

# The Battle of Neighbourhoods - Final

This notebook consist of six parts.

## 1 Introduction/Business Problem

1.a Discussion of the business problem and the audience who would be interested in this project.

## 2 Data Section

- 2.a What data is used?
- 2.b Importing Libraries
- 2.c Credentials and Core location
- 2.d Search for hotel & restaurant within 1 KM
- 2.e Location of Hotels

## 3 Methodology Section

- 3.a Removing Outlier - Hotel Bharani
- 3.b How Far are hotels from the core location
- 3.c Explore for other venues around Kanyakumari
- 3.d Extract Venues using Search Queries
- 3.e Location of all venues
- 3.f How far are venues from the core location?
- 3.g Venue Categories
- 3.h Rating of all Venues
- 3.i Number of Tips for all Venues
- 3.j Extracting Rated and Tips Venues
- 3.k Final list of Venues
- 3.l Clustering based on venues
- 3.m Center of all clusters & Midpoint of all venues

## 4 Results Section

- 4.a My hotel location
- 4.b Top Rated Venues
- 4.c Spot my hotel against others
- 4.d Few more Stats

## 5 Discussion Section

## 6 Conclusion Section

# 1. Introduction/Business Problem

Discussion of the business problem and the audience who would be interested in this project.

## **TOPIC: Opening a new Hotel / Restaurant in Kanyakumari, India**

### **About the place - Kanyakumari, India**

Kanyakumari,a beautiful **tourist spot** in southern India.Kanyakumari is a coastal town in the state of Tamil Nadu on India's southern tip. Jutting into the Laccadive Sea, the town was known as 'Cape Comorin'. A popular tourist destination in India, it is famous for its unique ocean sunrise, sunset and moonrise over the ocean, the 133 feet Thiruvalluvar Statue and Vivekananda Rock Memorial off the coast, and as a pilgrimage centre. Lying at the tip of peninsular India, it is the confluence of the Arabian sea, the Bay of Bengal and the Indian Ocean. Other historic sights that you can visit in Kanyakumari include the Padmanabhapuram Palace, the Vattakottai Fort, and the Gandhi Memorial.

### **Opening of Hotel/Restaurant**

Regarding opening any business problem, It would be better to open a hotel/restaurant near beach side.As it is a famous tourist spot,there is already lots of attention towards it. There will be many competitors in terms of hotel and restauramt.But keeping them in mind,the new hotel should be opened in a place where more people are attracted and comfortable for a stay and a good meal. IT will attract foreign and local peoples attention towards the new hotel. And the flavour new restaurant recipe with Italian, American, typical South & North Indian foods to grab their taste.

### **Business Problem**

The objective of this capstone project is to analyse and select the **suitable locations** in the city of Kanyakumari,India for opening a new hotel / restaurant attracted to all local and foreign people in the centre of all famous venues. Using data science methodology and machine learning techniques like clustering, this project aims to provide solutions to answer the business question.

### **Expected / Interested Visitors**

80% local and 20% foreign peoples visit kanyakumari once in a year.Some people stay for couple of days or more. Also they find some place for hangout or a good meal. Their main focus might be belonging to stay somewhere near to reach venues. Apart from these set of people, students and working professionals are common visitors here. So we may need to fascinate them all.

### **Target Audience**

The target audience would be any stakeholder that is willing to start hotel/restaurant business in Kanyakumari, India. This project is particularly useful to property developers and investors looking to open or invest for new business.

**Success Criteria:** The success criteria of the project will be a good recommendation of choice to the investors based on number of hotel/restaurant in the city.

## **2.Data section**

## 2.a What data is used?

- We will be completely working on **Foursquare data** to explore and try to locate our new hotel where more venues like church, temples, beach, museums, memorials that are present nearby.

To solve the problem, we will need the following data:

- List of neighbourhoods in Kanyakumari.
- Latitude and longitude coordinates of those neighbourhoods.
- Venue data related to Hotel/Resaurant. This will help us determine the most suitable place to open a Hotel/Resaurant.

## How will we be solving using this data?

We will looking for midpoint area of venues to locate our new hotel.Before that our major focus will be on all venues present in and around the core place of kanyakumari.

Just a heads up on how many hotels are distributed now around kanyakumari.We will perform some EDA(Exploratory Data Analysis) on hotels & restaurants present in the tourist spot.On furthur notebook we will use Foursquare data to determine other venues as well.

## 2. b Importing Libraries

```
In [13]: # Import Libraries
import pandas as pd # data analysis
import requests # HTTP Library
from bs4 import BeautifulSoup # scraping Library
import numpy as np # data in a vectorized manner manipulation

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

```
In [14]: from pandas.io.json import json_normalize # transform JSON file into a pandas dataframe
import json # JSON files manipulation
#!conda install -c conda-forge geopy --yes # uncomment this line if you have
n't completed the Foursquare API Lab
from geopy.geocoders import Nominatim # convert an address into latitude and longitude values

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

from sklearn.cluster import KMeans # clustering algorithm

#!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you
haven't completed the Foursquare API Lab
import folium # map rendering library

print("***** Loaded library *****")
```

\*\*\*\*\* Loaded library \*\*\*\*\*

## 2.c Credentials and Core location

```
In [15]: CLIENT_ID = '...'
CLIENT_SECRET = '...'
VERSION = '20200811'
LIMIT = 150

address = "Kanyakumari, Tamil Nadu"

geolocator = Nominatim(user_agent="foursquare_agent")
location = geolocator.geocode(address)
latitude = location.latitude #8.079252 # Location.Latitude
longitude = location.longitude #77.5499338 # Location.Longitude #

kan='Kanyakumari location : {},{}'.format(latitude,longitude)
print(kan)
```

Kanyakumari location : 8.079252,77.5499338

## 2.d Search for hotel & restaurant within 1 KM

In [16]: #Quering for hotel & restaurant using foursquare API

```
search_query = 'hotel'
search_query_res = 'restaurant'

radius = 1000
url_hotel = 'https://api.foursquare.com/v2/venues/search?client_id={}&client_s
ecret={}&ll={},{}&v={}&query={}&radius={}&limit={}'.format(CLIENT_ID, CLIENT_S
ECRET, latitude, longitude, VERSION, search_query, radius, LIMIT)
url_restaurant = 'https://api.foursquare.com/v2/venues/search?client_id={}&cli
ent_secret={}&ll={},{}&v={}&query={}&radius={}&limit={}'.format(CLIENT_ID, CLI
ENT_SECRET, latitude, longitude, VERSION, search_query_res, radius, LIMIT)
#url
```

**Send the GET Request of hotel & restaurants and examine the results**

In [17]: results\_hotel = requests.get(url\_hotel).json()
results\_restaurant = requests.get(url\_restaurant).json()
#results\_hotel

**Get relevant part of JSON and transform it into a pandas dataframe**

In [18]: venues\_hotel = results\_hotel['response']['venues']
venues\_restaurant = results\_restaurant['response']['venues']

# transform venues into a dataframe and merging both data
dataframe\_hotel = json\_normalize(venues\_hotel)
dataframe\_restaurant = json\_normalize(venues\_restaurant)

dataframe = pd.concat([dataframe\_hotel,dataframe\_restaurant])

print("There are {} restaurants and hotels at Kanyakumari".format(dataframe.sh
ape[0]))

There are 40 restaurants and hotels at Kanyakumari

**Define information of interest and filter dataframe**

```
In [19]: filtered_columns = ['name', 'categories'] + [col for col in dataframe.columns if col.startswith('location.')] + ['id']
dataframe_filtered = dataframe.loc[:, filtered_columns]

# function that extracts the category of the venue

def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']

# filter the category for each row
dataframe_filtered['categories'] = dataframe_filtered.apply(get_category_type, axis=1)

# clean column names by keeping only last term
dataframe_filtered.columns = [column.split('.')[ -1] for column in dataframe_filtered.columns]

#dataframe_filtered
hotels_df=dataframe_filtered[['name','categories','distance','lat','lng','id']]
hotels_df.head()
```

Out[19]:

	<b>name</b>	<b>categories</b>	<b>distance</b>	<b>lat</b>	<b>lng</b>	<b>id</b>
<b>0</b>	Hotel SeaView	Hotel	371	8.082333	77.551217	4cd42e2c558a370412d0c5a6
<b>1</b>	Hotel Sarvana	Hotel	179	8.080581	77.550861	4db052544df03036e8b9d615
<b>2</b>	Hotel Samudra	Motel	201	8.080642	77.551102	4d3c66e414aa8cfa4641a95e
<b>3</b>	Hotel Annapoorna	Indian Restaurant	206	8.080879	77.550835	50ed3a39e4b0ac50005eb3f1
<b>4</b>	Hotel Trisea	South Indian Restaurant	269	8.081475	77.548969	5030a43ee4b021f7a59c7456

## 2.e Location of Hotels

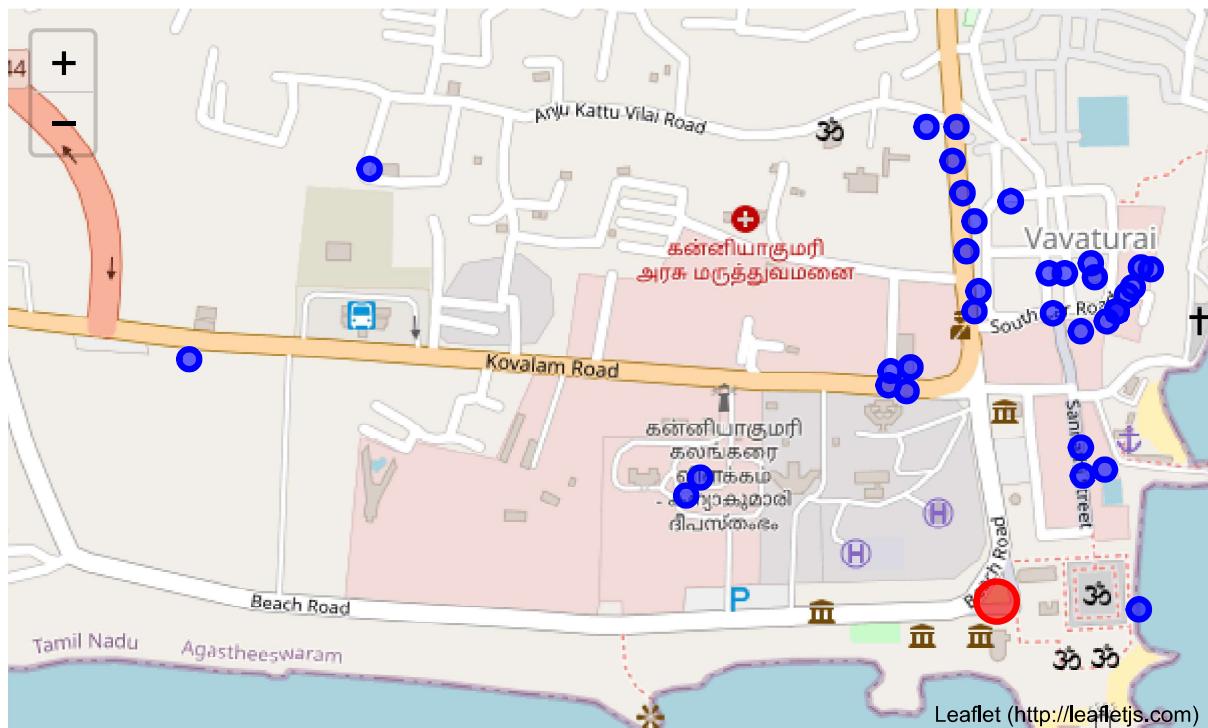
```
In [20]: hotels_map = folium.Map(location=[latitude, longitude], zoom_start=16) # generate map centred around the Kanyakumari

# add a red circle marker to represent the core location of kanyakumari
folium.features.CircleMarker(
    [latitude, longitude],
    radius=10,
    color='red',
    popup='Kanyakumari',
    fill = True,
    fill_color = 'red',
    fill_opacity = 0.6
).add_to(hotels_map)

# add the Italian restaurants as blue circle markers
for lat, lng, label in zip(hotels_df.lat, hotels_df.lng, hotels_df.name):
    folium.features.CircleMarker(
        [lat, lng],
        radius=5,
        color='blue',
        popup=label,
        fill = True,
        fill_color='blue',
        fill_opacity=0.6
    ).add_to(hotels_map)

# display map
hotels_map
```

Out[20]:



## 3.Methodology section

In this sections we will perform some data analysis and EDA to find insight from data.We will try to understand the current stats of all given data.Probably,clustering or centroid of all venues will help us to locate new hotel.

### 3.a Removing Outlier - Hotel Bharani

```
In [21]: dataframe_filtered=dataframe_filtered.drop(dataframe_filtered[dataframe_filtered.name =='Hotel Bharani'].index)
hotels_df=dataframe_filtered
print("So Now there are {} hotels & restaurants present in kanyakumari".format(dataframe_filtered.shape[0]))
```

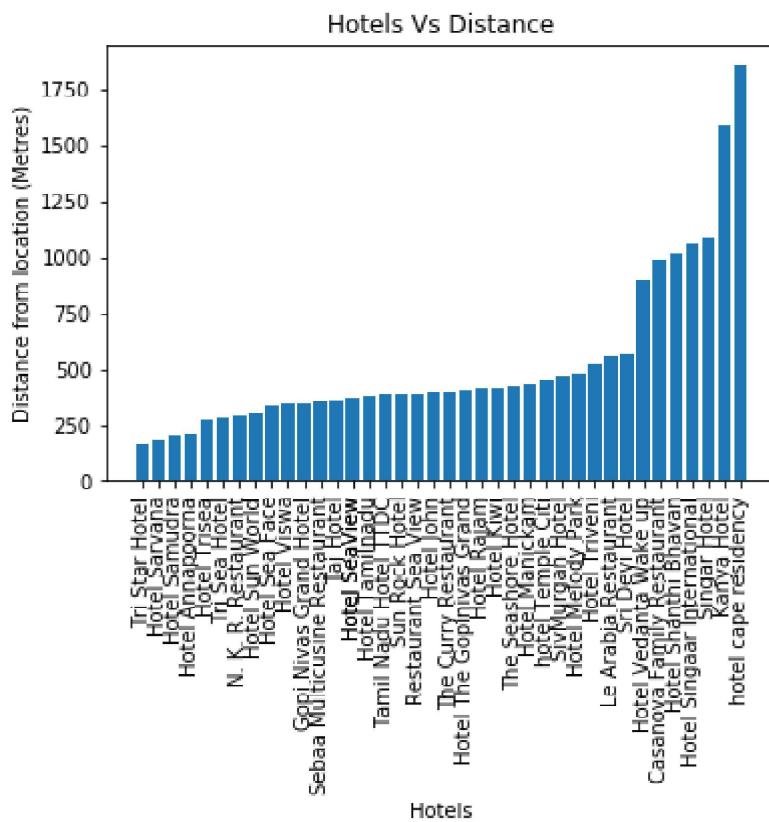
So Now there are 39 hotels & restaurants present in kanyakumari

### 3.b How Far are hotels from the core location

```
In [22]: distance_hotel_df=dataframe_filtered[['name','categories','distance','lat','lng']].sort_values('distance')

def plot_bar_x():
    # this is for plotting purpose
    index = np.arange(len(distance_hotel_df.name))
    plt.bar(distance_hotel_df.name, distance_hotel_df.distance)
    plt.xlabel('Hotels')
    plt.ylabel('Distance from location (Metres)')
    plt.xticks(distance_hotel_df.name, rotation=90)
    plt.title('Hotels Vs Distance')
    plt.show()
plot_bar_x()

print("Average distance between hotels and core location is {} metres".format(
int(sum(hotels_df['distance'])/hotels_df.shape[0])))
```



Average distance between hotels and core location is 521 metres

## Few Take Aways

- Singar hotel is far than rest of hotels.
- Tri Star remains close to the core spot.
- 521 metres is average distance from all hotels to core location

### 3.c Explore for other venues around Kanyakumari

A tourist person always wants to visit nearby iconic places. So he wants to reside somewhere nearby to all major venues. We will be exploring more venues around the core location.

We will be digging more on main areas or place around 1 km.

```
In [23]: radius=1000
url_venues = 'https://api.foursquare.com/v2/venues/explore?client_id={}&client_
_secret={}&ll={},{}&v={}&radius={}&limit={}'.format(CLIENT_ID, CLIENT_SECRET,
latitude, longitude, VERSION, radius, LIMIT)
#url_venues
```

```
In [24]: import requests

results_venues = requests.get(url_venues).json()
'There are {} venues around kanyakumari.'.format(len(results_venues['response']
]['groups'][0]['items']))
```

```
Out[24]: 'There are 16 venues around kanyakumari.'
```

**Get relevant part of JSON and transform it into a pandas dataframe**

```
In [25]: items_venues = results_venues['response']['groups'][0]['items']
#items_venues[0]
```

```
In [26]: dataframe_venues = json_normalize(items_venues) # flatten JSON

# filter columns
filtered_columns = ['venue.name', 'venue.categories'] + [col for col in dataframe_venues.columns if col.startswith('venue.location.')] + ['venue.id']
dataframe_filtered_venues = dataframe_venues.loc[:, filtered_columns]

# filter the category for each row
dataframe_filtered_venues['venue.categories'] = dataframe_filtered_venues.apply(get_category_type, axis=1)

# clean columns
dataframe_filtered_venues.columns = [col.split('.')[1] for col in dataframe_filtered_venues.columns]

dataframe_filtered_venues.name
```

```
Out[26]: 0           Sunrise Point
1   Vivekananda Rock Memorial
2           End of the Land
3      Kanyakumari Beach
4          Triveni Sangam
5      Sparsa Resorts and Spa
6          Hotel SeaView
7      Sangam Restaurtant
8          Hotel Sarvana
9      Thiruvalluvar Statue
10        Gandhi Memorial
11        Ferry Boat
12      Kanyakumari Lighthouse
13      The Seashore Hotel
14      Kanyakumari Bus Stantion
15      Thiruvalluvar Mandapam
Name: name, dtype: object
```

### 3.d Extract Venues using Search Queries

When I searched in google map,I could see there were some venues missing.Temples,Church,Parks and Museums are also more recognized by visitors and local audience.So lets bring their data inside.I am not sure why Foursquare hasnt captured it while trying venue query.

Below is the function to extract many queries at a time by passing them in a single list.

```
In [27]: # search query function
search_query_list = ['temple','church','park','museum']
radius =1000
temp_df=[]
search_df=[]

def search_query_fn():
    #Loop to run through urls and from json to pandas
    for i in range(len(search_query_list)):
        url= 'https://api.foursquare.com/v2/venues/search?client_id={}&client_
secret={}&ll={},{}&v={}&query={}&radius={}&limit={}'.format(CLIENT_ID, CLIENT_
SECRET, latitude, longitude, VERSION, search_query_list[i], radius, LIMIT)

        results=requests.get(url).json()
        venues = results['response']['venues']

        #Normalize from json
        dataframe = json_normalize(venues)

        #Removing unwanted column headers
        dataframe.columns = [col.split('.')[0] for col in dataframe.columns]
        temp_df.append(dataframe)

    #Loop to append dataframes to single dataframe
    for j in range(len(search_query_list)):
        data=temp_df[j]
        search_df.append(data)

# Function to run Loop over queries
search_query_fn()

search_df = pd.concat(search_df,sort=True)
search_df['categories'] = search_df.apply(get_category_type, axis=1)
search_df = pd.DataFrame(search_df[['name','categories','distance','lat','lng'
,'id']])
search_df
```

Out[27]:

	<b>name</b>	<b>categories</b>	<b>distance</b>	<b>lat</b>	<b>lng</b>	<b>i</b>
<b>0</b>	Bhagwati Aman Temple	Temple	127	8.079735	77.550979	4c7110d8d7fab1f7733e60c9
<b>1</b>	Kanyakumari Temple	Temple	209	8.080701	77.551147	5135e0ace4b05b6ad7b6e45
<b>2</b>	hotel Temple Citi	Hotel	448	8.083273	77.549709	58b591732520ae2198572be
<b>3</b>	Guganateeswara Temple	Temple	891	8.087151	77.548584	59361f0fd48ec1757c7d4ca4
<b>0</b>	St.Anthony's Church	Church	435	8.082916	77.551320	4db2dc880437fa536a056d3e
<b>1</b>	Our Lady Of Ransom Church	Church	680	8.085158	77.551544	4edb6b300e011b46ef9c3af5
<b>0</b>	Triangle Park	Park	8	8.079332	77.549930	5a17c667f96b2c105e79a65e
<b>1</b>	Hotel Melody Park	Hotel	482	8.083571	77.549568	52fbace0498e429e952167c

We will collate venues provided by foursquare and the ones extracted through hitting search query API

```
In [28]: # Data extracted from foursquare venues
four_sq_venue=pd.DataFrame(dataframe_filtered_venues[['name','categories','distance','lat','lng','id']])

# Data extracted from search queries
new_venues=pd.DataFrame(search_df)

# Concatenate both dataframe
df_venue=pd.concat([four_sq_venue, new_venues],sort=True)
```

Let us remove hotel & restaurants and get final list of venues.

We could see that there are some hotels/restaurants in the venues list. So we will remove them from the list. We have them in separate dataframe (hotels\_df).

```
In [29]: to_drop = ['Hotel', 'Restautant','hotel','Resort']
df_venues = df_venue[~df_venue['name'].str.contains('|'.join(to_drop))].reset_index()
print("There are {} venues in kanyakumari".format(df_venues.shape[0]))
df_venues[['name','distance','id']]
```

There are 17 venues in kanyakumari

Out[29]:

	<b>name</b>	<b>distance</b>	<b>id</b>
<b>0</b>	Sunrise Point	135	4f21fd64e4b0717a65eeddc3
<b>1</b>	Vivekananda Rock Memorial	312	4b9cbc7ef964a520e37836e3
<b>2</b>	End of the Land	148	4f22babfe4b0ed339695e61e
<b>3</b>	Kanyakumari Beach	10	4e8d9f944fc653e47d1afef1
<b>4</b>	Triveni Sangam	277	4eb57ae40cd688257829927c
<b>5</b>	Thiruvalluvar Statue	147	4ed9ed9530f83fb79c10cd14
<b>6</b>	Gandhi Memorial	26	4e8d8fc94fc653e47d19524a
<b>7</b>	Ferry Boat	259	4c71df7857b6a1436f4ec4cc
<b>8</b>	Kanyakumari Lighthouse	417	4c711c4334443704e6f5255f
<b>9</b>	Kanyakumari Bus Stantion	465	4edc1b4846907c1b44ba0ed8
<b>10</b>	Thiruvalluvar Mandapam	466	4cc0142397bc721ec6178967
<b>11</b>	Bhagwati Aman Temple	127	4c7110d8d7fab1f7733e60c9
<b>12</b>	Kanyakumari Temple	209	5135e0ace4b05b6ad7b6e450
<b>13</b>	Guganateeswara Temple	891	59361f0fd48ec1757c7d4ca4
<b>14</b>	St.Anthony's Church	435	4db2dc880437fa536a056d3e
<b>15</b>	Our Lady Of Ransom Church	680	4edb6b300e011b46ef9c3af5
<b>16</b>	Triangle Park	8	5a17c667f96b2c105e79a65e

### 3.e Location of all venues

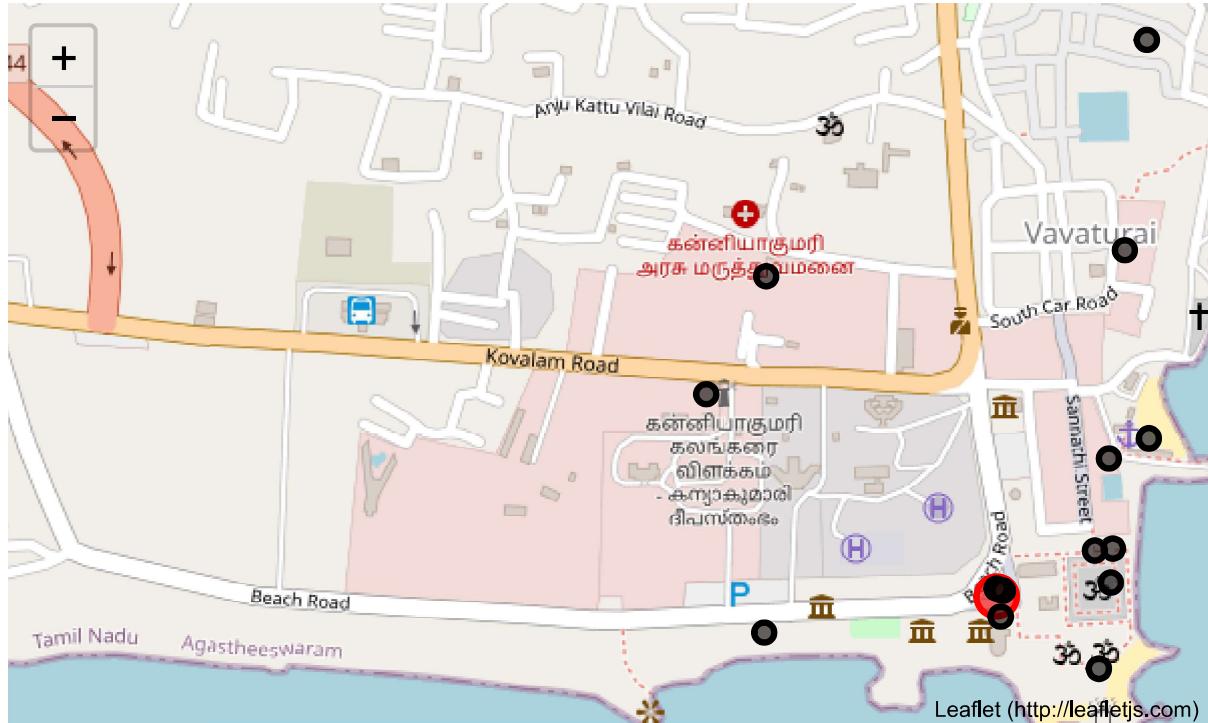
```
In [30]: venues_map = folium.Map(location=[latitude, longitude], zoom_start=16) # generate map centred around the Conrad Hotel

# add a red circle marker to represent the Kanyakumari
folium.features.CircleMarker(
    [latitude, longitude],
    radius=10,
    color='red',
    popup='kanyakumari',
    fill = True,
    fill_color = 'red',
    fill_opacity = 0.6
).add_to(venues_map)

# add the Italian restaurants as blue circle markers
for lat, lng, label in zip(df_venues.lat, df_venues.lng, df_venues.name):
    folium.features.CircleMarker(
        [lat, lng],
        radius=5,
        color='black',
        #popup=label,
        fill = True,
        fill_color='black',
        fill_opacity=0.6
    ).add_to(venues_map)

# display map
venues_map
```

Out[30]:

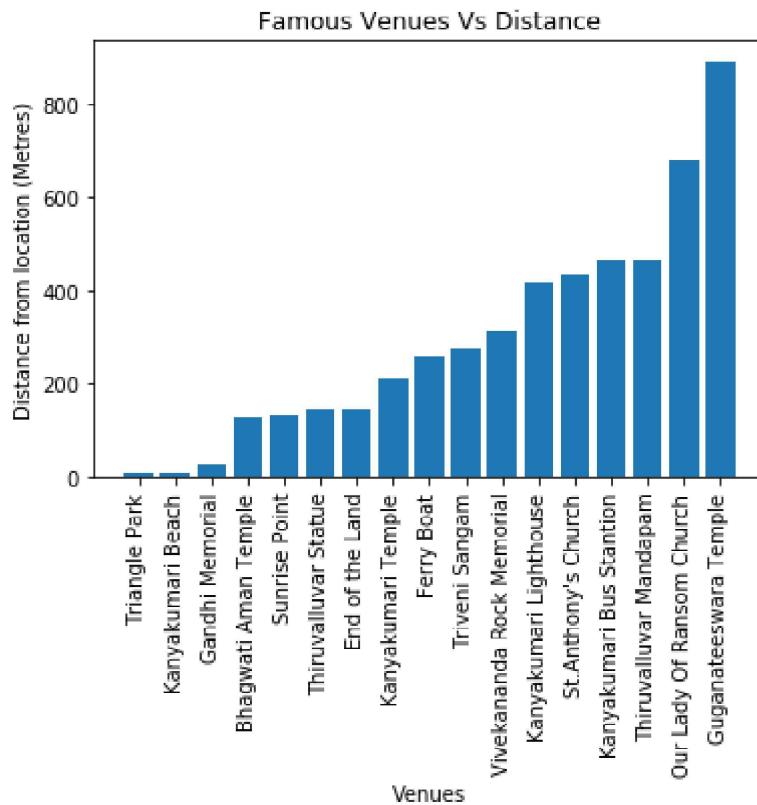


All venues seems to be dispersed except seashore areas.

We have listed out number of hotels and venues around kanyakumari. There are 39 Hotels/Restaurant and 17 Venues.

```
In [32]: distance_venues_df=df_venues.sort_values('distance')
```

```
def plot_bar_venue():
    # this is for plotting purpose
    index = np.arange(len(distance_venues_df.name))
    plt.bar(distance_venues_df.name, distance_venues_df.distance)
    plt.xlabel('Venues')
    plt.ylabel('Distance from location (Metres)')
    plt.xticks(distance_venues_df.name, rotation=90)
    plt.title('Famous Venues Vs Distance')
    plt.show()
plot_bar_venue()
```



## Few Take Aways

We could see Kanyakumari beach,Gandhi Memorial, Triangle Park are more closer to our location.

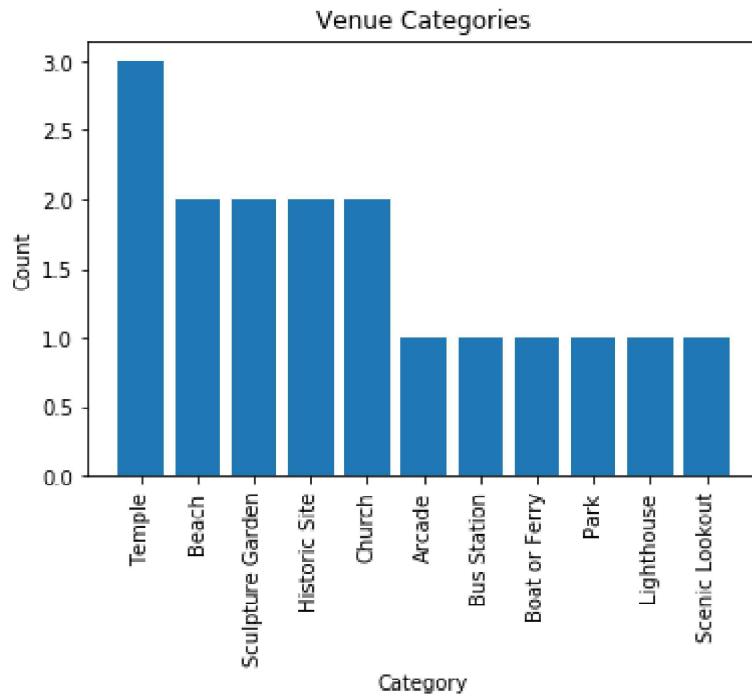
Guganateswara temple is far than rest of places.

Bus station is also an important venue which is 465 metres from our location

## 3.g Venue Categories

```
In [33]: freq_venue=df_venues['categories'].value_counts()
freq_venue=pd.DataFrame(freq_venue).reset_index()
freq_venue.columns=['Category', 'Count']
freq_venue

def plot_bar_categ():
    # this is for plotting purpose
    index = np.arange(len(freq_venue.Category))
    plt.bar(freq_venue.Category, freq_venue.Count)
    plt.xlabel('Category')
    plt.ylabel('Count')
    plt.xticks(freq_venue.Category, rotation=90)
    plt.title('Venue Categories')
    plt.show()
plot_bar_categ()
```



Eventhough we didnt have immense data to consider distribution of categories we could see that **Temple, Beach, Sculpture Garden, Historic sites and Church** are more common venues.

## 3.h Rating of all Venues

```
In [34]: #Rating of venues
rating_df=[]

for k in range(df_venues.shape[0]):
    venue_id=df_venues.id[k]
    url = 'https://api.foursquare.com/v2/venues/{}/?client_id={}&client_secret={}&v={}'.format(venue_id, CLIENT_ID, CLIENT_SECRET, VERSION)
    result = requests.get(url).json()
    #print(result)
    try:
        #print(df_venues.name[k],result['response']['venue']['rating'])
        rating=result['response']['venue']['rating']
        rating_df.append(rating)

    except:
        #print(df_venues.name[k],'This venue has not been rated yet.')
        rating='No Rating Yet'
        rating_df.append(rating)
```

```
In [35]: rate_dict = {'Venue': df_venues.name, 'Rating': rating_df,'distance':df_venues.distance}
rate_df=pd.DataFrame(rate_dict)
rate_df
```

Out[35]:

	Venue	Rating	distance
0	Sunrise Point	7.9	135
1	Vivekananda Rock Memorial	8	312
2	End of the Land	7.5	148
3	Kanyakumari Beach	7.1	10
4	Triveni Sangam	6.9	277
5	Thiruvalluvar Statue	No Rating Yet	147
6	Gandhi Memorial	5.5	26
7	Ferry Boat	No Rating Yet	259
8	Kanyakumari Lighthouse	No Rating Yet	417
9	Kanyakumari Bus Stantion	No Rating Yet	465
10	Thiruvalluvar Mandapam	No Rating Yet	466
11	Bhagwati Aman Temple	No Rating Yet	127
12	Kanyakumari Temple	No Rating Yet	209
13	Guganateeswara Temple	No Rating Yet	891
14	St.Anthony's Church	No Rating Yet	435
15	Our Lady Of Ransom Church	No Rating Yet	680
16	Triangle Park	No Rating Yet	8

### 3.i Number of Tips for all Venues

```
In [36]: tips_df=[]

for k in range(df_venues.shape[0]):
    venue_id=df_venues.id[k]
    url = 'https://api.foursquare.com/v2/venues/{}/client_id={}&client_secret={}&v={}'.format(venue_id, CLIENT_ID, CLIENT_SECRET, VERSION)
    result = requests.get(url).json()

#print(result['response']['venue']['tips']['count'],result['response']['venue'])
    tips=result['response']['venue']['tips']['count']
    tips_df.append(tips)
```

```
In [37]: tips_dict = {'Venue': df_venues.name, 'Tips': tips_df,'distance':df_venues.distance}
tips=pd.DataFrame(tips_dict)
tips=tips.sort_values('Tips',ascending = False)
tips
```

Out[37]:

	Venue	Tips	distance
1	Vivekananda Rock Memorial	16	312
0	Sunrise Point	4	135
7	Ferry Boat	4	259
3	Kanyakumari Beach	3	10
2	End of the Land	2	148
6	Gandhi Memorial	2	26
9	Kanyakumari Bus Stanton	1	465
8	Kanyakumari Lighthouse	1	417
4	Triveni Sangam	1	277
5	Thiruvalluvar Statue	0	147
10	Thiruvalluvar Mandapam	0	466
11	Bhagwati Aman Temple	0	127
12	Kanyakumari Temple	0	209
13	Guganateeswara Temple	0	891
14	St.Anthony's Church	0	435
15	Our Lady Of Ransom Church	0	680
16	Triangle Park	0	8

### 3.j Extracting Rated and Tips Venues

```
In [38]: # Add Tips column to Rating Dataframe
rate_df['Tips']=tips['Tips']

#Lets take values of only rated venues
only_rated_tips = rate_df[(rate_df['Rating']!='No Rating Yet') | (rate_df['Tips']!=0)]

only_rated_tips.reset_index(inplace = True,drop = True)
only_rated_tips
```

Out[38]:

	Venue	Rating	distance	Tips
0	Sunrise Point	7.9	135	4
1	Vivekananda Rock Memorial	8	312	16
2	End of the Land	7.5	148	2
3	Kanyakumari Beach	7.1	10	3
4	Triveni Sangam	6.9	277	1
5	Gandhi Memorial	5.5	26	2
6	Ferry Boat	No Rating Yet	259	4
7	Kanyakumari Lighthouse	No Rating Yet	417	1
8	Kanyakumari Bus Stantion	No Rating Yet	465	1

### 3.k Final list of Venues

```
In [39]: rated_list=[]
for i in range(len(only_rated_tips)):
    rated_tip_temp=only_rated_tips['Venue'][i]
    rated_list.append(rated_tip_temp)

#Masking all values present in list
mask = df_venues['name'].isin(rated_list)

final_venues = df_venues[mask]
#final_venues['Location']=final_venues['Lat'].astype(str).str.cat(final_venues['Lng'].astype(str), sep=' - ')
final_venues.reset_index(inplace = True,drop = True)

final_venues
```

Out[39]:

	<b>index</b>	<b>categories</b>	<b>distance</b>		<b>id</b>	<b>lat</b>	<b>lng</b>	<b>n</b>
<b>0</b>	0	Beach	135	4f21fd64e4b0717a65eeddc3	8.079398	77.551158	Sunrise Point	
<b>1</b>	1	Sculpture Garden	312	4b9cbc7ef964a520e37836e3	8.080707	77.552362	Vivekananda Rock Memorial	
<b>2</b>	2	Arcade	148	4f22babfe4b0ed339695e61e	8.078479	77.551035	End of the Land	
<b>3</b>	3	Beach	10	4e8d9f944fc653e47d1afef1	8.079311	77.550005	Kanyakumari Beach	
<b>4</b>	4	Historic Site	277	4eb57ae40cd688257829927c	8.078860	77.547448	Triveni Sangam	
<b>5</b>	10	Historic Site	26	4e8d8fc94fc653e47d19524a	8.079021	77.549976	Gandhi Memorial	
<b>6</b>	11	Boat or Ferry	259	4c71df7857b6a1436f4ec4cc	8.080931	77.551561	Ferry Beach	
<b>7</b>	12	Lighthouse	417	4c711c4334443704e6f5255f	8.081389	77.546820	Kanyakumari Lighthouse	
<b>8</b>	14	Bus Station	465	4edc1b4846907c1b44ba0ed8	8.082652	77.547469	Kanyakumari Bus Stand	

### 3.I Clustering based on venues

Now lets do some prediction to locate our new hotel in centre of final list of venues.

```
In [40]: # one hot encoding
neighbor_onehot = pd.get_dummies(final_venues[['categories']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
neighbor_onehot['name'] = final_venues['name']

# move neighborhood column to the first column
fixed_columns = [neighbor_onehot.columns[-1]] + list(neighbor_onehot.columns[:-1])
neighbor_onehot = neighbor_onehot[fixed_columns]

neighbor_onehot.head()
```

Out[40]:

	name	Arcade	Beach	Boat or Ferry	Bus Station	Historic Site	Lighthouse	Sculpture Garden
0	Sunrise Point	0	1	0	0	0	0	0
1	Vivekananda Rock Memorial	0	0	0	0	0	0	1
2	End of the Land	1	0	0	0	0	0	0
3	Kanyakumari Beach	0	1	0	0	0	0	0
4	Triveni Sangam	0	0	0	0	1	0	0

```
In [41]: neighbor_onehot.shape
neighbor_grouped = neighbor_onehot.groupby('name').mean().reset_index()
```

```
In [42]: # Top 10 venues
num_top_venues = 10

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['name']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['name'] = neighbor_grouped['name']
```

```
In [43]: # Clustering

# set number of clusters
kclusters = 3

neighbor_grouped_clustering = neighbor_grouped.drop('name', 1)

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

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

# add clustering labels
neighborhoods_venues_sorted.insert(0, 'Clustersss', kmeans.labels_)

neighbor_merged = final_venues

# merge toronto_grouped with toronto_data to add Latitude/Longitude for each neighborhood
neighbor_merged = neighbor_merged.join(neighborhoods_venues_sorted.set_index(
    'name'), on='name')

kmeans
```

```
Out[43]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
random_state=0, tol=0.0001, verbose=0)
```

### 3.m Center of all clusters & Midpoint of all venues

We will be collating the location of centroid of all clusters and midpoint of all venues to get more accurate location

```
In [44]: fin=neighbor_merged.groupby(['Clustersss']).mean()

lati=sum(fin.lat)/len(fin.lat)
longi=sum(fin.lng)/len(fin.lng)

#Taking midpoint of top ten closest hotel
venues_lan=sum(final_venues.lat)/len(final_venues.lat)
venues_lng=sum(final_venues.lng)/len(final_venues.lng)

final_latitude=(lati+venues_lan)/2
final_longitude=(longi+venues_lng)/2

print("Final location (Green Dot in our below given map) of our brand new hotel:({},{})".format(final_latitude,final_longitude))
```

Final location (Green Dot in our below given map) of our brand new hotel:8.07  
9896043302105,77.54973668986852

```
In [45]: map_clusters = folium.Map(location=[latitude, longitude], zoom_start=17)

# 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]

folium.features.CircleMarker(
    [final_latitude, final_longitude],
    radius=10,
    color='green',
    popup='My hotel',
    fill = True,
    fill_color = 'green',
    fill_opacity = 0.6
).add_to(map_clusters)

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(neighbor_merged['lat'], neighbor_merged['lon'],
                                   neighbor_merged['name'], neighbor_merged['Clustersss']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=6,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[45]:



The location (green colored) gives the central point to visit all other venues. Hence this can be locked down to attract all tourist.

## 4. Results section

### 4.a My hotel location

- Final location is pointed at 8.07985,77.54973
- This location is at Beach Road opposite to Gandhi Memorial and Kumari Temple.
- Located at exact junction of two cross roads which can give more attention to people who passby.

### 4.b Top Rated Venues

- Sunrise Point
- Vivekananda Rock Memorial
- End of the Land
- Kanyakumari Beach
- Triveni Sangam
- Gandhi Memorial

All these venues are rated well than other and also they have more tips and located within 320 metres to core location of kanyakumari.So tourists may like to visit these places.

### 4.c Spot my hotel against others

- Green - My hotel location
- Red - Kanyakumari core location.
- Black - Venues.
- Blue - Other hotels.
- My predicted location and core location are very close to each other which is expected.As this has central attraction,the predicted one almost matched with the core.

```
In [48]: my_hotel_vs_all = folium.Map(location=[latitude, longitude], zoom_start=16) # generate map centred around the Kanyakumari

# add a red circle marker to represent the my hotel location
folium.features.CircleMarker(
    [final_latitude, final_longitude],
    radius=10,
    color='green',
    popup='My Hotel',
    fill = True,
    fill_color = 'green',
    fill_opacity = 0.6
).add_to(my_hotel_vs_all)

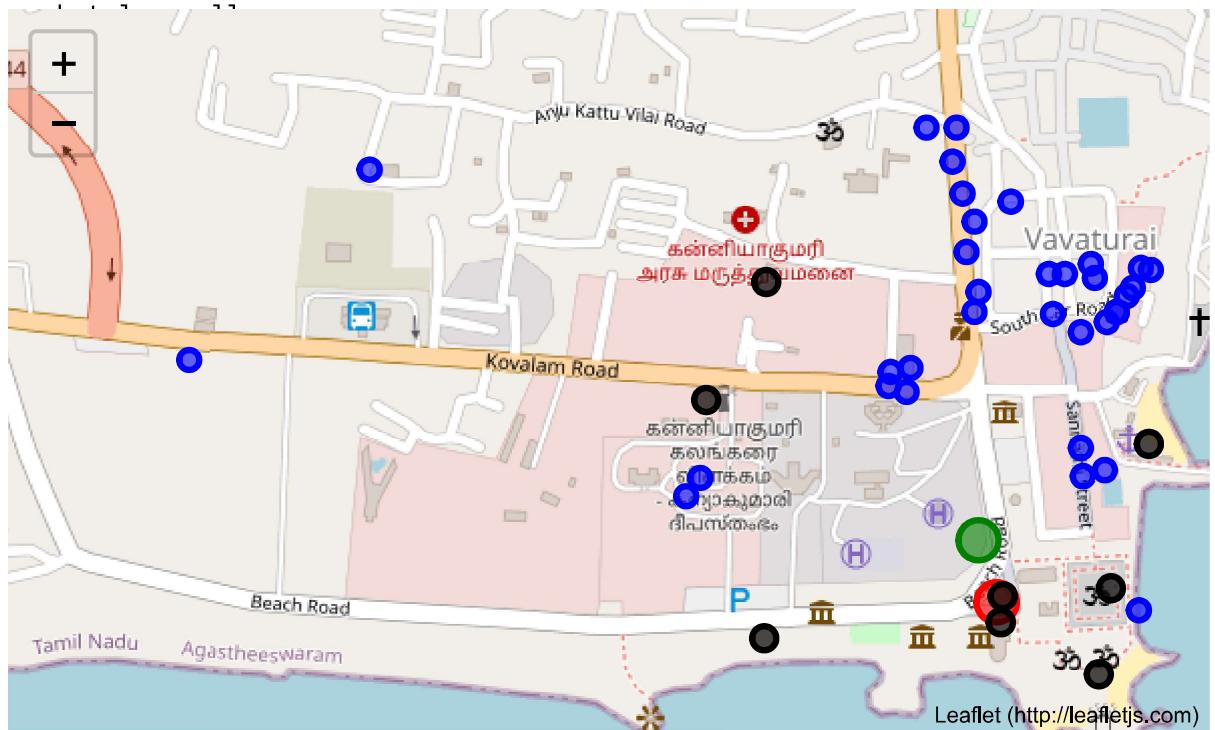
# add a red circle marker to represent the core Location of kanyakumari
folium.features.CircleMarker(
    [latitude, longitude],
    radius=10,
    color='red',
    popup='Kanyakumari',
    fill = True,
    fill_color = 'red',
    fill_opacity = 0.6
).add_to(my_hotel_vs_all)

# add the Italian restaurants as blue circle markers
for lat, lng, label in zip(hotels_df.lat, hotels_df.lng, hotels_df.name):
    folium.features.CircleMarker(
        [lat, lng],
        radius=5,
        color='blue',
        popup=label,
        fill = True,
        fill_color='blue',
        fill_opacity=0.6
    ).add_to(my_hotel_vs_all)

markers_colors = []
for lat, lon, poi, cluster in zip(neighbor_merged['lat'], neighbor_merged['lng'], neighbor_merged['name'], neighbor_merged['Clustersss']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=6,
        popup=label,
        color='black',
        fill=True,
        fill_color='black',
        fill_opacity=0.7).add_to(my_hotel_vs_all)
```

# display map

Out[48]:



#### 4.d Few more Stats

- Most common categories of venues are Temples, Church, Beach in Kanyakumari
- Average distance between all hotels is 454 metres.
- Tri Star hotel, Hotel Saravana, Hotel Samudra will be our competitors as they stay close to our predicted location.

### 5. Discussion section

From above reports,we could get an idea why the predicted one is pointed/clustered on the given spot. First most thing could be the center of attraction for the place.

KMeans have figured out the most common place for all the venues. This output was very adjacent to the core location. This proves the accurate spotting of our predicted algorithm.

Despite of the findings,there were some lack in data. Tips and ratings were missing for most of the venues. Also when I compared foursquare data with google map ,i could see there were many hotels and venues found missing in foursquare.

### 6. Conclusion section

As a business person,one would be able to set up a hotel/restaurant on given spot. This will bring revenue automatically as we have located in very near to core one. We proved this with Kmeans.

#### Future Expectation:

As mentioned earlier,most of data needs to be extracted from googlemaps. Even though we got somewhat accurate prediction. To be very confident on concluding our output,we may need more data to analyse.

Research based on hotel reviews and restaurant menus could be used for future purpose.

#### My Experience:

It was wonderful journey for me in IBM capstone and other courses. It can aid to layman people as well who dont know a pinch of Data science. Thanks to Coursera for keeping Skilful instructors with their awesome materials

**THANK YOU!! HAPPY DATA SCIENCE LEARNING !!!**