4M-04

Making Course Recommender Systems Interpretable: A Feature-aware Deep Learning-based Approach

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I. Introduction

As recommender systems have become a pervasive service on today's web, course recommender systems(CRS) show their potential to help students with course scheduling and alleviate the problem of information overload [1]. Traditional techniques, such as collaborative filtering(CF), represent users and items using the user-item interaction history. Previous research has identified the effectiveness of collaborative filtering approaches in suggesting relevant course recommendations [2]. However, the performance of CF is limited due to the sparseness of user-item interaction and falls short in explainability.

In recent years, Deep Learning techniques have achieved promising results in various domains, which have been widely deployed in nowadays recommender systems. While research has mainly focused on improving accuracy metrics, their models are becoming more and more complex thus making it extremely hard to understand the reasons behind model predictions. However, it is also important to make users understand and trust the recommender systems especially in course recommender systems. Knowledge graphs encapsulate personalized information about students and courses, enhancing recommender systems' ability to comprehend students' specific needs and the characteristics of courses. Consequently, recommender systems found on knowledge graphs are adept at furnishing more comprehensive explanations for students.

In this paper, we introduce a novel Feature-aware Course Recommender System based on Deep Learning, called FaCRS-DL, which can make recommendations interpretable by building students' profiles. Specifically, we exploit a knowledge graph including the category information of courses. Combining with the knowledge graph, we design a course recommender system based on a deep learning approach, which replaces the hidden layer in the neural network with course features, thereby generating recommendations and students' profiles. After obtaining the profiles and training the model, our approach to interpreting recommendations hinges on discerning the varying importance of different features within a student's profile.

II. The FaCRS-DL Model

A. Knowledge Graphs

Knowledge Graphs are directed graphs in which nodes represent resource entities and edges labeled relationships between them, which contain rich information about users and items. In the course recommendation domain, nodes can represent students, courses, and their associated features and attributes including categories, lecturers, types of courses(mandatory/elective) and so forth. Edges can represent direct relationships between two nodes, such as a student enrolling in a course, an instructor teaching a course, a course being a mandatory requirement, or a course being affiliated with a specific college. An example of KG is depicted in Figure 1. In this paper, we focus on the category information of the courses to construct the knowledge graphs.

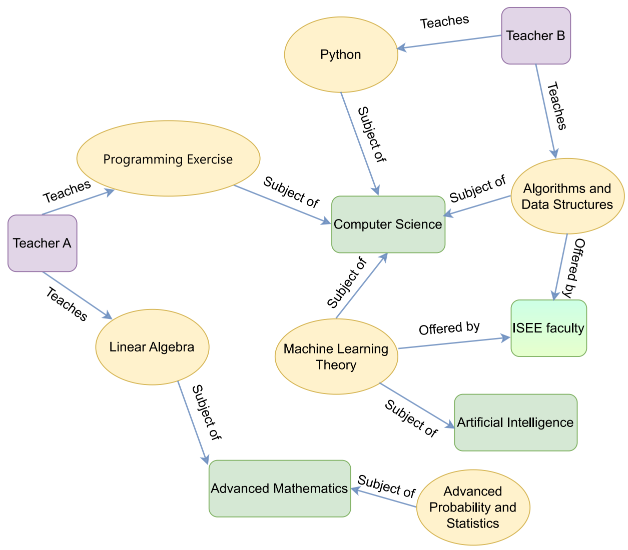

Fig. 1. Sample KG related to the course domain

B. Feature-aware CRS Based on Deep Learning

Based on the techniques of neural networks and deep learning, we integrate the knowledge graphs to design a feature-aware course recommender system. The architecture of our proposed model is shown in Figure 2. Considering the interpretability of the FaCRS-DL model, we propose to give meaning to the connection with the hidden layer and its each neuron by exploiting feature information explicitly in knowledge graphs. Inspired by the autoencoder [3], the FaCRS-DL model mainly contains three parts: *input layer, hidden layer*, and *output layer*. The hidden layer and its connections are substituted by the knowledge graph thus having an explicit representation on the meaning associated with both hidden nodes and their mutual connections. This means that each neuron represents an entity in the adopted KG and the edge between two autoencoder nodes exists if the corresponding KG entities are connected.

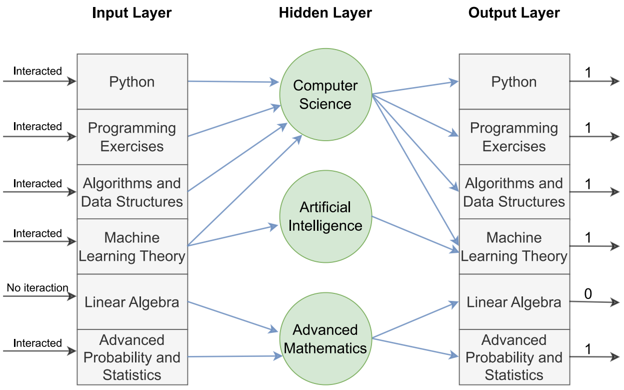

Fig. 2. The architectural overview of the proposed FaCRS-DL model

As previously mentioned, this model follows the main idea of an autoencoder, that the inputs and outputs are as consistent as possible. Hence, in the training process, the FaCRS-DL model learns how to reconstruct the input information using the latent embedding generated in the hidden layer. For each student, we have latent representations of the course features; in fact, these representations are no longer implicit in our model because each neuron corresponds to a feature entity in KGs.

To train our model, we inhibit the feedforward and back-propagation steps for those neurons that are not connected in the KGs by employing a masking multiplier matrix M, where rows and columns represent courses and features, respectively.

$$M_{m,n} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{pmatrix} \tag{1}$$

The matrix in Equation 1 represents the adjacency matrix of the KG indicating whether a connection among entities exists in it, as follows:

$$a_{i,j} \in M_{m,n} = \begin{cases} 1, & \text{if course } i \text{ is connected to feature } j \\ 0, & \text{otherwise} \end{cases}$$

Therefore, hidden layer(h) and output layer(o) can be obtained as follows:

$$\begin{aligned} h &= g\left(X \times (W_1 \circ M)\right) \\ o &= g\left(h \times \left(W_2 \circ M^T\right)\right) \end{aligned} \tag{2}$$

where X is the input embedding of a student, W_1 and W_2 represent the weight matrix between courses and features. In our work, SGD is employed as the optimization algorithm.

Obtaining user profile: After the model training, we extract the weights of the hidden layer and use them to generate a user profile $P(u)$ for user u, as follows:

$$P(u) = \{\langle f_{u1}, w_{u1}\rangle, \ldots, \langle f_{um}, w_{um}\rangle\}$$

where f_u means the entity associated to the hidden neuron and w_u represent its corresponding weight for user u.

III. Experiment

In our experiments, we choose a real-life dataset of MOOC, which is composed of 82,535 students and 1,302 courses [4]. To evaluate the performance of our model, we use two widely used metrics, Hit Ratio(HR@K) and d Normalized Discounted Cumulative Gain(NDCG@k) of top K recommendations. Table I shows the performance, and a student's profile:

TABLE I
Experimental Results & Case Study

Performance	
HR@10	NDCG@10
0.338700	0.491071

A Student's Profile		
Physics	Electronics	Mathematics
0.913346	0.804705	0.731921

This result demonstrates that our model can provide effective recommendations and generate a user profile with different weights of preferences on various features based on each user to provide reasonable explanations.

IV. Conclusion and Future Work

In this paper, we introduce the FaCRS-DL model, which can make recommendations interpretable and build students' profiles by incorporating knowledge graphs. Our experiments show the different weights of the hidden layer to indicate the student's preference on different features, which provides personal explanations for our recommendations.

In the future, we will extend the knowledge graph to include more information and compare the performance of our model with state-of-the-art models as baselines to prove the effectiveness of our model. Moreover, we will conduct user experiments to verify that the explanations generated by our model can improve the users' trust with recommender systems.

V. Acknowledgment

This work was supported by JSPS KAKENHI Grant Numbers JP20H00622,JP23H03507,JP23K02469.

References

[1] B. Ma, M. Lu, Y. Taniguchi, & S. Konomi, "Courseq: the impact of visual and interactive course recommendation in university environments," *Research and practice in technology enhanced learning*, 16, pp. 1–24, 2021.

[2] L. Wu, X. He, X. Wang, K. Zhang, & M. Wang, "A survey on accuracy-oriented neural recommendation: From collaborative filtering to information-rich recommendation," *IEEE Trans. Knowledge and Data Engineering*, 35(5), pp. 4425–4445, 2023.

[3] V. Bellini, A. Schiavone, T. Di Noia, A. Ragone, & E. Di Sciascio, "Knowledge-aware autoencoders for explainable recommender systems," in *Proc. 3rd Workshop Deep Learning for Recommender Systems*, 2018, pp. 24–31.

[4] J. Zhang, B. Hao, B. Chen, C. Li, H. Chen, & J. Sun, "Hierarchical reinforcement learning for course recommendation in moocs," in *Proc. AAAI conf artificial intelligence*, 33(1), 2019, pp. 435–442.