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Personalized Learning Path Recommendation based on Knowledge Graph

Qianyi Gu

School of Computer Science, Sichuan Normal University, Chengdu, China

Abstract. Due to the arrival of educational information age, the amounts of learning activities and digital learning resources in online education are growing rapidly accompanying with the produce of the big data in education. The paper explores the technology to find the personalized learning path based on the educational big data. It proposes to utilize the knowledge graph to make semantic integration of educational data from various online learning environments. The knowledge representation of the learning activities and resources are generated based on the dynamic harvested data. The individual leaning needs are derived from the representation and the personalized learning path is identified based on the articulated leaning needs. The identification method includes capturing the learner's evolving knowledge status and learning activities from various learning environments. It recommends the learning path which more precisely matches the learning goals and promotes intentional learning.

Keywords: Knowledge Graph; Big Data; Learning Path; Educational Resource.

1. Introduction

With a series of strategies and plans implemented for online education, the goal is to provide suitable education for every student with different knowledge states and leaning abilities. Thus, one of the key target for online education is reflected as striving to provide personalized learning and lifelong learning for every learner[1]. In the learning process, there are individual differences in learners' background knowledge about the current topic being studied, and these differences will have a significant impact on the learning process and learning outcomes[2]. Therefore, exploring approaches to achieve differentiated teaching and personalized learning has become an important task of current educational information age[3]. Under this demand and goal, the paper focuses on recommending personalized learning paths that adapt to learners' cognitive changes in online education by providing a sequence of learning contents and learning activities based on learners' cognitive levels and learning needs. The current formation and recommendation of learning paths are mainly based on some inherent characteristics and attributes of learners, with less consideration of learners' dynamic learning behaviors and the cognitive demand changes caused by the learning behaviors. The paper explores a dynamic personalized path recommendation technique based on knowledge graphs. The proposed technique use knowledge graphs to semantically integrate educational data in different online learning environments. Then it generates corresponding knowledge representations for the learning activities and educational resources. By mining the learners' constantly changing learning interests and needs from these knowledge representations, personalized learning paths based on learners' dynamic knowledge changes can be discovered. This technique are more accurate and effective in locating learning resources and recommending activity sequences that match learners' current learning characteristics.

To develop a personalized learning path recommendation technique based on knowledge graph, it aims to grasp the constantly changing learning needs of learners and integrates educational big data from different platforms into the path recommendation. The paper explores how to construct a knowledge graph of domain knowledge and learning behaviors. The knowledge graph can be used to effectively integrate heterogeneous learning data from different learning environments and to form the representation of learning needs. The paper describes the design and implementation of a personalized learning path recommendation technique based on dynamic learning interest demands. The demands are expressed through online learning activities. The evaluation of the effectiveness of the learning path recommendation is explained.

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2. Learning Path with a Personalized Approach

2.1. Learning Path

A learning path refers to the ordered composition of a series of learning activities in which learners actively or passively engage during the learning process[4]. In the online learning environment, a learning path can include browsing learning resources, interactions between teachers and students, web-based inquiry learning, online testing, and various learning behaviors and steps. The personalized learning path is regarded as an important component of implementing personalized learning. It should be based on learners' individual characteristics, cognitive levels, and learning needs, tailoring the optimal sequence combination of learning activities that align with their learning goals[5]. In recent years, various learners have joined in online education community, making it possible to collect and to analyze educational big data. The aggregation of the educational big data provides new ideas for discovering individual learning need and offering personalized learning path.

2.2. Extension Strategy for Deep Learning

To construct a learning path for the individual learner, one of the key question need to be answered is how the cognitive states of learners affect the choice of the learning path. During the learning process, learners often encounter contradictions and inconsistencies between information collected from different educational resources and learning contexts, as well as conflicts between these key concepts and their existing scientific understanding[6]. In these situations, learners often resort to rote memorization to remember these key concepts, making it difficult for learners to use the key concepts to construct their knowledge frameworks. This rote memorization learning approach caused by conflicting information during the learning process is very detrimental to deep learning. We believe that the main reason for these inconsistencies are that learners have biases in their understanding of the information collected in new contexts and cannot correctly apply their existing knowledge systems to help understand new concept. To solve this problem, the personalized learning path recommendation utilize cognitive extension strategy. The recommended learning path provides support for learners' information search and knowledge construction processes by establishing associations between the new information collected by learners and the concepts in their existing knowledge systems. The goal is to turn the new information in the learning process into an extension of learners' existing knowledge system. This strategy requires the learning path to prompt learners about the inherent connections between the key concepts encountered and their own knowledge system through cognitive activation. The learners are encouraged by the learning path to make comparison of the key concepts in the learning materials with their own knowledge system. The learning path makes the inherent semantic relationship between the newly collected information and the learners' own knowledge system. It helps learners to correctly use their own knowledge frameworks to interpret and deduce new information, ultimately eliminating conflicts and contradictions between new and old knowledge, and successfully completing knowledge construction.

2.3. Personalized need for Learning Path

Recommending personalized learning path to online learner still faces many difficulties and challenges[7]. The formation and recommendation of personalized learning paths mainly rely on learners' inherent characteristics and attributes, with less consideration of learners' dynamic learning behaviors and the cognitive demand changes caused by these behaviors. When learners engage in online education, their domain knowledge states may change at any time, which inevitably brings about real-time generated new learning needs. Therefore, rigid personalized learning paths cannot effectively optimize and promote online learning. Furthermore, learners from different schools and regions may use different learning environments and digital resources are distributed across various environments. Due to the heterogeneity of data, the selecting process of the learning path, can only rely on isolated data from one single learning environment. This approach can not truly leverage the advantages of educational big data generated in various online environments. A semantic integration

of educational data from different online environments are required. It is also necessary to generate the corresponding representations for learning activities and educational resources. By mining learners' changing learning interests and needs from the knowledge representations, a personalized learning path recommendation method based on learners' dynamic knowledge models are developed. The personalized learning path can meet learners' cognitive needs more scientifically. The recommended learning resources and learning activity sequences can align with learners' current learning characteristics more effectively and provide stronger support for promoting intentional learning.

3. Knowledge Graph Representation

The knowledge graph is used to achieve semantic integration of online behavior data from various learning environments. There are significant differences of how online learning environments describe learners' knowledge states, store educational resources, and set up interactions with learners. It is difficult to use the heterogeneous educational data generated from different platforms, which poses challenges for the application of educational big data in personalized learning path recommendation. The paper uses the conceptual model which applies knowledge representation technique to achieve the linguistic integration of heterogeneous educational data. The conceptual model utilizes knowledge graphs to represent teaching and learning activities on the platform and the internal structure of the knowledge domain. This hierarchical node connection structure can be used to represent the domain knowledge of learning topics and the semantics of teaching and learning activities. Graph matching is used to automatically transform the educational resources as well as learning behaviors from educational big data into the conceptual model. To acquire learners' online behavior data in a timely manner without interfering with the learning process, the online learning behavior capture system is developed to extract learners' online interaction data automatically.

In order to build the knowledge graph for domain knowledge and learning behaviors, the multi-document clustering and text mining techniques are used to develop knowledge mining algorithm for various knowledge domains. The mining algorithm effectively extract concept nodes related to teaching goals from a large amount of educational resources, forming the knowledge graph representation of domain knowledge. A semantic model is established based on the knowledge graph. The model automatically matches and annotates knowledge nodes and semantic relationships in educational data. It identifies the learning activities from different learning platforms, achieving semantic integration of cross-platform data. By using text entailment models to infer potential semantic contradictions between learners' knowledge states and domain knowledge, the algorithm discovers core concept omissions and misconceptions in learners' learning activities. The omissions and misconceptions are used to interpret learning interests and needs.

4. Technical Implementation

The technical implementation of the system includes the acquisition of cross platform educational data, the construction of a top down learning behavior knowledge graph and a bottom up domain knowledge graph. The system makes semantic integration of educational data based on these knowledge graphs and generates personalized learning paths under the dynamic knowledge representation of learners.

The system use web crawling technology to track and extract online learning behaviors and to collect educational data formed in various educational environments[8]. By analyzing the platform architecture, task composition, and learning activities in different educational environments, the online learning behaviors ontology is defined. The ontology guards the system extracts relevant information from online behavior data to generate the knowledge graph representations for learning activities. Natural language processing technology is used to extract core concepts and semantic associations from unstructured text in the crawled educational resources to form a domain knowledge

graph. The system use methods such as concept clustering and semantic structural difference analysis in the concept similarity framework model to complete entity alignment.

From a constructivist perspective, learners' understanding and cognition of new knowledge are built upon their existing knowledge[9]. During the acquisition of new knowledge, learners may go through a stage where they have grasped some related concepts but still have cognitive gaps or errors in understanding other important concepts related to them. This is defined as learners' personalized learning needs in the paper. By analyzing the knowledge graph that implements semantic fusion, the learner's current learning focus can be intelligently identified. Under this focus, the system inspects the text entailment of the knowledge graph representing domain knowledge and learner knowledge. The results reveals the learner's missing and misconceived concepts and provides a data basis for personalized learning path recommendation.

The task-centered design method are adopted with the developers of the online learning environments and k-12 teachers as the research subjects. The study explores the correlation between individual learners' learning needs and learning paths. Corresponding cognitive strategies are designed based on the findings from the study. The strategies are implemented with machine learning and natural language processing techniques. Classifiers are constructed for cognitive concept pairs. These classifiers are used to determine the sequential order of cognitive concepts under learners' current knowledge structure. Domain knowledge graphs and learners' cognitive representation data are used to construct concept vectors[10]. The practical cases for personalized learning path recommendations based on the discussion results are produced. The personalized learning path recommendation mechanisms based on the proposals and practical cases are implemented in the learning environment.

In order to reveal the underlying structural connections between various learning activities to learners, the paper use a different way of presenting knowledge compared to traditional learning paths. The new presentation help learners grasp the information provided by educational resources and identify the connections between learning themes. In traditional learning paths, educational resources are organized according to a certain structure of education units. When learners select the corresponding unit, the educational resources included in that unit are presented to them in sequential order. This organizational approach reflects that the resources are contained within the education unit, but it does not express the inherent semantic connections between these resources, as well as the connections between resources and the concepts within the learning theme. The system organizes learning path in the way to adopt a self-organizing presentation approach. This approach treats each learning activity as an equal central node, automatically organizes and generates a linked structure between nodes through semantic connections under the learning theme. It indicates learners the semantic connections between various activities and their relationship with the learning theme through semantic labels. This self-organizing learning path can dynamically form and evolve as the learning progresses and the learning theme transitions. It can also change with the deepening of individual learning and the change of learning interests, in order to adapt to learners' personalized learning needs.

5. Evaluation

5.1. Experiment Design

An experimental study is conducted to analyze the impact of personalized learning paths on learning effectiveness. The experiment is designed to compare the differences between self-directed learning path selection and personalized learning path recommendations implemented in this paper. The design includes selecting the teaching content, teaching tasks, format and process of the experiment, participants, data collection methods, and other specific details. During the experiment, the learning process data are collected, which includes all recorded learning behaviors, sequences adopted by each learner in completing the learning task. The learner behaviors include reading materials, searching and using learning resources, participating in forum interactions and completing assignments. Language protocol data are collected during the experiment, which includes tracking and recording

the language expressions, protocol coding of some learners' knowledge transformation processes. The learner knowledge status data including the mastery of relevant key concepts and completion of assignments are collected before and after the experiment.

5.2. Data Analysis and Results

The evaluation uses a combination of qualitative and quantitative method to analyze changes in learners' behaviors and cognition during online education. By classifying and coding learning behavior data, the patterns of changes in learning motivation during the learning process are found. By coding and analyzing language protocols, the patterns and changes in learners' cognitive processes are confirmed. After a thorough analysis of the patterns, we believe that the personalized learning path based on knowledge graph primarily impacts online education and learning behaviors in two ways. First, it provides support to learners in seeking and evaluating information during online learning, and promotes their engagements in deep learning. Second, it reveals the connections between new concepts and learners' existing knowledge, facilitating learners to effectively incorporate the content of educational resources into their own knowledge systems.

6. Summary

One major contribution of the paper is that it develops an effective semantic integration of educational data from various learning environments based on knowledge graph. Due to the significant diversity of protocols and implementations of online learning environments, how to effectively utilize educational big data from different types of learning activities across platforms has always been a hot topic of online education. From the perspective of semantic integration of big data, the paper explores the a graph based knowledge representation to reduce the complexity of data integration. The dynamic integration enables efficient and accurate discovery of learners' interests and knowledge needs in real-time manner, and provides possibilities for personalized learning services. The results of the research work presented in the paper provides the basis to build up an intelligent system for the individual learning path recommendation based on educational big data. As the individual learning needs constantly evolve throughout the learning process, the proposed intelligent mining technology can dynamically capture the needs from learning behaviors and provide personalized learning support in the form of intentional learning.

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