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To cite this article: Zulkarnain Lubis et al 2020 IOP Conf. Ser.: Mater. Sci. Eng. 725 012133

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Optimization of K Value at the K-NN algorithm in clustering using the expectation maximization algorithm

Zulkarnain Lubis^{1,*}, Poltak Sihombing², Herman Mawengkang²

¹Graduate School of Computer Science

zulkarnainlb@gmail.com

Abstract. Data is the most important thing in a study. The quality of the results of the research will be directly proportional to the quality of the data that will be used in the research is concerned. One of the problems that exist in the data set is the absence of a value in the data for a particular attribute or better known as the missing data. One method that is often used by researchers is the k-nearst Neighbor (KNN). However, this method has several drawbacks, one of which is the selection of appropriate values of k not to degrade the performance of the classification. In the process of calculating the parameters k KNN there that can affect the accuracy of the classification results. To use more than one parameter k then used by majority voting to determine the classification results. If the parameter k in KNN classification used 1 then the result was very tight because it will use the nearest neighbor to the results of the classification. Conversely, if the value of the parameter k used KNN is great then the classification results will blur. This research will optimize the parameters k in the UN tax cluster using the algorithmexpectation Maximation(EM). The results of the research in the form of clustering information by using the number of clusters k value optimization and the number of clusters without using the optimization of the value k. Then analysis the results after getting data already clustered. Results from the study showed that k obtained from the optimization algorithm can improve the results of the cluster where the 66% error can be reduced to 64%, yet very close to the best result of the measurement accuracy is tested.

1. Introduction

One way to classify the data is by using Clustering. Data grouping or clustering is a method used to classify into groups or clusters based on similarity, so that related data is placed in the same cluster. There are several clustering algorithms known ie partitional (Expectation-maximization, K-Means) and hierarchical (Centroid Linkage, Single Linkage), overlapping (Fuzzy C-Means) and hybrid. The algorithm can overcome the arbitrary grouping are partitional algorithm. Where in partitional algorithm, a document can be a member of a group or cluster to a process but the subsequent processes such documents can be moved to another cluster. One partitional algorithm that can group documents that have not been labeled is Expectation-Maximization, the algorithm used to find the value of Maximum Likelihood estimation of parameters in a probabilistic model. The characteristics of this algorithm is able to classify the data that has not been labeled or unlabeled data and also the results of the classification will always convergence. This algorithm has two phases: phase and phase Expectation Maximization.

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²Department of Information Technology, Faculty of Computer Science and Information Technology, University of North Sumatra, Medan, Indonesia

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In Expectation step (E-step) use the EM algorithm - Cluster for classifying data based on the model parameters. While on the Maximization step (M-step) will be done peng updates of the model parameters by using Multiple Linear Regression. Phase E-step and M-step is continued until the probability of each cluster achieve convergence. Before performing the necessary process of grouping data pre-processing, namely cleansing, tokenizing, parsing. Labeling of a cluster is done by finding the most actual label appears on a Cluster, and then adopt the label as the label Cluster. With the implementation of the EM algorithm - Cluster in the process of budget clusterisasi it can classify and determine the appropriate number of clusters,

2. Stages of Data Mining

Data mining is actually a part of the process of Knowledge Discovery in Databases (KDD), not as a technology intact and independent. Data mining is an important part of steps in the process of KDD primarily concerned with the extraction and calculation of the data patterns are analyzed, as shown by Figure 1 below:

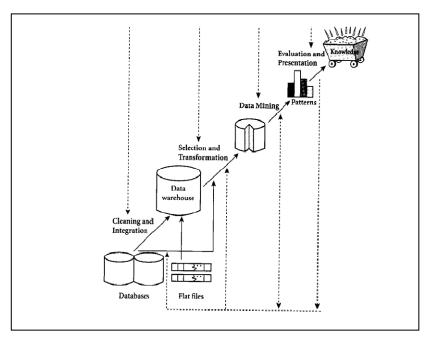


Figure 1. Stages in the process of knowledge discovery

a. Data cleaning

To eliminate the data noise (irrelevant data / dealing directly with the ultimate goal of data mining process, eg data mining that aims to analyze the results of the sale, then the data in the collection as "employee name", "age", and so on can -ignore) and inconsistent.

- b. Data integration
 - To combine multiple data sources.
- c. Data selection
 - To retrieve the appropriate data for analysis.
- d. Data transformation
 - To transform data into a form more suitable for mining. Data mining is the most important process in which a particular method is applied to generate the data pattern.

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e. Pattern evaluation

To identify whether interenting patterns obtained is sufficient to represent knowledge based on specific calculations.

f. Knowledge presentation

To present the knowledge that has been obtained from the user.

2.1 Method of KNN (K-Nearest Neighbor)

The working principle of the K-Nearest Neighbor (KNN) is seeking the shortest distance between the data to be evaluated by K neighbors (neighbor) closest to the training data. This technique is included in the nonparametric classification groups. Here we do not pay attention to the distribution of the data to be grouped. This technique is very simple and easy to implement. Similar to clustering techniques, we classify a new data based on the distance the new data into multiple data / neighbor (neighbor) nearby.

KNN algorithm purpose is to classify the new objects based on attributes and sample training. Clasifier not use any model to be matched and only based on memory. Given query point, will find a number of objects or k (training points) closest to the query point. Classification using the voting majority among the classification of k objects. KNN classification algorithm uses adjacency as the predicted value of the new query instance. Algorithm KNN method is simple, operates on the shortest distance from the query instance to the training sample to determine its KNN.

K best value for this algorithm depends on the data. In general, a high k value will reduce the effect of noise on klsifikasi, but draw the line between each classification is becoming increasingly blurred. Nice k value can be selected by optimization of parameters, for example by using cross-validation. The special case where the classification is based on the training data diprekdisikan closest (in other words, k = 1) is called Nearest Neighbor algorithm. excess KNN (*K-Nearest Neighbor*):

- 1. Resilient to training data that has a lot of noise.
- 2. Effective if training data is huge.

The weakness of KNN (*K-Nearest Neighbor*):

- 1. KNN need to determine the value of the parameter k (the number of nearest neighbors).
- 2. Training based on distance is not clear on what kind of distance that must be used.
- 3. Which attributes should be used to get the best results.
- 4. The computational cost is high because the necessary calculation of the distance of each query instance in the whole training sample.

2.2 KNN algorithm

- 1. Determine the parameter K
- 2. Calculate the distance between the data to be evaluated with all the training
- 3. Sort range formed (ascending)
- 4. Determine the shortest distance to the order of K
- 5. Pair the corresponding class
- 6. Find the number of classes from the nearest neighbor and set the class as a class data to be evaluated

KNN formula:

$$d_i = \sqrt{\sum_{i=1}^{p} (x_{2i} - x_{1i})^2} \dots 1$$

Information:

 $x_1 =$ Sample Data

 $x_2 = \text{Data Test} / \text{Testing}$

i = Variable Data

d = Distance formed

p = Dimension Data

Below is a flowchart of the method KNN:

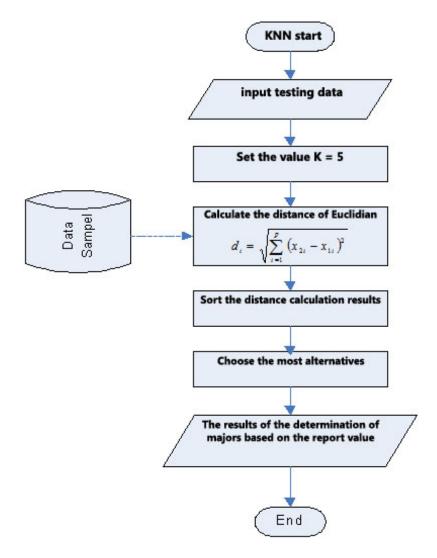


Figure 2. Flowchart of KNN Method

3. Methodology

Broadly speaking, the stages in this study is illustrated in Figure 3.

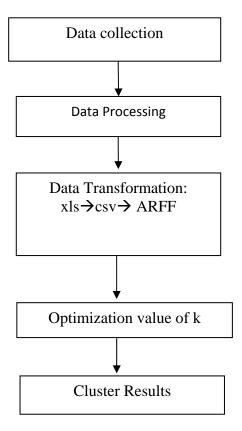


Figure 3. Block diagram of the stages of research

Figure 3 above is a research methodology that will be done by the author. The research methodology aims to outline all the activities carried out during the course of the study. From the picture above, it is known that there are three stages to be done to resolve the case at this research that includes: data collection, pre-process the data, data transformation, optimization of the value of k and cluster results. The preparation process includes three main things:

3.1 Data Selection

Select the data that will be used in the data mining process. In the process of the election is done also attributes that are tailored to the data mining process. In this study, the data used is in the form of data-ready, meaning that the data obtained has been the form of the target data. At this stage the problem to be faced is noisy data and missing values. Data cleaning process pelu done to clean data from duplicate data, the data is inconsistent, or typographical errors. So the data that has been through this process are ready to be processed in data mining. In this study, the data used is data that has been consistent, so that the data cleansing process is only performed on any data missing value.

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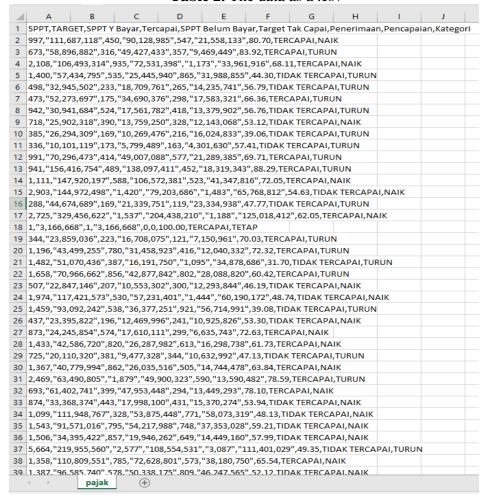
2 SPPT TARGET SPPT Belum Bayar | Target Tak Capai | Penerimaan | Pencapaian SPPT Y Bayar | Tercapai Kategori 997 111.687.118 90.128.985 21.558.133 NAIK 450 547 673 58.896.882 316 49.427.433 357 9,469,449 83,92 TERCAPAI TURUN 2.108 106,493,314 935 72.531.398 1.173 33.961.916 68,11 TERCAPAL NAIK 1.400 31.988.855 6 57,434,795 535 25,445,940 865 44.30 TIDAK TERCAPAI TURUN 498 32.945.502 233 18.709.761 265 14.235.741 56,79 TIDAK TERCAPAI TURUN 8 473 52.273.697 175 34.690.376 298 17.583.321 66,36 TERCAPAI TURUN 9 942 30.941.684 524 17.561.782 418 13.379.902 56,76 TIDAK TERCAPAI 10 718 25.902.318 390 13.759.250 328 12.143.068 53,12 TIDAK TERCAPAI 11 385 26.294.309 10.269.476 16.024.833 39,06 TIDAK TERCAPAI TURUN 169 216 12 336 10.101.119 173 5,799,489 163 4,301,630 57.41 TIDAK TERCAPAL TURUN 13 991 70.296.473 414 49.007.088 577 21.289.385 69.71 TERCAPAL TURUN 941 156.416.754 489 138.097.411 452 18.319.343 88,29 TERCAPAI TURUN 15 1.111 147.920.197 106.572.381 41.347.816 588 523 72.05 TERCAPAI NAIK 16 2,903 144.972.498 1.420 79.203.686 1.483 65.768.812 54,63 TIDAK TERCAPAI NAIK 17 288 44.674.689 169 21.339.751 119 23.334.938 47,77 TIDAK TERCAPAI TURUN 2.725 18 329,456,622 1.537 204,438,210 1.188 125,018,412 62.05 TERCAPAL NAIK 19 3.166.668 3.166.668 100,00 TERCAPAI TETAP 20 344 23.859.036 223 16.708.075 121 7.150.961 70,03 TERCAPAL TURUN 21 1.196 43,499,255 780 31.458.923 416 12,040,332 72.32 TERCAPAI 22 1.482 51.070.436 387 16.191.750 1.095 34.878.686 31,70 TIDAK TERCAPA 23 1.658 70,966,662 856 42.877.842 802 28.088.820 60,42 TERCAPAL TURUN 46,19 TIDAK TERCAPAI 22.847.146 10.553.302 24 507 207 300 12.293.844 NAIK 117.421.573 57.231.401 1.444 25 1.974 60,190,172 48.74 TIDAK TERCAPAI NAIK 530 26 1.459 93.092.242 538 36.377.251 921 56.714.991 39,08 TIDAK TERCAPAI TURUN 27 23,395,822 12,469,996 10.925.826 53.30 TIDAK TERCAPAI 28 873 24.245.854 574 17.610.111 299 6.635,743 72,63 TERCAPAI NAIK 29 1.433 42,586,720 820 26,287,982 613 16,298,738 61.73 TERCAPAL NAIK 9.477.328 10.632.992 47,13 TIDAK TERCAPAI TURUN 30 725 20.110.320 381 344 1.367 40.779.994 862 26.035.516 14.744.478 63,84 TERCAPAI 31 505 NAIK 32 2.469 63.490.805 1.879 49.900.323 590 13.590.482 78,59 TERCAPAI TURUN 33 693 61.402.741 399 47.953.448 294 13.449.293 78,10 TERCAPAI NAIK 34 874 33.368.374 443 17.998.100 431 15.370.274 53,94 TIDAK TERCAPAI NAIK 35 1.099 111.948.767 328 53.875.448 771 58.073.319 48,13 TIDAK TERCAPAI 1.543 91,571,016 795 54.217.988 748 37.353.028 59,21 TIDAK TERCAPAI 36 NAIK 37 1,506 34.395.422 857 19,946,262 649 14,449,160 57.99 TIDAK TERCAPAI NAIK 5.664 219.955.560 2.577 108.554.531 3.087 111.401.029 49,35 TIDAK TERCAPAI TURUN 38 1.358 110.809.551 785 72,628,801 38.180.750 65.54 TERCAPAI Sheet1 Sheet3

Table 1. The data in excel format

3.2 Data transformation

This study procedures carried out as in figure 3.1, namely, the data obtained from the database of the UN tax revenue Deli Serdang. Data will be modified. Data in the form of Excel 2016 spreadsheet files (.xls) as input to the Weka open source software. Before the data is transformed into ARFF, the data is converted first into the .csv format. Weka transform data from .csv be ARFF. The result of the transformation is preliminary data that will be used for optimization prosesn with k values. The results of the data transformation xls, csv, ARFF can be seen in the picture below.

Table 2. The data as a .csv



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pajak.arff Relation: pajak No. 1: SPPT 2: TARGET 3: SPPT Y Bayar 4: Tercapai 5: SPPT Belum Bayar 6: Target Tak Capai 7: Penerimaan 8: Pencapaian 9: Kategori 111,687... 450.0 90.128.... 547.0 21.558.133 80.7 TERCAPAI NAIK 83.92 TERCAPAI 58.896.... 316.0 49.427.... 357.0 9.469.449 TURUN 2,108 106,493... 935 0 72 531 1 173 33 961 916 68 11 **TERCAPAI** NAIK TURUN 57.434 535.0 25 445 865.0 31.988.855 44.3 TIDAKTER 1.400 32,945,... 265.0 5 498.0 233.0 18.709... 14.235.741 56.79 TIDAK TER... TURUN 473.0 52,273, 175.0 34.690... 298.0 17.583.321 66.36 **TERCAPAI** TURUN 942.0 30,941,. 524.0 17,561,... 418.0 13,379,902 56.76 TIDAKTER. TURUN 718.0 25.902... 390.0 13.759... 328.0 12.143.068 53.12 TIDAK TER.. 39.06 TIDAK TER.. 385.0 26.294.... 169 0 10,269,. 216.0 16,024,833 TURUN 10 336.0 5.799,489 57.41 TIDAK TER.. 10.101.... 173.0 163.0 4.301.630 TURUN 11 9910 70 296 4140 49 007 577 0 21,289,385 69.71 TERCAPAL TURUN 12 941.0 156,416... 489.0 138.097 452.0 18,319,343 88.29 TERCAPAL TURUN 588.0 106,572... 523.0 41,347,816 72.05 **TERCAPAI** 13 1,111 147,920... NAIK 14 2.903 144.972... 1.420 79.203.... 65.768.812 54.63 TIDAK TER. 15 288.0 44,674,... 21,339,... 119.0 23,334,938 47.77 TIDAK TER.. TURUN 169.0 16 2.725 329.456... 1.537 204.438... 1.188 125.018.412 62.05 TERCAPAI NAIK 17 10 3 166 668 1 0 3 166 668 0 0 0.0 100.0 TERCAPAL TETAP 18 344.0 23.859.... 223.0 16.708.... 121.0 7.150.961 70.03 **TERCAPAI** TURUN 31,458,... 12,040,332 72.32 TERCAPAI TURUN 19 1,196 43,499.... 780.0 416.0 20 1,482 51.070.... 387.0 16.191... 1.095 34.878.686 31.7 TIDAK TER. TURUN 802.0 60.42 TERCAPAI 21 1,658 70,966,... 856.0 42,877,... 28,088,820 TURUN 22 507.0 10.553... 300.0 22.847... 207.0 12.293.844 46.19 TIDAK TER. NAIK 23 1.974 117 421 530.0 57 231 1 444 60.190.172 48 74 TIDAK TER NAIK 93,092,... 24 1,459 538.0 36.377. 921.0 56.714.991 39.08 TIDAKTER.. TURUN 25 437.0 23,395 196.0 12,469,. 241.0 10,925,826 53.3 TIDAKTER. NAIK 26 873.0 24.245.... 574.0 17.610.... 299.0 6.635.743 72.63 TERCAPAI TERCAPAI 1,433 42,586,... 820.0 26,287... 613.0 16,298,738 61.73 NAIK 27 28 725.0 20.110.... 9.477.328 344.0 47.13 TIDAK TER. TURUN 381.0 10.632.992 29 1,367 40 779 862 0 26 035 505.0 14.744.478 63.84 TERCAPAL NAIK 30 2.469 63,490. 1.879 49.900. 590.0 13.590.482 78.59 TERCAPAL TURUN 31 693.0 399.0 47,953,. 13,449,293 78.1 TERCAPAI 61.402.... 294 0 NAIK 32 874.0 33.368.. 443.0 17.998... 431.0 15.370.274 53.94 TIDAK TER.. NAIK 33 1.099 111.948... 328.0 53.875.... 771.0 58.073.319 48.13 TIDAK TER... 795.0 54.217 748.0 NAIK 34 1.543 91.571... 37.353.028 59.21 TIDAK TER 35 1.506 34.395 857.0 19.946. 649.0 14.449.160 57.99 TIDAK TER... NAIK 36 5.664 219.955. 2.577 108.554... 3.087 111,401,029 49.35 TIDAK TER. TURUN 1,358 110,809.. 785.0 72,628, 573.0 38,180,750 65.54 **TERCAPAI** NAIK 38 1,387 96.585.... 578.0 50.338. 809.0 46.247.565 52.12 TIDAK TER... NAIK 16,045,. 173.0 5.071.953 75.98 TERCAPAI

Table 3. The data in ARFF format

3.3 Optimization Rated K

k-Nearest Neightbor (KNN) is a method using supervised algorithms where the results of the new query instance is classified based on the majority of categories on KNN. The purpose of this algorithm is to classify a new object attributes and training Based on the sample. Classifier does not use any model to be matched and only based on memory. Given query point, will find a number of objects or K (training points) closest to the query point.

3.4 Expectation Maximization Clustering

Expectation maximization algorithm is an algorithm unsupservised learning that has the ability to perform searches darisekumpulan knowledge of data that do not have labels or targets a particular class, by seeingthe value of any instances distributed into the Gaussian distribution, more tepatnyaadalah Gaussian mixture, then do iterations ascending to seek the highest likelihood value for each instance (see proximity to each cluster instances). Expectation Maximization algorithm (EM algorithm) is an algorithm that utilizes the mixture of Gaussian mixture.

Basically EM algorithm consists of two steps, ie, expectation and maximization. Calculating expektasi to a likelihood probability value, then the second step of fixing the value of the probability of the stretcher by changing parameters on Gaussian mixture so as to achieve maximum likelihood. There some things that need to be emphasized in the EM algorithm Algorithm namely:

- 1. Maximum Likelihood Estimation (MLE)
- 2. Mixtures of Gaussians
- **3.** Estimation-Maximization (EM)

But the EM algorithm using Gaussian mixture or words of a Gaussian lainlebih used or seeking mixture of yangdidapatkan distribution. EM Algorithm has the task of finding each Gaussian yangterdapat on Gaussian mixture distribution and develop each Gaussian yangditemukan at the optimum condition (so the model is more fit) that's called maximization, and the clustering process.

3.5. Interpretation / Evaluation

At this stage of the evaluation and interpretation of the patterns obtained based on the results of clustering data using EM-cluster method. If the results obtained are not appropriate, then the process would be repeated to the stage of the clustering process data. Knowledge of this stage is the final part of the KDD process where possible to investigate whether a pattern or information found in conflict with the facts. Pattern information generated from the data mining process should be presented in a form easily understood by the parties concerned.

4. Result and Discussion

Furthermore, from the data of the parameter with a k-nn algorithm, the data in the pull to get the Weka application cluster also using two parts of the cluster with no parameters and cluster k-nn-nn with parameter k. Both parts are in the cluster by using an algorithm *expectation Maximization* (EM). This algorithm is already available in Weka and can be directly used. The output from these two different parts and will be compared. For the results of the cluster with no parameters can be viewed as in Table 4.

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Table 4. Cluster results with the original data

			1	abic 4.	Jusici	i i courto wi	ui uie origii	iai uai	а		
hs-1.arff	hs-2.arff										
	jak_clustered		2: TADOET	4: CDDT V Daver	E: Taraanai	6: CDDT Dalum Daver	7: Torget Tak Consi 0:	Danarimaan	O: Densension	40: Katagori	44: Chater
	Ince_number Numeric	Nominal	Nominal	Nominal	Nominal	Nominal	7: Target Tak Capai 8: Nominal	Numeric	Nominal	Nominal	Nominal
1		997.0	111,687		90,128,	547.0	21,558,133		TERCAPAI	NAIK	cluster4
2	1.0	673.0	58,896,	316.0	49,427,	357.0	9,469,449		TERCAPAI	TURUN	cluster4
3	2.0	2,108	106,493	935.0	72,531,	1,173	33,961,916	68.11	TERCAPAI	NAIK	cluster10
4	3.0	1,400	57,434,	535.0	25,445,	865.0	31,988,855	44.3	TIDAK TER	TURUN	cluster2
5	4.0	498.0	32,945,	233.0	18,709,	265.0	14,235,741	56.79	TIDAK TER	TURUN	cluster3
6	5.0	473.0		175.0	34,690,	298.0	17,583,321		TERCAPAI	TURUN	cluster10
7	6.0	942.0	30,941,		17,561,	418.0	13,379,902	56.76	TIDAK TER	TURUN	cluster3
8	7.0	718.0	25,902,	390.0	13,759,	328.0	12,143,068		TIDAK TER	NAIK	cluster0
9	8.0	385.0	26,294,	169.0	10,269,	216.0	16,024,833		TIDAK TER	TURUN	cluster2
10	9.0	336.0	10,101,			163.0	4,301,630		TIDAK TER	TURUN	cluster3
11 12	10.0	991.0 941.0	70,296, 156,416		49,007, 138,097	577.0	21,289,385	69.71	TERCAPAI TERCAPAI	TURUN	cluster10
13	12.0		147,920		106,572		18,319,343 41,347,816		TERCAPAI	NAIK	cluster7 cluster9
14	13.0		144,972		79,203,	1,483	65,768,812		TIDAK TER	NAIK	cluster0
15	14.0		44,674		21,339,	119.0	23,334,938		TIDAK TER	TURUN	cluster6
16	15.0		329,456		204,438	1,188	125,018,412		TERCAPAI	NAIK	cluster10
17	16.0	1.0	3,166,668		3,166,668	0.0	0.0		TERCAPAI	TETAP	cluster1
18	17.0	344.0	23,859,	223.0	16,708,	121.0	7,150,961		TERCAPAI	TURUN	cluster10
19	18.0	1,196	43,499,	780.0	31,458,	416.0	12,040,332		TERCAPAI	TURUN	cluster9
20	19.0	1,482	51,070,	387.0	16,191,	1,095	34,878,686	31.7	TIDAK TER	TURUN	cluster2
21	20.0	1,658	70,966,	856.0	42,877,	802.0	28,088,820	60.42	TERCAPAI	TURUN	cluster10
22	21.0	507.0	22,847,	207.0	10,553,	300.0	12,293,844	46.19	TIDAK TER	NAIK	cluster6
23	22.0	1,974	117,421		57,231,	1,444	60,190,172	48.74	TIDAK TER	NAIK	cluster6
24		1,459	93,092,		36,377,	921.0	56,714,991	39.08	TIDAK TER	TURUN	cluster2
25	24.0	437.0	23,395,	196.0	12,469,	241.0	10,925,826	53.3	TIDAK TER	NAIK	cluster0
26		873.0	24,245,	574.0	17,610,	299.0	6,635,743		TERCAPAI	NAIK	cluster9
27	26.0		42,586,	820.0	26,287,	613.0	16,298,738		TERCAPAI	NAIK	cluster10
28	27.0	725.0	20,110,	381.0	9,477,328	344.0	10,632,992		TIDAK TER	TURUN	cluster6
29 30	28.0	1,367	40,779, 63,490,	862.0	26,035, 49,900,	505.0	14,744,478		TERCAPAL	NAIK	cluster10
31		2,469 693.0	61,402,	1,879 399.0	47,953,	590.0 294.0	13,590,482 13,449,293		TERCAPAI TERCAPAI	TURUN NAIK	cluster4 cluster9
32	31.0		33,368,	443.0	17,998,	431.0	15,370,274		TIDAK TER	NAIK	cluster0
33	32.0	1.099	111.948		53.875	771.0	58,073,319		TIDAK TER	NAIK	cluster6
34	33.0	1,543	91,571,		54,217,	748.0	37,353,028	59.21	TIDAK TER	NAIK	cluster3
35	34.0	1,506	34,395,	857.0	19,946,	649.0	14,449,160	57.99	TIDAK TER	NAIK	cluster3
36	35.0	5,664	219,955		108,554	3,087	111,401,029	49.35	TIDAK TER	TURUN	cluster6
37	36.0	1,358	110,809		72,628,	573.0	38,180,750		TERCAPAI	NAIK	cluster10
38	37.0	1,387	96,585,		50,338,	809.0	46,247,565		TIDAK TER	NAIK	cluster0
39	38.0	622.0	21,117,	449.0	16,045,	173.0	5,071,953	75.98	TERCAPAI	NAIK	cluster9
40	39.0	89.0	4,324,718	53.0	2,542,244	36.0	1,782,474		TIDAK TER	TURUN	cluster3
41	40.0		28,904,	357.0	11,189,	353.0	17,714,316		TIDAK TER	TURUN	cluster2
42	41.0		83,397,	2,346	57,677,	1,020	25,719,730		TERCAPAI	NAIK	cluster10
43	42.0	149.0	4,018,434		2,919,124		1,099,310		TERCAPAI	TURUN	cluster9
44	43.0	155.0	4,619,470		4,383,164		236,306		TERCAPAI	TURUN	cluster8
45	44.0	-,	72,942,	1,300	47,117,	777.0	25,824,935		TERCAPAI	NAIK	cluster10
46	45.0	2,312	168,610		130,836		37,774,270		TERCAPAI	NAIK	cluster9
47	46.0		28,197,		22,471,	192.0	5,725,451		TERCAPAL	NAIK	cluster4
48 49	47.0	3,591 414.0	112,869 15,922	2,468 390.0	79,228, 13,929,	1,123 24.0	33,640,598 1,992,601		TERCAPAI TERCAPAI	TURUN NAIK	cluster10 cluster7
50	49.0	2,190	15,922, 89,851,	1,471	13,929, 59,326,	719.0	30,525,407		TERCAPAI	TURUN	cluster/ cluster10
51		2,190	5,403,156			0.0	0.0		TERCAPAI	TETAP	cluster10 cluster1
52	51.0		36,361,	816.0	24,260,	497.0	12,100,889		TERCAPAI	NAIK	cluster10
53	52.0	1,950	56,221,	1,317	40,624,	633.0	15,596,724		TERCAPAI	NAIK	cluster9
54	53.0	1,133	38,172,	663.0	24,093,	470.0	14,079,098		TERCAPAI	NAIK	cluster10
55	54.0		9,051,527		8,110,587	62.0	940,940		TERCAPAI	TURUN	cluster5
56		337.0	12,270,	132.0		205.0	5,235,339		TIDAK TER	NAIK	cluster3
		0400	02.000	400.0	40.070	452.0	1001100	00.00	TEDOARM	KIAUZ	al. aka ad

Table 5. Results of Cluster Without Parameter K-NN

No.	cluster	Total Instant
1	0	15
2	1	31
3	2	10
4	3	14
5	4	12
6	5	6
7	6	19
8	7	11
9	8	14
10	9	25
11	10	48

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The second phase of testing is done with the data optimization results using the k value of K Nearest Neighbor with cluster model validation is performed on the original data. When implemented generate data as in Table 6.

e_number 2: SPPT 3: TARGET 4: SPPT Y Bayar Firman 9: Pencapaia
44.97 TIDAK TER.
84.95 TERCAPAI
47.13 TIDAK TER.
47.13 TIDAK TER.
66.03 TERCAPAI
47.77 TIDAK TER.
47.77 TIDAK TER.
78.59 TERCAPAI
64.77 TERCAPAI
64.77 TERCAPAI
67.14 TERCAPAI
48.74 TIDAK TER.
60.97 TIDAK TER. Nominal 140,089... 30,941,... 4,739,950 1,922 524.0 124.0 TURUN TURUN TURUN TURUN TURUN TURUN TURUN NAIK NAIK 4,026,752 9,477,328 59,326,... 21,339,... 84,942,... 713,198 10,632,992 30,525,407 23,334,938 88,179,478 cluster/ cluster8 cluster7 cluster5 cluster7 cluster7 NAIK 124.0 381.0 1,471 169.0 1,591 1,879 795.0 126,704 353.0 530.0 94.77 IERCAPA 187.14 TERCAPAI 187.14 TERCAPAI 187.14 TERCAPAI 187.14 TERCAPAI 187.15 TERCAPAI 187.16 T 117.421. 57,231,... 16,105,... 2,428,466 28,903,... 204,438... 4,969,121 13,929,... 72,628,... 755,400 4,624,147 15,665,036 168,445 7 289 873 259.0 19.0 751.0 1,537 177.0 390.0 785.0 1.0 NAIK NAIK NAIK TETAP NAIK NAIK TETAP TETAP 7,289,873 125,018,412 4,969,121 15,922,... 110,809... 755,400 cluster 4,624,147 57,434,... 9,051,527 148,257... 4,619,470 37,510,... 33,115,... 55,243,... 30,985,... 4,624,147 25,445,... 8,110,587 77,602,... 4,383,164 36,421,... 17,479,... 25,564,... 27,137,... 31,988,855 31,988,855 940,940 70,654,635 236,306 1,089,038 15,636,177 29,679,266 3,847,585 366.0 1,246 142.0 572.0 cluster8 cluster8 cluster7 cluster7 cluster0 87.58 TERCAPAI 82.4 TERCAPAI 70.06 TERCAPAI 65.76 TERCAPAI 67.1 TERCAPAI 68.98 TERCAPAI 62.11 TERCAPAI 100.0 TERCAPAI 57.33 TIDAK TER 58.22 TIDAK TER 1,120 281.0 926.0 324.0 4,193 410.0 552.0 46.0 453.0 232.0 1,895 184.0 324.0 cluster0 cluster3 cluster3 cluster4 cluster4 cluster4 8,801,052 0.0 5,235,339 6.984.362 9,730,674 28,474,... 16,266,... 3,360,665 2,205,752 31,458,... 133,343... TERCAPAI
TERCAPAI
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TERCAPAI
TERCAPAI
TERCAPAI
TIDAK TER.
TERCAPAI
TERCAPAI 402.0 656.0 141.0 780.0 645.0 414.0 442.0 841.0 486.0 357.0 149.0 663.0 578.0 23,391,... 3,360,665 2,205,752 43,499,... 156,487... 0.0 12,040,332 23,144,419 21,289,385 4,027,637 40,249,517 49,007,... 6,808,120 41,036.... cluster7 cluster5 cluster4 cluster4 cluster4 cluster2 cluster2 NAIK TURUN NAIK NAIK NAIK NAIK NAIK NAIK

Table 6. The results of Cluster with parameter k

Table 7. Results of Cluster Parameters K-NN

No.	cluster	Total Instant
1	0	26
2	1	10
3	2	16
4	3	22
5	4	28
6	5	24
7	6	32
8	7	31
9	8	16

4.1. Influence Selection of Parameter Values k

In the test will be analyzed the effect of optimization parameters k value the success rate with algorithms clusterexpectation *Maximization*, The k value is the number of nearest neighbors for use as consideration in determining the number of cluster decision.

Distance parameter used to optimize the use of simulation data that euclidean distance and the Hamming distance, while the value of k used is k = 13. Based on the above data processing results, when using early data without any additional parameters obtained by the

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number of clusters found and incorrect as many as 11 clusters of 66% then when using the optimization parameters obtained by the number of clusters k sebnayak 9 and can minimize incorrect cluster to 64%.

5. Conclusion

By using clustering algorithms can mengdentifikasi Cluster EM-attainment status and budget plans in the coming year. In the process of this grouping K-NN with k=13 an algorithm and can be used for the type of data berimensi high. Determination of parameter k in K-NN algorithm can affect and improve the number of clusters in advance.

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