Capstone Project- The Battle of the Neighborhoods (Week 2)

Applied Data Science Capstone

By: Chris Cothran

Table of Contents

I. Context

Each year, millions of homes are sold, constructed, or are renovated or repaired. These processes require materials, parts, and expertise that home improvement retailers can provide. The importance of siting a store to garner revenue from all of these activities while being sufficiently distant from competitors so that local activities increasingly rely on your store is one of many factors a company may consider in determining where to locate a new store. It provides a home improvement retailer extensive benefit to be able to predict where optimal zones to build a new store might be. This information can then be incorporated into a wide range of other factors to yield a final business decision.

II. Business Problem

In this project we will try to derive a high-graded list of optimal locations for a home improvement retailer. This report will be targeted to stakeholders considering expansion into the home improvement retail market in Houston, Texas, USA. There are multiple well-established home improvement retailers operating in Houston. For this initial exercise, we will consider optimality as a function in part derived from proximity to zones of higher home construction, renovation, and maintenance spending and distance from competing home improvement retail stores. The stakeholders are likely interested in zones that may be underserved in this regard in multiple categories as ideal locations. However, assuming the optimal conditions are met, we would like to locate the store as close to high-population zones within the city to ensure adequate day-to-day foot traffic.

III. Data

For this project, I will source data from the following locations: Foursquare, The U.S. Census Bureau, the U.S. Internal Revenue Service, the National Association of Realtors, and Foursquare.

1) Foursquare shall provide the data for the number of existing home improvement retailers in a city neighborhood, distance of neighborhoods from concentrated population zones, and proximity of existing shopping centers for convenience of access.
2) National Association of Realtor's data provided from Realtor.com shall provide number of housing listings by zip code.
3) U.S. Internal Revenue Service shall provide population data by zip code used to determine density proximity to potential sites based on number of filed income tax returns.
4) U.S. Internal Revenue Service data for two subsequent years shall provide economic growth indications based on the number of returns by income level in a given zip code year-over-year.
5) City center coordindates provided by Opendatasoft

IV. Data Preparation, Wrangling and Exploratory Data Analysis

In [281]:
```
#install Necessary Libraries

!pip install shapely
!pip install pyproj
!pip install wget
!pip install folium
```

```
Requirement already satisfied: shapely in /opt/conda/envs/Python36/lib/python
3.6/site-packages (1.7.1)
Requirement already satisfied: pyproj in /opt/conda/envs/Python36/lib/python
3.6/site-packages (2.6.1.post1)
Requirement already satisfied: wget in /opt/conda/envs/Python36/lib/python3.
6/site-packages (3.2)
Requirement already satisfied: folium in /opt/conda/envs/Python36/lib/python
3.6/site-packages (0.11.0)
Requirement already satisfied: requests in /opt/conda/envs/Python36/lib/pytho
n3.6/site-packages (from folium) (2.21.0)
Requirement already satisfied: jinja2>=2.9 in /opt/conda/envs/Python36/lib/py
thon3.6/site-packages (from folium) (2.10)
Requirement already satisfied: branca>=0.3.0 in /opt/conda/envs/Python36/lib/
python3.6/site-packages (from folium) (0.4.1)
Requirement already satisfied: numpy in /opt/conda/envs/Python36/lib/python3.
6/site-packages (from folium) (1.15.4)
Requirement already satisfied: urllib3<1.25,>=1.21.1 in /opt/conda/envs/Pytho
n36/lib/python3.6/site-packages (from requests->folium) (1.24.1)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/envs/Python3
6/lib/python3.6/site-packages (from requests->folium) (2020.6.20)
Requirement already satisfied: idna<2.9,>=2.5 in /opt/conda/envs/Python36/li
b/python3.6/site-packages (from requests->folium) (2.8)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /opt/conda/envs/Pytho
n36/lib/python3.6/site-packages (from requests->folium) (3.0.4)
Requirement already satisfied: MarkupSafe>=0.23 in /opt/conda/envs/Python36/l
ib/python3.6/site-packages (from jinja2>=2.9->folium) (1.1.0)
```

In [282]:
```
#import Libraries needed in the Project

import pandas as pd
import numpy as np
import wget
import folium
import geopy
import sklearn
import pylab as pl
import seaborn as sns
import matplotlib as mp
import matplotlib.cm as cm
import matplotlib.colors as colors
import random
import json
import requests
import scipy.optimize as opt
from geopy.geocoders import Nominatim
from matplotlib.ticker import NullFormatter
from matplotlib import pyplot as plt
from pandas.io.json import json_normalize
from sklearn.cluster import DBSCAN
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

#Lets set options to see maximum Columns and Rows
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

Get the datasets from the web

In [283]:
```
# we will define the urls for each of the downloadable files

url_NAR='https://github.com/Empcoth/Coursera_Capstone/raw/master/NAR2020.xlsx'
url_GOV_2017= 'https://github.com/Empcoth/Coursera_Capstone/raw/master/2017IR
S.xls'
```

In [284]:
```
#use the get library to download into local files

NAR=wget.download(url_NAR,r'\Users\Chris\Downloads\NAR.xlsx')
GOV_2017=wget.download(url_GOV_2017,r'\Users\Chris\Downloads\GOV_2017.xls')
```

In [285]:
```
#convert the files into pandas dataframes
NAR_df=pd.read_excel(r'\Users\Chris\Downloads\NAR.xlsx')

#As the columns have Mixed Data types, We specify these are parameters during
 the read_excel process
GOV_2017_df=pd.read_excel(r'\Users\Chris\Downloads\GOV_2017.xls',dtype={"ZIP":
str, "Adjusted Gross Income":str, "Number of returns":int})
```

In [286]:
```
#Look at the Shape of the Downloaded Files
print('The NAR July 2020 Data Consists of (Rows, Columns)', NAR_df.shape)
print('The IRS 2017 Data Consists of (Rows, Columns)', GOV_2017_df.shape)
```

```
The NAR July 2020 Data Consists of (Rows, Columns) (99286, 20)
The IRS 2017 Data Consists of (Rows, Columns) (9720, 3)
```

In [287]:
```
#Save each NAR dataframe to the defined set of columns needed for this project
NAR_df=NAR_df[['postal_code','month_date_yyyymm','median_listing_price','activ
e_listing_count']]
```

In [288]:
```
#Again Look at the Shape of the Downloaded Files
print('The NAR July 2020 Data Consists of (Rows, Columns)', NAR_df.shape)
print('The IRS 2017 Data Consists of (Rows, Columns)', GOV_2017_df.shape)
```

```
The NAR July 2020 Data Consists of (Rows, Columns) (99286, 4)
The IRS 2017 Data Consists of (Rows, Columns) (9720, 3)
```

In [289]:
```
NAR_df.dtypes
```

Out[289]:
```
postal_code               int64
month_date_yyyymm         int64
median_listing_price    float64
active_listing_count      int64
dtype: object
```

In [290]:
```
GOV_2017_df.dtypes
```

Out[290]:
```
ZIP                      object
Adjusted Gross Income    object
Number of returns         int64
dtype: object
```

We now download a file of Texas Longitude and Latitude coordinates and save it to a pandas dataframe

In [291]:
```
coord='https://raw.githubusercontent.com/Empcoth/Coursera_Capstone/master/Long
Lat.csv'
coordinates=wget.download(coord,r'\Users\Chris\Downloads\LongLat2.csv')
```

In [292]:
```
coor_df=pd.read_csv(r'\Users\Chris\Downloads\LongLat2.csv')
```

In [293]:
```
coor_df.head()
```

Out[293]:

	Zip	City	Latitude	Longitude
0	75016	Irving	32.767268	-96.777626
1	76385	Vernon	34.146356	-99.214088
2	77320	Huntsville	30.805099	-95.507190
3	77449	Katy	29.825908	-95.730100
4	76651	Italy	32.175783	-96.880180

V. Area Analysis

Now we will define the Houston area and look at the preliminary map using the Folium Library

In [294]:
```
#Define a dataframe with only City of Houston Coordinates to Find the City Cen
ter
Houston_df = coor_df.loc[coor_df['City'] =='Houston']
CityCenter_df=Houston_df.loc[Houston_df['Zip'] ==77002]
```

In [295]:
```
CityCenter_df.head()
```

Out[295]:

	Zip	City	Latitude	Longitude
1361	77002	Houston	29.755578	-95.36531

In [296]:
```
latitude=CityCenter_df['Latitude'][1361]
longitude=CityCenter_df['Longitude'][1361]
```

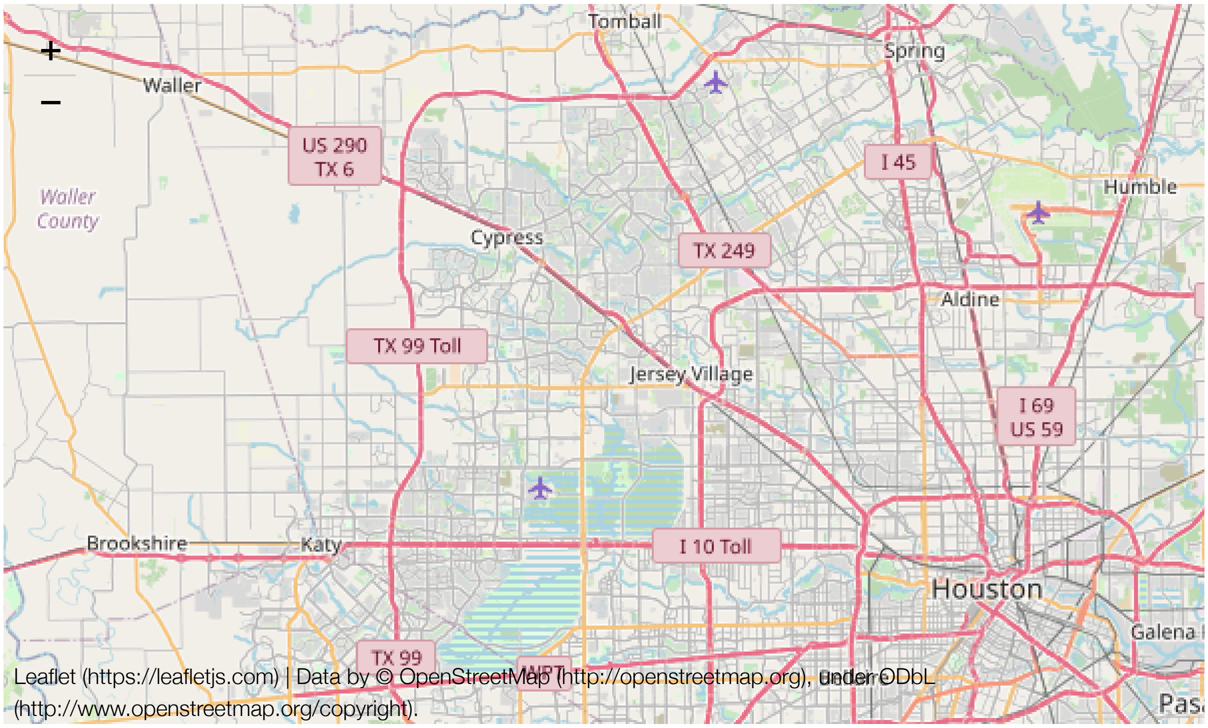
In [297]:
```
#Output of City Center Derivation
latitude, longitude
```

Out[297]:
```
(29.755578000000003, -95.36531)
```

In [298]:
```
#Define a Folium Map Object Variable
map_houston = folium.Map(location=[latitude, longitude], zoom_start=10)
```

In [299]:
```
#Display the Map
map_houston
```

Out[299]:



We need to include the greater metro area beyond Houston city limits in this analysis to be effective with this study. Thus, we will first define the 'Greater Houston' area with a list of Zip Codes traditionally included in that designation

In [300]:
```
#Import dataset of relevant zip codes

houzip='https://github.com/Empcoth/Coursera_Capstone/raw/master/HoustonAreaLongLat.xlsx'
houcord=wget.download(houzip,r'\Users\Chris\Downloads\HoustonAreaLongLat2.xlsx')
```

In [301]:
```
#Convert imported data to a pandas dataframe
hou_zip_df=pd.read_excel(r'\Users\Chris\Downloads\HoustonAreaLongLat2.xlsx')
```

In [302]:
```
#Look at the dataframe
hou_zip_df.head()
```

Out[302]:

	Zip
0	77002
1	77003
2	77004
3	77005
4	77006

In [303]:
```
#Look at the dataframe shape
hou_zip_df.shape
```

Out[303]: (236, 1)

In [304]:
```
#Check to see if Houston metro zips are in the Main List, to curate a list of
 Houston Metro Zip Codes and their Corresponding Longitude and Latitude Values
in a Combined List

import warnings
warnings.filterwarnings("ignore")
new_coor = coor_df.assign(result=coor_df['Zip'].isin(hou_zip_df['Zip']).astype
(int))
test_coor=new_coor[new_coor['result']==1]
test_coor.drop(['result'], axis=1, inplace=True)
test_coor.reset_index(drop=True)
test_coor.head()
```

Out[304]:

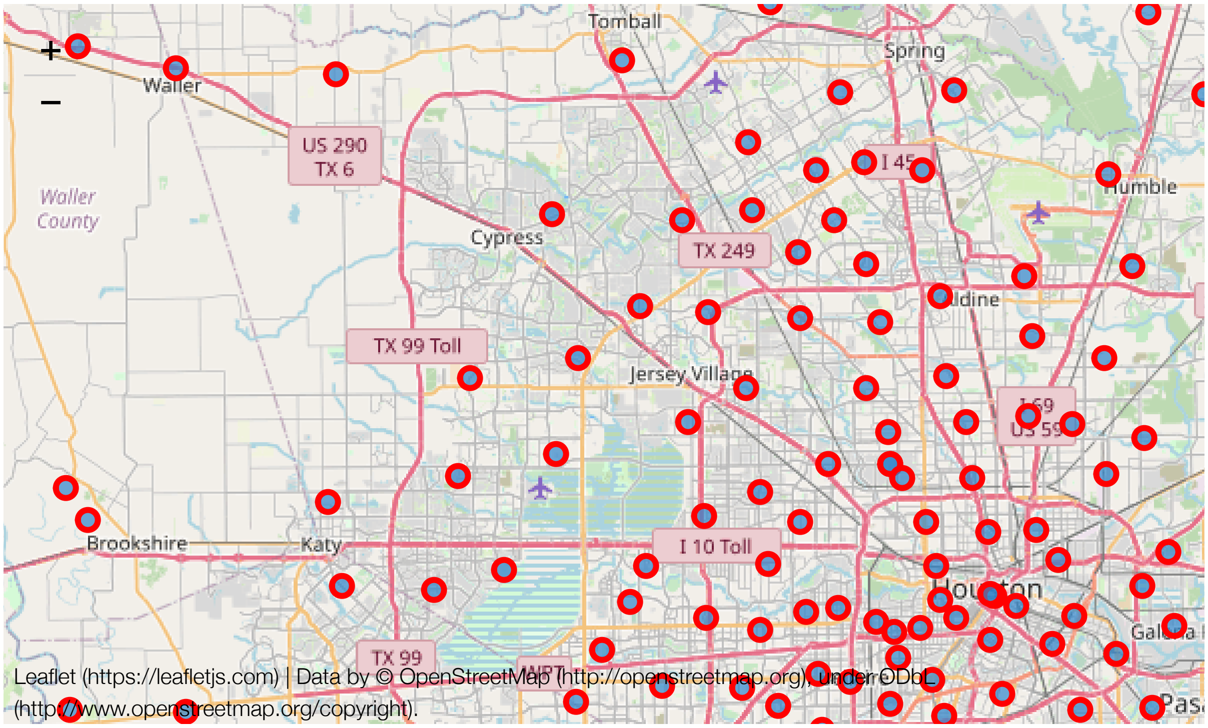
	Zip	City	Latitude	Longitude
3	77449	Katy	29.825908	-95.73010
29	77034	Houston	29.636430	-95.21789
45	77003	Houston	29.749278	-95.34741
57	78933	Cat Spring	29.773128	-96.39342
71	77479	Sugar Land	29.573345	-95.63213

Create a map of Houston with zip code centerpoints superimposed on top

In [305]:
```
#add markers to map
for lat, lng, Zip, city in zip(test_coor['Latitude'],test_coor['Longitude'],te
st_coor['Zip'],test_coor['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_houston)
```

In [306]:
```
map_houston
```

Out[306]:



We will now define viability ratings based on real estate listings and zip code performance

In [307]:
```
NAR_df.head()
```

Out[307]:

	postal_code	month_date_yyyymm	median_listing_price	active_listing_count
0	67801	202007	154050.0	26
1	34436	202007	263050.0	31
2	77423	202007	307550.0	89
3	84103	202007	849500.0	69
4	84027	202007	249050.0	13

Let's get a Year-to-Date Active Listing Count by Zip code in the Defined Greater Houston Metropolitan Area

In [308]:
```
#Define the Zip Codes into a Filtered Dataframe
test_nar_df=NAR_df.assign(result=NAR_df['postal_code'].isin(hou_zip_df['Zip'])
.astype(int))
NAR_filtered_df=test_nar_df[test_nar_df['result']==1]
NAR_filtered_df.drop(['result'], axis=1, inplace=True)
NAR_filtered_df.reset_index(drop=True).head()
```

Out[308]:

	postal_code	month_date_yyyymm	median_listing_price	active_listing_count
0	77423	202007	307550.0	89
1	77021	202007	292050.0	95
2	77532	202007	241495.0	132
3	77489	202007	189050.0	29
4	77069	202007	298750.0	88

In [309]:
```
#Lets Create a Composite Factor Based on median_listing_price multiplied by ac
tive_listing_count
import warnings
warnings.filterwarnings('ignore')
NAR_filtered_df['investment intensity']=NAR_filtered_df['median_listing_price'
]*NAR_filtered_df['active_listing_count']
NAR_filtered_df.reset_index(drop=True, inplace=True)
NAR_filtered_df.head()
```

Out[309]:

	postal_code	month_date_yyyymm	median_listing_price	active_listing_count	investment intensity
0	77423	202007	307550.0	89	27371950.0
1	77021	202007	292050.0	95	27744750.0
2	77532	202007	241495.0	132	31877340.0
3	77489	202007	189050.0	29	5482450.0
4	77069	202007	298750.0	88	26290000.0

In [310]:
```
NAR_grouped=NAR_filtered_df.groupby('postal_code').sum().reset_index()
NAR_grouped.head()
```

Out[310]:

	postal_code	month_date_yyyymm	median_listing_price	active_listing_count	investment intensity
0	77002	1414028	2212700.0	409	1.289000e+08
1	77003	1414028	2630900.0	766	2.878397e+08
2	77004	1414028	2583894.5	1502	5.545900e+08
3	77005	1414028	10130750.0	1134	1.644198e+09
4	77006	1414028	4327950.0	1144	7.071631e+08

In [311]:
```
#We can remove the date, listing price, and active listing columns
NAR=NAR_grouped.drop(columns=['month_date_yyyymm','median_listing_price','acti
ve_listing_count'])
NAR['investment intensity']=NAR['investment intensity'].div(1000000)
#As the Investment Intensity is quite large, we can Divide by 1 million to mak
e it more manageable while retaining relative difference across postal codes
NAR.head()
```

Out[311]:

	postal_code	investment intensity
0	77002	128.900050
1	77003	287.839725
2	77004	554.590012
3	77005	1644.197700
4	77006	707.163100

We will now define viability ratings based on combined filings times income factors for each zip code

In [312]:
```
GOV_2017_df.head()
```

Out[312]:

	ZIP	Adjusted Gross Income	Number of returns
0	75001	$1 under$25,000	2370
1	75001	$25,000 under$50,000	2440
2	75001	$50,000 under$75,000	1680
3	75001	$75,000 under$100,000	940
4	75001	$100,000 under$200,000	1320

We should take a look at adjusted gross income as it is a combination of string and integer values in the dataframe

In [313]:
```
#List the unique values in the Adjusted Gross Income column
print(GOV_2017_df['Adjusted Gross Income'].unique().tolist())
```

```
['$1 under $25,000', '$25,000 under $50,000', '$50,000 under $75,000', '$75,0
00 under $100,000', '$100,000 under $200,000', '$200,000 or more']
```

In [314]:
```
#Define a new dataframe and assign a Factor Score for each income level
GOV_df=GOV_2017_df
GOV_df['Adjusted Gross Income']=GOV_df['Adjusted Gross Income'].replace(['$1 under $25,000'],'1')
GOV_df['Adjusted Gross Income']=GOV_df['Adjusted Gross Income'].replace(['$25,000 under $50,000'],'2')
GOV_df['Adjusted Gross Income']=GOV_df['Adjusted Gross Income'].replace(['$50,000 under $75,000'],'3')
GOV_df['Adjusted Gross Income']=GOV_df['Adjusted Gross Income'].replace(['$75,000 under $100,000'],'4')
GOV_df['Adjusted Gross Income']=GOV_df['Adjusted Gross Income'].replace(['$100,000 under $200,000'],'5')
GOV_df['Adjusted Gross Income']=GOV_df['Adjusted Gross Income'].replace(['$200,000 or more'],'6')
GOV_df.head()
```

Out[314]:

	ZIP	Adjusted Gross Income	Number of returns
0	75001	1	2370
1	75001	2	2440
2	75001	3	1680
3	75001	4	940
4	75001	5	1320

In [315]:
```
# We can then rename the Adjusted Gross Income column
GOV_df.rename(columns={'Adjusted Gross Income':'Income Level Score'},inplace=True)
#Multiply the Income Level Score by the Number of Returns for a Relative Income Factor
GOV_df['Income Level Score']=GOV_df['Income Level Score'].astype(str).astype(int)
GOV_df['income intensity']=GOV_df['Income Level Score']*GOV_df['Number of returns']
GOV_df.reset_index(drop=True, inplace=True)
GOV_df.head()
```

Out[315]:

	ZIP	Income Level Score	Number of returns	income intensity
0	75001	1	2370	2370
1	75001	2	2440	4880
2	75001	3	1680	5040
3	75001	4	940	3760
4	75001	5	1320	6600

In [316]:
```
#We can then group by Zip
GOV_grouped=GOV_df.groupby('ZIP').sum().reset_index()
GOV_grouped.head()
```

Out[316]:

	ZIP	Income Level Score	Number of returns	income intensity
0	75001	21	9340	26190
1	75002	21	30620	94080
2	75006	21	23870	56750
3	75007	21	26370	73230
4	75009	21	6710	23100

In [317]:
```
#And remove the Income Level Score and Number of Returns Columns
GOV=GOV_grouped.drop(columns=['Income Level Score','Number of returns'])
GOV.head()
```

Out[317]:

	ZIP	income intensity
0	75001	26190
1	75002	94080
2	75006	56750
3	75007	73230
4	75009	23100

In [318]:
```
#Convert the Data Type of the Zip Column
GOV_Test=GOV
```

In [319]:
```
#GOV_Test
```

In [320]:
```
GOV_Test["ZIP"]=GOV_Test["ZIP"].astype(int)
```

In [321]:
```
GOV_Test.dtypes
```

Out[321]:
```
ZIP                 int64
income intensity    int64
dtype: object
```

In [322]:
```
#Define the Zips per the Greater Houston Metropolitan Area

GOV_Test=GOV_Test.assign(result=GOV_Test['ZIP'].isin(hou_zip_df['Zip']).astype
(int))
GOV_Test=GOV_Test[GOV_Test['result']==1]
GOV_Test.drop(['result'], axis=1, inplace=True)
GOV_Test.reset_index(drop=True).head()
```

Out[322]:

	ZIP	income intensity
0	77002	20090
1	77003	15410
2	77004	35300
3	77005	52810
4	77006	45200

In [323]:
```
#We Can Then Define a Dataframe Combining Investment Intensity and Income Inte
nsity by Zip

#First Lets Rename the Column Label of the NAR Df to Match the GOV DF

NAR_Renamed=NAR
NAR_Renamed.rename(columns={"postal_code": "ZIP"}, inplace=True)
```

In [324]:
```
NAR_Renamed.dtypes
```

Out[324]:
```
ZIP                          int64
investment intensity       float64
dtype: object
```

In [325]:
```
GOV_Test.dtypes
```

Out[325]:
```
ZIP                    int64
income intensity       int64
dtype: object
```

In [326]:
```
#We merge the Dataframes using the ZIP Key
merged_df=pd.merge(NAR_Renamed,GOV_Test, on=['ZIP','ZIP'])
```

In [327]:
```
#merged_df
```

In [328]:
```
#We Can Then Factor the Two Values by Multiplying Them
merged_df['Prospectivity Score']=merged_df['investment intensity']*merged_df[
'income intensity']
```

In [329]:
```
#We Can then Normalize the Prospectivity Score
normalized_df=merged_df
normalized_df['Prospectivity Score']=(normalized_df['Prospectivity Score']-nor
malized_df['Prospectivity Score'].mean())/normalized_df['Prospectivity Score']
.std()
```

In [330]:
```
#Sort by Prospectivity Score to Look at Top Prospects
normalized_df.sort_values(by=['Prospectivity Score'],ascending=False,inplace=T
rue)
normalized_df.reset_index(drop=True,inplace=True)
```

In [331]:
```
#We Can then Merge the Coordinate List with the Merged DF by eliminating Zip C
odes Not in the Merged List
test_coor_Renamed=test_coor
test_coor_Renamed.rename(columns={"Zip": "ZIP"}, inplace=True)
```

In [332]:
```
merge_test=pd.merge(test_coor_Renamed,normalized_df, on=['ZIP','ZIP'])
```

In [333]:
```
merge_test.head()
```

Out[333]:

	ZIP	City	Latitude	Longitude	investment intensity	income intensity	Prospectivity Score
0	77449	Katy	29.825908	-95.73010	293.667520	119820	0.494914
1	77034	Houston	29.636430	-95.21789	33.587138	30460	-0.495364
2	77003	Houston	29.749278	-95.34741	287.839725	15410	-0.396448
3	77479	Sugar Land	29.573345	-95.63213	1283.715325	143880	4.828698
4	77042	Houston	29.741565	-95.55996	421.325450	47340	0.053120

Now that we have our preliminary prospectivity table we can visualize the highly prospective zones

In [334]:
```
#Sort by Prospectivity Score in Descending Order and Take the Top 10 Rows
merge_test.sort_values(by=['Prospectivity Score'],ascending=False,inplace=True
)
merge_test.reset_index(drop=True,inplace=True)
```

In [335]:
```
#merge_test
```

In [336]:
```
sample_df=merge_test.head(11)
```

In [337]:
```
#sample_df
```

In [338]:
```
sample_df.head()
```

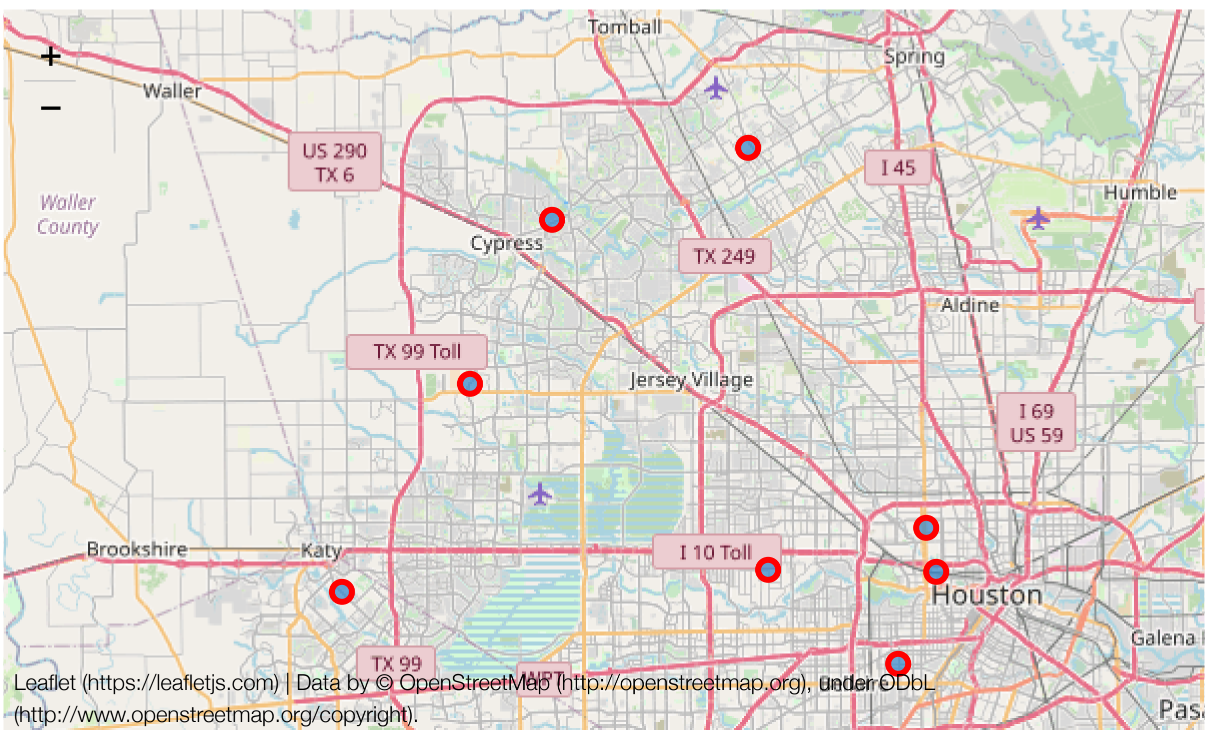
Out[338]:

	ZIP	City	Latitude	Longitude	investment intensity	income intensity	Prospectivity Score
0	77494	Katy	29.760833	-95.81104	1464.140459	168710	6.634928
1	77024	Houston	29.773994	-95.51771	3104.037550	74780	6.203177
2	77479	Sugar Land	29.573345	-95.63213	1283.715325	143880	4.828698
3	77433	Cypress	29.884175	-95.72219	1089.357898	126820	3.479447
4	77007	Houston	29.772627	-95.40319	1414.952830	88290	3.096075

In [339]:
```
map_sample = folium.Map(location=[latitude, longitude], zoom_start=10)

#add markers to map
for lat, lng, Zip, city in zip(sample_df['Latitude'],sample_df['Longitude'],sa
mple_df['ZIP'],sample_df['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_sample)
```

In [340]:
```
map_sample
```

Out[340]:



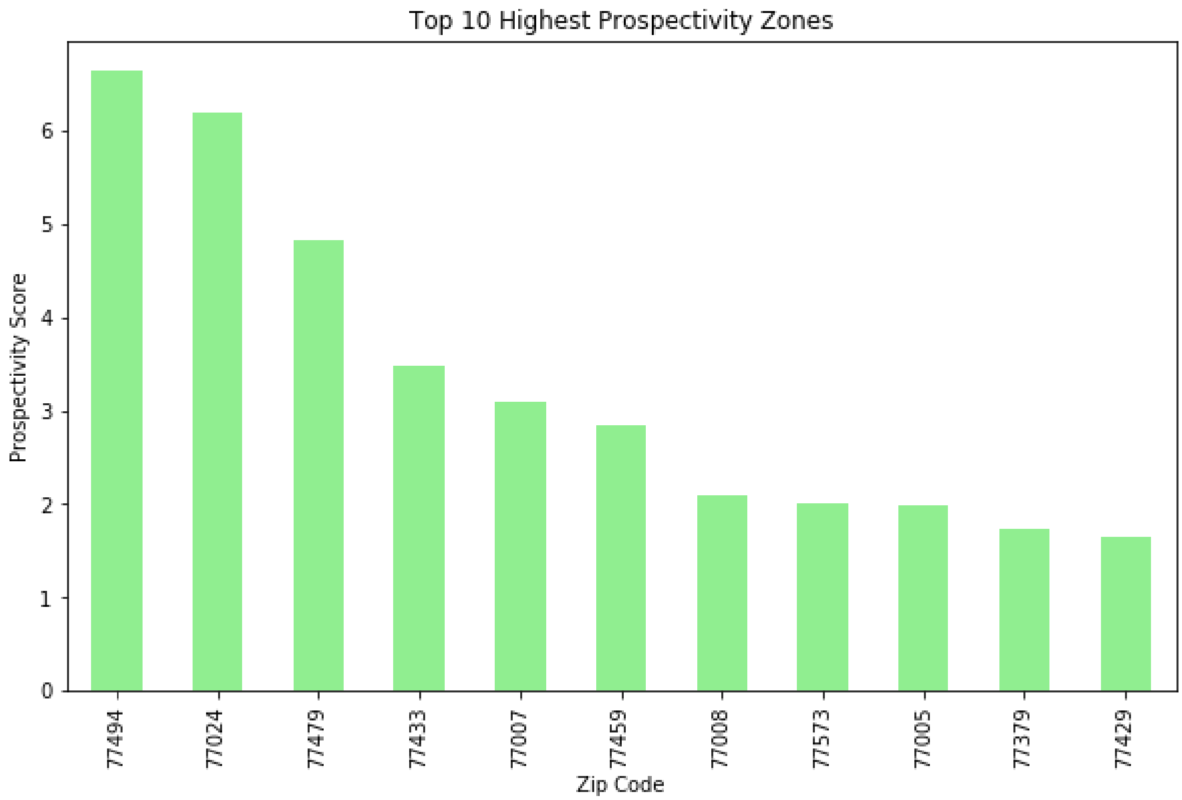
In [341]:
```
pie_df=sample_df.set_index('ZIP')
pie_df
```

Out[341]:

ZIP	City	Latitude	Longitude	investment intensity	income intensity	Prospectivity Score
77494	Katy	29.760833	-95.81104	1464.140459	168710	6.634928
77024	Houston	29.773994	-95.51771	3104.037550	74780	6.203177
77479	Sugar Land	29.573345	-95.63213	1283.715325	143880	4.828698
77433	Cypress	29.884175	-95.72219	1089.357898	126820	3.479447
77007	Houston	29.772627	-95.40319	1414.952830	88290	3.096075
77459	Missouri City	29.564347	-95.54762	1053.372022	110360	2.844592
77008	Houston	29.798777	-95.40951	1298.130485	69340	2.084068
77573	League City	29.502759	-95.08906	662.672050	131500	2.000849
77005	Houston	29.717529	-95.42821	1644.197700	52810	1.991826
77379	Spring	30.024749	-95.53215	670.548920	115730	1.724360
77429	Cypress	29.982746	-95.66597	604.343770	123870	1.644865

In [342]:
```
pie_df['Prospectivity Score'].plot(kind='bar', figsize=(10,6),rot=90, color='lightgreen')
plt.title('Top 10 Highest Prospectivity Zones')
plt.xlabel('Zip Code')
plt.ylabel('Prospectivity Score')
```

Out[342]: Text(0, 0.5, 'Prospectivity Score')



VI. Foursquare Data Selection

Next, we are going to utilize the Foursquare API to explore Home Improvement store locations in the Greater Houston Metropolitan Area

In [343]:
```
#Define Foursquare Credentials and Version
CLIENT_ID = '2XCT5GQNZACPUY0A1VHDEGFVHMBLP4SGF3ZARXFD21ZONABJ' # your Foursquare ID
CLIENT_SECRET = 'TYUIFCR35VAHSM3QZ5TR4FEZBVE2QHHLRPHYIC21KEM1ZGI3' # your Foursquare Secret
VERSION = '20180605' # Foursquare API version
CLIENT_ID, CLIENT_SECRET, VERSION, latitude, longitude
```

Out[343]:
```
('2XCT5GQNZACPUY0A1VHDEGFVHMBLP4SGF3ZARXFD21ZONABJ',
 'TYUIFCR35VAHSM3QZ5TR4FEZBVE2QHHLRPHYIC21KEM1ZGI3',
 '20180605',
 29.755578000000003,
 -95.36531)
```

In [344]:
```
LIMIT=100   #Limit the number of venues returned by the Forusquare API
radius=90000  #Define radius in meters from defined latitude and longitude coo
rdinates
query='Home Depot'
#create url to access the Foursquare API
url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secre
t={}&v={}&ll={},{}&radius={}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    latitude,
    longitude,
    radius,
    LIMIT)
url # display URL

url2='https://api.foursquare.com/v2/venues/search?&client_id={}&client_secret=
{}&v={}&ll={},{}&radius={}&limit={}&query={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    latitude,
    longitude,
    radius,
    LIMIT,
    query)

url2 # display URL2
```

Out[344]:
```
'https://api.foursquare.com/v2/venues/search?&client_id=2XCT5GQNZACPUY0A1VHDE
GFVHMBLP4SGF3ZARXFD21ZONABJ&client_secret=TYUIFCR35VAHSM3QZ5TR4FEZBVE2QHHLRPH
YIC21KEM1ZGI3&v=20180605&ll=29.755578000000003,-95.36531&radius=90000&limit=1
00&query=Home Depot'
```

In [345]:
```
#Get JSON file of the results from the API and store them in a variable
results=requests.get(url2).json()
```

In [346]:
```
#results
```

In [347]:
```
#see how many results were returned
counter=len(results['response']['venues'])
i=0

#Define a new dataframe to store the data
FS_df=pd.DataFrame(columns=['Hardware Store','Address','Longitude','Latitude'
],index=range(101))
cols=['name','longitude','latitude']

#Iterate to read data into a dictionary
while i<counter:
    FS_df['Latitude'][i]=results['response']['venues'][i]['location']['lat']
    FS_df['Longitude'][i]=results['response']['venues'][i]['location']['lng']
    FS_df['Hardware Store'][i]=results['response']['venues'][i]['name']
    FS_df['Address'][i]=results['response']['venues'][i]['location']['formatte
dAddress'][0]
    i=i+1
#FS_df
```

Next, we derive the locations for Lowe's, the other major Home Improvement Store covered in this Analysis

In [348]:
```
LIMIT=100   #Limit the number of venues returned by the Forusquare API
radius=90000  #Define radius in meters from defined latitude and longitude coo
rdinates
query='Lowe\'s'
url3='https://api.foursquare.com/v2/venues/search?&client_id={}&client_secret=
{}&v={}&ll={},{}&radius={}&limit={}&query={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    latitude,
    longitude,
    radius,
    LIMIT,
    query)

#Get JSON file of the results from the API and store them in a variable
results2=requests.get(url3).json()
```

In [349]:
```
#results2
```

In [350]:
```
#Let's check the length of the second request and append to the counter variab
le
counter=counter+len(results2['response']['venues'])
```

In [351]:
```
#Define a second counter for the additional rows
counter2=0
#Iterate to read data into a dictionary
while i<counter:
    FS_df['Latitude'][i]=results2['response']['venues'][counter2]['location'][
'lat']
    FS_df['Longitude'][i]=results2['response']['venues'][counter2]['location']
['lng']
    FS_df['Hardware Store'][i]=results2['response']['venues'][counter2]['name'
]
    FS_df['Address'][i]=results2['response']['venues'][counter2]['location'][
'formattedAddress'][0]
    i=i+1
    counter2=counter2+1
#FS_df
```

In [352]:
```
#We can see the following Incorrect Values based on external research

prob=['Lowes Theater', 'Lowest Energy Rate']

#Lets Define a Column to Flag these Values

FS_df['Flag']=FS_df['Hardware Store'].isin(prob)
```

In [353]:
```
FS_df=FS_df.dropna()
```

In [354]:
```
#FS_df
```

In [355]:
```
#Drop invalid values from the dataframe
FS_df.drop(FS_df[FS_df['Flag']==True].index, inplace=True)
```

In [356]:
```
FS_df.head()
```

Out[356]:

	Hardware Store	Address	Longitude	Latitude	Flag
0	The Home Depot	999 North Loop West	-95.4171	29.8114	False
1	The Home Depot	8400 Katy Freeway	-95.4936	29.7862	False
2	The Home Depot	5445 West Loop	-95.4573	29.7233	False
3	The Home Depot	18251 Gulf Freeway	-95.1532	29.5569	False
4	The Home Depot	10419 Highway 6 South	-95.6424	29.6638	False

In [357]:
```
#We can now remove the Flag column
FS_df.drop(columns=['Flag'], inplace=True)
```

In [358]:
```
#And reset the index and verify the DF
FS_df.reset_index(drop=True, inplace=True)
```

In [359]:
```
FS_df.head()
```

Out[359]:

	Hardware Store	Address	Longitude	Latitude
0	The Home Depot	999 North Loop West	-95.4171	29.8114
1	The Home Depot	8400 Katy Freeway	-95.4936	29.7862
2	The Home Depot	5445 West Loop	-95.4573	29.7233
3	The Home Depot	18251 Gulf Freeway	-95.1532	29.5569
4	The Home Depot	10419 Highway 6 South	-95.6424	29.6638

VII. Methodology

In this project, we ultimately seek to find a top 20 list of prospective Zip code centerpoints for sitign a new concept Home Improvement store in the Greater Houston Area. We limit our analysis to a radius of 90 kilometers from the Houston city center. We collect data from the Natinoal Association of Realtors (to define areas with housing listings for an intensity score relative to the number of houses listed for a given time period (YTD July 2020). We then use Internal Revenue Service Data on IRS filings by adjusted gross income of filers in a given zip code to determine aggregate wealth intensity.

We then implement the Haversine formula via a defined function for each of the queried competing Home Improvement store locations to obtain cumulative distances from stores. The areas with the most robust number of listings, highest total income levels, and longest cumulative distances from competitors establish our Top 20 listing results below.

In the third step, we will use K-Means clustering to define cluster labels based on proximity. These will then be mapped, and the Top 20 will be mapped. In the Report, there is a discussion on the data findings specific to these labels.

VIII. Prospective Candidate Areas Selection

As viability is in many ways associated with proximity to competitors, particularly in new concept startups, we will calculate the distance between each of the Hardware Store Locations Vs the Prospective Zip Code List

In [360]:
```
import math
from math import *
#We will need to define a function to calculate distance using the Haversine m
ethematical formula


def get_dist(lata, lona, latb, lonb):
    # approximate radius of earth in km
    R = 6378.0

    lat1 = radians(abs(lata))
    lon1 = radians(abs(lona))
    lat2 = radians(abs(latb))
    lon2 = radians(abs(lonb))

    dlon = lon2 - lon1
    dlat = lat2 - lat1

    a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))

    output = R * c

    return output
```

In [361]:
```
print(get_dist(29.8672, -95.3294, 29.773994,-95.51771),'kilometers apart')
```

```
20.937919756853088 kilometers apart
```

In [362]:
```
merge_test.head()
```

Out[362]:

	ZIP	City	Latitude	Longitude	investment intensity	income intensity	Prospectivity Score
0	77494	Katy	29.760833	-95.81104	1464.140459	168710	6.634928
1	77024	Houston	29.773994	-95.51771	3104.037550	74780	6.203177
2	77479	Sugar Land	29.573345	-95.63213	1283.715325	143880	4.828698
3	77433	Cypress	29.884175	-95.72219	1089.357898	126820	3.479447
4	77007	Houston	29.772627	-95.40319	1414.952830	88290	3.096075

In [363]:
```
#Define a dataframe for calculating distances from Hardware Store Locations

#Number of stores is defined by the length of the FS_df (Foursquare data Dataf
rame)
numstore=len(FS_df)
print(numstore)
```

```
97
```

In [364]:
```
#This defines the additional dataframe columns based on the total number of re
turned venues
counter=0
while counter<=numstore:
    merge_test[counter+7]=""
    counter=counter+1
```

In [365]:
```
merge_test.head()
```

Out[365]:

	ZIP	City	Latitude	Longitude	investment intensity	income intensity	Prospectivity Score	7	8	9	10	11	12
0	77494	Katy	29.760833	-95.81104	1464.140459	168710	6.634928						
1	77024	Houston	29.773994	-95.51771	3104.037550	74780	6.203177						
2	77479	Sugar Land	29.573345	-95.63213	1283.715325	143880	4.828698						
3	77433	Cypress	29.884175	-95.72219	1089.357898	126820	3.479447						
4	77007	Houston	29.772627	-95.40319	1414.952830	88290	3.096075						

Note that the following loop iterates the calls to the long/lat distance function defined above. This is calculated for 96 stores across more than 200 zip codes, requiring approximately 19,200 function calls. This process takes 43 minutes to complete. The results are saved in an Excel file made available on Github and re-imported as an Excel file into a DataFrame.

In [366]:
```
#colcounter=0
#rowcounter=0
#rowstore=0

#while rowstore<96:
    #while rowcounter<199:
        #merge_test[colcounter+7][rowcounter]=get_dist(merge_test['Latitude']
[rowcounter],merge_test['Longitude'][rowcounter],FS_df['Latitude'][rowstore],F
S_df['Longitude'][rowstore])
        #rowcounter=rowcounter+1
   # rowstore=rowstore+1
    #colcounter=colcounter+1
    #rowcounter=0
```

In [367]:
```
#merge_test.to_excel('Distances.xls')
```

In [368]:
```
#Get the Distances File with Calculated Values from Github Link (refer to note
above)

url4='https://github.com/Empcoth/Coursera_Capstone/raw/master/Distances.xls'
ditimport=wget.download(url4,'Distances.xls')
```

In [369]:
```
dist_import_df=pd.read_excel(ditimport, index_col=None, header=None)
```

In [370]:
```
dist_import_df.drop([0, 0],inplace=True)
dist_import_df.columns = dist_import_df. iloc[0]
```

In [371]:
```
dist_import_df.drop(dist_import_df.index[0],inplace=True)
```

In [372]:
```
dist_import_df.head()
```

Out[372]:

1	ZIP	City	Latitude	Longitude	Investment Intensity	Income Intensity	Prospectivity Score	Sum of Distances
2	77024	Houston	29.774	-95.5177	3104.04	74780	6.20318	2771.53
3	77479	Sugar Land	29.5733	-95.6321	1283.72	143880	4.8287	3960.68
4	77433	Cypress	29.8842	-95.7222	1089.36	126820	3.47945	3854.89
5	77007	Houston	29.7726	-95.4032	1414.95	88290	3.09607	2709.98
6	77459	Missouri City	29.5643	-95.5476	1053.37	110360	2.84459	3715.1

IX. K-Means Clustering Algorithm

In [373]:
```
#Install additional libraries
import matplotlib.pyplot as plt
%matplotlib inline
```

Pre-Processing

In [374]:
```
import pyproj
def xy_to_lonlat(x, y):
    proj_latlon = pyproj.Proj(proj='latlong',datum='WGS84')
    proj_xy = pyproj.Proj(proj="utm", zone=33, datum='WGS84')
    lonlat = pyproj.transform(proj_xy, proj_latlon, x, y)
    return lonlat[0], lonlat[1]
```

In [375]:
```
from sklearn.cluster import KMeans

number_of_clusters = 4

good_xys = dist_import_df[['Latitude', 'Longitude']].values
kmeans = KMeans(n_clusters=number_of_clusters, random_state=0).fit(good_xys)

cluster_centers = [xy_to_lonlat(cc[0], cc[1]) for cc in kmeans.cluster_centers
_]
```

In [376]:
```
labels=kmeans.labels_
```

In [377]:
```
labels
```

Out[377]:
```
array([2, 2, 2, 2, 2, 2, 3, 2, 1, 2, 1, 3, 2, 2, 2, 2, 1, 1, 2, 2, 2, 2,
       1, 2, 2, 2, 1, 1, 2, 2, 2, 2, 2, 3, 2, 1, 1, 1, 1, 0, 1, 2, 2, 2,
       2, 1, 3, 3, 2, 2, 2, 2, 2, 1, 3, 3, 2, 2, 1, 2, 1, 1, 1, 3, 1, 3,
       3, 1, 3, 3, 2, 2, 2, 1, 3, 2, 0, 3, 2, 2, 3, 3, 3, 2, 1, 1, 0, 1,
       3, 2, 2, 2, 1, 3, 2, 3, 2, 1, 0, 2, 2, 2, 3, 1, 1, 2, 2, 2, 2, 3,
       1, 3, 2, 1, 3, 2, 2, 3, 3, 3, 3, 2, 1, 3, 2, 1, 2, 2, 2, 1, 3, 0,
       2, 2, 2, 2, 2, 2, 3, 2, 2, 2, 3, 3, 3, 1, 1, 2, 1, 0, 3, 3, 3, 1,
       2, 2, 3, 3, 1, 2, 3, 3, 3, 0, 3, 1, 2, 3, 2, 3, 2, 0, 3, 3, 3, 3,
       3, 0, 2, 1, 3, 1, 2, 1, 3, 3, 3, 3, 1, 2, 3, 2, 3, 0, 2, 1, 3, 2,
       0], dtype=int32)
```

In [378]:
```
dist_import_df['Labels']=labels
```

In [379]:
```
dist_import_df.head()
```

Out[379]:

1	ZIP	City	Latitude	Longitude	Investment Intensity	Income Intensity	Prospectivity Score	Sum of Distances	Labels
2	77024	Houston	29.774	-95.5177	3104.04	74780	6.20318	2771.53	2
3	77479	Sugar Land	29.5733	-95.6321	1283.72	143880	4.8287	3960.68	2
4	77433	Cypress	29.8842	-95.7222	1089.36	126820	3.47945	3854.89	2
5	77007	Houston	29.7726	-95.4032	1414.95	88290	3.09607	2709.98	2
6	77459	Missouri City	29.5643	-95.5476	1053.37	110360	2.84459	3715.1	2

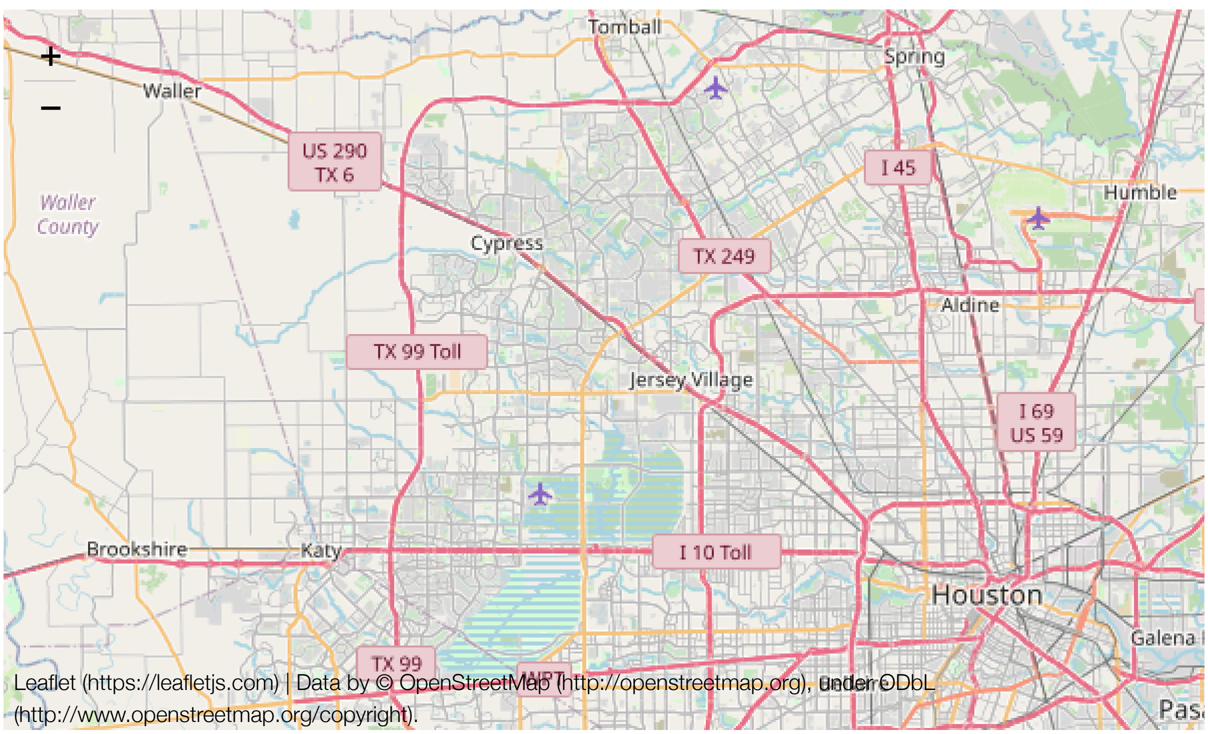
Now we will divide the dataframe into four separate datasets matching the cluster labels

In [380]:
```
#Define new Dataframe based on Cluster Labels
df_cluster0=dist_import_df[dist_import_df['Labels']==0]
df_cluster1=dist_import_df[dist_import_df['Labels']==1]
df_cluster2=dist_import_df[dist_import_df['Labels']==2]
df_cluster3=dist_import_df[dist_import_df['Labels']==3]
```

In [381]:
```
#Define Map objects

map_houston_cluster0 = folium.Map(location=[latitude, longitude], zoom_start=1
0)
map_houston_cluster1 = folium.Map(location=[latitude, longitude], zoom_start=1
0)
map_houston_cluster2 = folium.Map(location=[latitude, longitude], zoom_start=1
0)
map_houston_cluster3 = folium.Map(location=[latitude, longitude], zoom_start=1
0)

#We Can Map These Locations on the Houston Map

#add markers to map
for lat, lng, Zip, city in zip(df_cluster0['Latitude'],df_cluster0['Longitude'
],df_cluster0['ZIP'],df_cluster0['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_houston_cluster0)
```

In [382]:
```
map_houston_cluster0
```

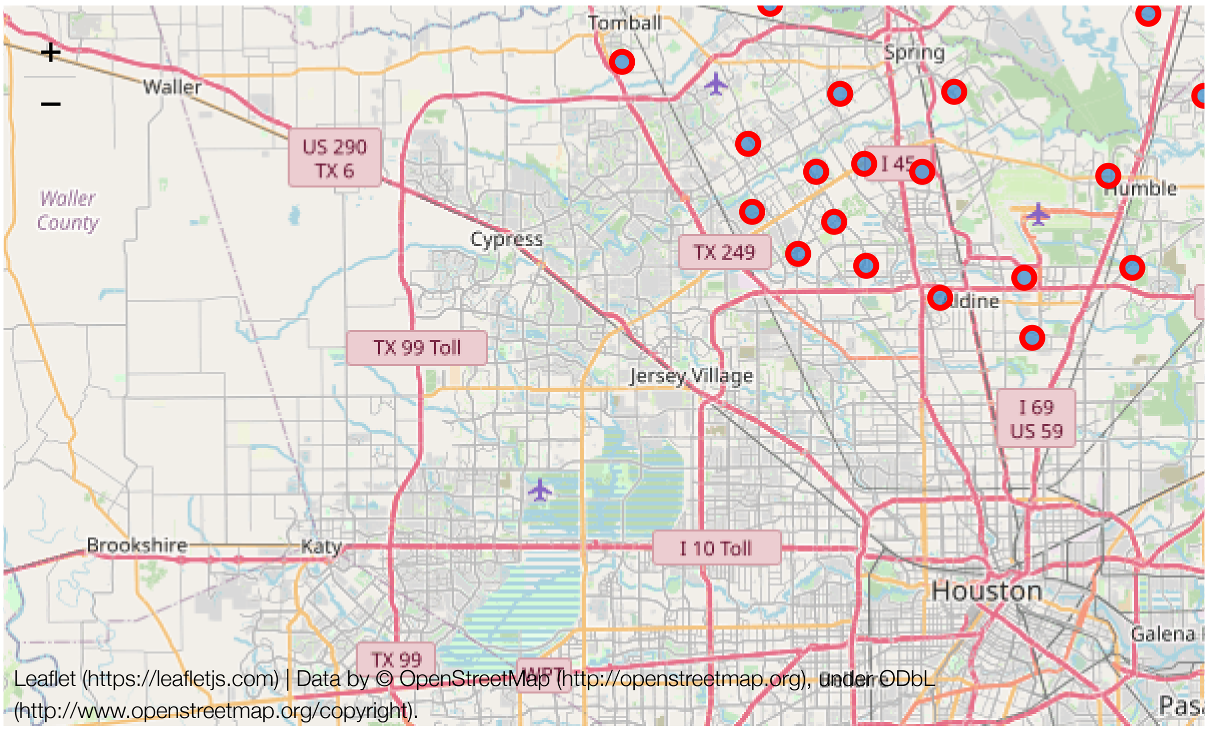
Out[382]:



In [383]:

```
#We Can Map These Locations on the Houston Map

#add markers to map
for lat, lng, Zip, city in zip(df_cluster1['Latitude'],df_cluster1['Longitude'
],df_cluster1['ZIP'],df_cluster1['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_houston_cluster1)
map_houston_cluster1
```

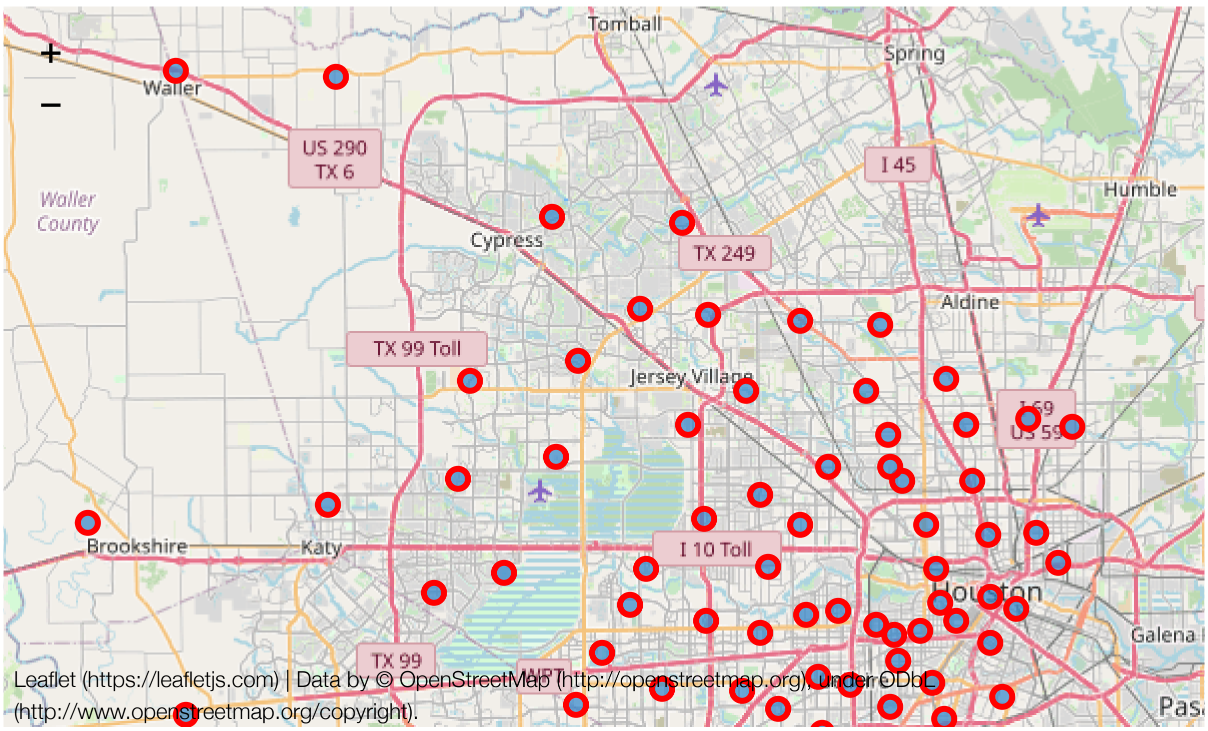
Out[383]:



In [384]:

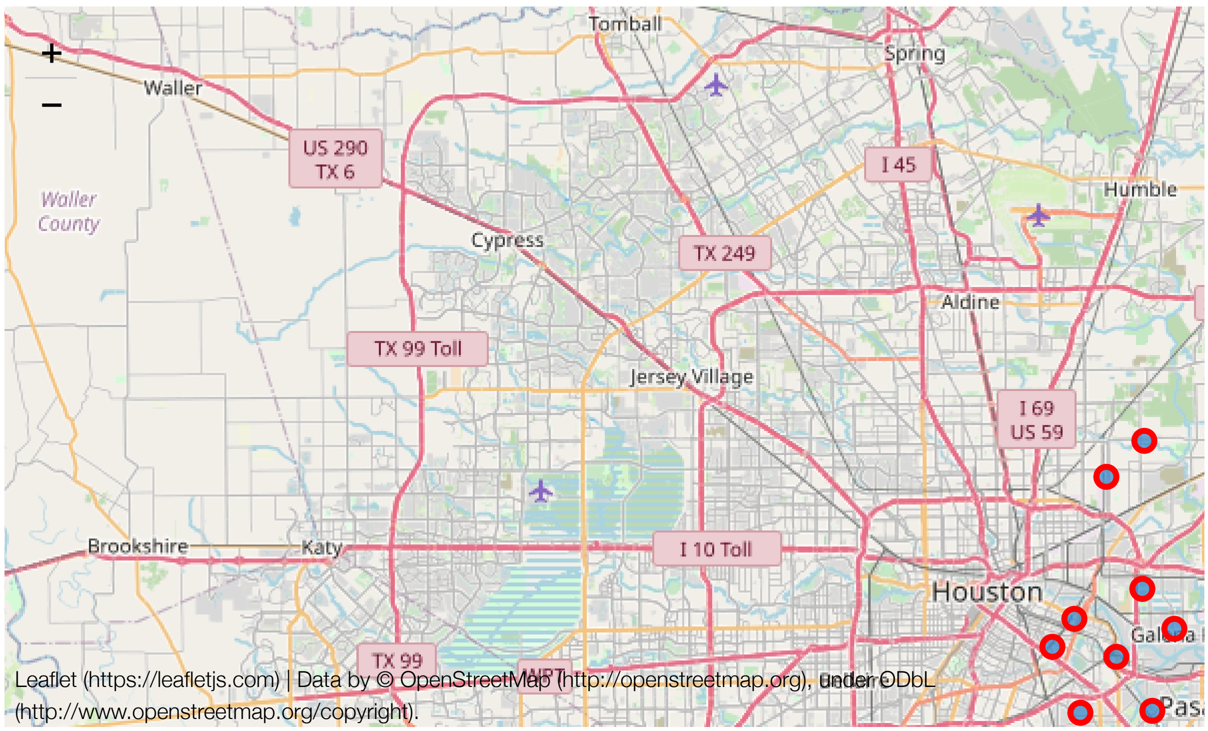
```
#add markers to map
for lat, lng, Zip, city in zip(df_cluster2['Latitude'],df_cluster2['Longitude'
],df_cluster2['ZIP'],df_cluster2['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_houston_cluster2)
map_houston_cluster2
```

Out[384]:



In [385]:
```
#add markers to map
for lat, lng, Zip, city in zip(df_cluster3['Latitude'],df_cluster3['Longitude'
],df_cluster3['ZIP'],df_cluster3['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_houston_cluster3)
map_houston_cluster3
```

Out[385]:



Now we will locate the best locations as a factor of the Prospectivity Score and the Sum of Distances from other Home Improvement stores

In [386]:
```
dist_import_df['Final Score']=dist_import_df['Prospectivity Score']*dist_impor
t_df['Sum of Distances']
```

In [387]:
```
df=dist_import_df
```

In [388]:
```
df.sort_values(by='Final Score', ascending=False)
df.reset_index(drop=True, inplace=True)
```

For a good sample of top prospects, let's take a top 20

In [389]:
```
df.head()
```

Out[389]:

1	ZIP	City	Latitude	Longitude	Investment Intensity	Income Intensity	Prospectivity Score	Sum of Distances	Labels	Fir Sco
0	77024	Houston	29.774	-95.5177	3104.04	74780	6.20318	2771.53	2	17192
1	77479	Sugar Land	29.5733	-95.6321	1283.72	143880	4.8287	3960.68	2	19124
2	77433	Cypress	29.8842	-95.7222	1089.36	126820	3.47945	3854.89	2	13412
3	77007	Houston	29.7726	-95.4032	1414.95	88290	3.09607	2709.98	2	8390
4	77459	Missouri City	29.5643	-95.5476	1053.37	110360	2.84459	3715.1	2	105(

In [390]:
```
df_top=df[df.index<20]
```

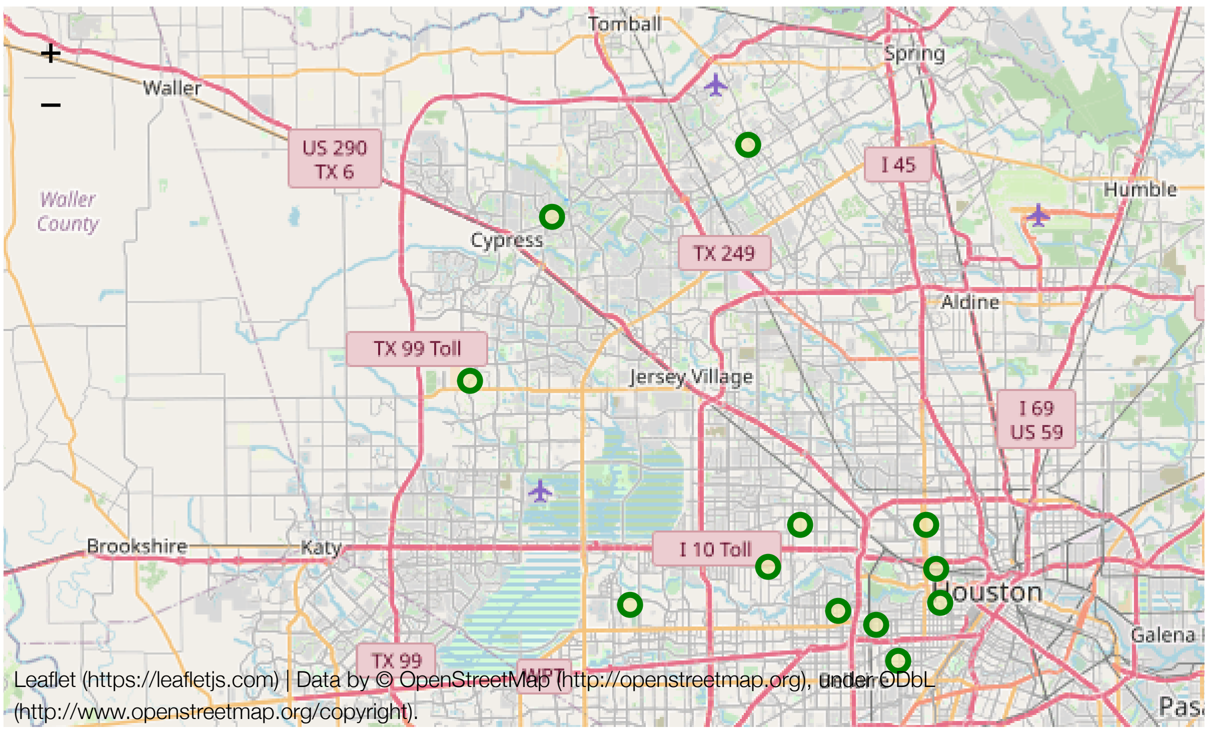
In [391]:
```
df_top
```

Out[391]:

1	ZIP	City	Latitude	Longitude	Investment Intensity	Income Intensity	Prospectivity Score	Sum of Distances	Labels	S
0	77024	Houston	29.774	-95.5177	3104.04	74780	6.20318	2771.53	2	171
1	77479	Sugar Land	29.5733	-95.6321	1283.72	143880	4.8287	3960.68	2	191
2	77433	Cypress	29.8842	-95.7222	1089.36	126820	3.47945	3854.89	2	134
3	77007	Houston	29.7726	-95.4032	1414.95	88290	3.09607	2709.98	2	83
4	77459	Missouri City	29.5643	-95.5476	1053.37	110360	2.84459	3715.1	2	1
5	77008	Houston	29.7988	-95.4095	1298.13	69340	2.08407	2695.13	2	561
6	77573	League City	29.5028	-95.0891	662.672	131500	2.00085	4759.28	3	952
7	77005	Houston	29.7175	-95.4282	1644.2	52810	1.99183	2784.67	2	554
8	77379	Spring	30.0247	-95.5322	670.549	115730	1.72436	3551.64	1	612
9	77429	Cypress	29.9827	-95.666	604.344	123870	1.64487	3854.03	2	633
10	77346	Humble	30.0019	-95.1696	805.103	88090	1.5307	4072.27	1	623
11	77584	Pearland	29.5437	-95.3404	556.37	124010	1.47487	3704.33	3	546
12	77056	Houston	29.7473	-95.4693	1411.95	47820	1.4321	2734.48	2	391
13	77019	Houston	29.7525	-95.3992	1338.49	48860	1.37061	2734.24	2	374
14	77055	Houston	29.7989	-95.4963	1266.87	50170	1.31728	2727.51	2	359
15	77406	Richmond	29.504	-95.9191	800.16	75730	1.23141	6139.18	2	755
16	77382	Spring	30.2147	-95.5321	949.881	59440	1.11155	5040.08	1	560
17	77386	Spring	30.1289	-95.419	659.7	80910	1.02214	4210.67	1	430
18	77077	Houston	29.7509	-95.6125	609.744	81250	0.910991	3145.19	2	286
19	77027	Houston	29.739	-95.4436	1217.47	37130	0.785273	2736.09	2	214

In [392]:
```
#Define Map objects

map_houston_top = folium.Map(location=[latitude, longitude], zoom_start=10)

#We Can Map These Locations on the Houston Map

#add markers to map
for lat, lng, Zip, city in zip(df_top['Latitude'],df_top['Longitude'],df_top[
'ZIP'],df_top['City']):
    label='{}, {}'.format(Zip, city)
    label=folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat,lng],
        radius=5,
        popup=label,
        color='green',
        fill=True,
        fill_color='#EEE8AA',
        fill_opacity=0.7,
        parse_html=False).add_to(map_houston_top)
map_houston_top
```

Out[392]:



In [ ]: