Hotel Reservations Prediction

August 29, 2024

1 Business Understanding

1.1 No perfect vacations?

The online hotel reservation channels have dramatically changed booking possibilities and customers' behavior. A significant number of hotel reservations 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.

1.2 Goals

So the goals of this project is (1) explore data to find insights about cancelations, and (2) to build a machine learning model capable of predicting cancelations or no-shows beforehand.

2 Data Understanding

2.1 The features

Feature	**Description**
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
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

Feature	Description
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

2.2 Libraries import and loading the data

[ ]:
```
# Data manipulation
import pandas as pd
import numpy as np

# EDA
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning
from lightgbm import LGBMClassifier

# Pre-processing
import optuna
from sklearn import metrics
from sklearn.model_selection import train_test_split, StratifiedKFold,
 ↪cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from feature_engine.imputation import MeanMedianImputer, CategoricalImputer
from category_encoders import TargetEncoder, OrdinalEncoder

# Notebook config
import warnings
warnings.filterwarnings('ignore')
plt.style.use('ggplot')
sns.set_palette('Dark2')
```

```
pd.set_option('display.max_rows', 50)
pd.set_option('display.max_columns', None)
```

[ ]:
```
data = pd.read_csv("../data/raw/Hotel Reservations.csv")
```

2.3 Data quality

[ ]:
```
print(f"The dataset has {data.shape[0]} rows and {data.shape[1]} columns.")
```

```
The dataset has 36275 rows and 19 columns.
```

[ ]:
```
print(f"The dataset has: {len(data.select_dtypes(include = 'object').columns.
 ↪to_list())} categorical columns.")
print(f"The dataset has: {len(data.select_dtypes(include = 'number').columns.
 ↪to_list())} numeric columns.")
```

```
The dataset has: 5 categorical columns.
The dataset has: 14 numeric columns.
```

[ ]:
```
data.nunique().sort_values()
```

[ ]:
```
arrival_year                               2
repeated_guest                             2
required_car_parking_space                 2
booking_status                             2
type_of_meal_plan                          4
market_segment_type                        5
no_of_adults                               5
no_of_children                             6
no_of_special_requests                     6
room_type_reserved                         7
no_of_weekend_nights                       8
no_of_previous_cancellations               9
arrival_month                             12
no_of_week_nights                         18
arrival_date                              31
no_of_previous_bookings_not_canceled      59
lead_time                                352
avg_price_per_room                      3930
Booking_ID                             36275
dtype: int64
```

[ ]:
```
data.dtypes
```

[ ]:
```
Booking_ID                              object
no_of_adults                             int64
no_of_children                           int64
no_of_weekend_nights                     int64
```

```
no_of_week_nights                        int64
type_of_meal_plan                       object
required_car_parking_space               int64
room_type_reserved                      object
lead_time                                int64
arrival_year                             int64
arrival_month                            int64
arrival_date                             int64
market_segment_type                     object
repeated_guest                           int64
no_of_previous_cancellations             int64
no_of_previous_bookings_not_canceled     int64
avg_price_per_room                     float64
no_of_special_requests                   int64
booking_status                          object
dtype: object
```

[ ]:
```
data.isnull().mean()
```

[ ]:
```
Booking_ID                              0.0
no_of_adults                            0.0
no_of_children                          0.0
no_of_weekend_nights                    0.0
no_of_week_nights                       0.0
type_of_meal_plan                       0.0
required_car_parking_space              0.0
room_type_reserved                      0.0
lead_time                               0.0
arrival_year                            0.0
arrival_month                           0.0
arrival_date                            0.0
market_segment_type                     0.0
repeated_guest                          0.0
no_of_previous_cancellations            0.0
no_of_previous_bookings_not_canceled    0.0
avg_price_per_room                      0.0
no_of_special_requests                  0.0
booking_status                          0.0
dtype: float64
```

[ ]:
```
data.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               65.00
1                                     0              106.68
2                                     0               60.00
3                                     0              100.00
4                                     0               94.50

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

2.4 Exploratory Data Analysis

[ ]:
```
data.describe().round(4).T
```

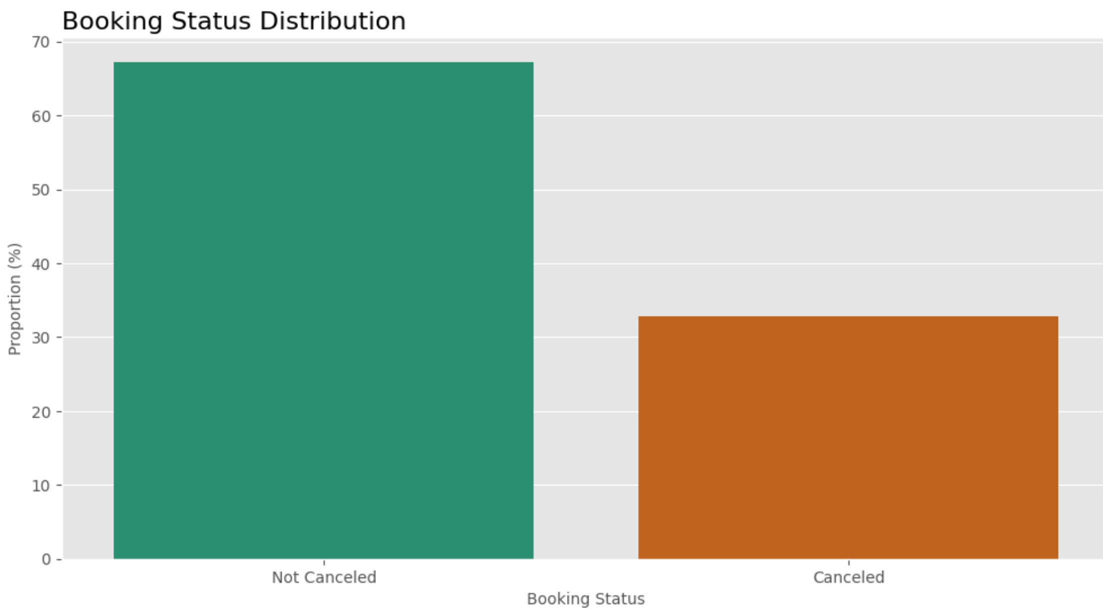
[ ]:
```
                                        count       mean      std      min  \
no_of_adults                          36275.0     1.8450   0.5187      0.0
no_of_children                        36275.0     0.1053   0.4026      0.0
no_of_weekend_nights                  36275.0     0.8107   0.8706      0.0
no_of_week_nights                     36275.0     2.2043   1.4109      0.0
required_car_parking_space            36275.0     0.0310   0.1733      0.0
```

```
lead_time                               36275.0     85.2326   85.9308      0.0
arrival_year                            36275.0   2017.8204    0.3838   2017.0
arrival_month                           36275.0      7.4237    3.0699      1.0
arrival_date                            36275.0     15.5970    8.7404      1.0
repeated_guest                          36275.0      0.0256    0.1581      0.0
no_of_previous_cancellations            36275.0      0.0233    0.3683      0.0
no_of_previous_bookings_not_canceled    36275.0      0.1534    1.7542      0.0
avg_price_per_room                      36275.0    103.4235   35.0894      0.0
no_of_special_requests                  36275.0      0.6197    0.7862      0.0

                                           25%       50%      75%      max
no_of_adults                               2.0      2.00      2.0      4.0
no_of_children                             0.0      0.00      0.0     10.0
no_of_weekend_nights                       0.0      1.00      2.0      7.0
no_of_week_nights                          1.0      2.00      3.0     17.0
required_car_parking_space                 0.0      0.00      0.0      1.0
lead_time                                 17.0     57.00    126.0    443.0
arrival_year                            2018.0   2018.00   2018.0   2018.0
arrival_month                              5.0      8.00     10.0     12.0
arrival_date                               8.0     16.00     23.0     31.0
repeated_guest                             0.0      0.00      0.0      1.0
no_of_previous_cancellations               0.0      0.00      0.0     13.0
no_of_previous_bookings_not_canceled       0.0      0.00      0.0     58.0
avg_price_per_room                        80.3     99.45    120.0    540.0
no_of_special_requests                     0.0      0.00      1.0      5.0
```

[ ]:
```
data.select_dtypes(exclude = 'number').describe().T
```

[ ]:
```
                    count  unique           top   freq
Booking_ID          36275   36275      INN00001      1
type_of_meal_plan   36275       4   Meal Plan 1  27835
room_type_reserved  36275       7   Room_Type 1  28130
market_segment_type 36275       5        Online  23214
booking_status      36275       2  Not_Canceled  24390
```

[ ]:
```
fig, ax = plt.subplots(figsize = (12, 6))
sns.countplot(x = data['booking_status'], hue = data['booking_status'], stat =␣
 ↪'percent')
ax.set_title("Booking Status Distribution", fontsize = 16, pad = 5, loc =␣
 ↪'left')
ax.set_xlabel("Booking Status", fontsize = 10)
ax.set_ylabel("Proportion (%)", fontsize = 10)
ax.set_xticklabels(['Not Canceled', 'Canceled'])
plt.show()
```



2.4.1 Lead time x Cancelations

Bookings made far in advance of the arrival date may have a higher probability of cancellation. Trips are always susceptible to changes in plans and unforeseen events, let's work on this hypothesis:

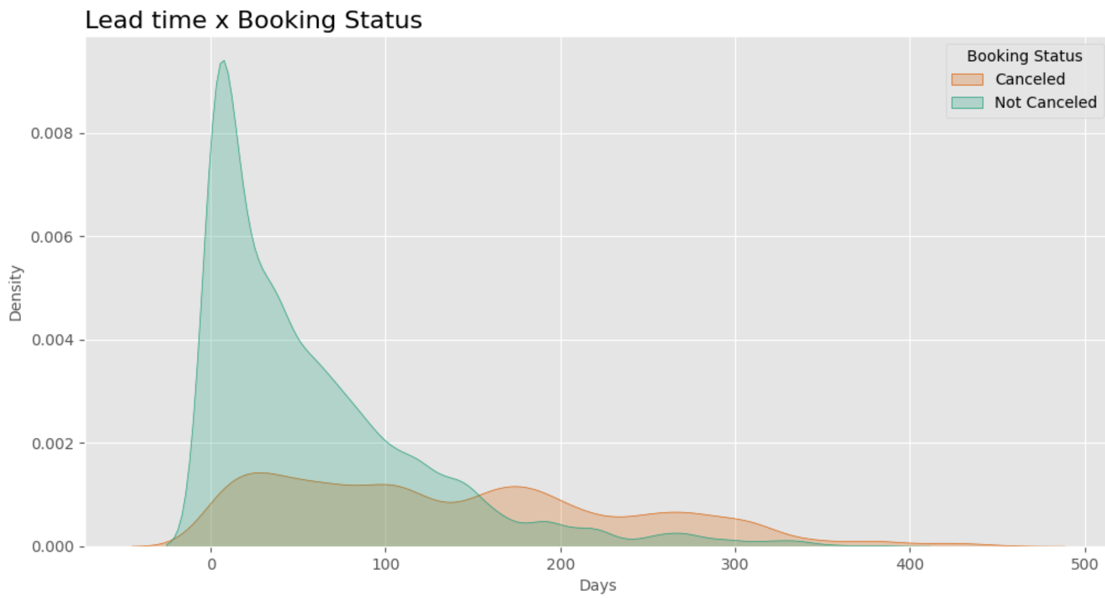
- H_0 : Lead time does not have a significant effect on cancellations.
- H_1 : A higher lead time increases the probability of cancellation.

[ ]:
```
from scipy.stats import mannwhitneyu

group_a = data[data['booking_status'] == 'Canceled']['lead_time']
group_b = data[data['booking_status'] == 'Not_Canceled']['lead_time']

_, p_value = mannwhitneyu(group_a, group_b, alternative = 'greater')

alpha = 0.05

if p_value < alpha:
    print("Reject H0: A higher lead time increases the probability of␣
 ↪cancellation.")
else:
    print("We do not reject H0: Lead time does not have a significant effect on␣
 ↪cancellations.")
```

```
Reject H0: A higher lead time increases the probability of cancellation.
```

[ ]:
```
fig, ax = plt.subplots(figsize = (12, 6))
sns.kdeplot(x = data['lead_time'], hue = data['booking_status'], fill = True)
```

```
ax.set_title("Lead time x Booking Status", fontsize = 16, pad = 5, loc = 'left')
ax.set_xlabel("Days", fontsize = 10)
ax.set_ylabel("Density", fontsize = 10)
ax.legend(title = 'Booking Status', labels = ['Canceled', 'Not Canceled'])
plt.show()
```



Bookings made between 150 and 300 days in advance have a higher probability of cancellation. It is advisable to create alerts and reservation confirmations starting from the 100-day mark.

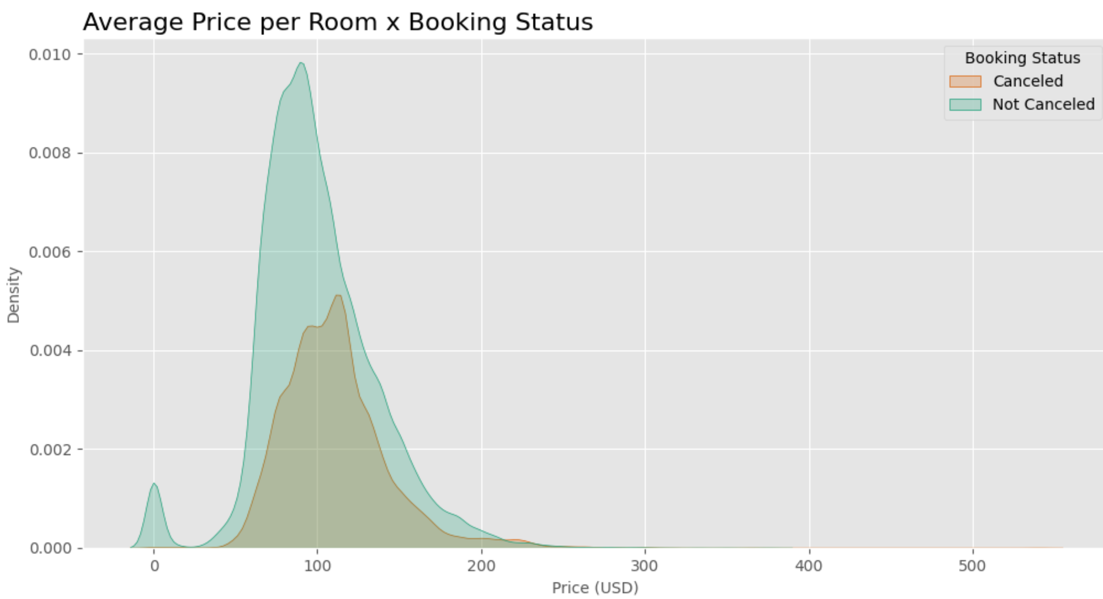
2.4.2 Average Price per Room x Cancelations

Does a higher priced room have higher probability of cancellation? - H_0 : The average price per room has no significant effect on the probability of cancellations. - H_1 : A higher average price per room is associated with a higher probability of cancellations.

[ ]:
```
group_a = data[data['booking_status'] == 'Canceled']['avg_price_per_room']
group_b = data[data['booking_status'] == 'Not_Canceled']['avg_price_per_room']

_, p_value = mannwhitneyu(group_a, group_b, alternative = 'greater')

alpha = 0.05

if p_value < alpha:
    print("Reject H0: A higher average price per room is associated with a␣
 ↪higher probability of cancellations.")
else:
    print("We do not reject H0: The average price per room has no significant␣
 ↪effect on the probability of cancellations.")
```

Reject H0: A higher average price per room is associated with a higher probability of cancellations.

```
[ ]: fig, ax = plt.subplots(figsize = (12, 6))

     sns.kdeplot(x = data['avg_price_per_room'], hue = data['booking_status'], fill␣
      ↪= True)
     ax.set_title("Average Price per Room x Booking Status", fontsize = 16, pad = 5,␣
      ↪loc = 'left')
     ax.set_xlabel("Price (USD)", fontsize = 10)
     ax.set_ylabel("Density", fontsize = 10)
     ax.legend(title = 'Booking Status', labels = ['Canceled', 'Not Canceled'])
     plt.show()
```



2.4.3 Number of Children x Cancelations

A higher number of children makes travel planning more difficult, as children tend to get sick more often, among other possible unforeseen events.

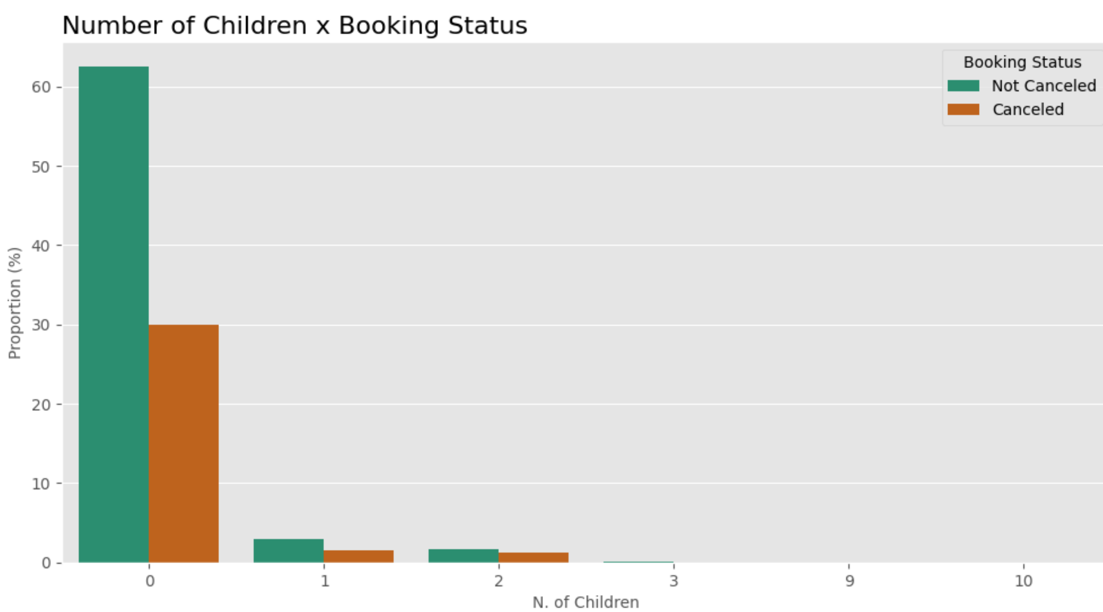
- H_0 : Number of children not have a significant effect on cancellations.
- H_1 : A higher number of children increases the probability of cancellation.

```
[ ]: group_a = data[data['booking_status'] == 'Canceled']['no_of_children']
     group_b = data[data['booking_status'] == 'Not_Canceled']['no_of_children']

     _, p_value = mannwhitneyu(group_a, group_b, alternative = 'greater')

     alpha = 0.05
```

```
if p_value < alpha:
    print("Reject H0: A higher number of children increases the probability of␣
 ↪cancellation.")
else:
    print("We do not reject H0: number of children does not have a significant␣
 ↪effect on cancellations.")
```

```
Reject H0: A higher number of children increases the probability of
cancellation.
```

[ ]:
```
fig, ax = plt.subplots(figsize = (12, 6))

sns.countplot(x = data['no_of_children'], hue = data['booking_status'], stat =␣
 ↪'percent')
ax.set_title("Number of Children x Booking Status", fontsize = 16, pad = 5, loc␣
 ↪= 'left')
ax.set_xlabel("N. of Children", fontsize = 10)
ax.set_ylabel("Proportion (%)", fontsize = 10)
ax.legend(title = 'Booking Status', labels = ['Not Canceled', 'Canceled'])
plt.show()
```



2.4.4 Room Type x Cancelation

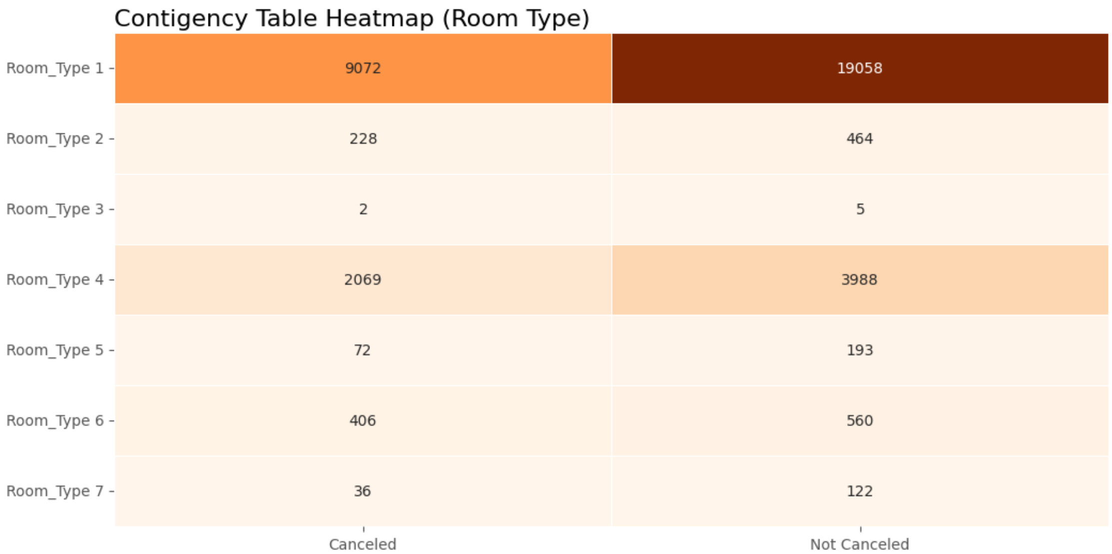
The room type may also be related to cancellations, let's investigate this.

- H_0 : Room Type is independent of Booking Status.
- H_1 : Room Type is not independent of Booking Status.

```
[ ]: from scipy.stats import chi2_contingency

contigency_table = pd.crosstab(data['room_type_reserved'],␣
 ↪data['booking_status'])
chi2, p_value, dof, expected = chi2_contingency(contigency_table)

alpha = 0.05
if p_value < alpha:
    print("Reject H0: Room Type and Booking Status are related.")
else:
    print("We do not reject H0: : There is not enough evidence to assert that␣
 ↪Room Type and Booking Status are related.")
```

```
Reject H0: Room Type and Booking Status are related.
```

```
[ ]: fig, ax = plt.subplots(figsize = (12, 6))

sns.heatmap(contigency_table, annot = True, linewidths=.5, fmt = 'd', cmap =␣
 ↪'Oranges', cbar=False)
ax.set_title("Contigency Table Heatmap (Room Type)", fontsize = 16, pad = 5,␣
 ↪loc = 'left')
ax.set_xlabel("")
ax.set_ylabel("")
ax.set_xticklabels(['Canceled', 'Not Canceled'])
plt.show()
```



- Room Type 1 is the most popular.
- Room Type 3 is the least popular.
- Room Type 6 has the highest cancelation rate.

As we can see, Room Type and the Booking Status are related.

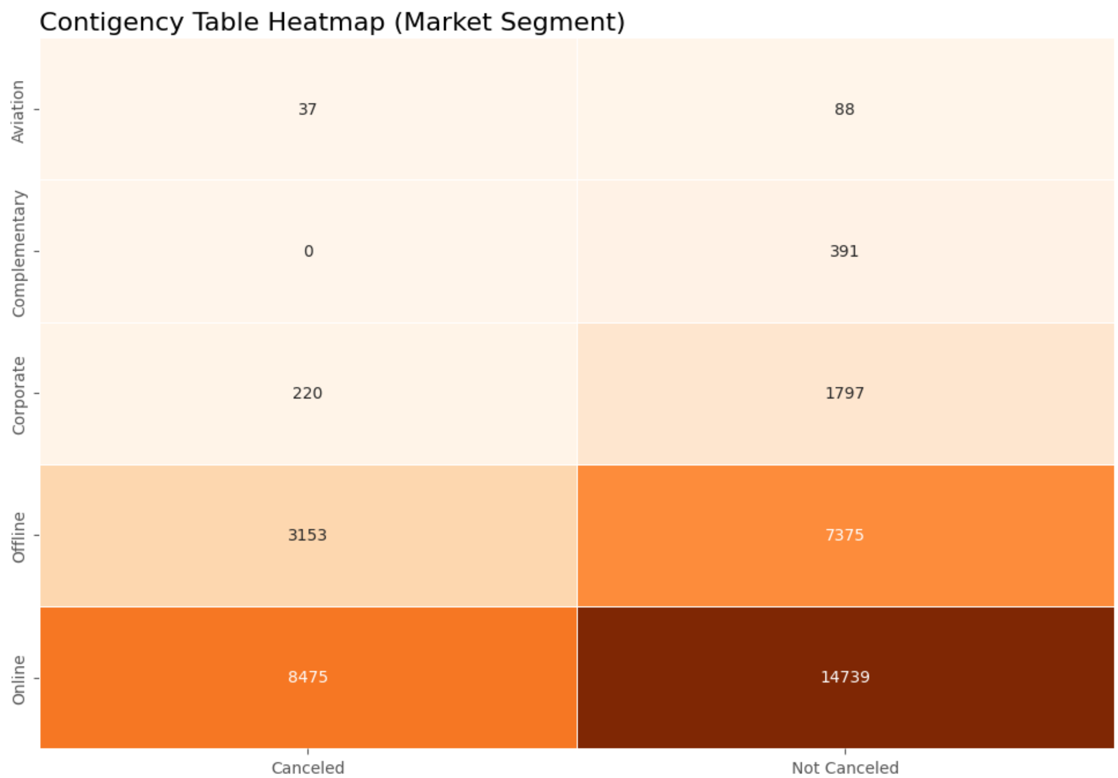
2.4.5 Market Segment x Booking Status

- H_0 : Market Segment is independent of Booking Status.
- H_1 : Market Segment is not independent of Booking Status

[ ]:
```
contigency_table_2 = pd.crosstab(data['market_segment_type'],␣
 ↪data['booking_status'])
chi2, p_value, dof, expected = chi2_contingency(contigency_table_2)

alpha = 0.05
if p_value < alpha:
    print("Reject H0: Marketing Segment and Booking Status are related.")
else:
    print("We do not reject H0: : There is not enough evidence to assert that␣
 ↪Marketing Segment and Booking Status are related.")
```

```
Reject H0: Marketing Segment and Booking Status are related.
```

[ ]:
```
fig, ax = plt.subplots(figsize = (12, 8))

sns.heatmap(contigency_table_2, annot = True, linewidths=.5, fmt = 'd', cmap =␣
 ↪'Oranges', cbar=False)
ax.set_title("Contigency Table Heatmap (Market Segment)", fontsize = 16, pad =␣
 ↪5, loc = 'left')
ax.set_xlabel("")
ax.set_ylabel("")
ax.set_xticklabels(['Canceled', 'Not Canceled'])
plt.show()
```



- Online segment is the most popular and also has the highest cancellation rate;
- Complementary segment has 0 cancellations;
- Corporate also has a low cancellation rate.

2.4.6 Correlation Matrix

[ ]:
```
dummies = data.drop(columns = 'Booking_ID', axis = 1).copy()
dummies = pd.get_dummies(dummies, prefix = ['type_of_meal_plan',␣
↪'room_type_reserved', 'market_segment_type','booking_status'], dtype = int)
corr = dummies.corr()
```

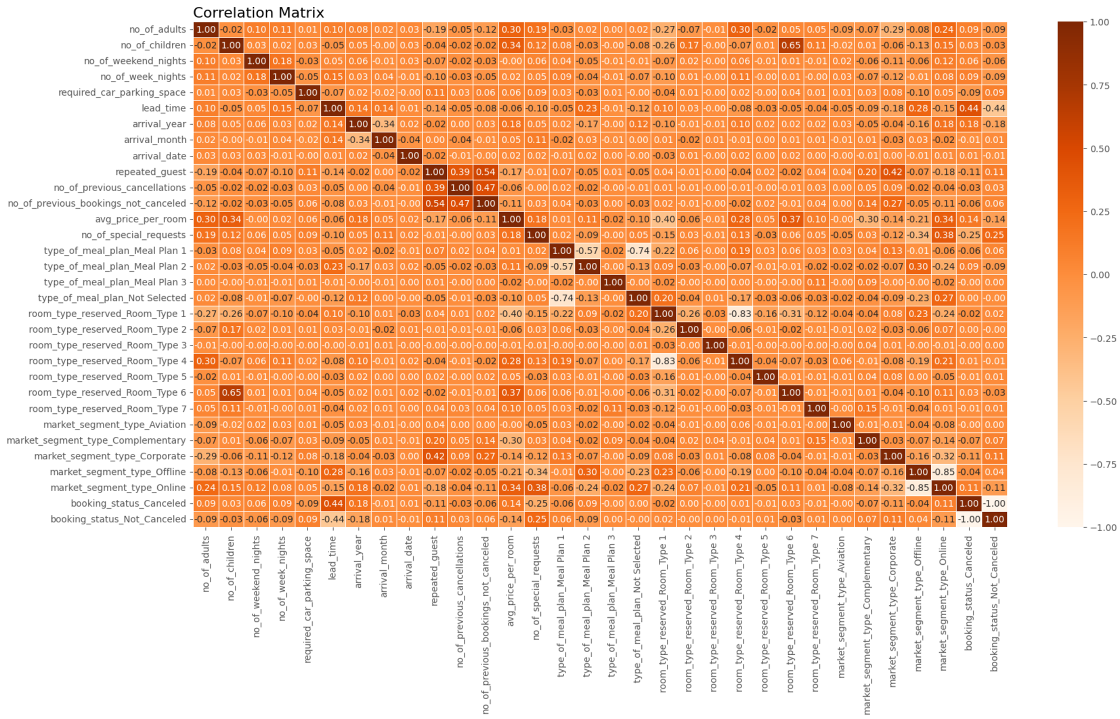
[ ]:
```
corr.loc['booking_status_Canceled'].sort_values(ascending = False)
```

[ ]:
```
booking_status_Canceled              1.000000
lead_time                            0.438538
arrival_year                         0.179529
avg_price_per_room                   0.142569
market_segment_type_Online           0.106362
no_of_week_nights                    0.092996
no_of_adults                         0.086920
type_of_meal_plan_Meal Plan 2        0.086370
no_of_weekend_nights                 0.061563
no_of_children                       0.033078
```

```
room_type_reserved_Room_Type 6          0.032652
room_type_reserved_Room_Type 4          0.013309
arrival_date                            0.010629
type_of_meal_plan_Not Selected          0.003072
room_type_reserved_Room_Type 2          0.000548
room_type_reserved_Room_Type 3         -0.001241
type_of_meal_plan_Meal Plan 3          -0.003193
market_segment_type_Aviation           -0.003964
room_type_reserved_Room_Type 5         -0.010224
arrival_month                          -0.011233
room_type_reserved_Room_Type 7         -0.014062
room_type_reserved_Room_Type 1         -0.020326
no_of_previous_cancellations           -0.033728
market_segment_type_Offline            -0.038351
no_of_previous_bookings_not_canceled   -0.060179
type_of_meal_plan_Meal Plan 1          -0.061267
market_segment_type_Complementary      -0.072867
required_car_parking_space             -0.086185
repeated_guest                         -0.107287
market_segment_type_Corporate          -0.112993
no_of_special_requests                 -0.253070
booking_status_Not_Canceled            -1.000000
Name: booking_status_Canceled, dtype: float64
```

[ ]:

```
fig, ax = plt.subplots(figsize = (20, 10))
sns.heatmap(corr, annot = True, fmt = '.2f', linewidths=.5, cmap = 'Oranges')
ax.set_title("Correlation Matrix",fontsize = 16, pad = 5, loc = 'left')
plt.show()
```



3 Data Preparation

3.1 Data manipulation

[ ]:
```
# Lets change the flag to int dtype

data['booking_status'] = data['booking_status'].map({'Canceled': 1,␣
↪'Not_Canceled': 0})
```

[ ]:
```
# We will drop the Booking_ID column and also the arrival_year. I believe month␣
↪e day columns may catch sazonality trends.

df = data.drop(columns = ['Booking_ID', 'arrival_year'], axis = 1).copy()
```

3.2 Pre-processing

[ ]:
```
features = df.drop(columns = 'booking_status', axis = 1).columns.to_list()
target = 'booking_status'

X = df[features]
y = df[target]
```

```
[ ]: cat_features = ['type_of_meal_plan', 'room_type_reserved',␣
      ↪'market_segment_type', 'repeated_guest', 'required_car_parking_space']
     num_features = ['no_of_adults', 'no_of_children', 'no_of_weekend_nights',␣
      ↪'no_of_week_nights', 'lead_time', 'no_of_previous_cancellations',␣
      ↪'no_of_previous_bookings_not_canceled', 'avg_price_per_room',␣
      ↪'no_of_special_requests']
     ordinal_features = ['arrival_date', 'arrival_month']
```

```
[ ]: cat_transformer = Pipeline([
         ('input_cat', CategoricalImputer(imputation_method='frequent')),
         ('encoder_cat', TargetEncoder())
     ])

     num_transformer = Pipeline([
         ('input_num', MeanMedianImputer(imputation_method='median'))
     ])

     ordinal_transformer = Pipeline([
         ('input_or', MeanMedianImputer(imputation_method='median')),
         ('encoder_or', OrdinalEncoder())
     ])

     preprocessor = ColumnTransformer(
         transformers=[
             ('cat', cat_transformer, cat_features),
             ('num', num_transformer, num_features),
             ('ordinal', ordinal_transformer, ordinal_features)
         ]
     )
```

4 Modeling

```
[ ]: X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.20,␣
      ↪random_state=21)

     X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size = 0.
      ↪25, random_state=21)
```

4.1 Base model

```
[ ]: model = LGBMClassifier(random_state=21)

     base_clf = Pipeline([
         ('preprocessor', preprocessor),
         ('classifier', model)
     ])
```

```
base_clf.fit(X_train, y_train)
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
[LightGBM] [Info] Number of positive: 7163, number of negative: 14602
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.001211 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 642
[LightGBM] [Info] Number of data points in the train set: 21765, number of used
features: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.329106 -> initscore=-0.712230
[LightGBM] [Info] Start training from score -0.712230
```

[ ]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
                                                  Pipeline(steps=[('imput_cat',
CategoricalImputer(imputation_method='frequent')),
('encoder_cat',
TargetEncoder())]),
                                                  ['type_of_meal_plan',
                                                   'room_type_reserved',
                                                   'market_segment_type',
                                                   'repeated_guest',
'required_car_parking_space']),
                                                 ('num',
                                                  Pipeline(steps=[('imput_num',
MeanMedianImputer(…
                                                   'no_of_weekend_nights',
                                                   'no_of_week_nights',
                                                   'lead_time',
'no_of_previous_cancellations',
'no_of_previous_bookings_not_canceled',
                                                   'avg_price_per_room',
                                                   'no_of_special_requests']),
                                                 ('ordinal',
                                                  Pipeline(steps=[('imput_or',
MeanMedianImputer()),
                                                                  ('encoder_or',
OrdinalEncoder())]),
                                                  ['arrival_date',
                                                   'arrival_month'])])),
                ('classifier', LGBMClassifier(random_state=21))])
```

[ ]:
```
y_proba_base = base_clf.predict_proba(X_val)[:,1]
y_pred_base = (y_proba_base > 0.5).astype(int)
```

```
[ ]: print(f"Validation Set - Results\n{'-'*25}")
print(f"Accuracy: {metrics.accuracy_score(y_val, y_pred_base):.4f}")
print(f"F1 Score: {metrics.f1_score(y_val, y_pred_base):.4f}")
print(f"ROC AUC: {metrics.roc_auc_score(y_val, y_proba_base):.4f}")
```

```
Validation Set - Results
-------------------------
Accuracy: 0.8815
F1 Score: 0.8111
ROC AUC: 0.9427
```

```
[ ]: print(f"{"="*15} Classification Report {"="*15}\n")
print(metrics.classification_report(y_val, y_pred_base))
```

```
=============== Classification Report ===============

              precision    recall  f1-score   support

           0       0.89      0.94      0.91      4854
           1       0.86      0.77      0.81      2401

    accuracy                           0.88      7255
   macro avg       0.87      0.85      0.86      7255
weighted avg       0.88      0.88      0.88      7255
```

In pursuit of balance and better results we will optimize our model around the F1 Score.

4.2 Optimized model

```
[ ]: def objective(trial):
    model = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', LGBMClassifier(
        verbosity = -1,
        n_estimators = 1000,
        learning_rate = trial.suggest_float("learning_rate", 1e-3, 0.1,␣
 ↪log=True),
        num_leaves = trial.suggest_int("num_leaves", 2, 2**10),
        subsample = trial.suggest_float("subsample", 0.05, 1.0),
        colsample_bytree = trial.suggest_float("colsample_bytree", 0.05, 1.0),
        min_data_in_leaf = trial.suggest_int("min_data_in_leaf", 1, 100),
        random_state = 21
    ))
    ])

    model.fit(X_train, y_train)
    predictions = model.predict(X_val)
```

```
    f1score = metrics.f1_score(y_val, predictions)
    return f1score
```

[ ]:
```
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=30)
```

```
[I 2024-08-28 19:07:27,017] A new study created in memory with name: no-name-
aba68665-add1-4220-8b18-be41fa816d11

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:07:33,767] Trial 0 finished with value: 0.780917929007461 and
parameters: {'learning_rate': 0.01575481934825425, 'num_leaves': 693,
'subsample': 0.07257609479264933, 'colsample_bytree': 0.17125373138867628,
'min_data_in_leaf': 45}. Best is trial 0 with value: 0.780917929007461.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:07:42,222] Trial 1 finished with value: 0.6798418972332015 and
parameters: {'learning_rate': 0.0019020911441208846, 'num_leaves': 694,
'subsample': 0.3050646418200134, 'colsample_bytree': 0.357559819519452,
'min_data_in_leaf': 77}. Best is trial 0 with value: 0.780917929007461.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:07:52,902] Trial 2 finished with value: 0.8106043585711076 and
parameters: {'learning_rate': 0.00417997101589838, 'num_leaves': 264,
'subsample': 0.903619087320658, 'colsample_bytree': 0.5527726641354044,
'min_data_in_leaf': 38}. Best is trial 2 with value: 0.8106043585711076.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:08:03,012] Trial 3 finished with value: 0.1109362706530291 and
parameters: {'learning_rate': 0.0014093559259069194, 'num_leaves': 434,
'subsample': 0.6025834173481727, 'colsample_bytree': 0.09841881011624212,
'min_data_in_leaf': 8}. Best is trial 2 with value: 0.8106043585711076.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:08:06,048] Trial 4 finished with value: 0.8253208614313683 and
parameters: {'learning_rate': 0.026133115786975702, 'num_leaves': 45,
'subsample': 0.3963810355072208, 'colsample_bytree': 0.6399645675048041,
'min_data_in_leaf': 25}. Best is trial 4 with value: 0.8253208614313683.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:08:13,874] Trial 5 finished with value: 0.74645129711209 and
parameters: {'learning_rate': 0.00224620501182298, 'num_leaves': 400,
```

```
'subsample': 0.6974639676180155, 'colsample_bytree': 0.42441623484664925,
'min_data_in_leaf': 86}. Best is trial 4 with value: 0.8253208614313683.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:08:30,775] Trial 6 finished with value: 0.7797177708682134 and
parameters: {'learning_rate': 0.0016793179828671248, 'num_leaves': 792,
'subsample': 0.9954077702592083, 'colsample_bytree': 0.6217547791545509,
'min_data_in_leaf': 35}. Best is trial 4 with value: 0.8253208614313683.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:08:38,083] Trial 7 finished with value: 0.7997308813635344 and
parameters: {'learning_rate': 0.010360282422196953, 'num_leaves': 573,
'subsample': 0.5083713046715959, 'colsample_bytree': 0.31037251024163015,
'min_data_in_leaf': 80}. Best is trial 4 with value: 0.8253208614313683.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:08:52,149] Trial 8 finished with value: 0.7175375064666322 and
parameters: {'learning_rate': 0.0010248832698531638, 'num_leaves': 866,
'subsample': 0.5769135461206005, 'colsample_bytree': 0.5988747669613056,
'min_data_in_leaf': 46}. Best is trial 4 with value: 0.8253208614313683.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:09:09,791] Trial 9 finished with value: 0.8353378526131642 and
parameters: {'learning_rate': 0.02331572881172912, 'num_leaves': 497,
'subsample': 0.7527103411997251, 'colsample_bytree': 0.7094172373716079,
'min_data_in_leaf': 21}. Best is trial 9 with value: 0.8353378526131642.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:09:30,957] Trial 10 finished with value: 0.8350583571900463 and
parameters: {'learning_rate': 0.07236371629528207, 'num_leaves': 1017,
'subsample': 0.8039120859624059, 'colsample_bytree': 0.9235415040873682,
'min_data_in_leaf': 1}. Best is trial 9 with value: 0.8353378526131642.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:09:52,764] Trial 11 finished with value: 0.8369947275922671 and
parameters: {'learning_rate': 0.06870145636595233, 'num_leaves': 997,
'subsample': 0.7862997832574106, 'colsample_bytree': 0.9347307739548064,
'min_data_in_leaf': 2}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

```
[I 2024-08-28 19:10:02,078] Trial 12 finished with value: 0.8320944468736335 and
parameters: {'learning_rate': 0.06965497395540485, 'num_leaves': 254,
'subsample': 0.8044826565417111, 'colsample_bytree': 0.9323368611352647,
'min_data_in_leaf': 17}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:10:21,536] Trial 13 finished with value: 0.8332968236582694 and
parameters: {'learning_rate': 0.03388057946718012, 'num_leaves': 563,
'subsample': 0.7467898498473614, 'colsample_bytree': 0.7820749504543442,
'min_data_in_leaf': 16}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:10:34,014] Trial 14 finished with value: 0.8326105810928014 and
parameters: {'learning_rate': 0.03400848144017518, 'num_leaves': 1019,
'subsample': 0.9366177052029995, 'colsample_bytree': 0.7762377249892383,
'min_data_in_leaf': 62}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:10:44,418] Trial 15 finished with value: 0.8336970755128764 and
parameters: {'learning_rate': 0.0711854874607767, 'num_leaves': 285,
'subsample': 0.6484383971849066, 'colsample_bytree': 0.7970522898684436,
'min_data_in_leaf': 22}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:11:17,849] Trial 16 finished with value: 0.8359392204360273 and
parameters: {'learning_rate': 0.0057547881485521535, 'num_leaves': 905,
'subsample': 0.8513299039068081, 'colsample_bytree': 0.8518738044870688,
'min_data_in_leaf': 1}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:11:26,300] Trial 17 finished with value: 0.8138414367060884 and
parameters: {'learning_rate': 0.005115963020062098, 'num_leaves': 901,
'subsample': 0.8816094583033557, 'colsample_bytree': 0.9791028516835338,
'min_data_in_leaf': 100}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:11:38,365] Trial 18 finished with value: 0.8226018396846255 and
parameters: {'learning_rate': 0.005634941979453718, 'num_leaves': 905,
'subsample': 0.36272372200044944, 'colsample_bytree': 0.8688692435154237,
'min_data_in_leaf': 60}. Best is trial 11 with value: 0.8369947275922671.
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:12:05,217] Trial 19 finished with value: 0.8343208251042352 and
parameters: {'learning_rate': 0.010569089182296588, 'num_leaves': 744,
'subsample': 0.8378139502092883, 'colsample_bytree': 0.9989885763129266,
'min_data_in_leaf': 4}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:12:35,348] Trial 20 finished with value: 0.8342105263157895 and
parameters: {'learning_rate': 0.0038046939695369933, 'num_leaves': 894,
'subsample': 0.4914044002693227, 'colsample_bytree': 0.8554287829901227,
'min_data_in_leaf': 10}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:12:55,418] Trial 21 finished with value: 0.8327153762268266 and
parameters: {'learning_rate': 0.017067892448375963, 'num_leaves': 620,
'subsample': 0.740606410105164, 'colsample_bytree': 0.692806049214498,
'min_data_in_leaf': 28}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:13:09,960] Trial 22 finished with value: 0.8349769888231426 and
parameters: {'learning_rate': 0.0395887904629496, 'num_leaves': 416,
'subsample': 0.6857375367321686, 'colsample_bytree': 0.7267485654384901,
'min_data_in_leaf': 11}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:13:26,397] Trial 23 finished with value: 0.8358143607705779 and
parameters: {'learning_rate': 0.09546613210785125, 'num_leaves': 815,
'subsample': 0.9650988537449217, 'colsample_bytree': 0.8565370650086939,
'min_data_in_leaf': 1}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:13:43,902] Trial 24 finished with value: 0.8334433443344335 and
parameters: {'learning_rate': 0.09167439419034766, 'num_leaves': 968,
'subsample': 0.9932367520659421, 'colsample_bytree': 0.8722914012228362,
'min_data_in_leaf': 1}. Best is trial 11 with value: 0.8369947275922671.

Warning: No categorical columns found. Calling 'transform' will only return
input data.

[I 2024-08-28 19:14:09,922] Trial 25 finished with value: 0.8278742580786986 and
parameters: {'learning_rate': 0.04947635285294934, 'num_leaves': 815,
```

```
'subsample': 0.8927404943074675, 'colsample_bytree': 0.5124175912309769,
'min_data_in_leaf': 12}. Best is trial 11 with value: 0.8369947275922671.
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

```
[I 2024-08-28 19:14:46,997] Trial 26 finished with value: 0.8360908890359585 and
parameters: {'learning_rate': 0.007301541653621315, 'num_leaves': 960,
'subsample': 0.8438933557474755, 'colsample_bytree': 0.8354528355029329,
'min_data_in_leaf': 1}. Best is trial 11 with value: 0.8369947275922671.
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

```
[I 2024-08-28 19:15:04,970] Trial 27 finished with value: 0.8316270964931387 and
parameters: {'learning_rate': 0.0074723146884285085, 'num_leaves': 948,
'subsample': 0.8533932837644331, 'colsample_bytree': 0.9342100440971319,
'min_data_in_leaf': 37}. Best is trial 11 with value: 0.8369947275922671.
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

```
[I 2024-08-28 19:15:28,042] Trial 28 finished with value: 0.8185448092280391 and
parameters: {'learning_rate': 0.0030149786777874076, 'num_leaves': 1020,
'subsample': 0.18347985925573962, 'colsample_bytree': 0.8028469948382004,
'min_data_in_leaf': 29}. Best is trial 11 with value: 0.8369947275922671.
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

```
[I 2024-08-28 19:15:34,402] Trial 29 finished with value: 0.7760785208856426 and
parameters: {'learning_rate': 0.013604830616288404, 'num_leaves': 704,
'subsample': 0.7876599624848081, 'colsample_bytree': 0.206640688757194,
'min_data_in_leaf': 56}. Best is trial 11 with value: 0.8369947275922671.
```

[ ]:
```
print(f"Best hyperparameters: {study.best_params}")
print(f"Best F1 Score: {study.best_value}")
```

```
Best hyperparameters: {'learning_rate': 0.06870145636595233, 'num_leaves': 997,
'subsample': 0.7862997832574106, 'colsample_bytree': 0.9347307739548064,
'min_data_in_leaf': 2}
Best F1 Score: 0.8369947275922671
```

[ ]:
```
param_dict = {'learning_rate': 0.06870145636595233, 'num_leaves': 997,␣
 ↪'subsample': 0.7862997832574106, 'colsample_bytree': 0.9347307739548064,␣
 ↪'min_data_in_leaf': 2}
param_dict
```

[ ]:
```
{'learning_rate': 0.06870145636595233,
 'num_leaves': 997,
 'subsample': 0.7862997832574106,
 'colsample_bytree': 0.9347307739548064,
```

```
 'min_data_in_leaf': 2}
```

[ ]:
```
model = LGBMClassifier(**param_dict, n_estimators=1000, random_state=21)

clf = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', model)
])

clf.fit(X_train, y_train)
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

[ ]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
                                                  Pipeline(steps=[('imput_cat',
CategoricalImputer(imputation_method='frequent')),
('encoder_cat',
TargetEncoder())]),
                                                   ['type_of_meal_plan',
                                                    'room_type_reserved',
                                                    'market_segment_type',
                                                    'repeated_guest',
'required_car_parking_space']),
                                                 ('num',
                                                  Pipeline(steps=[('imput_num',
MeanMedianImputer(…
                                                    'no_of_special_requests']),
                                                 ('ordinal',
                                                  Pipeline(steps=[('imput_or',
MeanMedianImputer()),
                                                                  ('encoder_or',
OrdinalEncoder())]),
                                                   ['arrival_date',
                                                    'arrival_month'])])),
                ('classifier',
                 LGBMClassifier(colsample_bytree=0.9347307739548064,
                                learning_rate=0.06870145636595233,
                                min_data_in_leaf=2, n_estimators=1000,
                                num_leaves=997, random_state=21,
                                subsample=0.7862997832574106))])
```

[ ]:
```
y_proba_op = clf.predict_proba(X_val)[:,1]
y_pred_op = (y_proba_op > 0.5).astype(int)
```

[ ]:
```
print(f"Validation Set - Results (Optimized)\n{'-'*25}")
print(f"Accuracy: {metrics.accuracy_score(y_val, y_pred_op):.4f}")
```

```
print(f"F1 Score: {metrics.f1_score(y_val, y_pred_op):.4f}")
print(f"ROC AUC: {metrics.roc_auc_score(y_val, y_proba_op):.4f}")
```

```
Validation Set - Results (Optimized)
-------------------------
Accuracy: 0.8977
F1 Score: 0.8370
ROC AUC: 0.9514
```

[ ]:
```
print(f"{"="*15} Classification Report {"="*15}\n")
print(metrics.classification_report(y_val, y_pred_op))
```

```
=============== Classification Report ===============

              precision    recall  f1-score   support

           0       0.90      0.95      0.93      4854
           1       0.89      0.79      0.84      2401

    accuracy                           0.90      7255
   macro avg       0.89      0.87      0.88      7255
weighted avg       0.90      0.90      0.90      7255
```

5 Evaluation

5.1 Metrics

[ ]:
```
y_pred = clf.predict(X_test)
y_proba = clf.predict_proba(X_test)[:,1]
```

[ ]:
```
print(f"Test Set - Results\n{'-'*25}")
print(f"Accuracy: {metrics.accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {metrics.f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC: {metrics.roc_auc_score(y_test, y_proba):.4f}")
```

```
Test Set - Results
-------------------------
Accuracy: 0.8983
F1 Score: 0.8359
ROC AUC: 0.9539
```

[ ]:
```
print(f"{"="*15} Classification Report {"="*15}\n")
print(metrics.classification_report(y_test, y_pred))
```

```
=============== Classification Report ===============

              precision    recall  f1-score   support
```

```
           0       0.91      0.94      0.93      4934
           1       0.86      0.81      0.84      2321

    accuracy                           0.90      7255
   macro avg       0.89      0.87      0.88      7255
weighted avg       0.90      0.90      0.90      7255
```

5.1.1 Best threshold

Let's find the best threshold for our main metric

[ ]:
```python
thresholds = np.arange(0.0, 1.01, 0.01)

f1_scores = []

for threshold in thresholds:
    y_predict = (y_proba > threshold).astype(int)

    f1 = metrics.f1_score(y_test, y_predict)
    f1_scores.append(f1)

best_threshold = thresholds[np.argmax(f1_scores)]
best_f1 = max(f1_scores)

print(f"Best threshold: {best_threshold}")
print(f"Best F1 Score: {best_f1:.4f}")
```

```
Best threshold: 0.6
Best F1 Score: 0.8369
```

5.2 Cross-validation

[ ]:
```python
scoring = metrics.make_scorer(metrics.f1_score)
cv = StratifiedKFold(n_splits=5, shuffle = True, random_state=21)

scores = cross_val_score(clf, X_train, y_train, cv = cv, scoring = scoring)
print(f"Mean F1 Score: {scores}")
print(f"General Mean F1 Score: {scores.mean()}")
print(f"F1 Score Standard Deviation: {scores.std()}")
```

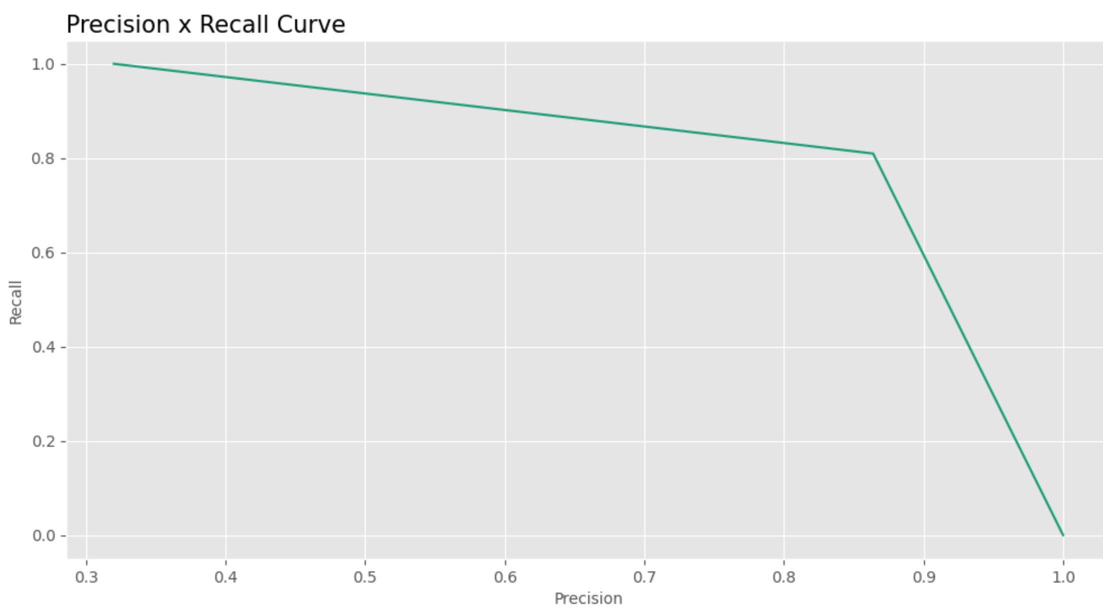
```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
Warning: No categorical columns found. Calling 'transform' will only return
input data.
Warning: No categorical columns found. Calling 'transform' will only return
input data.
Warning: No categorical columns found. Calling 'transform' will only return
input data.
```

```
Warning: No categorical columns found. Calling 'transform' will only return
input data.
Mean F1 Score: [0.83842795 0.82335766 0.83083512 0.83543392 0.83062477]
General Mean F1 Score: 0.8317358850779228
F1 Score Standard Deviation: 0.005112723493107408
```

The model demonstrated excellent generalization ability, with no signs of overfitting.

5.3 Graphics

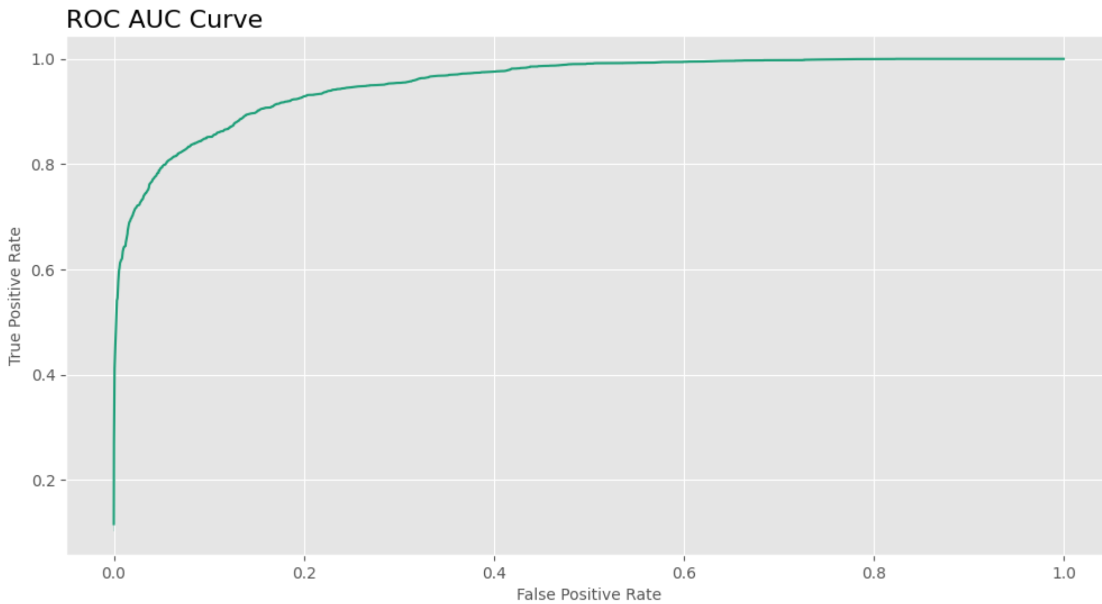
[ ]:
```python
precision, recall, thres = metrics.precision_recall_curve(y_test, y_pred)

fig, ax = plt.subplots(figsize = (12, 6))

sns.lineplot(x = precision, y = recall)
ax.set_title("Precision x Recall Curve", fontsize = 15, pad = 5, loc = 'left')
ax.set_xlabel("Precision", fontsize = 10)
ax.set_ylabel("Recall", fontsize = 10)
plt.show()
```



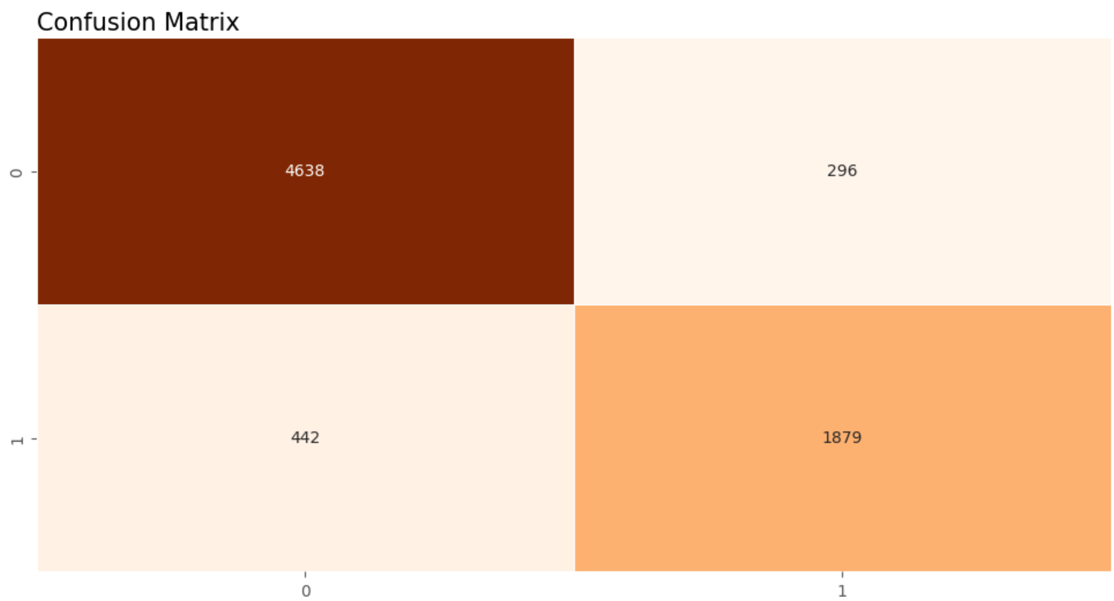
[ ]:
```python
curve = metrics.roc_curve(y_test, y_proba)
```

[ ]:
```python
fig, ax = plt.subplots(figsize = (12, 6))

sns.lineplot(x = curve[0], y = curve[1])
ax.set_title(f"ROC AUC Curve", fontsize = 16, pad = 5, loc = 'left')
ax.set_xlabel("False Positive Rate", fontsize = 10)
```

```
ax.set_ylabel("True Positive Rate", fontsize = 10)
plt.show()
```




```
[ ]: cf = metrics.confusion_matrix(y_test, y_pred)

fig, ax = plt.subplots(figsize = (12, 6))
sns.heatmap(cf, annot = True, fmt = 'd', linewidths=0.5, cmap = 'Oranges', cbar␣
 ↪= False)
ax.set_title("Confusion Matrix", fontsize = 15, pad = 5, loc = 'left')
plt.show()
```



6 Conclusions

6.0.1 Some insights

- Reservations with long lead times need to be closely tracked. Simple actions like periodic confirmation messages or emails can be a good plan, as we've seen that the probability of cancellation starts to rise with longer lead times.
- A higher number of children increases the probability of cancellation, so this is also something to keep track of.
- Room Type 1 is the most popular, while Room Type 6 has the highest number of cancellations.
- The Online segment is the most popular and also has the highest cancellation rate. The Complementary and Corporate segments have the lowest cancellation rates, so it may be a good idea to reward them.

6.0.2 About the model

The model achieved a good balance between precision and recall, as our main metric was the F1 Score. It demonstrated good generalization ability and strong metric results. To achieve a higher F1 Score, we can use a 0.6 threshold.