Restaurant Location Recommender (Using K-Means)

Introduction- Business Problem

The problem at hand is to find an optimal location for a restaurant. Specifically, this report will be targeted to stakeholders interested in opening an Indian Cuisine restaurant in Delhi, India. Finding a suitable location for restaurants in major cities like Delhi proves to be a daunting task. Various factors such as over-saturation or no demand ,for the type of restaurant that the customer wants to open, effect the success or failure of the restaurant. Hence, prospective investors can bolster their decisions using the descriptive and predictive capabilities of data science. We need to find locations(Neighbourhood) that have a **potentially unfulfilled demand** for Indian Restaurant. Also, we need locations that have **low competition and are not already crowded**. We would also prefer location as close to popular city Neighbourhood, assuming the first two conditions are met. We will use our data science powers to generate a few most promising neighbourhoods based on this criteria. Advantages of each area will then be clearly Expressed so that best possible final location can be chosen by stakeholders.

Data Acquisition and Preparation

Based on definition of our problem, factors that will influence our decision are:

- number of existing restaurants in the neighbourhood (any type of restaurant)
- number of and distance to Indian restaurants in the neighbourhood, if any
- distance of neighbourhood from popular neighbourhoods

In our project we will:

- acquire the names and boroughs of the neighbourhoods by scrapping a wikipedia page.
- After we have got the names of all the neighbourhoods, we will geocode them using the library geopy.geocoder (Nominatim).
- Next, we use the foursquare API to find all types of restaurants within a 1000 meter radius for every neighbourhood.

```
import numpy as np # library to handle data in a vectorized manner

import pandas as pd # library for data analsysis
pd.set_option("display.max_columns", None)
pd.set_option("display.max_rows", None)

import json # library to handle JSON files

from geopy.geocoders import Nominatim # convert an address into latitude and longitude values

import requests # library to handle requests
from bs4 import BeautifulSoup # library to parse HTML and XML documents

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.")
```

In order to create neighbourhood dataset following steps were followed:

- Scrapping the Wikipedia page. Link used- https://en.wikipedia.org/wiki/Neighbourhoods_of_Delhi
- Geocoding every neighbourhood

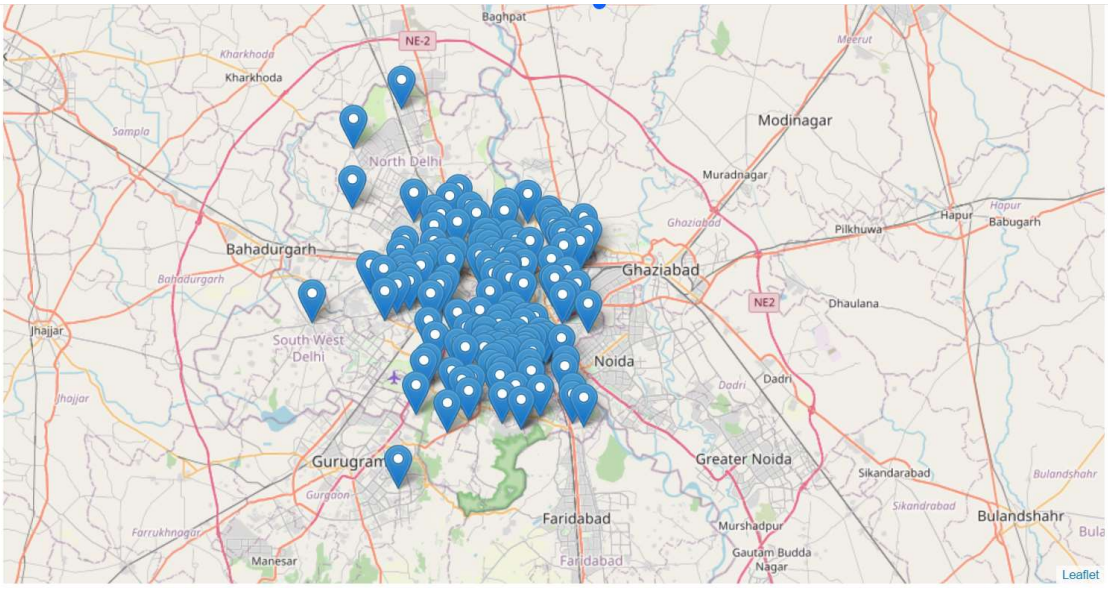
	Borough	Neighborhood	latitude	longitude
0	North West Delhi	Adarsh Nagar	28.614192	77.071541
1	North West Delhi	Ashok Vihar	28.699453	77.184826
2	North West Delhi	Azadpur	28.707657	77.175547
3	North West Delhi	Bawana	28.799660	77.032885
4	North West Delhi	Dhaka	39.031714	-90.261223

- Visualising the obtained dataset

```
locations = df_data_3[['latitude', 'longitude']]
locationlist = locations.values.tolist()
len(locationlist)
locationlist[7]
```

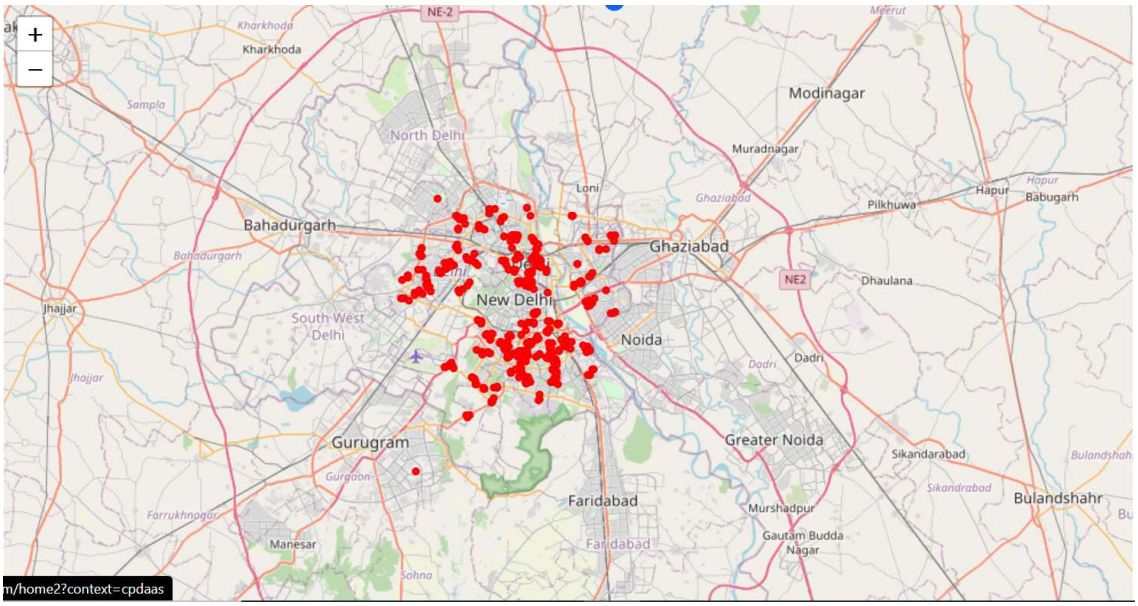
```
[28.688926399999996, 77.16168329999999]
```

```
map = folium.Map(location=[28.73, 77.03], zoom_start=12)
for point in range(0, len(locationlist)):
    folium.Marker(locationlist[point], popup=df_data_3['Borough'][point]).add_to(map)
map
```



Now that we had marked all the concerned neighbourhoods, we will use foursquare api to locate the nearby restaurants.

Here we have used the explore API call and filtered the search to find venues designated as restaurants.



Clustering and Analysis

The task at hand was not only to find the neighbourhoods with low density of Indian restaurants, but also the ones which have the potential for growth.

So we searched for neighbourhoods with similar pattern of restaurant trends.

This was achieved by clustering of neighbourhoods on the basis of restaurant data we had acquired. Clustering is a predominant algorithm of unsupervised Machine Learning. It is used to segregate data entries in cluster depending of the similarity of their attributes, calculated by using the simple formula of Euclidian distance.

We then analysed these clusters separately and used those clusters that showed high trends of Indian restaurants.

	Neighborhood	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	9th Most Common Venue	10th Most Common Venue
0	Adarsh Nagar	Fast Food Restaurant	Pizza Place	Indian Restaurant	Vegetarian / Vegan Restaurant	Dumpling Restaurant	Dhaba	Dim Sum Restaurant	Diner	Doner Restaurant	Donut Shop
1	Alaknanda	BBQ Joint	Indian Restaurant	New American Restaurant	Restaurant	Middle Eastern Restaurant	Pizza Place	Steakhouse	Deli / Bodega	Dhaba	Dim Sum Restaurant
2	Anand Vihar	Indian Restaurant	Pizza Place	Indian Sweet Shop	Soup Place	Punjabi Restaurant	Vegetarian / Vegan Restaurant	Donut Shop	Deli / Bodega	Dhaba	Dim Sum Restaurant
3	Ashok Vihar	Indian Restaurant	Bakery	Diner	Falafel Restaurant	Dhaba	Dim Sum Restaurant	Doner Restaurant	Donut Shop	Dumpling Restaurant	Eastern European Restaurant
4	Azadpur	Café	Argentinian Restaurant	Indian Restaurant	Restaurant	Vegetarian / Vegan Restaurant	Eastern European Restaurant	Dim Sum Restaurant	Diner	Doner Restaurant	Donut Shop

Applying the clustering algorithm

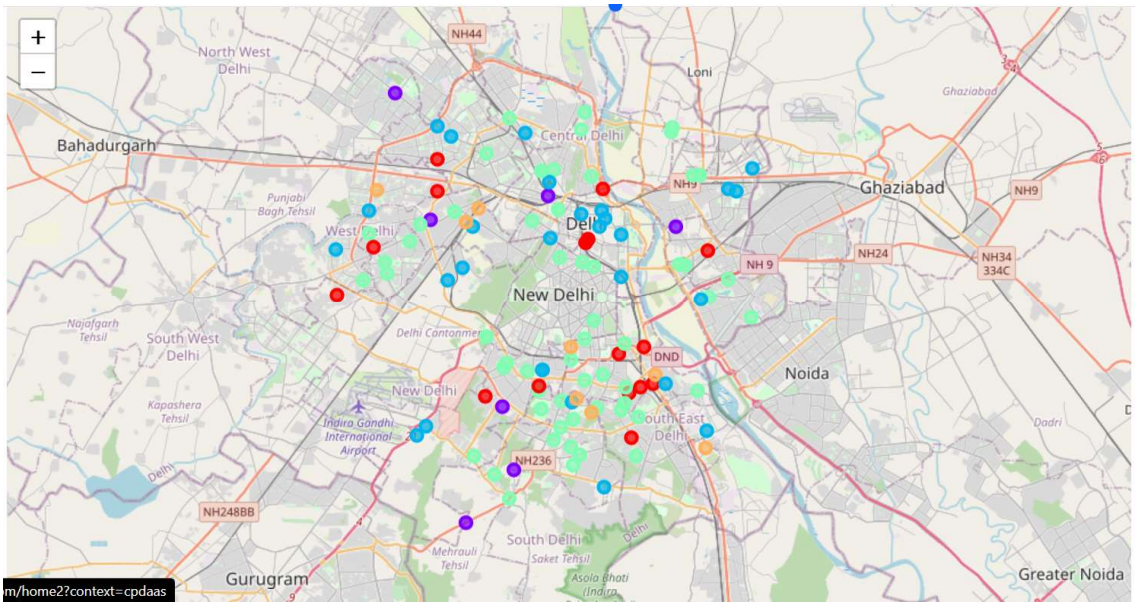
In [164]:
```
# set number of clusters
kclusters = 5

delhi_grouped_clustering = delhi_grouped.drop('Neighborhood', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(delhi_grouped_clustering)

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

Out[164]:
```
array([0, 3, 3, 2, 3, 1, 3, 3, 3, 0], dtype=int32)
```

In [165]:
```
# add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

delhi_merged = delhiData

# merge toronto_grouped with toronto_data to add latitude/longitude for each neighborhood
delhi_merged = delhi_merged.join(neighborhoods_venues_sorted.set_index('Neighborhood'), on='Neighborhood')

delhi_merged.dropna(inplace=True)
delhi_merged.head() # check the last columns!
```

	level_0	index	Borough	Neighborhood	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	7(Co
0	0	0	North West Delhi	Adarsh Nagar	28.614192	77.071541	0.0	Fast Food Restaurant	Pizza Place	Indian Restaurant	Vegetarian / Vegan Restaurant	Dumpling Restaurant	Dhaba	Dim Res
1	1	1	North West Delhi	Ashok Vihar	28.699453	77.184826	2.0	Indian Restaurant	Bakery	Diner	Falafel Restaurant	Dhaba	Dim Sum Restaurant	Dor Res
2	2	2	North West Delhi	Azadpur	28.707657	77.175547	3.0	Café	Argentinian Restaurant	Indian Restaurant	Restaurant	Vegetarian / Vegan Restaurant	Eastern European Restaurant	Dim Res
7	7	7	North West Delhi	Keshav Puram	28.688926	77.161683	3.0	Gastropub	Indian Restaurant	Café	Bakery	Food Truck	Food Stand	Foc Cou
9	9	9	North West Delhi	Kohat Enclave	28.698041	77.140539	2.0	Indian Restaurant	Bakery	Food Court	Food	Eastern European Restaurant	Dhaba	Dim Res

Cluster Visualisation

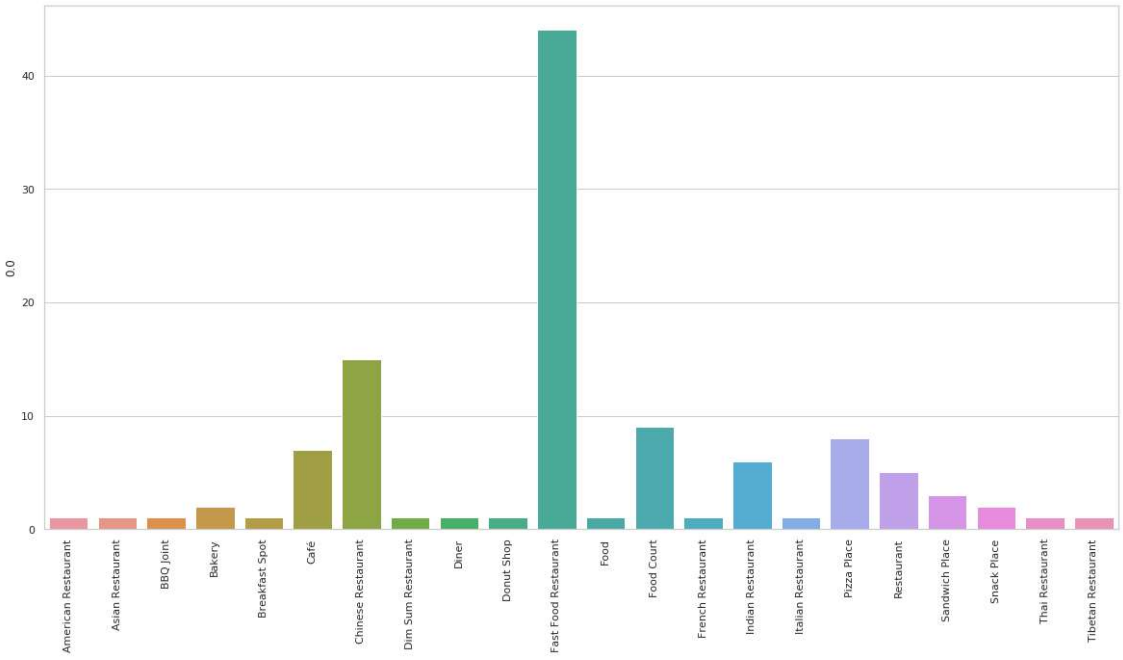


Out[167]:

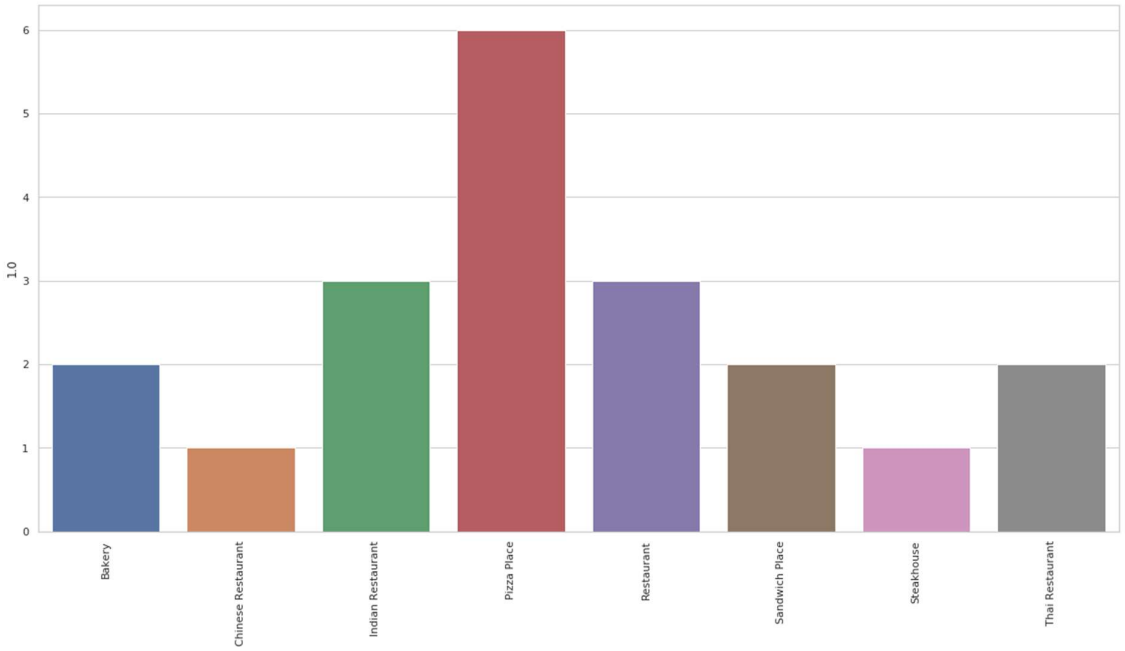
Cluster Labels	0.0	1.0	2.0	3.0	4.0
Afghan Restaurant	0	0	0	10	0
American Restaurant	1	0	1	11	0
Argentinian Restaurant	0	0	0	1	0
Asian Restaurant	1	0	2	18	0
Australian Restaurant	0	0	0	1	0

Analysing clusters

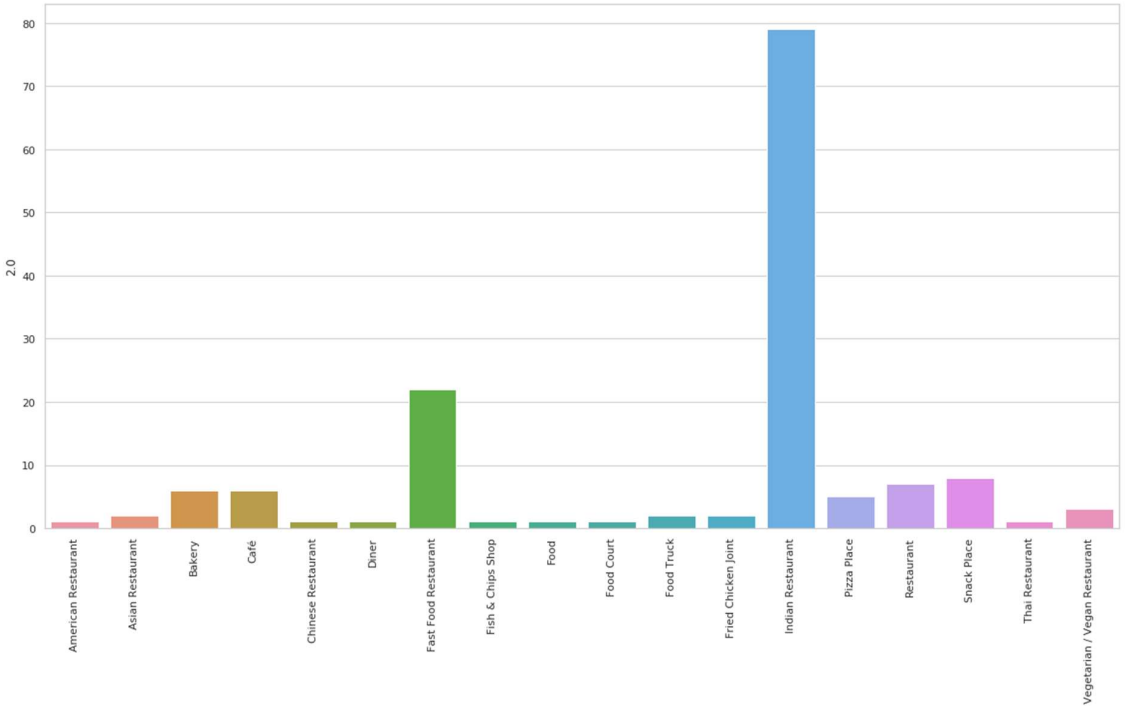
Plot_bar (0)



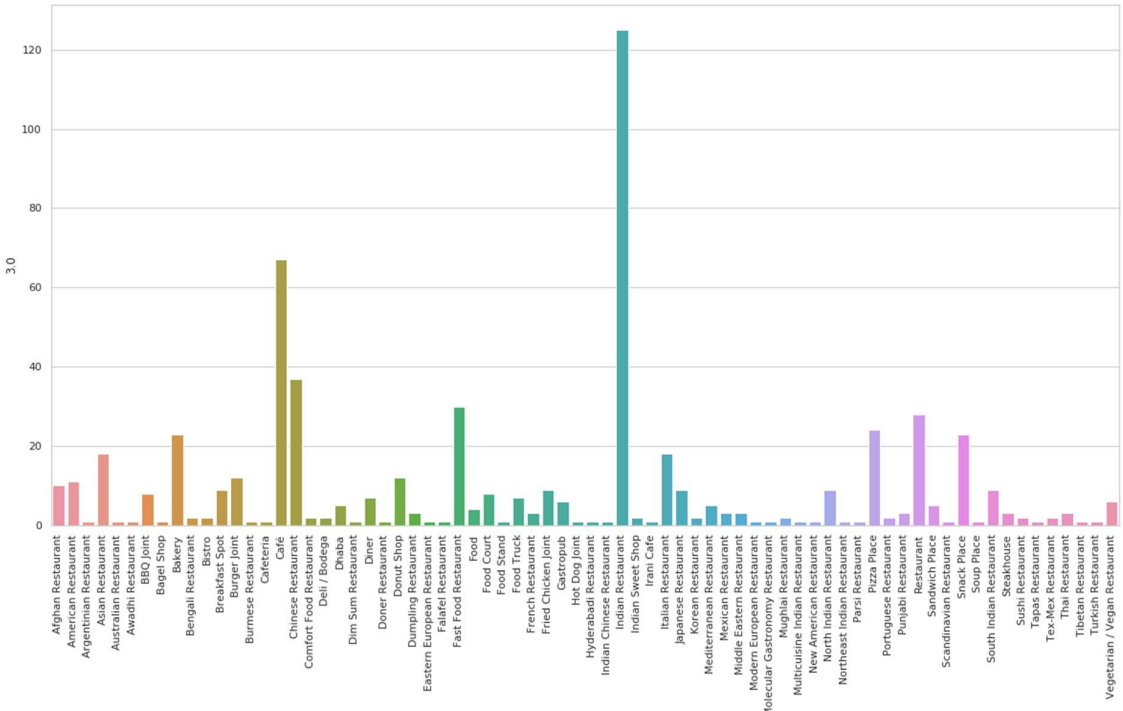
Plot_bar(1)



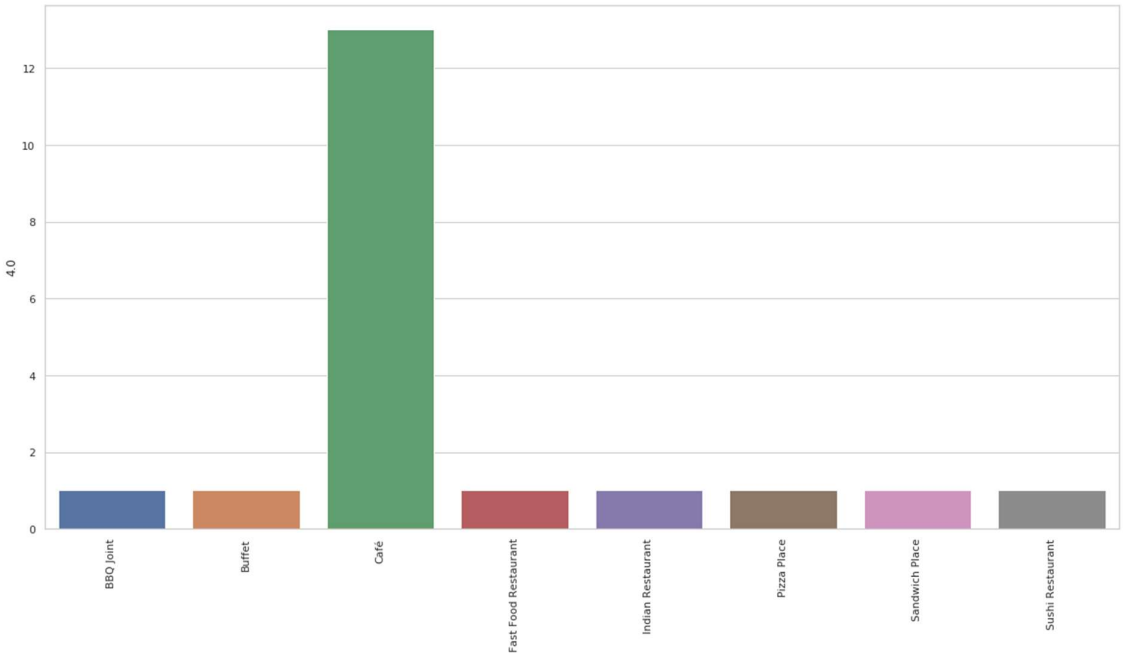
Plot_bar(2)



Plot_bar(3)



Plot_bar(4)



From the graphs it is evident that plots 1 and 2 have a high demand for Indian restaurants.

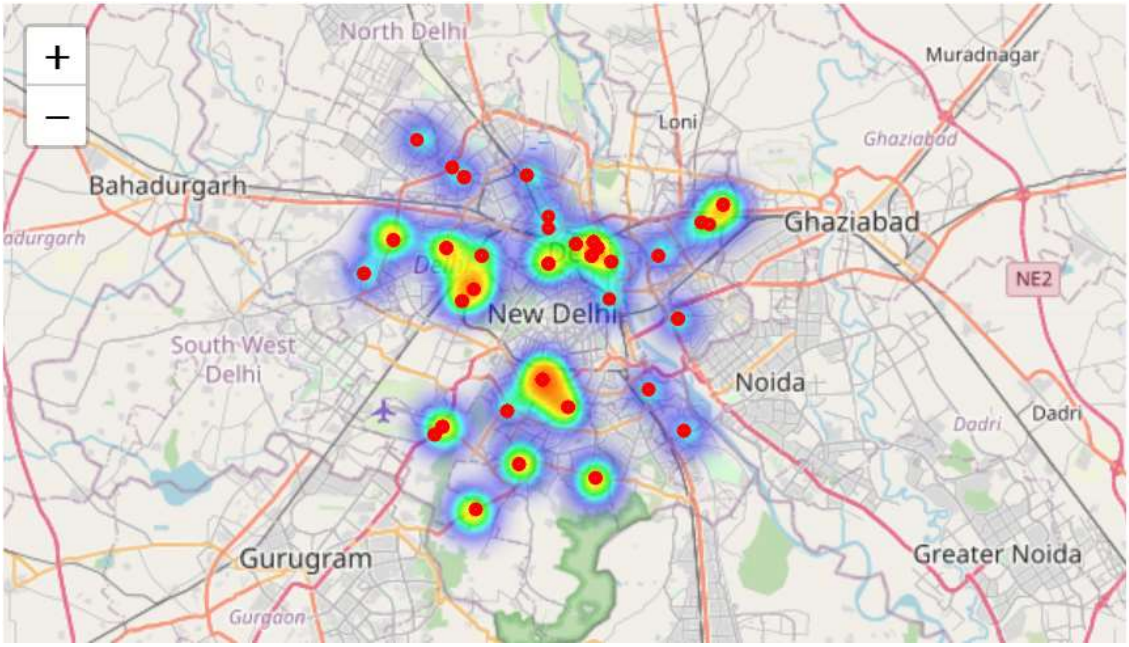
Recommendation

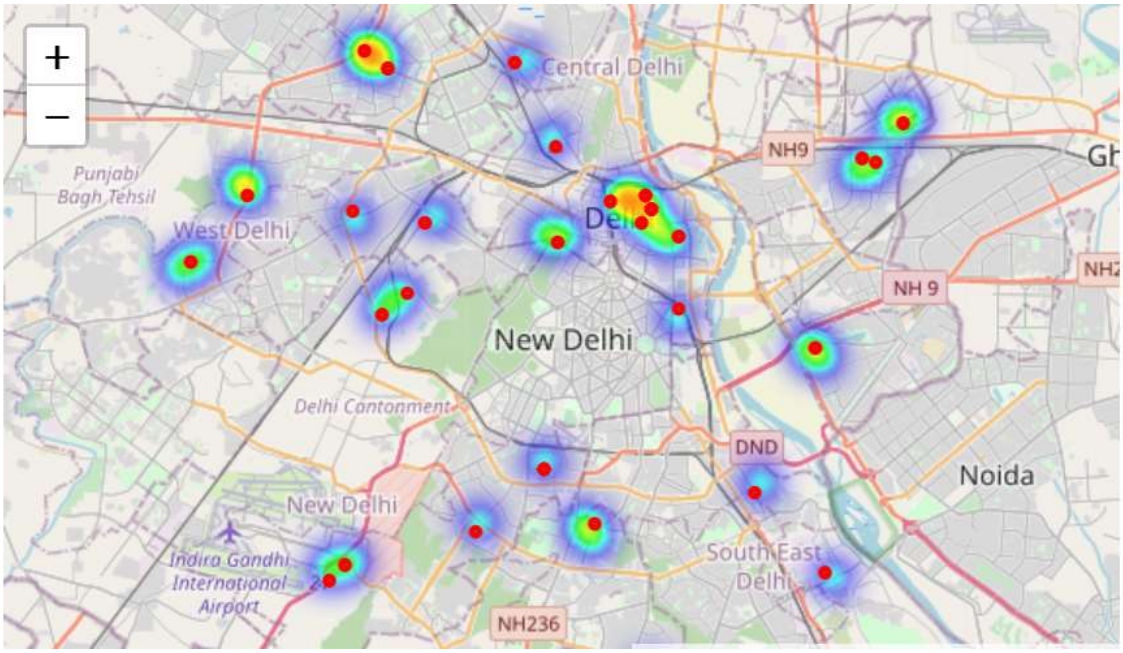
- we have first, analysed the density of the Indian Restaurants in generally for each neighbourhood.
- Then we eliminated the neighbourhoods that in the highest 70 percentile of density
- Found out the most popular neighbourhoods
- Then tried to find remaining neighbourhoods that are close to them
- Provided the a detailed recommendation of top 10 neighbourhoods

We know that when we were clustering the neighborhoods the data used contained the mean of all types of restaurants present in the particular neighborhood. Therefore, we can say that the neighborhoods are clustered on their restaurant trends.

Now, clusters 2 and 3 may collectively have the highest number of indian restaurant but there will be some neighborhoods in these clusters which would have a demand for Indian Restaurants, as these neighborhoods are in the same cluster, but would not have enough supply.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude
4	Ashok Vihar	28.699453	77.184826	Nat Khat Caterers	28.699630	77.187832
5	Ashok Vihar	28.699453	77.184826	Bakers Stop	28.700495	77.188716
6	Ashok Vihar	28.699453	77.184826	Invitation Banquet	28.696018	77.185953
7	Ashok Vihar	28.699453	77.184826	Gola Northend	28.701242	77.189288
17	Kohat Enclave	28.698041	77.140539	Peshawari	28.699012	77.139020





now we will remove all neighbourhoods with the following conditions:

- Number of Indian restaurants >30%
- Number of all restaurants >60%

'%' here refers to percentile

In [195]:
```
temp_recommend.head()
```

Out[195]:

	level_0	Neighborhood	latitude	longitude
1	1	Ashok Vihar	28.699453	77.184826
12	12	Pitam Pura	28.703268	77.132250
14	14	Rithala	28.720806	77.107181
19	19	Chawri Bazaar	28.649927	77.229788
25	25	Lahori Gate	28.656841	77.218534

In [197]:
```
temp_recommend.head()
```

Out[197]:

	level_0	Neighborhood	latitude	longitude	Hauz Khas Village	Khirki Village	Sarojini Nagar
1	1	Ashok Vihar	28.699453	77.184826	16.2236	19.1385	13.9746
12	12	Pitam Pura	28.703268	77.132250	17.7027	21.0274	15.6271
14	14	Rithala	28.720806	77.107181	20.4417	23.8370	18.4439
19	19	Chawri Bazaar	28.649927	77.229788	11.2216	13.4011	9.0732
25	25	Lahori Gate	28.656841	77.218534	11.6889	14.1214	9.4709

In [206]:
```
# top 5 neighborhoods near Connaught Place
neiNearHK = temp_recommend.sort_values(by=['Hauz Khas Village']).iloc[:,:4].head().set_index('Neighborhood')
neiNearHK
```

Out[206]:

Neighborhood	level_0	latitude	longitude
Gulmohar Park	93	28.557101	77.213006
Munirka	136	28.554886	77.171084
Mehrauli	108	28.521826	77.178323
Khanpur	102	28.512798	77.232395
Mahipalpur	134	28.544485	77.125691

In [207]:
```
# top 5 neighborhoods near Khirki Village
neiNearKV = temp_recommend.sort_values(by=['Khirki Village']).iloc[:,:4].head().set_index('Neighborhood')
neiNearKV
```

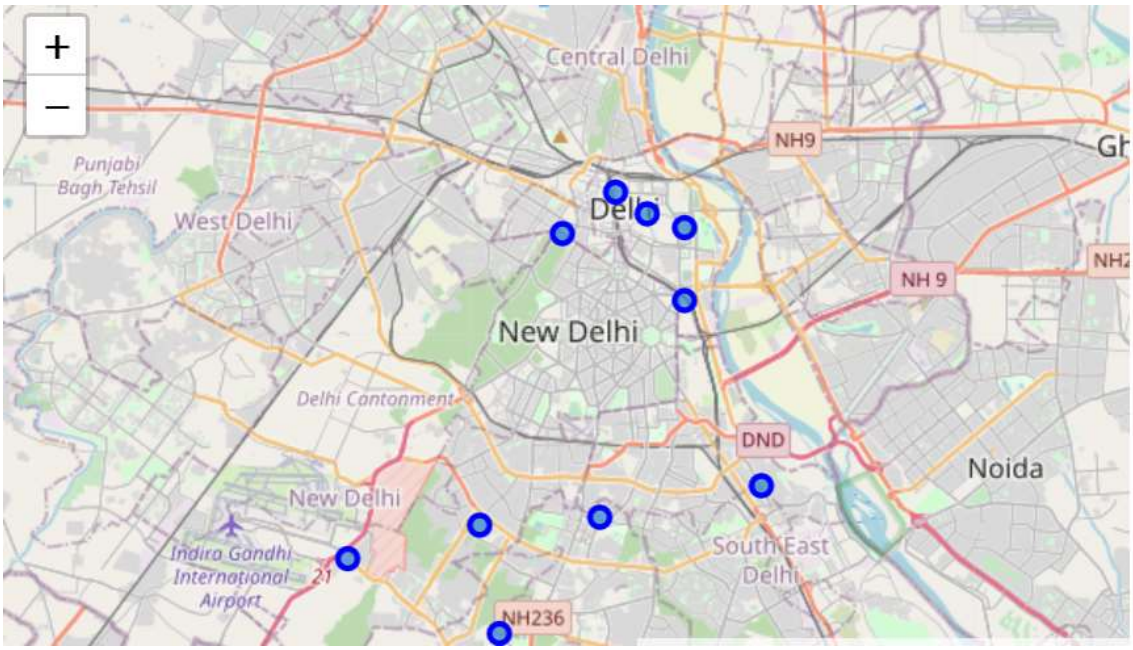
Out[207]:

Neighborhood	level_0	latitude	longitude
Khanpur	102	28.512798	77.232395
Gulmohar Park	93	28.557101	77.213006
Mehrauli	108	28.521826	77.178323
Munirka	136	28.554886	77.171084
New Friends Colony	112	28.567101	77.269764

In [208]:
```
# top 5 neighborhoods near Khirki Village
neiNearSN = temp_recommend.sort_values(by=['Sarojini Nagar']).iloc[:,:4].head().set_index('Neighborhood')
neiNearSN
```

Out[208]:

Neighborhood	level_0	latitude	longitude
Gulmohar Park	93	28.557101	77.213006
Munirka	136	28.554886	77.171084
Mehrauli	108	28.521826	77.178323
Pragati Maidan	64	28.623459	77.242512
New Friends Colony	112	28.567101	77.269764



Results and Discussions

Our analysis was conducted on more than 186 neighbourhoods, containing over 848 restaurants within 2km radius of every neighbourhood. We segregated these neighbourhoods on the basis of types and number of restaurants. Five clusters were obtained, each having a unique collection of restaurants. Since, we had an aim of finding optimal neighbourhoods for opening Indian restaurants, we selected cluster 2 and 3 which had the highest number of Indian restaurants. The above actions left us with the only those neighbourhoods that had a shared characteristics of and that had a high demand for Indian restaurants.

Next, we plotted a heat map for analysing the density of restaurants in the remaining neighbourhoods. This allowed us to select neighbourhoods that had few or no Indian restaurants and were not overcrowded by other kinds of restaurants. A total of 57 neighbourhoods were left. After this, we found out the top three most popular neighbourhoods(namely: Hauz khas Village, Khirki Village and Sarojini Nagar), and the

distance of every remaining neighbourhoods from all three of them. Then, we extracted top 5 closest neighbourhoods from each of three most popular neighbourhoods mentioned above. Taking the union of the resulting three dataset we get 11 neighbourhoods that satisfy all three conditions laid out in the business problem by the client.

The neighbourhoods recommendation obtained here are not completely accurate. This is due to the limitations in the dataset used in the project. Due to lack of cross referencing sources, we may have missed a few neighbourhoods from our consideration. The foursquare API does not contain, or does not rely, a comprehensive dataset about the restaurants present in Delhi. Surely, in a city like Delhi with a population of over 19 million, there are much more restaurants than 848.