Coursera Capstone Final

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Introduction: Welcome to my Coursera Capstone Final!

Hello! And welcome to my final project my Capstone Project for the Coursera - IBM Data Science course. I hope to illustrate just some of the things I've learned in the following paragraphs.

Before we begin, please note that this can be followed along wit Github : https://github.com/cjmarino/Coursera_Capstone_Final

For this project, I have chosen to think entrepreneurially and utilize my dataset to solve a rather simple, age old question - where, exactly, should I open a bar in Akron, OH to give myself the best chance of success?

In this, there are several considerations - do they already have an abundance of bars? What other things are popular in the area? If an area has no bars but seems like a culturally 'dry' area, I will want to avoid those as well.

Data: Where will I be getting my data?

I will be examining the Akron, OH location by zip codes. Since there was not a location I could find to properly scrape these zip codes from a site, manual input was required in the form a csv. This was taken from https://www.akronohio.gov/cms/AkronZipCodes2013/akron_area_zip_codes.pdf. Once those zip codes were entered, the coordinates was cross coordinated via google; that completed csv was then uploaded to my GitHub account, and can be found here: https://github.com/cjmarino/Coursera_Capstone/blob/master/Akron_Ohio_Zip_Codes.csv.

In the next section, we will walk through the methodology used to attempt to answer this question.

Please follow along my code here as you read this report: https://github.com/cjmarino/Coursera_Capstone/blob/master/Coursera_Capstone_Final.ipynb

Methodology: How do we get from here to there?

The first thing that is necessary is to import the library's that will be used as seen below.

```
#import libraries
!pip install folium
!pip install geopy
!pip install yellowbrick

import folium
from geopy.geocoders import Nominatim # convert an address into latitude and longitude values
import io
import matplotlib.cm as cm
import matplotlib.colors as colors
import numpy as np
import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
import requests
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer
print('Libraries imported.')
```

Next, we have to import the data; since Akron, OH did not have a nice clean table to use BeautifulSoup to scrape, this was entered manually in a csv file which was then uploaded to my Github account. If you are interested in downloading this csv, please visit the following: https://github.com/cjmarino/Coursera_Capstone_Final/blob/master/Akron_Ohio_Zip_Codes.csv

In [2]:
```
#import, clean, process, and display data
#read dataframe
df = pd.read_html('https://github.com/cjmarino/Coursera_Capstone_Final/blob/master/Akron_Ohio_Zip_Codes.csv', index_col=0)[0]
#reset index
df = df.reset_index(drop=True)
df.head()
```

Out[2]:

	Zip Code	City	Latitude	Longitude
0	44203	Barberton, New Franklin, Norton	41.0274	-81.6364
1	44221	Cuyahoga Falls, Stow	41.1362	-81.4828
2	44223	Cuyahoga Falls, Akron	41.1740	-81.5212
3	44260	Mogadore, Saint Joseph, Suffield	41.0263	-81.3509
4	44278	Tallmadge, Stow	41.0913	-81.4169

The next line looks at the last cell of the dataframe, and uses the .shape method to print the number of rows in the dataframe. We see from the output there is 20.

```
#In the last cell of your dataframe, use the .shape method to print the number of rows of your dataframe.
print('Number of rows in dataframe: ',df.shape[0])
```

```
Number of rows in dataframe:  20
```

Next, we provide our Foursquare login credentials. This has been hidden for security purposes, and thus will not include a screenshot of the code here.

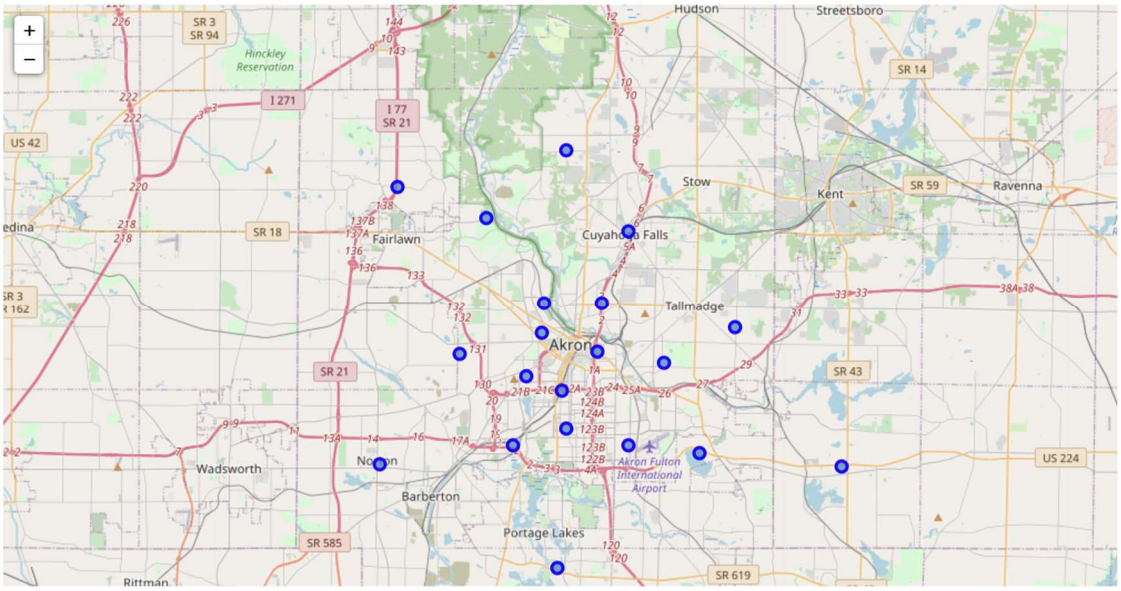
```
Your Foursquare credentials have been received: credentials are hidden.
```

Next, we use geolocator to get the coordinates of Akron, OH, and show us following points from our dataframe in a map.

In [6]:
```
#get geographical info of Akron
address = 'Akron, OH'

geolocator = Nominatim(user_agent="akron_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Akron are {}, {}. The following shows points in the areas surrounding Akron, OH.'.format(latitude

# create map of Manhattan using latitude and longitude values
map_akron = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to map
for lat, lng, label in zip(df['Latitude'], df['Longitude'], df['City']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_akron)
map_akron
```

```
The geograpical coordinate of Akron are 41.083064, -81.518485. The following shows points in the areas surrounding Akron, OH.
```

Out[6]:



We then check the latitude and longitude of the first city:

```
#get values of first city
df.loc[0, 'City']
city_latitude = df.loc[0, 'Latitude'] # city latitude value
city_longitude = df.loc[0, 'Longitude'] # city longitude value

city_name = df.loc[0, 'City'] # city name

print('Latitude and longitude values of {} are {}, {}.'.format(city_name,
                                                               city_latitude,
                                                               city_longitude))
```

```
Latitude and longitude values of Barberton, New Franklin, Norton are 41.0274, -81.6364.
```

Now we create a GET to use our Foursquare credentials to get venues near our first few cities, Barberton, New Franklin, and Norton.

```
#create GET request URL, send request an examine results
LIMIT = 100 # limit of number of venues returned by Foursquare API

#
radius = 500 # define radius

# # create URL
url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    city_latitude,
    city_longitude,
    radius,
    LIMIT)
url # display URL
results = requests.get(url).json()
results
```

```
Out[8]: {'meta': {'code': 200, 'requestId': '5fc3e9129e7d3348a3b7ecac'},
         'response': {'suggestedFilters': {'header': 'Tap to show:',
           'filters': [{'name': 'Open now', 'key': 'openNow'}]},
          'headerLocation': 'Norton',
          'headerFullLocation': 'Norton',
          'headerLocationGranularity': 'city',
          'totalResults': 21,
          'suggestedBounds': {'ne': {'lat': 41.0319000045, 'lng': -81.63044609257493},
           'sw': {'lat': 41.0228999955, 'lng': -81.64235390742506}},
          'groups': [{'type': 'Recommended Places',
            'name': 'recommended',
            'items': [{'reasons': {'count': 0,
               'items': [{'summary': 'This spot is popular',
                 'type': 'general',
                 'reasonName': 'globalInteractionReason'}]},
              'venue': {'id': '4d33946eeefa8cfa96a442b3',
               'name': 'Charger Lanes',
               'location': {'address': '1213 Norton Ave',
                'lat': 41.026438326378596,
                'lng': -81.63381402160235,
```

Now that we have venues nearby, we want to extract each category of the venues and display them neatly. We do this by doing the following.

```
# function that extracts the category of the venue
def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']
```

```
#clean json and structure it into pandas dataframe
venues = results['response']['groups'][0]['items']

nearby_venues = pd.json_normalize(venues) # flatten JSON

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

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

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

nearby_venues.head()
```

t[10]:

	name	categories	lat	lng
0	Charger Lanes	Bowling Alley	41.026438	-81.633814
1	Sweet Henrie's	Diner	41.024749	-81.637235
2	SUBWAY	Sandwich Place	41.028387	-81.637436
3	Chase Bank	Bank	41.025024	-81.637916
4	Dollar General	Discount Store	41.024201	-81.640551

Curious about how many venues it returned? Me too. Let's find out.

```
print('{} venues were returned by Foursquare.'.format(nearby_venues.shape[0]))
```

```
21 venues were returned by Foursquare.
```

We now want to look at different cities near Akron. We do that with the following code:

```
#create function to repeat with all neighborhoods in akron
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

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

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item in venue_list])
    nearby_venues.columns = ['City',
                  'City Latitude',
                  'City Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

```
#call function for toronto venues
akron_venues = getNearbyVenues(names=df['City'],
                               latitudes=df['Latitude'],
                               longitudes=df['Longitude']
                              )
```

```
Barberton, New Franklin, Norton
Cuyahoga Falls, Stow
Cuyahoga Falls, Akron
Mogadore, Saint Joseph, Suffield
Tallmadge, Stow
Akron
Akron
Akron
Akron
Akron
Akron
Akron
Akron
Akron
Akron, Green, Lakemore
Akron, Cuyahoga Falls, Fairlawn, Botzum
Akron
Akron, New Franklin, Portage Lakes, Green
Akron, Norton
Akron, Fairlawn, Cuyahoga Falls, Bath, Montrose-Ghent, Ghent
```

What size dataframe did we end up with? We run the following code to determine that:

```
#check size of resulting dataframe
print(akron_venues.shape)
akron_venues.head()
```

```
(149, 7)
```

ut[14]:

	City	City Latitude	City Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Barberton, New Franklin, Norton	41.0274	-81.6364	Charger Lanes	41.026438	-81.633814	Bowling Alley
1	Barberton, New Franklin, Norton	41.0274	-81.6364	Sweet Henrie's	41.024749	-81.637235	Diner
2	Barberton, New Franklin, Norton	41.0274	-81.6364	SUBWAY	41.028387	-81.637436	Sandwich Place
3	Barberton, New Franklin, Norton	41.0274	-81.6364	Chase Bank	41.025024	-81.637916	Bank
4	Barberton, New Franklin, Norton	41.0274	-81.6364	Dollar General	41.024201	-81.640551	Discount Store

And how many for each city?

```
#check how many venues were returned for each city
akron_venues.groupby('City').count()
```

ut[15]:

City	City Latitude	City Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Akron	58	58	58	58	58	58
Akron, Cuyahoga Falls, Fairlawn, Botzum	1	1	1	1	1	1
Akron, Fairlawn, Cuyahoga Falls, Bath, Montrose-Ghent, Ghent	2	2	2	2	2	2
Akron, Green, Lakemore	4	4	4	4	4	4
Akron, New Franklin, Portage Lakes, Green	11	11	11	11	11	11
Akron, Norton	4	4	4	4	4	4
Barberton, New Franklin, Norton	21	21	21	21	21	21
Cuyahoga Falls, Stow	41	41	41	41	41	41
Mogadore, Saint Joseph, Suffield	7	7	7	7	7	7

That's quite a bit. Let's find out how many we're working with.

```
#find out how many unique categories were pulled
print('There are {} uniques categories.'.format(len(akron_venues['Venue Category'].unique())))
```

```
There are 73 uniques categories.
```

To run an analysis on each city, we use one hot encoding as follows:

```
In [18]:
#analyze each city
# one hot encoding
akron_onehot = pd.get_dummies(akron_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
akron_onehot['City'] = akron_venues['City']

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

akron_onehot.head()
```

Out[18]:

	City	Accessories Store	American Restaurant	Antique Shop	Art Gallery	Arts & Crafts Store	Automotive Shop	Bank	Bar	Beer Garden	Bowling Alley	Candy Store	Chinese Restaurant	Clothing Store	Coffee Shop	Construction & Landscaping	Conv
0	Barberton, New Franklin, Norton	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	
1	Barberton, New Franklin, Norton	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	Barberton, New Franklin, Norton	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	Barberton, New Franklin, Norton	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	
4	Barberton, New Franklin, Norton	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

```
#examine dataframe shape
akron_onehot.shape
```

:[284]: (149, 74)

Group rows by city and take mean frequency of each category:

```
#group rows by city and take mean of the frequency of occurence of each category
akron_grouped = akron_onehot.groupby('City').mean().reset_index()
akron_grouped
```

:t[19]:

	City	Accessories Store	American Restaurant	Antique Shop	Art Gallery	Arts & Crafts Store	Automotive Shop	Bank	Bar	Beer Garden	Bowling Alley	Candy Store	Chinese Restaurant	Clothing Store	Coffee Shop	Cor Lar
0	Akron	0.00000	0.034483	0.00000	0.00000	0.00000	0.00000	0.000000	0.086207	0.00000	0.000000	0.017241	0.034483	0.017241	0.017241	
1	Akron, Cuyahoga Falls, Fairlawn, Botzum	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	Akron, Fairlawn, Cuyahoga Falls, Bath, Montros...	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	
3	Akron, Green, Lakemore	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	
4	Akron, New Franklin, Portage Lakes, Green	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.000000	0.090909	0.00000	0.090909	0.000000	0.000000	0.000000	0.000000	
5	Akron, Norton	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.000000	0.250000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	
6	Barberton, New Franklin, Norton	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.047619	0.047619	0.00000	0.047619	0.000000	0.047619	0.000000	0.000000	
7	Cuyahoga Falls, Stow	0.02439	0.073171	0.04878	0.02439	0.02439	0.02439	0.048780	0.048780	0.02439	0.000000	0.024390	0.000000	0.000000	0.024390	
8	Mogadore, Saint Joseph, Suffield	0.00000	0.000000	0.00000	0.00000	0.00000	0.00000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	

```
#confirm new shape
akron_grouped.shape
```

```
Out[20]: (9, 74)
```

Ok, we have data pulled. Let's take a look at the top 5 most common venues for each city.

```
#print each city along w top 5 most common venues
num_top_venues = 5

for hood in akron_grouped['City']:
    print("----"+hood+"----")
    temp = akron_grouped[akron_grouped['City'] == hood].T.reset_index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).reset_index(drop=True).head(num_top_venues))
    print('\n')
```

```
----Akron----
               venue  freq
0                Bar  0.09
1  Convenience Store  0.09
2  Electronics Store  0.05
3        Pizza Place  0.05
4               Park  0.05


----Akron, Cuyahoga Falls, Fairlawn, Botzum----
                    venue  freq
0  Health & Beauty Service   1.0
1           Historic Site   0.0
2  New American Restaurant   0.0
3           Movie Theater   0.0
4                  Lounge   0.0


----Akron, Fairlawn, Cuyahoga Falls, Bath, Montrose-Ghent, Ghent----
               venue  freq
0    Ice Cream Shop   0.5
1               Farm   0.5
2  Accessories Store   0.0
3               Lake   0.0
4     Movie Theater   0.0


----Akron, Green, Lakemore----
               venue  freq
0               Lake  0.25
1        Pizza Place  0.25
2  Convenience Store  0.25
3               Park  0.25
4  Accessories Store  0.00


----Akron, New Franklin, Portage Lakes, Green----
          venue  freq
0      Wine Bar  0.09
1  Bowling Alley  0.09
2           Lake  0.09
3     Gift Shop  0.09
4         Garden  0.09


----Akron, Norton----
                      venue  freq
0             Farmers Market  0.25
1                Golf Course  0.25
2                        Bar  0.25
3  Construction & Landscaping  0.25
4          Accessories Store  0.00


----Barberton, New Franklin, Norton----
```

Now let's write a function to sort the venues in descending order, create a new dtaframe and display the top 10 venues from each city:

```
#write function to sort venues in descending order
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]
```

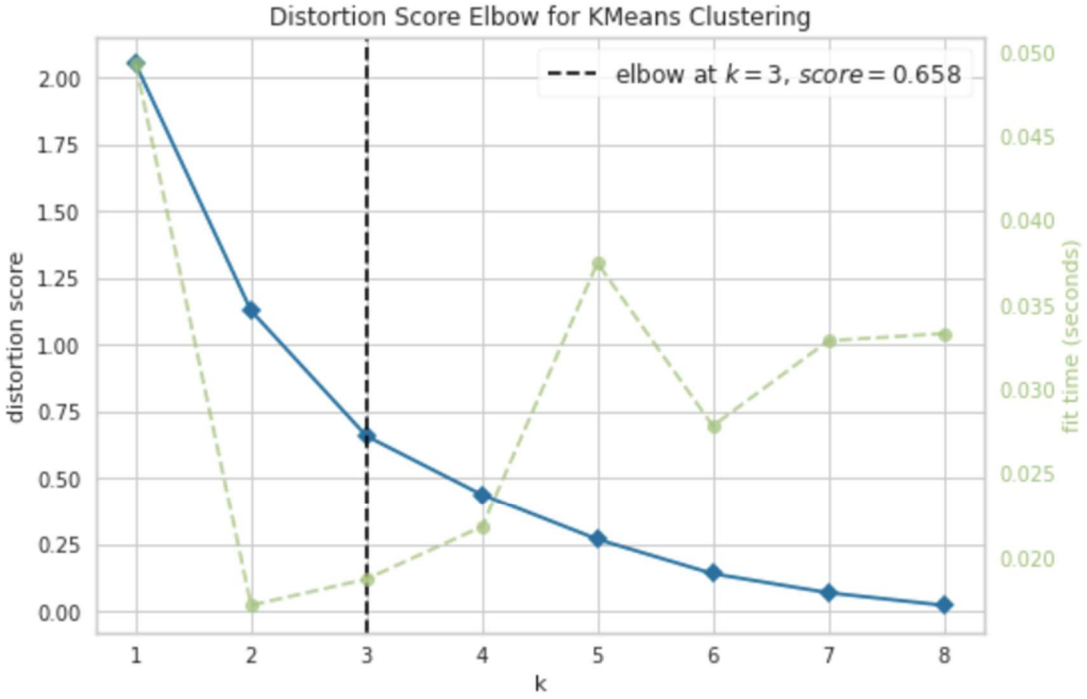
```
#create new dataframe and display top 10 venues for each city
num_top_venues = 10

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
akron_venues_sorted = pd.DataFrame(columns=columns)
akron_venues_sorted['City'] = akron_grouped['City']

for ind in np.arange(akron_grouped.shape[0]):
    akron_venues_sorted.iloc[ind, 1:] = return_most_common_venues(akron_grouped.iloc[ind, :], num_top_venues)

akron_venues_sorted.head()
```

ıt[24]:

	City	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	Akron	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
1	Akron, Cuyahoga Falls, Fairlawn, Botzum	Health & Beauty Service	Gym / Fitness Center	Discount Store	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farm	Farmers Market	Fast Food Restaurant
2	Akron, Fairlawn, Cuyahoga Falls, Bath, Montros...	Ice Cream Shop	Farm	Wine Bar	Fast Food Restaurant	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farmers Market	Food Truck
3	Akron, Green, Lakemore	Park	Convenience Store	Pizza Place	Lake	Wine Bar	Diner	Dog Run	Donut Shop	Dry Cleaner	Electronics Store
4	Akron, New Franklin, Portage Lakes, Green	Wine Bar	Bar	Lake	Pharmacy	Dry Cleaner	Pool	Farmers Market	Bowling Alley	Hot Spring	Garden

Now we want to start our clustering. To find a k-value, we run the following code:

```
akron_part_clustering = akron_grouped.drop('City', 1)
model = KMeans()
visualizer = KElbowVisualizer(model, k=(1,9))

visualizer.fit(akron_part_clustering)
visualizer.poof()
```



t[290]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0d15271bd0>

Since there did not seem to be much of a difference between 7 and 8 clusters, I chose to run it with 7 clusters just to speed things up a bit. After running the clusters, the result is as follows:

```
#cluster neighborhoods
# set number of clusters
kclusters = 7

akron_grouped_clustering = akron_grouped.drop('City', 1)

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

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
akron_venues_sorted.head(100)
```

t[26]:

	City	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	Akron	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
1	Akron, Cuyahoga Falls, Fairlawn, Botzum	Health & Beauty Service	Gym / Fitness Center	Discount Store	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farm	Farmers Market	Fast Food Restaurant
2	Akron, Fairlawn, Cuyahoga Falls, Bath, Montros...	Ice Cream Shop	Farm	Wine Bar	Fast Food Restaurant	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farmers Market	Food Truck
3	Akron, Green, Lakemore	Park	Convenience Store	Pizza Place	Lake	Wine Bar	Diner	Dog Run	Donut Shop	Dry Cleaner	Electronics Store
4	Akron, New Franklin, Portage Lakes, Green	Wine Bar	Bar	Lake	Pharmacy	Dry Cleaner	Pool	Farmers Market	Bowling Alley	Hot Spring	Garden
5	Akron, Norton	Farmers Market	Golf Course	Construction & Landscaping	Bar	Wine Bar	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farm
6	Barberton, New Franklin, Norton	Fast Food Restaurant	Pizza Place	Gift Shop	Pharmacy	Convenience Store	Bowling Alley	Discount Store	Diner	Dance Studio	Construction & Landscaping
7	Cuyahoga Falls, Stow	American Restaurant	Hotel	Bank	Italian Restaurant	Plaza	Bar	Cosmetics Shop	Gym / Fitness Center	Antique Shop	Historic Site
8	Mogadore, Saint Joseph, Suffield	Pizza Place	Liquor Store	Historic Site	Theme Park	Gas Station	Fast Food Restaurant	Wine Bar	Electronics Store	Discount Store	Dog Run

Ok, we're getting somewhere. Now we'll create a dataframe that includes the cluster, as well as the top 10 venues for each city.

```
#create dataframe that includes the cluster & top 10 venues for each city
# add clustering labels
akron_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

akron_merged = df

# merge manhattan_grouped with akron_venues_sorted to add Latitude/Longitude for each city
akron_merged = akron_merged.join(akron_venues_sorted.set_index('City'), on='City')

akron_merged.head(15) # check the last columns!
```

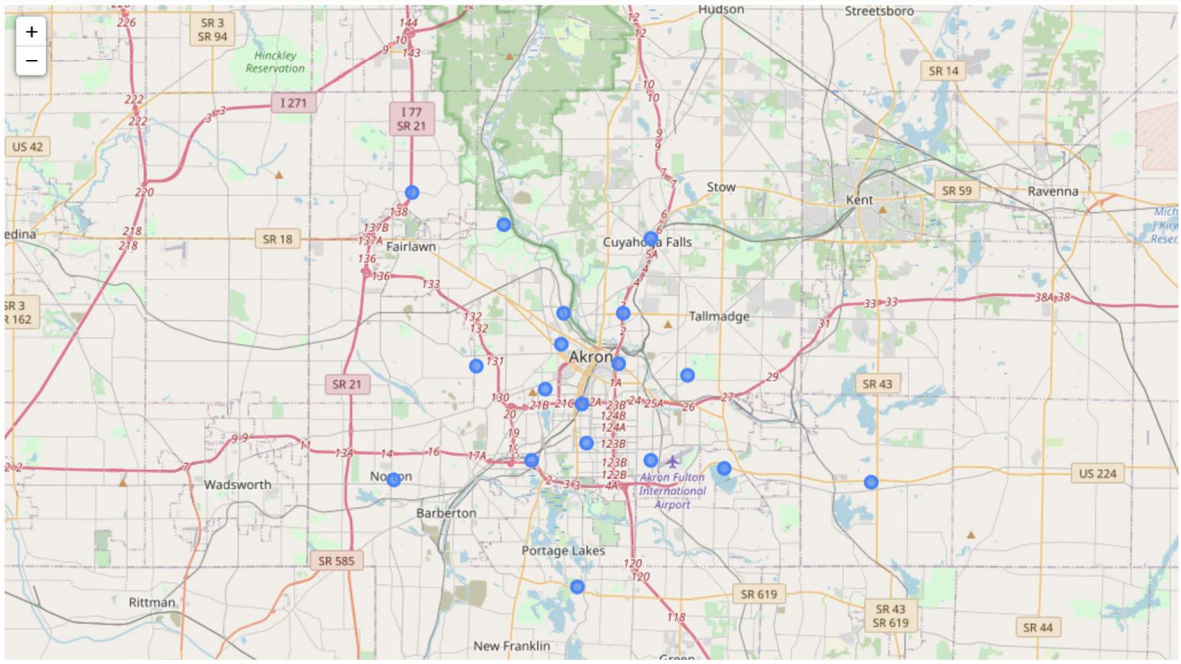
t[27]:

	Zip Code	City	Latitude	Longitude	Cluster Labels	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	
0	44203	Barberton, New Franklin, Norton	41.0274	-81.6364	3.0	Fast Food Restaurant	Pizza Place	Gift Shop	Pharmacy	Convenience Store	Bowling Alley	Discount Store	Diner	Dance Studio	Co La
1	44221	Cuyahoga Falls, Stow	41.1362	-81.4828	3.0	American Restaurant	Hotel	Bank	Italian Restaurant	Plaza	Bar	Cosmetics Shop	Gym / Fitness Center	Antique Shop	H
2	44223	Cuyahoga Falls, Akron	41.1740	-81.5212	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	44260	Mogadore, Saint Joseph, Suffield	41.0263	-81.3509	6.0	Pizza Place	Liquor Store	Historic Site	Theme Park	Gas Station	Fast Food Restaurant	Wine Bar	Electronics Store	Discount Store	

Visualizing these clusters on a map, we see the following:

```
#visualize resulting clusters
# create map
akron_merged = akron_merged.dropna().reset_index()
akron_merged.head()
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(akron_merged['Latitude'], akron_merged['Longitude'], akron_merged['City'], akron_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
```

t[28]:



Now, we can hone in on each cluster and make some decisions about where we want to open our bar.

Results: Our Cluster results

Cluster 1

```
#examine clusters
#cluster 1
akron_merged.loc[akron_merged['Cluster Labels'] == 0, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

9]:

	Zip Code	Cluster Labels	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
12	44312	0.0	Park	Convenience Store	Pizza Place	Lake	Wine Bar	Diner	Dog Run	Donut Shop	Dry Cleaner	Electronics Store

Cluster 2

```
#examine clusters
#cluster 2
akron_merged.loc[akron_merged['Cluster Labels'] == 1, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

0]:

	Zip Code	Cluster Labels	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
13	44313	1.0	Health & Beauty Service	Gym / Fitness Center	Discount Store	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farm	Farmers Market	Fast Food Restaurant

Cluster 3

```
#examine clusters
#cluster 3
akron_merged.loc[akron_merged['Cluster Labels'] == 2, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

1]:

	Zip Code	Cluster Labels	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
17	44333	2.0	Ice Cream Shop	Farm	Wine Bar	Fast Food Restaurant	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farmers Market	Food Truck

Cluster 4

```
#examine clusters
#cluster 4
akron_merged.loc[akron_merged['Cluster Labels'] == 3, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

2]:

	Zip Code	Cluster Labels	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	44203	3.0	Fast Food Restaurant	Pizza Place	Gift Shop	Pharmacy	Convenience Store	Bowling Alley	Discount Store	Diner	Dance Studio	Construction & Landscaping
1	44221	3.0	American Restaurant	Hotel	Bank	Italian Restaurant	Plaza	Bar	Cosmetics Shop	Gym / Fitness Center	Antique Shop	Historic Site
3	44301	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
4	44302	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
5	44303	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
6	44304	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
7	44305	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
8	44306	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
9	44307	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
10	44310	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
11	44311	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
14	44314	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store

Cluster 5

```
#examine clusters
#cluster 5
akron_merged.loc[akron_merged['Cluster Labels'] == 4, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

3]:

	Zip Code	Cluster Labels	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
16	44320	4.0	Farmers Market	Golf Course	Construction & Landscaping	Bar	Wine Bar	Dog Run	Donut Shop	Dry Cleaner	Electronics Store	Farm

Cluster 6

```
#examine clusters
#cluster 6
akron_merged.loc[akron_merged['Cluster Labels'] == 5, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

4]:

	Zip Code	Cluster Labels	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
15	44319	5.0	Wine Bar	Bar	Lake	Pharmacy	Dry Cleaner	Pool	Farmers Market	Bowling Alley	Hot Spring	Garden

Cluster 7

```
#examine clusters
#cluster 7
akron_merged.loc[akron_merged['Cluster Labels'] == 6, akron_merged.columns[[1] + list(range(5, akron_merged.shape[1]))]]
```

5]:

	Zip Code	Cluster Labels	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
2	44260	6.0	Pizza Place	Liquor Store	Historic Site	Theme Park	Gas Station	Fast Food Restaurant	Wine Bar	Electronics Store	Discount Store	Dog Run

Discussion: Observations and recommendations

Now that we have the results from all of our clustering groups, it's time to make a decision where to open our bar. I will walk through each of our choices below, and the reasoning it may or may not make a good locale. Remember, we broke this up in to seven clusters, so there are seven areas to look at.

Cluster 1: This cluster seems like it could be a decent candidate; there's a park and a lake, where people generally like to go before enjoying nightlife.

Cluster 2: This cluster seems to be very focused on healthy, beauty, and fitness, despite a donut shop. Considering one of the most common venues is a farm, it seems like this is a little more rural than I was looking to go.

Cluster 3: Despite having a farm as the 2nd most popular spot, this cluster has an ice cream shop, wine bar, and fast food in the top 5, indicating it's a bit closer together. This would make a better area than cluster 2.

Cluster 4: This cluster is hot! The 2nd most popular venue is a bar almost uniformly amongst zip codes in this area, however there are two zip codes where a bar is not in the top 5. This could be a great candidate to discuss further (see conclusion).

Cluster 5: This cluster has a golf course, bar, and wine bar within the top 5 most popular venues; competition may be stiff.

Cluster 6: This cluster has a wine bar and a bar as it's top two most popular spots; much like cluster 5, there's a bit too much competition for my risk level.

Cluster 7: This cluster has a wine bar as it's 7th most popular venue, but no bar in the top 10; further, with historic sites and theme parks in the top 5 spots, an opportunity for a great nightlife venue may be a possibility. See conclusion.

Conclusion: What did we decide?

When looking at each cluster, there were a few clusters that seemed like decent candidates; clusters 1, 3, 4, and 7.

With my particular level of risk aversion, and my desire to stay with tried and true, relatively close and similar zip codes, I would open my coffee shop in cluster number 4.

2]:

	Zip Code	Cluster Labels	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	44203	3.0	Fast Food Restaurant	Pizza Place	Gift Shop	Pharmacy	Convenience Store	Bowling Alley	Discount Store	Diner	Dance Studio	Construction & Landscaping
1	44221	3.0	American Restaurant	Hotel	Bank	Italian Restaurant	Plaza	Bar	Cosmetics Shop	Gym / Fitness Center	Antique Shop	Historic Site
3	44301	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
4	44302	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
5	44303	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
6	44304	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
7	44305	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
8	44306	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
9	44307	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
10	44310	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
11	44311	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store
14	44314	3.0	Convenience Store	Bar	Electronics Store	Fast Food Restaurant	Park	Pizza Place	Gym / Fitness Center	Chinese Restaurant	Gas Station	Grocery Store

When we look again at cluster number 4, we notice there are two zip codes that don't have a bar as the second most common venue; furthermore, only one of those two zip codes don't have a bar in the top 10… are you seeing it yet?

2]:

	Zip Code	Cluster Labels	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	44203	3.0	Fast Food Restaurant	Pizza Place	Gift Shop	Pharmacy	Convenience Store	Bowling Alley	Discount Store	Diner	Dance Studio	Construction & Landscaping

That's right! Only our first entry, 44203, does not appear to have a bar in the top 10 most popular venues in the zip code.

Seeing as how all the surrounding areas are extremely similar and share a lot in common, this is where I would open my bar to increase my chances of success.

Furthermore, it keeps me in a popular area, and around other things I need for personal entertainment.

It's a win/win!