Knowledge-aware Recommendation with Attention Mechanism and Contrastive Learning

Cuihong Chen, Gang Sun*

Abstract—**Knowledge graph (KG) is important in recommendation algorithms. For the past few years, graph neural networks (GNNs) models applied to knowledge-aware recommendation (KGR) have been a current research hotspot. However, GNN-based KGR models have some problems, eg. data sparsity, insufficient supervision indication, unbalanced information utilization, and insufficient knowledge extraction. This paper presents a knowledge-aware recommendation algorithm that integrates an attention mechanism with contrastive learning, thereby make the most of the rich entity information available in the KG. Through contrastive learning, the algorithm aims to derive more discriminative expressions for users and items, and the attention mechanism helps to identify key relationships between them. This dual way improves the accuracy and efficiency of recommendations. Firstly, by contrasting hierarchical structures within the KG, non-local graphs are constructed for users and items, facilitating the extraction of additional KG facts in KGR. Secondly, Intra-graph-level interactive contrastive learning is enforced within both non-local graphs to evaluate the levels of collaborative filtering alongside the KG part, so as to obtain more consistent information utilization. In addition, inter-graph-level interactive contrastive learning is implemented between non-local graphs to fully and effectively extract non-local KG indication. Finally, the attention mechanism is integrated to determine the consequence of node neighbors and adaptively propagate the embeddings from the neighbors of nodes. The proposed knowledge-aware recommendation algorithm (KGAC) in this paper, along with other recommendation algorithms, has been subjected to extensive experimentation across three benchmark data sets. The results of these tests confirm that KGAC outperforms other algorithms in terms of recommendation performance.**

Keywords: recommendation, knowledge graph, contrastive learning, attention mechanism.

I. Introduction

For the past few years, the progress of artificial intelligence, big data mining and other technologies has become more and more rapid, the society are becoming more and more informationalized, and there are more and more ways of information transmission. Recommender system is a key technology for providing users with personalized recommendations in massive amounts of information. It predicts the products or contents that users may be interested in by analyzing their behavior, preferences and historical data. recommendation systems usually use multiple algorithms [1-5], including collaborative filtering (CF), content filtering, hybrid recommendation, etc., to offer more exact personalized recommendations. However, traditional CF ways are often limited by data sparseness and cold-start matters, resulting in poor recommendation effects. To settle these matters, some research fellows have incorporated knowledge graph (KG) in the recommendation process [6-8]. KG is a structured semantic network for revealing relationships between entities in the actual world. As a structured representation of knowledge, KG encompass rich information regarding object attributes and relationships. Knowledge-aware recommendation (KGR) techniques for integrating knowledge graphs in recommender systems have garnered significant attention. In fact, there are many research works have been done about KGR [9-11], aiming to fully and consistently utilize the graphical information of CF (i.e., user-item interaction [4, 5]) and KG (i.e., item-entity relationship). A collaborative knowledge graph (CKG) has been proposed, which unites KG with user-item interaction data. This approach utilizes the intricate multi-level connectivity of knowledge graph to promote the nature of recommender systems. However, using such higher-order relationships would face many ignored challenges: 1) When the order raises, the amount of nodes with high-order connections with the object user will then raise dramatically, which will result in more computational burden and noise to the model. 2) The contributions of high-order relationships to prediction are unequal. This requires the model to assign different weights to them.

Contrastive learning can help address issues eg. insufficient supervised indication, unbalanced information utilization, and limited knowledge extraction. The attention mechanism makes the model more concern about vital information by giving it more weight [12][13]. For this reason, this paper designs a knowledge-aware recommendation algorithm (KGAC) that uses the attention mechanism and contrastive learning. Firstly, the KGAC algorithm acquires entity information from the KG. Then, it uses contrastive learning to study more discriminative user and object representations, incorporating the attention mechanism to capture key relationships between them. Finally, many tests are carried out on three benchmark data sets and compared with other recommendation algorithms.

Our achievements of this paper are summarized as below:

1. Novel Methodologies: Interaction between CF and KG information through intra-graph contrastive learning to promote the alignment of CF and KG partial information. Co-supervision of higher-order CF indication and their corresponding KG entities to integrate more KG information

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Cuihong Chen is an associate professor of School of Information Engineering, Anhui Business And Technology College, Hefei, China (e-mail: ahhfchench@163.com).

Gang Sun is a professor of School of Computer and Information Engineering, Fuyang Normal University, Fuyang, China (e-mail: ahfysungang@163.com).

through inter-graph contrastive learning. The pattern uses an attention mechanism to obtain key information.

2. Multifaceted tests: This study was subjected to extensive tests three benchmark data sets. The experimental results show that the knowledge-aware recommendation algorithm (KGAC) put forward in this research has excellent performance contrasted to other benchmark recommendation algorithms.

II. RELATED WORK

A. Knowledge Graph

KG is applied to recommender systems as an external data type capable of displaying large amounts of semantic knowledge and rich contextual content. There are three main modes of application of KG in recommender systems: 1) Embedding-based method: Map entities and relationships in the KG is a low-dimensional vector space for using mathematical operations to simulate and reason about the relationships between entities. TransE [14] is one of the earliest models with important influence in the field of KG embedding. It realizes embedding by regarding relationships as translations between entities. Subsequently, models eg. TransH [15] and TransR [16] emerged, improving some limitations of TransE, eg. handling symmetric and antisymmetric relationships. All of these ways mentioned above ignore the higher-order message in the KG. 2)Path-based method: Path-based way [17] [18][19] focus on using the path message in the KG to discover the reason about the relationships between entities. For example, the path ranking algorithm (PRA) takes the probability of each path as a feature and uses a logistic regression classifier for training and prediction. It can reveal the latent associations between entities and heighten the capabilities of recommendation systems and question answering systems by analyzing multi-hop paths. However, when there are multiple paths, an effective method is needed to comprehensively consider the information of these paths to avoid information overload. The above method extracts the meta-path by manually. The design of these meta-paths requires specific domain knowledge and a lot of time. And when the recommendation scenario or KG changes, the meta-paths need to be redesigned. 3) Graph neural network method (GNN): GNN-based ways[20][21][22] use GNNs to deal with KG data and can capture the topological structure and node features in the KG. Models eg. GCN and GAT are representatives in this field. GNN-KG can handle the dynamics and complexity of KG and can be employed to assignments eg. node classification and link prediction [23]. However, the computational cost is high, and for large-scale graphs, specific optimization techniques may be required. However, nodes with more connections in the graph may lose their original features in the message propagation course of GNN, resulting in overly smooth representations. And some ways use ways of aggregating a fixed number of neighbors or randomly selecting neighbor nodes when iteratively updating the representations of nodes in the network, which limits the utilization of graph information.

B. Attention Mechanism

The attention mechanisms can help recommender systems to better obtain the connection between users and items. Some researchers have drawn inspiration from the latest progress of GNNs and proposed some recommendation algorithms based on KG attention networks[24][25][26]. Generally, KG attention network-based algorithms use two designs to settle the challenge of high-order relationship modeling: one is recursive embedding propagation, which captures high-order connections with linear time complexity based on the embedding propagation of adjacent nodes; the other is attention-based aggregation. Utilizing a neural attention mechanism, the method learns the weight of each neighbor during the propagation process, thereby highlighting the significance of high-order connections. In contrast to existing approaches, this method not only bypasses the labor-intensive path materialization process, enhancing efficiency and usability, but also differs from regularization-based techniques by directly integrating high-order relationships into the prediction model. This allows customization of all relevant parameters to optimize the recommended target.

C. Contrastive Learning

Contrastive learning is a way for studying more discriminative representations, which can learn better feature representations by contrasting the imparities between samples. Drawing inspiration from classical self-supervised learning techniques, researchers have suggested leveraging self-supervision to address issues related to sparse supervision indication. A simple method involves augmenting or perturbing the input user-item-entity graph and then comparing the modified nodes with the original ones, adhering to a conventional contrastive paradigm akin to existing literature [27][28][29]. However, this paradigm conducts contrastive learning relatively independently, focusing solely on comparing the same components (CF or KG) across different graph views. This approach neglects the internal interactions between various segments of the graph, leading to a disconnection between CF and KG representation learning. The CF part has limited influence in the final user and object modeling. Under the traditional contrastive mechanism, the problems of unbalanced message utilization and insufficient knowledge extraction have not been effectively solved. Therefore, it is essential to promote the contrastive learning framework to facilitate effective message exchange between CF and KG. This approach enables the coherent integration of message from each component without the need for additional explicit labels. Recent research has introduced an interactive graph contrastive mechanism specifically for knowledge graph recommendation tasks (KGR), addressing limitations in the following ways: first, by comparing CF and KG components to equilibrate their contributions to expression studying; and second, by assessing both non-local graphs within KG to withdraw valuable non-local KG facts.

Contrastive learning and the attention mechanism is important in perfecting the recommendation nature of recommendation algorithms. The comprehensive application of contrastive learning, the attention mechanism, and KG is relatively rare in the research of recommendation algorithms. To this end, the KGAC proposed in this paper incorporates attention mechanisms and contrastive learning. Through contrastive learning and the attention mechanism, it integrates KG entity message, promotes the expressions of users and items, and improves the nature of the recommendation algorithm.

III. Problem Definition

Interaction data. We set M and N to represent a set of users and items severally in the recommendation scenario, i.e., $U=\{u_1,u_2,...,u_M\}$ and $I=\{i_1,i_2,...,i_N\}$. Constructing the interaction matrix $Y \in R^{M\times N}$ using veiled feedback from the users, where $y_{ui}=1$ signifies that a user has interacted with an item, eg. through clicking or buying, while $y_{ui}=0$ represents that no such interaction has occurred.

Knowledge graph. Storing object attributes or external common sense knowledge as a heterogeneous graph in a KG [30]. Let $G=\{(h,r,t)\,|\,h,t\in E, r\in R\}$ be the knowledge graph, where *h,r,t* severally represent the head, relationship, and tail corresponding to a knowledge triple, E and R severally represent the set of entities and relationships in G [31]. In many recommendation scenarios, we create a set of alignments between items and entities, referred to as $A=\{(i,e)\,|\,i\in I, e\in E\}$. Each pair (i,e) is the alignment of item *i* with entity *e*. This alignment between items and KG entities allows the KG to better analyze items and provide additional message to improve interaction data.

Problem statement. With known user-item interaction matrix Y and KG G, the main assignment of knowledge-aware recommendation is to design a likelihood feature that can forecast the user's interaction with a particular item.

IV. Methodology

A. The overall structure

The knowledge-aware recommendation algorithm (KGAC) integrates the attention mechanism and contrastive learning, which aims to unify partial message of CF and KG through interactive contrastive learning to achieve coherent message utilization and extract and integrate more KG facts. The attention mechanism is utilized to determine the weight of each neighbor during the propagation process, enabling the recursive transfer of embeddings from neighboring nodes to update their representations. The synergy between the contrastive learning module and the attention mechanism significantly promotes the accuracy and personalization of recommendations. Figure 1 reveals the overall structure of the KGAC algorithm.

B. Constructing the graph

Traditional recommendation algorithms depended on knowledge graphs often only employ the local adjacent entity message of users or items, which has certain limitations. Multilevel contrastive learning incorporates non-local KG message related to similar items conquering the restrictions of traditional recommendation algorithms depended on knowledge graphs. This approach aims to extract valuable message from the KG in a more comprehensive manner. Specifically, firstly, combine the CF signal with the KG to construct local and non-local graphs of users and items. Such a design helps to dig deeper into the potential relationships and facts in the KG.

The local graph extracts the first-order CF signal of users and items from the user-item interaction matrix Y. The components of the first-order CF indication are same with the knowledge graph (KG) after undergoing the item-entity alignment operation $A=\{(i,e)|i\in I, e\in E\}$, resulting in the incipient entity knowledge graph, as displayed in Eq. 1.

$$\mathrm{E}^0_{u,L}=\{e\,|\,(i,e)\in A, \text{and } i\in\{i|y_{ui}=1\}\},$$
$$\mathrm{E}^0_{i,L}=\{e|(i,e)\in A\} \tag{1}$$

In Eq. 1, $\mathrm{E}^0_{u,L}$ and $\mathrm{E}^0_{i,L}$ severally represent the primal entity sets of users and items in the KG of the local graph.

Then, we obtain more layers of relevant knowledge graph facts through natural propagation in the KG. In this way, a local graph centered around users and items is built. The triples in the local graph are seen in Eq. 2.

$$S^l_{o,L}=\{(h,r,t)\,|\,(h,r,t)\in G \text{ and } h\in E^{l-1}_{o,L}\}, l=1,...,L \tag{2}$$

$S^l_{u,L}$ and $S^l_{i,L}$ denote the triples at the l-th layer for users and items within the local graph. Each triple comprises the head entity from the (l-1)-th layer, the relationship, and the tail entity from the l-th layer. After the above course we construct the l-th layer local graph, which encompasses the heterogeneous structures of user-item-entity and item-entity relationships.

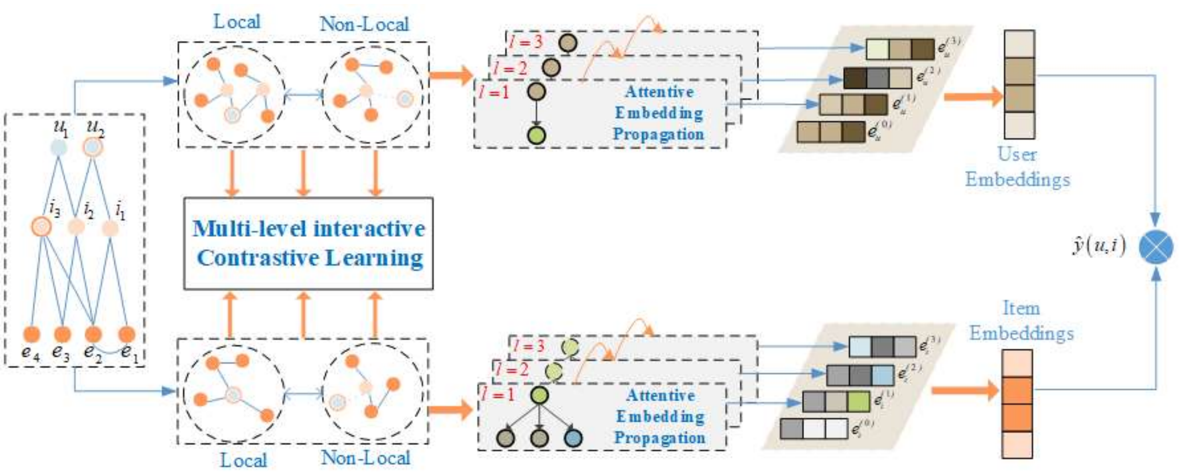

Fig. 1. The overall structure diagram of the KGAC algorithm

Align the higher order terms of CF with KG to form the non-local graph and enable the propagation of KG message. Incipiently, propagation in the user-item interaction graph derives higher-order items for users and items, where I_u and U_{sim} represents the high-order items related to user *u* and its similar users, while I_s indicates the high-order items associated with item *i*. Further obtain the aligned incipient entities $\mathrm{E}_{u,N}^{0}$ and $\mathrm{E}_{i,N}^{0}$ in the KG as displayed in Eq. 3.

$$\mathrm{E}_{u,N}^{0}=\left\{e\mid(i_u,e)\in A,\text{and } i_u\in I_u\right\},\quad \mathrm{E}_{i,N}^{0}=\left\{e\mid(i_s,e)\in A,\text{and } i_s\in I_s\right\} \tag{3}$$

In Eq. 3, $\mathrm{E}_{\mathrm{u,N}}^{0}$ and $\mathrm{E}_{\mathrm{i,N}}^{0}$ are the incipient entity sets of users and items in the non-local graph KG, severally.We constructed non-local graphs for users and items by propagating incipient entities in KG. The triple form as depicted in Eq. 4.

$$\mathrm{S}_{o,N}^{l}=\left\{(h,r,t)\mid(h,r,t)\in\mathrm{G}\text{ and } h\in E_{o,N}^{l-1}\right\},l=1,...,L \tag{4}$$

C. Contrastive Learning

This section will promote the balanced utilization of message across graphs through interactive contrastive learning intra-graph and inter-graph.

In the case of intra-graph interaction contrastive learning, the collaborative filtering component situated in the core layer of the local/non-local graph serves as the anchor. In this paper, knowledge message related to user and item representation learning is clarified as positive samples, while other KG entities are used as negative samples. In this way, we clarify the following contrastive loss function for users as displayed in Eq. 12, where τ is the temperature coefficient.

Analogously, the intra-graph contrastive loss for items, denoted as L_{Intra}^{I}, can be derived using the same approach. The total loss for the intra-graph interaction contrast is calculated as displayed in Eq. 5. This design enables the CF and KG indication to promote each other, thereby enhancing the coherence and sufficiency of representation learning.

$$L_{Intra}=L_{Intra}^{U}+L_{Intra}^{I} \tag{5}$$

Although intra-graph interaction contrastive learning achieves effective integration of message in a single graph, there are still challenges in fusing local and non-local message, especially the noise problem of non-local message. Given that the non-local graph incorporates rich external message, comprising high-order collaborative filtering indication and their corresponding knowledge graph facts, we introduce inter-graph interaction contrastive learning. This method aims to withdraw valuable non-local message by applying contrastive learning between the non-local and local graphs. Specifically, the inter-graph interaction contrastive learning selects a layer in the local graph as the target layer, where the corresponding layers of the non-local graphs are used as positive samples, and the layers of other non-local graphs are used as negative samples. In this way, we clarify the contrastive loss functionality for users as displayed in Eq. 6.

$$L_{Inter}^{U}=\sum_{u\in U}\sum_{k\in L}-\log\frac{e^{(E_{u,L}^{(k)}\bullet E_{u,N}^{(k)}/\tau)}}{e^{(E_{u,L}^{(K)}\bullet E_{u,N}^{(k)}/\tau)}+\sum_{k'\neq k}e^{(E_{u,L}^{(K)}\bullet E_{u,N}^{(k)}/\tau)}} \tag{6}$$

Similarly, the inter-graph contrastive loss of items can also be included through a similar method. The method of calculating the amount of user losses and item losses (i.e., final inter-graph contrastive losses) is displayed in Eq. 7. This method effectively utilizes local and non-local message and perfects the precision and robustness of the model's representation of users and items.

$$L_{Inter}=L_{Inter}^{U}+L_{Inter}^{I} \tag{7}$$

D. Attention Embedding Propagation

$N_h=\left\{(h,r,t)\mid(h,r,t)\in G\right\}$ represents the set of triples, where *h* is the head entity. We determine its connectivity by calculating the linear combination of entities, as displayed in Eq. 8.

$$e_{N_h}=\sum_{(h,r,t)\in N_h}\pi(h,r,t)e_t \tag{8}$$

Among them, $\pi(h,r,t)$ is the attention factor that affects the attention of each propagation along *h, r, t*. The attenuation factor determines the amount of reduction when message is transmitted between entities. The relation r determines the number of message spread from *t* to *h*.

This study utilises the associational attention mechanism to implement $\pi(h,r,t)$, and its expression is as seen in Eq. 9.

$$\pi(h,r,t)=(W_re_t)^T\tanh((W_re_h+e_r)) \tag{9}$$

In this study, the *tanh* activation function [26] allows the attention mark to reflect the spare between e_h and e_r in the association space. Additionally, the coefficients of all triplets associated with *h* are normalized using the softmax functionality, as detailed in Eq. 10.

$$\pi(h,r,t)=\frac{e^{\pi(h,r,t)}}{\sum_{(h,r',r')\in Nh}e^{\pi(h,r',t')}} \tag{10}$$

The attention grades included through this method ultimately reveal which neighboring nodes require greater focus to effectively capture collaborative indication. Our proposed model uses the adjacency structure of the graph to clarify the different meanings of different neighbors. Additionally, our approach incorporates not only node representations but also models the relationship between e_h and e_t, thereby encoding richer message throughout the propagation course.

We use a bidirectional interaction aggregator to achieve the new representation of entities, $e_h^{(1)}=f\left(e_h,e_{Nh}\right)$. The calculation of *f* is as displayed in Eq. 13.

Among them, the activation function is set as LeakyReLU [32], W1, W2 are trainable weight matrixes, and ⊙ is element-wise product. Different from aggregators eg. GCN and GraphSage, we perform additional encoding on the trait interaction between e_h and e_{Nh}.

We capture higher-order connectivity message and collect data spread from high-hop neighbors by piling up additional propagation layers. In the l-th step, the entity is represented using recursively, as illustrated in Eq. 11.

$$e_h^{(l)}=f(e_h^{(l-1)},e_{Nh}^{(l-1)}) \tag{11}$$

$$L_{Intra}^{U}=\sum_{u\in U}-log\frac{\sum_{k\in L}e^{((E_{u,L}^{(0)}\bullet E_{u,L}^{(k)}/\tau))}}{\sum_{k\in L}e^{((E_{u,L}^{(0)}\bullet E_{u,L}^{(k)}/\tau))}+\sum_{k^{'}>L}e^{((E_{u,L}^{(0)}\bullet E_{u,L}^{(k^{'})}/\tau))}}+\sum_{u\in U}-log\frac{\sum_{k\in L}e^{((E_{u,N}^{(0)}\bullet E_{u,N}^{(k)}/\tau))}}{\sum_{k\in L}e^{((E_{u,N}^{(0)}\bullet E_{u,N}^{(k)}/\tau))}+\sum_{k^{'}>L}e^{((E_{u,N}^{(0)}\bullet E_{u,N}^{(k^{'})}/\tau))}} \quad (12)$$

$$f=Leaky\,ReLU(W_1(e_h\,||\,e_{Nh}))+Leaky\,ReLU(W_2(e_h\odot e_{Nh})) \quad (13)$$

E. Model Prediction

The L-layer multi-order representation of user u is $\left\{e_u^{(1)},\cdots,e_u^{(L)}\right\}$ and the L-layer multi-order representation of an item i is $\left\{e_i^{(1)},\cdots,e_i^{(L)}\right\}$. The outputs from various layers highlight connection message of differing orders. The representation of each order is united into a vector, which serves as the ultimate embedded representation for u and i, as demonstrated in Eq. 14.

$$e_u=e_u^{(0)}\,||\ldots||\,e_u^{(L)},\ e_i=e_i^{(0)}\,||\ldots||\,e_i^{(L)} \quad (14)$$

Among them, || is the connection operation. The process uses embedding propagation to promote the incipient embedding while regulating the intensity of propagation. Ultimately, the matching scores between user and item representations can be predicted by calculating their inner product, as illustrated in Eq. 15.

$$\hat{y}(u,i)=e_u^T\cdot e_i \quad (15)$$

F. Model Optimization

The BPR loss function is applied to the recommendation model. This loss functionality is based on an assumption: for observed user interactions, it reflects the user's stronger preference. Therefore, the predicted score should be more than those unseen interactions. The BPR loss function is seen in Eq. 16.

$$L_{BPR}=\sum_{(u,i,j)\in O}-ln\,\sigma(\hat{y}_{ui}-\hat{y}_{uj}) \quad (16)$$

Among them, $O=\left\{(u,i,j)\ \ (u,i)\in O^{+},(u,j)\in O^{-}\right\}$ is the disciplinal data set contains two parts: 1) the seen interaction data sets O^{+}; 2) the unseen interaction data set O^{-}. The σ in Eq.16 denotes the sigmoid function. Minimization of the objective function (Eq. 17) is achieved by calculating the intra-graph and inter-graph interaction contrastive loss, the BPR loss and optimizing the model parameters.

In Eq. 17, Θ is the set of model parameters, while α is a hyperparameter that balances the weights of the intra-graph and inter-graph contrast losses. Additionally, $\lambda 1$ is the hyperparameter controlling the contrast loss and $\lambda 2$ is the hyperparameter of the $L2$ regularization.

$$L_{KGAC}=L_{BPR}+\lambda 1(\alpha L_{Intra}+L_{Inter})+\lambda 2\|\Theta\|_2^2 \quad (17)$$

V. EXPERIMENT

We experimented the KGAC recommendation algorithm put forward in this paper with other recommendation algorithms on three benchmark data sets with the aim of exploring the below three study matters:

RQ1: How does the nature of the KGAC recommendation algorithm contrast to other benchmark recommendation algorithms?

RQ2: What is the impact of attention mechanism and contrastive learning on the KGAC recommendation algorithm?

RQ3: What is the impact of temperature coefficient and model depth on the KGAC recommendation algorithm?

A. Datasets

To assess the validity of the KGAC, we utilized three benchmark data sets: Book-Crossing, MovieLens, and Last.FM. These publicly available data sets span various fields and disparate size and sparsity, thereby increasing the robustness of our tests. Fundamental statistical particulars for these data sets are summarized in Table I.

Book-Crossing: This data set is sourced from the book-crossing community and includes explicit ratings (0-10) for various books.

MovieLens: The data set is a film recommendation data set that includes about 1 million ratings (1-5).

Last-FM: It is a music data set comprising approximately 2,000 users, sourced from the Last.fm online music system.

We converted the specific feedback from the above three data sets to unexpressed feedback [33]. For the MovieLens data set, we clarify a rating of 4 as the positive threshold. For the sparsity of the Last.FM and Book-Crossing data sets, no threshold will be established for these data sets. We denote positive samples with a value of 1, while for negative samples, we discretionarily select an equal amount of items that have not been observed by each user.

In constructing the sub-KG, we adhere to the methodology outlined by RippleNet and utilize Microsoft's Satori tool to create sub-KG for the MovieLens, Book-Crossing, and Last.FM data sets. Each subset of the KG is a sub-KG that abide by a triple format (confidence level > 0.9). For each sub-KG graph, we collect the Satori IDs for all applicable movies, books, and musicians by aligning their names with the tails of the triples. Subsequently, we associate the object IDs with the heads of the triples and extract all triples from the sub-KG graph that exhibit a strong match.

TABLE I
STATISTICAL INFORMATION OF DATASETS

	User-item Interaction			Knowledge Graph		
	users	items	interactions	entities	relations	triplets
Book-Crossing	17,860	14,967	139,746	77,903	25	151,500
MovieLens	6,036	2,445	753,772	182,011	12	1,241,996
Last.FM	1,872	3,864	42,346	9,366	60	15,518

B. Evaluation Metrics

Two metrics broadly employed in the field of recommendation algorithms were used in this study[34][35], AUC (area under curve) and F1, to appraise the validity of the KGAC algorithm proposed in this paper.

AUC serves as a model evaluation metric within the machine learning domain. It essentially measures the likelihood that, for any given pair of positive and negative samples, the model is more prone to correctly identify a positive sample than to misclassify a negative sample as positive. A larger worth of AUC indicates that the pattern is more capable of distinguishing between positive and negative samples.

F1-score is another widely recognized metric in machine learning, particularly for assessing classification model performance. It is clarified as the harmonic average of accuracy and recall, and is widely employed to appraise the holistic effectiveness of a pattern. A higher F1 score indicates perfect nature of the pattern.

C. Baseline Algorithms

In this research, KGAC is experimented with other recommender system ways on three databases, Book-Crossing, MovieLens, and Last.FM. To confirm the validity of the KGAC model put forward in this paper, we contrast the KGAC model with the below models: BPRMF, CKE, PER, KGCN, KGAT, CKAN, KGIN. The details are as follows:

BPRMF [36]: This is a Bayesian optimization based individualized ranking BPR-Opt model.

CKE [10]: CKE integrates the framework's TransR-based heterogeneous network embedding method, stacked denoising self-encoder, and stacked convolutional self-encoder.

RippleNet [33]: It is an end-to-end framework for integrating KG into recommender systems.

PER [37]: This approach introduces meta-path based latent features that confirm recommendation patterns at global and individualized levels.

KGCN [38]: As a Graph Neural Network (GNN)-based method, KGCN incrementally incorporates neighboring message to promote object embeddings.

KGAT [39]: This GNN-based way utilizes an attention mechanism to iteratively integrate neighboring elements within the user-item-entity graph, facilitating the generation of user and item representations.

CKAN [40]: The approach combines collaboration indication with knowledge associations and employs a knowledge-aware attention mechanism to differentiate the achievements of disparate knowledge neighbors.

KGIN [41]: This method is a novel GNN message aggregation scheme that recursively integrates sequences of remotely connected relationships while extracting useful message about user intentions.

D. Performance Analysis (RQ1)

The proposed KGAC algorithm was subjected to multiple tests alongside other benchmark algorithms across three data sets: Book-Crossing, MovieLens, and Last.FM. The comparative consequences, derived from statistical analysis, are presented in Table Π. Each row's best performance in the baseline algorithms is marked by underlining, and the best performing consequences are noted in bold. As displayed in Table Π, the proposed KGAC algorithm outperforms other baseline algorithms across all three data sets. More specifically, on the Book-Crossing data set, the KGAC algorithm outperformed the best baseline algorithm (CKAN) by 3.18% in AUC and 2.20% in the F1; on the MovieLens data set, the KGAC algorithm outperformed the best baseline algorithms (RippleNet, KGIN) by 0.72% in AUC and 1.01% in the F1; on the Last.FM data set, the KGAC algorithm outperformed the best baseline algorithm (KGIN) by 0.68% in AUC and 1.71% in the F1.

We attribute this improvement to several elements: (1) By comparing CF indication with KG indication within non-local graphs, interactive contrastive learning at the intra-graph level facilitates interaction between the two components, enabling mutual supervision that promotes representation learning. (2) The comparison of non-local graphs for users and items allows interactive contrastive learning at the inter-graph level to fully integrate non-local KG facts, thereby enabling the pattern to study discriminative trait expressions from both types of graphs. (3) The attention mechanism makes the model to prioritize crucial message link to the nowaday assignment, thereby reducing the focus on less pertinent data. This selective attention promotes overall model performance by avoiding the equal treatment of all input data.

E. Ablation Experiment (RQ2)

To appraise the impact of the model's key parts, namely, the contrastive learning module and the attention module, on recommendation nature, we compared KGAC against several variants. (1) KGAC-A: This variant removes the attention network module and retains the interactive contrastive learning module; (2) KGAC-C: This specific variant omits the interactive contrastive learning module while preserving the attention network module.

Depended on the experimental consequences (displayed in Fig.2-Fig.4) we can easily conclude: (1) Interactive contrastive learning facilitates the representation studying of users and items, allows for the aggregation of more external message, and dramatically improves the nature of the pattern. (2) The attention mechanism can make the model focus on the key message instead of treating all message equally, and also make a certain contribution to the perfection of model nature.

TABLE II
COMPARISON RESULTS OF THE KGAC ALGORITHM AND OTHER BASELINE ALGORITHMS

Datasets		BPRMF	CKE	RippleNet	PER	KGCN	KGAT	CKAN	KGIN	KGAC
Book-Crossing	AUC	0.6581	0.6752	0.7206	0.6042	0.6836	0.7309	0.7414	0.7268	**0.7732**
	F1	0.6114	0.6231	0.6467	0.5721	0.6307	0.6538	0.6665	0.6609	**0.6885**
MovieLens	AUC	0.8916	0.9058	0.9185	0.7119	0.9084	0.9135	0.9076	0.9184	**0.9256**
	F1	0.7918	0.8019	0.8417	0.6665	0.8361	0.8436	0.8404	0.8437	**0.8538**
Last.FM	AUC	0.7558	0.7467	0.7756	0.6409	0.8019	0.8287	0.8412	0.8479	**0.8547**
	F1	0.7005	0.6735	0.7021	0.6027	0.7081	0.7419	0.7587	0.7593	**0.7764**

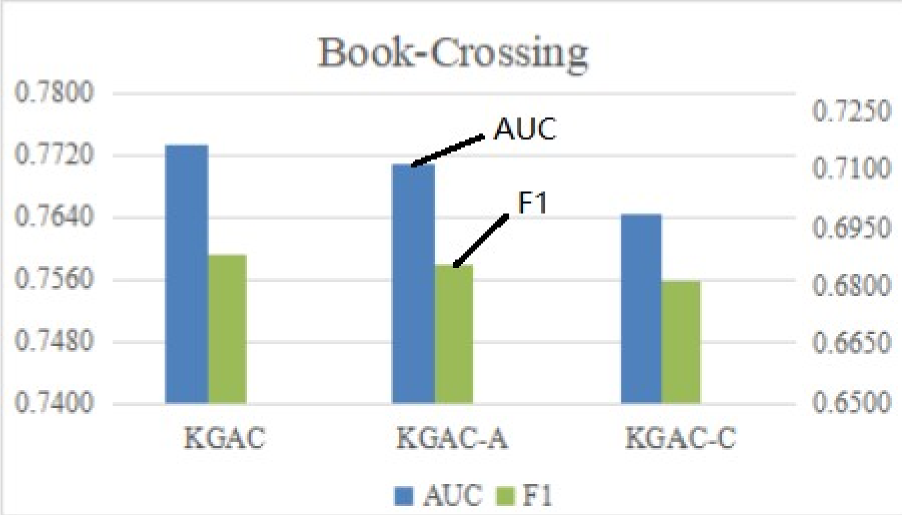

Fig. 2. Ablation experiment on the dataset Book-Crossing

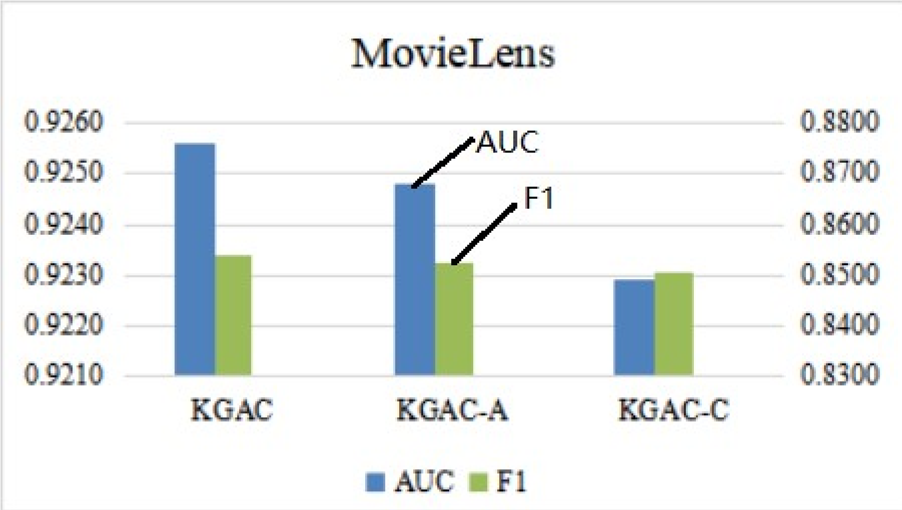

Fig. 3. Ablation experiment on the dataset MovieLens

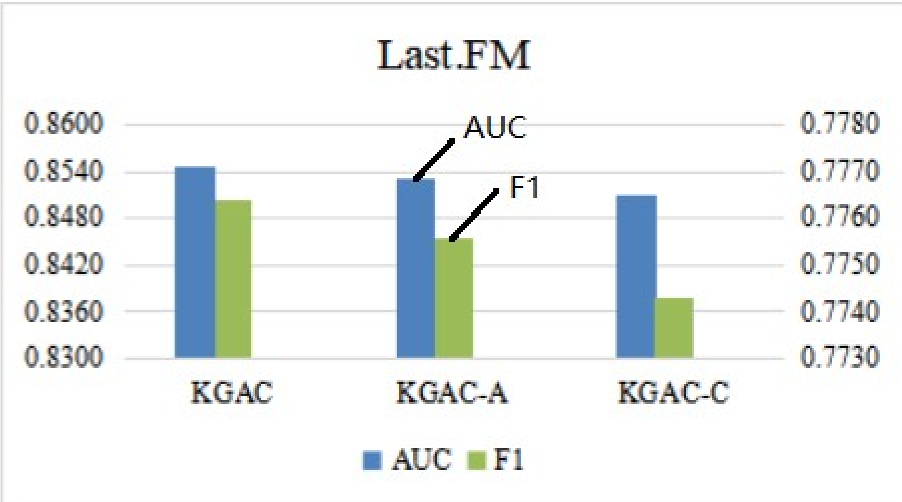

Fig. 4. Ablation experiment on the dataset Last.FM

F. Main Parameter Analysis (RQ3)

Model Depth

The model depth, designated as L, is the aggregation layers within both local and non-local graphs, as well as the number of layers in the positive pair utilized in the collaborative contrastive mechanism. To investigate the effects of model depth, we enforced tests with the KGAC algorithm for L values of 1, 2, 3, 4 across the Book-Crossing, MovieLens, Last.FM data sets, with the consequences illustrated in Figures 5 to 7. On the Book-Crossing data set, KGAC is best when $L = 1$; on the MovieLens data set, KGAC is best when $L = 2$; on the Last.FM data set, KGAC is best when $L = 3$. Experimental results indicate that an aggregation layer of three or fewer layers is ideal for gathering neighboring message from local and non-local graphs, providing adequate support for the collaborative contrastive learning of distinctive embeddings across CF and KG layers. Adding further layers tends to introduce additional noise rather than enhancing performance.

Temperature coefficient

The temperature coefficient τ is a critical factor in contrastive learning and significantly influences model performance. To investigate the impact of τ, we enforced tests with the KGAC algorithm for $\tau \in \{0.05, 0.075, 0.1, 0.2, 0.3, 0.4\}$ across the Book-Crossing, MovieLens, Last. FM data sets, with the consequences illustrated in Fig.8-Fig.10. Analysis of the findings indicates that the temperature coefficient τ regulates the extent to which contrastive loss focuses on challenging negative samples. A too large temperature coefficient τ will lead to poor model performance. If the temperature coefficient τ is small, it will lead to difficulties in model convergence, poor generalization ability, the model performance will also be adversely affected. Generally speaking, a temperature coefficient τ in the range of $\{0.1, 0.2\}$ can obtain satisfactory recommendation performance.

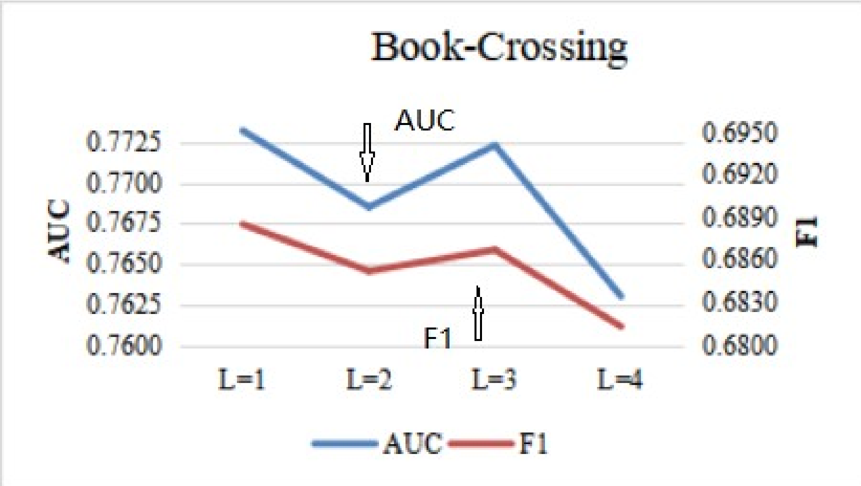

Fig. 5. The impact of model depth on the performance of KGAC on the dataset Book-Crossing

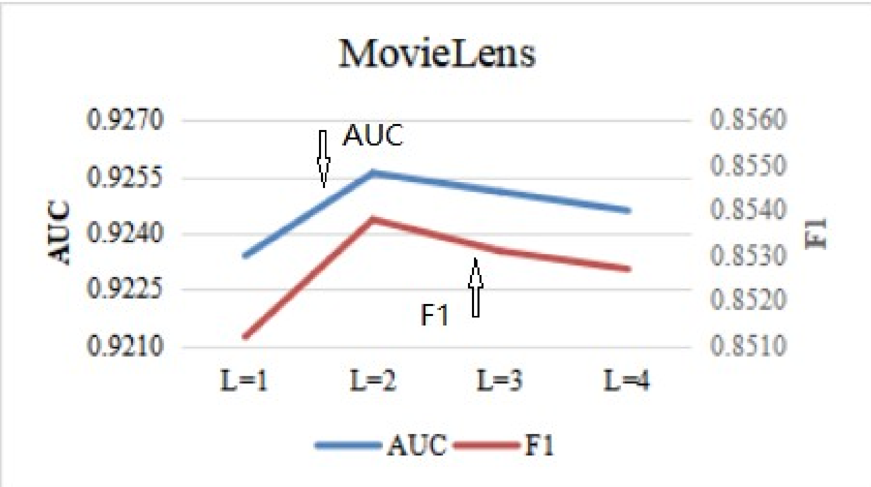

Fig. 6. The impact of model depth on the performance of KGAC on the dataset MovieLens

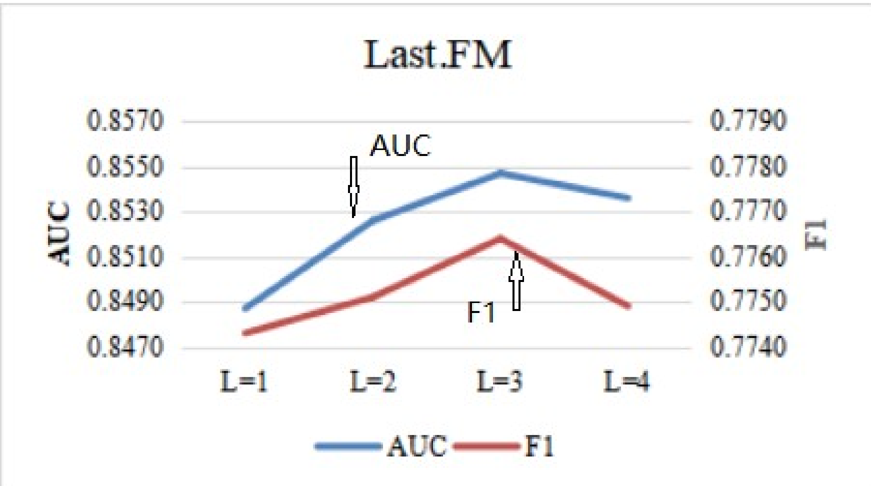

Fig. 7. The impact of model depth on the performance of KGAC on the dataset Last.FM

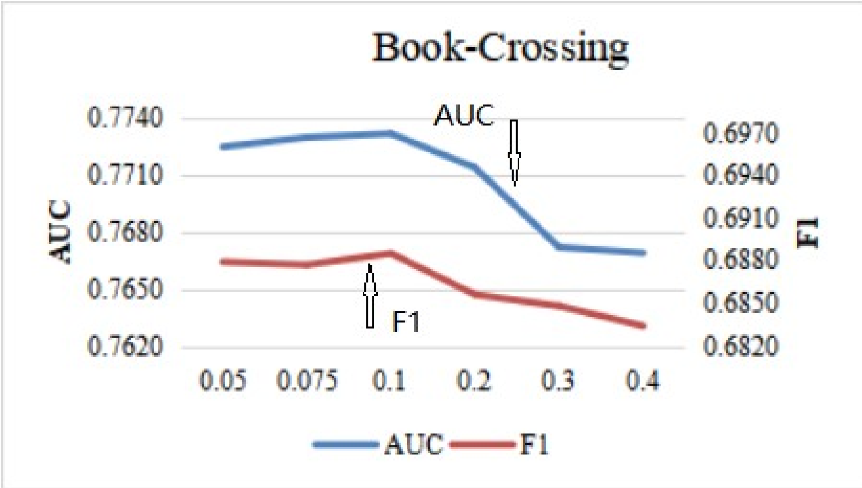

Fig. 8. The impact of temperature coefficient on the performance of KGAC on the dataset Book-Crossing

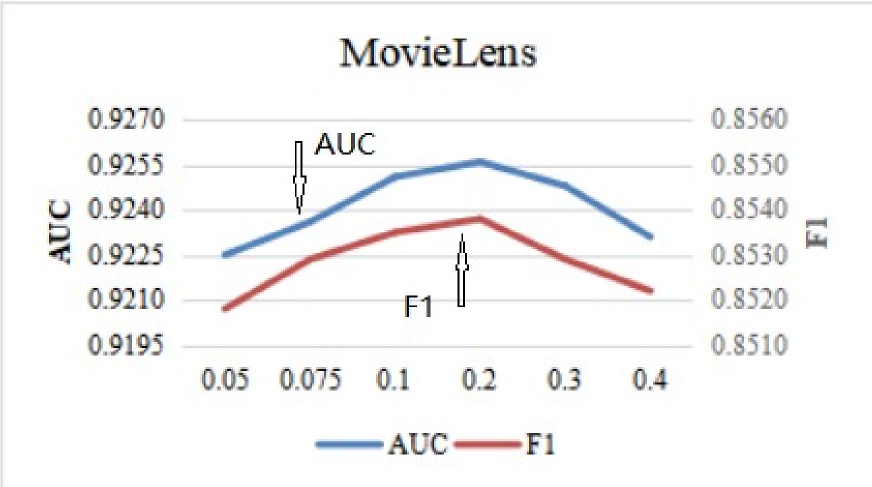

Fig. 9. The impact of temperature coefficient on the performance of KGAC on the dataset MovieLens

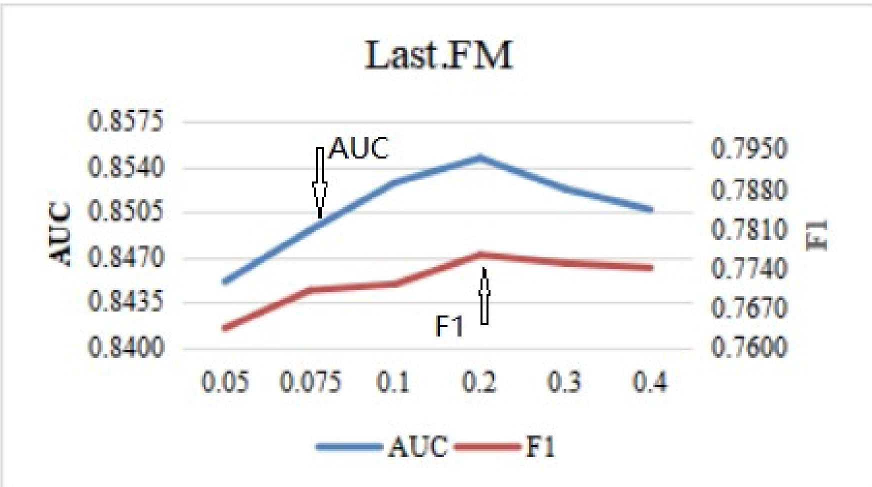

Fig. 10. The impact of temperature coefficient on the performance of KGAC on the dataset Last.FM

V. CONCLUSIONS

In view of some problems existing in current recommendation algorithms, this paper proposes the KGAC that integrates attention mechanism and contrastive learning. Through intra-graph interactive contrast of the layers of CF and KG parts, it coherently utilizes the CF and KG information in each local and non-local graph. By structuring non-local graphs and proceeding inter-graph interactive contrastive learning, more KG facts are fully extracted and integrated for user and item representation studying. Through the attention mechanism, the consequence of node neighbors is discriminated, important node message is focused on, and the embeddings from the neighbors of nodes are adaptively spread to update the representation of nodes. Many tests on three real-world data sets prove the reasonability and validity of KGAC. In addition to knowledge graph, there are many other structural information being in real-world scenarios, eg. social networks and object contexts. Future work will explore more precise and individualized recommendations for users by gathering social network and object context, and combining knowledge graphs.

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