Capstone Project : New Peruvian Restaurant in Manhattan, NY

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1. Introduction to Business Case

A Peruvian entrepreneur that counts with more than 50 restaurants in Peru hired my data science consulting company to investigate the possible location to open a new restaurant in New York City, specifically in Manhattan city. New York City has been the most populous city in the United States. It has a long history of multicultural immigration, which makes it very attractive to open a new Peruvian restaurant. Furthermore, most people associate Manhattan, NY, as the city never sleeps, which makes it an excellent feature to initiate a new culinary business. Peruvian food has experimented with an exponential change in the last ten years, and it has been considered one of the world's best culinary destinations. The biodiversity and multicultural heritage are the main features that make Peruvian food unique and the best place in the world to dine. Therefore, the gastronomic entrepreneur wants to take advantage of the Peruvian food excellent reputation and start a new business opportunity of opening a new restaurant in the borough's most popular restaurants, Manhattan city, NY.

2. Business Case Questions

The next questions should be answered after the evaluation of business case.

1. How many Peruvian restaurants are in Manhattan?
2. What is the best location in Manhattan City to open a Peruvian restaurant?
3. What are other potential neighborhoods in Manhattan for Peruvian Cuisine?
4. Which neighborhoods lack Peruvian restaurants?

3. Data Section

The following data is needed to get the solution for this case.

- List of Boroughs, Neighborhoods, as well as the latitudes and longitudes from each neighborhoods in New York: https://cocl.us/new_york_dataset (https://cocl.us/new_york_dataset) . The list of Boroughs, Neighborhoods, latitudes, and longitudes are needed to build the business case. After loading and exploring the data, it is then transformed into a data frame using Pandas. As the evaluation is focused on Manhattan, it is filtered to obtain only Manhattan's neighborhoods.
- List of 100 venues around 1000 meters of radius in Manhattan: Foursquare API. This list will provide information on venus around 1000 meters from Manhattan city.
- Venue data of Peruvian restaurants in Manhattan city: Foursquare API. The previous data is then filtered to obtain the existing business of Peruvian restaurants already in operation around Manhattan city. This data will be merged with the data of neighborhoods in Manhattan.

4. Metodology

The methodology established follows the process shown in figure 1. It starts by acquiring the data and cleaning it. In this process, the data is collected from the link https://cocl.us/new_york_dataset (https://cocl.us/new_york_dataset) and converted to a data frame format using Pandas. After the data is ready in a data frame format, the second process of exploratory data analysis starts by evaluating it to obtain relevant information that serves as input to the predictive model. Finally, one predictive model is chosen to observe the best location for opening a new Peruvian Restaurant in Manhattan. How we are exploring neighborhoods in Manhattan, the k-means clustering will be used for this proposal. K-means is an unsupervised machine learning algorithm that groups similar data points by trying to discover fundamental patterns. Hence it must fix numbers of K to make the clusters of the dataset.

Figure 1

Importing all the dependences needed for this evaluation

In [1]:
```
import numpy as np # library to handle data in a vectorized manner

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

import json # library to handle JSON files

#!conda install -c conda-forge geopy --yes # uncomment this line if you haven't c
from geopy.geocoders import Nominatim # convert an address into latitude and long

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

import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib.colors as colors

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

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

#!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you ha
import folium # map rendering library

print('Libraries imported.')
```

```
Libraries imported.
```

a) Data acquisition and cleaning.

The evaluation starts by acquiring the data of New York neighborhoods from the following URL link [https://cocl.us/new_york_dataset (https://cocl.us/new_york_dataset)](https://cocl.us/new_york_dataset) ,then the raw data in json extension is conversated to data frame format using pandas.

- Accessing to the data through the next link [https://geo.nyu.edu/catalog/nyu_2451_34572 (https://geo.nyu.edu/catalog/nyu_2451_34572)](https://geo.nyu.edu/catalog/nyu_2451_34572)

In [2]:
```
url='https://cocl.us/new_york_dataset'
resp=requests.get(url).json()
```

- Let's take a look at the first item in this list.

In [3]:
```
neighborhoods_data = resp['features']
neighborhoods_data[0]
```

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]}}
```


- define the dataframe columns and instantiate the dataframe

In [4]:
```
# define the dataframe columns
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']
# instantiate the dataframe
neighborhoods = pd.DataFrame(columns=column_names)
```

In [5]:
```
for data in neighborhoods_data:
    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]

    neighborhoods = neighborhoods.append({'Borough': borough,
                                          'Neighborhood': neighborhood_name,
                                          'Latitude': neighborhood_lat,
                                          'Longitude': neighborhood_lon}, ignore_
```

- Results of Data Frame

In [6]:
```
new_york_data=neighborhoods
new_york_data.head()
```

Out[6]:

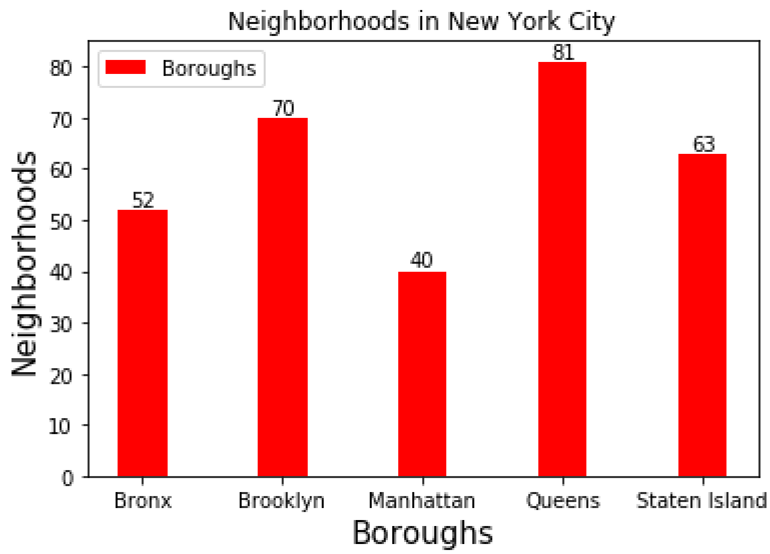
	Borough	Neighborhood	Latitude	Longitude
0	Bronx	Wakefield	40.894705	-73.847201
1	Bronx	Co-op City	40.874294	-73.829939
2	Bronx	Eastchester	40.887556	-73.827806
3	Bronx	Fieldston	40.895437	-73.905643
4	Bronx	Riverdale	40.890834	-73.912585

b) Exploratory data Analysis.

- Vizualise the Neighborhoods per Borough in New York

In [7]:

```
X=new_york_data.Borough
Y=new_york_data.groupby('Borough')['Neighborhood'].count()
N=[]
for i in Y:
    N.append(i)
#Nx=['Bronx', 'Brooklyn', 'Manhattan', 'Queens', 'Staten Island']
Borough = ['Bronx', 'Brooklyn', 'Manhattan', 'Queens', 'Staten Island']
labels=Borough


x = np.arange(len(Borough))  # the label locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots()
rects1 = ax.bar(x, N, width, label='Boroughs', color='red')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Neighborhoods',fontsize = 15)
ax.set_title('Neighborhoods in New York City')
ax.set_xlabel('Boroughs',fontsize = 15)
ax.set_xticks(x)
ax.set_xticklabels(labels)
ax.legend()


def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its height."""
    for rect in rects:
        height = rect.get_height()
        ax.annotate('{}'.format(height),
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 0),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')


autolabel(rects1)
#autolabel(rects2)

#fig.tight_layout()

plt.show()
```



- Revising the number of boroughs and neighborhoods

In [8]:
```
print('The dataframe has {} boroughs and {} neighborhoods.'.format(
        len(neighborhoods['Borough'].unique()),
        neighborhoods.shape[0]
    )
)
new_york_data.shape
```

```
The dataframe has 5 boroughs and 306 neighborhoods.
```

Out[8]:
```
(306, 4)
```

- Use geopy library to get the latitude and longitude values of New York City.

In [9]:
```
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,
```

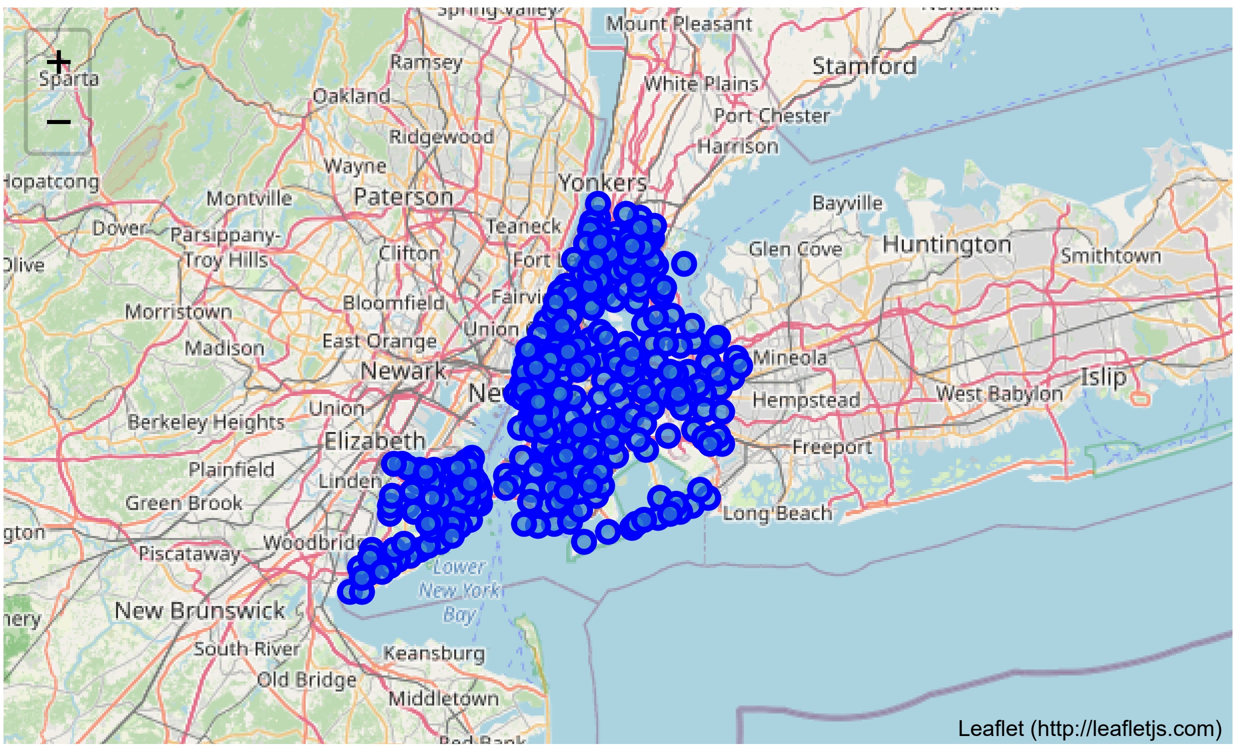
```
The geograpical coordinate of New York City are 40.7127281, -74.0060152.
```

- Create map of New York using latitude and longitude values

In [10]:

```
# 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(neighborhoods['Latitude'], neighborhoo
    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[10]:



In [ ]:

```
#![](map1.png)
```

- Define Foursquare Credentials and Version

In [11]:
```
CLIENT_ID = 'S5IVBRZHUGOEIVIGZ2QTK33VQXNV0ZSL0UV3UCZW3YWUY1QU' # your Foursquare
CLIENT_SECRET = 'O5POJ5RKMLAN5PM04OVGMQAMK5EYYECSJF0QEZ3OHQ1AA5Z0' # your Foursqu
VERSION = '20180605' # Foursquare API version

print('Your credentails:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: S5IVBRZHUGOEIVIGZ2QTK33VQXNV0ZSL0UV3UCZW3YWUY1QU
CLIENT_SECRET:O5POJ5RKMLAN5PM04OVGMQAMK5EYYECSJF0QEZ3OHQ1AA5Z0
```

- **Cluster only the neighborhoods in Manhattan : As mentioned in the introduction, the Peruvian Entrepreneur wants to open the new Peruvian restaurant in Manhattan city, hence the evaluation will be focused in Manhattan's neighborhoods**.

In [12]:
```
manhattan_data = neighborhoods[neighborhoods['Borough'] == 'Manhattan'].reset_inc
manhattan_data.head()
manhattan_data.shape
```

Out[12]: (40, 4)

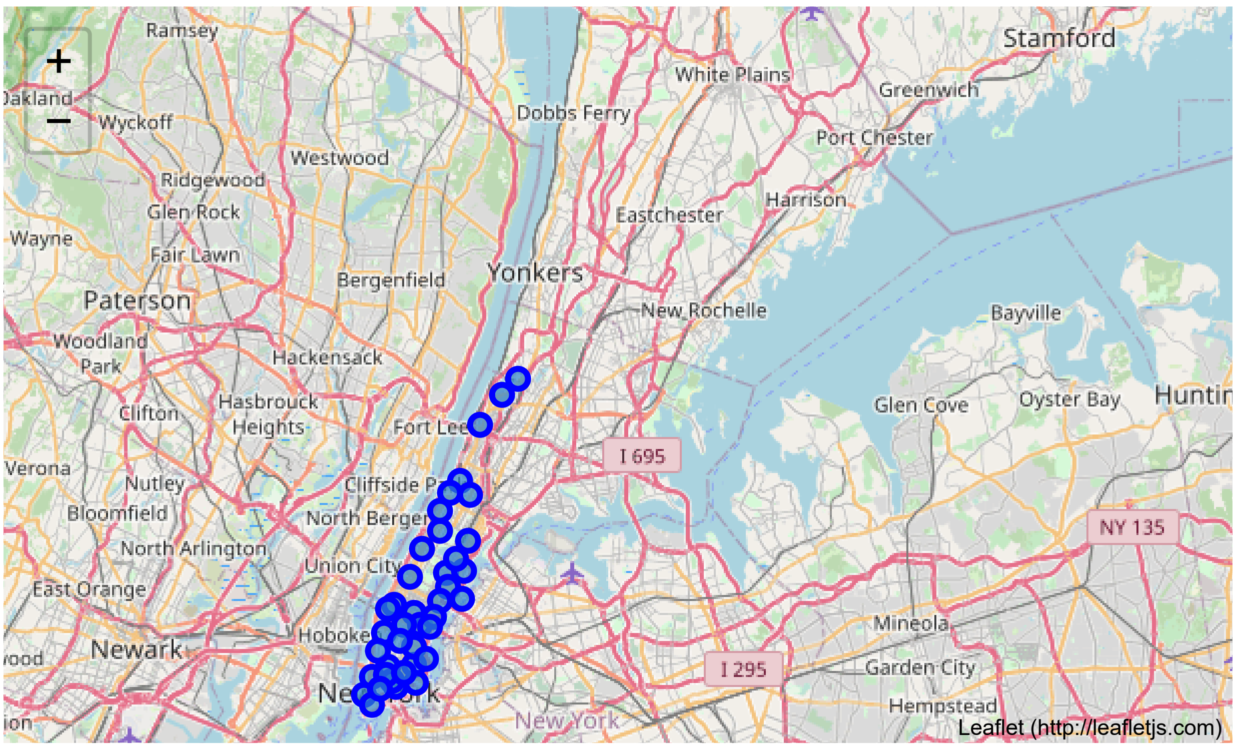
In [13]:
```
address = 'Manhattan, NY'
geolocator = Nominatim(user_agent="foursquare_agent")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(latitude, longitude)
```

```
40.7896239 -73.9598939
```

- Create map of Manhattan using latitude and longitude values

In [14]:
```
# 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['Longitude'
    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[14]:



In [1]:
```
#![](map2.png)
```

- Extracting 100 venues with 1000 meters of radius from Manhattan: Foursquare API with 100 venues of limit and 1000 meters radius is used to obtain the venues from Manhattan, which yields 3178 venues around the city.

In [15]:
```
radius = 1000
LIMIT=100
```

In [16]:
```
def getNearbyVenues(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={}&client_
            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])

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

    return(nearby_venues)
```

In [17]:
```
# type your answer here

manhattan_venues = getNearbyVenues(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
```

- Let's check the size of resulting data frame for nighborhoods in Manhattan

In [18]:
```
print(manhattan_venues.shape)
manhattan_venues.head()
```

```
(3178, 7)
```

Out[18]:

	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	Astral Fitness & Wellness Center	40.876705	-73.906372	Gym

- Revise the number of venues returned for each neighborhood and Checking the uniques categories

In [19]:
```
manhattan_venues.groupby('Venue').count()
print('There are {} uniques categories.'.format(len(manhattan_venues['Venue Categ
```

```
There are 325 uniques categories.
```

- **Cheking whether exist Peruvian Restaurants in the venues provided by Foursquare API**

In [20]:
```
"Peruvian Restaurant" in manhattan_venues['Venue Category'].unique()
```

Out[20]:
```
True
```

- Analyze Each Neighborhood in Manhattan: Once the venues from Manhattan are converted to data frame, we use dummies function to convert categorical data to numerical values. Then the data frame can be grouped by neighborhoods by taking the mean of the frequency of occurrence of each category.

In [21]:
```
to_onehot = pd.get_dummies(manhattan_venues[['Venue Category']], prefix="", prefi

# add neighborhood column back to dataframe
to_onehot['Neighborhoods'] = manhattan_venues['Neighborhood']

# move neighborhood column to the first column
fixed_columns = [to_onehot.columns[-1]] + list(to_onehot.columns[:-1])
to_onehot = to_onehot[fixed_columns]

print(to_onehot.shape)
to_onehot.head()
```

```
(3178, 326)
```

Out[21]:

	Neighborhoods	Accessories Store	Adult Boutique	African Restaurant	American Restaurant	Antique Shop	Arcade	Arepa Restaurant	Ar R
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	

In [22]:
```
to_grouped = to_onehot.groupby(["Neighborhoods"]).mean().reset_index()
print(to_grouped.shape)
to_grouped
```

(40, 326)

Out[22]:

	Neighborhoods	Accessories Store	Adult Boutique	African Restaurant	American Restaurant	Antique Shop	Arcade	Arep Restaura
0	Battery Park City	0.000000	0.00	0.000000	0.014493	0.00	0.000000	0.00000
1	Carnegie Hill	0.000000	0.00	0.000000	0.010870	0.00	0.000000	0.00000
2	Central Harlem	0.000000	0.00	0.066667	0.044444	0.00	0.000000	0.00000
3	Chelsea	0.000000	0.00	0.000000	0.040000	0.00	0.000000	0.01000
4	Chinatown	0.000000	0.00	0.000000	0.030000	0.00	0.000000	0.00000
5	Civic Center	0.000000	0.00	0.000000	0.030000	0.01	0.000000	0.00000
6	Clinton	0.000000	0.00	0.000000	0.040000	0.00	0.000000	0.00000
7	East Harlem	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
8	East Village	0.000000	0.00	0.000000	0.020000	0.00	0.000000	0.01000
9	Financial District	0.000000	0.00	0.000000	0.040000	0.00	0.000000	0.00000
10	Flatiron	0.000000	0.00	0.000000	0.030000	0.00	0.000000	0.00000
11	Gramercy	0.000000	0.00	0.000000	0.043011	0.00	0.010753	0.00000
12	Greenwich Village	0.000000	0.00	0.000000	0.020000	0.00	0.000000	0.00000
13	Hamilton Heights	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
14	Hudson Yards	0.000000	0.00	0.000000	0.071429	0.00	0.000000	0.00000
15	Inwood	0.000000	0.00	0.000000	0.035714	0.00	0.000000	0.00000
16	Lenox Hill	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
17	Lincoln Square	0.000000	0.00	0.000000	0.030612	0.00	0.000000	0.00000
18	Little Italy	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
19	Lower East Side	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
20	Manhattan Valley	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
21	Manhattanville	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
22	Marble Hill	0.000000	0.00	0.000000	0.038462	0.00	0.000000	0.00000
23	Midtown	0.000000	0.00	0.000000	0.010000	0.00	0.000000	0.00000
24	Midtown South	0.000000	0.00	0.000000	0.030000	0.00	0.000000	0.00000
25	Morningside Heights	0.000000	0.00	0.000000	0.073171	0.00	0.000000	0.00000
26	Murray Hill	0.000000	0.00	0.000000	0.030612	0.00	0.000000	0.00000

	Neighborhoods	Accessories Store	Adult Boutique	African Restaurant	American Restaurant	Antique Shop	Arcade	Arep Restaura
27	Noho	0.000000	0.00	0.000000	0.010000	0.00	0.000000	0.00000
28	Roosevelt Island	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
29	Soho	0.000000	0.00	0.000000	0.010000	0.00	0.000000	0.00000
30	Stuyvesant Town	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000
31	Sutton Place	0.000000	0.01	0.000000	0.030000	0.00	0.000000	0.00000
32	Tribeca	0.000000	0.00	0.000000	0.048193	0.00	0.000000	0.00000
33	Tudor City	0.000000	0.00	0.000000	0.013514	0.00	0.000000	0.00000
34	Turtle Bay	0.000000	0.00	0.000000	0.020000	0.00	0.000000	0.00000
35	Upper East Side	0.000000	0.00	0.000000	0.021277	0.00	0.000000	0.00000
36	Upper West Side	0.000000	0.00	0.000000	0.022989	0.00	0.000000	0.00000
37	Washington Heights	0.010989	0.00	0.000000	0.010989	0.00	0.000000	0.01098
38	West Village	0.000000	0.00	0.000000	0.040000	0.00	0.000000	0.00000
39	Yorkville	0.000000	0.00	0.000000	0.000000	0.00	0.000000	0.00000

- **Filtering the data to obtain the venues of Peruvian Restaurants**.

In [23]:
```
len(to_grouped[to_grouped["Peruvian Restaurant"] > 0])
```

Out[23]: 5

- **There are five Peruvian Restaurants in different neighborhoods around Manhattan**

In [24]:
```
to_Peruvian = to_grouped[["Neighborhoods","Peruvian Restaurant"]]
to_Peruvian.head()
```

Out[24]:

	Neighborhoods	Peruvian Restaurant
0	Battery Park City	0.0
1	Carnegie Hill	0.0
2	Central Harlem	0.0
3	Chelsea	0.0
4	Chinatown	0.0

C) Predictive Modeling

The next step is to cluster the current Peruvian restaurants inside the Manhattan neighborhoods. K-means is an unsupervised machine learning algorithm that groups similar data points by trying to discover fundamental patterns. Hence it must fix numbers of K to make the clusters of the dataset. It is very simple tool for clustering and clearly suited for modeling the data in this project. The Manhattan neighborhoods are grouped into 3 clusters based in the frequency of occurrence of Peruvian restaurants. The Manhattan neighborhoods are grouped into three clusters that display the information needed to make decisions about the best place to open a new Peruvian restaurant. The blue cluster contains Neighborhoods with more Peruvian Restaurants. The green cluster has less Peruvian Restaurants. On the other hand, the red cluster doesn't contain any Peruvian restaurant providing relevant evidence that the gastronomic business can be opened in any of the neighborhoods located in the red cluster.

- **Cluster Neighborhoods in Manhattan**

In [25]:
```
from sklearn.cluster import KMeans
toclusters = 3

to_clustering = to_Peruvian.drop(["Neighborhoods"], 1)

# run k-means clustering
kmeans = KMeans(n_clusters=toclusters, random_state=1)
kmeans.fit_transform(to_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:20]
```

Out[25]:
```
array([0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0])
```

In [26]:
```
to_merged = to_Peruvian.copy()

# add clustering labels
to_merged["Cluster Labels"] = kmeans.labels_
```

In [27]:
```
to_merged.rename(columns={"Neighborhoods": "Neighborhood"}, inplace=True)
to_merged.head(5)
```

Out[27]:

	Neighborhood	Peruvian Restaurant	Cluster Labels
0	Battery Park City	0.0	0
1	Carnegie Hill	0.0	0
2	Central Harlem	0.0	0
3	Chelsea	0.0	0
4	Chinatown	0.0	0

In [28]:
```
to_merged = to_merged.join(manhattan_venues.set_index("Neighborhood"), on="Neighb

print(to_merged.shape)
to_merged.head()
```

```
(3178, 9)
```

Out[28]:

	Neighborhood	Peruvian Restaurant	Cluster Labels	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Ven Longitu
0	Battery Park City	0.0	0	40.711932	-74.016869	Battery Park City Esplanade	40.711622	-74.0179
0	Battery Park City	0.0	0	40.711932	-74.016869	Waterfront Plaza, Brookfield Place	40.713241	-74.0162
0	Battery Park City	0.0	0	40.711932	-74.016869	Hudson Eats	40.712666	-74.0159
0	Battery Park City	0.0	0	40.711932	-74.016869	Equinox Brookfield Place	40.712704	-74.0149
0	Battery Park City	0.0	0	40.711932	-74.016869	Brookfield Place (BFPL)	40.713240	-74.0151

In [29]:
```
to_merged.sort_values(["Cluster Labels"], inplace=True)
to_merged.head()
```

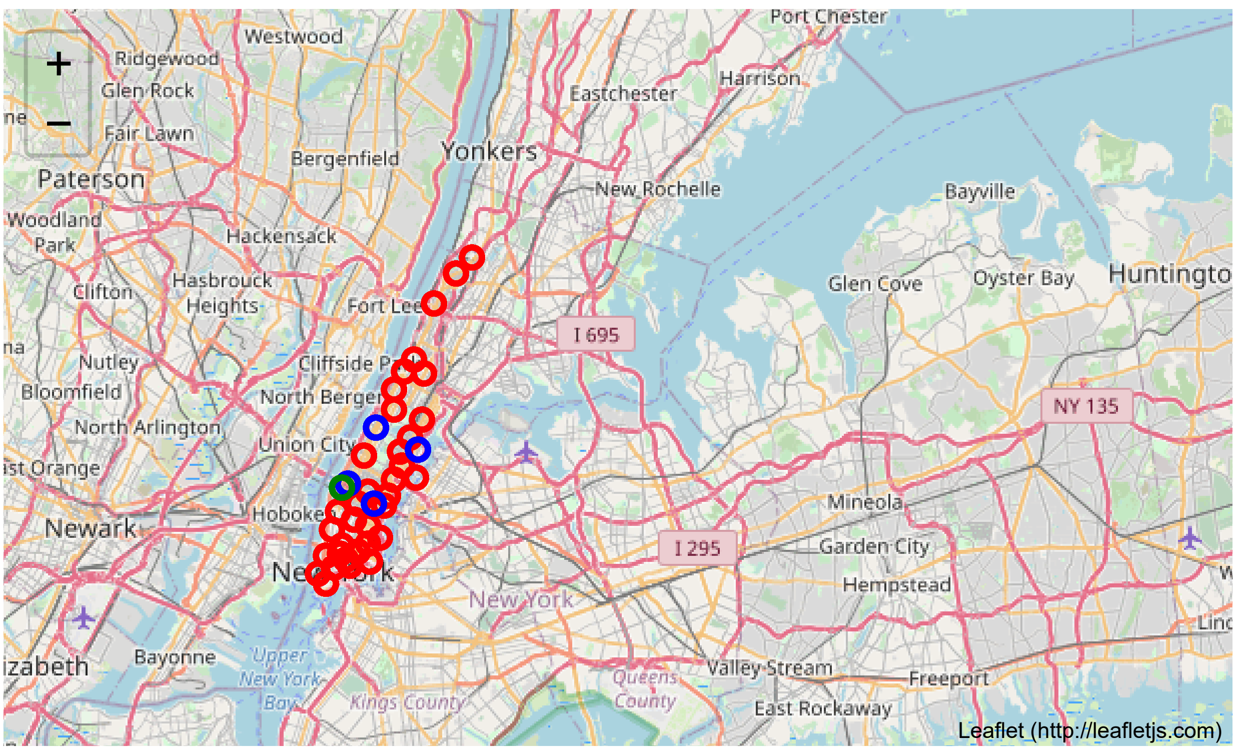
Out[29]:

	Neighborhood	Peruvian Restaurant	Cluster Labels	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Ve Longit
0	Battery Park City	0.0	0	40.711932	-74.016869	Battery Park City Esplanade	40.711622	-74.017
24	Midtown South	0.0	0	40.748510	-73.988713	Urban Outfitters	40.751170	-73.988
24	Midtown South	0.0	0	40.748510	-73.988713	Patent Pending	40.745133	-73.990
24	Midtown South	0.0	0	40.748510	-73.988713	&pizza	40.745205	-73.988
24	Midtown South	0.0	0	40.748510	-73.988713	Hangawi	40.746927	-73.984

- **Let's visualize the resuls of clustering**

In [30]:
```
map_clusters = folium.Map(location=[latitude, longitude],zoom_start=14)

# set color scheme for the clusters


# add markers to the map
markers_colors={}
markers_colors[0] = 'red'
markers_colors[1] = 'blue'
markers_colors[2] = 'green'
markers_colors[3] = 'yellow'
markers_colors[4] = 'cyan'
markers_colors[5] = 'black'
for lat, lon, cluster, poi in zip(to_merged['Neighborhood Latitude'], to_merged['
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)

    folium.features.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color =markers_colors[cluster],
        fill_color=markers_colors[cluster],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[30]:



In [ ]:
```
#![](map3.png)
```

Examine clusters

- **Examining the red cluster (cluster cero): Neighborhoods with cero Peruvian restaurants**

In [31]:
```
#Cluster 0
to_merged.loc[(to_merged['Cluster Labels'] ==0) & (to_merged['Venue Category'] ==
```

Out[31]:

Neighborhood	Peruvian Restaurant	Cluster Labels	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Ca

- **Examining the blue cluster (cluster 1) : Neighborhoods with more Peruvian Restaurants**

In [32]:
```
#Cluster 1
to_merged.loc[(to_merged['Cluster Labels'] ==1) & (to_merged['Venue Category'] ==
```

Out[32]:

	Neighborhood	Peruvian Restaurant	Cluster Labels	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude
26	Murray Hill	0.010204	1	40.748303	-73.978332	Pio Pio	40.745535	-73.977626
39	Yorkville	0.010000	1	40.775930	-73.947118	Pio Pio	40.779887	-73.947202
6	Clinton	0.010000	1	40.759101	-73.996119	Pio Pio	40.760636	-73.994714
36	Upper West Side	0.011494	1	40.787658	-73.977059	Flor de Mayo	40.785966	-73.976312

- **Examining the green cluster (cluster 2): Neighborhoods with less Peruvian Restaurants**

In [33]:
```
#Cluster 2
to_merged.loc[(to_merged['Cluster Labels'] ==2) & (to_merged['Venue Category'] ==
```

Out[33]:

	Neighborhood	Peruvian Restaurant	Cluster Labels	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude
14	Hudson Yards	0.017857	2	40.756658	-74.000111	Chirp	40.753377	-73.996116

5. Results

In this section, the answers released in the business case will be answered, having as basis the analyzed data.

1. **How many Peruvian restaurants are in Manhattan?** Based on the evaluated data, there are five Peruvian restaurants around Manhattan.

2. **What is the best location in Manhattan City to open a Peruvian restaurant?** Based on the k-means clustering algorithm used in Manhattan neighborhoods' data, the best place for opening a new Peruvian restaurant is in the red clustered neighborhoods. The optimal site can be in an area in the red cluster, not far from an existing Peruvian restaurant on the blue cluster. For example, a possible optimal location could be the East Harlem neighborhood. As shown in figure 5, the East Harlem area is not far from the Yorkville neighborhood that is clustered with blue color. The reason to open the new Peruvian restaurant not far from an actual Peruvian restaurant clustered in blue color is that actual restaurants already have a gained reputation, thus it can be favorable to open the new restaurant not far from a restaurant located in the blue cluster.
3. **What are other potential neighborhoods in Manhattan for Peruvian Cuisine?** Another option is to open a Peruvian restaurant in a red cluster neighborhood but far away from an existing Peruvian restaurant because it can be an excellent opportunity to obtain new customers without any similar competition around the neighborhood.
4. **What neighborhoods lack Peruvian restaurants?** The Manhattan neighborhoods in the red cluster don’t have a Peruvian restaurant. This information is relevant because it shows a great business opportunity to open a new Peruvian restaurant in one of these neighborhoods.

6. Recommendations

Based on the evaluation made, the Manhattan city provides a great business opportunity to initiate a new gastronomic business of Peruvian food. This evaluation shows that most of the Peruvian restaurants are in the blue cluster neighborhoods (cluster 1) which is around Murray Hill, Yorkville, Clinton, and Upper West Side. The green cluster neighborhoods (cluster 2) has the less Peruvian restaurants around Manhattan. Finally, the red clusters (cluster cero) doesn’t have Peruvian restaurants in its neighborhoods. Therefore, a new Peruvian restaurant can be opened in one of these neighborhoods clustered in red, not far from an existing Peruvian restaurant located in the blue cluster, for instance in the East Harlem neighborhood that is clustred in red.

Thank !

In [ ]:

In [ ]:

In [ ]: