

Process Mining on Learning Activities in a Learning Management System

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Abstract—A learning management system is a system that supports the management of teaching and learning activities in an educational institution. Telkom University has its own learning management system called CeLOE which was developed based on the open-source Moodle application. This study analyses an event log, automatically generated by the CeLOE LMS, that records student and lecturer activities in learning. The event log is mined to obtain a process model representing learning behaviours of the lecturers and students during the learning process. The case study in this research is learning in the study program 365 during the first semester of 2020/2021. The results of the analysis obtained are expected to increase understanding of the learning process and produce recommendations for improving the learning management system. The conclusions obtained from the analysis of the process model include the identification of activities and learning content that are used and carried out by students and lecturers, the most frequent learning activities and resources done by students and lecturers during the first semester of 2020/2021 in the study program 365, and the gap of activities and learning resources during the first semester of 2020/2021 in the study program 365.

Keywords— learning management system, event log, process mining, learning process, study program

I. INTRODUCTION

In this modern era, every organization strives to support its business processes with computer-based systems. Universities are no exception; more and more are implementing computer-based learning management systems (LMS). LMS allows universities to manage learning activities carried out by lecturers and students, in the form of material delivery, assignments, quizzes, exams, etc. One of the advantages of implementing LMS in universities is the automatic creation of an event log that is recorded by the LMS. The event log records step-by-step of the LMS usage by lecturers and students in the learning process.

The event log is useful to support process analysis. Process analysis allows understanding of business processes by analysing each activity and the activity sequence, identification of the most common activity sequence carried out by lecturers and students during the learning process, identification of exceptional sequence in certain groups of lecturers and students, and their conformity to learning process implementation guidelines at the university.

One of the main methods for process analysis is process mining. Process mining [1] is a process-based data analysis approach that describes user behaviours based on event log records of an information system. The event log is the main input in the *process discovery* stage, which is an approach to create a process model that displays the sequence of activities within a business process. The process model that has been produced will then be analysed at the *conformance checking* stage to check the conformity between the process model and the reference model. The results of process discovery and conformance checking can be used to recommend *enhancements* to a process that is currently running.

Process mining has been used in several case studies, including manufacturing [2], auditing [3], health [4], and education [5] [6]. In the education domain, process mining can be applied to analyse student and lecturer activities, patterns of learning activities in a study program, and provide recommendations to improve teaching and learning activities in a class. In general, process mining in education focuses on analysing how learning materials and learning activities are used to support the teaching and learning process [6]. There are many algorithms that can use to do process mining like heuristic miner, genetic miner, and fuzzy miner [7]. In this study, heuristic miner algorithm is used because this study need develop Petri net for further analysis. And heuristic miner algorithm can handle the event log with noise [8].

In this study, process mining is used to analyse the event log of CeLOE LMS, an LMS that is used at Telkom University. Based on previous research [8], CeLOE has met the readiness requirement to be analysed using process mining. In this study, an event log from one study program in one semester is used as a representative of learning process in study programs at Telkom University. This study aims to analyse student and lecturer activities, learning activity patterns, and provide recommendations to improve teaching and learning activities based on activities recorded in the CeLOE LMS event log. The algorithm used in the process discovery is the heuristic miner [9]. This algorithm is chosen because of its ability to handle noise, has been implemented in ProM as the main tool for process mining [10], and has been widely applied to various case studies [11]. The resulting process model will be analysed in conformance checking based on fitness, precision, and generalization [1].

II. RESEARCH METHODOLOGY

This research consists of 5 phases, which are: (1) Planning, (2) Extraction, (3) Data processing, (4) Mining and analysis, and (5) Evaluation. Data processing, mining and analysis, and evaluation phases are three iterative phases that need to be carried out repeatedly until sufficient results are found. General methodology is presented in Figure 1. Each stage will be described in the following subsections.

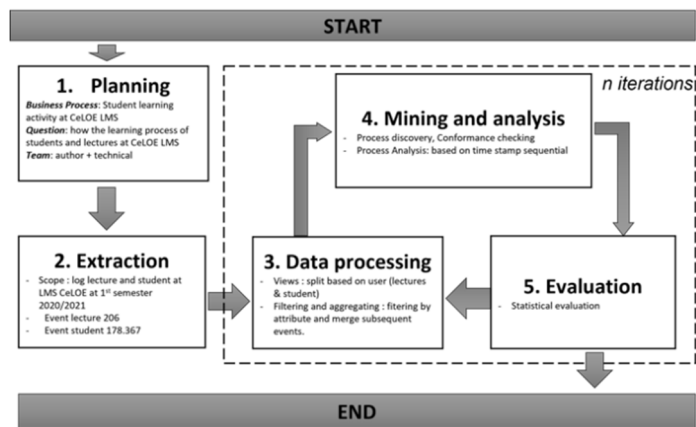


Figure 1. Process mining methodology

A. Planning

Process mining research starts with planning the scope of research, developing research questions, and building research team. The scope of this research is the teaching and learning activities of lecturers and students in the study program 365 during the first semester of 2020/2021, as recorded in the CeLOE LMS. The main research question is “How is the learning process of students and lecturers at CeLOE LMS?” and is divided into:

- Q1. How can we use process mining approach to analyse teaching and learning activities in an LMS?
- Q2. What is the most common sequence of activities in the teaching and learning process?
- Q3. What can we learn from analysing the teaching and learning activities of lecturers and students that have been carried out for one semester in the study program 365?

The research team consists of computer scientists as the process mining experts who are also the authors of this paper and the CeLOE team as the domain experts and the process owners.

The CeLOE LMS was developed from the open-source Moodle application. Lecturers design student learning process using those two-learning media, to support students to achieve an expected learning outcome [12]. Moodle has several learning media that can be used independently or guided, and can be divided into two types, i.e.:

- Activity: a collection of actions that allows students to interact with lecturers. Examples of activities include Assignment, Chat, Choice, Database, Feedback, Forum,

Glossary, H5P activity, Lesson, (LTI) External tool, Quiz, Survey, Wiki, and Workshop.

- Resource: learning resources prepared by lecturers to support student learning. Examples of resources are Book, File, Page, URL, and Glossary.

The database of CeLOE LMS consists of 388 tables [13] that are used to support the administration and operation of the CeLOE LMS. One of the tables contains the event log that is used in this study. The event log is stored in the `logstore_standard_log` table consisting of several attributes [14]:

- Courseid: a unique attribute of a record
- Components: modules or components referred to in an event, e.g., forums, wiki.
- Action: the type of action of an event, e.g., created, updated, viewed
- Target: related submodule information, e.g., post, discussion, page
- Contextinstanceid: a unique attribute that contains the course module, e.g., team message board, team wiki
- Timestamp: date and time

B. Extraction

In this phase, we extracted the CeLOE LMS event log obtained from the `logstore_standard_log` table. An event log can be defined as:

$$E = (c, a, t)$$

where E is a set of events parsed by case_id c , activity name a , and timestamp t . An event describes an activity a that occurs in a particular case c at timestamp t . Meanwhile, trace T is a temporal sequence of events that occur in a case, where $T \in E$. In this study, a case represents a lecturer or student who has a set of events related to their interaction with the CeLOE LMS for one semester.

The initial event log obtained is the event log of the entire study program from the university, then event log was grouped based on the existing study program. To get the event log for each study program, the `logstore_standard_log` table is matched with the course and `course_category` tables in the `courseid` attribute. After getting the event log for each study program, then separating the records based on the lecturer and student users, which is done by matching the `logstore_standard_log` table with the user table on the `userid` attribute.

After getting the separated event logs of student and lecturer, then filtering process is carried out based on component attributes. This filtering process sorts out activities and resources such as *assignments, quizzes, forums, chat, active quizzes*, and *feedback*. Resources in the form of *resources, URL, H5P, folders, pages, glossaries*, and *books*. The filtering process is done using the DISCO application from Fluxicon.

The characteristics of the event logs of lecturers and students are shown in Table 1 and Table 2. In both tables there are traces, events, event classes, variants, first event and last event. Traces are the number of sequences of activities that are formed.

Events are user activities, both lecturers and students, that are recorded in the event log. Event classes are types of activities in the event log (quiz, assignment, forum, etc.). Variants are the number of variations in the sequence of activities in the process. First and last events are activities carried out at the beginning and end of the process.

TABLE 1. CHARACTERISTICS OF LECTURER EVENT LOG

Characteristic	Description
Traces	26
Variants	17
Events	206
Event classes	8
First event	2020-09-02 14:02:58
Last event	2021-01-27 19:20:45

TABLE 2. CHARACTERISTICS OF STUDENT EVENT LOG

Characteristic	Description
Traces	3.994
Variants	3.391
Events	178.367
Event Classes	14
First event	2020-08-02 13:03:34
Last Event	2021-02-08 15:16:05

Table 1 shows that the lecturer log consists of 26 traces that correlate with 26 lecturers, with 17 variants (65%). In addition, there are 206 events that can be distinguished in 8 event classes. Table 2 shows that the student log consists of 3,994 traces that correlate with 3,994 student-class, with 3,391 variants (85%). In addition, there are 178,367 events with 14 event classes.

C. Data processing

Data pre-processing is the third phase of this research. Data pre-processing is carried out to ensure that the available event logs are ready to be processed with the heuristic miner algorithm. We undertake a role-based data processing to separately analyse lecturer and student records.

1. Lecturer data processing

The next step is filtering from the logstore_standard_log table attribute, namely CRUD (create-read-update-delete) by selecting records that have C and U. The selection of these 2 types of CRUD is because when the lecturer adds and changes activities or resources it will be recorded in the CRUD attribute with type C and U. Then do the merge subsequent events process assisted by ProM tools using the merge subsequent events plugin to ensure that there are no redundant records.

2. Student data processing

Student log data is processed by filtering event name attributes using Disco Fluxicon tools. This process selects several activities and one sub activity that is most relevant to represent the activities of the students. This filtering is done to minimize the looping of existing activities. For example, a quiz activity has sub-activities attempt viewed, attempt submitted, and course module viewed then in the log three records are recorded with the same quiz activity but different sub-activity. In this case, the selected sub-

activity was attempt submitted which stated that the student worked on the quiz until it was submitted. The results of the analysis of the selected activities and sub-activities can be seen in Table 3 where there are activities owned by student users, selected sub-activities to represent the activity and a description containing a description of the selected sub-activity.

TABLE 3. FILTERING ACTIVITY & SUB ACTIVITY STUDENT LOG

Activity	Sub Activity	Description
Forum	Course_module_viewed	View activity
Glossary	Course_module_viewed	View resource
H5P	Course_module_viewed	View resource
Page	Course_module_viewed	View resource
Quiz	Attempt_submitted	submitted
Resource	Course_module_viewed	View resource
URL	Course_module_viewed	View resource
Folder	Course_module_viewed	View resource
Feedback	Course_module_viewed	View activity
Choice	Answer_created	submitted
Chat	Message_sent	Message sent
Book	Course_module_viewed	View resource
Assignment	Assesable_submitted	submitted
Active_quiz	attempt_started	Attempt started

D. Mining and analysis

This is the main part of the study and consisting of *process discovery*, *conformance checking*, dan *analysis* steps. Process discovery was done using the heuristics miner on ProM tools [2]. Heuristics miner was chosen in this study because this algorithm is one of the most used algorithms for process discovery that can deal with noise and can be used to express the main behaviour recorded in an event log. In ProM, we used the interactive Data-aware Heuristics Miner (iDHM) plugin that allows interactive settings including several options of graphs to present the resulted process models.

The process model discovered using heuristics miner was then checked for its conformance to the traces in the event log, and vice versa. Conformance checking was done by measuring fitness, precision, and generalization [1], following the formulas:

1. **Fitness** (Q_f) indicates how well the resulting model represents traces in the event log.

$$Q_f = \frac{C_{me}}{\min(C_{me}, C_{em})}$$

Where

C_{me} = cost of aligning model to the event log

C_{em} = cost of aligning event log to the model

2. **Precision** (Q_p) indicates how accurate the model describes the traces in the event log. A model with low precision causes underfitting.

$$Q_p = \frac{n_{ae}}{\text{count}(n_{am})}$$

Where

n_{ae} = number of activities in the log

n_{am} = number of activities in the model

3. **Generalization** (Q_g) indicates the ability of the model to be generalized, that is, it can describe traces that are not in the event log. A model with low generalization causes *overfitting*.

$$Q_g = 1 - \frac{\Sigma(\sqrt{\#e})^{-1}}{\#n_m}$$

Where

n = number of nodes

e = number of executions

n_m = number of nodes in the model

E. Evaluation

Evaluation was done through an intensive discussion with the CeLOE team and further interview with representative of lecturers and questionnaire students to verify the findings. The detail about evaluation, and the finding discussed at section 4 about evaluation. More details about the research stages including the evaluation are described in Section 3.

III. RESULTS AND DISCUSSION

In the mining and analysis phase, process discovery is carried out using the heuristic miner algorithm on ProM tools which produces a process model. After getting the process models, then the results are converted into Petri net to make sure the models are consistent for conformance checking.

A. Mining and analysis of Lecturer activities

The discovered process model from the lecturer event log is shown as a directly-follow graph in Figure 2. Conformance checking was done and shown that the process model has a fitness of 87.196%, precision 37.472%, and generalization 99.9%. Those values indicate that the process model has a high conformance to the event log (high fitness) and can be generalized well (high generalization), but precision is low.

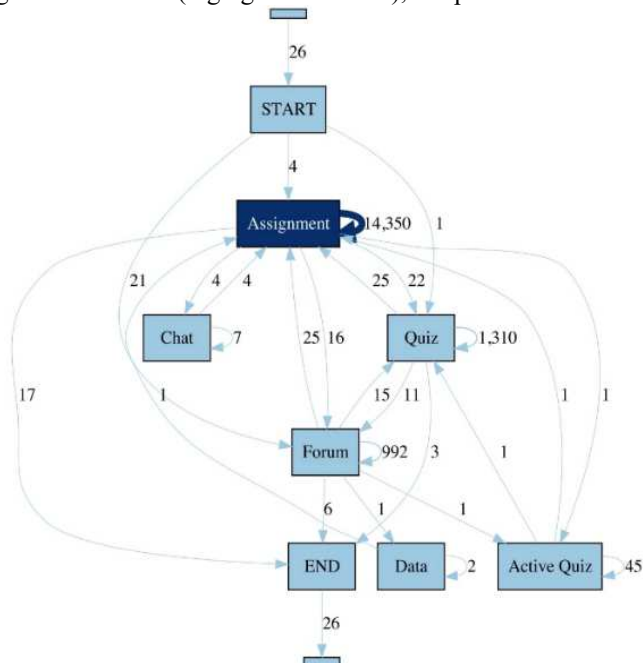


Figure 2. Process model of lecturer activities

Figure 2 also shows that lecturers performed several activities, with the three most frequent activities [frequency; percentage] being *Assignment* [14,410; 85.459%], *Quiz* [1,349; 8.001%], and *Forum* [1,040; 6.168%], as shown in Table 4. It is also shown in Table 4 that *Chat* and *Data* are rarely used by the lecturers during their teaching activities through the LMS. This finding suggests potential recommendation to promote *Chat* and *Data* to be used more often by the lecturers.

TABLE 4. LECTURER ACTIVITIES

Lectures Activities	Frequency	Relative frequency
Assignment	14,410	85.459%
Quiz	1,349	8.001%
Forum	1,040	6.168%
Chat	11	0.065%
Data	3	0.018%

Deeper analysis was done by checking the first and the last activities of lecturer traces, as presented in Figure 3. The most frequent first activities are *Forum* (21; 81%), *Assignment* (4; 15%), or *Quiz* (1; 4%). This finding reflects the reality based on interview to the lecturers (show on section 4. Evaluation), they are started using the LMS during a semester by a forum, assignment, or quiz. The most frequent last activities are *Assignment* (17; 65%), *Forum* (6; 23.1%), or *Quiz* (3; 11.5%). This finding also reflects the reality where lecturers are mostly used *Assignment*, *Forum*, or *Quiz* to end their teaching during the semester.

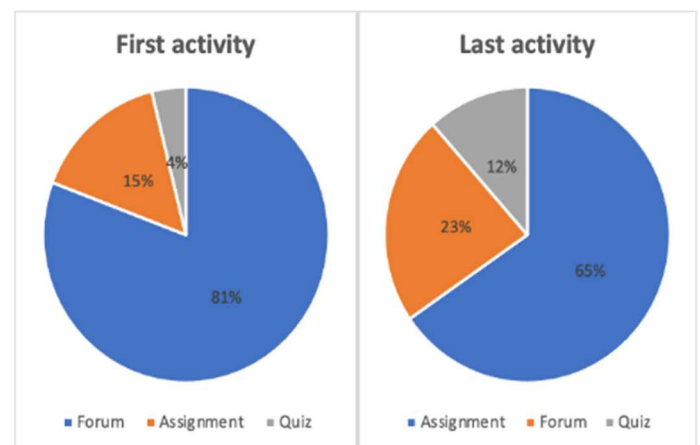


Figure 3. The first and last activities of lecturers

More detailed analysis also can be done by examining the dotted chart, as presented in Figure 3. It is shown in the dotted chart the most frequent activity is *Assignment* (light blue dots). This reflects the fact that most lecturers use LMS mostly for managing assignments for the students. The dotted chart also shows a high variance of the sequence of activities done by lecturers. The duration ranges from a few days up to nearly 5 months. This reflects the real situation where some lecturers have used LMS much more than the other lecturers.

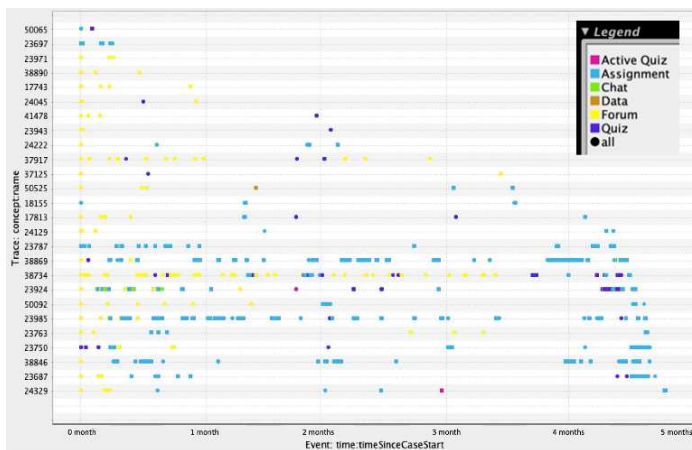


Figure 4. Dotted chart of lecturer activities. One row shows a sequence of activities of a lecturer. A colored dot represents an activity. The chart is ordered from the shortest to the longest duration of trace.

B. Mining and analysis of Student activities

The resulted model process of student log is presented as a directly-follow graph in Figure 5. Conformance checking of this model shows a fitness of 97.0%, precision 15.4%, and generalization 99.9%. Those values show that the process model is highly represent the event log (high fitness) and can be generalizable (high generalization) but is low in precision.

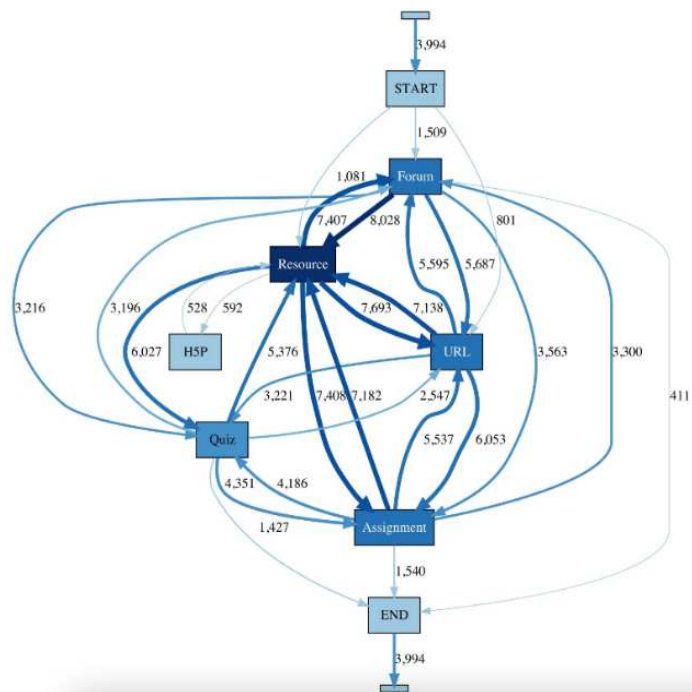


Figure 5. Process model of student activities

It can also be seen in Figure 5 that students performed several activities, with the top 6 most frequent activities are *Resource*, *Assignment*, *URL*, *Forum*, *Quiz*, and *H5P*. More detailed list of student activities is presented in Table 5. The three most frequent activities [frequency; percentage] are *Resource* [48,207; 27.027%], *Assignment* [36,312; 20.358%], and *URL* [35,902; 20.128%]. The other eight activities that are

infrequently used by students (frequency less than 1%) are *Page*, *Folder*, *Chat*, *Choice*, *Activequiz*, *Glossary*, *Book*, and *Feedback*.

TABLE 5. STUDENT ACTIVITIES

Students Activities	Frequency	Relative frequency
Resource	48,207	27.027%
Assignment	36,312	20.358%
URL	35,902	20.128%
Forum	28,639	16.056%
Quiz	20,835	11.681%
H5P	6,204	3.478%
Page	1,004	0.563%
Folder	953	0.534%
Chat	134	0.075%
Choice	91	0.051%
Activequiz	45	0.025%
Glossary	29	0.016%
Book	10	0.006%
Feedback	2	0.001%

Deeper analysis was done by checking the first and the last activities done by students, as presented in Figure 6. The top three most frequent first activities [frequency; percentage] are *Forum* [1,509; 38%], *Resource* [1,081; 27%], and *URL* [801; 20%]. This finding reflects the reality from questionnaire to students (show on section 4. Evaluation), where most students accessed *Forum*, *Resource*, or *URL* in the beginning of their learning activities in the LMS. Other activities are infrequent (less than 10%), which are: *Assignment*, *Quiz*, *H5P*, *Page*, *Chat*, *Glossary*, and *Book*.

The top three most frequent last activities [frequency; percentage] are *Assignment* [1,540; 39%], *Quiz* [1,427; 36%], and *Forum* [411; 10%]. This finding reflects the reality where most students accessed *Assignment*, *Quiz*, or *Forum* in the end of their learning activities during the semester. It also related to the fact that most lecturers give assignments or quizzes to assess student understanding in the end of semester, or forum to discuss further topics in the learning activities. Other activities are infrequent (less than 10%), which are *Resource*, *URL*, *Page*, *H5P*, *Folder*, and *Feedback*.

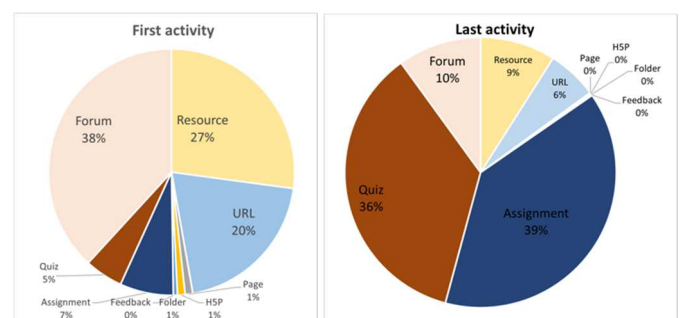


Figure 6. The first and last activities of students

Comparing the last activities of the lecturers (Figure 3) and the students (Figure 6), we have got similar list of the three most frequent last activities, which are *Assignment*, *Quiz*, and *Forum*. But, comparing the first activities of the lecturers and the students, we found that there are differences in their top

three most frequent first activities. Most lecturers used *Assignment*, *Quiz*, and *Forum*, while students used *Resource*, *Assignment*, and *URL*. In the list of the most frequent first activities of students, *Forum* is the fourth. This can be explained rationally that students needed to check on the *Resource* and *URL* to help them done *Assignment*, *Quiz*, and discuss further in the *Forum*.

More detailed analysis was done by examining the trace variant diagram. Figure 7 shows the top 8 most frequent trace variants covers 488 out of 3,994 traces (12.22%). Each row in a trace variant diagram represents a trace variant. The rows in the trace variant diagram are ordered from the most frequent variant to the least frequent one. Each coloured shape represents an activity. Figure 5 show that the top four variants consist of one activity each. There are 186 students (4.66%) only used *Forum*, 74 students (1.85%) only used *URL*, 64 students (1.6%) only used *Quiz*, and 50 students (1.25%) only used *Resource*.

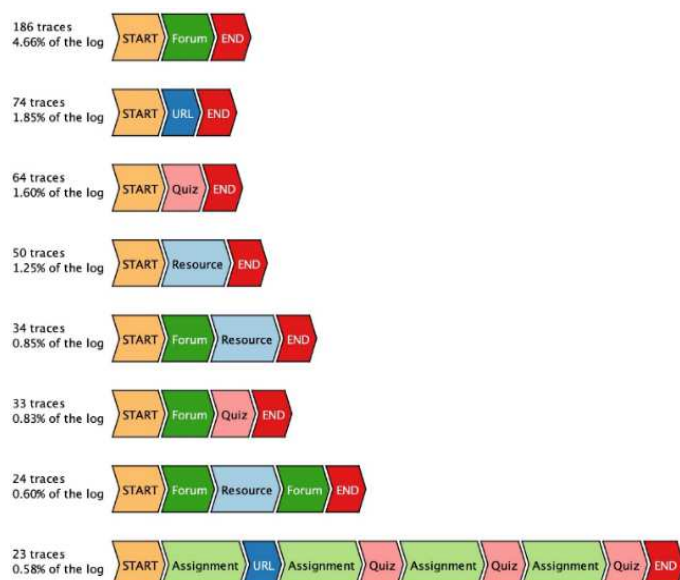


Figure 7. Top 8 trace variants of student activities

IV. EVALUATION

Evaluation was done through interview and questionnaire to lecturer and student. The evaluation was especially done by questionnaire to 34 students' respondent and interview to five lecturers. Questionnaire containing questions about what their activities at the beginning and the end of their class for each semester. Students can choose more than one activity for each question from the questionnaire. The lecturer respondents interviewed about whether the process model (figure 2) is compatible with their activities in the LMS and how they start and ending their semester.

From interview to five lecturers, they agree with the process model was developed use process mining show on figure 2. Three lectures initiate their lecturing activity in LMS with forum. In their first post at the forum, they can inform the student how they run the class. For the example at their first post in the forum, the lecturer usually publishes their email or

video conference link so the student can contact their class lecture at the time. And the two other lecture they use quiz or assignment at the beginning of the semester. Quiz or assignment containing pre-test. The pre-test is used to know the student knowledge about each topic. So, at the class meeting using video conference the lecture can initiate the material subject based on the student pre-test result.

At the end of semester, the lecturer agree that they used assignment and quiz to take final score at that semester. And forum used to know the student's opinion about student learning experience in that semester. The last forum is usually used to discuss about every topic in the class meet or the other topic.

Based on the 1st question result, the first activity that students most accessed is Forum (25%) then followed by resource file (25%), quiz (19%), assignment (17%), H5P (10%) and URL (3%). Both result between the most first students activity describe in process model (figure 5 and figure 6) and first activity from questionnaire result (figure 8) is forum. So between first activity in process model and the evaluation is match.

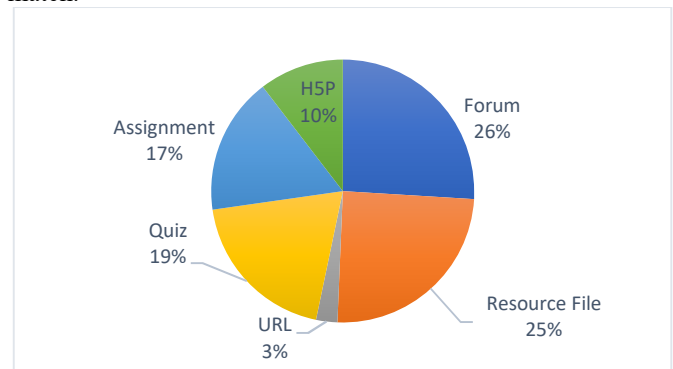


Figure 8. Students activities that accessed at the beginning of semester

The result from 2nd question about the activities that access at the end of semester is assignment (30%), then followed by quiz (27%), resource file (19%), H5P (10%), forum (8%), and URL (6%) that shown on figure 9. From the result of questionnaire that assignment is the most activity was accessed by student at the end of the semester. The questionnaire result match to process model from figure 5 and last activities on figure 6.

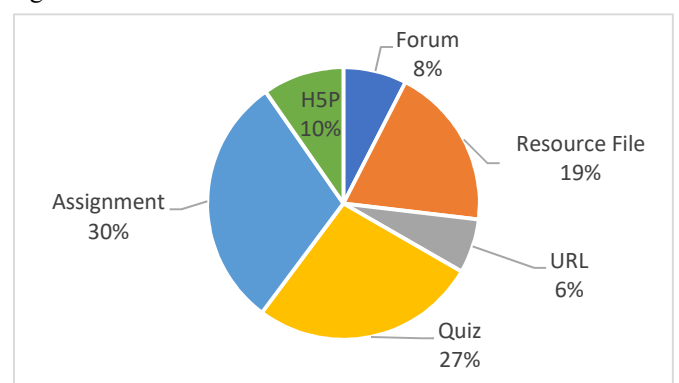


Figure 9. Students activities that accessed at the end of semester

V. CONCLUSIONS

Based on the study, it can be concluded that: (1) Process mining can be used to analyse the teaching/ learning activities carried out by lecturers and students during a semester. In this study, the most frequent activities carried out by lecturers in the Study Program 365 are assessments, among other activities including chats, quizzes, and forums. Meanwhile, the most frequent activities carried out by students in the Study Program 365 are assignments and quizzes. (2) Process mining can also be used to analyse the sequence of activities during the teaching/ learning process. We analysed the durations of lecturer activities and found that the durations ranged from a few days up to five months. We also analysed the first and last activities carried out by the lecturers and students. The most frequent first activities of the lecturers are the *Assignment*, *Forum*, and *Quiz*; while the most frequent first activities of the students are *Forum*, *Resource*, and *URL*. (3) The findings of the study experiments can be used to improve understanding on how the process has been carried out and suggest improvements. Based on the findings of the most frequent activities carried out by lecturers and students, we can suggest the University to promote other functionalities to be used by the lecturers and students. For example, the lecturers should be introduced to the LMS functionalities other than assignments, forums, and quizzes.

The evaluation about the finding in this study is done using interview five lecturer about the process model. And the other done by the questionnaire to 34 students about this study finding student process model. And the result is booth match between the finding and the evaluation.

This study can potentially be reproduced and further developed to implement process mining in a larger scope of study. Potential future work is to apply this approach to analyse and compare teaching/ learning process in several study program; to improve data processing approach by generating ontology mapping on the activities in the process; and to recommend improvements in the teaching/ learning process using the LMS.

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