Project_SLC_DSBA_INNHotels_FullCode

August 25, 2022

1 INN Hotels Project

1.1 Context

A significant number of hotel bookings are called-off due to cancellations or no-shows. The typical reasons for cancellations include change of plans, scheduling conflicts, etc. This is often made easier by the option to do so free of charge or preferably at a low cost which is beneficial to hotel guests but it is a less desirable and possibly revenue-diminishing factor for hotels to deal with. Such losses are particularly high on last-minute cancellations.

The new technologies involving online booking channels have dramatically changed customers' booking possibilities and behavior. This adds a further dimension to the challenge of how hotels handle cancellations, which are no longer limited to traditional booking and guest characteristics.

The cancellation of bookings impact a hotel on various fronts: * Loss of resources (revenue) when the hotel cannot resell the room. * Additional costs of distribution channels by increasing commissions or paying for publicity to help sell these rooms. * Lowering prices last minute, so the hotel can resell a room, resulting in reducing the profit margin. * Human resources to make arrangements for the guests.

1.2 Objective

The increasing number of cancellations calls for a Machine Learning based solution that can help in predicting which booking is likely to be canceled. INN Hotels Group has a chain of hotels in Portugal, they are facing problems with the high number of booking cancellations and have reached out to your firm for data-driven solutions. You as a data scientist have to analyze the data provided to find which factors have a high influence on booking cancellations, build a predictive model that can predict which booking is going to be canceled in advance, and help in formulating profitable policies for cancellations and refunds.

1.3 Data Description

The data contains the different attributes of customers' booking details. The detailed data dictionary is given below.

Data Dictionary

- Booking_ID: unique identifier of each booking
- no_of_adults: Number of adults
- no_of_children: Number of Children

- no_of_weekend_nights: Number of weekend nights (Saturday or Sunday) the guest stayed or booked to stay at the hotel
- no_of_week_nights: Number of week nights (Monday to Friday) the guest stayed or booked to stay at the hotel
- type_of_meal_plan: Type of meal plan booked by the customer:
  - Not Selected – No meal plan selected
  - Meal Plan 1 – Breakfast
  - Meal Plan 2 – Half board (breakfast and one other meal)
  - Meal Plan 3 – Full board (breakfast, lunch, and dinner)
- required_car_parking_space: Does the customer require a car parking space? (0 - No, 1- Yes)
- room_type_reserved: Type of room reserved by the customer. The values are ciphered (encoded) by INN Hotels.
- lead_time: Number of days between the date of booking and the arrival date
- arrival_year: Year of arrival date
- arrival_month: Month of arrival date
- arrival_date: Date of the month
- market_segment_type: Market segment designation.
- repeated_guest: Is the customer a repeated guest? (0 - No, 1- Yes)
- no_of_previous_cancellations: Number of previous bookings that were canceled by the customer prior to the current booking
- no_of_previous_bookings_not_canceled: Number of previous bookings not canceled by the customer prior to the current booking
- avg_price_per_room: Average price per day of the reservation; prices of the rooms are dynamic. (in euros)
- no_of_special_requests: Total number of special requests made by the customer (e.g. high floor, view from the room, etc)
- booking_status: Flag indicating if the booking was canceled or not.

1.4 Importing necessary libraries and data

[ ]:
```python
# To filter the warnings
import warnings
warnings.filterwarnings("ignore")

# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np

# libaries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Library to split data
from sklearn.model_selection import train_test_split
```

```
# To build linear model for statistical analysis and prediction
import statsmodels.stats.api as sms
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
from statsmodels.tools.tools import add_constant
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

# To get diferent metric scores
from sklearn import metrics
from sklearn.metrics import (
    f1_score,
    accuracy_score,
    recall_score,
    precision_score,
    confusion_matrix,
    roc_auc_score,
    plot_confusion_matrix,
    precision_recall_curve,
    roc_curve,
)

pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

1.5 Data Overview

- Observations
- Sanity checks

[ ]:
```
#mounting google colab drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[ ]:
```
# read the data
df = pd.read_csv('/content/drive/MyDrive/University Of Texas/Supervised␣
↪Learning - Classification/INNHotelsGroup.csv')
```

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

[ ]:
```
  Booking_ID  no_of_adults  no_of_children  no_of_weekend_nights  \
0   INN00001             2               0                     1
1   INN00002             2               0                     2
2   INN00003             1               0                     2
```

```
3   INN00004             2               0                      0
4   INN00005             2               0                      1

   no_of_week_nights type_of_meal_plan  required_car_parking_space  \
0                  2       Meal Plan 1                           0
1                  3      Not Selected                           0
2                  1       Meal Plan 1                           0
3                  2       Meal Plan 1                           0
4                  1      Not Selected                           0

  room_type_reserved  lead_time  arrival_year  arrival_month  arrival_date  \
0        Room_Type 1        224          2017             10             2
1        Room_Type 1          5          2018             11             6
2        Room_Type 1          1          2018              2            28
3        Room_Type 1        211          2018              5            20
4        Room_Type 1         48          2018              4            11

  market_segment_type  repeated_guest  no_of_previous_cancellations  \
0             Offline               0                             0
1              Online               0                             0
2              Online               0                             0
3              Online               0                             0
4              Online               0                             0

   no_of_previous_bookings_not_canceled  avg_price_per_room  \
0                                     0              65.000
1                                     0             106.680
2                                     0              60.000
3                                     0             100.000
4                                     0              94.500

   no_of_special_requests booking_status
0                       0   Not_Canceled
1                       1   Not_Canceled
2                       0       Canceled
3                       0       Canceled
4                       0       Canceled
```

[ ]:
```
df.shape
```

[ ]:
```
(36275, 19)
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36275 entries, 0 to 36274
Data columns (total 19 columns):
```

```
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Booking_ID                            36275 non-null  object
 1   no_of_adults                          36275 non-null  int64
 2   no_of_children                        36275 non-null  int64
 3   no_of_weekend_nights                  36275 non-null  int64
 4   no_of_week_nights                     36275 non-null  int64
 5   type_of_meal_plan                     36275 non-null  object
 6   required_car_parking_space            36275 non-null  int64
 7   room_type_reserved                    36275 non-null  object
 8   lead_time                             36275 non-null  int64
 9   arrival_year                          36275 non-null  int64
 10  arrival_month                         36275 non-null  int64
 11  arrival_date                          36275 non-null  int64
 12  market_segment_type                   36275 non-null  object
 13  repeated_guest                        36275 non-null  int64
 14  no_of_previous_cancellations          36275 non-null  int64
 15  no_of_previous_bookings_not_canceled  36275 non-null  int64
 16  avg_price_per_room                    36275 non-null  float64
 17  no_of_special_requests                36275 non-null  int64
 18  booking_status                        36275 non-null  object
dtypes: float64(1), int64(13), object(5)
memory usage: 5.3+ MB
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
Booking_ID                              0
no_of_adults                            0
no_of_children                          0
no_of_weekend_nights                    0
no_of_week_nights                       0
type_of_meal_plan                       0
required_car_parking_space              0
room_type_reserved                      0
lead_time                               0
arrival_year                            0
arrival_month                           0
arrival_date                            0
market_segment_type                     0
repeated_guest                          0
no_of_previous_cancellations            0
no_of_previous_bookings_not_canceled    0
avg_price_per_room                      0
no_of_special_requests                  0
booking_status                          0
dtype: int64
```

No null values

[ ]:
```
df.describe().T
```

[ ]:
```
                                            count     mean    std      min  \
no_of_adults                            36275.000    1.845  0.519    0.000
no_of_children                          36275.000    0.105  0.403    0.000
no_of_weekend_nights                    36275.000    0.811  0.871    0.000
no_of_week_nights                       36275.000    2.204  1.411    0.000
required_car_parking_space              36275.000    0.031  0.173    0.000
lead_time                               36275.000   85.233 85.931    0.000
arrival_year                            36275.000 2017.820  0.384 2017.000
arrival_month                           36275.000    7.424  3.070    1.000
arrival_date                            36275.000   15.597  8.740    1.000
repeated_guest                          36275.000    0.026  0.158    0.000
no_of_previous_cancellations            36275.000    0.023  0.368    0.000
no_of_previous_bookings_not_canceled    36275.000    0.153  1.754    0.000
avg_price_per_room                      36275.000  103.424 35.089    0.000
no_of_special_requests                  36275.000    0.620  0.786    0.000

                                            25%      50%      75%      max
no_of_adults                              2.000    2.000    2.000    4.000
no_of_children                            0.000    0.000    0.000   10.000
no_of_weekend_nights                      0.000    1.000    2.000    7.000
no_of_week_nights                         1.000    2.000    3.000   17.000
required_car_parking_space                0.000    0.000    0.000    1.000
lead_time                                17.000   57.000  126.000  443.000
arrival_year                           2018.000 2018.000 2018.000 2018.000
arrival_month                             5.000    8.000   10.000   12.000
arrival_date                              8.000   16.000   23.000   31.000
repeated_guest                            0.000    0.000    0.000    1.000
no_of_previous_cancellations              0.000    0.000    0.000   13.000
no_of_previous_bookings_not_canceled      0.000    0.000    0.000   58.000
avg_price_per_room                       80.300   99.450  120.000  540.000
no_of_special_requests                    0.000    0.000    1.000    5.000
```

Insights:

- `no_of_week_nights` is right skewed once that the MAX value is much higher than Q3 and median
- `lead_time` is right skewed
- Few variables can be trated as numerical, my hint: `avg_price_per_room`, `lead_time`

[ ]:
```
df.duplicated().sum()
```

[ ]:
```
0
```

No duplicated values

1.6 Exploratory Data Analysis (EDA)

- EDA is an important part of any project involving data.
- It is important to investigate and understand the data better before building a model with it.
- A few questions have been mentioned below which will help you approach the analysis in the right manner and generate insights from the data.
- A thorough analysis of the data, in addition to the questions mentioned below, should be done.

Leading Questions: 1. What are the busiest months in the hotel? 2. Which market segment do most of the guests come from? 3. Hotel rates are dynamic and change according to demand and customer demographics. What are the differences in room prices in different market segments? 4. What percentage of bookings are canceled? 5. Repeating guests are the guests who stay in the hotel often and are important to brand equity. What percentage of repeating guests cancel? 6. Many guests have special requirements when booking a hotel room. Do these requirements affect booking cancellation?

Univariate Analysiscat

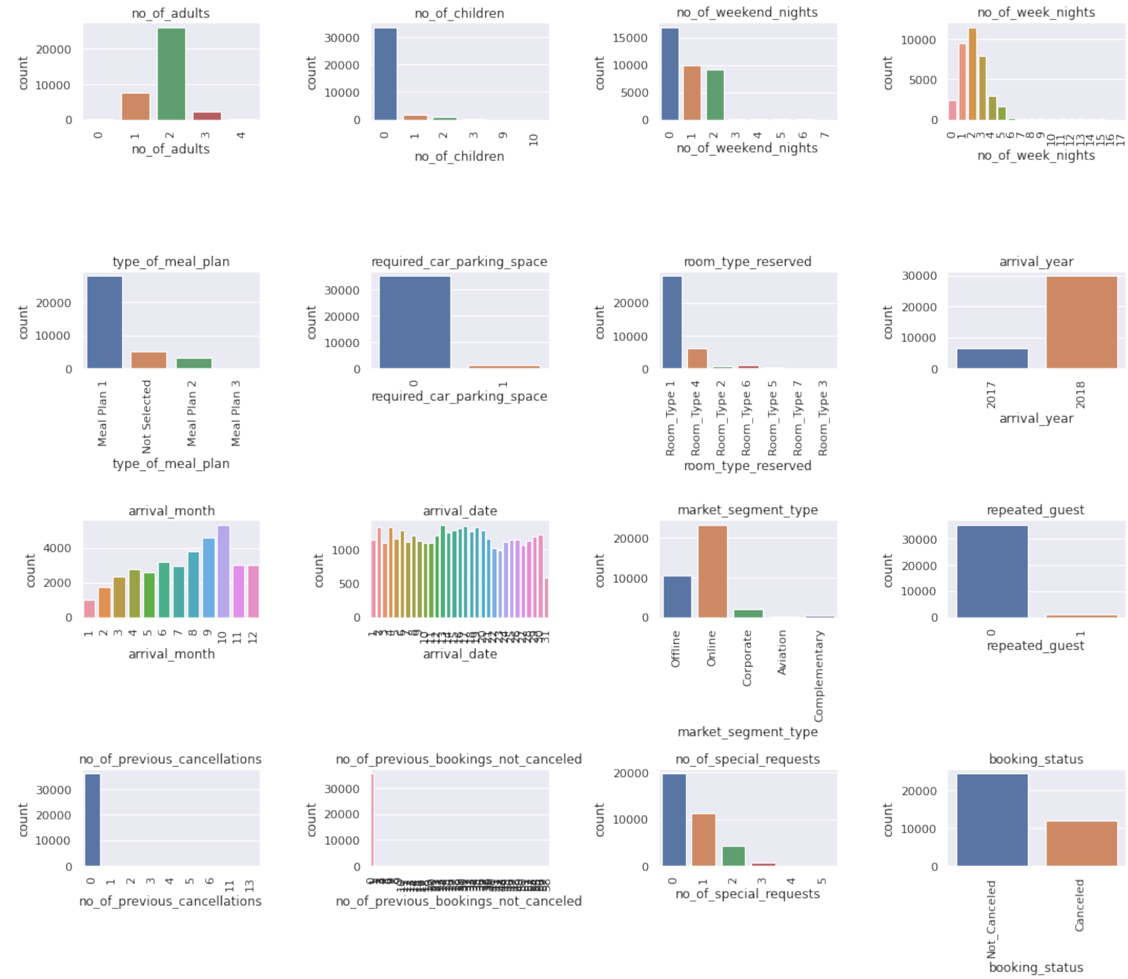
[ ]:
```
df.columns
```

[ ]:
```
Index(['Booking_ID', 'no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'type_of_meal_plan', 'required_car_parking_space',
       'room_type_reserved', 'lead_time', 'arrival_year', 'arrival_month',
       'arrival_date', 'market_segment_type', 'repeated_guest',
       'no_of_previous_cancellations', 'no_of_previous_bookings_not_canceled',
       'avg_price_per_room', 'no_of_special_requests', 'booking_status'],
      dtype='object')
```

[ ]:
```
cat = ['no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'type_of_meal_plan', 'required_car_parking_space',
       'room_type_reserved', 'arrival_year', 'arrival_month',
       'arrival_date', 'market_segment_type', 'repeated_guest',
       'no_of_previous_cancellations', 'no_of_previous_bookings_not_canceled',␣
↪'no_of_special_requests', 'booking_status']
```

[ ]:
```
#Ploting a countplot for all categorical features

plt.figure(figsize=(15,15))
sns.set_theme()

for i,column in enumerate(cat):
  plt.subplot(5, 4, i + 1)
  sns.countplot(data=df, x=df[column])
  plt.tight_layout()
  plt.title(column)
  plt.xticks(rotation=90)
```

```python
plt.show()
```



insights:

- Most of the bookins are for 2 adults and no kids
- Most of the bookings are from online market segment
- `arrival_date` forms an uniform distribution
- Far majority don't need car parking space
- Most of the bookings are for short stayage. Like one, two or three days. There are some outliers though

Will do some further investigation on: * `no_of_previos_bookings_no_canceled` * `no_of_previous_cancelations` * `no_of_weekend_nights` * `no_of_week_nights`

```python
[ ]: averigate = ['no_of_previous_bookings_not_canceled',
'no_of_previous_cancellations',
'no_of_weekend_nights',
'no_of_week_nights']
```

```
[ ]: for i in averigate:
       print(i+":", len(df[i].unique()))
```

```
no_of_previous_bookings_not_canceled: 59
no_of_previous_cancellations: 9
no_of_weekend_nights: 8
no_of_week_nights: 18
```

```
[ ]: for i in averigate:
       print(i+":", df[i].value_counts())
       print(50*'-')
```

```
no_of_previous_bookings_not_canceled: 0     35463
1       228
2       112
3        80
4        65
5        60
6        36
7        24
8        23
10       19
9        19
11       15
12       12
14        9
15        8
16        7
13        7
18        6
20        6
21        6
17        6
19        6
22        6
25        3
27        3
24        3
23        3
44        2
29        2
48        2
28        2
30        2
32        2
31        2
26        2
46        1
```

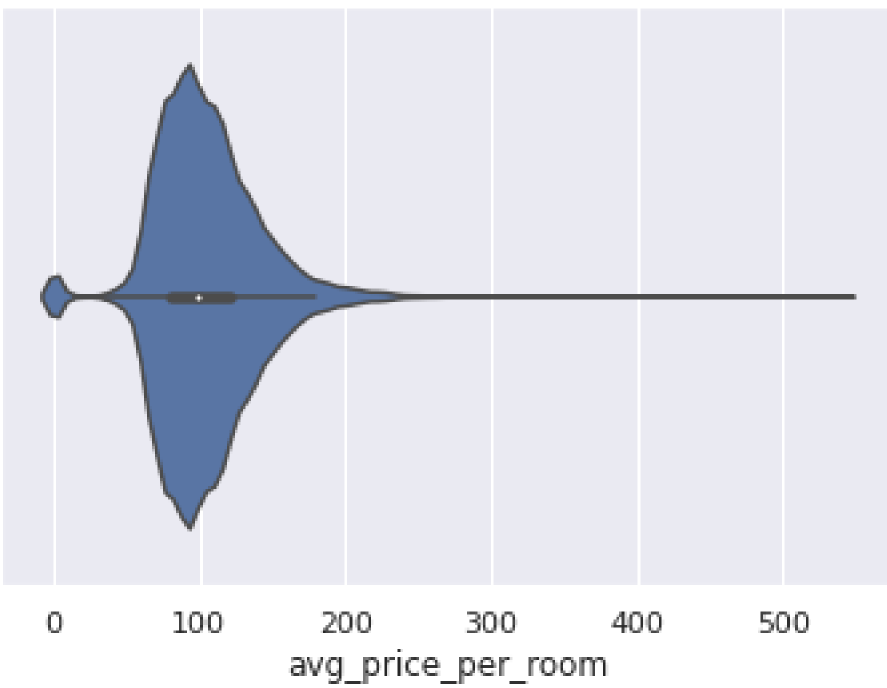
```
55        1
45        1
57        1
53        1
54        1
58        1
41        1
40        1
43        1
35        1
50        1
56        1
33        1
37        1
42        1
51        1
38        1
34        1
39        1
52        1
49        1
47        1
36        1
Name: no_of_previous_bookings_not_canceled, dtype: int64
--------------------------------------------------
no_of_previous_cancellations: 0     35937
1       198
2        46
3        43
11       25
5        11
4        10
13        4
6         1
Name: no_of_previous_cancellations, dtype: int64
--------------------------------------------------
no_of_weekend_nights: 0    16872
1     9995
2     9071
3      153
4      129
5       34
6       20
7        1
Name: no_of_weekend_nights, dtype: int64
--------------------------------------------------
no_of_week_nights: 2     11444
1      9488
```

```
3       7839
4       2990
0       2387
5       1614
6        189
7        113
10        62
8         62
9         34
11        17
15        10
12         9
14         7
13         5
17         3
16         2
Name: no_of_week_nights, dtype: int64
--------------------------------------------------
```

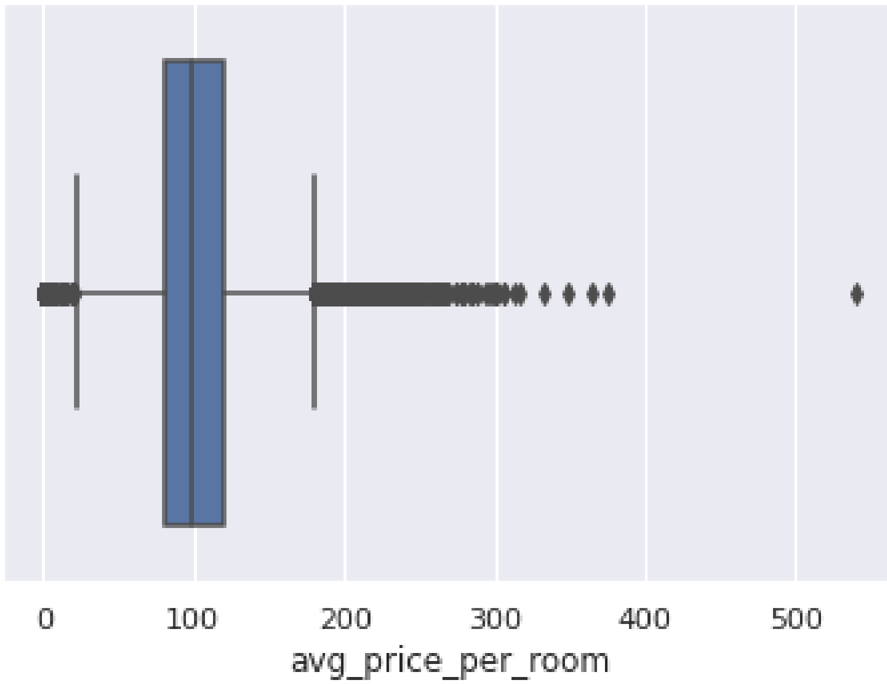
In the pre-processing part I'll simplify these variables into fewer categories to lower the model complexity

Understanding the distribution of the continuous features

[ ]:
```
sns.violinplot(data=df, x='avg_price_per_room');
```

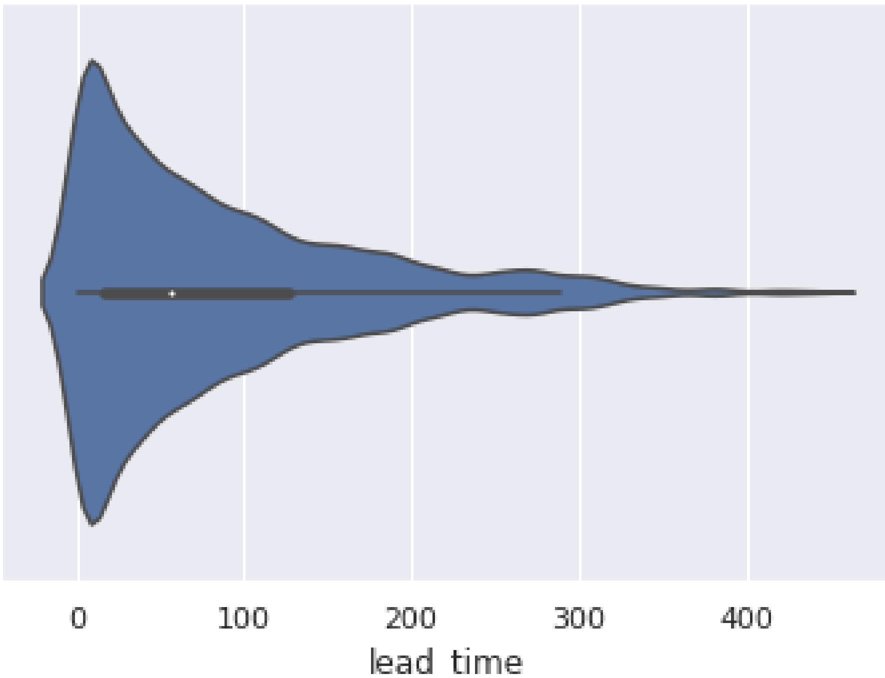


[ ]:
```
sns.boxplot(data=df, x='avg_price_per_room');
```

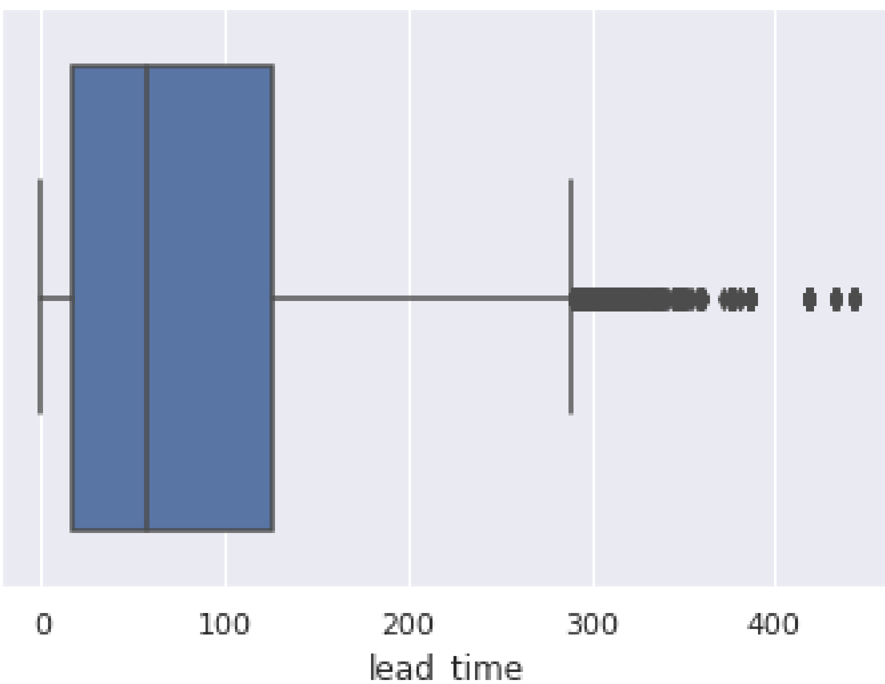


There's a lot of presence of non dense tail which indicates the presence of outliers. When looking at the boxplot seems close to a normal distribution, when looking at the *kde* we can notice the presence of outliers. I believe after the pre-processing this will look much closer to a normal curve if I replace outliers by the median. But, in order to preserv much of the possible variance I'll replace the outliers for the max and min IQR * 1.5

[ ]:
```
sns.violinplot(data=df, x='lead_time');
```



[ ]:
```
sns.boxplot(data=df, x='lead_time');
```



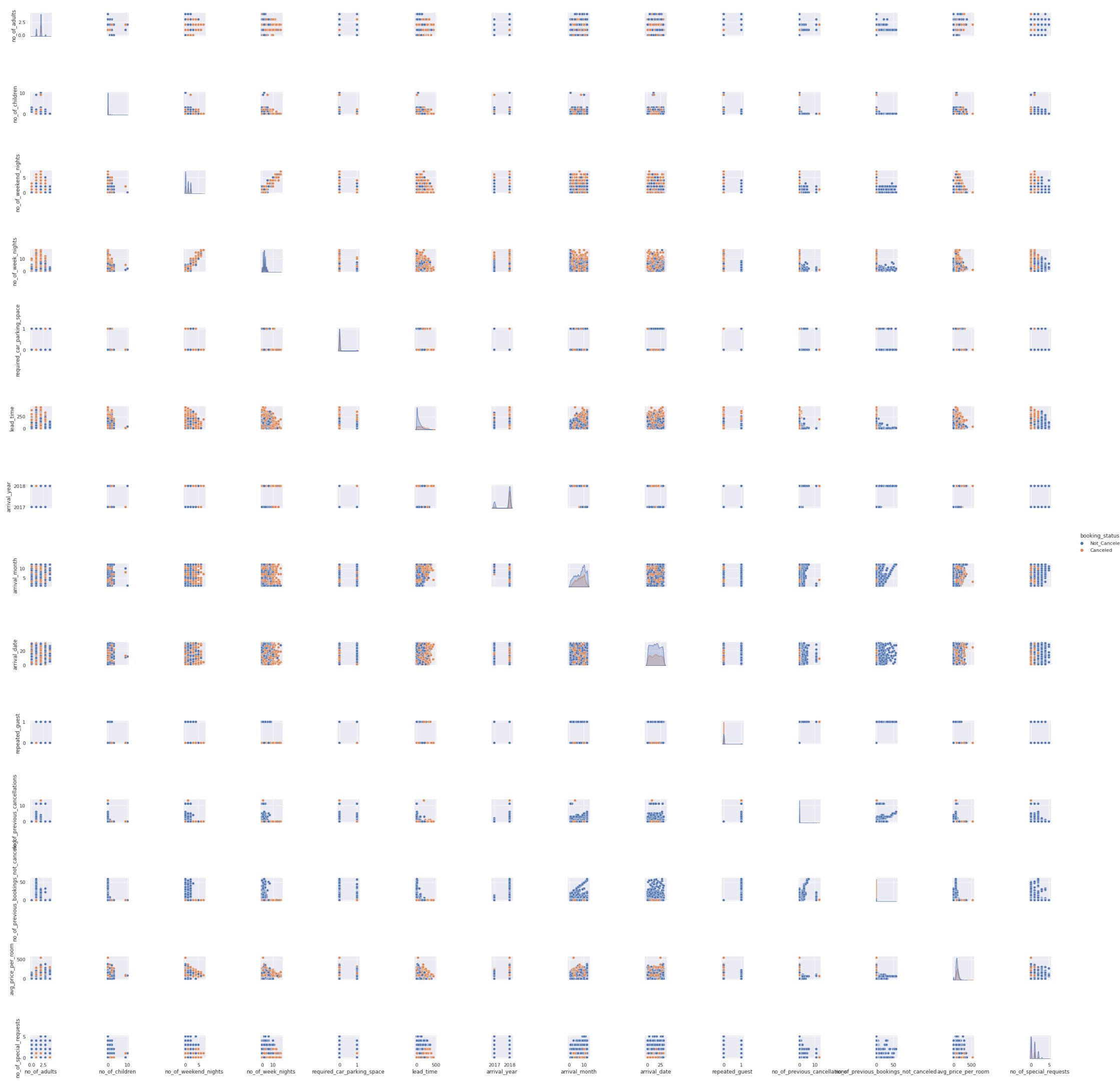
Also we can see the presence of outliers and the tail is more dense, so what deforms the distribution is not only the presence of outliers, but also the nature of the distribution itself. Even after the pre-processing step this distribution will still be right skewed

Bivariate Analysis

[ ]:
```
df_2 = df.copy()
df_2 = df_2.drop(["Booking_ID"], axis=1)
df_2.columns
```

[ ]:
```
Index(['no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'type_of_meal_plan', 'required_car_parking_space',
       'room_type_reserved', 'lead_time', 'arrival_year', 'arrival_month',
       'arrival_date', 'market_segment_type', 'repeated_guest',
       'no_of_previous_cancellations', 'no_of_previous_bookings_not_canceled',
       'avg_price_per_room', 'no_of_special_requests', 'booking_status'],
      dtype='object')
```

[ ]:
```
sns.pairplot(df_2, hue='booking_status');
```



Very poor visualization, but the goal here is to understand the shape of the scatterplot and check if there's concentration of colors, what would indicate information (patterns) that might explain the cancellation behaviour.

Some insights:

Insights:

- `avg_price_per_room` seems to have a negative correlation to `no_of_week_nights` also we can see that most of the cancellations are at the top of the scatterplot which indicates higher the price higher the cancelation
- At `no_of_week_nights` and `no_of_special_requests` we can see that the cancellations are concentrated at the median to the botton of the special requests, which indicates that the bookings that have less special requests tend to cancelate more
- `lead_time`and `avg_price_per_room` are negative correlated and there's a concentration of the cancellations from the median to the higher prices

- The higher the `lead_time` higher the cancellations

[ ]:
```
# read the data
df = pd.read_csv('/content/drive/MyDrive/University Of Texas/Supervised␣
↪Learning - Classification/INNHotelsGroup.csv')
```

[ ]:
```
df.columns
```

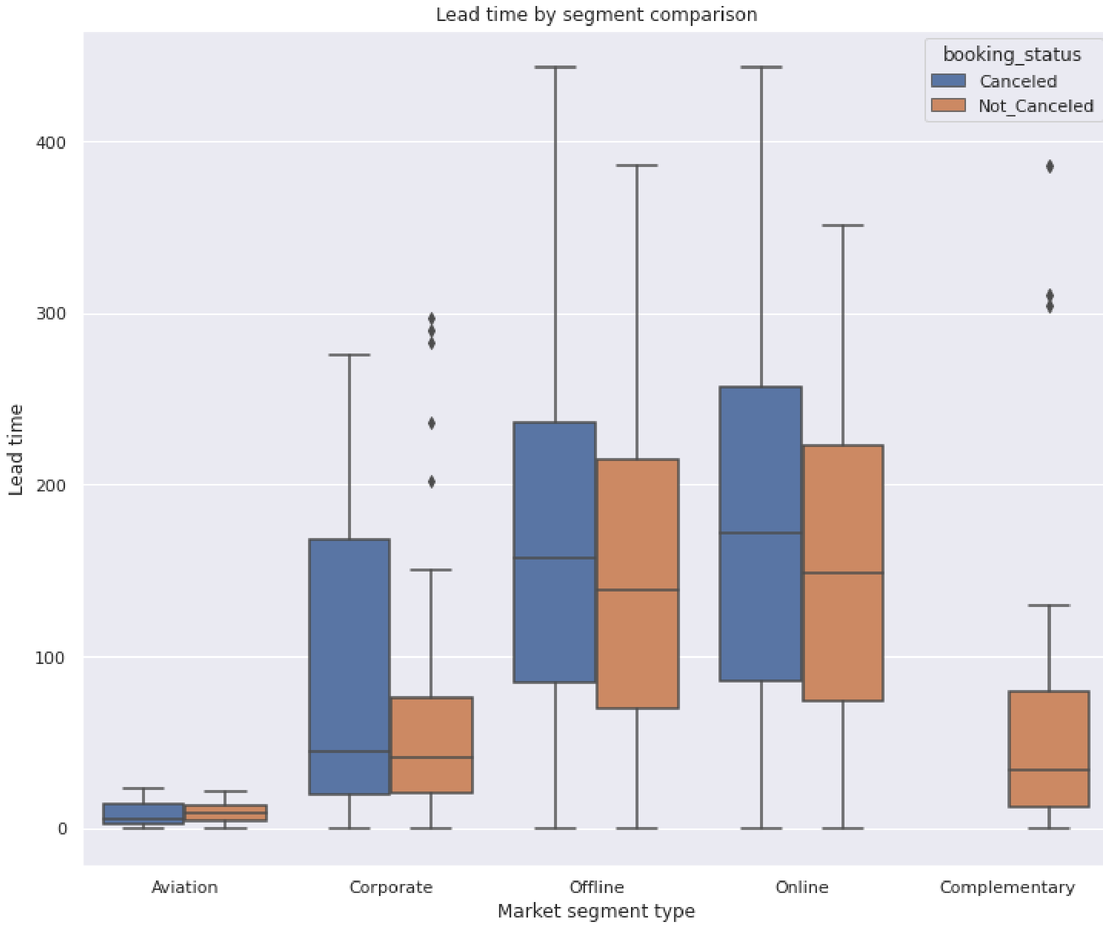
[ ]:
```
Index(['Booking_ID', 'no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'type_of_meal_plan', 'required_car_parking_space',
       'room_type_reserved', 'lead_time', 'arrival_year', 'arrival_month',
       'arrival_date', 'market_segment_type', 'repeated_guest',
       'no_of_previous_cancellations', 'no_of_previous_bookings_not_canceled',
       'avg_price_per_room', 'no_of_special_requests', 'booking_status'],
      dtype='object')
```

[ ]:
```
gb_lead = df.groupby(['lead_time','booking_status', 'market_segment_type'],␣
↪as_index=False)['Booking_ID'].count()
gb_lead.head(2)
```

[ ]:

	lead_time	booking_status	market_segment_type	Booking_ID
0	0	Canceled	Aviation	1
1	0	Canceled	Corporate	7

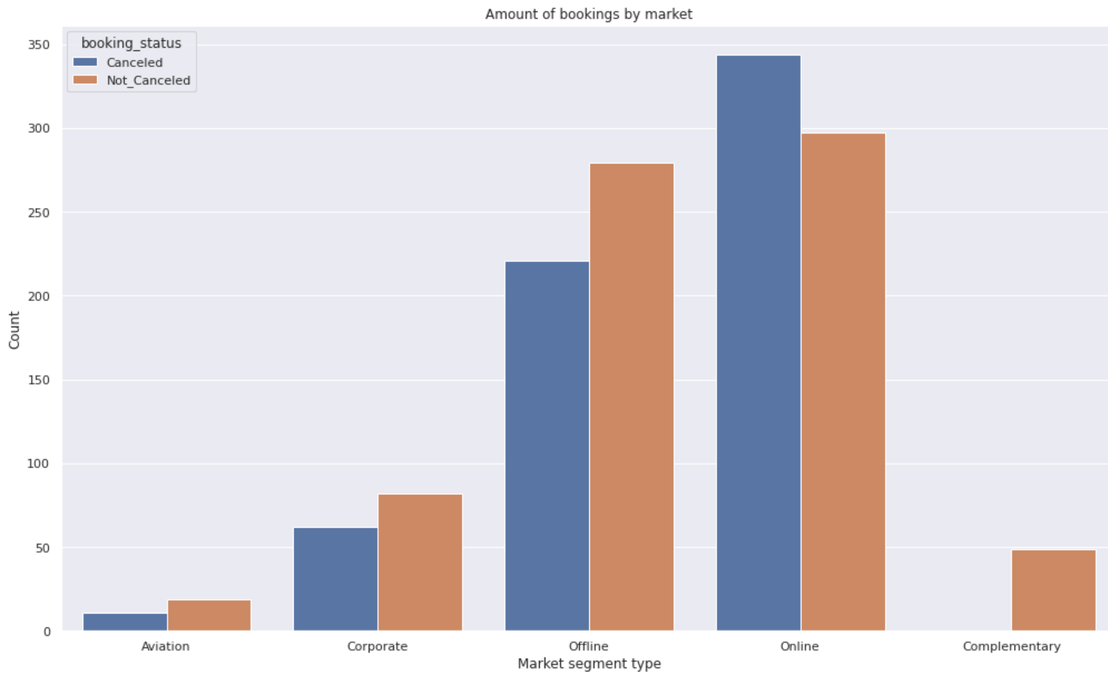
[ ]:
```
plt.figure(figsize=(12,10))
sns.boxplot(data=gb_lead, x='market_segment_type', y='lead_time',␣
↪hue='booking_status');
plt.title('Lead time by segment comparison');
plt.xlabel('Market segment type');
plt.ylabel('Lead time');
```



Insights:

- Aviation has no difference between cancelled and not cancelled
- Corporate has the biggest difference in behavior between cancelled and not cancelled
- Offline and online both have same behaviour when it comes to cancellation

[ ]:
```
plt.figure(figsize=(17,10))
sns.countplot(data=gb_lead, x='market_segment_type', hue='booking_status');
plt.title('Amount of bookings by market');
plt.xlabel('Market segment type');
plt.ylabel('Count');
```

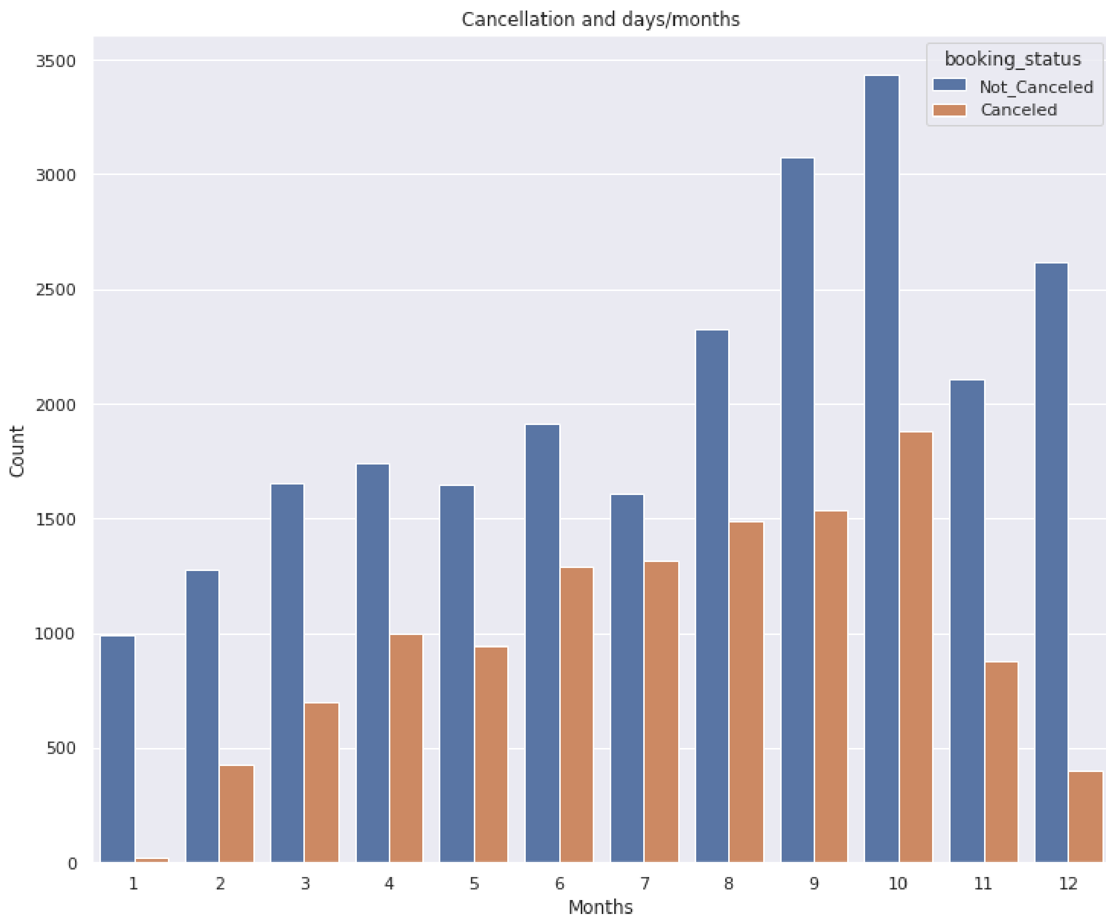


Insights:

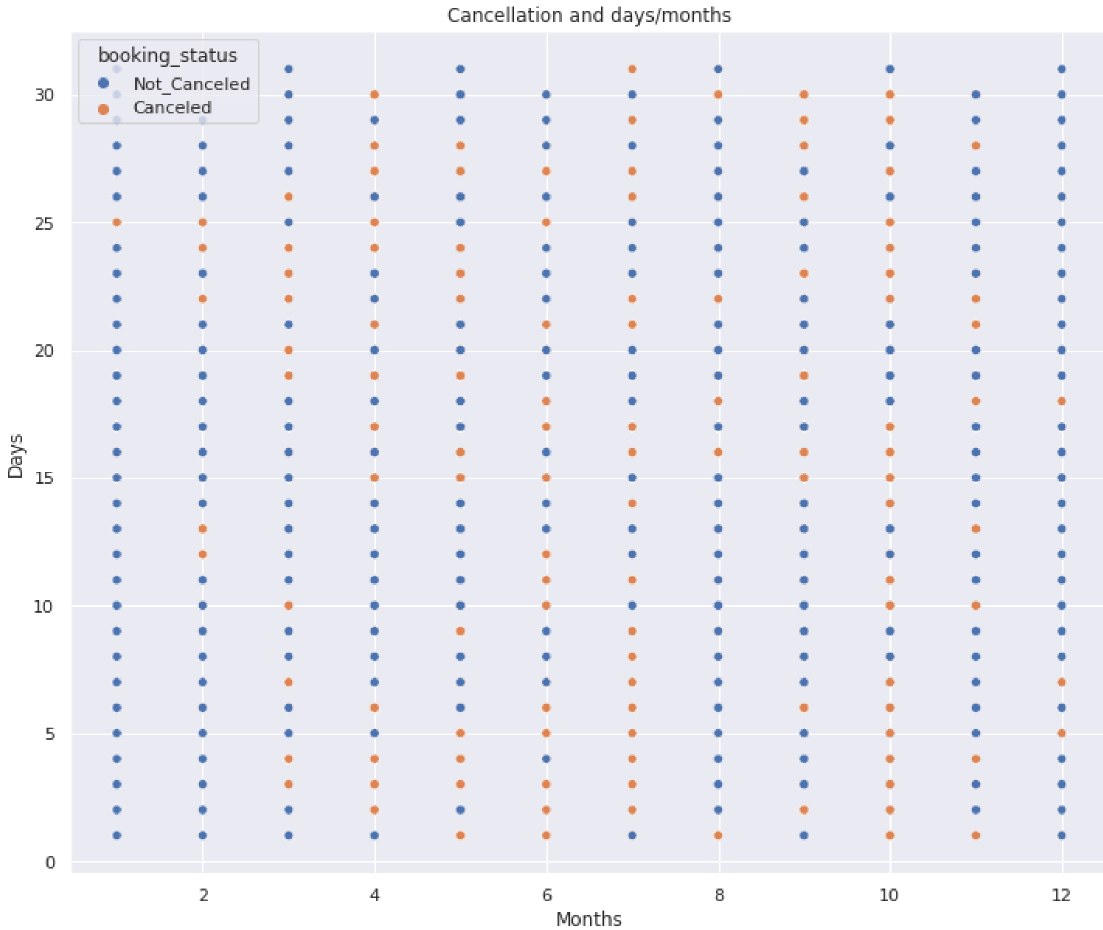
- Based on previous slide I though corporate would have a very different behaviour when compared to other segments, BUT when compared it presents same behaviour
- All features (excluding complementary which is only not cancelled) presents same cancelling behaviour

I'll search for seasonal patterns for cancellation:

[ ]:
```
plt.figure(figsize=(12,10))
sns.countplot(data=df, x='arrival_month', hue='booking_status')
plt.title('Cancellation and days/months');
plt.xlabel('Months');
plt.ylabel('Count');
```



[ ]:
```
plt.figure(figsize=(12,10))
sns.scatterplot(data=df, y='arrival_date', x='arrival_month',␣
 ↪hue='booking_status');
plt.title('Cancellation and days/months');
plt.xlabel('Months');
plt.ylabel('Days');
```



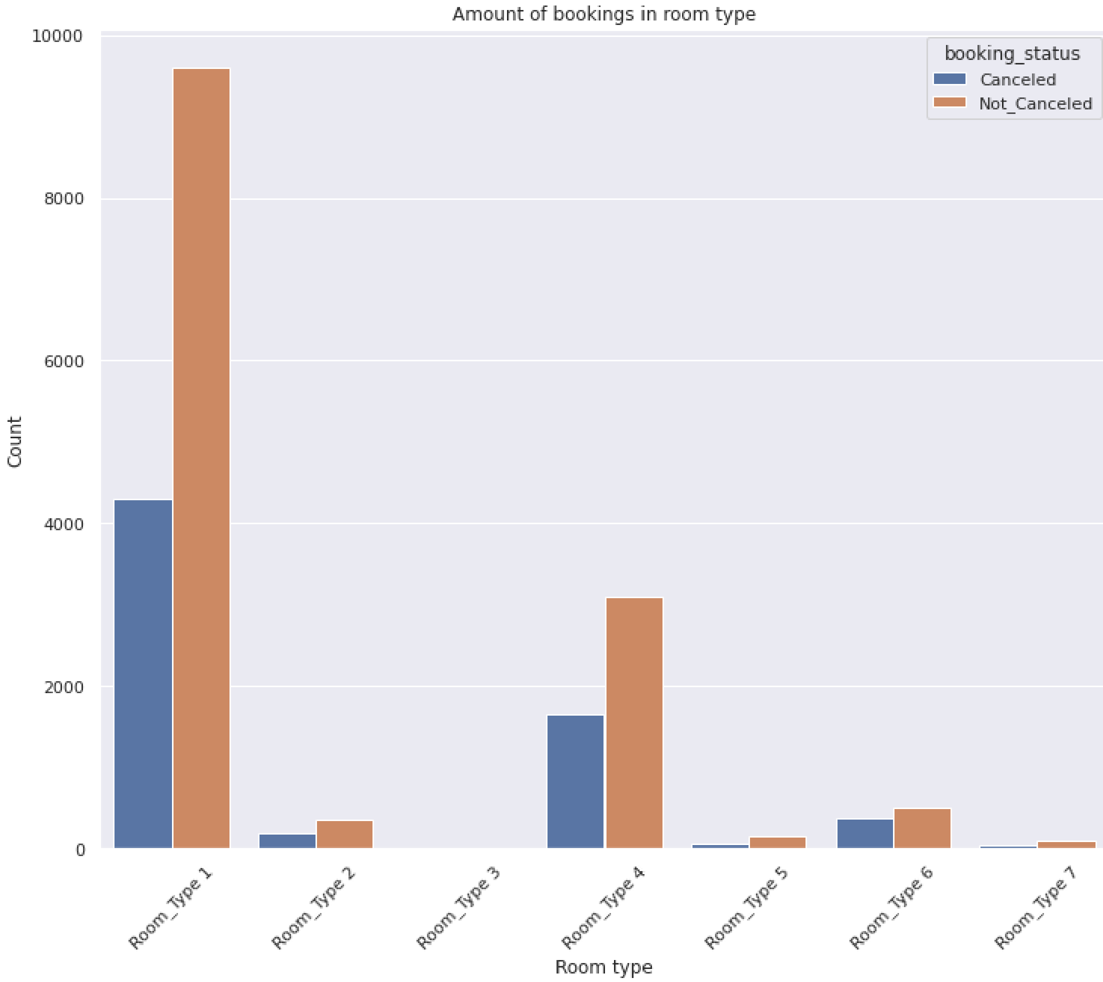
Insights:

- Based on both last graphs, couldn't identify any pattern of cancellation

```
[ ]: gb_room = df.groupby(['room_type_reserved', 'lead_time','booking_status',␣
     ↪'market_segment_type', 'avg_price_per_room'], as_index=False)['Booking_ID'].
     ↪count()
     gb_room.head(2)
```

```
[ ]:   room_type_reserved  lead_time booking_status market_segment_type  \
     0        Room_Type 1          0       Canceled            Aviation
     1        Room_Type 1          0       Canceled           Corporate

        avg_price_per_room  Booking_ID
     0              95.000           1
     1              65.000           1
```

```
[ ]: plt.figure(figsize=(12,10))
sns.countplot(data=gb_room, x='room_type_reserved', hue='booking_status');
plt.title('Amount of bookings in room type');
plt.xlabel('Room type');
plt.ylabel('Count');
plt.xticks(rotation=45);
```

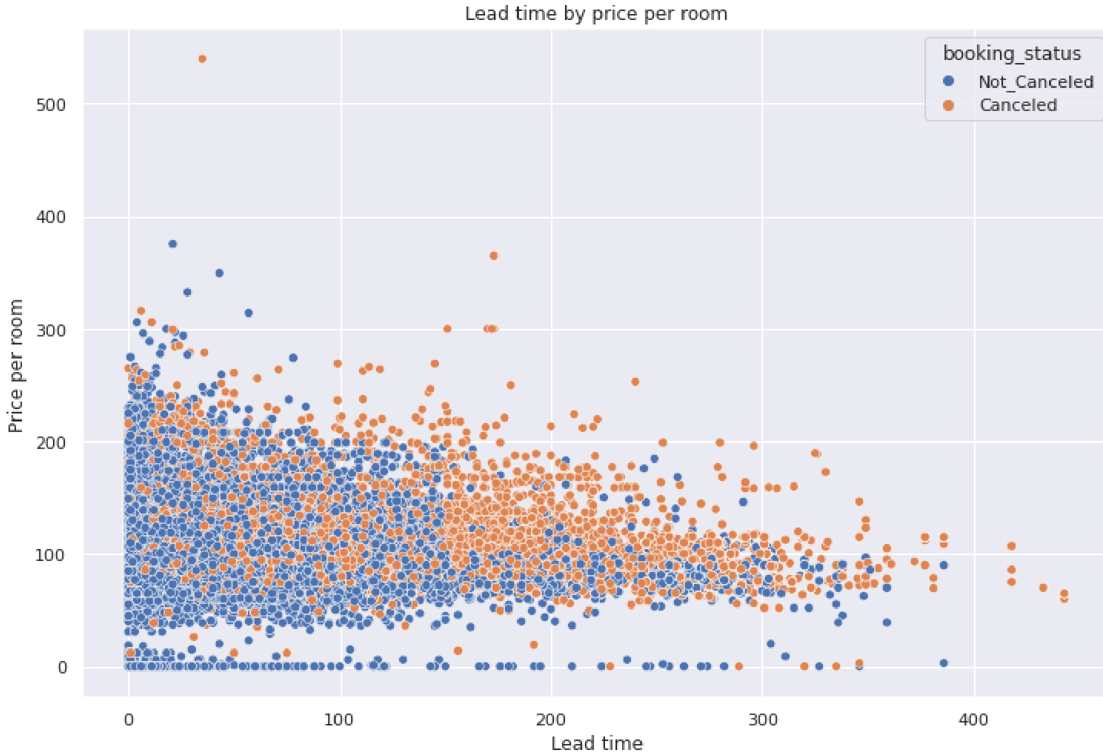


Insights:

- Concentration of booking for type 1 room
- All rooms shows similar behaviour when it comes to cancellations

```
[ ]: plt.figure(figsize=(12,8))
sns.scatterplot(data=df, x='lead_time', y='avg_price_per_room',␣
 ↪hue='booking_status')
plt.title('Lead time by price per room');
plt.xlabel('Lead time');
```

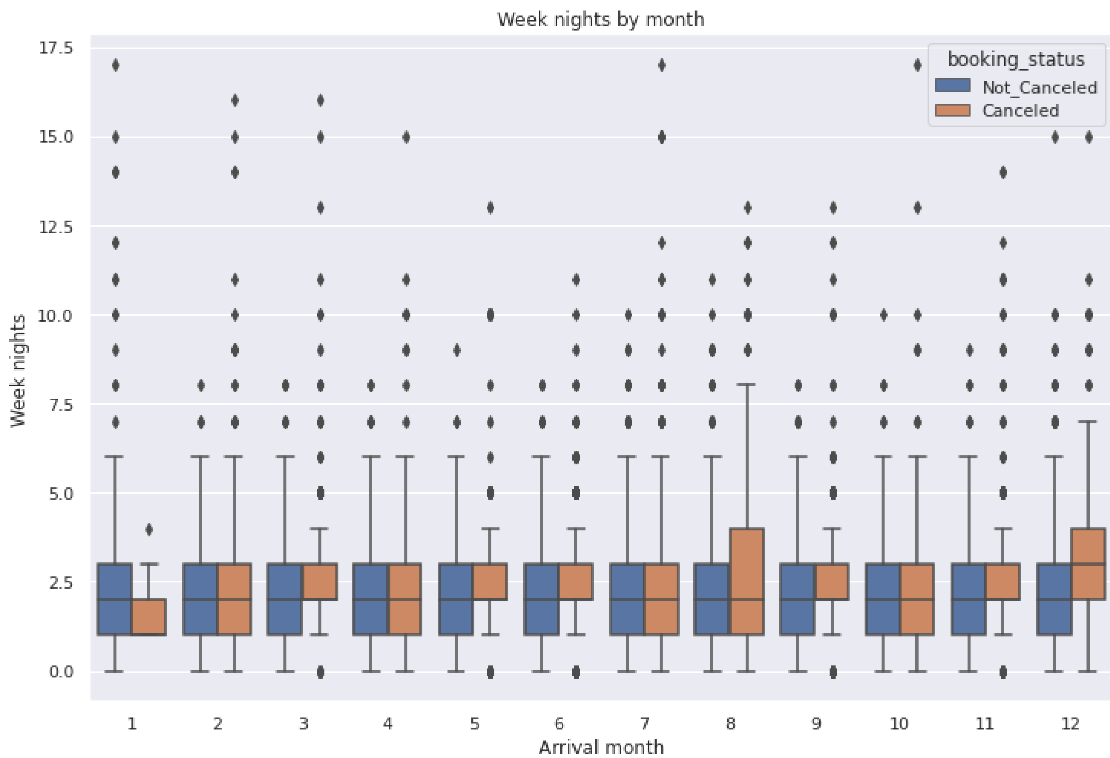
```
plt.ylabel('Price per room');
```



Insights:

- Weak negative correlation
- Concentration of cancellations in prices above 100 and with lead time higher than 150

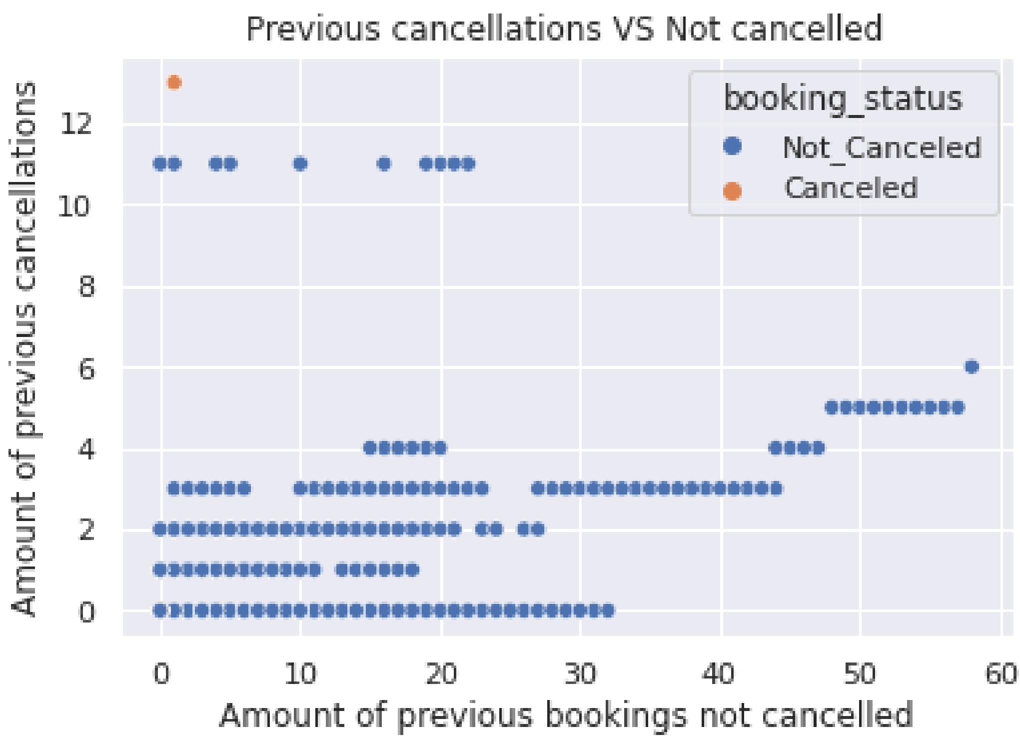
[ ]:
```
plt.figure(figsize=(12,8))
sns.boxplot(data=df, y='no_of_week_nights', x='arrival_month',␣
 ↪hue='booking_status')
plt.title('Week nights by month');
plt.xlabel('Arrival month');
plt.ylabel('Week nights');
```



Insights:

- In month 8 and 12 we can see difference in amount of nights presents in cancellations bookings. all others shows similar behaviour.

[ ]:
```
sns.scatterplot(data=df, y='no_of_previous_cancellations',␣
↪x='no_of_previous_bookings_not_canceled', hue='booking_status' );
plt.title('Previous cancellations VS Not cancelled');
plt.xlabel('Amount of previous bookings not cancelled');
plt.ylabel('Amount of previous cancellations');
```



Insights:

- Considering one exception, this group is homogeneous. Maybe `no_of_previous_bookings_not_canceled` would be usefull to the model, but this is a very imbalanced feature, so there might not be much use

I believe we understood much of the information of the dataset and the relationship between the x variables with the target variable and some relationship between some x variables too.

Considering that we still have to answer six business questions, I think the EDA is purpose is reached.

Answering Business Questions

1. What are the busiest months in the hotel?

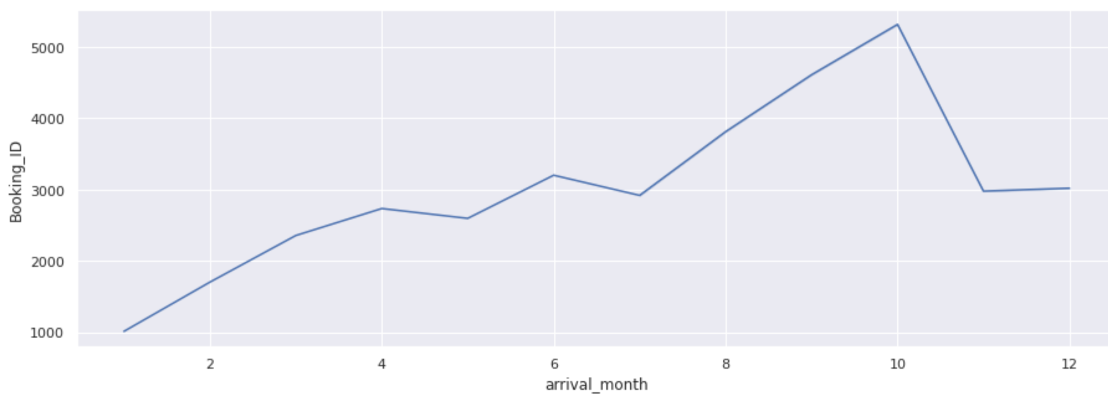
```
[ ]: gb_month = df.groupby(['arrival_year','arrival_month'],␣
     ↪as_index=False)['Booking_ID'].count()
     gb_month
```

[ ]:

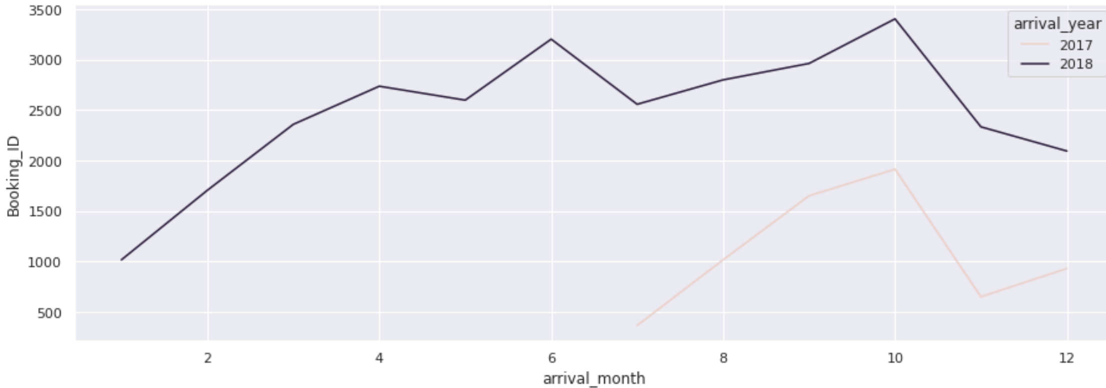
	arrival_year	arrival_month	Booking_ID
0	2017	7	363
1	2017	8	1014
2	2017	9	1649
3	2017	10	1913
4	2017	11	647

5	2017	12	928
6	2018	1	1014
7	2018	2	1704
8	2018	3	2358
9	2018	4	2736
10	2018	5	2598
11	2018	6	3203
12	2018	7	2557
13	2018	8	2799
14	2018	9	2962
15	2018	10	3404
16	2018	11	2333
17	2018	12	2093

[ ]:
```
plt.figure(figsize=(15,5))
sns.set_theme()

sns.lineplot(data=gb_month, x='arrival_month', y='Booking_ID', estimator='sum',␣
 ↪ci=False);
```



[ ]:
```
plt.figure(figsize=(15,5))

sns.lineplot(data=gb_month, x='arrival_month', y='Booking_ID',␣
 ↪hue='arrival_year');
```



The busiest months are October, September and August. Even though we don't have comple 2017 data, seems to follow same pattern as 2018.

2. Which market segment do most of the guests come from?

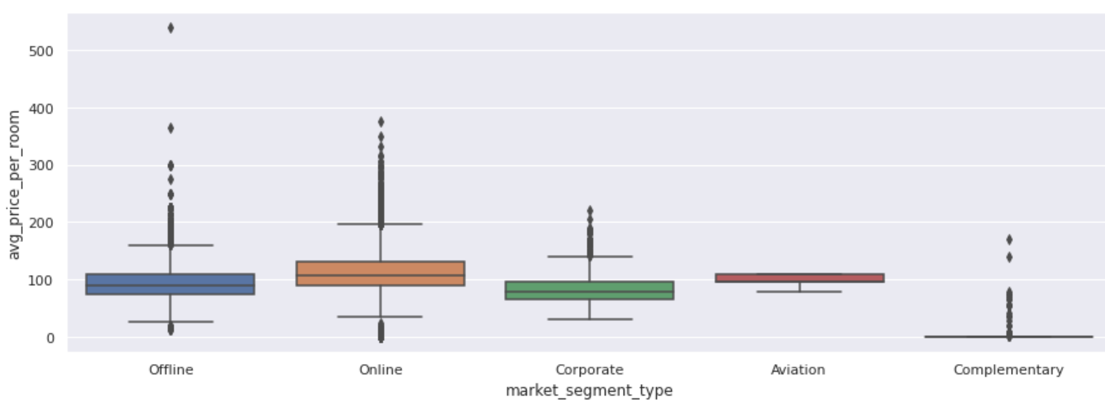
[ ]:
```
df['market_segment_type'].value_counts(normalize=True)*100
```

[ ]:
```
Online           63.994
Offline          29.023
Corporate         5.560
Complementary     1.078
Aviation          0.345
Name: market_segment_type, dtype: float64
```

64% of the bookings come from the online market segment

3. Hotel rates are dynamic and change according to demand and customer demographics. What are the differences in room prices in different market segments?

[ ]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=df, y='avg_price_per_room', x='market_segment_type');
```



Insights:

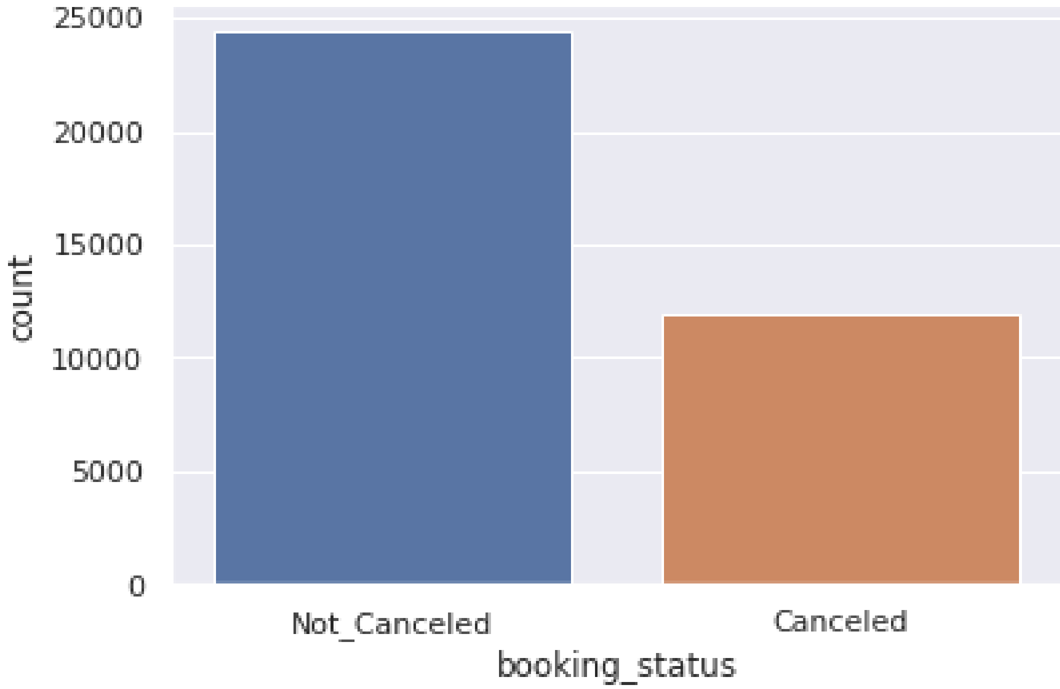
- In aviation seems to be a regular fare tha vary very little
- Complementary seems to be the opposit, high variance even though the prices are very low when compared to the others - I think that the complementary are the prices of promotions for the no-show (cancelled) bookings
- Offline segment seems to have balanced price when compared to Corporate and Onlie *but* presents some high average prices as outliers
- Online segment has the highers prices in general. Has the higgher Q3, higher median but not by far. Very close to aviation, offline and corporate segment

4. What percentage of bookings are canceled?

[ ]:
```
df.head(2)
```

[ ]:
```
  Booking_ID  no_of_adults  no_of_children  no_of_weekend_nights  \
0   INN00001             2               0                     1
1   INN00002             2               0                     2

   no_of_week_nights type_of_meal_plan  required_car_parking_space  \
0                  2       Meal Plan 1                           0
1                  3      Not Selected                           0

  room_type_reserved  lead_time  arrival_year  arrival_month  arrival_date  \
0        Room_Type 1        224          2017             10             2
1        Room_Type 1          5          2018             11             6

  market_segment_type  repeated_guest  no_of_previous_cancellations  \
0             Offline               0                             0
1              Online               0                             0

   no_of_previous_bookings_not_canceled  avg_price_per_room  \
0                                     0              65.000
1                                     0             106.680

   no_of_special_requests booking_status
0                       0   Not_Canceled
1                       1   Not_Canceled
```

[ ]:
```
sns.countplot(data=df, x='booking_status');
```



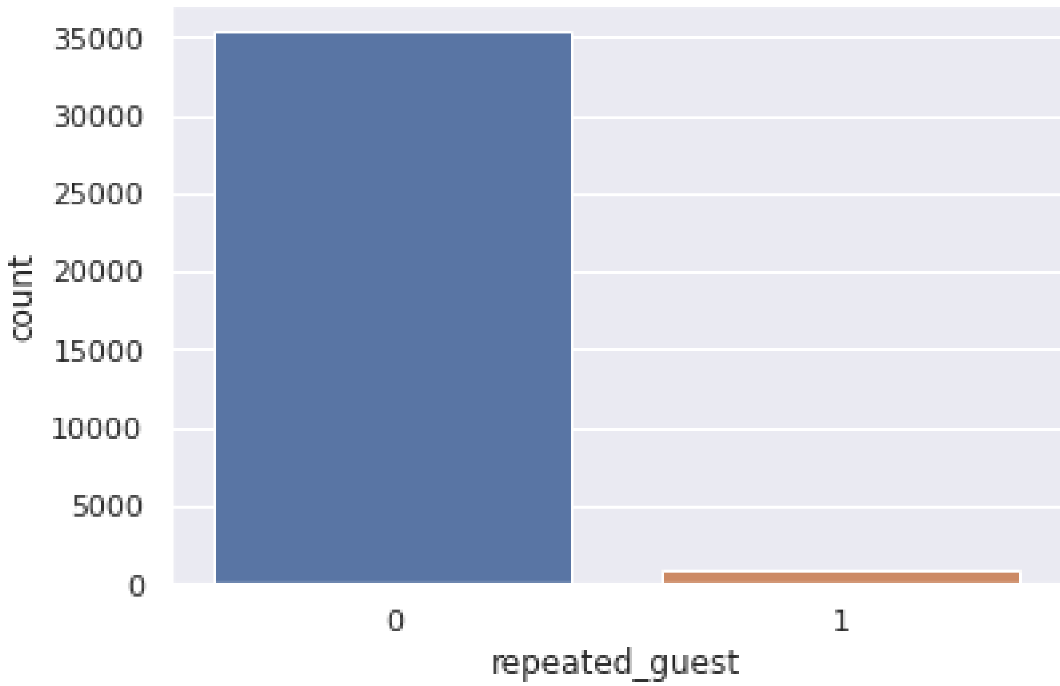
[ ]:
```
df['booking_status'].value_counts(normalize=True)*100
```

[ ]:
```
Not_Canceled    67.236
Canceled        32.764
Name: booking_status, dtype: float64
```

'booking_status' correspond to 67% of the dataset. Well balanced dataset for categories prediction

5. Repeating guests are the guests who stay in the hotel often and are important to brand equity. What percentage of repeating guests cancel?

[ ]:
```
sns.countplot(data=df, x='repeated_guest');
```



[ ]:
```
df['repeated_guest'].value_counts(normalize=True)*100
```

[ ]:
```
0    97.436
1     2.564
Name: repeated_guest, dtype: float64
```

97.5% of the guests are not repetead. Very imbalanced dataset by this optic. Only 2.5% of the bookings are from repeated clients

[ ]:
```
repeated_guests = df[df['repeated_guest'] == 1]

gb_rep = repeated_guests.groupby(['repeated_guest','booking_status'],␣
 ↪as_index=False)['Booking_ID'].count()
gb_rep
```

[ ]:

	repeated_guest	booking_status	Booking_ID
0	1	Canceled	16
1	1	Not_Canceled	914

[ ]:
```
perc_cancel = round(gb_rep['Booking_ID'][0]/gb_rep['Booking_ID'][1]*100,2)
perc_cancel
```

[ ]:
```
1.75
```

1.75% of the repeated guests cancel their bookings

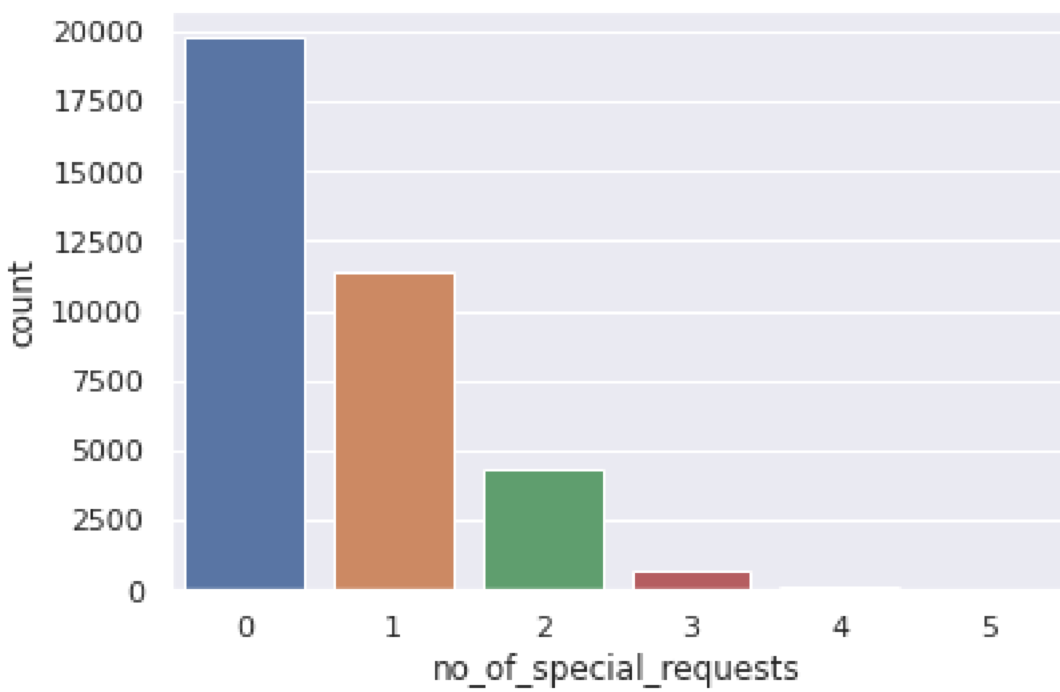
6. Many guests have special requirements when booking a hotel room. Do these requirements affect booking cancellation?

[ ]:
```
#first I'll understand the % of bookings with special requests

df['no_of_special_requests'].value_counts(normalize=True)*100
```

[ ]:
```
0    54.520
1    31.352
2    12.030
3     1.861
4     0.215
5     0.022
Name: no_of_special_requests, dtype: float64
```

54% of the bookings have no special requests

[ ]:
```
sns.countplot(data=df, x='no_of_special_requests');
```



[ ]:
```
gb_bs = df.groupby(['booking_status', 'no_of_special_requests'],␣
↪as_index=False)['Booking_ID'].count()
gb_bs
```

[ ]:

	booking_status	no_of_special_requests	Booking_ID
0	Canceled	0	8545

```
1       Canceled                          1        2703
2       Canceled                          2         637
3   Not_Canceled                          0       11232
4   Not_Canceled                          1        8670
5   Not_Canceled                          2        3727
6   Not_Canceled                          3         675
7   Not_Canceled                          4          78
8   Not_Canceled                          5           8
```

[ ]:
```
sns.barplot(data=gb_bs, x='no_of_special_requests', y='Booking_ID',␣
↪hue='booking_status');
```

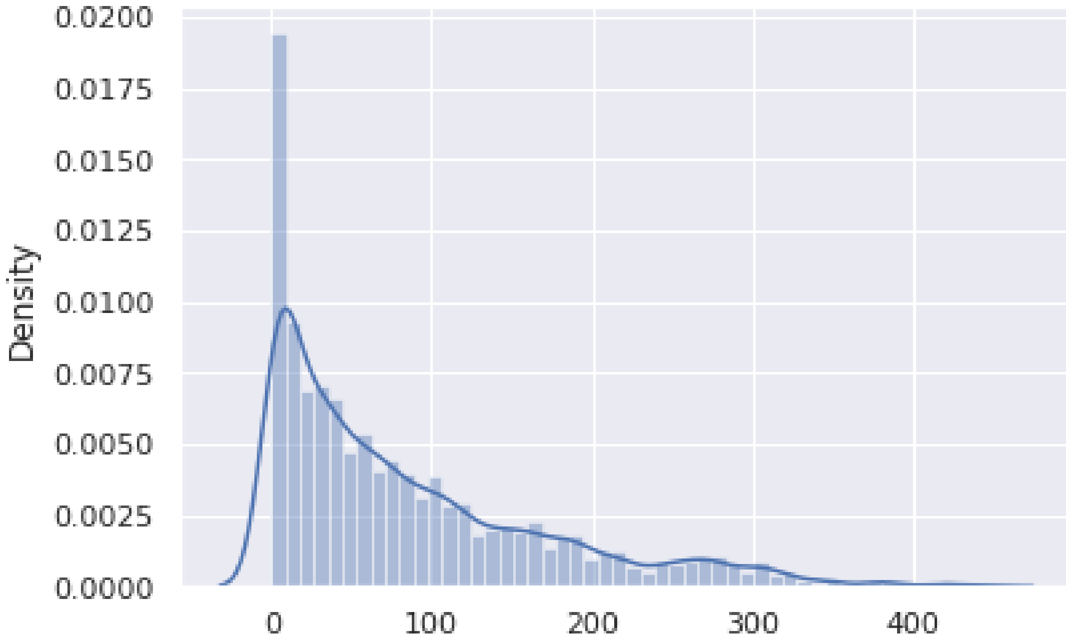
Seems to be a relationship between `no_of_special_requests` and `booking_status`. The more special requests, less the cancellation rate

1.7 Data Preprocessing

- Missing value treatment (if needed)
- Feature engineering (if needed)
- Outlier detection and treatment (if needed)
- Preparing data for modeling
- Any other preprocessing steps (if needed)

Outlier Treatment

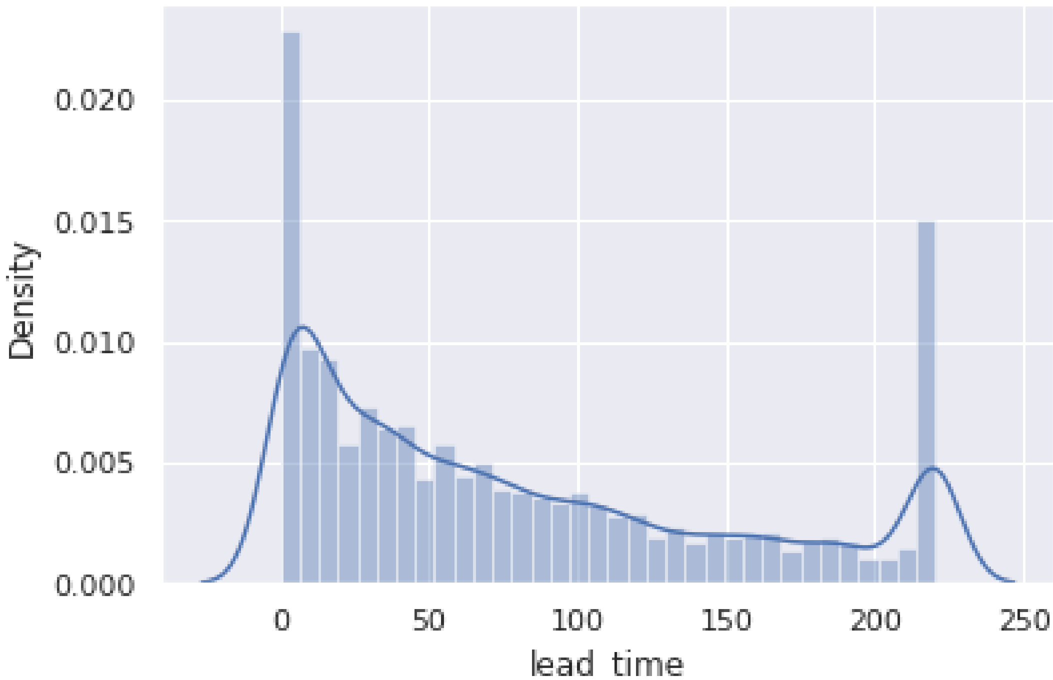
[ ]:
```
#verifying again the distribution

sns.distplot(x=df['lead_time']);
```



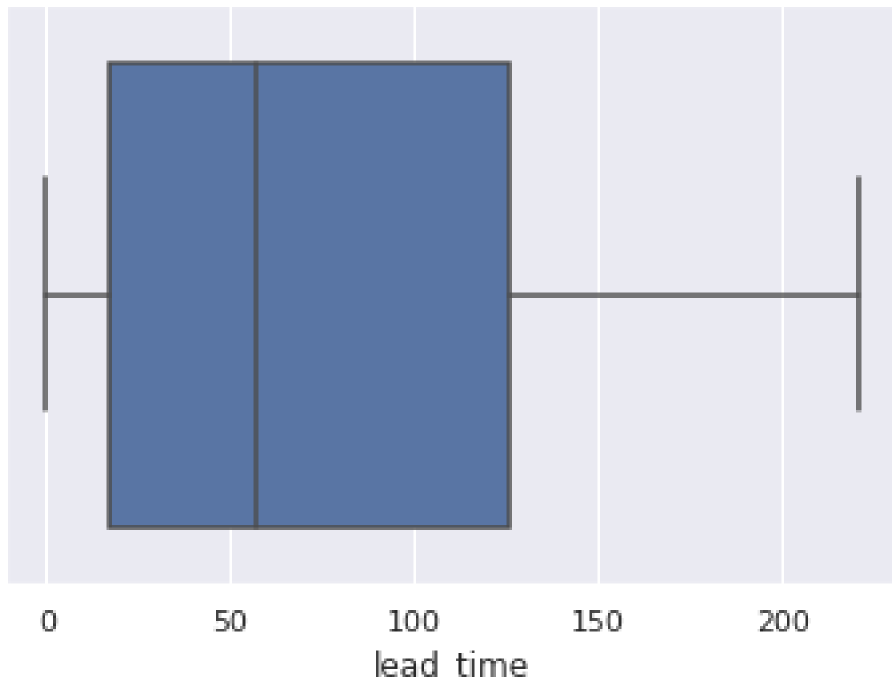
[ ]:
```
#calculate interquartile range
q3, q1 = np.percentile(df['lead_time'], [75 ,25])
iqr = q3 - q1

median = df['lead_time'].median()

#display interquartile range
print("IQR:",iqr)

#defining outliers range
lower_limit = median - (iqr * 1.5)
higher_limit = median + (iqr * 1.5)


print("Median:",median)
print("Lower limit:",lower_limit)
print("Higher limit:",higher_limit)
```

```
IQR: 109.0
Median: 57.0
Lower limit: -106.5
Higher limit: 220.5
```

[ ]:
```
df['lead_time'] = np.where(df["lead_time"] >higher_limit,␣
↪higher_limit,df['lead_time'])
df['lead_time'] = np.where(df["lead_time"] <lower_limit,␣
↪lower_limit,df['lead_time'])

sns.distplot(df['lead_time']);
```

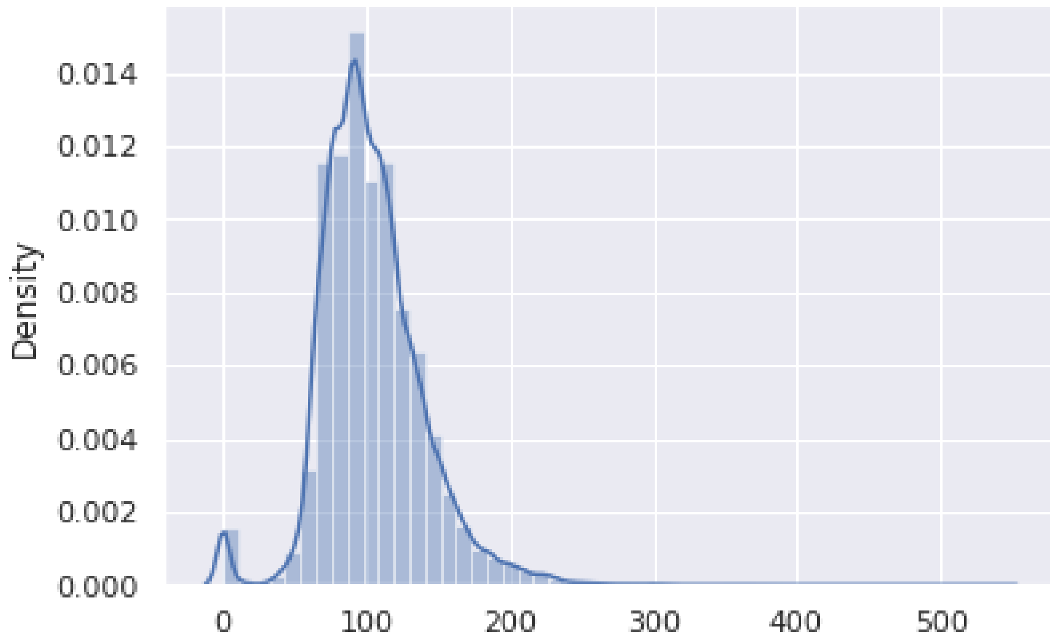


[ ]:
```
sns.boxplot(df['lead_time']);
```



Still an abnormal distribution, but the intent wasn't to transform into a normal curve, but to eliminate the outliers keeping most of the variance possible

[ ]:
```
#verifying again the distribution

sns.distplot(x=df['avg_price_per_room']);
```

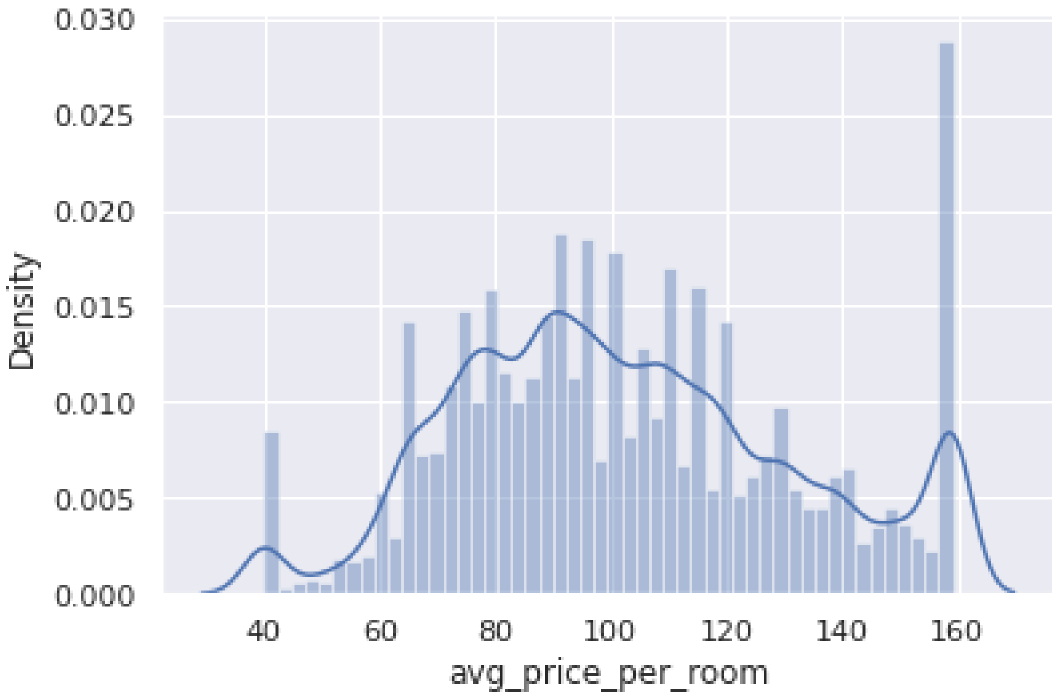


[ ]:
```
#calculate interquartile range
q3, q1 = np.percentile(df['avg_price_per_room'], [75 ,25])
iqr = q3 - q1

median = df['avg_price_per_room'].median()

#display interquartile range
print("IQR:",iqr)

#defining outliers range
lower_limit = median - (iqr * 1.5)
higher_limit = median + (iqr * 1.5)


print("Median:",median)
print("Lower limit:",lower_limit)
print("Higher limit:",higher_limit)
```

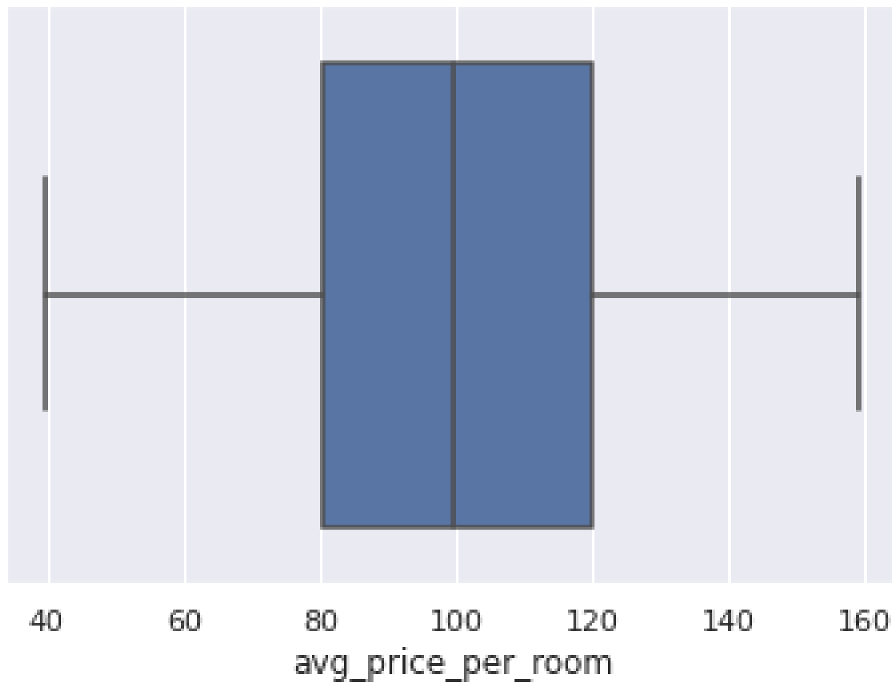
```
IQR: 39.7
Median: 99.45
Lower limit: 39.9
Higher limit: 159.0
```

[ ]:
```
df['avg_price_per_room'] = np.where(df["avg_price_per_room"] >higher_limit,␣
↪higher_limit,df['avg_price_per_room'])
```

```
df['avg_price_per_room'] = np.where(df["avg_price_per_room"] <lower_limit,␣
↪lower_limit,df['avg_price_per_room'])

sns.distplot(df['avg_price_per_room']);
```



[ ]:
```
sns.boxplot(df['avg_price_per_room']);
```



The goal here was to maintain the variance, once variance is importante both for logist regression and for decision trees

Feature Simplifying

```
[ ]: df['no_of_previous_bookings_not_canceled'] =␣
      ↪df["no_of_previous_bookings_not_canceled"].apply(lambda x: 1 if x > 0 else 0)
     df['no_of_weekend_nights'] = df["no_of_weekend_nights"].apply(lambda x: '0 to␣
      ↪3' if x < 4 else '4 or more')
     df['no_of_children'] = df["no_of_children"].apply(lambda x: 1 if x > 0 else 0)
     df['no_of_week_nights'] = df["no_of_week_nights"].apply(lambda x: '0 to 6' if x␣
      ↪< 7 else '7 or higher')
     df['booking_status'] = df["booking_status"].apply(lambda x: 0 if x ==␣
      ↪'Not_Canceled' else 1)

     print(df['no_of_previous_bookings_not_canceled'].value_counts())
     print(df['no_of_weekend_nights'].value_counts())
     print(df['no_of_children'].value_counts())
     print(df['no_of_week_nights'].value_counts())
     print(df['booking_status'].value_counts())
```

```
0    35463
1      812
Name: no_of_previous_bookings_not_canceled, dtype: int64
0 to 3       36091
```

```
4 or more      184
Name: no_of_weekend_nights, dtype: int64
0    33577
1     2698
Name: no_of_children, dtype: int64
0 to 6         35951
7 or higher      324
Name: no_of_week_nights, dtype: int64
0    24390
1    11885
Name: booking_status, dtype: int64
```

[ ]:
```
bins = [0,80,120,140,1000]
labels = ['0-79','80-119', '120-139', '140+']

df['avg_price_per_room'] = pd.cut(df['avg_price_per_room'], bins=bins,␣
 ↪labels=labels, include_lowest=True)
```

[ ]:
```
bins = [0,100,200,1000]
labels = ['0-99','100-199', '200+']

df['lead_time'] = pd.cut(df['lead_time'], bins=bins, labels=labels,␣
 ↪include_lowest=True)
```

[ ]:
```
#transforming all objects features into categorical

for feature in df.columns:
    if df[feature].dtype == 'object':
        df[feature] = pd.Categorical(df[feature])
```

[ ]:
```
#transforming some numerical features into categorical


numcat = ['no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'required_car_parking_space',
       'arrival_year', 'arrival_month',
       'arrival_date', 'repeated_guest',
       'no_of_previous_cancellations', 'no_of_previous_bookings_not_canceled',
       'no_of_special_requests','booking_status', 'lead_time',␣
 ↪'avg_price_per_room']


for feature in numcat:
    if df[feature].dtype == 'int64':
        df[feature] = pd.Categorical(df[feature])
```

The `arrival_year` is not relevant for the analysis, because of that I'll drop. `room_type_reserved` is very concentrated for that I'll drop.

```
[ ]: #saving the dataset with all the variables to the decision tree model
df_dtree = df.copy()
df_dtree.head(2)
```

```
[ ]:   Booking_ID no_of_adults no_of_children no_of_weekend_nights  \
0   INN00001            2              0               0 to 3
1   INN00002            2              0               0 to 3

  no_of_week_nights type_of_meal_plan required_car_parking_space  \
0            0 to 6       Meal Plan 1                          0
1            0 to 6      Not Selected                          0

  room_type_reserved lead_time arrival_year arrival_month arrival_date  \
0        Room_Type 1      200+         2017            10            2
1        Room_Type 1      0-99         2018            11            6

  market_segment_type repeated_guest no_of_previous_cancellations  \
0             Offline              0                            0
1              Online              0                            0

  no_of_previous_bookings_not_canceled avg_price_per_room  \
0                                    0               0-79
1                                    0             80-119

  no_of_special_requests booking_status
0                      0              0
1                      1              0
```

I'll have to drop `lead_time` and `avg_price_per_room` because they generate the error below when fitting the LG:

LinAlgError: Singular matrix

Also will drop `room_type_reserved` because it has concentration in one category and at the EDA it has shown no effect on the target variable Also will drop `arrival_year` because in my understanding it has no value in this analysis once that I don't have much historicak data and the season is captured by months and days

```
[ ]: df.drop(["Booking_ID", "arrival_year", 'room_type_reserved', 'lead_time',␣
 ↪'avg_price_per_room'], axis=1, inplace=True)
df.columns
```

```
[ ]: Index(['no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'type_of_meal_plan', 'required_car_parking_space',
       'arrival_month', 'arrival_date', 'market_segment_type',
       'repeated_guest', 'no_of_previous_cancellations',
       'no_of_previous_bookings_not_canceled', 'no_of_special_requests',
```

```
       'booking_status'],
      dtype='object')
```

[ ]:
```
#Taking a last look at tgge dataset before using it for the modelling
df.head()
```

[ ]:
```
  no_of_adults no_of_children no_of_weekend_nights no_of_week_nights  \
0            2              0               0 to 3            0 to 6
1            2              0               0 to 3            0 to 6
2            1              0               0 to 3            0 to 6
3            2              0               0 to 3            0 to 6
4            2              0               0 to 3            0 to 6

  type_of_meal_plan required_car_parking_space arrival_month arrival_date  \
0       Meal Plan 1                          0            10            2
1      Not Selected                          0            11            6
2       Meal Plan 1                          0             2           28
3       Meal Plan 1                          0             5           20
4      Not Selected                          0             4           11

  market_segment_type repeated_guest no_of_previous_cancellations  \
0             Offline              0                            0
1              Online              0                            0
2              Online              0                            0
3              Online              0                            0
4              Online              0                            0

  no_of_previous_bookings_not_canceled no_of_special_requests booking_status
0                                    0                      0              0
1                                    0                      1              0
2                                    0                      0              1
3                                    0                      0              1
4                                    0                      0              1
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36275 entries, 0 to 36274
Data columns (total 14 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   no_of_adults                          36275 non-null  category
 1   no_of_children                        36275 non-null  category
 2   no_of_weekend_nights                  36275 non-null  category
 3   no_of_week_nights                     36275 non-null  category
 4   type_of_meal_plan                     36275 non-null  category
 5   required_car_parking_space            36275 non-null  category
```

```
 6   arrival_month                         36275 non-null  category
 7   arrival_date                          36275 non-null  category
 8   market_segment_type                   36275 non-null  category
 9   repeated_guest                        36275 non-null  category
 10  no_of_previous_cancellations          36275 non-null  category
 11  no_of_previous_bookings_not_canceled  36275 non-null  category
 12  no_of_special_requests                36275 non-null  category
 13  booking_status                        36275 non-null  category
dtypes: category(14)
memory usage: 499.8 KB
```

all columns are categories and ready to go into the lg model

1.8 Building a Logistic Regression model

Spliting the dataset, adding the constant and creating the dummy variables

[ ]:
```
X = df.drop(["booking_status"], axis=1)
Y = df["booking_status"]

# adding a contstant to X variable
X = add_constant(X)

# creating dummies
X = pd.get_dummies(X, drop_first=True)


# Splitting data in train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.30, random_state=1, stratify=Y)
```

[ ]:
```
print("Shape of Training set : ", X_train.shape)
print("Shape of test set : ", X_test.shape)
print("Percentage of classes in training set:")
print(y_train.value_counts(normalize=True))
print("Percentage of classes in test set:")
print(y_test.value_counts(normalize=True))
```

```
Shape of Training set :  (25392, 72)
Shape of test set :  (10883, 72)
Percentage of classes in training set:
0    0.672
1    0.328
Name: booking_status, dtype: float64
Percentage of classes in test set:
0    0.672
1    0.328
Name: booking_status, dtype: float64
```

1.9 Checking Multicollinearity

```
[ ]: # let's check the VIF of the predictors
     from statsmodels.stats.outliers_influence import variance_inflation_factor

     vif_series = pd.Series(
         [variance_inflation_factor(X_train.values, i) for i in range(X_train.
      ↪shape[1])],
         index=X_train.columns,
     )
     print("VIF values: \n\n{}\n".format(vif_series))
```

```
VIF values:

const                        665.285
no_of_adults_1                49.982
no_of_adults_2                58.771
no_of_adults_3                18.168
no_of_adults_4                 1.176
                               …
no_of_special_requests_1       1.244
no_of_special_requests_2       1.267
no_of_special_requests_3       1.059
no_of_special_requests_4       1.016
no_of_special_requests_5       1.004
Length: 72, dtype: float64
```

```
[ ]: # fitting the model on training set
     logit = sm.Logit(y_train, X_train.astype(float))
     lg = logit.fit()
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.514180
         Iterations: 35
```

```
[ ]: # let's print the logistic regression summary
     print(lg.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:         booking_status   No. Observations:                25392
Model:                          Logit   Df Residuals:                    25320
Method:                           MLE   Df Model:                           71
Date:                Thu, 25 Aug 2022   Pseudo R-squ.:                  0.1870
Time:                        22:06:14   Log-Likelihood:                -13056.
converged:                      False   LL-Null:                       -16060.
Covariance Type:            nonrobust   LLR p-value:                     0.000
```

```
==============================================================================
==========================
                                            coef    std err          z
P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
--------------------------
const                                    -4.0743      0.476     -8.556
0.000      -5.008      -3.141
no_of_adults_1                           -0.3034      0.263     -1.155
0.248      -0.818       0.211
no_of_adults_2                            0.2167      0.260      0.834
0.404      -0.293       0.726
no_of_adults_3                            0.3682      0.268      1.374
0.169      -0.157       0.893
no_of_adults_4                           -0.3655      0.778     -0.470
0.639      -1.891       1.160
no_of_children_1                          0.2739      0.062      4.414
0.000       0.152       0.396
no_of_weekend_nights_4 or more            1.6255      0.284      5.730
0.000       1.069       2.182
no_of_week_nights_7 or higher             0.9213      0.193      4.761
0.000       0.542       1.301
type_of_meal_plan_Meal Plan 2             0.7327      0.053     13.698
0.000       0.628       0.837
type_of_meal_plan_Meal Plan 3            16.0472   2279.570      0.007
0.994   -4451.828    4483.923
type_of_meal_plan_Not Selected           -0.2679      0.046     -5.810
0.000      -0.358      -0.178
required_car_parking_space_1             -1.3192      0.128    -10.298
0.000      -1.570      -1.068
arrival_month_2                           3.0831      0.285     10.808
0.000       2.524       3.642
arrival_month_3                           3.1352      0.282     11.098
0.000       2.581       3.689
arrival_month_4                           3.3507      0.281     11.914
0.000       2.800       3.902
arrival_month_5                           3.5748      0.282     12.687
0.000       3.023       4.127
arrival_month_6                           3.8736      0.281     13.802
0.000       3.323       4.424
arrival_month_7                           3.9157      0.281     13.925
0.000       3.365       4.467
arrival_month_8                           3.5908      0.280     12.814
0.000       3.042       4.140
arrival_month_9                           3.5148      0.280     12.565
0.000       2.967       4.063
arrival_month_10                          3.7653      0.279     13.480
0.000       3.218       4.313
```

arrival_month_11	3.5713	0.282	12.681	0.000	3.019	4.123
arrival_month_12	2.1058	0.285	7.395	0.000	1.548	2.664
arrival_date_2	-0.7911	0.119	-6.647	0.000	-1.024	-0.558
arrival_date_3	-0.1987	0.118	-1.681	0.093	-0.430	0.033
arrival_date_4	-0.2044	0.113	-1.808	0.071	-0.426	0.017
arrival_date_5	-0.5015	0.120	-4.168	0.000	-0.737	-0.266
arrival_date_6	-0.2031	0.114	-1.781	0.075	-0.427	0.020
arrival_date_7	-0.3845	0.118	-3.249	0.001	-0.617	-0.153
arrival_date_8	-0.3915	0.118	-3.312	0.001	-0.623	-0.160
arrival_date_9	-0.7418	0.123	-6.028	0.000	-0.983	-0.501
arrival_date_10	-0.5723	0.122	-4.691	0.000	-0.811	-0.333
arrival_date_11	-0.6288	0.122	-5.171	0.000	-0.867	-0.390
arrival_date_12	-0.1334	0.114	-1.168	0.243	-0.357	0.090
arrival_date_13	-0.5866	0.114	-5.125	0.000	-0.811	-0.362
arrival_date_14	-0.7789	0.118	-6.612	0.000	-1.010	-0.548
arrival_date_15	-0.0182	0.114	-0.161	0.872	-0.241	0.204
arrival_date_16	-0.3682	0.113	-3.245	0.001	-0.591	-0.146
arrival_date_17	-0.2743	0.113	-2.433	0.015	-0.495	-0.053
arrival_date_18	-0.6036	0.116	-5.200	0.000	-0.831	-0.376
arrival_date_19	-0.1262	0.116	-1.091	0.275	-0.353	0.101
arrival_date_20	-0.3219	0.115	-2.803	0.005	-0.547	-0.097
arrival_date_21	-0.5087	0.119	-4.279	0.000	-0.742	-0.276
arrival_date_22	-0.3017	0.121	-2.484	0.013	-0.540	-0.064
arrival_date_23	-0.2850	0.122	-2.341	0.019	-0.524	-0.046

```
arrival_date_24                              -0.2595      0.118     -2.197
0.028      -0.491      -0.028
arrival_date_25                              -0.2807      0.118     -2.383
0.017      -0.512      -0.050
arrival_date_26                              -0.1089      0.117     -0.934
0.350      -0.337       0.120
arrival_date_27                              -0.2357      0.124     -1.895
0.058      -0.479       0.008
arrival_date_28                              -0.0655      0.118     -0.554
0.580      -0.297       0.166
arrival_date_29                              -0.4721      0.120     -3.919
0.000      -0.708      -0.236
arrival_date_30                              -0.0998      0.116     -0.859
0.391      -0.327       0.128
arrival_date_31                              -0.3518      0.151     -2.326
0.020      -0.648      -0.055
market_segment_type_Complementary           -25.1757   4448.946     -0.006
0.995   -8744.949    8694.597
market_segment_type_Corporate                -0.3890      0.287     -1.355
0.175      -0.951       0.174
market_segment_type_Offline                   0.0464      0.275      0.169
0.866      -0.493       0.586
market_segment_type_Online                    1.2657      0.275      4.601
0.000       0.727       1.805
repeated_guest_1                             16.2297   4.13e+07   3.93e-07
1.000   -8.09e+07    8.09e+07
no_of_previous_cancellations_1              -17.9946   4.13e+07  -4.36e-07
1.000   -8.09e+07    8.09e+07
no_of_previous_cancellations_2              -24.4687   1.86e+08  -1.32e-07
1.000   -3.64e+08    3.64e+08
no_of_previous_cancellations_3               -3.6001   1.31e+07  -2.75e-07
1.000   -2.57e+07    2.57e+07
no_of_previous_cancellations_4                6.3599   7.63e+05   8.34e-06
1.000   -1.49e+06    1.49e+06
no_of_previous_cancellations_5                7.9245   7.98e+05   9.93e-06
1.000   -1.56e+06    1.56e+06
no_of_previous_cancellations_6                2.8568   1.49e+07   1.92e-07
1.000   -2.91e+07    2.91e+07
no_of_previous_cancellations_11             -95.2932   6.65e+17  -1.43e-16
1.000     -1.3e+18     1.3e+18
no_of_previous_cancellations_13              50.3191   7.25e+05   6.94e-05
1.000   -1.42e+06    1.42e+06
no_of_previous_bookings_not_canceled_1      -47.0271   4.13e+07  -1.14e-06
1.000   -8.09e+07    8.09e+07
no_of_special_requests_1                     -1.4613      0.037    -39.538
0.000      -1.534      -1.389
no_of_special_requests_2                     -2.3598      0.061    -38.486
0.000      -2.480      -2.240
```

```
no_of_special_requests_3                -25.2921   1.06e+04     -0.002
0.998   -2.08e+04    2.07e+04
no_of_special_requests_4                -22.1142   6340.442     -0.003
0.997   -1.24e+04    1.24e+04
no_of_special_requests_5                -21.5983    1.2e+04     -0.002
0.999   -2.35e+04    2.34e+04
================================================================================
==========================
```

There are some features with P>0.05 but once they're dummy variables we will tolerate them

Visualizing the coefficients

[ ]:

```python
# converting coefficients to odds
odds = np.exp(lg.params)

# finding the percentage change
perc_change_odds = (np.exp(lg.params) - 1) * 100

# removing limit from number of columns to display
pd.set_option("display.max_columns", None)

# adding the odds to a dataframe
pd.DataFrame({"Odds": odds, "Change_odd%": perc_change_odds}, index=X_train.
 ↪columns).T
```

[ ]:

```
              const  no_of_adults_1  no_of_adults_2  no_of_adults_3  \
Odds          0.017           0.738           1.242           1.445
Change_odd% -98.300         -26.171          24.195          44.514

             no_of_adults_4  no_of_children_1  no_of_weekend_nights_4 or more  \
Odds                  0.694             1.315                           5.081
Change_odd%         -30.617            31.515                         408.107

             no_of_week_nights_7 or higher  type_of_meal_plan_Meal Plan 2  \
Odds                                 2.513                          2.081
Change_odd%                        151.258                        108.061

             type_of_meal_plan_Meal Plan 3  type_of_meal_plan_Not Selected  \
Odds                           9316049.791                           0.765
Change_odd%                  931604879.143                         -23.504

             required_car_parking_space_1  arrival_month_2  arrival_month_3  \
Odds                                0.267           21.825           22.993
Change_odd%                       -73.266         2082.532         2199.272

             arrival_month_4  arrival_month_5  arrival_month_6  \
Odds                  28.523           35.687           48.113
```

```
Change_odd%        2752.270        3468.739        4711.340

             arrival_month_7  arrival_month_8  arrival_month_9  \
Odds                  50.182           36.263           33.611
Change_odd%         4918.236         3526.280         3261.058

             arrival_month_10  arrival_month_11  arrival_month_12  \
Odds                   43.177            35.563             8.214
Change_odd%          4217.705          3456.274           721.391

             arrival_date_2  arrival_date_3  arrival_date_4  arrival_date_5  \
Odds                  0.453           0.820           0.815           0.606
Change_odd%         -54.667         -18.018         -18.490         -39.438

             arrival_date_6  arrival_date_7  arrival_date_8  arrival_date_9  \
Odds                  0.816           0.681           0.676           0.476
Change_odd%         -18.382         -31.924         -32.395         -52.375

             arrival_date_10  arrival_date_11  arrival_date_12  \
Odds                   0.564            0.533            0.875
Change_odd%          -43.578          -46.677          -12.489

             arrival_date_13  arrival_date_14  arrival_date_15  \
Odds                   0.556            0.459            0.982
Change_odd%          -44.380          -54.109           -1.808

             arrival_date_16  arrival_date_17  arrival_date_18  \
Odds                   0.692            0.760            0.547
Change_odd%          -30.803          -23.990          -45.318

             arrival_date_19  arrival_date_20  arrival_date_21  \
Odds                   0.881            0.725            0.601
Change_odd%          -11.852          -27.521          -39.870

             arrival_date_22  arrival_date_23  arrival_date_24  \
Odds                   0.740            0.752            0.771
Change_odd%          -26.047          -24.798          -22.860

             arrival_date_25  arrival_date_26  arrival_date_27  \
Odds                   0.755            0.897            0.790
Change_odd%          -24.472          -10.321          -20.996

             arrival_date_28  arrival_date_29  arrival_date_30  \
Odds                   0.937            0.624            0.905
Change_odd%           -6.341          -37.631           -9.494

             arrival_date_31  market_segment_type_Complementary  \
```

```
Odds                 0.703                              0.000
Change_odd%        -29.659                           -100.000

             market_segment_type_Corporate  market_segment_type_Offline  \
Odds                                 0.678                        1.048
Change_odd%                        -32.224                        4.754

             market_segment_type_Online  repeated_guest_1  \
Odds                              3.546      11180218.410
Change_odd%                     254.556    1118021740.991

             no_of_previous_cancellations_1  no_of_previous_cancellations_2  \
Odds                                  0.000                           0.000
Change_odd%                        -100.000                        -100.000

             no_of_previous_cancellations_3  no_of_previous_cancellations_4  \
Odds                                  0.027                         578.191
Change_odd%                         -97.268                       57719.088

             no_of_previous_cancellations_5  no_of_previous_cancellations_6  \
Odds                               2764.097                          17.405
Change_odd%                      276309.664                        1640.540

             no_of_previous_cancellations_11  no_of_previous_cancellations_13  \
Odds                                   0.000      7133772770655154995200.000
Change_odd%                         -100.000    713377277065515554045952.000

             no_of_previous_bookings_not_canceled_1  no_of_special_requests_1  \
Odds                                          0.000                     0.232
Change_odd%                                -100.000                   -76.808

             no_of_special_requests_2  no_of_special_requests_3  \
Odds                            0.094                     0.000
Change_odd%                   -90.556                  -100.000

             no_of_special_requests_4  no_of_special_requests_5
Odds                            0.000                     0.000
Change_odd%                  -100.000                  -100.000
```

The interpretation of the coefficients is harmed because I didn’t exclude the multicolinearity and high P Values, but still, i’m aiming to better predict instead of interpreting

1.10 Model performance evaluation

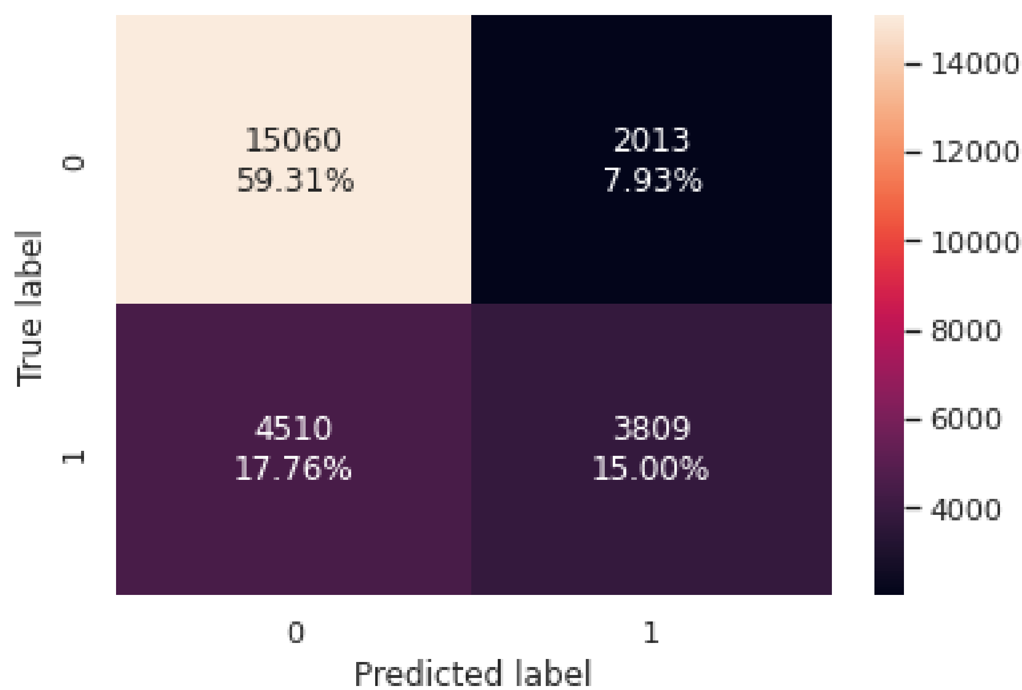
[ ]:
```
# predicting on training set
# default threshold is 0.5, if predicted probability is greater than 0.5 the␣
↪observation will be classified as 1

pred_train = lg.predict(X_train) > 0.5
pred_train = np.round(pred_train)
```

[ ]:
```
# defining a function to compute different metrics to check performance of a␣
↪classification model built using statsmodels
def model_performance_classification_statsmodels(
    model, predictors, target, threshold=0.5
):
    """
    Function to compute different metrics to check classification model␣
↪performance

    model: classifier
    predictors: independent variables
    target: dependent variable
    threshold: threshold for classifying the observation as class 1
    """

    # checking which probabilities are greater than threshold
    pred_temp = model.predict(predictors) > threshold
    # rounding off the above values to get classes
    pred = np.round(pred_temp)

    acc = accuracy_score(target, pred)  # to compute Accuracy
    recall = recall_score(target, pred)  # to compute Recall
    precision = precision_score(target, pred)  # to compute Precision
    f1 = f1_score(target, pred)  # to compute F1-score

    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {"Accuracy": acc, "Recall": recall, "Precision": precision, "F1": f1,},
        index=[0],
    )

    return df_perf
```

[ ]:
```
# defining a function to plot the confusion_matrix of a classification model


def confusion_matrix_statsmodels(model, predictors, target, threshold=0.5):
    """
```

```
    To plot the confusion_matrix with percentages

    model: classifier
    predictors: independent variables
    target: dependent variable
    threshold: threshold for classifying the observation as class 1
    """
    y_pred = model.predict(predictors) > threshold
    cm = confusion_matrix(target, y_pred)
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatten().
↪sum())]
            for item in cm.flatten()
        ]
    ).reshape(2, 2)

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=labels, fmt="")
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

[ ]:
```
confusion_matrix_statsmodels(lg, X_train, y_train)
```



The confusion matrix

- True Positives (TP): A booking is cancelled and the model predicted cancellation.
- True Negatives (TN): A booking is not cancelled and the model predicted no cancellation.
- False Positives (FP): The model predicted cancellation but the but the booking is not cancelled
- False Negatives (FN): The model predicted no cancellation but the booking is cancelled.

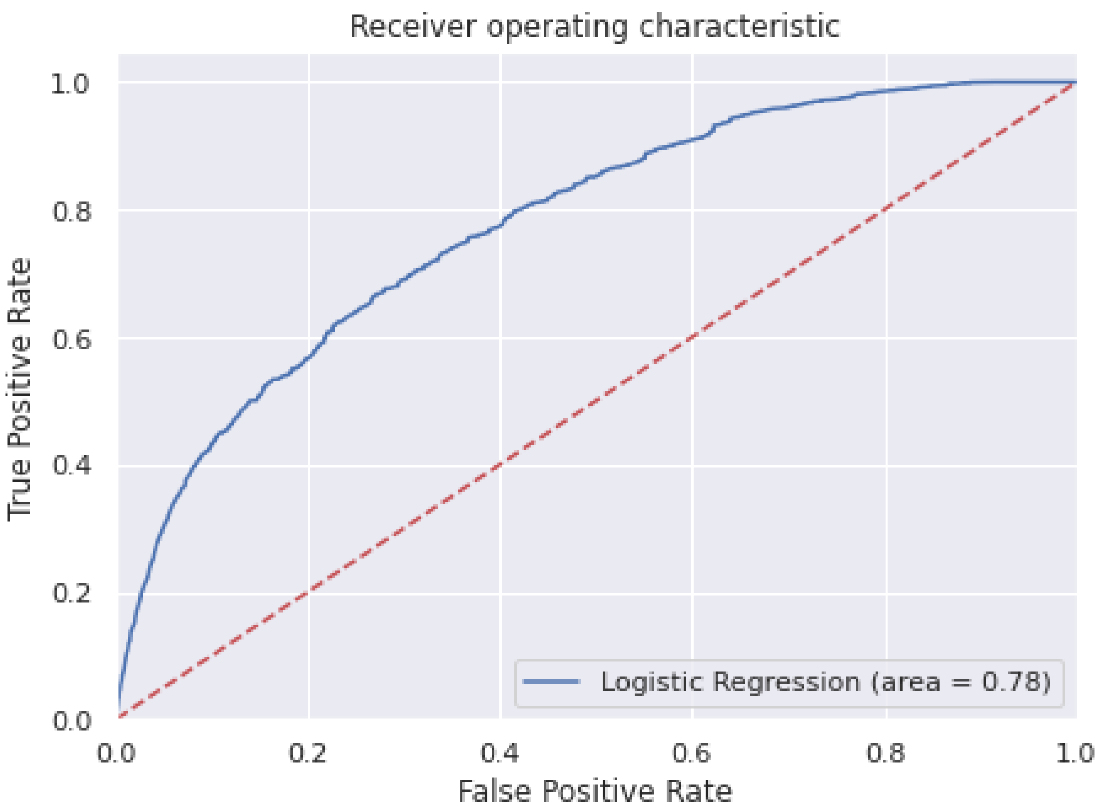
[ ]:
```
print("Training performance:")
model_performance_classification_statsmodels(lg, X_train, y_train)
```

```
Training performance:
```

[ ]:

	Accuracy	Recall	Precision	F1
0	0.743	0.458	0.654	0.539

[ ]:
```
logit_roc_auc_train = roc_auc_score(y_train, lg.predict(X_train))
fpr, tpr, thresholds = roc_curve(y_train, lg.predict(X_train))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="Logistic Regression (area = %0.2f)" %␣
 ↪logit_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

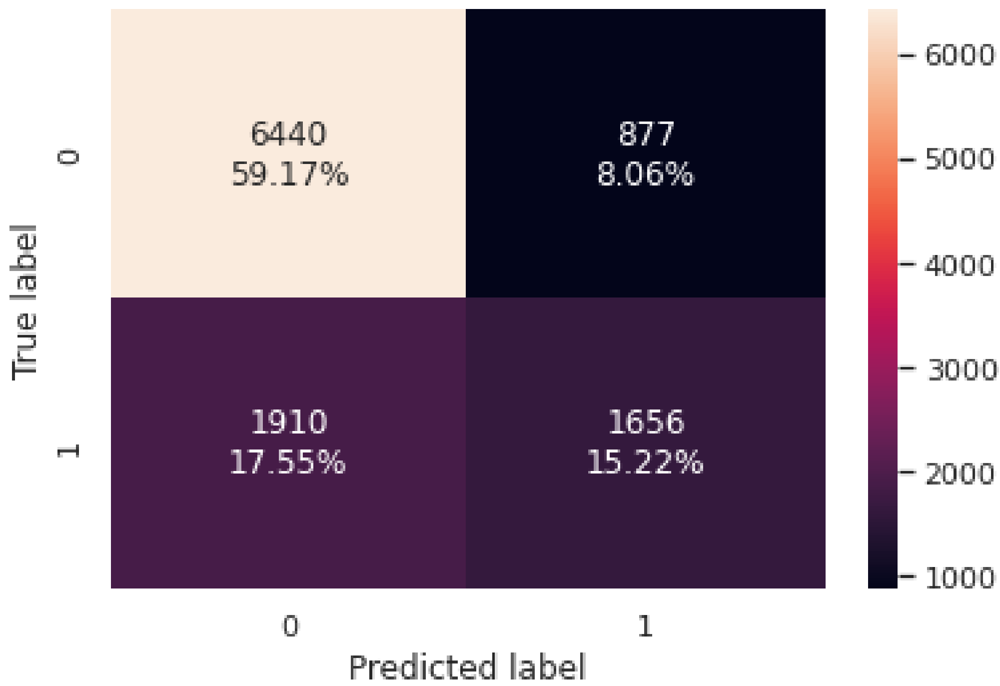


Logistic Regression model is giving a good performance on training set

Test Performance

[ ]:
```
X_test = X_test[list(X_train.columns)]
```

[ ]:
```
# creating confusion matrix
confusion_matrix_statsmodels(lg, X_test, y_test)
```




```
[ ]: log_reg_model_test_perf = model_performance_classification_statsmodels(
         lg, X_test, y_test
     )

     print("Test performance:")
     log_reg_model_test_perf
```

Test performance:

[ ]:

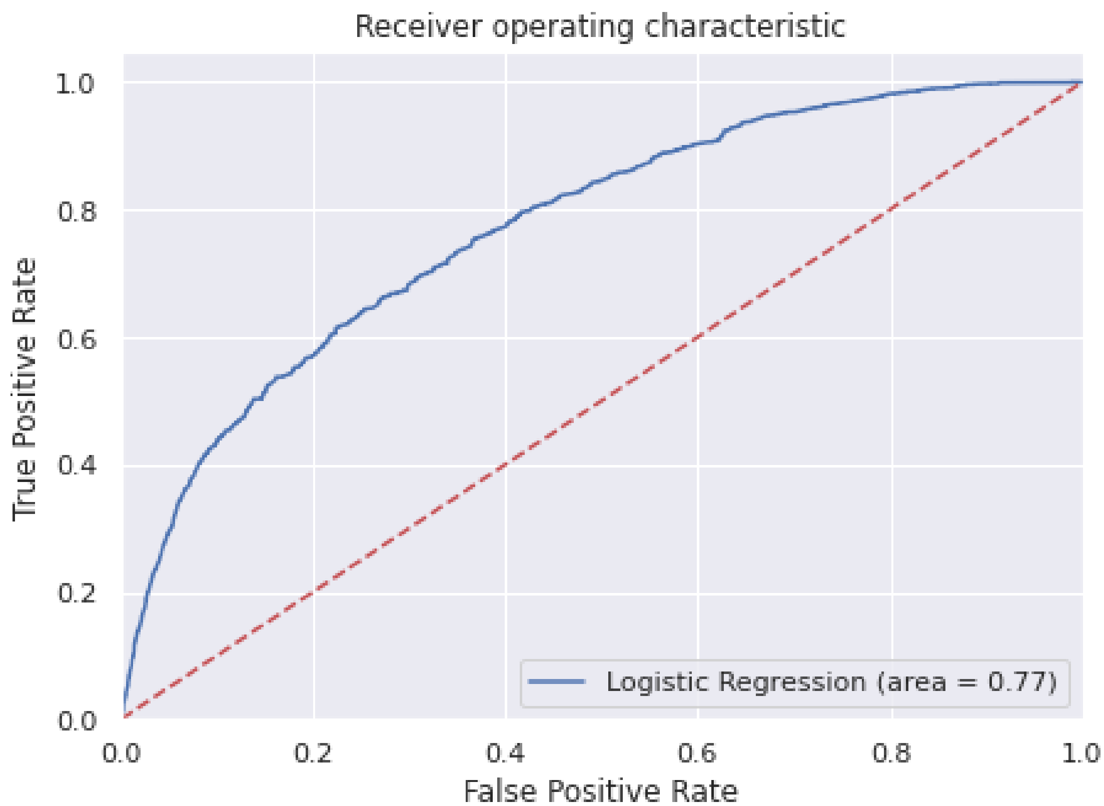
	Accuracy	Recall	Precision	F1
0	0.744	0.464	0.654	0.543

Insights:

- In this case `precision` is the most important metric and 65% is pretty acceptable
- Positive results for `precision` and `accuracy` and the test performance is close to the training performance which indicates we have no overfitting and by the `precision` value the model captured good amount of information

```
[ ]: logit_roc_auc_train = roc_auc_score(y_test, lg.predict(X_test))
     fpr, tpr, thresholds = roc_curve(y_test, lg.predict(X_test))
     plt.figure(figsize=(7, 5))
     plt.plot(fpr, tpr, label="Logistic Regression (area = %0.2f)" %␣
      ↪logit_roc_auc_train)
     plt.plot([0, 1], [0, 1], "r--")
```

```
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```



1.11 Final Model Summary

[ ]:
```
print(lg.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:         booking_status   No. Observations:                25392
Model:                          Logit   Df Residuals:                    25320
Method:                           MLE   Df Model:                           71
Date:                Thu, 25 Aug 2022   Pseudo R-squ.:                  0.1870
Time:                        22:06:16   Log-Likelihood:                -13056.
converged:                      False   LL-Null:                       -16060.
Covariance Type:            nonrobust   LLR p-value:                     0.000
```

```
================================================================================
=========================
                                                  coef    std err          z
P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
-------------------------
const                                          -4.0743      0.476     -8.556
0.000      -5.008      -3.141
no_of_adults_1                                 -0.3034      0.263     -1.155
0.248      -0.818       0.211
no_of_adults_2                                  0.2167      0.260      0.834
0.404      -0.293       0.726
no_of_adults_3                                  0.3682      0.268      1.374
0.169      -0.157       0.893
no_of_adults_4                                 -0.3655      0.778     -0.470
0.639      -1.891       1.160
no_of_children_1                                0.2739      0.062      4.414
0.000       0.152       0.396
no_of_weekend_nights_4 or more                  1.6255      0.284      5.730
0.000       1.069       2.182
no_of_week_nights_7 or higher                   0.9213      0.193      4.761
0.000       0.542       1.301
type_of_meal_plan_Meal Plan 2                   0.7327      0.053     13.698
0.000       0.628       0.837
type_of_meal_plan_Meal Plan 3                  16.0472   2279.570      0.007
0.994   -4451.828    4483.923
type_of_meal_plan_Not Selected                 -0.2679      0.046     -5.810
0.000      -0.358      -0.178
required_car_parking_space_1                   -1.3192      0.128    -10.298
0.000      -1.570      -1.068
arrival_month_2                                 3.0831      0.285     10.808
0.000       2.524       3.642
arrival_month_3                                 3.1352      0.282     11.098
0.000       2.581       3.689
arrival_month_4                                 3.3507      0.281     11.914
0.000       2.800       3.902
arrival_month_5                                 3.5748      0.282     12.687
0.000       3.023       4.127
arrival_month_6                                 3.8736      0.281     13.802
0.000       3.323       4.424
arrival_month_7                                 3.9157      0.281     13.925
0.000       3.365       4.467
arrival_month_8                                 3.5908      0.280     12.814
0.000       3.042       4.140
arrival_month_9                                 3.5148      0.280     12.565
0.000       2.967       4.063
arrival_month_10                                3.7653      0.279     13.480
0.000       3.218       4.313
```

```
arrival_month_11                               3.5713      0.282     12.681
0.000       3.019       4.123
arrival_month_12                               2.1058      0.285      7.395
0.000       1.548       2.664
arrival_date_2                                -0.7911      0.119     -6.647
0.000      -1.024      -0.558
arrival_date_3                                -0.1987      0.118     -1.681
0.093      -0.430       0.033
arrival_date_4                                -0.2044      0.113     -1.808
0.071      -0.426       0.017
arrival_date_5                                -0.5015      0.120     -4.168
0.000      -0.737      -0.266
arrival_date_6                                -0.2031      0.114     -1.781
0.075      -0.427       0.020
arrival_date_7                                -0.3845      0.118     -3.249
0.001      -0.617      -0.153
arrival_date_8                                -0.3915      0.118     -3.312
0.001      -0.623      -0.160
arrival_date_9                                -0.7418      0.123     -6.028
0.000      -0.983      -0.501
arrival_date_10                               -0.5723      0.122     -4.691
0.000      -0.811      -0.333
arrival_date_11                               -0.6288      0.122     -5.171
0.000      -0.867      -0.390
arrival_date_12                               -0.1334      0.114     -1.168
0.243      -0.357       0.090
arrival_date_13                               -0.5866      0.114     -5.125
0.000      -0.811      -0.362
arrival_date_14                               -0.7789      0.118     -6.612
0.000      -1.010      -0.548
arrival_date_15                               -0.0182      0.114     -0.161
0.872      -0.241       0.204
arrival_date_16                               -0.3682      0.113     -3.245
0.001      -0.591      -0.146
arrival_date_17                               -0.2743      0.113     -2.433
0.015      -0.495      -0.053
arrival_date_18                               -0.6036      0.116     -5.200
0.000      -0.831      -0.376
arrival_date_19                               -0.1262      0.116     -1.091
0.275      -0.353       0.101
arrival_date_20                               -0.3219      0.115     -2.803
0.005      -0.547      -0.097
arrival_date_21                               -0.5087      0.119     -4.279
0.000      -0.742      -0.276
arrival_date_22                               -0.3017      0.121     -2.484
0.013      -0.540      -0.064
arrival_date_23                               -0.2850      0.122     -2.341
0.019      -0.524      -0.046
```

```
arrival_date_24                            -0.2595      0.118     -2.197
0.028      -0.491      -0.028
arrival_date_25                            -0.2807      0.118     -2.383
0.017      -0.512      -0.050
arrival_date_26                            -0.1089      0.117     -0.934
0.350      -0.337       0.120
arrival_date_27                            -0.2357      0.124     -1.895
0.058      -0.479       0.008
arrival_date_28                            -0.0655      0.118     -0.554
0.580      -0.297       0.166
arrival_date_29                            -0.4721      0.120     -3.919
0.000      -0.708      -0.236
arrival_date_30                            -0.0998      0.116     -0.859
0.391      -0.327       0.128
arrival_date_31                            -0.3518      0.151     -2.326
0.020      -0.648      -0.055
market_segment_type_Complementary         -25.1757   4448.946     -0.006
0.995   -8744.949    8694.597
market_segment_type_Corporate              -0.3890      0.287     -1.355
0.175      -0.951       0.174
market_segment_type_Offline                 0.0464      0.275      0.169
0.866      -0.493       0.586
market_segment_type_Online                  1.2657      0.275      4.601
0.000       0.727       1.805
repeated_guest_1                           16.2297   4.13e+07   3.93e-07
1.000   -8.09e+07    8.09e+07
no_of_previous_cancellations_1            -17.9946   4.13e+07  -4.36e-07
1.000   -8.09e+07    8.09e+07
no_of_previous_cancellations_2            -24.4687   1.86e+08  -1.32e-07
1.000   -3.64e+08    3.64e+08
no_of_previous_cancellations_3             -3.6001   1.31e+07  -2.75e-07
1.000   -2.57e+07    2.57e+07
no_of_previous_cancellations_4              6.3599   7.63e+05   8.34e-06
1.000   -1.49e+06    1.49e+06
no_of_previous_cancellations_5              7.9245   7.98e+05   9.93e-06
1.000   -1.56e+06    1.56e+06
no_of_previous_cancellations_6              2.8568   1.49e+07   1.92e-07
1.000   -2.91e+07    2.91e+07
no_of_previous_cancellations_11           -95.2932   6.65e+17  -1.43e-16
1.000     -1.3e+18     1.3e+18
no_of_previous_cancellations_13            50.3191   7.25e+05   6.94e-05
1.000   -1.42e+06    1.42e+06
no_of_previous_bookings_not_canceled_1    -47.0271   4.13e+07  -1.14e-06
1.000   -8.09e+07    8.09e+07
no_of_special_requests_1                   -1.4613      0.037    -39.538
0.000      -1.534      -1.389
no_of_special_requests_2                   -2.3598      0.061    -38.486
0.000      -2.480      -2.240
```

```
no_of_special_requests_3                    -25.2921    1.06e+04     -0.002
0.998    -2.08e+04    2.07e+04
no_of_special_requests_4                    -22.1142    6340.442     -0.003
0.997    -1.24e+04    1.24e+04
no_of_special_requests_5                    -21.5983     1.2e+04     -0.002
0.999    -2.35e+04    2.34e+04
================================================================================
==========================
```

1.12 Building a Decision Tree model

[ ]:
```python
df_dtree.columns
```

[ ]:
```
Index(['Booking_ID', 'no_of_adults', 'no_of_children', 'no_of_weekend_nights',
       'no_of_week_nights', 'type_of_meal_plan', 'required_car_parking_space',
       'room_type_reserved', 'lead_time', 'arrival_year', 'arrival_month',
       'arrival_date', 'market_segment_type', 'repeated_guest',
       'no_of_previous_cancellations', 'no_of_previous_bookings_not_canceled',
       'avg_price_per_room', 'no_of_special_requests', 'booking_status'],
      dtype='object')
```

Spliting and creating the dummy variables

[ ]:
```python
X = df_dtree.drop('booking_status', axis=1)
Y = df_dtree["booking_status"]

X = pd.get_dummies(X, drop_first=True)

# Splitting data in train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.30, random_state=1
)
```

[ ]:
```python
print("Shape of Training set : ", X_train.shape)
print("Shape of test set : ", X_test.shape)
print("Percentage of classes in training set:")
print(y_train.value_counts(normalize=True))
print("Percentage of classes in test set:")
print(y_test.value_counts(normalize=True))
```

```
Shape of Training set :  (25392, 36357)
Shape of test set :  (10883, 36357)
Percentage of classes in training set:
0    0.671
1    0.329
Name: booking_status, dtype: float64
Percentage of classes in test set:
0    0.676
```

```
1    0.324
Name: booking_status, dtype: float64
```

Close to the same % of `booking_status` 1 in both training and testing sets

Fitting the model

```
[ ]: model0 = DecisionTreeClassifier(random_state=1)
     model0.fit(X_train, y_train)
```

```
[ ]: DecisionTreeClassifier(random_state=1)
```

Creating functions to evaluate the model:

```
[ ]: # defining a function to compute different metrics to check performance of a␣
     ↪classification model built using sklearn
     def model_performance_classification_sklearn(model, predictors, target):
         """
         Function to compute different metrics to check classification model␣
     ↪performance

         model: classifier
         predictors: independent variables
         target: dependent variable
         """

         # predicting using the independent variables
         pred = model.predict(predictors)

         acc = accuracy_score(target, pred)  # to compute Accuracy
         recall = recall_score(target, pred)  # to compute Recall
         precision = precision_score(target, pred)  # to compute Precision
         f1 = f1_score(target, pred)  # to compute F1-score

         # creating a dataframe of metrics
         df_perf = pd.DataFrame(
             {"Accuracy": acc, "Recall": recall, "Precision": precision, "F1": f1,},
             index=[0],
         )

         return df_perf
```

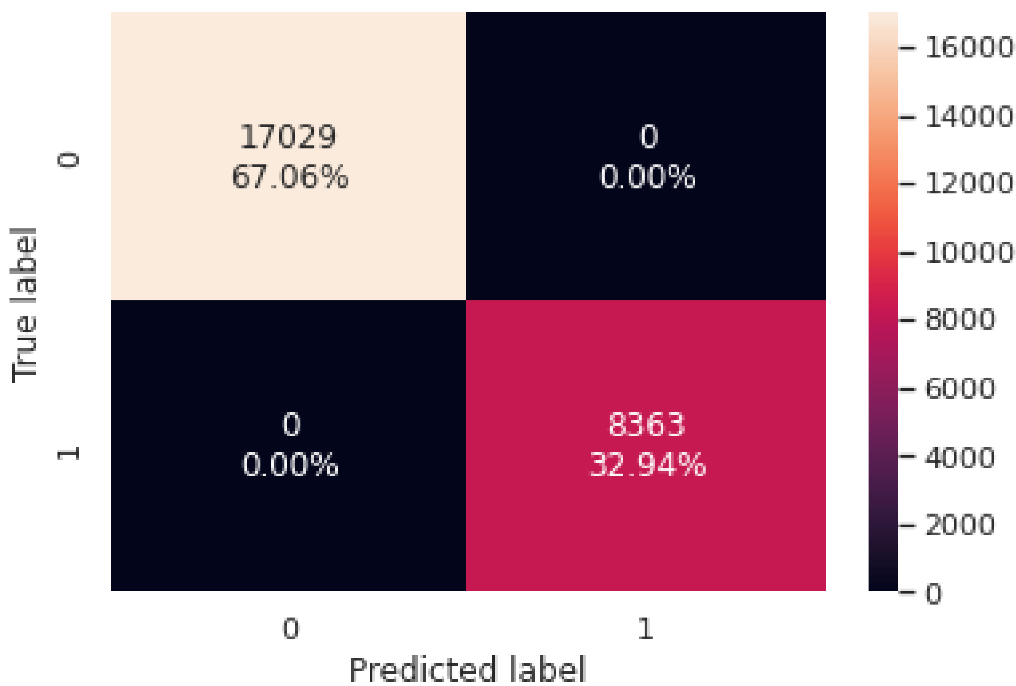
Creating function to make the confusion matrix with percentages:

```
[ ]: def confusion_matrix_sklearn(model, predictors, target):
         """
         To plot the confusion_matrix with percentages

         model: classifier
```

```
    predictors: independent variables
    target: dependent variable
    """
    y_pred = model.predict(predictors)
    cm = confusion_matrix(target, y_pred)
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatten().
↪sum())]
            for item in cm.flatten()
        ]
    ).reshape(2, 2)

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=labels, fmt="")
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

Training dataset results

[ ]:
```
confusion_matrix_sklearn(model0, X_train, y_train)
```



[ ]:
```
decision_tree_perf_train_without = model_performance_classification_sklearn(
    model0, X_train, y_train
```

```
)
decision_tree_perf_train_without
```

[ ]:

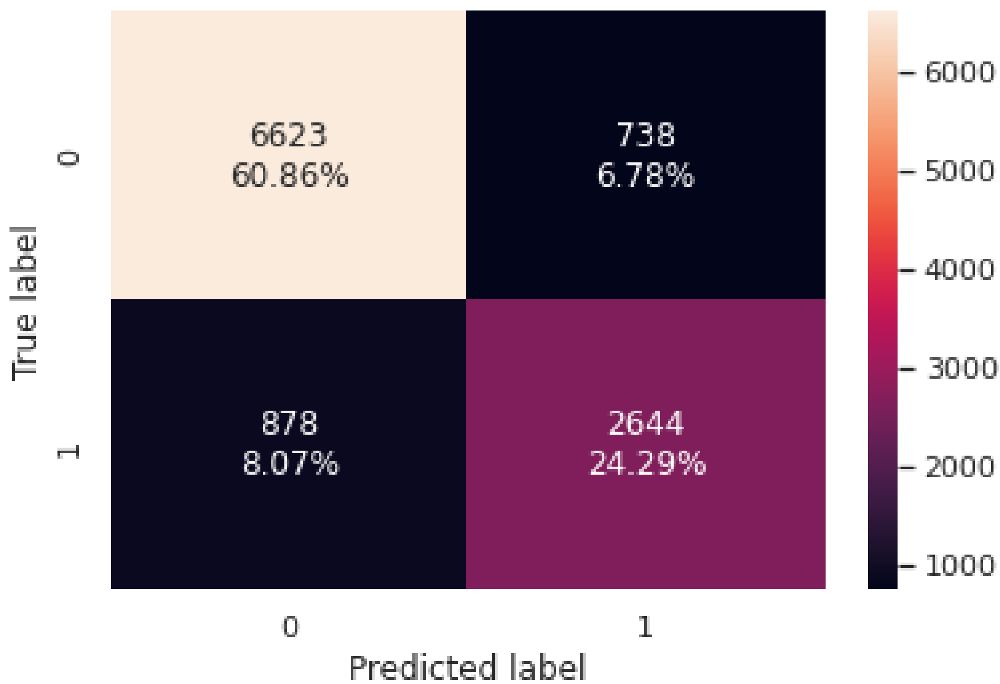
	Accuracy	Recall	Precision	F1
0	1.000	1.000	1.000	1.000

The training dataset has overfitted at the training data once we didn't pre-prune and the tree has grown to the max.

Let's check if it has the ability to generalise to the test data

Results on test dataset

[ ]:
```
confusion_matrix_sklearn(model0, X_test, y_test)
```



[ ]:
```
decision_tree_perf_test_without = model_performance_classification_sklearn(
    model0, X_test, y_test
)
decision_tree_perf_test_without
```

[ ]:

	Accuracy	Recall	Precision	F1
0	0.852	0.751	0.782	0.766

Altough the model has overfitted in the training data, the model has performed well into the test data. Specially when we look at `precision` which is the most important metric for this problem

1.13 Do we need to prune the tree?

The model has overfitted on the training dataset but presented satisfying performance no Precicion and F1 score.

The decision tree model presented better performance than Logistic Regression. For that reason, the tree don't need to be pruned.

But still we could post prune it and check if we're considering unrelevant data and lower the model complexity.

I tryied to perform post prunning seeking to improve the precision performance trying to find the best alpha but at the part of training the model it keeps processing and couldn't take that long.

So, once the result in the training dataset is satisfying for predicting purpose i'll leave as it is

1.14 Model Performance Comparison and Conclusions

[ ]:
```
print("Decision tree test performance:\n",  decision_tree_perf_test_without)
print("Logistic Regression test performance:\n", log_reg_model_test_perf)
```

```
Decision tree test performance:
    Accuracy  Recall  Precision    F1
0     0.852   0.751      0.782 0.766
Logistic Regression test performance:
    Accuracy  Recall  Precision    F1
0     0.744   0.464      0.654 0.543
```

The Decision Tree has higher `accuracy` and `precision` (which in this case is the most valuable metric) and `F1` score. So we would stay with Decision Tree model in order to predict which bookings will be canceled or not

1.15 Actionable Insights and Recommendations

- First of all, the company has to integrate the output of the model at some system, such as CRM or ERP so the data can be provided to other areas. After that the hotel is ready to use the data as a tool to decrease the cancellation rate.
- Lets pretend for a second that the output of the model is integrated to the company CRM system and now into the database there's this feature called `probably_cancel` and it will be filled with 0 or 1.
- The hotel could follow close to the bookings that are marked as `probably_cancel` and adopt some actions in order to reduce or have a B plan for the room, such as:

1. Having the reception to call to confirm withing certain periodos during the lead time;
2. Demanding some kind of pre certification of showing for those rooms;
3. Demanding some reservation fee that is part of the booking value and that would be not refundable in case of no show;

- The hotel could increase the fee of the clients/bookings market as `probably_cancel` in order to better balance with it's risk.

- The hotel has to make many tests through time to understand what reduces the % of False Negatives
- its important to keep track of the falses negatives and try to isolate the causes of it's change because it can be chaging because of the actions of the hotel to decrease the no-shows OR it can be changing because of the model itself or any other external phenomena.
- That's why it's important to experiment a lot and perform hypothesis testing, because the actions in order to avoid the cancelation will affected back the hability to predict of the model.
- Also, knowing that, it's important to review the model through time adding the data of the recomended actions so the actions the hotel take will be part of the predicting of the model.