Poster: Ensemble Federated Edge Learning for Recommender Systems

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***Abstract*—Given the explosion of e-services, it has become critical for recommender systems (RSs) to have expected suggestions. Traditional machine learning-based recommending models provide an interface for platforms to find the most relevant items for users. Nonetheless, those models are often trained with user data from a single domain at centralized cloud, which hinders the performance of RSs, causes significant data transmission overhead, and may harm data privacy. To address these issues, in this poster, we propose an ensemble federated edge learning scheme (eFEEL) on the basis of a semi-distributed architecture design. eFEEL aims to efficiently and effectively improve RSs without breaching user data privacy.**

***Index Terms*—federated edge learning, recommender systems, cross-domain data, smart edge device, smart gateway**

I. Introduction

Recommender systems (RSs) have been prominent to major e-service platforms (e.g., Amazon, Youtube, Facebook, etc.), as they provide suggestions about the most relevant items for users on the basis of user data (e.g., item attributes and behavior data). Traditional machine learning-based recommendation models primarily focus on data of a single domain and need the data to be centralized at cloud. Thus, they may face data sparsity and cold start issues, let alone the data transmission cost and data privacy concerns from users due to centralized data processing. In addition, we argue that real-world RSs are often complicated and require analytics of data from diverse domains. Thus, it will be a necessity to leverage the relatively information-rich cross-main data (e.g., browsing and watching history, thumb-ups, text information, etc.) to improve the recommendation performance of the data-sparse RSs [1]. It is also worth noting that the cross-domain data is collected from user activities on different platforms and is therefore privacy sensitive. Thus, it would be the best to not upload the data to a remote server.

In this poster, we consider federated edge learning (FEEL), a decentralized learning framework proposed by Google [2], to avoid data transmission from smart edge devices (SEDs) to centralized cloud and keep the recommendation model trained locally at the SEDs. By doing this, user data privacy is guaranteed and the data transmission cost is significantly reduced. Nonetheless, the conventional fully distributed architecture of FEEL is facing unprecedented challenges regardless of its wide usage in works [3]–[5]. For example, data at SEDs may have patterns with diverse distributions, which makes the performance of FEEL drops drastically.

In order to tackle the heterogeneity issue of the underlying user data [7], we design a semi-distributed architecture (as shown in Fig. 1), in which SEDs are classified into different groups based on diverse semantic associations, distributions, and densities of their data. Then, all the SEDs in each group are interconnected by a smart gateway (SG) and the data from each SED in the group will have similar patterns. On top of this semi-distributed architecture, we propose an ensemble federated edge learning (eFEEL) scheme. The intent of eFEEL is to efficiently and effectively improve the performance of RSs. Specifically, the SG of each group selects a general model to be trained, and this model will be downloaded by each SED in the group and is trained locally at the SED. The model updates from each SED in the group will be sent back to SG to generate an aggregated global model, and this global model will be utilized to construct the ensemble model. Finally, the global models from all the SGs will be combined together, e.g., weight-based methods, to form a super global model for the RS to make recommendations.

The remainder of this poster is organized as follows: In Section II, we introduce the system model. In Section III, we discuss a case study. In Section IV, we conclude the poster.

II. System Model

In this section, we introduce the system model, which consists of the smart edge devices (SEDs), smart gateways (SGs), and a centralized cloud server, as shown in Fig. 1.

In our semi-distributed architecture design, each SG organizes a group of SEDs with cache and computing capacities on the network edge. The SEDs in the group contain different applications to continuously collect user data, and the collected data has similar patterns. For example, customers with similar online shopping patterns in e-commerce will be grouped together and interconnected by an SG. It is worth noting that we have classified the mixed data into different domains.

Our proposed ensemble federated edge learning scheme (eFEEL) will first notify each SG to select a general model to be trained, and this general model should be suitable to the specific data in the group. The selected model at each SG will be sent to all the SEDs in its group, and each SED will train the model on its local data. Eventually, the model updates

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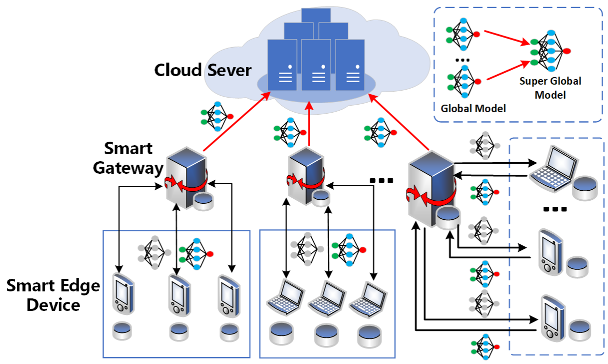

Fig. 1. Semi-Distributed Architecture Design

(e.g., model weights) from each SED will be sent back to the SG for aggregation, and a global model will be generated at each SG. The global models from all the SGs are diverse and will be combined together by the centralized server to form a super global model. This super global model will be utilized by the recommender system (RS) to find the most relevant items for the users.

It is worth noting that eFEEL trains the global model at individual SED and does not require the data to be transferred to SG. Thus, we have preserved data privacy and significantly reduced the data transmission overhead between the SG and the SEDs organized by it. We have also constructed an ensemble model with the cross-domain data instead of with the data from just a single domain, this will remarkably improve the performance of the RSs.

III. Case Study

In this section, we provide a use case of our proposed ensemble federated edge learning scheme (eFEEL) by looking at the news recommender systems (RSs).

Influential news websites (e.g., CNN: Cable News Network and BBC: British Broadcasting Corporation) contain a vast amount of diverse content (e.g., images, audio, video, and text) with topics ranging from politics to business and entertainment. In order to attract more users, the news outlets have continued to make efforts on recommending the most relevant items to individual users. Nonetheless, the news preference data of different users (e.g., sports fans and political enthusiasts) may exhibit significant heterogeneity in terms of statistical distributions, which poses unprecedented challenges to the RSs of news websites.

Our proposed scheme, designated as eFEEL, can be considered in this situation. Specifically, news website users often subscribe to the news outlet and access news from their personal devices (e.g., mobile phones and laptops; in our case the smart edge device (SEDs)). eFEEL can first group the users into different categories based on their behaviour data (e.g., clicks, like or dislike, written comments, etc.), which demonstrates different semantic associations, distributions, and densities. Then, the SEDs of each group, where data has similar patterns, will be interconnected by an SG.

Subsequently, eFEEL will tell each SG to choose a general model (e.g., a statistical model for the behaviour data of sports fans) to be trained. This model will be sent to the personal devices of the users in the group organized by the SG and trained locally based on the data at the devices. Then the model updates (e.g., model weights) from each device will be sent back to the SG for aggregation. With collaborative polling on all the training results from all the personal devices within the same group, a better global model could be generated for one specific type of users like sports fans.

Eventually, the well-trained global models from all the SGs will be combined together to form a fine-tuned ensemble super global model for the RS of the news outlet. For example, eFEEL can factor in each global model from individual SG differently by using diverse weights. If the news website focuses on politics, a higher weight will be assigned to the global model from the group of political enthusiasts, while a lower weight can be associated with the global model from the group of sports fans.

It is worth noting that eFEEL has trained global models for SGs locally at the personal devices, this preserves the data privacy of the users subscribed to the news outlets. Unlike the traditional machine techniques, eFEEL does not require user personal data to be sent over to SG, this significantly reduces the data transmission overhead and makes eFEEL more efficient in training models for RSs. In addition, we have also included ensemble modeling to combine all the global models of SGs together, this makes eFEEL more effective in training models for RSs.

IV. Conclusion

In summary, we proposed an ensemble federated edge learning scheme (eFEEL) for recommender systems on the basis of a semi-distributed architecture design. Nonetheless, this work is still at an early stage and needs further development in the future.

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