Final-Capstone

December 21, 2020

0.1 Week 4. The Battle of the Neighborhoods.

0.1.1 Part 1. Background.

Central America (**CAm**) is the natural land bridge between North and South America. After a century of dictatorships, civil wars and political unrest, things are looking good for this part of the world (see note), so much so that in Latin America, **CAm** has shown a bigger *average* economic growth than their neighbors in the South and the one up North (1) in the last decade. Although industry is still a big part of their respective economies (especially Guatemala and Panama), an important amount of the **CAm** economies depends on internal markets, either regional or country-specific. This includes restaurants, malls, and tourism, so important questions arise, are they the same avenues or do some countries share ones that others don't?. Even if they share the same avenues, do customers differ in their reviews depending on the country?

This information will be helpful to a preliminary market research, because it will let us know where the demand for a certain service is and where is it well evaluated (allowing us to investigate further what causes the better scores).

Note: Now signs of authoritarianism are blatant in most CAm (Guatemala, Honduras, El Salvador, Nicaragua), that might impact their economies in the near future.

0.1.2 Part 2. Problem.

- ¿Do Central American countries offer the same type of avenues or do some countries have some distinctive ones?
- If they have the same ¿do the reviews differ by country?

0.1.3 Part 3. Data Description.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
from sklearn.cluster import DBSCAN

plt.style.use('seaborn')
```

```
C:\Users\marina\Anaconda3\lib\site-packages\statsmodels\tools\_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
```

```
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

I will be using the Foursquare data on the Central American capitals. This includes:

- Belmopán (**Belize**),
- Guatemala City (**Guatemala**),
- San Salvador (**El Salvador**),
- Tegicigalpa (**Honduras**),
- Managua (**Nicaragua**),
- San José (**Costa Rica**),
- and Panamá City (**Panamá**).

[2]:
```
geo_capitals = pd.read_csv("./capitals-geolocation/concap.csv")

# Select only those that are marked as being in Central America
geo_capitals[geo_capitals['ContinentName'] == 'Central America'].head() # Only␣
↪first 5
```

[2]:
```
     CountryName   CapitalName  CapitalLatitude  CapitalLongitude CountryCode  \
29        Belize      Belmopan        17.250000        -88.766667          BZ
45        Canada        Ottawa        45.416667        -75.700000          CA
59    Costa Rica      San Jose         9.933333        -84.083333          CR
72   El Salvador  San Salvador        13.700000        -89.200000          SV
90     Greenland          Nuuk        64.183333        -51.750000          GL

      ContinentName
29  Central America
45  Central America
59  Central America
72  Central America
90  Central America
```

Thanks to the Kaggle user *Grecnik* for the geolocation data on the capitals of the world.

As we can see, although the countries stated before are there, we also have other countries like Canada or Greenland, which we know are not in Central America, so we'll have to clean that up. Knowing this is not a bad idea to make sure the geolacation data is correct, so we can make some Folium maps with the data.

[3]:
```
central_geo = geo_capitals[geo_capitals['ContinentName'] == 'Central America'].
↪copy(deep=True)
central_geo
```

[3]:
```
                          CountryName     CapitalName  CapitalLatitude  \
29                             Belize        Belmopan        17.250000
45                             Canada          Ottawa        45.416667
59                         Costa Rica        San Jose         9.933333
72                        El Salvador    San Salvador        13.700000
90                          Greenland            Nuuk        64.183333
```

```
93                          Guatemala  Guatemala City        14.616667
100                          Honduras     Tegucigalpa        14.100000
142                            Mexico     Mexico City        19.433333
156                         Nicaragua         Managua        12.133333
166                            Panama     Panama City         8.966667
183         Saint Pierre and Miquelon    Saint-Pierre        46.766667
184  Saint Vincent and the Grenadines       Kingstown        13.133333
227                     United States      Washington        38.883333

     CapitalLongitude CountryCode    ContinentName
29         -88.766667          BZ  Central America
45         -75.700000          CA  Central America
59         -84.083333          CR  Central America
72         -89.200000          SV  Central America
90         -51.750000          GL  Central America
93         -90.516667          GT  Central America
100        -87.216667          HN  Central America
142        -99.133333          MX  Central America
156        -86.250000          NI  Central America
166        -79.533333          PA  Central America
183        -56.183333          PM  Central America
184        -61.216667          VC  Central America
227        -77.000000          US  Central America
```

[4]:
```
central_geo.drop(index=[45, 90, 142, 183, 184, 227], inplace=True)
central_geo
```

[4]:
```
     CountryName     CapitalName  CapitalLatitude  CapitalLongitude  \
29        Belize        Belmopan        17.250000        -88.766667
59    Costa Rica        San Jose         9.933333        -84.083333
72   El Salvador    San Salvador        13.700000        -89.200000
93     Guatemala  Guatemala City        14.616667        -90.516667
100     Honduras     Tegucigalpa        14.100000        -87.216667
156    Nicaragua         Managua        12.133333        -86.250000
166       Panama     Panama City         8.966667        -79.533333

    CountryCode    ContinentName
29           BZ  Central America
59           CR  Central America
72           SV  Central America
93           GT  Central America
100          HN  Central America
156          NI  Central America
166          PA  Central America
```

With this information we'll use the ***Foursquare API*** to get all the venues in the different cities, and we'll be getting **the rating of each of them**. Since a free account only allows for 50 premium calls per day, in case that is not enough the data acquired will be stored in a csv file, with the help of the *Pandas* library.

[5]:
```
# The final Data Frame should look something like this, but with average scores
↪on each venue
ca_venues = pd.read_csv("ca_venues.csv")
ca_venues.head()
```

[5]:
```
   Unnamed: 0      City  City Latitude  City Longitude                   Venue  \
0           0  Belmopan          17.25      -88.766667           Moon Clusters
1           1  Belmopan          17.25      -88.766667           Bull Frog Inn
2           2  Belmopan          17.25      -88.766667                BBQ Spot
3           3  Belmopan          17.25      -88.766667       Betty's Fast Food
4           4  Belmopan          17.25      -88.766667  Belmopan City, Belize

                   Venue id  Venue Latitude  Venue Longitude  \
0  51411144e4b043b9424634d6       17.250410       -88.764992
1  5048b9fce4b0e33cddc0698f       17.251791       -88.764494
2  5691551a498e8f20fed364ee       17.246916       -88.765686
3  5c6709f212c8f0002c90a5c0       17.251902       -88.763106
4  53c3e05a498e5ef87c0027c8       17.246987       -88.770134

         Venue Category
0                  Café
1                 Hotel
2             BBQ Joint
3  Fast Food Restaurant
4          Intersection
```

[6]:
```
dummy = ca_venues[['City', 'Venue Category', 'Venue']]
```

0.1.4 Part 4. Analysis

[7]:
```
def return_most_common_venues(row, num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)

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

[8]:
```
import matplotlib.cm as cm
import matplotlib.colors as colors
```

[9]:
```
# Here we can see the different venue categories found in the capitals
pd.pivot_table(ca_venues,
               columns='Venue Category',
               index='City',
               aggfunc='count')
```

[9]:

```
                City Latitude                                           \
Venue Category   Art Gallery Asian Restaurant BBQ Joint Bakery  Bar
City
Belmopan                 NaN              NaN       1.0    NaN  NaN
Guatemala City           2.0              1.0       NaN    NaN  1.0
Managua                  NaN              NaN       NaN    NaN  NaN
Panama City              NaN              NaN       NaN    NaN  NaN
San Jose                 NaN              NaN       NaN    1.0  1.0
San Salvador             NaN              NaN       NaN    NaN  NaN
Tegucigalpa              NaN              NaN       NaN    NaN  NaN

                                                                     \
Venue Category Big Box Store Boutique Breakfast Spot Brewery Burger Joint
City
Belmopan                 NaN      NaN            NaN     NaN          NaN
Guatemala City           NaN      NaN            1.0     1.0          2.0
Managua                  1.0      NaN            2.0     NaN          NaN
Panama City              NaN      NaN            NaN     NaN          NaN
San Jose                 NaN      1.0            NaN     NaN          1.0
San Salvador             NaN      NaN            NaN     NaN          NaN
Tegucigalpa              NaN      NaN            NaN     NaN          NaN

                …  Venue id                                           \
Venue Category  … Public Art Rental Car Location Restaurant Sandwich Place
City            …
Belmopan        …        NaN                 NaN        NaN            NaN
Guatemala City  …        1.0                 1.0        2.0            1.0
Managua         …        NaN                 NaN        NaN            NaN
Panama City     …        NaN                 NaN        NaN            NaN
San Jose        …        NaN                 NaN        3.0            4.0
San Salvador    …        NaN                 NaN        NaN            NaN
Tegucigalpa     …        NaN                 NaN        1.0            NaN

                                                                    \
Venue Category Scenic Lookout Snack Place Sports Bar Steakhouse Theater
City
Belmopan                  NaN         NaN        NaN        NaN     NaN
Guatemala City            NaN         NaN        NaN        1.0     NaN
Managua                   NaN         NaN        1.0        NaN     NaN
Panama City               1.0         NaN        NaN        NaN     1.0
San Jose                  NaN         2.0        NaN        NaN     1.0
San Salvador              NaN         NaN        NaN        NaN     NaN
Tegucigalpa               NaN         NaN        NaN        NaN     NaN


Venue Category Vegetarian / Vegan Restaurant
City
```

```
Belmopan                                 NaN
Guatemala City                           1.0
Managua                                  NaN
Panama City                              NaN
San Jose                                 NaN
San Salvador                             NaN
Tegucigalpa                              NaN

[7 rows x 406 columns]
```

[10]:
```python
# And here we can see which city has the most varied venues
venue_counts = pd.pivot_table(ca_venues,
                              values='Venue Category',
                              index='City',
                              aggfunc='count').sort_values(by='Venue Category',
                                                           ascending=False)


venue_counts
```

[10]:
```
                Venue Category
City
San Jose                    40
Guatemala City              26
San Salvador                13
Panama City                 10
Managua                      9
Belmopan                     5
Tegucigalpa                  3
```

An alternative:

[11]:
```python
ca_venues.groupby(by=['City'])['Venue Category'].count().reset_index()
```

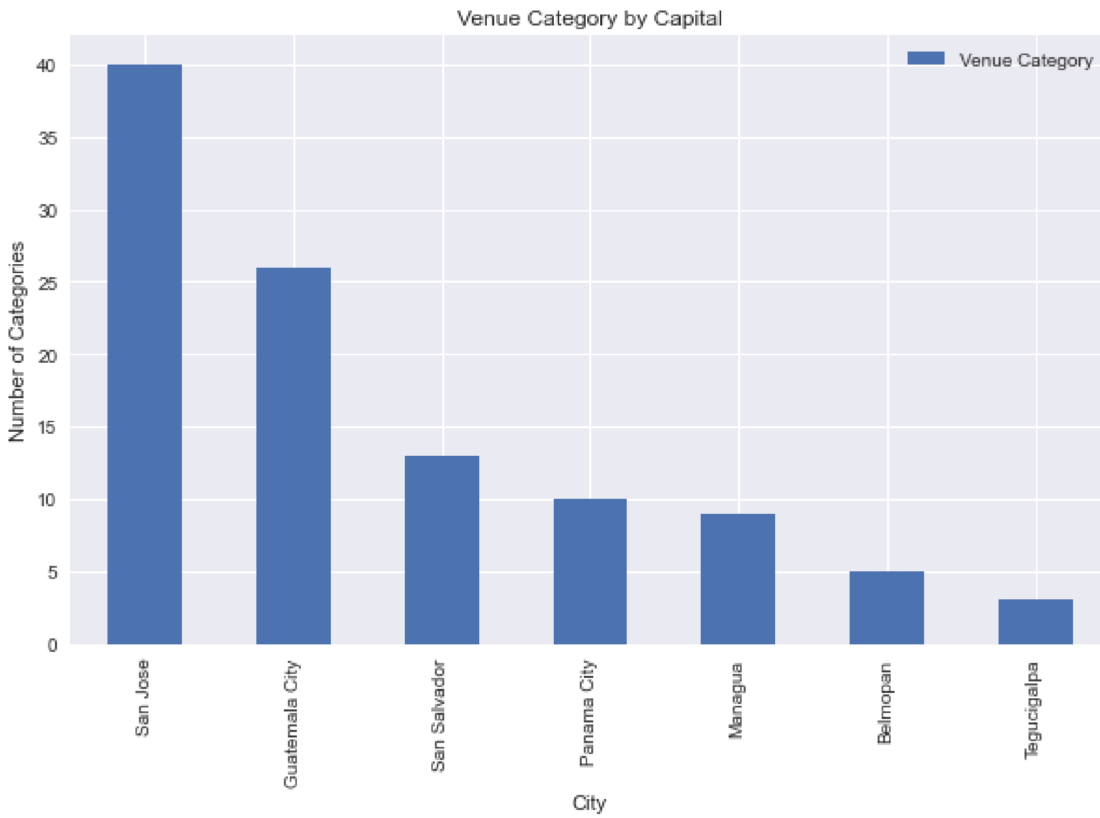
[11]:
```
             City  Venue Category
0        Belmopan               5
1  Guatemala City              26
2         Managua               9
3     Panama City              10
4        San Jose              40
5    San Salvador              13
6     Tegucigalpa               3
```

Once we have the entire dataset we'll use a clustering algorithm to know which countries share a commonality with each other. After that will use classification algorithm to see if the average avenue score per country is indicative of something.

[12]:
```python
ax = venue_counts.plot(kind='bar', figsize=(10, 6))
ax.set_title(label='Venue Category by Capital', fontdict={'fontsize':12})
```

```
ax.set_ylabel('Number of Categories')
```

[12]: Text(0, 0.5, 'Number of Categories')



[13]:
```
type_venue_counts = pd.pivot_table(ca_venues,
                               values='City',
                               index='Venue Category',
                               aggfunc='count').sort_values(by='City',
                                                            ascending=False)

type_venue_counts.head()
```

[13]:

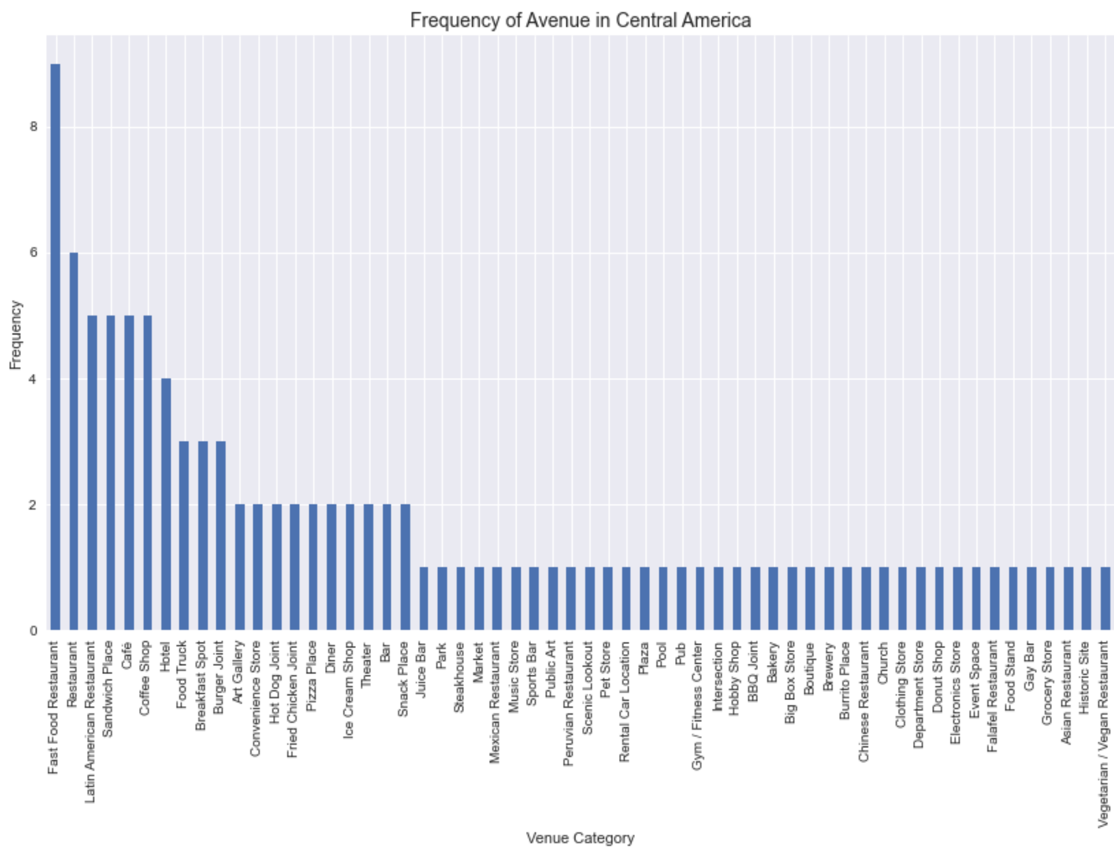
	City
Venue Category	
Fast Food Restaurant	9
Restaurant	6
Latin American Restaurant	5
Sandwich Place	5
Café	5

[14]:

```python
ax = type_venue_counts.plot(kind='bar', figsize=(14, 8), legend=False)
ax.set_title(label='Frequency of Avenue in Central America', fontdict={'fontsize':14})
ax.set_ylabel('Frequency')
```

[14]:

```
Text(0, 0.5, 'Frequency')
```



[ ]:

```python

```

[15]:

```python
# one hot encoding
ca_onehot = pd.get_dummies(ca_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
ca_onehot['City'] = ca_venues['City']

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

```python
ca_onehot.head()
```

[15]:
```
         City  Art Gallery  Asian Restaurant  BBQ Joint  Bakery  Bar  \
0  Belmopan            0                 0          0       0    0
1  Belmopan            0                 0          0       0    0
2  Belmopan            0                 0          1       0    0
3  Belmopan            0                 0          0       0    0
4  Belmopan            0                 0          0       0    0

   Big Box Store  Boutique  Breakfast Spot  Brewery  …  Public Art  \
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

   Rental Car Location  Restaurant  Sandwich Place  Scenic Lookout  \
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

   Snack Place  Sports Bar  Steakhouse  Theater  Vegetarian / Vegan 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

[5 rows x 59 columns]
```

[16]:
```python
ca_onehot.shape
```

[16]: (106, 59)

[17]:
```python
ca_grouped = ca_onehot.groupby('City').mean().reset_index()
ca_grouped
```

[17]:
```
             City  Art Gallery  Asian Restaurant  BBQ Joint  Bakery       Bar  \
0        Belmopan     0.000000          0.000000        0.2   0.000  0.000000
1  Guatemala City     0.076923          0.038462        0.0   0.000  0.038462
2         Managua     0.000000          0.000000        0.0   0.000  0.000000
3     Panama City     0.000000          0.000000        0.0   0.000  0.000000
4        San Jose     0.000000          0.000000        0.0   0.025  0.025000
5    San Salvador     0.000000          0.000000        0.0   0.000  0.000000
6     Tegucigalpa     0.000000          0.000000        0.0   0.000  0.000000
```

```
   Big Box Store  Boutique  Breakfast Spot   Brewery  …  Public Art  \
0       0.000000     0.000        0.000000  0.000000  …    0.000000
1       0.000000     0.000        0.038462  0.038462  …    0.038462
2       0.111111     0.000        0.222222  0.000000  …    0.000000
3       0.000000     0.000        0.000000  0.000000  …    0.000000
4       0.000000     0.025        0.000000  0.000000  …    0.000000
5       0.000000     0.000        0.000000  0.000000  …    0.000000
6       0.000000     0.000        0.000000  0.000000  …    0.000000

   Rental Car Location  Restaurant  Sandwich Place  Scenic Lookout  \
0             0.000000    0.000000        0.000000             0.0
1             0.038462    0.076923        0.038462             0.0
2             0.000000    0.000000        0.000000             0.0
3             0.000000    0.000000        0.000000             0.1
4             0.000000    0.075000        0.100000             0.0
5             0.000000    0.000000        0.000000             0.0
6             0.000000    0.333333        0.000000             0.0

   Snack Place  Sports Bar  Steakhouse  Theater  Vegetarian / Vegan Restaurant
0         0.00    0.000000    0.000000    0.000                       0.000000
1         0.00    0.000000    0.038462    0.000                       0.038462
2         0.00    0.111111    0.000000    0.000                       0.000000
3         0.00    0.000000    0.000000    0.100                       0.000000
4         0.05    0.000000    0.000000    0.025                       0.000000
5         0.00    0.000000    0.000000    0.000                       0.000000
6         0.00    0.000000    0.000000    0.000                       0.000000

[7 rows x 59 columns]
```

[18]:

```
num_top_venues = 10

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

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

# create a new dataframe
ca_venues_sorted = pd.DataFrame(columns=columns)
ca_venues_sorted['City'] = ca_grouped['City']

for ind in np.arange(ca_grouped.shape[0]):
```

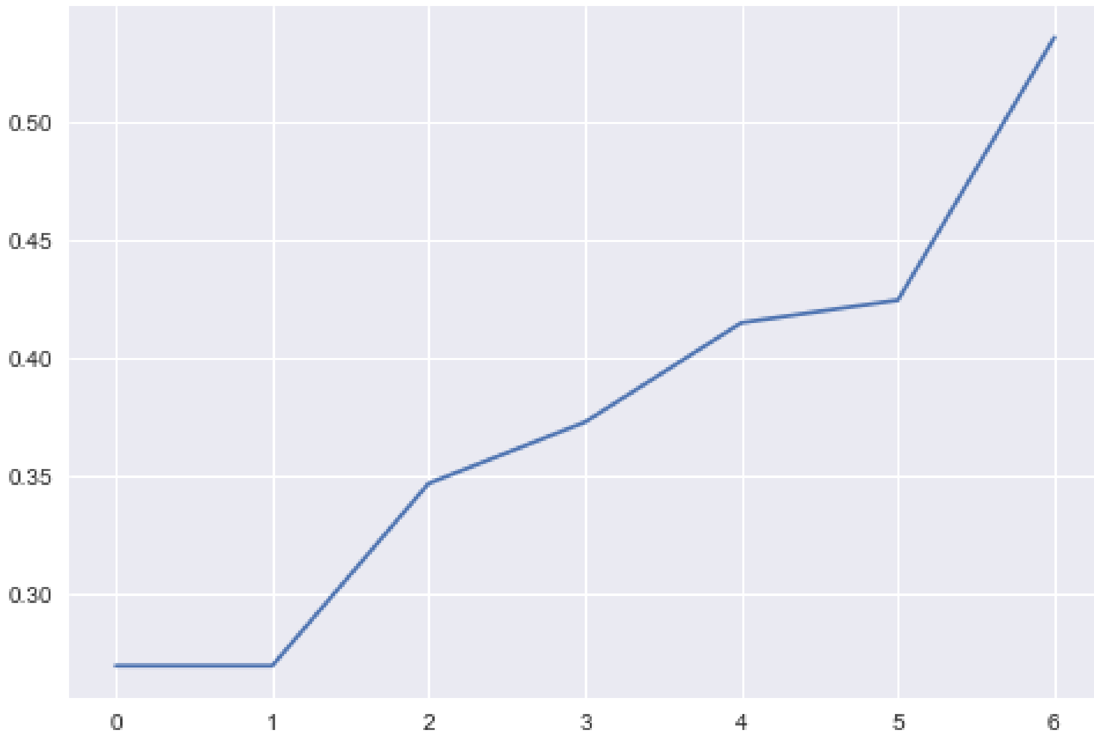
```
    ca_venues_sorted.iloc[ind, 1:] = return_most_common_venues(ca_grouped.
↪iloc[ind, :], num_top_venues)

ca_venues_sorted.head()
```

[18]:
```
             City 1st Most Common Venue 2nd Most Common Venue  \
0        Belmopan             BBQ Joint  Fast Food Restaurant
1  Guatemala City           Art Gallery          Burger Joint
2         Managua        Breakfast Spot    Chinese Restaurant
3     Panama City  Fast Food Restaurant                 Hotel
4        San Jose        Sandwich Place           Coffee Shop

  3rd Most Common Venue      4th Most Common Venue 5th Most Common Venue  \
0                 Hotel               Intersection                  Café
1            Restaurant                       Café          Hot Dog Joint
2     Convenience Store                 Sports Bar             Pet Store
3                  Park                       Pool               Theater
4  Fast Food Restaurant  Latin American Restaurant            Restaurant

          6th Most Common Venue      7th Most Common Venue  \
0  Vegetarian / Vegan Restaurant                Coffee Shop
1                         Hotel           Asian Restaurant
2                    Hobby Shop              Big Box Store
3                Scenic Lookout  Latin American Restaurant
4                  Snack Place              Ice Cream Shop

  8th Most Common Venue 9th Most Common Venue 10th Most Common Venue
0            Food Truck            Food Stand     Falafel Restaurant
1                   Bar        Breakfast Spot                Brewery
2    Mexican Restaurant            Donut Shop       Department Store
3                 Diner           Coffee Shop      Convenience Store
4         Grocery Store                Church                 Market
```

[19]:
```
from sklearn.neighbors import NearestNeighbors

ca_grouped_clustering = ca_grouped.drop('City', 1)

neigh = NearestNeighbors(n_neighbors=2).fit(ca_grouped_clustering)

distances, indices = neigh.kneighbors(ca_grouped_clustering)
```

[20]:
```
distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.plot(distances)
```

[20]: [<matplotlib.lines.Line2D at 0x2349dbdb208>]



[21]:
```
ca_grouped_clustering = ca_grouped.drop('City', 1)

# run k-means clustering
ca_dbscan = DBSCAN(eps=0.45).fit(ca_grouped_clustering)

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

[21]:
```
array([ 0,  0,  0,  0,  0,  0, -1], dtype=int64)
```

[22]:
```
# add clustering labels
ca_venues_sorted.insert(0, 'Cluster Labels', ca_dbscan.labels_)

ca_merged = central_geo

# merge manhattan_grouped with manhattan_data to add latitude/longitude for␣
 ↪each neighborhood
ca_merged = ca_merged.join(ca_venues_sorted.set_index('City'), on='CapitalName')

ca_merged.head() # check the last columns!
```

[22]:
```
     CountryName    CapitalName  CapitalLatitude  CapitalLongitude  \
29        Belize       Belmopan        17.250000        -88.766667
```

```
59    Costa Rica        San Jose         9.933333        -84.083333
72   El Salvador     San Salvador       13.700000        -89.200000
93     Guatemala  Guatemala City        14.616667        -90.516667
100     Honduras      Tegucigalpa       14.100000        -87.216667

    CountryCode    ContinentName  Cluster Labels 1st Most Common Venue  \
29           BZ  Central America               0            BBQ Joint
59           CR  Central America               0       Sandwich Place
72           SV  Central America               0           Food Truck
93           GT  Central America               0          Art Gallery
100          HN  Central America              -1  Fast Food Restaurant

    2nd Most Common Venue 3rd Most Common Venue  \
29   Fast Food Restaurant                 Hotel
59            Coffee Shop  Fast Food Restaurant
72         Clothing Store           Coffee Shop
93           Burger Joint            Restaurant
100            Restaurant      Electronics Store

             4th Most Common Venue 5th Most Common Venue  \
29                    Intersection                  Café
59        Latin American Restaurant            Restaurant
72              Fried Chicken Joint                  Café
93                             Café         Hot Dog Joint
100  Vegetarian / Vegan Restaurant                Church

             6th Most Common Venue 7th Most Common Venue  \
29   Vegetarian / Vegan Restaurant           Coffee Shop
59                     Snack Place        Ice Cream Shop
72                     Pizza Place                 Plaza
93                           Hotel      Asian Restaurant
100                     Food Truck            Food Stand

         8th Most Common Venue 9th Most Common Venue 10th Most Common Venue
29                  Food Truck            Food Stand     Falafel Restaurant
59               Grocery Store                Church                 Market
72   Latin American Restaurant           Music Store             Donut Shop
93                         Bar        Breakfast Spot                Brewery
100         Falafel Restaurant           Event Space             Donut Shop
```

[23]:
```
ca_dbscan.labels_
```

[23]:
```
array([ 0,  0,  0,  0,  0,  0, -1], dtype=int64)
```

[24]:
```
# create map
map_clusters = folium.Map(location=[12.769013, -85.602364], zoom_start=6)
```

```
# set color scheme for the clusters
x = np.arange(2)
ys = [i + x + (i*x)**2 for i in range(2)]
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(ca_merged['CapitalLatitude'],␣
 ↪ca_merged['CapitalLongitude'], ca_merged['CapitalName'], ca_merged['Cluster␣
 ↪Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

[24]: <folium.folium.Map at 0x2349dc48d08>

First Conclusions With only the basic avenue's information we can see that Honduras is the only one in the region that appears to be an outsider.

0.1.5 Part 5. Data with likes

We have thus far analised the venues only with their category, but Foursquare allows us to dig deeper, so that's what we are going to do. Since premium calls are restricted to 50 per day we did the requests days before and stored the results in csv files. After that we cleaned the data, until we were left with the premium_calls.csv file.

[25]:
```
venue_info = pd.read_csv("premium_calls.csv")
venue_info.head()
```

[25]:
```
   Unnamed: 0         response.venue.id    response.venue.name  \
0           0  51411144e4b043b9424634d6          Moon Clusters
1           1  5048b9fce4b0e33cddc0698f          Bull Frog Inn
2           2  5691551a498e8f20fed364ee               BBQ Spot
3           3  5c6709f212c8f0002c90a5c0      Betty's Fast Food
4           4  53c3e05a498e5ef87c0027c8  Belmopan City, Belize

  response.venue.price.message response.venue.likes.summary  \
0                        Cheap                       1 Like
```

```
1                        NaN                     2 Likes
2                   Moderate                         NaN
3                      Cheap                         NaN
4                        NaN                      1 Like

  response.venue.dislike
0                  False
1                  False
2                  False
3                  False
4                  False
```

First of all we need to clean this final table, removed the 'Unnamed: 0' column and change the column names.

[26]:
```
venue_info.drop(labels='Unnamed: 0',axis=1, inplace=True)
venue_info.columns
```

[26]:
```
Index(['response.venue.id', 'response.venue.name',
       'response.venue.price.message', 'response.venue.likes.summary',
       'response.venue.dislike'],
      dtype='object')
```

[27]:
```
venue_info.columns = ['id', 'Name', 'Price', 'Likes', 'Disliked?']
venue_info.head()
```

[27]:
```
                         id                   Name     Price    Likes  \
0  51411144e4b043b9424634d6          Moon Clusters     Cheap   1 Like
1  5048b9fce4b0e33cddc0698f          Bull Frog Inn       NaN  2 Likes
2  5691551a498e8f20fed364ee               BBQ Spot  Moderate      NaN
3  5c6709f212c8f0002c90a5c0      Betty's Fast Food     Cheap      NaN
4  53c3e05a498e5ef87c0027c8  Belmopan City, Belize       NaN   1 Like

  Disliked?
0     False
1     False
2     False
3     False
4     False
```

Now that we have done that, we need to extract the numbers in the 'Likes' column and change its type for it to be used as numbers in the analysis.

[28]:
```
# Let's extract only the number of likes for each venue
venue_info['Likes'] = venue_info['Likes'].str.extract(r'([0-9]+)', expand=False)
venue_info.head()
```

[28]:
```
                         id                 Name     Price Likes Disliked?
0  51411144e4b043b9424634d6         Moon Clusters     Cheap     1     False
1  5048b9fce4b0e33cddc0698f         Bull Frog Inn       NaN     2     False
2  5691551a498e8f20fed364ee              BBQ Spot  Moderate   NaN     False
3  5c6709f212c8f0002c90a5c0     Betty's Fast Food     Cheap   NaN     False
4  53c3e05a498e5ef87c0027c8  Belmopan City, Belize       NaN     1     False
```

[29]:
```python
ca_venues.drop(labels='Unnamed: 0', axis=1, inplace=True)
ca_venues.head()
```

[29]:
```
       City  City Latitude  City Longitude                  Venue  \
0  Belmopan          17.25      -88.766667          Moon Clusters
1  Belmopan          17.25      -88.766667          Bull Frog Inn
2  Belmopan          17.25      -88.766667               BBQ Spot
3  Belmopan          17.25      -88.766667      Betty's Fast Food
4  Belmopan          17.25      -88.766667  Belmopan City, Belize

                   Venue id  Venue Latitude  Venue Longitude  \
0  51411144e4b043b9424634d6       17.250410       -88.764992
1  5048b9fce4b0e33cddc0698f       17.251791       -88.764494
2  5691551a498e8f20fed364ee       17.246916       -88.765686
3  5c6709f212c8f0002c90a5c0       17.251902       -88.763106
4  53c3e05a498e5ef87c0027c8       17.246987       -88.770134

         Venue Category
0                  Café
1                 Hotel
2             BBQ Joint
3  Fast Food Restaurant
4          Intersection
```

Then we can join the ca_venues dataframe with the full information venues on the ids, so we can have the full scope.

[31]:
```python
full_venues = ca_venues.join(venue_info.set_index('id'), on='Venue id')
full_venues.head()
```

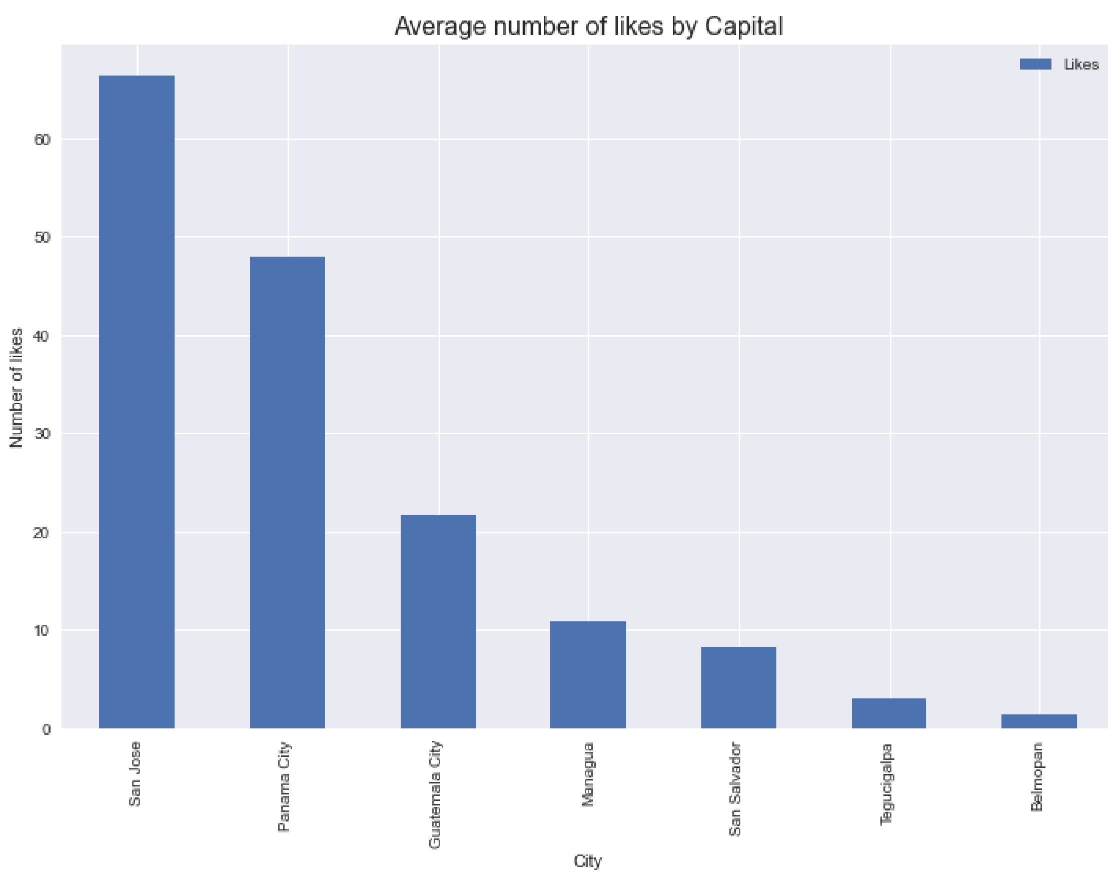
[31]:
```
       City  City Latitude  City Longitude                  Venue  \
0  Belmopan          17.25      -88.766667          Moon Clusters
1  Belmopan          17.25      -88.766667          Bull Frog Inn
2  Belmopan          17.25      -88.766667               BBQ Spot
3  Belmopan          17.25      -88.766667      Betty's Fast Food
4  Belmopan          17.25      -88.766667  Belmopan City, Belize

                   Venue id  Venue Latitude  Venue Longitude  \
0  51411144e4b043b9424634d6       17.250410       -88.764992
1  5048b9fce4b0e33cddc0698f       17.251791       -88.764494
2  5691551a498e8f20fed364ee       17.246916       -88.765686
```

```
3  5c6709f212c8f0002c90a5c0       17.251902       -88.763106
4  53c3e05a498e5ef87c0027c8       17.246987       -88.770134

         Venue Category                     Name     Price Likes Disliked?
0                  Café           Moon Clusters     Cheap     1     False
1                 Hotel            Bull Frog Inn       NaN     2     False
2             BBQ Joint                 BBQ Spot  Moderate   NaN     False
3  Fast Food Restaurant        Betty's Fast Food     Cheap   NaN     False
4          Intersection  Belmopan City, Belize       NaN     1     False
```

[32]:
```
full_venues['Likes'] = pd.to_numeric(full_venues['Likes'])
```

[33]:
```
ax = full_venues[['City', 'Likes']].groupby('City').mean().sort_values('Likes',
 ↪ascending=False).plot(kind='bar', figsize=(12, 8))

ax.set_title(label='Average number of likes by Capital', fontdict={'fontsize':
 ↪16})
ax.set_ylabel('Number of likes')
```

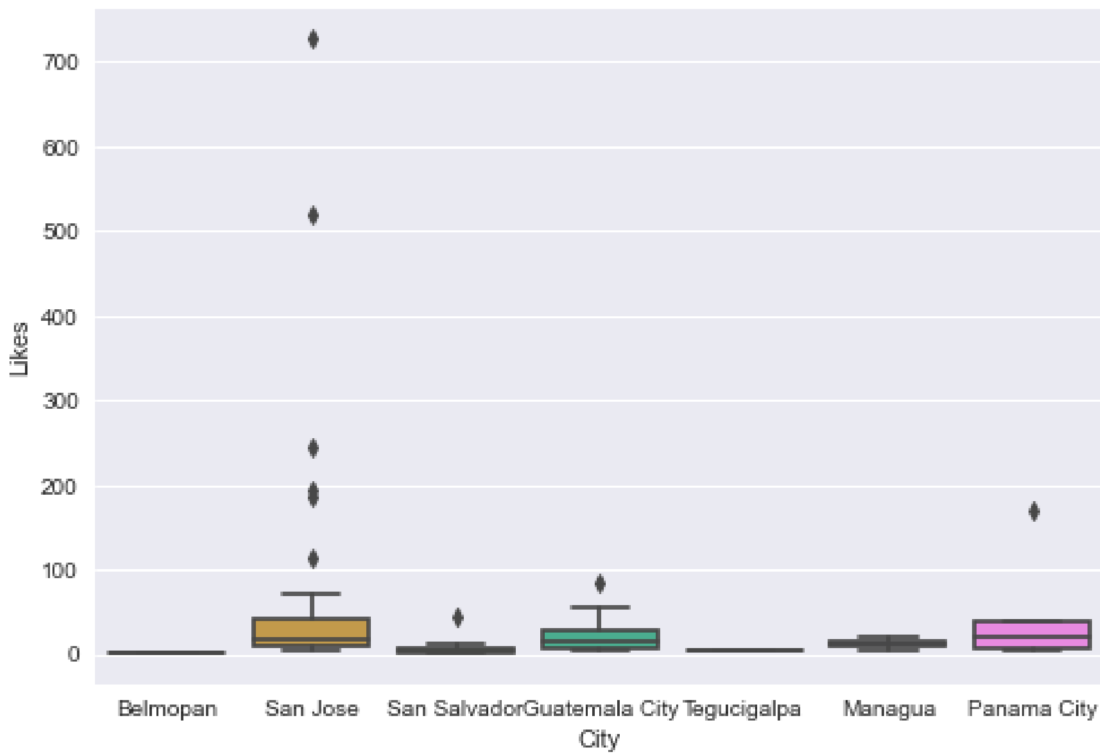
[33]: Text(0, 0.5, 'Number of likes')



In order for the machine learning algorithms to use the data we need to standardized it. First we begin with the numerical data.

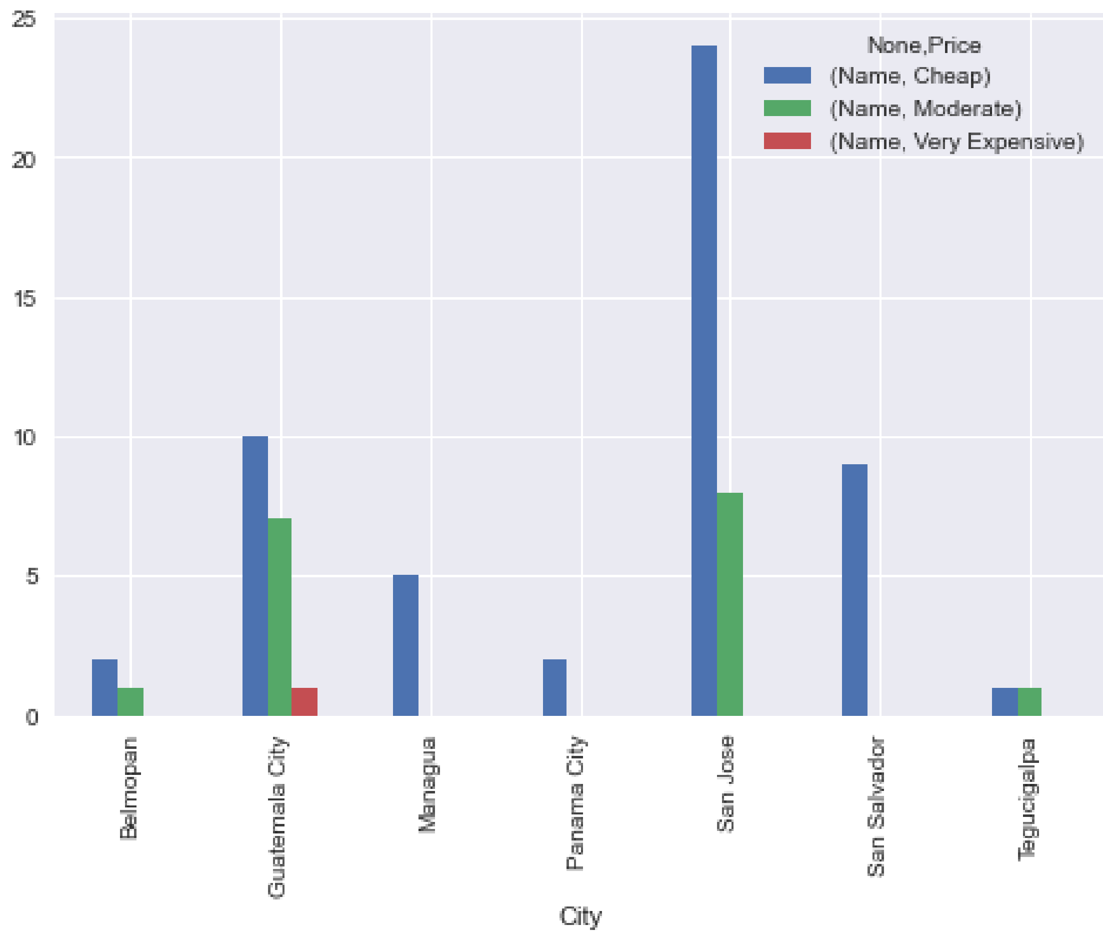
[34]:
```
sns.boxplot(x=full_venues['City'], y=full_venues['Likes'])
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x2349de1bbc8>



[35]:
```
full_venues[['City', 'Price', 'Name']].pivot_table(index='City',␣
 ↪columns='Price', aggfunc='count').plot(kind='bar')
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x2349e35ca08>



[36]:
```
# apply the robust scaling in Pandas using the .median() and .quantile() methods
def robust_scaling(df):
    # copy the dataframe
    df_robust = df.copy()
    # apply robust scaling
    df_robust = (df_robust - df_robust.median())  / (df_robust.quantile(0.75) -␣
↪df_robust.quantile(0.25))
    return df_robust

# call the robust_scaling function
likes_robust = robust_scaling(full_venues['Likes'])

likes_robust
```

[36]:
```
0     -0.586667
1     -0.533333
2           NaN
```

```
3          NaN
4    -0.586667
        ...
101        NaN
102        NaN
103        NaN
104        NaN
105        NaN
Name: Likes, Length: 106, dtype: float64
```

Then we proceed with the categorical values, that need to be transform into numeric ones. This can be achieved through one hot encoding.

[37]:
```
full_onehot = pd.get_dummies(full_venues[['Venue Category', 'Price', 'Disliked?
↪']],
                             prefix="",
                             prefix_sep="")

# add neighborhood column back to dataframe
full_onehot['Likes'] = likes_robust
full_onehot['City'] = full_venues['City']

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

full_onehot
```

[37]:
```
             City  Art Gallery  Asian Restaurant  BBQ Joint  Bakery  Bar  \
0        Belmopan            0                 0          0       0    0
1        Belmopan            0                 0          0       0    0
2        Belmopan            0                 0          1       0    0
3        Belmopan            0                 0          0       0    0
4        Belmopan            0                 0          0       0    0
..            ...          ...               ...        ...     ...  ...
101   Panama City            0                 0          0       0    0
102   Panama City            0                 0          0       0    0
103   Panama City            0                 0          0       0    0
104   Panama City            0                 0          0       0    0
105   Panama City            0                 0          0       0    0

     Big Box Store  Boutique  Breakfast Spot  Brewery  ...  Snack 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
..             ...       ...             ...      ...  ...          ...
```

```
101                0          0               0         0  …               0
102                0          0               0         0  …               0
103                0          0               0         0  …               0
104                0          0               0         0  …               0
105                0          0               0         0  …               0

     Sports Bar  Steakhouse  Theater  Vegetarian / Vegan Restaurant  Cheap  \
0             0           0        0                              0      1
1             0           0        0                              0      0
2             0           0        0                              0      0
3             0           0        0                              0      1
4             0           0        0                              0      0
..          …         …      …                          …    …
101           0           0        0                              0      0
102           0           0        0                              0      0
103           0           0        0                              0      0
104           0           0        0                              0      0
105           0           0        0                              0      0

     Moderate  Very Expensive  False     Likes
0           0               0      1 -0.586667
1           0               0      1 -0.533333
2           1               0      1       NaN
3           0               0      1       NaN
4           0               0      1 -0.586667
..        …             …    …       …
101         0               0      0       NaN
102         0               0      0       NaN
103         0               0      0       NaN
104         0               0      0       NaN
105         0               0      0       NaN

[106 rows x 64 columns]
```

[38]:
```python
full_grouped = full_onehot.groupby('City').mean().reset_index()
full_grouped
```

[38]:
```
            City  Art Gallery  Asian Restaurant  BBQ Joint  Bakery       Bar  \
0       Belmopan     0.000000          0.000000        0.2   0.000  0.000000
1  Guatemala City    0.076923          0.038462        0.0   0.000  0.038462
2        Managua     0.000000          0.000000        0.0   0.000  0.000000
3    Panama City     0.000000          0.000000        0.0   0.000  0.000000
4       San Jose     0.000000          0.000000        0.0   0.025  0.025000
5    San Salvador    0.000000          0.000000        0.0   0.000  0.000000
6    Tegucigalpa     0.000000          0.000000        0.0   0.000  0.000000

   Big Box Store  Boutique  Breakfast Spot   Brewery  …  Snack Place  \
```

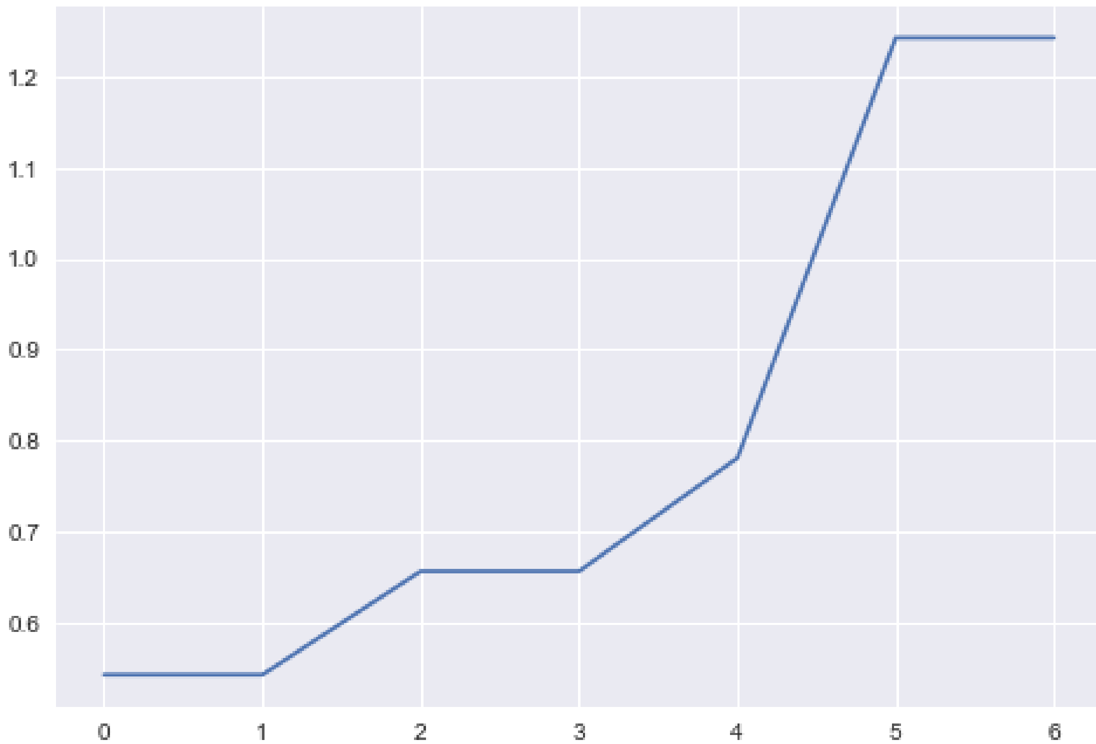
```
0       0.000000     0.000       0.000000  0.000000  …          0.00
1       0.000000     0.000       0.038462  0.038462  …          0.00
2       0.111111     0.000       0.222222  0.000000  …          0.00
3       0.000000     0.000       0.000000  0.000000  …          0.00
4       0.000000     0.025       0.000000  0.000000  …          0.05
5       0.000000     0.000       0.000000  0.000000  …          0.00
6       0.000000     0.000       0.000000  0.000000  …          0.00

   Sports Bar  Steakhouse  Theater  Vegetarian / Vegan Restaurant     Cheap  \
0    0.000000    0.000000    0.000                       0.000000  0.400000
1    0.000000    0.038462    0.000                       0.038462  0.384615
2    0.111111    0.000000    0.000                       0.000000  0.555556
3    0.000000    0.000000    0.100                       0.000000  0.200000
4    0.000000    0.000000    0.025                       0.000000  0.600000
5    0.000000    0.000000    0.000                       0.000000  0.692308
6    0.000000    0.000000    0.000                       0.000000  0.333333

   Moderate  Very Expensive     False     Likes
0  0.200000        0.000000  1.000000 -0.568889
1  0.269231        0.038462  1.000000  0.518400
2  0.000000        0.000000  1.000000 -0.059259
3  0.000000        0.000000  0.500000  1.920000
4  0.200000        0.000000  1.000000  2.897333
5  0.000000        0.000000  0.923077 -0.203636
6  0.333333        0.000000  1.000000 -0.480000

[7 rows x 64 columns]
```

Then to make sure what Epsilon value to use in the DBSCAN algorithm we ran Nearest Neighbors with this new data.

[39]:
```
full_grouped_clustering = full_grouped.drop('City', 1)

neigh = NearestNeighbors(n_neighbors=2).fit(full_grouped_clustering)

distances, indices = neigh.kneighbors(full_grouped_clustering)
```

[40]:
```
distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.plot(distances)
```

[40]:
```
[<matplotlib.lines.Line2D at 0x2349e422788>]
```



Even with the new data, we see that the elbow is not as well defined. Even so it seems that a epsilon value of 0.9 makes the separation better.

[41]:
```
full_grouped_clustering = full_grouped.drop('City', 1)

# run k-means clustering
full_dbscan = DBSCAN(eps=0.9).fit(full_grouped_clustering)

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

[41]:
```
array([ 0,  0,  0, -1, -1,  0,  0], dtype=int64)
```

[46]:
```
num_top_venues = 10

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

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

```
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
full_venues_sorted = pd.DataFrame(columns=columns)
full_venues_sorted['City'] = full_grouped['City']

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

full_venues_sorted.head()
```

[46]:

```
               City 1st Most Common Venue 2nd Most Common Venue  \
0          Belmopan                 False                 Cheap
1    Guatemala City                 False                 Likes
2           Managua                 False                 Cheap
3       Panama City                 Likes                 False
4          San Jose                 Likes                 False

  3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue  \
0              Moderate             BBQ Joint                 Hotel
1                 Cheap              Moderate            Restaurant
2        Breakfast Spot            Sports Bar    Mexican Restaurant
3  Fast Food Restaurant                 Cheap                 Hotel
4                 Cheap              Moderate        Sandwich Place

  6th Most Common Venue      7th Most Common Venue 8th Most Common Venue  \
0          Intersection       Fast Food Restaurant                  Café
1          Burger Joint                       Café         Hot Dog Joint
2    Chinese Restaurant          Convenience Store            Hobby Shop
3        Scenic Lookout                       Pool                 Diner
4           Coffee Shop  Latin American Restaurant            Restaurant

       9th Most Common Venue 10th Most Common Venue
0                 Hobby Shop            Event Space
1                Art Gallery     Fried Chicken Joint
2              Big Box Store              Pet Store
3  Latin American Restaurant                   Park
4       Fast Food Restaurant            Snack Place
```

[47]:

```
# add clustering labels
full_venues_sorted.insert(0, 'Cluster Labels', full_dbscan.labels_)

full_merged = central_geo

# merge manhattan_grouped with manhattan_data to add latitude/longitude for␣
 ↪each neighborhood
```

```
full_merged = full_merged.join(full_venues_sorted.set_index('City'),␣
↪on='CapitalName')

full_merged # check the last columns!
```

[47]:
```
    CountryName     CapitalName  CapitalLatitude  CapitalLongitude  \
29       Belize        Belmopan        17.250000        -88.766667
59   Costa Rica        San Jose         9.933333        -84.083333
72  El Salvador    San Salvador        13.700000        -89.200000
93    Guatemala  Guatemala City        14.616667        -90.516667
100    Honduras     Tegucigalpa        14.100000        -87.216667
156   Nicaragua         Managua        12.133333        -86.250000
166      Panama     Panama City         8.966667        -79.533333

    CountryCode    ContinentName  Cluster Labels 1st Most Common Venue  \
29           BZ  Central America               0                 False
59           CR  Central America              -1                 Likes
72           SV  Central America               0                 False
93           GT  Central America               0                 False
100          HN  Central America               0                 False
156          NI  Central America               0                 False
166          PA  Central America              -1                 Likes

    2nd Most Common Venue 3rd Most Common Venue 4th Most Common Venue  \
29                  Cheap              Moderate             BBQ Joint
59                  False                 Cheap              Moderate
72                  Cheap            Food Truck                 Plaza
93                  Likes                 Cheap              Moderate
100     Electronics Store              Moderate                 Cheap
156                 Cheap        Breakfast Spot            Sports Bar
166                 False  Fast Food Restaurant                 Cheap

    5th Most Common Venue 6th Most Common Venue      7th Most Common Venue  \
29                  Hotel          Intersection       Fast Food Restaurant
59         Sandwich Place           Coffee Shop  Latin American Restaurant
72                   Café  Fast Food Restaurant  Latin American Restaurant
93             Restaurant          Burger Joint                       Café
100  Fast Food Restaurant            Restaurant                 Hobby Shop
156    Mexican Restaurant    Chinese Restaurant          Convenience Store
166                 Hotel        Scenic Lookout                       Pool

    8th Most Common Venue      9th Most Common Venue 10th Most Common Venue
29                   Café                 Hobby Shop            Event Space
59             Restaurant       Fast Food Restaurant           Snack Place
72             Donut Shop                Music Store           Coffee Shop
93          Hot Dog Joint                Art Gallery    Fried Chicken Joint
100     Convenience Store           Department Store                  Diner
```

```
156            Hobby Shop              Big Box Store                Pet Store
166                 Diner  Latin American Restaurant                     Park
```

Once again we create the map.

[48]:
```python
# create map
map_clusters = folium.Map(location=[12.769013, -85.602364], zoom_start=6)

# set color scheme for the clusters
x = np.arange(2)
ys = [i + x + (i*x)**2 for i in range(2)]
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(full_merged['CapitalLatitude'],␣
 ↪full_merged['CapitalLongitude'], full_merged['CapitalName'],␣
 ↪full_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

[48]:
```
<folium.folium.Map at 0x2349f6659c8>
```

0.1.6 Part 6. Results and Discussion

We can see two different results, apparently drived by their respective data. In the first one, where we only compared venue types between the different capitals we saw Honduras as the odd one out, which was probably a result of its low variaty in venue types. In the second one, the data told us that both Costa Rica and Panamá City had a greater average of liked than the rest of Central American capitals. This might have resulted in the new map, where these two countries seem different from the other one.

The results are preliminary at best, as we know that Foursquare doesn't have a robust information on this countries. A better analysis would come out of a bigger and fuller data set. Having said that, it isn't surprising that Panamá and Costa Rica have better reviews, as they have the second and third biggest economies in the region and also don't suffer the violence that a richer country as Guatemala does.

0.1.7 Part 7. Conclusions

The goal of this analysis was to check if the capitals of all Central America countries share commonalities regarding their venues. It seems that they are not so far off, although with some minor differences. Honduras is the least known one, and Costa Rica is the highest liked, Panama being a close second. Other than that all of these seem to share some commonality. A more robust data is sure to make a clearer analysis, but a certain homogeneity seems to be the rule in Central America.

Stake holders would have a final answer, but Costa Rica looks like a more competitive ground, Honduras the least and San José has the cheapest places, Guatemala having the most expensive ones.