Suggest a Place to stay in New York City

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1. Introduction

Search for suitable area for accommodation.

Lots of people migrate to city in search of work, jobs like millions every month. Jobs are mainly concentrated on selective areas like IT parks, Malls and shopping complexes. There are also residential areas (based on cities) which are far from the city limit. All the parameters responsible for sustainable living should be available at a short distance for especially people like students or solo travelers.

Interest :
Here, we will convert addresses into their equivalent latitude and longitude values. Also, We will use the Foursquare API to explore neighborhoods in New York City. We will use the **explore** function to get the most common venue categories in each neighborhood, and then use this feature to group the neighborhoods into clusters. We will use the *k*-means clustering algorithm to complete this task. Finally, we will use the Folium library to visualize the neighborhoods in New York City and their emerging clusters.

2. The Data

Neighborhood has a total of 5 boroughs and 306 neighborhoods. In order to segment the neighborhoods and explore them, we will essentially need a dataset that contains the 5 boroughs and the neighborhoods that exist in each borough as well as the the latitude and logitude coordinates of each neighborhood.

This dataset exists for free on the web.

https://geo.nyu.edu/catalog/nyu_2451_34572

For our convenience, we can use the downloaded files, so we can simply run a *wget* command and access the data.

I. Week 3_newyork_data.json

3. Data Analysis

a. All the relevant data is in the features key, which is basically a list of the neighborhoods.

Let's see the first Item in the list..


```
{'type': 'Feature',
 'id': 'nyu_2451_34572.1',
 'geometry': {'type': 'Point',
  'coordinates': [-73.84720052054902, 40.89470517661]},
 'geometry_name': 'geom',
 'properties': {'name': 'Wakefield',
  'stacked': 1,
  'annoline1': 'Wakefield',
  'annoline2': None,
  'annoline3': None,
  'annoangle': 0.0,
  'borough': 'Bronx',
  'bbox': [-73.84720052054902,
   40.89470517661,
   -73.84720052054902,
   40.89470517661]}}
```


b. To process the data further we can convert them into a *Pandas* dataframe.

	Borough	Neighborhood	Latitude	Longitude
0	Bronx	Wakefield	40.894705	-73.847201
1	Bronx	Co-op City	40.874294	-73.829939
2	Bronx	Eastchester	40.887556	-73.827806
3	Bronx	Fieldston	40.895437	-73.905643
4	Bronx	Riverdale	40.890834	-73.912585

And ensure that the dataset has all 5 boroughs and 306 neighborhoods.

c. Use *'geopy'* library to get the latitude and longitude values of New York City.
In order to define an instance of the geocoder, we need to define a user_agent.

We will name our agent *ny_explorer*, as shown below.

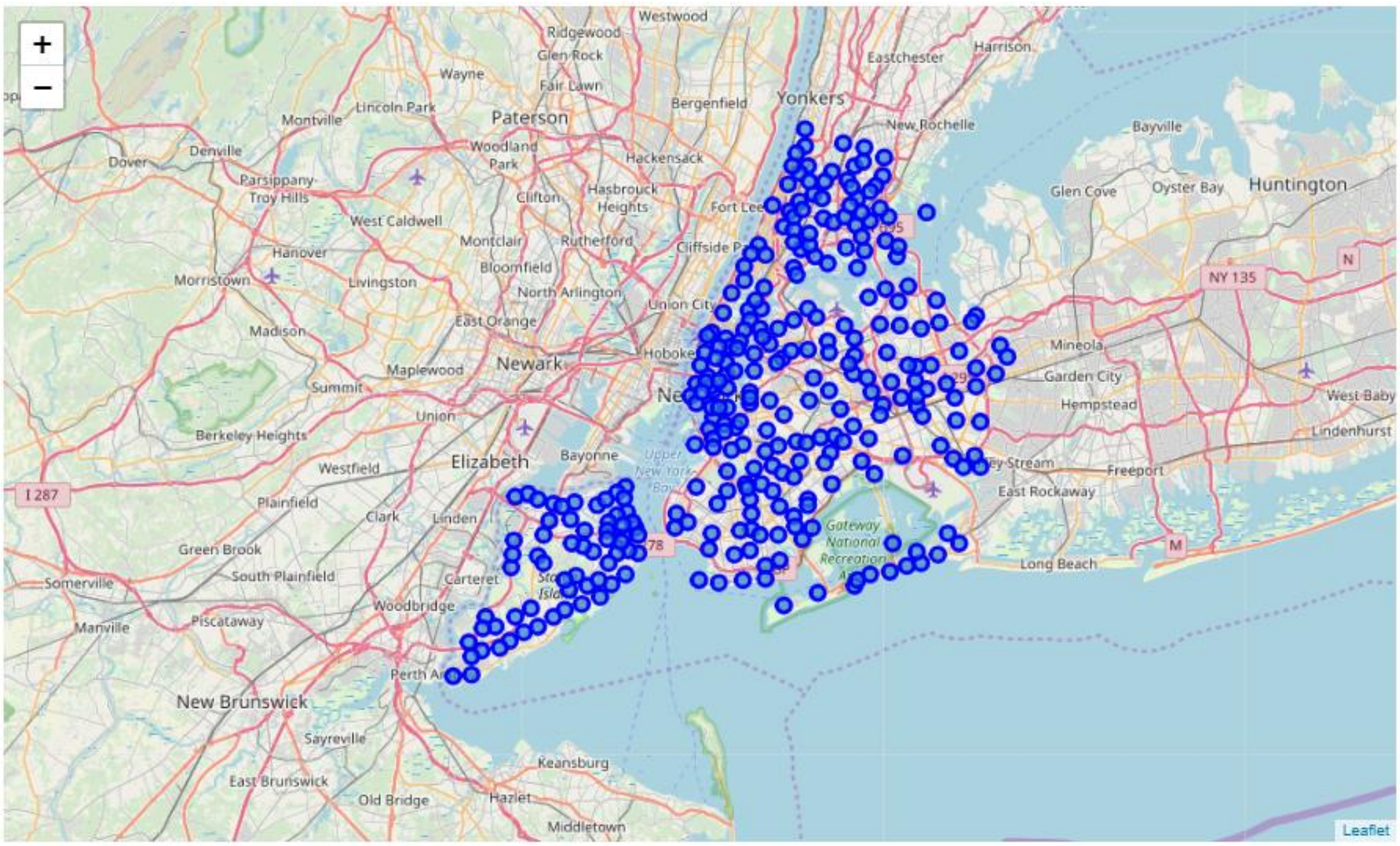
```
address = 'New York City, NY'

geolocator = Nominatim(user_agent="ny_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of New York City are {}, {}.'.format(latitude, longitude))
```

```
The geograpical coordinate of New York City are 40.7127281, -74.0060152.
```

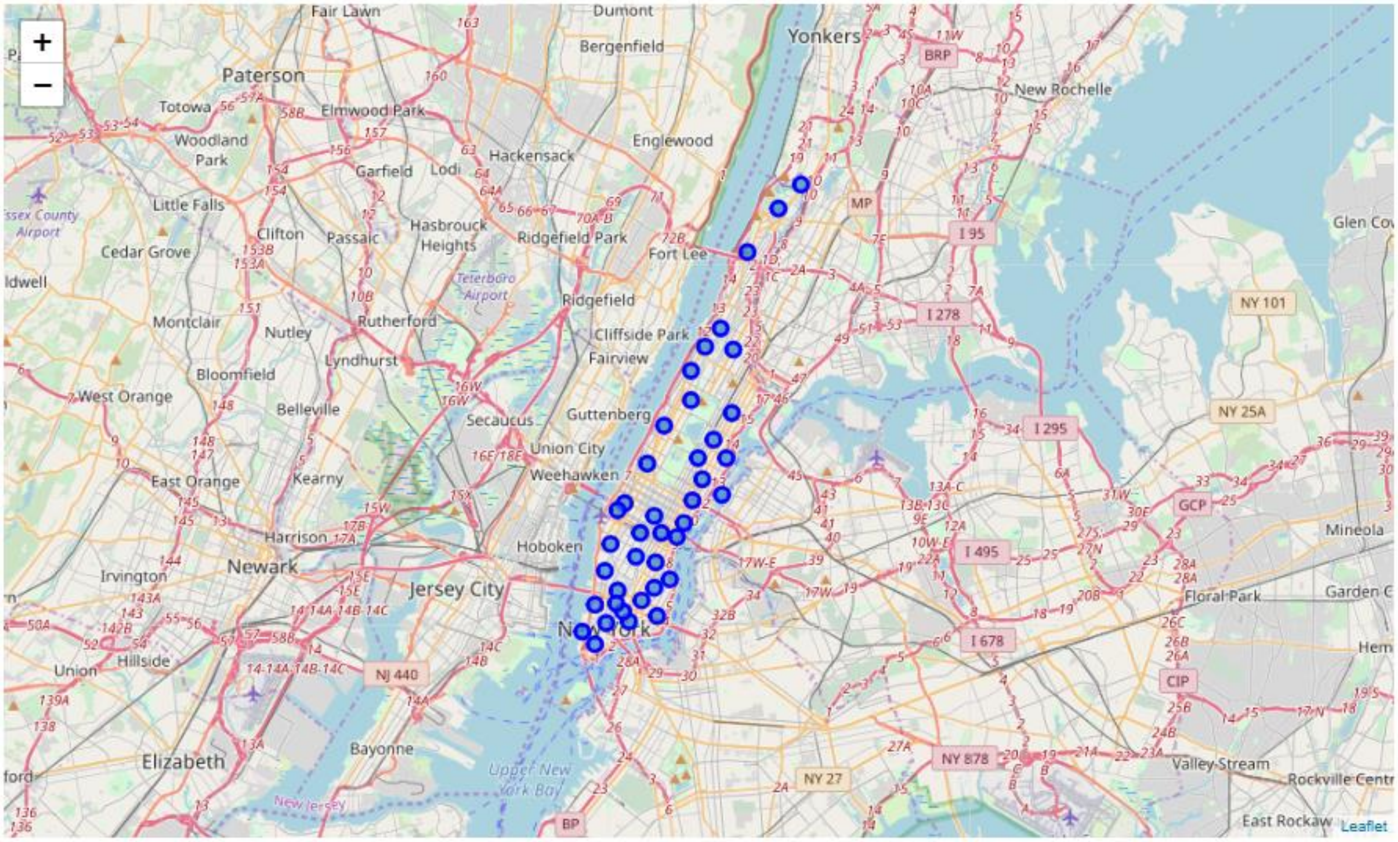
d. Create a map of New York with neighborhoods superimposed on top.

   We'll use Folium, which is a great visualization library. We can zoom into the above map, and click on each circle mark to reveal the name of the neighborhood and its respective borough.



   However, for illustration purposes, let's simplify the above map and segment and cluster only the neighborhoods in Manhattan. So let's slice the original dataframe and create a new dataframe of the Manhattan data.

e. So likewise New York City, let's visualize Manhattan the neighborhoods in it.



f. Next, we are going to start utilizing the Foursquare API to explore the neighborhoods and segment them.

g. Explore the first neighborhood in our dataframe.

   i. Get the neighborhood's name.

```
manhattan_data.loc[0, 'Neighborhood']
```

```
'Marble Hill'
```

   ii. Get the neighborhood's latitude and longitude values

```
neighborhood_latitude = manhattan_data.loc[0, 'Latitude'] # neighborhood latitude value
neighborhood_longitude = manhattan_data.loc[0, 'Longitude'] # neighborhood longitude value

neighborhood_name = manhattan_data.loc[0, 'Neighborhood'] # neighborhood name

print('Latitude and longitude values of {} are {}, {}.'.format(neighborhood_name,
                                                               neighborhood_latitude,
                                                               neighborhood_longitude))
```

```
Latitude and longitude values of Marble Hill are 40.87655077879964, -73.91065965862981.
```

   iii. Now, let's get the top 100 venues that are in Marble Hill within a radius of 500 meters.

   iv. Now clean the json and structure it into a *pandas* dataframe.
   E.g. Head()

	name	categories	lat	lng
0	Arturo's	Pizza Place	40.874412	-73.910271
1	Bikram Yoga	Yoga Studio	40.876844	-73.906204
2	Tibbett Diner	Diner	40.880404	-73.908937
3	Starbucks	Coffee Shop	40.877531	-73.905582
4	Dunkin'	Donut Shop	40.877136	-73.906666

v. Check the number venues returned by Foursquare

```
print('{} venues were returned by Foursquare.'.format(nearby_venues.shape[0]))
```

```
23 venues were returned by Foursquare.
```

h. Repeat the same process of step (g) for all the neighborhood. Write the code to run the above function on each neighborhood and create a new dataframe called manhattan_venues.

```
print(manhattan_venues.shape)
manhattan_venues.head()
```

```
(3329, 7)
```

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Marble Hill	40.876551	-73.91066	Arturo's	40.874412	-73.910271	Pizza Place
1	Marble Hill	40.876551	-73.91066	Bikram Yoga	40.876844	-73.906204	Yoga Studio
2	Marble Hill	40.876551	-73.91066	Tibbett Diner	40.880404	-73.908937	Diner
3	Marble Hill	40.876551	-73.91066	Starbucks	40.877531	-73.905582	Coffee Shop
4	Marble Hill	40.876551	-73.91066	Dunkin'	40.877136	-73.906666	Donut Shop

i. Let's check how many venues were returned for each neighborhood

	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Neighborhood						
Battery Park City	100	100	100	100	100	100
Carnegie Hill	100	100	100	100	100	100
Central Harlem	46	46	46	46	46	46
Chelsea	100	100	100	100	100	100
Chinatown	100	100	100	100	100	100
Civic Center	100	100	100	100	100	100
Clinton	100	100	100	100	100	100
East Harlem	40	40	40	40	40	40
East Village	100	100	100	100	100	100
Financial District	100	100	100	100	100	100
Flatiron	100	100	100	100	100	100
Gramercy	100	100	100	100	100	100
Greenwich Village	100	100	100	100	100	100
Hamilton Heights	62	62	62	62	62	62
Hudson Yards	84	84	84	84	84	84
Inwood	58	58	58	58	58	58
Lenox Hill	100	100	100	100	100	100
Lincoln Square	100	100	100	100	100	100
Little Italy	100	100	100	100	100	100
Lower East Side	55	55	55	55	55	55
Manhattan Valley	62	62	62	62	62	62
Manhattanville	41	41	41	41	41	41
Marble Hill	23	23	23	23	23	23
Midtown	100	100	100	100	100	100
Midtown South	100	100	100	100	100	100
Morningside Heights	43	43	43	43	43	43
Murray Hill	100	100	100	100	100	100
Noho	100	100	100	100	100	100
Roosevelt Island	30	30	30	30	30	30
Soho	100	100	100	100	100	100
Stuyvesant Town	21	21	21	21	21	21
Sutton Place	100	100	100	100	100	100
Tribeca	100	100	100	100	100	100
Tudor City	81	81	81	81	81	81
Turtle Bay	100	100	100	100	100	100
Upper East Side	100	100	100	100	100	100
Upper West Side	100	100	100	100	100	100
Washington Heights	83	83	83	83	83	83
West Village	100	100	100	100	100	100

Yorkville	100	100	100	100	100	100

j. So how many unique categories can be curated from all the returned venues?

```
print('There are {} uniques categories.'.format(len(manhattan_venues['Venue Category'].unique())))
```

```
There are 338 uniques categories.
```

k. Now, let's group rows by neighborhood and by taking the mean of the frequency of occurrence of each category.

	Neighborhood	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	American Restaurant	Antique Shop	Arcade	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Art Museum	
0	Battery Park City	0.000000	0.00	0.00	0.000000	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
1	Carnegie Hill	0.000000	0.00	0.00	0.000000	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.01	0.0
2	Central Harlem	0.000000	0.00	0.00	0.043478	0.043478	0.00	0.00	0.000000	0.000000	0.021739	0.00	0.0
3	Chelsea	0.000000	0.00	0.00	0.000000	0.030000	0.00	0.00	0.000000	0.000000	0.020000	0.00	0.0
4	Chinatown	0.000000	0.00	0.00	0.000000	0.040000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
5	Civic Center	0.000000	0.00	0.00	0.000000	0.030000	0.01	0.00	0.000000	0.000000	0.020000	0.00	0.0
6	Clinton	0.000000	0.00	0.00	0.000000	0.040000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
7	East Harlem	0.000000	0.00	0.00	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
8	East Village	0.000000	0.00	0.00	0.000000	0.020000	0.01	0.00	0.020000	0.010000	0.010000	0.00	0.0
9	Financial District	0.010000	0.00	0.00	0.000000	0.040000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
10	Flatiron	0.000000	0.00	0.00	0.000000	0.040000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
11	Gramercy	0.000000	0.00	0.00	0.000000	0.040000	0.00	0.01	0.000000	0.000000	0.010000	0.00	0.0
12	Greenwich Village	0.000000	0.00	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.000000	0.020000	0.00	0.0
13	Hamilton Heights	0.000000	0.00	0.00	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
14	Hudson Yards	0.000000	0.00	0.00	0.000000	0.059524	0.00	0.00	0.000000	0.000000	0.011905	0.00	0.0
15	Inwood	0.000000	0.00	0.00	0.000000	0.034483	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
16	Lenox Hill	0.000000	0.00	0.01	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.020000	0.00	0.0
17	Lincoln Square	0.000000	0.00	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
18	Little Italy	0.000000	0.00	0.00	0.000000	0.010000	0.00	0.00	0.000000	0.000000	0.010000	0.00	0.0
19	Lower East Side	0.000000	0.00	0.00	0.000000	0.018182	0.00	0.00	0.000000	0.018182	0.036364	0.00	0.0
20	Manhattan Valley	0.000000	0.00	0.00	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
21	Manhattanville	0.000000	0.00	0.00	0.000000	0.024390	0.00	0.00	0.000000	0.000000	0.024390	0.00	0.0
22	Marble Hill	0.000000	0.00	0.00	0.000000	0.043478	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
23	Midtown	0.000000	0.00	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.000000	0.010000	0.00	0.0
24	Midtown South	0.000000	0.00	0.00	0.000000	0.030000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
25	Morningside Heights	0.000000	0.00	0.00	0.000000	0.069767	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
26	Murray Hill	0.000000	0.00	0.00	0.000000	0.030000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
27	Noho	0.000000	0.01	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.010000	0.040000	0.00	0.0
28	Roosevelt Island	0.000000	0.00	0.00	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
29	Soho	0.010000	0.00	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.000000	0.040000	0.01	0.0
30	Stuyvesant Town	0.000000	0.00	0.00	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
31	Sutton Place	0.000000	0.01	0.00	0.000000	0.030000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0

32	Tribeca	0.000000	0.00	0.00	0.000000	0.040000	0.00	0.00	0.000000	0.010000	0.010000	0.00	0.0
33	Tudor City	0.000000	0.00	0.00	0.000000	0.012346	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
34	Turtle Bay	0.000000	0.00	0.00	0.000000	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
35	Upper East Side	0.000000	0.00	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.000000	0.050000	0.02	0.0
36	Upper West Side	0.010000	0.00	0.00	0.000000	0.020000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0
37	Washington Heights	0.012048	0.00	0.00	0.000000	0.012048	0.00	0.00	0.012048	0.000000	0.000000	0.00	0.0
38	West Village	0.010000	0.00	0.00	0.000000	0.040000	0.00	0.00	0.000000	0.000000	0.010000	0.00	0.0
39	Yorkville	0.000000	0.00	0.00	0.000000	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.00	0.0

l. Get each neighborhood along with the top 5 most common venues.
Like…

```
----Battery Park City----
           venue  freq
0           Park  0.08
1    Coffee Shop  0.07
2          Hotel  0.05
3  Memorial Site  0.04
4            Gym  0.04


----Carnegie Hill----
               venue  freq
0        Coffee Shop  0.06
1        Pizza Place  0.06
2               Café  0.05
3        Yoga Studio  0.03
4  French Restaurant  0.03


----Central Harlem----
                 venue  freq
0       Cosmetics Shop  0.07
1                  Bar  0.04
2   African Restaurant  0.04
3  American Restaurant  0.04
4    French Restaurant  0.04
```

m. Sort the venues and create a new dataframe and display the top 10 venues for each neighborhood.

	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	Battery Park City	Park	Coffee Shop	Hotel	Memorial Site	Gym	Boat or Ferry	Wine Shop	Grocery Store	Food Court	Shopping Mall
1	Carnegie Hill	Coffee Shop	Pizza Place	Café	Yoga Studio	Japanese Restaurant	Cosmetics Shop	Bar	Bakery	Spa	French Restaurant
2	Central Harlem	Cosmetics Shop	Seafood Restaurant	African Restaurant	American Restaurant	Bar	Chinese Restaurant	French Restaurant	Cafeteria	Bookstore	Boutique
3	Chelsea	Coffee Shop	Italian Restaurant	Bakery	Ice Cream Shop	Theater	American Restaurant	Seafood Restaurant	Nightclub	Hotel	Health & Beauty Service
4	Chinatown	Chinese Restaurant	Cocktail Bar	American Restaurant	Salon / Barbershop	Spa	Vietnamese Restaurant	Bubble Tea Shop	Bakery	Asian Restaurant	Mexican Restaurant

n. The next important step is to cluster the neighborhoods.

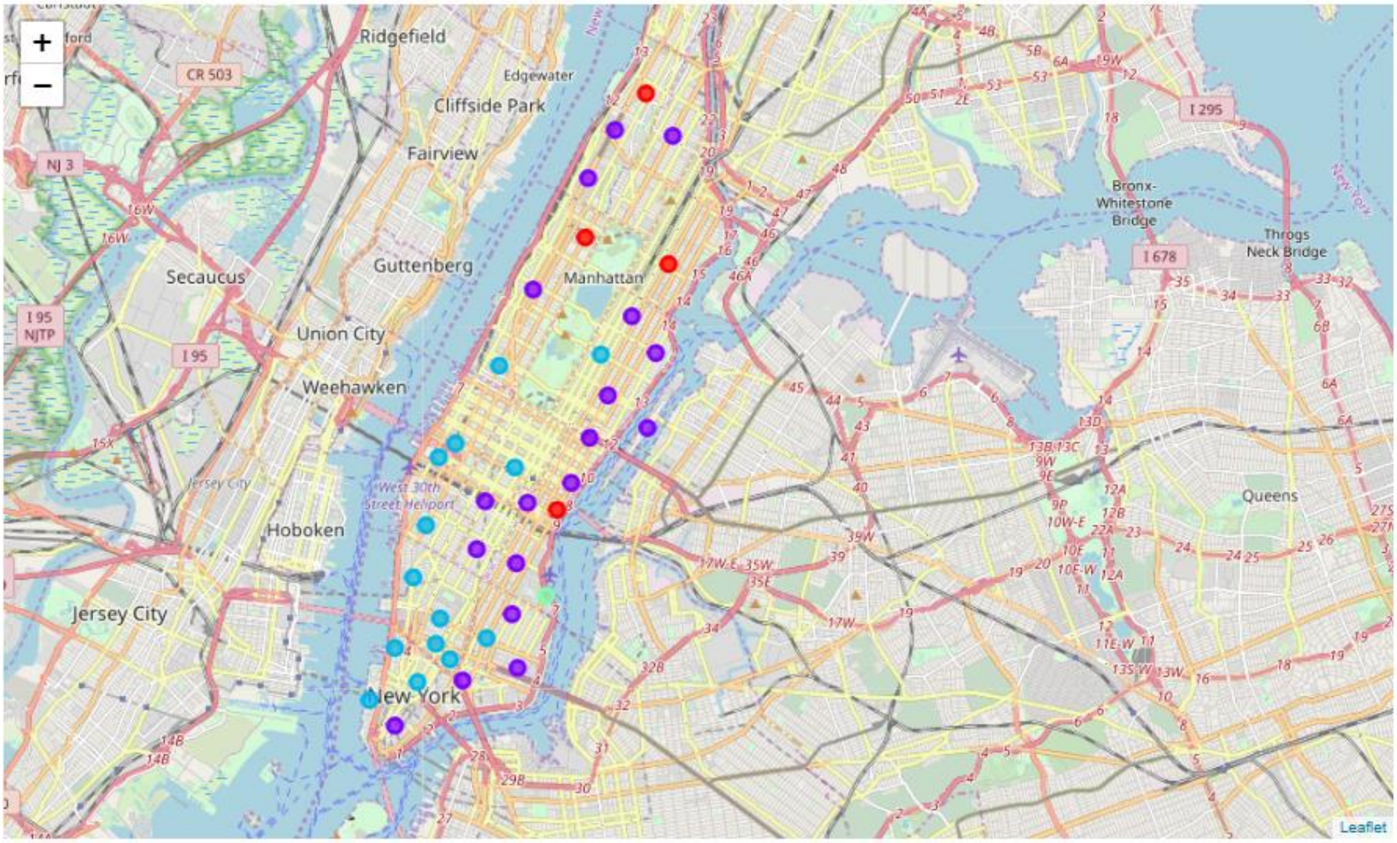
   i. Run *k*-means to cluster the neighborhood into 5 clusters. It will give us the below array as a result.

```
Out[38]: array([2, 1, 1, 2, 1, 2, 2, 0, 1, 1], dtype=int32)
```

   ii. Create a new dataframe that includes the cluster as well as the top 10 venues for each neighborhood.

	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	40.876551	-73.910660	4	Sandwich Place	Coffee Shop	Yoga Studio	Deli / Bodega	Supplement Shop	Steakhouse	Shopping Mall	Seafood Restaurant	Pizza Place	Department Store
1	Manhattan	Chinatown	40.715618	-73.994279	1	Chinese Restaurant	Cocktail Bar	American Restaurant	Salon / Barbershop	Spa	Vietnamese Restaurant	Bubble Tea Shop	Bakery	Asian Restaurant	Mexican Restaurant
2	Manhattan	Washington Heights	40.851903	-73.936900	1	Bakery	Café	Mobile Phone Shop	Grocery Store	Supplement Shop	Chinese Restaurant	Spanish Restaurant	Park	Deli / Bodega	New American Restaurant
3	Manhattan	Inwood	40.867684	-73.921210	0	Mexican Restaurant	Café	Lounge	Pizza Place	Spanish Restaurant	Park	Deli / Bodega	Chinese Restaurant	Restaurant	Wine Bar
4	Manhattan	Hamilton Heights	40.823604	-73.949688	0	Mexican Restaurant	Pizza Place	Café	Deli / Bodega	Coffee Shop	Yoga Studio	Sandwich Place	Sushi Restaurant	Liquor Store	Bakery

   iii. Visualize the final cluster



4. Result & Conclusion

Now, we can examine each cluster and determine the discriminating venue categories that distinguish each cluster. Based on the defining categories, we can then assign a name to each cluster and decide which one is better.

Cluster 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	Café	Lounge	Pizza Place	Spanish Restaurant	Park	Deli / Bodega	Chinese Restaurant	Restaurant	Wine Bar
4	Hamilton Heights	Mexican Restaurant	Pizza Place	Café	Deli / Bodega	Coffee Shop	Yoga Studio	Sandwich Place	Sushi Restaurant	Liquor Store	Bakery
7	East Harlem	Mexican Restaurant	Bakery	Deli / Bodega	Latin American Restaurant	Thai Restaurant	Liquor Store	Coffee Shop	Donut Shop	Beer Bar	Gas Station
25	Manhattan Valley	Indian Restaurant	Pizza Place	Coffee Shop	Bar	Yoga Studio	Playground	Café	Mexican Restaurant	Szechuan Restaurant	Thai Restaurant
36	Tudor City	Park	Café	Mexican Restaurant	Sushi Restaurant	Greek Restaurant	Deli / Bodega	Pizza Place	Garden	Coffee Shop	Spanish Restaurant

Cluster 2

	Neighborhood	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue
1	Chinatown	Chinese Restaurant	Cocktail Bar	American Restaurant	Salon / Barbershop	Spa	Vietnamese Restaurant	Bubble Tea Shop	Bakery	Asian Restaurant	Mexican Restaurant
2	Washington Heights	Bakery	Café	Mobile Phone Shop	Grocery Store	Supplement Shop	Chinese Restaurant	Spanish Restaurant	Park	Deli / Bodega	New American Restaurant
5	Manhattanville	Coffee Shop	Park	Mexican Restaurant	Seafood Restaurant	Italian Restaurant	Spanish Restaurant	Café	Sushi Restaurant	Supermarket	Lounge
6	Central Harlem	Cosmetics Shop	Seafood Restaurant	African Restaurant	American Restaurant	Bar	Chinese Restaurant	French Restaurant	Cafeteria	Bookstore	Boutique
9	Yorkville	Coffee Shop	Italian Restaurant	Gym	Pizza Place	Bar	Deli / Bodega	Sushi Restaurant	Wine Shop	Diner	Japanese Restaurant
10	Lenox Hill	Italian Restaurant	Coffee Shop	Sushi Restaurant	Pizza Place	Gym / Fitness Center	Gym	Sporting Goods Shop	Café	Burger Joint	Bakery
11	Roosevelt Island	Sandwich Place	Park	Coffee Shop	Hotel	Greek Restaurant	Dog Run	Outdoors & Recreation	Dry Cleaner	Liquor Store	Gym / Fitness Center
12	Upper West Side	Italian Restaurant	Bar	Wine Bar	Coffee Shop	Cosmetics Shop	Mediterranean Restaurant	Vegetarian / Vegan Restaurant	Indian Restaurant	Bakery	Pub
16	Murray Hill	Coffee Shop	Sandwich Place	Japanese Restaurant	Hotel	Italian Restaurant	American Restaurant	Gym / Fitness Center	Gym	Bar	Mediterranean Restaurant
19	East Village	Bar	Wine Bar	Ice Cream Shop	Pizza Place	Mexican Restaurant	Chinese Restaurant	Cocktail Bar	Ramen Restaurant	Dessert Shop	Vegetarian / Vegan Restaurant
20	Lower East Side	Pizza Place	Café	Chinese Restaurant	Park	Bakery	Ramen Restaurant	Art Gallery	Japanese Restaurant	Cocktail Bar	Coffee Shop
26	Morningside Heights	Bookstore	American Restaurant	Park	Coffee Shop	Tennis Court	Café	Burger Joint	Deli / Bodega	Food Truck	Sandwich Place
27	Gramercy	Bar	Italian Restaurant	Bagel Shop	American Restaurant	Pizza Place	Hotel	Thrift / Vintage Store	Mexican Restaurant	Coffee Shop	Cocktail Bar
29	Financial District	Coffee Shop	Wine Shop	American Restaurant	Pizza Place	Hotel	Food Truck	Cocktail Bar	Mediterranean Restaurant	Event Space	Gym
30	Carnegie Hill	Coffee Shop	Pizza Place	Café	Yoga Studio	Japanese Restaurant	Cosmetics Shop	Bar	Bakery	Spa	French Restaurant
33	Midtown South	Korean Restaurant	Hotel	Japanese Restaurant	Cosmetics Shop	Hotel Bar	Coffee Shop	Gym / Fitness Center	American Restaurant	Dessert Shop	Boutique
34	Sutton Place	Gym / Fitness Center	Furniture / Home Store	Indian Restaurant	Italian Restaurant	Gym	American Restaurant	Dessert Shop	Mexican Restaurant	Beer Garden	Sushi Restaurant
35	Turtle Bay	Italian Restaurant	Steakhouse	Wine Bar	Sushi Restaurant	Coffee Shop	Ramen Restaurant	Park	French Restaurant	Café	Japanese Restaurant
38	Flatiron	Gym / Fitness Center	Yoga Studio	Japanese Restaurant	Gym	American Restaurant	Cycle Studio	Café	Coffee Shop	New American Restaurant	Cosmetics Shop

Cluster 3

	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
8	Upper East Side	Italian Restaurant	Exhibit	Bakery	Art Gallery	Coffee Shop	Juice Bar	Hotel	Gym / Fitness Center	French Restaurant	Boutique
13	Lincoln Square	Theater	Café	Concert Hall	Plaza	Italian Restaurant	Gym / Fitness Center	Performing Arts Venue	Indie Movie Theater	Park	French Restaurant
14	Clinton	Theater	Gym / Fitness Center	American Restaurant	Italian Restaurant	Wine Shop	Spa	Gym	Hotel	Bar	Indie Theater
15	Midtown	Hotel	Theater	Coffee Shop	Clothing Store	Sporting Goods Shop	Bookstore	Spa	Bakery	Japanese Restaurant	Steakhouse
17	Chelsea	Coffee Shop	Italian Restaurant	Bakery	Ice Cream Shop	Theater	American Restaurant	Seafood Restaurant	Nightclub	Hotel	Health & Beauty Service
18	Greenwich Village	Italian Restaurant	Sushi Restaurant	Clothing Store	Indian Restaurant	French Restaurant	Café	Seafood Restaurant	Cosmetics Shop	Burger Joint	Caribbean Restaurant
21	Tribeca	Park	Italian Restaurant	Café	Spa	American Restaurant	Wine Bar	Gym	Boutique	Greek Restaurant	Coffee Shop
22	Little Italy	Bakery	Italian Restaurant	Café	Sandwich Place	Mediterranean Restaurant	Clothing Store	Seafood Restaurant	Salon / Barbershop	Yoga Studio	Cocktail Bar
23	Soho	Clothing Store	Boutique	Art Gallery	Shoe Store	Furniture / Home Store	Women's Store	Sporting Goods Shop	Bakery	Men's Store	Mediterranean Restaurant
24	West Village	Italian Restaurant	Cosmetics Shop	New American Restaurant	Wine Bar	Park	American Restaurant	Cocktail Bar	Bakery	Jazz Club	Theater
28	Battery Park City	Park	Coffee Shop	Hotel	Memorial Site	Gym	Boat or Ferry	Wine Shop	Grocery Store	Food Court	Shopping Mall
31	Noho	Italian Restaurant	Art Gallery	French Restaurant	Cocktail Bar	Bookstore	Coffee Shop	Mexican Restaurant	Pizza Place	Rock Club	Boutique
32	Civic Center	Gym / Fitness Center	French Restaurant	Hotel	Coffee Shop	Italian Restaurant	Sandwich Place	Yoga Studio	Spa	Park	Bakery
39	Hudson Yards	Café	American Restaurant	Italian Restaurant	Gym / Fitness Center	Restaurant	Hotel	Park	Coffee Shop	Dog Run	Boat or Ferry

Cluster 4

	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
37	Stuyvesant Town	Bar	Park	Boat or Ferry	Baseball Field	Heliport	Tennis Court	Basketball Court	Cocktail Bar	Gym / Fitness Center	Bistro

Cluster 5

	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	Sandwich Place	Coffee Shop	Yoga Studio	Deli / Bodega	Supplement Shop	Steakhouse	Shopping Mall	Seafood Restaurant	Pizza Place	Department Store

5. Future Direction

In this study , We have analyzed all relevant places that might be a suitable place to stay in the are of Manhattan. But one important aspect is missed out in this analysis i.e. price for that locality.

Price might play an important role to choose an area. Beside price, there are factors like public transport which is a big factor especially in Asian and EU countries.

Models in this study mainly focused on individual features. However, dataset with price and public transport details can be incorporated to have a better result. The performance of the model depends on the number of segmentation & clusters and their accuracy. These data are obviously more difficult to extract and quantify, but if somehow managed and optimized, could bring significant improvements to the models.

As a result, people are turning to big cities to start a business or work. For this reason, people can achieve better outcomes through their access to the platforms where such information is provided.

Not only for investors but also city managers can manage the city more regularly by using similar data analysis types or platforms.