IST 687

Data Science Project Report

Hotel Insights, Findings & Recommendations

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DESCRIPTION

- The Hotel Industry, in general, has always been volatile when it comes to reservation and cancellation of rooms. Some customers have reserved hotel rooms months, sometimes even a year before arrival. However, many of these customers potentially cancel bookings due to unforeseen reasons and other factors.
- Several attributes cause this to happen. After analysis, we found several factors that when targeted can significantly reduce cancellations. Thus, as data scientists, on behalf of the hotel industry, we aim to understand the historical data and analyze hotel booking trends. These factors can be used to report the trends and predict future bookings.
- With the various insights and analyses obtained, we aim to generate insights that can help drive business decisions on how to reduce cancellation bookings and essentially improve profits in the hotel business.

TECHNICAL DETAILS

- There are 20 features and 40,060 observations available in the dataset.
- The dataset is not overwritten, and columns are not renamed for ease of understanding and coding.
- Upon checking the NULL and missing values, we found out that there are no missing values; however, the NULL values were present in the country column as string values, which we converted into actual null type variables.
- We also identified the categorical values (by converting them into factor variables) and numerical data. We created separate datasets, one to perform association rules mining and another to perform ML classification.

GOALS/ OBJECTIVES

The overall goal of the project is to provide actionable recommendations, based on the insights.

OBJECTIVE

1. To perform analysis on columns such as cancellation, customer type, market segment, among other attributes.
2. Implement various Machine Learning algorithms to predict cancellation.
3. To analyze why people cancel hotel reservations and predict who will be canceling
4. To analyze:
   a) The number of cancellations:
      i) Number of bookings on a weekday vs weekends
      ii) Most preferred meal types
      iii) Country-wise bookings
      iv) New customers acquired
      v) Type of rooms preferred by customers
      vi) Booking types

vii) Assigned Rooms
viii) The number of guests in each booking

b) Analyze patterns associated with each segment, such as:
   i) Day of week
   ii) Type of customers
   iii) Type of rooms
   iv) Market Segment

c) Predict future cancellations based on machine learning algorithms such as the Apriori algorithm, linear modeling, support vector machines, and classification and regression trees.
d) Using these results, we can make critical business decisions regarding the customer experience they desire to deliver.

LIBRARIES USED

We used the following libraries for the project
Tidyverse, caret, rworldmap, skimr, ggplot2, arules, readr, rpart, e1071, rpart.plot

ANALYSIS:

DATASET

Upon exploring the structure of the data frame, we notice some variables are characters. Then, we replace those variables as factors to better analyze them.

```
-- Data Summary ------------------------
                           Values
Name                       data1
Number of rows             28519
Number of columns          19
_______________________
Column type frequency:
  character                1
  factor                   7
  numeric                  11
________________________
Group variables            None

-- Variable type: character ---------------------------------------------------------------------------
-
# A tibble: 1 x 8
  skim_variable n_missing complete_rate   min   max empty n_unique whitespace
* <chr>             <int>         <dbl> <int> <int> <int>    <int>      <int>
1 Children              0             1     4     8     0        2          0

-- Variable type: factor ------------------------------------------------------------------------------
-
# A tibble: 7 x 6
  skim_variable    n_missing complete_rate ordered n_unique top_counts
* <chr>                <int>         <dbl> <lgl>      <int> <chr>
1 Meal                     0             1 FALSE          5 BB: 21775, HB: 5473, Und: 879, FB: 311
2 Country                  0             1 FALSE        118 PRT: 10192, GBR: 5923, ESP: 3106, IRL: 1734
3 MarketSegment            0             1 FALSE          6 Onl: 11407, Off: 6308, Dir: 5492, Gro: 3358
4 IsRepeatedGuest          0             1 FALSE          2 0: 26856, 1: 1663
5 AssignedRoomType         0             1 FALSE          9 A: 10854, D: 8099, E: 4148, C: 1764
6 DepositType              0             1 FALSE          3 No : 28330, Ref: 120, Non: 69
7 CustomerType             0             1 FALSE          4 Tra: 20408, Tra: 6243, Con: 1619, Gro: 249

-- Variable type: numeric -----------------------------------------------------------------------------
-
# A tibble: 11 x 11
   skim_variable               n_missing complete_rate    mean    sd    p0   p25   p50   p75  p100 hist
 * <chr>                           <int>         <dbl>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <chr>
 1 LeadTime                            0             1 79.7    93.3      0     6    39   132   737 ▇▂▁▁▁
 2 StaysInWeekendNights                0             1  1.14    1.14     0     0     1     2    16 ▇▁▁▁▁
 3 StaysInWeekNights                   0             1  3.02    2.43     0     1     3     5    40 ▇▁▁▁▁
 4 Adults                              0             1  1.84    0.462    0     2     2     2     4 ▁▁▇▁▁
 5 PreviousCancellations               0             1  0.00680 0.104    0     0     0     0     5 ▇▁▁▁▁
 6 PreviousBookingsNotCanceled         0             1  0.173   1.07     0     0     0     0    30 ▇▁▁▁▁
 7 BookingChanges                      0             1  0.341   0.777    0     0     0     0    17 ▇▁▁▁▁
 8 RequiredCarParkingSpaces            0             1  0.190   0.400    0     0     0     0     8 ▇▁▁▁▁
 9 TotalOfSpecialRequests              0             1  0.673   0.832    0     0     0     1     5 ▇▁▁▁▁
10 totalfam                            0             1  1.96    0.662    0     2     2     2     5 ▁▇▁▁▁
11 duration                            0             1  4.17    3.34     0     2     3     7    56 ▇▁▁▁▁
```

Fig. 1: Data summary

Missing data:

The below plot displays the missing values to avoid any misinterpretations of data. We did not find missing values, however, NULL values were found and acted upon.

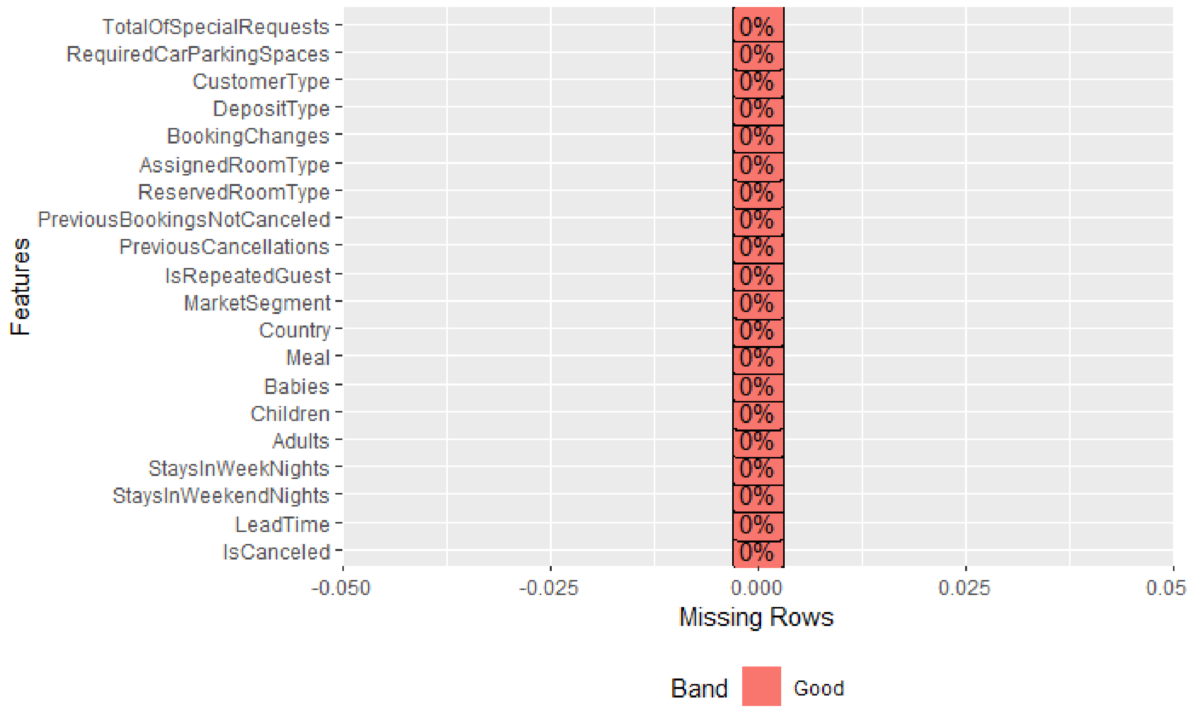
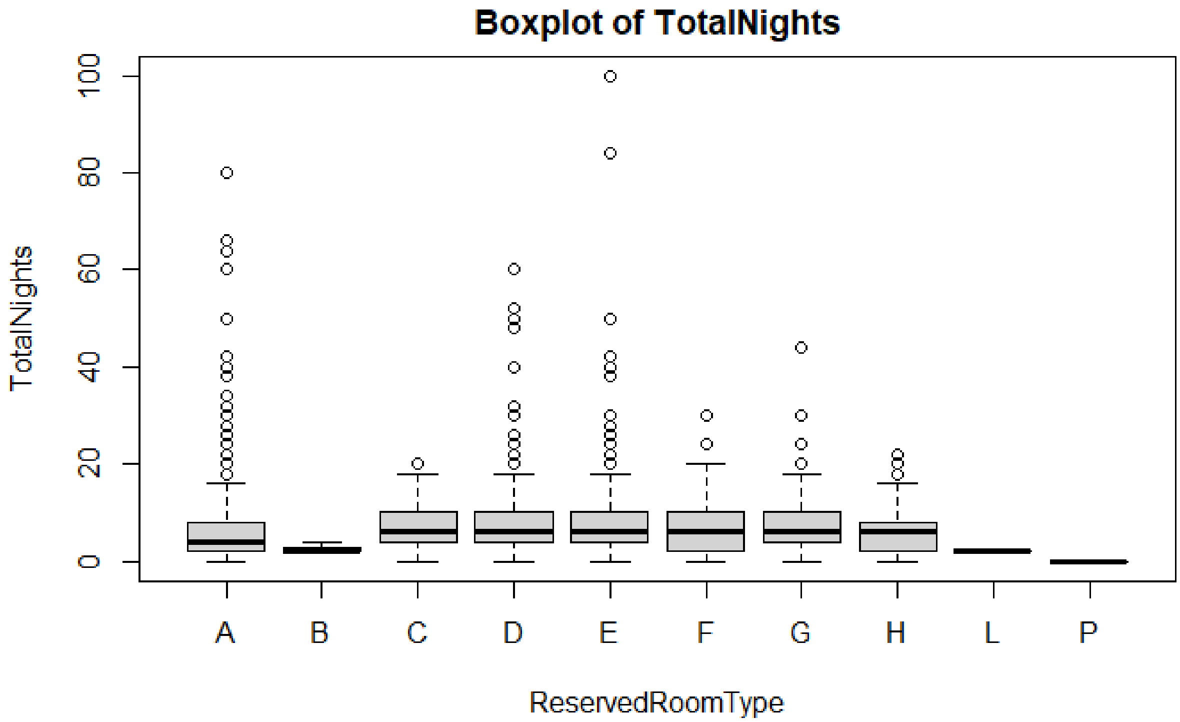


Fig. 2: Missing data percentage

Let's talk about the cancellations. It is very important to understand why the bookings are canceled in the first place to gain important information on areas of improvement. How many bookings were canceled? What are the factors that affect cancellations?

Fig 3: Box plot for total nights based on room type



Which country has the most cancellations?

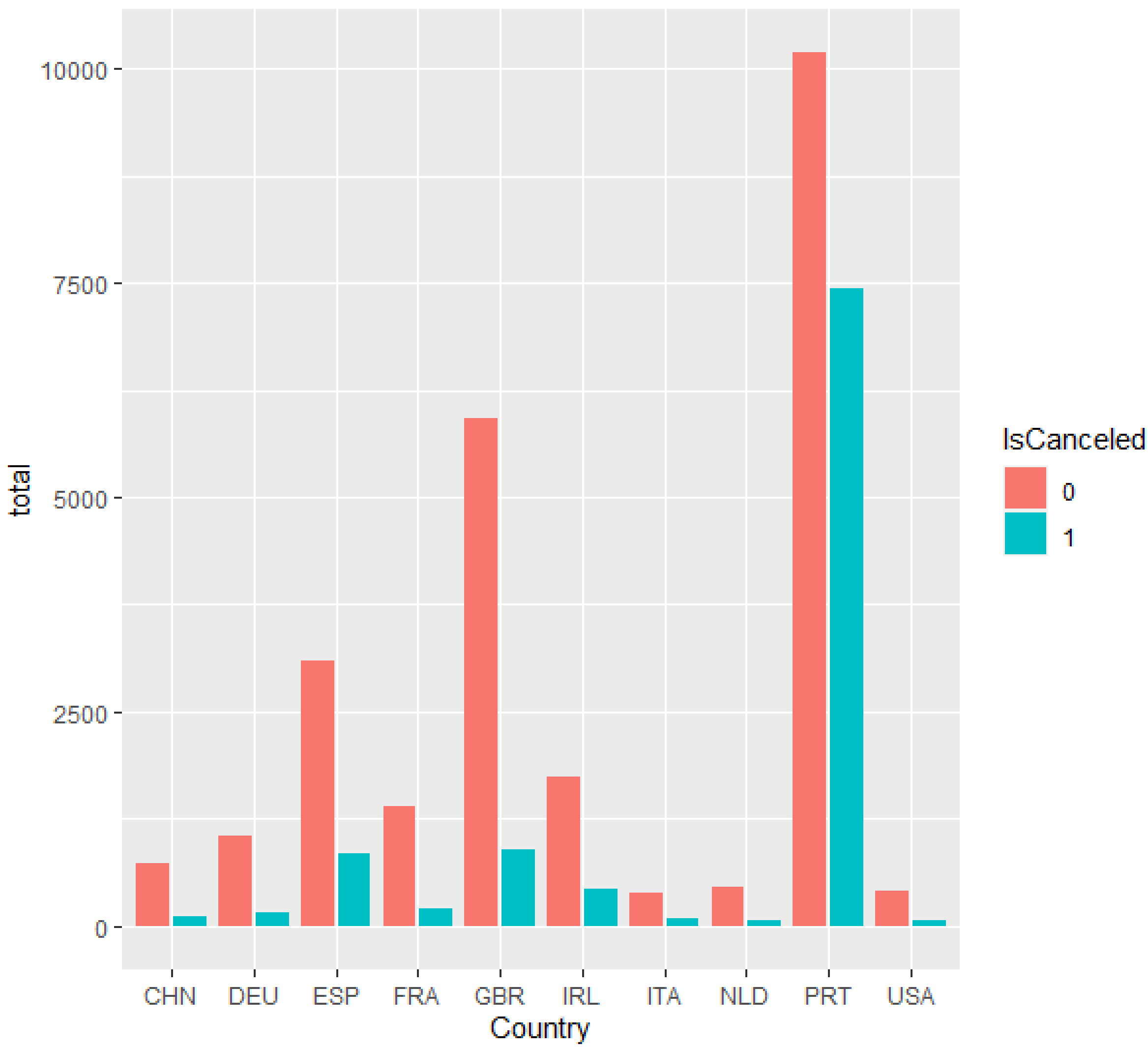


Fig. 4: Cancellations by top 10 countries

Based on the bar graph above, we can see that Portugal has the most bookings as well as cancellations. Great Britain (GBR) has a lot of successful bookings and very few cancellations comparatively.

Cancellation based on booking type:

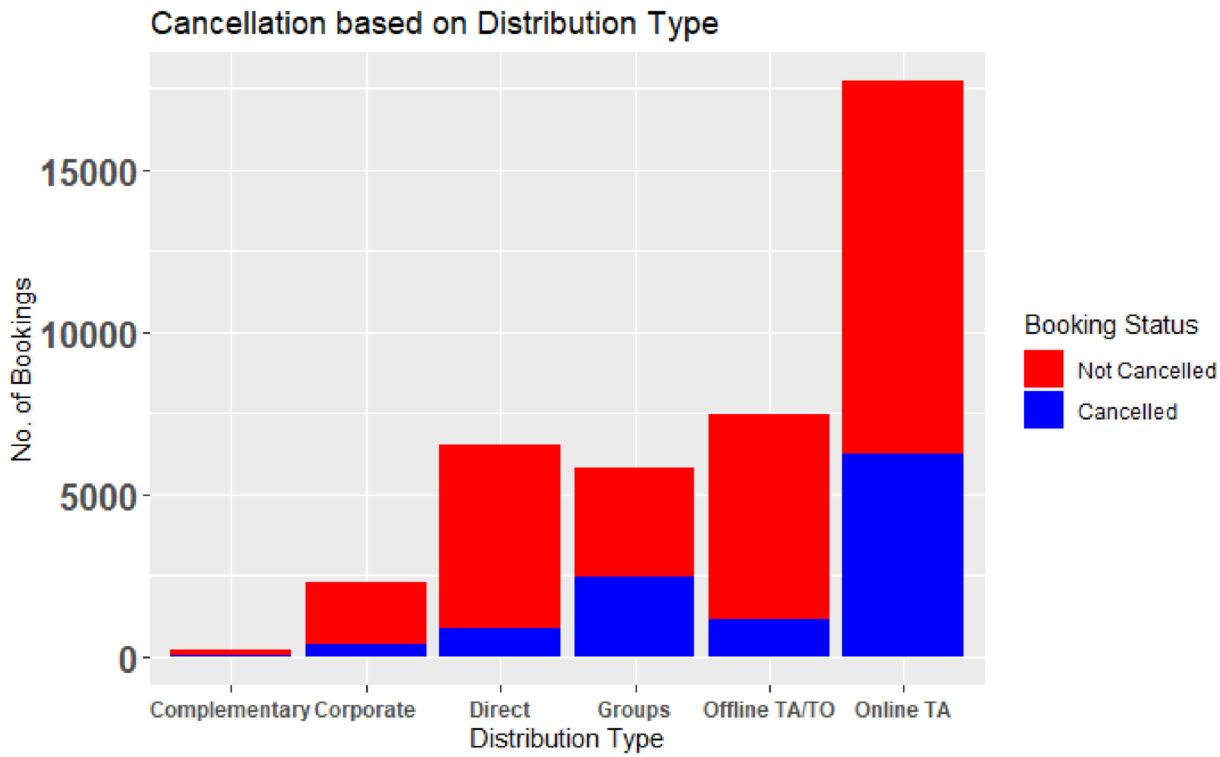


Fig. 5 Cancellation based on the distribution type

From the diagram, we can infer that the highest bookings and cancellations, both, majorly come through online travel agents.

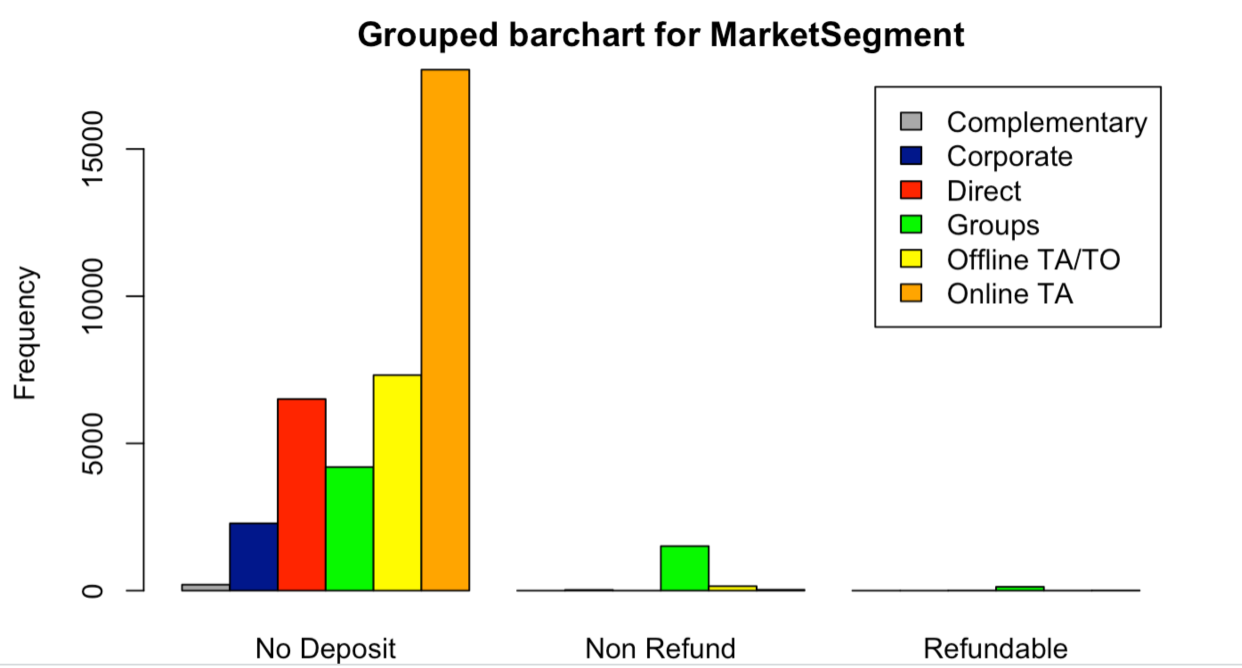


Fig 6 Market segmentation based on deposit type

The bookings done with no deposits have the majority of cancellations. Amongst them, the highest spike is through online booking.

1) How many times did each customer type perform booking changes?

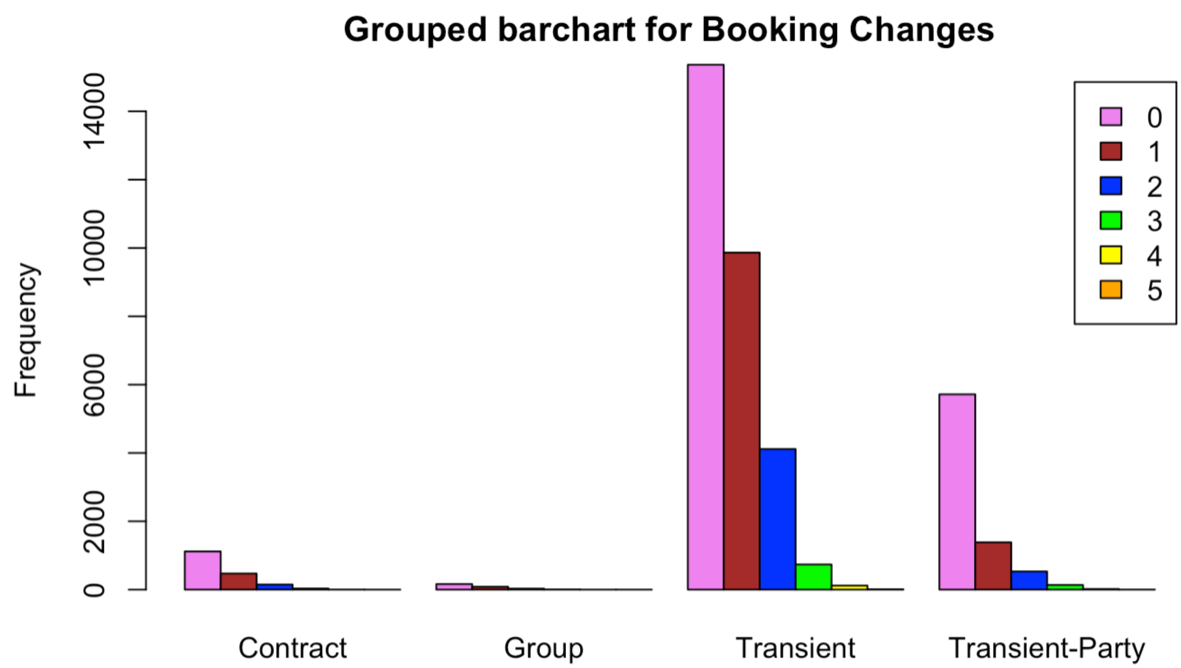


Fig 7 Booking changes based on customer type

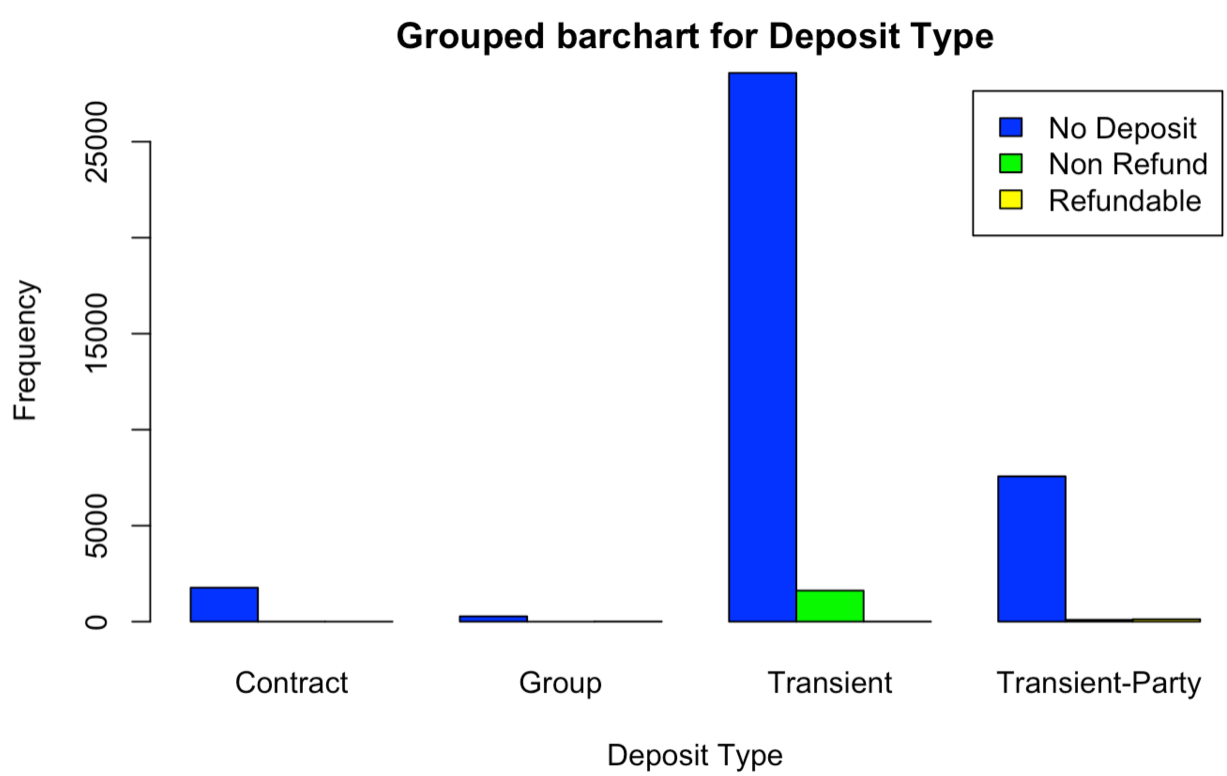


Fig 8 Deposit type based on customer type

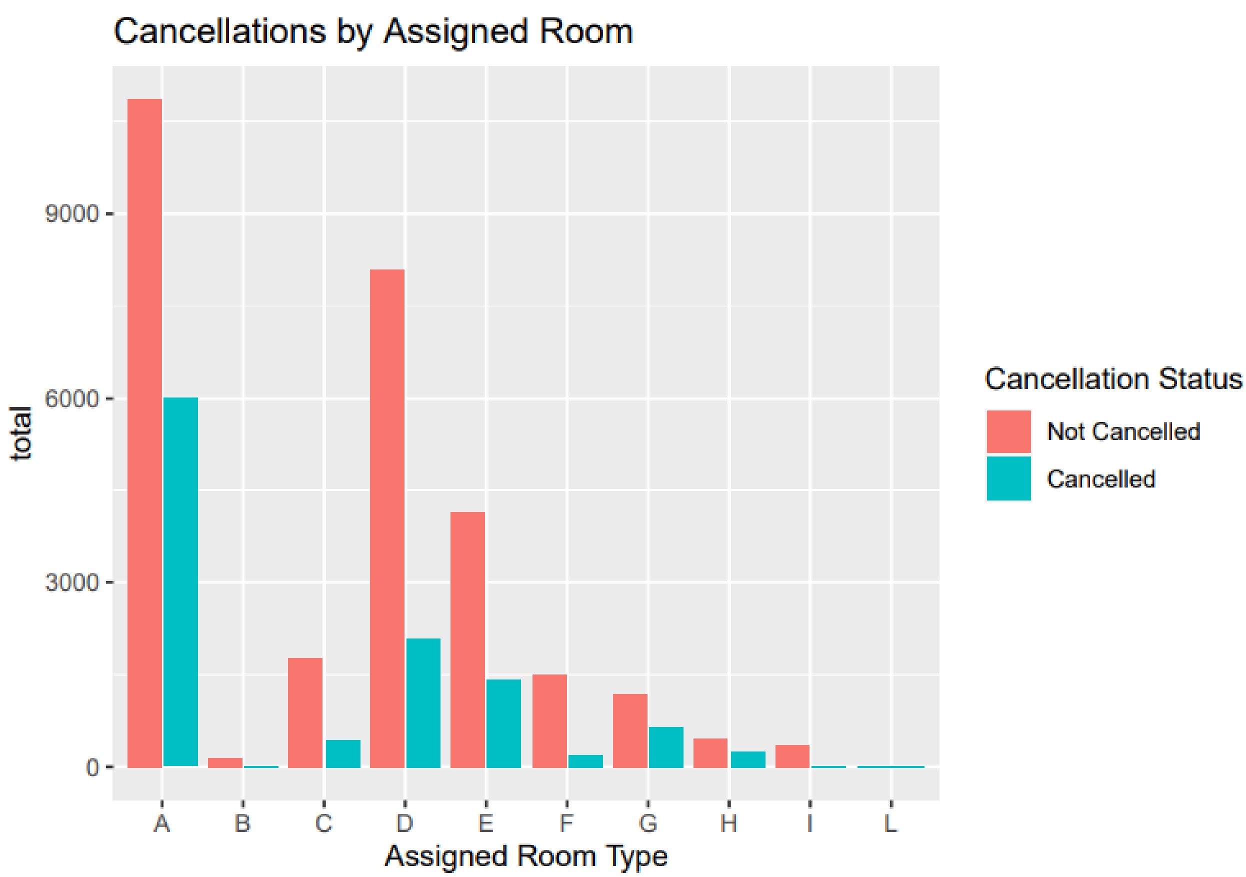


Fig 9 Cancellation based on room type

From this plot, we can see that more people have decided to reserve room A, but it's also, those people who have canceled more times

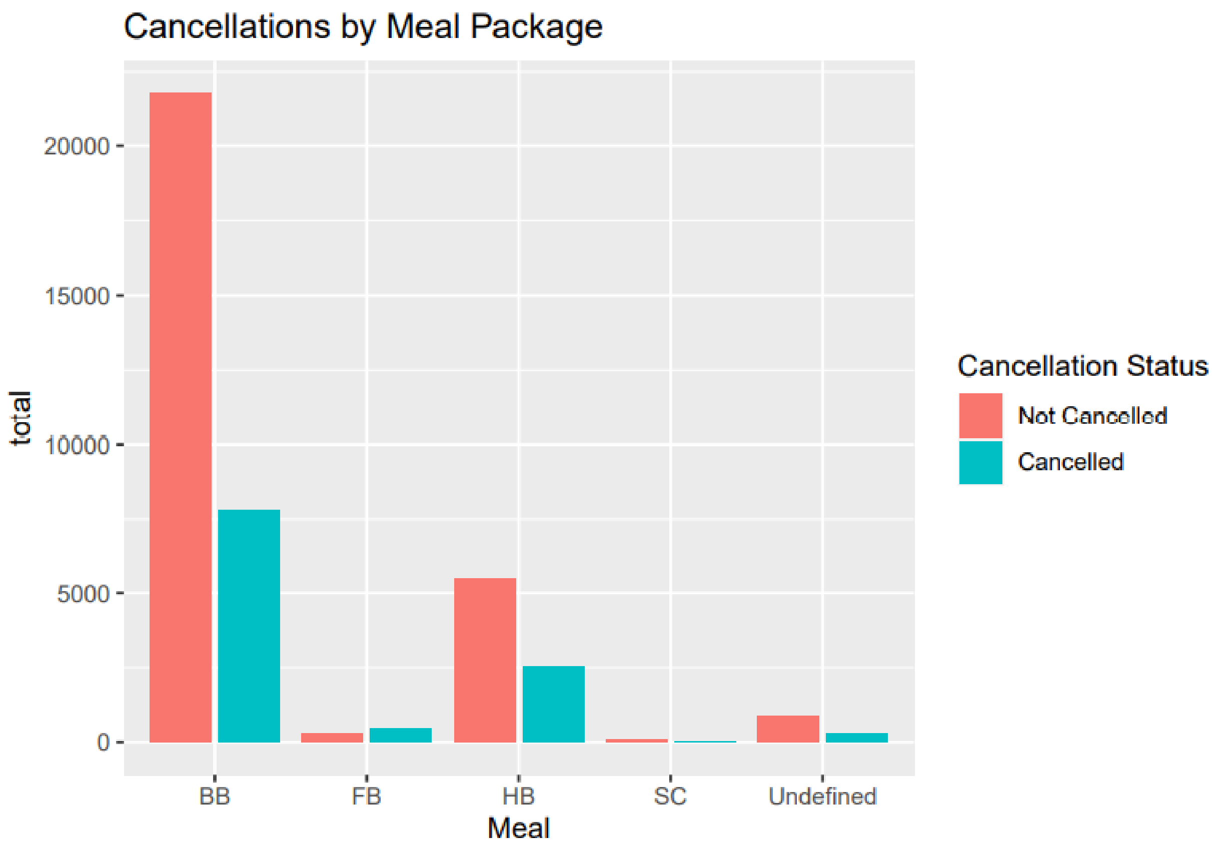


Fig 10 Cancellations by meal plans

Most people prefer the BB plan. The cancellation for HB and FB are significant if not more than their non-cancellations.

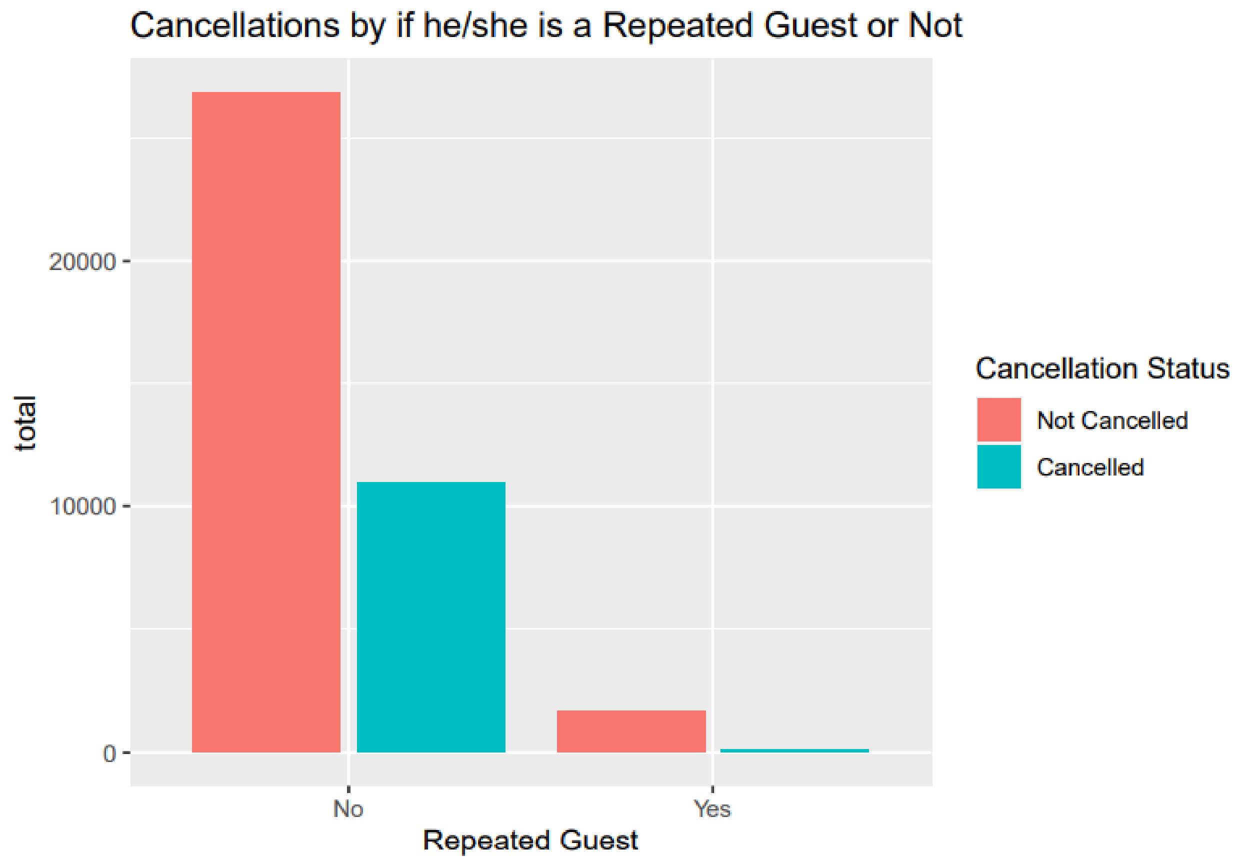
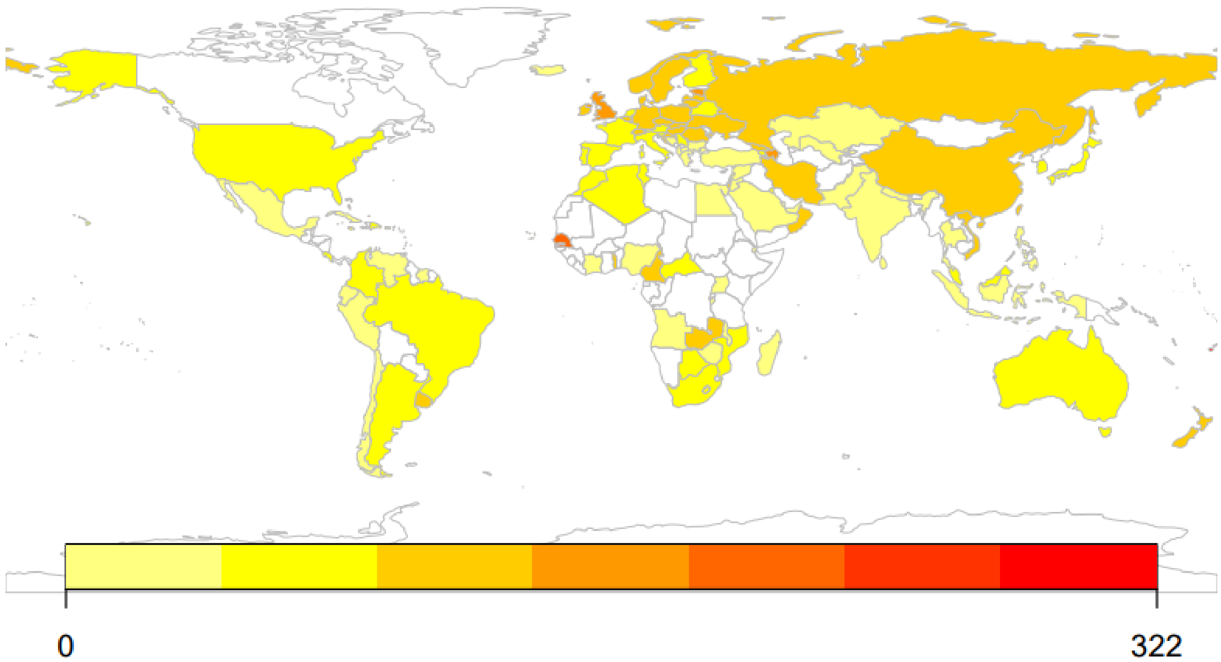


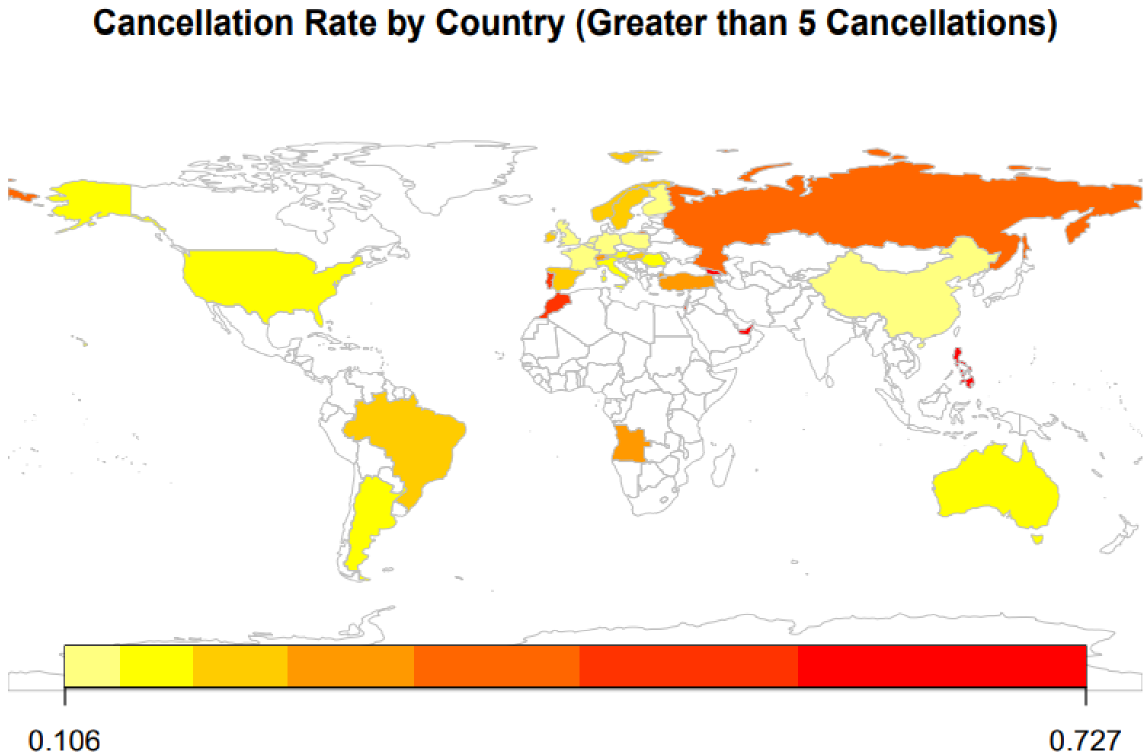
Fig 11 Cancellations in case of repeated guests

WORLD MAP ANALYSIS




```
#We can see that Asia oriental have a larger lead time on average
```

Fig 12: Lead time and the world




```
#From this plot we can see we should focus on Portugal and Morocco because they have both a high
#cancellation rate and a large amount of reservations
```

Fig 13 Countries and cancellations

LOGISTIC REGRESSION

Logistic Regression is one of the classification ML models and we pass the training data through the logistic regression model. family="binomial" as isCanceled is either '0' or '1'. It's a sophisticated statistical technique for modeling a binomial outcome using one or more explanatory variables. It estimates probabilities using a logistic function, which is the cumulative logistic distribution, to quantify the connection between the categorical dependent variable and one or more independent variables.

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 8028 1232
         1  653 2105

               Accuracy : 0.8432
                 95% CI : (0.8365, 0.8496)
    No Information Rate : 0.7223
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5869

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9248
            Specificity : 0.6308
         Pos Pred Value : 0.8670
         Neg Pred Value : 0.7632
             Prevalence : 0.7223
         Detection Rate : 0.6680
   Detection Prevalence : 0.7705
      Balanced Accuracy : 0.7778

       'Positive' Class : 0
```

RANDOM FOREST

A large number of decision trees are formed in the random forest approach. Every observation is input into the decision-making process. The final output is based on the most common conclusion for each observation. A new observation is fed into all the trees, with each categorization model obtaining a majority vote.

ntree - defines the number of trees to be generated. It is typical to test a range of values for this parameter (i.e. 100,200,300,400,500) and choose the one that minimizes the OOB estimate of error rate.

mtry - is the number of features used in the construction of each tree. These features are selected at random, which is where the “random” in “random forests” comes from. The default value for this parameter, when performing classification, is sqrt(number of features).

importance - enables the algorithm to calculate variable importance.

cutoff - Internally, random forest uses a cutoff of 0.5; i.e., if a particular unseen observation has a probability higher than 0.5, it will be classified as a positive class. In random forest, we have the option to customize the internal cutoff.

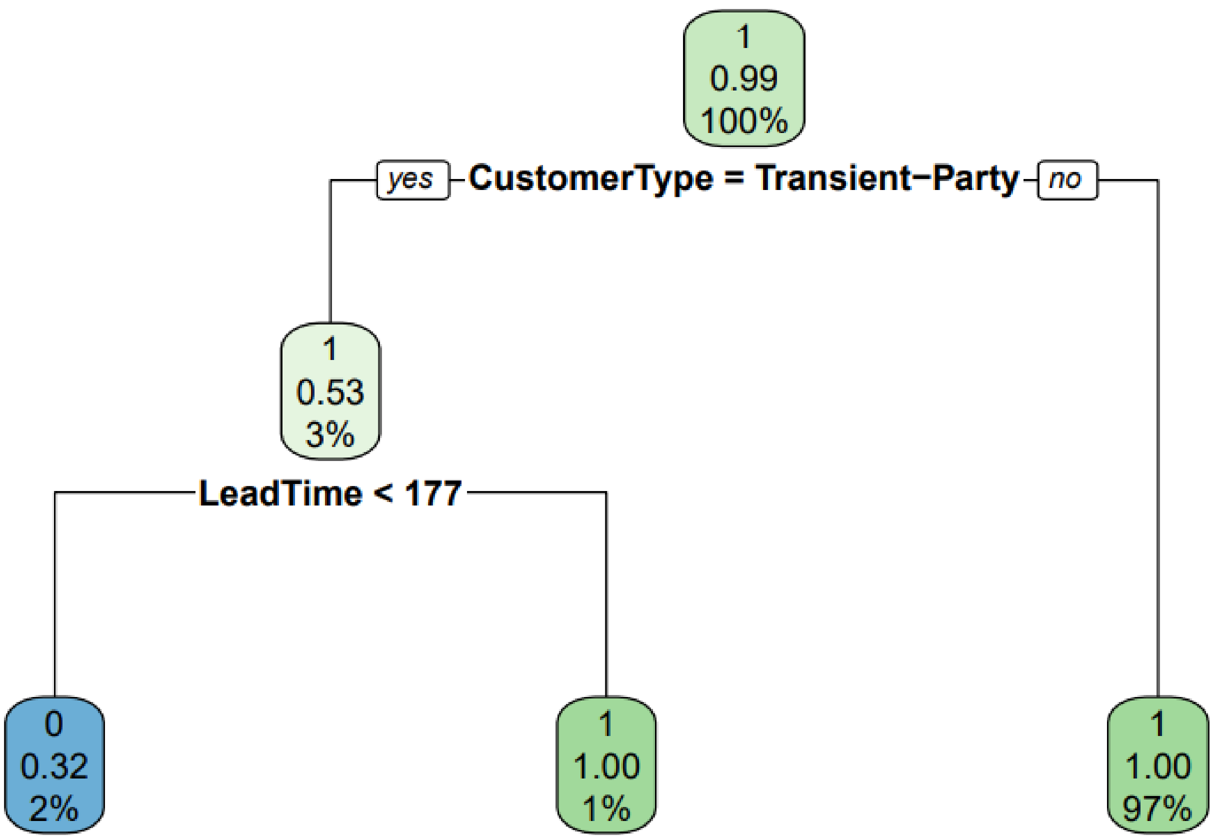
The Out-Of-Bag (OOB) data set is used to check the accuracy of the model, since the model wasn't created using this OOB data it will give us a good understanding of whether the model is effective or not.

Result: After Evaluating the probabilities and the class, the best random forest model gave an accuracy of 85.28% which is the best amongst all the models built.

REGRESSION TREE

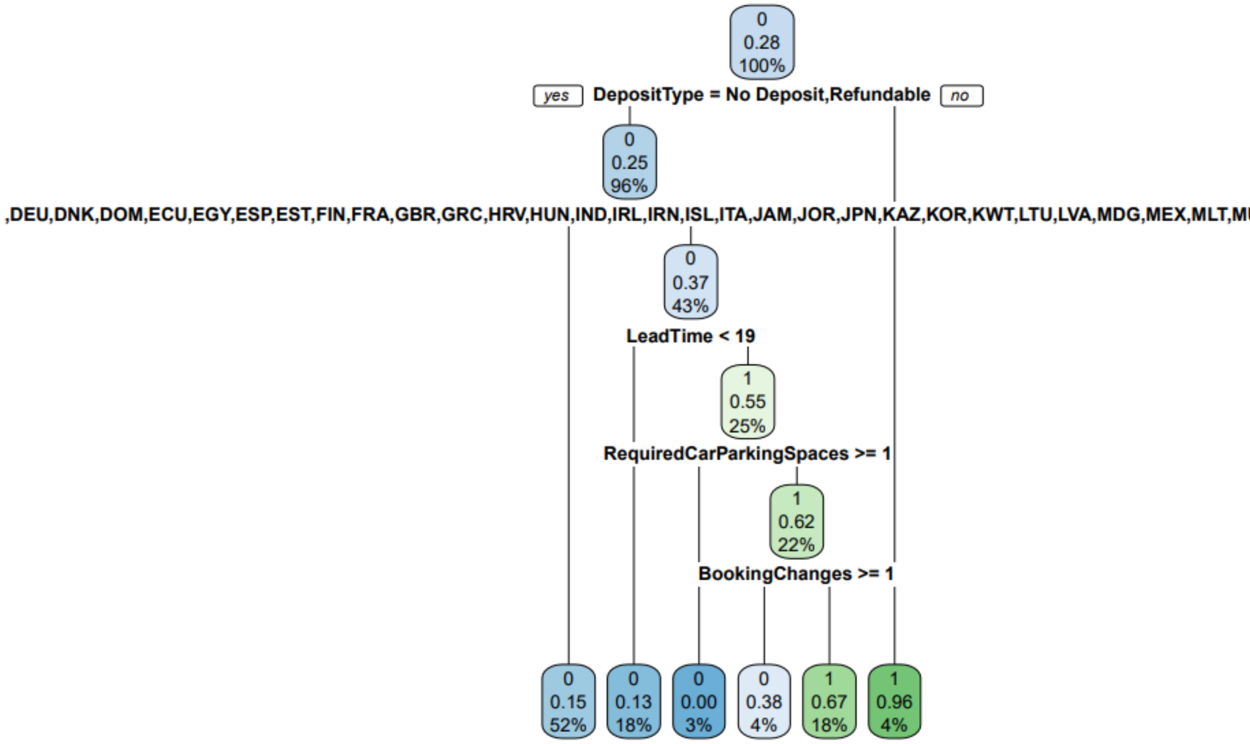
A regression tree is a decision tree that is used for the task of regression which can be used to predict continuous-valued outputs instead of discrete outputs.

We created a regression tree considering the five more significant variables



However, we see the model is not significant because the Mcnemar's Test P-Value is more than 0.05.

So, how the previous model wasn't significant. We started creating machine learning models to support our discovery that people from Portugal with a Non-Refundable deposit are people we should focus on.




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 6493 1202
##          1  636 1567
##
##                Accuracy : 0.8143
##                  95% CI : (0.8065, 0.8219)
##     No Information Rate : 0.7202
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5085
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9108
##             Specificity : 0.5659
##          Pos Pred Value : 0.8438
##          Neg Pred Value : 0.7113
##              Prevalence : 0.7202
##          Detection Rate : 0.6560
##    Detection Prevalence : 0.7774
##       Balanced Accuracy : 0.7383
##
##        'Positive' Class : 0
##
```

We infer that the model is significant because the Mcnemar's Test P-Value is less than 0.05. This model has an accuracy of 81.43%, which means the model predicted correctly the percentage of cases with the new data set.

Moreover, if we compare sensitivity and specificity, we can conclude that the model is better predicting when a person won't cancel (91.08% of the cases) than predicting when that person will cancel (56.59% of the cases).

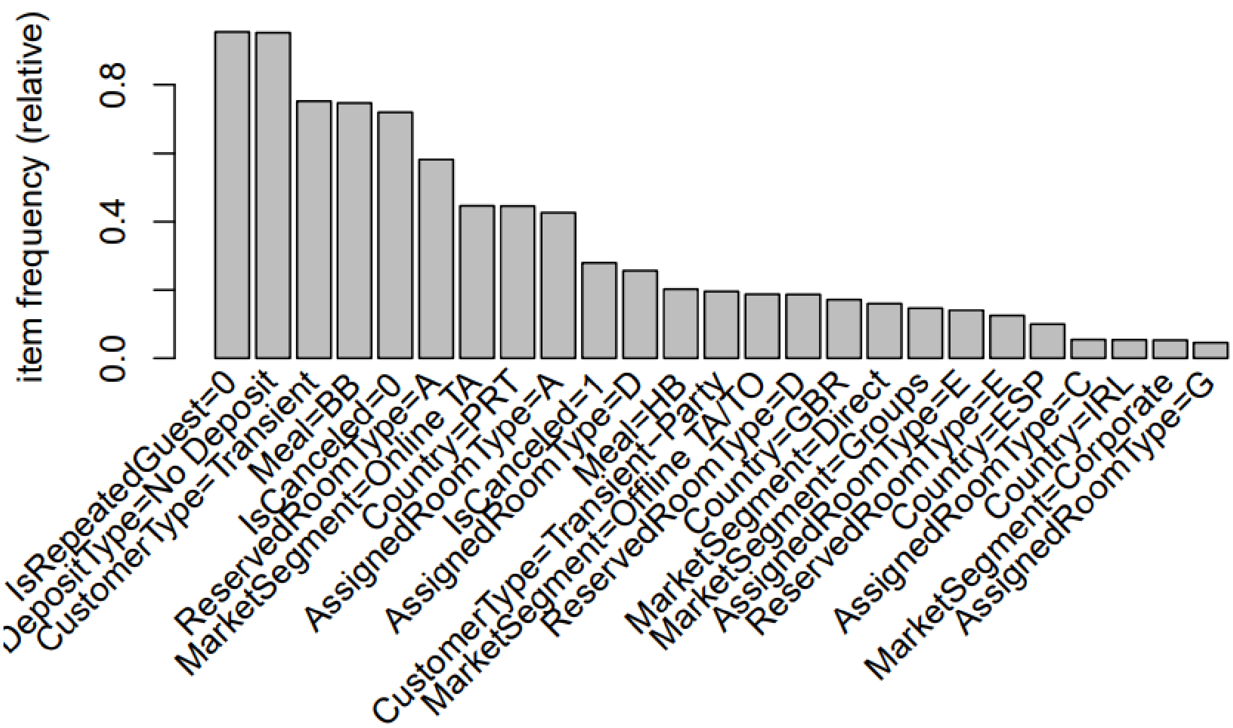
We also did a more complex regression tree with cross-validation to support our findings. From the results, we can determine if people are going to cancel: if they come from Portugal, they have a non-refundable deposit, and the customer is transient.
Therefore, this model supports our idea that people from Portugal and with a non-refundable deposit have a high probability to cancel.

ASSOCIATION RULE MINING

Association rule mining is a procedure that aims to observe frequently occurring patterns, correlations, or associations from datasets found in various kinds of databases such as relational databases, transactional databases, and other forms of repositories.

From the association rules
We should focus on people that come from Portugal, have a non-refundable deposit, and are considered transients. This is because they represent 12.67% of all the cancellations in the dataset.

We can observe that the bookings are the highest when done through an online Travel Agent. It also guarantees that through online travel agents, there is a greater probability of no cancellations.



SUPPORT VECTOR MACHINES

Support vector machines (SVMs) are supervised learning models that examine data for classification and regression analysis in machine learning.

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 5
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.0674652866495833
##
## Number of Support Vectors : 9470
##
## Objective Function Value : -38214.47
## Training error : 0.101926
## Cross validation error : 0.1258
## Probability model included.
```

```
#not a bad model after all!
#Training error : 0.102655
#Cross validation error : 0.126182
#both are pretty close
```

Insights:

- Maximum cancellations came from Portugal
- Direct market and Offline TA has lesser cancellations
- Online TAs had the most cancellations
- Bookings with children lead to lesser cancellations
- The higher lead time tends to have lesser cancellations
- No deposits promote cancellations
- When a parking spot is reserved, the probability of cancellation decreases significantly
- Room type ‘A’ had the highest number of cancellations
- Maximum cancellations of room A bookings are done online
- Repeated guests tend to cancel less frequently
- Portugal and Morocco have large reservations but also high cancellation rates

RECOMMENDATIONS

- Change deposit type for bookings from Portugal

A majority of our bookings are based out of Portugal. Those with a non-refundable deposit and transient customer type constitute 12.67% of the canceled population.

- Upgrade rooms or provide options for room switching.
  Since Room Type A is highly linked with cancellations, people who have booked room A could be provided an option to choose another room type on a last-minute basis.

- Improve graphics or data available for room type A online
  Since the majority of the cancellations of room type A are through online TA, maybe the customers had expected better rooms and were disappointed on seeing the actual room. Updating the room pictures provided to the online platforms, and keeping the rooms up to the mark may help.

- Special offers for group bookings with deposits
  Encourage customers of group type bookings to opt for deposit type bookings with special discount offers, provide gift vouchers or introduce a points-based system to avail discounts for future travel plans.

- Promote parking spaces and increase their availability:
  Since bookings with parking requirements have proved to be successful, we suggest advertising the availability of parking spaces effectively.

- Celebrate repeated customers:
  Repeated customers have proved to be loyal customers and rewarding them with special discounts or cashback or even a loyalty program seems like a good strategy.

- Breakfast plans:
  Since Room Type H and Meal Plan HB is highly linked with cancellations, people of the above subtype who have booked Room Type H or Meal Plan BB could be provided an option to choose another Room Type or Meal Plan on a last-minute basis.
  Generally, people tend to book BB plans for travel and holiday packages. We see a scope of improvement here.