Research Direction Proposal

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1 Abstract

In real-world scenarios, due to data security and user privacy [1], the graph data stored in each device is limited and often has bias [2]. Even though federated Graph Neural Network (GNN) models are proposed to solve the data isolation and heterogeneity problem with pseudo interacted items [3] and missing neighbor generation [4], these models lack explainability (e.g., the prediction of these models is not traceable). Thus, a trustworthy federated GNN framework is expected. In this proposal, we propose a Federated Learning (FL) framework that alleviates data heterogeneity while takes model explainability and fairness into consideration.

2 Proposed Idea

We aim to train an explainable GNN model orchestrated by a central server jointly with sub-graphs in each client.

- To improve the expressive ability of GNN with heterogenous data, inspired by LAGNN [5], we could use augmentation strategies. Regarding the graph in the client with a limited number of edges and nodes, we can add more neighbors and features based on the local neighbors with a generative model like the one used in LAGNN. Thus, we can ensure that each client shares a similar graph size.

- Moreover, to improve explainability, we want to focus on structural explainability [6]. After we have the augmented graphs, we feed them into a structural explainer. With the help of 2 components, the explainer aims to clarify the reasons for exhibited bias by masking bias edges (edge set s1) and identify edges (edge set s2) that contribute to prediction fairness level in the augmented graph, respectively. The edge sets, s1 and s2, can provide explanation on both bias and fairness. The explainer is then optimized by leveraging Wasserstein-1 distance and mutual information.

From the perspective of the FL system, another challenge that biases the trained model is slow-responding clients. In traditional synchronous FL systems

[7], due to the data heterogeneity, some clients take a longer time to complete each training round. The system then discards these clients, which biases the model training.

- Inspired by PAPAYA [8], an asynchronous FL system can be utilized to train our GNN model. The system makes sure weighs can be aggregated by the server as soon as they are ready. Thus, without discarding updates from slow clients, we can achieve a fairer model.

References

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