How to Put Users in Control of their Data via Federated Pair-Wise Recommendation

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Recommendation services are extensively adopted in several user-centered applications as a tool to alleviate the information overload problem and help users in orienteering in a vast space of possible choices. In such scenarios, privacy is a crucial concern since users may not be willing to share their sensitive preferences (e.g., visited locations, read books, bought items) with a central server. Unfortunately, data harvesting and collection is at the basis of modern, state-of-the-art approaches to recommendation. Decreased users’ willingness to share personal information along with data minimization/protection policies (such as the European GDPR), can result in the “data scarcity” dilemma affecting data-intensive applications such as recommender systems (RS). We argue that scarcity of adequate data due to privacy concerns can severely impair the quality of learned models and, in the long term, result in a turnover and disloyal customers with direct consequences for lives, society, and businesses. To address these issues, we present FPL, an architecture in which users collaborate in training a central factorization model while controlling the amount of sensitive data leaving their devices. The proposed approach implements pair-wise learning to rank optimization by following the Federated Learning principles conceived originally to mitigate the privacy risks of traditional machine learning. We have conducted an extensive experimental evaluation on three Foursquare datasets and have verified the effectiveness of the proposed architecture concerning accuracy and beyond-accuracy objectives. We have analyzed the impact of communication cost with the central server on the system’s performance, by varying the amount of local computation and training parallelism. Finally, we have carefully examined the impact of disclosed users’ information on the quality of the final model and suggested insights to strike a balance between utility-privacy trade-off.

CCS Concepts:
- Information systems → Recommender systems; Personalization.

Additional Key Words and Phrases: federated learning, recommender systems, BPR, privacy control

1 INTRODUCTION

With the increasing popularity of personalized services and the appearance of a plethora of smart devices responsible for the generation of a considerable amount of digital content, recommender systems (RSs) have emerged as a paradigm of information push to support better decision making to users and promote business by recommending novel and personalized items. Collaborative filtering (CF) models have been the mainstream of research in the RS community over the last two decades due to their performance accuracy [29, 42]. CF builds on the fundamental assumption that personal preferences correlate to each other, and users who expressed similar tastes in the past tend to agree in the future as well. Among them, a prominent class uses the matrix factorization (MF) approach as the inference model. The main aim of the MF model is to uncover user and item latent representations whose linear interaction explains observed feedback. To date, the majority of existing MF models are trained in a centralized fashion. Although it results in the best approach in terms of precision of computed recommendation, the centralized MF approach is facing, in recent years, several challenges about privacy of user data. Over the past year, the public awareness of privacy issues has been steadily increasing after large-scale data breaches such as Cambridge Analytica in 2018, which shared and harvested data from

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a massive number of users for political campaigning without their consent [11]. These incidents made international headlines, and have spurred the European Union, US Congress, and other jurisdictions to legislate new disclosure laws. As an example, in 2018 GDPR [1] was proposed by the EU that removes the default option for collecting, storing, and harnessing individual’s data and requires explicit authorization from the users to use their data. The consequent data scarcity dilemma can thereby jeopardize the training of MF models. Connecting it RSs, training high-quality MF models strongly relies on the availability of sufficient in-domain interaction data to ensure enough co-occurrence information exists to form similar behavioral/preference patterns in a user community. In recent years federated learning (FL) was proposed by Google, which offers a privacy-by-design solution [20, 21, 30] for machine-learned models. The goal in FL is to train a global machine learning (ML) model in a distributed fashion by leveraging both users’ data and personal devices’ computing capabilities while keeping data on the device they have been generated on (e.g., laptops, mobile phones, tablets), without the need of sharing them with a central server.

The proposed system envisioned in this work, FPL (short for Federated Pair-wise Learning), is a federated factorization model for collaborative recommendation, which builds on advances made in research involving federated representation/learning of knowledge by upholding real-world constraints about data privacy. It extends the state-of-the-art factorization approach, to build a RS that puts users in control of their sensitive data. Users participating in the federation process, can decide if and the extent by which they are willing to disclose their private sensitive (i.e. what they liked/consumed) preferences. The proposed system mainly leverages not-sensitive information (e.g., places she has non-visited) – which can be large and non-sensitive – to reach a competitive accuracy and respect a satisfactory balance between accuracy and privacy. In this work, we tackle to the following research questions:

**RQ1** Is it possible to integrate Pair-wise Learning with Federated Learning principles to build a federated version of factorization models? What is the impact of federated parameters (i.e., computation parallelism, and local computation amount) on the quality of recommendation?

**RQ2** The protection of the user’s feedback can put the recommendation service in jeopardy. Can user receive high-quality recommendation, while limiting the amount of disclosed sensitive data?

**RQ3** The sequentiality of the original pair-wise algorithms can be replicated at the price of increased communication costs. What is the optimal (or sub-optimal) trade-off between communication costs, and recommendation utility?

**RQ4** With limited training information, the recommendation algorithm might learn differently and unexpectedly. Does the federated recommendation (and the possible reduced information budget) inject additional biases in the final recommendation?

To answer the Research Questions, we have carried out extensive experiments on real-world datasets [40] in the Point of Interest (PoI) domain, by considering the accuracy of recommendation and diversity metrics (Item Coverage and Gini Index). Moreover, we analyzed communication cost and accuracy in a multi-objective perspective, as well as the fairness (i.e., the Bias Disparity) of FPL recommendations. The experimental evaluation shows that FPL can provide high-quality recommendations, putting the user in control of the amount of sensitive data to share.

### 2 BACKGROUND TECHNOLOGIES

This section is devoted to introducing the fundamentals of the federated learning paradigm, the pair-wise learning to rank approach, and the factorization models. In detail, it is designed to provide (i) a brief motivation of the technologies,
(ii) the essential mathematical background, (iii) the formal definition of the main concepts, and (iv) the notation that is adopted in the following.

2.1 Federated Learning

Federated learning (FL) is a paradigm initially envisioned by Google [20, 21, 30] to train a machine-learning model from data distributed among a loose federation of users’ devices (e.g., personal mobile phones). The rationale is to face the increasing issues of ownership and locality of data, to mitigate the privacy risks (and leaks) resulting from centralized machine learning [9, 19].

Definition 2.1 (Federated Learning). Let $\Theta$ denote the machine learning model parameters, and consider a learning scenario where the objective is to minimize a generic loss function $G(\Theta)$. Federated Learning is a learning paradigm in which the users of a federation $U$ collaborate to solve the learning problem under the coordination of a central server $S$ without sharing or exchanging their raw data.

From an algorithmic point of view, in the well-known implementation provided by McMahan et al. [30], authors realize a federated optimization inspired by Stochastic Gradient Descent (SGD). For a fixed number of rounds of communication, the central server $S$ selects a subset of clients $U' \subseteq U$ and sends them the current global model parameter $\Theta$. Each selected client $u \in U'$ locally updates the received model by using her own private data $K_u$ and returns to $S$ the gradient $\nabla G_{K_u}(\Theta)$. Hereby, the central server $S$ performs a weighted global aggregation of the received local gradients, and updates the model as follows:

$$\Theta \leftarrow \Theta - \alpha \sum_{u \in U'} w_u \nabla G_{K_u}(\Theta),$$

(1)

where $w_u$ is a client-dependent weight [5] and $\nabla$ is the differential operator. It should be noted that this approach builds on the assumption that $\sum_{u \in U'} w_u \nabla G_{K_u}(\Theta) \approx \nabla G_K(\Theta)$, where $K = \bigcup_{u \in U'} K_u$.

2.2 Factorization Models and Pair-Wise Recommendation

Let $U$ denote a set of users and $I$ a set of items (e.g., movies, songs, goods, places). Consider the recommendation problem as the maximization of a satisfaction-based utility function for each user in $U$.

Definition 2.2 (Recommendation Problem). Given a utility function $g: U \times I \to \mathbb{R}$, a recommendation problem is the activity of finding $\forall u \in U$ the item $i^*_u$, not already consumed by $u$, such that:

$$i^*_u = \arg\max_{i \in I} g(u, i).$$

(2)

Given $U$ and $I$, let $X = \mathbb{R}^{|U| \times |I|}$ be the user-item matrix containing for each $x_{ui}$ an explicit or implicit feedback (e.g., rating or check-in, respectively) of user $u \in U$ for item $i \in I$. In the work at hand, an implicit feedback scenario is considered — i.e., feedback is, e.g., purchases, visits, clicks, views, check-ins —, with $X$ containing binary values. Therefore, hereinafter $x_{ui} = 1$ and $x_{ui} = 0$ denote either user $u$ has consumed or not item $i$, respectively.

In FPL, the underlying data model is a Factorization model, inspired by MF [23], a recommendation model that became popular in the last decade thanks to its state-of-the-art recommendation accuracy [25].

Definition 2.3 (Matrix Factorization). Given a set of users $U$, a set of items $I$, and a matrix $X = \mathbb{R}^{|U| \times |I|}$, Matrix Factorization is a model $\Theta$ in which each user $u$ and each item $i$ is represented by the embedding vectors $p_u$ and $q_i$. 

respectively, in the shared latent space $\mathbb{R}^F$. The core of the algorithm relies on the assumption that $X$ can be factorized such that the dot product between $p_u$ and $q_i$ can explain any observed user-item interaction $x_{ui}$, and that any non-observed interaction can be estimated as:

$$
\hat{x}_{ui}(\theta) = b_i(\theta) + p_u^T(\theta)q_i(\theta) = b_i(\theta) + \sum_{f=1}^{F} p_{uf}(\theta)q_{if}(\theta),
$$

(3)

where $b_i$ is a term denoting the bias of the item $i$.

Hereinafter, the factorization model is denoted by using $\Theta = \langle P, Q, b \rangle$, where $P \in \mathbb{R}^{|U| \times F}$ is a matrix whose $u$-th row corresponds to the vector $p_u$, and $Q \in \mathbb{R}^{|I| \times F}$ is a matrix in which the $i$-th row corresponds to the vector $q_i$. Finally, $b \in \mathbb{R}^{|I|}$ is a vector whose $i$-th element corresponds to the value $b_i$.

Definition 2.4 (Bayesian Personalized Ranking). Let $\mathcal{K} : U \times I \times I$ be a training set defined by $\mathcal{K} = \{(u, i, j) \mid x_{ui} = 1 \land x_{uj} = 0\}$. Bayesian Personalized Ranking is an optimization approach aiming to learn a model $\Theta$ that solves the personalized ranking task according to the following optimization criterion:

$$
\max_{\Theta} \sum_{(u, i, j) \in \mathcal{K}} \ln \sigma(\hat{x}_{uij}(\Theta)) - \lambda ||\Theta||^2,
$$

(4)

where $\hat{x}_{uij}(\Theta)$ is a real value modeling the relation between user $u$, item $i$ and item $j$, $\sigma(\cdot)$ is the sigmoid function, and $\lambda$ is a model-specific regularization parameter to prevent overfitting.

Notably, the set $\mathcal{K}$ is composed of triples $(u, i, j)$, meaning that user $u$ has consumed item $i$ but not $j$, so that it is assumed she prefers item $i$ over $j$. BPR [33] optimization is a general criterion to train a wide range of recommendation models. In the context of MF, the model $\Theta$ of Definition 2.3 corresponds to the model $\Theta$ in Eq. 4 In MF, the value $\hat{x}_{uij}(\Theta)$ — hereinafter $\hat{x}_{uij}$ — can be decomposed as:

$$
\hat{x}_{uij}(\Theta) = \hat{x}_{ui}(\Theta) - \hat{x}_{uj}(\Theta),
$$

(5)

that is the core of the learning to rank approach, since it does not focus on predicting a single rating $x_{ui}$, but on classifying the difference of two predictions, i.e., it estimates the pair-wise relation between items. The learning algorithm searches the optimal parameter values of $\Theta$ by employing a stochastic gradient descent algorithm over the training triples in $\mathcal{K}$. Given a learning rate $\alpha$, the model is updated with:

$$
\Theta \leftarrow \Theta + \alpha \Delta \Theta, \quad \text{with} \quad \Delta \Theta = \frac{e^{-\hat{x}_{uij}}}{1 + e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta} \hat{x}_{uij} - \lambda \Theta.
$$

(6)

3 FPL: THE FEDERATED PAIR-WISE LEARNING FRAMEWORK

The advantage of FL is that users can collaboratively train a ML model with a server coordinating them, without the need to share their data. However, data protection usually leads to an accuracy loss [41], which is the price of letting users not share their sensitive data. In this section, we introduce FPL (summarized in Fig. 1), a framework in which users (or system designers) are completely in control of their data and are able to decide how much protect them². To the best of our knowledge, FPL is the first attempt to put pair-wise optimization in federated recommender systems, and to give the users the possibility to select the trade-off between data disclosure and recommendation utility.
3.1 FPL Framework

Following the aforementioned federated learning principles, let $\mathcal{U}$ be the set of users (clients) with a server $S$ coordinating them. Let us assume that users consume items from a catalog $I$ and give feedback about them (as in the recommendation problem of Section 2.2). $S$ is aware of the catalog $I$, while exclusively user $u$ knows her own set of consumed items.

To set up the federation for FPL, a global model is built on $S$ such that $\Theta = (Q, b)$, where $Q \in \mathbb{R}^{I \times F}$ and $b \in \mathbb{R}^{|I|}$ are the item-factor matrix and the bias vector (introduced in Section 2). On the other hand, on each user $u$’s device FPL builds a model $\Theta_u = (p_u)$, which corresponds to the representation of user $u$ in the latent space of dimensionality $F$. Each user $u$ holds her own private feedback dataset $x_u \in \mathbb{R}^I$, which — analogously to a centralized recommender system — corresponds to the $u$-th row of matrix $X$. Each FPL client $u$ hosts a user-specific training set $K_u : \mathcal{U} \times I \times I$ defined by $K_u = \{(u, i, j) \mid x_{ui} = 1 \land x_{uj} = 0\}$, where $x_{ui}$ represents the $i$-th element of $x_u$. Please note that, in the following, we refer to $X^+ = \sum_{u \in \mathcal{U}} |\{x_{ui} \mid x_{ui} = 1\}|$ as the number of positive interactions in the system.

The classic BPR-MF learning procedure [33] for model training can not be applied to the federated learning scheme [30]. Instead, we propose a novel learning paradigm that is executed for a number $E$ of epochs and works by rounds of communication that envisages transmission-computation-transmission-aggregation sequences between the server and the clients. The number of rounds of communication performed in each learning epoch is a parameter denoted by the symbol $rpe$ (round-per-epoch). Each round of communication is envisioned as a four-step protocol:

1. $S$ randomly selects (adopting a uniform distribution) a subset of users $\mathcal{U}^- \subseteq \mathcal{U}$ and delivers them the model $\Theta_S$;
2. local computation: each user $u$ generates $T$ triples from her dataset $K_u$ and performs BPR stochastic optimization on them to update her local model $\Theta_u$; moreover, user $u$ computes a variation $\Delta$ of the latent factor vector (and of the bias) of each item involved in training;
3. transmission: the clients in $\mathcal{U}^-$ send back to $S$ a portion of the computed item factor vector updates and item bias updates;
4. global aggregation: $S$ aggregates all the received updates in matrix $Q$ and vector $b$ to build the new $\Theta_S$ model.

![Fig. 1. Item-Factor Matrix (center) is sent by the server to the federation of devices (left side) which perform the local training phase. Local outputs are sent to the server which aggregates them (right side).](image-url)
It is noteworthy that, in FPL, only user \( u \) holds the embedding vector \( p_u \). Therefore, each user’s device autonomously computes her personalized item ranking, just pulling the updated global model (i.e., the matrix \( Q \)) from \( S \).

### 3.1.1 Local computation

In step 2, to update \( \Theta_u \) and compute the updates for item latent vectors, each client \( u \) needs to optimize Equation 4. This optimization is composed of iterative optimization steps over \( T \) training triples from \( \mathcal{K}_u \). In detail, in each step, user \( u \)’s device extracts a triple \((u, i, j)\) to compute the gradients for the local \( p_u \) vector of \( \Theta_u \), and for the vectors \( p_i \) and \( p_j \) of the received \( \Theta_S \). In detail, in the pair-wise learning, the partial derivatives, for the model parameter \( \theta \), are computed as follows:

\[
\frac{\partial}{\partial \theta} s_{uij} = \begin{cases} 
(q_i - q_j) & \text{if } \theta = p_u, \\
p_u & \text{if } \theta = q_i, \\
-p_u & \text{if } \theta = q_j, \\
1 & \text{if } \theta = b_i, \\
-1 & \text{if } \theta = b_j.
\end{cases} \tag{7}
\]

Thus, user \( u \)’s device updates the user embedding \( p_u \) by exploiting Eq. 6. The same procedure computes the item updates \((\Delta q_i, \Delta b_i)\) and \((\Delta q_j, \Delta b_j)\) for each training triple \((u, i, j)\). It is worth noticing that Rendle \cite{rendle2010} suggests, in a centralized scenario, to adopt a uniform distribution (over \( \mathcal{K} \)) to choose the training triples randomly. The purpose is to avoid data is traversed item-wise or user-wise, since this may lead to slow convergence. Conversely, a federated approach is required to train the model user-wise since the training of each round of communication is performed separately on each client \( u \) knowing only data in \( \mathcal{K}_u \). This is why, in FPL, the designer can control the number of triples \( T \) intended for training, to tune the degree of local computation — i.e., how much the sampling is user-wise traversing —.

### 3.1.2 Transmission

Once the local model update has taken place, the device sends the items updates back to \( S \) to contribute to the global \( Q \) matrix in \( \Theta_S \). Notably, the updates of a SGD iteration — i.e., the training output of a triple \((u, i, j)\) —, let the server distinguish the consumed item \( i \) from the non-consumed item \( j \), just by analyzing the positive sign of \((\Delta q_i, \Delta b_i)\), while they show the same absolute value. Consequently, sending all the updates computed by user \( u \)’s device may raise a privacy issue, since, in the long term, server \( S \) may be able to reconstruct the \( \mathcal{K}_u \) dataset. Since our primary goal is to put users in control of their data, FPL proposes a solution to overcome this vulnerability. By sending the sole update \((\Delta q_i, \Delta b_i)\) of each training triples \((u, i, j)\), user \( u \) would share with \( S \) indistinguishably negative or missing values, which are assumed to be not sensitive data. We introduce the parameter \( \pi \), which puts user in control of the amount of consumed items to share with the central server \( S \). For evaluation purposes, the parameter \( \pi \) works as a probability that clients send a specific positive item update \((\Delta q_i, \Delta b_i)\). Instead, the update \((\Delta q_j, \Delta b_j)\) for the negative item is always sent.

### 3.1.3 Global aggregation

Once \( S \) receives the updates from the clients in \( U^- \), it can update the global model with:

\[
\Theta_S \leftarrow \Theta_S + \alpha \sum_{u \in U^-} \Delta \Theta_u, \tag{8}
\]

with \( \alpha \) being the learning rate. Under a mathematical perspective, each row of the matrix \( Q \) is updated by summing up the contribution of all clients in \( U^- \) for the corresponding item.

### 3.2 Communication Cost

In a FL setting, communication rounds between clients and the server play a crucial role. In fact, a large amount of information exchanged might hinder the effectiveness of the overall approach as it requires high network costs. This perspective has led us to define a metric, the Communication Cost per Epoch (CCE), which calculates communication
costs that each particular FPL configuration requires. Since the communication in FPL is bidirectional, we compute the total cost $CCE$ of the training phase as the sum of the costs in each direction (i.e., server-to-clients - S2C, and clients-to-server - C2S). We formally define $CCE$ as follows:

$$CCE = \rho \cdot (\omega_{S2C} + \omega_{C2S}),$$

(9)

where $\omega_{S2C}$, and $\omega_{C2S}$ represent the amount of information sent by the server to each client, and by each client to the server, respectively. For FPL, we set $\omega_{S2C} = |I|$, since it is the number of item factor vectors the server sends to each client, while $\omega_{C2S} = T(1 + \pi)$, being $T$ the number of sent updates for non-consumed items and $\pi T$ the number of sent updates for consumed items. Let $\rho$ be the number of interactions between clients and server in one epoch, defined as:

$$\rho = |U^−| \cdot rpe,$$

(10)

To be completely agnostic to the underlying model, the value of $\omega_{S2C}$ and $\omega_{C2S}$ is computed by considering each exchanged update as a unit of information.

3.3 Model Freshness

A critical aspect of a FL approach is to decide how often the clients access to an updated global model. In a classic centralized approach, since the models are hosted on the same machine (or within the same ecosystem) this problem is not evident. In a distributed setting, the issue arises since the well-known recommendation algorithms make use of iterative updates [37]. In the FL scenario, if $|U^−| > 1$, the clients simultaneously work on the same copy of the global model, that is updated at the end of their computation. Let us define the freshness ($FRSH$) as a metric that computes the number of the updated global models delivered per epoch, that for FPL corresponds to $rpe$. Notably, by fixing $\rho$, the degree of parallelism is inversely correlated to the freshness. Let the normalized freshness ($nFRSH$) be the fraction between $FRSH$ and the ideal freshness $FRSH_{ideal}$ of the centralized system (in which each iteration exploits a fresh model). More formally, $nFRSH$ is defined as:

$$nFRSH = \frac{FRSH}{FRSH_{ideal}}.$$

(11)

4 EXPERIMENTAL SETUP

In this section, we introduce the experimental setting designed to answer the research questions. To this extent, we introduce the choice of the datasets with a brief analysis of their characteristics. Then, we describe the state-of-the-art algorithms we have involved. For the sake of reproducibility, for each method, we report the explored hyper-parameters in a specific section. Lastly, we present the evaluation protocol, and the metrics considered in the study.

4.1 Datasets

To evaluate FPL, we have chosen the Point-of-Interest (PoI) domain, which concerns data that users usually perceive as sensitive — i.e., visited places —. For this reason, we adopted the large-scale real-world Foursquare dataset [40]. It is well-known and considered as a reference for evaluating PoI recommendation models. Since the evaluation setting mimics the devices involved in a real federated scenario, we have extracted from Foursquare dataset check-ins for three countries, namely Brazil, Canada, and Italy, by supposing that the RS works on a per-country basis. To fairly evaluate FPL against the baselines, we have kept users with more than 20 interactions. Moreover, we have split the datasets by

3The limitations of the Collaborative Filtering in a cold-start user setting are well-known in literature. However, they are beyond the scope of this work.
adopting a realistic temporal hold-out 80-20 splitting on a per-user basis \cite{7,16}. Table 1 shows the characteristics of the resulting training sets adopted in the experiments. The table also shows the bias value $B_T$ \cite{28} of population on the different categories in training data, with a value above 1 denoting a higher susceptibility to choose the category items.

### 4.2 Collaborative Filtering Baselines

To evaluate the efficacy of FPL, we have conducted the experiments by considering five different recommendation approaches and two non-personalized methods. In detail, we computed recommendations with:

- **FCF** \cite{4}, to the best of our knowledge, the only federated MF approach in literature.
- **VAE** \cite{26}, a non-linear probabilistic model taking advantage of Bayesian inference to estimate model parameters;
- **BPR-MF** \cite{33}, the centralized vanilla BPR-MF implementation;
- **User-kNN**, and **Item-kNN** \cite{22}, user-based (and item-based) CF algorithms, that exploits cosine similarity to compute similarity between users;
- **Random**, a naive approach that randomly recommends items to users;
- **Top-Pop**, a non-personalized approach that recommends the most popular items;

To evaluate the impact of feedback deprivation on recommendation accuracy, we have evaluated different values of $\pi$ in $[0.0, 1.0]$. Hence, we have considered four different configurations regarding computation and communication:

- **sFPL**: it aims to reproduce the stochastic learning approach of centralized factorization model with pair-wise learning, where the central model is updated sequentially; therefore, we set $|U^-| = 1$ to involve just one random client per round, and it extracts solely one triple $(u, i, j)$ from its dataset ($T = 1$) for the training phase;
- **sFPL+**: we increase client local computation by raising to $X^+$ the number of triples $T$ extracted from $K_u$ by each client involved in the round of communication;
- **pFPL**: we enable parallelism by involving all clients in each round of communication ($|U^-| = |U|$); we keep $T = 1$;
- **pFPL+**: we extend pFPL by letting each client sample $T = X^+$ triples from $K_u$; the rationale is that the overall training samples are exactly $X^+$, as in centralized BPR-MF.

In \cite{33}, authors suggest to set the number of triples in one epoch of BPR to $X^+$, which corresponds to the number of optimizations steps. A particular choice is to randomly sampling $T = X^+$ triples per user. To make a federated training epoch of FPL comparable to BPR and among different configurations, we set $rpe$ in order to obtain always the same number of interactions $\rho$ between clients and server in one epoch (see Section 3.2), and such that this value is equal to the overall number of optimization steps in one epoch of the centralized pair-wise learning. In detail, we set $\rho = X^+$; then, $rpe = \rho/|U^-|$ results in $X^+$ for sFPL and sFPL+, while it is $X^+/|U^-|$ for pFPL and pFPL+.
4.3 Reproducibility

For the splitting strategy, we have adopted a temporal hold-out 80/20 to separate our datasets in training and test set. Moreover, to find the most promising learning rate $\alpha$, we have further split the training set, adopting a temporal hold-out 80-20 strategy on a user basis to extract her validation set. User-kNN and Item-kNN have been experimented for $k \in \{10, 20, ..., 10\}$ considering Cosine Vector Similarity. VAE has been trained by considering three autoencoder topologies, with the following number of neurons per layer: 200-100-200, 300-100-300, 600-200-600. We have chosen candidate models by considering the best models after training for 50, 100, and 200 epochs, respectively. For the factorization models, we have performed a grid search in BPR-MF for $\alpha \in \{0.005, 0.05, 0.5\}$ varying the number of latent factors in $\{10, 20, 50\}$. Then, to ensure a fair comparison, we have exploited the same learning rate and number of latent factors to train FPL and FCF, and we explored the models in the range of $\{10, \ldots, 50\}$ iterations. We have set user- and positive item-regularization parameter to $\frac{1}{20}$ of the learning rate. The negative item-regularization parameter is $\frac{1}{200}$ of the learning rate, as suggested in mymedialite implementation as well as by Anelli et al. [6].

4.4 Evaluation Metrics

The RQs (see Section 1) cover a broad spectrum of different recommendation dimensions. To this end, we have decided to measure several metrics to evaluate the approaches under the different perspectives. The accuracy of the models is measured by exploiting Precision ($P@N$) and Recall ($R@N$). They respectively represent, for each user, the proportion of relevant recommended items in the recommendation list, and the fraction of relevant items that have been altogether suggested. We have assessed the statistical significance of results by adopting Student’s paired T-test considering $p$-values $< 0.05$. To measure the diversity of recommendations, we have measured the Item Coverage ($IC@N$), and the Gini Index ($G@N$). $IC$ provides the number of diverse items recommended to users. It also conveys the sense of the degree of personalization [2]. Gini is a metric about distributional inequality. It measures how unequally different items a RS provides users with [12]. In the formulation adopted [16], a higher value of $G$ corresponds to higher personalization. Finally, to measure the Bias shift in the recommendation results, among the recently proposed fairness metrics [13, 44], we have decided to measure Bias Disparity ($BD@N$) [28], that measures, for each group of users, and category of items, the shift of the proposed recommendations from the initial dataset bias.

5 ANALYSIS OF THE EXPERIMENTAL RESULTS

In this Section, we focus on the different experiments conducted to explore the dimensions covered by the Research Questions (see Section 1). First, to position FPL with respect to the baselines, we analyze the accuracy, beyond-accuracy, and bias disparity of the recommendations. Once the analysis is completed, we investigate the impact of communication costs, and we study the multi-objective optimization of maximizing the accuracy while minimizing the communication costs. To this extent, we have explored the Pareto frontier, considering the two different dimensions.

5.1 Recommendation Accuracy

To answer RQ1, we want to assess whether it is possible to obtain a recommendation performance comparable to a centralized pair-wise learning approach while allowing the users to control their data. In this respect, Table 2 shows the accuracy and diversity results of the comparison between the state-of-the-art baselines and the four configurations of FPL presented in Section 4. By focusing on accuracy metrics, we may notice that User-kNN outperforms the other
Table 2. Results of accuracy and beyond-accuracy metrics for baselines and FPL on the three datasets. For each configuration of FPL and for each dataset, the experiment with the best $\pi$ is shown (see the bottom part for details). For all metrics, the greater the better.

|                      | Brazil | Canada | Italy |
|----------------------|--------|--------|-------|
|                      | P@10  | R@10  | IC@10 | G@10  | P@10  | R@10  | IC@10 | G@10  | P@10  | R@10  | IC@10 | G@10  |
| Random               | 0.00013 | 0.00015 | 46120 | 0.709455 | 0.00030 | 0.00035 | 10815 | 0.26809 | 0.00030 | 0.00029 | 10478 | 0.28914 |
| Top-Pop              | 0.01909 | 0.02375 | 19   | 0.000203 | 0.04239 | 0.04679 | 18    | 0.000321 | 0.04634 | 0.05506 | 19    | 0.00035 |
| User-kNN             | 0.10600 | 0.13480 | 3083  | 0.011593 | 0.07639 | 0.07533 | 609   | 0.00321 | 0.06881 | 0.07835 | 577   | 0.00282 |
| Item-kNN             | 0.01039 | 0.13153 | 5303  | 0.02117 | 0.06060 | 0.08317 | 1044  | 0.00652 | 0.10421 | 0.21324 | 163   | 0.02356 |
| VAE $*$              | 0.07702 | 0.09494 | 2552  | 0.00756 | 0.03694 | 0.03650 | 1216  | 0.00998 | 0.04560 | 0.05458 | 19    | 0.00036 |
| BPR-MF               | 0.03089 | 0.03749 | 911   | 0.00095 | 0.03724 | 0.03836 | 304   | 0.00174 | 0.03126 | 0.07084 | 403   | 0.00158 |
| sFPL                 | 0.07757 | 0.09581 | 1581  | 0.00561 | 0.04515 | 0.04550 | 451   | 0.00243 | 0.04701 | 0.05560 | 18    | 0.00036 |
| sFPL+                | 0.08682 | 0.11004 | 5200  | 0.01449 | 0.05701 | 0.05665 | 1510  | 0.01259 | 0.05595 | 0.06259 | 932   | 0.00789 |
| pFPL                 | 0.07771 | 0.09582 | 2114  | 0.00638 | 0.04582 | 0.04637 | 425   | 0.00213 | 0.04642 | 0.05465 | 96    | 0.00056 |
| pFPL+                | 0.08733 | 0.11085 | 3820  | 0.01106 | 0.05761 | 0.05755 | 1214  | 0.00981 | 0.05565 | 0.06291 | 936   | 0.00725 |

Best $\pi$ obtained for each the proposed FPL variations across three countries (Brazil, Canada, and Italy) are:
- $sFPL = (0.5, 0.1, 0.4)$,
- $sFPL+ = (0.9, 0.4, 0.2)$,
- $pFPL = (0.8, 0.1, 1)$,
- $pFPL+ = (0.8, 0.3, 0.1)$

* VAE does not always produce recommendations for all the users. For Italy, the reported results cover the 14% of the users.

![Fig. 2](image-url) Fig. 2. F1 performance at different values of $\pi$ in the range $[0, 1]$. The colors represent the four configurations: dark blue is $sFPL$, dark green is $sFPL+$, light blue is $pFPL$, light green is $pFPL+$.
the proposed system can generate recommendations with a quality that is comparable with the centralized pair-wise learning approach. Moreover, the increased local computation causes a considerable improvement in the accuracy of recommendation. On the other side, the training parallelism does not significantly affects results. Finally, when the local computation is combined with parallelism, the results show a further improvement.

To answer RQ2, we varied $\pi$ in the range $\{0.1, \ldots, 1.0\}$ to assess how removal of the updates for consumed items affects the final recommendation accuracy, and we plotted the accuracy performance by considering F1 in Figure 2. As previously observed, the best performance rarely corresponds to $\pi = 1$. On the contrary, a general trend can be observed: the training reaches a peak for a certain value of $\pi$ — depending on the dataset —, and then the system performance decays in accuracy when increasing the amount of shared positive updates. In rare cases, e.g., sFPL, and pFPL for Brazil dataset, the decay is absent, but results that are very close for different values of $\pi$. The general behavior suggests that the system learning exploits the updates of positive items to absorb information about popularity. This consideration is coherent with the mathematical formulation of the learning procedure, and it is also supported by the observation that for Canada and Italy FPL reaches the peak before with respect to Brazil. Indeed, Canada and Italy datasets are less sparse than Brazil, and the increase of information about positive items may lead to push up too much the popular items (this is a characteristic of pair-wise learning), while the same behavior in Brazil can be observed for values of $\pi$ very close to 1. The same mathematical background, for sFPL+ and pFPL+ with Brazil dataset, which is very sparse, explains the higher value of $\pi$ needed to reach good performance. Here, the lack of positive information with a vast catalog of items, confuses the training that cannot exploit item popularity. Now, we can positively answer to RQ2: user can receive high-quality recommendations also when decides to disclose a small amount of her sensitive data. However, it should be noted that the more the dataset is sparse, the more the amount of sensitive data should be large.

5.2 Accuracy or Diversity: exploring the trade-off between Precision and Item Coverage

In Table 2, we have also depicted the diversity metrics results of each experiment, i.e., item coverage, and Gini Index. What immediately catches our attention is an increase in IC and Gini in accord with the increase of local computation. In this sense, FPL shows a consistent prominence on BPR-MF. This performance is motivated by mere observation of the algorithm. By increasing local computation, each client compares each positive item with a significantly larger number of negative samples (i.e., wider spread). We have also explored the values of IC against the values of precision for each dataset and for each configuration while varying the parameter $\pi$. In Figure 3, we plot these values by considering increasing $\pi$ in the direction of the arrows. The plots unveil that, for Canada and Italy, by increasing the
Table 3. Different configurations of FPL in Brazil dataset, with the resulting number of rounds per epoch (rpe) and normalized freshness (with respect to sequential optimization). On the bottom, resulting values of CCE for each FPL configuration.

| Configuration | \(|U| \) | \(|T| \) | rpe | nFresh | \(rpe\) | nFresh | \(CCE\) |
|---------------|--------|--------|-----|--------|--------|--------|--------|
| sFPL          | 1      | 1      | 17473 | 100.00% | 0.0057% |
| sFPL+         | 1      | 34     | 34   | 100.00% | 0.0057% |
| \(\pi\)       | 0.0    | 28360614618 | 28380614992 | 28360614618 | 28380614992 |
| 0.2           | 28360734610 | 28384735058 | 28360734610 | 28384735058 |
| 0.4           | 28360854601 | 28388855125 | 28360854601 | 28388855125 |
| 0.6           | 28360974593 | 28392975191 | 28360974593 | 28392975191 |
| 0.8           | 28361094584 | 28397095258 | 28361094584 | 28397095258 |
| 1.0           | 28361214576 | 28401215324 | 28361214576 | 28401215324 |

Fig. 4. Reciprocal CCE versus Precision (P@10) with cutoff 10 on Brazil dataset. The colors represent the four configurations: dark blue is sFPL, dark green is sFPL+, light blue is pFPL, light green is pFPL+. The white points denote \(\pi = 1\) to specify the direction of increasing \(\pi\). The red line is the Pareto frontier.

5.3 Accuracy vs Communication Cost: a Multi-Objective Analysis

In this part of the analysis, we want to briefly consider which are the effects of changing the configuration and \(\pi\) on the communication cost associated with the exchange of data between clients and the server (see Section 3.2). For the sake of space, we focus the analysis on Brazil, the biggest and sparsest dataset. In Figure 4, we plot the values of precision against the reciprocal of the communication cost (in both cases, the higher, the better) considering the different configurations and values of \(\pi\). The red line represents the Pareto frontier, which in multi-objective optimization represents the set of optimal solutions — considered equally good — which dominates the other possible solutions. The configurations with high local computation (the green curves) also require high communication costs, regardless of the parallelism. The two configurations with low computation require lower communication costs, even though the difference, in absolute terms, is minimal. The small difference profoundly affects the Pareto analysis making these points lay on the Pareto frontier or very close to it. On the other side, the increase of local computation ensures that the points with high accuracy lie on the Pareto frontier. The multi-objective analysis between communication cost and accuracy may help the designer in providing the best setup for the federation of clients. Here, the analysis suggests holding low local computation configurations and the high-performance \(\pi\) (considering accuracy) of the high local computation configurations as the set of optimal settings. The experiment shows that a trade-off between accuracy and communication costs is possible, and, for the scenario at hand, it favors the settings with low local computation. In order to answer the RQ3 we can state that deciding to limit the communication costs does not particularly affect the recommendation accuracy. However, if a higher local computation cost is admitted, recommendation utility further improves.
Table 4. Results of recommendation bias disparity for each category in Brazil dataset (see Table 1) for baselines and FPL. For each configuration of FPL and for each dataset, the experiment with the best $\pi$ is shown. The closer to 0 the better.

|        | A&E | C&U | Food | NS  | O&R | P&OP | Residence | S&S | T&T |
|--------|-----|-----|------|-----|-----|------|-----------|-----|-----|
| Random | -0.3249 | 0.5593 | -0.0801 | -0.2448 | -0.1428 | 0.5490 | 0.9113 | 0.2026 | -0.2729 |
| Top-Pop | -1.0000 | -1.0000 | -0.3019 | -1.0000 | -0.9994 | -1.0000 | -1.0000 | -1.0000 | 6.6595 |
| User-kNN | 0.4446 | -0.8318 | 0.2608 | -0.2129 | 0.1615 | -0.8422 | -0.9694 | -0.4307 | 0.6206 |
| Item-kNN | 0.3459 | 0.1399 | 0.0676 | -0.1023 | 0.1525 | -0.3470 | -0.3805 | -0.2270 | 0.0830 |
| VAE    | 0.3926 | -0.7234 | 0.2225 | -0.3148 | 0.1938 | -0.7764 | -0.9107 | -0.3099 | 0.5723 |
| BPR-MF | 0.3009 | -0.7118 | 0.2322 | -0.7104 | 0.1421 | -0.7584 | -0.9923 | -0.4343 | 1.1648 |
| FCF    | -0.4642 | -0.9076 | 0.6872 | -0.9102 | 0.1352 | -0.9598 | -0.9936 | -0.9463 | 1.2391 |
| $sFPL$ | 0.2716 | -0.7380 | 0.2629 | -0.7558 | 0.1649 | -0.8136 | -0.9966 | -0.3682 | 1.0719 |
| $sFPL+$ | 0.3111 | -0.6752 | 0.1601 | -0.3963 | 0.2781 | -0.8057 | -0.9029 | -0.2906 | 0.8118 |
| $FPL$  | 0.2526 | -0.8128 | 0.2183 | -0.6132 | 0.1431 | -0.7386 | -0.9916 | -0.4791 | 1.2390 |
| $FPL+$ | 0.1535 | -0.5655 | 0.1901 | -0.3508 | 0.3449 | -0.7639 | -0.9130 | -0.4099 | 0.7783 |

5.4 Bias Disparity in FPL

When depriving the recommender of a part of the user’s feedback, one of the biggest concerns is the potential bias shift [10]. Bias analysis, and fairness are gaining momentum in the last years, they unveil several essential aspects of the recommenders’ behavior. To explore what happens the category biases in the different configurations and values of $\pi$, we measure the bias disparity (BD) in recommendation lists for the categories of the venues, i.e., we measure how much our system changes the original bias of a particular cluster of items and deviates the recommendation towards or against it. Table 4 shows the results in terms of BD for FPL and the other baselines. Here, the closer to 0, the closer to the initial bias. As expected, Top-Pop changed the recommendation towards T&T, which is the most popular category in the training set. By focusing on FPL, we may notice that it bias positively and negatively the same categories of the other state-of-the-art algorithms. Notably, it particularly pushes the bias of recommendation towards popular categories (e.g., A&E, Food, T&T), while it emphasizes the unpopularity of specific categories — above all C&U, P&OP, Residence —. This is probably due to the pair-wise nature of the approach, which works by iteratively increasing the difference values between enjoyed items and the others (the same behavior is evident for BPR-MF). The Bias Disparity analysis helps to answer RQ4. Hence, we draw the following consideration: the proposed system generates recommendations that are biased to the initial user preferences since it emphasizes the differences between consumed and non-consumed items. This behavior is also coherent with the recommendations of the other state-of-the-art algorithms.

6 RELATED WORK

Federated learning aims to meet ML privacy shortcomings by horizontally distributing the model’s training over user devices; thus, clients exploit private data without sharing them [30]. Despite its original formulation, the federated learning concept is extended to a more comprehensive idea of privacy-preserving decentralized collaborative ML techniques [41], both for horizontal federations, where different datasets share the same feature space, and vertical federations, where different datasets share the training samples but they differ in feature space. In the work at hand, we argued that RS can benefit, in terms of privacy, from the notion of federated learning, since all RS, in order to produce suggestions, exploit user sensitive information [18].

Weiss et al. [39] state that privacy can be preserved by limiting data collection, which is one of the main privacy concerns [18]. Indeed, the accuracy of RS based on the CF paradigm is strictly dependent on the amount of user ratings or, more generally, feedback (e.g. implicit feedback). In our idea, it is possible to put users in control of their sensitive
data by allowing to choose the amount of information to share with the server. Hence, if data collection from the server
side is reduced, other threats related to retention, sales, and unauthorised data browsing are limited as well.

Some important privacy-preserving schemes for RS [32, 43], exploit obfuscation and encryption strategies in
data collection. Alternatively, the obfuscation can be performed by decentralizing the user profile among multiple
repositories [8]. On the same research line we find BlurM(orange) [36] that obfuscates gender information in the user-item
matrix. Other researches focused the attention on the decentralized-matrix-factorization and distributed approach [14,
15]. The idea is very similar to that proposed in our work, namely inferring a function when the training data are
distributed among different nodes. The training process can be subdivided in two steps [15]: a distributed protocol
for computing the matrix and an optimization strategy. The former is based on the algorithm proposed by Ling et
al. [27] that is based on the idea to have a public matrix common to all agents and a private matrix held by single
agents. Another work that implements and idea very similar to ours is PDMFRec [14]. It pushes the computation of
the recommendation model to the user’s device and eliminates the need of exchanging sensitive personal information.
Even, the distributed version of Privacy-Preserving association rules (PPARM [38]), shares a similar idea. The aim of
this work is to reduce the number of involved users by applying distributed graph sampling. Regarding the idea of
reducing the amount of data shared by users, we found also JobMatch [34] which requires users to provide only a partial
ranking of their preferences. Regarding the work in the literature most similar to our model [4], the authors define a
federated implementation of collaborative filtering. Compared to our work, they use the SVD-MF method for implicit
datasets [17], which gives a linear least-squares fit to the dataset, and they train the model with a mixture of ALS and
SGD in order to preserve users’ privacy. However, rating prediction oriented optimization has shown its limits. Indeed,
learning to predict rankings has become a much more significant task than learning to predict ratings [31]. Therefore, a
class of learning-to-rank algorithms has been developed in the last decade, ranging from point-wise approaches [24], to
pair-wise [33] and list-wise [35] approaches. Among pair-wise methods, BPR [33], is one of the most broadly adopted,
thanks to its outstanding capabilities to correctly rank with acceptable computational complexity.

7 CONCLUSION AND FUTURE WORK

Inspired by the potential ubiquity of the federated learning paradigm, we propose FPL, a novel federated learning
framework that exploits pair-wise learning for factorization models. To this purpose, we have designed a model to
leave the user-specific information of the original factorization model in the clients’ devices. With FPL, a user may
be completely in control of her sensitive data and could share no positive feedback with the centralized server. The
framework can be envisioned as a general federated model in which clients (or system designer) can tune the amount
of information shared among devices. We have conducted an extensive experimental evaluation to analyze different
aspects: the degree of accuracy, the diversity of the recommendation results, the category shift, the optimal trade-off
between accuracy, and communication costs. Moreover, we have extensively analyzed the effects of a progressive
deprivation of positive feedback. We have assessed that the proposed model shows performance comparable with several
state-of-the-art baselines and the classic centralized factorization model with pair-wise learning. The experimental
evaluation shows that clients may share a small portion of their data with the server to achieve a high-performance
increase. Moreover, the analysis of the results demonstrates that further improvements can be achieved by increasing
local computation. These encouraging results suggest us to exploring whether a federated design can improve the
performance of other state-of-art recommendation families. We believe that the proposed privacy-oriented paradigm
may open the doors to a new class of ubiquitous recommendation engines.
