IBM Data Science Professional Certificate

Capstone project

'The battle of the Neighborhoods: How does population density influence business decisions?'

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1. Introduction

Background and problem

An important business strategy is to understand the factor that could be important for maximizing profit. One factor is location of business enterprise. The location of a business can influence the availability of demand and traffic of people seeking goods and services. Higher traffic can drive up the chance of increasing and maintaining profits. High demand of people correlates with location with higher population density. An example of a city with this high population density is New York city. New York city is one of the top ten cities in the world with the highest population density per square mile. New York city is considered the capital of the world, because of its unique multicultural population, and diverse business and entertainment enterprises. In this study, analysis of a good and service, the bakery industry, and the relationship of the population density in different neighborhoods, in the big Apple, are determined. The understanding of the relationship between these population density and the density of bakeries by neighborhood would enlighten business decision for potential stakeholders to determine what neighborhoods need to a particular good or service.

2. Data acquisition and cleaning

The data used for the study were gotten from different sources and via different techniques. The population data, the regular and polygon geoJSON of New York city containing the Manhattan Borough by Neighbourhood were downloaded from the internet. While the data of the top places to go in Manhattan were scraped from the FourSquare site using the developer API access provided by signing up for a developer account with a radius of 500 and limit of 1000 places. The data were sorted and combined into one dataframe for analysis by venue category, bakery. There were some setbacks with the data in the final dataframe. There were some missing neighborhoods in the dataframe of the top places to go in Manhattan (which includes the data of bakeries) and the in the dataframe of the population data. There were some mismatched spelling and alphabetization in neighborhoods in both dataframes, which were edited to correct and match both dataframes for inner joining of the dataframe by the contents in the neighborhood column. About 14 neighborhoods were not present in the population dataframe. Only about 60% of the neighborhoods were matched in the final dataframe.

In [123]:

```
import numpy as np
from bs4 import BeautifulSoup
import requests
import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json

#from geopy.geocoders import Nominatim # convert an address into latitude anc

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

# Matplotlib and associated plotting modules
# use the inline backend to generate the plots within the browser
%matplotlib inline

import matplotlib as mpl
import matplotlib.pyplot as plt

mpl.style.use('ggplot') # optional: for ggplot-like style

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

!pip install folium
import folium # map rendering library
from folium.plugins import MarkerCluster
from folium.plugins import FastMarkerCluster
from folium import plugins

from folium import plugins
from folium.plugins import HeatMap

print('Libraries imported.')
```

```
Requirement already satisfied: folium in c:\users\zada2\anaconda3\lib\sit
e-packages (0.10.1)
Requirement already satisfied: requests in c:\users\zada2\anaconda3\lib\s
ite-packages (from folium) (2.22.0)
Requirement already satisfied: numpy in c:\users\zada2\anaconda3\lib\site
-packages (from folium) (1.16.5)
Requirement already satisfied: jinja2>=2.9 in c:\users\zada2\anaconda3\li
b\site-packages (from folium) (2.10.3)
Requirement already satisfied: branca>=0.3.0 in c:\users\zada2\anaconda3
\lib\site-packages (from folium) (0.4.0)
Requirement already satisfied: idna<2.9,>=2.5 in c:\users\zada2\anaconda3
\lib\site-packages (from requests->folium) (2.8)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in c:\users\zada2\an
aconda3\lib\site-packages (from requests->folium) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
c:\users\zada2\anaconda3\lib\site-packages (from requests->folium) (1.24.
2)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\zada2\anaco
nda3\lib\site-packages (from requests->folium) (2019.9.11)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\zada2\anacond
```

```
a3\lib\site-packages (from jinja2>=2.9->folium) (1.1.1)
Requirement already satisfied: six in c:\users\zada2\anaconda3\lib\site-p
ackages (from branca>=0.3.0->folium) (1.12.0)
Libraries imported.
```

In [124]:

In [129]:

In [130]:

```python
NY_geo = newyork_data['features']
```

In [131]:

```python
# define the dataframe columns
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']

NY_geodf = pd.DataFrame(columns=column_names)
for data in NY_geo:
    borough = neighborhood_name = data['properties']['borough']
    neighborhood_name = data['properties']['name']

    neighborhood_latlon = data['geometry']['coordinates']
    neighborhood_lat = neighborhood_latlon[1]
    neighborhood_lon = neighborhood_latlon[0]

    NY_geodf = NY_geodf.append({'Borough': borough,
                                      'Neighborhood': neighborhood_name,
                                      'Latitude': neighborhood_lat,
                                      'Longitude': neighborhood_lon}, igr
NY_geodf.head()
```

Out[131]:

	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

In [132]:

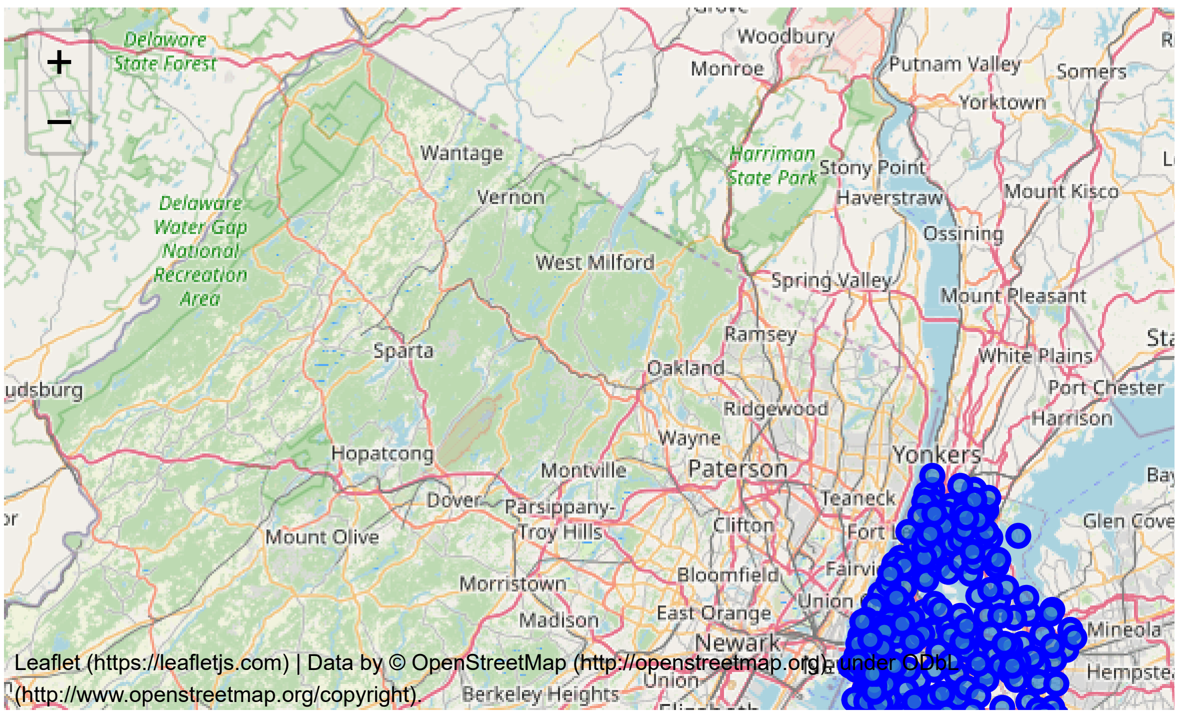
```
!pip install geopy

from geopy.geocoders import Nominatim # convert an address into latitude and

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(latitu
```

```
Requirement already satisfied: geopy in c:\users\zada2\anaconda3\lib\site-p
ackages (1.21.0)
Requirement already satisfied: geographiclib<2,>=1.49 in c:\users\zada2\ana
conda3\lib\site-packages (from geopy) (1.50)
The geograpical coordinate of New York City are 40.7127281, -74.0060152.
```

In [133]:

```python
# create map of New York using latitude and longitude values
map_newyork = folium.Map(location=[latitude, longitude], zoom_start=10)

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

map_newyork
```

Out[133]:



In [134]:

```
#Dataframe with manhanttan borough only
manhattan_data = NY_geodf[NY_geodf['Borough'] == 'Manhattan'].reset_index(drc
manhattan_data.head()
```

Out[134]:

	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

In [135]:

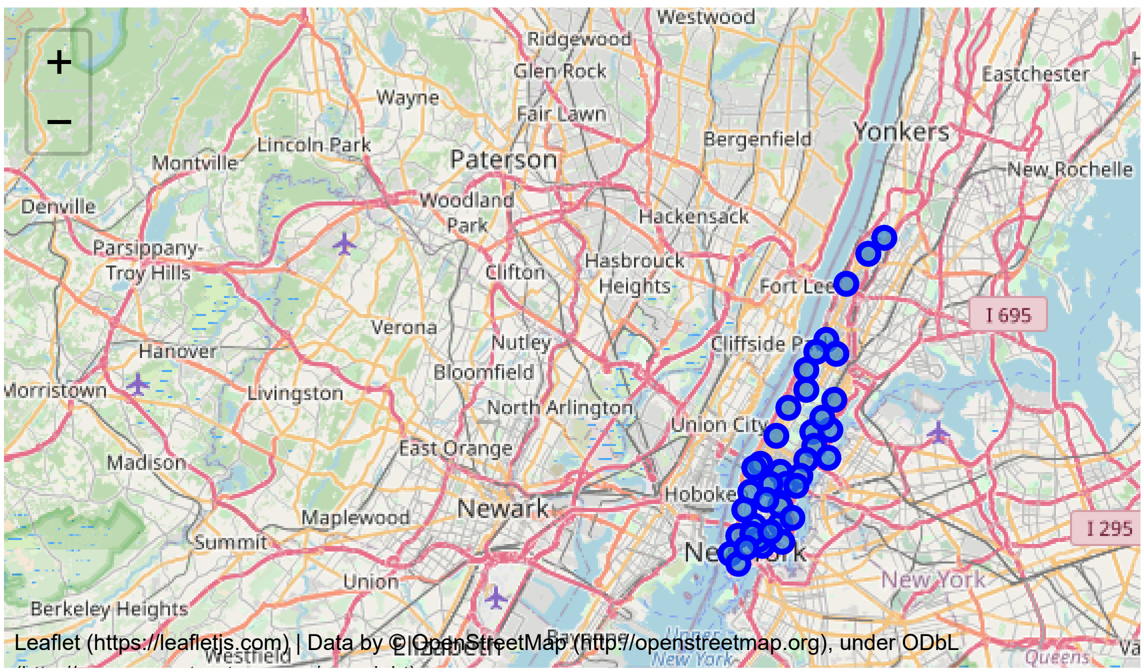
```
address = 'Manhattan, NY'

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

```
The geograpical coordinate of Manhattan are 40.7896239, -73.9598939.
```

In [136]:

```python
# create map of Manhattan using latitude and longitude values
map_manhattan = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to map
for lat, lng, label in zip(manhattan_data['Latitude'], manhattan_data['Longit
    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_manhattan)

map_manhattan
```

Out[136]:



In [137]:

```python
manhattan_data.tail()
```

Out[137]:

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

3. Methodology

In [138]:

```
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 [139]:

```
#Top 1000 venues in NYC
LIMIT = 1000 # limit of number of venues returned by Foursquare API
radius = 500 # define radius
def getplaces (names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&cli
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    placesNY = pd.DataFrame([item for venue_list in venues_list for item in v
    placesNY.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(placesNY)
```

In [140]:

```
#Get places withing Manhattan borough from the top 1000 venues in NYC (all 5

manhattan_venues = getplaces(names=manhattan_data['Neighborhood'],
                                   latitudes=manhattan_data['Latitude'],
                                   longitudes=manhattan_data['Longitude']
                                  )
```

```
Marble Hill
Chinatown
Washington Heights
Inwood
Hamilton Heights
Manhattanville
Central Harlem
East Harlem
Upper East Side
Yorkville
Lenox Hill
Roosevelt Island
Upper West Side
Lincoln Square
Clinton
Midtown
Murray Hill
Chelsea
Greenwich Village
East Village
Lower East Side
Tribeca
Little Italy
Soho
West Village
Manhattan Valley
Morningside Heights
Gramercy
Battery Park City
Financial District
Carnegie Hill
Noho
Civic Center
Midtown South
Sutton Place
Turtle Bay
Tudor City
Stuyvesant Town
Flatiron
Hudson Yards
```

In [141]:
```python
#Dataframe of top venues in manhanttan
print(manhattan_venues.shape)
manhattan_venues.head()
```

(3154, 7)

Out[141]:

	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

In [142]:
```python
#count by venue category
manhattan_venues.groupby('Venue Category').count()
```

Out[142]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude
Venue Category						
Accessories Store	2	2	2	2	2	2
Adult Boutique	1	1	1	1	1	1
Afghan Restaurant	1	1	1	1	1	1
African Restaurant	2	2	2	2	2	2
American Restaurant	77	77	77	77	77	77
Antique Shop	1	1	1	1	1	1
Arcade	1	1	1	1	1	1
Arepa Restaurant	2	2	2	2	2	2

In [143]:

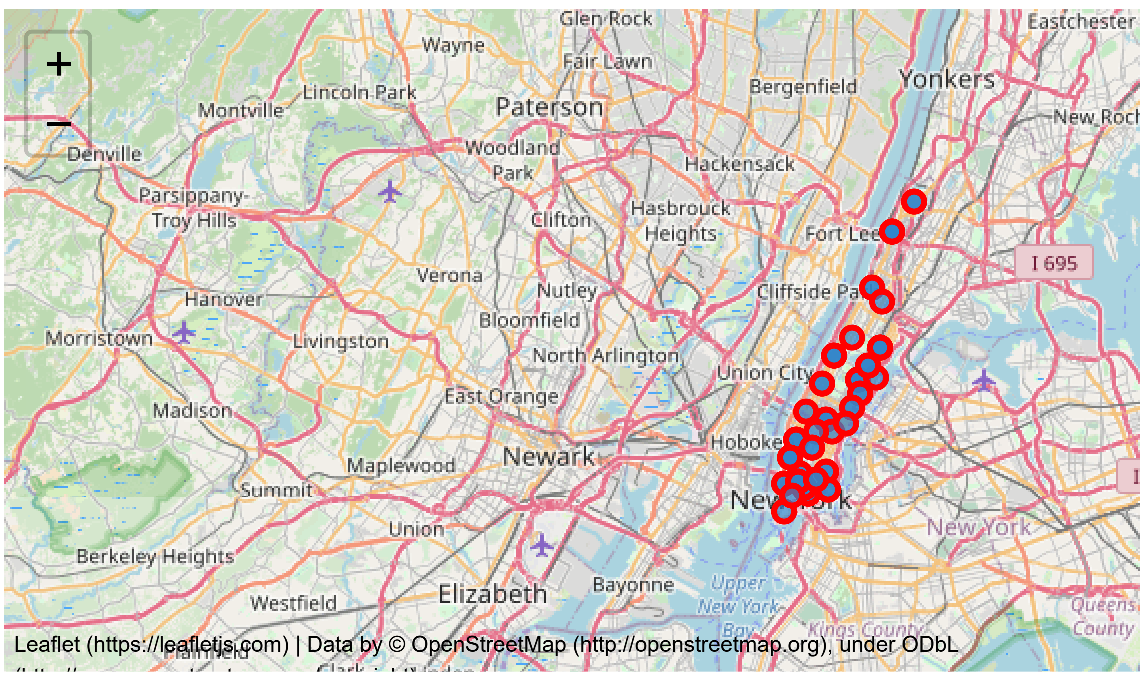
```
#Sort by bakery: venue category and make data frame

manhattan_sweetsbakery = manhattan_venues[manhattan_venues['Venue Category'].
manhattan_sweetsbakery.head()
print(manhattan_sweetsbakery.shape)
```

```
(72, 7)
```

In [144]:

```
# create map of Manhattan using latitude and longitude values
map_manhattan_sweetsbakery = folium.Map(location=[latitude, longitude], zoom_

# add markers to map
for lat, lng, label in zip(manhattan_sweetsbakery['Neighborhood Latitude'], m
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_manhattan_sweetsbakery)

map_manhattan_sweetsbakery
```

Out[144]:



In [145]:

```
#count by Neighborhood to count number of bakery
manhattan_sweetsbakery.groupby('Neighborhood').count()
```

Out[145]:

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Carnegie Hill	3	3	3	3	3	3
Central Harlem	1	1	1	1	1	1
Chelsea	3	3	3	3	3	3
Chinatown	4	4	4	4	4	4
Civic Center	1	1	1	1	1	1
Clinton	1	1	1	1	1	1
East Harlem	4	4	4	4	4	4
East Village	2	2	2	2	2	2
Financial District	1	1	1	1	1	1
Flatiron	2	2	2	2	2	2
Greenwich Village	2	2	2	2	2	2
Hamilton Heights	2	2	2	2	2	2
Inwood	2	2	2	2	2	2
Lenox Hill	2	2	2	2	2	2
Lincoln Square	2	2	2	2	2	2
Little Italy	6	6	6	6	6	6
Lower East Side	2	2	2	2	2	2
Manhattan Valley	1	1	1	1	1	1
Midtown	3	3	3	3	3	3
Midtown South	1	1	1	1	1	1
Murray Hill	1	1	1	1	1	1
Noho	2	2	2	2	2	2
Soho	3	3	3	3	3	3
Sutton Place	2	2	2	2	2	2
Tribeca	2	2	2	2	2	2
Turtle Bay	1	1	1	1	1	1
Upper East Side	4	4	4	4	4	4
Upper West Side	3	3	3	3	3	3

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Washington Heights	4	4	4	4	4	4
West Village	4	4	4	4	4	4
Yorkville	1	1	1	1	1	1

In [146]:

```
# Bakery store encoding
# one hot encoding
manhattan_onehot = pd.get_dummies(manhattan_sweetsbakery[['Venue Category']],

# add neighborhood column back to dataframe
manhattan_onehot['Neighborhood'] = manhattan_sweetsbakery['Neighborhood']
manhattan_onehot['Neighborhood Latitude'] = manhattan_sweetsbakery['Neighborh
manhattan_onehot['Neighborhood Longitude'] = manhattan_sweetsbakery['Neighbor


manhattan_onehot[['Neighborhood','Neighborhood Latitude','Neighborhood Longit
manhattan_onehot.head()
```

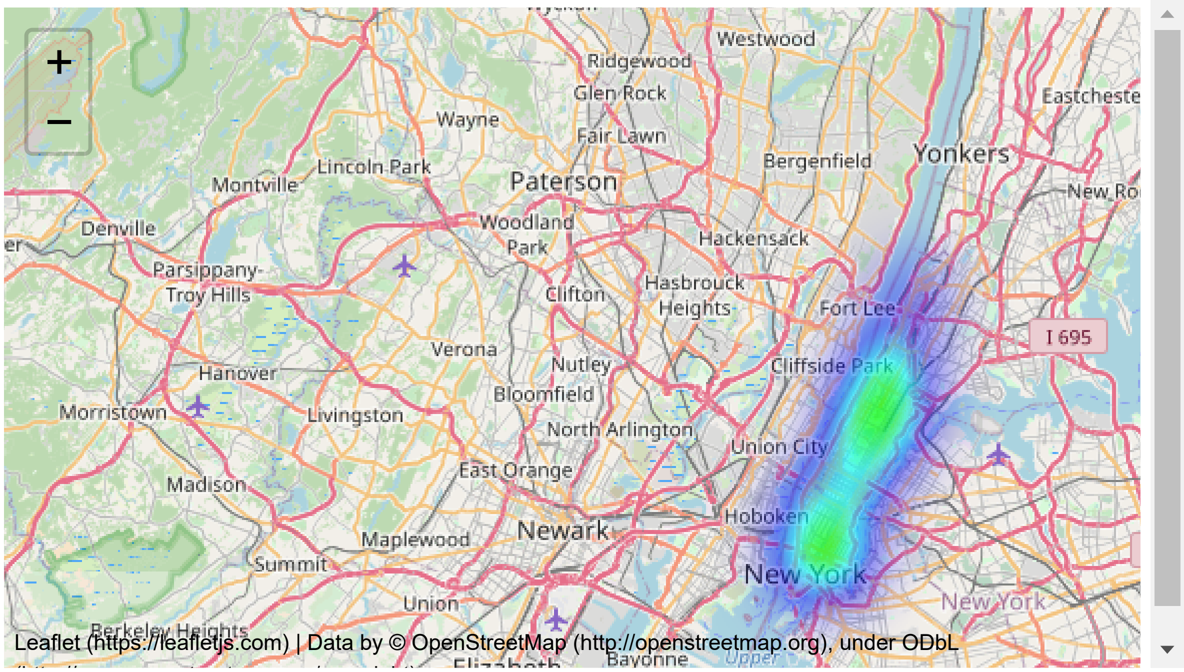
Out[146]:

	Bakery	Neighborhood	Neighborhood Latitude	Neighborhood Longitude
34	1	Chinatown	40.715618	-73.994279
96	1	Chinatown	40.715618	-73.994279
112	1	Chinatown	40.715618	-73.994279
124	1	Chinatown	40.715618	-73.994279
135	1	Washington Heights	40.851903	-73.936900

In [147]:

```
#needs to be correcly show neibohboods with less bakeries
map_manhattan_sweetsbakery2 = folium.Map(location=[latitude, longitude], zoom
# List of lists of bakery Loatitude and Longitude
heat_data = [[row['Neighborhood Latitude'],
              row['Neighborhood Longitude']] for index, row in manhattan_oneh
# Plot the bakeries on the map
HeatMap(heat_data,
        min_opacity=0.5,
        max_zoom=18,
        max_val=1.0,
        radius=20,
        blur=30,
        gradient=None,
        overlay=True).add_to(map_manhattan_sweetsbakery2)
map_manhattan_sweetsbakery2
```

Out[147]:



In [148]:

```
#count by Neighborhood to count number of bakery
manhattan_sweetsbakery2=manhattan_onehot.groupby(['Neighborhood'])['Bakery'].
manhattan_sweetsbakery2
```

Out[148]:

	Neighborhood	Bakery count
0	Carnegie Hill	3
1	Central Harlem	1
2	Chelsea	3
3	Chinatown	4
4	Civic Center	1
5	Clinton	1
6	East Harlem	4
7	East Village	2
8	Financial District	1
9	Flatiron	2
10	Greenwich Village	2
11	Hamilton Heights	2
12	Inwood	2
13	Lenox Hill	2
14	Lincoln Square	2
15	Little Italy	6
16	Lower East Side	2
17	Manhattan Valley	1
18	Midtown	3
19	Midtown South	1
20	Murray Hill	1
21	Noho	2
22	Soho	3
23	Sutton Place	2
24	Tribeca	2
25	Turtle Bay	1
26	Upper East Side	4
27	Upper West Side	3
28	Washington Heights	4
29	West Village	4
30	Yorkville	1

Make dataframe with count of bakeries by neighborhood and the histogram plot of each How to model and plot the plot clusters? What is the dependet or target viable or just what advice to give buiness person about opening a bakery base don what income?

Not Good enough, some neighborhoods missing

The next step is to perform an inner join of the two dataframes based on neighborhood:

There are a few obstacles here:

1. It was difficult finding data with popultion density for each neighborhood in manhattan.
2. Hence, the number of neighborhoods doesn't match between the two dataframes. The table from this website was the most diverse I could find, even from the NYC city data site, it wasn't a diverse population data per neighborhood.
3. Some of the neighborhoods names are not the same from the two data frames, so the names of the neighborhood data scrapped from the website using pandas will be editted to match the data from the FourSquare site and the corresponding ones in the geo dataset.

In [150]:

```python
# Instead of beautiful soup use pandas to pull data from the HTML/XML I founc
Manhanttan_pop2=pd.read_html('https://www.worldatlas.com/articles/manhattan-r
for dfManhanttan_pop2 in Manhanttan_pop2:
    print (dfManhanttan_pop2)
dfManhanttan_pop2.head()
```

```
    Rank           Neighborhood  Population
0      1                Midtown      391371
1      2       Lower Manhattan      382654
2      3                 Harlem      335109
3      4        Upper East Side      229688
4      5        Upper West Side      209084
5      6    Washington Heights      158318
6      7            East Harlem      115921
7      8              Chinatown      100000
8      9     Lower East Village       72957
9     10          Alphabet City       63347
10    11           East Village       62832
11    12         Lincoln Square       61489
12    13     Financial District       60976
13    14   Morningside Heights       55929
14    15      Hamilton Heights       48520
15    16                 Inwood       46746
16    17         Hell's Kitchen       45884
17    18      Battery Park City       39699
18    19                Chelsea       38242
19    20              Yorkville       35221
20    21        Hudson Heights       29000
21    22            Two Bridges       28915
22    23          Gramercy Park       27988
23    24                   NoHo       24846
24    25      Greenwich Village       22785
25    26       Stuyvesant Town        21049
26    27              Koreatown       20000
27    28                   SoHo       19573
28    29                Tribeca       17362
29    30            Murray Hill       10284
30    31            Marble Hill        9481
31    32     Flatiron District         8547
32    33                 NoLita        5713
33    34               Kips Bay        5330
34    35  Meatpacking District         1428
35    36           Little Italy        1211
```

Out[150]:

	Rank	Neighborhood	Population
0	1	Midtown	391371
1	2	Lower Manhattan	382654
2	3	Harlem	335109
3	4	Upper East Side	229688
4	5	Upper West Side	209084

In [151]:

```
list(dfManhanttan_pop2.columns)
```

Out[151]:

```
['Rank', '\ufeffNeighborhood', 'Population']
```

In [152]:

```
dfManhanttan_pop2.rename(columns={'Rank':'Rank','\ufeffNeighborhood':'Neighbo
list(dfManhanttan_pop2.columns)
```

Out[152]:

```
['Rank', 'Neighborhood', 'Population']
```

In [153]:

```
dfManhanttan_pop2['Neighborhood']
```

Out[153]:

```
0                  Midtown
1          Lower Manhattan
2                   Harlem
3          Upper East Side
4          Upper West Side
5       Washington Heights
6              East Harlem
7                Chinatown
8       Lower East Village
9            Alphabet City
10            East Village
11          Lincoln Square
12      Financial District
13     Morningside Heights
14        Hamilton Heights
15                  Inwood
16          Hell's Kitchen
17       Battery Park City
18                 Chelsea
19               Yorkville
20          Hudson Heights
21             Two Bridges
22           Gramercy Park
23                    NoHo
24       Greenwich Village
25         Stuyvesant Town
26               Koreatown
27                    SoHo
28                 Tribeca
29             Murray Hill
30             Marble Hill
31       Flatiron District
32                  NoLita
33                Kips Bay
34    Meatpacking District
35            Little Italy
Name: Neighborhood, dtype: object
```

In [154]:

```
# Harlem missing Central in the beginning
dfManhanttan_pop2.at[2,'Neighborhood'] = 'Central Harlem'
#Lower East Village is Lower East Side
dfManhanttan_pop2.at[8,'Neighborhood'] = 'Lower East Side'
#SoHo is Soho
dfManhanttan_pop2.at[27,'Neighborhood'] = 'Soho'
#Gramercy Park is Gramercy
dfManhanttan_pop2.at[22,'Neighborhood'] = 'Gramercy'
#NoHo is Noho
dfManhanttan_pop2.at[23,'Neighborhood'] = 'Noho'
#Flatiron District is Flatiron
dfManhanttan_pop2.at[31,'Neighborhood'] = 'Flatiron'
dfManhanttan_pop2
```

Out[154]:

	Rank	Neighborhood	Population
0	1	Midtown	391371
1	2	Lower Manhattan	382654
2	3	Central Harlem	335109
3	4	Upper East Side	229688
4	5	Upper West Side	209084
5	6	Washington Heights	158318
6	7	East Harlem	115921
7	8	Chinatown	100000
8	9	Lower East Side	72957
9	10	Alphabet City	63347
10	11	East Village	62832
11	12	Lincoln Square	61489
12	13	Financial District	60976
13	14	Morningside Heights	55929
14	15	Hamilton Heights	48520
15	16	Inwood	46746
16	17	Hell's Kitchen	45884
17	18	Battery Park City	39699
18	19	Chelsea	38242
19	20	Yorkville	35221
20	21	Hudson Heights	29000
21	22	Two Bridges	28915
22	23	Gramercy	27988
23	24	Noho	24846
24	25	Greenwich Village	22785
25	26	Stuyvesant Town	21049

	Rank	Neighborhood	Population
26	27	Koreatown	20000
27	28	Soho	19573
28	29	Tribeca	17362
29	30	Murray Hill	10284
30	31	Marble Hill	9481
31	32	Flatiron	8547
32	33	NoLita	5713
33	34	Kips Bay	5330
34	35	Meatpacking District	1428
35	36	Little Italy	1211

In [155]:

```python
# Inner join the new population dataframes by Neighborhoods
Manhanttan_bakery_pop2 = pd.merge(dfManhanttan_pop2, manhattan_sweetsbakery2,
Manhanttan_bakery_pop2.drop(columns=['Rank'], inplace=True)
Manhanttan_bakery_pop2.reset_index(inplace=True)
print(Manhanttan_bakery_pop2.shape)
Manhanttan_bakery_pop2
```

(22, 4)

Out[155]:

	index	Neighborhood	Population	Bakery count
0	0	Midtown	391371	3
1	1	Central Harlem	335109	1
2	2	Upper East Side	229688	4
3	3	Upper West Side	209084	3
4	4	Washington Heights	158318	4
5	5	East Harlem	115921	4
6	6	Chinatown	100000	4
7	7	Lower East Side	72957	2
8	8	East Village	62832	2
9	9	Lincoln Square	61489	2
10	10	Financial District	60976	1
11	11	Hamilton Heights	48520	2
12	12	Inwood	46746	2
13	13	Chelsea	38242	3
14	14	Yorkville	35221	1
15	15	Noho	24846	2
16	16	Greenwich Village	22785	2
17	17	Soho	19573	3
18	18	Tribeca	17362	2
19	19	Murray Hill	10284	1
20	20	Flatiron	8547	2
21	21	Little Italy	1211	6

Still, 14 neighborhoods from the bakery dataframe are missing

In [156]:

```python
# Inner join the new bakery with geo dataframes by Neighborhoods
Manhanttan_bakery_pop3 = pd.merge(Manhanttan_bakery_pop2, NY_geodf, on='Neigh
Manhanttan_bakery_pop3.drop(columns=['Borough'], inplace=True)
Manhanttan_bakery_pop3.reset_index(inplace=True)
print(Manhanttan_bakery_pop3.shape)
Manhanttan_bakery_pop3
```

```
(24, 7)
```

Out[156]:

	level_0	index	Neighborhood	Population	Bakery count	Latitude	Longitude
0	0	0	Midtown	391371	3	40.754691	-73.981669
1	1	1	Central Harlem	335109	1	40.815976	-73.943211
2	2	2	Upper East Side	229688	4	40.775639	-73.960508
3	3	3	Upper West Side	209084	3	40.787658	-73.977059
4	4	4	Washington Heights	158318	4	40.851903	-73.936900
5	5	5	East Harlem	115921	4	40.792249	-73.944182
6	6	6	Chinatown	100000	4	40.715618	-73.994279
7	7	7	Lower East Side	72957	2	40.717807	-73.980890
8	8	8	East Village	62832	2	40.727847	-73.982226
9	9	9	Lincoln Square	61489	2	40.773529	-73.985338
10	10	10	Financial District	60976	1	40.707107	-74.010665
11	11	11	Hamilton Heights	48520	2	40.823604	-73.949688
12	12	12	Inwood	46746	2	40.867684	-73.921210
13	13	13	Chelsea	38242	3	40.744035	-74.003116
14	14	13	Chelsea	38242	3	40.594726	-74.189560
15	15	14	Yorkville	35221	1	40.775930	-73.947118
16	16	15	Noho	24846	2	40.723259	-73.988434
17	17	16	Greenwich Village	22785	2	40.726933	-73.999914
18	18	17	Soho	19573	3	40.722184	-74.000657
19	19	18	Tribeca	17362	2	40.721522	-74.010683
20	20	19	Murray Hill	10284	1	40.748303	-73.978332
21	21	19	Murray Hill	10284	1	40.764126	-73.812763
22	22	20	Flatiron	8547	2	40.739673	-73.990947
23	23	21	Little Italy	1211	6	40.719324	-73.997305

In [157]:
```python
list(Manhanttan_bakery_pop3.columns)
```

Out[157]:
```
['level_0',
 'index',
 'Neighborhood',
 'Population',
 'Bakery count',
 'Latitude',
 'Longitude']
```

In [158]:
```python
Manhanttan_bakery_pop3.drop(columns=['level_0','index'], inplace=True)
Manhanttan_bakery_pop3
```

Out[158]:

	Neighborhood	Population	Bakery count	Latitude	Longitude
0	Midtown	391371	3	40.754691	-73.981669
1	Central Harlem	335109	1	40.815976	-73.943211
2	Upper East Side	229688	4	40.775639	-73.960508
3	Upper West Side	209084	3	40.787658	-73.977059
4	Washington Heights	158318	4	40.851903	-73.936900
5	East Harlem	115921	4	40.792249	-73.944182
6	Chinatown	100000	4	40.715618	-73.994279
7	Lower East Side	72957	2	40.717807	-73.980890
8	East Village	62832	2	40.727847	-73.982226
9	Lincoln Square	61489	2	40.773529	-73.985338
10	Financial District	60976	1	40.707107	-74.010665
11	Hamilton Heights	48520	2	40.823604	-73.949688
12	Inwood	46746	2	40.867684	-73.921210
13	Chelsea	38242	3	40.744035	-74.003116
14	Chelsea	38242	3	40.594726	-74.189560
15	Yorkville	35221	1	40.775930	-73.947118
16	Noho	24846	2	40.723259	-73.988434
17	Greenwich Village	22785	2	40.726933	-73.999914
18	Soho	19573	3	40.722184	-74.000657
19	Tribeca	17362	2	40.721522	-74.010683
20	Murray Hill	10284	1	40.748303	-73.978332
21	Murray Hill	10284	1	40.764126	-73.812763
22	Flatiron	8547	2	40.739673	-73.990947
23	Little Italy	1211	6	40.719324	-73.997305

In [161]:

```
#Drop Neighborhood duplicates
Manhanttan_bakery_pop3=Manhanttan_bakery_pop3.drop_duplicates(subset='Neighbo
Manhanttan_bakery_pop3
```

Out[161]:

	Neighborhood	Population	Bakery count	Latitude	Longitude
0	Midtown	391371	3	40.754691	-73.981669
1	Central Harlem	335109	1	40.815976	-73.943211
2	Upper East Side	229688	4	40.775639	-73.960508
3	Upper West Side	209084	3	40.787658	-73.977059
4	Washington Heights	158318	4	40.851903	-73.936900
5	East Harlem	115921	4	40.792249	-73.944182
6	Chinatown	100000	4	40.715618	-73.994279
7	Lower East Side	72957	2	40.717807	-73.980890
8	East Village	62832	2	40.727847	-73.982226
9	Lincoln Square	61489	2	40.773529	-73.985338
10	Financial District	60976	1	40.707107	-74.010665
11	Hamilton Heights	48520	2	40.823604	-73.949688
12	Inwood	46746	2	40.867684	-73.921210
13	Chelsea	38242	3	40.744035	-74.003116
15	Yorkville	35221	1	40.775930	-73.947118
16	Noho	24846	2	40.723259	-73.988434
17	Greenwich Village	22785	2	40.726933	-73.999914
18	Soho	19573	3	40.722184	-74.000657
19	Tribeca	17362	2	40.721522	-74.010683
20	Murray Hill	10284	1	40.748303	-73.978332
22	Flatiron	8547	2	40.739673	-73.990947
23	Little Italy	1211	6	40.719324	-73.997305

In [162]:

```
# @hidden_cell
with open('C:\\Users\\zada2\\downloads\\nyu-polygon-geojson.json') as json_da
    nyc_polygon_geo= json.load(json_data1)
latitude = 40.8021285
longitude = -73.9777254

print('Data downloaded!')
```

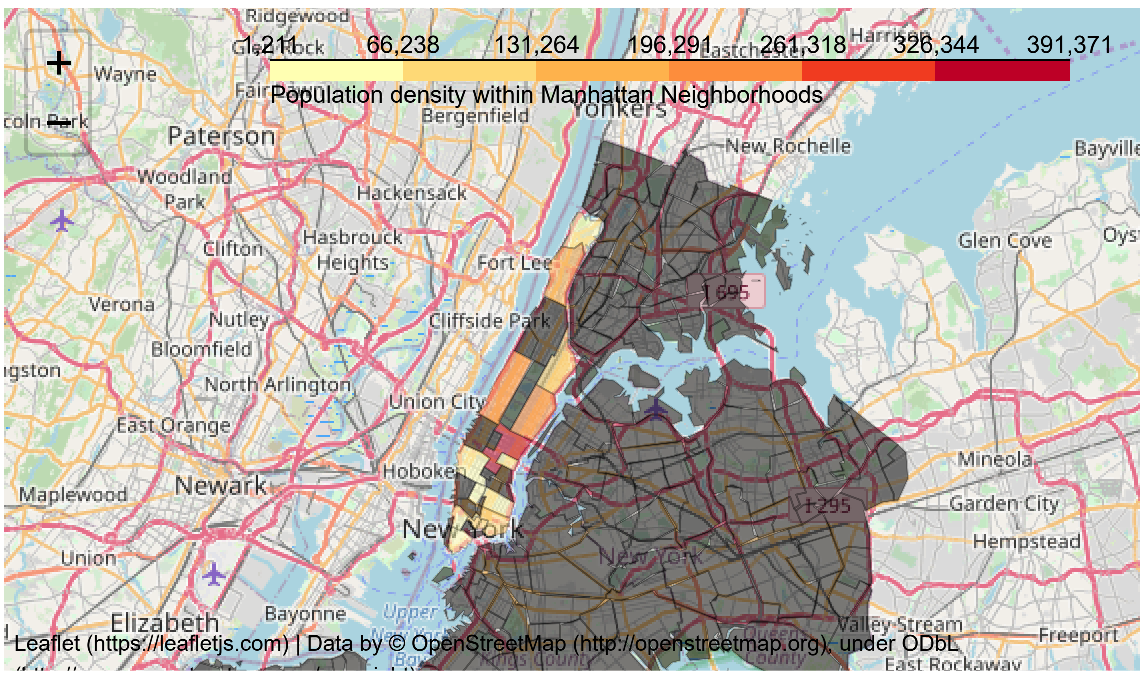
```
Data downloaded!
```

In [ ]:

```
#Polygon NYC geo.json:'https://geo.nyu.edu/catalog/nyu-2451-34561'
```

In [163]:
```python
address = 'Manhattan, NY'

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

#Map of neighborhood density and bakery count by neighnour hood
map_manhattan_popul_bakery = folium.Map(location=[latitude, longitude], zoom_
# generate choropleth map to show population distribution within Manhattan Ne
folium.Choropleth(
    geo_data=nyc_polygon_geo,
    data=Manhanttan_bakery_pop3,
    columns=['Neighborhood', 'Population'],
    key_on='feature.properties.neighborhood',
    fill_color='YlOrRd',
    fill_opacity=0.5,
    line_opacity=0.2,
    legend_name='Population density within Manhattan Neighborhoods').add_to(m



map_manhattan_popul_bakery
```

Out[163]:



In [167]:
```python
list(Manhanttan_bakery_pop3.columns)
```

Out[167]:
```
['Neighborhood', 'Population', 'Bakery count']
```

Regression plot: To visualize relationship between population density and bakery count...

In [170]:

```

```

Out[170]:

	Neighborhood	Population	Bakery count
0	Midtown	391371	3
1	Central Harlem	335109	1
2	Upper East Side	229688	4
3	Upper West Side	209084	3
4	Washington Heights	158318	4
5	East Harlem	115921	4
6	Chinatown	100000	4
7	Lower East Side	72957	2
8	East Village	62832	2
9	Lincoln Square	61489	2
10	Financial District	60976	1
11	Hamilton Heights	48520	2
12	Inwood	46746	2
13	Chelsea	38242	3
15	Yorkville	35221	1
16	Noho	24846	2
17	Greenwich Village	22785	2
18	Soho	19573	3
19	Tribeca	17362	2
20	Murray Hill	10284	1
22	Flatiron	8547	2
23	Little Italy	1211	6

In [191]:

```
Manhanttan_bakery_pop3.rename(columns={'Bakery count':'Bakerycount'},inplace
list(Manhanttan_bakery_pop3.columns)
```

Out[191]: ['Neighborhood', 'Population', 'Bakerycount']

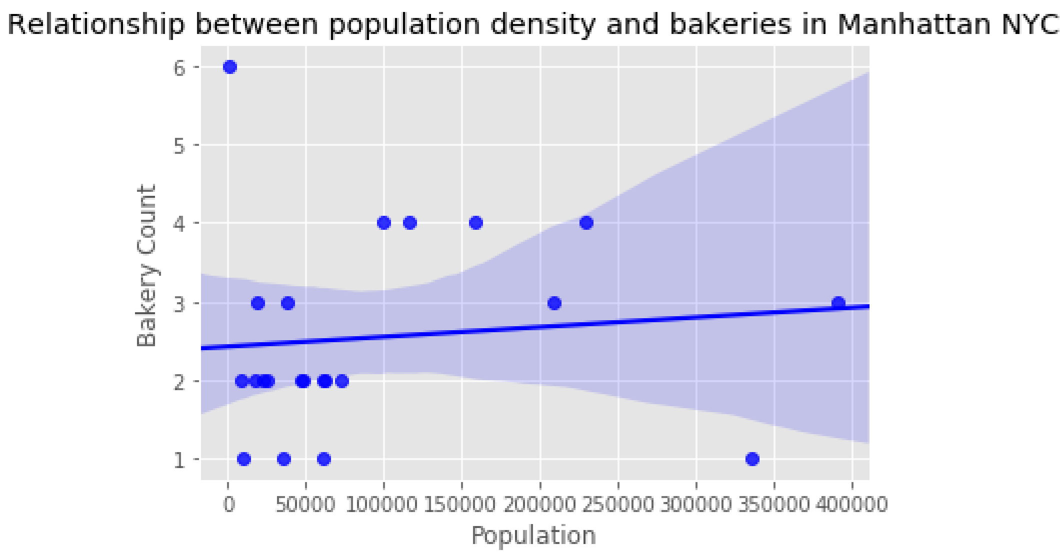
4. Results

In [192]:

```
#Plot data using seaborn
import seaborn as sns
ax1 = sns.regplot(x='Population', y='Bakerycount', data=Manhanttan_bakery_pop
ax1.set(xlabel='Population', ylabel='Bakery Count') # add x- and y-labels
ax1.set_title('Relationship between population density and bakeries in Manhat
```

Out[192]:

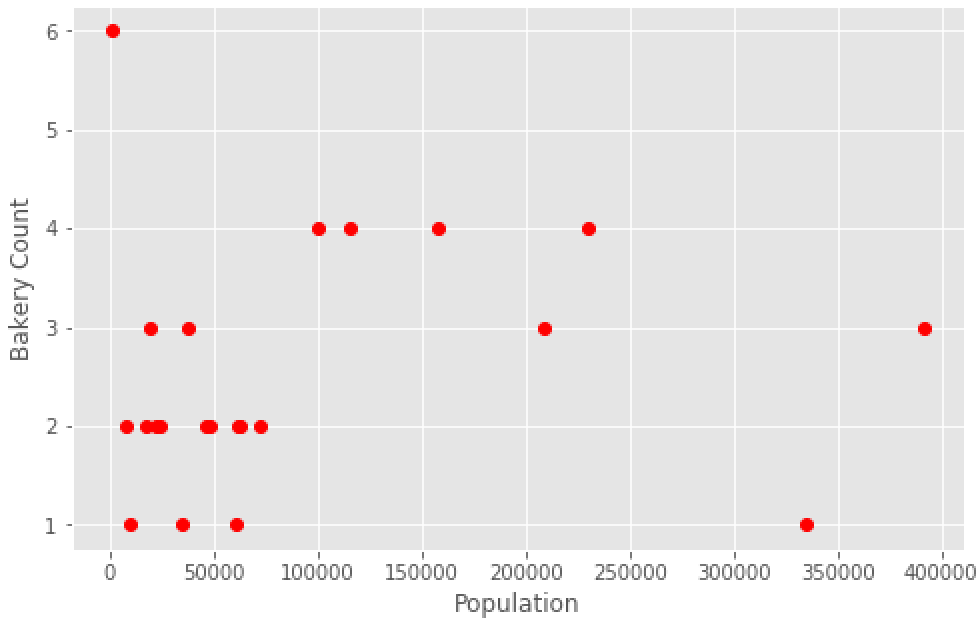
```
Text(0.5, 1.0, 'Relationship between population density and bakeries in Man
hattan NYC')
```



Relationship isn't linear, let's try polynomial regression

In [193]:

```
# Plot data
plt.figure(figsize=(8,5))
x_data, y_data = (Manhanttan_bakery_pop3["Population"].values, Manhanttan_bak
plt.plot(x_data, y_data, 'ro')
plt.ylabel('Bakery Count')
plt.xlabel('Population')
plt.show()
```



In [194]:

```
#Create train and test data
msk = np.random.rand(len(Manhanttan_bakery_pop2)) < 0.8
train = Manhanttan_bakery_pop3[msk]
test = Manhanttan_bakery_pop3[~msk]
```

In [195]:
```
#Polynomial fit of 2 power
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model
train_x = np.asanyarray(train[['Population']])
train_y = np.asanyarray(train[['Bakerycount']])

test_x = np.asanyarray(test[['Population']])
test_y = np.asanyarray(test[['Bakerycount']])


poly = PolynomialFeatures(degree=2)
train_x_poly = poly.fit_transform(train_x)
train_x_poly
```

Out[195]:
```
array([[1.00000000e+00, 3.91371000e+05, 1.53171260e+11],
       [1.00000000e+00, 2.09084000e+05, 4.37161191e+10],
       [1.00000000e+00, 1.58318000e+05, 2.50645891e+10],
       [1.00000000e+00, 1.15921000e+05, 1.34376782e+10],
       [1.00000000e+00, 7.29570000e+04, 5.32272385e+09],
       [1.00000000e+00, 6.28320000e+04, 3.94786022e+09],
       [1.00000000e+00, 6.14890000e+04, 3.78089712e+09],
       [1.00000000e+00, 6.09760000e+04, 3.71807258e+09],
       [1.00000000e+00, 4.85200000e+04, 2.35419040e+09],
       [1.00000000e+00, 4.67460000e+04, 2.18518852e+09],
       [1.00000000e+00, 3.52210000e+04, 1.24051884e+09],
       [1.00000000e+00, 2.27850000e+04, 5.19156225e+08],
       [1.00000000e+00, 1.95730000e+04, 3.83102329e+08],
       [1.00000000e+00, 1.73620000e+04, 3.01439044e+08],
       [1.00000000e+00, 1.02840000e+04, 1.05760656e+08],
       [1.00000000e+00, 8.54700000e+03, 7.30512090e+07],
       [1.00000000e+00, 1.21100000e+03, 1.46652100e+06]])
```

In [196]:
```
clf = linear_model.LinearRegression()
train_y_ = clf.fit(train_x_poly, train_y)
# The coefficients
print ('Coefficients: ', clf.coef_)
print ('Intercept: ',clf.intercept_)
```

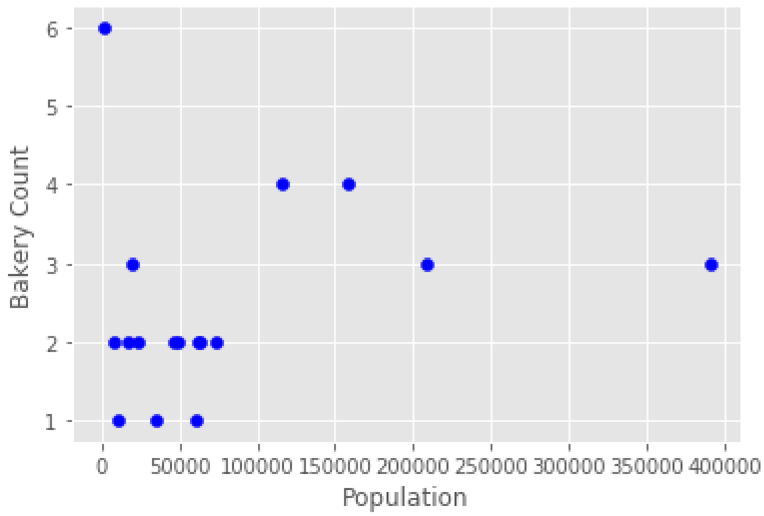
```
Coefficients:  [[ 0.00000000e+00  4.54239284e-06 -4.70396205e-12]]
Intercept:  [2.1834422]
```

In [197]:

```
plt.scatter(train.Population, train.Bakerycount,  color='blue')
XX = np.arange(0.0, 10.0, 0.1)
yy = clf.intercept_[0]+ clf.coef_[0][1]*XX+ clf.coef_[0][2]*np.power(XX, 2)
plt.plot(XX, yy, '-r' )
plt.xlabel("Population")
plt.ylabel("Bakery Count")
```

Out[197]:

```
Text(0, 0.5, 'Bakery Count')
```



In [198]:

```
from sklearn.metrics import r2_score

test_x_poly = poly.fit_transform(test_x)
test_y_ = clf.predict(test_x_poly)

print("Mean absolute error: %.2f" % np.mean(np.absolute(test_y_ - test_y)))
print("Residual sum of squares (MSE): %.2f" % np.mean((test_y_ - test_y) ** 2
print("R2-score: %.2f" % r2_score(test_y_ , test_y) )
```

```
Mean absolute error: 1.11
Residual sum of squares (MSE): 1.66
R2-score: -12.74
```

These results don't show a significant relationship between bakeries and population density for a polynomial fit at a power of 2. The R^2 score is negative. There is no significant coefficient correlations. Let's try a fit of the power of 6.

In [201]:

```python
# Poly fit power of 6
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model
train_x = np.asanyarray(train[['Population']])
train_y = np.asanyarray(train[['Bakerycount']])

test_x = np.asanyarray(test[['Population']])
test_y = np.asanyarray(test[['Bakerycount']])


poly2 = PolynomialFeatures(degree=6)
train_x_poly = poly2.fit_transform(train_x)
train_x_poly
```

Out[201]:

```
array([[1.00000000e+00, 3.91371000e+05, 1.53171260e+11, 5.99467891e+16,
        2.34614348e+22, 9.18212519e+27, 3.59361752e+33],
       [1.00000000e+00, 2.09084000e+05, 4.37161191e+10, 9.14034104e+15,
        1.91109907e+21, 3.99580237e+26, 8.35458343e+31],
       [1.00000000e+00, 1.58318000e+05, 2.50645891e+10, 3.96817562e+15,
        6.28233628e+20, 9.94606915e+25, 1.57464178e+31],
       [1.00000000e+00, 1.15921000e+05, 1.34376782e+10, 1.55770910e+15,
        1.80571197e+20, 2.09319937e+25, 2.42645764e+30],
       [1.00000000e+00, 7.29570000e+04, 5.32272385e+09, 3.88329964e+14,
        2.83313892e+19, 2.06697316e+24, 1.50800161e+29],
       [1.00000000e+00, 6.28320000e+04, 3.94786022e+09, 2.48051954e+14,
        1.55856003e+19, 9.79274441e+23, 6.15297717e+28],
       [1.00000000e+00, 6.14890000e+04, 3.78089712e+09, 2.32483583e+14,
        1.42951830e+19, 8.78996510e+23, 5.40486164e+28],
       [1.00000000e+00, 6.09760000e+04, 3.71807258e+09, 2.26713193e+14,
        1.38240637e+19, 8.42936107e+23, 5.13988721e+28],
       [1.00000000e+00, 4.85200000e+04, 2.35419040e+09, 1.14225318e+14,
        5.54221244e+18, 2.68908148e+23, 1.30474233e+28],
       [1.00000000e+00, 4.67460000e+04, 2.18518852e+09, 1.02148822e+14,
        4.77504885e+18, 2.23214434e+23, 1.04343819e+28],
       [1.00000000e+00, 3.52210000e+04, 1.24051884e+09, 4.36923141e+13,
        1.53888699e+18, 5.42011388e+22, 1.90901831e+27],
       [1.00000000e+00, 2.27850000e+04, 5.19156225e+08, 1.18289746e+13,
        2.69523186e+17, 6.14108579e+21, 1.39924640e+26],
       [1.00000000e+00, 1.95730000e+04, 3.83102329e+08, 7.49846189e+12,
        1.46767394e+17, 2.87267821e+21, 5.62269306e+25],
       [1.00000000e+00, 1.73620000e+04, 3.01439044e+08, 5.23358468e+12,
        9.08654972e+16, 1.57760676e+21, 2.73904086e+25],
       [1.00000000e+00, 1.02840000e+04, 1.05760656e+08, 1.08764259e+12,
        1.11853164e+16, 1.15029793e+20, 1.18296640e+24],
       [1.00000000e+00, 8.54700000e+03, 7.30512090e+07, 6.24368683e+11,
        5.33647914e+15, 4.56108872e+19, 3.89836253e+23],
       [1.00000000e+00, 1.21100000e+03, 1.46652100e+06, 1.77595693e+09,
        2.15068384e+12, 2.60447813e+15, 3.15402302e+18]])
```

In [202]:

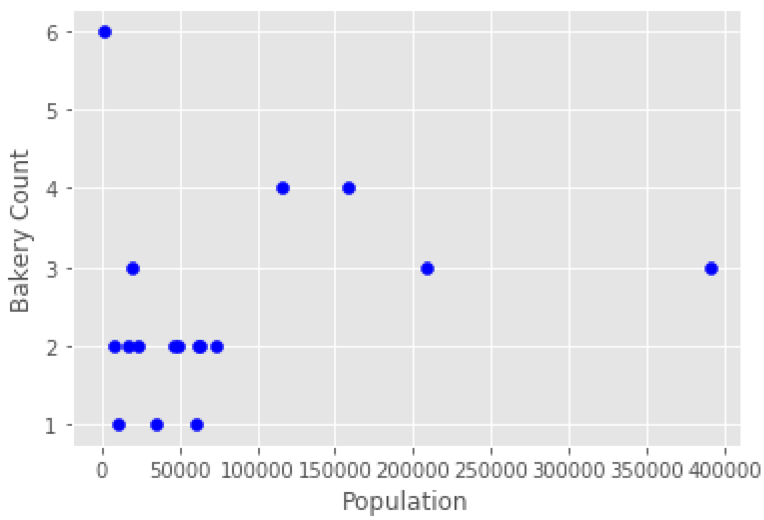
```
clf2 = linear_model.LinearRegression()
train_y_ = clf2.fit(train_x_poly, train_y)
# The coefficients
print ('Coefficients: ', clf2.coef_)
print ('Intercept: ',clf2.intercept_)
```

```
Coefficients:  [[ 0.00000000e+00  2.55041210e-24  2.26032192e-30  2.7600146
5e-25
   1.95239694e-20 -1.38697112e-25  2.27167686e-31]]
Intercept:  [2.12004753]
```

In [204]:

```
plt.scatter(train.Population, train.Bakerycount,  color='blue')
XX = np.arange(0.0, 10.0, 0.1)
yy = clf2.intercept_[0]+ clf2.coef_[0][1]*XX+ clf2.coef_[0][2]*np.power(XX, 2
plt.plot(XX, yy, '-r' )
plt.xlabel("Population")
plt.ylabel("Bakery Count")
```

Out[204]: Text(0, 0.5, 'Bakery Count')



In [207]:

```
from sklearn.metrics import r2_score

test_x_poly = poly2.fit_transform(test_x)
test_y_ = clf2.predict(test_x_poly)

print("Mean absolute error: %.2f" % np.mean(np.absolute(test_y_ - test_y)))
print("Residual sum of squares (MSE): %.2f" % np.mean((test_y_ - test_y) ** 2
print("R2-score: %.2f" % r2_score(test_y_ , test_y) )
```

```
Mean absolute error: 4.40
Residual sum of squares (MSE): 60.44
R2-score: -0.14
```

5. Conclusion and discussion

These results still don't show a significant relationship between bakeries and population density for a polynomial fit at a power of 6. However, the R^2 score increased.

There is no significant correlations or realtonship between the number of bakeries and population density. Business associates are advised to look at other variables such as access to public transportation, distribution of schools, parks and so on in different neighbourhoods in a city to determine where to open a bakery for the highest profit possible.

Thank you

In [ ]:

```

```