Research on knowledge graph model of diversified online resources and personalized recommendation

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Abstract. This paper proposes an improved knowledge graph model to match the distinctiveness in the education field, considering the lack of robustness and resource diversity in the existing research on knowledge graphs in the education field. A recommendation algorithm based on personalized features is given on the new knowledge graph model to improve recall and precision. Finally, we verify the robustness and expression ability in course resource diversity. The results show that the recall rate of curriculum resources is improved to 0.95-0.96, personalized satisfaction is up to 0.96 and the difference of recommended resources is up to 0.9.

1. Introduction

The traditional recommendation research on personalized learning resources mainly uses collaborative filtering, personalized browsing sequence or hybrid technology, etc. Their research collect learners, learning resources and other information online, and then mine personalized interests and recommended content. The efficiency of mining is seriously affected since the network information is increasingly overloaded. Google proposed Knowledge Graph (KG) and achieve a more intelligent search engine in 2012, arousing widespread concern in academia and engineering. Later, KG has extensive research and application in the field of chat robots, big data risk control, stock investment and intelligent medical. In recent years, many scholars have introduced KG into the field of education to improve the search speed and recommendation effect. Compared with other fields, these research are more theoretical (like review research) and less engineering application research. The main application research is as follows: [1] proposed a general recommendation KG in the field of education based on association rule mining and machine learning. [2] proposed an automatic construction and dependent KG based on association semantics; [3] proposed a personalized learning resource recommendation system structure based on KG. [4] proposed a recommendation algorithm based on KG ranking and so on.

These applied research mainly model online learning resources through KG related technologies. Compared with previous research, the current query speed has been greatly improved. Current KG lacks robustness considering the diversification, heterogeneity, and imbalance in online learning resources since KG formalizes and standardizes knowledge definition based on ontology. As a result, after modeling, the diversity of existing network learning resources KG is lost and the recall rate is poor. This paper proposed a multiple network courses resources KG model targeting on the specialty
of educational field. This model improves the insufficient of current KG in expressing the diversity of similar course network resources. At the same time, we give a personalized recommendation algorithm based on the new model. Finally, this paper verifies the diversified resource expression ability, inquiry capabilities, personal recommendation efficiency from experiments.

2. Diversified online course resources KG model

2.1. Conceptual model

The conceptual model of course KG is \( G = \{E, R, S\} \). E is the entity, R is the connection between the entities, and S is the entity set. Entity S includes course entity \( c = (\text{name, include, examples}) \) and resource entity \( rs = (\text{name, has, contribute /type}) \). The types of online resources and definitions of catalogs are shown in Table 1.

| Table.1 Definition of type symbols for online resources |
|---------------------------------------------------------|
| Notation | Description         | Notation | Description         |
| SY       | Syllabus            | LO       | learning objectives |
| CW       | courseware          | L/R      | live or recorded video |
| AM       | animation           | MC       | micro-classes       |
| CS       | cases               | ML       | material library    |
| TS       | test questions set  | P/S      | simulation platform or shareware |
| TL       | terminology         | OD       | online exchange discussion record |
| FQ       | FAQ                 | R/E      | reference resources or extended learning website |

2.2. Graph operation symbol

Course KG is a multilateral relationship graph including entities and relationships, in which nodes are entities, and edges are relationships between different types of entities. The specific operation symbols are shown in Table 2.

| Table.2 Graph operation symbol |
|--------------------------------|
| Notation | Description         | Notation | Description         |
| \( G \) | A knowledge graph of courses | \( S \) | A set of facts |
| \( c \) | Entity of course     | \( rs \) | Entity of resource |
| ( )     | Triad of head, relation and tail | ( ) | Embedding of head, relation and tail |
| \( r \in R, s \in S \) | Relation set and entity set | \( v \in V \) | Vertex in vertices set |
| \( e_G \in E_G \) | Edge in edges set | \( f \subseteq r \) | Follow-up courses relation |
| \( l \subseteq r \) | Leading course relation | \( c \subseteq S, rs \subseteq S \) | Course and resource entity set |
| \(<s_1, \ldots, s_n>\) | Resource corpus | \( f_G(e, s) \) | Scoring function |

2.3. Technical model

The overall technical structure model of knowledge graph mainly includes network course resource information extraction, knowledge fusion, processing, update and other parts, as shown in Figure 1.
For keeping the diversity of curriculum resources, the system sorts and merges the courses entities according to the differences in majors, directions, providers, or trends in the process of knowledge fusion. The relationship between examples and resource attributes is shown in Figure 2.

![Fig. 2 Course examples and resource attributes](image_url)

3. Personalized recommendations

3.1. Personalized features
The personalized characteristics mainly include educational background or learning foundation, interest, ability, learning time allocation and other factors. The definition of personality characteristic vector is shown in Equation (1). Among them, \( x_i \) is an instance of the \( i \)th learner, and the components \( \vec{b}_i \), \( \vec{n}_i \), \( \vec{a}_i \), and \( \vec{t}_i \) are respectively defined as equations (2), (3), (4), and (5). \( \alpha_i \), \( \beta_i \), \( \mu_i \), and \( \eta_i \) is the coefficient of each component. Each component value in formula (3) and (5) is obtained through mining statistics and evaluation of browsing content and browsing time [5]. In formula (4), \( a_{i1} \sim a_{i8} \) are attention, observation, memory, thinking, imagination, creativity, comprehension, language. The evaluation formulas for each ability value are \( a_{ik} = \frac{\text{avg}_{ik}}{\text{normal}_{ik} + \text{avg}_{ik}} \) (k=1~8, \( \text{avg}_{ik} \) is individual average value, \( \text{normal}_{ik} \) is general value).

\[
\vec{f}(x_i) = (\alpha_i, \vec{b}_i, \beta_i, \vec{n}_i, \vec{a}_i, \vec{t}_i) \quad (1)
\]

\[
\vec{b}_i = \frac{\sum_{j=1}^{n} \text{grade}_j / m \times \sum_{j=1}^{n} (\text{credit}_j * \text{poin}_j) \times \sum_{j=1}^{n} \text{credit}_j)}{} \quad (2)
\]

\[
\vec{n}_i = (\text{txt}, \text{video}, \text{excise}, \text{discuss}) \quad (3)
\]

\[
\vec{a}_i = (a_{i1}, a_{i2}, a_{i3}, a_{i4}, a_{i5}, a_{i6}, a_{i7}, a_{i8}) \quad (4)
\]

\[
\vec{t}_i = (\text{durate}, \text{dailydistr}, \text{weeklydistr}) \quad (5)
\]

3.2. Recommendation process
The process is as follows:

Step 1: Generate the course entity and all instance resource trees.

The system abstracts relevant courses entities and pre-requisite and following course entities based on personalized demand from KG diagram, and then generate resource tree (RT), as shown in Figure 3.

Step 2: prune RT.

The system prune RT trees according to the four component values of personality characteristics \( \vec{f}(x_i) \). \( \alpha_i \), \( \beta_i \), \( \mu_i \), and \( \eta_i \) are all set to 1. Then the system start machine learning and adjustment from
the learners’ feedback. In order to prevent over pruning, suboptimal values may be used in pruning algorithm. The designed algorithm NS graph is shown in Figure 4.

Fig. 3 RT with leading and following courses

![RT with leading and following courses](image)

**Case 1:** 
\[
\alpha_i = 1, \beta_i = 1, \mu_i = 1, \eta_i = 1
\]

| Text | Video | Exercise | Discussion |
|------|-------|----------|------------|
| Kill leaf-nodes of L/R, AM, MC and P/S | Kill leaf-nodes except L/R, AM, MC and P/S | Kill leaf-nodes except CS, ML, TS, P/S and F/Q | Kill leaf-nodes except LR, MC and OD |
| True | All instances have no leaf-node |
| Case 2: **Next-max** (txt, video, excise, discuss) |

Until an instance has a leaf-node

**Case 2:** 
\[
a_{d1} \text{ or } a_{d2} \text{ or } a_{d3} \text{ or } a_{d4} \text{ or } a_{d5} \text{ or } a_{d6} \text{ or } a_{d7} \text{ or } a_{d8}
\]

| Kill leaf-nodes except CW, L/R, AM, MC | Kill leaf-nodes of CS, ML, TS, P/S, OD, R/E | Kill leaf-nodes except CS, ML, P/S, R/E | Kill leaf-nodes except LR, OD |
| True | All instances have no leaf-node |
| Case 3: **Next-max** (a_{d1}, a_{d2}, a_{d3}, a_{d4}, a_{d5}, a_{d6}, a_{d7}, a_{d8}) |

Until an instance has a leaf-node

**Case 3:**

True

Living record time not in (dailystr, weeklystr,)

Kill leaf-nodes of LR

Delete instance-nodes which have no leaf-node

Fig. 4 Pruning algorithm

Step 3: Generate a personalized recommendation resource tree.

After pruning in the second step, if there are multiple course instances, the system combines into one instance. If there are more than one resource of the same kind, the system retains only the high-quality or optimal value and abandon all repeating resource types. The result of personalized recommendation resource tree is shown in Figure 5.
4. Experiment and result analysis

4.1. Experimental deployment

The experimental device is Intel Core I5-8500, main frequency 4GHz, memory 12GB, operating system 64-bit Windows 10. Network environment for Internet online learning platform, 10-100m adaptive bandwidth. The languages are Python3.7 and Cypher. The graph database management system is Neo4j.

4.2. Experiment process

The system searches and analyses course and resource information of an online education platform through web scraping, page content extraction and word association analysis technology. Firstly, we select the course Database Principles and Application Technology, and extract one course entity of Database and Application, 5 different course entities with a correlation degree (CD) greater than 0.8, 41 relevant course instances with a differentiation degree (DT) greater than 0.8, and 1,337 different learning resources. Then, we increase the number of courses to 5, 10 and 20 respectively, and extract the knowledge data is shown in Table 3. Finally, we take CD and DT as 0.6 and 0.4, repeating the previous experiment. At the same time, we collect the learning information of 13,548 people in 20 co-visited courses on the above platform to build the personality database. We select 50 people with significant, general and less significant individual features as the recommended objects from the personality database.

The system selects 5 courses out of the 20 courses randomly from overlapped visited. In each course, the system searches and extracts corresponding resource tree from the KG according to the personalized characteristics, and recommends to 10 people who have significant, general and not significant personalized characteristics. My team collect recommendation feedback information through online tracking and questionnaire survey.

| Number(N) | Course entity(C) | Associated course-entity(A) | Instance(I) | Resource(R) |
|-----------|-----------------|----------------------------|-------------|-------------|
| 1         | 1               | 5                          | 41          | 1337        |
| 5         | 5               | 27                         | 193         | 6113        |
| 10        | 10              | 59                         | 321         | 9985        |
| 20        | 20              | 121                        | 663         | 20961       |

4.3. Result analysis

When CD and DT are set as 0.8, 0.6 and 0.4, the comparison picture of resources obtained by searching 1, 5, 10 and 20 different courses are shown in Figure 6. When CD and DT are 0.8, the number of course entities, associated course entities and course instances is shown in Figure 7. The comparison picture of overall quality of resources under different thresholds (TH) is shown in Figure 8. The relationship curve between quality and quantity of resources is shown in Figure 9.

The results in Figure 6 illustrate that the lower the value of CD and DT, the faster the growth of course resources search. The results in Figure 7 show that as the number of searched courses increases, the number of associated course entities and course instances acquired increases faster. The results in
Figure 8 demonstrates that with the decrease of threshold (CD, DT), the overall quality of resources decreases faster. We conclude that the threshold for achieving a higher balance between quality and quantity of resources is around 0.8 from Figure 9.

In the KG diagram, the recall rate and accuracy of course resources are shown in Figure 10 and 11 respectively. Results in Figure 10 show that the recall rate of associated courses entities is between 0.96-0.98 and the recall rate of courses instances resources is between 0.95-0.96. Results in Figure 10 shows that the query precision of associated course entity is between 0.8-0.83 and the query precision of course instance resource is between 0.77 and 0.82.

We collect the feedback information recommended by 141 people in 5 courses and the satisfaction degree is shown in Figure 12. Results in Figure 12 show that the satisfaction of 49 people with significant personality is around 0.95, of 47 people with general personality is around 0.85, and of 45 people with no obvious personality are around 0.71.

Statistics on the difference of 150 personalized course resources are shown in Figure 13. It can be seen from the results in Figure 13 that for 50 people with significant personal characteristics, the difference of recommended resources is close to 0.86. For 50 people with general personal...
characteristics, the resource difference is about 0.6. The difference of resources was about 0.29 for 50 people with no significant personal characteristics.

![Fig.13 Differences of personalized recommendation resources](image)

5. Conclusion
Through the experiment and analysis in Part 4, the following are conclusions.

(1) The improved course resource KG model has strong robustness and flexibility in knowledge expression. As the threshold decreases, the number of resources searched will increase, but the quality of resources will decline faster. The optimal balance point between resource and quality is that the threshold is around 0.8.

(2) The query efficiency of resources has been optimized in the improved KG. The recall rate of course resources is between 0.95 and 0.96, and the precision rate is between 0.77 and 0.82.

(3) The more significant the personal characteristics are, the more accurate the recommendation will be, the higher the degree of satisfaction will be obtained, and the greater the difference of recommendation resources will be. The highest satisfaction was 0.96, and the highest difference in recommended resources was 0.9.

In the future, deep research could focus on students' personal characteristics elements and explore the differences of personal characteristics, to further improve the accuracy and difference of recommendations.

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