Federated Neural Collaborative Filtering

Vasileios Perifanis
Democritus University of Thrace and Athena Research
Center
Xanthi, Greece
vperifan@ee.duth.gr

ABSTRACT

In this work, we present a federated version of the state-of-the-art Neural Collaborative Filtering (NCF) approach for item recommendations. The system, named FedNCF, allows learning without requiring users to expose or transmit their raw data. Experimental validation shows that FedNCF achieves comparable recommendation quality to the original NCF system. Although federated learning (FL) enables learning without raw data transmission, recent attacks showed that FL alone does not eliminate privacy concerns. To overcome this challenge, we integrate a privacy-preserving enhancement with a secure aggregation scheme that satisfies the security requirements against an honest-but-curious (HBC) entity, without affecting the quality of the original model. Finally, we discuss the peculiarities observed in the application of FL in a collaborative filtering (CF) task as well as we evaluate the privacy-preserving mechanism in terms of computational cost.

KEYWORDS

Federated Learning, Privacy, Collaborative Filtering, Matrix Factorization, Neural Networks

1 INTRODUCTION

Recommendation systems have been widely used for creating personalized predictive models to help individuals identify content of interest [1]. Such systems collect various characteristics for an individual such as demographic features, ratings related to an item (explicit feedback) or user's interactions with specific items (implicit feedback) [2]. Their goal is to provide future preferences according to past interactions and they are widely adopted in various fields such as e-commerce and online streaming services. The most straightforward technique for generating recommendations is CF [3, 4].

In the case of centralized learning, a service provider should collect the user profiles along with their past interactions to a datacenter. On the one hand, the General Data Protection Regulation (GDPR) requires legal and transparent processing of the data. On the other hand, the information flow in conventional machine learning cannot be ensured and as a result, it is hard to make it comply with such regulations and laws [5].

In traditional recommendation systems, users' preferences and learned feature vectors can reveal sensitive information [6]. Besides, sophisticated techniques can result in the de-anonymization of a dataset [7]. Therefore, ways for building a robust recommender system without revealing users' private data are in demand.

The growing number of computation devices in the cloud, such as mobile phones and wearable devices, amplifies the adoption of machine learning [8]. However, conventional machine learning

Pavlos S. Efraimidis
Democritus University of Thrace and Athena Research
Center
Xanthi, Greece
pefraimi@ee.duth.gr

approaches require data transmission from those devices that hold much private information due to their sensors and rich users' interactions. To overcome the challenge of storing such information in a centralized server and enhance users' privacy, Google in 2016, proposed a new technique, named FL [9]. Since the federated setting facilitates machine learning without requiring the transmission of users' data, there are great promises for both privacy and fast distributed computations.

FL has attracted great interest, both in industry and academia. However, machine learning techniques such as MF and neural networks in the context of federated recommender systems remain highly unexplored. Moreover, private information can still be leaked. In conventional MF, users' latent feature vectors can reveal valuable information [10]. This also applies to the federated version of MF, since users share the same item and user latent feature space [11]. Hence, significant privacy concerns still remain, which in turn, can prevent the system from reaching its goals.

This work explores the use of MF and neural networks in a FL environment for creating recommender models. Recent work on recommender systems has shown the feasibility of applying deep neural architectures to increase the recommendation quality. One of the most successful systems is the NCF [12] approach which combines MF with deep neural architectures. In this work, we extend the state-of-the-art NCF method using a federated setting. In brief, federated CF (FedCF) lets participants in the learning process to locally compute the weights of their own model. Then, instead of the raw profile data, only the calculated weights are transmitted to the central entity.

Many of the existing works in the field of federated recommendation systems such as [13, 14], rely on the fact that the user's data does not leave the local devices. However, MF-based models use an embedding layer to represent the item profile¹. A participant updates an item's vector in the matrix only when the corresponding item is observed in the local dataset. Therefore, the transmission of the weight updates from embedding layers can reveal sensitive information [15].

The aim of this work is to develop an efficient recommendation system in a federated way so that users can enjoy recommendations, while their privacy is enhanced. We believe that effective federated recommenders can eventually lead to improved recommendations, because of the possibility to leverage personal data that were not accessible in the context of conventional machine learning. We summarize our main contributions as follows:

 We adapt the NCF approach to the FL setting for next item predictions. Unlike other solutions that have evaluated a

¹We use the terms matrix and profile interchangeably, while the vector term, represents a row in the matrix

FedCF setting, FedNCF leverages the non-linearity of neural networks to improve recommendations. To the best of our knowledge, FedNCF is the first approach that extends NCF in a federated fashion.

- We provide an extension to the federated averaging (FedAvg) algorithm [9] to handle the latent parameters of MF. While FedAvg has demonstrated its success both in the literature and in real-world applications in the context of neural networks, e.g. [16], we experimentally show that it leads to quality reduction in embedding-based models like MF.
- The original FedAvg algorithm requires the transmission of the updates in plain format by each participant. Therefore, FedAvg may sacrifice privacy for utility. We argue that integrating the SecAvg protocol [17] as a privacy-preserving mechanism, addresses privacy concerns against HBC entities.
- We study the effectiveness of our approach on four realworld datasets and compare the FedNCF against the centralized NCF to validate its recommendation quality. We also evaluate the computation overhead of the SecAvg integration against a privacy-preserving protocol based on homomorphic encryption (HE).

Our results show that FedNCF is a viable approach as it achieves comparable recommendations quality to the centralized NCF, while it enhances the privacy of the participants, without requiring heavy communication and computation overhead.

Organization: The remainder of the paper is structured as follows: Section 2 details the preliminaries, including an introduction to MF, a discussion about the machine learning models of the NCF approach and the scope of FL. Section 3 compares our approach with prior work in FedCF. Section 4 introduces FedNCF which is an adaptation of NCF [12] to the FL setting. The FedAvg integration to MF is described in Section 4.2, while the privacy-preserving protocol is presented in Section 5. The recommendation quality of FedNCF as well as the computation cost of the privacy-preserving scheme are evaluated in Section 6. Section 7 provides additional discussion, while Section 8 concludes our work.

2 PRELIMINARIES

2.1 Matrix Factorization

The goal of CF algorithms is to suggest new items to users based on their past behavior. In a typical scenario, the service provider has access to a set of M users, $U = \{u_1, u_2, ..., u_M\}$ and a set of N items, $I = \{i_1, i_2, ..., i_N\}$. Each user u_i has interacted with a subset of items n. The interaction generated by user i on item j is represented as $r_{ij} \in \mathbb{R}$. Similarly, the entire user-item interactions can be represented by a matrix $R \in \mathbb{R}^{M \times N}$ [18]. The objective of a CF system is to provide a ranked list of top-K items that a particular user has not interacted with and are suitable according to the user's preferences.

One of the most effective CF algorithms is MF and is based on latent factors [19]. The user-interaction matrix R is decomposed to $X \in \mathbb{R}^D$ and $Y \in \mathbb{R}^D$ matrices, where D denotes the dimension of the latent space. In MF, the similarity of two users can be measured

with the inner product of the matrices X and Y [10] and thus, $R \approx X \cdot Y$.

2.2 Neural Collaborative Filtering

The MF model estimates an interaction r_{ij} as the inner product of the latent vectors u_i and v_j . However, He et al. [12] argued that the product vector is inefficient in formulating the similarity of users and showed that this limitation can be overcome by learning the interaction function using deep neural networks. First, they presented a generalized MF (GMF) model, which employs embedding layers to obtain the latent user-item vectors. Then, the latent vectors are fed into a linear layer, at which the output layer returns the predicted score by minimizing the binary cross entropy (BCE) loss. Their second model is a multi-layer perceptron (MLP) with at least one hidden layer. In this architecture, the user and item latent vectors are concatenated into a single vector and the output is then fed to the hidden layers. Finally, they showed that the fusion of the linear GMF model and the non-linear MLP model, namely NeuMF, can result in higher quality recommendations and faster convergence. In NeuMF, the GMF outputs the product vector of the latent vectors and the MLP feeds the concatenation of the latent vectors in the deep neural network. The two outputs are concatenated in the last hidden layer, where a prediction is made. It is worth mentioning that NeuMF is one of the most used model baselines to evaluate recommendation systems [20].

2.3 Federated Learning

Federated Learning is a machine learning setting, which allows the training of models in decentralized environments. The main idea behind this learning technique is that different entities can collaboratively train a model under the coordination of a central server without sharing their data. Unlike conventional machine learning, which requires users to transmit their data, FL enables a higher level of privacy, as the model is trained locally on each device. After clients' operations, weight updates are sent back to the central server without revealing their raw data [21].

Upon receiving updates, the coordination server performs an aggregation [9] to achieve the learning objective. The aggregation of the transmitted updates is a crucial step in the FL pipeline, as it generates the new global parameters. In other words, the central entity is responsible for coordinating the training process and performing an aggregation function to generate the global parameters, while machine learning computations are only performed on the client side. Generally speaking, edge devices have much less computational power than regular servers, but there is also less data on them, making the training process easily handled. In addition, FL leverages the pool of mobile devices as a massive parallel platform comprising a large number of "small" computing nodes.

Federated Averaging. The most straightforward technique for weights' aggregation is the FedAvg algorithm [9]. Briefly, in each training round, the coordination server randomly selects a number of $C \in |U|$ online participants, where |U| is the total number of users. The current global model is transmitted to the selected participants and after some local gradient descent iterations, each user transmits its updated weights w^c , $c \in C$ and the total of number of its local training instances n_c back to the coordination server. After a time

threshold or when all selected participants have transmitted their updates, a weighted aggregation is performed based on the number of the training instances each participant owns. For completeness, the FedAvg algorithm is given in Appendix A.

Secure Aggregation. Although FedAvg does not require heavy computation and communication cost [9, 16], simply transmitting weight updates cannot ensure the privacy of the participants. Bonawitz et al. [17] introduced SecAvg, a Secure Multiparty Computation (SMC) algorithm, which only allows the disclosure of the sum of the weights updates, while any intermediate result from each participant remains secret. The algorithm is based on Shamir's secret sharing scheme [22]. A high level overview of SecAvg is given in Appendix B.

SecAvg is shown to be secure against HBC entities when a threshold of online participants is met. Note that the algorithm can also handle user dropouts, a property which is essential in FL as network failures may be a common event [16]. In learning environments based on embedding layers such as MF, SecAvg can effectively prevent the coordination server from deducing a user's interacted items. The coordination server is only allowed to learn that one or more participants updated a specific item but it cannot infer any information about the identity of a participant. Therefore, SecAvg fits the update procedure of MF.

Homomorphic Encryption. HE is an encryption method that allows algebraic operations on encrypted data such that the output of the computation is also a ciphertext. Only the entity that holds the secret key can decrypt the resulting ciphertext. In this work, we use the Paillier's partially HE scheme [23] to take advantage of the its additive property. We consider HE as a method for performing a privacy-preserving aggregation and compare this scheme against the SecAvg integration.

3 RELATED WORK

Ammad et al. [13] proposed a FedCF algorithm based on implicit feedback. Although their system only requires the updates of the item profile by each user, the raw gradients information can result in information leakage [24]. Furthermore, in their system, the coordination server waits for the transmission of the updates from all of the available participants and afterwards, an update procedure is initiated. Therefore, this approach is an asynchronous FL framework [25], where the coordination server waits for the updates from one to several clients, which can result in staleness [26], i.e. the received updates may be calculated on an outdated model.

Chai et al. [24] proposed FedMF, which is an extension of the system in [13] by integrating a HE scheme. In their scheme, a participant is selected at random to generate the public-secret key pair. The secret key is then shared among participants, enabling an HBC server to perform model updates additively without knowing neither the users' interactions nor the raw gradient updates.

Lin et al. [14] explored a federated MF system in the context of explicit feedback. Their system, FedRec, randomly samples some unrated items with a parameter $\rho \in \{0,1,2,3\}$ and assigns them a virtual score to hide a user's behavior and enhance the privacy of the participants. As their work is an extension of [13], the item

profile update is carried when all clients have transmitted their updates.

Ribero et al. [27] proposed a version of federated MF enhanced with the notion of differential privacy to protect sensitive data. In their work, the authors considered a number of entities who hold data for more than one participant. While their system does not require high communication cost and protects users' privacy, the grouping of individuals into entities that hold their data, does not apply in our scenario. In our work, the federated setting is intended to prevent the transmission of users' data to an external entity.

In summary, most of the above studies follow a common pattern:

- The coordination server maintains the item profile, which is transmitted to the participants in each training round.
- (2) Each participant updates the item profile received from the server with its local data and transmits the updates to the coordination server.
- (3) After each training round, the server performs an (asynchronous) aggregation on the updated item matrix and generates the new global item profile.

Therefore, none of the above systems does include the concept of a complete protocol for federated item recommendations in terms of aggregating the item profile. The update procedure is carried immediately by the coordination server when one or more updates are received [13, 14, 24], running an asynchronous version of SGD [28]. As a result, these systems do not require an aggregation algorithm such as the FedAvg [9], while the update procedure is carried internally by an optimizer.

In this work, we explore the application of CF in standard federated settings. We focus on the aggregation step, where the coordination server averages the updates received from the participants. Previous work on privacy-preserving CF [24], focused on the prediction task by updating the item profile when an update is received. Although this technique is promising in FL, the staleness problem may lead to the prevention of convergence [29].

The main concern of this work is to compare the centralized NCF's quality against FedNCF, to explore ways of accelerating the convergence speed in the case of MF and finally, to compare two privacy-preserving protocols in terms of computation and communication overhead.

Following the security definition for horizontal FL systems [5], in this work we assume that the participants and the coordination server are HBC entities, i.e., they follow the protocol faithfully but they attempt to infer additional information [30]. Moreover, we assume that the entities in FedNCF do not collude.

4 FEDERATED NEURAL COLLABORATIVE FILTERING

We propose the FedNCF framework, which comprises three federated learning algorithms: a generalized MF (FedGMF), a multi-layer perceptron (FedMLP) and a fusion of FedGMF and FedMLP (FedNeuMF). In essence, these models are the federated versions of the corresponding models presented in [12].

FedNCF adopts a client-server architecture, while allowing participants to keep their data locally and train a recommendation model collaboratively. In the following parts of this section, we first define the FedNCF's entities and their operations. Second, we

provide an adaptation of the FedAvg algorithm [9] to meet the training properties of MF.

4.1 The FedNCF framework

In this subsection we define the horizontal FedCF problem as well as the operations for the entities in the FedNCF solution. The primary goal of a federated recommendation system is to generate a global recommender based on local computations, without violating the privacy of the participants. The personal data needed for the federated training process can vary and are based on the learning objective. For instance, the data can be location-based.

In horizontal FedCF, users share the same user and item latent feature space [11]. For the FedCF, we define:

- M participants (data owners), $P_1, P_2, ..., P_M$.
- N items, $I_1, I_2, ..., I_N$.
- For $i = 1, 2, ..., M, U_i \in \mathbb{R}^D$ is the user profile, where D is the dimension of the latent space.
- For $j = 1, 2, ..., N, I_j \in \mathbb{R}^D$ is the item profile.
- Each P_i holds its rating matrix $R_i = r_{ij} \in \mathbb{R}$ and utilizes R_i to update the global model.

Definition 4.1. Given M participants, where each participant represents an individual user, $P_{i \in \{1,...,M\}} = \{U_i, I_i, R_i\}, U_i \neq U_j, I_i = I_j, i \neq j$, FedCF tries to generate a recommendation model by incorporating users' past interactions on a shared items set, without revealing anything for each participant.

In MF, the user latent vector is essential in the inference stage. However, the transmission of users' latent vectors poses privacy concerns [13]. The coordination server can directly infer private interactions data after accessing the transmitted updates. Therefore, we ask each participant to maintain the corresponding U_i locally. Consequently the global parameters concern the item profile. Our models also include a neural architecture, and hence, the global parameters contain the weights of the corresponding neural network.

FedNCF follows a client-server architecture similar to most federated systems such as [16]. Each participant is an agent that holds private interactions, capable of training a recommendation model. The coordination server maintains some global parameters and controls the learning process. Inside the server, there are two components: the user selection and the aggregation functions. The user selector is responsible for selecting a number of clients to perform a local update and the aggregator is responsible for summarizing their updates to form the new global parameters. The communication between the participants and the coordination server is performed over a secure channel (SSL/TLS). In this work, our main focus is to evaluate the recommendation quality of the federated system against the centralized one. Hence, we assume that all participants are available at any point of time. For more details for the architectures of our models, we refer our readers to [12].

4.1.1 Phases. The communication between the participants and coordination server enables the generation of the global parameters for the recommender system. The description below is similar to the protocol in [16]. However, we omit the selection phase, i.e., the selection of a number of participants based on some eligibility

criteria. In this work, we assume that the participants are available at any given time.

Federated Plan Configuration. The coordination server initiates a training plan to be transmitted to the participants. The coordination server publishes: (1) a description of the task, notifying the participants about the model's hyper-parameters, (2) the model's current global parameters w_0 and (3) a constant C that represents the number of participants that perform a local update before an aggregation. We term the process of aggregating C updates an aggregation round. A pass over all participants is referred as a global round.

The model's hyper-parameters contain information related to the training procedure. For instance, they include the local minibatch size B to use. The current w_0 holds information about the current weights of the model. Note that in the first round, w_0 is generated at random. In each aggregation round, the coordination server randomly chooses C participants and sends them the current global model.

Local Update. The selected participants use their local data along with some local steps, referred as local epochs, to update the global model. After its operation, the updated model weights, w^i , are transmitted to the coordination server for aggregation. In our models, there are three different types of weights: (1) the user profile U^i , (2) the item profile I^i and (3) the neural network's weights N^i_w . The transmission of the parameters I^i and N^i_w is sufficient for the learning objective.

Aggregation and Model Update. The coordination server waits for the transmission of the updated weights. Upon receiving ${\cal C}$ updates, it performs an aggregation function. Finally, it generates the new global parameters and the training procedure is repeated until model convergence.

4.2 Weights Aggregation

To effectively apply FedAvg in the case of MF, we consider an enhancement to the original FedAvg algorithm [9] to handle the item profile updates. The FedAvg algorithm is the most popular method for weight aggregation in the context of neural networks and in tasks such as classification. However, in a MF task, the aggregation algorithm must handle the additional latent vectors.

Unlike neural networks where a user affects every part of the network weights, in MF, the updates, in most cases, only concern a small portion of the item profile. Regarding the user profile, each participant only affects its corresponding user vector. Utilizing the original FedAvg algorithm to handle updates on the embedding layers of MF, will lead the aggregated parameters to be quite close to the aggregated parameters from the previous round. This is because of the peculiarity on the updates in the user/item profile. For instance, if a user has not interacted with an item, its local update on the item profile will return the same output as the original weight. The FedAvg algorithm includes this parameter in the calculation process and hence, the update for this item will remain close to the previous value and as a result, convergence is slowed down.

To overcome the above limitation and meet the weights update requirements in a MF task, we describe an adaptation of FedAvg, termed as MF-FedAvg, for handling the item profile updates. We **Algorithm 1:** *MF-FedAvg.* The C clients are indexed by c; E is the number of local epochs; B is the local minibatch size; D_c is the local dataset; N_w , I, n_c , n_I are the neural network's weights, the item profile's weights, the local training instances and the number of participants who updated a specific item, respectively.

assume that the data each participant owns are independent and non identically distributed (non-iid). In the rest of this work "non-iid" means that the data distributions D_i and D_j for two participants P_i and P_j can vary [31]. Moreover, each participant can hold a different number of training instances n_c . These assumptions are natural in FL because in the general case, each participant can have an arbitrary number of training instances, while the local datasets may not be representative of the overall distribution.

As noted, the item and the user latent vectors are updated independently by each client. In addition, when the MF module is fused with a neural architecture as in [12], the FedAvg algorithm has to deal with both the latent vectors and the neural network's weights. In our case, each of the three federated models contains a neural architecture. Hence, to effectively update the neural network's weights, i.e. parameters that do not correspond to either user or item latent vectors, we follow the update procedure as proposed in the original FedAvg [9]. That is, the weights that correspond to a neural architecture are updated as:

$$w_{t+1} \leftarrow \sum_{c=1}^{C} \frac{n_c}{n} w_{t+1}^c,$$

where C is the total number of selected participants in a training round, n_c is the number of the local training instances of a participant, $n = \sum_{c=1}^{C} n_c$ is the total number of training instances and w_{t+1}^c is the local weight updates generated by a participant.

The item profile is updated in such a way that a participant only contributes to the components that correspond to its interactions. For instance, if a participant has only interacted with two items, its local computation affects only these two items vectors. Therefore, the item profile is updated without taking into consideration the local training instances. Hence, in the server side, the item's

matrix can be updated by taking an average of the updates of the participants who updated a specific item in the profile.

Algorithm 1 shows the adaptation of FedAvg to MF, where each component in item profile is formed as an average of the learned parameters. In particular, the coordination server collects the updated weights I^c that correspond to the item updates for each selected participant $c \in C$. The coordination server calculates the difference between the updated weights I^c transmitted from a participant c and the item weights I from the previous round. The difference is zero only for items that a participant did not update, i.e. the participant did not interact with these items. This way, the coordination server can effectively calculate the sum of the item updates, while counting the number of participants who updated a specific vector in the item matrix. Finally, it averages the weights and updates the item profile.

4.3 FedNCF Threat Model

Below, we define the threat model and the privacy level that is achieved in the FedNCF system with the integration of the plain MF-FedAvg. We further show that a federated system alone does not provide strong privacy guarantees. In the next section, we proceed by describing a protocol by integrating a secure aggregation [17] approach, which meets the privacy requirements in the HBC model.

We consider two potential adversaries against the FedNCF system: (1) the coordination server and (2) the participants $P_{i \in \{1,...,M\}}$.

The required parameters during a local computation in FedNCF are the local interactions matrix R_i , the local user vector U^i , the global item profile I and the global neural network's weights N_w . At the end of a local computation, each participant P_i transmits the updated local I^i and N_w^i to the coordination server for aggregation. Hence, the coordination server has partial access to the local model of each participant. Recall that in FedNCF, participants do not transmit their updated user vectors.

Most horizontal FL systems define their threat model under the assumption of an HBC server [5, 32]. That is, it is assumed that the coordination server is honest in terms of its operations; yet, it may try to extract the private data of the participants. In this work, we also take into consideration an HBC participant, because it can learn additional information about another user by looking at the updated item profile.

As showed in [24], an aggregator, who has direct access to the updated parameters of a participant in two consecutive rounds, can extract this user's latent vector and as a result, to extract additional information, i.e., the original rating for an item. Although [24] showed that operating on encrypted gradients is sufficient for providing privacy guarantees against an HBC server, their privacy model does not hold against HBC participants. First, the reconstruction of the user profile applies against HBC participants even with the homomorphic encryption mechanism. Their system allows the update of the global item profile after a user's transmission. As such, the updates of the participant with sufficient computational resources and high bandwidth may always arrive first. On the one hand, this can be a bottleneck in the training procedure as the model updates will concern only one participant. On the other hand, HBC participants can inspect the model updates in two consecutive training rounds, leading to user's latent vector reconstruction. Second, as their system performs immediate gradients update, a participant has access to the global parameters in every step. An HBC participant, knowing the user who transmitted its updated item profile in the previous step and accessing the gradients of the global model from the current and previous step, can deduce the user's rating behavior.

To overcome the privacy threats caused by HBC entities, we argue that performing aggregation on masked parameters can ensure that: (1) the passive coordination server (aggregator) cannot learn any additional information beyond the aggregated parameters and (2) the passive user cannot infer the preferences of other participants.

5 SECURE WEIGHTS AGGREGATION

A plausible way for achieving a privacy-preserving aggregation is by adopting an efficient secure aggregation scheme like SecAvg [17]. On a higher level, SecAvg enables the coordination server to blindly calculate the sum of the updates of the participants, without revealing the produced weights that correspond to each individual. The protocol operates by pairing each user with every other selected participant and each pair agrees on a random matrix. After the agreement step, each user performs a simple calculation based on its order [17] (Appendix B). However, simply integrating this protocol in the case of MF will lead to the inconsistency described in Section 4.2. The aggregated parameters will remain close to the previous update, leading to quality reduction. Our goal is to generate an update with the calculated weights from the participants that actually interacted with an item, without revealing their identities.

To overcome this challenge and maintain high communication and computation efficiency, we show that combining SecAvg with the modified version of FedAvg will result in a privacy-preserving communication efficient protocol without quality reduction.

MF-SecAvg. The first concern is the update procedure for the item profile. Intuitively, only a small fraction of the selected participants have interacted with the same items. For instance, if only two out of *C* participants have interacted with a specific item, the aggregated result should only consider the updates of these two clients. Inevitably, in a similar manner with MF-FedAvg, the coordination server should be aware of the number of participants that interacted with specific items. A straightforward way for the coordination server to accomplish this, would be to ask clients to inform for their interactions. However, this method would result in immediate information leakage since the the coordination server can look at the interacted items and possibly infer additional information.

To protect the privacy of the participants, a protocol for generating only the total number of clients that interacted with each item is needed. One way is to perform SecAvg for the interacted items, as described in [17]. The secure aggregation protocol provides strong privacy guarantees against HBC entities and hence, it fits our goal. The participants generate a vector as large as the number of items in the item profile, which contains zeros for items that did not interact and ones, otherwise. Then, they can perform the SecAvg process for generating the masked vectors. This way, the coordination server will only collect the masked vectors. The masks will be canceled when added together, revealing the total number of participants interacted with each item, while the participants' plain interactions

Algorithm 2: *MF-SecAvg.* The *C* clients are indexed by c; *E* is the number of local epochs; *B* is the local minibatch size; D_c is the local dataset; N_w , I, n_c , n_I are the neural network's weights, the item profile's weights, the local training instances and the number of participants who updated a specific item, respectively; \mathcal{P} is the participants in the current training round.

```
Server executes:
initialize N_{w_0}, I_0
for each round t=1,2,... do
       S_t \leftarrow \text{set of } C \text{ clients}
       \begin{array}{l} \textbf{for } \textit{each client } c \in S_t \ \textbf{do} \\ & \max ked^c_{N_{w_{t+1}}}, masked^c_{I_{t+1}}, masked^c_{n_I} \leftarrow \\ & \text{ClientUpdate}(c, N_{w_t}, I_t) \end{array} 
     n_{I} \leftarrow \sum_{c=1}^{C} masked_{n_{I}}^{c}
N_{w_{l+1}} \leftarrow \sum_{c=1}^{C} \frac{1}{n} masked_{N_{w_{l+1}}}^{c}
I_{l+1} \leftarrow \sum_{c=1}^{C} \frac{1}{n_{I}} masked_{I_{l+1}}^{c}
Function ClientUpdate(c, N, I):
       \mathcal{B} \leftarrow \text{split } D_c \text{ into batches of size } B
       for each local epoch i=1,2,...,E do
              for batch b \in \mathcal{B} do
                      N_{w} \leftarrow N_{w} - \eta \nabla \mathcal{L}(N;b)
                  I \leftarrow I - \eta \nabla \mathcal{L}(I; b)
       masked_{N_w}, masked_I, masked_{n_I} \leftarrow SecAvg(N_w, I, \mathcal{P})
       return masked_{N_{n,i}}, masked_{I}, masked_{n_I}
Function SecAvg(N_w, I, \mathcal{P}):
       for each p in \mathcal{P} do
              Generate agreed vectors
              Compute masked weights
       return masked_{N_{W}}, masked_{I}, masked_{n_{I}}
```

are maintained secret. For handling the item profile updates, in a similar manner, the participants agree on random matrices as large as the item profile and perform the calculations according to the SecAvg protocol. The coordination server can now calculate the aggregated vector for each item in the item profile.

As noted earlier, FedNCF contains a neural architecture for each of the three models. Applying SecAvg on a neural network's weights is a simpler task than handling the item profile. After a local training operation each user multiplies its updated weights with the number of local training instances and perform the original SecAvg protocol. The coordination server sums the masked weights and divides the corresponding output with the total number of training instances. The participants also mask their number of local training instances using the SecAvg protocol, enabling a blind calculation of the total number of interactions. We summarize the MF-SecAvg protocol, which is the privacy-preserving integration to FedNCF, in Algorithm 2. A high level overview of FedNCF enhanced with MF-SecAvg is given in Fig. 1.

Putting it all together, the FedNCF learning process' main steps

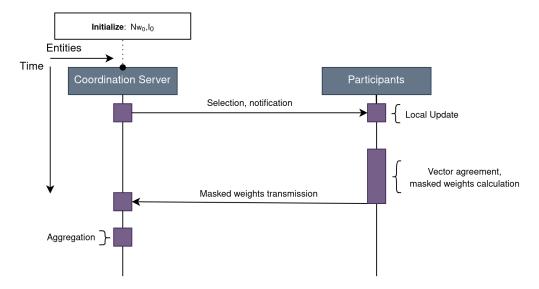


Figure 1: FedNCF communication protocol enhanced with SecAvg.

- (1) The coordination server randomly initializes the weights that correspond to the item profile, I_0 , and the neural architecture, N_{w_0} . It randomly selects C online participants to perform a local update and notifies them about the training plan, e.g. the model's architecture.
- (2) Each pair of participants agrees on two random matrices for the item profile and neural network's weights and two random vectors for the interacted items and the total number of local training instances, respectively.
- (3) The participants download the current global parameters and perform a specified number of gradient descent iterations.
- (4) Each participant perform a calculation to the generated weights according to MF-SecAvg, which is an extension of the SecAvg [17] protocol to handle the item profile updates.
- (5) The coordination server waits for the transmission of the masked weights within a specified time. If a specific threshold, thresh, of reports has been received in the specified time span, the round is considered successful and the coordination server can proceed with the aggregation step. The thresh parameter is used for correctness in the SecAvg protocol. For more details we refer to [17].

5.1 MF-SecAvg Security Analysis

Following the security analysis in [17], the masked parameters that are calculated independently by each participant look random if the agreed matrices between users, $\sum_{c \in C: c < v} R_{c,v}$ are generated uniformly at random. The random matrices hide the original weights calculated by each individual, in a way that the sum of the masked weights are equal to the sum of the weight updates generated by the participants.

First, each user, after its local computation, pairs its identifier with every other participant in the training round and each pair of users agree on random matrices. Finally, each participant performs an addition or a substraction to the calculated local update with the agreed matrix based on its identified order. The final output

is transmitted for aggregation. Therefore, the users in the current training round are only aware for their agreed random matrices, their output after a local training operation and the weights of the global model. Hence, they cannot learn anything other than their own updates.

In a similar manner, performing SecAvg, provides security guarantees against an HBC coordination server. The participants transmit their masked weights, which do not reveal anything about an individual's generated updates. The coordination server only learns the masked weights of a participant, the sum of those weights and the total number of the local training instances for this round's user group. Therefore, it cannot infer any additional information about the identity of the client that updated a specific vector. Note that, for correctness, the coordination server should collect the masked weights from at least a specified number of participants.

For handling the MF updates and to improve the model's quality, we ask participants to perform the SecAvg protocol for an additional vector, in order to notify the coordination server about the number of users who updated an item. Although this way reveals the number of participants who interacted with specific items, the coordination server cannot learn the identities of users that interacted with these items. Table 1 shows the access to learning parameters by system entities in FedNCF with MF-FedAvg and MF-SecAvg.

k-Anonymity of FedNCF. In this subsection we argue that the MF-SecAvg integration to FedNCF achieves k-anonymity for the participants in a training round.

The concept of k-anonymity is introduced by Samarati and Sweeney [33] and extended by Sweeney [34]. Briefly, a database release satisfies k-anonymity if every record is indistinguishable from at least k-1 other records, ensuring that individuals cannot be identified by linking attacks.

In the context of FedNCF k-anonymity is achieved by ensuring that no less than k=C participants can be associated with a specific item's vector update.

Data Items	Entities					
	MF-FedAvg			MF-SecAv _{		
	P_i	P_{j}	S	$\overline{P_i}$	P_j	S
local interactions r_{ij}	√	‡	✓	✓	X	X
training instances n_c	\checkmark	X	\checkmark	\checkmark	X	X
$local U_i$	\checkmark	#	#	\checkmark	X	X
$local I_i$	\checkmark	#	\checkmark	\checkmark	X	X
$local N_{w_i}$	\checkmark	#	\checkmark	\checkmark	X	X

Table 1: Access to learning parameters by system entities in two learning settings: MF-FedAvg and MF-SecAvg. ✓ denotes that the entity has access to the data item. ‡ denotes that an HBC adversary can deduce the value of this parameter.

We distinguish three entities in the FedNCF system: (i) the participants in an aggregation round, whose privacy needs to be protected, (ii) the coordination server (which is also the aggregator) and (iii) an HBC adversary. Note that the HBC adversary can be either a participant or the coordination server.

The participants control their local dataset as well as the local training iterations. In FedNCF, the participants' interactions are associated with the item's profile updates. The adversary has full knowledge of the global parameters in every aggregation round. The goal of the adversary is to perform a linking attack, i.e. to link an item's vector update with a specific user.

LEMMA 5.1. FedNCF enhanced with MF-SecAvg ensures the k-anonymity of the participants against an HBC adversary in an aggregation round.

PROOF. Recall that MF-SecAvg enables a blind calculation of the sum of the updates of the participants and the number of participants who updated a specific item. The participants in every aggregation round have only access to the current global parameters and their local interactions. Even if the same group of users is considered in consecutive aggregation rounds, an HBC participant cannot link any other user's interactions with item updates. Therefore, k-anonymity holds against HBC participants.

The coordination server collects and aggregates the masked updates received from the selected users. In the collection phase, the participants' weight updates are masked using the one-time-pad property of SecAvg. In the aggregation phase, the coordination server averages the sum of the masked updates for an item's vector based on the number of participants who updated a specific item. Although, the coordination server is aware of the number of participants who updated an item, it cannot deduce which user(s) updated this item. Hence, k-anonymity holds against an HBC coordination server.

5.2 Limitations of FedNCF

A limitation of the MF-SecAvg protocol is that an HBC adversary can still learn that the current group of participants did not interact with an item. However, k-anonymity still holds as the adversary cannot link an update with an individual's interaction.

A second limitation is that an HBC coordination server can manipulate the random selection process to select the same group of participants except one user in an effort to identify this user's interacted items.

Bluring property of FedNCF. Recall that FedNCF operates on an implicit feedback scenario. This means that only positive interactions are provided. To simulate negative interactions, a common strategy is to randomly sample some uninteracted items that extends a participant's training dataset. Negative sampling can also be extended to an explicit feedback scenario, e.g. by assigning a pseudo-rating to some randomly sampled uninteracted items [14]. Therefore, even if an HBC coordination server can force the selection of the same group of participants, negative sampling blurs a user's actual interactions.

Although a negative sampling strategy can enhance the privacy of the participants, an individual's behavior can still be deduced as interacted items are included in the training set. This limitation can be overcome by moving the selection process to a participant, who perform a random selection using a secure pseudo-random generator such as [35]. Another way is to ask the participants to perform a group checking operation by noticing the users' identities before the vectors' agreement step. A different approach may be to add noise in the local training step to offer differential privacy guarantees [36]. However, noising techniques may harm the model's quality. This study mainly concerns the comparison of centralized and federated learning without quality reduction. Therefore, we leave the integration of differential privacy in FedNCF for future work.

6 EXPERIMENTS

In this section we present the experimental settings as well as the results of our conducted experiments. We additionally provide an analysis for the impact of certain settings on the recommendation quality. We also compare the computation overhead of MF-SecAvg against a HE scheme, denoted as MF-HEAvg, that satisfies the security requirements against an HBC adversary. MF-HEAvg follows the concept of the protocol introduced in [24], which cannot be directly applied in our scenario as FedNCF operates in a synchronous setting. Briefly, in MF-HEAvg, each selected participant encrypts its corresponding updates with a shared public key. The coordination server collects the participants' updates and takes advantage of the Paillier's additive property to calculate the sum of the updates. Then, the selected participants in the next aggregation round, download the encrypted updated parameters, decrypt them with a shared secret key and perform an averaging based on the total number of training instances in the previous round. A detailed discussion for MF-HEAvg is given in Appendix C. For the implementation details refer to Appendix D.

6.1 Evaluation Settings

We evaluate the FedNCF system on four real-world datasets in recommender systems: MovieLens 100K², MovieLens 1M³ [37], Lastfm 2K⁴ [38] and Foursquare New York (NY)⁵ [39]. These datasets are widely used in the literature for evaluating CF algorithms. The

 $^{^2} https://grouplens.org/datasets/movielens/100 K/$

https://grouplens.org/datasets/movielens/1m/

⁴https://grouplens.org/datasets/hetrec-2011/

 $^{^5} https://sites.google.com/site/yangdingqi/home/foursquare-dataset$

first two datasets are movie ratings, where each user has interacted with at least 20 items, making them attractive for evaluating recommendation systems. Hence, we did not filter any user-item interaction. On the other hand, the Lastfm 2K and Foursquare NY datasets are highly sparse. Moreover, we observed that many users in both datasets have a small amount of interactions. Lastfm 2K contains artists tagged by users, while Foursquare NY contain users' check-ins. We excluded users with less than 5 interactions in both datasets. After user filtering, the datasets contain 1,600 users with 185,650 interactions and 1,083 users with 91,023 interactions, correspondingly. Table 2 shows the characteristics of the four datasets.

Dataset	#Interaction	#Item	#User	Sparsity
MovieLens 100K	100,000	1,682	943	93.7%
MovieLens 1M	1,000,209	3,706	6,040	95.53%
Lastfm 2K	185,650	12,454	1,600	99.07%
Foursquare NY	91,023	38,333	1,083	99.78%

Table 2: Evaluation datasets statistics

For pre-processing, we follow a common practice in recommendation systems by converting numeric ratings to implicit feedback [4, 12, 40] for the MovieLens datasets. Lastfm 2K and Foursquare NY only contain user interactions and thus, they are already in an implicit format. Next, we group the interactions by users and we sort their interactions by timestamps.

To evaluate the recommendation models, we adopt leave-one-out evaluation, a commonly used method in the literature [4, 12, 41]. That is, we hold out the last interaction for each user as validation data and utilize the remaining interactions for training. For quick evaluation, we pair each ground truth item in the test set with 100 randomly sampled uninteracted items [12]. Therefore, the CF task is transformed to rank the sampled negative items with the held-out item for each user. Although this kind of evaluation may falsely produce better results, our goal is not to present a state-of-the-art system, but to fairly compare the federated variant against the centralized one [12], on the same settings.

The ranked list is evaluated with the *Hit Ratio* (*HR*) and *Normalized Discounted Cumulative Gain* (*NDCG*) metrics. Briefly, *HR* calculates the appearance of the ground truth item in the top-K ranked items and *NDCG* takes into consideration the position of the hit [12, 42]. Note that HR@K is equivalent to Recall@K as there is only one ground truth item for each user. In this work we report the HR and NDCG with K=10. In the evaluation, we calculate both metrics for each user and report the average score.

6.2 Experimental Results

Aggregation Rounds Impact. We first demonstrate the sensitivity of FedNCF to the number of participants in an aggregation round. We evaluate the FedNCF system with $c = \{10, 20, 50, 100, 200, 300, |P|\}$ participants per aggregation round, where |P| is the total number of users present in the dataset, using the MF-FedAvg algorithm. Table 3 presents the highest HR observed for each model after 400 training iterations per participant in the MovieLens 100K dataset.

# P	FedGMF	FedMLP	FedNeuMF
10	0.58	0.39	0.6
20	0.59	0.4	0.61
50	0.56	0.4	0.6
100	0.54	0.41	0.56
200	0.49	0.4	0.51
300	0.44	0.39	0.48
943	0.35	0.38	0.39

Table 3: Impact of the number of participants per aggregation round, presenting the highest HR@10 observed in the MovieLens 100K dataset.

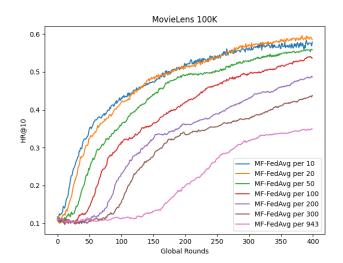


Figure 2: Impact of the number of participants per aggregation round on the convergence speed in the MovieLens 100K dataset, using the MF-FedAvg aggregation algorithm.

Bonawitz et al. [16], mentioned that the FedAvg algorithm can only effectively aggregate a small number of devices in parallel. In our experiments, we also observe similar behavior. The *HR* value decreases when the aggregation is performed with more than 100 participants in the case of MovieLens 100K dataset. A similar behavior is observed for the other three datasets: considering more participants per aggregation round than the observed optimal value, leads to quality reduction. In a similar manner, the number of participants considered in an aggregation round leads not only to quality reduction, but also to slower convergence. An example on the MovieLens 100K dataset is given in Fig. 2.

More precisely, we found that selecting 20, 120, 50 and 50 participants for each dataset, respectively, leads to the highest quality models. On the other hand, a significant drop (about 20%) in FedGMF and FedNeuMF is observed when all participants are considered for aggregation. Following the work in [43], the reduction in the model's quality and the convergence speed, when increasing the size of $\mathcal C$ per aggregation, can be attributed to the heterogeneity among participants, which leads to inconsistency between local models.

The quality of the FedMLP model is nearly the same, regardless of the number of participants in an aggregation round. However, FedMLP does not converge to an acceptable recommendation quality compared to FedGMF and FedNeuMF, as we show later in the comparison between NCF and FedNCF. This behavior can be attributed to the fact that, in MLP, the user and item profiles are concatenated before fed into the neural architecture. In FedMLP, each user only owns its corresponding user vector and hence, each training iteration leads to the inconsistency of the learning objective, resulting in the prevention of convergence.

Aggregation Function Impact. We additionally demonstrate the influence of the aggregation function, which is an integral step of the FedNCF approach. The primary purpose of this experiment is to highlight the efficacy of the MF-FedAvg adaptation to MF and to evaluate the convergence speed of FedAvg in a setting with additional learning parameters other than neural network's weights. We run MF-FedAvg, FedAvg and SimpleAvg algorithms, where SimpleAvg concerns a simple (non-weighted) averaging over the updated weights, with the same hyper-parameters, i.e., we conduct 400 training steps, while aggregating the local updates with the optimal C observed in the previous experiment. Table 4 shows the performance comparison between the two algorithms by measuring the HR@10 in the FedGMF model on the four datasets.

Dataset	MF-FedAvg	FedAvg	SimpleAvg
MovieLens 100K	0.59	0.56	0.55
MovieLens 1M	0.6	0.55	0.52
Lastfm 2K	0.62	0.59	0.58
Foursquare NY	0.21	0.16	0.12

Table 4: Influence on the recommendation quality using MF-FedAvg, FedAvg and SimpleAvg aggregation functions.

The recommendation performance shows that MF-FedAvg outperforms FedAvg, which outperforms SimpleAvg. Hence, there is evidence that the MF-FedAvg approach can be effectively applied as an optimization method in federated models based on MF.

MF-FedAvg also leads the model to faster convergence. Each of the three methods starts from an HR close to 0.1 in each of the four datasets, while MF-FedAvg converges much faster than FedAvg. An example of the convergence speed in the MovieLens 100K dataset for the three aggregation function is given in Fig. 3. At the end of the training iterations, we observe that the HR performance of MF-FedAvg is 3-5% greater than the corresponding HR of the FedAvg method. Therefore, our initial conjecture that the FedAvg does not respond well to models that contain additional parameters other than neural network's weights, is confirmed. The difference in the model's quality and the convergence speed can be attributed to the fact that the FedAvg algorithm is heavily dependent on the number of local training instances.

Data Federation Impact. Our primary goal in this experiment, is to compare the recommendation quality and the convergence speed of FedNCF against the centralized NCF system. In essence, we evaluate the federated variants of the three models presented in [12], namely, GMF, MLP and NeuMF. We compare FedNCF to the

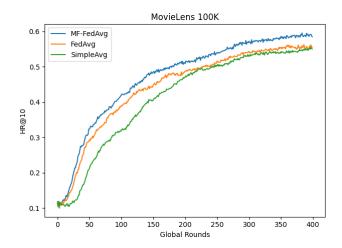


Figure 3: Convergence speed of the MF-FedAvg, FedAvg and SimpleAvg on the MovieLens 100K dataset.

centralized NCF by measuring the overall HR@10 and NDCG@10 metrics generated by each method. For each model we use the same hyper-parameters and we conduct 400 training iterations. For the federated models, we choose to aggregate the updated parameters with the optimal value observed in the first experiment, i.e. per 20, 100, 50, 50 participants for each dataset, respectively. Fig. 4 shows the recommendation quality and the convergence speed of the FedNCF models against the NCF baseline.

As expected, the recommendation quality of the centralized trained models is the upper-bound for FedNCF. Not surprisingly, the highest *HR* and *NDCG* values, in the NCF system, are generated by the NeuMF model, while GMF offers similar recommendation quality. We observed that the recommendation quality of the centralized system follows the same observation to the authors of NCF: NeuMF > MLP > GMF [12].

In the same way, FedNeuMF and FedGMF outperform FedMLP, while leading to faster convergence in each dataset except for the Foursquare NY. In the latter dataset, FedNeuMF and FedMLP overfit the training data, beginning from the 180th and 60th global round, respectively, while FedGMF has not reached its maximum performance after 400 global rounds. FedNeuMF and FedGMF offer similar recommendation quality in the rest of the datasets, while FedMLP cannot converge, as already discussed. Hence, the FedNCF system follows the same trend with NCF in terms of the recommendation quality of the three models. Table 5 presents the performance comparison for the highest *HR* and *NDCG* observed, between NCF and FedNCF in each dataset.

The experimental results show that the centralized models achieve higher recommendation quality. The difference between FedNeuMF and NeuMF is 8%, 12%, 16% and 3% for the *HR* metric in each dataset, respectively. On the one hand, we can conclude that the harder the task for centralized learning (see the recommendation quality for the Foursquare NY and MovieLens 100K datasets), the closer the performance of the federated variant. On the hand, the easier the task, the slower the recommendation quality of the federated variant against the centralized one.

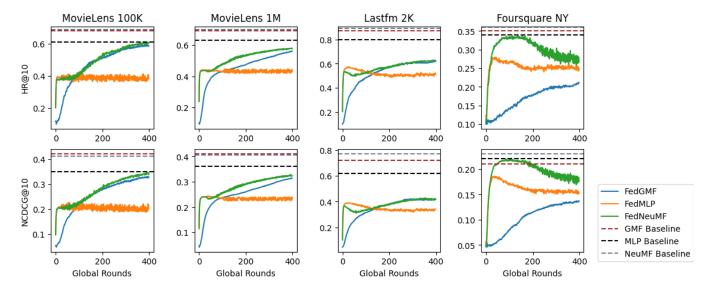


Figure 4: Performance comparison and convergence speed of NCF and FedNCF.

Although the difference between the two versions in the Movie-Lens 1M and Lastfm 100K datasets is over 10%, the federated models yield acceptable recommendation quality. Given that the federated setting is applied to data that are not available in centralized environments, it could be argued that FL may outperform traditional models in case of a large scale deployment.

Finally, it is worth mentioning that the client-server architecture for the FedNCF is simulated by partitioning the dataset into subsets according to users' interactions, i.e. each user is only aware for its local interactions. Hence, the data present on individuals vary in terms of size and distribution. As a result, the non-iid data leads to slow convergence [44] and efficiency reduction [43].

Secure Computations Performance. The integration of the MF-SecAvg and MF-HEAvg schemes to the FL pipeline offers the property of providing the same recommendation quality with the original FL models. The operations on random agreed weights with the MF-SecAvg and the encryption/decryption processes with the MF-HEAvg, will generate equivalent aggregated parameters with the MF-FedAvg approach. Hence, the objective of this experimental evaluation is to provide insights related to the computation overhead that is introduced. We choose to experiment with the FedGMF and FedNeuMF models as they comprise to the smallest and largest model of the NCF approach, correspondingly.

MF-SecAvg Performance In the MF-SecAvg approach, each participant agrees on a random matrix with each of the C-1 users for each weight parameter of the specified model and performs a simple operation based on its user order. Table 6 shows the average additional time needed for the random weights initialization and the masked weights generation in FedGMF and FedNeuMF models after a global round, considering the optimal value found in the first experiment as the number of users per aggregation round. Note that there is also an extra communication cost for the random matrix agreement phase. However, this extra cost is negligible as noted in [17].

Dataset		FedNCF	NCF			
		GMF				
MovieLens 100K	HR	0.59	0.68			
	NDCG	0.33	0.42			
MovieLens 1M	HR	0.56	0.69			
	NDCG	0.31	0.41			
Lastfm 2K	HR	0.62	0.87			
	NDCG	0.47	0.72			
Foursquare NY	HR	0.21	0.35			
	NDCG	0.14	0.21			
		ML	P			
MovieLens 100K	HR	0.43	0.61			
	NDCG	0.23	0.35			
MovieLens 1M	HR	0.44	0.63			
	NDCG	0.24	0.36			
Lastfm 2K	HR	0.57	0.8			
	NDCG	0.39	0.62			
Foursquare NY	HR	0.28	0.34			
	NDCG	0.19	0.22			
		NeuA	1F			
MovieLens 100K	HR	0.61	0.69			
	NDCG	0.34	0.42			
MovieLens 1M	HR	0.58	0.7			
	NDCG	0.33	0.41			
Lastfm 2K	HR	0.63	0.89			
	NDCG	0.43	0.77			
Foursquare NY	HR	0.33	0.36			
	NDCG	0.22	0.23			

Table 5: Performance comparison between FedNCF and NCF by measuring the highest HR@10 and NDCG@10 observed.

The additional computation cost is strongly dependent with the number of items present in each dataset. On the largest dataset (Foursquare NY) the overhead only concerns an extra computation time of 93ms with the NeuMF model. Therefore, it is easily observed that the MF-SecAvg protocol has an imperceptible influence on computation overhead. This suggest that integrating MF-SecAvg in federated recommender systems, provides both high computation and communication efficiency, while the privacy of the participants is maintained.

Dataset	FedGMF	FedNeuMF
MovieLens 100K	3ms	7ms
MovieLens 1M	5ms	12ms
Lastfm 2K	16ms	33ms
Foursquare NY	49ms	93ms

Table 6: MF-SecAvg impact on computation overhead in an aggregation round for each participant on a 4.0GHz, 8-core CPU.

MF-HEAvg Performance Unlike MF-SecAvg, MF-HEAvg incorporates an encryption scheme, which requires the generation of a public-secret key pair. Note that, according to NIST, the recommended key size is 3072 for 128-bits security [45]. Intuitively, it is expected that the larger the key size, the greater the computational complexity. Fixed-precision arithmetic and modulus operations for representing floating and negative point numbers, also contribute to the increased overhead. In addition, a ciphertext's size in the Paillier cryptosystem is inevitably as large as the size of the underlying public key. Therefore, storage requirements lead to an additional communication overhead, since each ciphertext should be sent to the coordination server for an update.

Table 7 summarizes the computation time needed for encryption/decryption with different key sizes as well as it shows the size of the encrypted parameters that a participant produces after its encryption operation in the MovieLens 100K dataset. Our results show that incorporating HE into the FL pipeline is computationally very expensive. The HE scheme introduces about 40 minutes of additional computation for producing the encrypted parameters, while an extra time of 14 minutes is needed for decrypting the updated parameters received from the coordination server, in the case of FedNeuMF with a 3072-bits key. In addition, a produced ciphertext's size is as high as 32.5 MB for a 3072-bits key in the Movielens 100K dataset, which contains a relative small number of items. Sending such large ciphertexts may further reduce the communication efficiency.

Although MF-HEAvg provides strong privacy guarantees, there is a significant communication and computation efficiency reduction, which may lead to user dropouts and as a result, to the failure of the learning objective. Therefore, the computation overhead may be unprofitable for "small" devices and hence, the MF-SecAvg approach is preferable to the MF-HEAvg, since the former only adds an additional overhead of a few extra milliseconds, without requiring complicated calculations.

7 DISCUSSION

The evaluation of the FedNCF system confirmed the viability of a FedCF framework. Our experiments showed the effectiveness of FL in recommender systems, supporting the concept that small contributions from low-resource computing nodes whose data remain local can lead to a high-quality machine learning model. We noted that the federated system leads to lower recommendation quality and slower convergence than the centralized approach. This is mainly due to the presence of non-iid data [43, 44]. Handling the non-iid data and optimizing or proposing new ways for aggregation will greatly benefit FL.

FL enables participants to build independent models, without exposing their raw data. We showed (Table 1) that participants' private data are still leaked by the output of their computations. To overcome this limitation, we presented a privacy-preserving approach by adapting the SecAvg protocol [17] to a MF approach. We showed that MF-SecAvg improves the privacy of the participants by ensuring the property of k-anonymity, while maintaining the original model's quality. The limitation of selecting the same group of participants (Section 5.2) can be overcome by enabling a group checking operation or by incorporating a randomized mechanism for differential privacy guarantees [36].

We also compared the MF-SecAvg approach against a HE scheme that offers the same privacy level under the constraint that the secret key is maintained secret among participants, while overcoming the challenge of linking an update with a specific user. However, HE introduces an additional overhead, which can be a bottleneck in the federated process.

FL is an active field of research; yet, industrial deployments and real world applications are still limited. We believe that leveraging privacy-enhancing mechanisms, will eventually lead to the large-scale participation of users. Such mechanisms include the utilization of cryptographic schemes such as efficient HE and SMC approaches, combined with the use of privacy definitions such as differential privacy [5, 8]. In this work, we chose not to alter the data by introducing noise to obtain differential privacy guarantees [36]. We showed (Fig. 4) that applying FL on non-iid data leads to slower convergence, even without altering the weight updates. Introducing noise may further reduce the convergence speed [46] and we leave "noising" before aggregation for future work. Noisebased methods either introduce additional overhead or reduce the convergence speed, making the deployment of FL applications even harder. Therefore, there is a trade-off between the privacy loss and model quality. On the one hand, the slow convergence prevents the deployment of a FL application and on the other hand, privacypreserving techniques will lead to the large-scale participation and eventually to the creation of smarter and more accurate models.

Open Issues. Although the analysis and evaluation of FL systems, there are still important open questions. A critical issue is the convergence against user dropouts and failures. In this work, we assumed that the participants and the coordination server are available and ready at any given time. In a real-world scenario, with a community comprised of many participants, failures from unreliable participants is a common event [16]. Although the MF-FedAvg algorithm and the MF-SecAvg and MF-HEAvg protocols provide tolerance against failures, user dropouts may lead to slow convergence. In addition, handling the failures of the coordination server is not an easy task. In case when the coordination server is

		Encrypti	on Time	(s)	Ι	Decrypti	on Time	(s)		Size	(MB)	
Model/Key Length	512	1024	2048	3072	512	1024	2048	3072	512	1024	2048	3072
FedGMF	9.05	52.48	358.93	1145.33	5.26	22.19	106.42	350.97	6.3	11.55	22.03	32.5
FedNeuMF	19.48	120.17	756.39	2360.71	13.41	57.43	264.78	806.17	13.04	23.89	45.55	67.22

Table 7: Time and storage consumption in an aggregation round for each participant with MF-HEAvg on a 4.0GHz, 8-core CPU.

down, the participants should wait for its liveness to be restored, leading to the delay of the learning process.

Besides fault tolerance, it is essential to address issues related to the learning process. In our experiments, each participant was selected once per global training round. That is, we considered *passive* selection, meaning that participants offer equal contribution to the global parameters in each global training round. A possible extension is to introduce *active* sampling to train the global model on participants with more beneficial contribution [47]. This way, the selected participants may lead the model to faster convergence.

Finally, we would like to emphasize an important issue for the reliability and acceptance of the FL systems. The success of FL is strongly dependent with the number of participants in the learning process. Currently, most FL frameworks assume the voluntary participation of users. However, without incentive mechanisms, users are not being motivated to adopt a FL system [48] and as a result, the concept of FL may fail. An incentive mechanism will not only attract more participants, but also encourage them to behave rationally [49], excluding targeted deviations from the protocol that may lead to biased models through poisoning attacks [50].

8 CONCLUSION

In this paper, we presented a federated version of the state-of-theart method Neural Collaborative Filtering for making high-quality recommendations. Although federated learning provides a higher privacy level than conventional machine learning, we showed that the federated setting alone, does not eliminate privacy concerns. Then, we introduced a privacy-preserving computation that utilises a SMC protocol to hide a participant's interactions. We evaluated the recommendation quality of the FedNCF approach and we discussed the impact of the utilized aggregation function and the number of participants that contribute in an aggregation round. Finally, we compared the SMC approach with a HE scheme that offers and equivalent protection level. We showed that both approaches enjoy the property of not declining the recommendation quality. It is easily observed that the HE scheme introduces heavy communication and computation overhead that may not be acceptable for low-resource devices.

We conclude that FL is a promising learning technique as private data sharing is no longer required. Therefore, training models by leveraging data that were not previously available, will eventually lead to smarter and more efficient systems. On the other hand, there are several open issues that need to be carefully investigated, such as choosing the optimal number of participants for a training round and handling network failure events. A critical future direction for improving FL, is to further focus on its security and privacy analysis. Even though FL enables a higher level of privacy than conventional machine learning, a formal estimation of the information leakage is

crucial. Finally, ways of building privacy-preserving solutions with no side information leakage, while maintaining the original model's quality and without requiring heavy computation overhead, are in demand.

9 ACKNOWLEDGMENTS

This work has been co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH - CREATE - INNOVATE (project code: T1EDK-02474, grant no.: MIS 5030446).

REFERENCES

- Resnick, P., & Varian, H. R. (1997). Recommender systems. Communications of the ACM, 40(3), 56-58
- [2] Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. Knowledge-based systems, 46, 109-132.
- [3] Mnih, A., & Salakhutdinov, R. R. (2008). Probabilistic matrix factorization. In Advances in neural information processing systems (pp. 1257-1264).
- [4] Rendle, S., Freudenthaler, C., Gantner, Z., & Schmidt-Thieme, L. (2012). BPR: Bayesian personalized ranking from implicit feedback. arXiv preprint arXiv:1205.2618.
- [5] Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2) 1-19
- [6] Weinsberg, U., Bhagat, S., Ioannidis, S., & Taft, N. (2012, September). BlurMe: Inferring and obfuscating user gender based on ratings. In Proceedings of the sixth ACM conference on Recommender systems (pp. 195-202).
- [7] Narayanan, A., & Shmatikov, V. (2008, May). Robust de-anonymization of large sparse datasets. In 2008 IEEE Symposium on Security and Privacy (sp 2008) (pp. 111-125). IEEE.
- [8] Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. *IEEE Signal Processing Magazine*, 37(3), 50-60.
- [9] McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017, April). Communication-efficient learning of deep networks from decentralized data. In Artificial Intelligence and Statistics (pp. 1273-1282). PMLR.
- [10] Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. Computer, 42(8), 30-37.
- [11] Gao, D., Tan, B., Ju, C., Zheng, V. W., & Yang, Q. (2020). Privacy Threats Against Federated Matrix Factorization. arXiv preprint arXiv:2007.01587.
- [12] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017, April). Neural collaborative filtering. In Proceedings of the 26th international conference on world wide web (pp. 173-182).
- [13] Ammad-Ud-Din, M., Ivannikova, E., Khan, S. A., Oyomno, W., Fu, Q., Tan, K. E., & Flanagan, A. (2019). Federated Collaborative Filtering for Privacy-Preserving Personalized Recommendation System. arXiv preprint arXiv:1901.09888.
- [14] Lin, G., Liang, F., Pan, W., & Ming, Z. (2020). FedRec: Federated Recommendation with Explicit Feedback. IEEE Intelligent Systems.
- [15] Melis, L., Song, C., De Cristofaro, E., & Shmatikov, V. (2019, May). Exploiting unintended feature leakage in collaborative learning. In 2019 IEEE Symposium on Security and Privacy (SP) (pp. 691-706). IEEE.
- [16] Bonawitz, K., Eichner, H., Grieskamp, W., Huba, D., Ingerman, A., Ivanov, V., et al., J. (2019). Towards federated learning at scale: System design. arXiv preprint arXiv:1902.01046.
- [17] Bonawitz, K., Ivanov, V., Kreuter, B., Marcedone, A., McMahan, H. B., Patel, S., et al., K. (2017, October). Practical secure aggregation for privacy-preserving machine learning. In proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security (pp. 1175-1191).
- [18] Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001, April). Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th international conference on World Wide Web (pp. 285-295).

- [19] Bell, R. M., & Koren, Y. (2007). Lessons from the Netflix prize challenge. Acm Sigkdd Explorations Newsletter, 9(2), 75-79.
- [20] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. ACM Computing Surveys (CSUR), 52(1), 1-38.
- [21] Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., et al., R. G. (2019). Advances and open problems in federated learning. arXiv preprint arXiv:1912.04977.
- [22] Shamir, A. (1979). How to share a secret. Communications of the ACM, 22(11), 612-613.
- [23] Paillier, P. (1999, May). Public-key cryptosystems based on composite degree residuosity classes. In *International conference on the theory and applications of* cryptographic techniques (pp. 223-238). Springer, Berlin, Heidelberg.
- [24] Chai, D., Wang, L., Chen, K., & Yang, Q. (2020). Secure federated matrix factorization. IEEE Intelligent Systems.
- [25] Chen, Y., Ning, Y., Slawski, M., & Rangwala, H. (2020, December). Asynchronous online federated learning for edge devices with non-iid data. In 2020 IEEE International Conference on Big Data (Big Data) (pp. 15-24). IEEE.
- [26] Damaskinos, G., Guerraoui, R., Kermarrec, A. M., Nitu, V., Patra, R., & Taiani, F. (2020, December). Fleet: Online federated learning via staleness awareness and performance prediction. In *Proceedings of the 21st International Middleware Conference* (pp. 163-177).
- [27] Ribero, M., Henderson, J., Williamson, S., & Vikalo, H. (2020). Federating Recommendations Using Differentially Private Prototypes. arXiv preprint arXiv:2003.00602.
- [28] Dean, J., Corrado, G. S., Monga, R., Chen, K., Devin, M., Le, Q. V., et al. (2012, December). Large scale distributed deep networks. In Proceedings of the 25th International Conference on Neural Information Processing Systems-Volume 1 (pp. 1223-1231).
- [29] Jiang, J., Cui, B., Zhang, C., & Yu, L. (2017, May). Heterogeneity-aware distributed parameter servers. In Proceedings of the 2017 ACM International Conference on Management of Data (pp. 463-478).
- [30] Goldreich, O. (2009). Foundations of cryptography: volume 2, basic applications. Cambridge university press, pp. 603.
- [31] Li, X., Huang, K., Yang, W., Wang, S., & Zhang, Z. (2019). On the convergence of fedavg on non-iid data. arXiv preprint arXiv:1907.02189.
- [32] Aono, Y., Hayashi, T., Wang, L., & Moriai, S. (2017). Privacy-preserving deep learning via additively homomorphic encryption. IEEE Transactions on Information Forensics and Security, 13(5), 1333-1345.
- [33] Samarati, P., & Sweeney, L. (1998). Protecting privacy when disclosing information: k-anonymity and its enforcement through generalization and suppression. Technical report, SRI International, 1998.
- [34] Sweeney, L. (2002). k-anonymity: A model for protecting privacy. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 10(05), 557-570.
- [35] Vazirani, U. V., & Vazirani, V. V. (1984, August). Efficient and secure pseudorandom number generation. In Workshop on the Theory and Application of Cryptographic Techniques (pp. 193-202). Springer, Berlin, Heidelberg.
- [36] Dwork, C., & Roth, A. (2014). The algorithmic foundations of differential privacy. Foundations and Trends in Theoretical Computer Science, 9(3-4), 211-407.
- [37] Harper, F. M., & Konstan, J. A. (2015). The movielens datasets: History and context. Acm transactions on interactive intelligent systems (tiis), 5(4), 1-19.
- [38] Cantador, I., Brusilovsky, P., & Kuflik, T. (2011, October). Second workshop on information heterogeneity and fusion in recommender systems (HetRec2011). In Proceedings of the fifth ACM conference on Recommender systems (pp. 387-388).
- [39] Yang, D., Zhang, D., Zheng, V. W., & Yu, Z. (2014). Modeling user activity preference by leveraging user spatial temporal characteristics in LBSNs. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 45(1), 129-142.
- [40] Hu, Y., Koren, Y., & Volinsky, C. (2008, December). Collaborative filtering for implicit feedback datasets. In 2008 Eighth IEEE International Conference on Data Mining (pp. 263-272). Ieee.
- [41] Tang, J., & Wang, K. (2018, February). Personalized top-n sequential recommendation via convolutional sequence embedding. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining (pp. 565-573).
- [42] He, X., Chen, T., Kan, M. Y., & Chen, X. (2015, October). Trirank: Review-aware explainable recommendation by modeling aspects. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management (pp. 1661-1670).
- [43] Zhao, Y., Li, M., Lai, L., Suda, N., Civin, D., & Chandra, V. (2018). Federated learning with non-iid data. arXiv preprint arXiv:1806.00582.
- [44] Wang, H., Kaplan, Z., Niu, D., & Li, B. (2020, July). Optimizing federated learning on non-iid data with reinforcement learning. In IEEE INFOCOM 2020-IEEE Conference on Computer Communications (pp. 1698-1707). IEEE.
- [45] Barker, E., Barker, É., Burr, W., Polk, W., & Smid, M. (2020). Recommendation for key management: Part 1: General (revision 5). NIST Special Publication 800-57.
- [46] Wei, K., Li, J., Ding, M., Ma, C., Yang, H. H., Farokhi, et al. (2020). Federated learning with differential privacy: Algorithms and performance analysis. IEEE Transactions on Information Forensics and Security, 15, 3454-3469.

- [47] Nishio, T., & Yonetani, R. (2019, May). Client selection for federated learning with heterogeneous resources in mobile edge. In ICC 2019-2019 IEEE International Conference on Communications (ICC) (pp. 1-7). IEEE.
- [48] Bao, X., Su, C., Xiong, Y., Huang, W., & Hu, Y. (2019, August). Flchain: A blockchain for auditable federated learning with trust and incentive. In 2019 5th International Conference on Big Data Computing and Communications (BIGCOM) (pp. 151-159). IEEE.
- [49] Toyoda, K., & Zhang, A. N. (2019, December). Mechanism design for an incentive-aware blockchain-enabled federated learning platform. In 2019 IEEE International Conference on Big Data (Big Data) (pp. 395-403). IEEE.
- [50] Bagdasaryan, E., Veit, A., Hua, Y., Estrin, D., & Shmatikov, V. (2020, June). How to backdoor federated learning. In *International Conference on Artificial Intelligence* and Statistics (pp. 2938-2948). PMLR.
- [51] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., et al., S. (2019). Pytorch: An imperative style, high-performance deep learning library. arXiv preprint arXiv:1912.01703.
- [52] Glorot, X., & Bengio, Y. (2010, March). Understanding the difficulty of training deep feedforward neural networks. In Proceedings of the thirteenth international conference on artificial intelligence and statistics (pp. 249-256). JMLR Workshop and Conference Proceedings.
- [53] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

A FEDAVG ALGORITHM

In this section we show the FedAvg algorithm for a weighted aggregation [9].

Algorithm 3: FedAvg. The C clients are indexed by c; E is the number of local epochs; B is the local minibatch size; D_c is the local dataset; $n_c = |D_c|$ is the number of local raining instances.

```
Server executes:
```

```
initialize w_0

for each round t=1,2,... do

Randomly select C clients

Transmit the currect global model w_t

S_t \leftarrow set of C clients

for each client c \in S_t do

w_{t+1}^c, n_c \leftarrow ClientUpdate(c, w)

w_{t+1} \leftarrow \sum_{c=1}^C \frac{n_c}{n} w_{t+1}^c

Function ClientUpdate(c, w):

\mathcal{B} \leftarrow split D_c into batches of size B

for each local epoch i=1,2,...,E do

for batch b \in \mathcal{B} do

w \leftarrow w - \eta \nabla \mathcal{L}(w; b)

return w_t \mid D_c \mid to server
```

B SECAVG PROTOCOL

In this section we show the SecAvg protocol for a simple (non-weighted) aggregation. The protocol operates by pairing the selected participants. Each pair of users agree on a common matrix and each participant masks its updated weights according to the agreed matrix and its user order. Finally, the generated masks are transmitted to the coordination server for aggregation.

In particular, each user generates the weight updates, w_{t+1}^c , where $c \in C$ is the indices of the selected participants in time step t+1 by performing some local gradient descent iterations. Each user perform the following operation before transmitting its

updates to the coordination server:

$$masked_{w_{t+1}}^c = w_{t+1}^c + \sum_{c \in C: c < v} R_{c,v} - \sum_{c \in C: c > v} R_{v,c},$$

where $R_{c,v}$ is the agreed matrix between user c and user v on an ordered set of users (c,v), c < v as described in [17]. The coordination server, after collecting each $masked_{w_{t+1}}^c$ calculates:

$$\begin{aligned} & masked_{w_{t+1}} = \sum_{c \in c} masked_{w_{t+1}}^c \\ &= \sum_{c \in c} w_{t+1}^c + \sum_{c \in C: c < v} R_{c,v} - \sum_{c \in C: c > v} R_{v,c} \\ &= \sum_{c \in c} (w_{t+1}^c). \end{aligned}$$

The $masked_{w_{l+1}}$ parameter contains the sum of the weight updates, which needs to be aggregated. In the simplest form of an aggregation step, the server can produce the updated weights by calculating:

$$w_{t+1} = masked_{w_{t+1}}/C,$$

where *C* is the number of selected participants.

C MF-HEAVG PROTOCOL

In this section we give a detailed description of the MF-HEAvg protocol, which is an adaptation of [24] in FedNCF. MF-HEAvg differs from its original proposal as it operates in a synchronous setting as well as it performs a weighted aggregation.

C.1 Integration to FedNCF

The integration of the Paillier's HE scheme to the FedNCF system requires a *public* and *secret* key (PK, SK) generation from a randomly selected participant. After the key generation process, the participant establishes a secure SSL/TLS channel for transmitting the PK to the coordination server. In addition, some SSL/TLS peer-to-peer connections are established with a number of online participants for sharing the corresponding SK. The SK propagates among participants, while it should be kept secret from the coordination server.

After the key generation/propagation, the coordination server initializes the global parameters, encrypts them with the shared PK and initiates the learning operation. In each round, every selected participant downloads the encrypted global parameters and perform an aggregation on (i) the neural network's weights based on the total number of training instances and (ii) the item profile based on the number of users who updated each item.

After the decryption phase, each user forms its local model X_i by decrypting the global parameters. Their local datasets are fed into the X_i to compute the updated weights. Subsequently, each participant computes the multiplication of its local training instances and the updated neural network's weights, $n_c * N_w^c$. This step is crucial as we use the FedAvg algorithm to perform aggregation on the parameters that correspond to the neural architecture. For the item profile, each user encrypts the whole updated item matrix. Moreover, the participants initialize an additional vector to include which items have been updated. This additional vector correspond to the item profile updates. This is because the item profile is being updated based on the number of participants who interacted with each item. Finally, they encrypt the updated weights, the additional

vector and a constant that corresponds to the number of their local training instances with the shared PK. Thus, each participant generates four encrypted vectors, $EncN_{w}^{c}$, $EncI^{c}$, $Enc_{n_{I}}^{c}$ and $Enc_{n_{c}}$, which are the encrypted parameters that correspond to the neural network's weights and the item profile, the items interacted and the number of local training instances, respectively. These values are transmitted to the coordination server.

Once the coordination server has collected the encrypted parameters, it calculates the sum of the updates, the total number of users who updated an item and the total number of training instances, based on the homomorphic additive property. Note that the coordination server does not hold the corresponding *SK* and hence, it cannot decrypt any of the received parameters. Consequently it cannot learn anything about the updated weights and the users who updated an item.

C.2 MF-HEAvg Security

The coordination server, after the summing operation, prepares the encrypted weights for the next round. The encrypted parameters are transmitted to the next group of selected participants, who can decrypt the corresponding ciphertexts. Note that the parameters are not in an aggregated form. Therefore, each participant, before feeding the weights to the local model, should perform an averaging step to the decrypted parameters based on the number of users who updated an item and the total number of training instances in the previous round, for the item profile and the neural network's weights, respectively.

We argue that MF-HEAvg protects the privacy of the participants against an HBC adversary, provided that the corresponding HE scheme is secure against chosen plaintext attacks.

The MF-HEAvg does not leak any information to the coordination server related to the updates of the participants nor the server can link an update with a user's identity provided that the SK does not get leaked. The homomorphic encryption scheme ensures that only the entity/ies that hold the SK can decrypt the corresponding ciphertexts. Moreover, the participants in every round, are only aware of the sum updates, the number of the participants who updated a specific item and the total number of the local training instances in the previous round. Hence, MF-HEAvg preserves the privacy of the participants as an HBC adversary cannot link any update with a specific user as the participants' identities are not revealed. Similarly to MF-SecAvg, integrating MF-HEAvg to FedNCF, ensures the k-anonymity of the participants. For more details refer to Section 5.1.

In addition to the above properties, MF-HEAvg eliminates the limitation of selecting the same group of participants except one user, identified in the MF-SecAvg integration (Section 5.2). The coordination server cannot inspect any of the updates as the participants transmit them in an encrypted form. However, MF-HEAvg comes at a high cost: HE schemes integrated on the weight updates of a machine learning model, significantly damage the communication and computation overhead due to the exponentiation and large modulus calculations, leading to large ciphertext expansion.

D IMPLEMENTATION DETAILS

We implement our proposed method with PyTorch [51]. The weight parameters in the neural architecture are initiated using the Xavier initialization [52]. For common hyper-parameters in all models, we consider D=12 latent factors and the hidden dimensions for the neural architectures are $h=\{48,24,12,6\}$. In addition, all weights are learnt by optimizing the BCE loss, where we sampled four negative instances per positive instance. For optimization, we utilized the Adam optimizer [53] with a learning rate of 1e-3. In each experiment, we conduct 400 epochs of training for our models.

We used the open-source library python-paillier⁶ to handle the encryption process and operate on encrypted ciphertexts. An extension of the Paillier cryptosystem for handling floating and negative numbers is given below.

D.1 Handling Floating and Negative Numbers

Typically, the Paillier cryptosystem [23] operates on non-negative integers, while a machine learning's computation generates floating and signed numbers. Hence, the Paillier cryptosystem should be extended to handle any real number, while preserving its properties.

We use fixed-precision arithmetic for integer representation. Briefly, an exponent is multiplied with the real number and the resulting integer is encrypted. In the decryption process, the floating representation is made by dividing the decrypted integer with the exponent used in the encryption process. Note that the exponent should be the same in both the encryption and decryption processes.

For negative numbers representation, a $max_{integer}$ parameter is used for which it is assumed that all of the data to be encrypted are smaller than this parameter. For instance, the $max_{integer}$ can be set to as large as $\frac{n}{3}$, where n=pq is part of the Paillier's PK and p,q are large prime numbers. Performing a modulus n operation for each of the data to be encrypted, will result in representing negative numbers with positive integers larger than the $max_{integer}$ parameter, while the positive numbers do not change.

E EXPERIMENTS SUPPLEMENTARY

In this section, we provide some additional details for the NCF and FedNCF approaches.

For the NCF approach we observe that NeuMF outperforms GMF, which outperforms the MLP model in terms of recommendation quality. Table 8 shows the highest HR observed after 400 training epochs in the four datasets considered.

Dataset	GMF	MLP	NeuMF
MovieLens 100K	0.68	0.61	0.69
MovieLens 1M	0.69	0.63	0.7
Lastfm 2K	0.87	0.8	0.89
Foursquare NY	0.35	0.34	0.36

Table 8: NCF's performance by measuring the highest HR@10 on the MovieLens 100K, MovieLens 1M, Lastfm 2K and Foursquare NY datasets.

In addition to the experiments conducted in Section 6, we also measured the impact of local epochs in terms of convergence. In each dataset we observed that the more the local epochs, the faster convergence for the FedNCF models. An example on the MovieLens 100K dataset is given in Fig. 5 using the MF-FedAvg aggregation function.

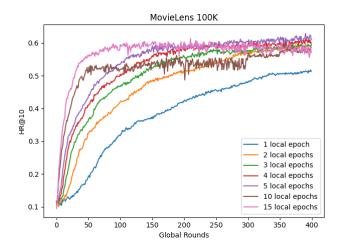


Figure 5: Impact of local epochs in the MovieLens 100K dataset.

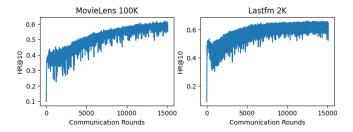


Figure 6: Convergence speed against communication rounds in the FedNeuMF model using a random selection order on the MovieLens 100K and Lastfm 2K datasets.

In Section 6, we selected each participant 400 times in an effort to fairly compare the FedNCF approach against NCF. However, in FL, each participant is not available at any given time, nor the participants equally contribute to the global parameters. In each aggregation round the coordination server randomly select a subset of participants. We simulated such a case and we observed that the selection order of the participants does not greatly impacts the model's quality. We experimented with 5 different selection orders using different seeds and we observed that the deviation is $\pm 2\%$ against the highest HR observed in Table 5. Finally, it is worth noting that using random selections, the first 100 communication (aggregation) rounds heavily affect the models' convergence. An example of the convergence speed in the MovieLens 100K and Lastfm 2K with the FedNeuMF model is given in Fig. 6.

⁶https://github.com/data61/python-paillier.