

In [2]:

```
#Importation of necessary libraries
import time
import pandas as pd # library for data analysis
import numpy as np # library to handle data in a vectorized manner
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
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

print('Done! Libraries imported.')
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: done
```

```
# All requested packages already installed.
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: done
```

```
# All requested packages already installed.
```

```
Done! Libraries imported.
```

## WEEK ONE

### 1. Description of the problem and a discussion of the background.

## Background

I am moving to New York City in a few months. I am looking for a single flat and I am hoping to use data science to help me find the most place to live in based on several factors. I want to be in Manhattan, near a tube station, walking distance to work-out studios, food, and entertainment. As much as possible, I want to be cost efficient.

## Problem to be solved

The task is to find the most cost efficient rental flat in Manhattan, NYC within walking distance to groceries, shops, a work-out studio, and a subway station. Additionally, flat must have 2 bedrooms, a living room, and bathroom. The rent must be around \$6000/ month.

## Interested Audience

This exercise will be beneficial to and interesting for other young professionals moving to Manhattan.

## WEEK TWO

### 2. Description of the data and how it will be used to solve the problem.

I require the the Geodata (longitude, latitude) of the following enterprises in Manhattan, NYC.

- Cycling studios
- Coffee shops
- Tube stations
- Places for rent and cost

## Source of Data

- Wikipedia ([https://en.wikipedia.org/wiki/List\\_of\\_New\\_York\\_City\\_Subway\\_stations\\_in\\_Manhattan](https://en.wikipedia.org/wiki/List_of_New_York_City_Subway_stations_in_Manhattan) ([https://en.wikipedia.org/wiki/List\\_of\\_New\\_York\\_City\\_Subway\\_stations\\_in\\_Manhattan](https://en.wikipedia.org/wiki/List_of_New_York_City_Subway_stations_in_Manhattan)))
- NY Transit authority and Google maps (<https://www.google.com/maps/search/manhattan+subway+metro+stations/@40.7837297,-74.1033043,1> (<https://www.google.com/maps/search/manhattan+subway+metro+stations/@40.7837297,-74.1033043,1>)
- Real estate websites (<http://www.rentmanhattan.com/index.cfm?page=search&state=results> (<http://www.rentmanhattan.com/index.cfm?page=search&state=results>)  
[https://www.nestpick.com/search?city=new-york&page=1&order=relevance&district=manhattan&gclid=CjwKCAiAjNjgBRAgEiwAGLI2hkP3A-cPxjZYkURqQEswQK2jKQEpv\\_MvKcrIhRWRzNkc\\_r-fGi0lxoCA7cQAvD\\_BwE&type=apartment&display=list](https://www.nestpick.com/search?city=new-york&page=1&order=relevance&district=manhattan&gclid=CjwKCAiAjNjgBRAgEiwAGLI2hkP3A-cPxjZYkURqQEswQK2jKQEpv_MvKcrIhRWRzNkc_r-fGi0lxoCA7cQAvD_BwE&type=apartment&display=list) ([https://www.nestpick.com/search?city=new-york&page=1&order=relevance&district=manhattan&gclid=CjwKCAiAjNjgBRAgEiwAGLI2hkP3A-cPxjZYkURqQEswQK2jKQEpv\\_MvKcrIhRWRzNkc\\_r-fGi0lxoCA7cQAvD\\_BwE&type=apartment&display=list](https://www.nestpick.com/search?city=new-york&page=1&order=relevance&district=manhattan&gclid=CjwKCAiAjNjgBRAgEiwAGLI2hkP3A-cPxjZYkURqQEswQK2jKQEpv_MvKcrIhRWRzNkc_r-fGi0lxoCA7cQAvD_BwE&type=apartment&display=list))  
[https://www.realtor.com/apartments/Manhattan\\_NY](https://www.realtor.com/apartments/Manhattan_NY) ([https://www.realtor.com/apartments/Manhattan\\_NY](https://www.realtor.com/apartments/Manhattan_NY)))

### 3. Methodology Section

Course lab generated cluster neighborhood data. Csv file is used for convenience of the project.

In [6]:

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

Out[6]:

	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

In [7]:

```
#Finding the 10 clustered neighborhoods I can move into
manhattan_merged = pd.read_csv('manhattan_merged.csv')
manhattan_merged.head()
```

Out[7]:

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

In [8]:

```

#Now I will map Manhattan neighborhoods, showing top 10 clusters

# 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 Label
s']):
    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['Longitud
e'], 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

```

Out[8]:

In [9]:

```
#Assign value to kk - cluster number to explore. I'm just going to pick any cluster.
```

```
kk = 2
```

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

Out[9]:

	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
0	Marble Hill	Coffee Shop	Discount Store	Yoga Studio	Steakhouse	Supplement Shop	Tennis Stadium	
1	Chinatown	Chinese Restaurant	Cocktail Bar	Dim Sum Restaurant	American Restaurant	Vietnamese Restaurant	Salon / Barbershop	
6	Central Harlem	African Restaurant	Seafood Restaurant	French Restaurant	American Restaurant	Cosmetics Shop	Chinese Restaurant	
9	Yorkville	Coffee Shop	Gym	Bar	Italian Restaurant	Sushi Restaurant	Pizza Place	M Res
14	Clinton	Theater	Italian Restaurant	Coffee Shop	American Restaurant	Gym / Fitness Center	Hotel	Wir
23	Soho	Clothing Store	Boutique	Women's Store	Shoe Store	Men's Store	Furniture / Home Store	Res
26	Morningside Heights	Coffee Shop	American Restaurant	Park	Bookstore	Pizza Place	Sandwich Place	
34	Sutton Place	Gym / Fitness Center	Italian Restaurant	Furniture / Home Store	Indian Restaurant	Dessert Shop	American Restaurant	
39	Hudson Yards	Coffee Shop	Italian Restaurant	Hotel	Theater	American Restaurant	Café	

Now we will use the csv of webscrapped Manhattan real estate data. to explore rental options. Use Nominatim.

In [11]:

```
# csv files with rental places with basic data but still without 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()
```

Out[11]:

	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

Now we need the latitude and longitude (geodata) of the rental places we webscrapped. We will use Nominatum.

In [ ]:

In [14]:

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

Out[14]:

	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	40.799771	-73.966213
1	East 97th Street	Upper East Side	3.57	3.0	2100	7500	40.788585	-73.955277
2	West 105th Street	Upper West Side	1.89	4.0	2800	5300	40.799771	-73.966213
3	CARMINE ST.	West Village	3.03	2.0	1650	5000	40.730523	-74.001873
4	171 W 23RD ST.	Chelsea	3.45	2.0	1450	5000	40.744118	-73.995299

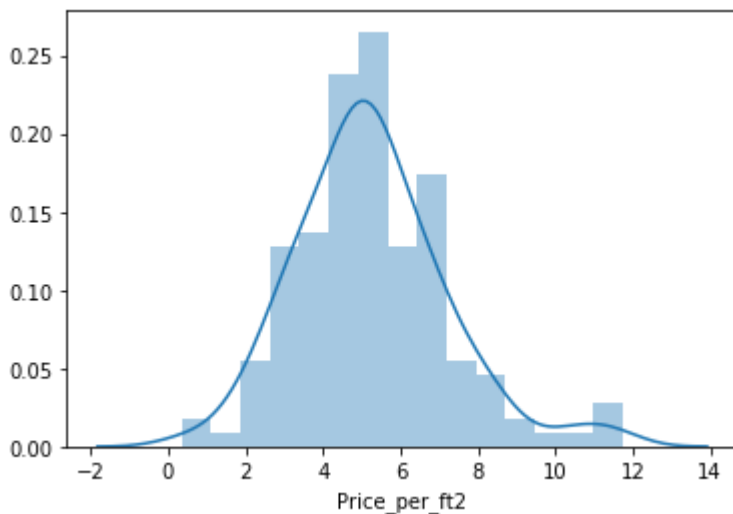


In [16]:

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

Out[16]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x1a1d1e1f50>



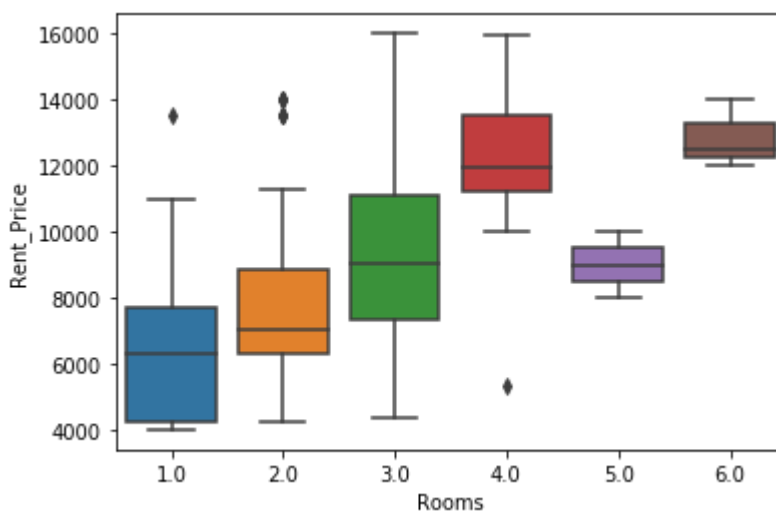
This graph shows that the mean rental price is within our \$6000 range.

In [17]:

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

Out[17]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x1a1d9526d0>



Now we will check the monthly rental prices and addresses so that we can select which apartment matches our price range.

In [19]:

```
# 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='green',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_manhattan_rent)

map_manhattan_rent
```

Out[19]:

We need to determine rental places that match us based on pricess and location of amenities around the apartment.

In [20]:

```
# 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
```

Out[20]:

Time to drill down on a particular apartment and the venues near it - i.e. Near subway stations?

In [21]:

```
kk = 3
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == kk, manhattan_merged.
columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

Out[21]:

	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
3	Inwood	Mexican Restaurant	Lounge	Pizza Place	Café	Wine Bar	Bakery	Art Res
5	Manhattanville	Deli / Bodega	Italian Restaurant	Seafood Restaurant	Mexican Restaurant	Sushi Restaurant	Beer Garden	
10	Lenox Hill	Sushi Restaurant	Italian Restaurant	Coffee Shop	Gym / Fitness Center	Pizza Place	Burger Joint	Ice Cream Shop
12	Upper West Side	Italian Restaurant	Bar	Bakery	Vegetarian / Vegan Restaurant	Indian Restaurant	Coffee Shop	Coffee Shop
16	Murray Hill	Sandwich Place	Hotel	Japanese Restaurant	Gym / Fitness Center	Coffee Shop	Salon / Barbershop	
17	Chelsea	Coffee Shop	Italian Restaurant	Ice Cream Shop	Bakery	Nightclub	Theater	Art
18	Greenwich Village	Italian Restaurant	Sushi Restaurant	French Restaurant	Clothing Store	Chinese Restaurant	Café	Res
27	Gramercy	Italian Restaurant	Restaurant	Thrift / Vintage Store	Cocktail Bar	Bagel Shop	Coffee Shop	
29	Financial District	Coffee Shop	Hotel	Gym	Wine Shop	Steakhouse	Bar	Res
31	Noho	Italian Restaurant	French Restaurant	Cocktail Bar	Gift Shop	Bookstore	Grocery Store	M Res
32	Civic Center	Gym / Fitness Center	Bakery	Italian Restaurant	Cocktail Bar	French Restaurant	Sandwich Place	
35	Turtle Bay	Italian Restaurant	Coffee Shop	Steakhouse	Wine Bar	Sushi Restaurant	Hotel	
36	Tudor City	Café	Park	Pizza Place	Mexican Restaurant	Greek Restaurant	Sushi Restaurant	
38	Flatiron	Italian Restaurant	American Restaurant	Gym	Gym / Fitness Center	Yoga Studio	Vegetarian / Vegan Restaurant	

We need to map out subway stations against the rental apartments. We do this by using the csv file from our webscrapping.

In [23]:

```
mh=pd.read_csv('NYC_subway_list.csv')
mh.head()
```

Out[23]:

	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

In [25]:

```
# 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)
#After this we need to get the geodata for each station and add to our dataframe
```

In [26]:

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

(76, 4)

Out[26]:

	sub_station	sub_address	lat	long
0	Dyckman Street Subway Station	170 Nagle Ave, New York, NY 10034, USA	40.861857	-73.924509
1	57 Street Subway Station	New York, NY 10106, USA	40.764250	-73.954525
2	Broad St	New York, NY 10005, USA	40.730862	-73.987156
3	175 Street Station	807 W 177th St, New York, NY 10033, USA	40.847991	-73.939785
4	5 Av and 53 St	New York, NY 10022, USA	40.764250	-73.954525

In [27]:

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

Out[27]:

(22, 4)

Generate map of subway stations using Noninativim geolocator to show desirable rental apartemnts and their nearest stations.

In [28]:

```
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
```

Out[28]:

In [29]:

```
mh_rent.head()
```

Out[29]:

	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	40.799771	-73.966213
1	East 97th Street	Upper East Side	3.57	3.0	2100	7500	40.788585	-73.955277
2	West 105th Street	Upper West Side	1.89	4.0	2800	5300	40.799771	-73.966213
3	CARMINE ST.	West Village	3.03	2.0	1650	5000	40.730523	-74.001873
4	171 W 23RD ST.	Chelsea	3.45	2.0	1450	5000	40.744118	-73.995299

In [30]:

```

# 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/AEAAQAAAAAAAAA1gAAAAJGE
3OTA4YTdlLTkzZjU0NDYyYy1lZThlLWQ5OTNkYzlhNm40OQ.jpg')
FloatImage(url, bottom=5, left=85).add_to(map_manhattan_rent)

map_manhattan_rent

```



Out[30]:

## 4. Results Section

Finally! Now we can use our data to pick out our perfect apartment! We begin by mapping the apartments, subway stations, and amenity venues.

In [31]:

```
# 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 Label
s']):
    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/AEEAAQAAAAAAAAAAlgAAAAJGE3OTA4YTdlLTkzZjUtNDYyYy1iZThlLWQ5OTNkYzlhNzM4OQ.jpg')
FloatImage(url, bottom=5, left=85).add_to(map_mh_one)

map_mh_one
```

Out[31]:

**19 Dutch Street in the Financial District Neighborhood and near 'Fulton Street Subway' station, Cluster # 3 Monthly rent : \$6935, looks like a good apartmnet.**

Time to find the cafes, restaurants, gyms, and other amenities hear this apartment.

In [32]:

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

Out[32]:

	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
3	Inwood	Mexican Restaurant	Lounge	Pizza Place	Café	Wine Bar	Bakery	Art Res
5	Manhattanville	Deli / Bodega	Italian Restaurant	Seafood Restaurant	Mexican Restaurant	Sushi Restaurant	Beer Garden	
10	Lenox Hill	Sushi Restaurant	Italian Restaurant	Coffee Shop	Gym / Fitness Center	Pizza Place	Burger Joint	I
12	Upper West Side	Italian Restaurant	Bar	Bakery	Vegetarian / Vegan Restaurant	Indian Restaurant	Coffee Shop	Co:
16	Murray Hill	Sandwich Place	Hotel	Japanese Restaurant	Gym / Fitness Center	Coffee Shop	Salon / Barbershop	
17	Chelsea	Coffee Shop	Italian Restaurant	Ice Cream Shop	Bakery	Nightclub	Theater	Art
18	Greenwich Village	Italian Restaurant	Sushi Restaurant	French Restaurant	Clothing Store	Chinese Restaurant	Café	Res
27	Gramercy	Italian Restaurant	Restaurant	Thrift / Vintage Store	Cocktail Bar	Bagel Shop	Coffee Shop	
29	Financial District	Coffee Shop	Hotel	Gym	Wine Shop	Steakhouse	Bar	Res
31	Noho	Italian Restaurant	French Restaurant	Cocktail Bar	Gift Shop	Bookstore	Grocery Store	M Res
32	Civic Center	Gym / Fitness Center	Bakery	Italian Restaurant	Cocktail Bar	French Restaurant	Sandwich Place	
35	Turtle Bay	Italian Restaurant	Coffee Shop	Steakhouse	Wine Bar	Sushi Restaurant	Hotel	
36	Tudor City	Café	Park	Pizza Place	Mexican Restaurant	Greek Restaurant	Sushi Restaurant	
38	Flatiron	Italian Restaurant	American Restaurant	Gym	Gym / Fitness Center	Yoga Studio	Vegetarian / Vegan Restaurant	

COOL. Basically this apartment is within budget range of \$6000, located near a subway station, and have multiple amenities nearby.

## 5. Discussion Section

This course take time to digest and apply but it is very rewarding once you see how much you have learned and progressed.

I am quite proud of myself and I feel like I have a good background as I continue learning about the world of data science.

## 6. Conclusion Section

This program is such a great way to get into the world of data science. This course covered topics really well and I look forward to applying this in my work.

Stay home and we will get through this COVID-19 - this too shall pass!