A number of factors contribute to a hotel booking being fulfilled or Canceled The Basic Procedure implemented to achieve the goal of thisresearch are ;

1.Understanding the problem 2.Gathering the Data 3.Data Cleaning and validation 4.Exploratory Data Analysis 5.Feature Preprocessing 6.Modeling 7.Model Evaluation 8.Feature Importance 9.Model Deployment

1. Understanding the Problem The first crucial step for any data science problem is understanding the problem one is trying to solve. It is necessary to explicitly and accurately define the data problem that is to be solved. This will lay a good foundation for the project.

Problem Statement: As a data scientist, you are supporting a hotel with a project aimed at increasing revenue from their room bookings. They believe that they can use data science to help them reduce the number of cancellations. You are to use any appropriate methodology to identify what contributes to whether a booking will be fulfilled or canceled. The results of your work will be used to reduce the chance someone cancels their booking. As a data scientist, an in-depth understanding of this problem statement will determine the success of the project. After understanding the problem statement, the goal of the project has to be defined;

Goal: 1. To develop/build a system/web app that predicts whether a hotel booking will be Online or Offline Or canceled. 2. To determine the factors with high importance in predicting whether a hotel booking will be fulfilled or canceled

2.1. Gathering the Data After determining the end goal, the next step is to gather data that is labeled according to the end goal. The data used for this project was obtained from Kaggle.

First, the required libraries were imported;

In [7]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, classification_report, ConfusionMatrixDisplay
from sklearn.model_selection import RandomizedSearchCV
```

In [8]:
```
df = pd.read_csv("Hotel Reservations.csv")
df.head()
```

Out[8]:

	Booking_ID	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_meal_plan	required_car_parking_space	roo
0	INN00001	2	0	1	2	Meal Plan 1	0	
1	INN00002	2	0	2	3	Not Selected	0	
2	INN00003	1	0	2	1	Meal Plan 1	0	
3	INN00004	2	0	0	2	Meal Plan 1	0	
4	INN00005	2	0	1	1	Not Selected	0	

Data Dictionary 1.1 Booking_ID: unique identifier of each booking 1.2 no_of_adults: Number of adults 1.3 no_of_children: Number of Children 1.4 no_of_weekend_nights: Number of weekend nights (Saturday or Sunday) the guest stayed or booked to stay at the hotel 1.5 no_of_week_nights: Number of week nights (Monday to Friday) the guest stayed or booked to stay at the hotel 1.6 type_of_meal_plan: Type of meal plan booked by the customer: 1.7 required_car_parking_space: Does the customer require a car parking space? (0 - No, 1- Yes) 1.8 room_type_reserved: Type of room reserved by the customer. The values are ciphered (encoded) by INN Hotels. 1.9 lead_time: Number of days between the date of booking and the arrival date 1.10 arrival_year: Year of arrival date 1.11 arrival_month: Month of arrival date 1.12 arrival_date: Date of the month 1.13 market_segment_type: Market segment designation. 1.14 repeated_guest: Is the customer a repeated guest? (0 - No, 1- Yes) 1.15 no_of_previous_cancellations: Number of previous bookings that were canceled by the customer prior to the current booking 1.16 no_of_previous_bookings_not_canceled: Number of previous bookings not canceled by the customer prior to the current booking 1.17 avg_price_per_room: Average price per day of the reservation; prices of the rooms are dynamic. (in euros) 1.18 no_of_special_requests: Total number of special requests made by the customer (e.g. high floor, view from the room, etc) 1.19 booking_status: Flag indicating if the booking was canceled or not.

In [9]:
```
df.shape
```

Out[9]:
```
(36275, 19)
```

shape of the dataset The dataset has 36275 rows and 19 columns.

In [10]:
```
df.columns
```

Out[10]:
```
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')
```

3.3. Data Cleaning and Validation Now that the data needed for the project is ready, the next step is to ensure that the data is properly clean and well-validated. Effective data cleaning is a vital part of any data science project. Before any analysis can be done, your data must be void of inconsistencies or errors unless you're aiming at a flawed result.

The first step is to check for null values;

In [11]:
```
df.isnull().values.any()
```

Out[11]:
```
False
```

In [12]:
```
df.isna().sum()
```

Out[12]:
```
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
```

Next, I checked for duplicate rows.

In [13]:
```
df.duplicated().sum()
```

Out[13]:
```
0
```

In [14]:
```
df.duplicated()
```

Out[14]:
```
0        False
1        False
2        False
3        False
4        False
         ...
36270    False
36271    False
36272    False
36273    False
36274    False
Length: 36275, dtype: bool
```

The data is void of duplicate rows. Next, I described the quantitative columns, to check for any abnormalities.

In [15]:
```
df.describe()
```

Out[15]:

	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	required_car_parking_space	lead_time	arrival_year	arı
count	36275.000000	36275.000000	36275.000000	36275.000000	36275.000000	36275.000000	36275.000000	3(
mean	1.844962	0.105279	0.810724	2.204300	0.030986	85.232557	2017.820427	
std	0.518715	0.402648	0.870644	1.410905	0.173281	85.930817	0.383836	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	2017.000000	
25%	2.000000	0.000000	0.000000	1.000000	0.000000	17.000000	2018.000000	
50%	2.000000	0.000000	1.000000	2.000000	0.000000	57.000000	2018.000000	
75%	2.000000	0.000000	2.000000	3.000000	0.000000	126.000000	2018.000000	
max	4.000000	10.000000	7.000000	17.000000	1.000000	443.000000	2018.000000	

The code above was used to achieve that. Then, I specifically checked the year and date columns to ensure there were no abnormal values. The data spans from 2017 to 2018.

In [17]:
```
df['arrival_year'].value_counts()
```

Out[17]:
```
2018    29761
2017     6514
Name: arrival_year, dtype: int64
```

4. Exploratory Data Analysis

This is the core of any data science project. It is said a data scientist involves almost a major percentage of his work in doing EDA. EDA helps to discover hidden patterns in data and uncovers relationships between variables. Therefore, there is no data science project without EDA. The EDA for this project is divided into two parts;

In [18]:
```
df['no_of_adults'].value_counts()
```

Out[18]:
```
2    26108
1     7695
3     2317
0      139
4       16
Name: no_of_adults, dtype: int64
```

In [19]:
```
df['no_of_children'].value_counts()
```

Out[19]:
```
0     33577
1      1618
2      1058
3        19
9         2
10        1
Name: no_of_children, dtype: int64
```

In [20]:
```
df['no_of_previous_cancellations'].unique()
```

Out[20]:
```
array([ 0,  3,  1,  2, 11,  4,  5, 13,  6], dtype=int64)
```

In [21]:
```
df['no_of_previous_cancellations'].value_counts()
```

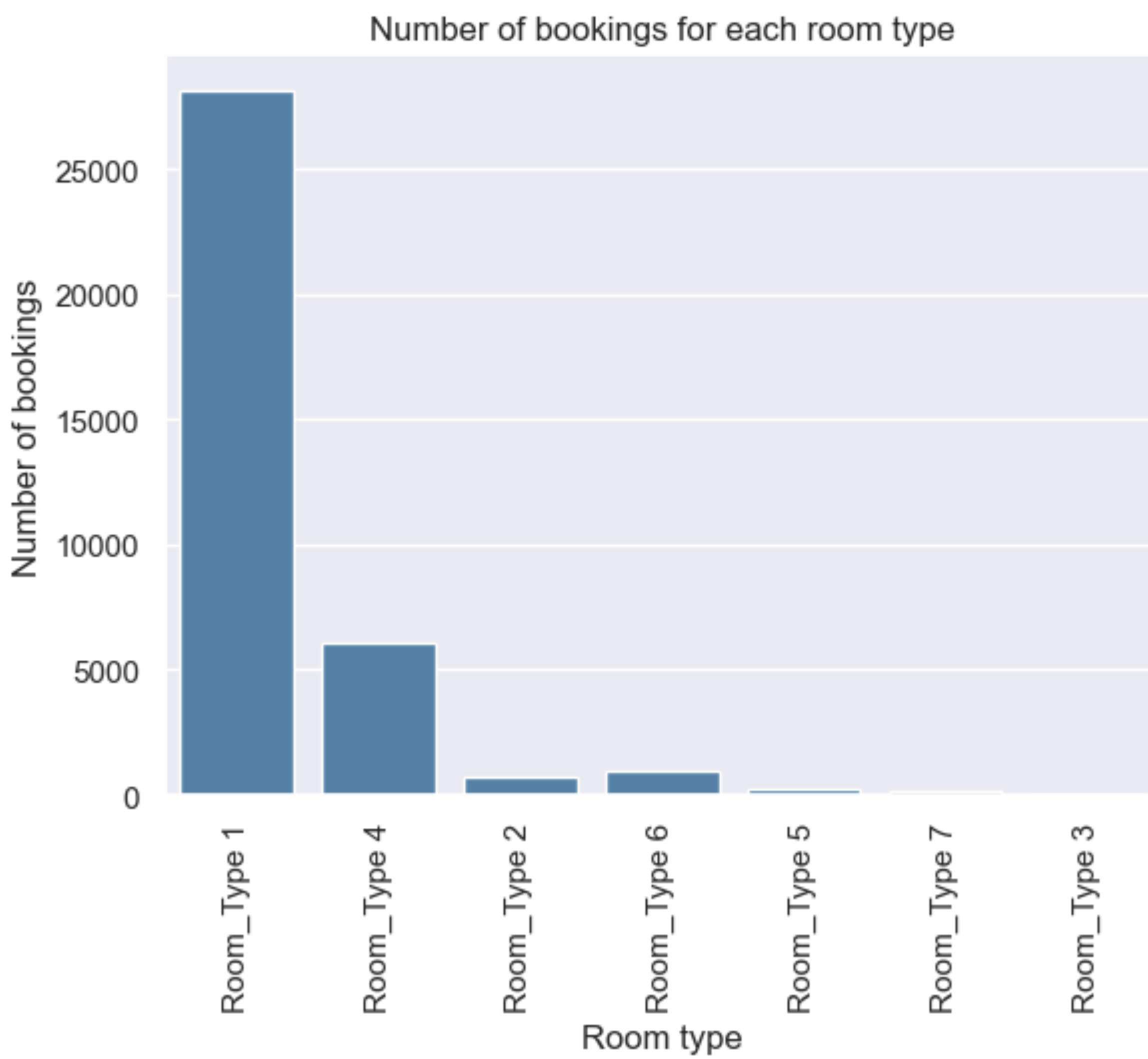
Out[21]:
```
0     35937
1       198
2        46
3        43
11       25
5        11
4        10
13        4
6         1
Name: no_of_previous_cancellations, dtype: int64
```

Exploratory Data Analysis

In [23]:
```
sns.kdeplot(df['avg_price_per_room'], fill=True)
plt.xlabel('Average price per room')
plt.title('Distribution of the average price per day of the reservation')

plt.savefig('price.png', bbox_inches='tight', dpi=300)
plt.show()
```

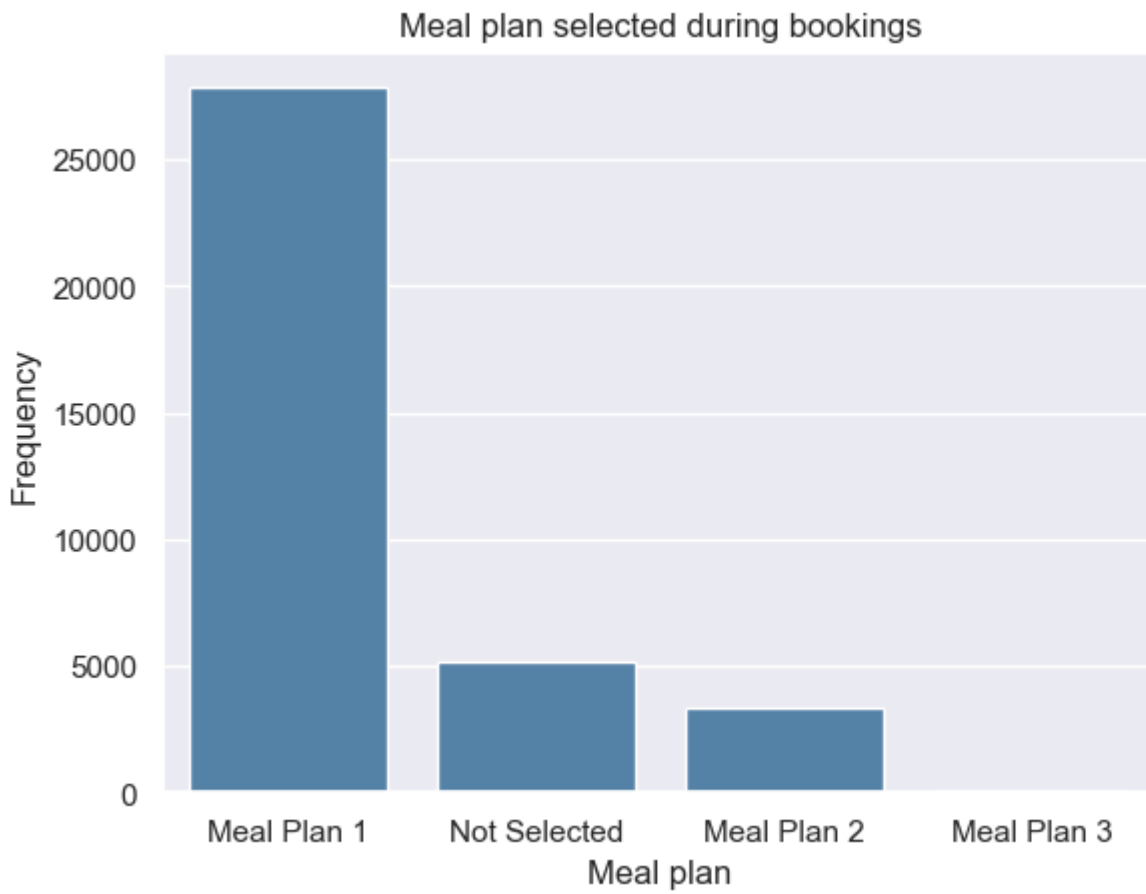
the distribution is approximately right skewed as most of the prices are kind of betwwen 50-200. This is kind of okay since the variable is calculated per day.

In [24]:
```
sns.countplot(x='room_type_reserved',data=df, color='steelblue')
plt.xticks(rotation=90)
plt.ylabel('Number of bookings')
plt.xlabel('Room type')
plt.title('Number of bookings for each room type')

plt.savefig('roomtype.png', bbox_inches='tight', dpi=300)
plt.show()
```



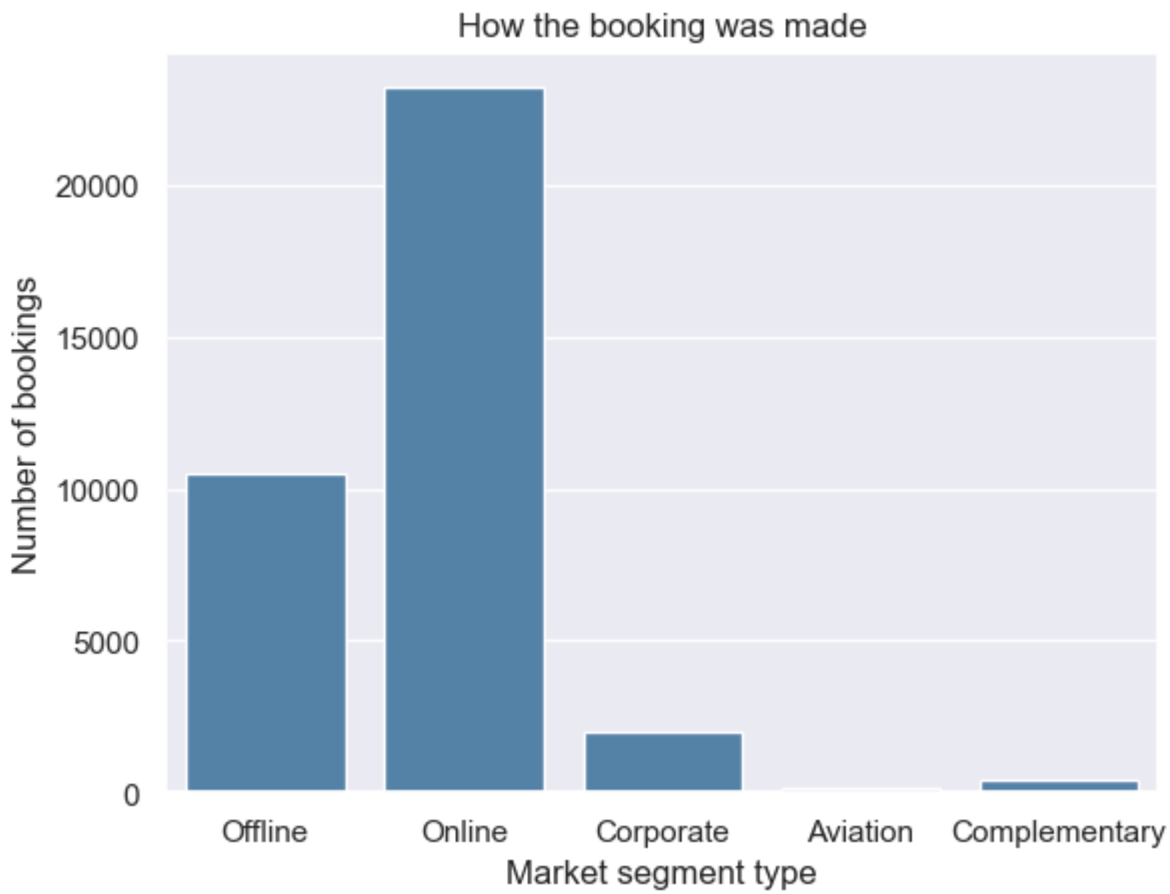
the room_type 1 has the highest number of bookings with over 20000 bookings.

In [25]:
```
sns.countplot(x='type_of_meal_plan', data=df, color='steelblue')
plt.xlabel('Meal plan')
plt.ylabel('Frequency')
plt.title('Meal plan selected during bookings')

plt.savefig('meal.png', bbox_inches='tight', dpi=300)
plt.show()
```



the meal plan 1 was mostly selected during bookings. N.B.; the not selected was not filtered out because it's possible to not select a meal plan when making a booking.

In [26]:
```
sns.countplot(x='market_segment_type', data=df, color='steelblue')
plt.xlabel('Market segment type')
plt.ylabel('Number of bookings')
plt.title('How the booking was made')

plt.savefig('market.png', bbox_inches='tight', dpi=300)
plt.show()
```

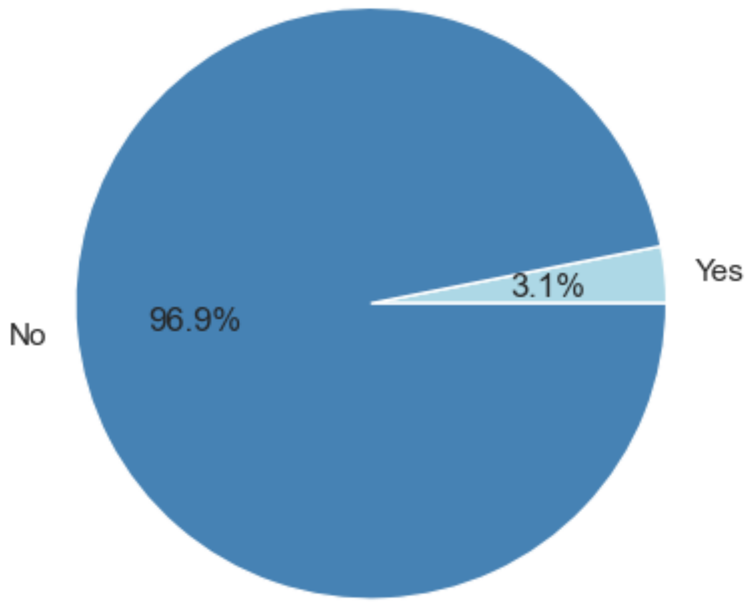


Most bookings were made online, least is avaiation medium.

In [27]:
```
car_space_yes = df['required_car_parking_space'].sum()
required_car_space = ['Yes', 'No']
data = [car_space_yes, (len(df)-car_space_yes)]
data
```

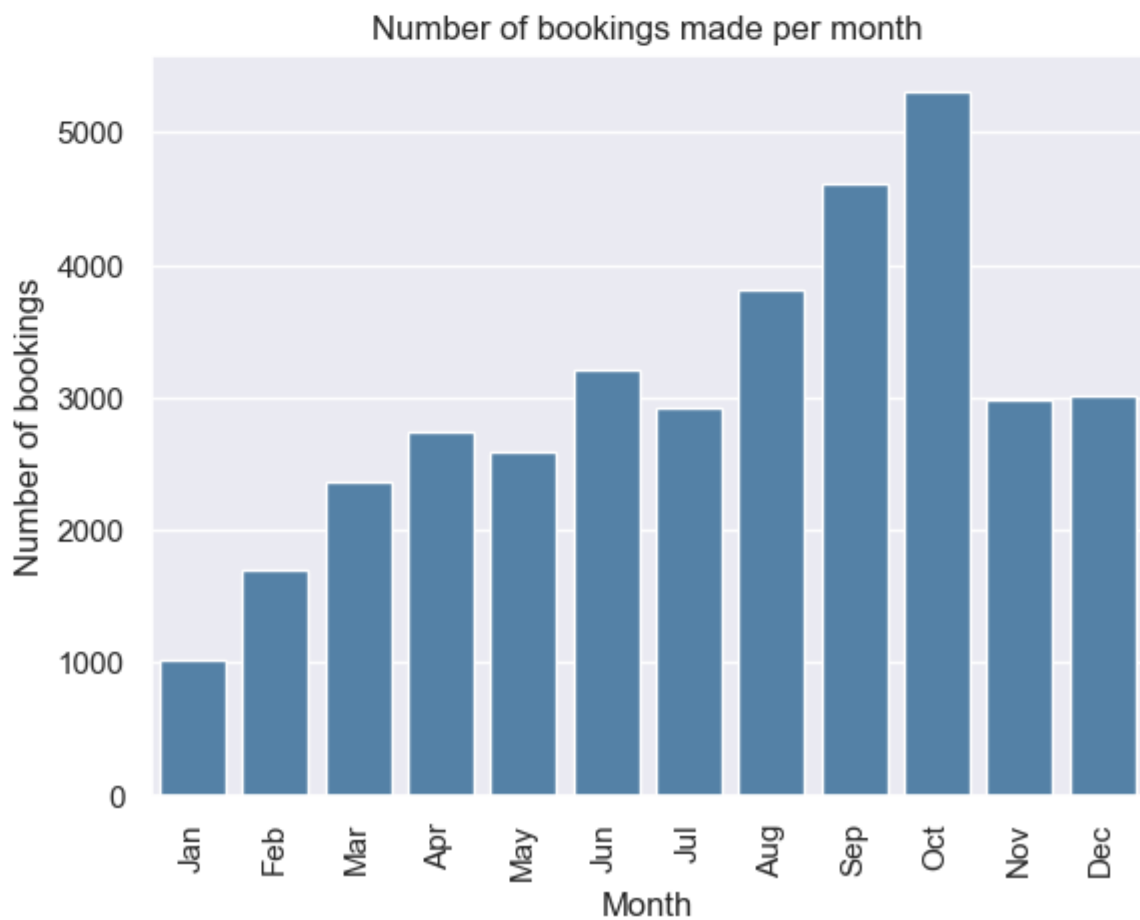
Out[27]: [1124, 35151]

In [28]:
```
plt.pie(data, labels=required_car_space, autopct='%1.1f%%', colors=['Lightblue', 'Steelblue'])

plt.savefig('car.png', bbox_inches='tight', dpi=300)
plt.show()
```



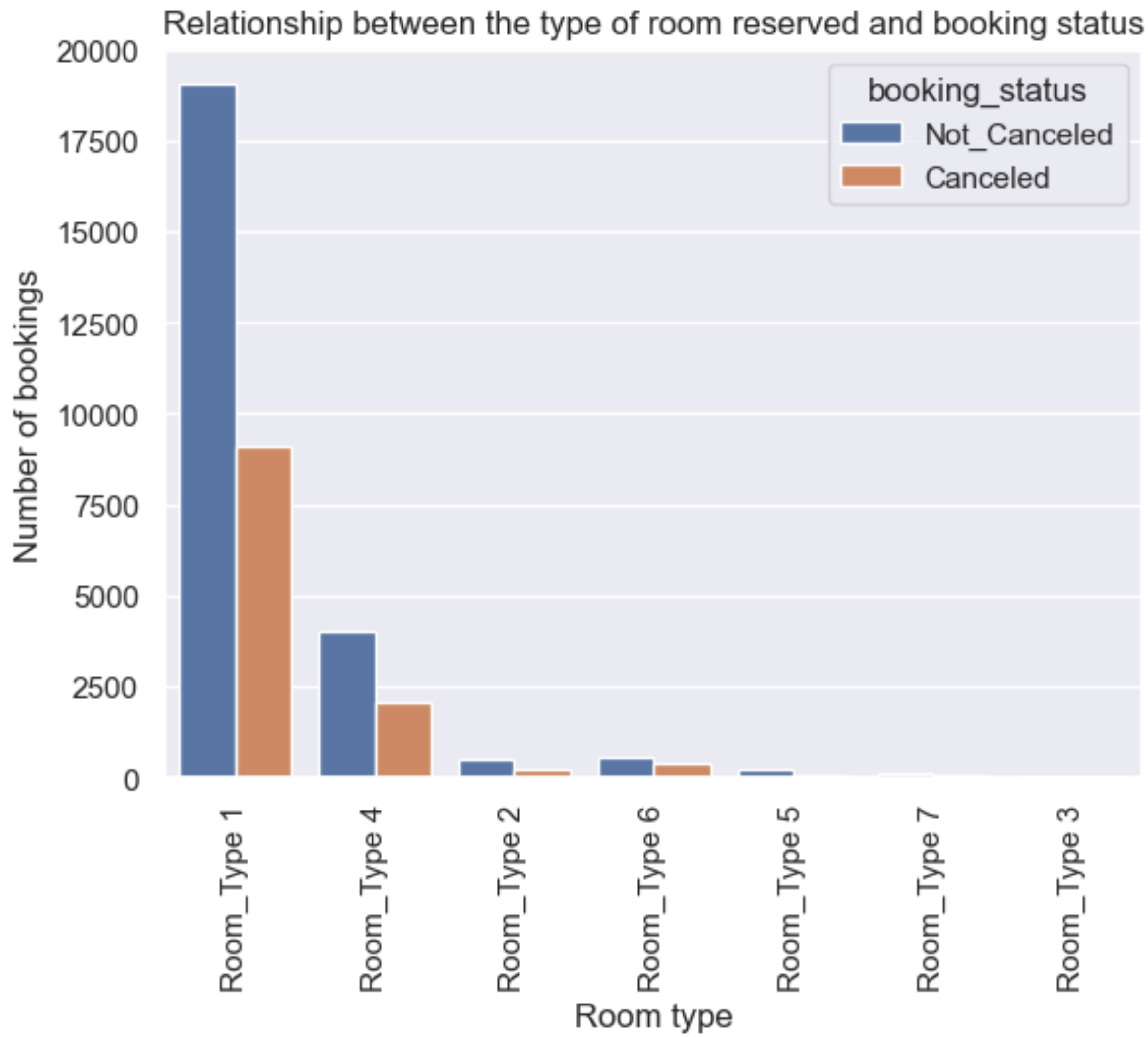
96.9% indicated no need for car parking space, while 3.1% indicated need for car parking space.

In [29]:
```
sns.countplot(x='arrival_month', data=df, color='Steelblue')
plt.xlabel('Month')
plt.ylabel('Number of bookings')
plt.title('Number of bookings made per month')
x = range(0, 12)
labels = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
plt.xticks(x, labels, rotation=90)

plt.savefig('month.png', bbox_inches='tight', dpi=300)
plt.show()
```



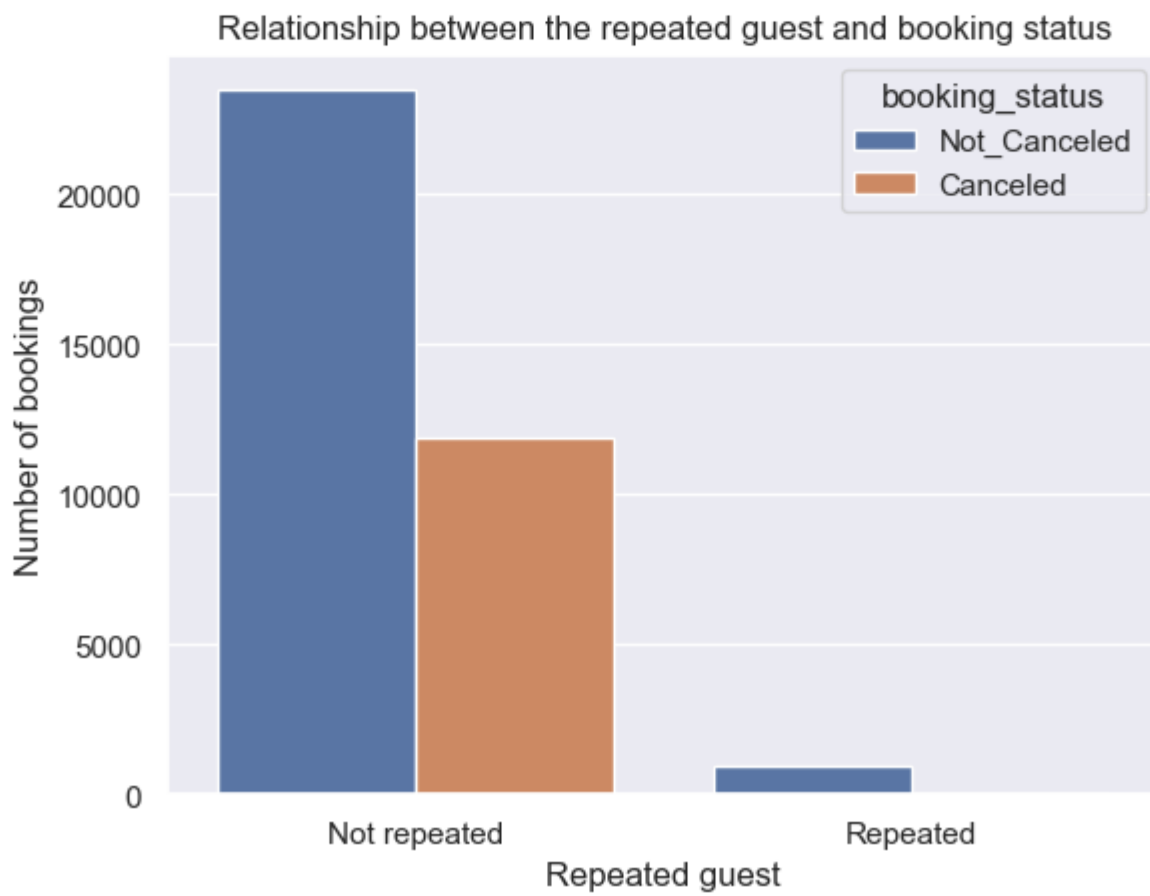
October has the highest number of bookings with over 4000 bookings made, while the January has the least amount number of bookings.
Bivariate Analysis

In [30]:
```
sns.countplot(x='room_type_reserved', hue='booking_status', data=df)
plt.xticks(rotation=90)
plt.ylabel('Number of bookings')
plt.xlabel('Room type')
plt.title('Relationship between the type of room reserved and booking status')

plt.savefig('roomvstatus.png', bbox_inches='tight', dpi=300)
plt.show()
```



In [31]:
```
sns.boxplot(x='booking_status', y='avg_price_per_room', data=df, sym='')
plt.xlabel('Booking status')
plt.ylabel('Average price per room')
plt.title('Relationship between the booking status and average price per room')


plt.savefig('pricevstatus.png', bbox_inches='tight', dpi=300)
plt.show()
```

In [32]:
```
sns.countplot(x='repeated_guest',hue='booking_status', data=df)
plt.ylabel('Number of bookings')
plt.xlabel('Repeated guest')
plt.title('Relationship between the repeated guest and booking status')
x = range(2)
labels = ['Not repeated', 'Repeated']
plt.xticks(x, labels)


plt.savefig('repeatedvstatus.png', bbox_inches='tight', dpi=300)
plt.show()
```



In [33]:
```
df.groupby(['repeated_guest','booking_status'])[['booking_status']].count()
```

Out[33]:

repeated_guest	booking_status	booking_status
0	Canceled	11869
	Not_Canceled	23476
1	Canceled	16
	Not_Canceled	914

In [34]:
```
df['no_of_previous_cancellations'].value_counts()
```

Out[34]:
```
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
```

Feature preprocessing

In [35]:
```
model_data = df.copy()
```

In [36]:
```
model_data.columns
```

Out[36]:
```
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')
```

Feature engineering

In [37]:
```
model_data['no_of_individuals'] = model_data['no_of_adults'] + model_data['no_of_children']
```

In [38]:
```
model_data['no_of_days_booked'] = model_data['no_of_weekend_nights'] + model_data['no_of_week_nights']
```

In [39]:
```
model_data.head()
```

Out[39]:

	Booking_ID	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_meal_plan	required_car_parking_space	roo
0	INN00001	2	0	1	2	Meal Plan 1	0	
1	INN00002	2	0	2	3	Not Selected	0	
2	INN00003	1	0	2	1	Meal Plan 1	0	
3	INN00004	2	0	0	2	Meal Plan 1	0	
4	INN00005	2	0	1	1	Not Selected	0	

5 rows × 21 columns

Feature encoding

In [40]:
```
cat_features = ['type_of_meal_plan','no_of_weekend_nights', 'room_type_reserved', 'market_segment_type']
```

In [41]:
```
lab = LabelEncoder()
for col in cat_features:
    model_data[col] = lab.fit_transform(model_data[col])
```

In [42]:
```
model_data.head()
```

Out[42]:

	Booking_ID	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_meal_plan	required_car_parking_space	roo
0	INN00001	2	0	1	2	0	0	
1	INN00002	2	0	2	3	3	0	
2	INN00003	1	0	2	1	0	0	
3	INN00004	2	0	0	2	0	0	
4	INN00005	2	0	1	1	3	0	

5 rows × 21 columns

In [43]:
```
model_data['market_segment_type'].value_counts()
```

Out[43]:
```
4    23214
3    10528
2     2017
1      391
0      125
Name: market_segment_type, dtype: int64
```

In [44]:
```
df['arrival_year'].value_counts()
```

Out[44]:
```
2018    29761
2017     6514
Name: arrival_year, dtype: int64
```

In [46]:
```
model_data['booking_status'] = model_data['booking_status'].replace({'Canceled':0, 'Not_Canceled':1})
```

In [47]:
```
model_data['booking_status'].value_counts()
```

Out[47]:
```
1    24390
0    11885
Name: booking_status, dtype: int64
```

In [48]:
```
sns.countplot(x='booking_status', data=df)

plt.savefig('class.png', bbox_inches='tight', dpi=300)
plt.show()
```

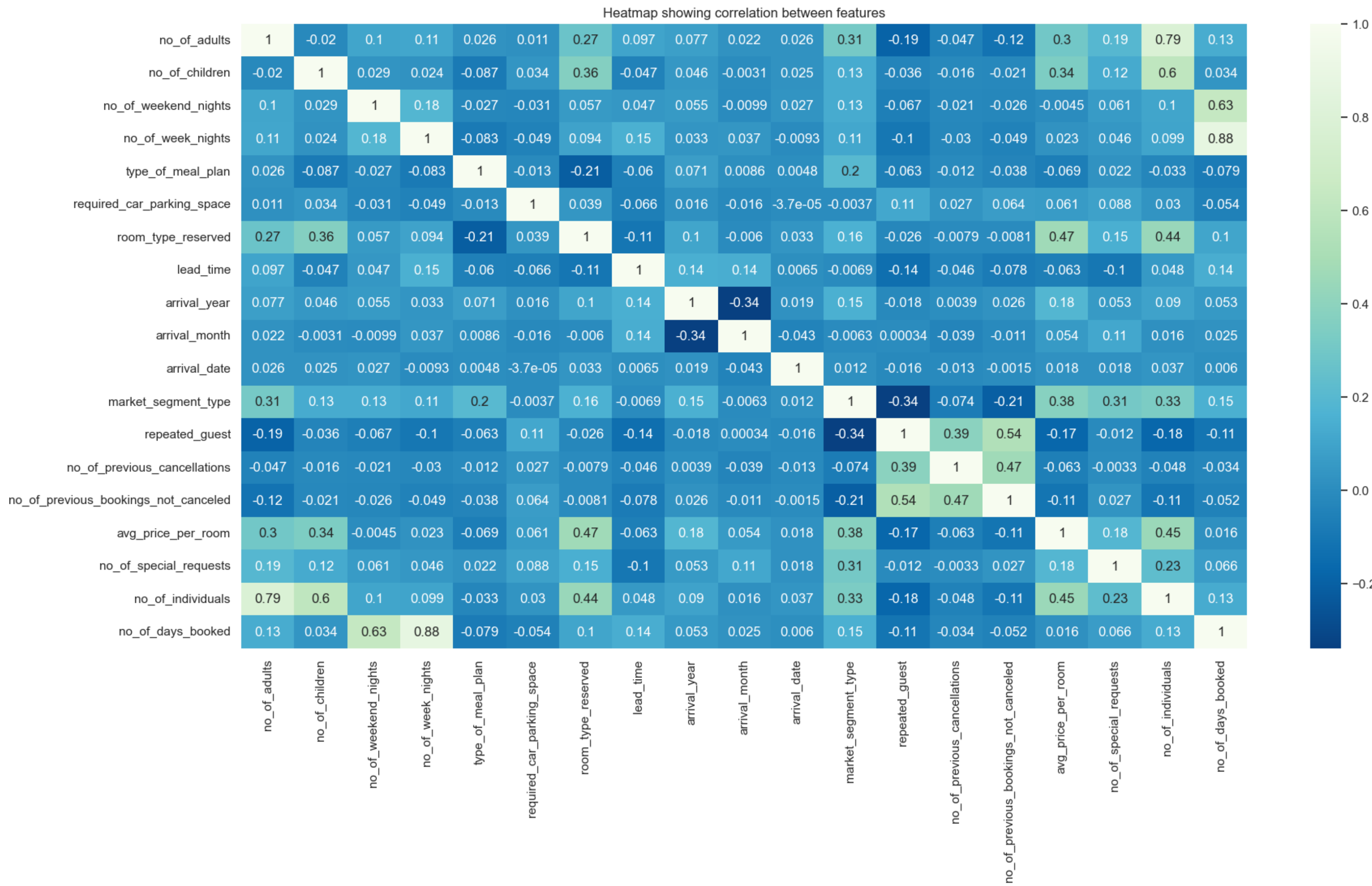
Feature correlation

In [49]:
```
features = model_data.drop(['Booking_ID', 'booking_status'], axis=1)
features.head()
```

Out[49]:

	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_meal_plan	required_car_parking_space	room_type_reserv
0	2	0	1	2	0	0	
1	2	0	2	3	3	0	
2	1	0	2	1	0	0	
3	2	0	0	2	0	0	
4	2	0	1	1	3	0	

In [50]:
```
plt.figure(figsize=(20,10))
sns.heatmap(features.corr(), annot=True, cmap='GnBu_r')
plt.title('Heatmap showing correlation between features')
plt.savefig('corr.png', bbox_inches='tight', dpi=300)
plt.show()
```



Train-test split validation
The dataset is split into explanatory variables — X and target variable — y. Then, it further, split into train and test data in a ratio of 80:20 respectively. Splitting the data helps to assess the model’s performance on unseen data after being trained on the training data. Scikit-learn’s train-test split is

used to accomplish this task.

In [154...
```
X = features
y = model_data['booking_status']
```

In [155...
```
print(X.shape, y.shape)
```

```
(36275, 19) (36275,)
```

In [156...
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [157...
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(29020, 19) (7255, 19) (29020,) (7255,)
```

Feature scaling
Before going into modeling proper, the data needs to be scaled to handle skewed features. Scikit-learn's standard scaler ensures that for each feature the mean is 0 and the variance is 1, bringing all the features to the same magnitude. Doing this will significantly affect the model's performance.

In [158...
```
scaler = StandardScaler()
scaledX_train = scaler.fit_transform(X_train)
scaledX_test = scaler.transform(X_test)
```

6. Modeling The hotel booking cancelations problem is a classification problem, therefore about three classification models were trained and the optimal model was chosen.

In [159...
```
f1scores = []
```

Logistic Regression

In [160...
```
logit = LogisticRegression()
logit.fit(scaledX_train, y_train)
```

Out[160]:
```
▾ LogisticRegression

LogisticRegression()
```

In [161...
```
pred_logit = logit.predict(scaledX_test)
pred_logit
```

Out[161]:
```
array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```

In [162...
```
print(f'The accuracy score of the logistic regression model is {accuracy_score(y_test, pred_logit)}')
```

```
The accuracy score of the logistic regression model is 0.8056512749827704
```

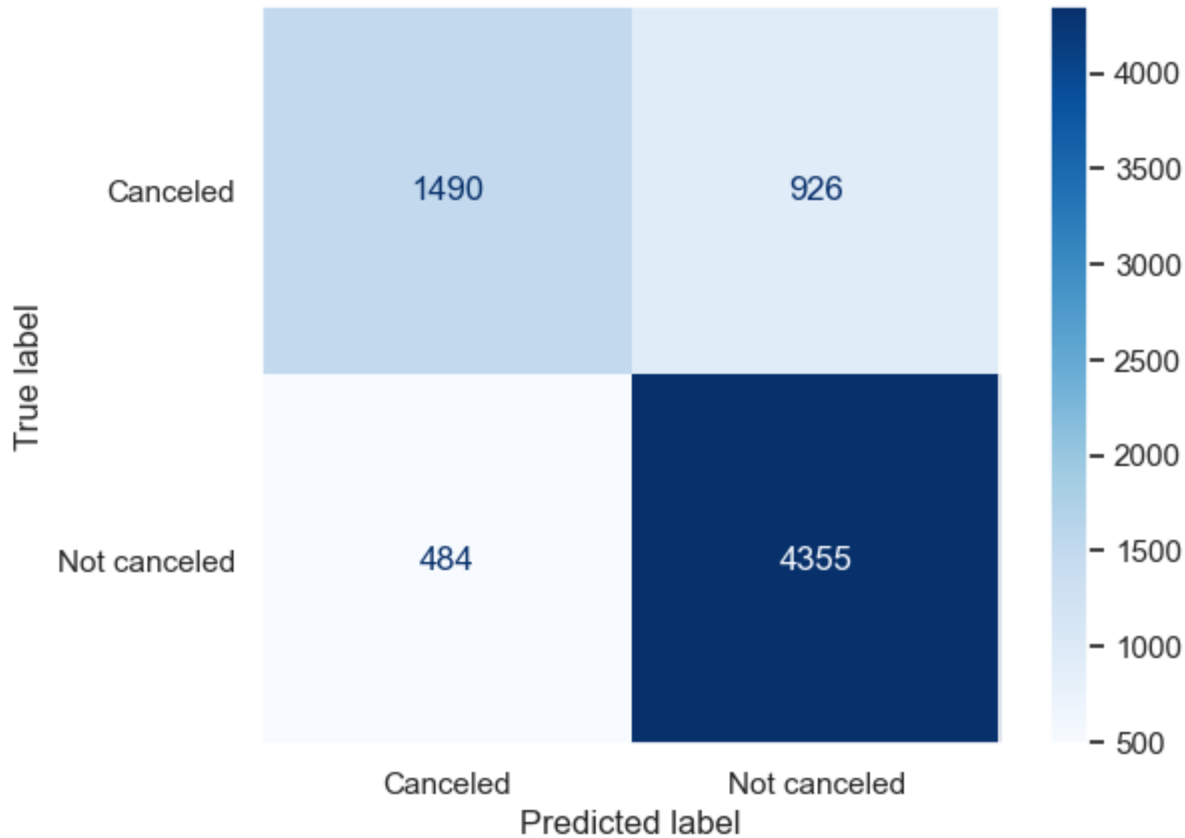
In [163...
```
print(f'The f1_score of the logistic regression model is {f1_score(y_test, pred_logit)}')
f1scores.append(f1_score(y_test, pred_logit))
```

```
The f1_score of the logistic regression model is 0.8606719367588934
```

In [164...
```
print(classification_report(y_test, pred_logit))
```

```
              precision    recall  f1-score   support

           0       0.75      0.62      0.68      2416
           1       0.82      0.90      0.86      4839

    accuracy                           0.81      7255
   macro avg       0.79      0.76      0.77      7255
weighted avg       0.80      0.81      0.80      7255
```

In [165...
```
confusion_matrix_log = confusion_matrix(y_test, pred_logit)
cm_display_log = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix_log, display_labels = ['Canceled', 'Not c
cm_display_log.plot(cmap=plt.cm.Blues)
plt.grid(False)

plt.savefig('logcm.png', bbox_inches='tight', dpi=300)
plt.show()
```



DecisionTreeClassifier

In [166…

```
df.head()
```

Out[166]:

	Booking_ID	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_meal_plan	required_car_parking_space	roo
0	INN00001	2	0	1	2	Meal Plan 1	0	
1	INN00002	2	0	2	3	Not Selected	0	
2	INN00003	1	0	2	1	Meal Plan 1	0	
3	INN00004	2	0	0	2	Meal Plan 1	0	
4	INN00005	2	0	1	1	Not Selected	0	

In [167…

```
forest = DecisionTreeClassifier(random_state = 1)
forest.fit(scaledX_train, y_train)
```

Out[167]:

```
▾         DecisionTreeClassifier

DecisionTreeClassifier(random_state=1)
```

In [168…

```
pred_decision = forest.predict(scaledX_test)
pred_decision
```

Out[168]:

```
array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```

In [169…

```
print(f'The accuracy score of the Decision Tree model is {accuracy_score(y_test, pred_decision)}')
```

```
The accuracy score of the Decision Tree model is 0.8734665747760165
```

In [170…

```
print(f'The f1_score of the DecisionTreeClassifier model is {f1_score(y_test, pred_decision)}')
f1scores.append(f1_score(y_test, pred_decision))
```

```
The f1_score of the DecisionTreeClassifier model is 0.9047520232413364
```

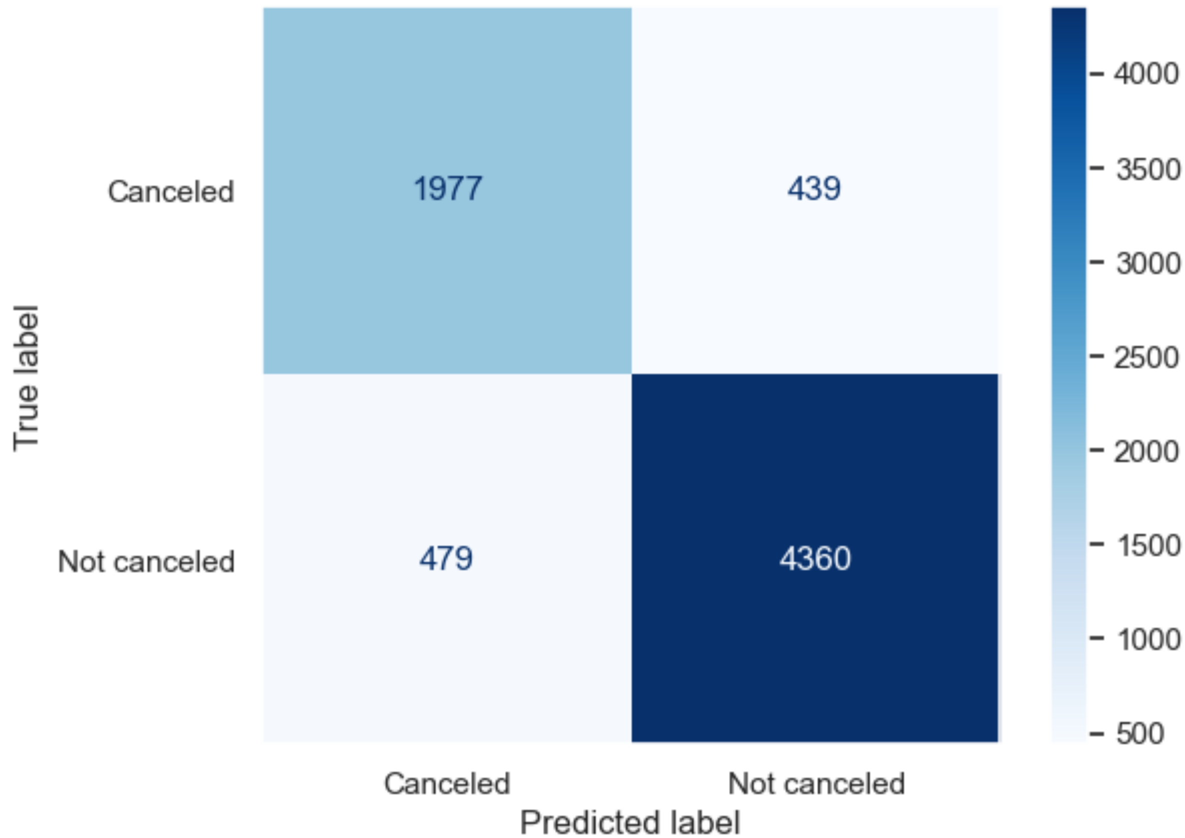
In [171…

```
print(classification_report(y_test, pred_decision))
```

```
              precision    recall  f1-score   support

           0       0.80      0.82      0.81      2416
           1       0.91      0.90      0.90      4839

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

In [172…

```
confusion_matrix_forest = confusion_matrix(y_test, pred_decision)
cm_display_forest = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix_forest, display_labels = ['Canceled',
cm_display_forest.plot(cmap=plt.cm.Blues)
plt.grid(False)

plt.savefig('forestcm.png', bbox_inches='tight', dpi=300)
plt.show()
```



RandomForest

In [173…
```
forest = RandomForestClassifier(random_state = 1)
forest.fit(scaledX_train, y_train)
```

Out[173]:
```
▾         RandomForestClassifier
RandomForestClassifier(random_state=1)
```

In [174…
```
pred_forest = forest.predict(scaledX_test)
pred_forest
```

Out[174]:
```
array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```

In [175…
```
print(f'The accuracy score of the random forest model is {accuracy_score(y_test, pred_forest)}')
```

```
The accuracy score of the random forest model is 0.9061337008959338
```

In [176…

```
print(f'The f1_score of the random forest model is {f1_score(y_test, pred_forest)}')
f1scores.append(f1_score(y_test, pred_forest))
```

```
The f1_score of the random forest model is 0.9309260574094737
```

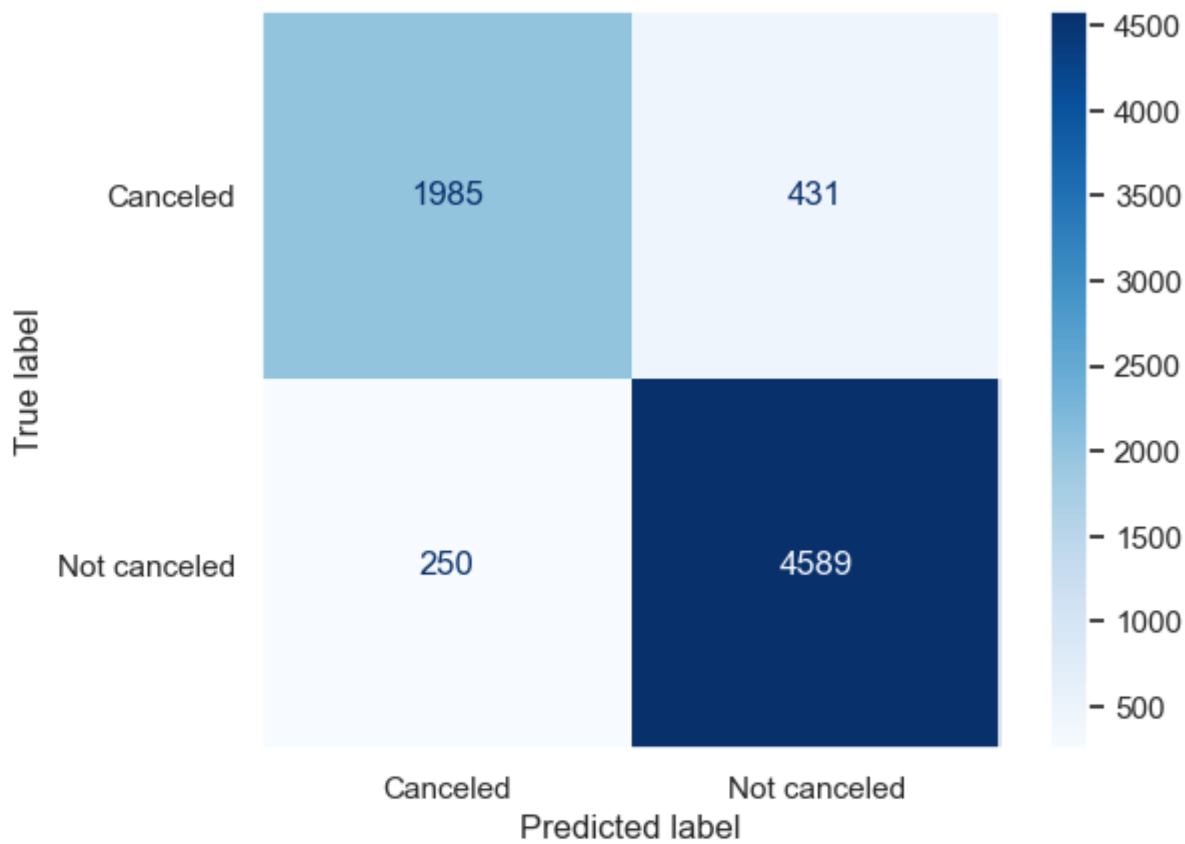
In [177…

```
print(classification_report(y_test, pred_forest))
```

```
              precision    recall  f1-score   support

           0       0.89      0.82      0.85      2416
           1       0.91      0.95      0.93      4839

    accuracy                           0.91      7255
   macro avg       0.90      0.88      0.89      7255
weighted avg       0.91      0.91      0.91      7255
```

In [178…

```
confusion_matrix_forest = confusion_matrix(y_test, pred_forest)
cm_display_forest = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix_forest, display_labels = ['Canceled',
cm_display_forest.plot(cmap=plt.cm.Blues)
plt.grid(False)

plt.savefig('forestcm.png', bbox_inches='tight', dpi=300)
plt.show()
```



In [179…

```
models = ['Logistic Regression', 'Random Forest','decision_tree']
print(f1scores)
```

```
[0.8606719367588934, 0.9047520232413364, 0.9309260574094737]
```

In [180…

```
models_scores = list(zip(models, f1scores))
evaluation = pd.DataFrame(models_scores, columns=['Model', 'F1score'])
evaluation
```

Out[180]:

	Model	F1score
0	Logistic Regression	0.860672
1	Random Forest	0.904752
2	decision_tree	0.930926

Conclusion
1. Regularised models and trees do not get impacted by outliers, hence the models show good results despite some outliers in the data
2.After gridSearch and hyperparameter tunnig we found Random Forest is the best model in indentifying whether a user cancelled his booking or not.
3. Random Forest worked the best because it adds regularization to the loss function to reduce model complexity and increase generalisation.
4. We adjusted the model weights due to class imbalance in target variable. Our final model has a overall balanced accuracy score 0.930926
5. It classifies 85% of the users who cancelled correctly and 91% who did not cancel correctly.
1.10 How can this model be used?
1.1 This model will be helpful in highlighting the bookings which have high propensity of cancellation
1.2 The hotels can use this model to impose high cancellation fee on bookings which the model has detected as likely to be cancelled. This will discourage the customer from cancelling or the booking will be done by a user who is less likely to cancel