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A new agglomerative hierarchical clustering to model student activity in online learning

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Abstract

In this paper, a new technique of agglomerative hierarchical clustering (AHC), which is known as SLG (single linkage dissimilarity increment distribution, global cumulative score standard), can work well in analyzing students' activity in online learning as evidenced by obtaining the highest score in testing the validity index of cophenetic correlation coefficient (CPCC) ie 0.9237, 0.9015, 0.9967, 0.8853, 0.9875 of the five datasets compared with conventional agglomerative hierarchical clustering methods.

Keywords: AHC, CPCC, SLG, students activity, validity index

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1. Introduction

Online learning models that commonly come up are collaborative and asynchronous ones [1, 2]. Computer-based communication tools such as emails and discussion forums are often used in online learning, but they require a lot of arrangements and interactions with the instructor to fit the pedagogical model that combines the richness of learning experiences and reflection necessary for in-depth learning [3]. The mechanism of arranging popular learning models in a conventional system aims to consider individual learning styles to be adopted in an online learning system, such as the one designed by [4] characterized by the view that considers students as activists, reflectors, theorists, and pragmatists [5].

Therefore, this research argues that online student learning styles and models are more complex than conventional methods, which is attributable to a simple classification of cognitive styles. If any, individual learning strategies that are based on socio-cultural phenomena arising from membership in particular groups tend to be more professional or disciplined than cognition-based ones [6]. This view is supported by the work of, who argue that by focusing on individual learning, educators have failed to understand the social structure and dynamics necessary for knowledge building processes [7]. To describe the patterns of individual and social behavior of students in the context of online learning, one of the methods that can be used is the method of clustering in data mining science [8, 9].

Cluster analysis is aimed at discovering structures existing in data in order to find an appropriate and valid cluster from the data rather than setting rules for separating data into a number of categories [10, 11]. However, clusters must reflect the mechanism that causes some objects to become more similar to each other [12]. The clustering algorithm plays an important role in the analysis of data exploration and data generation, providing a means to ensure the data structure. There are two main strategies used in clustering: hierarchical and partitional methods. The partitional structure deals with the inward pattern of a number of small clusters [13]. While the hierarchical method proposes accumulation of clusters by providing additional information about the data structure, which is represented graphically as a dendrogram. A particular algorithm can be obtained by defining the same measurements between the pattern and the cluster, which ultimately will determine conditions of the structure of a cluster that is identifiable [14].

The first literature [15] used a total of 95 participants in this course. Ward procedures prove effective to restore the underlying data structures. There were three groups representing a special approach to online learning. The data show that those three groups can be interpreted to reflect the three approaches to learning. Cluster 1: Mastery-Oriented or 'Self-Driven' Approach. Cluster 1 is the largest cluster with a total of 35 participants representing 59.3% of

the research sample. Cluster 2: Focus of the Task or 'To Complete' Approach. The second cluster accounted for 22% of the research sample (n=13). Cluster 3: Minimum Efforts or 'Procrastinator' Approach. The third cluster consists of 11 participants or 18.7% of the research sample. The disadvantage of this first literature is that the use of non-optimal methods of the three clusters formed does not reflect the behavior of all members of the course.

The second literature [16] to represent the interaction of communication between users, this research modeled the interaction as the main graph. This research employed five different techniques of validation: Rand, RS, Silhouette, DB Index, and Root Mean Square. The mean of the nine features and the number of users in each cluster were used to construct quantitative description of the type of role played by clusters/users. Single clusters 1 to 6 have a composition that is significantly different from that of any other forums. Silent users constitute 95% of the total number of users on the Personal Issues forum (Cluster 1). This shows that, regardless of the name, there is little dialogue going on. Cluster 2 has a powerful component of popular initiators, which shows that some users regularly initiate a thread that later leads to a discussion. Cluster 6, the weather forum, is also heavily grounded by popular initiators and popular participants, but consists of a larger number of grunts. Clusters 7, 9, and 10 each consist of four forums. The disadvantage of this second literature is that too many forums are formed for grouping students as a consequence the mapping of students from each forum is not focused.

The third literature [17], this research was obtained from the Web access logs to study two programs, i.e. first, to teach "data structures". The second course is "Introduction to Computing Science and Programming". The results are good enough to reflect students' behavior towards the course. Each cluster is characterized by the following: 1) the number of Bad Students is significantly lower than the number of visitors who are either a Worker or a Regular Student, and the Bad Student class is characterized by a high number of clicks and downloads of documents; 2) the size of the Working Student class is the largest and is characterized by the lowest number of clicks and downloads of documents; 3) the size of the Regular Student class is smaller than that of the Working Student class and greater than that of the Bad Student class, and is characterized by a moderate number of hits and downloads of documents, and the behaviour of downloading on a regular basis. The disadvantage of this third literature is the use of improper and unclear clustering methods for the purpose of this grouping.

The fourth literature [18] in this research, cluster analysis was used to group 95 students based on seven variables, generating a ratio of 13.6 cases per variable, both within acceptable limits. The Ward hierarchical clustering method and the squared Euclidean distance model were used to determine the distance between clusters. In total, 95 participants performed 17,695 actions in the system with an average of 186 (n=127) actions per students. Cluster 1: Superficial Listener, Intermittent Speaker. The first cluster accounts for 31% of the participants (n=29). Cluster 2: Concentrated Listener, Integrated Speaker. The second cluster consists of the largest number of students, i.e. 49% of the total number of participants (n=47). Cluster 3: General Audience, Reflective Speaker. The last cluster consists of a small group of students accounting for 20% of the total research sample (n=19). The disadvantage of this fourth literature is the use of standard deviations for the clustering of student behavior in incorrect clustering methods, as evidenced by the clustering results in which many cluster imbalances are due to the different variables of each group.

The fifth literature [19], in this research, data were obtained from two programs offered to 412 groups of students majoring in engineering. Results of Course 1 show that only 9% (Clusters 2 and 3) of those groups have accessed all modules greater than the total mean while 41% (Cluster 4) have accessed all modules lower than the mean. Therefore, Clusters 2 and 3 consist of the most active self-students while Cluster 4 becomes a passive online student group in a non-graded environment. 34% only accessed resources but showed extremely poor participation in the discussion. In Course 2, only 5% (Cluster 1) had a higher mean for all three input parameters and 42% generated a lower score for the three of them (Cluster 4). In Cluster 0 (19%), students have used forums to get marks by not using cognition as they already got a lower mean for the resource hits. The students belonging to Clusters 2 and 3 (34%) with higher scores in accessing resources and viewing forums and lower scores in terms of participation in forums illustrate that they lack communication skills and have problems with written language. The weakness of this fifth literature is that the results analyzed are limited to the level of student

participation in online forums, the results obtained are also limited to the contribution and activity of the students.

The sixth literature [20] in this study, taken from 1523 student posts. The clustering technique used is ALG clustering and applied to the online community of inquiry. From the results of this study produced 10 clusters divided into 8 models of student behavior patterns and the value obtained is a comparison of the number of students and student graduation rates. Initiator (20%;97.2%), contributor (2.78%;80%), facilitator (17.2%;87.1%), knowledge-elicitor (0.55%;100%), vicarious-acknowledger (19.4%;77.1%), complicator (6.11%;63.6%), closer (13.8%;48%) and passive learner (20%;44.4%). The weakness of the last literature is that there is no comparison of the ALG clustering method with conventional agglomerative hierarchical clustering methods, so it is not known how much the cluster validation differs.

2. Problem Statement

From the background of the problems and the literature study in this paper can be summarized two main problems, the first is the clustering method used in many papers for the analysis of student interpersonal personality is mostly less appropriate evidenced by the number of clusters (K) that are not optimal and the results of groupings have many inequities. The second method of interpersonal personality used in many papers can not produce complete and detailed output such as the comparison of whether students with high activity levels can get high final value and how much the comparison of the level of cluster validation of the SLG method compared to conventional agglomerative hierarchical clustering methods.

3. A New Algorithm of Hierarchical Clustering

In this paper, it is introduced a new hierarchical clustering algorithm namely single linkage dissimilarity increment distribution-global cumulative score standart (SLG). This algorithm is a development of previous research that discusses the ALG algorithm [21], and the algorithm discussed in this paper is SLG. The fundamental difference between the two is the characteristics of conventional agglomerative hierarchical clustering algorithms, namely average linkage and single linkage. This new algorithm is the result of a combination of agglomerative hierarchical clustering (AHC) based on Dissimilarity Increment Distribution (DID) [22] and parameter-free algorithm Global Cumulative Score Standart (GCSS) [23].

Algorithm 1. SLG Algorithm

- 1: Input: dataset X
- 2: procedure
- 3: $M_p : M_p(i,j)$
- 4: Select the most similar clusters (C_i, C_j) $minDist = \min\{d(x_i, x_j) : x_i \in C_i, x_j \in C_j\}$
- 5: if $|C_i| < 6$ and $|C_j| < 6$ then
- 6: Merge clusters C_i, C_j into a new cluster C_b using SLDID (eq.2) and GCSS (eq.3)
- 7: end if
- 8: if $|C_i| \geq 6$ and $|C_j| < 6$ then
- 9: if $dissinc(x_i, x_j, x_k) = |d(x_i, x_j) - d(x_j, x_k)|$ of (C_j) is not in the tail then
- 10: the $pdissinc(w, \lambda)$ (eq.1) then $dissinc(x_i, x_j, x_k) = |d(x_i, x_j) - d(x_j, x_k)|$ of (C_j) then
- 11: Merge clusters C_i, C_j into a new cluster C_b using SLDID (2) and GCSS (3)
- 12: else
- 13: Do not merge C_i, C_j
- 14: end if
- 15: end if
- 16: if $|C_i| \geq 6$ and $|C_j| \geq 6$ then
- 17: Compute $gap_{C_i}(C_j)$ and $gap_{C_j}(C_i)$
- 18: Compute $DC(C_i), DC(C_j)$ and $DC(C_i \cup C_j)$
- 19: if $gap_{C_i}(C_j)$ is in the tail of the $pdissinc(w, \lambda)$ (eq.1) then
- 20: $disinc(x_i, x_j, x_k) = |d(x_i, x_j) - d(x_j, x_k)|$ of (C_i) then
- 21: Freeze cluster C_i
- 22: else if $gap_{C_j}(C_i)$ is in the tail of the $pdissinc(w, \lambda)$ (eq.1) then
- 23: $disinc(x_i, x_j, x_k) = |d(x_i, x_j) - d(x_j, x_k)|$ of (C_j) then

- 24: Freeze cluster C_j
 25: else if $DC(C_i \cup C_j) \leq DC(C_i) + DC(C_j)$ then
 26: Merge clusters C_i, C_j into a new cluster C_b using SLDID (2) and GCSS (3)
 27: else
 28: Do not merge C_i, C_j
 29: end if
 30: end if
 31: until all pairs of clusters should not be merged

The DID was derived in, using the Euclidean distance as the dissimilarity measure $d(\cdot, \cdot)$, under the hypothesis of Gaussian distribution of data. This distribution was written as a function of the mean value of the dissimilarity increments, which is denoted as λ [24].

$$pdissinc(w; \lambda) = \frac{\pi\beta^2}{4\lambda^2} w \exp\left(-\frac{\pi\beta^2}{4\lambda^2} w^2\right) + \frac{\pi^2\beta^3}{8\sqrt{2}\lambda^3} X\left(\frac{4\lambda^2}{\pi\beta^2} - w^2\right) \exp\left(-\frac{\pi\beta^2}{8\lambda^2} w^2\right) \operatorname{erfc}\left(\frac{\sqrt{\pi}\beta}{2\sqrt{2}\lambda} w\right) \quad (1)$$

The assumption of the SLDID algorithm is to consider the newly formed cluster, $C_b = C_i \cup C_j$, obtained by combining C_i and C_j , and C_a is one of the remaining groups formed in the preceding steps. Also, let's consider $|C_i|$ and $|C_j|$ as the number of patterns on the C_i and C_j clusters, respectively. We define the SLDID algorithm by characterizing the merging function, according to the size of the $d^*(C_a, C_b)$ distance between the clusters [22].

$$d_S(C_a, C_b) = \min \{d(C_i, C_a), d(C_j, C_a)\} \quad (2)$$

GCSS algorithm in essence compares the closeness level of a new cumulative hypothetical cluster (cd_k) with the closeness level of cumulative of both prospective groups (cd_i and cd_j). The GCSS criterion determines that the union between C_i and C_j into a new cluster C_k is a suitable merging if their cumulative standard score statistics (css_i and css_j) are greater than or equal to the following dynamic merging threshold [23]:

$$\begin{aligned} gcss_{th}(C_k, C_i, C_j, Y_{MIN}) = \\ gcss_{th}(css_k, N_i, \gamma_i, \mu_i, \sigma_i, N_j, \gamma_j, \mu_j, \sigma_j, Y_{MIN}) = \\ css_k Y(N_i, N_j) \Psi_G(N_i, \gamma_i, \mu_i, \sigma_i, N_j, \gamma_j, \mu_j, \sigma_j, Y_{MIN}) \end{aligned} \quad (3)$$

where css_k is the cumulative standard score of C_k , $Y_{MIN}=0.01$, $N_i, \gamma_i = d_{ij} - d_i$, $\gamma_j = d_{ij} - d_j$ and μ_i, σ_i, μ_j and σ_j . The value of Y_{MIN} is defined as 1% of the number of clusters in C ($Y_{MIN}=0.01 Y$).

4. Evaluation of Clustering Result with Cophenetic Correlation Coefficient (CPCC)

Cophenetic correlation coefficient to measure the degree of similarity between P_c and the proximity matrix P . The cophenetic matrix P_c is defined in such a way that the element $P_c(i, j)$ represents the proximity level at which the two data points x_i and x_j are found in the same cluster for the first time. The CPCC ranges from -1 to $+1$. The high value indicates great similarity between P and P_c . The CPCC index is defined as [25]

$$CPCC = \frac{\frac{1}{M} \sum_{i=1}^{n-1} \sum_{j=i+1}^n d_{ij} c_{ij} - \mu_p \mu_c}{\sqrt{\left(\frac{1}{M} \sum_{i=1}^{n-1} \sum_{j=i+1}^n d_{ij}^2 - \mu_p^2\right) \left(\frac{1}{M} \sum_{i=1}^{n-1} \sum_{j=i+1}^n c_{ij}^2 - \mu_c^2\right)}} \quad (4)$$

5. Interpersonality of Student Activity

Interpersonality is social or personally oriented interaction or informal communication aimed at the creation of relationships among participants. Impersonality is task-oriented communication in which information is offered or requested [26]. The concept of social presence is closely related to interpersonality. Social presence refers to "the ability of participants in a community of inquiry to project themselves socially and emotionally, as 'real' people (i.e., their full personality), through the medium of communication being used" [27].

- Support/alignment; someone who is not critical, acceptance is passive.
- Disclosure; someone who often talks about himself or other personal information.
- Appraisal; someone who likes to praise; satisfied with the ideas of others.
- Humor; someone who often jokes, or comments to remove tension.
- Inquiry; someone who often asks others for opinions about a problem.
- Inform/offer; someone who forwards factual information.
- Opposition/adversariality; a person involved in intellectual conflicts, or conflicts.
- Reserve; someone who often ends a discussion or no attempt to pursue it further.
- Chastisement; an angry person, spreading open hostility; personal attack; provoke
- Sarkasm; someone who often throws mock phrases;
- Advocacy; someone who is selfish
- Ask/request; someone who asks for factual information (other than opinion).
- Other; someone who uses rhetorical questions and questions for himself.

6. Data Set and Research Methodology

Experiments carried out in this paper to analyze the activities carried out by students in online learning to two different subjects in the Bachelor of Information and Communication Technology (Computer Security, Knowledge Management) in January 2017 until May 2017 at the School and Science Technology, Asia e University, Malaysia. All courses took place in the teaching and learning environment based online, the entire dataset involving a total of 36 students were distributed in five post dataset of total 1523 student posts shown in Figure 1.

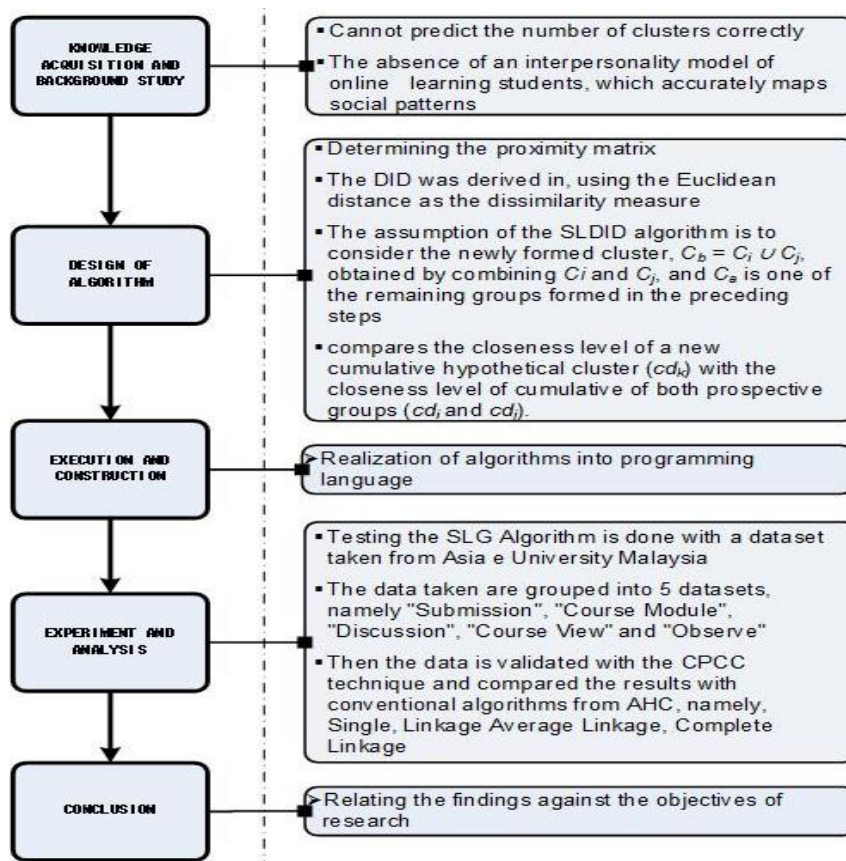


Figure 1. Research methodology

7. Results and Analysis

7.1. Characterisation

Number of posting activity and days used by online learner:

$P^{(1)}$ $D^{(1)}$: Submission (assignment); $P^{(2)}$ $D^{(2)}$: Course module (forum); $P^{(3)}$ $D^{(3)}$: Discussion (forum); $P^{(4)}$ $D^{(4)}$: Course view; $P^{(5)}$ $D^{(5)}$: Observe.

7.2. Cluster Analysis

In the “submission (assignment)” data set, there are two clusters, i.e. the first cluster that represents the “support” interpersonal pattern with a considerably large population of 18.89% and the rate of graduation of 94.1%. The second cluster represents the “disclosure” interpersonal pattern with a population of 1.11% and the rate of graduation of 100% shown in Figure 2. In the second data set, i.e. “course module (forum)”, the cluster analysis discovered two clusters, where the first cluster represents the “appraisal” interpersonal pattern with a population of 2.23% and the rate of graduation of 75%. The second cluster represents the “inquiry” interpersonal pattern with a population of 17.22% and the rate of graduation of 87.1% shown in Figure 3.

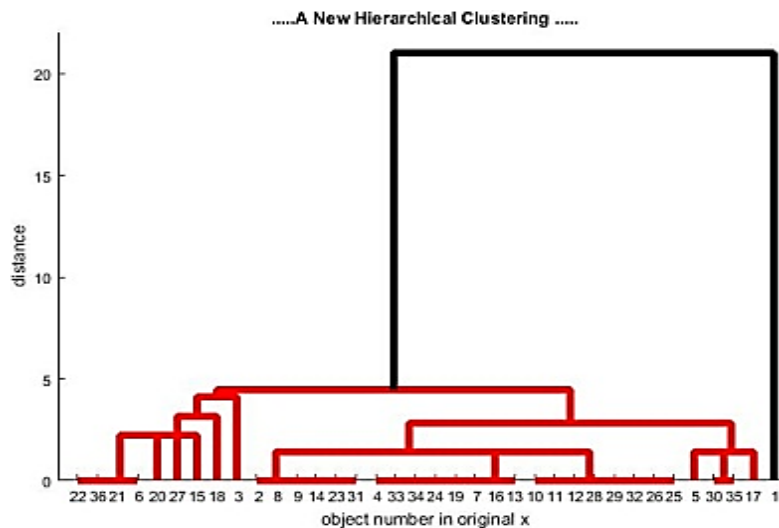


Figure 2. Dendrogram dataset submission

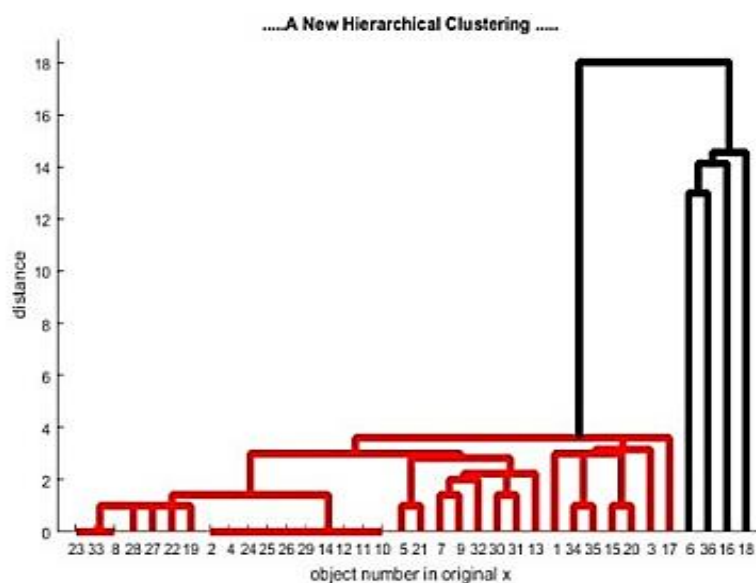


Figure 3. Dendrogram dataset course module

In relation to the cluster analysis of the “discussion (forum)” data set, after carrying out the cluster analysis, there were two clusters generated where the first cluster represents the “inform” interpersonal pattern with a population of 0.55% and the rate of graduation of 100%. The second cluster represents the “opposition” interpersonal pattern with a population of 18.9% and the rate of graduation of 77.1%. The third cluster represents the “humor” interpersonal pattern with a population of 0.55% and the rate of graduation of 100% as shown in Figure 4.

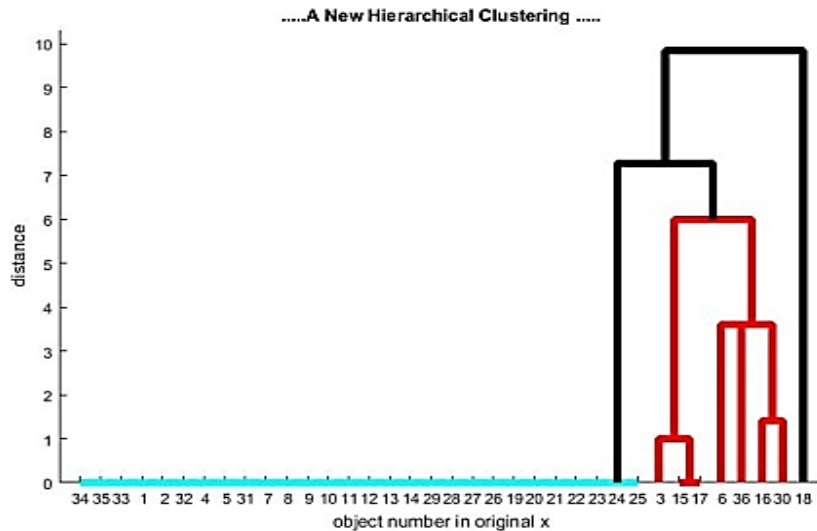


Figure 4. Dendrogram dataset discussion

In the fourth data set, i.e. “course view”, after carrying out cluster analysis, there were two clusters generated where the first cluster represents the “other” interpersonal pattern with a population of 5% and the rate of graduation of 66.7%. The second cluster represents the “chastisement” interpersonal pattern with a population of 1.11% and the rate of graduation of 50%. The third cluster represents the “advocacy” interpersonal pattern with a population of 13.89% and the rate of graduation of 48% as shown in Figure 5.

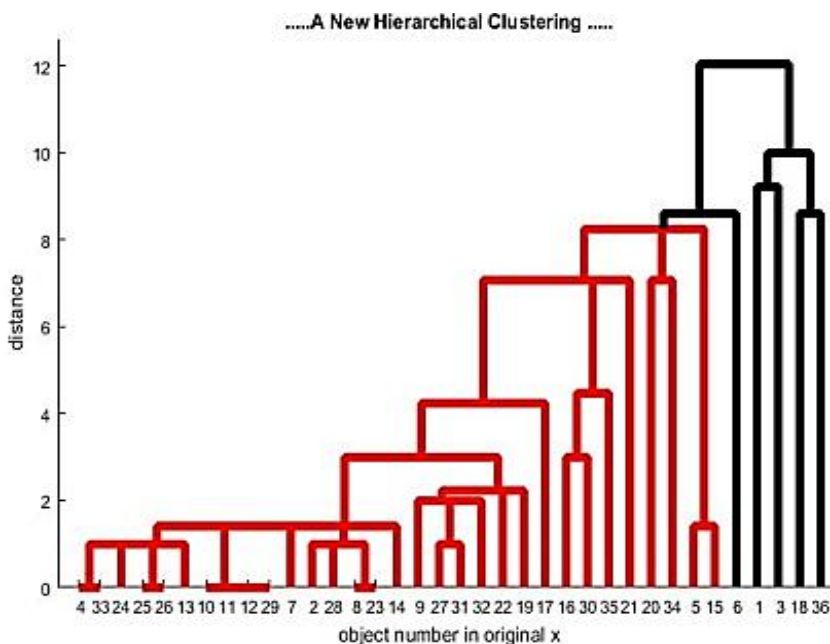


Figure 5. Dendrogram dataset course view

Lastly, the “observe” data set after conducting the cluster analysis generated two clusters where the first cluster represents the “sarcasm” interpersonal pattern with a population of 1.11% and the rate of graduation of 50%. The second cluster represents the “ask” interpersonal pattern with a population of 1.11% and the rate of graduation of 50%. The third cluster represents the “reserve” interpersonal pattern with a population of 17.78% and the rate of graduation of 41.2% as shown in Figure 6. From Table 1 also the method of interpersonality used can map students based on their activities in online learning and compared with the final grade of students in the course. The comparison of SLG method with conventional AHC method (single, average, complete) in Table 2 resulted in SLG method able to get the highest score when tested using CPCC validity index of five datasets, it can be proven that this algorithm is suitable for analyzing student activity in online learning.



Figure 6. Dendrogram dataset observe

Table 1. Interpretation of Student Activity in Interpersonality Analysis; %L (percentage of Student in each Cluster and %P (Percentage of Student in Each Cluster that Pass the Subject)

	CLUSTER	%L	%P	MODEL
P ⁽¹⁾ , D ⁽¹⁾	C ₁	18.89%	94.1%	Support / Alignment
	C ₂	1.11%	100%	Disclosure
P ⁽²⁾ , D ⁽²⁾	C ₁	2.78%	75%	Appraisal
	C ₂	17.22%	87.1%	Inquiry
P ⁽³⁾ , D ⁽³⁾	C ₁	0.55%	100%	Inform/offer
	C ₂	18.9%	77.1%	Opposition/adversariality
	C ₃	0.55%	100%	Humor
P ⁽⁴⁾ , D ⁽⁴⁾	C ₁	5%	66.7%	Other
	C ₂	1.11%	50%	Chastisement
	C ₂	13.89%	48%	Advocacy
P ⁽⁵⁾ , D ⁽⁵⁾	C ₁	1.11%	50%	Sarkasm
	C ₂	1.11%	50%	Ask/request
	C ₂	17.78%	41.2%	Reserve

Table 2. Comparison of SLG Methods and Conventional AHC Methods

Dataset	SLG	Single Linkage	Average Linkage	Complete Linkage
	CPCC	CPCC	CPCC	CPCC
Submission	0.9237	0.8956	0.8994	0.8352
Course Modul	0.9015	0.8881	0.8975	0.8931
Discussion	0.9967	0.9059	0.9307	0.9224
Course View	0.8853	0.8614	0.8519	0.8695
Observe	0.9875	0.9738	0.9781	0.9780

8. Conclusion

Research on patterns of behavior in online learning is always interesting to review, because at this time the development of online learning very rapidly, in this paper the discussion of the pattern of student behavior from the liveliness contribution to the comparison with the final grade of students from a course. The two main problems discussed in this paper are first, how to find the right number of clusters (K) as the optimal solution of clustering where the right grouping solution will form a strategy in knowing the interpersonalities of students in online learning, the results of the analysis in this paper can be proven that the SLG method can find the right number of clusters (K) and this new algorithm after being evaluated get the highest score compared to other conventional Agglomerative Hierarchical Clustering methods (single, average, complete) using the CPCC validity index of the five batch data. The second problem discussed in this paper is how to generate students' 'interpersonality models in detailed online learning of the students' active contribution in online learning and compared to the final grades of students of a course, from the experiments conducted in this paper can be produced a complete interpersonal model that can be used as a reference for schools and teachers in guiding students in online learning.

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