Capstone Project

The Battle of Neighborhoods

Find the best place to open a restaurant in Milan

1. Introduction

Now that you have been equipped with the skills and the tools to use location data to explore a geographical location, over the course of two weeks, you will have the opportunity to be as creative as you want and come up with an idea to leverage the Foursquare location data to explore or compare neighborhoods or cities of your choice or to come up with a problem that you can use the **Foursquare** location data to solve. If you cannot think of an idea or a problem, here are some ideas to get you started:

1. In Module 3, we explored **New York City** and the city of **Toronto** and segmented and clustered their neighborhoods. Both cities are very diverse and are the financial capitals of their respective countries. One interesting idea would be to compare the neighborhoods of the two cities and determine how similar or dissimilar they are. Is New York City more like Toronto or Paris or some other multicultural city? I will leave it to you to refine this idea.
2. In a city of your choice, if someone is looking to open a **restaurant**, where would you recommend that they open it? Similarly, if a contractor is trying to start their own business, where would you recommend that they set up their office?

These are just a couple of many ideas and problems that can be solved using location data in addition to other datasets. No matter what you decide to do, make sure to provide sufficient justification of why you think what you want to do or solve is important and why would a client or a group of people be interested in your project.

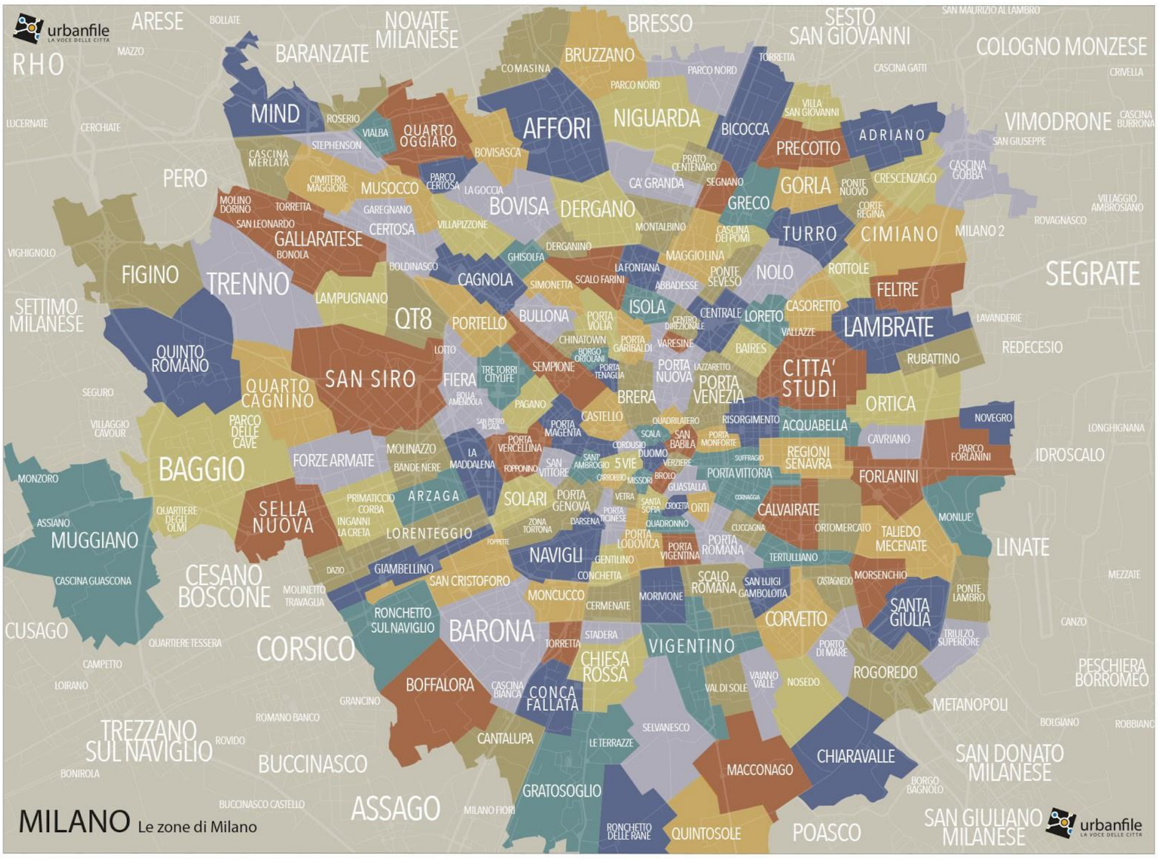
So I decided to try to answer this simple question: where would you recommend to open a new restaurant?

1.1. Business problem

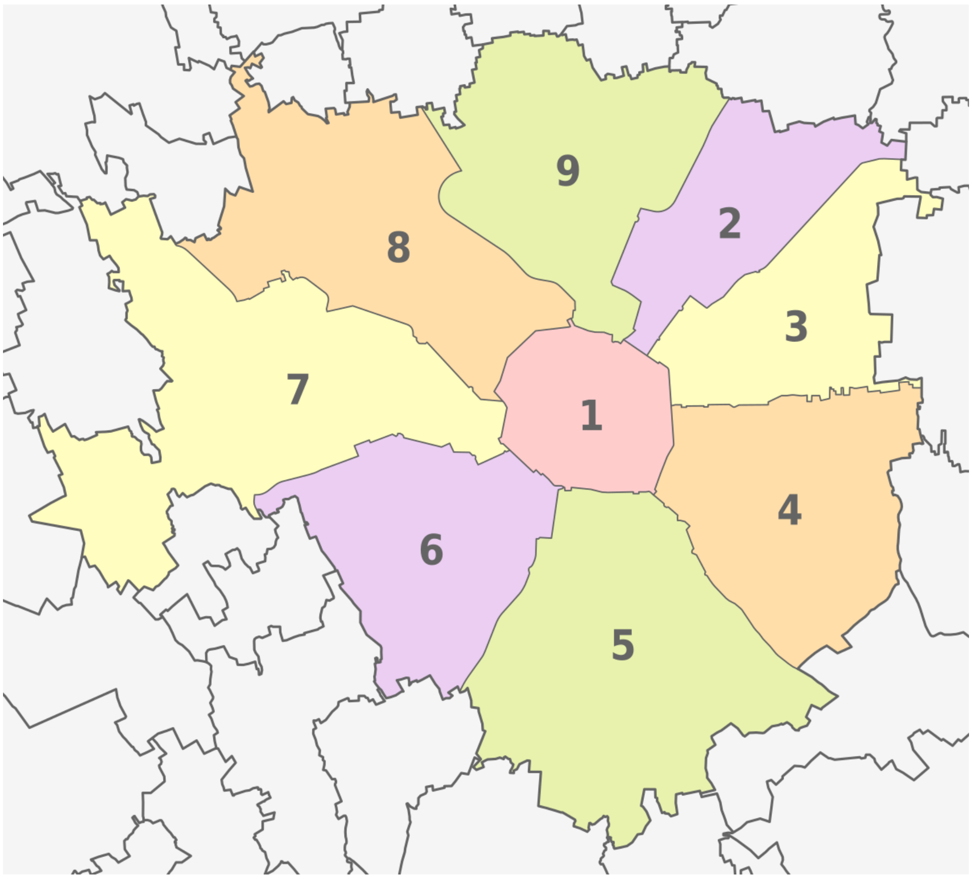
The city chosen to answer the initial question is **Milan** a city in northern Italy, capital of Lombardy, and the second-most populous city in Italy after Rome. Its continuously built-up urban area, that stretches well beyond the boundaries of the administrative metropolitan city, is the fourth largest in the EU with 5.27 million inhabitants.

Milan is considered a leading alpha global city, with strengths in the field of the art, commerce, design, education, entertainment, fashion, finance, healthcare, media, services, research and tourism. Its business district hosts Italy's stock exchange (Italian: Borsa Italiana), and the headquarters of national and international banks and companies. In terms of GDP, it has the second-largest economy among EU cities after Paris, and is the wealthiest among EU non-capital cities. Milan is also considered part of the Blue Banana and one of the "Four Motors for Europe".

Let's see how many neighborhood there are and how they are distributed:



As you can see there are many of them, so the town is also divided in districts (municipi):



After this short **presentation**, I suppose that the city of Milan is place with a great competition, especially, if you want to **open** a **restaurant** so I would like to help a possible stakeholder to understand better the town and the market with useful insights.

1.2. Target audience

A business entrepreneur that wants open a new restaurant in Milan.

Business Analyst or Data Scientists, who wish to analyze the neighborhoods of Milan using python, Jupiter notebook and some machine learning techniques.

Someone curious about data that want to have an idea, how beneficial it is to open a restaurant and what are the pros and cons of this business.

2. Data section

First of all we need some information about the area of Milan such as borough\districts, population, latitude\longitude etc… so I think Wikipedia is the first place to take a look:

https://it.wikipedia.org/wiki/Municipi_di_Milano

The borough are 9 with these coordinates:

	Borough	Name	Area(km2)	Population(31/12/2018)	Population_Density(km2)	Latitude	Longitude
0	1	Centro storico	967	98 531	10 189	45.471282	9.184999
1	2	Stazione Centrale, Gorla, Turro, Greco, Cresce...	1258	162 090	12 884	45.486117	9.203635
2	3	Città Studi, Lambrate, Venezia	1423	144 110	10 127	45.482506	9.241047
3	4	Vittoria, Forlanini	2095	161 551	7 711	45.431573	9.244738
4	5	Vigentino, Chiaravalle, Gratosoglio	2987	126 089	4 221	45.416987	9.238333
5	6	Barona, Lorenteggio	1828	151 291	8 276	45.440087	9.155924
6	7	Baggio, De Angeli, San Siro	3134	175 465	5 598	45.461244	9.089917
7	8	Fiera, Gallaratese, Quarto Oggiaro	2372	188 367	7 941	45.515925	9.140196
8	9	Stazione Garibaldi, Niguarda	2112	187 773	8 890	45.516888	9.191866

Now I need to find a list of all the **neighborhood** with the correspondent **borough**. Unfortunately the wikipedia tables aren't up to date so I found this paper from the official website of Milan:

https://www.pgt.comune.milano.it/sites/default/files/allegati/NIL_Intro.pdf

Elenco schede NIL per i municipi

Municipio 1
1. Duomo
2. Brera
3. Giardini Porta Venezia
4. Guastalla
7. Magenta- San Vittore
8. Parco Sempione
(5. Vigentina)
(6. Ticinese)
(68. Pagano)
(69. Sarpi)

Municipio 2
10. Stazione Centrale - Ponte Seveso
16. Gorla - Precotto
17. Adriano
19. Padova - Turro - Crescenzago

Municipio 5
5. Porta Vigentina - Porta Lodovica
6. Porta Ticinese - Conca del Naviglio
36. Scalo Romana
34. Chiaravalle
37. Morivione
38. Vigentino - Q.re Fatima
39. Quintosole
40. Ronchetto delle Rane
41. Gratosoglio - Q.re Missaglia - Q.re Terrazze
42. Stadera - Chiesa Rossa - Q.re Torretta - Conca Fallata
43. Tibaldi
85. Parco delle Abbazie
86. Parco dei Navigli
(47. Cantalupa)

Municipio 8
59. Tre Torri
64. Trenno
65. Q.re Gallaratese - Q.re San Leonardo - Lampugnano
66. QT8
67. Portello
68. Pagano
69. Sarpi
70. Ghisolfa
71. Villapizzone - Cagnola - Boldinasco
72. Maggiore - Musocco - Certosa
73. MIND - Cascina Triulza
74. Roserio
75. Stephenson
76. Quarto Oggiaro - Vialba - Musocco
(88. Parco Bosco in città)

Scraping the pdf file was impossible, so I created and uploaded this dataset on github:

https://github.com/NicMil/Coursera_Capstone/blob/master/Milano_Municipi_NIL.csv

This is a sample:

Num_NIL	NIL	Municipio	prezzo_mq
17	Adriano	2	€ 2.800 /m²
80	Affori	9	€ 2.350 /m²
87	Assiano	7	€ 2.400 /m²
55	Baggio - Q.re degli Olmi - Q.re Valsesia	7	€ 2.400 /m²
52	Bande Nere	6	€ 3.857 /m²
46	Barona	6	€ 3.250 /m²

Note: the information about average land price is taken from these two websites (national reference points for the real estate market in Italy):

https://www.immobiliare.it/mercato-immobiliare/lombardia/milano/

https://www.mercato-immobiliare.info/lombardia/milano/milano.html

For the **final step**, I need to get the coordinates of every neighborhood.

Fortunately the statistics office of Milan created a very interesting portal about open data https://dati.comune.milano.it/ (licenceCreative Commons http://www.opendefinition.org/licenses/cc-by) and I found what I was looking for: a shape file (**GeoJSON**).

https://dati.comune.milano.it/dataset/e8e765fc-d882-40b8-95d8-16ff3d39eb7c/resource/9c4e0776-56fc-4f3d-8a90-f4992a3be426/download/ds964_nil_wm.geojson

	ID_NIL	NIL	Valido_dal	Valido_al	Fonte	Shape_Length	Shape_Area	OBJECTID	geometry
0	48	RONCHETTO SUL NAVIGLIO - Q.RE LODOVICO IL MORO	05/02/2020	Vigente	Milano 2030 - PGT Approvato	8723.368714	2.406306e+06	89	POLYGON ((9.15422 45.43775, 9.15274 45.43887, ...
1	64	TRENNO	05/02/2020	Vigente	Milano 2030 - PGT Approvato	3309.998800	4.896921e+05	90	POLYGON ((9.10623 45.49016, 9.10591 45.49084, ...
2	67	PORTELLO	05/02/2020	Vigente	Milano 2030 - PGT Approvato	3800.750663	9.096022e+05	91	POLYGON ((9.15636 45.48785, 9.15495 45.48852, ...
3	81	BOVISASCA	05/02/2020	Vigente	Milano 2030 - PGT Approvato	7105.469715	1.578028e+06	92	POLYGON ((9.16803 45.52234, 9.16763 45.52272, ...
4	84	PARCO NORD	05/02/2020	Vigente	Milano 2030 - PGT Approvato	11741.717005	1.532331e+06	93	POLYGON ((9.20040 45.52848, 9.20028 45.52846, ...

After some steps of data cleaning and data preparation, the final result is:

	Id	Neighborhood	Borough	Population(31/12/2018) Borough	Average Price(€/sm)	Latitude	Longitude
0	48	Ronchetto Sul Naviglio - Q.Re Lodovico Il Moro	6	151 291	€ 2.563 /m²	45.438460	9.137260
1	64	Trenno	8	188 367	€ 2.350 /m²	45.492822	9.101675
2	67	Portello	8	188 367	€ 4.300 /m²	45.484490	9.153947
3	81	Bovisasca	9	187 773	€ 2.000 /m²	45.517433	9.156731
4	84	Parco Nord	9	187 773	€ 6.800 /m²	45.523514	9.184235

Now I am rady to use the foursquare API:

https://developer.foursquare.com/docs/places-api/

3. Methodology

3.1. Business Understanding

The aim of this project is to find the best neighborhood of Milan to open a new restaurant.

3.2. Analytical Approach

The total number of neighborhoods in Milan are 89 so we need to find a way to cluster them based on their similarities, that are the number and the kind of restaurant.
Briefly, after some steps of Data Cleaning and Data Exploration, I will use a K-Means algorithm to extract the clusters, produce a map and make an argument on the final result.

3.3. Data Exploration

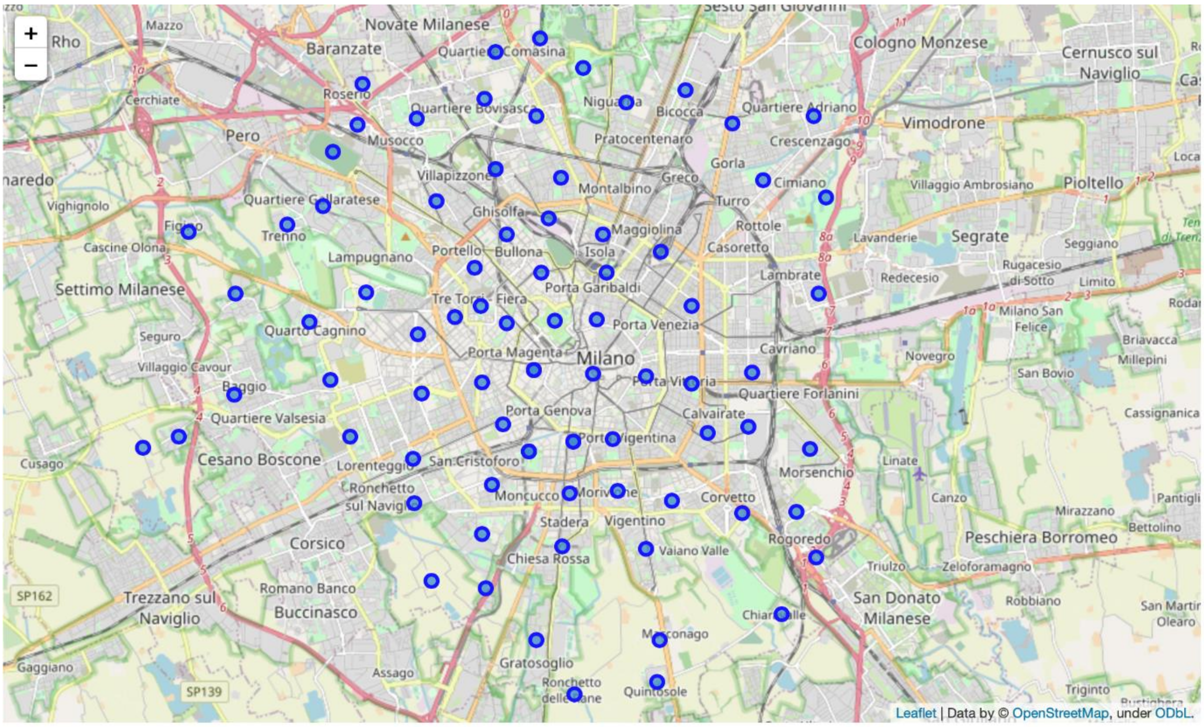
To explore the data, I will use "Folium" a python library that can create interactive leaflet map using coordinate data.

The code below is an example how to check the centroids of every neighborhood in Milan:

```
map_milan = folium.Map(location=[latitude, longitude], zoom_start=12)

# add markers to map
for lat, lng, borough, neighborhood in zip(df_milan_complete['Latitude'],
                                           df_milan_complete['Longitude'],
                                           df_milan_complete['Id'],
                                           df_milan_complete['Neighborhood']):
    label = '{}, {}'.format(neighborhood, borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_milan)

map_milan
```

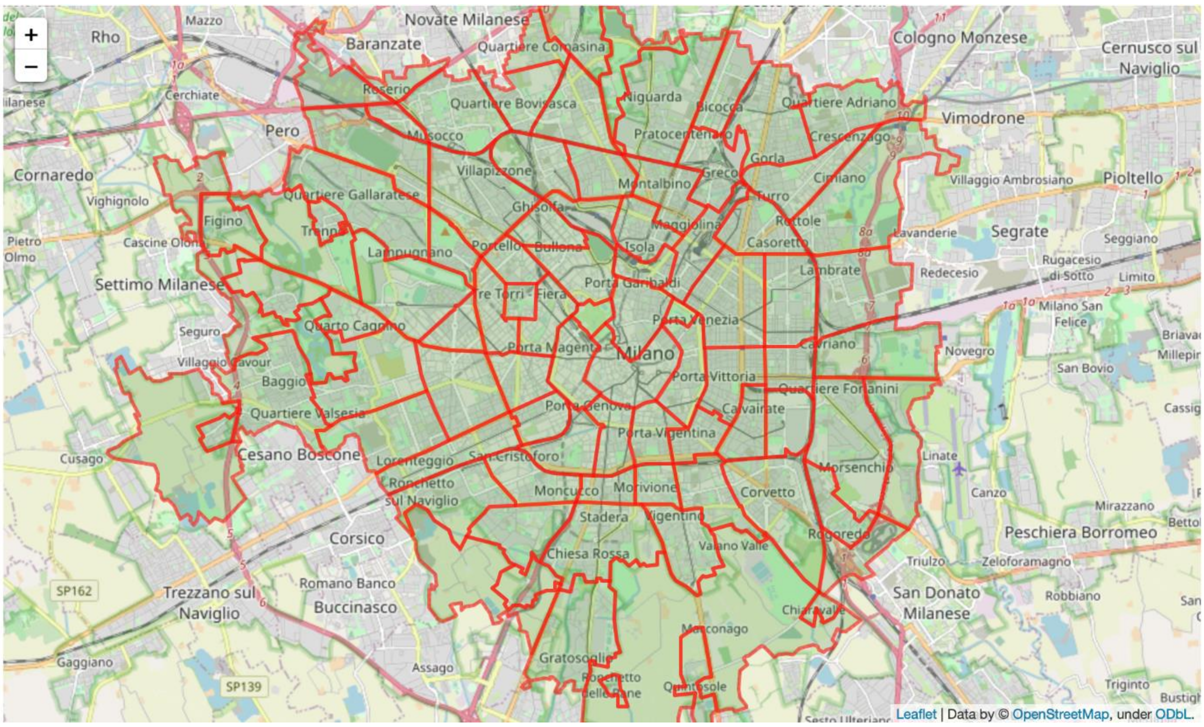


Another interesting function is a GeoJSON map. Let's see:

```
m = folium.Map([latitude, longitude], zoom_start=12)

folium.GeoJson(milan_neighborhood_geodf,
    style_function=lambda x: {
        'color' : 'red',
        'opacity': 0.6,
        'fillColor' : 'green',
        }).add_to(m)

m
```



Now it’s time to use the foursquare API (Link) to extract the venues of each neighborhood in Milan:

```
        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&section=food&client_id={}&client_secret={}&v={}&ll={},{}&radius=
{}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)
```

```
rest_unique = milan_restaurants.groupby(['Venue',
                                          'Venue Latitude',
                                          'Venue Longitude',
                                          'Venue Category']).size().reset_index(name='Counts')
print(rest_unique.shape)
rest_unique.head(10)
```

	Venue	Venue Latitude	Venue Longitude	Venue Category	Counts
0	"Carmen" (ristorante - pizzeria - grill)	45.440161	9.224682	Pizza Place	2
1	'A Tarantella	45.490889	9.233899	Pizza Place	1
2	100 Montaditos	45.446989	9.176994	Sandwich Place	2
3	100 Montaditos	45.453823	9.163722	Sandwich Place	2
4	100 Montaditos	45.522432	9.214766	Sandwich Place	2
5	13 Giugno	45.469227	9.215788	Restaurant	2
6	150up	45.490257	9.184895	Bistro	1
7	212 Hamburger & Delicious	45.454765	9.161157	Burger Joint	2
8	212 Rotisserie & Delicious	45.452686	9.201624	Fried Chicken Joint	5
9	22	45.474928	9.193852	Bistro	1

Unfortunately if two centroids are too close together, I could extract duplicates venues (see the column “Counts”). To solve this problem, I will link a unique venue with the right neighborhood using his polygon (“geometry”).

```
from shapely.geometry import shape, Point

rest_list = []

for ind1, rest in rest_unique.iterrows():
    point = Point(rest[["Venue Longitude"]].item(), rest[["Venue Latitude"]].item())
    # print(point)
    for ind2, neighborhood in df_milan_complete.iterrows():
        polygon = shape(neighborhood[["Geometry"]].item())
        if (polygon.contains(point)):
            # print("match with " + str(polygon))
            frame = {'Neighborhood': neighborhood[["Neighborhood"]].item(),
                     'Neighborhood Latitude': neighborhood[["Latitude"]].item(),
                     'Neighborhood Longitude': neighborhood[["Longitude"]].item(),
                     'Venue': rest[["Venue"]].item(),
                     'Venue Latitude': rest[["Venue Latitude"]].item(),
                     'Venue Longitude': rest[["Venue Longitude"]].item(),
                     'Venue Category': rest[["Venue Category"]].item()
                    }
            rest_list.append(frame)

cn = ['Neighborhood', 'Neighborhood Latitude', 'Neighborhood Longitude',
      'Venue', 'Venue Latitude', 'Venue Longitude', 'Venue Category']
milan_restaurants_unique = pd.DataFrame(rest_list, columns = cn)
milan_restaurants_unique.head()
```

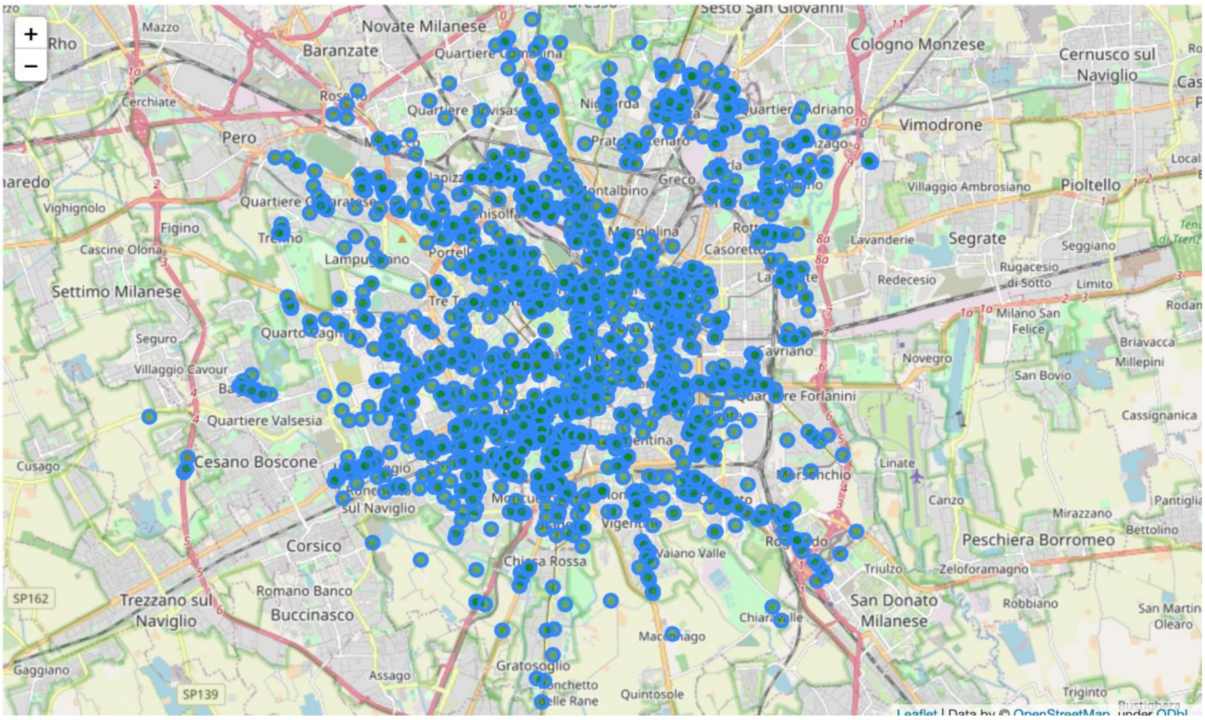
Let’s compare the two dataset:

```
print(milan_restaurants.shape)
print(milan_restaurants_unique.shape)
```

```
(5141, 7)
(1852, 7)
```

As you can see, I removed a lot of duplicates.

Now we can use “milan_restaurant_unique” dataset as input for a folium map:



Before to continue, it could be a good idea to check what kind of venue are popular in Milan.

Let’s see:

```python
venueDF = milan_restaurants_unique.groupby('Venue Category').size().reset_index(name='Counts')
venueDF.sort_values(by=['Counts'], ascending=False).head(10)
```

	Venue Category	Counts
45	Italian Restaurant	398
17	Café	293
62	Pizza Place	263
65	Restaurant	92
46	Japanese Restaurant	80
8	Bakery	52
71	Seafood Restaurant	49
81	Sushi Restaurant	47
69	Sandwich Place	46
21	Chinese Restaurant	42

So if we exclude Café and Bakery, Italian Restaurant and Pizza place are the most popular.

Let's keep in mind and continue with our analysis.

3.4. Clustering

To analyze which neighborhood of Milan is good to open a new restaurant, I will use a K-means clustering: a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K. The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity.

So the first step is identify the best "K" using a famous analytical approach: the elbow method.

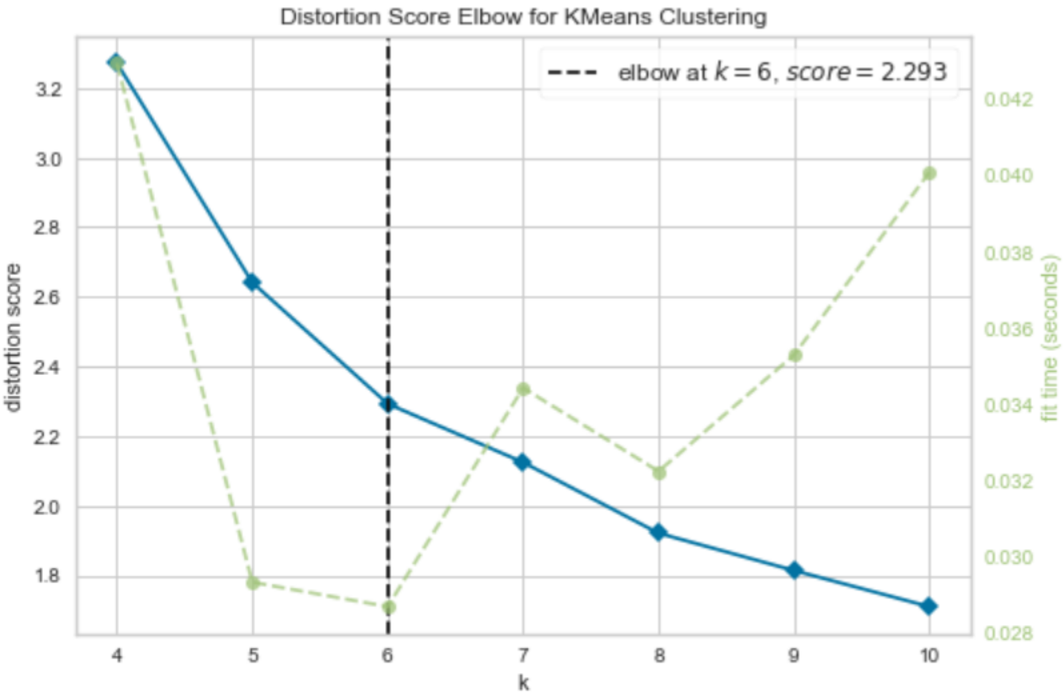
```python
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs

from yellowbrick.cluster import KElbowVisualizer

milan_part_clustering = milan_grouped.drop('Neighborhood', 1)

# Instantiate the clustering model and visualizer
model = KMeans()
visualizer = KElbowVisualizer(model, k=(4,11))

visualizer.fit(milan_part_clustering)        # Fit the data to the visualizer
visualizer.poof()     # Draw/show/poof the data
```



From the plot up here, I can easily say that the best K is 6.

Finally, we can try to cluster the neighborhood based on the venue categories and use K-Means clustering. The 6 clusters are partitioned based on similar

type of restaurants that belong to neighborhoods.

To run the cluster, I have used the code snippet below.

```
# set number of clusters
kclusters = 6

milan_grouped_clustering = milan_grouped.drop('Neighborhood', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(milan_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

And merge to obtain the final dataset:

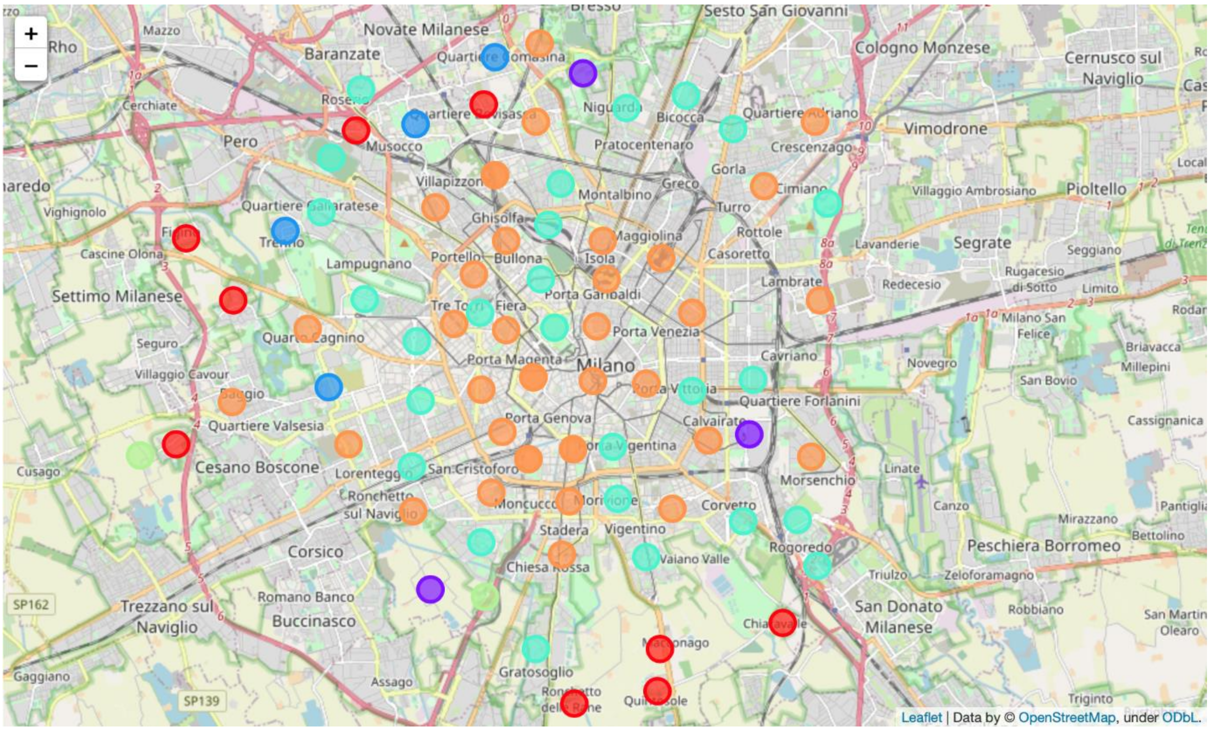
```
milan_merged = df_milan_complete.join(milan_venues_sorted.set_index('Neighborhood'), on='Neighborhood')
milan_merged['Cluster Labels'] = milan_merged['Cluster Labels'].fillna(0)
milan_merged['Cluster Labels'] = milan_merged['Cluster Labels'].astype(int)
milan_merged.drop(columns='Geometry', inplace=True)

milan_merged.head()
```

	Id	Neighborhood	Borough	Population(31/12 /2018) Borough	Average Price(€/sm)	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
0	48	Ronchetto Sul Naviglio - Q.Re Lodovico Il Moro	6	151 291	€ 2.563 /m²	45.438460	9.137260	5	Italian Restaurant	Pizza Place	Food Court	Noodle House
1	64	Trenno	8	188 367	€ 2.350 /m²	45.492822	9.101675	2	Pizza Place	Sandwich Place	Spanish Restaurant	Asian Restaurant
2	67	Portello	8	188 367	€ 4.300 /m²	45.484490	9.153947	5	Italian Restaurant	Japanese Restaurant	Seafood Restaurant	Mediterranean Restaurant
3	81	Bovisasca	9	187 773	€ 2.000 /m²	45.517433	9.156731	0	Italian Restaurant	Restaurant	Asian Restaurant	Steakhouse
4	84	Parco Nord	9	187 773	€ 6.800 /m²	45.523514	9.184235	1	Italian Restaurant	Sardinian Restaurant	Steakhouse	Breakfast Spot

4. Result and discussion

Before to start to analyze all the clusters, let's take a look on a folium map:



As we can see, each cluster belong to a color with different characteristics. You can read the complete list below:

Cluster 1 (Red):

	Neighborhood	Average Price(€/sm)	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
3	Bovisasca	€ 2.000 /m²	45.517433	9.156731	0	Italian Restaurant	Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
5	Figino	€ 2.000 /m²	45.491381	9.074376	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10	Quinto Romano	€ 2.250 /m²	45.479418	9.087541	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
19	Stephenson	€ 3.079 /m²	45.512246	9.121394	0	Italian Restaurant	Steakhouse	Restaurant	Asian Restaurant	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
21	Quintosole	€ 2.910 /m²	45.403412	9.204756	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
38	Muggiano	€ 2.200 /m²	45.451403	9.071630	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
43	Ronchetto Delle Rane	€ 4.350 /m²	45.401107	9.181961	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50	Chiaravalle	€ 2.700 /m²	45.416749	9.239611	0	Italian Restaurant	Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
51	Parco Delle Abbazie	€ 4.300 /m²	45.411618	9.205639	0	Italian Restaurant	Restaurant	Japanese Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria

Cluster 2 (Purple):

	Neighborhood	Average Price(€/sm)	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
4	Parco Nord	€ 6.800 /m²	45.523514	9.184235	1	Italian Restaurant	Sardinian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant	Vegetarian / Vegan Restaurant
36	Ortomercato	€ 4.005 /m²	45.453417	9.230270	1	Italian Restaurant	Pizza Place	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
75	Parco Dei Navigli	€ 1.800 /m²	45.423321	9.141989	1	Italian Restaurant	Sardinian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant	Vegetarian / Vegan Restaurant

Cluster 3 (Blue):

	Neighborhood	Average Price(€/sm)	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
1	Trenno	€ 2.350 /m²	45.492822	9.101675	2	Pizza Place	Sandwich Place	Spanish Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria
6	Quarto Oggiaro - Vialba - Musocco	€ 1.700 /m²	45.513636	9.137731	2	Pizza Place	Spanish Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
14	Comasina	€ 1.750 /m²	45.526441	9.159969	2	Pizza Place	Spanish Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
48	Forze Armate	€ 2.700 /m²	45.462489	9.113830	2	Pizza Place	Fast Food Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant

Cluster 4 (Cyan):

	Neighborhood	Average Price(€/sm)	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
9	Stadio - Ippodromi	€ 3.265 /m²	45.479641	9.123833	3	Seafood Restaurant	Pizza Place	Italian Restaurant	Mediterranean Restaurant	Food Truck	Diner	Burger Joint
13	San Siro	€ 3.150 /m²	45.471382	9.138358	3	Chinese Restaurant	Pizza Place	Italian Restaurant	Sushi Restaurant	Trattoria/Osteria	Food Truck	Sardinian Restaurant
17	Farini	€ 5.652 /m²	45.493963	9.174605	3	Italian Restaurant	Pizza Place	Restaurant	Breakfast Spot	Seafood Restaurant	Indian Restaurant	Chinese Restaurant
22	Parco Sempione	€ 5.800 /m²	45.474131	9.176251	3	Spanish Restaurant	Sardinian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant	Vegetarian / Vegan Restaurant
23	Barona	€ 3.250 /m²	45.432353	9.156192	3	Food Court	Italian Restaurant	Pizza Place	Japanese Restaurant	Trattoria/Osteria	Asian Restaurant	Breakfast Spot
25	Gorla - Precotto	€ 2.800 /m²	45.512660	9.225630	3	Pizza Place	Italian Restaurant	Breakfast Spot	Restaurant	Japanese Restaurant	Seafood Restaurant	Puglia Restaurant
26	Niguarda - Ca' Granda - Prato Centenaro - Q.Re...	€ 2.550 /m²	45.516696	9.196117	3	Pizza Place	Restaurant	Sushi Restaurant	Italian Restaurant	Korean Restaurant	Asian Restaurant	Breakfast Spot
27	Triulzo Superiore	€ 2.626 /m²	45.427941	9.249243	3	Fast Food Restaurant	Pizza Place	Restaurant	Japanese Restaurant	Trattoria/Osteria	Diner	Steakhouse

Cluster 5 (Green):

	Neighborhood	Average Price(€/sm)	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
20	Cantalupa	€ 3.717 /m²	45.421741	9.157204	4	Restaurant	Mediterranean Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant
32	Assiano	€ 2.400 /m²	45.449368	9.061547	4	Restaurant	Mediterranean Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot	Trattoria/Osteria	Kebab Restaurant

Cluster 6 (Orange):

	Neighborhood	Average Price(€/sm)	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
0	Ronchetto Sul Naviglio - Q.Re Lodovico Il Moro	€ 2.563 /m²	45.438460	9.137260	5	Italian Restaurant	Pizza Place	Food Court	Noodle House	Asian Restaurant	Breakfast Spot
2	Portello	€ 4.300 /m²	45.484490	9.153947	5	Italian Restaurant	Japanese Restaurant	Seafood Restaurant	Mediterranean Restaurant	Restaurant	Pizza Place
7	Isola	€ 5.550 /m²	45.490894	9.189617	5	Italian Restaurant	Pizza Place	Bistro	Ramen Restaurant	Restaurant	Seafood Restaurant
8	Quarto Cagnino	€ 2.241 /m²	45.473740	9.108096	5	Italian Restaurant	Pizza Place	Sushi Restaurant	Asian Restaurant	Steakhouse	Breakfast Spot
11	Duomo	€ 7.100 /m²	45.463707	9.186948	5	Italian Restaurant	Pizza Place	Sandwich Place	Restaurant	Bistro	Sushi Restaurant
12	Guastalla	€ 7.300 /m²	45.463219	9.201891	5	Italian Restaurant	Pizza Place	Seafood Restaurant	Indian Restaurant	Bistro	Sandwich Place
15	Tibaldi	€ 2.750 /m	45.440348	9.180459	5	Italian Restaurant	Pizza Place	Japanese Restaurant	Sushi Restaurant	Food Court	Breakfast Spot

Here we are at the end of the analysis, I tried to set up a realistic data-analysis scenario using several different ways such as: web scraping on Wikipedia, open data from public administration (Mayor of Milan), some powerful python libraries eg. Folium and GeoPandas, Foursquare API, etc…

So now we have the opportunity to make some argument about the clusters. Let's see what we have found:

1. The most common venues in Milan are Italian Restaurant and Pizza Place.
2. Cluster 3 and 5 don't have an Italian Restaurant.
3. From the geographical representation of the clusters, Comasina and Quarto Oggiaro, seems a good place open an Italian Restaurant. Also the land price isn't so high.
4. If our stakeholder thinks that there are too much Italian Restaurant, It can also be suggested that Assiano (cluster 5) could be a great area to open a Vegan\Vegetarian restaurant because of low profile and land price.

5. Conclusion

As the analysis is performed on small set of data, we can achieve better results by increasing the neighborhood information (see the next chapter). Anyway Milan is an international city with many different types of new restaurant business to offer and I think we have gone through the process of identifying the business problem, specifying the data required, clean the datasets, performing a machine learning algorithm using k-means clustering and providing some useful tips to our stakeholder.

6. Next development

Next steps I would recommend are:

- Use a different Venue API with more data. Unfortunately foursquare isn't pretty famous in Italy.

  Mostly users prefer Google Maps or Facebook.

- Find and use updated demographics data about Milan's Neighborhood.

- Try a Neighborhood-Based Clustering.