# CAPSTONE PROJECT: BATTLE OF THE NEIGHBORHOODS

## Venue Recommendation for United States of America Visitor's

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## I. PURPOSE

This document provides the details of how i reached conclusion on mostly commonly visited place and also provide recommendation on best value stay while in USA

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## II. INTRODUCTION

There are lot of websites that scrapes different websites to provide us a comparison on places to stay or visit.However, most of these websites provides recommendation simply based on usual tourist attractions or key residential areas that are mostly expensive or already known for travelers based on certain keywords like "Hotel", or "Backpackers" etc. The intention on this project is to collect and provide a data driven recommendation that can supplement the recommendation with statistical data. This will also be utilizing data retrieved from New York open data sources and FourSquare API venue recommendations.

The sample recommender in this notebook will provide the following use case scenario:

- A person planning to visit United States as a Tourist or an Expat and looking for a reasonable accommodation.
- The user wants to receive venue recommendation where he or she can stay or rent with close proximity to places of interest or search category option.
- The recommendation should not only present the most viable option, but also present a comparison table of all possible town venues.

For this demonstration, this notebook will make use of the following data:

- Median Rental Prices by town.
- Popular Food venues in the vicinity. (Sample category selection)

Note: While this demo makes use of Food Venue Category, Other possible categories can also be used for the same implementation such as checking categories like:

- Outdoors and Recreation
- Nightlife
- Nearby Schools, etc.

I will limit the scope of this search as FourSquare API only allows 50 free venue query limit per day when using a free user access.

## III. DATA ACQUISITION

This demonstration will make use of the following data sources:

### USA median residential rental prices.

Data will retrieved from open dataset from median rent by town and flattype (https://www.quandl.com/data/ZILLOW/M1300_MPPRSF-Zillow-Home-Value-Index-Metro-Median-Price-Of-Reduction-Single-Family-Residence-Canon-City-CO) from https://www.quandl.com (https://www.quandl.com) website.

The original data source contains median rental prices of Singapore HDB units from 2005 up to 2nd quarter of 2018. I will retrieve rental the most recent recorded rental prices from this data source (Q2 2018) being the most relevant price available at this time. For this demonstration, I will simplify the analysis by using the average rental prices of all available flat type.

### Location data retrieved using Google maps API.

Data coordinates of Town Venues will be retrieved using google API. I also make use of MRT stations coordinate as a more important center of for all towns included in venue recommendations.

### Top Venue Recommendations from FourSquare API

(FourSquare website: www.foursquare.com (http://www.foursquare.com))

I will be using the FourSquare API to explore neighborhoods in selected towns in Singapore. The Foursquare explore function will be used to get the most common venue categories in each neighborhood, and then use this feature to group the neighborhoods into clusters. The following information are retrieved on the first query:

- Venue ID
- Venue Name
- Coordinates : Latitude and Longitude
- Category Name

Another venue query will be performed to retrieve venue ratings for each location. Note that rating information is a paid service from FourSquare and we are limited to only 50 queries per day. With this constraint, we limit the category analysis with only one type for this demo. I will try to retrieve as many ratings as possible for each retrieved venue ID.

# IV. METHODOLOGY

### United States Cities or Towns List with median residential rental prices obtained from New York free data source

The source data contains median rental prices of United States from 2008 up to of 2019. I will retrive the most recent recorded rental prices from this data source (Q2 2018) being the most relevant price available at this time. For this demonstration, I will simplify the analysis by using the average rental prices of all available flat type.

**Data Cleanup and re-grouping.** The retrieved table contains some un-wanted entries and needs some cleanup.

The following tasks will be performed:

- Drop/ignore cells with missing data.
- Use most current data record.

- Fix data types.

### Importing Python Libraries

This section imports required python libraries for processing data.
While this first part of python notebook is for data acquisition, we will use some of the libraries make some data visualization.

In [4]:

```
#!conda install -c conda-forge folium=0.5.0 --yes # comment/uncomment if not yet installed.
#!conda install -c conda-forge geopy --yes        # comment/uncomment if not yet installed

import numpy as np # library to handle data in a vectorized manner
import pandas as pd # library for data analsysis

# Numpy and Pandas libraries were already imported at the beginning of this notebook.
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files
from geopy.geocoders import Nominatim # convert an address into latitude and longitude valu
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
import folium # map rendering library

import requests # library to handle requests
import bs4 as bs
import urllib.request

print('Libraries imported.')
```

```
Libraries imported.
```

### 1. Downloading towns list with and median residential rental prices

In [5]:

```
data = pd.read_csv('Sale_Prices_Msa.csv')
data.head()
#Taking only region name and # Taking the most recent report which is "2019-04"

df = pd.DataFrame(data[['RegionName','2019-04']])
#renaming RegionName to City and year to median_rent
df.rename(columns = {'RegionName':'Town','2019-04':'median_rent'}, inplace = True)

df.head()
#sgp_median_rent_by_town_data.head()
```

Out[5]:

| | Town | median_rent |
|---|---|---|
| **0** | United States | NaN |
| **1** | New York, NY | NaN |
| **2** | Los Angeles-Long Beach-Anaheim, CA | 632800.0 |
| **3** | Chicago, IL | 244400.0 |
| **4** | Dallas-Fort Worth, TX | NaN |

### Data Cleanup and re-grouping.

The retrieved table contains some un-wanted entries and needs some cleanup. The following tasks will be performed:

- Drop/ignore cells with missing data.
- Use most current data record.
- Fix data types.

In [6]:

```
# Drop rows with rental price == 'na'.
df.dropna(subset=['median_rent'],axis = 0,inplace = True)

#drop column index as it isnt required
# Ensure that median_rent column is float64.
df['median_rent']=df['median_rent'].astype(np.float64)

df = df.reset_index(drop=True)

df.head()
```

Out[6]:

| | Town | median_rent |
|---|---|---|
| **0** | Los Angeles-Long Beach-Anaheim, CA | 632800.0 |
| **1** | Chicago, IL | 244400.0 |
| **2** | San Francisco, CA | 789400.0 |
| **3** | Riverside, CA | 353000.0 |
| **4** | Phoenix, AZ | 247300.0 |

- Note:For this demonstration, We will do a simplier analysis by using a median price for all available rental units regardless of its size.

In [7]:

```
df_avg = df.groupby(['Town'])['median_rent'].mean().reset_index()
df_avg
```

Out[7]:

| | Town | median_rent |
|---|---|---|
| **0** | Adrian, MI | 145800.0 |
| **1** | Akron, OH | 141600.0 |
| **2** | Albany, OR | 258600.0 |
| **3** | Anchorage, AK | 311700.0 |
| **4** | Astoria, OR | 287700.0 |
| **5** | Barnstable Town, MA | 396700.0 |
| **6** | Bartlesville, OK | 113200.0 |
| **7** | Bay City, MI | 82200.0 |
| **8** | Beaver Dam, WI | 156200.0 |
| **9** | Bellingham, WA | 379500.0 |

- Adding geographical coordinates of each town location.

In [6]:

```
# The code was removed by Watson Studio for sharing.
```

```
google_key=hidden_from_view
```

**2. Retrieve town coordinates.**

Google api will be used to retrive the coordinates (latitude and longitude of each town centers. The town coordinates will be used in retrieval of Foursquare API location data.

In [8]:

```
df_avg['Latitude'] = 0.0
df_avg['Longitude'] = 0.0

for idx,town in df_avg['Town'].iteritems():
    address = town + " United States" ; # I prefer to use MRT stations as more important ce
    url = 'https://maps.googleapis.com/maps/api/geocode/json?address={}&key={}'.format(addr
    print(url)
    lat = requests.get(url).json()["results"][0]["geometry"]["location"]['lat']
    lng = requests.get(url).json()["results"][0]["geometry"]["location"]['lng']
    df_avg.loc[idx,'Latitude'] = lat
    df_avg.loc[idx,'Longitude'] = lng
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-8-454c1173519d> in <module>
      4 for idx,town in df_avg['Town'].iteritems():
      5     address = town + " United States" ; # I prefer to use MRT statio
ns as more important central location of each town
----> 6     url = 'https://maps.googleapis.com/maps/api/geocode/json?address
={}&key={}'.format(address,google_key)
      7     print(url)
      8     lat = requests.get(url).json()["results"][0]["geometry"]["locati
on"]['lat']

NameError: name 'google_key' is not defined
```

In [13]:

```
#reading from saved file to avoid call to google api multiple times
df_avg = pd.read_csv('United_States_average.csv')
df_avg.head()
```

Out[13]:

| | Unnamed: 0 | Town | median_rent | Latitude | Longitude |
|---|---|---|---|---|---|
| **0** | 0 | Adrian, MI | 145800.0 | 41.897547 | -84.037166 |
| **1** | 1 | Akron, OH | 141600.0 | 41.081445 | -81.519005 |
| **2** | 2 | Albany, OR | 258600.0 | 44.636511 | -123.105928 |
| **3** | 3 | Anchorage, AK | 311700.0 | 61.218056 | -149.900278 |
| **4** | 4 | Astoria, OR | 287700.0 | 46.187884 | -123.831253 |

In [ ]:

```

```

In [14]:

```
df_avg.set_index("Town")
```

Out[14]:

| | Unnamed: 0 | median_rent | Latitude | Longitude |
|---|---|---|---|---|
| **Town** | | | | |
| **Adrian, MI** | 0 | 145800.0 | 41.897547 | -84.037166 |
| **Akron, OH** | 1 | 141600.0 | 41.081445 | -81.519005 |
| **Albany, OR** | 2 | 258600.0 | 44.636511 | -123.105928 |
| **Anchorage, AK** | 3 | 311700.0 | 61.218056 | -149.900278 |
| **Astoria, OR** | 4 | 287700.0 | 46.187884 | -123.831253 |
| **Barnstable Town, MA** | 5 | 396700.0 | 41.700321 | -70.300202 |
| **Bartlesville, OK** | 6 | 113200.0 | 36.747311 | -95.980818 |
| **Bay City, MI** | 7 | 82200.0 | 43.594468 | -83.888865 |
| **Beaver Dam, WI** | 8 | 156200.0 | 43.457769 | -88.837329 |

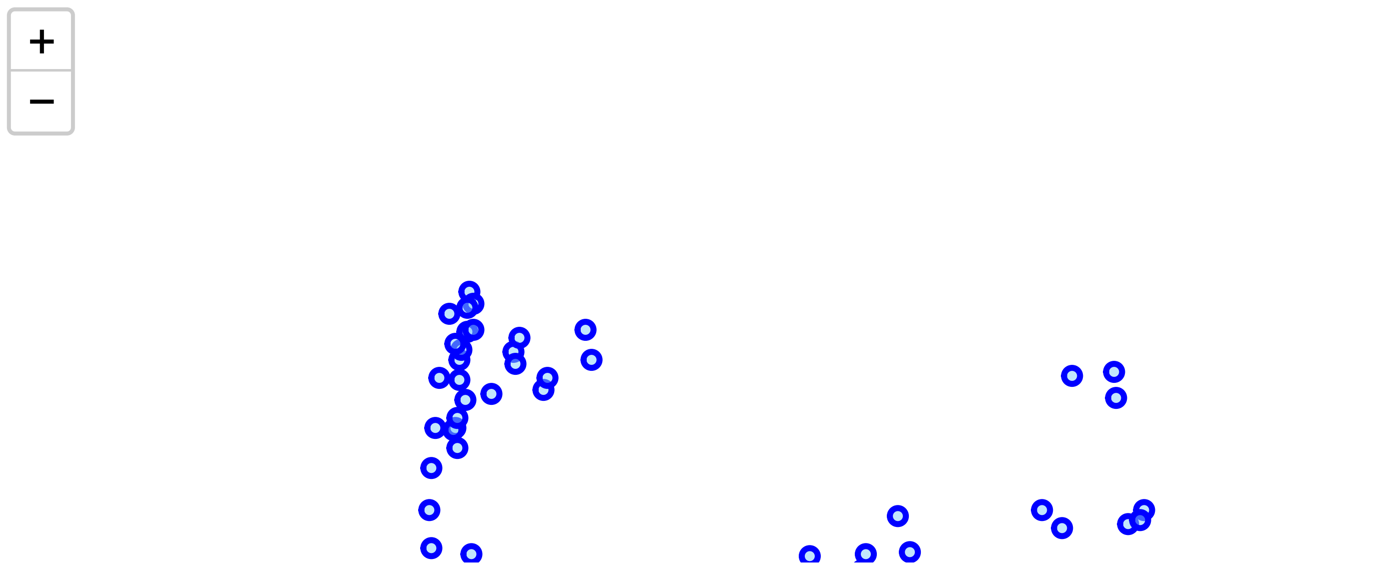
**Generate Singapore basemap.**

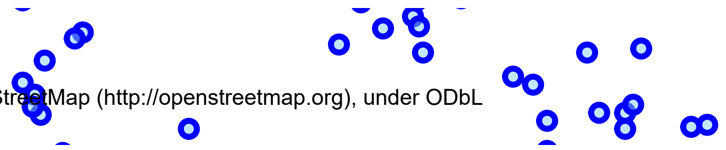
In [15]:

```
geo = Nominatim()
address = 'United States'
location = geo.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geographical coordinate of United States {}, {}.'.format(latitude, longitude))

# create map of USA using latitude and longitude values
map_USA = folium.Map(location=[latitude, longitude],tiles="OpenStreetMap", zoom_start=4)

# add markers to map
for lat, lng, town in zip(
    df_avg['Latitude'],
    df_avg['Longitude'],
    df_avg['Town']):
    label = town
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=4,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#87cefa',
        fill_opacity=0.5,
        parse_html=False).add_to(map_USA)
map_USA
```

```
c:\users\msvdp\appdata\local\programs\python\python37\lib\site-packages\ipyk
ernel_launcher.py:1: DeprecationWarning: Using Nominatim with the default "g
eopy/1.20.0" `user_agent` is strongly discouraged, as it violates Nominati
m's ToS https://operations.osmfoundation.org/policies/nominatim/ (https://op
erations.osmfoundation.org/policies/nominatim/) and may possibly cause 403 a
nd 429 HTTP errors. Please specify a custom `user_agent` with `Nominatim(use
r_agent="my-application")` or by overriding the default `user_agent`: `geop
y.geocoders.options.default_user_agent = "my-application"`. In geopy 2.0 thi
s will become an exception.
  """Entry point for launching an IPython kernel.

The geographical coordinate of United States 39.7837304, -100.4458825.
```

Out[15]:





Leaflet (http://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

In [18]:

```
fileName = "United_States_average.csv"
linkName = "United_States Average Rental Prices"
create_download_link(df_avg,linkName,fileName)
```

Out[18]:

United_States Average Rental Prices
(data:text/csv;base64,LFVubmFtZWQ6IDAsVG93bixtZWRpYW5fcmVudCxMYXRpdHVkZSxMb2

In [17]:

```
from IPython.display import HTML
import base64

# Extra Helper scripts to generate download links for saved dataframes in csv format.
def create_download_link( df, title = "Download CSV file", filename = "data.csv"):
    csv = df.to_csv()
    b64 = base64.b64encode(csv.encode())
    payload = b64.decode()
    html = '<a download="{filename}" href="data:text/csv;base64,{payload}" target="_blank">
    html = html.format(payload=payload,title=title,filename=filename)
    return HTML(html)
```

## V. Segmenting and Clustering Cities or Towns in USA

### Retrieving FourSquare Places of interest.

Using the Foursquare API, the **explore** API function was be used to get the most common venue categories in each neighborhood, and then used this feature to group the neighborhoods into clusters. The *k*-means clustering algorithm was used for the analysis. Fnally, the Folium library is used to visualize the recommended neighborhoods and their emerging clusters.

In the ipynb notebook, the function **getNearbyVenues** extracts the following information for the dataframe it generates:

- Venue ID
- Venue Name
- Coordinates : Latitude and Longitude
- Category Name

The function **getVenuesByCategory** performs the following:

1. **category** based venue search to simulate user venue searches based on certain places of interest. This search extracts the following information:

    - Venue ID
    - Venue Name
    - Coordinates : Latitude and Longitude

- Category Name
2. For each retrieved **venueID**, retrive the venues category rating.

In [12]:

```
# The code was removed by Watson Studio for sharing.
```

```
Hidden Foursqure API Keyset
```

In [13]:

```
# The code was removed by Watson Studio for sharing.
```

```
CLIENT_ID     = hidden
CLIENT_SECRET = hidden
VERSION       = 20190102
LIMIT         = 80
```

# 1. Exploring Neighbourhood in USA

#### Using the following foursquare api query url, search venues on all boroughs in selected USA Cities.

> `https://api.foursquare.com/v2/venues/` **search** `?`
> `client_id=` **CLIENT_ID** `&client_secret=` **CLIENT_SECRET** `&ll=` **LATITUDE** **,** **LONGITUDE** `&v=` **VI**

Retrieving data from FourSquare API is not so straight forward. It returns a json list top venues to visit to city. The scores however, is retrieved on a separate query to the FourSquare Venue API and is limited to 50 queries per day when using a free FourSquare subscription.
The following functions generates the query urls and processes the returned json data into dataframe.

The function **getNearbyVenues** extracts the following information for the dataframe it generates:

- Venue ID
- Venue Name
- Coordinates : Latitude and Longitude
- Category Name

The function **getVenuesByCategory** performs the following:

1. **category** based venue search to simulate user venue searches based on certain places of interest. This search extracts the following information:
    - Venue ID
    - Venue Name
    - Coordinates : Latitude and Longitude
    - Category Name
2. For each retrieved **venueID**, retrive the venues category rating.

The generated data frame in the second function contains the following column:

| Column Name | Description |
|---|---|
| Town | Town Name |
| Town Latitude | Towns MRT station Latitude |
| Town Longitude | Town MRT station Latitude |
| VenueID | FourSquare Venue ID |
| VenueName | Venue Name |
| score | FourSquare Venue user rating |
| category | Category group name |
| catID | Category ID |
| latitude | Venue Location - latitude |
| longitude | Venue Location - longitude |

In [19]:

```
# Foursquare Credentials
CLIENT_ID = '' # your Foursquare ID
CLIENT_SECRET = '' # your ou Secretr key
VERSION = '20180605' # Foursquare API version
LIMIT = 80

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

```
Your credentials:
CLIENT_ID: 2FPN1CICVCJC3FTJJVN1VJG04RJ0IWGB3HGYL3HTAENMFUK1
CLIENT_SECRET:SXYV152RCW3DLF3RLTOMMSRU0LIZWJSFFRCFOQ2PXIWXK12X
```

In [20]:

```
import time
# ---------------------------------------------
# The following function retrieves the venues given the names and coordinates and stores it
FOURSQUARE_EXPLORE_URL = 'https://api.foursquare.com/v2/venues/explore?'
FOURSQUARE_SEARCH_URL = 'https://api.foursquare.com/v2/venues/search?'

def getNearbyVenues(names, latitudes, longitudes, radius=500):
    global CLIENT_ID
    global CLIENT_SECRET
    global FOURSQUARE_EXPLORE_URL
    global FOURSQUARE_SEARCH_URL
    global VERSION
    global LIMIT
    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print('getNearbyVenues',names)
        # create the API request URL
        url = '{}&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            FOURSQUARE_EXPLORE_URL,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']['id'],v['venue']['name'],
            v['venue']['location']['lat'],v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])
        time.sleep(2)

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item in venue_list
    nearby_venues.columns = ['Town','Town Latitude','Town Longitude','Venue','Venue Latituc

    return(nearby_venues)
```

In [21]:

```
FOURSQUARE_SEARCH_URL = 'https://api.foursquare.com/v2/venues/search?'
# SEARCH VENUES BY CATEGORY

# Dataframe : venue_id_recover
# - store venue id to recover failed venues id score retrieval later if foursquare limit is
venue_id_rcols = ['VenueID']
venue_id_recover = pd.DataFrame(columns=venue_id_rcols)

def getVenuesByCategory(names, latitudes, longitudes, categoryID, radius=500):
    global CLIENT_ID
    global CLIENT_SECRET
    global FOURSQUARE_EXPLORE_URL
    global FOURSQUARE_SEARCH_URL
    global VERSION
    global LIMIT
    venue_columns = ['Town','Town Latitude','Town Longitude','VenueID','VenueName','score',
    venue_DF = pd.DataFrame(columns=venue_columns)
    print("[#Start getVenuesByCategory]")
    for name, lat, lng in zip(names, latitudes, longitudes):
        #print('getVenuesByCategory',categoryID,name) ; # DEBUG: be quiet
        # create the API request URL
        url = '{}client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}&categoryId=
            FOURSQUARE_SEARCH_URL,CLIENT_ID,CLIENT_SECRET,VERSION,lat,lng,radius,LIMIT,cate
        # make the GET request
        results = requests.get(url).json()
        # Populate dataframe with the category venue results
        # Extracting JSON  data values

        for jsonSub in results['response']['venues']:
            #print(jsonSub)
            # JSON Results may not be in expected format or incomplete data, in that case,
            ven_id = 0
            try:
                # If there are any issue with a restaurant, retry or ignore and continue
                # Get location details
                ven_id   = jsonSub['id']
                ven_cat  = jsonSub['categories'][0]['pluralName']
                ven_CID  = jsonSub['categories'][0]['id']
                ven_name = jsonSub['name']
                ven_lat  = jsonSub['location']['lat']
                ven_lng  = jsonSub['location']['lng']
                venue_DF = venue_DF.append({
                    'Town'       : name,
                    'Town Latitude' : lat,
                    'Town Longitude': lng,
                    'VenueID'    : ven_id,
                    'VenueName'  : ven_name,
                    'score'      : 'na',
                    'category'   : ven_cat,
                    'catID'      : ven_CID,
                    'latitude'   : ven_lat,
                    'longitude'  : ven_lng}, ignore_index=True)
            except:
                continue
    # END OF LOOP, return.
    print("\n[#Done getVenuesByCategory]")
    return(venue_DF)
```

In [34]:

```
FOURSQUARE_SEARCH_URL = 'https://api.foursquare.com/v2/venues/search?'
# SEARCH VENUES BY CATEGORY

# Dataframe : venue_id_recover
# - store venue id to recover failed venues id score retrieval later if foursquare limit is
venue_id_rcols = ['VenueID','Score']
venue_id_recover = pd.DataFrame(columns=venue_id_rcols)

def getVenuesIDScore(venueID):
    global CLIENT_ID
    global CLIENT_SECRET
    global FOURSQUARE_EXPLORE_URL
    global FOURSQUARE_SEARCH_URL
    global VERSION
    global LIMIT
    global venue_id_recover
    print("[#getVenuesIDScore]")
    venID_URL = 'https://api.foursquare.com/v2/venues/{}?client_id={}&client_secret={}&v={}
    venID_score = 0.00
    # Process results
    try:
        venID_result = requests.get(venID_URL).json()
        venID_score  = venID_result['response']['venue']['rating']
    except:
        venue_id_recover = venue_id_recover.append({'VenueID' : venueID, 'Score' : 0.0},igr
        return ["error",0.0]
    return ["success",venID_score]
```

In [25]:

```
df_avg.dtypes
```

Out[25]:

```
Town            object
median_rent    float64
Latitude       float64
Longitude      float64
dtype: object
```

In [22]:

```
venue_columns = ['Town','Town Latitude','Town Longitude','VenueID','VenueName','score','cat
df_venue = pd.DataFrame(columns=venue_columns)
```

**Search Venues with recommendations on : Food Venues (Restaurants,Fastfoods, etc.)**

To demonstrate user selection of places of interest, We will use this Food Venues category in our further analysis.

- This Foursquare search is expected to collect venues in the following category:
    - category
    - Food Courts
    - Coffee Shops

- Restaurants
- Cafés
- Other food venues

In [23]:

```
# Food Venues : Restaurants, Fastfoods, Etc
categoryID = "4d4b7105d754a06374d81259"
town_names = df_avg['Town']
lat_list   = df_avg['Latitude']
lng_list   = df_avg['Longitude']
df_food_venues = getVenuesByCategory(names=town_names,latitudes=lat_list,longitudes=lng_lis
df_food_venues
```

```
[#Start getVenuesByCategory]

[#Done getVenuesByCategory]
```

- Save collected USA food venues by town into csv for future use.

In [24]:

```
# Save collected USA food venues by town into csv for future use.
fileName = "food_venues.Category.csv"
linkName = "IBM Storage Link:food_venues.Category.csv"
create_download_link(df_food_venues,linkName,fileName)
```

Out[24]:

IBM Storage Link:food_venues.Category.csv
(data:text/csv;base64,LFRvd24sVG93biBMYXRpdHVkZSxUb3duIExvbmdpdHVkZSxWZW51ZUl

**Search Venues with recommendations on : Outdoors and Recreation**

Note:

- 2nd Test: Retrieve venues for Outdoors and Recreation.
- This section can be ran separately due to maximum limit encountered when using Foursquare free API version. I have saved simmilar results in github to run the same analyis.

In [25]:

```
# Disable for this run demo.
if (1):
    # Outdoors & Recreation,
    categoryID = "4d4b7105d754a06377d81259"
    town_names = df_avg['Town']
    lat_list   = df_avg['Latitude']
    lng_list   = df_avg['Longitude']
    df_outdoor_venues_by_town = getVenuesByCategory(names=town_names,latitudes=lat_list,lor
    fileName = "outdoorAndRecration.Category.csv"
    linkName = "IBM Storage Link:outdoorAndRecration.Category.csv"
    create_download_link(df_outdoor_venues_by_town,linkName,fileName)
```

```
[#Start getVenuesByCategory]

[#Done getVenuesByCategory]
```

In [26]:

```
    fileName = "outdoorAndRecration.Category.csv"
    linkName = "IBM Storage Link:outdoorAndRecration.Category.csv"
    create_download_link(df_outdoor_venues_by_town,linkName,fileName)
```

Out[26]:

IBM Storage Link:outdoorAndRecration.Category.csv
(data:text/csv;base64,LFRvd24sVG93biBMYXRpdHVkZSxUb3duIExvbmdpdHVkZSxWZW51ZUl

In [27]:

```
df_food_venues.head()
# The code was removed by Watson Studio for sharing.
```

Out[27]:

| | Town | Town Latitude | Town Longitude | VenueID | VenueName | score | category |
|---|---|---|---|---|---|---|---|
| **0** | Adrian, MI | 41.897547 | -84.037166 | 4d2a426febacb1f7ff040250 | Pizza Bucket | na | Pizza Places |
| **1** | Adrian, MI | 41.897547 | -84.037166 | 4d9e29ec71ac6a31ed9a4c06 | The Grasshopper El Chapulin - Adrian | na | Mexican Restaurants |
| **2** | Adrian, MI | 41.897547 | -84.037166 | 5b9c2550270ee70039c5657f | Downtown Dempsey's | na | Pizza Places |
| **3** | Adrian, MI | 41.897547 | -84.037166 | 4fd257c5e4b069289209c46e | governor croswell tea room restaurant | na | Tea Rooms |
| **4** | Adrian, MI | 41.897547 | -84.037166 | 5af8842232b61d002cf554c3 | Farver’s | na | Bistros |

**In this section, We use the FourSquare API to retrieve venue scores of locations. Note that there is max**

**query limit of 50 in FourSquare API for free subscription. So use or query carefully.**

In [37]:

```
score_is_NAN = len(df_food_venues[df_food_venues['score'].isna()].index.tolist())
print("Current score=NaN count=",score_is_NAN)
for idx in df_food_venues[df_food_venues['score'].isna()].index.tolist():
    venueID = df_food_venues.loc[idx,'VenueID']
    print(venueID)
    status,score = getVenuesIDScore(venueID)
    if status == "success":
        df_food_venues.loc[idx,'score'] = score
score_is_NAN = len(df_food_venues[df_food_venues['score'].isna()].index.tolist())
print("PostRun score=NaN count=",score_is_NAN)
print('Done',end='')
```

```
Current score=NaN count= 0
PostRun score=NaN count= 0
Done
```

In [29]:

```

fileName = "food_venues_with_Score.Category.csv"
linkName = "IBM Storage Link:food_venues_score.Category.csv"
create_download_link(df_food_venues,linkName,fileName)
```

Out[29]:

IBM Storage Link:food_venues_score.Category.csv
(data:text/csv;base64,LFRvd24sVG93biBMYXRpdHVkZSxUb3duIExvbmdpdHVkZSxWZW51ZUl

- Note: Re-run continuation, reload saved csv file. # Reloading previously saved runs to avoid re-running FourSquare API.

In [26]:

```
# The code was removed by Watson Studio for sharing.
```

- Combine venues collection into one dataframe : df_venue

In [38]:

```
# If all categories are called
if (1):
    df_venue = pd.concat([df_food_venues,df_outdoor_venues_by_town], ignore_index=True)
#else
df_venue = df_food_venues
df_venue.shape
```

Out[38]:

```
(4461, 10)
```

**Data cleanup uneeded entries**

- Eliminate possible venue duplicates.
- Improve the quality of our venue selection by removing venues with no ratings or 0.0

In [39]:

```
# Eliminate possible venue duplicates.
df_venue = df_venue[venue_columns]

# Drop rows with missing elements
df_venue = df_venue.dropna(axis='columns')
```

In [40]:

```
df_venue.shape
```

Out[40]:

```
(4461, 10)
```

In [41]:

```
df_venue.head()
```

Out[41]:

| | Town | Town Latitude | Town Longitude | VenueID | VenueName | score | category |
|---|---|---|---|---|---|---|---|
| **0** | Adrian, MI | 41.897547 | -84.037166 | 4d2a426febacb1f7ff040250 | Pizza Bucket | na | Pizza Places |
| **1** | Adrian, MI | 41.897547 | -84.037166 | 4d9e29ec71ac6a31ed9a4c06 | The Grasshopper El Chapulin - Adrian | na | Mexican Restaurants |
| **2** | Adrian, MI | 41.897547 | -84.037166 | 5b9c2550270ee70039c5657f | Downtown Dempsey's | na | Pizza Places |
| **3** | Adrian, MI | 41.897547 | -84.037166 | 4fd257c5e4b069289209c46e | governor croswell tea room restaurant | na | Tea Rooms |
| **4** | Adrian, MI | 41.897547 | -84.037166 | 5af8842232b61d002cf554c3 | Farver's | na | Bistros |

In [295]:

```
# Save town venues collection.
# This list is already intersting data for display in different webpages.
fileName = "recommended.USA_town_venues.csv"
linkName = "IBM Storage Link:recommended_USA_town_venues.csv"
create_download_link(df_food_venues,linkName,fileName)
```

Out[295]:

IBM Storage Link:recommended_USA_town_venues.csv
(data:text/csv;base64,LFRvd24sVG93biBMYXRpdHVkZSxUb3duIExvbmdpdHVkZSxWZW51ZU

**Check venue count per town.**

In [70]:

```
df_venue.groupby('Town').count()
```

Out[70]:

| | Town Latitude | Town Longitude | VenueID | VenueName | score | category | catID | latitude | longitude |
|---|---|---|---|---|---|---|---|---|---|
| **Town** | | | | | | | | | |
| **Adrian, MI** | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 |
| **Akron, OH** | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| **Albany, OR** | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 |
| **Anchorage, AK** | 49 | 49 | 49 | 49 | 49 | 49 | 49 | 49 | 49 |
| **Astoria, OR** | 45 | 45 | 45 | 45 | 45 | 45 | 45 | 45 | 45 |
| **Barnstable Town, MA** | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| **Bartlesville, OK** | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| **Bay City, MI** | 32 | 32 | 32 | 32 | 32 | 32 | 32 | 32 | 32 |

In [44]:

```
# Verify the dtypes
df_venue.dtypes
```

Out[44]:

```
Town                object
Town Latitude      float64
Town Longitude     float64
VenueID             object
VenueName           object
score               object
category            object
catID               object
latitude           float64
longitude          float64
dtype: object
```

**How many unique categories can be curated from all the returned venues?**

In [45]:

```
# Count number of categories that can be curated.
print('There are {} uniques categories.'.format(len(df_venue['category'].unique())))
```

```
There are 159 uniques categories.
```

**What are the top 20 most common venue types?**

In [46]:

```
# Check top 10 most frequently occuring venue type
df_venue.dropna(subset=['score'])
df_venue.groupby('category')['VenueName'].count().sort_values(ascending=False)[:20]
```

Out[46]:

```
category
Coffee Shops               433
American Restaurants       375
Mexican Restaurants        267
Pizza Places               256
Sandwich Places            193
Cafés                      186
Restaurants                156
Bakeries                   145
Italian Restaurants        133
Ice Cream Shops            115
Fast Food Restaurants      112
Burger Joints               89
Food                        89
Food Trucks                 80
Diners                      72
Bars                        72
Seafood Restaurants         71
Breakfast Spots             70
Delis / Bodegas             70
Chinese Restaurants         69
Name: VenueName, dtype: int64
```

**What are the top 20 venues given with highest score rating?**

In [74]:

```python
# Top 10 venues with highest given score rating

df_venue.groupby(['Town','category']).count().sort_values(by='score',ascending=False)[:20]
```

Out[74]:

| | | Town Latitude | Town Longitude | VenueID | VenueName | score | catID | latitude | lo |
|---|---|---|---|---|---|---|---|---|---|
| **Town** | **category** | | | | | | | | |
| **Portland, OR** | **Coffee Shops** | 16 | 16 | 16 | 16 | 16 | 16 | 16 | |
| **Seattle, WA** | **Coffee Shops** | 15 | 15 | 15 | 15 | 15 | 15 | 15 | |
| **Salinas, CA** | **Mexican Restaurants** | 10 | 10 | 10 | 10 | 10 | 10 | 10 | |
| **El Paso, TX** | **Mexican Restaurants** | 10 | 10 | 10 | 10 | 10 | 10 | 10 | |
| **Las Vegas, NV** | **American Restaurants** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Edwards, CO** | **American Restaurants** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Fort Collins, CO** | **Food Trucks** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Santa Cruz, CA** | **Coffee Shops** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Naples, FL** | **Italian Restaurants** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Redding, CA** | **Coffee Shops** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Tucson, AZ** | **Mexican Restaurants** | 9 | 9 | 9 | 9 | 9 | 9 | 9 | |
| **Dodge City, KS** | **Mexican Restaurants** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Tulsa, OK** | **American Restaurants** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Des Moines, IA** | **Coffee Shops** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Riverside, CA** | **Mexican Restaurants** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **St. Cloud, MN** | **Pizza Places** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Madison, WI** | **Coffee Shops** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Akron, OH** | **Cafés** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Sacramento, CA** | **Coffee Shops** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| **Cleveland, OH** | **Coffee Shops** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |

## Analyze Each USA 's nearby recommended venues

In [75]:

```
# one hot encoding
sg_onehot = pd.get_dummies(df_venue[['category']], prefix="", prefix_sep="")

# add Town column back to dataframe
sg_onehot['Town'] = df_venue['Town']

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

# Check returned one hot encoding data:
print('One hot encoding returned "{}" rows.'.format(sg_onehot.shape[0]))

# Regroup rows by town and mean of frequency occurrence per category.
sg_grouped = sg_onehot.groupby('Town').mean().reset_index()

print('One hot encoding re-group returned "{}" rows.'.format(sg_grouped.shape[0]))
sg_grouped.head()
```

```
One hot encoding returned "4461" rows.
One hot encoding re-group returned "143" rows.
```

Out[75]:

| | Town | Afghan Restaurants | African Restaurants | American Restaurants | Antique Shops | Arcades | Arepa Restaurants | Art Galleries |
|---|---|---|---|---|---|---|---|---|
| **0** | Adrian, MI | 0.0 | 0.0 | 0.176471 | 0.0 | 0.0 | 0.0 | 0.0 |
| **1** | Akron, OH | 0.0 | 0.0 | 0.125000 | 0.0 | 0.0 | 0.0 | 0.0 |
| **2** | Albany, OR | 0.0 | 0.0 | 0.047619 | 0.0 | 0.0 | 0.0 | 0.0 |
| **3** | Anchorage, AK | 0.0 | 0.0 | 0.040816 | 0.0 | 0.0 | 0.0 | 0.0 |
| **4** | Astoria, OR | 0.0 | 0.0 | 0.066667 | 0.0 | 0.0 | 0.0 | 0.0 |

Type *Markdown* and LaTeX: $\alpha^2$

## Analyze USA's most visited venues

In [76]:

```
num_top_venues = 10
for town in sg_grouped['Town']:
    print("# Town=< "+town+" >")
    temp = sg_grouped[sg_grouped['Town'] == town].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_ver
    print('\n')
```

```
# Town=< Adrian, MI >
                  venue  freq
0          Pizza Places  0.24
1  American Restaurants  0.18
2   Italian Restaurants  0.12
3              Bakeries  0.06
4             Tea Rooms  0.06
5               Bistros  0.06
6   Chinese Restaurants  0.06
7         Burger Joints  0.06
8     Cuban Restaurants  0.06
9       Ice Cream Shops  0.06


# Town=< Akron, OH >
                       venue  freq
0                      Cafés  0.20
1       American Restaurants  0.12
2                Food Trucks  0.10
```

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

In [77]:

```
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]
```

In [78]:

```
num_top_venues = 10

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

# create columns according to number of top venues
columns = ['Town']
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
town_venues_sorted = pd.DataFrame(columns=columns)
town_venues_sorted['Town'] = sg_grouped['Town']

for ind in np.arange(sg_grouped.shape[0]):
    town_venues_sorted.iloc[ind, 1:] = return_most_common_venues(sg_grouped.iloc[ind, :], r

print(town_venues_sorted.shape)
town_venues_sorted.head()
```

```
(143, 11)
```

Out[78]:

| | Town | 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 Mo Comm Ven |
|---|---|---|---|---|---|---|---|---|
| **0** | Adrian, MI | Pizza Places | American Restaurants | Italian Restaurants | Burger Joints | Cuban Restaurants | Chinese Restaurants | Baker |
| **1** | Akron, OH | Cafés | American Restaurants | Coffee Shops | Food Trucks | Sandwich Places | Delis / Bodegas | Restaura |
| **2** | Albany, OR | Cafés | Sandwich Places | Thai Restaurants | Bakeries | Italian Restaurants | Mexican Restaurants | Fc |
| **3** | Anchorage, AK | Coffee Shops | Cafés | Seafood Restaurants | Pizza Places | Sandwich Places | Restaurants | Americ Restaura |
| **4** | Astoria, OR | Seafood Restaurants | Coffee Shops | Pizza Places | Food | American Restaurants | Italian Restaurants | T Restaura |

## Clustering Neighborhoods

Run *k*-means to cluster the Towns into 5 clusters.

In [79]:

```
# set number of clusters
kclusters = 5
sg_grouped_clustering = sg_grouped.drop('Town', 1)
# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=1).fit(sg_grouped_clustering)

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

```
[1 0 1 1 1 0 0 1 1 1]
143
```

In [206]:

```
town_venues_sorted.head()
```

Out[206]:

| | Town | 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 Mo Comm Ven |
|---|---|---|---|---|---|---|---|---|
| 0 | Adrian, MI | Pizza Places | American Restaurants | Italian Restaurants | Burger Joints | Cuban Restaurants | Chinese Restaurants | Baker |
| 1 | Akron, OH | Cafés | American Restaurants | Coffee Shops | Food Trucks | Sandwich Places | Delis / Bodegas | Restaura |
| 2 | Albany, OR | Cafés | Sandwich Places | Thai Restaurants | Bakeries | Italian Restaurants | Mexican Restaurants | Fc |
| 3 | Anchorage, AK | Coffee Shops | Cafés | Seafood Restaurants | Pizza Places | Sandwich Places | Restaurants | Americ Restaura |
| 4 | Astoria, OR | Seafood Restaurants | Coffee Shops | Pizza Places | Food | American Restaurants | Italian Restaurants | T Restaura |

In [80]:

```
#town_venues_sorted = town_venues_sorted.set_index("Town")
sg_merged = df_avg.set_index("Town")
# add clustering labels
sg_merged['Cluster Labels'] = pd.Series(kmeans.labels_)
# merge sg_grouped with df_avg to add latitude/longitude for each neighborhood
sg_merged = sg_merged.join(town_venues_sorted)
sg_merged
```

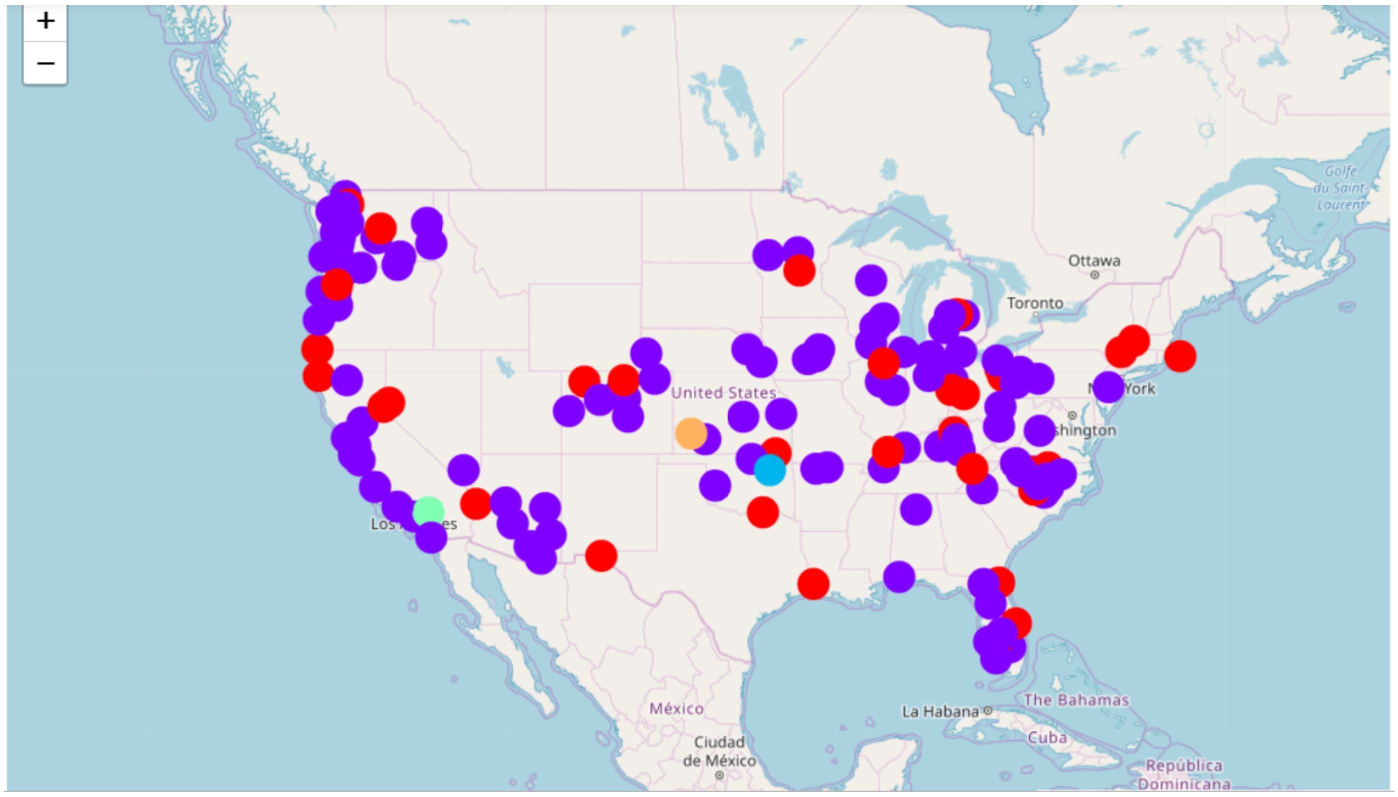
Out[80]:

| | Unnamed: 0 | median_rent | Latitude | Longitude | Cluster Labels | Town | 1st Most Common Venue | 2nd Most Common Venue | 3rd Mos Commo Venu |
|---|---|---|---|---|---|---|---|---|---|
| **Town** | | | | | | | | | |
| **Adrian, MI** | 0 | 145800.0 | 41.897547 | -84.037166 | NaN | NaN | NaN | NaN | Na |
| **Akron, OH** | 1 | 141600.0 | 41.081445 | -81.519005 | NaN | NaN | NaN | NaN | Na |
| **Albany, OR** | 2 | 258600.0 | 44.636511 | -123.105928 | NaN | NaN | NaN | NaN | Na |
| **Anchorage, AK** | 3 | 311700.0 | 61.218056 | -149.900278 | NaN | NaN | NaN | NaN | Na |
| **Astoria, OR** | 4 | 287700.0 | 46.187884 | -123.831253 | NaN | NaN | NaN | NaN | Na |
| **Barnstable Town, MA** | 5 | 396700.0 | 41.700321 | -70.300202 | NaN | NaN | NaN | NaN | Na |

- Save csv copy of merged data

In [81]:

```
# create map
map_clusters = folium.Map(location=[latitude, longitude], tiles="Openstreetmap", zoom_start

# 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(sg_merged['Latitude'], sg_merged['Longitude'], sg_merged.
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=10,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=1).add_to(map_clusters)

map_clusters
```



## VI. Discussion and Conclusion

On this notebook, Analysis of best venue recommendations based on Food venue category has been presented. Recommendations based on other user searches like available outdoor and recreation areas are also available.The information extracted in this notebook, will be a good supplement to web based recommendations for visitors to find out nearby venues of interest and be a useful aid in deciding a place to stay or where to go during their visits.

Using Foursquare API, we have collected a good amount of venue recommnedations. Sourcing from the venue recommendations from FourSquare has its limitation, The list of venues is not exhaustive list of all the available venues is the area. Furthermore, not all the venues found in the the area has a stored ratings. For this reason, the number of analyzed venues are only about 50% of all the available venues initially collected. The results therefore may significantly change, when more information are collected on those with missing data.

The generated clusters from our results shows that there are very good and interesting places located in areas where the median rents are cheaper. This kind of results may be very interesting for travelers who are also on budget constraints. Our results also yielded some interesting findings. For instance, The initial assumption among websites providing recommendations is that the Central Area that have the highest median rent also have better food venues. Result shows that most popular food venue among residents and visitors are **Coffee Shops, American Restaurants, Mexican Restaurants**.

```
In [ ]:
```