Restaurant Location Recommender (Using K-Means)

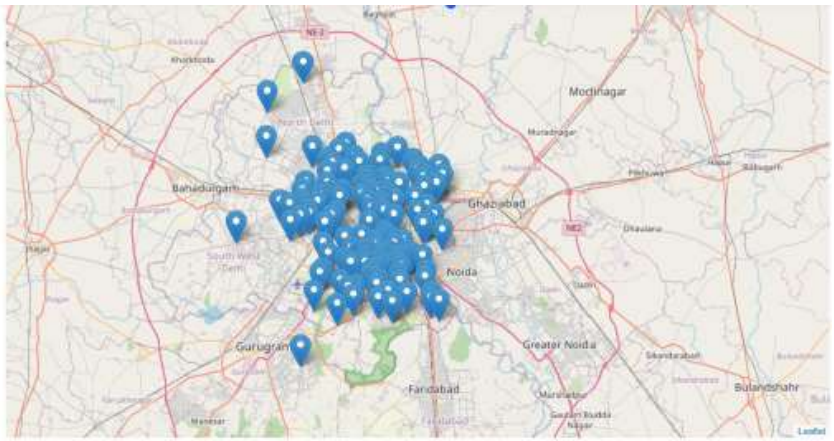
Introduction- Business Problem

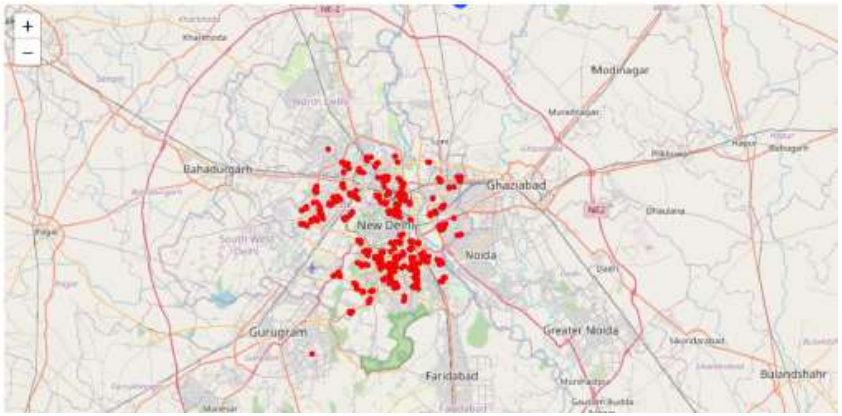
- The problem at hand is to find an optimal location for a restaurant
- Specifically, this report will be targeted to stakeholders interested in opening an Indian Cuisine restaurant in Delhi, India

Data Acquisition and Preparation

- https://en.wikipedia.org/wiki/Neighbourhoods_of_Delhi this link was used in addition to the datasets downloaded from kaggle.com
- 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.

Locating neighbourhoods and restaurants





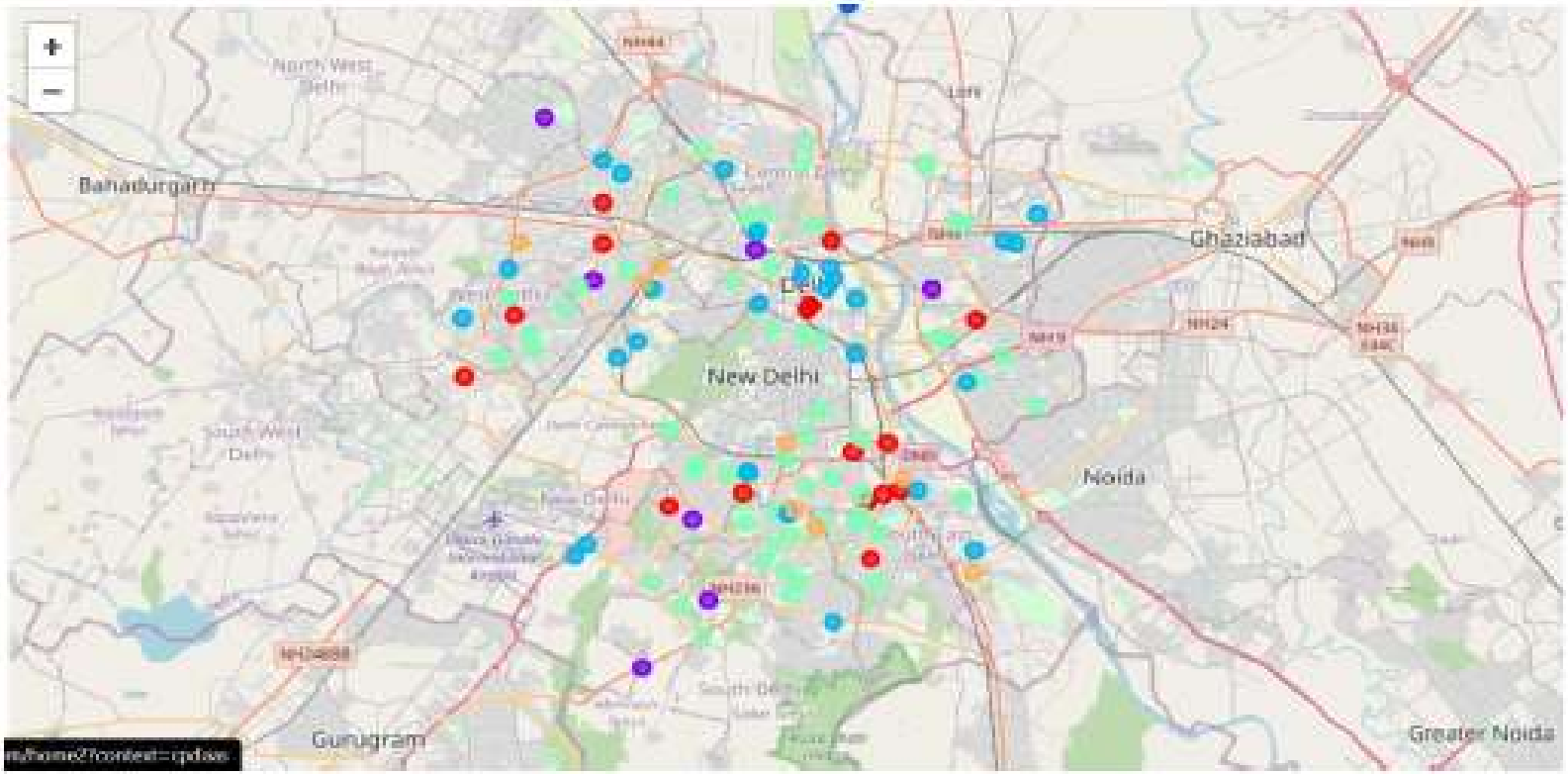
Clustering and Analysis

	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

Clustering and Analysis

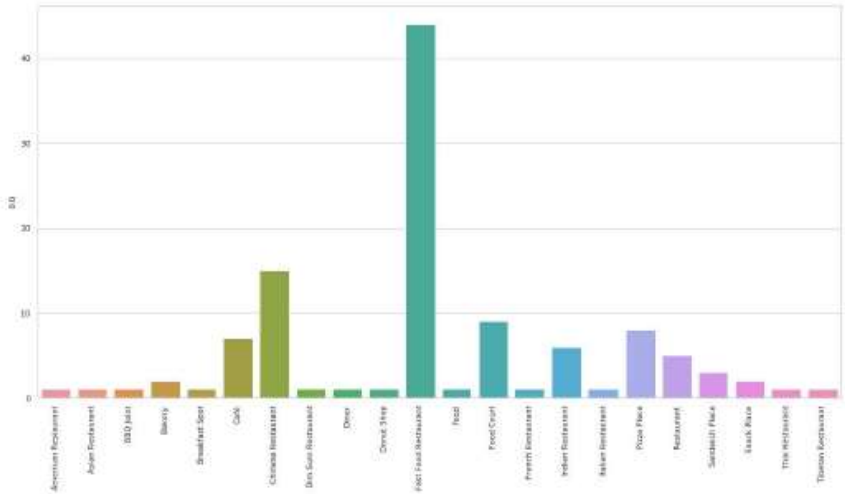
	level_0	index	Borough	Neighborhood	latitude	longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7t Co
0	0	0	North West Delhi	Adarsh Nagar	28.614192	77.071541	0.0	Fast Food Restaurant	Pizza Place	Indian Restaurant	Vegetarian / Vegan Restaurant	Dumpling Restaurant	Dhaba	Din 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	Do 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	Din Res
7	7	7	North West Delhi	Keshav Puram	28.688926	77.161683	3.0	Gastropub	Indian Restaurant	Café	Bakery	Food Truck	Food Stand	Foo 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	Din Res

Cluster Visualisation

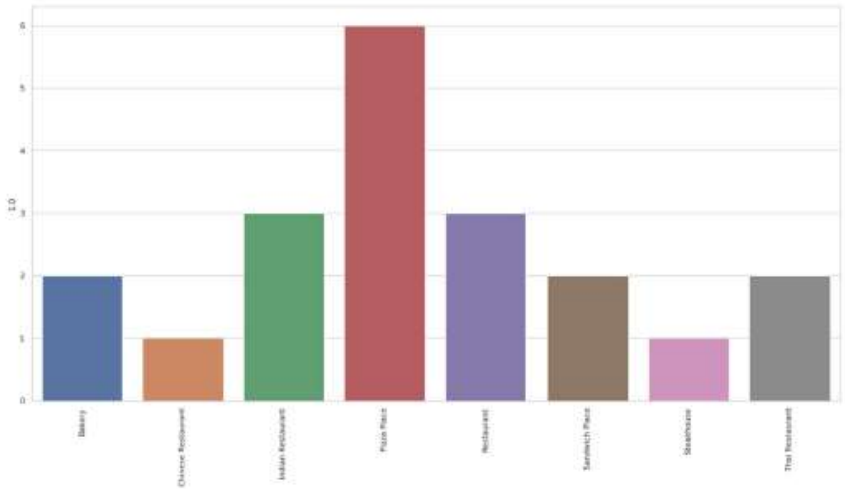


Comparing clusters

Plot_bar (0)



Plot_bar(1)



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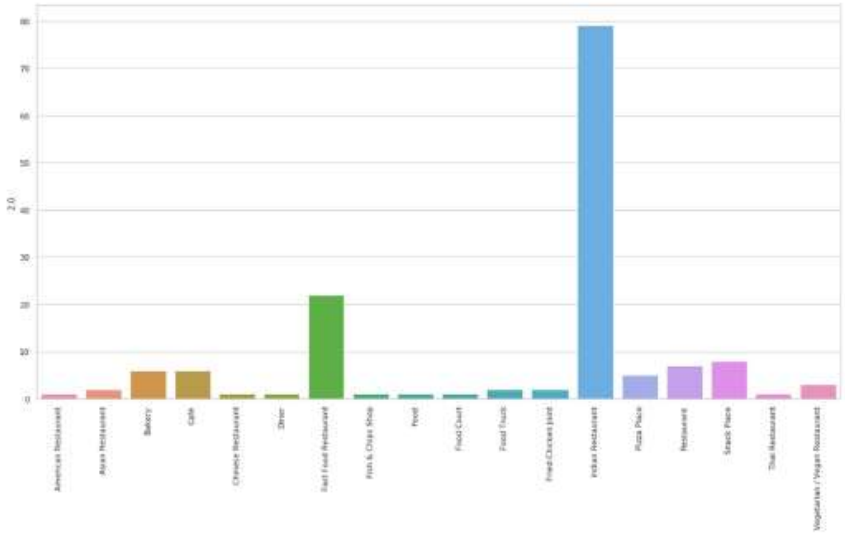
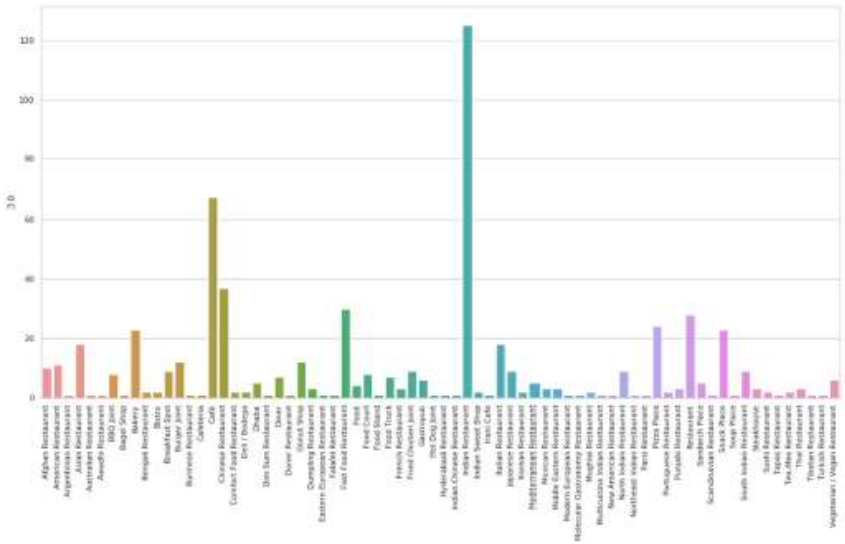
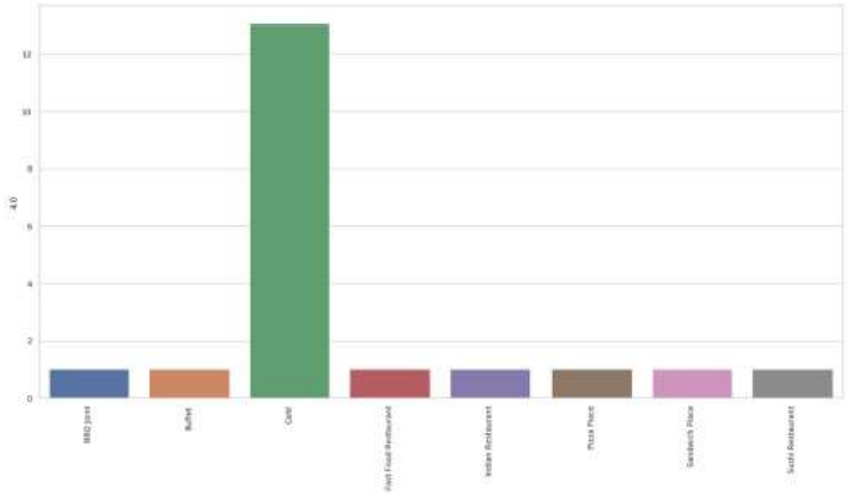
Plot_bar(2)



Plot_bar(3)



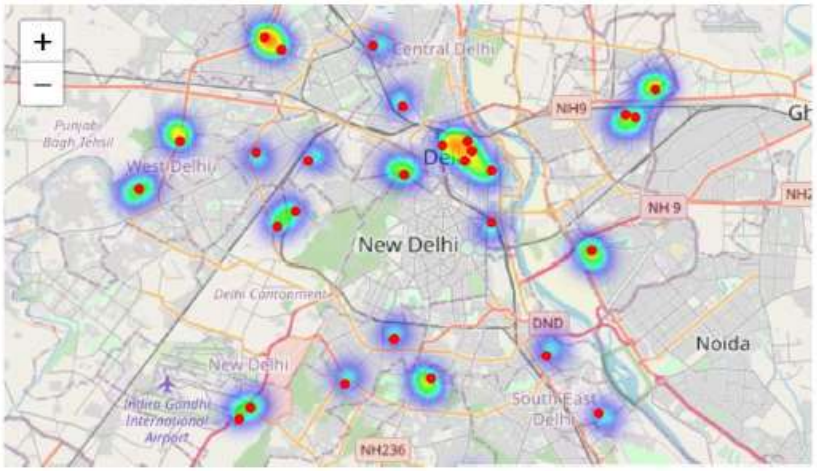
Plot_bar(4)

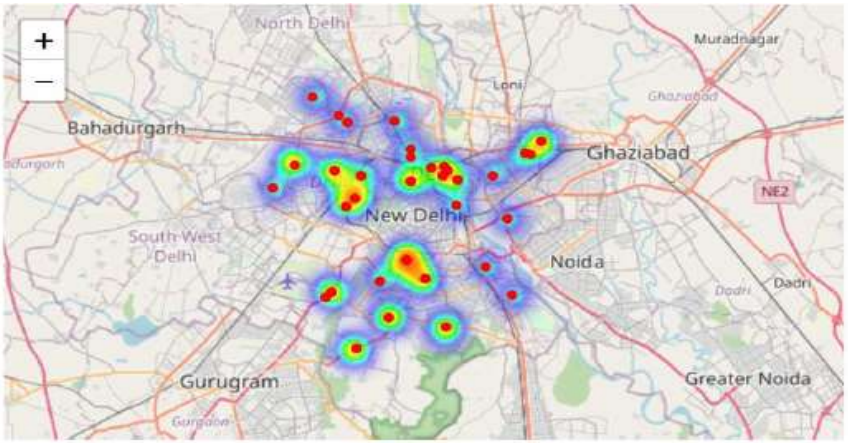


From the graphs it is evident that plots 1 and 2 have a high demand for Indian restaurants.

Recommendation

	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





Recommendation

```
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	77.126691

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

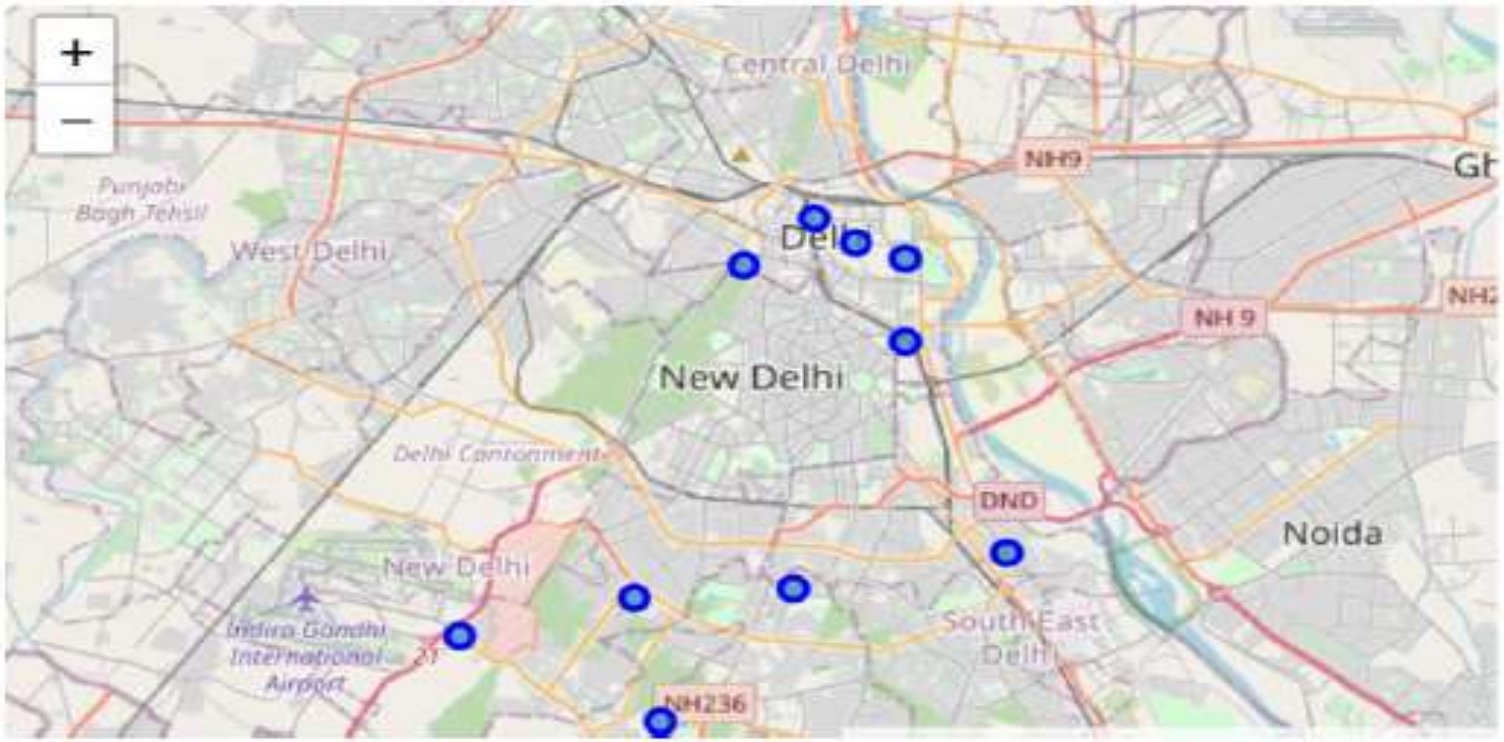
Out[207]:

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

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	84	28.623459	77.242512
New Friends Colony	112	28.567101	77.269764

Recommendation



Results and discussions

- we plotted a heat map for analysing the density of restaurants in the remaining neighbourhoods
- 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

Results and discussions

- 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