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Modular Federated Cross-Domain Recommendation (MFCDR) System with a Projected Attention Network

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Abstract: In today's digital age, data is considered a new currency. It drives many aspects related to research, business strategies, and decisions across various industries, providing recommendations. As data becomes more valuable, the privacy of user data becomes crucial. This article introduces an innovative, novel privacy-preserving federated learning approach, with the advancement of attention networks for cross-domain recommendation. A decentralized approach to federated learning has replaced traditional machine learning to enhance user privacy and data security. The research employs a projected attention network (PRADO) within a real federated environment to improve local device training. The proposed framework is examined through a use case of book recommendation based on emotions extracted from social media reviews, utilizing GoEmotions and customized book dataset. The results showed assurance of the system with better performance in terms of precision, recall, and the F1-score over benchmarking models such as Embedding and Mapping framework for Cross-Domain Recommendation (EMCDR), Cross-Domain based on Latent Feature Mapping (CDFLM), Aspect-based Neural Recommender (ANR), and Meta-learning-based model for Federated Personalized Cross-Domain Recommendation (MFPCDR), with the suggested system reaching a precision of 0.96 and an F1-score of 0.89. The findings indicate that the real implementation of a federated learning environment is modular, scalable, efficient, and preserves privacy.

Keywords: federated learning, attention network, privacy, cross-domain recommendation, data security

1. Introduction

Recommendations for services or products require detailed information about the user to ensure optimal performance. This information includes both contextual and behavioral data. However, when a user interacts with multiple platforms, their interests may span across different domains. Therefore, it is necessary to extract user preferences from these various domains and recommend relevant products—a process known as a cross-domain recommendation (CDR) system. CDR systems help recommend products in domains with little or no data availability by leveraging information from data-rich sources. CDR effectively addresses the cold-start problem and the issue of new users. However, the process involves data sharing across domains, which increases the risk of privacy breaches due to the transfer of data between source and target domains [1]. General Data Protection Regulation (GDPR), the California Consumer Privacy Act (CCPA), and others are becoming increasingly common, and many users are likely to opt out of sharing their information with service providers. Federated learning (FL) aligns with these regulatory requirements by minimizing data exposure and giving users greater control over their personal information. FL is a collaborative learning technique in which machine learning models are trained across multiple devices using decentralized data—ensuring privacy is preserved [2].

Although there has been significant development in the field of FL, a gap still exists in the practical implementation of an efficient FL framework—particularly in handling client data transmission by servers and managing resource constraints for model training on client devices. This research aims to bridge that gap by evaluating the capability of the proposed model through a case study on emotion-based book recommendations. The study demonstrates CDR within an FL framework that maintains both accuracy and user privacy.

The selection of a case study on emotion-based book recommendations serves a specific purpose. Traditional book recommendation systems rely on collaborative filtering or content-based methods that focus on user behavior, such as ratings and reading history, or on book attributes, such as genre and author. However, emotions play a crucial role in human decision-making. In the context of reading, incorporating emotional analysis into the recommendation system enables more personalized suggestions, which can lead to greater user satisfaction.

The remainder of this paper is organized as follows: Section 2 reviews previous research on recommendation systems within an FL environment. Section 3 provides an overview of the methodology employed in this study. Section 4 presents the implementation and evaluation. Sections 5 and 6 discuss the results and conclusions, respectively.

2. Literature Review

The FL concept was invented by Google in 2016 for the security and privacy of personal data [3]. FL enables recommendation models to leverage a vast and diverse range of data sources distributed across multiple devices and locations. This decentralized approach enhances scalability, as the model can learn from a larger and more varied dataset

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without relying on a central server. By aggregating insights from diverse user populations, federated recommendation systems can capture a broader spectrum of preferences, trends, and behaviors, resulting in more accurate and diverse recommendations. The integration of FL with recommendation systems offers a viable approach known as a federated recommendation system. Researchers continue to explore various techniques and enhancements in this evolving field. The literature is reviewed across different categories, including traditional approaches, advanced methods for FL recommendation systems, security in federated recommendation systems, CDR systems, and, finally, federated CDR systems.

2.1. Federated learning recommendation system – a traditional approach

In an era of information overload, an effective recommender system is essential to enhance search and recommendation quality. Data security and user privacy are also critical concerns. Ammad-ud-din et al. [3] presented the first federated collaborative filtering implementation using stochastic gradient model updates. As a classical machine learning case study, this work explores a recommendation system based on users' implicit input. The method is demonstrated using the Movie Lens dataset and an in-house dataset, showcasing its adaptability. However, simulator-based systems bypass the complexities of real-world asynchronous client data transfer, highlighting the need for further research in this area.

Tan et al. [4] proposed FedRecSys, a Federated Recommender System for online services like product, content, and advertisement recommendations. The algorithm's implementation is open source. Su [5] proposed a federated online learning system to enhance the accuracy of recommendation systems through information sharing. A recommender system for mobile social networks was presented, along with an incentive scheme based on contracts to encourage user participation in model training, enhancing utility for both users and the third party (TTP). Liang et al. [6] explored privacy-aware recommendations using explicit feedback. A new federated recommendation technique, FedRec++, was suggested. It is lossless and denoises clients to eliminate noise from virtual ratings assigned to randomly sampled items. The authors also examined the privacy of FedRec++ and found that it offers strong protection for users' privacy.

Eren et al. [7] proposed FedSPLIT, in which an unsupervised one-shot federated collaborative filtering implementation that uses nonnegative matrix factorization for joint factorization. Clients utilize local CF simultaneously as the initial step to create unique recommenders tailored to each client. The processor conducts joint factorization and identifies global item patterns. Next, knowledge distillation is used to perform pattern aggregation, which is then transferred to each client to update their local models.

Aneli et al. [8] addressed user privacy in recommendations. Recommendations can be made without exploiting sensitive data. The authors introduced FedeRank, an algorithm for federated recommendations. The system learns a distinct factorization model for each device. The central server and federated clients collaborate in sync to train the model. FedeRank manages recommendations in a distributed way, allowing users to control how much information they share. Comparing state-of-the-art (SOTA) algorithms shows that recommendation accuracy is effective with only a small percentage of user-shared data. The research by Lin et al. [9] aims to ensure fairness, meaning consistent recommendation performance among FL participants. Cali3F is a framework that integrates the near network into a federated collaborative filtering recommendation system. It uses a multitask learning framework to train both local and global models. The recommendation performance sampling strategy uses user profile representatives and incorporates a new block update component-based similarity. This leads to faster and fairer outcomes.

Researchers are elaborating on the different techniques and enhancements in this field. Yang et al. [10] provided a detailed description based on the FL concept of horizontal, vertical, and transfer learning for a recommendation system. The division is based on user and item-sharing scenarios (feature space). They discussed the challenges in the design of federated recommender systems. Kalloori and Klingler [11] utilized FL to benefit stakeholders and recommender systems. They developed an FL approach in which the updates of models are averaged to collaboratively learn a federated recommendation model from either other stakeholders or the client's training data. In this approach, two popular algorithms, Bayesian Personalized Ranking and Neural Collaborative Filtering, are discussed.

Otari et al. [12] discussed challenges and advancements in federated recommendation systems.

2.2. Advanced techniques for recommendation in FL

To address the issue of asynchronous data transfer, Wang et al. [13] developed a deep neural network (DNN)-based recommender system called PrivRec, which utilizes users' secondary data to learn user–item interactions and generate recommendations. To handle challenges such as inactive users and data heterogeneity in FL-based recommender systems, they proposed a practical and efficient meta-learning approach for PrivRec. Additionally, to mitigate the risk of exposing private data to malicious FL clients, the privacy of PrivRec was enhanced using differential privacy techniques at the user level, resulting in a more robust and secure model named DP-PrivRec.

As DP-based systems typically incur computational overhead, Yang et al. [14] introduced a personalized mask technique to safeguard data privacy without compromising the training process or degrading model performance. They demonstrated the effectiveness of this approach in a recommendation context using the FedMMF algorithm. Moreover, by incorporating an adaptive secure aggregation protocol, FedMMF was shown—both theoretically and empirically—to deliver superior performance.

In a similar vein, Jalalirad et al. [15] proposed a straightforward yet effective application of FL for recommendation systems aimed at enhancing personalization. They also discussed related meta-learning algorithms. Compared to existing SOTA FL-based recommenders, their proposed algorithm was simpler and more effective in real-world contexts. The algorithms were evaluated on benchmark datasets, and performance was measured using Root Mean Squared Error (RMSE) for predicting user ratings. The authors emphasized that to ensure user privacy, reconstruction of gradients or parameter updates must be encrypted.

Chen et al. [16] employed federated meta-learning, training user-specific recommendation models via a shared, parameterized algorithm that leverages information from other users to improve learning. Their findings indicated that the recommendation model trained using this method outperformed existing approaches in both accuracy and scalability.

To further enhance model performance, Hidasir et al. [17], proposed several parallel RNN (p-RNN) architectures for session-based modeling using click data, incorporating additional features such as images and text associated with the items users clicked on.

Qin et al. [18] introduced an innovative Privacy-Preserving Recommender System Framework (PPRSF) based on FL, which supports both training and inference phases of recommendation algorithms. By leveraging PPRSF, the risk of privacy exposure is significantly reduced, while complying with legal and regulatory requirements. Moreover, the framework supports a variety of recommendation algorithms, adding to its flexibility and utility.

To support recommendation among social connections, Perifanis et al. [19] proposed FedPOIRec, an FL approach for top-N Point of Interest (POI) recommendations that integrates features derived from users' social circles. In the FedPOIRec framework, local data remains on the client side, while the server aggregates updates. Additionally, FedPOIRec facilitates knowledge sharing among friends by allowing users to communicate learned parameters.

2.3. Security in federated recommendation systems

The authors integrate users' federated computational preferences through a privacy-preserving protocol that leverages the capabilities of the CKKS fully homomorphic encryption system. Song et al. [20] proposed a Federated Gradient Boosting Decision Tree (FGBDT) system that utilizes Secure Boost, a federated ensemble model based on gradient boosting decision trees (GBDTs). This system aims to enhance user classification for healthcare providers by utilizing data shared with mobile network operators (MNOs), each possessing different features. The FGBDT system enables privacy-preserving joint modeling between MNOs and healthcare providers (HPs), allowing collaborative data usage while preserving data privacy. The proposed system is particularly useful for healthcare recommendation applications, as it allows more accurate user classification using data from both MNOs and HPs.

Guillén et al. [21] noted that recommendation systems are effective for generating personalized correlations and predictions. FL provides significant privacy benefits, as users' private information remains on their local devices. The trained model is communicated via a secure protocol, and communication costs are reduced by distributing the data across multiple devices. This "privacy-by-design" strategy ensures compliance with ethical and legal requirements while enabling personalized user recommendations.

Zhang and Jiang [22] proposed a hybrid clustering personalized vertical federated matrix recommendation algorithm based on matrix factorization. This approach incorporates user clustering into the recommendation model and ensures the security of user data through homomorphic encryption.

Dogra et al. [23] introduced a novel framework for FL-based recommender systems (RSs) that employs fixed-size encoding for both items and users, making it independent of the number of items or users. This approach is memory-efficient and well-suited for large-scale RS applications. The framework was validated through a next-app recommendation use case, achieving performance comparable to existing solutions while significantly reducing memory consumption.

2.4. Cross-domain recommendation systems

CDR techniques can be classified as content-based, feature-based, embedding transformation-based, rating-based, or as a combination of these types. Gao et al. [24] proposed a neural network approach called NATR, which combines item-level and domain-level attention mechanisms. Item embeddings are transferred from the secondary domain to help prevent user privacy leakage, thereby addressing key challenges in CDR learning. However, the scalability of the proposed technique has not been explored.

Zhu et al. [25] introduced a system based on matrix factorization to generate user and item latent factors, which are then mapped across domains using deep neural networks. Other CDR approaches focus on dual-target learning [26–28]. All of these systems require the user's relevant data to be shared across different domains to enable effective recommendations.

2.5. Federated CDR systems

The research goals in references [1, 29–35] are to address the issue of data privacy and cold-start users during the recommendation. For this purpose, they utilize an information-rich source domain to improve recommendations. While these problems are being solved, user data privacy remains a high priority. The authors proposed a federated framework for CDR while ensuring privacy. The proposed methods train a common recommender model on every user's device to gain the embeddings of users and items. After this, every user's weights are uploaded to the server located at the center. User privacy is protected using different techniques such as local differential privacy, homomorphic encryption, etc., which are applied to weights before gradients are uploaded to the server. Additionally, embedding transformation techniques are used on the server side to refine the relationship of user embedding between two domains. These methods provide a privacy-preserving solution for CDR while maintaining accuracy. A federated framework integrated with CDR provides substantial benefits in terms of privacy preservation and personalized recommendations.

The reviewed literature provides insights from conventional approaches like collaborative filtering and matrix factorization in a federated framework to the utilization of deep neural networks and transformer-based methods to enhance recommendation systems. However, many challenges exist regarding:

Scalability: Existing practices become expensive as the size of the user-item matrix increases with the number of clients.

Communication efficiency: Incorporating deep neural networks into a federated framework incurs significant communication overhead.

Resource constraints: Cross-device FL requires training on edge devices, which are often resource-constrained.

2.6. Research contribution

To address the above challenges, our contributions are as follows:

1) We develop a real-time, efficient FL framework capable of handling a large number of clients, thereby addressing scalability issues.
2) We integrate federated transfer learning with a projected attention network (PRADO) to create a novel system that efficiently supports on-device training, reducing communication overhead and addressing resource constraints.
3) We provide empirical evidence to evaluate the performance of the proposed model.

3. Research Methodology

3.1. Problem definition

Assume that M local clients and a centralized server participate in the training. The local clients represent users, forming the set $U = \{u_1, u_2, \ldots, u_m\}$. For each user, emotions are extracted from their reviews, represented as $E = \{e_1, e_2, \ldots, e_m\}$, where $e_i \in \mathbb{R}^d$ denotes the emotion embedding vector. Let $B = \{b_1, b_2, \ldots, b_n\}$ be the set of books, with corresponding reviews $V = \{v_1, v_2, \ldots, v_n\}$ extracted for each book. The goal is to predict the correct emotion e_i and identify the most relevant book that aligns with that emotion.

3.2. Proposed framework

The proposed approach uses a projected attention network, PRADO, as shown in Figure 1 [36]. Trainable projections are combined with attention mechanisms and convolutions. PRADO's strength in classifying longer texts makes the model more efficient [36]. This leads to enhanced performance and accuracy in recommendation systems.

Figure 1
Projected attention network (PRADO) architecture

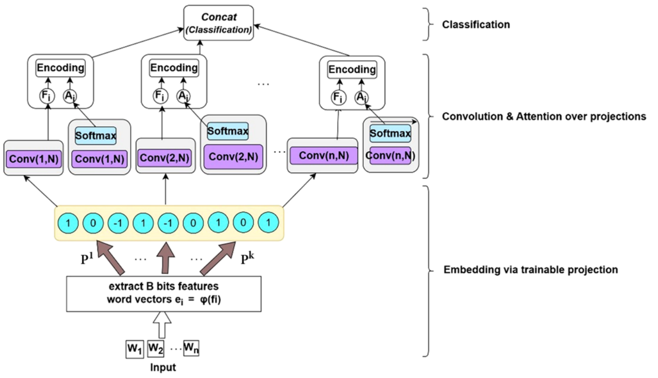


Figure 2 illustrates the framework for the federated multi-objective CDR system. It comprises the following modules:

Emotion prediction at the local layer: User reviews are collected and processed using PRADO for emotion prediction.

Aggregator: The FL-based aggregator combines model weights received from the local clients.

Recommendation layer: This layer provides recommendations from the source domain to the target domain for all users, including cold-start cases.

3.2.1. Emotion prediction at the local layer

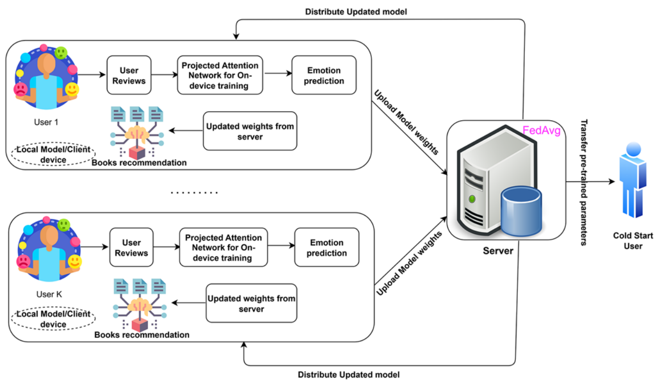
Local model training occurs at this layer, where each user acts as a client. Considering the challenges of the FL framework, particularly the resource limitations of edge devices, the concept of a projected attention network (PRADO) is employed [37]. To process the text, the NLP model represents it as a one-hot vector $\delta_i \in \mathbb{R}$^|V| and uses a word embedding matrix W that maps this vector to a dense representation, $e_i = W\,\delta_i$. However, this method requires a large amount of storage, which is impractical for devices participating in FL training. PRADO addresses this challenge by replacing the embedding layer with a projection-based method, thereby reducing memory requirements.

Projection-based method: A bit vector is generated by hashing a word ωi and mapped to vector $fi \in \{-1,0,1\}^B$ by the projection operator P. B is the dimension of the projection. Map fi to the word embedding using ϕ.

$$e_i = \phi(f_i) = \Theta f_i \ldots\ldots \quad (1)$$

where $\Theta \in \mathbb{R}^{d \times B}$ is a weight matrix.

Figure 2
FL-PRADO model architecture for cross-domain recommendation



Convolution and Attention process: PRADO applies the convolution and attention process to each word on receipt of embeddings e_i to encode the sequence into a fixed-length vector. Convolutional Feature extraction is done using:

$$F_n^i = Conv(e_i) \ldots\ldots \quad (2)$$

To capture important features, the attention score is computed using $Conv_n^{att}$,

$$W_i^n = Conv_n^{att}(e_i) \ldots\ldots \quad (3)$$

The SoftMax function is applied over the sequence dimension to produce normalized attention weights. The array A_i^(n)represents a vector of probabilities. Each value's probability corresponds to its relative size in the vector.

$$A_i^n = \frac{e^{W_i^n}}{\sum_i e^{W_j^n}} \ldots\ldots \quad (4)$$

Weighted pooling: The goal of pooling is to capture relevant details while compressing the input's spatial size. The weighted sum of convolutional features is obtained,

$$E^n = \sum_i A_i^n \odot F_n^i \ldots\ldots \quad (5)$$

where $\odot$ denotes element-wise multiplication. Thus, the most relevant text is maintained from the long text. Concatenation of encodings: PRADO uses multiple convolution kernels to capture different features, and finally, text encoding is done.

$$TextEncoder = concat\left(E^1, E^2, E^3 \ldots\right) \ldots\ldots \quad (6)$$

Here x is the inputted text by a user, and the TextEncoder comprehensively represents the input.

Prediction layer: The encoded text is passed through the fully connected layer and produces the output.

$$output = \Psi(TextEncoder(x)) \ldots\ldots \quad (7)$$

Ψ is a feed-forward neural network. The output generated, i.e., the trained model's weights, further communicated to the FL environment.

3.2.2. FL aggregator

In FL, each client holds its own local dataset and trains a local model using the projected attention network as described above. The global model W is updated by aggregating the models from all clients. Many existing FL approaches utilize synchronous, semi-synchronous [38], or asynchronous [39] communication protocols for aggregation. However, these methods often perform poorly in heterogeneous environments. In the synchronous approach, faster clients may remain idle while waiting for slower ones, leading to underutilization of available resources. Conversely, the asynchronous approach ensures full resource utilization but incurs a high cost in terms of network communication [40].

To address these issues, a hybrid technique called Buffered FedAvg is employed to train the global model [39].

In Buffered FedAvg, the server does not initiate the aggregation process immediately upon receiving an update from each client; instead, these updates are stored in a buffer. A threshold value 'M' is defined for the buffer size. The server performs an update only when 'M' client updates are available in the buffer, as shown in Equation (1).

$$w_{server}^{t+1}(aggr_p) = \frac{1}{M}\sum_{i\in B_t} w_i^t \,|B_t \geq M \ldots\ldots \quad (8)$$

Aggregation occurs only when the buffer size reaches the threshold value 'M'. Until then, the server continues to collect client updates without performing aggregation.

3.2.3. Recommendation layer

Once the server sends the aggregated updates, each client incorporates them to refine its local recommendation process. For a specific user '*i*' and book '*j*' the recommendation score 'ŷ' at client '*k*' is computed using the following function:

$$\hat{y}_{ij}^{k} = f\left(u_i^k, v_j^k, aggr_p, \text{rec\_score}k\right) \ldots\ldots \quad (9)$$

In Equation (9), f represents the client's recommendation function. The variable u_i^k is the user representation, v_j^k, is the book representation, $aggr_p$ denotes the aggregated emotional data received from the server, and rec_score$k$ includes the parameters of the local recommendation model at client '*k*'.

The client's recommendation function is implemented using the enhanced random forest algorithm to support CDR. The steps are presented in algorithm in Table 1.

Table 1
Enhanced random forest algorithm for cross-domain recommendation in FL-environment

Algorithm 2: Enhanced Random Forest algorithm for Cross-Domain recommendation in FL environment

Input:
Emotion vector (E) from FL server, Book Reviews(V), Number of trees (B), Number of Features per split (m)

Output:
Predicted book

Training phase of model

Step 1. For each client participating in model training, Combine the features from source domain and target domain i.e. concatenate (E, V) and add to training set S.
Step 2. Initialize random forest.
Step 3. For c_d_b = 1 to B:
  a. Draw a bootstrap sample s_c_d_b from S
  b. Build decision tree T_c_d_b:
At each node:
  i. Apply emotion weighted feature sampling
  ii. Evaluate split using Gini score
  iii. Split on features with maximum split score
  iv. Stop when node size reach to minimum sample node
  c. Add T_c_d_b to Forest
Step 4. Return Forest

Client-Side: Prediction Phase
For reviews from new user '*i*' and book '*j*':
  i. Extract emotions vector 'E' from FL -PRADO.
  ii. Extract book reviews V′
  iii. Concatenate ('E', V′) in input vector S′
  iv. Predict:
For each tree T_c_d_b in Forest:
  Predict_book = T_c_d_b (S′)
Calculate majority_vote (Predict_book)
*c_d_b – cross domain book
*S_c_d_b – c_d_b from sample set
*T_c_d_b – Tree for c_d_b

3.3. Dataset details

3.3.1. GoEmotions

Human emotions can often be expressed through just a few words. Google researchers developed GoEmotions [41], a dataset comprising 58K Reddit comments. The dataset was created by extracting comments from English-language subreddits. It was carefully designed by the researchers, taking into account human psychology and the applicability of the data.

The emotions in the dataset are categorized into 27 labels plus a neutral category. To enrich the dataset, emojis are included as proxies for emotions. Table 2 presents a sample of review text along with its corresponding emotion categories. To minimize noise, researchers filtered out emotion labels assigned by only a single annotator.

3.3.2. Books_dataset

The original book dataset 'Books_rating' from Kaggle contains 194,640 book titles along with their reviews and ratings. From this dataset, 10,000 unique titles were extracted based on the helpfulness of the book reviews.

The reader reviews contain, on average, 300–500 words. These book titles are further categorized into 27 emotions plus a neutral category, based on the reviews and content of the books. This new dataset is used for generating recommendations.

Tables 3 and 4 present samples of book reviews and the corresponding emotional percentages related to specific books, respectively.

Table 2
Sample of the GoEmotions dataset

Review text	Emotion label
We can hope...	Optimism
Shhh don't give them the idea...	Anger
Thank you so much, kind stranger. I really need that…	Gratitude
Ion knows but it would be better for you ….	Neutral
Still better than YouTube rewind….	Admiration
I want a pizza flair!!	Desire

Table 3
Sample of book reviews from the original dataset

Book_Id	Book_Title	Review and content summary by the reader
B000UYJ2NM	Thinking of the Sensible: Merleau-Ponty's A-Philosophy.	The Thinking of the Sensible is not like most secondary source...
B000UZS5ZM	Leopard in the Sun	One cannot help but feel saddened at the feud between the Barragans and the Monsalves, utterly amazing story!
B0064P287I	Rush: Time Machine	I am a lifelong fan of Rush. I have seen then about 50 times, begining with the Moving Pictures Tour.
B000UYFWP	Romantic Poetry: Recent Revisionary Criticism.	Romantic poetry and would like to know more about how it has been interpreted in light of the …

Table 4
Sample of a new book dataset for emotion categorization

Book Title	Admiration	Amusement	….	Relief
Big Brother Dustin	0.3107	0.2830	…	0.1460
The Unstrung Harp; Or, Mr. Earbrass Writes A Novel	0.2683	0.8600	…	0.3544
Paul Bowles: A Life	0.3366	0.3031	…	0.3483
The Complete Idiot's Guide to Writing Well	0.6293	0.2896	…	0.3574
Germanicus	0.2946	0.2987	…	0.3576

4. Experimental Setup

The research outlines a production-ready FL system that enables secure and efficient aggregation of model weights and their distribution among clients in an FL environment. This facilitates a decentralized model training while preserving data privacy. The implementation is performed via Spring Boot, Kotlin, and SeqFlowLight library.

Given a review text for emotion prediction and a dataset, we retain most of the hyperparameters as defined by the PRADO authors, modifying only the batch size and learning rate. We observe that training the model for at least 5 epochs on the local device is necessary to ensure proper convergence. The Adam optimizer is employed for model optimization, with a learning rate of 0.005. A sigmoid activation function is used in the hidden layer, while a SoftMax activation function is applied in the output layer.

The number of clients should be equal to the threshold value set for buffered Federated Averaging (FedAvg). For example, if N = 20, aggregation is triggered only when this number of clients has contributed their updates. The experiments are conducted over five communication rounds to distribute and aggregate the learned parameters. The macro average of each evaluation metric is considered for performance assessment.

The evaluation is organized into two segments. Initially, we evaluate the model for emotion prediction, and subsequently, we use it for book recommendations based on the predicted emotions.

To assess the performance of the proposed model in emotion prediction, baseline models are run without an FL environment—namely, LSTM, Bi-LSTM, BERT, and PRADO—on a single dataset, GoEmotions, along with the FL-based PRADO model.

The second part of the evaluation involves capturing emotions from user reviews, extracting emotions from book reviews, and identifying similarities between them to provide better recommendations. The original book dataset, 'Books_rating', from Kaggle contains 194,640 book titles along with their reviews and ratings. From this dataset, 10,000 unique titles were extracted based on the helpfulness of the reviews. On average, each review contains 300–500 words. These book titles are then categorized into 27 emotions plus a neutral category, based on the reviews and content.

The GoEmotions dataset presents inherent challenges due to imbalanced distributions of reviews across different emotions; therefore, accuracy was not used as an evaluation metric. Instead, the evaluation metrics adopted for this research are precision, recall, and F1-score.

Precision is the proportion of relevant predictions among all positive predictions. A higher precision indicates fewer false positives.

Recall reflects the proportion of relevant instances that were correctly predicted out of all actual relevant instances.

The F1-score provides a balance between precision and recall [42].

5. Results and Discussion

We want to make it clear that the primary goal of our research is to develop an efficient on-device approach using PRADO within an FL environment. Our aim is to achieve performance that is close to state-of-the-art while adhering to the constraints of edge devices and ensuring user data privacy.

Considering these factors, it may not be entirely fair to directly compare PRADO/FL-PRADO with models trained in cloud environments, where privacy and resource limitations are not present. Nevertheless, we present comparisons with well-established baselines and previous non-on-device techniques, while carefully accounting for the differences in goals and operational contexts.

5.1. Evaluation of emotion prediction

As discussed in Section 4, while evaluating the performance of the proposed model for emotion prediction, the baseline models—LSTM, Bi-LSTM, BERT, and PRADO—are run without an FL environment.

The strength of PRADO lies in its ability to perform effectively under constrained computational power and limited memory, making it well-suited for on-device applications. Table 5 presents the precision, recall, and F1-score values calculated for the different language models.

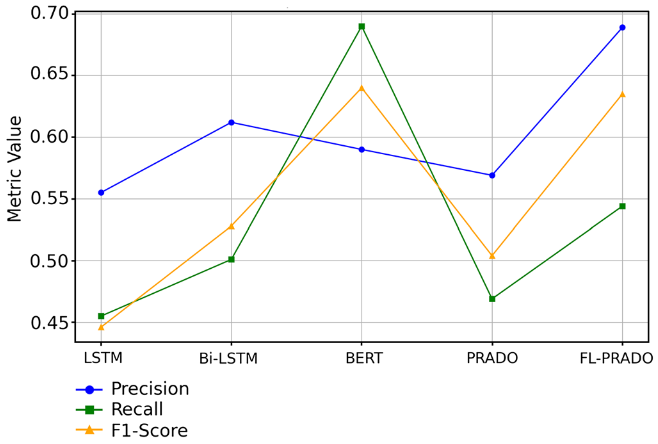
All baseline models (LSTM, Bi-LSTM, BERT, and PRADO) are executed in a standard (non-FL) environment.

The FL-PRADO shows substantial improvement over various models. Figure 3 shows comparative line chart. In comparison with LSTM, FL-PRADO's precision is improved by 23.11%, recall is improved by 17.39%, and F1 score is significantly improved i.e., by 42.2%. In comparison with Bi-LSTM, FL-PRADO's precision is improved by 13.11%, recall is improved by 8%, and F1 score is improved i.e., by 20.75%. In comparison with BERT, FL-PRADO's precision is improved by 16.95%, recall is declined by 21.74%, and no change for F1 score. It is noticeable that FL version of PRADO performs better than original PRADO model. In comparison with PRADO, FL-PRADO's precision is increased by 21.05%, recall is improved by 14.89%, and

Table 5
Emotion prediction metrics (precision, recall, and F1 score) on the GoEmotions dataset

Model	Precision	Recall	F1-score
LSTM	0.56	0.46	0.45
Bi-LSTM	0.61	0.50	0.53
BERT	0.59	0.69	0.64
PRADO	0.57	0.47	0.50
FL-PRADO	0.69	0.54	0.64

Figure 3
Comparative line chart for metrics



F1 score gain of 28%. Relative to other language models, FL-PRADO exhibits the highest precision, 11% improvement on average, indicating high relevance for emotion prediction. FL-PRADO effectively balances recall and precision and can be used in diverse situations.

To provide the statistical measure of reliability and variability of precision, recall, and F1-score, we calculated the confidence intervals (CI) at 95% of these metrics. Figures 4 and 5 demonstrate macro and weighted-average scores of the precision, Figures 6 and 7 present the confidence intervals of macro and weighted average scores of recalls. Finally, Figures 8 and 9 show macro and weighted average of the F1-score across different training rounds and clients.

The performance of BERT is relatively similar to that of FL-PRADO but fails to balance precision and comes at a higher computational cost.

5.2. Evaluation of the recommendation model

The classification performance of the recommendation model is evaluated in terms of precision, recall, F1, and other parameters related to implementation variations.

Figure 4
Macro averaged precision with 95% CI

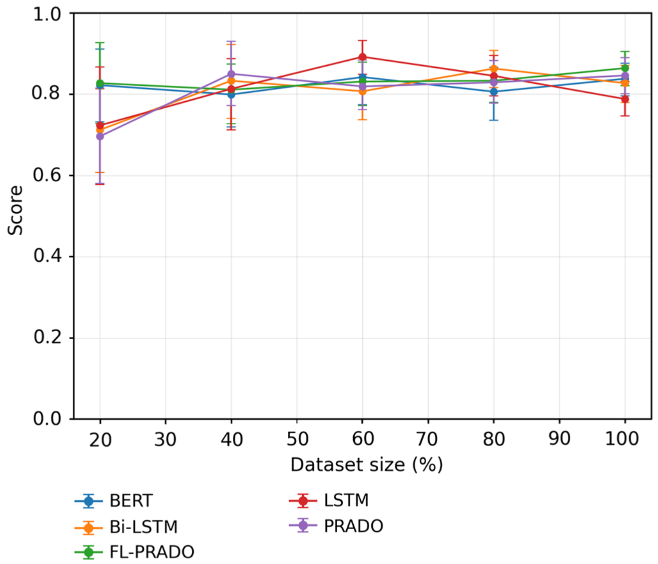


Figure 5
Weighted averaged precision with 95% CI

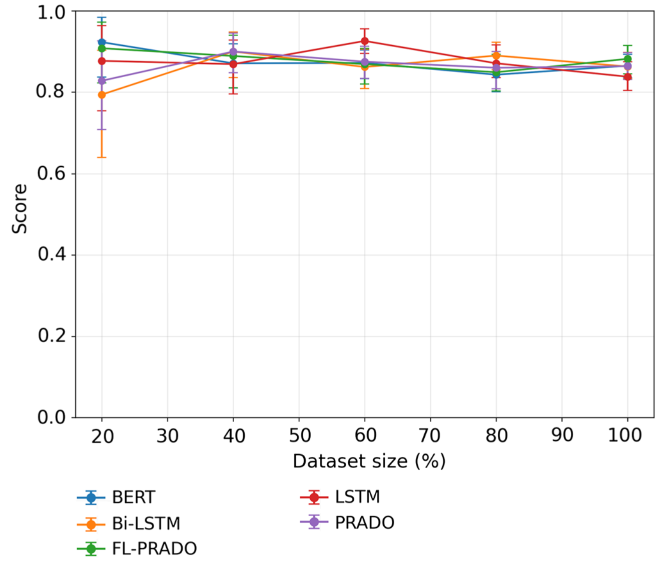
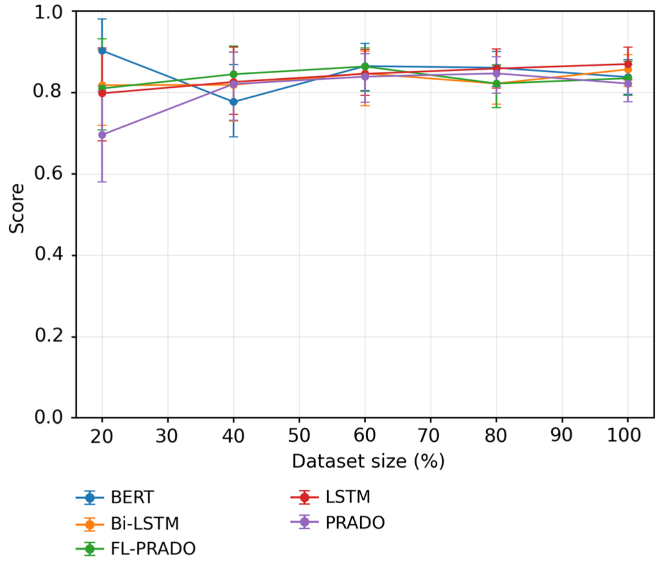


Figure 6
Macro averaged recall with 95% CI



Baseline models for CDR: Due to the absence of directly comparable baseline methods, we selected representative and widely adopted models — EMCDR, CDFLM, ANR, and MFPCDR. Baseline model selection is performed considering the methods used in the proposed model and its relevance to the proposed model, as shown in Table 6.

EMCDR (famous model for CDR): This framework is developed for cross-domain mapping and recommendation with the help of a multilayer perceptron that captures nonlinear mapping functions across domains.

ANR (attention-based model): This aspect-based model uses attention-based techniques to perform CDR. First, the model is trained on the target domain, and correlated source domain comments are applied to deliver recommendations [43].

CDLFM (CDR): The cross-domain model based on latent feature mapping applies the similarity relationship between users' rating

Figure 7
Weighted averaged Recall with 95% CI

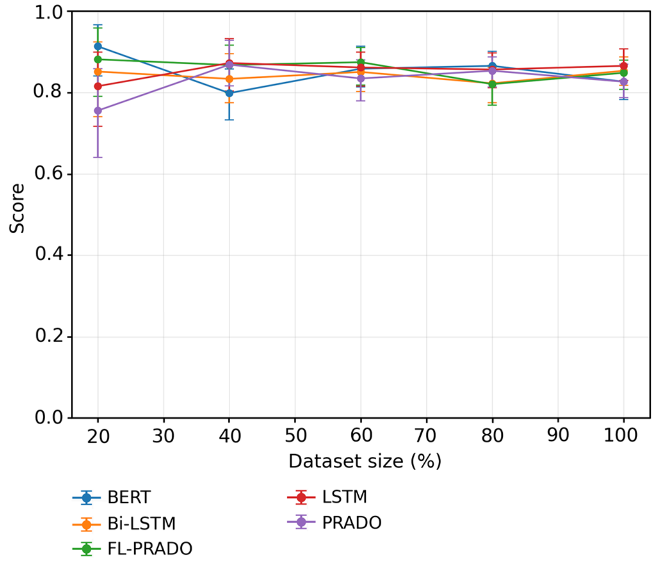
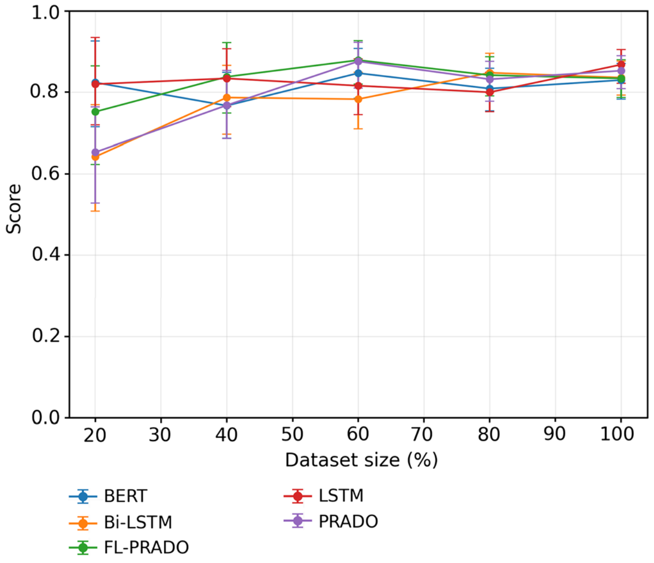


Figure 8
Macro averaged F1 with 95% CI

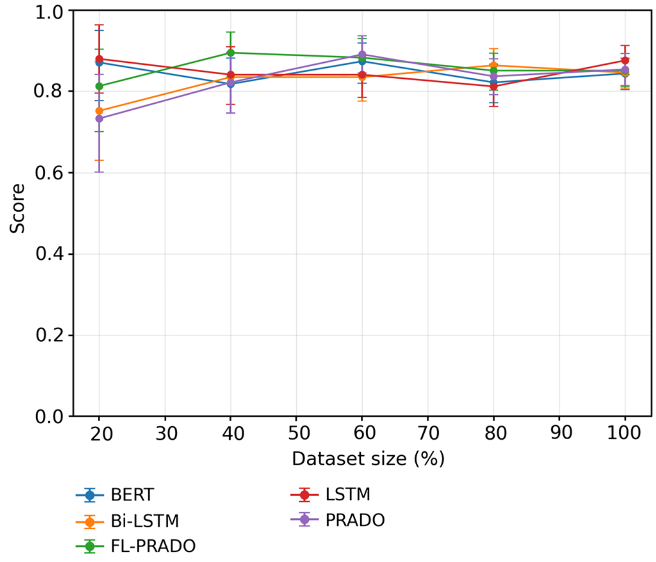


behavior. A cross-domain knowledge transfer is performed using a domain-based gradient boosting tree approach. The model also handles cold-start user problems using latent attributes [44].

MFPCDR (federated CDR): A meta-learning federated CDR model for a personalized recommendation based on an attention mechanism and transfer learning [45].

The classification performances of the experimental outputs in terms of precision, recall, and F1 score are given in Table 7. With experimental setup mentioned in Section 4, the proposed approach achieves best performance in comparison with all base models with and without privacy preservation. The precision of our model is 0.96 which performs better than EMCDR by 28%, CDFLM by 21.52%, ANR by 10.34%, and MFPCDR by 9.09%. This comparison clearly indicates that attention-based mechanisms outperform as compared to other.

Figure 9
Weighted averaged F1 with 95% CI



Compared with MFPCDR, having CDR model in FL environment has the slight difference in performance as compared to our approach. MFPCDR has used attention mechanism in local embeddings and applied transfer learning approach. But use of meta-data in recommendation effects on overall performance of the model whereas our model not only applies the projected attention mechanism and uses enhanced the random forest algorithm to handle CDR. This resulted into enhancement not only in precision but also in recall and F1-score by 2.53% and 5.95% respectively.

To demonstrate the experimental outcome, plot graph is produced as shown in Figure 10. As shown in Table 7, for the proposed model, modular federated CDR with PRADO has the highest performance in CDR, indicating that, compared with any other domain for personalized recommendation, emotions play an important role.

Most of the existing federated CDR system including MFPCDR [45] and FedCDR [1] uses the standard FedAvg mechanism, but in our proposed framework, we applied buffered FedAvg which enhanced the overall performance of the model. Table 8 shows the ablated buffered FedAvg strategy by replacing it with standard FedAvg. There is drop in precision by 2.08%, in recall by 4.9%, and in F1-score drop by 4.5% confirming that buffering improves convergence stability and overall performance.

6. Conclusion

This research presents a novel Modular Federated Cross-Domain Recommendation (MFCDR) system built on a projected attention network, designed to provide highly personalized recommendations while ensuring strong user privacy. By using FL, our approach enables collaborative model training without sharing raw user data, addressing critical privacy concerns that are increasingly important in today's data-sensitive environment. Our extensive experiments demonstrate that the MFCDR system substantially outperforms several well-established baseline models including EMCDR, CDFLM, ANR, and MFPCDR achieving a precision of 0.96 and an F1-score of 0.89. These improvements reflect the effectiveness of combining attention mechanisms with FL to deliver accurate, emotion-driven recommendations across different domains. Overall, our research highlights a promising direction for building recommendation systems that respect user privacy without

Table 6
Evaluation features and descriptions

Methods	Domain (source/target)	Privacy-preserving	Method used
EMCDR	Books/CDs	No	Multilayer perceptron
CDFLM	Books/Movies	No	Gradient boosting Tree approach
ANR	Movies/CDs	No	Attention mechanism
MFPCDR	Books/CDs	Yes	Attention mechanism and transfer learning
MFCDR with PRADO	Emotions/Books	Yes	Projected attention network and transfer learning

Table 7
Classification performance

Methods	Precision	Recall	F1-score
EMCDR	0.75	0.62	0.70
CDFLM	0.79	0.66	0.70
ANR	0.87	0.72	0.78
MFPCDR	0.88	0.79	0.84
MFCDR with PRADO	0.96	0.81	0.89

Figure 10
Performance evaluation metrics

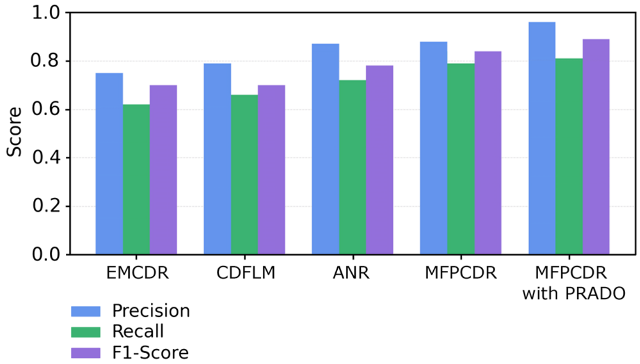


Table 8
Ablation of buffered FedAvg's impact on classification performance

Model variant	Precision	Recall	F1-score
MFCDR PRADO - Buffered FedAvg	0.96	0.81	0.89
MFCDR PRADO - FedAvg	0.94	0.77	0.85

compromising on quality. The MFCDR framework is both scalable and practical, making it well-suited for real-world applications where data privacy regulations and cross-domain personalization are paramount. This approach ultimately paves the way for more secure, user-centric recommendation platforms in the digital age.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Manisha Shrirang Otari: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Dipika Patil:** Validation, Formal analysis, Supervision. **Mithun Basawaraj Pati:** Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Yan, D., Zhao, Y., Yang, Z., Jin, Y., & Zhang, Y. (2022). FedCDR: Privacy-preserving federated cross-domain recommendation. *Digital Communications and Networks*, *8*(4), 552–560. https://doi.org/10.1016/j.dcan.2022.04.034

[2] Aledhari, M., Razzak, R., Parizi, R. M., & Saeed, F. (2020). Federated learning: A survey on enabling technologies, protocols, and applications. *IEEE Access*, *8*, 140699–140725. https://doi.org/10.1109/ACCESS.2020.3013541

[3] 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: 1901.09888*. https://doi.org/10.48550/arXiv.1901.09888

[4] Tan, B., Liu, B., Zheng, V., & Yang, Q. (2020). A federated recommender system for online services. In *Proceedings of the 14th ACM Conference on Recommender Systems*, 579–581. https://doi.org/10.1145/3383313.3411528

[5] Su, G. (2021). Federated online learning based recommendation systems for mobile social applications. In *2021 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress*, 936–939. https://doi.org/10.1109/DASC-PICom-CBDCom-CyberSciTech52372.2021.00156

[6] Liang, F., Pan, W., & Ming, Z. (2021). FedRec++: Lossless federated recommendation with explicit feedback. *Proceedings of the AAAI Conference on Artificial Intelligence*, *35*(5), 4224–4231. https://doi.org/10.1609/aaai.v35i5.16546

[7] Eren, M. E., Richards, L. E., Bhattarai, M., Yus, R., Nicholas, C., & Alexandrov, B. S. (2022). FedSPLIT: One-shot federated recommendation system based on non-negative joint matrix factorization and knowledge distillation. *arXiv Preprint: 2205.02359*. https://doi.org/10.48550/arXiv.2205.02359

[8] Anelli, V. W., Deldjoo, Y., di Noia, T., Ferrara, A., & Narducci, F. (2021). FedeRank: User controlled feedback with federated recommender systems. In *Advances in Information Retrieval: 43rd European Conference on IR Research*, 32–47. https://doi.org/10.1007/978-3-030-72113-8_3

[9] Lin, G., Liang, F., Pan, W., & Ming, Z. (2021). FedRec: Federated recommendation with explicit feedback. *IEEE Intelligent Systems*, *36*(5), 21–30. https://doi.org/10.1109/MIS.2020.3017205

[10] Yang, L., Tan, B., Zheng, V. W., Chen, K., & Yang, Q. (2020). Federated recommendation systems. In Q. Yang, L. Fan, & H. Yu (Eds.), *Federated learning: Privacy and incentive* (pp. 225–239). Springer. https://doi.org/10.1007/978-3-030-63076-8_16

[11] Kalloori, S., & Klingler, S. (2021). Horizontal cross-silo federated recommender systems. In *Proceedings of the 15th ACM Conference on Recommender Systems*, 680–684. https://doi.org/10.1145/3460231.3478863

[12] Otari, M. S., Kumar, B. S., & Patil, M. B. (2024). Challenges and advancement in federated recommendation system: A comprehensive review. In *Accelerating Discoveries in Data Science and Artificial Intelligence I*, 225–234. https://doi.org/10.1007/978-3-031-51167-7_22

[13] Wang, Q., Yin, H., Chen, T., Yu, J., Zhou, A., & Zhang, X. (2022). Fast-adapting and privacy-preserving federated recommender system. *The VLDB Journal*, *31*(5), 877–896. https://doi.org/10.1007/s00778-021-00700-6

[14] Yang, L., Zhang, J., Chai, D., Wang, L., Guo, K., Chen, K., & Yang, Q. (2023). Practical and secure federated recommendation with personalized mask. In *Trustworthy Federated Learning: First International Workshop*, 33–45. https://doi.org/10.1007/978-3-031-28996-5_3

[15] Jalalirad, A., Scavuzzo, M., Capota, C., & Sprague, M. (2019). A simple and efficient federated recommender system. In *Proceedings of the 6th IEEE/ACM International Conference on Big Data Computing, Applications and Technologies*, 53–58. https://doi.org/10.1145/3365109.3368788

[16] Chen, F., Luo, M., Dong, Z., Li, Z., & He, X. (2019). *Federated meta-learning with fast convergence and efficient communication arXiv Preprint: 1802.07876*. https://doi.org/10.48550/arXiv.1802.07876

[17] Hidasi, B., Quadrana, M., Karatzoglou, A., & Tikk, D. (2016). Parallel recurrent neural network architectures for feature-rich session-based recommendations. In *Proceedings of the 10th ACM Conference on Recommender Systems*, 241–248. https://doi.org/10.1145/2959100.2959167

[18] Qin, J., Liu, B., & Qian, J. (2021). A novel privacy-preserved recommender system framework based on federated learning. In *Proceedings of the 2021 4th International Conference on Software Engineering and Information Management*, 82–88. https://doi.org/10.1145/3451471.3451485

[19] Perifanis, V., Drosatos, G., Stamatelatos, G., & Efraimidis, P. S. (2023). FedPOIRec: Privacy-preserving federated poi recommendation with social influence. *Information Sciences*, *623*, 767–790. https://doi.org/10.1016/j.ins.2022.12.024

[20] Song, Y., Xie, Y., Zhang, H., Liang, Y., Ye, X., Yang, A., & Ouyang, Y. (2021). Federated learning application on telecommunication-joint healthcare recommendation. In *2021 IEEE 21st International Conference on Communication Technology*, 1443–1448. https://doi.org/10.1109/ICCT52962.2021.9657870

[21] Guillen, I., Sanchez-Corcuera, R., & Casado-Mansilla, D. (2021). A recommender system that safeguards the user privacy through Federated Learning. In *2021 6th International Conference on Smart and Sustainable Technologies*, 01–05. https://doi.org/10.23919/SpliTech52315.2021.9566466

[22] Zhang, J., & Jiang, Y. (2021). A vertical federation recommendation method based on clustering and latent factor model. In *2021 International Conference on Electronic Information Engineering and Computer Science*, 362–366. https://doi.org/10.1109/EIECS53707.2021.9587935

[23] Dogra, M., Meher, B. P., Mani, P. V., & Min, H.-K. (2022). Memory efficient federated recommendation model. In *2022 IEEE 16th International Conference on Semantic Computing*, 139–142. https://doi.org/10.1109/ICSC52841.2022.00028

[24] Gao, C., Chen, X., Feng, F., Zhao, K., He, X., Li, Y., & Jin, D. (2019). Cross-domain recommendation without sharing user-relevant data. In *The World Wide Web Conference*, 491–502. https://doi.org/10.1145/3308558.3313538

[25] Zhu, F., Wang, Y., Chen, C., Liu, G., Orgun, M., & Wu, J. (2018). A deep framework for cross-domain and cross-system recommendations. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence*, 3711–3717. https://doi.org/10.24963/ijcai.2018/516

[26] Zhu, F., Chen, C., Wang, Y., Liu, G., & Zheng, X. (2019). DTCDR: A framework for dual-target cross-domain recommendation. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, 1533–1542. https://doi.org/10.1145/3357384.3357992

[27] Hu, G., Zhang, Y., & Yang, Q. (2018). CoNet: Collaborative cross networks for cross-domain recommendation. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, 667–676. https://doi.org/10.1145/3269206.3271684

[28] Liu, M., Li, J., Li, G., & Pan, P. (2020). Cross domain recommendation via bi-directional transfer graph collaborative filtering networks. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, 885–894. https://doi.org/10.1145/3340531.3412012

[29] Cai, J., Liu, Y., Liu, X., Li, J., & Zhuang, H. (2023). Privacy-preserving federated cross-domain social recommendation. In *Trustworthy Federated Learning: First International Workshop*, 144–158. https://doi.org/10.1007/978-3-031-28996-5_11

[30] Zhao, P., Jin, Y., Ren, X., & Li, Y. (2024). A personalized cross-domain recommendation with federated meta learning. *Multimedia Tools and Applications*, *83*(28), 71435–71450. https://doi.org/10.1007/s11042-024-18495-3

[31] Di, Y., Shi, H., Wang, Q., Jia, S., Bao, J., & Liu, Y. (2025). Federated cross-domain recommendation system based on bias eliminator and personalized extractor. *Knowledge and Information Systems*, *67*(3), 2935–2965. https://doi.org/10.1007/s10115-024-02316-y

[32] Li, R., Shu, Y., Cao, Y., Luo, Y., Zuo, Q., Wu, X., .., & Zhang, W. (2024). Federated cross-view e-commerce recommendation based on feature rescaling. *Scientific Reports*, *14*(1), 29926. https://doi.org/10.1038/s41598-024-81278-1

[33] Guo, L., Lu, Z., Yu, J., Nguyen, Q. V. H., & Yin, H. (2024). Prompt-enhanced federated content representation learning for cross-domain recommendation. In *Pro-*

ceedings of the ACM Web Conference 2024, 3139–3149. https://doi.org/10.1145/3589334.3645337

[34] Liu, Z., He, X., Ma, X., Wang, B., Shen, G., & Kong, X. (2024). FedOCD: A one-shot federated framework for heterogeneous cross-domain recommendation. In *Web and Big Data: 8th International Joint Conference*, 69–83. https://doi.org/10.1007/978-981-97-7241-4_5

[35] Goyal, S. J., Goyal, R., Singh, V. K., Arunachalam, R., & Tripathi, K. N. (2025). Privacy-preserving cross-domain recommendation using hybrid federated transfer learning. *Multimedia Tools and Applications*, *84*(18), 19343–19377. https://doi.org/10.1007/s11042-024-19747-y

[36] Kaliamoorthi, P., Ravi, S., & Kozareva, Z. (2019). PRADO: Projection attention networks for document classification on-device. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing*, 5011–5020. https://doi.org/10.18653/v1/D19-1506

[37] Otari, M. S., Patil, D., & Patil, M. B. (2024). Revolutionizing emotion-driven sentiment analysis using federated learning on edge devices for superior privacy and performance. *Nanotechnology Perceptions*, *20*(S6), 769–784. https://doi.org/10.62441/nano-ntp.vi.1342

[38] Stripelis, D., Thompson, P. M., & Ambite, J. L. (2022). Semi-synchronous federated learning for energy-efficient training and accelerated convergence in cross-silo settings. *ACM Transactions on Intelligent Systems and Technology*, *13*(5), 78. https://doi.org/10.1145/3524885

[39] Nguyen, J., Malik, K., Zhan, H., Yousefpour, A., Rabbat, M., Malek, M., & Huba, D. (2022). Federated learning with buffered asynchronous aggregation. In *Proceedings of the 25th International Conference on Artificial Intelligence and Statistics*, *151*, 3581–3607.

[40] Pu, P., Chen, L., & Hu, R. (2011). A user-centric evaluation framework for recommender systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems*, 157–164. https://doi.org/10.1145/2043932.2043962

[41] Demszky, D., Movshovitz-Attias, D., Ko, J., Cowen, A., Nemade, G., & Ravi, S. (2020). GoEmotions: A dataset of fine-grained emotions. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4040–4054. https://doi.org/10.18653/v1/2020.acl-main.372

[42] Yacouby, R., & Axman, D. (2020). Probabilistic extension of precision, recall, and F1 score for more thorough evaluation of classification models. In *Proceedings of the First Workshop on Evaluation and Comparison of NLP Systems*, 79–91. https://doi.org/10.18653/v1/2020.eval4nlp-1.9

[43] Chin, J. Y., Zhao, K., Joty, S., & Cong, G. (2018). ANR: Aspect-based neural recommender. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, 147–156. https://doi.org/10.1145/3269206.3271810

[44] Wang, X., Peng, Z., Wang, S., Yu, P. S., Fu, W., & Hong, X. (2018). Cross-domain recommendation for cold-start users via neighborhood based feature mapping. In *Database Systems for Advanced Applications: 23rd International Conference*, 158–165. https://doi.org/10.1007/978-3-319-91452-7_11

[45] Di, Y., & Liu, Y. (2023). MFPCDR: A meta-learning-based model for federated personalized cross-domain recommendation. *Applied Sciences*, *13*(7), 4407. https://doi.org/10.3390/app13074407

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