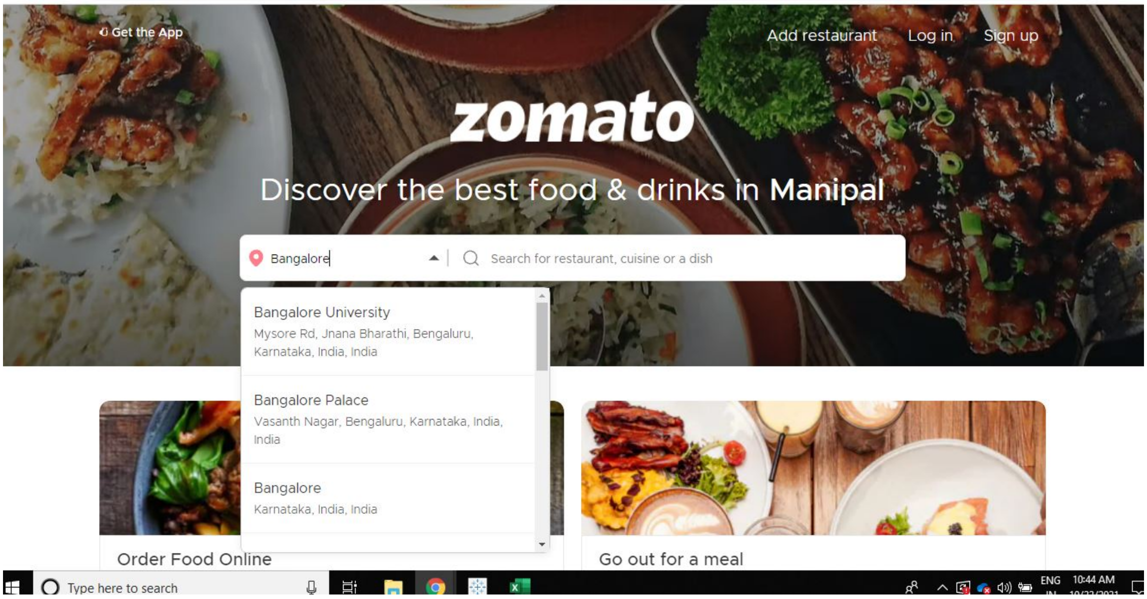


The Kaggle dataset was downloaded using the Zomato API. It contains dimensional information of restaurants listed on the platform. The columns available are listed below.

```
Restaurant Id: Unique id of every restaurant across various cities
of the world
Restaurant Name: Name of the restaurant
Country Code: Country in which restaurant is located
City: City in which restaurant is located
Address: Address of the restaurant
Locality: Location in the city
Locality Verbose: Detailed description of the locality
Longitude: Longitude coordinate of the restaurant’s location
Latitude: Latitude coordinate of the restaurant’s location
Cuisines: Cuisines offered by the restaurant
Average Cost for two: Cost for two people in different currencies
(local currency)
Currency: Currency of the country
Has Table booking: yes/no
Has Online delivery: yes/ no
Is delivering: yes/ no
Switch to order menu: yes/no
Price range: range of price of food
Aggregate Rating: Average rating out of 5
Rating color: depending upon the average rating color
Rating text: text on the basis of rating of rating
Votes: Number of ratings given
Switch to order menu is NO for all observations, hence it’s of no
value.
Price range ranges from one to four, with four being premium-
priced restaurants.
```

1. Importing Libraries

In [1]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
%matplotlib inline
import seaborn as sns
from collections import Counter
import warnings
warnings.filterwarnings("ignore")
```

2. Reading file

In [2]:
```
df = pd.read_csv('zomato.csv',encoding='latin-1')
```

In [3]:
```
df.head()
```

Out[3]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitu
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027!
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057!

5 rows × 21 columns

In [4]:
```
df.columns
```

Out[4]:
```
Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address',
       'Locality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines',
       'Average Cost for two', 'Currency', 'Has Table booking',
       'Has Online delivery', 'Is delivering now', 'Switch to order menu',
       'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
       'Votes'],
      dtype='object')
```

2.1 Combining Country Code with the original dataset

In [5]:
```python
country_codes = pd.read_excel('Country-Code.xlsx')
country_codes.head()
```

Out[5]:

	Country Code	Country
0	1	India
1	14	Australia
2	30	Brazil
3	37	Canada
4	94	Indonesia

In [6]:
```python
data = pd.merge(df,country_codes,how='left',on='Country Code')
```

In [7]:
```python
data.drop(['Country Code','Address','Locality','Locality Verbose','Longitude', 'La
```

In [8]:
```python
data.head()
```

Out[8]:

	Restaurant ID	Restaurant Name	City	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	deliveri n
0	6317637	Le Petit Souffle	Makati City	French, Japanese, Desserts	1100	Botswana Pula(P)	Yes	No	
1	6304287	Izakaya Kikufuji	Makati City	Japanese	1200	Botswana Pula(P)	Yes	No	
2	6300002	Heat - Edsa Shangri-La	Mandaluyong City	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	Yes	No	
3	6318506	Ooma	Mandaluyong City	Japanese, Sushi	1500	Botswana Pula(P)	No	No	
4	6314302	Sambo Kojin	Mandaluyong City	Japanese, Korean	1500	Botswana Pula(P)	Yes	No	

3. Basic Exploration

In [9]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9551 entries, 0 to 9550
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant ID         9551 non-null   int64  
 1   Restaurant Name       9551 non-null   object 
 2   City                  9551 non-null   object 
 3   Cuisines              9542 non-null   object 
 4   Average Cost for two  9551 non-null   int64  
 5   Currency              9551 non-null   object 
 6   Has Table booking     9551 non-null   object 
 7   Has Online delivery   9551 non-null   object 
 8   Is delivering now     9551 non-null   object 
 9   Switch to order menu  9551 non-null   object 
 10  Price range           9551 non-null   int64  
 11  Aggregate rating      9551 non-null   float64
 12  Rating color          9551 non-null   object 
 13  Rating text           9551 non-null   object 
 14  Votes                 9551 non-null   int64  
 15  Country               9551 non-null   object 
dtypes: float64(1), int64(4), object(11)
memory usage: 1.2+ MB
```

3.1 Exploring contnious features

Note: Here `Restaurant ID` may not be considered a continous variable

In [10]:
```
data.describe()
```

Out[10]:

	Restaurant ID	Average Cost for two	Price range	Aggregate rating	Votes
count	9.551000e+03	9551.000000	9551.000000	9551.000000	9551.000000
mean	9.051128e+06	1199.210763	1.804837	2.666370	156.909748
std	8.791521e+06	16121.183073	0.905609	1.516378	430.169145
min	5.300000e+01	0.000000	1.000000	0.000000	0.000000
25%	3.019625e+05	250.000000	1.000000	2.500000	5.000000
50%	6.004089e+06	400.000000	2.000000	3.200000	31.000000
75%	1.835229e+07	700.000000	2.000000	3.700000	131.000000
max	1.850065e+07	800000.000000	4.000000	4.900000	10934.000000

3.2 Exploring categorical features

In [11]:
```
data.describe(include='object')
```

Out[11]:

	Restaurant Name	City	Cuisines	Currency	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Rating color	R
count	9551	9551	9542	9551	9551	9551	9551	9551	9551	
unique	7446	141	1825	12	2	2	2	1	6	
top	Cafe Coffee Day	New Delhi	North Indian	Indian Rupees(Rs.)	No	No	No	No	Orange	Av
freq	83	5473	936	8652	8393	7100	9517	9551	3737	

3.3 Exploring unique values for each categorical feature

In [12]:

```
for col in data.describe(include='object').columns:
    print(col)
    print(data[col].unique())
    print('-'*50)
```

```
Restaurant Name
['Le Petit Souffle' 'Izakaya Kikufuji' 'Heat - Edsa Shangri-La' ...
 'Huqqa' 'A\x81ô\x81ôk Kahve' "Walter's Coffee Roastery"]
--------------------------------------------------
City
['Makati City' 'Mandaluyong City' 'Pasay City' 'Pasig City' 'Quezon City'
 'San Juan City' 'Santa Rosa' 'Tagaytay City' 'Taguig City' 'Brasí_lia'
 'Rio de Janeiro' 'Sí£o Paulo' 'Albany' 'Armidale' 'Athens' 'Augusta'
 'Balingup' 'Beechworth' 'Boise' 'Cedar Rapids/Iowa City' 'Chatham-Kent'
 'Clatskanie' 'Cochrane' 'Columbus' 'Consort' 'Dalton' 'Davenport'
 'Des Moines' 'Dicky Beach' 'Dubuque' 'East Ballina' 'Fernley' 'Flaxton'
 'Forrest' 'Gainesville' 'Hepburn Springs' 'Huskisson' 'Inverloch'
 'Lakes Entrance' 'Lakeview' 'Lincoln' 'Lorn' 'Macedon' 'Macon' 'Mayfield'
 'Mc Millan' 'Middleton Beach' 'Miller' 'Monroe' 'Montville'
 'Ojo Caliente' 'Orlando' 'Palm Cove' 'Paynesville' 'Penola' 'Pensacola'
 'Phillip Island' 'Pocatello' 'Potrero' 'Princeton' 'Rest of Hawaii'
 'Savannah' 'Singapore' 'Sioux City' 'Tampa Bay' 'Tanunda' 'Trentham East'
 'Valdosta' 'Vernonia' 'Victor Harbor' 'Vineland Station' 'Waterloo'
 'Weirton' 'Winchester Bay' 'Yorkton' 'Abu Dhabi' 'Dubai' 'Sharjah' 'Agra'
 'Ahmedabad' 'Allahabad' 'Amritsar' 'Aurangabad' 'Bangalore' 'Bhopal'
 'Bhubaneshwar' 'Chandigarh' 'Chennai' 'Coimbatore' 'Dehradun' 'Faridabad'
 'Ghaziabad' 'Goa' 'Gurgaon' 'Guwahati' 'Hyderabad' 'Indore' 'Jaipur'
 'Kanpur' 'Kochi' 'Kolkata' 'Lucknow' 'Ludhiana' 'Mangalore' 'Mohali'
 'Mumbai' 'Mysore' 'Nagpur' 'Nashik' 'New Delhi' 'Noida' 'Panchkula'
 'Patna' 'Puducherry' 'Pune' 'Ranchi' 'Secunderabad' 'Surat' 'Vadodara'
 'Varanasi' 'Vizag' 'Bandung' 'Bogor' 'Jakarta' 'Tangerang' 'Auckland'
 'Wellington City' 'Birmingham' 'Edinburgh' 'London' 'Manchester' 'Doha'
 'Cape Town' 'Inner City' 'Johannesburg' 'Pretoria' 'Randburg' 'Sandton'
 'Colombo' 'Ankara' 'ÛÁstanbul']
--------------------------------------------------
Cuisines
['French, Japanese, Desserts' 'Japanese'
 'Seafood, Asian, Filipino, Indian' ... 'Burger, Izgara'
 'World Cuisine, Patisserie, Cafe' 'Italian, World Cuisine']
--------------------------------------------------
Currency
['Botswana Pula(P)' 'Brazilian Real(R$)' 'Dollar($)' 'Emirati Diram(AED)'
 'Indian Rupees(Rs.)' 'Indonesian Rupiah(IDR)' 'NewZealand($)'
 'Pounds(\x8c£)' 'Qatari Rial(QR)' 'Rand(R)' 'Sri Lankan Rupee(LKR)'
 'Turkish Lira(TL)']
--------------------------------------------------
Has Table booking
['Yes' 'No']
--------------------------------------------------
Has Online delivery
['No' 'Yes']
--------------------------------------------------
Is delivering now
['No' 'Yes']
--------------------------------------------------
Switch to order menu
['No']
--------------------------------------------------
Rating color
['Dark Green' 'Green' 'Yellow' 'Orange' 'White' 'Red']
--------------------------------------------------
Rating text
['Excellent' 'Very Good' 'Good' 'Average' 'Not rated' 'Poor']
--------------------------------------------------
Country
['Phillipines' 'Brazil' 'United States' 'Australia' 'Canada' 'Singapore'
 'UAE' 'India' 'Indonesia' 'New Zealand' 'United Kingdom' 'Qatar'
 'South Africa' 'Sri Lanka' 'Turkey']
--------------------------------------------------
```

In [13]:
```
data.shape
```

Out[13]:
```
(9551, 16)
```

4. Missing Values

In [14]:
```
data.isna().sum()
```

Out[14]:
```
Restaurant ID           0
Restaurant Name         0
City                    0
Cuisines                9
Average Cost for two    0
Currency                0
Has Table booking       0
Has Online delivery     0
Is delivering now       0
Switch to order menu    0
Price range             0
Aggregate rating        0
Rating color            0
Rating text             0
Votes                   0
Country                 0
dtype: int64
```

`Observation:`

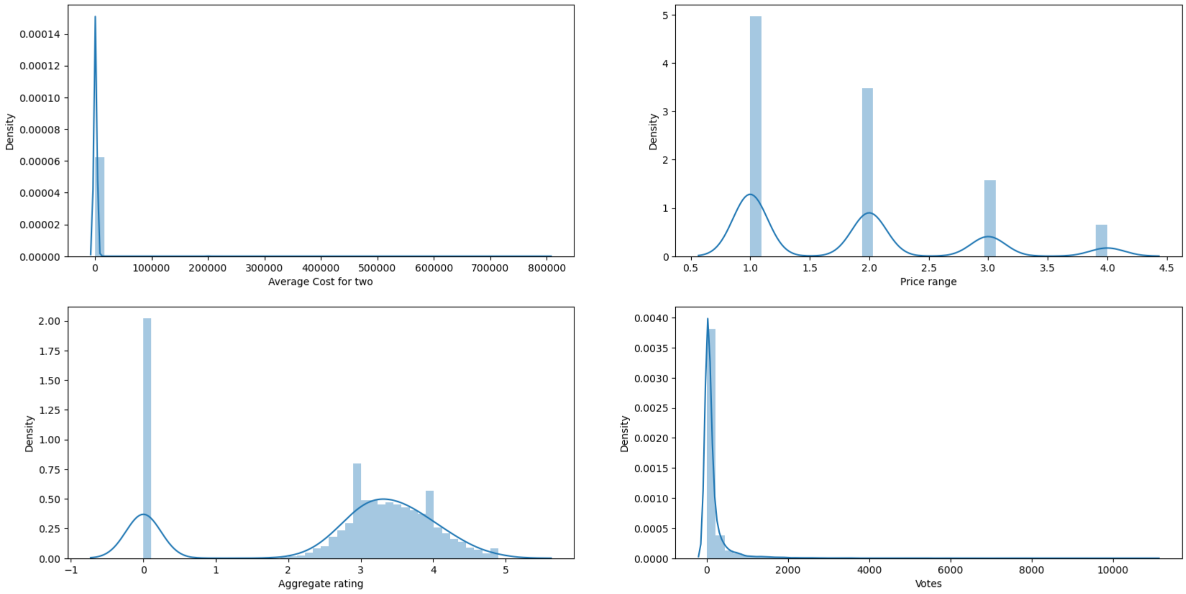
We can see only `Cuisines` have 9 missing values which can be dropped from the dataset

In [15]:
```
data['Cuisines'].dropna(axis=0,inplace=True)
```

4. Outlier Analysis

4.1 Plotting Distribution for continous features

In [16]:
```
labels = list(data.describe().columns)[1:]
c=0
plt.figure(figsize=(20,10))
for i in labels:
    c=c+1
    plt.subplot(2,2,c)
    sns.distplot(df[i],kde=True,)

plt.show()
```



4.2 Z-Score Analysis to remove outliers

In [17]:
```python
import scipy.stats as st
zr = np.abs(st.zscore(df['Restaurant ID']))
```

In [18]:
```python
continous_df = df[list(data.describe().columns)[1:]]
z = np.abs(st.zscore(continous_df))
continous_df = continous_df[(z<3).all(axis=1)]
continous_df.shape
```

Out[18]:
```
(9362, 4)
```

`Observation:`

We can see that datapoints have been reduced from 9551 to 9362 removing outliers with z-score > 3

In [19]:
```python
clean_data = data.iloc[continous_df.index]
```

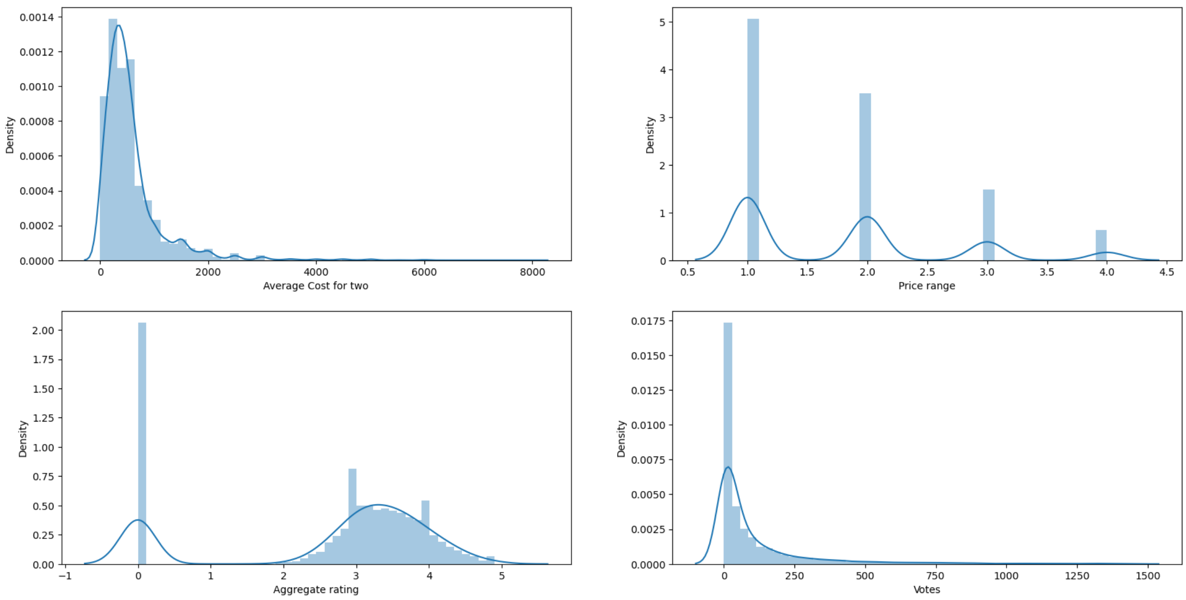
In [20]:
```python
clean_data.head()
```

Out[20]:

	Restaurant ID	Restaurant Name	City	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	deliveri n
0	6317637	Le Petit Souffle	Makati City	French, Japanese, Desserts	1100	Botswana Pula(P)	Yes	No	
1	6304287	Izakaya Kikufuji	Makati City	Japanese	1200	Botswana Pula(P)	Yes	No	
2	6300002	Heat - Edsa Shangri-La	Mandaluyong City	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	Yes	No	
3	6318506	Ooma	Mandaluyong City	Japanese, Sushi	1500	Botswana Pula(P)	No	No	
4	6314302	Sambo Kojin	Mandaluyong City	Japanese, Korean	1500	Botswana Pula(P)	Yes	No	

4.3 Verifying using distribution plot

In [21]:
```
labels = list(data.describe().columns)[1:]
c=0
plt.figure(figsize=(20,10))
for i in labels:
    c=c+1
    plt.subplot(2,2,c)
    sns.distplot(clean_data[i],kde=True,)

plt.show()
```

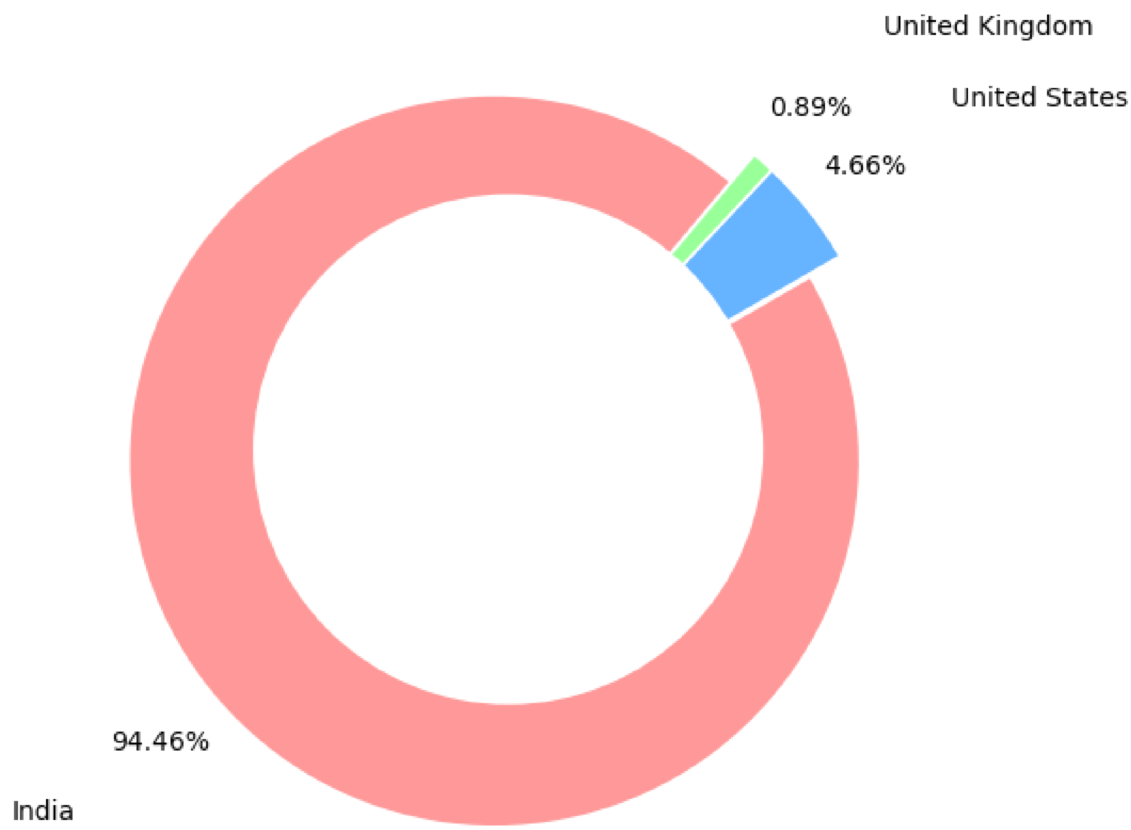


5. Extracting Insights using Visualizations

5.1 Top 3 countries for which data represents

In [22]:
```
country_counts = clean_data['Country'].value_counts()
```

In [23]:
```
fig1, ax1 = plt.subplots()

colors = ['#ff9999','#66b3ff','#99ff99']
#explsion
explode = (0.05,0.05,0.05)
plt.pie(x=country_counts[:3],labels=country_counts[:3].index,autopct='%1.2f%%',
        radius=1,pctdistance=1.2,startangle=50,labeldistance=1.5,
        counterclock=True,explode=explode,colors=colors)
centre_circle = plt.Circle((0,0),0.70,fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
# Equal aspect ratio ensures that pie is drawn as a circle
ax1.axis('equal')
plt.tight_layout()
plt.show()
```



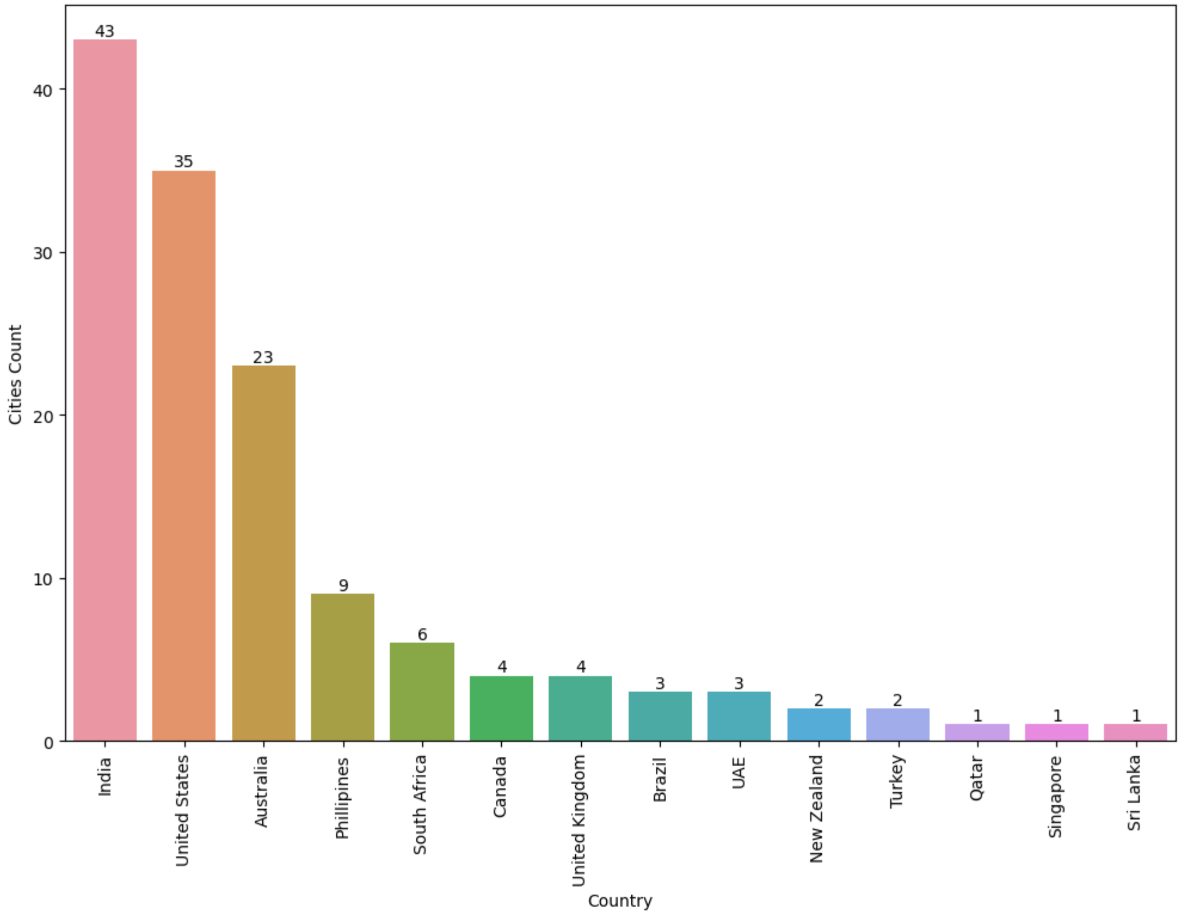
Observation:

Cleary the data is dominating for India as more than 90% of it comes from Indian Restaurants. The top 3 on list are India, USA and UK

5.2 Penetration across cities for each Country

In [24]:
```
city_counts = list()
for i in clean_data.groupby(['Country','City']).count().index:
    city_counts.append(i[0])
city_counts = dict(Counter(city_counts))
city_counts = dict(sorted(city_counts.items(),key=lambda x:x[1],reverse=True))
country = list(city_counts.keys())
```

```
counts = list(city_counts.values())
fig = plt.figure(figsize=(12,8))
plt.xlabel('Country')
plt.ylabel('Cities Count')
plt.xticks(rotation=90)
ax = sns.barplot(x=country,y=counts)
ax.bar_label(ax.containers[0])
plt.show()
```

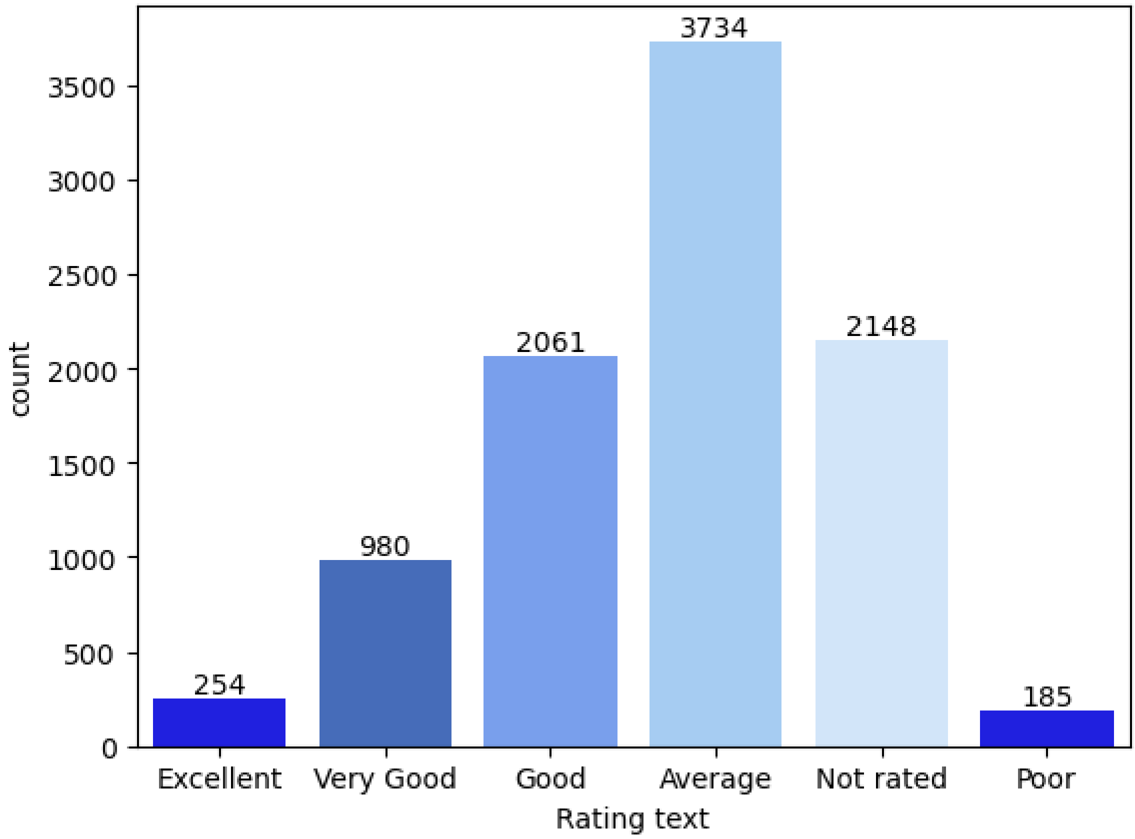


`Observation:`

Zomato is present in 43 cities in India and 35 in the USA and 23 in Australia and the rest 12 cities are in single digits. So it validates the previous assumption that India and USA can be compared.

5.3 Count for each rating types

In [25]:
```
ax = sns.countplot(data=clean_data,x='Rating text',palette=['#0000FF', '#3366CC',
ax.bar_label(ax.containers[0])
plt.show()
```



`Observation:`

It can be observed that most popular rating is for 'Average'. But this does'nt give much insights for a particular contry.

5.4 Fuction definition:

1. Distribution of Aggregate Rating for a particular country

2. % Distribution of Restaurants Based on rating for a particular country

`Note` : Here we have only compared India and USA

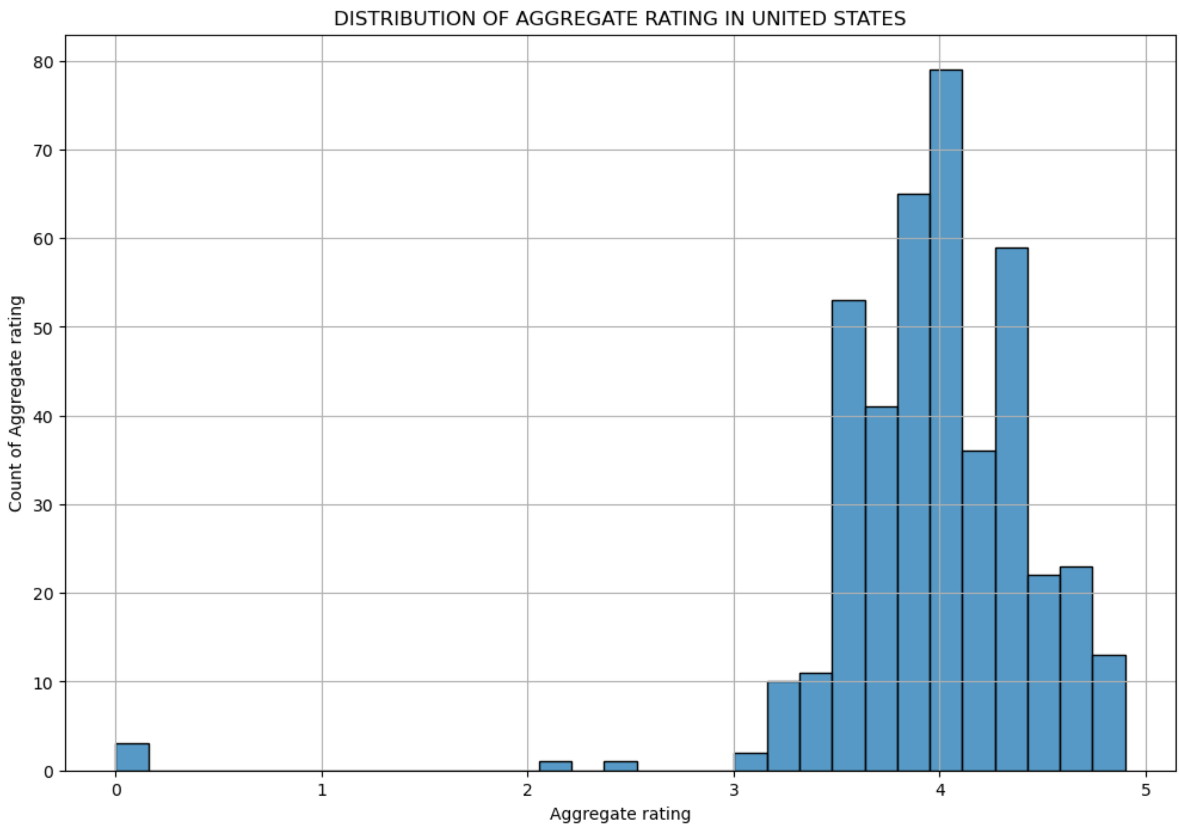
In [26]:
```
def get_ratingdist(clean_data,country):
    agg = None
    for i, j in clean_data.groupby('Country'):
        if i == country:
            agg = j['Aggregate rating']
    fig = plt.figure(figsize=(12,8))
    plt.title(f'DISTRIBUTION OF AGGREGATE RATING IN {country.upper()}')
    plt.xlabel('Aggregate rating')
    plt.ylabel('Count of Aggregate rating')
    plt.grid()
    sns.histplot(data=agg)
```

In [27]:
```
def get_restdist(clean_data,country):

    df = clean_data[clean_data['Country']==country]
```

```
    ratings = df['Rating text'].unique()
    ratings_count = np.zeros(len(ratings))
    for i in range(len(ratings)):
        ratings_count[i] = (df.groupby('Rating text').count().loc[ratings[i]][0])

    sort_indices = np.argsort(ratings_count)[::-1]
    ratings = ratings[sort_indices]
    ratings_count = ratings_count[sort_indices]

    total_rest = len(df)
    ratings_dist = (ratings_count/total_rest)*100
    ratings_dist = np.round(ratings_dist,decimals=2)
    fig = plt.figure(figsize=(12,8))
    plt.title(f'% DISTRIBUTION OF RESTAURANTS BASED ON RATINGS {country.upper()}')
    plt.xlabel('% Distribution of Resteraunts')
    plt.ylabel('Ratings')
    ax = sns.barplot(x=ratings,y=ratings_dist)
    ax.bar_label(ax.containers[0])
    plt.show()
```

5.4.1 USA Ratings

In [28]:
```
get_ratingdist(clean_data,'United States')
```



Observation:

Here we can observe that in USA people usually rate if the food is between Average - Excellent. A few ratings are given for poor restaurants This can mean two things:

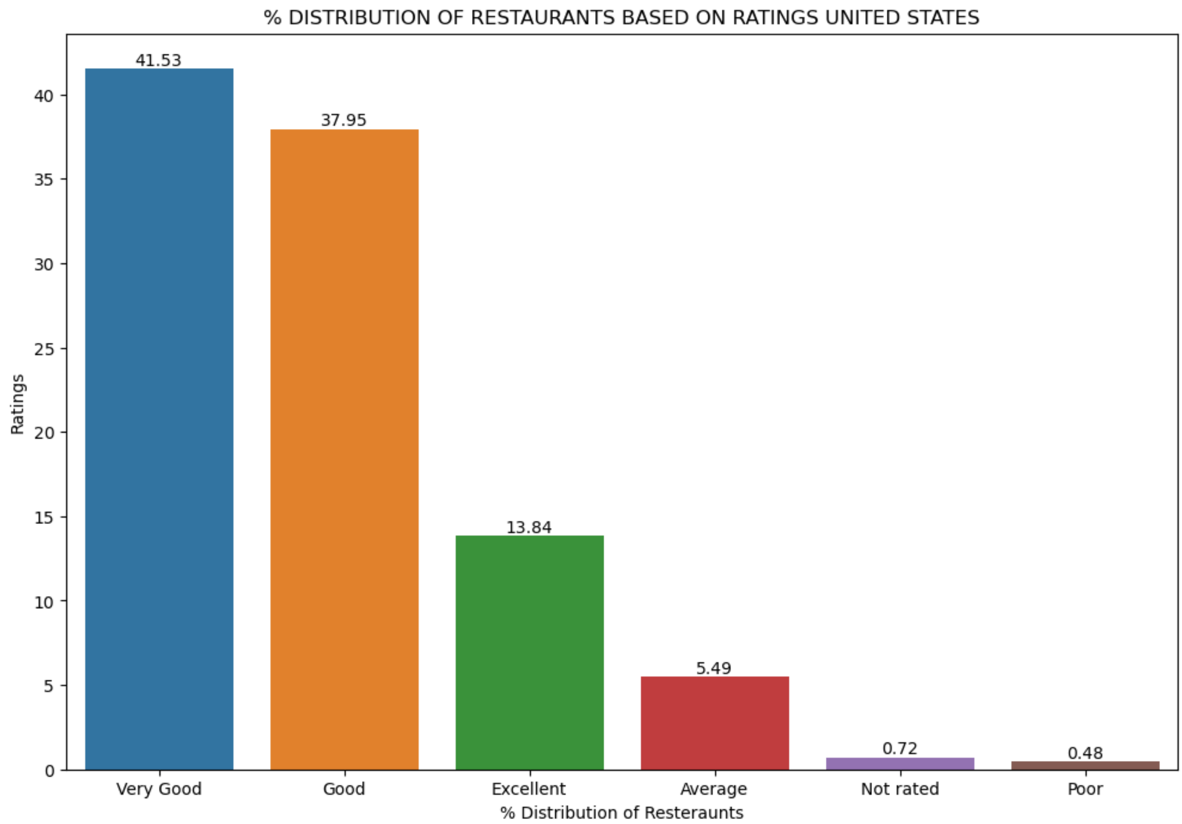
1. Either people in USA tend to avoid rating negatively

2. Or most of the restuarants in USA serve quite good food

`Note` : This may also result of lack of datapoints for USA as well

5.4.2 % Distribution of Resteraunts based on ratings in USA

In [29]:
```
get_restdist(clean_data,'United States')
```

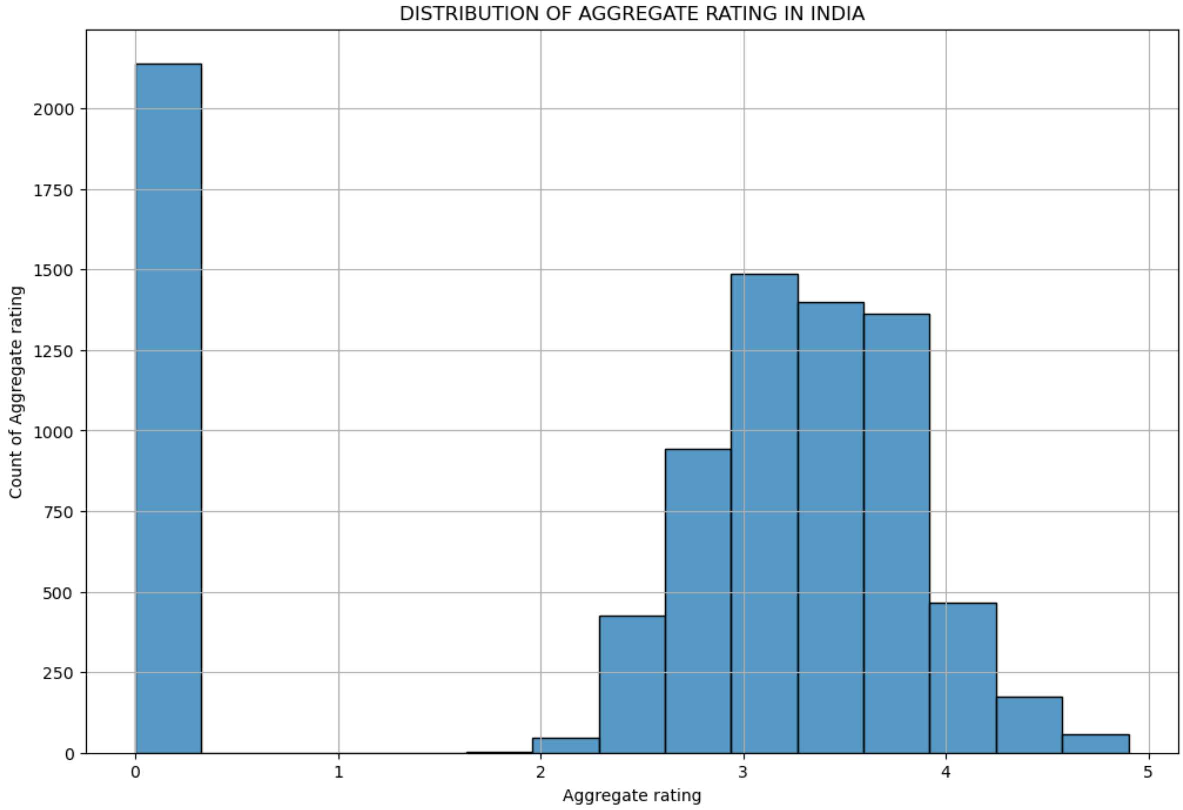


`Observation:`

With this graph we can cleary notice that 40% of restaurants in USA are raitng 'Very Good'. A major percentage of distribution are rated 'Very Good','Good' or 'Excellent'.

5.4.3 India Ratings

In [30]:
```
get_ratingdist(clean_data,'India')
```



`Observation:`

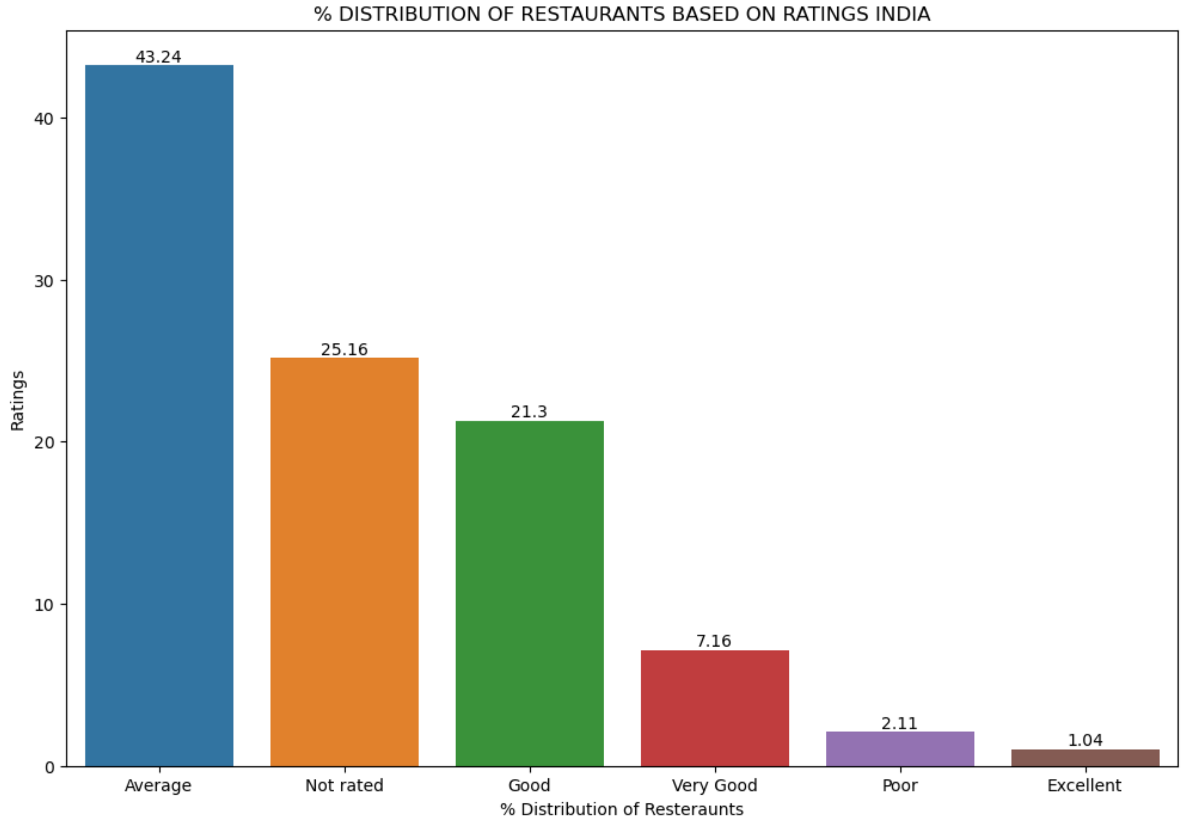
Here we can observe that in India people usually rate if the food is between Average - Excellent. But here interestingly they penealize heavily for bad food/service. This is very different from the behaviour of customers in USA. This can be result of one of the following:

1. People are senstive towards quality of food/service
2. Major restaurants in India aren't able to provide good quality food.
3. In India, people tend to rate poor so as avail free exchanges or cashbacks

`Note` : The datapoints for India are huge as compared to USA

5.4.4 % Distribution of Resteraunts based on ratings in India

In [31]:
```
get_restdist(clean_data,'India')
```



`Observation:`

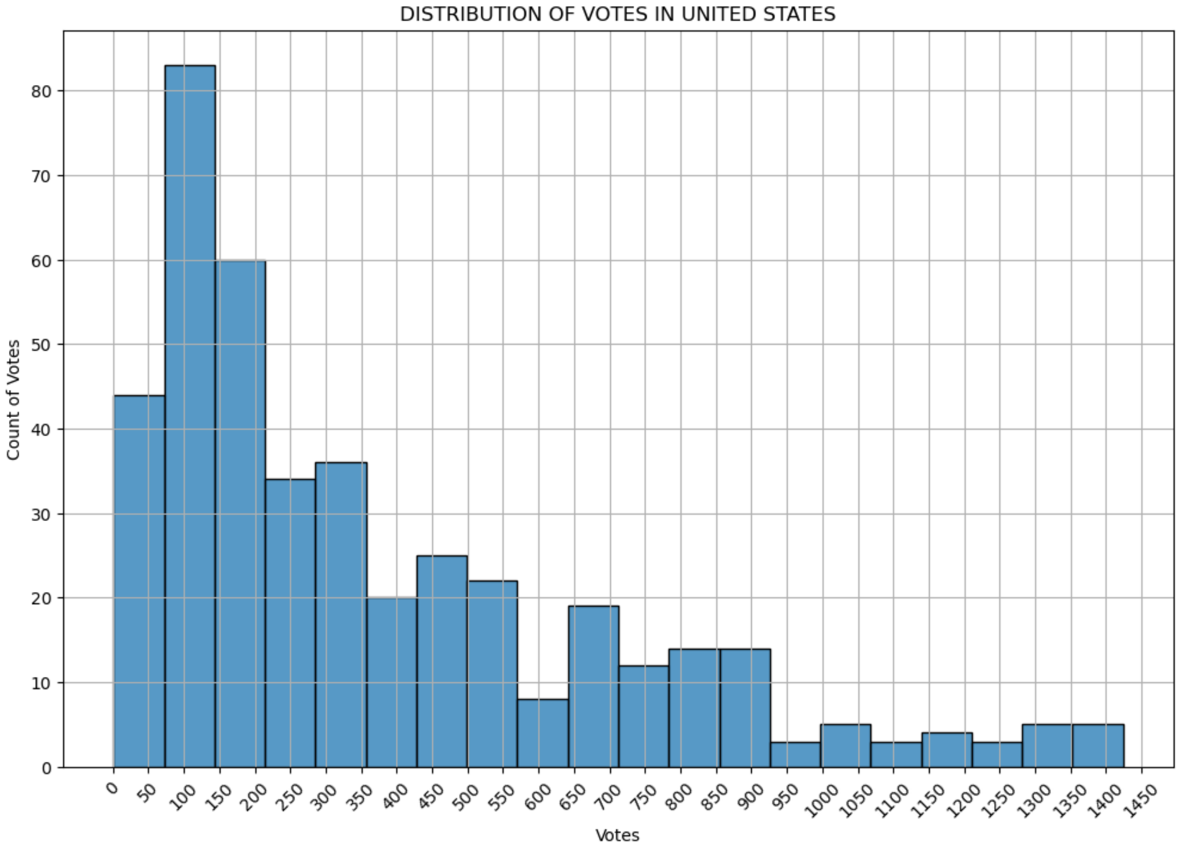
Here we can observe that when it comes to rating, Indian consumer is not generous with rating as 25% of restaurants are not rated (although this might be because data is large compared to USA). But this might also because of the fact that major chunk of Indian Restuarants fail to provide good food

5.5 Distribution of Votes

In [32]:
```
def get_country_votes(clean_data,country):
    df = clean_data[clean_data['Country']==country]
    fig = plt.figure(figsize=(12,8))
    plt.title(f'DISTRIBUTION OF VOTES IN {country.upper()}')
    plt.xlabel('Votes')
    plt.ylabel('Count of Votes')
    plt.xticks(np.arange(0,1500,50),rotation=45)
    plt.grid()
    sns.histplot(data=df['Votes'],bins=20)
```

5.5.1 Distribution of Votes in USA

In [33]:
```
get_country_votes(clean_data,'United States')
```

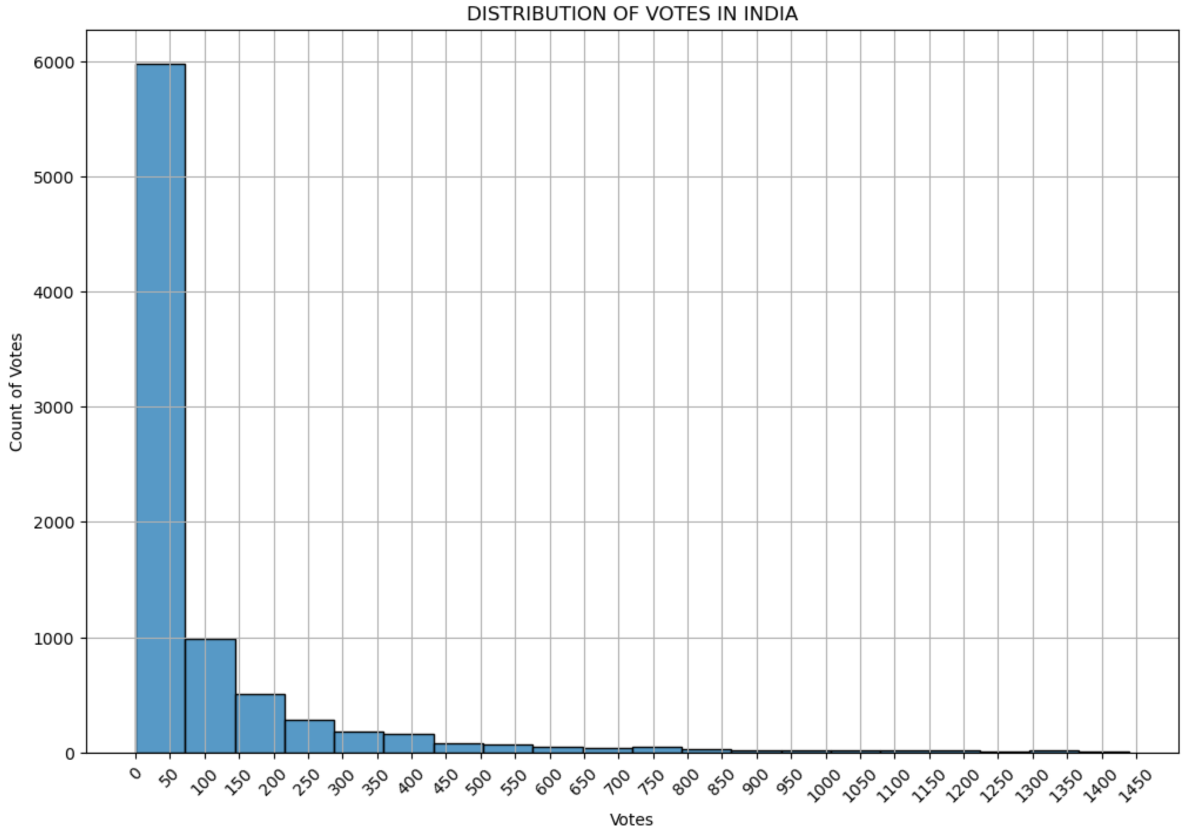


`Observation:`

Clearly, there is a good variation in number of votes in USA. People tend to give more feedbacks in USA

5.5.2 Distribution of Votes in India

In [34]:
```
get_country_votes(clean_data,'India')
```



`Observation:`

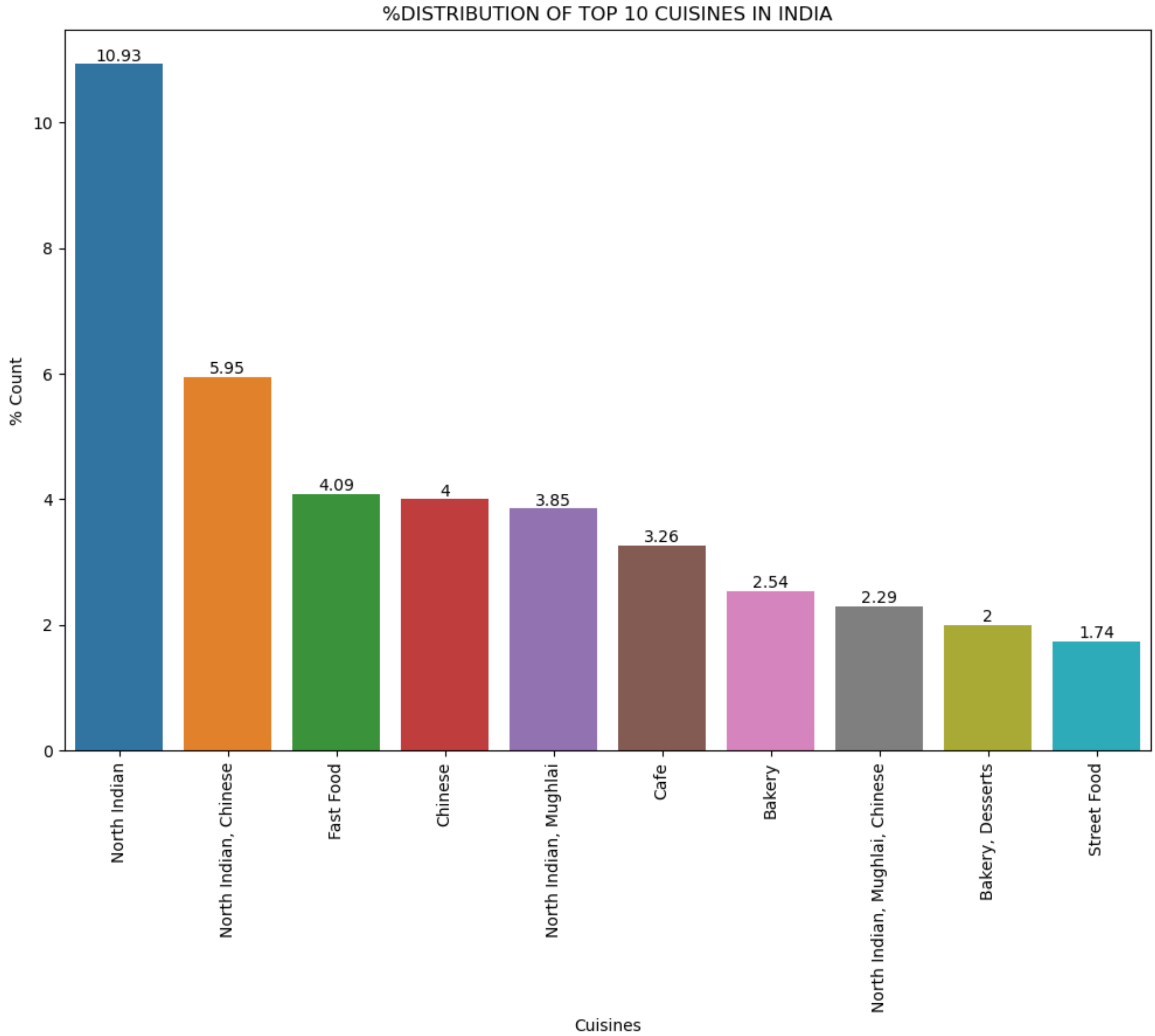
Clearly, there is a less variation in number of votes in India. People tend to give less feedbacks in India

5.6 Understanding Cuisines

In [35]:
```
def get_cuisines(clean_data,country):

    df = clean_data[clean_data['Country']==country]
    top_10 = df['Cuisines'].value_counts().nlargest(10)
    total = len(df)
    cuisine_type = np.array(top_10.keys())
    cuisine_count = np.array(top_10.values)

    cuisine_count = (cuisine_count/total)*100
    cuisine_count = np.round(cuisine_count,decimals=2)


    fig = plt.figure(figsize=(12,8))
    plt.title(f'%DISTRIBUTION OF TOP 10 CUISINES IN {country.upper()}')
    plt.xlabel('Cuisines')
    plt.ylabel('% Count')
    plt.xticks(rotation=90)
    ax = sns.barplot(x=cuisine_type,y=cuisine_count)
    #ax = sns.countplot(x='Cuisines',data=df,order=top_10.index)
    ax.bar_label(ax.containers[0])
    plt.show()
```

5.6.1 Top 10 Cuisines in India

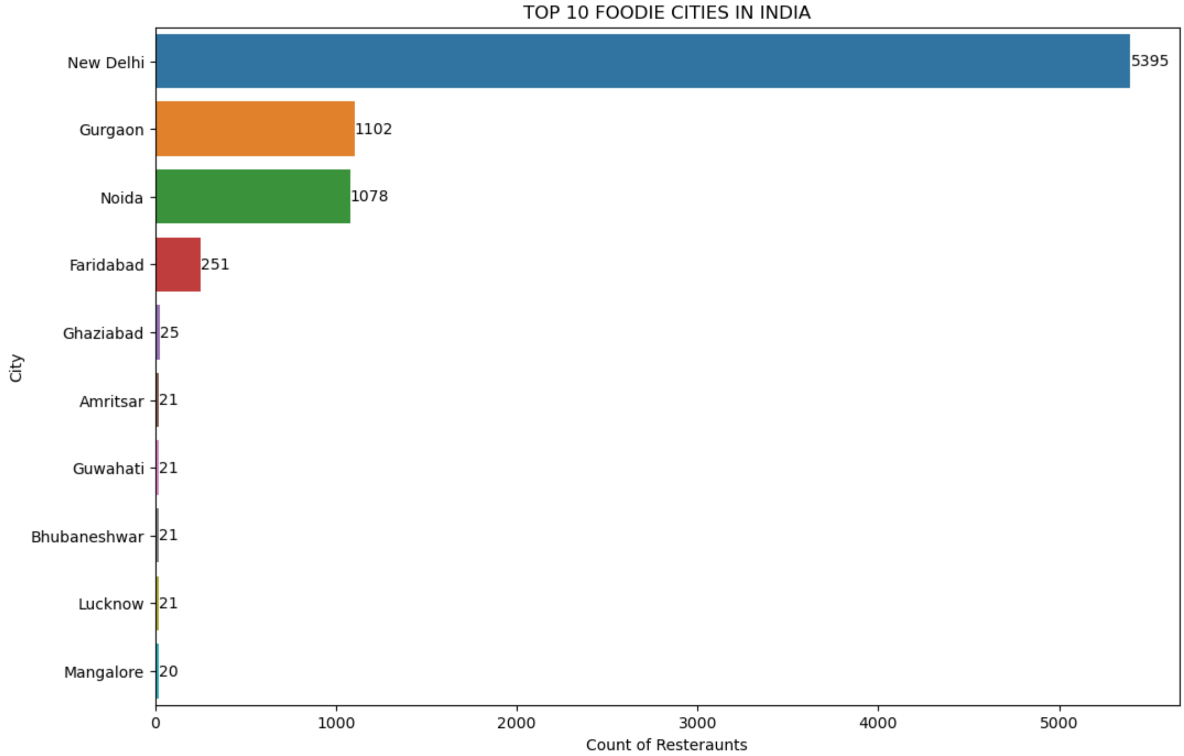
In [36]:
```python
get_cuisines(clean_data,'India')
```



Observation:

Clearly, North Indian food tend to dominate the market. But this might be because the data is concentrated more in North Indian States!! Lets verify

In [37]:
```python
df = clean_data[clean_data['Country']=='India']
fig = plt.figure(figsize=(12,8))
plt.title('TOP 10 FOODIE CITIES IN INDIA')
plt.xlabel('Count of Resteraunts')
plt.ylabel('City')
top_10 = df['City'].value_counts().nlargest(10)
ax = sns.barplot(x=top_10.values,y=top_10.index)
ax.bar_label(ax.containers[0])
plt.show()
```

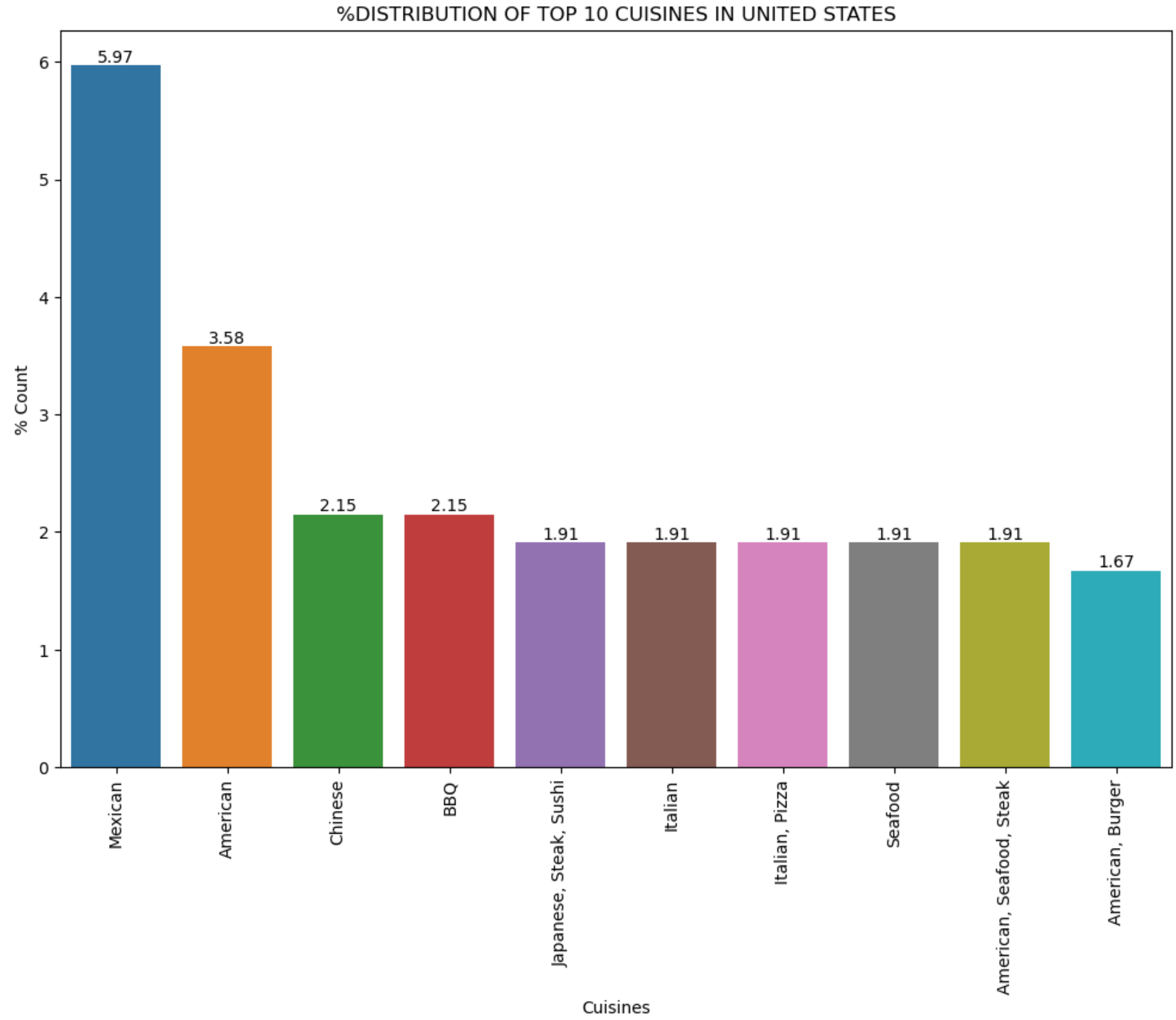


Observation:

We can see that most of restaurants are located in Delhi- NCR Region and thats why the popularity of North Indian food is validated

5.6.2 Top 10 Cuisines in USA

In [38]:
```
get_cuisines(clean_data,'United States')
```



`Observation:`

We can see that Mexican cuisines is most popular among the folks in USA, but there is not much difference in popularity of other cuisines like American, Chinese etc

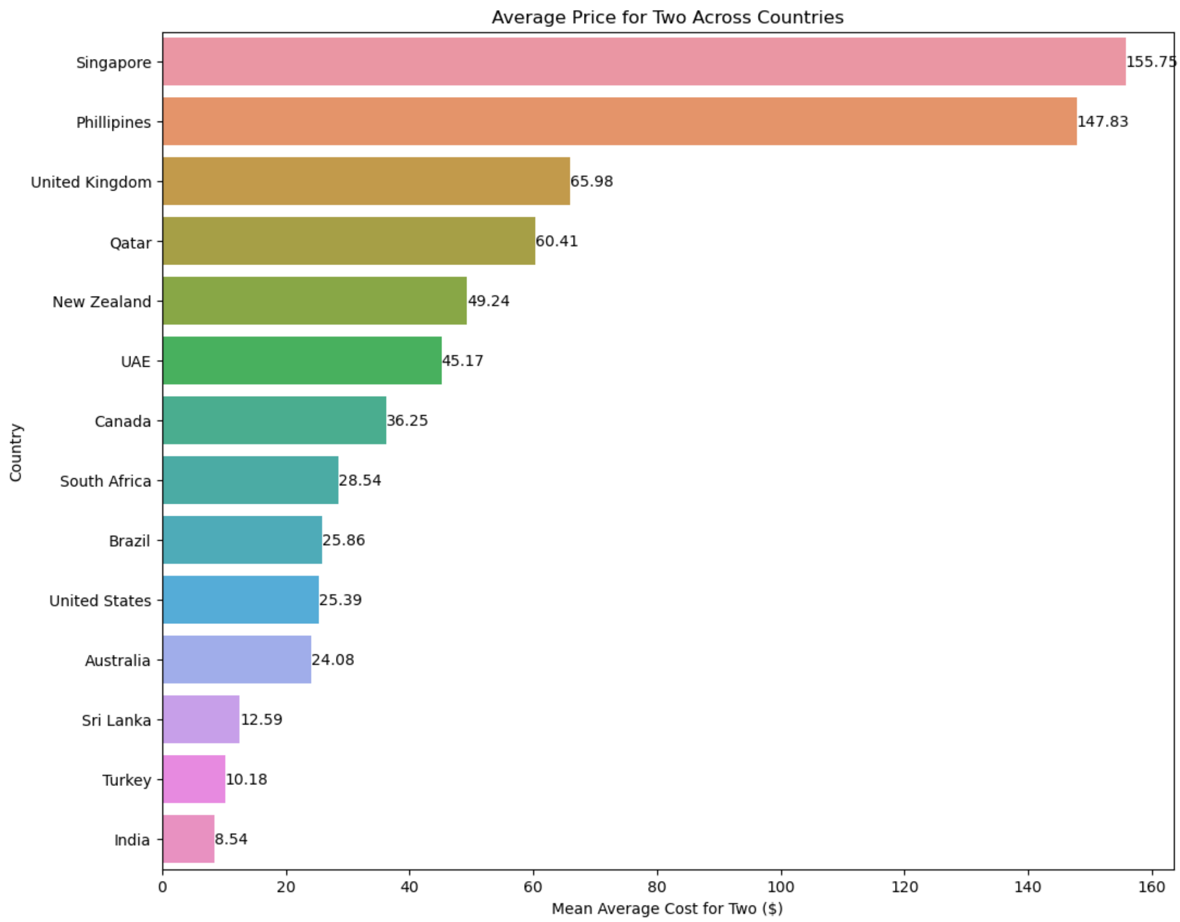
5.7 Which country has the cheaper food?

In [39]:
```
def convert_to_dollar(value, currency):
    # Dictionary of currency conversion rates with respect to Dollar
    conversion_rates = {
        'Botswana Pula(P)': 0.092,
        'Brazilian Real(R$)': 0.192,
        'Dollar($)': 1.0,
        'Emirati Diram(AED)': 0.272,
        'Indian Rupees(Rs.)': 0.014,
        'NewZealand($)': 0.706,
        'Pounds(\x8c£)': 1.38,
        'Qatari Rial(QR)': 0.27,
        'Rand(R)': 0.068,
        'Sri Lankan Rupee(LKR)': 0.0053,
        'Turkish Lira(TL)': 0.12
    }

    # Convert the value to Dollar
    if currency in conversion_rates:
        value_in_dollar = value * conversion_rates[currency]
        return value_in_dollar
```

```
    else:
        return None
```

In [40]:
```
clean_data['Average Cost for two ($)'] = clean_data.apply(lambda x:convert_to_doll
```

In [41]:
```
fig = plt.figure(figsize=(12,10))
plt.title('Average Price for Two Across Countries')
plt.xlabel('Mean Average Cost for Two ($)')
plt.ylabel('Country')
avg_cost = clean_data.groupby('Country').mean()['Average Cost for two ($)']
avg_cost = avg_cost.sort_values(ascending=False)
avg_cost = avg_cost.round(2)
ax = sns.barplot(x=avg_cost.values,y=avg_cost.index)
ax.bar_label(ax.containers[0])
plt.show()
```



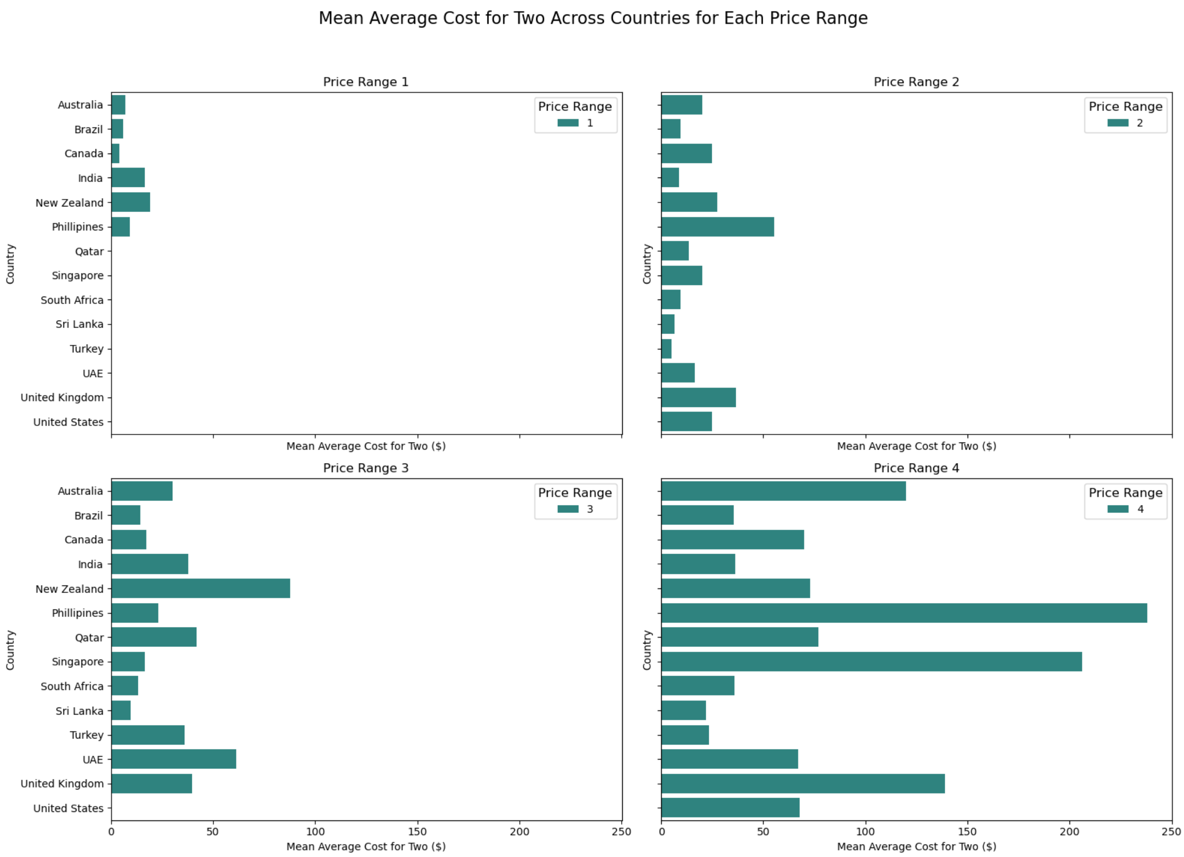
Observation:

Here we can observe that if we consider "Average Cost for Two (Dollar)", then Singapore tends to serve most expensive food across all countries whereas India tends to serve cheapest of all.

5.7 Distibution of Avg Cost for Two across all Price range

In [42]:
```
grouped_data = clean_data.groupby(['Country', 'Price range'])['Average Cost for tw

# Get the unique price range values
price_ranges = sorted(grouped_data['Price range'].unique())
```

```python
# Create the subplots for each price range
fig, axs = plt.subplots(2, 2, figsize=(16, 12), sharex=True, sharey=True)

# Flatten the axes for easier indexing
axs = axs.ravel()

# Create the partitioned bar plots for each price range value
for i, price_range in enumerate(price_ranges):
    filtered_data = grouped_data[grouped_data['Price range'] == price_range]
    sns.barplot(x='Average Cost for two ($)', y='Country', data=filtered_data, hue
    axs[i].set_title(f'Price Range {price_range}')
    axs[i].legend(title='Price Range', title_fontsize='large')
    axs[i].set_xlabel('Mean Average Cost for Two ($)')
    axs[i].set_ylabel('Country')

plt.suptitle('Mean Average Cost for Two Across Countries for Each Price Range', fo
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



Observation:

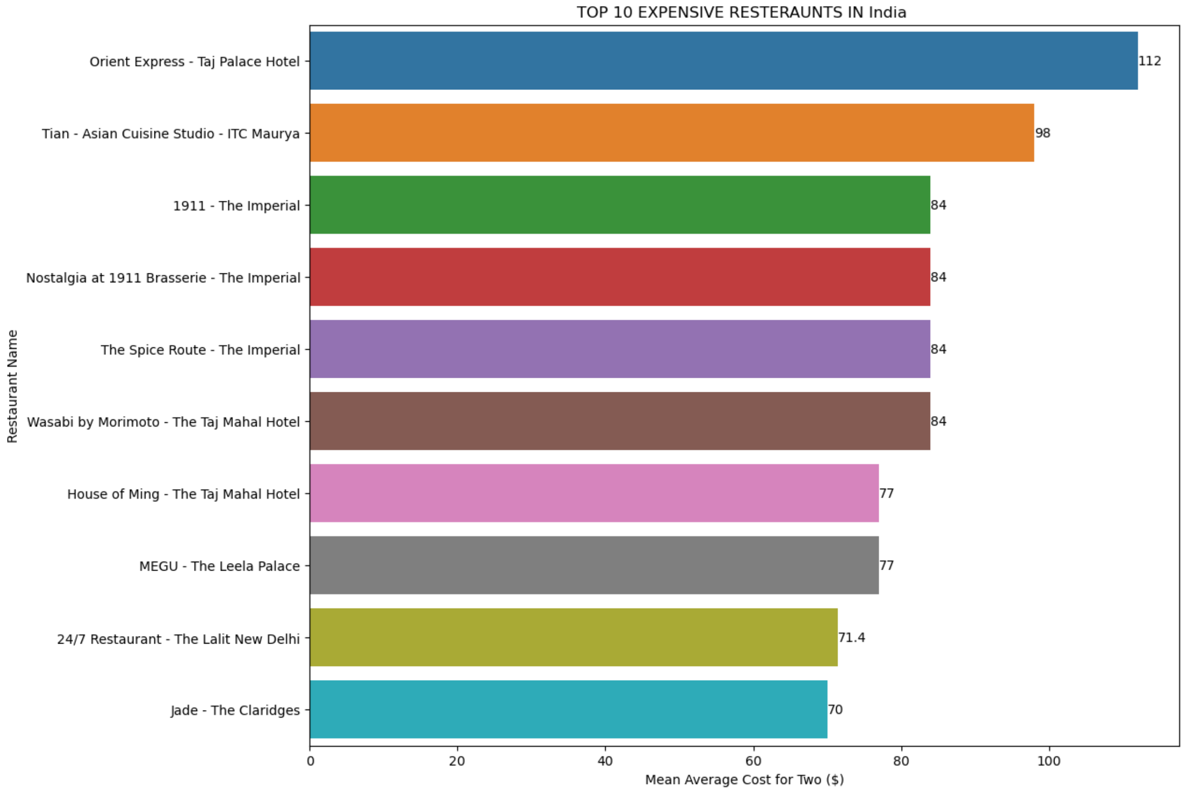
40% of restaurants across geographies fall into the cheaper price range of 1, with 32%, 14%, 6% of restaurants falling into 2,3,4 respectively, this is because Indian price range 1 restaurants are dominating the dataset. Similar distribution can be found for Indian restaurants as well.

Overall Philippines, the UK, and Singapore have higher food prices(Price range 4) and Indonesia, Turkey and Sri Lanka (price range 2) have lower prices.

5.8 Top 10 Expensive Restaurants in India

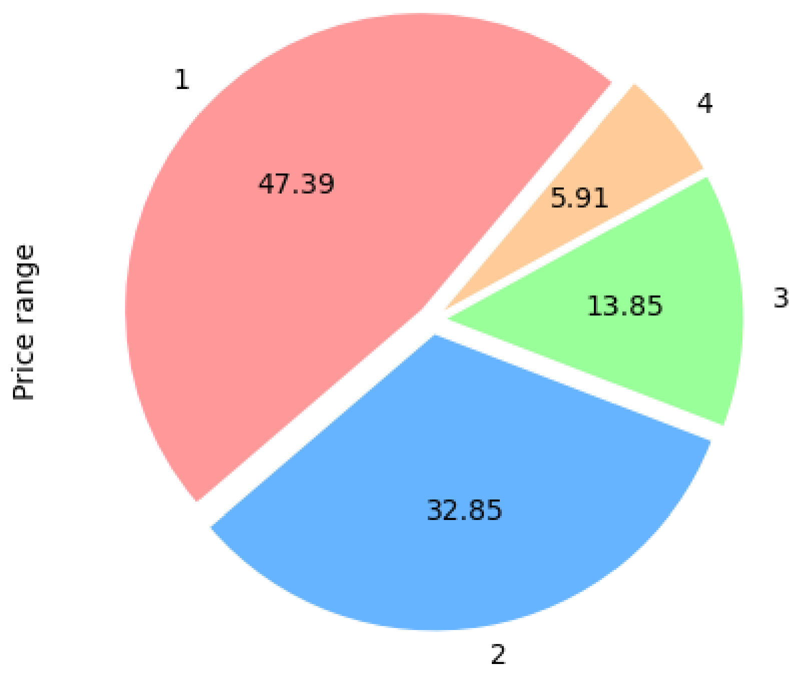
In [43]:
```
def get_expensive(clean_data,country):
    top_10 = clean_data[clean_data['Country']==country].groupby('Restaurant Name')
    names = top_10.index
    cost = top_10.values
    fig = plt.figure(figsize=(12,10))
    plt.title(f'TOP 10 EXPENSIVE RESTERAUNTS IN {country} ')
    plt.xlabel('Mean Average Cost for Two ($)')
    plt.ylabel('Restaurant Name')
    ax = sns.barplot(x=cost,y=names)
    ax.bar_label(ax.containers[0])
    plt.show()
```

In [44]:
```
get_expensive(clean_data,'India')
```



5.9 Distribution of Price Ranges

In [45]:
```
clean_data['Price range'].value_counts().plot(kind='pie', autopct = '%.2f',
                                              radius=1,startangle=50,counterclock=
                                              explode=[0.05,0.05,0.05,0.05],colors
plt.show()
```

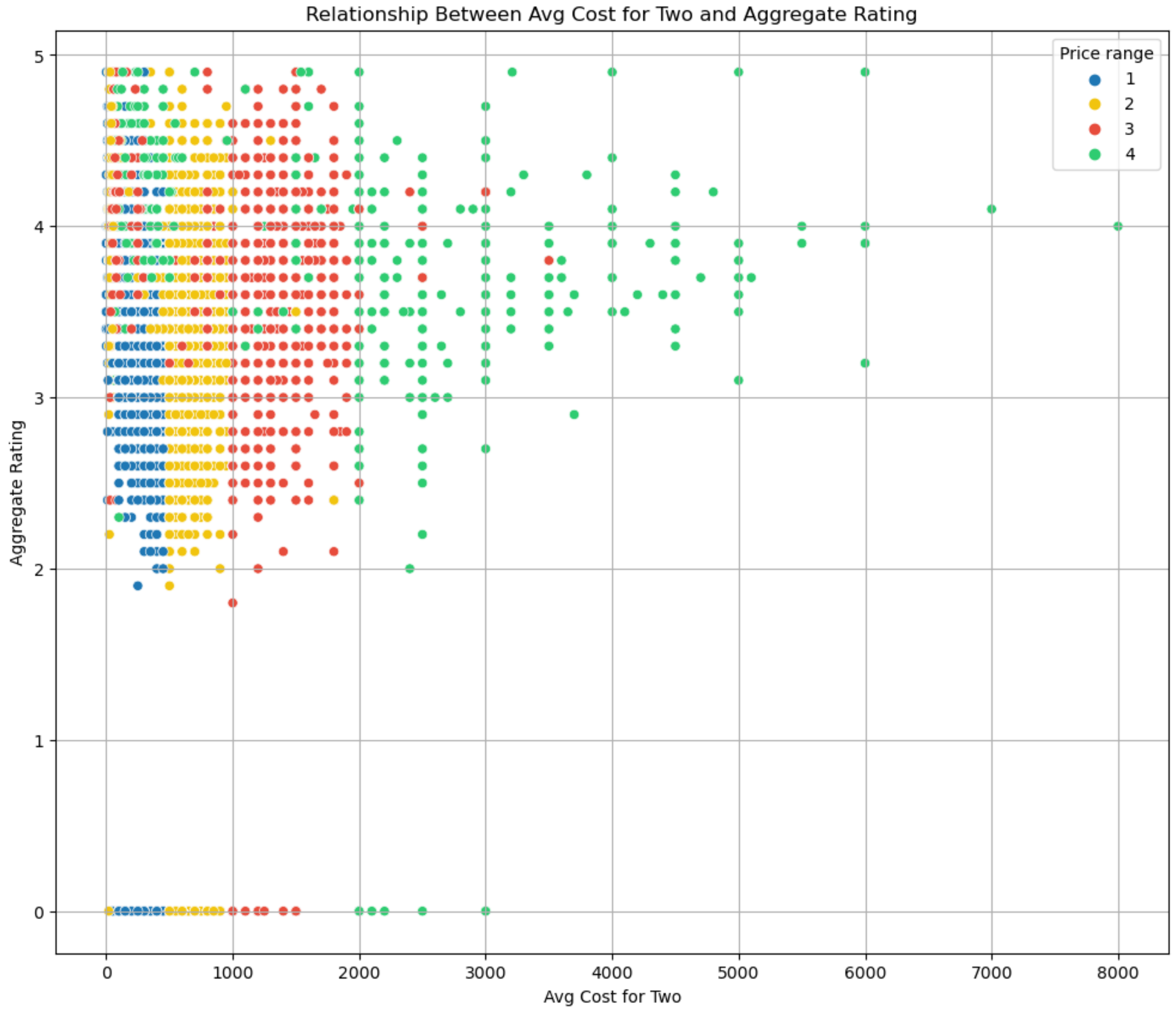


Observation:

Here we can see that 47% of the data falls under price range 1 and 32% of it falls under price range 2. This might be because dataset is dominating with Indian Restaurants

6.0 Relationship Between Avg Cost for Two and Aggregate Rating

In [46]:
```
fig = plt.figure(figsize=(12,10))
sns.scatterplot(x='Average Cost for two',y='Aggregate rating',data=clean_data,hue=
plt.title(f'Relationship Between Avg Cost for Two and Aggregate Rating')
plt.xlabel('Avg Cost for Two')
plt.ylabel('Aggregate Rating')
plt.grid()
plt.show()
```



`Observation:`

We can observe that expensive restaurants are rated highly whereas cheap restuarants are not rated that much

Summary

1. 90% of observations belong to India.
2. USA(4) has higher ratings than India(3.5) and a majority of Indian restaurants have 0 ratings. Either Zomato should nudge customers to rate or these are newly onboarded restaurants.
3. US customers provide ratings more frequently and consistently than Indians.
4. Popular Indian cuisine is North Indian owing to major North Indian cities and for the USA it's all Americana food.
5. India and US have moderate food prices as compared to the rest of the countries.
6. Positive relation exists between ratings and the average cost for two, this could be because of the assumed notion that premium restaurants have good ambiance or

better service, whereas regular restaurants cannot provide such an experience which could lead to lower ratings.