Towards Better Course Recommendations: Integrating Multi-Perspective Meta-Paths and Knowledge Graphs

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Abstract

Course recommender systems demonstrate their potential in assisting students with course selection and effectively alleviating the problem of information overload. Current course recommender systems focus predominantly on collaborative information and fail to consider the multi-perspective information and the bi-directional relationship between students and courses. This paper introduces a novel Multi-perspective Aware Explainable Course Recommendation model (MAECR) that leverages knowledge graphs and multi-perspective meta-paths to enhance both the accuracy and explainability of course recommendations. By the dual-side modeling from both the student and the course for each meta-path, MAECR can identify and understand the interests and needs of students in each course, as well as evaluate the attractiveness and suitability of the courses for individual students. Following the dual-side modeling for each meta-path, we aggregate multi-perspective meta-paths of each student and course using a carefully designed attention mechanism. The attention weights generated by this mechanism serve as explanations for the recommendation results, representing the preference score for each perspective. MAECR thus provides personalized and explainable recommendations. Comprehensive experiments are implemented to demonstrate the effectiveness and improved interpretability of the proposed model.

CCS Concepts

• Applied computing → Collaborative learning; **• Information systems → Data mining**; **• Social and professional topics → Computing education**.

Keywords

Course recommendation, Explainable recommender systems, Knowledge graphs

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1 Introduction

Massive Open Online Courses (MOOCs) have garnered considerable attention as an alternative educational pattern to traditional university classrooms, democratizing educational resources. However, with a vast array of courses available, it can be challenging for students to select the appropriate ones based on their various needs. Course recommender systems demonstrate their potential in assisting students with course selection and effectively alleviating the problem of information overload [15, 19]. Given a set of historical courses that a user enrolled in, the key factor of generating effective recommendations relies on the accurate modeling of user preferences and course attributes [35].

Recent works proposed to generate precise and individualized course recommendations based on their historical data [5, 9, 20, 22, 25, 40]. While the aforementioned methods excel in modeling user preferences, they do have some limitations. One significant limitation of previous research is the insufficient integration of external entities or relations information (e.g., knowledge concept entity and prerequisite relation) [7, 36]. Previous research often relies on course content and student interactions to model the embeddings of the student and course while considering only a single perspective, either from the user to the course or from the course to the user [3]. Students may have different orientations based on their own reasons, which serve as different criteria for course selection and influence their course selection process [18]. A useful course recommendation system should better account for student motivations in their designs [17], which means it should consider multi-criteria personalized recommendations based on students' goals. Correspondingly, each course contains specific content, specialized knowledge, and target audiences, students are likely to consider multi-perspective information when selecting a course. An illustrative example is shown in the left part of Fig 1, the target student expresses interest in the course *Database*. The motivation behind this choice could be the specific knowledge concepts such as

Programming Language covered in the course, prior course enrollment experience with similar courses such as *Pattern Recognition* (e.g., Learning-oriented), or even the instructor *Teacher*'s expertise and teaching style that aligns with the target student's preferences (e.g., Social-oriented). Previous studies have primarily focused on modeling users based solely on course content and individual interaction data. We consider that the integration of information from multiple perspectives can facilitate comprehensively capturing the factors that influence users' preferences for target courses.

Another limitation of previous research is that they only considered student-side preferences, neglecting whether the course is suited to the student. These studies employed one-way modeling, focusing solely on student interest in courses [35]. However, courses vary in terms of difficulty and prerequisite requirements, which raises the possibility that although a student may express interest in a course, the instructor's teaching style or the course's difficulty level may not be appropriate for that student. As shown in the right part of Fig 1, the target student's interest in course *Computer Vision* is considered without accounting for the student's lack of *Machine Learning Basics* knowledge concept, the recommendation may be inappropriate. Conversely, by employing bi-directional modeling of both student and course sides, the system can recommend course *Computer Vision* to students who possess the necessary knowledge *Machine Learning Basics*, thereby ensuring the appropriateness of the recommendation. Bi-directional modeling allows us to evaluate both the student's interest in and need for the course, as well as whether the course aligns with the student's abilities. Additionally, previous research lacked attention to the explainability of the recommendations, which has often been on improving model accuracy and neglects the crucial aspect of explainability in recommendations. One approach to address the issue of limited explainability in course recommender systems is to incorporate a knowledge graph that integrates multi-dimensional information about both the user and the courses. By analyzing the knowledge graph, the system can take into account individual pieces of information about the user and the courses. Explicitly presenting the user's attention to various dimensions of information and the degree of alignment with each dimension of the target course offers an opportunity to enhance the user's comprehension of the recommendation results.

To address the limitations of existing methods, this paper proposes a novel **M**ulti-perspective **A**ware **E**xplainable **C**ourse **R**ecommendation model integrating knowledge graphs and multi-perspective meta-paths called MAECR. MAECR integrates multi-perspective information from both sides of users and courses within the knowledge graph and models them from their respective perspectives. Specifically, we first construct the knowledge graph containing rich entity and relation information, then extract multi-perspective meta-paths between users and courses. These multi-perspective meta-paths are encoded using the Bi-directional Long Short-Term Memory technique (BiLSTM) and integrated through a well-designed attention mechanism. The multi-perspective meta-paths and dual-side modeling allow us to personalized model users and courses, taking into account the various attention different users pay to distinct aspects. The learned attention weights can also be employed to explain the reasons behind the recommendations, as they reveal the relative importance of different meta-paths to the target users. By modeling users and courses through the knowledge graph and meta-paths, MAECR can enhance recommendation effectiveness and provide explanations to users. Through extensive experiments, including performance comparisons with baselines, modeling studies, and case studies, we validate the effectiveness and explainability of MAECR. Our findings indicate that entity information plays a more crucial role than relational information in modeling student preferences.

2 Related Work

2.1 Course Recommendation

Historically, the development of course recommendation systems predominantly focused on content-based or collaborative filtering (CF) methods [9, 22–24]. Scholars Walk [27] employed a randomized wandering approach to acknowledge sequential course relationships. Wagner et al. [31] employed the traditional machine learning technique KNN to assist students in mitigating dropout risks. With the development of deep learning, this technique is also widely used in course recommendation [6, 8, 25, 26, 40]. Yu et al. [39] presented an end-to-end hierarchical reinforcement learning (HRL) model for concept expansion in MOOCs, which employed a two-level HRL mechanism of seed selection and concept expansion. Gao et al. [5] introduced the Relation Map Driven Cognitive Diagnosis (RCD) model, which enhances cognitive diagnosis accuracy by comprehensively modeling student-exercise-concept interactions using a multi-layer relation map. Gao et al. [4] proposed a novel online course recommendation model that integrates a deep convolutional neural network with negative sequence mining. Despite their performance efficacy, they did not provide discussions about the explainability of their model. The 'black box' nature of deep learning models raises interpretability concerns [15, 16].

Course recommendation in the educational environment presents a multifaceted challenge, largely due to the diversity of factors influencing student course selection, including future career, learning goals, and credit requirements [19]. Moreover, as noted by [32], '*the trust educators and learners place in a model is contingent on its explainability*'. Therefore, our primary goal is to integrate user and course multi-perspective information to achieve effective and explainable recommendations.

2.2 Knowledge Graph-based Recommendation

Knowledge graphs, which encapsulate personalized information about students and courses, offer valuable context by mapping entities and their relationships, enhancing the representation learning capabilities of the course recommender systems [34, 37, 41].

Jiang et al. [7] formulated the knowledge concept recommendation as an intensive learning task combined with MOOC knowledge graphs. Recent studies have also explored the extraction and modeling of meta-paths in knowledge graphs. Yang et al. [36] explored how meta-graphs facilitate the discovery of nuanced user/item representations and the extraction of meaningful structures, enriching the semantics of recommendations. Frej et al. [3] incorporated meta-path information to make recommendations explainable, which also determined the suitable length of meta-paths in recommendations. Wu et al. [33] proposed a Graph-based Student Knowledge Profile Model (GSKPM) to accurately profile students' knowledge by leveraging graph structures, addressing cold start problems in online

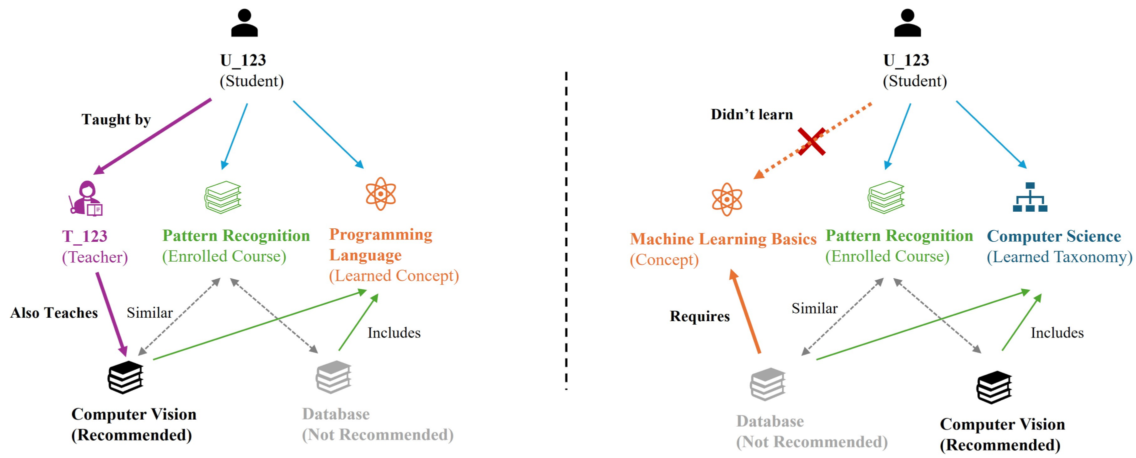

Figure 1: Two illustrative examples of multi-perspectives and dual-side modeling are shown on the left and right parts, respectively.

learning, and ensuring consistency between training and prediction outcomes. Ain et al [1] explored how personal knowledge graphs can be leveraged to enhance learner modeling and recommend personalized learning resources in MOOCs. Ma et al. [21] introduced a multi-graph recommendation method based on contrastive learning that enhances fairness in course recommendations by considering learners' diverse knowledge backgrounds. Although they utilized various information from the knowledge graph to enhance recommendations, they performed limited mining of the information covered by the meta-paths within the knowledge graph, making it difficult to learn the influence of different meta-paths on student recommendations. Additionally, their modeling process only considered student preferences while neglecting the suitability of the courses.

Distinct from other knowledge graph-based recommender systems [3, 35], our approach explicitly models users and courses, aggregating each meta-path with students and courses as starting points, respectively. Moreover, we introduce an attention mechanism in the aggregation process. This strategy allows each user to gain a deeper understanding of their individual preferences and suitability to recommended courses, thereby enhancing the explainability of our model.

3 Preliminaries

We aim to provide course recommendations that are both accurate and explainable. To facilitate understanding of the subsequent sections, we first explain relevant concepts and define our recommendation goal.

Knowledge Graph: Knowledge Graphs (KGs) are directed graphs in which nodes represent resource entities and edges labeled relationships between them. We construct a knowledge graph $\mathcal{G}_k = \{(s, r, d) \mid s, d \in \mathcal{E}, r \in \mathcal{R}\}$, where $\mathcal{E}$ represents the set of entities including students, courses and their associated attributes such as concepts, taxonomies, teachers, schools, etc. And $\mathcal{R}$ denotes the set of relations between entities, such as a student *enrolling* in a course, an instructor *teaching* a course, a course being *related to* some knowledge concepts or taxonomies, a university *offering* a course, etc. Each triplet (s, r, d) denotes a source entity node s, relation edge r and destination entity node d. For example, (Student A, Learn, Binary Tree) means Student A learned knowledge concept Binary Tree.

Meta-path: A meta-path is a sequence of entity nodes and relation edges, indicating a specific semantic path among entities. For example, a meta-path of "Student - LearnConcept - Concept - RequiredBy - Course" indicates that a student has learned a concept required by the target course. We pre-define a set of meta-path patterns and extract all meta-paths from the knowledge graph $\mathcal{G}_k$. A meta-path $p \in \mathcal{P}$ can be defined as $(e_1, r_1, e_2, \cdots, r_{n-1}, e_n)$, where e_i denotes entities and r_i represents relations in the knowledge graph. Frej et al. [3] have verified that learners prefer paths that are neither too long nor overly complex. Following their work, we limit the length of meta-paths to an appropriate range in our work.

Recommendation Goal: Given the user-course interaction history graph $\mathcal{G}_i$ and knowledge graph $\mathcal{G}_k$, our goal is to predict missing links in the interaction graph $\mathcal{G}_i$, which indicates the enrollment probability between the target user and the target course.

4 The Proposed MAECR Model

In this section, we introduce our model MAECR, a Meta-path Aware Explainable Course Recommendation model. The overview of the proposed model is shown in Figure 2. It consists of three components: *Multi-Perspective Meta-path Extraction* component, *Dual-Side Meta-path Modeling* component, and *Attention-based Meta-path Aggregation* component.

4.1 Multi-Perspective Meta-path Extraction

To analyze the multi-perspective preferences of students and the multi-dimensional information of courses, we first construct an overall graph $\mathcal{G} = \mathcal{G}_i \cup \mathcal{G}_k$ from the original dataset. After constructing graph $\mathcal{G}$, we record the interactions between each pair (student, course) and extract the meta-paths that include various attribute information entities between them. Our goal is to extract

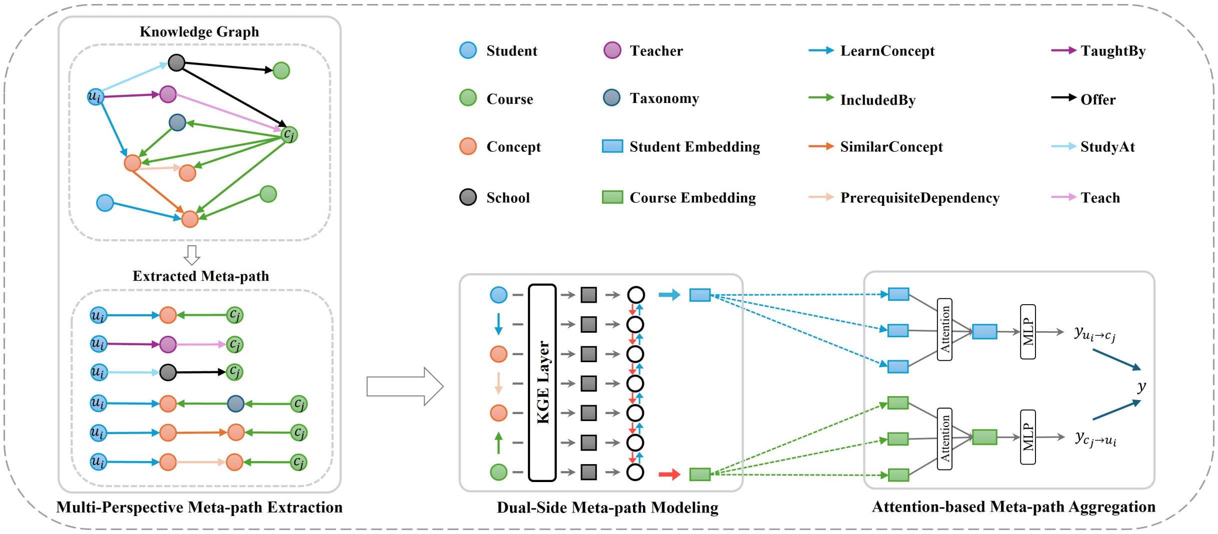

Figure 2: The architectural overview of the proposed MAECR model

meta-paths with multiple perspectives and appropriate lengths. In this paper, according to the original dataset, we focus on concept, taxonomy, similarity, teacher, and school information within the knowledge graph. Concept and taxonomy information is explored by previous research [35], which shows the usefulness of improving the accuracy of recommendations. The concept knowledge entities we use are detailed information, similar to *Inequalities* in *Mathematics* and *String-Matching algorithms* in *Computer Science*. Taxonomy knowledge entities, on the other hand, are relatively broad classifications, similar to category information such as *Mathematics* and *Computer Science*. Similarity information implies collaborative information containing interactions between students and courses, which is widely used in the recommender systems [5, 31, 35]. However, the influence of school and instructor information on course recommendations has been rarely explored. We believe this information plays a significant role in students' decision-making when selecting courses. Students often adopt a social-oriented approach when choosing a course [17], taking into consideration factors such as the instructor teaching the course and the institution offering it. Considering the multi-perspective information based on the dataset, the well-designed meta-paths in this paper are shown in Fig. 3:

We categorize meta-paths into two groups based on students' motivations for taking courses and the attributes of the courses: *Knowledge-oriented Meta-paths* and *Social-oriented Meta-paths*. Social-oriented meta-paths include *(Student, TaughtBy, Teacher, Teach, Course)* and *(Student, StudyAt, School, Offer, Course)* meta-paths. The meta-path containing teacher information *(Student, TaughtBy, Teacher, Teach, Course)* indicates that the student has enrolled in a course taught by this teacher. The meta-path containing school information *(Student, StudyAt, School, Offer, Course)* represents that this school offers the course the student has enrolled in. We incorporate teacher and school meta-paths into our model since we consider that students can be attracted to information beyond course knowledge information.

Due to the diversity of knowledge information and the complex connections between knowledge, we designed multiple perspective meta-paths about various aspects of information. When designing knowledge-oriented meta-paths, we categorize them into four types based on the different relationships between entities: *simple content meta-paths*, *similarity meta-paths*, *prerequisite meta-paths*, *and hierarchical meta-paths*. Simple content meta-paths consist of basic information derived from course content such as concept and taxonomy. These meta-paths highlight the direct influence of knowledge concepts and taxonomies relevant to students when selecting a course. The meta-paths *(Student, LearnConcept, Concept, IncludedBy, Course)* and *(Student, LearnConcept, Concept, RequiredBy, Course)* indicate that the student has learned the related concepts, which are included and required by the course. To address the potential issue of information cocoons and enhance the diversity of recommendations, we considered the meta-path *(Student, LearnTaxonomy, Taxonomy, IncludedBy, Course)*, as users may be interested in courses within similar categories.

Similarity meta-paths indicate that the meta-path contains similarity relationships. We compute similar concepts and similar courses based on collaborative information, aligning with the principles of collaborative filtering in recommender systems. The meta-path *(Student, Enroll, Course, SimilarCourse, Course)* considers that users may be interested in courses similar to those they have previously interacted with. Similarly, the meta-paths *(Student, LearnConcept, Concept, SimilarConcept, Concept, IncludedBy, Course)* and *(Student, LearnConcept, Concept, SimilarConcept, Concept, RequiredBy, Course)* suggest that if a student has learned concept A, they may be interested in a course that includes or requires a similar concept B. It is worth noting that we do not simply calculate similarity based on the interaction history between students and courses or between students and concepts. Instead, we use the Word2Vec technique to calculate 10 similar concepts for each concept, feeding all concepts into the word vector model to output the 10 most similar concepts for each one. Similarly, we select 10 similar courses for each course

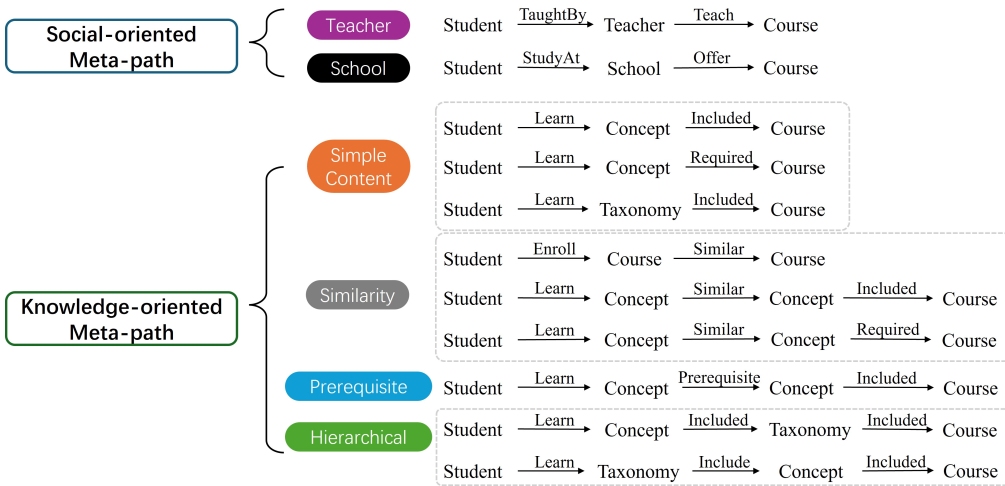

Figure 3: An illustrative example about Multi-Perspective Meta-path Extraction

by calculating the cosine similarity from the interaction history between students and courses to select the 10 most similar courses.

Prerequisite meta-paths capture the prerequisite-dependency relationship, which typically reflects a learning sequence between knowledge concepts, where mastering a specific concept requires prior knowledge of others. We design meta-paths incorporating prerequisite relationships based on this principle. The meta-path *(Student, LearnConcept, Concept, PrerequisiteDependency, Concept, IncludedBy, Course)* indicates concept A and concept B are prerequisite dependencies, which the student has learned concept A and concept B is included in the course. Hierarchical meta-paths capture the hierarchical relationships between knowledge concepts and taxonomies, revealing the connections between course content across different levels of granularity. Therefore, we considered meta-paths *(Student, LearnConcept, Concept, IncludedBy, Taxonomy, IncludedBy, Course)* and *(Student, LearnTaxonomy, Taxonomy, Include, Concept, IncludedBy, Course)* that reflect student-course interactions involving these two types of knowledge entities. This indicates that the student has learned related concepts or taxonomies, which are then related to a certain taxonomy or concept, and the course contains the latter's taxonomy or concept. Through our detailed and careful design and extraction of meta-paths, these meta-paths incorporate multi-perspective information, which is utilized in the subsequent parts of our research.

4.2 Dual-Side Meta-path Modeling

To capture the diverse preferences of students from various perspectives, as well as the attractiveness and suitability of courses in different aspects, we consider a dual-side meta-path modeling strategy that can consider each meta-path from the student's perspective as the source point and from the course's perspective as the source point. Since the same meta-path, it will reflect the intentions and preferences of the student side, as well as provide information about the attributes of the course and its appropriateness and attractiveness to different students. For example, the meta-path "*Student - LearnConcept - Concept A - PrerequisiteDependency - Concept B - IncludedBy - Course*" indicates that the student has learned Prerequisite Concept A, suggesting an interest in the target course or a goal to take a related course. On the other hand, the target course includes Concept B, and to understand it, one needs to have studied Concept A. In other words, the course is suitable for a student who has studied Concept A. Therefore, it is essential to model the meta-paths separately for students and courses.

We first model each meta-path from the student side and the course side, respectively. Inspired by recent research on reciprocal recommender systems [12], our approach employs a bi-directional LSTM (Bi-LSTM) technique to model each meta-path, as it effectively handles sequences consisting of entities and relations. LSTM can be used for feature extraction from sequential data, which can handle complex relations within the sequence. By considering both the student and the course as the starting points of the sequence in each of the two LSTM directions, the BiLSTM is able to learn a two-view representation of each meta-path. This approach enables the model to capture the user's preferences and goals, as well as the potential requirements of the course for each meta-path.

For modeling each meta-path $p = (e_1, r_1, e_2, \cdots, r_{n-1}, e_n) \in \mathcal{P}_{ij}$ between student u_i and course c_j, we first represent each entity and relation in the meta-path as a low-dimensional embedding using Knowledge Graph Embeddings (KGE) technique, which initialized by TransR [14]. These vector embeddings capture the complex semantic information between entities and relations, thereby enhancing the model's ability to understand and utilize the information in the knowledge graph and meta-path. Specifically, the embedding of each meta-path can be represented as follows:

$$\mathbf{Emb_p} = [\mathbf{emb}_1, \mathbf{emb}_2, \ldots, \mathbf{emb}_T],$$

where $\mathbf{Emb_p}$ denotes the embedding of meta-path p, and $\mathbf{emb_t}$ is the low-dimensional knowledge graph embedding of the t-th element, which includes entity embedding and relation embedding. T means the length of the meta-path.

To learn two-view information of each meta-path, the embedding sequence $\mathbf{Emb_p}$ of the meta-path p is fed into a bi-directional LSTM model to capture the contextual information, which consists of the forward LSTM and the backward LSTM:

$$\mathbf{h}_{ij}^{t} = \mathrm{LSTM}_{forward}\left(\mathbf{emb}_t, \mathbf{h}_{ij}^{t-1}\right),$$
$$\mathbf{h}_{ji}^{t} = \mathrm{LSTM}_{backward}\left(\mathbf{emb}_t, \mathbf{h}_{ji}^{t-1}\right),$$

where $\mathbf{h}_{ij}^{t}$ and $\mathbf{h}_{ji}^{t}$ are the hidden states of the forward direction (from student u_i to course c_j) and backward direction (from course c_j to student u_i) at the step t, respectively.

To model the dual side of each meta-path p from the student u_i and the course c_j, the dual side embedding of each meta-path can be computed by averaging the hidden states from two directions as follows:

$$\mathbf{p}_{u_i} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{h}_{ij}^{t},$$
$$\mathbf{p}_{c_j} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{h}_{ji}^{t},$$

where $\mathbf{p}_{u_i}$ and $\mathbf{p}_{c_j}$ are the embedding of the meta-path p from student side and course side respectively. Though modeling the meta-path from two sides of the student and course, the bi-directional LSTM model is able to learn the preferences and goals of students, as well as the potential requirements and attractiveness of the course.

4.3 Attention-based Meta-path Aggregation

For different meta-paths, students have various attention and preferences regarding different aspects of a course. Similarly, courses have different focuses and are suitable for different types of students based on their content. To capture the heterogeneity of multi-perspective preferences among users, we use an attention mechanism to aggregate the meta-paths of students and courses that have interacted. This approach allows us to dynamically evaluate the preferences of different users for different perspectives using attention weights. The aggregated meta-path can be systematically obtained as follows:

$$\mathbf{x}_i = \sum_{l=1}^{L_1}\alpha_l^i \mathbf{p}_{u_i}^l,$$
$$\mathbf{y}_j = \sum_{l=1}^{L_2}\alpha_l^j \mathbf{p}_{c_j}^l,$$

where $\mathbf{x}_i$ and $\mathbf{y}_j$ represent the aggregated final embedding of the student u_i and course c_j, which incorporate the heterogeneity of multi-perspective information. $L1$ and $L2$ mean the number of the meta-paths student and course interacted, respectively. $\mathbf{p}_{u_i}^l$ and $\mathbf{p}_{c_j}^l$ indicate the $l-th$ meta-path embedding of the student and the course from the dual side. And attention weights α_l^i and α_l^j can be obtained as follows:

$$\alpha_l^i = \sigma\left(W_1\mathbf{p}_{u_i}^l + b_1\right),$$
$$\alpha_l^j = \sigma\left(W_2\mathbf{p}_{c_j}^l + b_2\right),$$

where W_1, W_2, b_1 and b_2 represent the weight and bias, respectively. And σ represents a sigmoid activation function. The attention weights α_l^i and α_l^j indicate the relative importance of different meta-paths for the student and course, which can be used to explain the recommendation results.

4.4 Recommendation and Explanation

We utilize the MAECR model to accomplish the task of interaction prediction in course recommendations. After obtaining the embeddings of students and courses, we compute the students' preferences for courses and the courses' suitability and attractiveness for students, respectively. These two perspectives scores are aggregated to generate the final recommendation result.

Specifically, the preference score $\hat{y}_{u_i\to c_j}$ of the student u_i to course c_j is systematically obtained through MLP, which takes the final embedding of student $\mathbf{x}_i$ as input:

$$\hat{y}_{u_i\to c_j} = \sigma\left(W_1\mathbf{x}_i + b_1\right),$$

Similarly, the suitability and attractiveness score $\hat{y}_{c_j\to u_i}$ of the course c_j to student u_i is systematically obtained through MLP, which takes the final embedding of course $\mathbf{y}_j$ as input:

$$\hat{y}_{c_j\to u_i} = \sigma\left(W_2\mathbf{y}_j + b_2\right),$$

where W_1, W_2, b_1 and b_2 represent the weight and bias, respectively. $\hat{y}_{u_i\to c_j}$ predicts the probability that course c_j satisfying student u_i's preference, while $\hat{y}_{c_j\to u_i}$ predicts the probability that student u_i meets the requirements of the course and is suitable for the course.

To consider the dual-side factors of the student and the course, we average the two scores as the final probability of the prediction:

$$\hat{y}_{i,j} = \frac{1}{2}\left(\hat{y}_{u_i\to c_j} + \hat{y}_{c_j\to u_i}\right).$$

In our work, we utilize the Bayesian Personalized Ranking (BPR) [28] loss function to optimize the model parameters as follows:

$$\mathcal{L}_{bpr} = -\frac{1}{|\mathcal{D}|}\sum_{(i,j,k)\in\mathcal{D}}\log\left(\sigma\left(\hat{y}_{i,j} - \hat{y}_{i,k}\right)\right),$$

where the triad (i, j, k) denotes that student u_i interacted with course c_j, while un-interacted with course c_k. $|D|$ represents the count of triads and σ represents a sigmoid function. In our work, Adam [10] is employed as the optimization algorithm.

After calculating the probability of a user interacting with each course, we generate a personalized list of Top-N recommendations tailored to each user. To enhance the user's understanding of the reason behind the recommendations, we display each meta-path with weights to the recommended courses and identify which knowledge concepts or attributes of the course are more important to the user by analyzing these weights. This approach provides a clear rationale for each recommendation, ensuring they align with the user's preferences and goals. Meanwhile, by employing bi-directional modeling, we ensure that the recommended courses are appropriate for the target user.

5 Evaluation

5.1 Dataset

In the context of this work, we focus on the scenario of course recommendation within an MOOC environment. The datasets in our analysis are collected from the XuetangX [1] MOOC [38]. We preprocessed the data to better model users and courses by filtering out users with few interactions. Specifically, we retained users with more than five interactions and courses with more than ten

[1] http://www.xuetangx.com

interactions in our work. The dataset statistics are introduced in Table 1.

Table 1: Statistics of the XuetangX dataset

Dataset	Users	Courses	Knowledge Entity Types	Knowledge Relation Types	Knowledge Entities	AVG Knowledge Entities per Course	Interactions	Interactions Density
XuetangX	34,916	629	6	14	25,796	249.07	273,072	1.0795%

In the XuetangX dataset, each course contains rich knowledge entities. It allows us to construct knowledge graphs and extract meta-paths containing rich information in our work, which includes concept, taxonomy, teacher and school information. Such as course *Database Systems Principles and Development* has *Minimum Spanning Tree*, *Computer Science* concepts, *Database Technology* taxonomy attribute and so forth. We extract these knowledge entities and attempt to construct knowledge graphs based on multi-perspective information about the students and courses.

5.2 Experiment Setup

5.2.1 Metrics. Our model is implemented with the Pytorch library. The datasets were split into training, validation, and testing sets, with 90% used for training and validation, and 10% used for testing. For fair comparisons with baselines, we carefully tuned each parameter and selected the optimal results for each model.

To estimate the effectiveness of our model, we rely on four widely recognized metrics following previous research [3, 36, 40]: Precision@K, Recall@K, Hit Ratio(HR@K) and Normalized Discounted Cumulative Gain(NDCG@k) of Top-K recommendations. It's important to mention that the higher metrics values signify superior performance.

5.2.2 Baselines. We compared our model to different baseline methods given below.

- **PMF** [29], a traditional recommendation model that relies solely on the user-item rating matrix.
- **NMF** [13], factorizes a non-negative matrix into the product of two or more non-negative matrices based on the user-item interaction matrix.
- **Item-based KNN** [30], models user and item based on item similarity obtained by interaction information.
- **Popularity[2]**, provides the most popular items for users.
- **LightFM + BPR/WARP** [11], a hybrid recommender system combining collaborative filtering and content-based technique, these two baselines differ in the loss function.
- **KEAM** [35], introduces knowledge graphs into explainable course recommender systems utilizing autoencoder architecture technique.

6 Results

6.1 Performance Comparison

Table 2 presents the overall results, summarized as follows: (1) MAECR outperforms all baseline models and significantly enhances recommendation performance on the XuetangX dataset. It can be attributed to our model leveraging multi-perspective meta-paths to mine preference information and model students and courses by utilizing a dual-side view. (2) NMF and PMF consistently show the worst performance. As traditional models that rely on matrix decomposition, they focus on the rating task in recommendation. (3) Item-based KNN performs relatively poorly, even compared to popularity-based algorithms. Since the quality and intrinsic value of a course often play a crucial role. (4) Although LightFM + BPR and LightFM + WARP show commendable performance, there remains a gap compared to the effectiveness demonstrated by our proposed model. This gap may be due to their failure to incorporate the valuable information from the knowledge graph and meta-paths. (5) KEAM performs well among the baselines, second only to our proposed model MAECR. The ability of KEAM to mine information from the knowledge graph enables it to better learn user preferences. However, KEAM does not consider the valuable information contained in the various meta-paths within the knowledge graph, nor does it account for the heterogeneity of different meta-paths' influences on students.

6.2 Model Study

Next, we present an in-depth analysis of the different components of the MAECR model and determine their impact on its performance.

6.2.1 Effectiveness of Each Component in MAECR. To verify the effectiveness of each component of our proposed MAECR model, we conducted ablation experiments comparing the performance of MAECR and its various variants to illustrate the rationality of the model design. Specifically, we compared three variants:

- **MAECR w/o KGE**: This variant removes the Knowledge Graph Embeddings (KGE) layer and directly randomizes the initial embeddings of entities and relationships.
- **MAECR w/o DSMM**: This variant replaces the Dual-Side Meta-path Modeling component with a shared LSTM, meaning that the embeddings of each meta-path for both students and courses are the same.
- **MAECR w/o AMA**: This variant replaces the attention mechanism in the mete-paths aggregation process with a simple mean pooling.

These comparisons help demonstrate the importance and impact of each component in the overall model performance. Based on the results presented in Figure 4, we observe that (1) MAECR achieved the optimal performance, indicating that every component of the model we designed is effective. (2) MAECR w/o AMA produced the worst results, highlighting the importance of the attention mechanism in the student and course modeling process. In a heterogeneous knowledge graph structure, which contains complex entity and relationship information, the attention mechanism is crucial for capturing this complexity. Additionally, the attention weights can be utilized to explain our recommendations. (3) MAECR w/o DSMM demonstrated the best performance among the variants, suggesting that the bidirectional modeling of students and courses in the same meta-path process provides only a minor improvement over the modeling results of LSTM using shared weights. (4) MAECR w/o KGE demonstrates better performance than MAECR w/o AMA, though not as strong as MAECR w/o DSMM. This finding indicates that initializing the embeddings of entities and relations within the meta-paths using knowledge graph information has a positive impact on recommendation performance. However, its

Table 2: Performance comparison(%) on XuetangX dataset

	K = 5				K = 10			
Model	Precision@5	Recall@5	HR@5	NDCG@5	Precision@10	Recall@10	HR@10	NDCG@10
NMF	0.7426	3.5014	4.1742	2.1586	0.5834	5.7223	7.7952	4.6882
PMF	1.7449	6.2680	8.4064	5.3152	1.2925	10.1819	13.3001	7.8732
Item-based KNN	3.4849	15.7647	18.7612	13.0186	3.0265	19.4349	22.2497	14.3728
Popular	4.5827	20.3531	23.3910	15.9767	3.5745	29.3086	33.1577	20.5101
LightFM + BPR	5.7270	22.7200	24.8587	17.1764	4.5236	30.6093	34.5323	21.8579
LightFM + WARP	6.8992	28.1926	31.5301	22.0286	5.7847	39.2849	43.4644	27.6882
KEAM	8.7503	31.8533	40.1347	28.5454	6.9825	44.2884	52.0843	34.1118
MAECR	**11.9426**	**50.7875**	**59.1121**	**46.0129**	**7.1953**	**63.1065**	**71.8926**	**51.7822**

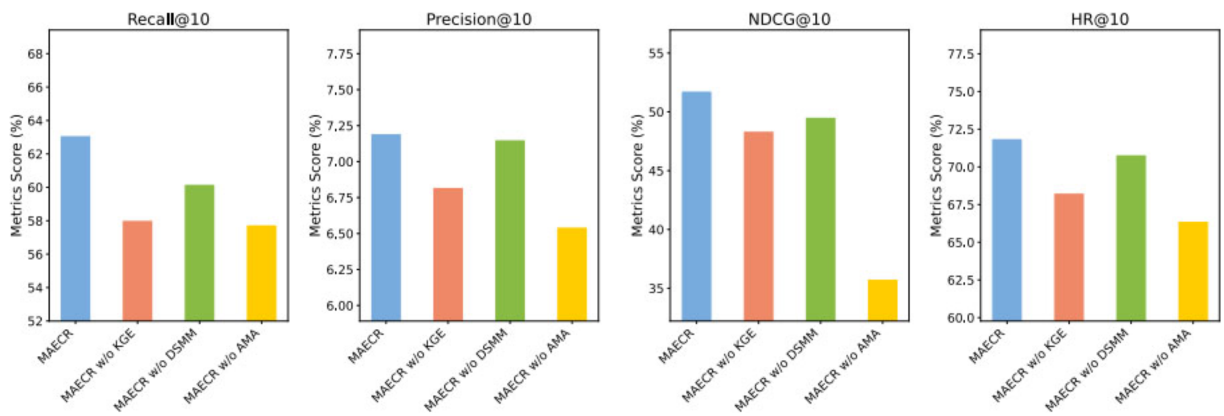

Figure 4: The effectiveness of each component in MAECR.

effect is more sensitive to changes in epoch values and learning rates.

6.2.2 Influence of Different Perspective Meta-paths. To explore the impact of each entity and relationship, we evaluated the performance of MAECR using a combination of multiple sets of meta-paths with different perspectives. Specifically, we tested the performance of the model based on the meta-path design in Section 4.1 after removing information about the concept, taxonomy, school, and teacher entities, denoted as MAECR **w/o** concept, MAECR **w/o** taxonomy, MAECR **w/o** school, and MAECR **w/o** teacher. After removing information about different relations, we also tested the model performance, including the similar relation and the prerequisite-dependency relation for the concept, the similar relation for the course, and the hierarchical relation between the concept and taxonomy. These variants are denoted as MAECR **w/o** SimConcept, MAECR **w/o** Pre-Dep, MAECR **w/o** SimCourse, and MAECR **w/o** Hierarchical. This allows us to determine which information is more important to the student population and the influence of various entities and relationships. The results are shown in Table 3 and we discuss the following observations:

From the perspective of entity information as shown in Table 3, we can know that: (1) MAECR achieves the best performance compared to its variants without specific entity information. This demonstrates that entity information from various perspectives helps the model better learn students' preferences for different aspects of entity information. (2) Among the entity information ablation variants, MAECR **w/o** taxonomy achieves the best performance, indicating that broad taxonomy information has a limited impact on users' course selection. This may be because courses within the same taxonomy are not always strongly related. Students typically prioritize other types of entity information over broad taxonomy classifications. (3) Interestingly, MAECR **w/o** teacher shows the worst performance, contrary to common expectations. This suggests that students place significant importance on the teacher when selecting courses. When the courses are similar, differences in instructors' experience and attractiveness can lead students to prefer courses taught by instructors who better align with their preferences.

From the perspective of relation information as shown in Table 3, we can observe that: (1) MAECR achieves the best performance compared to its variants that exclude certain relational information. This suggests that the effective use of various complex relations enhances the modeling of student preferences. (2) Among these relation variants, MAECR **w/o** SimCourse achieved the best performance, indicating that similar course relations have minimal impact on students' course selection. This likely occurs because students typically have specific goals in mind when choosing courses and

Table 3: The influence of different perspective meta-paths in MAECR

	Model/Variant	Precision@10	Recall@10	HR@10	NDCG@10
	MAECR	**7.1953**	**63.1065**	**71.8926**	**51.7822**
Entity	MAECR w/o taxonomy	6.9725	58.9289	69.3281	41.8913
	MAECR w/o concept	6.0945	53.0089	62.3634	40.6962
	MAECR w/o teacher	5.9521	50.2306	59.0948	41.1421
	MAECR w/o school	6.5519	55.7059	65.5363	42.4686
Relation	MAECR w/o SimCourse	7.0154	59.0204	69.4358	50.0215
	MAECR w/o SimConcept	6.7928	57.7250	67.9118	44.2494
	MAECR w/o Pre-Dep	6.6723	56.7368	66.7492	44.1108
	MAECR w/o Hierarchical	6.9012	57.9136	68.1336	48.5187

thus do not repeatedly enroll in courses with similar content. (3) Consequently, students place greater emphasis on the prerequisite-dependency relationship of concepts, which explains why MAECR **w/o** Pre-Dep shows the worst performance among these variants. (4) When comparing the performance drop between entity ablation and relational ablation variants, we observed that the performance decrease is more significant after entity ablation. We believe this is because entity information plays a more critical role in the model. While relationships between entities are important, the information carried by the entities themselves is more essential for accurate prediction and recommendation. The detailed structure of relationships, by comparison, is less critical. This result aligns with previous research by Yang et al. [35], who found that even when using entities generated by ChatGPT in the knowledge graph, performance still improved compared to scenarios where such entities were absent.

6.3 Case Study

Our work not only focuses on performance improvement but also emphasizes the explainability of our model. During the recommendation process, we extract and display the weights of individual meta-paths connecting the target student to the key features of the recommended course for each student. Additionally, we present the student preference scores and attention weights for each meta-path from the student's perspective, as well as the course attractiveness scores and attention weights from the course's perspective.

We illustrate our approach with two case studies of recommendation results, as shown in Fig 5. One successful case and one failure case are presented at the top and bottom of the figure, respectively. In the successful prediction case, our model generates a high prediction score due to the elevated student preference scores and course attractiveness scores that we calculated. These attention weights highlight the primary factors influencing the prediction, thereby enhancing the transparency and interpretability of our model. For the target student, the most important factors are the instructor responsible for the course and the logical coherence of the knowledge points being taught (e.g., learning exponentiation before convolution). From the course perspective, its attractiveness is linked to the fact that it is offered by a specific instructor and institution, which appeals to most students.

In the case of a failed prediction, despite high student preference scores, the attractiveness score of the course is low, leading to an unsuccessful recommendation. Although the students expressed strong interest in courses related to linear algebra and subjects within the mathematics taxonomy, the course instructor may not have been a suitable match for the students, resulting in a low attractiveness score for the course. This example underscores the importance of considering multi-perspective information from both the student and course dual-sides in the prediction process and demonstrates the nuanced interpretability that our model provides in real-world recommendation scenarios.

7 Conclusion

In this paper, we introduce a novel **M**ulti-perspective **A**ware **E**xplainable **C**ourse **R**ecommendation (MAECR) model that leverages meta-path and knowledge graph information. The model enhances both the explainability and effectiveness of recommendations by employing dual-side modeling from the perspectives of both students and courses. We emphasize the importance of multi-perspective meta-paths in capturing user preferences across different dimensions, which helps generate more accurate and interpretable recommendations. Additionally, we use a bi-directional LSTM to model each meta-path in both directions, obtaining embeddings for students and courses along those paths. Finally, we design an attention mechanism to aggregate these embeddings and use the attention weights to provide explanations for the recommendations. Through extensive experiments, including performance comparisons with baselines, modeling studies, and case studies, we validate the effectiveness and explainability of MAECR. Our findings indicate that entity information plays a more crucial role than relational information in modeling student preferences.

However, our current study has some limitations. A significant limitation is the absence of real user experiments to evaluate the effectiveness and explainability of our course recommender system. Therefore, we plan to conduct a comprehensive user study in the future. Moreover, we plan to implement our model on more datasets to evaluate MAECR's performance.

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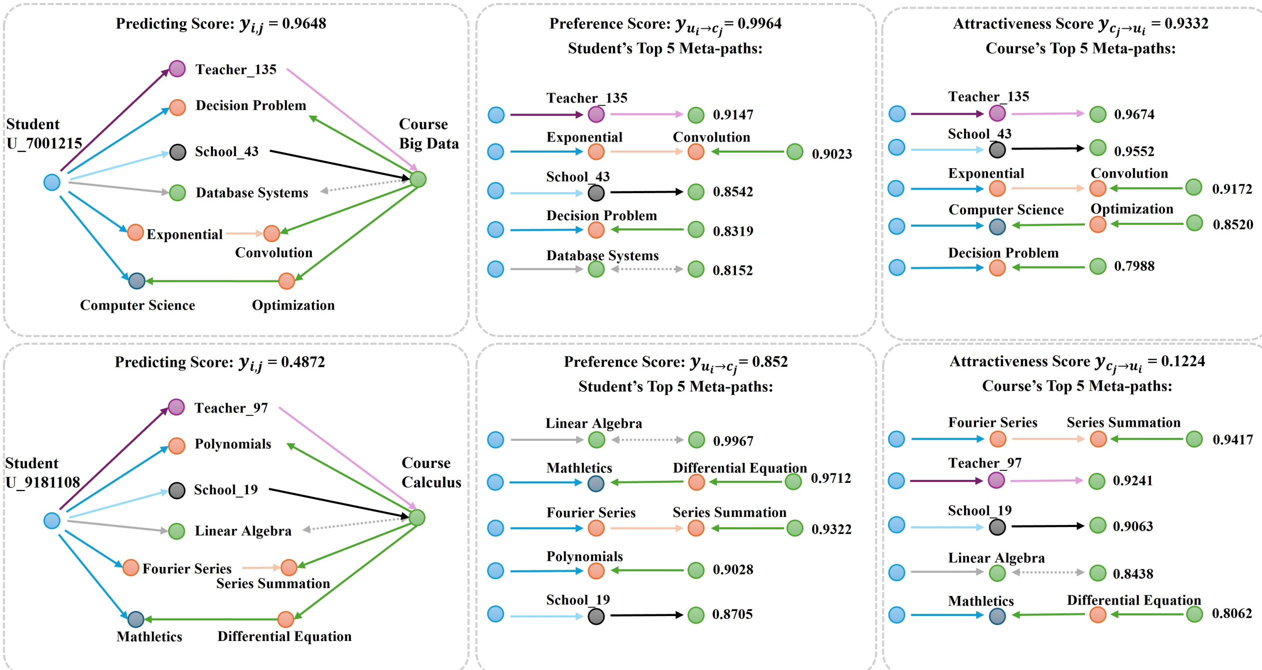

Figure 5: Examples of a successful case (Top) and an unsuccessful case (Bottom).

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