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A STUDY ON DEVELOPMENT OF WEB APPLICATION TO VISUALIZE COURSE ATTITUDE INDICATOR BASED ON COMMUNICATION HISTORY

Hiroshi Shiratsuchi[1], Kazuhisa Hatta[2], Kozo Horiuchi[3]
and Takanori Matsuzaki[1]

[1]Graduate School of Humanity-Oriented Science and Engineering
[2]Faculty of Humanity-Oriented Science and Engineering
Kindai University
11-6 Kayanomori, Iizuka-shi, Fukuoka 820-8555, Japan
{ sira; takanori }@fuk.kindai.ac.jp; khatta@iis.elec.fuk.kindai.ac.jp

[3]Gururi Co., Ltd.
2-1-6 Uomachi, Kokurakita-ku, Fukuoka 802-0006, Japan
kozo.horiuchi@gururi.co.jp

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Abstract. *The number of dropouts at universities and other higher education institutions is on the rise, and academic failure and changes in living conditions are cited as contributing factors. As part of efforts to prevent dropouts and provide academic support, research is being conducted on methods of analyzing the learning process by utilizing student grade information, attendance information, and learning records obtained from electronic learning materials such as LMS, e-learning, and tablet terminals, known as "education big data". One study aimed at helping students avoid dropping out of college is visualizing student behavior and course indicators as student guidance indicators based on campus Wi-Fi access and communication history. The history of student smartphone connections to campus Wi-Fi was collected as a student behavior indicator, and visualized the time spent and tracking information in our previous research. This paper describes how to visualize application usage during lectures based on information output by the Layer 7 Firewall (L7FW) as an attitude indicator. Specifically, from the massive log data processed by L7FW, the amount of communication and the number of sessions belonging to the category of applications used by students via Wi-Fi that have little relevance to lectures are extracted. By visualizing the usage status during a single lecture or a series of lectures, the system aims to provide a basis for student attitude indicators. Since wireless connection history and communication history are personal information, a method of protecting user information by pseudonymization using a cryptographic key or hash value should also be considered.*

Keywords: Behavior analytics, Learning analytics, Course attitude indicator, Usage visualization

1. **Introduction.** With the tightening of enrollment capacity at universities in Japan, measures to reduce the rate of student absences and withdrawals have become an increasingly critical issue for universities. There are no effective measures to prevent students from dropping out of school, and course guidance by university faculty and interviews with counselors are the only contact points for students. Course guidance by faculty members is based on limited information such as high school grades, admission examinations, and post-enrollment performance. In recent years, however, an increasing number of universities have electronically recorded the results of student interviews conducted by faculty members as "student charts". Furthermore, an increasing number of universities have adopted a system that provides real-time attendance information by utilizing student ID

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cards with built-in wireless IC tags [1, 2]. Also, a broad range of other information related to education is being digitized, such as class evaluation questionnaires and records of reports and quizzes taken using LMS (Learning Management System) and e-portfolios.

The above kind of information is called Education Big Data (EBD), and various researches have been conducted in Japan and abroad to collect and utilize this data [3]. EBD is analyzed as Learning Analytics (LA), but in LA, it is a method of clarifying the process by which the participants proceeded with their learning behaviors by analyzing the history of each lecture using electronic materials such as LMS and pre-managed tablet devices [4]. Because of the limited number of lectures to which this method can be applied, it is difficult to target all classes. However, with the digitization of class content since the Corona disaster, it may become a valuable method in the future. A common predictor for many students who take time off or leave school is a decline in grades and a gradual increase in tardiness and attendance at college. These can be inferred from the attendance management system and grade reports mentioned above. However, it is difficult to judge whether a student has an elevated level of awareness but lacks academic ability, or whether a student attends lectures but cannot concentrate in class, leaves the room halfway through, or looks only at their smartphone. In previous research, the relationship between social media usage and academic performance among college students and the impact of smartphone use on learning had been examined by analyzing based on survey results [5, 6]. Therefore, if students' behavior patterns and concentration in lectures can be quantified, it may lead to more accurate and early support.

Smartphone ownership among college students is said to be around 95% or more. In line with this, the campus wireless LAN connection service has been provided so that students can view the educational system, LMS, and other information on their smartphones. As a result, students' location information, which could only be obtained by attending lectures or using their student ID cards, can now be obtained through their connection history to wireless LAN [7]. This information can be used as a continuous behavior history if the student has Wi-Fi enabled on campus [8]. In our previous research, the history of student smartphone connections to campus Wi-Fi was collected as a student behavior indicator, and visualized the time spent and tracking information at each facility on campus [9]. Furthermore, if communication history by these terminals can be obtained by the Layer 7 Firewall (L7FW), it would be possible to visualize this as a student attitude indicator based on application usage. Thus, it is inferred that the travel and communication history of EBD as a new amount of information is closely related to attendance and performance of lectures.

In this paper, in addition to the connection history of student terminals to the campus wireless LAN system, L7FW collects various application usage information during lectures as communication data volume and session information, categorizes them in consideration of relevance to the classes, and stores them in a database. Then, it aims to visualize it as a student's attitude toward attending a lecture during a single classroom time or a continuous class period. Specifically, L7FW records connection destinations, applications used, data volume and so on for each session for all communication traffic on campus. From this vast amount of data, only student access is extracted and classified into categories based on relevance to lectures and application types, which are then constructed into a database. These are developed as a Web Application that designates a date or a time by student or lecture from the accumulated and generates the relevant information as a cumulative graph for each application type on the time axis. Since wireless connection histories and communication logs are personal information, we will also consider ways to protect user information by pseudonymizing it using encryption keys and hash values. By using our proposed system described above, we expect to be able to discuss the relationship between the use of smartphones, social media, etc. and academic performance for various lectures without limiting the evaluation to lectures using the LMS or conducting a large-scale questionnaire survey.

Section 2 describes the procedure for visualizing students' course attitude indicators, and Section 3 outlines the logs output by L7FW and categorizes them based on their relevance to the information and classes used in our proposed method. Section 4 describes the construction of a Web Application that visualizes application usage during a lecture by specifying users, lecture names, and periods. Section 5 analyzes the application usage in actual classes, and examines the relationship between results, and Section 6 concludes.

2. **Visualization of Course Attitude Indicator.** In the previous study, an integrated network management system was developed as a Web Application to visualize the behavior history of students by extracting their connection history by the time of day based on user information obtained when they connect to wireless access points installed on the university campus [9]. This research aims to formulate an indicator of students' class attendance status by analyzing network connection time, application types used, and traffic volume using smartphones. In other words, we will examine a method to obtain the amount of traffic per application during the lecture hours for each student from PaloAlto's L7FW, analyze the amount of data unrelated to the lecture, connection time and frequency, and quantify the degree of concentration on the lecture as an attendance index. At this time, the number of sessions, which indicates the number of connections additionally to the traffic volume per unit time and the destination, is obtained from the L7FW. That will make it possible to identify services such as SNS and game applications that require frequent sessions, although the amount of communication per session is small. In addition, students' behavior histories obtained in previous studies are linked to individual timetables to track attendance for specific lectures.

Course attitude indicator should be created comprehensively for all courses that the target students are taking, weighing the importance of subject and the expertise of the contents. First, as a course attitude indicator of the target students toward one course, visualization of the transition of smartphone usage time during lecture time and the amount of data used will be performed as a transition graph. Also, a method to visualize the transition of the amount of communication that is unrelated to the lecture during the lecture period (about 16 weeks) for a specific lecture as a graph will be implemented. The following sections describe the diverse types of information from the L7FW and discuss the calculation of course attitude indicator based on the relevance to lectures utilizing the application type information specified by the equipment.

3. **Getting Application Logs from L7FW.** Figure 1 shows an example of logs per session acquired by L7FW transferred to the log server in CSV format using the syslog protocol. As can be seen from the figure, the L7FW records various information about all communications passing through the device, such as the transmission and reception address, port used, protocol type, application type, category, amount of data transmitted and received, and possibility for each session. To record the entire communication log, approximately 300,000∼500,000 lines per hour (about 40 to 60 MB/hour) are output in

```
May 11 00:03:03 FW_1,016201006876,TRAFFIC,0.0.0.0,0.0.0.0,outside_dmz_005_3,dns-base,vsys1,outside,dmz,
  udp,allow,241,87,United States,Japan,infrastructure, network-protocol,dns,dns-base
May 11 00:03:03 FW_1,016201006876,TRAFFIC,0.0.0.0,0.0.0.0,outside_dmz_005_3,dns-base,vsys1,outside,dmz,
  udp,allow,297,89,India,Japan,infrastructure,network-protocol,dns,dns-base
May 11 00:03:04 FW_1,016201006876,TRAFFIC,0.0.0.0,0.0.0.0,in_out_apply_permit,quic,vsys1,inside,outside,
  udp,allow,12412,5693,unknown,United States,infrastructure,browser-based,no,no
May 11 00:03:04 FW_1,016201006876,TRAFFIC,0.0.0.0,0.0.0.0,permit,sharepoint-online,vsys1,Gloval,outside,
  tcp,allow,46971,4958,Japan,United States,social-business,browser-based,is-saas
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Figure 1. Example of application logs collected by L7FW

our environment as weekday daytime with roughly 2,000 active users. The application log also contains information related to system administration, such as DNS inquiries and SNMP. For this reason, the minimum amount of information related to sending and receiving shown in Table 1, excluding the information, should be stored in the database. By constructing a database of campus Wi-Fi usage information, including connection information from the wireless LAN controller (WLC), authentication information from the RADIUS server, and IP address assignment information from the DHCP server, the IP address, MAC address, and connection location of each terminal used by users can be referenced in real time. For this purpose, IP addresses logged by L7FW, and the above information are tied together and stored in the database. The ER (entity relationship) diagram of the newly created database is shown in Figure 2.

For the purpose of protecting personal information when creating a database, pseudonyms are used for user information using encryption keys and hash values. Specifically, as shown in Figure 3, for example, for a 10-digit User ID, a private key is inserted into each of the third and seventh digits by three bytes, and then a disguised User ID is generated by

Table 1. Examples of principal information recorded by L7FW

Attribute	Description	Example
datetime	Recorded datetime	May 1 00:00:00
srcIP	source IP Address	172.16.1.1
destIP	destination IP Address	10.13.1.1
protocol	Protocol Type	tcp
identifier	Application Type	slack-base
category	Application Category	saas
sub-category	Application Sub-Category	instant-messaging
direction	traffic direction	outside
sent	transmitted data (byte)	244
incoming	received data (byte)	97

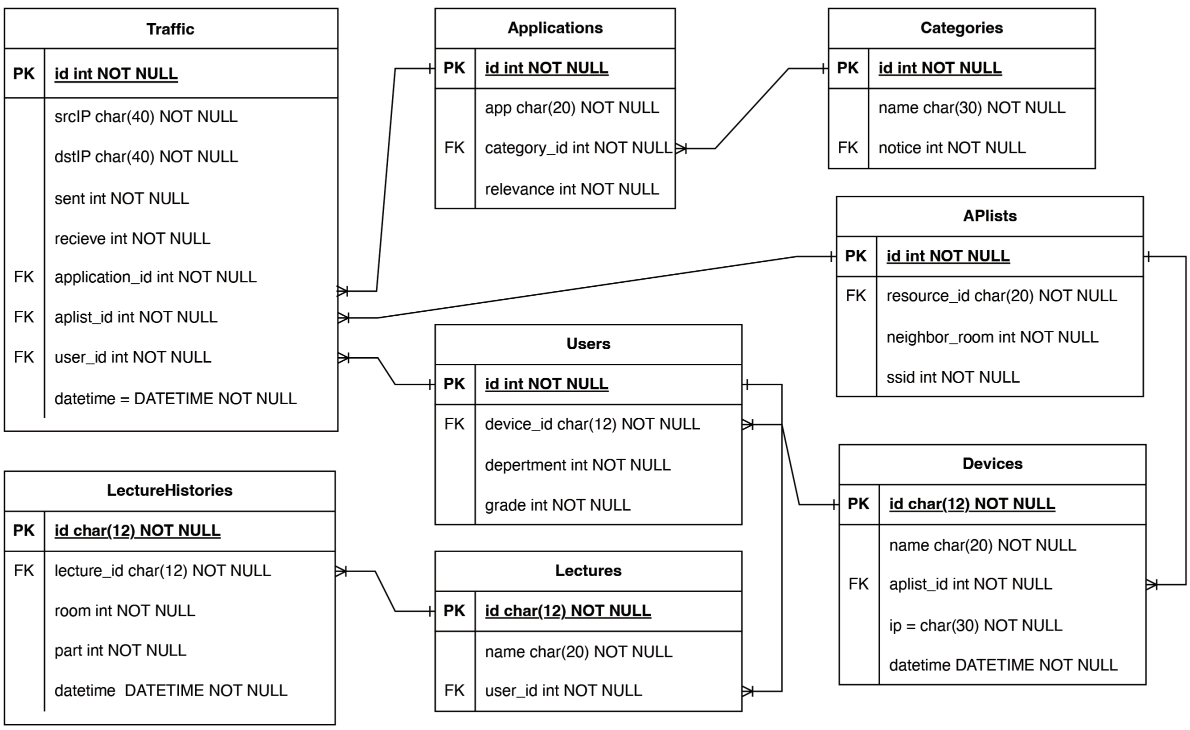

Figure 2. ER diagram of the proposed database structure

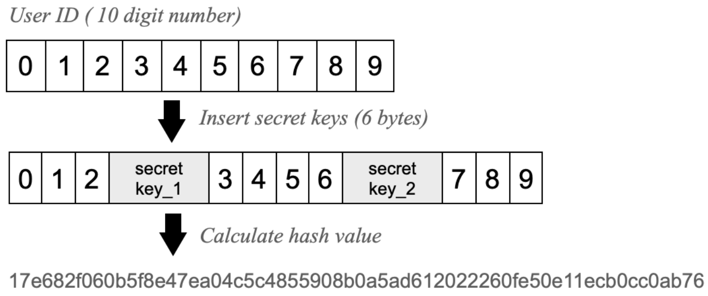

Figure 3. Pseudonymization procedure for user information

a hash calculation algorithm such as SHA-2 (Secure Hash Algorithm). IP addresses and MAC (media access control) addresses were excluded from pseudonyms. This is because the Dynamic Host Configuration Protocol (DHCP) assigns a different IP address every period of time, disguising the MAC address as a standard feature of smartphones.

4. **Development of Web Applications to Visualize Usage.** This section aims to develop a Web Application to visualize information necessary for course indicators from the created database. Specifically, from the information stored in the database, communication information for each application used by any student during a lecture is extracted at 3-minute intervals. Then, a method of displaying the communication information as a time transition graph showing course attitude indicator during the lecture period is discussed.

The application name and classification category defined by L7FW are shown in Table 2. The category name in the table has a wide meaning and is not an appropriate taxonomy for calculating course attitude indicators. Subcategory names, on the other hand, match the purpose of the application categorizing. The problem, however, is that social networking sites such as Facebook/Instagram (facebook-base) and Twitter (twitter-base), which are not usually associated with lectures, and access to LMS content such as Google Classroom

Table 2. An example of application type detection and categorization by L7FW

Application identifier	Category	Subcategory
youtube-base	media	photo-video
facebook-base	saas	social-networking
google-classroom	saas	social-networking
zoom-base	saas	internet-conferencing
twitter-base	collaboration	social-networking
quic	networking	infrastructure
gmail-base	saas	email
icloud-mail	saas	email
apex-legends	media	gaming
minecraft	media	gaming
slack-base	saas	instant-messaging
ntp-base	networking	infrastructure
ssl	networking	encrypted-tunnel
amazon-music-base	media	audio-streaming
web-browsing	general-internet	internet-utility
skype	saas	instant-messaging
apple-push-notifications	general-internet	internet-utility
google-message	collaboration	instant-messaging

TABLE 3. Proposed application classification based on relevance of lectures

Category	Applications	Relevance to lectures
SNS	Instagram, Twitter, etc.	False
Movie	Youtube, Netflix, etc.	False
Music	Spotify, iTunes Music, etc.	False
Game	Apex-legends, Minecraft, etc.	False
LMS	Classroom, Teams, etc.	True
Web meeting	Zoom, Google Meet, etc.	True
Storage	Google/iCloud/One Drive, etc.	Gray zone
Message	Slack, Discord, etc.	Gray zone
Browser	browsing web page and LMS contents, etc.	Gray zone
Notification	push notification	Gray zone

(google-classroom) fall into the same instant-messaging category. Therefore, by improving the subcategory classification in Table 2, the application classification for a course attitude indicator is proposed as Table 3.

Based on the classifications in Table 3, we developed a Web Application using the Python language and the Django framework to display the foundational graphs for the various forms of course attitude indicators from a database built in MySQL. Specifically, this system can graphically display the amount of communication data and the number of sessions for each application and category for any user and time. In addition, by specifying a lecture name, it is also possible to display trends in application usage for the entire course or for the whole period of a single lecture. For example, a graph showing the communication data by application used by a student between 14:50 and 15:50 on a someday can be visualized as shown in Figure 4. In the figure, the horizontal axis shows the time of day, and the vertical axis shows the total amount of communication for each application aggregated in 3-minute increments as a stacked graph. Furthermore, by focusing on the use of applications that are less relevant to the lecture based on Table 3, they can be displayed as a stacked graph according to relevance, as shown in Figure 5.

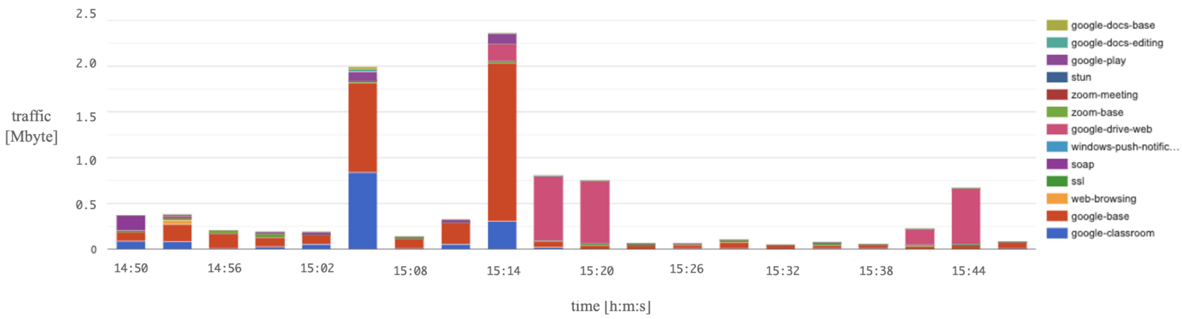

FIGURE 4. (color online) Amount of traffic sent/received for each application during a certain lecture period

5. **Experimental Results.** In this section, we examine the relationship between smartphone application usage and grades during the entire 16 times lecture period (including exams) for 61 students in an actual lecture course offered in the first semester of 2022. The target lecture consisted of classroom lectures and exercises related to the C programming language. In principle, the students were not allowed to use smartphones during the lectures. However, since the lecture is in a computer classroom, students may use their smartphones without being detected by the teacher. Since this subject, days of the week and time limits for conducting this lecture have already planned, it would be necessary

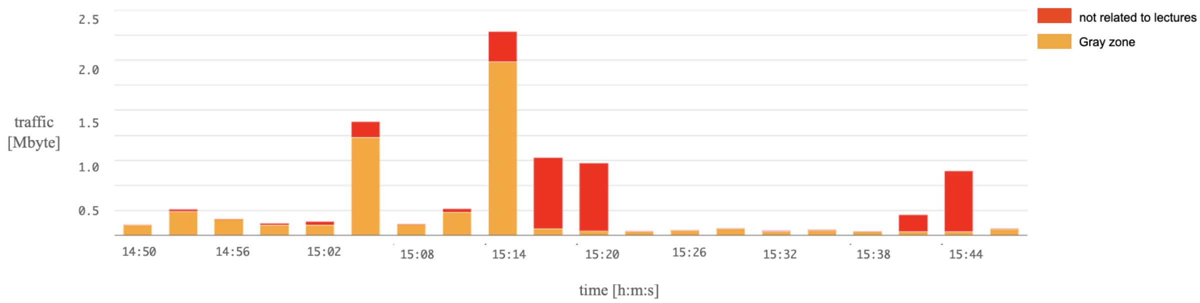

Figure 5. (color online) Usage of applications that appear to have little relevance to the lecture

to survey application usage on students' smartphone devices connected to Wi-Fi access points installed near the classrooms during these periods.

Figure 6 shows the transition of cumulative time spent on applications unrelated to lectures for each student in lecture period. In this figure, the horizontal axis represents the number of classes, and the vertical axis represents the cumulative time. The median of all students is indicated by a bold line, which is used as a basis to classify students into three groups. Attitudes toward attending classes are shown as bad attitude (orange line), normal attitude (blue line), and good attitude (green line), in order from the group with the most time spent, because the more time spent using applications that are less relevant to lectures, the less favorable. On the other hand, some students increased their usage time in the first half or near the end of the lecture period. These can be interpreted as abandonment in the middle of a course or the need to concentrate on the lecture due to insufficient understanding.

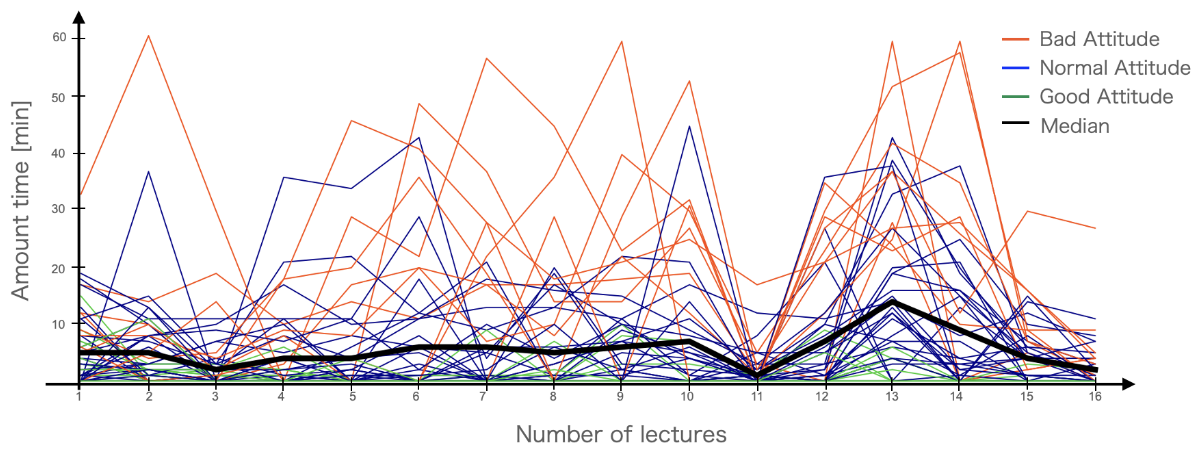

Figure 6. (color online) Cumulative usage time of applications with low relevance during the lecture period

Table 4 shows the three attitude indices and grade categories for examining the relationship between attitude and actual grades. In the table, scores of 50 or more out of a possible 100 are divided into groups of 10, and the respective scores are shown. As can be seen from the table, no correlation can be found between grades and attitudes in this experiment. One of the reasons for this is that the amount of communication by the *quic* protocol among the application IDs shown in Table 2 is remarkably high. The *quic* is a new communication protocol that replaces Google's proposed TCP/UDP protocol and features high-speed communication. For that reason, it is used in various applications,

TABLE 4. Experimental results on the relationship between course attitude and grades

Grade sections	Good attitude	Normal attitude	Bad attitude
90∼100	1	1	0
80∼90	3	8	1
70∼80	5	8	7
60∼70	3	11	2
50∼60	0	4	0
40∼50	1	1	0
0∼40	2	3	0

including Google Mail, Message, Classroom, and YouTube. However, since the *quic* multiplexes communications, L7FW cannot identify the actual application name. It is conceivable that applications with many users could not be classified, making it difficult to determine the attitude toward attending classes. By blocking the *quic* protocol on the L7FW, this problem is solved. However, changing the policy rules needs careful investigation of the scope of impact beforehand.

6. **Conclusion.** The purpose of this study is to visualize the course attitude indicator toward attending lectures based on the communication logs of students connected to the campus Wi-Fi. As a result, we constructed a Web Application that can display the application usage during class hours for any student or lecture unit, the utilization considering the relevance to the lecture, and the student's lecture attendance throughout the lecture period as transition graphs. Although the relationship between attendance attitudes and grade evaluation was examined for actual classes, the relationship between them could not be determined. The reason for this is thought to be that the multiplexing by the *quic* protocol made it impossible to classify categories such as LMS, Mail, and video distribution in spite of a large number of users. In this regard, we plan to add a rule to block the *quic* protocol in L7FW and proceed with verification covering more lectures.

If the above results can be used as a basis for quantitative evaluation of course indicators in the future, and if the behavior and performance indicators that are being developed in parallel can also be quantified, they can be used as effective indicators for preventing students from dropping out of school.

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