Mobility-Aware Routing and Caching: A Federated Learning Assisted Approach

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Abstract—We develop mobility-aware routing and caching strategies to solve the network cost minimization problem for dense small-cell networks. The challenge mainly stems from the insufficient backhaul capacity of small-cell networks and the limited storing capacity of small-cell base stations (SBSs). The optimization problem is NP-hard since both the mobility patterns of the mobilized users (MUs), as well as the MUs’ preference for contents, are unknown. To tackle this problem, we start by dividing the entire geographical area into small sections, each of which containing one SBS and several MUs. Based on the concept of one-stop-shop (OSS), we propose a federated routing and popularity learning (FRPL) approach in which the SBSs cooperatively learn the routing and preference of their respective MUs, and make caching decision. Notably, FRPL enables the completion of the multi-tasks in one shot, thereby reducing the average processing time per global aggregation. Theoretical and numerical analyses show the effectiveness of our proposed approach.

Index Terms: Routing, caching, dense small-cell networks, one-stop-shop, federated learning.

I. INTRODUCTION

Wireless caching is a promising concept to reduce the peak traffic and backhaul load, particularly for video content delivery [1], [2]. The concept stems from the content reuse property of video streaming, i.e., users are likely to request the same video content. As such, saving popular content at the local small-cell base stations (SBSs) during the off-peak time or pushing them at user devices directly through broadcasting improves the network’s throughput performance and user-perceived quality of experience (QoE) [3], [4].

Realizing the potential of wireless caching necessitates the optimization of several parameters. To do this, one can take advantage of a recently-emerged concept, namely federated learning (FL). FL enables several partners to jointly learn the parameters of a specific model in a distributed manner, i.e., without requiring any data exchange [5]. Thus, using FL largely reduces the amount of data that should be uploaded via the wireless uplink channel. Besides, FL maintains the benefits of reacting cognitively to the mobile communication environment and conditions of cellular networks, as well as preserving personal data privacy [6].

Mobility-aware caching technology that exploits the user mobility statistics for the allocation of caching resources has been recently investigated in [7]–[9]. More explicitly, [7] proposes a mobility-aware cache placement strategy that maximizes the data offloading ratio in device-to-device (D2D) networks. Reference [8] develops a green mobility-aware caching model to jointly optimize the cache placement and power allocation among SBSs and mobile devices. Besides, [9] explores the mobility-aware content caching problem for small-cell networks to maximize the caching gain.

Against this background, we primarily focus on developing mobility-aware routing and caching strategies for dense small-cell networks based on the FL framework. To jointly optimize the routing and cache placement, we first formulate the network cost minimization problem, which is an NP-hard mixed integer programming (MIP) problem. To tackle this intricacy, we propose a federated routing and popularity learning (FRPL) approach by which the SBSs learn the popularity of files by learning the pedestrian- and request-density. Next, to avoid the unnecessary data retransmission over a backhaul, we develop a novel content transmission protocol to improve the cache-efficiency (CE) performance of SBSs. Moreover, to ensure the minimum network cost for dense small-cell networks, we optimize the cache placement by developing an algorithm that greedily approximates the minimizer of the MIP problem. The contributions of this paper are as follows:

• Motivated by the notion of one-stop-shop (OSS), we propose an FRPL approach that enables SBSs to complete multiple tasks, thereby reducing the processing time. Reducing the processing time is crucial as the duration of the time-slot within one global aggregation is limited.
• The proposed FRPL is a model to predict the pedestrian-density of each cell and to generate the request-density of specific files for dense small-cell networks.
• By exploiting the prediction results and using a novel content transmission protocol, we develop a cache placement policy to optimize the storage for SBSs.
• Numerical results show that our cache placement policy guarantees a high CE for SBSs compared to the existing schemes, although mobile users’ (MUs’) demand information is unknown. The effectiveness of our FRPL approach has been verified as well.

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II. System Model and Problem Formulation

We consider a network consisting of a finite but time-varying number of SBSs, denoted by $K_t$ and a single macro-cell base station (MBS) that are deployed to serve $U$ MUs simultaneously. Due to the dense deployment, the coverage areas the SBSs and also the MBS overlap; Hence, at each time, an MU might be in the communication range of multiple contributors. Due to the limited duration of every time slot, an MU can download at most $b_k$ data bytes in each contact with SBS $k$.

A. Federated Learning Model

To generate an FRPL model, we exploit an FL algorithm by which the MBS and SBSs (also called potential contributors or participants) collaboratively learn a shared model while keeping all the training data at the participants’ side. The FL model trained at the participant’s side is referred to as the local model. The MBS integrates the local models and generates the global model, which improves the local model of each participant. The working schematic of our local and global models is illustrated in Fig. 1. More details follow.

Assume that there are $I$ participants. The $i$th participant, $i \in \{1, \cdots, I\}$, collects a matrix $X_i = [x_{i,1}, \cdots, x_{i,q_i}]$ of input data, where the subscript $Q_i$ indicates the number of the samples collected by a participant $i$. $X_i$ is thus the entry vector for training the local FL model of participant $i$. The output vector is $y_i = [y_{i,1}, \cdots, y_{i,q_i}]^T$. We define a vector $\rho_i$ to capture the parameters related to the local FL model trained by $X_i$ and $y_i$. Under a linear model assumption we have $y_i = X_i \rho_i + n$, where $n$ is measurement noise typically approximated as Gaussian i.i.d. samples.

In standard gradient descent (SGD) methods [10], the unknown model is iteratively estimated by computing $\rho_i$ at each epoch, evaluating a gradient associated to the squared error cost function

$$f(\rho_i, X_i, y_i) = ||X_i \rho_i - y_i||^2,$$

where $||\cdot||$ denotes the $l_2$-norm operation. Thus the training procedure of the FL algorithm is given by

$$\min_{\rho_1, \cdots, \rho_I} \frac{1}{Q} \sum_{i=1}^{I} \sum_{j=1}^{Q} f(\rho_i, x_{i,j}, y_{i,j})$$

subject to $\rho_1 = \cdots = \rho_I = \beta$, \hspace{1cm} (2a)

where $\beta$ captures the parameters related to the global FL model. In addition, (2b) guarantees that all the participants and MBS share the same FL model when the FL algorithm convergences, say after $\theta$ rounds. The update of the global model is given by $\beta = \frac{1}{Q} \sum_{i=1}^{I} Q_i \rho_i$. \hspace{1cm} (2b)

B. Content Request Model

Consider a content library with $M$ contents. The size of each content $f \in \{1, \cdots, M\}$ is $g_f$. Each MU requests the content $f$ randomly and independently from the content library with some time-invariant probability $p_{f,t} \in [0,1]$. Traditionally, when an MU requests some content within the time deadline $\tau$, she can obtain it through random caching, local SBS caching, or MBS caching [1]. However, such naive caching mechanisms can barely guarantee a high CE performance due to the following reasons: (i) The aforementioned mechanisms largely neglect the limited storing capacity and the finite bandwidth; (ii) Often they result in an unnecessary re-transmission of data. Therefore, in this paper, we decompose the cache domain of the required contents of an MU into three categories, as listed below:

- **Local Caching**: The MU would firstly check the local SBS. If the required content is cached on the local SBS, then the MU obtains the required content directly from the local cache within the time deadline $\tau$. Otherwise, the MU receives the required contents from one of the following sources:
  - **Intra-Cell Caching**: If the local SBS does not have the required content, it can fetch it from another SBS in the intra-cell domain if any of them have stored it, so that the MU is served within the deadline $\tau$.
  - **Inter-Cell Caching**: If no SBS in the intra-cell domain has the required content, the local SBS fetches it via the backhaul link, from an external SBS deployed in the other overlapped cells or, in the worst case, from the MBS.

C. Problem Formulation

This paper focuses primarily on the following challenges that are associated with small-cell networks: (i) When MUs intensively migrate into one area, it is challenging to properly retrieve the large number of objects requested by MUs over a backhaul while guaranteeing a minimum network cost; (ii) The MUs’ preferences affect the CE of SBSs. Moreover, distributed caching might result in duplicate files in a small area; (iii) Joint learning and cache placement, as well as service provisioning, might result in a high delay.

Now we are in the position to formalize the joint cache placement and content routing problem. Let $C \in \{0,1\}^{K_t \times M}$ be a binary caching strategy of the required contents in SBSs, where $c_{k,f} = 1$ indicates the $k$th SBS stores the file $f \in \{1, \cdots, M\}$, and $c_{k,f} = 0$ indicates otherwise. Let $\alpha_{C_f} = \sum_{k=1}^{K_t} \sum_{f=1}^{M} c_{k,f} \cdot \alpha_{C_f}$ denote the SBSs’ aggregated cost as a result of caching, where $\alpha_{C_f}$ is the cost of caching content $f$. The cost mainly depends on the file size $g_f$.\hspace{1cm}
Moreover, the expected cost for retrieving content $f$ from SBS $k \in \{1, \ldots, K_t\}$ via backhaul within a global aggregation period can be written as

$$J^*_k(f) = \psi_k \cdot p_{f,t} \cdot (c_k f - \alpha_{S_k} + (1 - c_k f) \cdot d_k f),$$

(3)

where $\psi_k$ represents the pedestrian-density at time slot $t$ at the site of SBS $k$. Besides, $\lambda_{f,t} = \psi_k \cdot p_{f,t}$ indicates the expected request-density (i.e., the number of requests per time slot) of a specific file at time $t$. Finally, $d_k f = \prod_{f} (1 - c_k f) (\alpha_{M} + \alpha_{M_k})$ corresponds to the costs w.r.t. the worst case, i.e., when file $f$ has not been stored, and shall be fetched from MBS. Herein, $\alpha_M$ is a constant cost for retrieving $f$ via an MBS backhaul, and $\alpha_{M_k}$ denotes the cost of retrieving $f$ for SBS $k$ from MBS. $\lambda_{f,t} c_k f - \alpha_{S_k}$ stands for the expected cost for retrieving $f$ from SBS $k$ that has stored $f$.

Minimizing the aggregate cost $J^*_k(f) \psi_k \cdot p_{f,t}$ in (3) over the $K_t$ SBSs, i.e., minimize $\sum_{k=1}^{K_t} J^*_k(f) \psi_k \cdot p_{f,t}$, yields an optimal routing strategy for each file.

Based on the discussion above, the mobility-aware routing strategy and cache placement is equivalent to minimizing the network cost per global aggregation.\(^1\) Formally,

$$\begin{align*}
\min \{C, p, \psi_k\} & \sum_{k=1}^{K_t} \sum_{f=1}^{M} c_k f \cdot \alpha_{C_f} + \sum_{k=1}^{K_t} \sum_{f=1}^{M} J^*_k(f) \psi_k \cdot p_{f,t}, \\
\text{s.t.} & \sum_{f=1}^{M} c_k f g_{f,k} \leq C_k, \forall k \in \{1, \ldots, K_t\}, t = 1, 2, \ldots \tag{4b}
\end{align*}$$

(4a)

$$c_k f \in \{0, 1\}, \forall k, f, t, \tag{4c}$$

where constraint (4b) means that the total size of cached files cannot exceed the cache capacity of SBS $k$.

We observe that problem (4) is a mixed integer programming problem which is at least NP-hard. Moreover, the objective function is not available since it involves unknown popularity $p_{f,t}$ and pedestrian-density $\psi_k f$. In particular, there exists $2^{M+K_t}$ possible caching strategy matrices $\{C\}$, implying an exponential growth in complexity as a function of $M$ and $K_t$. Therefore, it is essential to develop an efficient approach to solve the problem (4) while maintaining a low delay.

III. FEDERATED ROUTING AND POPULARITY LEARNING

Based on the OSS concept, we propose an FRPL approach to learn the pedestrian- and request-density, also generating the popularity of specific files while ensuring a fast model aggregation. This approach consists of the following three major stages:

Geographical Location Division: We divide the entire geographical area uniformly into $K_t$ small areas. Each area includes an SBS and a set of currently connected MUs $U_k, k \in \{1, \ldots, K_t\}$, at time slot $t$. Note that usually MUs in the set $U_k$ have the same network cell ID at this moment.

\(^1\)We focus primarily on minimizing the total cost in terms of content caching and retrieving, and thereby omitting the other kind of costs such as the computation, prediction, and learning cost.

### Algorithm 1: Federated Routing and Popularity Learning (FRPL)

**Input:** Initialize the points $T \leftarrow 0, t \leftarrow 0, \kappa \leftarrow 0$, and $\eta > 0$.

**Output:** The pedestrian-density $\psi^*_k f, t$ and the expected request-density $\lambda^*_f, t, \kappa$.

1. for $T = 1, 2, \ldots$
   2. for $t = 1, 2, \ldots \theta$
      \> Pedestrian-Density Prediction
      3. For each local FL model, the respective SBS searches the $\kappa$ neighboring areas to find the candidates of pedestrian clusters.
      4. Calculate the gradient of the loss function $L(p_{1,1,t})$.
      5. Monitor the statistic of clusters and estimate the number of clusters by following the criterion in (5).
      6. Update the local FL model $p_{1,1,t}$ and the centroids of $\kappa$ clusters.
      7. Estimate the pedestrian-density: $\psi_k^* f, t \leftarrow \sum_{t=1}^{N} N(i) + N(k) - N^- (k)$.
   \> Request-Density Prediction
   8. Learn the request density $\lambda^* f, t$ for each file $f \in \{1, \ldots, M\}$, by minimizing the mean square error between the estimated and actual request-density.
   9. Update the local FL model $p_{2,1,t}$.
   10. Estimate the expected request-density: $\lambda^*_f, t \leftarrow \frac{\sum_{t=1}^{N} N(i) + N(k) - N^- (k)}{\sum_{f=1}^{M} \lambda^*_f, t}$.
11. end for
12. The distributed $K_t$ SBSs invoke the SGD method to update the local FL models $\{p_{0,1,t}, \ldots, p_{0,K_t}\}$, $q = \{1, 2\}$, to MBSs to aggregate the local FL models.
13. Update the global FL model $p_{2,1,t}$ by following (10).
14. Update the gradient function of global FL model by (11).
15. end for

**Dual-Task Execution:** The SBS of each small area aims at learning the pedestrian-density and the request-density of each file by fully exploiting the location- and request-context. Details follow.

* TASK 1 (Pedestrian-Density Prediction): To predict the pedestrian-density of a cell $k_t$, the corresponding SBS derives the following statistics for the set of MUs at $K_t$ areas: (i) The number of pedestrian clusters in the transition region of $\kappa$ neighboring cells that have $k_t$ as the predicted next cell; (ii) The number of pedestrians already transited to $k_t$ [11]; (iii) The number of pedestrians that are predicted to leave this current cell $k_t$.

To search the $\kappa$ neighboring areas to find the candidates of pedestrian clusters, the SBS uses the $K$-means clustering algorithm [12] with the loss function given by $L_1(p_{1,i}) := \sum_{k=1}^{K_t} || x_j - f(p_{1,i}, x_j)||^2$, where $f(p_{1,i}, x_j)$ is the centroid of all objects assigned to $x_j$'s class.

In words, the pedestrian clustering minimizes the sum of squared errors between data points and their respective centroids, until reaching a stationary centroid.

To obtain the number of pedestrian clusters that are approaching the desired cell $k_t$, the SBS uses the following
detectation criterion:
\[
\frac{\sqrt{(x_0 - x_k(t))^2 + (y_0 - y_k(t))^2}}{\sqrt{(x_0 - x_k(t-1))^2 + (y_0 - y_k(t-1))^2}} < 1, \tag{5}
\]
where \((x_0, y_0)\) is the location of the SBS (cell \(k_t\)), \((x_k(t), y_k(t))\) is the final location of the centroid of cluster \(k\) with \(k = \{1, \ldots, k\}\). We use \(N(i)\) to denote the statistical function of pedestrian-density at cluster \(i\), and \(N(k_t)\) to denote the statistical function of pedestrian-density associated with the number of pedestrians already transited to this cell. Besides, \(N^-(k_t)\) represents the statistical function of pedestrian-density associated with the number of pedestrians might leave this current cell. In this case, the pedestrian-density of the desired cell yields \(\psi_{k,t} = \frac{\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)}{\sum_{t=1}^{T} \lambda_{f,t}} \), given that their respective centroids of clusters \(1, \ldots, \kappa\) satisfy the detection criterion in (5) accordingly.

> TASK 2 (Request-Density Prediction): Using the files’ rating together with users’ features, the SBS learns the request density of file \(f, f = \{1, \ldots, M\}\), by minimizing the least squared error between the estimated request-density and the actual one. By exploring the linear regression model to predict \(\lambda_{f,t}\), the SBS uses the following loss function
\[
L_2(\rho_{2,i}) := \frac{1}{2} \|y_j - f(\rho_{2,i}, x_j)\|^2 + \alpha \|\rho_{2,i}\|^2, \tag{6}
\]
where the \(\alpha\) is a hyperparameter for regularization. Then, the popularity of file \(f\) yields \(p_{f,t} = \frac{\lambda_{f,t}}{\sum_{i=1}^{\kappa} \lambda_{f,t}} \). Thus, the expected request-density \(\lambda^*_{f,t}\) of file is given by
\[
\lambda^*_{f,t} = \psi_{k,t} \cdot p_{f,t} = \left(\frac{\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)}{\sum_{t=1}^{T} \lambda_{f,t}}\right) \cdot \lambda_{f,t}. \tag{7}
\]
Later in Section IV, the SBS uses this metric for cache placement.

**Fast Model Aggregation:** In the framework of federated learning, \(K_t\) SBSs send the local models \(\{\rho_{q,1}, \ldots, \rho_{q,K_t}\}\) to the MBS with \(q = \{1, 2\}\) being the indices of prediction tasks. Then \(\beta_{q,t}\) is the global model at time slot \(t\) that is given by
\[
\beta_{q,t} = \frac{1}{Q} \sum_{i=1}^{K_t} Q_i \cdot \rho_{q,i,t}, \quad q \in \{1, 2\}. \tag{8}
\]
Note that \(\sum_{i=1}^{K_t} Q_i \cdot \rho_{q,i,t}\) indicates the total number of training data points. The MBS then sends \(\beta_{q,t}\) back to the SBSs. After receiving \(\beta_{q,t}\) from the MBS, the SBSs use the SGD method to update the local models \(\{\rho_{q,1}, \ldots, \rho_{q,K_t}\}\). The update of local model \(\rho_{q,i,t}\) follows as
\[
\rho_{q,i,t+1} = \beta_{q,t} - \frac{\eta}{Q_i} \sum_{j=1}^{Q_i} \nabla f(\beta_{q,t}, x_{i,j}, y_{i,j}) \tag{9}
\]
w.r.t. the task \(q\), where \(\eta\) denotes the learning rate. Moreover, \(\nabla f(\beta_{q,t}, x_{i,j}, y_{i,j})\) corresponds to the gradient function of \(f(\beta_{q,t}, x_{i,j}, y_{i,j})\) w.r.t. \(\beta_{q,t}\). For simplicity, we hereby define \(F(\beta_{q,t}, x_{i,j}, y_{i,j}) = \frac{1}{Q} \sum_{i=1}^{K_t} Q_i \sum_{j=1}^{Q_i} f(\beta_{q,t}, x_{i,j}, y_{i,j})\) as the squared error cost function of the global model.

After receiving the updated local models, the MBS also updates the global model \(\beta_{q,t}\) as \([13]\)
\[
\beta_{q,t+1} = \beta_{q,t} - \eta \left(\nabla F(\beta_{q,t}, x_{i,j}, y_{i,j}) - \Theta_q\right), \quad q \in \{1, 2\}, \tag{10}
\]
where \(\nabla F(\beta_{q,t}, x_{i,j}, y_{i,j})\) is the gradient function of \(F(\beta_{q,t}, x_{i,j}, y_{i,j})\) w.r.t. \(\beta_{q,t}\). Besides, \(\Theta_q\) is given by
\[
\Theta_q = \nabla F(\beta_{q,t}, x_{i,j}, y_{i,j}) - \frac{1}{Q} \sum_{i=1}^{K_t} Q_i \cdot \rho_{q,i,t}, \quad q \in \{1, 2\}. \tag{11}
\]
Algorithm 1 summarized the described stages. Finally, we note that the dimension of the raw pedestrians’ data (including geographic location, date, time, sojourn time) affects the outcome of \(K\)-means clustering algorithm \([12]\). We therefore state the following proposition.

**Proposition 1.** The expected request-density \(\lambda^*_{f,t}\) has the following properties:

- When the datasets utilized for user clustering in transition region of neighboring cells are insufficient, the associated \(\lambda^*_{f,t}\) has a lower bound of \(\lambda^*_{f,t} \geq \frac{\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)}{\sum_{t=1}^{T} \lambda_{f,t}} \).
- In contrast, when the number of dimensions of datasets is larger than 10, the associated \(\lambda^*_{f,t}\) has an upper bound of \(\lambda^*_{f,t} \leq \frac{\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)}{\sum_{t=1}^{T} \lambda_{f,t}} \lambda_{f,t}\), where \(\kappa^*\) indicates the maximum number of desired non-empty clusters.

**Proof:** We observe that one drawback of the \(K\)-means clustering occurs when it is applied to datasets with \(m\) data points in \(n \geq 10\) dimensional real space \(\mathbb{R}^n\) \([12]\). As a result, the \(K\)-means clustering often converges with at least one or more clusters with either empty or very few data points. In this case, to facilitate fast model aggregation, we discard the clusters which are empty or summarize very few data point when performing the pedestrian-density prediction, and thus resulting in \(\kappa^*\) desired non-empty clusters. Note that cluster filtration is required in that the modest values of \(\kappa^*\) can enable solution that summarizes the underlying data \([12]\) better.

Accordingly, when the datasets utilized for user clustering in transmission region of neighboring cells are scarce, the estimated pedestrian-density \(\psi_{k,t}\) reaches trough of \(N(k_t) - N^-(k_t)\), thus resulting in a lower bound of \(\lambda^*_{f,t} \geq \frac{\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)}{\sum_{t=1}^{T} \lambda_{f,t}} \).

In contrast, when the number of dimensions of datasets is larger than 10, the estimated pedestrian-density \(\psi_{k,t}\) arrives at a peak value of \(\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)\), thereby yielding an upper bound of \(\lambda^*_{f,t} \leq \frac{\sum_{i=1}^{\kappa} N(i) + N(k_t) - N^-(k_t)}{\sum_{t=1}^{T} \lambda_{f,t}} \lambda_{f,t}\).
IV. CACHE PLACEMENT POLICY

In this section, we develop an algorithm that greedily optimizes the cache placement for $K_t$ SBs. After learning $\psi_{k,t}$ and $p_{f,t}$, the expected request density can be calculated as $\lambda_{f}^{*} = \psi_{k, t} \cdot p_{f,t}^{*}$. The optimal cache placement problem is equivalent to minimizing the network cost $D(\{c_{k,f}^{*}\})$ that is given by

$$D(\{c_{k,f}^{*}\}) := \sum_{k=1}^{K_t} \sum_{f=1}^{M} c_{k,f}^{*} \cdot \alpha_{c_{k,f}^{*}} +$$

$$\sum_{k=1}^{K_t} \sum_{f=1}^{M} \psi_{k,t} \cdot p_{f,t}^{*} \cdot \left( c_{k,f}^{*} \cdot \alpha_{s_{k}} + (1 - c_{k,f}^{*}) \cdot d_{k,f}^{*} \right).$$

The optimization problem thus follows as

$$\text{minimize} \quad D(\{c_{k,f}^{*}\}) \quad \text{subject to} \quad \sum_{f=1}^{M} c_{k,f}^{*} g_{f} \leq C_{k}^{S}, \quad \forall k \in \{1, \ldots, K_t\}, \quad t = 1, 2, \ldots,$$

$$c_{k,f}^{*} \in \{0, 1\}, \quad \forall k, f, t. \quad (13c)$$

Problem (13) is an integer programming, which is NP-hard in general. Given cache placement policy $\{c_{k,f}^{*}\}$, the content retrieval policy is determined based on our content transmission protocol introduced in Section II-C.

As a low-complexity and efficient solution to problem (13), we develop Algorithm 2, which greedily places the files to a cache. The solution is an approximate minimizer of $D(\{c_{k,f}^{*}\})$ in (13a). Details follow.

Let $I_{k}$ be the total size of files that are already cached at the SBS $k$ during each iteration of our algorithm. Naturally, the initial $I_{0}$ is 0. Let $\mathcal{L}_{k,f}$ denote the set collecting all the pairs $\{k, f\}$ for which the placement of file $f$ at the cache of SBS $k$ has not been performed yet, and the cache of $k$ is not full yet. For the $j$'th iteration, our algorithm conducts the cache placement by picking the pair $\{k^{*}, f^{*}\} \in \mathcal{L}_{j,f}$ with the lowest $D(\{c_{k,f}^{*}\})$ given that this is lower than the one in the previous iteration. Formally, we have

$$\{k^{*}, f^{*}\} = \arg\min_{\{k,f\} \in \mathcal{L}_{j,f}} D(\{c_{k,f}^{*}\}). \quad (14)$$

Then, if $I_{k}^{j} < C_{k}^{S}$, our algorithm updates $I_{k}^{j+1} = I_{k}^{j} + c_{k^{*}, f^{*}} g_{f}$ and $\mathcal{L}_{k,f}^{j+1} = \mathcal{L}_{k,f}^{j} \setminus \{k^{*}, f^{*}\}$, respectively; Otherwise, when $I_{k}^{j} = C_{k}^{S}$ implies that the cache of SBS $k^{*}$ is full, our algorithm excludes all pairs $\{k^{*}, f\}$ from $\mathcal{L}_{k,f}^{j}$, and thereby terminating the cache placement at SBS $k^{*}$. The algorithm terminates when all the caches become full. The described cache placement optimization, referred to as the greedy cache placement, is summarized in Algorithm 2.

V. SIMULATION RESULTS AND ANALYSIS

A. Datasets and System Parameter Sets

We consider a real-world datasets, i.e., MovieLens 1M [14], to evaluate the proposed strategies Algorithm 1 and Algorithm 2. Similar to [15], we assume that the moving rating process in the datasets can be viewed as a streaming request. TABLE I lists the most important parameters of our experiments.

**TABLE I**

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| $T$       | 3400  | $M$       | 3952  |
| $U$       | 6040  | $\epsilon$ | [0.1, 0.8] |
| $\eta$    | 0.003 | $\alpha$  | [1, 10] |
| $C_{k}^{S}$ | [50 : 500] | $\alpha_{c_{k,f}}$ | 1.5 mW |
| $g_{f}$   | 1     | $\alpha_{M_{SBS}}$ | 370 mW |
| $\alpha_{M_{SBS}}$ | 180 mW |

B. Performance Evaluation

We evaluate the average CE (the average ratio of cache hits within one global aggregation period compared to the total requests) of our proposals in comparison with the following cache placement approaches:

- **Optimal with Full Information:** This scheme has access to full information of users’ demands; thus, it has the potential of providing the best CE performance.
- **$\epsilon$-Greedy:** Also known as $m$-$\epsilon$-greedy, this is a variant of the multi-armed bandit algorithms without any prior- or contextual-information. The policy randomly selects a set of $m$ files with probability $\epsilon < 1$, while with probability $1 - \epsilon$, it selects the $m$ files with the highest estimated popularity so far.
- **Random:** This scheme selects a random set of files to cache in each time slot.

In Fig. 2, we compare the average CE performances of different caching approaches. The figure shows that our proposed greedy algorithm achieves a CE gain significantly higher than that of the random- and $\epsilon$-greedy approaches under different $\epsilon$. The reason is that the proposed algorithm greedily places the cache to SBSs after learning the expected request densities of files by Algorithm 1.
algorithm to optimize the cache placement and to minimize the network cost. Numerical results revealed that our proposed cache placement is a near-optimal solution for improving the CE performance while ensuring a minimum network cost.

VI. CONCLUSION

We developed mobility-aware routing and caching strategies for dense small-cell networks based on the FL framework. To optimize the routing and cache placement, we first formulated a network cost minimization problem, which is NP-hard. To tackle this problem, we first proposed an approach by which SBSs learn the pedestrian density and request density. Afterward, based on the predictions, we developed a greedy algorithm to optimize the cache placement and to minimize the network cost. Numerical results revealed that our proposed cache placement is a near-optimal solution for improving the CE performance while ensuring a minimum network cost.

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