Cab Booking Cancellation

By Nivetha Sivaprakasam

Introduction

As technology improves the importance for a safe and fast transportation is in need. Many people rely on cab services, whether it be long distance or point to point. However; traffic, late bookings, and vehicle issues often lead to bookings getting cancelled or forgotten. A new issue is the confusion between a mobile booking or online booking which might not be received by the company. Due to the lack of service the company is held accountable for the mistakes of the drivers. In this paper I will explore the effects of different variables and how they affect the chance of a cab getting cancelled or not. This data could be used by the government, cab companies, and airports to improve their business.

Dataset

For this project I used the dataset from kaggle's class competition "Predicting Cab Booking Cancellations". The data comes from YourCabs, a trustworthy cab service in Bangalore, India. Similarly the company has issues with cab bookings getting cancelled due to the unavailability of the car, causing customers to search for an alternative. The csv file contains various id's used to distinguish between the customer (based on the mobile number), booking, and vehicle. The package id is a binary value that distinguishes between the number of hours driven and kilometers. The travel type id is a unique id that distinguishes between the type of travel (1=long type, 2=point to point, 3=hourly rental). Similarly the other id's show the from_city, to_city, from_area and to_area value. The date and time is also included to see if there is a correlation between the 'from_date' and 'to_date'. As mentioned in the introduction online and mobile bookings are taken into consideration to see if they impact the chance of a Cab getting cancelled.

Data Wrangling

In terms of wrangling the data I first worked on the package_id and decided to set the NULL values to 0, so that NULL values would represent the package_id value of 0. For the to_date variable I worked on setting an origin, typically 01-01-1900, and modifying

the format to be **‘mm/dd/yyyy’**. For better understanding of the data and future modeling purposes I decided to parse the from_date and to_date into month, day, and time creating the variables from_month, from_day, from_time, to_month, to_day, and to_time. For parsing the dates I made sure the format of the from_date was ‘MM/DD/YYYY H:M’ and then I modified that format to be m, d, and H:M. I set the variable to be numeric since I ran into issues while modeling. For the to_month I set the NULL values to be 0 since I ran into issues with modeling.

```
mydata$from_date <- as.POSIXct(mydata$from_date, format='%d/%m/%Y %H:%M')
mydata$from_month <- format(mydata$from_date, format='%m')
mydata$from_month<-as.numeric(mydata$from_month)
mydata$from_month
```

For a better comparison, I choose to compare the difference in days between from_date and booking_created. To create this variable I set the format of the booking_created and from_date to be ‘MM/DD/YYYY H:M’ and I got the difference by using difftime. Afterwards to set the value to be numeric I used as.numeric and rounded the number for easy reference.

```
mydata$booking_created <-
as.POSIXct(mydata$booking_created,format='%m/%d/%Y %H:%M')
mydata$from_date <- as.POSIXct(mydata$from_date,format='%m/%d/%Y %H:%M')
mydata$diffs<- difftime(mydata$from_date ,mydata$booking_created , units =
c("days"))
mydata$diffs<-as.numeric(mydata$diffs)
mydata$diffs<-round(mydata$diffs)
mydata$diffs
```

Finally, I wrote the data frame to a csv file (cab_final.csv).

diffs	from_month	from_day	from_time	to_month
0	1	1	2:00	0
0	1	1	9:00	0
0	1	1	3:30	0
0	1	1	5:45	0
0	1	1	9:00	0
1	1	1	22:30	0
0	1	1	9:45	1
0	1	1	11:00	0
0	1	1	16:00	0
0	1	1	11:00	0
0	1	1	11:00	0
0	1	1	12:45	0
0	1	1	12:30	0
0	1	1	12:45	0
0	1	1	15:00	0
1	1	2	2:00	0
1	1	2	0:30	1
11	1	12	8:00	1

Logistic Regression

Logistic regression is the statistical method for analyzing data in which there is at least one independent variable that could determine an outcome. In this case the outcome would be whether the cab was cancelled or not which is determined by the value 1 (cancelled) or 0 (not cancelled). In order to find the variables that impact the cab cancellation I used both the Weight of Evidence and Information Value.

Weight of Evidence/ Information Value

The Weight of Evidence is used to determine the predictive power of an independent variable compared to the dependent. The woe package is used and contains the function iv.mult. This function can also be used to determine the information value (IV). The information value is used to determine the importance of the variable. Based on the IV value I was able to determine whether the variable is useful or not. If the IV value is less than 0.02 the variable is considered not useful, 0.02 to 0.1 means the predictor is weak, 0.1 to 0.3 is a medium strength variable, 0.3 to 0.5 is a strong indicator, and greater than 0.5 represents a suspicious relationship. The run below represents the IV value for the variable diffs in which the IV determines the relationship to be Medium.

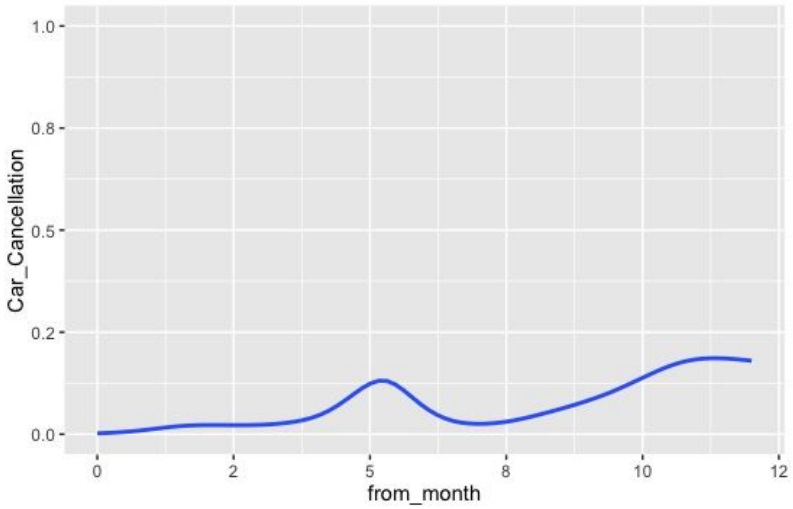
```
Information Value 0.13
[[1]]
  variable  class outcome_0 outcome_1 pct_0 pct_1 odds  woe  miv
1    diffs (;0.5)     24593      2434   0.6   0.8  0.8 -0.2 0.04
2    diffs <0.5;)     15706       698   0.4   0.2  1.7  0.6 0.09
                                      sql
1 when diffs < 0.5 then -0.241729021585819
2 when diffs >= 0.5 then 0.558924104552018
```

I decided to test 10 variables excluding the id variables to determine 4 important variables. By repeating this call: **iv.mult(mydata,"Car_Cancellation",vars=c("online_booking")),** with other variables I was able to determine the importance of the variables.

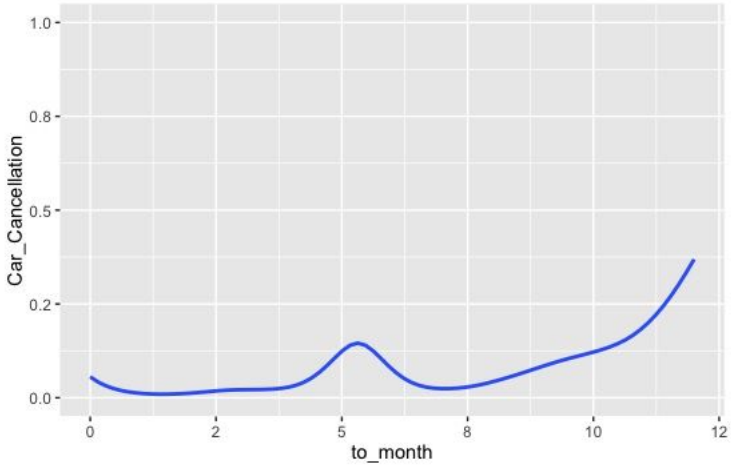
Modeling

For the logistic modeling I used the library ggplot2 and the function ggplot to plot the curve. Based on the variable I was able to see either an increasing or decreasing slope in the curve. By checking the WOE and IV values I decided to model the variables

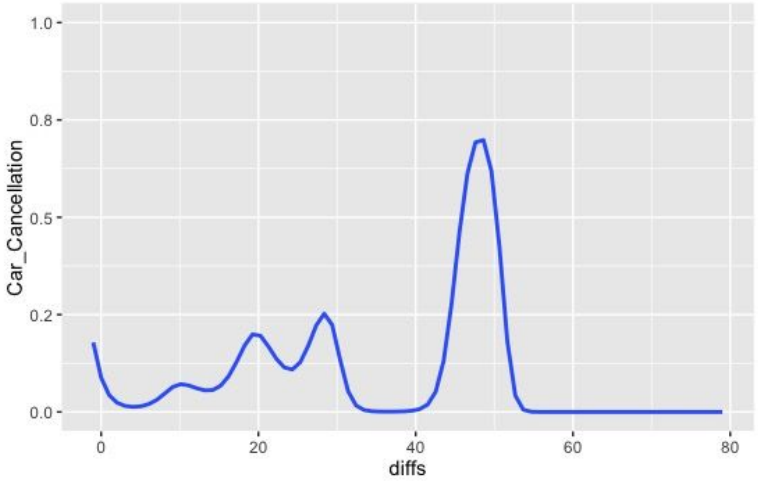
from_month, online_booking, diffs, and to_month to see if the values impact the chance of a cab getting cancelled.



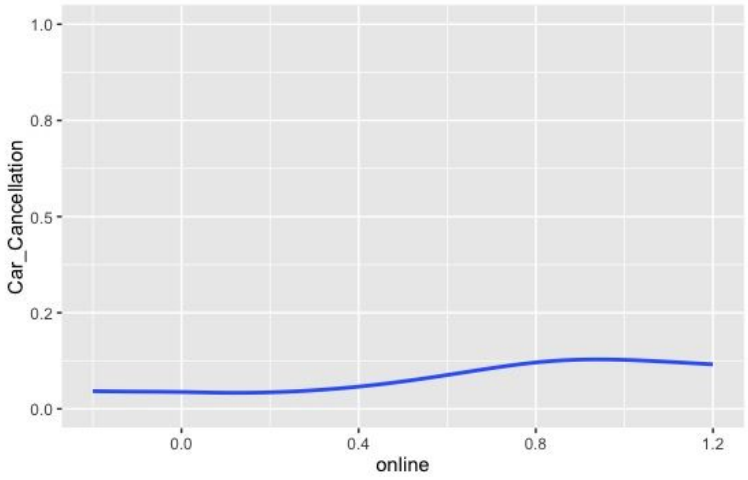
This curve is for the variable from_month and Car_Cancellation. Based on the curve we can predict as the from_month increases the chances for car cancellation increases. Around the month June and November is when the highest chance for car cancellation occurs compared to July and January.



This curve represents the variable to_month and the chance of a cab getting cancelled. As the month increases, we can see an increase in Car_Cancellation. Similar to the from_month curve there is an increase around June and November, and a decrease in January and July.



This curve represents the variable diffs which is the difference in days from the booking created and from date. The chances for a cab getting cancelled is highest around 50 days and 0 days; while the lowest is 60 to 80 days.



This curve represents the chance of Car Cancellation for the variable online_booking. If the online_booking is 1 the cancellation chance is higher compared to a value of 0. For all the models I set the y limit to be from 0 to 1, for accuracy purpose.

Decision Tree

A decision tree is a method that uses a tree like model of decisions and their consequences, including the number of nodes, and chance of probability. To calculate the most important variables it is important to use information gain.

Information Gain

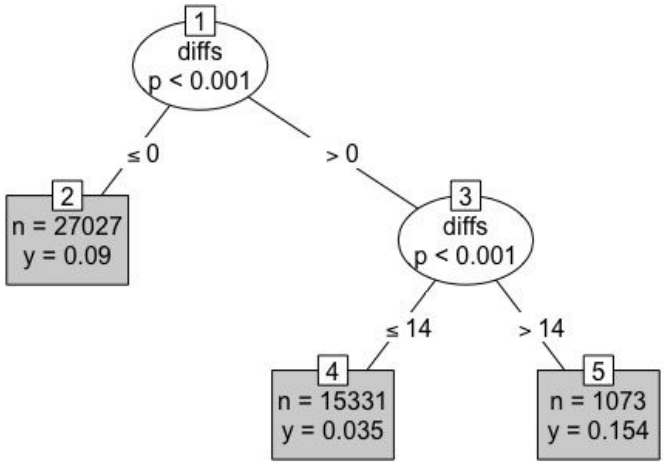
Information gain is a method to see how much information is gained by doing the split using the particular variable. The higher the value the more important the variable is.

```
           attr_importance
from_month        1.216516
```

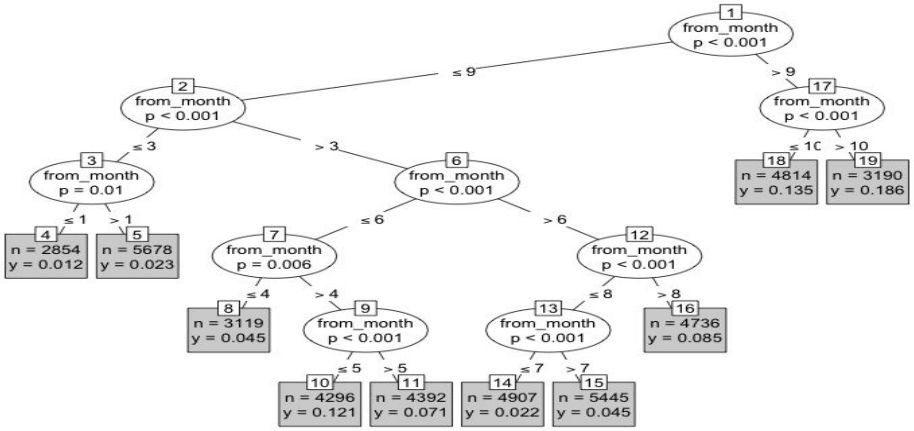
Above is an example run for the variable from_month. I decided to model the variables from_month, to_month, and diffs to see if there was a difference based on the value.

Modeling

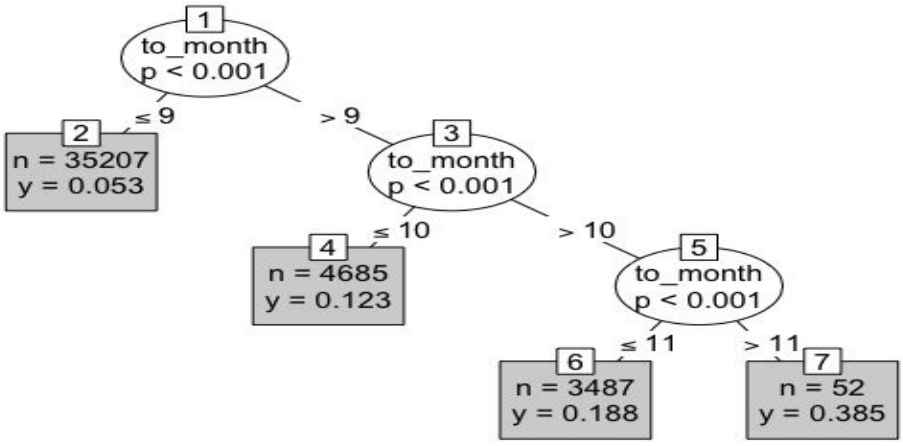
For the decision tree I used the package party which contains the function ctree. The function takes the parameter of the y value, x value, and dataset; while the plot function takes the type of plotting. In this case I set the plot type to be simple in order to clearly see the results.



Based on the tree above, we can see the decisions made to the variable diffs. Starting from node 1 we can decide which way to go based on the diff value. The value ‘n’ represents the number of records which that value, while ‘y’ represents the chance of cab cancellation. The most common value is < 0 and the highest chance of cab cancellation occurs in a diff value greater than 14.



The tree above is used for the variable from_month and displays the variable possibilities from 1 to 12. Based on the tree we can see the most common value is for the month January while the highest chance for cancellation occurs in November. The lowest chance for cab cancellation occurs around January.



This tree represents the decision for the variables to_month and Car_Cancellation. Based on the tree we can see that the most common value is for the months before September, while the least common value are for the months November and December. The months with the highest chance of cancellation are November and December, and the least chance are for the months September and before.

Results

The graphs presented above show that the chance of cab cancellation is higher during popular holidays including Christmas hence an increase during December and

November. One common problem to notice if the difference is days is low there is a high chance of not getting a cab, while a longer difference decreases the chance of cancellation. One major issue with the data was that most of the variables were id with no legend, including the car id, area id, and city id. If there was a key it would have been helpful to use the id to gain more results. For the variable package_id, a value of 1 (4 hr & 40 km) and 7(12 hrs & 120 km) resulted in the higher chance of cancellations compared to 3(6 hrs & 60 km). As expected for mobile bookings, if the value is 1 then the chance of cancellation is high compared to 0. A travel type of long distance has a low chance of cancellation possibly since they are expensive and companies would prefer long distance over short distances.

Future/Recommendations

In the future companies should try to prioritize their cabs to help customers early morning and late nights to get them to their locations safely. Companies should take safety over money as their priority; however, this will take some time to achieve. Companies should give an early notice for a change so customers could find a backup. Customers should prepare early in advance for cab bookings and should prioritize the use for long distance. Customers should avoid online and mobile booking and resort to phone bookings to ensure a cab. In general simple changes and backup plans can ensure a customer has a cab instead of being estranged. In the future this study can be done in other countries to see if a location has an impact on the cancellation. The distance traveled can be of great use for research and company records.

R Code

cab.R (Data Wrangling)

```
mydata = read.csv("cab.csv", na.strings='NULL')
mydata$package_id[is.na(mydata$package_id)] <- 0

#FORMAT
mydata$to_date <- as.Date(mydata$to_date, origin = "1900-01-01")
mydata$to_date


#TIME DIFF
```

```
mydata$booking_created <- as.POSIXct(mydata$booking_created,
                                     format='%m/%d/%Y %H:%M')
mydata$from_date <- as.POSIXct(mydata$from_date,
                                     format='%m/%d/%Y %H:%M')
mydata$diffs<- difftime(mydata$from_date ,mydata$booking_created , units =
c("days"))
mydata$diffs<-as.numeric(mydata$diffs)
mydata$diffs<-round(mydata$diffs)
mydata$diffs

#OTHER STUFF
mydata$from_date <- as.POSIXct(mydata$from_date, format='%d/%m/%Y %H:%M')
mydata$from_month <- format(mydata$from_date, format='%m')
mydata$from_month<-as.numeric(mydata$from_month)
mydata$from_month

mydata$from_day <- format(mydata$from_date, format='%d')
mydata$from_day <-as.numeric(mydata$from_day)
mydata$from_day

mydata$from_time <- format(mydata$from_date, format='%H:%M')
mydata$from_time

#TO DATE
mydata$to_date <- as.POSIXct(mydata$to_date, format='%d/%m/%Y %H:%M')
mydata$to_month <- format(mydata$to_date, format='%m')
mydata$to_month<-as.numeric(mydata$to_month)
mydata$to_month
mydata$to_month[is.na(mydata$to_month)] <- 0

mydata$to_day <- format(mydata$to_date, format='%d')
mydata$to_day <-as.numeric(mydata$to_day)
mydata$to_day

mydata$to_time <- format(mydata$to_date, format='%H:%M')
mydata$to_time

mydata$from_month[is.na(mydata$from_month)] <- 0
mydata$diffs[is.na(mydata$diffs)] <- 0
summary(mydata)

write.csv(mydata, file = "cab_final.csv")
-------------------------
```

Cab_Model.R (Logistic Modeling)

```
library(ggplot2)
library(woe)
library(riv)
mydata <- read.csv("cab_final.csv")

iv.mult(mydata, "Car_Cancellation", vars = c("package_id"))
iv.mult(mydata, "Car_Cancellation", vars = c("travel_type_id"))
iv.mult(mydata, "Car_Cancellation", vars = c("online_booking"))
iv.mult(mydata, "Car_Cancellation", vars = c("mobile_site_booking"))
iv.mult(mydata, "Car_Cancellation", vars = c("diffs"))
iv.mult(mydata, "Car_Cancellation", vars = c("from_month"))
iv.mult(mydata, "Car_Cancellation", vars = c("from_day"))
iv.mult(mydata, "Car_Cancellation", vars = c("to_month"))
iv.mult(mydata, "Car_Cancellation", vars = c("to_day"))
#-----------------------------------------------------------

#Variable Declaration
diffs <- mydata$diffs
Car_Cancellation <- mydata$Car_Cancellation
online_booking <- mydata$online_booking
from_month <- mydata$from_month
to_month <- mydata$to_month

#From Month
library(ggplot2)
ggplot(mydata, aes(x=from_month, y=Car_Cancellation)) + ylim(0, 1) +
  stat_smooth(method.args=list(family="binomial"), se=FALSE)

#To Month
library(ggplot2)
ggplot(mydata, aes(x=to_month, y=Car_Cancellation)) + ylim(0,1) +
  stat_smooth(method.args=list(family="binomial"), se=FALSE)

#Diff
library(ggplot2)
ggplot(mydata, aes(x=diffs, y=Car_Cancellation))  + ylim(0, 1) +
  stat_smooth(method.args=list(family="binomial"), se=FALSE)

#Online Booking
online <- jitter(as.numeric(online_booking))
```

```
library(ggplot2)
ggplot(mydata, aes(x=online, y=Car_Cancellation)) + ylim(0,1) +
  stat_smooth(method.args=list(family="binomial"), se=FALSE)

--------------------
```

cab_Decision.R (Decision Tree Modeling)

```
library(party)

mydata <- read.csv("cab_final.csv")

library(FSelector)
print(information.gain(Car_Cancellation~package_id, mydata))
print(information.gain(Car_Cancellation~travel_type_id, mydata))
print(information.gain(Car_Cancellation~online_booking, mydata))
print(information.gain(Car_Cancellation~mobile_site_booking, mydata))
print(information.gain(Car_Cancellation~diffs, mydata))
print(information.gain(Car_Cancellation~from_month, mydata))
print(information.gain(Car_Cancellation~from_day, mydata))
print(information.gain(Car_Cancellation~to_month, mydata))
print(information.gain(Car_Cancellation~to_day, mydata))

Car_Cancellation <- mydata$Car_Cancellation
diffs <- mydata$diffs
from_month <- mydata$from_month
to_month <- mydata$to_month

# Create the tree.

output.tree <- ctree(Car_Cancellation ~ from_month, data = mydata)
png("airct.png", res=80, height=500, width=710)
plot(output.tree, type = "simple")
dev.off()

output.tree <- ctree(Car_Cancellation ~ to_month, data = mydata)
plot(output.tree, type = "simple")

output.tree <- ctree (Car_Cancellation ~ diffs, data = mydata)
plot(output.tree, type = "simple")
```