Predicting Zomato Restaurants Rate

1. Business Problem

1.1 Problem Description

Restaurants from all over the world can be found here in Bengaluru. From United States to Japan, Russia to Antarctica, you get all type of cuisines here. Delivery, Dine-out, Pubs, Bars, Drinks,Buffet, Desserts you name it and Bengaluru has it. Bengaluru is best place for foodies. The number of restaurant are increasing day by day. Currently which stands at approximately 12,000 restaurants. With such an high number of restaurants. This industry hasn't been saturated yet. And new restaurants are opening every day. However it has become difficult for them to compete with already established restaurants. The key issues that continue to pose a challenge to them include high real estate costs, rising food costs, shortage of quality manpower, fragmented supply chain and over-licensing. This Zomato data aims at analysing demography of the location. Most importantly it will help new restaurants in deciding their theme, menus, cuisine, cost etc for a particular location. It also aims at finding similarity between neighborhoods of Bengaluru on the basis of food.

- Does demography of area matters?
- Does location of particular type of restraurant depends on people living in that area>
- Does theme of restraurant matters?
- Is food chain category restraurant likely to have more customers than its counter part?
- Are any neighbourhood on similar based on the type of food?
- Is particular neighbours is famous for itw own kind of food?

- If two neighbours are similar does that mean these are related or particular group of people live in neighbourhood or these are places to eat.
- What kind of food is famous in locality.
- Do entire locality loves veg food, if yes then locality populated by particular set of people eg Jain, Gujarati,Marwadi who are basically veg.

1.2 Problem Statement

The dataset also contains reviews for each of the restaurant which will help in finding overall rating for the place. So we will try to predict rating for particular restaurant.

1.3 Real world/Business Objectives

We need to predict rating based on different parameters like Average_cost for two people, Online Order available, foods,menu list, most liked dishes etc features.

1.4 Machine Learning Formulation

Here we suppose to predicted rating of restaurant, so it is basically **Regression** problem.

1.5 Perfomance Metric

We will try to reduce Mean Square Error ie **MSE** as minimum as possible. So it is **Regression** problem reducing **MSE**.

- Ideal MSE is 0.

2. Machine Learning Problem

2.1 Data

Data Acquire

https://www.kaggle.com/himanshupoddar/zomato-bangalore-restaurants (https://www.kaggle.com/himanshupoddar/zomato-bangalore-restaurants)

2.1.1 Understanding the data

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import ast

from wordcloud import WordCloud, STOPWORDS
from sklearn.preprocessing import OneHotEncoder

from joblib import dump,load
#%matplotlib notebook
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from sklearn.linear_model import LinearRegression
from sklearn import linear_model
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import  make_scorer
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
```

In [2]:

```
data = pd.read_csv('data/zomato.csv')
data.shape
```

Out[2]:

```
(51717, 17)
```

In [3]:

```
data.head()
```

Out[3]:

	url	address	name	online_order	book_table
0	https://www.zomato.com/bangalore/jalsa-banasha...	942, 21st Main Road, 2nd Stage, Banashankari, ...	Jalsa	Yes	Yes
1	https://www.zomato.com/bangalore/spice-elephan...	2nd Floor, 80 Feet Road, Near Big Bazaar, 6th ...	Spice Elephant	Yes	No
2	https://www.zomato.com/SanchurroBangalore?cont...	1112, Next to KIMS Medical College, 17th Cross...	San Churro Cafe	Yes	No
3	https://www.zomato.com/bangalore/addhuri-udupi...	1st Floor, Annakuteera, 3rd Stage, Banashankar...	Addhuri Udupi Bhojana	No	No
4	https://www.zomato.com/bangalore/grand-village...	10, 3rd Floor, Lakshmi Associates, Gandhi Baza...	Grand Village	No	No

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51717 entries, 0 to 51716
Data columns (total 17 columns):
url                            51717 non-null object
address                        51717 non-null object
name                           51717 non-null object
online_order                   51717 non-null object
book_table                     51717 non-null object
rate                           43942 non-null object
votes                          51717 non-null int64
phone                          50509 non-null object
location                       51696 non-null object
rest_type                      51490 non-null object
dish_liked                     23639 non-null object
cuisines                       51672 non-null object
approx_cost(for two people)    51371 non-null object
reviews_list                   51717 non-null object
menu_item                      51717 non-null object
listed_in(type)                51717 non-null object
listed_in(city)                51717 non-null object
dtypes: int64(1), object(16)
memory usage: 6.7+ MB
```

Observation

Rate, dish_liked, phone , approx_cost(for two people) values are missing.

In [5]:

```
data['votes'].describe()
```

Out[5]:

```
count    51717.000000
mean       283.697527
std        803.838853
min          0.000000
25%          7.000000
50%         41.000000
75%        198.000000
max      16832.000000
Name: votes, dtype: float64
```

Observation

- Minimum vote's value is 0, can be interpret as there are some restaurants who have 0 vote
- Maximum vote's value is 16832, there is a restaurant who has 16832.
- Average vote's values is 284, so average 284 votes for restaurant

In [6]:

```
data.columns
```

Out[6]:

```
Index(['url', 'address', 'name', 'online_order', 'book_table', 'rate',
'votes',
       'phone', 'location', 'rest_type', 'dish_liked', 'cuisines',
       'approx_cost(for two people)', 'reviews_list', 'menu_item',
       'listed_in(type)', 'listed_in(city)'],
      dtype='object')
```

Columns description

- url: contains the url of the restaurant in the zomato website
- address: contains the address of the restaurant in Bengaluru
- name: contains the name of the restaurant
- online_order: whether online ordering is available in the restaurant or not
- book_table: table book option available or not
- rate: contains the overall rating of the restaurant out of 5
- votes: contains total number of rating for the restaurant as of the above mentioned date
- phone: contains the phone number of the restaurant
- location: contains the neighborhood in which the restaurant is located
- rest_type: restaurant type
- dish_liked: dishes people liked in the restaurant
- cuisines: food styles, separated by comma
- approx_cost(for two people): contains the approximate cost for meal for two people
- reviews_list: list of tuples containing reviews for the restaurant, each tuple
- menu_item: contains list of menus available in the restaurant
- listed_in(type): type of meal
- listed_in(city): contains the neighborhood in which the restaurant is listed

2.2 Data Preprocess

2.2.1 Adjust column names and dropped irrelevant columns

In [7]:

```
# explore columns related to the addrress
data.loc[:,['address','location','listed_in(city)']].sample(8,random_state=1)
```

Out[7]:

	address	location	listed_in(city)
8157	2A/3, 15th Cross, Green Garden Layout, Shirdi ...	Marathahalli	Brookefield
32498	18, Shreenidhi Arcade, Maruthi Nagar Main Road...	BTM	Koramangala 6th Block
4679	56, Near Passport Office, Outer Ring Road, Bel...	Bellandur	Bellandur
2445	14/6, 9th Main Road, Opposite Water Tank, 100 ...	BTM	Bannerghatta Road
27316	321/3A, Sharif Complex, Hosur Main Road, Oppos...	Hosur Road	Koramangala 4th Block
2735	4/5, 5th Cross, Laxmi Road, Shanti Nagar, Bang...	Shanti Nagar	Basavanagudi
34577	9, Maruthi Nagar, Madiwala, BTM, Bangalore	BTM	Koramangala 6th Block
32233	13th cross, 16th main, Tavarekere Main Road, B...	BTM	Koramangala 6th Block

Here, we can see that 3 column are representing same information, so just dropping column which are not important.

- we are going to keep the location column and drop the address and listed_in(city) columns
- columns url , phone , we are not interested in ,to be dropped too

In [8]:

```
# drop unnecessary columns
column_to_drop = ['address','url' ,'listed_in(city)', 'phone']
data.drop(columns=column_to_drop, axis=1,inplace=True)
```

In [9]:

```
data.columns
```

Out[9]:

```
Index(['name', 'online_order', 'book_table', 'rate', 'votes', 'locatio
n',
       'rest_type', 'dish_liked', 'cuisines', 'approx_cost(for two peo
ple)',
       'reviews_list', 'menu_item', 'listed_in(type)'],
      dtype='object')
```

2.2.2 Remove Duplicates

Q.1) Is there duplicate values present in dataset? If yes then many of them are duplicate?

In [10]:

```
# check for duplicate values
print("No of Duplicates in dataset:  ",data.duplicated().sum())
```

```
No of Duplicates in dataset:   9809
```

In [11]:

```
# drop the duplicates
data.drop_duplicates(inplace=True)
```

2.2.3 Removing Null values

Q.2) Is there NULL values present in dataset? If yes then many they are (in %)?

In [12]:

```
# check for null values
((data.isna().sum()/data.shape[0])*100).round(2)
```

Out[12]:

```
name                            0.00
online_order                    0.00
book_table                      0.00
rate                           10.15
votes                           0.00
location                        0.03
rest_type                       0.41
dish_liked                     48.22
cuisines                        0.09
approx_cost(for two people)     0.60
reviews_list                    0.00
menu_item                       0.00
listed_in(type)                 0.00
dtype: float64
```

Observation:

- We can oberve that 54% dish_liked is missing as well as 15% rate values are missing.
- If we throw everything out, mean we are loosing more than 60% points.

Q.3) Can we do something, can we save some of the points?

But before removing NULL values lets understand, Rate colomn.

In [13]:

```
# check for unique values in the rate column
data.rate.unique()
```

Out[13]:

```
array(['4.1/5', '3.8/5', '3.7/5', '3.6/5', '4.6/5', '4.0/5', '4.2/5',
       '3.9/5', '3.1/5', '3.0/5', '3.2/5', '3.3/5', '2.8/5', '4.4/5',
       '4.3/5', 'NEW', '2.9/5', '3.5/5', nan, '2.6/5', '3.8 /5', '3.4/
5',
       '4.5/5', '2.5/5', '2.7/5', '4.7/5', '2.4/5', '2.2/5', '2.3/5',
       '3.4 /5', '-', '3.6 /5', '4.8/5', '3.9 /5', '4.2 /5', '4.0 /5',
       '4.1 /5', '3.7 /5', '3.1 /5', '2.9 /5', '3.3 /5', '2.8 /5',
       '3.5 /5', '2.7 /5', '2.5 /5', '3.2 /5', '2.6 /5', '4.5 /5',
       '4.3 /5', '4.4 /5', '4.9/5', '2.1/5', '2.0/5', '1.8/5', '4.6 /
5',
       '4.9 /5', '3.0 /5', '4.8 /5', '2.3 /5', '4.7 /5', '2.4 /5',
       '2.1 /5', '2.2 /5', '2.0 /5', '1.8 /5'], dtype=object)
```

Observation:

- There are some points which has 'NEW' rating and '-' rating, which is completely incorrect.

In [14]:

```
data['rate'] = data['rate'].replace('NEW',np.NaN)
data['rate'] = data['rate'].replace('-',np.NaN)
```

We can see that by default it has '/5' (divide by 5) arithmatic character, first we will remove this then proceed.

In [15]:

```
data['rate'] = data.loc[:,'rate'].replace('[ ]','',regex = True)
data['rate'] = data['rate'].astype(str)
data['rate'] = data['rate'].apply(lambda r: r.replace('/5',''))
data['rate'] = data['rate'].apply(lambda r: float(r))

data['rate'].head(2)
```

Out[15]:

```
0    4.1
1    4.1
Name: rate, dtype: float64
```

As we understood Rate colomn above, lets understand, dish_liked

But before that first go throght "Review_List"

In [16]:

```
type(data.reviews_list[0])
```

Out[16]:

```
str
```

In [17]:

```
# return to a list of tuples
data.reviews_list = data.reviews_list.apply(lambda x: ast.literal_eval(x))
type(data.reviews_list[0])
```

Out[17]:

```
list
```

In [18]:

```
# check for the first input
data.reviews_list[0][0]
```

Out[18]:

```
('Rated 4.0',
 'RATED\n  A beautiful place to dine in.The interiors take you back to
the Mughal era. The lightings are just perfect.We went there on the oc
casion of Christmas and so they had only limited items available. But
the taste and service was not compromised at all.The only complaint is
that the breads could have been better.Would surely like to come here
again.')
```

Observation:

- We can see that in "Review_List" starting line come up with rating. 'Rated 4.0'.
- We can use this values and filled up 'Rate' colomn.

Q3A. Can we use this values as fill up in 'Rate' Colomn wherever it is missing? If yes then image we have saved that data point,ie information.

In [19]:

```
# extract the rate for the first input from the review column
extracted = [float(i[0].replace('Rated','').strip()) for i in data.reviews_list[0]]
extracted
```

Out[19]:

```
[4.0, 4.0, 2.0, 4.0, 5.0, 5.0, 4.0, 4.0, 5.0, 4.0, 4.0, 4.0]
```

Above are review for particular restaurant, we can use mean value.

In [20]:

```
extracted_mean = round((sum(extracted)/len(extracted)),1)
extracted_mean
```

Out[20]:

```
4.1
```

- This is great. Lets Compare this value with 'Rate' colomn value.

In [21]:

```
print("Extracted Rate: ",extracted_mean)
print("Original Rate: ",data.rate[0])
```

```
Extracted Rate:  4.1
Original Rate:  4.1
```

- This is brillliant, lets do for all.

In [22]:

```
def extract_features_from_review_list(x):
    '''
    extract the rate value out of a string inside tuple
    '''
    # ensure that x is not Null and there is more than one rate
    if not x or len(x) <= 1:
        return None
    rate = [float(i[0].replace('Rated','').strip())  for i in x if type(i[0])== str
    return round((sum(rate)/len(rate)),1)
```

In [23]:

```
# create new column
data['review_rate']  = data.reviews_list.apply(lambda x : extract_features_from_rev
```

In [24]:

```
## Compare "Original Rate" vs "Rate extracted from Review List"
data.loc[:,['rate','review_rate']].sample(10,random_state=1)
```

Out[24]:

	rate	review_rate
43076	4.0	4.0
49259	3.3	NaN
43257	4.5	4.2
30157	3.3	3.1
41110	3.8	4.0
34220	4.0	4.0
42520	3.0	3.3
45657	3.2	2.3
38218	3.3	3.9
4568	NaN	3.5

- Quite Closer.
- Ok, so we can replace missing value with this new adjustment.

In [25]:

```
# get the before number of null values
data.rate.isna().sum()
```

Out[25]:

5914

In [26]:

```
# apply the changes
nan_index = data.query('rate != rate & review_rate == review_rate').index
for i in nan_index:
    data.loc[i,'rate'] = data.loc[i,'review_rate']
```

In [27]:

```
# update the number of null values now
data.rate.isna().sum()
```

Out[27]:

4861

- Please notice we have saved more than 1000 points.

In [28]:

```
# check now
((data.isna().sum()/data.shape[0])*100).round(2)
```

Out[28]:

```
name                            0.00
online_order                    0.00
book_table                      0.00
rate                           11.60
votes                           0.00
location                        0.03
rest_type                       0.41
dish_liked                     48.22
cuisines                        0.09
approx_cost(for two people)     0.60
reviews_list                    0.00
menu_item                       0.00
listed_in(type)                 0.00
review_rate                    25.71
dtype: float64
```

- Purpose behind filling missing values has being accomplished, we can remove 'review_rate' colomn

In [29]:

```
# # first let's drop the review_rate column now
# data.drop(columns='review_rate',axis=1,inplace=True)
```

Now we will remove missing values, from 'rate' and 'average_cost' colomn

In [30]:

```
# drop null values
data.dropna(subset=['rate', 'approx_cost(for two people)'],inplace=True)
```

In [31]:

```
# check shape
data.shape
```

Out[31]:

```
(36840, 14)
```

In [32]:

```
data.isna().sum()
```

Out[32]:

```
name                               0
online_order                       0
book_table                         0
rate                               0
votes                              0
location                           0
rest_type                        121
dish_liked                     15277
cuisines                           8
approx_cost(for two people)        0
reviews_list                       0
menu_item                          0
listed_in(type)                    0
review_rate                     5889
dtype: int64
```

Observation:

- Here count 0 means there is no missing value.

In [33]:

```
# remove cuisines missing values
data=data[data.cuisines.isna()==False]
```

In [34]:

```
data.rename(columns={'approx_cost(for two people)': 'average_cost'}, inplace=True)
```

In [35]:

```
# check for percentage of null values
((data.isna().sum()/data.shape[0])*100).round(2)
```

Out[35]:

```
name                0.00
online_order        0.00
book_table          0.00
rate                0.00
votes               0.00
location            0.00
rest_type           0.33
dish_liked         41.46
cuisines            0.00
average_cost        0.00
reviews_list        0.00
menu_item           0.00
listed_in(type)     0.00
review_rate        15.98
dtype: float64
```

In [36]:

```
# make lower case
data.dish_liked = data.dish_liked.apply(lambda x:x.lower().strip() if isinstance(x,
```

In [37]:

```
menu_list = []

# collect the dishes' names and make a menu list for all kind of dishes
for dish in data.dish_liked.tolist():
    if isinstance(dish,str) and len(dish)>0:
        for e in dish.split(','):
            menu_list.append(e)
len(menu_list)
```

Out[37]:

```
118363
```

In [38]:

```
# Now collect the unique dish name
menu_set = set(menu_list)
```

As we replace review_rate into missing rate values can we do the same here.

Q.3B) Can we replace missing 'dish_liked' with 'menu_list' values?

In [39]:

```
# clear the text
def clear_text(t):
    '''
    clear the input text t
    '''
    return ' '.join([i[1].replace("RATED\n  ",'') for i in t]).encode('utf8').decod
           replace('?','').replace('�','').replace('\n','').replace('.',' ').strip(
```

In [40]:

```
# make a new column reviews_text
data['reviews_text'] = data.reviews_list.apply(lambda x: clear_text(x))
```

In [41]:

```
# check part of reviews text for the first restaurant
data.reviews_text[0][:500]
```

Out[41]:

```
'a beautiful place to dine in the interiors take you back to the mugha
l era  the lightings are just perfect we went there on the occasion of
christmas and so they had only limited items available  but the taste
and service was not compromised at all the only complaint is that the
breads could have been better would surely like to come here again  i
was here for dinner with my family on a weekday  the restaurant was co
mpletely empty  ambience is good with some good old hindi music  seati
ng arrange'
```

Clean up dist_like

- convert text to lower case.
- missing value could extract from review_list

In [42]:

```
data.dish_liked.nunique()
```

Out[42]:

```
5250
```

In [43]:

```
# make lower case
data.dish_liked = data.dish_liked.apply(lambda x:x.lower().strip() if isinstance(x,
```

In [44]:

```
# example
data.dish_liked[10000]
```

Out[44]:

```
nan
```

In [45]:

```
# the solution
menu_set.intersection(data.reviews_text[10000].split(' '))
```

Out[45]:

```
{'chicken', 'fish', 'rice', 'thali'}
```

In [46]:

```
#creat a new column for the reviewed dish
data['dish_n_review'] = data.reviews_text.apply(lambda x: ', '.join(list(menu_set.i
```

In [47]:

```
# get sample to compare
data.query('dish_liked != dish_liked')[['dish_liked','dish_n_review']].sample(5,ran
```

Out[47]:

	dish_liked	dish_n_review
32901	NaN	halwa, kheer
44323	NaN	rice, prawn, shawarma, tikka, chicken
6479	NaN	
11046	NaN	rice
50112	NaN	cappuccino, coffee

So now, we can replace this missed values from the dish_n_review

In [48]:

```
# fill in the missing values in dish_liked column with data from reviews
nan_index = data.query('dish_liked != dish_liked & dish_n_review == dish_n_review')
for i in nan_index:
    data.loc[i,'dish_liked'] = data.loc[i,'dish_n_review']
```

In [49]:

```
# Now let's test our work
data.dish_liked[10000]
```

Out[49]:

```
'chicken, fish, thali, rice'
```

- Now we can drop the menu_list & menu_set

In [50]:

```
del menu_list
del menu_set
```

In [51]:

```
# first let's drop the review_rate column now
data.drop(columns=['reviews_text','review_rate','dish_n_review'],axis=1,inplace=Tru
```

In [52]:

```
# check for null values
((data.isna().sum()/data.shape[0])*100).round(3)
```

Out[52]:

```
name               0.000
online_order       0.000
book_table         0.000
rate               0.000
votes              0.000
location           0.000
rest_type          0.329
dish_liked         0.000
cuisines           0.000
average_cost       0.000
reviews_list       0.000
menu_item          0.000
listed_in(type)    0.000
dtype: float64
```

In [53]:

```
data.shape
```

Out[53]:

```
(36832, 13)
```

- Now thing looked quite good. There is no missing values.

2.1.2 Data Visualizations

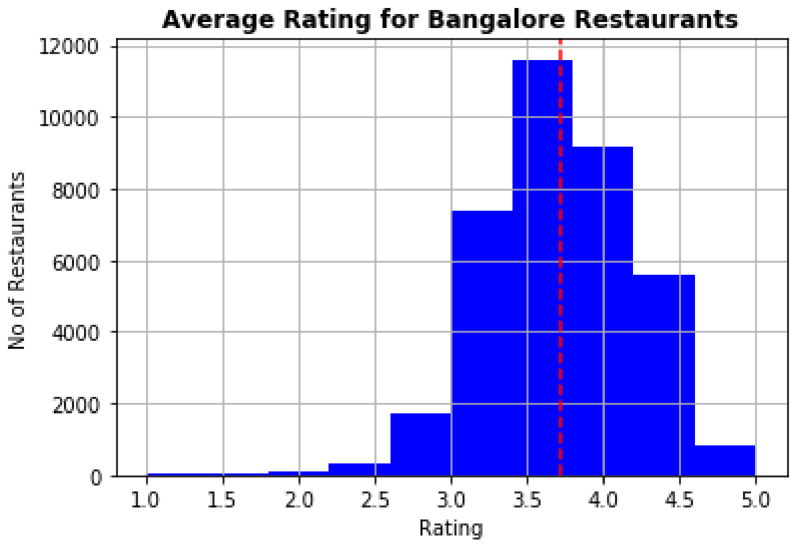
Q.4) What is distrubution of 'Rate column'?

Now it is fine, now we can proceed.

In [54]:

```
data.rate.hist(color='blue')
plt.axvline(x= data.rate.mean(),ls='--',color='red')
plt.title('Average Rating for Bangalore Restaurants',weight='bold')
plt.xlabel('Rating')
plt.ylabel('No of Restaurants')
print("Mean is : ",data.rate.mean())
```

```
Mean is :  3.7208921589921835
```



Observation:

- Average rating is 3.7 in banglore for zomato.

Q.5) Which are the top 20 restaurant in the Banglore? What is their count

In [55]:

```
data.name.value_counts().head()
```

Out[55]:

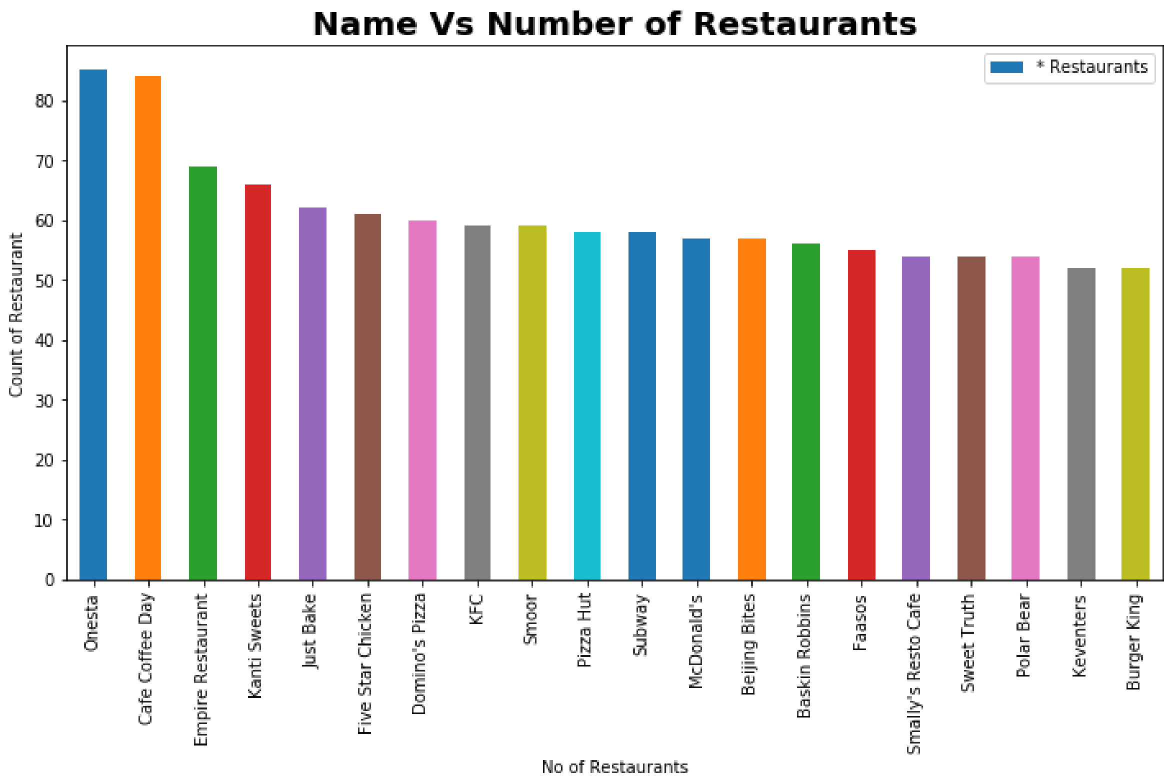
```
Onesta                85
Cafe Coffee Day       84
Empire Restaurant     69
Kanti Sweets          66
Just Bake             62
Name: name, dtype: int64
```

In [56]:

```
plt.figure(figsize=(12,6))
ax =data.name.value_counts()[:20].plot(kind='bar')
ax.legend(['* Restaurants'])
plt.xlabel('No of Restaurants')
plt.ylabel('Count of Restaurant')
plt.title("Name Vs Number of Restaurants", fontsize=20, weight='bold')
```

Out[56]:

```
Text(0.5,1,'Name Vs Number of Restaurants')
```



Observation

- we can say that 'Onesta' day has highest count among all

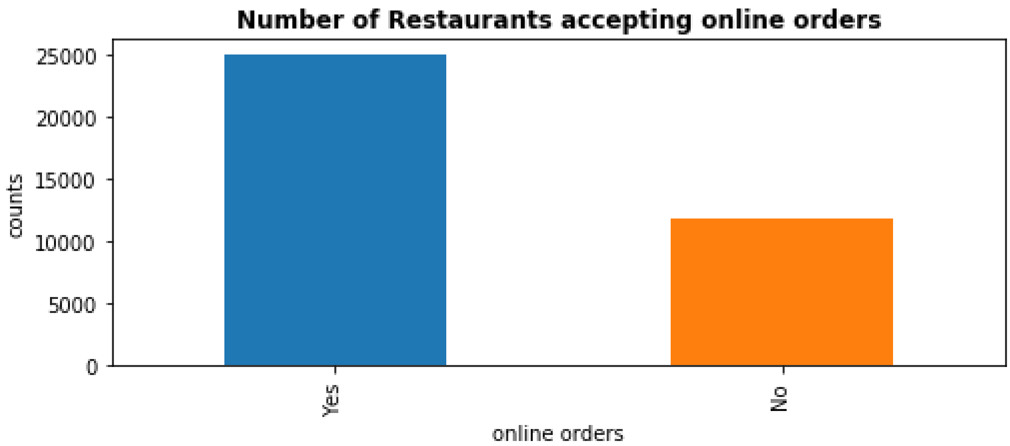
Q.6) How many Restaurant accepting online orders?

In [57]:

```
plt.figure(figsize=(8,3))
ax =data.online_order.value_counts().plot(kind='bar')
plt.title('Number of Restaurants accepting online orders', weight='bold')
plt.xlabel('online orders')
plt.ylabel('counts')

data.online_order.value_counts()
```

Out[57]:

```
Yes    24969
No     11863
Name: online_order, dtype: int64
```



Observation:

- Most of order are onlines.
- no missing values in online order colomn

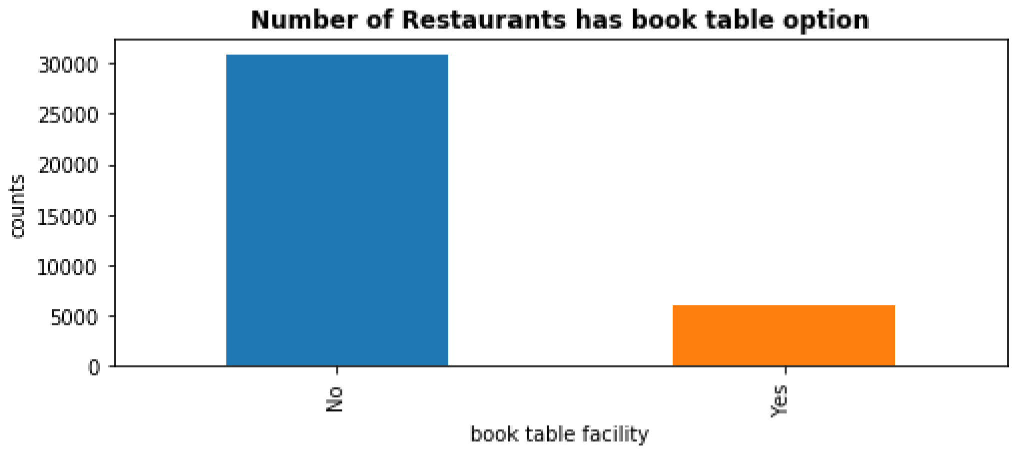
Q.7) How many Restaurant have option to book a table?

In [58]:

```
plt.figure(figsize=(8,3))
ax =data.book_table.value_counts().plot(kind='bar')
plt.title('Number of Restaurants has book table option', weight='bold')
plt.xlabel('book table facility')
plt.ylabel('counts')

data.book_table.value_counts()
```

Out[58]:

```
No     30799
Yes     6033
Name: book_table, dtype: int64
```



Observation

- Most of restaurant do not have book table facility

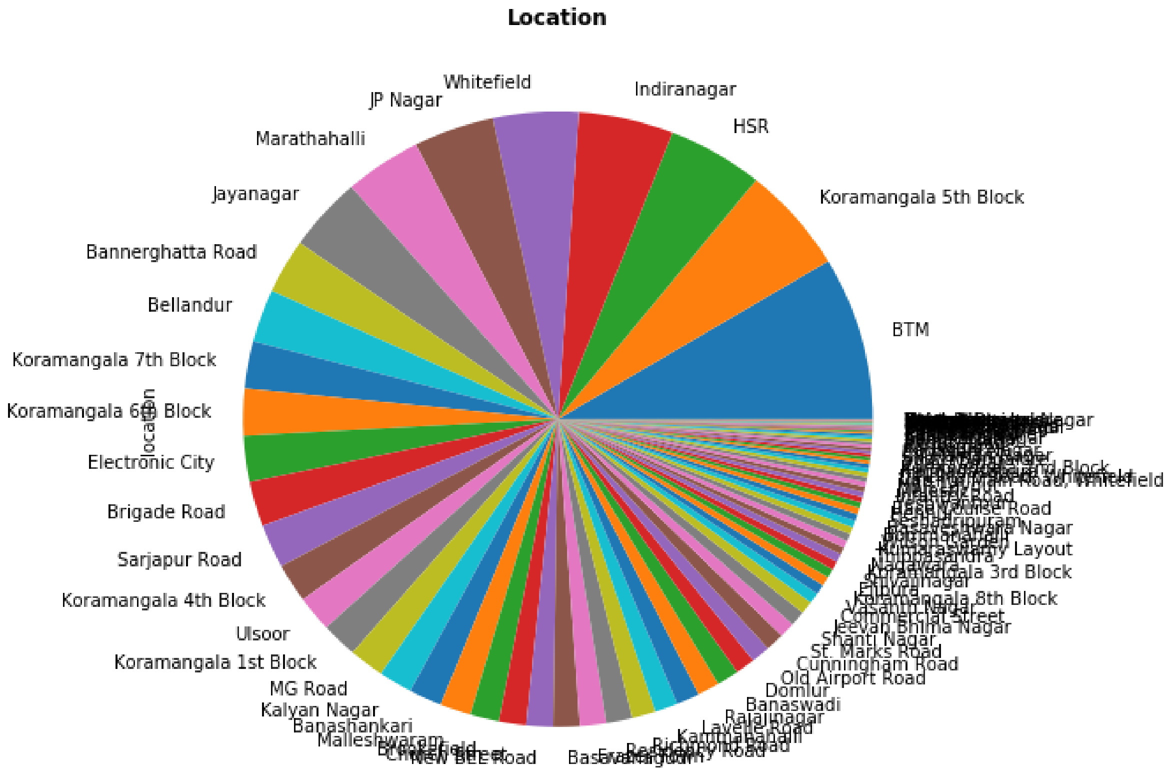
Q.8) In banglore city,in which area has maximum number of restaurants? Also find percetage for the same.

In [59]:

```
plt.figure(figsize=(8,8))
ax =data.location.value_counts().plot(kind='pie')
plt.title('Location', weight='bold')
```

Out[59]:

```
Text(0.5,1,'Location')
```



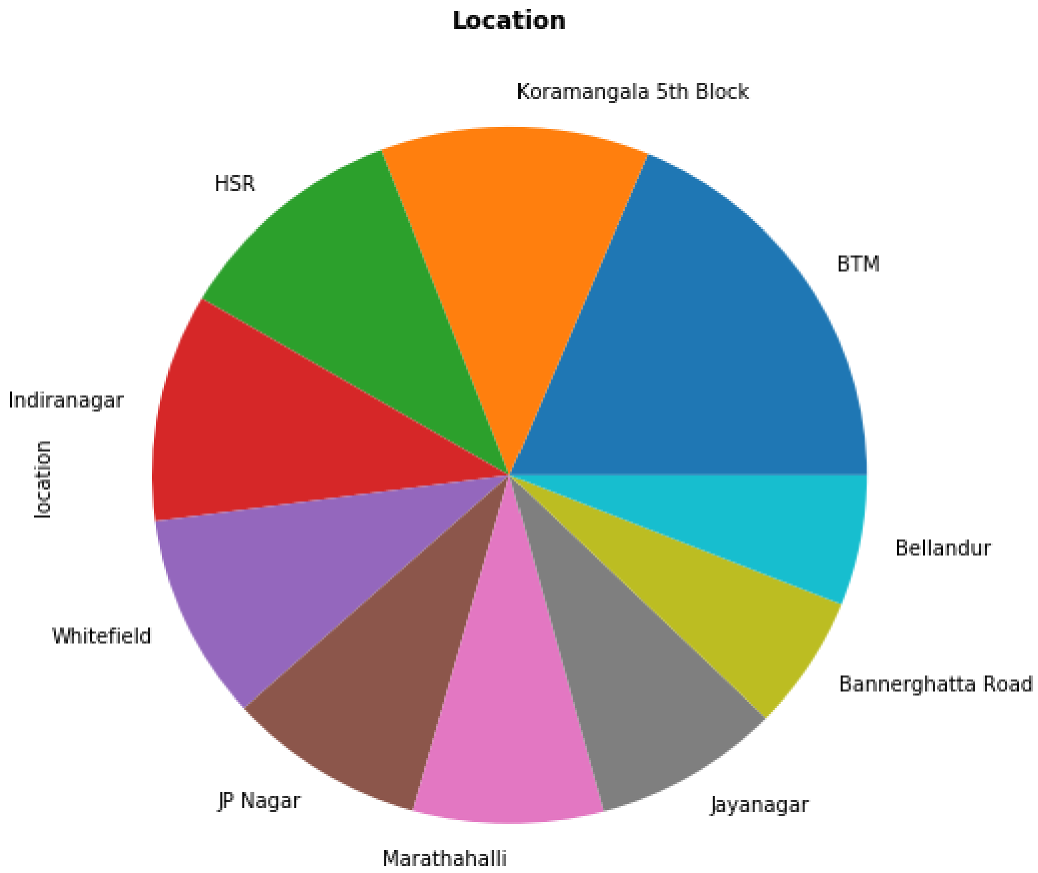
Its very complicated to understand so we will limit ourself to TOP 10 locations

In [60]:

```
plt.figure(figsize=(8,8))
ax =data.location.value_counts()[:10].plot(kind='pie')
plt.title('Location', weight='bold')
```

Out[60]:

```
Text(0.5,1,'Location')
```



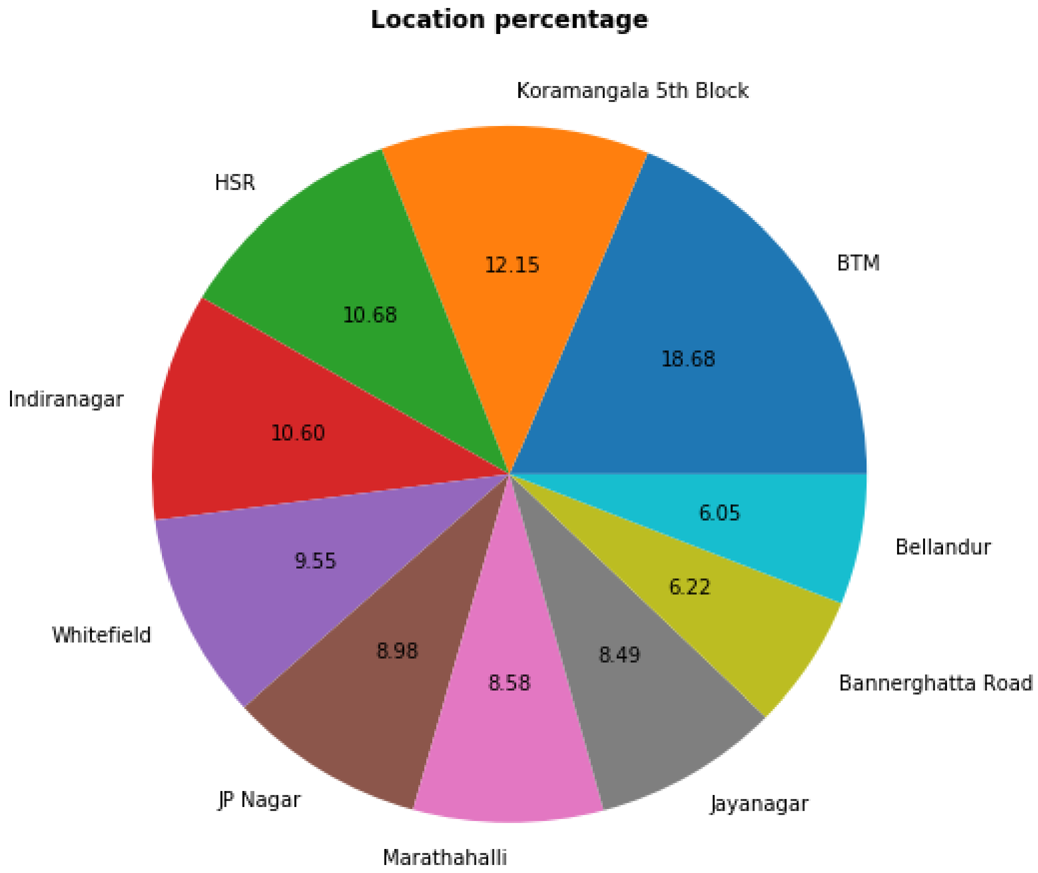
Observation

- We can say that BTM location, where most of restaurant are available

Q9.1) Percentage.

In [61]:

```
## https://stackoverflow.com/questions/6170246/how-do-i-use-matplotlib-autopct

plt.figure(figsize=(8,8))
values = data.location.value_counts()[:10]
labels = data['location'].value_counts()[:10].index
plt.pie(values, labels=labels, autopct='%.2f')
plt.title('Location percentage', weight='bold')
plt.show()
```



Observation:

Now picture seems very clear, maximum restaurant are in BTM follows by HSR,Koramangla, JP Nagar, .. so on.

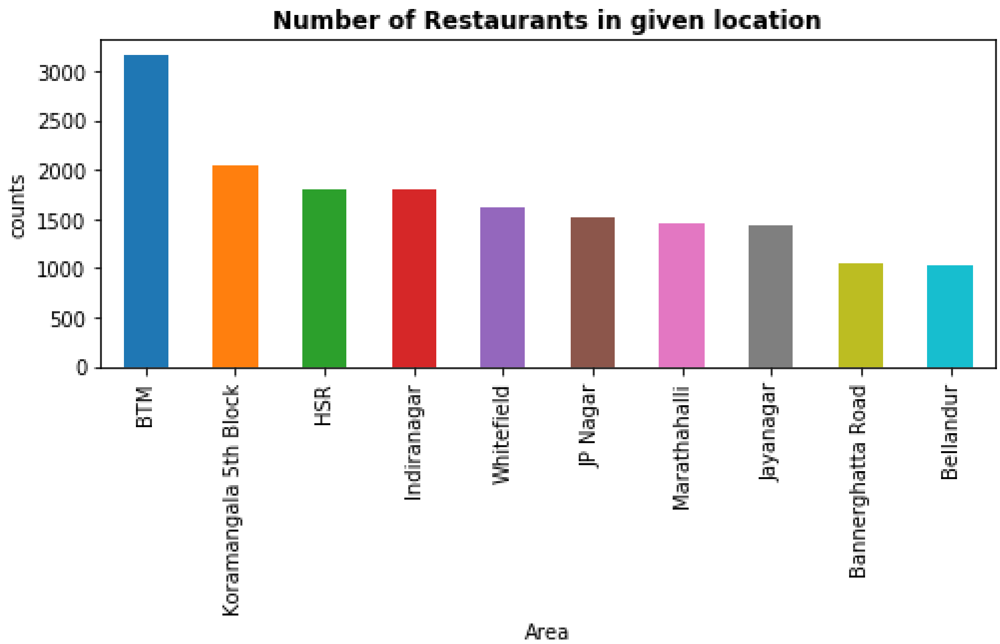
Q9.2 Now, we know percentage of top 10 area, lets find count of each area.

In [62]:

```
plt.figure(figsize=(8,3))
ax =data.location.value_counts()[:10].plot(kind='bar')
plt.title('Number of Restaurants in given location', weight='bold')
plt.xlabel('Area')
plt.ylabel('counts')
```

Out[62]:

```
Text(0,0.5,'counts')
```



Observation

- BTM area has around 3k restaurants.

In [63]:

```
data['location'].nunique() ## Neighbourhoods in banglore
```

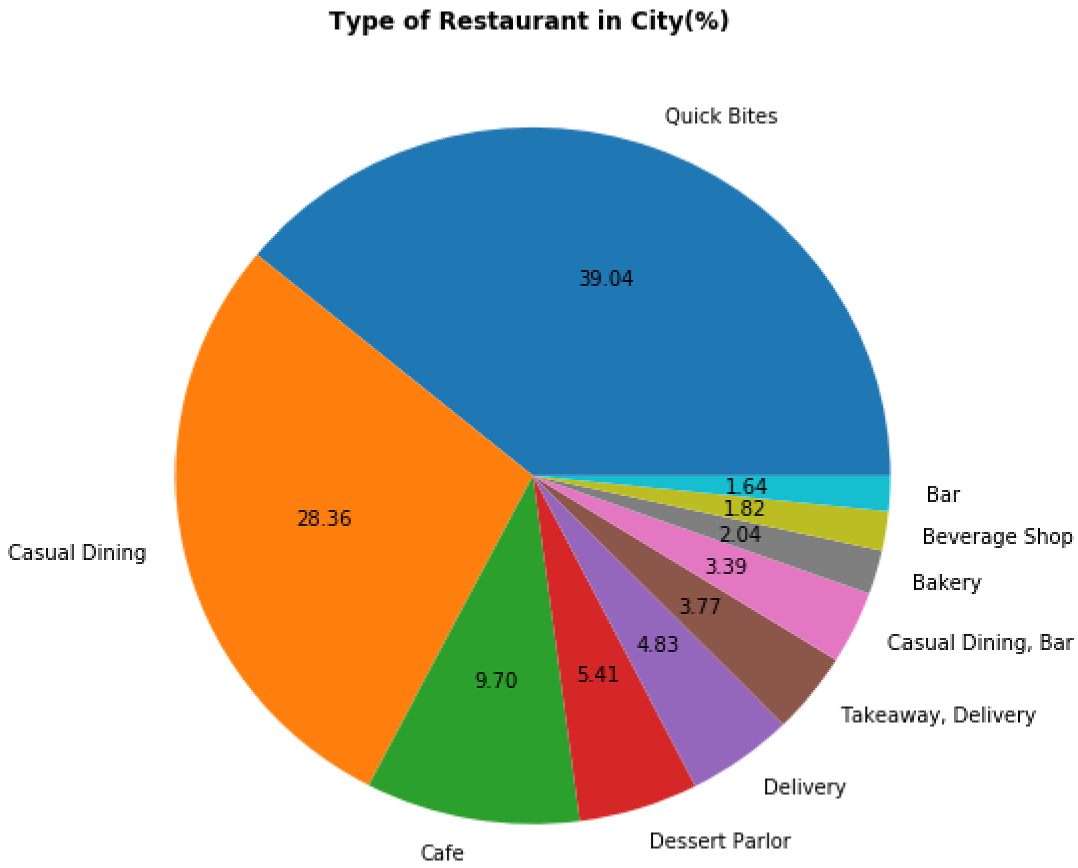
Out[63]:

```
92
```

Q.10) What type of restaurant are there in banglore? also percetage and counts

In [64]:

```
plt.figure(figsize=(8,8))
values = data.rest_type.value_counts()[:10]
labels = data['rest_type'].value_counts()[:10].index
plt.pie(values, labels=labels, autopct='%.2f')
plt.title('Type of Restaurant in City(%) ', weight='bold')
plt.show()
```

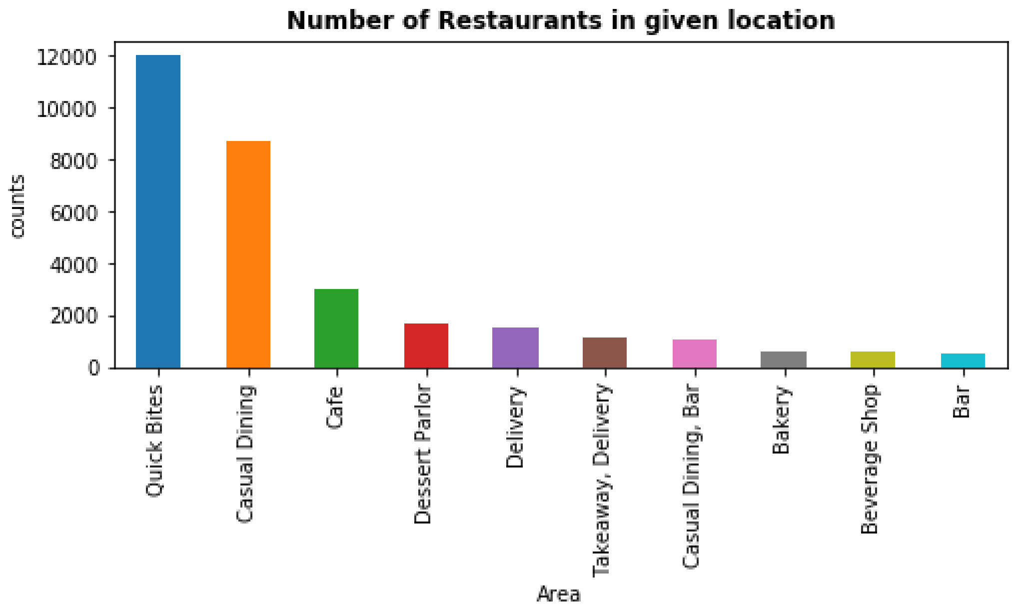


In [65]:

```
plt.figure(figsize=(8,3))
ax =data.rest_type.value_counts()[:10].plot(kind='bar')
plt.title('Number of Restaurants in given location', weight='bold')
plt.xlabel('Area')
plt.ylabel('counts')
```

Out[65]:

```
Text(0,0.5,'counts')
```



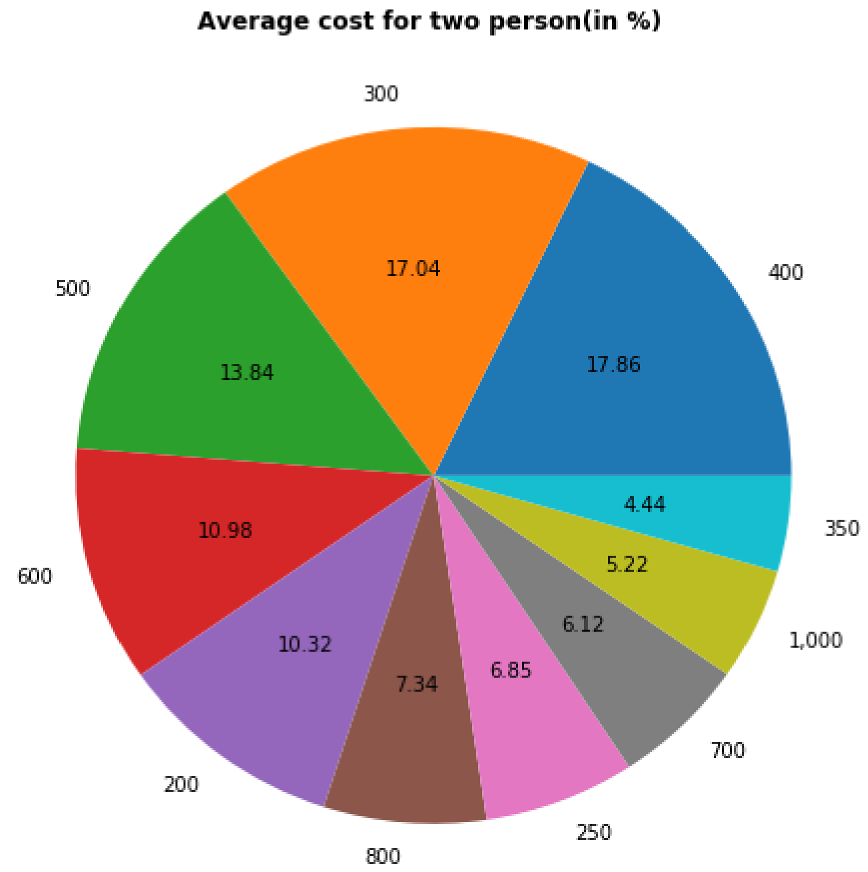
Observation

- "Quick beats" is leading in the race, which is close to 12k follow by "Causal Dining" which is around 8K

Q.11) What is the Average cost in restaurants?

In [66]:

```
plt.figure(figsize=(8,8))
values = data.average_cost.value_counts()[:10]
labels = data['average_cost'].value_counts()[:10].index
plt.pie(values, labels=labels, autopct='%.2f')
plt.title('Average cost for two person(in %) ', weight='bold')
plt.show()
```



Observation

There is 17.86% percetage chances that for two person average cost will be 400 and 17.04% chance that cost will be 300. so on.

Q.12) Which dish are most famous/favourite dish in restaurants?

In [67]:

```
data.dish_liked.nunique()
```

Out[67]:

```
7482
```

Before we dive in remember that at initial stages we observe that dist_like colomn has some missing values. so first remove missing values then proceed.

In [68]:

```
#lets delete the nulll values

data1 = data.copy()

dishes_data = data1[data1.dish_liked.notnull()]
dishes_data.dish_liked = dishes_data.dish_liked.apply(lambda x:x.lower().strip())
```

In [69]:

```
dishes_data.isnull().sum()
```

Out[69]:

```
name                0
online_order        0
book_table          0
rate                0
votes               0
location            0
rest_type         121
dish_liked          0
cuisines            0
average_cost        0
reviews_list        0
menu_item           0
listed_in(type)     0
dtype: int64
```

In [70]:

```
dishes_data.dish_liked[:10]
```

Out[70]:

```
0    pasta, lunch buffet, masala papad, paneer laja...
1    momos, lunch buffet, chocolate nirvana, thai g...
2    churros, cannelloni, minestrone soup, hot choc...
3                                          masala dosa
4                                  panipuri, gol gappe
5    onion rings, pasta, kadhai paneer, salads, sal...
6                                              chicken
7    farmhouse pizza, chocolate banana, virgin moji...
8    pizza, mocktails, coffee, nachos, salad, pasta...
9    waffles, pasta, coleslaw sandwich, choco waffl...
Name: dish_liked, dtype: object
```

We can see that each row has contained multiple dishes separated by "commma".

In [71]:

```python
# count each dish to see how many times each dish repeated
dish_count = []
for i in dishes_data.dish_liked: ## iterate in each rows in table
    for t in i.split(','):
        t = t.strip() # remove the white spaces to get accurate results
        dish_count.append(t)
```

In [72]:

```python
dish_count[:10] #lets see favourite top 10 dishes
```

Out[72]:

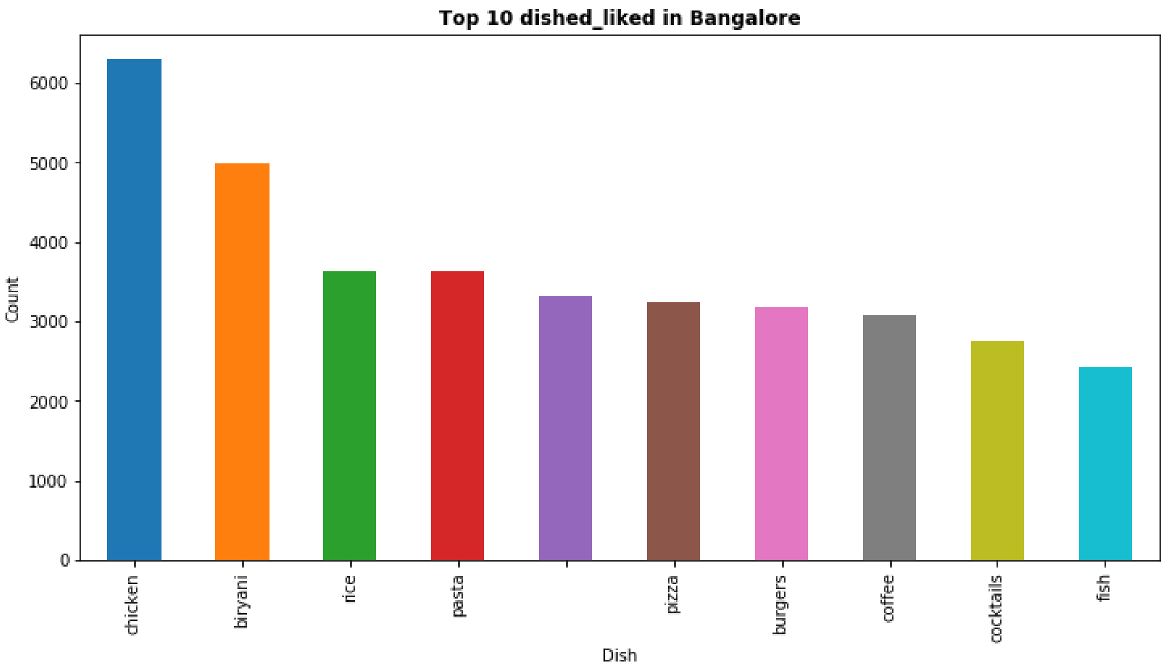
```
['pasta',
 'lunch buffet',
 'masala papad',
 'paneer lajawab',
 'tomato shorba',
 'dum biryani',
 'sweet corn soup',
 'momos',
 'lunch buffet',
 'chocolate nirvana']
```

In [73]:

```python
plt.figure(figsize=(12,6))
pd.Series(dish_count).value_counts()[:10].plot(kind='bar')
plt.title('Top 10 dished_liked in Bangalore',weight='bold')
plt.xlabel('Dish')
plt.ylabel('Count')
```

Out[73]:

```
Text(0,0.5,'Count')
```

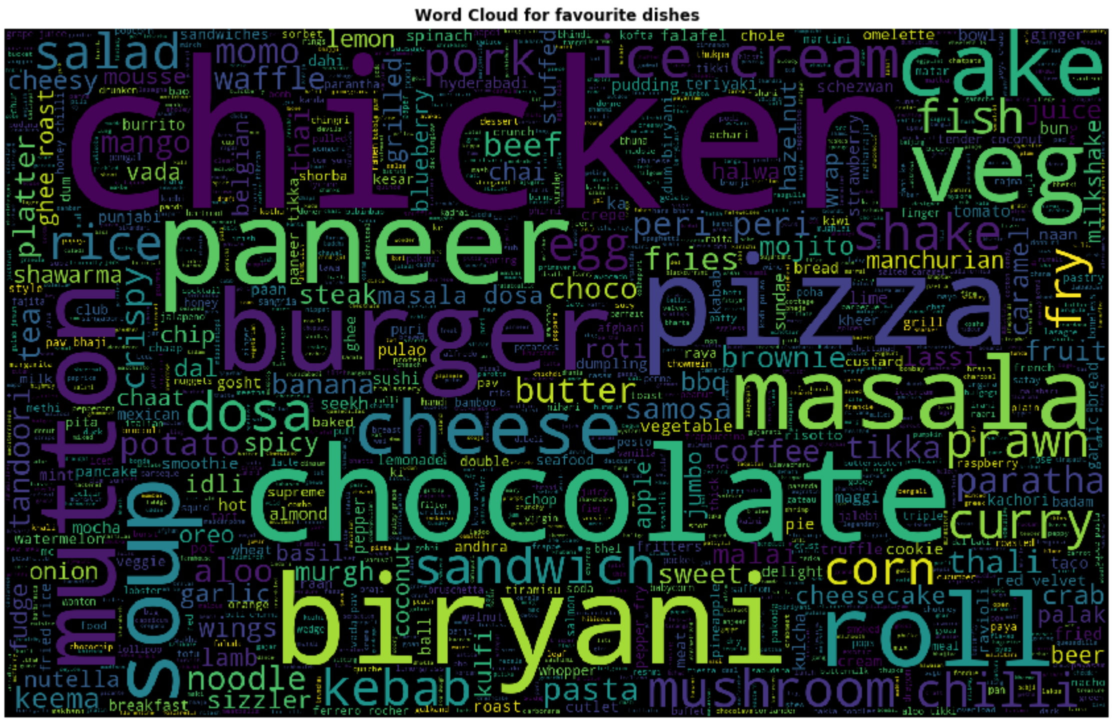


Observation

- We can see that 'pasta' is most favourite dish followed by 'burger' followed by 'cocktails'.

In [74]:

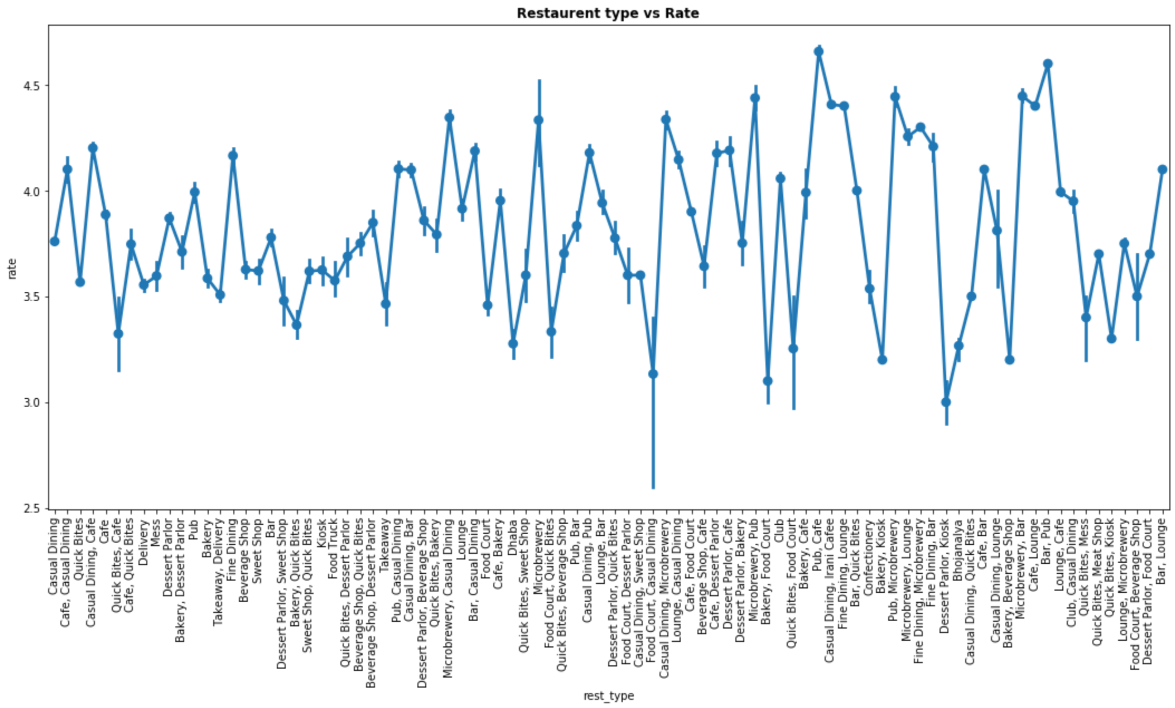
```
dish_set = set(dish_count)
dish_word_cloud = ', '.join(dish_set)

plt.figure( figsize=(15,10) )
wc = WordCloud(width=1600, height=1000,background_color="black", max_words=len(dish
wc.generate(dish_word_cloud)
plt.imshow(wc, interpolation='bilinear')
plt.title('Word Cloud for favourite dishes',weight='bold')
plt.axis("off")
plt.imshow(wc)
plt.show()
```



Q.9) Lets see 'Rate' vs 'Restaurant type' graph.

In [75]:

```
f,ax=plt.subplots(figsize=(18,8))
g = sns.pointplot(x=data["rest_type"], y=data["rate"], data=data)
g.set_xticklabels(g.get_xticklabels(), rotation=90)
plt.title('Restaurent type vs Rate', weight = 'bold')
plt.show()
```



Q.10) Print top 10 Cuisines

In [76]:

```
cuisines_data = data[data.cuisines.notnull()]
cuisines_data.cuisines = cuisines_data.cuisines.apply(lambda x:x.lower().strip())
```

In [77]:

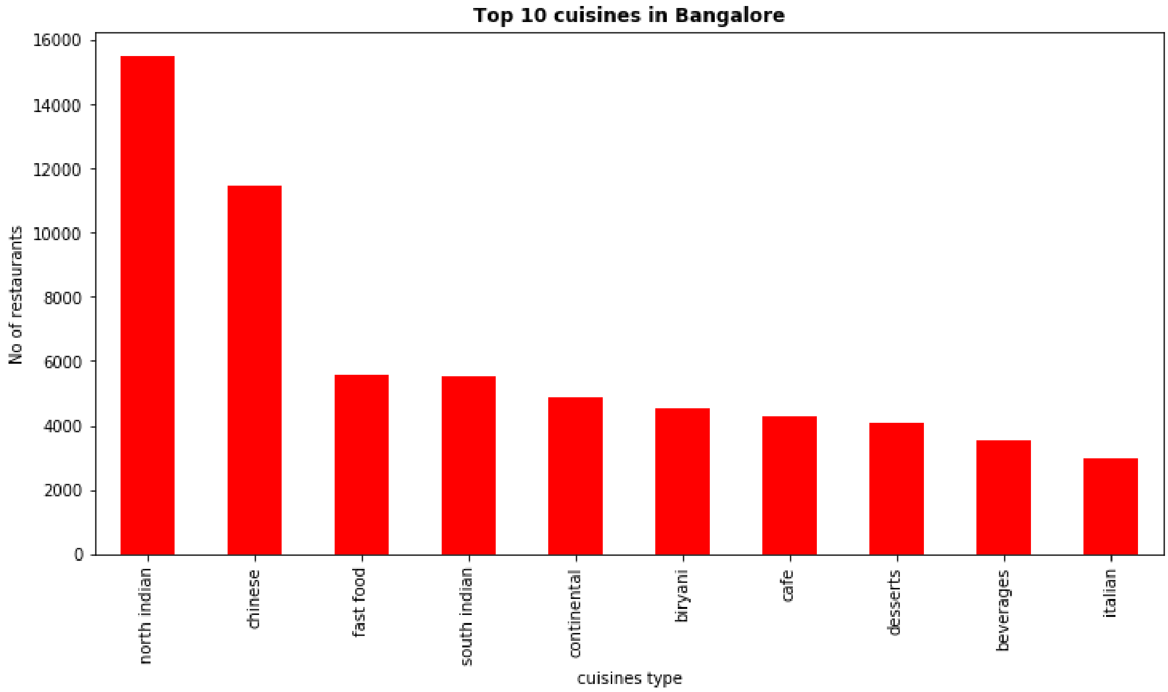
```
cuisines_count= []

for i in cuisines_data.cuisines:
    for j in i.split(','):
        j = j.strip()
        cuisines_count.append(j)
```

In [78]:

```
plt.figure(figsize=(12,6))
pd.Series(cuisines_count).value_counts()[:10].plot(kind='bar',color= 'r')
plt.title('Top 10 cuisines in Bangalore',weight='bold')
plt.xlabel('cuisines type')
plt.ylabel('No of restaurants')
```

Out[78]:

```
Text(0,0.5,'No of restaurants')
```



Observation

- North Indian food is at top, followed by chinease and so on.

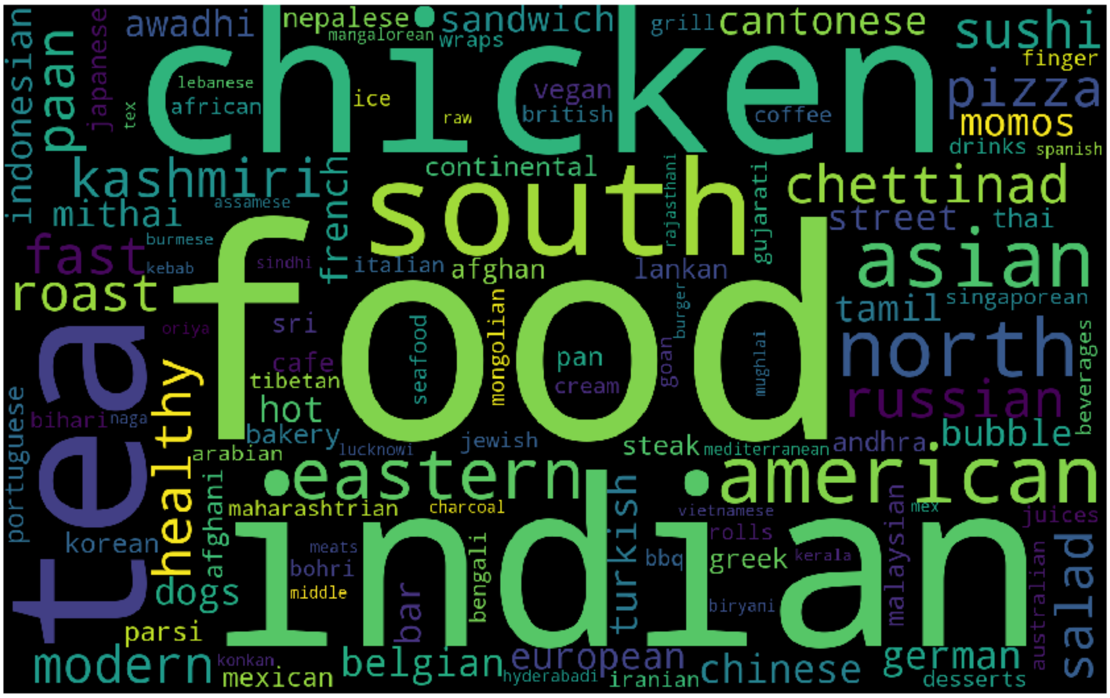
In [79]:

```
cuisines_set = set(cuisines_count)
cuisines_word_cloud = ', '.join(cuisines_set)
```

In [80]:

```
plt.figure( figsize=(15,10) )
wc = WordCloud(width=1600, height=1000,background_color="black", max_words=len(cuis
wc.generate(cuisines_word_cloud)
plt.title('Word Cloud for cuisines',weight='bold')
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.imshow(wc)
plt.show()
```

Word Cloud for cuisines



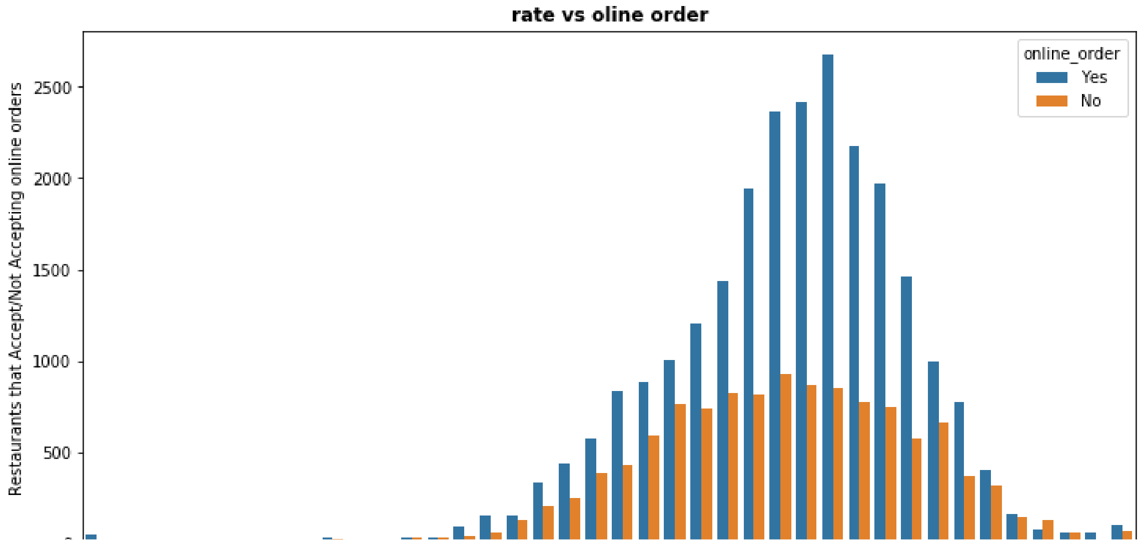
Q.11) Lets plot 'Rate' vs 'Online order'

In [81]:

```
plt.figure(figsize = (12,6))
sns.countplot(x=data['rate'], hue = data['online_order'])
plt.ylabel("Restaurants that Accept/Not Accepting online orders")
plt.title("rate vs oline order",weight = 'bold')
```

Out[81]:

```
Text(0.5,1,'rate vs oline order')
```



3. Model

Till now we were understanding, visualising data. Now let move to build proper Machine Learning model.

In [82]:

```
# pd.get_dummies ==> Convert categorical variable into dummy/indicator variables.(C

data['online_order']= pd.get_dummies(data.online_order, drop_first=True)
data['book_table']= pd.get_dummies(data.book_table, drop_first=True)
data
```

Out[82]:

	name	online_order	book_table	rate	votes	location	r
0	Jalsa	1	1	4.1	775	Banashankari	Casu
1	Spice Elephant	1	0	4.1	787	Banashankari	Casu
2	San Churro Cafe	1	0	3.8	918	Banashankari	Cafe

In [83]:

```
data.columns
```

Out[83]:

```
Index(['name', 'online_order', 'book_table', 'rate', 'votes', 'locatio
n',
       'rest_type', 'dish_liked', 'cuisines', 'average_cost', 'reviews
_list',
       'menu_item', 'listed_in(type)'],
      dtype='object')
```

In [84]:

```
data.drop(columns=['dish_liked','reviews_list','menu_item','listed_in(type)'], inpl
```

In [85]:

```
data['rest_type'] = data['rest_type'].str.replace(',' , '')
data['rest_type'] = data['rest_type'].astype(str).apply(lambda x: ' '.join(sorted(x
data['rest_type'].value_counts().head()
```

Out[85]:

```
Bites Quick       12006
Casual Dining      8720
Cafe               2982
Dessert Parlor     1665
Delivery           1486
Name: rest_type, dtype: int64
```

In [86]:

```
data['cuisines'] = data['cuisines'].str.replace(',' , '')
data['cuisines'] = data['cuisines'].astype(str).apply(lambda x: ' '.join(sorted(x.s
data['cuisines'].value_counts().head()
```

Out[86]:

```
Chinese Indian North                 1956
Indian North                         1907
Indian South                         1034
Chinese Indian Indian North South     941
Bakery Desserts                       698
Name: cuisines, dtype: int64
```

In [87]:

```
data['average_cost'] = data['average_cost'].str.replace(',' , '')
data['average_cost'] = data['average_cost'].apply(int)
```

In [88]:

```
data.head(3)
```

Out[88]:

	name	online_order	book_table	rate	votes	location	rest_type	cuisines	average_c
0	Jalsa	1	1	4.1	775	Banashankari	Casual Dining	Chinese Indian Mughlai North	
1	Spice Elephant	1	0	4.1	787	Banashankari	Casual Dining	Chinese Indian North Thai	
2	San Churro Cafe	1	0	3.8	918	Banashankari	Cafe Casual Dining	Cafe Italian Mexican	

In [89]:

```
x = data.drop(['rate','name'],axis = 1)
y = data['rate']
```

In [90]:

```
print(x.shape)
print(y.shape)
```

```
(36832, 7)
(36832,)
```

3.1 Splitting the data for Model Building

In [92]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state =
```

In [93]:

```
# from joblib import dump,load

dump(X_train, 'pkl_files/more_feature_X_train')
dump(X_test, 'pkl_files/more_feature_X_test')
dump(y_train, 'pkl_files/more_feature_y_train')
dump(y_test, 'pkl_files/more_feature_y_test')
```

Out[93]:

```
['pkl_files/more_feature_y_test']
```

In [2]:

```
X_train = load('pkl_files/more_feature_X_train')
X_test = load('pkl_files/more_feature_X_test')
y_train = load('pkl_files/more_feature_y_train')
y_test = load('pkl_files/more_feature_y_test')
```

In [3]:

```
X_train.head(2)
```

Out[3]:

	online_order	book_table	votes	location	rest_type	cuisines	average_cost
34072	0	1	1390	Koramangala 5th Block	Lounge	Continental Indian North	1400
51088	1	1	1218	Whitefield	Pub	American Asian Mexican	1200

In [58]:

```
enc = OneHotEncoder( handle_unknown='ignore')
```

In [80]:

```
## ALWAYS AVOID DATA LEAKAGE

# this method is for training data set
def one_hot_fit_transform(df,name):
    output_data = df[name].values.reshape(-1, 1)
    return enc.fit_transform(output_data).toarray()

# this method is for test data set
def one_hot_transform(df,name):
    output_data1 = df[name].values.reshape(-1, 1)
    return enc.transform(output_data1).toarray()
```

In [8]:

```
# one hot encoding apply to 'rest_type' features on train/test dataset
tr_dummy_rest_type = one_hot_fit_transform(X_train,'rest_type' )
te_dummy_rest_type= one_hot_transform(X_test,'rest_type' )

# one hot encoding apply to 'location' features on train/test dataset
tr_dummy_city = one_hot_fit_transform(X_train,'location' )
te_dummy_city= one_hot_transform(X_test,'location')

# one hot encoding apply to 'cuisines' features on train/test dataset
tr_dummy_cuisines = one_hot_fit_transform(X_train,'cuisines' )
te_dummy_cuisines=one_hot_transform(X_test,'cuisines')
```

In [9]:

```
tr_dummy_rest_type.shape, te_dummy_rest_type.shape
```

Out[9]:

```
((25782, 67), (11050, 67))
```

In [10]:

```
tr_dummy_city.shape, te_dummy_city.shape
```

Out[10]:

```
((25782, 92), (11050, 92))
```

In [11]:

```
tr_dummy_cuisines.shape, te_dummy_cuisines.shape
```

Out[11]:

```
((25782, 1674), (11050, 1674))
```

In [12]:

```
## combine all 'one-hot' encoded features as Tr.
tr =pd.DataFrame(pd.np.column_stack([ tr_dummy_rest_type,tr_dummy_city, tr_dummy_cu

## CONCAT both dataframe ### ie Tr and X_train(original dataframe)
## https://stackoverflow.com/questions/45963799/pandas-concat-resulting-in-nan-rows

l1=X_train.values.tolist()
l2=tr.values.tolist()

for i in range(len(l1)):
    l1[i].extend(l2[i])

X_train=pd.DataFrame(l1,columns=X_train.columns.tolist()+tr.columns.tolist())
X_train.shape
```

Out[12]:

```
(25782, 1840)
```

In [15]:

```
## combine all 'one-hot' encoded features as Te.
te =pd.DataFrame(pd.np.column_stack([ te_dummy_rest_type,te_dummy_city,te_dummy_cui

## CONCAT both dataframe ### ie Te and X_test(original dataframe)
## https://stackoverflow.com/questions/45963799/pandas-concat-resulting-in-nan-rows

l3=X_test.values.tolist()
l4=te.values.tolist()
for i in range(len(l3)):
    l3[i].extend(l4[i])

X_test=pd.DataFrame(l3,columns=X_test.columns.tolist()+te.columns.tolist())
X_test.shape
```

Out[15]:

```
(11050, 3673)
```

In [16]:

```
# after onehot encoding DONE. 'location','rest_type','cuisines' are redundant featu

X_train =X_train.drop(['location','rest_type','cuisines'],axis = 1)
X_test =X_test.drop(['location','rest_type','cuisines'],axis = 1)
```

In [17]:

```
X_train.head(3)
```

Out[17]:

	online_order	book_table	votes	average_cost	0	1	2	3	4	5	...	1823	1824
0	0	1	1390	1400	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
1	1	1	1218	1200	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
2	1	0	34	300	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0

3 rows × 1837 columns

Now it is looking good. We can proceed.

In [26]:

```
# checking final train set shape
X_train.shape, y_train.shape
```

Out[26]:

```
((25782, 1837), (25782,))
```

In [27]:

```
# # checking final test set shape
X_test.shape, y_test.shape
```

Out[27]:

```
((11050, 3670), (11050,))
```

In [21]:

```
dump(X_train, 'max_features_pkl/more_feature_X_train')
dump(X_test, 'max_features_pkl/more_feature_X_test')
dump(y_train, 'max_features_pkl/more_feature_y_train')
dump(y_test, 'max_features_pkl/more_feature_y_test')
```

Out[21]:

```
['max_features_pkl/more_feature_y_test']
```

In [4]:

```
X_train= load('max_features_pkl/more_feature_X_train')
X_test= load('max_features_pkl/more_feature_X_test')
y_train= load('max_features_pkl/more_feature_y_train')
y_test= load('max_features_pkl/more_feature_y_test')
```

In [2]:

```
def mse(y, y_pred):
    return np.mean((y_pred - y)**2)

mse_scorer = make_scorer(mse, greater_is_better=False)
```

In [3]:

```
# https://github.com/erykml/medium_articles/blob/master/Machine%20Learning/feature_

# function for creating a feature importance dataframe
def imp_df(column_names, importances):
    df = pd.DataFrame({'feature': column_names,
                       'feature_importance': importances}) \
           .sort_values('feature_importance', ascending = False) \
           .reset_index(drop = True)
    return df

# plotting a feature importance dataframe (horizontal barchart)
def var_imp_plot(imp_df, title):
    imp_df.columns = ['feature', 'feature_importance']
    sns.barplot(x = 'feature_importance', y = 'feature', data = imp_df, orient = 'h
         .set_title(title, fontsize = 20)
```

Model -1 Linear Regression

In [19]:

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_train,y_train)
y_pred_lr = lr.predict(X_test)

mse(y_test, y_pred_lr)
```

Out[19]:

```
0.12780356343784205
```

Model - 2 SGD Regressor

In [20]:

```
from sklearn import linear_model

sgdReg = linear_model.SGDRegressor()
sgdReg.fit(X_train,y_train)
y_pred_sgdr = sgdReg.predict(X_test)

mse(y_test, y_pred_sgdr)
```

Out[20]:

```
2.0696763974475958e+28
```

Model -3 Random Forest Regressor

In [21]:

```
from sklearn.ensemble import RandomForestRegressor

rfr = RandomForestRegressor()
rfr.fit(X_train,y_train)
y_pred_rfr = rfr.predict(X_test)

mse(y_test, y_pred_rfr)
```

Out[21]:

```
0.037061256486730365
```

Without any hyper param tuning RFR ie Random Forest Regressor it learning something. so let experiment on RFR.

Hyperparam Tuning on RFR

In [ ]:

```
tuned_parameters = {'n_estimators': [250,500,1000,1200]}

grd_regressor = GridSearchCV(RandomForestRegressor(), tuned_parameters, cv=10,
                    n_jobs=-1, verbose=1, scoring=mse_scorer)
grd_regressor.fit(X_train, y_train)
```

After above experiment we got below result

- MSE: 0.0348536002293039999 == 200 (n_estimators)
- MSE: 0.034615859400387666 ==250 (n_estimators)
- MSE: 0.0333620113806332284 == 500 (n_estimators)
- MSE: 0.033503516544483965 ===1000 (n_estimators)
- MSE: 0.033083536144839625 ===1200 (n_estimators)

We can clearly see that MSE values is dropping but fact is to run 1200 estimators it take more than 4.5 hours on my system(i5 7Gen, 16GB RAM), to run 1000 n_estimators is took almost 3 hours.

So we can reduce MSE value further but training time is increases accordingly so I decide to stop on this experiments.

Final n_estimators choose 200.

Best Parameter Model

In [7]:

```

rfr = RandomForestRegressor(max_depth=None,n_estimators=200,min_samples_split= 2)
rfr.fit(X_train,y_train)
y_pred_rfr = rfr.predict(X_test)

mse(y_test, y_pred_rfr)
```

Out[7]:

```
0.03485360022930399
```

Let's Visualise output by comparing y_true vs y_pred

In [8]:

```
Randpred = pd.DataFrame({ "actual": y_test, "pred": y_pred_rfr })
Randpred
```

Out[8]:

	actual	pred
17780	3.6	3.582500
35810	3.8	3.782500
25324	4.1	4.088500
13990	3.5	3.470500
8655	3.1	3.060275
48193	4.3	4.298000
36352	3.7	3.692857
45728	3.2	3.199500
965	4.2	4.209500
51331	3.3	3.373000
51383	3.8	3.635167
44222	3.2	3.541000
27867	3.7	3.733188
11630	4.2	4.195500
35034	4.1	4.086500
28163	4.6	4.588000
10271	4.1	4.102500
37911	2.5	2.505500
48264	4.2	4.204500
18437	3.2	3.239500
733	3.3	3.254500
7135	3.4	3.804150
24160	4.1	4.098500
21946	3.5	3.460500
25816	2.6	3.439000
13740	3.1	3.163724
20946	4.4	4.253500
29830	3.5	3.507596
49270	4.2	4.204000
14590	3.0	3.044000
...	...	...
36456	3.6	3.608474
15310	4.1	4.353500
3560	3.7	3.698000

	actual	pred
45640	3.8	3.779500
2003	2.8	2.867006
51664	3.9	3.904500
20149	3.4	3.400000
50255	3.5	3.298000
33714	4.1	4.103000
50234	3.4	3.822000
48580	3.9	3.812500
30897	3.9	3.895000
38034	3.7	3.689500
27862	3.9	3.906000
28251	3.3	3.300000
11185	3.9	3.882500
26053	3.6	3.659000
23917	3.7	3.671500
39343	4.5	4.500000
2041	3.4	3.526750
47365	3.4	3.332369
32371	3.9	3.900000
45065	1.0	1.076500
40135	3.9	3.839000
15512	3.7	3.630976
46443	3.9	3.900000
24395	4.0	3.970000
21119	3.7	3.628000
43452	4.0	3.994000
43432	3.7	3.703500

11050 rows × 2 columns

MSE = 0.0348 , It is good Model still can we still improved Model?

Not Null Features only

Till now, we have considered **ONE-HOT** encoding of on below features.

- rest_type
- location
- cuisines
- online_order

- book_table

Here we are going to include below features also,

- dish_liked
- cuisines

Obviously we have to deal with large features set.

In [15]:

```
onehot = pd.read_csv("data/zomato.csv")
onehot.head()
```

Out[15]:

	url	address	name	online_order	book_table	rate	votes
0	https://www.zomato.com/bangalore/jalsa-banasha...	942, 21st Main Road, 2nd Stage, Banashankari, ...	Jalsa	Yes	Yes	4.1/5	775
1	https://www.zomato.com/bangalore/spice-elephan...	2nd Floor, 80 Feet Road, Near Big Bazaar, 6th ...	Spice Elephant	Yes	No	4.1/5	787
		1112, Next to	San				

In [16]:

```
onehot.shape
```

Out[16]:

```
(51717, 17)
```

In [17]:

```
# check for duplicate values
print("No of Duplicates in dataset:  ",onehot.duplicated().sum())
# drop the duplicates
onehot.drop_duplicates(inplace=True)
```

```
No of Duplicates in dataset:   0
```

In [18]:

```
# check for duplicate values
print("No of Duplicates in dataset:  ",onehot.duplicated().sum())
```

```
No of Duplicates in dataset:   0
```

This time we will drop all Null values. Last time we saved some Null values by converting them to relative values. But in this run we will neglect all values null. Initially there are 51k values by removing NULL it will be somewhere around 23k. Frankly speaking 23k is also good enough points to experiment.

In [19]:

```
onehot['rate'] = onehot['rate'].replace('NEW',np.NaN) # replace 'NEW' values with N
onehot['rate'] = onehot['rate'].replace('-',np.NaN) # replace '-' value with NaN
onehot.dropna(how = 'any', inplace = True) # remove all NaN

onehot['rate'] = onehot.loc[:,'rate'].replace('[ ]','',regex = True) # replace [] w
onehot['rate'] = onehot['rate'].astype(str) # convert to string
onehot['rate'] = onehot['rate'].apply(lambda r: r.replace('/5','')) # replace '/5'
onehot['rate'] = onehot['rate'].apply(lambda r: float(r)) # convert string back to
```

In [20]:

```
onehot.shape
```

Out[20]:

```
(23046, 17)
```

In [21]:

```
onehot['cuisines'] = onehot['cuisines'].str.replace(',' , '') # replace ',' with ''
onehot['cuisines'] = onehot['cuisines'].astype(str).apply(lambda x: ' '.join(sorted
onehot['cuisines'].unique() # find unique values
```

Out[21]:

```
array(['Chinese Indian Mughlai North', 'Chinese Indian North Thai',
       'Cafe Italian Mexican', ...,
       'BBQ Continental Indian Italian North', 'Nepalese Tibetan',
       'Andhra Biryani Hyderabadi'], dtype=object)
```

In [22]:

```
onehot['rest_type'] = onehot['rest_type'].str.replace(',' , '')
onehot['rest_type'] = onehot['rest_type'].astype(str).apply(lambda x: ' '.join(sort
onehot['rest_type'].value_counts().head()
```

Out[22]:

```
Casual Dining        7298
Bites Quick          5224
Cafe                 2321
Bar Casual Dining    1308
Dessert Parlor       1074
Name: rest_type, dtype: int64
```

In [23]:

```
onehot['dish_liked'] = onehot['dish_liked'].str.replace(',' , '')
onehot['dish_liked'] = onehot['dish_liked'].astype(str).apply(lambda x: ' '.join(so
onehot['dish_liked'].value_counts().head()
```

Out[23]:

```
Biryani            179
Friendly Staff      68
Waffles             67
Biryani Chicken     66
Paratha             56
Name: dish_liked, dtype: int64
```

In [24]:

```
onehot['approx_cost(for two people)'] = onehot['approx_cost(for two people)'].str.r
onehot.rename(columns={'approx_cost(for two people)': 'average_cost'}, inplace=True
```

In [25]:

```
x = onehot.drop(['rate','name'],axis = 1)
y = onehot['rate']
```

Train Test Split

In [26]:

```
train_data,test_data,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_s
```

In [27]:

```
# dump(train_data, 'without_featurization/train_data')
# dump(test_data, 'without_featurization/test_data')
# dump(y_train, 'without_featurization/y_train')
# dump(y_test, 'without_featurization/y_test')
```

Out[27]:

```
['without_featurization/y_test']
```

In [60]:

```
train_data.shape
```

Out[60]:

```
(16132, 15)
```

In [29]:

```
test_data.shape
```

Out[29]:

```
(6914, 15)
```

In [27]:

```
train_data = load('without_featurization/train_data')
test_data = load('without_featurization/test_data')
y_train = load('without_featurization/y_train')
y_test = load('without_featurization/y_test')
```

In [8]:

```
all_features =[]
# test_feature=[]
```

One Hot Encoding

In [6]:

```
enc = OneHotEncoder( handle_unknown='ignore')
```

In [4]:

```
## ALWAYS AVOID DATA LEAKAGE

# this method is for training data set
def one_hot_fit_transform(df,name):
    output_data = df[name].values.reshape(-1, 1)
    return enc.fit_transform(output_data).toarray(), enc.get_feature_names([name])

# this method is for test data set
def one_hot_transform(df,name):
    output_data1 = df[name].values.reshape(-1, 1)
    return enc.transform(output_data1).toarray()
```

In [9]:

```
tr_dummy_rest_type,rest_tr = one_hot_fit_transform(train_data,'rest_type' )
te_dummy_rest_type = one_hot_transform(test_data,'rest_type' )
all_features.extend(rest_tr)


tr_dummy_online_order, oo_tr = one_hot_fit_transform(train_data,'online_order' )
te_dummy_online_order = one_hot_transform(test_data,'online_order' )
all_features.extend(oo_tr)

tr_dummy_book_table,bt_tr = one_hot_fit_transform(train_data,'book_table' )
te_dummy_book_table = one_hot_transform(test_data,'book_table' )
all_features.extend(bt_tr)
# test_feature.append(bt_te)

tr_dummy_city,loc_tr = one_hot_fit_transform(train_data,'location' )
te_dummy_city = one_hot_transform(test_data,'location')
all_features.extend(loc_tr)
# test_feature.append(loc_te)

tr_dummy_cuisines,cui_tr = one_hot_fit_transform(train_data,'cuisines' )
te_dummy_cuisines =one_hot_transform(test_data,'cuisines')
all_features.extend(cui_tr)
# test_feature.append(rest_tr)

tr_dummy_dishliked,dish_tr = one_hot_fit_transform(train_data,'dish_liked' )
te_dummy_dishliked=one_hot_transform(test_data,'dish_liked')
all_features.extend(dish_tr)
# test_feature.append(rest_tr)
```

In [10]:

```
len(all_features)
```

Out[10]:

5831

In [30]:

```
tr_dummy_rest_type.shape, te_dummy_rest_type.shape
```

Out[30]:

```
((16132, 52), (6914, 52))
```

In [31]:

```
tr_dummy_online_order.shape, te_dummy_online_order.shape
```

Out[31]:

```
((16132, 2), (6914, 2))
```

In [32]:

```
tr_dummy_book_table.shape, te_dummy_book_table.shape
```

Out[32]:

```
((16132, 2), (6914, 2))
```

In [33]:

```
tr_dummy_city.shape, te_dummy_city.shape
```

Out[33]:

```
((16132, 88), (6914, 88))
```

In [34]:

```
tr_dummy_cuisines.shape, te_dummy_cuisines.shape
```

Out[34]:

```
((16132, 1254), (6914, 1254))
```

In [35]:

```
tr_dummy_dishliked.shape, te_dummy_dishliked.shape
```

Out[35]:

```
((16132, 4433), (6914, 4433))
```

In [36]:

```
type(tr_dummy_dishliked)
```

Out[36]:

```
numpy.ndarray
```

In [37]:

```
type(train_data)
```

Out[37]:

```
pandas.core.frame.DataFrame
```

Create Final Train DF (Concate two Dataframes)

In [39]:

```
tr =pd.DataFrame(pd.np.column_stack([tr_dummy_rest_type, tr_dummy_online_order,tr_d
                                 tr_dummy_cuisines,tr_dummy_dishliked]), columns=al
## https://stackoverflow.com/questions/45963799/pandas-concat-resulting-in-nan-rows

l1=train_data.values.tolist()
l2=tr.values.tolist()

for i in range(len(l1)):
    l1[i].extend(l2[i])

X_train=pd.DataFrame(l1,columns=train_data.columns.tolist()+tr.columns.tolist())
```

In [41]:

```
X_train.shape
```

Out[41]:

```
(16132, 5846)
```

Create Final Test DF (Concate two Dataframes)

In [11]:

```
te =pd.DataFrame(pd.np.column_stack([te_dummy_rest_type, te_dummy_online_order,te_d
                                          te_dummy_cuisines,te_dummy_dishliked]),co


# X_test =pd.concat([test_data,te],axis=1)

l3=test_data.values.tolist()
l4=te.values.tolist()
for i in range(len(l3)):
    l3[i].extend(l4[i])

X_test=pd.DataFrame(l3,columns=test_data.columns.tolist()+te.columns.tolist())
X_test.shape
```

Out[11]:

```
(6914, 5846)
```

Deleting the Unwanted columns

After OneHot enconding Achieved we will simply remove, redudant features.

In [42]:

```
X_train.drop(columns=['rest_type','location','cuisines','dish_liked','menu_item','u
```

In [12]:

```
X_test.drop(columns=['rest_type','location','cuisines','dish_liked','menu_item','ur
```

In [43]:

```
X_train.head(2)
```

Out[43]:

	votes	average_cost	rest_type_Bakery	rest_type_Bakery Bites Quick	rest_type_Bakery Cafe	rest_type_Bakery Dessert Parlor
0	326	500	0.0	0.0	0.0	0.0
1	33	300	0.0	0.0	0.0	0.0

2 rows × 5833 columns

In [48]:

```
X_train.shape
```

Out[48]:

```
(8407, 5833)
```

In [13]:

```
X_test.head(2)
```

Out[13]:

	votes	average_cost	rest_type_Bakery	rest_type_Bakery Bites Quick	rest_type_Bakery Cafe	rest_type_Bakery Dessert Parlor
0	1519	900	0.0	0.0	0.0	0.0
1	48	1500	0.0	0.0	0.0	0.0

2 rows × 5833 columns

In [14]:

```
X_test.shape
```

Out[14]:

```
(6914, 5833)
```

Persistence Object to local disk

In [15]:

```
# # from joblib import dump,load

dump(X_train, 'one_hot_X_train')
dump(X_test, 'one_hot_X_test')
dump(y_train, 'one_hot_y_train')
dump(y_test, 'one_hot_y_test')
```

Out[15]:

```
['one_hot_y_test']
```

In [16]:

```
X_train = load('one_hot_X_train')
X_test = load('one_hot_X_test')
y_train = load('one_hot_y_train')
y_test = load('one_hot_y_test')
```

In [17]:

```
X_train.shape, y_train.shape
```

Out[17]:

```
((16132, 5833), (16132,))
```

In [18]:

```
X_test.shape, y_test.shape
```

Out[18]:

```
((6914, 5833), (6914,))
```

Model -1 Linear Regression

In [21]:

```
lr = LinearRegression()
lr.fit(X_train,y_train)
y_pred_lr = lr.predict(X_test)

mse(y_test, y_pred_lr)
```

Out[21]:

```
0.043088530367839446
```

Model -2 SGDRegressor

In [22]:

```
sgdReg = linear_model.SGDRegressor()
sgdReg.fit(X_train,y_train)
y_pred_sgdr = sgdReg.predict(X_test)

mse(y_test, y_pred_sgdr)
```

Out[22]:

```
9.866490108561476e+28
```

Model -3 Random Forest Regressor

In [23]:

```
rfr = RandomForestRegressor()
rfr.fit(X_train,y_train)
y_pred_rfr = rfr.predict(X_test)

mse(y_test, y_pred_rfr)
```

Out[23]:

```
0.015422974956058898
```

Feature Importance

In [31]:

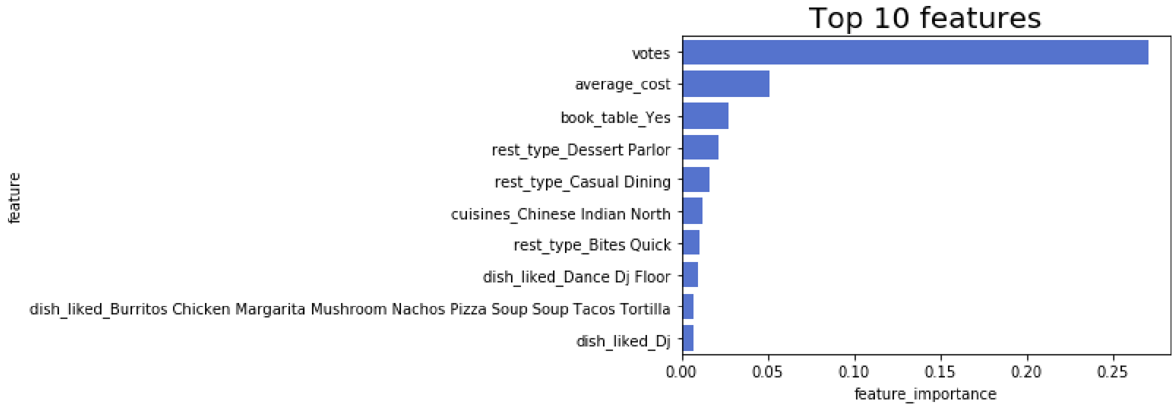
```
base_imp = imp_df(X_train.columns, rfr.feature_importances_)
base_imp[:10]
```

Out[31]:

	feature	feature_importance
0	votes	0.269980
1	average_cost	0.051038
2	book_table_Yes	0.027400
3	rest_type_Dessert Parlor	0.021658
4	rest_type_Casual Dining	0.016629
5	cuisines_Chinese Indian North	0.012381
6	rest_type_Bites Quick	0.010144
7	dish_liked_Dance Dj Floor	0.009564
8	dish_liked_Burritos Chicken Margarita Mushroom...	0.007177
9	dish_liked_Dj	0.006743

In [35]:

```
var_imp_plot(base_imp[:10],"Top 10 features")
```



Observation:

- This is brilliant, last we saw MSE = 0.015, **without hyperparam tuning.**

Hyperparam Tuning for RFR One Hot Encoding

In [ ]:

```
tuned_parameters = {'n_estimators': [250,500,1000,1200]}

grd_regressor = GridSearchCV(RandomForestRegressor(), tuned_parameters, cv=10,
                         n_jobs=-1, verbose=1, scoring=mse_scorer)
grd_regressor.fit(X_train, y_train)
```

After above experiment we got below result

- MSE: 0.014044408085530756 == 200 (n_estimators)
- MSE: 0.014195859400387666 ==250 (n_estimators)
- MSE: 0.014120113806332284 == 500 (n_estimators)
- MSE: 0.014103516544483965 ===1000 (n_estimators)
- MSE: 0.014083536144839625 ===1200 (n_estimators)

We can clearly see that MSE values is dropping but fact is to run 1200 estimators it take more than 4.5 hours on my system(i5 7Gen, 16GB RAM), to run 1000 n_estimators is took almost 3 hours.

So we can reduce MSE value further but training time is increases accordingly so I decide to stop on this experiments.

Final n_estimators choose 300.

In [36]:

```
from sklearn.ensemble import RandomForestRegressor

rfr = RandomForestRegressor(n_estimators =300)
rfr.fit(X_train,y_train)
y_pred_rfr = rfr.predict(X_test)

mse(y_test, y_pred_rfr)
```

Out[36]:

```
0.01410025081577405
```

Final model Features Importance

In [37]:

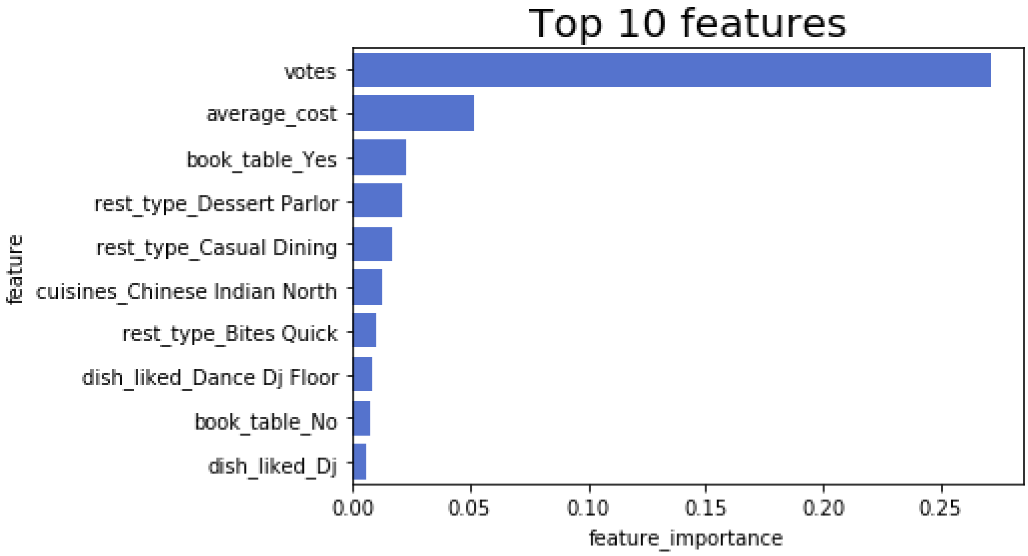
```
base_imp = imp_df(X_train.columns, rfr.feature_importances_)
base_imp[:10]
```

Out[37]:

	feature	feature_importance
0	votes	0.271175
1	average_cost	0.052279
2	book_table_Yes	0.023298
3	rest_type_Dessert Parlor	0.020897
4	rest_type_Casual Dining	0.017309
5	cuisines_Chinese Indian North	0.012555
6	rest_type_Bites Quick	0.010289
7	dish_liked_Dance Dj Floor	0.008446
8	book_table_No	0.008088
9	dish_liked_Dj	0.006187

In [38]:

```
var_imp_plot(base_imp[:10],"Top 10 features")
```



Visualise Output

In [39]:

```
Randpred = pd.DataFrame({ "actual": y_test, "pred": y_pred_rfr })
Randpred
```

Out[39]:

	actual	pred
35957	4.0	4.000333
4975	4.0	3.996667
21830	3.9	3.896000
11982	3.7	3.708333
2597	3.8	3.849000
35155	4.5	4.500000
24001	3.4	3.491000
42314	3.8	3.801000
2249	3.9	3.904000
18336	2.8	2.901814
820	4.0	3.813306
10761	3.5	3.525526
12522	4.2	4.200000
31459	4.3	4.300000
8342	4.4	4.399000
36069	3.7	3.701000
25002	3.5	3.528333
37829	3.4	3.538667
41124	3.9	3.875667
26851	4.1	4.097000
47398	4.3	4.300000
26270	4.0	3.936847
31431	2.7	2.717667
51701	4.1	4.098333
31128	3.9	3.900000
9524	3.7	3.755575
15519	3.8	3.800000
45828	4.3	4.294333
32301	4.1	4.100000
45778	2.9	2.956750
...	...	...
1224	4.0	3.999667
46128	3.8	3.801333
26131	3.9	4.038333

	actual	pred
51097	4.2	4.060729
182	4.1	3.993167
18800	3.8	3.800333
39157	4.0	4.000000
30265	3.7	3.700000
50934	3.1	3.459000
7913	4.3	4.195000
49007	3.9	3.899667
12534	4.3	4.284000
9397	3.8	3.799667
36828	4.1	4.100000
22484	3.7	3.704000
1119	4.0	3.924333
15077	4.3	4.303000
16855	4.2	4.192333
38739	3.8	3.801667
11724	4.0	4.010333
23198	4.0	3.922865
29237	4.1	4.100000
33928	4.3	4.300000
50417	3.5	3.560333
6961	3.9	3.984000
19450	4.1	4.100667
32469	3.5	3.507667
3181	4.0	3.911111
3029	4.1	4.117333
42550	3.6	3.600000

6914 rows × 2 columns

4. Feature Engineering

Let's try ***response coding*** in categorical variable on regression model.

Basically what we are going to do replace categorical features with response coded features. In simple words we are going to consider each categorical feature once and find mean value of 'Rate' column.

Eg.==>
Consider "online_order" feature, which has two categories, 'Yes' and 'No'. So we will do a small hack, which is explained as below,

.

- consider category as 'Yes' in 'online_order', take mean value of 'Rate'
- similarly consider second category as 'No' in 'online_order', take mean value of 'Rate' column.
- We will perform above logic using ***group_by*** on desired categorical column and simple take a mean of 'Rate' column.
- Create new column which will contain mean values.
- we will called it as **MEAN VALUE REPLACEMENT**

In [121]:

```
train_data = load('without_featurization/train_data')
test_data = load('without_featurization/test_data')
y_train = load('without_featurization/y_train')
y_test = load('without_featurization/y_test')
```

In [122]:

```
train_data.shape, y_train.shape
```

Out[122]:

```
((16132, 15), (16132,))
```

In [123]:

```
test_data.shape,y_test.shape
```

Out[123]:

```
((6914, 15), (6914,))
```

In [124]:

```
train_data.head(2)
```

Out[124]:

	url	address	online_order	book_table	votes	
28653	https://www.zomato.com/bangalore/kaaram-korama...	11, Eat Street, 80 Feet Road, Opposite Indian ...	Yes	No	326	4
5935	https://www.zomato.com/bangalore/brownie-heave...	110-A, Westminister Building, Cunningham Road,...	Yes	No	33	

Response Coded Features

In [125]:

```
# re-insert rate column in train data
train_data.insert(2, 'Rate', y_train, allow_duplicates = False)
```

In [126]:

```
# check shape
train_data.shape
```

Out[126]:

```
(16132, 16)
```

In [127]:

```
train_data.head(2)
```

Out[127]:

	url	address	Rate	online_order	book_table	vo
28653	https://www.zomato.com/bangalore/kaaram-korama...	11, Eat Street, 80 Feet Road, Opposite Indian ...	3.9	Yes	No	
5935	https://www.zomato.com/bangalore/brownie-heave...	110-A, Westminister Building, Cunningham Road,...	4.2	Yes	No	

In [128]:

```
# Re-Insert 'rate' column in test dataframe.
test_data.insert(2, 'Rate', y_test, allow_duplicates = False)
test_data.shape
```

Out[128]:

```
(6914, 16)
```

In [129]:

```
test_data.head(2)
```

Out[129]:

	url	address	Rate	online_order	book_table	vo
35957	https://www.zomato.com/bangalore/154-breakfast...	154, 8th Main Road, 3rd Block, Koramangala 3rd...	4.0	Yes	Yes	15
4975	https://www.zomato.com/bangalore/kitchen-on-ta...	Shantala nagar, Ashok Nagar, Brigade Road, Ban...	4.0	Yes	No	

In [130]:

```
# # https://www.geeksforgeeks.org/python-creating-a-pandas-dataframe-column-based-c

key_dict = dict()
def provide_response_coded_features(groupByVal,columnName, df):

    '''
    This function is used to convert categorical features into response coded featu
    It simply perform MEAN VALUE REPLACEMENT.
    '''
    mean_df = df.groupby([groupByVal]).mean()
    mean_dict =mean_df['Rate'].to_dict()
    key_dict.update([ (groupByVal, mean_dict) ] )
    for k, v in mean_dict.items():
            mean_dict[k] = round(v,2)
    df[columnName] = df[groupByVal].map(mean_dict)
    return df
```

In [134]:

```
# create response coded feature for online_order feature.
mean_online_order =provide_response_coded_features('online_order','mean_online_orde
mean_online_order[['Rate','online_order','mean_online_order']][:10]
```

Out[134]:

	Rate	online_order	mean_online_order
28653	3.9	Yes	3.89
5935	4.2	Yes	3.89
11546	4.4	No	3.93
17899	3.9	Yes	3.89
50256	3.9	Yes	3.89
8289	4.3	No	3.93
43207	4.1	No	3.93
34447	4.2	Yes	3.89
50330	4.1	Yes	3.89
32243	3.9	Yes	3.89

In [135]:

```
# create response coded feature for book_table feature.

mean_book_table =provide_response_coded_features('book_table','mean_book_table',tra
mean_book_table[['Rate','book_table','mean_book_table']][:10]
```

Out[135]:

	Rate	book_table	mean_book_table
28653	3.9	No	3.81
5935	4.2	No	3.81
11546	4.4	Yes	4.16
17899	3.9	No	3.81
50256	3.9	No	3.81
8289	4.3	Yes	4.16
43207	4.1	No	3.81
34447	4.2	No	3.81
50330	4.1	No	3.81
32243	3.9	No	3.81

In [136]:

```
# create response coded feature for rest_type feature.

mean_rest_type =provide_response_coded_features('rest_type','mean_rest_type',train_
mean_rest_type[['Rate','rest_type','mean_rest_type']][:20]
```

Out[136]:

	Rate	rest_type	mean_rest_type
28653	3.9	Casual Dining	3.84
5935	4.2	Dessert Parlor	4.09
11546	4.4	Dining Fine	4.20
17899	3.9	Casual Dining	3.84
50256	3.9	Beverage Bites Quick Shop	3.94
8289	4.3	Casual Dining	3.84
43207	4.1	Dining Fine	4.20
34447	4.2	Bites Quick	3.74
50330	4.1	Bakery Dessert Parlor	4.01
32243	3.9	Delivery	3.76
40054	4.4	Dessert Parlor	4.09
35813	4.6	Cafe	3.99
40708	3.9	Casual Dining	3.84
42263	3.8	Casual Dining	3.84
26024	3.8	Casual Dining	3.84
41032	4.1	Bites Quick	3.74
45653	3.9	Bites Quick	3.74
18997	3.8	Casual Dining	3.84
8355	4.1	Bar Cafe	4.10
2910	3.6	Casual Dining	3.84

In [137]:

```
# create response coded feature for location feature.

mean_location =provide_response_coded_features('location','mean_location',train_dat
mean_location[['Rate','location','mean_location']][:10]
```

Out[137]:

	Rate	location	mean_location
28653	3.9	Koramangala 6th Block	3.94
5935	4.2	Cunningham Road	4.08
11546	4.4	Lavelle Road	4.22
17899	3.9	Brigade Road	3.95
50256	3.9	Brookefield	3.70
8289	4.3	Koramangala 7th Block	3.99
43207	4.1	MG Road	3.95
34447	4.2	BTM	3.74
50330	4.1	ITPL Main Road, Whitefield	3.62
32243	3.9	Koramangala	4.00

In [138]:

```
# create response coded feature for cuisines feature.

mean_cuisines =provide_response_coded_features('cuisines','mean_cuisines',train_dat
mean_cuisines[['Rate','cuisines','mean_cuisines']][:10]
```

Out[138]:

	Rate	cuisines	mean_cuisines
28653	3.9	Andhra Biryani	3.88
5935	4.2	Desserts Fast Food	4.11
11546	4.4	Continental Indian Italian North	4.02
17899	3.9	Continental Desserts Italian Pizza	4.00
50256	3.9	Beverages Fast Food	3.99
8289	4.3	Arabian Beverages Indian North	4.28
43207	4.1	Chinese	3.84
34447	4.2	Chinese Indian Kerala South	4.16
50330	4.1	Bakery Desserts	3.94
32243	3.9	American Biryani Burger Chinese Continental Fo...	3.63

In [139]:

```
# create response coded feature for dish_liked feature.

mean_dish_liked =provide_response_coded_features('dish_liked','mean_dish_liked',tra
mean_dish_liked[['Rate','dish_liked','mean_dish_liked']][:10]
```

Out[139]:

	Rate	dish_liked	mean_dish_liked
28653	3.9	Biryani Biryani Biryani Biryani Biryani Dum Gu...	3.90
5935	4.2	Brownie Brownie Chocolate Chocolate Chocolate ...	4.19
11546	4.4	Breakfast Buffet Cake Chicken Chocolate Lasagn...	4.40
17899	3.9	Fries Mocktails Mozzarella Pasta Pizza Salad S...	3.90
50256	3.9	Banana Cake Cake Chai Coffee Ginger Ginger Poh...	3.90
8289	4.3	Arabic Baklava Biryani Biryani Chicken Cuisine...	4.30
43207	4.1	Chicken Clear Crabmeat Crispy Duck Food Jasmin...	4.10
34447	4.2	Appam Beef Chicken Curry Curry Egg Fish Fry Gh...	4.20
50330	4.1	Blueberry Blueberry Brownie Cheesecake Chocola...	4.10
32243	3.9	Bowl Burgers Burrito Fish Pasta Pizza Salads S...	3.90

In [140]:

```
for feature,values in key_dict.items():
    print(feature)
```

```
online_order
book_table
rest_type
location
cuisines
dish_liked
```

In [141]:

```
def return_dict_mean_value(query_feature):

    '''
    'key_dict' is dictionary object which has all the Categorical variable names st
    This is function is used to return mean value for query_feature.

    KEY ==>
    Value ==> Mean value response to that key

    query_feature ==>  Desired key
    Return ==> Categorical feature and their corresponding mean values.
    '''

    result_dict=dict()

    for feature_name, values in key_dict.items():
        if feature_name == query_feature:
            for key in values:
                result_dict.update([ (key, values[key]) ] )

                print(key + ':', values[key])
    return result_dict
return_dict_mean_value('online_order')
```

```
No: 3.93
Yes: 3.89
```

Out[141]:

```
{'No': 3.93, 'Yes': 3.89}
```

In [142]:

```
## similarly we will create same response coded features for test dataset
## Test data

dict_online = return_dict_mean_value('online_order')
dict_book_table = return_dict_mean_value('book_table')
dict_rest_type = return_dict_mean_value('rest_type')
dict_location = return_dict_mean_value('location')
dict_cuisines = return_dict_mean_value('cuisines')
dict_dish_liked = return_dict_mean_value('dish_liked')
```

```
North Bangalore: 3.6
Old Airport Road: 3.82
Old Madras Road: 3.17
RT Nagar: 3.65
Race Course Road: 3.99
Rajajinagar: 3.84
Rajarajeshwari Nagar: 3.85
Rammurthy Nagar: 3.58
Residency Road: 4.04
Richmond Road: 4.04
Sadashiv Nagar: 3.99
Sahakara Nagar: 3.73
Sanjay Nagar: 3.89
Sankey Road: 4.12
Sarjapur Road: 3.88
Seshadripuram: 4.05
Shanti Nagar: 3.64
Shivajinagar: 3.88
South Bangalore: 3.36
St. Marks Road: 4.13
```

In [143]:

```
test_data['mean_online_order'] = test_data['online_order'].map(dict_online)
```

In [144]:

```
test_data['mean_book_table'] = test_data['book_table'].map(dict_book_table)
```

In [145]:

```
test_data['mean_rest_type'] = test_data['rest_type'].map(dict_rest_type)
```

In [146]:

```
test_data['mean_location'] = test_data['location'].map(dict_location)
```

In [147]:

```
test_data['mean_cuisines'] = test_data['cuisines'].map(dict_cuisines)
```

In [148]:

```
test_data['mean_dish_liked'] = test_data['dish_liked'].map(dict_dish_liked)
```

In [149]:

```
##check NaN values. NaN value arise because there are some categories those are not
test_data.isna().sum()
```

Out[149]:

```
url                    0
address                0
Rate                   0
online_order           0
book_table             0
votes                  0
phone                  0
location               0
rest_type              0
dish_liked             0
cuisines               0
average_cost           0
reviews_list           0
menu_item              0
listed_in(type)        0
listed_in(city)        0
mean_online_order      0
mean_book_table        0
mean_rest_type         2
mean_location          0
mean_cuisines         64
mean_dish_liked      489
dtype: int64
```

In [183]:

```
print("There are some category which is not present in train set which is % ",((2+6
```

```
There are some category which is not present in train set which is %
7.103825136612022
```

- It is not large number so we can simply neglect those data points.

In [151]:

```
# drop null values
test_data.dropna(subset=['mean_dish_liked','mean_rest_type','mean_cuisines'],inplac
```

In [152]:

```
test_data.isna().sum()
```

Out[152]:

```
url                 0
address             0
Rate                0
online_order        0
book_table          0
votes               0
phone               0
location            0
rest_type           0
dish_liked          0
cuisines            0
average_cost        0
reviews_list        0
menu_item           0
listed_in(type)     0
listed_in(city)     0
mean_online_order   0
mean_book_table     0
mean_rest_type      0
mean_location       0
mean_cuisines       0
mean_dish_liked     0
dtype: int64
```

In [154]:

```
y_test= test_data['Rate']
```

Delete Redudant columns

In [155]:

```
train_data.columns
```

Out[155]:

```
Index(['url', 'address', 'Rate', 'online_order', 'book_table', 'vote
s',
       'phone', 'location', 'rest_type', 'dish_liked', 'cuisines',
       'average_cost', 'reviews_list', 'menu_item', 'listed_in(type)',
       'listed_in(city)', 'mean_online_order', 'mean_book_table',
       'mean_rest_type', 'mean_location', 'mean_cuisines', 'mean_dish_
liked'],
      dtype='object')
```

In [156]:

```
h_liked','menu_item','url','phone','reviews_list','listed_in(type)','listed_in(city
```

In [160]:

```
train_data.columns
```

Out[160]:

```
Index(['votes', 'average_cost', 'mean_online_order', 'mean_book_tabl
e',
       'mean_rest_type', 'mean_location', 'mean_cuisines', 'mean_dish_
liked'],
      dtype='object')
```

In [163]:

```
test_data.columns
```

Out[163]:

```
Index(['url', 'address', 'Rate', 'online_order', 'book_table', 'vote
s',
       'phone', 'location', 'rest_type', 'dish_liked', 'cuisines',
       'average_cost', 'reviews_list', 'menu_item', 'listed_in(type)',
       'listed_in(city)', 'mean_online_order', 'mean_book_table',
       'mean_rest_type', 'mean_location', 'mean_cuisines', 'mean_dish_
liked'],
      dtype='object')
```

In [164]:

```
one','reviews_list','listed_in(type)','listed_in(city)','address','online_order','bo
```

In [165]:

```
test_data.columns
```

Out[165]:

```
Index(['votes', 'average_cost', 'mean_online_order', 'mean_book_tabl
e',
       'mean_rest_type', 'mean_location', 'mean_cuisines', 'mean_dish_
liked'],
      dtype='object')
```

Checking Shape

In [161]:

```
# always verify shapes
train_data.shape, y_train.shape
```

Out[161]:

```
((16132, 8), (16132,))
```

In [166]:

```python
# always verify shapes
test_data.shape, y_test.shape
```

Out[166]:

```
((6405, 8), (6405,))
```

Model - 1 Linear Regression Model

In [167]:

```python
lr = LinearRegression()
lr.fit(train_data,y_train)
y_pred_lr = lr.predict(test_data)

mse(y_test, y_pred_lr)
```

Out[167]:

```
0.009480108537376686
```

feature Importance

In [169]:

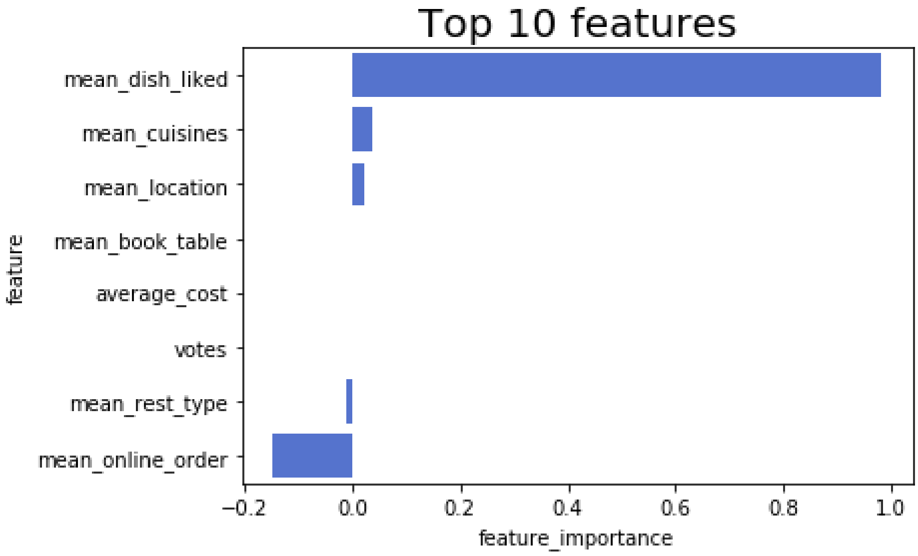
```python
base_imp = imp_df(train_data.columns, lr.coef_)
base_imp
```

Out[169]:

	feature	feature_importance
0	mean_dish_liked	9.827036e-01
1	mean_cuisines	3.537434e-02
2	mean_location	2.377197e-02
3	mean_book_table	1.934189e-04
4	average_cost	-1.964055e-07
5	votes	-9.667180e-07
6	mean_rest_type	-1.007759e-02
7	mean_online_order	-1.484983e-01

In [170]:

```
var_imp_plot(base_imp[:10],"Top 10 features")
```



In below blog explained negative feature value meaning.

- [https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-random-forest-d9166011959e (https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-random-forest-d9166011959e)](https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-random-forest-d9166011959e)
- In short, it is saying we can remove those features.

Output Visualization

In [171]:

```
Randpred = pd.DataFrame({ "actual": y_test, "pred": y_pred_lr })
Randpred
```

Out[171]:

	actual	pred
35957	4.0	4.004962
4975	4.0	4.007328
21830	3.9	3.888549
11982	3.7	3.700317
2597	3.8	3.789058
35155	4.5	4.500518
24001	3.4	3.372919
42314	3.8	3.745710
2249	3.9	3.891765
18336	2.8	3.695511
10761	3.5	3.324357
12522	4.2	4.202476
31459	4.3	4.305275
8342	4.4	4.407281
36069	3.7	3.695148
25002	3.5	3.537053
37829	3.4	3.476825
41124	3.9	3.898060
26851	4.1	3.979687
47398	4.3	4.290773
26270	4.0	3.997477
31431	2.7	2.672473
51701	4.1	4.101982
31128	3.9	3.908352
9524	3.7	3.757555
15519	3.8	3.794292
45828	4.3	4.306590
32301	4.1	4.100993
45778	2.9	2.905917
11425	3.7	3.688375
...	...	...
32173	4.5	4.511601
1224	4.0	3.989808
46128	3.8	4.066222

	actual	pred
26131	3.9	3.990516
51097	4.2	4.190791
182	4.1	4.103322
18800	3.8	3.802567
39157	4.0	4.008525
30265	3.7	3.696365
50934	3.1	3.123672
7913	4.3	4.242368
49007	3.9	3.899826
12534	4.3	4.307094
9397	3.8	3.801117
36828	4.1	4.110287
22484	3.7	3.711893
1119	4.0	3.972426
15077	4.3	4.354720
16855	4.2	4.166887
38739	3.8	3.798697
11724	4.0	4.006563
23198	4.0	3.938653
29237	4.1	4.108550
33928	4.3	4.303713
50417	3.5	3.599997
6961	3.9	4.003845
19450	4.1	4.100658
32469	3.5	3.419166
3029	4.1	4.079376
42550	3.6	3.609086

6405 rows × 2 columns

Model - 2 SGD Regression Model

In [172]:

```
sgdReg = linear_model.SGDRegressor()
sgdReg.fit(train_data,y_train)
y_pred_sgdr = sgdReg.predict(test_data)

mse(y_test, y_pred_sgdr)
```

Out[172]:

```
3.352623320908809e+30
```

- No need to find feature importance, model is not learning.

Model - 3 Random Forest Regressor Model

In [173]:

```
rfr = RandomForestRegressor()
rfr.fit(train_data,y_train)
y_pred_rfr = rfr.predict(test_data)

mse(y_test, y_pred_rfr)
```

Out[173]:

```
0.0035328634537601226
```

Hyperparam Tuning

In [174]:

```
tuned_parameters = {'n_estimators': [250,500,1000,1200]}

grd_regressor = GridSearchCV(RandomForestRegressor(), tuned_parameters, cv=10,
                   n_jobs=-1, verbose=1, scoring=mse_scorer)
grd_regressor.fit(train_data, y_train)
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent wor
kers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:  4.9min finished
```

Out[174]:

```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=RandomForestRegressor(bootstrap=True, criterion='ms
e', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=N
one,
           oob_score=False, random_state=None, verbose=0, warm_start=F
alse),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'n_estimators': [250, 500, 1000, 1200]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=make_scorer(mse, greater_is_better=False), verbose=1)
```

In [175]:

```
print(grd_regressor.best_params_)
```

```
{'n_estimators': 500}
```

Best Model "Random forest Regreesion"

In [176]:

```
rfr = RandomForestRegressor(n_estimators=500)
rfr.fit(train_data,y_train)
y_pred_rfr = rfr.predict(test_data)

mse(y_test, y_pred_rfr)
```

Out[176]:

```
0.003185935434390344
```

In [177]:

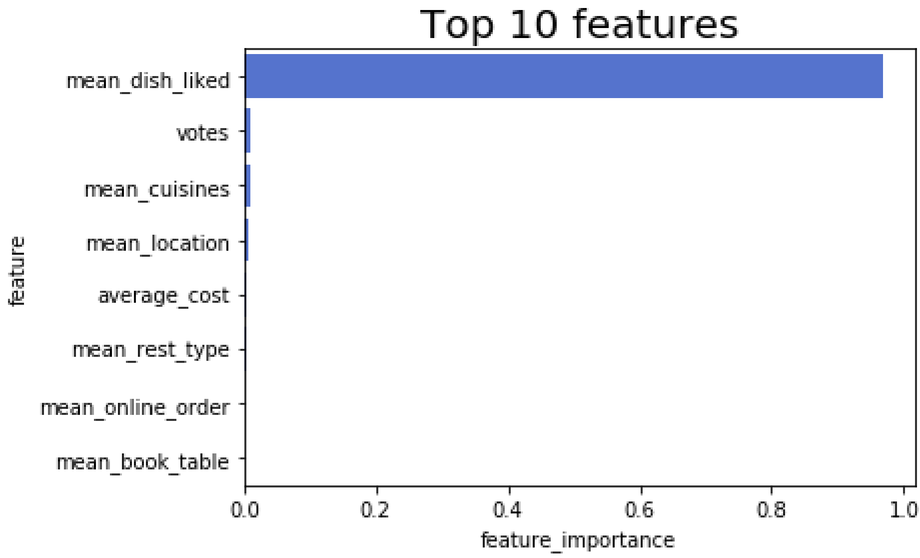
```
base_imp = imp_df(train_data.columns, rfr.feature_importances_)
base_imp[:10]
```

Out[177]:

	feature	feature_importance
0	mean_dish_liked	0.967695
1	votes	0.009489
2	mean_cuisines	0.009386
3	mean_location	0.005334
4	average_cost	0.004089
5	mean_rest_type	0.002658
6	mean_online_order	0.000911
7	mean_book_table	0.000439

In [178]:

```
var_imp_plot(base_imp[:10],"Top 10 features")
```



Output Visualization

In [179]:

```
Randpred = pd.DataFrame({ "actual": y_test, "pred": y_pred_rfr })
Randpred
```

Out[179]:

	actual	pred
35957	4.0	4.000000
4975	4.0	4.000000
21830	3.9	3.900000
11982	3.7	3.700600
2597	3.8	3.800200
35155	4.5	4.500000
24001	3.4	3.304673
42314	3.8	3.780370
2249	3.9	3.900000
18336	2.8	2.857532
10761	3.5	3.520978
12522	4.2	4.200000
31459	4.3	4.300000
8342	4.4	4.400000
36069	3.7	3.700000
25002	3.5	3.513400
37829	3.4	3.446067
41124	3.9	3.896800
26851	4.1	4.096800
47398	4.3	4.300000
26270	4.0	4.000000
31431	2.7	2.699800
51701	4.1	4.100000
31128	3.9	3.900000
9524	3.7	3.757384
15519	3.8	3.800000
45828	4.3	4.300000
32301	4.1	4.100000
45778	2.9	2.902000
11425	3.7	3.700000
...	...	...
32173	4.5	4.500000
1224	4.0	4.000000
46128	3.8	3.804000

	actual	pred
26131	3.9	4.000000
51097	4.2	4.200000
182	4.1	4.100000
18800	3.8	3.800000
39157	4.0	4.000000
30265	3.7	3.700000
50934	3.1	3.100000
7913	4.3	4.267434
49007	3.9	3.899200
12534	4.3	4.300000
9397	3.8	3.800000
36828	4.1	4.100000
22484	3.7	3.700000
1119	4.0	3.933800
15077	4.3	4.300400
16855	4.2	4.196600
38739	3.8	3.800000
11724	4.0	4.000000
23198	4.0	3.925964
29237	4.1	4.100000
33928	4.3	4.300000
50417	3.5	3.559600
6961	3.9	4.000000
19450	4.1	4.100000
32469	3.5	3.493816
3029	4.1	4.100000
42550	3.6	3.600600

6405 rows × 2 columns

5. Model Compare

In [182]:

```
from prettytable import PrettyTable


x = PrettyTable()
x.field_names =  ['Model','MSE']

x.add_row(["SGD Regressor 7 ONEHOT Features", 8.091e+30])
x.add_row(["SGD Regressor Response coded Features", 6.926e+29])
x.add_row(["SGD Regressor 5 ONEHOT Features", 2.069e+28])

x.add_row(["Linear Regression 5 ONEHOT Features", 0.12780])
x.add_row(["Random Forest Regressor 5 ONEHOT Features", 0.03485])

x.add_row(["Linear Regression 7 ONEHOT Features", 0.04308])
x.add_row(["Random Forest Regressor 7 ONEHOT Features", 0.01404])

x.add_row(["Linear Regression Response coded Features", 0.00948])
x.add_row(["Random Forest Regressor Response coded Features", 0.00353])



print('\n')
print(x)
```

```
+-------------------------------------------------+-----------+
|                      Model                      |    MSE    |
+-------------------------------------------------+-----------+
|         SGD Regressor 7 ONEHOT Features         | 8.091e+30 |
|      SGD Regressor Response coded Features      | 6.926e+29 |
|         SGD Regressor 5 ONEHOT Features         | 2.069e+28 |
|       Linear Regression 5 ONEHOT Features       |   0.1278  |
|    Random Forest Regressor 5 ONEHOT Features    |  0.03485  |
|       Linear Regression 7 ONEHOT Features       |  0.04308  |
|    Random Forest Regressor 7 ONEHOT Features    |  0.01404  |
|    Linear Regression Response coded Features    |  0.00948  |
| Random Forest Regressor Response coded Features |  0.00353  |
+-------------------------------------------------+-----------+
```

6. Summary

We collect data from CSV file, half of values were missing, we did not throw up all values, instead of throw NULL value we tried to fill estimate values using related colomn.
We tried only 5 one-hot encoded features and try different models Random Forest Regressor was most learning model, so we tune model using **gridsearch** technic, **minimal MSE** = 0.03485.
Then we tried with 7 one-hot encoded features and try on different models.Again Random Forest regressor was winning the race.
we achieved **MSE = 0.01404**.

Then we done some **Feature Engineering**, used response coded feature, but this time "Linear Regression" perform well than previous model , Random Forest Regressor is winning the race as usual. Finally we achieved **MSE =0.00353**.

End of the day,below model are best among all the version.

- Random Forest Regressor Response coded Features ==> 0.00353

Reference:

- https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-random-forest-d9166011959e (https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-random-forest-d9166011959e)
- https://medium.com/@purnasaigudikandula/zomato-bangalore-restaurant-analysis-and-rating-prediction-df277321c7cd (https://medium.com/@purnasaigudikandula/zomato-bangalore-restaurant-analysis-and-rating-prediction-df277321c7cd)
- https://www.kaggle.com/hindamosh/funny-banglore-restaurants-analysis (https://www.kaggle.com/hindamosh/funny-banglore-restaurants-analysis)