

# Capstone Project

## EDA Of Hotel Booking Analysis

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# Content:

- **Introduction**
- **Loading Libraries (Numpy,Pandas,Matplotlib,Seaborn)**
- **Reading input dataset by df.info(), df.describe(), df.columns()**
- **Cleaning the Data and dropping unnecessary columns**
- **Analyzing the data and plotting the charts from the given Dataset**
- **Conclusion**

# Introduction :

- **Hotel industry is a very volatile industry and the bookings depend on variety of factors such as type of hotels, seasonality, days of week and many more.**
- **This makes analyzing the patterns available in the past data more important to help the hotels plan better.**
- **Using the hotels data . We can use the patterns to predict the bookings**

# Loading Libraries

```
▶ # Importing the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import datetime as dt
```

- Numpy is python library used for working with arrays
- Pandas allows importing data from various file format such as CSV, Excel, Json, SQL
- Matplotlib is a plotting library for the Python Programming Language and its numerical Mathematics extension library
- Seaborn is a data visualization library built on top of matplotlib and closely integrated with pandas data structure in python
- DateTime is used to import to work with the date as well as time

# Reading the information of Dataset by .info() and .columns

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 32 columns):
#   Column                                     Non-Null Count  Dtype
---  --
0   hotel                                     119390 non-null  object
1   is_canceled                             119390 non-null  int64
2   lead_time                               119390 non-null  int64
3   arrival_date_year                       119390 non-null  int64
4   arrival_date_month                     119390 non-null  object
5   arrival_date_week_number               119390 non-null  int64
6   arrival_date_day_of_month              119390 non-null  int64
7   stays_in_weekend_nights                 119390 non-null  int64
8   stays_in_week_nights                   119390 non-null  int64
9   adults                                  119390 non-null  int64
10  children                                119386 non-null  float64
11  babies                                  119390 non-null  int64
12  meal                                    119390 non-null  object
13  country                                 118902 non-null  object
14  market_segment                         119390 non-null  object
15  distribution_channel                   119390 non-null  object
16  is_repeated_guest                      119390 non-null  int64
17  previous_cancellations                 119390 non-null  int64
18  previous_bookings_not_canceled         119390 non-null  int64
19  reserved_room_type                     119390 non-null  object
20  assigned_room_type                     119390 non-null  object
21  booking_changes                        119390 non-null  int64
22  deposit_type                           119390 non-null  object
23  agent                                  103050 non-null  float64
24  company                                6797 non-null   float64
25  days_in_waiting_list                   119390 non-null  int64
26  customer_type                           119390 non-null  object
27  adr                                    119390 non-null  float64
28  required_car_parking_spaces            119390 non-null  int64
29  total_of_special_requests              119390 non-null  int64
30  reservation_status                     119390 non-null  object
31  reservation_status_date                119390 non-null  object
dtypes: float64(4), int64(16), object(12)
memory usage: 29.1+ MB
```

df.columns

```
Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_year',
       'arrival_date_month', 'arrival_date_week_number',
       'arrival_date_day_of_month', 'stays_in_weekend_nights',
       'stays_in_week_nights', 'adults', 'children', 'babies', 'meal',
       'country', 'market_segment', 'distribution_channel',
       'is_repeated_guest', 'previous_cancellations',
       'previous_bookings_not_canceled', 'reserved_room_type',
       'assigned_room_type', 'booking_changes', 'deposit_type',
       'customer_type', 'adr', 'required_car_parking_spaces',
       'total_of_special_requests', 'reservation_status',
       'reservation_status_date'],
      dtype='object')
```

# Most important step is to clean the data.

- We have NaN values in Agent and Company but that columns are negligible so we drop that columns.

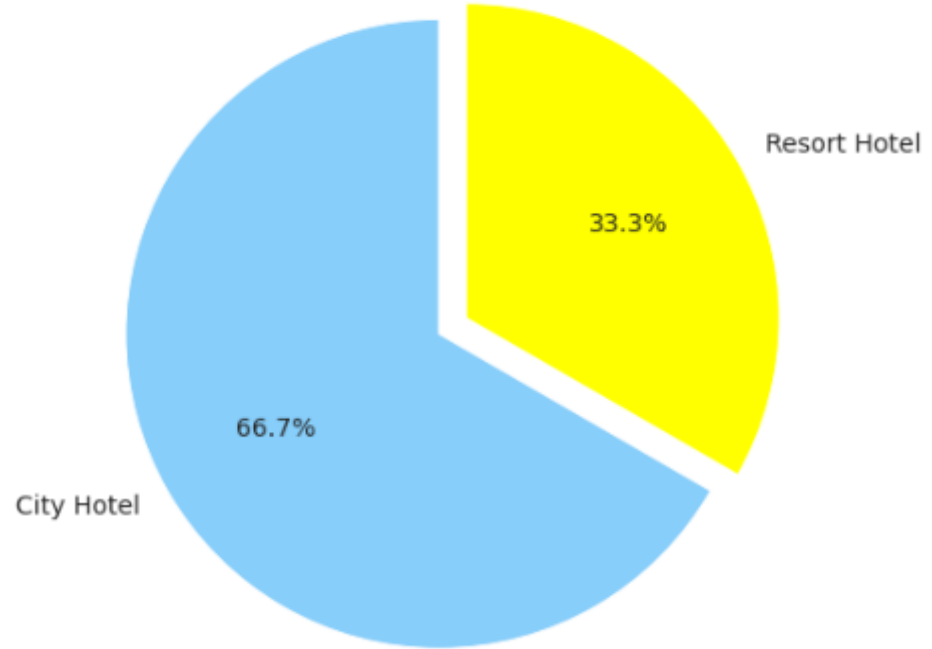
| deposit_type | agent | company |
|--------------|-------|---------|
| No Deposit   | NaN   | NaN     |
| No Deposit   | NaN   | NaN     |
| No Deposit   | NaN   | NaN     |
| No Deposit   | 304.0 | NaN     |
| No Deposit   | 240.0 | NaN     |

```
[11] #Lets drop columns with high missing values "agent" and "company".  
df.drop(['agent','company'], axis = 1 , inplace = True)
```

## EDA

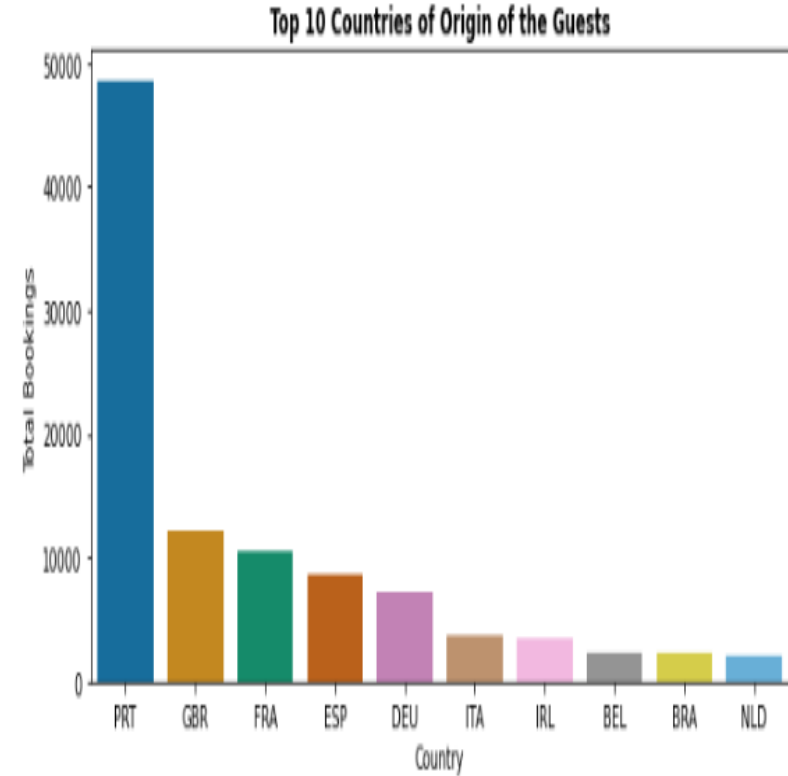
### 1. Hotel Comparison :

Here we just compared the  
Resort hotel and City Hotel  
In terms of bookings.



## 2. Country wise Guests :

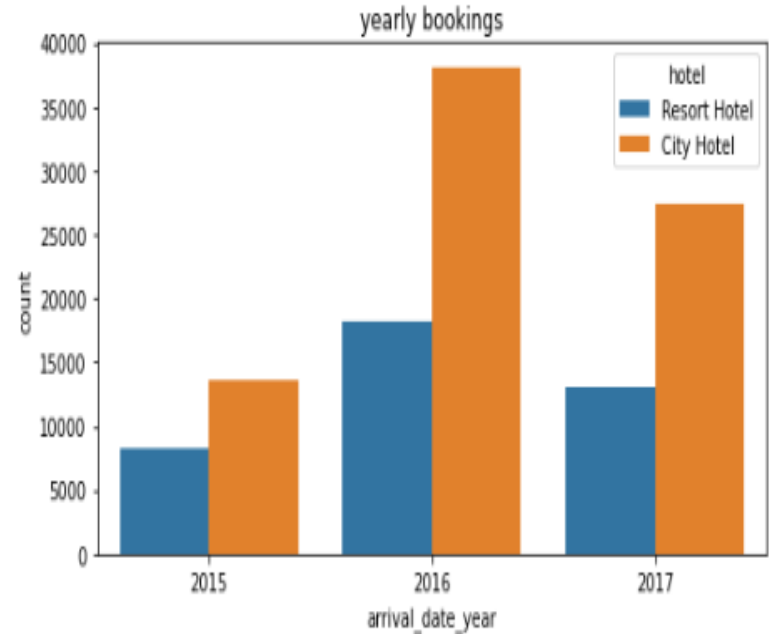
- **Portugal, UK and France, Spain and Germany are the top countries from most guests come, more than 80% come from these 5 countries.**





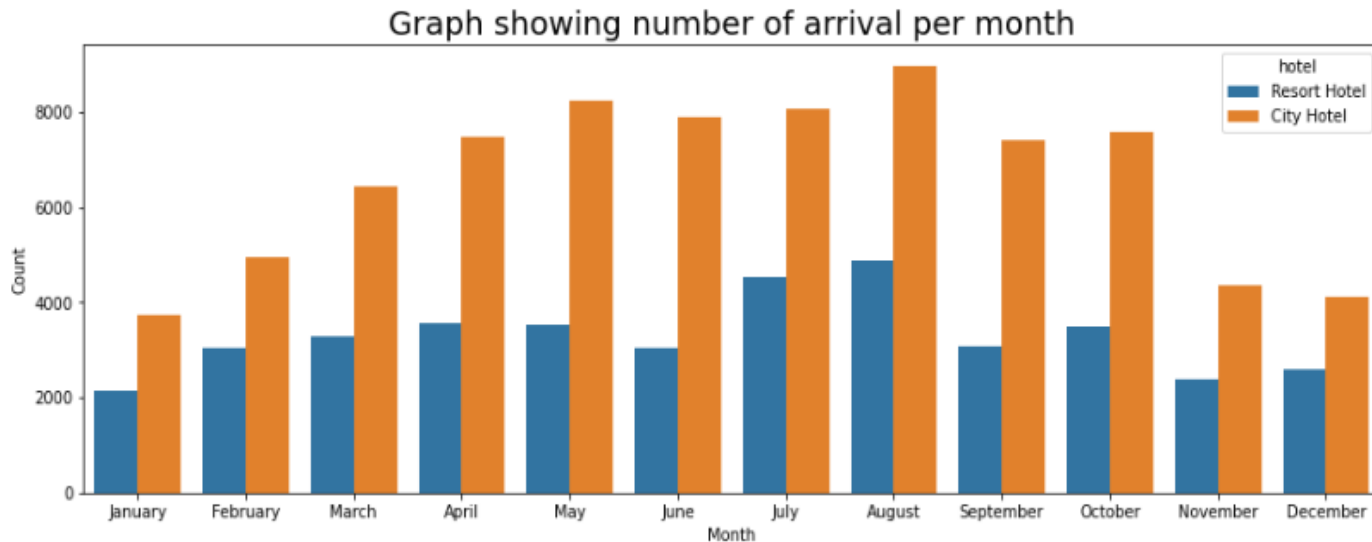
### 3. Year-wise and hotel-wise bookings :

➤ Here we can see that 2016 seems to be the year where hotel booking is at its highest.



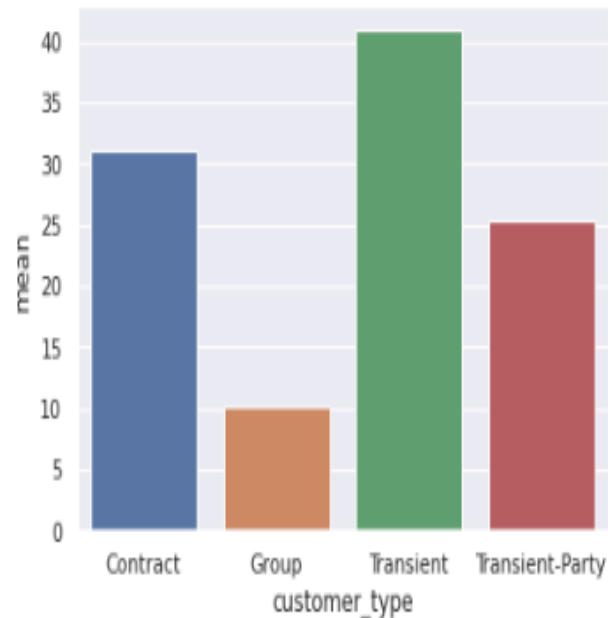
## 4. Month-wise and hotel-wise arrivals :

We see an increasing trend in booking around the middle of the year, with August being the highest



## 5. Customer Type Bookings:

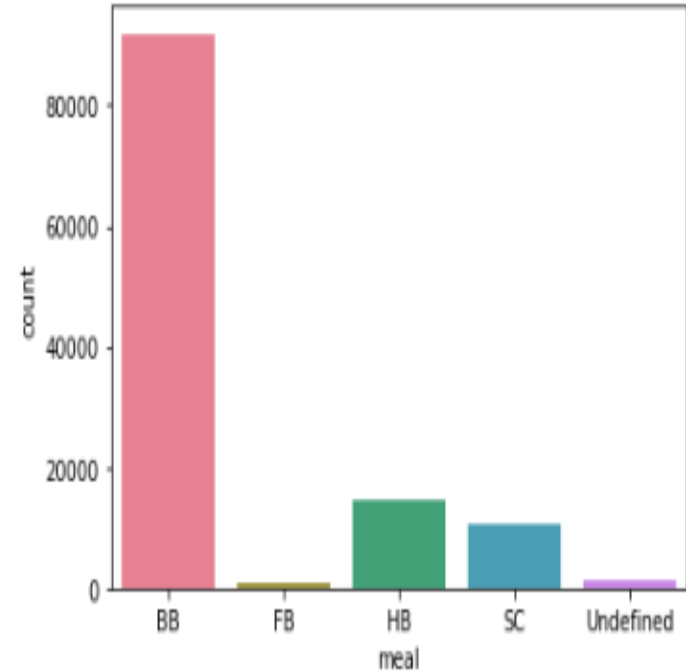
- **Majority of the bookings are transient.** with the ease of booking directly from the website, most people tend to skip the middleman to ensure quick response from their booking.



## 6. Meal Type :

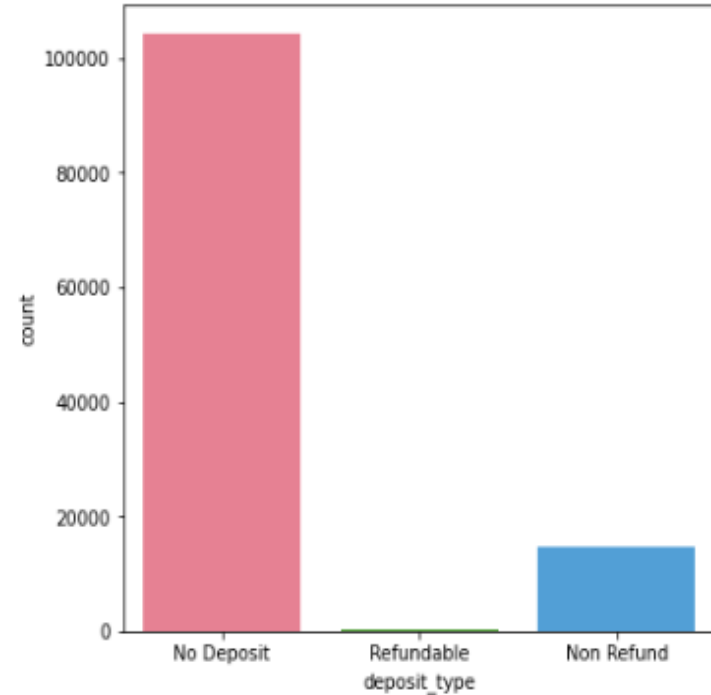
```
BB          0.772620
HB          0.121398
SC          0.089472
Undefined   0.009798
FB          0.006712
Name: meal, dtype: float64
```

As we can see that bed and breakfast as the high count with respect to other meal type



## 7. Deposit Type :

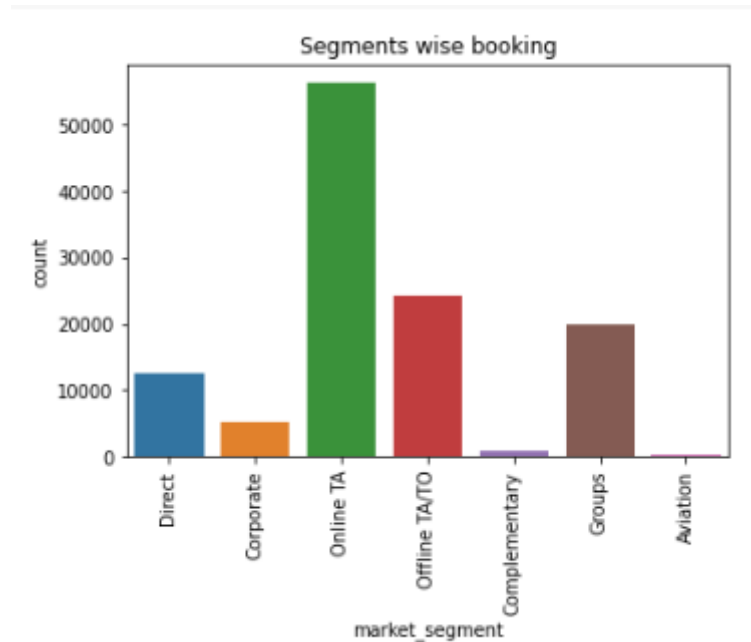
- Majority of the booking does not require deposit. That could explain why cancellation rate was actually 50% of non-cancellation rate.



## 8. Market Type Segment :

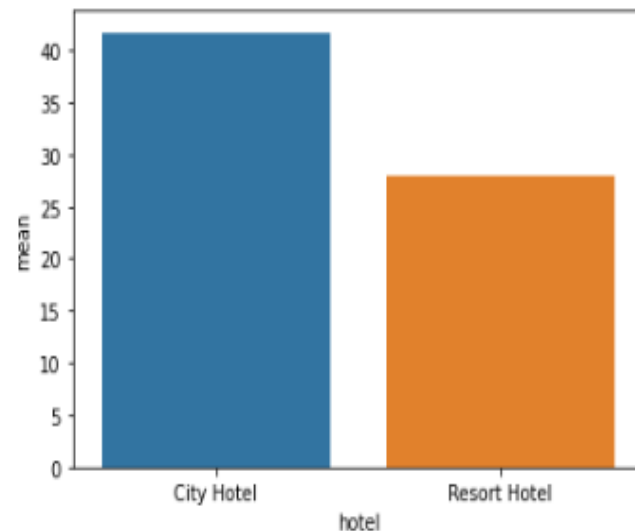
```
↳ Online TA      0.474373  
   Offline TA/TO  0.203199  
   Groups         0.166580  
   Direct         0.104695  
   Corporate      0.042986  
   Complementary  0.006173  
   Aviation       0.001993  
   Name: market_segment, dtype: float64
```

- Indirect bookings through online and offline travel agents are higher compared to direct bookings and same is the case with group bookings which are also high.



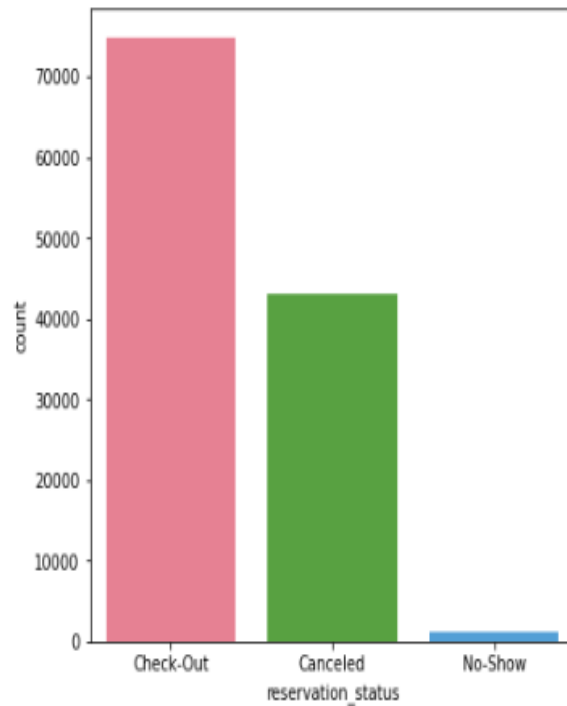
## 9. Bookings Cancelled :

➤ Here we have seen a huge proportion of cancellation from city hotel. This was expected since 3/4 of the hotel .bookings belong to city hotels.



## 10. Reservation status :

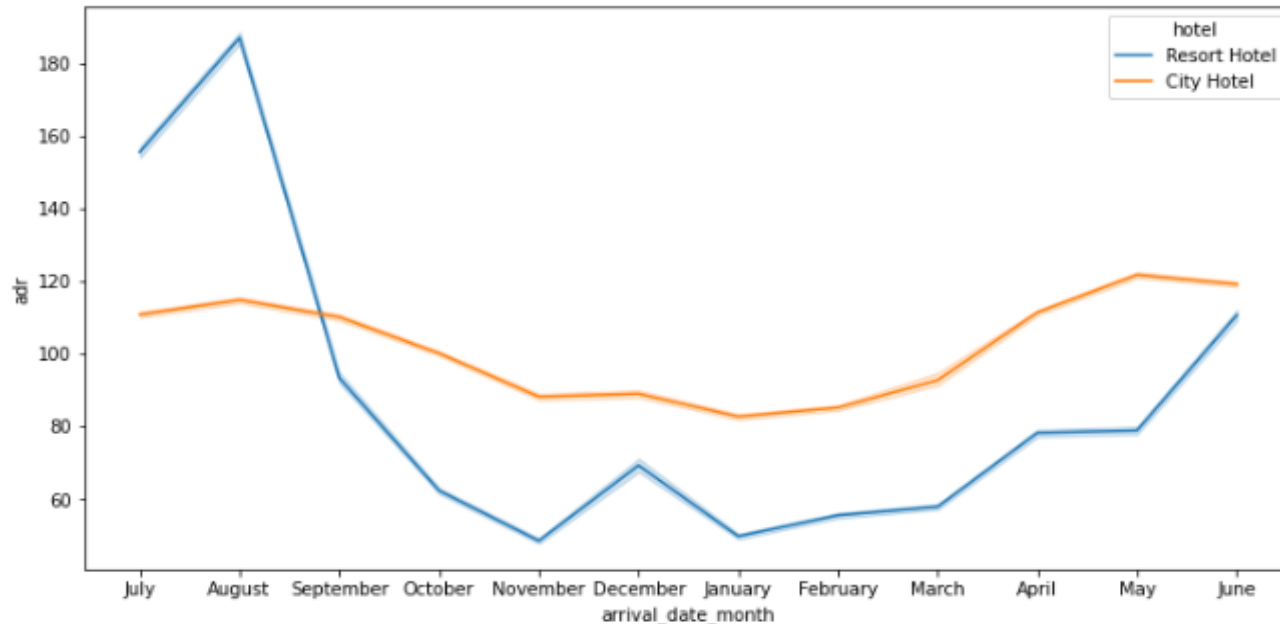
- **Canceled** — booking was canceled by the customer;
- **Check-Out** — customer has checked in but already departed;
- **No-Show** — customer did not check-in and did inform the hotel of the reason why.





## 11. Average Daily Rate (ADR) :

- Prices of resort hotel are much higher. It seems that that is definitely the case since resort hotels specialize in that.
- Prices of city hotel do not fluctuate that much.



## Conclusion :

- Majority of the hotels booked are city hotel.
- We also realize that the high rate of cancellations can be due high no deposit policies.
- The target months between May to Aug. Those are peak months due to the summer period.
- Majority of the guests are from Western Europe.
- Given that we do not have repeated guests.

**Q & A**