with the highest LRU-2 scores (the inverse of the time elapsed since the previous two requests for a content). Then we calculate the "recall" as the fraction of the actual contents requested within the upcoming 30 minutes that are covered by each list. Table 1 reports the recall ratios for contents in different popularity groups. It is clear that both lists cover the more popular contents better. It is also interesting to notice that LRU2 score is better than the predictive score when predicting the most popular contents, while predictive score is better than LRU2 for the rest of the popularity groups. The relative recall gap gets larger for the less popular groups. This suggests that our predictive scores can be used to improve caching performance for contents with medium popularity.

We now present PEC, a hybrid caching system, that takes advantage of the complementary prediction power of predictive and reactive caching scores. PEC partitions the cache into two portions, proactive portion and reactive portion. The proactive portion is used to prefetch contents with high predictive caching scores, while the reactive portion stores

contents without predictive scores and is updated reactively using any reactive caching algorithm. For our experiments in Section.5, we uses LRU2 for reactive caching.

Algorithm 1 Per-request Processing and Reactive Cache Replacement

Input: user u requests content c_t at time t ;
Output: updated predictive caching scores, refreshed reactive cache portion.

- 1: **if** c_t in cache **then**
- 2: $hit++$
- 3: **else**
- 4: download c_t to reactive portion, evict content with lowest reactive caching score
- 5: **end if**
- 6: reset user u 's contributions to predictive scores of contents in u 's last top- n list $L_u(n, t')$;
- 7: add $\langle c_t, t \rangle$ to u 's request history, generate new top- n list $L_u(n, t)$;
- 8: for each contents in the new top- n list $L_u(n, t)$, update their proactive caching scores;

4.2.2 Content Prefetching and Replacement. Algorithm 1 describes how our hybrid caching algorithm processes each new requested content c_t by user u at time t . If c_t is either in the proactive or the reactive portion, it will be directly served from the cache and counted as a new cache hit. Otherwise, c_t will be downloaded from the server and stored in the reactive portion. If the reactive portion is full, the content with the lowest reactive caching score, such as the LRU2 score, will be evicted from the reactive portion. Since u has just generated a new content request, the top- n next-content list $L_u(n, t')$ generated when u requested the previous content at t' expires. All predictive caching scores $\mathcal{S}(u, c, t)$ calculated for $c \in L_u(n, t')$ will be reset. We then generate a new top- n list $L_u(n, t)$ using the fusion model in Section 3.1.3 with $\langle c_t, t \rangle$ as the most recent content request, and update the predictive caching scores of all contents in the new list according to (5), (6) and (7).

Algorithm 2 Periodic Predictive Score Update and Proactive Cache Replacement

Input: predictive scores \mathcal{P}_1 and \mathcal{P}_2 for all active contents;
Output: updated predictive caching scores, refreshed proactive cache portion.

- 1: **while** true **do**
- 2: **if** periodic update timer expires **then**
- 3: update \mathcal{P}_1 and \mathcal{P}_2 for all active contents;
- 4: restart update timer;
- 5: **end if**
- 6: **if** link to server is idle, and prefetch quota³ available **then**
- 7: prefetch the content with the highest $(\mathcal{P}_1, \mathcal{P}_2)$ score not in cache, replace the content with the lowest $(\mathcal{P}_1, \mathcal{P}_2)$ score in proactive portion.
- 8: **end if**
- 9: **end while**

Algorithm 2 describes how the predictive caching scores are updated periodically over time, and how the proactive portion is refreshed through prefetching. We periodically update the predictive caching scores of all content in the top- n lists of all active users according to (5), (6) and (7). Whenever there is a chance for prefetching, we will prefetch the content with the highest $(\mathcal{P}_1, \mathcal{P}_2)$ scores but not in the cache (proactive nor reaction portion) into the proactive portion. If needed, the content with the lowest $(\mathcal{P}_1, \mathcal{P}_2)$ score will be evicted from the proactive portion.

4.2.3 Dynamic Partition Adjustment. In PEC, the predictive scores are time-varying, the number of contents with predictive scores can be dynamic. To avoid assigning too much storage for proactive caching when there are only a small number of contents can be prefetched, we impose the dynamic partitioning mechanism. We first set up lower and upper bounds for proactive portion as $\alpha * Cache_Size$, $\beta * Cache_Size$, with hyper-parameters $0 < \alpha < \beta < 1$. At time t , $n(t)$ is the number of contents with predictive scores. We set $\gamma * n(t)$ as the target size for proactive portion (γ can be larger or smaller than one, depending on the prediction quality). After each request, $n(t)$ is updated. If the current proactive cache size is less than $\gamma * n(t)$, we increase it by one (up to $\beta * Cache_Size$); if the current proactive cache size is larger than $\gamma * n(t)$, we decrease it by one (down to $\alpha * Cache_Size$).

4.2.4 Controlling Prefetching Bandwidth Overhead. Although proactive caching gives us more freedom to update the cache and boosts the caching performance by predicting the content popularity in the near future, it consumes extra bandwidth to prefetch content. We propose a three-level bandwidth overhead controlling strategy.

- (1) Firstly, prefetching is only conducted in the background. Whenever a missed content is being downloaded from the server, the prefetching is banned. In other words, prefetching only utilizes idle bandwidth to improve caching performance without interfering with the regular content downloads.
- (2) Secondly, after each user content request, if the link becomes idle, we allow at most one content prefetching to control prefetching traffic.
- (3) Thirdly, to further limit the bandwidth overhead, we can introduce *prefetching gap* K to limit the prefetching frequency. Prefetching gap is the minimum number of user content requests between two prefetchings. For example, if $K = 3$, it means a new prefetching is allowed only after three new user content requests.

³Prefetch quota means the three-level bandwidth overhead controlling strategy is satisfied.

The bandwidth overhead and prefetching efficiency tradeoff will be studied in Section 5.6.

5 EVALUATION

In this section, we evaluate the performance of PEC on real world datasets from two content providers. Datasets details are introduced in Section 5.1. Prediction accuracy of per-user next-content and next-request-time are evaluated in Section 5.2 and 5.3 accordingly. Section 5.4 presents caching simulator setup, evaluation metrics, and PEC settings and its computation complexity. We compare PEC with several state-of-the-art reactive and proactive caching benchmarks in Section 5.5. The trade-off between bandwidth overhead and proactive caching gain is investigated in Section 5.6.

5.1 Dataset

The first dataset, datasetA is content request trace with timestamps. It was collected from IPTV users in different provinces of China, and each user is identified by her IP address. On average, 61.90% of the video requests are for TV series, 24.91% for movies, 8.94% for TV shows, and 4.25% for other types of videos. DatasetB was collected from users of a major OTT video service in a major city of China. The data format is similar to datasetA, except each user has a unique ID, instead of IP address. 51.99% of requests are for TV series and 48.01% are for the other types of videos. datasetB only contains active users who generates at least 10 requests each day.

To emulate Edge Caching scenarios, we use a subset of

Table 2: DATASET Details

Dataset	A_1	A_2	B_1	B_2
# of users	58,016	5,363	507	263
# of contents	65k	20k	26k	16k
# of requests	536k	59k	100k	50k
time span	13 days		7 days	
training set	First 11 days		First 5 days	
testing set	Last 2 days			

datasetA based on user’s IP prefix. We call it $datasetA_1$. We further sample a smaller subset, $datasetA_2$, of users sharing the same /16 IP prefix. Similarly, we randomly sample one subset from datasetB as $datasetB_1$, and another smaller $datasetB_2$ from $datasetB_1$. The details are shown in Table 2.

5.2 Next-Content Prediction

5.2.1 Model Training and Configuration. We tried different configurations and the best one is shown in Table 3. The input of our TSAS next-content prediction model is a user’s past 50 requests with timestamps. If the number of the past

Table 3: Hyper-parameter Configuration

Parameter	Value
input sequence length for TSAS	50
max time interval capping k	5 hours
learning rate	0.001
latent vector dimension d	50
# of self-attention blocks	2
batch size	128
drop rate	0.2
n-gram selection	$n = 3$
download time for each content	0.5s

requests is less than 50, empty contents will be padded with the timestamp of the start of the dataset. The maximal time interval between two requests is capped at 5 hours. Other parameters are set as default values in Tensorflow 1.12.0. Following practices in [21] [17], to reduce the content/user space and improve prediction accuracy, we only predict the next requests for active users and active contents, since the requests generated by active users are the most important for caching. Users having at least 3 requests and contents requested at least 3 times are considered as active. For the n-gram model, we set $n = 3$ to achieve the best complexity-performance tradeoff in our experiments. Similarly, 3-gram model is built on active users and contents as well.

5.2.2 Prediction Accuracy. The accuracy of the top-n next-content list is measured by the *top-n hit ratio*, which is defined as the fraction of predictions that the next content watched by u is indeed in the predicted top-n list. For TV series, our simple heuristics only predict the next episode as the next content, i.e, $n = 1$. The top-1 hit ratio is 45.31% for $datasetA_1$ and 32.48% for $datasetB_1$ respectively. The prediction accuracy for non-TV videos of $datasetA_1$ are presented in Table 4. The upper bound for fusing top-n lists of TSAS and 3-gram is calculated as the hit ratio of the combined top-n lists of the two models. It is clear that users are less predictable when watching non-TV videos, self-attention TSAS model outperforms the 3-gram model at larger n . The simple CombSum fusion can significantly improve the prediction accuracy of individual models to approach the fusion upper bound. This suggests that the two prediction models are complementary, and can be easily combined. Similarly, for $datasetB_1$, TSAS and 3-gram also have complementary performance, and fusion hit ratios are 0.1039, 0.1705, and 0.2548 for top-1, top-3 and top-10 prediction lists respectively.

Table 4: Hit Ratio for non-TV videos in $datasetA_1$

Hit@n	Fusion	TSAS	3-gram	Upper bound
n=10	0.1483	0.1263	0.1117	0.1603
n=3	0.1132	0.0911	0.0944	0.1296
n=1	0.0779	0.0691	0.0725	0.1012

5.3 Next-Request-Time Prediction

As discussed in Section 3.2, a user consumes video following ON-OFF pattern. In each ON session, the user will request the next video as soon as she finishes the last video, and we can use the time interval between request for c and the next request in the training set to approximate the watching time for c . This approximation is problematic if c is the last video of an ON session. To filter out such intervals, we first estimate the length of a video based on the largest mode of the distribution of the watch time approximations from all users (assuming a significant portion of users will finish watching the video). We then discard all approximations larger than the estimated video length. Finally, we take the sample mean and sample variance of the filtered watch time approximations to estimate the next request arrival range as described in Sec. 3.2. For a content that has never showed up in the training set, we simply use 20 mins as an estimation. The difference between the estimated mean arrival time and the actual arrival time for $datasetA_1$ is shown in Table 5. The prediction errors for $datasetB_1$ are 11.92 minutes and 15.27 minutes for TV-Series and non-TV-Series, respectively. Knowing that the exact arrival time cannot be very accurately predicted, the predictive score in Equation 5 is calculated using a time interval $[a(\tau_{k+1}^{(u)}), b(\tau_{k+1}^{(u)})]$ for loss tolerance.

Table 5: Next Request Arrival Prediction Error (mins) on Testing Set ($datasetA_1$)

Type	TV-Series	Movie	Show
Error (mins)	15.5197	25.3991	12.1609

5.4 Caching and PEC Configurations

5.4.1 Caching Configuration and Performance Metrics. We simulate a single edge cache with variable storage size. The edge cache is connected to a content server hosting all the contents. If the content requested by a user is in the cache, it can access it with zero latency, otherwise, the requested content will be downloaded from the server, incurring longer latency. Cache **hit ratio** is a classic performance metric. Additionally, users are directly impacted by the content retrieval latency. Since prefetching generated by proactive caching will consume some bandwidth on the link to server, it may

introduce additional delays to retrieve missed contents from server. Besides, delayed hit may happen if multiple requests are requested at same time in a queue [3]. So **latency** is another important metric, which indicates how long one request needs to wait till it is pushed to the user. In the experiments, we calculate latency reduction resulted from caching by comparing the latency of cache supported content retrieval with cacheless content retrieval. We simulate the content transmission on the link to the server to evaluate the total latency of serving all requests. In our simulator, content will be downloaded sequentially from the server, the active content download occupies the whole link bandwidth. Following the common research practices [50, 54, 53, 45, 19], we assume each content has the same size, and the transmission time for all contents is set to 0.5s in the following experiments if no explicit declaration. Finally, we monitor the bandwidth utilization on the link to quantify the traffic overhead of proactive caching.

5.4.2 PEC Hyper-parameter Settings and Computation Complexity. PEC employs two cache portions, with the reactive portion controlled by LRU-2, and the proactive portion updated by predictive caching scores. To maintain up-to-date predictive scores, the periodic update timer in Algorithm 2 is set to 5 minutes. We set the prefetching gap K as 1 in the following experiments if no explicit declaration. As discussed in Section 4.2.3, dynamic partitioning is employed in PEC. We set $\alpha = 0.5, \beta = 0.9, \gamma = 1.2$ for *datasetA* and $\alpha = 0.3, \beta = 0.6, \gamma = 0.4$ for *datasetB*. Fig. 8 compares the cache hit ratios of dynamic partitioning with static partitioning in the first day of *datasetA*₁ testing set. Cache hit ratio is calculated for every 5K requests. Our dynamic partitioning can adapt well to the user activity variations over the day and dominates static partitioning at different fixed ratios most of the time.

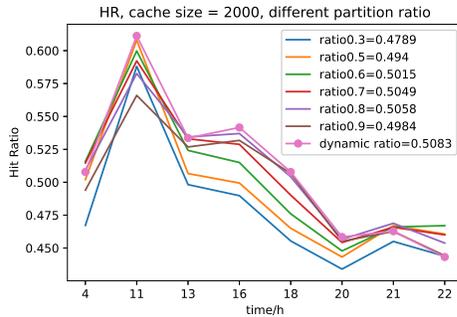


Figure 8: Hybrid Caching Performance Comparison between Dynamic Partitioning and Static Partitioning at Different Fixed Ratios.

On our local computer with GTX 1660 Ti and Intel Core i5-9400, it takes 12ms to update all predictive scores every 5 minutes as described in Equation (5), and 23ms to make time-sensitive prediction (TSAS, 3-gram and fusion) after each user content request on average. This makes PEC implementable for real-time operation on reasonably configured edge cache nodes.

5.5 Caching Experiments & Comparison with Other Benchmarks

After training the prediction models using the training data, we now use the content requests in the testing set to conduct predictive caching experiments.

5.5.1 Comparison with Reactive Caching Policies. We first compare PEC with following reactive caching policies:

- (1) LRU-2: evicts content based on the time elapsed since the previous two requests. In PEC, LRU2 is also used to manage the reactive portion;
- (2) LRU: evicts content based on the time elapsed since the last request;
- (3) LFU: evicts content based on the request frequency in the whole history;
- (4) LRB: Learning Relaxed Belady, an online learning approach using the concept of Belady boundary [32]
- (5) NOC: an online learning based caching algorithm with worst-case performance guarantee [51];
- (6) CEC: dynamically selects reactive caching policies using reinforcement learning [54];

The results for cache size of 2,000 over two-day testing data on *datasetA*₁ is shown in Fig. 9a. Cache hit ratio is calculated every 5k requests⁴. PEC has much better performance during the off-peak time, for example, from 3:00am - 15:00pm. It is because during off-peak time, there is more idle bandwidth, and PEC gets more chances to prefetch contents and update its proactive portion. Fig. 9b plots the user request rate and the prefetching rate by PEC, respectively. During the peak time, prefetching rate is only less than half of the request rate; during off-peak time, PEC can almost launch one prefetching after each user request, so that the proactive portion can be updated in-time to achieve high hit ratio. Table 6 reports the average latency reduction of different caching policies that were adopted into our cache system simulator over the cacheless system. PEC has the largest latency reductions over all the cache sizes, thanks to its predictive prefetching. Besides, latency reduction are up to 53.23%,

⁴We couldn't customize the instantaneous hit ratio calculation of the LRB code, we only report the average hit ratio of LRB in Figure 10

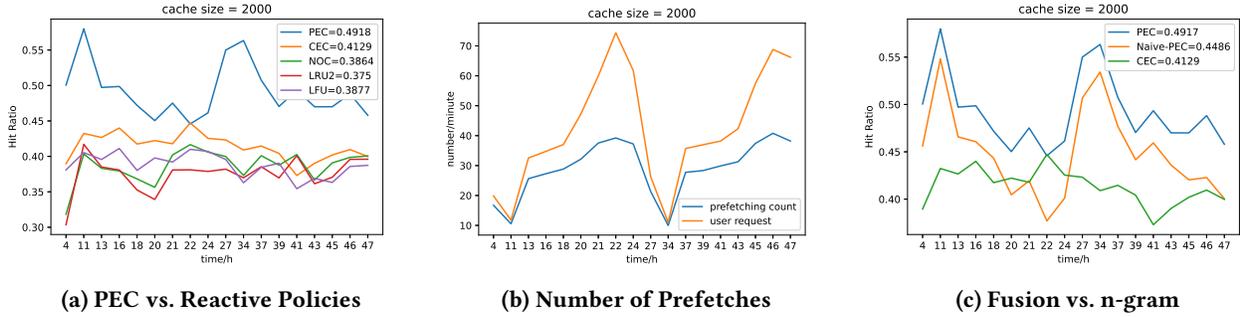


Figure 9: Comparison of Hit Ratio over Two Days between PEC and Reactive Caching Policies as well as Prefetching with Simple Prediction Model.

63.48%, 57.85% on the $datasetA_2$, $datasetB_1$, $datasetB_2$ respectively, where the latency reduction of CEC are 46.81%, 58.94%, and 52.48%.

Table 6: Latency reduction percentage over a cacheless system on $datasetA_1$ (first day on testing set)

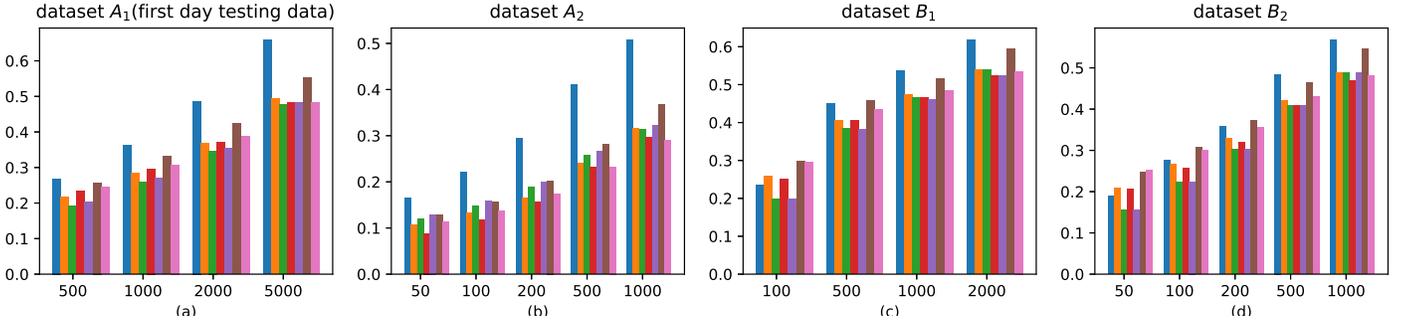
Cache size	500	1000	2000	5000
PEC	33.59%	44.36%	57.73%	73.79%
LRU2	28.71%	37.09%	46.51%	60.74%
LRU	27.50%	36.48%	45.90%	59.28%
LFU	30.78%	38.30%	47.05%	58.86%
CEC	29.78%	43.43%	56.02%	67.54%

We also compare PEC with these benchmarks on the other three datasets and the results are shown in Fig.10. In most cases, PEC outperforms the benchmarks, except on $datasetB_1$ and $datasetB_2$ when the cache size is small. It is because $datasetB_1$ and $datasetB_2$ are for active users and top popular contents dominate their content requests. The traditional caching policies such as LRU/LFU can perform well on these top popular contents. When the cache size is small, LRU/LFU can outperform PEC sometimes. When the cache size gets larger, it becomes equally important to cache medium popular contents. As demonstrated in Table 1, our predictive score is better than the traditional caching scores to hit contents with medium popularity. Consequently, PEC achieves much higher hit ratio on larger cache sizes. LRU focuses on large-scale datasets and considers contents with different sizes. It was not designed for edge caching. As a result, it was not sufficiently warmed up with our edge cache traces to achieve good performance.

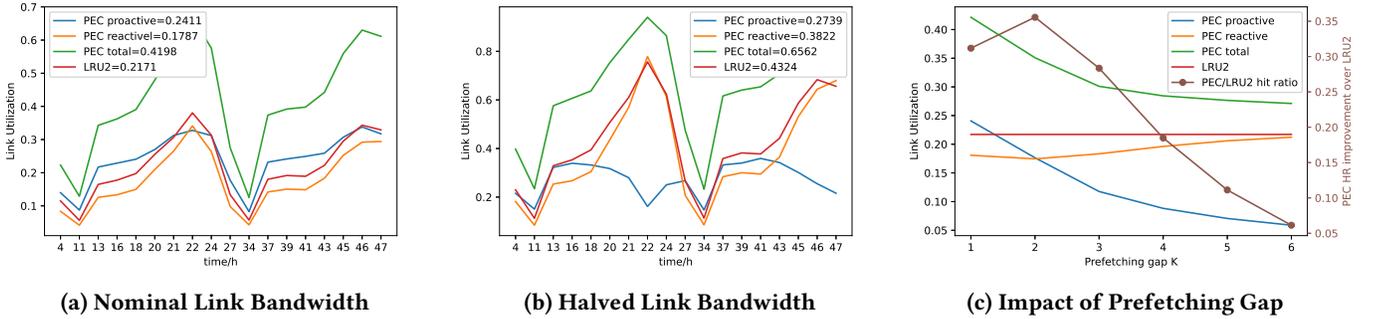
5.5.2 Comparison with Simple Periodically Proactive Caching. The traditional proactive caching policy controls the whole storage, periodically (the period is set to 3 hours) estimate the content popularity using the past request frequencies,

and load the cache with the most popular contents in batch. There is no cache replacement between two batch updates. For a more fair comparison with PEC, we also implement a hybrid proactive-reactive caching policy, called modified proactive caching, which uses the same partition ratio as PEC, the reactive portion is also controlled by LRU-2, but the proactive portion is periodically updated using past content request frequencies. The caching results are reported in Table 7 for different cache sizes on the first day of testing set of $datasetA_1$. PEC significantly outperforms the two periodic proactive cache updating policies. The performance improvement is mostly due to: 1) predictive caching scores can better reflect the future content popularity than the statistics of the past requests, 2) PEC updates proactive scores in realtime and the proactive portion is constantly updated through background prefetching so that it can better adapt to dynamic content popularity evolution.

5.5.3 Comparison with Naive-PEC Driven by Simple Prediction Model. In PEC, we leverage time-aware TSAS model with fusion process to capture user’s short-term and long-term preferences. To justify the complexity of TSAS and fusion model, we compare PEC with proactive caching guided only by the 3-gram prediction model, called Naive-PEC. To have a fair comparison, PEC and Naive-PEC use the same dynamic partition ratio, and for TV-series contents, PEC and Naive-PEC use the same heuristic method. The only difference between them is the prediction model on the other contents. The hit ratio result is shown in Fig.9c with the best reactive benchmark CEC as the reference line. We can notice that thanks to the prefetching method, Naive-PEC can still have a better overall performance than CEC. Our time-aware TSAS model with fusion process achieves more than 10% improvement over the Naive-PEC and it’s worthy to use TSAS and fusion model.


Figure 10: Hit Ratio Comparison with Benchmarks on Four Different Datasets under Different Cache Sizes
Table 7: Hit Ratio and Latency Reduction Comparison with Periodic Proactive Caching

The First Day in Testing Set	Periodic Proactive		Modified Proactive		PEC	
	latency	HR	latency	HR	latency	HR
Cache Size						
500	23.81%	0.1637	27.48%	0.2020	33.59%	0.2685
1000	29.38%	0.2061	34.03%	0.2520	33.59%	0.3624
2000	36.65%	0.2692	41.81%	0.3212	57.72%	0.4869
5000	47.41%	0.3652	52.80%	0.4211	73.79%	0.6593


Figure 11: PEC Bandwidth Overhead and Caching Gain Trade-off

5.6 Bandwidth Overhead Analysis

We report the link utilization for proactive updates and reactive updates in Fig. 11a. We also report the link utilization for the pure reactive policy LRU-2. Due to prefetching, the overall link utilization of PEC is higher than LRU-2, but is controlled within an acceptable range by the three-level bandwidth overhead control mechanism. Fig. 11b reports the link utilization when the link capacity is halved and then each content download takes 1 second to complete. As a result, the server spends a larger fraction of its link bandwidth to serve the missed contents, and the prefetching is suppressed to a lower fraction. This suggests that PEC can elastically adjust its prefetching traffic to minimize its negative impact

on the regular traffic. In this case, the hit ratio of PEC is 0.4632, still higher than the LRU2 hit ratio of 0.3718.

Fig. 11c shows the how the tradeoff between hit ratio and link utilization can be controlled by the prefetching gap K . Larger K gives less chance for prefetching, leading to lower link utilization, at the same time, degrades the performance of PEC. But PEC always outperforms LRU2 with a resealable prefetching gap. Interestingly, there is a slightly hit rate increases when the prefetching gap increases from 1 to 2. The reason can be that the predictive caching score is not perfect, if PEC prefetches into cache too many contents that never become popular, it will hurt the caching performance. But still, the difference is small, does not change the overall trend of the bandwidth-performance tradeoff.

6 CONCLUSION

In this paper, we develop a novel predictive edge caching system, called PEC, which leverages on learning-based user sequential behavior predictions and real-time background proactive content prefetches to estimate and keep track of the highly dynamic content popularity in the near future. In our experiments driven by real-world user traces, compared with the traditional periodic proactive caching, PEC significantly improves the hit ratio by up to 80%, and reduces the latency by up to 55%. Meanwhile, PEC also outperforms the state-of-art machine learning based reactive caching policy by 19.10% in terms of hit ratio, and reduces the content retrieval latency by 9.2%. PEC prefetching works in the background and utilizes the spare bandwidth to boost the caching performance. Its bandwidth overhead and caching gain tradeoff can be flexibly controlled. Our work demonstrates that per-user sequential prediction models can lead to more accurate future content popularity estimation than simple history-based statistics, and opportunistic content prefetching can be used to tradeoff spare network bandwidth for reduced latency, which is critical for the emerging edge applications.

REFERENCES

- [1] Bahman Abolhassani, John Tadrous, and Atilla Eryilmaz. 2021. Single vs distributed edge caching for dynamic content. *IEEE/ACM Transactions on Networking*.
- [2] Zahaib Akhtar, Yaguang Li, Ramesh Govindan, Emir Halepovic, Shuai Hao, Yan Liu, and Subhabrata Sen. 2019. Avic: a cache for adaptive bitrate video. In *Proceedings of the 15th International Conference on Emerging Networking Experiments And Technologies (CoNEXT '19)*. Association for Computing Machinery, Orlando, Florida, 305–317. ISBN: 9781450369985. DOI: 10.1145/3359989.3365423.
- [3] Nirav Atre, Justine Sherry, Weina Wang, and Daniel S Berger. 2020. Caching with delayed hits. In *Proceedings of the Annual conference of the ACM Special Interest Group on Data Communication on the applications, technologies, architectures, and protocols for computer communication*, 495–513.
- [4] Ejder Bastug, Mehdi Bennis, and Mérouane Debbah. 2014. Living on the edge: the role of proactive caching in 5g wireless networks. *IEEE Communications Magazine*, 52, 8, 82–89. DOI: 10.1109/MCOM.2014.6871674.
- [5] Chia-Tai Chan, Shuo-Cheng Hu, Pi-Chung Wang, and Yaw-Chung Chen. 2000. A fifo-based buffer management approach for the atm gfr services. *IEEE communications letters*, 4, 6, 205–207.
- [6] Zheng Chang, Lei Lei, Zhenyu Zhou, Shiwen Mao, and Tapani Ristaniemi. 2018. Learn to cache: machine learning for network edge caching in the big data era. *IEEE Wireless Communications*, 25, 3, 28–35. DOI: 10.1109/MWC.2018.1700317.
- [7] Ludmila Cherkasova. 1998. *Improving WWW proxies performance with greedy-dual-size-frequency caching policy*. Hewlett-Packard Laboratories.
- [8] Mostafa Dehghan, Anand Seetharam, Bo Jiang, Ting He, Theodoros Salonidis, Jim Kurose, Don Towsley, and Ramesh Sitaraman. 2015. On the complexity of optimal routing and content caching in heterogeneous networks. In *2015 IEEE conference on computer communications (INFOCOM)*. IEEE, 936–944.
- [9] Qilin Fan, Xiuhua Li, Jian Li, Qiang He, Kai Wang, and Junhao Wen. 2021. Pa-cache: evolving learning-based popularity-aware content caching in edge networks. *IEEE Transactions on Network and Service Management*, 18, 2, 1746–1757.
- [10] N Choungmo Fofack, Philippe Nain, Giovanni Neglia, and Don Towsley. 2012. Analysis of ttl-based cache networks. In *6th international ICST conference on performance evaluation methodologies and tools*. IEEE, 1–10.
- [11] Maria Gregori, Jesús Gómez-Vilardebó, Javier Matamoros, and Deniz Gündüz. 2016. Wireless content caching for small cell and d2d networks. *IEEE Journal on Selected Areas in Communications*, 34, 5, 1222–1234.
- [12] Gerhard Hasslinger, Juho Heikkinen, Konstantinos Ntougias, Frank Hasslinger, and Oliver Hohlfeld. 2018. Optimum caching versus lru and lfu: comparison and combined limited look-ahead strategies. In *2018 16th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt)*, 1–6. DOI: 10.23919/WIOPT.2018.8362880.
- [13] Gerhard Hasslinger, Konstantinos Ntougias, Frank Hasslinger, and Oliver Hohlfeld. 2016. Performance evaluation for new web caching strategies combining lru with score based object selection. In *2016 28th International Teletraffic Congress (ITC 28)*. Vol. 01, 322–330. DOI: 10.1109/ITC-28.2016.150.
- [14] Ruining He and Julian McAuley. 2016. Fusing similarity models with markov chains for sparse sequential recommendation. In *2016 IEEE 16th International Conference on Data Mining (ICDM)*. IEEE, 191–200.
- [15] Balázs Hidasi and Alexandros Karatzoglou. 2018. Recurrent neural networks with top-k gains for session-based recommendations. In *Proceedings of the 27th ACM international conference on information and knowledge management*, 843–852.
- [16] Wei Jiang, Gang Feng, Shuang Qin, Tak Shing Peter Yum, and Guohong Cao. 2019. Multi-agent reinforcement learning for efficient content caching in mobile d2d networks. *IEEE Transactions on Wireless Communications*, 18, 3, 1610–1622.
- [17] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In *2018 IEEE International Conference on Data Mining (ICDM)*. IEEE, 197–206.
- [18] Vadim Kirilin, Aditya Sundarajan, Sergey Gorinsky, and Ramesh K Sitaraman. 2020. Rl-cache: learning-based cache admission for content delivery. *IEEE Journal on Selected Areas in Communications*, 38, 10, 2372–2385.
- [19] Jeongho Kwak, Yeongjin Kim, Long Bao Le, and Song Chong. 2018. Hybrid content caching in 5g wireless networks: cloud versus edge caching. *IEEE Transactions on Wireless Communications*, 17, 5, 3030–3045. DOI: 10.1109/TWC.2018.2805893.
- [20] Guangyu Li, Qiang Shen, Yong Liu, Houwei Cao, Zifa Han, Feng Li, and Jin Li. 2018. Data-driven approaches to edge caching. In *Proceedings of the 2018 Workshop on Networking for Emerging Applications and Technologies*, 8–14.
- [21] 2020. *Time interval aware self-attention for sequential recommendation*. *Proceedings of the 13th International Conference on Web Search and Data Mining*. Association for Computing Machinery, New York, NY, USA, 322–330. ISBN: 9781450368223.
- [22] Zhan-sheng Li, Da-wei Liu, and Hui-juan Bi. 2008. Crfp: a novel adaptive replacement policy combined the lru and lfu policies. In *2008 IEEE 8th International Conference on Computer and Information Technology Workshops*, 72–79. DOI: 10.1109/CIT.2008.Workshops.22.
- [23] Shangsong Liang, Zhaochun Ren, and Maarten De Rijke. 2014. Fusion helps diversification. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*, 303–312.

- [24] N Blefari Melazzi, Giuseppe Bianchi, Alberto Caponi, and Andrea Detti. 2014. A general, tractable and accurate model for a cascade of lru caches. *IEEE Communications Letters*, 18, 5, 877–880.
- [25] Konstantinos Poularakis, George Iosifidis, Vasilis Sourlas, and Leandros Tassiulas. 2016. Exploiting caching and multicast for 5g wireless networks. *IEEE Transactions on Wireless Communications*, 15, 4, 2995–3007.
- [26] Kaiqiang Qi, Shengqian Han, and Chenyang Yang. 2019. Learning a hybrid proactive and reactive caching policy in wireless edge under dynamic popularity. *IEEE Access*, 7, 120788–120801.
- [27] Alireza Sadeghi, Fatemeh Sheikholeslami, and Georgios B Giannakis. 2017. Optimal and scalable caching for 5g using reinforcement learning of space-time popularities. *IEEE Journal of Selected Topics in Signal Processing*, 12, 1, 180–190.
- [28] Alireza Sadeghi, Fatemeh Sheikholeslami, Antonio G Marques, and Georgios B Giannakis. 2019. Reinforcement learning for adaptive caching with dynamic storage pricing. *IEEE Journal on Selected Areas in Communications*, 37, 10, 2267–2281.
- [29] Alireza Sadeghi, Gang Wang, and Georgios B Giannakis. 2019. Deep reinforcement learning for adaptive caching in hierarchical content delivery networks. *IEEE Transactions on Cognitive Communications and Networking*, 5, 4, 1024–1033.
- [30] Avik Sengupta, SaiDhiraj Amuru, Ravi Tandon, R Michael Buehrer, and T Charles Clancy. 2014. Learning distributed caching strategies in small cell networks. In *2014 11th International Symposium on Wireless Communications Systems (ISWCS)*. IEEE, 917–921.
- [31] Samuel O Somuyiwa, András György, and Deniz Gündüz. 2018. A reinforcement-learning approach to proactive caching in wireless networks. *IEEE Journal on Selected Areas in Communications*, 36, 6, 1331–1344.
- [32] Zhenyu Song, Daniel S. Berger, Kai Li, and Wyatt Lloyd. 2020. Learning relaxed belady for content distribution network caching. In *17th USENIX Symposium on Networked Systems Design and Implementation (NSDI 20)*. USENIX Association, Santa Clara, CA, (Feb. 2020), 529–544. ISBN: 978-1-939133-13-7.
- [33] Zhenyu Song et al. 2020. Learning relaxed belady for content distribution network caching. In *17th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 20)*, 529–544.
- [34] John Tadrous and Atila Eryilmaz. 2016. On optimal proactive caching for mobile networks with demand uncertainties. *IEEE/ACM Transactions on Networking*, 24, 5, 2715–2727. doi: 10.1109/TNET.2015.2478476.
- [35] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In <https://arxiv.org/pdf/1706.03762.pdf>.
- [36] Fangxin Wang, Feng Wang, Jiangchuan Liu, Ryan Shea, and Lifeng Sun. 2020. Intelligent video caching at network edge: a multi-agent deep reinforcement learning approach. In *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*. IEEE, 2499–2508.
- [37] Jie Wang, Li Zhu, Tao Dai, and Yabin Wang. 2020. Deep memory network with bi-lstm for personalized context-aware citation recommendation. *Neurocomputing*, 410, 103–113.
- [38] Jingyi Wang, Qiang Liu, Zhaocheng Liu, and Shu Wu. 2019. Towards accurate and interpretable sequential prediction: a cnn & attention-based feature extractor. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, 1703–1712.
- [39] Xiaofei Wang, Chenyang Wang, Xiuhua Li, Victor CM Leung, and Tarik Taleb. 2020. Federated deep reinforcement learning for internet of things with decentralized cooperative edge caching. *IEEE Internet of Things Journal*, 7, 10, 9441–9455.
- [40] Xianglin Wei, Jianwei Liu, Yangang Wang, Chaogang Tang, and Yongyang Hu. 2021. Wireless edge caching based on content similarity in dynamic environments. *Journal of Systems Architecture*, 115, 102000.
- [41] Pingyang Wu, Jun Li, Long Shi, Ming Ding, Kui Cai, and Fuli Yang. 2019. Dynamic content update for wireless edge caching via deep reinforcement learning. *IEEE Communications Letters*, 23, 10, 1773–1777.
- [42] Gang Yan, Jian Li, and Don Towsley. 2021. Learning from optimal caching for content delivery. In *Proceedings of the 17th International Conference on emerging Networking EXperiments and Technologies*, 344–358.
- [43] Chenchen Yang, Yao Yao, Zhiyong Chen, and Bin Xia. 2015. Analysis on cache-enabled wireless heterogeneous networks. *IEEE Transactions on Wireless Communications*, 15, 1, 131–145.
- [44] Jiahui Ye, Zichun Li, Zhi Wang, Zhuobin Zheng, Han Hu, and Wenwu Zhu. 2021. Joint cache size scaling and replacement adaptation for small content providers. In *IEEE INFOCOM 2021-IEEE Conference on Computer Communications*. IEEE, 1–10.
- [45] Jiaying Yin, Lixin Li, Huisheng Zhang, Xu Li, Ang Gao, and Zhu Han. 2018. A prediction-based coordination caching scheme for content centric networking. In *2018 27th Wireless and Optical Communication Conference (WOCC)*, 1–5. doi: 10.1109/WOCC.2018.8372711.
- [46] Cong Zhang, Haitian Pang, Jiangchuan Liu, Shizhi Tang, Ruixiao Zhang, Dan Wang, and Lifeng Sun. 2019. Toward edge-assisted video content intelligent caching with long short-term memory learning. *IEEE access*, 7, 152832–152846.
- [47] Feixiong Zhang, Chenren Xu, Yanyong Zhang, K. K. Ramakrishnan, Shreyasee Mukherjee, Roy Yates, and Thu Nguyen. 2015. Edgebuffer: caching and prefetching content at the edge in the mobilityfirst future internet architecture. In *2015 IEEE 16th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, 1–9. doi: 10.1109/WoWMoM.2015.7158137.
- [48] Chen Zhong, M Cenk Gursoy, and Senem Velipasalar. 2018. A deep reinforcement learning-based framework for content caching. In *2018 52nd Annual Conference on Information Sciences and Systems (CISS)*. IEEE, 1–6.
- [49] Chen Zhong, M Cenk Gursoy, and Senem Velipasalar. 2020. Deep reinforcement learning-based edge caching in wireless networks. *IEEE Transactions on Cognitive Communications and Networking*, 6, 1, 48–61.
- [50] Chen Zhong, M. Cenk Gursoy, and Senem Velipasalar. 2018. A deep reinforcement learning-based framework for content caching. In *2018 52nd Annual Conference on Information Sciences and Systems (CISS)*, 1–6. doi: 10.1109/CISS.2018.8362276.
- [51] Shiji Zhou, Zhi Wang, Chenghao Hu, Yanan Mao, Haopeng Yan, Chuan Wu, Shanghang Zhang, and Wenwu Zhu. 2021. Caching in dynamic environments: a near-optimal online learning approach. *IEEE Transactions on Multimedia*, 1–1. doi: 10.1109/TMM.2021.3132156.
- [52] Hao Zhu, Yang Cao, Wei Wang, Tao Jiang, and Shi Jin. 2018. Deep reinforcement learning for mobile edge caching: review, new features, and open issues. *IEEE Network*, 32, 6, 50–57.
- [53] Tongyu Zong, Chen Li, Yuanyuan Lei, Guangyu Li, Houwei Cao, and Yong Liu. 2022. Cocktail edge caching: ride dynamic trends of content popularity with ensemble learning. *IEEE/ACM Transactions on Networking*, 1–12. doi: 10.1109/TNET.2022.3193680.
- [54] Tongyu Zong, Chen Li, Yuanyuan Lei, Guangyu Li, Houwei Cao, and Yong Liu. 2021. Cocktail edge caching: ride dynamic trends of content popularity with ensemble learning. In *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*, 1–10.