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Hybrid clustering based on multi-criteria segmentation for higher education marketing

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ABSTRACT

Market segmentation in higher education institutions is still rarely applied although it can assist in defining the right strategies and actions for the targeted market. The problem that often arises in market segmentation is how to exploit the preferences of students as customers. To overcome this, the combination of hybrid clustering method with multiple criteria will be applied to the case of the market segmentation for students in higher education institutions. The integration of geographic, demographic, psychographic, and behavioral criteria from students is used to get more insightful information about student preference. Data result of the integration will be processed using hybrid clustering using K-means and self organizing map (SOM) algorithm. The hybrid clustering conducted to get promising clustering result along with the visualization of segmentation. This study successfully produces five student segments. It received 1,386 as the Davies-Bouldin index (DBI) value and 2,752 as the quantization error (QE) value which indicates a good clustering result for market segmentation. In addition, the visualization of the clustering result can be seen in a hexagonal map.

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1. INTRODUCTION

Market segmentation is increasingly being implemented in Higher Education Institutions (HEIs). It is used to find the model that help define the right strategies and actions for the targeted market [1]. Based on the resulting market segment, HEIs can also gain insights into potential bases for segmentation, positioning and communication strategies targeting the specific characteristics of each segment [2].

The key point of market segmentation problem is how to exploit the preferences of customers, because it provides a basis for the following segmentation decision [3]. Customer preferences can be obtained by determining segmentation criteria in order to obtain information that will be used for market segmentation [4]. These criteria can be a single criterion or a combination of several criteria called multiple criteria. Market segmentation involving multiple criteria has been carried out to analyze the readiness of the crisis periods in terms of food security using the volume of agricultural production, the balance of foreign trade of agri-food products as well as the structure of total agri-food product trade [5]. It also used to divide the tourist segment in choosing outbound destinations [6]. The combination of demographic, psychographic, and behavioral criteria has also been used for segmentation of the wine market where the results show the use of these combination is more promising [7]. The integration between psychographic, demographic, and behavioral criteria of market segments in financial services provides useful insight into their unique customer behavior [8]. The involvement of multi criteria in market segmentation is proven to be able to add useful information about customers in the researched field. Even though the use of multiple criteria has been done in market segmentation and other fields, but this has not been widely implemented in market segmentation for HEIs. For market segmentation on HEIs, the criteria used are as in the following studies. M. Davari *et al.* [1], socio-demographic and geographic information is used as segmentation criteria for the purpose of market segmentation in the education industry. Another criterion used in market segmentation for HEIs is psychographic information [2], [9] which provides a deeper understanding of students as customers. While the behavioral criterion is applied as the basis for market segmentation to help private HEIs recognize the behavior of prospective students who will choose their place to study [10]. To obtain more useful information regarding customers, this study will apply market segmentation with multiple criteria. The criteria that will be involved are criteria that have been widely used in previous studies include geographic, demographic, psychographic, and behavioral.

Then, information obtained based on multiple criteria becomes the input for partitioning method in market segmentation. The most popular partitioning method is K-means clustering [4]. This method has been implemented for segmentation of the organic food market [11], mobile service providers customers [12], and internet banking customers [13]. Meanwhile, for market segmentation in HEI, K-means clustering is conducted in the second stage after internal validation with three clusters as the best result [2]. In addition, it is also used in the higher education market segmentation to determine the right media to target prospective students [9]. Although K-means provides promising segmentation results, there is still a chance to improve the results by using hybrid method. E. B. Baylan [14], proposed the hybrid method using analytic hierarchy process (AHP)-technique for order preference by similarity to the ideal solution (TOPSIS) which is applied to the project risk assessment is able to provide a platform that can be analyzed qualitatively. Whereas in the case of network security, the integration of methods between internet of things (IoT) and blockchain is applied to industrial processes for solving the security issues in real-time [15]. The hybrid method was also adopted by energy companies in the process of implementing the strategy of adaptation [16].

Menawhile, several studies have integrated K-means with other clustering algorithms to improved clustering result. The visualization capabilities of self organizing map (SOM) combined with K-means were used to determine the spatiotemporal pattern of water quality data and identify sources of pollution [17]. The application of the SOM algorithm with K-means for market segmentation in insurance companies is able to support visualization and provide better results when compared using single algorithm [18]. It can be seen that the hybrid method between K-means and SOM algorithm can help in terms of visualization and accuracy of clustering results. However, the use of the combination of hybrid clustering method with multiple criteria has not been applied to the case of the market segmentation for HEIs.

Therefore, this study proposes hybrid clustering based on multi-criteria segmentation for higher education marketing. The integration of geographic, demographic, psychographic, and behavioral criteria from students is used to get more insightful information about student preference in choosing HEIs. Whereas, hybrid clustering using K-means and SOM algorithm will be conducted to get promising clustering result along with the visualization of segmentation.

2. RESEARCH METHOD

The stages of market segmentation on HEIs using hybrid clustering based on the multi-criteria segmentation is explained in Figure 1. There are four stages consisting of data collection, data exploration, extracting segments, and describing segments. The first stage is collecting data from higher education students with the specified criteria. The most common segmentation criteria are geographic, demographic, psychographic and behavioural [4]. Demographic and geographic information is obtained from internal data storage owned by HEIs as research sites. Survey data were collected to obtain psychographic and behavioral criteria. Preprocessing is performed at the data exploration stage. This stage includes data cleaning, data integration, and data transformation [19], [20]. All data obtained from the previous stage will be processed at the exploration stage. The results of the preprocessed data are the dataset without missing values and inconsistencies with the transformation into numeric values.

At the extracting segments stage, students are clustered based on the data obtained from the exploration stage. Hybrid clustering using K-means and SOM algorithm is processed following Figure 2. The first clustering algorithm that implemented to data is SOM algorithm. The main steps of this clustering method are as follows [21]:

- Initialize the number of neurons d.and the size of a plane grid map of neurons m. The input layer accept training data $x \in R^d$ with d neurons while the output layer is often laid out as a plane grid map with $M = m \times m$ neurons.
- Trained SOM model in an iterative process including competition and convergence. the weights keep connection from each input neuron to each output neuron and can be denoted as $W = \{w_i | w_i \in R^d, i = 1, \ldots, M\}$.
- Found the winner in the competition, that is, the closest neuron c to the input sample x(t) in the tth iterative step. The value of c can be obtained by (1).

$$c = \arg\min\{\|x(t) - w_i(t)\|\} \quad (1)$$

- The weight vectors update based on the neighborhood relationships with the winner neuron by (2).

$$w_i(t+1) = w_i(t) + h_{ci}(t)(x(t) - w_i(t)) \quad (2)$$

where $h_{ci}(t)$ is the neighborhood function that determines the neighbor update scheme for topology-preserving nature of SOM which follows (3) in the form of Gaussian function.

$$h_{ci}(t) = \alpha(t) exp\left(\frac{-sqdist(c,i)}{2\sigma^2(t)}\right) \quad (3)$$

where $\alpha(t)$ is the learning rate that monotonically decreases with step t, $sqdist(c,i)$ is the square of distance between neuron c and neuron i on the plane grid map and $\sigma(t)$ is the kernel radius that determines the range of neighborhood relationships.

The SOM training model can be represented using U matrix, histogram collision and other indexes to visual the data sets [22]. In this paper, grayscale of U matrix and hit histogram is used level to determine the relationships between the multiple criteria of higher education students and to reduce them to a few independent features. It also produces visual images of each cluster [23].

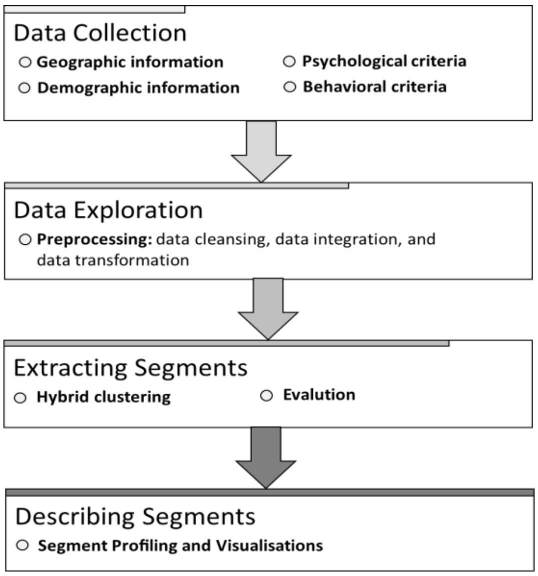

Figure 1. The stages of the proposed research methodology

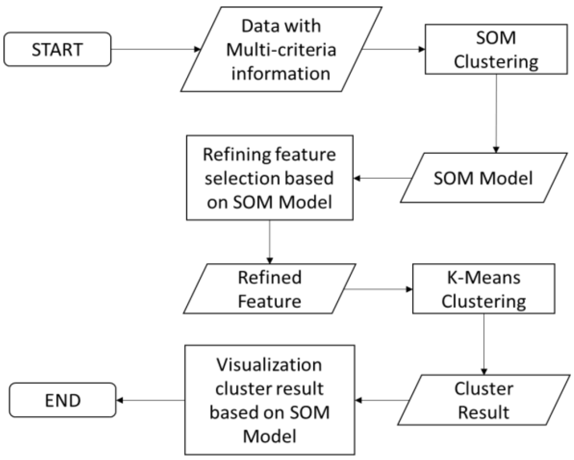

Figure 2. Hybrid clustering using K-means and SOM algorithm

Then, K-means is used to re-cluster the features resulted from SOM. The steps of clustering with K-means method are as follows [24]:

- Select the number of clusters k and initialize the cluster center k. Cluster centers are assigned initial values with random numbers.

- Allocate all data objects to the nearest cluster. The proximity of a data to a particular cluster is determined the distance D_{ij} between the data X_{ki} with the cluster center X_{kj}. To distance all data to each cluster center point can use Euclidean distance theory formulated as follows (4):

$$D_{ij} = \sqrt{\left(X_{1i} - X_{1j}\right)^2 + \left(X_{2i} - X_{2j}\right)^2 + \cdots + \left(X_{ki} - X_{kj}\right)^2} \quad (4)$$

- Recalculate cluster center with current cluster membership. The new cluster center is the average of all data in a particular cluster.
- Reassign each object using the new cluster center. If the cluster center does not change again then the clustering process is complete.
- Otherwise, return to step number 2 until the center of the cluster does not change anymore.

The evaluation method of cluster results uses the Davies-Bouldin index (DBI) and quantization error. DBI represents how well clustering has been done by calculating the quantity and the derivative features of the dataset [25]. DBI is the internal validity, which if it is closer to non-negative zero then shows the the better cluster results. The quantization error (QE) measures the average squared distance from each point to the centroid of the cluster where it belongs, according to the partition into number of subsets [26]. Lower values for QE are better.

For the last stage, the cluster labels which are the result of K-means clustering are mapped to SOM models that have been obtained from the previous cluster process. The visualization of cluster results from SOM algorithm in the form of U Matrix can help in understanding the structure of each student segment obtained from the clustering results [27].

3. RESULTS AND ANALYSIS

This research was applied to 230 students from the Sahid University of Surakarta as one of the private HEIs in the region of Central Java, Indonesia. The resulting dataset from the data collection stage consists of 230 objects with a total of 48 features. The features of the dataset represent the criteria that have been determined to be used in this study (geographic, demographic, psychographic, and behavioral).

A feature representing geographic criteria is an address. Meanwhile, age, religion and gender are features that represent demographic criteria. For features that represent psychographic and behavioral criteria are the answers of questionnaires to students. Each questionnaire item represents one feature. There are 36 items that become a feature to represent the psychographic criteria. For behavioral criteria are based on the answers of 7 items in the questionnaire. All items in the questionnaire were arranged on 5-point Likert-type scales (1=completely disagree to 5=completely agree) [28].

3.1. Hybrid clustering segmentation

Data features with categorical types is transformed into numeric value so that it can be maximally processed by the clustering method. All features are processed with SOM clustering in order to obtain a SOM model that can be visualized in the form of U matrix.

Figure *3* shows the feature maps for every cluster and for all input attributes. The SOM maps were formed using an 8×9 hexagonal architecture with a Gaussian neighbourhood function based on the optimum number of neurons (*M*=76). The optimum number of neurons is calculated (5).

$$M \approx 5\sqrt{N} \quad (5)$$

where *M* is the number of neurons, which is an integer close to the result of the righthand side of the equation and *N* is the number of objects [29].

Relationships between features could be inspected by visually comparing the pattern of shaded pixels for each map [23]. The features with similar patterns are considered highly correlated and be removed from the feature set [30]. Therefore, based on

Figure *3*, a detailed inspection of the similar feature pattern is carried out. For example, several features such as C3 and C4 have the same pattern as C2. Thus, C3 and C4 can be removed from the feature set. Finally, we got 26 features as new inputs for the next clustering process.

This research uses elbow method to determine the optimal number of clusters [31]. From the graph shown in Figure 4, the optimal number of clusters is five. The value of the cluster k=4 to k=5, then from k=5 to k=6, it shows a drastic decrease to form the elbow at point k=5 then the ideal number of cluster k is 5. Then, K-means algorithm is used to divide the data of students with 26 features into 5 clusters.

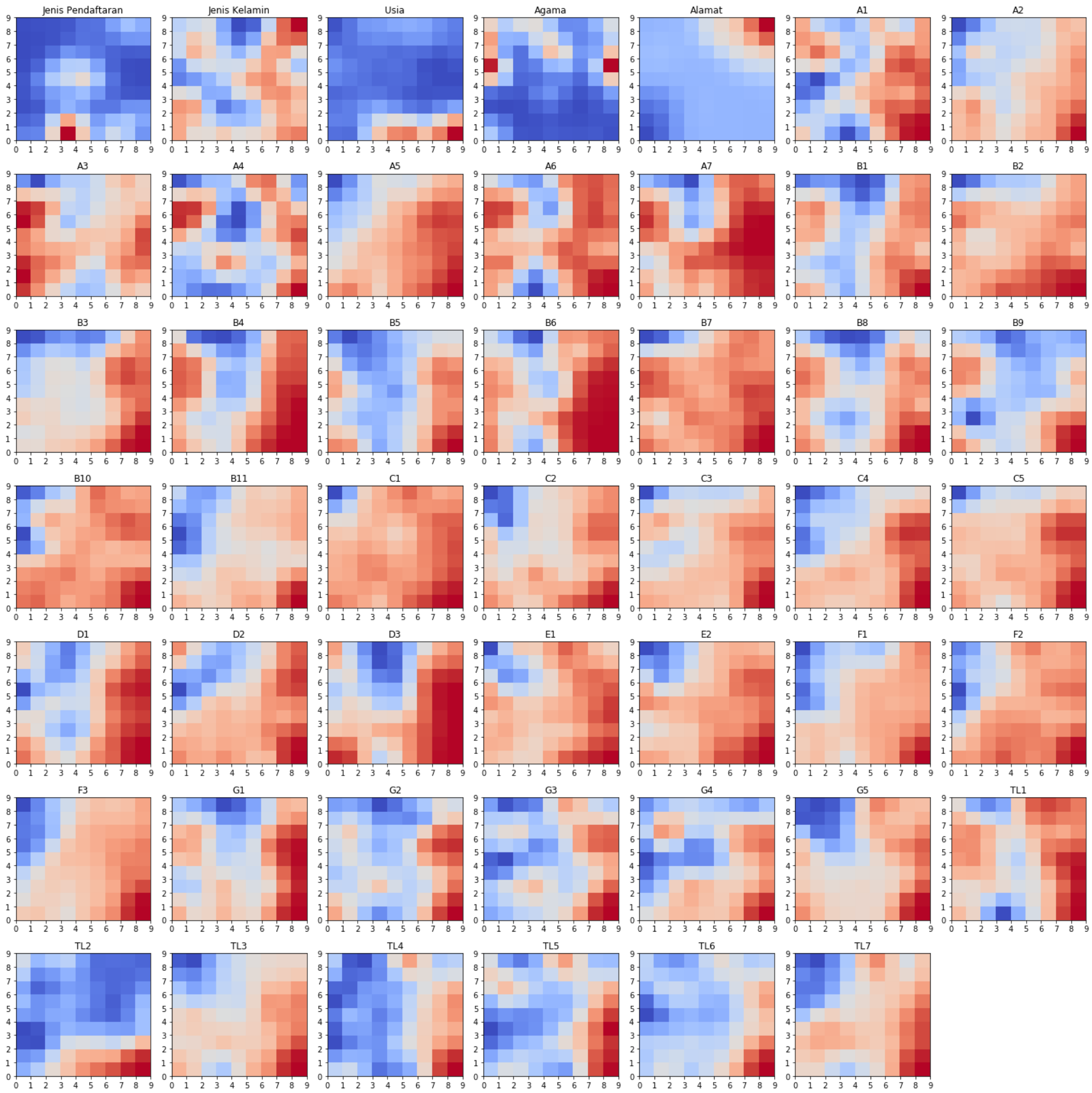

Figure 3. Feature map of SOM model based on multi-criteria segmentation

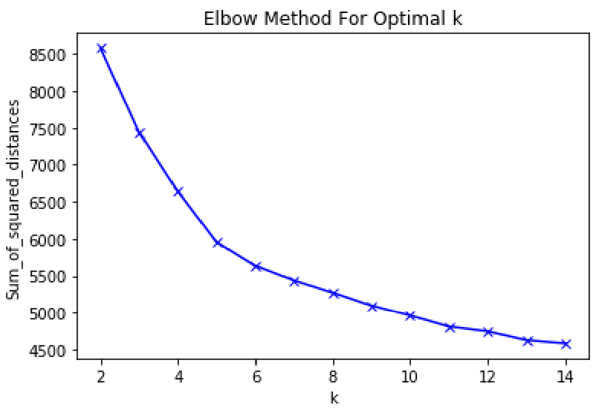

Figure 4. The graph of elbow method for optimal number of cluster

3.2. Market segmentation evaluation

The evaluation of market segmentation with cluster analysis is done by finding the DBI value and quantization error (QE). The results from Table 1. show a small value of DBI and QE, so it can be concluded that clustering based on multi-criteria segmentation performs an optimal result. It means that the distance between the clusters is large and the distance between the objects in the cluster is small [32].

In addition, the DBI value is 1,386 and the QE value is 2,752 when using hybrid clustering. While using single clustering the DBI value is 1,562 and the QE value is 4,033. From the Table 1, it can also be seen that the DBI and QE values using hybrid clustering are smaller than using single clustering. This indicates that the performance of hybrid clustering using K-means and SOM algorithm has exceeded the performance using a single clustering method.

Table 1. The performance comparison of clustering using single and hybrid method

Method	DBI	QE
Single clustering using K-means	1,562	4,033
Hybrid clustering using K-means and SOM	1,386	2,752

3.3. Visualization of segmentation result

The results of market segmentation using hybrid clustering method based on multi-criteria are visualized in Figure 5. The figure is SOM model generated from the experiments. All objects from the dataset are classified into each neuron in the form of a hexagon hits map. From the visualization results, it can be seen the number of objects for each cluster and their distribution on the map. The variation in the color scheme from light blue to dark blue is showing the average Euclidean distance between adjacent nodes. The color degrade between dark blue to light blue showing the reduction in distance between nodes [18]. Dark blue areas are representing dissimilarity (large Euclidean distances between objects). While the light blue areas are representing similarity (small Euclidean distances between objects). Cluster 02 and Cluster 03 have the most members and occupy light blue areas. Meanwhile, the dark blue area is occupied by a cluster with fewer members, namely, Cluster 00, Cluster 01, and Cluster 04.

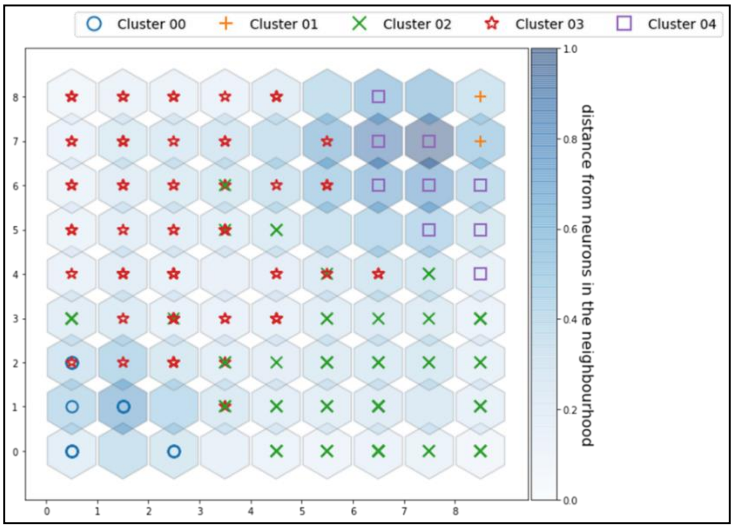

Figure 5. Visualization of cluster results with the hits map

3.4. Analysis of segment profiles

To study the characteristic of customers within each cluster, the feature plane of SOM model (

Figure *3*) and the hits map (Figure 5) are used. By comparing the clustering map with the feature planes of SOM model, the following analysis of segment results can be concluded:

- Cluster 00: Members of this cluster are dominated by students from the Kalimantan region, Indonesia. The characteristics of this cluster are similar to Cluster 04. The ages of students who are members of this

cluster are 16-25. When viewed from the reasons for choosing their university, the quality factor of education got a lower score when compared to the score of Cluster 04 members. The involvement of students from members of this cluster in campus and social media activities was higher than in cluster 4.
- Cluster 01: Members of this cluster are students from Papua, Indonesia, with the least number of members and dominated by female students. The age of the students in this cluster is 16-25 years. Among all the clusters, family motivation is the highest factor that encourages continuing education to higher education. In addition, the influence of advertisements and promotions, especially recommendations from friends and family, is the highest factor for choosing their university compared to other clusters.
- Cluster 02: The members of this cluster are dominated by students from Java, Indonesia with the second largest number of members of all clusters. The age of the students who are members of this cluster varies with some students aged over 36 years. The number of male and female students is equal. Compared to Cluster 01, members of this cluster have higher economic motivation, especially related to affordable tuition fees and scholarship offers. Another highest factor when compared to other clusters is easy transportation to their universities. Members of this cluster have the highest activity in participating in campus activities and social media.
- Cluster 03: The members of this cluster are dominated by students from Java, Indonesia with the largest number of cluster members. The age of students who are members of this cluster is more varied than other clusters, namely between 16-35 years. Compared to all clusters, students who were members of this cluster scored the lowest in terms of the factors that motivated them to choose their university to study. The factor with the lowest score is the influence of advertising and promotion. The involvement of students who are members of this cluster in campus activities and social media has the lowest score.
- Cluster 04: Members of this cluster are dominated by students from the Sumatra region, Indonesia. The characteristics of this cluster are similar to Cluster 00. The age of the students in this cluster is 16-25 years. When viewed from the reasons for choosing their university, the quality factor of education gets a higher score when compared to the score given by members of Cluster 00. The economic factors related to tuition fees and the effect of promotion have lower scores when compared to the scores given by members of Cluster 00.

Based on the results of the segmentation, it appears that each criterion can be linked to one another to describe the segment profile. For example, Cluster 00 and Cluster 04 are clusters that are dominated by students from outside Java and have similar profiles. They are students from Sumatra and Kalimantan. Students from Sumatra are more concerned with the quality of education in choosing higher education than students from Kalimantan. Meanwhile, the economic factor is a higher reason for students from Kalimantan to choose higher education when compared to students from Sumatra. For behavior criteria, students from Kalimantan students are more involved in campus activities than students from Sumatra.

For Cluster 02 and Cluster 03, they are students from Java. The significant difference between the two student profiles in the two clusters is that Cluster 02 has more motivation to pursue higher education. In addition, they are more often involved with campus activities. Meanwhile, Cluster 03 has the lowest motivation in pursuing higher education. They are also not much involved in campus activities. Students from Papua included in Cluster 01. Motivation and recommendations from family becomes the highest reason in continuing higher education. Students from Papua are members of Cluster 01. The motivation and recommendation from their families are the highest reasons in continuing higher education.

4. CONCLUSION

Hybrid clustering using K-means and SOM algorithm based on multi-criteri segmentation performs an optimal clustering result. It is shown by a small value of DBI and QE. When using hybrid clustering, the DBI value is 1,386 and the QE value is 2,752. In addition, the performance of hybrid clustering using K-means and SOM algorithm has exceeded the performance using a single clustering method. The SOM algorithm is used to obtain a model that helps visualize the features of the data and cluster results. Based on observations from the feature map, unnecessary features can be removed so that the quality of the cluster improves. The SOM model also helps create a visualization of the cluster labels produced by K-means clustering.

Segmentation in marketing the higher education students successfully done using the hybrid clustering method based on multi-criteria segmentation. The proposed method produces five student segments. The segmentation criteria based on geography, demographics, psychographics, and behavior provide interesting information, especially the relationship between the criteria used. The characteristics of each cluster can be distinguished according to the criteria, so that the information obtained is richer.

Future research that needs to be done is to explore other clustering methods that can be integrated. A comprehensive evaluation also needs to be included to compare some standard techniques/parameters with the existing work. In addition, it is necessary to improve the quality of the data sources by improving the questionnaire items and enhancing the features of geographic and demographic criteria.

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