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Analysis and Application of The Mining Process to Identify Student Learning Behaviour On The Use of E-Learning After The Covid-19 Pandemic

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Abstract

SMK Telkom Malang is a vocational high school in the field of Technology and Information Technology that implements technological advances and developments in the system, distance learning. E-learning is one of the learning media supported by computer and internet technology, which contains learning content. Student learning behavior in machine learning or E-Learning has a strong relationship in its use. The higher the quality of the application of learning in machine learning or E-Learning, the higher the achievement in obtaining data on student learning behavior in the use of e-learning recorded in the event log. This research uses Disco and ProM tools using the Heuristic Miner. Heuristic Miner is used because it is most suitable for handling process mining on event logs from Learning Management System because heuristic miners can express event logs well and reveal main events recorded in event logs and are able to handle data that has noise. The use of Petri Net in ProM tools helps in analyzing the process model to provide an overview of student learning behavior towards e-learning the actual Result of heuristic miner can model the event log into the process model well, seen from the average fitness of the RPL majors shows a value of 0.970.

Keywords: Process Mining, Disco tools, ProM tools, E-Learning, Event Log

1. Introduction

Student learning behavior in machine learning or E-Learning has a strong connection to its use. The higher the quality of the application of learning in machine learning or E-Learning, the higher the achievement in obtaining data on student learning behavior in using e-learning recorded in the event log, event logs are historical transactions stored in information systems. The event log has several events for specific cases, event logs stored in the information system will be able to carry out analysis using the mining process, process mining is a method that automatically detects and rebuilds business process workflows from event logs, the mining process is important to find activities running at the same time,The goal of process mining is to use event logs to extract process-related information. For example, to find a process model by observing events recorded by several systems in the organization Process mining was chosen because of its ability to process event log data such as that obtained by this research. The mining process (process mining) requires special algorithms designed to achieve the desired results from the mining process (process mining) (Van der Aalst, 2016a).

There are many process mining algorithms that can be used when implementing process mining, the heuristic miner algorithm is used because it is most suitable for handling process mining on event logs from the Learning Management System. The heuristic miner algorithm was also chosen because of its ability to handle event logs with noise, and can display the main behavior of the existing process model (Fitriansah et al., 2019). The Heurisitc Miner algorithm also supports all general forms of process models so that it is proven to be able to be implemented well for various types of cases (Mangunsong et al., 2015).

This research uses the process mining tools Disco tools and ProM tools using the Heuristic Miner algorithm. The use of Petri Net in ProM tools helps in analyzing the best process model to provide an overview of student learning behavior regarding actual use of e-learning. Disco is a mining process tool from Fluxicon that makes the mining process simple, easy and fast. The function of the Disco Tools is to change file extensions in the form of .xls, .txt, and .csv into file extensions that can be analyzed by the mining process in the form of xes and .mxml. ProM is a tool used to analyze and describe processes based on data, ProM is also used to analyze event logs through the mining process which is generated through certain algorithms. From the results of observations or learning observations after the Covid-19 pandemic at

Telkom Malang Vocational School, the level of student learning behavior towards participating in learning via e-learning is not yet known. This is because each student's understanding ability is different in the online learning process. This is due to the composition of Telkom Malang Vocational School students who have many extracurricular activities and little time is one of the factors.

2. Conceptual Background

2.1 Process Mining

Process mining is an activity aimed at building process models based on event log data. Techniques in process mining aim to detect, monitor and improve processes using event logs. Process mining is a process-oriented data analysis method that processes event logs to explain the processes that occur (Van der Aalst, 2016a). Process mining has been applied in various fields, including education (Trčka et al., 2010) (Cairns et al., 2015).

According to (Ikhsan et al., 2021), E-Learning provides a means of information technology-based education, which focuses on the effectiveness of distance learning in. E-Learning as a supporter of the face-to-face teaching process through online media, taking into account student learning behavior patterns, the overall effectiveness of the success obtained from learning using E-Learning is gradually being developed.

states that Disco tools can examine and display each case by displaying detailed customs of a process so that it can be identified as a whole. ProM is a tool used to analyze and describe processes based on data. ProM is also used to analyze event logs through the mining process which is generated through certain algorithms. ProM makes it easier for users to apply all existing techniques in process mining (Van der Aalst, 2016).ProM supports conversion and import of various types of modeling languages, including Petri net, Heuristic net, EPCs, and so on.

Event logs are historical transactions stored in information systems. Event logs contain information about activities in the form of certain cases or events that occur on a system and are recorded by the system itself. Currently, event logs are needed as input for process mining and the event log will be extracted so that it becomes a form of process model (Fitriansah et al., 2019). Event logs can be easily found and techniques for analyzing them are not limited to certain application domains (Van der Aalst, 2016b).

The heuristic miner algorithm is a process mining algorithm that uses a local approach in problem solving. Since this algorithm works from a control flow perspective in the model, it only provides information about the course of events of the case to determine dependencies or dependencies between activities in the process model. Heuristic miner is a proven algorithm for process mining that can be implemented well for various types of cases Heuristic Miner can handle noise, and can be used to express the main events recorded in the event log (Weijters et al., 2006). Heuristic Miner determines three threshold cases, namely: Relative-tobest Threshold, Positive Observation Threshold, and Dependency Threshold (Weijters et al., 2006).

3. Research Methodology

The research method used in this research adopts an approach with the DSR (*Design Science Research*) concept as well as a framework or framework for finding solutions (Hevner et al., 2004) in IS *Research.* Research to solve problems is carried out in several stages including the Data Collection Stage, Data Preprocessing Stage, Transformation Stage for weighting words, Processing Stage where the text mining process is carried out, and Model Evaluation Stage and delivery of research results.

Figure 1. Research Model

4. Data analysis and results

The default value for the PT parameter, namely 10 to 25, causes all low frequency activities to be included in the process model. This causes the resulting fitness value to be low. Conversely, if the PT value is increased, the fitness value also increases. This is because as the PT parameters increase, fewer low-frequent activities participate in the process model. However, there are times when a PT value that is too large also results in a decreased fitness value. This is because there is very little activity that has a frequency above the threshold value that is too large. So, it can be concluded that in Indonesian language subjects majoring in RPL, the fitness value that is close to 1 is with PT parameters worth 50 and 20, RT 0.05, and DT 0.9 which has a fitness value of 0.938.

Table 1. Testing RT scores for Indonesian Language Subjects, RPL Department

RT	PT	DT	*Fitness*
0.05	50	0.9	0.938
0.25	50	0.9	0.938
0.50	50	0.9	0.938
0.75	50	0.9	0.938
1.00	50	0.9	0.938

The resulting fitness values are also similar when testing different Relative-to-best Threshold (RT) parameters. It can be concluded that testing on RT parameters will provide the same process model even if the parameter values are changed.

Table 2. Testing DT scores for Indonesian Language Subjects, RPL Department

RT	PT	DT	*Fitness*
0.05	50	0.9	0.938
0.05	50	0.7	0.938
0.05	50	0.5	0.938
0.05	50	0.3	0.938
0.05	50	0.1	0.938

Table 3. Testing PT scores for Indonesian Language Subjects, RPL Department

RT	PT	DT	*Fitness*
0.05	10	0.9	0.842
0.05	15	0.9	0.883
0.05	20	0.9	0.938
0.05	25	0.9	0.934
0.05	50	0.9	0.938

Testing the RT parameters will provide the same process model even if the parameter values are changed.

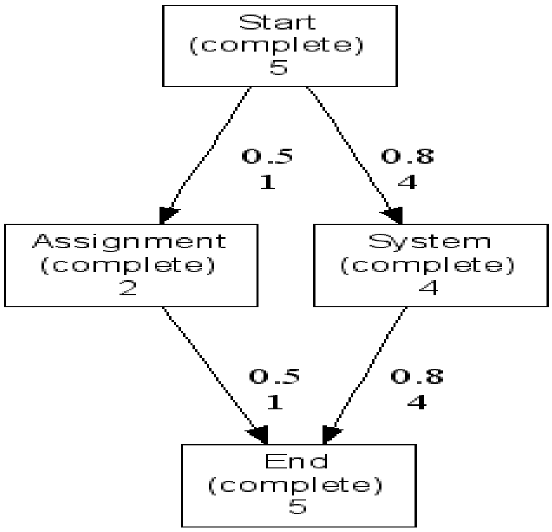

Figure 2. Process model of scenario results in the Indonesian language subject of the RPL Department

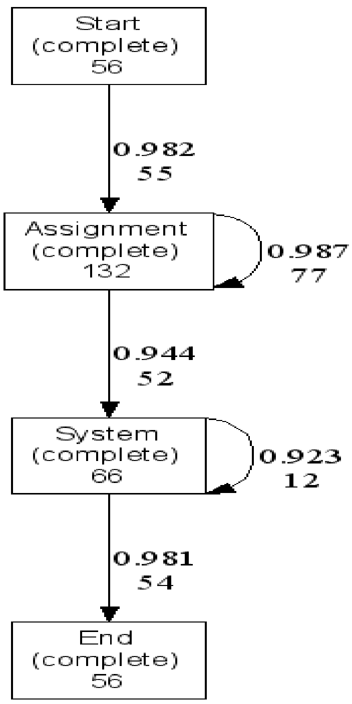

Figure 3. Process model resulting from scenarios in the Chemistry subject of the RPL Department

This process model is the result of process mining by applying the Heuristic Miner algorithm, using the parameter settings used, namely for the RPL department, PT is 15, RT is 0.05, and

DT is 0.9. while for the TKJ major, PT is worth 25, RT is 0.05, and DT is worth 0.9. This process model is the best process model resulting from testing scenario one.

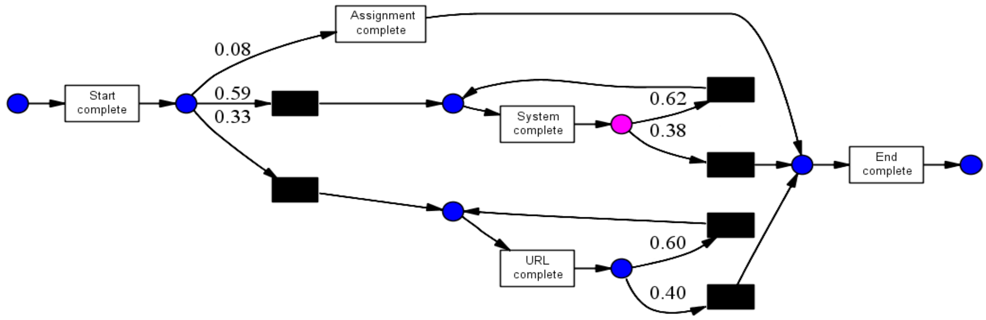

Figure 4. Results of Performance Analysis for Indonesian Language subjects in the RPL Department

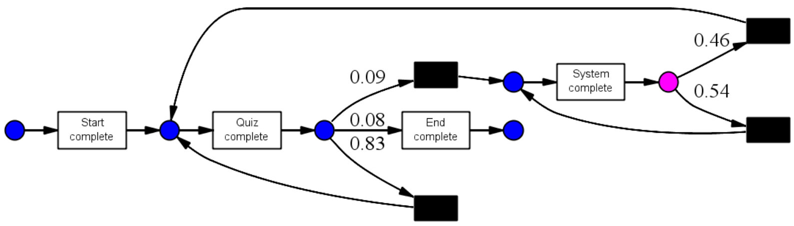

Figure 5. Results of Performance Analysis for RPL Department English subjects

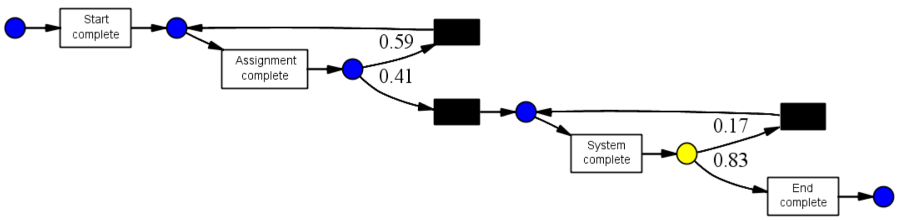

Figure 6. Results of Performance Analysis for Chemistry subjects in the RPL Department

Activity	Total		
	Bahasa Indonesia	Bahasa Inggris	Kimia
Assignment	8	-	132
System	88	27	66
Quiz	-	150	-
URL	48	-	-

Table 4. Frequency of Access to Software Engineering Department

Frequency results in the Software Engineering department show that the student patterns described with the most frequency are 88 system activities in Indonesian subjects, 150 quiz activities in English subjects, and 132 assignment activities in chemistry subjects. This activity is the activity most frequently used by the average RPL student when accessing the Telkom Vocational School LMS.

6. Discussion and implications

Based on the results of this research, there are several conclusions obtained by the author, including the following:

1. Heuristic Miner can model *the event log* into a process model well, seen from the average *fitness value* of the RPL major subjects showing a value of 0.970.
2. Changes in the *Positive Observations Threshold* (PT) parameter affect the *fitness value*.
3. The pattern of student learning behavior at LMS SMK Telkom Malang based on the highest access frequency is as follows: bMost access frequency for the Software Engineering major:

system activities for Indonesian subjects, 150 *quiz activities* for English subjects, and 132 assignment activities for chemistry subjects. By applying text mining techniques to e-learning data after the COVID-19 pandemic, institutions can gain valuable insights into student behavior, tailor their educational strategies, and support students more effectively in a remote learning environment. This approach can lead to improved learning outcomes and a better overall e-learning experience.

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