Cache Placement Optimization in Mobile Edge Computing Networks With Unaware Environment—An Extended Multi-Armed Bandit Approach

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Abstract—Caching high-frequency reuse contents at the edge servers in the mobile edge computing (MEC) network omits the part of backhaul transmission and further releases the pressure of data traffic. However, how to efficiently decide the caching contents for edge servers is still an open problem, which refers to the cache capacity of edge servers, the popularity of each content, and the wireless channel quality during transmission. In this paper, we discuss the influence of unknown user density and popularity of content on the cache placement solution at the edge server. Specifically, towards the implementation of the cache placement solution in the practical network, there are two problems needing to be solved. First, the estimation of unknown users’ preference needs a huge amount of records of users’ previous requests. Second, the overlapping serving regions among edge servers cause the wrong estimation of users’ preference, which hinders the individual decision of caching placement. To address the first issue, we propose a learning-based solution to adaptively optimize the cache placement policy without any previous knowledge of the user density and the popularity of the contents. We develop the extended multi-armed bandit (Extended MAB), which combines the generalized global bandit (GGB) and Standard Multi-armed bandit (MAB), to iteratively estimate both a global parameter, i.e., the user density, and individual parameters, i.e., the popularity of each content. For the second problem, a multi-agent Extended MAB based solution is presented to avoid the mis-estimation of parameters and achieve the decentralized cache placement policy. The proposed solution determines the primary time slot and secondary time slot for each edge server. The edge servers estimate expected satisfied user number of caching a content with the overlap information and determine the cache placement solution. The proposed strategies are proven to achieve the bounded regret according to the mathematical analysis. Extensive simulations verify the optimality of the proposed strategies when comparing with baselines.

Index Terms—Multi-armed bandit, cooperative cache placement, edge computing.

I. INTRODUCTION

EMERGING 5G networks provides the high-efficiency transmission under challenge of the increasing amount of data traffic and user number, which brings economic and technical benefits. Specifically, mobile edge computing (MEC) is introduced in the 5G network to shorten the back-haul transmission distance by deploying part of tasks at the edge server. Caching popular data contents at the edge serves enables part of users’ requests to be directly responded to by the edge servers rather than by the faraway data center, which reduces the delivery latency and greatly improves the efficiency of the wireless transmission. However, because of the limitation of the cache capacity, the edge servers cannot cache all contents. In this paper, we aim to find the optimal cache placement policy at edge servers to maximize the number of satisfied user requests by caching contents. There are two challenges we address in the paper.

First, the cache placement solution depends on the popularity of each content, which is hard to acquire for edge servers. Meanwhile, the user number is dynamic as time goes by and unknown. With the unknown user density, the number of requesting a content at a time slot cannot directly reflect the popularity of the content. Second, to cover all mobile devices in the wireless network, some of the edge servers are placed with the overlapped serving region. In this case, devices in the overlapped serving region could be served by multiple edge servers. The optimal cache placement solution not only depends on the practical popularity of the content but also the cache placement of the adjacent edge servers that have the overlapping region with it.

Towards the two problems, we propose a learning-based cache placement solution without any prior knowledge of the user density and the content popularity. Moreover, the proposed cache placement solution could avoid inaccurate
estimation of parameters and performance loss under the overlapped region when multiple edge servers have overlapping serving region.

For the first problem, we conduct the cache placement optimization with the multi-armed bandit (MAB) model under the unknown user density and popularity of each content. The standard MAB, which regards each arm individual, and Generalized global bandit (GGB), which assumes the arms have a known relationship with an unknown parameter, cannot handle the two different unknown parameters concurrently. To fill the gap between the practical requirement of diverse parameter estimation and constraints of the MAB models, we propose the Extended MAB for cache placement optimization, which considers both the individual parameter and the global parameter. The user density and popularity of each content are estimated concurrently, which improves the learning efficiency of the optimal cache placement solution.

For the second problem, we first propose a centralized cache placement policy, in which one of the dimensions represents all cache placement choices, and the other one covers all edge servers, to eliminate the inaccuracy of parameter estimation. Moreover, to reduce the complexity, we propose a multi-agent Extended-MAB for edge servers to individually make cache placement. Each edge server in the network is regarded as an agent and has its exclusive time slot to make parameter estimation. With the information of the overlapped region, the edge server estimates the expected serving user number and further derives the optimal cache placement solution.

The main contributions of this paper are summarized as follows:

- We propose a cache placement solution under unknown user density and popularity of content. To the best of our knowledge, this is the first work that considers both user density and popularity of content unknown in the cache placement solution. Specifically, we propose the Extended MAB, which is first used to deal with the cache placement in an individual edge server scenario where edge servers own a non-overlapping serving region. The regret is discussed to specify its theoretical performance.
- To avoid the miscalculation due to the overlapped serving region in a large-scale MEC network, the proposed Extended-MAB is modified to deal with the joint caching placement optimization in a cooperative edge server scenario. A dedicated edge server manager is first set to collect overall network information and output the cache placement action combination for all edge servers. Moreover, a multi-agent Extended-MAB in which the edge servers individually perform actions is proposed to release the burden of computation complexity overhead of the joint cache placement optimization.
- We conduct a series of experiments with different parameters and network settings. We choose 5 different baselines and 3 metrics to verify the availability of the proposed cache placement solution. According to the experiment, the proposed cache placement solution shows the best performance in all the scenarios.

II. RELATED WORKS

In this section, we introduce existing research relevant to the cache placement policy and MAB. In what follows, we mainly review the research of the cache placement policy under the unknown environment of the MEC network. After that, we review some extension studies of the standard MAB theory and discuss the applications, which are relevant to the proposed extended MAB model in this paper. We also emphasize the difference between the mentioned research and proposed solution in this paper.

A. Cache Placement with Unknown Environment of MEC Network

The cache placement policy in the MEC network is influenced by the wireless channel condition, such as the signal to noise ratio (SNR), and the attributes of mobile users, such as the user density and popularity of requesting contents.

Reference [1], [2] investigate the cache placement optimization with unknown channel conditions. Since the noise and fading of wireless channel influence the transmission error rate, unknown characteristics of wireless channel conditions may decrease the successful transmission probability or waste the bandwidth. In particular, [1] models a cache-enabled network and assumes the channel state as a Markov decision process. The value function and state-action cost are discussed in different channel cases. Reference [1] discusses the optimal cache scheduling under the dynamic wireless network. Reference [2] divides the entire wireless cell into several groups to avoid interference in the D2D network and proposes the primal-dual adaptive cache placement algorithm.

One way to estimate the popularity of content is to record the users’ requests, such as [3], [4]. Specifically, [4] discusses the optimization of the recording period for the popularity estimation. However, according to [5], the online content has different evolution patterns, thus the recording period is hard to be determined. The pre-determined record period makes the mentioned methods not flexible enough to be implemented in the practical network.

Other researchers consider predicting the popularity of contents using machine learning-based methods. Reference [6] proposes probabilistic dynamic factor analysis model and predicts the evolution of content popularities. Later, based on this solution, [6] extends the cooperative caching strategy for a multi-cell network with Variational Bayes (VB) approach under the unknown model parameters. References [8], [9] employ the deep learning-based prediction by firstly collecting users’ requests as the training data. In [10], [11], transfer learning is introduced to estimate the popularity, which is further used to design the cache placement strategy. Specifically, [11] studies the cache placement in a heterogeneous network where the content popularity information is unaware. Reference [10] discusses content correlation and information transition between periods and uses the auto-regressive (AR) model to predict the users’ requests. The above model-based
algorithms need the assumption about the users’ requests, which is hard to be obtained in the practical network.

The exploration and exploitation trade-off is further discussed to avoid the prior assumption of the popularity of the content for the cache placement solution. Reference [12] introduces the content controller to learn the unknown popularities of contents by observing the instantaneous demand from users and discusses the relationship between the cache placement solution and the factors, such as the number of files, the number of users, the cache size, and the skewness of the popularity profile. Reference [13] and [14] both consider using a multi-armed bandit for the cache placement problem. Reference [13] applies the semidefinite relaxation approach in the centralized cache placement situation, where the cache placement strategy of all base stations is jointly derived. Besides, [13] also provides a distributed algorithm such that each base station could make its own decision. Reference [14] indicates that the cache placement is influenced not only by the popularity of each content but also by the users’ preference. Because of the unknown users’ preference, the proposed model observes the historical content and derives the cooperative cache content strategy. It is noted that [12]–[14] do not discuss the influence of unknown user density on the cache placement solution. Specifically, [13], [14] assume the fixed user number in the wireless environment and optimize the cache placement solution. However, the unknown user density will slow down the learning efficiency because the popularity of content is calculated based on the number of users’ requests. In this paper, we consider the cache placement under the dynamic environment. At each time slot, the user number in the wireless network changes following a random distribution. We propose the Extended MAB to learn the user density and popularity concurrently. With the Extended MAB, the cache placement solution under the unknown user density and popularity could be learned faster, which further improves the efficiency of the cache placement solution.

The unknown user density is another challenging problem in wireless transmission optimization. Reference [15] indicates the importance of user density in the cache-enabled network. The research estimates the expected user density based on the coverage area of the edge server. Later, [15] proposes an approach that optimizes the caching probability given the expected user density. To estimate the user number in a multi-user scenario, different methods are proposed. Reference [16] proposes a two-step detection method for detecting the set of active users using random-set theory and reduces the complexity of detection with the increase of active users. Reference [17] discusses the number estimation of co-channel users with a statistical mixture model. Reference [18] proposes a statistical approach based on spin glass theory to calculate the number of users under the unknown interference. Reference [19] proposes an accurate prediction of user density with the previous time observations and simulates the prediction method practically in Tsinghua campus. Even though the above researches consider the influence of unknown user number and propose the estimation methods, they do not include them in the study of the cache placement problem.

How the overlapped region among multiple edge servers affect the caching design is still an open problem. Little research focuses on the how to make full use of the benefit from the multiple edge servers responding the requests. Reference [20] assumes part of base stations know about the popularity of content and proposes Gibbs sampling-based method based on the knowledge of contents stored in its neighboring base stations. This method cannot be conducted at a environment with totally unknown popularity of content. In [21], the number and location of mobile users are defined in advance and fixed. However, the assumption of the pre-determined location and requests of mobile users is still unrealistic in the practical network. In this work, we propose a general cache placement strategy without the determined number and locations of users and maximize the number of satisfied users in the whole region. We discuss the influence of the mis-calculation of the user density and popularity, which is caused by multiple edge servers responding the requests. To solve the problem, we propose a time-division method for addressing the problem introduced by the mis-calculation of user density and popularity.

B. Multi-Armed Bandit

Reference [22] points out that the independence of arms in the multi-armed bandit causes the increase of convergence time with a large number of arms. To solve the problem, [22] introduces a bandit with the mean reward of arms following a linear function. Reference [23] proposes a multi-dimensional linear bandit and the cumulative Bayes risk under an arbitrary policy is at least \( O(\sqrt{T}) \), where \( T \) denotes the running time of the proposed algorithm. The complexity is lower than \( O(\log T) \) in a standard multi-armed bandit problem.

Reference [24] proposes a Global Multi-Armed Bandit (GMAB), in which arms are globally informative through a global parameter. The rewards in GMAB follow different distributions but with the same parameter. The GMAB model has fewer constraints on the reward distribution, hence can cover more scenarios. Reference [25] extends the GMAB to GGB to handle nonmonotonic but decomposable reward functions, multidimensional global parameters, and switching costs. The proposed greedy algorithm converges to the optimal arm in a finite time period. According to the results, the proposed algorithm significantly outperforms existing bandits solutions. Reference [26] proposes group-based multi-armed bandits by combining the standard multi-armed bandit and the GGB. Moreover, the paper proposes Upper Confidence Bound-greedy (UCB-g) algorithm to solve the regional bandit model. The proposed strategy achieves order-optimal regret by exploiting the intra-region correlation and inter-region independence.

Combinatorial MAB (CMAB) is proposed in [27], which allows the agents to play a set of arms at each time. By minimizing the \((\alpha,\beta)\) approximation regret, the online CMAB could converge to the optimal solution. The CMAB achieves \(O(\log n)\) distribution-dependent regret after \( n \) times playing. [13], [14], [28] all refer to the structure of the CMAB to solve the cache placement problems in different MEC models.
In this paper, we take the benefits from the CMAB and propose the Extended MAB, which admits choosing multiple arms at each time, to solve the cache placement in the MEC network. The main difference between the proposed Extended MAB and other MABs lies in that the proposed Extended-MAB includes both the individual parameter and global parameter.

III. SYSTEM MODEL

We consider a cache-enabled MEC network with $M$ edge servers and use $m$ to denote the index of the edge server. There are $N$ contents in the network and the contents form the content set $\mathcal{N}$, $\mathcal{N} \triangleq \{1, 2, \ldots, N\}$. In this paper, we consider the data size of each content is the same. \footnote{If the data size of each content is different, we divide them into small pieces with same size and regard them as multiple individual contents.} We define $m$ could cache $K$ contents and the set of caching contents at edge server $m$ forms an combination $\mathcal{P}_{m,t}$. We use $i_{m,t}$ to denote the index of caching contents of edge server $m$ at $t$. The number of combination is denoted as $C$, $C = \binom{N}{K}$.

In this paper, we study the influence of unknown users’ preferences on the cache placement solution and ignore the attributes of wireless transmission. We assume that edge servers could successfully transmit content to the users in its serving region. At each time slot $t$, the edge servers broadcast the caching contents to all users in its serving region, and the caching content could be successfully received. In this case, if the requested contents are cached at edge servers, the requests are directly satisfied without needing to fetch the contents from the central server. The edge server only needs to receive a signal to indicate whether the user device is satisfied by the caching content. Based on the satisfied user number, the edge server estimates the user density and popularity of contents to further optimize the cache placement solution.

We investigate two different scenarios of the distribution of edge servers as illustrated in Fig. 1 and Fig. 2. Fig. 1 presents an individual edge server scenario in which the serving region of each edge server does not overlap with other edge servers. The yellow circle in Fig. 1 indicates the serving region of an edge server. If the user requests a cached content, the edge server is capable of transmitting the content without backhaul transmission as the green lines showing. Otherwise, the central server transmits them to the user. The corresponding transmissions are denoted by red lines.

In Fig. 2, we discuss the cooperative edge server scenario, where the users have the chance of being served by multiple edge servers. As illustrated in Fig. 2, the users in region 1 and region 3 are served by their corresponding edge servers, but the users in region 2 could be served by both two edge servers. If the user in the overlapped location requires a content, it takes the benefit from the cache space so long as one of the edge servers caches this content. In this case, if all edge servers choose the most popular content to cache, the overall cache placement policy may only achieve a sub-optimal performance. We define the location of each edge server is deterministic, the information of the overlapped region is assumed to be known by all edge servers.

We define the serving region of $m$ as $R_m$, and the overall region of the MEC network is $R^*$. The relationship between the serving region of edge server $m$ and the whole region is

$$\forall m, R_m \leq R^* \leq \sum_{m=1}^{M} R_m.$$  \hfill (1)

When the serving region of all edge server are non-overlapped, $R^* = \sum_{m=1}^{M} R_m$ holds.

We consider users distributed in the network following Poisson point process (PPP) at each time slot $t$. The user density reflects the ratio of actual user number $u_t^*$ to the area size of serving region, which is denoted as $v_t$, $v_t = \frac{u_t^*}{R_t^*}$. We assume that the user density follows a certain distribution $v_t(\theta)$ with expectation $\mu(\theta)$, where $\theta$ is unknown. Moreover, the expectation of user density function satisfies the following conditions \cite{24}.

- For $\theta, \theta' \in \Theta$, there exists $D_1 > 0$ and $0 < \gamma_1 < 1$ such that $|\mu^{-1}(\theta) - \mu^{-1}(\theta')| \leq D_1 |\theta - \theta'|^{\gamma_1}$, where $\mu^{-1}$ is the inverse function of $\mu$.\footnote{If the data size of each content is different, we divide them into small pieces with same size and regard them as multiple individual contents.}
- For $\theta, \theta' \in \Theta$, there exists $D_2 > 0$ and $0 < \gamma_2 \leq 1$, such that $|\mu(\theta) - \mu(\theta')| \leq D_2 |\theta - \theta'|^{\gamma_2}$

Specifically, in this paper, we apply function $\mu(\theta) = w\theta^k + b$ as the expectation of user density. The exponential parameter $k$ reflects the influence from the variable $\theta$. The parameter $w$ and $b$ could be changed to adapt to the different environment.
The user number of requesting content \( n \) at \( t \) in the overall region is \( u_{n,t} \). Without loss of generality, we assume that the popularity of the contents are \( p_1, p_2, \ldots, p_N \) with \( p_1 \geq p_2 \geq \ldots \geq p_N \) and \( \sum_{n=1}^{N} p_n = 1 \). Under the above description of the popularity of contents and the user density, we could derive the amount of requiring content \( n \) denoted by \( u_{n,t} = p_n u_{m,t}^* \). It is noted that both the parameter of user density \( \theta \) and the popularity \( p_n \) of certain content \( n \) are unknown in a practical MEC network. The optimal cache placement of each edge server depends on the accurate estimation of the parameters.

When users’ requests are satisfied by the cached content at the edge server, the user device sends a signal to inform the edge server. The edge servers aim to maximize the number of serving users by the caching contents, which is written as \( u_{m,t} \). The problem is formulated as

**Problem 1:**

\[
\max \lim_{T \to \infty} \sum_{t=1}^{T} \sum_{m=1}^{M} u_{m,t} \\
= \max \lim_{T \to \infty} \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{i,m,t} p_{i,m,t} v_t(\theta) R_m \\
\text{s.t. (1), } ||u_{m,t}|| \leq K. \tag{2}
\]

According to problem 1, the formulated optimization problem is difficult to solve as the user density and preference are unknown. In this paper, we refer to the MAB model to learn the unknown parameter and further adjust the cache placement solution online, which overcomes the weakness of traditional method in the environment with unknown parameters. We propose the Extended MAB, which combines the attributes of the MAB and the GGB and provides a more efficient way to determine the cache placement in the MEC network in scenarios of both individual edge servers and cooperative edge servers. The edge server estimates the expected parameters at each time slots based on the number of the user satisfied by cached contents and does not need to record the user number for fetching each specific content.

### IV. EXTENDED MULTI-ARMED BANDIT

In this section, we present the Extended MAB for following cache placement optimization, which incorporates the global parameter and the individual local parameters concurrently.

We first briefly introduce the model of standard MAB. The MAB is proposed to solve the exploration and exploitation dilemma in the unknown environment optimization. Given the countable arms, i.e., the optional actions, the agent chooses one of the arms as action at each time. A reward is returned after the arm is taken. In the beginning, the agent does not know the reward of each arm and explores the environment by randomly choosing the arms and acquires the rewards. With the accumulation of knowledge of the reward of each arm, the agent could choose the optimal arm to maximize the summary of the reward. If the agent chooses the best-estimated arm too early, the loss of the reward may occur because of the lack of knowledge of the environment. However, if the agent always chooses an arm randomly, it cannot make full use of the knowledge of environment and derive the optimal action.

At each time \( t \), the agent takes \( a_t \) and acquire the reward \( r_{a_t} \), the objective is written as

\[
\lim_{T \to \infty} \max_{a_t} \sum_{i=1}^{T} r_{a_t}. \tag{3}
\]

In the GGB, the reward is determined by the reward distribution function \( v_{a_t}(\theta) \), whose expectation is \( \mu_{a_t}(\theta) \). The global parameter \( \theta \) is shared by all arms. The agent chooses the arm and acquires the knowledge of the parameter \( \theta \). If \( \theta \) is accurately estimated, the optimal arm could be chosen directly without any other exploration. The objective in GGB is written as

\[
\lim_{T \to \infty} \max_{a_t} \sum_{i=1}^{T} v_{a_t}(\theta) = \lim_{T \to \infty} \max_{a_t} \sum_{i=1}^{T} \mathbb{E}(v_{a_t}(\theta)) \\
= \lim_{T \to \infty} \max_{a_t} \sum_{i=1}^{T} \mu_{a_t}(\theta). \tag{4}
\]

The Extended MAB to integrate the global parameter and the individual parameter of each arm in one bandit model. The reward of each arm depends on two types of parameters, which is denoted as \( r_{a_t} = p_{a_t} v(\theta) \). We use \( \mu(\theta) \) to denote the expectation of distribution function \( v(\theta) \). The objective of Extended MAB is to maximize the accumulated reward, which is

\[
\lim_{T \to \infty} \sum_{t=1}^{T} \max_{a_t} p_{a_t} \mathbb{E}(v(\theta)) = \lim_{T \to \infty} \sum_{t=1}^{T} \max_{a_t} p_{a_t} \mu(\theta). \tag{5}
\]

The knowledge of global parameter could be obtained no matter which cache placement policy is chosen, while the individual parameter can only be obtained when this content is cached.

### V. CACHE PLACEMENT IN INDIVIDUAL EDGE SERVER SCENARIO

In the individual edge server scenario, all edge servers have their exclusive serving regions and make independent cache placement. Given the constraints of the cache capacity \( K \), the edge server \( m \) chooses a cache combination \( \mathbb{I}_{i,m,t} \). The \( u_{i,m,t} \) indicates the total amount of all satisfied users by the caching combination \( \mathbb{I}_{i,m,t} \) at time \( t \), which can be written as

\[
u_{i,m,t} = \sum_{i,m,t} u_{i,m,t}. \tag{6}
\]

We transform Problem 1 as maximizing the average number of satisfied user’s requests in the infinite time duration, which is presented as

\[
\lim_{T \to \infty} \sum_{t=1}^{T} \max_{i,m,t} u_{i,m,t} = \lim_{T \to \infty} \sum_{t=1}^{T} \max_{i,m,t} \sum_{i,m,t} \mathbb{E}(u_{i,m,t}). \tag{7}
\]

The user number of requesting a content depends on the user density in the serving region and the popularity of the content. To maximize the satisfied user number by the caching content, we use the Extended MAB to learn the cache placement policy.
We define the cache combination $\mathbb{I}_{m,t}$ as the arm that the agent chooses. The process is divided into 3 parts, which are initialization, exploration and exploitation, and parameter estimation. The details are shown as follows.

1) Initialization: At the beginning of the algorithm, the edge server $m$ does not know the information of contents and caches nothing. The users in the region send requests to $m$ and $m$ fetches the requesting contents from the central server. The estimated parameters of user density $\hat{\theta}$ and popularity $\hat{p}_n$ of each content $n$ are initialized by 0. We use $B$ to denote the size of a batch, in which the edge server makes the same cache placement policy.

2) Exploration and Exploitation: The trade-off between exploration and exploitation follows a determined rule. If time $t$ satisfies $\log_2(t+B) \in \mathbb{N}$, the random cache placement combination is chosen. Otherwise, the edge server chooses the best combination according to the estimated parameters. With this policy, when the parameters are correctly estimated, the policy decreases the randomness and makes cache placement decisions according to the estimated parameters.

3) Parameters Estimation: The expected reward $\bar{X}_{i,m,t}$ of combination $\mathbb{I}_{m,t}$ until time $t$ is updated after choosing it, which is calculated based on the previously acquired reward and current reward. We use $\bar{X}_{i,m,t}$ to denote the updated expected reward of combination $\mathbb{I}_{m,t}$. Once the combination $\mathbb{I}_{m,t}$ is chosen, the expected reward of $\mathbb{I}_{m,t}$ at time $t$ is updated as

$$\bar{X}_{i,m,t}^{t} = \frac{M_{i,m,t}(t-1)\bar{X}_{i,m,t} + X_{i,m,t}}{M_{i,m,t}(t-1) + 1} \quad (8)$$

where $M_{i,m,t}(t-1)$ denotes the number of times $\mathbb{I}_{m,t}$ is chosen from time $t-1$. Since the combination with content $n$ has $K-1$ remaining space to cache, the combination with $n$ has $\binom{N-1}{K-1}$ different choices. Hence, the combination set, which includes content $n$, is composed by $\binom{N-1}{K-1}$ combinations. If we sum up the reward of all combinations, we have

$$\sum_{c_{i}=1}^{C} \bar{X}_{c_{i}} = \binom{N-1}{K-1} \sum_{n_{i}=1}^{N} \bar{X}_{n_{i}} = \binom{N-1}{K-1} \mu(\hat{\theta}). \quad (9)$$

The estimated global parameter $\hat{\theta}$ is derived from the sum of expectation rewards of all combinations. Based on Eq. (9), the expected global parameter is given as

$$\hat{\theta} = \arg \min_{\theta \in \Theta} \left\{ \binom{N-1}{K-1} \mu(\theta) - \sum_{c_{i}=1}^{C} \bar{X}_{c_{i}} \right\}. \quad (10)$$

The popularity of each cache placement combination $c$ could be derived by

$$\hat{p}_c = \frac{\bar{X}_c}{\mu(\hat{\theta})}. \quad (11)$$

Until now, we could derive the estimated popularity of each combination, which supports choosing the cache placement solution. Hence, we do not need to know the estimated popularity of each individual content. The details of the process are given in Algorithm 1.

We show the regret analysis and complexity analysis in the following part of the section. We indicate the proposed

Algorithm 1 Cache Placement for Individual Edge Server Scenario Based on Extended MAB

| Initialize the cache size $K$; the number of combinations $C = \binom{N}{K}$; the distribution function of user density $\mu(\theta)$; $\hat{\theta} = 0$; $\hat{a}_c = 0$; $M_c = 0$; $t = 1$; the batch size $B$;
| while $t \geq 1$ do
| $b = 0$
| while $b < B$ do
| if $\log_2(t) \in \mathbb{N}$ then
| Select combination $\mathbb{I}_{m,t}$ randomly for set $C$;
| else
| Select combination $\mathbb{I}_{m,t}$ which satisfies $I_{m,t} = \arg \max_{c \in C \setminus \mathbb{I}_{m,t}} \hat{p}_c, t(\hat{\theta})$;
| end if
| $X_{c_t} = X_{c_t}$ for $c \in C \setminus I_{m,t}$;
| Update $X_{c_{i,m,t}}$ with (8);
| Update $\hat{\theta}$ with (10);
| Update $\hat{p}_c$ with (11);
| $M_{i,m,t}(t) = M_{i,m,t}(t-1) + 1$;
| $b = b + 1$;
| end while
| end while

Extended MAB based cache placement solution approaches to optimal cache placement policy.

Proposition 1: In the individual edge server scenario, the proposed Extended MAB converges to the expected regret $\left( \frac{\log T}{T} + 2 \exp\left( -2 \left( \frac{\log T}{T} \right) \right) \right) * g_{\text{max}}$ at time $T$, where parameters $D_1, D_2, \gamma_1, \gamma_2$ and $\sigma_1, \sigma_2$ satisfy $D_1 > 0, D_2 > 0, 0 < \gamma_1 < 1, 0 < \gamma_2 < 1, \sigma_1 > 0, \sigma_2 > 0, g_{\text{max}}$ denotes the maximal gap value between the optimal reward and any other rewards.

Proof: To find the optimal $K$ arms, we need to reduce the gap between the practical maximum reward and the evaluated maximum reward as much as possible. We define the chosen arms indexed by $I_1, I_2, \ldots, I_K \subseteq I_{m,t}$. The regret of expected regret between the ideal best cache placement and the estimated cache placement action at each time slot is denoted as

$$\text{Reg} = \sum_{k=1}^{K} a_{k}\mu(\theta) - a_{I_k}\mu(\theta). \quad (12)$$

We analyze the expected regret $\text{Reg}(T)$ to prove that the Extended MAB could find the best cache placement, which is written as

$$\text{Reg}(T) = \frac{1}{T} \sum_{t=1}^{T} \left( \frac{\log T}{T} + 2 \exp\left( -2 \left( \frac{\log T}{T} \right) \right) \right) * g_{\text{max}} * K. \quad (13)$$

We separately discuss the regrets of the algorithm with exploration action and exploitation action. We firstly calculate the regret of random cache placement. The regret of random cache placement is defined as $\text{Reg}_{1}(T)$, which satisfies

$$\text{Reg}_{1}(T) \leq \frac{\log_2 T}{T} + B * \text{gap}_{\text{max}} * K. \quad (14)$$

The proof of Eq.(14) is shown as appendix VIII.
The regret with the exploitation action $Reg_2(T)$ is written as
\[
Reg_2(T) \leq 2^{(N-1)} \frac{1}{K-1} \frac{2}{\gamma_1} T + 2N \exp \left(-2\left(\frac{N-1}{\gamma_2} \frac{\mu(\theta^*)}{\gamma_2} T \right) \right) \cdot \text{gap}_{\text{max}}.
\]

The proof of Eq.(15) is shown as appendix VIII.

Since $\rho_n < 1$ is always satisfied, by summing up $Reg_1(T)$ and $Reg_2(T)$, the total regret of Algorithm 1 is written as
\[
Reg(T) \leq \frac{\log T}{T} \cdot B \cdot \text{gap}_{\text{max}} \cdot K + 2^{(N-1)} \frac{1}{K-1} \frac{2}{\gamma_1} T \cdot \text{gap}_{\text{max}} + 2N \exp \left(-2\left(\frac{N-1}{\gamma_2} \frac{\mu(\theta^*)}{\gamma_2} T \right) \right) \cdot \text{gap}_{\text{max}}.
\]

The estimated optimal cache placement is taken in the exploitation policy.

The complexity of the Extended MAB based cache placement solution in individual scenario depends on the number of contents and the capacity of cache size. At each iteration, estimating the parameters requires computing the expected reward of all combinations, the complexity of which is $O\left(\binom{N}{K}\right)$. While finishing the estimation of parameters, the edge server searches the cache placement solution with the highest expected reward. The complexity of searching algorithm is $O\left(\binom{N}{K}\right)$. Hence, the complexity of the Extended MAB based cache placement solution is $O\left(\binom{N}{K}\right)$.

VI. CACHE PLACEMENT IN COOPERATIVE EDGE SERVER SCENARIO

In this section, we discuss the cache placement in cooperative edge server scenarios with overlapped serving regions. We first draw the lesson from Algorithm 1 and propose a centralized Extended MAB algorithm with the assistance of the central server. Then, to reduce the size of the action space of the centralized algorithm, we propose a decentralized multi-agent Extended MAB algorithm, where the edge server makes decisions individually but achieves the global optimal cache placement with low computational complexity.

A. Centralized Extended MAB Based Cache Placement Solution

In a real large-scale MEC network, the users in the overlapped region could receive the requesting content from one or more edge servers. If all edge servers choose the most popular contents to cache, the users in the overlapped regions will lose the extra chance to be satisfied. To make full use of the cache space, we firstly propose a centralized cache placement solution, in which a central server is introduced to make cache placement policy. The scope of the serving region and the overlapped region is aware by the central server in advance.

The cache placement combination of each edge server is regarded as a sub-combination. The central server chooses $M$ sub-combinations for $M$ edge servers. Assembling all $M$ sub-combinations $\mathbb{1}_{m,i}$ produces a macro-combination $C_i$. The reward is determined by the number of satisfied users in the global network. The popularity of contents and user density are iteratively estimated according to the accumulated reward from the beginning to the present. The cache placement based on the centralized Extended MAB bandit is described as follows.

1) Initialization: Given the cache size $K$ and the amount of the total contents $N$. The macro-combination space $C$ has $C$ elements, where $C = \binom{N}{K}^M$. The reward is recorded in the $\hat{X}_c$ for macro-combination $c$. The parameters of the user density and the popularity of each macro-combination are initialized by 0.

2) Exploration and Exploitation: The policy of balancing exploration and exploitation is the same as the situation with individual edge server. If $t$ satisfies $\log_2(t) \in \mathbb{N}$, the central server randomly chooses the macro-combination. Otherwise, the central server chooses the estimated best macro-combination. It is noted $B$ in the cooperative scenario should be set larger than the individual scenario because of more choice of macro-combination.

3) Parameter Estimation: The parameter of the user density is estimated after obtaining the reward at each time slot. Later, we estimate the popularity of each combination under the estimated user density. We firstly determine how many times that content $n$ is shown in all macro-combinations. As there are $\binom{N-1}{K-1}$ sub-combinations without content $n$, we have $\binom{N-1}{K}$ macro-combinations in the environment excluding the content $n$. Hence we obtain that $\binom{N}{K}^M - \binom{N-1}{K}^M$ macro-combinations contain combination $n$. The user density is derived as
\[
\bar{\mu}(\bar{\theta}) = \frac{\sum_{c=1}^{C} \hat{X}_c}{\binom{N}{K}^M - \binom{N-1}{K}^M}.
\]

After that, the popularity of each macro-combination could be derived according to Eq. (11).

B. Decentralized Extended MAB Based Cache Placement Solution

With the increase of the edge servers’ amount, the space of the cache placement combination grows exponentially. When adding an extra content, the number of cache placement combinations is increased by $\binom{N+1}{K}^M - \binom{N}{K}^M$, which makes it difficult to be implemented in a practical large-scale wireless network. To solve this problem, we introduce a decentralized framework and let edge servers make their own cache placement solution based on the proposed Extended MAB.

There are two issues to be addressed in the cooperative edge server scenario as they do not occur in the individual edge server case. First, the overlapped serving region leads to a miscalculation of the parameters. We take a case with 2 edge servers sharing the overlapped serving region as an example and denote two edge servers as $E_0$ and $E_1$. When the edge
servers $B_0$ and $B_1$ both cache content $n$, the users requesting content $n$ in the overlapped region are satisfied only by one of them. The reward received by the edge server, which reflects the actual satisfied user number, is always no more than the reward in the individual case.

To avoid the mis-estimation, we propose a time-division parameter estimation framework, in which each edge server is assigned a dedicated primary time slot and multiple sharing secondary time slots. Edge servers update the parameters only when they are in the primary time slot. Since there are $M$ edge servers in the network, $M$ time slots are set as a group. In each group, the edge servers have 1 exclusive primary slot and $M − 1$ shared secondary slot. The proposed time-division framework is shown in Fig. 3. The users in the overlapped region tend to be served by the edge server in the primary slot. Based on this scheme, if $B_0$ and $B_1$ cache the same content $n$ and $B_0$ is in the primary state slot, $B_0$ has priority to receive the response from the users in the overlapped region, which reflects the actual satisfied user number of the overlapped region. Then $B_0$ updates the parameters according to the reward. Meantime, $B_1$ neglects the parameter estimation of policy adjustment and only broadcasts all caching contents.

Second, the best cache placement of each edge server is determined not only by the estimated user density and popularity of the content but also by the cache placement of adjacent edge servers. Under the accurately estimated parameters, the edge server cannot directly choose the cache placement solution with maximal expected reward because the edge servers which has overlapped region with it may have the same choice.

We assume each of $M$ edge servers have overlapped region with at least 1 other edge server. In the decentralized cache placement solution, to find the best cache placement strategy, the edge servers transmit the cache placement solution to adjacent edge servers after it makes decisions in the primary time slot. With the cache placement solution and size of the overlapped region, the edge servers derive the popularity of each content under the exclusive primary time slot. Given the popularity $p_{m,t}$ of each combination $\Pi_{m,t}$, we first calculate the popularity of combinations including $n$, denoted by $s_n$, as

$$s_n = \sum_{t \in T} p_{m,t}. \quad (18)$$

It is noted that there are $\binom{N−1}{K−1}$ combinations including $n$, and $\binom{N−2}{K−2}$ combinations with other contents. Hence, the estimated popularity $\hat{p}_n$ is given by

$$\hat{p}_n = \frac{s_n}{\binom{N−1}{K−1} − \binom{N−2}{K−2}}. \quad (19)$$

The serving region is divided into different sub-regions based on the overlap with other edge servers. Since the location of each edge server is predefined, we could identify edge servers that each sub-region belongs to and calculate the area size of each sub-region. Under the estimated popularity of each content, we choose the content for $M + K$ cache units at all edge servers.

**Proposition 2:** We order the estimated popularity $p_n$ of each content $n$ from highest to lowest and use $f_i$ denote the index after the ordering. We define $S$ as the best cache placement set, $s \triangleq \{f_1, f_2, \ldots, f_{M+K}\}$. In other word, the $M + K$ content with highest estimated popularity forms the best cache placement set $S$. The contents of optimal cache placement solution for the cooperative edge server scenario always belong to best cache placement set $S$.

**Proof:** We define the optimal cache placement solution of edge servers as $i^*$ and the obtained reward is $r^*$. Under
the accurate estimation, if the content $n, n \in i^*$ does not belong to the cache placement set $S$, there is at least one content $n', n' \in S$ is not cached at edge servers. In this case, if we replace all caching $n$ with $n'$, we must acquire a higher reward. Hence, $i^*$ is not the optimal cache placement solution.

The final cache placement solution is chosen from the cache placement set rather than the content set, which reduces the search complexity. For each content, the edge server $m$ calculates the expected reward of caching it. The expected reward of content $n$ is the summary of the expected reward of content $n$ in different sub-regions. We assume that $R_{m,n}$ is divided to $P$ sub-regions, where $R_{m,p}$ denotes the $p$th sub-region of $R_m$. We assume that $k_{m,p,n}$ edge servers share the sub-region $R_{m,p}$ and cache content $n$. If $k_{m,p,n}$ edge servers cache the same content $n$, the satisfied user number of caching $n$ is evenly assigned to each of the expected reward $\bar{r}_{m,n}$ is defined as

$$\bar{r}_{m,n} = \frac{\sum_{p=1}^{P} R_{m,p} \mu(\theta) \hat{p}_n}{k_{m,p,n}}.$$  \hspace{1cm} (20)

After calculating the expected reward of $N$ contents, according to Problem 1, the edge server chooses $K$ content with the highest expected reward as the cache placement solution. The detail of decentralized cache placement solution is shown as Algorithm 2.

The regret analysis of each agent in the cooperative edge server MEC network is given as Proposition 3.

**Proposition 3:** Until time $T$, the regret in decentralized Extended MAB based cache placement solution is

$$Reg(T) \leq \frac{2}{T} \sum_{m=1}^{M} \sum_{m=1}^{T} \bar{r}_{m,n} - \bar{r}_{1,m}.$$  \hspace{1cm} (21)

The accumulated regret is the sum of accumulated regret of random cache placement and the estimated optimal cache placement.

As we mentioned before, the random cache placement solution only happens when $\log_2(t) \in N$. Given the highest gap $\text{gap}_{\text{max}}$ of reward between the optimal cache placement solution and an arbitrary cache placement solution, the regret in the random cache can be written as

$$Reg_1(T) = \frac{1}{T} \sum_{t=1}^{T} \sum_{k=1}^{K} 1(\log_2(t) \in N) B * \text{gap}_{\text{max}}$$

$$= \log_2 T \cdot B * \text{gap}_{\text{max}} * K.$$  \hspace{1cm} (22)

The regret of estimated optimal cache placement is represented as

$$Reg_2(T) \leq (2 \exp \left(-2 T \sum_{k=1}^{K} \frac{\sigma_1}{(K-1)} \frac{2^{\gamma_1}T}{D_1} \right) + 2N \exp \left(-2 T \sum_{k=1}^{K} \frac{\sigma_2}{D_2} \mu(\theta) \frac{2^{\gamma_2}T}{D_1} \right)) * \text{gap}_{\text{max}}.$$  \hspace{1cm} (23)

The proof of (23) is shown as appendix 3.

By summing up $Reg_1(T)$ and $Reg_2(T)$, Proposition 3 is derived.

The complexity of the centralized cache placement solution depends on the number of the macro-combinations. At each time slot, the central server updates the parameters of the user density and popularity of each macro-combination, then searches the macro-combination with the highest popularity as the cache placement solution. The complexity is $O((N^K)M)$.

The complexity of the decentralized cache placement solution of edge server $m$ is determined not only by the number of contents, but the sub-regions overlapping with other edge servers. The complexity of updating parameters is the same as the individual scenario. In this case, the complexity is determined by the number of sub-regions $P$ and the maximal edge server number $k_{m,p,n}$ that share the same sub-region. The complexity is written as $O(P * k_{m,p,n} * N)$.

VII. SIMULATION RESULTS

To evaluate the performance of our proposed algorithm, we compare them with both intelligent cache placement solutions and common cache placement solutions. We choose the least frequently used (LFU) cache placement solution and least recently used (LRU) cache placement solution as the common solution. LFU solution replaces the content with the shortest request time. LRU solution considers replacing the least recently used content in the cache space. We use the UCB bandit based solution, which is proposed in [12], and $\epsilon$-greedy bandit as the intelligent baselines. The $\epsilon$-greedy bandit lets the agent choose the arms randomly with probability $1 - \epsilon$ and choose the best arm with probability $\epsilon$. Specifically, we set $\epsilon = 0.95$ in the $\epsilon$-greedy bandit. The UCB bandit based solution focuses not only on the reward but also on the exploration duration of each arm. The UCB bandit based solution adjusts the trade-off between exploration and exploitation according to the accumulated reward and the time required for playing different arms. It is noted that in the UCB bandit and $\epsilon$-greedy bandit baselines, the unknown user density is regarded as part of the environment. During the learning of the environment, the user density is learned implicitly. Furthermore, we refer to the collaborative cache placement method in [21] as a baseline to evaluate the performance of the cooperative server scenario. The collaborative cache placement method also discusses how the overlapped region influences the performance of cache placement and proposes a multi-agent cache placement solution. Different from the solution in this paper, [21] assumes that the user number and the location of each user are pre-defined.

We choose three different metrics to compare the performance of the proposed cache placement solution, which are the
accumulated regret, convergence time, and average satisfying user number. For the first and second metrics, we mainly discuss the performance of the proposed Extended MAB. With the third metric, we show the effects of using different cache placement solutions with different settings.

A. Performance in Individual Server Scenario

To evaluate the performance of the Extended MAB cache placement in the individual edge server scenario, we first compare the performance with different content numbers. We choose $N = 5$ and $N = 10$ and that the cache capacity of the edge server is 2. The batch $B$ is set as 20. We define the radius of the serving region of each edge server as 5 and the parameter of user density as 5. The popularity of each content follows the Zipf distribution.

Fig. 4 and Fig. 5 presents the accumulated regret of different cache placement solution with $N = 5$ and $N = 10$. The accumulated regret reflects the performance gap between the practical cache placement policy and the optimal cache placement policy. According to Fig. 4 and Fig. 5, we could see that the Extended MAB cache placement solution could achieve the optimal cache placement solution when it learns the environment well. According to Fig. 4 and Fig. 5, the Extended MAB based solution has minimal accumulated regret. The LRU method shows an unstable performance as the LRU policy does not depend on the accumulated experience.

Fig. 6 and Fig. 7 show the average satisfied user number by the cache placement with different solutions. The proposed algorithm has a better average reward and a faster convergence behavior than those of the others. According to Fig. 6 and Fig. 7, we could see that with the experience knowledge, the learning based algorithms show better performance than the general cache solution. With the accurate estimation of the content popularity, the edge server could choose the optimal cache placement solution.

Moreover, we compare the accuracy of the parameter estimation among the proposed algorithm and the baselines.
Table I illustrates the user density estimation accuracy under different numbers of iterations. Table I presents the accuracy of estimating the parameter in different iteration times. It is observed that the Extended MAB solution can estimate the parameters more accurately and faster, which leads to a more accurate search of the optimal cache placement solution.

### B. Performance in Cooperative Server Scenario

The centralized cache placement solution could be regarded as the large-scale individual cache placement solution, which has the similar performance as the last subsection. In this section, we only evaluate the decentralized cache placement solution. It is noted that we introduce a new baseline from [21] to verify the availability of the decentralized Extended MAB based cache placement solution. In the following presentation, we call the baseline as Collab MAB. In the cooperative edge server scenario, we assume that the number of overlapping edge servers is 2 and 3 in the following experiments. We set the content number as $N = 10$ and $N = 20$ and the cache size as 3 and 5 for each edge server. The overlap size between two edge servers is the half size of the serving region. We first give the accumulated regret and the average reward when $M = 2$.

**The accumulated regret when $N = 10$ and $N = 20$ are shown as Fig. 8 and Fig. 9.**

According to Fig. 8 and Fig. 9, the proposed Extended MAB solution has the minimum accumulated reward. Moreover, the UCB solution, $\epsilon$-greedy solution, and the Collab MAB solution have a better performance when the number of content is small. With the increase of the content number, these three baselines do not share the global parameter, i.e., the user density, which hinders the cache placement learn the environment and derive a better policy. Meantime, because of the influence of the overlapped region, these three baselines do not estimate the actual reward accurately, which further increases the accumulated regret.

The average number of satisfied user are shown as Fig. 10 and Fig. 11. According to Fig. 10 and Fig. 11, the average satisfied user number improves when the user number increases. With the same Zipf distribution parameter, if the content number increases, the popularity of each content tends to be evenly distributed. In this case, the proposed Extend MAB cache placement solution could adjust the policy based on the overlapped region, which leads to better performance.

Since the popularity of each content influences the optimal cache placement solution, we also adjust the Zipf parameter to evaluate the performance with different popularity of contents. The Zipf parameter is chosen as $\{0, 0.5, 1, 1.5\}$ to further
evaluate the performance of the average satisfied user number. According to Fig. 12, the propose Extended MAB always shows the best performance with the change of Zipf parameter.
better if the overlapped region is considered in the cache placement solution.

VIII. Conclusion

In this paper, we study cache placement in the practical MEC network with unknown user behaviors. We develop an extended MAB based on the standard MAB and GGB to formulate the problem. To solve the problem, we first give a cache placement strategy for the individual edge server scenario, where edge servers share a non-overlapping serving region. After that, the joint cache placement is proposed for the cooperative edge server scenario with overlapping serving regions. To reduce the complexity of the proposed centralized algorithm, a decentralized Extended MAB is proposed. The simulation results show that the proposed algorithm has the best performance compared to the baseline algorithms in different situations.

APPENDIX A

Proof of Equation (14)

When \( \log_2(t) \in \mathbb{N} \) is satisfied, the algorithm chooses the cache placement randomly. It is noted that as the reward from a certain action is limited, the regret between the best cache placement and other cache placement is limited. We denote the upper bound of the regret is denoted as \( \text{gap}_{\max} \). Hence, after a batch of random action, the regret of the exploration action is

\[
\text{Reg}(T) = \frac{1}{T} \sum_{t=1}^{T} 1(\log_2(t) \in \mathbb{N}) B \ast (a_k \mu(\theta) - X_{1_{k,t}}) \\
\leq \log_2 T \ast B \ast \text{gap}_{\max} \ast K \tag{24}
\]

where \( 1(\log_2(t) \in \mathbb{N}) = 1 \) if \( \log_2(t) \in \mathbb{N} \) is satisfied, otherwise, \( 1(\log_2(t) \in \mathbb{N}) = 0 \).

APPENDIX B

Proof of Equation 15

It is noted that if the unknown parameters are estimated correctly, the practical cache placement is the same as the best cache placement. The regret between the optimal cache placement and the practical cache placement is caused by the wrong estimation of the parameters. According to the analysis, we could derive that

\[
\{I_{\max} \neq I_{\text{chosen}}\} \subseteq \{\hat{\theta} \neq \theta\} \cup \{\exists n, \hat{p}_n \neq p_n \cap \{\hat{\theta} = \theta\}\}. \tag{25}
\]

Based on (25), we separate analyze the regret with different wrong parameters. We firstly discuss the probability of \( \hat{\theta} \neq \theta \). If \( \hat{\theta} \neq \theta \), there exists \( \sigma_1 > 0 \) which conforms \( |\theta - \hat{\theta}| \geq \sigma_1 \). We establish the relationship between the estimated parameter of the user density and the expected reward of each combination until \( t \), that is, there exists \( D_1 > 0 \) and \( 1 > \gamma_1 > 0 \) satisfying

\[
\Pr\{\hat{\theta} \neq \theta\} = \Pr(|\hat{\theta} - \theta| \geq \sigma_1) \leq \Pr(D_1 \frac{1}{(K-1)^{N-1}}) \\
\times (X_1 + \ldots + X_n) - \mu(\theta)^|\theta| \geq \sigma_1. \tag{26}
\]

We define \( X \) as a variable which satisfies \( X = \frac{1}{(K-1)^{N-1}}(X_1 + \ldots + X_n) \). It could be easily concluded that the expectation of \( X \) is \( \mu(\theta) \). Eq. (26) could be rewritten as

\[
\Pr(D_1 \frac{1}{(K-1)^{N-1}}(X_1 + \ldots + X_n) - \mu(\theta)^|\theta| \geq \sigma_1) \\
= \Pr(|X - \frac{(N-1)}{(K-1)} \mu(\theta)^|\theta| | \geq \frac{(N-1)}{(K-1)} \gamma_1 D_1 |) \\
\leq 2 \exp \left(-2 \left(\frac{(N-1)}{(K-1)} \gamma_1 D_1 \right)^2 T\right). \tag{27}
\]

where (1) succeeds due to Hoeffding’s inequality.

Next we determine the probability \( \Pr\{\exists n, \hat{p}_n \neq p_n | \hat{\theta} = \theta\} \) following the similar analysis. There exists \( \sigma_2 > 0 \) satisfying

\[
\Pr\{\exists n, \hat{p}_n \neq p_n | \hat{\theta} = \theta\} \leq \sum_{n=1}^{N} \Pr(|\hat{p}_n - p_n| \geq \sigma_2 | \hat{\theta} = \theta). \tag{28}
\]

Since we already discussed the situation of \( \hat{\theta} = \theta \), we could remove the condition directly. Based on Assumption 1, there exists \( D_2 > 0 \) and \( 1 > \gamma_2 > 0 \) which satisfies

\[
\Pr(\hat{p}_n \neq p_n | \hat{\theta} = \theta) \leq 2 \exp \left(-2 \left(\frac{\sigma_2^2}{D_2} p_n \mu(\theta)^{2\gamma_2} T\right)^2\right). \tag{29}
\]

APPENDIX C

Proof of Equation (23)

When the edge server \( m \) chooses the expected optimal cache placement solution, the regret is

\[
\text{Reg}(T) = \text{gap}_{\max} \ast \Pr(I_{\max} \neq I_{\text{chosen}}) \\
\leq \text{gap}_{\max} \ast \Pr(p_1 \neq \hat{p}_1 \cup \ldots \cup p_N \neq \hat{p}_N \cup \theta \neq \hat{\theta}) \\
\leq \text{gap}_{\max} \ast (\Pr(\theta \neq \hat{\theta}) + \sum_{n=1}^{N} \Pr(p_n \neq \hat{p}_n | \theta \neq \hat{\theta})). \tag{30}
\]
According to Eq. (27) and Eq. (29), we have the following inequality regarding the expected regret of optimal cache placement policy

\[
Reg(T) \leq (2 \exp \left( -2 \left( \frac{N-1}{K-1} \frac{\sigma_1}{D_1} T \right)^2 \right) + 2N \exp \left( -2 \left( \frac{\sigma_2}{D_2} \mu(\theta)^{2T} T \right) \right)) \cdot gap_{max}.
\]

(31)

We obtain the expected regret of each edge server in cooperative scenario given by

\[
Reg(T) \leq \left( \frac{\log T}{T} \right) \star K + 2 \exp \left( -2 \left( \frac{N-1}{K-1} \frac{\sigma_1}{D_1} \right)^2 T \right) + 2N \exp \left( -2 \left( \frac{\sigma_2}{D_2} \mu(\theta)^{2T} \right) \right) \cdot gap_{max}.
\]

(32)

REFERENCES

[1] B. Zhou, Y. Cui, and M. Tao, “Optimal dynamic multicast scheduling for cache-enabled content-centric wireless networks,” IEEE Trans. Commun., vol. 65, no. 7, pp. 2956–2970, Jul. 2017.

[2] X. Zhang and Q. Zhu, “Spectrum efficiency maximization using primal-dual adaptive algorithm for distributed mobile devices caching over edge computing networks,” in Proc. 51st Annu. Conf. Inf. Sci. Syst. (CISS), Baltimore, MD, USA, Mar. 2017, pp. 1–6.

[3] M. M. Kamran and S. Khorsandian, “Popularity estimation in a popularity-based hybrid peer-to-peer network,” in Proc. 13th Int. Conf. Adv. Commun. Technol. (ICACT), Gangwon, South Korea, Nov. 2011, pp. 399–404.

[4] T. Wang et al., “Estimating video popularity from past request arrival times in a VoD system,” IEEE Access, vol. 8, pp. 19934–19947, 2020, doi: 10.1109/ACCESS.2020.2966495.

[5] J. Wu, Y. Zhou, D. M. Chiu, and Z. Zhu, “Modeling dynamics of online video popularity,” IEEE Trans. Multimedia, vol. 18, no. 9, pp. 1882–1895, Sep. 2016.

[6] S. Mehrizi, A. Tsakmalis, S. ShahbazzPanahi, S. Chatzinotas, and B. Ottersten, “Popularity tracking for proactive content caching with dynamic factor analysis,” in Proc. IEEE/CIC Int. Conf. Commun. China (ICCC), Changzhou, China, Aug. 2019, pp. 875–880.

[7] S. Mehrizi, S. Chatterjee, S. Chatzinotas, and B. Ottersten, “Online spatiotemporal popularity learning via variational Bayes for cooperative caching,” IEEE Trans. Commun., vol. 68, no. 11, pp. 7068–7082, Nov. 2020.

[8] J. Yin, L. Li, H. Zhang, X. Li, A. Gao, and Z. Han, “A prediction-based coordination caching scheme for content centric networking,” in Proc. WOCC, Apr./May 2018, pp. 1–5.

[9] W.-X. Liu, J. Zhang, Z.-W. Liang, L.-X. Peng, and J. Cai, “Content popularity prediction and caching for ICN: A deep learning approach with SDN,” IEEE Access, vol. 6, pp. 5075–5089, 2018.

[10] B. N. Bharath, K. G. Nagavanda, and H. P. Voon, “A learning-based approach to caching in heterogeneous small cell networks,” IEEE Trans. Commun., vol. 64, no. 4, pp. 1674–1686, Apr. 2016.

[11] B. B. Nagaraja and K. G. Nagavanda, “Caching with unknown popularity profiles in small cell networks,” in Proc. IEEE Global Commun. Conf. (GLOBECOM), San Diego, CA, USA, Dec. 2015, pp. 1–6.

[12] P. Blasco and D. Gunduz, “Learning-based optimization of cache content in a small cell base station,” in Proc. IEEE Int. Conf. Commun. (ICC), Sydney, NSW, Australia, Jun. 2014, pp. 1897–1903.

[13] J. Song, M. Sheng, T. Q. S. Quek, C. Xu, and X. Wang, “Learning-based content caching and sharing for wireless networks,” IEEE Trans. Commun., vol. 65, no. 10, pp. 4309–4324, Oct. 2017.

[14] W. Jiang, G. Feng, S. Qin, and Y. Liu, “Multi-agent reinforcement learning based cooperative content caching for mobile edge networks,” IEEE Access, vol. 7, pp. 61856–61867, 2019.

[15] E. Gruppi, K.-K. Wong, M. Z. Bocus, and W. H. Chin, “Ultra dense edge caching networks with arbitrary user spatial density,” IEEE Wireless Commun., vol. 19, no. 7, pp. 4363–4377, Jul. 2020.

[16] D. Angelosante, E. Biglieri, and M. Lops, “Low-complexity receivers for multiuser detection with an unknown number of active users,” in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., Las Vegas, NV, USA, Mar. 2008, pp. 3481–3484.

[17] E. G. Larsson, “Multiuser detection with an unknown number of users,” IEEE Trans. Signal Process., vol. 53, no. 2, pp. 724–728, Feb. 2005.

[18] A. T. Campo and E. Biglieri, “Large–system analysis of static multiuser detection with an unknown number of users,” in Proc. 2nd IEEE Int. Workshop Comput. Adv. Multi-Sensor Adapt. Process., Saint Thomas, VI, USA, Dec. 2007, pp. 81–84.

[19] Y. Gao, A. Hong, Q. Zhou, X. Li, S. Liu, and B. Shao, “Prediction of traffic density and interest using real time mobile traffic data,” in Proc. Int. Conf. Identificat., Infl. Knowl. Internet Things (IIKI), Beijing, China, Oct. 2016, pp. 250–254.

[20] A. Chattopadhyay, B. Blaszczyszyn, and H. P. Keeler, “Gibbsian on-line distributed content caching strategy for cellular networks,” IEEE Trans. Wireless Commun., vol. 17, no. 2, pp. 969–981, Feb. 2018.

[21] X. Xu, M. Tao, and C. Shen, “Collaborative multi-agent multi-armed bandit learning for small-cell caching,” IEEE Trans. Wireless Commun., vol. 19, no. 4, pp. 2570–2585, Apr. 2020.

[22] A. J. Mersereau, P. Rusmevichientong, and J. N. Tsitsiklis, “A structured multiarmed bandit problem and the greedy policy,” in Proc. 47th IEEE Conf. Decis. Control, Cancún, Mexico, Dec. 2008, pp. 4945–4950.

[23] P. Rusmevichientong and J. N. Tsitsiklis, “Linearly parameterized bandits,” Math. Oper. Res., vol. 35, no. 2, pp. 395–411, May 2010.

[24] O. Atan, C. Tekin, and M. Schaar, “Global multi-armed bandits with Holder continuity,” in Proc. 18th Int. Conf. Artif. Intell. Statist., vol. 38, 2015, pp. 28–36.

[25] C. Shen, R. Zhou, C. Tekin, and M. van der Schaar, “Generalized global bandit and its application in cellular coverage optimization,” IEEE J. Sel. Topics Signal Process., vol. 12, no. 1, pp. 218–232, Feb. 2018.

[26] Z. Wang, R. Zhou, and C. Shen, “Regional multi-armed bandits with partial informativeness,” IEEE Trans. Signal Process., vol. 66, no. 21, pp. 5705–5717, Nov. 2018.

[27] W. Chen, W. Wang, Y. Yuan, and Q. Wang, “Combinatorial multi-armed bandit and its extension to probabilistically triggered arms,” J. Mach. Learn. Res., vol. 17, no. 1, pp. 1746–1778, 2014.

[28] W. Jiang, G. Feng, S. Qin, T. S. P. Yum, and G. Cao, “Multi-agent reinforcement learning for efficient content caching in mobile D2D networks,” IEEE Trans. Wireless Commun., vol. 18, no. 3, pp. 1610–1622, Mar. 2019.

[29] J. Li, B. Liu, and H. Wu, “Energy-efficient in-network caching for content-centric networking,” IEEE Commun. Lett., vol. 17, no. 4, pp. 797–800, Apr. 2013.

[30] T. Fukushima, M. Iio, K. Hirata, and M. Yamaomoto, “Popularity-based content cache management for in-network caching,” in Proc. Int. Conf. Inf. Netw. (ICOIN), Kuala Lumpur, Malaysia, Jan. 2019, pp. 411–413.

[31] S. P. Romano, M. Luglió, C. Rosetti, and M. Zito, “The SHINE testbed for secure in-network caching in hybrid satellite-terrestrial networks,” in Proc. Eur. Conf. Netw. Commun. (EuCNC), Valencia, Spain, Jun. 2019, pp. 172–176.

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