# Best Restaurant Locations in Manhattan

# 1- Introduction

Manhattan is one of the five boroughs that make up New York City, and is the center of the New York metropolitan area. It is also located over the same area as a county of New York state called New York County. Although it is the smallest borough, it is the most densely populated borough. Manhattan is an important commercial, financial, and cultural center of both the United States and the world,it has many famous landmarks, tourist attractions, museums, and universities. In this project we'll identify the best Neighborhoods in Manhattan to open a resturant in Manhattan, this will be suitable for investors who are looking for the best place in Manhattan for a resturant that will be with a high profit potentials.

# 2- Data

To check the best Neighborhoods in Manhattan for a restaurant, there are alot of factors that will affect this purpose, but as we'll make a study for a general type restaurant, so we'll focus only on the following aspects: the competition and Prking availability. the datasets to be used are as following:

1- Newyork data : a dataset that contains Newyork's boroughs and neighborhood along with it's coordinates, we'll slice the dataset on borough column, to get the related data to manhattan only.

2- Manhattan venues : a dataset includes all venues in each neighborhood, latitude & longitude for each neighborhood, venue names and it's category. we'll do some explatory analysis on the dataset to get the most common venues in each neighborhood, then merge it to the manhattan data that created from above.

3- Parking Meters GPS Coordinates and Status : a dataset that contains parking meters number, latitude & longitude, and borough, from "NYC opendata". we'll use Nominatim reverse geocoding service, to convert the coordinates to an address then to the corresponding Neighborhood from that address, then we'll group the Neighborhoods by the count of parking meters. then we'll merge it to the above manhattan data, and then prepare it for the clustering model that we'll use to group the neighborhoods by there similarty to each other, and based on that we'll check the clusters and identify which groups are suitable for our purpose.

# 3- Methodology

Before we get the data and start exploring it, let's download all the dependencies that we will need.

```
Libraries imported.
```

Let's download Neywork data.

```
Data downloaded!
```

Now we load and explore the data

- Let's start by Newyork data

Out[3]:

```
{'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]}}
```


Out[4]:

| | 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 |

Let's slice the dataframe to include Manhattan boroughs only.

```
Manhattan has 40 Neighborhood
```

Out[5]:

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

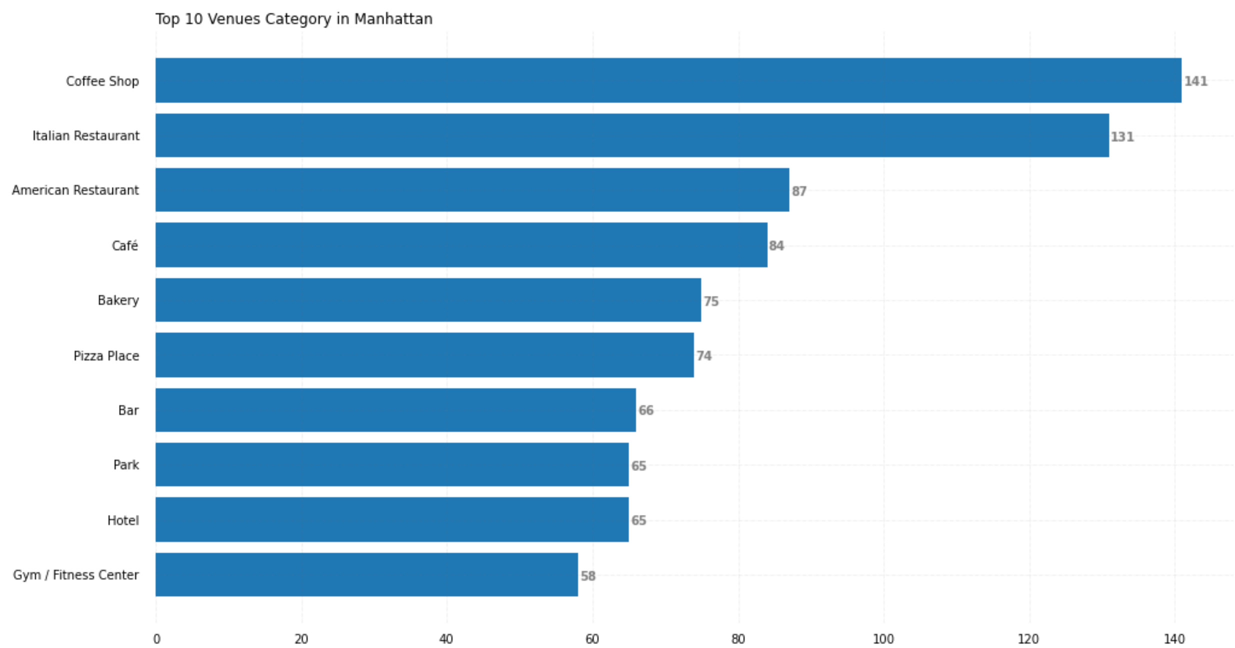
- Now let's download and explore Manhattan venues dataset.

Out[6]:

| | 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 | Dunkin' | 40.877136 | -73.906666 | Donut Shop |
| **4** | Marble Hill | 40.876551 | -73.91066 | Starbucks | 40.877531 | -73.905582 | Coffee Shop |

```
Manhattan has 40 Neighborhood with total 3240 venues
```

- we'll check the top 10 venues in Manhattan.




- Let's identify the nature of each Neighborhood by getting the top 5 most common venues in each neighborhood.

Out[9]:

| | Neighborhood | Accessories Store | Adult Boutique | Afghan Restaurant | African Restaurant | American Restaurant | Antique Shop | Arepa Restaurant | Argen Resta |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Marble Hill | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1 | Marble Hill | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 2 | Marble Hill | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 3 | Marble Hill | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 4 | Marble Hill | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |

we'll group rows by neighborhood and by taking the mean of the frequency of occurrence of each category

Out[10]:

| | Neighborhood | Accessories Store | Adult Boutique | Afghan Restaurant | African Restaurant | American Restaurant | Antique Shop | Arepa Restaurant | Argen Resta |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Battery Park City | 0.0 | 0.0 | 0.0 | 0.000000 | 0.012987 | 0.0 | 0.0 | 0.0 |
| 1 | Carnegie Hill | 0.0 | 0.0 | 0.0 | 0.000000 | 0.010526 | 0.0 | 0.0 | 0.0 |
| 2 | Central Harlem | 0.0 | 0.0 | 0.0 | 0.066667 | 0.044444 | 0.0 | 0.0 | 0.0 |
| 3 | Chelsea | 0.0 | 0.0 | 0.0 | 0.000000 | 0.040000 | 0.0 | 0.0 | 0.0 |
| 4 | Chinatown | 0.0 | 0.0 | 0.0 | 0.000000 | 0.030000 | 0.0 | 0.0 | 0.0 |

Now let's create a new dataframe and display the top 5 venues for each neighborhood.

Out[11]:

| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue |
|---|---|---|---|---|---|---|
| 0 | Battery Park City | Park | Coffee Shop | Gym | Clothing Store | Hotel |
| 1 | Carnegie Hill | Coffee Shop | Café | Bar | Italian Restaurant | Pizza Place |
| 2 | Central Harlem | African Restaurant | Seafood Restaurant | Cosmetics Shop | Bar | French Restaurant |
| 3 | Chelsea | Coffee Shop | Art Gallery | Bakery | American Restaurant | Italian Restaurant |
| 4 | Chinatown | Chinese Restaurant | Bakery | Dessert Shop | Cocktail Bar | Hotpot Restaurant |

- Now let's merge neighborhoods_venues_sorted data with Manhattan data.

Out[12]:

| | Borough | Neighborhood | Latitude | Longitude | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Manhattan | Marble Hill | 40.876551 | -73.910660 | Gym | Discount Store | Coffee Shop | Sandwich Place | Yoga Studio |
| **1** | Manhattan | Chinatown | 40.715618 | -73.994279 | Chinese Restaurant | Bakery | Dessert Shop | Cocktail Bar | Hotpot Restaurant |
| **2** | Manhattan | Washington Heights | 40.851903 | -73.936900 | Café | Bakery | Mobile Phone Shop | Deli / Bodega | Gym |
| **3** | Manhattan | Inwood | 40.867684 | -73.921210 | Mexican Restaurant | Café | Restaurant | Lounge | Chinese Restaurant |
| **4** | Manhattan | Hamilton Heights | 40.823604 | -73.949688 | Pizza Place | Café | Coffee Shop | Deli / Bodega | Mexican Restaurant |

- Next step is to get number of parkings available in each neighborhood.
- so let's download the Parking Meters GPS Coordinates and Status dataset and explore it.

As most of the Datasets, Parkint meters data contains only coordinates, so we had to convert those coordinates and get the Neighborhood. to do this we used reverse geocoding service from Nominatim. the following line of codes commented because the reverese geocoding takes some time with 5000 coordinates in our dataset.

- After we got the corresponding Neighborhood to each coordinate, we saved it to a new CSV file named "manhattan_parking", so let's load the file and start exploring it.

Out[15]:

| | MeterNo | LAT | LONG | Neighborhood |
|---|---|---|---|---|
| **0** | 1068277 | 40.863244 | -73.925681 | Fort George |
| **1** | 1068276 | 40.862876 | -73.925443 | Fort George |
| **2** | 1068275 | 40.862783 | -73.925016 | Fort George |
| **3** | 1068274 | 40.862670 | -73.924983 | Fort George |
| **4** | 1068273 | 40.862289 | -73.925066 | Fort George |

- Let's check if there are empty values in Neighborhood coloumn, and remove it if any.

Out[16]:
```
False    4833
True      133
Name: Neighborhood, dtype: int64
```

- removing empty values and check again.

Out[17]:
```
False    4833
Name: Neighborhood, dtype: int64
```

- Now we'll group the dataset by Neighborhood.

Out[19]:

| | Neighborhood | Parking_No. |
|---|---|---|
| **0** | Alphabet City | 3 |
| **1** | Battery Park City | 2 |
| **2** | Brighton Beach | 1 |
| **3** | Bronx County | 2 |
| **4** | Carnegie Hill | 79 |

- Let's merge the parking data with the manhattan merged data.

Out[20]:

| | Borough | Neighborhood | Latitude | Longitude | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Commor Venue |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Manhattan | Marble Hill | 40.876551 | -73.910660 | Gym | Discount Store | Coffee Shop | Sandwich Place | Yoga Studic |
| **1** | Manhattan | Chinatown | 40.715618 | -73.994279 | Chinese Restaurant | Bakery | Dessert Shop | Cocktail Bar | Hotpo Restauran |
| **2** | Manhattan | Washington Heights | 40.851903 | -73.936900 | Café | Bakery | Mobile Phone Shop | Deli / Bodega | Gym |
| **3** | Manhattan | Inwood | 40.867684 | -73.921210 | Mexican Restaurant | Café | Restaurant | Lounge | Chinese Restauran |
| **4** | Manhattan | Hamilton Heights | 40.823604 | -73.949688 | Pizza Place | Café | Coffee Shop | Deli / Bodega | Mexicar Restauran |

- Replace the Nan values in Parking_No. column with the mean value.

Out[21]:

| | Borough | Neighborhood | Latitude | Longitude | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Manhattan | Marble Hill | 40.876551 | -73.910660 | Gym | Discount Store | Coffee Shop | Sandwich Place | Yoga Studio |
| 1 | Manhattan | Chinatown | 40.715618 | -73.994279 | Chinese Restaurant | Bakery | Dessert Shop | Cocktail Bar | Hotpot Restaurant |
| 2 | Manhattan | Washington Heights | 40.851903 | -73.936900 | Café | Bakery | Mobile Phone Shop | Deli / Bodega | Gym |
| 3 | Manhattan | Inwood | 40.867684 | -73.921210 | Mexican Restaurant | Café | Restaurant | Lounge | Chinese Restaurant |
| 4 | Manhattan | Hamilton Heights | 40.823604 | -73.949688 | Pizza Place | Café | Coffee Shop | Deli / Bodega | Mexican Restaurant |

- Merge the parking data to manhattan_grouped dataset, to prepare a data set for clustering model.

Out[22]:

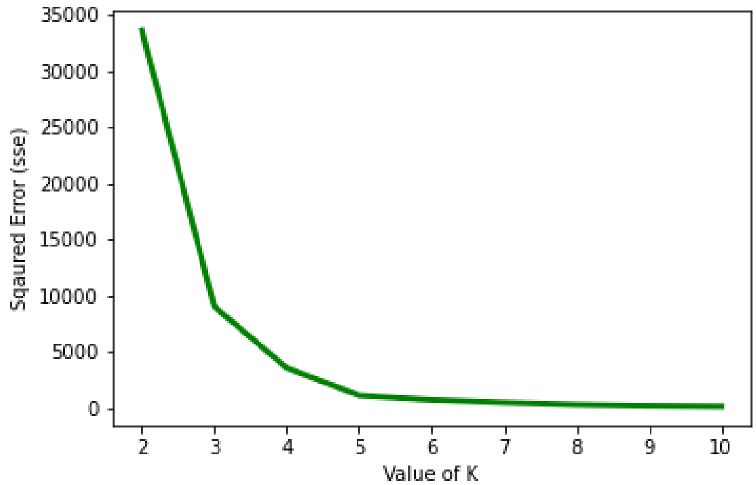
| | Neighborhood | Accessories Store | Adult Boutique | Afghan Restaurant | African Restaurant | American Restaurant | Antique Shop | Arepa Restaurant | Argen Resta |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Battery Park City | 0.0 | 0.0 | 0.0 | 0.000000 | 0.012987 | 0.0 | 0.0 | 0.0 |
| 1 | Carnegie Hill | 0.0 | 0.0 | 0.0 | 0.000000 | 0.010526 | 0.0 | 0.0 | 0.0 |
| 2 | Central Harlem | 0.0 | 0.0 | 0.0 | 0.066667 | 0.044444 | 0.0 | 0.0 | 0.0 |
| 3 | Chelsea | 0.0 | 0.0 | 0.0 | 0.000000 | 0.040000 | 0.0 | 0.0 | 0.0 |
| 4 | Chinatown | 0.0 | 0.0 | 0.0 | 0.000000 | 0.030000 | 0.0 | 0.0 | 0.0 |

Out[23]:

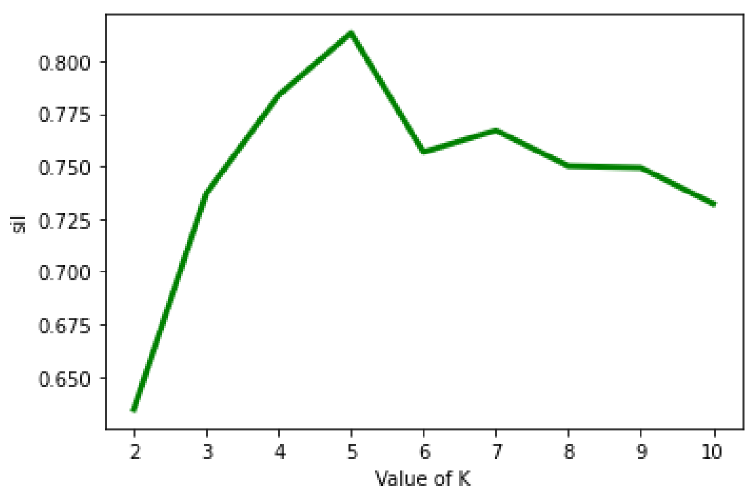
| | Neighborhood | Accessories Store | Adult Boutique | Afghan Restaurant | African Restaurant | American Restaurant | Antique Shop | Arepa Restaurant | Argen Resta |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Battery Park City | 0.0 | 0.0 | 0.0 | 0.000000 | 0.012987 | 0.0 | 0.0 | 0.0 |
| 1 | Carnegie Hill | 0.0 | 0.0 | 0.0 | 0.000000 | 0.010526 | 0.0 | 0.0 | 0.0 |
| 2 | Central Harlem | 0.0 | 0.0 | 0.0 | 0.066667 | 0.044444 | 0.0 | 0.0 | 0.0 |
| 3 | Chelsea | 0.0 | 0.0 | 0.0 | 0.000000 | 0.040000 | 0.0 | 0.0 | 0.0 |
| 4 | Chinatown | 0.0 | 0.0 | 0.0 | 0.000000 | 0.030000 | 0.0 | 0.0 | 0.0 |

- Now our dataset is ready, let's build a clustering model for Manhattan Neighborhoods.

- We'll use K-means to cluster the Neighborhoods, and to do that let's get the optimal value of K.
- Elbow method :




- Silhouette_score method :




From the two methods, the optimal value of K is 5, so let's run the model based on this value.

Out[26]:
```
array([2, 0, 0, 1, 0, 2, 0, 0, 1, 0, 0, 0, 0, 4, 2, 4, 1, 2, 4, 3, 0, 2,
       0, 0, 3, 4, 3, 0, 0, 0, 0, 0, 4, 2, 3, 0, 0, 0, 0, 0])
```

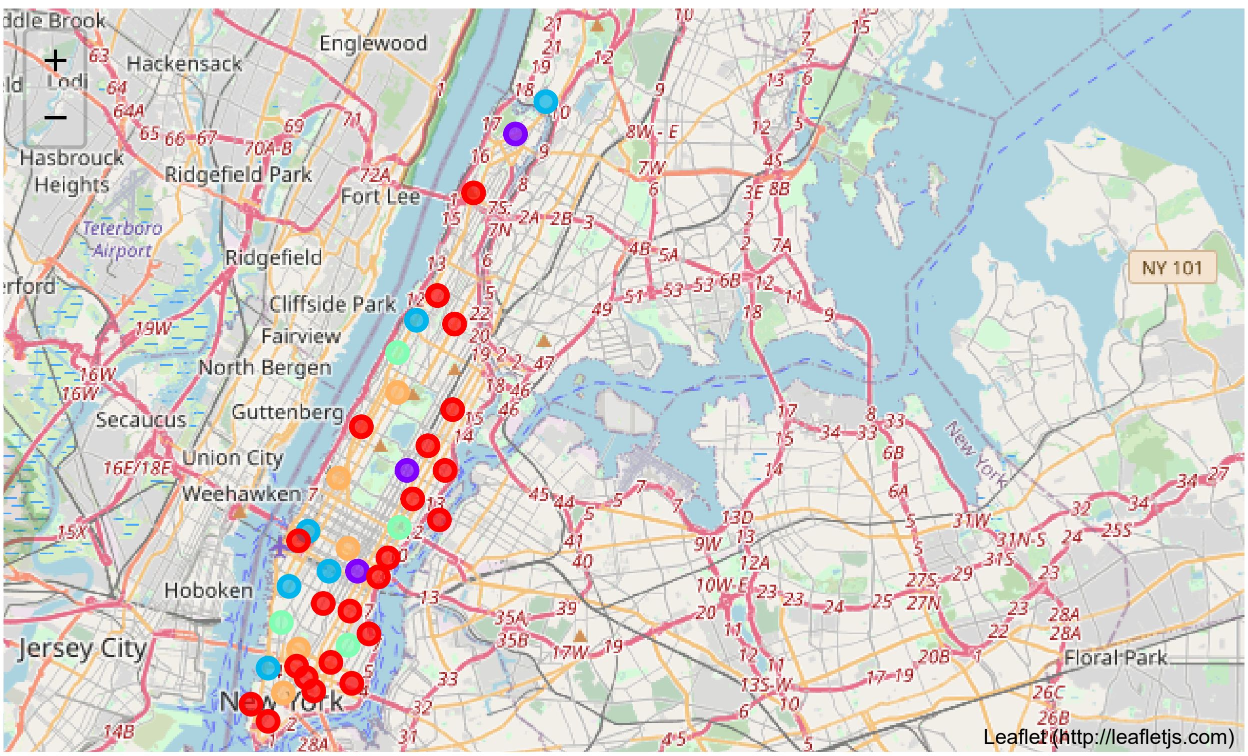
- Let's add the cluster labels to manhattan merged dataset.

Out[27]:

| | Borough | Neighborhood | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Manhattan | Marble Hill | 40.876551 | -73.910660 | 2 | Gym | Discount Store | Coffee Shop | Sandwich Place |
| **1** | Manhattan | Chinatown | 40.715618 | -73.994279 | 0 | Chinese Restaurant | Bakery | Dessert Shop | Cocktail Bar |
| **2** | Manhattan | Washington Heights | 40.851903 | -73.936900 | 0 | Café | Bakery | Mobile Phone Shop | Deli / Bodega |
| **3** | Manhattan | Inwood | 40.867684 | -73.921210 | 1 | Mexican Restaurant | Café | Restaurant | Lounge |
| **4** | Manhattan | Hamilton Heights | 40.823604 | -73.949688 | 0 | Pizza Place | Café | Coffee Shop | Deli / Bodega |

- Let's create a map to visualize the Clusters.

Out[28]:




- Examining each Cluster :

## Cluster 1

Out[29]:

| | Neighborhood | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | Parking_No. |
|---|---|---|---|---|---|---|---|---|
| **1** | Chinatown | 0 | Chinese Restaurant | Bakery | Dessert Shop | Cocktail Bar | Hotpot Restaurant | 74.0 |
| **2** | Washington Heights | 0 | Café | Bakery | Mobile Phone Shop | Deli / Bodega | Gym | 72.0 |
| **4** | Hamilton Heights | 0 | Pizza Place | Café | Coffee Shop | Deli / Bodega | Mexican Restaurant | 44.0 |
| **6** | Central Harlem | 0 | African Restaurant | Seafood Restaurant | Cosmetics Shop | Bar | French Restaurant | 72.0 |
| **7** | East Harlem | 0 | Mexican Restaurant | Bakery | Latin American Restaurant | Thai Restaurant | Sandwich Place | 74.0 |
| **9** | Yorkville | 0 | Italian Restaurant | Bar | Gym | Coffee Shop | Deli / Bodega | 82.0 |
| **10** | Lenox Hill | 0 | Italian Restaurant | Pizza Place | Sushi Restaurant | Cocktail Bar | Coffee Shop | 192.0 |
| **11** | Roosevelt Island | 0 | Park | Restaurant | Residential Building (Apartment / Condo) | Dry Cleaner | Metro Station | 72.0 |
| **12** | Upper West Side | 0 | Italian Restaurant | Mediterranean Restaurant | Bakery | Bar | Wine Bar | 72.0 |
| **20** | Lower East Side | 0 | Chinese Restaurant | Bakery | Café | Ramen Restaurant | Art Gallery | 127.0 |
| **22** | Little Italy | 0 | Bakery | Café | Italian Restaurant | Bubble Tea Shop | Hotel | 42.0 |
| **23** | Soho | 0 | Clothing Store | Italian Restaurant | Boutique | Mediterranean Restaurant | Coffee Shop | 72.0 |
| **27** | Gramercy | 0 | Bar | Bagel Shop | Italian Restaurant | American Restaurant | Pizza Place | 85.0 |
| **28** | Battery Park City | 0 | Park | Coffee Shop | Gym | Clothing Store | Hotel | 2.0 |
| **29** | Financial District | 0 | Coffee Shop | American Restaurant | Pizza Place | Gym | Cocktail Bar | 88.0 |
| **30** | Carnegie Hill | 0 | Coffee Shop | Café | Bar | Italian Restaurant | Pizza Place | 79.0 |
| **31** | Noho | 0 | Italian Restaurant | Coffee Shop | Mexican Restaurant | French Restaurant | Pizza Place | 72.0 |
| **35** | Turtle Bay | 0 | Coffee Shop | Italian Restaurant | Sushi Restaurant | Japanese Restaurant | Ramen Restaurant | 109.0 |
| **36** | Tudor City | 0 | Park | Mexican Restaurant | Café | Pizza Place | Coffee Shop | 3.0 |
| **37** | Stuyvesant Town | 0 | Bar | Park | Coffee Shop | Boat or Ferry | Pet Service | 72.0 |
| **38** | Flatiron | 0 | Gym / Fitness Center | Italian Restaurant | American Restaurant | New American Restaurant | Japanese Restaurant | 72.0 |
| **39** | Hudson Yards | 0 | American Restaurant | Gym / Fitness Center | Café | Hotel | Italian Restaurant | 6.0 |

## Cluster 2

Out[30]:

| | Neighborhood | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | Parking_No. |
|---|---|---|---|---|---|---|---|---|
| **3** | Inwood | 1 | Mexican Restaurant | Café | Restaurant | Lounge | Chinese Restaurant | 32.0 |
| **8** | Upper East Side | 1 | Coffee Shop | Italian Restaurant | Bakery | Gym / Fitness Center | Exhibit | 72.0 |
| **16** | Murray Hill | 1 | Hotel | Coffee Shop | Japanese Restaurant | Sandwich Place | American Restaurant | 110.0 |

## Cluster 3

Out[31]:

| | Neighborhood | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | Parking_No. |
|---|---|---|---|---|---|---|---|---|
| **0** | Marble Hill | 2 | Gym | Discount Store | Coffee Shop | Sandwich Place | Yoga Studio | 72.0 |
| **5** | Manhattanville | 2 | Seafood Restaurant | Coffee Shop | Deli / Bodega | Park | Sushi Restaurant | 17.0 |
| **14** | Clinton | 2 | Italian Restaurant | Gym / Fitness Center | Theater | American Restaurant | Coffee Shop | 72.0 |
| **17** | Chelsea | 2 | Coffee Shop | Art Gallery | Bakery | American Restaurant | Italian Restaurant | 183.0 |
| **21** | Tribeca | 2 | Park | American Restaurant | Italian Restaurant | Spa | Wine Bar | 32.0 |
| **33** | Midtown South | 2 | Korean Restaurant | Hotel | Hotel Bar | Japanese Restaurant | Cosmetics Shop | 115.0 |

## Cluster 4

Out[32]:

| | Neighborhood | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | Parking_No. |
|---|---|---|---|---|---|---|---|---|
| **19** | East Village | 3 | Bar | Mexican Restaurant | Pizza Place | Vegetarian / Vegan Restaurant | Speakeasy | 184.0 |
| **24** | West Village | 3 | Italian Restaurant | American Restaurant | New American Restaurant | Cosmetics Shop | Cocktail Bar | 81.0 |
| **26** | Morningside Heights | 3 | Coffee Shop | Bookstore | Park | American Restaurant | Burger Joint | 37.0 |
| **34** | Sutton Place | 3 | Italian Restaurant | Pizza Place | Park | Gym / Fitness Center | Gym | 72.0 |

## Cluster 5

Out[33]:

| | Neighborhood | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | Parking_No. |
|---|---|---|---|---|---|---|---|---|
| **13** | Lincoln Square | 4 | Plaza | Café | Concert Hall | Performing Arts Venue | Theater | 16.0 |
| **15** | Midtown | 4 | Hotel | Coffee Shop | Clothing Store | Theater | American Restaurant | 72.0 |
| **18** | Greenwich Village | 4 | Italian Restaurant | Clothing Store | Sushi Restaurant | Gym | Coffee Shop | 76.0 |
| **25** | Manhattan Valley | 4 | Mexican Restaurant | Bar | Thai Restaurant | Pizza Place | Coffee Shop | 77.0 |
| **32** | Civic Center | 4 | Coffee Shop | Cocktail Bar | Gym / Fitness Center | American Restaurant | French Restaurant | 1.0 |

- Clusters Venues summary :

Out[34]:

| | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue |
|---|---|---|---|---|---|
| **cluster 1** | Italian Restaurant | Bakery | Café | Cocktail Bar | Pizza Place |
| **cluster 2** | Mexican Restaurant | Coffee Shop | Restaurant | Sandwich Place | American Restaurant |
| **cluster 3** | Seafood Restaurant | Hotel | Hotel Bar | American Restaurant | Cosmetics Shop |
| **cluster 4** | Italian Restaurant | Pizza Place | Park | American Restaurant | Speakeasy |
| **cluster 5** | Mexican Restaurant | Café | Gym / Fitness Center | Gym | Coffee Shop |

# 4- Results & Discussion

- our analysis shows that Neighborhoods in cluster 1,2 & 4 represents a perfect location for a restaurant, the most common venues in these Neighborhoods are a variety of restaurants cuisine and coffe shops, with a fare numbers of parking spots.
- Other clusters can be choosed if you are willing to open a specific restaurant cuisine, based on the Neighborhoods that have the same type of restaurants.
- we choosed the nehighborhoods that have a variety of restaurants and the competition is high because up to the 5th common venue there are restaurants and coffeshops, and there are a lot of parkings too. ofcourse if the restaurant cuisine is konwn, there will be more factors to consider while building the model, such as the distance from the suppliers, the population study of each neighborhood, is it a breakfast restaurant to check the traffic where people are heading to businees centers and work zones, and so on.

# 5- Conclusion

- Purpose of this project was to identify Manhattan Neighborhoods that have a high competition in restaurants and coffeshops in order to aid stakeholders in narrowing down the search for optimal location for a new restaurant, by using a cluster model to group Manhattan Neighborhoods to different clusters that have neighborhoods with similar charactarestics.
- Final decission on optimal restaurant location will be made by stakeholders based on specific characteristics in every recommended neighborhood, taking into consideration additional factors like attractiveness of each location (proximity to park or water), levels of noise / proximity to major roads, real estate availability, prices, social and economic dynamics of every neighborhood etc