Capstone Project - The Battle of Neighborhoods(Final)

0.1 Exploring venues in Indore, India

0.1.1 Table of Contents

0.1.2 Introduction

The aim of the project is to identify venues in Indore, India based on their rating and average prices. In this notebook, we will identify various venues in the city of **Indore, India**, using **Foursquare API** and **Zomato API**, to help visitors select the restaurants that suit them the best.
Whenever a user is visiting a city they start looking for places to visit during their stay. They primarily look for places based on the venue ratings across all venues and the average prices such that the locations fits in their budget.
Here, we'll **identify places that are fit for various individuals** based on the information collected from the two APIs and Data Science. Once we have the plot with the venues, any company can launch an application using the same data and suggest users such information.

0.1.3 Data Collection from APIs

To begin with, we will take a look at **Indore on the Map** using the folium library.
We will also fetch the data from **two different APIs**.

- **Foursquare API**: We will use the Foursquare API to fetch venues in Indore starting from the middle upto 44 Kilometers in each direction.

- **Zomato API**: The Zomato API provides information about various venues including the complete address, user ratings, price for two people, price range and a lot more.

0.1.4 Indore

Indore is composed of a number of sectors spread across a total area of 530 sq Km. There are many venues (especially restaurants, hotels and cafes) which can be explored.

We can use the geopy library to extract the latitude and longitude values of Pune but it seems off and thus, we'll directly supply the values in this case.

[2]:
```
TARGET_LATITUDE = 22.7196
TARGET_LONGITUDE = 75.8577
TARGET = 'Indore'
print('The geograpical coordinates of {} are {}, {}.'.format(TARGET,␣
↪TARGET_LATITUDE, TARGET_LONGITUDE))
```

```
The geograpical coordinates of Indore are 22.7196, 75.8577.
```

[3]:
```
import folium

target_location_map = folium.Map(location = [TARGET_LATITUDE,␣
↪TARGET_LONGITUDE], zoom_start = 12.5)
folium.Marker([TARGET_LATITUDE, TARGET_LONGITUDE]).add_to(target_location_map)
target_location_map.save("TargetMap.html")
target_location_map
```

[3]:
```
<folium.folium.Map at 0x7f9abfc07b70>
```

0.1.5 Foursquare API

We begin by fetching a total of all venues in Indore upto a range of 4 Kilometers using the Foursquare API. The Foursquare API has the explore API which allows us to find venue recommendations within a given radius from the given coordinates. We will use this API to find all the venues we need.

[4]:
```
FOURSQUARE_CLIENT_ID = '0HH2B0MRFB2FALD3CL3SQAGF5KPCVO53DS5OEOKOP4MWUCJO'
FOURSQUARE_CLIENT_SECRET = 'D5KMPZK1RAFC0RSUS3VCUOIAIIA2KVCOWHIP1RJX3D1L0UQS'
RADIUS = 6000 # 6 Km
NO_OF_VENUES = 100
VERSION = '20200426' # Current date
```

We define the get_category_type method to get the correct category for each venue.

[5]:
```
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']
```

We'll call the API over and over till we get all venues from the API within the given distance. The maximum venues this API can fetch is 100, so we will fetch all venues by iteratively calling this API and increasing the offset each time.

- Foursquare API requires client_id, and client_secret to function which can be accessed after creating a developer account.
- We will set the radius as 4 Kilometers.
- The version is a required parameter which defines the date on which we are browsing so that it retrieves the latest data.

[6]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib.colors as colors

from pandas.io.json import json_normalize
import requests

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

offset = 0
total_venues = 0
foursquare_venues = pd.DataFrame(columns = ['name', 'categories', 'lat', 'lng'])

while (True):
    url = ('https://api.foursquare.com/v2/venues/explore?client_id={}'
           '&client_secret={}&v={}&ll={},{}&radius={}&limit={}&offset={}').
 ↪format(FOURSQUARE_CLIENT_ID,
                                                                          ␣
 ↪FOURSQUARE_CLIENT_SECRET,
                                                                           VERSION,
                                                                          ␣
 ↪TARGET_LATITUDE,
                                                                          ␣
 ↪TARGET_LONGITUDE,
                                                                           RADIUS,
                                                                          ␣
 ↪NO_OF_VENUES,
                                                                           offset)
    result = requests.get(url).json()
    venues_fetched = len(result['response']['groups'][0]['items'])
    total_venues = total_venues + venues_fetched
```

```
    print("Total {} venues fetched within a total radius of {} Km".
↪format(venues_fetched, RADIUS/1000))

    venues = result['response']['groups'][0]['items']
    venues = json_normalize(venues)

    # Filter the columns
    filtered_columns = ['venue.name', 'venue.categories', 'venue.location.lat',␣
↪'venue.location.lng']
    venues = venues.loc[:, filtered_columns]

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

    # Clean all column names
    venues.columns = [col.split(".")[-1] for col in venues.columns]
    foursquare_venues = pd.concat([foursquare_venues, venues], axis = 0, sort =␣
↪False)

    if (venues_fetched < 100):
        break
    else:
        offset = offset + 100

foursquare_venues = foursquare_venues.reset_index(drop = True)
print("\nTotal {} venues fetched".format(total_venues))
```

```
Total 75 venues fetched within a total radius of 6.0 Km

Total 75 venues fetched

/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/ipykernel_launcher.py:33: FutureWarning: pandas.io.json.json_normalize
is deprecated, use pandas.json_normalize instead
```

0.1.6 Zomato API

The Zomato API allows using its search API to search for any given venue based on certain search filters such as query, latitude, longitude and more. Zomato also requires a Zomato user key which can be accessed with a developer account.

We'll use the name, lat, and lng values of various venues fetched from Foursquare API to use the search API and get more information regarding each venue.

- The query will be the name of the venue.
- The start defines from what offset we want to start, so we'll keep it at 0.
- The count defines the number of restaurants we want to fetch. As we have the exact location coordinates, we'll fetch only one.
- We will supply the latitude and longitude values.

- We will set the sorting criteria as real_distance so each time we get the venue we're searching based on location coordinates.

[7]:
```
headers = {'user-key': 'df1145140716bb75945b27ee861a1c62'}
venues_information = []

for index, row in foursquare_venues.iterrows():
    print("Fetching data for venue: {}".format(index + 1))
    venue = []
    url = ('https://developers.zomato.com/api/v2.1/search?q={}' +
           '&start=0&count=1&lat={}&lon={}&sort=real_distance').
 ↪format(row['name'], row['lat'], row['lng'])
    try:
        result = requests.get(url, headers = headers).json()
    except:
        print("There was an error...")
    try:

        if (len(result['restaurants']) > 0):
            venue.append(result['restaurants'][0]['restaurant']['name'])
            venue.
 ↪append(result['restaurants'][0]['restaurant']['location']['latitude'])
            venue.
 ↪append(result['restaurants'][0]['restaurant']['location']['longitude'])
            venue.
 ↪append(result['restaurants'][0]['restaurant']['average_cost_for_two'])
            venue.append(result['restaurants'][0]['restaurant']['price_range'])
            venue.
 ↪append(result['restaurants'][0]['restaurant']['user_rating']['aggregate_rating'])
            venue.
 ↪append(result['restaurants'][0]['restaurant']['location']['address'])
            venues_information.append(venue)
        else:
            venues_information.append(np.zeros(6))
    except:
        pass

zomato_venues = pd.DataFrame(venues_information,
                                    columns = ['venue', 'latitude',
                                               'longitude', 'price_for_two',
                                               'price_range', 'rating',␣
 ↪'address'])
```

```
Fetching data for venue: 1
Fetching data for venue: 2
Fetching data for venue: 3
Fetching data for venue: 4
Fetching data for venue: 5
```

```
Fetching data for venue: 6
Fetching data for venue: 7
Fetching data for venue: 8
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```

```
Fetching data for venue: 54
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Fetching data for venue: 72
Fetching data for venue: 73
Fetching data for venue: 74
Fetching data for venue: 75
```

[8]:
```
zomato_venues = pd.DataFrame(venues_information,
                                    columns = ['venue', 'latitude',
                                               'longitude', 'price_for_two',
                                               'price_range', 'rating',␣
 ↪'address'])
```

0.1.7 Data Cleaning

The data from multiple resources might not always align. Thus, it is important to combine the data retrieved from multiple resources properly.

We'll first plot the two data points on the map. We'll then try to combine data points that have their latitude and longitude values very close to one another. From the remaining selected venues, we will inspect the venues to ensure that any remaining mismatched venues are also removed from the final dataset of venues before we begin any analysis.

We will first plot the Foursquare data on the map.

[9]:
```
target_location_map = folium.Map(location = [TARGET_LATITUDE,␣
 ↪TARGET_LONGITUDE], zoom_start = 13)

for name, latitude, longitude in zip(foursquare_venues['name'],␣
 ↪foursquare_venues['lat'], foursquare_venues['lng']):
    label = '{}'.format(name)
    label = folium.Popup(label, parse_html = True)
```

```
    folium.CircleMarker(
        [latitude, longitude],
        radius = 5,
        popup = label,
        color = 'green',
        fill = True,
        fill_color = '#3186cc',
        fill_opacity = 0.7,
        parse_html = False).add_to(target_location_map)

target_location_map.save("Venues by Foursquare.html")
target_location_map
```

[9]: <folium.folium.Map at 0x7f9abef9c358>

From the map, we can infer that there are clusters of venues around Vijay Nagar, Palasia and Indore Junction. We can also plot the category count and see the major type of venues that exist.

We will also plot the Zomato data on the map.

[10]:
```
target_location_map = folium.Map(location = [TARGET_LATITUDE,␣
↪TARGET_LONGITUDE], zoom_start = 13)

for venue, address, latitude, longitude in zip(zomato_venues['venue'],␣
↪zomato_venues['address'],
                                               zomato_venues['latitude'],␣
↪zomato_venues['longitude']):
    UPDATED_LG = float(longitude)
    UPDATED_LT = float(latitude)
    label = '{}, {}'.format(name, address)
    label = folium.Popup(label, parse_html = True)
    folium.CircleMarker(
        [UPDATED_LT, UPDATED_LG],
        radius = 5,
        popup = label,
        color = 'red',
        fill = True,
        fill_color = '#cc3535',
        fill_opacity = 0.7,
        parse_html = False).add_to(target_location_map)

target_location_map.save("Venues by Zomato.html")
target_location_map
```

[10]: <folium.folium.Map at 0x7f9abcb525c0>

[11]:
```
foursquare_venues['lat'] = foursquare_venues['lat'].apply(lambda lat:␣
↪round(float(lat), 4))
foursquare_venues['lng'] = foursquare_venues['lng'].apply(lambda lng:␣
↪round(float(lng), 4))
zomato_venues['latitude'] = zomato_venues['latitude'].apply(lambda lat:␣
↪round(float(lat), 4))
zomato_venues['longitude'] = zomato_venues['longitude'].apply(lambda lng:␣
↪round(float(lng), 4))
```

[12]:
```
dataset = pd.concat([foursquare_venues, zomato_venues], axis = 1)
dataset['lat_diff'] = dataset['latitude'] - dataset['lat']
dataset['lng_diff'] = dataset['longitude'] - dataset['lng']
```

[13]:
```
selected_venues = dataset[(abs(dataset['lat_diff']) <= 0.0004) &␣
↪(abs(dataset['lng_diff']) <= 0.0004)].reset_index(drop = True)
selected_venues
```

[13]:

	name	categories	lat	lng	\
0	Shreemaya Hotel Indore	Hotel	22.7151	75.8746	
1	56 Dukan	Plaza	22.7241	75.8848	
2	Lotus Hut Cafe	Coffee Shop	22.7209	75.8759	
3	Mr Beans	Cafeteria	22.7233	75.8969	
4	Bablu Sandwich	Sandwich Place	22.7036	75.8554	
5	Ccd,apollo Square	Café	22.7264	75.8810	
6	Sky Sheesha Lounge	Hookah Bar	22.7441	75.8946	
7	Celebrations Shreemaya	Restaurant	22.7153	75.8751	
8	Top n town	Ice Cream Shop	22.7257	75.8774	
9	Cafe Palette	Café	22.7214	75.8875	
10	Subway	Sandwich Place	22.7445	75.8942	
11	The Roof	Indian Restaurant	22.7241	75.8855	
12	Tinku Ice Cream	Ice Cream Shop	22.7213	75.8739	
13	Cafe Coffee Day	Coffee Shop	22.6975	75.8772	
14	Shoppers Stop Indore	Shopping Mall	22.7362	75.8910	
15	10 downing street	Pub	22.7444	75.8943	
16	Malhar Mega Mall	Shopping Mall	22.7446	75.8945	
17	Chaibar	Tea Room	22.7254	75.8829	
18	saket pan conner	Dessert Shop	22.7254	75.8949	
19	Chappan	Snack Place	22.7247	75.8837	
20	cafe coffee day	Café	22.7542	75.9002	
21	Crown Palace	Indian Restaurant	22.7195	75.8836	
22	Sreemaya	Indian Restaurant	22.7399	75.8924	
23	Johney Hot-Dog	Hot Dog Joint	22.7246	75.8845	
24	Pizza Hut	Pizza Place	22.7447	75.8940	
25	KFC	Fast Food Restaurant	22.7446	75.8939	
26	McDonald's	Fast Food Restaurant	22.7521	75.8962	
27	The Chocolate Room	Dessert Shop	22.7542	75.9002	
28	Bake n shake	Bakery	22.7542	75.9001	

```
29            Hotel Mangal City                Motel  22.7526  75.8964
30               FYI Vijaynagar  Fast Food Restaurant  22.7559  75.8943
31  Fairfield by Marriott Indore                Hotel  22.7479  75.9038

                         venue  latitude  longitude  price_for_two  \
0                   Cheers Cafe   22.7152    75.8749          200.0
1                    Chaap Adda   22.7241    75.8848          300.0
2                     Lotus Hut   22.7209    75.8758          350.0
3                     Mr. Beans   22.7232    75.8967          800.0
4                   Prem Prakash   22.7035    75.8555          350.0
5                Cafe Coffee Day   22.7262    75.8810          500.0
6            Sky Blue Sports Bar   22.7440    75.8944         1800.0
7                Hotel Shreemaya   22.7152    75.8750         1100.0
8                   Top 'N' Town   22.7257    75.8775          200.0
9                     Coksa Cafe   22.7214    75.8872          250.0
10                        Subway   22.7447    75.8943          500.0
11                     The Roof    22.7240    75.8856          900.0
12         Sheetal Gazak & Kulfi   22.7209    75.8739          250.0
13               Cafe Coffee Day   22.6977    75.8772          500.0
14               Cafe Coffee Day   22.7362    75.8911          500.0
15                  Cafe Paprika   22.7447    75.8944          350.0
16                   Cafe Idiots   22.7447    75.8945          400.0
17                  The Chai Bar   22.7253    75.8830          300.0
18            New Mahaveer Dairy   22.7255    75.8948          200.0
19                   Eat N Treat   22.7246    75.8840          250.0
20            The Chocolate Room   22.7541    75.9002          700.0
21                    Tea De Pot   22.7195    75.8837          400.0
22           Shreemaya Celebrity   22.7399    75.8922          500.0
23                 Johny Hot Dog   22.7244    75.8845          150.0
24                     Pizza Hut   22.7448    75.8941          600.0
25                           KFC   22.7447    75.8940          450.0
26       SGF - Spice Grill Flame   22.7523    75.8958          500.0
27            The Chocolate Room   22.7541    75.9002          700.0
28            The Chocolate Room   22.7541    75.9002          700.0
29                       Level 3   22.7526    75.8965         1500.0
30                         F.Y.I   22.7558    75.8944          400.0
31  Kava - Fairfield by Marriott   22.7481    75.9039         1500.0

    price_range rating                                        address  \
0           1.0    2.9       G-1/1, Sapna Chamber, 12/1, RNT Marg, Indore
1           1.0    3.5  Shop 56, Lower Ground 02, One Centre, New Pala…
2           2.0    3.9                17, MG Road, South Tukoganj, Indore
3           3.0    4.3                    100, Saket, Old Palasia, Indore
4           2.0    3.8  Prem Nagar Square, Manik Bagh Overbridge Corne…
5           2.0    3.7  Apollo Square, Race Course Road, Near Janjeerw…
6           4.0    3.5  3rd Floor, C21 Mall, AB Road, Vijay Nagar, Indore
7           3.0    4.4                12, South Tukoganj, RNT Marg Indore
```

8	1.0	4.2	14/8, Race Course Road, YN Road, Indore
9	1.0	0	24/2, Manorama Ganj, Near Sanghi Motors, Geeta…
10	2.0	3.9	Ground Floor, Malhar Mega Mall, Vijay Nagar, I…
11	3.0	3.5	Hotel Kanchan Tilak, 582/2, MG Road, New Palas…
12	1.0	4.1	Near Rajani Bhawan, YN Road, Indore
13	2.0	3.7	BCM City Building, AB Road, Near Navalakha Squ…
14	2.0	3.3	Inside Hotel Ginger, Near Shoppers Stop Buildi…
15	2.0	3.2	Shop 7, 3rd Floor, Malhar Mega Mall, Vijay Nag…
16	2.0	2.8	3, Third Floor, Food Court, Malhar Mega Mall, …
17	1.0	3.9	G 1, Chetak Vihar, 7 R.S Bhandari Marg, Near 5…
18	1.0	3.7	28/2, Saket Chouraha, Old Palasia, Indore
19	1.0	3.9	LG 15, Silver Arcade, Chappan Dukan, Opposite …
20	2.0	4.0	Scheme 54, PU 4, Upper Ground 7, BCM Heights, …
21	2.0	0	22/3, Basement, Kanchan Bagh, Gita Bhawan Road…
22	2.0	4.4	Hotel Shreemaya, AB Road, Press Complex, Indore
23	1.0	4.6	Shop UD-49-50-51, Arcade Silver 56/1, New Pala…
24	2.0	3.6	Anchor 1, II Floor, Malhar Mega Mall, Vijay Na…
25	2.0	4.1	Malhar Mega Mall, Vijay Nagar, Indore
26	2.0	4.0	S-24, Shahid Bhagat Singh, Parisar, Vijay Naga…
27	2.0	4.0	Scheme 54, PU 4, Upper Ground 7, BCM Heights, …
28	2.0	4.0	Scheme 54, PU 4, Upper Ground 7, BCM Heights, …
29	4.0	3.5	Second Floor, Mangal City Mall, AB Road, Vijay…
30	2.0	3.8	Ankur Annexe, Scheme 54, Near SBI, Vijay Nagar…
31	4.0	3.9	Plot 18/C, Scheme 94, Ring Road, Vijay Nagar, …

	lat_diff	lng_diff
0	0.0001	0.0003
1	0.0000	0.0000
2	0.0000	-0.0001
3	-0.0001	-0.0002
4	-0.0001	0.0001
5	-0.0002	0.0000
6	-0.0001	-0.0002
7	-0.0001	-0.0001
8	0.0000	0.0001
9	0.0000	-0.0003
10	0.0002	0.0001
11	-0.0001	0.0001
12	-0.0004	0.0000
13	0.0002	0.0000
14	0.0000	0.0001
15	0.0003	0.0001
16	0.0001	0.0000
17	-0.0001	0.0001
18	0.0001	-0.0001
19	-0.0001	0.0003
20	-0.0001	0.0000

```
21    0.0000    0.0001
22    0.0000   -0.0002
23   -0.0002    0.0000
24    0.0001    0.0001
25    0.0001    0.0001
26    0.0002   -0.0004
27   -0.0001    0.0000
28   -0.0001    0.0001
29    0.0000    0.0001
30   -0.0001    0.0001
31    0.0002    0.0001
```

Taking a look at the names of venues from both APIs, some names are a complete mismatch.

Category 1: There are venues that have specific restaurants/cafes inside them as provided by Zomato API .

Category 2: Two locations are so close by that they have practically same latitude and longitude values .

Category 3: Some have been replaced with new restaurants.

The venues which belong to category 1 and category 3 are alright to keep, the venues that fall in category 2 should be removed.

[14]:
```
selected_venues = selected_venues.drop([0]).reset_index(drop = True)
```

[15]:
```
selected_venues['average_price'] = selected_venues['price_for_two']/2
selected_venues = selected_venues.drop(columns = ['name', 'lat', 'lng',␣
↪'lat_diff', 'lng_diff', 'price_for_two'])
```

[16]:
```
selected_venues.head(5)
```

[16]:

	categories	venue	latitude	longitude	price_range	rating	address	average_price
0	Plaza	Chaap Adda	22.7241	75.8848	1.0	3.5	Shop 56, Lower Ground 02, One Centre, New Pala…	150.0
1	Coffee Shop	Lotus Hut	22.7209	75.8758	2.0	3.9	17, MG Road, South Tukoganj, Indore	175.0
2	Cafeteria	Mr. Beans	22.7232	75.8967	3.0	4.3	100, Saket, Old Palasia, Indore	400.0
3	Sandwich Place	Prem Prakash	22.7035	75.8555	2.0	3.8	Prem Nagar Square, Manik Bagh Overbridge Corne…	175.0
4	Café	Cafe Coffee Day	22.7262	75.8810	2.0	3.7	Apollo Square, Race Course Road, Near Janjeerw…	250.0

I'll drop the venues which have 0.0 rating as it means it's not been rated yet.

[17]:
```
selected_venues = selected_venues[selected_venues['rating'] != 0.0]
print("Total venues available: {}".format(selected_venues.shape[0]))
```

```
Total venues available: 29
```

0.1.8 Methodology

This project aims at identifying the venues in **Indore** based on their rating and average costs. This would enable any visitor to identify the venues he/she wants to visit based on their rating and cost preference.

As a first step, we retrieved the **data from two APIs (Foursquare and Zomato)**. We extract venue information from the center of Indore, upto a distance of 6 Km. The latitude and longitude values are then used to fetch venue rating and price from Zomato.

Secondly, we then **explored the data** retrieved from the two APIs on the map and identified the top category types. The **data from the two sources is carefully combined** based on the name, latitude and longitude values from the two sources. The final dataset would include the rating and price values for each venue.

Next, we'll **analyse the data** that we created based on the ratings and price of each venue. We'll **identify places where many venues are located** so that any visitor can go to one place and enjoy the option to choose amongst many venue options. We'll also explore **areas that are high rated and those that are low rated** while also plotting the map of high and low priced venues. Lastly, we'll cluster the venues based on the available information of each venue. This will allow us to clearly identify which venues can be recommended and with what characteristics.

Finally, we'll discuss and conclude which venues to be explored based on visitor requirement of rating and cost.

0.1.9 Analysis

The complete dataset is now in its final form.

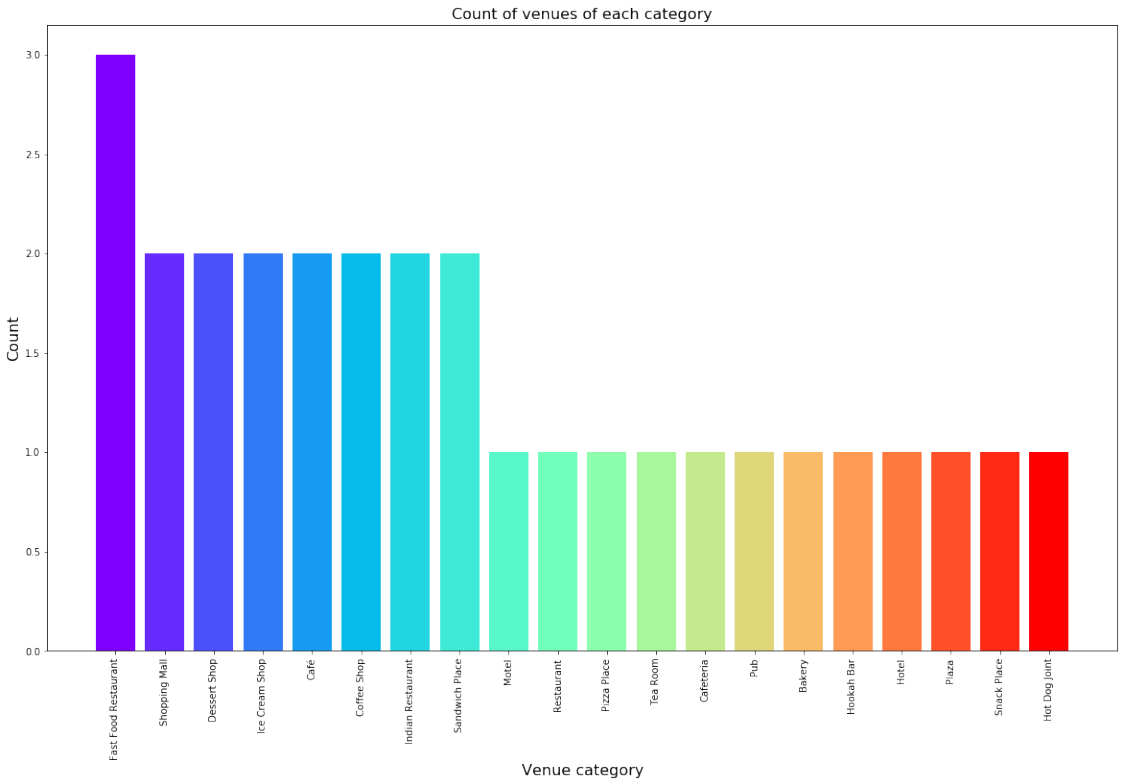
We will **inspect these venues based on their rating**. The rating of a venue are based on user reviews and belongs to a range from 1 to 5. We'll also **analyse the venues based on their price per person as well as the price range**.

0.1.10 Categories

We have various types of venues in the final dataset. We will take a look at the venues and check which are the majority venue categories in the list.

[18]:
```
venue_distribution = selected_venues['categories'].value_counts()
colors = cm.rainbow(np.linspace(0, 1, len(venue_distribution.index)))
plt.figure(figsize = (20, 12))
plt.xticks(rotation = 90)
plt.xlabel("Venue category", fontsize = 16)
plt.ylabel("Count", fontsize = 16)
plt.title("Count of venues of each category", fontsize = 16)
plt.bar(venue_distribution.index, venue_distribution.values, color = colors)
```

[18]: <BarContainer object of 20 artists>



As we can see the majority venues are **Hotel** and **Indian Restaurant**. So, if as a tourist, you're looking for cafes and Indian restaurants, you're in luck.

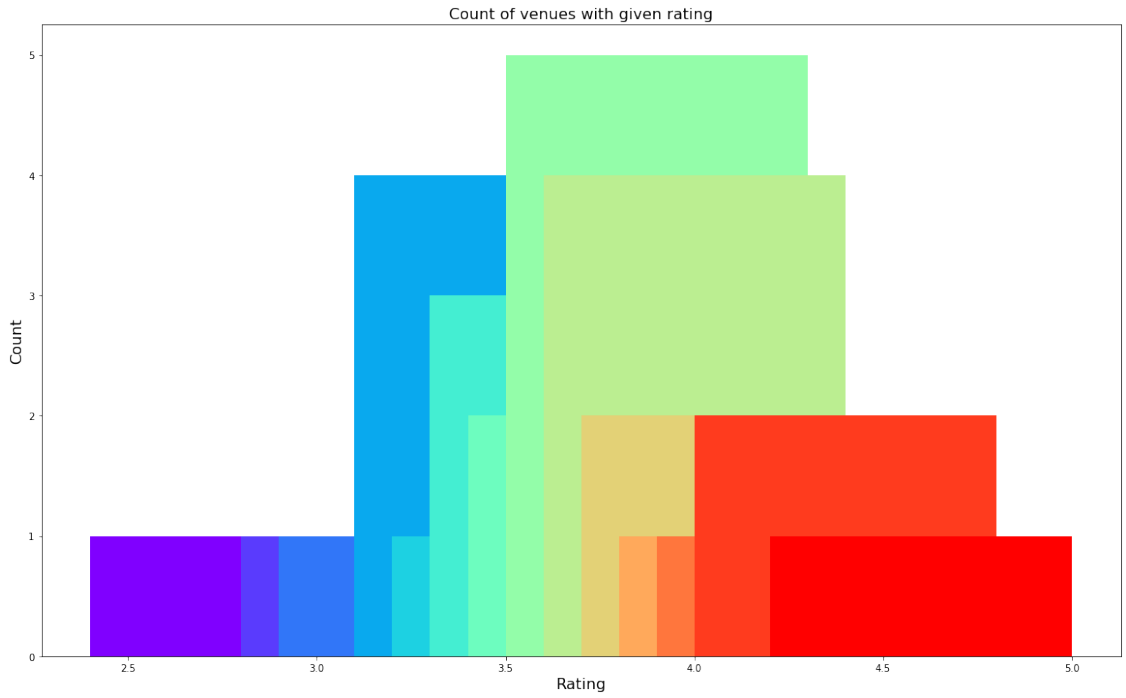
0.1.11 Rating

Rating of a venue is an important factor on which a visitor decides whether it is worth it to visit the place. To cater to this, we will first see what is the average rating for all the venues in the city. Next, we will plot the venues on the map and color code them.

We'll first identify the various rating values and plot them as a bar plot with their counts to see the most common rating.

[19]:
```
selected_venues['rating'] = selected_venues['rating'].astype(float)
rating = selected_venues['rating'].value_counts().sort_index()
plt.figure(figsize = (20, 12))
plt.bar(rating.index, rating.values, color = cm.rainbow(np.linspace(0, 1,␣
 ↪len(rating.index))))
plt.xlabel("Rating", fontsize = 16)
plt.ylabel("Count", fontsize = 16)
plt.title("Count of venues with given rating", fontsize = 16)
```

[19]: Text(0.5, 1.0, 'Count of venues with given rating')



From the plot above, it is clear that majority venues have their rating close to 4.

Let's create bins for various ratings and plot them in different colors on the map. The ratings will be divided between 4 bins:

- 1 to 2
- 2 to 3
- 3 to 4
- 4 to 5

[34]:
```
bins = [1.0, 2.0, 3.0, 4.0, 5.0]
labels = ['Low', 'Okay', 'Good', 'Very good']
selected_venues['rating_bin'] = pd.cut(selected_venues['rating'].astype(float),␣
↪bins = bins, labels = labels, include_lowest = True)
```

[36]:
```
color_map = {'Low': 'red', 'Okay': 'orange', 'Good': 'green', 'Very good':␣
↪'darkgreen'}

target_location_map = folium.Map(location = [TARGET_LATITUDE,␣
↪TARGET_LONGITUDE], zoom_start = 13)

for name, address, latitude, longitude, rating_bin in␣
↪zip(selected_venues['venue'],
```

```
                                                                    ␣
↪selected_venues['address'],
                                                                    ␣
↪selected_venues['latitude'],
                                                                    ␣
↪selected_venues['longitude'],
                                                                    ␣
↪selected_venues['rating_bin']):
    label = '{}, {}'.format(name, address)
    label = folium.Popup(label, parse_html = True)
    folium.Marker(
        [latitude, longitude],
        icon = folium.Icon(color = color_map[rating_bin]),
        popup = label).add_to(target_location_map)

target_location_map.save("Venues Ratings.html")
target_location_map
```

[36]:
```
<folium.folium.Map at 0x7f9ab7627940>
```

The map has the location of all the venues. It appears that many venues are located near about Vijay Nagar, Palasia and High Street with rating above 3. If someone wants to explore new venues, they should definitely check out these areas.

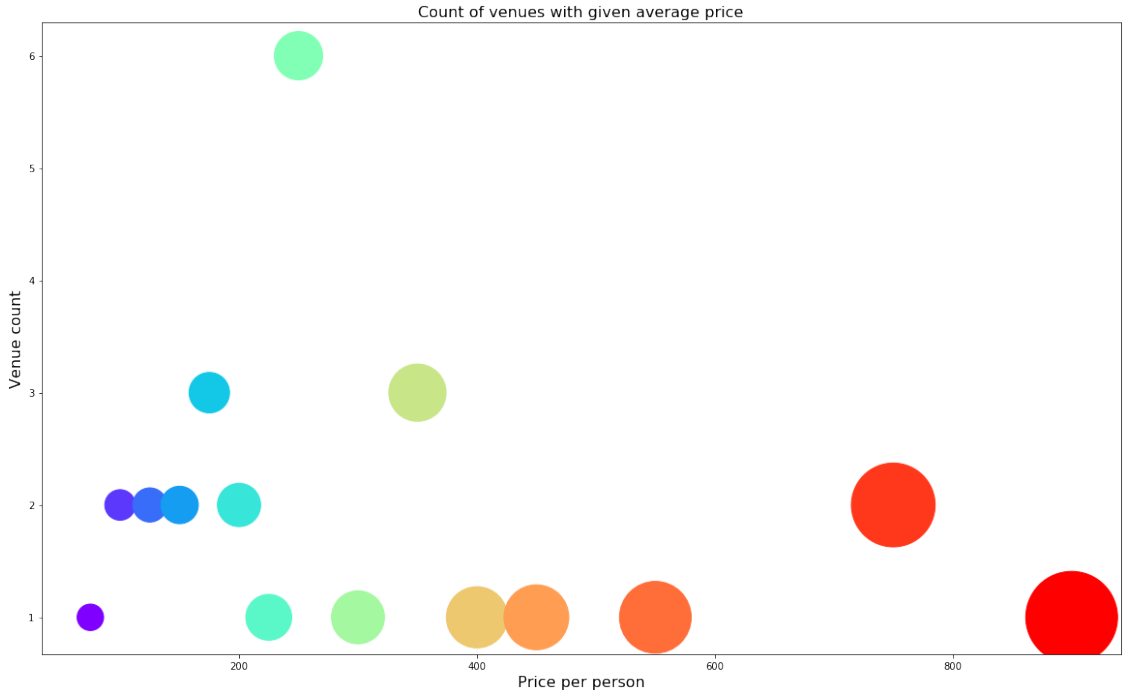
0.1.12 Price

We will now take a look the venues based on the price values. We have two price features for our venues, one is average_price which defines the average cost for one person and the other is price_range which determines the price range as defined by Zomato.

We will first explore the average_price using a scatter plot between the price and the count of venues with that average price. We'll size the points based on the price to highlight their price.

[37]:
```
average_prices = selected_venues['average_price'].value_counts().sort_index()
plt.figure(figsize = (20, 12))
plt.scatter(average_prices.index,
            average_prices.values,
            s = average_prices.index*10,
            c = cm.rainbow(np.linspace(0, 1, len(average_prices.index))))
plt.xlabel("Price per person", fontsize = 16)
plt.ylabel("Venue count", fontsize = 16)
plt.title("Count of venues with given average price", fontsize = 16)
```

[37]:
```
Text(0.5, 1.0, 'Count of venues with given average price')
```



From the plot above we can see that a large number of venues have an average price between Rs 400 and Rs 700.

Users might also be interested in going to a place that fits in their budget. I'll use the price_range column to plot the venues on a map. We'll represent the venues with lower price in green and move towards red as the price increases.

[38]:
```
color_map = {1: 'green', 2: 'darkgreen', 3: 'orange', 4: 'red'}

target_location_map = folium.Map(location = [TARGET_LATITUDE,␣
 ↪TARGET_LONGITUDE], zoom_start = 13)

for name, address, latitude, longitude, price_range in␣
 ↪zip(selected_venues['venue'],
                                                        ␣
 ↪selected_venues['address'],
                                                        ␣
 ↪selected_venues['latitude'],
                                                        ␣
 ↪selected_venues['longitude'],
                                                        ␣
 ↪selected_venues['price_range'].astype(str)):
    label = '{}, {}'.format(name, address)
    label = folium.Popup(label, parse_html = True)
    folium.Marker(
```

```
        [latitude, longitude],
        icon = folium.Icon(color = color_map[_bin]),
        popup = label).add_to(target_location_map)

target_location_map.save("Venues Prices.html")
target_location_map
```

```
      ␣
↪---------------------------------------------------------------------------

       NameError                                 Traceback (most recent call␣
↪last)

       <ipython-input-38-c81054179188> in <module>
        12     folium.Marker(
        13         [latitude, longitude],
   ---> 14         icon = folium.Icon(color = color_map[_bin]),
        15         popup = label).add_to(target_location_map)
        16


       NameError: name '_bin' is not defined
```

0.1.13 Clustering

We will now cluster all these venues based on their price range, location and more to identify similar venues and the relationship amongst them. We'll cluster the venues into two separate groups.

[39]:
```
from sklearn.cluster import KMeans

NO_OF_CLUSTERS = 2

clustering = selected_venues.drop(['venue', 'address', 'rating_bin',␣
 ↪'categories'], 1)
kMeans = KMeans(n_clusters = NO_OF_CLUSTERS, random_state = 0).fit(clustering)
selected_venues.insert(0, 'cluster_labels', kMeans.labels_)
selected_venues.head(5)
```

[39]:

	cluster_labels	categories	venue	latitude	longitude	\
0	0	Plaza	Chaap Adda	22.7241	75.8848	
1	0	Coffee Shop	Lotus Hut	22.7209	75.8758	
2	0	Cafeteria	Mr. Beans	22.7232	75.8967	
3	0	Sandwich Place	Prem Prakash	22.7035	75.8555	
4	0	Café	Cafe Coffee Day	22.7262	75.8810	

```
   price_range  rating                                              address  \
0          1.0     3.5  Shop 56, Lower Ground 02, One Centre, New Pala…
1          2.0     3.9                17, MG Road, South Tukoganj, Indore
2          3.0     4.3                    100, Saket, Old Palasia, Indore
3          2.0     3.8  Prem Nagar Square, Manik Bagh Overbridge Corne…
4          2.0     3.7  Apollo Square, Race Course Road, Near Janjeerw…

   average_price rating_bin
0          150.0       Good
1          175.0       Good
2          400.0  Very good
3          175.0       Good
4          250.0       Good
```

[40]:
```
target_location_map = folium.Map(location = [TARGET_LATITUDE,␣
↪TARGET_LONGITUDE], zoom_start = 13)
color_map = { 0: 'green', 1: 'red'}

# add venues to the map
markers_colors = []
for venue, address, cluster, latitude, longitude in␣
↪zip(selected_venues['venue'],
                                                    ␣
↪selected_venues['address'],
                                                    ␣
↪selected_venues['cluster_labels'],
                                                    ␣
↪selected_venues['latitude'],
                                                    ␣
↪selected_venues['longitude']):
    label = folium.Popup(str(venue) + ', ' + str(address), parse_html = True)
    folium.CircleMarker(
        [latitude, longitude],
        radius = 5,
        popup = label,
        color = color_map[cluster],
        fill = True,
        fill_color = color_map[cluster],
        fill_opacity = 0.7).add_to(target_location_map)

# add cluster centers to the map
for index, cluster in enumerate(kMeans.cluster_centers_):
    latitude = cluster[0]
    longitude = cluster[1]
    label = folium.Popup("Cluster: " + str(index), parse_html = True)
    folium.CircleMarker(
```

```
        [latitude, longitude],
        radius = 10,
        popup = label,
        color = color_map[index],
        fill = True,
        fill_color = color_map[index],
        fill_opacity = 0.7).add_to(target_location_map)

target_location_map.save("Venues Clusters.html")
target_location_map
```

[40]: <folium.folium.Map at 0x7f9ab74a3ac8>

From the map, we see the two clusters:

The first cluster is spread across the whole city and includes the majority venues. The second cluster is very sparsely spread and has very limited venues.

[41]:
```
result = selected_venues[selected_venues['cluster_labels'] == 0]
print("Cluster 0")
result.head(10).reset_index(drop = True)
```

```
Cluster 0
```

[41]:

	cluster_labels	categories	venue	latitude	longitude	price_range	rating
0	0	Plaza	Chaap Adda	22.7241	75.8848	1.0	3.5
1	0	Coffee Shop	Lotus Hut	22.7209	75.8758	2.0	3.9
2	0	Cafeteria	Mr. Beans	22.7232	75.8967	3.0	4.3
3	0	Sandwich Place	Prem Prakash	22.7035	75.8555	2.0	3.8
4	0	Café	Cafe Coffee Day	22.7262	75.8810	2.0	3.7
5	0	Ice Cream Shop	Top 'N' Town	22.7257	75.8775	1.0	4.2
6	0	Sandwich Place	Subway	22.7447	75.8943	2.0	3.9
7	0	Indian Restaurant	The Roof	22.7240	75.8856	3.0	3.5
8	0	Ice Cream Shop	Sheetal Gazak & Kulfi	22.7209	75.8739	1.0	4.1
9	0	Coffee Shop	Cafe Coffee Day	22.6977	75.8772	2.0	3.7

```
                                              address  average_price rating_bin
0  Shop 56, Lower Ground 02, One Centre, New Pala…          150.0       Good
1                17, MG Road, South Tukoganj, Indore          175.0       Good
2                    100, Saket, Old Palasia, Indore          400.0  Very good
3  Prem Nagar Square, Manik Bagh Overbridge Corne…          175.0       Good
4  Apollo Square, Race Course Road, Near Janjeerw…          250.0       Good
5           14/8, Race Course Road, YN Road, Indore          100.0  Very good
6  Ground Floor, Malhar Mega Mall, Vijay Nagar, I…          250.0       Good
7  Hotel Kanchan Tilak, 582/2, MG Road, New Palas…          450.0       Good
8                Near Rajani Bhawan, YN Road, Indore          125.0  Very good
9  BCM City Building, AB Road, Near Navalakha Squ…          250.0       Good
```

[42]:
```
print("These venues for cluster 0 have mean price range of {:.02f} and rating␣
↪spread around {:.02f}".
      format(result['price_range'].mean(), result['rating'].astype(float).
↪mean()))
```

```
These venues for cluster 0 have mean price range of 1.80 and rating spread
around 3.84
```

[43]:
```
result = selected_venues[selected_venues['cluster_labels'] == 1]
print("Cluster 1")
result.head(10).reset_index(drop = True)
```

```
Cluster 1
```

[43]:
```
   cluster_labels  categories                        venue  latitude  \
0               1  Hookah Bar          Sky Blue Sports Bar   22.7440
1               1  Restaurant              Hotel Shreemaya   22.7152
2               1       Motel                      Level 3   22.7526
3               1       Hotel  Kava - Fairfield by Marriott   22.7481

   longitude  price_range  rating  \
0    75.8944          4.0     3.5
1    75.8750          3.0     4.4
2    75.8965          4.0     3.5
3    75.9039          4.0     3.9

                                              address  average_price rating_bin
0  3rd Floor, C21 Mall, AB Road, Vijay Nagar, Indore          900.0       Good
1                12, South Tukoganj, RNT Marg Indore          550.0  Very good
2  Second Floor, Mangal City Mall, AB Road, Vijay…          750.0       Good
3  Plot 18/C, Scheme 94, Ring Road, Vijay Nagar, …          750.0       Good
```

[44]:
```
print("These venues for cluster 1 have mean price range of {:.02f} and rating␣
↪spread around {:.02f}".
```

```
    format(result['price_range'].mean(), result['rating'].astype(float).
↪mean()))
```

```
These venues for cluster 1 have mean price range of 3.75 and rating spread
around 3.83
```

0.1.14 Results and Discussion

Based on our analysis above, we can draw a number of conclusions that will be useful to aid any visitor visiting the city of Indore, India.

After collecting data from the Foursquare and Zomato APIs, we got a list of 90 different venues. However, not all venues from the two APIs were identical. Hence, we had to inspect their latitude and longitude values as well as names to combine them and remove all the outliers. This resulted in a total venue count of 35.

We identified that from the total set of venues, majority of them were Cafes and Indian Restaurants. A visitor who loves Cafes/Indian Restaurants would surely benefit from coming to Indore.

While the complete range of ratings range from 1 to 5, the majority venues have ratings close to 4. This means that most restaurants provide good quality food which is liked by the people of the city, thus indicating the high rating. When we plot these venues on the map, we discover that there are clusters of venues around Vijay Nagar, Palasia and Rajbada. These clusters also have very high ratings (more than 3).

When we take a look at the price values of each venue, we explore that many venues have prices which are in the range of Rs 400 to Rs 700 for one person. However, the variation in prices is very large, given the complete range starts from Rs 100 and goes uptil Rs 1200. On plotting the venues based on their price range on the map, we discovered that venues located near Vijay Nagar and Rajbada are relatively priced lower than venues in Palasia.

Finally, through clusters we identified that there are many venues which are relatively lower priced but have an average rating of 3.57. On the other hand, there are few venues which are high priced and have average rating of 4.03.

- If you're looking for cheap places with relatively high rating, you should check Vijay Nagar.
- If you're looking for the best places, with the highest rating but might also carry a high price tag, you should visit Palasia and Rajbada. A company can use this information to build up an online website/mobile application, to provide users with up to date information about various venues in the city based on the search criteria (name, rating and price).

0.1.15 Conclusion

The purpose of this project was to explore the places that a person visiting Indore could visit. The venues have been identified using Foursquare and Zomato API and have been plotted on the map. The map reveals that there are three major areas a person can visit: Vijay Nagar, Rajbada & Palasia. Based on the visitor's venue rating and price requirements, he/she can choose amongst the three places.

[ ]: