Best U.S. City to Open a Dispensary in 2019

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1 Battle of the Neighborhoods - New Dispensary

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2 Introduction

With the legal landscape rapidly changing, regulation and decriminalization of Marijuana is significantly increasing. A substance that was once considered dangerous through urban legends and propaganda has been debunked and is being touted for a combination of its medicinal benefits, increased safety vs alternative substances, plant by-products and more. In the changing environment, it is the perfect time to invest in this growing $16 Billion industry.

The goal of this project is to determine the optimal location for opening a new dispensary in cities in which marijuana is recreationally legal. The initial location and underlying data may then be used to find a storefront, establish a supply chain, build marketing campaign and develop a fiscal business plan to get investor contribution.

3 Data

3.1 To determine the best location for opening a number of factors will be looked at:

2019 State Laws https://disa.com/map-of-marijuana-legality-by-state

2019 Local Venue Data https://foursquare.com

2017-2018 Population and Crime Statistics https://ucr.fbi.gov/crime-in-the-u.s/2018/preliminary-report/tables/table-4/table-4.xls/view

2019 State Tax Rate https://taxfoundation.org/sales-tax-rates-2019/

List of US States https://simple.wikipedia.org/wiki/List_of_U.S._states

2018 Cost of Living Index

https://www.kaggle.com/andytran11996/cost-of-living/version/3

- First, the legality will be assessed for each state and city.

- The legality will be cross referenced against a US-population database to find the most densely populated cities with population > 100,000 people.
- Locations of current dispensaries within 1 mile (1.609 km) will be checked.

- If a dispensary exists, the location will be ruled out.

- Another factor that will be assessed is the demographic of the area.

- Cities or neighborhoods with children and families will not be looked at in order to keep them family-friendly.

- Since the goal of this project is to open a recreational dispensary
- I will be looking in areas with active nightlife and adult activities
- I will be looking for places with nearby fast-food, pizza restaurants and convenience stores. Establishments are often frequented by target clientele
- I will be verifying crime rates in cities and aim for lower property crime rate locations
- Many dispensaries have been robbed since installation due to the nature of the product. Try to minimize this risk as much as possible.

Stipulations and Assumptions

1. The following states did not have crime data available and were not included in this assessment. This was not a major problem since none of these states had recreational marijuana legal except for Vermont.

    - Delaware
    - Maine
    - Mississippi
    - Vermont*
    - West Virginia
    - Wyoming

2. Although a legalized area, District of Columbia was not considered in this report since it is not a state and therefore did not have state data available.

3. Only property crime was considered. Violent crimes, although bad, were not taken into account since the risk posed in this endeavor is robbery, burglary or larceny.

4. Since this project is created to get investors and not based on a specific region, only cities with 100,000 residents or more were considered, additionally, anywhere in the United States was considered to be Viable.

5. Tax data was initially collected and looked at but it was determined that a cost of living indices would be a better indicator.

3.2 Methodology

In order to gather the appropriate data, signficant data cleansing was performed to get information into a usable format, remove bad data, exclude cities that are not in scope and generate a streamlined dataset.

I began with consolidating all data based on state/city. To do this I took the tax information which had abbreviated state names and combined them with a list of the 50 states from wikipedia. Once I had the taxes and state names available in its own dataframe I was able to combine it with the crime statistics dataframe. I also got geospatial data from GeoPy using the city and state names to add to the city database. Finally, I calculated a crime-index which is a ratio of property crime to population for each city to complete the database.

Once the database was established, I used the Geo-coordinate data to query the Foursquare server API and gather local venue data for each city. Cities that had dispensaries were dropped from the dataset. The venue data was then transformed with one-hot encoding and grouped along venue frequency by the counts in each city. This data was then used to cluster the cities into 5 different clusters based on what types of venue and overall culture is present in the area.

I started performing exploratory analysis by creating a map of all of the cities that were in my dataset. After clustering was performed, a new map was generated color coding the clusters on the map. Finally, once the target cluster was identified, the crime rate and sales tax were cross referenced to determine the top choice of city to open the dispensary.

In [1]:
```
import numpy as np # library to handle data in a vectorized manner
import matplotlib as mpl
import matplotlib.cm as cm
import matplotlib.colors as colors
import pandas as pd # library for data analsysis
import json # library to handle JSON files
import requests # library to handle requests
import folium # map rendering library
from sklearn.cluster import KMeans # import k-means from clustering stage
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe
from geopy.geocoders import Nominatim # convert an address into latitude and longitude values
from bs4 import BeautifulSoup
#!conda install beautifulsoup4 --yes
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

print('Libraries imported.')
```

```
Libraries imported.
```

3.3 Get updated legalization data

In [2]:
```
url = "disa.com/map-of-marijuana-legality-by-state"
r  = requests.get("http://" +url)
data = r.text
soup = BeautifulSoup(data)
```

```
In [3]: text = []
        legalized = []
        medical = []
        i=0
        for table in soup.find_all('td'):
            text.append([i, table])
            i+=1

        for j in range(0,len(text)-1):
            if str(text[j+1][1]) == "<td>Fully Legal</td>":
                s = str(text[j][1])
                state = s[4:-5]
                legalized.append(state.upper())
            elif str(text[j+1][1]) == "<td>Mixed</td>":
                s = str(text[j][1])
                state = s[4:-5]
                medical.append(state.upper())
```

```
In [4]: legalized
```

```
Out[4]: ['ALASKA',
         'CALIFORNIA',
         'COLORADO',
         'DISTRICT OF COLUMBIA',
         'MAINE',
         'MASSACHUSETTS',
         'MICHIGAN',
         'NEVADA',
         'OREGON',
         'VERMONT',
         'WASHINGTON']
```

3.4 State Sales Tax

```
In [5]: url = "taxfoundation.org/sales-tax-rates-2019/"
        r  = requests.get("http://" +url)
        data = r.text
        soup = BeautifulSoup(data)
```

```
In [6]: text = []

        for table in soup.find_all('td'):
            text.append(table)
        text.pop(0)

        state = []
        tax = []

        for i in range(0,len(text)):
```

```
        if i % 7 == 0:
            s = str(text[i])
            t = str(text[i+1])
            state.append(s[4:-5])
            tax.append(t[4:-5])
```

```
In [7]: for j in range(0,len(tax)):
            try :
                tax[j] = float(tax[j].strip('%'))/100
            except :
                tax[j] = float(0)
```

```
In [8]: for k in range(0,len(tax)):
            try :
                state[k] = state[k].split(' ', 1)[0]
                state[k] = state[k].split('\xa0', 1)[0]
            except :
                next
```

3.5 Correct State Names

```
In [9]: url = "simple.wikipedia.org/wiki/List_of_U.S._states"
        r  = requests.get("http://" +url)
        data = r.text
        soup = BeautifulSoup(data)
```

```
In [10]: text = []


         for table in soup.find_all('area'):
             text.append(str(table))
         statelist =[]

         for k in range(0,len(text)):
             try :
                 text[k] = text[k][11:].split('"', 1)[0]
                 text[k] = text[k].split(' CA', 1)[0]
                 statelist.append(text[k].upper())
             except :
                 next
```

```
In [11]: statelist.sort()
         statelist = list(dict.fromkeys(statelist))
```

```
In [12]: taxes = pd.DataFrame([statelist,tax[0:50]]).transpose()
```

```
In [13]: taxes.rename(columns={0:'State',1:'Tax'},inplace=True)
         taxes.head()
```

```
Out[13]:         State    Tax
         0     ALABAMA   0.04
         1      ALASKA      0
         2     ARIZONA  0.056
         3    ARKANSAS  0.065
         4  CALIFORNIA 0.0725
```

3.5.1 Get cost of living data

```
In [14]: costol = pd.read_csv(r'cost-of-living-2018.csv')

In [15]: costol.head()

Out[15]:    Rank                 City  Cost of Living Index  Rent Index  \
         0   NaN    Hamilton, Bermuda                145.43      110.87
         1   NaN  Zurich, Switzerland                141.25       66.14
         2   NaN  Geneva, Switzerland                134.83       71.70
         3   NaN   Basel, Switzerland                130.68       49.68
         4   NaN    Bern, Switzerland                128.03       43.57

            Cost of Living Plus Rent Index  Groceries Index  Restaurant Price Index  \
         0                          128.76           143.47                  158.75
         1                          105.03           149.86                  135.76
         2                          104.38           138.98                  129.74
         3                           91.61           127.54                  127.22
         4                           87.30           132.70                  119.48

            Local Purchasing Power Index
         0                        112.26
         1                        142.70
         2                        130.96
         3                        139.01
         4                        112.71

In [16]: coldb = pd.DataFrame()

In [17]: coldb.head()

Out[17]: Empty DataFrame
         Columns: []
         Index: []

In [18]: for i in range(0,len(costol)):
             coldb.loc[i,'City'] = costol['City'][i].split(', ')[0].upper()
             coldb.loc[i,'CLI'] = costol['Cost of Living Index'][i]

In [19]: coldb.head()
```

Out[19]:
```
         City     CLI
0  HAMILTON  145.43
1    ZURICH  141.25
2    GENEVA  134.83
3     BASEL  130.68
4      BERN  128.03
```

3.5.2 Generate Legalization Map

In [20]:
```
!wget --quiet https://raw.githubusercontent.com/python-visualization/folium/master/examples/data/us-s
```

In [21]:
```
legal_map = folium.Map(location=[39.83, -98.58], zoom_start=4, tiles='Mapbox Bright')
```

In [22]:
```
legaldf = pd.DataFrame(legalized)
```

In [23]:
```
medicaldf = pd.DataFrame(medical)
```

In [24]:
```
medicaldf.head()
```

Out[24]:
```
             0
0      ARIZONA
1     ARKANSAS
2  CONNECTICUT
3     DELAWARE
4      FLORIDA
```

In [25]:
```
legaldf['Legal'] = 2
medicaldf['Legal'] = 1
```

In [26]:
```
legaldf.rename(columns={0:'State'},inplace=True)
medicaldf.rename(columns={0:'State'},inplace=True)
```

In [27]:
```
legdb = pd.concat([legaldf,medicaldf])
```

In [28]:
```
legdb.head()
```

Out[28]:
```
                  State  Legal
0                ALASKA      2
1            CALIFORNIA      2
2              COLORADO      2
3  DISTRICT OF COLUMBIA      2
4                 MAINE      2
```

In [29]:
```
newdb = taxes.merge(legdb, on="State",how="outer")
```

In [30]:
```
newdb = newdb.fillna(0)
```

In [31]:
```
newdb["Legal"] = newdb["Legal"].astype(int)
for i in range(0,len(newdb["State"])):
    newdb.loc[i,"State"]= newdb["State"][i].capitalize()
```

In [32]: newdb.head()

Out[32]:

	State	Tax	Legal
0	Alabama	0.0400	0
1	Alaska	0.0000	2
2	Arizona	0.0560	1
3	Arkansas	0.0650	1
4	California	0.0725	2

In [33]:
```
statemap = r'states.json' # geojson file

# create a plain world map
legal_map = folium.Map(location=[39.83, -98.58], zoom_start=4, tiles='Mapbox Bright')
legal_map.choropleth(
    geo_data=statemap,
    data=newdb,
    columns=["State","Legal"],
    key_on='feature.properties.name',
    fill_color="GnBu",
    fill_opacity=0.7,
    line_opacity=0.2,
    threshold_scale=[0.001,1.001,2.001],
    legend_name='Legalization in the US 2019 - Blue: Fully Legal, Green: Medicinal only'

)

# display map
legal_map
```

Out[33]: <folium.folium.Map at 0x7f0c98080f28>

3.6 Import Crime Statistics

In [34]:
```
crime = pd.read_csv(r'crime_stats.csv',skiprows=4)
crime = crime[:-9]
```

In [35]: taxes.head()

Out[35]:

	State	Tax
0	ALABAMA	0.04
1	ALASKA	0
2	ARIZONA	0.056
3	ARKANSAS	0.065
4	CALIFORNIA	0.0725

In [36]:
```
states = list(crime['State'].unique())
del states[1]
```

In [37]:
```
crime = crime.merge(taxes, on='State', how='left')
```

```
In [38]: for i in range (1,len(crime)):
             if i%2 != 0:
                 crime.loc[i, 'City'] = crime.loc[i-1, 'City']
             if pd.isnull(crime.loc[i,'State']):
                 crime.loc[i, 'State'] = crime.loc[i-1, 'State']
                 crime.loc[i, 'Tax'] = crime.loc[i-1, 'Tax']

In [39]: crime.rename(columns={"Population1":"Population","Property \ncrime":"Property Crime", "Larceny-\n
         crime.drop(columns=["Unnamed: 2","Violent \ncrime","Murder","Rape2", "Aggravated \nassault","Moto
         crime = crime[:-9]

In [40]: crime = crime.fillna(0)

In [41]: crime["Population"] = crime["Population"].str.replace(",","").astype(float)
         crime["Property Crime"] = crime["Property Crime"].str.replace(",","").astype(float)

In [42]: crime = crime[crime['Population'] != 0]

In [43]: crime['Crime Index'] = crime['Property Crime']/crime['Population']

In [44]: crime.dropna(axis=0,inplace=True)

In [45]: crime = crime.reset_index(drop=True)
         crime.head()
```

Out[45]:

	State	City	Population	Property Crime	Tax	Crime Index
0	ALABAMA	BIRMINGHAM	212178.0	6472.0	0.04	0.030503
1	ALABAMA	MOBILE4	248431.0	6493.0	0.04	0.026136
2	ALABAMA	MONTGOMERY	199099.0	4246.0	0.04	0.021326
3	ALABAMA	TUSCALOOSA	101124.0	1953.0	0.04	0.019313
4	ALASKA	ANCHORAGE	296188.0	7708.0	0.00	0.026024

```
In [46]: coldb.head()
```

Out[46]:

	City	CLI
0	HAMILTON	145.43
1	ZURICH	141.25
2	GENEVA	134.83
3	BASEL	130.68
4	BERN	128.03

```
In [47]: crime = crime.merge(coldb, on='City', how='left')

In [48]: try:
             crime.drop(['Country'],inplace=True,axis=1)
         except:
             next

In [49]: crime=crime.fillna(0)
```

In [50]: crime.head()

Out[50]:

	State	City	Population	Property Crime	Tax	Crime Index	CLI
0	ALABAMA	BIRMINGHAM	212178.0	6472.0	0.04	0.030503	74.64
1	ALABAMA	BIRMINGHAM	212178.0	6472.0	0.04	0.030503	71.60
2	ALABAMA	MOBILE4	248431.0	6493.0	0.04	0.026136	0.00
3	ALABAMA	MONTGOMERY	199099.0	4246.0	0.04	0.021326	0.00
4	ALABAMA	TUSCALOOSA	101124.0	1953.0	0.04	0.019313	0.00

In [51]:
```
try:
    for i in range(0,len(crime)):
        if crime['State'][i] not in legalized:
            crime.drop([i],axis=0, inplace=True)
except:
    next
```

In [52]: crime.head()

Out[52]:

	State	City	Population	Property Crime	Tax	Crime Index	\
5	ALASKA	ANCHORAGE	296188.0	7708.0	0.0000	0.026024	
16	CALIFORNIA	ANAHEIM	353400.0	4629.0	0.0725	0.013098	
17	CALIFORNIA	ANTIOCH	112252.0	1873.0	0.0725	0.016686	
18	CALIFORNIA	BAKERSFIELD	381154.0	7570.0	0.0725	0.019861	
19	CALIFORNIA	BERKELEY	122687.0	2827.0	0.0725	0.023042	

	CLI
5	94.99
16	0.00
17	0.00
18	69.20
19	87.82

3.6.1 Find the city with lowest Property Crime City to open a dispensary in each state

In [53]:
```
crime = crime[crime.City != 'RIALTO5']
crime = crime[crime.City != 'LAS VEGAS METROPOLITAN POLICE DEPARTMENT']
```

In [54]:
```
cities = pd.concat([crime['State'],crime['City'],crime['Tax'],crime['Crime Index'],crime['CLI']],axis=1)
```

In [55]:
```
cities.reset_index(inplace=True,drop=True)
```

In [56]: cities.head()

Out[56]:

	State	City	Tax	Crime Index	CLI
0	ALASKA	ANCHORAGE	0.0000	0.026024	94.99
1	CALIFORNIA	ANAHEIM	0.0725	0.013098	0.00
2	CALIFORNIA	ANTIOCH	0.0725	0.016686	0.00
3	CALIFORNIA	BAKERSFIELD	0.0725	0.019861	69.20
4	CALIFORNIA	BERKELEY	0.0725	0.023042	87.82

3.6.2 Get Geospatial Data using GeoPy for City, State

In [57]:
```
lat = []
lon = []
for i in range(0,len(cities)):
    address = '{}, {}'.format(cities['City'][i],cities['State'][i])
    geolocator = Nominatim(user_agent='capstone')
    location = geolocator.geocode(address)
    lat.append(location.latitude)
    lon.append(location.longitude)
```

In [62]:
```
city2 = pd.concat([cities,pd.Series(lat),pd.Series(lon)],axis=1)
```

In [63]:
```
city2.rename(columns={0:'Latitude',1:'Longitude'},inplace=True)
```

In [164]:
```
city2.head()
```

Out[164]:

	State	City	Tax	Crime Index	CLI	Latitude	Longitude
0	ALASKA	ANCHORAGE	0.0000	0.026024	94.99	61.216313	-149.894852
1	CALIFORNIA	ANAHEIM	0.0725	0.013098	0.00	33.834752	-117.911732
2	CALIFORNIA	ANTIOCH	0.0725	0.016686	0.00	38.004921	-121.805789
3	CALIFORNIA	BAKERSFIELD	0.0725	0.019861	69.20	35.373871	-119.019464
4	CALIFORNIA	BERKELEY	0.0725	0.023042	87.82	37.870839	-122.272864

3.6.3 Create map of all viable US cities with population over 100,000 and legalized Recreational Marijuana

In [65]:
```
# create map of Cities using latitude and longitude values
cities_map = folium.Map(location=[39.83, -98.58], zoom_start=4)

# add markers to map
for lat, lng, city, state in zip(city2['Latitude'], city2['Longitude'], city2['City'], city2['State']):
    label = '{}, {}'.format(state, city)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=10,
        popup=label,
        color='green',
        fill=True,
        fill_color='#228B22',
        fill_opacity=0.7,
        parse_html=False).add_to(cities_map)

cities_map
```

Out[65]: <folium.folium.Map at 0x7f0c97932898>

3.6.4 Get local venue data for each city from Foursquare API

In [66]:
```
CLIENT_ID = 'K5HRW4OC5J4EZS14DH2OKQBNZV5GNXIOZKY03QXJ4RDCPTUD' # your Foursq
CLIENT_SECRET = '4ZWZFMI0VAL01GTTVLUJSJOL0YPARUAQB225RMYILABEIQ0Q' # your Fo
VERSION = '20190420'
limit = 100
radius = 1609
latitude = 1
longitude = 1
print('Your credentials:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentials:
CLIENT_ID: K5HRW4OC5J4EZS14DH2OKQBNZV5GNXIOZKY03QXJ4RDCPTUD
CLIENT_SECRET:4ZWZFMI0VAL01GTTVLUJSJOL0YPARUAQB225RMYILABEIQ0Q
```

In [81]:
```
url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={},{}&
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    latitude,
    longitude,
    radius,
    limit)
```

In [82]:
```
results = requests.get(url).json()
```

In [83]:
```
def getNearbyVenues(states, names, latitudes, longitudes, radius=1609):

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

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={
            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([(
```

```
                    state,
                    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 = ['State',
                    'City',
                     'City Latitude',
                     'City Longitude',
                     'Venue',
                     'Venue Latitude',
                     'Venue Longitude',
                     'Venue Category']

    return(nearby_venues)
```

In [84]:
```
# 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']
```

In [85]:
```
city2.head()
```

Out[85]:

	State	City	Tax	Crime Index	CLI	Latitude	Longitude
0	ALASKA	ANCHORAGE	0.0000	0.026024	94.99	61.216313	-149.894852
1	CALIFORNIA	ANAHEIM	0.0725	0.013098	0.00	33.834752	-117.911732
2	CALIFORNIA	ANTIOCH	0.0725	0.016686	0.00	38.004921	-121.805789
3	CALIFORNIA	BAKERSFIELD	0.0725	0.019861	69.20	35.373871	-119.019464
4	CALIFORNIA	BERKELEY	0.0725	0.023042	87.82	37.870839	-122.272864

In [86]:
```
city_venues = getNearbyVenues(states=city2['State'],
                              names= city2['City'],
                              latitudes = city2['Latitude'],
                              longitudes = city2['Longitude'],
                              radius=1609
                             )
```

In [87]:
```
venues = results['response']['groups'][0]['items']

nearby_venues = 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]
```

In [88]:
```
city_venues.head()
```

Out[88]:
```
    State       City  City Latitude  City Longitude  \
0  ALASKA  ANCHORAGE      61.216313     -149.894852
1  ALASKA  ANCHORAGE      61.216313     -149.894852
2  ALASKA  ANCHORAGE      61.216313     -149.894852
3  ALASKA  ANCHORAGE      61.216313     -149.894852
4  ALASKA  ANCHORAGE      61.216313     -149.894852

                               Venue  Venue Latitude  Venue Longitude  \
0                  Glacier BrewHouse       61.217719      -149.896839
1   Humpy's Great Alaskan Alehouse       61.216427      -149.894146
2                        Crow's Nest       61.217838      -149.899718
3                 49th State Brewing       61.219736      -149.895975
4  Apple Anchorage 5th Avenue Mall       61.217140      -149.888671

      Venue Category
0            Brewery
1                Bar
2  Seafood Restaurant
3            Brewery
4   Electronics Store
```

3.6.5 Prepare the venue data to perform K-means clustering

In [89]:
```
# one hot encoding
city_onehot = pd.get_dummies(city_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
city_onehot['State'] = city_venues['State']
city_onehot['City'] = city_venues['City']

# move neighborhood column to the first column
fixed_columns = [city_onehot.columns[-2]] + [city_onehot.columns[-1]] + list(city_onehot.columns[:-2])
```

```
city_onehot = city_onehot[fixed_columns]
city_onehot.head()
```

Out[89]:

	State	City	ATM	Accessories Store	Advertising Agency	\
0	ALASKA	ANCHORAGE	0	0	0	
1	ALASKA	ANCHORAGE	0	0	0	
2	ALASKA	ANCHORAGE	0	0	0	
3	ALASKA	ANCHORAGE	0	0	0	
4	ALASKA	ANCHORAGE	0	0	0	

	Afghan Restaurant	African Restaurant	Airport	American Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Animal Shelter	Antique Shop	Aquarium	Arcade	Art Gallery	Art Museum	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Arts & Crafts Store	Arts & Entertainment	Asian Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Athletics & Sports	Australian Restaurant	Auto Dealership	Auto Garage	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Auto Workshop	Automotive Shop	BBQ Joint	Bagel Shop	Bakery	Bank	Bar	\
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	1	
2	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

	Baseball Field	Baseball Stadium	Basketball Court	Basketball Stadium	\
0	0	0	0	0	
1	0	0	0	0	

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Bath House	Beach	Bed & Breakfast	Beer Bar	Beer Garden	Beer Store \
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Belgian Restaurant	Big Box Store	Bike Shop	Bistro	Board Shop \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Boat or Ferry	Bookstore	Boutique	Bowling Alley	Boxing Gym \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Brazilian Restaurant	Breakfast Spot	Brewery	Bridal Shop \
0	0	0	1	0
1	0	0	0	0
2	0	0	0	0
3	0	0	1	0
4	0	0	0	0

	Bubble Tea Shop	Buffet	Building	Burger Joint	Burmese Restaurant \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Burrito Place	Bus Station	Bus Stop	Business Service	Butcher	Café \
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Cajun / Creole Restaurant	Cambodian Restaurant	Camera Store	Campground \
0	0	0	0	0

1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Candy Store	Cantonese Restaurant	Capitol Building	Caribbean Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Carpet Store	Casino	Cheese Shop	Chinese Restaurant	Chiropractor	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Chocolate Shop	Church	Circus	City Hall	Climbing Gym	Clothing Store	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Cocktail Bar	Coffee Shop	College Academic Building	College Auditorium	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	College Baseball Diamond	College Basketball Court	College Bookstore	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	College Gym	College Rec Center	College Theater	Comedy Club	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Comfort Food Restaurant	Comic Shop	Community Center	Concert Hall	\

0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Construction & Landscaping	Convenience Store	Convention Center \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Cosmetics Shop	Creperie	Cuban Restaurant	Cupcake Shop	Cycle Studio \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Dance Studio	Deli / Bodega	Department Store	Dessert Shop \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Dim Sum Restaurant	Diner	Disc Golf	Discount Store	Dive Bar \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Doctor's Office	Dog Run	Donburi Restaurant	Donut Shop \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Dumpling Restaurant	Eastern European Restaurant	Electronics Store \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	1

	Elementary School	Empanada Restaurant	Entertainment Service	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Ethiopian Restaurant	Event Service	Event Space	Exhibit	Eye Doctor	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Fabric Shop	Falafel Restaurant	Farm	Farmers Market	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Fast Food Restaurant	Filipino Restaurant	Financial or Legal Service	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Fish & Chips Shop	Fish Market	Flea Market	Flower Shop	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Fondue Restaurant	Food	Food & Drink Shop	Food Court	Food Truck	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Football Stadium	Fountain	French Restaurant	Fried Chicken Joint	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Frozen Yogurt Shop	Furniture / Home Store	Gaming Cafe	Garden	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Garden Center	Gas Station	Gastropub	Gay Bar	General Entertainment	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	German Restaurant	Gift Shop	Go Kart Track	Golf Course	Gourmet Shop	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Greek Restaurant	Grocery Store	Gun Shop	Gym	Gym / Fitness Center	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Gym Pool	Gymnastics Gym	Halal Restaurant	Harbor / Marina	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Hardware Store	Hawaiian Restaurant	Health & Beauty Service	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Health Food Store	Herbs & Spices Store	High School	Historic Site	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	

4	0	0	0	0

	History Museum	Hobby Shop	Hockey Arena	Home Service	Hookah Bar	Hostel \
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

	Hot Dog Joint	Hotel	Hotel Bar	Hotel Pool	Ice Cream Shop \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Indian Chinese Restaurant	Indian Restaurant	Indie Movie Theater \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Indie Theater	Indonesian Restaurant	Inn	Insurance Office	Intersection \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Irish Pub	Israeli Restaurant	Italian Restaurant \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Japanese Curry Restaurant	Japanese Restaurant	Jazz Club	Jewelry Store \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Juice Bar	Karaoke Bar	Kids Store	Kitchen Supply Store	Knitting Store \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0

3	0	0	0	0	0
4	0	0	0	0	0

	Korean Restaurant	Lake	Latin American Restaurant	Laundromat	Lawyer \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Library	Light Rail Station	Lingerie Store	Liquor Store	Lounge \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Malay Restaurant	Marijuana Dispensary	Market	Martial Arts Dojo \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Massage Studio	Medical Center	Mediterranean Restaurant	Men's Store \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Metro Station	Mexican Restaurant	Middle Eastern Restaurant \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Miscellaneous Shop	Mobile Phone Shop	Monument / Landmark	Motel \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Motorcycle Shop	Motorsports Shop	Movie Theater	Multiplex	Museum \
0	0	0	0	0	0
1	0	0	0	0	0

2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Music School	Music Store	Music Venue	Nail Salon	National Park \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Nature Preserve	Neighborhood	New American Restaurant	Nightclub \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Non-Profit	Noodle House	Office	Opera House	Optical Shop \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Organic Grocery	Other Great Outdoors	Other Nightlife	Other Repair Shop \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Outdoor Sculpture	Paintball Field	Paper / Office Supplies Store	Park \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Parking	Pastry Shop	Pedestrian Plaza	Performing Arts Venue \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Persian Restaurant	Peruvian Restaurant	Pet Service	Pet Store	Pharmacy \
0	0	0	0	0	0

1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Piano Bar	Pie Shop	Pier	Pilates Studio	Pizza Place	Platform	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Playground	Plaza	Poke Place	Pool	Pool Hall	Portuguese Restaurant	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Print Shop	Pub	Public Art	Racetrack	Ramen Restaurant	Record Shop	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Rental Car Location	Rental Service	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	Residential Building (Apartment / Condo)	Resort	Restaurant	Rock Club	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Salad Place	Salon / Barbershop	Salvadoran Restaurant	Sandwich Place	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Satay Restaurant	Scandinavian Restaurant	Scenic Lookout	School	\

0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Science Museum	Sculpture Garden	Seafood Restaurant	Shipping Store \
0	0	0	0	0
1	0	0	0	0
2	0	0	1	0
3	0	0	0	0
4	0	0	0	0

	Shoe Store	Shop & Service	Shopping Mall	Shopping Plaza	Skate Park \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Skating Rink	Ski Chalet	Smoke Shop	Smoothie Shop	Snack Place \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Soccer Field	Soccer Stadium	Social Club	Soup Place \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	South American Restaurant	South Indian Restaurant \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	Southern / Soul Food Restaurant	Souvenir Shop	Souvlaki Shop	Spa \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Spanish Restaurant	Speakeasy	Sporting Goods Shop	Sports Bar	Stadium	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	State / Provincial Park	Stationery Store	Steakhouse	Storage Facility	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Street Food Gathering	Strip Club	Supermarket	Supplement Shop	Surf Spot	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Sushi Restaurant	Szechuan Restaurant	Taco Place	Tailor Shop	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Taiwanese Restaurant	Tanning Salon	Tapas Restaurant	Tattoo Parlor	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Tea Room	Tennis Court	Tennis Stadium	Tex-Mex Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Thai Restaurant	Theater	Theme Park	Theme Park Ride / Attraction	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Theme Restaurant	Thrift / Vintage Store	Tiki Bar	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Tourist Information Center	Toy / Game Store	Track	Track Stadium	Trail	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Train Station	Tree	Turkish Restaurant	Udon Restaurant	Used Bookstore	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Vape Store	Vegetarian / Vegan Restaurant	Video Game Store	Video Store	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Vietnamese Restaurant	Warehouse Store	Waterfront	Weight Loss Center	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Whisky Bar	Wine Bar	Wine Shop	Winery	Wings Joint	Women's Store	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	Yoga Studio	Yoshoku Restaurant
0	0	0
1	0	0
2	0	0
3	0	0

```
4           0                  0
```

In [90]:
```
city_group = city_onehot.groupby(['State','City']).mean().reset_index()
```

In [91]:
```
city_group.head()
```

Out[91]:
```
        State         City  ATM  Accessories Store  Advertising Agency  \
0      ALASKA    ANCHORAGE  0.0               0.03                 0.0
1  CALIFORNIA      ANAHEIM  0.0               0.00                 0.0
2  CALIFORNIA      ANTIOCH  0.0               0.00                 0.0
3  CALIFORNIA  BAKERSFIELD  0.0               0.00                 0.0
4  CALIFORNIA     BERKELEY  0.0               0.00                 0.0

   Afghan Restaurant  African Restaurant  Airport  American Restaurant  \
0                0.0                0.00      0.0             0.010000
1                0.0                0.00      0.0             0.016129
2                0.0                0.00      0.0             0.028571
3                0.0                0.00      0.0             0.021277
4                0.0                0.01      0.0             0.020000

   Animal Shelter  Antique Shop  Aquarium  Arcade  Art Gallery  Art Museum  \
0             0.0           0.0       0.0     0.0     0.000000        0.00
1             0.0           0.0       0.0     0.0     0.016129        0.00
2             0.0           0.0       0.0     0.0     0.000000        0.00
3             0.0           0.0       0.0     0.0     0.010638        0.00
4             0.0           0.0       0.0     0.0     0.000000        0.01

   Arts & Crafts Store  Arts & Entertainment  Asian Restaurant  \
0                  0.0                   0.0          0.020000
1                  0.0                   0.0          0.016129
2                  0.0                   0.0          0.000000
3                  0.0                   0.0          0.000000
4                  0.0                   0.0          0.020000

   Athletics & Sports  Australian Restaurant  Auto Dealership  Auto Garage  \
0                 0.0                    0.0              0.0          0.0
1                 0.0                    0.0              0.0          0.0
2                 0.0                    0.0              0.0          0.0
3                 0.0                    0.0              0.0          0.0
4                 0.0                    0.0              0.0          0.0

   Auto Workshop  Automotive Shop  BBQ Joint  Bagel Shop    Bakery      Bank  \
0       0.000000         0.000000        0.0         0.0  0.020000  0.000000
1       0.000000         0.016129        0.0         0.0  0.016129  0.000000
2       0.028571         0.028571        0.0         0.0  0.028571  0.000000
3       0.000000         0.000000        0.0         0.0  0.010638  0.010638
4       0.000000         0.000000        0.0         0.0  0.010000  0.000000
```

	Bar	Baseball Field	Baseball Stadium	Basketball Court	\
0	0.040000	0.0	0.0	0.0	
1	0.016129	0.0	0.0	0.0	
2	0.000000	0.0	0.0	0.0	
3	0.042553	0.0	0.0	0.0	
4	0.000000	0.0	0.0	0.0	

	Basketball Stadium	Bath House	Beach	Bed & Breakfast	Beer Bar	\
0	0.0	0.00	0.0	0.0	0.00	
1	0.0	0.00	0.0	0.0	0.00	
2	0.0	0.00	0.0	0.0	0.00	
3	0.0	0.00	0.0	0.0	0.00	
4	0.0	0.01	0.0	0.0	0.01	

	Beer Garden	Beer Store	Belgian Restaurant	Big Box Store	Bike Shop	\
0	0.00	0.0	0.0	0.0	0.0	
1	0.00	0.0	0.0	0.0	0.0	
2	0.00	0.0	0.0	0.0	0.0	
3	0.00	0.0	0.0	0.0	0.0	
4	0.01	0.0	0.0	0.0	0.0	

	Bistro	Board Shop	Boat or Ferry	Bookstore	Boutique	Bowling Alley	\
0	0.0	0.0	0.0	0.00	0.0	0.000000	
1	0.0	0.0	0.0	0.00	0.0	0.000000	
2	0.0	0.0	0.0	0.00	0.0	0.000000	
3	0.0	0.0	0.0	0.00	0.0	0.010638	
4	0.0	0.0	0.0	0.02	0.0	0.000000	

	Boxing Gym	Brazilian Restaurant	Breakfast Spot	Brewery	Bridal Shop	\
0	0.0	0.00	0.020000	0.020000	0.0	
1	0.0	0.00	0.016129	0.032258	0.0	
2	0.0	0.00	0.000000	0.000000	0.0	
3	0.0	0.00	0.021277	0.000000	0.0	
4	0.0	0.02	0.010000	0.020000	0.0	

	Bubble Tea Shop	Buffet	Building	Burger Joint	Burmese Restaurant	\
0	0.00	0.0	0.0	0.010000	0.0	
1	0.00	0.0	0.0	0.032258	0.0	
2	0.00	0.0	0.0	0.028571	0.0	
3	0.00	0.0	0.0	0.021277	0.0	
4	0.01	0.0	0.0	0.010000	0.0	

	Burrito Place	Bus Station	Bus Stop	Business Service	Butcher	Café	\
0	0.0	0.0	0.0	0.0	0.00	0.010000	
1	0.0	0.0	0.0	0.0	0.00	0.000000	
2	0.0	0.0	0.0	0.0	0.00	0.000000	
3	0.0	0.0	0.0	0.0	0.00	0.021277	
4	0.0	0.0	0.0	0.0	0.01	0.030000	

	Cajun / Creole Restaurant	Cambodian Restaurant	Camera Store	Campground	\
0	0.010000	0.0	0.0	0.0	
1	0.016129	0.0	0.0	0.0	
2	0.000000	0.0	0.0	0.0	
3	0.010638	0.0	0.0	0.0	
4	0.000000	0.0	0.0	0.0	

	Candy Store	Cantonese Restaurant	Capitol Building	Caribbean Restaurant	\
0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	

	Carpet Store	Casino	Cheese Shop	Chinese Restaurant	Chiropractor	\
0	0.0	0.0	0.00	0.000000	0.0	
1	0.0	0.0	0.00	0.016129	0.0	
2	0.0	0.0	0.00	0.057143	0.0	
3	0.0	0.0	0.00	0.031915	0.0	
4	0.0	0.0	0.01	0.030000	0.0	

	Chocolate Shop	Church	Circus	City Hall	Climbing Gym	Clothing Store	\
0	0.0	0.0	0.0	0.0	0.0	0.05	
1	0.0	0.0	0.0	0.0	0.0	0.00	
2	0.0	0.0	0.0	0.0	0.0	0.00	
3	0.0	0.0	0.0	0.0	0.0	0.00	
4	0.0	0.0	0.0	0.0	0.0	0.00	

	Cocktail Bar	Coffee Shop	College Academic Building	College Auditorium	\
0	0.00	0.060000	0.0	0.0	
1	0.00	0.048387	0.0	0.0	
2	0.00	0.028571	0.0	0.0	
3	0.00	0.085106	0.0	0.0	
4	0.01	0.020000	0.0	0.0	

	College Baseball Diamond	College Basketball Court	College Bookstore	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
4	0.0	0.0	0.0	

	College Gym	College Rec Center	College Theater	Comedy Club	\
0	0.00	0.0	0.00	0.0	
1	0.00	0.0	0.00	0.0	
2	0.00	0.0	0.00	0.0	
3	0.00	0.0	0.00	0.0	

4	0.01	0.0	0.01	0.0

	Comfort Food Restaurant	Comic Shop	Community Center	Concert Hall \
0	0.000000	0.000000	0.0	0.000000
1	0.016129	0.016129	0.0	0.000000
2	0.000000	0.000000	0.0	0.028571
3	0.000000	0.000000	0.0	0.000000
4	0.010000	0.010000	0.0	0.000000

	Construction & Landscaping	Convenience Store	Convention Center \
0	0.0	0.000000	0.0
1	0.0	0.048387	0.0
2	0.0	0.028571	0.0
3	0.0	0.021277	0.0
4	0.0	0.000000	0.0

	Cosmetics Shop	Creperie	Cuban Restaurant	Cupcake Shop	Cycle Studio \
0	0.03	0.000000	0.0	0.0	0.0
1	0.00	0.016129	0.0	0.0	0.0
2	0.00	0.000000	0.0	0.0	0.0
3	0.00	0.000000	0.0	0.0	0.0
4	0.00	0.000000	0.0	0.0	0.0

	Dance Studio	Deli / Bodega	Department Store	Dessert Shop \
0	0.0	0.000000	0.02	0.00
1	0.0	0.016129	0.00	0.00
2	0.0	0.028571	0.00	0.00
3	0.0	0.000000	0.00	0.00
4	0.0	0.010000	0.00	0.01

	Dim Sum Restaurant	Diner	Disc Golf	Discount Store	Dive Bar \
0	0.0	0.010000	0.0	0.000000	0.010000
1	0.0	0.016129	0.0	0.000000	0.000000
2	0.0	0.000000	0.0	0.028571	0.028571
3	0.0	0.010638	0.0	0.000000	0.021277
4	0.0	0.000000	0.0	0.000000	0.000000

	Doctor's Office	Dog Run	Donburi Restaurant	Donut Shop \
0	0.0	0.00	0.0	0.0
1	0.0	0.00	0.0	0.0
2	0.0	0.00	0.0	0.0
3	0.0	0.00	0.0	0.0
4	0.0	0.01	0.0	0.0

	Dumpling Restaurant	Eastern European Restaurant	Electronics Store \
0	0.0	0.0	0.01
1	0.0	0.0	0.00
2	0.0	0.0	0.00

3	0.0	0.0	0.00
4	0.0	0.0	0.00

	Elementary School	Empanada Restaurant	Entertainment Service \
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	0.0
3	0.0	0.0	0.0
4	0.0	0.0	0.0

	Ethiopian Restaurant	Event Service	Event Space	Exhibit	Eye Doctor \
0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0

	Fabric Shop	Falafel Restaurant	Farm	Farmers Market \
0	0.00	0.0	0.0	0.010000
1	0.00	0.0	0.0	0.016129
2	0.00	0.0	0.0	0.000000
3	0.00	0.0	0.0	0.000000
4	0.01	0.0	0.0	0.010000

	Fast Food Restaurant	Filipino Restaurant	Financial or Legal Service \
0	0.000000	0.0	0.0
1	0.016129	0.0	0.0
2	0.114286	0.0	0.0
3	0.063830	0.0	0.0
4	0.000000	0.0	0.0

	Fish & Chips Shop	Fish Market	Flea Market	Flower Shop \
0	0.0	0.01	0.0	0.00
1	0.0	0.00	0.0	0.00
2	0.0	0.00	0.0	0.00
3	0.0	0.00	0.0	0.00
4	0.0	0.00	0.0	0.01

	Fondue Restaurant	Food	Food & Drink Shop	Food Court	Food Truck \
0	0.0	0.0	0.0	0.010000	0.000000
1	0.0	0.0	0.0	0.016129	0.016129
2	0.0	0.0	0.0	0.000000	0.000000
3	0.0	0.0	0.0	0.000000	0.000000
4	0.0	0.0	0.0	0.000000	0.000000

	Football Stadium	Fountain	French Restaurant	Fried Chicken Joint \
0	0.0	0.0	0.00	0.000000
1	0.0	0.0	0.00	0.016129

2	0.0	0.0	0.00	0.000000
3	0.0	0.0	0.00	0.000000
4	0.0	0.0	0.03	0.000000

	Frozen Yogurt Shop	Furniture / Home Store	Gaming Cafe	Garden \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

	Garden Center	Gas Station	Gastropub	Gay Bar	General Entertainment \
0	0.0	0.0	0.010000	0.010000	0.000000
1	0.0	0.0	0.016129	0.000000	0.000000
2	0.0	0.0	0.000000	0.000000	0.000000
3	0.0	0.0	0.000000	0.010638	0.021277
4	0.0	0.0	0.010000	0.000000	0.000000

	German Restaurant	Gift Shop	Go Kart Track	Golf Course	Gourmet Shop \
0	0.0	0.03	0.0	0.0	0.01
1	0.0	0.00	0.0	0.0	0.00
2	0.0	0.00	0.0	0.0	0.00
3	0.0	0.00	0.0	0.0	0.00
4	0.0	0.00	0.0	0.0	0.01

	Greek Restaurant	Grocery Store	Gun Shop	Gym	Gym / Fitness Center \
0	0.0	0.000000	0.0	0.00	0.000000
1	0.0	0.000000	0.0	0.00	0.016129
2	0.0	0.028571	0.0	0.00	0.000000
3	0.0	0.010638	0.0	0.00	0.000000
4	0.0	0.010000	0.0	0.02	0.000000

	Gym Pool	Gymnastics Gym	Halal Restaurant	Harbor / Marina \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

	Hardware Store	Hawaiian Restaurant	Health & Beauty Service \
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	0.0
3	0.0	0.0	0.0
4	0.0	0.0	0.0

	Health Food Store	Herbs & Spices Store	High School	Historic Site \
0	0.0	0.0	0.0	0.00

1	0.0	0.0	0.0	0.00
2	0.0	0.0	0.0	0.00
3	0.0	0.0	0.0	0.00
4	0.0	0.0	0.0	0.01

	History Museum	Hobby Shop	Hockey Arena	Home Service	Hookah Bar	Hostel	\
0	0.01	0.0	0.000000	0.0	0.0	0.0	
1	0.00	0.0	0.000000	0.0	0.0	0.0	
2	0.00	0.0	0.000000	0.0	0.0	0.0	
3	0.00	0.0	0.021277	0.0	0.0	0.0	
4	0.00	0.0	0.000000	0.0	0.0	0.0	

	Hot Dog Joint	Hotel	Hotel Bar	Hotel Pool	Ice Cream Shop	\
0	0.0	0.020000	0.000000	0.0	0.010000	
1	0.0	0.000000	0.000000	0.0	0.048387	
2	0.0	0.000000	0.000000	0.0	0.000000	
3	0.0	0.021277	0.010638	0.0	0.021277	
4	0.0	0.010000	0.000000	0.0	0.030000	

	Indian Chinese Restaurant	Indian Restaurant	Indie Movie Theater	\
0	0.0	0.000000	0.0	
1	0.0	0.048387	0.0	
2	0.0	0.000000	0.0	
3	0.0	0.000000	0.0	
4	0.0	0.020000	0.0	

	Indie Theater	Indonesian Restaurant	Inn	Insurance Office	Intersection	\
0	0.0	0.00	0.0	0.0	0.0	
1	0.0	0.00	0.0	0.0	0.0	
2	0.0	0.00	0.0	0.0	0.0	
3	0.0	0.00	0.0	0.0	0.0	
4	0.0	0.01	0.0	0.0	0.0	

	Irish Pub	Israeli Restaurant	Italian Restaurant	\
0	0.0	0.0	0.000000	
1	0.0	0.0	0.016129	
2	0.0	0.0	0.000000	
3	0.0	0.0	0.031915	
4	0.0	0.0	0.020000	

	Japanese Curry Restaurant	Japanese Restaurant	Jazz Club	Jewelry Store	\
0	0.0	0.01	0.0	0.0	
1	0.0	0.00	0.0	0.0	
2	0.0	0.00	0.0	0.0	
3	0.0	0.00	0.0	0.0	
4	0.0	0.03	0.0	0.0	

	Juice Bar	Karaoke Bar	Kids Store	Kitchen Supply Store	Knitting Store	\

0	0.000000	0.0	0.01	0.0	0.0
1	0.016129	0.0	0.00	0.0	0.0
2	0.000000	0.0	0.00	0.0	0.0
3	0.000000	0.0	0.00	0.0	0.0
4	0.000000	0.0	0.00	0.0	0.0

	Korean Restaurant	Lake	Latin American Restaurant	Laundromat	Lawyer \
0	0.0	0.0	0.000000	0.0	0.0
1	0.0	0.0	0.000000	0.0	0.0
2	0.0	0.0	0.000000	0.0	0.0
3	0.0	0.0	0.010638	0.0	0.0
4	0.0	0.0	0.010000	0.0	0.0

	Library	Light Rail Station	Lingerie Store	Liquor Store	Lounge \
0	0.0	0.0	0.01	0.000000	0.00
1	0.0	0.0	0.00	0.032258	0.00
2	0.0	0.0	0.00	0.000000	0.00
3	0.0	0.0	0.00	0.010638	0.00
4	0.0	0.0	0.00	0.000000	0.01

	Malay Restaurant	Marijuana Dispensary	Market	Martial Arts Dojo \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

	Massage Studio	Medical Center	Mediterranean Restaurant	Men's Store \
0	0.0	0.0	0.000000	0.0
1	0.0	0.0	0.000000	0.0
2	0.0	0.0	0.000000	0.0
3	0.0	0.0	0.010638	0.0
4	0.0	0.0	0.000000	0.0

	Metro Station	Mexican Restaurant	Middle Eastern Restaurant \
0	0.0	0.020000	0.0
1	0.0	0.080645	0.0
2	0.0	0.085714	0.0
3	0.0	0.095745	0.0
4	0.0	0.020000	0.0

	Miscellaneous Shop	Mobile Phone Shop	Monument / Landmark	Motel \
0	0.0	0.01	0.0	0.0
1	0.0	0.00	0.0	0.0
2	0.0	0.00	0.0	0.0
3	0.0	0.00	0.0	0.0
4	0.0	0.00	0.0	0.0

	Motorcycle Shop	Motorsports Shop	Movie Theater	Multiplex	Museum \
0	0.0	0.0	0.00	0.000000	0.000000
1	0.0	0.0	0.00	0.000000	0.016129
2	0.0	0.0	0.00	0.000000	0.000000
3	0.0	0.0	0.00	0.010638	0.000000
4	0.0	0.0	0.01	0.000000	0.000000

	Music School	Music Store	Music Venue	Nail Salon	National Park \
0	0.0	0.0	0.00	0.0	0.0
1	0.0	0.0	0.00	0.0	0.0
2	0.0	0.0	0.00	0.0	0.0
3	0.0	0.0	0.00	0.0	0.0
4	0.0	0.0	0.02	0.0	0.0

	Nature Preserve	Neighborhood	New American Restaurant	Nightclub \
0	0.0	0.0	0.01	0.000000
1	0.0	0.0	0.00	0.000000
2	0.0	0.0	0.00	0.000000
3	0.0	0.0	0.00	0.010638
4	0.0	0.0	0.03	0.000000

	Non-Profit	Noodle House	Office	Opera House	Optical Shop \
0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0

	Organic Grocery	Other Great Outdoors	Other Nightlife	Other Repair Shop \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

	Outdoor Sculpture	Paintball Field	Paper / Office Supplies Store \
0	0.01	0.000000	0.0
1	0.00	0.000000	0.0
2	0.00	0.028571	0.0
3	0.00	0.000000	0.0
4	0.00	0.000000	0.0

	Park	Parking	Pastry Shop	Pedestrian Plaza	Performing Arts Venue \
0	0.050000	0.00	0.0	0.0	0.01
1	0.016129	0.00	0.0	0.0	0.00
2	0.000000	0.00	0.0	0.0	0.00
3	0.021277	0.00	0.0	0.0	0.00
4	0.020000	0.01	0.0	0.0	0.00

	Persian Restaurant	Peruvian Restaurant	Pet Service	Pet Store	Pharmacy	\
0	0.0	0.0	0.0	0.00	0.000000	
1	0.0	0.0	0.0	0.00	0.000000	
2	0.0	0.0	0.0	0.00	0.028571	
3	0.0	0.0	0.0	0.00	0.010638	
4	0.0	0.0	0.0	0.01	0.000000	

	Piano Bar	Pie Shop	Pier	Pilates Studio	Pizza Place	Platform	\
0	0.0	0.0	0.0	0.0	0.030000	0.0	
1	0.0	0.0	0.0	0.0	0.016129	0.0	
2	0.0	0.0	0.0	0.0	0.085714	0.0	
3	0.0	0.0	0.0	0.0	0.010638	0.0	
4	0.0	0.0	0.0	0.0	0.020000	0.0	

	Playground	Plaza	Poke Place	Pool	Pool Hall	Portuguese Restaurant	\
0	0.01	0.0	0.000000	0.0	0.0	0.0	
1	0.00	0.0	0.016129	0.0	0.0	0.0	
2	0.00	0.0	0.000000	0.0	0.0	0.0	
3	0.00	0.0	0.000000	0.0	0.0	0.0	
4	0.00	0.0	0.000000	0.0	0.0	0.0	

	Print Shop	Pub	Public Art	Racetrack	Ramen Restaurant	Record Shop	\
0	0.0	0.020000	0.0	0.000000	0.00	0.0	
1	0.0	0.000000	0.0	0.000000	0.00	0.0	
2	0.0	0.000000	0.0	0.028571	0.00	0.0	
3	0.0	0.010638	0.0	0.000000	0.00	0.0	
4	0.0	0.000000	0.0	0.000000	0.01	0.0	

	Rental Car Location	Rental Service	\
0	0.010000	0.0	
1	0.000000	0.0	
2	0.000000	0.0	
3	0.021277	0.0	
4	0.000000	0.0	

	Residential Building (Apartment / Condo)	Resort	Restaurant	Rock Club	\
0	0.0	0.0	0.020000	0.000000	
1	0.0	0.0	0.000000	0.016129	
2	0.0	0.0	0.028571	0.000000	
3	0.0	0.0	0.000000	0.000000	
4	0.0	0.0	0.000000	0.000000	

	Salad Place	Salon / Barbershop	Salvadoran Restaurant	Sandwich Place	\
0	0.00	0.010000	0.0	0.000000	
1	0.00	0.000000	0.0	0.016129	
2	0.00	0.028571	0.0	0.028571	
3	0.00	0.000000	0.0	0.063830	

4	0.01	0.000000	0.0	0.000000

	Satay Restaurant	Scandinavian Restaurant	Scenic Lookout	School \
0	0.0	0.0	0.00	0.0
1	0.0	0.0	0.00	0.0
2	0.0	0.0	0.00	0.0
3	0.0	0.0	0.00	0.0
4	0.0	0.0	0.01	0.0

	Science Museum	Sculpture Garden	Seafood Restaurant	Shipping Store \
0	0.0	0.0	0.050000	0.010000
1	0.0	0.0	0.016129	0.000000
2	0.0	0.0	0.028571	0.000000
3	0.0	0.0	0.000000	0.010638
4	0.0	0.0	0.000000	0.000000

	Shoe Store	Shop & Service	Shopping Mall	Shopping Plaza	Skate Park \
0	0.0	0.0	0.01	0.0	0.000000
1	0.0	0.0	0.00	0.0	0.000000
2	0.0	0.0	0.00	0.0	0.028571
3	0.0	0.0	0.00	0.0	0.000000
4	0.0	0.0	0.00	0.0	0.000000

	Skating Rink	Ski Chalet	Smoke Shop	Smoothie Shop	Snack Place \
0	0.000000	0.0	0.0	0.0	0.01
1	0.016129	0.0	0.0	0.0	0.00
2	0.000000	0.0	0.0	0.0	0.00
3	0.000000	0.0	0.0	0.0	0.00
4	0.000000	0.0	0.0	0.0	0.00

	Soccer Field	Soccer Stadium	Social Club	Soup Place \
0	0.0	0.0	0.0	0.00
1	0.0	0.0	0.0	0.00
2	0.0	0.0	0.0	0.00
3	0.0	0.0	0.0	0.00
4	0.0	0.0	0.0	0.01

	South American Restaurant	South Indian Restaurant \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	Southern / Soul Food Restaurant	Souvenir Shop	Souvlaki Shop	Spa \
0	0.000000	0.0	0.0	0.0
1	0.016129	0.0	0.0	0.0
2	0.000000	0.0	0.0	0.0

3	0.000000	0.0	0.0	0.0
4	0.010000	0.0	0.0	0.0

	Spanish Restaurant	Speakeasy	Sporting Goods Shop	Sports Bar	Stadium \
0	0.0	0.000000	0.03	0.000000	0.0
1	0.0	0.016129	0.00	0.000000	0.0
2	0.0	0.000000	0.00	0.028571	0.0
3	0.0	0.000000	0.00	0.000000	0.0
4	0.0	0.000000	0.01	0.000000	0.0

	State / Provincial Park	Stationery Store	Steakhouse	Storage Facility \
0	0.0	0.0	0.030000	0.0
1	0.0	0.0	0.016129	0.0
2	0.0	0.0	0.000000	0.0
3	0.0	0.0	0.031915	0.0
4	0.0	0.0	0.000000	0.0

	Street Food Gathering	Strip Club	Supermarket	Supplement Shop	Surf Spot \
0	0.0	0.0	0.0	0.01	0.0
1	0.0	0.0	0.0	0.00	0.0
2	0.0	0.0	0.0	0.00	0.0
3	0.0	0.0	0.0	0.00	0.0
4	0.0	0.0	0.0	0.00	0.0

	Sushi Restaurant	Szechuan Restaurant	Taco Place	Tailor Shop \
0	0.020000	0.00	0.000000	0.0
1	0.016129	0.00	0.032258	0.0
2	0.000000	0.00	0.000000	0.0
3	0.010638	0.00	0.010638	0.0
4	0.020000	0.01	0.010000	0.0

	Taiwanese Restaurant	Tanning Salon	Tapas Restaurant	Tattoo Parlor \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

	Tea Room	Tennis Court	Tennis Stadium	Tex-Mex Restaurant \
0	0.00	0.000000	0.0	0.0
1	0.00	0.000000	0.0	0.0
2	0.00	0.000000	0.0	0.0
3	0.00	0.010638	0.0	0.0
4	0.01	0.000000	0.0	0.0

	Thai Restaurant	Theater	Theme Park	Theme Park Ride / Attraction \
0	0.010000	0.000000	0.0	0.0
1	0.016129	0.000000	0.0	0.0

2	0.000000	0.000000	0.0	0.0
3	0.021277	0.010638	0.0	0.0
4	0.030000	0.010000	0.0	0.0

	Theme Restaurant	Thrift / Vintage Store	Tiki Bar	\
0	0.01	0.000000	0.000000	
1	0.00	0.000000	0.000000	
2	0.00	0.000000	0.000000	
3	0.00	0.010638	0.010638	
4	0.00	0.010000	0.000000	

	Tourist Information Center	Toy / Game Store	Track	Track Stadium	Trail	\
0	0.01	0.01	0.0	0.0	0.01	
1	0.00	0.00	0.0	0.0	0.00	
2	0.00	0.00	0.0	0.0	0.00	
3	0.00	0.00	0.0	0.0	0.00	
4	0.00	0.00	0.0	0.0	0.00	

	Train Station	Tree	Turkish Restaurant	Udon Restaurant	Used Bookstore	\
0	0.010000	0.0	0.00	0.0	0.0	
1	0.000000	0.0	0.00	0.0	0.0	
2	0.028571	0.0	0.00	0.0	0.0	
3	0.021277	0.0	0.00	0.0	0.0	
4	0.000000	0.0	0.01	0.0	0.0	

	Vape Store	Vegetarian / Vegan Restaurant	Video Game Store	Video Store	\
0	0.0	0.000000	0.0	0.000000	
1	0.0	0.016129	0.0	0.000000	
2	0.0	0.000000	0.0	0.028571	
3	0.0	0.000000	0.0	0.000000	
4	0.0	0.020000	0.0	0.000000	

	Vietnamese Restaurant	Warehouse Store	Waterfront	Weight Loss Center	\
0	0.00	0.0	0.0	0.0	
1	0.00	0.0	0.0	0.0	
2	0.00	0.0	0.0	0.0	
3	0.00	0.0	0.0	0.0	
4	0.01	0.0	0.0	0.0	

	Whisky Bar	Wine Bar	Wine Shop	Winery	Wings Joint	Women's Store	\
0	0.0	0.02	0.0	0.0	0.0	0.0	
1	0.0	0.00	0.0	0.0	0.0	0.0	
2	0.0	0.00	0.0	0.0	0.0	0.0	
3	0.0	0.00	0.0	0.0	0.0	0.0	
4	0.0	0.00	0.0	0.0	0.0	0.0	

	Yoga Studio	Yoshoku Restaurant
0	0.00	0.0

```
1          0.00                0.0
2          0.00                0.0
3          0.00                0.0
4          0.03                0.0
```

3.6.6 Drop cities that already have dispensaries

```
In [92]: city_group = city_group[city_group['Marijuana Dispensary'] == 0]
         city_group.reset_index(drop=True,inplace=True)
         print(city_group.shape)
```

```
(99, 387)
```

```
In [93]: def return_most_common_venues(row, num_top_venues=10):
             row_categories = row.iloc[1:]
             row_categories_sorted = row_categories.sort_values(ascending=False)
             return  row_categories_sorted.index.values[0:num_top_venues]
```

3.6.7 Find top 10 most common venue types for each city

```
In [94]: num_top_venues = 10

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

         # create columns according to number of top venues
         columns = ['State','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
         neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
         neighborhoods_venues_sorted['State'] = city_group['State']
         neighborhoods_venues_sorted['City'] = city_group['City']

         for row in np.arange(city_group.shape[0]):
             neighborhoods_venues_sorted.iloc[row, 2:] = return_most_common_venues(city_group.iloc[row,1:],10
         neighborhoods_venues_sorted.head()
```

```
Out[94]:         State         City 1st Most Common Venue 2nd Most Common Venue  \
         0      ALASKA    ANCHORAGE           Coffee Shop                  Park
         1  CALIFORNIA      ANAHEIM    Mexican Restaurant           Coffee Shop
         2  CALIFORNIA      ANTIOCH  Fast Food Restaurant           Pizza Place
         3  CALIFORNIA  BAKERSFIELD    Mexican Restaurant           Coffee Shop
         4  CALIFORNIA     BERKELEY   Chinese Restaurant   Japanese Restaurant
```

```
   3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue  \
0          Clothing Store    Seafood Restaurant                   Bar
1           Ice Cream Shop     Indian Restaurant     Convenience Store
2      Mexican Restaurant    Chinese Restaurant             Racetrack
3    Fast Food Restaurant        Sandwich Place                   Bar
4  New American Restaurant       Thai Restaurant     French Restaurant

  6th Most Common Venue 7th Most Common Venue 8th Most Common Venue  \
0      Accessories Store            Steakhouse   Sporting Goods Shop
1             Taco Place          Liquor Store          Burger Joint
2        Paintball Field                Bakery         Grocery Store
3     Chinese Restaurant    Italian Restaurant            Steakhouse
4                   Café          Yoga Studio         Ice Cream Shop

  9th Most Common Venue           10th Most Common Venue
0        Cosmetics Shop                      Pizza Place
1               Brewery  Southern / Soul Food Restaurant
2            Sports Bar                     Burger Joint
3        Breakfast Spot            General Entertainment
4           Coffee Shop                      Pizza Place
```

3.6.8 Performing K-Means Clustering using 5 clusters

I used SciKit Learn K-Means Clustering unsupervised learning in order to group different cities based on their top 10 most common venues. Once the clustering was performed, I reviewed the venues in the cluster to classify the clusters:
cluster 0: Shops cluster 1:

In [95]:
```
k_means = KMeans(init = "k-means++", n_clusters = 5, n_init = 12)
```

In [96]:
```
city_group = city_group.merge(city2,on=['City','State'],how="left")
```

In [111]:
```
city_group.drop(52,inplace=True)
```

In [112]:
```
# set number of clusters
kclusters = 5
from sklearn.preprocessing import StandardScaler

city_clusters = city_group.drop(['State','City','Latitude','Longitude'], axis=1)
city_fit = StandardScaler().fit_transform(city_clusters)
```

In [113]:
```
# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(city_fit)

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

Out[113]:
```
array([1, 1, 1, 1, 4, 1, 1, 1, 1, 1], dtype=int32)
```

In [115]:
```
kmeans.labels_.shape
```

Out[115]: (99,)

In [103]: city2.reset_index(drop=True,inplace=True)

In [108]: len(neighborhoods_venues_sorted)

Out[108]: 99

In [116]: # add clustering labels
neighborhoods_venues_sorted['Cluster']=kmeans.labels_

In [117]: city_full = city2.merge(neighborhoods_venues_sorted, on=['State','City'], how='inner')

In [118]: city_full.dropna(inplace=True, axis=0)

In [119]: city_full['Cluster'] = city_full['Cluster'].astype(int)

In [120]: city_full.head()

Out[120]:

```
        State          City     Tax  Crime Index    CLI   Latitude   Longitude  \
0      ALASKA     ANCHORAGE  0.0000     0.026024  94.99  61.216313 -149.894852
1  CALIFORNIA       ANAHEIM  0.0725     0.013098   0.00  33.834752 -117.911732
2  CALIFORNIA       ANTIOCH  0.0725     0.016686   0.00  38.004921 -121.805789
3  CALIFORNIA   BAKERSFIELD  0.0725     0.019861  69.20  35.373871 -119.019464
4  CALIFORNIA      BERKELEY  0.0725     0.023042  87.82  37.870839 -122.272864

  1st Most Common Venue 2nd Most Common Venue    3rd Most Common Venue  \
0           Coffee Shop                  Park           Clothing Store
1    Mexican Restaurant           Coffee Shop           Ice Cream Shop
2  Fast Food Restaurant           Pizza Place       Mexican Restaurant
3    Mexican Restaurant           Coffee Shop     Fast Food Restaurant
4    Chinese Restaurant   Japanese Restaurant  New American Restaurant

  4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
0   Seafood Restaurant                    Bar     Accessories Store
1    Indian Restaurant      Convenience Store            Taco Place
2   Chinese Restaurant              Racetrack       Paintball Field
3       Sandwich Place                    Bar    Chinese Restaurant
4      Thai Restaurant      French Restaurant                  Café

  7th Most Common Venue 8th Most Common Venue 9th Most Common Venue  \
0            Steakhouse   Sporting Goods Shop        Cosmetics Shop
1          Liquor Store          Burger Joint               Brewery
2                Bakery         Grocery Store            Sports Bar
3   Italian Restaurant             Steakhouse        Breakfast Spot
4           Yoga Studio        Ice Cream Shop           Coffee Shop

  10th Most Common Venue  Cluster
0            Pizza Place        1
```

```
1  Southern / Soul Food Restaurant        1
2                      Burger Joint        1
3             General Entertainment        1
4                       Pizza Place        4
```

In [320]: city_full.shape

Out[320]: (102, 18)

In [121]:
```
# create map
map_clusters = folium.Map(location=[39.83, -98.58], 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(city_full['Latitude'], city_full['Longitude'], city_full['City'], city_full['Clust
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=10,
        popup=label,
        color=rainbow[cluster],
        fill=True,
        fill_color=rainbow[cluster],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[121]: <folium.folium.Map at 0x7f0c95e08588>

3.7 Review Clusters

Cluster 0

In [122]:
```
city_full.loc[city_full['Cluster'] == 0, city_full.columns[[1] + list(range(2, city_full.shape[1]))]]
```

Out[122]:
```
              City     Tax  Crime Index  CLI   Latitude   Longitude  \
49  SAN BERNARDINO  0.0725     0.018655  0.0  34.108345 -117.289765

   1st Most Common Venue 2nd Most Common Venue 3rd Most Common Venue  \
49     Convenience Store        Clothing Store        Discount Store

   4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
49  Fast Food Restaurant         Grocery Store           Pizza Place
```

```
  7th Most Common Venue 8th Most Common Venue 9th Most Common Venue  \
49             Nightclub            Shoe Store      Department Store

  10th Most Common Venue  Cluster
49     Mexican Restaurant        0
```

Cluster 1

```
In [123]: city_full.loc[city_full['Cluster'] == 1, city_full.columns[[1] + list(range(2, city_full.shape[1]))]]
```

Out[123]:

	City	Tax	Crime Index	CLI	Latitude	Longitude
0	ANCHORAGE	0.0000	0.026024	94.99	61.216313	-149.894852
1	ANAHEIM	0.0725	0.013098	0.00	33.834752	-117.911732
2	ANTIOCH	0.0725	0.016686	0.00	38.004921	-121.805789
3	BAKERSFIELD	0.0725	0.019861	69.20	35.373871	-119.019464
5	BURBANK	0.0725	0.014175	0.00	34.181648	-118.325855
6	CARLSBAD	0.0725	0.008791	0.00	33.158093	-117.350597
7	CHULA VISTA	0.0725	0.007034	0.00	32.640054	-117.084196
8	CLOVIS	0.0725	0.013983	0.00	36.825228	-119.702919
9	CONCORD	0.0725	0.016411	0.00	37.976852	-122.033562
10	CORONA	0.0725	0.010682	0.00	33.875295	-117.566445
11	COSTA MESA	0.0725	0.020571	0.00	33.663339	-117.903317
12	DALY CITY	0.0725	0.007722	0.00	37.705767	-122.461921
13	DOWNEY	0.0725	0.014721	0.00	33.942215	-118.123565
14	EL CAJON	0.0725	0.011556	0.00	32.794773	-116.962527
15	ELK GROVE	0.0725	0.006830	0.00	38.408799	-121.371618
16	ESCONDIDO	0.0725	0.008303	0.00	33.121675	-117.081485
17	FAIRFIELD	0.0725	0.012314	0.00	38.249358	-122.039966
18	FONTANA	0.0725	0.008688	0.00	34.092233	-117.435048
19	FREMONT	0.0725	0.011516	0.00	37.548270	-121.988572
20	FRESNO	0.0725	0.019484	72.36	36.729529	-119.708861
21	FULLERTON	0.0725	0.014008	0.00	33.870821	-117.929417
22	GARDEN GROVE	0.0725	0.012589	0.00	33.774629	-117.946372
23	GLENDALE	0.0725	0.007674	0.00	34.192912	-118.246249
24	HAYWARD	0.0725	0.015630	0.00	37.668821	-122.080796
25	HUNTINGTON BEACH	0.0725	0.010547	0.00	33.678334	-118.000017
26	INGLEWOOD	0.0725	0.012327	0.00	33.956200	-118.353132
27	IRVINE	0.0725	0.006508	83.73	33.685697	-117.825982
28	JURUPA VALLEY	0.0725	0.012886	0.00	33.979847	-117.451575
29	LANCASTER	0.0725	0.009717	0.00	34.698106	-118.136615
30	LONG BEACH	0.0725	0.013322	78.23	33.785389	-118.158049
32	MODESTO	0.0725	0.020026	0.00	37.639097	-120.996878
33	MORENO VALLEY	0.0725	0.015924	0.00	33.937517	-117.230594
34	MURRIETA	0.0725	0.007406	0.00	33.577752	-117.188454
35	NORWALK	0.0725	0.009315	0.00	33.909280	-118.084917
36	OAKLAND	0.0725	0.030660	85.11	37.804456	-122.271356
37	OCEANSIDE	0.0725	0.011877	0.00	33.195870	-117.379483

38	ONTARIO	0.0725	0.012694	0.00	34.065846	-117.648430
40	OXNARD	0.0725	0.012863	0.00	34.197631	-119.180382
41	PALMDALE	0.0725	0.008084	0.00	34.579313	-118.117111
43	POMONA	0.0725	0.014517	0.00	34.055381	-117.751750
44	RANCHO CUCAMONGA	0.0725	0.011890	0.00	34.103319	-117.575174
45	RICHMOND	0.0725	0.019259	70.98	37.935758	-122.347749
46	RIVERSIDE	0.0725	0.016063	0.00	33.953355	-117.396162
47	ROSEVILLE	0.0725	0.012634	0.00	38.752124	-121.288006
48	SALINAS	0.0725	0.014825	0.00	36.674412	-121.655037
52	SAN MATEO	0.0725	0.009554	0.00	37.496904	-122.333057
54	SANTA CLARA	0.0725	0.012059	0.00	37.354113	-121.955174
55	SANTA CLARITA	0.0725	0.007566	0.00	34.391664	-118.542586
56	SANTA MARIA	0.0725	0.011338	0.00	34.953130	-120.435858
57	SANTA ROSA	0.0725	0.008885	90.23	38.440467	-122.714431
58	SIMI VALLEY	0.0725	0.007241	0.00	34.269447	-118.781482
59	STOCKTON	0.0725	0.018623	0.00	37.957702	-121.290780
60	SUNNYVALE	0.0725	0.008075	0.00	37.368830	-122.036350
61	TEMECULA	0.0725	0.012463	0.00	33.494635	-117.147366
62	THOUSAND OAKS	0.0725	0.006476	0.00	34.171427	-118.910588
63	TORRANCE	0.0725	0.010483	0.00	33.835849	-118.340629
64	VALLEJO	0.0725	0.019390	0.00	38.104086	-122.256637
65	VICTORVILLE	0.0725	0.013789	0.00	34.536107	-117.291156
66	VISALIA	0.0725	0.016111	0.00	36.330228	-119.292058
67	VISTA	0.0725	0.007242	0.00	33.200037	-117.242536
68	WEST COVINA	0.0725	0.011708	0.00	34.068621	-117.938953
70	COLORADO SPRINGS	0.0290	0.015192	75.42	38.833958	-104.825349
71	FORT COLLINS	0.0290	0.012820	73.57	40.550853	-105.066808
72	GREELEY	0.0290	0.011897	0.00	40.423314	-104.709132
73	PUEBLO	0.0290	0.029836	0.00	38.254447	-104.609141
74	WESTMINSTER	0.0290	0.015327	0.00	39.836653	-105.037205
77	LOWELL	0.0625	0.010297	0.00	42.633425	-71.316172
78	SPRINGFIELD	0.0625	0.014286	66.40	42.101483	-72.589811
79	WORCESTER	0.0625	0.010178	0.00	42.262593	-71.802293
80	ANN ARBOR	0.0600	0.007332	70.01	42.268157	-83.731229
81	CLINTON TOWNSHIP	0.0600	0.007386	0.00	42.584852	-82.934824
83	GRAND RAPIDS	0.0600	0.009319	70.58	42.963240	-85.667864
84	LANSING	0.0600	0.014394	0.00	42.733771	-84.555380
85	STERLING HEIGHTS	0.0600	0.005351	0.00	42.580312	-83.030203
86	WARREN	0.0600	0.010428	0.00	42.493257	-83.006275
87	HENDERSON	0.0685	0.008818	0.00	36.039146	-114.981923
88	NORTH LAS VEGAS	0.0685	0.012398	0.00	36.200837	-115.112096
90	EUGENE	0.0000	0.018294	78.94	44.050505	-123.095051
91	GRESHAM	0.0000	0.017143	0.00	45.506741	-122.436706
92	HILLSBORO	0.0000	0.009960	0.00	45.522894	-122.989827
93	SALEM	0.0000	0.021874	69.81	44.939157	-123.033121
94	BELLEVUE	0.0650	0.015553	88.85	47.614422	-122.192337
95	EVERETT	0.0650	0.022710	77.63	47.967306	-122.201400
96	KENT	0.0650	0.026390	0.00	47.382690	-122.227027

98	SPOKANE	0.0650	0.036404	69.26	47.657942	-117.421227

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	\
0	Coffee Shop	Park	Clothing Store	
1	Mexican Restaurant	Coffee Shop	Ice Cream Shop	
2	Fast Food Restaurant	Pizza Place	Mexican Restaurant	
3	Mexican Restaurant	Coffee Shop	Fast Food Restaurant	
5	Mexican Restaurant	Sandwich Place	American Restaurant	
6	Beach	Mexican Restaurant	Café	
7	Mexican Restaurant	Grocery Store	Convenience Store	
8	Mexican Restaurant	Sandwich Place	Coffee Shop	
9	Mexican Restaurant	Sandwich Place	Discount Store	
10	Mexican Restaurant	Convenience Store	Rental Car Location	
11	Sushi Restaurant	Mexican Restaurant	Playground	
12	Chinese Restaurant	Sandwich Place	Fast Food Restaurant	
13	Mexican Restaurant	Coffee Shop	Fast Food Restaurant	
14	Mexican Restaurant	Clothing Store	Coffee Shop	
15	Pizza Place	Pharmacy	Fast Food Restaurant	
16	Mexican Restaurant	Fast Food Restaurant	American Restaurant	
17	Coffee Shop	Mexican Restaurant	Convenience Store	
18	Fast Food Restaurant	Mexican Restaurant	Convenience Store	
19	Grocery Store	Chinese Restaurant	Pizza Place	
20	Fast Food Restaurant	Chinese Restaurant	Sandwich Place	
21	Sushi Restaurant	Italian Restaurant	Burger Joint	
22	Vietnamese Restaurant	Fast Food Restaurant	Korean Restaurant	
23	Trail	Park	Golf Course	
24	Mexican Restaurant	Pizza Place	Coffee Shop	
25	Coffee Shop	Pizza Place	Mexican Restaurant	
26	Mexican Restaurant	Fast Food Restaurant	Grocery Store	
27	Sandwich Place	Bakery	Ice Cream Shop	
28	Fast Food Restaurant	Convenience Store	Pizza Place	
29	Mexican Restaurant	Diner	Fast Food Restaurant	
30	Mexican Restaurant	Pizza Place	Thai Restaurant	
32	Coffee Shop	Park	American Restaurant	
33	Fast Food Restaurant	Mexican Restaurant	Pizza Place	
34	Mexican Restaurant	Pizza Place	Fast Food Restaurant	
35	Fast Food Restaurant	Mexican Restaurant	Coffee Shop	
36	Bar	Coffee Shop	Chinese Restaurant	
37	American Restaurant	Beach	Ice Cream Shop	
38	Mexican Restaurant	Burger Joint	Convenience Store	
40	Mexican Restaurant	Grocery Store	Pharmacy	
41	Fast Food Restaurant	Mexican Restaurant	Discount Store	
43	Mexican Restaurant	Pizza Place	Coffee Shop	
44	Mobile Phone Shop	Mexican Restaurant	Burger Joint	
45	Mexican Restaurant	Convenience Store	Pharmacy	
46	Fast Food Restaurant	Mexican Restaurant	Pizza Place	
47	Mexican Restaurant	Park	Pizza Place	
48	Hotel	Mexican Restaurant	Fast Food Restaurant	

52	Trail	Intersection	Yoshoku Restaurant
54	Korean Restaurant	Fast Food Restaurant	Mexican Restaurant
55	Pizza Place	Pharmacy	Convenience Store
56	Mexican Restaurant	Fast Food Restaurant	Convenience Store
57	Mexican Restaurant	Coffee Shop	Pizza Place
58	Mexican Restaurant	Sushi Restaurant	Sandwich Place
59	Mexican Restaurant	Fast Food Restaurant	Coffee Shop
60	Coffee Shop	Indian Restaurant	Burger Joint
61	American Restaurant	Mexican Restaurant	Italian Restaurant
62	Hotel	Martial Arts Dojo	Park
63	Clothing Store	Cosmetics Shop	Japanese Restaurant
64	Mexican Restaurant	Harbor / Marina	Seafood Restaurant
65	Pizza Place	Convenience Store	Mexican Restaurant
66	Mexican Restaurant	Fast Food Restaurant	Pizza Place
67	Fast Food Restaurant	Mexican Restaurant	Sandwich Place
68	Clothing Store	Mexican Restaurant	Bubble Tea Shop
70	Bar	Coffee Shop	Brewery
71	Coffee Shop	Clothing Store	Cosmetics Shop
72	Bar	Mexican Restaurant	Convenience Store
73	Mexican Restaurant	Pizza Place	Italian Restaurant
74	Mexican Restaurant	Convenience Store	Fast Food Restaurant
77	Sandwich Place	Pizza Place	Asian Restaurant
78	Donut Shop	Sandwich Place	American Restaurant
79	Italian Restaurant	Café	Bar
80	Coffee Shop	Pizza Place	Bar
81	Convenience Store	Food	Liquor Store
83	Coffee Shop	Museum	Bar
84	Bar	Coffee Shop	Bakery
85	Sandwich Place	Fast Food Restaurant	Shipping Store
86	Fast Food Restaurant	American Restaurant	Fried Chicken Joint
87	Fast Food Restaurant	Coffee Shop	Convenience Store
88	Fast Food Restaurant	Convenience Store	Mexican Restaurant
90	Brewery	Coffee Shop	Pizza Place
91	Coffee Shop	Pizza Place	Bar
92	Mexican Restaurant	Coffee Shop	Fast Food Restaurant
93	Coffee Shop	American Restaurant	Bar
94	Coffee Shop	Steakhouse	Spa
95	Coffee Shop	Mexican Restaurant	Gym
96	Coffee Shop	Mexican Restaurant	Pub
98	Bar	Pizza Place	American Restaurant

	4th Most Common Venue	5th Most Common Venue \
0	Seafood Restaurant	Bar
1	Indian Restaurant	Convenience Store
2	Chinese Restaurant	Racetrack
3	Sandwich Place	Bar
5	Pizza Place	Burger Joint
6	Coffee Shop	Hotel

7	Clothing Store	Taco Place
8	Pizza Place	Burger Joint
9	Japanese Restaurant	Coffee Shop
10	Fast Food Restaurant	Indian Restaurant
11	Hotel	Concert Hall
12	Pizza Place	Playground
13	Pizza Place	Burger Joint
14	Convenience Store	Fast Food Restaurant
15	American Restaurant	Coffee Shop
16	Convenience Store	Pizza Place
17	American Restaurant	Thai Restaurant
18	Gas Station	Pizza Place
19	Coffee Shop	Bakery
20	Pharmacy	Pizza Place
21	Mexican Restaurant	Ice Cream Shop
22	Coffee Shop	Convenience Store
23	Scenic Lookout	Yoshoku Restaurant
24	Bar	Fast Food Restaurant
25	Fast Food Restaurant	Gym / Fitness Center
26	Convenience Store	Southern / Soul Food Restaurant
27	Café	Coffee Shop
28	Golf Course	Pharmacy
29	Convenience Store	Bar
30	Bar	Fast Food Restaurant
32	Sandwich Place	Italian Restaurant
33	Pharmacy	Sandwich Place
34	Pharmacy	Park
35	Pizza Place	Pharmacy
36	Mexican Restaurant	Sandwich Place
37	Mexican Restaurant	Seafood Restaurant
38	Pizza Place	Sandwich Place
40	Convenience Store	Italian Restaurant
41	Pizza Place	Thai Restaurant
43	Bar	Pharmacy
44	Asian Restaurant	Coffee Shop
45	Liquor Store	Food Truck
46	Coffee Shop	Sandwich Place
47	Bar	Grocery Store
48	Coffee Shop	American Restaurant
52	Farm	Empanada Restaurant
54	Thai Restaurant	Bubble Tea Shop
55	Park	Coffee Shop
56	Burger Joint	Sushi Restaurant
57	Hotel	American Restaurant
58	Coffee Shop	Fast Food Restaurant
59	American Restaurant	Deli / Bodega
60	Sandwich Place	Grocery Store
61	Coffee Shop	Sushi Restaurant

62	Gym	Sandwich Place
63	Lingerie Store	American Restaurant
64	Coffee Shop	Food Truck
65	Sandwich Place	Platform
66	Sandwich Place	Italian Restaurant
67	Coffee Shop	Convenience Store
68	Vietnamese Restaurant	Korean Restaurant
70	Italian Restaurant	Pizza Place
71	Mexican Restaurant	Seafood Restaurant
72	Fast Food Restaurant	Sandwich Place
73	Fast Food Restaurant	Bakery
74	Sushi Restaurant	Grocery Store
77	Donut Shop	Pharmacy
78	Burger Joint	Discount Store
79	Coffee Shop	Mexican Restaurant
80	Sandwich Place	Korean Restaurant
81	Baseball Field	Diner
83	Brewery	Hotel
84	Mexican Restaurant	Pharmacy
85	Shopping Mall	Discount Store
86	Coffee Shop	Intersection
87	Pizza Place	Mexican Restaurant
88	Fried Chicken Joint	Casino
90	Sushi Restaurant	Café
91	American Restaurant	Furniture / Home Store
92	Sandwich Place	Pizza Place
93	Sandwich Place	Pizza Place
94	Grocery Store	Vietnamese Restaurant
95	Hockey Arena	Asian Restaurant
96	Clothing Store	Fast Food Restaurant
98	Coffee Shop	Brewery

	6th Most Common Venue	7th Most Common Venue \
0	Accessories Store	Steakhouse
1	Taco Place	Liquor Store
2	Paintball Field	Bakery
3	Chinese Restaurant	Italian Restaurant
5	Diner	Bakery
6	Breakfast Spot	Pizza Place
7	Sandwich Place	Italian Restaurant
8	Hotel	Ice Cream Shop
9	Café	Chinese Restaurant
10	Sandwich Place	Diner
11	Convenience Store	Flea Market
12	Convenience Store	Rental Car Location
13	Sushi Restaurant	Restaurant
14	Middle Eastern Restaurant	Sandwich Place
15	Rental Car Location	Sports Bar

16	Coffee Shop	Sandwich Place
17	Gas Station	Sushi Restaurant
18	American Restaurant	Café
19	Pet Store	Intersection
20	Mobile Phone Shop	Mexican Restaurant
21	Pizza Place	Café
22	Bar	Café
23	Electronics Store	Empanada Restaurant
24	Chinese Restaurant	Sandwich Place
25	Spa	Grocery Store
26	Burger Joint	Pizza Place
27	Japanese Restaurant	Burger Joint
28	Ice Cream Shop	Movie Theater
29	Vegetarian / Vegan Restaurant	Coffee Shop
30	Convenience Store	Sandwich Place
32	Fast Food Restaurant	Café
33	American Restaurant	Grocery Store
34	Chinese Restaurant	Coffee Shop
35	Park	Chinese Restaurant
36	Cocktail Bar	Japanese Restaurant
37	Surf Spot	Coffee Shop
38	Seafood Restaurant	ATM
40	Fast Food Restaurant	Thrift / Vintage Store
41	Train Station	Convenience Store
43	Convenience Store	Music Venue
44	Japanese Restaurant	Furniture / Home Store
45	Park	Metro Station
46	Convenience Store	American Restaurant
47	Convenience Store	Coffee Shop
48	Convenience Store	Breakfast Spot
52	Entertainment Service	Ethiopian Restaurant
54	Coffee Shop	Asian Restaurant
55	Fast Food Restaurant	Bank
56	Pharmacy	Pizza Place
57	Thai Restaurant	Italian Restaurant
58	Grocery Store	Burger Joint
59	Baseball Stadium	Chinese Restaurant
60	Park	Mexican Restaurant
61	Steakhouse	Brewery
62	Sushi Restaurant	Thrift / Vintage Store
63	Coffee Shop	Mexican Restaurant
64	Pizza Place	Rental Car Location
65	Performing Arts Venue	Donut Shop
66	American Restaurant	Coffee Shop
67	Chinese Restaurant	Ice Cream Shop
68	Noodle House	Pizza Place
70	Gastropub	Mexican Restaurant
71	Breakfast Spot	Gym

72	Pizza Place	Pharmacy
73	American Restaurant	Bar
74	Sandwich Place	Vietnamese Restaurant
77	Discount Store	Coffee Shop
78	Hotel	Shipping Store
79	Pizza Place	Sandwich Place
80	Thrift / Vintage Store	College Auditorium
81	Sandwich Place	Coffee Shop
83	Music Venue	Steakhouse
84	Convenience Store	Middle Eastern Restaurant
85	Rental Car Location	American Restaurant
86	Discount Store	Pharmacy
87	Grocery Store	Gym / Fitness Center
88	Bakery	Pizza Place
90	Breakfast Spot	Indie Movie Theater
91	Burger Joint	Mexican Restaurant
92	Convenience Store	Grocery Store
93	Restaurant	Italian Restaurant
94	Sushi Restaurant	Sandwich Place
95	Sushi Restaurant	Bakery
96	Sandwich Place	Bakery
98	Sushi Restaurant	Lounge

	8th Most Common Venue	9th Most Common Venue \
0	Sporting Goods Shop	Cosmetics Shop
1	Burger Joint	Brewery
2	Grocery Store	Sports Bar
3	Steakhouse	Breakfast Spot
5	Donut Shop	Deli / Bodega
6	Italian Restaurant	American Restaurant
7	Seafood Restaurant	Cosmetics Shop
8	American Restaurant	Fast Food Restaurant
9	Pizza Place	Italian Restaurant
10	Discount Store	Sushi Restaurant
11	Italian Restaurant	Video Store
12	Park	Dive Bar
13	Pharmacy	American Restaurant
14	Chinese Restaurant	Cosmetics Shop
15	Salon / Barbershop	Sandwich Place
16	Vietnamese Restaurant	Cosmetics Shop
17	Burger Joint	Chinese Restaurant
18	Discount Store	Fried Chicken Joint
19	Café	Mexican Restaurant
20	Salon / Barbershop	Grocery Store
21	Coffee Shop	Sports Bar
22	Chinese Restaurant	Asian Restaurant
23	Entertainment Service	Ethiopian Restaurant
24	Shipping Store	Italian Restaurant

25	Japanese Restaurant	Sandwich Place
26	Coffee Shop	Pharmacy
27	Mediterranean Restaurant	Mexican Restaurant
28	Fried Chicken Joint	Park
29	Plaza	Fried Chicken Joint
30	Cosmetics Shop	Grocery Store
32	New American Restaurant	Mexican Restaurant
33	Video Store	Discount Store
34	Sandwich Place	Gym
35	Cosmetics Shop	Donut Shop
36	Vietnamese Restaurant	Café
37	Breakfast Spot	Beer Garden
38	Candy Store	Fried Chicken Joint
40	Chinese Restaurant	Park
41	Burger Joint	Bus Station
43	Nightclub	Gay Bar
44	Pizza Place	Bakery
45	Performing Arts Venue	Gym
46	Pet Store	Grocery Store
47	Fast Food Restaurant	Gas Station
48	Shipping Store	Thai Restaurant
52	Event Service	Event Space
54	Sandwich Place	Convenience Store
55	Mexican Restaurant	Martial Arts Dojo
56	Sandwich Place	Steakhouse
57	Brewery	Clothing Store
58	Breakfast Spot	Park
59	Sandwich Place	Rental Car Location
60	Chinese Restaurant	Bubble Tea Shop
61	Wine Bar	Pizza Place
62	Liquor Store	Beer Store
63	Chinese Restaurant	Shoe Store
64	Pet Store	Southern / Soul Food Restaurant
65	Bakery	Fast Food Restaurant
66	Salon / Barbershop	Breakfast Spot
67	Pizza Place	American Restaurant
68	Asian Restaurant	Ice Cream Shop
70	Sandwich Place	Steakhouse
71	Grocery Store	Vietnamese Restaurant
72	Discount Store	Bank
73	Café	Sandwich Place
74	Rental Car Location	Pizza Place
77	Café	Chinese Restaurant
78	Sports Bar	Gas Station
79	American Restaurant	Breakfast Spot
80	Park	Gourmet Shop
81	Clothing Store	Park
83	American Restaurant	Pizza Place

84	Intersection	Irish Pub
85	Pub	Bank
86	Video Store	Chinese Restaurant
87	Big Box Store	Shoe Store
88	Pharmacy	Coffee Shop
90	Japanese Restaurant	Burger Joint
91	Fast Food Restaurant	Thai Restaurant
92	Flea Market	Ice Cream Shop
93	Park	Fast Food Restaurant
94	Shopping Mall	Food Truck
95	Burger Joint	Tattoo Parlor
96	Gym / Fitness Center	Chinese Restaurant
98	Italian Restaurant	Concert Hall

	10th Most Common Venue	Cluster
0	Pizza Place	1
1	Southern / Soul Food Restaurant	1
2	Burger Joint	1
3	General Entertainment	1
5	Pet Store	1
6	Bar	1
7	Coffee Shop	1
8	Italian Restaurant	1
9	Thai Restaurant	1
10	Furniture / Home Store	1
11	Coffee Shop	1
12	Supermarket	1
13	Department Store	1
14	Bar	1
15	New American Restaurant	1
16	Thai Restaurant	1
17	Sandwich Place	1
18	Latin American Restaurant	1
19	Fried Chicken Joint	1
20	Coffee Shop	1
21	Breakfast Spot	1
22	Arts & Crafts Store	1
23	Event Service	1
24	Sushi Restaurant	1
25	Pharmacy	1
26	Cosmetics Shop	1
27	Asian Restaurant	1
28	Sporting Goods Shop	1
29	American Restaurant	1
30	Thrift / Vintage Store	1
32	Convenience Store	1
33	Convenience Store	1
34	Grocery Store	1

35	Burger Joint	1
36	Vegetarian / Vegan Restaurant	1
37	Brewery	1
38	Mobile Phone Shop	1
40	Ice Cream Shop	1
41	Sushi Restaurant	1
43	Taco Place	1
44	Sushi Restaurant	1
45	Fried Chicken Joint	1
46	Sushi Restaurant	1
47	Sandwich Place	1
48	Chinese Restaurant	1
52	Exhibit	1
54	Indian Restaurant	1
55	Chinese Restaurant	1
56	Shoe Store	1
57	French Restaurant	1
58	Gym	1
59	Cosmetics Shop	1
60	Hotel	1
61	Gastropub	1
62	Italian Restaurant	1
63	Brewery	1
64	Chinese Restaurant	1
65	History Museum	1
66	Brewery	1
67	ATM	1
68	Grocery Store	1
70	American Restaurant	1
71	Brewery	1
72	Steakhouse	1
73	Hotel	1
74	Storage Facility	1
77	Gym	1
78	Rental Car Location	1
79	Middle Eastern Restaurant	1
80	Sushi Restaurant	1
81	Bar	1
83	Ice Cream Shop	1
84	Sandwich Place	1
85	Bar	1
86	Clothing Store	1
87	Cosmetics Shop	1
88	Discount Store	1
90	Beer Store	1
91	Women's Store	1
92	Sports Bar	1
93	Mexican Restaurant	1

```
94              Mexican Restaurant        1
95                      Beer Store        1
96                    Hockey Arena        1
98                           Hotel        1
```

Cluster 2

In [124]:
```
city_full.loc[city_full['Cluster'] == 2, city_full.columns[[1] + list(range(2, city_full.shape[1]))]]
```

Out[124]:
```
           City    Tax  Crime Index  CLI   Latitude   Longitude  \
69  CENTENNIAL  0.029     0.008221  0.0  39.568064 -104.977831

   1st Most Common Venue 2nd Most Common Venue 3rd Most Common Venue  \
69  Fast Food Restaurant        Sandwich Place         Grocery Store

   4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
69           Pizza Place   American Restaurant    Mexican Restaurant

   7th Most Common Venue 8th Most Common Venue 9th Most Common Venue  \
69  Gym / Fitness Center             BBQ Joint     Salon / Barbershop

   10th Most Common Venue  Cluster
69                    Spa        2
```

Cluster 3 This is our ideal cluster. Active nightlife, pubs, breweries and trendy areas and activities.

In [125]:
```
cluster3 = city_full.loc[city_full['Cluster'] == 3, city_full.columns[[1] + list(range(2, city_full.shape[1])
cluster3
```

Out[125]:
```
           City     Tax  Crime Index    CLI   Latitude   Longitude  \
31  LOS ANGELES  0.0725     0.012505  82.30  34.053691 -118.242767
39       ORANGE  0.0725     0.009155   0.00  33.750038 -117.870493
42     PASADENA  0.0725     0.010903   0.00  34.147645 -118.144478
50    SAN DIEGO  0.0725     0.009250  77.01  32.717421 -117.162771
51     SAN JOSE  0.0725     0.012075  82.87  37.336191 -121.890583
53    SANTA ANA  0.0725     0.011227   0.00  33.749495 -117.873221
75       BOSTON  0.0625     0.009736  87.05  42.360253  -71.058291
76    CAMBRIDGE  0.0625     0.008119  82.96  42.375100  -71.105616
82      DETROIT  0.0600     0.022378  70.20  42.331551  -83.046640
89         RENO  0.0685     0.014195  62.88  39.529270 -119.813674
97      SEATTLE  0.0650     0.025904  88.04  47.603832 -122.330062

   1st Most Common Venue 2nd Most Common Venue 3rd Most Common Venue  \
31     Sushi Restaurant           Coffee Shop   Japanese Restaurant
39    Mexican Restaurant     Convenience Store                   Bar
42   American Restaurant           Coffee Shop           Pizza Place
50                 Hotel    Mexican Restaurant   Italian Restaurant
```

51	Mexican Restaurant	Coffee Shop	Cocktail Bar
53	Mexican Restaurant	Fast Food Restaurant	Bar
75	Italian Restaurant	Seafood Restaurant	Historic Site
76	New American Restaurant	Coffee Shop	Pub
82	Coffee Shop	Bar	American Restaurant
89	Bar	Pub	Mexican Restaurant
97	Coffee Shop	Cocktail Bar	Seafood Restaurant

	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue \
31	Plaza	Mexican Restaurant	Ramen Restaurant
39	Restaurant	Fast Food Restaurant	Coffee Shop
42	Italian Restaurant	Bar	Steakhouse
50	Café	Bar	American Restaurant
51	Bar	Sushi Restaurant	Sandwich Place
53	Convenience Store	Restaurant	Pharmacy
75	Park	Coffee Shop	Pizza Place
76	Café	Gastropub	Brewery
82	Restaurant	Diner	Park
89	Brewery	Coffee Shop	Café
97	Vietnamese Restaurant	American Restaurant	Sushi Restaurant

	7th Most Common Venue	8th Most Common Venue \
31	Ice Cream Shop	Bookstore
39	Pizza Place	Sandwich Place
42	Bakery	Cosmetics Shop
50	Coffee Shop	Seafood Restaurant
51	Theater	Pizza Place
53	Sandwich Place	Pizza Place
75	Sandwich Place	Market
76	Vegetarian / Vegan Restaurant	Portuguese Restaurant
82	Lounge	Steakhouse
89	Hotel	Breakfast Spot
97	Italian Restaurant	Breakfast Spot

	9th Most Common Venue	10th Most Common Venue	Cluster
31	Bar	Mediterranean Restaurant	3
39	American Restaurant	Diner	3
42	Pub	Beer Garden	3
50	New American Restaurant	Burger Joint	3
51	Pub	Ice Cream Shop	3
53	American Restaurant	Coffee Shop	3
75	Bakery	Hotel	3
76	Ice Cream Shop	Tapas Restaurant	3
82	Burger Joint	Hotel	3
89	Steakhouse	Pizza Place	3
97	Hotel	Art Museum	3

Cluster 4

In [126]:
```
city_full.loc[city_full['Cluster'] == 4, city_full.columns[[1] + list(range(2, city_full.shape[1]))]]
```

Out[126]:
```
       City     Tax  Crime Index    CLI   Latitude   Longitude  \
4  BERKELEY  0.0725     0.023042  87.82  37.870839 -122.272864

  1st Most Common Venue 2nd Most Common Venue    3rd Most Common Venue  \
4   Chinese Restaurant   Japanese Restaurant  New American Restaurant

  4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
4       Thai Restaurant     French Restaurant                  Café

  7th Most Common Venue 8th Most Common Venue 9th Most Common Venue  \
4           Yoga Studio        Ice Cream Shop           Coffee Shop

  10th Most Common Venue  Cluster
4            Pizza Place        4
```

In [127]:
```
# create map
map_clusters = folium.Map(location=[39.83, -98.58], 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(cluster3['Latitude'], cluster3['Longitude'], cluster3['City'],cluster3['Cluster'])
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=10,
        popup=label,
        color=rainbow[cluster],
        fill=True,
        fill_color=rainbow[cluster],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[127]: <folium.folium.Map at 0x7f0c984c0dd8>

In [135]:
```
sort3 = cluster3[cluster3['CLI']!=0]
```

In [149]:
```
safe = sort3.sort_values('Crime Index').head(6)
safe
```

Out[149]:
```
           City     Tax  Crime Index    CLI   Latitude   Longitude  \
76    CAMBRIDGE  0.0625     0.008119  82.96  42.375100  -71.105616
50    SAN DIEGO  0.0725     0.009250  77.01  32.717421 -117.162771
75       BOSTON  0.0625     0.009736  87.05  42.360253  -71.058291
51     SAN JOSE  0.0725     0.012075  82.87  37.336191 -121.890583
31  LOS ANGELES  0.0725     0.012505  82.30  34.053691 -118.242767
89         RENO  0.0685     0.014195  62.88  39.529270 -119.813674

   1st Most Common Venue 2nd Most Common Venue 3rd Most Common Venue  \
76  New American Restaurant           Coffee Shop                   Pub
50                    Hotel    Mexican Restaurant    Italian Restaurant
75       Italian Restaurant    Seafood Restaurant          Historic Site
51       Mexican Restaurant           Coffee Shop          Cocktail Bar
31        Sushi Restaurant           Coffee Shop   Japanese Restaurant
89                      Bar                   Pub    Mexican Restaurant

  4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
76                  Café              Gastropub               Brewery
50                  Café                    Bar   American Restaurant
75                  Park            Coffee Shop           Pizza Place
51                   Bar       Sushi Restaurant        Sandwich Place
31                 Plaza     Mexican Restaurant      Ramen Restaurant
89               Brewery            Coffee Shop                  Café

          7th Most Common Venue  8th Most Common Venue  \
76  Vegetarian / Vegan Restaurant  Portuguese Restaurant
50                    Coffee Shop     Seafood Restaurant
75                 Sandwich Place                 Market
51                        Theater            Pizza Place
31                 Ice Cream Shop              Bookstore
89                          Hotel         Breakfast Spot

     9th Most Common Venue    10th Most Common Venue  Cluster
76          Ice Cream Shop          Tapas Restaurant        3
50  New American Restaurant                Burger Joint        3
75                   Bakery                     Hotel        3
51                      Pub            Ice Cream Shop        3
31                      Bar  Mediterranean Restaurant        3
89               Steakhouse               Pizza Place        3
```

In [150]:
```
lowcol = sort3.sort_values('CLI').head(6)
lowcol
```

Out[150]:
```
           City     Tax  Crime Index    CLI   Latitude   Longitude  \
89         RENO  0.0685     0.014195  62.88  39.529270 -119.813674
82      DETROIT  0.0600     0.022378  70.20  42.331551  -83.046640
50    SAN DIEGO  0.0725     0.009250  77.01  32.717421 -117.162771
31  LOS ANGELES  0.0725     0.012505  82.30  34.053691 -118.242767
```

```
51     SAN JOSE  0.0725     0.012075  82.87  37.336191 -121.890583
76    CAMBRIDGE  0.0625     0.008119  82.96  42.375100  -71.105616

      1st Most Common Venue 2nd Most Common Venue 3rd Most Common Venue  \
89                      Bar                   Pub    Mexican Restaurant
82              Coffee Shop                   Bar   American Restaurant
50                    Hotel    Mexican Restaurant    Italian Restaurant
31          Sushi Restaurant          Coffee Shop   Japanese Restaurant
51        Mexican Restaurant          Coffee Shop           Cocktail Bar
76  New American Restaurant           Coffee Shop                    Pub

   4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
89               Brewery           Coffee Shop                  Café
82            Restaurant                 Diner                  Park
50                  Café                   Bar   American Restaurant
31                 Plaza    Mexican Restaurant      Ramen Restaurant
51                   Bar      Sushi Restaurant        Sandwich Place
76                  Café             Gastropub               Brewery

          7th Most Common Venue  8th Most Common Venue  \
89                        Hotel         Breakfast Spot
82                       Lounge             Steakhouse
50                  Coffee Shop     Seafood Restaurant
31               Ice Cream Shop              Bookstore
51                      Theater            Pizza Place
76  Vegetarian / Vegan Restaurant  Portuguese Restaurant

      9th Most Common Venue    10th Most Common Venue  Cluster
89               Steakhouse               Pizza Place        3
82              Burger Joint                    Hotel        3
50  New American Restaurant               Burger Joint        3
31                       Bar  Mediterranean Restaurant        3
51                       Pub            Ice Cream Shop        3
76           Ice Cream Shop         Tapas Restaurant        3
```

In [157]:
```
reno = sort3[sort3['City']=='RENO']
```

3.8 Results

3.8.1 City Selection

Of the 11 cities in the target cluster, the top 6 safest and 6 lowest cost of living index cities were cross-referenced to highlight Reno, NV and Cambridge, MA as the top choices to open a Dispensary in 2019. After city review, Reno was chosen over Cambridge due to lower cost of living and more active nightlife, however, Cambridge is still a viable choice due to the trendy culture and diversity.

In [163]:
```
# create map
renomap = folium.Map(location=[39.529,-119.813], zoom_start=10)
```

```
# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(reno['Latitude'], reno['Longitude'], reno['City'], reno['Cluster']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=200,
        popup=label,
        color='darkgreen',
        fill=True,
        fill_color='green',
        fill_opacity=0.7).add_to(renomap)

renomap
```

Out[163]: <folium.folium.Map at 0x7f0c9848d208>

3.9 Discussion

Upon review of the 5 different cluster datasets, I was able to determine which clusters contain the target demographic and culture that is becoming of a new dispensary such as an active nightlife scene from bars, pubs, liquor stores, activities, lots of restaurants such as fast food and convenience stores. The recommendation would be to focus investment on opening a dispensary in Reno, NV followed by Cambridge, MA as a backup option or expansion location. These cities are both highly populated, very trendy, have an active nightlife, are relatively safe, and have a decent state sales tax compared to other cities assessed.

3.10 Conclusion

Recreational marijuana is a rapidly materializing industry, estimated to surpass $16 Billion in 2019 and exponentially growing. With the influx of new users and change of legal status, there is a huge demand for recreational marijuana with very limited supply. This is the prime chance to seize this opportunity and open a new legal marijuana supply chain in the United States. Based on the data reviewed and analyzed, Reno, Nevada is the top city in the US to open the next Marijuana Dispensary based on its population, safety, cost of living index and overall culture.

In [ ]: