

# project hotell

presented by  
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# PROBLEM STATEMENT

## OBJECTIVE

It is the design and implementation of a machine learning model for a hotel to predict whether the booking will be canceled or not.

- **Goal:** He did the classification correctly.



# FIRST STEP

## IMPORT DATA AND LIBRARYS

- **pandas** : To maintain and retrieve the data
- **seaborn , matplotlib** : To create a visualization for the data
- **train\_test\_splite** : To split the data into test data and train data
- **KNeighborsClassifier** : To create a model of type KNN
- **Confusion\_matrix** : He is doing a test for the model.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
```

```
data = pd.read_csv(r"C:\Users\karem\Downloads\first inten project.csv")
data.head(10)
```

# DATA EXAMINATION AND PROCESSING

```
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36285 entries, 0 to 36284
Data columns (total 17 columns):
#   Column                Non-Null Count  Dtype  
---  -
0   Booking_ID            36285 non-null  object  
1   number of adults       36285 non-null  int64   
2   number of children     36285 non-null  int64   
3   number of weekend nights 36285 non-null  int64   
4   number of week nights  36285 non-null  int64   
5   type of meal           36285 non-null  object  
6   car parking space      36285 non-null  int64   
7   room type              36285 non-null  object  
8   lead time              36285 non-null  int64   
9   market segment type    36285 non-null  object  
10  repeated               36285 non-null  int64   
11  P-C                    36285 non-null  int64   
12  P-not-C                36285 non-null  int64   
13  average price          36285 non-null  float64 
14  special requests       36285 non-null  int64   
15  date of reservation    36285 non-null  object  
16  booking status         36285 non-null  object  
dtypes: float64(1), int64(10), object(6)
memory usage: 4.7+ MB

data[data.duplicated() == True]
```

## NULL CHECK

- Null does not exist in the data.

## DUPLICATED CHECK

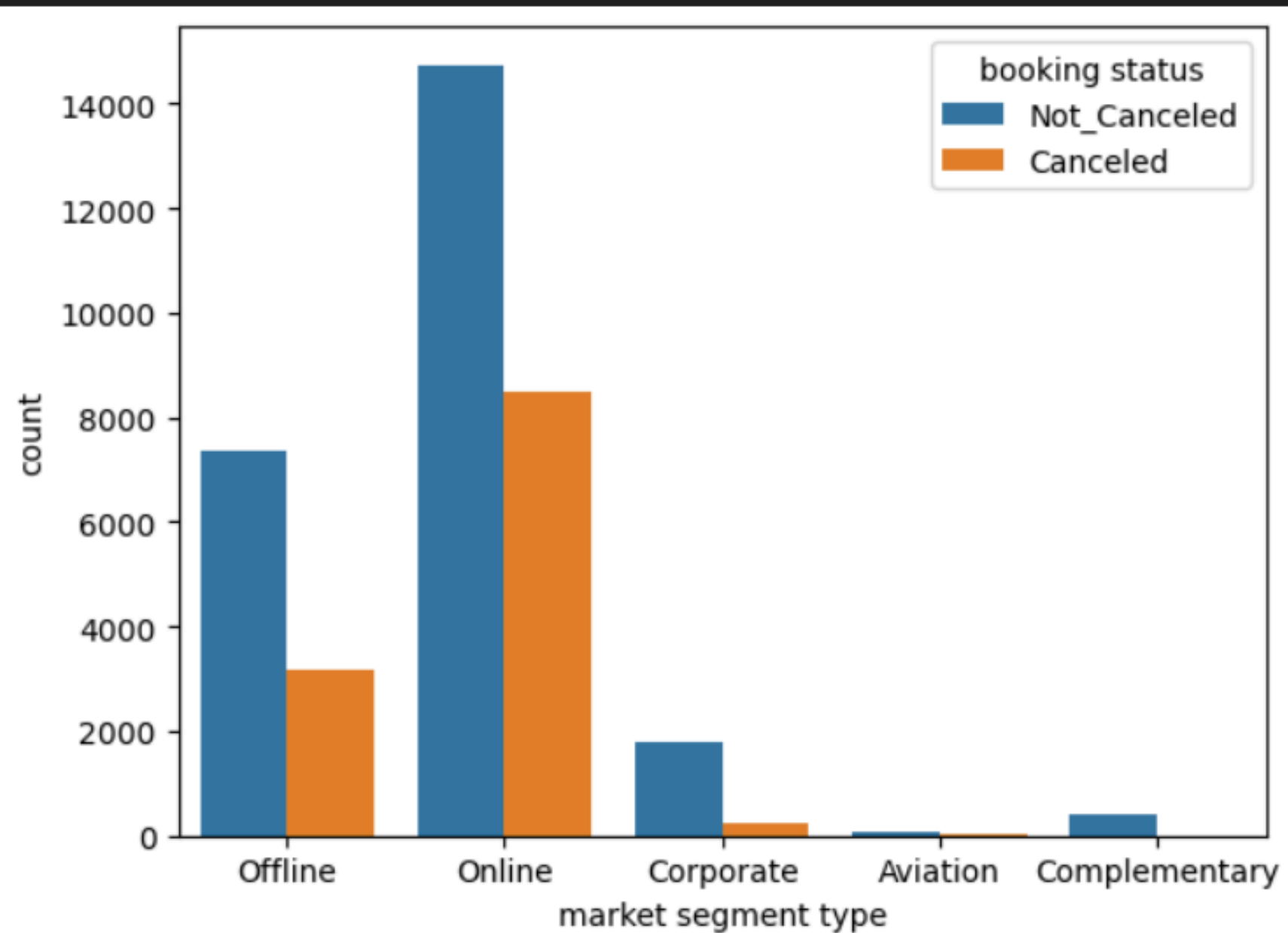
- There are no duplicates.

## CHECK DATA TYPE

- The type of data for the date of reservation is incorrect and we will change it to date, time, but we faced some problems that there is a date of 2018-2-29 which is wrong, so I replaced it with 1/3/2018.

# DATA ANALYSIS

```
sns.countplot(data=data, x='market segment type', hue='booking status')  
plt.show()
```

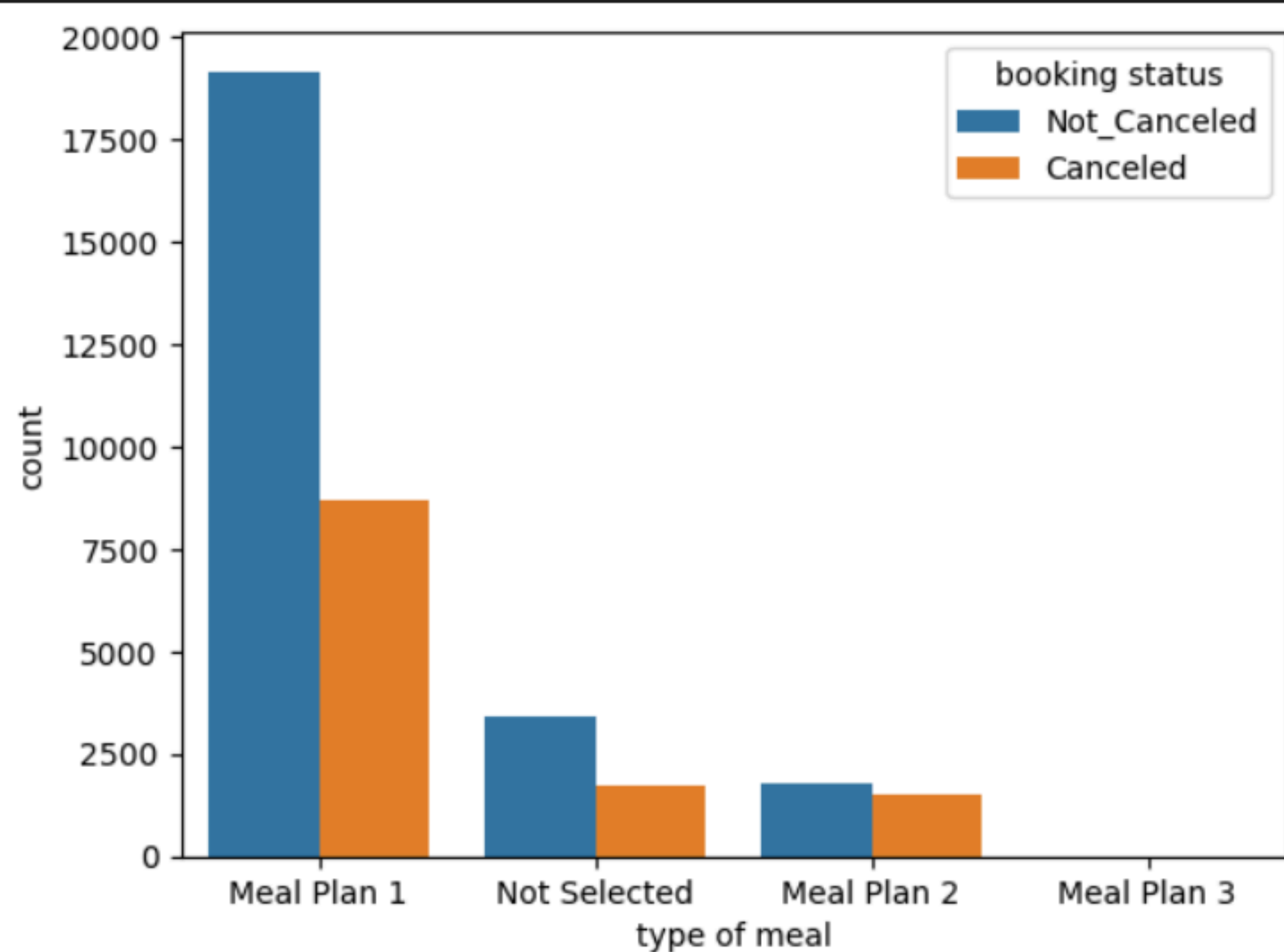


# Here I wanted to study if there is a relationship between 'booking status' and 'market segment type'.

- In that case, it turned out that the highest number of bookings was online, and there was a higher number of cancellations.
- Also, the difference between 'canceled' and 'not canceled' is in 'complementary.'

# It is clear that the 'market segment type' affects the 'booking status,' so we will take the 'market segment type.'

```
sns.countplot(data=data, x='type of meal', hue='booking status')  
plt.show()
```



# HERE I WANTED TO STUDY IF THERE IS A RELATIONSHIP BETWEEN 'BOOKING STATUS' AND 'TYPE OF MEAL' BY BAR PLOT.

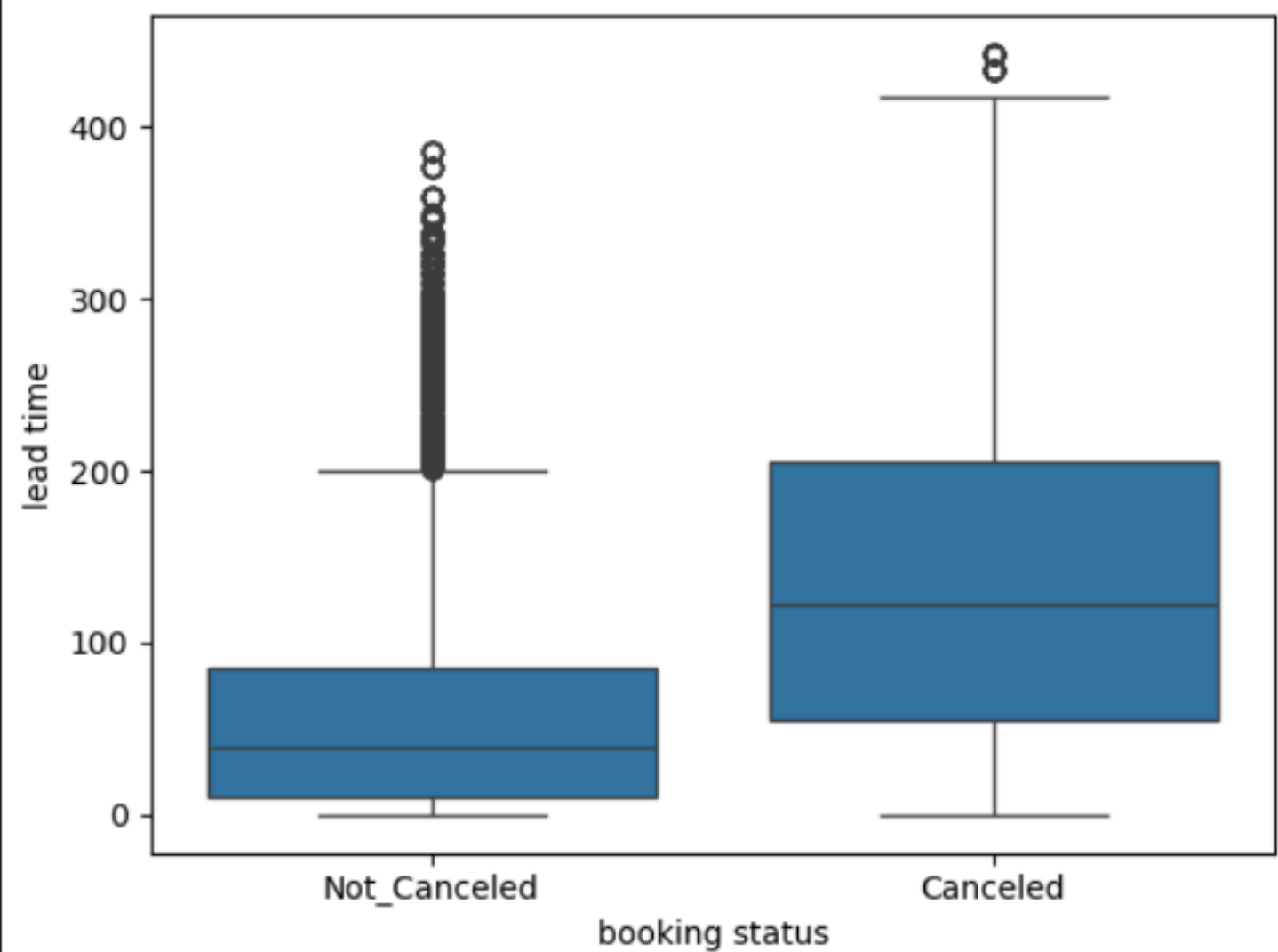
- It is clear that plan 1 is the best in terms of performance and that plan 2 is less efficient regarding the difference between canceled and not canceled.
- Plan 3 is to be the least plan in terms of quantity and may reach zero.

# It is clear that the 'type of meal' affects the 'booking status'.

```
sns.boxplot(data=data, x='booking status', y='lead time')  
plt.show()
```

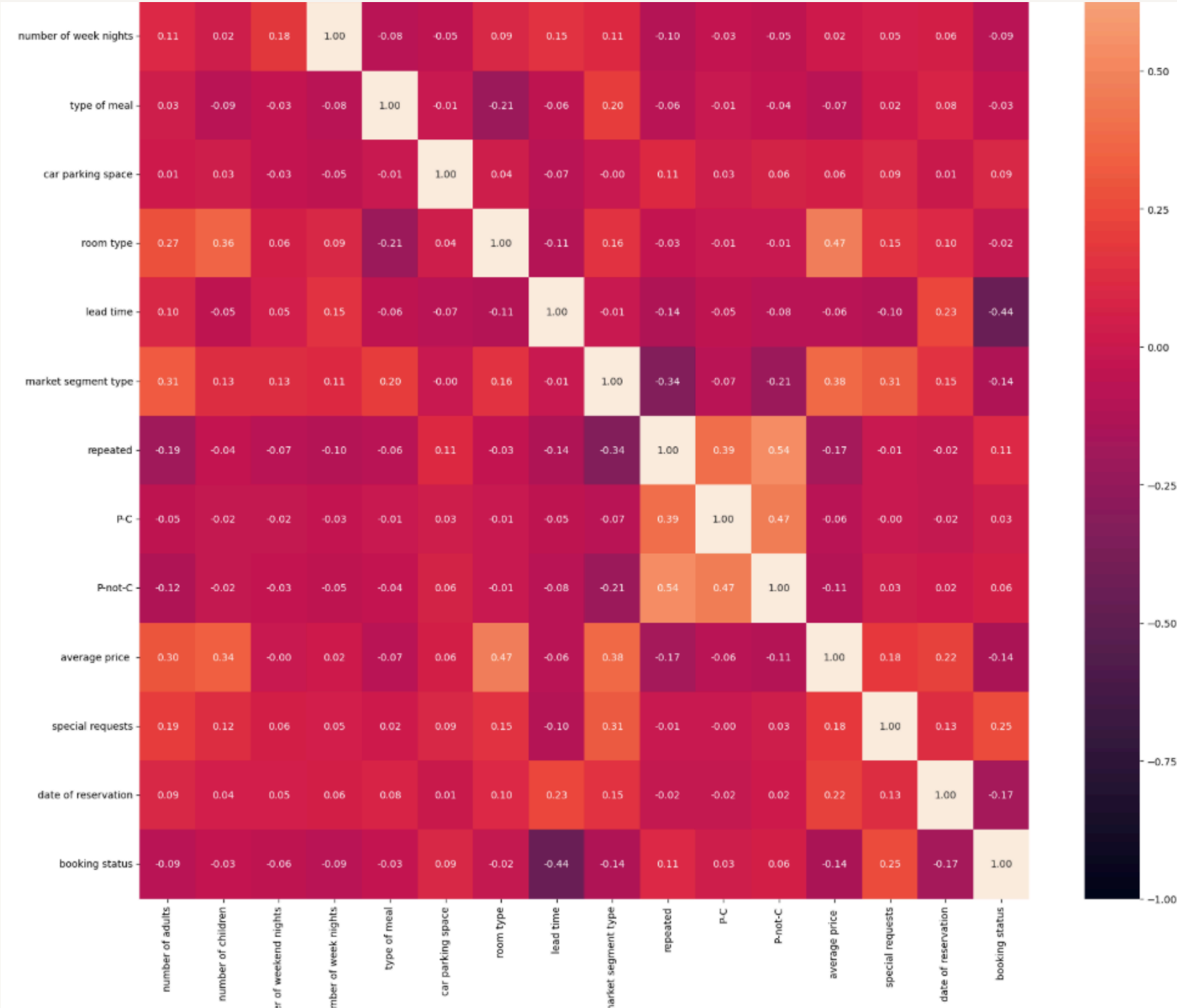
# HERE I WANTED TO STUDY IF THERE IS A  
RELATIONSHIP BETWEEN 'BOOKING STATUS' AND 'LEAD  
TIME' BY BOX PLOT.

- It is clear that the longer the lead time, the higher the number of cancellations.
- It is clear that the shorter the lead time, the higher the number of Not\_canceled.



```
le = LabelEncoder()
data['type of meal'] = le.fit_transform(data['type of meal'])
data['market segment type'] = le.fit_transform(data['market segment type'])
data['booking status'] = le.fit_transform(data['booking status'])
data['room type'] = le.fit_transform(data['room type'])
data.drop(['Booking_ID','month'] , inplace= True ,axis= 1)
```

- This is to do encoding for the column categories because the KNN model cannot accept non-numeric data.



- This heatmap represents the correlation between the column and then.

| <i>column</i>       | correlation |
|---------------------|-------------|
| date of reservation | -0.17       |
| special requests    | 0.25        |
| average price       | -0.14       |
| p-not-c             | 0.06        |
| p-c                 | 0.03        |
| repeated            | 0.11        |
| market segment type | -0.14       |
| lead time           | -0.44       |



# SELECT BEST COLUMNS

```
data_traning = data.loc[ :,[ 'type of meal','repeated', 'car parking space','lead time', 'market segment type', 'average price ', 'special requests']]
targetcolum = data['booking status']
data_traning
```

```
X_train, X_test, y_train, y_test = train_test_split(data_traning, targetcolum, test_size=0.3, random_state=42)
```

```
model = KNeighborsClassifier(n_neighbors=5)
model.fit(X_train, y_train)
```

## BEST COLUMNS

- 'type of meal' , 'repeated' , 'car parking space' , 'lead time' , 'market segment type' , 'average price ' , 'special requests'

## TRAIN MODEL

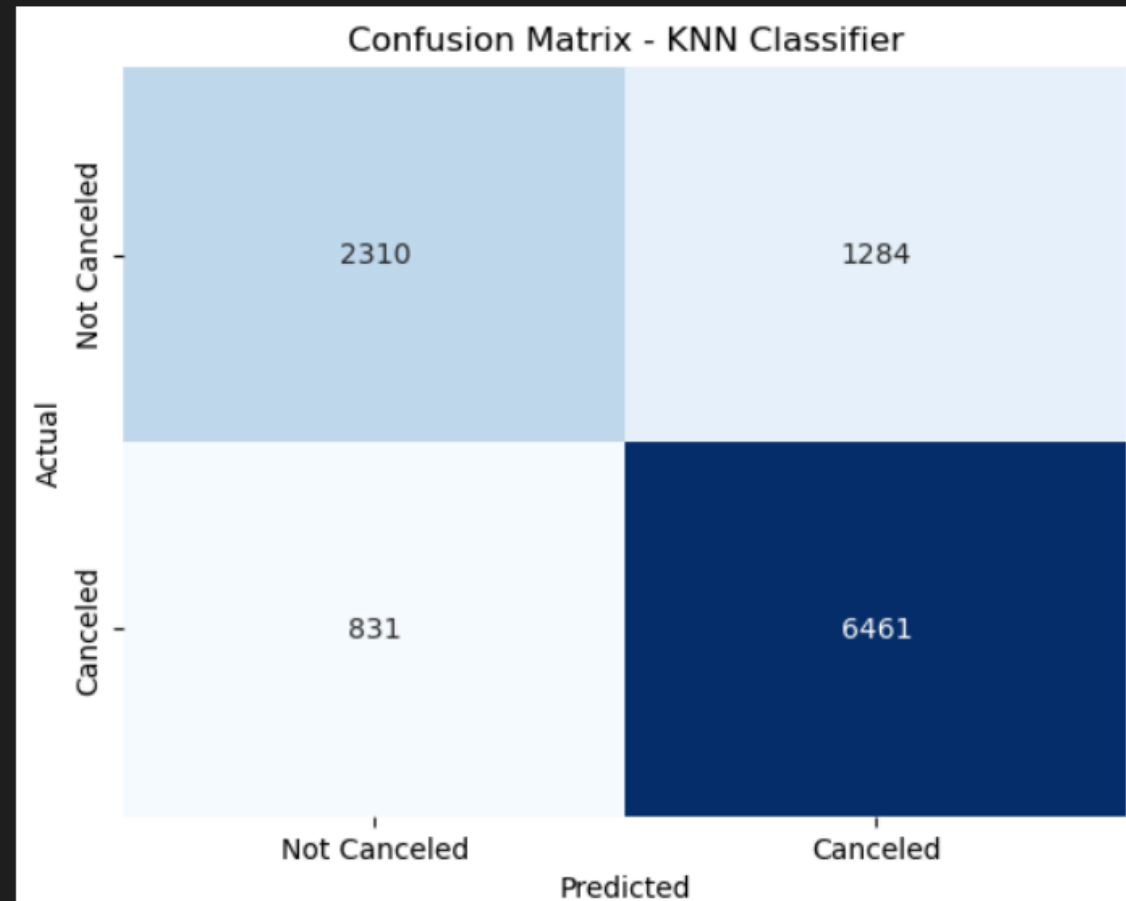
- I chose here that it takes 5 from neighbors because it was giving the best result.

## SPLIT DATA

- Here I did a split of the data with a 70 to 30 ratio, and this was the best ratio used.

# EVALUATING THE MODEL

```
y_pred = model.predict(x_test)
report = classification_report(y_test, y_pred )
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cbar=False,xticklabels=['Not Canceled', 'Canceled'],yticklabels=['Not Canceled', 'Canceled'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - KNN Classifier')
plt.show()
```



## HIS RESULTS

- It is clear that the model predicts canceled cases very accurately, as it predicted 6461 correctly and 2310 correctly for not canceled cases.

**PRESENTED BY :**

karem atef

THANKS

*karem atef*