Capstone Project (3)

June 26, 2020

Determine similar neighborhoods from New York and Toronto

0.1 Table of contents

0.2 Introduction

Toronto and New York are both financial capitals in their respective countries. Many people travel between Toronto and New York often for business and family purposes. There are also many technology and software companies that have offices in both cities. For people who need to travel between these two cities, how should they decide which neighborhood of the city they should stay in? There are many studies and data that report different attributes of neighborhoods in each city but there are very few studies that show the similarity between Toronto and New York. The purpose of this study is to find out what neighborhoods are similar in Toronto and New York based on the types of venues around the neighborhoods.

0.3 Data

In order to analyze the similarity among all the neighborhoods in Toronto and New York, Foursquare Location data will be used to provide venues information in each cities by their neighborhoods. The data of neighborhoodsToronto neighborhoods coordinates is obtained from Wikipedia and the data of New York neighborhoods is obtained from NYU Spatial Data Repository.

The neighborhoods data will have the Neighborhood Names, postal codes and their Latitudes and Longitudes.

The venues data will contain Venues Names, Venues Category and their Latitudes and Longitudes.

Toronto Neighborhoods Data

We will form the Toronto neighborhoods data from the table on wikipedia page: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M

We will perform basic data cleaning by removing any Null values and grouping the neighborhoods by Borough

[47]:
```
import pandas as pd
import numpy as np
raw_wiki = pd.read_html("https://en.wikipedia.org/wiki/
↪List_of_postal_codes_of_Canada:_M")
wiki = pd.DataFrame(raw_wiki[0])
wiki.drop(wiki[wiki['Borough'] == 'Not assigned'].index, inplace=True)
wiki.rename(columns = {'Postal Code': 'PostalCode'}, inplace=True)
trt_neighborhoods = wiki.groupby('Borough').agg({'Neighborhood':', '.join}).
↪reset_index()
```

[48]:
```
trt_neighborhoods.head()
```

[48]:
```
            Borough                                       Neighborhood
0   Central Toronto  Lawrence Park, Roselawn, Davisville North, For…
1  Downtown Toronto  Regent Park, Harbourfront, Queen's Park, Ontar…
2      East Toronto  The Beaches, The Danforth West, Riverdale, Ind…
3         East York  Parkview Hill, Woodbine Gardens, Woodbine Heig…
4         Etobicoke  Islington Avenue, Humber Valley Village, West …
```

Next we will add coordinates to each set of Neighborhoods

[50]:
```
import json # library to handle JSON files

#!conda install -c conda-forge geopy
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
```

[51]:
```
Latitude = []
Longitude = []
geolocator = Nominatim(user_agent="ny_explorer")
for b in trt_neighborhoods['Borough']:
    address = b + ", Toronto"
    location = geolocator.geocode(address)
    Latitude.append(location.latitude)
    Longitude.append(location.longitude)


trt_neighborhoods['Latitude'] = Latitude
trt_neighborhoods['Longitude'] = Longitude
trt_neighborhoods
```

[51]:
```
            Borough                                       Neighborhood  \
0   Central Toronto  Lawrence Park, Roselawn, Davisville North, For…
```

```
1  Downtown Toronto  Regent Park, Harbourfront, Queen's Park, Ontar…
2      East Toronto  The Beaches, The Danforth West, Riverdale, Ind…
3         East York  Parkview Hill, Woodbine Gardens, Woodbine Heig…
4         Etobicoke  Islington Avenue, Humber Valley Village, West …
5       Mississauga              Canada Post Gateway Processing Centre
6        North York  Parkwoods, Victoria Village, Lawrence Manor, L…
7       Scarborough  Malvern, Rouge, Rouge Hill, Port Union, Highla…
8      West Toronto  Dufferin, Dovercourt Village, Little Portugal,…
9              York  Humewood-Cedarvale, Caledonia-Fairbanks, Del R…

    Latitude  Longitude
0  43.653482 -79.383935
1  43.654174 -79.380812
2  43.653482 -79.383935
3  43.699971 -79.332520
4  43.643556 -79.565633
5  43.678524 -79.629129
6  43.754326 -79.449117
7  43.773077 -79.257774
8  43.653482 -79.383935
9  43.689619 -79.479188
```

New York Neighborhoods Data

Now we need to perform the steps on data of neighborhoods in New York

[10]:
```
!wget -q -O 'newyork_data.json' https://cocl.us/new_york_dataset
```

[13]:
```
with open('newyork_data.json') as json_data:
    newyork_data = json.load(json_data)
neighborhoods_data = newyork_data['features']
```

[14]:
```
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']

# instantiate the dataframe
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)
```

Merge neighborhoods by Borough

[25]:
```
ny_neighborhoods = neighborhoods.groupby('Borough').agg({'Neighborhood':', '.
↪join}).reset_index()
ny_neighborhoods
```

[25]:
```
         Borough                                       Neighborhood
0          Bronx  Wakefield, Co-op City, Eastchester, Fieldston,…
1       Brooklyn  Bay Ridge, Bensonhurst, Sunset Park, Greenpoin…
2      Manhattan  Marble Hill, Chinatown, Washington Heights, In…
3         Queens  Astoria, Woodside, Jackson Heights, Elmhurst, …
4  Staten Island  St. George, New Brighton, Stapleton, Rosebank,…
```

Next we will add coordinates to each set of Neighborhoods

[157]:
```
Latitude = []
Longitude = []
geolocator = Nominatim(user_agent="ny_explorer")
for b in ny_neighborhoods['Borough']:
    address = b + ", NY"
    location = geolocator.geocode(address)
    Latitude.append(location.latitude)
    Longitude.append(location.longitude)
```

[158]:
```
ny_neighborhoods['Latitude'] = Latitude
ny_neighborhoods['Longitude'] = Longitude
```

[159]:
```
ny_neighborhoods
```

[159]:
```
         Borough                                       Neighborhood  \
0          Bronx  Wakefield, Co-op City, Eastchester, Fieldston,…
1       Brooklyn  Bay Ridge, Bensonhurst, Sunset Park, Greenpoin…
2      Manhattan  Marble Hill, Chinatown, Washington Heights, In…
3         Queens  Astoria, Woodside, Jackson Heights, Elmhurst, …
4  Staten Island  St. George, New Brighton, Stapleton, Rosebank,…

    Latitude  Longitude
0  40.846651 -73.878594
1  40.650104 -73.949582
2  40.789624 -73.959894
3  40.749824 -73.797634
4  40.583456 -74.149605
```

[160]:
```
neighborhoods_location = pd.concat([trt_neighborhoods, ny_neighborhoods])
neighborhoods_location.drop('Neighborhood', axis = 1, inplace=True)
neighborhoods_location.reset_index(drop=True)
```

[160]:

	Borough	Latitude	Longitude
0	Central Toronto	43.653482	-79.383935
1	Downtown Toronto	43.654174	-79.380812
2	East Toronto	43.653482	-79.383935
3	East York	43.699971	-79.332520
4	Etobicoke	43.643556	-79.565633
5	Mississauga	43.678524	-79.629129
6	North York	43.754326	-79.449117
7	Scarborough	43.773077	-79.257774
8	West Toronto	43.653482	-79.383935
9	York	43.689619	-79.479188
10	Bronx	40.846651	-73.878594
11	Brooklyn	40.650104	-73.949582
12	Manhattan	40.789624	-73.959894
13	Queens	40.749824	-73.797634
14	Staten Island	40.583456	-74.149605

Now that we have the data of Boroughs and neighborhoods in Toronto and New York, we will plot them on a map and review their distribution

[57]:
```
!pip install folium
import matplotlib.cm as cm
import matplotlib.colors as colors

import folium # map rendering library
```

```
Requirement already satisfied: folium in
/opt/conda/envs/Python36/lib/python3.6/site-packages (0.11.0)
Requirement already satisfied: branca>=0.3.0 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from folium) (0.4.1)
Requirement already satisfied: jinja2>=2.9 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from folium) (2.10)
Requirement already satisfied: requests in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from folium) (2.21.0)
Requirement already satisfied: numpy in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from folium) (1.15.4)
Requirement already satisfied: MarkupSafe>=0.23 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from jinja2>=2.9->folium)
(1.1.0)
Requirement already satisfied: idna<2.9,>=2.5 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from requests->folium)
(2.8)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from requests->folium)
```

```
(3.0.4)
Requirement already satisfied: urllib3<1.25,>=1.21.1 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from requests->folium)
(1.24.1)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/envs/Python36/lib/python3.6/site-packages (from requests->folium)
(2020.6.20)
```

[63]:
```
trt_location = [43.6532, -79.3832]

trt_map = folium.Map(location=trt_location, zoom_start=11)

# add markers to the map on each Borough
for lat, lon, neigh in zip(trt_neighborhoods['Latitude'],␣
↪trt_neighborhoods['Longitude'], trt_neighborhoods['Borough']):
    label = folium.Popup((str(neigh)), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        fill=True,
        fill_opacity=0.7).add_to(trt_map)
trt_map
```

[63]: `<folium.folium.Map at 0x7f8ce3701470>`

[64]:
```
ny_location = [40.7128, -74.0060]
ny_map = folium.Map(location=ny_location, zoom_start=11)
for lat, lon, neigh in zip(ny_neighborhoods['Latitude'],␣
↪ny_neighborhoods['Longitude'], ny_neighborhoods['Borough']):
    label = folium.Popup((str(neigh)), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        fill=True,
        fill_opacity=0.7).add_to(ny_map)
ny_map
```

[64]: `<folium.folium.Map at 0x7f8ce371b518>`

Toronto Venues Data

[65]:
```
CLIENT_ID = 'XWOIXYORH4AD3IOTCCRPITM25V04X3CROI1Q2TJQMBCXYS5G' # your␣
↪Foursquare ID
CLIENT_SECRET = 'VZ2RYOIVJMQZI3RHSCZG4CWPZNPVXUGI2MGZFF1HCNJG3JGB' # your␣
↪Foursquare Secret
VERSION = '20200626' # Foursquare API version
```

```
LIMIT = 100
```

[66]:
```
import json

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

[70]:
```
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        # 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 = ['Borough',
                  'Borough Latitude',
                  'Borough Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

[71]:
```
trt_venues = getNearbyVenues(names=trt_neighborhoods['Borough'],
                                   latitudes=trt_neighborhoods['Latitude'],
                                   longitudes=trt_neighborhoods['Longitude']
                                  )
trt_venues.head()
```

[71]:
```
           Borough  Borough Latitude  Borough Longitude  \
0  Central Toronto         43.653482         -79.383935
1  Central Toronto         43.653482         -79.383935
2  Central Toronto         43.653482         -79.383935
3  Central Toronto         43.653482         -79.383935
4  Central Toronto         43.653482         -79.383935

                      Venue  Venue Latitude  Venue Longitude   Venue Category
0          Downtown Toronto       43.653232       -79.385296     Neighborhood
1    Nathan Phillips Square       43.652270       -79.383516            Plaza
2                Chatime       43.655542       -79.384684  Bubble Tea Shop
3  Textile Museum of Canada       43.654396       -79.386500       Art Museum
4                    Indigo       43.653515       -79.380696        Bookstore
```

Let's perform the same steps on new york neighborhoods data

[72]:
```
ny_venues = getNearbyVenues(names=ny_neighborhoods['Borough'],
                                   latitudes=ny_neighborhoods['Latitude'],
                                   longitudes=ny_neighborhoods['Longitude']
                                  )
ny_venues.head()
```

[72]:
```
  Borough  Borough Latitude  Borough Longitude                 Venue  \
0   Bronx         40.846651         -73.878594           JungleWorld
1   Bronx         40.846651         -73.878594         African Lions
2   Bronx         40.846651         -73.878594  Congo Gorilla Forest
3   Bronx         40.846651         -73.878594         Giraffe House
4   Bronx         40.846651         -73.878594        Grizzly Corner

   Venue Latitude  Venue Longitude Venue Category
0       40.845227       -73.877181            Zoo
1       40.847058       -73.878024    Zoo Exhibit
2       40.847774       -73.881604            Zoo
3       40.847875       -73.880127    Zoo Exhibit
4       40.849023       -73.877739    Zoo Exhibit
```

Analyze each Borough in Toronto and New York and convert venue Category to a categorical variable

[73]:
```
# one hot encoding
trt_onehot = pd.get_dummies(trt_venues[['Venue Category']], prefix="",␣
 ↪prefix_sep="")
```

```
# add borough column back to dataframe
trt_onehot['Borough'] = trt_venues['Borough']
# move neighborhood column to the first column
fixed_columns = [trt_onehot.columns[-1]] + list(trt_onehot.columns[:-1])
trt_borough = trt_onehot[fixed_columns]

trt_borough.head()
```

[73]:

```
           Borough  Airport  Airport Terminal  American Restaurant  \
0  Central Toronto        0                 0                    0
1  Central Toronto        0                 0                    0
2  Central Toronto        0                 0                    0
3  Central Toronto        0                 0                    0
4  Central Toronto        0                 0                    0

   Art Gallery  Art Museum  Bakery  Bank  Bar  Bookstore  …  Tanning Salon  \
0            0           0       0     0    0          0  …              0
1            0           0       0     0    0          0  …              0
2            0           0       0     0    0          0  …              0
3            0           1       0     0    0          0  …              0
4            0           0       0     0    0          1  …              0

   Tea Room  Thai Restaurant  Theater  Toy / Game Store  \
0         0                0        0                 0
1         0                0        0                 0
2         0                0        0                 0
3         0                0        0                 0
4         0                0        0                 0

   Vegetarian / Vegan Restaurant  Video Game Store  Vietnamese Restaurant  \
0                              0                 0                      0
1                              0                 0                      0
2                              0                 0                      0
3                              0                 0                      0
4                              0                 0                      0

   Wine Shop  Women's Store
0          0              0
1          0              0
2          0              0
3          0              0
4          0              0

[5 rows x 93 columns]
```

[74]:

```
# one hot encoding
```

```
ny_onehot = pd.get_dummies(ny_venues[['Venue Category']], prefix="",␣
↪prefix_sep="")
# add borough column back to dataframe
ny_onehot['Borough'] = ny_venues['Borough']
# move neighborhood column to the first column
fixed_columns = [ny_onehot.columns[-1]] + list(ny_onehot.columns[:-1])
ny_borough = ny_onehot[fixed_columns]

ny_borough.head()
```

[74]:

```
  Borough  Athletics & Sports  Bakery  Bank  Baseball Field  \
0   Bronx                   0       0     0               0
1   Bronx                   0       0     0               0
2   Bronx                   0       0     0               0
3   Bronx                   0       0     0               0
4   Bronx                   0       0     0               0

   Bike Rental / Bike Share  Bike Trail  Boat or Ferry  Burger Joint  \
0                         0           0              0             0
1                         0           0              0             0
2                         0           0              0             0
3                         0           0              0             0
4                         0           0              0             0

   Bus Line  …  Souvenir Shop  Sports Club  Tennis Court  Theater  \
0         0  …              0            0             0        0
1         0  …              0            0             0        0
2         0  …              0            0             0        0
3         0  …              0            0             0        0
4         0  …              0            0             0        0

   Theme Park  Theme Park Ride / Attraction  Trail  Yoga Studio  Zoo  \
0           0                             0      0            0    1
1           0                             0      0            0    0
2           0                             0      0            0    1
3           0                             0      0            0    0
4           0                             0      0            0    0

   Zoo Exhibit
0            0
1            1
2            0
3            1
4            1

[5 rows x 54 columns]
```

Next, let's group rows by taking the mean of the frequency of occurrence of each category for each Borough. We will use the mean value as the main factor to evaluate similarity

[77]:
```
trt_mean = trt_borough.groupby('Borough').mean().reset_index()
trt_mean
```

[77]:
```
           Borough  Airport  Airport Terminal  American Restaurant  \
0  Central Toronto      0.0               0.0             0.013514
1 Downtown Toronto      0.0               0.0             0.010417
2     East Toronto      0.0               0.0             0.013514
3        East York      0.0               0.0             0.000000
4        Etobicoke      0.0               0.0             0.000000
5      Mississauga      0.6               0.4             0.000000
6       North York      0.0               0.0             0.000000
7      Scarborough      0.0               0.0             0.023256
8     West Toronto      0.0               0.0             0.013514
9             York      0.0               0.0             0.000000

   Art Gallery  Art Museum    Bakery      Bank       Bar  Bookstore  …  \
0     0.000000    0.013514  0.000000  0.013514  0.000000   0.013514  …
1     0.010417    0.010417  0.000000  0.010417  0.020833   0.010417  …
2     0.000000    0.013514  0.000000  0.013514  0.000000   0.013514  …
3     0.000000    0.000000  0.000000  0.000000  0.000000   0.000000  …
4     0.000000    0.000000  0.000000  0.000000  0.000000   0.000000  …
5     0.000000    0.000000  0.000000  0.000000  0.000000   0.000000  …
6     0.000000    0.000000  0.000000  0.000000  0.000000   0.000000  …
7     0.000000    0.000000  0.023256  0.023256  0.023256   0.000000  …
8     0.000000    0.013514  0.000000  0.013514  0.000000   0.013514  …
9     0.000000    0.000000  0.000000  0.000000  0.000000   0.000000  …

   Tanning Salon  Tea Room  Thai Restaurant   Theater  Toy / Game Store  \
0       0.013514  0.013514         0.027027  0.027027          0.000000
1       0.020833  0.010417         0.010417  0.020833          0.000000
2       0.013514  0.013514         0.027027  0.027027          0.000000
3       0.000000  0.000000         0.000000  0.000000          0.000000
4       0.000000  0.000000         0.000000  0.000000          0.000000
5       0.000000  0.000000         0.000000  0.000000          0.000000
6       0.000000  0.000000         0.000000  0.000000          0.000000
7       0.000000  0.046512         0.000000  0.000000          0.023256
8       0.013514  0.013514         0.027027  0.027027          0.000000
9       0.000000  0.000000         0.000000  0.000000          0.000000

   Vegetarian / Vegan Restaurant  Video Game Store  Vietnamese Restaurant  \
0                       0.013514          0.013514               0.013514
1                       0.000000          0.010417               0.010417
2                       0.013514          0.013514               0.013514
3                       0.000000          0.000000               0.000000
```

```
4                       0.000000          0.000000               0.000000
5                       0.000000          0.000000               0.000000
6                       0.000000          0.000000               0.000000
7                       0.000000          0.023256               0.000000
8                       0.013514          0.013514               0.013514
9                       0.000000          0.000000               0.000000

   Wine Shop  Women's Store
0   0.000000       0.013514
1   0.000000       0.010417
2   0.000000       0.013514
3   0.000000       0.000000
4   0.000000       0.000000
5   0.000000       0.000000
6   0.000000       0.000000
7   0.000000       0.000000
8   0.000000       0.013514
9   0.166667       0.000000

[10 rows x 93 columns]
```

[112]:
```python
ny_mean = ny_borough.groupby('Borough').mean().reset_index()
ny_mean
```

[112]:
```
         Borough  Athletics & Sports    Bakery      Bank  Baseball Field  \
0          Bronx            0.000000  0.000000  0.000000        0.000000
1       Brooklyn            0.000000  0.037037  0.037037        0.000000
2      Manhattan            0.064516  0.000000  0.000000        0.225806
3         Queens            0.000000  0.000000  0.000000        0.000000
4  Staten Island            0.000000  0.000000  0.000000        0.000000

   Bike Rental / Bike Share  Bike Trail  Boat or Ferry  Burger Joint  \
0                  0.000000    0.000000       0.000000      0.037037
1                  0.000000    0.000000       0.000000      0.000000
2                  0.032258    0.000000       0.000000      0.000000
3                  0.000000    0.166667       0.166667      0.000000
4                  0.000000    0.000000       0.000000      0.000000

   Bus Line  …  Souvenir Shop  Sports Club  Tennis Court   Theater  \
0  0.000000  …       0.037037     0.000000      0.000000  0.037037
1  0.037037  …       0.000000     0.000000      0.000000  0.000000
2  0.000000  …       0.000000     0.000000      0.032258  0.000000
3  0.000000  …       0.000000     0.166667      0.000000  0.000000
4  0.000000  …       0.000000     0.000000      0.000000  0.000000

   Theme Park  Theme Park Ride / Attraction  Trail  Yoga Studio       Zoo  \
0    0.037037                      0.037037    0.0     0.000000  0.111111
```

```
1     0.000000                          0.000000    0.0     0.037037  0.000000
2     0.000000                          0.000000    0.0     0.000000  0.000000
3     0.000000                          0.000000    0.0     0.000000  0.000000
4     0.000000                          0.000000    0.5     0.000000  0.000000

   Zoo Exhibit
0     0.259259
1     0.000000
2     0.000000
3     0.000000
4     0.000000

[5 rows x 54 columns]
```

Finally, let's merge both New York and Toronto venues data into one data frame in preparation of model building in the next step.

[122]:
```python
borough = pd.concat([ny_mean, trt_mean],sort=False)
borough.fillna(0,inplace=True)
borough.reset_index(drop=True)
```

[122]:
```
             Borough  Athletics & Sports    Bakery      Bank  Baseball Field  \
0              Bronx            0.000000  0.000000  0.000000        0.000000
1           Brooklyn            0.000000  0.037037  0.037037        0.000000
2          Manhattan            0.064516  0.000000  0.000000        0.225806
3             Queens            0.000000  0.000000  0.000000        0.000000
4      Staten Island            0.000000  0.000000  0.000000        0.000000
5    Central Toronto            0.000000  0.000000  0.013514        0.000000
6   Downtown Toronto            0.000000  0.000000  0.010417        0.000000
7       East Toronto            0.000000  0.000000  0.013514        0.000000
8          East York            0.000000  0.000000  0.000000        0.000000
9          Etobicoke            0.000000  0.000000  0.000000        0.000000
10       Mississauga            0.000000  0.000000  0.000000        0.000000
11        North York            0.000000  0.000000  0.000000        0.000000
12       Scarborough            0.000000  0.023256  0.023256        0.000000
13      West Toronto            0.000000  0.000000  0.013514        0.000000
14              York            0.000000  0.000000  0.000000        0.000000

    Bike Rental / Bike Share  Bike Trail  Boat or Ferry  Burger Joint  \
0                   0.000000    0.000000       0.000000      0.037037
1                   0.000000    0.000000       0.000000      0.000000
2                   0.032258    0.000000       0.000000      0.000000
3                   0.000000    0.166667       0.166667      0.000000
4                   0.000000    0.000000       0.000000      0.000000
5                   0.000000    0.000000       0.000000      0.000000
6                   0.000000    0.000000       0.000000      0.000000
7                   0.000000    0.000000       0.000000      0.000000
```

```
8                    0.000000    0.000000       0.000000      0.000000
9                    0.000000    0.000000       0.000000      0.000000
10                   0.000000    0.000000       0.000000      0.000000
11                   0.000000    0.000000       0.000000      0.000000
12                   0.000000    0.000000       0.000000      0.000000
13                   0.000000    0.000000       0.000000      0.000000
14                   0.000000    0.000000       0.000000      0.000000

    Bus Line  …  Sushi Restaurant  Tanning Salon  Tea Room  Thai Restaurant  \
0   0.000000  …          0.000000       0.000000  0.000000         0.000000
1   0.037037  …          0.000000       0.000000  0.000000         0.000000
2   0.000000  …          0.000000       0.000000  0.000000         0.000000
3   0.000000  …          0.000000       0.000000  0.000000         0.000000
4   0.000000  …          0.000000       0.000000  0.000000         0.000000
5   0.000000  …          0.013514       0.013514  0.013514         0.027027
6   0.000000  …          0.010417       0.020833  0.010417         0.010417
7   0.000000  …          0.013514       0.013514  0.013514         0.027027
8   0.000000  …          0.000000       0.000000  0.000000         0.000000
9   0.000000  …          0.000000       0.000000  0.000000         0.000000
10  0.000000  …          0.000000       0.000000  0.000000         0.000000
11  0.000000  …          0.000000       0.000000  0.000000         0.000000
12  0.000000  …          0.000000       0.000000  0.046512         0.000000
13  0.000000  …          0.013514       0.013514  0.013514         0.027027
14  0.000000  …          0.000000       0.000000  0.000000         0.000000

    Toy / Game Store  Vegetarian / Vegan Restaurant  Video Game Store  \
0           0.000000                       0.000000          0.000000
1           0.000000                       0.000000          0.000000
2           0.000000                       0.000000          0.000000
3           0.000000                       0.000000          0.000000
4           0.000000                       0.000000          0.000000
5           0.000000                       0.013514          0.013514
6           0.000000                       0.000000          0.010417
7           0.000000                       0.013514          0.013514
8           0.000000                       0.000000          0.000000
9           0.000000                       0.000000          0.000000
10          0.000000                       0.000000          0.000000
11          0.000000                       0.000000          0.000000
12          0.023256                       0.000000          0.023256
13          0.000000                       0.013514          0.013514
14          0.000000                       0.000000          0.000000

    Vietnamese Restaurant  Wine Shop  Women's Store
0                0.000000   0.000000       0.000000
1                0.000000   0.000000       0.000000
2                0.000000   0.000000       0.000000
3                0.000000   0.000000       0.000000
```

```
4                  0.000000   0.000000       0.000000
5                  0.013514   0.000000       0.013514
6                  0.010417   0.000000       0.010417
7                  0.013514   0.000000       0.013514
8                  0.000000   0.000000       0.000000
9                  0.000000   0.000000       0.000000
10                 0.000000   0.000000       0.000000
11                 0.000000   0.000000       0.000000
12                 0.000000   0.000000       0.000000
13                 0.013514   0.000000       0.013514
14                 0.000000   0.166667       0.000000

[15 rows x 130 columns]
```

At this stage, we have cleaned the location data for both cities as well as mean of the frequency of each type of venue in each Borough. We are ready to move to the model building stage.

0.4 Methodology

To determine what boroughs are similar to each other in Toronto and New York, we will use one of the most popular unsupervised machine learning clustering algorithsm **KMeans** to group the data into different categories.

Since we do not know how many groups we should assign the boroughs to, we will use the **Elbow Method** of KMeans to determine the optimal clustering methods

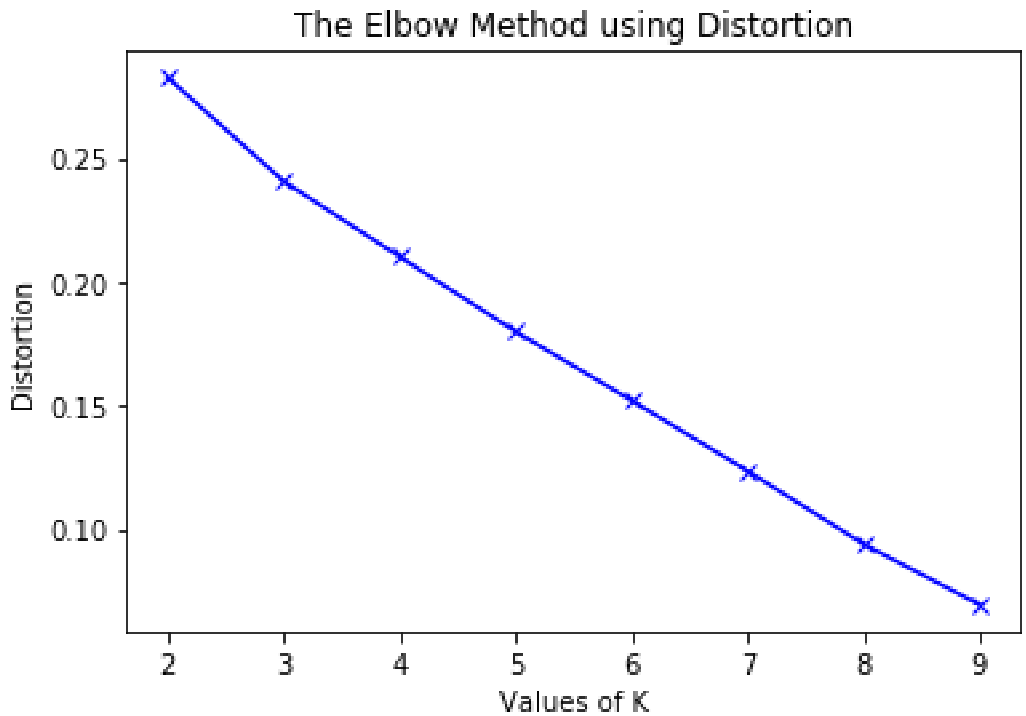
0.5 Analysis

[124]:
```
borough_mean = borough.drop('Borough', axis =1)
```

[126]:
```
from sklearn.cluster import KMeans
from sklearn import metrics
from scipy.spatial.distance import cdist
import numpy as np
import matplotlib.pyplot as plt
distortions = []
inertias = []
mapping1 = {}
mapping2 = {}
K = range(2,10)

for k in K:
    #Building and fitting the model
    kmeanModel = KMeans(n_clusters=k).fit(borough_mean)

    distortions.append(sum(np.min(cdist(borough_mean, kmeanModel.
 ↪cluster_centers_,
                         'euclidean'),axis=1)) / borough_mean.shape[0])
```

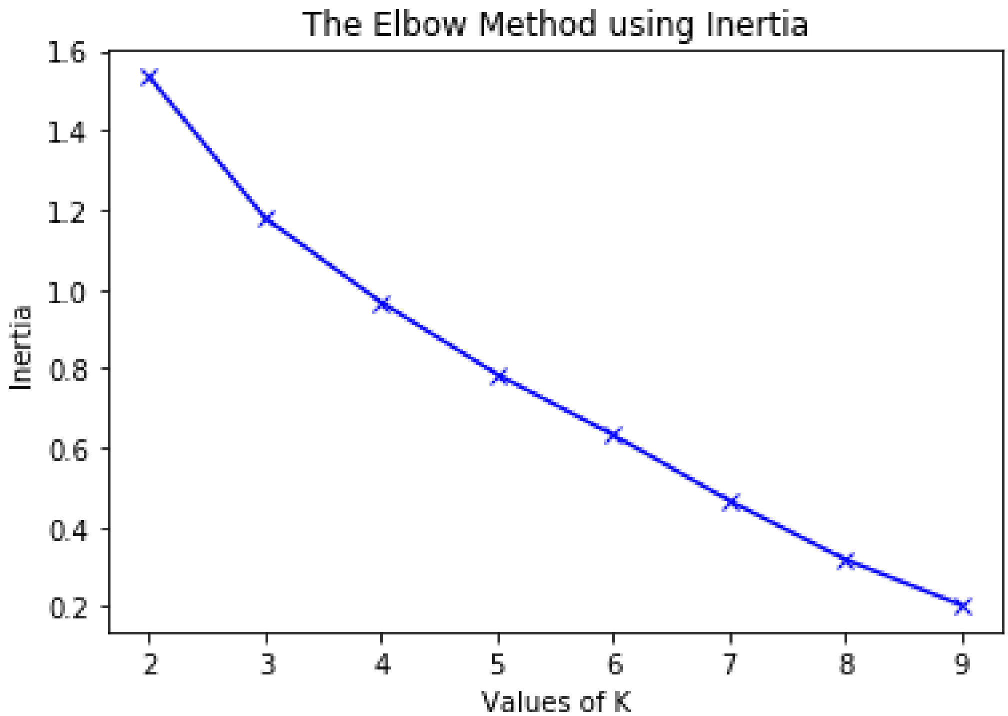
```
    inertias.append(kmeanModel.inertia_)

    mapping1[k] = sum(np.min(cdist(borough_mean, kmeanModel.cluster_centers_,
                 'euclidean'),axis=1)) / borough_mean.shape[0]
    mapping2[k] = kmeanModel.inertia_
```

[127]:
```
plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```



It is not obvious what the optimal K is. Let's try with a different evaluator

[128]:
```
plt.plot(K, inertias, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```



Observing the two plots above, we can say that **k=3** is the optimal groupings for our data.

[134]:
```
kmeanModel = KMeans(n_clusters=3).fit(borough_mean)
```

[135]:
```
kmeanModel.labels_
```

[135]:
```
array([0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int32)
```

[136]:
```
borough.insert(0, 'Cluster Labels', kmeanModel.labels_)
```

[137]:
```
borough
```

[137]:
```
   Cluster Labels            Borough  Athletics & Sports    Bakery      Bank  \
0               0              Bronx            0.000000  0.000000  0.000000
1               0           Brooklyn            0.000000  0.037037  0.037037
2               0          Manhattan            0.064516  0.000000  0.000000
3               0             Queens            0.000000  0.000000  0.000000
4               2      Staten Island            0.000000  0.000000  0.000000
0               0    Central Toronto            0.000000  0.000000  0.013514
1               0   Downtown Toronto            0.000000  0.000000  0.010417
2               0       East Toronto            0.000000  0.000000  0.013514
3               0          East York            0.000000  0.000000  0.000000
4               0          Etobicoke            0.000000  0.000000  0.000000
5               1        Mississauga            0.000000  0.000000  0.000000
```

6	0	North York	0.000000	0.000000	0.000000
7	0	Scarborough	0.000000	0.023256	0.023256
8	0	West Toronto	0.000000	0.000000	0.013514
9	0	York	0.000000	0.000000	0.000000

	Baseball Field	Bike Rental / Bike Share	Bike Trail	Boat or Ferry	\
0	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	
2	0.225806	0.032258	0.000000	0.000000	
3	0.000000	0.000000	0.166667	0.166667	
4	0.000000	0.000000	0.000000	0.000000	
0	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.000000	0.000000	
4	0.000000	0.000000	0.000000	0.000000	
5	0.000000	0.000000	0.000000	0.000000	
6	0.000000	0.000000	0.000000	0.000000	
7	0.000000	0.000000	0.000000	0.000000	
8	0.000000	0.000000	0.000000	0.000000	
9	0.000000	0.000000	0.000000	0.000000	

	Burger Joint	…	Sushi Restaurant	Tanning Salon	Tea Room	\
0	0.037037	…	0.000000	0.000000	0.000000	
1	0.000000	…	0.000000	0.000000	0.000000	
2	0.000000	…	0.000000	0.000000	0.000000	
3	0.000000	…	0.000000	0.000000	0.000000	
4	0.000000	…	0.000000	0.000000	0.000000	
0	0.000000	…	0.013514	0.013514	0.013514	
1	0.000000	…	0.010417	0.020833	0.010417	
2	0.000000	…	0.013514	0.013514	0.013514	
3	0.000000	…	0.000000	0.000000	0.000000	
4	0.000000	…	0.000000	0.000000	0.000000	
5	0.000000	…	0.000000	0.000000	0.000000	
6	0.000000	…	0.000000	0.000000	0.000000	
7	0.000000	…	0.000000	0.000000	0.046512	
8	0.000000	…	0.013514	0.013514	0.013514	
9	0.000000	…	0.000000	0.000000	0.000000	

	Thai Restaurant	Toy / Game Store	Vegetarian / Vegan Restaurant	\
0	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.000000	
4	0.000000	0.000000	0.000000	
0	0.027027	0.000000	0.013514	
1	0.010417	0.000000	0.000000	

```
2         0.027027           0.000000                           0.013514
3         0.000000           0.000000                           0.000000
4         0.000000           0.000000                           0.000000
5         0.000000           0.000000                           0.000000
6         0.000000           0.000000                           0.000000
7         0.000000           0.023256                           0.000000
8         0.027027           0.000000                           0.013514
9         0.000000           0.000000                           0.000000

   Video Game Store  Vietnamese Restaurant  Wine Shop  Women's Store
0          0.000000               0.000000   0.000000       0.000000
1          0.000000               0.000000   0.000000       0.000000
2          0.000000               0.000000   0.000000       0.000000
3          0.000000               0.000000   0.000000       0.000000
4          0.000000               0.000000   0.000000       0.000000
0          0.013514               0.013514   0.000000       0.013514
1          0.010417               0.010417   0.000000       0.010417
2          0.013514               0.013514   0.000000       0.013514
3          0.000000               0.000000   0.000000       0.000000
4          0.000000               0.000000   0.000000       0.000000
5          0.000000               0.000000   0.000000       0.000000
6          0.000000               0.000000   0.000000       0.000000
7          0.023256               0.000000   0.000000       0.000000
8          0.013514               0.013514   0.000000       0.013514
9          0.000000               0.000000   0.166667       0.000000

[15 rows x 131 columns]
```

Let's visualize the outcome and observe the distribution of clusters

[164]:
```
borough = borough.join(neighborhoods_location.set_index('Borough'),␣
 ↪on='Borough')
borough
```

[164]:
```
   Cluster Labels           Borough  Athletics & Sports    Bakery      Bank  \
0               0             Bronx            0.000000  0.000000  0.000000
1               0          Brooklyn            0.000000  0.037037  0.037037
2               0         Manhattan            0.064516  0.000000  0.000000
3               0            Queens            0.000000  0.000000  0.000000
4               2     Staten Island            0.000000  0.000000  0.000000
0               0   Central Toronto            0.000000  0.000000  0.013514
1               0  Downtown Toronto            0.000000  0.000000  0.010417
2               0      East Toronto            0.000000  0.000000  0.013514
3               0         East York            0.000000  0.000000  0.000000
4               0         Etobicoke            0.000000  0.000000  0.000000
5               1       Mississauga            0.000000  0.000000  0.000000
6               0        North York            0.000000  0.000000  0.000000
```

7	0	Scarborough	0.000000	0.023256	0.023256
8	0	West Toronto	0.000000	0.000000	0.013514
9	0	York	0.000000	0.000000	0.000000

	Baseball Field	Bike Rental / Bike Share	Bike Trail	Boat or Ferry	\
0	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	
2	0.225806	0.032258	0.000000	0.000000	
3	0.000000	0.000000	0.166667	0.166667	
4	0.000000	0.000000	0.000000	0.000000	
0	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.000000	0.000000	
4	0.000000	0.000000	0.000000	0.000000	
5	0.000000	0.000000	0.000000	0.000000	
6	0.000000	0.000000	0.000000	0.000000	
7	0.000000	0.000000	0.000000	0.000000	
8	0.000000	0.000000	0.000000	0.000000	
9	0.000000	0.000000	0.000000	0.000000	

	Burger Joint	…	Tea Room	Thai Restaurant	Toy / Game Store	\
0	0.037037	…	0.000000	0.000000	0.000000	
1	0.000000	…	0.000000	0.000000	0.000000	
2	0.000000	…	0.000000	0.000000	0.000000	
3	0.000000	…	0.000000	0.000000	0.000000	
4	0.000000	…	0.000000	0.000000	0.000000	
0	0.000000	…	0.013514	0.027027	0.000000	
1	0.000000	…	0.010417	0.010417	0.000000	
2	0.000000	…	0.013514	0.027027	0.000000	
3	0.000000	…	0.000000	0.000000	0.000000	
4	0.000000	…	0.000000	0.000000	0.000000	
5	0.000000	…	0.000000	0.000000	0.000000	
6	0.000000	…	0.000000	0.000000	0.000000	
7	0.000000	…	0.046512	0.000000	0.023256	
8	0.000000	…	0.013514	0.027027	0.000000	
9	0.000000	…	0.000000	0.000000	0.000000	

	Vegetarian / Vegan Restaurant	Video Game Store	Vietnamese Restaurant	\
0	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.000000	
2	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.000000	
4	0.000000	0.000000	0.000000	
0	0.013514	0.013514	0.013514	
1	0.000000	0.010417	0.010417	
2	0.013514	0.013514	0.013514	

```
3                0.000000      0.000000          0.000000
4                0.000000      0.000000          0.000000
5                0.000000      0.000000          0.000000
6                0.000000      0.000000          0.000000
7                0.000000      0.023256          0.000000
8                0.013514      0.013514          0.013514
9                0.000000      0.000000          0.000000

   Wine Shop  Women's Store   Latitude  Longitude
0   0.000000       0.000000  40.846651 -73.878594
1   0.000000       0.000000  40.650104 -73.949582
2   0.000000       0.000000  40.789624 -73.959894
3   0.000000       0.000000  40.749824 -73.797634
4   0.000000       0.000000  40.583456 -74.149605
0   0.000000       0.013514  43.653482 -79.383935
1   0.000000       0.010417  43.654174 -79.380812
2   0.000000       0.013514  43.653482 -79.383935
3   0.000000       0.000000  43.699971 -79.332520
4   0.000000       0.000000  43.643556 -79.565633
5   0.000000       0.000000  43.678524 -79.629129
6   0.000000       0.000000  43.754326 -79.449117
7   0.000000       0.000000  43.773077 -79.257774
8   0.000000       0.013514  43.653482 -79.383935
9   0.166667       0.000000  43.689619 -79.479188

[15 rows x 133 columns]
```

[169]:

```python
# create map
map_clusters = folium.Map(location=[43.111, -76.825], zoom_start=7)

# set color scheme for the clusters
x = np.arange(3)
ys = [i + x + (i*x)**2 for i in range(3)]
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(borough['Latitude'], borough['Longitude'],␣
 ↪borough['Borough'], borough['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[int(cluster-1)],
        fill=True,
```

```
        fill_color=rainbow[int(cluster-1)],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

[169]: <folium.folium.Map at 0x7f8cdb03b7b8>

0.6 Results and Discussion

In this study, we analyze 15 boroughs from New York and Toronto by evaluating different venues in each borough. We then cluster these boroughs into 3 clusters and determind their smiliarity using KMeans algorithms. From the results, we can see that there are 12 out of 15 boroughs are actually very similar to each other and the only borough that stands out are Misissauga and Staten Island. This result is not suprising as Mississauga and Staten Island are both very far away from the downtown area in both cities. We also noticed that Misissauga and Staten Island are very different from each other in terms of the types of venues in both boroughs. Overall, this study has shown that New York is extermely similar to Toronto in terms of venues.

0.7 Conclusion

In conclusion, this study has shown that New York and Toronto are two very similar cities. For people who constantly travel between these two cities, they should not experience too much difference in terms of their access to different types of venues in the majority parts of both cities except in Mississauga and Staten Island.