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Utilizing Clustering Methods for Categorizing Delivery Requirements Based on Analysis of E-Commerce Product Data

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Abstract: This study presents the implementation of the K-Means algorithm model, revealing novel insights into risk categorization in the delivery process. Two distinct clusters were identified: Cluster 1 (C0) indicating high risk, comprising 53 data points out of a dataset of 360, and Cluster 2 (C1) indicating low risk, encompassing 307 data points from the same dataset. Analysis conducted using RapidMiner Studio corroborated these findings, further delineating the cluster membership: C0 with 53 data points and C1 with 307 data points. Each cluster was characterized by optimal centroid values, recorded at 131.717 & 385.075 for C0, and 119.932 & 111.414 for C1. The model's effectiveness was assessed using the Davies-Bouldin Index, yielding a value of 0.626.

Keywords: Data Mining; K-Means; Clustering; E-Commerce; Product Analysis.

1. Introduction

The growth of information technology and the evolution of the digital world have indirectly necessitated rapid processes and have had a significant and profound impact on daily human life. One such development is the advent of internet technology. Among the activities facilitated by the internet is online business, commonly known as e-commerce. In a warehouse, the product is a critical element for managing inventory and ensuring efficient delivery processes to avoid shortages and damage. The arrangement and management of products for shipment are crucial in e-commerce operations. The volume of goods processed daily, weekly, and monthly is continually increasing, necessitating precise placement and grouping according to shipping needs. This surge in products leads to challenges in warehouse space management, requiring organized and data-driven approaches to storage and shipping. This study focuses on categorizing warehouse products into fast-moving and slow-moving groups, employing clustering processes and developing the K-Means algorithm method. This method is a non-hierarchical (partitioning) clustering technique that partitions data into two or more groups (clusters) with similar characteristics.

Relevant studies include Ainur, Heri (2021), which focused on text mining analysis of electronic products sold on the e-commerce platform Shopee, using the Kmeans algorithm and Python programming language. Data scraped included text comments, sales numbers, and star ratings. The study revealed that low-cost and high-cost smartphones on Shopee Indonesia's marketplace showed similar patterns in word clouds, with dominant words being neutral and positive, while negative words were less prominent. Words like "send", "fast", and "good" appeared frequently, with accuracy percentages of 92% for low-cost smartphones and 94% for medium to high-cost ones. The use of the K-means algorithm is effective for clustering e-commerce products to strategize customer delivery needs. Clustering, a data mining technique, aims to identify groups of objects with similar characteristics and differentiate them from others. Objects within the same group are more homogeneous compared to those in different groups. The number of identifiable groups depends on the quantity and variety of data objects.

2. Research Method

In carrying out analysis and looking for results on retail data, these steps are made to research in research, namely to make it easier and in accordance with the desired goals. The following is a general description of the steps taken during this research:

2.1 Data Collection
The data that will be used as a dataset in this research is product data or delivery data, then the data is analyzed and looked for patterns to make research easier so that it can run systematically and meet the desired objectives and the data that will be used as a dataset in this research is product data or delivery data. taken in August, obtained in Excel format and the data is still undergoing selection, preprocessing and transformation processes. The following are the steps in the research stages that will be carried out as follows.

1) Data Selection
The data selection stage is a data cleaning process that will be used to delete data by removing missing values, duplicate data, checking data for inconsistencies and correcting errors in the data. The data cleaning process is carried out manually with the help of spreadsheet software. Below is the data in orange for the data selection process [18].

Table 1. Data Selection

Code	Initial Delivery	Final Delivery	Receipt
SPXID03207925659A	22	2	0
SPXID03546691247A	31	27	124.508
SPXID03175764966A	10	9	38.614
SPXID03224436054A	3	12	0
SPXID03706201890A	3	1	14.800
SPXID03813160790A	12	10	50.112
SPXID03075511929A	10	18	5.524
SPXID03375556911A	6	8	0
SPXID03527462199A	12	6	0

2) Data Selection
Data Selection is the process of selecting data from a collection of existing operational data before entering the data and information mining stage. At this stage the following steps will be taken:

a. Data was taken by random sampling by selecting the most product data for each product category from a set of stock data contained in the spreadsheet and previously cleaned.
b. From the sampling selection process, 100 testing data and 360 data were obtained which will be used in calculating and processing the data to the next stage.
c. The attributes that will be used and analyzed are selected, because in
d. In the initial data there are several attributes that are not needed, such as attributes. Removing attributes from the main data is because there is no connection in the calculation of the K-Means algorithm that will be used. There are only 2 attributes that will be used, namely initial and final delivery. The following are the results of initial data processing after going through the stages above to be used as a dataset in the next stage, shown in Table 2:

Table 2. Data Selection

Code	Initial Delivery	Final Delivery
SPXID03207925659A	22	21
SPXID03546691247A	31	27
SPXID03175764966A	10	9
SPXID03224436054A	4	12
SPXID03706201890A	4	1
SPXID03813160790A	12	10
SPXID03075511929A	10	18
SPXID03375556911A	6	8
SPXID03527462199A	12	6

3) Data Transformation
Data Transformation is the process of changing the initial data format into a standard data format for the data reading process with the K-Means algorithm in the program or tool used. The following are the results of initial data processing after going through the stages above to be used as a dataset at the next stage [19].

Table 3. K-Means Clusterization Dataset

Code	Initial Delivery	Final Delivery
SPXID03207925659A	22	21
SPXID03546691247A	31	27
SPXID03175764966A	10	9
SPXID03224436054A	4	12
SPXID03706201890A	4	1
SPXID03813160790A	12	10
SPXID03075511929A	10	18
SPXID03375556911A	6	8
SPXID03527462199A	12	6

2.2 Modeling
Data modeling in this research was carried out using the clustering method using the K-Means algorithm [20]. The sequence of steps carried out in using the K-Means algorithm is as follows:

1) Determining the number of clusters to be used, in this study 3 types of clusters were used, including Low Sales Product (C1) for products that have a low sales potential level, Medium Sales Product (C2) for products that have a medium sales potential level, and High Sales Product (C3) for products that have the potential for high sales levels [21].
2) Determining the centroid value at the initial stage for the 0th iteration, is done randomly using the formula for determining the initial target k-means to get the target data or distance between groups, using the following formula:

$$\text{Cn Initial} = \frac{\text{Total Number of Data Points}}{\text{Number of Clusters} + 1}$$

   So, if you apply the formula above, you will get results like the following :
   Cn Initial = $\frac{217}{3+1}$ = 54.25, so that the initial value of the centroid is set 54.25.

3) Then determine the starting point of each cluster. In this study, the starting point of the cluster was taken randomly by calculating the average value contained in the 145th data to the 217th data for the 1st cluster starting point, the average of the 73rd data and the 144th data for the 2nd cluster starting point, and the average of the 1st data to the 72nd data for the 3rd cluster starting point. Consequently, the results of determining the starting points for the 1st iteration stage established the initial centroids for each cluster. These centroids act as reference points around which the data points are clustered during the initial phase of the K-Means algorithm. The iterative process of K-Means then commences, where each data point is assigned to the nearest centroid, and the centroid positions are recalculated based on the mean of the assigned points. This process continues iteratively, adjusting the centroids and the grouping of data points until the centroids stabilize, signifying the formation of distinct, well-defined clusters.

2.3 Evaluation
Evaluation can be done by observing and analyzing the results of the algorithm used to ensure that the test results are truly in accordance with the discussion. Check each attribute value and model that has been built. Then carry out an evaluation by observing and analyzing the results of the k-means algorithm used to ensure that the test results are correct and match the results of the discussion. Testing is carried out to measure the accuracy of the results of each proposed model. Iteration is defined as the degree of closeness between the K value and the actual value. Evaluation can be done by observing and analyzing the results of the algorithm used to ensure that the test results are truly in accordance with the discussion. Analyze each attribute value and model that has been built and ensure that the test results produce a value defined as the level of closeness between the value and the actual value of the model that has been built.

3. Result and Discussion

3.1 Results
3.1.1 Formation of Cluster Groups
From the data pre-processing process, 360 data records were obtained which will be processed using the K-Means algorithm. Through several stages such as in the data modeling section, the result was that the clustering process with the

K-Means algorithm stopped at the 9th iteration, because the position of the objects from each cluster had not changed and obtained optimal values. The following is the form of the cluster obtained:

1) The first cluster (C0) has a cluster center (131.72, & 385.08), so it can be interpreted that this cluster is a group of coded data that has a high risk of delivery. There are 53 code data records included in the first cluster, some data samples included in this cluster include Sample 4 (197, 543), Sample 5 (189, 846), Sample 70 (154, 284), Sample 357 (146, 330) and Sample 360 (97, 600).
2) The second cluster (C1) has a cluster center (119.93 & 111.41), so it can be interpreted that this cluster is a group of Code data that has low risk. This cluster has many members, namely 307 code data records included in the cluster. Some data samples included in the following cluster include Sample 1 (89, 94), Sample 30 (95, 38), Sample 55 (99, 51) , Sample 310 (95, 66) and Sample 355 (76, 44). The following is a table of 4 cluster categories.

Table 4. Data Cluster Groups

No.	Code	Cluster Category
1	SPXID03977565467A	Low Risk
2	SPXID03825879985A	High Risk
3	SPXID03650911376A	High Risk
4	SPXID03023446268A	Low Risk
5	SPXID03656365082A	High Risk
6	SPXID03353515134A	Low Risk
7	SPXID03784910144A	Low Risk
8	SPXID03464321345A	High Risk

3.1.2 Test Results

In this process, the clustering method with the K-Means algorithm is applied to form cluster groups with proper accuracy. In this research the author used calculation testing with the help of the RapidMiner Studio application. Testing the model obtained using the RapidMiner Studio application is done with the following steps:

1) Import the data needed for the process in the Rapid Miner tool. In the RapidMiner Studio application, select and click Import Data, then select the data that will be used and then determine the attributes and labels that will be used.
2) Click the Design menu, in the process view, add the dataset in the folder to the process view screen. In the Names & Roles menu, look for the Set Role function which will later be used to set role attributes, then drag it to the process display screen.
3) Next, in the Normalization menu, select Normalize and drag it to the process display screen. Through this function you can set the data normalization that will be carried out from the dataset used in this process.
4) Then on the Modeling menu, in the Segmentation submenu, select the k-Means function, to apply the K-Means algorithm to the clustering process that will be carried out. In this function we can determine the number (k) of clusters that will be used in data modeling.
5) The next step is to add the Performance function to display the Bouldin-Index value obtained from the data clustering process used.
6) Connect all the commands so that the process display screen shows the following flow:

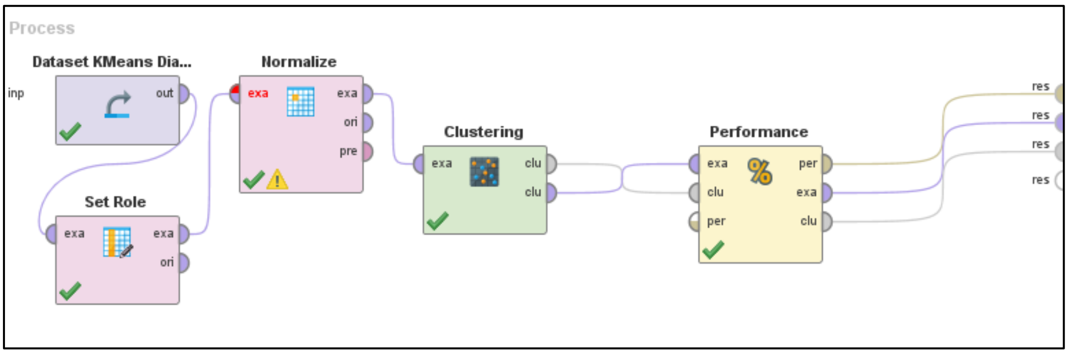

Figure 1. K-Means Clustering Rapid Miner Process

7) Carry out a Running Process to get clustering results from the 360 dataset records that we use.

3.1.3 Analysis of Test Results

After carrying out the stages of searching for cluster groups using the clustering method, the use of the K-Means algorithm used produces a cluster grouping of each data. The code data used is 360 data records which will be tested in the process of forming cluster groups using the K-Means algorithm. The results of the cluster model in testing the RapidMiner application show that of the 360 data, there are 53 data in the first cluster group (C0) and 307 data in the second cluster group (C1), which can be seen in the following figure.

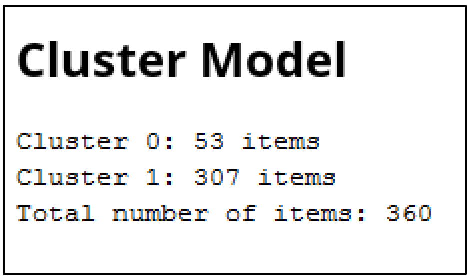

Figure 2. Cluster Model results in the RapidMiner Studio application

From the results above it can be seen that the formation of cluster members obtained through testing with the RapidMiner application is relevant to examples of K-Means model calculations carried out manually. The members of each cluster also have similarities with the manual calculations carried out. It's just that in the process of using the Rapid Miner tool the initial cluster value is not determined as is done in the manual calculation process. The most optimal cluster points for each variable for Cluster 0 (C0) are 131,717 & 385,075 and for Cluster 1 (C1) are 119,932 & 111,414 as can be seen in the image below.

cluster_0	cluster_1
131.717	119.932
385.075	111.414

Figure 3. Optimal Cluster Results in the RapidMiner Studio application

The optimal point for this cluster when compared with the results of the K-Means model calculation which was carried out manually also has the same number, namely as in the following table.

Table 5. Optimal cluster values in manual calculations

Initial Center Point	Initial Delivery	Final Delivery
C0	131,72	385,08
C1	119,93	111,41

Performance testing of models and algorithms is carried out with the aim of knowing the results of the calculations being analyzed and measuring whether the methods and algorithms used are functioning properly or not.

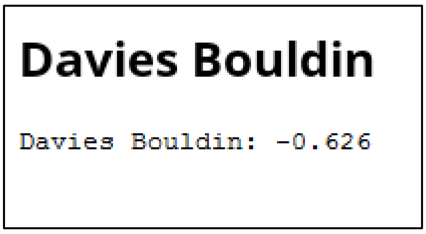

Figure 4. Davies-Bouldin Index results in the RapidMiner Study application

The results of the evaluation value with the Davies Bouldin Index or DBI based on the RapidMiner Studio application obtained from testing obtained from the test results on the RapidMiner Studio application show the number 0.626 as in Figure 4.

3.2 Discussion

The main findings and implications of this research in categorizing shipping requirements using the K-Means algorithm and clustering analysis of e-commerce product data. The discussion is structured around the formation of cluster groups, test results, and analysis of test results. The research successfully applied the K-Means algorithm to create two different cluster groups based on product data characteristics: Cluster 0 (C0) which represents high-risk products and Cluster 1 (C1) which represents low-risk products. Cluster 0 consists of 53 data points, while Cluster 1 includes a larger 307 data points. The optimal centroid values for this cluster were identified at 131.717 & 385.075 for C0 and 119.932 & 111.414 for C1. These findings show that our clustering approach effectively separates products into risk categories, which is very useful for optimizing warehouse management and shipping processes in e-commerce. To evaluate the accuracy and effectiveness of the model, researchers conducted tests using the RapidMiner Studio application. These test results align with our manual calculations, thus strengthening the reliability of our clustering methodology. The Davies-Bouldin Index (DBI) value calculated during the evaluation resulted in a score of 0.626. This value indicates the closeness of the clusters and shows that our clustering model performs well in grouping similar products. The consistency between the results obtained through manual calculations and those produced by the RapidMiner Studio application is a convincing validation of our methodology. The optimal cluster values for C0 and C1 closely match the manually obtained values, further confirming the accuracy of our clustering approach. The DBI score of 0.626, indicating the quality of the clusters, indicates that our model effectively captures the patterns inherent in the product data. In practical terms, the formation of high-risk and low-risk product clusters has significant implications for e-commerce operations. Warehouse managers can use this categorization to simplify inventory management, allocate storage space more efficiently, and prioritize shipping of high-risk products. Additionally, this approach can increase customer satisfaction by ensuring timely delivery of important goods while optimizing logistics costs. The research shows the practical utility of using the K-Means algorithm and clustering analysis to categorize delivery requirements in the context of e-commerce product data. The formation of distinct clusters and the alignment between manual and automated results underscore the power of our approach. This research offers valuable insights into improving e-commerce logistics and potentially improving the overall customer experience in digital markets.

4. Related Work

In research topics related to product data analysis in e-commerce, several related studies have been conducted. Rachmarwi et al. (2018) conducted a study on online shopping in Indonesia, which can provide relevant context to our research on product grouping [1]. Furthermore, Rahman and Suroyo (2021) have applied the K-Means algorithm method in analyzing electronic product data in e-commerce using Python [2]. This research may provide additional insight into the use of K-Means in the context of e-commerce products, which is in line with our research focus. In addition, Darmi and Setiawan (2016) studied the application of the K-Means clustering method in grouping product sales, which can be an additional reference in the context of e-commerce product analysis [3]. The use of data mining and the K-Means algorithm in the context of e-commerce has also been investigated by several other studies. Hamdani (2020) combines RFM (Recency, Frequency, Monetary) with the K-Means algorithm to group customer loyalty [4]. Hasanah and Larasati (2019) utilize data mining to group product sales categories [5]. Khormarudin (2016) provides further views on the K-Means clustering algorithm in data mining techniques [6]. Apart from that, the development of e-commerce and its important role for small businesses has been researched by Suhayati (2017) [8] and Alwendi (2020) [12]. This research provides important context on how e-commerce can increase business competitiveness. The role of e-commerce in business development was also studied by Rehatalanit (2021), which can provide further understanding of the implications of e-commerce in business growth [13]. Other related research includes the application of the fuzzy time series method [15] and sentiment analysis of e-commerce products using the Naïve Bayes algorithm [19] as well as sentiment analysis of Twitter user tweet data regarding online shop products using the K-Means method [20]. All these studies provide diverse frameworks for analyzing product data and e-commerce usage in various contexts.

Research on grouping products in e-commerce using the K-Means algorithm has significant differences compared to previous research and the findings of this research. One difference is that in our research we focus on risk analysis in the product delivery process, which has not been widely explored in the e-commerce context. The author uses the K-Means algorithm to identify two different clusters, namely high risk and low risk clusters, which can help warehouse and logistics managers manage stock and delivery more efficiently. In addition, this research provides added value by combining the results of manual analysis with testing using the RapidMiner Studio application. These results prove the consistency of the grouping results and optimal centroid values between the two methods. We also measure the quality of grouping with the Davies-Bouldin Index, which provides a deeper understanding of the effectiveness of the K-Means algorithm in grouping products in e-commerce. By focusing on risk analysis in product delivery, combining manual analysis methods and testing using software, and measuring the quality of grouping, our research makes a new contribution to the understanding of product grouping in e-commerce. This can help e-commerce companies optimize inventory management, warehouse space management, and delivery of high-risk products, thereby increasing operational efficiency and customer satisfaction.

5. Conclusion

In this research, the application of the K-Means algorithm model has produced significant findings, namely the grouping of risk levels in the delivery process into two different clusters. The first cluster (C0) indicates a high level of risk and consists of 53 data from a total of 360 datasets tested, while the second cluster (C1) indicates a low risk level with 307 data from the same dataset. Testing using the RapidMiner Studio application also yielded similar insights, with each cluster consisting of the appropriate group members. The optimal centroid values for these two clusters are 131,717

& 385,075 for C0 and 119,932 & 111,414 for C1. In addition, the Davies-Bouldin Index evaluation value of 0.626 shows good grouping quality, indicating that this grouping model is effective in classifying products with similar characteristics. The results of this research have important implications in the context of warehouse management and delivery processes in e-commerce. Grouping products by risk can help warehouse managers optimize inventory management, allocate storage space more efficiently, and prioritize delivery of high-risk products. Thus, this research makes an important contribution to improving e-commerce operational efficiency and has the potential to increase customer satisfaction through on-time delivery and more efficient logistics management.

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