# Hotel Booking Analysis EDA Capstone Project AlmaBetter

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## **Points to Discuss**

- Agenda
- Data summary
- Data cleaning
- Hotel wise analysis
- Distribution Channel wise analysis
- Cancellation related analysis
- Time and Stay related analysis
- Heat Correlation
- Challenges

## **Agenda**

To extract, observe and analyse the given hotel bookings data set from 2015-2017.

The analysis of given data set in following ways:

- Hotel wise analysis
- Distribution Channel wise analysis
- Booking cancellation analysis
- Timewise analysis

## **Data Summary**

#### Given data set has different columns of variables crucial for hotel bookings:

hotel: The category of hotels, which has two values resort hotel and city hotel.

is\_cancelled: The value of column show the cancellation type. If the booking was cancelled or not. Values[0,1], where 0 indicates not cancelled.

lead time: The time between reservation and actual arrival.

stayed\_in\_weekend\_nights: The number of weekend nights stay per reservation

stayed\_in\_weekday\_nights: The number of weekday nights stay per reservation.

meal: Meal preferences per reservation.[BB,FB,HB,SC,Undefined]

Country: The origin country of guest.

market\_segment: This column show how reservation was made and what is the purpose of reservation. Eg, corporate means corporate trip, TA for travel agency.

distribution\_channel: The medium through booking was made. [Direct,Corporate,TA/TO,undefined,GDS.]

Is\_repeated\_guest: Shows if the guest is who has arrived earlier or not. Values[0,1]-->0 indicates no and 1 indicated yes person is repeated guest.

days\_in\_waiting\_list: Number of days between actual booking and transact.

customer type: Type of customers( Transient, group, etc.)

#### **Data information**

#	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_n	umber 119390 non-null int64
6	arrival_date_day_of_	month 119390 non-null int64
7	stays_in_weekend_r	nights 119390 non-null int64
8	stays_in_week_nigh	ts 119390 non-null int64
9	adults	119390 non-null int64
10	) children	119386 non-null float64
11	babies	119390 non-null int64
12	2 meal	119390 non-null object
13	3 country	118902 non-null object
14	market_segment	119390 non-null object
15	distribution_channe	l 119390 non-null object

dtypes: float64(4), int64(16), object(12) No. of Rows: 119390 entries, 0 to 119389

No. of Data columns: 32 columns

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

## **Data Cleaning**

Data Cleaning is a crucial step before EDA as it will remove the ambiguous data that can affect the outcome of EDA.

While cleaning data we will perform the following steps:

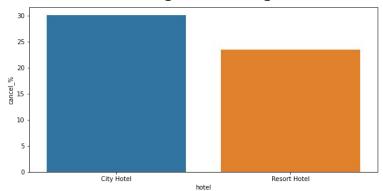
- 1) Remove duplicate rows (df1[df1.duplicated()].shape)+df1.drop\_duplicates(inplace = True)

  No. of duplicate rows : 31980
- 2) Handling missing values. (hotelbookings.isnull().sum().sort\_values(ascending=False)
  hotelbookings[['company','agent']] = hotelbookings[['company','agent']].fillna(0)
  hotelbookings['children'].fillna(hotelbookings['children'].mean(), inplace = True)
  hotelbookings['country'].fillna('others', inplace = True)
- 3) Convert columns to appropriate data types. (df1[['children', 'company', 'agent']] = df1[['children', 'company', 'agent']].astype('int64'))
- 4) Removing the Outliers (adr,lead\_time,days\_in\_waiting\_list,required\_car\_parking\_space)

## Hotel wise analysis

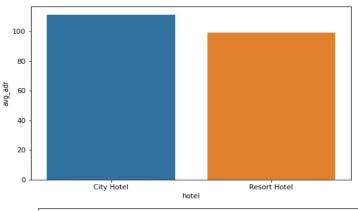
- Hotel with higher bookings cancellation rate.
- Hotel with longest waiting time
- Hotel with most revenue.
- Chances of customer returning to hotel for another stay
- Factors Governing Booking
- Special requests by the guests

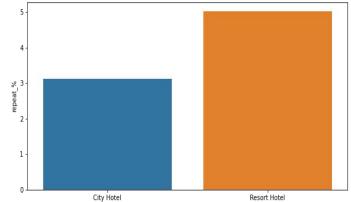
#### Hotel with higher bookings cancellation rate



- 30% of customers of City Hotel have cancelled their booking. Whereas 20-25% of customers have cancelled their booking in Resort Hotel.
- City hotel generates most revenue.
- Both the customers have less chances of its customer returning for the stay.

#### Hotel with most revenue



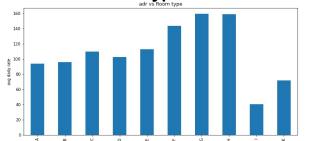


Chances of customer returning to hotel for another stay

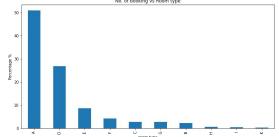
#### Factors governing booking

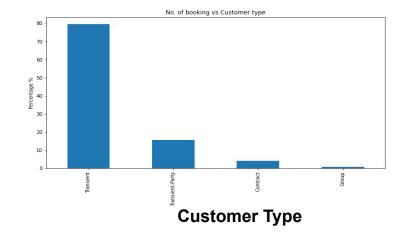






#### Room type with highest no. of bookings

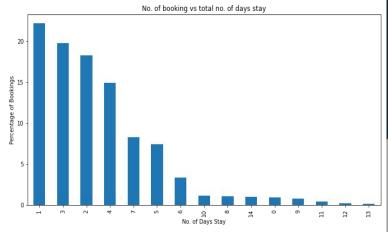




- Most number of customers used No Deposit option
- Room type A has the highest number of bookings compared to the other room types.
- The most number of bookings was made by Transient Customer Type and the least was by Group customer type..

## Hotel Type No. of booking vs Hotel Type 50 10 Hotel Type No. of booking vs total no. of guests 10 12 Total No. of Guest Total Number of Guest

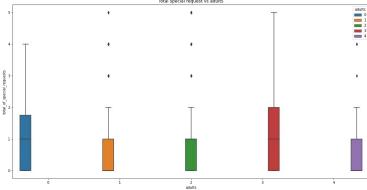
#### Total number of days stays



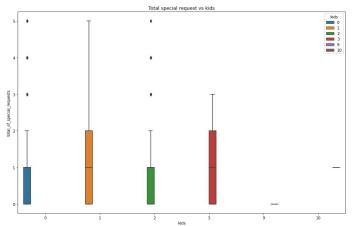
- Most preferred hotel was City Hotel.
- The number of days stay was mostly1
- Most number of bookings was done by couples.

#### Special requests by the guests

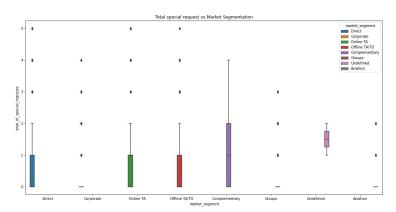
#### Special Requests According to Adults



#### Special Requests According to Kids



#### Special Requests According to Market Segmentation

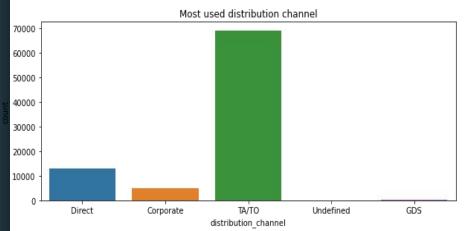


- The most number of special request demand was from Complementary market segment.
- The cases where the number of adults is more than 3 ,there was a high demand of special requests.
- When the no. of kids were 1 and 3, we can expect more special requests.

## **Distribution Channel wise analysis**

- Most used Distribution Channel
- Which distribution channel brings better revenue generating deals for hotels?
- Market segments used by the guests
- Distribution Channel with highest cancellation

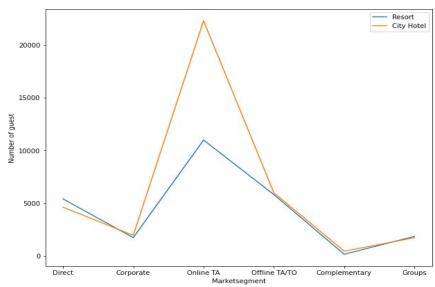
#### Most used distribution channel



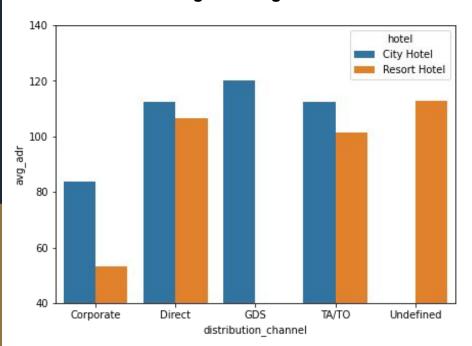
Most number of customers have used TA/TO(Travel Agency/Travel Operator) distribution channel for hotel bookings.

Mostly used market segment by the guests was Online TA to book City hotel and Resort hotel.

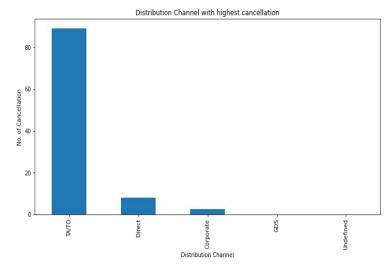
#### Most used market segment



## Distribution channel bringing highest revenue generating deals



#### **Distribution Channel with highest cancellation**



 GDS channel brings higher revenue for City hotel. Whereas for Resort hotel gets more revenue by direct and TA/TO channel.

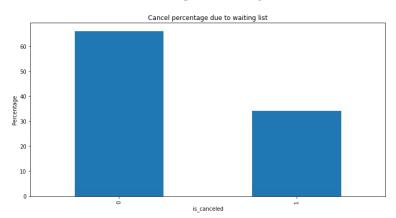
## **Cancellation related Analysis**

- Waiting time(days)
- Lead Time
- Cancellation for not assigning same room
- Car parking space

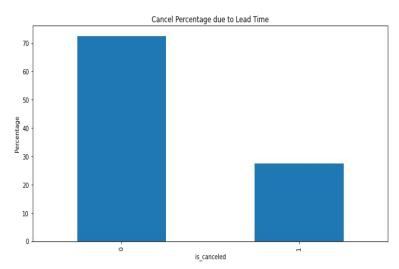
#### Waiting time(days)

#### **Cancellation related analysis**

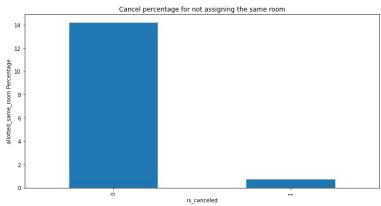
#### **Lead Time**



 The parameters like lead time and days in waiting list have no significant impact on the cancellation rate.

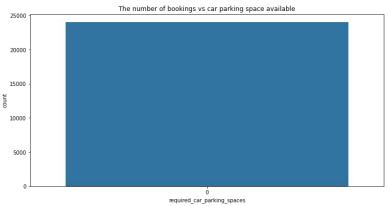


#### Cancellation for not assigning same room



 The booking change from assigned room to reserved room parameter not had any influence on cancellation of bookings.

#### Car parking space

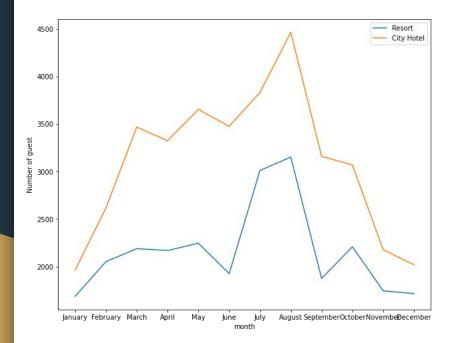


 Main reason for cancellation has been because of no car parking space.

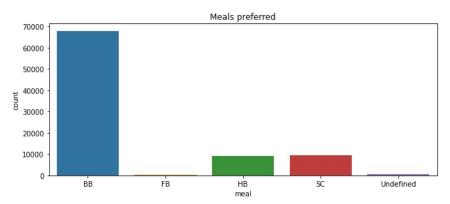
## **Time and Stay related Analysis**

- Customer type with maximum Average Daily Rate
- Type of customers booking the most
- Best time to book a hotel room
- Countries from which most customers are coming

#### Best time to book a hotel room



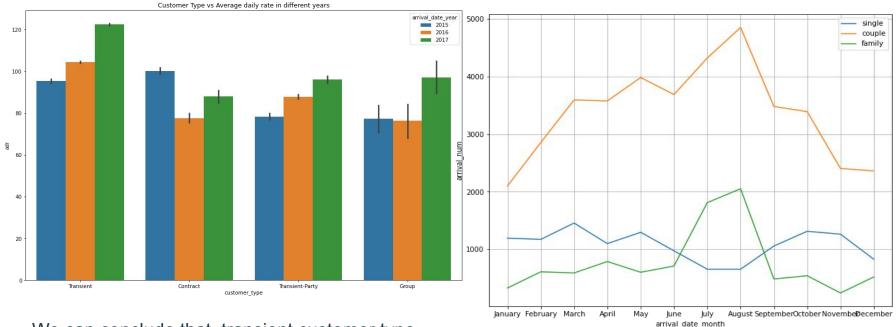
#### **Meal preferred**



- As per the plot graph, we can conclude that most of the customers visit in the month of August.
- In this analysis, we have concluded that the most preferred meal type by the customer is Bed and Breakfast(BB).

#### **Customer type with maximum Average Daily Rate**

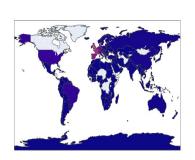
#### Type of customers booking the most

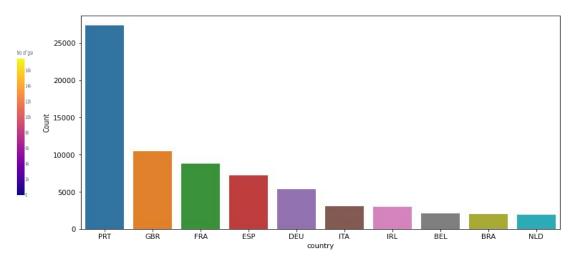


We can conclude that, transient customer type generates maximum adr. The adr of transient-party has been increasing with the year. The group customer type does not show much of a progression.

According to the above graph, it shows that mostly couples or families that has been visiting during the month of July and August.

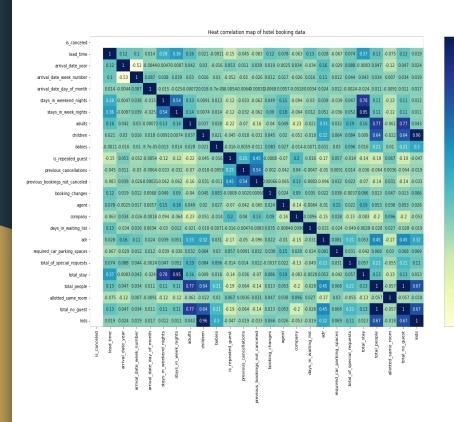
#### Countries from which most customers are coming





 Most of the guests were from Portugal with 25k customers. Second by Great Britain with 10k customers. Followed by France, Spain and Germany respectively.

#### **Heat Correlation Map**



The average daily rate is positively correlated with total number of guest. Hence we can understand that when number of guest increases ,the average daily rate of hotel also increases with it.

The average daily rate is positively correlated with the number of special request. Hence we can understand that when the number of special request increases the revenue of the hotel increases.

The total number of days stay and lead time have slight positive correlation to each other. Thus we can say that higher number of days stay result in higher lead time.

## **Challenges**

A lot of null values were present in the dataset.

There were a lot of duplicate data.

Removing the outliers from the given dataset.

Selecting appropriate visualization techniques was a tedious job.

# Thank You !!!