Capstone Project - Dry Bars/ Beauty Express

Applied Data Science Capstone by IBM/Coursera
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Introduction

In order to study possible locations for opening a business that has not yet been explored in Brazil, this project brings the DryBar concept, and aims to identify more suitable locations for the location of this type of establishment. The result may allow extrapolating the profile of the most successful locations to other cities with similar characteristics.

The concept

DryBar can be defined as spaces of beauty, at more convenient prices, when compared to traditional services. It appeared in California in 2010 and became a common presence in cities such as New York and Los Angeles, due to its agility, facilities and inviting prices.

For the development of the project, the option was to map a region of the city of New York, seeking to understand elements of geolocation and its relevance, for the installation of DryBar. It is considered that this type of service is highly dependent on the flow of female people, with little time available and a profile that values good presentation in the work environment. These are factors considered to be decisive for the success of this business model.

Project's goal

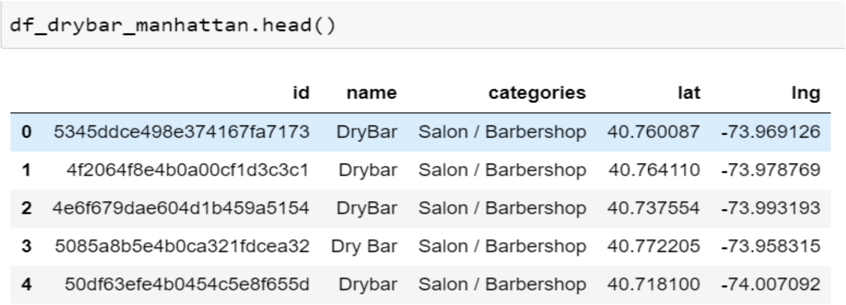
Finding DryBar in the observation region, analyzing its surroundings from the study of clusters, complemented with customer evaluations, considering that, in addition to the quality of the service, ease of access, an element related to location, is implicit.

A map of the Midtown region on Manhattan Island was made, one of the main hubs of large companies in New York City. Due to these characteristics, the region concentrates public with a profile for this type of business; women with lots of activities and little time for traditional beauty salons.

Based on these criteria, Foursquare (https://developer.foursquare.com/docs) was used as the only source of data. The ‘k-means clustering’ unsupervised learning algorithm was the means to identify the advantages of each area, so that the profile of the best location can be defined, for future referrals to those interested in implementing this business in large Brazilian capitals.

Development

In the Foursquare API a search was made with a radius of 9.5km from the center of the Manhattan district, to find the drybar establishments in the region and afterwards, manipulate and organize the data in a data frame

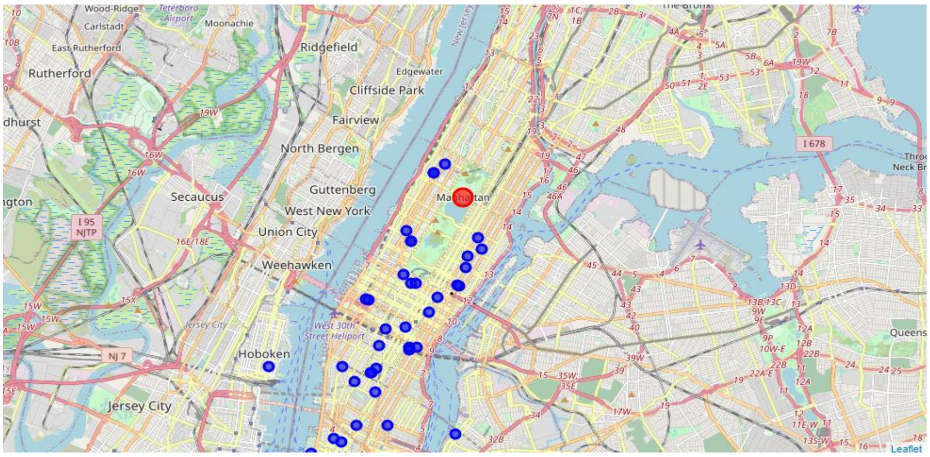


```
df_drybar_manhattan.head()
```

	id	name	categories	lat	lng
0	5345ddce498e374167fa7173	DryBar	Salon / Barbershop	40.760087	-73.969126
1	4f2064f8e4b0a00cf1d3c3c1	Drybar	Salon / Barbershop	40.764110	-73.978769
2	4e6f679dae604d1b459a5154	DryBar	Salon / Barbershop	40.737554	-73.993193
3	5085a8b5e4b0ca321fdcea32	Dry Bar	Salon / Barbershop	40.772205	-73.958315
4	50df63efe4b0454c5e8f655d	Drybar	Salon / Barbershop	40.718100	-74.007092

Parte data frame com a localização dos Drybars

41 Drybars returned, in the graph below it is possible to see how they are distributed on the island of Manhattan



Localização gráfica dos Drybars

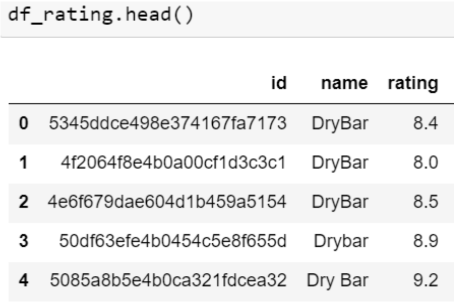
It is possible to observe that the Drybars are concentrated in a part of the island of Manhattan and not in its entire extension. The spots are in the Midtown, Upper and Lower regions, three of the

five that divide Manhattan Island. It is in these regions that large companies, various government agencies and different businesses are concentrated, in fact the proximity to other establishments seems to have an influence on the choice of the location for the opening of this business model, since the other side of the island are areas considered residential.
https://www.rodei.com.br/amp/para-entender-melhor-os-bairros-de-manhattan-parte-ii/

Drybars Notes

The scope of the project is to verify if there is a relationship between the success of the business and its location, in this case, to know what types of categories, services that permeate these establishments and to measure the success of the business that is associated with the quality of service will be used. customer notes, which is implicitly located, is based on the hypothesis that establishments with good scores tend to be at strategic points.

Again, a search is made on Foursquare with the ID of each Drybar in order to obtain the evaluations given by the customers (details of the search in the notebook), after manipulating a dataframe, df_rating, as shown below.

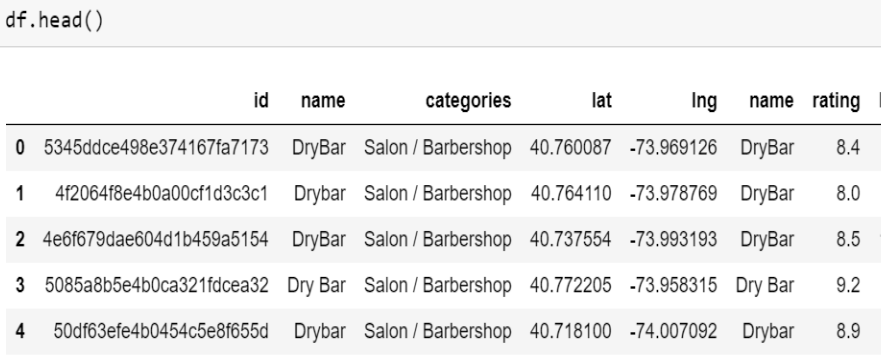


```
df_rating.head()
```

	id	name	rating
0	5345ddce498e374167fa7173	DryBar	8.4
1	4f2064f8e4b0a00cf1d3c3c1	DryBar	8.0
2	4e6f679dae604d1b459a5154	DryBar	8.5
3	50df63efe4b0454c5e8f655d	Drybar	8.9
4	5085a8b5e4b0ca321fdcea32	Dry Bar	9.2

Part of the dataframe with customer notes

The step now is to concatenate the first data frame that contains the categories and the location of each drybar, with the second data frame, which contains notes.



```
df.head()
```

	id	name	categories	lat	lng	name	rating
0	5345ddce498e374167fa7173	DryBar	Salon / Barbershop	40.760087	-73.969126	DryBar	8.4
1	4f2064f8e4b0a00cf1d3c3c1	Drybar	Salon / Barbershop	40.764110	-73.978769	DryBar	8.0
2	4e6f679dae604d1b459a5154	DryBar	Salon / Barbershop	40.737554	-73.993193	DryBar	8.5
3	5085a8b5e4b0ca321fdcea32	Dry Bar	Salon / Barbershop	40.772205	-73.958315	Dry Bar	9.2
4	50df63efe4b0454c5e8f655d	Drybar	Salon / Barbershop	40.718100	-74.007092	Drybar	8.9

Dataframe part after concatenation

With the Fousquare search data previously organized, the next step will be to use the Machine learning algorithm to extract information that will later be transformed into knowledge.

Machine Learning

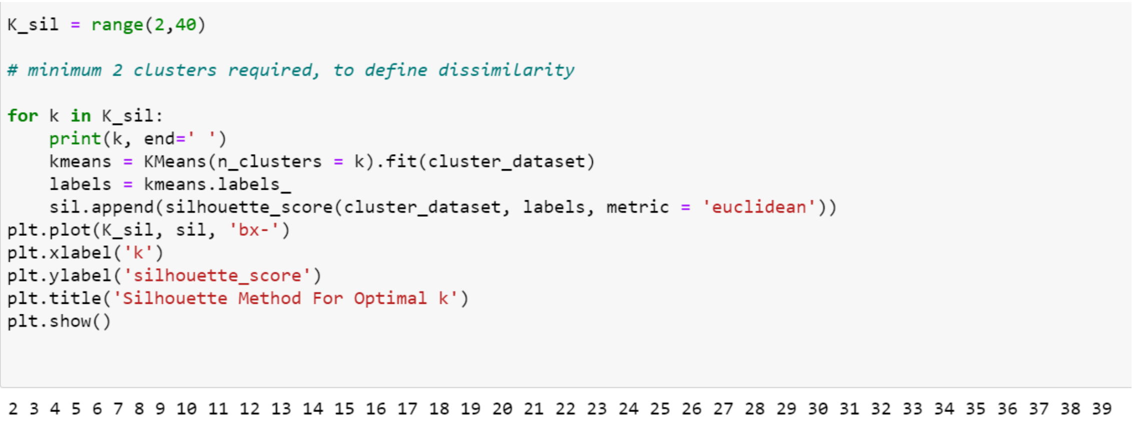
The unsupervised Machine Learning algorithm “K-means” groups data by similarities around each other around a central point, the centroid. For processing, input variables are given, in this case, latitudes and longitudes, and it returns groups, called clusters, as output.

Once you have the clusters, the next step is to calculate the average of the grades evaluated by the customers of each group. The two clusters that have the highest average score, will make a new search on Foursquare from the centroid of these two clusters to discover the categories of the neighboring establishments and draw conclusions from that.

K-means

To start the algorithm it is necessary to define the best value of k, as it is not known what is the best value to choose, so we use the silhouette method, which calculates the average between how cohesive the points are within the cluster and how distant are from the other clusters so the closer to 1 the better the k value.

To carry out this process, it is necessary to provide values for the algorithm so that it tests and finds out what is the best value for k, there is no rule for choosing these numbers, it is up to each one, in the case of the project the choice is numbers ranging from 2 to 39 represented by range (2.40) as shown in the image below.

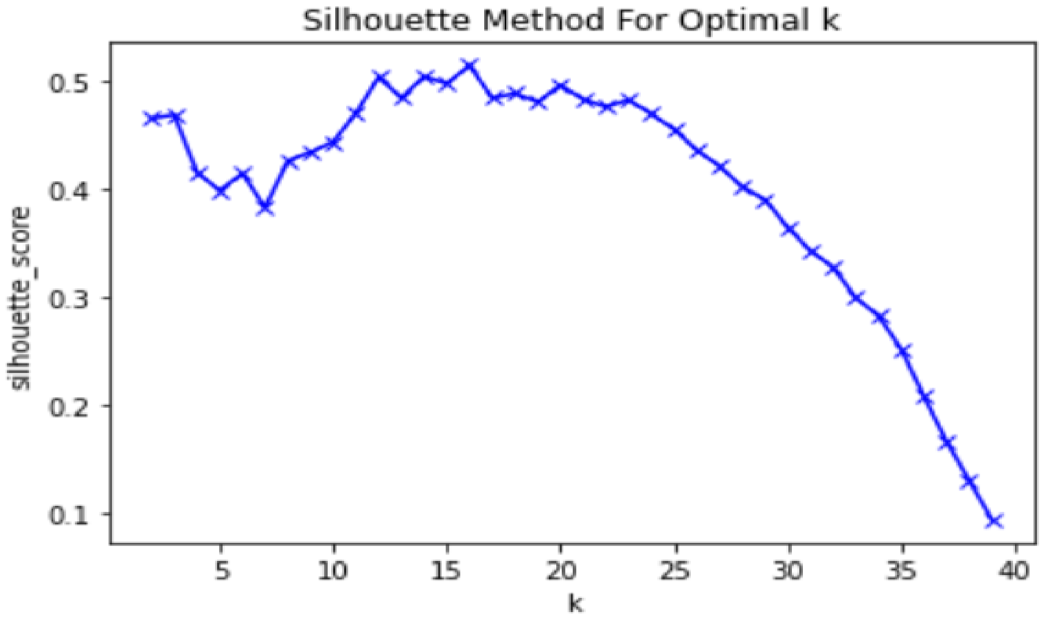


```
K_sil = range(2,40)

# minimum 2 clusters required, to define dissimilarity

for k in K_sil:
    print(k, end=' ')
    kmeans = KMeans(n_clusters = k).fit(cluster_dataset)
    labels = kmeans.labels_
    sil.append(silhouette_score(cluster_dataset, labels, metric = 'euclidean'))
plt.plot(K_sil, sil, 'bx-')
plt.xlabel('k')
plt.ylabel('silhouette_score')
plt.title('Silhouette Method For Optimal k')
plt.show()
```

```
2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39
```

Execution to find out which best value for k

The code above returned the graph to assess which k will be chosen.

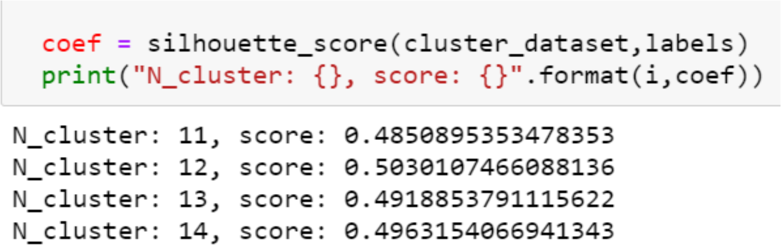


Silhouette graphic

It is possible to see in the graph two peaks, the first approximately between 11 and 14 and the second between 15 and 17, for the data scientist the decision between choosing which one has the best for k is personal, but in the case of the project with a small sample of data is not very interesting to have many clusters.

When choosing the first peak of the graph it is not yet known which is the best value for k, it could be 11.12, 13 or 14, which is the best among them?

It is not always possible to make this decision just by looking at the graphs, so it is important to check through the values of the silhouette coefficients, as shown below.

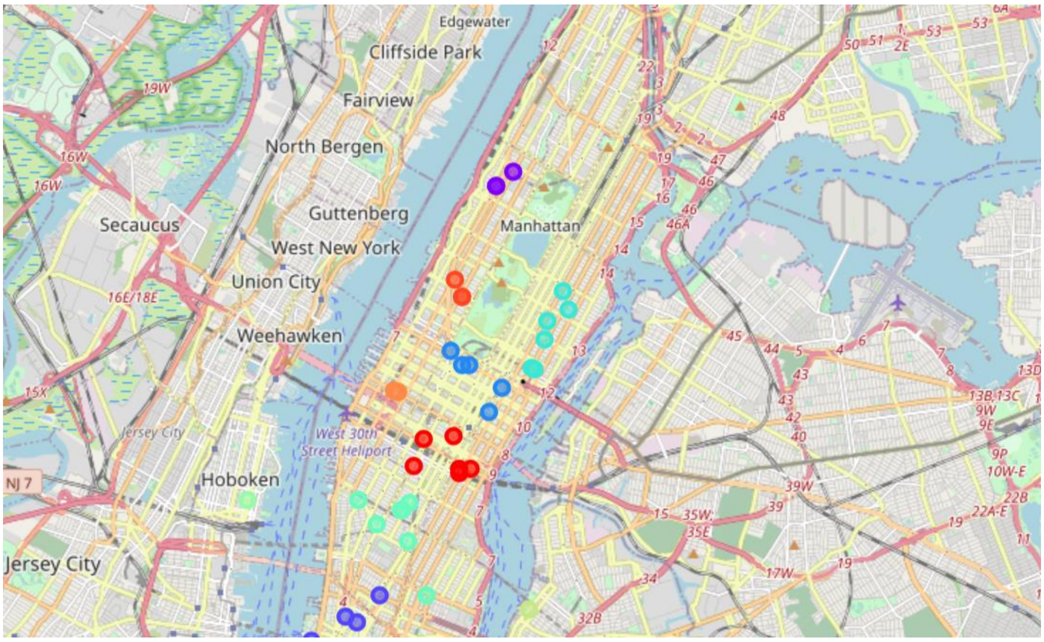


```
coef = silhouette_score(cluster_dataset,labels)
print("N_cluster: {}, score: {}".format(i,coef))
```

```
N_cluster: 11, score: 0.4850895353478353
N_cluster: 12, score: 0.5030107466088136
N_cluster: 13, score: 0.4918853791115622
N_cluster: 14, score: 0.4963154066941343
```

Values of the coefficients of clusters 11,12,13 and 14

This processed generated the information that the best value for k is 12, it means that the unsupervised k-means algorithm based on the input variables: latitude and longitude, will return 12 similar clusters, as can be seen in the graph below.

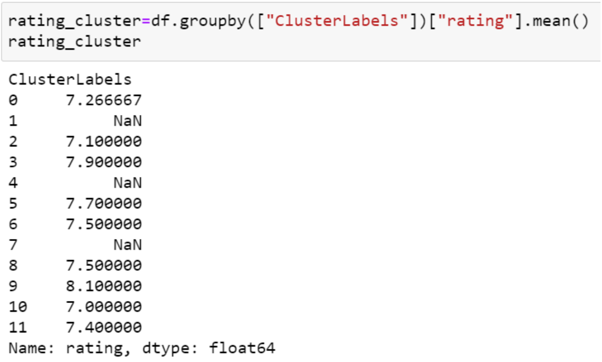


The clusters

Getting to know the clusters

As part of the project, it is not exploring all the clusters, but the establishments considered as success cases based on customer evaluations. One way to obtain this information is by averaging the scores for each cluster.

As the idea is to know the influence of neighboring establishments, the comparison between two clusters of higher average seems to be considerable.To know the averages of each cluster, it is necessary to use the groupby function, as shown below.

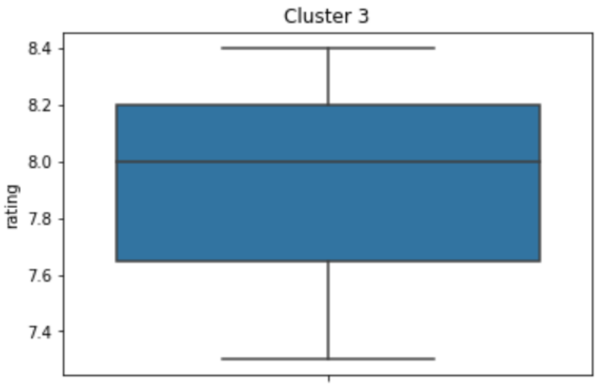


```
rating_cluster=df.groupby(["ClusterLabels"])["rating"].mean()
rating_cluster
```

```
ClusterLabels
0     7.266667
1          NaN
2     7.100000
3     7.900000
4          NaN
5     7.700000
6     7.500000
7          NaN
8     7.500000
9     8.100000
10    7.000000
11    7.400000
Name: rating, dtype: float64
```

Average customer ratings for each cluster

Clusters 3 and 9 have the highest average, only these two groups will serve as a parameter for the completion of the project, for which all establishments related to each of these clusters are selected.

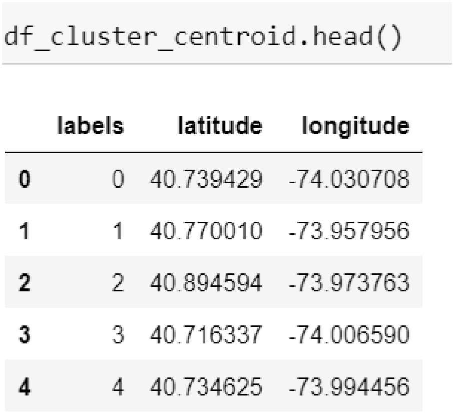


Cluster 5 boxplot

Cluster 3 has a good concentration of grades considered good above 7.5 (as shown in the graph below). Cluster 9, on the other hand, has only 1 element, that is, 1 establishment, for this reason it is not necessary to plot the graph, but as its score had a significant value, it is worth knowing the categories of its neighboring establishments. (details on notebook)

In search of the neighboring categories of clusters 3 and 9

As stated earlier, the k-means algorithm returns the clusters and also the central point of each one with the “kmeans.cluster_centers” function, these centroides are coordinated. Thus, after being handled, they are organized in a data frame. (details on notebook)

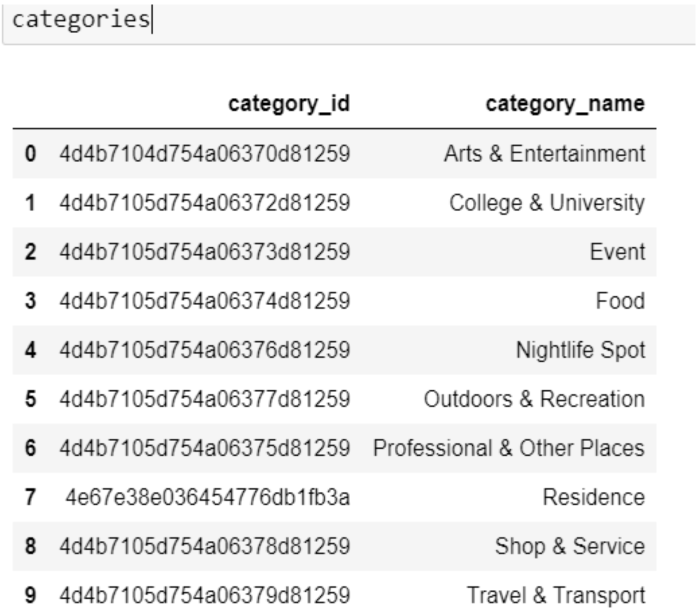


```
df_cluster_centroid.head()
```

	labels	latitude	longitude
0	0	40.739429	-74.030708
1	1	40.770010	-73.957956
2	2	40.894594	-73.973763
3	3	40.716337	-74.006590
4	4	40.734625	-73.994456

Location of the 12 centroides

To search for categories from a location point first, you need to know how many categories the Fourquare API makes available, so with the code and registration keys previously made it is possible to have this information on a dataframe like the one below.

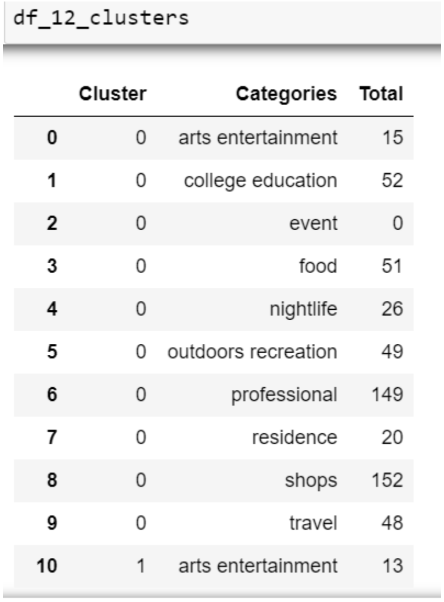


```
categories
```

	category_id	category_name
0	4d4b7104d754a06370d81259	Arts & Entertainment
1	4d4b7105d754a06372d81259	College & University
2	4d4b7105d754a06373d81259	Event
3	4d4b7105d754a06374d81259	Food
4	4d4b7105d754a06376d81259	Nightlife Spot
5	4d4b7105d754a06377d81259	Outdoors & Recreation
6	4d4b7105d754a06375d81259	Professional & Other Places
7	4e67e38e036454776db1fb3a	Residence
8	4d4b7105d754a06378d81259	Shop & Service
9	4d4b7105d754a06379d81259	Travel & Transport

The 10 categories that the Foursquare API provides

With the information of the categories and knowing the location of the centroides, it is already possible to search how many categories there are for each cluster. After manipulated and organized in a dataframe, this is the result. (Details of this process on the notebook)



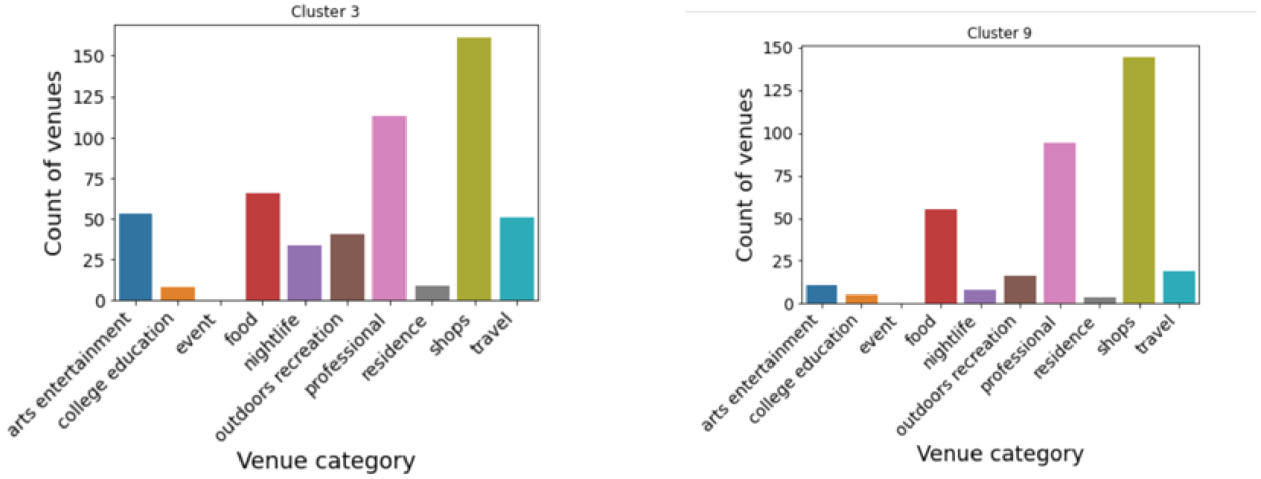
```
df_12_clusters
```

	Cluster	Categories	Total
0	0	arts entertainment	15
1	0	college education	52
2	0	event	0
3	0	food	51
4	0	nightlife	26
5	0	outdoors recreation	49
6	0	professional	149
7	0	residence	20
8	0	shops	152
9	0	travel	48
10	1	arts entertainment	13

Part of the iframe with total categories within a radius of 300 meters from the clusters' centroides

Results of

A way to visualize which categories are within a radius of 300 meters from the centroides of clusters 3 and 9 and through the graph.



Categories within a radius of 300 meters from the centroid

There is a high concentration of categories such as shop and professional in both cases, these categories have establishments such as: Business Center, Distribution Center, Town Hall, Industrial Estate, Wedding Hall etc. To know more details, it is necessary to specify the search even more, which will certainly be for a little while, with this information it is possible to draw some conclusions.

Conclusion

According to the Brazilian Franchising Association - ABF, the definition of the best location is a little more complex than it appears, because it involves antagonistic variables, such as the flow of people and costs. The best location is not necessarily the one that will provide the highest revenue, but the one that will bring the best result, being one of the factors to be considered in the evaluations given by customers.

Several factors are taken into account when starting a business, such as the flow of people, the level of demand and operating costs. With this, it is possible to conjecture, with the information extracted, which would be the best places to open the business, based on the K-means algorithm, serving as one of the reference factors.

When clustering, k-means returned groups with shorter distances from each other. Associated with the verification of the marks given by the customers, it was observed that the clusters with the highest averages had around them business categories such as shop and professional, which indicates a significant presence of trades and companies and which helps to justify the hypothesis that, well-evaluated and well-frequented places are strategically positioned, in relation to an environment composed of companies and extensive commerce.

This is the contribution that this project offers, and the future interested in the promising business of express salons should also consider other elements, such as the flow of public with interest in this type of service, demand capacity, among others, for a greater possibility of success in choosing the localization.