Exploring the Neighborhoods in Alaska: Restaurants according to Classes of region

This is the final project of IBM Specialization courses (9) by Coursera. Firstly I want to make research about my own city - Baku in Azerbaijan, but unfortunately the latitudes and the longitudes of our region don't exist in anywhere. Gathering information about it can take a long time than you think. That is why I decided to find better place for my research and decided in Alaska (USA). So this is my Capstone project.

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[1]:

```
import numpy as np # library to handle data in a vectorized manner

import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files

!conda install -c conda-forge geopy --yes # uncomment this line if you haven't completed the Foursquare API lab
from geopy.geocoders import Nominatim # convert an address into latitude and longitude values
!pip install beautifulsoup4

!python3 -m pip install lxml

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

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# import k-means from clustering stage
from sklearn.cluster import KMeans

!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you haven't completed the Foursquare API lab
import folium # map rendering library

print('Libraries imported.')
```

```
Solving environment: done


==> WARNING: A newer version of conda exists. <==
  current version: 4.5.11
  latest version: 4.7.10

Please update conda by running

    $ conda update -n base -c defaults conda



# All requested packages already installed.

Requirement already satisfied: beautifulsoup4 in /home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (4.8.0)
Requirement already satisfied: soupsieve>=1.2 in /home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from beautifulsoup4) (1.9.2)
Requirement already satisfied: lxml in /home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (4.4.0)
Solving environment: done


==> WARNING: A newer version of conda exists. <==
  current version: 4.5.11
  latest version: 4.7.10

Please update conda by running

    $ conda update -n base -c defaults conda



# All requested packages already installed.

Libraries imported.
```

1. Discussion and Background of the Business Problem

You won't be surprised to hear that Alaska's specialty is fresh fish. Salmon, halibut, and crab—plucked right from some of the world's most pristine waters—may well be one of the main reasons you visit Alaska.

But here's the rub: it's hard to find a restaurant that serves memorable meals. And it's expensive: even a basic dinner entrée can run you up to $30.

Imagine that we want to open new restaurant in Alaska. But we should find better borough for it. We should find it in **Unified Home-Rule** classed place due to the some reasons. (A "unified municipality" is an organized borough (unified, home-rule borough). A unified municipality is defined as such by the Local Boundary Commission in 3 AAC 110.990(1). The Alaska Constitution recognizes only two types of municipalities, cities and boroughs. The legislature consistently treats unified municipalities as boroughs. For example, State statutes utilize the same standards for incorporation of a borough as they do for incorporation of a unified municipality . By contrast, the legislature has established separate standards for incorporation of a city.)

2. Data Preparation:

2.1. Get The Names of Areas, Regions and Squares from Wikipedia

[2]:
```
from bs4 import BeautifulSoup
response_obj = requests.get('https://en.wikipedia.org/wiki/List_of_boroughs_and_census_areas_in_Alaska').text
print(type(response_obj))
```

```
<class 'str'>
```

[3]:
```
soup = BeautifulSoup(response_obj,'html.parser')
#print (soup.prettify())
```

Processing the Information From Wiki To Make Necessary Lists

[4]:
```
#pinpointing the location of the table and its contents
Alaska_Table = soup.find('table', class_ = 'wikitable sortable')
#Districts_Alaska_Table
```

[5]:
```
Name = []
Region = []
Area = []

for row in Alaska_Table.findAll("tr"):
    #print (row)
    Ward = row.findAll('td')
    #print (len(Ward))

    if len(Ward)==10: #Only extract table body not heading
        Name.append(Ward[0].find(text=True).rstrip())
        Region.append(Ward[2].find(text=True).rstrip())
        Area.append(Ward[8].find(text=True).rstrip())
```

[6]:
```
Alaska_data=pd.DataFrame(Name,columns=['Name'])
Alaska_data['Region']=Region
Alaska_data['Area_SqKm']=Area
Alaska_data
```

[6]:

	Name	Region	Area_SqKm
0	013	Second	6,988
1	020	Unified Home Rule	1,697
2	060	Second	505
3	068	Home Rule	12,750
4	090	Second	7,366
5	100	Home Rule	2,344
6	110	Unified Home Rule	2,716
7	122	Second	16,013
8	130	Second	4,840
9	150	Second	6,560
10	164	Home Rule	23,782
11	170	Second	24,682
12	185	Home Rule	88,817
13	188	Home Rule	35,898
14	195	Home Rule	3,829
15	220	Unified Home Rule	2,874
16	230	First	452
17	-	-	323,440
18	275	Unified Home Rule	2,570
19	282	Home Rule	7,650

[7]:
```
Alaska_data['Name']='Aleutians East Borough','Anchorage','Bristol Bay Borough','Denali Borough','Fairbanks North Star Borough','Haines Borough','Juneau','Kenai Peninsula Borough','Ketchikan G
Alaska_data
```

[7]:

	Name	Region	Area_SqKm
0	Aleutians East Borough	Second	6,988
1	Anchorage	Unified Home Rule	1,697
2	Bristol Bay Borough	Second	505
3	Denali Borough	Home Rule	12,750
4	Fairbanks North Star Borough	Second	7,366
5	Haines Borough	Home Rule	2,344
6	Juneau	Unified Home Rule	2,716
7	Kenai Peninsula Borough	Second	16,013
8	Ketchikan Gateway Borough	Second	4,840
9	Kodiak Island Borough	Second	6,560
10	Lake and Peninsula Borough	Home Rule	23,782
11	Matanuska-Susitna Borough	Second	24,682
12	North Slope Borough	Home Rule	88,817
13	Northwest Arctic Borough	Home Rule	35,898
14	Petersburg Borough	Home Rule	3,829
15	Sitka	Unified Home Rule	2,874
16	Skagway	First	452
17	Unorganized Borough	-	323,440
18	Wrangell	Unified Home Rule	2,570
19	Yakutat	Home Rule	7,650

Get the Coordinates of the Areas

[8]:
```
from geopy.geocoders import Nominatim
geolocator = Nominatim()
Alaska_data['Area_Name_Coord']= Alaska_data['Name'].apply(geolocator.geocode).apply(lambda x: (x.latitude, x.longitude))
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:2: DeprecationWarning: Using Nominatim with the default "geopy/1.20.0" `user_agent` is strongly discourage
d, as it violates Nominatim's ToS https://operations.osmfoundation.org/policies/nominatim/ and may possibly cause 403 and 429 HTTP errors. Please specify a custom `user_agent` with `Nominatim
(user_agent="my-application")` or by overriding the default `user_agent`: `geopy.geocoders.options.default_user_agent = "my-application"`. In geopy 2.0 this will become an exception.
```

[9]:
```
Alaska_data[['Latitude', 'Longitude']] = Alaska_data['Area_Name_Coord'].apply(pd.Series)
```

[10]:
```
Alaska_data.drop(['Area_Name_Coord'], axis=1, inplace=True)
Alaska_data
```

[10]:

	Name	Region	Area_SqKm	Latitude	Longitude
0	Aleutians East Borough	Second	6,988	55.051244	-162.891689
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852
2	Bristol Bay Borough	Second	505	58.737034	-156.875387
3	Denali Borough	Home Rule	12,750	63.878678	-149.650166
4	Fairbanks North Star Borough	Second	7,366	64.864904	-146.775162
5	Haines Borough	Home Rule	2,344	59.083123	-135.343057
6	Juneau	Unified Home Rule	2,716	58.301950	-134.419734
7	Kenai Peninsula Borough	Second	16,013	60.096827	-151.788033
8	Ketchikan Gateway Borough	Second	4,840	55.489748	-131.011963
9	Kodiak Island Borough	Second	6,560	57.543377	-153.357412
10	Lake and Peninsula Borough	Home Rule	23,782	58.327711	-156.154765
11	Matanuska-Susitna Borough	Second	24,682	62.340248	-149.479329
12	North Slope Borough	Home Rule	88,817	69.533513	-153.822068
13	Northwest Arctic Borough	Home Rule	35,898	67.238513	-159.981635
14	Petersburg Borough	Home Rule	3,829	56.751221	-133.458841
15	Sitka	Unified Home Rule	2,874	57.052497	-135.337612
16	Skagway	First	452	59.622636	-135.409437
17	Unorganized Borough	-	323,440	63.417431	-157.671865
18	Wrangell	Unified Home Rule	2,570	56.204567	-132.043255
19	Yakutat	Home Rule	7,650	59.572735	-139.578312

Final Data-Frame with Coordinates of the Major Areas

[11]:
```
Alaska_data
```

[11]:

	Name	Region	Area_SqKm	Latitude	Longitude
0	Aleutians East Borough	Second	6,988	55.051244	-162.891689
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852
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8	Ketchikan Gateway Borough	Second	4,840	55.489748	-131.011963
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12	North Slope Borough	Home Rule	88,817	69.533513	-153.822068
13	Northwest Arctic Borough	Home Rule	35,898	67.238513	-159.981635
14	Petersburg Borough	Home Rule	3,829	56.751221	-133.458841
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17	Unorganized Borough	-	323,440	63.417431	-157.671865
18	Wrangell	Unified Home Rule	2,570	56.204567	-132.043255
19	Yakutat	Home Rule	7,650	59.572735	-139.578312

Use geopy library to get the latitude and longitude values of Singapore.

In order to define an instance of the geocoder, we need to define a user_agent. We will name our agent ny_explorer, as shown below.

[12]:
```
address = 'Alaska'

geolocator = Nominatim(user_agent="foursquare_agent")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Alaska areas are {}, {}.'.format(latitude, longitude))
```

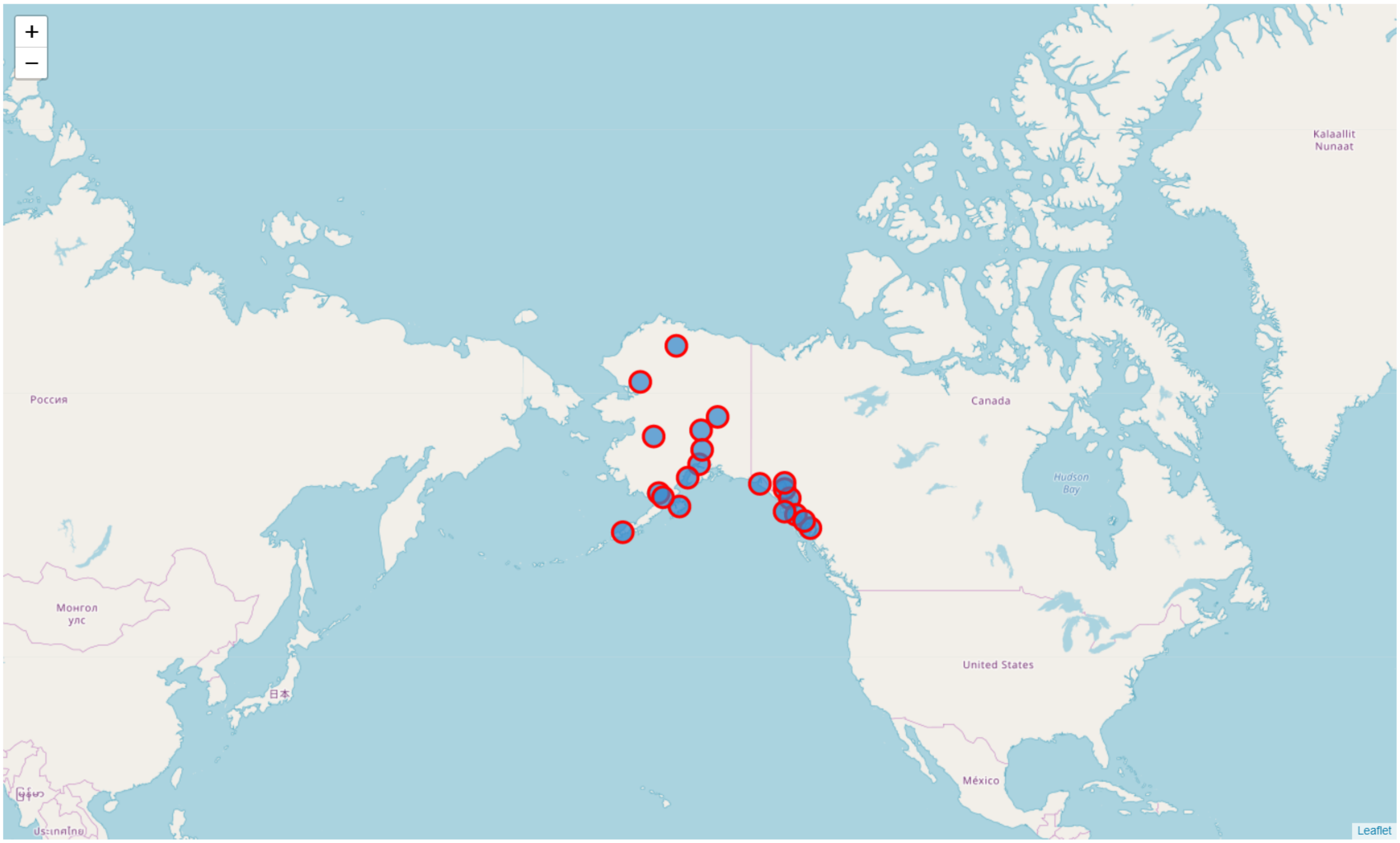
```
The geograpical coordinate of Alaska areas are 64.4459613, -149.680909.
```

Create a map of Singapore with neighborhoods superimposed on top.

[13]:
```
# create map of Toronto using latitude and longitude values
map_alaska= folium.Map(location=[latitude, longitude], zoom_start=3)
```

```python
# add markers to map
for lat, lng , Name , Region in zip(Alaska_data['Latitude'], Alaska_data['Longitude'], Alaska_data['Name'], Alaska_data['Region']):
    label = '{}, {}'.format(Region, Name)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=10,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_alaska)

map_alaska
```

[13]:



3. Explore regions in Alaska

[14]:

```python
CLIENT_ID = 'BURPSDHBL0XRO133LCY4VBS5QUUGYFT13GKQXWYNEGIBQVLA' # your Foursquare ID
CLIENT_SECRET = 'TLE5JH52YACWQORB2GDVM22OIYZTTUHI0GX003C2WJYXGGQL' # your Foursquare Secret
VERSION = '20190729' # Foursquare API version

print('Your credentails:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: BURPSDHBL0XRO133LCY4VBS5QUUGYFT13GKQXWYNEGIBQVLA
CLIENT_SECRET:TLE5JH52YACWQORB2GDVM22OIYZTTUHI0GX003C2WJYXGGQL
```

Let's create a function to get the venues to all the regions in Alaska

Exploring the regions

1.Create the get request url (Foursquare ID and Secret are necessary) 1.a. Number of Venues we will look for is 100 2.a. Radius of Search Would be 100 m.

2.Create a json from the request object (Need requests Module)

3.Create the lists Containing all the information

4.From the lists create the dataframe.

[15]:

```python
def getNearbyVenues(names, latitudes, longitudes, radius=500):
    LIMIT = 100 # limit of number of venues returned by Foursquare API

    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)
```

```python
        # 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 = ['Neighborhood',
                  'Neighborhood_Latitude',
                  'Neighborhood_Longitude',
                  'Venue',
                  'Venue_Latitude',
                  'Venue_Longitude',
                  'Venue_Category']

    return(nearby_venues)
```

Use the Function Above to Create the Dataframe of Venues Around areas of Alaska

[16]:
```python
alaska_Venues = getNearbyVenues(names=Alaska_data['Name'],
                                   latitudes=Alaska_data['Latitude'],
                                   longitudes=Alaska_data['Longitude']
                                  )
```

```
Aleutians East Borough
Anchorage
Bristol Bay Borough
Denali Borough
Fairbanks North Star Borough
Haines Borough
Juneau
Kenai Peninsula Borough
Ketchikan Gateway Borough
Kodiak Island Borough
Lake and Peninsula Borough
Matanuska-Susitna Borough
North Slope Borough
Northwest Arctic Borough
Petersburg Borough
Sitka
Skagway
Unorganized Borough
Wrangell
Yakutat
```

Let's check the size of the resulting dataframe

[17]:
```python
print(alaska_Venues.shape)
alaska_Venues.head()
```

```
(147, 7)
```

[17]:

	Neighborhood	Neighborhood_Latitude	Neighborhood_Longitude	Venue	Venue_Latitude	Venue_Longitude	Venue_Category
0	Anchorage	61.216313	-149.894852	Glacier BrewHouse	61.217719	-149.896839	Brewery
1	Anchorage	61.216313	-149.894852	Humpy's Great Alaskan Alehouse	61.216427	-149.894146	Bar
2	Anchorage	61.216313	-149.894852	Alaska Center for the Performing Arts	61.216989	-149.893718	Performing Arts Venue
3	Anchorage	61.216313	-149.894852	Wild Scoops	61.217839	-149.891494	Ice Cream Shop
4	Anchorage	61.216313	-149.894852	Orso	61.217657	-149.895940	Seafood Restaurant

[18]:
```python
# Create a Data-Frame out of it to Concentrate Only on Restaurants

Alaska_Venues_only_restaurant = alaska_Venues[alaska_Venues['Venue_Category']\
                                                           .str.contains('Restaurant')].reset_index(drop=True)
Alaska_Venues_only_restaurant.index = np.arange(1, len(Alaska_Venues_only_restaurant)+1)
print ("Shape of the Data-Frame with Venue Category only Restaurant: ", Alaska_Venues_only_restaurant.shape)
Alaska_Venues_only_restaurant.head()

alaska_restuarant = Alaska_data

# merge alaska_grouped with singapore to add latitude/longitude for each neighborhood
alaska_restuarant = alaska_restuarant.join(Alaska_Venues_only_restaurant.set_index('Neighborhood'), on='Name')

alaska_restuarant.head()
```

```
Shape of the Data-Frame with Venue Category only Restaurant:  (27, 7)
```

[18]:

	Name	Region	Area_SqKm	Latitude	Longitude	Neighborhood_Latitude	Neighborhood_Longitude	Venue	Venue_Latitude	Venue_Longitude	Venue_Category
0	Aleutians East Borough	Second	6,988	55.051244	-162.891689	NaN	NaN	NaN	NaN	NaN	NaN
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Orso	61.217657	-149.895940	Seafood Restaurant
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Ginger	61.217682	-149.890564	Asian Restaurant
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Crow's Nest	61.217838	-149.899718	Seafood Restaurant
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Bubbly Mermaid Oyster Bar	61.218149	-149.889501	Seafood Restaurant

3.1 Central Alaska Area

[19]:
```python
Central_Alaska_restuerent = alaska_restuarant[alaska_restuarant['Region'] == 'Unified Home Rule'].reset_index(drop=True)
Central_Alaska_restuerent.head()
```

[19]:

	Name	Region	Area_SqKm	Latitude	Longitude	Neighborhood_Latitude	Neighborhood_Longitude	Venue	Venue_Latitude	Venue_Longitude	Venue_Category
0	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Orso	61.217657	-149.895940	Seafood Restaurant
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Ginger	61.217682	-149.890564	Asian Restaurant
2	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Crow's Nest	61.217838	-149.899718	Seafood Restaurant
3	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Bubbly Mermaid Oyster Bar	61.218149	-149.889501	Seafood Restaurant
4	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	61.216313	-149.894852	Pangaea Restaurant and Lounge	61.216479	-149.891934	Restaurant

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

[20]:
```
### Number of Unique Categories in the Dataframe
print('There are {} unique categories.'.format(len(Central_Alaska_restuarent['Venue_Category'].unique())))
```

```
There are 12 unique categories.
```

We have seen that there are 12 unique categories in the Central Alaska Venues Data-Frame. Let's see the Frequency of Each Category

[21]:
```
print (Central_Alaska_restuarent['Venue_Category'].value_counts())
```

```
Seafood Restaurant           7
American Restaurant          4
Restaurant                   3
Sushi Restaurant             3
Asian Restaurant             2
Mexican Restaurant           2
Thai Restaurant              2
Cajun / Creole Restaurant    1
Japanese Restaurant          1
Mediterranean Restaurant     1
Theme Restaurant             1
Name: Venue_Category, dtype: int64
```

Create a Data-frame with the 10 Most Frequently Occuring Venue_Category

[22]:
```
# create a dataframe of top 10 categories
alaska_Central_Venues_Top10 = Central_Alaska_restuarent['Venue_Category'].value_counts()[0:10].to_frame(name='frequency')
alaska_Central_Venues_Top10=alaska_Central_Venues_Top10.reset_index()
#Singapore_Venues_Top10

alaska_Central_Venues_Top10.rename(index=str, columns={"index": "Venue_Category", "frequency": "Frequency"}, inplace=True)
alaska_Central_Venues_Top10
```

[22]:

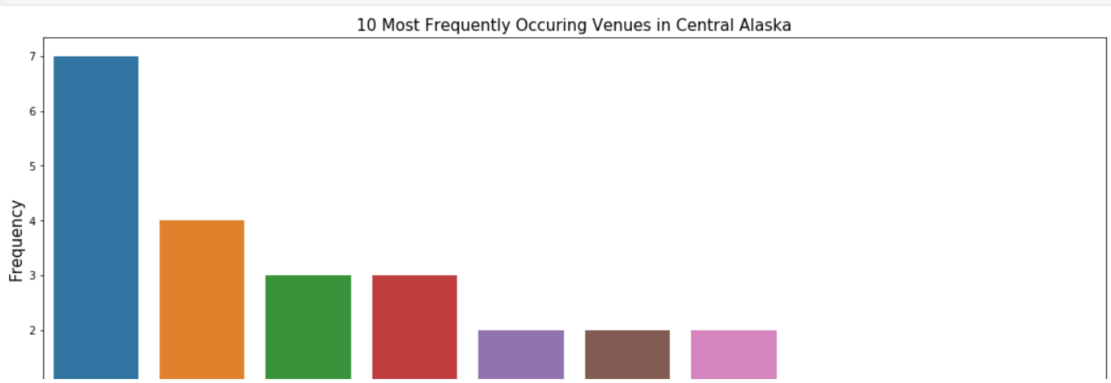
	Venue_Category	Frequency
0	Seafood Restaurant	7
1	American Restaurant	4
2	Restaurant	3
3	Sushi Restaurant	3
4	Asian Restaurant	2
5	Mexican Restaurant	2
6	Thai Restaurant	2
7	Cajun / Creole Restaurant	1
8	Japanese Restaurant	1
9	Mediterranean Restaurant	1

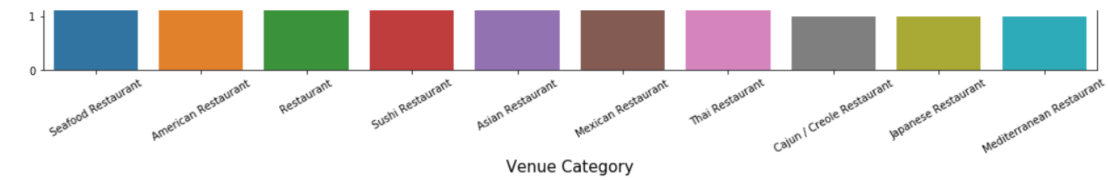
[23]:
```
import seaborn as sns
from matplotlib import pyplot as plt
fig = plt.figure(figsize=(18,7))
s=sns.barplot(x="Venue_Category", y="Frequency", data=alaska_Central_Venues_Top10)
s.set_xticklabels(s.get_xticklabels(), rotation=30)
plt.title('10 Most Frequently Occuring Venues in Central Alaska', fontsize=15)
plt.xlabel("Venue Category", fontsize=15)
plt.ylabel ("Frequency", fontsize=15)
plt.savefig("Most_Freq_Venues.png", dpi=300)
plt.show()
```

```
<Figure size 1800x700 with 1 Axes>
```

Seafood ,American, Ordinary, Sushi and Asian Restaurant is the frequent venues in Unified Home Rule classed areas of Alaska

[24]:
```
# create a dataframe of top 10 categories
alaska_Central_Venues_Top10 = Central_Alaska_restuarent['Venue_Category'].value_counts()[0:10].to_frame(name='frequency')
alaska_Central_Venues_Top10=alaska_Central_Venues_Top10.reset_index()
#Alaska_Venues_Top10

alaska_Central_Venues_Top10.rename(index=str, columns={"index": "Venue_Category", "frequency": "Frequency"}, inplace=True)
#alaska_Central_Venues_Top10

import seaborn as sns
from matplotlib import pyplot as plt
fig = plt.figure(figsize=(18,7))
s=sns.barplot(x="Venue_Category", y="Frequency", data=alaska_Central_Venues_Top10)
s.set_xticklabels(s.get_xticklabels(), rotation=30)
plt.title('10 Most Frequently Occuring Venues in Central Alaska', fontsize=15)
plt.xlabel("Venue Category", fontsize=15)
plt.ylabel ("Frequency", fontsize=15)
plt.savefig("Most_Freq_Venues.png", dpi=300)
plt.show()
```





4. Analyze Each Neighborhood

[25]:
```
# one hot encoding
alaska_onehot = pd.get_dummies(Alaska_Venues_only_restaurant[['Venue_Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
alaska_onehot['Neighborhood'] = Alaska_Venues_only_restaurant['Neighborhood']

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

alaska_onehot.head()
```

[25]:

	Neighborhood	American Restaurant	Asian Restaurant	Cajun / Creole Restaurant	Japanese Restaurant	Mediterranean Restaurant	Mexican Restaurant	Restaurant	Seafood Restaurant	Sushi Restaurant	Thai Restaurant	Theme Restaurant
1	Anchorage	0	0	0	0	0	0	0	1	0	0	0
2	Anchorage	0	1	0	0	0	0	0	0	0	0	0
3	Anchorage	0	0	0	0	0	0	0	1	0	0	0
4	Anchorage	0	0	0	0	0	0	0	1	0	0	0
5	Anchorage	0	0	0	0	0	0	1	0	0	0	0

[26]:
```
alaska_onehot.shape
```

[26]: (27, 12)

Next, let's group rows by neighborhood and by taking the mean of the frequency of occurrence of each category

[27]:
```
alaska_grouped = alaska_onehot.groupby('Neighborhood').mean().reset_index()
alaska_grouped
```

[27]:

	Neighborhood	American Restaurant	Asian Restaurant	Cajun / Creole Restaurant	Japanese Restaurant	Mediterranean Restaurant	Mexican Restaurant	Restaurant	Seafood Restaurant	Sushi Restaurant	Thai Restaurant	Theme Restaurant
0	Anchorage	0.125000	0.062500	0.0625	0.000000	0.000000	0.062500	0.125000	0.250000	0.125	0.125	0.0625
1	Juneau	0.500000	0.000000	0.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.500	0.000	0.0000
2	Sitka	0.111111	0.111111	0.0000	0.111111	0.111111	0.111111	0.111111	0.333333	0.000	0.000	0.0000

Let's confirm the new size

[28]:
```
alaska_grouped.shape
```

[28]: (3, 12)

Let's print each neighborhood along with 3 common venues

[31]:
```
num_top_venues = 3
for hood in alaska_grouped['Neighborhood']:
    print("----"+hood+"----")
    temp = alaska_grouped[alaska_grouped['Neighborhood'] == 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')
```

```
----Anchorage----
                venue  freq
0   Seafood Restaurant  0.25
1  American Restaurant  0.12
2           Restaurant  0.12


----Juneau----
                venue  freq
0  American Restaurant   0.5
1     Sushi Restaurant   0.5
2     Asian Restaurant   0.0


----Sitka----
                venue  freq
0   Seafood Restaurant  0.33
1  American Restaurant  0.11
2     Asian Restaurant  0.11
```

Let's put that into a pandas dataframe

First, let's write a function to sort the venues in descending order.

[32]:
```
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]
```

Now let's create the new dataframe and display the top 10 venues for each neighborhood.

[33]:
```
num_top_venues = 10
```

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

# create columns according to number of top venues
columns = ['Neighborhood']
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
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhood'] = alaska_grouped['Neighborhood']

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

neighborhoods_venues_sorted.head()
```

[33]:

	Neighborhood	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	Anchorage	Seafood Restaurant	Thai Restaurant	Sushi Restaurant	Restaurant	American Restaurant	Theme Restaurant	Mexican Restaurant	Cajun / Creole Restaurant	Asian Restaurant	Mediterranean Restaurant
1	Juneau	Sushi Restaurant	American Restaurant	Theme Restaurant	Thai Restaurant	Seafood Restaurant	Restaurant	Mexican Restaurant	Mediterranean Restaurant	Japanese Restaurant	Cajun / Creole Restaurant
2	Sitka	Seafood Restaurant	Restaurant	Mexican Restaurant	Mediterranean Restaurant	Japanese Restaurant	Asian Restaurant	American Restaurant	Theme Restaurant	Thai Restaurant	Sushi Restaurant

[34]:
```python
#neighborhoods_venues_sorted
```

5. Cluster Neighborhoods

Run k-means to cluster the neighborhood into 5 clusters.

[35]:
```python
# import k-means from clustering stage
from sklearn.cluster import KMeans

# set number of clusters
kclusters = 3

alaska_grouped_clustering = alaska_grouped.drop('Neighborhood', 1)

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

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

[35]:
```
array([0, 1, 2], dtype=int32)
```

Let's create a new dataframe that includes the cluster as well as the top 10 venues for each neighborhood.

[36]:
```python
# add clustering labels
neighborhoods_venues_sorted.insert(0, 'ClusterLabels', kmeans.labels_)

alaska_merged = Alaska_data

# merge alaska_grouped with singapore to add latitude/longitude for each neighborhood
alaska_merged = alaska_merged.join(neighborhoods_venues_sorted.set_index('Neighborhood'), on='Name')

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

[36]:

	Name	Region	Area_SqKm	Latitude	Longitude	ClusterLabels	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	Aleutians East Borough	Second	6,988	55.051244	-162.891689	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	0.0	Seafood Restaurant	Thai Restaurant	Sushi Restaurant	Restaurant	American Restaurant	Theme Restaurant	Mexican Restaurant	Cajun / Creole Restaurant	Asian Restaurant	Mediterranean Restaurant
2	Bristol Bay Borough	Second	505	58.737034	-156.875387	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Denali Borough	Home Rule	12,750	63.878678	-149.650166	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	Fairbanks North Star Borough	Second	7,366	64.864904	-146.775162	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

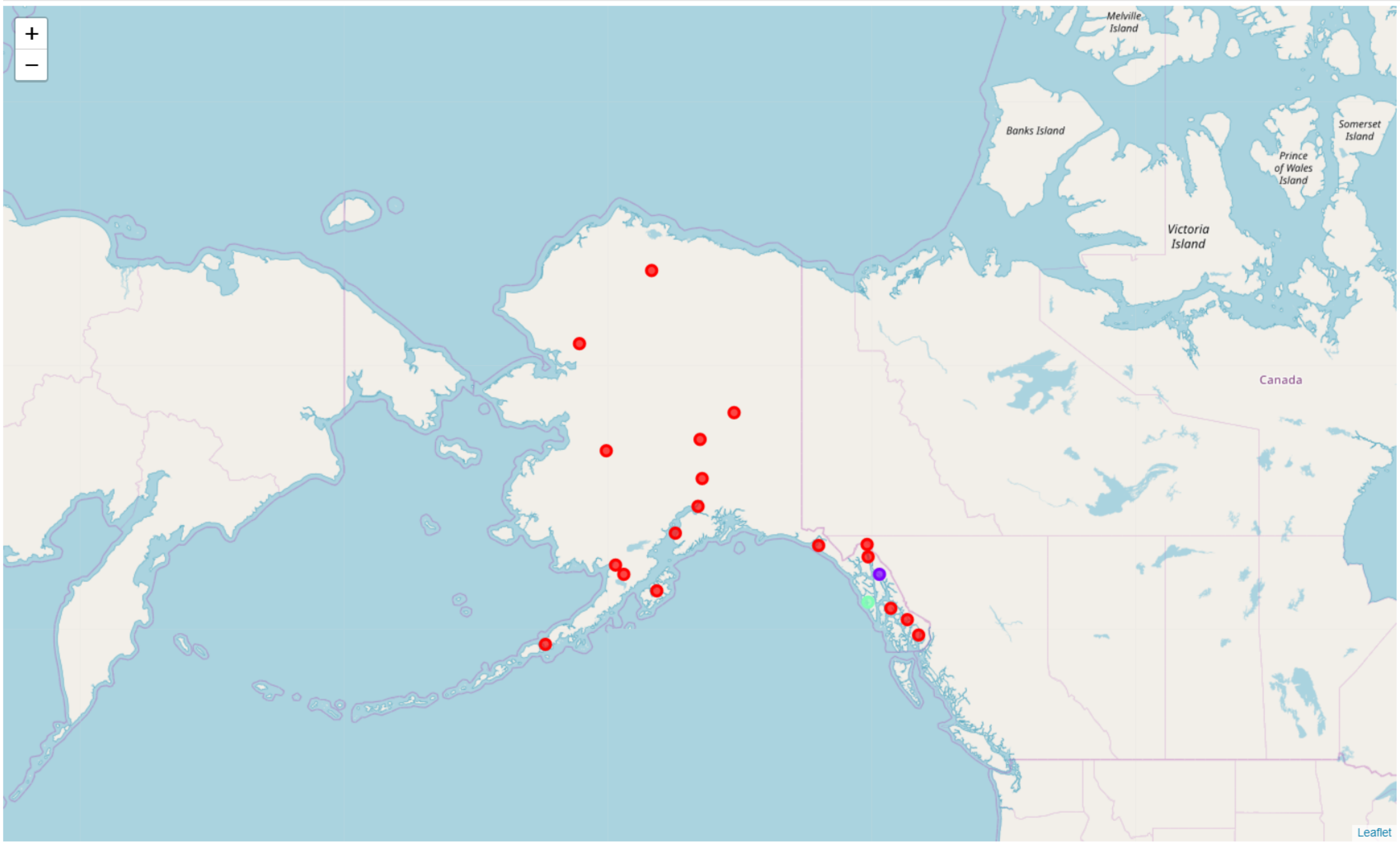
[37]:
```python
alaska_merged['ClusterLabels'].fillna(0, inplace=True)
alaska_merged['ClusterLabels'] = alaska_merged['ClusterLabels'].apply(np.int64)
alaska_merged['ClusterLabels']
```

[37]:
```
0     0
1     0
2     0
3     0
4     0
5     0
6     1
7     0
8     0
9     0
10    0
11    0
12    0
13    0
14    0
15    2
16    0
17    0
18    0
19    0
Name: ClusterLabels, dtype: int64
```

Finally, let's visualize the resulting clusters

[38]:
```
# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors


# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=4)

# 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(alaska_merged['Latitude'], alaska_merged['Longitude'], alaska_merged['Name'], alaska_merged['ClusterLabels']):
    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
```

[38]:



6. Examine Clusters

Cluster 1

[39]:
```
alaska_cluster1=alaska_merged.loc[alaska_merged['ClusterLabels'] == 0, alaska_merged.columns[[0] + list(range(1, alaska_merged.shape[1]))]]
print ("No of Neighbourhood in Cluster Label 0: %d" %(alaska_cluster1.shape[0]))
alaska_cluster1
```

```
No of Neighbourhood in Cluster Label 0: 18
```

[39]:

	Name	Region	Area_SqKm	Latitude	Longitude	ClusterLabels	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	Aleutians East Borough	Second	6,988	55.051244	-162.891689	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	Anchorage	Unified Home Rule	1,697	61.216313	-149.894852	0	Seafood Restaurant	Thai Restaurant	Sushi Restaurant	Restaurant	American Restaurant	Theme Restaurant	Mexican Restaurant	Cajun / Creole Restaurant	Asian Restaurant	Mediterranean Restaurant
2	Bristol Bay Borough	Second	505	58.737034	-156.875387	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Denali Borough	Home Rule	12,750	63.878678	-149.650166	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	Fairbanks North Star Borough	Second	7,366	64.864904	-146.775162	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5	Haines Borough	Home Rule	2,344	59.083123	-135.343057	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

7	Kenai Peninsula Borough	Second	16,013	60.096827	-151.788033	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
8	Ketchikan Gateway Borough	Second	4,840	55.489748	-131.011963	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9	Kodiak Island Borough	Second	6,560	57.543377	-153.357412	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10	Lake and Peninsula Borough	Home Rule	23,782	58.327711	-156.154765	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11	Matanuska-Susitna Borough	Second	24,682	62.340248	-149.479329	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
12	North Slope Borough	Home Rule	88,817	69.533513	-153.822068	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
13	Northwest Arctic Borough	Home Rule	35,898	67.238513	-159.981635	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14	Petersburg Borough	Home Rule	3,829	56.751221	-133.458841	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
16	Skagway	First	452	59.622636	-135.409437	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
17	Unorganized Borough	-	323,440	63.417431	-157.671865	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
18	Wrangell	Unified Home Rule	2,570	56.204567	-132.043255	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
19	Yakutat	Home Rule	7,650	59.572735	-139.578312	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Cluster 2

alaska_cluster2=alaska_merged.loc[alaska_merged['ClusterLabels'] == 1, alaska_merged.columns[[0] + list(range(1, alaska_merged.shape[1]))]] print ("No of Neighbourhood in Cluster Label 1: %d" % (alaska_cluster2.shape[0])) alaska_cluster2

[41]:

```
alaska_cluster3=alaska_merged.loc[alaska_merged['ClusterLabels'] == 2, alaska_merged.columns[[0] + list(range(1, alaska_merged.shape[1]))]]
print ("No of Neighbourhood in Cluster Label 2: %d" %(alaska_cluster3.shape[0]))
alaska_cluster3
```

```
No of Neighbourhood in Cluster Label 2: 1
```

[41]:

	Name	Region	Area_SqKm	Latitude	Longitude	ClusterLabels	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	Sitka	Unified Home Rule	2,874	57.052497	-135.337612	2	Seafood Restaurant	Restaurant	Mexican Restaurant	Mediterranean Restaurant	Japanese Restaurant	Asian Restaurant	American Restaurant	Theme Restaurant	Thai Restaurant	Sushi Restaurant

Discussion

The first important observation noticed while creating this report is that the Foursquare data returned is not the same each time an API call is made and hence, the results are not reproducible unless one does save this data to a file for future use. Because of this, a high limit for each call needs to be used in order to maximize the number fo results. Morover, the radius used during the search had an important impact on the number of results because some central of neighborhoods are too dense compared to others. When it comes to performing k-means on the grouped data, special attention mus be placed when choosing the number of clusters as well as the top number of venues to be used. For instance, all previous values tried (<9) resulted in contradictory results. Also, the number of top venues (10) had an impact on the resultst, but not as important the number of clusters so we sticked to 10.

Conclusion

We have used the city's data set to obtain each neighborhood's location in the form of a GEOJSON file from which we extracted each neighborhoods polygon's centroid. Using this location information and Foursquare data we obtained 3 clusters using the top 10 venues for each individual neighborhood. Finally, this information allowed us to recommend three areas of the city to customers interested in cheap restaurant, these areas were chosen because of their proximity to the city and their respective clusters, however one must notice that cluster 3 includes both near and far neighborhoods.

[ ]: