GraphP-FL: Personalized Federated Graph Learning via Dynamic Structure Awareness and Fisher Information Elastic Alignment

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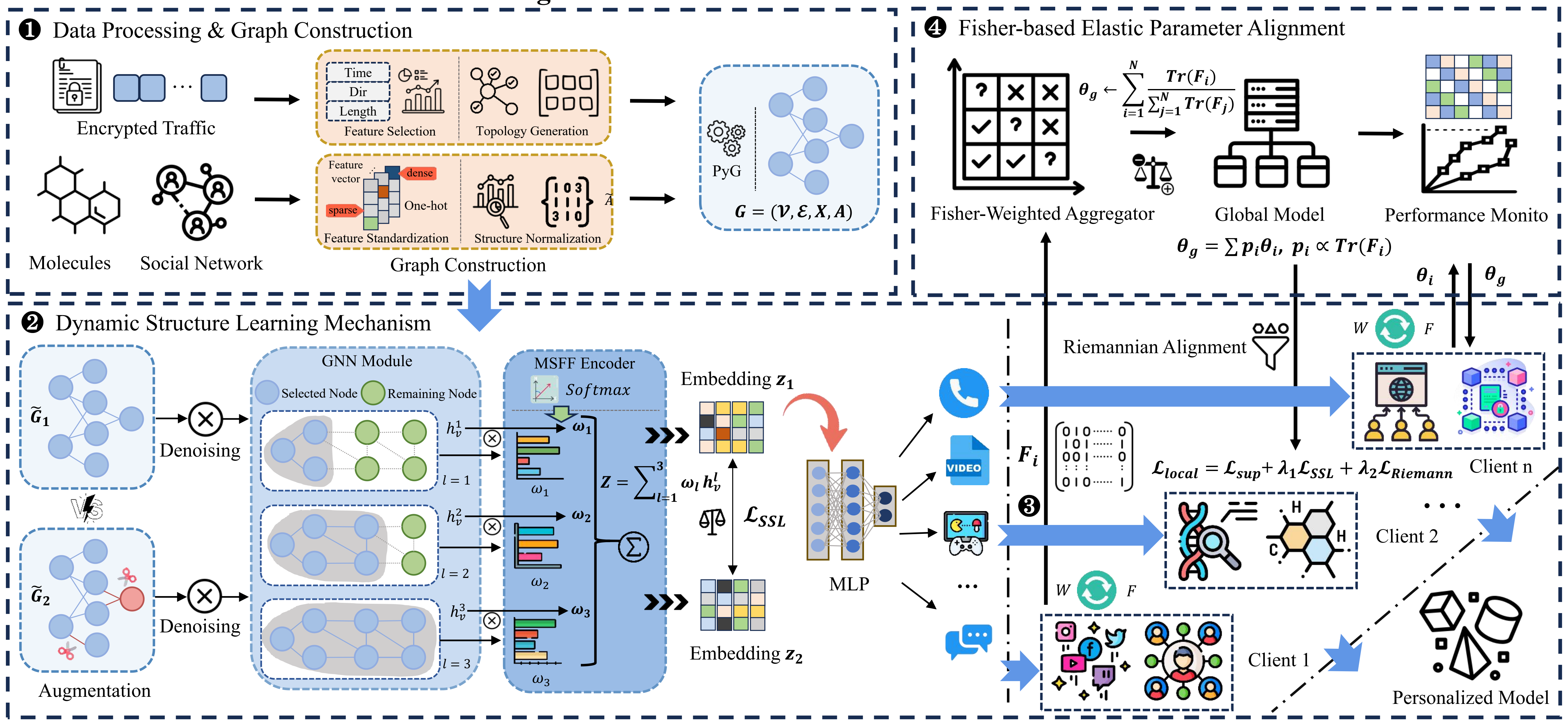
Background

- **Graph Quality & Supervision Scarcity Challenget**: Existing FGL methods face noisy/sparse local graphs and label scarcity, making adaptive latent structure reconstruction under limited supervision an urgent challenge.
- **Non-IID Induced Catastrophic Forgetting**: Non-IID data causes model drift and forgetting. Current methods fail to balance local knowledge preservation and topology correction, ignoring the coupling between parameters and graph structures.

The proposed GraphP-FL



Limitations of Existing Methods

- **Unreliable Graph Assumption**: Existing FGL methods implicitly assume local graph structures are reliable, leading to representation degradation under topological noise.
- **Lack of Elastic Parameter Awareness**: They lack fine-grained awareness of parameter importance during aggregation, causing catastrophic forgetting due to model drift.

Our Main Contributions

- Noisy/Sparse Local Graphs and Label Scarcity

→ **Dynamic Structure Learning Mechanism**

- Non-IID Induced Catastrophic Forgetting

→ **Fisher-based Elastic Parameter Alignment**

Performance Comparison Chart

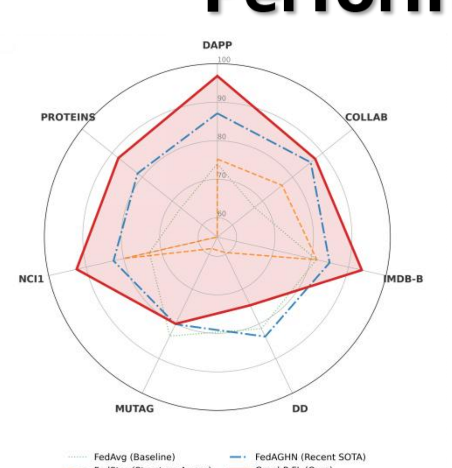


Figure 1: Performance comparison radar chart

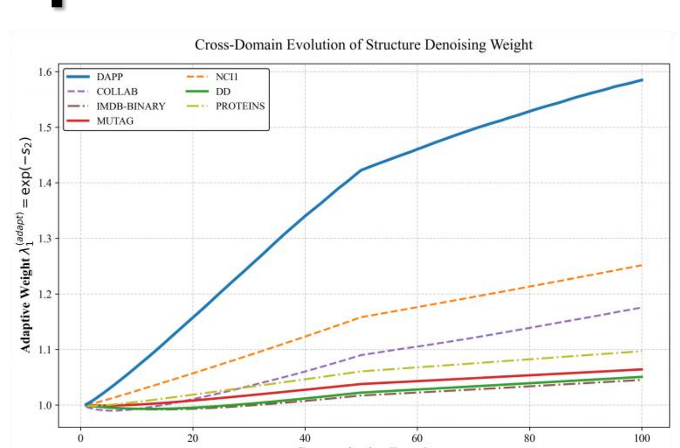


Figure 2: Hyperparameter performance chart

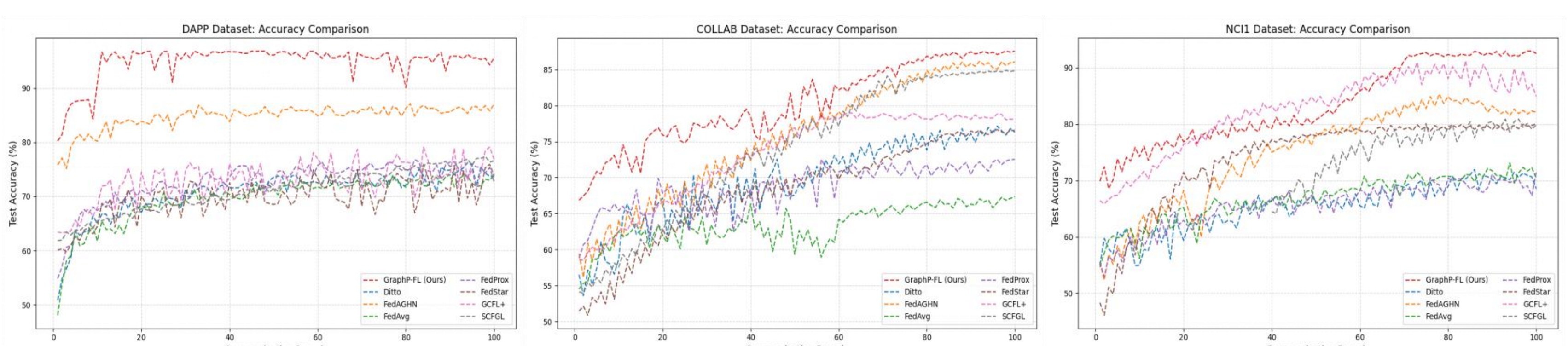


Figure 3: Accuracy performance chart

Experimental Results

Table 1: Test accuracy comparison (Mean ± Std) on seven benchmarks. The best results are highlighted in bold

Method	DAPP	COLLAB	IMDB-BINARY	DD	MUTAG	NCI1	PROTEINS
FedAvg	74.00±2.15	67.36±1.88	81.40±1.25	81.41±2.45	83.51±4.12	73.11±1.67	67.12±2.05
FedProx	76.73±1.92	72.54±1.65	81.90±1.10	70.63±2.30	84.04±3.85	71.48±1.55	67.21±1.98
Ditto	76.23±1.45	77.14±1.42	80.20±0.98	68.25±2.10	**85.11±3.50**	71.95±1.32	67.65±1.75
GCFL+	77.28±1.12	78.46±1.25	83.23±0.85	57.94±3.25	71.67±5.20	86.42±1.05	85.92±1.15
FedStar	75.24±1.35	76.54±1.30	81.56±0.92	59.44±2.88	58.33±6.50	80.00±1.22	55.03±2.45
FedAGHN	87.12±0.88	86.09±0.75	84.95±0.65	**83.68±1.15**	80.12±3.25	82.70±0.82	81.54±0.95
SCFGL	88.45±0.76	84.85±0.82	80.12±0.78	63.96±2.55	58.33±5.80	80.71±0.95	54.35±2.10
Ours	**96.81±0.21**	**87.56±0.35**	**93.55±0.28**	74.66±1.85	80.00±3.05	**92.55±0.42**	**87.92±0.55**

Table 2: Performance comparison using the adaptive hyperparameter mechanism

Model	DAPP	COLLAB	IMDB-B	DD	MUTAG	NCI1	PROTEINS
FedAvg	74.00 ± 2.15	67.36 ± 1.88	81.40 ± 1.25	81.41 ± 2.45	83.51 ± 4.12	73.11 ± 1.67	67.12 ± 2.05
FedAGHN	87.12 ± 0.88	86.09 ± 0.75	84.95 ± 0.65	83.68 ± 1.15	80.12 ± 3.25	82.70 ± 0.82	81.54 ± 0.95
Ours (Adapt)	**95.79 ± 0.43**	**87.86 ± 0.33**	**92.43 ± 0.54**	**82.56 ± 0.88**	**86.25 ± 0.47**	**92.75 ± 0.53**	**90.27 ± 0.65**

Conclusion

We proposed GraphP-FL, a general personal ized FGL framework to address the dual heterogeneity of graph data. Specifically, the self-supervised dynamic topology reconstruction mechanism adaptively rectifies noisy structures, while the Fisher-based Elastic Parameter Align ment mechanism precisely protects local key knowl edge.

Future work

We will explore the potential of GraphP-FL in han dling adversarial clients by leveraging Fisher information for anomaly detection.