Flattened Graph Convolutional Networks For Recommendation

Yue Xu
yuexu.xy@foxmail.com
Alibaba Group.

Hao Chen
sundaychenhao@gmail.com
Tencent Inc.

Yuanchen Bei
yuanchenbei@zju.edu.cn
Zhejiang University.

Feiran Huang
huangfr@jnu.edu.cn
Jinan University.

ABSTRACT
Graph Convolutional Networks (GCNs) and their variants have achieved significant performances on various recommendation tasks. However, many existing GCN models tend to perform recursive aggregations among all related nodes, which can arise severe computational burden to hinder their application to large-scale recommendation tasks. To this end, this paper proposes the flattened GCN (FlatGCN) model, which is able to achieve superior performance with remarkably less complexity compared with existing models. Our main contribution is three-fold. First, we propose a simplified but powerful GCN architecture which aggregates the neighborhood information using one flattened GCN layer, instead of recursively. The aggregation step in FlatGCN is parameter-free such that it can be pre-computed with parallel computation to save memory and computational cost. Second, we propose an informative neighbor-infomax sampling method to select the most valuable neighbors by measuring the correlation among neighboring nodes based on a principled metric. Third, we propose a layer ensemble technique which improves the expressiveness of the learned representations by assembling the layer-wise neighborhood representations at the final layer. Extensive experiments on three datasets verify that our proposed model outperforms existing GCN models considerably and yields up to a few orders of magnitude speedup in training efficiency.

ACM Reference Format:
Yue Xu, Hao Chen, Zengde Deng, Yuanchen Bei, and Feiran Huang. 2022. Flattened Graph Convolutional Networks For Recommendation. In Proceedings of 4th Workshop on Deep Learning Practice and Theory for High-Dimensional Sparse and Imbalanced Data with KDD 2022 (DLP-KDD 2022). ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/nmnnnn.nnmmnn

1 INTRODUCTION
Graph Convolutional Networks (GCNs), which generalize the Convolutional Neural Networks (CNNs) on graph-structured data [1], have achieved impressive performance on various graph-based learning tasks [2–4], including recommendation [5]. The core idea behind GCNs is to iteratively aggregate information from locally nearby neighbors in a graph using neural networks [6]. Each node at one GCN layer performs graph convolution operations to aggregate information from its nearby neighbors at the previous layer. By stacking multiple GCN layers, the information can be propagated across the far reaches of a graph, which makes GCNs capable of learning from both content information as well as the graph structure. As such, GCN-based models are widely adopted in recommendation tasks [5, 7–14] which require learning from relational datasets. However, although existing GCN-based recommendation models have set new standards on various benchmark tasks [5, 7, 8, 11, 15–19], many of them suffer from two pitfalls.

First, many existing GCN models suffer from high computational complexity due to the use of multi-layer architectures and complicated modeling techniques. This may largely hinder their application to large-scale real-world recommender systems. For example, the metapath-guided GCN models [8, 20] propose to construct manifold metapaths for neighborhood aggregation, which introduces high complexity on data pre-processing and information aggregation. Meanwhile, the attention-based GCN (GAT) models propose to generalize graph convolution with the attention mechanism [2, 9, 15], which, however, introduces an excessive amount of additional parameters to fit. On the other hand, the recent advances on simplified GCNs such as [18, 21], indicate that it is feasible to remove certain components from existing architectures while still maintaining comparable performances. This motivates us to rethink the essential components of building an expressive GCN model for recommendations.

Second, the recursive neighborhood aggregation among all nodes arises severe computational burden but may have limited contribution in recommendation tasks. Specifically, as pointed out in [22], the convolution in the GCN model is indeed a special form of Laplacian smoothing, which makes the feature of nodes within the same cluster similar to greatly ease the classification or regression task. Therefore, it is critical for GCN models to ensure that similar nodes have been grouped into the same cluster before performing neighborhood aggregations. In homogeneous networks, it is highly likely for two similar nodes to form a direct edge [23]. However, the networks are heterogeneous in the context of recommendation. As such, the difficulty of recognizing similar nodes arises since we need to measure the correlation between any user-item pair based on their indirect relationships. Existing models usually measure the correlation by counting the historical interactions [8, 9, 11, 12]. However, such intuitive measurements can be easily dominated by the popular user/items. Besides, the correlations are unlikely to scale linearly with the number of historical interactions. Therefore, it is worth exploring the definition of a principled metric to
2.1 Neighbor Information Measurement

Starting from GraphSAGE [4] and FastGCN [6], GCN models down-sample the neighbors to accelerate the recursive message passing. Since this downsampling process would inevitably lose information, it is critical to preserve as much information as possible in the preserved neighbor, which could maximally represent the root node. To this end, we introduce the mutual information measurement to evaluate to what extent a neighbor can describe the given root node. Besides, we also propose a simplified version of neighbor-root-node information measurement for efficient computation.

Neighbor-Root-Node Mutual Information. Let $u$ denote the root node. We first select an arbitrary node $v \in N_u$. Let the random variable $v$ be the feature of a randomly picked node in $N_u$, then the distribution of $v$ is $P_v = P(\{v = v_u\})$, where $v_u$ is the outcome feature of node $v$. Similarly, we assume $u$ to be the feature associated with the root node $u$, then the distribution of $u$ is $P_u = P(\{u = u_u\})$, where $u_u$ is the outcome feature of node $u$. After defining these notations, their mutual information $I(v, u)$ is the KL-divergence between the joint distribution $P_{v \cup u} = P(\{v = v_u, u = u_u\})$ and the product of marginal distributions $P_v \otimes P_u$:

$$I(v, u) = \text{KL}(P_{v \cup u} \ || \ P_v \otimes P_u)$$

where $(\cdot)$ follows from $f$-divergence representation based on KL-divergence [25]; random variable $u'$ denotes the feature associate with an arbitrary node $u' \in U \cup I$; $T \in T$ is an arbitrary function that maps a pair of features to a real value, which reflecting the correlation of two features. After replacing the $f$-divergence in Eq. (1) with a GAN-like divergence, Eq. (1) is written as follows,

$$I_{GAN}(v, u) \geq \sup_{T \in T'} \mathbb{E}_{P_{v \cup u} \sim T'} \mathbb{E}_{P_v \sim P_{v'}} \mathbb{E}_{P_u \sim P_{u'}} \{e^T(e_u, e_u') - 1\},$$

where $(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

2.1.1 Neighbor Information Measure. Let $u$ denote the root node. We first select an arbitrary node $v \in N_u$. Let the random variable $v$ be the feature of a randomly picked node in $N_u$, then the distribution of $v$ is $P_v = P(\{v = v_u\})$, where $v_u$ is the outcome feature of node $v$. Similarly, we assume $u$ to be the feature associated with the root node $u$, then the distribution of $u$ is $P_u = P(\{u = u_u\})$, where $u_u$ is the outcome feature of node $u$. After defining these notations, their mutual information $I(v, u)$ is the KL-divergence between the joint distribution $P_{v \cup u} = P(\{v = v_u, u = u_u\})$ and the product of marginal distributions $P_v \otimes P_u$:

$$I(v, u) = \text{KL}(P_{v \cup u} \ || \ P_v \otimes P_u)$$

where $(\cdot)$ follows from $f$-divergence representation based on KL-divergence [25]; random variable $u'$ denotes the feature associate with an arbitrary node $u' \in U \cup I$; $T \in T$ is an arbitrary function that maps a pair of features to a real value, which reflecting the correlation of two features. After replacing the $f$-divergence in Eq. (1) with a GAN-like divergence, Eq. (1) is written as follows,

$$I_{GAN}(v, u) \geq \sup_{T \in T'} \mathbb{E}_{P_{v \cup u} \sim T'} \mathbb{E}_{P_v \sim P_{v'}} \mathbb{E}_{P_u \sim P_{u'}} \{e^T(e_u, e_u') - 1\},$$

where $(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

To this end, we introduce the mutual information measurement to evaluate to what extent a neighbor can describe the given root node. Besides, we also propose a simplified version of neighbor-root-node information measurement for efficient computation.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.

Practical Simplification. In practice, we cannot go over the entire functional space to evaluate the exact value of $I_{GAN}(v, u)$. Since the feature of nodes are learned collaborative filtering embeddings, we parameterize $T(a, b)$ by computing their inner product as $T(a, b) = a^\top \cdot b$. Through the trained CF embeddings, we obtain a lower bound of GAN-based mutual information as:

$$I_{CF}(v, u) = \log \sigma(e_u^\top \cdot e_u)$$

where $\sigma(\cdot)$ is the sigmoid function.
2.2 Flattened Layer Aggregation
Mathematically, let $G(\{U,I,R\})$ denote the user-item interaction graph. $U = \{u_1, \ldots, u_N\}$ denotes the user set, and $I = \{i_1, \ldots, i_M\}$ denotes the item set, while $R \in \mathbb{R}^{N \times M}$ describes the user-item interaction matrix. After introducing the notations, the argument adjacent matrix for users and items can be defined as follows,

$$A = \begin{bmatrix} 0 & R \\ R^T & 0 \end{bmatrix} \in \mathbb{R}^{(N+M) \times (N+M)}.$$  

Therefore, we can define the multi-hop neighbors of a given node $u$ according to the adjacent matrix $A$. Specially, $N_u^0 = \{u\}$. The first-order neighbor set is given by $N_u^1 = \{v|A_{uv} = 1\}$, while the second-order neighbor set is denoted by $N_u^2 = \{v|A_{uv}^2 \geq 1\}$, so on and so forth.

As shown in Fig. 1, for a given root node $u$, we select the most informative subset $S_u^k$ from a given neighbor set $N_u^k$ by greedily selecting the top-$S_u^k$ informative neighbors, namely,

$$S_u^k = \text{top-rank}(C(u,u) \text{ for } v \in N_u^k, \ S^k),$$

where top-rank is the function that returns the indices of the top-$S_u^k$ value and $S^k$ denotes the sampling size of the $k$-th layer. Based on the definition of the neighbor infomax selection in Eq. (6), we can utilize flat infomax aggregation to extract the information of different layers,

$$h_u^k = \frac{1}{S^k} \sum_{v \in S_u^k} e_{uv}.$$

Noted that the aggregation step Eq. (6) and Eq. (7) is a parameter-free operation such that it can be done in a pre-processing manner only once, thereby saving vast memory and computational cost to ease the training on large-scale graphs and application to real-world recommender systems.

2.3 Layer Ensemble Architecture
With Eq. (7), FlatGCN aggregates the information of a $K$-layer subgraph into $K$ vectors. Thus for any given user-item pair $(u, i)$, we have $\{h_u^1, \ldots, h_u^K\}$ to represent the user subgraph and $\{h_i^1, \ldots, h_i^K\}$ to represent the item subgraph.

The success of FM [26, 27] inspires that a hand-crafted cross-interaction function may be better than brutally learning with Multi-Layer Perception (MLP) function. As shown in Fig. 1, we first compute the interactions between different layers combinations for every layer of user’s and the item’s subgraphs. In such a way, we can easily take full advantage of the aggregation embedding of each subgraph layer for both user and item, and thus we model the complex interaction from user $u$ to item $i$ as,

$$\tilde{y}_{u,i} = \text{MLP}[\|h_u^k\|^p, (h_u^k)^T \cdot h_i^k],$$

where $\|$ indicates the concatenation operation, $(h_u^k)^T \cdot h_i^k$ denotes the relevance score between the $k$-th layer representation of the user subgraph and $j$-th layer of the item subgraph. It is noteworthy that Eq. (8) actually summarize the complicated relations between the user-item pair $(u, i)$ into a $K^2$-dimension vectors, that greatly reduce the number of the parameters in the followed MLP function.

3 EXPERIMENTS
3.1 Experiment Setup
Datasets. We utilize two benchmark datasets and a commercial dataset to evaluate the recommendation performance: AmazonBook and WeChat dataset contains users’ clicks on different articles recorded by the WeChat platform. We use Meta2Vec [24] and the state-of-the-art (SOTA) LightGCN [18] to produce the pre-trained embeddings of users and items in datasets to feed into the GCN model as the raw features.

Evaluation Protocols. We randomly split the entire user-item recommendation records of each dataset into an embedding training set, GCN model training (validation) set, and a test set to evaluate the performance, where each of them contains 65%, 15%, and 20% of the full records, respectively. Besides, we apply the wildly used full-rank evaluation protocols [18] to evaluate the recommendation performance.

Comparison Methods. We compare the following SOTA baselines: I. GCN [4] applies 2-layer GCN to process input embeddings following PinSAGE [7], followed by an inner product function. II. IntentGC [5] introduces a fast architecture named IntentNet to avoid unnecessary feature interactions for efficient training. III. NGCF* [17] is an embedding learning method. We fix its inputs as the given user-item embeddings and only train its propagation layers. We denote it as NGCF*. IV. LightGCN* [18] is the SOTA recommendation model. Similar to NGCF*, we fix its inputs as the given user-item embeddings and only train its propagation layers.

Parameter Settings. The optimal parameter settings for all comparison methods are achieved by either empirical study or suggested settings by the original papers. We consider the 3-layer subgraphs and set the sampling size $S_k = 25$ for $k = 1, 2$. Especially, we adopt Adam [28] as the optimizer with learning rate as 0.001; the $L_2$ regularization weight as $10^{-5}$.

3.2 Result Analysis
Performance Comparison. Table 1 reports the performance on the three datasets w.r.t. precision (PRE@20), recall (REC@20), and ndcg (NCDG@20) metrics. The improvement gives the relative enhancement of FlatGCN over the best baseline (underlined). The superscript * denotes statistical significance against the best baseline with $p < 0.05$.

Overall, our proposed FlatGCN statistically significantly outperforms the best baselines among all three datasets w.r.t. all evaluation metrics and both Meta2Vec and LightGCN embeddings. These results verify the consistent superiority of FlatGCN on characterizing the relevance between users and items than SOTA GCN-based recommendation methods. Particularly for the commercial WeChat dataset, FlatGCN leads to an enhanced performance by more than 30% on Meta2Vec embeddings. With LightGCN embeddings, FlatGCN outperforms the best baselines by over 60%.

Learning Efficiency. One main advantage of FlatGCN is the low training complexity. In Fig. 2, we present the average training time of FlatGCN and the other baselines. We also present the preprocessing time of FlatGCN. The results in Fig. 2 shows that FlatGCN achieves superior performance with one or two orders of magnitude speedup in training time. Notably, FlatGCN is 10 times faster than the fastest baseline: NGCF. Moreover, the preprocessing time of FlatGCN can be neglected, comparing with the training time of the baselines.
Table 1: Overall Performance Comparison

| Embeddings | AmazonBook PRE | AmazonBook REC | AmazonBook NDCG | Yelp2018 PRE | Yelp2018 REC | Yelp2018 NDCG | WeChat PRE | WeChat REC | WeChat NDCG |
|------------|----------------|----------------|------------------|-------------|--------------|--------------|-------------|-------------|-------------|
| IntentGC   | 0.0259         | 0.0517         | 0.0458           | 0.0274      | 0.0592       | 0.0490       | 0.0116      | 0.0908      | 0.0512      |
| GCN        | 0.0271         | 0.0543         | 0.0476           | 0.0299      | 0.0648       | 0.0527       | 0.0181      | 0.1425      | 0.0789      |
| NGCF       | 0.0384         | 0.0769         | 0.0678           | 0.0363      | 0.0769       | 0.0666       | 0.0189      | 0.1493      | 0.0837      |
| LightGCN   | 0.0448         | 0.0919         | 0.0833           | 0.0388      | 0.0842       | 0.0704       | 0.0191      | 0.1478      | 0.0940      |
| FlatGCN    | **0.0498**     | **0.1014**     | **0.0918**       | **0.0430**  | **0.0932**   | **0.0807**   | **0.0258**  | **0.2019**  | **0.1233**  |

| Improve    | 11.16%*        | 10.34%*        | 10.20%*          | 10.82%*     | 10.69%*      | 14.63%*      | 35.08%*     | 35.23%*     | 31.17%*     |

| Embeddings | AmazonBook PRE | AmazonBook REC | AmazonBook NDCG | Yelp2018 PRE | Yelp2018 REC | Yelp2018 NDCG | WeChat PRE | WeChat REC | WeChat NDCG |
|------------|----------------|----------------|------------------|-------------|--------------|--------------|-------------|-------------|-------------|
| IntentGC   | 0.0307         | 0.0609         | 0.0540           | 0.0335      | 0.0723       | 0.0616       | 0.0230      | 0.1835      | 0.1057      |
| GCN        | 0.0317         | 0.0649         | 0.0576           | 0.0291      | 0.0625       | 0.0529       | 0.0233      | 0.1872      | 0.1079      |
| NGCF       | 0.0433         | 0.0880         | 0.0785           | 0.0401      | 0.0853       | 0.0737       | 0.0425      | 0.3533      | 0.2015      |
| LightGCN   | 0.0450         | 0.0919         | 0.0823           | 0.0410      | 0.0874       | 0.0752       | 0.0342      | 0.2831      | 0.1671      |
| FlatGCN    | **0.0485**     | **0.0982**     | **0.0884**       | **0.0450**  | **0.0954**   | **0.0818**   | **0.0709**  | **0.5932**  | **0.3543**  |

| Improve    | 7.78%*         | 6.86%*         | 7.41%*           | 9.76%*      | 9.15%*       | 8.78%*       | 66.82%*     | 67.90%*     | 75.83%*     |

4 CONCLUSION

In this paper, we introduced the FlatGCN model which is able to achieve superior performance along with a few orders of magnitude speedup in training compared with existing models. Specifically, we proposed a flattened GCN architecture which is able to perform neighborhood propagation only once over a single GCN layer instead of recursively. Moreover, we proposed an informative sampling method named neighbor-informax to select the top informative neighbors for neighborhood aggregation. Finally, we proposed a layer ensemble technique to improve the model expressiveness. Extensive experiments verified the superiority of the proposed FlatGCN on both learning performance and training speed.

REFERENCES

[1] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. In ICLR, 2017.
[2] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. In ICLR, 2018.
[3] William Hamilton, Rex Ying, and Jure Leskovec. Representation learning on graphs: Methods and applications. IEEE Data Engineering Bulletin, 2017.
[4] William Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. In NIPS, pages 1024–1034, 2017.
[5] Jun Zhao, Zhou Zhou, Ziyu Guan, Wei Zhao, Wei Ning, Guang Qiu, and Xiaofei He. IntentGC: a scalable graph convolution framework fusing heterogeneous information for recommendation. In KDD, pages 2347–2357, 2019.
[6] Jie Chen, Tengfei Ma, and Cao Xiao. FastGCN: fast learning with graph convolutional networks for recommendation learning. In KDD, 2018.
[7] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In KDD, pages 974–983, 2018.
[8] Shaohua Fan, Junxiong Zhu, Xiaotian Han, Chuan Shi, Limin Hu, Biyu Ma, and Yongkang Li. Metapath-guided heterogeneous graph neural network for intent recommendation. In KDD, pages 2478–2486, 2019.
[9] Qitian Wu, Hengrui Zhang, Xiaofeng Gao, Peng He, Paul Weng, Han Gao, and Guihai Chen. Dual graph attention networks for deep latent representation of multifaceted social effects in recommender systems. In WWW, pages 2091–2102, 2019.
[10] Hao Chen, Zhong Huang, Yue Xu, Zengde Deng, Feiran Huang, Peng He, and Zhoujun Li. Neighbor enhanced graph convolutional networks for node classification and recommendation. Knowledge-Based Systems, 246:108594, 2022.
[11] Hongwei Wang, Fuzheng Zhang, Mengdi Zhang, Jure Leskovec, Miao Zhao, Wenjie Li, and Zhongyuan Wang. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. In KDD, pages 968–977, 2019.
[12] Hongwei Wang, Miao Zhao, Xing Xie, Wenjie Li, and Minyi Guo. Knowledge graph convolutional networks for recommender systems. In WWW, page 3307–3313, New York, NY, USA, 2019.

[13] Hao Chen, Zengde Deng, Yue Xu, and Zhoujun Li. Non-recursive graph convolutional networks. In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 3205–3209. IEEE, 2021.

[14] Hao Chen, Zefan Wang, Feiran Huang, Xiao Huang, Yue Xu, Yishi Lin, Peng He, and Zhoujun Li. Generative adversarial framework for cold-start item recommendation. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 2565–2571, 2022.

[15] Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua. KGAT: Knowledge graph attention network for recommendation. In KDD, pages 950–958, 2019.

[16] Hao Chen, Yue Xu, Feiran Huang, Zengde Deng, Wenbing Huang, Senzhang Wang, Peng He, and Zhoujun Li. Label-aware graph convolutional networks. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management, pages 1977–1980, 2020.

[17] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. Neural graph collaborative filtering. In SIGIR, pages 165–174, 2019.

[18] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang. LightGCN: Simplifying and powering graph convolution network for recommendation. SIGIR, 2020.

[19] Hao Chen, Wenbing Huang, Yue Xu, Fuchun Sun, and Zhoujun Li. Graph unfolding networks. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management, pages 1981–1984, 2020.

[20] Binbin Hu, Chuan Shi, Wayne Xin Zhao, and Philip S Yu. Leveraging meta-path based context for top-N recommendation with a neural co-attention model. In KDD, pages 1531–1540, 2018.

[21] Felix Wu, Tianyi Zhang, Amauri Holanda de Souza Jr, Christopher Fifty, Tao Yu, and Kilian Q Weinberger. Simplifying graph convolutional networks. In ICML, 2019.

[22] Qimai Li, Zhichao Han, and Xiao-Ming Wu. Deeper insights into graph convolutional networks for semi-supervised learning. In AAAI, 2018.

[23] Miller McPherson, Lynn Smith-Lovin, and James M Cook. Birds of a feather: Homophily in social networks. Annual Review of Sociology, 27(1):415–444, 2001.

[24] Yuxiao Dong, Nitesh V Chawla, and Ananthram Swami. Metapath2vec: Scalable representation learning for heterogeneous networks. In KDD, pages 135–144, 2017.

[25] Ishmael Belghazi Mohamed, Baratin Aristide, Rajeshwar Sai, Ozair Sherjil, Bengio Yoshua, Courville Aaron, and Hjelm Devon. Inductive representation learning on large graphs. In ICML, 2018.

[26] Huifeng Guo, Ruiming Tang, Yunning Ye, Zhenguo Li, and Xiuqiang He. DeepFM: a factorization-machine based neural network for ctr prediction. arXiv preprint arXiv:1703.04247, 2017.

[27] Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. Field-aware factorization machines for ctr prediction. In Proceedings of the 10th ACM Conference on Recommender Systems, pages 43–50, 2016.

[28] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.