SneakerStoresNYC

July 1, 2020

1 Sneaker Stores in NYC

1.0.1 Introduction/Business Problem

This final project explores the best locations for new sneaker and lifestyle stores throughout the streets of New York City. New York is a major metropolitan area with more than 8.4 million (Quick Facts, 2018) inhabitants. Its the largest city in the US with a long history of international immigration and style innovation for the whole world. As Jay-Z and Alicia Keys once put it, if you can make it here, you can make it everywhere. In 2017, the total global sneakers market was valued at approximately 62.5 billion U.S. dollars and was forecast to reach a value of 97.8 billion U.S. dollars by 2024. (https://www.statista.com/statistics/1017918/sneakers-market-value-forecast-worldwide/)

Since the competion is very high, the project aims to answer the question where are good locations to open a new sneaker store and what kind of target audience and clients can be expected. We also will try to answer the question if the store should be a classical retail store or a resell aka commission based to store.

1.0.2 Data section

For this project we use the New Zork citz data used in the previous weeks. This contains the following: 1. New York City data that contains Borough, Neighborhoods along with there latitudes and longitudes - Data Source: https://cocl.us/new_york_dataset - Description: This data set contains the required information. And we will use this data set to explore various neighborhoods of new york city.

2. Sneaker and fashion retails store in Manhatten and Brooklyn (NYC).
    - Data Source: Foursquare API
    - Description: By using this API we will get all the venues in Queens neighborhood. We can filter these venues to get only Indian restaurants.

1.0.3 Approach

Approach Collect the new york city data from https://cocl.us/new_york_dataset * Using Foursquare API we will get all venues for each neighborhood. * Filter out all venues which are sneaker and fashion related. * Data Visualization and some statistical analysis. * Analysing using Clustering (Specially K-Means): 1. Find the best value of K 2. Visualize the neighborhood with number of Indian Restaurants. * Compare the Neighborhoods to Find the Best Place for Starting up a Restaurant * Inference From these Results and related Conclusions

1.0.4 Libaries

[4]:
```
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␣
↪completed the Foursquare API lab
from geopy.geocoders import Nominatim # convert an address into latitude and␣
↪longitude values

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

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

# 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␣
↪haven't completed the Foursquare API lab
import folium # map rendering library

print('Libraries imported.')
```

```
Libraries imported.
```

1.0.5 Download Data

[5]:
```
!wget -q -O 'newyork_data.json' https://cocl.us/new_york_dataset
print('Data downloaded!')
with open('newyork_data.json') as json_data:
    newyork_data = json.load(json_data)
```

```
Data downloaded!
```

1.0.6 Transform to DataFrame

[6]:
```
neighborhoods_data = newyork_data['features']
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']
neighborhoods = pd.DataFrame(columns=column_names)
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_index=True)

manhattan_data = neighborhoods[neighborhoods['Borough'] == 'Manhattan'].
 ↪reset_index(drop=True)
manhattan_data.head()
```

[6]:

	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

1.0.7 Location Data

[7]:
```
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,␣
 ↪longitude))
```

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

1.0.8 Create a map of New York with neighborhoods superimposed on top.

[8]:
```
# 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'], 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_manhattan)

map_manhattan
```

[8]:
```
<folium.folium.Map at 0x7f179208b4a8>
```

1.0.9 Foursqure Data

[9]:
```
CLIENT_ID = 'I3LSPZJQ13UVYQPGCIABQUPMLL1HU35WL3Y3IU3AFSCVCSHO' # your␣
↪Foursquare ID
CLIENT_SECRET = 'KTOWTE2HOIRPDYPFKPFACFZ5CF4QABRP400TY002ZXNYBVWR' # your␣
↪Foursquare Secret
VERSION = '20200605' # Foursquare API version

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

```
Your credentails:
CLIENT_ID: I3LSPZJQ13UVYQPGCIABQUPMLL1HU35WL3Y3IU3AFSCVCSHO
CLIENT_SECRET:KTOWTE2HOIRPDYPFKPFACFZ5CF4QABRP400TY002ZXNYBVWR
```

1.0.10 Process Manhatten Neighborhood Data

[10]:
```
manhattan_data.loc[0, 'Neighborhood']
neighborhood_latitude = manhattan_data.loc[0, 'Latitude'] # neighborhood␣
↪latitude value
neighborhood_longitude = manhattan_data.loc[0, 'Longitude'] # neighborhood␣
↪longitude value
neighborhood_name = manhattan_data.loc[0, 'Neighborhood'] # neighborhood name
```

[11]:
```python
# type your answer here
LIMIT = 200
radius = 500

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={}&v={}&ll={},{}&radius={}&limit={}'.format(
            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_list])
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)

manhattan_venues = getNearbyVenues(names=manhattan_data['Neighborhood'],
```

```python
                                    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
```

[12]:

```python
# one hot encoding
```

```
manhattan_onehot = pd.get_dummies(manhattan_venues[['Venue Category']],␣
↪prefix="", prefix_sep="")

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

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

manhattan_onehot.head()

manhattan_onehot = manhattan_onehot[['Neighborhood','Shoe Store','Sporting␣
↪Goods Shop','Bank']]
```

[13]:
```
manhattan_grouped = manhattan_onehot.groupby('Neighborhood').mean().
↪reset_index()
manhattan_grouped.head()
```

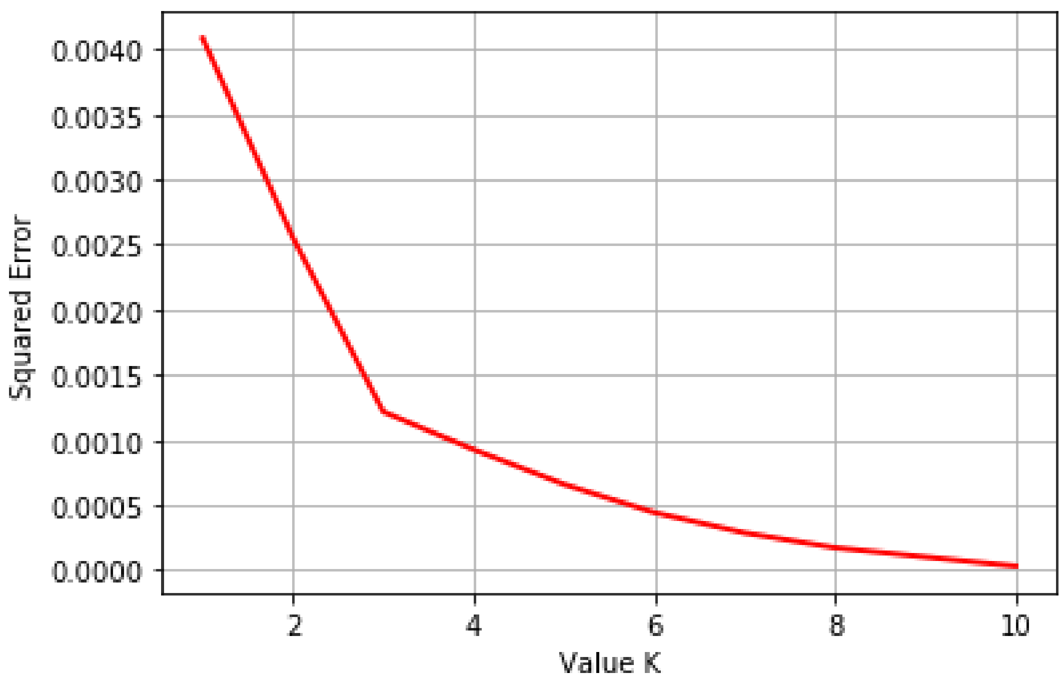
[13]:

	Neighborhood	Shoe Store	Sporting Goods Shop	Bank
0	Battery Park City	0.000000	0.0	0.000000
1	Carnegie Hill	0.011494	0.0	0.011494
2	Central Harlem	0.000000	0.0	0.000000
3	Chelsea	0.010000	0.0	0.000000
4	Chinatown	0.010000	0.0	0.000000

1.0.11 Some Clustering

[14]:
```
manhattan_grouped_clustering = manhattan_grouped.drop('Neighborhood', 1)
cost=[]
for i in range(1,11):
    KM = KMeans(n_clusters = i, max_iter = 500)
    KM.fit(manhattan_grouped_clustering)
    cost.append(KM.inertia_)

plt.plot(range(1,11), cost, color='r', linewidth='2')
plt.xlabel('Value K')
plt.ylabel('Squared Error')
plt.grid()
plt.show()
```



From the above image we see that best value of K will be 3 according to Elbow method.

We will merge above table with our New York dataframe so that we will get coordinates of all neighborhoods.

[15]:
```
def return_most_common_venues(row, num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)

    return row_categories_sorted.index.values[0:num_top_venues]
```

[16]:
```
num_top_venues = 3

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['Neighborhood']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
```

```
neighborhoods_venues_sorted['Neighborhood'] = manhattan_grouped['Neighborhood']

for ind in np.arange(manhattan_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] =␣
 ↪return_most_common_venues(manhattan_grouped.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

[16]:
```
        Neighborhood 1st Most Common Venue 2nd Most Common Venue  \
0  Battery Park City                  Bank   Sporting Goods Shop
1      Carnegie Hill                  Bank            Shoe Store
2     Central Harlem                  Bank   Sporting Goods Shop
3            Chelsea            Shoe Store                  Bank
4          Chinatown            Shoe Store                  Bank

  3rd Most Common Venue
0            Shoe Store
1   Sporting Goods Shop
2            Shoe Store
3   Sporting Goods Shop
4   Sporting Goods Shop
```

[17]:
```
# set number of clusters
kclusters = 3

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).
 ↪fit(manhattan_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

[17]:
```
array([0, 2, 0, 0, 0, 1, 1, 0, 0, 0], dtype=int32)
```

[18]:
```
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)
manhattan_merged = manhattan_data.copy()
manhattan_merged = manhattan_merged.join(neighborhoods_venues_sorted.
 ↪set_index('Neighborhood'), on='Neighborhood')
manhattan_merged = manhattan_merged.join(manhattan_grouped.
 ↪set_index('Neighborhood'), on='Neighborhood')
manhattan_merged.head()
```

[18]:
```
     Borough        Neighborhood   Latitude  Longitude  Cluster Labels  \
0  Manhattan         Marble Hill  40.876551 -73.910660               0
1  Manhattan           Chinatown  40.715618 -73.994279               0
2  Manhattan  Washington Heights  40.851903 -73.936900               2
3  Manhattan              Inwood  40.867684 -73.921210               0
```

```
4  Manhattan    Hamilton Heights  40.823604 -73.949688             2

  1st Most Common Venue 2nd Most Common Venue 3rd Most Common Venue  \
0                  Bank   Sporting Goods Shop            Shoe Store
1            Shoe Store                  Bank   Sporting Goods Shop
2                  Bank   Sporting Goods Shop            Shoe Store
3                  Bank   Sporting Goods Shop            Shoe Store
4                  Bank   Sporting Goods Shop            Shoe Store

   Shoe Store  Sporting Goods Shop      Bank
0    0.000000             0.000000  0.000000
1    0.010000             0.000000  0.000000
2    0.011494             0.011494  0.022989
3    0.000000             0.000000  0.000000
4    0.000000             0.000000  0.016949
```

1.0.12 Visualize the three clusters

[19]:
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# 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 Labels']):
    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
```

[19]: <folium.folium.Map at 0x7f1791eeeb70>

1.1 Analyze the Clusters

Cluster 0

[20]:
```
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == 0, manhattan_merged.
 ↪columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

[20]:
```
           Neighborhood 1st Most Common Venue 2nd Most Common Venue  \
0            Marble Hill                  Bank   Sporting Goods Shop
1              Chinatown            Shoe Store                  Bank
3                 Inwood                  Bank   Sporting Goods Shop
6         Central Harlem                  Bank   Sporting Goods Shop
7            East Harlem                  Bank   Sporting Goods Shop
11      Roosevelt Island                  Bank   Sporting Goods Shop
12       Upper West Side            Shoe Store                  Bank
13        Lincoln Square                  Bank   Sporting Goods Shop
16           Murray Hill                  Bank   Sporting Goods Shop
17               Chelsea            Shoe Store                  Bank
18      Greenwich Village                  Bank   Sporting Goods Shop
19          East Village                  Bank   Sporting Goods Shop
20       Lower East Side                  Bank   Sporting Goods Shop
21               Tribeca                  Bank   Sporting Goods Shop
22          Little Italy                  Bank   Sporting Goods Shop
24          West Village                  Bank   Sporting Goods Shop
25      Manhattan Valley                  Bank   Sporting Goods Shop
26   Morningside Heights                  Bank   Sporting Goods Shop
28      Battery Park City                  Bank   Sporting Goods Shop
29    Financial District                  Bank   Sporting Goods Shop
31                  Noho                  Bank   Sporting Goods Shop
33        Midtown South                   Bank   Sporting Goods Shop
37       Stuyvesant Town                  Bank   Sporting Goods Shop
39          Hudson Yards                  Bank   Sporting Goods Shop

   3rd Most Common Venue  Shoe Store  Sporting Goods Shop  Bank
0             Shoe Store    0.000000                  0.0   0.0
1    Sporting Goods Shop    0.010000                  0.0   0.0
3             Shoe Store    0.000000                  0.0   0.0
6             Shoe Store    0.000000                  0.0   0.0
7             Shoe Store    0.000000                  0.0   0.0
11            Shoe Store    0.000000                  0.0   0.0
12   Sporting Goods Shop    0.011236                  0.0   0.0
13            Shoe Store    0.000000                  0.0   0.0
16            Shoe Store    0.000000                  0.0   0.0
17   Sporting Goods Shop    0.010000                  0.0   0.0
18            Shoe Store    0.000000                  0.0   0.0
19            Shoe Store    0.000000                  0.0   0.0
20            Shoe Store    0.000000                  0.0   0.0
21            Shoe Store    0.000000                  0.0   0.0
22            Shoe Store    0.000000                  0.0   0.0
```

```
24           Shoe Store   0.000000            0.0  0.0
25           Shoe Store   0.000000            0.0  0.0
26           Shoe Store   0.000000            0.0  0.0
28           Shoe Store   0.000000            0.0  0.0
29           Shoe Store   0.000000            0.0  0.0
31           Shoe Store   0.000000            0.0  0.0
33           Shoe Store   0.000000            0.0  0.0
37           Shoe Store   0.000000            0.0  0.0
39           Shoe Store   0.000000            0.0  0.0
```

Cluster 1

[21]:
```
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == 1, manhattan_merged.
↪columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

[21]:
```
    Neighborhood 1st Most Common Venue 2nd Most Common Venue  \
10    Lenox Hill    Sporting Goods Shop                  Bank
14       Clinton    Sporting Goods Shop                  Bank
15       Midtown    Sporting Goods Shop            Shoe Store
23          Soho    Sporting Goods Shop                  Bank
32  Civic Center    Sporting Goods Shop                  Bank
38      Flatiron    Sporting Goods Shop                  Bank

   3rd Most Common Venue  Shoe Store  Sporting Goods Shop  Bank
10            Shoe Store        0.00                 0.02   0.0
14            Shoe Store        0.00                 0.01   0.0
15                  Bank        0.01                 0.02   0.0
23            Shoe Store        0.00                 0.01   0.0
32            Shoe Store        0.00                 0.02   0.0
38            Shoe Store        0.00                 0.02   0.0
```

Cluster 2

[22]:
```
manhattan_merged.loc[manhattan_merged['Cluster Labels'] == 2, manhattan_merged.
↪columns[[1] + list(range(5, manhattan_merged.shape[1]))]]
```

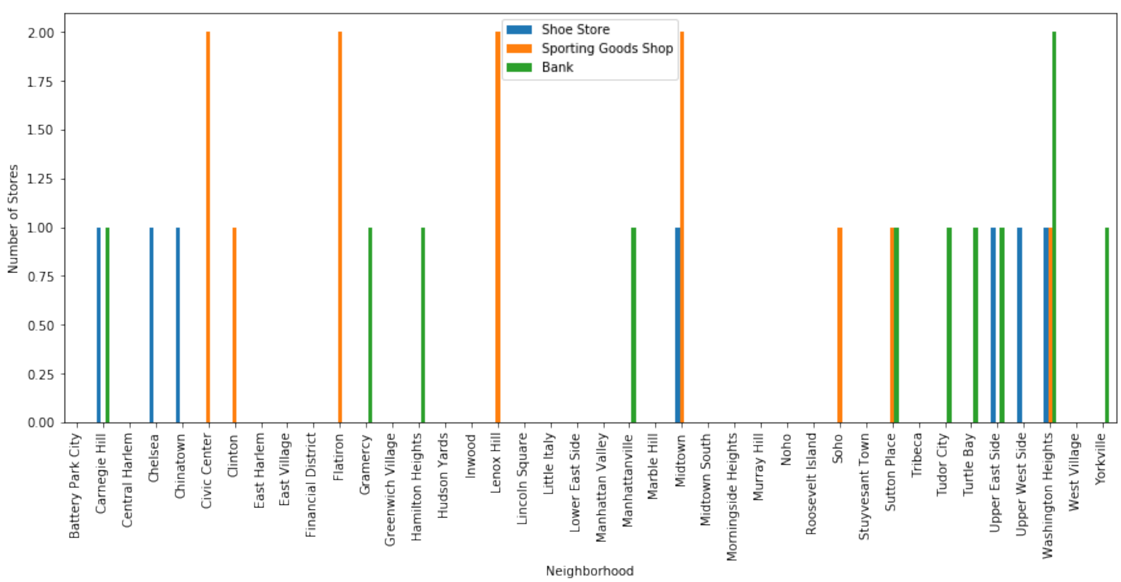
[22]:
```
          Neighborhood 1st Most Common Venue 2nd Most Common Venue  \
2   Washington Heights                  Bank   Sporting Goods Shop
4     Hamilton Heights                  Bank   Sporting Goods Shop
5       Manhattanville                  Bank   Sporting Goods Shop
8      Upper East Side                  Bank            Shoe Store
9            Yorkville                  Bank   Sporting Goods Shop
27            Gramercy                  Bank   Sporting Goods Shop
30       Carnegie Hill                  Bank            Shoe Store
34        Sutton Place                  Bank   Sporting Goods Shop
35          Turtle Bay                  Bank   Sporting Goods Shop
36          Tudor City                  Bank   Sporting Goods Shop
```

	3rd Most Common Venue	Shoe Store	Sporting Goods Shop	Bank
2	Shoe Store	0.011494	0.011494	0.022989
4	Shoe Store	0.000000	0.000000	0.016949
5	Shoe Store	0.000000	0.000000	0.023810
8	Sporting Goods Shop	0.011236	0.000000	0.011236
9	Shoe Store	0.000000	0.000000	0.010000
27	Shoe Store	0.000000	0.000000	0.011364
30	Sporting Goods Shop	0.011494	0.000000	0.011494
34	Shoe Store	0.000000	0.010000	0.010000
35	Shoe Store	0.000000	0.000000	0.010000
36	Shoe Store	0.000000	0.000000	0.013158

Some plotting

[23]:
```
graph = pd.DataFrame(manhattan_onehot.groupby('Neighborhood')['Shoe Store','Sporting Goods Shop','Bank'].sum())
#graph = graph.sort_values(by='Shoe Store', ascending=False)
graph.plot(kind='bar',figsize=(15,6))
plt.xlabel('Neighborhood')
plt.ylabel('Number of Stores')
plt.show()
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/ipykernel_launcher.py:1: FutureWarning: Indexing with multiple keys
(implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  """Entry point for launching an IPython kernel.
```



In the above picture we see that * not all neighborhoods have a sneaker or shoe store or a bank

* Midtown with a one shoe and two sporting shops has the most amount of shops * Washington Heights has the most number of banks

1.1.1 Results

The results of the exploratory data analysis and clustering is summarized below : 1. Midtown has the highest density of sneaker shops 2. Washington Heights has the most number of banks 3. Cluster 0 neighborhoods have the least number of shoe shops 4. Opening a restaurant would most likely be a good idea in a neighborhood with a lot of banks and many clients and not so many shoe shops, for example Upper East side

1.1.2 Discussion

It is hard to tell where to open a sneaker shop. The data provides a first glimpse. But some more correlation analysis would be required to figure out the ideal location.

Some drawbacks of analysis are: the clustering is completely based on the data provided by Foursquare API. Since land price, the distance of venues from the closest station, the number of potential customers, could all play a major role and thus, this analysis is definitely far from being conclusory. However, it definitely gives us some very important preliminary information on the possibilities of opening a high fashion and sneaker store in Manhattan.

1.1.3 Conlcusion and Course Remarks

To conclude this project, I liek to comment of the nature of such a real-life data science project. We applied some frequently used python libraries to handle JSON file, plotting graphs, and other exploratory data analysis. Using the Foursquare API to major boroughs of New York City and the neighborhoods in Manhattan. This is suitable for real-life business problems. Also, some of the drawbacks and chances for improvements to represent even more realistic pictures are mentioned. As a final note, all of the above analyses is depended on the adequacy and accuracy of Foursquare data. A more comprehensive analysis and future work would need to incorporate data from other external databases.