Low-pass Personalized Subgraph Federated Recommendation

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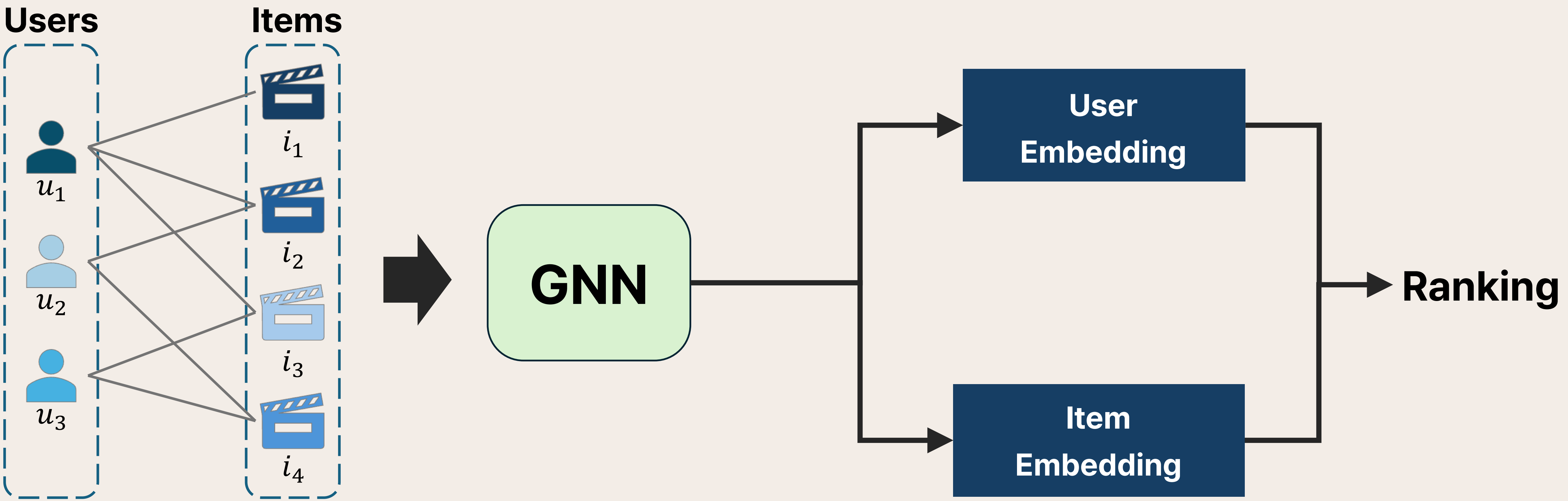
Table of Contents

1. Introduction
2. Preliminaries
3. Methodology
4. Experiment
5. Conclusion

1. Introduction

Graph Neural Network(GNN)-based Recommender System



Bipartite Graph Construction

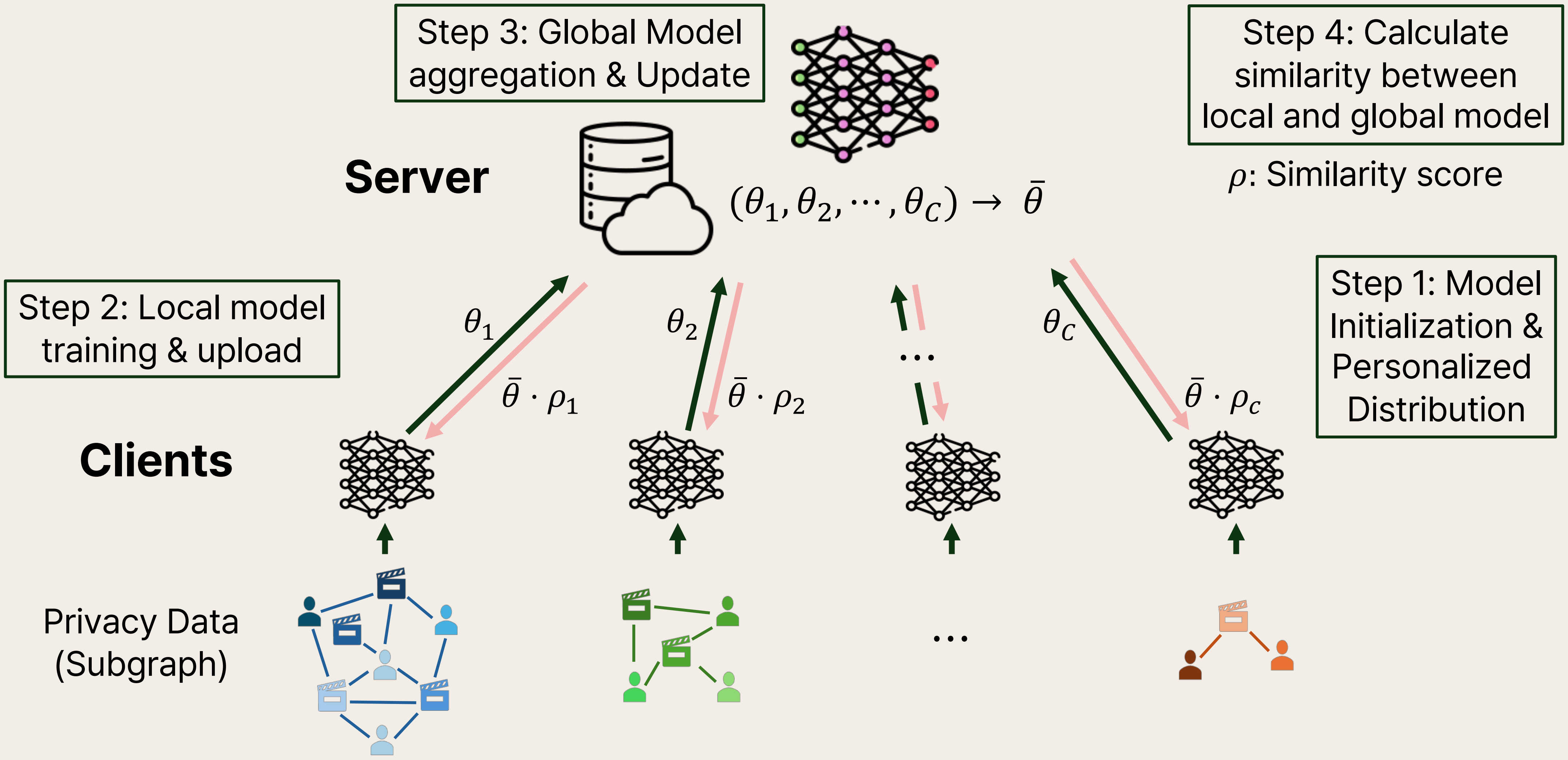
Information Aggregation Via GNN

Recommend contents based on score function with embeddings

LightGCN: Simplifying and Powering Graph Convolution Network for Recommendation, 2020, SIGIR

1. Introduction

Personalized Federated Learning



Communication-Efficient Learning of Deep Networks from Decentralized Data, 2017, AISTATS

1. Introduction

Limitations of Subgraph Federated Recommendation

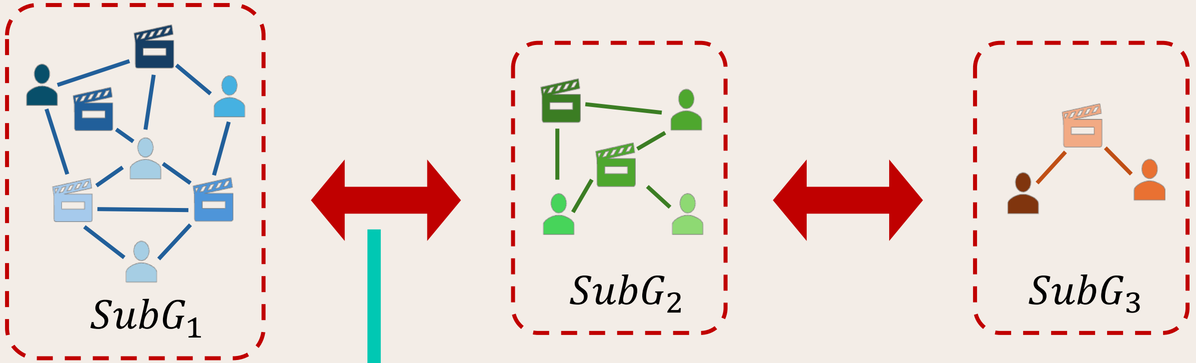
Subgraph Structural Imbalance

- Drastic variations in **subgraph scale (user/item counts)** and **connectivity (item degree)**

1. Introduction

Limitations of Subgraph Federated Recommendation

Drastic Variations
Client's
Privacy Dataset



Large-**D**ense   **M**edium-**B**alanced   **S**mall-**S**parse

subgraph scale (user/item counts)

➔ GNN Representation Misalignment

➔ Structural Incompatibility

(FedPUB) NDCG drops ~80%
(0.0605 → 0.0123) in Small-Sparse Clients.

connectivity (item degree)

➔ Localized Popularity Bias

➔ Reinforced Feedback Loops

(FedAvg) x23 accuracy gap between
Head (0.0924) and Tail (0.0040) items.

1. Introduction

Solutions to the Limitations

[Limitations]

1. Subgraph scale (user/item counts)

- **Spatial GNNs**: Sensitive to local topology; scale variations cause **misaligned representations**.
- **Spectral FL**: Designed for homogeneous graphs; ineffective on **bipartite FRS graphs**.

2. Connectivity (item degree)

- **Degree imbalance**: Dense clients overfit to hubs; sparse clients over-rely on few popular items.
- **Client isolation**: Amplifies vicious popularity **feedback loop**, suppressing the long-tail.

[Solutions]

1. Leveraging denoised subgraph structural signals

→ Extracts robust structural signals via **low-pass filter.**

→ Personalizes updates using **structural similarity** to a neutral anchor graph.

2. Sharing Popularity Bias information

→ Shares global bias context via a **privacy-preserving scalar value.**

→ Applies a **bias-aware margin** to boost long-tail exposure.

Our method

2. Preliminaries

Low-pass Graph Convolution (Graph Signal Processing)

$G = \{V, E\}$

$D = \mathrm{diag}(\deg(v_1), \ldots \deg(v_N))$

$L = D - A$ (Laplacian Matrix)

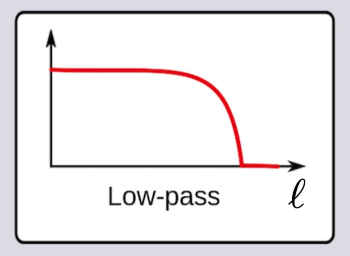
Eigen-Decomposition $\longrightarrow$

$$L = \underbrace{\begin{bmatrix} | & & | \\ \chi_0 & \cdots & \chi_{N-1} \\ | & & | \end{bmatrix}}_{\chi} \underbrace{\begin{bmatrix} \lambda_0 & & 0 \\ & \ddots & \\ 0 & & \lambda_{N-1} \end{bmatrix}}_{\Lambda} \underbrace{\begin{bmatrix} - & \chi_0 & - \\ & \cdots & \\ - & \chi_{N-1} & - \end{bmatrix}}_{\chi^T}$$

Apply filter with transfer function $\hat{g}(\cdot)$ to a graph signal $f : V \to \mathbb{R}^N$

$$f \xrightarrow{\text{GFT}} \hat{f}(l) \xrightarrow{\hat{g}(\lambda_l)} \hat{g}(\lambda_l)\hat{f}(l) \xrightarrow{\text{IGFT}} f(i) = \sum_{l=0}^{N-1} \hat{g}(\lambda_l)\hat{f}(l)\chi_l(i)$$

$$\underbrace{\begin{bmatrix} \lambda_0 & & 0 \\ & \ddots & \\ 0 & & \lambda_{N-1} \end{bmatrix}}_{\Lambda} \rightarrow$$



$$\rightarrow \underbrace{\begin{bmatrix} \lambda_0 & & 0 \\ & \ddots & \\ 0 & & 0 \end{bmatrix}}_{\hat{g}(\Lambda)}$$

Denoised Graph Structural Signal

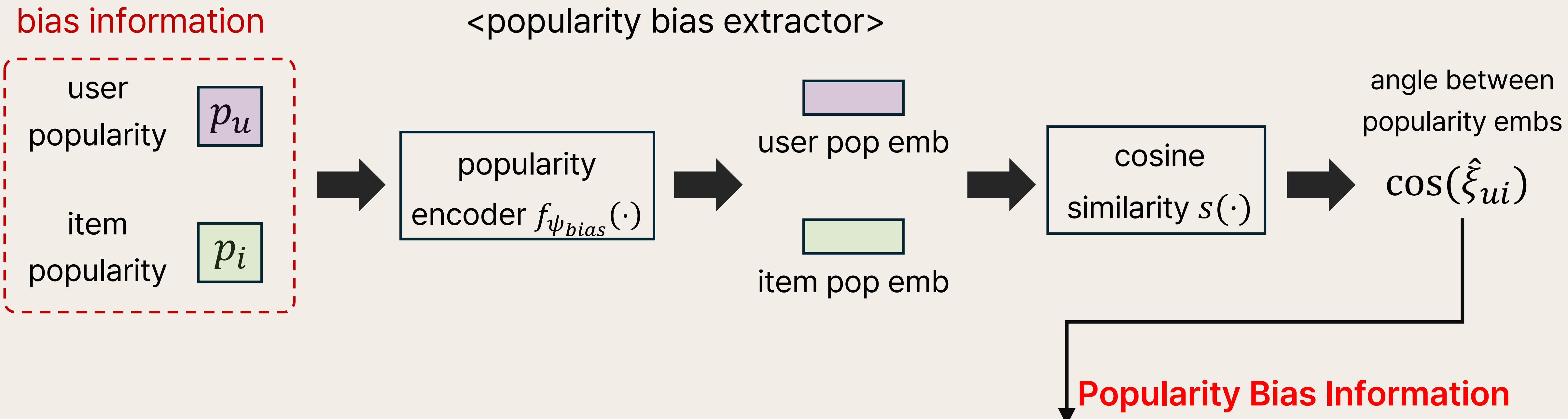
$0 = \lambda_0 < \lambda_1 \leq \cdots \leq \lambda_{N-1}$ - eigenvalues are usually sorted increasingly.

Learning graphs from data: A signal representation perspective, 2018, IEEE Signal Processing

- GFT: Graph Fourier Transform
- IGFT: Inverse Graph Fourier Transform

2. Preliminaries

Popularity Bias-aware Margin Loss



$$\mathcal{L}_{BC} = -\sum_{(u,i)\in O^+} \log \frac{\exp(\cos(\hat{R}_{ui} + \boxed{\widetilde{\mathcal{M}}^c_{ui}})/\tau)}{\exp(\cos(\hat{R}_{ui} + \widetilde{\mathcal{M}}^c_{ui})/\tau) + \sum_{j\in N_u} \exp(\cos(\hat{R}_{uj})/\tau)}$$

positive angle

sampled negative item

negative angle

Model Architecture (LPSFed)

Low-pass Personalized Subgraph Federated Recommendation (LPSFed)

[Client Side]

Stage1: Training of Client Models

- Low-pass GCN - model parameters, denoised structural signals
- Popularity bias-aware loss – localized popularity bias information

Stage2: Computing Structural Similarity

- denoised structural signals ↔ server-provided neutral structural anchor

[Server Side]

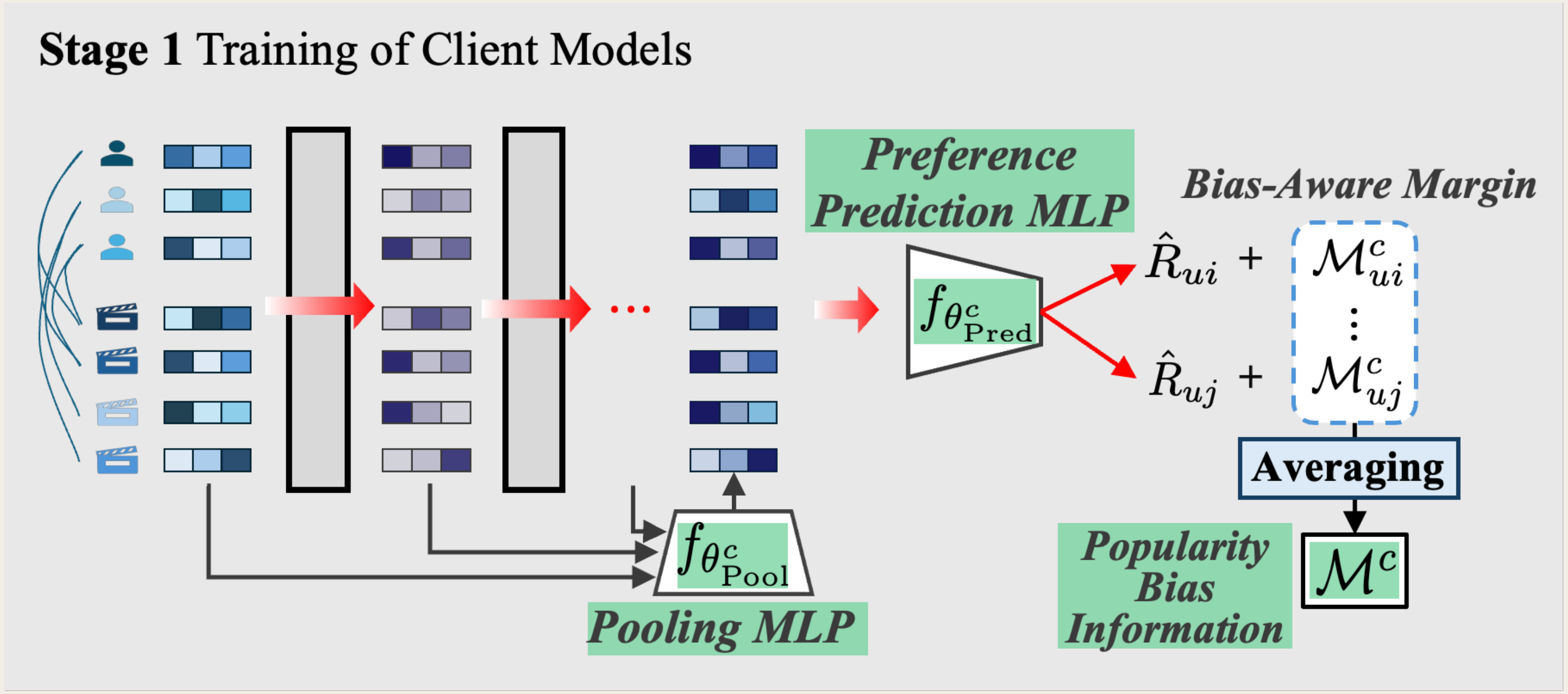
Stage3: Aggregating and Distributing Parameters on the Server

- Aggregates client parameters and Distributes personalized similarity score

3.1. Training of Client Models

[Client Side] Stage1: Training of Client Models

- Low-pass GCN - model parameters, denoised structural signals
- Popularity bias-aware loss – localized popularity bias information

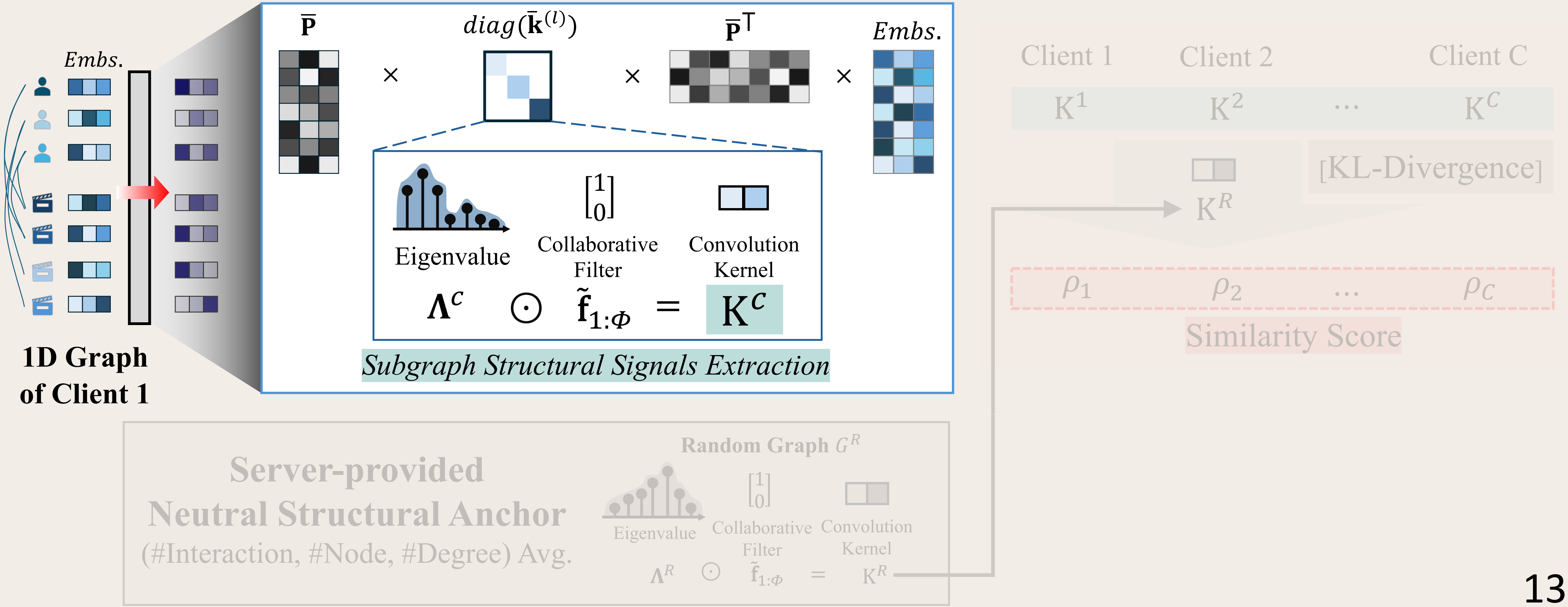


3. Method

3.2.1. Computing Structural Similarity

[Client Side] Stage2: Computing Similarity between Client and Random Graph

- denoised structural signals ↔ server-provided neutral structural anchor

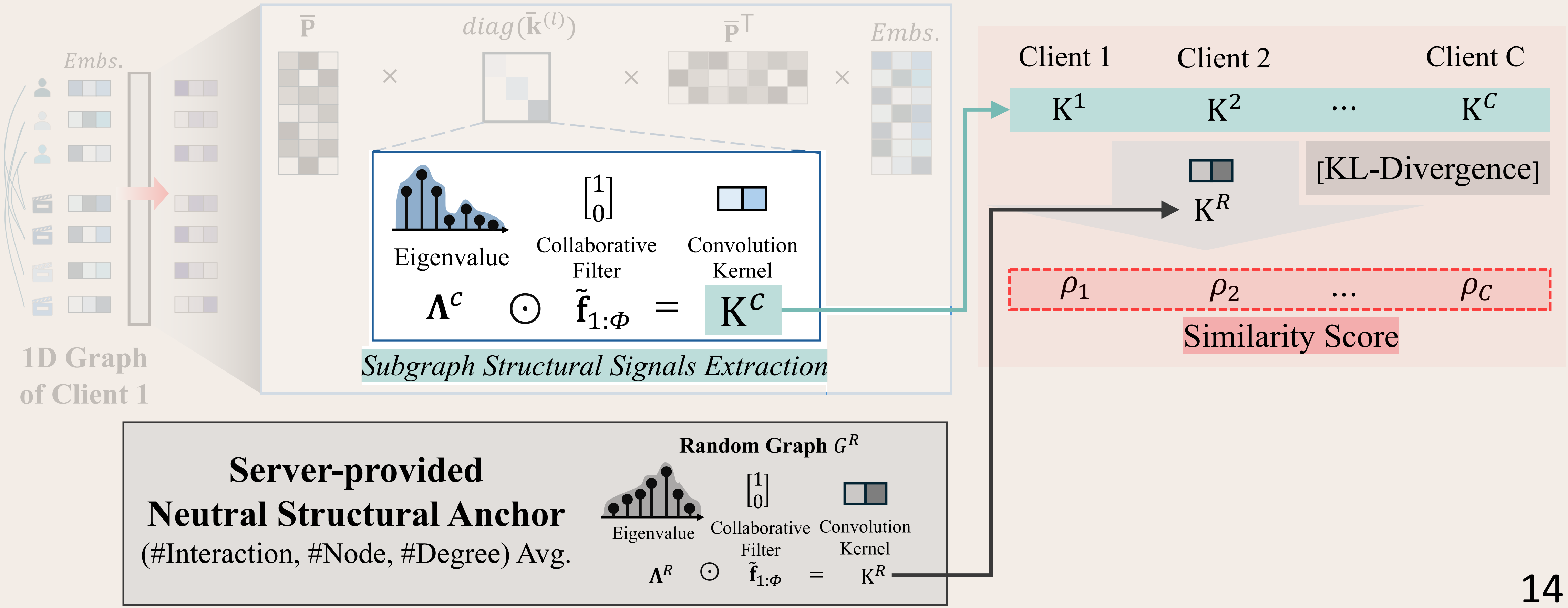


3. Method

3.2.2. Computing Structural Similarity

[Client Side] Stage2: Computing Similarity between Client and Random Graph

- denoised structural signals ↔ server-provided neutral structural anchor

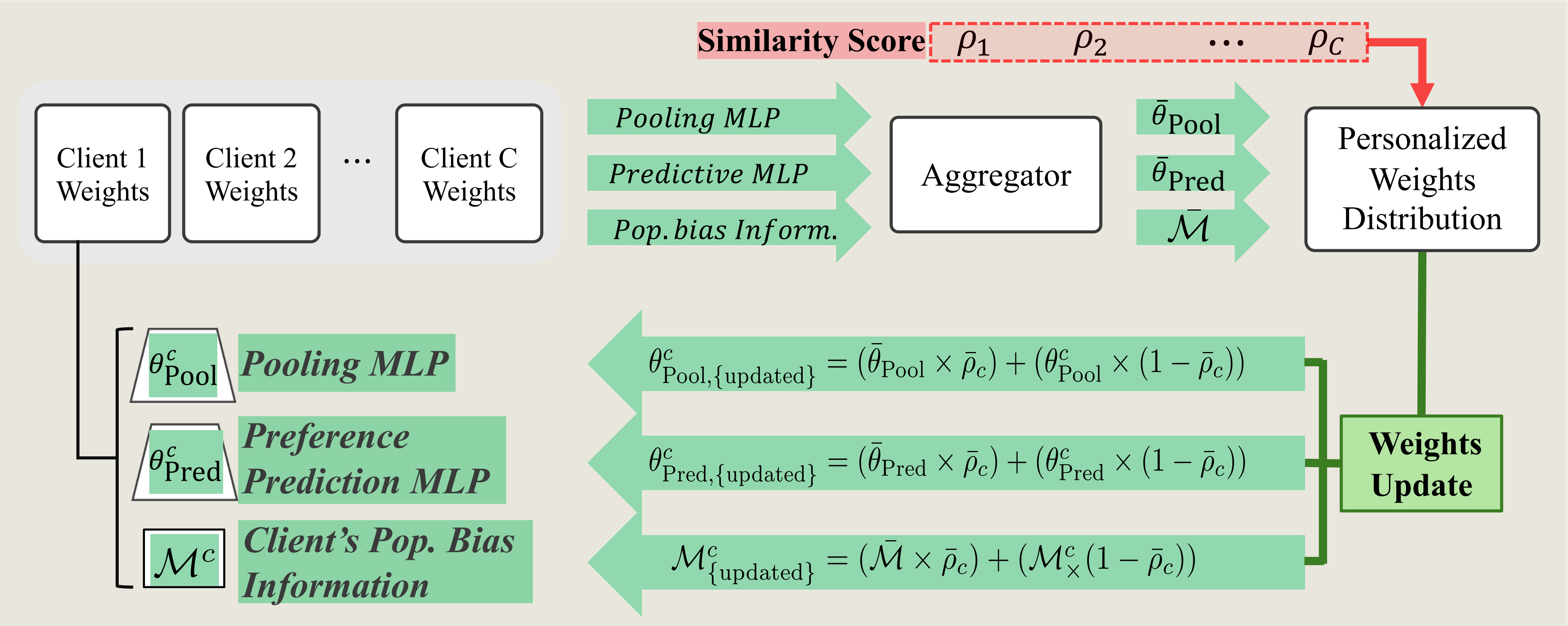


3. Method

3.3. Aggregating and Distributing Parameters on the Server

[Server Side] Stage3: Aggregating and Distributing Parameters on the Server

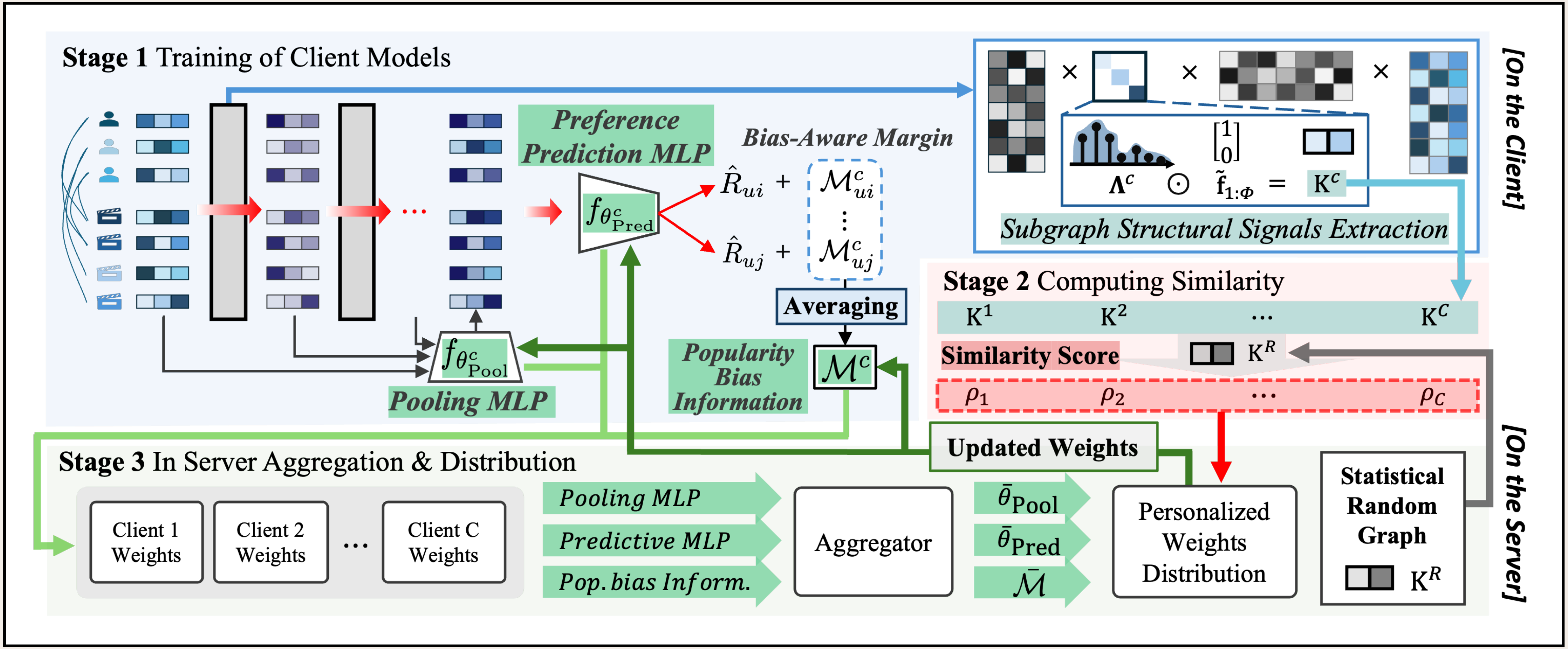
- Aggregates client parameters and Distributes personalized similarity score



3. Method

Overall Framework (LPSFed)

Low-pass Personalized Subgraph Federated Recommendation (LPSFed)



Experiments

4.1 Datasets & Baselines

Datasets

Dataset	#User	#Item	#Interact.
ML-1M	6,040	3,900	1,000,290
Gowalla	29,858	40,981	1,027,370
Yelp2018	31,668	38,048	1,561,406
Amazon-Book	52,643	91,599	2,984,108
Tmall-Buy	885,759	1,114,123	7,592,214

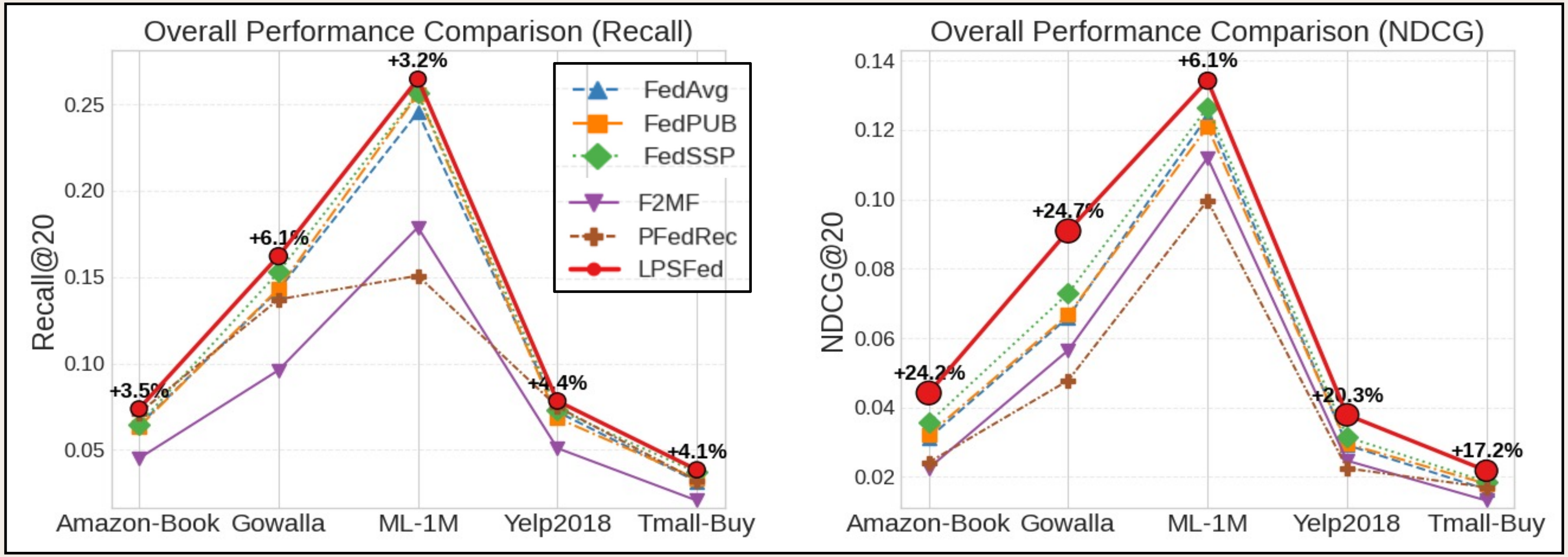
Baselines

- **Standard FL**: FedAvg (foundational approach)
- **MF**: FedMF, F2MF (fairness-aware)
- **Personalized FRS**: PFedRec, FedRAP
- **Spatial GNN-based** : FedPerGNN, FedHGNN, FedPUB
- **Spectral-based**: FedSSP
- **Ours**: Spectral + Personalization + Bias-aware

- **Imbalance Simulation:** Spectral Clustering (4 clients)
- **Data Split:** 8:1:1 ratio (Train/Val/Test)
- **Metrics:** Recall@20, NDCG@20
- **RQ:** Research Question
- **Improvements (%):** Compared to the second-best model

4.2 (RQ1) Overall Performance Comparison

(RQ1) Overall Performance Comparison



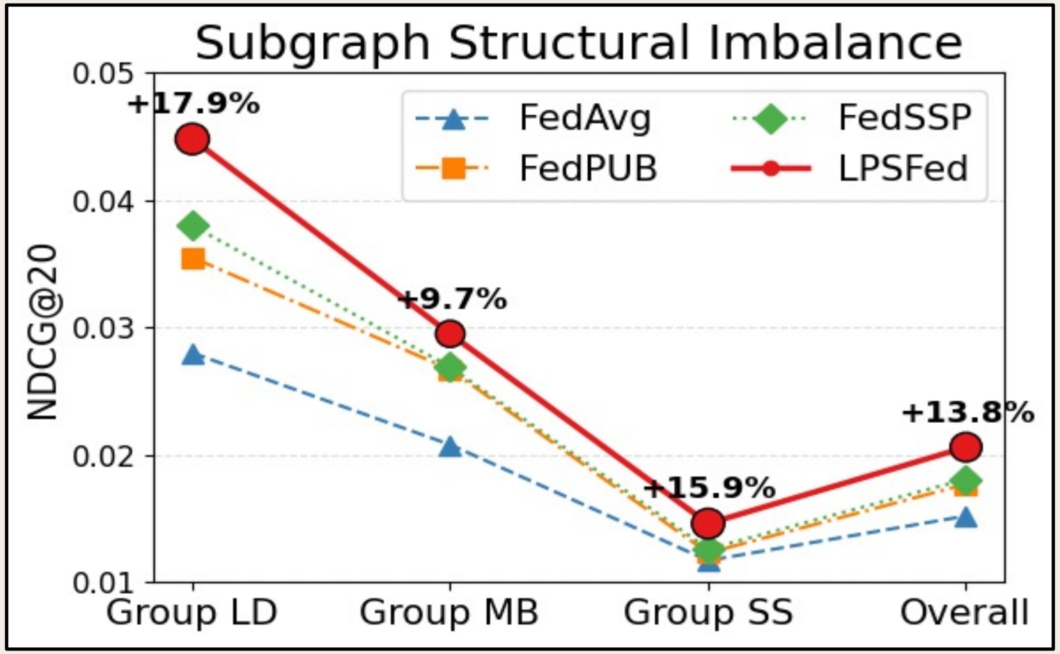
[Key Takeaways]

- **(RQ1)** Overall Dominance: Consistent SOTA across all five benchmarks; significantly outperforms nine competitive baselines.
- **(RQ1)** Synergistic Gain: High-precision ranking (NDCG) achieved through spectral personalization and bias-aware margin.

4. Experiment

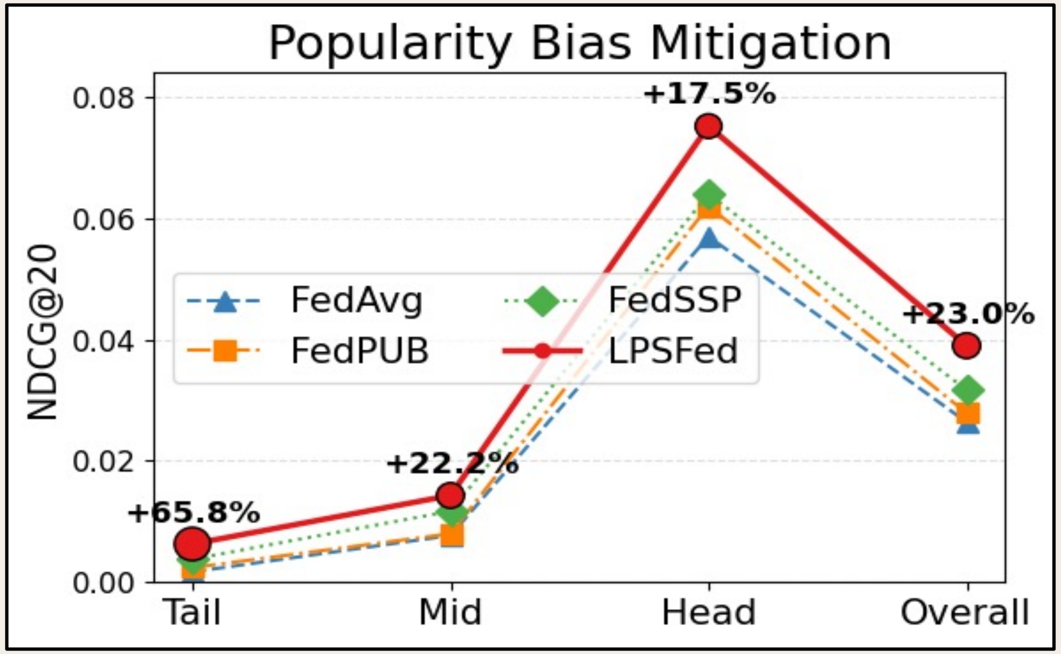
4.3 (RQ 2 & 3) Robustness Analysis

(RQ2) Robustness to Subgraph Imbalance



LD: Large-Dense / **MB**: Medium-Balanced / **SS**: Small-Sparse

(RQ3) Localized Popularity Bias Mitigation



(Node Proportion) **Tail** – 3 / **Mid** – 2 / **Head** – 1

- Split based on item node's degree distribution

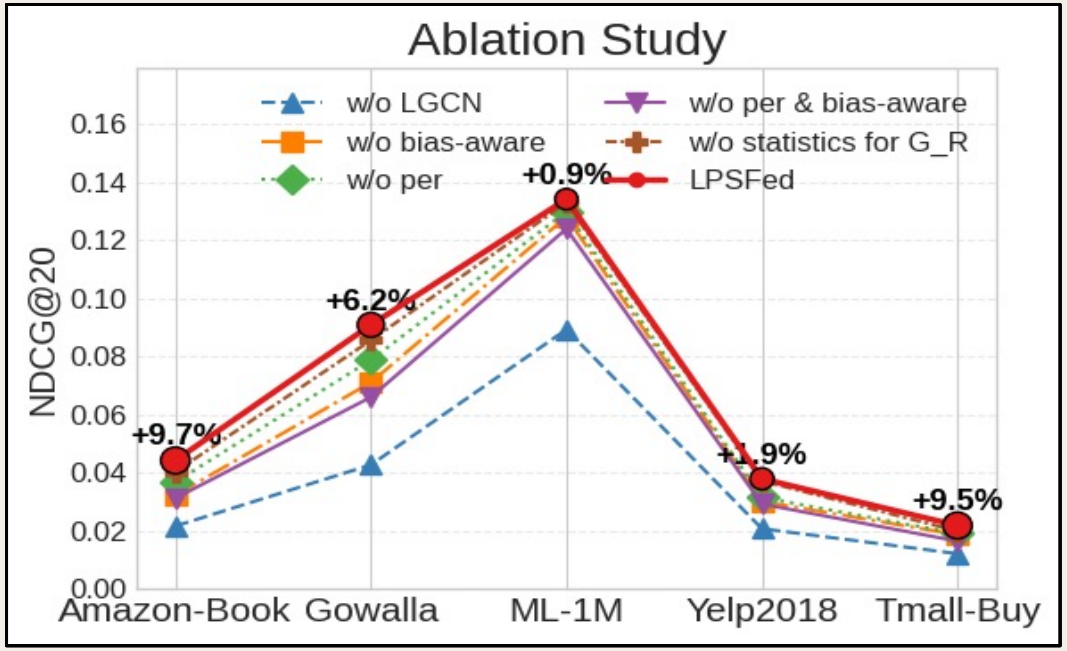
[Key Takeaways]

- **(RQ2)** Subgraph Imbalance: Consistent robustness across all scales; breaks feedback loops and popularity dependence.
- **(RQ3)** Popularity Bias: "No-trade-off" performance gains across the entire item spectrum, from Tail to Head.

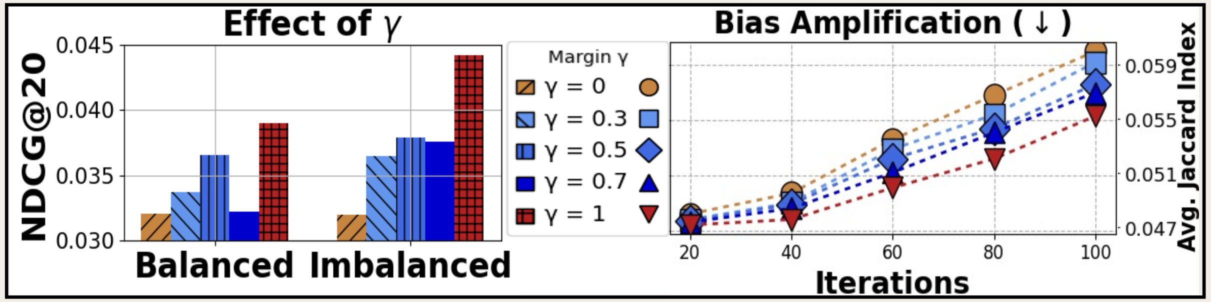
4. Experiment

4.4 (RQ4) Ablation Study & (RQ5) Hyperparameter Analysis

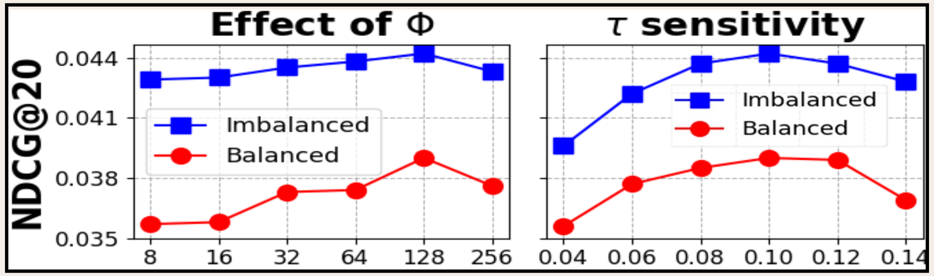
(RQ4) Ablation Study



(RQ5) Hyperparameter Analysis



(a) Varying Margin Strength γ



(b) Loss Temperature Sensitivity

[Key Takeaways]

- **(RQ4)** Ablation: All component is essential, with the **low-pass filtering** being critical for structural divergence.
- **(RQ5)** Hyperparameter: **Stronger bias margin** (γ) and **optimal frequency cut-offs** (Φ) are the primary drivers of peak performance.

5. Conclusion

1. Subgraph Scale (user/item counts)

- Leveraging denoised subgraph structural signals

  → Improves similarity measurement & Preserves subgraph's core structural pattern

2. Connectivity (item degree)

- Sharing Popularity Bias Information

  → Enhances recommendation diversity

3. Privacy Preserving Personalized FRS

- Utilizing server-provided neutral structural anchor

  → Preserves privacy during learning

Thank You

E-Mail: dntjr41@g.skku.edu

Code: https://github.com/dntjr41/LPSFed