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Price Intelligence Using K-Means Clustering and Linear Regression, Case Study of Store Dk Nutritionindo at Tokopedia

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- Abstract: The ability to find the right price recommendation will determine the fate of product sales in the market. This is necessary to prevent whey concentrate products from being sold in the market and to avoid customers fleeing or switching to other competitors. This study uses a price intelligence approach using the k-means clustering method for price grouping based on the closest competitor and demand forecasting using linear regression to determine fair and competitive prices. The results of the k-means clustering price of 145000 from dk nutritionindo are included in C4. The closest competitor has 7 prices cheaper and 5 prices more expensive. The highest price is 495000 and the lowest price is 90000. The results of the 26th month to 33rd month demand forecasting have 2 graphs up and 6 graphs down. Forecasting confusion matrix test produces 62.5% accuracy, 75% precision, 60% recall. With MAPE = 28.95% according to Lewis (1982) then the influence of forecasting is declared feasible (good enough). Because the trend chart illustrates a decline, it is recommended that the shop lowers the price with a recommended price range from 135000 to 90000.
 - **Keywords:** Intelligence Price, K-Means Clustering, Demand Forecasting, Linear Regression, Tokopedia

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1. Introduction

The pandemic occurred in recent years has had a major impact on the world economy. The issues of rapid environmental change insist the companies to adapt more quickly in a new environment called the "New Normal" [1]. Quick response situations are needed by companies all over the world for business adaptation. In a short time the world was forced to be more professional in doing business.

Dk Nutritionindo, which was established in 2009, is a virtual/online-based sales store for fitness supplements in Tokopedia marketplace. Rapid environmental changes and the widespread exodus of traditional businesses to the digital world due to the pandemic have made business competition in the digital world increasingly inevitable, so an adaptation is needed to attract consumers and increase competitiveness.

Adaptation must be fast, efficient, and measurable so that the results will always be relevant to current conditions. The amount of data that was previously unused can now be processed in such a way. It can produce output in the form of insight of useful information to support decisions in the company's business [2]. Example of Examples of such insight can be in the form of competitor price grouping [3] and sales prediction [4] to estimate the right price to design a competitor-based pricing strategy [5]. With focused data, the results will always be relevant to the lastes environmental changes.

2. Theoretical Review

2.1. Price

Price is a measurement of the exchange rate which is equated with money or other goods for the benefits obtained from an item or service for a person or group at a certain time and a certain place [3]. From the consumer's point of view, price is an indicator of the value associated with the perceived benefits of a good or service. Consumers usually compare the ability and quality of an item or service in fulfil their needs [6].

2.2. Pricing Strategy

Every company needs to understand the nature of the market and the demands, one of them is the elasticity of demand [7]. According to Kotler & Armstrong, "how responsive demand will be to a change in price". The number of requests will determine the upper limit of the possible price range for a product. Demand will decrease drastically if the price is too high. This requires a reasonable price range that the company can offer for its products, while costs determine the lower limit. Cost is a factor that determines the minimum price that must be set so that the company does not suffer losses [7].

Based on the discussion of pricing strategies according to consumer psychology [6], a table of recommendations for proceeding is made according to Table 1.

Table 1.	Pricing	Strategy
----------	---------	----------

Act Recom-	
mendation	
Increase the price	
Keep the price	
Keep the price	
Decrease the price	

In Table 1, it is explained that if the results of the demand forecasting graph increase, then there are two choices of recommended action. They are to keep the price or increase the price to enhance the company's profit. If the results of the demand forecasting chart are stable, then the recommended action is to keep the price. If the results of the demand forecasting graph fall, then the recommended action is to lower prices by giving discounts or providing promotional prices to minimize the decline in sales so that sales volume can return to normal.

2.3. Price Intelligence

Price intelligence is a branch of business intelligence [9] which is a business decision support system that focuses on prices, its function is to support pricing decisions. In the price intelligence process there are 5 stages, namely exploration, matching, extraction, data quality assurance, analytics and reporting. The price intelligence process itself refers to the optimization of price determination using the fundamental basis of price techniques and methodologies. It has been determined according to certain market areas to produce insight into price information and have a function to support decisions in pricing strategies in the company [10]. Company managers can apply price intelligence to find the right price and correct deficiencies in implementing pricing strategies, driving higher revenue and reducing the risk of losing customers.

2.4. K-Means Clustering

It is one of the methods in unsupervised machine learning. This method is used to break down and divide one part of the data into several data to produce data grouping based on the similarity of the feature data used in the form of distance and proximity[11]. For example, in the case of the closest competitor grouping. The closest competitor cluster is obtained based on the nature or character approach of the data. Other examples are used for segmentation, grouping by price, grouping competitors, and others. The k-means clustering algorithm can be seen in Figure 1.

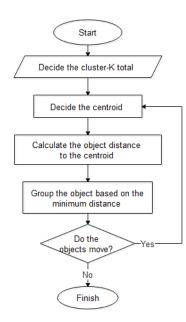


Figure 1. K-means clustering algorithm.

The calculation of the distance from the object to this cluster uses the Euclidean Distance

formula (1).

$$D_e = \sqrt{(x_i - s_i)^2 + (y_i - t_i)^2} \tag{1}$$

Description :

 D_e = Distance, i = The number of objects, x, y = Objects coordinate, s, t = The coordinate of the random centroid point.

2.5. Linear Regression

Linear regression is a supervised machine learning method that creates data predictions based on previous data[12]. This method is often used in forecasting the demand for a product (demand analytics) [13]. An example of BI dashboard usage containing treding deman analitics. The linear regression formlula is found in formula (2).

$$\beta_{i} = \frac{\sum_{i=1}^{n} y_{i} x_{i} - \frac{\left(\sum_{i=1}^{n} y_{i}\right) \left(\sum_{i=1}^{n} x_{i}\right)}{n}}{\sum_{i=1}^{n} X_{i}^{2} - \frac{\left(\sum_{i=1}^{n} x_{i}\right)^{2}}{n}}$$
(2)

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \tag{3}$$

$$y = \beta_0 + \beta_1 x \tag{4}$$

Description :

 β_1 = Coefficient/direction of regression determining forecasting track, β_0 = Constant Value, y = Demand Forecasting, x = Predicted nth period, \bar{y} = Demand Forecasting Average, \bar{y} = Predicted period average, n = Amount of data

3. Methodology and Implementation

3.1. Literature Review

Marwala and Hurwitz stated that price is something fundamental and technical for economic theory [8]. Secapramana examined the problem of effective price placement to maintain the flow of consumer demand. Olga Miroshnichenko solved the price problem by making a price position recommendation concept using data from the Ruukki Rus company [9]. In 2009, Chen, et al. created dynamic price modeling for data mining-based marketplaces [10]. Siburian T et al, carried out the process of grouping the rice prices using k-means clustering which resulted in grouping areas with high, medium, and low rice prices [3]. The book entitled "A Guide to Basic Econometric Techniques" introduces the use of linear regression concepts to describe and create models for the purpose of forecasting demand.

3.2. Equipments and Materials

This study applies the python programming language version 3.7.3, while the compilation tools used are Jupyter lab and PySpark as data processing tools. LibreCalc version 7 is used for storage, data processing, and visualization. The hardware used is an HP brand laptop with AMD A8-7410 processor specifications, Core 4, CPU Clock 1.331 Mhz, 4 GB RAM, Kali Linux 2020-2 64bit operating system. The data which will be used for price grouping applies data on product prices and the location of competitors. It uses the competitors who have similar characteristics and product types with 85 data extracted directly from the Tokopedia website.

No	Price	Store Location
*1	IDR145.000	Yogyakarta
2	IDR 140.000	Jakarta
3	IDR 127.999	Jakarta
4	IDR 140.000	Jakarta
5	IDR 155.000	Kudus
6	IDR 127.000	Jakarta
7	IDR 145.000	Jakarta
83	IDR 169.000	Semarang
84	IDR 90.000	Kendari
85	IDR 110.000	Jakarta Selatan

Table 2. The results of data extraction from Tokopedia

The * row is dk nutrition

To get clean data, pre-processing the data is done. The data for the application of k-means clustering is pre-processed by means of data cleaning, data integration, data transformation, and data normalization. Thus, each variable has the same scale so that the output will be more accurate. The data normalization formula (5) below.

$$x_{new} = \frac{x_{old}}{x_{max}} \tag{5}$$

Description :

 x_{new} = The result of data normalization, x_{old} = Old Data, x_{max} = The data with maximum parameter.

No	Price	Area	
*1	0.11	0.67	
2	$0,\!117$	$0,\!33$	
3	$0,\!10$	$0,\!33$	
4	$0,\!11$	$0,\!33$	
83	$0,\!13$	$0,\!33$	
84	$0,\!07$	$1,\!00$	
85	$0,\!09$	$0,\!33$	

Table 3. The pre-processing data result for k-means

The * row is dk nutrition

While the second data for demand forecasting is sales transaction data for whey concentrate products gained from the internal store of DK Nutritionindo by 25 data in a range of 2016-2018.

		Veen Cel	A 4
	Month	Year Sales	amount
1	January	2016	218
2	February	2016	402
3	March	2016	386
4	April	2016	434
5	May	2016	486
6	June	2016	257
7	July	2016	204
8	August	2016	269
9	September	2016	324
10	October	2016	231
11	November	2016	395
12	December	2016	346
13	January	2017	98
14	February	2017	183
15	March	2017	188
16	April	2017	259
17	May	2017	172
18	June	2017	128
19	July	2017	212
20	August	2017	225
21	September	2017	173
22	October	2017	271
23	November	2017	156
24	December	2017	254
25	January	2018	123

 Table 4.
 Store sales in dk nutritionindo

In data cleaning for demand forecasting, pre-processing is used by means of data cleaning, data integration, and data transformation. The results are as Table 5.

Month	Sales Amount	Month	Sales Amount
1	218	14	183
2	402	15	188
3	386	16	259
4	434	17	172
5	486	18	128
6	257	19	212
7	204	20	225
8	269	21	173
9	324	22	271
10	231	23	156
11	395	24	254
12	346	25	123
13	98		

Table 5. The pre-processing data result for linear regression

3.3. Design Stages

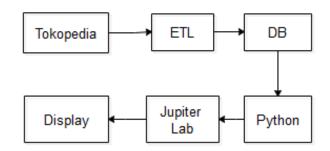


Figure 2. The design of architecture system

At this stage, the design for the system architecture is carried out. The stages of system architecture design consist of 6 stages, namely:

- 1. Retrieve data from the website www.tokopedia.com.
- 2. Process the ETL according to the data requirements.

- 3. Save to the database.
- 4. Use Phyton as a programming language.
- 5. Use Jupyter lab to process data.
- 6. Display the output as the insight.

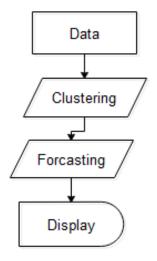


Figure 3. Process Design

For the design stage, this process is carried out in 4 stages according to Figure 5, namely:

- 1. Retrieve the data.
- 2. Do clustering the data.
- 3. Do forecasting the data.
- 4. Present analytic result.

3.4. Implementation Stage

The implementation of price intelligence has several stages. They are the stages of data discovery, reporting, and analytics. In this study, review was performed and the stages were divided into 6 stages. An explanation in the form of an image can be seen in Figure 4.

Arma Fauzi , Bambang Purnomosidi DP, Faizal Makhrus, and Widyastuti Andriyani

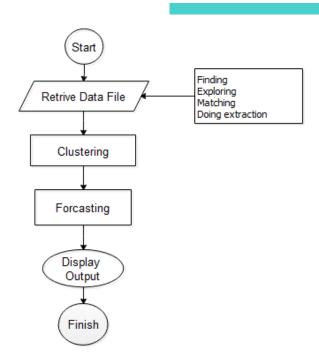


Figure 4. Price Intelligence Stages

There are six stages in Price Intelligence Staged, as follows :

- 1. Start.
- 2. Retrieve the Data.
- 3. Clustering by k-means.
- 4. Demand forecasting by linear regression.
- 5. Present the result.
- 6. Finish.

4. Results and Discussion

4.1. Price Grouping Using K-Means

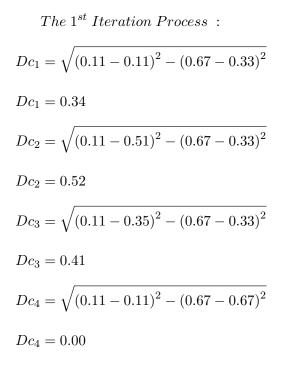
4.1.1. Clustering

Stage 1 in grouping data using k-means, it takes a centroid point. This study declares the centroid point into 4 points which are summarized in Table 6.

Cluster	No	Price	Store Location
c1	2	0,11	0,33
c2	18	$0,\!51$	$0,\!33$
c3	22	$0,\!35$	$0,\!33$
c4	28	$0,\!11$	$0,\!67$

Table 6.Centroid Point

Stage 2 is calculating the distance of the object to the centroid point using the Euclidean Distance formula. This 1st iteration process is used to find dc1, dc2, dc3, dc4.



Stage 3 repeats the distance calculation process again from the 2^{nd} data to the 85^{th} data until it is completed. The results of iteration-1 are summarized in Table 4.1.1.

No	Dc1	Dc2	Dc3 Dc4	
1	0,34	$0,\!52$	0,41	0,00
2	0,00	$0,\!41$	$0,\!24$	0,33
3	$0,\!01$	$0,\!41$	$0,\!25$	0,33
4	0,00	$0,\!41$	$0,\!24$	0,33
83	$0,\!02$	$0,\!38$	$0,\!22$	$0,\!33$
84	$0,\!67$	0,80	0,72	0,34
85	$0,\!02$	$0,\!43$	$0,\!27$	0,33

Table 7.	The 1^{st}	Iteration
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In step 4 after the distance calculation process is accomplished, the distance between the

data is calculated. The data that has the shortest distance are grouped according to their respective clusters. The results of the shortest distance cluster can be seen in Table 8.

No	Dc1	Dc2	Dc3	Dc4	Shortest Distance	Cluster
1	0,34	$0,\!52$	0,41	0,01	0,01	4
2	0,00	$0,\!41$	$0,\!24$	$0,\!33$	0,00	1
3	$0,\!01$	$0,\!41$	$0,\!25$	$0,\!33$	0,01	1
4	0,00	$0,\!41$	0,24	0,33	0,00	1
83	$0,\!02$	$0,\!38$	$0,\!22$	$0,\!33$	0,02	1
84	$0,\!67$	$0,\!80$	$0,\!72$	$0,\!34$	$0,\!34$	4
85	$0,\!02$	0,43	0,27	0,33	$0,\!02$	1

 Table 8.
 The Shortest Distance Result

In the step 5, if the data distance changes, then repeat steps 3 to step 5 using the new centroid of the average iteration distance until no more centroid changes. If the distance of the data in each cluster has not changed, then the clustering process is accomplished. The results of member clustering can be seen in Table 9.

Table 9. The results of member clustering.

Cluster	Members	Total
C1	2, 3, 4, 6, 7, 8, 9, 10, 13, 14, 15, 16,	45
	17,19,20,21,24,25,26,29,31,34,	
	37, 39, 40, 41, 42, 43, 44, 46, 48, 49,	
	50, 53, 56, 58, 60, 63, 66, 69, 70, 72,	
	79, 83, 85.	
C2	18,23,27,30,35,36,55,62,64,67,	13
	77, 80, 82.	
C3	22,32,38,47,51,52,57,59,61,65,	14
	68, 73, 75, 76.	
C4	$1,\ 5,\ 11,\ 12,\ 28,\ 33,\ 45,\ 54,\ 71,\ 74,$	13
	78, 81, 84.	

Cluster	Members	Total
C1	76000, 85000, 89000, 93000, 93000,	45
	95000, 98000, 99000, 99000, 99000,	
	99000, 99000, 110000, 110000,	
	110000, 110000, 110000, 110000,	
	115000, 115000, 115000, 115000,	
	115000, 125000, 127000, 127999,	
	135000, 140000, 140000, 140000,	
	140000, 145000, 145000, 155000,	
	169000, 200000, 212500, 215000,	
	225000, 225000, 230000, 240000,	
	250000, 290000, 299000.	
C2	650000, 650000, 650000, 650000,	13
	660000, 675000, 675000, 700000,	
	720000, 880000, 880000, 920000,	
	1282500.	
C3	315000, 450000, 485000, 490000,	14
	493000, 495000, 495000, 495000,	
	495000, 495000, 495000, 495000,	
	495000, 620000.	
C4	90000, 93000, 98000, 99000, 115000,	13
	125000, 135000, 145000 , 147000,	
	155000, 290000, 495000, 495000.	

Table 10. The result of price clustering.

Based on Table 9 and Table 10, it can be concluded that Store Dk Nutritiondo is included in cluster C4 where the cluster has 13 members.

Validation The validation for clustering is executed by comparing the results of manual calculations with the results using tools, namely librecalc and pyspark. The results of clustering validation can be seen in Table 11.

No.	Clustering Result			Validation		
110.	Manual	Libre Calc	Pyspark	Appropriate	Inappropriate	
*1	4	4	4		-	
2	1	1	1		-	
3	1	1	1	\checkmark	-	
4	1	1	1		-	
5	1	1	1	\checkmark	-	
84	4	4	4	\checkmark	-	
85	1	1	1		-	
Total	85	85	85	85	0	

Table 11. Validation

From the results of the validation on Table 10, the result is in 100% appropriate and 0% inappropriate. It can be concluded that the process and results of clustering using k-means are appropriate and feasible to apply.

4.2. Forecasting Demand Using Linear Regression

4.2.1. Linear Regression

Based on the distribution procedure on the training data and test data of 70% and 30%, this study will predict 30% of the data in the next 8 months using a 12-month regression model. The method is to do a forecast for the 26^{th} month, then repeat the forecast from the 27^{th} month to the 33^{rd} month.

$$\beta_{1} = \frac{45693 - \frac{2344*234}{12}}{4706 - \frac{234^{2}}{12}}$$

$$\beta_{1} = \frac{-72}{143}$$

$$\beta_{1} = -0.50$$

$$then \beta_{1} is - 0.50$$

$$\beta_{0} = \bar{y} - \beta_{1}\bar{x}$$

$$\beta_{0} = 195 - (-0.50(20))$$

$$\beta_{0} = 205$$

$$thus \beta_{0} is 205$$

$$y = \beta_{0} + \beta_{1}x$$

$$y = 205 + (-0.50(26))$$

$$y = 192$$

$$ANd so y is 192$$

After forecasting using a 12-month period regression, 192 results were obtained for sales in the 26th month. To get the forecasting results for the 27^{th} month to the 33^{rd} month, then repeat the previous steps by doing a forecast from the 27^{th} month to the 33^{rd} month so the result is similar to Table 12.

No	Month -	Month	Demand	Graphic
	25	January	123	-
1	26	February	192	upward
2	27	March	188	downward
3	28	April	184	downward
4	29	May	193	upward
5	30	June	191	downward
6	31 July		177	downward
7	32	August	174	downward
8	33 September		173	downward
	Crophic d	inaction	upward	2
	Graphic d	irrection	downward	6

Table 12. The forecasting results in the next 8 month

From Table 12, there are forecasting of decline in sales as 6 times. It happened in March, April, June, July, August, and September. Moreover, there was an increase in sales about 2 times in February and May. The confusion matrix test is illustrated in Table 13, 14, 15.

4.2.2. Confusion Matrix Test

Month	Actual Graphic	Forecasting Graphic	Accuracy
18	downward	downward	right
19	upward	downward	wrong
20	upward	upward	right
21	downward	upward	wrong
22	upward	upward	right
23	downward	upward	wrong
24	upward	upward	right
25	downward	downward	right

Table 13. The forecasting result in the next 8 months

Output	Forecasting					
	Graphic	Upward	Downward	Actual Total		
Actual	Upward	3	2	5		
Actual	Downward	1	2	3		
	Forecasting Total	4	4	8		

 Table 14.
 Confusion Matrix

 Table 15.
 Confusion Matrix Result

Value					
Acuracy	62,5%				
Precise	75%				
Recall	60%				

4.2.3. MAPE Test

The 12-month regression validation test was assessed using MAPE. MAPE (Mean Absolute Percentage Error) is a relative error measurement whose function is to determine the percentage deviation or error from the forecasting results. The smaller the MAPE result, the smaller the forecast error. The MAPE value is an absolute value, meaning that the MAPE value will always be positive.

$$MAPE = \sum_{i=1} \left| \frac{A_i - F_i}{A - i} \right| \times 100\%$$
(6)

Description :

 $\mathrm{MAPE}=\mathrm{Mean}$ Absolute Percentage Error, $A_i=\mathrm{Actual}$ data total, $F_i=\mathrm{Forecast}$ data total

$$MAPE = \frac{128 - 159}{128} \times 100\%$$
$$MAPE = \frac{-31}{128} \times 100\%$$
$$MAPE = -0.2422 \times 100\%$$
$$MAPE = 24.22\%$$

The results presented above are the results of the values in the first validation column using data starting from month 18. For columns 2-8, do the same calculations using data 19-25, then explore the average value by adding up all MAPE results and then dividing total amount of test data. MAPE test results can be observed in Table 16.

No	Actual	Forecast	MAPE
18	128	159	24.22%
19	212	146	31.13%
20	225	150	33.33%
21	173	151	12.72%
22	271	172	36.53%
23	156	187	19.87%
24	254	236	7.09%
25	123	205	66.67%
Av	erage o	28.95%	

Table 16.The average of MAPE

According to Lewis (1982) [17], as shown in Table 16 stated that, If MAPE $\leq 10\%$ then the forecasting result is very accurate If MAPE > 10% - 20% then the forecasting result is good If MAPE > 20% - 50% then the forecasting result is feasible (good enough) If MAPE > 50% then the forecasting result is very weak/inaccurate

MAPE	Forecasting Power
$\leq 10\%$	Very accure
${>}10\%$ - 20%	Good
*>20% - 50%	Feasible (good enough)
> 50%	weak / inacurate

Table 17. Forecasting Power Table

Because the MAPE value is 28.95%, the forecasting power is declared feasible (good enough).

4.3. Data Visualization

Data visualization is a representation of information and data in the form of tables, graphs, pictures, and so on. In other words, data visualization will clarify the information presented to make it more efficient and easier to understand. Reporting or data visualization in this study include:

4.3.1. The closest competitor table.

The	The Closest Competitor Price Cluster (C4)						
No	Member	Price	No	Member	Price		
1	84	90000	8	1	145000		
2	11	93000	9	74	147000		
3	12	98000	10	5	155000		
4	81	99000	11	78	290000		
5	71	115000	12	33	495000		
6	54	125000	13	45	495000		
7	28	135000					

 Table 18.
 The closest competitor price cluster.

4.3.2. The closest competitor table in lower price.

Ine	Inexpensive Closest Competitor Cluster						
No	Member	Price	No	Member	Price		
1	84	90000	5	71	115000		
2	11	93000	6	54	125000		
3	12	98000	7	28	135000		
4	81	99000					

Table 19. Inexpensive Closest Competitor Cluster.

4.3.3. The closest competitor table in higher price

Exp	Expensive Closest Competitor Cluster							
No	Member	Price	No	Member	Price			
9	74	147000	12	33	495000			
10	5	155000	13	45	495000			
11	78	290000						

Table 20. Expensive Closest Competitor Cluster

4.3.4. The closest competitor price bar chart



Figure 5. Closest competitor price bar chart.

4.3.5. Demand Forecasting Graph

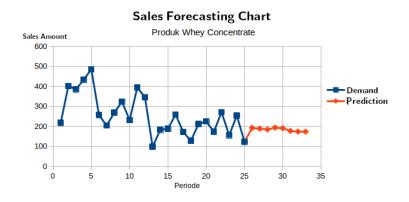


Figure 6. Demand Forecasting Graph

4.3.6. Action recommendation

 Table 21.
 Action Recomendation

Trend Graph Direction	Action Recommendation
Downward	Lower the price

4.3.7. Price Recommendation

 Table 22.
 Price Recommendation

No	Price Recommendation
1	135000
2	125000
3	115000
4	99000
5	98000
6	93000
7	90000

5. Conclusions and Suggestions

This research develops the price intelligence with the results of k-means clustering of 4 competitor clusters. The Dk nutritionindo store applies the price of 145000 to enter cluster-4. The closest competitor has 7 prices cheaper and 5 prices more expensive. The highest price of the closest competitor is 495000 and the lowest price is 90000. The results of the 26th month to 33rd month demand forecast have 2 graphs up and 6 graphs down. The average percentage of absolute error (MAPE) is 28.95% so that the power of forecasting is declared feasible (good enough) according to Lewis (1982) [17]. Because the demand trend chart illustrates a decline, the store is advised to lower the price with a recommended price range from 135000 to 90000. Suggestions from the author for further researchers are as follows:

- a By changing several methods such as Trend Moment, Bayesian, Facebook Prophet, and others, it is possible that the research results will more preferable and more accurate.
- b To examine the level of system performance deeper, the process of training and testing data can be improved with other variables or criteria.
- c The preparation and pre-processing of data should be automatically so that the extraction can be faster and more accurate.
- d The selection of the cluster center point is still random, it is expected that further research can apply other methods which are more accurate.

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