The battle of the neighbourhoods: Discovering Casablanca

By: Ahmed KCHIKECHE

Introduction to the business problem

As the largest city in Morocco, Casablanca is one of the best investment destinations in north Africa. Casablanca is located in the centre of the Casablanca-Settat region who according to the ministry of finance[i] contribute 26.5 per cent to the nation's GDP.

Casablanca's strategic location, the availability of undertrial and logistical infrastructure and its attractive business climate makes the city the main destination for startups and large-scale investment project. However, the publicly available microdata on the locations of venues is extremely scarce. This can make it hard to choose the best location for an investment project.

The objective of this project is to facilitate the choice of businesses locations in Casablanca based on the frequency of nearby venues.

The goals of this project are:

- Identify the geographical position of all the neighbourhoods in the city of Casablanca
- Identify the nearby venues to each neighbourhood by frequency
- Cluster the neighbourhoods based on each neighbourhood by frequency

Data

To achieve the goals of our project, we will need to get the following datasets

1. The names and postal codes of all neighbourhoods in the city of Casablanca;
2. The coordinates of each neighbourhood;
3. The nearby venues data for each neighbourhood.

The data on postal codes in Casablanca was obtained from a webpage[ii] from the postal service of morocco website. We scraped the webpage using the .read_html() pandas method. After processing the data, we obtained a table containing two columns (The neighbourhood name and its corresponding postal code) and 3048 rows.

The second step of our data gathering process was to get the coordinates (Latitude, Longitude) of each neighbourhood. To do so, we used ArcGIS geocoder. After extracting the coordinates of each neighbourhood, we added two new columns to our previous dataset. This version of the dataset was cleaned to fill missing data and remove duplicate and redundant information.

Finally, we used the Foursquare API to get the nearby venues for each neighbourhood in the processed dataset. This data was then processed and made available for clustering. The final dataset consisted of the neighbourhoods names, coordinates and the 10 most frequent nearby venues for each neighbourhood.

Methodology

I- Getting and Cleaning Data

The first part of any data project is Data acquisition and wrangling. In this project, I needed to get the following data

- The names and postal codes of all neighbourhoods in the city of Casablanca;
- The coordinates of each neighbourhood in Casablanca;

- Venues data for each neighbourhood in Casablanca.

1. Neighbourhoods data acquisition

The data on postal codes in Casablanca is obtained from The postal service of Morroco.

To prepare the dataset for modelling, we need first to scrap it and store it in a pandas data frame. To scrap the data from the webpage tables we will use the .read_html() pandas method. To do so, we used the following code

```
#store the as in an object
url = 'http://www.codepostal.ma/search_mot.aspx?keyword=CASABLANCA'
#read all the table in the webpage and store them in an object
tables = pd.read_html(url)
#get the number of tables in the webpage
print('the number of tables in the webpage is:')
print(len(tables))
```

We found that the data contains 10 tables. We checked each of them and found that the tables that contain all the neighbourhoods in Casablanca are table 5 shown below.

	0	1	2
0	Ville	Quartier/Voie	Code postal
1	CASABLANCA	4 EME TRANCHE	20450
2	CASABLANCA	6 EME TRANCHE	20450
3	CASABLANCA	AABIR	20400
4	CASABLANCA	AAHD AL JADID	20450
5	CASABLANCA	ABATTOIRES	20320
6	CASABLANCA	ABOUAB NASSIM	20190
7	CASABLANCA	ABOUAB OUM RABII	20220
8	CASABLANCA	ABRAJ ABDELMOUMEN	20340
9	CASABLANCA	ABRAJ EL FIDA	20530
10	CASABLANCA	ADDAMANE	20460

We then Saved the table in a pandas data frame, verified the data in it, dropped non-essential column and translated the column names to English.

Using the .info() method we can check the processed dataframe main properties

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3048 entries, 1 to 3048
Data columns (total of 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   neighborhood  3048 non-null   object
 1   postalcode    3048 non-null   object
dtypes: object(2)
memory usage: 47.8+ KB
```

2. Adding the coordinates data to our data frame

This was challenging. After trying to use Google geocoder in vain, The loop took a very long time, we used ArcGIS geocoder to extract the neighbourhoods coordinates.

The Python function used the extract the data from the geocoder is the following.

```
def get_latlng(neighborhood):
    # initialize your variable to None
    lat_lng_coords = None
    # loop until you get the coordinates
    while(lat_lng_coords is None):
        g = geocoder.arcgis('{}, Casablanca, MAR'.format(neighborhood))
        lat_lng_coords = g.latlng
    return lat_lng_coords
```

We defined the function, called the function to get the coordinates and store in a new list using list comprehension. Afterwards, we created a temporary data frame to populate the coordinates into Latitude and Longitude, then merge the coordinates into the original data frame.

Finally, we checked the resulting data frame for missing data and found that the geocoder didn’t get the coordinates for one of the neighbourhoods. To solve this problem, we used google map to find the coordinates manually and added them to our data frame.

The resulting dataframe was the following

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3048 entries, 0 to 0
Data columns (total of 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   neighborhood  3048 non-null   object
 1   postalcode    3048 non-null   object
 2   Latitude      3048 non-null   object
 3   Longitude     3048 non-null   object
dtypes: object(4)
memory usage: 119.1+ KB
```

3. Removing duplicate neighbourhoods

To make sure we don't have any redundant data (e.i. Duplicate neighbourhoods or neighbourhoods with the same coordinates), we filtered the data to get distinct neighbourhoods.

First, we dropped 67 duplicate neighbourhoods from our dataset. The duplicate neighbourhoods could result from neighbourhoods with more than one postal code. This could be due to inconsistencies in the postal service data or to the fact that different addresses in the same neighbourhoods have different postal codes. The resulting data frame can be seen below.

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2981 entries, 0 to 0
Data columns (total of 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   neighborhood  2981 non-null   object
 1   postalcode    2981 non-null   object
 2   Latitude      2981 non-null   object
 3   Longitude     2981 non-null   object
dtypes: object(4)
memory usage: 116.4+ KB
```

We then dropped neighbourhoods that have the same coordinates. These neighbourhoods could be close enough that the geocoder didn't have distinct coordinates for each of them. One problem with the postal service data that is collected to give addresses to each building and this is extremely detailed. To achieve this, the same neighbourhood is devised into partitions with different postal codes. We don't need this level because we will get the nearby venues for each neighbourhood and we don't want these venues to intersect.

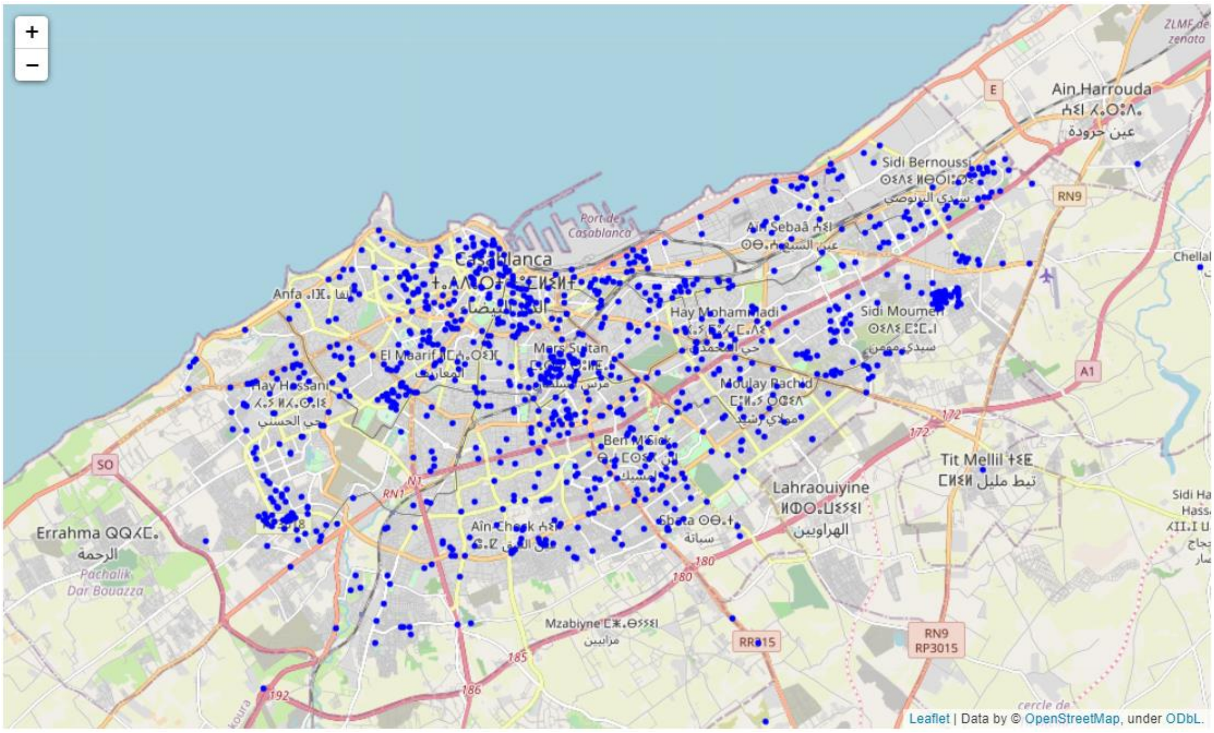
After dropping neighbourhoods with similar coordinates we got the following data frame. This operation reduced the number of distinct neighbourhoods to 1038 dropping 1943 neighbourhoods.

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1038 entries, 0 to 0
Data columns (total of 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   neighborhood    1038 non-null   object
 1   postalcode      1038 non-null   object
 2   Latitude        1038 non-null   object
 3   Longitude       1038 non-null   object
dtypes: object(4)
memory usage: 40.5+ KB
```

Finally, we decided to drop neighbourhoods with the same postal code and got our final neighbourhoods positions data frame.

4. Exploring Casablanca and verifying data usability

To show a visualisation of the neighbourhoods in Casablanca. we created a map using the coordinates that we got before and added markers of the neighbourhoods on top.



Unfortunately, Some data points are outside Casablanca.

Ideally, We should only take into account neighbourhoods in 'Prefecture of Casablanca'. To do so we need to get the coordinates of the city's administrative polygon boundary.

This is done by following these steps

1) use OpenStreetMap https://nominatim.openstreetmap.org/ to search for the city
2) Get the city details https://nominatim.openstreetmap.org/ui/details.html?osmtype=R&osmid=2523504&class=boundary
3) Copy the OSM ID. 2523504
4) use http://polygons.openstreetmap.fr/index.py to search for the polygon using the OSM ID.

5) Get the polygon from http://polygons.openstreetmap.fr/index.py?id=2523504
6) Calculate if a point is inside the polygon or not and filter out the points outside the polygon.

All the credit for the method to get the polygon goes to https://gis.stackexchange.com/a/192298

However, we could not implement this solution with our current knowledge and experience with python programming and due to time restrictions. the number of data points outside Casablanca is very low and can be tolerated.

5. Getting Venues information

The last step of data collection is getting nearby venues to each neighbourhood in our dataset using the Foursquare API using a developer account. To do so, we used a python function to get nearby venues and store them in a data frame. The resulting data frame information is shown bellow

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7995 entries, 0 to 7994
Data columns (total of 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Neighborhood            7995 non-null   object
 1   Neighbourhood Latitude  7995 non-null   float64
 2   Neighbourhood Longitude 7995 non-null   float64
 3   Venue                   7995 non-null   object
 4   Venue Latitude          7995 non-null   float64
 5   Venue Longitude         7995 non-null   float64
 6   Venue Category          7995 non-null   object
dtypes: float64(4), object(3)
memory usage: 437.4+ KB
```

The data frame contains 4 new columns containing information about nearby venues like their position and category.

II- Modeling

1. Feature engeneering

To apply the clustering algorithm to our dataset, we did the following

- Used one-hot encoding to get dummies for our categorical variables;
- Grouped rows by neighbourhood and by taking the mean of the frequency of occurrence of each category;
- Sorted the venues in descending order of venues categories frequency;
- Created a new data frame displaying the top 10 venues for each neighbourhood.

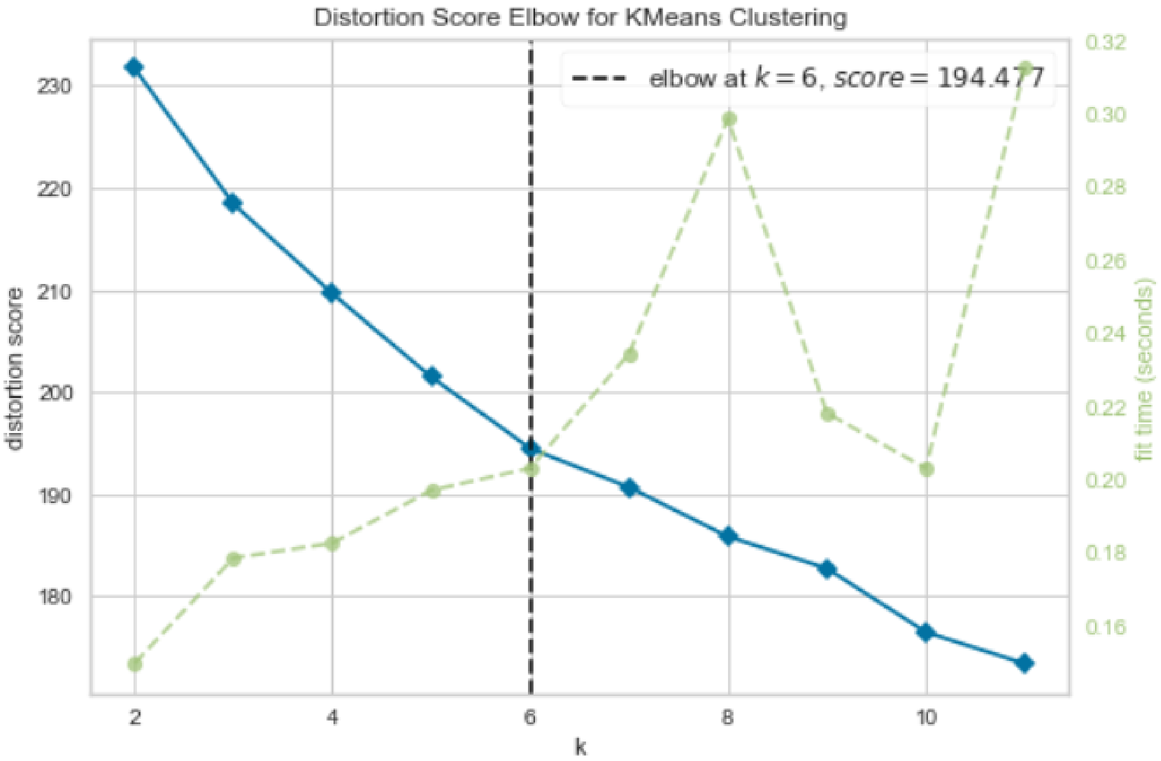
The resulting data frame is shown below.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 971 entries, 0 to 970
Data columns (total of 11 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Neighborhood           971 non-null    object
 1   1st Most Common Venue  971 non-null    object
```

```
 2   2nd Most Common Venue    971 non-null    object
 3   3rd Most Common Venue    971 non-null    object
 4   4th Most Common Venue    971 non-null    object
 5   5th Most Common Venue    971 non-null    object
 6   6th Most Common Venue    971 non-null    object
 7   7th Most Common Venue    971 non-null    object
 8   8th Most Common Venue    971 non-null    object
 9   9th Most Common Venue    971 non-null    object
 10  10th Most Common Venue   971 non-null    object
dtypes: object(11)
memory usage: 83.6+ KB
```

2. Clustering

To apply k-mean clustering, we used the Elbow method to choose the optimal k. The figure below shows a visualization of the optimal k.



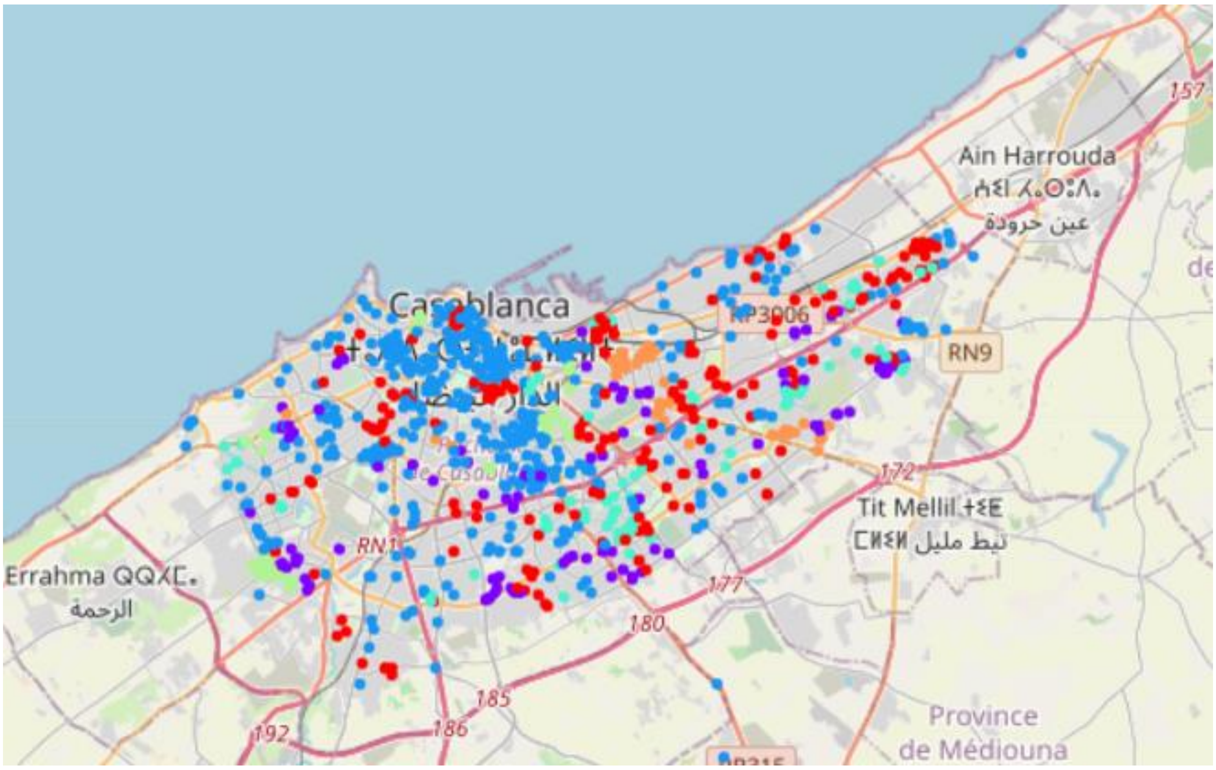
As we can see. The k-mean algorithm should be initialized with 6 clusters.

After applying the clustering algorithm, we added the cluster labels and the coordinates to the previous data frame, the results are shown below

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 971 entries, 0 to 970
Data columns (total of 15 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Neighborhood             971 non-null    object
 1   postalcode               971 non-null    object
 2   Latitude                 971 non-null    object
 3   Longitude                971 non-null    object
 4   Cluster Labels           971 non-null    int32
```

```
 5   1st Most Common Venue   971 non-null    object
 6   2nd Most Common Venue   971 non-null    object
 7   3rd Most Common Venue   971 non-null    object
 8   4th Most Common Venue   971 non-null    object
 9   5th Most Common Venue   971 non-null    object
 10  6th Most Common Venue   971 non-null    object
 11  7th Most Common Venue   971 non-null    object
 12  8th Most Common Venue   971 non-null    object
 13  9th Most Common Venue   971 non-null    object
 14  10th Most Common Venue  971 non-null    object
dtypes: int32(1), object(14)
memory usage: 117.6+ KB
```

Using this new data frame, we can visualize the clusters on the map.



Results

After applying the clustering algorithm, we can show the number of neighbourhoods in each cluster. Furthermore, we aggregated the data by calculating the frequency of occurrence of venues categories as the 1st, 2nd and 3rd most common venue category in each cluster.

This information could be used by potential investors to analyse the neighbourhoods according to the frequency of venues. The results of our analysis are shown below.

Let's first see the number of neighbourhoods in each cluster :

The cluster	The number of neighbourhoods
0	216
1	121
2	463
3	76
4	54

5	41

Lets now see the frequency of the most common venues in each cluster

The most common venues in cluster 0	Venues categories	frequency
1st Most Common Venue	Coffee Shop	74.5%
	Zoo Exhibit	3.7%
	Fast Food Restaurant	2.3%
2nd Most Common Venue	Coffee Shop	34.3%
	Fast Food Restaurant	7.4%
	Hotel	3.2%
3rd Most Common Venue	Yoga Studio	13.0%
	Coffee Shop	16.7%
	Fast Food Restaurant	6.9%

The most common venues in cluster 1	Venues categories	frequency
1st Most Common Venue	Coffee Shop	61.2%
	Zoo Exhibit	18.2%
	Convenience Store	4.1%
2nd Most Common Venue	Coffee Shop	44.6%
	Fast Food Restaurant	9.9%
	Snack Place	5.0%
3rd Most Common Venue	Coffee Shop	24.0%
	Yoga Studio	9.9%
	Pizza Place	9.9%

The most common venues in cluster 2	Venues categories	Frequency
1st Most Common Venue	Coffee Shop	24.2%
	Fast Food Restaurant	11.2%
	Hotel	6.0%
2nd Most Common Venue	Yoga Studio	10.8%
	Fast Food Restaurant	8.9%
	Hotel	7.3%
3rd Most Common Venue	Coffee Shop	5.4%
	Pizza Place	4.5%
	Bakery	4.1%

The most common venues in cluster 3	Venues categories	Frequency
1st Most Common Venue	Coffee Shop	100.0%
2nd Most Common Venue	Yoga Studio	51.3%
	Ice Cream Shop	6.6%
	Bistro	5.3%
3rd Most Common Venue	Donut Shop	59.2%
	Yoga Studio	32.9%

	Doner Restaurant	3.9%

The most common venues in cluster 4	Venues categories	Frequency
1st Most Common Venue	Shopping Mall	27.8%
	Snack Place	13.0%
	Coffee Shop	18.5%
2nd Most Common Venue	Yoga Studio	10.8%
	Fast Food Restaurant	8.9%
	Hotel	7.3%
3rd Most Common Venue	Shopping Mall	35.2%
	Yoga Studio	11.1%
	Pool Hall	11.1%

The most common venues in cluster 5	Venues categories	Frequency
1st Most Common Venue	Tram Station	46.3%
	Coffee Shop	31.7%
	Hot Dog Joint	12.2%
2nd Most Common Venue	Coffee Shop	51.3%
	Tram Station	6.6%
	Pizza Place	5.3%
3rd Most Common Venue	Donut Shop	31.7%
	Yoga Studio	24.4%
	Doner Restaurant	12.2%

Discussion

The objective of this project was to provide potential investor in Casablanca with an easy way to access location data neighbourhoods locations and the frequency of venues categories in each neighbourhood. This task however was complicated by various factors related to data availability and accuracy. This is a very incomplete project; however, we hope that it could be a starting point to more extensive analysis.

This section of the report will discuss various problems that we encountered in the various stages of this project.

First of all, the only exhaustive list of neighbourhood names and their postal codes was found on a website of the postal code of Morocco. We found that some neighbourhoods have the same postal code and thus could be close to each other and thus redundant. Removing neighbourhoods with duplicate postal code would reduce the number of neighbourhoods dramatically (to less than 100 neighbourhood) we did not remove these neighbourhoods because we are not sure to which degree neighbourhoods with the same postal code are close to each other. This needs more testing and could have a damaging effect on our data quality.

The second source of data instability was the ArcGIS geocoder that we used to get the coordinates for our neighbourhoods. The geocoder did assign wrong coordinates to some of the neighbourhoods (coordinates outside Casablanca). This could result from the fact that the geocoder uses different naming conventions for neighbourhoods or due to some error in our code. This problem could be solved partially if we can exclude the neighbourhoods that are outside Casablanca. We couldn't however implement this solution due to inexperience with Python.

We could also improve our results using cross-validation to choose the optimal k or by using multiple clustering algorithms and comparing the results.

Conclusion

The objective of this project is to facilitate the choice of businesses locations in Casablanca based on the frequency of nearby venues. Using various data source we compiled an exhaustive list of all the neighbourhoods in Casablanca, their location and the most common venue categories in each neighbourhood. We then used k-mean clustering to make 6 clusters and we aggregated the data for each cluster.

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[i] https://www.finances.gov.ma/Publication/depf/2019/profils-regionaux.pdf

[ii] http://www.codepostal.ma/search_mot.aspx?keyword=CASABLANCA