A Metaverse-based Student's Spatiotemporal Digital Profile for Representing Learning Situation

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***Abstract*—In recent years, the metaverse becomes a promising method to provide an intelligent teaching platform for the teaching-learning process. Existing teaching evaluation methods rely on the exam results and the educator's teaching experience, which is hard to reflect the detailed teaching outcomes and each student's learning situation. Therefore, this paper proposes a four-layer metaverse architecture to build students' virtual entities of learning situations, containing a data acquisition layer, a technology layer, a model building layer, and an application layer. Furthermore, the virtual entities are constructed on the event logs recorded in the Learning Management System (LMS) and visualized as spatiotemporal digital profiles for students. In the spatial dimension, the profile can reflect a student's learning situation in different aspects, including the completion of an assignment, the mastery of knowledge, the practical ability, etc. In the temporal dimension, it can reflect a student's learning situation at different learning stages. Students' practical abilities are obtained by the Machine Learning method GBDT (Gradient Boosting Decision Tree), and other dimensions of the profile are generated by the Knowledge Graph technology. With these profiles, educators can do teaching intervention, teaching evaluation, and personalized cultivation, providing a new path for intelligent teaching. We take the CG (Course Grading) platform and Data Structure and Algorithm course as examples to validate our model strategy. The experimental results show that the spatiotemporal digital profiles can better describe students' learning situations, providing data support for teaching evaluation.**

Index Terms*—*metaverse*, *education*, *teaching evaluation*, *spatiotemporal digital profile*, *Graph Knowledge

I. Introduction

Nowadays, the metaverse has attracted a lot of research interests with the development of related technologies. Metaverse is an online digital space parallel to the real world, which is a virtual world that maps and interacts with the real world [1]. Although the metaverse is still in its infancy, it has been applied in many fields, including online games, social application, medical training, and education [1]–[3]. There are many applications of metaverse on curriculum resources and teaching methods. However, the learning situation analysis and teaching evaluation are also central concerns in education. Due to the ability of metaverse to describe entities, we use it to generate students' profiles for their learning situations and do teaching evaluations according to the profiles.

Traditional teaching evaluation takes the exam results as student profiles and the evaluation is conducted based on the educator's teaching experiences. The evaluation criterion cannot fully reflect students' learning situations. Meanwhile, the teaching evaluation is for the cohorts, lacking the personalized analysis of each learner. Although most courses adopt the formative evaluation and take the exam results in different teaching stages as the evaluation standard, it is still hard to reflect the students' comprehensive learning situations. Therefore, the key is how to get detailed event logs of students' learning processes.

The use of the Learning Management System (LMS) has grown exponentially in recent years for both online learning courses and blended-learning courses [4], [5]. LMS has many advantages including freedom of learning and practicing, collecting data on all student activities at different levels of granularity [5], [6]. Besides their traditional classrooms, nowadays most universities use the LMS, and the exemplar platforms include BlackBoard [7], Moodle [8] and EDx [9]. In LMS, the learning process data is stored in the event logs, revealing the students' learning situations. These data contributed affluent resources for constructing profiles of students. The question is, how can we build the profiles?

Several studies have proposed to extract knowledge from the event logs recorded by the LMS with the EPM (Educational Process Mining) technology [5], [10]–[16]. They aim to understand the factors that influence skill acquisition and create models for the educational process [5], [14], [15], [17]. These methods analyze students' learning patterns, for example, the learning behavior of high-score students and that of the low-

978-1-7348995-2-8/22/$31.00

score ones. With the mining results, teachers can check the students' learning situation that is good or bad. These methods have provided more ways to reflect the students' learning situation, but they only have two or three fixed patterns. However, we want to get more detailed information about students' learning situations, such as how many questions have been completed, the completion of questions, the mastery of knowledge, etc. The existing methods are difficult to satisfy such requirements.

With the idea of the metaverse, this paper constructs the virtual entities of students' learning situations based on the event logs on the LMS platform. We propose a four-layer metaverse for the virtual entity from the macro perspective, containing the data acquisition layer, the technology layer, the model building layer, and the application layer. Furthermore, we visualize these virtual entities as students' spatiotemporal digital profiles, including profiles of individuals and cohorts.

In the spatial dimension, the profile can reflect a student's learning situation in different aspects, including the completion of assignments and experiments, the mastery degree of knowledge, and practical ability. In the temporal dimension, it can reflect a student's learning situation at different learning stages. With the profiles, educators can monitor and analyze each student's learning situation. Moreover, they can dynamically adjust the teaching methods to accomplish the teaching intervention. Students can also check their strengths and shortages at any time. These are convenient for teachers and students to complete personalized cultivation. Finally, teachers can make accurate teaching evaluations at the end of a course. The profiles of students' practical ability are obtained by the machine learning method GBDT (Gradient Boosting Decision Tree) [18], [19], and the profiles of other dimensions are generated by the Knowledge Graph technology.

The main contributions of this paper are as follows.

- We propose a four-layer architecture of metaverse to construct the virtual entities of students' learning situations. These virtual entities are visualized as students' spatiotemporal digital profiles. To our knowledge, it is the first time to describe the learning situation with metaverse.
- The profiles are built with Graph Knowledge with LMS event logs, including students' learning situations in different aspects and learning stages. Furthermore, we will generate the profiles of individuals and cohorts, providing a more comprehensive description of students' learning outcomes.
- With the profiles, we can observe learners' knowledge acquisition and ability acquisition at any time and do dynamic teaching interventions in teaching. Meanwhile, we can conduct an accurate teaching evaluation at the end of a course, which is more scientific, convenient, and comprehensive.

The rest of this paper is organized as follows. In Section II, we review the related work. Architecture of our four-layer metaverse is introduced in Section III. Spatiotemporal Digital Profiles and Teaching is described in detail in Section IV. In Section V, experimental results are given and analyzed. The conclusion is given in Section VI.

II. Relate work

A. Metaverse

The concept of metaverse originates from the science fiction novel "Snow Crash" written by Neal Stephenson in 1992 [1]. David Baszucki, CEO of Robles, believed that the metaverse is a 3D virtual world that connects everyone in the real world [2]. The metaverse is the integration of the real and the virtual worlds [3], which is supported by the related technologies. At present, most technologies or products that embody the metaverse are mainly limited to the field of electronic entertainment. The text-based interactive game is the primary category of metaverse [20], such as MUSHs (Multi-User Shared Hallucination) [21]. With the rapid advances in computer graphics, virtual worlds equipped with 3D graphics appeared, such as ActiveWorlds [22]. Nowadays, massively multiplayer online video games are probably the most popular version of the metaverse, for example, Second Life [23] and Fortnite [24]. However, it is inappropriate to regard the metaverse as a video game. The metaverse can be applied to various fields, such as education, which breaks through the limitations of the physical world and creates a new virtual educational world through the online teaching platform [25]–[28].

B. Educational Process Mining

EPM is to extract knowledge from event logs recorded by Learning Management System, Massive Open Online Courses (MOOCs), or Intelligent Tutoring System (ITS). It focuses on the development of a set of intelligent tools and techniques aimed at extracting process-related knowledge from event logs [12], [15], [29]. The application of EPM can be divided into five dimensions, which are discovering learning behavior patterns, predicting the trend of learning outcome, improving teaching evaluation and feedback, providing teaching decision support, and improving education management service. Trcka et al. [30] converted students' examination records of multiple courses into event logs to analyze the elective courses' learning paths. Mukala et al. [31] used a fuzzy mining algorithm to extract students' learning patterns in MOOCs. It has been found that the learning behavior pattern of unsuccessful students is poor and unpredictable, while the behavior pattern of successful students is generally similar. Pechenizkiy et al. [32] applied process discovery and other technologies to analyze online multiple-choice question data and evaluate feedback on the trend of students' answering behavior. Cairns et al. [33] used conformance checking to analyze the fitness degree between the employees' training paths and the established curriculum constraints. Anuwatvisit et al. [34] used conformance checking to detect discrepancies

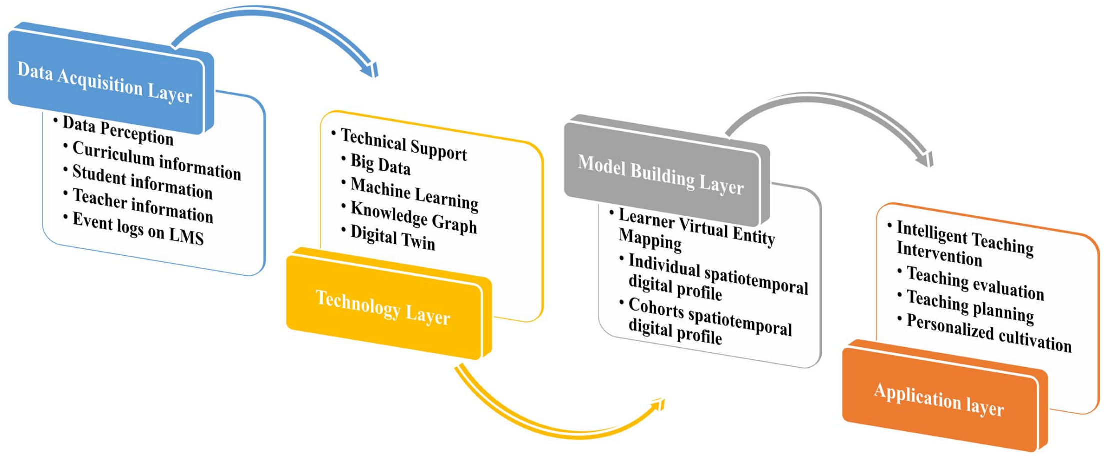

Fig. 1. Architecture of the learning virtual entity.

between the flows prescribed in students' registration models and the actual process instances.

C. Educational Process Mining and Learning Management System

The LMS allows collecting records corresponding to all events, actions, and activities of students at different granularity levels [5]. Ardimento et al. [14] adopted the fuzzy-based process mining techniques to model the developers' coding process. The event logs include low-level logs such as keyboard and mouse events and high-level logs such as commands issued at the IDE (Integrated Development Environment) level. Damevski et al. [35] presented a semi-automatic approach for mining frequent developer's behavior patterns of IDE usage. This method recognized sequences of activities executed by developers, focusing on how developers interact with the IDE. Real et al. [5] aimed to adopt the EPM techniques to mine the students learning paths in an Introductory Programming course. The analysis of these results provided general and specific information on students' learning paths and can help teachers observe students' behavior patterns. Ardimento et al. [13] used conformance checking to test coding behaviors from event logs on IDE and studied how developers carry out coding activities and what hurdles they usually face. Etinger et al. [36] attempted to uncover and analyze the patterns of behavior performed by students with higher scores and lower scores, understanding the online course usage patterns and their relationship with learning outcomes.

III. Architecture of the Four-Layer Metaverse

At present, the application of metaverse in education mostly focuses on providing virtual learning platforms for learners and educators. Education contains two aspects, which are teaching and learning. But the existing studies mainly focus on teaching. Furthermore, the traditional teaching evaluation method often adopts exam scores, which are not objective and scientific. In this paper, we use metaverse technology to construct the learner's virtual entity.

According to the characteristics of our application, we propose a four-layer architecture, as shown in Fig. 1, including the data acquisition layer, the technology layer, the model building layer, and the application layer.

- Data acquisition layer. In the data acquisition layer, learners' learning process data on the LMS teaching platform, teaching evaluation data, and other interaction data are collected as the basis of the system.
- Technology layer. This layer integrates Big Data technology, Machine Learning technology, Knowledge Graph technology, and Digital Twin technology. The Big Data technology can help the system obtain, analyze, and normalize the educational data. The Machine Learning technology constructs students' practical ability model by analyzing and processing learners' log data. Digital Twins and Knowledge Graph provide algorithmic support for constructing learners' virtual entities.
- Model building layer. This layer is the core for constructing the learner virtual entity, including the learners' learning state model and practical ability model. With the visualization of the virtual entity, teachers and learners can better understand learners' learning situations, and the horizontal comparison between entities is also more intuitive. The model is built on the Knowledge Graph and the Machine Learning technology, providing a new path for intelligent learning.
- Application layer. This layer provides a friendly interactive interface for students, teachers, managers, and other users to monitor and analyze the teaching process. Through the reports, charts, and other visual means, students' knowledge network, cognitive ability, and learning behavior data are displayed to users, providing support for optimizing teaching methods, accurate teaching evaluation, and education management. Moreover, it can further stimulate learners to actively learn and enhance teachers' confidence in cultivating students' high-level thinking ability.

IV. Spatiotemporal Digital Profile and Teaching

A. Digital Profile Based on Knowledge Graph

Knowledge Graph uses visualization techniques to describe the relationship between entities in the world. It can mine a large amount of heterogeneous data and extract their associated relations to construct a knowledge structure network. Triple is a general representation of the Knowledge Graph. The forms of triples include (entity 1 - relationship - entity 2) and (entity - attribute - attribute value). This paper uses the Knowledge Graph technology to handle event logs in LMS. It includes the following steps, data preprocessing, entity extraction, and digital profile generation.

1) Data Preprocessing: There is much information in the LMS platform, such as course information, questions, and learning process log data. Firstly, we extract these data from the learning platform. Secondly, we deal with these data to complete the data cleaning. Finally, data slicing, labeling, and normalizing are done according to the requirements of profile generation.

2) Entity Extraction: This paper extracts the following entity information, including courses, questions, assignments, experiments, exams, students, etc. According to the analysis results, we define the following entities and their attributes in Table I.

TABLE I. The entities and their attributes.

ID	Entity	Attributes
1	Course	Name, chapter, section, teacher
2	Question	ID, type, content, chapter, section, difficulty
3	Assignment	ID, questions, chapter, score, completion
4	Experiment	ID, questions, chapter, score, completion
5	Exam	ID, questions, completion time, score
6	Student	Student NO., name, password
7	Knowledge	ID, name, chapter
8	Practical ability	High, low

We can complete the query and display students' learning situations according to these entities. Furthermore, analyzing the relationship between these elements to visualize the knowledge structure.

3) Digital Profile Generation : The individual spatiotemporal digital profiles are generated based on the event logs of their learning process and the Knowledge Graph technology. It can reflect students' learning outcomes in different aspects, including knowledge mastery, completion of an assignment, learning situation in each chapter, practical ability, etc. Moreover, we also show the cohorts' learning situations. For the cohorts' profile, we will make statistics on their average learning situations, for example, high score, low score, average score, completion degree, etc. Furthermore, we can query students' learning situations at any time to check their learning outcomes, providing real-time learning status data. The profile can also avoid the disadvantage that the teaching evaluation can only be carried out at the end of the course.

B. Multi-Granularity Practical Ability Model Based on GBDT

The cultivation of practical ability is one of the most important objectives of a course. Meanwhile, the log data of the learning process in LMS can reflect the students' acquisition of practical ability for most STEM courses. Therefore, we model students' practical ability with these log data and the Machine Learning technology GBDT.

Our curriculum system is a long and continuous cultivation process for students' abilities. Students in different learning stages have different practical abilities. To effectively utilize the feedback data of the prerequisite courses and do fine management for teaching, we propose a multi-granularity modeling strategy for students' practical abilities at different learning stages, for example, before and after a course. Before a course, we can build students' primary ability model with the log data of the prerequisite course, and at the end of the course, we can build the advanced ability model with the log data of this course.

This paper adopts the Machine Learning method GBDT to model students' practical ability, dividing into two steps, feature preprocessing and practical ability modeling.

1) Feature Preprocessing: We define the input dataset as $D = \{(x_i, y_i)\}$, $i \in 1, 2, ..., n$, where $x_i \in \mathbb{R}^z$ is the log feature of student i with z dimensions, $y_i \in [0, 1]$ is the label of this sample, and n is the number of samples. The label y represents a student's practical ability, and we define it as high and low.

2) The Practical Ability Model: According to the learning behavior logs of the prerequisite course and the target course, we build the students' primary practical ability model pF_M and the advanced practical ability model aF_M respectively. Both models are built with GBDT [18], [37] in the same way. The modeling approach is in the [18], [37].

C. Teaching Intervention Based on the Digital Profile

The teaching process should match students' learning situations to obtain better teaching outcomes. However, existing teaching methods cannot fully adapt to the idea of student-centered, and the teaching contents seldom change in the teaching process. Therefore, this paper does dynamic planning and intervention to the teaching strategy of a course based on the profiles. The teaching plan is divided into two levels, the global plan and the individual plan. The global teaching plan designs the teaching strategy before a course, and the individual teaching plan carries out personalized cultivation for students. Furthermore, we also conduct teaching interventions according to the real-time profiles of students in a course.

D. Teaching Evaluation Based on the Digital Profile

At the end of a course, students' learning profiles are generated with their event logs of the learning process. With these profiles and the grades of each stage, we can analyze the learning outcomes of this course. In addition, we can also compare students' profiles at different learning stages

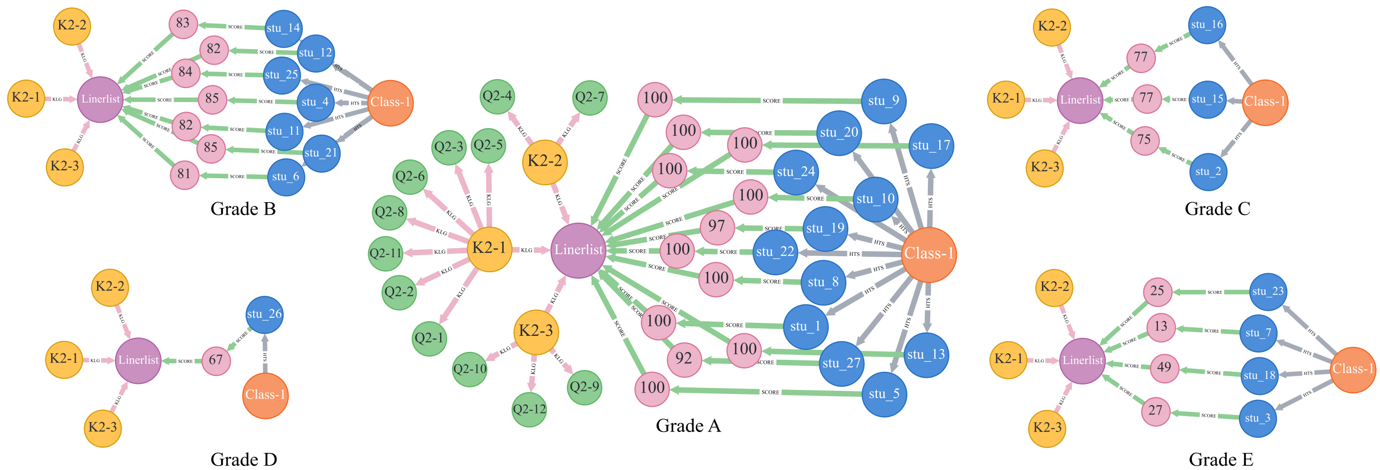

Fig. 2. The score of assignment for each student in chapter *linear list*.

to analyze the changes in cohorts' abilities and individual abilities. With the above analysis results, the teaching outcome of the course is summarized. Meanwhile, the practical ability model is updated based on the new event logs. Finally, the closed-loop teaching process of the course is completed.

V. Experiments

A. Experiment Settings

We take the CG (Course Grading) [38] platform and the Data Structure and Algorithm course to validate our instructional strategy. The study involved three grades in the School of Computer Science. The event logs of the two grades of 620 students are used as training data for the practical ability models. Meanwhile, the building of the student spatiotemporal profiles is conducted on 27 students of the last grade. We use Python language and the Neo4j toolkit to generate students' spatiotemporal digital profiles.

B. Spatiotemporal Digital Profiles

We visualize students' spatiotemporal digital profiles for learning situations based on the event logs on the CG platform, including individual completion of assignments and knowledge mastery, and cohorts' learning situations. Our goal is to display students' learning situations in each learning stage. Therefore, the profiles are not only displayed by course but also by chapter.

1) Completion of Assignments for Students: We can check the completion of students' assignments at any time to supervise students to work hard. The score of the assignment for each student in chapter *linear list* is in Fig. 2.

Fig. 2 clearly shows the score of each student's assignment in this chapter. We have graded the results and displayed them at different levels. Grade A to E denotes the grades from excellent to fail. Qi_j represents question j in chapter i, Ki_j represents knowledge j in chapter i, and one knowledge can contain multiply questions. With this result, we can understand the cohorts' completion of assignments and supervise the students with poor progress, for example, stu_3, stu_7, stu_18, and stu_23.

Furthermore, we can also visualize a student's score for each question in an assignment to check the complete details. The knowledge of each question is also displayed. Student stu_27's score of each question in chapter *graph* is as Fig. 3.

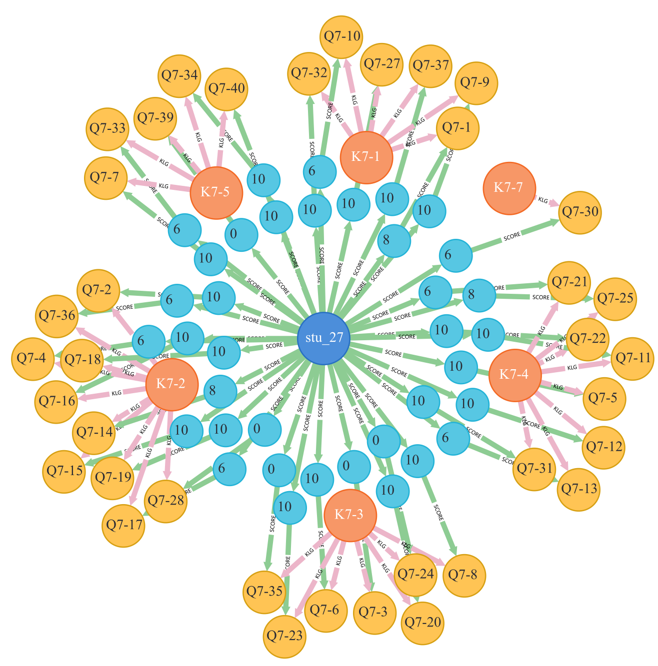

Fig. 3. Student stu_27's score of each question in chapter *graph*.

In Fig. 3, we can figure out what questions and knowledge are not well mastered, facilitating the improvement of weak knowledge. For example, $Q7\_3$, $Q7\_24$, and $Q7\_35$, and their knowledge $K7\_3$. While knowledge $K7\_1$ is better mastered.

Moreover, we can show the scores and completion degrees of each assignment, which are shown in Fig. 4. It intuitively displays the reason why a student does not get full marks. Is it because you didn't complete all the questions or didn't correct all the questions. In addition to the profiles shown in the paper, we can also click on the entity to view its detailed attributes, for example, student number, ID, and practical ability, which are shown in the upper right of Fig. 4.

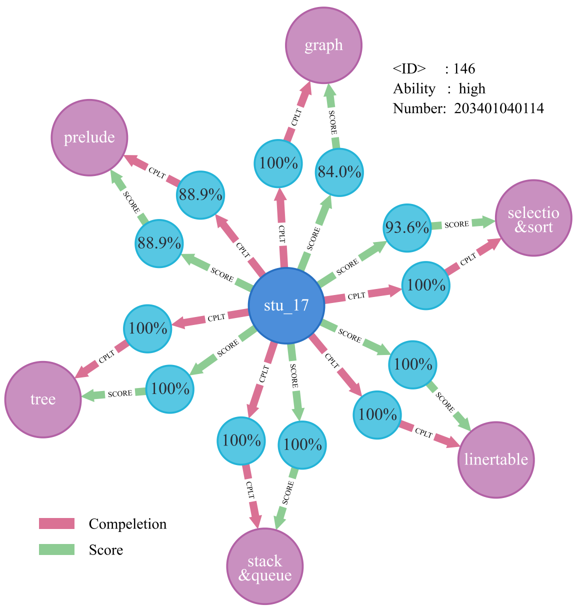

Fig. 4. Student stu_17's score and completion of each assignment.

2) Student's Knowledge Mastery: In this section, we display the knowledge mastery of the individual and the cohorts, which are shown in Fig. 5 and Fig. 6.

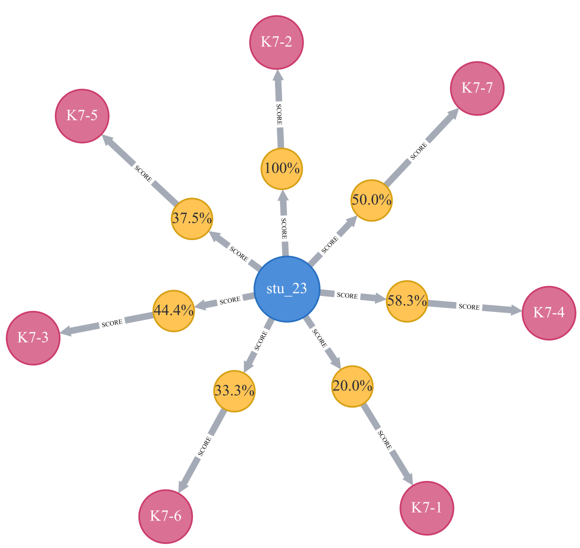

Fig. 5. Student stu_23's mastery of each knowledge in chapter *graph*.

The mastery of each knowledge is the average score of all the questions under this knowledge. In Fig. 5, stu_23's mastery of all knowledge in chapter *graph* is low, showing that his grasp of these contents is not ideal. Therefore, we

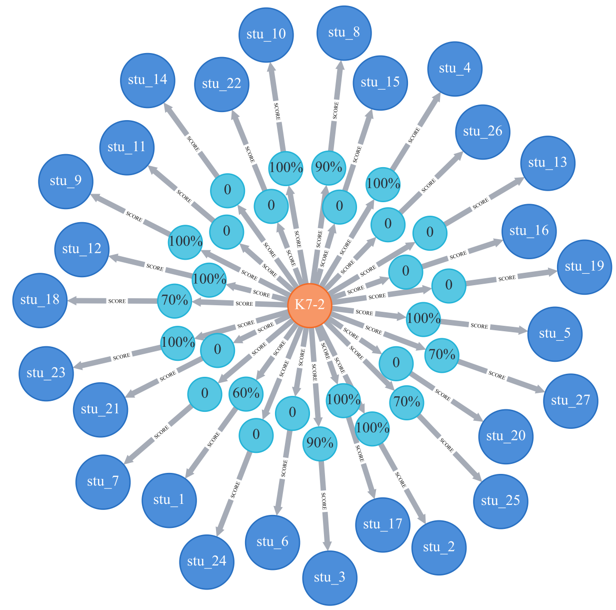

Fig. 6. The knowledge mastery of $k7\_2$ in chapter *graph* for all students.

should pay more attention to him. Furthermore, the contents in this chapter are hard for most students, which can also be seen in Fig. 6. For this part, teachers should strengthen the guidance to students and urge them to do more exercises.

3) The Cohorts' Learning Situations: Moreover, we can analyze the cohorts' learning situations in a class at different teaching stages. The average scores, average completion, and max score of all students for some knowledge are in Fig. 7. The score is normalized by 0 to 10.

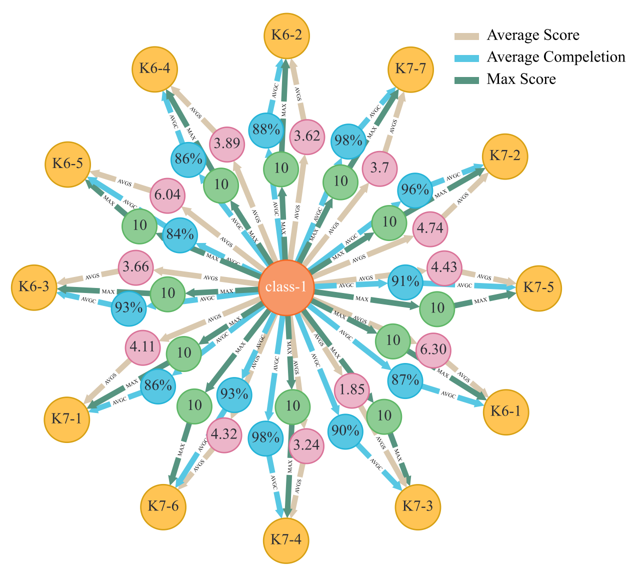

Fig. 7. The cohorts' learning situations for some knowledge.

In Fig. 7, we can figure out the cohorts' learning situations for some knowledge. The max scores of all knowledge are 10, indicating that some students are doing well. The completion of questions related to knowledge is high, but the average scores of most knowledge are not ideal. For example, $k7\_3$, $k7\_4$, $k7\_7$, $k6\_2$, $k6\_3$, and $k6\_4$. This figure shows that most students' mastery degrees of knowledge are not ideal, and everyone needs to do harder. With the cohorts' profiles, we can easily understand the average mastery of knowledge and strengthen the training of weak points. Compared with the traditional method of score statistics, it is more diversified and effective.

In addition to the above profiles, we can also make various queries according to the log data on CG to display different aspects of students' learning situations, providing data support for teaching design and teaching evaluation.

VI. Conclusion

To generate detailed spatiotemporal digital profiles for students' learning situations, this paper employs metaverse technology to build students' learning virtual entities. We propose a four-layer architecture to construct the virtual entity with the events logs on LMS. We extract the features from these logs and use Knowledge Graph to generate the digital profiles, including the learning status of different learning links and teaching stages. Furthermore, a multi-granularity practical ability model built with GBDT is proposed to describe students' practical abilities at different teaching stages. Finally, we take the CG platform and the Data Structure and Algorithm course as examples to validate our model strategy. The experimental results show that the spatiotemporal digital profiles can be more intuitive and detailed for describing students' learning outcomes. Therefore, educators' can do accurate teaching evaluations based on the profiles. Furthermore, the digital profiles can also provide strong data support for teaching intervention, teaching evaluation, and personalized cultivation, forming a new path for intelligent teaching. In the future, we should continue to refine students' digital profiles.

Acknowledgement

This paper is partly supported by the Education and Teaching Research Project of Shenyang Institute of Engineering (2019JYYB13), the Science Foundation of Liaoning Provincial Department of Education (LJKZ1052), the Undergraduate Education Reform Funding of Shenyang Aerospace University (JG202202C).

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