Capstone Project: Battle of the Neighborhoods

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by Pete Gil

Introduction

An eager venture capitalist is interested in investing into a hot new restaurant in Brooklyn, NY. This will be a new construction and investment. This will initially focus on finding the best neighborhood based on the number of restaurants within a neighborhood.

The data will come from a public New York City source and will focus on the borough of Brooklyn. Foursquare data will also be integrated to get coordinates and venue info to establish a better idea in which what area in Brooklyn would be the best to invest in.

Data

Data used is from a public website for New York City. The data consists of all boroughs in New York City and their corresponding coordinates. In order to help solve the problem, data will be used to determine all data for the borough of Brooklyn and coordinates to use in conjunction with Foursquare data will use for extracting venue information.

Data source:

https://geo.nyu.edu/catalog/nyu_2451_34572

Pre-Processing

The pre-processing of the data was executed by pulling data from the original data source, merged into a Python data frame, and then integrated with Foursquare data to find venues to corresponding neighborhoods and coordinates. The final data set has neighborhood, coordinates, and venue information.

Importing data from source

Luckily, New York City dataset exists for free on the web. https://geo.nyu.edu/catalog/nyu_2451_34572

I downloaded the files and placed it on the server to import easier.

In [2]:
```
!wget -q -O 'newyork_data.json' https://ibm.box.com/shared/static/fbpwbovar71f8p5sgddm06cgipa2rxpe.json
print('Data downloaded!')
```

```
Data downloaded!
```

Load and explore the data

Next, let's load the data.

In [4]:
```
with open('newyork_data.json') as json_data:
    newyork_data = json.load(json_data)
```

Let's take a quick look at the data.

In [4]:
```
newyork_data
```

Out[4]:

```
{'type': 'FeatureCollection',
 'totalFeatures': 306,
 'features': [{'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]}},
  {'type': 'Feature',
   'id': 'nyu_2451_34572.2',
   'geometry': {'type': 'Point',
    'coordinates': [-73.82993910812398, 40.87429419303012]},
   'geometry_name': 'geom',
   'properties': {'name': 'Co-op City',
    'stacked': 2,
```


Importing data into a python dataframe

Tranform the data into a *pandas* dataframe

The next task is essentially transforming this data of nested Python dictionaries into a *pandas* dataframe. So let's start by creating an empty dataframe.

In [10]:
```
# define the dataframe columns
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']

# instantiate the dataframe
neighborhoods = pd.DataFrame(columns=column_names)
```

Take a look at the empty dataframe to confirm that the columns are as intended.

In [11]:
```
neighborhoods
```

Out[11]:

	Borough	Neighborhood	Latitude	Longitude

Then let's loop through the data and fill the dataframe one row at a time.

In [12]:
```
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)
```

Quickly examine the resulting dataframe.

In [13]:
```
neighborhoods.head()
```

Out[13]:

	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

Pre-Processing (cont'd)

Foursquare Data is pulled for further processing

Focused on Top 20 Venues in Brooklyn and created new dataframe for the venues

Now there's a dataframe with venue name and coordinates

Now, let's get the top 20 venues that are in Brooklyn within a radius of 500 meters.

First, let's create the GET request URL. Name your URL **url**.

In [21]:
```
# type your answer here
#<!-- The correct answer is:
LIMIT = 20 # limit of number of venues returned by Foursquare API
#-->

#<!--
radius = 500 # define radius
#-->

##\\ # create URL
url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={},{}&
radius={}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    neighborhood_latitude,
    neighborhood_longitude,
    radius,
    LIMIT)
url # display URL
#-->
```

Out[21]:
```
'https://api.foursquare.com/v2/venues/explore?&client_id=ORJ4K1W3IW3A50CGBGY3LY4SN0NMECQNSZJ2FN2M
2UHWIUFG&client_secret=B4IFZSJU4DRSW4Z2CG5RRF1DYM41NU2B04DFPBFSBHUSNH42&v=20180605&ll=40.62580106
5010656,-74.03062069353813&radius=500&limit=20'
```

In [22]:
```
results = requests.get(url).json()
results
```

Out[22]:
```
{'meta': {'code': 200, 'requestId': '5c1b1860f594df03ec9b713b'},
 'response': {'suggestedFilters': {'header': 'Tap to show:',
   'filters': [{'name': '$-$$$$', 'key': 'price'},
    {'name': 'Open now', 'key': 'openNow'}]},
  'headerLocation': 'Bay Ridge',
  'headerFullLocation': 'Bay Ridge, Brooklyn',
  'headerLocationGranularity': 'neighborhood',
  'totalResults': 92,
  'suggestedBounds': {'ne': {'lat': 40.63030106951066,
    'lng': -74.02470273356597},
   'sw': {'lat': 40.62130106051065, 'lng': -74.03653865351028}},
  'groups': [{'type': 'Recommended Places',
```

Before we proceed, let's borrow the **get_category_type** function from the Foursquare lab.

In [23]:
```
# 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']
```

Now we are ready to clean the json and structure it into a *pandas* dataframe.

In [24]:
```
venues = results['response']['groups'][0]['items']

nearby_venues = json_normalize(venues) # flatten JSON

# filter columns
filtered_columns = ['venue.name', 'venue.categories', 'venue.location.lat', 'venue.location.lng']
nearby_venues =nearby_venues.loc[:, filtered_columns]

# filter the category for each row
nearby_venues['venue.categories'] = nearby_venues.apply(get_category_type, axis=1)

# clean columns
nearby_venues.columns = [col.split(".")[-1] for col in nearby_venues.columns]

nearby_venues.head()
```

Out[24]:

	name	categories	lat	lng
0	Pilo Arts Day Spa and Salon	Spa	40.624748	-74.030591
1	Bagel Boy	Bagel Shop	40.627896	-74.029335
2	Cocoa Grinder	Juice Bar	40.623967	-74.030863
3	Pegasus Cafe	Breakfast Spot	40.623168	-74.031186
4	Ho' Brah Taco Joint	Taco Place	40.622960	-74.031371

In [25]:
```
#let's see how many venues returned
print('{} venues were returned by Foursquare.'.format(nearby_venues.shape[0]))
```

```
20 venues were returned by Foursquare.
```

Pre-Processing (cont'd)

Let's assign the corresponding neighborhoods in Brooklyn. Below is the dataframe with neighborhoods, venue, coordinates, venue category. Also, knowing a count of each neighborhood gives an idea of what we are working with.

In [28]:
```
#### Let's check the size of the resulting dataframe
print(brooklyn_venues.shape)
brooklyn_venues.head()
```

```
(1231, 7)
```

Out[28]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Bay Ridge	40.625801	-74.030621	Pilo Arts Day Spa and Salon	40.624748	-74.030591	Spa
1	Bay Ridge	40.625801	-74.030621	Bagel Boy	40.627896	-74.029335	Bagel Shop
2	Bay Ridge	40.625801	-74.030621	Cocoa Grinder	40.623967	-74.030863	Juice Bar
3	Bay Ridge	40.625801	-74.030621	Pegasus Cafe	40.623168	-74.031186	Breakfast Spot
4	Bay Ridge	40.625801	-74.030621	Ho' Brah Taco Joint	40.622960	-74.031371	Taco Place

Let's check how many venues were returned for each neighborhood

In [29]:
```
##Let's check how many venues were returned for each neighborhood
brooklyn_venues.groupby('Neighborhood').count()
```

Out[29]:

	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Neighborhood						
Bath Beach	20	20	20	20	20	20
Bay Ridge	20	20	20	20	20	20
Bedford Stuyvesant	20	20	20	20	20	20
Bensonhurst	20	20	20	20	20	20
Bergen Beach	6	6	6	6	6	6
Boerum Hill	20	20	20	20	20	20

Pre-Processing (cont'd)

Finally, we get total sum of restaurants for the kmeans ml experiment

In [41]:
```
# one hot encoding
brooklyn_onehot = pd.get_dummies(brooklyn_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
brooklyn_onehot['Neighborhood'] = brooklyn_venues['Neighborhood']

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

brooklyn_onehot.head()
```

Out[41]:

n / od ant	Spa	Spanish Restaurant	Sporting Goods Shop	Sports Bar	Steakhouse	Supermarket	Surf Spot	Sushi Restaurant	Taco Place	Taiwanese Restaurant	Tapas Restaurant	Tattoo Parlor
	1	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	1	0	0	0

And let's examine the new dataframe size.

In [43]:
```
brooklyn_onehot.shape
```

Out[43]: (1231, 220)

In [44]:
```
#let's group rows by neighborhood and by taking the mean of the frequency of occurrence of each c
ategory
brooklyn_grouped = brooklyn_onehot.groupby('Neighborhood').sum()
brooklyn_grouped
```

Out[44]:

rant	Used Bookstore	Varenyky restaurant	Vegetarian / Vegan Restaurant	Video Game Store	Video Store	Vietnamese Restaurant	Waterfront	Whisky Bar	Wine Bar	Wine Shop	Women's Store	Total Restaurants

Methodology

With all the pre-processing done, the kmeans machine learning algorithm and clustering on the dataframe is ready for execution. Five clusters were used to determine totals. The end results show Total Restaurants, Total Sum, and the cluster. The end results also show that the K5 cluster has the most restaurants.

In [46]:
```
# import k-means from clustering stage
from sklearn.cluster import KMeans

# run k-means clustering
kmeans = KMeans(n_clusters = 5, random_state = 0).fit(brooklyn_grouped)
```

In [47]:
```
means_df = pd.DataFrame(kmeans.cluster_centers_)
means_df.columns = brooklyn_grouped.columns
means_df.index = ['K1','K2','K3','K4','K5']
means_df['Total Sum'] = means_df.sum(axis = 1)
means_df.sort_values(axis = 0, by = ['Total Sum'], ascending=False)

#K5 shows as the best group
```

Out[47]:

	Yoga Studio	American Restaurant	Antique Shop	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	Auto Worksh
K5	0.375000	0.000000	-6.938894e-18	1.250000e-01	-1.734723e-18	1.387779e-17	-6.938894e-18	1.387779e-17	-6.938894e-18	-1.7347 18
K1	0.400000	0.533333	6.666667e-02	6.666667e-02	6.666667e-02	1.333333e-01	6.666667e-02	1.333333e-01	6.666667e-02	-3.4694 18
K4	0.454545	0.272727	9.090909e-02	-6.938894e-18	-3.469447e-18	9.090909e-02	1.818182e-01	9.090909e-02	-1.387779e-17	-3.4694 18
K3	0.083333	0.083333	-6.938894e-18	-6.938894e-18	-3.469447e-18	8.333333e-02	-6.938894e-18	1.666667e-01	8.333333e-02	-3.4694 18
K2	0.083333	0.250000	4.166667e-02	-6.938894e-18	-3.469447e-18	1.250000e-01	1.387779e-17	8.333333e-02	8.333333e-02	4.16666 02

Total Restaurants	Total Sum
7.500000	27.500000
6.533333	26.400000
3.545455	23.545455
4.000000	22.333333
1.458333	15.208333

Results

We can see what Neighborhoods belong to what Group/cluster from the kmeans experiment and also what Neighborhoods are in the Group 5

```
In [76]: #lets find a the group for each neighbourhood
neigh_summary = pd.DataFrame([brooklyn_grouped.index, 1 + kmeans.labels_]).T
neigh_summary.columns = ['Neighborhood', 'Group']
neigh_summary
```

Out[76]:

	Neighborhood	Group
0	Bath Beach	1
1	Bay Ridge	1
2	Bedford Stuyvesant	4
3	Bensonhurst	1
4	Bergen Beach	2
5	Boerum Hill	1
6	Borough Park	3
7	Brighton Beach	1
8	Broadway Junction	2
9	Brooklyn Heights	1
10	Brownsville	3
11	Bushwick	5
12	Canarsie	2
13	Carroll Gardens	4
14	City Line	3
15	Clinton Hill	1
16	Cobble Hill	1
17	Coney Island	2
18	Crown Heights	2
19	Cypress Hills	5
20	Ditmas Park	5

```
In [77]: neigh_summary[neigh_summary['Group'] == 5]
```

Out[77]:

	Neighborhood	Group
11	Bushwick	5
19	Cypress Hills	5
20	Ditmas Park	5
28	Flatbush	5
30	Fort Greene	5
56	Prospect Park South	5
62	South Side	5
64	Sunset Park	5

Results (cont'd)

Final results show kmeans, Total Restaurants, and Total Sum. The decision of the investment would likely focus on K5, K1, and K2. Between these three, you can invest on an area that has the least amount of restaurants (K2) or the most (K1, K5)

```
In [106]: brooklyn_final.head()
```

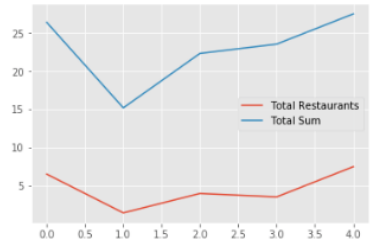
Out[106]:

	kmean	Total Restaurants	Total Sum
0	K1	6.533333	26.400000
1	K2	1.458333	15.208333
2	K3	4.000000	22.333333
3	K4	3.545455	23.545455
4	K5	7.500000	27.500000

Discussion

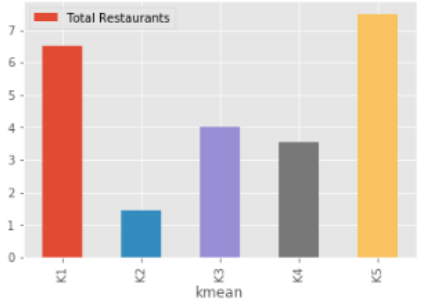
These charts show graphically where the results fall. The charts make the discussion of what cluster is the best to focus on for the new restaurant development. It's clear there are many choices - either the new development can focus on the cluster with the most or less totals.

```
In [92]: #let plot this data

         %matplotlib inline

         import matplotlib as mpl
         import matplotlib.pyplot as plt

         mpl.style.use('ggplot') # optional: for ggplot-like style
         print ('Matplotlib version: ', mpl.__version__) # >= 2.0.0

Matplotlib version:  3.0.2

In [108]: # plot bar chart
          lines = brooklyn_final.plot.line()
```




```
In [118]: # a scatter plot comparing num_children and num_pets
          brooklyn_final.plot(kind='line',x='kmean',y='Total Restaurants',color='red')
          plt.show()

          brooklyn_final.plot(kind='bar',x='kmean',y='Total Restaurants')
```


```
Out[118]: <matplotlib.axes._subplots.AxesSubplot at 0x7f60a14d5a90>
```



Conclusion

Final results show that the final decision of the investment would likely focus on K5, K1, and K2. Between these three, the investment will most likely not focus on an area that has the least amount of restaurants (K2), but with the most (K1, K5). The final recommendation would focus on these neighborhoods in K5.

	Neighborhood	Group
11	Bushwick	5
19	Cypress Hills	5
20	Ditmas Park	5
28	Flatbush	5
30	Fort Greene	5
56	Prospect Park South	5
62	South Side	5
64	Sunset Park	5