FedSSP: Federated Graph Learning with Spectral Knowledge and Personalized Preference

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NEURAL INFORMATION PROCESSING SYSTEMS

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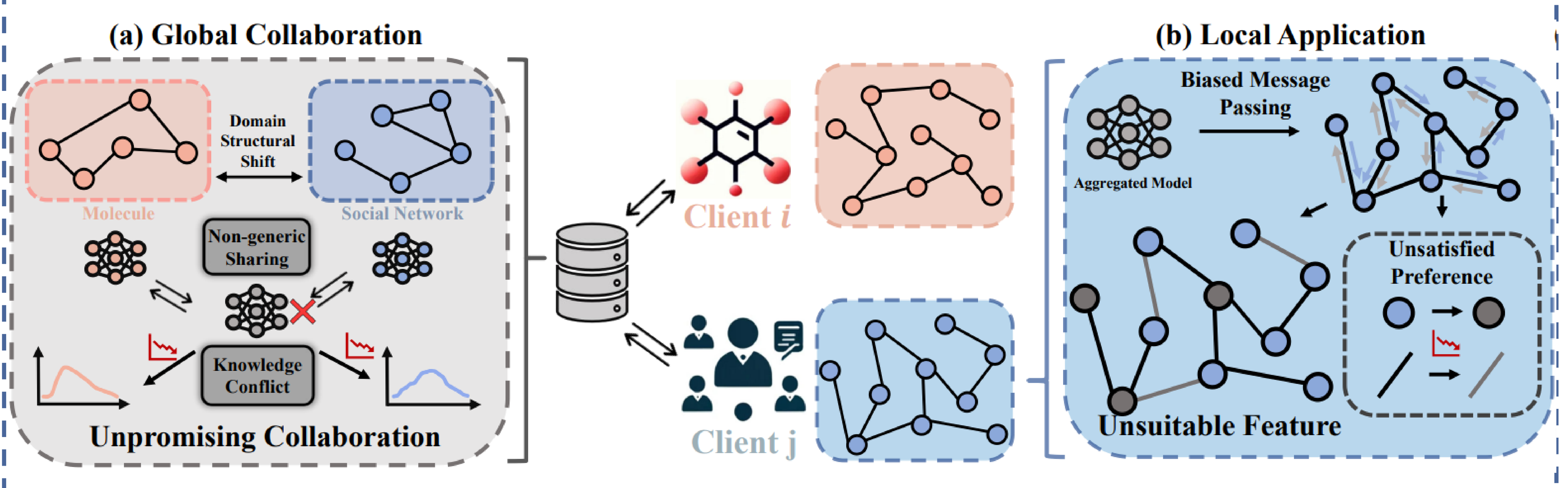
https://github.com/OakleyTan/FedSSP

Contribution

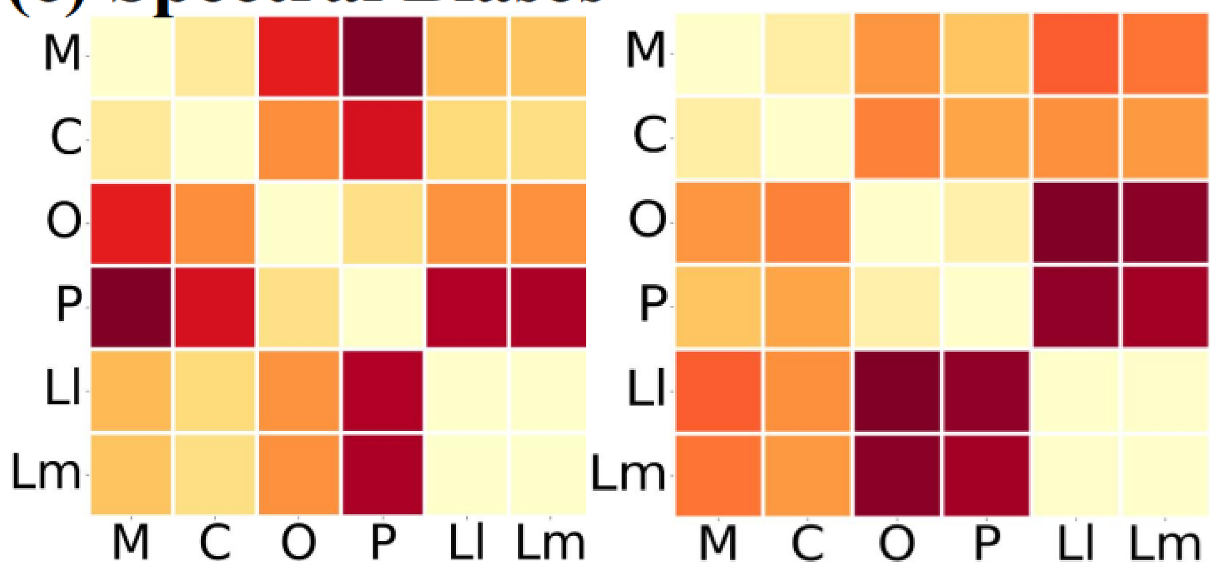
- We are the first to reveal domain structural shifts through **spectral biases**, as well as consider the inconsistent **preferences** of distinct datasets from various clients.
- We propose FedSSP, which innovatively overcomes knowledge conflicts from a spectral perspective and implements personalized graph preference adjustments for each client.

Motivation



- (a) Clients struggle with knowledge conflict caused by **non-generic** sharing which arises from the shifts.
- (b) The aggregated message-passing scheme suffers from unsatisfied **inconsistent preferences**.

(c) Spectral Biases



- (c) Spectral characteristics exhibit significant biases across domains but are more similar within a same domain.

References: FedSSP: Federated Graph Learning with Spectral Knowledge and Personalized Preference. **NeurIPS, 2024. Zihan Tan,** Guancheng Wan, Wenke Huang, Mang Ye.

Introduction

- The limitations of existing methods prompt two questions for us:
  - How to address theknowledge conflict under domain structural shift by extracting and sharing generic knowledge?
  - How to design personalized plans to deal with inconsistentpreferences of specific graph datasets from various clients?

Proposed Method

- **Generic Spectral Knowledge Sharing**

$$\theta_g^{t+1} = \theta_g^t + \frac{\sum_{i=1}^{N} \Delta\theta_i^t}{N} (i \in [1..N]) \begin{cases} \hat{B} = \phi^f(\theta^f; B), \\ \phi^e(\theta^e; \lambda) = \begin{cases} \sin(\beta\lambda / c^{q/d}), & \text{if } q \text{ is even,} \\ \cos(\beta\lambda / c^{(q-1)/d}), & \text{if } q \text{ is odd,} \end{cases} \end{cases}$$

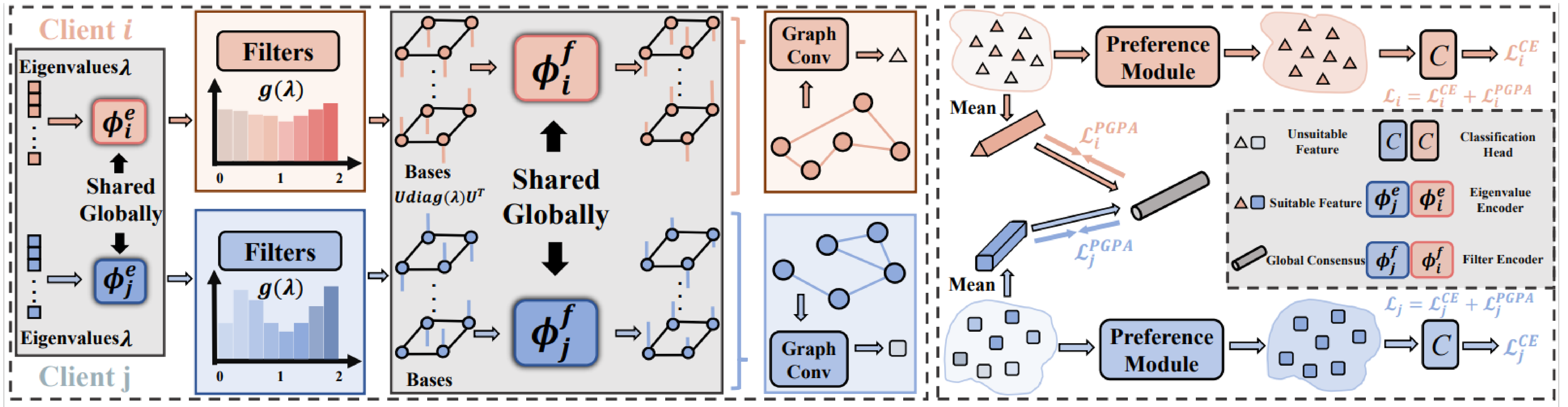
- ☐ Generic spectral knowledge extracted from eigenvalue encoder and filter encoder are shared globally.

- **Personalized Graph Preference Adjustment**

$$h = \mathcal{F}(\theta^F; \mathcal{G}), \quad h' := h + \delta \qquad \bar{h}_i = (1-\mu)\cdot \bar{h}_i^{\text{pre}} + \mu \cdot \bar{h}_i^{\text{cur}} \qquad \bar{h}_g = \frac{\sum_{i=1}^{N} \bar{h}_i}{N},$$

$$\mathcal{L}_i = \mathbb{E}_{(z_i', y_i)\sim\mathcal{D}_i}(\mathcal{L}_i^{CE} + \mathcal{L}_i^{PGPA}) = \mathbb{E}_{(z_i', y_i)\sim\mathcal{D}_i}[\text{CE}(z_i', y_i) + \tau \cdot \text{MSE}(\bar{h}_i, \bar{h}_g)]$$

- ☐ Preference module is leveraged for suitable feature adjusting, while a regulazation term is utilized to sovle the over-reliance issue.



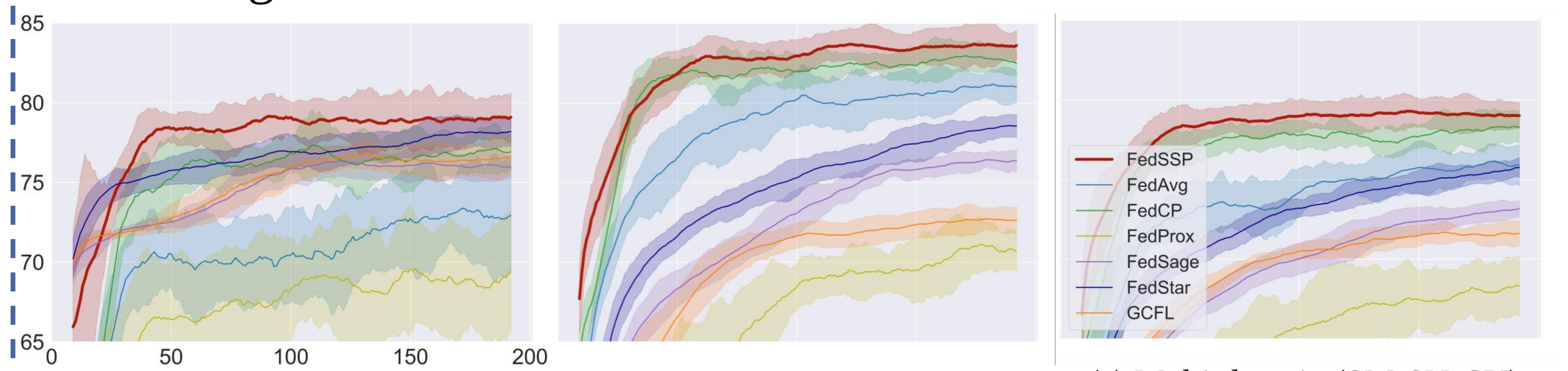
(a) Generic Spectral Knowledge Sharing (b) Personalized Graph Preference Adjustment

Experiments

- We perform experiments on graph classification tasks in various cross-dataset and cross-domainscenarios to validate the superiority of our framework FedSSP.

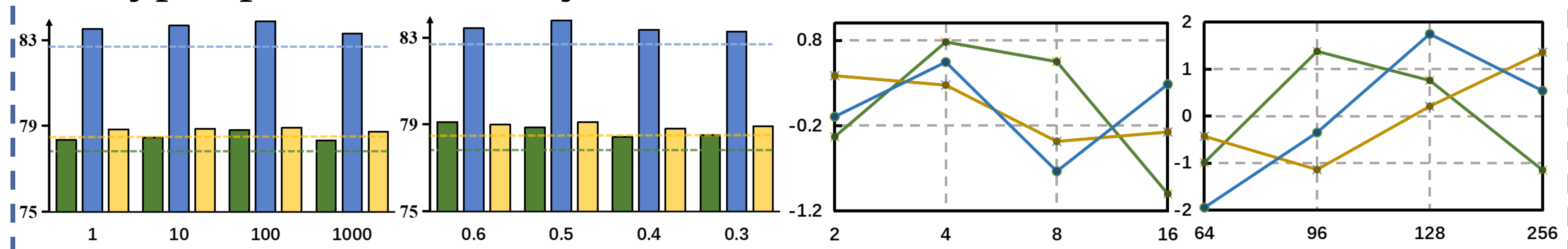
Methods	single-domain	double-domain		Multi-Domain		
	SM	SM-BIO	SM-CV	SM-BIO-SN	BIO-SN-CV	SM-SN-CV
Local	77.33 ± 1.15	72.52 ± 1.86	82.24 ± 1.73	71.13 ± 1.32	72.59 ± 2.70	77.83 ± 0.54
FedAvg [ASTAT17]	74.12 ± 2.10	67.82 ± 1.63	81.21 ± 1.00	67.31 ± 2.56	70.93 ± 2.91	75.33 ± 1.06
FedProx [arXiv18]	69.35 ± 3.36	67.27 ± 4.17	70.02 ± 2.27	63.89 ± 4.33	69.32 ± 1.75	67.15 ± 2.25
FedSage [NeurIPS21]	75.61 ± 1.16	72.60 ± 3.18	76.23 ± 0.49	70.84 ± 0.88	69.69 ± 1.11	73.36 ± 0.86
GCFL [NeurIPS21]	77.71 ± 1.53	72.05 ± 2.20	72.64 ± 0.71	70.43 ± 1.39	67.91 ± 2.15	71.79 ± 0.21
APPLE [IJCAI22]	74.29 ± 1.89	70.40 ± 2.13	76.07 ± 2.55	71.07 ± 1.64	72.52 ± 1.03	72.33 ± 0.42
FedCP [KDD23]	77.58 ± 2.00	71.15 ± 1.77	81.59 ± 0.40	71.32 ± 1.23	73.74 ± 2.53	78.17 ± 1.78
FGSSL [IJCAI23]	77.90 ± 0.85	72.47 ± 2.15	82.60 ± 0.48	68.13 ± 1.71	73.44 ± 1.33	77.90 ± 0.62
FedStar [AAAI23]	78.63 ± 2.11	72.71 ± 1.22	78.84 ± 1.07	**72.60 ± 2.45**	69.51 ± 3.24	75.94 ± 0.40
FedSSP (ours)	**79.62 ± 2.23**	**73.66 ± 2.34**	**84.29 ± 0.68**	72.37 ± 2.18	**75.07 ± 2.70**	**79.12 ± 1.23**

- Convergence



(a) single-domain (SM) (b) double-domain(SM-CV) (c) Multi-domain (SM-SN-CV)

- Hyper-parameter Study



(a) PGPA Parameter τ (b) Momentum μ (c) Attention Heads (d) Hidden Dimension

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