Feature Re-enhanced Meta-Contrastive Learning for Recommendation

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***Abstract*—Enhancing the performance of recommendation systems through joint modeling of user-item interactions and knowledge graph (KG) information using Graph Neural Networks (GNN) has shown promising results. However, due to the cold-start problem and inherent sparsity in graph data, the effectiveness of extracting informative features from the graph data is often limited. Existing approaches mostly focus on enhancing the original embeddings.It is imperative to develop a comprehensive and effective multi-faceted feature enhancement strategy that assists in augmenting information during the feature transfer process.In this paper, we present a novel framework for recommendation called Feature Re-enhanced Meta Contrastive Learning (FReML). The framework employs a simple self-gating mechanism to handle the features in the interaction view, enhancing the correlation between user and item features. It utilizes a multi-layer perceptron approach for meta-feature extraction on both the interaction view and the knowledge graph view, aiming to enhance the performance of contrastive learning. We evaluate our proposed framework on real-world datasets and demonstrate improved training results compared to state-of-the-art approaches. Further ablation analysis validates the rationality of the key component designs.**

***Keywords*-artificial intelligence; recommendation systems; feature re-enhancement; self-gating;meta-learning**

I. Introduction

In recent years, the development of smart cities has presented new opportunities and challenges for recommendation systems [3]. As urban areas expand and people demand more convenient and personalized services, recommendation systems play a crucial role in smart cities [4]. Traditional recommendation algorithms are mainly based on modeling user-item interaction data and predicting future preferences by analyzing users' historical behavior [1] [2]. However, the sparsity of interaction data due to factors such as low user engagement, behavioral inertia, and privacy concerns often renders this approach inadequate in addressing the challenges of cold-start and data sparsity. To overcome these issues, researchers have begun incorporating knowledge graphs (KGs) into recommendation systems to enrich the representation of relationships between users and items [5] [18]. KG is a structured data representation that organizes information in terms of entities and relationships and provides rich semantic information and contextual associations [6]. By jointly modeling user-item interaction data with KG, complex relationships between users and items can be more accurately captured, thus improving the performance of recommendation systems.KGAT [13] focuses on various edge types in collaborative knowledge graphs (CKG) and improves recommendation performance by aggregating messages through attention mechanisms.DPAO [18] uses reinforcement learning to adaptively aggregate higher-order features to enhance feature representation.KGCL [17] integrates the knowledge enhancement mode into the cross view CL module to reduce the influence of information noise on the knowledge graph enhancement recommendation system.

However, despite achieving some success in recommendation systems, joint modeling approaches still face certain challenges. The cold-start problem and sparsity of graph data remain issues [19], as valuable information in the graph data often cannot be fully extracted and utilized. To tackle the aforementioned challenges, this study proposes a new framework called Feature re-enhancement based Meta Contrastive Learning. Aiming to assist recommendation systems, our approach not only applies GNN for feature transformation but also conducts information enhancement during the process of feature transfer. Inspired by [20] and [21], we adopt a simple yet effective self-gating mechanism to process features from the interaction view, allowing for adaptive learning during optimization to strengthen the feature correlations between users and items while mitigating the influence of redundant information. Furthermore, by leveraging the concept of simple residual learning [23] and employing a multilayer perceptron approach [22], we extract meta-features from both the interaction view and the knowledge graph view. Through nonlinear transformations, higher-level features are extracted to facilitate better learning of sample similarities or differences, ultimately enhancing the performance of dual-view contrastive learning.

Our contributions are outlined as follows: We propose a new approach for enhancing information in the representation of user/item features in the interaction view by utilizing a self-gating mechanism;We employ multilayer perceptrons in the meta-network to extract meta-features and perform contrastive learning on both the interaction and knowledge graph views through nonlinear transformations, which helps address performance issues resulting from sparse data;Compared to existing state-of-the-art methods, our approach yields better training results. Further ablation analysis validates the rationale behind our key component design.

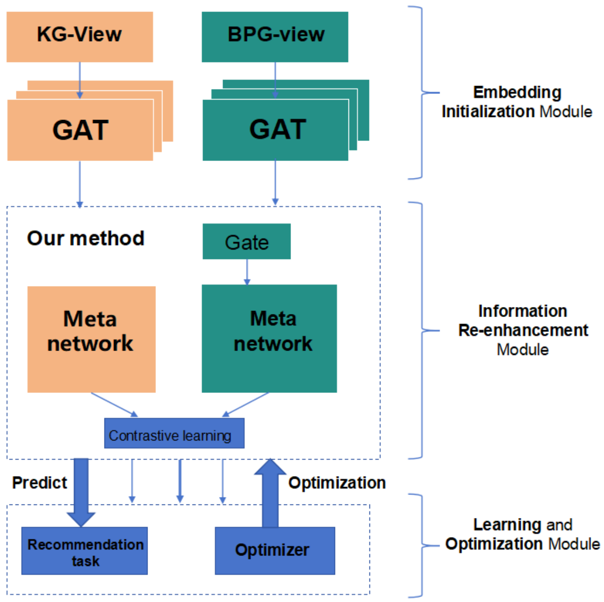

Figure 1. An overview of the FReML framework.

II. Related Work

A. GNN-based Recommender Systems

In general, Graph Neural Networks (GNNs) adhere to the concept of propagating messages across different graph layers. Within the framework of GNN, numerous GNN-based recommendation systems have been proposed to capture various graph structural relationships in recommendation settings. For instance, LightGCN [29]modifies the aggregation process by removing activation functions and feature transformation matrices. KGAT [13] focuses on various types of edges in the Collaborative Knowledge Graph (CKG) and aggregates messages based on attention scores.

By incorporating GNN architectures into recommendation systems, researchers have developed various GNN-based models that exploit the power of message passing and aggregation mechanisms. These models aim to capture the rich interactions and dependencies between users, items, and other entities present in recommendation graphs. The GNN-based recommendation models often incorporate techniques such as graph convolutional networks (GCNs) [31], graph attention networks (GATs) [30], and graph pooling operations to effectively capture and leverage the graph structure [32]. In summary, GNN-based recommendation systems can produce more accurate and personalized recommendations, efficiently handle sparse and noisy data, and capture higher-order dependencies in the data.

B. Contrastive Learning for Recommendation

Recently, contrastive self-supervised learning has gained significant attention in academia. Its primary motivation lies in enriching user representation learning by generating self-supervised signals [7]. In the field of recommendation systems, contrastive learning is regarded as a powerful technique that combines self-supervised signals with the consistency between contrastive representation views to achieve data augmentation. Among various contrastive learning models, contrastive methods based on InfoNCE [7] are more widely used due to their ability to improve embedding uniformity.

Contrastive self-supervised learning is an unsupervised learning approach that generates self-supervised signals by comparing differences between different samples or views. In the context of recommendation systems, contrastive learning leverages user behavior data and item attributes to construct sample pairs or view pairs for comparison. The model learns to distinguish positive sample pairs from negative sample pairs, i.e., pairs with high similarity and low similarity, thereby capturing underlying patterns and correlations in the data, leading to a better understanding of user interests and preferences [8]. In our approach, re-enhancing feature representation contributes to the improvement of contrastive learning effectiveness.

III. Methodology

In this section, we will introduce our model, **FReML**. We propose a feature re-enhancement approach based on a self-gating mechanism, aiming to improve the effectiveness of dual-view contrastive learning results in the context of recommendation systems. Additionally, we utilize a meta-network to extract meta-features [22], further enhancing the quality of our approach. The ultimate goal is to boost the recommendation performance and demonstrate the efficacy of our proposed method.

A. Embedding Initialization Module

1) Dual-view embedding: Our study employs two views, with the knowledge graph serving as the raw data for the knowledge view and the user/item bipartite graph serving as the raw data for the interaction view. In the embedding process of these two views, we utilize the dropout mechanism to filter out noise and information that is irrelevant to the recommendation task [24]. This involves applying a combination of non-learnable perturbations and learnable removals to a subset of edges. The following is the initial embed:

$$E_f^0 = h_u^0 || h_v^0 \tag{1}$$

$$E_k^0 = M_r^k(e_h^0 || h_t^0) \tag{2}$$

Where E_k^0, E_f^0 can be translated as the initial embedding of the knowledge view and the interaction view . M_r^k represents

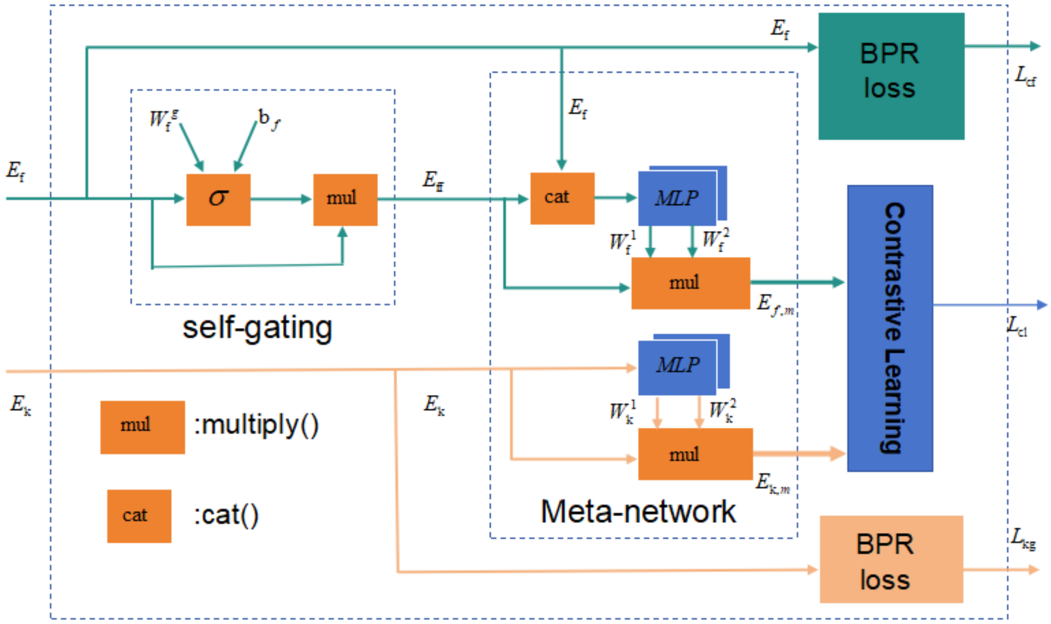

Figure 2. The figure shows Feature the Re-enhancement module and the Meta-feature Extraction module in detail.

the transformation matrix of the relation r. Regarding the learnable removal method, we utilize a dropout approach whereby edges are selectively eliminated based on their probability score. During training, each edge is assigned a specific dropout probability, and edges with probabilities exceeding a predefined threshold are removed. By applying this approach, we enable the model to effectively discard edges that are noisy or unrelated to the recommendation task, leading to improved embeddings in both views:

$$p_e^f = sigmoid((log(\varepsilon) - log(1-\varepsilon) + MLP(E_f^0))/\tau_f) \tag{3}$$

The random variable ε ranges from 0 to 1 [25]. $MLP(\cdot)$ denotes the multilayer perceptron embedding layer. τ_f and τ_k are temperature hyperparameters, respectively p_e^f is calculated using a similar method.

2) Graph Attention Network: For the filtered interaction and knowledge views, we employ graph neural network-based encoders to capture the higher-order structural context of node representations. Inspired by [13], an attention mechanism is adopted to better capture the importance of different relationships between nodes, allowing the model to adaptively weight them. Additionally, the model exhibits robustness to outliers and noise:

$$\alpha_{ij} = \frac{\exp(\sigma(a_f[W_f h_i || W_f h_j]))}{\sum_{k\in\mathcal{N}_i}\exp(\sigma(a_f[W_f h_i || W_f h_k])} \tag{4}$$

$$\alpha_{ht} = \frac{\exp(\sigma(a_k[W_k e_h || W_r m_r || W_k e_t]))}{\sum_{k\in\mathcal{N}_h}\exp(\sigma(a_k[W_k e_h || W_r m_r || W_k e_k])} \tag{5}$$

Where α_{ij} represents the attention score from node i to node j in the interaction view, while α_{ht} represents the attention score from entity h to entity t in the knowledge view. m_r denotes the embedded representation of the relationship between the respective entities. W_f and a_f are trainable parameters. $\sigma(\cdot)$ is the $LeakReLU$ activation function.

B. Information Re-enhancement Module

1) Feature Re-enhancement: Through the self-gating module, the interactive view can dynamically update weights according to users' different behaviors to better express the relationship between users and items. It can help solve the sparsity problem in the interactive view, where many users have only rated or interacted with a small number of items, resulting in a lot of missing data and sparse matrices [20]. The self-gating module can dynamically update weights by focusing more attention on important items in the user interaction process, thus facilitating the resolution of the sparsity problem. From the perspective of computational efficiency and model complexity, the self-gating module introduces additional parameters and computational operations, which increases the model complexity. For the knowledge graph view, it already meets the requirements and achieves good performance, and adding the self-gating module is unnecessary for reducing computational costs and model complexity [21]. Here we present a method for feature enhancement via the self-gating module:

$$E_f^{'} = softmax(E_f W_f^g + b_f) \tag{6}$$

$$E_{ff} = E_f \odot E_f^{'} \tag{7}$$

Here, $W_f^g \in \mathbb{R}^{d \times d}$ and $b_f \in \mathbb{R}^{d \times 1}$ are the hyperparameters that we need to learn. $\odot$ represents element-wise multiplication.

2) Meta-feature Extraction: The purpose of performing meta-feature extraction is to enhance the contrastive learning of dual-view images, in order to adapt to contrast-enhanced personalized knowledge transformers. Simultaneously, more meaningful representations are learned, and the embedded vectors transformed by the meta-network may contain more useful information, enabling better description of the similarity or dissimilarity between samples [23]. The meta-network can extract higher-level features through nonlinear transformations, thereby assisting the model in better discriminating samples from different categories. Additionally, it can reduce noise or variations among samples. By using the meta-network [26], it is possible to normalize or regularize the embedded vectors, reducing the impact of such variations on the final contrastive learning results. The relevant formula is as follows:

$$F_{mlp}^{1,f}(E_{ff}, E_f) \rightarrow W_f^1 \tag{8}$$

$$F_{mlp}^{1,k}(E_k) \rightarrow W_k^1 \tag{9}$$

Where E_{ff} is the embedded output of the interactive view after feature re-enhancement. $F_{mlp}^{1,f}(\cdot)$ and $F_{mlp}^{1,k}()$ are multi-layer perceptron processing functions for two views, respectively [22]. W_f^2 and W_k^2 are calculated in a similar way.

$$E_{f,m} = W_f^1 W_f^2 E_{ff} \tag{10}$$

$$E_{k,m} = W_k^1 W_k^2 E_k \tag{11}$$

The embedded output E_{ff} and E_k of the previous module are multiplied by the weight parameters W^1 and W^2 of this module respectively using the idea of simple residuals.

C. Learning and Optimization

1) Dual-view Learning: We have employed the Bayesian Personalized Ranking (BPR) loss[7], which is a pairwise loss. This loss encourages predictions on observed items over unobserved items of the same kind. The original interaction view and the knowledge view use similar computational loss calculation functions. The formula for BPR loss of interactive view is as follows:

$$\mathcal{L}_{cf(u,v^+,v^-)} = -log(sigmoid(y(u, v^+) - y(u, v^-))) \tag{12}$$

where (u, v^+) is the positive interaction, (u, v^-) is a random negative interaction. $y(\cdot)$ is the user preference function for interactive view loss calculation. The formula for knowledge view [27] BPR loss is as follows:

$$\mathcal{L}_{kg(h,r,t^+,t^-)} = -log(sigmoid(e_h^T R_r e_{t^+} - e_h^T R_r e_{t^-})) \tag{13}$$

where (h, r, t^+) is a positive triplet in knowledge graph and (h, r, t^-) is a negative one by replacing tail entity randomly.

2) Contrast learning and optimization: Through the work of the feature enhancement module, we get two sets of embedded representations $E_{f,m}$ and $E_{k,m}$ We adopted InfoNCE [7]information loss calculation method as a comparative learning between the two views in order to obtain a more effective information representation. We use the choices in [8] to compare matching strategies. The goal is to encourage the retention of information shared in both the interactive view and the knowledge view.:

$$\mathcal{L}_{cl(v)} = -log \frac{\exp(s(e_v^f, e_v^k)/\tau_{cl})}{\sum_{j \in \mathcal{N}} \exp(s(e_v^f, e_j^k)/\tau_{cl}) + \exp(s(e_j^f, e_v^k)/\tau_{cl})} \tag{14}$$

where $s(\cdot)$ measures the cosine similarity of two vectors, and τ_{cl} is the temperature hyper-parameter. Where $[e_v^f, e_v^k]$ represents an embedded representation of the same item in both views. $\mathcal{N}$ is the set of negative samples. The following is the overall optimization function:

$$\mathcal{L} = \mathcal{L}_{cf} + \beta_1 \mathcal{L}_{cl} + \beta_2 \mathcal{L}_{kg} \tag{15}$$

IV. EXPERIMENTS

A. Datasets and Setting

We utilize the last-fm dataset [18] and the movie-lens dataset [8]. The former is a music recommendation class dataset that, for each user in the dataset, contains a list of their most popular artists and the number of plays. The latter is a collection of movie ratings. Both include the interaction of user items and social information between users, as well as the connections between items. The dataset last-fm, in particular, exhibits a larger magnitude and higher degree of sparsity.

We used the following recommendation system models as our baseline: Classical model BPR-MF [9] based only on interaction graphs, and models CKE [10], KGCN [11], KGNNLS [12], KGAT [13], CKAN [14], KGPL [15], KACL [8], DSKReG [16], KGCL [17] based on knowledge graphs. Hyperparameters β_1 and β_2 that integrate the three losses are 0.1 and 1, respectively. All learning rates were set to 0.0001, and the decay rate was set to 0.7. The output dimension of each layer in the graph attention network is [64, 32, 16]. We implemented an early stopping mechanism to halt the training process after 10 consecutive iterations without improvement. The training was conducted on an RTX3090 graphics card.

B. Experimental Result

1) Main Results: We compared our proposed FReML model with state-of-the-art baselines using the Recall@K and NDCG@K evaluation metrics, where K=20. As shown

Table I
PERFORMANCE OF OTHER METHODS ON DIFFERENT DATA SETS COMPARED WITH OURS ON NDCG@20 AND RECALL@20.

%	Metric	BPR-MF	CKE	KGCN	KGNNLS	KGAT	CKAN	KGPL	KGCL	KACL	OUR
Movielens	RECALL	-11.89	-10.72	-7.87	-8.28	-1.45	-6.20	-3.96	-1.80	0.0	**+0.72**
Movielens	NDCG	-14.82	-12.86	-10.12	-10.51	-1.83	-5.62	-6.50	-3.13	0.0	**+1.31**
LastFM	RECALL	-21.26	-17.84	-9.80	-11.23	-3.41	-10.57	-1.32	-0.99	0.0	**+1.21**
LastFM	NDCG	-19.37	-17.47	-10.76	-12.03	-5.19	-12.67	-4.94	+0.38	0.0	**+1.77**

Table II
STATISTICS OF EXPERIMENTED DATASETS.

datasets	Entities	Relations	Triplets	Users	Items	Interactions	Sparsity
Movielens	24882	20	237155	27385	9904	539300	**99.8012%**
LastFM	106389	9	464567	23566	48123	3034763	**99.7324%**

Table III
ABLATION STUDY.

%	Movielens	Movielens	LastFM	LastFM
Metric	RECALL	NDCG	RECALL	NDCG
F-En w/o	-6.13	-7.86	-1.96	-2.11
M-Con w/o	-0.71	-1.29	-1.20	-1.74
OUR	0.0	0.0	0.0	0.0

in Table 1, our FReML model demonstrates significant improvements over the current state-of-the-art models, indicating that our feature enhancement method based on gate mechanism and meta-network successfully extracts more effective representations from the knowledge view and interaction view. Based on the results, we observed performance improvements over the baselines, with more pronounced improvements on the last-fm dataset. By comparing the data features in Table 2, we infer that our method can perform even better on larger-scale datasets. The relative improvement in NDCG is more prominent, reflecting the model's better performance in ranking, thus confirming the positive impact of our feature enhancement method on improving the accuracy of recommendation rankings, which aligns with our intention.

2) Ablation Results: As shown in Table 3, this part is designed to evaluate the effectiveness of each component. "F-En w/o" indicates the removal of the feature enhancement module based on gate mechanism, while "M-Con w/o" indicates the removal of the meta-contrastive learning module. By comparing the experimental data from the ablation experiments, we found that removing the feature enhancement module while keeping the meta-contrastive learning module actually decreases the performance compared to the baseline, indicating that conducting only meta-feature extraction would increase the complexity of the model and reduce the expressive power of features. Furthermore, it also demonstrates the indispensable auxiliary role of feature enhancement in meta-contrastive learning. The removal of modules leads to a relatively greater decrease in the NDCG metric, once again validating the positive effect of our model on recommendation ranking. Overall, it reflects the effectiveness of jointly applying both modules in our model.

V. CONCLUSION

Through this research, we propose a feature re-enhanced meta-contrastive learning framework called FReML, which aims to address the challenges of cold-start and data sparsity in recommendation systems [28]. This framework employs self-gating mechanisms and multi-layer perceptron methods to process the features from interaction views, reinforcing the feature association between users and items. By employing meta-feature extraction and contrastive learning, we enhance the performance of the model. This framework holds significant implications for improving the performance of recommendation systems. Future research can further explore and optimize this method to adapt to more complex and larger-scale recommendation system scenarios.

REFERENCES

[1] Wu, Shiwen and Sun, Fei and Zhang, Wentao and Xie, Xu and Cui, Bin, *Graph Neural Networks in Recommender Systems: A Survey*. ACM Comput. Surv., 1999.

[2] Xiao Li and Li Sun and Mengjie Ling and Yan Peng, *A survey of graph neural network based recommendation in social*. Neurocomputing, 2023.

[3] Zhang C, Duan X, Liu F, Li X, Liu S, *Three-way naive Bayesian collaborative filtering recommendation model for smart city*. Sustainable Cities and Society, 2022.

[4] Ahmed ST, Kumar V, Kim J, *AITel: eHealth Augmented Intelligence based Telemedicine Resource Recommendation Framework for IoT devices in Smart cities*. IEEE Internet of Things Journal, 2023.

[5] Ma, Ting and Huang, Longtao and Lu, Qianqian and Hu, Songlin, *KR-GCN: Knowledge-Aware Reasoning with Graph Convolution Network for Explainable Recommendation*. Association for Computing Machinery, 2023.

[6] Fanourakis, N., Efthymiou, V., Kotzinos, D. et al, *Knowledge graph embedding methods for entity alignment: experimental review*. Applied Sciences, 2023.

[7] Xiao Wang, Nian Liu, Hui Han, and Chuan Shi, *Self-supervised heterogeneous graph neural network with co-contrastive learning*. KDD '21, 2021.

[8] Wang, Hao, Yao Xu, Cheng Yang, Chuan Shi, Xin Li, Ning Guo, and Zhiyuan Liu, *Knowledge-Adaptive Contrastive Learning for Recommendation*. Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining, 2023.

[9] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme, *BPR: Bayesian personalized ranking from implicit feedback*. arXiv, 2012.

[10] Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian, Xing Xie, and Wei-Ying Ma, *Collaborative knowledge base embedding for recommender systems*. Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, 2016.

[11] HongweiWang, Miao Zhao, Xing Xie,Wenjie Li, and Minyi Guo, *Knowledge Graph Convolutional Networks for Recommender Systems*. WWW, 2019.

[12] Hongwei Wang, Fuzheng Zhang, Mengdi Zhang, Jure Leskovec, Miao Zhao, Wenjie Li, and ZhongyuanWang, *Knowledge-aware graph neural networks with label smoothness regularization for recommender systems*. Proceedings ofthe 25th ACMSIGKDD international conference on knowledge discovery and data mining, 2019.

[13] Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua, *Kgat: Knowledge graph attention network for recommendation*. Proceedings ofthe 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2019.

[14] Ze Wang, Guangyan Lin, Huobin Tan, Qinghong Chen, and Xiyang Liu, *CKAN: Collaborative Knowledge-aware Attentive Network for Recommender Systems*. SIGIR, 2020.

[15] Xiang Wang, Tinglin Huang, Dingxian Wang, Yancheng Yuan, Zhenguang Liu, Xiangnan He, and Tat-Seng Chua, *Learning Intents behind Interactions with Knowledge Graph for Recommendation*. Proceedings ofthe Web Conference, 2021.

[16] Yu Wang, Zhiwei Liu, Ziwei Fan, Lichao Sun, and Philip S Yu, *Dskreg: Differentiable sampling on knowledge graph for recommendation with relational gnn*. Proceedings ofthe 30th ACM International Conference on Information and Knowledge Management, 2021.

[17] Yuhao Yang, Chao Huang, Lianghao Xia, and Chenliang Li, *Knowledge Graph Contrastive Learning for Recommendation*. arXiv, 2022.

[18] Jung, Heesoo, Sangpil Kim, and Hogun Park, *Dual Policy Learning for Aggregation Optimization in Graph Neural Network-based Recommender Systems*. Proceedings of the ACM Web Conference, 2023.

[19] Ahmadian, Milad, Mahmood Ahmadi, and Sajad Ahmadian, *A reliable deep representation learning to improve trust-aware recommendation systems*. Expert Systems with Applications, 2022.

[20] Junliang Yu, Hongzhi Yin, Jundong Li, Qinyong Wang, Nguyen Quoc Viet Hung, and Xiangliang Zhang, *Self-supervised multi-channel hypergraph convolutional network for social recommendation*. WWW '21, 2021.

[21] Liu C, Li Y, Lin H, Zhang C, *GNNRec: Gated graph neural network for session-based social recommendation model*. Journal of Intelligent Information Systems, 2023.

[22] Yannam VR, Kumar J, Babu KS, Sahoo B, *Improving group recommendation using deep collaborative filtering approach*. International Journal of Information Technology, 2023.

[23] Cafer Budak, Vasfiye Menc¸ik, and Veysel Gider, *Determining similarities of covid-19 – lung cancer drugs and affinity binding mode analysis by graph neural network-based gefa method*. Journal of Biomolecular Structure and Dynamics, 2023.

[24] Mengru Chen, Chao Huang, Lianghao Xia, Wei Wei, Yong Xu, and Ronghua Luo, *Heterogeneous graph contrastive learning for recommendation*. WSDM '23, 2023.

[25] Dongsheng Luo, Wei Cheng, Dongkuan Xu,Wenchao Yu, Bo Zong, Haifeng Chen, and Xiang Zhang, *Parameterized Explainer for Graph Neural Network*. Advances in Neural Information Processing Systems, 2020.

[26] Chen, Mengru and Huang, Chao and Xia, Lianghao and Wei, Wei and Xu, Yong and Luo, Ronghua, *Heterogeneous Graph Contrastive Learning for Recommendation*. Association for Computing Machinery, 2023.

[27] Bishan Yang, Wen-tau Yih, Xiaodong He, Jianfeng Gao, and Li Deng, *Embedding entities and relations for learning and inference in knowledge bases*. arXiv, 2014.

[28] Shalaby W, Oh S, Afsharinejad A, Kumar S, Cui X, *M2TRec: Metadata-aware Multi-task Transformer for Large-scale and Cold-start free Session-based Recommendations*. Proceedings of the 16th ACM Conference on Recommender Systems, 2022.

[29] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang, *Lightgcn: Simplifying and powering graph convolution network for recommendation*. Proc. ofSIGIR, 2020.

[30] Wang S, Hu L, Wang Y, He X, Sheng QZ, Orgun MA, Cao L, Ricci F, Yu PS, *Graph learning based recommender systems: A review*. arXiv, 2021.

[31] Liu H, Wei Y, Yin J, Nie L, *HS-GCN: hamming spatial graph convolutional networks for recommendation*. IEEE Transactions on Knowledge and Data Engineering, 2022.

[32] Abadal S, Jain A, Guirado R, López-Alonso J, Alarcón E, *Computing graph neural networks: A survey from algorithms to accelerators*. ACM Computing Surveys (CSUR), 2021.