The Battle of Neighborhoods

Capstone Project Presentation

IBM Data Science Professional Certificate - Applied Data Science Capstone

Introduction

In an average month in the UK, around 100,000 households will move into a new home. In January 2017, more people moved than any month since March the previous year. Each year, approximately 4-5% of the population will move to a different city or county in the UK. London has the most movements as it is increasing in population density. On a yearly basis, nearly 200,000 people move from elsewhere in the UK to live in London, while only 25,000 move the opposite way.

So, this raising lots of questions: What is the most factor influences people to move? Is it safety, desire, Work location, the neighborhood itself or something else?

The crime statistics dataset of London found on Kaggle has crimes in each Boroughs of London from 2008 to 2016. The year 2016 being the latest we will be considering the data of that year which is actually old information as of now. The crime rates in each borough may have changed over time.

This project aims to select the safest borough in London based on the total crimes, explore the neighborhoods of that borough to find the 10 most common venues in each neighborhood and finally cluster the neighborhoods using k-mean clustering.

Expats who are considering to relocate to London will be interested to identify the safest borough in London and explore its neighborhoods and common venues around each neighborhood.

Data Acquisition and Cleansing

Data collected from three sources:

1. The first data source is London crime report displaying total crime per borough in London;
2. The second data source is scraped from a Wikipedia website by using Beautiful Soup library in python;
3. The third data source is a list of Neighborhoods in the Royal Borough of Kingston upon Thames, found on Wikipedia.

Cleansing data:

With the libraries are in place data has been manipulated and transformed and ready to be used for visualization

```
import requests # library to handle requests
import pandas as pd # library for data analsysis
import numpy as np # library to handle data in a vectorized manner
import random # library for random number generation
from bs4 import BeautifulSoup # library for web scrapping

#!conda install -c conda-forge geocoder --yes
import geocoder

#!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim # module to convert an address into latitude and longitude values

# libraries for displaying images
from IPython.display import Image
from IPython.core.display import HTML

# tranforming json file into a pandas dataframe library
from pandas.io.json import json_normalize

#!conda install -c conda-forge folium=0.5.0 --yes
import folium # plotting library
```

Methodology

Statistical summary of crimes

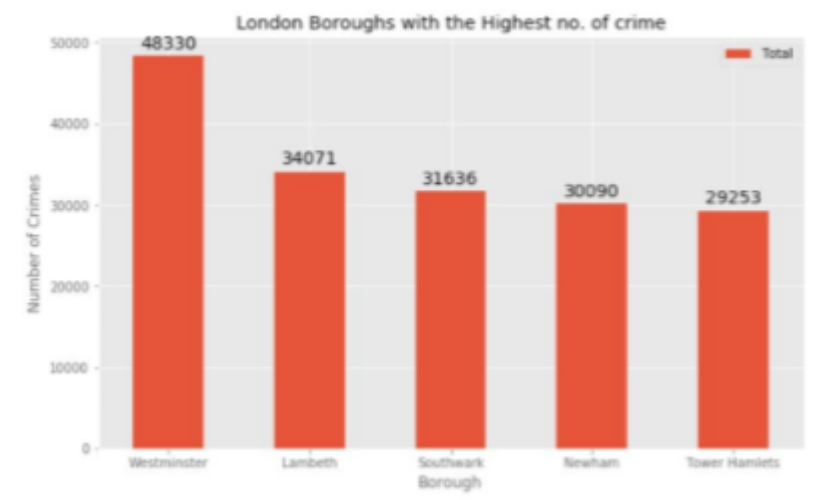
- The describe function in python is used to get statistics of the London crime data, this returns the mean, standard deviation, minimum, maximum, 1st quartile (25%), 2nd quartile (50%), and the 3rd quartile (75%) for each of the major categories of crime
- The count for each of the major categories of crime returns the value 33 which is the number of London boroughs. 'Theft and Handling' is the highest reported crime during the year 2016 followed by 'Violence against the person', 'Criminal damage'. The lowest recorded crimes are 'Drugs', 'Robbery' and 'Other Notifiable offenses.

	Burglary	Criminal Damage	Drugs	Other Notifiable Offences	Robbery	Theft and Handling	Violence Against the Person	Total
count	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000
mean	2069.242424	1941.545455	1179.212121	479.060606	682.666667	8913.121212	7041.848485	22306.696970
std	737.448644	625.207070	586.406416	223.298698	441.425366	4620.565054	2513.601551	8828.228749
min	2.000000	2.000000	10.000000	6.000000	4.000000	129.000000	25.000000	176.000000
25%	1531.000000	1650.000000	743.000000	378.000000	377.000000	5919.000000	5936.000000	16903.000000
50%	2071.000000	1989.000000	1063.000000	490.000000	599.000000	8925.000000	7409.000000	22730.000000
75%	2631.000000	2351.000000	1617.000000	551.000000	936.000000	10789.000000	8832.000000	27174.000000
max	3402.000000	3219.000000	2738.000000	1305.000000	1822.000000	27520.000000	10834.000000	48330.000000

Methodology – Cont'd[1]

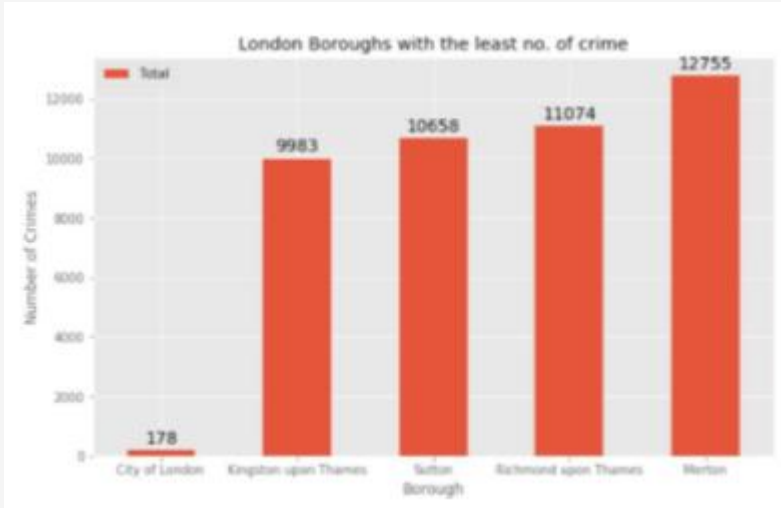
Boroughs with the highest crime rates

- Comparing five boroughs with the highest crime rate during the year 2016 it is evident that Westminster has the highest crimes recorded followed by Lambeth, Southwark, Newnham
- and Tower Hamlets. Westminster has a significantly higher crime rate than the other 4 boroughs.



Boroughs with the lowest crime rates

- Comparing five boroughs with the lowest crime rate during the year 2016, City of London has the lowest recorded crimes followed by Kingston upon Thames, Sutton, Richmond upon Thames and Merton.
- City of London has a significantly lower crime rate because it is the 33rd principal division of Greater London but it is not a London borough. It has an area of 1.12 square miles and a population of 7000 as of 2013 which suggests that it is a small area. Hence, we will consider the next borough with the lowest crime rate as the safest borough in London which is Kingston upon Thames.



Methodology – Cont'd[2]

Neighborhoods in Kingston upon Thames

- There are 15 neighborhoods in the royal borough of Kingston upon Thames, they are visualized on a map using folium on python.

Modelling

Using the final dataset containing the neighborhoods in Kingston upon Thames along with the latitude and longitude, we can find all the venues within a 500-meter radius of each neighborhood by connecting to the Foursquare API. This returns a json file containing all the venues in each neighborhood which is converted to a pandas dataframe. This data frame contains all the venues along with their coordinates and category.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Berrylands	51.393781	-0.284802	Surbiton Racket & Fitness Club	51.392676	-0.290224	Gym / Fitness Center
1	Berrylands	51.393781	-0.284802	Alexandra Park	51.394230	-0.281206	Park
2	Berrylands	51.393781	-0.284802	K2 Bus Stop	51.392302	-0.281534	Bus Stop
3	Berrylands	51.393781	-0.284802	Cafe Rosa	51.390175	-0.282490	Café
4	Canbury	51.417499	-0.305553	The Boater's Inn	51.418546	-0.305915	Pub

Modelling – Cont'd

One hot encoding is done on the venues data. (One hot encoding is a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction). The Venues data is then grouped by the Neighborhood and the mean of the venues are calculated, finally the 10 common venues are calculated for each of the neighborhoods.

To help people find similar neighborhoods in the safest borough we will be clustering similar neighborhoods using K - means clustering which is a form of unsupervised machine learning algorithm that clusters data based on predefined cluster size. We will use a cluster size of 5 for this project that will cluster the 15 neighborhoods into 5 clusters. The reason to

Conduct a K- means clustering is to cluster neighborhoods with similar venues together so that people can shortlist the area of their interests based on the venues/amenities around each neighborhood.

Results

After running the K-means clustering we can access each cluster created to see which neighborhoods were assigned to each of the five clusters. Looking into the neighborhoods in the first cluster (see fig 4.1)

	Neighborhood	Borough	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue
1	Canbury	Kingston upon Thames	51.417499	-0.305553	0	Pub	Café	Plaza	Fish & Chips Shop	Supermarket	Spa	Shop & Service	Park
4	Hook	Kingston upon Thames	51.367898	-0.307145	0	Bakery	Convenience Store	Indian Restaurant	Fish & Chips Shop	Wine Shop	Food	Electronics Store	Farmers Market
5	Kingston upon Thames	Kingston upon Thames	51.409627	-0.306262	0	Coffee Shop	Café	Burger Joint	Sushi Restaurant	Pub	Record Shop	Cosmetics Shop	Market
7	Malden Rushett	Kingston upon Thames	51.341052	-0.319076	0	Convenience Store	Pub	Garden Center	Restaurant	Fast Food Restaurant	Discount Store	Dry Cleaner	Electronics Store
9	New Malden	Kingston upon Thames	51.405335	-0.263407	0	Gastropub	Gym	Sushi Restaurant	Supermarket	Korean Restaurant	Indian Restaurant	Fish & Chips Shop	Dry Cleaner
10	Norbiton	Kingston upon Thames	51.409999	-0.287396	0	Indian Restaurant	Pub	Food	Italian Restaurant	Platform	Grocery Store	Farmers Market	Dry Cleaner
12	Seething Wells	Kingston upon Thames	51.392642	-0.314366	0	Indian Restaurant	Coffee Shop	Italian Restaurant	Pub	Café	Wine Shop	Fast Food Restaurant	Chinese Restaurant
13	Surbiton	Kingston upon Thames	51.393756	-0.303310	0	Coffee Shop	Pub	Supermarket	Breakfast Spot	Grocery Store	Gastropub	French Restaurant	Train Station
14	Tolworth	Kingston upon Thames	51.378876	-0.282960	0	Grocery Store	Pharmacy	Furniture / Home Store	Train Station	Pizza Place	Discount Store	Coffee Shop	Bus Stop

Results – Cont'd[1]

The cluster one is the biggest cluster with 9 of the 15 neighborhoods in the borough Kingston upon Thames. Upon closely examining these neighborhoods we can see that the most common venues in these neighborhoods are Restaurants, Pubs, Cafe, Supermarkets, and stores. Looking into the neighborhoods in the second, third and fifth clusters, we can see these clusters have only one neighborhood in each. This is because of the unique venues in each of the neighborhoods, hence they couldn't be clustered into similar neighborhoods

The second cluster has one neighborhood which consists of Venues such as Restaurants, Golf courses, and wine shops.

The third cluster has one neighborhood which consists of Venues such as Train stations, Restaurants, and Furniture shops.

The fourth cluster has two neighborhoods in it, these neighborhoods have common venues such as Parks, Gym/Fitness centers, Bus Stops, Restaurants, Electronics Stores and Soccer fields etc.

The fifth cluster has one neighborhood which consists of Venues such as Grocery shops, Bars, Restaurants, Furniture shops, and Department stores. We will look into the neighborhoods in the fourth cluster.

Results – Cont'd[2]

Visualizing the clustered neighborhoods on a map using the folium library.

Each cluster is color coded for the ease of presentation; we can see that majority of the neighborhood falls in the red cluster which is the first cluster. Three neighborhoods have their own cluster (Blue, Purple and Yellow), these are clusters two three and five. The green cluster consists of two neighborhoods which is the 4th cluster.

Discussion

The aim of this project is to help people who want to relocate to the safest borough in London, expats can choose the neighborhoods to which they want to relocate based on the most common venues in it. For example, if a person is looking for a neighborhood with good connectivity and public transportation, we can see that Clusters 3 and 4 have Train stations and Bus stops as the most common venues. If a person is looking for a neighborhood with stores and restaurants in a close proximity then the neighborhoods in the first cluster is suitable. For a family I feel that the neighborhoods in Cluster 4 are more suitable dues to the common venues in that cluster, these neighborhoods have common venues such as Parks, Gym/Fitness centers, Bus Stops, Restaurants, Electronics Stores and Soccer fields which is ideal for a family. The choices of neighborhoods may vary from person to person.

Conclusion

This project helps a person get a better understanding of the neighborhoods with respect to the most common venues in that neighborhood. It is always helpful to make use of technology to stay one step ahead i.e. finding out more about places before moving into a neighborhood. We have just taken safety as a primary concern to shortlist the safest borough of London. The future of this project includes taking other factors such as cost of living in the areas into consideration to shortlist the borough, such as filtering areas based on a predefined budget.