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FGCLR: An Effective Graph Contrastive Learning For Recommendation

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Abstract

Graph contrastive learning(GCL) has become a prevalent technique for graph-based recommendation. Most GCL-based methods perform stochastic augmentation on the user-item interaction graph which may change the intrinsic semantics completely and easily biased by the noise perturbation. At the same time, they adopt the traditional components of graph neural network that may not be indispensable for the collaborative filtering. We argue that these methods ignore the the inherent semantic nature and the much more sparsity data of recommendation. In this paper, we propose an eFfective Graph Contrastive Learning model for Recommendation named FGCLR. In FGCLR, graph contrastive augmentation utilizes principal component analysis(PCA) to distill global collaborative feature, and graph neural network is refined to improve its ability to fit collaborative filtering task. Empirical results on several real-world datasets show that FGCLR archives superior recommendation performance compared to state-of-the-art algorithms.

Keywords: Recommendation, Collaborative Filtering, Graph Contrastive Learning, Principal Component Analysis

1. **Introduction.** While the ever increasing use of social media and e-commerce systems, recommender systems are widely used for filtering personally interested information for users [1, 2, 3, 4, 5]. The key role of a recommender system is to extract ascertain patterns of user interest in items and provide targeted recommendations that meet users' needs. Collaborative filtering (CF) is a common strategy towards achieving effective personalized recommendations, which studies the relationships between users and the interrelationships among items to predict new user-item associations. Most collaborative filtering algorithms are dedicated to learning latent representation of users and items, and perform prediction based on the embedding vectors.

Meanwhile, recommender systems are relying more and more on deep learning techniques to acquire valuable representations of users and items through low-dimensional embeddings [6, 7, 8, 9]. Especially, Graph convolution network(GCN), who focuses on using neural networks to collect feature information from neighboring nodes within a graph, achieves promising success on collaborative filtering for recommender systems [10, 11, 12]. However, most GCN-based collaborative filtering methods are trained in a supervised manner and require abundant quality labeled data for training. To remedy this issue, graph contrastive learning(GCL) has been introduced into collaborative filtering for recommendation [13, 14]. Following the contrastive learning framework of computer vision, GCL generates a pair of different augmentations for every graph [15] , and then aims to enhancing the reciprocal information between these augmentations.

While graph contrastive learning have achieved remarkable accomplishments on collaborative filtering for recommender systems [16, 17], there are three key research gaps remain less explored: Firstly, it's worth noting that most of the existing graph contrastive learning methods adopt stochastic augmentation techniques, such as node perturbation. For example, GraphCL [14] formulates several kinds of graph augmentations. These augmentations consist of subgraph, edge perturbation, node dropping, and attribute masking. However, the intrinsic semantics of the graph could be completely altered by these augmentations and easily biased by the noise perturbation even if the perturbation is weak. For instance, changing an entry in user-item interaction graph will turn the item purchased from a handbag to a screwdriver, and inevitably it is going to hurt the inherit semantic structure by altering historical purchase information. Secondly, since the information of each node(user or item) is only denotes by a one-hot ID [10, 18], the semantic information of the user-item interaction graph is relatively rare. Furthermore, the user-item interaction usually has more sparse data than other tasks such as node classification. Therefore, it is essential to obtain key collaborative information and concrete semantics from the global perspective. Thirdly, as we all known, GCN is initially designed for node classification and integrated with multiple basic neural network operations. However, the core components of graph convolution network including nonliner function and dropout operation are not indispensable for the collaborative filtering. We argue that the design of the models should not be identical for different tasks that have the inconsistent inherent semantics data.

To solve the above questions, we attempt to revisit the graph contrastive learning paradigm for recommendation and propose an effective method FGCLR. More specifically, we utilize original graph data as $views1$ and PCA-based graph augmentation as $view2$ for contrastive learning. $View2$ is performed to not only preserve the graph intrinsic semantics but also obtain the global collaborative information from highly spare data. To

obtain the final embedding for prediction, we incorporate residual connection to combine the embeddings learned at multiple layers. Meanwhile, we perform ablation studies to prove that non-linear function and dropout operation has no contribution for collaborative filtering.

In summary, this work presents several significant contributions including:

- We introduce a novel graph contrastive learning framework to enhance the recommender systems by PCA-based graph augmentation. To the best of our knowledge, we are the first to use PCA on graph contrastive learning for recommendation.
- We propose an effective algorithm termed as FGCLR, which optimizes the GCN model design to address the identified key challenges pertaining to recommender systems.
- Experiments on several real-world datasets demonstrate that the proposed approach is capable of producing performance that is equal or superior in quality to the current state-of-the-art methods.

The ensuing sections of this work are structured as follows. Section 2 introduces related work in collaborative filtering, graph-base recommendation models and graph contrastive learning. Section 3 explains the proposed FGCLR neural networks method. Subsequently, the empirical findings are presented in Section 4. Finally, Section 5 provides our conclusions of this work.

2. **Related Works.**

In this section, we introduce collaborative filtering, graph-base recommendation models and graph contrastive learning.

2.1. **Collaborative Filtering.**

Collaborative filtering is a popular technique utilized in recommendation systems to predict user preferences. This approach involves analyzing the historical data and behavior of users, along with similar users, to generate recommendations [2, 19]. To predict potential engagement between users and items, the approach involves representing the ID of each user and item as an embedding vector, followed by utilizing dot product [20]. The core technique is the effectiveness of embedding models, since many works merge supplemental information into representation learning such as knowledge graph [21], attention mechanism [22], and user latent review [23]. Attentive collaborative filtering, for instance, can allocate weights automatically to the two levels of feedback.

2.2. **Graph-base Recommendation Models.**

Researchers are increasingly focusing on leveraging the strong nonlinear representation capabilities of deep learning to address the complex relationship between users and items [24, 25, 26]. Utilizing the intrinsic semantics of graph structures in user-item relationships for recommendation systems has been the primary focus of most research efforts [27]. Graph convolution techniques such as Laplacian eigen-decomposition [28] and Chebyshev polynomials [29] work in the spectral domain, with some recent works applying to the spatial domain, such as GCN [8], which aggregates the embeddings of neighbors to capture the target node's representation, quickly becoming a popular algorithm within GNNs [30, 31]. Since the power of graph convolution, a flood of efforts such as NGCF [32] have sprung up to draw GCN into CF using user-item interaction graph by the high-order connectivity. It is important to note that the design of different neural networks is contingent upon the specific tasks they aim to accomplish. Especially for recommendation systems, we utilize residual connection with combining embedding of layers and discard dropout operation and non-linear function.

2.3. **Graph Contrastive Learning.** The contrast between local and global representations has been harnessed by graph contrastive learning, making it a powerful self-supervised learning paradigm [33, 34, 35]. For node-level tasks, Zhu et al. [36] propose that data augmentation methods should uphold the intrinsic traits and attributes of graphs, and accordingly introduce an adaptive augmentation method that leverages diverse priors for both topological and semantic facets of the graph. On the other hand, for graph-level tasks, You et al. [14] introduce GraphCL, a method that employs four types of graph augmentations to incorporate a range of priors, and demonstrate its efficacy in the case of graph-level tasks. For CL-based recommendation systems, Lin et al. [19] propose NCL, a composite model that combines factor and neighborhood models while considering both implicit and explicit feedback from users. LightGCL [37] utilizes singular value decomposition for contrastive augmentation, which enables the unconstrained structural refinement with global collaborative relation modeling. Furthermore, we employ PCA [38] for contrastive augmentation to address the sparsity issue for recommendation.

3. **Method.** In this section, we will expound our model, as illustrated in Figure1. First, we feed the original user-item interaction graph into Local graph convolution network. Second, the PCA-based augmentation distills the global collaborative feature for graph contrastive learning. Meanwhile, only neighbor embeddings is aggregated and performed to next layer without nonlinear activation and dropout operation. Finally, we combine the InfoNCE loss [39] with pairwise loss [37] to optimize the model.

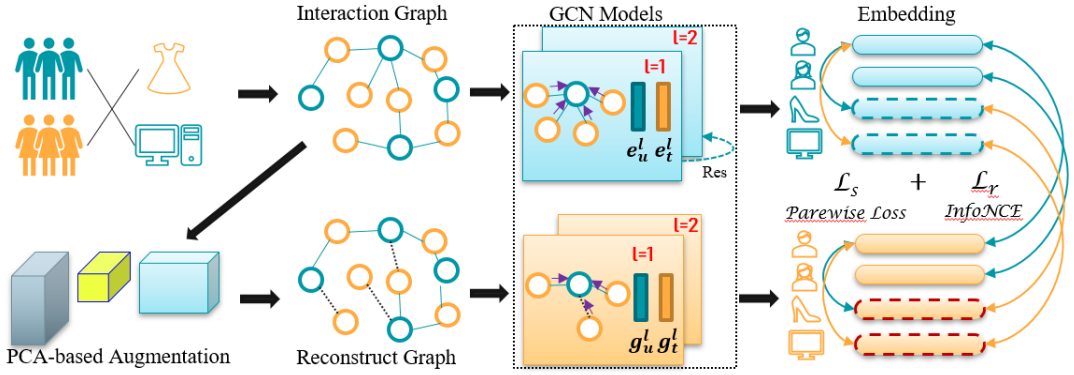

FIGURE 1. The overall framework of FGCLR.

3.1. **Matrix Form.** Consider the user-item interaction matrix denoted as $A \in \mathbb{R}^{m \times n}$, where m and n represent respectively the count of users and items involved in the interaction. For each entry a_{ut}, if user u has interacted with item t, then $a_{ij} = 1$, otherwise $a_{ij} = 0$. From the user-item interaction matrix A, we define the normalized adjacent matrix $\widetilde{A}$ as below:

$$\widetilde{A} = D_u^{-1/2} \cdot \widetilde{A} \cdot D_t^{-1/2} \tag{1}$$

where $D_u \in \mathbb{R}^{I \times I}$, $D_t \in \mathbb{R}^{J \times J}$ denotes users and items diagonal degree matrices. Each entry is calculated as:

$$\widetilde{A}_{i,j} = \frac{A_{i,j}}{\sqrt{|N_i| \cdot |N_j|}} \tag{2}$$

where N_i and N_j denote the neighboring items and users of each user or item interacted.

3.2. **Local Graph Convolution.** The primary function of Graph Convolutional Networks (GCN) is to effectively aggregate the semantic features of neighboring nodes, thereby enhancing the learning process of the representation of the target nodes. Inspired by LightGCN [37], we adopt our local graph convolution for target node as follows:

$$e_u^{l+1} = \widetilde{A} \cdot e_t^l \tag{3}$$

$$e_t^{l+1} = \widetilde{A} \cdot e_u^l \tag{4}$$

where e_u^{l+1} and e_t^{l+1} is the aggregated embedding of the l-th layer for user u and item t. $\widetilde{A}$ is the normalized adjacent matrix calculated in section 3.1.

Most of graph-based recommender models perform nonlinear activation in their paradigm. Although they perform well on some tasks such as node or graph classification whose input features have deep semantic information, nonlinear activation is found to be insignificant for collaborative filtering task [10]. Meanwhile, we also find that dropout operation imposes negative effect. In ensuring clarity regarding the impact of various operations, we perform ablation studies in Section 4.3.

3.3. **Residual Connection.** For a user or item, we obtain the ultimate representation by aggregating embedding of each layer as follows:

$$e_u = \sum_{l=0}^{L} \alpha_l \cdot e_u^l \tag{5}$$

$$e_t = \sum_{l=0}^{L} \alpha_l \cdot e_t^l \tag{6}$$

where α means the attention coefficient of the $l-th$ layer embedding in calculating the final representation. In FGCLR, we define α of each layer as follows:

$$\alpha_l = 1 - \frac{l}{L} \tag{7}$$

3.4. **PCA-based graph contrastive augmentation.** In the field of graph contrastive learning, various graph augmentations have been proposed, including but not limited to edge perturbation, attribute masking, node classification, and subgraph. Although they perform well in multiple graph-based tasks such as edge classification, those augmentations may destroy the intrinsic semantic of user-item interaction. In our model, the graph augmentation is performed by principal component analysis (PCA) to not only alleviate the sparsity issue but also draw useful global information of user-item interactions. Specifically, we employ principal component analysis on the adjacency matrix A:

$$U, S, V = PCA(\widetilde{A}, q) \tag{8}$$

where q is the required rank of $\widetilde{A}$, and $U \in \mathbb{R}^{I \times q}$, $S \in \mathbb{R}^{q \times q}$, $V \in \mathbb{R}^{q \times J}$.

The reconstruct matrix $\widehat{A}$, which is the contrastive augmentation of user-item interaction graph, is calculated using the following formula:

$$\widehat{A} = U \cdot S \cdot V \tag{9}$$

We preform feature propagation on $\widehat{A}$ as follows:

$$g_u^{l+1} = \widehat{A} \cdot e_t^l \tag{10}$$

$$g_t^{l+1} = \widehat{A} \cdot e_u^l \tag{11}$$

3.5. **Model prediction and constrastive learning.** The model's prediction is formulated as the dot product between the final representations of user and item:

$$\hat{y_{ut}} = e_u^T e_t \tag{12}$$

which is used as the prediction score for recommendation task.

Motivated by [37], we contrast the PCA-augmented view embeddings $g_{i,l}^u$ with the main-view embedding $e_{i,l}^u$ in the InfoNCE loss [40]:

$$L_s^u = \sum_i \sum_l -\log \frac{\exp\left(sim(e_{i,l}^u, g_{i,l}^u)/\tau\right)}{\sum_{i',i' \neq i} \exp\left(sim(e_{i,l}^u, g_{i',l}^u)/\tau\right)} \tag{13}$$

$$L_s^t = \sum_i \sum_l -\log \frac{\exp\left(sim(e_{i,l}^t, g_{i,l}^t)/\tau\right)}{\sum_{i',i' \neq i} \exp\left(sim(e_{i,l}^t, g_{i',l}^t)/\tau\right)} \tag{14}$$

Where sim means the cosine similarity and the temperature of the InfoNCE loss is denoted as τ. For the recommendation task, we employ the pair-wise loss as:

$$L_r = \sum_i \sum_s max(0, 1 - \hat{y}_{i,p_s} + \hat{y}_{i,n_s}) \tag{15}$$

Finally, we integrate the constrastive learning loss with pair-wise loss into a unified objective loss:

$$L = L_r + \lambda_1 \cdot (L_s^u + L_s^t) + \lambda_2 \cdot \|e^0\|^2 \tag{16}$$

We use the Adam optimizer to minimize L and implement it in a mini-batch manner.

4. **Experiments.** The datasets and experimental settings are detailed in Section 4.1, followed by a comprehensive comparison of our model against other state-of-the-art methods in Section 4.2. To justify the effective of FGCLR, we perfrom ablation studies and hyperparameter studies.

4.1. Experimental Settings.

4.1.1. *Datasets.* Our method was evaluated on three real-world datasets: $Yelp$, *Gowalla* and $Tmall$. $Yelp$ is a dataset collected from the Yelp Dataset Challenge. *Gowalla* is a dataset collected from the popular location-based social networking platform named Gowalla. $Tmall$ is a dataset collected users' puchase information in Tmall. These datasets' statistics are shown in Table 1.

The datasets are partitioned into training, validation, and test sets with a division ratio of 7:1:2. The evalutation metrics are recall@20, recall@40, ndcg@20 and ndcg@40 which are widely used in recommendation task.

TABLE 1. Datasets statistics

Datasets	User #	Item #	Interaction #	Density
Yelp	29601	24734	1517326	0.00207
Gowalla	50821	57440	1172425	0.00040
Tmall	47939	41390	2357450	0.00119

4.1.2. *Comparision Methods.* In the experiments, we compared FGCLR against some state-of-the-art baselines with typical recommendation paradigms including GNN-based collaborative filtering model and self-supervised learning for recommendation.

GRACE [36]**:** This baseline proposes to destroy the graph structure through random edge discarding and random node feature dropping, and uses the destroyed graph as a comparison view.

LightGCN [10]**:** This model adopts a simplified GCN structure which leverages a linear propagation technique to determine the aggregated sum of the acquired embeddings across all layers through weight computation.

LightGCL [37]**:** This method proposes to utilizes singular value decomposition for contrastive augmentation which enables the unconstrained structural refinement with global collaborative.

4.1.3. *Hyper-parameter Settings.* In FGCLR, we use Adam optimizer [39] with the default learning rate 0.001 and mini-batch size of 256. The regularization coefficient λ_1 and λ_2 are respectively searched in the list of $\{1e-5, 1e-6, 1e-7\}$ and $\{1e-4, 1e-5\}$. The temperature τ is searched from $\{0.1, 0.3, 0.5, 1, 2\}$. The rank of PCA is searched from $\{2, 4, 6, 10, 20\}$. A constant embedding size of 32 is fixed across all models, while employing the Xavier method for embedding parameter initialization[41]. For GCN networks, we use two convolution layers.

4.2. **Performance Comparison and Analysis.** Table 2 shows the performance comparison with competing methods mentioned in Section 4.1.2 with three datasets. Bold text highlights the best results in these tables. Based on the information in the table, we can make the following observations.

1. Our model consistently demonstrates superior performance when compared to other methods on all three datasets. It is worth noting that in Tmall dataset, the recall@20 evalutation metrics of FGCLR is six percentage points better than LightGCL, which was the best among the evaluated baselines. This outcome provides compelling evidence of the efficacy and suitability of our model for recommendation tasks.
2. LightGCL demonstrated the most superior performance among the evaluated baselines, outperforming both GRACE and LightGCN. However, our FGCLR performs better than LightGCL in all datasets, the observed increase in performance can be attributed to the optimized graph convolution. We discard nonlinear activation and dropout operation which have no contribution even negative effect for collaborative filtering.
3. It is noteworthy from our empirical findings that the performance of GRACE is at par with that of LightGCN. Compared with GRACE and LightGCN, FGCLR adopts PCA-based augmentation without biased by stochastic augmentation, and distills the global semantics information from highly spare data.

4.3. **Ablation and Effectiveness Analysis.** We perform the ablation study to explore the effect of dropout operation and nonlinear activation. We implement three simplified variants of FGCLR:

TABLE 2. Experimental results on three real-world datasets

Datasets	Yelp				Gowalla				Tmall			
Method	R@20	N@20	R@40	N@40	R@20	N@20	R@40	N@40	R@20	N@20	R@40	N@40
GRACE	0.0680	0.0495	0.1012	0.0702	0.0891	0.0543	0.1332	0.0697	0.0258	0.0160	0.0426	0.0217
LightGCN	0.0525	0.0449	0.880	0.0607	0.1185	0.0785	0.1612	0.0925	0.0257	0.0211	0.0425	0.0269
LightGCL	0.0782	0.0667	0.1291	0.0854	0.1579	0.0934	0.2261	0.1111	0.0526	0.0361	0.0860	0.0479
ours	**0.0833**	**0.0707**	**0.1352**	**0.0897**	**0.1622**	**0.0957**	**0.2293**	**0.1133**	**0.0558**	**0.0380**	**0.0889**	**0.0496**

$FGCLR_{-d+l}$**:** which utilizes the non-linear activation function but removes dropout operation.

$FGCLR_{+d-l}$**:** which includes dropout operation but discards the non-linear activation function.

$FGCLR_{+d+l}$**:** which implements not only dropout operation but also non-linear activation function.

We keep all hyper-parameters to be same for the three variants. As shown in Table 3, discarding dropout operation and non-linear activation function leads to consistent improvements. From these observations, we can draw following conclusions:

- Adding dropout operation cannot improve the effect on FGCLR.
- Adding nonlinear activation imposes negative effect significantly.
- As a whole, dropout operation and nonlinear activation improve to be negative in results. In order to keep graph representation learning simple and effective, we discard both of them on our model.

TABLE 3. Ablation study on FGCLR

Datasets	Yelp				Gowalla				Tmall			
Method	R@20	N@20	R@40	N@40	R@20	N@20	R@40	N@40	R@20	N@20	R@40	N@40
$FGCLR_{-d+l}$	0.0829	0.0701	0.1337	0.0888	0.1597	0.0939	0.2304	0.1122	0.0548	0.0367	0.0870	0.0489
$FGCLR_{+d-l}$	0.0812	0.0685	0.1312	0.0869	0.1584	0.0938	0.2255	0.1114	0.0542	0.0361	0.0863	0.0478
$FGCLR_{+d+l}$	0.0809	0.0685	0.1305	0.0868	0.1574	0.0933	0.2259	0.1111	0.0533	0.0349	0.0848	0.0467
FGCL	**0.0833**	**0.0707**	**0.1352**	**0.0897**	**0.1622**	**0.0957**	**0.2293**	**0.1133**	**0.0558**	**0.0380**	**0.0889**	**0.0496**

4.4. **Hyper-parameter Sensitivity Analysis.** For our model, the important hyper-parameters include regularization coefficient λ_1, the temperature τ and q the rank of PCA.

- As shown in Figure2, FGCLR is relatively insensitive to λ_1. For the three datasets, the optimal value is $1e^{-7}$.
- The hyper-parameter q determines the rank of PCA. Figure 3 shows that $q = 6$ can obtain satisfactory experiment results. when q is larger than 10, the performance drops quickly.
- The temperature parameter τ determines the degree of attention paid to difficult negative samples by comparison loss. From results in Figure 4, by setting the parameter τ to a value of 0.5, it is evident that optimal beat performance can be achieved.

5. **Conclusion.** In this paper, we propose an effective graph contrastive learning model named FGCLR for recommendation. FGCLR consists of two major components, *i.e.*, PCA-based graph augmentation and improved graph convolution. In PCA-based graph

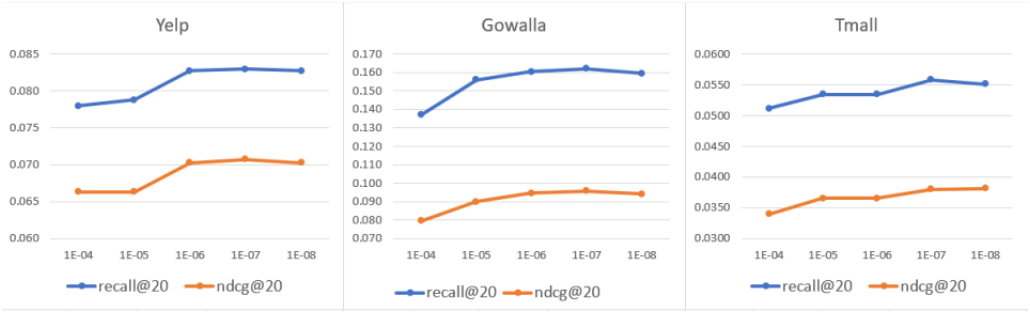

FIGURE 2. Performance w.r.t different λ

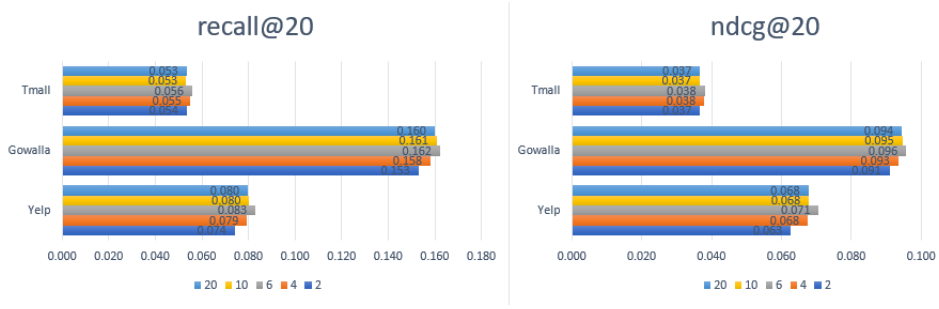

FIGURE 3. Recall and ndcg w.r.t q

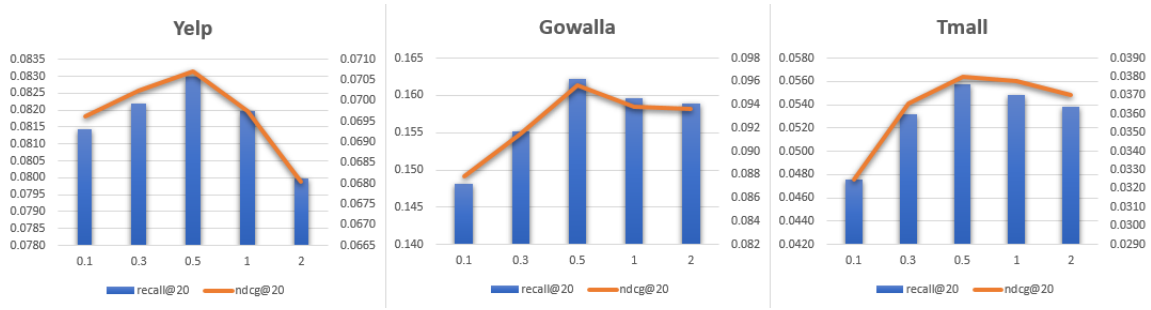

FIGURE 4. Performance w.r.t different τ

augmentation, we distill significant collaborative signals from the origin graph. In improved graph convolution, we discard nonlinear activation and dropout operation which have no contribution for collaborative filtering. Our experimental analysis demonstrates that the proposed model outperforms existing state-of-the-art solutions on several real world public datasets.

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