Heterogeneity-Aware Knowledge Sharing for Graph Federated Learning

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joint work with Sheng Wan, Shuo Chen, Bo Han, Chen Gong

TLDR: We address heterogeneity by aligning semantic knowledge and structural knowledge across clients.

paper: https://arxiv.org/abs/2601.21589
code: https://github.com/blgpb/FedSSA

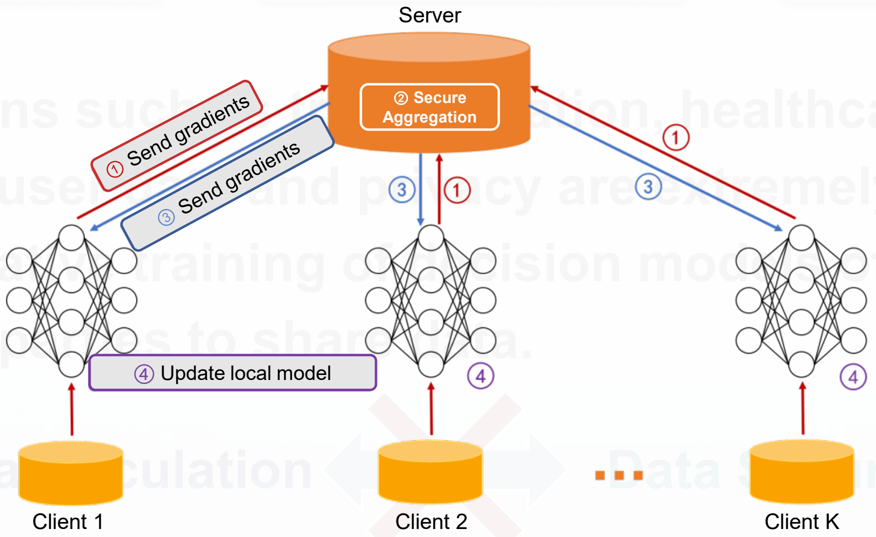
Contents

Motivation

Federated Learning

Goal : Data remains strictly local on each client, fully respecting ensuring **data security** and **user privacy** while enabling synergistic modeling across decentralized clients.

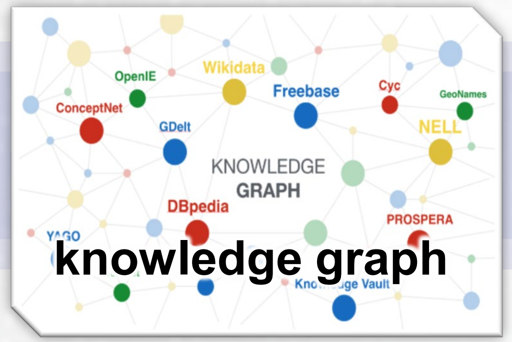
Insight : Data Stays Local, Models Move: Usable yet Invisible

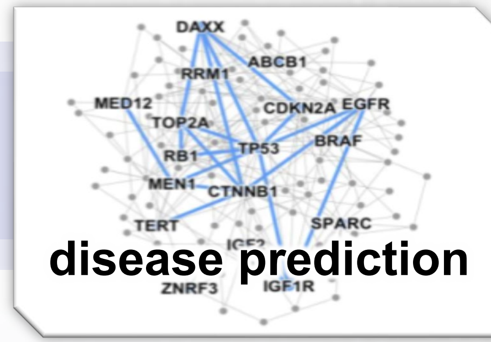


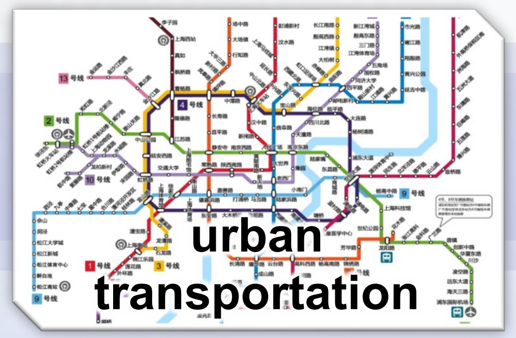
Motivation

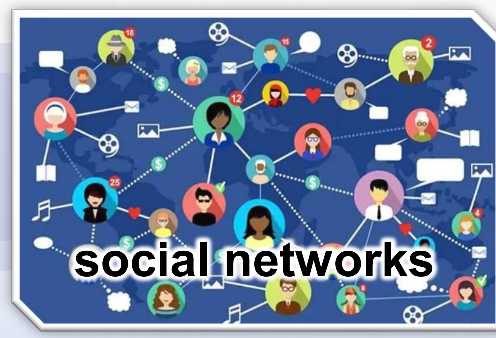
Graph Data

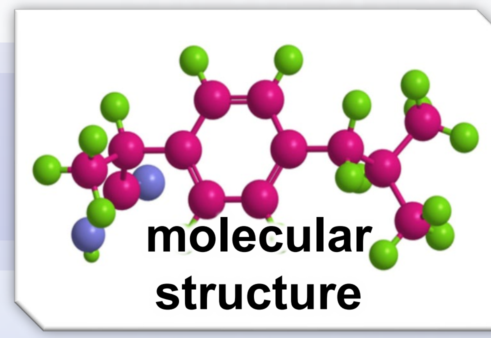
Most existing federated learning methods focus on unstructured data, while research on structured graph data remains very limited.





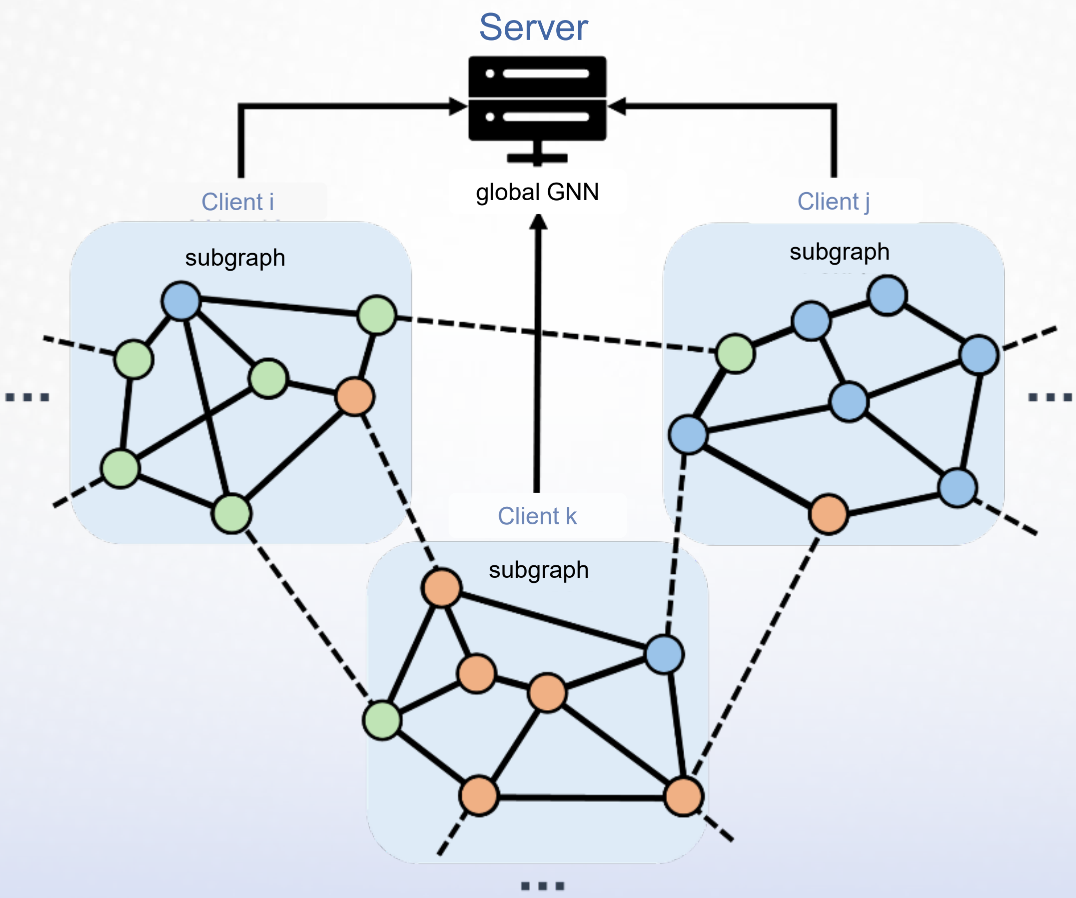






Motivation

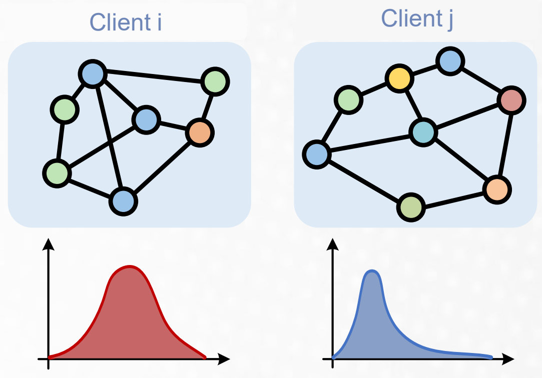
Challenges in Graph Federated Learning: Heterogeneity Caused by Inconsistent Graph Data Distributions Across Clients



Motivation

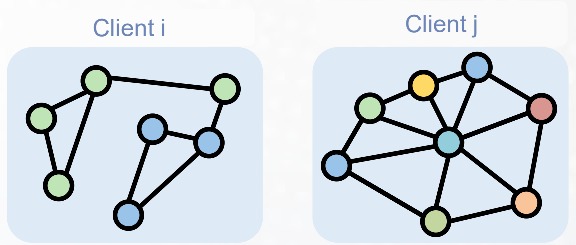
■ Node Feature Heterogeneity

Inconsistent Node Feature Distributions
Across Graphs from Different Clients



■ Structural Heterogeneity

Inconsistent Node Connection Patterns
Across Graphs from Different Clients



How can we explicitly address node feature heterogeneity and structural heterogeneity in graph federated learning?

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Methodology

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Research Question: How to address node feature heterogeneity and structural heterogeneity?

Problems:

Node Feature Heterogeneity

Structural Heterogeneity

Solutions:

semantic knowledge sharing

We infer class-wise node distributions, so that we can cluster clients based on inferred distributions and construct cluster-level representative distributions. We then **minimize the divergence** between local and cluster-level distributions to facilitate semantic knowledge sharing.

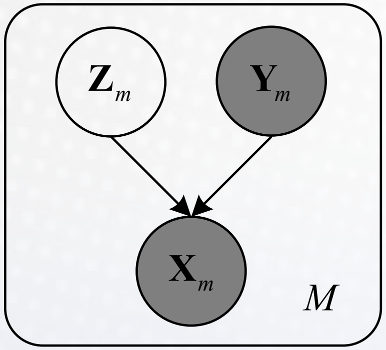
structural knowledge sharing

We propose a spectral energy measure to characterize structural information, so that we can cluster clients based on spectral energy and build cluster-level spectral GNNs. We then **align** the spectral characteristics of local spectral GNNs with those of cluster-level spectral GNNs to enable structural knowledge sharing.

For Node Feature Heterogeneity

■ **Key Innovations : inferring class-wise node distributions**

① **On the client side, we use latent variables to characterize the graph data distribution of each class-wise node feature.**



The graphical model of our proposed variational model, where $\mathbf{Z}_m$ is a latent variable, $\mathbf{X}_m$ and $\mathbf{Y}_m$ are observed variables.

log marginal likelihood:

$$\log p(\mathbf{X}_m, \mathbf{Y}_m) \geq \mathbb{E}_{\mathbf{Z}_m \sim q(\mathbf{Z}_m|\mathbf{X}_m,\mathbf{Y}_m)} \log \frac{p(\mathbf{X}_m|\mathbf{Z}_m,\mathbf{Y}_m)p(\mathbf{Z}_m)p(\mathbf{Y}_m)}{q(\mathbf{Z}_m|\mathbf{X}_m,\mathbf{Y}_m)}$$

ELBO:

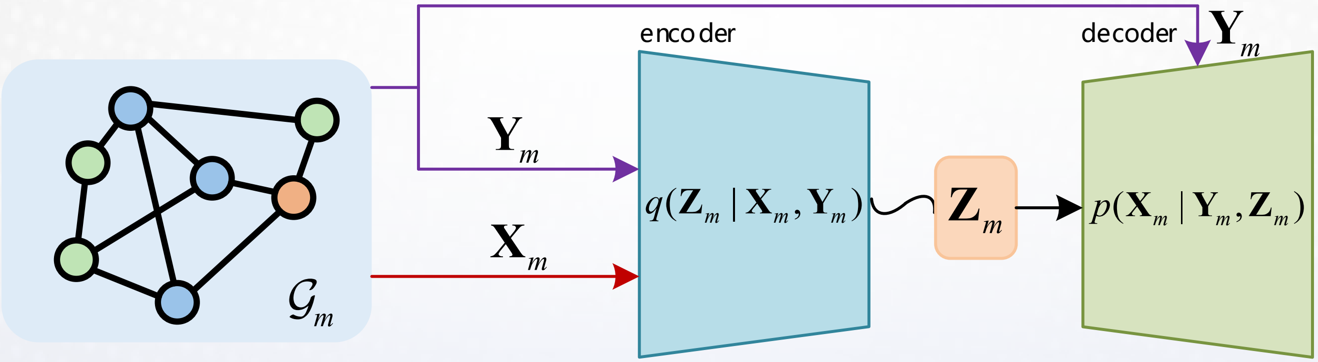
$$\mathcal{L}_{\mathrm{ELBO}}(\mathbf{X}_m, \mathbf{Y}_m) = \mathbb{E}_{\mathbf{Z}_m \sim q(\mathbf{Z}_m|\mathbf{X}_m,\mathbf{Y}_m)} \log p(\mathbf{X}_m|\mathbf{Z}_m,\mathbf{Y}_m) + \log p(\mathbf{Y}_m) - D_{\mathrm{KL}}(q(\mathbf{Z}_m|\mathbf{X}_m,\mathbf{Y}_m)||p(\mathbf{Z}_m))$$

For Node Feature Heterogeneity

- **Key Innovations : inferring class-wise node distributions**

  ① **On the client side, we use latent variables to characterize the graph data distribution of each class-wise node feature.**

the architecture of VGAE:



the latent distribution $q(\mathbf{Z}_m^c)$ of nodes with class label c on the m-th client:

$$\mathcal{I}_m^c \triangleq \{i \in \{1,2,\cdots,n_m\} \mid (\mathbf{Y}_m)_{[i,1]} = c\},$$

$$q(\mathbf{Z}_m^c) \triangleq q\left((\mathbf{Z}_m)_{[\mathcal{I}_m^c,:]} \,\middle|\, (\mathbf{X}_m)_{[\mathcal{I}_m^c,:]}, (\mathbf{Y}_m)_{[\mathcal{I}_m^c,:]}\right)$$

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For Node Feature Heterogeneity

- **Key Innovations : clustering via inferred distributions**

② **Cluster based on node feature distribution uploaded by the client.**

client upload:

$$q(\mathbf{Z}_m^c) = \mathcal{N}(\boldsymbol{\mu}_m^c, \boldsymbol{\Sigma}_m^c) \text{ for c} = 1,2,\cdots,C$$

reparameterization sampling:

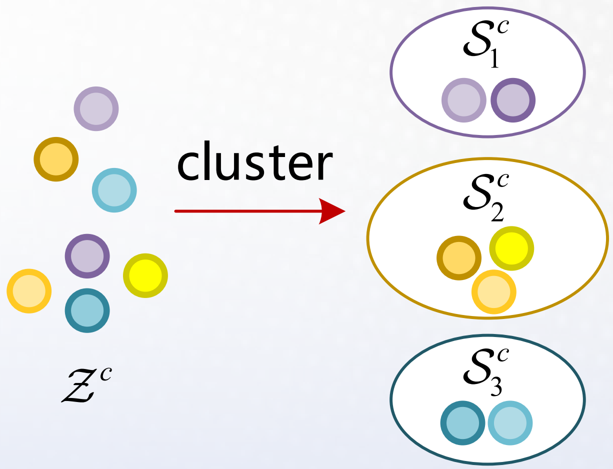
$$\tilde{\mathbf{Z}}_m^c = \boldsymbol{\mu}_m^c + (\boldsymbol{\Sigma}_m^c)^{\frac{1}{2}}\epsilon_m^c, \epsilon_m^c \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

the collection of clients with class c:

$$\mathcal{Z}^c = \{\tilde{\mathbf{Z}}_m^c | m \in \mathcal{M}\}$$

cluster into K_{node} clusters:

$$\text{Cluster}: \mathcal{Z}^c \rightarrow \{\mathcal{S}_1^c, \mathcal{S}_2^c, \cdots, \mathcal{S}_{K_{\text{node}}}^c\}$$



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For Node Feature Heterogeneity

- **Key Innovations : cluster-based node feature distribution alignment**

③ **Approximate the node feature distributions of all nodes within a cluster into a single Gaussian distribution.**

mixed Gaussian distributions in cluster $\mathcal{S}_i^c$:

$$p(\mathbf{S}_i^c) = \sum_{m \in \mathcal{S}_i^c} w_m^c \cdot \mathcal{N}(\boldsymbol{\mu}_m^c, \boldsymbol{\Sigma}_m^c),$$

To reduce the computational complexity of mixed Gaussian distributions, we approximate them as a representative Gaussian distribution using moment matching:

$$q(\mathbf{S}_i^c) = \mathcal{N}(\boldsymbol{\mu}_i^c, \boldsymbol{\Sigma}_i^c)$$

the first moment:

$$\boldsymbol{\mu}_i^c = \sum_{m \in \mathcal{S}_i^c} w_m^c \boldsymbol{\mu}_m^c,$$

the second moment:

$$\Sigma_i^c = \left(\sum_{m \in \mathcal{S}_i^c} \omega_m^c (\boldsymbol{\Sigma}_m^c + \boldsymbol{\mu}_m^c (\boldsymbol{\mu}_m^c)^\top) \right) - \boldsymbol{\mu}_i^c (\boldsymbol{\mu}_i^c)^\top$$

minimize KL divergence to facilitate semantic knowledge sharing:

$$\mathcal{L}_{\text{node}} = \sum_{c=1}^{C} \sum_{i=1}^{K_{\text{node}}} \sum_{m \in \mathcal{S}_i^c} D_{\text{KL}} \left(q(Z_m^c) \parallel q(\mathcal{S}_i^c) \right)$$

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For Structural Heterogeneity

■ Key Innovations : construct spectral energy measure

① **Construct the spectral energy measure and characterize graph structural information on each client.**

K-order polynomial graph filters:

$$\mathbf{P}_m = \sum_{k=0}^{K} \underbrace{w_m^k}_{\text{coefficients}} \overbrace{\mathbf{H}_m^k}^{\text{polynomial}}$$

The Laplacian matrix describes the structural information of graph and is reflected in the energy distribution along the spectral bands.

where $\mathbf{H}_m^k = (\mathbf{L}_m)^k \mathbf{X}_m \in \mathbb{R}^{n_m \times d}$

Since $\mathbf{L}_m = \mathbf{U}_m \Lambda_m \mathbf{U}_m^{\mathrm{T}}$, $\widetilde{\mathbf{X}}_m = \mathbf{U}_m^{\mathrm{T}} \mathbf{X}_m$

Therefore, $\mathbf{H}_m^k = \mathbf{U}_m \Lambda_m^k \widehat{\mathbf{X}}_m$. Its physical meaning represents the signal of the k-th spectral band. $w_m^k \in \mathbb{R}$ represents learnable coefficients of the k-th spectral band.

compute the average response vector for each band:

$$\mathbf{F}_m^k = w_m^k \mathbf{H}_m^k \in \mathbb{R}^{n_m \times d},$$

$$\mathbf{E}_m^k = \frac{1}{n_m} \sum_{i=1}^{n_m} \left(\mathbf{F}_m^k\right)_{[i,:]} \in \mathbb{R}^d$$

define the spectral energy measure:

$$\mathbf{S}_m = \left[\mathbf{E}_m^0, \mathbf{E}_m^1, \cdots, \mathbf{E}_m^K\right] \in \mathbb{R}^{d \times (K+1)}$$

This measure essentially acts as a **spectral fingerprint**, which reflects the energy distribution of structural topologies as learned by spectral GNN.

Methodology

For Structural Heterogeneity

- **Key Innovations : clustering via spectral energies**

② **Clustering clients based on the subspace distance spanned by the spectral energy measure.**

QR decomposition:

$$\mathbf{S}_m = \mathbf{Q}_m \mathbf{R}_m$$

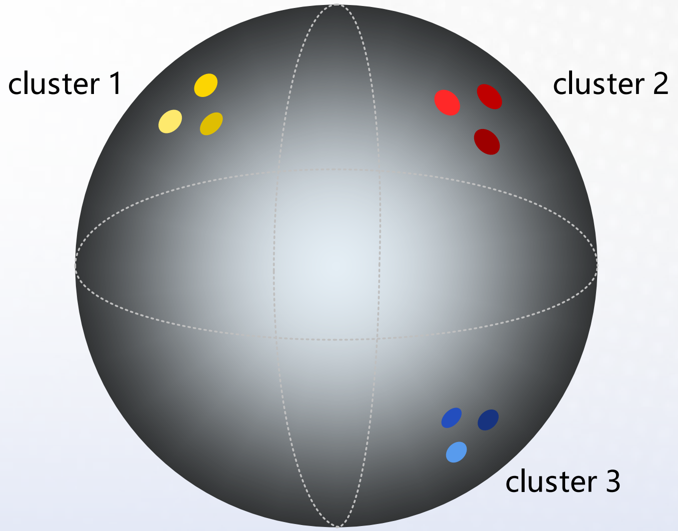
$$\mathbf{Q}_{\mathrm{m}}^{\top} \mathbf{Q}_{\mathrm{m}} = \mathbf{I}_{\mathrm{K+1}}$$

Chordal distance between two spectral energy measures:

$$d_{\mathrm{Chordal}}(\mathbf{Q}_m, \mathbf{Q}_n) = \left(K + 1 - \|\mathbf{Q}_m^{\top} \mathbf{Q}_n\|_{\mathrm{F}}^2\right)^{\frac{1}{2}}$$

cluster into K_{struct} clusters:

$$\text{Cluster:} \{\mathbf{S}_m\}_{m=1}^{M} \rightarrow \{\mathcal{T}_1^c, \mathcal{T}_2^c, \cdots, \mathcal{T}_{K_{\mathrm{struct}}}^c\}$$



For Structural Heterogeneity

- **Key Innovations : structural knowledge alignment**

③ **Align the spectral characteristics of local spectral GNNs with those of cluster-level spectral GNNs.**

compute the mean of learnable coefficients:

$$\overline{w}_j^k \leftarrow \frac{1}{|\mathcal{T}_j|} \sum_{m \in \mathcal{T}_j} w_m^k$$

minimize the discrepancy between the coefficients of local spectral GNNs and those of cluster-level spectral GNNs:

$$\mathcal{L}_{\text{align}} = \sum_{k=0}^{K} \sum_{j=1}^{K_{\text{struct}}} \sum_{m \in \mathcal{T}_j} \left| w_m^k - \overline{w}_j^k \right|$$

add a regularization term:

$$\mathcal{L}_{\text{reg}} = \sum\nolimits_{m=1}^{M} \sum\nolimits_{k=0}^{K} \left(\lambda_1 \left| w_m^k \right| + \frac{\lambda_2}{2} \left(w_m^k \right)^2 \right)$$

$$\mathcal{L}_{\text{struct}} = \mathcal{L}_{\text{align}} + \mathcal{L}_{\text{reg}}$$

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Experimental Results

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■ **Main Results**: node classification performance on **homophilic** graph datasets

	Cora			CiteSeer			PubMed			-
Methods	5 Clients	10 Clients	20 Clients	5 Clients	10 Clients	20 Clients	5 Clients	10 Clients	20 Clients	-
Local	81.30±0.21	79.94±0.24	80.30±0.25	69.02±0.05	67.82±0.13	65.98±0.17	84.04±0.18	82.81±0.39	82.65±0.03	-
FedAvg (McMahan et al., 2017)	74.45±5.64	69.19±0.67	69.50±3.58	71.06±0.60	63.61±3.59	64.68±1.83	79.40±0.11	82.71±0.29	80.97±0.26	-
FedProx (Li et al., 2020)	72.03±4.56	60.18±7.04	48.22±6.18	71.73±1.11	63.33±3.25	64.85±1.35	79.45±0.25	82.55±0.24	80.50±0.25	-
FedPer (Arivazhagan et al., 2019)	81.68±0.40	79.35±0.04	78.01±0.32	70.41±0.32	70.53±0.28	66.64±0.27	85.80±0.21	84.20±0.28	84.72±0.31	-
GCFL (Xie et al., 2021)	81.47±0.65	78.66±0.27	79.21±0.70	70.34±0.57	69.01±0.12	66.33±0.05	85.14±0.33	84.18±0.19	83.94±0.36	-
FedGNN (Wu et al., 2021)	81.51±0.68	70.12±0.99	70.10±3.52	69.06±0.92	55.52±3.17	52.23±6.00	79.52±0.23	83.25±0.45	81.61±0.59	-
FedSage+(Zhang et al., 2021)	72.97±5.94	69.05±1.59	57.97±12.60	70.74±0.69	65.63±3.10	65.46±0.74	79.57±0.24	82.62±0.31	80.82±0.25	-
FED-PUB (Baek et al., 2023)	83.70±0.19	81.54±0.12	81.75±0.56	72.68±0.44	72.35±0.53	67.62±0.12	86.79±0.09	86.28±0.18	85.53±0.30	-
FedGTA (Li et al., 2023)	80.06±0.63	80.59±0.38	79.01±0.31	70.12±0.10	71.57±0.34	69.94±0.14	87.75±0.01	86.80±0.01	87.12±0.05	-
AdaFGL (Li et al., 2024)	82.01±0.51	80.09±0.08	79.74±0.05	71.44±0.27	72.34±0.09	70.95±0.45	86.91±0.28	86.97±0.10	86.59±0.21	-
FedTAD (Zhu et al., 2024)	80.31±0.26	80.87±0.11	80.07±0.15	70.34±0.37	69.43±0.75	68.09±0.69	84.00±0.13	84.61±0.17	84.33±0.18	-
FedIIH (Yu et al., 2025a)	84.11±0.17	81.85±0.09	83.01±0.15	72.86±0.25	76.50±0.06	73.36±0.41	87.80±0.18	87.65±0.18	87.19±0.25	-
FedSSA (Ours)	**84.67±0.05**	**82.32±0.04**	**84.13±0.09**	**73.06±0.08**	**77.65±0.10**	**74.09±0.09**	**88.11±0.07**	**87.78±0.13**	**87.37±0.14**	-

	Amazon-Computer			Amazon-Photo			ogbn-arxiv			Avg.
Methods	5 Clients	10 Clients	20 Clients	5 Clients	10 Clients	20 Clients	5 Clients	10 Clients	20 Clients	All
Local	89.22±0.13	88.91±0.17	89.52±0.20	91.67±0.09	91.80±0.02	90.47±0.15	66.76±0.07	64.92±0.09	65.06±0.05	79.57
FedAvg (McMahan et al., 2017)	84.88±1.96	79.54±0.23	74.79±0.24	89.89±0.83	83.15±3.71	81.35±1.04	65.54±0.07	64.44±0.10	63.24±0.13	74.58
FedProx (Li et al., 2020)	85.25±1.27	83.81±1.09	73.05±1.30	90.38±0.48	80.92±4.64	82.32±0.29	65.21±0.20	64.37±0.18	63.03±0.04	72.84
FedPer (Arivazhagan et al., 2019)	89.67±0.34	89.73±0.04	87.86±0.43	91.44±0.37	91.76±0.23	90.59±0.06	66.87±0.05	64.99±0.18	64.66±0.11	79.94
GCFL (Xie et al., 2021)	89.07±0.91	90.03±0.16	89.08±0.25	91.99±0.29	92.06±0.25	90.79±0.17	66.80±0.12	65.09±0.08	65.08±0.04	79.90
FedGNN (Wu et al., 2021)	88.08±0.15	88.18±0.41	83.16±0.13	90.25±0.70	87.12±2.01	81.00±4.48	65.47±0.22	64.21±0.32	63.80±0.05	75.23
FedSage+(Zhang et al., 2021)	85.04±0.61	80.50±1.13	70.42±0.85	90.77±0.44	76.81±8.24	80.58±1.15	65.69±0.09	64.52±0.14	63.31±0.20	73.47
FED-PUB (Baek et al., 2023)	90.74±0.05	90.55±0.13	90.12±0.09	93.29±0.19	92.73±0.18	91.92±0.12	67.77±0.09	66.58±0.08	66.64±0.12	81.59
FedGTA (Li et al., 2023)	86.69±0.18	86.66±0.23	85.01±0.87	93.33±0.12	93.50±0.21	92.61±0.15	60.32±0.04	60.22±0.09	58.74±0.14	79.45
AdaFGL (Li et al., 2024)	80.20±0.05	83.62±0.26	84.53±0.23	86.69±0.19	89.85±0.83	88.11±0.05	52.73±0.19	51.77±0.36	50.94±0.08	76.97
FedTAD (Zhu et al., 2024)	82.20±1.20	85.50±0.33	83.91±1.54	92.29±0.39	90.59±0.09	89.18±0.84	65.35±0.14	64.06±0.25	64.45±0.13	78.87
FedIIH (Yu et al., 2025a)	90.74±0.13	90.86±0.23	90.44±0.05	93.42±0.02	94.22±0.08	93.55±0.09	70.30±0.06	69.34±0.02	68.65±0.04	83.10
FedSSA (Ours)	**91.09±0.07**	**91.30±0.13**	**90.62±0.09**	**93.86±0.15**	**94.62±0.14**	**93.76±0.07**	**70.86±0.13**	**69.47±0.08**	**68.77±0.13**	**83.53**

achieve the best performance among all methods

Experimental Results

■ **Main Results:** node classification performance on heterophilic graph datasets

Methods	Roman-empire 5 Clients	Roman-empire 10 Clients	Roman-empire 20 Clients	Amazon-ratings 5 Clients	Amazon-ratings 10 Clients	Amazon-ratings 20 Clients	Minesweeper 5 Clients	Minesweeper 10 Clients	Minesweeper 20 Clients	-
Local	33.65±0.13	28.42±0.26	23.89±0.32	45.03±0.31	**45.89±0.19**	46.02±0.02	71.35±0.17	69.96±0.16	69.31±0.09	-
FedAvg (McMahan et al., 2017)	38.93±0.32	35.43±0.32	32.00±0.39	41.26±0.53	41.66±0.14	42.20±0.21	72.60±0.08	69.68±0.09	71.36±0.16	-
FedProx (Li et al., 2020)	27.95±0.59	26.43±1.41	23.12±0.49	36.92±0.02	36.86±0.14	36.96±0.05	71.91±0.27	70.66±0.20	71.50±0.37	-
FedPer (Arivazhagan et al., 2019)	20.75±1.75	15.51±1.13	15.45±2.76	36.62±0.30	32.34±1.01	36.96±0.03	58.73±10.45	65.35±7.02	53.80±11.40	-
GCFL (Xie et al., 2021)	40.65±0.14	40.51±0.24	37.85±0.25	36.92±0.05	36.86±0.14	36.96±0.02	72.04±0.13	71.88±0.12	69.20±0.18	-
FedGNN (Wu et al., 2021)	30.26±0.11	29.09±0.13	26.60±0.02	36.80±0.06	36.72±0.00	36.45±0.09	72.15±0.13	71.08±0.07	71.71±0.27	-
FedSage+(Zhang et al., 2021)	57.26±0.00	49.07±0.00	38.36±0.00	36.82±0.00	36.71±0.00	37.03±0.02	77.74±0.00	72.80±0.00	69.70±0.00	-
FED-PUB (Baek et al., 2023)	40.80±0.26	36.77±0.30	32.67±0.39	44.41±0.41	44.85±0.17	45.39±0.50	72.18±0.02	71.69±0.71	71.41±0.87	-
FedGTA (Li et al., 2023)	61.56±0.27	60.94±0.19	59.65±0.28	41.22±0.66	39.40±0.44	39.24±0.12	73.54±1.56	72.65±1.21	69.63±4.54	-
AdaFGL (Li et al., 2024)	67.64±0.18	64.55±0.09	62.42±0.26	41.70±0.06	42.30±0.00	42.59±0.14	73.24±1.13	70.79±2.14	71.26±1.31	-
FedTAD (Zhu et al., 2024)	45.26±0.19	44.71±0.38	42.04±0.13	43.59±0.33	43.35±0.29	44.50±0.26	72.39±0.43	71.99±0.13	72.74±0.03	-
FedIIH (Yu et al., 2025a)	68.32±0.05	66.44±0.28	64.61±0.13	44.26±0.24	44.24±0.10	45.19±0.04	74.29±0.02	73.23±0.04	72.81±0.02	-
FedSSA (Ours)	**68.67±0.10**	**66.81±0.09**	**65.14±0.15**	**45.18±0.14**	45.11±0.15	**46.13±0.05**	**82.26±0.14**	**82.16±0.08**	**82.60±0.11**	-

Methods	Tolokers 5 Clients	Tolokers 10 Clients	Tolokers 20 Clients	Questions 5 Clients	Questions 10 Clients	Questions 20 Clients	Avg. 5 Clients	Avg. 10 Clients	Avg. 20 Clients	Avg. All
Local	67.81±0.17	70.04±0.23	62.34±0.67	66.73±0.57	57.96±0.10	60.00±0.21	56.91	54.45	52.31	54.56
FedAvg (McMahan et al., 2017)	60.74±0.31	54.73±0.50	56.36±0.39	65.68±0.23	58.91±0.22	60.33±0.15	55.84	52.08	52.45	53.46
FedProx (Li et al., 2020)	42.90±0.24	41.15±0.22	40.42±0.62	47.36±0.38	45.46±0.34	46.83±0.11	45.41	44.11	43.77	44.43
FedPer (Arivazhagan et al., 2019)	46.61±9.88	54.97±13.23	44.82±11.61	58.38±9.39	59.40±9.71	62.32±1.56	44.22	45.51	42.67	44.13
GCFL (Xie et al., 2021)	64.39±1.17	59.90±0.85	58.82±0.70	60.51±1.18	59.85±0.16	60.31±0.48	54.90	53.80	52.63	53.78
FedGNN (Wu et al., 2021)	43.10±0.27	41.57±0.07	40.70±0.74	47.55±0.02	45.65±0.12	47.39±0.13	45.97	44.82	44.57	45.12
FedSage+(Zhang et al., 2021)	75.06±0.00	71.31±0.00	69.73±0.00	64.95±0.00	65.06±0.00	59.33±0.00	62.37	58.99	54.83	58.73
FED-PUB (Baek et al., 2023)	70.88±0.58	72.46±0.68	65.26±0.59	67.71±3.99	59.64±0.52	62.48±2.92	59.20	57.08	55.44	57.24
FedGTA (Li et al., 2023)	60.83±0.45	55.18±1.20	57.89±1.61	65.56±1.91	58.29±1.57	61.70±0.35	60.54	57.29	57.62	58.49
AdaFGL (Li et al., 2024)	59.26±2.18	54.78±2.12	56.61±2.93	64.23±2.09	58.82±1.14	62.84±0.49	61.21	58.25	59.14	59.54
FedTAD (Zhu et al., 2024)	60.91±0.25	53.39±1.73	56.47±1.58	68.89±1.20	58.44±1.06	61.51±1.56	58.21	54.38	55.45	56.01
FedIIH (Yu et al., 2025a)	71.09±0.26	71.32±0.09	70.30±0.10	68.32±0.03	67.99±0.09	65.40±0.07	65.26	64.64	63.66	64.52
FedSSA (Ours)	**75.82±0.05**	**73.96±0.10**	**72.29±0.11**	**69.51±0.15**	**68.69±0.18**	**65.74±0.07**	**68.29**	**67.35**	**66.10**	**67.34**

Compared with SOTA, the average performance improvement is 2.82%.

achieve the best average performance among all methods

Experimental Results

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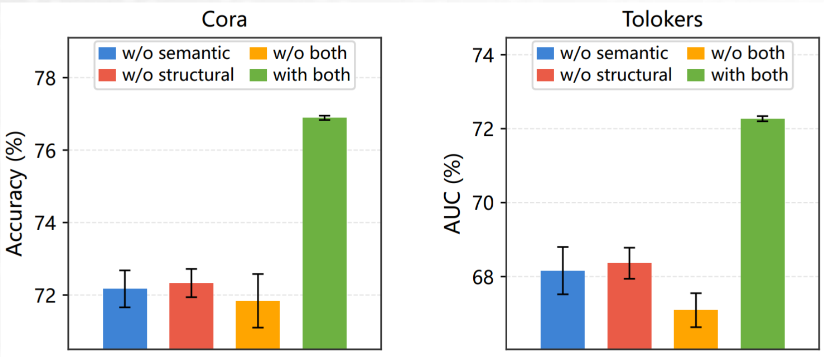
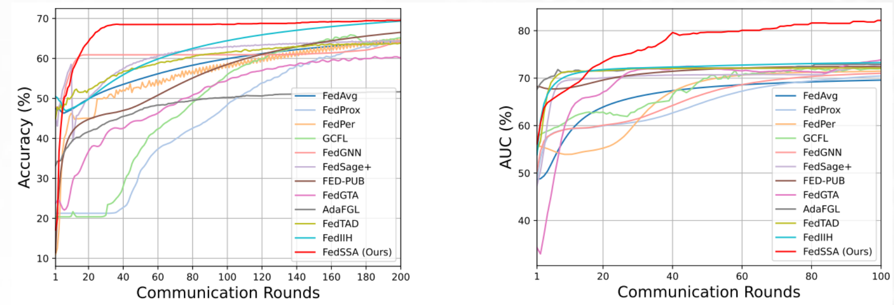
ablation studies:

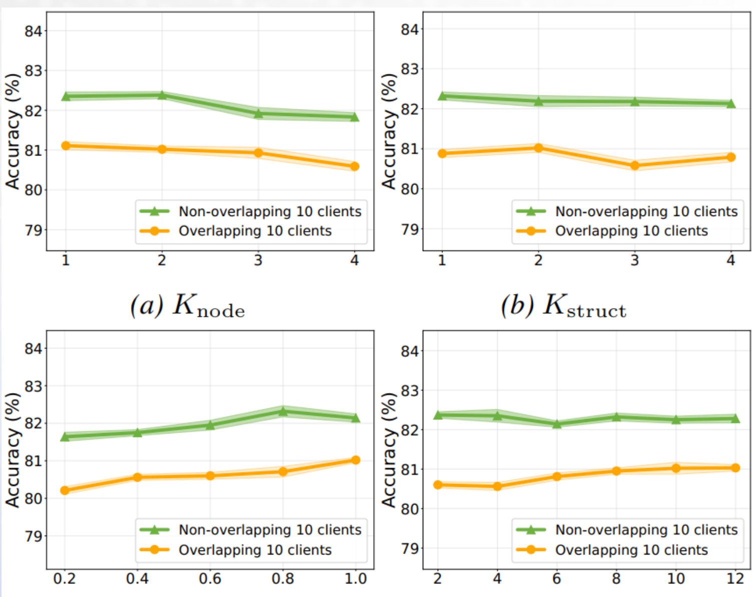


convergence curves:



(a) ogbn-arxiv (b) Minesweeper

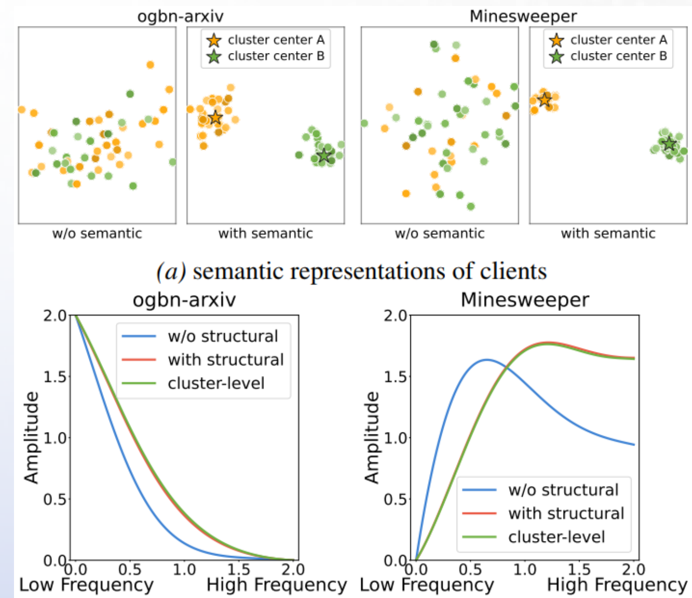
sensitivity analysis:



(a) K_{node} (b) K_{struct}

(c) λ_1 (d) λ_2

case studies:



(a) semantic representations of clients

(b) spectral properties of local models

Contents

Conclusion

We propose a graph **Fed**erated learning method via **S**emantic and **S**tructural **A**lignment (FedSSA) to address heterogeneity in Graph Federated Learning (GFL).

- On one hand, we **minimize the divergence** between local distributions and cluster-level distributions to mitigate the heterogeneity in node features.
- On the other hand, we **align the spectral characteristics** of local spectral GNNs with those of cluster-level spectral GNNs to address the heterogeneity in structural topologies.

Our proposed FedSSA achieves strong performance on eleven datasets and outperforms the second-best method by a large margin of **2.82%** in terms of classification accuracy.

Thank you!

Wentao Yu

joint work with Sheng Wan, Shuo Chen, Bo Han, Chen Gong

paper: https://arxiv.org/abs/2601.21589

code: https://github.com/blgpb/FedSSA