The Toll Of Traffic

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Business Problem Intorduction

No Development is a better prospect for a city if its heading for an unplanned one.

Bangalore (known officially as *Bengaluru*) has seen rapid expansion and development in the recent decades. Though it has been beneficial to its economy and population, the sudden influx of population and increasing number of vehicles on the road has put a huge strain on the city's roads and its commuters.

The city's condition is so bad that it is regularly placed on top for world's most congested cities.

References:

Why is Bangalore stuck in Traffic Jams (https://www.bbc.com/news/world-asia-india-38155635)

Bangalore - The World's most traffic congested city (https://www.indianfolk.com/nama-bengaluru-worlds-traffic-congested-city/)

Tom-Tom Traffic Index - Bangalore (https://www.tomtom.com/en_gb/traffic-index/bengaluru-traffic/)

The main culprit of the problem seems to be unplanned development of infrastructure and a road network not suitable for daily commutes.

The picture below describes the problem aptly. It is a view of Bangalore's Richmond Neighbourhood. We see that some roads remain quite empty and others are occupied 18 - 20 hours a day. Credits for the picture go to Deccan Herald.

The traffic also takes a toll on the economy of the city.

The Cost Of Traffic on Cities in India (https://timesofindia.indiatimes.com/india/traffic-congestion-costs-four-major-indian-cities-rs-1-5-lakh-crore-a-year/articleshow/63918040.cms#:~:text=NEW%20DELHI%3A%20Traffic%20congestion%20during,c

The recent introduction of metro lines seemed a way forward in tackling this problem. But alas, delayed projects for building the required infrastructure for metros to operate on a full scale and the high price of metro travel seem to give little hope. And thus would not provide a solution in the recent future.

This project aims to cluster neighbourhoods in Bangalore to find points is the road network which form a bottleneck for traffic flow.

Data sources

The project uses the following data sources:

- [Geospacial Coordinates for Bangalore (https://www.kaggle.com/rmenon1998/bangalore-neighborhoods)](https://www.kaggle.com/rmenon1998/bangalore-neighborhoods)

  The dataset provides the data for location coordinates of all nighborhoods in Bangalore and some.

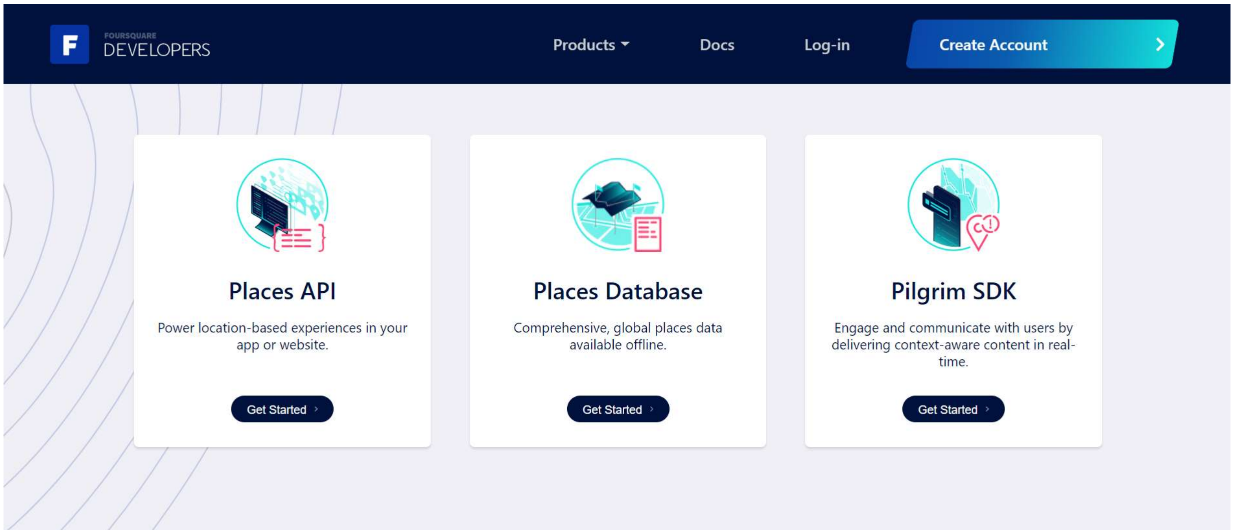
- **Goepy Library** is used to get revese geocoding for locations.

- **Foursquare API** to get data for venues in a neighborhood.

  "Foursquare is the most trusted, independent location data platform for understanding how people move through the real world."

  We need a Foursquare Developer account to use its API.
  The regular account provides 950 API calls a day for extracting location data in any neighborhood.

[Foursquare API - Getting Started Guide (https://developer.foursquare.com/docs/places-api/getting-started/)](https://developer.foursquare.com/docs/places-api/getting-started/)

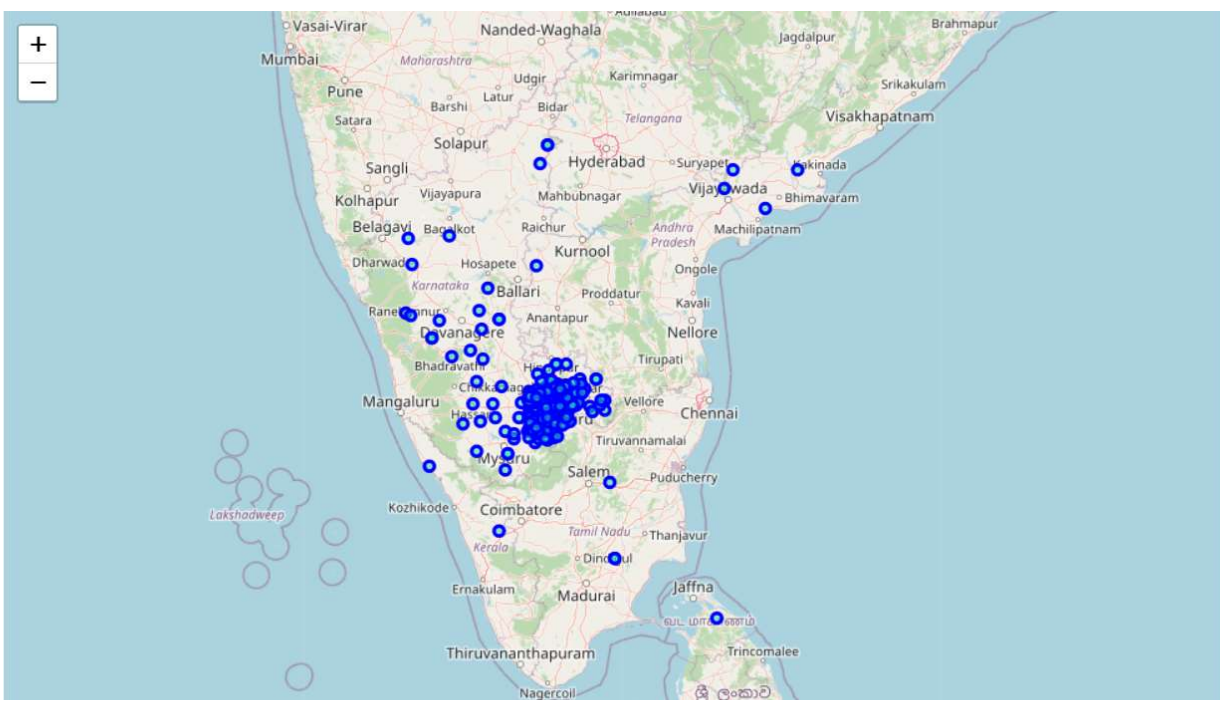


Data cleaning

The data source used for plotting neighborhoods contains data for *latitude* and *longitude* of neighborhoods.

The data is mostly comoposed of neighborhoods in Bangalore but has many outliers.

Folium library is used to create the following map depicting neighborhoods in the dataset.



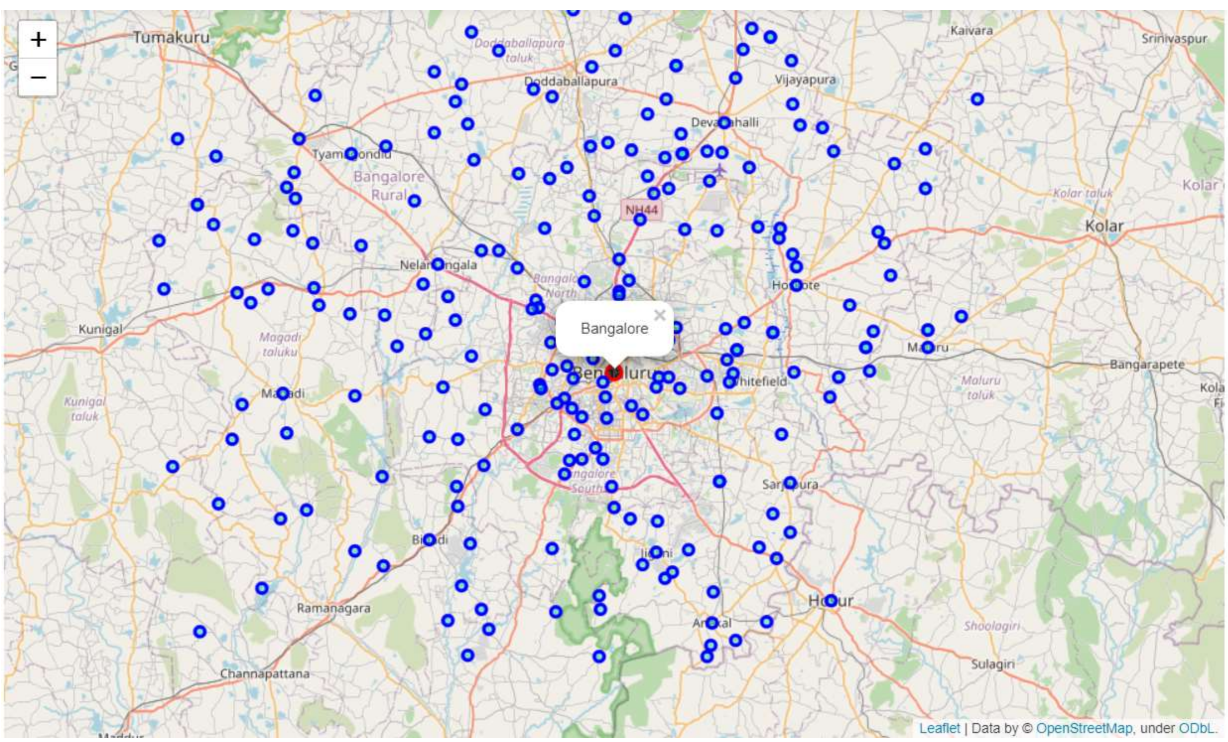
We see that the DataSet contains areas beyond the state of Karnataka and indeed beyond India.

We now clean the dataset to remove the outlieres and restrict the neighborhoods to Bangalore and its outskirts.

Here is the top 5 rows of the cleaned dataset for coordinates.

	Neighborhood	Latitude	Longitude
0	Amruthahalli	13.066513	77.596624
1	Banaswadi	13.014162	77.651854
2	Bhattarahalli	13.025800	77.714279
3	Byatarayanapura	13.062074	77.596392
4	Devanagundi	12.973613	77.839402

The map after cleaning of dataset is as follows.



We see that a total of 101 neighborhoods remain after cleaning the data

As we now have a cleaned dataset ready for analysis.

Let us proceed with analysis.

Methodology

I utilized the Foursquare API to explore the neighnorhoods and segment them.

The limit was set capped at 100 venues and a search radius of 1000 meters for each neighnorhood from their given latitude and longitude information.

Here is a head of the dataframe created with Venues name, category, latitude and longitude informations returned from Forsquare API.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Amruthahalli	13.066513	77.596624	The Druid Garden	13.063946	77.591492	Brewery
1	Amruthahalli	13.066513	77.596624	Big Straw	13.063414	77.591192	Bubble Tea Shop
2	Amruthahalli	13.066513	77.596624	Shivas Kabab Corner	13.062748	77.591789	Indian Restaurant
3	Amruthahalli	13.066513	77.596624	Swensen's	13.063476	77.590793	Ice Cream Shop
4	Amruthahalli	13.066513	77.596624	McDonald's	13.063687	77.589573	Fast Food Restaurant

The table is a merged form of neighborhoods with the nearby venues to each one.

The newly created dataset contains longitude and latitude values for venues as well as the neighborhood.

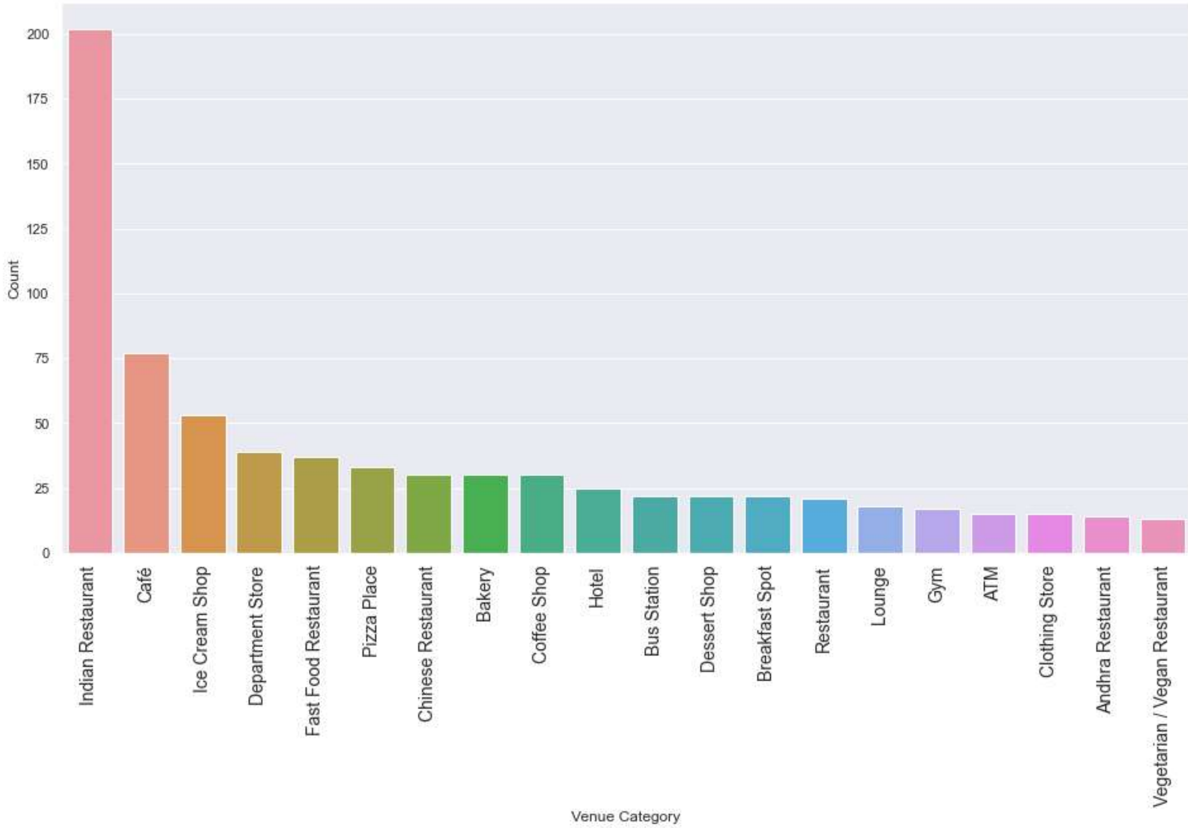
The Category of venue was also saved.

A total of 1215 venues were returned from the API.

Next, we count and plot the number of venue categories returned .

We see that a total of 182 unique categories of venues were returned.

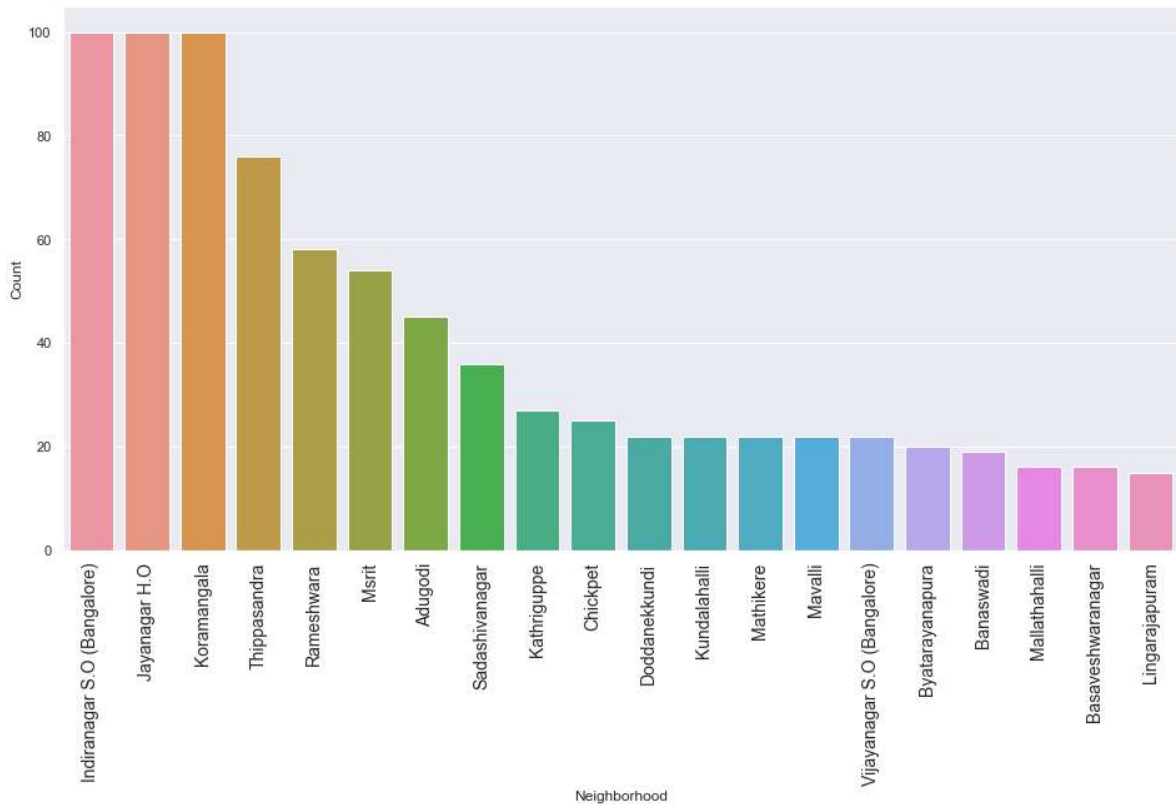
Plotting the top 20 venues that have the highest frequency we see the following bar graph.



The bar plot shows us that the most common venues returned are:

- **Indian Restaurants**
- **Cafes**
- **Ice Cream Shops**

Next, we plot the number of veneus returned per neighborhood to see the distribution of venues provided for each neighborhood.



An observation was made that the **number of venues returned for each neighborhood differ greatly**.

With posh areas like **Indiranagar, Jayanagar and Koramangala** having reached the 100 cap.

While no venues were returned for many neighborhoods.

This could be a problem with the foursquare API.

As the next course of action we try to find the most common venues in each neighborhood

We create a dataframe to show the top 10 most common venues of each neighborhood by grouping the last dataframe by neighborhood values.

A summary of the dataframe is as follows.

	Neighborhoods	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	Achitnagar	Bakery	Food & Drink Shop	Asian Restaurant	Yoga Studio	Food	Flower Shop	Flea Market	Financial or Legal Service	Field	Fast Food Restaurant
1	Adugodi	Indian Restaurant	Dessert Shop	Café	Lounge	Multiplex	Bookstore	Brewery	Coffee Shop	Donut Shop	Salon / Barbershop
2	Alahalli	Food & Drink Shop	Food Court	Food	Flower Shop	Flea Market	Financial or Legal Service	Field	Fast Food Restaurant	Farmers Market	Farm
3	Amruthahalli	Indian Restaurant	Bus Station	Pizza Place	Fast Food Restaurant	Bubble Tea Shop	Chinese Restaurant	Brewery	Hotel	Ice Cream Shop	Diner
4	Anekal	ATM	Business Service	Movie Theater	Department Store	Dessert Shop	Food	Flower Shop	Flea Market	Financial or Legal Service	Field
...	...	...	...	...	...	...	...	...	...	...	...
97	Vimanapura	Indian Restaurant	Fast Food Restaurant	Café	Pizza Place	Hotel	Restaurant	Bus Stop	Farmers Market	Gym	Event Service
98	Virgonagar	Breakfast Spot	University	Lake	Event Space	Food & Drink Shop	Food	Flower Shop	Flea Market	Financial or Legal Service	Field
99	Yadavanahalli	Resort	Hotel Bar	Restaurant	Yoga Studio	Electronics Store	Flea Market	Financial or Legal Service	Field	Fast Food Restaurant	Farmers Market
100	Yelachenahalli	Café	Pizza Place	Department Store	Indian Restaurant	Restaurant	Metro Station	Athletics & Sports	Motorcycle Shop	Flower Shop	Flea Market
101	Yelahanka	Ice Cream Shop	Café	Clothing Store	American Restaurant	Food Truck	Vegetarian / Vegan Restaurant	Smoke Shop	Multiplex	Train Station	Fast Food Restaurant

102 rows × 11 columns

Analysis

We now analyse the data at hand using K means clustering.

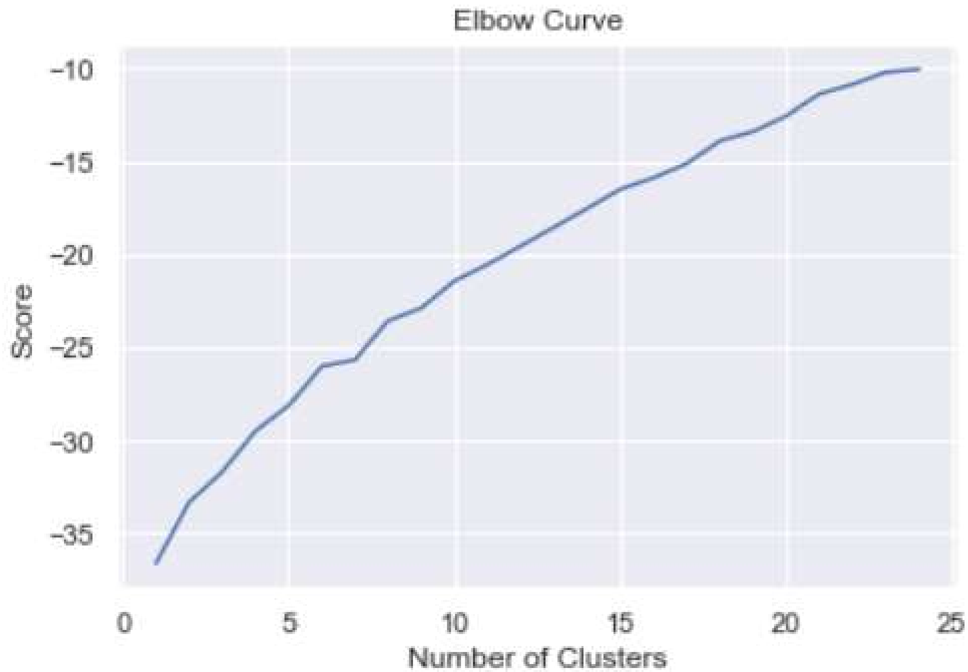
We have some common venue categories in the dataframe.

K-Means algorithm is one of the most common cluster method of unsupervised learning and thus will be an effective algorithm for clustering this kind of data.

First we find the number of clusters the neighborhoods should be grouped into.

For this purpose the elbow method was used where we run the K means algorithm for a different number of clusters and find the knee of the graph or where the graph flattens.

The following graph is obtained while running the K means for number of clusters rangind from 1 to 25.



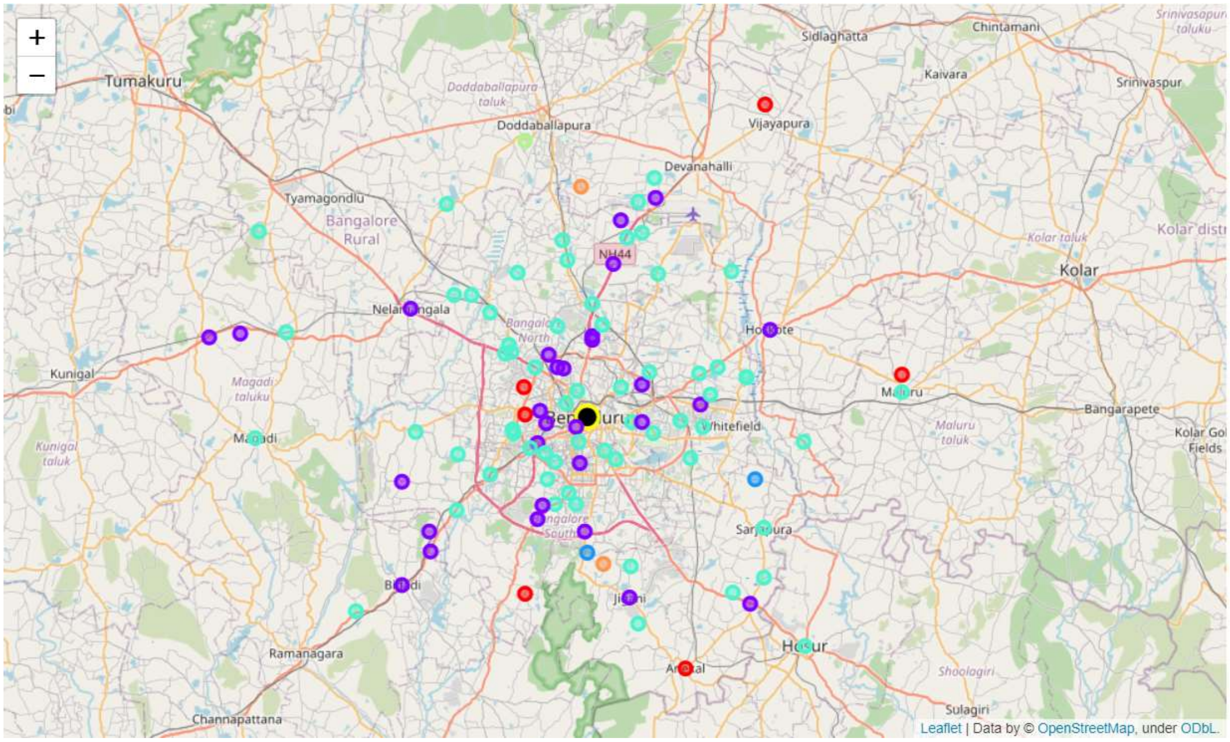
The elbow is not definite in the curve but the curve starts to become stable around 6.

Thus 6 was used as the number of clusters.

Results and Discussion

After clustering the neighborhoods, the custer labels were added back to the dataset for plotting.

The neighborhoods were grouped into 6 clusters by KNN as shown below.



The following observations were made.

- Cluster 0 is mainly composed of financial areas and markets.
- Cluster 1 is mainly composed of resteraunts and shopping districts along with areas for public transport.
- Custer 2 is composed of 2 locations both on the outskirts of the city and have a remarkebly similar layout in terms of most common locations. These are most likely locations on which the API couldn't get enough data.
- Cluster 4 is just a town on city outskirts with marksets, restaurants and farms.
- Cluster 5 like Cluster 2 is composed of 2 neighborhoods for which the API would't have provided enough data. The two neighborhoods here too are almost identical in their common venues.

Conclusion

I made the following conclusions from the result:

We can conculde from the above results that cluster 1 and 3 were the largest clusteres formed.

Cluster 0 appears to be a financial district and thus will recieve highest traffic and footfall on weekdays composed of people going for jobs.

Cluster 1 is composed of shopping districts and public transport stops. These neighborhoods tend to have traffic in rush hours as due to commuters going to work or returning from it.

Cluster 2, 4 and 5 are mostly composed of towns on the outskirts of the city which do not have a problem of packed roads.

Cluster 3 is the largest cluster and is composed mostly of food courts and places of Entertainment like movie theatres.
These places are most likely to recieve a higher amount of traffic and more footfall on weekends composed of families shopping and people out for leisure.

The solutions for the problem at hand seem to be:

1. The roads are choked due to a large number of people commuting to work through same highways. So more flyovers should be built.
2. Neigborhoods lie mostly near specific parts of Ring Road which will be a problem as many try to commute to same areas at same time. The roads in these areas should recieve constant monitoring.
3. Promotion and encouragement of public transports.
4. Metro seems a very viable option for this pupose so more metro lines should be laid and prices should be lowered.
5. Avoid central parts of city for commute during weekwnds.

“The road is hard, and you have to get accustomed to it.”