Paper(s) discussed

(1) Wang, A. Li, M. Pang, H. Li and Y. Chen, "GraphFL: A Federated Learning Framework for Semi-Supervised Node Classification on Graphs," 2022 IEEE International Conference on Data Mining (ICDM), Orlando, FL, USA, 2022, pp. 498-507.

(2) Fair and Robust Federated Learning Through Personalization, Tian Li, Shengyuan Hu, Ahmad Beirami, Virginia Smith, Proceedings of the 38th International Conference on Machine Learning

Summary

(1) The paper "GraphFL: A Federated Learning Framework for Semi-Supervised Node Classification on Graphs" proposes a novel federated learning framework for semi-supervised node classification on graphs. In this framework, multiple clients with their own local graph datasets and partially labeled nodes collaboratively learn a global model without sharing the raw data.

(2) "Fair and Robust Federated Learning Through Personalization" proposes FairFed, a novel federated learning framework that personalizes the global model for each client to improve fairness and robustness. FairFed consists of two phases: personalization and aggregation. Personalization reduces bias and variance, while aggregation ensures proportional contributions and is not affected by demographic or other characteristics. FairFed outperforms state-of-the-art frameworks and effectively mitigates security threats. It provides an efficient and decentralized solution for fair and robust federated learning while preserving privacy.

Pros

(1)
- The experimental results on benchmark datasets demonstrate that GraphFL achieves competitive performance compared to state-of-the-art methods while preserving data privacy and confidentiality.
- The proposed techniques significantly improve the performance of GraphFL in terms of accuracy and convergence speed.

(2)
- The proposed FairFed framework addresses the issue of fairness in federated learning by personalizing the global model for each client based on their local data.
- The FairFed framework is also shown to be robust to security threats such as data poisoning and model backdoor attacks.

Cons

(1)
- The paper focuses on semi-supervised node classification on graphs and does not address other graph learning tasks, such as link prediction or graph clustering.
- The paper assumes that clients have access to local datasets, which may not always be feasible in real-world scenarios.

(2)
- The FairFed framework assumes that clients have access to labeled data, which may not be the case in some scenarios.
- The paper evaluates the FairFed framework on a limited set of benchmark datasets, which may not fully represent the diversity and complexity of real-world data.

Questions for discussion

(1)
- How does GraphFL preserve data privacy and confidentiality?
- What are the challenges of federated learning in graph learning tasks?
- How do personalized aggregation and label propagation improve the performance of GraphFL?
- Can GraphFL be applied to other graph learning tasks besides semi-supervised node classification?

(2)
- What are some potential future research directions for FairFed and federated learning in general?
- What are some potential real-world applications of the FairFed framework?

(1) Presentation and Discussion Feedback

Name of Presenters: Brian, Edward and Caroline

How was the presentation? Did it help you?

The presentation was very well structured for someone like with little to none experience on the subject. I could follow and somewhat understand the chain of events and the flow of paper discussed.

Feedback for the presenters:

- Everyone were well prepared and understood the subject they were talking about.
- A more interactive approach might be better for these kind of talks so they know how fast-paced the talk is or if the audience is following the topics.

Novel points raised during the presentation or discussion that you thought were crucial. Carefully consider all issues raised and list only those you feel were most important.

- The proposed framework could be evaluated on more challenging graph datasets with larger graph sizes, higher label sparsity, and more heterogeneous client populations to better assess its scalability and robustness.
- The proposed framework could be extended to incorporate other types of federated learning algorithms, such as secure aggregation or differential privacy, to enhance the privacy and security of the communication among the clients and the server.

(2) Presentation and Discussion Feedback

Name of Presenters: KC, Cheng-Hao, Saarika

How was the presentation? Did it help you?

The paper and subject at hand seemed interesting, however, it could have been presented in a better structured way. I could not follow the presentation as well as the previous one so it didn't really help me in understanding the topics. This might be influenced by my lack of knowledge on the topic.

Feedback for the presenters:

- Explanation of topics was thorough and detailed and presenters were very well familiar with subject.
- The speed and flow of presentation was a bit off, I couldn't really follow how things were going and I kept getting distracted. Maybe less explanation on some subjects could help this issue.

Novel points raised during the presentation or discussion that you thought were crucial. Carefully consider all issues raised and list only those you feel were most important.

- The FairFed framework consists of two phases: personalization and aggregation, which are designed to reduce bias and variance and ensure proportional contributions, respectively.
- The FairFed framework provides an efficient and decentralized solution for fair and robust federated learning while preserving privacy, which is a crucial requirement for many real-world applications.