Decentralized Collaborative Learning Framework for Next POI Recommendation

JING LONG and TONG CHEN, The University of Queensland, Australia
QUOC VIET HUNG NGUYEN, Griffith University, Australia
HONGZHI YIN, The University of Queensland, Australia

Next Point-of-Interest (POI) recommendation has become an indispensable functionality in Location-based Social Networks (LBSNs) due to its effectiveness in helping people decide the next POI to visit. However, accurate recommendation requires a vast amount of historical check-in data, thus threatening user privacy as the location-sensitive data needs to be handled by cloud servers. Although there have been several on-device frameworks for privacy-preserving POI recommendations, they are still resource intensive when it comes to storage and computation, and show limited robustness to the high sparsity of user-POI interactions. On this basis, we propose a novel decentralized collaborative learning framework for POI recommendation (DCLR), which allows users to train their personalized models locally in a collaborative manner. DCLR significantly reduces the local models’ dependence on the cloud for training, and can be used to expand arbitrary centralized recommendation models. To counteract the sparsity of on-device user data when learning each local model, we design two self-supervision signals to pretrain the POI representations on the server with geographical and categorical correlations of POIs. To facilitate collaborative learning, we innovatively propose to incorporate knowledge from either geographically or semantically similar users into each local model with attentive aggregation and mutual information maximization. The collaborative learning process makes use of communications between devices while requiring only minor engagement from the central server for identifying user groups, and is compatible with common privacy preservation mechanisms like differential privacy. We evaluate DCLR with two real-world datasets, where the results show that DCLR outperforms state-of-the-art on-device frameworks and yields competitive results compared with centralized counterparts.

CCS Concepts: • Information systems → Recommender systems;

Additional Key Words and Phrases: Point-of-Interest recommendation, decentralized collaborative learning, user privacy

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Authors’ addresses: J. Long, T. Chen, and H. Yin (corresponding author), The University of Queensland, Brisbane, QLD, 4072, Australia; emails: {jing.long, tong.chen, h.yin1}@uq.edu.au; Q. V. H. Nguyen, Griffith University, Brisbane, QLD, 4111, Australia; email: henry.nguyen@griffith.edu.au.

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1 INTRODUCTION

Recently, next Point-of-Interest (POI) recommendation has gained immense attention in e-commerce due to the rapid growth of Location-based Social Networks (LBSNs), such as Weeplace and Yelp. Such services generate large volumes of historical check-in data, which is valuable for understanding users’ behavioral patterns and predicting their preferences on the next movement. Next POI recommendation has wide applications like mobility prediction, route planning, and location-based advertising [4, 30].

To facilitate personalized POI recommendations by analyzing users’ check-in data, early models mainly focused on Markov chains [38, 54] and matrix factorization (MF) [25]. Recently, models based on recurrent neural networks (RNNs) [10, 15] and graph neural networks (GNNs) [23] have demonstrated advantages in capturing temporal and structural dependencies among POIs. To alleviate the data sparsity problem in POI recommendation, recent models exploit geographical and temporal information to represent the spatiotemporal connections between movements [24, 52]. However, those models ignore correlations of non-adjacent POIs and non-consecutive check-ins. On this basis, Luo et al. [31] utilize self-attention layers to capture relative spatiotemporal information of all check-in activities along the sequence.

Given the rise of intensive computing resources and massive training data, current deep neural networks (DNNs) have achieved the state-of-the-art performance in POI recommendation. In addition, such recommenders are typically trained in a centralized way. That is, all users’ data and the recommendation model are centrally hosted, and both the training and inference of the recommender are performed on the powerful cloud server. In this paradigm, users’ devices only act as a terminal for uploading new data and recommendation requests, as well as displaying the recommended POIs to users.

However, such a centralized POI recommendation paradigm brings three significant real-world issues: (1) High cost of resources. To provide precise and fast recommendations, large-scale data is stored and processed on the server, which consumes excessive storage and computing resources. Consequently, it is financially and environmentally expensive to maintain such resource-intensive services. (2) Privacy issues. Despite the successful applications of centralized deep learning in various online services, users’ privacy is increasingly prone to breaches, causing huge losses for both users and enterprises such as Facebook [16] and Netflix [33]. In addition, POI recommendation is especially sensitive to privacy concerns as historical check-in data directly reveals users’ physical trajectories [41]. However, if users choose not to share their personal data with the POI recommender, they will possibly face a decreased service quality as a consequence. (3) Weak resilience. Centralized POI recommendation highly relies on the stability of the server and internet connectivity. Once the server is impaired or overcrowded, or network quality cannot be guaranteed, the recommendation services are unable to ensure timeliness and may even go offline [34, 48]. Many tourist attractions are located in remote areas with limited telecom infrastructures, weakening the resilience of cloud-based POI recommendation.

As such, there has been a recent surge in developing on-device POI recommendation. In on-device recommender frameworks, users can keep their personal check-in data on their own devices, which can significantly reduce the risk of privacy breaches. Specifically, Wang et al. [40] deployed compressed models on mobile devices for secure and stable POI recommendation. In such a framework, all personal information including check-in data and compressed models is stored on users’ own devices. To address the data sparsity problem, those compressed models inherit the knowledge from the teacher model, which is trained with public data. However, both the teacher and student models are still trained on the cloud server and all users share the same model. In addition, Guo et al. [13] proposed a federated learning framework for next POI recommendation. However,
the framework is still resource intensive for storage and computation, because the central server is responsible for collecting and aggregating locally trained models, as well as redistributing the aggregated model to all users. Moreover, all users share the same global model, which ignores the dynamics and diversity of users’ spatial activities and interests, leading to suboptimal performance. Although some approaches [37, 44] can cluster clients to provide group-based personalized models, this commonly involves the transmission of sensitive user attribute information. To conclude, we are still in pursuit of a decentralized POI recommendation paradigm that requires minimal engagements and resources from the central party and can collaboratively learn personalized models amid highly sparse interaction data at the individual device level.

To this end, we propose a new decentralized POI recommendation paradigm that allows user devices to mutually communicate and collaborate to learn performant recommenders. Unlike standard federated learning, in this paradigm, the central server is only responsible for providing pretrained parameters (i.e., POI embeddings) and grouping similar users in a secure way, such that collaborative model learning is enabled for user devices within the same group. On the server side, to alleviate the data sparsity problem and speed up the training for local models, we design two self-supervised pretraining tasks to inject categorical and geographical information into POI representations. The first task is to create correlations between POIs and their associated categorical tags by Mutual Information Maximization (MIM) [55], while the second one is to enhance POI representations by learning and predicting distances between POIs. The pretrained POI embeddings, as a key part of model parameters, will be incrementally updated with each user’s on-device interaction data. In addition, we propose two metrics to identify similar users for collaborative learning. First, semantic neighbors are decided by category distribution similarities. That is, the higher the category distribution similarity between two users is, the more likely they are neighbors. In addition, geographical neighbors are decided by the physical distances, where the distance between two users is the minimal distance between their two sets of centroids, while multiple centroids of a user are obtained by clustering all visited POIs with their longitudes and latitudes. To calculate category distribution similarity and physical distances, the server has to collect category distributions and centroids from devices. Although such information is far less sensitive compared to check-in trajectories or personalized models, only perturbed category distributions and centroids are uploaded to the server.

On this basis, our proposed framework is more performant than the decentralized framework proposed by Chen et al. [3] that also allows local models to exchange knowledge with geographically close users decided by the random walk theory. [3] is subject to a performance drop compared with the state-of-the-art centralized POI recommendation frameworks, since the limited knowledge from a single type of neighbor cannot utilize the knowledge from similar users effectively. Based on two types of neighbors informed by the server, we design a novel MIM task to jointly learn and combine knowledge from both types of neighbors in a unified and elegant way. As such, we can obtain a high-quality, fully personalized local recommender for each user.

To conclude, our contributions are listed as follows:

- We propose a novel decentralized collaborative learning framework for POI recommendation (DCLR), where users receive a fully personalized local recommendation model while retaining all personal data on-device. The new paradigm allows for collaborative model learning with minimal dependency on the cloud, and is generalizable to arbitrary centralized recommendation models.
- To alleviate data sparsity when learning each local POI recommender, we design two self-supervised learning objectives to make full use of the side information on geographical correlations and categorical tags of POIs.
We propose two metrics to identify neighbors based on categorical similarity and geographical distances. In addition, we propose an effective way to learn knowledge from neighbors with both attentive aggregation and mutual information maximization.

We evaluate DCLR with two real-world datasets. The results show the effectiveness and efficiency of our proposed model. Specifically, DCLR outperforms all on-device frameworks and provides competitive POI recommendation accuracy compared with advanced centralized models.

2 PRELIMINARIES

In this section, we first introduce important notations used in this article, and then formulate our major tasks.

We denote the set of user, POI, and category as \( U = \{ u_1, u_2, \ldots, u_{|U|} \} \), \( P = \{ p_1, p_2, \ldots, p_{|P|} \} \), \( C = \{ c_1, c_2, \ldots, c_{|C|} \} \), respectively. Each POI \( p \in P \) is associated with a category \( c \in C \) and geographical coordinates \((\text{lon}_p, \text{lat}_p)\).

Definition 1 (Check-in Activity). A check-in activity of a user indicates a user \( u \in U \) has visited a POI \( p \in P \) at a timestamp \( t \). It can be denoted by a tuple \( x = (u, p, t) \).

Definition 2 (Check-in Sequence). A check-in sequence contains \( M \) consecutive check-in activities visited by a user \( u_i \), denoted by \( X(u_i) = \{x_1, x_2, \ldots, x_M\} \).

Task 1: Decentralized Next POI Recommendation. In our decentralized framework, the server is only responsible for providing pretrained parameters (i.e., POI embeddings) and identifying neighbors for each client in a privacy-preserving manner. No user profiles are used by either local models or the server. After receiving the anonymized neighbor IDs from the server, each mobile device will obtain and aggregate knowledge from its neighbors to update the local model. Note that each device hosts only one user’s data and model. Given \( X(u_i) \) and neighbor IDs, the local model is trained to provide a ranked list of POIs based on each user’s recent interest as recommendations.

3 THE PROPOSED FRAMEWORK

In this section, we formally introduce our techniques to build DCLR for next POI recommendation. The overview of DCLR is illustrated in Figure 1. Overall, our proposed DCLR consists of (1) a base recommender that will be deployed on each user device, (2) two self-supervised learning tasks that enhance POI representation learning with public data on the server side, (3) a neighbor identification strategy deployed on the server that consists of two metrics for securely identifying similar users in collaborative learning, and (4) a neighbor communication strategy to jointly learn and combine knowledge from both types of neighbors in an effective, secure, and on-device manner. In what follows, we unfold the design of each module of our proposed approach.

3.1 Base POI Recommender

The key component of our decentralized framework is to exchange knowledge with homogeneous models learned with different users’ own data. Thus, our decentralized framework is scalable and flexible, which can be applied to almost any next POI recommenders. Our work is based on the Spatio-Temporal Attention Network (STAN) [31], which is one of the newest POI recommender models. As our main contributions lie in the decentralized collaborative learning paradigm rather than the base model, we keep the introduction of STAN brief.
Fig. 1. Overview of our proposed DCLR. All individual check-in trajectories are stored on the device side. The server is responsible for providing model parameters pretrained with public data (i.e., geographical coordinates and categorical tags of POIs) and identifying neighbors for each client in a privacy-preserving manner. After receiving the pretrained model and neighbor IDs, each device first optimizes the personalized model with individual check-in data, and further enhances the model with the knowledge from two types of neighbors.

We use $e_p \in \mathbb{R}^d$ and $e_t \in \mathbb{R}^d$ to denote the embedded representations of POI and time, respectively. For time discretization, we follow [31] to divide continuous timestamps into $7 \times 24 = 168$ intervals to represent the exact hours in a week. Therefore, the input dimensions of the embeddings $e_p$ and $e_t$ are $|P|$ and 168, and the output for each check-in activity $x$ is $e_x = e_p + e_t \in \mathbb{R}^d$. 

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Then, the input embedding of each user’s sequence is \( X_u = [e_{x_1}, e_{x_2}, \ldots, e_{x_M}] \in \mathbb{R}^{M \times d} \). STAN further encodes the spatiotemporal gaps between two check-ins \( x_a \) and \( x_b \) via \( e_{ab} \in \mathbb{R}^d \):

\[
e_{ab}^\Delta = \Delta_{ab}^s \times e_{\Delta_s} + \Delta_{ab}^t \times e_{\Delta_t},
\]

where \( e_{\Delta_s} \) and \( e_{\Delta_t} \) are two unit embeddings to represent a specific amount of spatial (e.g., 1 kilometer) or time (e.g., 1 hour) difference, and \( \Delta_{ab}^s \) and \( \Delta_{ab}^t \) are the true spatiotemporal differences of \( x_a \) and \( x_b \) (e.g., 10 kilometers and 5 hours). On this basis, the embedding of trajectory spatio-temporal relation matrix is \( \Delta \in \mathbb{R}^{M \times M} \):

\[
\Delta = \begin{bmatrix}
e^\Delta_{11} & e^\Delta_{12} & \cdots & e^\Delta_{1M} \\
e^\Delta_{21} & e^\Delta_{22} & \cdots & e^\Delta_{2M} \\
\vdots & \vdots & \ddots & \vdots \\
e^\Delta_{M1} & e^\Delta_{M2} & \cdots & e^\Delta_{MM}
\end{bmatrix},
\]

where \( e^\Delta_{ab} \) is the element-wise sum of \( e_{ab}^\Delta \). Then, we adopt the self-attention mechanism to further combine embedded sequences and spatiotemporal differences. Given three parameters \( W_Q, W_K, \) and \( W_V \in \mathbb{R}^{d \times d} \), the final embedded sequence \( E_u \in \mathbb{R}^{M \times d} \) is defined as follows:

\[
E_u = \text{Softmax} \left( \frac{QK^T + \Delta}{\sqrt{d}} \right) \cdot V,
\]

where \( Q = X_u W_Q, K = X_u W_K, \) and \( V = X_u W_V \). Given the final embedding of the sequence \( E_u \in \mathbb{R}^{M \times d} \), the embedding of \( h \) candidate POIs \( E_{\text{cand}} = [e_{p_1}, e_{p_2}, \ldots, e_{p_h}] \in \mathbb{R}^{h \times M} \), and the spatio-temporal relation matrix \( \Delta_{\text{cand}} \in \mathbb{R}^{h \times M} \) for those \( h \) candidate POIs and \( M \) visited POIs, the likelihood \( \alpha \in \mathbb{R}^h \) of candidate POIs to be visited by a user is calculated as

\[
\alpha = \text{Sum} \left( \text{Softmax} \left( \frac{E_{\text{cand}}E_u^T + \Delta_{\text{cand}}}{\sqrt{d}} \right) \right),
\]

where Sum(\( \cdot \)) is the sum of the last dimension.

Afterward, for each user’s on-device model, we adopt cross-entropy to define the POI prediction loss for optimization:

\[
L_{\text{POI}} = - \sum_{n=1}^{N_{\text{pos}}} \log \sigma(\alpha_i) + \frac{1}{N_{\text{neg}}} \sum_{j=1,j \neq i}^{N_{\text{neg}}} \log(1 - \sigma(\alpha_j)),
\]

where \( N_{\text{pos}} \) is the number of positive samples for a user, \( N_{\text{neg}} \) is the number of negative samples for each positive sample \( p_i \) that are randomly drawn from users’ unvisited POIs, \( \sigma(\cdot) \) is the sigmoid function, and \( \alpha_i \) and \( \alpha_j \) are respectively the scores assigned to the positive and negative samples.

### 3.2 Self-supervised Tasks for POI Embedding Pretraining

The sparsity of user-POI interactions has been a long-standing issue in POI recommendation, which deteriorates further in decentralized settings as each client now needs to independently learn a local model with only the on-device user data. Though parameter sharing via a central server (e.g., federated learning) can help alleviate this problem, the low-quality models submitted by clients at the first place harms the convergence efficiency and bottlenecks the performance of the final model. On this basis, we propose two self-supervision signals to enhance POI representations with the geolocations and categorical tags that are widely available in POI recommendation datasets. The self-supervised tasks are used for pretraining the POI embeddings on the server before they are further optimized on-device with users’ own interactions. Compared with self-supervised learning tasks requiring interaction sequences, e.g., mask prediction tasks [55], the
parameter pretraining in DCLR only involves the commonly available and insensitive public data about POIs, i.e., geolocations and category tags. In contrast, if we perform mask prediction on the server, all users need to upload their personal trajectories to the server, bringing significant problems including high communication costs and privacy issues. Mask prediction tasks are unsuitable to be performed on-device, as POI embeddings trained only with the target user’s trajectories are heavily biased, while it is infeasible to obtain travel records from other users.

On one hand, geographical information is indispensable in next POI recommendation as users’ preferences on next POIs are highly dependent on their distances to users’ current POIs [24, 29]. However, current POI recommenders only capture the geographical correlation between observed POIs in trajectories. Thus, we further encode the geographical properties with a pairwise distance prediction task between POIs. On the other hand, while users’ check-ins on specific POIs are sparse, their interactions at the category level (e.g., restaurants, entertainment, etc.) are relatively denser. The prediction of category-wise preferences is able to provide strong predictive signals on user interests at the POI level. For example, a user’s strong preference on entertainment venues indicates she/he is likely to visit POIs like cinemas and pubs under this category. Therefore, we create correlations between POIs and their associated categories by maximizing their mutual information [55].

**Geolocation-guided Self-supervised Learning.** First, we enhance POI representations by injecting geographical information. Each POI $p_i$ is associated with a geographical coordinate $(lon_{p_i}, lat_{p_i})$. Hence, the true distance in kilometer between any pair of POIs can be calculated by adopting the Haversine function [39]:

$$\text{dis}(p_i, p_j) = \text{Haversine}((lon_{p_i}, lat_{p_i}), (lon_{p_j}, lat_{p_j})).$$

(6)

Then, we assign labels for different distances: small if $\text{dis}(p_i, p_j) \leq 5km$, medium if $5km < \text{dis}(p_i, p_j) \leq 10km$, and large for distances $\text{dis}(p_i, p_j) > 10km$. Our choice of cut-off points is based on the observation from [2], which is generalizable across common LBSNs. On this basis, we can enhance POI representations by learning and predicting distances between POIs. Then, we formulate the **distance prediction (DP)** objective below:

$$L_{DP} = -\sum_{\forall p_i, p_j} \sum_{l=1}^{L} y_{ij}^l \log (\hat{y}_{ij}^l),$$

(7)

where $L = 3$ is the number of distance labels (i.e., small, medium, and large), $y_{ij}^l$ is the one-hot indicator for label $l$, and $\hat{y}_{ij}^l$ is the predicted probabilities for label $l$. The $L$-dimensional probability distribution $\hat{y}_{ij}$ over all distance intervals is calculated as follows:

$$\hat{y}_{ij} = \text{Softmax} \left( w_{DP} e_{p_i}^T \cdot e_{p_j} \right),$$

(8)

where $e_{p_i}, e_{p_j} \in \mathbb{R}^d$ are embeddings of POI $p_i$ and POI $p_j$, and $w_{DP} \in \mathbb{R}^{3 \times 1}$ are learnable parameters. It is worth noting that it makes little sense to perform distance prediction for all POI pairs given the limited on-device computing resources and the low possibility of traveling to long-distance POIs from the current one. Hence, for each POI, training samples consist of all short-distance POIs and a certain amount (i.e., 500 in our case) of medium-distance and long-distance POIs that are randomly selected.

**Category-aware Self-supervised Learning.** We further propose to enrich POI embeddings with category information by leveraging Mutual Information Maximization [55]. Mutual information (MI) refers to dependencies between two variables. That is, conditioned on one variable, MI estimates certain knowledge of the other via the following:

$$MI(X, Y) = P(X) - P(X|Y) = P(Y) - P(Y|X).$$

(9)
MI has been widely used for learning feature representations. However, directly optimizing this objective is computationally intractable. Instead, we maximize its lower bond via the InfoNCE loss \[19\]. Back to our scenario, we treat a POI \(p\) and its associated category \(c\) as two views of the POI. Inspired by InfoNCE, we design a category prediction (CP) loss to maximize the mutual information between these two views, which is defined below:

\[
L_{CP} = -\sum_{p_i} \log \frac{\exp(f_{CP}(p_i, c_{p_i}))}{\sum_{n=1}^{N_{CP}} \exp(f_{CP}(p_i, c_n))},
\]

(10)

where \(c_{p_i}\) is a POI's associated category, \(N_{CP}\) negative pairs \((p_i, c_n)\) are sampled from the categorical set \(C \setminus c_{p_i}\), and \(f_{CP}(\cdot, \cdot)\) is a function of the pairwise similarity between the POI and the category to a single value. In DCLR, it is implemented by a bilinear network with a scalar output:

\[
f_{CP}(p, c) = \sigma(e_p^T W_{CP} e_c),
\]

(11)

where \(e_p \in \mathbb{R}^d\) and \(e_c \in \mathbb{R}^d\) are embeddings of POI and category, and \(W_{CP} \in \mathbb{R}^{d \times d}\) is a learnable parameter matrix. By optimizing the loss function, we can maximize the mutual information between positive pairs while minimizing that between negative pairs.

### 3.3 Privacy-aware Neighbor Identification

In DCLR, each user’s personalized model is obtained by further optimizing the network parameters and pretrained POI embeddings through the recommendation loss \(L_{POI}\). Although self-supervised learning helps to learn better POI representations despite sparsity, it is still a challenge to estimate a user’s exact preference with a limited amount of interactions. To address the problem, we propose to let each user device communicate with its neighbors who are similar to the current user. However, in our proposed framework, users only have access to their own check-in data, and thus, they cannot get the information to decide their neighbors. To tackle this issue, we ask the server to perform neighbor identification for each user on the server side. Compared with federated frameworks that also cluster similar users to facilitate better model personalization [37, 44], DCLR avoids collecting users’ raw data, which is highly sensitive, and instead leverages implicit user preference indicators to support accurate yet privacy-aware neighbor identification. Furthermore, after the self-supervised pretraining task, the server is only responsible for identifying neighbors for users, and is released from the hefty role of aggregating all local models throughout the training cycle, which is computationally expensive. In addition, privacy can be rigorously guaranteed when such implicit information is masked by privacy mechanisms (e.g., differential privacy) before sharing. In this section, we provide details of the privacy-aware neighbor identification on the server side.

**Geographical Neighbors.** In the scenario of POI recommendation, if two users frequently visit venues in the same area, they possess high geographical similarity because they might have visited the same POIs in the past, and are likely to visit the same POIs in the future. In addition, users from the same or nearby POIs may share similar mobility patterns, which are easily influenced by the environment [6, 36]. We term such neighbors as **Geographical Neighbors.** On this basis, we propose to identify similar users by measuring the distances between the centroids (i.e., averaged coordinates) of two users’ visited POIs. The smaller the distance between two centroids, the higher affinity two users share. However, in some cases, a single centroid coordinate is unable to comprehensively represent a user’s frequent activity zones. For example, if a user’s visited POIs are distributed in two different cities, the centroid might be somewhere that is far away from both. In this situation, the centroid is not helpful for finding neighbors. To address this problem, we advocate generating multiple centroids for each user by applying k-means clustering [32] on the coordinates of all her/his visited POIs. The number of centroids is adaptively determined for each
user, such that no visited POIs have a distance above our predefined threshold (i.e., 10 km in our case) with their nearest centroids. Then, we can obtain a set of centroids for each user \( u_n \):

\[
O(u_n) = \{o^1, o^2, \ldots, o^v\},
\]

where \( v \) is the number of centroids. In addition, \( v \) is not supposed to be the same for every user as different users’ visited places may vary in numbers and geolocations. Afterward, the geographical distance of two users is calculated by the function below:

\[
d_{geo}(u_n, u_m) = \min(Haversine(o_n, o_m)),
\]

where \( o_n \in O(u_n), o_m \in O(u_m) \).

**Semantic Neighbors.** Meanwhile, it is worth pointing out not only that users who are physically close to each other are regarded similar but also that users can be highly relevant at the semantic level. Having visited similar places indicates that users have the same interests, and thus, such users are considered to be similar. Such neighbors are termed **Semantic Neighbors**. Although both categorical preferences and POI-level preferences can reflect such affinity between users [14, 49, 50], we leverage categorical preferences as the metric of semantic similarity for the following reasons. First, people with the same interests might locate far away from each other and are hence unlikely to have similar POI-level preferences. Furthermore, compared with users’ check-ins on specific POIs, their interactions at the category level are relatively denser, making categorical preference a more accurate indicator of semantic similarity. Lastly, revealing users’ POI-level preferences in the cyber environment is more prone to privacy breaches.

Formally, we use \( CP(u_n) = \{cp^n_1, cp^n_2, \ldots, cp^n_{|C|}\} \) to denote the user’s distribution over \(|C|\) POI categories, which can be directly derived from all visited POIs in the user’s training data. For example, a dataset has three categories including Bar, Music Venue, and Steakhouse, and a user has visited Bar two times, Music Venue three times, and Steakhouse five times. Then, the category distribution of the user is \( CP(u_n) = \{0.2, 0.3, 0.5\} \). Thus, we adopt **Kullback-Leibler (KL)** divergence [1, 11] to quantify the distance between two users’ categorical preferences, which is formulated as follows:

\[
d_{cat}(u_n, u_m) = \sum_{c=1}^{|C|} cp^n_c \cdot \log \frac{cp^n_c}{cp^m_c}. 
\]

Based on the methods above, the server is able to calculate geographical and categorical distances between any pair of users, and we use \( D_{geo} \in \mathbb{R}_{\geq 0}^{U \times U} \) and \( D_{cat} \in \mathbb{R}_{\geq 0}^{U \times U} \) to denote the generated geographical and categorical distance matrices among users. The \( i \)th row of the two matrices represents geographical distances and categorical distances between the \( i \)th user and all other users. In addition, the \( q \) nearest neighbors of the \( i \)th user can be decided by sorting the \( i \)th row, excluding the \( i \)th user, and selecting \( q \) users with the smallest distances. Then, for user \( u_n \), we use \( N_{geo}(u_n) = \{(u_m, d_{geo}(u_n, u_m))\}_{m=1}^q \) and \( N_{cat}(u_n) = \{(u_m, d_{cat}(u_n, u_m))\}_{m=1}^q \) to carry the identified geographical and categorical neighbor IDs and their distances with \( u_n \). Specifically, those two sets are the information that the server will hand over to all users for subsequent computations after the neighbor identification.

**Incorporating Differential Privacy.** In our proposed framework, we maintain a server to collect centroids \( O(u_n) \) and categorical preferences \( CP(u_n) \) of all users. After calculating the geographical distance matrix and categorical distance matrix, the server can inform all users of their neighbor IDs. Although in DCLR the risk of sending geolocation centroids and category distributions to the server is considered lower than directly transmitting raw user trajectories [7], our framework fully accounts for the compatibility with privacy preservation mechanisms when communicating with the server. Specifically, we propose to inject noise into centroids and distributions to further reduce the privacy risk with the well-established differential privacy [8]. In DCLR, noise
from Laplace distribution is injected into both centroids $O(u_n)$ and category distributions $CP(u_n)$ to achieve $\epsilon$-differential privacy:

$$M(D) = f(D) + \text{Lap}\left(\frac{\Delta f}{\epsilon}\right),$$

(15)

where $D$ is the data to be submitted by a user; $f(\cdot)$ denotes an arbitrary randomized function; $\epsilon$ is the privacy budget, referring to the degree of privacy protection offered; and $\Delta f$ is the sensitivity of the function $f(\cdot)$, which is calculated as below:

$$\Delta f = \max_{D, D'} ||f(D) - f(D')||_1,$$

(16)

where $D$ and $D'$ are two adjacent datasets that differ in only one record. Back to our scenario, for $O(u_n)$, the sensitivity can be easily obtained via the sum of longitude and latitude differences between the two farthest centroids. For $CP(u_n)$, as mentioned above, category distribution is derived from a user’s visiting counts over all POI categories. In addition, the sensitivity of the counting query is $1 \cdot \frac{1}{8}$. Thus, we can add noise satisfying $\text{Lap}(\epsilon)$ distribution to the visiting counts of all categories before converting them into the category distribution. By adjusting the magnitude of privacy budget $\epsilon$, we can conveniently control the user privacy by trading off the informativeness of identified neighbors for each user.

### 3.4 Collaborative Model Learning

Given the geographical neighbors $N_{\text{geo}}(u_n)$ and semantic neighbors $N_{\text{cat}}(u_n)$, the new challenge is how to enhance the personalized model with both types of neighbors. As two different types of neighbors carry vastly different knowledge, simply aggregating all neighbors will cause considerable information loss, leading to a significant drop of recommendation quality. Hence, we propose a two-step method to solve the problem. First, we generate two enhanced models by separately exchanging knowledge with geographical and semantic neighbors. Then, we further combine these two enhanced models into a fully personalized local recommender for each user.

In decentralized deep learning, the basic method to communicate with other homogeneous models is model aggregation [51]. In our framework, both geographical and semantic neighbors have different weights as they have different distances to the current user. On this basis, we propose an affinity-based model aggregation strategy to learn knowledge from neighbors. To learn the enhanced model with geographical neighbors, we first calculate the similarity between a neighbor and the current user based on its distance to the current user:

$$s(u_n, u_m) = \frac{1}{1 + d_{\text{geo}}(u_n, u_m)}.$$

After that, we define the weight of each neighbor model $\Theta_m$ of $u_m \in N_{\text{geo}}(u_n)$ via

$$w(\Theta_n) = \frac{s(\Theta_m)}{\sum_{k=1}^{q} s(\Theta_k)}.$$

(18)

On this basis, the enhanced model for user $u_n$ with geographical neighbors is defined as below:

$$\Theta_n^{\text{geo}} \leftarrow (1 - \mu)\bar{\Theta}_n + \mu \sum_{m=1}^{q} w(\Theta_m) \Theta_m,$$

(19)

where $\bar{\Theta}_n$ is the original model for the current user and $\mu$ is a hyperparameter that controls the proportion of the current model and the aggregated model based on neighbors.
The enhanced model $\Theta_n^{\text{cat}}$ with semantic/categorical neighbors can be done analogously to geographical neighbor aggregation, where $\mu$ is the same for both geographical neighbors and semantic neighbors. Given two enhanced models $\Theta_n^{\text{geo}}$ and $\Theta_n^{\text{cat}}$, another challenge is how to losslessly combine these two models to obtain the final model for each user. Both $\Theta_n^{\text{geo}}$ and $\Theta_n^{\text{cat}}$ are enhanced models, and they can be treated as two different views of the current model. Therefore, we adopt Mutual Information Maximization [55] to let these two enhanced models gain knowledge from each other. Intuitively, the most important component of these two models is their embedded POI representations. Thus, we construct positive training samples by pairing the embeddings of the same POI from two models. For each positive pair, we generate negative samples by swapping one POI embedding with the embedding for a different POI randomly drawn from the corresponding model. Inspired by InfoNCE loss [19], we define the combination loss $L_{\text{comb}}$ for two models as below:

$$L_{\text{comb}} = -\sum_{p_i} \log \frac{\exp\left(f_{\text{comb}}(e_{p_i}^{\text{geo}}, e_{p_i}^{\text{cat}})\right)}{\sum_{j=1, j\neq i}^{N_1} \exp\left(f_{\text{comb}}(e_{p_i}^{\text{geo}}, e_{p_j}^{\text{cat}})\right) + \sum_{j'=1, j'=i}^{N_2} \exp\left(f_{\text{comb}}(e_{p_{j'}}^{\text{geo}}, e_{p_i}^{\text{cat}})\right)},$$

(20)

where $e_{p_i}^{\text{geo}}$ and $e_{p_i}^{\text{cat}}$ are embeddings of the same POI from two models, $e_{p_j}^{\text{cat}}$ and $e_{p_{j'}}^{\text{geo}}$ are respectively the negative embeddings from $\Theta_n^{\text{cat}}$ and $\Theta_n^{\text{geo}}$, $N_1 = N_2$ are the numbers of negative samples from each of the models, and $f_{\text{comb}}(\cdot, \cdot)$ is the function of pairwise similarity implemented as the bilinear network below:

$$f_{\text{comb}}(e_{p_i}^{\text{geo}}, e_{p_i}^{\text{cat}}) = \sigma(e_{p_i}^{\text{geo}}^T W_{\text{comb}} e_{p_i}^{\text{cat}}),$$

(21)

where $W_{\text{comb}}$ is a learnable parameter matrix. Once the fine-tuning of both enhanced models is finished by minimizing $L_{\text{comb}}$, we further average the two fine-tuned models to get the final personalized model:

$$\Theta_u \leftarrow \left(\Theta_u^{\text{geo}} + \Theta_u^{\text{cat}}\right) / 2.$$  

(22)

To achieve the above process, users must collect model weights of their neighbors, which may lead to privacy breaches. To this end, users only share their perturbed weights. Similar to the strategy when sharing centroids and category distributions, we propose to inject noise satisfying Laplace distribution into model weights. During model weights exchange, the sensitivity of the model weights is $2\eta N_{\text{pos}}$, where $\eta$ is the absolute difference between the largest and smallest weights of the model $\Theta_u$, and $N_{\text{pos}}$ is the number of positive samples used to train the model [45]. Thus, for each user, we inject noise satisfying $\text{Lap}\left(\frac{2\eta}{N_{\text{pos}}\epsilon}\right)$ to the model weights before transmitting them to neighboring user devices.

3.5 Learning Personalized Next POI Recommendation Model with DCLR

The implementation of DCLR is described in Algorithm 1. Starting from the server side, lines 1–5 initialize the recommender and pretrain POI representations with two self-supervised learning signals. With perturbed centroid and category preferences received from all user devices (line 6), the server calculates the geographical distance matrix and categorical distance matrix via lines 7–8, then sends the neighbor information to all users (line 9). The server’s engagement in the decentralized learning ends from here. Back to the user’s side, after obtaining the pretrained POI embeddings (lines 10–12), we record the updated user model parameters as $\Theta_n$ in every training epoch (lines 14–16). Then, in lines 17–22, $\Theta_n$ is enhanced by the models of geographically and semantically similar users, which will undergo a mutual information maximization step and be
We now analyze the communication and computation complexities of Algorithm 1. Recall that $q$ denotes the neighbor size for both geographical and semantic neighbors, $|P|$ denotes the number of POIs, and $M$ denotes the maximum number of check-in activities. Besides, we use $E$ to denote the maximum number of epochs.

**Communication Complexity.** Before the training process, each user needs to upload their centroid $O(u_n)$ and category preferences $CP(u_n)$ to the server. After that, each user needs to receive the pretrained model $\Theta$, geographical neighbor ids $N_{geo}(u_n)$, and semantic neighbor ids $N_{cat}(u_n)$ from the server. During the training process, for each epoch, each user needs to collect $2q$ models from two types of neighbors. Simultaneously, each user needs to send out their model a certain number of times. The average times of sending out are $2q$ as the number of models collected should be the same as the number of models sent out. Thus, the total communication complexity of each user is $(4q + 1) \times \Theta + O(u_n) + CP(u_n) + N_{geo}(u_n) + N_{cat}(u_n)$. The size of $\Theta$ is much larger than the sizes of $O(u_n)$, $CP(u_n)$, $N_{geo}(u_n)$, and $N_{cat}(u_n)$, and the most important component of $\Theta$ is POI embeddings. Thus, the total communication complexity for each user is linear with the POI set size $|P|$.
### Computation Complexity
Since the parameter pretraining in DCLR is a one-off process performed on the server, we only analyze the computation complexity of the training process on-device. For each epoch, the computation cost mainly relies on two parts including local model optimization with personal trajectory and model enhancement via learning knowledge from neighbors. For local model optimization, the time complexity is $M$ since $M - 2$ check-ins are used for training. For model enhancement, the first step is to obtain two enhanced models by aggregating models from two types of neighbors, and the time complexity is $2q$. The second step is to combine the two enhanced models by MIM, and the time complexity is $|P|$ since each POI embedding is a training sample. Thus, the total computation complexity of each user is $E(M + 2q + |P|)$. Since $M$ and $|P|$ are relatively larger than $q$, the total computation complexity of each user mainly depends on the number of training samples on-device and the POI set size.

The above complexity analysis shows that DCLR is efficient and can be scaled to very large datasets.

### 4 EXPERIMENTS
In this section, we evaluate the recommendation performance of DCLR in POI recommendation w.r.t. state-of-the-art baselines. All experiments are processed on the computer equipped with Intel (R) Core i7-10700K CPU, 3.80GHz and one NVIDIA’s GeForce RTX 2070, 8GB Graphics Card.

#### 4.1 Datasets and Evaluation Protocols
We evaluate our proposed DCLR on two publicly available real-world Location-Based Social Network datasets: Weeplace \[28\] and Yelp \[9\]. Both datasets contain user check-ins in the cities of New York, Los Angeles, and Chicago. Inspired by previous works \[2, 22\], we remove users with fewer than 10 check-ins for both datasets, as well as POIs that have fewer than 10 visits. Table 1 summarizes the statistics of the two datasets.

For evaluation, we adopt the leave-one-out protocol, which is widely used in previous work \[42, 43\]. That is, for each check-in sequence, we use the last check-in POI for test, the second to last POI for validation, and the remaining for training. The maximum sequence length is set to 200. The most recent 200 check-ins will be used in the evaluation if the sequence length is larger than 200. For each ground truth, we pair it with 200 unvisited POIs as the candidates for ranking. Those 200 POIs are the closest ones to the user’s last check-in location. Note that, different from ranking e-commerce products \[20, 35\], our evaluation is based on the location-sensitive nature of POI recommendation tasks, as a user rarely travels long distances between two consecutive check-ins. Then, the local recommendation model generates a ranked list for those 201 POIs based on their scores, and the ground truth is expected to be ranked at the top. Then, we adopt Hit Ratio at Rank $k$ (HR@$k$) and Normalized Discounted Cumulative Gain at Rank $k$ (NDCG@$k$) \[46\] to measure the recommendation on the top-$k$ POIs in the ranking list, where HR@$k$ calculates the times that the ground truth is among the top-$k$ list, while NDCG@$k$ further considers the ground truth’s position in the top-$k$ list.

#### Table 1. Dataset Statistics

|          | Weeplace | Yelp |
|----------|----------|------|
| #users   | 4,504    | 6,070|
| #POIs    | 35,675   | 46,527|
| #categories | 450   | 428  |
| #check-ins | 886,408 | 951,832|
| #check-ins per user | 196.80 | 156.81|
4.2 Baseline Methods

We compare DCLR with the following baseline methods, including both centralized POI recommenders and state-of-the-art on-device ones:

- **POP** is a simple method that ranks the POIs based on their popularity.
- **DIS** is a basic method for POI recommendation that ranks the POIs based on their distances to the user’s historical check-in POIs.
- **MF [25]** is a classic collaborative filtering algorithm for centralized POI recommender systems.
- **LSTM [15]** is a recurrent neural network that has shown its ability to capture both short-term and long-term dependencies in sequential data. Thus, LSTM is naturally applied to solve the next POI recommendation problem.
- **STAN [31]** is a state-of-the-art model that explicitly exploits relative spatiotemporal information of both consecutive and non-consecutive check-in activities. It proposes a bi-attention architecture for personalized item frequency where the first layer aggregates spatiotemporal information and the second layer matches the target to all check-ins.
- **DMF [3]** is a decentralized MF framework. To overcome the data sparsity issues, on-device models learn knowledge from neighbors who are physically close to the current user decided by the random walk theory.
- **LLRec [40]** is an on-device framework that adopts the teacher-student training strategy. It trains a teacher RNN-based model with public data on the cloud and sends the compressed model to the end devices for local model training. In this way, end devices keep private check-in data without exposure to the cloud and the simplified model significantly reduces the computation burden for end devices.
- **PREFER [13]** is a federated learning framework for next POI recommendation. First, users train personalized models locally with their individual check-in data in parallel. After that, the edge services collect and aggregate multi-dimensional user-independent parameters to build a federated POI recommendation model. Then, the federated model is sent back to users.

For DCLR’s hyperparameters, we set the latent dimension $d = 32$, the neighbor size $q = 30$ for both geographical and semantic neighbors, the tradeoff between the current model and aggregated model of neighbors $\mu = 0.3$ for both geographical and semantic neighbors, and the privacy budget $\epsilon = 0.1$. The impacts of the above hyperparameters will be further discussed in Section 4.5. During training, we adopt a learning rate of 0.002, dropout of 0.2 on all deep layers, and batch size of 16, and the maximum training epoch is set to 50. In addition, the numbers of negative samples for POI prediction loss ($N_{neg}$), category prediction LOSS ($N_{CP}$), and combination loss ($N_1 = N_2$) are set to 5. For all baselines, we adopt the same general hyperparameters including latent dimension, learning rate, dropout, batch size, and the maximum training epoch.

4.3 Recommendation Performance

Table 2 summarizes the experimental results on recommendation effectiveness. From such results, we have the following observations. Among the centralized POI recommendation, POP and DIS have poor performance on both datasets since they cannot capture users’ preferences. After that, the fact that LSTM outperforms MF shows LSTM’s ability to capture both short-term and long-term dependencies on next POI recommendation. In addition, thanks to the effective use of spatiotemporal information of both consecutive and non-consecutive check-in activities, STAN shows higher accuracy than LSTM. Compared to the advanced centralized baseline STAN, our proposed model also has competitive performance. Intuitively, on Weeplace, DCLR achieves light improvements...
over STAN (1% on average for all metrics). On Yelp, DCLR outperforms STAN by 5% to 8% on all metrics. For this result, a possible reason is that STAN is trained with check-ins across three different cities where the information learned from other cities might be noisy, leading to inferior performance of STAN. With this observation, we further show the effectiveness of DCLR as users under DCLR only exchange knowledge with similar users without overfitting the noise from dissimilar users. On this basis, for Yelp, we train and test three STAN models separately with check-ins from each of the three cities in the dataset. Then, we compare their test results with DCLR’s performance over three cities separately. It is worth noting that DCLR is trained with the whole Yelp dataset and personalized models can still exchange knowledge with semantic neighbors from the other two cities. In addition, we also evaluate the performance of STAN when a unified model is trained over three cities. The results are shown in Table 3, where we can observe noticeable performance improvements for all cities if three STAN models are trained separately rather than only one STAN model being used, which proves the above assumption. Even so, DCLR outperforms city-specific STAN models by 2%, 4%, and 3% in New York, Los Angeles, and Chicago, respectively. This is because DCLR can achieve better personalization and learn more expressive models with the collaborative learning architecture. Considering that DCLR significantly reduces the dependency on the cloud server and the risk of privacy breaches, the above results have demonstrated the effectiveness of our proposed method.

In addition, our method consistently and significantly outperforms all three on-device POI recommendation models in terms of every metric on both datasets. In detail, our work shows the advantage against a decentralized matrix factorization framework (DMF) by an obvious margin, where the improvement achieves 147% on average for all metrics. This is because our work exploits multiple components to handle the data sparsity issues. First, we propose two self-supervised learning objectives to inject geographical and categorical information into POI representations. Then, we propose an effective way to learn knowledge from two types of neighbors, while DMF only learns knowledge from geographical neighbors. Furthermore, our proposed model outperforms LLRec by 10% on average for all metrics. To completely protect users’ privacy, LLRec does not
allow any form of personal information to leave users’ devices. Instead, our proposed method is able to bring a large improvement on the recommendation quality with negligible privacy risks given the information shared and the differential privacy guarantee. Meanwhile, both the teacher model and the compressed model are trained on the cloud, showing high demand of on-cloud computing and storage resources. Thus, DCLR has shown its advantages over LLRec. Compared to PREFFER, our work has a noticeable advantage on recommendation accuracy. In addition, PREFFER needs to collect and aggregate users’ personalized models, exposing user privacy to potential breaches. Therefore, DCLR is more capable than PREFFER since it can provide both stronger privacy protection and more accurate recommendations with less reliance on the cloud server.

4.4 Ablation Study

To better understand the performance gain from various components of our methods, we conduct an ablation study on different degraded versions of DCLR. Table 4 summarizes the results. We denote the full model as DCLR and drop different components as variants. In what follows, we introduce all variants and discuss the effectiveness of responding model components.

**Remove Category Prediction Loss (CP).** In DCLR, we exploit category prediction loss and distance prediction loss to infuse categorical and geographical information into POI representations. To testify to the usefulness of category prediction loss, we remove category prediction loss and use only distance prediction loss to enhance POI representations. As a result, we observe performance drops (6% on average for all metrics) for both datasets. This is because users’ interactions at the category level are relatively denser compared to the POI level, helping the model capture the preferences on POIs.

**Remove Distance Prediction Loss (DP).** To evaluate the effectiveness of distance prediction loss, we remove distance prediction loss and use only category prediction loss to enhance POI representations. Consequently, there is a noticeable decrease in recommendation performance (9% on average for all metrics) for both datasets. Hence, the inclusion of distance prediction loss is necessary since it can help to capture transformation rules among sequential check-in activities. In addition, representative POI embeddings with categorical and geographical information are necessary for personal models to exchange knowledge from neighbors with highly relevant patterns. As such, the two self-supervised losses have shown their strong effectiveness to improve the recommendation quality.

**Remove All Neighbors (AN).** The crucial component of DCLR is allowing users to exchange knowledge with two types of neighbors, which is supposed to address the data sparsity issues caused by the fact that all personalized models are trained locally with individual check-in data.

We mark DCLR’s performance with boldface numbers.

|        | Weeplace |       | Yelp |       |
|--------|----------|-------|------|-------|
|        | HR@5    | NDCG@5| HR@10| NDCG@10| HR@5    | NDCG@5| HR@10| NDCG@10|
| DCLR   | 0.4452  | 0.3083| 0.5569| 0.3861| 0.4388  | 0.3031| 0.5466| 0.3794 |
| -CP    | 0.4247  | 0.2898| 0.5253| 0.3584| 0.4179  | 0.2821| 0.5139| 0.3593 |
| -DP    | 0.4119  | 0.2801| 0.5027| 0.3498| 0.4035  | 0.2700| 0.4951| 0.3433 |
| -AN    | 0.2819  | 0.1948| 0.3183| 0.2450| 0.2632  | 0.1858| 0.3491| 0.2252 |
| -GN    | 0.3432  | 0.2430| 0.3959| 0.3033| 0.3289  | 0.2242| 0.4282| 0.2746 |
| -SN    | 0.3743  | 0.2558| 0.4135| 0.3199| 0.3401  | 0.2426| 0.4534| 0.2979 |
| -MIM   | 0.4164  | 0.2829| 0.5251| 0.3741| 0.3896  | 0.2724| 0.5123| 0.3597 |
| -PP    | 0.4618  | 0.3214| 0.5746| 0.4059| 0.4400  | 0.3074| 0.5648| 0.3878 |

In Table 4, we list the results of the ablation study. The performance of each degradation is compared to the full model DCLR. The results show that each component is crucial to the recommendation quality, and their removal leads to a noticeable decrease in performance.
To verify its efficacy, we remove the neighbor-based aggregation for both types of neighbors, and each user learns a single local recommendation model with his/her own data. Consequently, the collaborative learning component and privacy protection are also removed. The resulting variant model has experienced serious performance drops (39% on average for all metrics) for both datasets. Among all components of DCLR, the performance drops of removing all neighbors are the most significant. Such results have shown that our strategy of exchanging knowledge with both types of neighbors can effectively handle the data sparsity issues in the decentralized environment. Meanwhile, this strategy also avoids learning biased information from irrelevant users.

**Remove Geographical Neighbors (GN).** Although the combination of both types of neighbors has proven its effectiveness, we are still interested in the performance gain from the single neighbor type. To testify to the effectiveness of geographical neighbors, we only allow local models to exchange knowledge with semantic neighbors, and thus, we don’t need to combine knowledge of two types of neighbors via mutual information maximization. As a consequence, significant performance drops (24% on average for all metrics) for both datasets are observed, showing the effectiveness of exchanging knowledge with geographical neighbors.

**Remove Semantic Neighbors (SN).** To verify the usefulness of semantic neighbors, we only allow local models to learn knowledge from geographical neighbors. Similarly, mutual information maximization for aggregating knowledge from two types of neighbor is removed. Accordingly, we observe obvious performance drops (20% on average for all metrics) from both datasets. As such, the knowledge learned from semantic neighbors is indispensable for addressing the data sparsity issues. In addition, considering the performance of removing geographical neighbors, it can be proven that geographical neighbors can provide more valuable information compared with semantic neighbors. Besides, as mentioned above, distance prediction is a more influential self-supervised task compared with category prediction. Thus, we can conclude that, in POI recommendation, although semantic factors significantly affect the recommendation performance, geographical factors do play more important roles. On this basis, in future research and deployment of decentralized POI recommendation systems, resources can be slightly skewed to geographical factors (e.g., assigning more geographical neighbors).

**Remove Mutual Information Maximization (MIM).** Given two enhanced models learned separately from two types of neighbors with the attention mechanism, we design a mutual information maximization task to further combine these enhanced models into a fully personalized local model. To verify the effectiveness of this task, we simply use the average method rather than MIM to combine the two enhanced models. As a consequence, we observe a noticeable decrease of recommendation performance (7% on average for all metrics) for both datasets. Thus, the inclusion of MIM is important to the information fusion of two different types of neighbors.

However, the MIM process is fully performed on-device and high computational overhead might crash the devices. To verify whether the computational overhead added is reasonable for low-power devices, we record the training time where MIM is not included and MIM is included. Please note the time is the average time per user per epoch. The results are shown in Figure 2. We can observe significant increases of training time if MIM is included. This is because all POI embeddings are updated during the MIM process. However, the MIM component is able to significantly improve each local model’s recommendation accuracy with only around 6 seconds’ time added to the aggregation step on top of its plain counterpart without MIM. Furthermore, as MIM is performed during the model aggregation, this does not affect the inference time of the final model.

**Remove Privacy Protection (PP).** In DCLR, we exploit a differential privacy mechanism to avoid privacy breaches during the processes of neighbor identification and communication. To measure the influence of the differential privacy mechanism on the performance of DCLR, we remove the privacy protection. After that, the performance is slightly improved by 3% on average
forallmetricsandbothdatasets. This reflectsthatourmodelcanprovidestrongprivacyprotection with only a little sacrifice in recommendation quality.

4.5 Hyperparameter Sensitivity

In this section, we investigate the performance fluctuations of our proposed DCLR with varying hyperparameters including the latent dimension $d$, the neighbor size $q$ used for both geographical and semantic neighbors, the trade-off between the current model and the aggregated model $\mu$ in Equation (19), and the privacy budget $\epsilon$. The results are shown in Figure 3.

**Impact of $d$.** First, we study the impact of the latent dimension $d \in \{8, 16, 32, 64, 128\}$. As $d$ increases from 8 to 32, significant improvements of DCLR’s performance are observed for both datasets. However, when $d$ is larger than 32, the performance starts to decrease. A possible reason is that, in DCLR, personalized models are trained with limited data, and larger dimension might cause overfitting problems.

**Impact of $q$.** Then, we experiment on a series of neighbor sizes $q \in \{15, 30, 50, 70\}$. Generally, DCLR benefits from larger $q$ on both datasets. However, the performance growth tends to slow down when $q$ is large enough (50 and 70). In addition, the drop of accuracy (Weeplace) also can be observed. The reason is that neighbors who have larger geographical distances and smaller categorical preference similarities contain biased information. Moreover, the increase of $q$ also leads to huge computing resources. Thus, the neighbor size should be controlled within a reasonable range.

**Impact of $\mu$.** $\mu$ is a hyperparameter that controls the proportion of the current model and the aggregated model. The value of $\mu$ is examined in $\mu \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. On Weeplace, DCLR achieves the best performance when $\mu = 0.3$. However, on Yelp, DCLR achieves the best performance when $\mu = 0.5$. This is because the users of the Yelp dataset have fewer check-in activities, leading to more serious data sparsity problems. Hence, more information from the neighbors will greatly help improve the performance of the final local models.
Impact of $\epsilon$. $\epsilon$ is the privacy budget that controls the amount of noise added to centroids, category distributions, and model weights. The higher $\epsilon$ is, the less noise is added. We evaluate the impact of different privacy budgets $\epsilon \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. As the privacy budget increases from 0.1 to 0.9, there is generally an upward trend in DCLR’s performance, but the improvement tends to stop when $\epsilon$ is larger than 0.5. The reason is that when $\epsilon$ is relative large, the limited amount of noise will have minor side effects on the recommendation accuracy. But meanwhile, a lower noise injection will be less effective in protecting users’ privacy. In addition, the noise added to model weights can be regarded as the regularization term, which can effectively prevent overfitting. Hence, by default, $\epsilon$ is set to 0.1, which can provide strong privacy protection with acceptable sacrifice of accuracy.

4.6 Effect of Neighbor Sizes on Convergence Speed

In decentralized machine learning, convergence speed is a crucial performance metric, as it determines the efficiency of the model deployment, as well as the ability to ensure timeliness when processing new data. In this work, we further evaluate the convergence speed on various neighbor
sizes $q \in \{15, 30, 50, 70\}$ by displaying the average training loss on iteration number. The results are shown in Figure 4. The first observation is that, among all neighbor sizes, the convergence speed of DCLR on Weeplace is faster than that of Yelp, as Weeplace data is relatively denser compared to Yelp. Second, when the neighbor size is increased from 15 to 30, the convergence speeds have experienced a noticeable rise. This is because, with more neighbors, personalized models can obtain richer information to capture users’ preferences more quickly. However, as the neighbor size continues to rise, the quality of neighbors become worse since those neighbors have larger geographical distances and smaller categorical preference similarities. Thus, knowledge learned from such neighbors is biased, which reduces the efficiency of learning users’ preferences. As a result, with the increase of neighbor size, the convergence speed increases at first. Then, the convergence will gradually slow down as the neighbor size continues to increase further.

5 RELATED WORK
In this section, we review recent literature on related areas including POI recommendation and decentralized learning.
5.1 Next POI Recommendation

Similar to traditional item recommenders, early POI recommender systems exploit the collaborative filtering technique to capture the correlations among users, POIs, and contextual features [5, 25]. Intuitively, GeoMF [25] captures the spatial clustering phenomenon in terms of two-dimensional kernel density estimation by augmenting users’ and POIs’ latent factors in the factorization model with activity area vectors of users and influence area vectors of POIs, respectively. FPMC-LR [5] extends the learning of latent features to personalized Markov chains and the localized regions. As a result, it can exploit the personalized Markov chain in the check-in sequences and takes into account users’ movement constraints.

Recent POI recommendation models are mainly based on RNNs and their variants, which achieve state-of-the-art performance. To improve model performance, ST-RNN [27] models local temporal and spatial contexts in each layer with time-specific transition matrices for different time intervals and distance-specific transition matrices for different geographical distances. SERM [47] combines spatiotemporal information and semantic contexts (e.g., keywords and categorical tags) to reflect user preferences and effectively captures semantics-aware spatiotemporal transition regularities to improve POI prediction accuracies. However, the above RNN models ignore long-term dependencies within the check-in trajectories. To solve this problem, DeepMove [10] first uses a recurrent layer to learn short-term sequential regularity from highly correlated trajectories, and then combines it with long-term periodicity learned by an attention layer. STGN [53] adds time and distance gates to the standard LSTM for better capturing short-term and long-term spatiotemporal preference. To further improve the performance of LSTM, ARNN [12] models both the sequential regularity and transition regularities of similar POIs to build the knowledge graph.

Inspired by sequential item recommendation [18], GeoSAN [24] utilizes self-attention to capture user preference with point-to-point interactions among the trajectory. To make use of correlations of non-adjacent POIs and non-consecutive check-ins, STAN [31] uses a bi-layer attention architecture, where the first layer aggregates spatiotemporal correlations within the trajectory and the second layer recalls the target with consideration of personalized item frequency (PIF).

Nevertheless, all the above methods are trained and deployed on cloud services, causing significant problems including huge cost of resources, privacy issues, and high demand of powerful networks. Instead, our proposed DCLR deploys personalized models on mobile devices, which can stably provide accurate and secure POI recommendations.

5.2 On-device Frameworks for Next POI Recommendation

On-device frameworks appear to overcome most shortcomings of centralized learning and have been applied to many areas such as multiarmed bandit [17], network distance prediction [26], hash function learning [21], and health analysis [48]. There are also multiple works to deploy on-device POI recommendation models. First, Chen et al. [3] proposed a DMF for next POI recommendation, where personalized models are trained and stored locally. To improve the recommendation precision, DMF exchanges knowledge with neighbors who are physically close to the current user. Then, Wang et al. [40] deployed compressed models on mobile devices for secure and stable POI recommendations. To maintain the robustness of the whole on-device framework, local compressed models inherit the knowledge from the teacher model, which is trained with public data. Nevertheless, all users share the same model trained with the public data, ignoring the dynamics and diversity of users’ spatial activities and interests. Instead, our proposed work allows users to obtain high-quality, fully personalized local recommenders by collaboratively learning knowledge with other similar users. In addition, Guo et al. [13] proposed a federated learning framework for next POI recommendation. That is, personalized models are trained and stored locally. Then, the edge
servers collect and aggregate all personalized models. After that, the aggregated model is sent back to all users. Consequently, the federated framework is still resource intensive for storage and computation. Besides, all users in the federated framework also share the same global model. However, in our proposed work, the central server is only responsible for providing pretrained parameters and grouping similar users in a secure way, and local models are fully personalized via an efficient collaborative learning strategy.

The most similar work to ours is the decentralized matrix factorization for next POI recommendation [3]. We summarize two major differences: (1) To alleviate the sparsity issues, we propose two self-supervised learning objectives to enhance POI representations with geographical coordinates and categorical tags. Specifically, the first task is to create correlations between POIs and their associated categorical tags by mutual information maximization, and the second is to learn and predict geographical distances between POIs. (2) Their personalized models are enhanced by knowledge from users who are physically close to the current user. However, such limited knowledge cannot effectively address the data sparsity problem. On the contrary, we propose two types of neighbors based on geographical distances and categorical preference similarities. Then, we design a mutual information maximization task to jointly learn and combine knowledge from both types of neighbors in an effective way.

6 CONCLUSION

Advanced performance of current next POI recommenders is highly dependent on the collection, storage, and training, which involve massive check-in data, leading to problems including huge cost of computing resources, privacy issues, and high demand of network connectivity. In our article, the proposed solution DCLR is a decentralized paradigm that locally trains personalized recommenders for all users. To address the data sparsity issues, we first design two self-supervised signals to enhance POI representations with coordinate information and categorical tags. Then, for decentralized collaborative learning, we define two metrics to identify neighbors concerning geographical distances and categorical preference similarities. Finally, we exploit attention mechanism and mutual information maximization technology to jointly learn and combine knowledge from both types of neighbors. We evaluate the proposed DCLR with two real-world datasets. The experimental results have demonstrated our model’s superiority in next POI recommendation. This is because, compared to state-of-the-art POI recommenders, it can provide more accurate personalized POI recommendations and stronger privacy protection with less reliance on the cloud server. Through the ablation study and sensitivity analysis, we also show the significant effect of the two self-supervised learning tasks, the strategies for neighbor identification and communication, and the privacy protection mechanism in addressing data sparsity issues and providing privacy protection. Future work can include the fusion of social relationships for neighbor identification, and dynamic addition and removal of users with respect to timestamps.

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