Capstone Project - The Battle of the Neighborhoods

COVID Risk Categories Applied For Reopening Restaraunts

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Introduction: Business Problem

Among the numerous and diverse challenges humanity has faced through modern history, the recent Corona Virus pandemic showed itself as one of the most urgent and formidable one. Not only it brought unparalleled distress to every nation's healthcare system, but inflicted heavy losses in it's economies, specially regarding the survival of small businesses - mainly composed of family restaurants and stores. Still, despite minimal improvements in the infection curve scenarios, many countries are starting to reopen their economies due to the agrravating economical factors.

Invariably, the small food business are soon to receive quarantine eager clients, when the pandemic, despite still existing, has began to be treated as a "new normal" situation. In this scenario, this project aims to provide both businesses and clients a dynamic tool for evaluating the risk of attending/providing services at each neighbourhood, based on infection rate, populational density and quantity of stores avaliable (as wait lines and maximum capacity are a crucial factor imposed by health authorities and overall safety practices).

The initial goal of the project is to evaluate risks specifically for the **food service industry**. This model must not be used to analyse the risk of individual restaurants, but the risk associated with it's operation in it's neighbourhood. It's also expected to stabilish a relationship between clusters of venues and infection rate over neighborhoods.

This is an easily replicable experiment for every city in the world, but, due to ease of access of data

Data Sources

The data needed for the project is listed below (besides the restaurants location data obtained from Foursquare API):

1. Geographical data of buroughs and neighbourhoods of NYC and their latitude/longitude. Avaliable at: https://geo.nyu.edu/catalog/nyu_2451_34572. The data has been conviniently uploaded at the server as: https://cocl.us/new_york_dataset

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

2. COVID-19 infection data, kill rate and quantity of registered cases. Avaliable at: https://www1.nyc.gov/site/doh/covid/covid-19-data.page (downloaded on 07/21/2020 as a csv for this project)

ZIP Neighborhood Borough Cases Cases per 100,000 Deaths per 100,000 Percent positive (of people tested) 10001 Chelsea/NoMad/West Chelsea Manhattan 415 1761,23 101,85 7,78 10002 Chinatown/Lower East Side Manhattan 1214 1581,65 208,45 11 10003 East Village/Gramercy/Greenwich Village Manhattan 504 936,77 63,2 5,92 10004 Financial District Manhattan 36 986,14 27,39 6,36 10005 Financial District Manhattan 76 905,18 23,82 5,71

3. NYC population data per burough/neighbourhood. Avaliable at https://data.cityofnewyork.us/City-Government/New-York-City-Population-By-Neighborhood-Tabulatio/swpk-hqdp. Data extracted via SODA API JSON: https://data.cityofnewyork.us/resource/swpk-hqdp.json

Dataset Structuring

Libraries

```
1 import numpy as np #Vectorized data
2
3 import pandas as pd #Dataframes
4 pd.set_option('display.max_columns', None)
5 pd.set_option('display.max_rows', None)
```

```
import json #JSON Files
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe

import requests #Requests

#!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim #Adress into lat/long

import matplotlib.cm as cm #Plotting and plotting modules
import matplotlib.colors as colors

import matplotlib.pyplot as plt #Plotting additional graphs
from matplotlib.ticker import PercentFormatter

from sklearn.cluster import KMeans #K-Means and Clustering

#!conda install -c conda-forge folium=0.5.0 --yes
import folium #Map Rendering (Folium)

print('Success!')
```

```
Success!
```

Data Import

```
# NYC Neighbouhood Names

!wget -q -O 'newyork_data.json' https://cocl.us/new_york_dataset #Get JSON
with open('newyork_data.json') as json_data:
    newyork_data = json.load(json_data) #Load data from JSON
neighborhoods_data = newyork_data['features']
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude'] #Specifying columns fo
neighborhoods = pd.DataFrame(columns=column_names) #Create DF header

for data in neighborhoods_data: #Fill DF rows
    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_index=Tru


neighborhoods.drop_duplicates(subset ="Neighborhood", keep = False, inplace = True) #Drop
```

```
neighborhoods.drop_duplicates(subset = "Neighborhood", keep = False, inplace = True) #Drop
print("Rows:",len(neighborhoods['Neighborhood'].unique())) #Checking size with data source

neighborhoods.sort_values("Neighborhood",inplace=True) #Sort alphabetically
neighborhoods.head()
```

```
Rows: 298
```

	Borough	Neighborhood	Latitude	Longitude
298	Bronx	Allerton	40.865788	-73.859319
215	Staten Island	Annadale	40.538114	-74.178549
241	Staten Island	Arden Heights	40.549286	-74.185887
227	Staten Island	Arlington	40.635325	-74.165104
228	Staten Island	Arrochar	40.596313	-74.067124

```
#COVID Infection Data

covid_df=pd.read_csv('https://raw.githubusercontent.com/rafzss/Coursera_Capstone/master/Da
covid_df=covid_df.rename(columns={"Cases per 100,000":"Cases per 100k"})
covid_df=covid_df.rename(columns={"Deaths per 100,000":"Deaths per 100k"})
covid_df=covid_df.rename(columns={"Percent positive<br>(of people tested)":"Percent Positi
covid_df.drop(["ZIP"],axis=1,inplace=True)
print("Rows before splitting:",len(covid_df['Neighborhood'].unique())) #Checking size with

#Splitting rows of grouped neighborhoods

def splitDataFrameList(df,target_column,separator): # Based on: https://gist.github.com/jl

    # df = dataframe to split,
    # target_column = the column containing the values to split
    # separator = the symbol used to perform the split
    # returns: a dataframe with each entry for the target column separated, with each elem
    #The values in the other columns are duplicated across the newly divided rows.

    row_accumulator = []
    def splitListToRows(row, separator):
        split_row = row[target_column].split(separator)
        for s in split_row:
            new_row = row.to_dict()
            new_row[target_column] = s
            row_accumulator.append(new_row)

    df.apply(splitListToRows, axis=1, args = (separator, ))
    new_df = pd.DataFrame(row_accumulator)
    return new_df

covid_df=splitDataFrameList(covid_df,"Neighborhood","/")

covid_df=covid_df.sort_values('Cases per 100k').drop_duplicates('Neighborhood',keep='last'
```

```
covid_df.sort_values("Neighborhood",inplace=True) #Sort alphabetically

print("Rows after splitting:",len(covid_df['Neighborhood'].unique())) #Checking size with
covid_df.head()
```

```
Rows before splitting: 162
Rows after splitting: 225
```

	Neighborhood	Borough	Cases	Cases per 100k	Deaths per 100k	Percent Positive
285	Airport	Queens	1690	4634.93	490.92	23.11
156	Allerton	Bronx	3164	4424.66	496.45	20.93
12	Alphabet City	Manhattan	774	1317.49	117.45	7.94
104	Annadale	Staten Island	1597	2648.23	97.84	16.97

```
# NYC Population

nycpop=pd.read_csv('https://raw.githubusercontent.com/rafzss/Coursera_Capstone/master/Data
print("Latest Year:",nycpop["Year"].max()) #Get latest year of poll
nycpop=nycpop[nycpop['Year']==nycpop["Year"].max()] #Filter dataset by latest year

# This step approximates the population for neighborhoods that were grouped from the loade
# The total population is simply divided by the number of occurrances of neighborhoods in

nycpop=splitDataFrameList(nycpop,"NTA Name","-") #Split rows with more than one neighborho
dupsdf=nycpop.pivot_table(index=['NTA Code'],aggfunc='size') #Count duplicates of each nei
nycpop=nycpop.merge(dupsdf.rename('Count').to_frame(),on=['NTA Code'],how='left') #Add pre
nycpop['Population']=round(nycpop['Population']/nycpop['Count']) #Approximate population o

nycpop.drop_duplicates(subset ="NTA Name", keep = False, inplace = True) #Drop duplicates
nycpop=nycpop.drop(['FIPS County Code','NTA Code','Count'],axis=1) #Drop unnecessary colum
print("Rows:",len(nycpop['NTA Name'].unique())) #Checking size with data source

nycpop.head()
```

```
Latest Year: 2010
Rows: 298
```

	Borough	Year	NTA Name	Population
0	Bronx	2010	Claremont	15539.0
1	Bronx	2010	Bathgate	15539.0
2	Bronx	2010	Eastchester	11506.0
3	Bronx	2010	Edenwald	11506.0
4	Bronx	2010	Baychester	11506.0

Data Preparation

```
neighborhoods.set_index('Neighborhood') #Set index as neighborhood
nycpop.set_index('NTA Name') #Set index as neighborhood
covid_df.set_index('Neighborhood') #Set index as neighborhood

df1 = pd.merge(nycpop, covid_df, how='inner', left_on='NTA Name', right_on='Neighborhood')
df = pd.merge(neighborhoods,df1,how='inner',left_on='Neighborhood',right_on='NTA Name') #M
df.drop_duplicates(subset ="Neighborhood_x", keep = False, inplace = True) #Drop duplicate
df=df.drop(['Borough_x','Year','NTA Name','Neighborhood_y','Borough_y'],axis=1) #Drop redu
df=df.rename(columns={"Neighborhood_x":"Neighborhood"}) #Rename 'neighborhood'
df.set_index('Neighborhood') #Set index as neighborhood
print(df.shape)
df.head()
```

```
(150, 9)
```

	Borough	Neighborhood	Latitude	Longitude	Population	Cases	Cases per 100k	Deaths per 100k	Per Posi
0	Bronx	Allerton	40.865788	-73.859319	14452.0	3164	4424.66	496.45	2
1	Staten Island	Annadale	40.538114	-74.178549	6942.0	1597	2648.23	97.84	1
2	Staten Island	Arrochar	40.596313	-74.067124	5360.0	1315	3089.68	187.97	1

We see that the dataset went from the original 298 rows of the neighborhood dataset to 150, due to removal of duplicates and wrong matchings of the neighborhood strings of each dataset. Python allows for ease to use matching alghoritms through pre-built libraries, such as Levenshtein's alghoritm in the 'fuzzywuzzy' library. This will not be applied in this project so as to not overextend it.

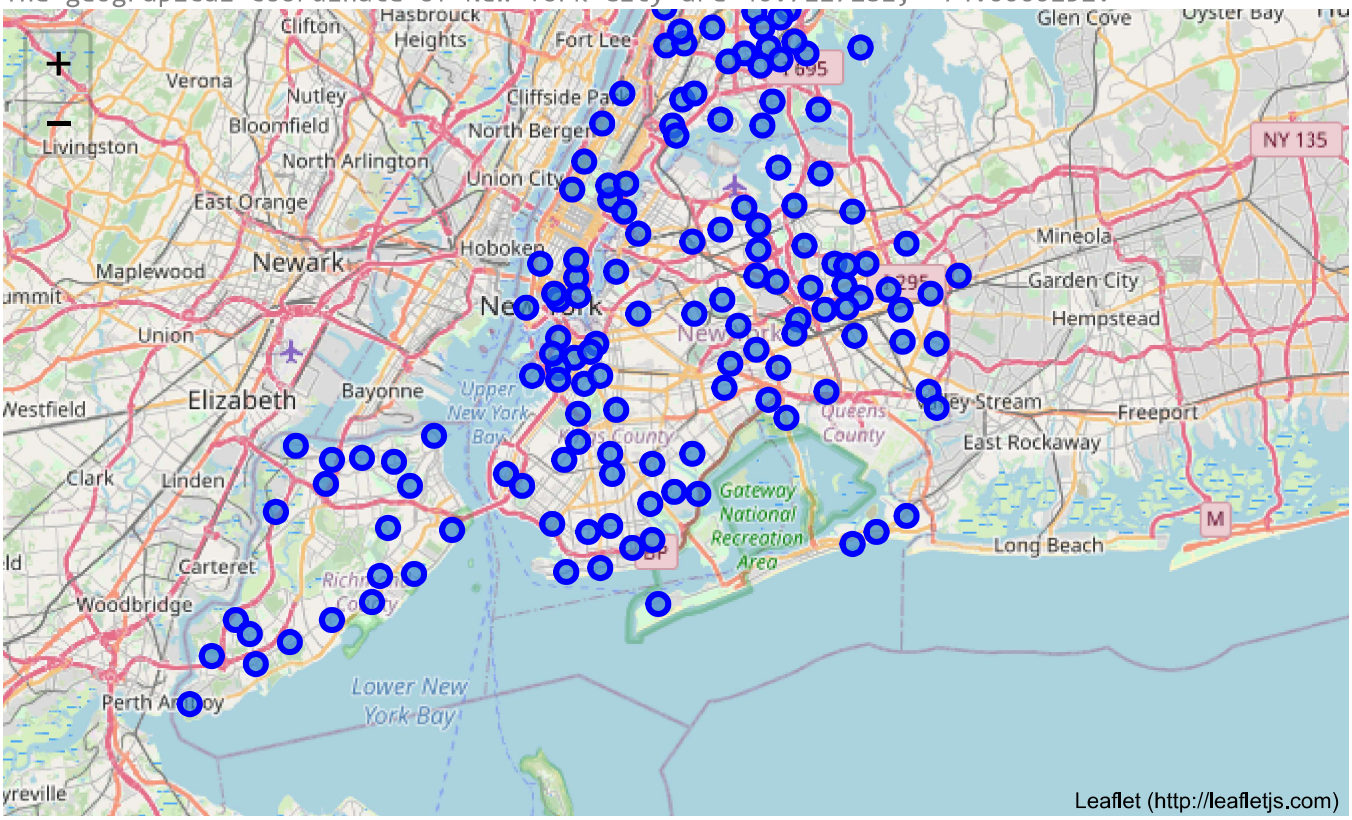
Data Visualization

```
#Locate NYC Coordinates

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

```
# 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(df['Latitude'], df['Longitude'], df['Borough'],
    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
```

```
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_secret={}
            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 venue_lis
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)

# Function that extracts the category of the venue

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']
```

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



Analysis

Foursquare Connection

```
1 CLIENT_ID = 'VLXFKV40KQLKJP3NM3U2VTOWIZYHKJXM3CXWH3SUVILRPA5D' # your Foursquare ID
2 CLIENT_SECRET = 'QJVKBVYQLA52BKUEV3AQGQPUBB0UFP0ORLPQTMYXBAPGZMZD' # your Foursquare Secre
3 VERSION = '20180605' # Foursquare API version
4
5 print('Your credentails:')
6 print('CLIENT_ID: ' + CLIENT_ID)
7 print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: VLXFKV40KQLKJP3NM3U2VTOWIZYHKJXM3CXWH3SUVILRPA5D
CLIENT_SECRET:QJVKBVYQLA52BKUEV3AQGQPUBB0UFP0ORLPQTMYXBAPGZMZD
```

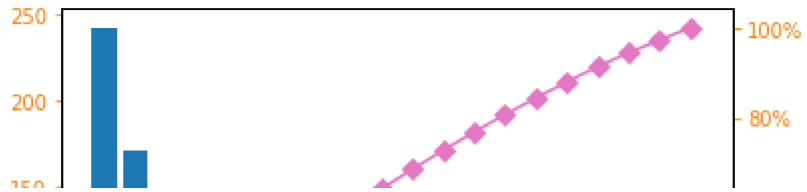
Foursquare Venues and Categories

```
1 #Standard Function for fetching Foursquare data
2
```

```
        return categories_list[0]['name']
```

```
# Fetching Foursquare Data:

LIMIT=100 #Limit of venues returned by Foursquare API (for each neighborhood)
radius=500 #Limit of radius for getting venues

nyc_venues = getNearbyVenues(names=df['Neighborhood'],
                                   latitudes=df['Latitude'],
                                   longitudes=df['Longitude']
                                  )

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

```
# Pareto Chart

df_pareto = nyc_venues.groupby(['Venue Category'])['Venue Category'].count().to_frame(name
df_pareto.index=df_pareto['Venue Category']
df_pareto = df_pareto.sort_values(by='Venues',ascending=False)
df_pareto = df_pareto.nlargest(20,['Venues'])
df_pareto["cumulative_percent"] = df_pareto["Venues"].cumsum()/df_pareto["Venues"].sum()*1
df_pareto

fig, ax = plt.subplots()
ax.bar(df_pareto.index, df_pareto["Venues"], color="C0")
ax2 = ax.twinx()
ax2.plot(df_pareto.index, df_pareto["cumulative_percent"], color="C6", marker="D", ms=7)
ax2.yaxis.set_major_formatter(PercentFormatter())

ax.tick_params(axis="y", colors="C1")
ax2.tick_params(axis="y", colors="C1")

for tick in ax.get_xticklabels():
        tick.set_rotation(90)
        tick.set_color("C0")
plt.show()
```



As imagined, food services places correspond to the vast majority of the venues analysed (at least from the top 20 venues).


```
# Grouping venues into neighborhoods

nyc_grouped=nyc_venues.groupby(['Neighborhood'])['Venue Category'].count().to_frame(name='
nyc_grouped.sort_values
print(nyc_grouped.shape)


# Merging venue data with dataset:

df2 = pd.merge(df,nyc_grouped,how='left',left_on='Neighborhood',right_on='Neighborhood')
print(df2.shape)

df2.head() #This is the final dataset for analysis
# Some columns will not be used, but they provide details for future analysis and comparis
```

```
(150, 2)
(150, 10)
There are 357 uniques categories.
```

	Borough	Neighborhood	Latitude	Longitude	Population	Cases	Cases per 100k	Deaths per 100k	Per Posi
0	Bronx	Allerton	40.865788	-73.859319	14452.0	3164	4424.66	496.45	2
1	Staten Island	Annadale	40.538114	-74.178549	6942.0	1597	2648.23	97.84	1
2	Staten Island	Arrochar	40.596313	-74.067124	5360.0	1315	3089.68	187.97	1

Cluster Neighborhoods

```
# K-Means for clustering neighborhoods into 4 risk rates (Low, Average, High and Critical)

df_kcluster = df2.filter(['Cases per 100k','Venues Qty']) # Dataframe with X

k=4
kmeans = KMeans(n_clusters=k, random_state=0).fit(df_kcluster) # Run k-means clustering
kmeans.labels_[0:10] # Check cluster labels generated for each row in the dataframe

```

```
# Create new dataframe with clusters

# add clustering labels
df_kcluster.insert(0, 'Cluster Labels', kmeans.labels_)
df_kcluster=df_kcluster.drop(['Cases per 100k','Venues Qty'],axis=1) # Drop redundant colu
df_final = df2.merge(df_kcluster,left_index=True,right_index=True) # Merge Cluster Labels

print(df_final.shape)
df_final.head()
```

```
(150, 11)
```

	Borough	Neighborhood	Latitude	Longitude	Population	Cases	Cases per 100k	Deaths per 100k	Per Posi
0	Bronx	Allerton	40.865788	-73.859319	14452.0	3164	4424.66	496.45	2
1	Staten Island	Annadale	40.538114	-74.178549	6942.0	1597	2648.23	97.84	1
2	Staten Island	Arrochar	40.596313	-74.067124	5360.0	1315	3089.68	187.97	1

Visualize Clusters

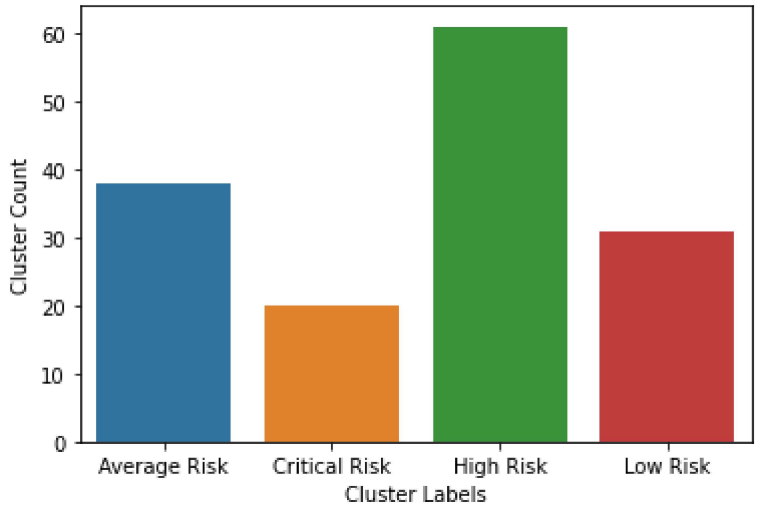
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
x = np.arange(k)
ys = [i + x + (i*x)**2 for i in range(k)]
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(df_final['Latitude'], df_final['Longitude'], df_final['N
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```


Poughkeepsie
Plattekill
Beekman
Washington
New Milford
East Fishkill
Bridgewater
Patterson
Newburgh
Brookfield
Deerpark
Blooming Grove
Carmel
Newtown
Danbury
Woodbury
Ridgebury
Monroe
Putnam Valley
Somers
Yorktown
Ridgefield
Wantage
Harriman State Park
Stony Point
Lewisboro
Vernon
Haverstraw
Mount Kisco
Wilton
Ossining
West Milford
Spring Valley
Norwalk
Mount Pleasant
Ramsey
Sparta
Oakland
White Plains
Stamford
Port Chester
Ridgewood
Harrison
Leaflet (http://leafletjs.com)

Results and Discussion

```
import seaborn as sns # Plotting library

# Bar Plot

df_plot = df_final.filter(['Cases per 100k','Venues Qty','Cluster Labels'],axis=1)
df_plot['Cluster Labels']=df_plot['Cluster Labels'].replace(0,'High Risk').replace(1,'Low
df_count = df_plot.groupby(['Cluster Labels'])['Cluster Labels'].count().to_frame(name='Cl
df_count.head()

sns.barplot(x='Cluster Labels',y='Cluster Count',data=df_count) # Bar Plot
```

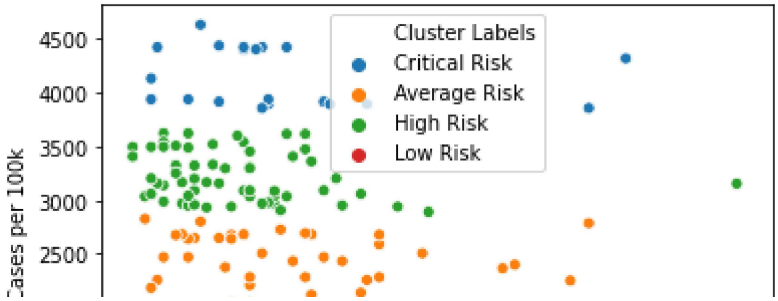
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55b996b160>
```



In the atual scenario (07-23-2020), New York City shows a higher amount of neighborhoods with 'High Risk' cases.

```
# Scatterplot of Cluster Labels

sns.scatterplot(x='Venues Qty',y='Cases per 100k',data=df_plot,hue='Cluster Labels')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55ba8150b8>
```



We can see then the classification by clusters that represent the healthcare precautions strictness for each risk group (cluster labels). It's intuitive to think that neighborhoods with a high avaliability of stores and low infection rate may present lower risks than the opposite scenario. It is noted as well that the clusters have their frontiers in a clear geospacial manner, but this probably represents the correlation between amount of venues, people transit and socioeconomic bias of each region, meaning that the relationship of geography is not of causation.

- Group 0: High Risk
- Group 1: Low Risk
- Group 2: Critical Risk
- Group 3: Average Risk

In summary, the results did not display abnormalities or an excessive amount of outliers. The data showed a rather clear clustering, indexed by the independent variables of the study. It's important to remember that K-means is an unsupervised alghoritm and should not be artificially labed. The previous results show a interpretation of the randomic data generated in this session.

Conclusion

Despite discarding an elevated amount of data due to string mismatching of geospacial data definitions and numeric data of pandemic, the model showed itself to clearly define well structured cluster labels, without evident outliers.

The ease of use of Foursquare API and Python's libraries allowed for an agile and assertive approach to such urgent and delicate problem. The complexity of the pandemic scenario which we live on is not denied, but the model could - simply - stabilish action response levels for the variety of healthcare solutions according to the social context of each neighborhood, where it could serve as a response guide, particularly to small towns that do not rely on a structured core of medical scientists.

Future refinement of this project involve better string comparison tools for merging different sourced datasets and inclusion of other variables to the predicted model.

```
1
```