VIT-CAT: PARALLEL VISION TRANSFORMERS WITH CROSS ATTENTION FUSION FOR POPULARITY PREDICTION IN MEC NETWORKS

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ABSTRACT

Mobile Edge Caching (MEC) is a revolutionary technology for the Sixth Generation (6G) of wireless networks with the promise to significantly reduce users’ latency via offering storage capacities at the edge of the network. The efficiency of the MEC network, however, critically depends on its ability to dynamically predict/update the storage of caching nodes with the top-K popular contents. Conventional statistical caching schemes are not robust to the time-variant nature of the underlying pattern of content requests, resulting in a surge of interest in using Deep Neural Networks (DNNs) for time-series popularity prediction in MEC networks. However, existing DNN models within the context of MEC fail to simultaneously capture both temporal correlations of historical request patterns and the dependencies between multiple contents. This necessitates an urgent quest to develop and design a new and innovative popularity prediction architecture to tackle this critical challenge. The paper addresses this gap by proposing a novel hybrid caching framework based on the attention mechanism. Referred to as the parallel Vision Transformers with Cross Attention (VIT-CAT) Fusion, the proposed architecture consists of two parallel ViT networks, one for collecting temporal correlation, and the other for capturing dependencies between different contents. Followed by a Cross Attention (CA) module as the Fusion Center (FC), the proposed ViT-CAT is capable of learning the mutual information between temporal and spatial correlations, as well, resulting in improving the classification accuracy, and decreasing the model’s complexity about 8 times. Based on the simulation results, the proposed ViT-CAT architecture outperforms its counterparts across the classification accuracy, complexity, and cache-hit ratio.

Index Terms— Mobile Edge Caching, Popularity Prediction, Deep Neural Networks, Vision Transformer, Cross-Attention.

1. INTRODUCTION

The phenomenal growth in demand for mobile wireless data services, together with the emergence of advanced Internet of Things (IoT) applications bring new technical challenges to wireless communications. According to Ericsson’s mobility report [1], global mobile data traffic is projected to exponentially grow from 67 exabytes/month in 2021 to 282 exabytes/month in 2027. To accommodate the huge amount of mobile data traffic, Mobile Edge Caching (MEC) [2–5] has emerged as a promising solution for potential deployment in the Sixth Generation (6G) of communication networks. MEC networks provide low-latency communication for IoT devices by storing multimedia contents in the storage of nearby caching nodes [6, 7]. The limited storage of caching nodes, however, makes it impossible to preserve all contents on nearby devices. To tackle this challenge, predicting the most popular content is of paramount importance, as it can significantly influence the content availability in the storage of caching nodes and reduce users’ latency.

Existing popularity prediction solutions are typically developed based on statistical models [6–10], Machine Learning (ML)-based architectures [11–14], and Deep Neural Networks (DNNs) [15–24], among which the latter is the most efficient one for popularity prediction. This is mainly due to the fact that DNN-based models can capture users’ interests from raw historical request patterns without any feature engineering or pre-processing. In addition, DNN-based popularity prediction models are not prone to sparsity and cold-start problems with new mobile user/multimedia contents. As a result, recent research has shifted its primary attention to DNN-based frameworks to monitor and forecast the popularity of content using its historical request pattern. A critical aspect of a DNN-based popularity prediction architecture is its ability to accurately capture both temporal and spatial correlations within the time-variant request patterns of multiple contents. While the temporal correlation illustrates the variation of users’ preferences over time, spatial correlation reflects the dependency between different multimedia contents. The majority of works in this field [18–21], however, are not appropriately designed to simultaneously capture both dependencies. This necessitates an urgent quest to develop and design a new and innovative popularity prediction architecture, which is the focus of this paper.

Literature Review: Recently, a variety of promising strategies have been designed to forecast the popularity of multimedia contents with the application to MEC networks. In [25], an auto-encoder architecture was proposed to improve content popularity prediction by learning the latent representation of historical request patterns of contents. To boost the decision-making capabilities of caching strategies, Reinforcement Learning (RL) [26, 27] and Convolutional Neural Network (CNN) [28]-based caching frameworks were introduced to exploit the contextual information of users. Despite all the benefits that come from the aforementioned works, they relied on a common assumption that the content popularity/historical request patterns of contents would remain unchanged over time, which is not applicable in highly dynamic practical systems.

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To capture the temporal correlation of historical request patterns of contents, several time-series-based DNN caching strategies [18, 29] were introduced, among which Long Short Term Memory (LSTM) [19, 24] is one of the most effective learning models. LSTM, however, suffers from computation/time complexity, unsuitability to capture long-term dependencies, parallel computing, and capturing dependencies between multiple contents. To take into account the correlation among historical request patterns of various contents, a Clustering-based LSTM (C-LSTM) model [30] was proposed to predict the number of content requests in the upcoming time. C-LSTM framework, however, is still prone to computation/time complexity, and parallel computing issues. To tackle the aforementioned challenges, Transformer architectures [31] have been developed as a time-series learning model, while the sequential data need not be analyzed in the same order, resulting in less training complexity and more parallelization. There has been a recent surge of interest in using Transformers in various applications [31–33]. The paper aims to further advance this emerging field.

**Contribution:** A crucial aspect of Transformers that has a significant potential for widespread implementation in various Artificial Intelligence (AI) applications is the self-attention mechanism. This can deal with time-series data need not be analyzed in the same order, resulting in less training complexity and more parallelization. There has been a recent surge of interest in using Transformers in various applications [31–33]. The paper aims to further advance this emerging field.

Consequently, an $(T \times N_c)$ indicator request matrix, denoted by $R$ is generated, where $T$ denotes the total number of timestamps, and $N_c$ is the total number of distinct contents, where $r_{t,l} = 1$ (the element in the $t^{th}$ row and $l^{th}$ column), if content $c_l$ is requested at time $t$.

**Step 2 - Time Windowing:** Relying on a common assumption that the most popular contents will be cached during the off-peak period [35], it is unnecessary to predict the content popularity at each timestamp. Accordingly, we define an $(N_W \times N_c)$ window-based request matrix, denoted by $R^{(W)}$, where $N_W = \frac{T}{W}$ represents the number of time windows with the length of $W$, where $W$ is the time interval between two consecutive updating times. For instance, $r_{t,l}^{(W)} = \sum_{i=i-1}^{i=W+1} r_{t,i}$ represents the total number of requests of content $c_l$ between two updating times $t_u - 1$ and $t_u$.

**Step 3 - Data Segmentation:** To generate 2D input samples, the window-based request matrix $R^{(W)}$ is segmented via an overlapping sliding window of length $L$. Accordingly, the modified dataset, denoted by $D = \{(X_u, y_u)\}_{u=1}^{M}$, is prepared, where $M$ is the total number of input samples. Term $X_u \in \mathbb{R}^{L \times N_c}$ is 2D input samples, representing the request patterns of all contents before updating time $t_u$ with the length of $L$. Finally, the term $y_u \in \mathbb{R}^{N_c \times 1}$ represents the corresponding labels, where $\sum_{i=1}^{K} y_{u,i} = K$, with $K$ denoting the storage capacity of caching nodes. Note that $y_{u, l} = 1$ indicates that content $c_l$ would be popular at $t_{u+1}$, otherwise it would be zero. Next, we describe the data labeling method.

**Step 4 - Data Labeling:** Given the historical request patterns of contents $X_u$ as the input of the ViT-CAT architecture, we label contents as popular and non-popular, according to the following criteria:

1. **Probability of Requesting a Content:** Probability of requesting content $c_l$, for $(1 \leq l \leq N_c)$, at updating time $t_u$, is obtained by $p_l^{(u)} = \frac{r_{t,u,l}^{(W)}}{\sum_{l=1}^{N_c} r_{t,u,l}^{(W)}}$.

2. **Skewness of the Request Pattern:** The skewness of the request pattern of content $c_l$, for $(1 \leq l \leq N_c)$, is denoted by $\zeta_c$, where negative skew for content $c_l$ indicates that the number of requests for content $c_l$ increases throughout $T$ timestamps. This metric is considered along with the request probability to avoid misclassifying the older popular content with a large number of requests that lose their popularity over time.

Accordingly, the Top-$K$ popular contents will be labeled with $y_{u, l} = 1$, where $c_l$ for $(1 \leq l \leq K)$ has negative skew and the highest probability. This completes the presentation of data preparation. Next, we present the proposed ViT-CAT architecture.

### 2.2. ViT-CAT Architecture

In this subsection, we present different components of the proposed ViT-CAT architecture, which is developed based on the attention mechanism. As shown in Fig. 1(a), the ViT-CAT architecture consists of two parallel paths, named Time-Series (TS)-path and Multi-Content (MC)-path, performed based on self-attention mechanism, followed by a Cross-Attention (CA) module as the fusion layer.

**A. Patching**

Generally speaking, the input of the Transformer encoder in the ViT network is a sequence of embedded patches, consisting of patch embedding and positional embedding. In this regard, the 2D input samples $X_u$ is split into $N$ non-overlapping patches, denoted by $X_u^{(p)} = \{X_u^{(l)}\}_{l=1}^{N}$. As can be seen from Fig. 1(a), we apply two following patching methods for TS-path and MC-path:
embedded patches. Finally, to encode the order of the input sequences, a learnable embedding token is added to the beginning of the embedded patches. This is referred to as the patch embedding, a linear projection of each patch to the model’s dimension. In this regard, the output of the SA block, except that the Query module is set to 1, is given by

$$Z_0 = [x^{p_1}; x^{p_2}; E; x^{p_1}; x^{p_2}; E; \ldots; x^{p_1}; x^{p_2}; E] + E^{pos},$$

where $z_{c0}$, which is provided to an LL module, is utilized for the classification task, as follows

$$y = LL(LayerNorm(z_{c0})).$$

This completes the description of the Transformer encoder. Next, we briefly explain the SA, MSA, and CA modules, respectively.

**1. Self-Attention (SA):** To capture the correlation between different parts of the input sample, the SA module is used [31], where its input is embedded vectors $Z \in \mathbb{R}^{N \times d}$, where $Z$ consists of $N$ vectors with an embedding dimension of $d$. This is the weighted sum over all values $V$, obtained by

$$SA(Z) = \text{softmax}(QK^T / \sqrt{d_h}) V,$$

where the scaled similarity is converted to the probability using softmax, and $QK^T$ is the scaled dot-product of $Q$ and $K$ by $\sqrt{d_h}$.

**2. Multihead Self-Attention (MSA):** The primary objective of the MSA module is to pay attention to input samples from various representation subspaces at multiple spots. More precisely, the MSA module consists of $h$ heads with different trainable weight matrices $W_{i}^{QKV} \in \mathbb{R}^{d_{h} \times d}$, performed $h$ times in parallel. Finally, the outputs of $h$ heads are concatenated into a single matrix and multiplied by $W_{i}^{MSA} \in \mathbb{R}^{hd_h \times d}$, where $d_h$ is set to $d/h$. The output of the MSA module is, therefore, given by

$$MSA(Z) = [SA_1(Z); SA_2(Z); \ldots; SA_h(Z)] W^{MSA}.$$

**3. Cross-Attention (CA):** The CA module is the same as the SA block, except that the Query $Q$, Key $K$, and Value $V$ are obtained from different input features as shown in Fig. 1(a). More precisely, to
Table 1. Variants of the ViT-CAT Architecture.

| Model ID | Layers | Model dimension | MLP layers | MLP size | Heads | Params  | Accuracy |
|----------|--------|-----------------|------------|----------|-------|---------|----------|
| 1        | 1      | 25              | 1          | 128      | 5     | 201,188 | 84.35%   |
| 2        | 1      | 50              | 1          | 128      | 5     | 435,788 | 94.77%   |
| 3        | 1      | 50              | 1          | 128      | 4     | 415,488 | 80.35%   |
| 4        | 1      | 50              | 1          | 64       | 5     | 342,793 | 93.49%   |
| 5        | 1      | 50              | 2          | 64       | 5     | 435,788 | 94.82%   |
| 6        | 2      | 50              | 1          | 128      | 5     | 568,185 | 94.84%   |

Table 2. Classification accuracy using different fusion networks.

| Model   | CA     | FC     | SA     |
|---------|--------|--------|--------|
| Accuracy| 94.77% | 92.58% | 79.93% |
| Parameters| 435,788 | 417,171 | 400,788 |

Fig. 2. Comparison with state-of-the-arts based on the cache-hit ratio.

3. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed ViT-CAT architecture through a series of experiments. Given the users’ ZIP code in Movielens dataset [28], we assume there are six caching nodes, where the classification accuracy is averaged over all caching nodes. In all experiments, we use the Adam optimizer, where the learning and weight decay are set to 0.001 and 0.01, respectively, and binary cross-entropy is used as the loss function for the multi-label classification task. In Transformers, the MLP layers’ activation function is ReLU, whereas their output layer’s function is sigmoid.

Effectiveness of the ViT-CAT Architecture: In this subsection, different variants of the proposed ViT-CAT architecture are evaluated to find the best one through trial and error. According to the results in Table 1, increasing the MLP size from 64 (Model 4) to 128 (Model 6), the model dimension from 25 to 50 (Model 1 to Model 2), the number of MLP layers from 1 to 2 (Models 4 and 5), the number of heads from 4 to 5 (Models 2 and 3), and the number of Transformer layers from 1 (Model 2) to 2 (Model 6) increase the classification accuracy while increasing the number of parameters.

Effect of the Fusion Layer: In this experiment, we evaluate the effect of the fusion layer in the proposed ViT-CAT architecture with other baselines, where the parallel ViT architecture in all networks is the same (Model 2), i.e., the TS and MC paths perform based on the SA mechanism. In this regard, we consider two fusion layers, i.e., the Fully Connected (FC) and the SA layers. According to the results in Table 2, the CA module outperforms the others, since it captures the mutual information between two parallel networks.

Performance Comparisons: Finally, we compare the performance of the proposed ViT-CAT architecture in terms of the cache-hit ratio with other state-of-the-art caching strategies, including LSTM-C [19], TRansformer (TR) [36], ViT architecture [15], and some statistical approaches, such as Least Recently Used (LRU), Least Fre-

4. CONCLUSION

In this paper, we presented a parallel Vision Transformers with Cross Attention (ViT-CAT) Fusion architecture to predict the Top-K popular contents in Mobile Edge Caching (MEC) networks. To capture the temporal correlation and the dependency between multiple contents, we employed two parallel ViT networks, followed by a Cross Attention (CA), which was used to learn the mutual information between two networks. Simulation results showed that the proposed ViT-CAT architecture improved the cache-hit ratio, classification accuracy, and complexity when compared to its state-of-the-art.
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