DFDG: Federated GNNs Learning from Dynamic Graphs for traffic forecasting

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Abstract

DFDG is introduced as a pioneering fusion of federated graph neural networks (GNNs) with dynamic graphs and unsupervised learning for dynamic traffic forecasting in urban settings. Utilizing self-organizing map clustering, speed patterns are clustered at various time intervals, and resulting clusters are assigned to Federated Learning participants. Within the federated setup, participants use neural ordinary differential equations coupled with attention spatial-temporal graph convolution networks to form the DFDG architecture collectively. During training, participants contribute local updates to a global GNN model, with performance weightage reflecting their reliability. This dynamic weighting system influences each participant's significance in subsequent communication rounds, promoting adaptive learning across the federated network. We group homogeneous participants based on their previous round performance and data distribution. Grouping contributes to federated learning systems' overall efficiency and effectiveness, enhancing model generalization, reducing communication overhead, preserving privacy by aggregating updates from homogeneous client groups, and allowing adaptability to local data characteristics. Extensive benchmark testing validates DFDG's superiority in traffic forecasting, surpassing current state-of-the-art methods. Our method not only advances traffic forecasting but can be adapted for broader discourse on real-time dynamic graph applications.

Our Contributions

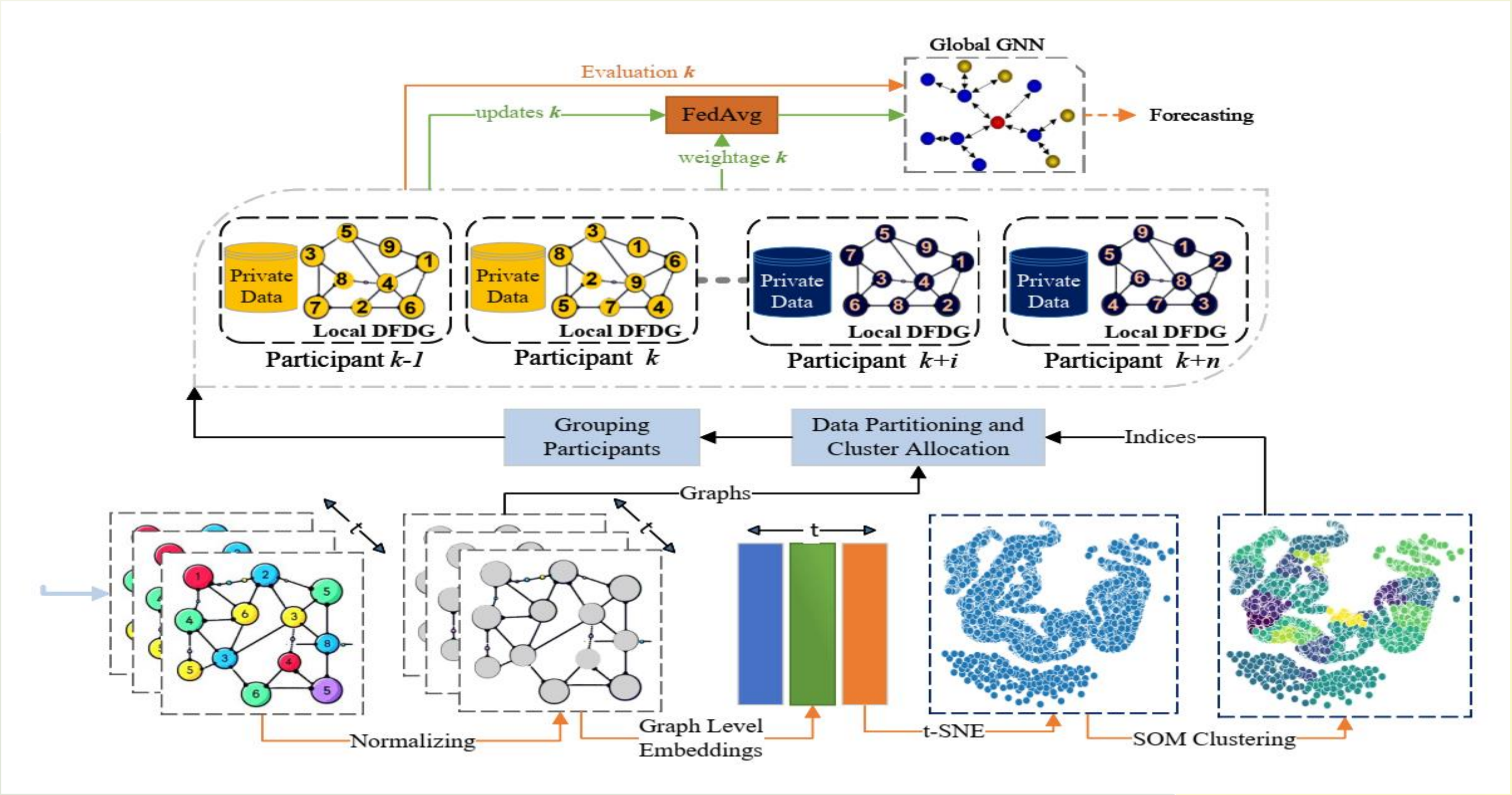
1. **Integration of Federated Learning with Dynamic Graphs**
2. **Clustering Speed Patterns**
3. **Participants' Data Assignment and Custom GNN Architecture**
4. **Dynamic Weighting System**
5. **Homogeneous Grouping:**
6. **Benefits of Grouping:**

- Enhanced efficiency and effectiveness.
- Improved model generalization.
- Reduced communication overhead.
- Privacy preservation through homogeneous client group updates.
- Adaptability to local data characteristics.

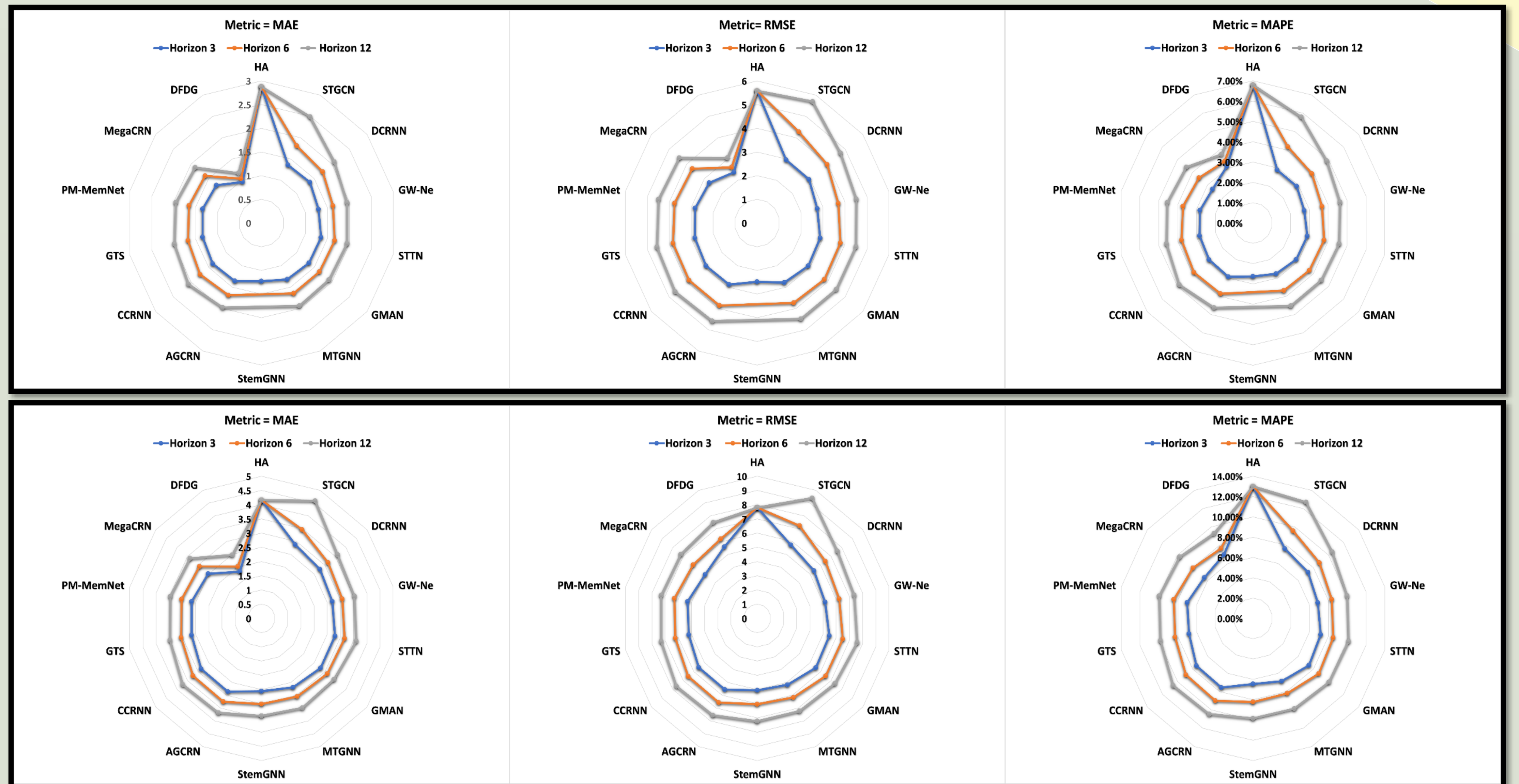
Methods and Materials

DATA SOURCES

1. METR_LA, 2. PEMS_Bay, 3. PEMS_D7M, 4. EXPY-TKY



Results



Conclusion

In conclusion, the Federated GNN Learning from Dynamic Graphs project introduces the innovative Dynamic Federated Graphs (DFDG) framework, seamlessly integrating Federated Learning with Graph Neural Networks (GNNs) to address urban traffic forecasting challenges. The project's key components include self-organizing map clustering, participant assignment, and the DFDG architecture, featuring neural ordinary differential equations and attention spatial-temporal GNNs. The dynamic weighting system and adaptive learning mechanisms enhance the federated network's adaptability, while homogeneous grouping based on participant performance and data distribution improves efficiency and privacy preservation. Rigorous benchmark testing confirms DFDG's superiority in traffic forecasting, positioning it as a leader in the field. Beyond traffic forecasting, the project underscores the versatility and potential impact of its approach in real-time dynamic graph applications across various domains.

References

[1] J. Bai, J. Zhu, Y. Song, L. Zhao, Z. Hou, R. Du, and H. Li, "A3t-gcn: Attention temporal graph convolutional network for traffic forecasting," ISPRS International Journal of Geo-Information, vol. 10, no. 7, 2021.

[2] Y. Li, R. Yu, C. Shahabi, and Y. Liu, "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," in International Conference on Learning Representations, 2018.

[3] B. Yu, H. Yin, and Z. Zhu, "Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting," in Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI, 2018, pp. 3634–3640.

[4] Z. Wu, S. Pan, G. Long, J. Jiang, and C. Zhang, "Graph wavenet for deep spatial-temporal graph modeling," in Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19, 7 2019, pp. 1907–1913.

[5] M. Xu, W. Dai, C. Liu, X. Gao, W. Lin, G.-J. Qi, and H. Xiong, "Spatial-temporal transformer networks for traffic flow forecasting," arXiv preprint arXiv:2001.02908, 2020.

[6] C. Zheng, X. Fan, C. Wang, and J. Qi, "Gman: A graph multi-attention network for traffic prediction," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 01, pp. 1234–1241, Apr. 2020.

[7] Z. Wu, S. Pan, G. Long, J. Jiang, X. Chang, and C. Zhang, "Connecting the dots: Multivariate time series forecasting with graph neural networks," in Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, ser. KDD '20, 2020, p. 753–763.

[8] D. Cao, Y. Wang, J. Duan, C. Zhang, X. Zhu, C. Huang, Y. Tong, B. Xu, J. Bai, J. Tong, and Q. Zhang, "Spectral temporal graph neural network for multivariate time-series forecasting," in Advances in Neural Information Processing Systems, vol. 33, 2020, pp. 17 766–17 778

Acknowledgments

I Acknowledge the invention of LLM for making this complex project possible.