Coursera Capstone Project - Report

The Battle of Neighborhoods

• Introduction

I am a data scientist residing in Downtown Dubai. I currently live within walking distance to Downtown BurjKhalifa/Dubai Mall metro station and I enjoy many amenities and venues in the area, such as various international cousin restaurants, cafes, food shops and entertainment. I have been offered a great opportunity to work for a leader firm in Manhattan, NY. The key question is : **How can I find a convenient and enjoyable place similar to mine now in Dubai?** In order to make a comparison and evaluation of the rental options in Manhattan NY, I must set some basis, therefore the apartment in Manhattan must meet the following demands:

- apartment must be 2 or 3 bedrooms
- desired location is near a metro station in the Manhattan area and within 1.0 mile (1.6 km) radius
- price of rent not exceed $7,000 per month
- top amenities in the selected neighborhood shall be similar to current residence
- desirable to have venues such as coffee shops, restaurants Asian Thai, gym and food shops
- as a reference, I have included a map of venues near current residence in Dubai.

Business Problem:

The challenge is to find a suitable apartment for rent in Manhattan NY that complies with the demands on location, price and venues. The data required to resolve this challenge is described in the following part 2, below.

Interested Audience:

I believe this is a relevant challenge with valid questions for anyone moving to other large city in US, EU, Africa or Asia. The same methodology can be applied in accordance to demands as applicable.

This case is also applicable for anyone interested in exploring starting or locating a new business in any city. Lastly, it can also serve as a good practical exercise to develop Data Science skills.

• Data

Description of the Data:

The following data is required to answer the issues of the problem:

- List of Boroughs and neighborhoods of Manhattan with their geodata (lat and long).
- List of Subway metro stations in Manhattan with their address location.
- List of apartments for rent in Manhattan area with their addresses and price.
- Preferably, a list of apartment for rent with additional information, such as price, address, area, No. of bedrooms, etc.
- Venues for each Manhattan neighborhood (then can be clustered).
- Venues for subway metro stations, as needed.

How the data will be used to solve the problem

The data will be used as follows:

- Use Foursquare and geopy data to map top 10 venues for all Manhattan neighborhoods and clustered in groups (as per Course LAB)
- Use foursquare and geopy data to map the location of subway metro stations, separately and on top of the above clustered map in order to be able to identify the venues and ammenities near each metro station, or explore each subway location separately
- Use Foursquare and geopy data to map the location of rental places, in some form, linked to the subway locations.
- create a map that depicts, for instance, the average rental price per square ft, around a radious of 1.0 mile (1.6 km) around each subway station, or a similar metrics. I will be able to quickly point to the popups to know the relative price per subway area.
- Addresses from rental locations will be converted to geodata(lat, long) using Geopy-distance and Nominatim.

- Data will be searched in open data sources if available, from real estate sites (if open to reading), libraries or other government agencies such as Metro New York MTA, etc.

The processing of these DATA will allow to answer the key questions to make a decision:

- what is the cost of rent (per square ft) around a mile radius from each subway metro station?
- what is the area of Manhattan with best rental pricing that meets criteria established?
- What is the distance from work place (Park Ave and 53 rd St) and the tentative future home?
- What are the venues of the two best places to live in? How the prices compare?
- How venues distribute among Manhattan neighborhoods and around metro stations?
- Are there tradeoffs between size and price and location?
- Any other interesting statistical data findings of the real estate and overall data.

• Methodology

Mapping of Data:

The following maps were created to facilitate the analysis and the choice of the place to live:

- Manhattan map of Neighborhoods
- manhattan subway metro locations
- Manhattan map of places for rent
- Manhattan map of clustered venues and neighborhoods
- Combined maps of Manhattan rent places with subway locations
- Combined maps of Manhattan rent places with subway locations and venues clusters

Upload Libraries Required:

In [2]:

```
import numpy as np # library to handle data in a vectorized manner
import time
```

```
import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files
import requests # library to handle requests
from pandas.io.json import json_normalize # tranform
JSON file into a pandas dataframe


!conda install -c conda-forge geopy --yes # uncomment
this line if you haven't completed the Foursquare API
lab
from geopy.geocoders import Nominatim # convert an
address into latitude and longitude values

!conda install -c conda-forge folium=0.5.0 --yes #
uncomment this line if you haven't completed the
Foursquare API lab
import folium # map rendering library
from folium import plugins

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

import seaborn as sns

# import k-means from clustering stage
from sklearn.cluster import KMeans
```

Dubai Map - Current residence and venues in neighborhood

for comparison to future Manhattan renting place

```
# Al Murooj Complex, Dubai
address = 'Doha St, Sheik Zayed Rd, Trade Centre 2,
DIFC Area - Dubai'
```

```
geolocator = Nominatim()
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Dubai home are
{}, {}.'.format(latitude, longitude))
```

Al Murooj Complex, Dubai
Address: 'Doha St, Sheik Zayed Rd, Trade Centre 2, DIFC Area - Dubai'

From google : the latitude and longitude for my place where I reside in Dubai, are as follows:

```
neighborhood_latitude=25.203558
neighborhood_longitude=55.276660
```

Dial FourSquare to find venues around current residence in Dubai

```
# @hidden_cell
CLIENT_ID = 'xxxxxxxxxxxxxxxxxxx' # your Foursquare
ID
CLIENT_SECRET = 'xxxxxxxxxxxxxxxxxxx' # your
Foursquare Secret
VERSION = 'xxxxxxxxxxxxxxxxxxx' # Foursquare API
version

#print('Your credentails:')
#print('CLIENT_ID: ' + CLIENT_ID)
#print('CLIENT_SECRET:' + CLIENT_SECRET)
In [13]:
LIMIT = 100 # limit of number of venues returned by
Foursquare API
radius = 500 # define radius
# create URL
url = 'https://api.foursquare.com/v2/venues/explore?
&client_id={}&client_secret={}&v={}&ll={},{}
&radius={}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
```

```
    VERSION,
    neighborhood_latitude,
    neighborhood_longitude,
    radius,
    LIMIT)
url # display URL

# results display is hidden for report simplification
results = requests.get(url).json()      #results
```

function that extracts the category of the venue - borrow from the Foursquare lab.

```
def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']
In [16]:
venues = results['response']['groups'][0]['items']
DUnearby_venues = json_normalize(venues) # flatten
JSON
# filter columns
filtered_columns = ['venue.name', 'venue.categories',
'venue.location.lat', 'venue.location.lng']
DUnearby_venues =DUnearby_venues.loc[:,
filtered_columns]
# filter the category for each row
DUnearby_venues['venue.categories'] =
DUnearby_venues.apply(get_category_type, axis=1)
# clean columns
DUnearby_venues.columns = [col.split(".")[-1] for col
in DUnearby_venues.columns]

DUnearby_venues.shape
```

```
(46, 4)
```

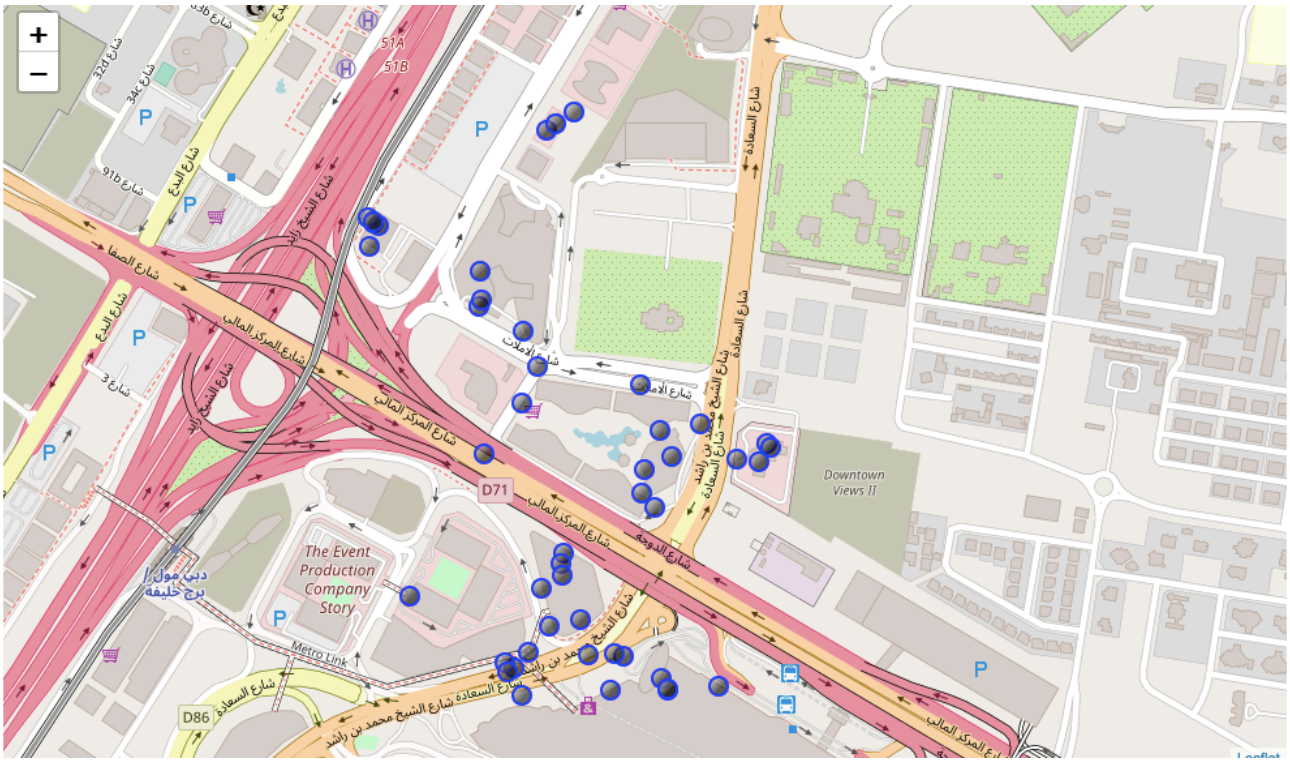
```
# Venues near current Dubai residence place
DUnearby_venues.head(10)
```

	name	categories	lat	lng
0	Barry's Bootcamp	Gym / Fitness Center	25.204714	55.275379
1	Home Bakery Jumeriah	Bakery	25.202852	55.277807
2	Sumo Sushi & Bento	Japanese Restaurant	25.202885	55.274721
3	Address Boulevard Lobby Lounge	Coffee Shop	25.201401	55.276044
4	Address Boulevard	Hotel	25.201249	55.275992
5	Roda Al Murooj	Hotel	25.203229	55.277613
6	Rove Downtown Dubai	Hotel	25.203030	55.279384
7	Starbucks	Coffee Shop	25.202806	55.278896
8	Double Decker Pub	Pub	25.202295	55.277326
9	Mama'esh	Middle Eastern Restaurant	25.205077	55.274650

Map of Dubai residence place with venues in Neighborhood - for reference

```
latitude=25.203558
longitude=55.276660
# create map of Dubai place  using latitude and
longitude values
map_sg = folium.Map(location=[latitude, longitude],
zoom_start=18)
# add markers to map
for lat, lng, label in zip(DUnearby_venues['lat'],
DUnearby_venues['lng'], DUnearby_venues['name']):
    label = folium.Popup(label, parse_html=True)
    folium.RegularPolygonMarker(
        [lat, lng],
```

```
        number_of_sides=30,
        radius=7,
        popup=label,
        color='blue',
        fill_color='#0f0f0f',
        fill_opacity=0.6,
    ).add_to(map_sg)

map_sg
```



MANHATTAN NEIGHBORHOODS - DATA AND MAPPING

Cluster neighborhood data was produced with Foursquare during course lab work. A csv file was produced containing the neighborhoods around the 40 Boroughs. Now, the csv file is just read for convenience and consolidation of report.

```
# Read csv file with clustered neighborhoods with geodata
manhattan_data  = pd.read_csv('mh_neigh_data.csv')
manhattan_data.head()
```

	Borough	Neighborhood	Latitude	Longitude	Cluster Labels
0	Manhattan	Marble Hill	40.876551	-73.910660	2
1	Manhattan	Chinatown	40.715618	-73.994279	2
2	Manhattan	Washington Heights	40.851903	-73.936900	4
3	Manhattan	Inwood	40.867684	-73.921210	3
4	Manhattan	Hamilton Heights	40.823604	-73.949688	0

```
manhattan_data.tail()
```

	Borough	Neighborhood	Latitude	Longitude	Cluster Labels
35	Manhattan	Turtle Bay	40.752042	-73.967708	3
36	Manhattan	Tudor City	40.746917	-73.971219	3
37	Manhattan	Stuyvesant Town	40.731000	-73.974052	4
38	Manhattan	Flatiron	40.739673	-73.990947	3
39	Manhattan	Hudson Yards	40.756658	-74.000111	2

Manhattan Borough neighborhoods - data with top 10 clustered venues

```
manhattan_merged =
pd.read_csv('manhattan_merged.csv')
manhattan_merged.head()
```

	Borough	Neighborhood	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	9th Most Common Venue	10th Most Common Venue
0	Manhattan	Marble Hill	40.8	-73.	2	Coffee Shop	Discount Store	Yoga Studio	Steakhouse	Supplement Shop	Tennis Stadium	Shoe Store	Gym	Bank	Seafood Restaurant
1	Manhattan	Chinatown	40.7	-73.	2	Chinese Restaurant	Cocktail Bar	Dim Sum Restaurant	American Restaurant	Vietnamese Restaurant	Salon / Barbershop	Noodle House	Bakery	Bubble Tea Shop	Ice Cream Shop
2	Manhattan	Washington Heights	40.8	-73.	4	Café	Bakery	Mobile Phone Shop	Pizza Place	Sandwich Place	Park	Gym	Latin American Restaurant	Tapas Restaurant	Mexican Restaurant

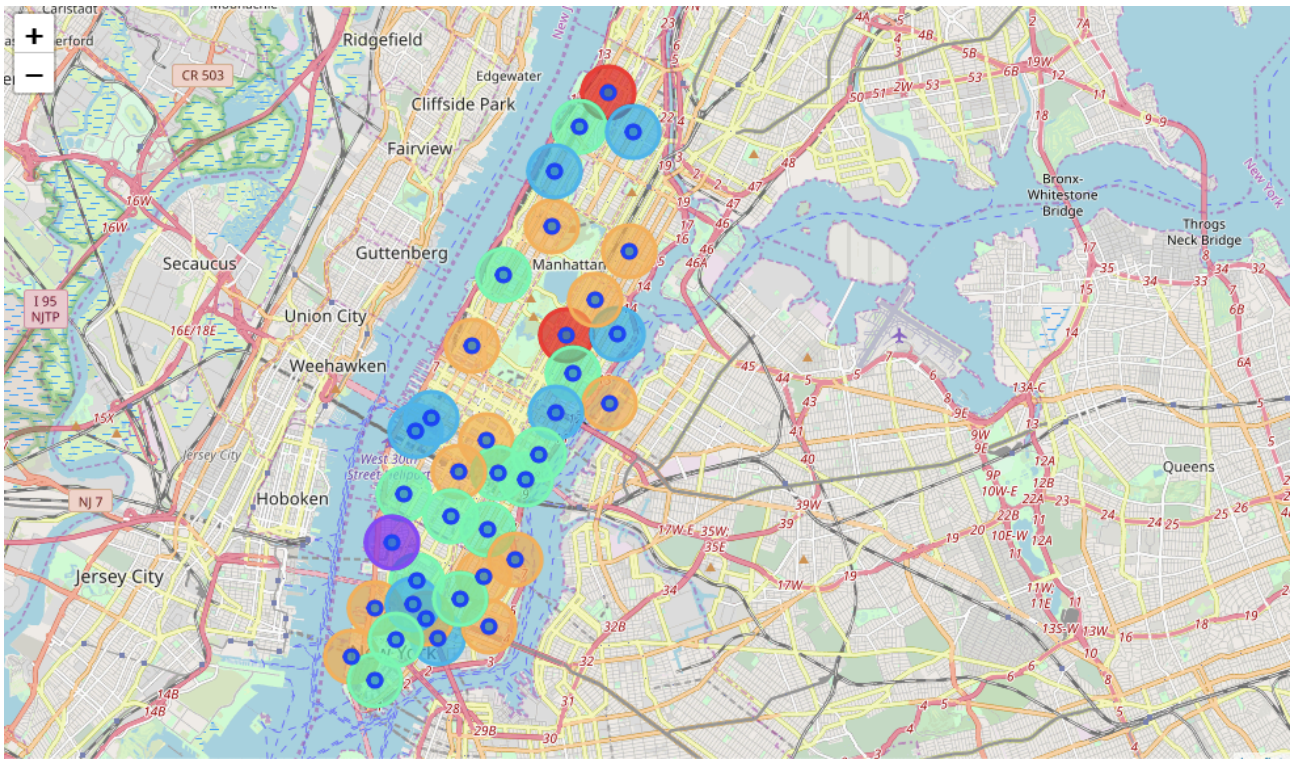
3	Manhattan	Inwood	40.8	-73.	3	Mexican Restaurant	Lounge	Pizza Place	Café	Wine Bar	Bakery	American Restaurant	Park	Frozen Yogurt Shop	Spanish Restaurant
4	Manhattan	Hamilton Heights	40.8	-73.	0	Mexican Restaurant	Coffee Shop	Café	Deli / Bodega	Pizza Place	Liquor Store	Indian Restaurant	Sushi Restaurant	Sandwich Place	Yoga Studio

Map of Manhattan neighborhoods with top 10 clustered venues

popus allow to identify each neighborhood and the cluster of venues around it in order to proceed to examine in more detail in the next cell

```
# create map of Manhattan using latitude and
longitude values from Nominatim
latitude= 40.7308619
longitude= -73.9871558

kclusters=5
map_clusters = folium.Map(location=[latitude,
longitude], zoom_start=13)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i+x+(i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in
zip(manhattan_merged['Latitude'],
```

```
manhattan_merged['Longitude'],
manhattan_merged['Neighborhood'],
manhattan_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' +
str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=20,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)
  # add markers for rental places to map
for lat, lng, label in
zip(manhattan_data['Latitude'],
manhattan_data['Longitude'],
manhattan_data['Neighborhood']):
    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_clusters)


map_clusters
```



Examine a particular Cluster - print venues

After examining several cluster data , I concluded that cluster # 2 resembles closer the Singapore place, therefore providing guidance as to where to look for the future apartment.

Assign a value to 'kk' to explore a given cluster.

```
## kk is the cluster number to explore
kk = 2
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == kk, manhattan_merged.columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

	Neighborhood	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	9th Most Common Venue	10th Most Common Venue

0	Marble Hill	Coffee Shop	Discount Store	Yoga Studio	Steakhouse	Supplement Shop	Tennis Stadium	Shoe Store	Gym	Bank	Seafood Restaurant
1	Chinatown	Chinese Restaurant	Cocktail Bar	Dim Sum Restaurant	American Restaurant	Vietnamese Restaurant	Salon / Barbershop	Noodle House	Bakery	Bubble Tea Shop	Ice Cream Shop
6	Central Harlem	African Restaurant	Seafood Restaurant	French Restaurant	American Restaurant	Cosmetics Shop	Chinese Restaurant	Event Space	Liquor Store	Beer Bar	Gym / Fitness Center
9	Yorkville	Coffee Shop	Gym	Bar	Italian Restaurant	Sushi Restaurant	Pizza Place	Mexican Restaurant	Deli / Bodega	Japanese Restaurant	Pub
14	Clinton	Theater	Italian Restaurant	Coffee Shop	American Restaurant	Gym / Fitness Center	Hotel	Wine Shop	Spa	Gym	Indie Theater
23	Soho	Clothing Store	Boutique	Women's Store	Shoe Store	Men's Store	Furniture / Home Store	Italian Restaurant	Mediterranean Restaurant	Art Gallery	Design Studio
26	Morningside Heights	Coffee Shop	American Restaurant	Park	Bookstore	Pizza Place	Sandwich Place	Burger Joint	Café	Deli / Bodega	Tennis Court

34	Sutton Place	Gym / Fitness Center	Italian Restaurant	Furniture / Home Store	Indian Restaurant	Dessert Shop	American Restaurant	Bakery	Juice Bar	Boutique	Sushi Restaurant
39	Hudson Yards	Coffee Shop	Italian Restaurant	Hotel	Theater	American Restaurant	Café	Gym / Fitness Center	Thai Restaurant	Restaurant	Gym

Map of Manhattan places for rent

Several Manhattan real estate webs were webscrapped to collect rental data, as mentioned in section 2.0 . The result was summarized in a csv file for direct reading, in order to consolidate the proces.

The initial data for 144 apartment did not have the latitude and longitude data (NaN) but the information was established in the following cell using an algorythm and Nominatim.

```
# csv files with rental places with basic data but
still wihtout geodata ( latitude and longitude)
# pd.read_csv(' le.csv', header=None, nrows=5)
mh_rent=pd.read_csv('MH_flats_price.csv')
mh_rent.head()
```

	Address	Area	Price_per_ft2	Rooms	Area-ft2	Rent_Price	Lat	Long
0	West 105th Street	Upper West Side	2.94	5.0	3400	10000	NaN	NaN
1	East 97th Street	Upper East Side	3.57	3.0	2100	7500	NaN	NaN

2	West 105th Street	Upper West Side	1.89	4.0	2800	5300	NaN	NaN
3	CARMINE ST.	West Village	3.03	2.0	1650	5000	NaN	NaN
4	171 W 23RD ST.	Chelsea	3.45	2.0	1450	5000	NaN	NaN

```
mh_rent.tail()
```

	Address	**Area**	**Price_ per_ft2**	**Rooms**	**Area -ft2**	**Rent_ Price**	**Lat**	**Long**
139	200 East 72nd Street	Rental in Lenox Hill	5.15	3.0	1700	8750	NaN	NaN
140	50 Murray Street	No fee rental in Tribeca	7.11	2.0	1223	8700	NaN	NaN
141	300 East 56th Street	No fee rental in Midtown East	3.87	3.0	2100	8118	NaN	NaN
142	1930 Broadway	No fee rental in Central Park West	5.06	2.0	1600	8095	NaN	NaN
143	33 West 9th Street	Rental in Greenwich Village	6.67	2.0	1500	10000	NaN	NaN

Obtain geodata (lat, long) for each rental place in Manhattan with Nominatim

Data was stored in a csv file for simplifaction report purposes and saving code processing time in future.

This coding section was 'markedown' for the report because its execution takes few minutes . Therefore, the csv saved will be just read directly in the following cell.

for n in range(len(mh_rent)): address= mh_rent['Address'][n] address=(mh_rent['Address'][n]+ ' , '+' Manhattan NY ') geolocator =

Nominatim() location = geolocator.geocode(address) latitude = location.latitude longitude = location.longitude mh_rent['Lat'][n]=latitude mh_rent['Long'][n]=longitude

print(n,latitude,longitude)

time.sleep(2)
print('Geodata completed')

save dataframe to csv file

mh_rent.to_csv('MH_rent_latlong.csv',index=False) mh_rent.shape

```
mh_rent=pd.read_csv('MH_rent_latlong.csv')
mh_rent.head()
```

	Address	Area	Price_per_ft2	Rooms	Area-ft2	Rent_Price	Lat	Long
0	West 105th Street	Upper West Side	2.94	5.0	3400	10000	40.7997	-73.966
1	East 97th Street	Upper East Side	3.57	3.0	2100	7500	40.7885	-73.955
2	West 105th Street	Upper West Side	1.89	4.0	2800	5300	40.7997	-73.966
3	CARMINE ST.	West Village	3.03	2.0	1650	5000	40.7305	-74.001
4	171 W 23RD ST.	Chelsea	3.45	2.0	1450	5000	40.7441	-73.995

```
mh_rent.tail()
```

	Address	Area	Price_per_ft2	Rooms	Area-ft2	Rent_Price	Lat	Long
139	200 East 72nd Street	Rental in Lenox Hill	5.15	3.0	1700	8750	40.769	-73.960

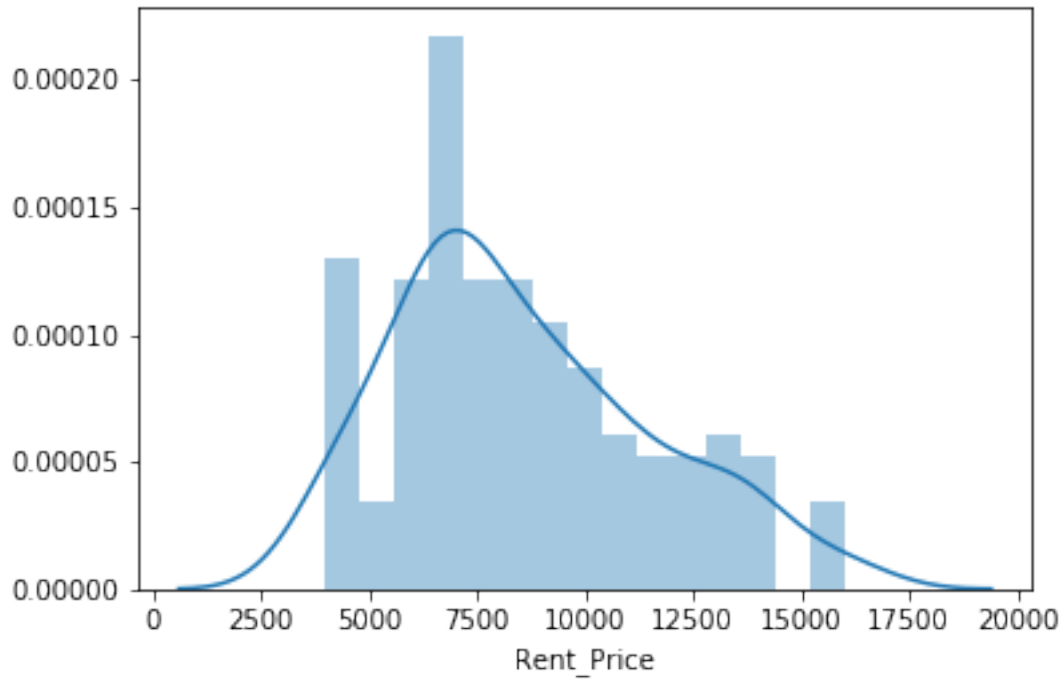
140	50 Murray Street	No fee rental in Tribeca	7.11	2.0	1223	8700	40.714	-74.009
141	300 East 56th Street	No fee rental in Midtown East	3.87	3.0	2100	8118	40.758	-73.965
142	1930 Broadway	No fee rental in Central Park West	5.06	2.0	1600	8095	40.772	-73.981
143	33 West 9th Street	Rental in Greenwich Village	6.67	2.0	1500	10000	40.733	-73.997

Manhattan apartment rent price statistics

A US 7000 Dollar per month rent is actually around the mean value - almost similar to Dubai!

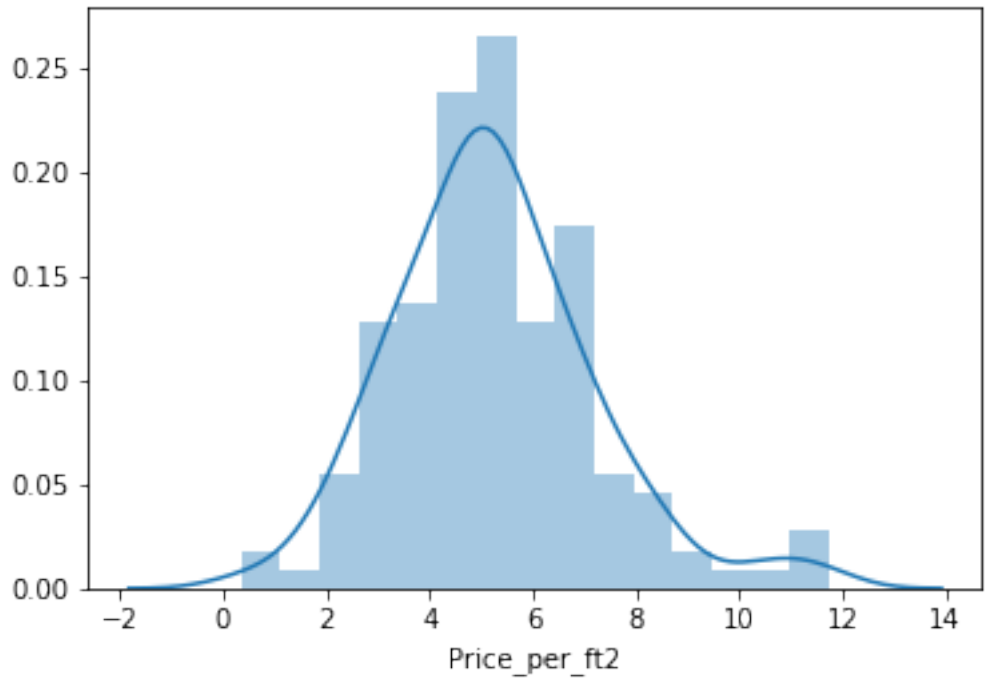
```
import seaborn as sns
sns.distplot(mh_rent['Rent_Price'],bins=15)
```

```
<matplotlib.axes._subplots.AxesSubplot at
0x7f1298c3e400>
```



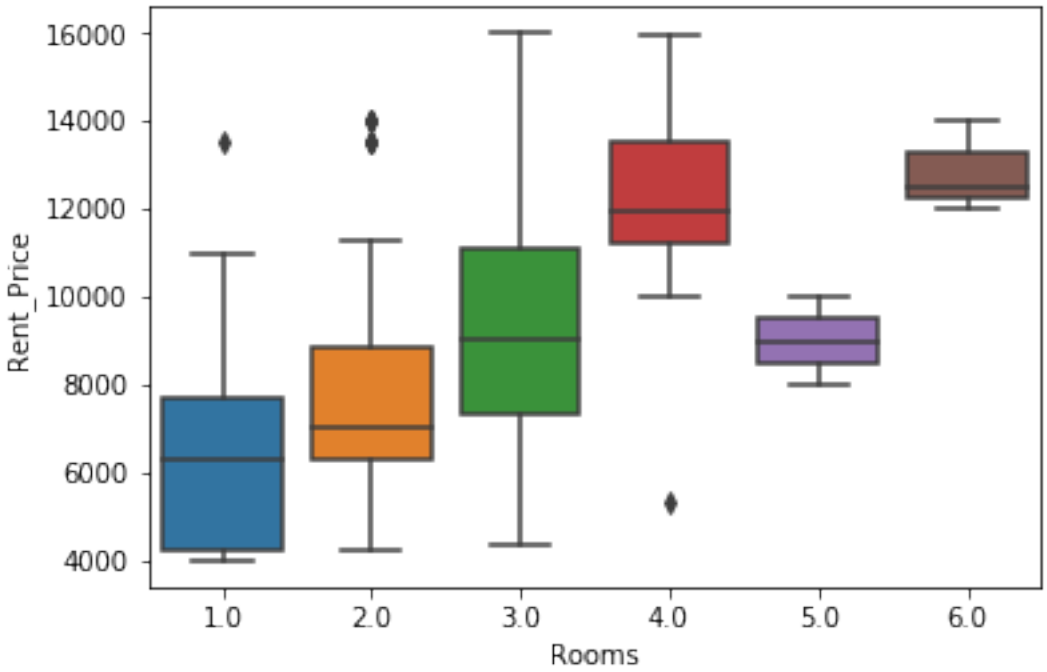
```
import seaborn as sns
sns.distplot(mh_rent['Price_per_ft2'],bins=15)
```

```
<matplotlib.axes._subplots.AxesSubplot at
0x7f129176ad30>
```




```
sns.boxplot(x='Rooms', y= 'Rent_Price', data=mh_rent)
```

```
<matplotlib.axes._subplots.AxesSubplot at
0x7f12916bc278>
```



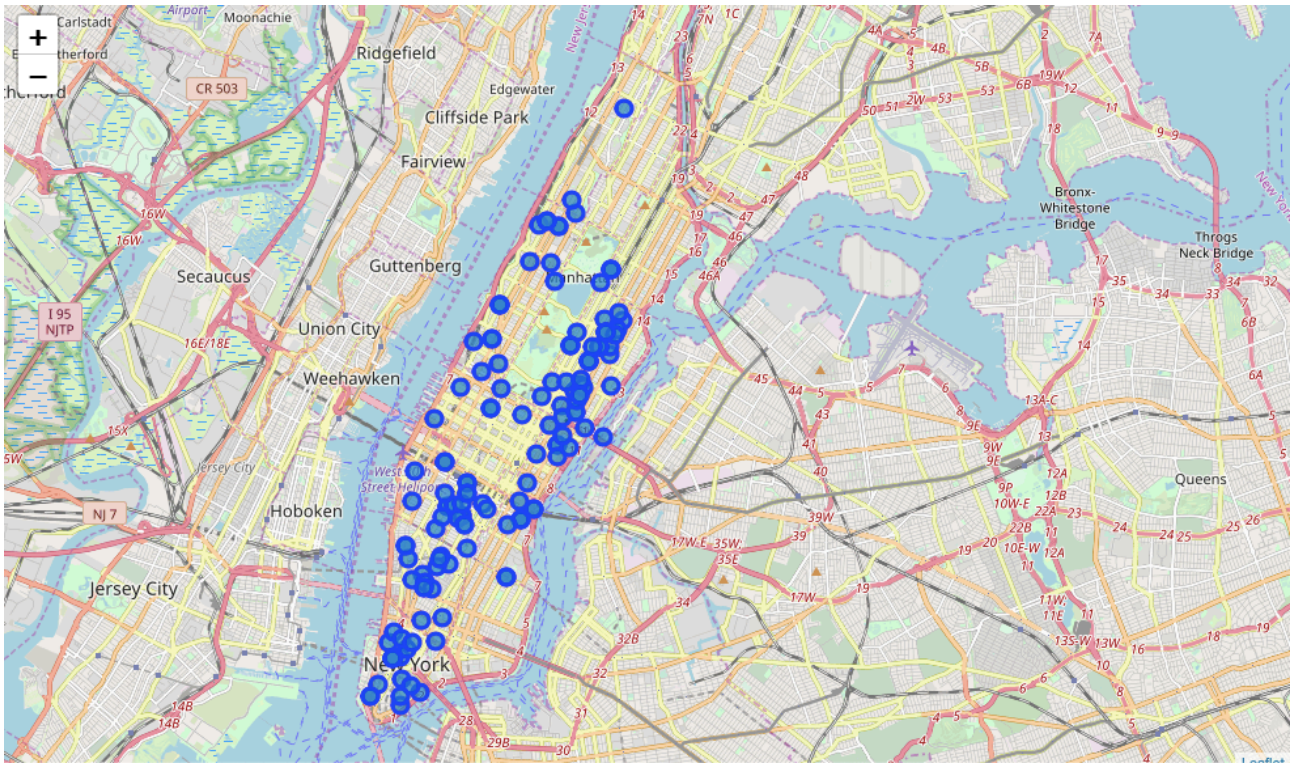
Map of Manhattan apartments for rent

The popups will indicate the address and the monthly price for rent thus making it convenient to select the target appartment with the price condition estipulated (max US7000)

```
# create map of Manhattan using latitude and
longitude values from Nominatim
latitude= 40.7308619
longitude= -73.9871558

map_manhattan_rent = folium.Map(location=[latitude,
longitude], zoom_start=12.5)

# add markers to map
for lat, lng, label in zip(mh_rent['Lat'],
mh_rent['Long'],'$ ' +
mh_rent['Rent_Price'].astype(str)+ ',  '+
mh_rent['Address']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=6,
```

```
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_manhattan_rent)
```

```
map_manhattan_rent
```



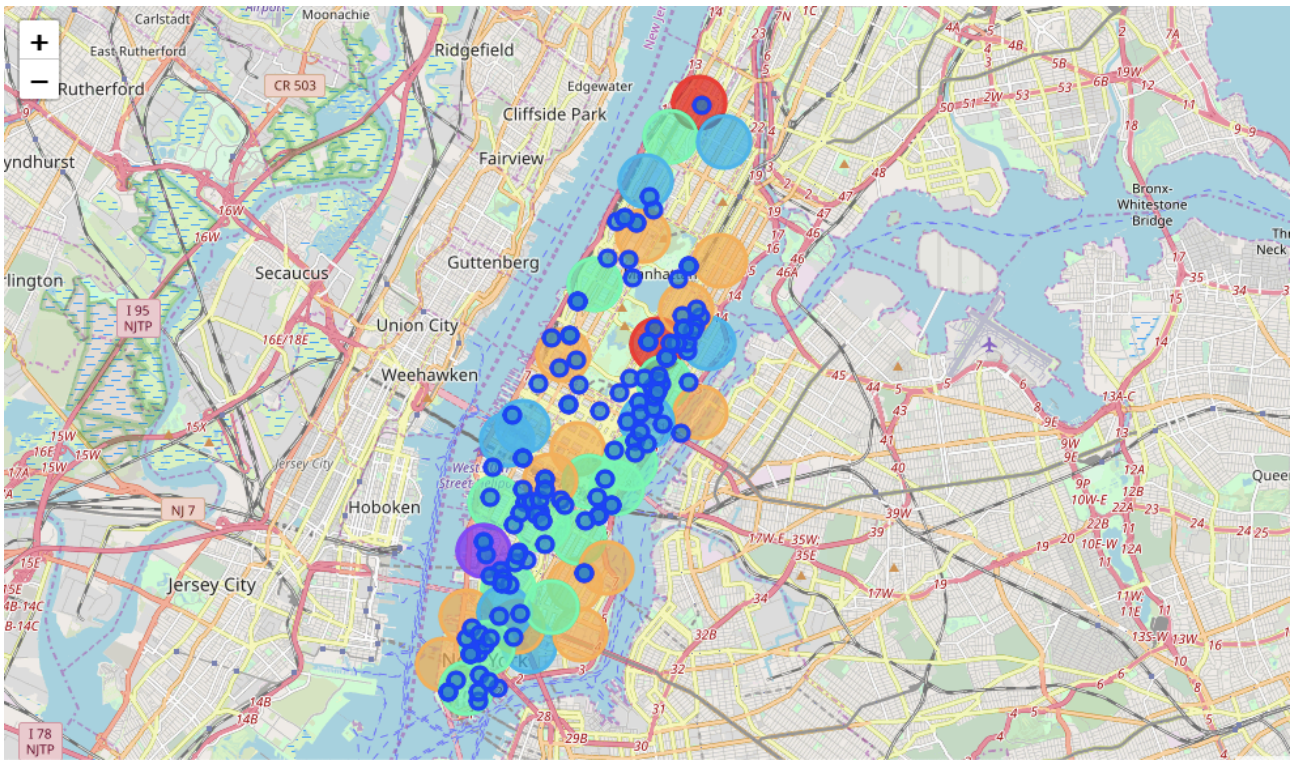
Map of Manhattan showing the places for rent and the cluster of venues

Now, one can point to a rental place for price and address location information while knowing the cluster venues around it.

This is an insightful way to explore rental possibilites

```
# create map of Manhattan using latitude and
longitude values from Nominatim
latitude= 40.7308619
longitude= -73.9871558

# create map with clusters
kclusters=5
map_clusters2 = folium.Map(location=[latitude,
longitude], zoom_start=13)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i+x+(i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in
zip(manhattan_merged['Latitude'],
manhattan_merged['Longitude'],
manhattan_merged['Neighborhood'],
manhattan_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' +
str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=20,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters2)

# add markers to map for rental places
for lat, lng, label in zip(mh_rent['Lat'],
mh_rent['Long'],'$ ' +
mh_rent['Rent_Price'].astype(str)+
mh_rent['Address']):
    label = folium.Popup(label, parse_html=True)
```

```
    folium.CircleMarker(
        [lat, lng],
        radius=6,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_clusters2)

    # Adds tool to the top right
from folium.plugins import MeasureControl
map_manhattan_rent.add_child(MeasureControl())

# FMeasurement ruler icon to establish distnces on
map
from folium.plugins import FloatImage
url = ('https://media.licdn.com/mpr/mpr/
shrinknp_100_100/
AAEAAQAAAAAAAAlgAAAAJGE3OTA4YTdlLTkzZjUtNDFjYy1iZThlL
WQ5OTNkYzlhNzM4OQ.jpg')
FloatImage(url, bottom=5,
left=85).add_to(map_manhattan_rent)

map_clusters2
```



Now one can explore a particular rental place and its venues in detail

In the map above, examination of apartments with rental place below 7000/month is straightforward while knowing the venues around it.
We could find an apartment with at the right price and in a location with desirable venues.

The next step is to see if it is located near a subway metro station, in next cells work.

```
## kk is the cluster number to explore
kk = 3
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == kk, manhattan_merged.columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

	Neighborhood	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	9th Most Common Venue	10th Most Common Venue
3	Inwood	Mexican Restaurant	Lounge	Pizza Place	Café	Wine Bar	Bakery	American Restaurant	Park	Frozen Yogurt Shop	Spanish Restaurant
5	Manhattanville	Deli / Bodega	Italian Restaurant	Seafood Restaurant	Mexican Restaurant	Sushi Restaurant	Beer Garden	Coffee Shop	Falafel Restaurant	Bike Trail	Other Nightlife

10	Lenox Hill	Sushi Restaurant	Italian Restaurant	Coffee Shop	Gym / Fitness Center	Pizza Place	Burger Joint	Deli / Bodega	Gym	Sporting Goods Shop	Thai Restaurant
12	Upper West Side	Italian Restaurant	Bar	Bakery	Vegetarian / Vegan Restaurant	Indian Restaurant	Coffee Shop	Cosmetics Shop	Wine Bar	Mexican Restaurant	Sushi Restaurant
16	Murray Hill	Sandwich Place	Hotel	Japanese Restaurant	Gym / Fitness Center	Coffee Shop	Salon / Barbershop	Burger Joint	French Restaurant	Bar	Italian Restaurant
17	Chelsea	Coffee Shop	Italian Restaurant	Ice Cream Shop	Bakery	Nightclub	Theater	Art Gallery	Seafood Restaurant	American Restaurant	Hotel
18	Greenwich Village	Italian Restaurant	Sushi Restaurant	French Restaurant	Clothing Store	Chinese Restaurant	Café	Indian Restaurant	Bakery	Seafood Restaurant	Electronics Store
27	Gramercy	Italian Restaurant	Restaurant	Thrift / Vintage Store	Cocktail Bar	Bagel Shop	Coffee Shop	Pizza Place	Mexican Restaurant	Grocery Store	Wine Shop

29	Financial District	Coffee Shop	Hotel	Gym	Wine Shop	Steakhouse	Bar	Italian Restaurant	Pizza Place	Park	Gym / Fitness Center
31	Noho	Italian Restaurant	French Restaurant	Cocktail Bar	Gift Shop	Bookstore	Grocery Store	Mexican Restaurant	Hotel	Sushi Restaurant	Coffee Shop
32	Civic Center	Gym / Fitness Center	Bakery	Italian Restaurant	Cocktail Bar	French Restaurant	Sandwich Place	Coffee Shop	Gym	Yoga Studio	Park
35	Turtle Bay	Italian Restaurant	Coffee Shop	Steakhouse	Wine Bar	Sushi Restaurant	Hotel	Noodle House	Indian Restaurant	Japanese Restaurant	French Restaurant
36	Tudor City	Café	Park	Pizza Place	Mexican Restaurant	Greek Restaurant	Sushi Restaurant	Hotel	Deli / Bodega	Diner	Dog Run
38	Flatiron	Italian Restaurant	American Restaurant	Gym	Gym / Fitness Center	Yoga Studio	Vegetarian / Vegan Restaurant	Bakery	Clothing Store	Cosmetics Shop	Cycle Studio

Mapping Manhattan Subway locations

Manhattan subway metro locations (address) was obtained from web-scrapping sites such as Wikipedia, Google and NY Metro Transit. For simplification, a csv file was produced from the

'numbers' (Apple excel) so that the reading of this file is the starting point here.
The geodata will be obtain via Nominatim using the algorythm below.

```
# A csv file summarized the subway station and the addresses for next step to determine geodata
mh=pd.read_csv('NYC_subway_list.csv')
mh.head()
```

	sub_station	sub_address
0	Dyckman Street Subway Station	170 Nagle Ave, New York, NY 10034, USA
1	57 Street Subway Station	New York, NY 10106, USA
2	Broad St	New York, NY 10005, USA
3	175 Street Station	807 W 177th St, New York, NY 10033, USA
4	5 Av and 53 St	New York, NY 10022, USA

Add column labeled 'lat' and 'long' to be filled with geodata

```
#  Add columns 'lat'  and 'long' to mh dataframe - with random temporary numbers to get started
sLength = len(mh['sub_station'])
lat = pd.Series(np.random.randn(sLength))
long=pd.Series(np.random.randn(sLength))
mh = mh.assign(lat=lat.values)
mh = mh.assign(long=long.values)
```

Algorythm to find latitude and longitud for each subway metro station and add them to dataframe

This coding has been 'Markdown' just to simplify the file report, and the csv file will be read in cell below.

for n in range(len(mh)): address= mh['sub_address'][n] geolocator = Nominatim() location = geolocator.geocode(address) latitude =

location.latitude longitude = location.longitude mh['lat'][n]=latitude mh[‘long'][n]=longitude

print(n,latitude,longitude)

time.sleep(2)
print('Geodata completed')

save dataframe to csv file

mh.to_csv('MH_subway.csv',index=False) mh.shape

Read csv file that produced the subway stations list with geodata

```
mh=pd.read_csv('MH_subway.csv')
print(mh.shape)
mh.head()
```

```
(76, 4)
```

	sub_station	sub_address	lat	long
0	Dyckman Street Subway Station	170 Nagle Ave, New York, NY 10034, USA	40.86185	-73.92450
1	57 Street Subway Station	New York, NY 10106, USA	40.76425	-73.95452
2	Broad St	New York, NY 10005, USA	40.73086	-73.98715
3	175 Street Station	807 W 177th St, New York, NY 10033, USA	40.84799	-73.93978
4	5 Av and 53 St	New York, NY 10022, USA	40.76425	-73.95452

```
# removing duplicate rows and creating new set mhsub1
mhsub1=mh.drop_duplicates(subset=['lat','long'],
keep="last").reset_index(drop=True)
mhsub1.shape
```

```
(22, 4)
```

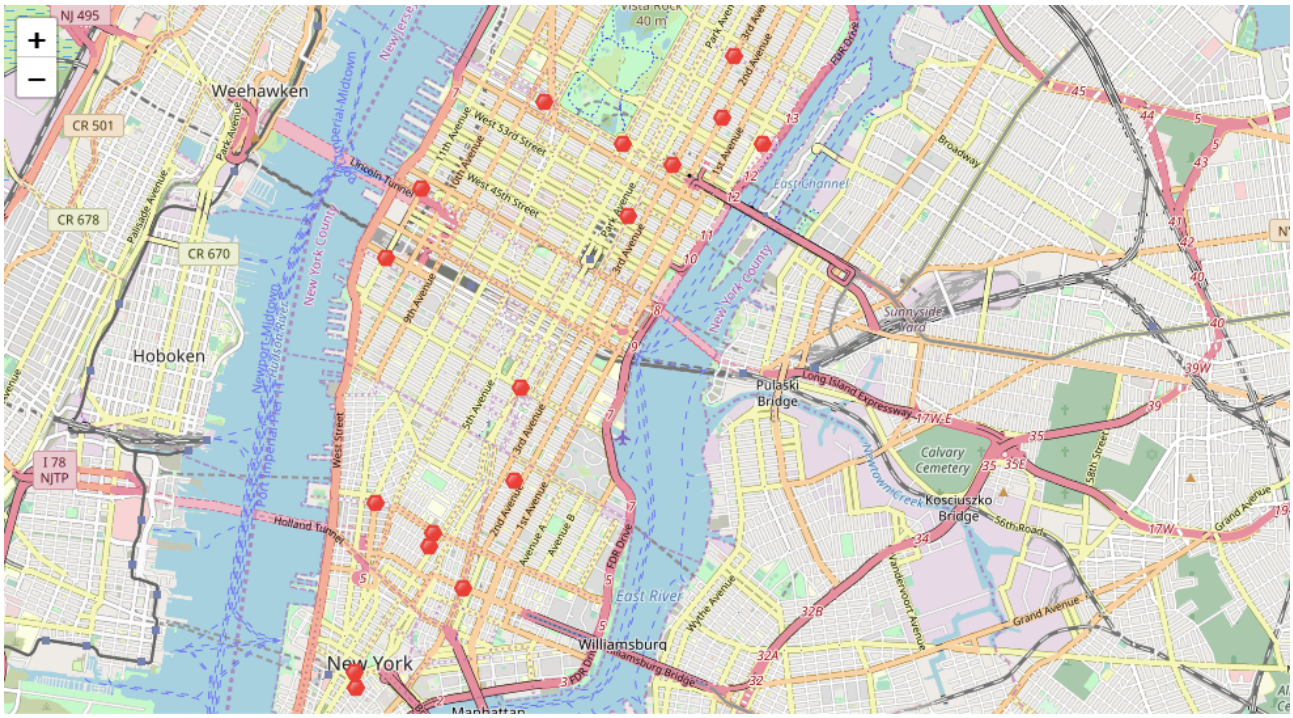
```
mhsub1.tail()
```

	sub_station	sub_address	lat	long
17	190 Street Subway Station	Bennett Ave, New York, NY 10040, USA	40.858113	-73.932983
18	59 St-Lexington Av Station	E 60th St, New York, NY 10065, USA	40.762259	-73.96627
19	57 Street Station	New York, NY 10019, United States	40.764250	-73.954525
20	14 Street / 8 Av	New York, NY 10014, United States	40.730862	-73.987156
21	MTA New York City	525 11th Ave, New York, NY 10018, USA	40.759809	-73.999282

MAP of Manhattan showing the location of subway stations

```
# map subway stations
# create map of Manhattan using latitude and
longitude values obtain previoulsy via Moninatim
geolocator
latitude=40.7308619
longitude=-73.9871558

map_mhsub1 = folium.Map(location=[latitude,
longitude], zoom_start=12)

# add markers of subway locations to map
for lat, lng, label in zip(mhsub1['lat'],
mhsub1['long'],  mhsub1['sub_station'].astype(str) ):
    label = folium.Popup(label, parse_html=True)
    folium.RegularPolygonMarker(
        [lat, lng],
        number_of_sides=6,
        radius=6,
        popup=label,
        color='red',
        fill_color='red',
        fill_opacity=2.5,
```

```
    ).add_to(map_mhsub1)
map_mhsub1
```



Map of Manhattan showing places for rent and the subway locations nearby

Now, we can visualize the desirable rental places and their nearest subway station. Popups display rental address and monthly rental price and the subway station name.

Notice that the icon in the top-right corner is a "ruler" that allows to measure the distance from a rental place to an specific subway station

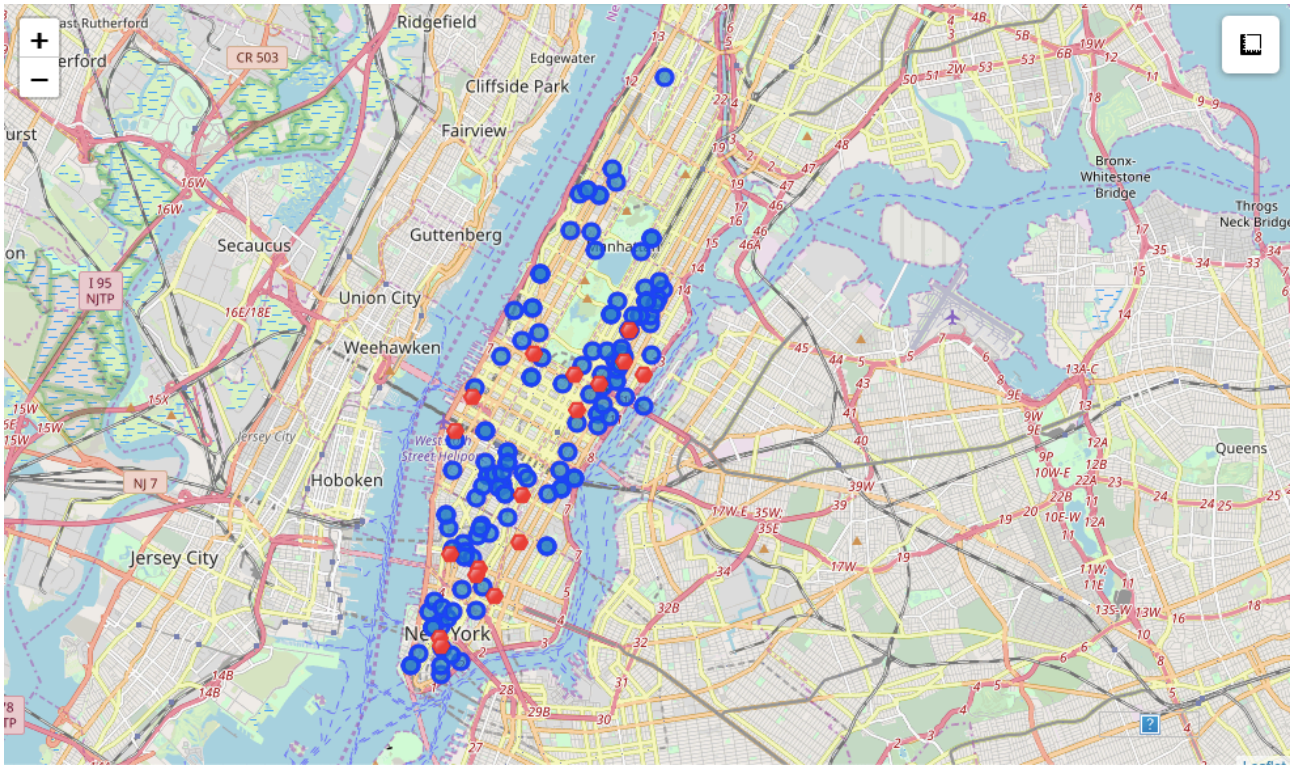
```
mh_rent.head()
```

	Address	Area	Price_per_ft2	Rooms	Area-ft2	Rent_Price	Lat	Long
0	West 105th Street	Upper West Side	2.94	5.0	3400	10000	40.7997	-73.966

1	East 97th Street	Upper East Side	3.57	3.0	2100	7500	40.7885	-73.955
2	West 105th Street	Upper West Side	1.89	4.0	2800	5300	40.7997	-73.966
3	CARMINE ST.	West Village	3.03	2.0	1650	5000	40.7305	-74.001
4	171 W 23RD ST.	Chelsea	3.45	2.0	1450	5000	40.7441	-73.995

```
# create map of Manhattan using latitude and
longitude values from Nominatim
latitude= 40.7308619
longitude= -73.9871558

map_manhattan_rent = folium.Map(location=[latitude,
longitude], zoom_start=13.3)

# add markers to map
for lat, lng, label in zip(mh_rent['Lat'],
mh_rent['Long'],'$ ' +
mh_rent['Rent_Price'].astype(str)+
mh_rent['Address']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=6,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_manhattan_rent)

    # add markers of subway locations to map
for lat, lng, label in zip(mhsub1['lat'],
mhsub1['long'],  mhsub1['sub_station'].astype(str) ):
```

```
    label = folium.Popup(label, parse_html=True)
    folium.RegularPolygonMarker(
        [lat, lng],
        number_of_sides=6,
        radius=6,
        popup=label,
        color='red',
        fill_color='red',
        fill_opacity=2.5,
    ).add_to(map_manhattan_rent)

    # Adds tool to the top right
from folium.plugins import MeasureControl
map_manhattan_rent.add_child(MeasureControl())

# Measurement ruler icon tool to measure distances in map
from folium.plugins import FloatImage
url = ('https://media.licdn.com/mpr/mpr/shrinknp_100_100/AAEAAQAAAAAAAAlgAAAAJGE3OTA4YTdlLTkzZjUtNDFjYy1iZThlLWQ5OTNkYzlhNzM4OQ.jpg')
FloatImage(url, bottom=5, left=85).add_to(map_manhattan_rent)
map_manhattan_rent
```



Results

ONE CONSOLIDATE MAP

Let's consolidate all the required information to make the apartment selection in one map

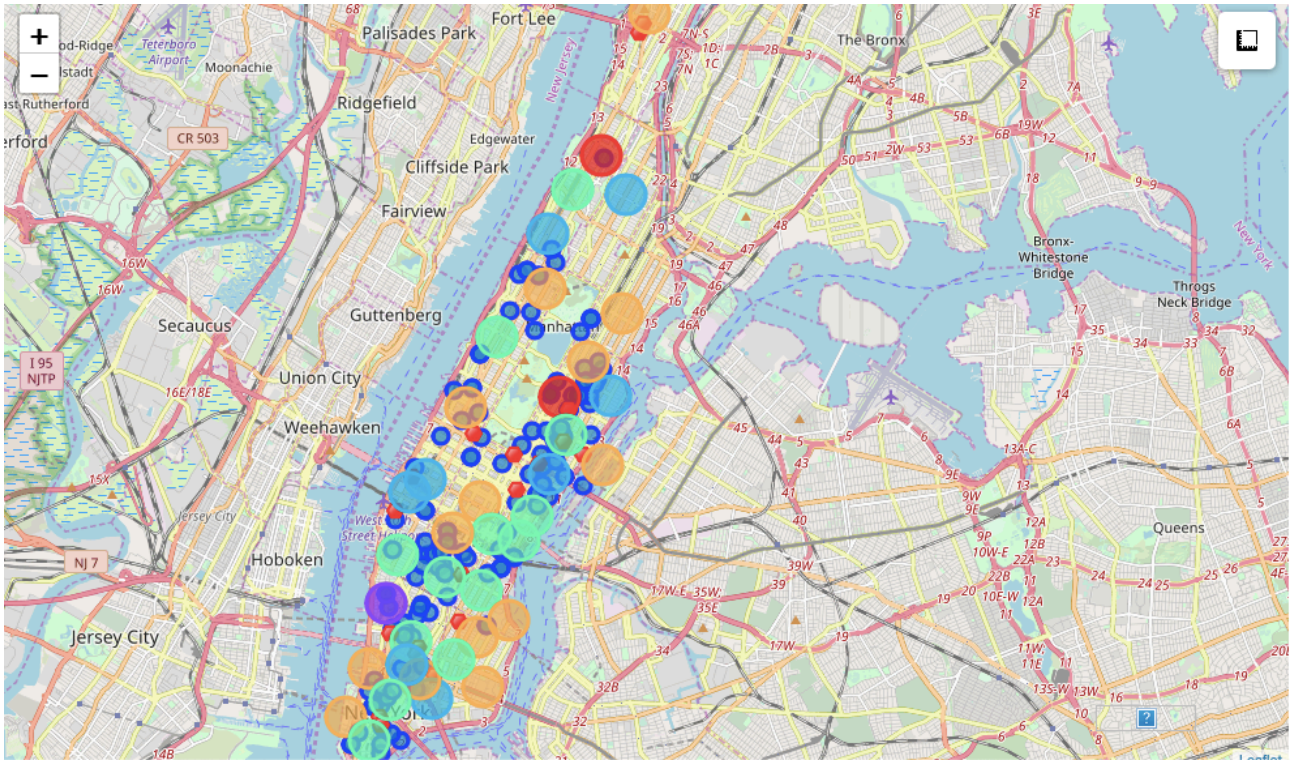
Map of Manhattan with rental places, subway locations and cluster of venues

Red dots are Subway stations, Blue dots are apartments available for rent, Bubbles are the clusters of venues

```
# create map of Manhattan using latitude and
longitude values from Nominatim
latitude= 40.7308619
longitude= -73.9871558

map_mh_one = folium.Map(location=[latitude,
longitude], zoom_start=13.3)

# add markers to map
for lat, lng, label in zip(mh_rent['Lat'],
mh_rent['Long'],'$ ' +
mh_rent['Rent_Price'].astype(str)+ ',
'+mh_rent['Address']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=6,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_mh_one)

    # add markers of subway locations to map
```

```
for lat, lng, label in zip(mhsub1['lat'],
mhsub1['long'],  mhsub1['sub_station'].astype(str) ):
    label = folium.Popup(label, parse_html=True)
    folium.RegularPolygonMarker(
        [lat, lng],
        number_of_sides=6,
        radius=6,
        popup=label,
        color='red',
        fill_color='red',
        fill_opacity=2.5,
    ).add_to(map_mh_one)


# set color scheme for the clusters
kclusters=5
x = np.arange(kclusters)
ys = [i+x+(i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in
zip(manhattan_merged['Latitude'],
manhattan_merged['Longitude'],
manhattan_merged['Neighborhood'],
manhattan_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' +
str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=15,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_mh_one)

    # Adds tool to the top right
```

```
from folium.plugins import MeasureControl
map_mh_one.add_child(MeasureControl())

# Measurement ruler icon tool to measure distances in
map
from folium.plugins import FloatImage
url = ('https://media.licdn.com/mpr/mpr/
shrinknp_100_100/
AAEAAQAAAAAAAAlgAAAAJGE3OTA4YTdlLTkzZjUtNDFjYy1iZThlL
WQ5OTNkYzlhNzM4OQ.jpg')
FloatImage(url, bottom=5, left=85).add_to(map_mh_one)

map_mh_one
```



Problem Resolution - Select the apartment for rent

The above consolidate map was used to explore options.

After examining, I have chosen two locations that meet the requirements which will assess to make a choice:

- Apartment 1: 305 East 63rd Street in the Sutton Place Neighborhood and near 'subway 59th Street' station, Cluster # 2 Monthly rent : 7500 Dollars
- Apartment 2: 19 Dutch Street in the Financial District Neighborhood and near 'Fulton Street Subway' station, Cluster # 3 Monthly rent : 6935 Dollars

Venues for Apartment 1 - Cluster 2

```
## kk is the cluster number to explore
kk = 2
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == kk, manhattan_merged.columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

	Neighborhood	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	9th Most Common Venue	10th Most Common Venue
0	Marble Hill	Coffee Shop	Discount Store	Yoga Studio	Steakhouse	Supplement Shop	Tennis Stadium	Shoe Store	Gym	Bank	Seafood Restaurant
1	Chinatown	Chinese Restaurant	Cocktail Bar	Dim Sum Restaurant	American Restaurant	Vietnamese Restaurant	Salon / Barbershop	Noodle House	Bakery	Bubble Tea Shop	Ice Cream Shop
6	Central Harlem	African Restaurant	Seafood Restaurant	French Restaurant	American Restaurant	Cosmetics Shop	Chinese Restaurant	Event Space	Liquor Store	Beer Bar	Gym / Fitness Center

9	Yorkville	Coffee Shop	Gym	Bar	Italian Restaurant	Sushi Restaurant	Pizza Place	Mexican Restaurant	Deli / Bodega	Japanese Restaurant	Pub
14	Clinton	Theater	Italian Restaurant	Coffee Shop	American Restaurant	Gym / Fitness Center	Hotel	Wine Shop	Spa	Gym	Indie Theater
23	Soho	Clothing Store	Boutique	Women's Store	Shoe Store	Men's Store	Furniture / Home Store	Italian Restaurant	Mediterranean Restaurant	Art Gallery	Design Studio
26	Morningside Heights	Coffee Shop	American Restaurant	Park	Bookstore	Pizza Place	Sandwich Place	Burger Joint	Café	Deli / Bodega	Tennis Court
34	Sutton Place	Gym / Fitness Center	Italian Restaurant	Furniture / Home Store	Indian Restaurant	Dessert Shop	American Restaurant	Bakery	Juice Bar	Boutique	Sushi Restaurant
39	Hudson Yards	Coffee Shop	Italian Restaurant	Hotel	Theater	American Restaurant	Café	Gym / Fitness Center	Thai Restaurant	Restaurant	Gym

Venues for Apartment 2 - Cluster 3

```
## kk is the cluster number to explore
kk = 3
```

```
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == kk, manhattan_merged.columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

	Neighborhood	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	9th Most Common Venue	10th Most Common Venue
3	Inwood	Mexican Restaurant	Lounge	Pizza Place	Café	Wine Bar	Bakery	American Restaurant	Park	Frozen Yogurt Shop	Spanish Restaurant
5	Manhattanville	Deli / Bodega	Italian Restaurant	Seafood Restaurant	Mexican Restaurant	Sushi Restaurant	Beer Garden	Coffee Shop	Falafel Restaurant	Bike Trail	Other Nightlife
10	Lenox Hill	Sushi Restaurant	Italian Restaurant	Coffee Shop	Gym / Fitness Center	Pizza Place	Burger Joint	Deli / Bodega	Gym	Sporting Goods Shop	Thai Restaurant
12	Upper West Side	Italian Restaurant	Bar	Bakery	Vegetarian / Vegan Restaurant	Indian Restaurant	Coffee Shop	Cosmetics Shop	Wine Bar	Mexican Restaurant	Sushi Restaurant

16	Murray Hill	Sandwich Place	Hotel	Japanese Restaurant	Gym / Fitness Center	Coffee Shop	Salon / Barbershop	Burger Joint	French Restaurant	Bar	Italian Restaurant
17	Chelsea	Coffee Shop	Italian Restaurant	Ice Cream Shop	Bakery	Nightclub	Theater	Art Gallery	Seafood Restaurant	American Restaurant	Hotel
18	Greenwich Village	Italian Restaurant	Sushi Restaurant	French Restaurant	Clothing Store	Chinese Restaurant	Café	Indian Restaurant	Bakery	Seafood Restaurant	Electronics Store
27	Gramercy	Italian Restaurant	Restaurant	Thrift / Vintage Store	Cocktail Bar	Bagel Shop	Coffee Shop	Pizza Place	Mexican Restaurant	Grocery Store	Wine Shop
29	Financial District	Coffee Shop	Hotel	Gym	Wine Shop	Steakhouse	Bar	Italian Restaurant	Pizza Place	Park	Gym / Fitness Center
31	Noho	Italian Restaurant	French Restaurant	Cocktail Bar	Gift Shop	Bookstore	Grocery Store	Mexican Restaurant	Hotel	Sushi Restaurant	Coffee Shop
32	Civic Center	Gym / Fitness Center	Bakery	Italian Restaurant	Cocktail Bar	French Restaurant	Sandwich Place	Coffee Shop	Gym	Yoga Studio	Park

35	Turtle Bay	Italian Restaurant	Coffee Shop	Steakhouse	Wine Bar	Sushi Restaurant	Hotel	Noodle House	Indian Restaurant	Japanese Restaurant	French Restaurant
36	Tudor City	Café	Park	Pizza Place	Mexican Restaurant	Greek Restaurant	Sushi Restaurant	Hotel	Deli / Bodega	Diner	Dog Run
38	Flatiron	Italian Restaurant	American Restaurant	Gym	Gym / Fitness Center	Yoga Studio	Vegetarian / Vegan Restaurant	Bakery	Clothing Store	Cosmetics Shop	Cycle Studio

Apartment Selection

Using the "one map" above, I was able to explore all possibilities since the popups provide the information needed for a good decision.

Apartment 1 rent cost is US7500 slightly above the US7000 budget. Apt 1 is located 400 meters from subway station at 59th Street and work place (Park Ave and 53rd) is another 600 meters way. I can walk to work place and use subway for other places aroung. Venues for this apt are as of Cluster 2 and it is located in a fine district in the East side of Manhattan.

Apartment 2 rent cost is US6935, just under the US7000 budget. Apt 2 is located 60 meters from subway station at Fulton Street, but I will have to ride the subway daily to work , possibly 40-60 min ride. Venues for this apt are as of Cluster 3.

Based on current Dubai venues, I feel that Cluster 2 type of venues is a closer resemblance to my current place. That means that APARTMENT 1 is a better choice since the extra monthly rent is worth the conveniences it provides.

• DISCUSSION

In general, I am positively impressed with the overall organization, content and lab works presented during the Coursera IBM Certification Course.

I feel this Capstone project presented me a great opportunity to practice and apply the Data Science tools and methodologies learned.

I have created a good project that I can present as an example to show my potential.

I feel I have acquired a good starting point to become a professional Data Scientist and I will continue exploring to creating examples of practical cases.

• CONCLUSIONS

I feel rewarded with the efforts, time and money spent. I believe this course with all the topics covered is well worthy of appreciation.

This project has shown me a practical application to resolve a real situation that has impacting personal and financial impact using Data Science tools.

The mapping with Folium is a very powerful technique to consolidate information and make the analysis and decision thoroughly and with confidence. I would recommend for use in similar situations.

One must keep abreast of new tools for DS that continue to appear for application in several business fields.

End of Project