Capstone Project

June 24, 2019

1 Introduction

Hello and welcome to my IBM Data Science Capstone Project on Coursera. This notebook holds the source code for the project and has detailed headers explaining each step along the way. The last cell of the notebook contains the code necessary to generate the final outcomes (though be sure to run all preceding code cells beforehand). Thank you for reviewing my project and I hope you find it interesting!

In [1]:
```
#All relevent imports
import numpy as np
import pandas as pd
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)
import json
from geopy.geocoders import Nominatim
import geocoder
import requests
from pandas.io.json import json_normalize
import matplotlib.cm as cm
import matplotlib.colors as colors
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import folium

from bs4 import BeautifulSoup
```

2 Goal

to determine the best place a buisness owner can open up his/her buisness in chicago.

- we will utalize chicago census data and the foursquare api to generate a heatmap of recommended locations
- clustering will be used to translate the unstructured foursquare data into meaningful insights about the buisness enviroment of chicago neighborhoods

In [2]:
```
#Some Resources Used
#base API
```

```
#https://api.foursquare.com/v2/
#https://api.foursquare.com/v2/venues/
#https://api.foursquare.com/v2/users/
#https://api.foursquare.com/v2/tips/
#https://github.com/blackmad/neighborhoods/blob/master/chicago.geojson
#https://github.com/OpenDataDE/State-zip-code-GeoJSON/blob/master/il_illinois_zip_code
```

3 Getting Soup Output from website

Here we will be pulling the names and zipcodes of chicago neighborhoods from a website for later use

```
In [2]: df_chicago = pd.DataFrame(columns=['Zipcode','Neighborhood'])
        df_chicago
```

```
Out[2]: Empty DataFrame
        Columns: [Zipcode, Neighborhood]
        Index: []
```

```
In [3]: addr = 'https://data.mongabay.com/igapo/zip_codes/metropolitan-areas/metro-zip/Chicago%
        source = requests.get(addr).text
        soup = BeautifulSoup(source,'lxml')
```

```
In [4]: table = soup.find('table',class_='boldtable')
```

```
In [5]: for i in table.find_all('tr'):
            content = i.td.text.split()
            df_chicago = df_chicago.append(dict(zip(df_chicago.columns,content)),ignore_index=T
        df_chicago.head()
```

```
Out[5]:   Zipcode Neighborhood
        0   60001        Alden
        1   60002      Antioch
        2   60002          Old
        3   60002          Old
        4   60002    Wadsworth
```

```
In [7]: #df_chicago.to_csv(r'D:\Desktop\outcomes\chicago.csv')
```

```
In [6]: df_chicago_only = df_chicago[df_chicago["Neighborhood"] == "Chicago"]
```

```
In [7]: codes = df_chicago.groupby(df_chicago["Neighborhood"]).groups
```

```
In [8]: #Create Empty Pandas DF
        df_grouped = pd.DataFrame(columns=['Neighborhood','Zipcode'])
        df_grouped
```

```
Out[8]: Empty DataFrame
        Columns: [Neighborhood, Zipcode]
        Index: []
```

4 Combining Data By Neighborhood

For easy lookback here we combine the neightborhood names by each zipcode. This will aid in individual research outside of the datasets can we can later use to formulate a cost function.

```
In [9]: for nb in codes.keys():
            #print("NB",nb)
            zc = []
            for i in codes[nb]:
                zc.append(df_chicago.iloc[i][0])
                zc = list(set(zc))
                zcf = ', '.join(zc)
```

```
In [12]: for nb in codes.keys():
             content = [nb]
             zc = []
             for i in codes[nb]:
                 zc.append(df_chicago.iloc[i][0])
                 zc = list(set(zc))
                 zcf = ', '.join(zc)
             content.append(zcf)
             df_grouped = df_grouped.append(dict(zip(df_grouped.columns,content)),ignore_index=
         df_grouped.head()
```

```
Out[12]:   Neighborhood       Zipcode
         0           AT         60572
         1       Abbott         60064
         2      Addison         60101
         3        Alden  60001, 60033
         4    Algonquin  60156, 60102
```

5 Illinois geodata

In this section of code geojson data for the state of illinois is sorted to be used later in folium mapping. The file is rather large so it is sorted into only relevent sections and the remainder is dropped.

```
In [13]: #loading GeoJSON file
         with open('illinois.json','r') as jsonFile:
             data = json.load(jsonFile)

         geo = data
```

```
In [14]: #geo['features'][0]['properties']["ZCTA5CE10"]
         geo['features'][0]
```

```
Out[14]: {'type': 'Feature',
          'properties': {'STATEFP10': '17',
```

```
 'ZCTA5CE10': '62359',
 'GEOID10': '1762359',
 'CLASSFP10': 'B5',
 'MTFCC10': 'G6350',
 'FUNCSTAT10': 'S',
 'ALAND10': 10360074,
 'AWATER10': 7921,
 'INTPTLAT10': '+40.0338795',
 'INTPTLON10': '-091.2014548',
 'PARTFLG10': 'N'},
'geometry': {'type': 'Polygon',
 'coordinates': [[[-91.182899, 40.026881],
   [-91.182577, 40.026761],
   [-91.182428, 40.026711],
   [-91.182125, 40.026608],
   [-91.181677, 40.02648],
   [-91.181419, 40.026419],
   [-91.18093, 40.026323],
   [-91.180498, 40.026255],
   [-91.180081, 40.026205],
   [-91.179637, 40.026169],
   [-91.179213, 40.026161],
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   [-91.178347, 40.026177],
   [-91.177816, 40.026225],
   [-91.177419, 40.026285],
   [-91.177051, 40.026348],
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   [-91.176692, 40.02387],
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   [-91.176684, 40.021291],
   [-91.176632, 40.021046],
   [-91.176601, 40.020977],
   [-91.17656, 40.020918],
   [-91.176809, 40.020901],
   [-91.181786, 40.020983],
   [-91.183933, 40.021028],
   [-91.184539, 40.021028],
   [-91.185146, 40.021048],
   [-91.186161, 40.021048],
   [-91.187006, 40.021065],
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   [-91.189561, 40.021092],
   [-91.190867, 40.021127],
   [-91.192906, 40.021143],
   [-91.195194, 40.02118],
   [-91.195837, 40.021186],
```

```
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[-91.223745, 40.01823],
[-91.223765, 40.018575],
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```

```
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 [-91.195771, 40.039127],
 [-91.195772, 40.038993],
 [-91.195803, 40.035795],
 [-91.195442, 40.035798],
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 [-91.176672, 40.028705],
 [-91.177306, 40.02852],
 [-91.182777, 40.026919],
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[[-91.182899, 40.026881],
 [-91.183078, 40.026948],
```

```
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            [-91.184535, 40.027364],
            [-91.184908, 40.027436],
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            [-91.185982, 40.027566],
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            [-91.189076, 40.027318],
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            [-91.189847, 40.027106],
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            [-91.190878, 40.026716],
            [-91.1912, 40.026561],
            [-91.191838, 40.026201],
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            [-91.194698, 40.024203],
            [-91.195045, 40.024042],
            [-91.195471, 40.023859],
            [-91.195954, 40.023686],
            [-91.195981, 40.023445],
            [-91.196013, 40.023319],
            [-91.196045, 40.023137],
            [-91.196055, 40.023002],
            [-91.192161, 40.024143],
            [-91.188828, 40.025144],
            [-91.182899, 40.026881]]]}}
```

In [15]:
```
#Create Empty Pandas DF
df_geoZips = pd.DataFrame(columns=['Zipcode','Latitude','Longitude'])
df_geoZips
```

Out[15]:
```
Empty DataFrame
Columns: [Zipcode, Latitude, Longitude]
Index: []
```

In [16]:
```
validZips = []
#zz = set(df_chicago.iloc[:,0].values)
```

```
zz = set(df_chicago_only.iloc[:,0].values)
for i in range(len(geo['features'])):
    zi = geo['features'][i]['properties']["ZCTA5CE10"]
    lat = geo['features'][i]['properties']['INTPTLAT10']
    long = geo['features'][i]['properties']['INTPTLON10']

    if(zi in zz):
        validZips.append(geo['features'][i])
        df_geoZips = df_geoZips.append(dict(zip(df_geoZips.columns,[zi,lat,long])),ig
df_geoZips.head()
```

Out[16]:

	Zipcode	Latitude	Longitude
0	60656	+41.9742801	-087.8271313
1	60638	+41.7814424	-087.7705341
2	60652	+41.7479398	-087.7148066
3	60629	+41.7758678	-087.7114956
4	60641	+41.9466055	-087.7467867

In [17]:
```
#validZips = set(df_chicago.iloc[:,0].values)
#geoData = []
#for i in range(len(geo['features'])):
#    z = geo['features'][i]['properties']["ZCTA5CE10"]
#    if(z in zz):
#
#df_geoZips.to_csv(r'D:\Desktop\outcomes\chicago_geozips.csv')
```

In [18]:
```
geo['features'][0]
```

Out[18]:
```
{'type': 'Feature',
 'properties': {'STATEFP10': '17',
  'ZCTA5CE10': '62359',
  'GEOID10': '1762359',
  'CLASSFP10': 'B5',
  'MTFCC10': 'G6350',
  'FUNCSTAT10': 'S',
  'ALAND10': 10360074,
  'AWATER10': 7921,
  'INTPTLAT10': '+40.0338795',
  'INTPTLON10': '-091.2014548',
  'PARTFLG10': 'N'},
 'geometry': {'type': 'Polygon',
  'coordinates': [[[-91.182899, 40.026881],
    [-91.182577, 40.026761],
    [-91.182428, 40.026711],
    [-91.182125, 40.026608],
    [-91.181677, 40.02648],
    [-91.181419, 40.026419],
    [-91.18093, 40.026323],
    [-91.180498, 40.026255],
```

```
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```

```
[-91.216864, 40.017106],
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[-91.223732, 40.015201],
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```

```
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 [-91.195707, 40.043059],
 [-91.195754, 40.039882],
 [-91.195772, 40.039441],
 [-91.195771, 40.039127],
 [-91.195772, 40.038993],
 [-91.195803, 40.035795],
 [-91.195442, 40.035798],
 [-91.193694, 40.035771],
 [-91.192651, 40.035747],
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 [-91.184871, 40.035597],
 [-91.183401, 40.035576],
 [-91.18266, 40.035561],
 [-91.180703, 40.035531],
 [-91.17831, 40.035483],
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 [-91.17664, 40.031975],
 [-91.176666, 40.029181],
 [-91.176675, 40.028789],
 [-91.176672, 40.028705],
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 [-91.185605, 40.027535],
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 [-91.187246, 40.02758],
 [-91.187975, 40.027517],
 [-91.188361, 40.027459],
 [-91.188724, 40.027393],
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 [-91.189458, 40.027223],
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 [-91.190531, 40.026856],
 [-91.190878, 40.026716],
```

```
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            [-91.193824, 40.024716],
            [-91.194436, 40.024343],
            [-91.194698, 40.024203],
            [-91.195045, 40.024042],
            [-91.195471, 40.023859],
            [-91.195954, 40.023686],
            [-91.195981, 40.023445],
            [-91.196013, 40.023319],
            [-91.196045, 40.023137],
            [-91.196055, 40.023002],
            [-91.192161, 40.024143],
            [-91.188828, 40.025144],
            [-91.182899, 40.026881]]]}}
```

6 Folium Beta Visual

This is a pre-calculations visual of our selected zipcodes. Each marker is placed in the center of our target zipcodes.

```
In [77]: map_chicago = folium.Map(location=[41.88, -87.62], zoom_start=10)

         for i in df_geoZips.values:
             t1 = float(i[1])
             t2 = float(i[2])
             #folium.Marker([t1,t2]).add_to(map_chicago)
             folium.CircleMarker([t1,t2],radius=5,color='blue',fill=True,fill_color='#3186cc',

         map_chicago

Out[77]: <folium.folium.Map at 0x21c821a2208>
```

7 Folium Geo visual

This is a pre-calculations visual of our illinois geojson data trimmed to the relevant zipcodes.

```
In [37]: map_chicago = folium.Map(location=[41.82, -87.62], zoom_start=9.5)

         print(len(validZips))
         for i in range(len(validZips)):
             folium.GeoJson(validZips[i],overlay=True,style_function= lambda x :{'fillColor':'
```

```
map_chicago
```

65

Out[37]: <folium.folium.Map at 0x21c81cf4f28>

```
In [38]: #map_chicago.save("chicago.html")
```

8 chicago buisness data

Here we are bringing in data from the US Census to judge how many of each size of buisness are in our target areas. We can sort the data by NAICS code to mirror our foursquare data and gain further insight into where a good place for our buisness might be.

```
In [39]: #SOURCE
         #zbp16totals
         #https://www.census.gov/data/datasets/2016/econ/cbp/2016-cbp.html
```

Field Data
Name Type Description * ZIP C ZIP Code * NAICS C Industry Code - 6-digit NAICS code * EST N Total Number of Establishments * N1_4 N Number of Establishments: 1-4 Employee Size Class * N5_9 N Number of Establishments: 5-9 Employee Size Class * N10_19 N Number of Establishments: 10-19 Employee Size Class * N20_49 N Number of Establishments: 20-49 Employee Size Class * N50_99 N Number of Establishments: 50-99 Employee Size Class * N100_249 N Number of Establishments: 100-249 Employee Size Class * N250_499 N Number of Establishments: 250-499 Employee Size Class * N500_999 N Number of Establishments: 500-999 Employee Size Class * N1000 N Number of Establishments: 1,000 or More Employee Size Class

```
In [40]: df_ccd = pd.read_csv("zbp16detail.csv")
```

```
In [41]: print(df_ccd.head())
         #df_geoZips
         print(df_ccd.shape)
         distinct_zips = set(df_geoZips.iloc[:,0].values)
```

```
   zip   naics  est  n1_4  n5_9  n10_19  n20_49  n50_99  n100_249  n250_499  \
0  501  ------    2     1     0       0       1       0         0         0
1  501  81----    2     1     0       0       1       0         0         0
2  501  813///    2     1     0       0       1       0         0         0
3  501  8131//    2     1     0       0       1       0         0         0
4  501  81311/    2     1     0       0       1       0         0         0

   n500_999  n1000
0         0      0
1         0      0
2         0      0
3         0      0
```

```
4          0      0
(8418283, 12)
```

```
In [42]: df_ccd = df_ccd[df_ccd["zip"].isin(distinct_zips)]
```

```
         df_ccd.shape
```

```
Out[42]: (42701, 12)
```

```
In [43]: codes = df_ccd.groupby(df_ccd["zip"]).groups
         print(len(codes.keys()))
```

```
65
```

9 Foursquare Data

The bulk of our insight is gained from foursquare data. Here we will utalize the API to gain insight into the buisnesses in each zipcode and cluster different zipcodes accordingly. Those clusters can then be compaired to our target buisness to find which cluster best fits our target buisness and further compaired to our Census dataset

```
In [44]: #trending venues endpoint
         #means venues with the most people checked in
         #we can use this data for each zipcode along with the chicago buisness data
         #to find the zipcodes with the least amount of establishments but most
         #trending
```

```
In [45]: #Foursquare credentials
         client_id = 'your_ud'
         client_secret = 'your_secret'
         version = '20190526'
```

```
In [46]: radius = 100000
         LIMIT = 50
```

url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={},{}&radius=
CLIENT_ID, CLIENT_SECRET, VERSION, lat, lng, radius, LIMIT)

```
In [47]: def getTrending(lat,long):
             url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={
                     client_id,
                     client_secret,
                     version,
                     lat,
                     long,
                     radius,
```

```
                    LIMIT)
             # make the GET request
            #results = requests.get(url).json()["response"]['groups'][0]['items']
            results = requests.get(url).json()
            return results
```

```
In [48]: #60649        +41.7634204        -087.5658787
         fTest = getTrending(+41.7634204,-087.5658787)
```

```
In [49]: k = fTest['response']['groups'][0]['items']
         k[0]['venue']
```

```
Out[49]: {'id': '42eeb780f964a520b4261fe3',
          'name': 'Museum of Science and Industry',
          'location': {'address': '5700 S Lake Shore Dr',
           'crossStreet': 'at 57th Dr',
           'lat': 41.791617208319984,
           'lng': -87.58306656501914,
           'labeledLatLngs': [{'label': 'display',
             'lat': 41.791617208319984,
             'lng': -87.58306656501914}],
           'distance': 3447,
           'postalCode': '60637',
           'cc': 'US',
           'city': 'Chicago',
           'state': 'IL',
           'country': 'United States',
           'formattedAddress': ['5700 S Lake Shore Dr (at 57th Dr)',
            'Chicago, IL 60637',
            'United States']},
          'categories': [{'id': '4bf58dd8d48988d191941735',
            'name': 'Science Museum',
            'pluralName': 'Science Museums',
            'shortName': 'Science Museum',
            'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_entertainment/museu
             'suffix': '.png'},
            'primary': True}],
          'photos': {'count': 0, 'groups': []},
          'venuePage': {'id': '85626555'}}
```

```
In [50]: i = [1234]
         for j in fTest['response']['groups'][0]['items']:
             v = dict(j)['venue']
             content = [i[0],v['name'],v['location']['lat'],v['location']['lng'],]
             print(content)
             break;
```

```
[1234, 'Museum of Science and Industry', 41.791617208319984, -87.58306656501914]
```

10 Testing out Locations

Here we gain human insight into our data by seeing what categorys tend to show up for each zip-code. This insight was also useful because it exposed that some buisnesses were being duplicated by the API (Airports, resturants, ect) and this was corrected.

```
In [51]: #Create Empty Pandas DF
         df_trends = pd.DataFrame(columns=['Zipcode','Name','Latitude','Longitude','Category'])
         target_category = '5454144b498ec1f095bff2f2'
         #https://developer.foursquare.com/docs/resources/categories
         df_trends

Out[51]: Empty DataFrame
         Columns: [Zipcode, Name, Latitude, Longitude, Category]
         Index: []

In [52]: #df_geoZips

         for i in df_geoZips.values:
             trending_venues = getTrending(i[1],i[2])['response']['groups'][0]['items']
             for j in trending_venues:
                 v = dict(j)['venue']
                 content = [i[0],v['name'],v['location']['lat'],v['location']['lng'],v['categor
                 df_trends = df_trends.append(dict(zip(df_trends.columns,content)),ignore_index


In [53]: df_trends.drop_duplicates(["Zipcode","Name"],inplace = True)
         len(df_trends)
         df_trends.head()

Out[53]:   Zipcode                                  Name   Latitude  Longitude  \
         0   60656                   The Capital Grille  41.974923 -87.862916
         1   60656  Frank Lloyd Wright Home and Studio  41.894157 -87.799517
         2   60656                           Smoque BBQ  41.950168 -87.727684
         3   60656                        Trader Joe's  41.890123 -87.804593
         4   60656                          Portillo's  41.907365 -87.912586

                      Category
         0  American Restaurant
         1        Historic Site
         2            BBQ Joint
         3        Grocery Store
         4        Hot Dog Joint

In [54]: # one hot encoding
         df_trends_onehot = pd.get_dummies(df_trends[['Category']], prefix="", prefix_sep="")

         # add neighborhood column back to dataframe
         df_trends_onehot['Zipcode'] = df_trends['Zipcode']
```

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

df_trends_onehot.head()
```

Out[54]:

	Zipcode	African Restaurant	American Restaurant	Amphitheater	Antique Shop	Art Gallery	Art Museum	Asian Restaurant	BBQ Joint	Bakery	Bar	Baseball Stadium	Beach	Beer Bar	Beer Store	Boat or Ferry	Bookstore	Breakfast Spot	Brewery	Butcher	Café	Chinese Restaurant	Chocolate Shop	Climbing Gym	Clothing Store	Cocktail Bar	Coffee Shop	Comedy Club	Concert Hall	Cosmetics Shop	Cupcake Shop	Cycle Studio
0	60656	0	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
1	60656	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
2	60656	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	60656	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
4	60656	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

```
   Deli / Bodega  Dessert Shop  Diner  Donut Shop  Electronics Store  \
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

   Farmers Market  Field  Flower Shop  French Restaurant  Frozen Yogurt Shop  \
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

   Furniture / Home Store  Garden  Garden Center  Gourmet Shop  Grocery Store  \
0                       0       0              0             0              0
1                       0       0              0             0              0
2                       0       0              0             0              0
3                       0       0              0             0              1
4                       0       0              0             0              0

   Gym  Gym / Fitness Center  Historic Site  History Museum  Hot Dog Joint  \
0    0                     0              0               0              0
1    0                     0              1               0              0
2    0                     0              0               0              0
3    0                     0              0               0              0
4    0                     0              0               0              1

   Hotel  Ice Cream Shop  Indie Movie Theater  Italian Restaurant  \
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

   Japanese Restaurant  Korean Restaurant  Lingerie Store  Liquor 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

   Mediterranean Restaurant  Mexican Restaurant  \
0                         0                   0
1                         0                   0
2                         0                   0
3                         0                   0
```

```
4                         0                   0

   Molecular Gastronomy Restaurant  Museum  Music School  Music Venue  \
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

   Nature Preserve  New American Restaurant  Optical Shop  \
0                0                        0             0
1                0                        0             0
2                0                        0             0
3                0                        0             0
4                0                        0             0

   Other Great Outdoors  Outdoor Sculpture  Park  Pie Shop  Pizza Place  \
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

   Rock Club  Salad Place  Salon / Barbershop  Sandwich Place  Science Museum  \
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

   Seafood Restaurant  Spa  Stadium  Sushi Restaurant  Tapas Restaurant  \
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

   Theater  Trail  Vegetarian / Vegan Restaurant  Waterfront  Yoga Studio  \
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

   Zoo  Zoo Exhibit
0    0            0
1    0            0
2    0            0
```

```
3    0            0
4    0            0
```

```
In [55]: df_trends_grouped = df_trends_onehot.groupby('Zipcode').mean().reset_index()
         df_trends_grouped.head()
```

Out[55]:

	Zipcode	African Restaurant	American Restaurant	Amphitheater	Antique Shop	Art Gallery	Art Museum	Asian Restaurant	BBQ Joint	Bakery	Bar	Baseball Stadium	Beach	Beer Bar	Beer Store	Boat or Ferry	Bookstore	Breakfast Spot	Brewery	Butcher	Café	Chinese Restaurant	Chocolate Shop	Climbing Gym	Clothing Store	Cocktail Bar	Coffee Shop	Comedy Club	Concert Hall	Cosmetics Shop
0	60411	0.021277	0.0	0.021277	0.0	0.021277	0.021277	0.021277	0.021277	0.021277	0.042553	0.0	0.0	0.0	0.0	0.021277	0.0	0.021277	0.042553	0.0	0.0	0.021277	0.021277	0.0	0.0	0.0	0.021277	0.0	0.021277	0.000000
1	60415	0.020833	0.0	0.000000	0.0	0.020833	0.020833	0.020833	0.020833	0.020833	0.041667	0.0	0.0	0.0	0.0	0.000000	0.0	0.020833	0.062500	0.0	0.0	0.020833	0.000000	0.0	0.0	0.0	0.020833	0.0	0.020833	0.000000
2	60601	0.000000	0.0	0.020000	0.0	0.000000	0.020000	0.000000	0.020000	0.000000	0.020000	0.0	0.0	0.0	0.0	0.040000	0.0	0.000000	0.000000	0.0	0.0	0.000000	0.020000	0.0	0.0	0.0	0.040000	0.0	0.020000	0.020000
3	60602	0.000000	0.0	0.020408	0.0	0.000000	0.020408	0.000000	0.020408	0.000000	0.020408	0.0	0.0	0.0	0.0	0.040816	0.0	0.000000	0.000000	0.0	0.0	0.000000	0.020408	0.0	0.0	0.0	0.061224	0.0	0.020408	0.020408
4	60603	0.000000	0.0	0.020408	0.0	0.000000	0.020408	0.000000	0.020408	0.000000	0.020408	0.0	0.0	0.0	0.0	0.040816	0.0	0.000000	0.000000	0.0	0.0	0.000000	0.020408	0.0	0.0	0.0	0.061224	0.0	0.020408	0.020408

	Cupcake Shop	Cycle Studio	Deli / Bodega	Dessert Shop	Diner	Donut Shop
0	0.00	0.0	0.021277	0.0	0.0	0.000000
1	0.00	0.0	0.020833	0.0	0.0	0.000000
2	0.02	0.0	0.020000	0.0	0.0	0.020000
3	0.00	0.0	0.020408	0.0	0.0	0.020408
4	0.00	0.0	0.020408	0.0	0.0	0.020408

	Electronics Store	Farmers Market	Field	Flower Shop	French Restaurant
0	0.000000	0.0	0.0	0.000000	0.000000
1	0.000000	0.0	0.0	0.020833	0.020833
2	0.020000	0.0	0.0	0.000000	0.020000
3	0.020408	0.0	0.0	0.000000	0.020408
4	0.020408	0.0	0.0	0.000000	0.020408

	Frozen Yogurt Shop	Furniture / Home Store	Garden	Garden Center
0	0.0	0.0	0.000000	0.0
1	0.0	0.0	0.020833	0.0
2	0.0	0.0	0.000000	0.0
3	0.0	0.0	0.000000	0.0
4	0.0	0.0	0.000000	0.0

	Gourmet Shop	Grocery Store	Gym	Gym / Fitness Center	Historic Site
0	0.000000	0.021277	0.021277	0.000000	0.000000
1	0.000000	0.041667	0.020833	0.000000	0.020833
2	0.020000	0.020000	0.020000	0.020000	0.000000
3	0.020408	0.020408	0.020408	0.020408	0.000000
4	0.000000	0.020408	0.020408	0.020408	0.000000

	History Museum	Hot Dog Joint	Hotel	Ice Cream Shop
0	0.042553	0.021277	0.042553	0.042553
1	0.041667	0.020833	0.020833	0.062500
2	0.000000	0.000000	0.100000	0.000000
3	0.000000	0.000000	0.102041	0.000000
4	0.020408	0.000000	0.102041	0.000000

	Indie Movie Theater	Italian Restaurant	Japanese Restaurant
0	0.0	0.000000	0.0
1	0.0	0.000000	0.0
2	0.0	0.020000	0.0
3	0.0	0.020408	0.0
4	0.0	0.020408	0.0

	Korean Restaurant	Lingerie Store	Liquor Store	Mediterranean Restaurant
0	0.0	0.021277	0.021277	0.021277
1	0.0	0.020833	0.020833	0.020833
2	0.0	0.020000	0.020000	0.040000
3	0.0	0.020408	0.020408	0.040816
4	0.0	0.020408	0.020408	0.020408

	Mexican Restaurant	Molecular Gastronomy Restaurant	Museum
0	0.0	0.0	0.000000
1	0.0	0.0	0.000000
2	0.0	0.0	0.020000
3	0.0	0.0	0.020408
4	0.0	0.0	0.020408

	Music School	Music Venue	Nature Preserve	New American Restaurant
0	0.0	0.0	0.021277	0.000000
1	0.0	0.0	0.020833	0.000000
2	0.0	0.0	0.000000	0.020000
3	0.0	0.0	0.000000	0.020408
4	0.0	0.0	0.000000	0.020408

	Optical Shop	Other Great Outdoors	Outdoor Sculpture	Park	Pie Shop
0	0.000000	0.021277	0.021277	0.127660	0.0
1	0.000000	0.000000	0.000000	0.083333	0.0
2	0.020000	0.000000	0.020000	0.080000	0.0
3	0.020408	0.000000	0.020408	0.081633	0.0
4	0.020408	0.000000	0.020408	0.102041	0.0

	Pizza Place	Rock Club	Salad Place	Salon / Barbershop	Sandwich Place
0	0.021277	0.021277	0.000000	0.00	0.000000
1	0.041667	0.020833	0.000000	0.00	0.020833
2	0.000000	0.000000	0.020000	0.02	0.000000
3	0.000000	0.000000	0.020408	0.00	0.020408
4	0.000000	0.000000	0.020408	0.00	0.000000

	Science Museum	Seafood Restaurant	Spa	Stadium	Sushi Restaurant
0	0.021277	0.000000	0.0	0.000000	0.0
1	0.020833	0.000000	0.0	0.020833	0.0
2	0.000000	0.040000	0.0	0.000000	0.0
3	0.000000	0.040816	0.0	0.000000	0.0
4	0.000000	0.040816	0.0	0.000000	0.0

	Tapas Restaurant	Theater	Trail	Vegetarian / Vegan Restaurant
0	0.0	0.021277	0.021277	0.0
1	0.0	0.020833	0.000000	0.0
2	0.0	0.060000	0.020000	0.0
3	0.0	0.061224	0.020408	0.0
4	0.0	0.081633	0.020408	0.0

	Waterfront	Yoga Studio	Zoo	Zoo Exhibit
0	0.042553	0.021277	0.0	0.0
1	0.020833	0.041667	0.0	0.0
2	0.040000	0.040000	0.0	0.0
3	0.040816	0.020408	0.0	0.0

```
4    0.040816     0.020408  0.0           0.0
```

11 Venue Categories

To make calculations easier later on and create a nicer input interface the venue categories are called down from the API and sorted according to category teirs.

```
In [56]: #https://api.foursquare.com/v2/venues/categories
         #Create Empty Pandas DF
         df_category = pd.DataFrame(columns=['Category','Subcategory','Sub-Subcategory'])
         df_category

Out[56]: Empty DataFrame
         Columns: [Category, Subcategory, Sub-Subcategory]
         Index: []

In [57]: url = 'https://api.foursquare.com/v2/venues/categories?&client_id={}&client_secret={}&
                     client_id,
                     client_secret,version )

         categories = requests.get(url).json()['response']['categories']

In [58]: categories[0]['categories'][20]['categories']

Out[58]: [{'id': '4bf58dd8d48988d18f941735',
           'name': 'Art Museum',
           'pluralName': 'Art Museums',
           'shortName': 'Art Museum',
           'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_entertainment/museum
            'suffix': '.png'},
           'categories': []},
          {'id': '559acbe0498e472f1a53fa23',
           'name': 'Erotic Museum',
           'pluralName': 'Erotic Museums',
           'shortName': 'Erotic Museum',
           'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/nightlife/stripclub_',
            'suffix': '.png'},
           'categories': []},
          {'id': '4bf58dd8d48988d190941735',
           'name': 'History Museum',
           'pluralName': 'History Museums',
           'shortName': 'History Museum',
           'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_entertainment/museum
            'suffix': '.png'},
           'categories': []},
          {'id': '4bf58dd8d48988d192941735',
           'name': 'Planetarium',
           'pluralName': 'Planetariums',
```

```
  'shortName': 'Planetarium',
  'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_entertainment/museum
   'suffix': '.png'},
  'categories': []},
 {'id': '4bf58dd8d48988d191941735',
  'name': 'Science Museum',
  'pluralName': 'Science Museums',
  'shortName': 'Science Museum',
  'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_entertainment/museum
   'suffix': '.png'},
  'categories': []}]
```

In [59]:
```
for k in categories:
    for i in k['categories']:
        if(len(i['categories']) > 0):
            for j in i['categories']:
                df_category = df_category.append(dict(zip(df_category.columns,[k['name
            else:
                df_category = df_category.append(dict(zip(df_category.columns,[k['name
```

```
df_category.head()
```

Out[59]:

	Category	Subcategory	Sub-Subcategory
0	Arts & Entertainment	Movie Theater	Drive-in Theater
1	Arts & Entertainment	Movie Theater	Indie Movie Theater
2	Arts & Entertainment	Movie Theater	Multiplex
3	Arts & Entertainment	Movie Theater	Movie Theater
4	Arts & Entertainment	Museum	Art Museum

In [60]:
```
index = df_category[df_category['Subcategory'] == 'Stadium']
print(index)
df_trends[df_trends['Category'].isin(index['Sub-Subcategory'].values)]
```

```
                Category Subcategory     Sub-Subcategory
22  Arts & Entertainment     Stadium    Baseball Stadium
23  Arts & Entertainment     Stadium  Basketball Stadium
24  Arts & Entertainment     Stadium      Cricket Ground
25  Arts & Entertainment     Stadium    Football Stadium
26  Arts & Entertainment     Stadium        Hockey Arena
27  Arts & Entertainment     Stadium       Rugby Stadium
28  Arts & Entertainment     Stadium      Soccer Stadium
29  Arts & Entertainment     Stadium      Tennis Stadium
30  Arts & Entertainment     Stadium       Track Stadium
31  Arts & Entertainment     Stadium             Stadium
```

Out[60]:

	Zipcode	Name	Latitude	Longitude	Category
67	60638	United Center	41.880759	-87.673974	Stadium

129	60652	United Center	41.880759	-87.673974		Stadium
174	60629	United Center	41.880759	-87.673974		Stadium
278	60625	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
373	60626	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
591	60630	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
627	60651	United Center	41.880759	-87.673974		Stadium
678	60645	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
788	60803	United Center	41.880759	-87.673974		Stadium
836	60712	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
854	60623	United Center	41.880759	-87.673974		Stadium
911	60608	United Center	41.880759	-87.673974		Stadium
950	60612	United Center	41.880759	-87.673974		Stadium
1076	60659	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
1132	60415	United Center	41.880759	-87.673974		Stadium
1209	60624	United Center	41.880759	-87.673974		Stadium
1332	60607	United Center	41.880759	-87.673974		Stadium
1367	60657	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
1405	60613	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
1584	60805	United Center	41.880759	-87.673974		Stadium
1720	60640	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
1811	60632	United Center	41.880759	-87.673974		Stadium
1895	60643	United Center	41.880759	-87.673974		Stadium
1940	60620	United Center	41.880759	-87.673974		Stadium
1988	60636	United Center	41.880759	-87.673974		Stadium
2033	60609	United Center	41.880759	-87.673974		Stadium
2339	60655	United Center	41.880759	-87.673974		Stadium
2420	60644	United Center	41.880759	-87.673974		Stadium
2484	60618	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
2670	60660	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
2713	60804	United Center	41.880759	-87.673974		Stadium
2793	60707	United Center	41.880759	-87.673974		Stadium
2944	60621	United Center	41.880759	-87.673974		Stadium
3089	60646	Wrigley Field	41.948160	-87.655562	Baseball	Stadium
3147	60639	United Center	41.880759	-87.673974		Stadium
3178	60622	United Center	41.880759	-87.673974		Stadium

12 Collection of Dataframes

Below is a detail of all of our collected dataframe thusfar and their held data. In total 7 dataframe were examined to give us great insight into the chicago buisness climate. With this data we can now proceed into final calculations.

- df_category = [CATEGORY,SUBCATEGORY,SUB-Subcategory]
- df_trends_grouped = [Onehot encoded near buisnesses by category]
- df_trends = [closest buisnesses and their categories]

- df_ccd = [chicago census data for buisnesses]
- df_geoZips = [zip, lat ,long]
- df_grouped = [all zipcodes for each neighborhood]
- df_chicago = [original scrapped data]

```
In [61]: def mainCatPrintout():
             types = df_category.Subcategory.unique()
             print("Please Select a type:")
             for i in range(0,len(types),3):
                 print("%-30s %-30s %s" %(str(i)+":"+types[i],str(i+1)+":"+types[i+1],str(i+2)+

         def getmainCatSelection(index):
             index = int(index)
             if(index >= 0 and index < 52):
                 sc = getGeoCats(df_category.Subcategory.unique()[index])
                 #print(sc)
                 return sc
             else:
                 return "Selection Not Found. Please Try Again"

         def getGeoCats(category_name):
             index = df_category[df_category['Subcategory'] == category_name]
             mc = index.values[0,0]
             sc = index['Sub-Subcategory'].values
             #print(sc)
             return sc

         #mapping of input below to a NAICS code
         #https://www.naics.com/business-lists/counts-by-naics-code/?#countsByNAICS
         naics_codes = {0:71,1:61,2:71,3:71,4:81,5:71,6:71,7:71,8:61,9:61,10:72,
                        11:72,12:72,13:72,14:72,15:72,16:72,17:72,18:72,19:72,20:72,
                        21:72,22:72,23:72,24:72,25:72,26:72,27:72,28:72,29:72,30:72,
                        31:72,32:44,33:11,34:11,35:92,36:71,37:71,38:92,39:62,40:55,
                        41:61,42:71,43:62,44:44,45:72,46:42,47:81,48:48,49:53,50:48}

         def getNaicsData(index):
             return df_ccd[df_ccd["naics"].str[0:2] == str(naics_codes[int(selection)])]

         def getFoursquareData():
             limit = 10
             indicators = ['st', 'nd', 'rd']
             # create columns according to number of top venues
             columns = ['Zipcode']
             for ind in np.arange(limit):
```

```
            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
        df_commons = pd.DataFrame(columns=columns)
        df_commons['Zipcode'] = df_trends_grouped['Zipcode']
        for ind in np.arange(df_trends_grouped.shape[0]):
            df_commons.iloc[ind, 1:] = getMostCommon(df_trends_grouped.iloc[ind, :], limit
        return df_commons

    def getMostCommon(row, limit):
        row_categories = row.iloc[1:]
        row_categories_sorted = row_categories.sort_values(ascending=False)

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

In [62]:
```
getFoursquareData().head()
```

Out[62]:

	Zipcode	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	60411	Park	History Museum	Waterfront	Hotel	Ice Cream Shop	Bar	Brewery	Mediterranean Restaurant	Nature Preserve	Concert Hall
1	60415	Park	Brewery	Ice Cream Shop	Grocery Store	Bar	Pizza Place	History Museum	Yoga Studio	Coffee Shop	Garden
2	60601	Hotel	Park	Theater	Coffee Shop	Yoga Studio	Waterfront	Mediterranean Restaurant	Seafood Restaurant	Boat or Ferry	Gym / Fitness Center
3	60602	Hotel	Park	Theater	Coffee Shop	Seafood Restaurant	Mediterranean Restaurant	Boat or Ferry	Waterfront	Cosmetics Shop	Concert Hall
4	60603	Park	Hotel	Theater	Coffee Shop	Seafood Restaurant	Boat or Ferry	Waterfront	Mediterranean Restaurant	New American Restaurant	Museum

13 Clustering on Foursqure Data

Here we utalize the encoded data from the foursquare API to cluster zipcodes according to buisness climates. This will form a large part of our predictions

In [63]:
```
#Num clusters
k = 5
#dataSet = getFoursquareData().drop('Zipcode',1)

kmc = KMeans(random_state=0)
kmc.fit(df_trends_grouped.drop('Zipcode',1))
```

Out[63]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=8, n_init=10, n_jobs=None, precompute_distances='auto',
    random_state=0, tol=0.0001, verbose=0)
```

In [64]:
```
kmc.labels_
```

Out[64]:
```
array([5, 5, 4, 4, 4, 4, 4, 4, 4, 1, 1, 4, 4, 3, 6, 0, 1, 1, 1, 2, 1, 1,
       1, 3, 3, 3, 6, 6, 5, 5, 2, 2, 5, 1, 7, 1, 1, 5, 7, 6, 7, 0, 5, 3,
       6, 2, 7, 1, 3, 5, 1, 4, 5, 2, 0, 6, 6, 4, 7, 7, 2, 5, 3, 5, 5])
```

In [65]:
```
df_geoZips.sort_values(by=["Zipcode"],inplace=True)
df_geoZips.insert(3,"Cluster",kmc.labels_,True)
```

In [66]:
```
df_geoZips.head()
```

Out[66]:

	Zipcode	Latitude	Longitude	Cluster
44	60411	+41.5087744	-087.5903141	5
22	60415	+41.7029482	-087.7788303	5
20	60601	+41.8853104	-087.6221295	4
52	60602	+41.8830726	-087.6291494	4
33	60603	+41.8801879	-087.6255095	4

In [67]:
```
validZips[0]['properties']['ZCTA5CE10']

for i in validZips[0:1]:
    print(i['properties']['ZCTA5CE10'])
```

```
60656
```

In [68]:
```
df_geoZips.head()
```

Out[68]:

	Zipcode	Latitude	Longitude	Cluster
44	60411	+41.5087744	-087.5903141	5
22	60415	+41.7029482	-087.7788303	5
20	60601	+41.8853104	-087.6221295	4
52	60602	+41.8830726	-087.6291494	4
33	60603	+41.8801879	-087.6255095	4

14 Cluster Map

This map represents the clustered data. All that remains is a cost function analysis cloropleth map to be overlayed atop it to create final recommendations.

```
In [69]: map_chicago = folium.Map(location=[41.88, -87.62], zoom_start=10)
         numClusters = df_geoZips["Cluster"].max()
         x = np.arange(numClusters)
         ys = [i + x + (i*x)**2 for i in range(numClusters)]
         colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
         rainbow = [colors.rgb2hex(i) for i in colors_array]


         for i in df_geoZips.values:
             t1 = float(i[1])
             t2 = float(i[2])
             folium.CircleMarker([t1,t2],radius=5,color=rainbow[int(i[3]-1)],fill=True,fill_co


         for i in range(len(validZips)):
             clust = df_geoZips[df_geoZips["Zipcode"]==validZips[i]['properties']['ZCTA5CE10']]
             folium.GeoJson(validZips[i],style_function= lambda x: {'fillColor':'grey','color'


         map_chicago

Out[69]: <folium.folium.Map at 0x21c821a2ef0>
```

15 Recommendation Logic

Here lays the recommendation cost function for our analysis it attempts to score zipcodes based on the business opportunity by balancing the right amount of existing business presence (signaling a market/want) and threat of competition (too many small businesses or a few large businesses)

```
In [70]: fqd = getFoursquareData()
         def zipcodeScore(zipCode,ccdSmallBuisnessNum,selection):
             buisMod = 0
             clusterMod = 0
             if(ccdSmallBuisnessNum != 0 and (ccdSmallBuisnessNum > 8 or ccdSmallBuisnessNum <
                 buisMod = (abs(ccdSmallBuisnessNum-6)-2)*-1
             weight = -5
             for i in fqd[fqd["Zipcode"]==str(zipCode)].values[0]:
                 if(i not in getmainCatSelection(selection)):
                     clusterMod-=(5-abs(weight))
                     weight+=1
             return clusterMod+buisMod
```

```
        def recommendationEngine(selection):
            naics = getNaicsData(selection)
            scores = []
            for i in df_geoZips.values:
                buisnesses = naics[naics["zip"]==int(i[0])]
                bNum = buisnesses["n1_4"].sum() + buisnesses["n5_9"].sum()
                scores.append(zipcodeScore(i[0],bNum,selection))
            df_geoZips.insert(4,"Score",scores,True)
            bestCluster = df_geoZips.iloc[df_geoZips[['Score']].idxmax()].values[0][3]
            for i in range(len(df_geoZips)):
                if(df_geoZips.iloc[i,3]==bestCluster):
                    df_geoZips.iloc[i,4]+=30
            return df_geoZips
```

```
In [71]: df_geoZips.head()
```

Out[71]:

	Zipcode	Latitude	Longitude	Cluster
44	60411	+41.5087744	-087.5903141	5
22	60415	+41.7029482	-087.7788303	5
20	60601	+41.8853104	-087.6221295	4
52	60602	+41.8830726	-087.6291494	4
33	60603	+41.8801879	-087.6255095	4

```
In [76]: mainCatPrintout()
         selection = input()
         if((selection != None) and int(selection) >= 0 and int(selection) < 51):
             getmainCatSelection(selection)
             recommendationEngine(selection)
             map_chicago = folium.Map(location=[41.88, -87.62], zoom_start=10)

             # Add the color for the chloropleth:
             map_chicago.choropleth(
              geo_data=dict({"Type":"FeatureCollection","features":list(validZips)}),
              name='choropleth',
              data=df_geoZips,
              columns=['Zipcode', 'Score'],
              key_on='properties.ZCTA5CE10',
              fill_color='BuGn',
              fill_opacity=0.9,
              line_opacity=0.5,
              legend_name="Recommedation Cost Estimate"
             )
             folium.LayerControl().add_to(map_chicago)

             for i in df_geoZips.values:
                 t1 = float(i[1])
                 t2 = float(i[2])
                 folium.CircleMarker([t1,t2],radius=5,color=rainbow[int(i[3]-1)],fill=True,fil
```

```
            display(map_chicago)
            df_geoZips.drop(["Score"], axis=1,inplace=True)
        else:
            print("Please enter a valid Selection")
```

```
Please Select a type:
0:Movie Theater                 1:Museum                        2:Music Venue
3:Performing Arts Venue         4:Public Art                    5:Stadium
6:Theme Park                    7:Zoo                           8:College Academic Building
9:College Stadium               10:African Restaurant           11:American Restaurant
12:Asian Restaurant             13:Caribbean Restaurant         14:Dessert Shop
15:Eastern European Restaurant  16:French Restaurant            17:German Restaurant
18:Greek Restaurant             19:Hawaiian Restaurant          20:Indian Restaurant
21:Italian Restaurant           22:Jewish Restaurant            23:Latin American Restaurant
24:Mediterranean Restaurant     25:Mexican Restaurant           26:Middle Eastern Restaurant
27:Russian Restaurant           28:Spanish Restaurant           29:Turkish Restaurant
30:Ukrainian Restaurant         31:Bar                          32:Athletics & Sports
33:Beach                        34:Ski Area                     35:States & Municipalities
36:Convention Center            37:Event Space                  38:Government Building
39:Medical Center               40:Office                       41:School
42:Spiritual Center             43:Child Care Service           44:Clothing Store
45:Food & Drink Shop            46:Furniture / Home Store       47:Airport
48:Bus Station                  49:Hotel                        50:Train Station
12
```

```
<folium.folium.Map at 0x21c828ddcf8>
```

In [ ]: