Machine Learning Project - CLUSTERING

Description:

A bank wishes to generate groups of its customers based on the data from the dataset mentioned in the following section in order to generate differential customer service policies for each type of customer.

Create the best possible clustering model to meet the objectives defined above, using the dataset found in the "BankChurners.csv" file.

References to variables:

- **CLIENTNUM:** Number of clients → quantitative variable.
- Attrition Flag: Account status the following month → qualitative variable.
- Customer_Age: quantitative variable.
- Gender: qualitative variable.
- **Dependent_count:** Number of people in charge → quantitative variable.
- **Education_Level:** qualitative variable.
- Marital Status: qualitative variable.
- **Income_Category:** qualitative variable.
- Card_Category: qualitative variable.
- Months_on_book: Account's age → qualitative variable.
- **Total_Relationship_Count:** Number of customer's products (accounts and cards) > quantitative variable.
- Months_Inactive_12_mon: Number of months inactive in the last 12 months →
 quantitative variable.
- Contacts_Count_12_mon: Number of contacts in the last 12 months (inquiries/claims to the bank)→ quantitative variable.
- **Credit_Limit**: quantitative variable.
- Total_Revolving_Bal: Uncovered balance of the card (it would be what the client has used of the amount on his card, it is the difference between Credit_Limit y Avg_Open_To_Buy)→ quantitative variable.
- Avg Open To Buy: Available amount in the card → quantitative variable.
- **Total_Amt_Chng_Q4_Q1:** Percentage change in the amount of consumption quantitative variable.
- Total_Trans_Amt: Amount of consumption in the last 12 months → quantitative variable.
- **Total_Trans_Ct:** Number of transactions in the last 12 months → quantitative variable
- Total_Ct_Chng_Q4_Q1: Percentage change in amount of consumption → quantitative variable.
- Avg_Utilization_Ratio: Card utilization ratio (it is the result of doing Total_Revolving_Bal divided by Credit_Limit) → quantitative variable.

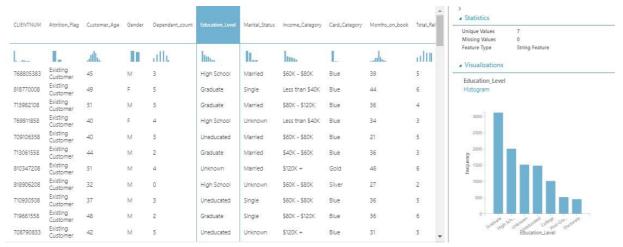
Experiment in Azure:

https://gallery.cortanaintelligence.com/Experiment/Obligatorio-Clustering-Correa-Lopez-Mosco

Categorical variables:

The categorical variables are:

- Attrition_Flag: It is the target variable.
- **Gender:** Indicates the gender categories of a person.
- **Education_Level:** Indicates the categories of a person's level of education.
- Marital_Status: Indicates the marital categories of a person.
- Income_Category: Indicates a person's income categories.
- Card_Category: Indicates the categories of type of cards that a person can have.



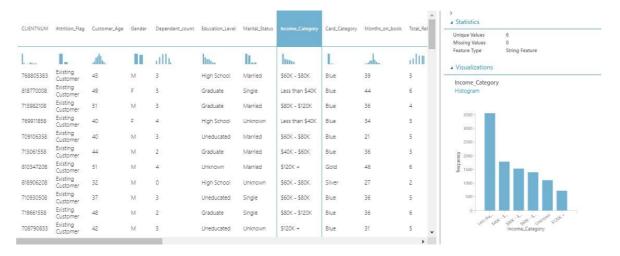
We have 7 educational levels.

We observe that the clients with the highest occurrence are graduates.



We have 4 marital statuses.

We note that most of the clients are married.



We have 6 income categories.

We note that most clients earn less than \$40,000 per year.



We have 4 categories of cards.

We note that most customers have a blue card.

We detail the script below, where we will convert the categorical variables to dummy variables:

```
select *,

case when Attrition_Flag = 'Existing Customer' then 1 else 0 end as AF_Existing,

case when Attrition_Flag = 'Attrited Customer' then 1 else 0 end as AF_Attrited,

case when Education_Level = 'Graduate' or 'High School' or 'Unknown' or 'Uneducated' then 1 else 0 end as EL_Graduate_HighSchool_Unk_Uned,

case when Gender = 'M' then 1 else 0 end as G_Male,

case when Gender = 'F' then 1 else 0 end as G_Female,

case when Marital_Status = 'Married' or 'Single 'then 1 else 0 end as MS_Married_Single,

case when Income_Category = 'Less than $40K' then 1 else 0 end as IC_less40,

case when Card_Category = 'Blue' then 1 else 0 end as CC_Blue

from t1:
```

We group the variables "Income_Category" and "Card_Category" according to the category with the greatest presence in each of them, we do this because they have more than 2 categories. In the case of "Education_Level" and "Marital_Status", we group according to the number of observations.

Variables selection:

The attributes that we are going to exclude are:

- **CLIENTNUM:** it is not going to give us any type of information when running our model because it is a unique identifier of the customer and of the purchase and we are not going to need it to train our model.
- Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_De pendent_count_Education_Level_Months_Inactive_12_mon_1: We have no information on this variable.
- Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_De pendent_count_Education_Level_Months_Inactive_12_mon_2: We have no information on this variable.

We include all the numerical variables.

We select n-1 dummy variables from each category and leave out the categorical variables.

Models creation:

We create models with different amounts of clusters and initializations to be able to make a comparison between them.

	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center
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Model 1	Combined Evaluation	3.964208	4.776239	10127	17.082005
	Evaluation For Cluster No.0	3.9167	4.577475	3963	9.062044
	Evaluation For Cluster No.1	4.451164	5.68277	1785	12.766739
	Evaluation For Cluster No.2	3.808706	4.586593	4379	17.082005
	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center
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Model 2	Combined Evaluation	3.823517	4.683694	10127	16.857249
	Evaluation For Cluster No.0	3.652997	4.455474	3541	13.631124
	Evaluation For Cluster No.1	3.777042	4.429969	3868	16.857249
	Evaluation For Cluster No.2	3.781661	4.928076	1409	6.763225
	Evaluation For Cluster No.3	4.467177	5.787748	1309	8.864923

	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center	
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Model 3	Combined Evaluation	3.755299	4.552568	10127	16.923625	
•	Evaluation For Cluster No.0	3.82054	4.566546	2464	16.923625	
	Evaluation For Cluster No.1	3.73955	4.882459	1376	9.264381	
	Evaluation For Cluster No.2	3.720525	4.278655	2379	11.520104	
	Evaluation For Cluster No.3	3.645633	4.294681	3225	13.684122	
	Evaluation For Cluster No.4	4.190605	6.00931	683	8.971392	
	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center	
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Model 4	Combined Evaluation	3.664318	4.487967	10127	16.58289	
	Evaluation For Cluster No.0	4.331757	5.639923	987	8.616508	
	Evaluation For Cluster No.1	3.531336	4.135216	2621	9.138488	
	Evaluation For Cluster No.2	3.807243	4.404777	1524	16.58289	
	Evaluation For Cluster No.3	3.433325	4.165296	2811	8.142655	
	Evaluation For Cluster No.4	3.730986	4.924397	855	6.122369	
	Evaluation For Cluster No.5	3.712688	4.825242	1329	6.505187	
	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center	
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Model 5	Combined Evaluation	3.594814	4.389162	10127	16.683463	
	Evaluation For Cluster No.0	4.309915	5.586348	969	8.663584	
	Evaluation For Cluster No.1	3.623942	4.277714	1344	9.012923	
	Evaluation For Cluster No.2	3.585866	4.17148	2111	16.683463	
	Evaluation For Cluster No.3	3.283491	3.897258	1339	6.07147	
	Evaluation For Cluster No.4	3.672448	4.697677	1281	6.505907	
	Evaluation For Cluster No.5	3.363932	4.063562	2221	10.97827	
	Evaluation For Cluster No.6	3.730554	4.894791	862	6.101905	

	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center
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Model 6	Combined Evaluation	3.520916	4.336695	10127	16.615414
	Evaluation For Cluster No.0	3.289297	3.967522	2080	10.982242
	Evaluation For Cluster No.1	3.612587	4.818386	791	6.242033
	Evaluation For Cluster No.2	3.520041	4.466297	1057	8.13017
	Evaluation For Cluster No.3	3.283972	3.889126	1430	6.143182
	Evaluation For Cluster No.4	3.625765	4.657121	1227	6.187032
	Evaluation For Cluster No.5	3.577249	4.239381	1317	8.988261
	Evaluation For Cluster No.6	3.594182	4.180553	1554	16.615414
	Evaluation For Cluster No.7	4.165199	5.629598	671	8.976103
	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center
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Model 7	Combined Evaluation	3.501791	4.262666	10127	16.619757
	Evaluation For Cluster No.0	3.697956	4.262214	459	9.194493
	Evaluation For Cluster No.1	3.491492	4.138816	854	6.56281
	Evaluation For Cluster No.2	3.585117	4.168153	1547	16.619757
	Evaluation For Cluster No.3	3.545472	4.176825	1305	8.990393
	Evaluation For Cluster No.4	3.494618	4.446631	1046	8.124066
	Evaluation For Cluster No.5	4.160079	5.625996	669	8.976396
	Evaluation For Cluster No.6	3.612864	4.817784	790	6.240901
	Evaluation For Cluster No.7	3.268567	3.950198	2032	10.981204
	Evaluation For Cluster No.8	3.281524	3.880988	1425	6.137569
	Result Description	Average Distance to Cluster Center	Average Distance to Other Center	Number of Points	Maximal Distance To Cluster Center
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Model 8	Combined Evaluation	3.445449	4.229891	10127	13.714954
viouei o	Evaluation For Cluster No.0	3.495047	4.407154	908	6.451621
	Evaluation For Cluster No.1	4.287735	5.331909	345	13.714954
	Evaluation For Cluster No.2	3.539103	4.116333	885	5.789362
	Evaluation For Cluster No.3	3.520454	4.163197	1063	6.066266
	Evaluation For Cluster No.4	3.149588	3.81526	1043	5.257454
	Evaluation For Cluster No.5	3.161535	3.794018	1783	5.556301
	Evaluation For Cluster No.6	4.132433	5.567458	664	7.722296
	Evaluation For Cluster No.7	3.607802	4.776258	748	6.223827
	Evaluation For Cluster No.8	3.151672	3.629424	1491	5.360525
	Evaluation For Cluster No.9	3.593312	4.596087	1197	6.038759

Model	k	Initialization	Result description	Average distance to cluster center	Average distance to other center	Number of points	Maximal distance
Model 1	3	Evenly	Combined Evaluation	3.964208	4.776239	10127	17.082005
Model 2	4	K-Means++	Combined Evaluation	3.823517	4.683694	10127	16.857249
Model 3	5	Random	Combined Evaluation	3.755299	4.552568	10127	16.923625
Model 4	6	First N	Combined Evaluation	3.664318	4.487967	10127	16.58289
Model 5	7	Evenly	Combined Evaluation	3.594814	4.389162	10127	16.683463
Model 6	8	K-Means++	Combined Evaluation	3.520916	4.336695	10127	16.615414
Model 7	9	Random	Combined Evaluation	3.501791	4.262666	10127	16.619757
Model 8	10	First N	Combined Evaluation	3.445449	4.229891	10127	13.714954

We tried from k=3 to k=10 and different initialization methods.

The best model is the one with the smallest intra-cluster distance (Average distance to cluster center) and the largest distance between clusters (Average distance to other center).

As a business condition we randomly say that the number of observations cannot be less than 800. Then we must discard the models:

- *Model 3:* Cluster 5 (Cluster 4 in Azure) has 683 observations.
- *Model 6:* Cluster 2 (Cluster 1 in Azure) has 791 observations and Cluster 8 (Cluster 7 in Azure) has 671 observations.
- *Model 7:* Cluster 1 (Cluster 0 in Azure) has 459 observations, Cluster 6 (Cluster 5 in Azure) has 669 observations and Cluster 7 (Cluster 6 in Azure) has 790 observations.
- *Model 8:* Cluster 2 (Cluster 1 in Azure) has 345 observations, Cluster 7 (Cluster 6 in Azure) has 664 observations and Cluster 8 (Cluster 7 in Azure) has 748 observations.

In this instance, without having made a characterization that is the optimal method to select a model, we would choose model 4 because it is the one with the second smallest intra-cluster distance. We can call this model "hand-made" because we vary "k" values manually.

We perform the characterization of the best model found:

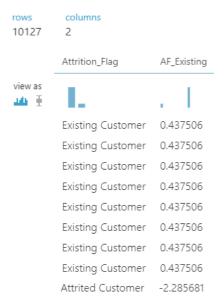
To decide on which model, we must make a characterization, so we write a SQL script and this way be able to characterize the representative individual of each cluster.

```
select assignments
, avg(Customer_Age) as Customer_Age_avg
, avg(Dependent_count) as Dependent_count_avg
, avg(Months_on_book) as Months_on_book_avg
, avg(Total_Relationship_Count) as Total_Relationship_Count_avg
, avg(Months_Inactive_12_mon) as Months_Inactive_12_mon_avg
, avg(Contacts_Count_12_mon) as Contacts_Count_12_mon_avg
, avg(Credit_Limit) as Credit_Limit_avg
, avg(Total_Revolving_Bal) as Total_Revolving_Bal_avg
, avg(Avg_Open_To_Buy) as Avg_Open_To_Buy_avg
, avg(Total\_Amt\_Chng\_Q4\_Q1) as Total\_Amt\_Chng\_Q4\_Q1\_avg
, avg(Total_Trans_Amt) as Total_Trans_Amt_avg
, avg(Total_Trans_Ct) as Total_Trans_Ct_avg
, avg(Total_Ct_Chng_Q4_Q1) as Total_Ct_Chng_Q4_Q1_avg
, avg(Avg_Utilization_Ratio) as Utilization_Ratio_avg
, avg(AF_Existing) as AF_Existing_avg
, avg(EL_Graduate_HighSchool_Unk_Uned) as EL_Graduate_HighSchool_Unk_Uned_avg
, avg(G_Male) as G_Male_avg
, avg(MS_Married_Single) as MS_Married_single_avg
, avg(IC_less40) as IC_less40_avg
, avg(CC_Blue) as CC_Blue_avg
, count(*) as Cantidad_casos
from t1
```

Cantidad casos = Amount of cases.

For each cluster we will calculate the average value of each attribute.

Name each of the groups:



As Attrition_Flag is a categorical variable (it can take two values: 1 or 0, which after Normalization are 0.437506 and -2.285681 respectively), its interpretation is not the same as with numeric variables.

The same thing happens with all categorical variables.

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Gender	G_Male		Education_Level	EL_Graduate_HighSchool_Un k_Uned		Marital_Status	MS_Married_Single
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М	1.05995	6	High School	-0.668521		Married	1.077338
F	-0.9434	36	Graduate	1.495838		Single	-0.928214
М	1.05995		Graduate	1.495838		Married	1.077338
F	-0.9434		High School	-0.668521		Unknown	-0.928214
			Uneducated	-0.668521		Married	1.077338
М	1.05995		Graduate	1.495838		Married	1.077338
М	1.05995	6	Unknown Post-Graduate	-0.668521 -0.668521		Married	1.077338
М	1.05995	6	Uneducated	-0.668521		Unknown	-0.928214
			Doctorate	-0.668521		Single	-0.928214
			Uneducated	-0.668521		Single	-0.928214
			Unknown	-0.668521		Divorced	-0.928214
			College	-0.668521			
Income_	Category	IC_less4	40	Card_Category	CC_Blu	ie .	
100		L					
\$60K -	\$80K	-0.736	437	Blue	0.270	611	
Less tha	an \$40K	1.3578	9	Blue	0.270	611	
\$80K -	\$120K	-0.736	437				
Less tha	an \$40K	1.3578	9	Blue	0.270		
\$60K -	\$80K	-0.736	437	Blue	0.270	611	
\$40K -	\$60K	-0.736	437	Blue	0.270	611	
\$120K +		-0.736		Blue	0.270	611	
\$60K -		-0.736		Gold	-3.695	5345	
\$60K -		-0.736		Silver	-3.695	5345	
Unknov		-0.736		Platinum	-3.695	5345	

If we <u>analyze each attribute</u> (using color rules), we can see if they help to distinguish between clusters.



Cantidad_casos =Amount_cases

If the attributes have values very close to 0 and therefore very similar to the mean, then they do not "help" to differentiate between clusters; we observe that most are close to zero.

On the other hand, if we <u>use color rules by cluster</u>, we can see within each one which attributes are most striking, the variables that best separate them and how they are characterized. Based on the table we see above for k=6:

- Cluster 1 (Assignment 0) has most of the values of the attributes close to the mean because they are around zero, so we say that the cluster does not stand out in any of them and they are not useful for the analysis, but the values that do rise above the mean are Credit_Limit (2,28510158) and Avg_Open_To_Buy (2,283833635). We can consider it as a client with a high credit limit and with an available balance on his/her card. It has 987 observations.
- Cluster 2 (Assignment 1) has most of the values of the attributes close to the mean because they are close to zero, so we say that the cluster does not stand out in any of them, and they are not useful for the analysis. However, CC_Blue has a value of 0.270610758, so we say that all observations are of CC_Blue=1 from what we see in the analysis of this attribute. In short, we can consider it as an average customer who has a blue card. It has 2621 observations.
- Cluster 3 (Assignment 2) has all the values of the attributes close to the mean because they are close to zero, so we say that the cluster does not stand out in any of them, and they are not useful for the analysis.

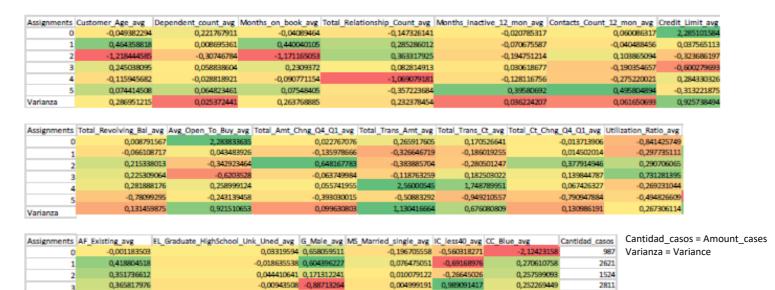
We can consider it as an average customer. It has 1524 observations.

At this point we do NOT stop considering this cluster, as we could stop considering an attribute for not "helping" to differentiate between clusters.

- Cluster 4 (Assignment 3) has all the values of the attributes close to the mean because they are close to zero, so we say that the cluster does not stand out in any of them, and they are not useful for the analysis. We can consider it as an average customer. It has 2811 observations.
- Cluster 5 (Assignment 4) has most of the values of the attributes close to the mean because they are close to zero, so we say that the cluster does not stand out in any of them, and they are not useful for the analysis. However, the values that do rise above the mean are Total_Trans_Amt (2.5600544) and Total_Trans_Ct (1.74878995).
 - We can consider it as a customer who has a high amount consumed in the last 12 months and a high number of transactions in the last 12 months. It has 855 observations.
- Cluster 6 (Assignment 5) has all the values of the attributes close to the mean because they are close to zero, so we say that the cluster does not stand out in any of them, and they are not useful for the analysis. We can consider him as an average customer. It has 1329 observations.

Variables that contribute discriminating groups:

0,418396214



We calculate the variance of each attribute. High variances indicate different values, more separated, so the more separated they are, the better because they discriminate the groups better.

0,006363688

0,02277282 0,079861898

0.301544346

0.026256075

0,231816612

855

1329

-0,0052908 0,270314847

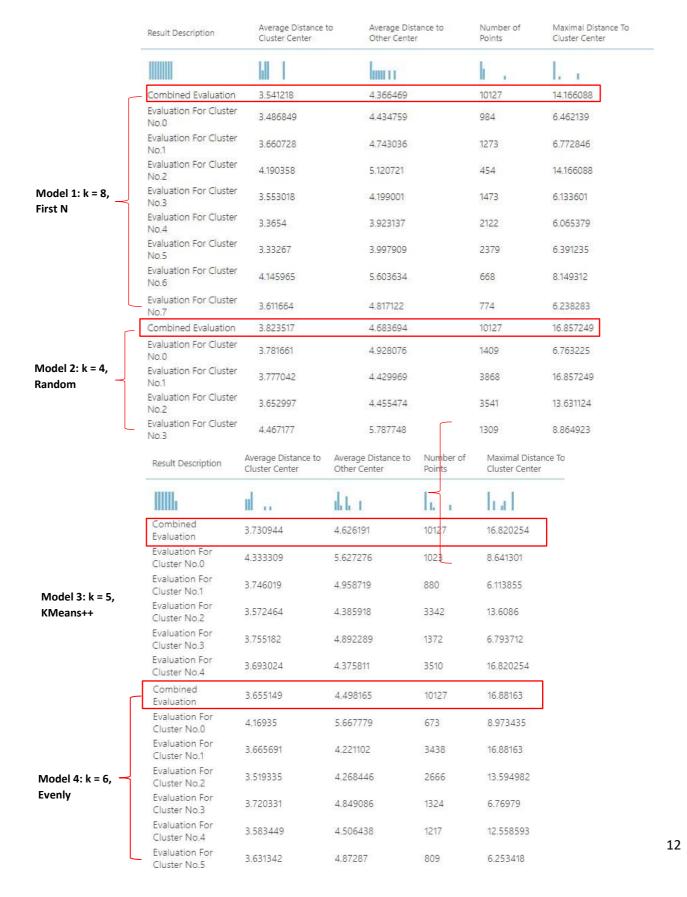
0,015467887 -0,17463992

0.000606634 0.274916354

If <u>we see each attribute by its variance</u>, the category that contributes the most, because it is the one with the greatest variance and greater than 1, is Total_Trans_Amt (1.130416657) and it was the one that separated the clusters the most. Those that contribute to a lesser extent and do not completely detach from the average because they are still values close to zero are: Credit_Limit, Avg_Open_To_Buy, Total_Trans_Ct, AF_Existing and CC_Blue_avg (the green ones in the Variance row).

We look for the new "best model" using the Hyper Parameter Tuning technique (Sweep Clustering):

In the "Sweep Clustering" module we are going to define different values of "k" and Azure is going to create as many models as values of "k" we have given it. Once finished, it will throw which of them is the best.

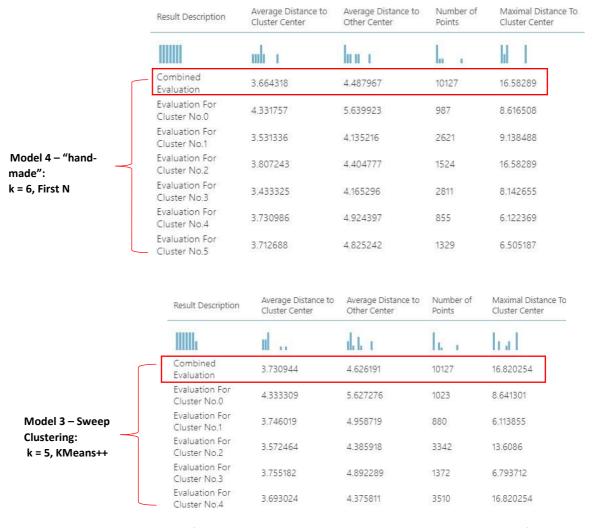


Model	k	Initialization	Result description	Average distance to cluster center	•	Number of points	Maximal distance
Model 1	8	First N	Combined Evaluation	3.541218	4.366469	10127	14.166088
Model 2	4	Random	Combined Evaluation	3.823517	4.683694	10127	16.857249
Model 3	5	K-Means++	Combined Evaluation	3.730944	4.626191	10127	16.820254
Model 4	6	Evenly	Combined Evaluation	3.655149	4.498165	10127	16.88163

We choose model 3 since the intra-cluster and inter-cluster distances do not vary as much respect to model 2 and neither with respect to the extremes (models 1 and 4).

Conclusion:

Model	k	Initialization	Result description	Average distance to cluster center	Average distance to other center	Number of points	Maximal distance
Model 4 – "hand- made"	6	First N	Combined Evaluation	3.664318	4.487967	10127	16.582890
Model 3 - Sweep							
Clustering	5	K-Means++	Combined Evaluation	3.730944	4.626191	10127	16.820254



The distribution of observations is very similar and greater than 800 as defined above, so it is not a decisive factor in our selection.

Therefore, we say that the best model is the one with the smallest intra-cluster distance (Average distance to cluster center) \rightarrow Model 4 – "hand-made".