Hotel Booking Demand

2022-08-17

Introduction

For my project, I analyzed the hotel booking demand dataset, comprising over 119,000 reservations from two prestigious hotels in Portugal: a Resort Hotel and a City Hotel in Lisbon. The dataset spans check-in dates from July 2015 to August 2017, providing a comprehensive view of booking trends and guest preferences during this period. The primary research questions addressed include identifying the optimal time of year for booking hotels in Portugal, the most common distribution channels for bookings, peak months for hotel occupancy, the top countries of origin for guests, and potential factors contributing to high cancellation rates.

Importing Packages

I utilized various R packages such as tidyverse, ggplot2, and readr to import, clean, and visualize the data.

Loading in the Data set

The dataset was loaded into R as a tibble for efficient data manipulation and analysis.

```r
hoteldata <- read.csv("_data/hotel_bookings.csv", stringsAsFactors=TRUE)
```

```r
hoteldata <- as_tibble(hoteldata)
glimpse(hoteldata)
```

```
Rows: 119,390
Columns: 32
$ hotel                          <fct> Resort Hotel, Resort Hotel, Resort Hote~
```

```
$ is_canceled                    <int> 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, ~
$ lead_time                      <int> 342, 737, 7, 13, 14, 14, 0, 9, 85, 75, ~
$ arrival_date_year              <int> 2015, 2015, 2015, 2015, 2015, 2015, 201~
$ arrival_date_month             <fct> July, July, July, July, July, July, Jul~
$ arrival_date_week_number       <int> 27, 27, 27, 27, 27, 27, 27, 27, 27, 27,~
$ arrival_date_day_of_month      <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~
$ stays_in_weekend_nights        <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ stays_in_week_nights           <int> 0, 0, 1, 1, 2, 2, 2, 2, 3, 3, 4, 4, 4, ~
$ adults                         <int> 2, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, ~
$ children                       <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ babies                         <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ meal                           <fct> BB, BB, BB, BB, BB, BB, BB, FB, BB, HB,~
$ country                        <fct> PRT, PRT, GBR, GBR, GBR, GBR, PRT, PRT,~
$ market_segment                 <fct> Direct, Direct, Direct, Corporate, Onli~
$ distribution_channel           <fct> Direct, Direct, Direct, Corporate, TA/T~
$ is_repeated_guest              <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ previous_cancellations         <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ previous_bookings_not_canceled <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ reserved_room_type             <fct> C, C, A, A, A, A, C, C, A, D, E, D, D, ~
$ assigned_room_type             <fct> C, C, C, A, A, A, C, C, A, D, E, D, E, ~
$ booking_changes                <int> 3, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ deposit_type                   <fct> No Deposit, No Deposit, No Deposit, No ~
$ agent                          <fct> NULL, NULL, NULL, 304, 240, 240, NULL, ~
$ company                        <fct> NULL, NULL, NULL, NULL, NULL, NULL, NUL~
$ days_in_waiting_list           <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ customer_type                  <fct> Transient, Transient, Transient, Transi~
$ adr                            <dbl> 0.00, 0.00, 75.00, 75.00, 98.00, 98.00,~
$ required_car_parking_spaces    <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ total_of_special_requests      <int> 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 3, ~
$ reservation_status             <fct> Check-Out, Check-Out, Check-Out, Check-~
$ reservation_status_date        <fct> 2015-07-01, 2015-07-01, 2015-07-02, 201~
```

Displaying the first 10 elements of the data set gives a better idea.

```r
head(hoteldata, n=10)
```

```
# A tibble: 10 x 32
   hotel        is_canceled lead_time arrival_date_year arrival_date_month
   <fct>              <int>     <int>             <int> <fct>
 1 Resort Hotel           0       342              2015 July
 2 Resort Hotel           0       737              2015 July
 3 Resort Hotel           0         7              2015 July
```

```
 4 Resort Hotel           0        13               2015 July
 5 Resort Hotel           0        14               2015 July
 6 Resort Hotel           0        14               2015 July
 7 Resort Hotel           0         0               2015 July
 8 Resort Hotel           0         9               2015 July
 9 Resort Hotel           1        85               2015 July
10 Resort Hotel           1        75               2015 July
# i 27 more variables: arrival_date_week_number <int>,
#   arrival_date_day_of_month <int>, stays_in_weekend_nights <int>,
#   stays_in_week_nights <int>, adults <int>, children <int>, babies <int>,
#   meal <fct>, country <fct>, market_segment <fct>,
#   distribution_channel <fct>, is_repeated_guest <int>,
#   previous_cancellations <int>, previous_bookings_not_canceled <int>,
#   reserved_room_type <fct>, assigned_room_type <fct>, ...
```

Displaying the number of rows, columns and summary of the data set.

```r
dim(hoteldata)
```

```
[1] 119390     32
```

```r
summary(hoteldata)
```

```
          hotel         is_canceled       lead_time   arrival_date_year
 City Hotel   :79330   Min.   :0.0000   Min.   :  0   Min.   :2015
 Resort Hotel:40060   1st Qu.:0.0000   1st Qu.: 18   1st Qu.:2016
                      Median :0.0000   Median : 69   Median :2016
                      Mean   :0.3704   Mean   :104   Mean   :2016
                      3rd Qu.:1.0000   3rd Qu.:160   3rd Qu.:2017
                      Max.   :1.0000   Max.   :737   Max.   :2017

 arrival_date_month arrival_date_week_number arrival_date_day_of_month
 August :13877      Min.   : 1.00            Min.   : 1.0
 July   :12661      1st Qu.:16.00            1st Qu.: 8.0
 May    :11791      Median :28.00            Median :16.0
 October:11160      Mean   :27.17            Mean   :15.8
 April  :11089      3rd Qu.:38.00            3rd Qu.:23.0
 June   :10939      Max.   :53.00            Max.   :31.0
 (Other):47873
 stays_in_weekend_nights stays_in_week_nights     adults
```

```
Min.   : 0.0000        Min.   : 0.0        Min.   : 0.000
1st Qu.: 0.0000        1st Qu.: 1.0        1st Qu.: 2.000
Median : 1.0000        Median : 2.0        Median : 2.000
Mean   : 0.9276        Mean   : 2.5        Mean   : 1.856
3rd Qu.: 2.0000        3rd Qu.: 3.0        3rd Qu.: 2.000
Max.   :19.0000        Max.   :50.0        Max.   :55.000

   children          babies                 meal          country
Min.   : 0.0000   Min.   : 0.000000   BB       :92310   PRT    :48590
1st Qu.: 0.0000   1st Qu.: 0.000000   FB       :  798   GBR    :12129
Median : 0.0000   Median : 0.000000   HB       :14463   FRA    :10415
Mean   : 0.1039   Mean   : 0.007949   SC       :10650   ESP    : 8568
3rd Qu.: 0.0000   3rd Qu.: 0.000000   Undefined: 1169   DEU    : 7287
Max.   :10.0000   Max.   :10.000000                     ITA    : 3766
NA's   :4                                               (Other):28635
      market_segment  distribution_channel is_repeated_guest
Online TA    :56477   Corporate: 6677      Min.   :0.00000
Offline TA/TO:24219   Direct   :14645      1st Qu.:0.00000
Groups       :19811   GDS      :  193      Median :0.00000
Direct       :12606   TA/TO    :97870      Mean   :0.03191
Corporate    : 5295   Undefined:    5      3rd Qu.:0.00000
Complementary:  743                        Max.   :1.00000
(Other)      :  239
previous_cancellations previous_bookings_not_canceled reserved_room_type
Min.   : 0.00000       Min.   : 0.0000                A      :85994
1st Qu.: 0.00000       1st Qu.: 0.0000                D      :19201
Median : 0.00000       Median : 0.0000                E      : 6535
Mean   : 0.08712       Mean   : 0.1371                F      : 2897
3rd Qu.: 0.00000       3rd Qu.: 0.0000                G      : 2094
Max.   :26.00000       Max.   :72.0000                B      : 1118
                                                      (Other): 1551
assigned_room_type booking_changes      deposit_type        agent
A      :74053      Min.   : 0.0000   No Deposit:104641   9      :31961
D      :25322      1st Qu.: 0.0000   Non Refund: 14587   NULL   :16340
E      : 7806      Median : 0.0000   Refundable:   162   240    :13922
F      : 3751      Mean   : 0.2211                       1      : 7191
G      : 2553      3rd Qu.: 0.0000                       14     : 3640
C      : 2375      Max.   :21.0000                       7      : 3539
(Other): 3530                                            (Other):42797
   company       days_in_waiting_list         customer_type
NULL   :112593   Min.   :  0.000      Contract       : 4076
40     :   927   1st Qu.:  0.000      Group          :  577
223    :   784   Median :  0.000      Transient      :89613
```

```
67      :   267   Mean   :  2.321      Transient-Party:25124
45      :   250   3rd Qu.:  0.000
153     :   215   Max.   :391.000
(Other):  4354
     adr          required_car_parking_spaces total_of_special_requests
Min.    :  -6.38   Min.   :0.00000            Min.   :0.0000
1st Qu.:  69.29   1st Qu.:0.00000            1st Qu.:0.0000
Median :  94.58   Median :0.00000            Median :0.0000
Mean   : 101.83   Mean   :0.06252            Mean   :0.5714
3rd Qu.: 126.00   3rd Qu.:0.00000            3rd Qu.:1.0000
Max.   :5400.00   Max.   :8.00000            Max.   :5.0000

reservation_status reservation_status_date
Canceled :43017    2015-10-21:  1461
Check-Out:75166    2015-07-06:   805
No-Show  : 1207    2016-11-25:   790
                   2015-01-01:   763
                   2016-01-18:   625
                   2015-07-02:   469
                   (Other)   :114477
```

The hotel data set is composed of 119,390 rows and 32 columns.

Tidying the Data

Before analysis, I conducted data tidying processes to ensure data accuracy and consistency. This involved addressing missing values, removing unnecessary columns like 'Company' due to high null values, and refining categorical variables such as meal options and room types.

```r
table(hoteldata$hotel)
```

```
City Hotel Resort Hotel
     79330        40060
```

```r
table(hoteldata$meal)
```

```
       BB        FB        HB        SC Undefined
    92310       798     14463     10650      1169
```

```r
table(hoteldata$arrival_date_year)
```

```

 2015  2016  2017 
21996 56707 40687 
```

Here there are four meal options: BB: Bed and Breakfast (Breakfast is included in the hotel's price). FB: Full Board (Breakfast, lunch and dinner are all included in the hotel's price). HB: Half Board (Price includes breakfast and dinner in the hotel's price). SC / Undefined: Self Catering meals.

```r
# Replacing the undefined values with "SC" and then displaying it's unique values
hoteldata$meal <-replace(hoteldata$meal,hoteldata$meal=='Undefined','SC')
hoteldata$meal <- factor(hoteldata$meal)
levels(hoteldata$meal)
```

```
[1] "BB" "FB" "HB" "SC"
```

Removing unwanted columns

Columns deemed irrelevant or containing excessive null values, such as 'Company' and 'arrival_date_week_number,' were removed to streamline the dataset and focus on essential variables for analysis.

```r
hoteldata = subset(hoteldata, select = -c(company, arrival_date_week_number))
```

Dealing with missing values

I handled missing values in the dataset, particularly in the 'agent' column, by removing rows with null values. Additionally, I replaced NaN values in the 'children' column with corresponding values from the 'babies' column to maintain data integrity.

```r
hoteldata <- hoteldata[!hoteldata$agent == "NULL", ]
glimpse(hoteldata)
```

```
Rows: 103,050
Columns: 30
$ hotel                          <fct> Resort Hotel, Resort Hotel, Resort Hote~
```

```
$ is_canceled                    <int> 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, ~
$ lead_time                      <int> 13, 14, 14, 9, 85, 75, 23, 35, 68, 18, ~
$ arrival_date_year              <int> 2015, 2015, 2015, 2015, 2015, 2015, 201~
$ arrival_date_month             <fct> July, July, July, July, July, July, Jul~
$ arrival_date_day_of_month      <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~
$ stays_in_weekend_nights        <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ stays_in_week_nights           <int> 1, 2, 2, 2, 3, 3, 4, 4, 4, 4, 4, 4, 4, ~
$ adults                         <int> 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ~
$ children                       <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, ~
$ babies                         <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ meal                           <fct> BB, BB, BB, FB, BB, HB, BB, HB, BB, HB,~
$ country                        <fct> GBR, GBR, GBR, PRT, PRT, PRT, PRT, PRT,~
$ market_segment                 <fct> Corporate, Online TA, Online TA, Direct~
$ distribution_channel           <fct> Corporate, TA/TO, TA/TO, Direct, TA/TO,~
$ is_repeated_guest              <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ previous_cancellations         <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ previous_bookings_not_canceled <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ reserved_room_type             <fct> A, A, A, C, A, D, E, D, D, G, E, D, E, ~
$ assigned_room_type             <fct> A, A, A, C, A, D, E, D, E, G, E, E, E, ~
$ booking_changes                <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, ~
$ deposit_type                   <fct> No Deposit, No Deposit, No Deposit, No ~
$ agent                          <fct> 304, 240, 240, 303, 240, 15, 240, 240, ~
$ days_in_waiting_list           <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ customer_type                  <fct> Transient, Transient, Transient, Transi~
$ adr                            <dbl> 75.00, 98.00, 98.00, 103.00, 82.00, 105~
$ required_car_parking_spaces    <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ total_of_special_requests      <int> 0, 1, 1, 1, 1, 0, 0, 0, 3, 1, 0, 3, 0, ~
$ reservation_status             <fct> Check-Out, Check-Out, Check-Out, Check-~
$ reservation_status_date        <fct> 2015-07-02, 2015-07-03, 2015-07-03, 201~
```

Checking if there are any missing values (NA/NaN) in the data set. Finding the number of missing values in every column.

```
colSums(is.na(hoteldata))
```

```
                  hotel                 is_canceled
                      0                           0
              lead_time           arrival_date_year
                      0                           0
     arrival_date_month   arrival_date_day_of_month
                      0                           0
stays_in_weekend_nights        stays_in_week_nights
```

```
                      0                                0
                 adults                         children
                      0                                2
                 babies                             meal
                      0                                0
                country                   market_segment
                      0                                0
   distribution_channel                is_repeated_guest
                      0                                0
 previous_cancellations previous_bookings_not_canceled
                      0                                0
     reserved_room_type               assigned_room_type
                      0                                0
        booking_changes                     deposit_type
                      0                                0
                  agent             days_in_waiting_list
                      0                                0
          customer_type                              adr
                      0                                0
required_car_parking_spaces    total_of_special_requests
                      0                                0
     reservation_status          reservation_status_date
                      0                                0
```

We can observe that only one column, the one with 'children' as the column name, seems to have values missing. Substituting the values in the children column for the ones in the babies column.

```
n <- length(hoteldata)
for (i in n) {
        if (is.na(hoteldata$children[i]))
                hoteldata$children[i] <- hoteldata$babies

}
```

```
# Checking for outliers
hoteldata%>%
  filter(adr>800)
```

```
# A tibble: 1 x 30
  hotel      is_canceled lead_time arrival_date_year arrival_date_month
```

```
  <fct>             <int>     <int>            <int> <fct>
1 City Hotel            1        35             2016 March
# i 25 more variables: arrival_date_day_of_month <int>,
#   stays_in_weekend_nights <int>, stays_in_week_nights <int>, adults <int>,
#   children <int>, babies <int>, meal <fct>, country <fct>,
#   market_segment <fct>, distribution_channel <fct>, is_repeated_guest <int>,
#   previous_cancellations <int>, previous_bookings_not_canceled <int>,
#   reserved_room_type <fct>, assigned_room_type <fct>, booking_changes <int>,
#   deposit_type <fct>, agent <fct>, days_in_waiting_list <int>, ...
```

Here it is visible that there in only one outlier where the average daily rate (adr) is greater than 800. Updating the outlier value by the mean of adr (average daily rate).

```r
hoteldata = hoteldata%>%
  mutate(adr = replace(adr, adr>1000, mean(adr)))
```

```r
hoteldata%>%group_by(arrival_date_month, arrival_date_year)%>%tally()
```

```
# A tibble: 26 x 3
# Groups:   arrival_date_month [12]
   arrival_date_month arrival_date_year     n
   <fct>                          <int> <int>
 1 April                           2016  4854
 2 April                           2017  4904
 3 August                          2015  3357
 4 August                          2016  4692
 5 August                          2017  4633
 6 December                        2015  2367
 7 December                        2016  3264
 8 February                        2016  3056
 9 February                        2017  3405
10 January                         2016  1784
# i 16 more rows
```

July and August are the only 2 months where they had bookings all the three years 2015,2016,2017. This could typically corelate with the weather and summer breaks for children.

Exploratory Data Analysis

I performed comprehensive exploratory data analysis (EDA) to uncover insights into hotel booking patterns, customer behavior, and market trends. This included visualizations depicting booking distributions by hotel type, booking status, market segments, and geographical origin of guests.

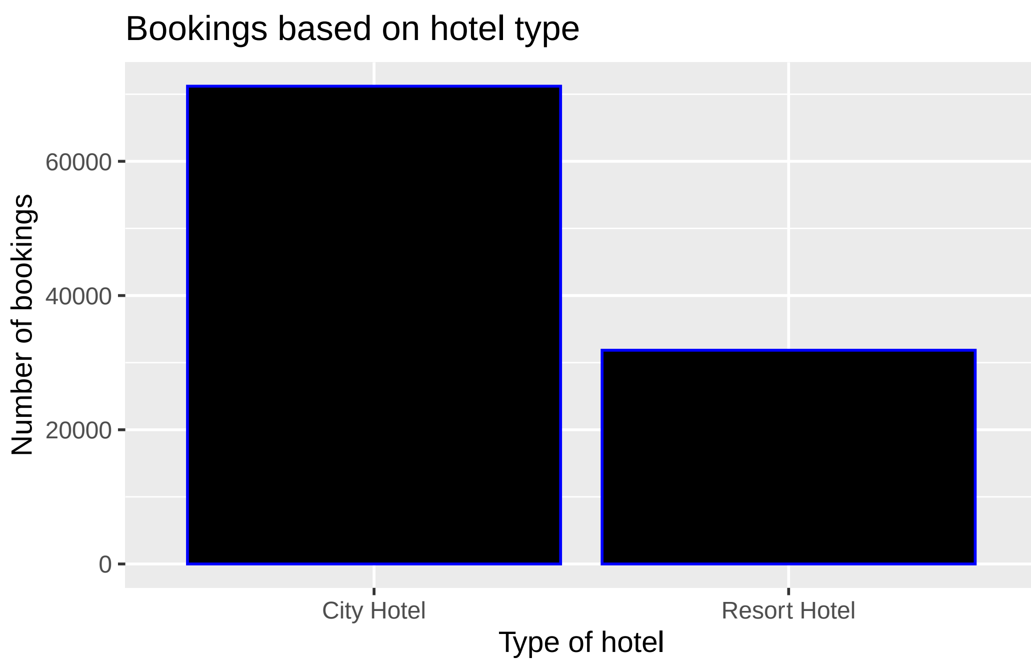
##Visualizing Booking Trends My approach to exploratory data analysis (EDA) was thorough and aimed at revealing deep insights into hotel booking patterns, customer behavior, and market trends. Through a series of insightful visualizations, I delved into various aspects such as booking distributions based on hotel types, booking statuses, market segments, and the geographical origins of guests. These visualizations not only provided a clear picture of the current booking landscape but also allowed for the identification of key trends and patterns that can inform strategic decision-making in the hospitality industry.

```
table(hoteldata$hotel)
```

```

  City Hotel Resort Hotel 
       71199        31851 
```

Visualizing this graphically gives us a better picture.

```
#The percentage of city hotels is more

ggplot(hoteldata, aes(x = hotel)) + geom_bar(mapping = aes(x = hotel), color = "blue", fil
```



We can see that City Hotel has been booked more times than the Resort Hotel between 2015 - 2017. This uneven distribution was the primary reason why I chose this data set.

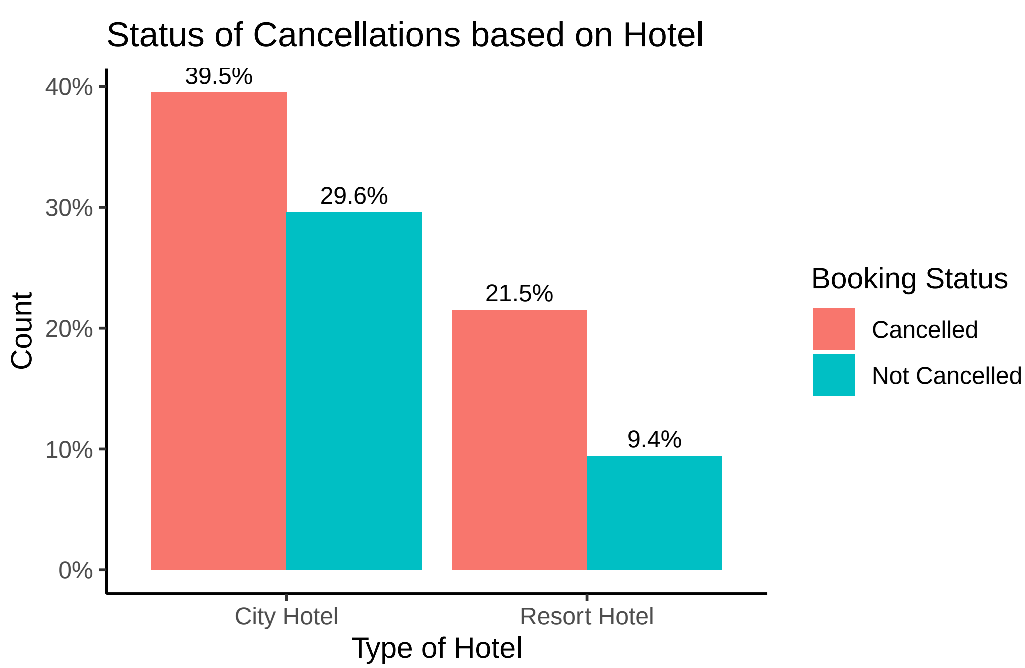
```
#Check the number of cancellations made by respective hotels.
table(hoteldata$is_canceled, hoteldata$hotel)
```

```
  City Hotel Resort Hotel
0      40706        22150
1      30493         9701
```

```
#Visualizing the number of cancellations based on type of hotel.
ggplot(data = hoteldata,
       aes(
         x = hotel,
         y = prop.table(stat(count)),
         fill = factor(is_canceled), width = 0.5,
         label = scales::percent(prop.table(stat(count)))
       )) +
  geom_bar(position = position_dodge()) +
  geom_text(
```

```
    stat = "count",
    position = position_dodge(.9),
    vjust = -0.5,
    size = 3
  ) + scale_y_continuous(labels = scales::percent) +
  labs(title = "Status of Cancellations based on Hotel",
       x = "Type of Hotel",
       y = "Count") +
  theme_classic() +
  scale_fill_discrete(
    name = "Booking Status",
    labels = c("Cancelled", "Not Cancelled")
  )
```

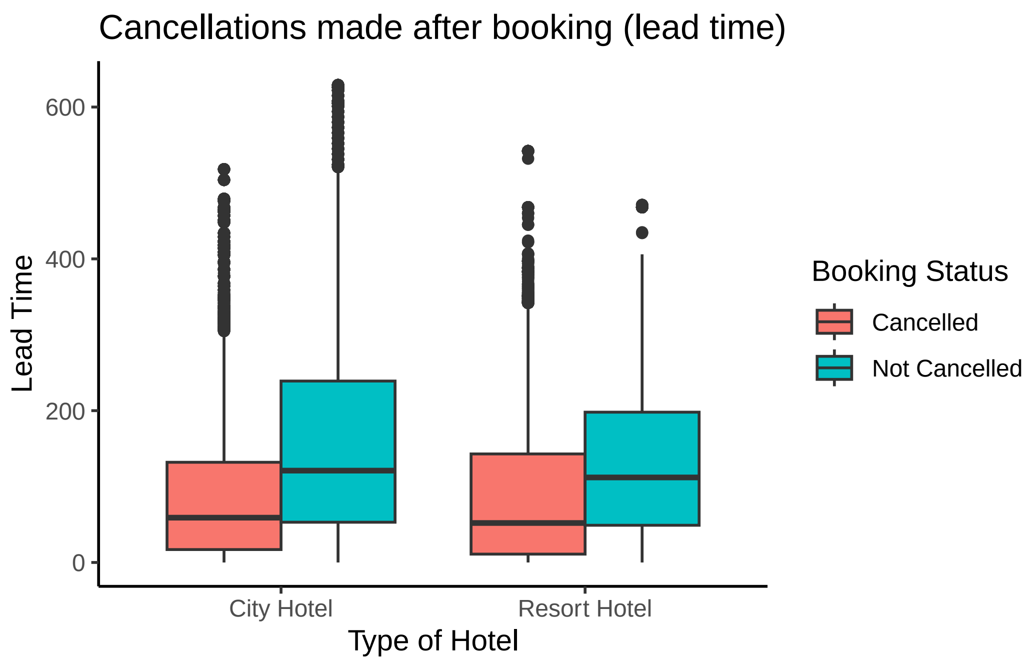
```
Warning: `stat(count)` was deprecated in ggplot2 3.4.0.
i Please use `after_stat(count)` instead.
```



It is evident that City Hotel has more bookings than the Resort Hotel. However, the number of 'Cancelled' bookings is more for both the hotels than the bookings 'Not Cancelled'. This could be related to something after the booking has been made.

Lead Time is the amount of time between the booking made and the actual date of check in.

```
ggplot(data = hoteldata, aes(x = hotel,y = lead_time,fill    =factor(is_canceled))) + geom
labs(title = "Cancellations made after booking (lead time)",
x = "Type of Hotel",y = "Lead Time") + scale_fill_discrete(name = "Booking Status",breaks
```



Lead time is the actual time between the day when booking made and actual day of checking in. From the plot we can see that cancellation of bookings normally occurs soon after booking. The cancellations seem to be less when enough time has passed after the booking has been made.

Checking the unique values in the arrival_date_year column.

```
unique(hoteldata$arrival_date_year)
```

```
[1] 2015 2016 2017
```

Checking which year had most bookings.

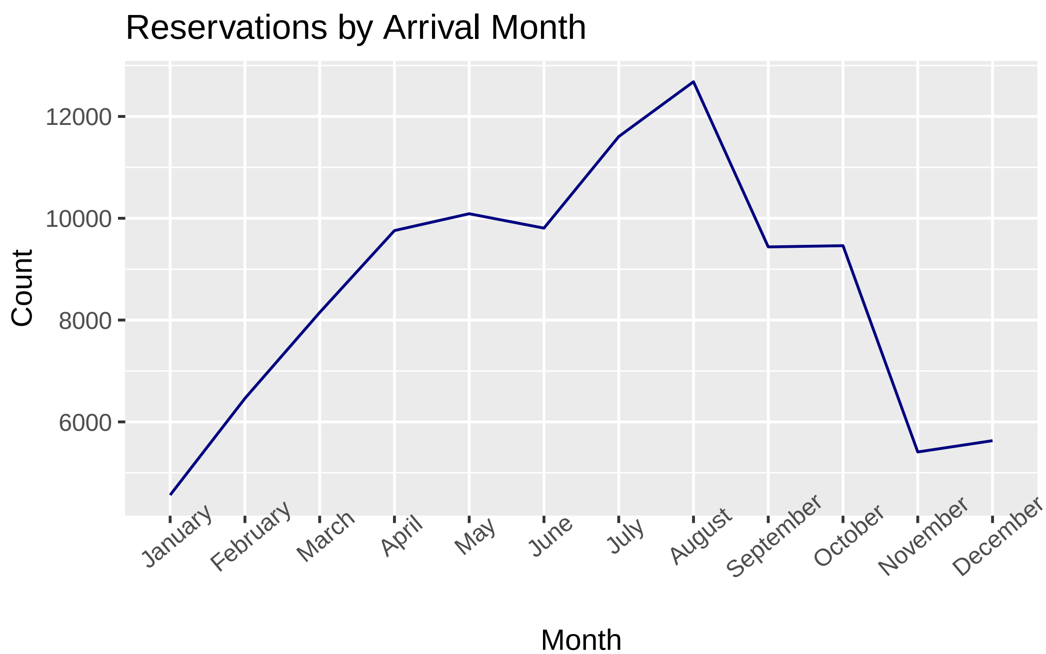
```
ggplot(hoteldata, aes(x = arrival_date_year)) + geom_bar(mapping = aes(x = arrival_date_ye
```

Comparison of year of Arrival date versus cancellation, year 2016 is the one with the most bookings as well as cancellations. More than double bookings were made in 2016, compared to the previous year. But the bookings decreased by almost 15% the next year. **Inference:** Bookings over the years are consistently greater for city hotels than resort hotels and do not increase proportionately over the years.

It will be interesting to see which month was most favoured by visitors to travel. We will select the arrival_date_month feature to answer this question and get its value count. We must first sort the data because it is not organized according to the order of months.

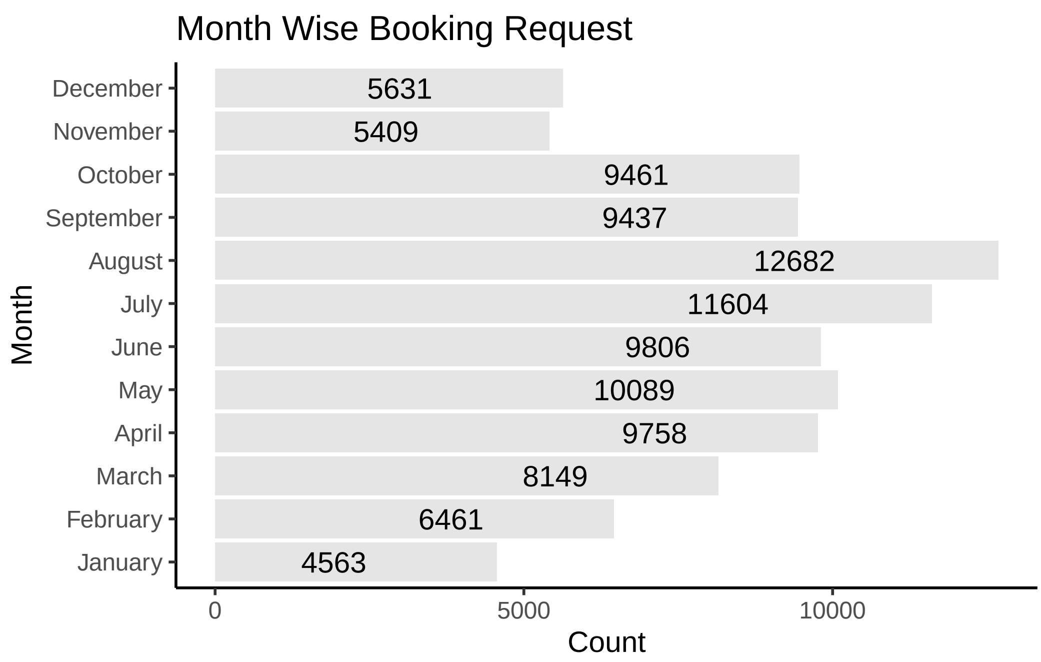
```
#Arranging months in correct order :

hoteldata$arrival_date_month <-
  factor(hoteldata$arrival_date_month, levels = month.name)

# Visualize Hotel bookings on Monthly basis

arrival_date_month <- hoteldata$arrival_date_month
reservemonth<-table(arrival_date_month)
 reservemonth<-data.frame(reservemonth)
 reservemonth$arrival_date_month<-factor(reservemonth$arrival_date_month, levels=month.nam
 ggplot(reservemonth, aes(x=arrival_date_month, y=Freq, group=1)) + geom_line(col="navy")
```

```r
  ggtitle("Reservations by Arrival Month") + ylab("Count") + xlab("Month")+
  theme(axis.text.x=element_text(angle=40))
```



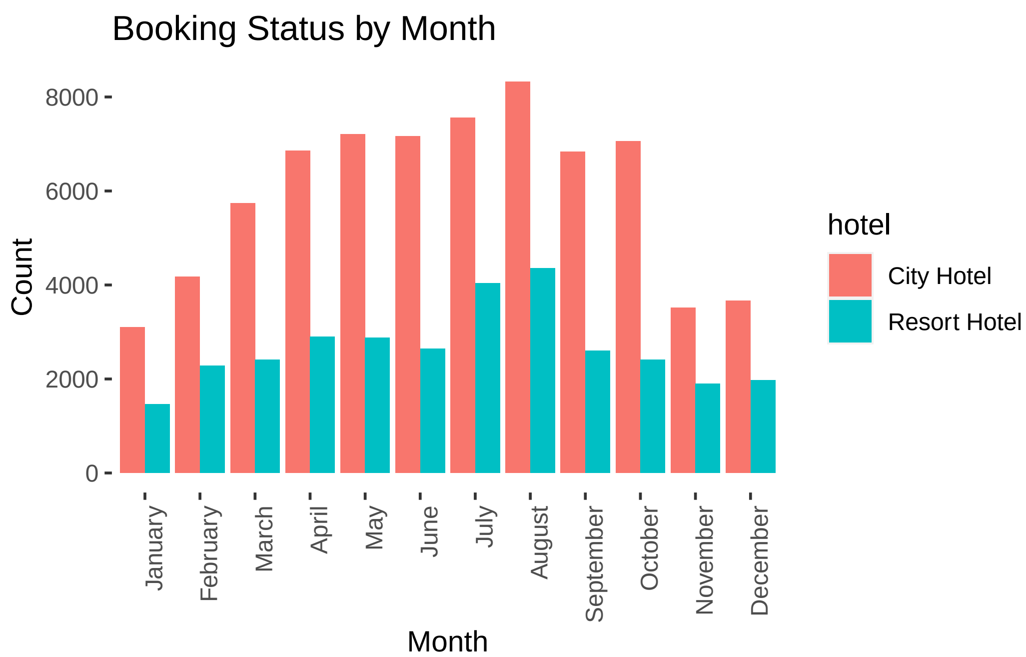

```r
ggplot(data = hoteldata, aes(x = arrival_date_month)) +
  geom_bar(fill = "black", alpha = 0.1) + geom_text(stat = "count", aes(label = ..count..)
  coord_flip() + labs(title = "Month Wise Booking Request",
                      x = "Month",
                      y = "Count") +
  theme_classic()
```

```
Warning: The dot-dot notation (`..count..`) was deprecated in ggplot2 3.4.0.
i Please use `after_stat(count)` instead.
```



We can observe that August and July are the most frequently booked months. Weather variations can be to blame for this. The winter season saw few reservations (November, December, and January). The month of August receives the most reservations because it is when most kids take their summer vacations. The month with the slightest reservations is January, which may be related to the climate.

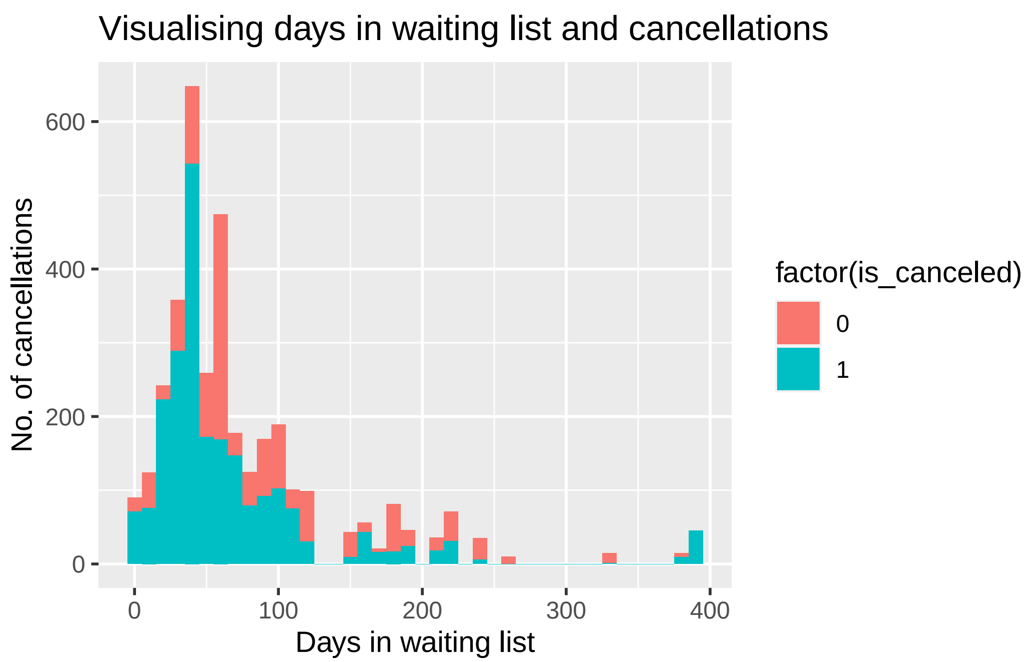
```r
arrival_date_month <- hoteldata$arrival_date_month
ggplot(hoteldata, aes(x=arrival_date_month, fill = hotel)) +
  geom_bar(position = position_dodge(), stat = "count") +
  labs(title = "Booking Status by Month",
       x = "Month",
       y = "Count") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        panel.background = element_blank())
```



Seasonally, the combined revenue for the two hotels rose from year to year. This is particularly crucial for the resort hotel because the majority of its annual revenue is generated during the summer. The city hotel's seasonal revenue is relatively stable during the fall, spring, and summer seasons but decreases during the winter.

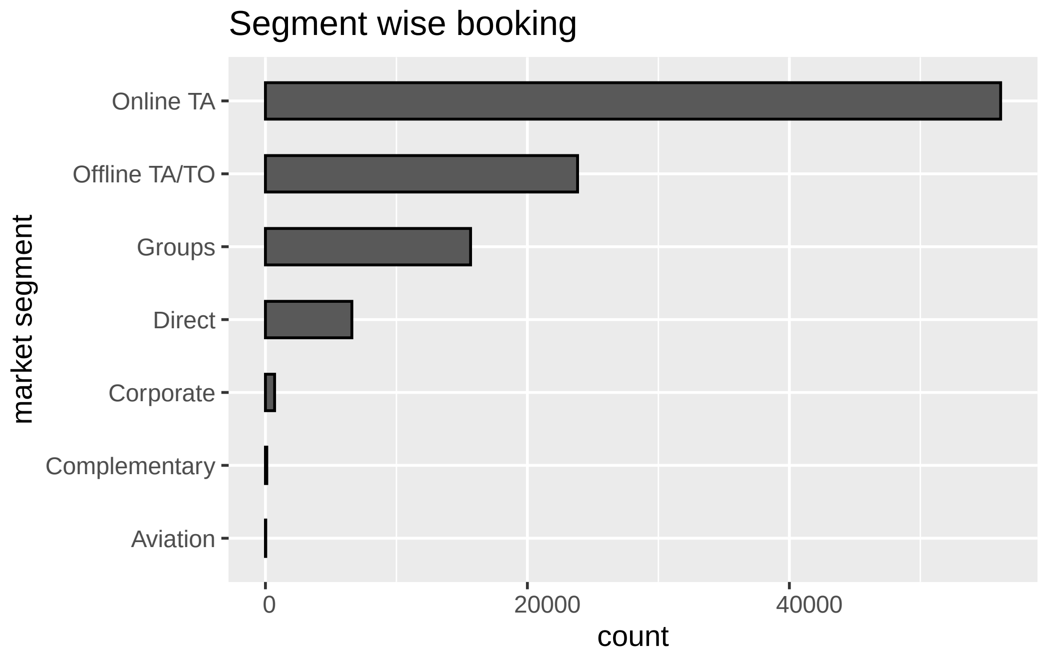
Shows when there are lesser days on the waiting list, there is a lesser number of cancellations.

```
#Histogram illustrating Days in waiting list and cancellations
hoteldata%>%
  filter(days_in_waiting_list>1)%>%
  ggplot(aes(x=days_in_waiting_list,fill= factor(is_canceled)))+
  geom_histogram(binwidth = 10) + labs(title = "Visualising days in waiting list and cance
```



Inference: From this we can infer that when the number of days in the waiting list is low there seems to be lower cancellations. This could also be related to cancellation when they were informed they would not get the requested room.

```
#Checking the purpose of the reservation and visualizing it.
ggplot(hoteldata, aes(y= market_segment)) + geom_bar(mapping = aes(y= market_segment), col
```



Indirect bookings through online and offline travel agents are higher than direct bookings, and the same is true with group bookings, which are also high. For most countries and continents, online travel companies were the most common way to make reservations. Relying on these conclusions, the hotel advertising department might direct most of its marketing funds to these online travel agencies to draw current and potential visitors to their hotels.

```
#Checking the assigned room types:

hoteldata%>%
  ggplot(aes(x = assigned_room_type, fill = factor(is_canceled))) +
  geom_bar() + labs(title = "Bookings based on assigned room type", x= "Assigned room type
```

Inference: We can observe that room type 'A' was booked the most by customers. However, the number of cancellations of room type 'A' also is the highest. This could be due to the non-availability of the room, or the customer could have been reassigned to another room, which could be the reason for such a high number of cancellations.

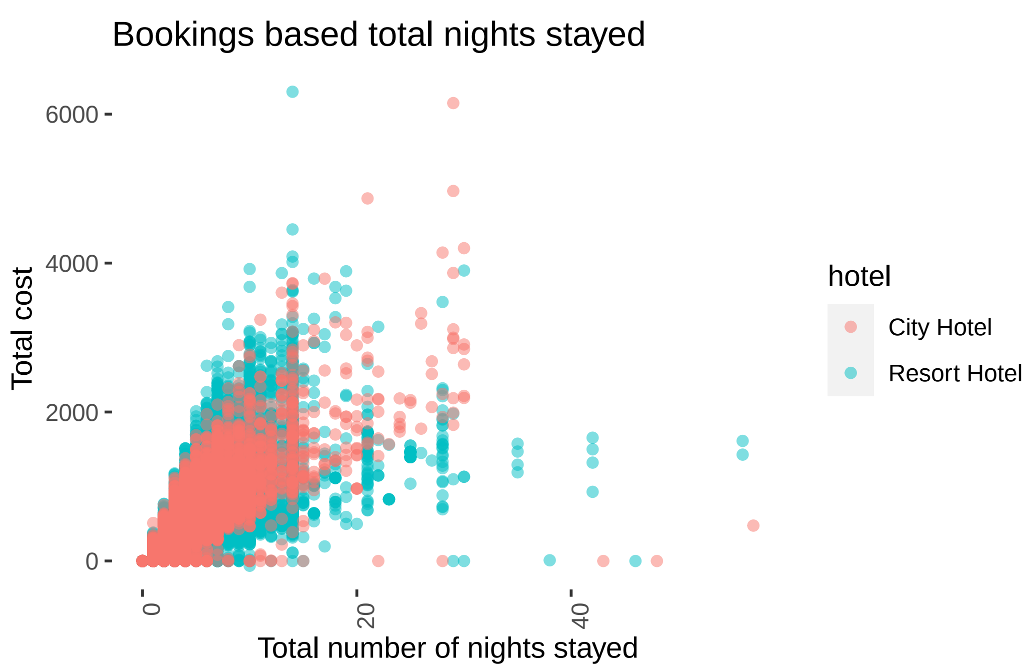
Visualizing the total number of nights stayed at the City Hotel and the Resort Hotel. We calculate total number of nights stayed by adding values of two columns stays_in_weekend_nights and stays_in_week_nights.

```
totalnights <- hoteldata$stays_in_weekend_nights + hoteldata$stays_in_week_nights

totalcost <- totalnights*hoteldata$adr

hoteldata%>%mutate(totalnights, totalcost)
```

```
# A tibble: 103,050 x 32
   hotel        is_canceled lead_time arrival_date_year arrival_date_month
   <fct>              <int>     <int>             <int> <fct>
 1 Resort Hotel           0        13              2015 July
 2 Resort Hotel           0        14              2015 July
 3 Resort Hotel           0        14              2015 July
 4 Resort Hotel           0         9              2015 July
```

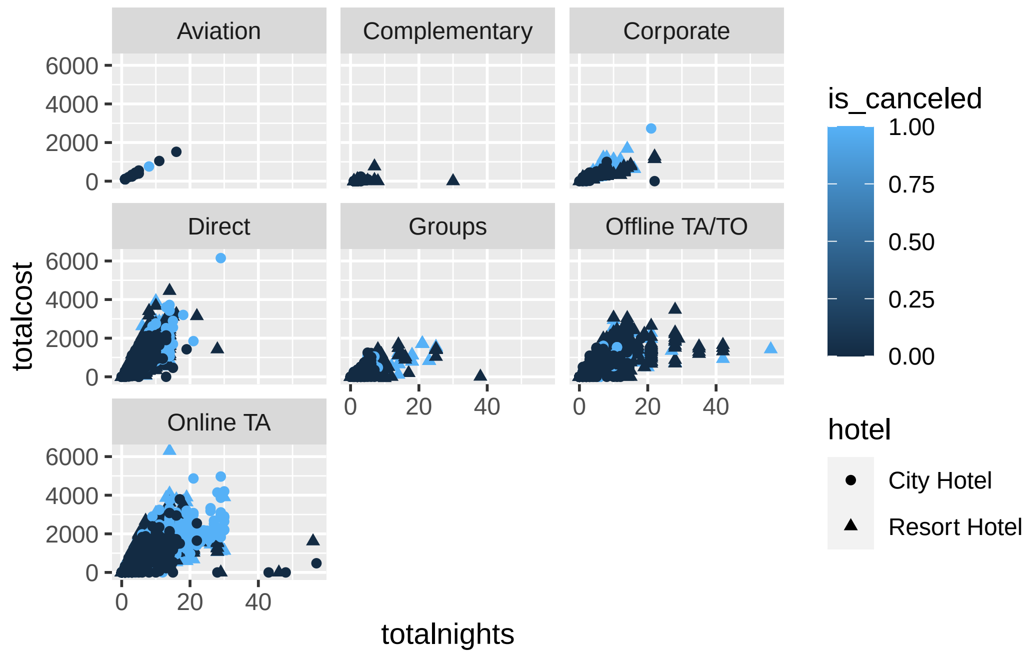
```
 5 Resort Hotel            1        85                2015 July
 6 Resort Hotel            1        75                2015 July
 7 Resort Hotel            1        23                2015 July
 8 Resort Hotel            0        35                2015 July
 9 Resort Hotel            0        68                2015 July
10 Resort Hotel            0        18                2015 July
# i 103,040 more rows
# i 27 more variables: arrival_date_day_of_month <int>,
#   stays_in_weekend_nights <int>, stays_in_week_nights <int>, adults <int>,
#   children <int>, babies <int>, meal <fct>, country <fct>,
#   market_segment <fct>, distribution_channel <fct>, is_repeated_guest <int>,
#   previous_cancellations <int>, previous_bookings_not_canceled <int>,
#   reserved_room_type <fct>, assigned_room_type <fct>, ...
```

```
ggplot(hoteldata, aes(x= totalnights, y= totalcost, color = hotel )) + geom_point(alpha=0.
        panel.background = element_blank())
```



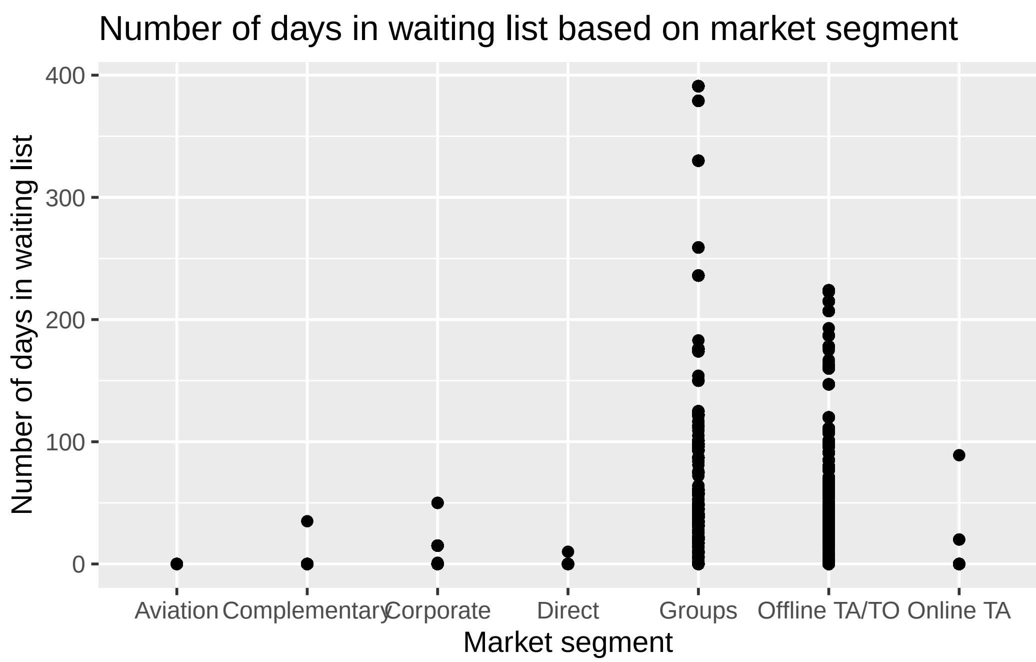
Inference: From this we can see majority of the customers stayed for a period less than 2 weeks and most people stayed at the city hotel.

```
#Exploring the data across different market segments
ggplot(hoteldata, aes(x=totalnights,y=totalcost,shape=hotel,color=is_canceled))+
  geom_point()+
  facet_wrap(~market_segment)
```



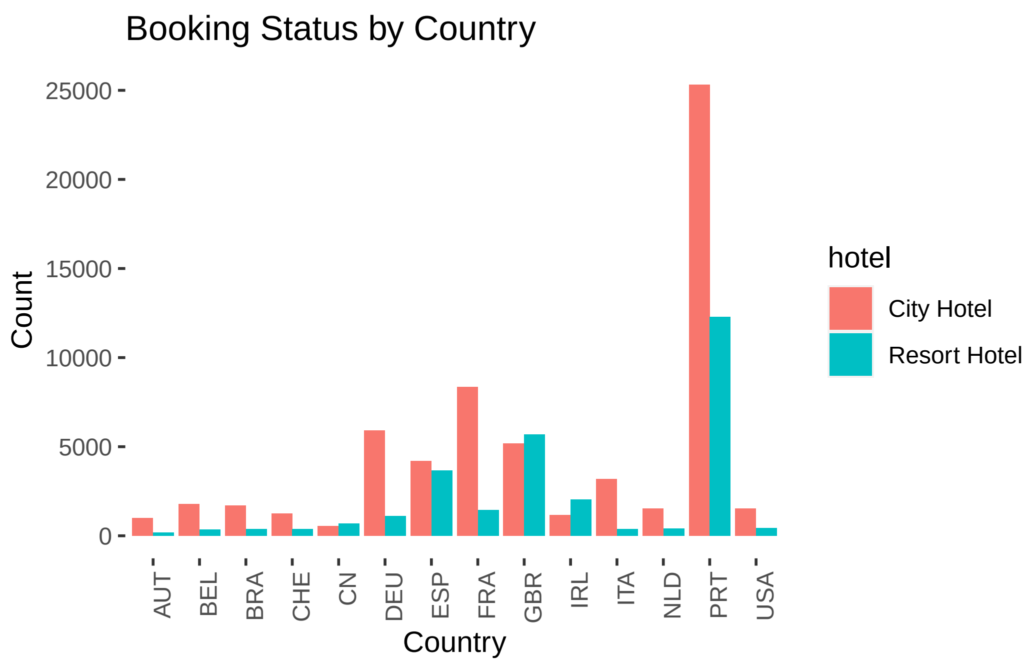
Here we can see nobody from Aviation segment stayed at the Resort Hotel. Majority of the customers that booked through Offline TA/TO and Online TA have more cancellations than other market segments. Groups segment has cancellation rate around 50%.

```
#Number of days in waiting list based on market segment
ggplot(hoteldata, aes(x = market_segment, y = days_in_waiting_list)) +
   geom_point()+
   ylab('Number of days in waiting list')+
  xlab('Market segment')+
  ggtitle('Number of days in waiting list based on market segment')
```



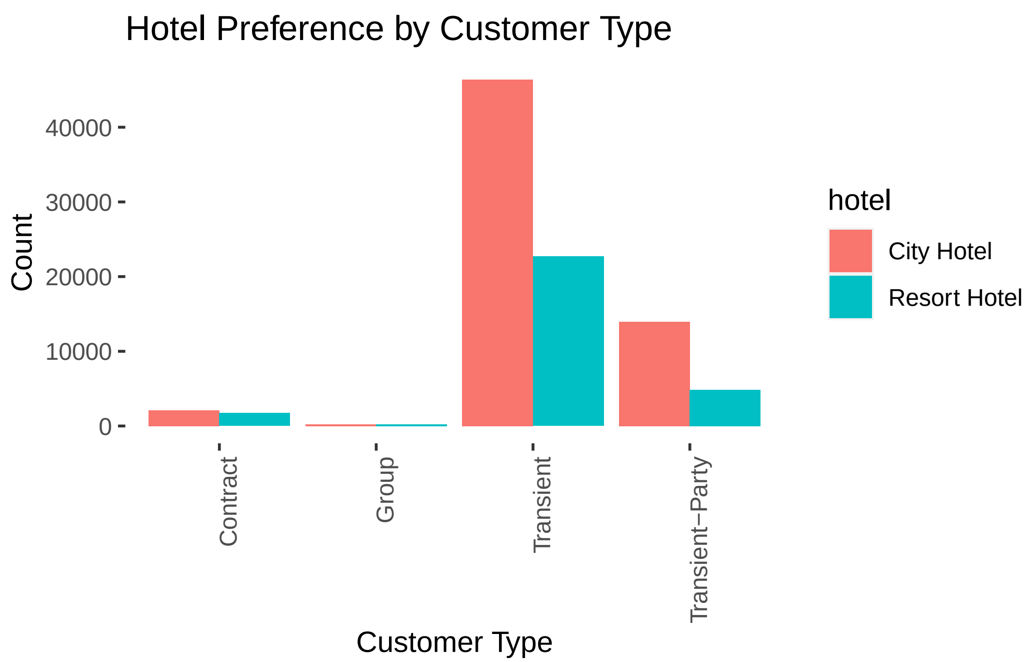
The shortest period on the waiting list is in the aviation sector. The explanation may be because airlines have to arrange stay and meals for their employees or passengers, and therefore, they do not want to book hotels that would put them on a waiting list.

```
#Visulizing bookings based on country:
hoteldatasample <- hoteldata[hoteldata$reservation_status == "Check-Out",]

hoteldatasubset <- hoteldata%>%group_by(country)%>%filter(n() >1000)

ggplot(hoteldatasubset, aes(country, fill = hotel)) +
  geom_bar(position = position_dodge(), stat = "count") +
  labs(title = "Booking Status by Country",
       x = "Country",
       y = "Count") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        panel.background = element_blank())
```



Portugal, UK and France, Spain and Germany are the top countries from most guests come, more than 80% come from these 5 countries. The fact that these hotels are in Portugal may help to explain why most reservations are from European nations, with Portugal accounting for the most significant percentage.

```
#Visualizing bookings based on customer type:
ggplot(hoteldatasubset, aes(customer_type, fill = hotel)) +
  geom_bar(position = position_dodge(), stat = "count") +
  labs(title = "Hotel Preference by Customer Type",
       x = "Customer Type",
       y = "Count") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        panel.background = element_blank())
```



One of the leading market segments, transient guests, are people or groups who book fewer than ten rooms per night. Typically, they are drop-in visitors, last-minute travelers, or people who need to reserve a room at a hotel property for a brief period.

Conclusion

This analysis delved into various aspects of the hotel booking dataset to uncover valuable insights. My exploration aimed to understand the origins of the majority of customers, the prevalent hotel types, the peak booking year, the market segment with the shortest waiting list days, and the busiest months for both city hotels and resorts. One intriguing discovery was the consistent demand for resort hotels throughout the year compared to the fluctuating trend observed in city hotels, contrary to initial expectations.

While this analysis provided valuable insights, there are notable limitations in the dataset. One limitation is the absence of information regarding potential accommodation upgrades or amenities associated with encoded room types. This missing data hinders a comprehensive understanding of customer preferences and their impact on booking behavior. Additionally, the inability to discern specific room features limits the depth of analysis regarding factors influencing guest satisfaction and potential booking cancellations.

Moving forward, refining these insights by incorporating data on accommodation upgrades, amenities, and guest preferences could enhance the predictive accuracy of models and provide more nuanced recommendations for hotel management. Understanding the factors influencing guest satisfaction and booking decisions is crucial in optimizing hotel operations and delivering exceptional guest experiences.

Overall, this analysis underscores the complexity of the hotel booking industry and the importance of leveraging comprehensive data to drive informed decision-making and enhance customer experiences.

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