

Introduction

Athens and Thessaloniki are the two major cities in Greece. Together, they are inhabited by the 50% of the Greek population. Both cities were struck by the financial crisis but recently have started to come back in all sorts of aspects such as the residential, tourism, education and job employment. They have also an extended history over the centuries and as such they attract tourist both from abroad and within Greece.

Athens is the capital and largest city of Greece. Athens dominates the Attica region and is one of the world's oldest cities, with its recorded history spanning over 3,400 years and its earliest human presence starting somewhere between the 11th and 7th millennium BC. The Athens Urban Area today consists of 40 municipalities, 35 of which make up what is referred to as the Greater Athens municipalities, located within 4 regional units (North Athens, West Athens, Central Athens, South Athens); and a further 5, which make up the Greater Piraeus municipalities, located within the regional unit of Piraeus as mentioned above. The densely built up urban area of the Greek capital sprawls across 412 km² (159 sq mi) throughout the Attica Basin and has a total population of 3,074,160 (in 2011).

Thessaloniki is the second-largest city in Greece, with over 1 million inhabitants in its metropolitan area, and the capital of Greek Macedonia, the administrative region of Central Macedonia and the Decentralized Administration of Macedonia and Thrace.[Its nickname is "the co-capital", a reference to its historical status as the or "co-reigning" city of the Eastern Roman (Byzantine) Empire, alongside Constantinople.

Obejective

In this project, we will aim to to study:

1. the similarity or dissimilarity of both cities
2. classification of the areas inside the city to determine whether it is suitable for locals or it is more touristic. To achieve that we will utilize data from Foursquare and use Machine Learning techniques such as clustering and segmentation.

Data

The data was collected from a Greek webpage specializing in information 'https://www.xo.gr/greek-postal-codes-zips'.

As next step, the data was cleaned and saved in csv files in order to be easy to handle.

The data sets to be used can be found in the project repository:

1. Athens -

https://github.com/amstersam/Coursera_CapStone_Final_Project/blob/master/Athens.csv

2. Thessaloniki -

https://github.com/amstersam/Coursera_CapStone_Final_Project/blob/master/Thessaloniki.csv

To start, let's get and look at the data. I've already upload it on Jupyter, so let us have a look and load it to dataframe.

```
[112]: #import the required library
import numpy as np
import pandas as pd

#read csv file contain KL data
df_athens = pd.read_csv('Athens.csv')
df_athens.head()
```

```
[112]:
```

| | District | Area | PostCode |
|---|---------------|--------------|----------|
| 0 | North Suburbs | EKALI | 14578 |
| 1 | North Suburbs | NEA ERITHREA | 14671 |
| 2 | North Suburbs | PEFKI | 15121 |
| 3 | North Suburbs | MAROUSI | 15122 |
| 4 | North Suburbs | MELISIA | 15127 |

We can explore the data with some basic queries in order to understand where we can focus and which areas may be more convenient to work with.

```
[113]: #examine data
print('Athens dataframe has {} districts and {} areas.'.format(
    len(df_athens['District'].unique()),
    df_athens.shape[0]
))

#grouping data to find District with highest number of area
df_athens.groupby('District').count()
```

Athens dataframe has 6 districts and 50 areas.

```
[113]:
```

| | Area | PostCode |
|-----------------------|------|----------|
| District | | |
| Center | 4 | 4 |
| East Suburbs | 10 | 10 |
| North Suburbs | 11 | 11 |
| South Suburbs | 11 | 11 |
| South Suburbs Suburbs | 2 | 2 |
| West Suburbs | 12 | 12 |

As we can see below, we have loaded as well an extra csv file containing all Greek postal codes and their equivalent latitude and longitude values (<https://github.com/MentatInnovations/grpostcodes>).

```
[131]: #read and load JB data
df_geo = pd.read_csv('postcode_lat_long_gr.csv')
df_geo.head()
```

```
[131]:
```

| | tk | lat | lon |
|---|-------|-----------|-----------|
| 0 | 10021 | 37.974511 | 23.733071 |
| 1 | 10431 | 37.984438 | 23.728117 |
| 2 | 10432 | 37.987244 | 23.726373 |
| 3 | 10433 | 37.978381 | 23.780513 |
| 4 | 10434 | 37.993469 | 23.727507 |

We could have used the geocoder instead but as long as we have everything we need we shall proceed faster. Now, we are in a position to perform a join and assign coordinates to every point and we can take a quick look at the results.

```
[117]: athens_full = pd.merge(df_athens, df_geo, how='left',
                             left_on='PostCode', right_on='tk', validate="1:1")
athens_full.drop(labels='tk', axis=1, inplace=True)
athens_full.head()
```

```
[117]:
```

| | District | Area | PostCode | lat | lon |
|---|---------------|--------------|----------|-----------|-----------|
| 0 | North Suburbs | EKALI | 14578 | 38.100877 | 23.835080 |
| 1 | North Suburbs | NEA ERITHREA | 14671 | 38.092649 | 23.820048 |
| 2 | North Suburbs | PEFKI | 15121 | 38.052949 | 23.790560 |
| 3 | North Suburbs | MAROUSI | 15122 | 38.054956 | 23.807655 |
| 4 | North Suburbs | MELISIA | 15127 | 38.057229 | 23.833602 |

```
[118]: df_athens = df_athens.drop_duplicates().reset_index(drop=True)
```

```
[32]: df_athens
```

```
[32]:
```

| | District | Area | PostCode |
|----|-----------------------|-------------------|----------|
| 0 | North Suburbs | EKALI | 14578 |
| 1 | North Suburbs | NEA ERITHREA | 14671 |
| 2 | North Suburbs | PEFKI | 15121 |
| 3 | North Suburbs | MAROUSI | 15122 |
| 4 | North Suburbs | MELISIA | 15127 |
| 5 | North Suburbs | HALANDRI | 15231 |
| 6 | North Suburbs | VRILISIA | 15235 |
| 7 | North Suburbs | PENTELI | 15236 |
| 8 | North Suburbs | FILOTHEI | 15237 |
| 9 | North Suburbs | HALANDRI - PATIMA | 15238 |
| 10 | North Suburbs | AGIA PARASKEVI | 15341 |
| 11 | East Suburbs | GERAKAS | 15344 |
| 12 | East Suburbs | STAVROS | 15345 |
| 13 | East Suburbs | ANTHOUSA | 15349 |
| 14 | East Suburbs | PALINI | 15351 |
| 15 | East Suburbs | GLIKA NERA | 15354 |
| 16 | East Suburbs | PSIHIKO | 15451 |
| 17 | East Suburbs | HOLARGOS | 15561 |
| 18 | East Suburbs | PAPAGOU | 15669 |
| 19 | Center | ZOGRAFOU | 15771 |
| 20 | Center | KESARIANI | 16121 |
| 21 | Center | VIRONAS | 16231 |
| 22 | South Suburbs | ILIOUPOLI | 16341 |
| 23 | South Suburbs | ARGIROUPOLI | 16450 |
| 24 | South Suburbs | GLIFADA | 16561 |
| 25 | South Suburbs | VOULIAGMENI | 16671 |
| 26 | South Suburbs Suburbs | VARI | 16672 |

We shall do the same for Thessaloniki.

```
[132]: #read and load Thessaloniki data
df_thessaloniki = pd.read_csv('Thessaloniki.csv')
df_thessaloniki.head()
```

```
[132]:
```

| | District | Area | PostCode |
|---|--------------------|--------------------|----------|
| 0 | South-east Suburbs | HARILAOU | 54248 |
| 1 | South-east Suburbs | HARILAOU | 54249 |
| 2 | South-east Suburbs | KATO TOUMBA | 54250 |
| 3 | South-east Suburbs | KOSTADINOUPOLITIKA | 54351 |
| 4 | South-east Suburbs | ANO TOUMBA | 54352 |

```
[116]: #examine
print('Thessaloniki dataframe has {} districts and {} areas.'.format(
    len(df_thessaloniki['District'].unique()),
    df_thessaloniki.shape[0]
))

#group by district
df_thessaloniki.groupby('District').count()
```

Thessaloniki dataframe has 4 districts and 29 areas.

```
[116]:
```

| | Area | PostCode |
|--------------------|------|----------|
| District | | |
| CENTER | 3 | 3 |
| North Suburbs | 2 | 2 |
| South-east Suburbs | 14 | 14 |
| West Suburbs | 10 | 10 |

We also change the columns names to be more homogenous from the aspect of detail.

```
[134]: thessaloniki_full = pd.merge(df_thessaloniki, df_geo, how='left',
    left_on='PostCode', right_on='tk', validate="1:1")
thessaloniki_full.drop(labels='tk', axis=1, inplace=True)
thessaloniki_full.head()
```

```
[134]:
```

| | District | Area | PostCode | lat | lon |
|---|--------------------|--------------------|----------|-----------|-----------|
| 0 | South-east Suburbs | HARILAOU | 54248 | 39.677124 | 22.580364 |
| 1 | South-east Suburbs | HARILAOU | 54249 | 40.602356 | 22.965986 |
| 2 | South-east Suburbs | KATO TOUMBA | 54250 | 40.602126 | 22.972760 |
| 3 | South-east Suburbs | KOSTADINOUPOLITIKA | 54351 | 40.617032 | 22.974236 |
| 4 | South-east Suburbs | ANO TOUMBA | 54352 | 40.612080 | 22.983126 |

```
[135]: thessaloniki_full.rename(columns={'lat': 'Latitude'}, inplace=True)
```

```
[136]: thessaloniki_full.rename(columns={'lon': 'Longitude'}, inplace=True)
```

Methodology

In this project, we will try to use the basic methodology, which was presented during Week 3 and the respective lab.

Then we will use the Foursquare API to explore neighborhoods in both cities, Athens and Thessaloniki. After that, explore function to get the most common venue categories in each neighborhood, and then use this feature to group the neighborhoods into clusters K-means clustering algorithm will be use to complete this task. And also, the Folium library to visualize the neighborhoods in Athens and Thessaloniki and their emerging clusters.

Based on dataframe analysis above, we found out that North Suburbs area in Athens and West Suburbs area in Thessaloniki contain the largest area within and from an online research we found out that the population density there is quite high.

one_W5.ipynb

: Python 3

EKALI

NEA ERITHREA

PEFKI

MAROUSI

MELISIA

HALANDRI

VRILISIA

PENTELI

FILOTHEI

HALANDRI – PATIMA

AGIA PARASKEVI

(249, 7)

[155]:

| | Area | Area Latitude | Area Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|--------------|---------------|----------------|-----------------|----------------|-----------------|---------------------|
| 0 | EKALI | 38.100877 | 23.835080 | Πλατεία Μουσίων | 38.102017 | 23.832907 | Plaza |
| 1 | EKALI | 38.100877 | 23.835080 | Nike Store | 38.097062 | 23.836865 | Sporting Goods Shop |
| 2 | NEA ERITHREA | 38.092649 | 23.820048 | Family Project | 38.091214 | 23.819720 | Bakery |
| 3 | NEA ERITHREA | 38.092649 | 23.820048 | Πανερυθραϊκός | 38.090214 | 23.818901 | Souvlaki Shop |
| 4 | NEA ERITHREA | 38.092649 | 23.820048 | Κοράλλι | 38.092371 | 23.820113 | Ouzeri |

one_W5.ipynb

: Python 3

HARILAOU

HARILAOU

KATO TOUMBA

KOSTADINOUPOLITIKA

ANO TOUMBA

TOUMBA

TOUMBA

NEA REDESTOS

ANALIPSI

ANTHEON

KALAMARIA

PANORAMA

TRIANDRIA

THERMI

(414, 7)

[159]:

| | Area | Area Latitude | Area Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|----------|---------------|----------------|----------------|----------------|-----------------|-------------------------|
| 0 | HARILAOU | 40.602356 | 22.965986 | Πατσάς 92 | 40.602313 | 22.964555 | Patsa Restaurant |
| 1 | HARILAOU | 40.602356 | 22.965986 | Fregio | 40.603232 | 22.969078 | Ice Cream Shop |
| 2 | HARILAOU | 40.602356 | 22.965986 | Σείριος | 40.600558 | 22.964317 | Liquor Store |
| 3 | HARILAOU | 40.602356 | 22.965986 | Εστία | 40.602769 | 22.969260 | Bakery |
| 4 | HARILAOU | 40.602356 | 22.965986 | Θανάσης & Υιοί | 40.603772 | 22.968866 | Grilled Meat Restaurant |

Analysis of Athens

Firstly, we will get the most common venues for Athens.

[163]:

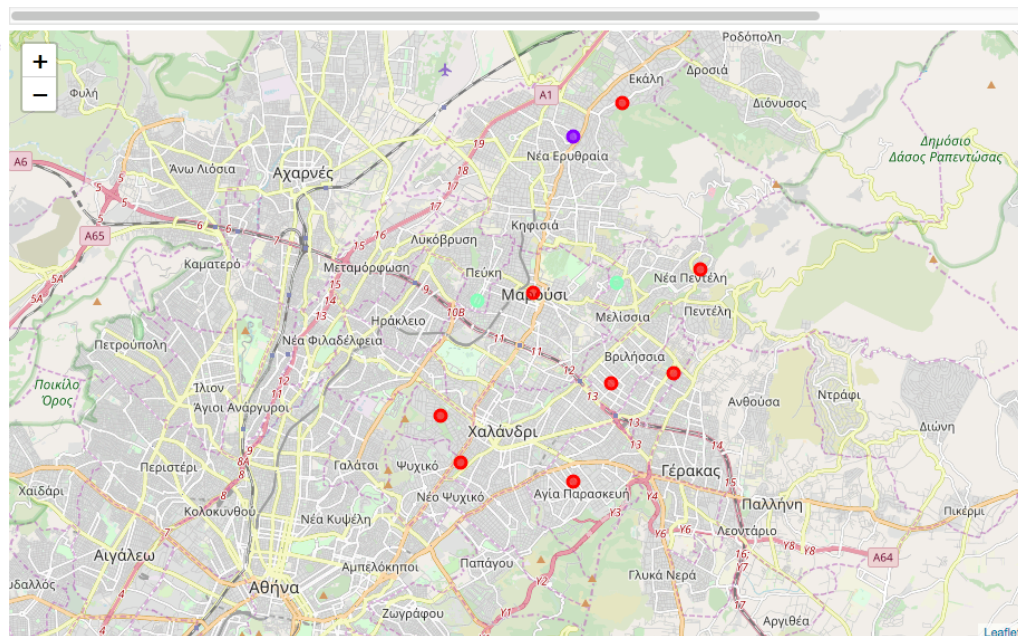
| | Area | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue |
|---|-------------------|-----------------------|-----------------------|-------------------------|-----------------------|-----------------------|-----------------------|-----------------------|------------------------|
| 0 | AGIA PARASKEVI | Bakery | Clothing Store | Bar | Pharmacy | Pizza Place | Cosmetics Shop | Café | Mobile Phone Shop |
| 1 | EKALI | Plaza | Sporting Goods Shop | Grilled Meat Restaurant | Greek Restaurant | Dog Run | Donut Shop | Electronics Store | Farmers Market |
| 2 | FILOTHEI | Park | Plaza | Tennis Stadium | Stadium | Snack Place | French Restaurant | Dog Run | Donut Shop |
| 3 | HALANDRI | Gym / Fitness Center | Café | Bakery | Basketball Court | Burger Joint | Mobile Phone Shop | Coffee Shop | Furniture / Home Store |
| 4 | HALANDRI - PATIMA | Cupcake Shop | Park | Racetrack | Farmers Market | Steakhouse | Dog Run | Yoga Studio | French Restaurant |

Secondly, we will move on to apply k-means.

[164] :

| | District | Area | PostCode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue |
|---|---------------|--------------|----------|-----------|-----------|----------------|-----------------------|-----------------------|-------------------------|-----------------------|-----------------------|-------------------------|-------------------------|
| 0 | North Suburbs | EKALI | 14578 | 38.100877 | 23.835080 | 0 | Plaza | Sporting Goods Shop | Grilled Meat Restaurant | Greek Restaurant | Dog Run | Donut Shop | Electronics Store |
| 1 | North Suburbs | NEA ERITHREA | 14671 | 38.092649 | 23.820048 | 1 | Dessert Shop | Bar | Nail Salon | Cocktail Bar | Italian Restaurant | Ice Cream Shop | Fire Station |
| 2 | North Suburbs | PEFKI | 15121 | 38.052949 | 23.790560 | 2 | Greek Restaurant | Bakery | Park | Café | Souvlaki Shop | Gym / Fitness Center | Grilled Meat Restaurant |
| 3 | North Suburbs | MAROUSI | 15122 | 38.054956 | 23.807655 | 0 | Café | Bakery | Bar | Coffee Shop | Souvlaki Shop | Multiplex | Plaza |
| 4 | North Suburbs | MELISIA | 15127 | 38.057229 | 23.833602 | 2 | Souvlaki Shop | Bakery | Café | Pharmacy | Seafood Restaurant | Grilled Meat Restaurant | Grocery Store |

[166] :



Analysis of Thessaloniki

As far as Thessaloniki is concerned we will follow the same method.


```
[244]: #create the new dataframe and display the top 10 venues for each neighborhood
num_top_venues = 8

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['Area']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
areas_venues_sorted = pd.DataFrame(columns=columns)
areas_venues_sorted['Area'] = thessaloniki_grouped['Area']

for ind in np.arange(thessaloniki_grouped.shape[0]):
    areas_venues_sorted.iloc[ind, 1:] = return_most_common_venues(thessaloniki_grouped.iloc[ind, :], num_top_venues)

areas_venues_sorted.head()
```

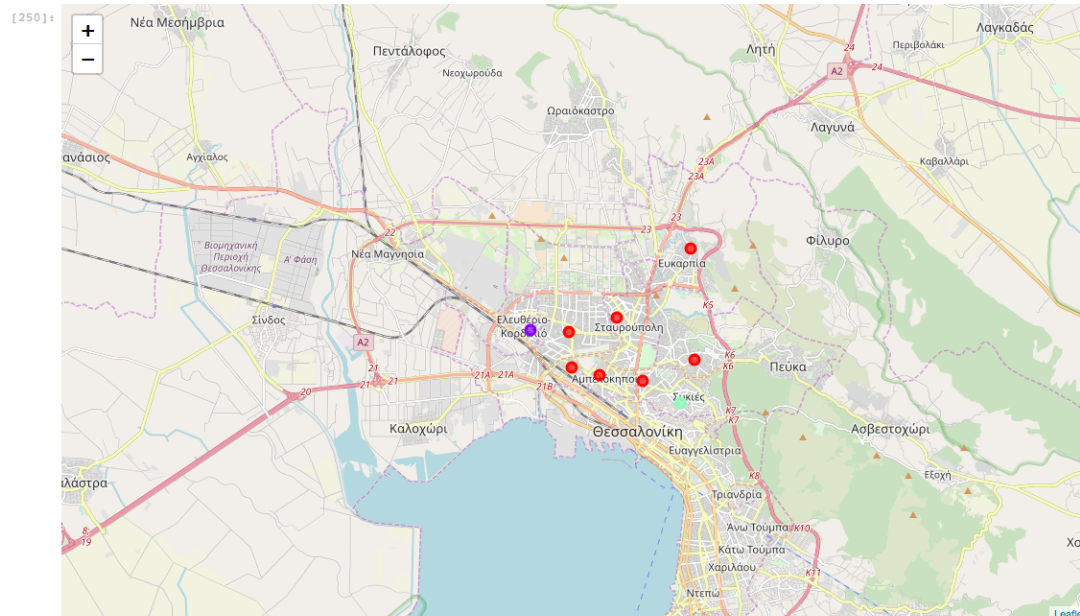
[244]:

| | Area | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue |
|---|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 0 | AMPELOKIPI | Café | Bar | Mobile Phone Shop | Supermarket | Souvlaki Shop | Coffee Shop | Snack Place | Fast Food Restaurant |
| 1 | ELEUTHERIO - KORDELIO | Café | Supermarket | Coffee Shop | Fish Taverna | Jewelry Store | Meze Restaurant | Mobile Phone Shop | Electronics Store |
| 2 | EVOSMOS | Bar | Café | Snack Place | Meze Restaurant | Fast Food Restaurant | Greek Restaurant | Bakery | Mobile Phone Shop |
| 3 | MENEMENI | Pub | Soccer Field | Plaza | Pier | Seafood Restaurant | Café | Supermarket | Fast Food Restaurant |
| 4 | NEAPOLI | Café | Video Store | Gym | Electronics Store | Dessert Shop | Men's Store | Meze Restaurant | Mobile Phone Shop |

K-means for Thessaloniki

[245]:

| | District | Area | PostCode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue |
|---|--------------|-----------------------|----------|-----------|-----------|----------------|-----------------------|-------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 0 | West Suburbs | AMPELOKIPI | 56121 | 40.655333 | 22.921503 | 0 | Café | Bar | Mobile Phone Shop | Supermarket | Souvlaki Shop | Coffee Shop | Snack Place | Fast Food Restaurant |
| 1 | West Suburbs | MENEMENI | 56122 | 40.657488 | 22.911517 | 0 | Pub | Soccer Field | Plaza | Pier | Seafood Restaurant | Café | Supermarket | Fast Food Restaurant |
| 2 | West Suburbs | EVOSMOS | 56224 | 40.667036 | 22.910492 | 0 | Bar | Café | Snack Place | Meze Restaurant | Fast Food Restaurant | Greek Restaurant | Bakery | Mobile Phone Shop |
| 3 | West Suburbs | ELEUTHERIO - KORDELIO | 56334 | 40.667525 | 22.896978 | 1 | Café | Supermarket | Coffee Shop | Fish Taverna | Jewelry Store | Meze Restaurant | Mobile Phone Shop | Electronics Store |
| 4 | West Suburbs | STAVROUPOLI | 56429 | 40.689740 | 22.954117 | 0 | Gym | Grilled Meat Restaurant | Bakery | Greek Restaurant | Basketball Court | Plaza | Café | Salon / Barbershop |



Results

| | | | | | | | | | | | |
|--------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------|-----------------------|-----------------------|-------------------------|-------------------------|-----------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| [251]: | #Cluster 1 for Athens athens_merged.loc[athens_merged['Cluster Labels'] == 0, athens_merged.columns[[2] + list(range(5, athens_merged.shape[1]))]] | | | | | | | | | | |
| [251]: | PostCode | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | |
| | 0 | 14578 | 0 | Plaza | Sporting Goods Shop | Grilled Meat Restaurant | Greek Restaurant | Dog Run | Donut Shop | Electronics Store | Farmers Market |
| | 3 | 15122 | 0 | Café | Bakery | Bar | Coffee Shop | Souvlaki Shop | Multiplex | Plaza | Gaming Cafe |
| | 5 | 15231 | 0 | Gym / Fitness Center | Café | Bakery | Basketball Court | Burger Joint | Mobile Phone Shop | Coffee Shop | Furniture / Home Store |
| | 6 | 15235 | 0 | Park | Plaza | Convenience Store | Japanese Restaurant | Farmers Market | Pharmacy | Flower Shop | Coffee Shop |
| | 7 | 15236 | 0 | Pharmacy | Plaza | Grilled Meat Restaurant | Greek Restaurant | Yoga Studio | Souvlaki Shop | Meze Restaurant | Pizza Place |
| | 8 | 15237 | 0 | Park | Plaza | Tennis Stadium | Stadium | Snack Place | French Restaurant | Dog Run | Donut Shop |
| | 9 | 15238 | 0 | Cupcake Shop | Park | Racetrack | Farmers Market | Steakhouse | Dog Run | Yoga Studio | French Restaurant |
| | 10 | 15341 | 0 | Bakery | Clothing Store | Bar | Pharmacy | Pizza Place | Cosmetics Shop | Café | Mobile Phone Shop |
| [252]: | #Cluster 2 for Athens athens_merged.loc[athens_merged['Cluster Labels'] == 1, athens_merged.columns[[2] + list(range(5, athens_merged.shape[1]))]] | | | | | | | | | | |
| [252]: | PostCode | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | |
| | 1 | 14671 | 1 | Dessert Shop | Bar | Nail Salon | Cocktail Bar | Italian Restaurant | Ice Cream Shop | Fire Station | Health & Beauty Service |
| [253]: | #Cluster 3 for Athens athens_merged.loc[athens_merged['Cluster Labels'] == 2, athens_merged.columns[[2] + list(range(5, athens_merged.shape[1]))]] | | | | | | | | | | |
| [253]: | PostCode | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | |
| | 2 | 15121 | 2 | Greek Restaurant | Bakery | Park | Café | Souvlaki Shop | Gym / Fitness Center | Grilled Meat Restaurant | Pool |
| | 4 | 15127 | 2 | Souvlaki Shop | Bakery | Café | Pharmacy | Seafood Restaurant | Grilled Meat Restaurant | Grocery Store | Gym |
| [254]: | #Cluster 1 for Thessaloniki thessaloniki_merged.loc[thessaloniki_merged['Cluster Labels'] == 0, thessaloniki_merged.columns[[2] + list(range(5, thessaloniki_merged.shape[1]))]] | | | | | | | | | | |
| [254]: | PostCode | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | |
| | 0 | 56121 | 0 | Café | Bar | Mobile Phone Shop | Supermarket | Souvlaki Shop | Coffee Shop | Snack Place | Fast Food Restaurant |
| | 1 | 56122 | 0 | Pub | Soccer Field | Plaza | Pier | Seafood Restaurant | Café | Supermarket | Fast Food Restaurant |
| | 2 | 56224 | 0 | Bar | Café | Snack Place | Meze Restaurant | Fast Food Restaurant | Greek Restaurant | Bakery | Mobile Phone Shop |
| | 4 | 56429 | 0 | Gym | Grilled Meat Restaurant | Bakery | Greek Restaurant | Basketball Court | Plaza | Café | Salon / Barbershop |
| | 5 | 56431 | 0 | Café | Taverna | Bar | Fast Food Restaurant | Plaza | Snack Place | Coffee Shop | Mobile Phone Shop |
| | 6 | 56532 | 0 | BBQ Joint | Gym / Fitness Center | Snack Place | Park | Pizza Place | Playground | Plaza | Café |
| | 8 | 56727 | 0 | Café | Video Store | Gym | Electronics Store | Dessert Shop | Men's Store | Meze Restaurant | Mobile Phone Shop |
| | 9 | 57002 | 0 | Bar | Pub | Greek Restaurant | Video Store | Grilled Meat Restaurant | Frozen Yogurt Shop | Fried Chicken Joint | Fish Taverna |
| [255]: | #Cluster 2 for Thessaloniki thessaloniki_merged.loc[thessaloniki_merged['Cluster Labels'] == 1, thessaloniki_merged.columns[[2] + list(range(5, thessaloniki_merged.shape[1]))]] | | | | | | | | | | |
| [255]: | PostCode | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | |
| | 3 | 56334 | 1 | Café | Supermarket | Coffee Shop | Fish Taverna | Jewelry Store | Meze Restaurant | Mobile Phone Shop | Electronics Store |
| [256]: | #Cluster 3 for Thessaloniki thessaloniki_merged.loc[thessaloniki_merged['Cluster Labels'] == 2, thessaloniki_merged.columns[[2] + list(range(5, thessaloniki_merged.shape[1]))]] | | | | | | | | | | |
| [256]: | PostCode | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | |
| | 7 | 56625 | 2 | Café | Gym | Bougatsa Shop | Theater | Supermarket | Restaurant | Beer Bar | Scenic Lookout |

Discussion

Based on cluster for each city above, we believe that classification for each cluster can be done better with calculation of venues categories (most common) in each city. Referring to each cluster, we can determine to some extent what represents each cluster by using Foursquare - Most Common Venue data.

We can summarize the following based on the clustering produced by our code.

| Cluster | Athens | Thessaloniki |
|---------|------------------|------------------|
| 1 | Residential area | Residential area |
| 2 | Residential area | Residential area |
| 3 | Residential area | Residential area |

Unfortunately, the kind of data provided by Foursquare reaches to a certain extent, meaning that there are several limitations as far as the statistical or other quantitative aspect of the data is concerned. In other words, we have no information about the range of ages of the people visiting those venues, or the income and educational level of those people. Those categorical variables could have another kind of value to our project leading perhaps to several remarks or observations.

Conclusion

Using the Foursquare API, we can capture data of common places for the two major Greek cities. Going back to our initial objectives we could almost safely come to the conclusion that the two cities and more specifically the North suburbs of Athens and the West suburbs of Thessaloniki are similar and both be classified as residential areas.

However, to declare both cities are similar or dissimilar based on common venues visited is quite difficult. Both cities are similar in some venues also dissimilar in certain venues. Consequently, both areas consist of many different districts that are quite attractive for locals mostly, since they have to offer venues to cover the daily needs of the people but also sports, entertainment and other.