Predicting the Success of a Restaurant

In this project, we will go trough a complete Data Analysis and Visualization on Restaurants dataset. The goal of this project is to provide decision power for decision makers when looking at informations about restaurants in their region. For this we can do the following work:

- Get intuition about the data;
- Document an exploratory data analysis;
- Point out conclusions in every step of analysis;
- Use graphical modules (matplotlib and seaborn) to answear questions;
- Apply a predictive point of view for helping people to choose the best restaurant.
- Using this predictive approach for predicting the success of a new restaurant in the relevant region.

Libraries

In [15]:
```
import pandas as pd
import numpy as np
from warnings import filterwarnings
filterwarnings('ignore')
pd.set_option('display.max_columns', 500)
from collections import Counter
from PIL import Image

# Viz libs
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from matplotlib.gridspec import GridSpec
from mpl_toolkits.axes_grid.inset_locator import InsetPosition
import folium
from folium.plugins import HeatMap, FastMarkerCluster
from wordcloud import WordCloud

# Geolocation libs
from geopy.geocoders import Nominatim

# Utils modules
from custom_transformers import *
```

```
from viz_utils import *
from ml_utils import *

# ML libs
from sklearn.model_selection import train_test_split
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import lightgbm as lgb
import shap
```

Load the Data

In [16]:
```
# Reading restaurants data
data_path = r'../input/restaurants/dataset.csv'
df_restaurants = import_data(path=data_path, n_lines=5000)

# Results
print(f'Dataset shape: {df_restaurants.shape}')
df_restaurants.head()
```

```
This dataset has 17 columns, which 1 is/are applicable to optimization.

-----------------------------------------------------
Memory usage (5000 lines): 0.6486 MB
Memory usage after optimization (5000 lines): 0.6295 MB
-----------------------------------------------------

Reduction of 2.94% on memory usage

Dataset shape: (51717, 17)
```

Out[16]:

	url	address	name	online_order	book_table	rate	votes	phone	location
0	https://www.zomato.com/bangalore/jalsa-banasha...	942, 21st Main Road, 2nd Stage, Banashankari, ...	Jalsa	Yes	Yes	4.1/5	775	080 42297555\r\n+91 9743772233	Banashankari
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	080 41714161	Banashankari
2	https://www.zomato.com/SanchurroBangalore?cont...	1112, Next to KIMS Medical College, 17th Cross...	San Churro Cafe	Yes	No	3.8/5	918	+91 9663487993	Banashankari
3	https://www.zomato.com/bangalore/addhuri-udupi...	1st Floor, Annakuteera, 3rd Stage, Banashankar...	Addhuri Udupi Bhojana	No	No	3.7/5	88	+91 9620009302	Banashankari
4	https://www.zomato.com/bangalore/grand-village...	10, 3rd Floor, Lakshmi Associates, Gandhi Baza...	Grand Village	No	No	3.8/5	166	+91 8026612447\r\n+91 9901210005	Basavanagudi

Overview the Data

In [17]:
```
df_overview = data_overview(df_restaurants)
df_overview
```

Out[17]:

	feature	qtd_null	percent_null	dtype	qtd_cat
0	dish_liked	28078	0.542916	object	5271
1	rate	7775	0.150337	object	64
2	phone	1208	0.023358	object	14926
3	approx_cost(for two people)	346	0.006690	object	70
4	rest_type	227	0.004389	object	93
5	cuisines	45	0.000870	object	2723
6	location	21	0.000406	object	93
7	listed_in(type)	0	0.000000	object	7
8	menu_item	0	0.000000	object	9098
9	reviews_list	0	0.000000	object	22513
10	url	0	0.000000	object	51717
11	address	0	0.000000	object	11495
12	votes	0	0.000000	int32	0
13	book_table	0	0.000000	object	2
14	online_order	0	0.000000	object	2
15	name	0	0.000000	object	8792
16	listed_in(city)	0	0.000000	object	30

approx_cost(for two people):

- Change the data type from object to float;

rate:

- change data type from object to float

In [18]:
```
# Changing the data type from approx_cost columns
df_restaurants['approx_cost'] = df_restaurants['approx_cost(for two people)'].astype(str).apply(lambda x: x.replace(','
df_restaurants['approx_cost'] = df_restaurants['approx_cost'].astype(float)

# Extracting the rate in a float column
df_restaurants['rate_num'] = df_restaurants['rate'].astype(str).apply(lambda x: x.split('/')[0])
while True:
    try:
        df_restaurants['rate_num'] = df_restaurants['rate_num'].astype(float)
        break
    except ValueError as e1:
        noise_entry = str(e1).split(":")[-1].strip().replace("'", "")
        print(f'Threating noisy entrance on rate: {noise_entry}')
        df_restaurants['rate_num'] = df_restaurants['rate_num'].apply(lambda x: x.replace(noise_entry, str(np.nan)))

# Dropping old columns
df_restaurants.drop(['approx_cost(for two people)', 'rate'], axis=1, inplace=True)
df_restaurants.head()
```

```
Threating noisy entrance on rate: NEW
Threating noisy entrance on rate: -
```

Out[18]:

	url	address	name	online_order	book_table	votes	phone	location	rest_
0	https://www.zomato.com/bangalore/jalsa-banasha...	942, 21st Main Road, 2nd Stage, Banashankari, ...	Jalsa	Yes	Yes	775	080 42297555\r\n+91 9743772233	Banashankari	C D
1	https://www.zomato.com/bangalore/spice-elephan...	2nd Floor, 80 Feet Road, Near Big Bazaar, 6th ...	Spice Elephant	Yes	No	787	080 41714161	Banashankari	C D
2	https://www.zomato.com/SanchurroBangalore?cont...	1112, Next to KIMS Medical College, 17th Cross...	San Churro Cafe	Yes	No	918	+91 9663487993	Banashankari	C D
3	https://www.zomato.com/bangalore/addhuri-udupi...	1st Floor, Annakuteera, 3rd Stage, Banashankar...	Addhuri Udupi Bhojana	No	No	88	+91 9620009302	Banashankari	C
4	https://www.zomato.com/bangalore/grand-village...	10, 3rd Floor, Lakshmi Associates, Gandhi Baza...	Grand Village	No	No	166	+91 8026612447\r\n+91 9901210005	Basavanagudi	C D

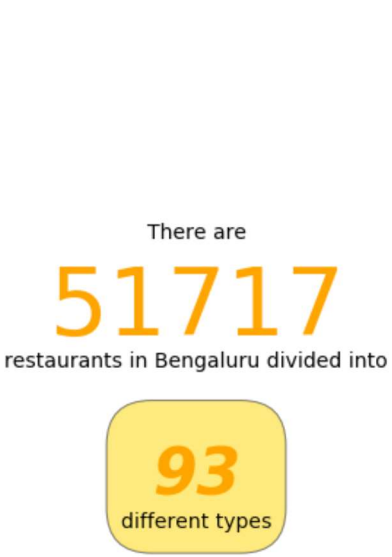
Data Visualization Exploration

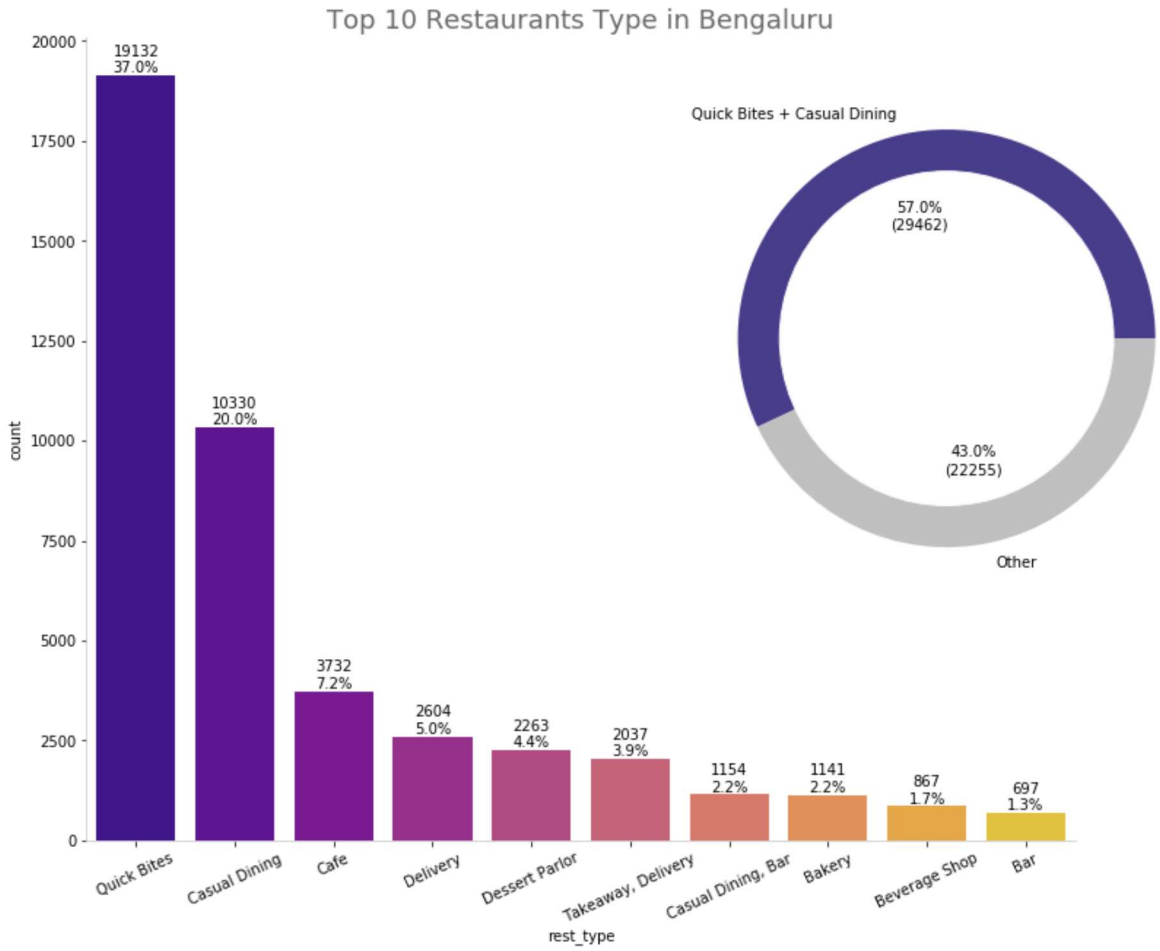
Restaurants Overview

- *How many types of restaurants we have?*

In [19]:

```
# Building a figure
fig = plt.figure(constrained_layout=True, figsize=(15, 9))

# Axis definition with GridSpec
gs = GridSpec(1, 3, figure=fig)
ax1 = fig.add_subplot(gs[0, 0])
ax2 = fig.add_subplot(gs[0, 1:3])

# Axis 1 - Big Number for total restaurants and total types in the data
total_restaurants = len(df_restaurants)
total_types = len(df_restaurants['rest_type'].value_counts())
ax1.text(0.00, 0.75, 'There are', fontsize=14, ha='center')
ax1.text(0.00, 0.63, f'{total_restaurants}', fontsize=64, color='orange', ha='center')
ax1.text(0, 0.59, 'restaurants in Bengaluru divided into', fontsize=14, ha='center')
ax1.text(0.00, 0.43, total_types, fontsize=44, ha='center', color='orange', style='italic', weight='bold',
         bbox=dict(facecolor='gold', alpha=0.5, pad=14, boxstyle='round, pad=.7'))
ax1.text(0, 0.39, 'different types', fontsize=14, ha='center')
ax1.axis('off')

# Axis 2 - Total number of restaurants per type (Top N)
top = 10
single_countplot(df_restaurants, ax2, x='rest_type', top=top)
ax2.set_title(f'Top {top} Restaurants Type in Bengaluru', color='dimgrey', size=18)
for tick in ax2.get_xticklabels():
    tick.set_rotation(25)

# Axis 3 - Representative of the top two restaurant type
df_restaurants['top_types'] = df_restaurants['rest_type'].apply(lambda x: 'Quick Bites + Casual Dining' if x in ('Quick
ip = InsetPosition(ax2, [0.57, 0.3, 0.6, 0.65])
ax3.set_axes_locator(ip)
donut_plot(df_restaurants, col='top_types', ax=ax3, colors=['darkslateblue', 'silver'], title='')
```





- *What are the most popular restaurants?*

---

let's group our data into some numerical variables that could probably show a good overview from restaurant's indicators like `total votes`, `mean approx cost`, `rate` and others. By the end, we will have in hands a new DataFrame with grouped information about all the restaurant's franchise in the dataset.

It's important to say that here we are grouping by `restaurant name` and, as long as there are restaurants with the same name in the dataset (same name but different locations, for example), we will also see how many unities each "franchise" have.

In [20]:
```
popular_franchises = df_restaurants.groupby(by='name', as_index=False).agg({'votes': 'sum',
                                                                            'url': 'count',
                                                                            'approx_cost': 'mean',
```

```
                                                                'rate_num': 'mean'})
popular_franchises.columns = ['name', 'total_votes', 'total_unities', 'mean_approx_cost', 'mean_rate_num']
popular_franchises['votes_per_unity'] = popular_franchises['total_votes'] / popular_franchises['total_unities']
popular_franchises = popular_franchises.sort_values(by='total_unities', ascending=False)
popular_franchises = popular_franchises.loc[:, ['name', 'total_unities', 'total_votes', 'votes_per_unity',
                                                'mean_approx_cost', 'mean_rate_num']]

# Correcting a restaurant name
bug_name = 'SantÃ\x83Â\x83Ã\x82Â\x83Ã\x83Â\x82Ã\x82Â\x83Ã\x83Â\x83Ã\x82Â\x82Ã\x83Â\x82Ã\x82Â\x83Ã\x83Â\x83Ã\x82Â\x83Ã\x8
popular_franchises['name'] = popular_franchises['name'].apply(lambda x: 'Santa Spa Cusisine' if x == bug_name else x)


popular_franchises.head(10)
```

Out[20]:

	name	total_unities	total_votes	votes_per_unity	mean_approx_cost	mean_rate_num
1320	Cafe Coffee Day	96	3089	32.177083	844.791667	3.256977
5549	Onesta	85	347520	4088.470588	600.000000	4.410588
3788	Just Bake	73	2898	39.698630	400.000000	3.405970
2446	Empire Restaurant	71	229808	3236.732394	685.211268	4.030435
2577	Five Star Chicken	70	3134	44.771429	257.857143	3.425000
3958	Kanti Sweets	68	7336	107.882353	400.000000	3.898529
5790	Petoo	66	4242	64.272727	659.848485	3.833333
5840	Polar Bear	65	8121	124.938462	361.538462	4.031034
827	Baskin Robbins	64	2487	38.859375	251.562500	3.572581
1655	Chef Baker's	62	5073	81.822581	516.071429	3.590909

In [21]:

```
# Creating a figure for restaurants overview analysis
fig, axs = plt.subplots(3, 3, figsize=(15, 15))

# Plot Pack 01 - Most popular restaurants (votes)
sns.barplot(x='total_votes', y='name', data=popular_franchises.sort_values(by='total_votes', ascending=False).head(),
            ax=axs[1, 0], palette='plasma')
axs[1, 0].set_title('Top 5 Most Voted Restaurants', size=12)
sns.barplot(x='total_votes', y='name',
            data=popular_franchises.sort_values(by='total_votes', ascending=False).query('total_votes > 0').tail(),
            ax=axs[2, 0], palette='plasma_r')
axs[2, 0].set_title('Top 5 Less Voted Restaurants\n(with at least 1 vote)', size=12)
```

```
for ax in axs[1, 0], axs[2, 0]:
    ax.set_xlabel('Total Votes')
    ax.set_xlim(0, popular_franchises['total_votes'].max())
    format_spines(ax, right_border=False)
    ax.set_ylabel('')

# Annotations
axs[0, 0].text(0.50, 0.30, int(popular_franchises.total_votes.mean()), fontsize=45, ha='center')
axs[0, 0].text(0.50, 0.12, 'is the average of votes', fontsize=12, ha='center')
axs[0, 0].text(0.50, 0.00, 'received by restaurants', fontsize=12, ha='center')
axs[0, 0].axis('off')

# Plot Pack 02 - Cost analysis
sns.barplot(x='mean_approx_cost', y='name', data=popular_franchises.sort_values(by='mean_approx_cost', ascending=False)
            ax=axs[1, 1], palette='plasma')
axs[1, 1].set_title('Top 5 Most Expensives Restaurants', size=12)
sns.barplot(x='mean_approx_cost', y='name',
            data=popular_franchises.sort_values(by='mean_approx_cost', ascending=False).query('mean_approx_cost > 0').t
            ax=axs[2, 1], palette='plasma_r')
axs[2, 1].set_title('Top 5 Less Expensive Restaurants', size=12)
for ax in axs[1, 1], axs[2, 1]:
    ax.set_xlabel('Avg Approx Cost')
    ax.set_xlim(0, popular_franchises['mean_approx_cost'].max())
    format_spines(ax, right_border=False)
    ax.set_ylabel('')

# Annotations
axs[0, 1].text(0.50, 0.30, round(popular_franchises.mean_approx_cost.mean(), 2), fontsize=45, ha='center')
axs[0, 1].text(0.50, 0.12, 'is mean approx cost', fontsize=12, ha='center')
axs[0, 1].text(0.50, 0.00, 'for Bengaluru restaurants', fontsize=12, ha='center')
axs[0, 1].axis('off')

# Plot Pack 03 - Rate analysis
sns.barplot(x='mean_rate_num', y='name', data=popular_franchises.sort_values(by='mean_rate_num', ascending=False).head(
            ax=axs[1, 2], palette='plasma')
axs[1, 2].set_title('Top 5 Rstaurants with Highest Rates', size=12)
sns.barplot(x='mean_rate_num', y='name',
            data=popular_franchises.sort_values(by='mean_rate_num', ascending=False).query('mean_rate_num > 0').tail(),
            ax=axs[2, 2], palette='plasma_r')
axs[2, 2].set_title('Top 5 Restaurants with Lowest Rate', size=12)
for ax in axs[1, 2], axs[2, 2]:
    ax.set_xlabel('Avg Rate')
    ax.set_xlim(0, popular_franchises['mean_rate_num'].max())
    format_spines(ax, right_border=False)
    ax.set_ylabel('')
```

```
# Annotations
axs[0, 2].text(0.50, 0.30, round(popular_franchises.mean_rate_num.mean(), 2), fontsize=45, ha='center')
axs[0, 2].text(0.50, 0.12, 'is mean rate given by customers', fontsize=12, ha='center')
axs[0, 2].text(0.50, 0.00, 'for Bengaluru restaurants', fontsize=12, ha='center')
axs[0, 2].axis('off')

plt.tight_layout()
plt.suptitle('The Best and the Worst Restaurants to Visit in Bengaluru', size=16)
plt.show()
```

The Best and the Worst Restaurants to Visit in Bengaluru

1668

is the average of votes

received by restaurants

496.62

is mean approx cost

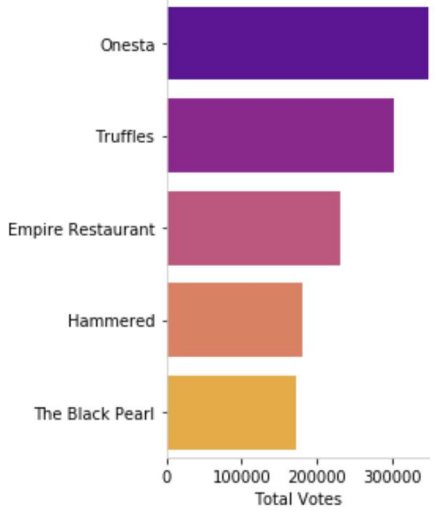
for Bengaluru restaurants

3.62

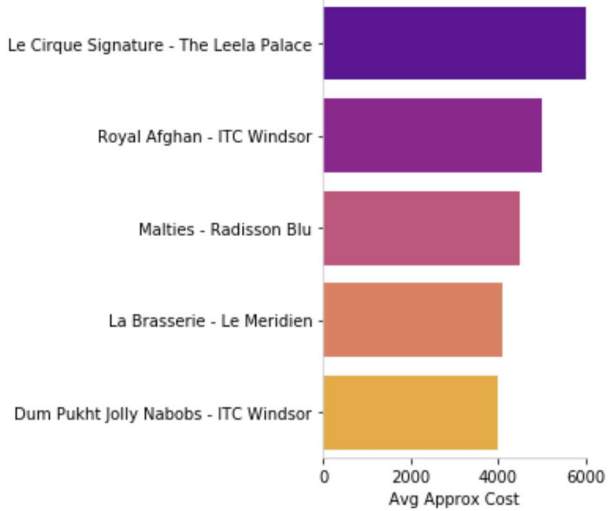
is mean rate given by customers

for Bengaluru restaurants

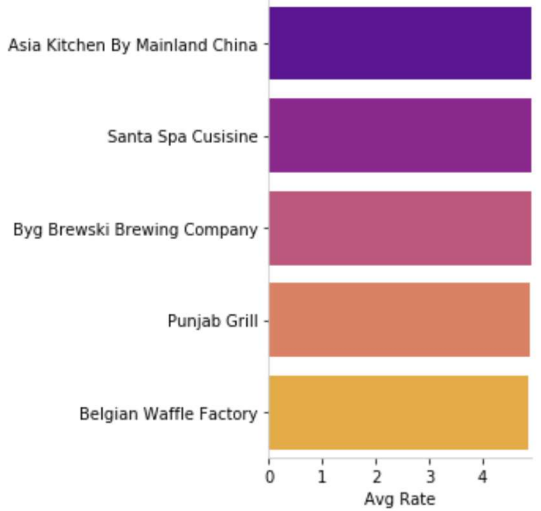
Top 5 Most Voted Restaurants



Top 5 Most Expensives Restaurants



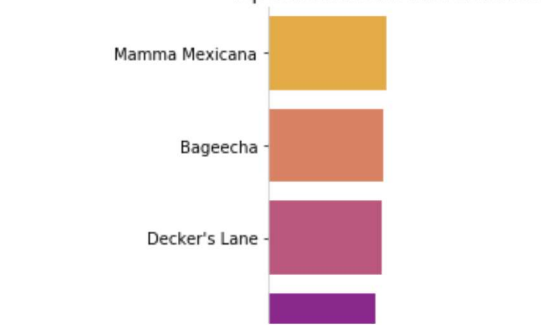
Top 5 Rstaurants with Highest Rates

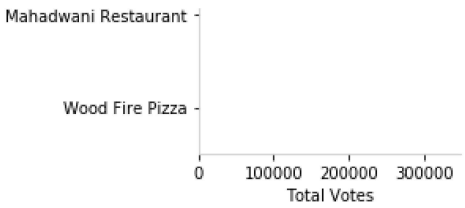


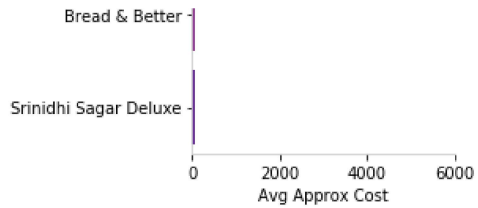
Top 5 Less Voted Restaurants
(with at least 1 vote)

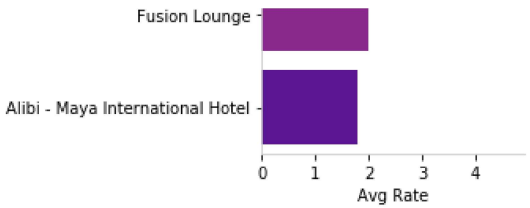
Top 5 Less Expensive Restaurants

Top 5 Restaurants with Lowest Rate





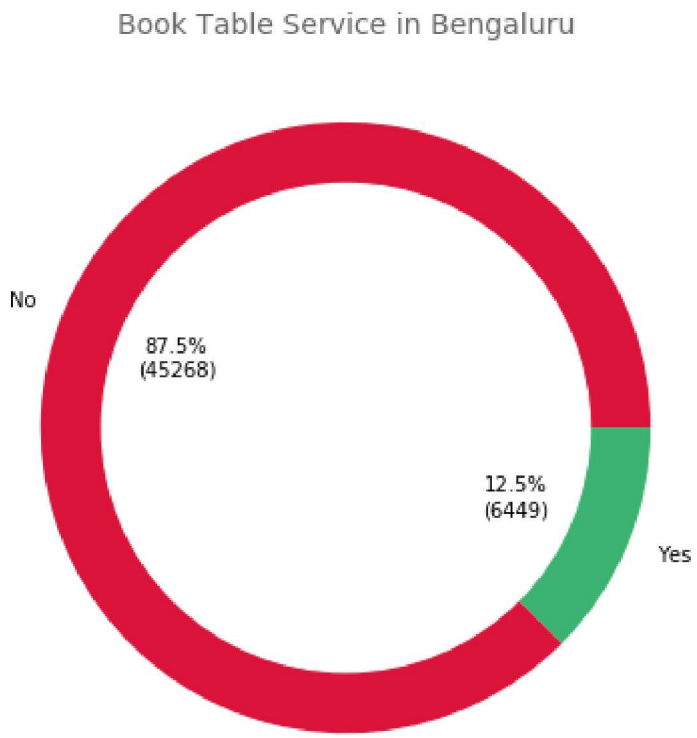


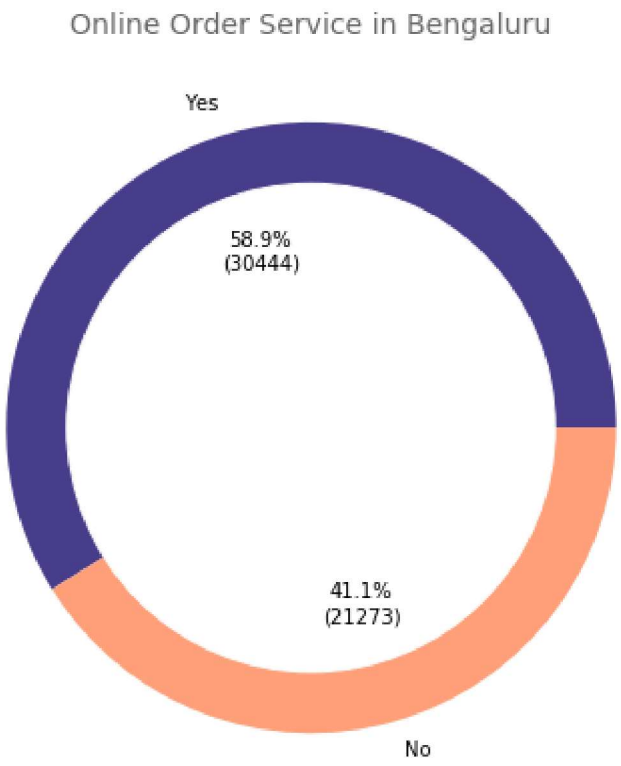


Restaurants Services

- *How many restaurants offer Book Table service? And how about Online Order service?*

In [22]:
```
fig, axs = plt.subplots(1, 2, figsize=(15, 10))
donut_plot(df_restaurants, col='book_table', colors=['crimson', 'mediumseagreen'], ax=axs[0],
           title='Book Table Service in Bengaluru')
donut_plot(df_restaurants, col='online_order', colors=['darkslateblue', 'lightsalmon'], ax=axs[1],
           title='Online Order Service in Bengaluru')
```





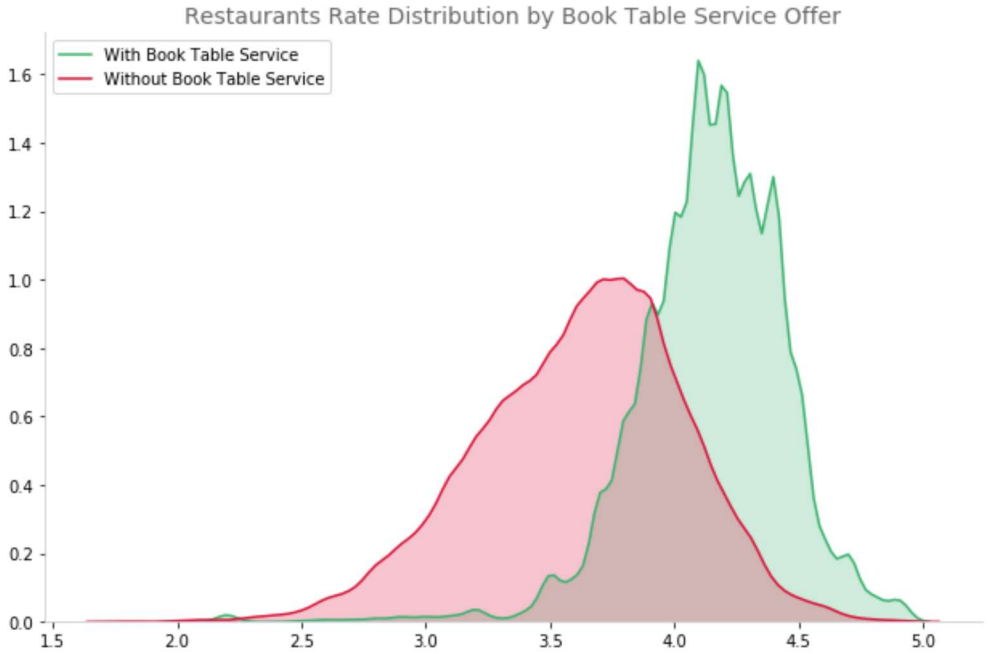
With the donuts above we can clearly see the proportions of Bengaluru restaurants who offers book table and online order service. In the first case, we can see that just 12.5% of restaurants have book table, while 87.5% don't offer this service.

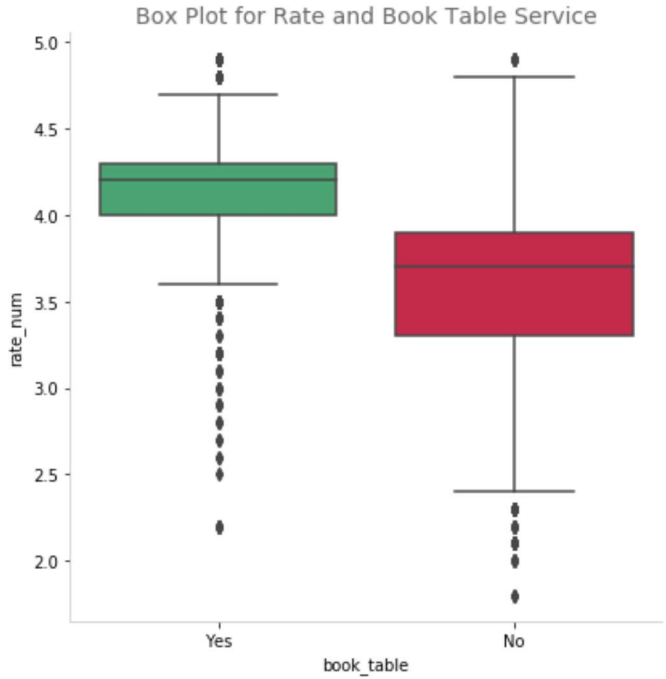
By the other hand, we have almost 59% of restaurants who have online order service.

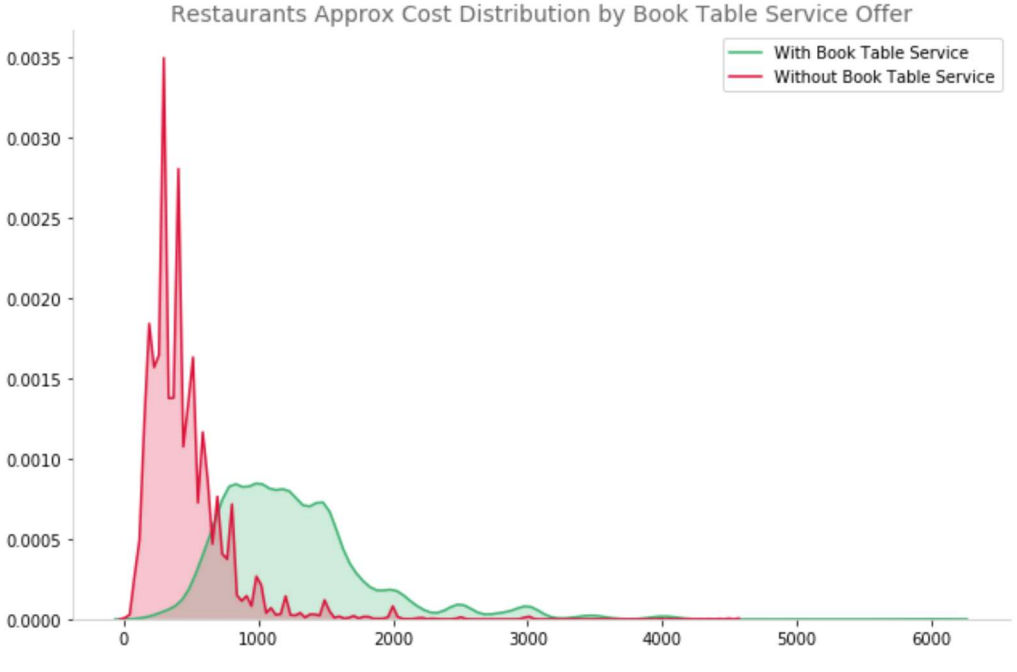
- *How the offering of Book Table service impact on Rate and Approx Cost?*

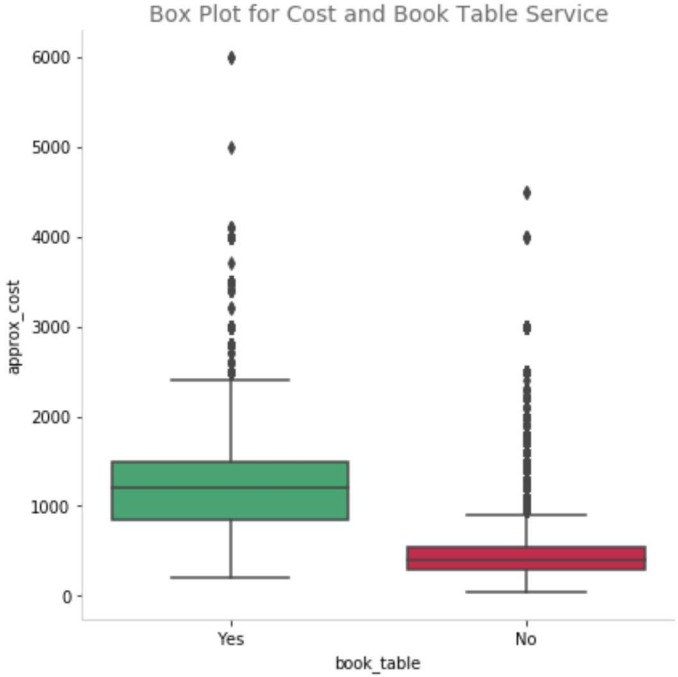
In [23]:
```
# Building a figure
fig = plt.figure(constrained_layout=True, figsize=(15, 12))

# Axis definition with GridSpec
gs = GridSpec(2, 5, figure=fig)
ax2 = fig.add_subplot(gs[0, :3])
ax3 = fig.add_subplot(gs[0, 3:])
ax4 = fig.add_subplot(gs[1, :3])
```

```
ax5 = fig.add_subplot(gs[1, 3:])

# First Line (01) - Rate
sns.kdeplot(df_restaurants.query('rate_num > 0 & book_table == "Yes"')['rate_num'], ax=ax2,
            color='mediumseagreen', shade=True, label='With Book Table Service')
sns.kdeplot(df_restaurants.query('rate_num > 0 & book_table == "No"')['rate_num'], ax=ax2,
            color='crimson', shade=True, label='Without Book Table Service')
ax2.set_title('Restaurants Rate Distribution by Book Table Service Offer', color='dimgrey', size=14)
sns.boxplot(x='book_table', y='rate_num', data=df_restaurants, palette=['mediumseagreen', 'crimson'], ax=ax3)
ax3.set_title('Box Plot for Rate and Book Table Service', color='dimgrey', size=14)

# First Line (01) - Cost
sns.kdeplot(df_restaurants.query('approx_cost > 0 & book_table == "Yes"')['approx_cost'], ax=ax4,
            color='mediumseagreen', shade=True, label='With Book Table Service')
sns.kdeplot(df_restaurants.query('approx_cost > 0 & book_table == "No"')['approx_cost'], ax=ax4,
            color='crimson', shade=True, label='Without Book Table Service')
ax4.set_title('Restaurants Approx Cost Distribution by Book Table Service Offer', color='dimgrey', size=14)
sns.boxplot(x='book_table', y='approx_cost', data=df_restaurants, palette=['mediumseagreen', 'crimson'], ax=ax5)
ax5.set_title('Box Plot for Cost and Book Table Service', color='dimgrey', size=14)


# Customizing plots
for ax in [ax2, ax3, ax4, ax5]:
    format_spines(ax, right_border=False)

plt.tight_layout()
```


Restaurants Rate Distribution by Book Table Service Offer
With Book Table Service
Without Book Table Service
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Box Plot for Rate and Book Table Service
rate_num
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Yes
No
book_table

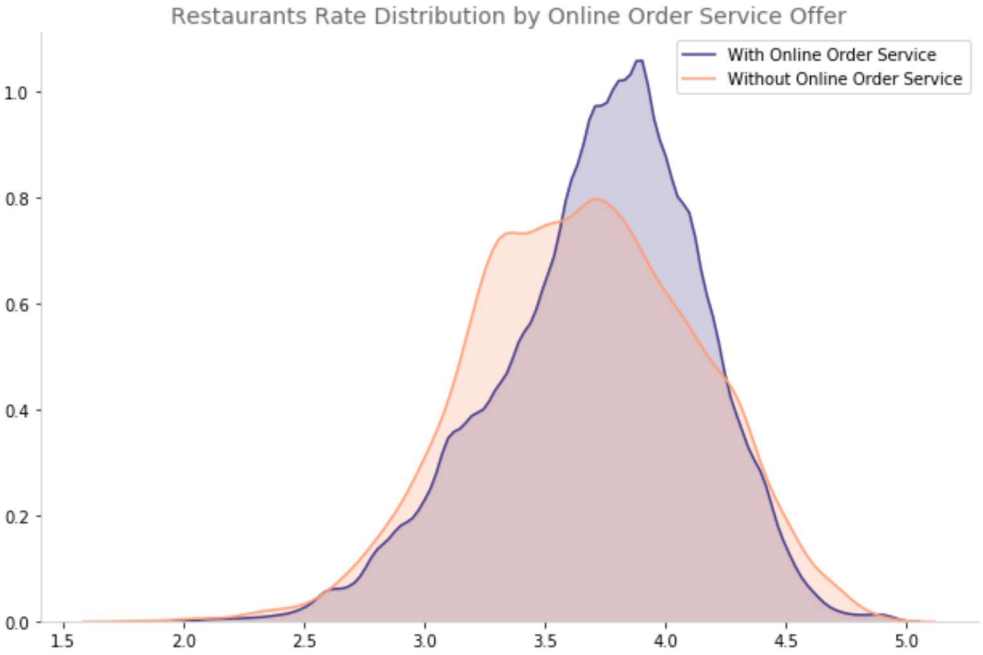

Restaurants Approx Cost Distribution by Book Table Service Offer
With Book Table Service
Without Book Table Service
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
0.0035
0
1000
2000
3000
4000
5000
6000

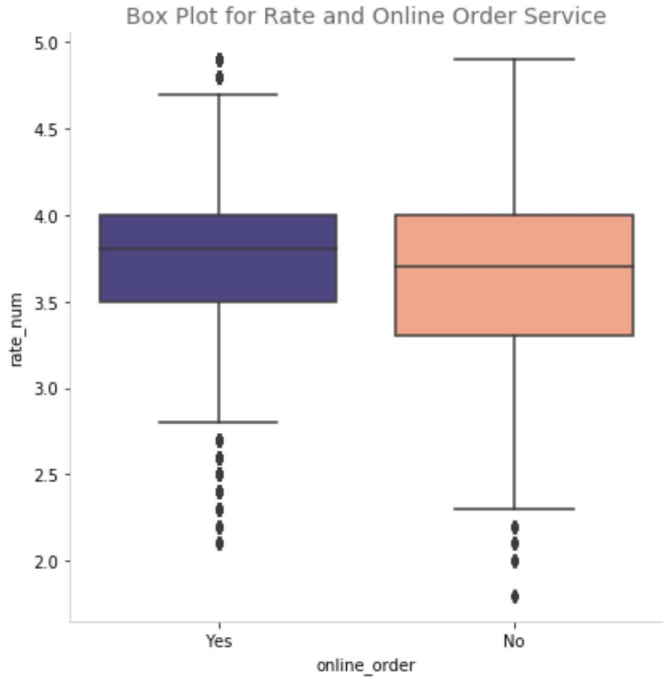

Box Plot for Cost and Book Table Service
approx_cost
0
1000
2000
3000
4000
5000
6000
Yes
No
book_table

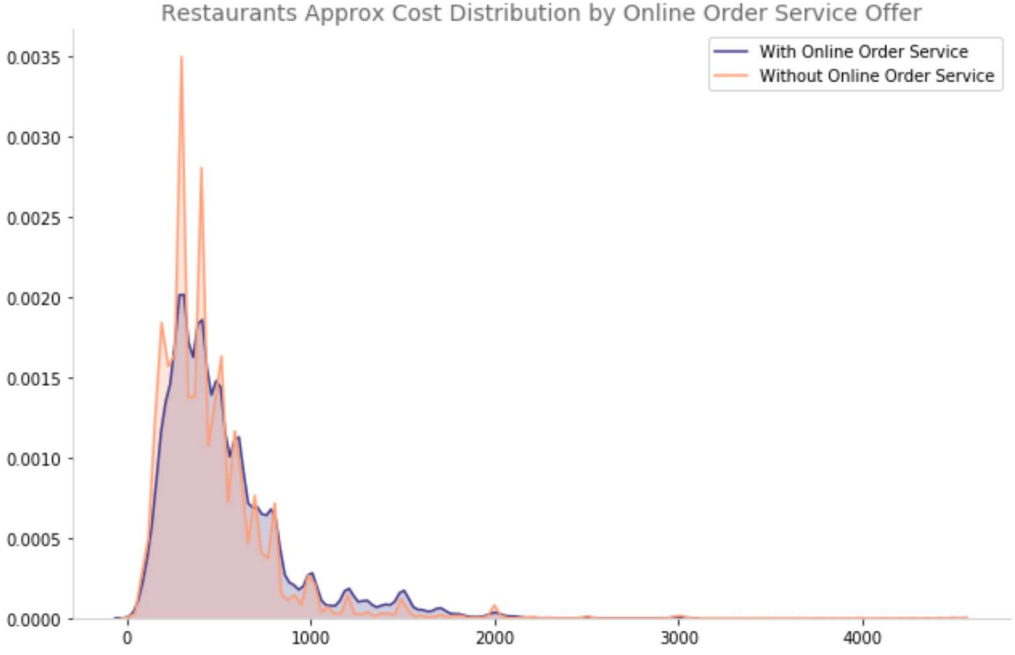
The distplot and the boxplot above show us the importance given by the customers for book table service in restaurants: on the first line we notice that, in general, restaurants with book table service usually receive highest rate notes. Meanwhile, we can conclude by the second line that those same restaurants are usually more expensive.

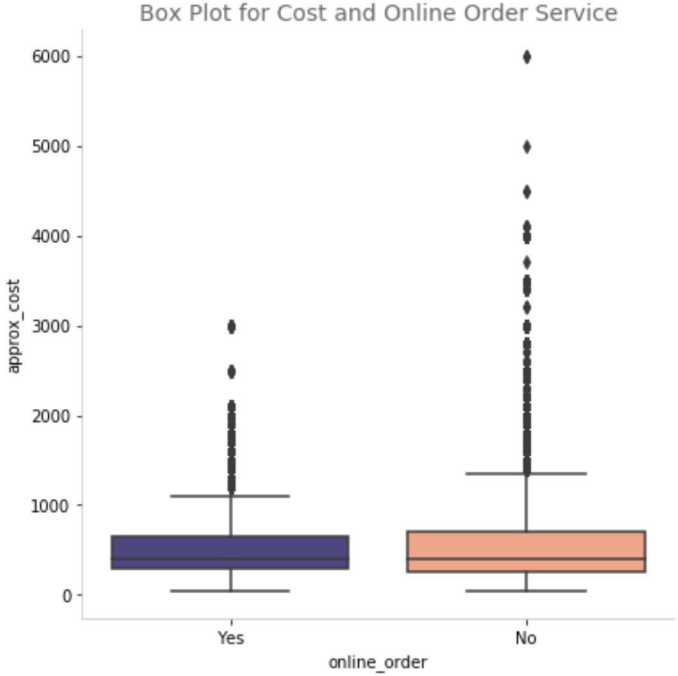
- *How the offering of Online Order service impact on Rate and Approx Cost?*

In [24]:
```
# Building a figure
fig = plt.figure(constrained_layout=True, figsize=(15, 12))

# Axis definition with GridSpec
gs = GridSpec(2, 5, figure=fig)
ax2 = fig.add_subplot(gs[0, :3])
ax3 = fig.add_subplot(gs[0, 3:])
ax4 = fig.add_subplot(gs[1, :3])
ax5 = fig.add_subplot(gs[1, 3:])

# First Line (01) - Rate
sns.kdeplot(df_restaurants.query('rate_num > 0 & online_order == "Yes"')['rate_num'], ax=ax2,
            color='darkslateblue', shade=True, label='With Online Order Service')
sns.kdeplot(df_restaurants.query('rate_num > 0 & online_order == "No"')['rate_num'], ax=ax2,
            color='lightsalmon', shade=True, label='Without Online Order Service')
ax2.set_title('Restaurants Rate Distribution by Online Order Service Offer', color='dimgrey', size=14)
sns.boxplot(x='online_order', y='rate_num', data=df_restaurants, palette=['darkslateblue', 'lightsalmon'], ax=ax3)
ax3.set_title('Box Plot for Rate and Online Order Service', color='dimgrey', size=14)

# First Line (01) - Cost
sns.kdeplot(df_restaurants.query('approx_cost > 0 & online_order == "Yes"')['approx_cost'], ax=ax4,
            color='darkslateblue', shade=True, label='With Online Order Service')
sns.kdeplot(df_restaurants.query('approx_cost > 0 & book_table == "No"')['approx_cost'], ax=ax4,
            color='lightsalmon', shade=True, label='Without Online Order Service')
ax4.set_title('Restaurants Approx Cost Distribution by Online Order Service Offer', color='dimgrey', size=14)
sns.boxplot(x='online_order', y='approx_cost', data=df_restaurants, palette=['darkslateblue', 'lightsalmon'], ax=ax5)
ax5.set_title('Box Plot for Cost and Online Order Service', color='dimgrey', size=14)


# Customizing plots
for ax in [ax2, ax3, ax4, ax5]:
    format_spines(ax, right_border=False)

plt.tight_layout()
```


Restaurants Rate Distribution by Online Order Service Offer
With Online Order Service
Without Online Order Service
1.0
0.8
0.6
0.4
0.2
0.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Box Plot for Rate and Online Order Service
rate_num
5.0
4.5
4.0
3.5
3.0
2.5
2.0
Yes
No
online_order


Restaurants Approx Cost Distribution by Online Order Service Offer
With Online Order Service
Without Online Order Service
0.0035
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0
1000
2000
3000
4000


Box Plot for Cost and Online Order Service
approx_cost
6000
5000
4000
3000
2000
1000
0
Yes
No
online_order

Now if we look for online order service, it's fair to say that the customer don't give importance for this service as much they give for book table one. The rate distribution shows customers usually give highest rates for restaurants who offer online order service (even if the difference is little).

Looking at the cost comparison between restaurants who offer online order service, we can conclude that they are almost the same.

Where Are the Good Ones?

Searching for useful insights for predicting the success of a restaurant in Bengaluru, let's dive into locations to answer the question in the session title. By the way, where are the good restaurants?*

**Good restaurants are relative and we will point that the good ones have a high rate*

In [25]:
```
# Grouping data into location
good_ones = df_restaurants.groupby(by='location', as_index=False).agg({'votes': 'sum',
                                                                        'url': 'count',
                                                                        'approx_cost': 'mean',
                                                                        'rate_num': 'mean'})
good_ones.columns = ['location', 'total_votes', 'total_unities', 'mean_approx_cost', 'mean_rate_num']
good_ones['votes_per_unity'] = good_ones['total_votes'] / good_ones['total_unities']
good_ones = good_ones.sort_values(by='total_unities', ascending=False)
good_ones = good_ones.loc[:, ['location', 'total_unities', 'total_votes', 'votes_per_unity',
                                          'mean_approx_cost', 'mean_rate_num']]
good_ones.head(10)
```

Out[25]:

	location	total_unities	total_votes	votes_per_unity	mean_approx_cost	mean_rate_num
0	BTM	5124	619376	120.877440	396.480973	3.573740
22	HSR	2523	499720	198.065795	475.610048	3.672164
45	Koramangala 5th Block	2504	2219506	886.384185	663.663845	4.005821
29	JP Nagar	2235	586593	262.457718	522.771300	3.675306
89	Whitefield	2144	466829	217.737407	598.152836	3.621618
27	Indiranagar	2083	1196007	574.175228	653.788027	3.828154
32	Jayanagar	1926	488080	253.416407	476.407716	3.780280
56	Marathahalli	1846	445201	241.170639	513.750683	3.541927
3	Bannerghatta Road	1630	219077	134.403067	443.679654	3.507449
6	Bellandur	1286	206027	160.207621	527.503888	3.525692

In [26]:

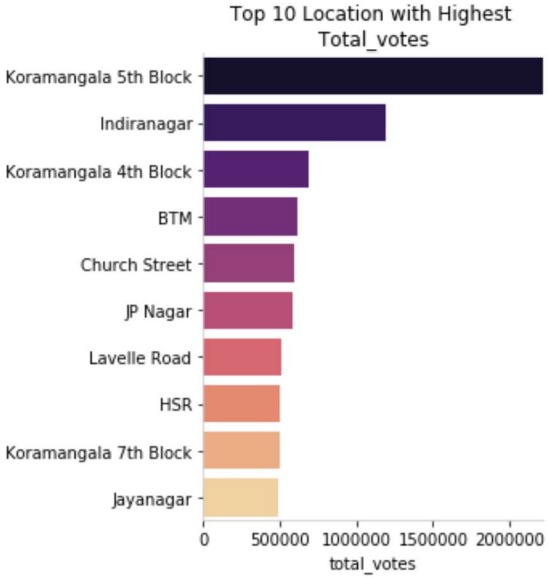
```
# Creating a figure for restaurants overview analysis
fig, axs = plt.subplots(3, 3, figsize=(15, 15))
list_cols = ['total_votes', 'mean_approx_cost', 'mean_rate_num']

# PLotting best and worst by grouped data
answear_plot(grouped_data=good_ones, grouped_col='location', axs=axs, list_cols=list_cols, top=10, palette='magma')

# Finishing the chart
plt.suptitle('Where Are the Top Restaurants in Bengaluru?', size=16)
plt.tight_layout()
plt.show()
```

Where Are the Top Restaurants in Bengaluru?

157763.28

is the average of total_votes

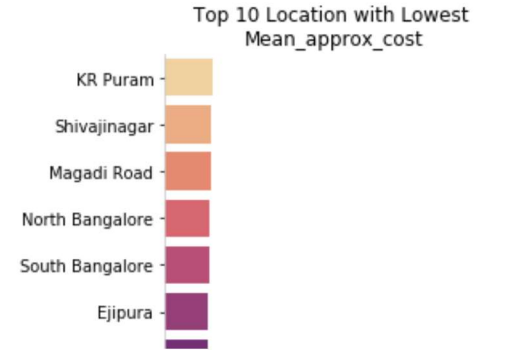
by location



547.97

is the average of mean_approx_cost

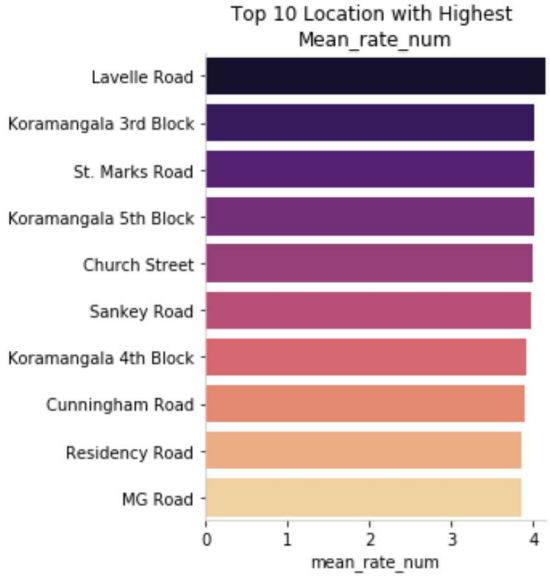
by location

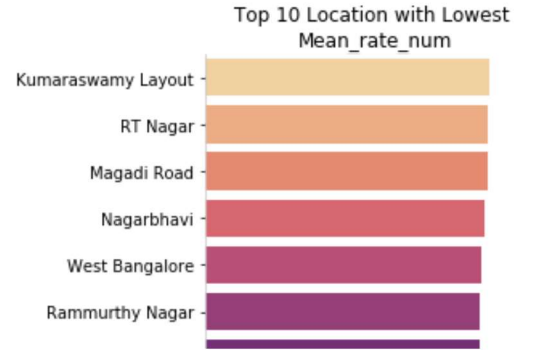


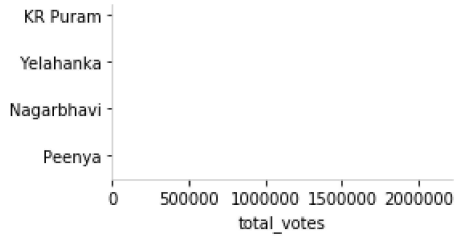
3.64

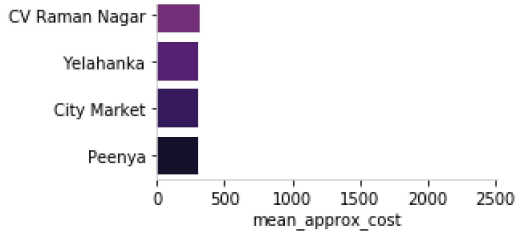
is the average of mean_rate_num

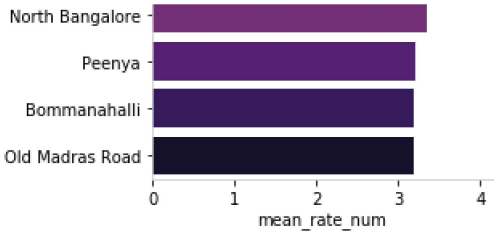
by location







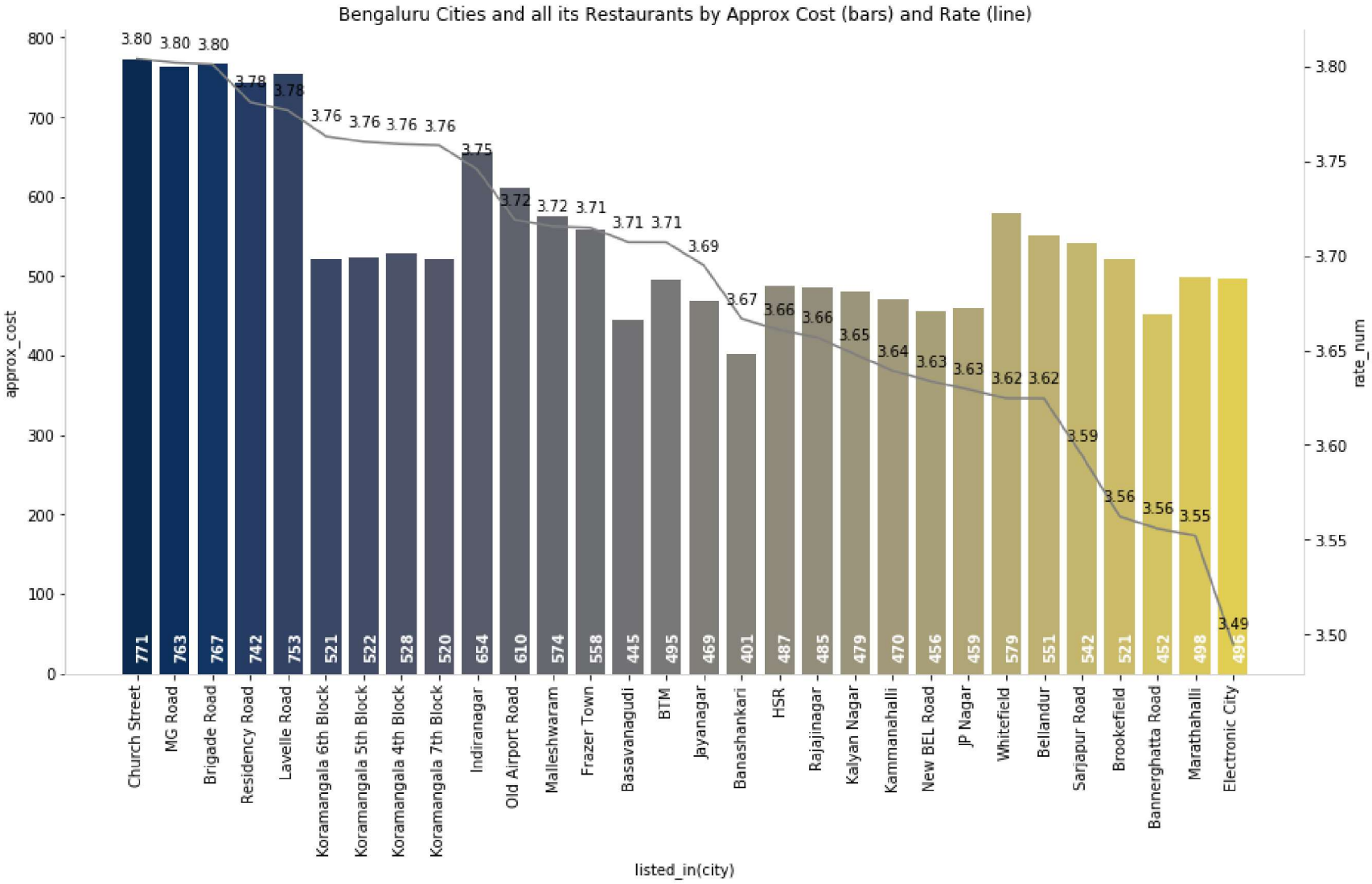




Now let's purpose a clearly view for cities with restaurants in Bengaluru and take a look at the average cost and rate of restaurants in each one. The idea is to see how these two variables are related and to present customers the insight of choosing the best city to visit (eating purposes) in Bengaluru.

In [27]:
```
# Grouping data by city
city_group = df_restaurants.groupby(by='listed_in(city)', as_index=False).agg({'rate_num': 'mean',
                                                                               'approx_cost': 'mean'})
city_group.sort_values(by='rate_num', ascending=False, inplace=True)

# Ploting
fig, ax = plt.subplots(figsize=(15, 8))
sns.barplot(x='listed_in(city)', y='approx_cost', data=city_group, palette='cividis',
            order=city_group['listed_in(city)'])
ax2 = ax.twinx()
sns.lineplot(x='listed_in(city)', y='rate_num', data=city_group, color='gray', ax=ax2, sort=False)

# Labeling line chart (rate)
xs = np.arange(0, len(city_group), 1)
ys = city_group['rate_num']
for x,y in zip(xs, ys):
    label = "{:.2f}".format(y)
    plt.annotate(label, # this is the text
                 (x,y), # this is the point to label
                 textcoords="offset points", # how to position the text
                 xytext=(0,10), # distance from text to points (x,y)
                 ha='center', # horizontal alignment can be left, right or center
                 color='black')

# Labeling bar chart (cost)
for p in ax.patches:
    x = p.get_bbox().get_points()[:, 0]
    y = p.get_bbox().get_points()[1, 1]
    ax.annotate('{}'.format(int(y)), (x.mean(), 15), va='bottom', rotation='vertical', color='white',
                fontweight='bold')
```

```
# Customizing chart
format_spines(ax)
format_spines(ax2)
ax.tick_params(axis='x', labelrotation=90)
ax.set_title('Bengaluru Cities and all its Restaurants by Approx Cost (bars) and Rate (line)')
plt.show()
```



In the following steps, the real idea was to extract lat and long features from the address in the dataset, but there are huge differences between address formats that made it difficult. the best we can do here is to extract geolocation features based in the restaurant city.

In [28]:

```
# Extracting lat and long from the restaurant city using an API service
geolocator = Nominatim(user_agent="Y_BzShFZceZ_rj_t-cI13w")

# Creating a auxiliar dataset with cities location (reducing the API calls and time consuming by consequence)
cities_aux = pd.DataFrame(df_restaurants['listed_in(city)'].value_counts())
cities_aux.reset_index(inplace=True)
cities_aux.columns = ['city', 'total_restaurants']

# Extracting cities lat and long features
cities_aux['lat'] = cities_aux['city'].apply(lambda x: geolocator.geocode(x)[1][0])
cities_aux['lng'] = cities_aux['city'].apply(lambda x: geolocator.geocode(x)[1][1])

# Adding more features do further analysis
city_group = df_restaurants.groupby(by='listed_in(city)', as_index=False).agg({'votes': 'sum',
                                                                               'approx_cost': 'mean',
                                                                               'rate_num': 'mean'})
city_group.columns = ['city', 'total_votes', 'avg_approx_cost', 'avg_rate_num']

# Creating an unique city data
cities_aux = cities_aux.merge(city_group, how='left', on='city')

# Merging the original data to the grouped cities lat and long
df_restaurants = df_restaurants.merge(cities_aux, how='left', left_on='listed_in(city)', right_on='city')
df_restaurants.drop(['city', 'total_restaurants'], axis=1, inplace=True)

# Results on cities grouped data
cities_aux
```

Out[28]:

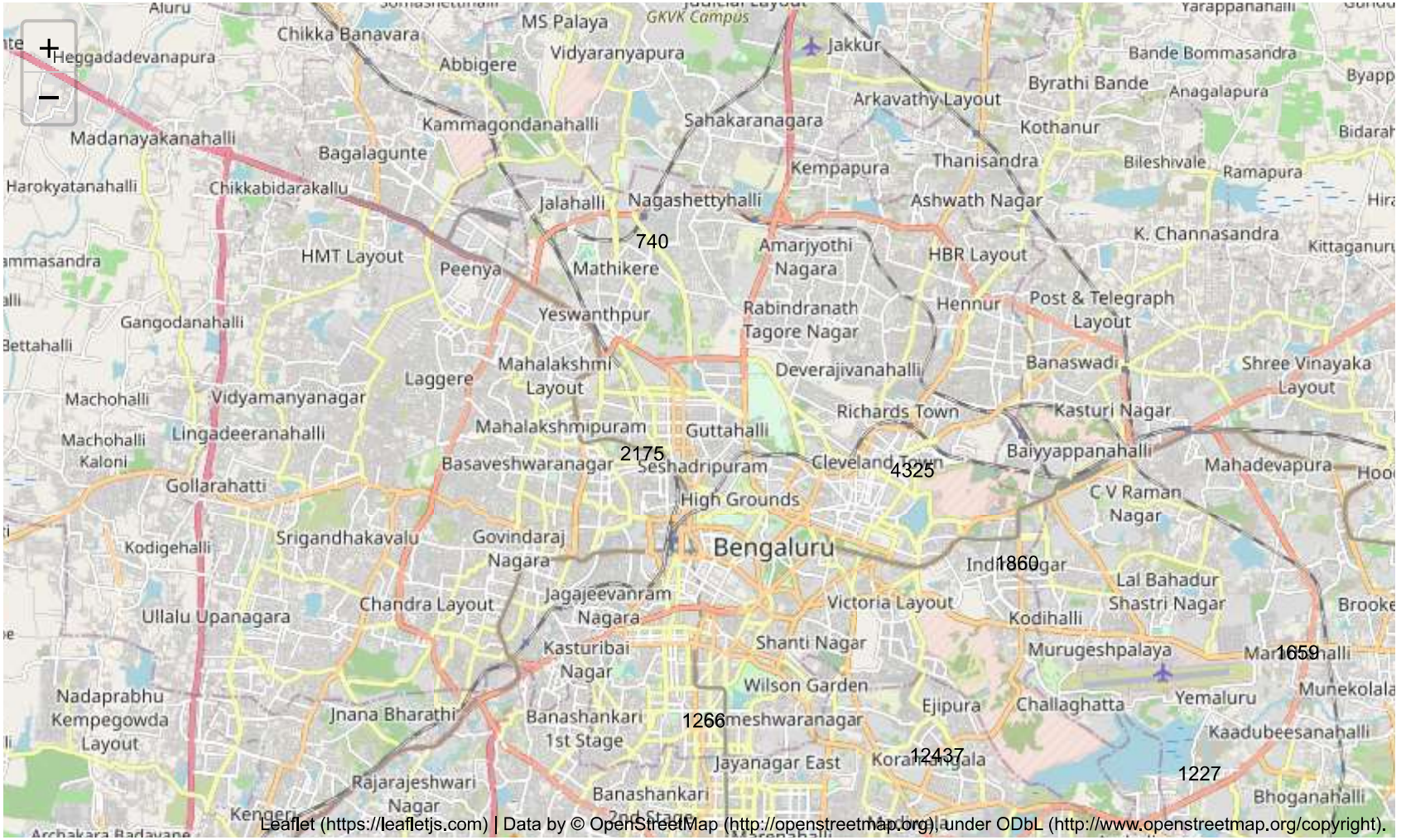
	city	total_restaurants	lat	lng	total_votes	avg_approx_cost	avg_rate_num
0	BTM	3279	12.911276	77.604565	985690	495.485145	3.707241
1	Koramangala 7th Block	2938	12.936485	77.613478	1065901	520.497598	3.758410
2	Koramangala 5th Block	2836	12.934843	77.618977	1040312	522.979026	3.760255
3	Koramangala 4th Block	2779	12.932778	77.629405	992065	528.353924	3.759035
4	Koramangala 6th Block	2623	12.939025	77.623848	978900	521.340524	3.763153
5	Jayanagar	2371	27.349301	95.315941	563880	469.077053	3.694969
6	JP Nagar	2096	12.265594	76.646540	395852	459.774904	3.629472
7	Indiranagar	1860	12.973291	77.640467	781831	654.753655	3.745659
8	Church Street	1827	31.197743	-4.311452	687895	771.990104	3.804262
9	MG Road	1811	12.975526	77.606790	722679	763.987696	3.802023
10	Brigade Road	1769	44.621621	-84.790422	648458	767.091115	3.801146
11	Lavelle Road	1744	40.771868	-76.370470	583177	753.584873	3.776818
12	HSR	1741	29.152347	75.724580	376409	487.814302	3.660821
13	Marathahalli	1659	12.955257	77.698416	365313	498.232078	3.552207
14	Whitefield	1620	53.553368	-2.296902	336835	579.159925	3.624712
15	Residency Road	1620	38.738885	-77.527626	588107	742.960723	3.781222
16	Bannerghatta Road	1617	12.875498	77.595048	244843	452.534077	3.555875
17	Brookefield	1518	33.593506	-79.034563	270959	521.246702	3.562348
18	Old Airport Road	1425	33.542388	-81.687340	584215	610.877698	3.719040
19	Kammanahalli	1329	13.009346	77.637709	174171	470.659591	3.639265
20	Kalyan Nagar	1309	19.160229	76.277282	176749	479.753657	3.647913
21	Basavanagudi	1266	12.941726	77.575502	281606	445.137549	3.707276
22	Sarjapur Road	1261	12.924036	77.639433	314662	542.102729	3.594706
23	Electronic City	1229	15.675090	73.810836	109957	496.955102	3.494807
24	Bellandur	1227	12.931032	77.678247	356853	551.098361	3.624614

	city	total_restaurants	lat	lng	total_votes	avg_approx_cost	avg_rate_num
25	Frazer Town	1185	12.998683	77.615525	283348	558.237288	3.714838
26	Malleshwaram	1096	13.002735	77.570325	262331	574.789762	3.715523
27	Rajajinagar	1079	12.988234	77.554883	198247	485.874649	3.656948
28	Banashankari	863	15.887678	75.704678	151573	401.551564	3.666758
29	New BEL Road	740	13.038442	77.564753	149167	456.648575	3.633741

Geo Analysis: where are the restaurants located in Bengaluru?

In [29]:
```
# Zipping locations for folium map
locations = list(zip(df_restaurants['lat'].values, df_restaurants['lng'].values))

# Creating a map using folium
map1 = folium.Map(
    location=[12.97, 77.63],
    zoom_start=11.5
)

# Plugin: FastMarkerCluster
FastMarkerCluster(data=locations).add_to(map1)

map1
```

Out[29]:



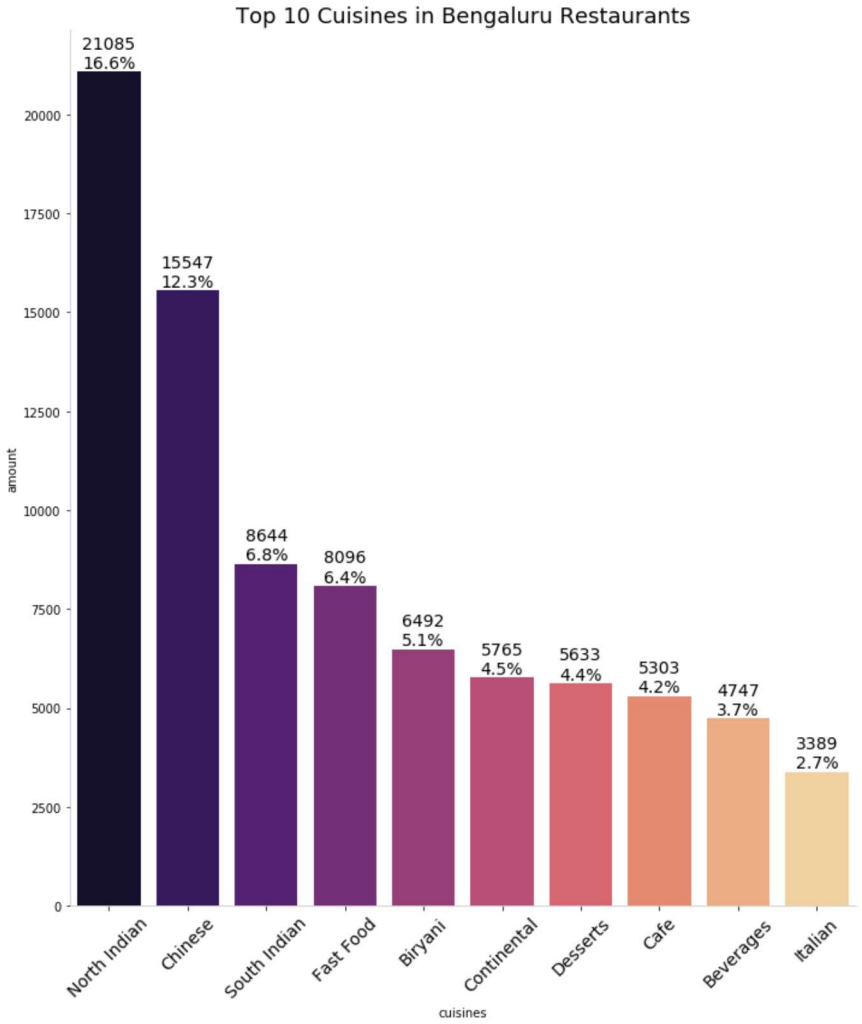
Food Options

In this session we will discuss the customer's food preferences. The goal is to go trough the text presented in the columns like `cuisines` and `dish_liked` to extract valuable information about options available in Bengaluru restaurants.

- *What we can conclude about main options available on Bengaluru restaurants?*

In [32]:
```
# Creating a list with all options available
cuisines = list(df_restaurants['cuisines'].astype(str).values)
```

```
cuisines_word_list = []
for lista in [c.split(',') for c in cuisines]:
    for word in lista:
        cuisines_word_list.append(word.strip())

# Creating a Counter for unique options and generating the wordcloud
cuisines_wc_dict = Counter(cuisines_word_list)

wordcloud = WordCloud(width=1280, height=720, collocations=False, random_state=42,
                      colormap='magma', background_color='white').generate_from_frequencies(cuisines_wc_dict)

# Visualizing the WC created and the total for each cuisine
fig, axs = plt.subplots(1, 2, figsize=(20, 12))
ax1 = axs[0]
ax2 = axs[1]
ax1.imshow(wordcloud)
ax1.axis('off')
ax1.set_title('WordCloud for Cuisines Available on Bengaluru Restaurants', size=18, pad=20)

# Total for each cuisine
df_cuisines = pd.DataFrame()
df_cuisines['cuisines'] = cuisines_wc_dict.keys()
df_cuisines['amount'] = cuisines_wc_dict.values()
df_cuisines.sort_values(by='amount', ascending=False, inplace=True)
sns.barplot(x='cuisines', y='amount', data=df_cuisines.head(10), palette='magma', ax=ax2)
format_spines(ax2, right_border=False)
ax2.set_title('Top 10 Cuisines in Bengaluru Restaurants', size=18)

# Customizing chart
ncount = df_cuisines['amount'].sum()
x_ticks = [item.get_text() for item in ax2.get_xticklabels()]
ax2.set_xticklabels(x_ticks, rotation=45, fontsize=14)
for p in ax2.patches:
    x = p.get_bbox().get_points()[:, 0]
    y = p.get_bbox().get_points()[1, 1]
    ax2.annotate('{}\n{:.1f}%'.format(int(y), 100. * y / ncount), (x.mean(), y), fontsize=14, ha='center', va='bottom')

plt.tight_layout()
plt.show()
```



We can see a lot of North Indian, Chinese, South Indian, Fast Food, Desserts and other patterns related to options available in Bengaluru area.

Predicting the Success of a Restaurant

Well, finally we arrived at our main task on this notebook: predict the success of a restaurant in Bengaluru using the data provided and extracting some additional features. At this point probably you're asking: but how we will do it? That's what a thought for this task:

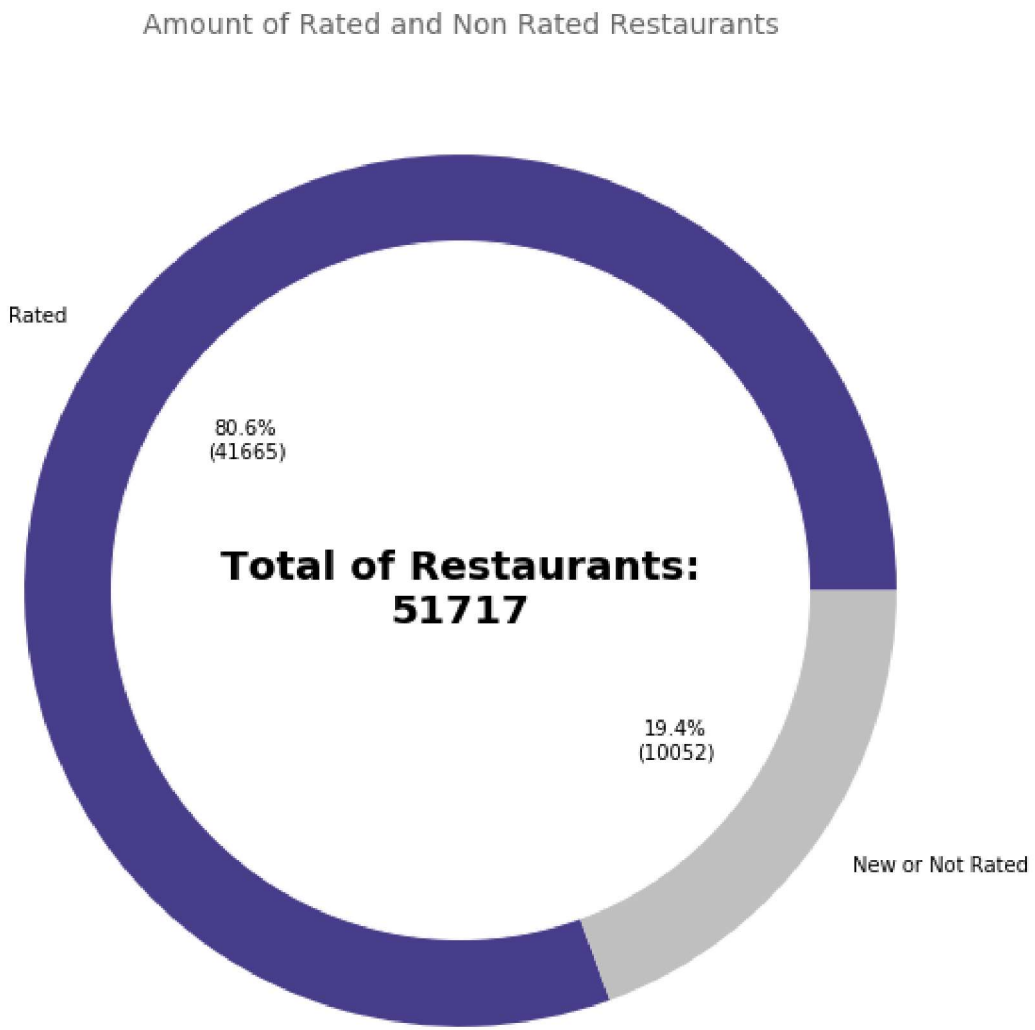
1. Use the restaurant rate to classify our data in two classes: good and bad (thresholds to be defined)

2. Create a target variable using a pre-defined rate threshold
3. Extract features from the data
4. Create a classification model using a supervisioned approach
5. Predict the "probability for being a good restaurant" for the ones marked as NEW or without rate

First of all, let's split the data we will use for train/validation and the data we want to do a real prediction.

Target Definition

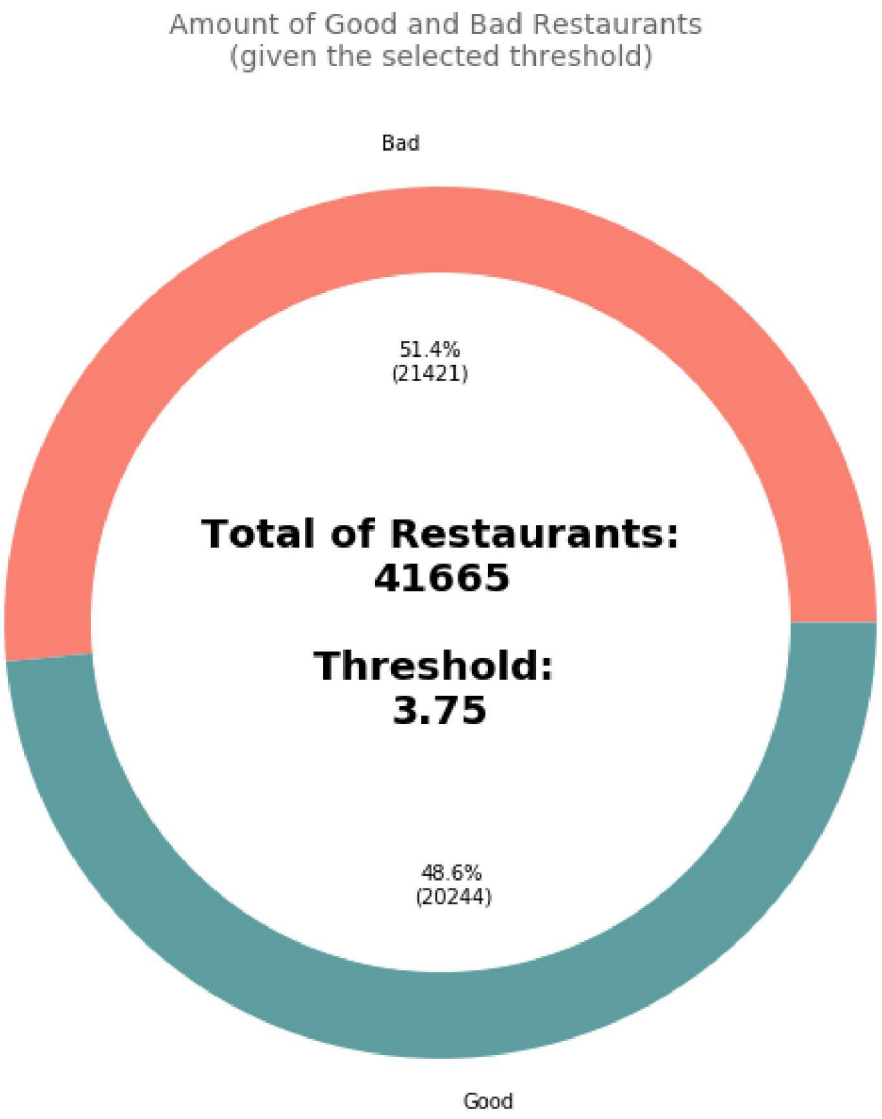
In [34]:
```
# Splitting restaurants data
df_restaurants['rated'] = df_restaurants['rate_num'].apply(lambda x: 1 if x >= 0 else 0)
new_restaurants = df_restaurants.query('rated == 0')
train_val_restaurants = df_restaurants.query('rated == 1')

# PLotting a donut chart for seeing the distribution
fig, ax = plt.subplots(figsize=(10, 10))
donut_plot(df_restaurants, col='rated', ax=ax, label_names=['Rated', 'New or Not Rated'],
           colors=['darkslateblue', 'silver'], title='Amount of Rated and Non Rated Restaurants',
           text=f'Total of Restaurants:\n{len(df_restaurants)}')
```



By now we've already splitted our original data into `new_restaurants` and `train_val_restaurants` pandas DataFrames. Let's keep the first one aside for now and let's work only with the training and validation set. The next step is to create our target variable to be used in this classification task.

The main point here is to define a fair threshold for splitting the restaurants data into `good` and `bad` ones. It would be a really experimental decision and we must keep in mind that this approach is not the best one. Probably it would let margin for classification errors.

In [35]:
```
# Defining a custom threshold for splitting restaurants into good and bad
threshold = 3.75
train_val_restaurants['target'] = train_val_restaurants['rate_num'].apply(lambda x: 1 if x >= threshold else 0)

# Donut chart
fig, ax = plt.subplots(figsize=(10, 10))
label_names = ['Bad' if target == 0 else 'Good' for target in train_val_restaurants['target'].value_counts().index]
color_list = ['salmon' if label == 'Bad' else 'cadetblue' for label in label_names]
donut_plot(train_val_restaurants, col='target', ax=ax, label_names=label_names,
           colors=color_list, title='Amount of Good and Bad Restaurants \n(given the selected threshold)',
           text=f'Total of Restaurants:\n{len(train_val_restaurants)}\n\nThreshold: \n{threshold}')
```



The meaning of all this is that we marked as `good` restaurants with a rate greater or equal to **3.75**. Correct or not, let's continue to see what we can get from this.

The next step is to prepare some features for training our classification model.

Feature Extraction

After defining the target and splitting the data into train+val and test sets, let's define the features to be used on training. Here we will take a look at the raw data to select valuable features and apply some steps to create another ones.

The initial set of selected features inclue:

- online_order;
- book_table;
- location;
- rest_type;
- cuisines;
- listed_in(type);
- listed_in(city);
- approx_cost

In [36]:
```
# Selecting initial features
initial_features = ['online_order', 'book_table', 'location', 'rest_type', 'cuisines',
                    'listed_in(type)', 'listed_in(city)', 'approx_cost', 'target']
train_val_restaurants = train_val_restaurants.loc[:, initial_features]

# Extracting new features
train_val_restaurants['multiple_types'] = train_val_restaurants['rest_type'].astype(str).apply(lambda x: len(x.split(',
train_val_restaurants['total_cuisines'] = train_val_restaurants['cuisines'].astype(str).apply(lambda x: len(x.split(','

# Dropping another ones
train_val_restaurants.drop('cuisines', axis=1, inplace=True)
train_val_restaurants.head()
```

Out[36]:

	online_order	book_table	location	rest_type	listed_in(type)	listed_in(city)	approx_cost	target	multiple_types	total_cuisines
0	Yes	Yes	Banashankari	Casual Dining	Buffet	Banashankari	800.0	1	1	3
1	Yes	No	Banashankari	Casual Dining	Buffet	Banashankari	800.0	1	1	3
2	Yes	No	Banashankari	Cafe, Casual Dining	Buffet	Banashankari	800.0	1	2	3
3	No	No	Banashankari	Quick Bites	Buffet	Banashankari	300.0	0	1	2
4	No	No	Basavanagudi	Casual Dining	Buffet	Banashankari	600.0	1	1	2

Some considerations:

- We won't use the `votes` feature as long as this is a information we only know after launching a restaurant. As we want to be predictive, the idea is to return the probability of success of a restaurant before launching it.
- We created the `multiple_types`, `total_dishes` and `total_cuisines` features in a way of counting the food services offered by the restaurant. This is information can be gotten before the launching of the establishment.

For the last act on this topic, let's split the data into training and validation sets.

In [37]:
```
# Splitting the data
X = train_val_restaurants.drop('target', axis=1)
y = train_val_restaurants['target'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.20, random_state=42)
```

Encoding

Upon examining the data we have prepared for training our classification model, it is essential to emphasize the necessity of applying encoding techniques to handle categorical features. By doing so, we can determine the 'global reach' of our restaurant success predictor. When using features such as 'location' and 'listed_in(city)' for training, it confines the applicability of our model to the Bengaluru area exclusively. For the time being, let's retain these features while acknowledging that, at least in this initial phase, our classification model can only predict the success of restaurants within the Bengaluru region."

In [38]:
```
# Splitting features by data type
cat_features= [col for col, dtype in X_train.dtypes.items() if dtype == 'object']
num_features = [col for col, dtype in X_train.dtypes.items() if dtype != 'object']

# Apply encoding for categorical features
X_train_cat = X_train[cat_features]
for col in cat_features:
    col_encoded = pd.get_dummies(X_train_cat[col], prefix=col, dummy_na=True)
    X_train_cat = X_train_cat.merge(col_encoded, left_index=True, right_index=True)
    X_train_cat.drop(col, axis=1, inplace=True)

print(f'Total categorical features after encoding: {X_train_cat.shape[1]}')
```

```
Total categorical features after encoding: 226
```

Pipeline

It's time to develop a comprehensive data preprocessing pipeline. This pipeline will receive the raw data containing restaurant information and apply all the steps we've selected to prepare the data for training and prediction. In our initial approach, the pipeline will encompass the following:

Preparing the 'cost' and 'rate' attributes from the raw data. Selecting the initial features to be included in the data preparation. Creating new features based on the original data. Establishing a target variable for training purposes. Segregating restaurants into rated and non-rated categories. Encoding categorical features within the data. Imputing missing data by using the median for numerical features.

In [39]:

```
# Class for applying initial prep on key columns
class PrepareCostAndRate(BaseEstimator, TransformerMixin):

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        # Extracting the approx cost feature
        X['approx_cost'] = X['approx_cost(for two people)'].astype(str).apply(lambda x: x.replace(',', '.'))
        X['approx_cost'] = X['approx_cost'].astype(float)

        # Extracting the rate feature
        X['rate_num'] = X['rate'].astype(str).apply(lambda x: x.split('/')[0])
        while True:
            try:
                X['rate_num'] = X['rate_num'].astype(float)
                break
            except ValueError as e1:
                noise_entry = str(e1).split(":")[-1].strip().replace("'", "")
                #print(f'Threating noisy entrance on rate feature: {noise_entry}')
                X['rate_num'] = X['rate_num'].apply(lambda x: x.replace(noise_entry, str(np.nan)))

        return X

# Class for selection the initial features
class InitialFeatureSelection(BaseEstimator, TransformerMixin):

    def __init__(self, initial_features=['online_order', 'book_table', 'location', 'rest_type', 'cuisines',
                                         'listed_in(type)', 'listed_in(city)', 'approx_cost', 'rate_num']):
        self.initial_features = initial_features

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        return X[self.initial_features]

# Class for creating some features
class RestaurantAdditionalFeatures(BaseEstimator, TransformerMixin):

    def __init__(self, multiples_types=True, total_cuisines=True, top_locations=10, top_cities=10, top_types=10):
        self.multiples_types = multiples_types
        self.total_cuisines = total_cuisines
        self.top_locations = top_locations
```

```
        self.top_cities = top_cities
        self.top_types = top_types

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):

        # Adding features based on counting of restaurant types and cuisines
        if self.multiples_types:
            X['multiple_types'] = X['rest_type'].astype(str).apply(lambda x: len(x.split(',')))
        if self.total_cuisines:
            X['total_cuisines'] = X['cuisines'].astype(str).apply(lambda x: len(x.split(',')))
            X.drop('cuisines', axis=1, inplace=True)

        # Creating for features for reducing granularity on location
        main_locations = list(X['location'].value_counts().index)[:self.top_locations]
        X['location_feature'] = X['location'].apply(lambda x: x if x in main_locations else 'Other')
        X.drop('location', axis=1, inplace=True)

        # Creating for features for reducing granularity on city
        main_cities = (X['listed_in(city)'].value_counts().index)[:self.top_cities]
        X['city_feature'] = X['listed_in(city)'].apply(lambda x: x if x in main_cities else 'Other')
        X.drop('listed_in(city)', axis=1, inplace=True)

        # Creating for features for reducing granularity on restaurant type
        main_rest_type = (X['rest_type'].value_counts().index)[:self.top_types]
        X['type_feature'] = X['rest_type'].apply(lambda x: x if x in main_rest_type else 'Other')
        X.drop('rest_type', axis=1, inplace=True)

        return X

# Class for creating a target based on a threshold (training only)
class CreateTarget(BaseEstimator, TransformerMixin):

    def __init__(self, threshold=3.75):
        self.threshold = threshold

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        X['target'] = X['rate_num'].apply(lambda x: 1 if x >= self.threshold else 0)

        return X
```

```python
# Class for splitting the data into new (not rated) and old (rated) restaurants
class SplitRestaurants(BaseEstimator, TransformerMixin):

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        # Splits the restaurants based on rate column (rated and non rated)
        rated = X[~X['rate_num'].isnull()]
        non_rated = X[X['rate_num'].isnull()]

        # Dropping the rate column
        rated.drop('rate_num', axis=1, inplace=True)
        non_rated.drop('rate_num', axis=1, inplace=True)

        return rated, non_rated
```

In [40]:
```python
# Reading raw data
data_path = r'../input/zomato-bangalore-restaurants/zomato.csv'
raw_data = import_data(path=data_path, n_lines=5000)

# Defining a commoon pipeline to be applied after reading the raw data
common_pipeline = Pipeline([
    ('initial_preparator', PrepareCostAndRate()),
    ('selector', InitialFeatureSelection()),
    ('feature_adder', RestaurantAdditionalFeatures()),
    ('target_creator', CreateTarget()),
    ('new_splitter', SplitRestaurants())
])

# Applying the initial pipeline
train_restaurants, new_restaurants = common_pipeline.fit_transform(raw_data)
print(f'Total restaurants to be used on training: {len(train_restaurants)}')
print(f'Total restaurants to be used on prediction: {len(new_restaurants)}')
```

```
This dataset has 17 columns, which 1 is/are applicable to optimization.

---------------------------------------------------
Memory usage (5000 lines): 0.6486 MB
Memory usage after optimization (5000 lines): 0.6295 MB
---------------------------------------------------

Reduction of 2.94% on memory usage

Total restaurants to be used on training: 41665
Total restaurants to be used on prediction: 10052
```

Let's take a look at our `train_restaurants` data:

In [41]:
```
train_restaurants.head()
```

Out[41]:

	online_order	book_table	listed_in(type)	approx_cost	multiple_types	total_cuisines	location_feature	city_feature	type_feature	target
0	Yes	Yes	Buffet	800.0	1	3	Other	Other	Casual Dining	1
1	Yes	No	Buffet	800.0	1	3	Other	Other	Casual Dining	1
2	Yes	No	Buffet	800.0	2	3	Other	Other	Other	1
3	No	No	Buffet	300.0	1	2	Other	Other	Quick Bites	0
4	No	No	Buffet	600.0	1	2	Other	Other	Casual Dining	1

Let's define and apply a categorical and a numerical pipeline for preparing the data:

In [43]:
```
# Splitting into training and testing data
X = train_restaurants.drop('target', axis=1)
y = train_restaurants['target'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.20, random_state=42)

# Splitting into cat and num data
cat_features = [col for col, dtype in X_train.dtypes.items() if dtype == 'object']
num_features = [col for col, dtype in X_train.dtypes.items() if dtype != 'object']

# Building a numerical processing pipeline
num_pipeline = Pipeline([
```

```
    ('imputer', SimpleImputer(strategy='median'))
])

# Building a categorical processing pipeline
cat_pipeline = Pipeline([
    ('encoder', DummiesEncoding(dummy_na=True))
])

# Building a complete Pipeline
full_pipeline = ColumnTransformer([
    ('num', num_pipeline, num_features),
    ('cat', cat_pipeline, cat_features)
])

# Applying the full pipeline into the data
X_train_prep = full_pipeline.fit_transform(X_train)
X_test_prep = full_pipeline.fit_transform(X_test)
print(f'Shape of X_train_prep: {X_train_prep.shape}')
print(f'Shape of X_test_prep: {X_test_prep.shape}')

# returning categorical features after encoding and creating a new set of features after the pipeline
encoded_features = full_pipeline.named_transformers_['cat']['encoder'].features_after_encoding
model_features = num_features + encoded_features
print(f'\nSanity check! Number of features after the pipeline (must be the same as shape[1]): {len(model_features)}')
```

```
Shape of X_train_prep: (33332, 53)
Shape of X_test_prep: (8333, 53)

Sanity check! Number of features after the pipeline (must be the same as shape[1]): 53
```

We are now ready to train classification models and select the best one for our task.

Training a Model

Finally, we arrive at the focal point of our project: training a classification model to predict the probability of success (a high rating) for a given restaurant. We have already completed approximately 80% of the necessary preparation and transformations.

For this task, let's train a `LogisticRegression`, `DecisionTrees`, `RandomForest` and `LightGBM` classifiers, each one using `RandomizedGridSearchCV` with 5 k-folds and hyperparameters pre-defined.

In [44]:
```
# Logistic Regression hyperparameters
logreg_param_grid = {
    'C': np.linspace(0.1, 10, 20),
    'penalty': ['l1', 'l2'],
```

```
    'class_weight': ['balanced', None],
    'random_state': [42],
    'solver': ['liblinear']
}

# Decision Trees hyperparameters
tree_param_grid = {
    'criterion': ['entropy', 'gini'],
    'max_depth': [3, 5, 10, 20],
    'max_features': np.arange(1, X_train.shape[1]),
    'class_weight': ['balanced', None],
    'random_state': [42]
}

# Random Forest hyperparameters
forest_param_grid = {
    'bootstrap': [True, False],
    'max_depth': [3, 5, 10, 20, 50],
    'n_estimators': [50, 100, 200, 500],
    'random_state': [42],
    'max_features': ['auto', 'sqrt'],
    'class_weight': ['balanced', None]
}

# LightGBM hyperparameters
lgbm_param_grid = {
    'num_leaves': list(range(8, 92, 4)),
    'min_data_in_leaf': [10, 20, 40, 60, 100],
    'max_depth': [3, 4, 5, 6, 8, 12, 16],
    'learning_rate': [0.1, 0.05, 0.01, 0.005],
    'bagging_freq': [3, 4, 5, 6, 7],
    'bagging_fraction': np.linspace(0.6, 0.95, 10),
    'reg_alpha': np.linspace(0.1, 0.95, 10),
    'reg_lambda': np.linspace(0.1, 0.95, 10),
}

lgbm_fixed_params = {
    'application': 'binary',
    'objective': 'binary',
    'metric': 'auc',
    'is_unbalance': 'true',
    'boosting_type': 'gbdt',
    'num_leaves': 31,
    'feature_fraction': 0.5,
    'bagging_fraction': 0.5,
```

```
    'bagging_freq': 20,
    'learning_rate': 0.05,
    'verbose': 0
}
```

In [45]:
```
# Setting up classifiers
set_classifiers = {
    'LogisticRegression': {
        'model': LogisticRegression(),
        'params': logreg_param_grid
    },
    'DecisionTrees': {
        'model': DecisionTreeClassifier(),
        'params': tree_param_grid
    },
    'RandomForest': {
        'model': RandomForestClassifier(),
        'params': forest_param_grid
    },
    'LightGBM': {
        'model': lgb.LGBMClassifier(**lgbm_fixed_params),
        'params': lgbm_param_grid
    }
}
```

Training and evaluating classifiers

In [46]:
```
# Creating an instance for the homemade class BinaryClassifiersAnalysis
clf_tool = BinaryClassifiersAnalysis()
clf_tool.fit(set_classifiers, X_train_prep, y_train, random_search=True, cv=5, verbose=5)
```

```
Training model LogisticRegression

Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    4.7s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   17.3s finished
Training model DecisionTrees

Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  12 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:    1.4s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
```

```
Training model RandomForest

Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   12.6s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  1.2min finished
Training model LightGBM

Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   11.7s finished
```

In [47]:
```
# Evaluating metrics
df_performances = clf_tool.evaluate_performance(X_train_prep, y_train, X_test_prep, y_test, cv=5)
df_performances.reset_index(drop=True).style.background_gradient(cmap='Blues')
```

```
Evaluating model LogisticRegression

Evaluating model DecisionTrees

Evaluating model RandomForest

Evaluating model LightGBM
```

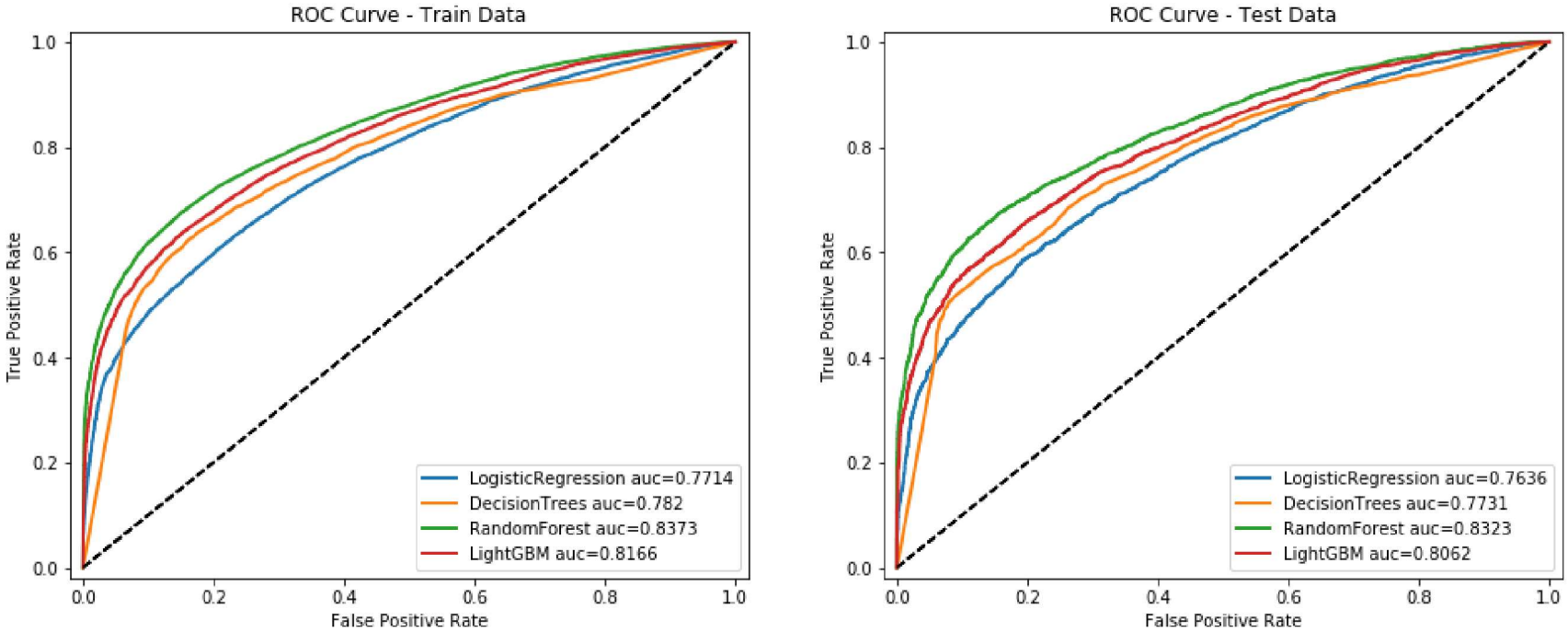
Out[47]:

	model	approach	acc	precision	recall	f1	auc	total_time
0	LogisticRegression	Treino 5 K-folds	0.7016	0.7316	0.612	0.6664	0.7714	9.337
1	LogisticRegression	Teste	0.6978	0.7274	0.5946	0.6543	0.7636	0.033
2	DecisionTrees	Treino 5 K-folds	0.7286	0.7506	0.6641	0.7044	0.782	1.927
3	DecisionTrees	Teste	0.7107	0.7447	0.6063	0.6684	0.7731	0.02
4	RandomForest	Treino 5 K-folds	0.7638	0.8044	0.6805	0.7373	0.8373	45.672
5	RandomForest	Teste	0.7617	0.8086	0.6609	0.7273	0.8323	0.208
6	LightGBM	Treino 5 K-folds	0.7455	0.7991	0.6378	0.7094	0.8166	10.576
7	LightGBM	Teste	0.7318	0.7831	0.6118	0.6869	0.8062	0.07

It's very interesting to see that the `RandomForest` was the best classification model for our task. Meanwhile it's also the heaviest one in terms of time consuming. Let's use it for further evaluation.

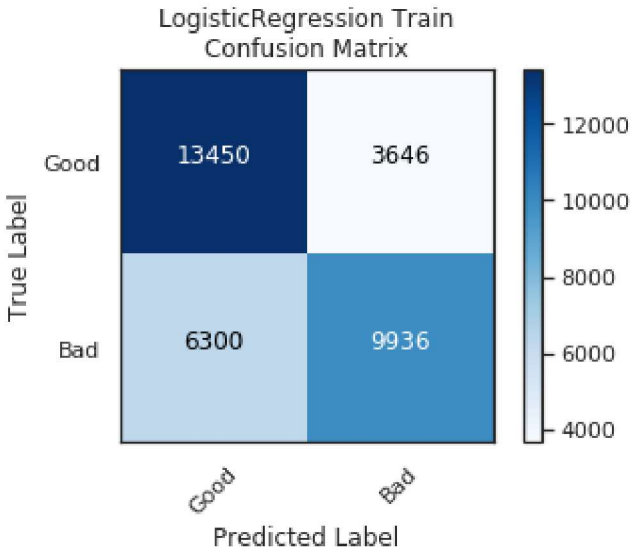
Plotting the ROC Curve for the classifiers (train and test)

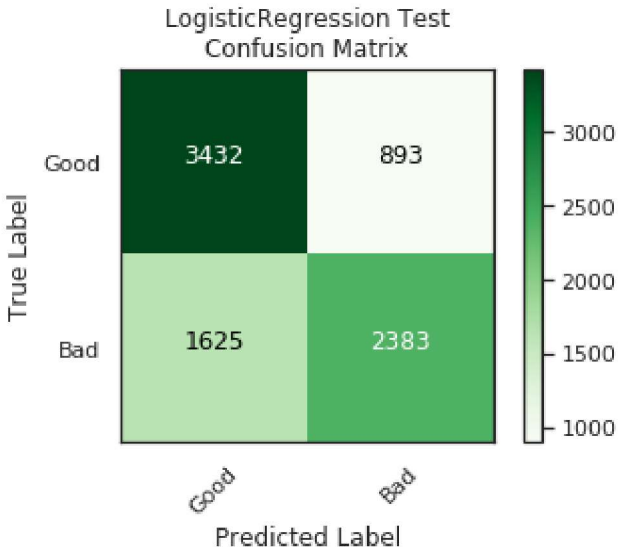
In [48]:
```
clf_tool.plot_roc_curve()
```

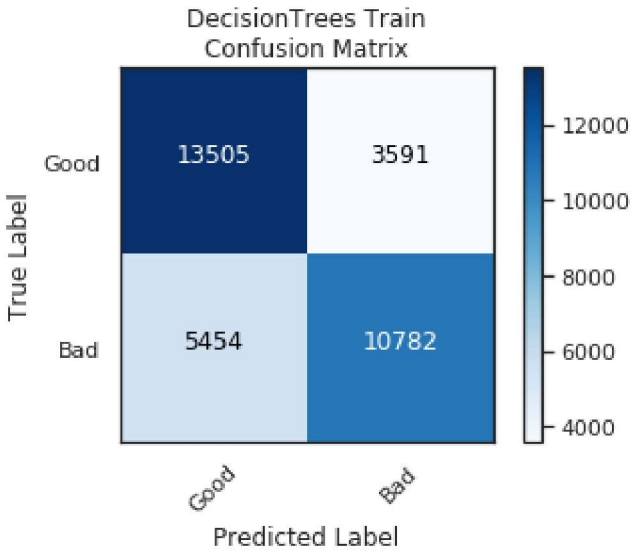


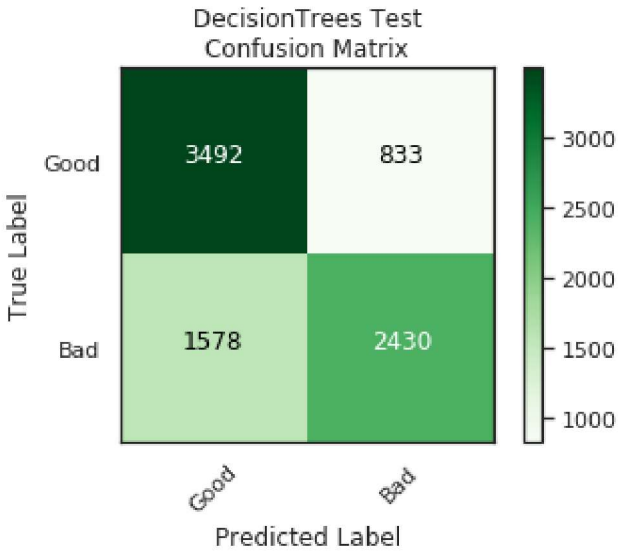
Plotting Confusion Matrix for each classifier (train and test)

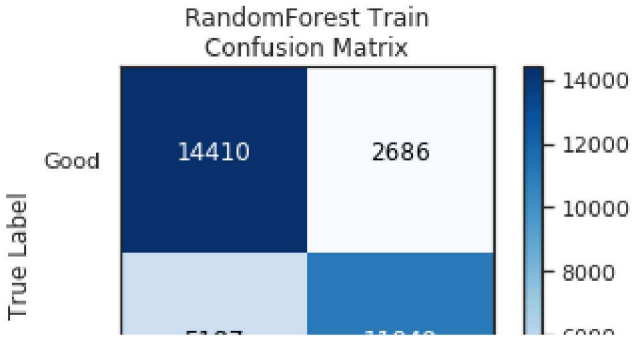
In [49]:
```
clf_tool.plot_confusion_matrix(classes=['Good', 'Bad'])
```

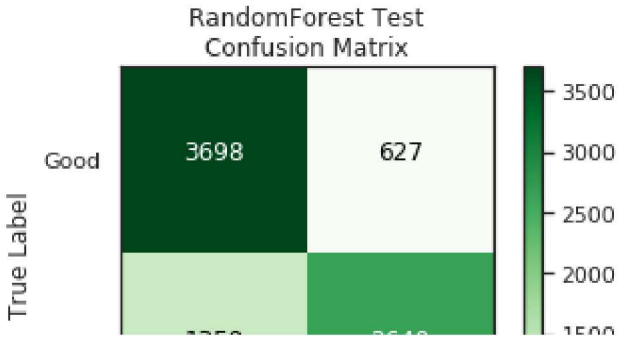

LogisticRegression Train
Confusion Matrix
Good
Bad
True Label
13450
3646
6300
9936
12000
10000
8000
6000
4000
Good
Bad
Predicted Label

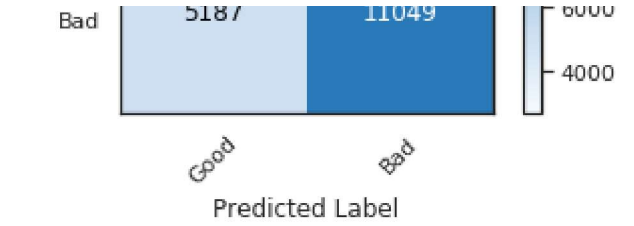

LogisticRegression Test
Confusion Matrix
Good
Bad
True Label
3432
893
1625
2383
3000
2500
2000
1500
1000
Good
Bad
Predicted Label

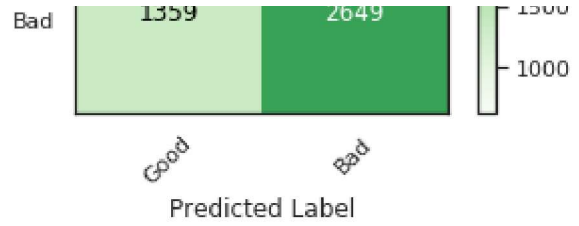

DecisionTrees Train
Confusion Matrix
Good
Bad
True Label
13505
3591
5454
10782
12000
10000
8000
6000
4000
Good
Bad
Predicted Label

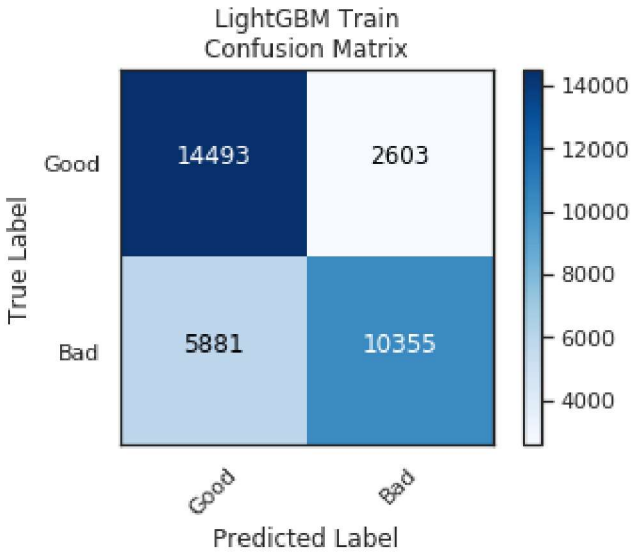

DecisionTrees Test
Confusion Matrix
Good
Bad
True Label
3492
833
1578
2430
3000
2500
2000
1500
1000
Good
Bad
Predicted Label

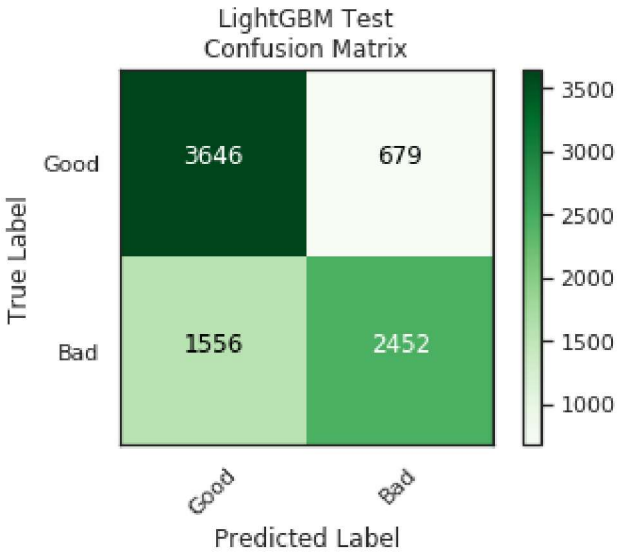

RandomForest Train
Confusion Matrix
Good
True Label
14410
2686
14000
12000
10000
8000


RandomForest Test
Confusion Matrix
Good
True Label
3698
627
3500
3000
2500
2000



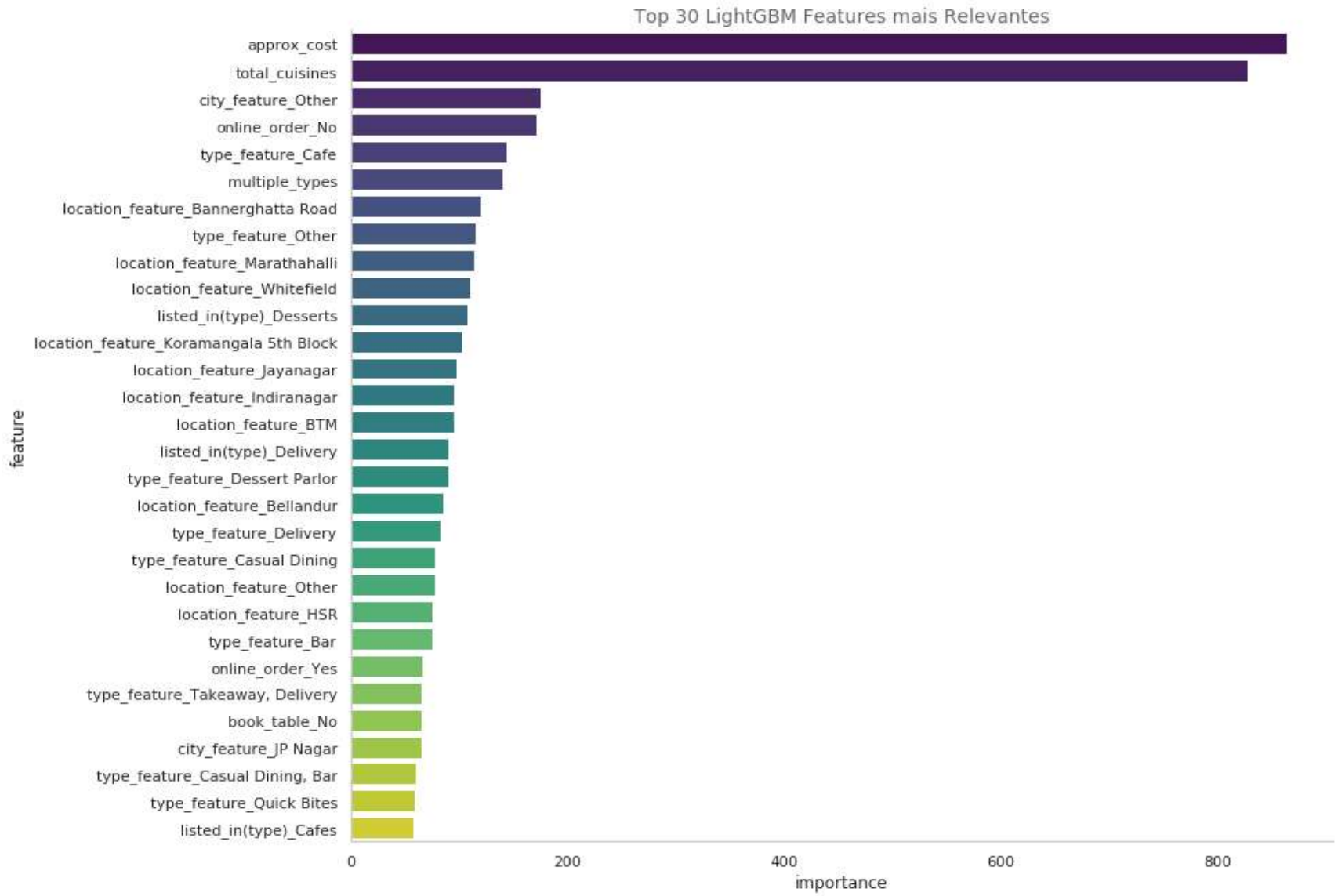






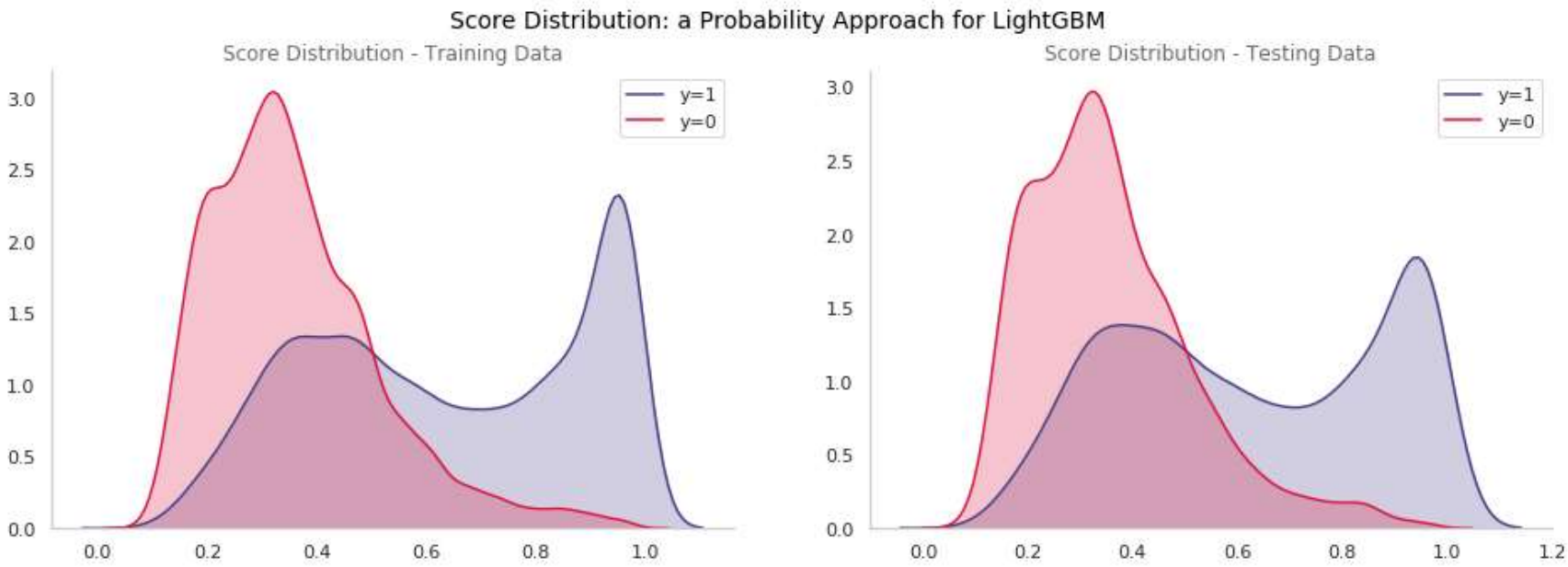
Looking at the feature importance of a specific model

In [50]:
```
fig, ax = plt.subplots(figsize=(13, 11))
forest_feature_importance = clf_tool.feature_importance_analysis(model_features, specific_model='LightGBM', ax=ax)
plt.show()
```



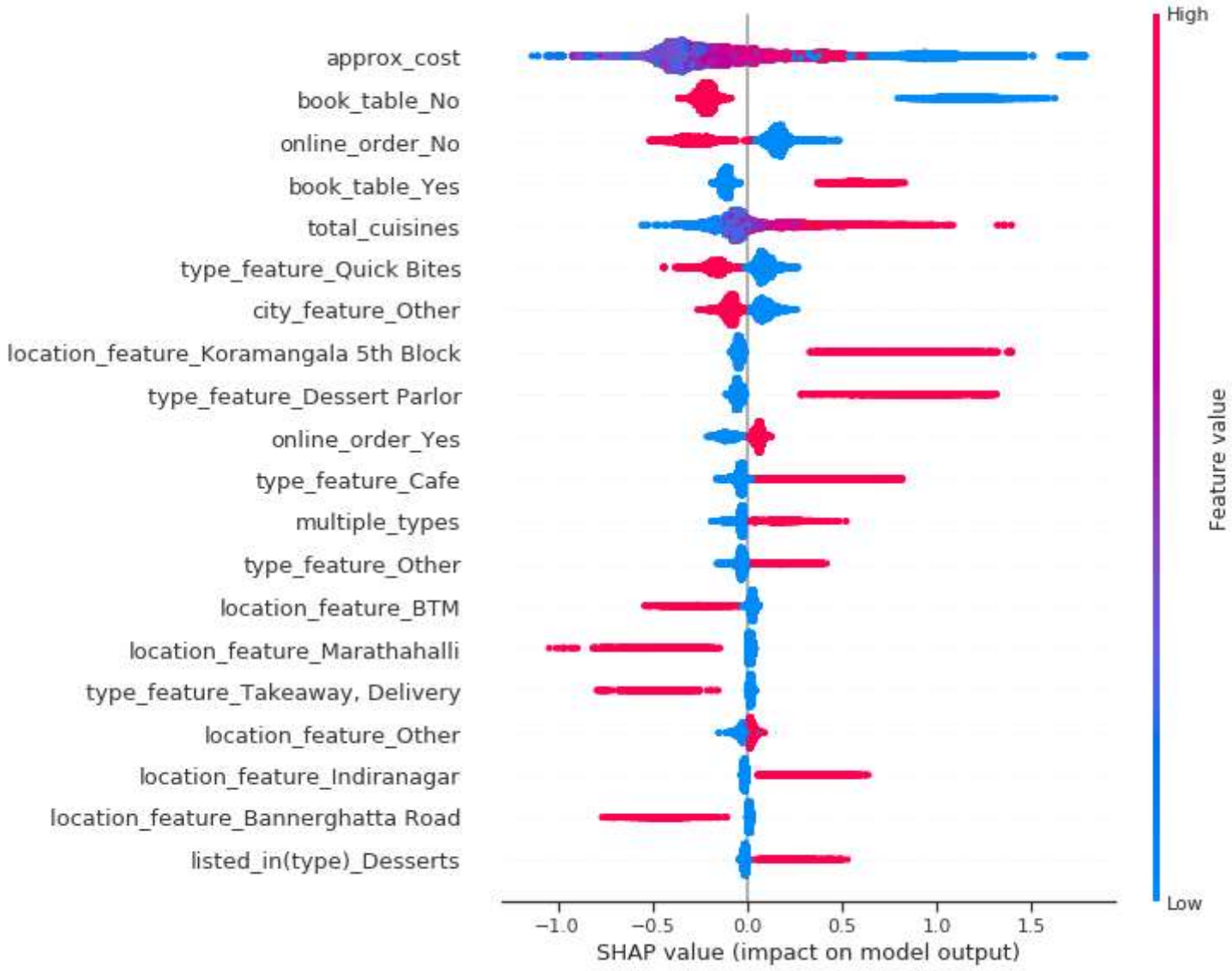
Looking at score (proba) distribution for a specific model

In [51]:
```
clf_tool.plot_score_distribution('LightGBM', shade=True)
```



- *Using shap analysis for evaluating features patterns*

In [53]:
```
# Returning the LightGBM model and applying shap value
model = clf_tool.classifiers_info['LightGBM']['estimator']
explainer = shap.TreeExplainer(model)
df_X_train_prep = pd.DataFrame(X_train_prep, columns=model_features)
shap_values = explainer.shap_values(df_X_train_prep)

# Plotting a summary plot using shap
shap.summary_plot(shap_values, df_X_train_prep)
```



Conclusion

After going through all the tasks, we can conclude that it is indeed possible to predict the success of new restaurants added to the Zomato service, particularly in terms of their ratings. This capability holds significant value for businesses looking to assess key restaurant concepts and customer preferences in the Bengaluru region. With this valuable information, one can thoroughly examine a restaurant's features before its launch. Both business owners and customers would greatly appreciate such insights.

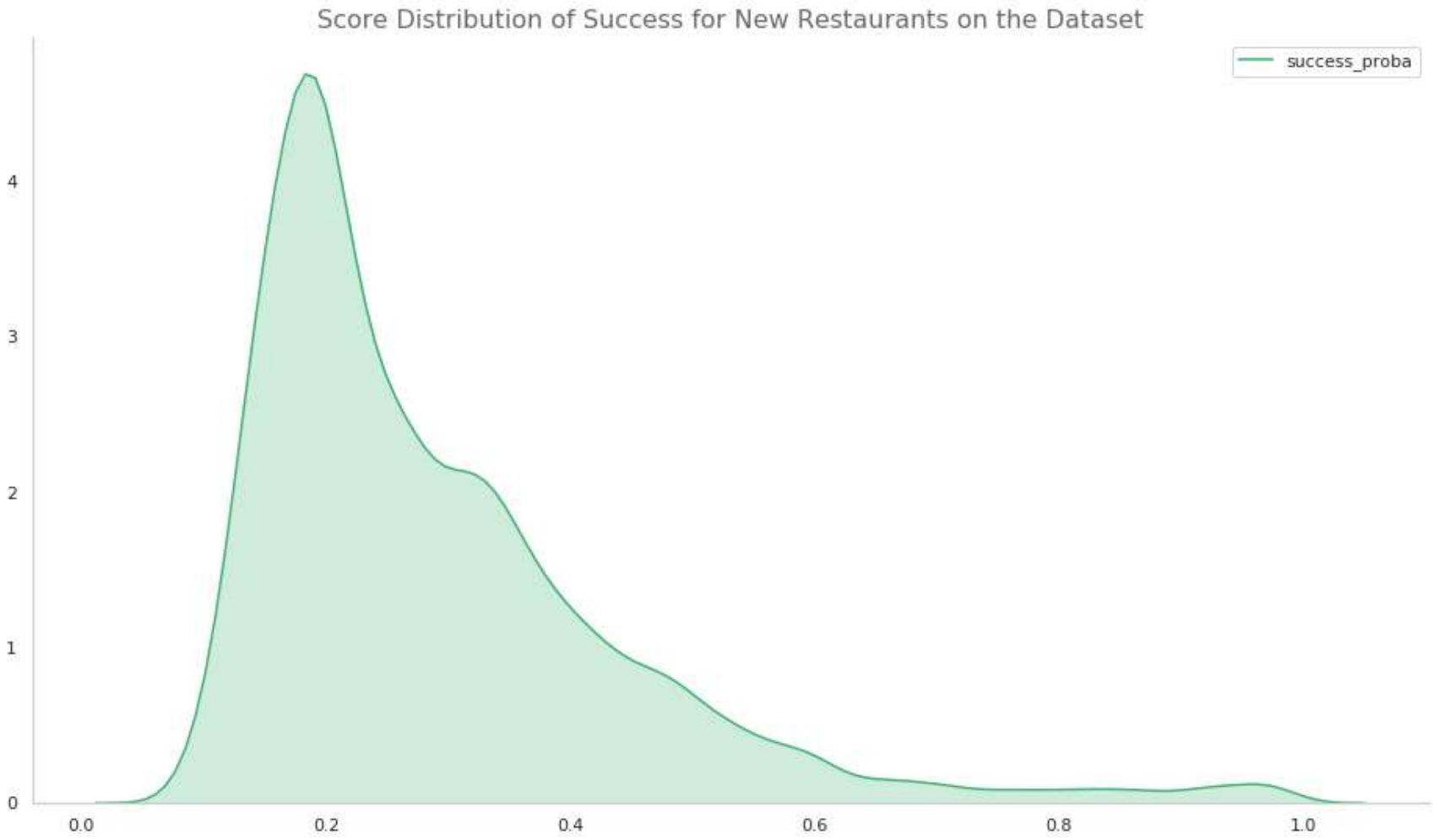
Now, considering a developer's perspective, it would be beneficial to code this process as a production script that receives data from new restaurants on a monthly (or even daily) basis and provides a 'success score probability.' To achieve this, we need to encapsulate several steps, such as building (or reading) a complete pipeline in a pickle (pkl) format, constructing (or reading) a classification model, also in pkl format, and finally, applying the predict or predict_proba methods to score the new data. Let's simulate this scenario.

In [54]:
```
# Applying the full pipeline into new restaurants
new_restaurants_prep = full_pipeline.fit_transform(new_restaurants.drop('target', axis=1))

# Returning the best model and predicting the rate for new restaurants
model = clf_tool.classifiers_info['LightGBM']['estimator']
y_pred = model.predict(new_restaurants_prep)
y_probas = model.predict_proba(new_restaurants_prep)
y_scores = y_probas[:, 1]

# Labelling new data
new_restaurants['success_class'] = y_pred
new_restaurants['success_proba'] = y_scores
new_restaurants.head()
```

Out[54]:

	online_order	book_table	listed_in(type)	approx_cost	multiple_types	total_cuisines	location_feature	city_feature	type_feature	target	s
72	No	No	Delivery	150.0	1	1	Other	Other	Quick Bites	0	
75	No	No	Delivery	500.0	2	2	Other	Other	Takeaway, Delivery	0	
84	No	No	Delivery	100.0	1	2	Other	Other	Quick Bites	0	
90	No	No	Delivery	500.0	1	2	Other	Other	Delivery	0	
91	No	No	Delivery	400.0	2	1	Other	Other	Takeaway, Delivery	0	

In [55]:
```
# Looking at the score distribution for new restaurants
fig, ax = plt.subplots(figsize=(16, 9))
sns.kdeplot(new_restaurants['success_proba'], ax=ax, shade=True, color='mediumseagreen')
format_spines(ax, right_border=False)
ax.set_title('Score Distribution of Success for New Restaurants on the Dataset', size=16, color='dimgrey')
plt.show()
```



What are the most promissing restaurants (with the highest proba score)?

In [56]:
```
# Ordering new restaurants by proba score
new_restaurants_data = new_restaurants.reset_index().merge(raw_data.reset_index()[['name', 'index']], how='left', on='i
top_new = new_restaurants_data.sort_values(by='success_proba', ascending=False).head(10)
top_new = top_new.loc[:, ['name', 'success_proba', 'online_order', 'book_table', 'listed_in(type)',
                          'approx_cost', 'multiple_types', 'total_cuisines', 'location_feature',
                          'city_feature', 'type_feature']]
top_new
```

Out[56]:

	name	success_proba	online_order	book_table	listed_in(type)	approx_cost	multiple_types	total_cuisines	location_feature	city_fe
2198	Biergarten	0.985066	No	Yes	Dine-out	2.1	2	7	Koramangala 5th Block	
2302	Biergarten	0.985066	No	Yes	Pubs and bars	2.1	2	7	Koramangala 5th Block	
2298	Biergarten	0.984221	No	Yes	Drinks & nightlife	2.1	2	7	Koramangala 5th Block	
3941	Inntense Restobar	0.983622	No	Yes	Pubs and bars	1.6	2	5	Indiranagar	Indira
3937	Inntense Restobar	0.982903	No	Yes	Drinks & nightlife	1.6	2	5	Indiranagar	Indira
4283	The Coastal Crew by Fujian on 24th	0.980410	Yes	Yes	Dine-out	1.1	2	5	JP Nagar	Jaya
8480	By Chance	0.979379	No	Yes	Dine-out	1.1	2	4	Other	MG
6483	Cheers Pub Bar & Restro	0.978530	No	Yes	Pubs and bars	1.1	2	5	Other	Korama 5th
8958	Inntense Restobar	0.978381	No	Yes	Pubs and bars	1.6	2	4	Indiranagar	
6294	Cheers Pub Bar & Restro	0.977792	No	Yes	Dine-out	1.1	2	5	Other	Korama 5th

What are the restaurants with the lowest likely probability? (the ones that maybe customers won't order for Zomato)

In [57]:
```
# Ordering new restaurants by proba score
bottom_new = new_restaurants_data.sort_values(by='success_proba', ascending=True).head(10)
bottom_new = bottom_new.loc[:, ['name', 'success_proba', 'online_order', 'book_table', 'listed_in(type)',
                          'approx_cost', 'multiple_types', 'total_cuisines', 'location_feature',
                          'city_feature', 'type_feature']]
bottom_new
```

Out[57]:

	name	success_proba	online_order	book_table	listed_in(type)	approx_cost	multiple_types	total_cuisines	location_feature	city_featu
4582	Sapid	0.076830	No	No	Delivery	250.0	1	1	Bannerghatta Road	JP Nag
4590	Jugz Cafe	0.076830	No	No	Delivery	250.0	1	1	Bannerghatta Road	JP Nag
1890	Sapid	0.084764	No	No	Delivery	250.0	1	1	Bannerghatta Road	BT
231	Kitchen King	0.088447	No	No	Delivery	250.0	1	3	Bannerghatta Road	Oth
4614	Ambur Hotel	0.088475	No	No	Delivery	250.0	1	1	Bannerghatta Road	JP Nag
590	Super Chef's (New Royal treat)	0.089171	No	No	Delivery	NaN	1	3	Bannerghatta Road	Oth
355	Super Chef's (New Royal treat)	0.089171	No	No	Delivery	NaN	1	3	Bannerghatta Road	Oth
435	Kitchen King	0.089865	No	No	Dine-out	250.0	1	3	Bannerghatta Road	Oth
4607	Chef Snow	0.091352	No	No	Delivery	300.0	1	2	Bannerghatta Road	JP Nag
4785	Ambur Hotel	0.091792	No	No	Dine-out	250.0	1	1	Bannerghatta Road	JP Nag

We have finally completed our work here, and we can be very excited about what we have accomplished. With this implementation, we were able to provide valuable information for business areas and Zomato customers, aiding them in selecting the best restaurants for ordering, especially the newly established ones. This serves as an example of what predictive models can achieve in practical applications.