BaltimoreFinalVersion

June 9, 2020

1 Opening a fast food restaurant in Baltimore, MD

1.1 1. Introduction

1.1.1 1.1 Business Problem

The objective of this capstone project is to find the most suitable location for the entrepreneur to open a new fast food restaurant in Baltimore, MD. By using data science methods and unsupervised machine learning methods such as clustering, this project aims to provide solutions to answer the business question: In Baltimore, if an entrepreneur wants to open a fast food restaurant, where should he consider opening it?

1.1.2 1.2 Target Audience

The entrepreneur who wants to find the location to open a fast food restaurant in Baltimore

1.2 2. Data

1.2.1 2.1 Baltimore rent prices dataset

This dataset contains average rent prices for standard 1 bedroom apartment for each of 272 Baltimore neighborhoods. Unfortunately, I did not find the similar dataset for commercial real estate, however rent prices ratio among neighborhoods should be more or less similar for residential and commercial real estate. Rent price amount is one of the most important factors in terms of choosing the place for future restaurant. Thats why this variable will be included in the analysis

1.2.2 2.2 Baltimore crime dataset

Baltimore is very far from being a safe city. That is why this dataset will help to determine the safest neighborhoods as every entrepreneur wants to have his business located in a safe area

1.2.3 2.3 Baltimore population dataset

This dataset contains information about population of each of 272 Baltimore neighborhoods. I need this data to determine criminal level in each neighborhood, because absolute number of crimes per neighborhood does not represent safety level since in highly populated neighborhoods there is higher probability of happening more crimes. So, I will divide number of crimes by population to calculate number of crimes per person in Baltimore neighborhoods

1.2.4 2.4 Foursquare API

Foursquare API will allow to retrieve information about the number of popular spots in each neighborhood in Baltimore. This will be a good indication of foot traffic. Calling the Foursquare API returns a JSON file, which can be turned into a dataframe for analysis in python

1.3 3. Data Preparation

[1]:
```
#First, we need to import all dependencies
import numpy as np
import pandas as pd
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
import json # library to handle JSON files

!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim

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

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

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

!conda install -c conda-forge folium=0.5.0 --yes
import folium # map rendering library

print('Libraries imported.')
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /home/jupyterlab/conda/envs/python

  added / updated specs:
    - geopy


The following packages will be downloaded:

    package                    |            build
```

```
    ---------------------------|-----------------
    ca-certificates-2020.4.5.2 |       hecda079_0         147 KB  conda-forge
    certifi-2020.4.5.2         |   py36h9f0ad1d_0         152 KB  conda-forge
    geographiclib-1.50         |             py_0          34 KB  conda-forge
    geopy-1.22.0               |     pyh9f0ad1d_0          63 KB  conda-forge
    ------------------------------------------------------------
                                           Total:         395 KB

The following NEW packages will be INSTALLED:

  geographiclib      conda-forge/noarch::geographiclib-1.50-py_0
  geopy              conda-forge/noarch::geopy-1.22.0-pyh9f0ad1d_0

The following packages will be UPDATED:

  ca-certificates                     2020.4.5.1-hecc5488_0 -->
2020.4.5.2-hecda079_0
  certifi                         2020.4.5.1-py36h9f0ad1d_0 -->
2020.4.5.2-py36h9f0ad1d_0



Downloading and Extracting Packages
geopy-1.22.0         | 63 KB     | ##################################### | 100%
certifi-2020.4.5.2   | 152 KB    | ##################################### | 100%
ca-certificates-2020 | 147 KB    | ##################################### | 100%
geographiclib-1.50   | 34 KB     | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Collecting package metadata (current_repodata.json): done
Solving environment: failed with initial frozen solve. Retrying with flexible
solve.
Collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /home/jupyterlab/conda/envs/python

  added / updated specs:
    - folium=0.5.0


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
```

```
    altair-4.1.0               |            py_1         614 KB  conda-forge
    branca-0.4.1               |            py_0          26 KB  conda-forge
    brotlipy-0.7.0             |py36h8c4c3a4_1000         346 KB  conda-forge
    chardet-3.0.4              |py36h9f0ad1d_1006         188 KB  conda-forge
    cryptography-2.9.2         |   py36h45558ae_0         613 KB  conda-forge
    folium-0.5.0               |            py_0          45 KB  conda-forge
    pandas-1.0.4               |   py36h830a2c2_0        10.1 MB  conda-forge
    pysocks-1.7.1              |   py36h9f0ad1d_1          27 KB  conda-forge
    toolz-0.10.0               |            py_0          46 KB  conda-forge
    vincent-0.4.4              |            py_1          28 KB  conda-forge
    ------------------------------------------------------------
                                           Total:        12.0 MB

The following NEW packages will be INSTALLED:

  altair             conda-forge/noarch::altair-4.1.0-py_1
  attrs              conda-forge/noarch::attrs-19.3.0-py_0
  branca             conda-forge/noarch::branca-0.4.1-py_0
  brotlipy           conda-forge/linux-64::brotlipy-0.7.0-py36h8c4c3a4_1000
  chardet            conda-forge/linux-64::chardet-3.0.4-py36h9f0ad1d_1006
  cryptography       conda-forge/linux-64::cryptography-2.9.2-py36h45558ae_0
  entrypoints        conda-forge/linux-64::entrypoints-0.3-py36h9f0ad1d_1001
  folium             conda-forge/noarch::folium-0.5.0-py_0
  idna               conda-forge/noarch::idna-2.9-py_1
  importlib_metadata conda-forge/noarch::importlib_metadata-1.6.0-0
  jinja2             conda-forge/noarch::jinja2-2.11.2-pyh9f0ad1d_0
  jsonschema         conda-forge/linux-64::jsonschema-3.2.0-py36h9f0ad1d_1
  markupsafe         conda-forge/linux-64::markupsafe-1.1.1-py36h8c4c3a4_1
  pandas             conda-forge/linux-64::pandas-1.0.4-py36h830a2c2_0
  pyopenssl          conda-forge/noarch::pyopenssl-19.1.0-py_1
  pyrsistent         conda-forge/linux-64::pyrsistent-0.16.0-py36h8c4c3a4_0
  pysocks            conda-forge/linux-64::pysocks-1.7.1-py36h9f0ad1d_1
  pytz               conda-forge/noarch::pytz-2020.1-pyh9f0ad1d_0
  requests           conda-forge/noarch::requests-2.23.0-pyh8c360ce_2
  toolz              conda-forge/noarch::toolz-0.10.0-py_0
  urllib3            conda-forge/noarch::urllib3-1.25.9-py_0
  vincent            conda-forge/noarch::vincent-0.4.4-py_1


Downloading and Extracting Packages
pysocks-1.7.1        | 27 KB     | ##################################### | 100%
toolz-0.10.0         | 46 KB     | ##################################### | 100%
chardet-3.0.4        | 188 KB    | ##################################### | 100%
pandas-1.0.4         | 10.1 MB   | ##################################### | 100%
folium-0.5.0         | 45 KB     | ##################################### | 100%
branca-0.4.1         | 26 KB     | ##################################### | 100%
cryptography-2.9.2   | 613 KB    | ##################################### | 100%
```

```
brotlipy-0.7.0       | 346 KB    | ##################################### | 100%
altair-4.1.0         | 614 KB    | ##################################### | 100%
vincent-0.4.4        | 28 KB     | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Libraries imported.
```

1.3.1 Crimes dataset

[2]:
```python
#read crimes dataset
df_crimes = pd.read_csv('https://data.baltimorecity.gov/api/views/wsfq-mvij/
↪rows.csv?accessType=DOWNLOAD')
df_crimes.head()
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/IPython/core/interactiveshell.py:3063: DtypeWarning: Columns (7) have
mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

[2]:
```
    CrimeDate CrimeTime CrimeCode                   Location     Description  \
0  05/30/2020  18:18:00        4E            1200 MCCULLOH ST  COMMON ASSAULT
1  05/30/2020  18:35:00        5A  1000 N PATTERSON PARK AVE        BURGLARY
2  05/30/2020  17:50:00        4E          4800 GWYNN OAK AVE  COMMON ASSAULT
3  05/30/2020  02:14:00        4E           3000 GRANTLEY AVE  COMMON ASSAULT
4  05/30/2020  16:20:00        6J     YORK RD & MONTPELIER ST         LARCENY

  Inside/Outside Weapon Post   District      Neighborhood  Longitude  \
0              I    NaN  123    CENTRAL             UPTON -76.627035
1              I    NaN  322    EASTERN       MIDDLE EAST -76.585380
2              I    NaN  622  NORTHWEST       HOWARD PARK -76.697653
3              I    NaN  613  NORTHWEST  TOWANDA-GRANTLEY -76.669235
4              O    NaN  513   NORTHERN               NaN -76.608855

    Latitude  Location 1            Premise  vri_name1  Total Incidents
0  39.301886         NaN  ROW/TOWNHOUSE-OCC        NaN                1
1  39.301852         NaN  ROW/TOWNHOUSE-OCC  Eastern 2                1
2  39.330594         NaN  ROW/TOWNHOUSE-OCC        NaN                1
3  39.336714         NaN  ROW/TOWNHOUSE-OCC        NaN                1
4  39.326454         NaN             STREET        NaN                1
```

[3]:
```python
#we need only 2 columns
df_crimes=df_crimes[['CrimeDate','Neighborhood']]
```

[4]:
```python
print(df_crimes.dtypes)
```

```
CrimeDate       object
Neighborhood    object
```

```
dtype: object
```

[5]:
```
#CrimeDate is an object. We need to convert it to datetime
df_crimes['CrimeDate'] = df_crimes['CrimeDate'].astype('datetime64[ns]')
```

[6]:
```
#We need only current crime situation. Lets keep only last 3 years data
df_crimes = df_crimes.loc[df_crimes['CrimeDate'] > '2017-01-01']
```

[7]:
```
#time to drop null values
df_crimes = df_crimes.dropna()
df_crimes.shape
```

[7]:
```
(155562, 2)
```

[8]:
```
#Lets count crimes by neighborhoods
df_crimes_grouped = df_crimes.groupby('Neighborhood',as_index = False).count()
df_crimes_grouped.head()
```

[8]:

	Neighborhood	CrimeDate
0	4X4	318
1	ABELL	368
2	ALLENDALE	969
3	ARCADIA	161
4	ARLINGTON	692

1.3.2 Population and coordinates dataset

[9]:
```
df_population = pd.read_csv('https://query.data.world/s/
↪d2f7awf7nlopf4afgl3el47ghm6dv7') #read dataset
df_population = df_population[['Name','Population','the_geom']] #we need only 3␣
↪columns
df_population['Name'] = df_population['Name'].str.upper() #make neighborhoods␣
↪names uppercase to merge with crimes dataset
df_population.rename(columns={'Name': 'Neighborhood'}, inplace = True) #rename␣
↪neighborhood names columm
df_population.head()
```

[9]:

	Neighborhood	Population	the_geom
0	ABELL	889.0	MULTIPOLYGON (((-76.61113021264933 39.32343829…
1	ALLENDALE	3554.0	MULTIPOLYGON (((-76.67262514014695 39.29183630…
2	ARCADIA	1235.0	MULTIPOLYGON (((-76.56852496130239 39.33594331…
3	BOYD-BOOTH	822.0	MULTIPOLYGON (((-76.65153098537668 39.28642992…
4	ARLINGTON	2598.0	MULTIPOLYGON (((-76.68626338505344 39.34790493…

[10]:
```
#time to merge two datasets
df_merged=pd.
↪merge(df_crimes_grouped,df_population,how="outer",on="Neighborhood")
```

```
df_merged=df_merged.dropna()  #drop NA values
df_merged.head()
```

[10]:

```
         Neighborhood  CrimeDate  Population  \
1               ABELL      368.0       889.0
2           ALLENDALE      969.0      3554.0
3             ARCADIA      161.0      1235.0
4           ARLINGTON      692.0      2598.0
5    ARMISTEAD GARDENS      582.0      3458.0

                                            the_geom
1  MULTIPOLYGON (((-76.61113021264933 39.32343829…
2  MULTIPOLYGON (((-76.67262514014695 39.29183630…
3  MULTIPOLYGON (((-76.56852496130239 39.33594331…
4  MULTIPOLYGON (((-76.68626338505344 39.34790493…
5  MULTIPOLYGON (((-76.55879992777896 39.30645665…
```

1.3.3 Cleaning and preparing merged dataset

[11]:

```
df_merged = df_merged[(df_merged != 0).all(1)] #drop zero values
df_merged = df_merged[df_merged['Population'] > 499] #we are not interested in␣
↪neighborhoods with less than 500 tenants
#Crimes per population shows safety level of a neighborhood better than just␣
↪number of crimes
df_merged['Crimes per 1 person'] = df_merged['CrimeDate'] /␣
↪df_merged['Population']
df_merged = df_merged.sort_values(by= ['Crimes per 1 person'], ascending =␣
↪False)
df_merged.rename(columns={'the_geom': 'Coordinates'}, inplace = True)
#Making new columns Latitude and Longitude out of initial coordinates column
df_merged['Coordinates'] = df_merged['Coordinates'].map(lambda x: x.
↪lstrip('MULTIPOLYGON ((('))
df_merged['Coordinates'] = df_merged['Coordinates'].str[:35]
df_merged[['Longitude','Latitude']] = df_merged['Coordinates'].str.split(' ',␣
↪expand=True)
```

[12]:

```
#drop unneeded columns
df_merged = df_merged[['Neighborhood','Population','Crimes per 1␣
↪person','Latitude','Longitude']]
df_merged.head()
```

[12]:

```
          Neighborhood  Population  Crimes per 1 person          Latitude  \
122       INNER HARBOR      1484.0             1.580863   39.2843612174191
66            DOWNTOWN      4448.0             1.218525   39.2894922456335
157        MIDDLE EAST      1484.0             1.042453  39.29872242913879
45       CHARLES NORTH      1059.0             0.891407   39.3142726593081
```

```
207  REISTERSTOWN STATION      1968.0             0.634654   39.3512380859961

                 Longitude
122  -76.61332268206179
66   -76.60549025746245
157   -76.5851275142668
45   -76.61571455479564
207  -76.70885511420639
```

1.3.4 Baltimore rent prices dataset

[13]:
```
df_rent = pd.read_excel("Rent Prices.xlsx") #read Baltimore rent prices dataset
df_rent.head()
```

[13]:
```
        Neighborhood  price
0              Abell   1445
1          Allendale    956
2            Arcadia    916
3          Arlington   1001
4   Armistead Gardens   1428
```

[14]:
```
#small dataset preparations before merging
df_rent['price'] = df_rent['price'].astype('int')
df_rent['Neighborhood'] = df_rent['Neighborhood'].str.upper()
df_rent.rename(columns={'price': 'Rent Price'}, inplace = True)
df_rent.head()
```

[14]:
```
        Neighborhood  Rent Price
0              ABELL        1445
1          ALLENDALE         956
2            ARCADIA         916
3          ARLINGTON        1001
4   ARMISTEAD GARDENS        1428
```

[15]:
```
#Adding Baltimore rent prices dataset to the main dataset
df_supermerged=pd.merge(df_merged,df_rent,how="outer",on="Neighborhood")
df_supermerged['Latitude'] = df_supermerged['Latitude'].str[:14]
df_supermerged = df_supermerged.dropna()
```

[16]:
```
#Changing coordinate columns type from string to float
df_supermerged['Latitude'] = df_supermerged['Latitude'].astype(float)
df_supermerged['Longitude'] = df_supermerged['Longitude'].astype(float)
df_supermerged.head()
```

[16]:
```
          Neighborhood  Population  Crimes per 1 person   Latitude  \
0         INNER HARBOR      1484.0             1.580863  39.284361
1             DOWNTOWN      4448.0             1.218525  39.289492
```

```
2           MIDDLE EAST      1484.0             1.042453  39.298722
3          CHARLES NORTH     1059.0             0.891407  39.314273
4   REISTERSTOWN STATION     1968.0             0.634654  39.351238

   Longitude  Rent Price
0 -76.613323      1792.0
1 -76.605490      1582.0
2 -76.585128      1408.0
3 -76.615715      1551.0
4 -76.708855      1001.0
```

1.4 4. Methodology / Modelling

My initial plan was to 1. Use Foursquare API to get the information about number of venues per neighborhood 2. Use k-means clustering to cluster neighborhoods in purpose to get cluster with low rent prices and crimes per person and high number of venues, that is evidence of high foot traffic of neighborhood.

Unfortunately, Foursquare API doesnt work properly and is not able to get data for almost 200 neighborhoods without errors. Thats why I decided 1.to cluster my current dataset to choose the most suitable cluster 2. Use Foursquare API for chosen cluster only 3. Finally, select from this cluster a few neighborhoods with a lot of venues around

So, its time for K-means clustering. However, firstly we need to normalize values and define the right K - number of clusters

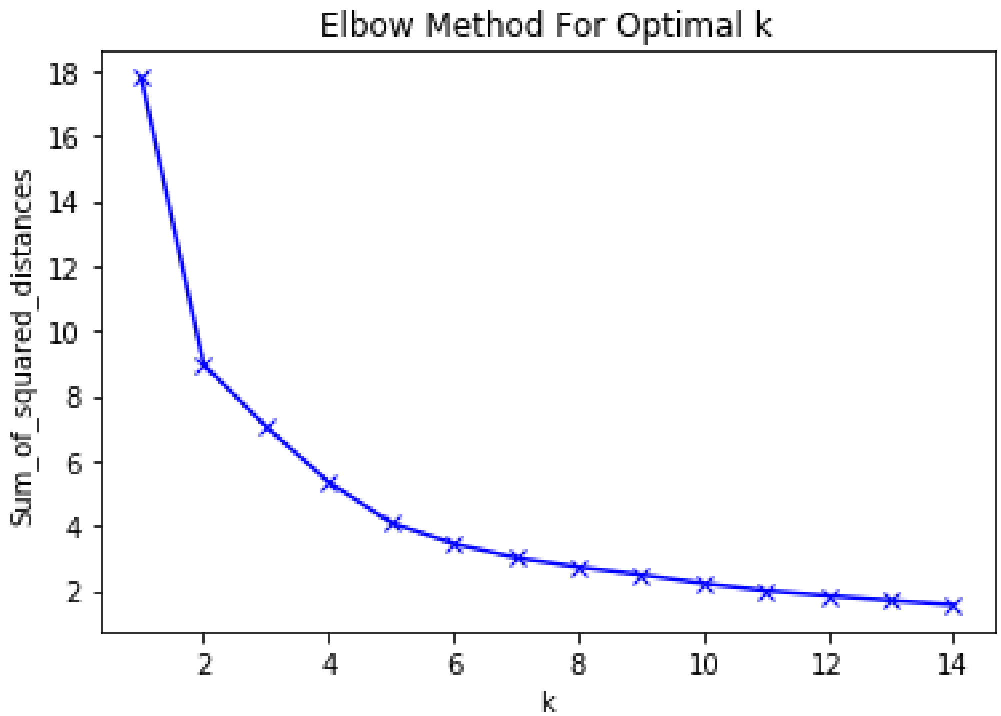
[17]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
```

[18]:
```
#Using MinMaxScaler to normalize values in different columns
df_clustering = df_supermerged.drop(['Neighborhood','Latitude','Longitude'], 1)
mms = MinMaxScaler()
mms.fit(df_clustering)
data_transformed = mms.transform(df_clustering)
```

[19]:
```
#Defining the right value for K - number of clusters. We are using Elbow Method
Sum_of_squared_distances = []
K = range(1,15)
for k in K:
    km = KMeans(n_clusters=k)
    km = km.fit(data_transformed)
    Sum_of_squared_distances.append(km.inertia_)
```

[20]:
```
#PLot elbow method graph
plt.plot(K, Sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum_of_squared_distances')
```

```
plt.title('Elbow Method For Optimal k')
plt.show()
```



[21]:
```
# Elbow method suggests to use 2 clusters, but im afraid that Foursquare API␣
↪will not be able to work with such big clusters. So, lets set K=3
kclusters = 3
```

[22]:
```
# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(data_transformed)

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

[22]:
```
array([2, 2, 2, 2, 1, 1, 2, 1, 2, 2], dtype=int32)
```

[23]:
```
df_supermerged.insert(0, 'Cluster Labels', kmeans.labels_)
df_supermerged.head()
```

[23]:

	Cluster Labels	Neighborhood	Population	Crimes per 1 person	\
0	2	INNER HARBOR	1484.0	1.580863	
1	2	DOWNTOWN	4448.0	1.218525	
2	2	MIDDLE EAST	1484.0	1.042453	
3	2	CHARLES NORTH	1059.0	0.891407	

```
4                1  REISTERSTOWN STATION      1968.0             0.634654

    Latitude  Longitude  Rent Price
0  39.284361 -76.613323      1792.0
1  39.289492 -76.605490      1582.0
2  39.298722 -76.585128      1408.0
3  39.314273 -76.615715      1551.0
4  39.351238 -76.708855      1001.0
```

Mapping clusters

[24]:
```python
#First we need to get Baltimore coordinates
address = 'Baltimore, MD'

geolocator = Nominatim(user_agent="baltimore_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Baltimore  are {}, {}.'.format(latitude,␣
 ↪longitude))

# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

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

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(df_supermerged['Latitude'],␣
 ↪df_supermerged['Longitude'], df_supermerged['Neighborhood'],␣
 ↪df_supermerged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

```
The geographical coordinate of Baltimore  are 39.2908816, -76.610759.
```

[24]:
```
<folium.folium.Map at 0x7f9fbeca9a90>
```

[25]:
```python
#Making the datasets of each cluster
cluster_0 = df_supermerged.loc[df_supermerged['Cluster Labels'] == 0,␣
↪df_supermerged.columns[[1,2,3,4,5] + list(range(6, df_supermerged.
↪shape[1]))]]
cluster_1 = df_supermerged.loc[df_supermerged['Cluster Labels'] == 1,␣
↪df_supermerged.columns[[1,2,3,4,5] + list(range(6, df_supermerged.
↪shape[1]))]]
cluster_2 = df_supermerged.loc[df_supermerged['Cluster Labels'] == 2,␣
↪df_supermerged.columns[[1,2,3,4,5] + list(range(6, df_supermerged.
↪shape[1]))]]
```

[26]:
```python
cluster_0.describe()
# big population, low criminal level, low rent price. Just what we need!
```

[26]:

	Population	Crimes per 1 person	Latitude	Longitude	Rent Price
count	22.000000	22.000000	22.000000	22.000000	22.000000
mean	7790.909091	0.183235	39.328702	-76.625446	1209.000000
std	3581.558864	0.084477	0.035886	0.055042	215.651836
min	4219.000000	0.048281	39.234504	-76.709871	860.000000
25%	5471.500000	0.121359	39.311495	-76.664780	1080.000000
50%	6563.000000	0.200475	39.335068	-76.626312	1228.000000
75%	8492.250000	0.233515	39.355447	-76.589351	1303.500000
max	17694.000000	0.339715	39.371964	-76.529975	1720.000000

[27]:
```python
cluster_1.describe()
# Small population, low criminal level, very low rent price.
# Looks like this cluster is suburbs, map proves it. Definetely, not the best␣
↪neighborhoods to open restaurant
```

[27]:

	Population	Crimes per 1 person	Latitude	Longitude	Rent Price
count	100.000000	100.000000	100.000000	100.000000	100.000000
mean	1957.826457	0.220191	39.322920	-76.642646	1042.110000
std	1041.812374	0.110125	0.029341	0.048646	115.289963
min	562.325500	0.021340	39.223828	-76.711206	850.000000
25%	1171.000000	0.147955	39.300160	-76.680856	956.000000
50%	1783.500000	0.202491	39.325201	-76.658645	1001.000000
75%	2617.500000	0.271709	39.347583	-76.607069	1080.000000
max	4974.000000	0.634654	39.372000	-76.529691	1325.000000

[28]:
```python
cluster_2.describe()
# Small population, relatively high criminal level, high rent price.
# The worst choice in terms of opening a restaurant
```

[28]:

	Population	Crimes per 1 person	Latitude	Longitude	Rent Price
count	55.000000	55.000000	55.000000	55.000000	55.000000
mean	2188.654545	0.333739	39.302328	-76.603164	1629.290909
std	1286.399069	0.281875	0.025130	0.026491	207.716480
min	576.000000	0.033695	39.253584	-76.655543	1359.000000
25%	1245.000000	0.170480	39.286935	-76.619326	1445.000000
50%	1823.000000	0.273752	39.297023	-76.609417	1582.000000
75%	2989.500000	0.412277	39.318855	-76.589541	1738.000000
max	5671.000000	1.580863	39.371998	-76.529808	2063.000000

1.4.1 Foursquare API to understand foot traffic in the neighborhoods

[29]:
```
#Define foursquare credentials and version
CLIENT_ID = 'MTBEPPARHYKOB1AEQOHT3LM1PCQK2TATB430OZZ5502NZ3YH' # my Foursquare␣
↪ID
CLIENT_SECRET = 'Q1ASXWOQJYGAFL230KLUZFM4EJTIVCV4JYVEEYODGOZA3R5H' # my␣
↪Foursquare Secret
VERSION = '20180605' # Foursquare API version
```

[30]:
```
#let's get for all neighborhoods the top 100 venues within a radius of 500␣
↪meters.¶
def getNearbyVenues(names, latitudes, longitudes, radius=500):

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

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

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

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
```

```
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

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

    return(nearby_venues)
limit=100
```

[31]:

```
#getting list of venues for each neighborhood
baltimore_venues = getNearbyVenues(names=cluster_0['Neighborhood'],
                                   latitudes=cluster_0['Latitude'],
                                   longitudes=cluster_0['Longitude'])
```

```
UPTON
BROOKLYN
BROADWAY EAST
SANDTOWN-WINCHESTER
CHERRY HILL
CENTRAL PARK HEIGHTS
FRANKFORD
RESERVOIR HILL
BELAIR-EDISON
HAMPDEN
CANTON
CHARLES VILLAGE
HOWARD PARK
NEW NORTHWOOD
WALTHERSON
LOCH RAVEN
GLEN
FALLSTAFF
ROLAND PARK
NORTH HARFORD ROAD
CROSS COUNTRY
CHESWOLDE
```

[32]:
```
print(baltimore_venues.shape)
baltimore_venues.head()
```

```
(234, 7)
```

[32]:
```
  Neighborhood  Neighborhood Latitude  Neighborhood Longitude  \
0        UPTON              39.300173              -76.624831
1        UPTON              39.300173              -76.624831
2        UPTON              39.300173              -76.624831
3        UPTON              39.300173              -76.624831
4        UPTON              39.300173              -76.624831

                                                Venue  Venue Latitude  \
0                                        Land of Kush       39.300180
1  Eubie Blake National Jazz Institute And Cultur…      39.299596
2                                        The Bun Shop       39.300658
3                                         Linden Deli       39.301302
4                              Hip Hop Fish & Chicken       39.300345

   Venue Longitude                Venue Category
0       -76.621671  Vegetarian / Vegan Restaurant
1       -76.619939                History Museum
2       -76.619488                        Bakery
3       -76.620002                  Deli / Bodega
4       -76.621890              Fish & Chips Shop
```

[33]:
```
#Choosing neighborhoods with a lot of venues
baltimore_venues.groupby('Neighborhood').count()
df = baltimore_venues.groupby('Neighborhood').filter(lambda x : len(x)>20)
df.iloc[:, 0]
```

[33]:
```
Neighborhood
CANTON             34
CHARLES VILLAGE    30
GLEN               30
HAMPDEN            30
Name: Neighborhood Latitude, dtype: int64
```

[34]:
```
#Selected_Neighborhoods is a final dataset.
#It shows the best neighborhoods to open restaurant
Selected_Neighborhoods = cluster_0.loc[(cluster_0['Neighborhood']=='CANTON') |␣
 ↪(cluster_0['Neighborhood']=='CHARLES VILLAGE') |␣
 ↪(cluster_0['Neighborhood']=='GLEN') | (cluster_0['Neighborhood']=='HAMPDEN')]
Selected_Neighborhoods
```

[34]:
```
        Neighborhood  Population  Crimes per 1 person   Latitude  Longitude  \
99           HAMPDEN      6963.0             0.202786  39.327068 -76.627793
```

```
102          CANTON     12192.0              0.201198  39.286136 -76.580042
104  CHARLES VILLAGE     8906.0              0.199753  39.317899 -76.615389
155             GLEN     7876.0              0.120112  39.356230 -76.702458

     Rent Price
99       1306.0
102      1720.0
104      1445.0
155      1001.0
```

1.5 Results

I have pulled data on population, rent prices and crime rates for every neighborhood in Baltimore and used this information to narrow down our neighborhood options to 1 cluster of 22 neighborhoods. Then I used Foursquare API for these 22 neighborhoods and retrieved number of popular venues in every neighborhood. It allowed me to select 4 neighborhoods with the highest foot traffic.

[47]:
```
map_baltimore = folium.Map(location=[latitude, longitude], zoom_start=10)

for lat, lng, neighborhood in zip(Selected_Neighborhoods['Latitude'],␣
 ↪Selected_Neighborhoods['Longitude'], Selected_Neighborhoods['Neighborhood']):
    label = '{}'.format(neighborhood)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_baltimore)

map_baltimore
```

[47]: <folium.folium.Map at 0x7f9fba1ad748>

[48]:
```
df = df.reset_index()
df = df[['Neighborhood','Venue']]
Results = pd.merge(Selected_Neighborhoods,df,how="outer",on="Neighborhood")
Results = Results[['Neighborhood','Population','Crimes per 1 person','Rent␣
 ↪Price','Venue']]
Results.rename(columns={'Venue': 'Venues'}, inplace = True)
Results
```

[48]:

	Neighborhood	Population	Crimes per 1 person	Rent Price	Venues
0	HAMPDEN	6963.0	0.202786	1306.0	30

1	CANTON	12192.0	0.201198	1720.0	34
2	CHARLES VILLAGE	8906.0	0.199753	1445.0	30
3	GLEN	7876.0	0.120112	1001.0	30

Let's now analyze 4 retrieved neighborhoods: Hampden, Canton, Charles Village and Glen. First of all, each neighborhood is densely populated and safe compared to other Baltimore neighborhoods (average Baltimore neighborhood population - 2755, average crimes per person - 0,25). In terms of foot traffic these 4 neighborhoods are also one of the best (only 17 out of 270 have more than 34 popular venues). Rent prices significantly differs between 4 neighborhoods (from 1001 to 1720. Anyway its much lower than maximum of 2063). So, I can conclude that each of 4 selected neighborhoods could be a very good location to open a restaurant.

GLEN Extremely low rent price and safety level, but located in Baltimore suburbs. Perfect place to open cheap fast food restaurant with small budget.

HAMPDEN and CHARLES VILLAGE Good safety level and medium rent prices. Located relatively close to city center. Very well-balanced choices in terms of opening a fast food restaurant.

CANTON The most populated neighborhood and located in the city center near the biggest city park! It's fair that rent price is higher than average. Canton is a perfect location to open a restaurant, if an entrepreneur can afford a rent

Ultimately, the optimal spot depends on what type of restaurant you would like to open.

1.6 Discussion

A major drawback of this analysis is that the clustering was completely based on Foursquare' s data for popular venues. There are plenty other ways to assess popularity of neighborhoods and the spots inside them, venue popularity is just one of them. It may also be helpful to look exclusively at cafes and restaurants in an area, how many there are, and how popular they are on weekdays and weekends.

1.7 Conclusion

Finally, we have executed an end-to-end data science project using common python libraries to manipulate datasets, Foursquare API to explore the neighborhoods of Baltimore, Folium leaflet map and unsupervised machine learning algorithm K-means with elbow method to cluster and segment neighborhoods. Thanks for reading!