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Study on Learning Analytics Data Collection Model using Edge Computing

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Abstract – *In this study, we study a learning analytics model using edge computing that can collect learner data generated from various smart toy tools. As a method, a scenario is composed of a learning management system provided to learners, a learning analytics edge node, and a learning analytics cloud server. The learning analytics model of this study aims to overcome the limited situation and provide learning services for support and motivation for developing learners. In this way, we will use edge computing to analyze big data in learning using smart teaching tools, reduce the delay time for feedback, interaction, and response from learning activities, and perform efficient distributed computing. In the future, the proposed model will be developed and applied directly to the field.*

Keywords: *Learning Analytics, Edge Computing, Smart Toys, Smart Learning, Intelligent Tutoring System.*

I. INTRODUCTION

According to a recent IDATE forecast, the profits of the global smart toy industry were €4.98 billion in 2016; they are expected to increase to €8.38 billion by 2020 [1]. In Korea, since coding education became mandatory in middle schools in 2018, it is also being provided through toys. Diverse smart toys (block-type, interactive-type, and coding education-type) are thus being released.

As the importance of data-based decision-making increases, interest in collecting and analyzing learner data has also increased in the learning industry. Conventional learning analytics use conventional learning management systems, which mostly use standard data. Now, by including non-standard data, along with the standard data, and also using big data, machine learning, and cloud computing technologies, learning effectiveness and tutoring and learning support can be improved [2].

Systems such as Blackboard, Moodle, and Canvas already use learning analytics to identify poor learners, abandoners, and dropouts. However, only simple learning activity information, such as a learner's login time, progress, or quiz results, is collected. Data such as sensor data, location, voices, or codes, which are unique to learning activities when using smart toys, are not collected [3]. In particular, the need for learning analytics increases as schools adopts the distance learning approach owing to COVID19.

To implement learning analytics in a class using smart toys, a study is required to collect data on the state of sensors, changes in the location, state of teaching tools, conversations with smart toys, code blocks or source codes entered by learners, and learning activities. However, no such study has been conducted yet. Therefore, in this study, a system that provides learning analytics services for block-type teaching tools, control-type teaching tools, interactive smart toys, code education-type teaching tools, and so on is proposed.

For smart toy-based learning, unlike conventional learning, short feedback time and quasi-real-time interaction are required. Sending massive amounts of learning activity information from a smart toy to a cloud server for analysis will require a considerable amount of time. Therefore, edge computing should be adopted for feedback and interaction at a location close to the smart toy.

II. LEARNING ANALYTICS

In learning analytics, diverse and sporadic data from students are analyzed in real-time, and an effective learning model is established. Learning analytics is a special application area of big data analysis technology. Its purpose is to improve the learning system by collecting and analyzing learning data to obtain meaningful results [4].

Learning analytics has a different unit depending on the analysis target. Micro-level tracks and interprets data on learning activities of individual learners or groups, Meso-level analyzes at the level of institutional or existing business intelligence, and at Macro-level accumulates individual and institutional level data analysis at the regional or national level will be performed to derive overall trends.

At present, learning analytics technology remains at the level of providing personalized learning feedback for developing learners. However, in the near future, it is expected that we will be able to provide all-around customized education by collecting various data such as student behavior and personality as well as simple grade data based on artificial intelligence and providing a richer profile.

Recently, many studies have been conducted on dashboard visualization based on the learning analytics of a learner.

Most studies on the dashboard using learning analytics monitor the learning environment or learning activities of students. They provide visualizations of learner participation in learning, learning attitude, learning time, utilization frequency of learning materials, and so on. [5].

The international standardization organization, IMS Global Learning Consortium (IMS Global), is actively performing data identification for learning analytics. Learning data collected and analyzed are classified into five categories: learning content data, learning activity data, operational data, career data, and learner-educator profile data. The collected data for learning analytics is shown in Fig.1[6].

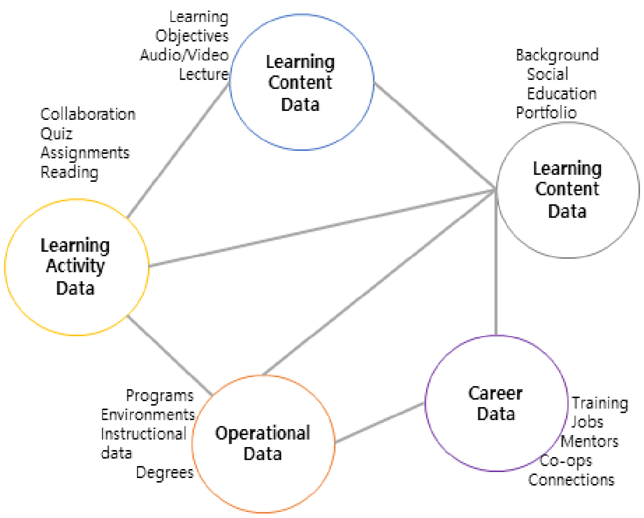

Figure 1. Collected data for learning analytics

When learning analytics using such big data is introduced, the following values can be provided for each target. From the learner's point of view, First, learning activities and progress can be measured to support learning. Second, improved feedback can be provided through records generated in the course of learning activities, formative evaluation, general evaluation, and stealth evaluation. Third, it is possible to create personalized learning paths and provide learning resources based on data such as learners' prior learning level, preference, and concentration time.

From the instructor's point of view, First, it is possible to compare and analyze learning contents, learning organization, and learning patterns through the pattern analysis of excellent learners, and based on these data, it is possible to derive the direction of improvement of one's own teaching method. Second, students and groups with poor participation in learning can be detected early and intensively managed for the students and groups. Third, quantitative data such as content exposure frequency, learner participation rate, learner's attitude, etc., can provide learning design ability incorporating improved learning experiences based on facts.

III. EDGE COMPUTING

In computing and data storage, edge computing collects, processes, and analyzes data at an edge that is physically closer to the user than a cloud datacenter. Edge computing is a distributed computing paradigm that improves response time and saves bandwidth by analyzing data at the edge [7]. The edge computing environment is shown in Fig. 2[8].

Edge computing, which is a form of cloud computing, is becoming popular because it can be used to share and send large amounts of data collected from various Internet of Things (IoT) devices via the Internet without time or space constraints. In cloud computing technology, there is a centralized cloud in which all the data processing and computing are performed at the cloud data center. In contrast, edge computing is a distributed cloud model, with distributed data processing in IoT and neighboring devices.

Edge computing is used where rapid data analysis for real-time response and collection and processing of vast amounts of data is required. Edge computing is a method of processing data in places where data is generated, such as smartphones and IoT, and is a concept opposite to cloud computing in which data is processed/stored/analyzed in existing data centers.

The advantages of edge computing are as follows. Data load can be reduced because it only processes data that occurs at the location. The delay is reduced because it can be processed directly without the process of transmitting data to the cloud. There is no need to transfer data to the cloud, so the security is good. Not affected by cloud server failure.

Edge computing is applied in smart factories, self-driving cars, virtual reality, augmented reality, biometrics, drones, communication services in the 5G environment, and so on. [8-10]. Until now, in order to learn artificial intelligence, the data was collected in one place, and the model was trained. However, unlike the existing method, federated learning sends the model to the place where the data to be learned is located. This method does not require data to be transmitted to the server, so it is expected that privacy issues can be solved. It is not yet used for learning analytics. However, if big data learning analytics is required for online video, real-time classes, or collecting learning data from various IoT, edge computing will be required.

Figure 2. Edge computing environment

IV. LEARNING ANALYTICS SERVICE MODEL FOR SMART TOYS

This study proposes a learning analytics service model for smart toys that can instantly provide an intelligent tutoring system after collecting and analyzing learning information based on a learner's use of various smart toys. The model is shown in Fig. 3.

The entire service system consists of an open learning management system (Open LMS), a learning analytics edge node, and a learning analytics cloud server.

First, the Open LMS provides learning content (learning path, project, feedback, etc.) from the learning analytics cloud server to a learner. The learning activity information in the LMS is converted to a standard protocol by a learning analytics agent in the system, which is then sent to the learning analytics cloud server via the learning analytics edge node. The learning content is based on the standard protocol received from the learning analytics cloud server and is provided to the user via the learning management system.

Second, the learning analytics edge node broadcasts the learning activity information received from the Open LMS and the learning content received from the learning analytics cloud server. The edge node analyzes the learning activity information received from the Open LMS in real-time and sends feedback.

Third, the learning analytics cloud server saves the learning activity information received from edge nodes in a database (LRS: Learning Record Store). It performs statistical/SNS/pattern/estimation analysis of the learning activity information saved in the database and then sends it to Open LMS via edge nodes after visualization to create customized learning paths, projects, and feedback for learners.

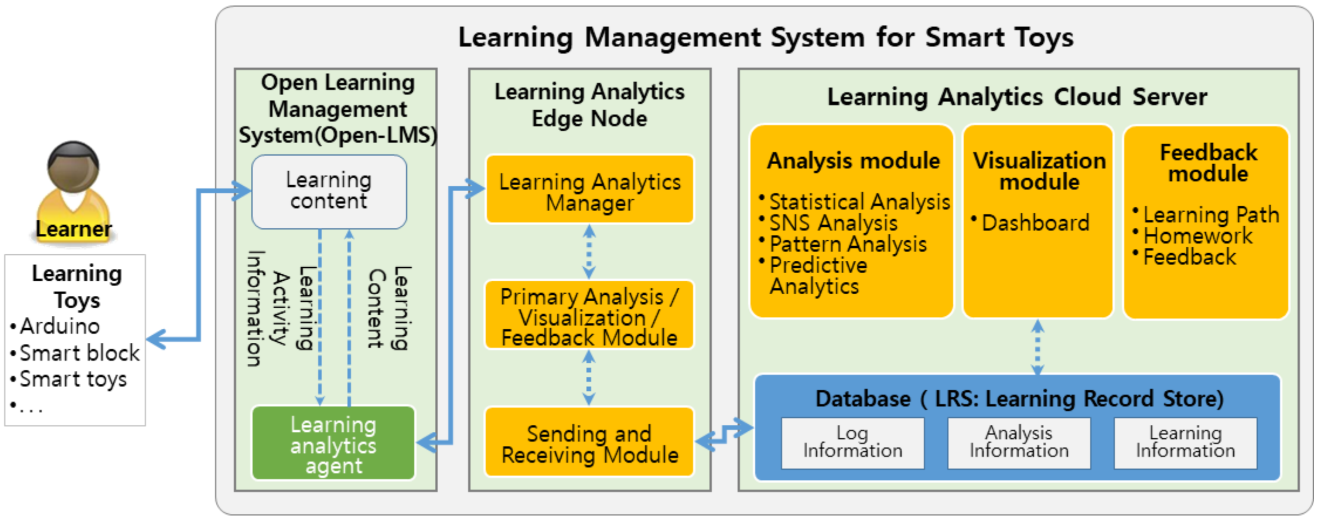

Figure 3. Configuration of learning service system for smart toys

V. CONCLUSION

Conventional offline education faces limitations in both educations at the learner's level and individual learning. Often, only final evaluation data, such as test results, are manually recorded, and no meaningful activity records are accumulated during the learning process. In addition, it can be difficult to provide personalized feedback based on learning habits, cognitive level, and so forth because only standardized tests are used to measure the academic level of students. In particular, such testing ignores information such as sensor data, location, voice, and code, which are unique learning activities available with smart toys. To overcome this situation and provide support and motivation for individual learners, in this study, we seek to provide a new data-based learning service. Using smart toys where edge computing is utilized, we seek to implement feedback, interaction, and fast response after big data analysis, reduce the response latency for learning activities and implement efficient distributed computing. A system will be developed as outlined here and applied to learning in the future.

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