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Capturing Students' Dynamic Learning Pattern Based on Activity Logs Using Hierarchical Clustering

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Abstract

Students can have various characteristics and learning patterns. By understanding the characteristics and learning pattern of individual students, teachers can provide individualized learning strategies based on students' needs. Students' learning patterns may experience changes depending on their conditions during the learning process. If the learning pattern analysis is only run once, then the progress and changes in student learning patterns throughout the learning process cannot be recognized. On the other hand, periodical analysis is expected to describe the dynamics of student learning patterns from time to time. This research is intended for capturing students' dynamic learning pattern using Hierarchical Clustering. We clustered the learning patterns based on Learning Management Systems (LMS) activity logs. The activity log data were partitioned into several periodical datasets. The results of the periodic clustering indicated that students' learning patterns varied from one another and changed from time to time. Most students experienced change in learning patterns throughout the semester. The analysis also indicated that learning pattern also has the potential to be improved and maintained.

Keywords: *learning pattern, activity logs, learning management systems, hierarchical clustering.*

1. Introduction

Students can have various characteristics and learning patterns. Students can differ in terms of learning styles, motivation levels, knowledge levels, learning awareness, learning speed, and learning preferences [1]. These differences affect the individual learning process and can ultimately affect learning outcomes.

Teachers need to embrace student differences wisely. By understanding the characteristics and learning pattern of individual students, teachers can provide individualized learning strategies based on students' needs. In traditional learning, student recognition relies on the reliability and foresight of the teacher in observing student behavior directly. With e-learning, the characteristics of students can be reflected by their behavior during their activities[2].

Learning analytics has been utilized for the purpose of understanding and optimizing learning by collecting, analyzing and reporting of student data and the contexts associated with them [3]. It incorporates multidisciplinary science that aims to support the improvement of the learning process through the collection and analysis of student behavior and performance data [4]. Besides students' behavior and performance data, some scholar utilized learning analytics based on students' emotional data and network data[5].

The data is then processed using descriptive, predictive, and prescriptive analytics approaches to offer different insights into learning and teaching[6]**.** Over the past decade, these approaches have enabled educational institutions and teachers to make decisions based on academic data and activity tracking to optimize student learning process [7],[8]. Learning analysis can be tailored to student needs, enabling a better picture of student conditions and performance. Some studies applied this approach to detect students who are slow to learn, but then show progress due to special treatment from teachers [9],[10]**.** The application of learning analytics in modeling students, for example, analyzing the level of knowledge of students, analyzing students' pace and effort[11], recognizing student learning patterns[12] and behaviors [13], and analyzing students' learning progress[14].

Students' learning patterns may evolve depending on their conditions during the learning process. The intensity of a student at the end of the semester can increase or decrease when compared to the intensity at

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the beginning of the semester. The knowledge and ability of a student can also gradually progress as the topics being taught.

If the learning pattern analysis is only run once, then the progress and changes in student learning patterns throughout the learning process cannot be recognized. On the other hand, periodical analysis is expected to describe the dynamics of student learning patterns from time to time. Time-dependent analysis of learning can provide important insights, so that teachers and institutions can predict in a timely manner to adjust the learning process[12]. For example, in students who are at risk of not graduating, learning analytics can be used in (relatively) real-time as a tool to monitor student activity and encourage teachers to offer support according to student needs [14].

This research is intended for capturing students' dynamic learning pattern. We analyzed the learning pattern based on Learning Management Systems (LMS) activity logs. The activity log data were partitioned based on several periodical dataset. Afterwards, the learning pattern and its dynamic structure will be observed. To analyze learning patterns, we can use the unsupervised method.

Clustering, as one of the unsupervised methods, can be used to identify patterns and structures of previously unlabeled data [15],[16]. Another advantage of clustering is its ability to analyze small amounts of data[17]. The main purpose is to group students into clusters that have similar learning patterns with each other with the aim of improving learning outcomes through personalization [15]. Several clustering method have been used for learning analytics, such as in analyzing students' learning strategies [18], exploring students engagement [19],[20], exploring students' learning performance[21],[22], analysis of students who have the potential to drop out [23],[24] and understanding students cognitive presence [25].

On this study, we use hierarchical clustering because of its great performance on previous research. The hierarchical clustering is able to describe the outliers data[26]. It also does not demand pre-defined number of cluster [27]. Consequently, we can decide the best cluster number without having to run the clustering process several times.

2. Research Methods

The focus of this research is to conduct hierarchical clustering on LMS activity logs periodically. The clustering analysis is performed not only to obtain learning pattern but also to observe the change that may occurred on the pattern from one period to another. This research was conducted following some steps as shown on Figure 1.

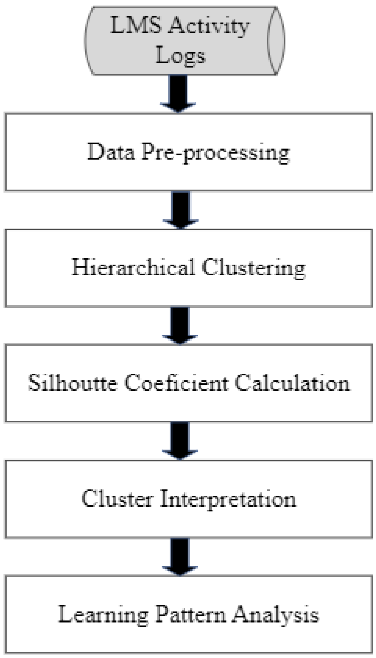

Figure 1. Research Steps

Datasets that have gone through preprocessing then went through a clustering process using agglomerative hierarchical clustering. Silhouette coefficients were calculated to get the optimal number of clusters in each dataset. Furthermore, the clustering structure with the best silhouette coefficient was analyzed to determine student learning patterns. After the cluster structures in each dataset were generated, we analyze changes in student learning patterns. The following subsections describe the research steps in detail.

2.1 Data Description and Pre-processing

This research aimed to identify changes in student learning patterns from time to time. Therefore, activity log data collection was carried out at four different times: at the end of the 4th week, at the end of the 8th week, at the end of the 12th week, and at the end of the 16th week (end of the semester). Figure 2 shows the details of the partitioned dataset used in the clustering.

In this research, pattern analysis was simulated using data obtained from activity logs on a Moodle-based LMS implemented at the Faculty of Computer Science in an Indonesian university. The analysis was carried out using activity data involving 117 students in 2 classes of Interaction Systems Course. The Interaction System Course used e-Learning as a complementary to the in-class face-to-face learning.

Activity log data processed in our research only represents the learning activities of students through e-Learning. Thus, the learning pattern analyzed only describes how students learn through e-Learning and does not include face-to-face learning or independent

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learning outside of e-Learning. We include the available variables in our LMS activity log.

The variables are the number of views of the assignment page, the number of views of the course page, the number of views of learning resources, the interval between submission and the final deadline (in hours), the number of forum page access, the number of discussion forum initiations, the number of discussion page access, the number of messages in the discussion forum, and the average score of the assignments.

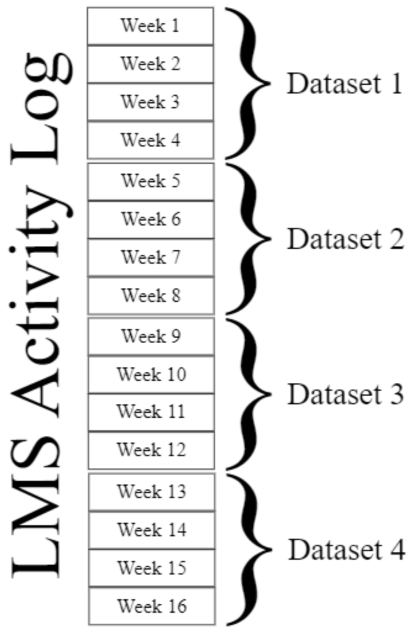

Figure 2. Activity Log Partitioning

2.2 Clustering Method

The process of analyzing learning patterns is carried out by agglomerative hierarchical clustering of each periodic data as described in Figure 2. Agglomerative hierarchical clustering considers the relationship between data points. This method follows the bottom-up mode, the data objects are represented in dendrogram. It begins with each case being a separate cluster and then merging these clusters into a larger cluster based on the similarities of the two clusters. This process is repeated, until all data points are grouped together in one cluster [15], [19].

The clustering results then be validated using the Silhouette Coefficient [28]. Silhouette coefficients were calculated to obtain the optimal number of clusters on each dataset. It computes the cluster density and how far the clusters are apart from each other[29]. A higher coefficient value indicates a denser cluster structure and is different from other clusters[18],[30]. Furthermore, the results of clustering were analyzed to understand the characteristics and changes in learning patterns.

3. Results and Discussions

After the data has been preprocessed, then clustering analysis was carried out on the four datasets. From the clustering results, the Silhouette Coefficient was calculated to determine the optimal number of clusters for each dataset. Then, the clusters formed were interpreted and analyzed for the learning patterns of students from each period.

3.1 Clustering Result

Different datasets acquire different clustering result. However, all the datasets produce relatively similar patterns on the dendrograms. The clustering dendrograms are illustrated in Figure 3.

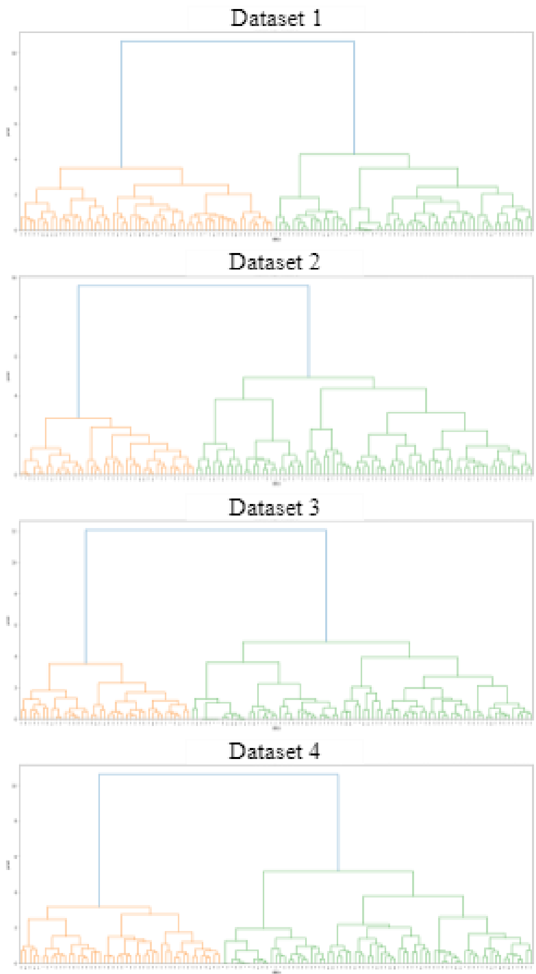

Figure 3. Hierarchical Clustering Dendrograms

We used Silhouette Coefficient as cluster evaluation parameter. It combines intra-cluster distance and inter-cluster distance for each cluster to calculate the quality of the obtained structure. The best cluster structure is indicated by higher value of Silhouette Coefficient.

Figure 4 shows that the highest values of Silhouette Coefficient on all datasets were in the number of two clusters consistently. It can also be seen from the

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dendrograms that the farthest distance between clusters in each dataset is obtained when there are two clusters. As a result, the analysis of students' learning patterns was based on two clusters.

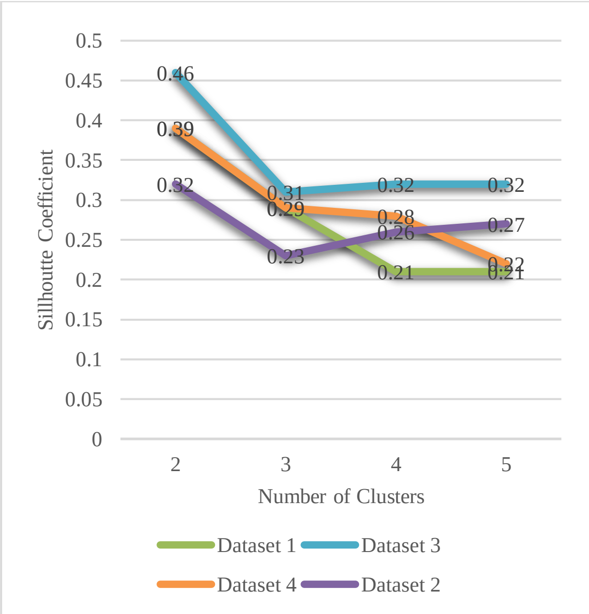

Figure 4. Silhouette Coefficient based on Number of Clusters

Figure 5-8 give visualization of the clustered data on dataset 1, dataset 2, dataset 3, and dataset 4 respectively. The visualizations depicted two different clusters of students on each dataset. The cluster interpretation and learning pattern analysis will be discussed in the following subsections.

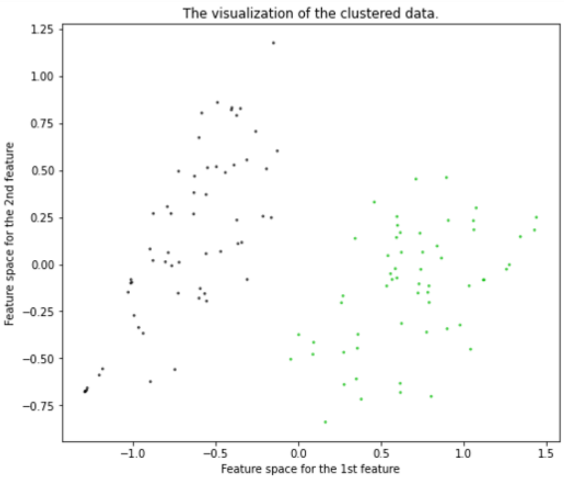

Figure 5. Dataset 1 Cluster Visualization

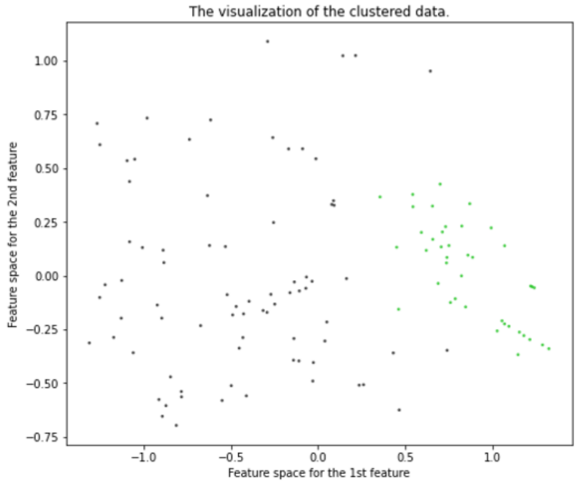

Figure 6. Dataset 2 Cluster Visualization

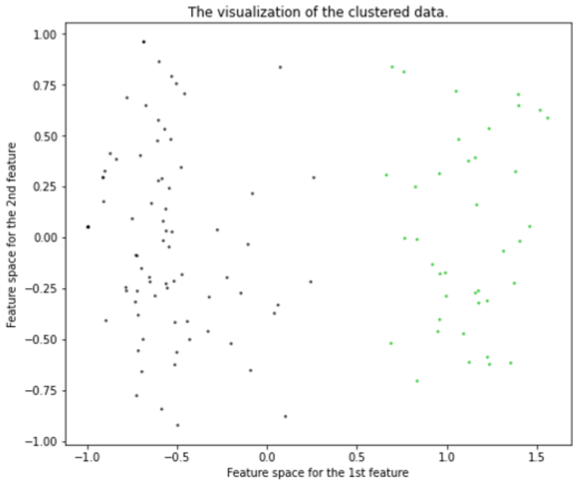

Figure 7. Dataset 3 Cluster Visualization

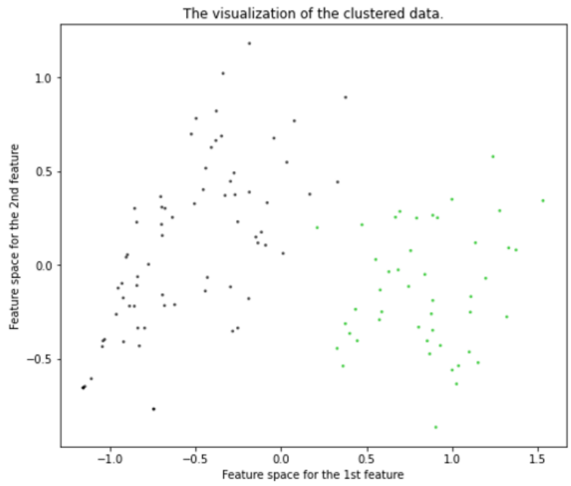

Figure 8. Dataset 4 Cluster Visualization

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3.2 Cluster Interpretation

Two extreme patterns were identified from the resulting structure in the four datasets. Table 1 shows the average value per attribute of each cluster in the datasets 1, 2, 3, and 4. The first cluster (C0) has a learning pattern with poor student performance in terms of results (grades/scores), learning activities, and participation in discussion forums. While in the second cluster (C1) has the opposite learning pattern.

The first characteristic that can be identified was the difference between students who are C0 and C1 based on the frequency of accessing the LMS. The average value of number of course page visits and number of learning resource access in all datasets illustrates this fact. Students on C1 access the course page at least twice as often as students on C0. Likewise, when viewed from the number of accesses to learning resources.

The interesting thing was shown by the average number of task page accesses and the interval between assignment submission and deadline attributes. Although students in C1 had better average scores on these two attributes, the difference was not large. In dataset 1 the values of these two attributes tended to be high in both clusters, but in other datasets the values of both attributes dropped significantly.

The C0 consisted of students that have low assignment grades. In contrast, C1 comprised students with higher assignment grades. This happened in all datasets. Similarly for the assignment page visit attribute and the interval between assignment submission and deadline attributes. Although in the last two attributes, the differences were not too significant.

All four datasets produced the distinguishing characteristics that can be seen from attributes related to the discussion forum. CO contained students that rarely accessed forum discussions and never participated in forum discussions. Meanwhile C1 contained students that were active in the forum discussions as they regularly visited the forum page, read the discussions, initiated the conversations, and replied to messages on the discussions.

Table 1. Average Value of Attributes on Clusters

	Dataset 1		Dataset 2		Dataset 3		Dataset 4	
Attributes	C0 59 students	C1 58 students	C0 40 students	C1 77 students	C0 78 students	C1 39 students	C0 71 students	C1 46 students
Number of course page visit	13,07	28,22	10,15	25,10	4,99	14,64	12,61	23,43
Number of learning resource access	5,85	8,36	8,90	17,81	3,03	6,13	3,82	7,26
Number of assignment page visit	11,03	16,48	2,10	3,36	2,69	3,00	7,55	11,70
Interval between assignment submission and deadline (in hours)	11,56	14,98	0,00	0,70	1,27	2,28	2,37	2,39
Average score of the assignments (0-100)	69,32	87,38	59,43	83,81	80,46	95,90	78,70	94,04
Number of forum page access	2,47	16,48	1,60	14,68	0,47	11,74	1,90	12,91
Number of discussion page access	1,05	16,52	0,80	15,64	0,26	13,44	0,96	12,74
Number of discussion forum initiations	0,00	3,21	0,00	2,51	0,00	3,36	0,00	2,63
Number of messages in the discussion forum	0,00	3,38	0,00	2,71	0,00	3,54	0,00	2,11

From the cluster characteristics, we could conclude that the activity of students in learning (accessing the course page and learning materials), participation in discussions, and enthusiasm on assignments (submission time and number of assignment page visits) are related to the scores achieved by these students. If a student is active, then it is likely that she/he will get good grades. On the other hand, students with poor grades are generally not diligent in learning activities and not participating in discussion.

3.4 Learning Pattern Analysis

After the cluster structures in each dataset were generated, we analyzed the changes in student learning patterns. For example, if a student in dataset 1 is assigned to C0 and in dataset 2 the same student is assigned to C1 then it is said that the student experienced a change in learning patterns. Table 2 shows the changes in student learning patterns in each dataset.

The results obtained indicated that individual learning patterns have the potential to change from time to time. For example, the comparison of dataset 1 and dataset 2 resulted in 37 students moving clusters, even though most students remained in their clusters. There were 28 students who moved from cluster C0 to C1, and 9 students moved from C1 to C0. Meanwhile, 31 students remained in cluster C0, and 49 students remained in cluster C1.

Changes also occurred in the comparison between dataset 2 and dataset 3 and the comparison between dataset 3 and dataset 4. From the results of dataset 2 to dataset 3, the most changes occurred in the shifting of

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members of cluster C1 to cluster C0 as many as 40 students (34%). This number was greater than the number of students who remained in cluster C1 in both dataset 2 and dataset 3, which was 37 people (32%). In the comparison of dataset 3 and dataset 4, 50 students experienced changes in learning patterns. This is the highest number of shifting between datasets, compared to changes in dataset 1 to dataset 2 (37 students) and changes from dataset 2 to dataset 3 (42 students).

Table 2. Learning Pattern Changes between Datasets

Learning Pattern				Number of Students
Dataset 1	Dataset 2	Dataset 3	Dataset 4	
C0	C0	C0	C0	15
C0	C0	C0	C1	15
C0	C0	C1	C0	1
C0	C0	C1	C1	0
C0	C1	C0	C0	12
C0	C1	C0	C1	4
C0	C1	C1	C0	4
C0	C1	C1	C1	8
C1	C0	C0	C0	6
C1	C0	C0	C1	2
C1	C0	C1	C0	0
C1	C0	C1	C1	1
C1	C1	C0	C0	16
C1	C1	C0	C1	8
C1	C1	C1	C0	16
C1	C1	C1	C1	9

On the other hand, if we look at the overall comparison of dataset 1 to dataset 4, only 24 students (20%) have an unchanging learning pattern. 15 students remained at cluster C0, which showed no improvement in learning patterns. Only 9 students were consistently active and perform well, indicated by staying on cluster C1.

Most students, 93 people (80%), experienced change in learning patterns at least once during the semester. 49 students who in period 1 (dataset 1) were classified as having a good learning pattern (cluster C1) but in the next periods experienced a lessening in activity so they moved to cluster C0. In contrast, 44 students who in period 1 (dataset 1) were in cluster C0 improved their learning patterns in the following periods.

These results signified that students' learning patterns diverse from one student to another. The learning pattern of one student may change during the semester. It means that students should improve their activities and participation on the learning process and keep up their good work.

4. Conclusion

The results of the periodic clustering indicated that students' learning patterns varied from one another and changed from time to time. From the Silhouette Coefficient calculation, students were best grouped into two clusters of learning patterns. The first cluster (C0) has a learning pattern with poor student performance in terms of results (grades/scores), learning activities, and participation in discussion forums. While in the second cluster (C1) has the opposite learning pattern.

We also analyzed the changes in student learning patterns. Only a small percentage of students (20%) were consistent in a certain learning pattern throughout the semester. Most students (80%), experienced change in learning patterns at least once during the semester.

Students who experienced cluster change increases as the course progresses. There were 37 students shifting clusters between period 1 and period 2, 42 students between period 2 and period 3, and 50 students between period 3 and period 4. On the other hand, it also shown that learning pattern also has the potential to be improved and maintained.

The variety of student learning patterns can be utilized by providing personalized learning according to the individual needs of students. The dynamics of learning patterns should be accompanied by dynamic learning treatments for everyone. The dynamics of student learning patterns can be used to see student learning progress and anticipate declines in learning performance.

The results of clustering show the structure and characteristics of clusters derived from activity logs for the same course and different periods. Thus, in the activity logs of other courses, it is very possible to produce different cluster structures and characteristics.

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