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Explicable recommendation based on knowledge graph

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ABSTRACT

Most of the existing researches on recommendation system assemble in how to enhance precision of recommendation, ignoring acceptance and recognition of users. To work out the problem, a model of explainable recommendation on account of knowledge graph as well as many-objective evolutionary algorithm is proposed, which combines recommendation and explanation. In this work, embedding vectors obtained by embedding-based method are used to quantify the explainability, so as to obtain the explainability of paths between users and items. Candidate recommendation list of users is gained from constructed knowledge graph. Many-objective evolutionary algorithm is used to optimize the list of candidate recommendation so as to seek a set of tradeoff solutions to the four objective functions of accuracy, diversity, novelty and explainability. Then, the best path among object user and recommended items is chosen in knowledge graph as the explanation. Finally, the conclusion that can be drawn from various experiments is that the presented model can boost explainability without reducing the precision, diversity as well as novelty.

1. Introduction

As technology develops, the amount of data increases. To deal with overloading information, recommendation system (RS) is produced (Jin, Guo, Xu, Wang, & Wang, 2021; Wu, Sun, Hong, Ge, & Wang, 2021; Zhu et al., 2021). RS is widely used in social networks, search engines and other platforms (Jin et al., 2021; Mohamed Ariff et al., 2021). The goal of RS is to recommend accurate and diverse items for users and improve users' satisfaction with recommendation algorithms. A good recommendation system not only needs to accurately grasp the needs of users, but also needs to understand the psychology of users and give appropriate recommendations in a way that users can easily accept. Therefore, it is essential to provide users with reasons to recommend items. Explainable recommendation is to provide users with recommendations as well as a reason for recommendations (Wang et al., 2019). When recommending to users, explaining reasons for recommendation can not only improve the transparency of recommendation system, but also improve trust and acceptance of users on recommendation system, enhance users' satisfaction with the recommended items (Zarzour, Al shboul, Al-Ayyoub, & Jararweh, 2020; Lin et al., 2019).

Explanation of recommended items generated by existing explainable recommendation is limited to one of items, users and features as media, and the correlation among these three types of media has not been excavated enough (Ozsoy et al., 2020; Tintarev & Masthoff, 2011). Knowledge graph is used to connect the three types of media, so as to select appropriate way to make explainable recommendations to users (Wang, Zhao, Xie, Li, & Guo, 2019; Zhang & Chen, 2018). At present, there are two various ways to apply knowledge graph to recommendation system: path-based method as well as embedding-based method. Fig. 1 is a typical example of recommendation based on knowledge graph. The movie "A Bug's Life" can be recommended to Marry through the path of director, and in the same way, the movie "Pretty in Pink" and "Jumpin' Jack Flash" can also be recommended to Marry through the path of actor. The above approach can produce explanatory recommendations, the path-based method uses semantically connected information, which takes advantage of only one aspect of knowledge graph (Guo et al., 2020). Meta-path is a valid way to utilize information about knowledge graph, which can make utmost of different relationships between object user and disparate items so as to make recommendations explainable. The method of path-based leverages the calculation of semantic similarity among entities under different paths, which results in some limits because it relies heavily on predefined *meta*-paths (Li, Hong, Jia, Zhou, & Yue, 2018). Embedding vectors of entities and relationships in knowledge graph are acquired by embedding-based method, which simultaneously preserves original structure or semantic information of the knowledge graph (Zhou et al., 2021). However, Embedding-based method ignores the information connectivity of knowledge graph and lacks explanation. It has become a trend to combine the advantages of

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embedding-based method and path-based method, which can consider both semantic information and path to further mine various information contained in knowledge graph. Thus, this unified method has a better ability to explain recommended items (Guo et al., 2020).

A model of explainable recommendation on account of knowledge graph as well as many-objective evolutionary algorithms (MaOEA) is come up with in the paper, which can optimize accuracy, novelty, diversity and explainability to achieve the goal of comprehensively improving recommendation performance. In the proposed model, knowledge graph is constructed by triples, and a list of candidate recommendations for object user is gained through the constructed knowledge graph. Embedding vectors of entities and relationships are obtained through embedding-based method, and the product of vectors corresponding to nodes and relationships is used to represent the importance of relationships to nodes. All paths starting from target user are obtained in knowledge graph, and the explainability of recommended items corresponding to each path is quantified according to the importance of relationships to nodes. Further, GrEA is employed to optimize the list of candidate recommendation in order to get final recommendation result. The dominating contributions to the paper are overview blew:

(1) In this paper, an explainable recommendation model is proposed in which accuracy, diversity, novelty and explainability can be optimized simultaneously.
(2) Entities and relationships are extracted to construct triples. The structure of knowledge graph is on the basis of constructed triples, then the list of candidate recommendation for object user is gained in accordance with association among entities through constructed knowledge graph.
(3) Embedding vectors of entities and relationships are obtained. The product of corresponding vector of entity and relation is used to reflect the importance of relation to entity, and the explainability of recommended items corresponding to each path of knowledge graph is quantified in conformity with the importance.

The structure of the rest of this paper is as shown. Related work about knowledge graph embedding algorithm is described in section 2. The preliminary about this paper reveals in section 3, including may-objective optimization and TransH. The proposed model is mentioned particularly in section 4. Section 5 accounts for experiments of presented model. The conclusion is introduced in section 6.

2. Related work

For the past few years, knowledge graph has appealed to keen interest as edge information generation recommendation. Knowledge graph can not only relieve the matters of sparse data as well as cold start, but also provide more accurate recommendations and explain the recommended items, so that the recommended items can be tracked (Wang, Zhang, Wang, Miao, & Guo, 2018; Xian, Fu, Muthukrishnan, Melo, & Zhang, 2019). According to recent researches, it is found that the prime approaches of the introduction of knowledge graph to recommendation system are two types: (1) the embedding-based method; (2) the path-based method. The advantages of embedding-based method are as follows: low-dimensional vectors are obtained for entities and relationships in knowledge graph through knowledge graph embedding, which reduces the high-dimensional of knowledge graph. Meanwhile, the obtained vectors can fully represent the relationships among entities, enhancing the flexibility of the application of knowledge graph. Although embedding-based method can easily introduce knowledge graph into recommendation system, this method ignores the relationships among various entities, resulting in unexplainable recommendation results. The advantage of path-based method is that it can get the utmost out of the network structure of knowledge graph, the disadvantage is that the interaction paths among entities need to be designed manually, and the manually designed paths cannot be transferred to other fields.

There have been a lot of researches on embedding-based methods in the realm of explicable recommendation systems. Zhang et al. (Zhang, Yuan, Xie, & Ma, 2016) came up with model of recommendation, in which semantic features are extracted from structured content, text content and visual content with an item, respectively, and the implicit vector of collaborative filtering into joint learning is used to generate recommendations. Wang et al. (Wang, Zhang, Hou, et al., 2018) constructed a heterogeneous information network containing users, attributes and emotions, mapped users into a low-dimensional feature space according to users' emotional network, social network and information network, and finally used special fusion methods to get the final heterogeneous embedded representation to predict users' emotional

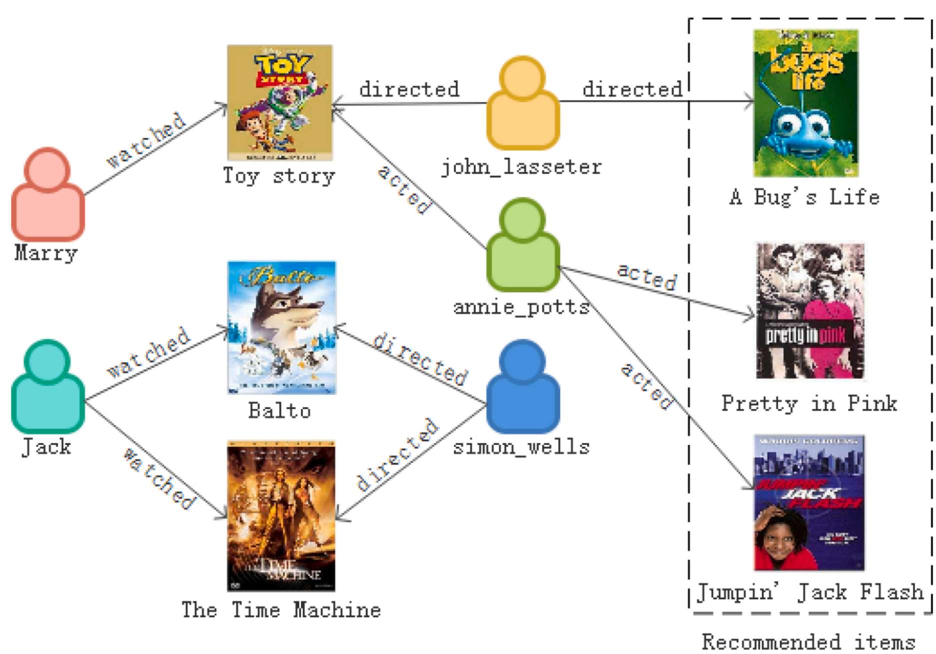

Fig. 1. An illustration of recommendation based on knowledge graph.

tendency and generate recommendation results. Cao et al. (Cao, Xiang, He, Hu, & Chua, 2019) introduced knowledge graph into RS and proposed a model, which especially considered various preferences for users to improve recommendation performance and at the same time completed the facts missing in knowledge graph. Although the above-mentioned models on the basis of embedding to retain original structure and semantic equivalency about constructed knowledge graph, they ignore links between items, resulting in unexplainable recommendation results (He, Kang, & Mcauley, 2017).

At present, many scholars have introduced path-based methods into explicable recommendation system. Xiao et al. (Xiao, Xiang, Sun, Sturt, & Han, 2013) took advantage of heterogeneity of information network to acquire the preference for user along disparate paths in order to come about feasible candidate recommended items under diverse semantics hypothesis. Shi et al. (Shi et al., 2019) fused information about multiple *meta*-paths for recommendation, gaining disparate types of analogical users via various paths, which produce recommended items. Wang et al. (Wang, Wang, Xu, He, & Chua, 2019) explored the connectivity of paths and brought path weights together so that foretell reciprocity between user and recommended items, while differentiating the advantages of various paths to enable comprehensive reasoning and explanation of recommendations. Sun et al. (Sun et al., 2018) put forward a model of recommendation that mines all paths of knowledge graph and codes them through cyclic network to distinguish the significance of various paths of describing the preferences to user for items. These recommended models for path-based method depend on manually extracted characteristics to expression the semantics of paths. Manually designed features usually can not overlay the whole probable entities and relationships, which also affects the boost of recommended performance to a certain extent (Shi, Hu, Zhao, & Yu, 2017). Embedded-based method in combination with path-based method to take full advantage of knowledge graph has turn into a vogue research theme (Wang, Zhang, et al., 2019).

Intelligent optimization algorithms are used in different fields (Cui, Jing, Zhao, Zhang, & Chen 2021). In the area of RS, Jain et al. (Jain, Singh, & Dhar, 2020) came up with a recommendation framework that includes precision and variety, and within this framework proposes a multi-parent crossover mechanism that can obtain items that contain good diversity and novelty. Cui et al. (Cui, Peng, Fu, Wen, & Nan, 2017) put forward an improved multi-objective optimization algorithm, which proposed a probabilistic genetic operation, and applied this algorithm to recommendation system to balance the accuracy and diversity. With the increasing complexity of recommendation environment, precision and diversity as objective functions can no longer satisfy the demand of users. Therefore, it is essential to take into account many-objective evolutionary algorithms (MaOEA) that can optimize concurrently four or more objective functions to comprehensively improve the recommendation performance. Cui et al. (Cui et al., 2021) put forward the model of two-layer recommendation that used improved matrix decomposition to obtain the items of unrated goods, and then used multi-objective optimization of accuracy, diversity, novelty and recall rate to obtain diverse and novel recommended items in a more effective way.

Based on the above researches, considering the constraints on embedding-based method as well as path-based method, unified method is used to complement each other's advantages. In the area of explainable recommendation, a good explainable recommendation system aims to improve explainability without affecting accuracy. Therefore, the paper proposes a model of recommendation on the basis of knowledge graph and MaOEA that integrates the embedding-based method as well as the path-based method for the sake of getting the utmost out of the path and semantic information about knowledge graph. MaOEA is employed to optimize accuracy, diversity, novelty as well as explainability synchronously, which improves the recommendation performance and has the explainability.

3. Preliminary

3.1. Embedding-based method

Knowledge graph is essentially a lexeme network composed of many triples, which can provide a deeper and broader range of associations between users and various items to enhance the property of recommendation (Xian et al., 2019). Knowledge graph embedding algorithm can obtain low-dimensional vectors of entities and relationships, the obtained vectors maintain structure and semantic information of knowledge graph, so we can easily introduce knowledge graph into recommendation system by using knowledge graph embedding (KGE) algorithms (Ai, Azizi, Chen, & Zhang, 2018). In general, KGE algorithms are mainly divided into the model of translational distance as well as the model of semantic matching. In this paper, TransH is used to acquire the embedding vectors for entities and relationship. TransH abstracts relationship in triple into a hyperplane, then maps head node and tail node to the hyperplane, and calculates the difference between head node and tail node through translation vectors on the hyperplane (Zhen, Zhang, Feng, & Zheng, 2014). The illustration of TransH is revealed in Fig. 2.

According to the illustration, we can obtain a mathematical representation of triplet, where h and t denote the vectors of head node as well as tail node. For relation$r$, we position specific translation vector d_r in relation specific hyperplanew_r. For a triple, we first need to map h and t to hyperplane, so as to obtain the mapping vector $h_\perp$ and$t_\perp$. The specific formula is as follows:

$$h_\perp = h - w_r^\top h w_r \tag{1}$$

$$t_\perp = t - w_r^\top t w_r \tag{2}$$

where $w_r^\top h$ indicates the length of projection of h in the direction ofw_r.

After getting the projection, we can calculate the difference of triples according to the function below:

$$f_r(h,t) = \left\| \left(h - w_r^\top h w_r\right) + d_r - \left(t - w_r^\top t w_r\right) \right\|_2^2 \tag{3}$$

If the triplet is correct, the function value is smaller, otherwise it is larger. For the purpose of achieving the desired results above, the following function is employed to drill the model:

$$Loss = \sum_{(h,r,t)\in\Delta} \sum_{(h',r',t')\in\Delta'_{(h,r,t)}} \left[f_r(h,t) + r - f_{r'}(h',t')\right]_+ \tag{4}$$

where Δ represents correct triplets set, Δ' denotes negative examples set.

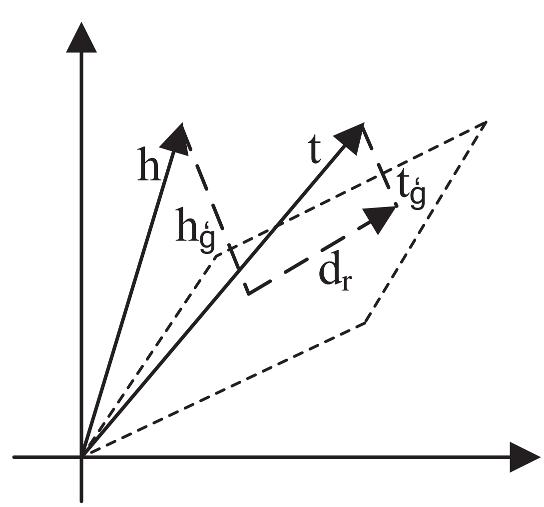

Fig. 2. An illustration of TransH.

3.2. Many-objective optimization

Algorithm that can make three or more objective functions in a given region simultaneously as best as possible is called many-objective evolutionary algorithm, the definition of MaOEA is as follows:

$$minimize F(a) = (f_1(a), f_2(a), \ldots, f_n(a))^T (n > 3) \tag{5}$$

where, $a = (a_1, a_2, \ldots, a_m) \in \Omega$ is called decision variable, Ω denotes decision space, the number of target functions is indicated by n, the dimension of decision variable is represented by m.

Given two different decision vectors, $a \prec b$ if and only if the listed blew conditions are met:

$$\begin{aligned} &\forall i \in \{1, 2, \cdots, n\} : f_i(a) \leqslant f_i(b) \\ &\exists i \in \{1, 2, \cdots, n\} : f_i(a) < f_i(b) \end{aligned} \tag{6}$$

If there is no $a \in \Omega$ such that $a \prec a^*$, $a^* \in \Omega$ is identified as Pareto optimal.

Many-objective optimization algorithm can only try its best to make each objective function draw near to the optimal, so optimal solutions of many-objective optimization problem are a group of tradeoff solutions.

$$PS = \{a \in \Omega | \neg \exists a^* \in \Omega, a^* \succ a\} \tag{7}$$

4. Proposed the model of explicable recommendation based on MaOEA

The model of explicable recommendation system on the basis of MaOEA is introduced. Unified method is used to quantify explainability, and MaOEA is employed to concurrently optimize precision, novelty, diversity, and explainability in order to improve explainability without affecting accuracy.

4.1. Problem definition

Recommendation problem in explicable recommendation model based on knowledge graph and many-objective optimization can be expressed as follows. Knowledge graph is a heterogeneous information network, which contains rich semantic associations among entities. In the constructed knowledge graph, nodes represent entities and edges denote semantic relationships among entities. By introducing knowledge graph into recommendation system, unified method is used to measure the explainability of items.

Accuracy is a basic indicator used to measure the merits and demerits of recommendation algorithms, diversity provides a list of recommendations that cover the user's different areas of interest to meet the user's preferences, novelty refers to the ability to recommend items that are not popular, explainability reflects the probability that user chooses the recommended items. Four objective functions are critical, and they contradict each other. It is our goal to compromise among four objective functions, so that each objective function can be as optimal as possible, and finally get a set of Pareto solutions that satisfy all objective functions.

4.2. The framework of proposed model

Primarily, (user, item, rating), (actor, item, acted) and (director, item, directed) these triples are extracted to construct knowledge graph. There are four different nodes in these triples: user, item, actor and director, these nodes of disparate types are regarded as entities in knowledge graph. The relationships existing in various triples that contain ratings ranging from 2.5 to 5, acted and directed are looked on as the connections among entities in knowledge graph. The constructed knowledge graph is rich in semantic relations, which effectively compensates for the sparsity of interactive information. The list of candidate recommendations of target user can be obtained on the basis of constructed knowledge graph. Then, the vectors of entities and the vectors of relations are acquired by embedding-based method in knowledge graph embedding algorithm, and these embedding vectors are boring into explicable recommendation system. In addition, the product between vectors corresponding to entity and relationship is calculated to reflect the importance of relationship to entity. According to constructed knowledge graph, the path from target user to recommended item is obtained, and the importance of corresponding relationship to entity in the path is summed up to measure the explainability of recommended item. The specific calculation of explainability is in section 4.3. The meaning of accuracy, diversity and novelty and the method of calculation are described in detail in section 4.4. Eventually, accuracy, diversity, novelty and explainability are taken as four objective functions, and GrEA is used to optimize the list of candidate recommendations of target user obtained through knowledge graph constructed by the above triples, so that these objective functions are optimized as much as possible, in order to obtain the final recommendation results satisfying the four objective functions. The framework of this explicable recommendation system model is exhibited in Fig. 3.

4.3. Explainability

Explainability measures the ability to improve a user's choice of items in recommendation results. For purpose of getting the utmost out of semantic information about knowledge graph and path information between nodes, embedding-based method as well as path-based method is combined to provide better explainability for recommended items and improve the probability of users choosing recommended items. Firstly, TransH is used to transform nodes and relationships in knowledge graph into vectors, and the corresponding vectors of nodes and relationships are multiplied to indicate the importance of relationship to nodes. A higher value manifests that the relationship is more significant to the node. Then, all paths starting from target user in knowledge graph are obtained, and the product of node vector and relation vector on each path is summed up to evaluate the explainability of recommendation results corresponding to the path. High explainability indicates that relationship of the path is more significant to node, and the recommended item is more easily accepted by the target user. The definition of explainability is as:

$$Explainability = \frac{\sum_{i \in R_u} \sum_{l \in L} e_u^{(l)} \cdot r_u^{(l)}}{|R_u|} \tag{8}$$

where L represents all paths from user u to item i, $e_u^{(l)}$ is on behalf of the embedding of entity e_u that is in the path from object user u to recommended item i, $r_u^{(l)}$ is the embedding of relation r_u that is in the paths from object user u to recommended item i, the embedded vector dimension is 50.

4.4. Objective functions

The proposed explicable model based on MaOEA and knowledge graph which can optimize precision, diversity, novelty, as well as explainability meanwhile in this paper. Accuracy is the most intuitive indicator used to measure whether users like items in recommendation results. Higher precision denotes that the recommendation performance of the presented model is much better. Items rated higher than 3 are considered to be preferred by users. Accuracy is calculated as follows:

$$Accuracy = Precision = \frac{|R_u \cap T_u|}{|R_u|} \tag{9}$$

where $|R_u|$ represents recommendation lists of user u, T_u signifies the items that user u likes, $|R_u|$ stands for the length of recommendation results on user u, $|R_u \cap T_u|$ manifests the length of items that preferred by user u.

Novelty signifies the popularity of items in recommendation results, the low mean prevalent of items in a list of recommended results in-

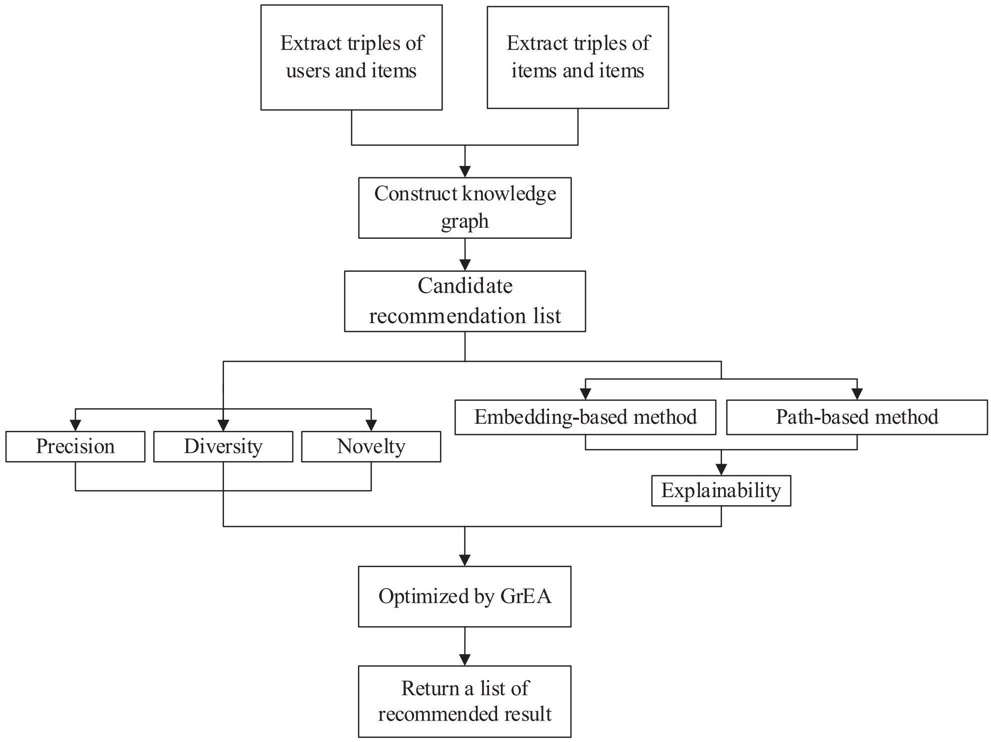

Fig. 3. the framework about proposed model.

dicates that the corresponding recommended items are relatively novelty. The reciprocal of the amounts of times that all users rate an item indicates novelty of the item, hence, a higher novelty value means a lower popularity of list of recommended results. Novelty is defined as:

$$Novelty = \frac{\sum_{i \in R_u} \log_2\left(\frac{num}{r_i}\right)}{|R_u|} \tag{10}$$

where r_i represents the amounts of times that all users rate the item$i$, *num* is the quantity of users.

When making recommendations, the diversity of users' interests should be considered to provide users with a variety of items, so as to explore the interest points of users. Diversity pays more attention to the richness of items in recommendation results that is measured by the total dissimilarity between items in recommendation results, which is calculated as:

$$Diversity = 1 - \frac{\sum_{i \in R_u} \sum_{j \in R_u} s(i,j)}{\frac{1}{2}|R_u|(|R_u| - 1)} \tag{11}$$

where $s(i,j)$ denotes the similarity of different items in recommendation results ($i \neq j$).

To recommend relevant items, accuracy, diversity, novelty and explainability should be as large as possible. The larger values of four objective functions are, the better performance of proposed model is. Therefore, the four objective functions that are mentioned should be maximized at the same time. The optimization problems of corresponding recommendation in this paper are as follows:

$$\begin{cases} \max Accuracy = Precision = \dfrac{|R_u \cap T_u|}{|R_u|} \\ \max Novelty = \dfrac{\sum\limits_{i \in R_u} \log_2\left(\dfrac{num}{r_i}\right)}{|R_u|} \\ \max Diversity = 1 - \dfrac{\sum\limits_{i \in R_u} \sum\limits_{j \in R_u} s(i,j)}{\dfrac{1}{2}|R_u|(|R_u| - 1)} \\ \max Explainability = \dfrac{\sum\limits_{i \in R_u} \sum\limits_{l \in L} e_u^{(l)} \cdot r_u^{(l)}}{|R_u|} \end{cases} \tag{12}$$

4.5. Individual representation

Real number encoding is suitable for recommendation scenarios, hence, chromosome is encoded by integer that is the corresponding to item number in candidate recommendation list. What calls for special attention is that duplicates elements can not occur to an individual, that is because an individual represents a recommendation generated for user, in which items can not be recommended repeatedly. An explanation of individual coding is revealed in Fig. 4.

4.6. Genetic operators

Genetic operators, including selection, crossover as well as mutation, play an indispensable role in genetic algorithm, which are essential to seek optimal solutions, genetic algorithm has better search ability through selection with retaining individuals of high fitness in the population, crossover with global search ability and mutation with local search ability, so as to increase the diversity and convergence of individuals.

In this paper, we principally improve the crossover and mutation in genetic algorithm. Therefore, the operation of selection is briefly

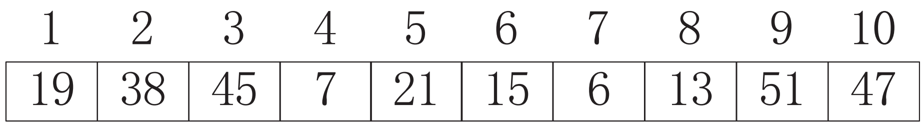

Fig. 4. An explanation of individual coding.

introduced, and the improved crossover and mutation are explained meticulously in the following subsections. Matching selection used in this paper: a strategy of tournament selection on the basis of dominance relation and density information is used to select individuals. Environmental selection: the goal of obtaining the best individuals is achieved by selecting the best solutions from the former population and the population of newly created.

4.6.1. Crossover

Crossover refers to substitution of parts of different individuals to produce a new individual. Crossover can obtain two different offspring by randomly selecting two parent individuals, dividing the parent individuals at the randomly location and exchanging the right part of them. The detailed crossover is described as follows: primarily, two various individuals P1 as well as P2 is choosing randomly from the entire population. Next, a stochastic point i is picked, and the parent individuals P1 and P2 are swapped from the right of i, new progeny individuals C1 as well as C2 are generated by crossover. Then, Duplicate element may be generated after crossover. For the repeated element, its position is obtained, and a parent individual P3 is randomly selected to replace the repeated element with its element of the same position, and the process is repeated until there is no repeated element in the individuals. The detailed process of crossover is shown in Fig. 5.

4.6.2. Mutation

Mutation refers to the replacement of some gene values in individual chromosomes with other alleles to form a new individual. The mutation point is selected randomly, then, an element is chosen from the candidate recommendation list that has not appeared in the individual, and replace the element corresponding to the mutation point. The detailed description of mutation is displayed in Fig. 6.

5. Experimental

The validity of the proposed model is testified by analyzing experiments on different data sets. Design of experiments and the result of experiments are analyzed concretely.

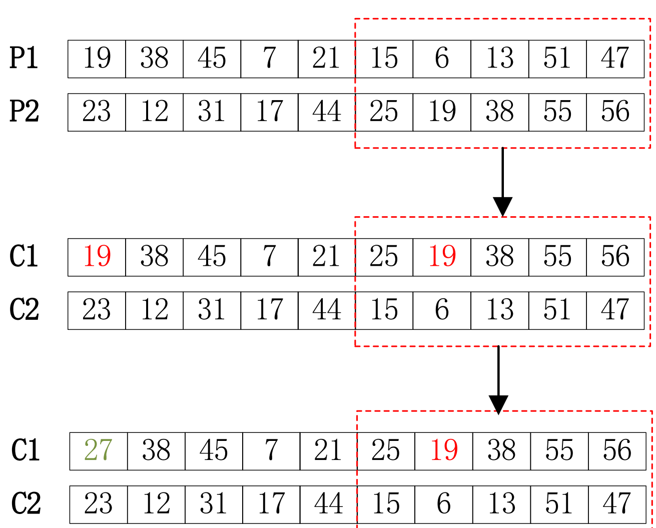

Fig. 5. An illustration of the crossover operator.

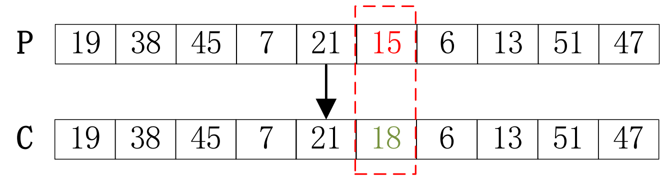

Fig. 6. An illustration of the mutation operator.

5.1. The set of data

An extension of MovieLens10M data set which published by GroupLeans research group is applied to estimate the property of proposed model (https://www.grouplens.org). The set of data involves 2112 users as well as 10,197 items, and 80 percent of the entire data set is employed as the training set and the rest of 20 percent as test set. The entire dataset is divided into four various relatively small datasets. Table 1 reveals the analysis of various data sets.

5.2. Parameter settings

Candidate recommendation list is obtained by constructed knowledge graph, which is optimized by MaOEA to acquire the top-N recommendation list. The main parameters in algorithm are set in Table2.

5.3. The metrics of evaluation

For the purpose of revealing the validity of a recommendation model is directly reflected on its performance in evaluation indicators, so the evaluation indicators of recommendation results have always been very important. Precision reflects the ability of generating recommendation results that preferred by user on the basis of implicit interaction both user and item. Novelty refers to the ability to recommend non-popular products to users. Recommendation results are diversified to meet users' broad interests, which can cover users' different areas of interest. Explainability increases the likelihood that users will accept recommended items, increasing transparency and persuasiveness of recommendations. Therefore, the objective functions mentioned in Section 4.2 are regarded as evaluation indicator of the paper.

5.4. Experimental results

The analysis of experiment contains two parts, one is the comparison between algorithms to find an algorithm that enables the model of presented with the most significant recommendation performance, the other is contrasted of other models to prove the availability of proposed model.

Table 1
Analysis of various data sets.

Data set	Users	Items
Movielens1	528	10197
Movielens2	528	10197
Movielens3	528	10197
Movielens4	528	10197

Table2
The setting of main parameters.

Parameters	value
Individual dimension (n)	10
The probability of crossover	1
The probability of mutation	1/n
Population size	100
Max generation	100

5.4.1. *Comparison results of algorithms*

MaOEA is a valid way to settle the matter of many-objective optimization by looking for a set of compromise solutions among different objective functions. In this section, NSGA-III (Jain & Deb, 2014), GrEA (Yang, Li, Liu, & Zheng, 2013) and RVEA (Cheng, Jin, Olhofer, & Sendhoff, 2016) are applied to estimate the model which is presented in the paper. A set of non-dominant solutions are obtained through these three algorithms, which represents a list of recommendation result. Therefore, we obtain maximum, minimum as well as mean value of each evaluation indicator on this set of solution. The experimental results of each indicator are shown in Fig. 7. It can be clearly concluded from Fig. 7 that although maximum value of precision is the same, minimum value and average value are the best obtained by GrEA. In terms of novelty, maximum value gained by GrEA and RVEA is the same and the largest among three algorithms, while the minimum value obtained by GrEA is still higher than the other two algorithms. Generally speaking, GrEA has the best effective in novelty, its maximum value and minimum value are the best among three algorithms. What can be seen from Fig. 7 is that maximum value of diversity obtained by GrEA and NSGA-III is the same, which is higher than maximum value acquired by RVEA. Meanwhile, minimum value and mean value acquired by GrEA are the best. In the aspect of explainability, the maximum and average values of GrEA are the best compared with other algorithms.

Fig. 8 reveals the boxplots of various algorithms on evaluation indicators, which use a more intuitional way to describe the distribution of solutions obtained by different algorithms. In terms of accuracy, diversity, and explainability, it is very explicit that the median of objective function obtained by GrEA is significantly better than the median obtained by NSGA-III and RVEA. Especially in the indicators of diversity and explainability, the performance of GrEA is more outstanding. The upper quartile of GrEA is closest to the top, indicating that most of the corresponding the values of solutions are relatively large. From the overall distribution of solutions obtained by each algorithm, GrEA has the best performance on diverse evaluation indicators. Theregore, it can draw a conclusion of the results from three algorithms on different evaluation indicators that GrEA is the best among comparison algorithms, which makes the proposed model have the best recommendation performance. Therefore, GrEA is selected for the model comparison experiment in the second part.

5.4.1.1. *Comparison results of models.*

In this subsection, the presented model on the basis MaOEA and knowledge graph embedding (MaORS-KGE) is compared with collaborative filtering (Yang, Guo, Liu, & Steck,

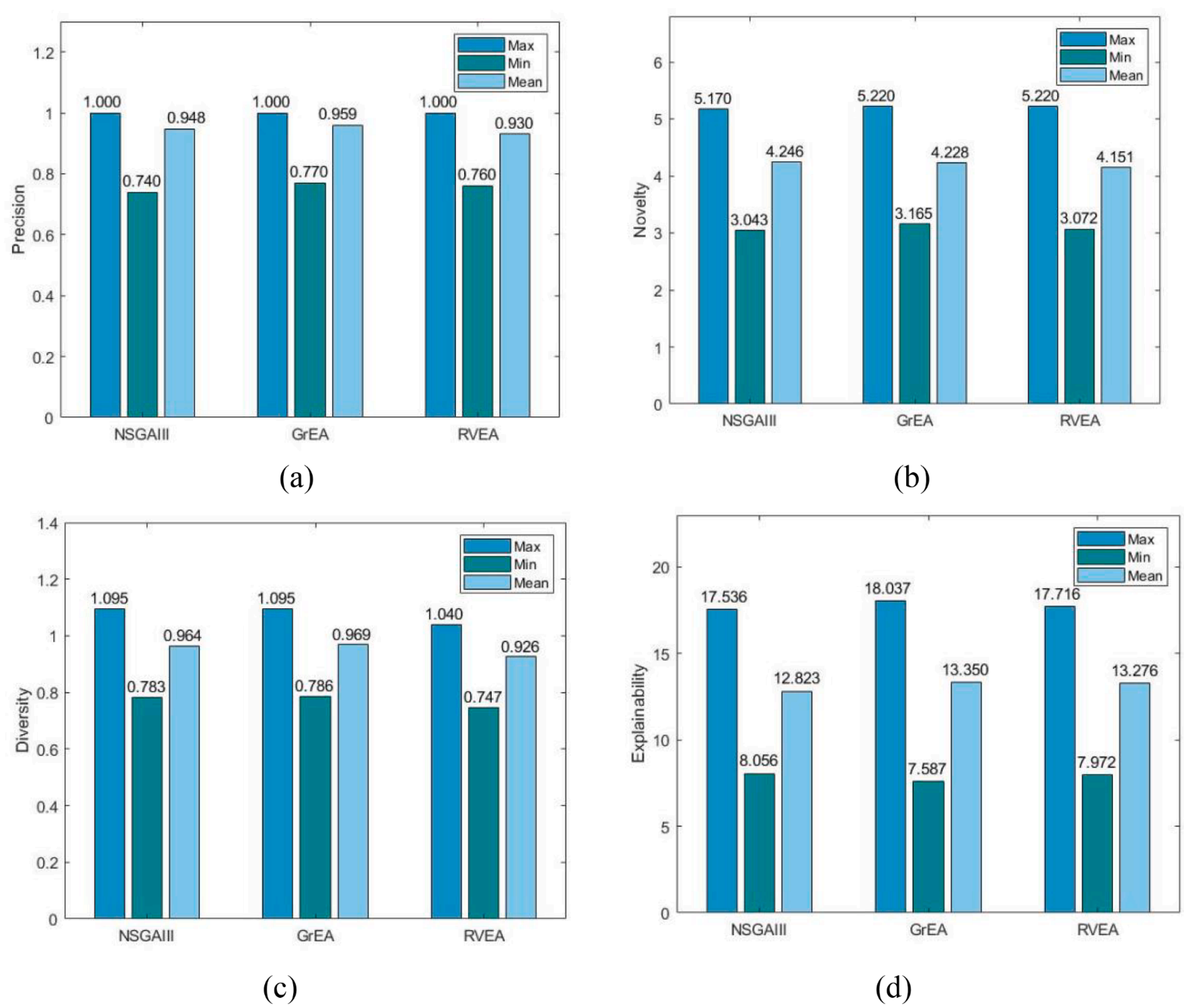

Fig. 7. Recommendation performance of three algorithms on different evaluation indicators. (a) Precision (b) Novelty (c) Diversity (d) Explainability.

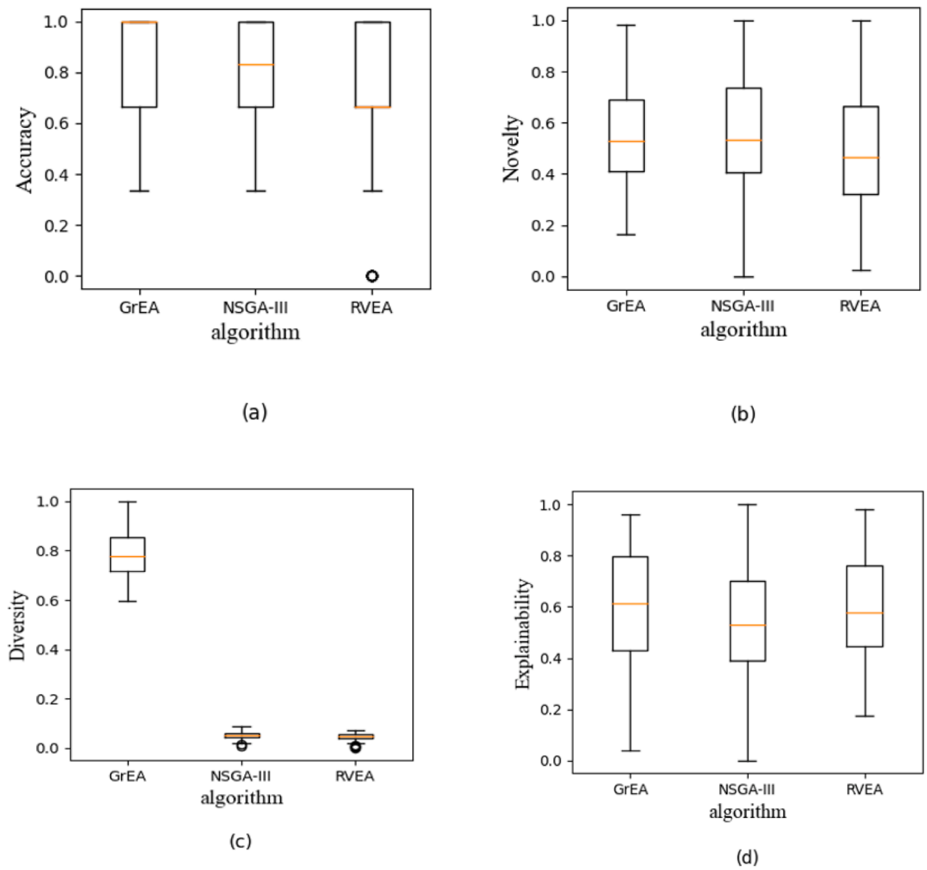

Fig. 8. The boxplots of three algorithms on various evaluation indicators. (a) Accuracy (b) Novelty (c) Diversity (d) Explainability.

2014), MORS (Wang, Gong, Li, & Yang, 2016) and MaORA (Cui et al., 2021) to certify the availability of proposed model. What is obtained through MaOEA is a list of tradeoff solutions, and we compare maximum, minimum, as well as mean values of those solutions to other models. The recommended performance of comparison models in Movielens1 is shown in Table 3.

As can be seen from Table 3, in terms of precision and novelty, although maximum, average and minimum values obtained by the model proposed in this paper are not the best, the overall performance of the model proposed is still better than that of collaborative filtering. As can be seen from Table 3, compared with other models, maximum value and average value of the model proposed in this paper are the best in terms of diversity and explainability, and the value of average is higher than that of collaborative filtering. In general, on the dataset of Movielens1, the performance of MaORS-KGE in the other three evaluation indicators is good except novelty.

Table3
The performance of comparison models in Movielens1.

		Precision	Novelty	Diversity	Explainability
Item -Based CF		0.900	3.421	0.880	8.913
User-Based CF		0.900	2.926	0.791	7.177
Best	MORS	0.930	7.443	0.935	12.183
	MaORA	1.000	6.714	0.885	6.249
	MaORS-KGE	1.000	5.220	1.095	18.037
Mean	MORS	0.910	7.320	0.885	11.028
	MaORA	0.993	6.087	0.665	3.115
	MaORS-KGE	0.959	4.228	0.969	13.350
Worst	MORS	0.890	7.296	0.877	10.749
	MaORA	0.870	4.779	0.523	0.891
	MaORS-KGE	0.770	3.165	0.786	7.587

Table 4 demonstrates the property of different models on other data sets. Holistic performance of presented model is the greatest on various data sets. The mean values of evaluation indicators except accuracy and novelty gained by proposed model are superior to the values acquired by other comparison models in Movielens2 and in Movielens3. In Movielens3, the maximum value of proposed model in novelty is the best, and the average value is second only to MaORA, in terms of accuracy, the maximum of presented model is the best as MaORA, but the average value of MaORS-KGE is still lower than MaORA. In Movielens4, although explainability gained by MaORS-KGE are the best among four models, the average values of accuracy and diversity obtained by the model of MaORS-KGE are lower than those obtained by comparison models. From the analysis of the above results, it can be clearly concluded that in different data sets, MaORA always has the best values in novelty and accuracy, because MaORA adopts the improved matrix decomposition algorithm with regularization constraint to provide users with novel and diverse recommendation more efficiently. Although MaORS-KGE performs second to MOPA in terms of novelty and accuracy, it is consistently the best among comparison models in terms of explainability, and MaORS-KGE is far ahead in terms of diversity in most data sets.

Presented model optimizes candidate recommendation list to make recommendations, which is obtained from knowledge graph. Recommendation result is concerned to the construction of knowledge graph, therefore, the average performance of property model is relatively stable in different data sets. MORS and collaborative filtering need to obtain predicted ratings, and then generate recommendations based on the predicted ratings. Errors will inevitably occur in the process of predicting ratings, thus affecting recommendation results. Therefore, recommendation performance of MORS and collaborative filtering fluctuates greatly in different data sets. To sum up, overall performance

Table 4
The performance of comparison models in other data sets.

		User-based CF	Item-based CF	MORS Best	MORS Mean	MaORA Best	MaORA Mean	MaORS-KGE Best	MaORS-KGE Mean
Movielens2	Precision	0.500	0.800	0.900	0.850	0.990	0.8625	1.000	0.797
	Novelty	3.929	4.188	5.513	5.420	7.156	6.544	7.613	5.375
	Diversity	1.092	1.088	0.945	0.936	0.980	0.658	1.282	1.095
	Explainability	15.933	13.468	12.415	12.217	14.849	4.684	65.918	35.112
Movielens3	Precision	0.600	0.300	0.200	0.150	1.000	0.845	1.000	0.646
	Novelty	3.909	3.032	3.762	3.733	5.725	4.879	5.885	4.522
	Diversity	1.072	1.018	1.022	1.004	0.929	0.696	1.276	1.075
	Explainability	14.598	15.818	21.908	21.657	27.485	8.763	89.192	44.966
Movielens4	Precision	0.900	0.800	0.800	0.750	1.000	0.934	1.000	0.788
	Novelty	2.883	3.429	3.509	3.501	6.198	5.674	5.605	4.517
	Diversity	0.956	1.043	1.103	1.081	0.979	0.755	1.234	1.056
	Explainability	20.155	15.646	23.735	21.109	23.922	9.600	80.793	49.398

of presented model is the best compared with other models, and the improvement of recommended performance is also the most comprehensive.

6. Case study on path explanation

For the sake of intuitively show how the proposed model produces explainable recommendation results, we randomly select a user to get the recommendation results of the user, and explain how to explain through corresponding path of recommendation results. Firstly, user 78 is randomly selected, and a group of compromise solutions satisfying four objective functions are obtained. Taking item 4467 randomly selected as an example, how to generate an explanation for the user through the corresponding path is illustrated in Fig. 9.

From Fig. 9 we can visually see that there are five different paths from user 78 to item 4467, and each paths represent different semantics. These paths can be divided into two types, which are shown in Fig. 9, the first type of path pattern is {*user→item←actor→item*}, the second type of path pattern is{*user→item←director→item*}. The embedding vectors of entities as well as relationships in constructed knowledge graph are obtained through TransH. The product of vectors corresponding to entities as well as relationships is employed to reflect the significant of relationships to various entities, which measures the explainability of paths. The best path is chosen to explain to user to improve the probability of user to choose recommended items. Corresponding explainability of each path is listed as bellow:

- Movie 4467 is recommended because user 78 has seen movie 41, the actor of movie 41 is alison_steadman, who also appeared in movie 4467. The explainability of this path calculated by embedding vectors is 3.327.
- Movie 4467 is recommended because user 78 has seen movie 296, the actor of movie 296 is bill_paterson, who also appeared in movie 4467. The explainability of this path calculated by embedding vectors is 3.271.
- Movie 4467 is recommended because user 78 has seen movie 4280, the actor of movie 4280 is robin_williams, who also appeared in movie 4467. The explainability of this path calculated by embedding vectors is 2.879.
- Movie 4467 is recommended because user 78 has seen movie 4981, the actor of movie 4981 is uma_thurman, who also appeared in movie

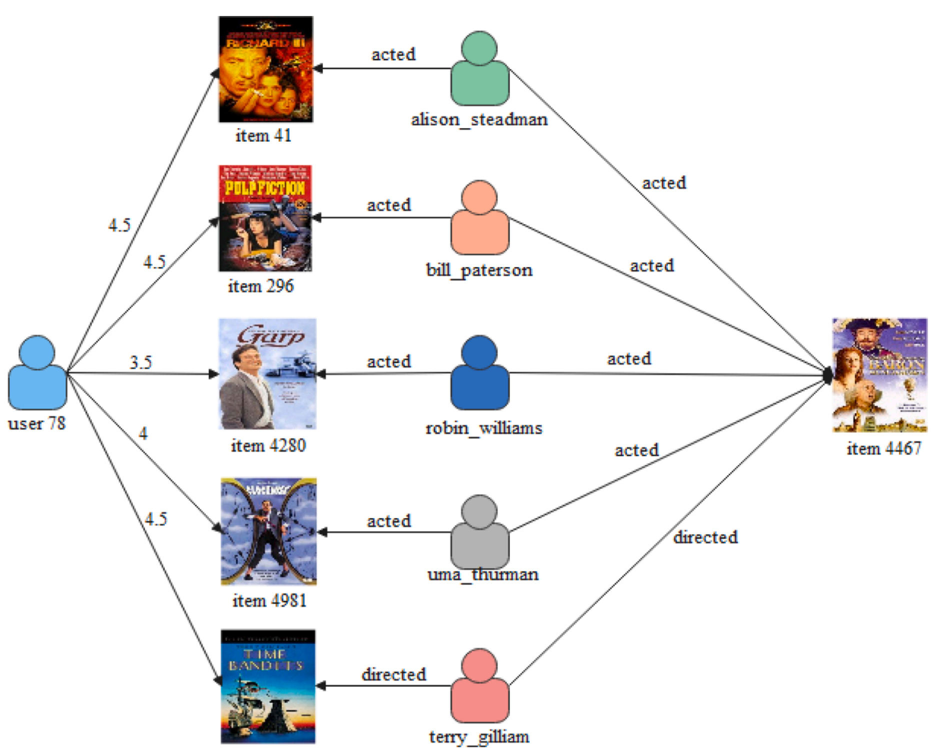

Fig. 9. An illustration of explanation paths between user 78 and item 4467.

4467. The explainability of this path calculated by embedding vectors is 2.799.

• Movie 4467 is recommended because user 78 has seen movie 2968, the director of movie 2968 is terry_gilliam, who also directed movie 4467. The explainability of this path calculated by embedding vectors is 3.470.

Among these paths, the best explanation path is the last one. In the last path, user 78 gives a high rating to movie 2968, and movie 4467 with the same director as movie 2968 are more acceptable for the target user.

7. Conclusion

An explainable recommendation model is presented on the basis of knowledge graph as well as many-objective evolutionary algorithm (MaORS-KGE), and the embedding vectors of entities and relationships are obtained by knowledge graph embedding in the paper. The embedding vectors are used to measure the explainability of paths in knowledge graph, and then many-objective evolutionary algorithm is employed to optimize accuracy, diversity, novelty and explainability simultaneously. Through a lot of various experiments, it is attested that the monolithic performance of MaORS-KGE is much greater than that of collaborative filtering and MORS, and the effectiveness and explainability of MaORS-KGE are also proved.

Although the model presented in the paper has favourable performance on all evaluation indicators, the preference of user affects the explainability of proposed model. The factors affecting preference for user should be comprehensively considered to boost the ability of explanation in future research.

CRediT authorship contribution statement

Xingjuan Cai: Conceptualization, Writing – review & editing. **Lijie Xie:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Rui Tian:** Writing – review & editing. **Zhihua Cui:** Supervision, Project administration, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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