Fast-adapting and Privacy-preserving Federated Recommender System

Qinyong Wang\textsuperscript{1} · Hongzhi Yin\textsuperscript{1,*} · Tong Chen\textsuperscript{1} · Junliang Yu\textsuperscript{1} · Alexander Zhou\textsuperscript{2} · Xiangliang Zhang\textsuperscript{3}

Abstract In the mobile Internet era, recommender systems have become an irreplaceable tool to help users discover useful items, thus alleviating the information overload problem. Recent research on deep neural network (DNN)-based recommender systems have made significant progress in improving prediction accuracy, largely attributed to the widely accessible large-scale user data. Such data is commonly collected from users’ personal devices, and then centrally stored in the cloud server to facilitate model training. However, with the rising public concerns on user privacy leakage in online platforms, online users are becoming increasingly anxious over abuses of user privacy. Therefore, it is urgent and beneficial to develop a recommender system that can achieve both high prediction accuracy and strong privacy protection.

To this end, we propose a DNN-based recommendation model called PrivRec running on the decentralized federated learning (FL) environment, which ensures that a user’s data is fully retained on her/his personal device while contributing to training an accurate model. On the other hand, to better embrace the data heterogeneity (e.g., users’ data vary in scale and quality significantly) in FL, we innovatively introduce a first-order meta-learning method that enables fast on-device personalization with only a few data points. Furthermore, to defend against potential malicious participants that pose serious security threat to other users, we further develop a user-level differentially private model, namely DP-PrivRec, so attackers are unable to identify any arbitrary user from the trained model. Finally, we conduct extensive experiments on two large-scale datasets in a simulated FL environment, and the results validate the superiority of both PrivRec and DP-PrivRec.

Keywords Recommender System · Federated Learning · Meta Learning

1 Introduction

With the immense popularity of mobile phones, users can gain access to a large number of online content and services with only one click, such as news, e-commerce, movies and music. However, it has also become difficult for users to accurately find information relevant to their interests. Therefore, recommender systems have become an essential tool for alleviating such information overload by automatically generating a recommendation list based on a user’s preference.
Meanwhile, the past decade has seen the enormous advancement of deep neural network (DNN)-based recommender systems [52], which are able to achieve superior performance in terms of many aspects compared to conventional models. On the other hand, it is well-known that the overwhelming performance of DNN-based models is largely attributed to the increased access to large-scale training data. Such recommender systems are usually deployed on a cloud server to acquire the sufficient resource for data storage and efficient training, which then provides services to connected users in an on-demand manner. This means that they require to collect users’ behavioral data (e.g., browsing history) and then centrally store it in the service providers’ central servers. Unfortunately, this centralized recommendation paradigm inevitably leads to increasing concerns on user privacy as user data stored on the server might be accidentally leaked or misused. Even though the data sent to the server can be anonymized, users’ information can still be identified when linked with other data sources [13].

Therefore, it is important and desirable to offer a privacy-by-design solution where the recommendation service providers do not need to access personal data, while still building robust and accurate recommendation models. Over the past decade, the capacities of storage and computation increase dramatically on personal devices (e.g., smart phones and laptops), making it possible to distribute the resource-intensive model training process from the server to edge devices owned by users. In this regard, federated learning (FL) [19, 13] has emerged as a popular framework in the development of privacy-preserving machine learning systems. Training an FL model consists of several key steps. First, the server selects a batch of available devices and sends them the current global model. Then, based on locally stored user data, each device computes the gradients w.r.t. an objective function of the model. Finally, the central system aggregates the gradients from different devices in order to update the global model. These training steps are iterated until the global model converges. Each user’s data is fully kept on her/his personal device in the FL setting and thus they retain control over his/her own data.

Motivated by the idea of FL, there have been some attempts [51, 19, 37] to facilitate privacy-preserving recommendation but they ignore two important problems in real-world scenarios, which are data heterogeneity and malicious participants. In this paper, to address both challenges in a unified way, we propose two DNN-based recommender systems that smoothly run in the FL setting, namely PrivRec and the more secure DP-PrivRec enhanced by differential privacy. In what follows, we elaborate on these two challenges and our corresponding solutions.

**Data Heterogeneity.** It is common that users have highly different personal preferences when consuming online products. Hence, the data heterogeneity problem arises in FL-based recommenders where the local data generated by different users vary significantly in both distribution and scale. This problem will be exacerbated for recommendation models due to two reasons. First, frequent users have far more interaction records with items than other inactive (e.g., new or cold-start) users. Therefore, in a typical FL setting, straightforwardly minimizing the average loss for all users will mostly advantage the recommendation performance for active users while the inactive users’ preferences can be hardly estimated. On this occasion, the ultimate recommendation model is clearly unfair for a huge number of users due to biased service quality. Second, the difficulty in achieving optimal personalization also arises with data heterogeneity. Existing FL-based recommendation paradigms are only designed to let all devices contribute to a global model, hence the final model is only good on average recommendation accuracy. Since they do not account for the heterogeneity of data distribution among users, there is no guarantee that the global model is fully customized for every user, impeding the delivery of personalized recommendations.

In light of this, we resort to the notion of meta-learning [12] as a natural solution to address the data heterogeneity problem in the FL setting. Meta learning was originally proposed to quickly adapt the global model to a new task (a user in our case) using only a few data points. In a similar vein, some methods [5, 10] utilize the recently proposed Model-Agnostic Meta-Learning (MAML) [11] to enable an FL recommender to achieve fast on-device personalization with only a small amount of user-generated data. However, inheriting the drawbacks of MAML, these methods incur huge computational cost when computing the second-order gradients, which is unbearable for the resource-constrained edge devices. Furthermore, they require to divide the local data into support and query sets for the two-stage training, which is impractical for users with a highly limited number of interaction records. Hence, in this paper, we propose to use only the approximated first-order gradient for meta-learning (i.e., REPTILE [31]), thus reducing computational burden while maintaining a comparable performance. Also no data splitting is required in our approach, making the model a better fit for both active and inactive users and easier to run in the FL environment. Furthermore, we add a proximal term in the local learning objective function, which effectively caps the contribution of a
single client. By doing so, we can ensure the fairness and accuracy of the final model for every user regardless of the amount of data she/he holds.

We term this novel DNN-based FL recommender system coupled with the first-order meta-learning as PrivRec.

**Malicious Participants.** We show that PrivRec can effectively prevent it from sharing each users’ sensitive data with the central server while training an accurate model. However, in an open Internet environment, it is insufficient to protect sensitive user data by simply decoupling the model training process from the need for direct access to the raw user data. More specifically, the unique settings of FL would increase the risk of privacy leakage by unintentionally allowing malicious clients to participate in the training. In [29], it is shown that a curious client in FL can infer not only membership (the presence of exact data points in other participants’ training data), but also properties that characterize subsets of the data (e.g., sensitive user attributes). Nasr et al. [30] comprehensively explore membership inference on gradient parameters, including an analysis in an FL setting. Orekondy et al. [33] show that clients can be identified in an FL setting by model updates alone.

Therefore, it is necessary to take further defensive measures so that the participating adversaries are unable to infer from the trained model whether a client has joined the decentralized training (i.e., membership inference). We present DP-PrivRec, an extension of PrivRec, to strengthen our FL-based recommender with differential privacy (DP) [1,7,8]. DP is a well-established method to defend against such attacks, whose basic idea is adding additional noise to ensure that the published information does not vary much whether one individual is present or not. In this way, the attackers cannot infer the private information of any user with high confidence, as no user significantly affects the final output.

The pipeline of running our proposed DP-PrivRec is briefly shown in Figure 1. Instead of only protecting a single data point like in conventional DP mechanisms, DP-PrivRec enforces differential privacy at the entire user level, which is more suited to FL-based recommenders as each user’s published information is actually their gradient computed with the entire local dataset. To achieve this, we employ the Gaussian mechanism [7] to perturb the gradients which are sent from the FL clients to the central server, so that the resulting recommender model satisfies a given privacy budget. In addition, we introduce a novel approach that learns to adaptively clip a client’s gradient, which controls the contribution of each client, during training. As such, we can effectively bypass the need for setting such gradient clipping bounds with heavy human supervision and abundant task-specific knowledge.

We highlight our contributions below:

- We develop a privacy-preserving recommendation model called PrivRec based on FL. Apart from preventing users from sharing their own data for model training, we propose an efficient and practical meta-learning approach to enable PrivRec to quickly adapt to inactive users, alleviating the critical data heterogeneity problem for existing FL-based recommenders.
- To defend against the malicious participants who may conduct membership inference attacks on the trained model, we further propose DP-PrivRec with a user-level differential privacy mechanism. We also introduce a learnable gradient clipping bound to adaptively adjust each user’s importance during model optimization.
- We perform extensive experiments to validate the effectiveness of our proposed models and results show that PrivRec and DP-PrivRec achieve superior performance over the state-of-the-art baselines.

The rest of this paper is organized as follows. Section 2 details our proposed methodologies, Section 3 introduces the experimental settings, Section 4 presents the experimental results, Section 5 reviews related work and finally Section 6 concludes this paper.

### 2 Methodologies

In this section, we describe our proposed privacy-preserving PrivRec and DP-PrivRec models in detail.
2.1 PrivRec in the Federated Learning Setting

The federated learning (FL) framework aims to train a shared global model with a central server from decentralized data spanning over a large number of different clients. In recommendation tasks, examples of such clients include personal devices like smartphones, wearable devices, computers, etc. Machine learning algorithms designed for FL commonly solve the optimization problem by multiple training rounds, where at each round the central server sends the current model to a fraction of the users for the next round of training. In this way, a model that solves the optimization problem is obtained, which in theory performs well on average over a model that solves the optimization problem by multiple training rounds, where at each round the central server sends the current model to a fraction of the users and those users update the model w.r.t. their own loss functions. Then, these users return their model updates to the central server that combines the received updates to optimize the global model and then sends the updated model to another fraction of the users for the next round of training. In this way, a model that solves the optimization problem is obtained, which in theory performs well on average over all clients. One core advantage of FL is that users’ data can safely reside on their own devices, making it an attractive and popular learning paradigm for building a recommender system by viewing each user’s personal device as a client.

Though deep neural networks (DNNs) dominate contemporary recommender systems with promising performance, directly deploying them in the FL setting can still lead to serious privacy disclosure. This is because they usually train a user/item embedding matrix to store the user preference/item features, whose entries are uniquely identifiable to users/items (i.e., the use of user/item IDs). Consequently, the embedding matrices are also sent to selected clients to facilitate training in FL. Once there exists a malicious participating client, they can obtain any user’s embedding, from which a user’s personal preferences and attributes can be easily inferred.

To avoid the dependency of user and item identities for modelling, we instead take only features related to users (e.g., age and occupation) and items (e.g., genre and textual description) as the input. Specifically, we learn a unique embedding for each categorical feature like gender, and for numerical features such as ages, raw values are used. These embeddings and numerical values are concatenated as a single embedding to act as the user and item representations, which are denoted as and respectively. Then, the paired user and item embeddings are fed into a multi-layer neural network, which models the user-item interactions. The output can be either an explicit rating or implicit feedback, and is a pairwise user-item score indicating the willingness of user to interact with item . This feed-forward process is formulated as:

\[
\begin{align*}
x_0 &= [U; V], \\
x_i &= ReLU \left( W_i x_0 + b_i \right), \\
&\vdots \\
x_N &= ReLU \left( W_N x_{N-1} + b_N \right), \\
\hat{Y}_{uv} &= f \left( W_o x_N + b_o \right),
\end{align*}
\]

where \( W_i \) and \( b_i \) are the weight and bias for the \( i \)-th hidden network layer, and \( W_o \) and \( b_o \) are the weight and bias for the output layer. \( \hat{Y}_{uv} \) is user \( u \)'s estimated preference for item \( v \). \( ReLU() \) denotes the rectified linear unit activation function for the hidden layers and \( f() \) is the activation function of the output layer, which depends on how user preferences are modeled. For example, Sigmoid function can be used for implicit feedback and a linear function can be considered for rating prediction.

Taking the implicit feedback as an example, we adopt the cross-entropy function to measure the training loss:

\[
\mathcal{L} = \sum_{(u,v) \in Y^+ \cup Y^-} Y_{uv} \log \hat{Y}_{uv} + (1 - Y_{uv}) \log \left( 1 - \hat{Y}_{uv} \right),
\]

where \( Y^+ \) and \( Y^- \) respectively contain the positive and negative user-item pairs for training, and \( Y_{uv} \in \{0, 1\} \) is the ground-truth value with 1 indicating that user \( u \) has visited item \( v \) and 0 otherwise.

2.2 PrivRec with On-device Personalization

It is known that FL suffers from the presence of non-IID data, that is, the participants may have heterogeneous local data in terms of both size and distribution. To address these problems, we exploit the meta-learning framework that was first proposed to address the multi-task learning problem, which can quickly adapt to a new task with only a small amount of training data. The rationale is that as we may consider making a recommendation for each client as a task, we can estimate an inactive user’s preferences even when only a small number of items have been consumed. In particular, we build PrivRec upon the gradient-based meta-learning framework Model-Agnostic Meta-Learning (MAML), which works purely by gradient-based optimization without requiring additional parameters or model modification. In what follows, we give some preliminaries of MAML, then describe how PrivRec addresses data heterogeneity with the notion of meta-learning.

\footnote{We use the term “client” and “user” interchangeably.}
2.2.1 Model-Agnostic Meta-Learning (MAML)

Given a model parameterized by \( \theta \), and some related tasks (supervised or unsupervised), MAML runs several training rounds until the model converges or some condition is met.

In each round, the current global model parameter is denoted as \( \theta_0 \), and the following steps are sequentially performed to further optimize \( \theta_0 \).

(1) **Task Sampling:** A mini-batch of \( M \) tasks (i.e., clients in our case) \( T_i \) are uniformly sampled.

(2) **Local Update:** Within each task \( \tau \in T_i \), the model parameter denoted as \( \theta_\tau \) is initialized to be \( \theta_0 \):

\[
\theta_\tau = \theta_0. \tag{3}
\]

Also, its own data is split into support set \( \mathcal{D}_s^\tau \) and query set \( \mathcal{D}_q^\tau \). Then \( \theta_\tau \) is updated by gradient \( \nabla_{\theta_\tau} \mathcal{L}(\theta_\tau, \mathcal{D}_q^\tau) \) where \( \mathcal{L}(\theta_\tau, \mathcal{D}_s^\tau) \) denotes the training loss on support set w.r.t. \( \theta \). Finally, we obtain the locally updated parameter \( \theta_\tau \):

\[
\theta_\tau \leftarrow \theta_\tau - \alpha_1 \nabla_{\theta_\tau} \mathcal{L}(\theta_\tau, \mathcal{D}_q^\tau), \tag{4}
\]

where \( \alpha_1 \) is the learning rate. Note that there could be more than one gradient descent step, and we show the case with only one step.

(3) **Meta Update:** After local updates, the initial parameter \( \theta_0 \) is globally updated based on the gradients of \( \mathcal{L}(\theta_\tau, \mathcal{D}_s^\tau) \), i.e., the meta-loss for task \( \tau \) using the locally updated parameter \( \theta_\tau \) on query set \( \mathcal{D}_q^\tau \):

\[
\theta_0 \leftarrow \theta_0 - \alpha_2 \nabla_{\theta_0} \sum_{\tau \in T_i} \mathcal{L}(\theta_\tau, \mathcal{D}_s^\tau), \tag{5}
\]

where \( \alpha_2 \) is the learning rate and the summation is over all sampled tasks \( \tau \in T_i \).

When training is completed, we obtain the optimal model parameter \( \theta^* \). Given an unseen task, starting from the optimal parameter \( \theta^* \), the model can quickly adapt to it by taking a small number of local gradient descent steps using the support set (i.e., Eq. (3)).

2.2.2 Faster-adapting PrivRec for Federated Learning

Naturally, it is plausible to consider a client as a task in the context of FL, and implement the techniques of meta-learning. Recently, [5] proposed a federated framework that integrates the aforementioned MAML for recommendation, in which a parameterized meta-algorithm is used to train the recommendation models, and parameters within both the local models and the meta-algorithm need to be optimized. However, it is subject to inevitable deficiencies due to its straightforward application of the vanilla MAML. First, the MAML meta-gradient update involves a gradient-of-gradient (also known as second-order gradient) calculation, which can be computationally expensive [13]. This also creates potentially infeasible memory requirements, especially for resource-constrained personal devices [44]. Second, it requires the split of local data for each client into support and query sets for the two-stage update, which may be impossible for inactive users with very few historical records. Moreover, in recommendation tasks, the majority of users are inactive because the number of user interactions commonly follows the long-tail distribution [50].

To address the problems caused by such data heterogeneity, we innovatively introduce a faster-adapting mechanism to PrivRec based on the REPTILE algorithm [31]. As an approximation of MAML, REPTILE executes stochastic gradient descent for a fixed number of iterations on a given task, and then gradually moves the initialization weights in the direction of the weights obtained from the tasks. By ignoring the second-order gradients, REPTILE avoids the heavy computation and needs to split the local data while still achieving promising results in the meta-learning task [31]. Motivated by this, we reformulate the meta update in Eq. (5) to be:

\[
\theta_0 \leftarrow \theta_0 + \alpha_3 \frac{1}{M} \sum_{\tau=1}^{M} (\theta_\tau - \theta_0), \tag{6}
\]

where \( \alpha_3 \) is the learning rate, \( M \) is the number of sampled tasks and \( \theta_\tau \) denotes the locally updated parameters in task \( \tau \). This is different from Eq. (5) since it does not need to take any derivatives from a different dataset. This is also different from the ordinary SGD as we allow for multiple local update iterations to obtain \( \theta_\tau \), which is the key to better on-device personalization in practice [20].

To further improve model flexibility and handle the complicated heterogeneous FL environments, we append a proximal term [23] to the local objective function \( \mathcal{L} \). Specifically, denoting the local objective function for client \( \tau \) as \( \mathcal{L}(\theta_\tau, \mathcal{B}_s^\tau) \) where \( \mathcal{B}_s^\tau \) denotes a training data batch on \( \tau \), we rewrite it as the following:

\[
\mathcal{L}'(\theta_\tau, \mathcal{B}_s^\tau) = \mathcal{L}(\theta_\tau, \mathcal{B}_s^\tau) + \frac{\mu}{2} \| \theta_\tau - \theta_0 \|,
\]

where \( \mu \) is a constant coefficient. By restricting the locally updated parameters to be close to the global (initial) ones, we can avoid potential divergence caused by the underlying heterogeneous data, and safely incorporate varied numbers of local training iterations as needed due to data heterogeneity.

With these ingredients, we formally list the details of training PrivRec in Algorithm 1, where steps executed on the server side (i.e., task sampling and meta update) and client side (i.e., local update) are respectively summarized in lines 2-8 and 10-19.
We hereby present some necessary preliminaries regarding DP. The adjacent datasets is the core concept in DP. Two datasets are considered adjacent when they are identical except for one record. With respect to a record, most prior work such as [1] and [34] tend to derive their task-specific definitions, such as a single training sample, a mini-batch of training samples, or all the data from a single user. As we aim to enforce the user-level privacy, the adjacent datasets in our paper are defined below.

**Definition 1 (Adjacent Datasets)** Let $d$ and $d'$ be two datasets where each entry is associated with a user. $d$ and $d'$ are adjacent if we can obtain $d'$ by replacing all data points associated with only one user in $d$ with the examples of a different user from $d'$.

Different from the definition in [28] that would lead to a variable size of mini-batch of clients at each training round, this definition instead yields a fixed mini-batch size. This makes it easier to analytically compute the privacy loss by using the composition rule [27], and further accelerate computation.

Recall that our goal is to ensure that the presence or absence of any specific user’s data in the training set should have slight impact on the parameters of the learned model, which means that it is impossible for an adversary to infer whether any specific user’s data has been used in the training data (i.e., whether it is $d$ or $d'$) by examining the trained model. This goal can be formally expressed as $(\varepsilon, \delta)$-Differential Privacy below.

**Definition 2 ($(\varepsilon, \delta)$-Differential Privacy)** A randomizing mechanism $M : \mathcal{D} \to \mathcal{R}$ with domain $\mathcal{D}$ and range $\mathcal{R}$ satisfies $(\varepsilon, \delta)$-differential privacy if for any two adjacent inputs $d, d' \in \mathcal{D}$ and for any subset of outputs $O \subseteq \mathcal{R}$, it holds that $\Pr[M(d) \in O] \leq e^{\varepsilon} \Pr[M(d') \in O] + \delta$ where $Pr[\cdot]$ denotes the probability.

To achieve $(\varepsilon, \delta)$-DP, a common method is to add noise drawn from the Gaussian distribution to the output of mechanism $M$. Note that in DP-PrivRec, the outputs of $M$ from the clients are gradients, so we leverage noisy stochastic gradient descent (NoisySGD), which is a popular option when deploying DP-enhanced DNNs [14][28]. According to NoisySGD, within each iteration of model training, a gradient w.r.t. the model loss function on a randomly subsampled dataset is obtained and then the gradient is clipped (or bounded) in $\ell_2$ norm. Clipping the gradients effectively bounds the sensitivity of the system w.r.t. the addition or removal of an arbitrary individual from the training set. After gradient clipping, the Gaussian noise perturbation on the gradients ensures $(\varepsilon, \delta)$-DP for this iteration.

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**Algorithm 1: Procedures for Training PrivRec**

**Input:** The number of global rounds $E_1$ and local epochs $E_2$, the number of clients sampled each time $M$, initialized model parameter set $\theta_0 = \{U, V, W, b\}$, constant $\mu$ and learning rates $\alpha_1, \alpha_3$.

1. **[Server Execution]:**
   2. for round $i \leftarrow 1, 2, \ldots, E_1$
   3. Randomly sample $M$ clients to form a task set $T_i$.
   4. for client $\tau \in T_i$, do
   5. \[ \theta_s \leftarrow \text{CLIENTUPDATE}(\tau, \theta_0); \]
   6. end
   7. $\theta_0 \leftarrow \theta_0 + \alpha_3 \frac{1}{M} \sum_{\tau=1}^{M} \Delta_s$.
   8. end

9. **[Client Execution, i.e., CLIENTUPDATE($\tau$, $\theta_0$)]**:
10. $B_s \leftarrow$ (divide the local data into mini-batches); \[ \tau \theta_0 \leftarrow \theta_0; \]
11. for $j \leftarrow 1, 2, \ldots, E_2$
12. for batch $B_s' \in B_s$, do
13. \[ \ell'(\theta_0, B_s') = \ell(\theta_0, B_s') + \frac{\mu}{2} ||\theta_s - \theta_0||; \]
14. \[ \theta_s \leftarrow \theta_s - \alpha_1 \nabla_{\theta_s} \ell'(\theta_s, B_s'); \]
15. end
16. $\Delta_s = \theta_s - \theta_0$;
17. return $\Delta_s$ to the server;

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2.3 Differentially Private PrivRec (DP-PrivRec)

So far, by running PrivRec in the FL setting, we ensure that user data is retained in the local device, facilitating privacy protection regarding personal data. However, risk still exists if there are potential participating clients who are able to infer whether a given user is present during training solely based on the model parameters or gradients they receive [29][34], thus leaking user identities and even sensitive attributes.

To defend PrivRec against such attacks, we bridge the model with the notion of differential privacy (DP) [9][1], which is the state-of-the-art framework for quantifying and limiting information disclosure about individuals due to its strong privacy guarantee. A conventional DP mechanism usually introduces a level of uncertainty into the released data, such that the contribution of any data point will not lead to obvious changes in the data. However, in the FL setting, instead of only protecting a single training data point, we need to protect each user’s entire dataset from attacks. Hence, we extend PrivRec with our proposed user-level DP mechanism, which is named DP-PrivRec and is introduced in this section.

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**2.3.1 Differential Privacy (DP)**

We hereby present some necessary preliminaries regarding DP. The adjacent datasets is the core concept in DP. Two datasets are considered adjacent when they are identical except for one record. With respect to a record, most prior work such as [1] and [34] tend to derive their task-specific definitions, such as a single training sample, a mini-batch of training samples, or all the data from a single user. As we aim to enforce the user-level privacy, the adjacent datasets in our paper are defined below.

**Definition 1 (Adjacent Datasets)** Let $d$ and $d'$ be two datasets where each entry is associated with a user. $d$ and $d'$ are adjacent if we can obtain $d'$ by replacing all data points associated with only one user in $d$ with the examples of a different user from $d'$.

Different from the definition in [28] that would lead to a variable size of mini-batch of clients at each training round, this definition instead yields a fixed mini-batch size. This makes it easier to analytically compute the privacy loss by using the composition rule [27], and further accelerate computation.

Recall that our goal is to ensure that the presence or absence of any specific user’s data in the training set should have slight impact on the parameters of the learned model, which means that it is impossible for an adversary to infer whether any specific user’s data has been used in the training data (i.e., whether it is $d$ or $d'$) by examining the trained model. This goal can be formally expressed as $(\varepsilon, \delta)$-Differential Privacy below.

**Definition 2 ($(\varepsilon, \delta)$-Differential Privacy)** A randomizing mechanism $M : \mathcal{D} \to \mathcal{R}$ with domain $\mathcal{D}$ and range $\mathcal{R}$ satisfies $(\varepsilon, \delta)$-differential privacy if for any two adjacent inputs $d, d' \in \mathcal{D}$ and for any subset of outputs $O \subseteq \mathcal{R}$, it holds that $\Pr[M(d) \in O] \leq e^{\varepsilon} \Pr[M(d') \in O] + \delta$ where $Pr[\cdot]$ denotes the probability.

To achieve $(\varepsilon, \delta)$-DP, a common method is to add noise drawn from the Gaussian distribution to the output of mechanism $M$. Note that in DP-PrivRec, the outputs of $M$ from the clients are gradients, so we leverage noisy stochastic gradient descent (NoisySGD), which is a popular option when deploying DP-enhanced DNNs [14][28]. According to NoisySGD, within each iteration of model training, a gradient w.r.t. the model loss function on a randomly subsampled dataset is obtained and then the gradient is clipped (or bounded) in $\ell_2$ norm. Clipping the gradients effectively bounds the sensitivity of the system w.r.t. the addition or removal of an arbitrary individual from the training set. After gradient clipping, the Gaussian noise perturbation on the gradients ensures $(\varepsilon, \delta)$-DP for this iteration.
2.3.2 Building DP-PrivRec

McMahan et al. [28] added a differential privacy mechanism to the FL optimization algorithm to achieve user-level privacy protection, and used moments accountant [1] to verify that it satisfies user-level differential privacy. Motivated by this, we propose our user-level differentially private recommender DP-PrivRec. Specifically, at the $i$-th round of training DP-PrivRec, we implement the following steps.

(1) Subsampling Clients: Given $N$ clients, we uniformly sample a batch of $M$ clients $\mathcal{T}_i$ with probability $q$, where the ratio $q = M/N$ is defined as the sampling parameter and is important for measuring privacy loss. It is also worth noting that subsampling can amplify the privacy guarantee [21] since it decreases the chances of leaking information about a particular individual, and makes it impossible to infer the information about this individual when she/he is not included in $\mathcal{T}_i$.

(2) Clipping Gradient: On client $\tau$, we compute the gradients w.r.t. the loss function on mini-batches of local datasets. After each computation, we obtain a new gradient, denoted by $\Delta_{\tau}$, whose $\ell_2$ norm is bounded by a predefined threshold $S$:

$$\Delta_{\tau} \leftarrow \Delta_{\tau} \cdot \min \{1, \frac{S}{\|\Delta_{\tau}\|}\}. \quad (8)$$

After gradient clipping, the gradient is sent back to the server. We will investigate a flexible method for adaptively setting $S$ in the next subsection.

(3) Estimating Gradients: On the server side, these clipped gradients are aggregated on the central server using a query function, which is in accordance with Eq. (6):

$$f(\mathcal{T}_i) := \frac{\sum_{\tau \in \mathcal{T}_i} \Delta_{\tau}}{M}. \quad (9)$$

**Theorem 1.** The sensitivity of $f(\mathcal{T}_i)$ is upper-bounded by $\frac{2S}{M}$.

**Proof of Theorem 1.** Given any two adjacent batch $\mathcal{T}_i$ and $\mathcal{T}_i'$, and assuming, by definition, that they are only different in user $u$ and user $u'$, we have:

$$\|f(\mathcal{T}) - f(\mathcal{T}')\| = \left\| \frac{\sum_{\tau \in \mathcal{T}_i} \Delta_{\tau}}{M} - \frac{\sum_{\tau \in \mathcal{T}_i'} \Delta_{\tau}}{M} \right\|$$

$$= \left\| \frac{\Delta_u - \Delta_{u'}}{M} \right\|$$

$$\leq \frac{2S}{M}. \quad \Box$$

(4) Adding Noise: Finally, we draw noise from the Gaussian distribution $N(0, \sigma^2)$, which is used to perturb the aggregated gradient, where $\sigma$ is proportional to the sensitivity of the query function, i.e., $\sigma = z \cdot \frac{2S}{M}$.

In Section 2.3.3 we will discuss a privacy guarantee of such mechanism.

2.3.3 Adaptive Gradient Clipping

Obviously, for DP-PrivRec, an appropriate bound $S$ is critical for privacy guarantees and utility. If it is too high, excessive noise might be introduced to the global model. However, if it is too low, severe information loss will occur. Both cases can seriously affect the performance of the learned recommender. On the other hand, as the norm of the gradients varies dramatically throughout the whole FL process with a large number of rounds, setting a constant threshold $S$ is potentially harmful to overall system performance.

Most previous work consider $S$ as a hyperparameter and empirically tune it based on the specific tasks and datasets. This labor-intensive process requires substantial domain knowledge, which hurts the model flexibility. Therefore, it is necessary for DP-PrivRec to automatically determine the value of $S$ during training. In this regard, a common practice is to adjust $S$ corresponding to the norm of the updates [41,35]. Formally, at each round, the updating rule for $S$ is:

$$S \leftarrow S - \alpha_4(\beta - \gamma), \quad (9)$$

where $\beta$ is the fraction of samples in the batch whose value is at most $S$, the previous bound, and $\alpha_4$ is the learning rate. With coefficient $\gamma$, the optimal $S$ is the $\gamma$-th quantile of the norm of the user update [41].

Formally, in any round, at each of the sampled clients, say $\tau$, we calculate $b_\tau$, the proportion of elements whose norm is at most $S$ in the final update vector $\Delta_{\tau}$: $b_\tau = \frac{1}{\|\Delta_{\tau}\|} \sum_{\tau \in \mathcal{T}_i} \Delta_{\tau}$, whose $\ell_2$ norm is at most $S$ in the final update vector $\Delta_{\tau}$: $b_\tau = \frac{1}{\|\Delta_{\tau}\|} \sum_{\tau \in \mathcal{T}_i} \Delta_{\tau}$. On the server side, $\beta$ is aggregated from the values sent from sampled clients using another query function: $\beta = \frac{\sum_{\tau \in \mathcal{T}_i} b_\tau}{M}$. Note that $\beta$ also contains sensitive information and needs to be injected with noise, so we apply Gaussian mechanism using the sensitivity $2/M$, which can proved easily following our proof sketch for Theorem 1 knowing that the proportion $b_\tau$ is naturally bounded by 1.

We list the detailed procedures for training DP-PrivRec in Algorithm 2.

2.3.4 A Privacy Guarantee

In [1] it is discussed that privacy spent for multiple access to the sensitive data can be measured by the moments accountant technique. Next, we demonstrate that our model is also applicable for moments accountant.
Proof that our model is applicable for moments accountant. (1) At each round, each batch is randomly sampled by the ratio \( q \), which meets the condition of privacy amplification. (2) The gradient from each client is clipped to \( S \) and the proportion \( b_\tau \) for client \( \tau \) is also bounded by 1. (3) There are two query functions (i.e., for calculating \( \Delta \) and \( \beta \) separately) and they are upper-bounded by \( \frac{2\sqrt{\tau^2-1}}{M} \) and \( \frac{2\sqrt{\tau^2}}{M} \) respectively. To fix the privacy spent by each round, we introduce a balance factor \( h \) to these two query functions. The new noise scale for them is \( z_1 = \frac{1}{\sqrt{h}} \) and \( z_2 = \frac{1}{\sqrt{h}} \), where \( z \) is a fixed noise variance. According to [27], if we apply the Gaussian mechanisms \( \frac{2\sqrt{\tau^2-1}}{M} \) and \( \frac{2\sqrt{\tau^2}}{M} \) in the same training round, then the resulting Gaussian mechanism is with privacy tuple \((S^*, z)\), where \( S^* = 2\sqrt{\frac{\tau^2-1}{M}} \). (4) The moments are upper-bounded by that of the sampled Gaussian mechanism with sensitivity 1, noise scale \( z \) and sampling probability \( q \). (5) Although the clipping bound \( S \) is adaptively changed, it does not affect the noise scale \( z \), which we use to generate the noise irrespective of the private data. Hence, we can safely apply the composability property of moments accountant. □

These Gaussian mechanisms are applied to \( N/M \) subsamples sequentially, whose privacy losses are recorded by the moment accountant data structure. Abadi et al. [11] apply composability and tail bound properties of these moment accountants to obtain \( \epsilon \) given budget \( \delta \), achieving \((\epsilon, \delta)\)-DP.

In our work, we employ a numerically stable analytical Moment Accountant implementation named autodp [3] which is based on Renyi Differential Privacy (RDP) [17], to calculate \( \epsilon \).

3 Evaluation Setup

We introduce our evaluation settings in this section.

3.1 Experimental Environment

Our experiments follow the FL environment simulation widely used in FL research [23][10]. Specifically, we build our models using the popular PySyft [35] FL framework, where each user is modeled as a virtual worker object and behaves exactly like normal remote edge devices. A virtual server object is also created for conducting the global model update and controlling the training process. By following the standard simulation setting, we focus on the core logic of our problem in a real-life production scenario.

3.2 Datasets

In this section, we introduce the two datasets Frappe and Movielens-1M, which have ample user and item features for representation learning. We introduce their properties as follows:

Frappe Frappe is a context-aware mobile application discovery tool. We adopt the extended version of the dataset used in [13]. The dataset contains eight features, which are “count”, “daytime”, “weekday”, “is weekend”, “homework”, “cost”, “weather”, “country” and “city”. We consider “count” and “cost” as item-related features while the rest as user features. We convert the ratings greater than 3 stars as positive ratings (i.e., 1) and the others as negative ratings (i.e., 0). This

\[ \text{https://github.com/yuxiangw/autodp} \]

\[ \text{http://baltrunas.info/research-menu/frappe} \]
dataset contains 957 users, 4,082 items and 288,609 interactions.

**Movielens**4: Movielens provides datasets containing the movie ratings by users. We select Movielens-1M in this experiment, which contains user demographic information: age, gender and occupation, and 18 movie genres. Similarly, we denote every feature (including each genre) as a one-hot feature vector. Similarly, we consider the genres as item related features and user demographic information as user features. We binarize the user ratings into implicit feedbacks via the same strategy as used for Frappe. This dataset contains 6,040 users, 3,706 items and 1,000,209 interactions.

### 3.3 Evaluation Protocols

We randomly select 80% of the users as *training users* and the rest 20% as *testing users*. Similar to the settings in prior work [5, 10], we use the following method to split our datasets. In the training phase, we use all the data from training users to train the model. After obtaining a fully pretrained model after the training phase, we move to the testing phase. Specifically, for each testing user/client, we evenly split her/his data into the training set $D^\tau_{\text{train}}$ and testing set $D^\tau_{\text{test}}$. For each user $\tau$, we fine-tune the pretrained model on the client device using $D^\tau_{\text{train}}$ to facilitate on-device personalization, and then evaluate the recommendation performance on $D^\tau_{\text{test}}$ from all testing users.

To measure the recommendation accuracy, we use two evaluation metrics commonly used in recommender system research [6, 45, 44], namely hits ratio at rank $k$ ($\text{Hits@}k$) and normalized discounted cumulative gain at rank $k$ ($\text{nDCG@}k$). Specifically, for each positive user-item interaction in the test set $D^\tau_{\text{test}}$, we proceed as follows:

1. We compute ranking scores for the positive item as well as the negative items that the user has never interacted with.
2. We form a top-$k$ recommendation list by picking $k$ items with the highest ranking scores. If the ground-truth item appears in the top-$k$ recommendation list, we have a hit. Otherwise, we have a miss.

Then, $\text{Hits@}k$ for each $D^\tau_{\text{test}}$ is defined as:

\[
\text{Hits@}k = \frac{\# \text{hit@}k}{|D^\tau_{\text{test}}|},
\]

where $\# \text{hit@}k$ denotes the number of hits in all testing cases from user $\tau$. A high $\text{Hits@}k$ value is expected for a good recommender model. Meanwhile, for $D^\tau_{\text{test}}$, $\text{nDCG@}k$ is defined as:

\[
\text{nDCG@}k = \sum_{i=1}^{k} \frac{2^v_i - 1}{\log_2(i + 1)},
\]

where $r_i$ is the graded relevance of item at position $i$. We use the simple binary relevance in the experiments, meaning that $r_i = 1$ if the ground-truth item $v$ is in the hits set and $r_i = 0$ otherwise. After evaluating on each individual user, the $\text{Hits@}k$ and $\text{nDCG@}k$ scores are averaged over all testing users as the overall results.

### 4 Experimental Results and Discussions

Following the settings in Section 3, we conduct experiments to evaluate our proposed models. Specifically, we aim to verify our major claims made in this paper by answering the following research questions (RQs):

| Metric | Hits@5 | Hits@10 | Hits@20 | Hits@30 | nDCG@5 | nDCG@10 | nDCG@20 | nDCG@30 |
|--------|--------|---------|---------|---------|--------|---------|---------|---------|
| $k$    | 5      | 10      | 20      | 30      | 5      | 10      | 20      | 30      |
| FOLF-SELF | 0.118  | 0.149   | 0.142   | 0.123   | 0.101  | 0.130   | 0.109   | 0.207   |
| NN-SELF | 0.109  | 0.130   | 0.138   | 0.122   | 0.088  | 0.124   | 0.102   | 0.201   |
| FCF    | 0.082  | 0.126   | 0.186   | 0.228   | 0.088  | 0.118   | 0.156   | 0.196   |
| PrivRec| 0.123  | 0.160   | 0.205   | 0.249   | 0.106  | 0.137   | 0.174   | 0.210   |
| PrivRec-CEN | 0.127 | 0.163   | 0.207   | 0.252   | 0.109  | 0.138   | 0.178   | 0.212   |

| Metric | Hits@5 | Hits@10 | Hits@20 | Hits@30 | nDCG@5 | nDCG@10 | nDCG@20 | nDCG@30 |
|--------|--------|---------|---------|---------|--------|---------|---------|---------|
| $k$    | 5      | 10      | 20      | 30      | 5      | 10      | 20      | 30      |
| FOLF-SELF | 0.536  | 0.618   | 0.658   | 0.682   | 0.479  | 0.584   | 0.680   | 0.621   |
| NN-SELF | 0.531  | 0.613   | 0.651   | 0.677   | 0.472  | 0.550   | 0.595   | 0.616   |
| FCF    | 0.527  | 0.596   | 0.646   | 0.671   | 0.469  | 0.544   | 0.591   | 0.612   |
| PrivRec| 0.544  | 0.624   | 0.661   | 0.688   | 0.483  | 0.560   | 0.607   | 0.626   |
| PrivRec-CEN | 0.543 | 0.628   | 0.665   | 0.690   | 0.484  | 0.563   | 0.608   | 0.628   |

4 https://grouplens.org/datasets/movielens/
RQ1. Without DP, how does PrivRec perform compared with similar state-of-the-art models?

RQ2. What are the effects of different FL hyperparameter settings on the performance of PrivRec?

RQ3. What is the performance difference between DP-PrivRec and PrivRec?

RQ4. How do the DP parameters affect the privacy guarantee?

4.1 Recommendation Performance of PrivRec (RQ1)

To answer RQ1, we implement PrivRec without DP according to Algorithm 1. For its DNN structure, the embedding dimension for each category feature is 64, the number of hidden layers is 4, and the nonlinear activation is the Sigmoid function.

Before we proceed, we validate the correctness of PrivRec in the FL environment. We compare the performance of PrivRec and PrivRec-CEN, where PrivRec-CEN means running the same neural network model in the centralized environment. For PrivRec-CEN, we simply run it in the centralized multi-task setting where we treat each user as a task. Their results are shown in the last two rows of Table 1 and Table 2 for the Movielens and Frappe datasets respectively. On both datasets, there exists a slight performance degradation for PrivRec compared with PrivRec-CEN, but this is natural and inevitable due to the distribution design and how the gradients are merged for global model updates. Overall, the performance of PrivRec is comparable to that of PrivRec-CEN, hence we are confident that our PrivRec model produces almost identical results as the centralized setting.

As the core of PrivRec is its capability of performing recommendation in an FL environment, we compare PrivRec with the following three state-of-the-art FL recommender systems that are most relevant to ours:

**NN-SELF** [5]. In this work, the authors propose a DNN-based recommender system running in the FL environment, and it employs a two-stage meta-learning scheme to achieve fast on-device personalization. We adopt its SELF setting where the training set is the support set of the corresponding testing user. The rest setting is identical to ours, including the input features and neural network structures.

**FOFL-SELF** [19]. This FL recommender system is proposed to address the flaws of second-order meta-learning by employing REPTILE to implement the first-order meta-learning. This is also a DNN-based model but does not utilize the side information of users and items.

**FCF** [2]. Federated Collaborative Filtering (FCF) is an FL-based implementation of matrix factorization. The authors formulate the updating rules to update the model parameters to suit the FL setting.

The comparison results are also shown in Table 1 and Table 2 for the Movielens and Frappe datasets respectively. From the results, we can draw the following observations: (1) FOFL-SELF and PrivRec outperform NN-SELF, demonstrating that the first-order REPTILE meta-learning is more capable of handling the scarce data of user clients than MAML that requires the local dataset to be split into support and query sets for training, and this is especially crucial for building an FL recommender system where a large portion of users are inactive. (2) PrivRec, FOFL-SELF and NN-SELF have higher accuracy than FCF. This is because the PrivRec, FOFL-SELF and NN-SELF adopt deep neural networks as their main building blocks, which have larger learning capacities in capturing user preferences from raw data. (3) Our PrivRec consistently outperforms all baseline methods. In particular, PrivRec outperforms FOFL-SELF. One of the main reasons is that FOFL-SELF does not utilize the side information of users and items, weakening its ability of addressing the data sparsity problem. In contrast, PrivRec fully takes advantage of the user/item features for representation learning. Another reason is that we add a proximal term in the loss function in the local client, which can significantly limit the contribution of a single user, thus tackling the complicated heterogeneity issue in the FL environment.

4.2 Impact of FL Hyperparameters (RQ2)

To answer RQ2, we vary several important FL hyperparameters of PrivRec and report the corresponding Hits@20 on both datasets. These hyperparameters include the number of training epochs on the server and clients $E_1$ and $E_2$, and the number of clients in each training batch $M$. Specifically, we vary the values of $E_1$, $E_2$ and $M$ in \{5, 20, 40, 60, 80, 100\}, \{5, 20, 40, 60, 80, 100, 120\} and \{2, 5, 10, 15, 20, 25, 30, 35, 40\} respectively.

The experimental results are illustrated in Figure\[2\]. For $E_1$, the model performance increases dramatically when $E_1$ is smaller than 40, especially on Frappe dataset. When $E_1$ is over 40, the recommendation performance tends to remain stable on both datasets. For $E_2$, the model performance gradually increases, and remains stable when it reaches 100. This demonstrates that, our meta-learning based approach is able to achieve on-device personalization with sufficient iterations of local updates, yielding high recommendation accuracy at both the individual and system level. At the same time, varying $M$ shows the smallest impact to model
4.3 Influence of Differential Privacy (RQ3)

To answer RQ3, we run DP-PrivRec and PrivRec on both datasets, and compare their performances ($\text{Hits}@k$). Recall that the main difference between them is that DP-PrivRec adds a Gaussian noise to the gradients used to update the global model. For the hyper-parameters $\epsilon$ and $\delta$ of DP-PrivRec in this experiment, we use $\gamma = 0.9, h = 0.7, M = 30$, and the initial bound $S$ is set as 40 for Movielens and 35 for Frappe respectively.

We show the results in Figure 3 and Figure 4 for both datasets. From these figures, we can come to two major conclusions. First, DP-PrivRec has lower prediction accuracy than PrivRec, which is within our expectation because we add a noise in the gradients during training to achieve user-level DP, making the model update less effective. Second, DP-PrivRec exhibits comparable performance with PrivRec. Moreover, the performance gap between them is within 10%, which is a tolerable trade off considering the much stronger privacy protection that DP-PrivRec offers.

4.4 Effects of Privacy Protection (RQ4)

In this study, we vary the key DP parameters in DP-PrivRec and investigate the corresponding privacy loss $\epsilon$ and model performance.
Privacy Loss. First, we compute the upper bound of the privacy loss $\epsilon$ in ($\epsilon, \delta$)-DP using the RDP-based analytical Moment Accountant, when given different values of $\delta$, the sampling ratio $q = M/N$ and the number of mechanism composition $E_1$. Note that we measure the privacy loss during the model training stage, meaning that $N$ is 80% of the total users (i.e., 4800 and 760 in Movielens and Frappe respectively). We fix the noise variance $\sigma = 1$ for Gaussian Mechanism following previous work [11,28], and set $E_1 = 1000$ for both datasets. We show the results for Movielens and Frappe in Table 3 and Table 4 respectively. Clearly, we can achieve different levels of privacy as needed by choosing different combinations of parameters. In particular, $\epsilon$ obtained on Movielens is clearly less than that on Frappe. This implies that using smaller sampling probability yields a tighter privacy budget, which is consistent with the privacy amplification rule [21]. Therefore, for Frappe which has a smaller $N$, we need a smaller batch size ($M$) to achieve a similar level of privacy as on Movielens.

Effects of Adaptive Clipping Approach. We also study the relationship between the adaptive norm unclipped quantile $\gamma$ and the initial clipping bound $S$. We show the evaluation results of $\text{Hits}@20$ on Movielens by tuning $\gamma \in \{0.1, 0.4, 0.7, 0.9\}$ and $S$ in the range [20, 45]. We fix the balance factor $h = 0.7$ in this experiment. Since the optimal $S$ is the $\gamma$-th quantile of the norm of the user update, it is expected that a larger $\gamma$ yields better performance because more of the gradient values are kept. But it is also at the risk of increasing the sensitivity of the query function. On the other hand, the initial $S$ should be carefully chosen. An $S$ that is too large in the beginning makes the model harder to converge, degrading the overall performance. A similar pattern can also be observed in the Frappe dataset.

5 Related Work

In this section, we review recent advances relevant to our work in three lines: federated learning, personalized FL algorithms and private FL algorithms.

5.1 Federated Learning

With the boom of machine learning, especially deep neural networks (DNN) over the past decade, numerous practical applications based on these techniques have emerged to help users address real-world problems, such as recommender system, facial recognition and AI assistance. These models usually run in a cloud-based paradigm, namely these machine learning models are trained and hosted on cloud servers, and they provide on-demand services for users. However, DNN-based models are notoriously known to be data-hungry, and thus require access to a huge amount of user data. Meanwhile, many countries enforce laws and regulations to protect the personal information privacy and security. These laws and regulations make online service providers hard to collect and centrally store user data for training purposes.

Federated learning (FL) is a new attempt to solve the data dilemma faced by traditional machine learning methods, which enables training a shared global model with a central server while keeping all the sensitive data in local institutions where the data belong. Google was the first to propose federated learning concept in 2016, and applied this technology to their application Gboard - a virtual keyboard of Google for touchscreen mobile devices with support for more than 600 language varieties [28,10,30]. Since then, various machine learning algorithms have been proposed to adapt to the FL setting. Based on how the data across parties are utilized in FL, these algorithms can be categorized into three categories according to [49]: horizontal federated learning such as the aforementioned Gboard, vertical federated learning such as [17,32] and federated transfer learning.

The exploration of building an FL recommender system, which falls into the horizontal federated learning category, is still rare. There are some work aiming to develop an FL matrix factorization recommender system [12,24]. [2] introduce a Federated Collaborative Filter (FCF) model that generates recommendation results based on implicit feedback data by deriving a federated version of the widely used CF method. To update the global model, FCF aggregates user-specific gradient updates of the model weights from the clients. In [12], the authors propose a federated multi-view matrix factorization method for recommendation, which
enhances the performance by including side information from both users and items.

We are the first few work to propose a DNN-based personalized FL recommender system that fully utilizes the user/item side information to learn their representations.

5.2 Personalizing FL algorithms

On the other hand, a typical solution to obtain an optimal FL model is only good on average, and it does not fully consider the heterogeneity of data distribution of users [10]. This contradicts our goal to develop a practical recommender system that can generate personalized results for each user. Therefore, it is necessary to “personalize” the vanilla FL algorithm. Currently, there are three major lines of work addressing this challenge: local fine-tuning, multi-task learning and adding user context.

**Local fine-tuning** The mainstream approach to personalize an FL algorithm is local fine-tuning, where each client receives a global model and tunes it using their own local data and several gradient descent steps. Recently, this approach is predominantly used in meta-learning methods such as MAML [11]. In [20], a personalized FedAvg algorithm in which the classic FedAvg algorithm is first deployed, and then they switch to REPTILE, a meta-learning algorithm proposed in [31], and finally runs local updates to achieve personalization. They found that FL with a single objective of performance of the global model could limit the capacity of the learned model for personalization. ARUBA proposed in [22] is a meta-learning algorithm inspired by online convex optimization, and it achieves improved personalization when applied to FedAvg. The most closely related work to ours is [5] where the authors build an FL recommender system based on MAML, where a parameterized meta-algorithm is used to train parameterized recommendation models and both meta-algorithm and local model parameters need to be optimized. However, [5] is based on MAML, which requires computationally expensive second-order gradients.

**Multi-task learning** The second category of such work is to view the personalization problem as multi-task learning [49,44]. The most well-known work in this category is MOCHA [39], which considers the optimization on each client as a new task such that the approaches of multi-task learning can be applied. In another work [23], the authors propose to cluster clients into groups based on some features and consider each of them as similar tasks, and then train a model for each group. However, in such setting, all clients are required to participate in every training round, which is infeasible for a large-scale federated learning system.

**Adding user context** Finally, we introduce the third category that the personalization of a global FL model could be achieved by adapting to different contexts. For example, Hard et al. in [16] develop an FL next-word prediction model in a virtual keyboard for smartphones and personalize it on the local device by incorporating different contexts.

Our work falls into the first category, but different from their work, our proposed (DP-)PrivRec only utilize the more efficient first-order gradient to adapt to the resource-constraint edge devices, while achieving great on-device personalization.

5.3 Private FL Algorithms

In a pure FL environment, the clients do not need to transfer data to the third party during model training. However, transferring parameters or gradients may still be susceptible to leaking sensitive information [29,46,48]. To address this problem, differential privacy (DP) is used in federated learning for protecting the transaction of models or data such as [11,25,15,51,37]. The common goal of such work is to ensure that a learned model does not reveal whether a client participated during decentralized training. This requires the protection of the client’s whole dataset against differential attacks from other clients.

Specifically, the FedMEC framework in [51] is an efficient federated learning service on the mobile edge computing environment, which allocates the heavy computations to the edge devices and makes the computation results differentially private before sending back to the server. On the other hand, [28] and [14] independently propose a user-level DP algorithm in the federated learning setting and provide a tight privacy guarantee. In [37], the authors also propose a FL recommender with differential privacy, which divides users into multiple groups, and separately learns a DP prototype recommendation model for each entity. However, this assumes that there is no privacy concerns for users within a group. Most recently, [24] introduce a DP-based Upper Confidence Bound (UCB) strategy to the proposed federated private bandits framework in order to protect the client’s data from exposure, and based on this scheme, the authors build a recommender system.

In our work, we formulate a user-level differentially private PrivRec called DP-PrivRec. Compared to the DP techniques used in [28,14,37,24], DP-PrivRec is different from them in two aspects. First, we sample an equal-sized batch of clients instead of varied-size,
which helps us easily analytically measure the privacy used during training and accelerate the computation. Second, we introduce an adaptive method to set the gradient clipping bound, reducing human supervision during training.

6 Conclusions

When widely used recommender systems meet the dramatically rising concerns of personal privacy protection in the mobile Internet era, it is urgent and practical to develop a recommender system that can balance privacy and recommendation performance.

In this paper, we aim to address this dilemma. We first proposed a DNN-based recommender system called PrivRec that utilizes the side information of users and items to learn the user/item representations, and then generate recommendations. In particular, PrivRec can smoothly run on the FL setting, which is a fully distributed framework to design privacy-perserving algorithms. With PrivRec, sensitive user data never has to leave their devices, while still enjoying the recommendation service. Since the trivial FL training paradigm can hardly provide personalized results for every individual user, we introduced an efficient method based on meta-learning to fast adapt to a new user or inactive user using a few local data examples. Furthermore, as there are still risks to leak personal information to potential malicious FL participants, we enhanced the privacy protection of PrivRec by introducing a user-level DP mechanism, and developed a more powerful model called DP-PrivRec. We also provided an analytical sketch to measure the privacy spent when training DP-PrivRec. Finally, we performed extensive experiments on two datasets within a simulated FL environment, whose results demonstrate the effectiveness of our proposed PrivRec and DP-PrivRec.

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