Advancing Recommendation Systems Using Graph Neural Networks

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Abstract

We introduce an adaptive graph-based recommender system that balances accuracy and diversity through a multi-channel architecture. By decomposing the interaction graph into α-β cores, residuals, and a diffusion-enhanced view, our model captures both dense and long-tail patterns. Trainable channel gating and contrastive alignment enable dynamic control over recommendation behavior. With tunable hyperparameters, the system flexibly targets accuracy-oriented, diversity-promoting, or balanced objectives—making it well-suited for real-world, long-tail recommendation scenarios. Our architecture outperforms the SOTA models in all metrics.

Related Work

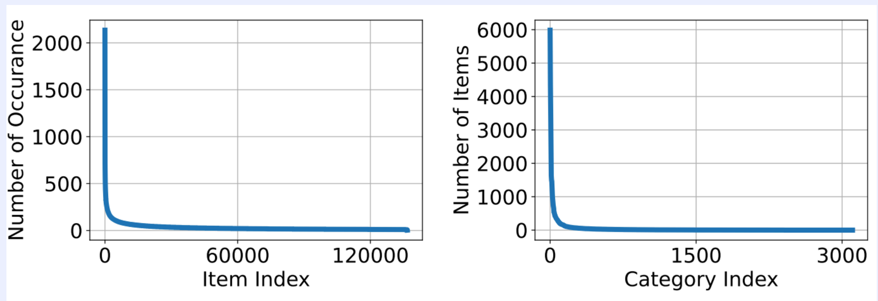
In recent literature, LightGCN[1] simplifies GCN-based collaborative filtering by removing feature transformations and nonlinear activations—relying solely on linear neighborhood aggregation and a weighted sum of layer-wise embeddings—to achieve ≈16 % relative improvement over NGCF[2] with far less complexity. Building on this, DGRec[3] tackles diversity shortfalls by combining submodular neighbor selection, layer attention, and long-tail loss reweighting, boosting recommendation variety without sacrificing accuracy.

Methodology

- Heterogeneous Graph Neural Networks (GNNs) handling distinct user-item interactions.
- Flexible layer factory enabling the interchange of convolutional layers, such as LightGCN and diffusion-based PPR.
- Diffusion-based Personalized PageRank (PPR) to refine embedding propagation.
- Alpha-beta core decomposition to effectively isolate and prioritize core user-item interactions from peripheral ones.
- Bayesian Personalized Ranking (BPR) loss combined with category-balanced weighting to address data imbalance.
- Contrastive learning using InfoNCE loss differentiating between core and peripheral user-item interactions, improving representation quality.
- Weighted random sampling based on category and item popularity distributions to enhance diversity and accuracy.

Experiment and Dataset

- Used NVIDIA GeForce GTX 1080 8-GB GPU.
- Training takes ~4.8 hours.
- Hyper-parameter tuning based on the validation set.
- Dataset - Taobao[3]
  - Users: 82,633
  - Items: 136,710
  - Interactions: 4,230,631
  - Categories: 3,108
  - Mean Category Size: 43,986



Formulation

$$\mathcal{L}\text{InfoNCE} = -\frac{1}{N}\sum i = 1^N \log \frac{\exp\left(\frac{\mathbf{p}_i^\top \mathbf{q}i}{\tau}\right)}{\sum j = 1^N \exp\left(\frac{\mathbf{p}_i^\top \mathbf{q}j}{\tau}\right)} \tag{1}$$

$$\mathbf{h}^{(k)}\text{item} = \text{GNN}(\mathcal{G}u \to i, \mathbf{h}^{(k-1)})\ \mathbf{h}^{(k)}\text{user} = \text{GNN}(\mathcal{G}_{i\to u}, \mathbf{h}^{(k-1)})\ \mathbf{h}^{(k)} = \alpha_d \cdot \mathbf{h}^{(0)} + (1-) \cdot \mathbf{h}^{(k)}\text{GNN} \tag{2}$$

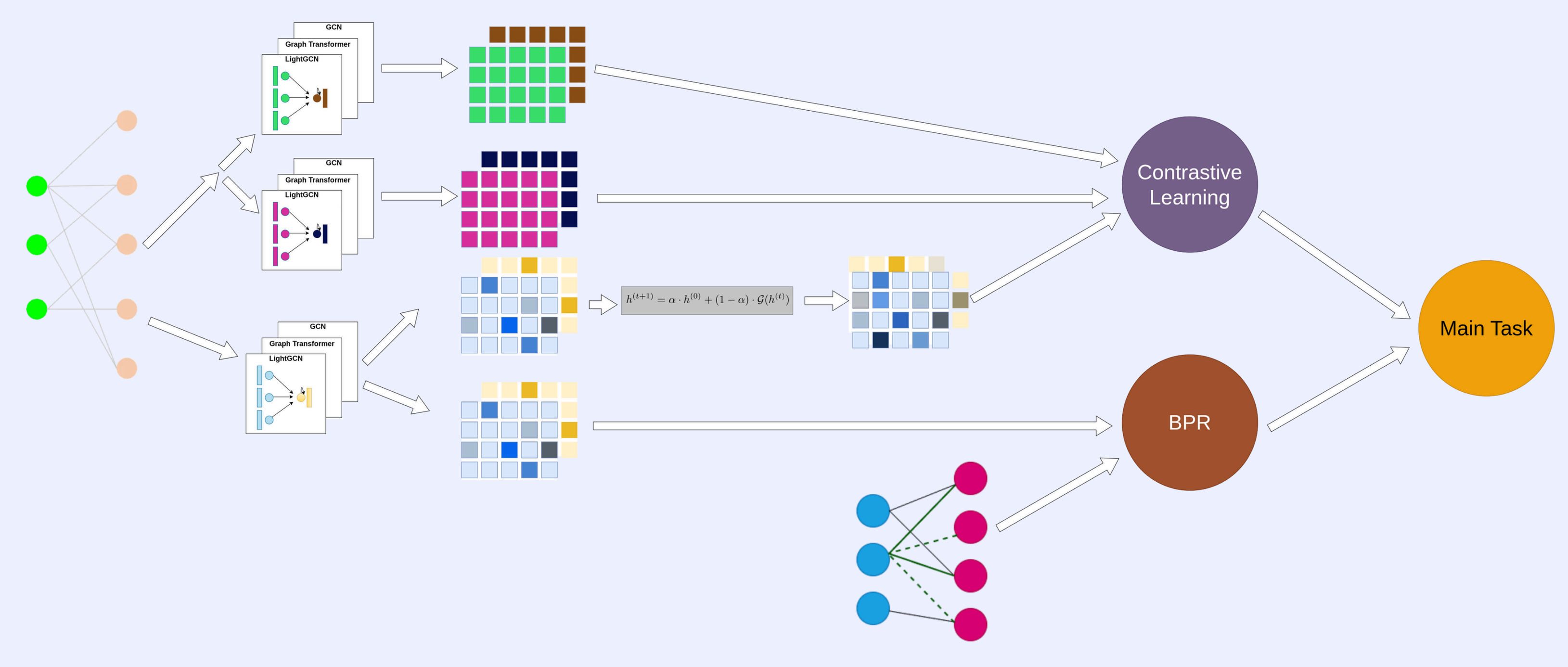
$$\mathcal{L}\text{BPR} = -\frac{1}{B}\sum (u, i^+, i^-) \log \sigma\left(sui^+ - sui^-\right) \tag{3}$$

$$\mathcal{L}\alpha\text{-}\beta = \text{InfoNCE}(\mathbf{ecore}, \mathbf{erest}) \tag{4}$$

$$\mathcal{L}\text{diff} = \text{InfoNCE}(\mathbf{ecore}, \mathbf{ediff}) + \text{InfoNCE}(\mathbf{erest}, \mathbf{ediff}) \tag{5}$$

$$\mathcal{L}\text{total} = \lambda\text{bpr} \cdot \mathcal{L}\text{BPR} + \lambda\text{con} \cdot \mathcal{L}\alpha\text{-}\beta + \lambda\text{diff} \cdot \mathcal{L}_{\text{diff}} \tag{6}$$

Model Architecture



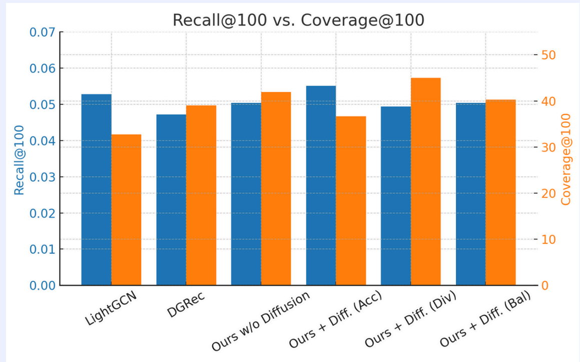
Evaluation and Metrics

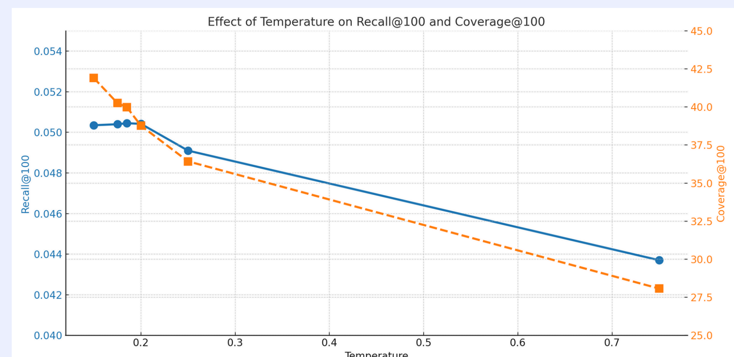
- Recall@k: Measures system's ability to retrieve relevant items.
- Hit Ratio@k: Indicates the proportion of users for whom relevant items were successfully recommended.
- Coverage@k: Assesses the diversity and breadth of recommendations across categories.

Ablation Study

Our model outperforms both DGRec and LightGCN in all metrics. Adding the diffusion channel improves Recall@100 by 9.4% over the no-diffusion variant, confirming the benefit of global smoothing. The diversity-oriented setup achieves the highest Coverage@300 (107.77), highlighting its strength in long-tail recommendation. The balanced version delivers competitive accuracy and diversity, demonstrating the effectiveness of our gated multi-channel fusion and tunable training objectives.

Method	Recall@100	Recall@300	HR@100	HR@300	Cov.@100	Cov.@300
LightGCN (raw)	0.05280	**0.10630**	0.32610	**0.50970**	32.7069	69.3502
DGRec (raw)	0.04720	0.09510	0.30260	0.48170	39.0597	89.1684
Ours w/o Diffusion	0.05035	0.09547	0.30625	0.46798	41.9031	100.4957
Ours + Diffusion (Acc-Oriented)	**0.05507**	0.10533	**0.32831**	0.49753	36.6667	87.8693
Ours + Diffusion (Div-Oriented)	0.04940	0.09600	0.30930	0.47670	**44.9904**	**107.7740**
Ours + Diffusion (Balanced)	0.05040	0.09990	0.31550	0.49230	40.2589	93.8764





Conclusion

In conclusion, our adaptive multi-channel framework effectively balances accuracy and diversity, demonstrating superior performance across all metrics and offering a practical solution for real-world, long-tail, and graph-based over-smoothing recommendation tasks.

References

- [1] X. He, K. Deng, X. Wang, Y. Li, Y. Zhang, and M. Wang, "LightGCN: Simplifying and Powering Graph Convolution Network for Recommendation," arXiv:2002.02126 [cs], Jul. 2020, Available: https://arxiv.org/abs/2002.02126
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