SFedRec: A Federated Learning Framework for Dynamic Session-based Recommendation

Extended Abstract

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ABSTRACT

Session-based recommendation systems are critical for capturing users' evolving interests in real-time interactions. However, applying such systems in a federated learning (FL) setting presents challenges related to decentralized data and privacy preservation. To address this, we propose SFedRec, a session-based federated recommendation framework that integrates long-term user preferences with dynamicd session-based behaviors. SFedRec builds decentralized heterogeneous knowledge graphs to model user-item interactions and social connections, utilizing a graph neural network to learn user representations while ensuring privacy through Local Differential Privacy (LDP). Extensive experiments on three real-world datasets demonstrate that SFedRec outperforms state-of-the-art federated recommendation models, showing significant improvements in both general and cold-start scenarios.

KEYWORDS

session-based recommendation; federated learning; heterogeneous knowledge graph; privacy preservation

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1 INTRODUCTION

With the growing emphasis on data privacy, *federated learning (FL)* has emerged as a compelling solution to train machine learning models in decentralized environments without the need to collect user data centrally [2, 7, 15–17, 23, 29, 47, 53, 60–62]. FL enables collaborative learning across clients while preserving user privacy, crucial with regulations like the General Data Protection Regulation (GDPR) [44]. While this approach has been successfully applied in various static tasks, its application in *recommender systems* – where user interactions are dynamic and personalized – presents a unique set of challenges.

In the context of FL, several works rely on centralized data for user preference modeling [1, 4, 18–20, 30, 31, 34, 40, 58]. They distribute the training of user-specific models across devices and share model updates, not raw data, with a central server. However, these models mainly learn static, long-term preferences and fail to capture dynamic user behavior well, especially in real-time scenarios like session-based recommendation systems [5, 8, 14, 21, 26, 32, 42, 45, 48, 50–52, 54]. More recently, graph neural networks (GNNs) are being integrated into federated recommendation systems to better capture the complex relationships [9, 24, 27, 28, 35, 36, 43, 49, 55, 59]. However, existing approaches using GNNs on static *user-item bipartite graphs*, which limits their ability to model *session-based recommendations*, where user preferences shift rapidly over short periods [11–13, 22, 37, 41, 46, 63]. Additionally, while social network can help with cold-start problem and accuracy [3, 25, 33, 38, 39, 57], most FL frameworks do not fully leverage the social context due to data privacy and integration complexity.

The primary goal of this research is to introduce a novel FL framework to address these gaps. Our aim is to capture the dynamic, session-based preferences of users in a privacy-preserving manner, while also leveraging social network information to improve recommendation performance in federated environments.

2 PROBLEM FORMULATION

Let U and I denote a sets of users and items, respectively. The dataset of user's historical behaviors $\mathcal{D}$ contains all sessions of all users. Each user $u \in U$ is associated with a set of sessions denoted by $D_u \in (S_1^u, S_2^u, ..., S_{D_u}^u)$, where S_T^u is the T^{th} session of u. Each session S_T^u is a sequence of items clicked by an anonymous user, where $S_T^u[t] \in I$ denotes the I^{th} item in the session S_T^u. For brevity, we may drop the superscript u and/or superscript T in S_T^u, apart

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Table 1: Experiment Results Compared with Baseline Methods in %

Model	Gowalla				Delicious				Foursquare			
	HR@10	MRR@10	HR@20	MRR@20	HR@10	MRR@10	HR@20	MRR@20	HR@10	MRR@10	HR@20	MRR@20
FedMF	18.27	7.63	22.48	8.34	12.58	6.39	15.46	8.42	22.35	7.55	25.24	8.06
FedPerGNN	31.36	15.58	36.98	16.41	26.14	12.97	29.92	14.19	40.93	18.56	49.20	20.18
FeSoG	34.25	17.02	40.12	18.66	32.33	15.20	40.67	16.68	47.66	23.91	56.45	25.06
SFedRec	**37.53**	**17.35**	**42.05**	**19.48**	**32.92**	**15.95**	**42.42**	**17.10**	**49.69**	**24.50**	**57.02**	**25.64**

from the session component, we have a social network which is a graph $S = (U, E)$ about social relations. The set of nodes in S is the user set U, and the set E of edges represents the social relationships between users. An edge (u, v) from u to v means that u is followed by v.

Given a sub-graph of local user-item interactions and social relationships, a user u_i stored in client c_i, the interaction data are denoted as D_u, We denote the $C = (c_1, c_2, ...)$ as clients set, each users' data is placed in different clients respectively, we define session-based federated social recommendation as the task of predicting the next project, that is, predicting the next item of a new session $S \notin \mathcal{D}$, which needs to build a prediction model from all the users' data stored in their own private devices with a centralized server. Our work will be processed in a privacy preserving manner based on locally stored user historical data and auxiliary information extracted from local sub-graph which is built by the local user-user, user-item and item-item interaction.

3 METHODOLOGY

Our proposed method mainly comprises three components: long-term interests representation component, session-based representation component and federated learning component. To be specific, each component is explained as follows:

- **Long-term interests representation component**: This module firstly constructs local heterogeneous knowledge graph from all historical user behaviors $\mathcal{D}$ and the social network S for each users to capture user-item interactions, item transitions, and social relationships, These sub-graphs endow the system with the ability to conduct local modeling of user behavior; then learns knowledge-enhanced long-term user and item representations by employing heterogeneous knowledge graph neural network to incorporate both historical trends and collaborative information from neighboring nodes in the graph.
- **Session-based representation component**: During the active session, this network focuses on modeling the transitions between items. By learning item embeddings at the session level, it can effectively incorporate real-time interaction information and capture the immediate interest changes of users in the current session. Meanwhile, it also takes full account of the long-term preferences of users, avoiding the situation of only focusing on session-level behaviors and ignoring the overall interest trends of users. The prediction part can comprehensively consider the long-term interests of users and the real-time needs of the current session, providing users with highly accurate next-item recommendations.
- **Federated learning component**: This module undertakes crucial tasks of data transmission and privacy protection in the federated learning framework. Its main responsibility is to upload the gradients of model parameters to the server. However, during the transmission of original gradient updates, there is a risk of sensitive information leakage. To effectively prevent this problem, this module adopts the Local Differential Privacy (LDP) technology. Specifically, before the client transmits parameters to the server, the LDP technology adds carefully controlled noise to the parameters. The addition of this noise can not only ensure the statistical usability of the data but also maximize the protection of user privacy information, making it difficult for attackers to obtain sensitive data from the transmitted parameters. Finally, the central server is responsible for collecting the parameters from various clients and aggregating these parameters. The aggregated results will be sent back to the clients for the clients to update their local models, thereby achieving the collaborative training and optimization of the entire federated learning system.

4 EXPERIMENT

We develop two experiments to validate our proposed SFedRec, we choose three representative benchmark public real-world datasets, i.e., *Gowalla [6]*, *Delicious [10]* and *Foursquare [56]*, to evaluate our proposed model. Table 1 shows the overall results of all baselines on three datasets, we highlight the best results in bold. Our SFedRec outperforms all the FedRec models by a big margin, this superiority of SFedRec can be mainly attributed to its innovative utilization of the multi-relation knowledge graph to learn the representation. The multi-relation knowledge graph enables SFedRec to capture a vast amount of complex information. It not only includes the direct relationships between users and items but also takes into account the indirect associations and semantic connections. By leveraging knowledge source, SFedRec can generate more accurate and comprehensive user and item representations, which demonstrates the effectiveness of our model.

5 CONCLUSION

In this paper, we first explore the challenge problem of dynamic recommendation and personalized in FedRec, considering the superiority of session-based recommendation systems in solving user dynamic interest problem. In the future, we will consider efficient aggregation of client private models and explore adversarial training and robustness enhancement techniques for dynamic federated recommendation.

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