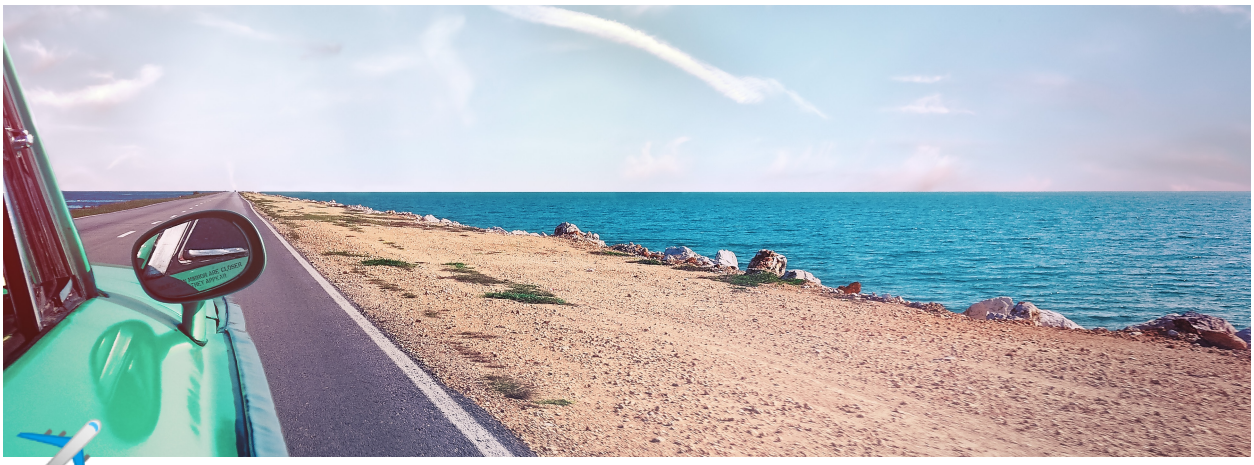


DemoDay_M2

Proyecto: “Demanda reservaciones de hotel”

Perla Peña

Experto: Erick

14 marzo 2022

Descripción del dataset

Tomado del artículo “Hotel booking demand datasets” de Nuno Antonio publicado en la Science direct en 2019.

> “This data article describes two datasets with hotel demand data. One of the hotels (H1) is a resort hotel and the other is a city hotel (H2). Both datasets share the same structure, with 31 variables describing the 40,060 observations of H1 and 79,330 observations of H2. Each observation represents a hotel booking. Both datasets comprehend bookings due to arrive between the 1st of July of 2015 and the 31st of August 2017, including bookings that effectively arrived and bookings that were canceled. Since this is hotel real data, all data elements pertaining hotel or costumer identification were deleted. Due to the scarcity of real business data for scientific and educational purposes, these datasets can have an important role for research and education in revenue management, machine learning, or data mining, as well as in other fields.”
> https://www.sciencedirect.com/science/article/pii/S2352340918315191

Descripción de las variables

Table 1 (*continued*)

Variable	Type	Description	Source/Engineering
DistributionChannel	Categorical	Booking distribution channel. The term "TA" means "Travel Agents" and "TO" means "Tour Operators"	BO, BL and DC
IsCanceled	Categorical	Value indicating if the booking was canceled (1) or not (0)	BO
IsRepeatedGuest	Categorical	Value indicating if the booking name was from a repeated guest (1) or not (0)	BO, BL and C/ Variable created by verifying if a profile was associated with the booking customer. If so, and if the customer profile creation date was prior to the creation date for the booking on the PMS database it was assumed the booking was from a repeated guest
LeadTime	Integer	Number of days that elapsed between the entering date of the booking into the PMS and the arrival date	BO and BL/ Subtraction of the entering date from the arrival date
MarketSegment	Categorical	Market segment designation. In categories, the term "TA" means "Travel Agents" and "TO" means "Tour Operators"	BO, BL and MS
Meal	Categorical	Type of meal booked. Categories are presented in standard hospitality meal packages: Undefined/SC – no meal package; BB – Bed & Breakfast; HB – Half board (breakfast and one other meal – usually dinner); FB – Full board (breakfast, lunch and dinner)	BO, BL and ML
PreviousBookingsNotCanceled	Integer	Number of previous bookings not cancelled by the customer prior to the current booking	BO and BL / In case there was no customer profile associated with the booking, the value is set to 0. Otherwise, the value is the number of bookings with the same customer profile created before the current booking and not canceled.
PreviousCancellations	Integer	Number of previous bookings that were cancelled by the customer prior to the current booking	BO and BL/ In case there was no customer profile associated with the booking, the value is set to 0. Otherwise, the value is the number of bookings with the same customer profile created before the current booking and canceled.
RequiredCardParkingSpaces	Integer	Number of car parking spaces required by the customer	BO and BL
ReservationStatus	Categorical	Reservation last status, assuming one of three categories: 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	BO

ReservationStatusDate	Date	Date at which the last status was set. This variable can be used in conjunction with the *ReservationStatus* to understand when was the booking canceled or when did the customer checked-out of the hotel	BO
ReservedRoomType	Categorical	Code of room type reserved. Code is presented instead of designation for anonymity reasons	BO and BL
StaysInWeekendNights	Integer	Number of weekend nights (Saturday or Sunday) the guest stayed or booked to stay at the hotel	BO and BL/ Calculated by counting the number of weekend nights from the total number of nights
StaysInWeekNights	Integer	Number of week nights (Monday to Friday) the guest stayed or booked to stay at the hotel	BO and BL/Calculated by counting the number of week nights from the total number of nights
TotalOfSpecialRequests	Integer	Number of special requests made by the customer (e.g. twin bed or high floor)	BO and BL/Sum of all special requests

Hotel booking demand datasets

This data article describes two datasets with hotel demand data. One of the hotels (H1) is a resort hotel and the other is a city hotel (H2). Both datasets share the same structure, with 31 variables describing the 40,060 observations of H1

https://www.sciencedirect.com/science/article/pii/S2352340918315191

Data in Brief

Procesamiento del data

```
#Descripción del dataset
summary(booking)
dim(booking)
head(booking)
str(booking)

> dim(booking)
[1] 119390     32
> str(booking)
'data.frame': 119390 obs. of  32 variables:
 $ hotel                         : chr  "Resort Hotel" "Resort Hotel" "Resort Hotel" "Resort Hotel" ...
 $ is_canceled                   : int  0 0 0 0 0 0 0 0 1 1 ...
 $ lead_time                     : int  342 737 7 13 14 14 0 9 85 75 ...
 $ arrival_date_year             : int  2015 2015 2015 2015 2015 2015 2015 2015 2015 2015 ...
 $ arrival_date_month            : chr  "July" "July" "July" "July" ...
 $ 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 ...
 $ stays_in_weekend_nights       : int  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 ...
 $ adults                        : int  2 2 1 1 2 2 2 2 2 2 ...
 $ children                      : int  0 0 0 0 0 0 0 0 0 0 ...
 $ babies                        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ meal                          : chr  "BB" "BB" "BB" "BB" ...
 $ country                       : chr  "PRT" "PRT" "GBR" "GBR" ...
 $ market_segment                : chr  "Direct" "Direct" "Direct" "Corporate" ...
 $ distribution_channel          : chr  "Direct" "Direct" "Direct" "Corporate" ...
 $ is_repeated_guest             : int  0 0 0 0 0 0 0 0 0 0 ...
 $ previous_cancellations        : int  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 ...
 $ reserved_room_type            : chr  "C" "C" "A" "A" ...
 $ assigned_room_type            : chr  "C" "C" "C" "A" ...
 $ booking_changes               : int  3 4 0 0 0 0 0 0 0 0 ...
```

```
 $ deposit_type                  : chr  "No Deposit" "No Deposit" "No Deposit" "No Deposit" ...
 $ agent                         : int  0 0 0 304 240 240 0 303 240 15 ...
 $ company                       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ days_in_waiting_list          : int  0 0 0 0 0 0 0 0 0 0 ...
 $ customer_type                 : chr  "Transient" "Transient" "Transient" "Transient" ...
 $ adr                           : num  0 0 75 75 98 ...
 $ required_car_parking_spaces   : int  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 ...
 $ reservation_status            : chr  "Check-Out" "Check-Out" "Check-Out" "Check-Out" ...
 $ reservation_status_date       : chr  "01/07/2015" "01/07/2015" "02/07/2015" "02/07/2015" ...
```

Revisar si existen NA

```
#Después de la limpieza de datos verificamos que no existan NA
(colSums(is.na(booking)))

hotel                     is_canceled
                            0                               0
                      lead_time              arrival_date_year
                            0                               0
            arrival_date_month       arrival_date_week_number
                            0                               0
     arrival_date_day_of_month        stays_in_weekend_nights
                            0                               0
          stays_in_week_nights                          adults
                            0                               0
                      children                          babies
                            0                               0
                          meal                         country
                            0                               0
                market_segment           distribution_channel
                            0                               0
             is_repeated_guest         previous_cancellations
                            0                               0
previous_bookings_not_canceled             reserved_room_type
                            0                               0
            assigned_room_type                booking_changes
                            0                               0
                  deposit_type                           agent
                            0                               0
                       company           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
```

Modificación de la base de datos

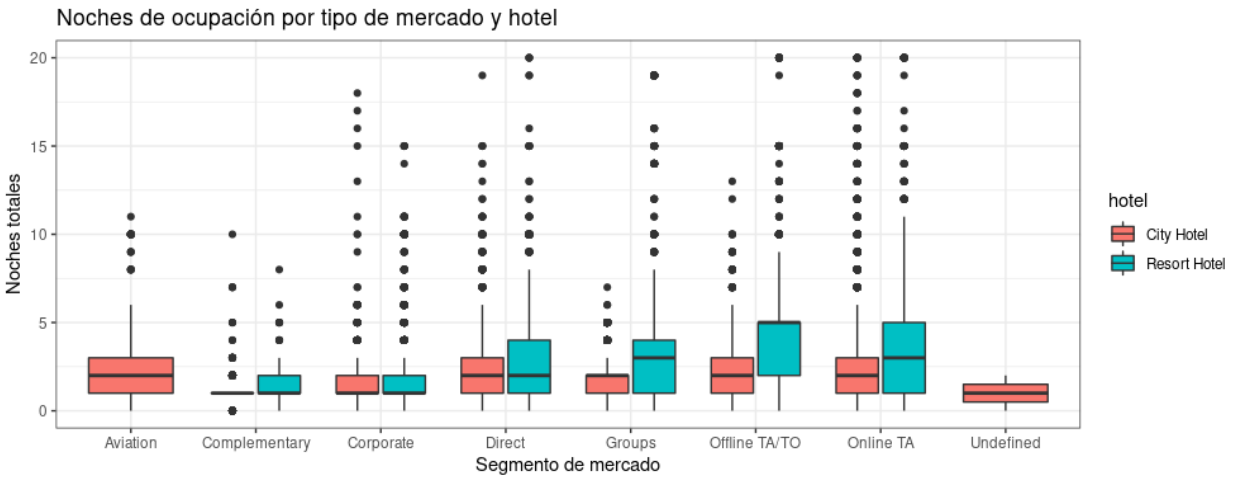
```
#cambiar a formato fecha reservation_status_date
bforest <- mutate(booking, reservation_status_date = as.Date(reservation_status_date, "%d/%m/%Y"),
                  is_canceled = factor(is_canceled))

b1 <- mutate(booking, reservation_status_date = as.Date(reservation_status_date, "%d/%m/%Y"),
             hotel = factor(hotel),
             is_canceled = factor(is_canceled),
             market_segment = factor(market_segment))

>str(bforest)
'data.frame': 119390 obs. of  32 variables:
 $ hotel                         : chr  "Resort Hotel" "Resort Hotel" "Resort Hotel" "Resort Hotel" ...
 $ is_canceled                   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 2 ...

> str(b1)
'data.frame': 119390 obs. of  32 variables:
 $ hotel                         : Factor w/ 2 levels "City Hotel","Resort Hotel": 2 2 2 2 2 2 2 2 2 ...
 $ is_canceled                   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 2 ...
 $ lead_time                     : int  342 737 7 13 14 14 0 9 85 75 ...

#Estandarización de la base de datos (usada para SVM)
## Preparar los datos
hotel_df <- hotel_stays%>%
  select(is_canceled, hotel, arrival_date_month, meal,
         adr, deposit_type, lead_time, adults, required_car_parking_spaces,
         total_of_special_requests, market_segment,
         stays_in_week_nights, stays_in_weekend_nights)%>%
  mutate_if(is.character,factor)

#Instalar biblioteca
install.packages("tidymodels")
library(tidymodels)

#Normalización base de datos
hotel_rec <- recipe(is_canceled ~., data = hotel_train) %>%
  step_dummy(all_nominal(), -all_outcomes()) %>%
  step_zv(all_numeric())%>%
  step_normalize(all_numeric()) %>%
  prep()
```

EDA

Percnotación por tipo de mercado

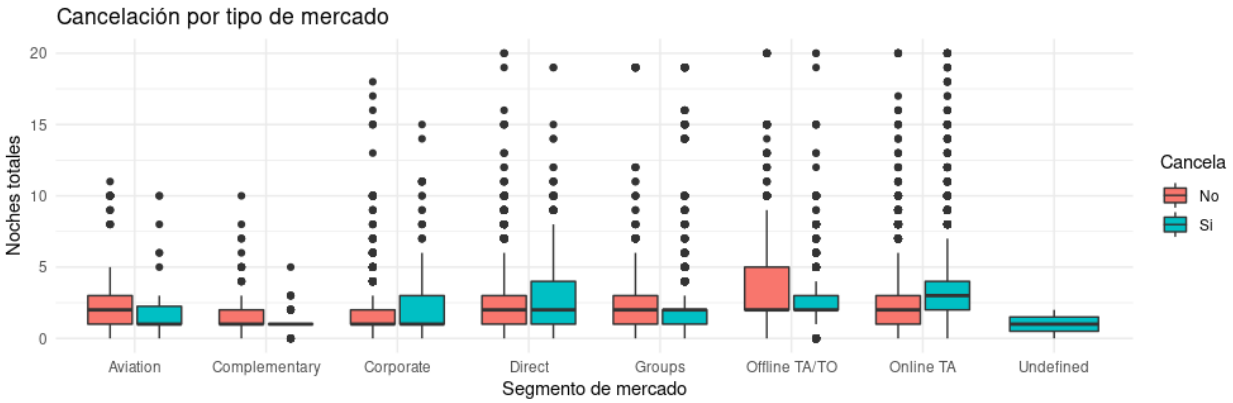
```
b1 %>%
  ggplot(aes(x= market_segment, y = stays_in_week_nights, fill=  hotel))+
  geom_boxplot()+
  ggtitle("Noches de ocupación por tipo de mercado y hotel") +
  xlab("Segmento de mercado") +
  ylab("Noches totales")+
```

```
  theme(plot.title = element_text(size=12))+
  theme_bw()+
  ylim(0,20)
```



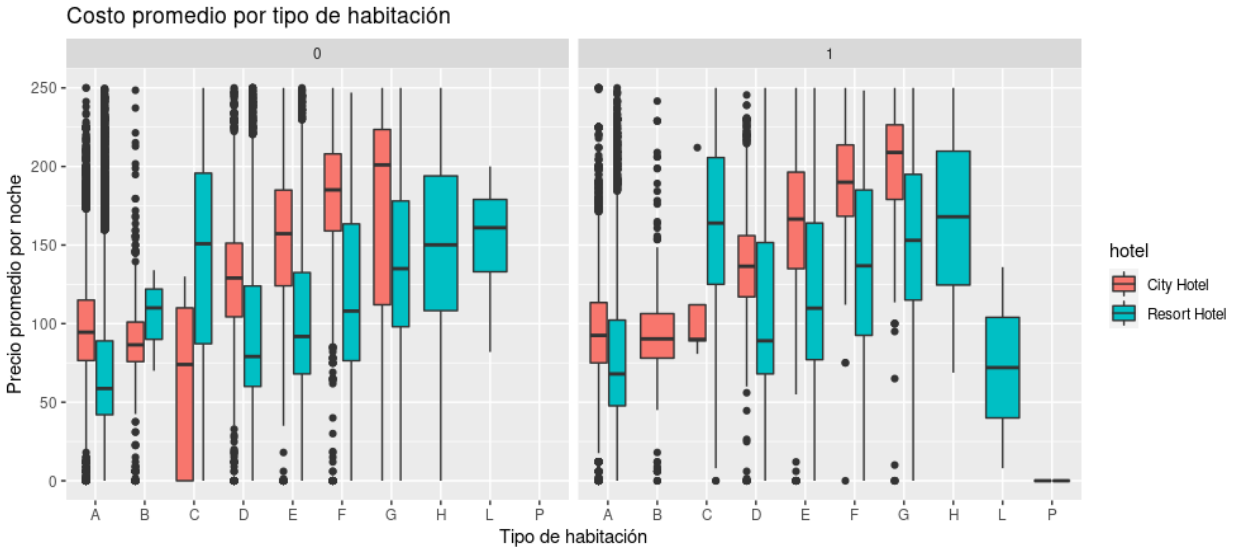
Cancelación de la reservación por tipo de mercado

```
b1 %>%
  ggplot(aes(x=market_segment, y = stays_in_week_nights, fill = is_canceled))+
  geom_boxplot()+
  ggtitle("Cancelación por tipo de mercado") +
  xlab("Segmento de mercado") +
  ylab("Noches totales")+
  theme(plot.title = element_text(size=12))+
  theme_minimal() +
  ylim(0,20)+
  scale_fill_discrete(name = "Cancela", labels = c("No", "Si"))
```



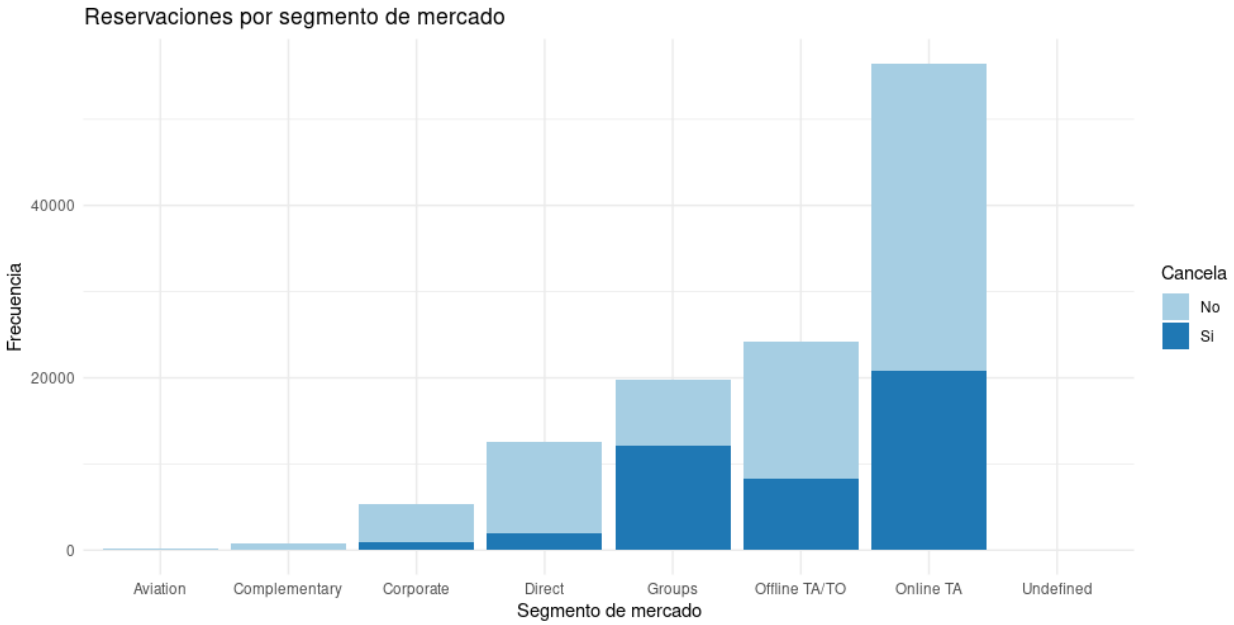
Costo promedio por tipo de habitación

```
b1 %>%
  ggplot(aes(x=reserved_room_type, y = adr, fill = hotel))+
  geom_boxplot()+
  facet_wrap("is_canceled") +
  ylim(0,250)+
  ggtitle("Costo promedio por tipo de habitación") +
  xlab("Tipo de habitación") +
  ylab("Precio promedio por noche")+
  theme(plot.title = element_text(size=12))+
  theme_gray()
```



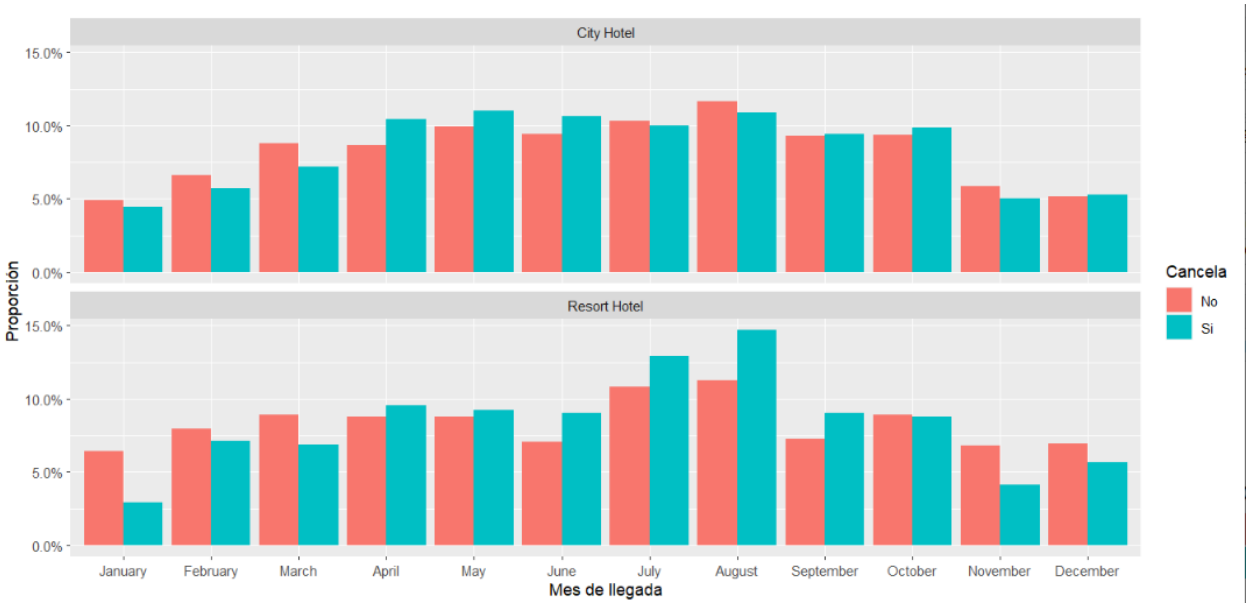
Frecuencia por tipo de mercado

```
b1 %>%
  ggplot(aes(x=market_segment, y=frequency(market_segment), fill=is_canceled)) +
  geom_bar(stat="identity")+
  scale_fill_brewer(palette="Paired", name = "Cancela", labels = c("No", "Si"))+
  theme_minimal()+
  ggtitle("Reservaciones por segmento de mercado") +
  xlab("Segmento de mercado") +
  ylab("Frecuencia")
```



Estado de las reservaciones por mes y tipo de hotel

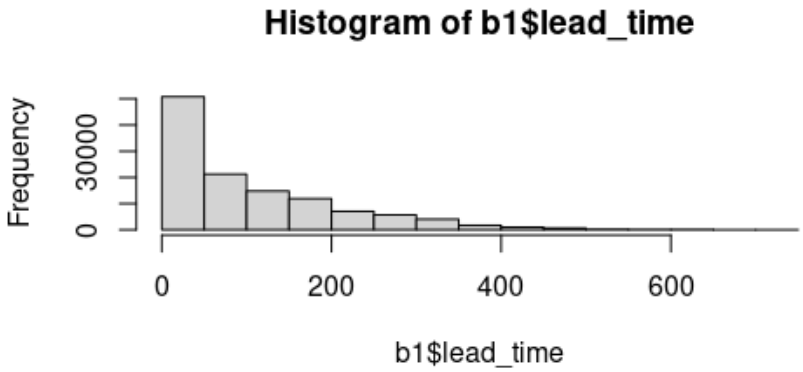
```
#Seleccionar datos
hotel_stays <- bforest %>%
  mutate(hotel = factor(hotel), children = case_when(children + babies > 0 ~ "children",
                              TRUE ~ "none"),
         required_car_parking_spaces = case_when(required_car_parking_spaces > 0 ~ "parking",
                                                 TRUE ~ "none")) %>%
                                                select(-reservation_status, -babies)

#Hacer el plot
hotel_stays%>%
  mutate(arrival_date_month = factor(arrival_date_month,
                                     levels = month.name)) %>%
  count(hotel, arrival_date_month, is_canceled)%>%
  group_by(hotel, is_canceled)%>%
  mutate(proportion = n / sum(n))%>%
  ggplot(aes(arrival_date_month, proportion, fill = is_canceled))+
  geom_col(position = "dodge")+
  scale_y_continuous(labels = scales::percent_format())+
  facet_wrap(~hotel, nrow = 2)+
  xlab("Mes de llegada") +
  ylab("Proporción")+
  scale_fill_discrete(name = "Cancela", labels = c("No", "Si"))
```

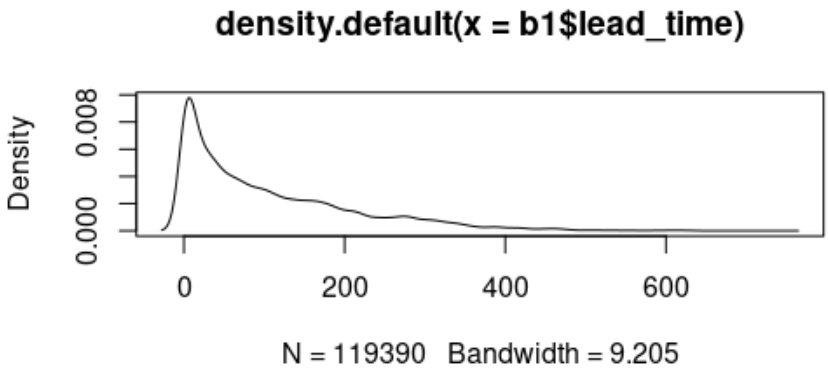


Pruebas estadísticas de hipótesis

Prueba de normalidad de los datos

```
##Verificar la normalidad de los datos con un histograma
#opción 1
hist(b1$lead_time)

#opción 2
install.packages("skimr")
library(skimr)
skim(hotel_stays)

#Densidad
d <- density(b1$lead_time)
plot(d)

#Prueba de  shapiro test
lt.test <- shapiro.test(b1$lead_time[0:5000])
lt.test

Shapiro-Wilk normality test

data:  b1$lead_time[0:5000]
W = 0.88581, p-value < 2.2e-16
```





Valor de p < 0.05 por lo que rechazamos H0. Los valores no son gaussianos a una significancia del 5%

```
skim(hotel_stays)
-- Data Summary ------------------------
                           Values
Name                       hotel_stays
Number of rows             119390
Number of columns          30
_________________________
Column type frequency:
  character                11
  Date                     1
  factor                   2
  numeric                  16
_________________________
Group variables            None

-- Variable type: character ----------------------
# A tibble: 11 x 8
   skim_variable               n_missing
 * <chr>                           <int>
 1 arrival_date_month                  0
 2 children                            0
```

```
 3 meal                              0
 4 country                           0
 5 market_segment                    0
 6 distribution_channel              0
 7 reserved_room_type                0
 8 assigned_room_type                0
 9 deposit_type                      0
10 customer_type                     0
11 required_car_parking_spaces       0
   complete_rate   min   max empty n_unique
 *         <dbl> <int> <int> <int>    <int>
 1             1     3     9     0       12
 2             1     4     8     0        2
 3             1     2     9     0        5
 4             1     2     4     0      178
 5             1     6    13     0        8
 6             1     3     9     0        5
 7             1     1     1     0       10
 8             1     1     1     0       12
 9             1    10    10     0        3
10             1     5    15     0        4
11             1     4     7     0        2
   whitespace
 *      <int>
 1          0
 2          0
 3          0
 4          0
 5          0
 6          0
 7          0
 8          0
 9          0
10          0
11          0

-- Variable type: Date ---------------------------
# A tibble: 1 x 7
  skim_variable           n_missing complete_rate
* <chr>                       <int>         <dbl>
1 reservation_status_date         0             1
  min        max        median     n_unique
* <date>     <date>     <date>        <int>
1 2014-10-17 2017-09-14 2016-08-07      926

-- Variable type: factor -------------------------
# A tibble: 2 x 6
  skim_variable n_missing complete_rate ordered
* <chr>             <int>         <dbl> <lgl>
1 hotel                 0             1 FALSE
2 is_canceled           0             1 FALSE
  n_unique top_counts
*    <int> <chr>
1        2 Cit: 79330, Res: 40060
2        2 0: 75166, 1: 44224

-- Variable type: numeric ------------------------
# A tibble: 16 x 11
   skim_variable                 n_missing
 * <chr>                             <int>
 1 lead_time                             0
```

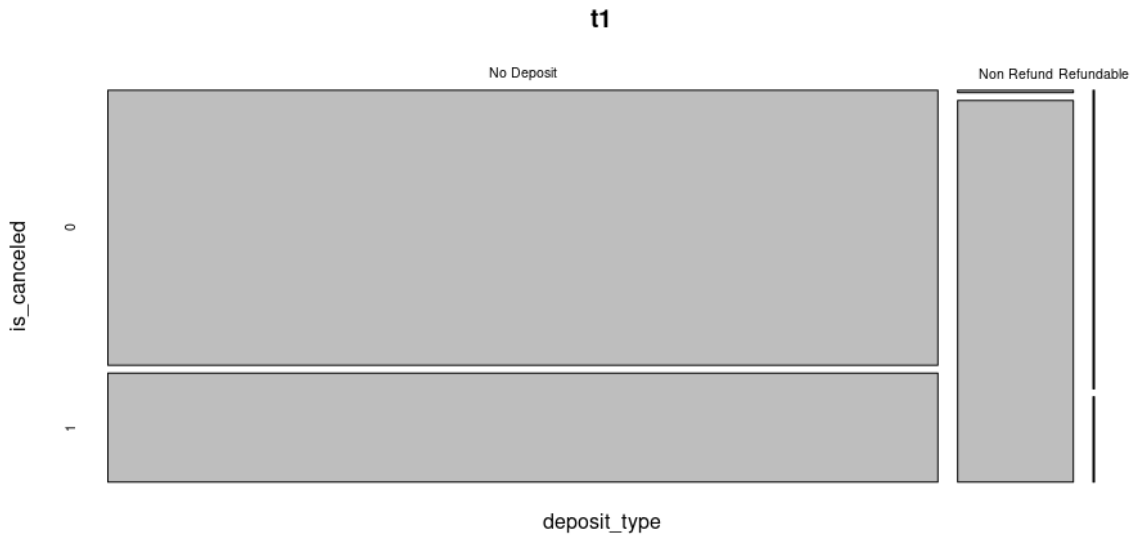
```
 2 arrival_date_year                       0
 3 arrival_date_week_number                0
 4 arrival_date_day_of_month               0
 5 stays_in_weekend_nights                 0
 6 stays_in_week_nights                    0
 7 adults                                  0
 8 is_repeated_guest                       0
 9 previous_cancellations                  0
10 previous_bookings_not_canceled          0
11 booking_changes                         0
12 agent                                   0
13 company                                 0
14 days_in_waiting_list                    0
15 adr                                     0
16 total_of_special_requests               0
   complete_rate      mean      sd      p0    p25
 *         <dbl>     <dbl>   <dbl>   <dbl>  <dbl>
 1             1  104.     107.       0      18
 2             1 2016.       0.707 2015    2016
 3             1   27.2     13.6      1      16
 4             1   15.8      8.78     1       8
 5             1    0.928    0.999    0       0
 6             1    2.50     1.91     0       1
 7             1    1.86     0.579    0       2
 8             1    0.0319   0.176    0       0
 9             1    0.0871   0.844    0       0
10             1    0.137    1.50     0       0
11             1    0.221    0.652    0       0
12             1   74.8    107.       0       7
13             1   10.8     53.9      0       0
14             1    2.32    17.6      0       0
15             1  102.      50.5     -6.38   69.3
16             1    0.571    0.793    0       0
      p50   p75  p100 hist
 *  <dbl> <dbl> <dbl> <chr>
 1   69     160   737 ▇▁▁▁▁
 2 2016    2017  2017 ▃▁▅▁▇
 3   28      38    53 ▇▇▇▇▅
 4   16      23    31 ▇▇▇▇▅
 5    1       2    19 ▇▁▁▁▁
 6    2       3    50 ▇▁▁▁▁
 7    2       2    55 ▇▁▁▁▁
 8    0       0     1 ▇▁▁▁▁
 9    0       0    26 ▇▁▁▁▁
10    0       0    72 ▇▁▁▁▁
11    0       0    21 ▇▁▁▁▁
12    9     152   535 ▇▁▂▁▁
13    0       0   543 ▇▁▁▁▁
14    0       0   391 ▇▁▁▁▁
15   94.6   126  5400 ▇▁▁▁▁
16    0       1     5 ▇▁▁▁▁
```

Pruebas de correlación

De acuerdo a las pruebas de normalidad se detectó que los datos no cumplen con esta condición por lo que se optó por utilizar prueba no paramétrica.

Comprobar si existe correlación entre el tipo de deposito y la cancelación

```
#verificar otras variables
attach(booking)
t1 <- table(deposit_type, is_canceled)
plot(t1)
t1.cor <-round(cor(t1),1)
t1.cor
install.packages("corrplot")
install.packages("PerformanceAnalytics")
library(corrplot)
library(PerformanceAnalytics)

#correlación
corrplot(t1.cor, method="number", type="upper")
chart.Correlation(t1, histogram = F, pch = 19)

> t1
is_canceled
deposit_type     0     1
  No Deposit 74947 29694
  Non Refund    93 14494
  Refundable   126    36

#no se agregan resultados ya que no tienen lógica los plot
```



Métodos de clasificación

Random Forest

```
#Instalar paquetes
urlPackage <- "https://cran.r-project.org/src/contrib/Archive/randomForest/randomForest_4.6-12.tar.gz"
install.packages(urlPackage, repos=NULL, type="source")
library(randomForest)

#Crear semilla, datos test y datos tain
set.seed(101)
tamano.total <- nrow(bforest)
tamano.entreno <- round(tamano.total*0.7)
datos.indices <- sample(1:tamano.total , size=tamano.entreno)
datos.entreno <- bforest[datos.indices,]
datos.test <- bforest[-datos.indices,]

#Modelo Random Forest
modelo <- randomForest(is_canceled~., data=datos.test)
modelo

#gráficos y resultados
varImpPlot(modelo)
plot(modelo)
legend("right", colnames(modelo$err.rate), lty = 1:5, col = 1:6)
importance(modelo2)

# Separar árboles
> split_var_1 <- sapply(seq_len(modelo$ntree),
+                       function(i) getTree(modelo, i, labelVar=TRUE)[1, "split var"])
> table(split_var_1)
split_var_1
```

Modelo

```
Call:
 randomForest(formula = is_canceled ~ ., data = datos.test
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 5

        OOB estimate of  error rate: 0.01%
Confusion matrix:
      0     1  class.error
0 22522     0 0.0000000000
1     2 13293 0.0001504325
> |
```

Importancia

```
importance(modelo)
                            MeanDecreaseGini
```

```
hotel                                64.451176
lead_time                          1060.414075
arrival_date_year                   145.024817
arrival_date_month                   78.903162
arrival_date_week_number            156.995166
arrival_date_day_of_month            92.282868
stays_in_weekend_nights              58.899494
stays_in_week_nights                 97.893647
adults                               40.672072
children                             16.697532
babies                                1.422965
meal                                 43.000536
country                            1390.876412
market_segment                      662.677977
distribution_channel                148.391380
is_repeated_guest                    18.708229
previous_cancellations              597.263148
previous_bookings_not_canceled       49.835286
reserved_room_type                   56.435486
assigned_room_type                  197.988419
booking_changes                     232.813508
deposit_type                       3112.127408
agent                               331.114216
company                              27.670444
days_in_waiting_list                  9.898190
customer_type                       225.226143
adr                                 259.516468
required_car_parking_spaces         315.916987
total_of_special_requests           720.081914
reservation_status                27901.715443
reservation_status_date             782.833377
> importance(modelo2)
                               MeanDecreaseGini
hotel                              0.000000e+00
lead_time                          1.574528e-02
arrival_date_year                  0.000000e+00
arrival_date_month                 0.000000e+00
arrival_date_week_number           0.000000e+00
arrival_date_day_of_month          0.000000e+00
stays_in_weekend_nights            0.000000e+00
stays_in_week_nights               0.000000e+00
adults                             0.000000e+00
children                           0.000000e+00
babies                             0.000000e+00
meal                               0.000000e+00
country                            6.459493e-01
market_segment                     0.000000e+00
distribution_channel               0.000000e+00
is_repeated_guest                  0.000000e+00
previous_cancellations             0.000000e+00
previous_bookings_not_canceled     0.000000e+00
reserved_room_type                 0.000000e+00
assigned_room_type                 0.000000e+00
booking_changes                    0.000000e+00
deposit_type                       2.480106e+02
agent                              0.000000e+00
company                            0.000000e+00
days_in_waiting_list               0.000000e+00
customer_type                      1.772218e-01
adr                                0.000000e+00
required_car_parking_spaces        0.000000e+00
```

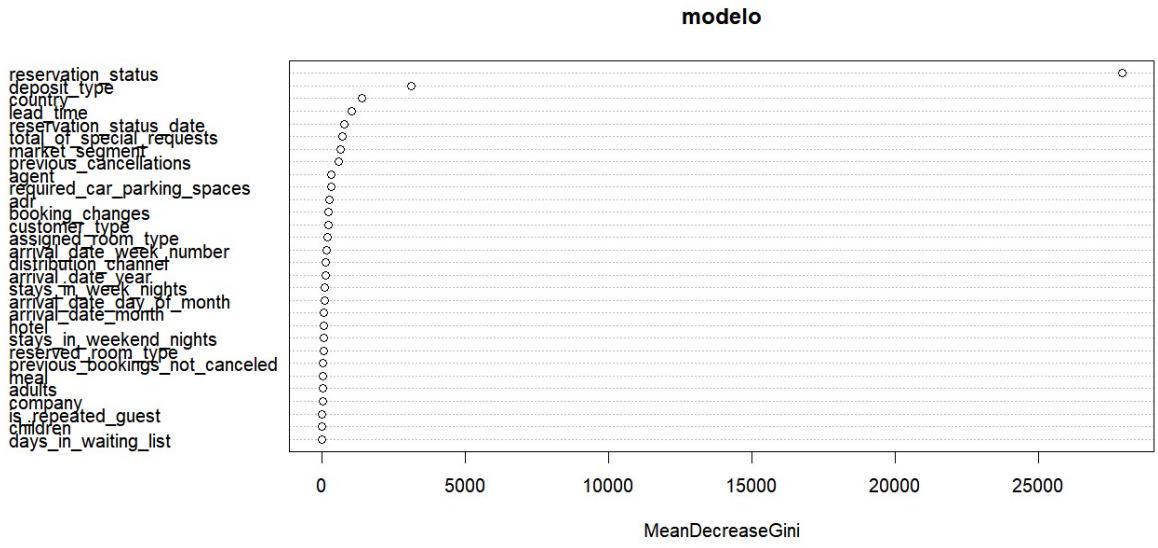
```
total_of_special_requests          0.000000e+00
reservation_status                 3.871516e+04
reservation_status_date            0.000000e+00
```

Matriz de confusión y predicción

```
> pred <- predict(modelo, newdata = datos.entreno)
> caret::confusionMatrix(pred, datos.entreno$is_canceled)
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 22522     0
         1     0 13295

               Accuracy : 1
                 95% CI : (0.9999, 1)
    No Information Rate : 0.6288
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 1

 Mcnemar's Test P-Value : NA

            Sensitivity : 1.0000
            Specificity : 1.0000
         Pos Pred Value : 1.0000
         Neg Pred Value : 1.0000
             Prevalence : 0.6288
         Detection Rate : 0.6288
   Detection Prevalence : 0.6288
      Balanced Accuracy : 1.0000

       'Positive' Class : 0
```

Se destaca de la matriz de confusión que el modelo analizó todos los datos.

Importancia de las variables



- Se excluye reservation_status ya que indica si fue cancelada o no
- Se rescatan del modelo:
  - deposit_type
  - country
  - lead_time
  - total_of_special_requests

Separación árboles

```
split_var_1
                            adr
                             17
                         adults
                              0
                          agent
                              0
     arrival_date_day_of_month
                              0
             arrival_date_month
                              0
      arrival_date_week_number
                              0
               arrival_date_year
                              0
             assigned_room_type
                             23
                         babies
                              0
                booking_changes
```

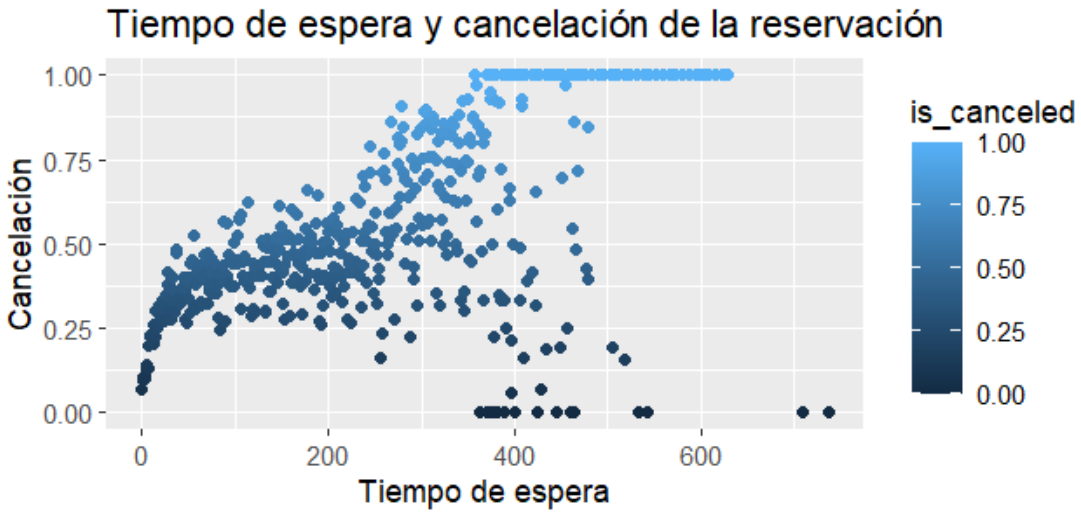
```
                           22
                     children
                            0
                      company
                            2
                      country
                           63
                customer_type
                            8
          days_in_waiting_list
                            2
                 deposit_type
                           86
          distribution_channel
                            7
                        hotel
                           12
             is_repeated_guest
                            1
                    lead_time
                           37
               market_segment
                           17
                         meal
                            0
previous_bookings_not_canceled
                            1
        previous_cancellations
                           40
   required_car_parking_spaces
                           20
            reservation_status
                           91
       reservation_status_date
                           21
            reserved_room_type
                            0
          stays_in_week_nights
                            0
       stays_in_weekend_nights
                            0
     total_of_special_requests
                           30
```

Grafica de las variables resultantes de Random Forest

```
#agrupar por lead_time (Tiempo de espera)
grouplead_time <- aggregate(booking["is_canceled"], by=booking["lead_time"], mean)
grouplead_time

grouplead_time %>%
  ggplot(aes(x=lead_time, y = (is_canceled), color = is_canceled))+
  geom_point()+
  geom_smooth(method = "lm", se = FALSE)+
  ggtitle("Tiempo de espera y cancelación de la reservación") +
  xlab("Tiempo de espera") +
  ylab("Cancelación")
```

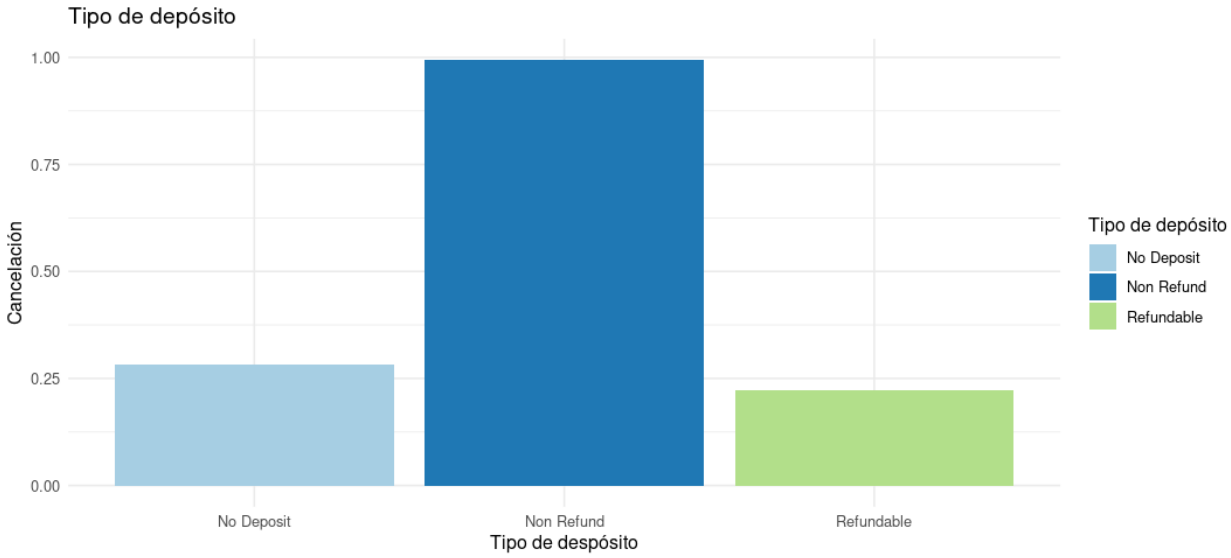
```
#agrupar por deposit_type (Tipo de deposito)
groupdeposit_type <- aggregate(booking["is_canceled"], by=booking["deposit_type"], mean)
groupdeposit_type

plot(factor(groupdeposit_type$deposit_type), groupdeposit_type$is_canceled)

groupdeposit_type %>%
  ggplot(aes(x= factor(deposit_type), y = is_canceled, fill= factor(deposit_type)))+
  geom_bar(stat = "identity")+
  theme_minimal()+
  ggtitle("Tipo de depósito") +
  xlab("Tipo de despósito") +
  ylab("Cancelación")+
  scale_fill_brewer(palette="Paired", name = "Tipo de depósito")


#agrupar por adr (Tarifa diaria promedio)
groupadr <- aggregate(booking["is_canceled"], by=booking["adr"], mean)
groupadr

groupadr %>%
  ggplot(aes(x=adr, y = (is_canceled)))+
  geom_point(shape = 18,  fill="blue", color="darkred", size=1)+
  xlim(0,500)+
  geom_smooth(method = "lm", se = FALSE)+
  ggtitle("Precio promedio por noche") +
  xlab("Precio promedio") +
  ylab("Cancelación")

#agrupar por market_segment (Tipo de segmento de mercado)
groupmarket_segment <- aggregate(booking["is_canceled"], by=booking["market_segment"], mean)
groupmarket_segment

plot(factor(groupmarket_segment$market_segment), groupmarket_segment$is_canceled)

groupmarket_segment %>%
  ggplot(aes(x= factor(market_segment), y = is_canceled, fill=factor(market_segment)))+
  geom_bar(stat = "identity")+
  theme_minimal()+
  ggtitle("Tipo de segmento de mercado") +
  xlab("Tipo de segmento de mercado") +
  ylab("Cancelación")+
  scale_fill_brewer(palette="Paired")


#agrupar por total_special_request (Total de requerimientos especiales)
grouprequest <- aggregate(booking["is_canceled"], by=booking["total_of_special_requests"], mean)
grouprequest


grouprequest %>%
  ggplot(aes(x= factor(total_of_special_requests), y = is_canceled))+
  geom_point()
```

Tiempo de espera



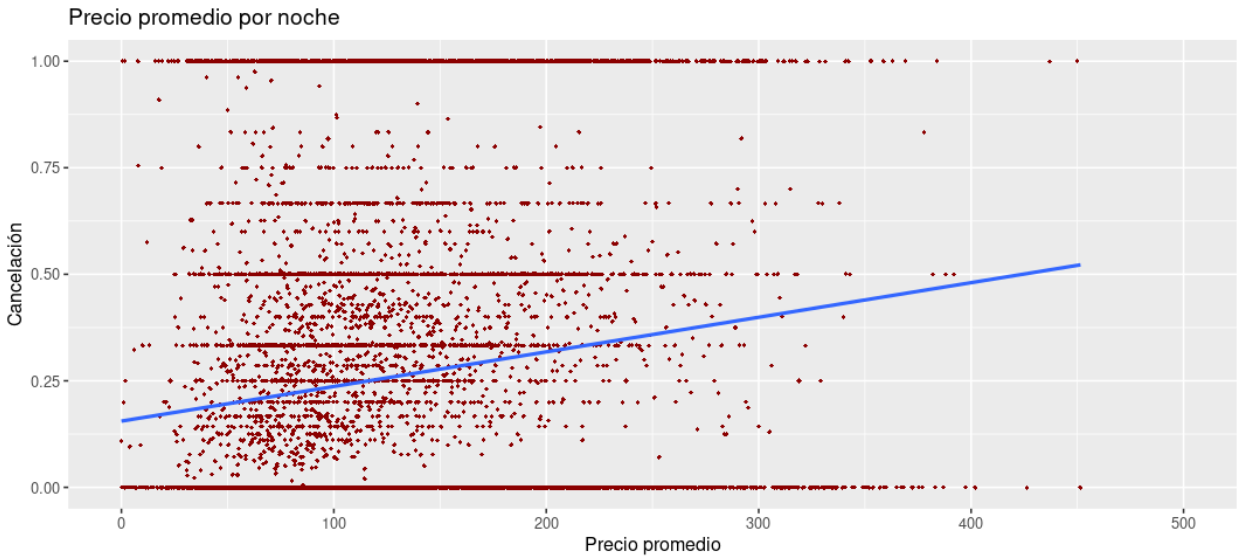
Entre mayor es el tiempo de espera aumenta la cancelación de las reservación.

Tipo de depósito

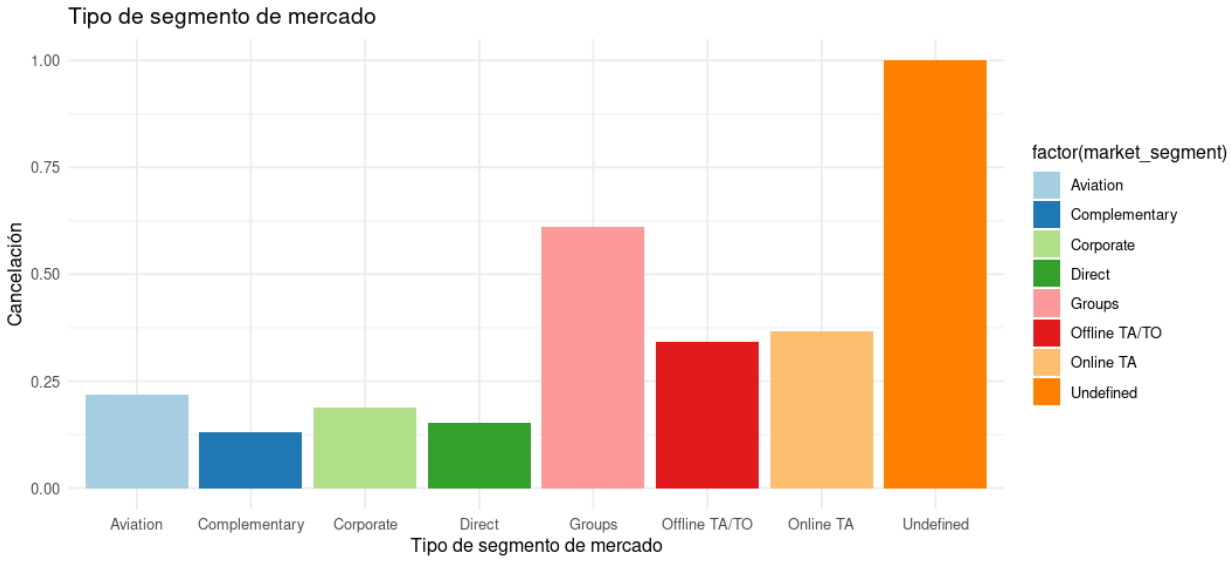


El 99% de los que pagaron la cifra completa cancelaron, es neesario revisar la base completa para tomar una decisión.

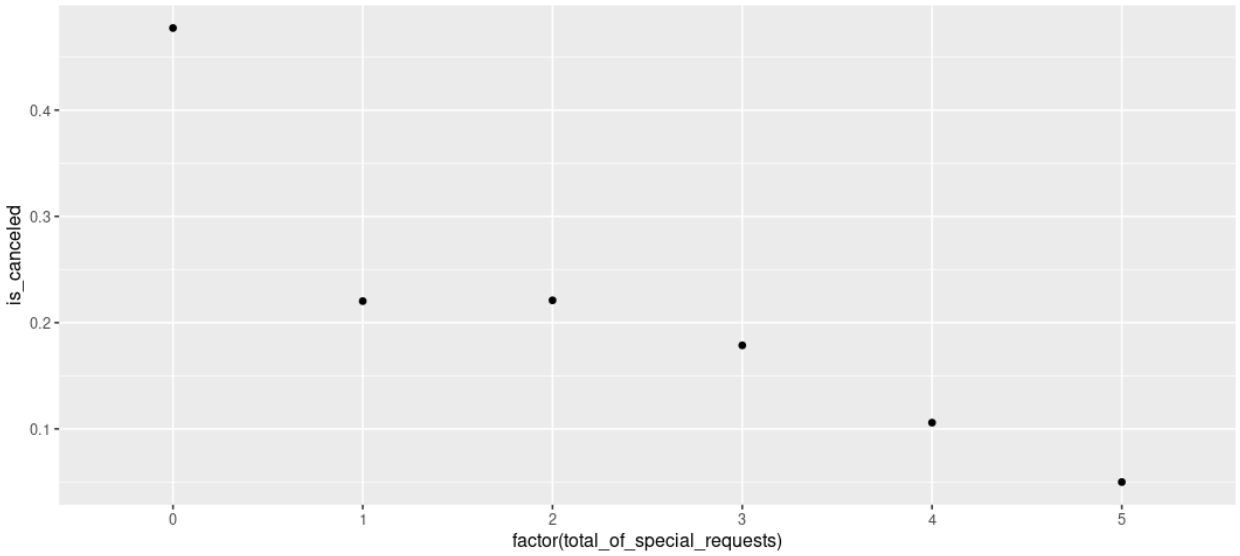
Precio promedio por noche



Tipo de segmento de mercado



Requisitos especiales



Regresión logística

```
#set.seed(1)
df <- bforest
nobs <- nrow(bforest)
itrain <- sample(nobs, 0.8 * nobs)
train <- df[itrain, ]
test <- df[-itrain, ]

#Regresión logística con todas las variables
rl <- glm(is_canceled ~., data = train)
rl
summary(rl)
#Regresión logística con las variables de random forest
rl2 <- glm(is_canceled ~ deposit_type + country + lead_time +
            market_segment + adr, family = binomial, data = train)
rl2
summary(rl2)
#Ajuste de la regresión logística sin la variable que no aporta
rl3 <- update(rl2, ~. -country)
summary(rl3)
#Ajuste de la regresión logística con la variable faltante
rl4 <- update(rl3, ~. +total_of_special_requests)
summary(rl4)
#coeficientes
rl4$coef
plot(rl4)
```

Coeficientes de la regresión logística

```
Call:
glm(formula = is_canceled ~ deposit_type + country + lead_time +
```

```
    market_segment + adr, family = binomial, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2576  -0.7322  -0.4590   0.1997   2.7651

Coefficients:
                             Estimate Std. Error z value
(Intercept)                -1.500e+01  5.354e+02  -0.028
deposit_typeNon Refund      5.475e+00  1.191e-01  45.978
deposit_typeRefundable     -3.617e-02  2.260e-01  -0.160
countryAGO                  1.482e+01  5.354e+02   0.028
countryAIA                 -1.305e-01  7.572e+02   0.000
countryALB                  1.246e+01  5.354e+02   0.023
countryAND                  1.507e+01  5.354e+02   0.028
countryARE                  1.536e+01  5.354e+02   0.029
countryARG                  1.257e+01  5.354e+02   0.023
countryARM                  1.377e+01  5.354e+02   0.026
countryASM                  5.838e-02  7.572e+02   0.000
countryATA                  9.178e-01  6.486e+02   0.001
countryATF                 -2.872e-01  7.572e+02   0.000
countryAUS                  1.251e+01  5.354e+02   0.023
countryAUT                  1.217e+01  5.354e+02   0.023
countryAZE                  1.360e+01  5.354e+02   0.025
countryBDI                  1.585e+00  7.572e+02   0.002
countryBEL                  1.222e+01  5.354e+02   0.023
countryBEN                  2.613e+01  6.112e+02   0.043
countryBFA                  4.973e-01  7.572e+02   0.001
countryBGD                  1.524e+01  5.354e+02   0.028
countryBGR                  1.193e+01  5.354e+02   0.022
countryBHR                  1.416e+01  5.354e+02   0.026
countryBHS                  1.158e+00  7.572e+02   0.002
countryBIH                  1.278e+01  5.354e+02   0.024
countryBLR                  1.348e+01  5.354e+02   0.025
countryBOL                  3.287e-01  5.721e+02   0.001
countryBRA                  1.324e+01  5.354e+02   0.025
countryBRB                  8.131e-01  6.182e+02   0.001
countryBWA                 -1.192e-01  7.572e+02   0.000
countryCAF                  4.464e-01  6.176e+02   0.001
countryCHE                  1.249e+01  5.354e+02   0.023
countryCHL                  1.265e+01  5.354e+02   0.024
countryCHN                  1.372e+01  5.354e+02   0.026
countryCIV                  1.369e+01  5.354e+02   0.026
countryCMR                  2.177e-01  5.664e+02   0.000
countryCN                   1.229e+01  5.354e+02   0.023
countryCOL                  1.285e+01  5.354e+02   0.024
countryCOM                  4.049e-02  6.510e+02   0.000
countryCPV                  1.426e+01  5.354e+02   0.027
countryCRI                  1.113e+01  5.354e+02   0.021
countryCUB                  1.134e+00  5.696e+02   0.002
countryCYM                  1.545e-01  7.572e+02   0.000
countryCYP                  1.264e+01  5.354e+02   0.024
countryCZE                  1.247e+01  5.354e+02   0.023
countryDEU                  1.198e+01  5.354e+02   0.022
countryDJI                 -1.592e-01  7.572e+02   0.000
countryDNK                  1.238e+01  5.354e+02   0.023
countryDOM                  1.344e+01  5.354e+02   0.025
countryDZA                  1.292e+01  5.354e+02   0.024
countryECU                  1.339e+01  5.354e+02   0.025
countryEGY                  1.356e+01  5.354e+02   0.025
countryESP                  1.283e+01  5.354e+02   0.024
```

```
countryEST                  1.233e+01  5.354e+02   0.023
countryETH                  1.361e+01  5.354e+02   0.025
countryFIN                  1.206e+01  5.354e+02   0.023
countryFRA                  1.234e+01  5.354e+02   0.023
countryFRO                  1.337e+01  5.354e+02   0.025
countryGAB                  1.397e+01  5.354e+02   0.026
countryGBR                  1.231e+01  5.354e+02   0.023
countryGEO                  1.426e+01  5.354e+02   0.027
countryGGY                  2.748e+01  6.552e+02   0.042
countryGHA                  1.406e+01  5.354e+02   0.026
countryGIB                  1.408e+01  5.354e+02   0.026
countryGLP                  2.687e+01  6.557e+02   0.041
countryGNB                  1.315e+01  5.354e+02   0.025
countryGRC                  1.282e+01  5.354e+02   0.024
countryGTM                  5.159e-01  5.984e+02   0.001
countryGUY                  7.913e-01  7.572e+02   0.001
countryHKG                  1.555e+01  5.354e+02   0.029
countryHND                  2.760e+01  7.572e+02   0.036
countryHRV                  1.271e+01  5.354e+02   0.024
countryHUN                  1.285e+01  5.354e+02   0.024
countryIDN                  1.497e+01  5.354e+02   0.028
countryIMN                  2.692e+01  7.572e+02   0.036
countryIND                  1.246e+01  5.354e+02   0.023
countryIRL                  1.260e+01  5.354e+02   0.024
countryIRN                  1.298e+01  5.354e+02   0.024
countryIRQ                  1.047e+00  5.587e+02   0.002
countryISL                  1.140e+01  5.354e+02   0.021
countryISR                  1.276e+01  5.354e+02   0.024
countryITA                  1.319e+01  5.354e+02   0.025
countryJAM                  4.666e-01  5.830e+02   0.001
countryJEY                  2.665e+01  5.939e+02   0.045
countryJOR                  1.182e+01  5.354e+02   0.022
countryJPN                  1.188e+01  5.354e+02   0.022
countryKAZ                  1.302e+01  5.354e+02   0.024
countryKEN                  5.989e-01  6.097e+02   0.001
countryKHM                  2.743e+01  6.557e+02   0.042
countryKNA                  1.092e+00  7.572e+02   0.001
countryKOR                  1.334e+01  5.354e+02   0.025
countryKWT                  1.290e+01  5.354e+02   0.024
countryLAO                  1.539e-01  6.557e+02   0.000
countryLBN                  1.312e+01  5.354e+02   0.024
countryLBY                  1.111e+00  5.699e+02   0.002
countryLCA                  4.353e-01  7.572e+02   0.001
countryLIE                  4.864e-01  7.572e+02   0.001
countryLKA                  8.119e-01  5.756e+02   0.001
countryLTU                  1.189e+01  5.354e+02   0.022
countryLUX                  1.310e+01  5.354e+02   0.024
countryLVA                  1.209e+01  5.354e+02   0.023
countryMAC                  1.612e+01  5.354e+02   0.030
countryMAR                  1.360e+01  5.354e+02   0.025
countryMCO                  1.276e+01  5.354e+02   0.024
countryMDG                  2.203e+00  7.572e+02   0.003
countryMDV                  1.511e+01  5.354e+02   0.028
countryMEX                  1.148e+01  5.354e+02   0.021
countryMKD                  1.225e+01  5.354e+02   0.023
countryMLI                  5.000e-01  7.572e+02   0.001
countryMLT                  1.323e+01  5.354e+02   0.025
countryMMR                  2.881e-01  7.572e+02   0.000
countryMNE                  1.299e+01  5.354e+02   0.024
countryMOZ                  1.258e+01  5.354e+02   0.024
countryMRT                 -3.662e-01  7.572e+02   0.000
```

```
countryMUS                    1.267e+01  5.354e+02   0.024
countryMWI                    5.158e-01  6.557e+02   0.001
countryMYS                    1.210e+01  5.354e+02   0.023
countryMYT                    2.617e+01  6.532e+02   0.040
countryNGA                    1.460e+01  5.354e+02   0.027
countryNLD                    1.221e+01  5.354e+02   0.023
countryNOR                    1.267e+01  5.354e+02   0.024
countryNPL                    4.974e-01  7.572e+02   0.001
countryNULL                   1.287e+01  5.354e+02   0.024
countryNZL                    1.100e+01  5.354e+02   0.021
countryOMN                    1.283e+01  5.354e+02   0.024
countryPAK                    1.426e+01  5.354e+02   0.027
countryPAN                    2.652e-01  5.711e+02   0.000
countryPER                    1.317e+01  5.354e+02   0.025
countryPHL                    1.443e+01  5.354e+02   0.027
countryPOL                    1.234e+01  5.354e+02   0.023
countryPRI                    1.265e+01  5.354e+02   0.024
countryPRT                    1.402e+01  5.354e+02   0.026
countryPRY                    2.089e-01  5.984e+02   0.000
countryPYF                    8.238e-01  7.572e+02   0.001
countryQAT                    1.496e+01  5.354e+02   0.028
countryROU                    1.263e+01  5.354e+02   0.024
countryRUS                    1.329e+01  5.354e+02   0.025
countryRWA                    6.659e-01  6.501e+02   0.001
countrySAU                    1.453e+01  5.354e+02   0.027
countrySDN                    1.848e+00  7.572e+02   0.002
countrySEN                    1.461e+01  5.354e+02   0.027
countrySGP                    1.388e+01  5.354e+02   0.026
countrySLE                   -9.023e-02  7.572e+02   0.000
countrySLV                   -5.289e-04  6.551e+02   0.000
countrySMR                    1.268e+00  7.572e+02   0.002
countrySRB                    1.079e+01  5.354e+02   0.020
countrySTP                    1.967e+00  7.572e+02   0.003
countrySUR                    3.121e-01  5.828e+02   0.001
countrySVK                    1.294e+01  5.354e+02   0.024
countrySVN                    1.271e+01  5.354e+02   0.024
countrySWE                    1.232e+01  5.354e+02   0.023
countrySYC                    1.420e+01  5.354e+02   0.027
countrySYR                    7.974e-01  6.098e+02   0.001
countryTGO                    4.698e-01  6.338e+02   0.001
countryTHA                    1.336e+01  5.354e+02   0.025
countryTJK                    2.729e+01  5.783e+02   0.047
countryTMP                    1.366e+01  5.354e+02   0.026
countryTUN                    1.400e+01  5.354e+02   0.026
countryTUR                    1.354e+01  5.354e+02   0.025
countryTWN                    1.285e+01  5.354e+02   0.024
countryTZA                    1.326e+01  5.354e+02   0.025
countryUGA                    3.980e-01  6.546e+02   0.001
countryUKR                    1.324e+01  5.354e+02   0.025
countryUMI                    2.717e+01  7.572e+02   0.036
countryURY                    1.283e+01  5.354e+02   0.024
countryUSA                    1.264e+01  5.354e+02   0.024
countryUZB                    1.412e+01  5.354e+02   0.026
countryVEN                    1.401e+01  5.354e+02   0.026
countryVNM                    1.310e+01  5.354e+02   0.024
countryZAF                    1.327e+01  5.354e+02   0.025
countryZMB                    1.363e+01  5.354e+02   0.025
countryZWE                    1.473e+01  5.354e+02   0.028
lead_time                     5.643e-03  9.897e-05  57.018
market_segmentComplementary -9.322e-01  2.187e-01  -4.263
market_segmentCorporate     -1.017e+00  1.859e-01  -5.469
```

```
market_segmentDirect        -9.241e-01  1.821e-01  -5.075
market_segmentGroups        -4.593e-01  1.822e-01  -2.521
market_segmentOffline TA/TO -8.000e-01  1.815e-01  -4.408
market_segmentOnline TA      6.181e-01  1.802e-01   3.431
market_segmentUndefined      1.449e+01  3.786e+02   0.038
adr                          3.582e-03  1.801e-04  19.887
                            Pr(>|z|)
(Intercept)                 0.977645
deposit_typeNon Refund       < 2e-16 ***
deposit_typeRefundable      0.872881
countryAGO                  0.977911
countryAIA                  0.999862
countryALB                  0.981432
countryAND                  0.977540
countryARE                  0.977118
countryARG                  0.981266
countryARM                  0.979486
countryASM                  0.999938
countryATA                  0.998871
countryATF                  0.999697
countryAUS                  0.981354
countryAUT                  0.981859
countryAZE                  0.979733
countryBDI                  0.998330
countryBEL                  0.981786
countryBEN                  0.965897
countryBFA                  0.999476
countryBGD                  0.977286
countryBGR                  0.982226
countryBHR                  0.978898
countryBHS                  0.998780
countryBIH                  0.980950
countryBLR                  0.979907
countryBOL                  0.999542
countryBRA                  0.980271
countryBRB                  0.998951
countryBWA                  0.999874
countryCAF                  0.999423
countryCHE                  0.981385
countryCHL                  0.981152
countryCHN                  0.979553
countryCIV                  0.979608
countryCMR                  0.999693
countryCN                   0.981685
countryCOL                  0.980849
countryCOM                  0.999950
countryCPV                  0.978756
countryCRI                  0.983418
countryCUB                  0.998411
countryCYM                  0.999837
countryCYP                  0.981165
countryCZE                  0.981413
countryDEU                  0.982147
countryDJI                  0.999832
countryDNK                  0.981551
countryDOM                  0.979978
countryDZA                  0.980744
countryECU                  0.980051
countryEGY                  0.979793
countryESP                  0.980877
countryEST                  0.981621
```

```
countryETH                0.979724
countryFIN                0.982036
countryFRA                0.981608
countryFRO                0.980076
countryGAB                0.979188
countryGBR                0.981657
countryGEO                0.978755
countryGGY                0.966549
countryGHA                0.979051
countryGIB                0.979026
countryGLP                0.967317
countryGNB                0.980412
countryGRC                0.980891
countryGTM                0.999312
countryGUY                0.999166
countryHKG                0.976836
countryHND                0.970923
countryHRV                0.981065
countryHUN                0.980847
countryIDN                0.977688
countryIMN                0.971640
countryIND                0.981438
countryIRL                0.981224
countryIRN                0.980665
countryIRQ                0.998505
countryISL                0.983017
countryISR                0.980988
countryITA                0.980350
countryJAM                0.999361
countryJEY                0.964201
countryJOR                0.982382
countryJPN                0.982303
countryKAZ                0.980599
countryKEN                0.999216
countryKHM                0.966638
countryKNA                0.998849
countryKOR                0.980120
countryKWT                0.980775
countryLAO                0.999813
countryLBN                0.980454
countryLBY                0.998445
countryLCA                0.999541
countryLIE                0.999487
countryLKA                0.998875
countryLTU                0.982278
countryLUX                0.980481
countryLVA                0.981983
countryMAC                0.975979
countryMAR                0.979734
countryMCO                0.980983
countryMDG                0.997678
countryMDV                0.977493
countryMEX                0.982892
countryMKD                0.981748
countryMLI                0.999473
countryMLT                0.980294
countryMMR                0.999696
countryMNE                0.980645
countryMOZ                0.981251
countryMRT                0.999614
countryMUS                0.981115
```

```
countryMWI                  0.999372
countryMYS                  0.981964
countryMYT                  0.968044
countryNGA                  0.978250
countryNLD                  0.981806
countryNOR                  0.981125
countryNPL                  0.999476
countryNULL                 0.980816
countryNZL                  0.983610
countryOMN                  0.980881
countryPAK                  0.978751
countryPAN                  0.999630
countryPER                  0.980372
countryPHL                  0.978492
countryPOL                  0.981611
countryPRI                  0.981146
countryPRT                  0.979111
countryPRY                  0.999721
countryPYF                  0.999132
countryQAT                  0.977708
countryROU                  0.981183
countryRUS                  0.980202
countryRWA                  0.999183
countrySAU                  0.978345
countrySDN                  0.998052
countrySEN                  0.978234
countrySGP                  0.979321
countrySLE                  0.999905
countrySLV                  0.999999
countrySMR                  0.998663
countrySRB                  0.983921
countrySTP                  0.997927
countrySUR                  0.999573
countrySVK                  0.980716
countrySVN                  0.981057
countrySWE                  0.981648
countrySYC                  0.978837
countrySYR                  0.998957
countryTGO                  0.999409
countryTHA                  0.980092
countryTJK                  0.962358
countryTMP                  0.979643
countryTUN                  0.979133
countryTUR                  0.979825
countryTWN                  0.980853
countryTZA                  0.980248
countryUGA                  0.999515
countryUKR                  0.980271
countryUMI                  0.971373
countryURY                  0.980880
countryUSA                  0.981159
countryUZB                  0.978960
countryVEN                  0.979126
countryVNM                  0.980479
countryZAF                  0.980226
countryZMB                  0.979686
countryZWE                  0.978049
lead_time                    < 2e-16 ***
market_segmentComplementary 2.02e-05 ***
market_segmentCorporate     4.52e-08 ***
market_segmentDirect        3.88e-07 ***
```

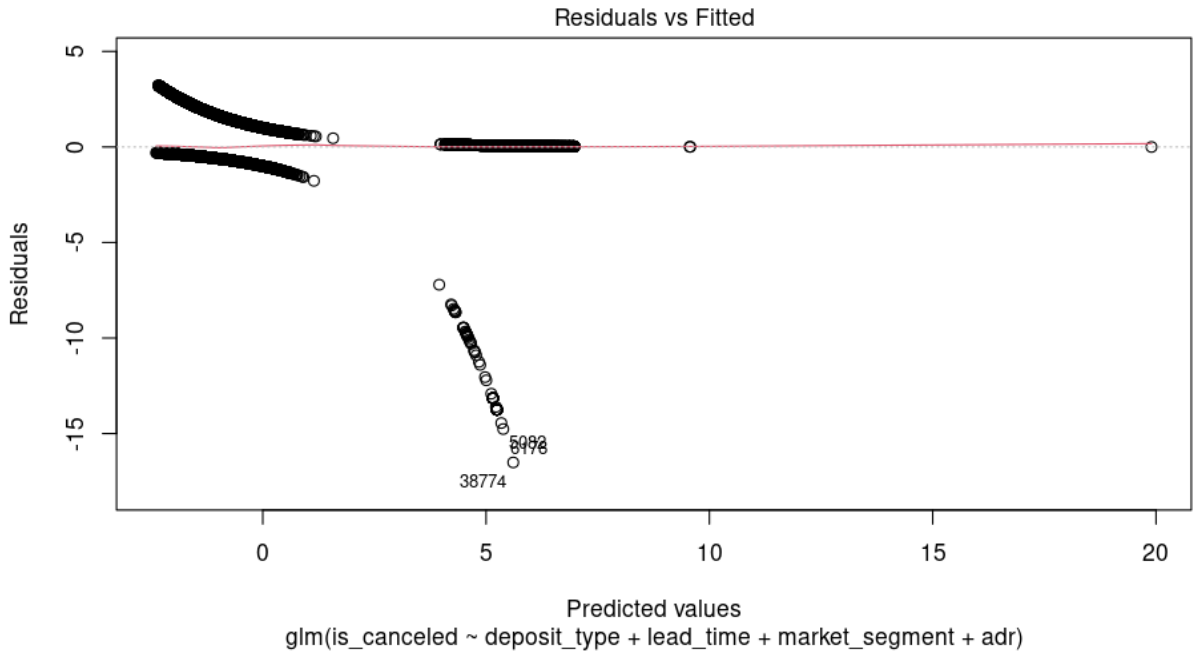
```
market_segmentGroups        0.011708 *
market_segmentOffline TA/TO 1.04e-05 ***
market_segmentOnline TA     0.000602 ***
market_segmentUndefined     0.969474
adr                          < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 125869  on 95511  degrees of freedom
Residual deviance:  86109  on 95331  degrees of freedom
AIC: 86471

Number of Fisher Scoring iterations: 12

> rl3 <- update(rl2, ~. -country)
> summary(rl3)

Call:
glm(formula = is_canceled ~ deposit_type + lead_time + market_segment +
    adr, family = binomial, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.3501  -0.8429  -0.5397   0.1737   2.2036

Coefficients:
                             Estimate Std. Error z value
(Intercept)                -1.540e+00  1.724e-01  -8.932
deposit_typeNon Refund      6.123e+00  1.186e-01  51.631
deposit_typeRefundable     -2.658e-01  2.067e-01  -1.286
lead_time                   3.925e-03  8.776e-05  44.724
market_segmentComplementary -4.413e-01  2.117e-01  -2.084
market_segmentCorporate     -6.177e-01  1.779e-01  -3.472
market_segmentDirect        -7.840e-01  1.740e-01  -4.507
market_segmentGroups        -2.633e-01  1.739e-01  -1.514
market_segmentOffline TA/TO -7.958e-01  1.734e-01  -4.591
market_segmentOnline TA      3.001e-01  1.720e-01   1.745
market_segmentUndefined      1.106e+01  5.124e+01   0.216
adr                          2.958e-03  1.710e-04  17.295
                            Pr(>|z|)
(Intercept)                  < 2e-16 ***
deposit_typeNon Refund       < 2e-16 ***
deposit_typeRefundable      0.198390
lead_time                    < 2e-16 ***
market_segmentComplementary 0.037156 *
market_segmentCorporate     0.000517 ***
market_segmentDirect        6.59e-06 ***
market_segmentGroups        0.130061
market_segmentOffline TA/TO 4.41e-06 ***
market_segmentOnline TA     0.081027 .
market_segmentUndefined     0.829173
adr                          < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 125869  on 95511  degrees of freedom
Residual deviance:  94305  on 95500  degrees of freedom
```

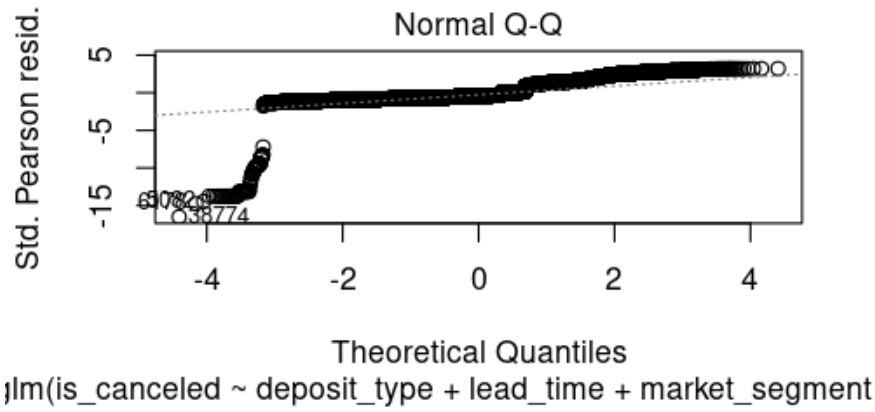
```
AIC: 94329

Number of Fisher Scoring iterations: 8
```

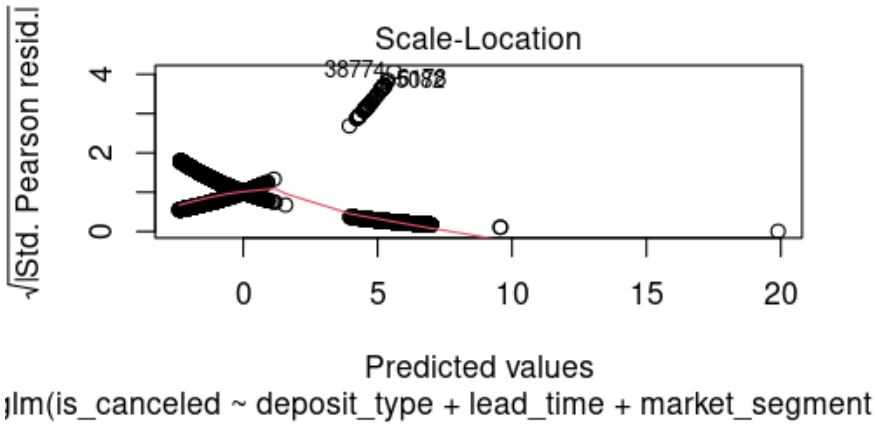
De acuerdo al modelo de regresión logística las variables que tienen mayor significancia de acuerdo al valor de P son:

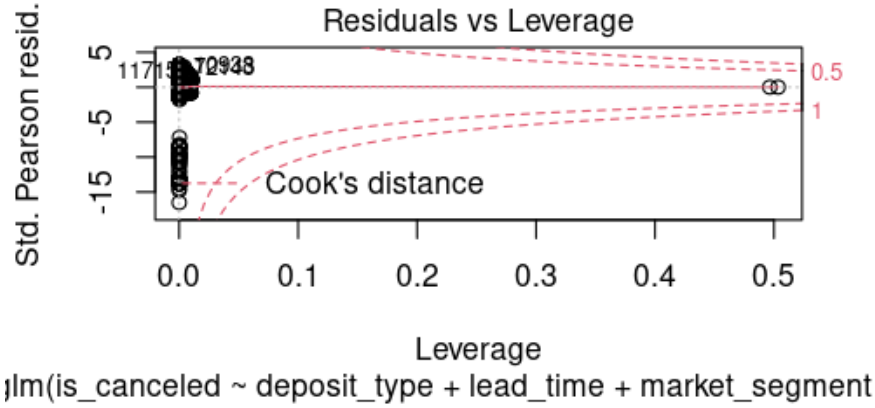
deposit_typeNon Refund < 2e-16 ***
deposit_typeRefundable 0.198390
lead_time < 2e-16 ***
market_segmentComplementary 0.037156 *
market_segmentCorporate 0.000517 ***
market_segmentDirect 6.59e-06 ***
market_segmentOffline TA/TO 4.41e-06 ***
adr < 2e-16 **

Se usará deposit_type, lead_time, market_segment y adr para ex




Normal Q-Q
Std. Pearson resid.
5
-5
-15
38774
-4
-2
0
2
4
Theoretical Quantiles
glm(is_canceled ~ deposit_type + lead_time + market_segment


Scale-Location
√|Std. Pearson resid.|
4
2
0
38774
0
5
10
15
20
Predicted values
glm(is_canceled ~ deposit_type + lead_time + market_segment


Residuals vs Leverage
Std. Pearson resid.
5
-5
-15
0.5
1
Cook's distance
0.0
0.1
0.2
0.3
0.4
0.5
Leverage
glm(is_canceled ~ deposit_type + lead_time + market_segment

SVM

```
## Preparar los datos
hotel_stays <- bforest %>%
  mutate(hotel = factor(hotel), children = case_when(children + babies > 0 ~ "children",
                               TRUE ~ "none"),
         required_car_parking_spaces = case_when(required_car_parking_spaces > 0 ~ "parking",
                                                 TRUE ~ "none")) %>%
                                                select(-reservation_status, -babies)


hotel_df <- hotel_stays%>%
  select(is_canceled, hotel, arrival_date_month, meal,
         adr, deposit_type, lead_time, adults, required_car_parking_spaces,
         total_of_special_requests, market_segment,
         stays_in_week_nights, stays_in_weekend_nights)%>%
  mutate_if(is.character,factor)

#Instalar biblioteca
install.packages("tidymodels")
library(tidymodels)

#Crear semilla, data train - test y normalizar los datos
hotel_split <- initial_split(hotel_df)

hotel_train <- training(hotel_split)
hotel_test <- testing(hotel_split)

hotel_rec <- recipe(is_canceled ~., data = hotel_train) %>%
  step_dummy(all_nominal(), -all_outcomes()) %>%
  step_zv(all_numeric())%>%
  step_normalize(all_numeric()) %>%
  prep()

#data para crear modelo
test_proc <-bake(hotel_rec, new_data = hotel_test)
hotel_rec_juice <- juice(hotel_rec)

#svm
best6 <- svm(is_canceled ~ .,  data = juice(hotel_rec),
             kernel = "radial")
best6
summary(best6)

#matriz de confusión train
table(juice(hotel_rec)$is_canceled, fitted(best6), dnn = c("Actual", "Predicho"))
pred <- predict(best6, juice(hotel_rec))

#matriz de conusión test
mac <- table(true = test_proc$is_canceled,
            pred = predict(best6,
                           newdata = test_proc))
mac

#accurancy
round(sum(diag(mac))/sum(colSums(mac)), 5)
```

Summary

```
> best6

Call:
svm(formula = is_canceled ~ ., data = juice(hotel_rec),
    kernel = "radial")


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1

Number of Support Vectors:  40492

> str(best6)
List of 30
 $ call           : language svm(formula = is_canceled ~ ., data = juice(hotel_rec), kernel = "radial")
 $ type           : num 0
 $ kernel         : num 2
 $ cost           : num 1
 $ degree         : num 3
 $ gamma          : num 0.0312
 $ coef0          : num 0
 $ nu             : num 0.5
 $ epsilon        : num 0.1
 $ sparse         : logi FALSE
 $ scaled         : logi [1:32] TRUE TRUE TRUE TRUE TRUE TRUE ...
 $ x.scale        :List of 2
```

Matriz de confusión

```
#train
> table(juice(hotel_rec)$is_canceled, fitted(best6), dnn = c("Actual", "Predicho"))
      Predicho
Actual     0     1
     0 52817  3555
     1 13773 19397

#Matriz de confusión con la base test
> mac <- table(true = test_proc$is_canceled,
+             pred = predict(best6,
+                            newdata = test_proc))
> mac
    pred
true     0     1
   0 17552  1242
   1  4622  6432

> #accurancy
> round(sum(diag(mac))/sum(colSums(mac)), 5)
[1] 0.80354

#Ajustar el modelo
>fit.hotel <- svm(is_canceled ~ ., data = juice(hotel_rec),
           kernel = "radial",
```

```
           decision.values = TRUE)

>summary(fit.hotel)
>str(fit.hotel)

fitted <- attributes(predict(fit.hotel, test_proc,
                             decision.values = TRUE))$decision.values

#Resultado del modelo ajustado
>mc <- table(true = test_proc,
            pred = predict(fit.hotel,
                           newdata = test_proc))
>mc
pred
true    No  Yes
  No  4163  657
  Yes   82   98

#accurancy
> round(sum(diag(mc))/sum(colSums(mc)), 5)
[1] 0.8522

# Verificar las proporciones
> rs <- apply(mc, 1, sum)
> r1 <- round(mc[1,]/rs[1], 5)
> r2 <- round(mc[2,]/rs[2], 5)
> rbind(No=r1, Yes=r2)
         No     Yes
No  0.86369 0.13631
Yes 0.45556 0.54444
```

El modelo tiene un accurancy del 80.35%, solo el 19.64% no quedo correctamente clasificado. Con el ajuste el accurancy llega a un 85%.

Weighted k-Nearest Neighbor Classifier

```
#Instalar bibliotecas
install.packages("kknn")
library(kknn)

#Ejecutar modelo
knn_spec <- nearest_neighbor()%>%
  set_engine("kknn")%>%
  set_mode("classification")

knn_fit <- knn_spec %>%
  fit(is_canceled~.,
      data=juice(hotel_rec))

#summary
> summary(knn_fit)
        Length Class            Mode
lvl      2     -none-           character
spec     5     nearest_neighbor list
fit     10     train.kknn       list
preproc  1     -none-           list
elapsed  1     -none-           list
```

```
> knn_fit
parsnip model object


Call:
kknn::train.kknn(formula = is_canceled ~ ., data = data, ks = min_rows(5,     data, 5))

Type of response variable: nominal
Minimal misclassification: 0.1929821
Best kernel: optimal
Best k: 5

#evaluar knn
set.seed(1234)
validation_splits <- mc_cv(juice(hotel_rec), prop =0.9,
                           strata = is_canceled)
validation_splits

knn_res <- fit_resamples(
  knn_spec,
  is_canceled ~.,
  validation_splits,
  control = control_resamples(save_pred = TRUE)
)
```

Conclusiones

- En este proyecto la finalidad es predecir si se cancelará o no la reservación para ello se utilizaron los métodos random forest, regresión logística y SVM.
- Del random forest se obtuvieron las variables que tienen mayor significancia para el objetivo,
- Una vez detectadas, con la regresión logística se midió su nivel de significancia.
- Con el modelo SVM se realizó la clasificación de las variables.
- Se sugiere hacer tuning del SVM para modelos futuros, así como ajuste en el random forest.
- Se sugiere estudiar el data con weghted k-nearest neighbor classifier.