Preliminary Results

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Project Overview

Customer: ABC Hotels.

Business Need: ABC Hotels would like to identify bookings that have a high risk of cancellation. The risk of cancellation should be a value between 0 and 1, so it can be interpreted as the probability of cancellation. With this capability, hotel management can target bookings that have a high risk (i.e., probability) of cancellation with additional advertisements and/or offers in an effort to prevent them from being cancelled.

Data: ABC Hotels has provided a data set containing over 35,000 bookings for which it is known whether or not the booking was cancelled. Students are required to use this data set provided in the zipped folder below.

Questions to Answer

1.) What is the label (i.e., the target or dependent variable) for the supervised classification problem?

2.) What data processing is needed and how will it be performed?

3.) What features will be initially included?

4.) What are the expected analytic and informational outcomes to be produced?

5.) How will the model be used in practice?

Below, we included the R code of within this analysis, we will be addressing and answering the questions above.

Preliminary Results R Code

```r
# Libraries Used
library(dplyr)

library(lubridate)

library(purrr)
library(caret)
library(ggplot2)
library(MESS)
library(reticulate)

library(tensorflow)

library(keras)

use_virtualenv("my_tf_workspace", required = TRUE)

getwd()

## [1] "/Users/doojerthekid/Documents/Merrimack Grad School
Documents/DSE6211/Final_Project"

# Read in CSV
hotel_df = read.csv("project_data.csv")

# Check for NA values
colSums(is.na(hotel_df))

##                           Booking_ID                         no_of_adults
##                                    0                                    0
##                       no_of_children                no_of_weekend_nights
##                                    0                                    0
##                    no_of_week_nights                    type_of_meal_plan
##                                    0                                    0
##           required_car_parking_space                   room_type_reserved
##                                    0                                    0
##                            lead_time                         arrival_date
##                                    0                                    0
##                  market_segment_type                       repeated_guest
##                                    0                                    0
##         no_of_previous_cancellations no_of_previous_bookings_not_canceled
##                                    0                                    0
##                    avg_price_per_room               no_of_special_requests
##                                    0                                    0
##                       booking_status
##                                    0

# No NA values in data frame. This is great!

# Check unique values of booking status. This will be our response variable
for our analysis.
unique(hotel_df$booking_status)

## [1] "not_canceled" "canceled"
```

Our response variable will be whether the customer canceled, or did not cancel their reservation. We want our response variable to be a binary variable. Let us have 0 represent not canceled and 1 represent canceled and let us convert booking_status to binary response variable. We also will remove the Booking_ID column as we will not be interested in what their booking identification number will be for our analysis.

```
hotel_df = hotel_df %>%
  mutate(booking_status = ifelse(booking_status == "canceled", 1, 0))

# We will not need the booking ID code for each observation. Let us remove
that
# variable
hotel_df = hotel_df[, -which(names(hotel_df) == "Booking_ID")]
```

Now, we are left with 16 total variables. With 1 response variable, we have 15 predictors to use in our modeling. Let us look at a summary of our variables.

Variable Summary

We will now run through what each of our variables in the data set represent. We will identify what type of variable each one is and make any changes we see necessary to help make simplify syntax.

booking_status: This is our response variable. It is a binary variable with values 0 and 1. This is a classification variable, meaning we will be constructing qualitative predictive models in our analysis.

no_of_adults: This represents the number of adults in the reservation. This is a discrete quantitative variable. Let us change the name of the variable from no_of_adults to just adults to help with syntax during modeling. We will have a snippet of code below for all of the variables that get a column name change.

no_of_children: This represents the number of children in the reservation. This is a discrete quantitative variable. We will change name to children for easier syntax.

no_of_weekend_nights: This represents the number of weekend nights in the reservation. This is a discrete quantitative variable. We will change name to weekend_nights for easier syntax.

no_of_week_nights: This represents the number of week nights in the reservation. This is a discrete quantitative variable. We will change name to week_nights for easier syntax.

type_of_meal_plan: This variable represents type of meal plan for each reservation. Let us look at the values.

```
unique(hotel_df$type_of_meal_plan)

## [1] "meal_plan_1"  "not_selected" "meal_plan_2"  "meal_plan_3"

# There is four options: not selected, 1, 2, or 3
# Check counts of each value
hotel_df %>%
  count(type_of_meal_plan)
```

```
##   type_of_meal_plan     n
## 1       meal_plan_1 27802
## 2       meal_plan_2  3302
## 3       meal_plan_3     5
## 4      not_selected  5129
```

```
#  type_of_meal_plan     n
# 1       meal_plan_1 27802
# 2       meal_plan_2  3302
# 3       meal_plan_3     5
# 4       not_selected  5129
# Let us change values to none, one, two or three
hotel_df = hotel_df %>%
  mutate(type_of_meal_plan = ifelse(type_of_meal_plan ==
                                      "not_selected", "meal_none",
type_of_meal_plan)) %>%
  mutate(type_of_meal_plan = ifelse(type_of_meal_plan ==
                                      "meal_plan_1", "meal_one",
type_of_meal_plan)) %>%
  mutate(type_of_meal_plan = ifelse(type_of_meal_plan ==
                                      "meal_plan_2", "meal_two",
type_of_meal_plan)) %>%
  mutate(type_of_meal_plan = ifelse(type_of_meal_plan ==
                                      "meal_plan_3", "meal_three",
type_of_meal_plan))
# Check count again to make sure code worked
hotel_df %>%
  count(type_of_meal_plan)
```

```
##   type_of_meal_plan     n
## 1         meal_none  5129
## 2          meal_one 27802
## 3        meal_three     5
## 4          meal_two  3302
```

```
# type_of_meal_plan     n
# 1              none  5129
# 2               one 27802
# 3             three     5
# 4               two  3302

# The code worked.
# This variable is a qualitative variable with four unique values.
# Let us change variable to meal_plan
```

required_car_parking_space: This represents number of parking spaces needed. This is a discrete quantitative variable. Let us change the variable name to parking_space.

room_type_reserved: This represents type of room reserved. Let us check values

```
unique(hotel_df$room_type_reserved)
```

```
## [1] "room_type1" "room_type4" "room_type2" "room_type6" "room_type5"
## [6] "room_type7" "room_type3"

# Check counts of each
hotel_df %>%
  count(room_type_reserved)

##   room_type_reserved     n
## 1         room_type1 28105
## 2         room_type2   692
## 3         room_type3     7
## 4         room_type4  6049
## 5         room_type5   263
## 6         room_type6   964
## 7         room_type7   158

# room_type_reserved     n
# 1         room_type1 28105
# 2         room_type2   692
# 3         room_type3     7
# 4         room_type4  6049
# 5         room_type5   263
# 6         room_type6   964
# 7         room_type7   158

# There are 7 unique values. Let us change the names of unique values
hotel_df = hotel_df %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type1", "room_one",
room_type_reserved)) %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type2", "room_two",
room_type_reserved)) %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type3", "room_three",
room_type_reserved)) %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type4", "room_four",
room_type_reserved)) %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type5", "room_five",
room_type_reserved)) %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type6", "room_six",
room_type_reserved)) %>%
  mutate(room_type_reserved = ifelse(room_type_reserved ==
                                      "room_type7", "room_seven",
room_type_reserved))
hotel_df %>%
  count(room_type_reserved)
```

```
##   room_type_reserved     n
## 1          room_five   263
## 2          room_four  6049
## 3           room_one 28105
## 4         room_seven   158
## 5           room_six   964
## 6         room_three     7
## 7           room_two   692

# Code worked.
# This is a qualitative variable with seven different unique values.
# We will change the variable name to room_type
```

lead_time: We will be removing the lead_time predictor. We will treat this as we did with the booking ID variable. This is more of a time stamp observation on the reservation. Therefore we will remove it.

```
hotel_df = hotel_df[, -which(names(hotel_df) == "lead_time")]
```

arrival_date: This represents arrival date of each customer. Let us pull just the months of the arrival time and group our observations into fours seasons rather than months. We will group them into Spring, Summer, Fall and Winter.

```
# We can use month function from the lubridate package for this
hotel_df = hotel_df %>%
  mutate(arrival_season = case_when(
      month(arrival_date) %in% c(1, 2, 12) ~ "winter",
      month(arrival_date) %in% c(3, 4, 5) ~ "spring",
      month(arrival_date) %in% c(6, 7, 8) ~ "summer",
      month(arrival_date) %in% c(9, 10, 11) ~ "fall"))
# Let us drop arrival date column now
hotel_df = hotel_df[, -which(names(hotel_df) == "arrival_date")]
```

market_segment_type: This is a qualitative variable with five unique values that represents how the engaged customer booked.

```
unique(hotel_df$market_segment_type)

## [1] "offline"       "online"        "corporate"     "aviation"
## [5] "complementary"
```

The customer either booked offline (phone call), online, corporate, aviation or complementary. Let us change the variable to market_type

repeated_guest: This is a binary qualitative variable with 0 representing not a repeat guest and 1 representing repeat guest

```
unique(hotel_df$repeated_guest)

## [1] 0 1
```

Let us change variable name to repeat_guest.

no_of_previous_cancellations: This represents the number of previous cancellations by customer.

```
unique(hotel_df$no_of_previous_cancellations)

## [1]  0  3  1  2 11  4  5 13  6
```

This is a continuous quantitative variable. Let us change name to previous_cancellations

no_of_previous_bookings_not_canceled: This represents number of previous bookings that were not canceled.

```
unique(hotel_df$no_of_previous_bookings_not_canceled)

##  [1]  0  5  1  3  4 12 19  2 15 17  7 20 16 50 13  6 14 34 18  8 10 23 11
49 47
## [26] 53  9 33 22 24 52 21 48 28 39 25 31 38 26 51 42 37 35 56 44 27 32 55
45 30
## [51] 57 46 54 43 58 41 29 40 36
```

This is a continuous quantitative variable. Let us change name to prev_not_cancel.

avg_price_per_room: This represents average booking price per room. This is a continuous quantitative variable.We will not change this variable for now.

no_of_special_requests: This represents number of special requests made by each customer. This is a continuous quantitative variable. We will change this variable to spec_requests

Let us change the variable names:

```
hotel_df = hotel_df %>%
  rename(adults = no_of_adults,
         children = no_of_children,
         weekend_nights = no_of_weekend_nights,
         week_nights = no_of_week_nights,
         meal_plan = type_of_meal_plan,
         parking_spaces = required_car_parking_space,
         room_type = room_type_reserved,
         market_type = market_segment_type,
         repeat_guest = repeated_guest,
         prev_cancel = no_of_previous_cancellations,
         prev_not_cancel = no_of_previous_bookings_not_canceled,
         spec_requests = no_of_special_requests)
```

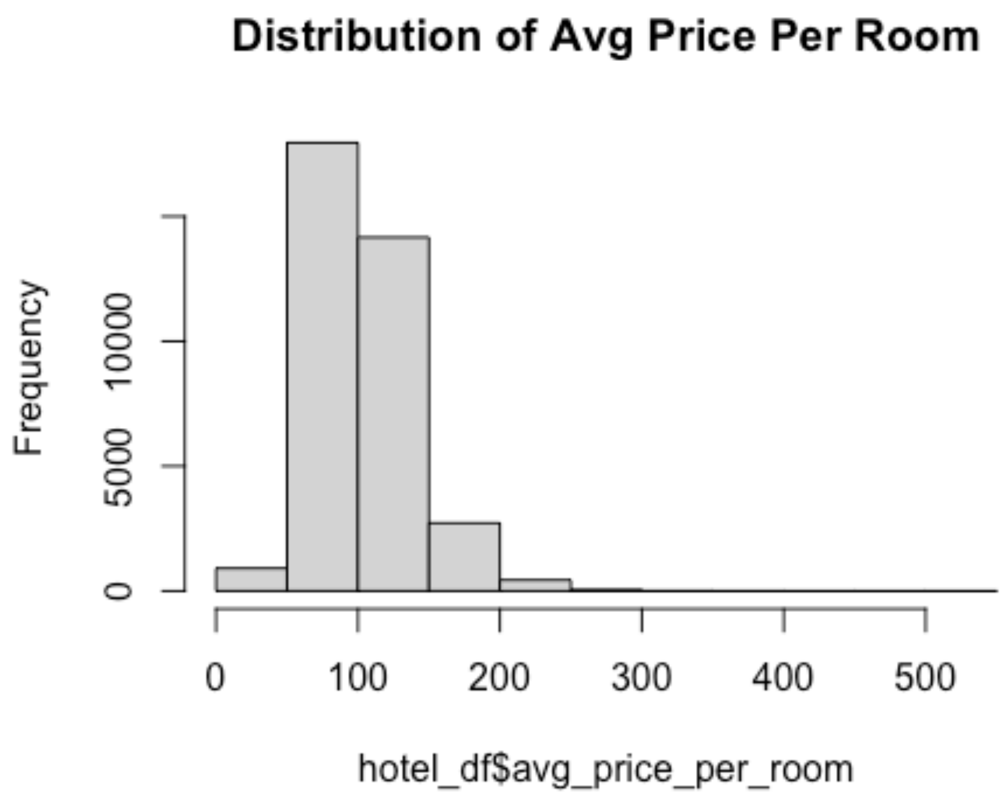
We have now summarized and started our data pre-processing. There will be more data pre-processing in the following feature engineering section.

Feature Engineering

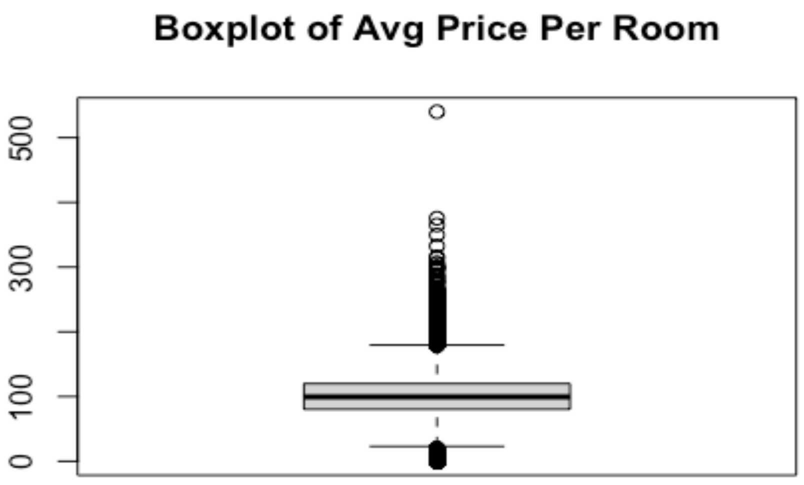
What variables do we want to include in our analysis? We have already removed the customer ID variable and lead time varaible.

Let us look at the average price per room variable. Looking at all of the other continuous variables, this specific continuous variable has the most unique values. Let us look at the distribution of it and see if we need to make any transformations to make distribution more normal:

```r
par(mfrow = c(1, 1))
hist(hotel_df$avg_price_per_room, main = "Distribution of Avg Price Per
Room")
```



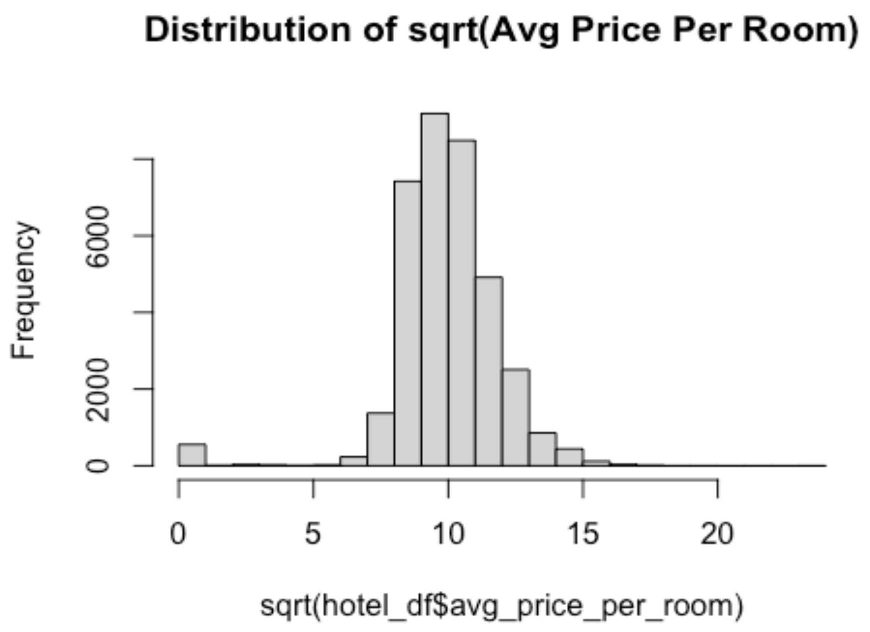
```r
boxplot(hotel_df$avg_price_per_room, main = "Boxplot of Avg Price Per Room")
```



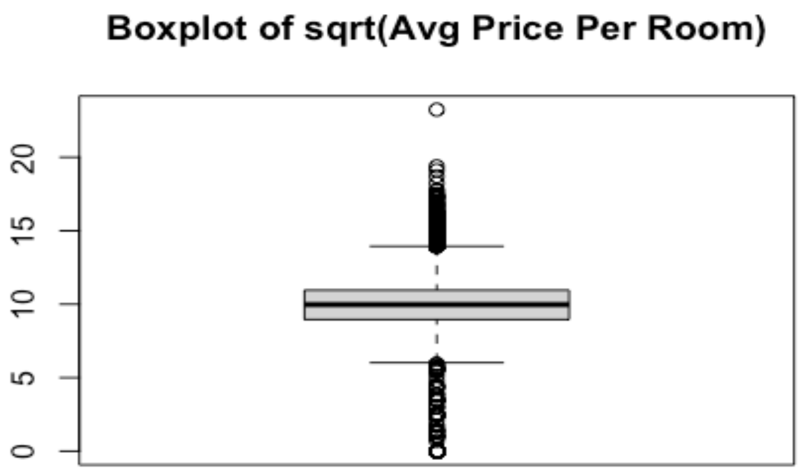
We see that the boxplot is heavily skewed right with a lot of outliers. Let us try some transformations to make the distribution more normal and minimize the number of outliers.

Square root:

```r
par(mfrow = c(1, 1))
hist(sqrt(hotel_df$avg_price_per_room), main = "Distribution of sqrt(Avg
Price Per Room)")
```



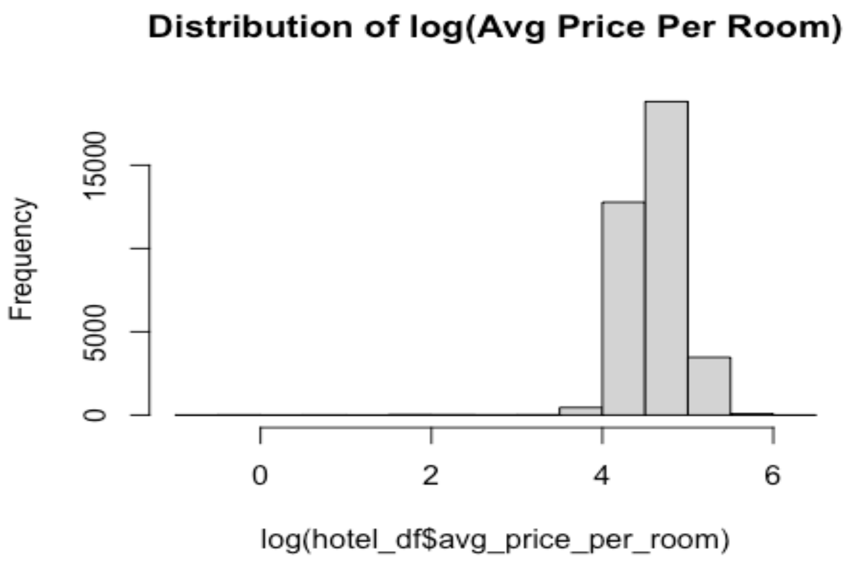
```r
boxplot(sqrt(hotel_df$avg_price_per_room), main = "Boxplot of sqrt(Avg Price
Per Room)")
```



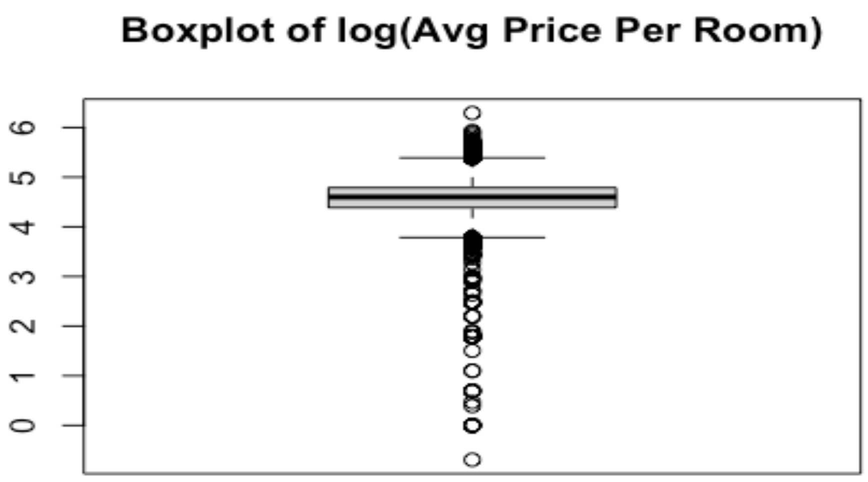
Made distribution slightly more normal. Still a lot of outliers.

Log:

```r
par(mfrow = c(1, 1))
hist(log(hotel_df$avg_price_per_room), main = "Distribution of log(Avg Price
Per Room)")
```



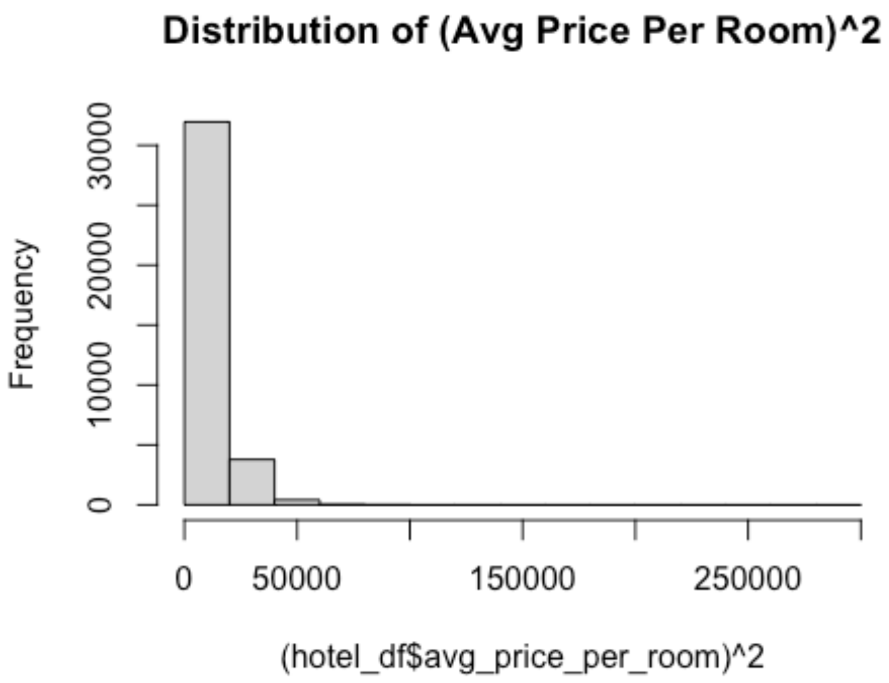
```r
boxplot(log(hotel_df$avg_price_per_room), main = "Boxplot of log(Avg Price
Per Room)")

## Warning in bplt(at[i], wid = width[i], stats = z$stats[, i], out =
## z$out[z$group == : Outlier (-Inf) in boxplot 1 is not drawn
```



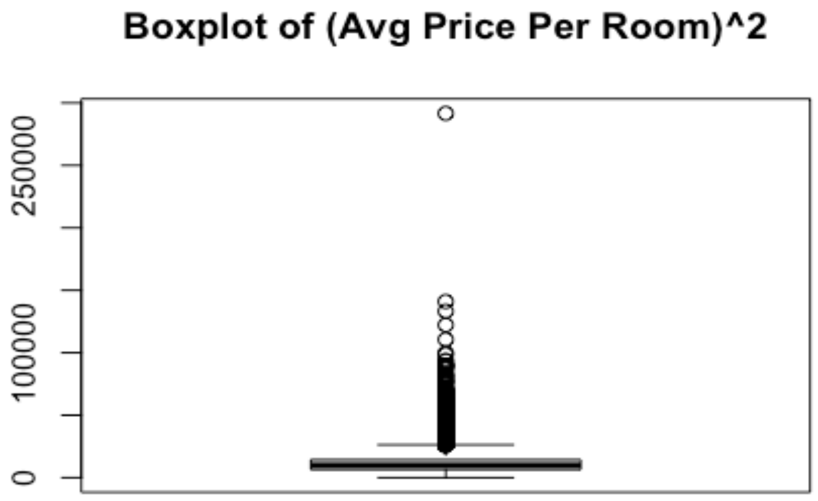
This did not make distribution more normal.

Squared:

```r
par(mfrow = c(1, 1))
hist((hotel_df$avg_price_per_room)^2, main = "Distribution of (Avg Price Per
Room)^2")
```



```
boxplot((hotel_df$avg_price_per_room)^2, main = "Boxplot of (Avg Price Per
Room)^2")
```



This did not make distribution more normal. The transformations did not help minimize the outliers or make the distribution more normal. Therefore, we will not be transforming this variable for our analysis.

One-Hot Encoding Categorical Variables

Now let us focus on one-hot encoding all of our categorical variables. Let us first convert all of our character variables to factors. Once the variables are converted to factors, we can then one-hot encode them. Once that is done, we then want to scale all the non-response variables.

```
# Let us find all of the character variables
character_variables = hotel_df %>%
  keep(is.character) %>%
  names()
print(character_variables)

## [1] "meal_plan"      "room_type"      "market_type"    "arrival_season"

# Now, let us convert all the character variables to factors
hotel_df = hotel_df %>%
  mutate(meal_plan = as.factor(meal_plan),
         room_type = as.factor(room_type),
         market_type = as.factor(market_type),
         arrival_season = as.factor(arrival_season))

# Confirm variables were converted to factors
factor_variables = hotel_df %>%
  keep(is.factor) %>%
  names()
print(factor_variables)

## [1] "meal_plan"      "room_type"      "market_type"    "arrival_season"

# Now, let us one-hot encode our factor variables
dummy_vars = dummyVars(~ meal_plan + room_type + market_type +
arrival_season,
                       data = hotel_df,
                       levelsOnly = TRUE,
                       fullRank = TRUE)
encoded_hotel_df = predict(dummy_vars, newdata = hotel_df)

# Now let us combine data hotel_df and encoded_hotel_df
hotel_df = cbind(hotel_df, encoded_hotel_df)

# Now let us remove our original categorical variables
hotel_df = hotel_df[, -which(names(hotel_df) == "meal_plan")]
hotel_df = hotel_df[, -which(names(hotel_df) == "room_type")]
hotel_df = hotel_df[, -which(names(hotel_df) == "market_type")]
hotel_df = hotel_df[, -which(names(hotel_df) == "arrival_season")]
```

```
# Now, let us scale all of the predictors in the data frame. We will not be
scaling the response variable. This will conclude our data pre-processing.
After that, we can start building our neural networks
response_var = hotel_df$booking_status
predictors_scaled = scale(hotel_df[, -which(names(hotel_df) ==
"booking_status")])
hotel_df = cbind(response_var, as.data.frame(predictors_scaled))
hotel_df = hotel_df %>%
  rename(booking_status = response_var)
```

Analysis Gameplan

This will be a qualitative regression analysis. Our response variable is a binary qualitative variable with two values: 0 for not-cancelled and 1 for cancelled reservation. We have 26 predictor variables and the 1 response variable for our analysis.

What is our goal? Our goal is to fit a predictive model to help the ABC Hotels to identify bookings that have a high risk of cancellation using the data set given. The risk of cancellation will be a value between 0 and 1. The closer the probability is to 1, the higher risk of cancellation. Since we are trying to predict a qualitative response variable, we will fit at least one dense neural network model. In this portion of the project, we will specify the following aspects of the neural network(s) and discuss why/how they were chosen: number of layers, number of units for each layer, activation functions for each layer, loss function and optimization algorithm.

We have already started our data pre-processing above. We have one-hot encoded our categorical variables and scaled all of our predictors.

We will create a training and test data set. We will train the model using the training data set and will use that trained model to predict the response variable in the test set. We will then be using confidence matrices, ROC, AUC, Confidence Curves, etc. to measure accuracy.

We will evaluate the neural networks using learning curves on training and validation sets. Is the model(s) underfitting or overfitting? Based on this, changes will be made to the architecture of the dense neural network(s). Based on the evaluation of the preliminary model(s), we will provide further data processing and feature engineering steps that will be implemented and investigated for the Final Report.

Training and Test Data

Let us look at the dimension of our data set:

```
dim(hotel_df)

## [1] 36238    27
```

There are 36238 observations and 27 variables. Let us define our training and test data. Since we have a good amount of observations, will be using 70% of our data to be the training data and 30% to be our test data.

```r
set.seed(1)
train = sample(nrow(hotel_df), 0.7 * nrow(hotel_df))
train_df = hotel_df[train, ]
test_df = hotel_df[-train, ]
```

We have 25366 observations in our training data and 10872 observations in our test data. These data sets will be used to train our neural networks. We will use the trained neural network models to predict our booking_status response variables in the the test data.

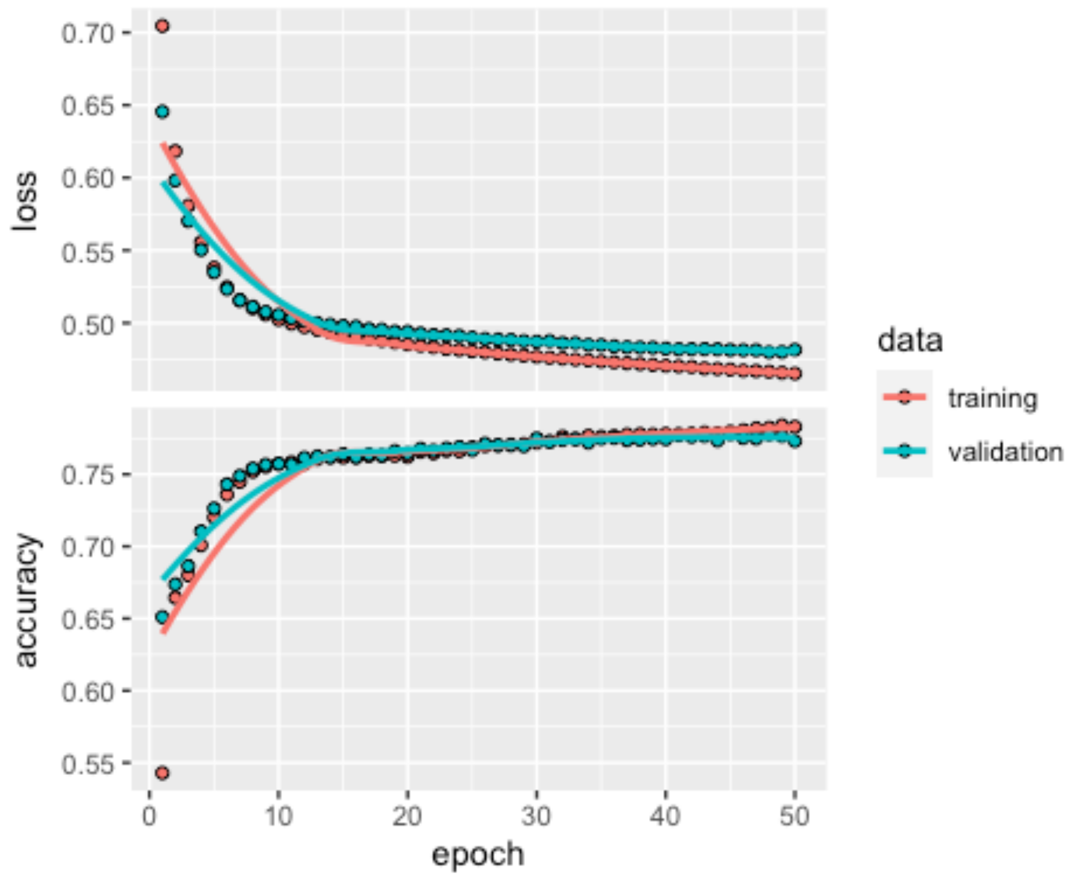
Neural Network Model

Let us fit a neural network model on the training data and use that to predict our test data. First we will need to separate the training features and labels and the test features and labels. Once that is done, we can choose how many nodes we want in each layer. We will use the rectified linear unit (relu) as the activation function in the intermediate layers. The final layer will use a sigmoid activation. This will output a probability between 0 and 1, indicating how likely a customer is to the target 1, which would represent them cancelling their reservation. Since our problem is a binary classification problem, we will use the binary_crossentropy loss function. We will use the rmsprop optimizer. We will use accuracy as our metric.

We will start with two layers. The first layer will have 20 nodes and the second layer will have 10. We will start with 100 epochs, a batch size of 100 and a validation split of 0.3. This means that 70% of our training data will be used to train the model and 30% of our training data will be used to validate the trained model.

We will then used the train model to predict the booking status labels in our test data.

```r
# Training data
train_feat = train_df[, -which(names(train_df) == "booking_status")]
train_feat = as.matrix(train_feat)

train_labels = train_df[, which(names(train_df) == "booking_status")]
train_labels = as.matrix(train_labels)

# Test data
test_feat = test_df[, -which(names(test_df) == "booking_status")]
test_feat = as.matrix(test_feat)

test_labels = test_df[, which(names(test_df) == "booking_status")]
test_labels = as.matrix(test_labels)

# Fit neural network model
model = keras_model_sequential(list(
  layer_dense(units = 20, activation = "relu"),
  layer_dense(units = 10, activation = "relu"),
  layer_dense(units = 1, activation = "sigmoid")
))

compile(model,
        optimizer = "rmsprop",
        loss = "binary_crossentropy",
        metrics = "accuracy")

history = fit(model, train_feat, train_labels,
              epochs = 50, batch_size = 500, validation_split = 0.3)

plot(history)
```

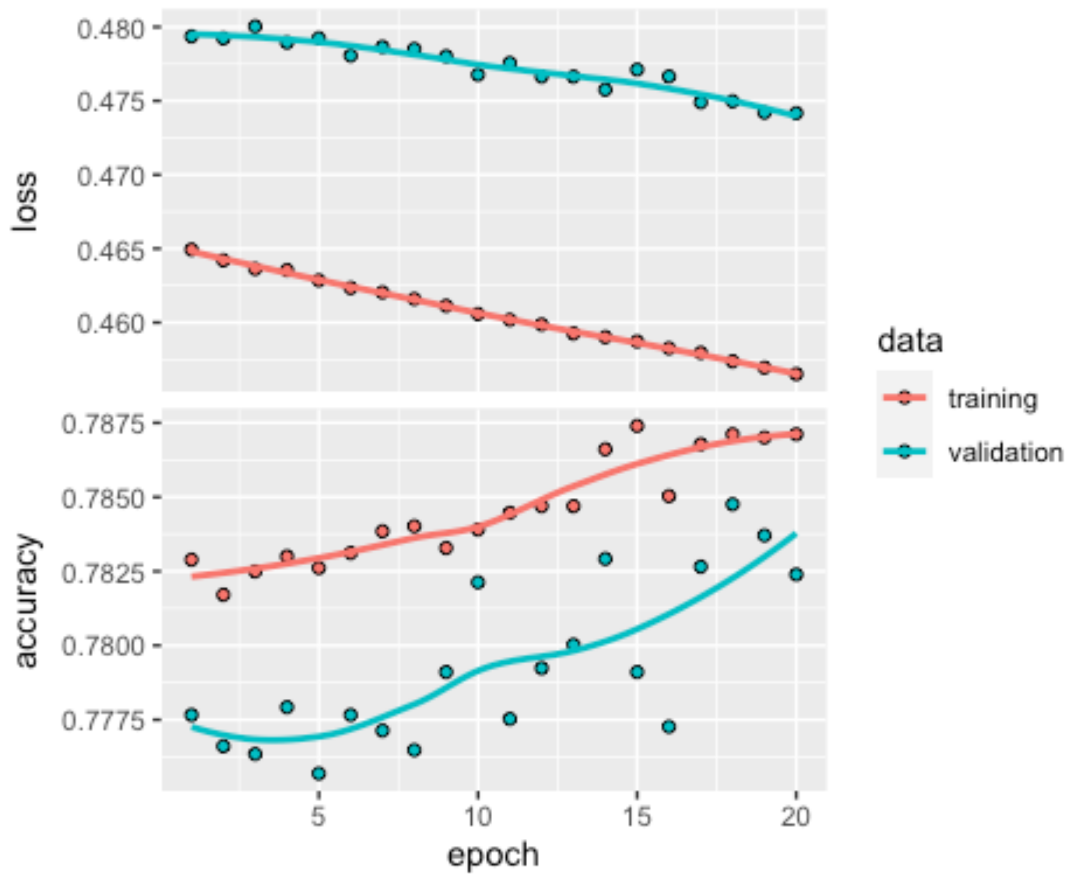


```
set.seed(123)
results = model %>%
  evaluate(test_feat, test_labels)

## 340/340 - 0s - loss: 0.4766 - accuracy: 0.7796 - 269ms/epoch - 790us/step

print(results)

##      loss  accuracy
## 0.4766257 0.7796174
```

We used 50 epochs and a batch size of 500. We used a validation split of 30%.

We see that our validation accuracy starts to level out around 20 epochs. This model produced an accuracy of 78% when predicting the test labels. Let us change the epoch size to 20.

```r
history = fit(model, train_feat, train_labels,
              epochs = 20, batch_size = 500, validation_split = 0.3)

plot(history)
```

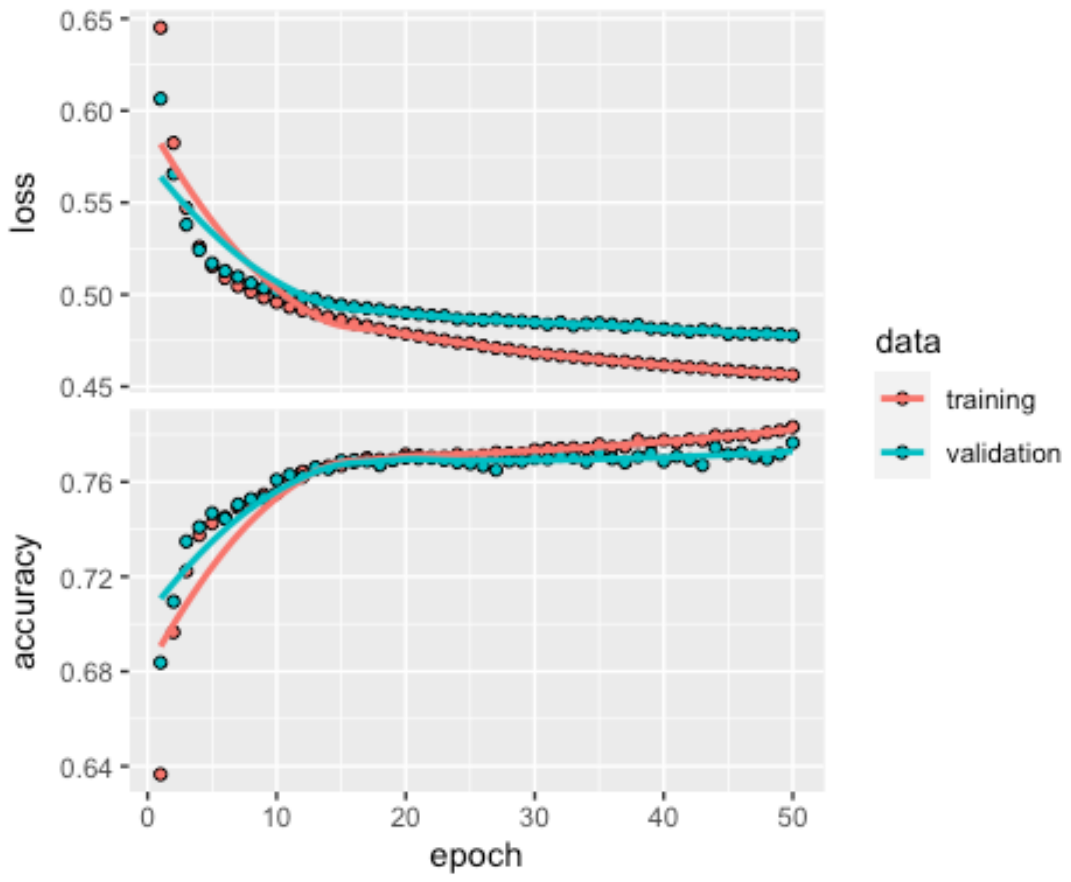


```r
set.seed(123)
results = model %>%
  evaluate(test_feat, test_labels)

## 340/340 - 0s - loss: 0.4700 - accuracy: 0.7815 - 267ms/epoch - 785us/step

print(results)

##      loss  accuracy
## 0.4699659 0.7814569
```

Now let us add another layer into our neural network model to see if we can increase the accuracy of predicting our test labels. Let us use 5 nodes in the layer that we added.

```r
model_1 = keras_model_sequential(list(
  layer_dense(units = 20, activation = "relu"),
  layer_dense(units = 10, activation = "relu"),
  layer_dense(units = 5, activation = "relu"),
  layer_dense(units = 1, activation = "sigmoid")
))
```

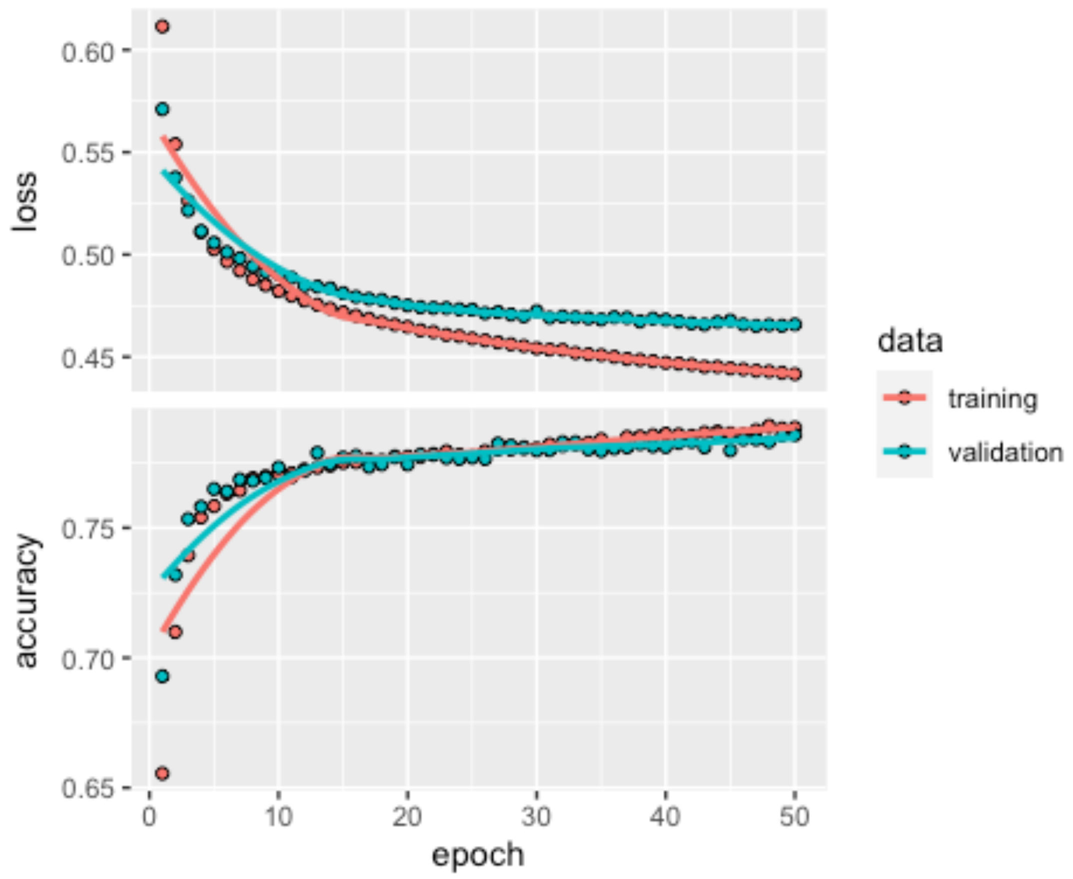
```
compile(model_1,
        optimizer = "rmsprop",
        loss = "binary_crossentropy",
        metrics = "accuracy")

history = fit(model_1, train_feat, train_labels,
              epochs = 50, batch_size = 500, validation_split = 0.3)

plot(history)
```



```
set.seed(123)
results = model_1 %>%
  evaluate(test_feat, test_labels)

## 340/340 - 0s - loss: 0.4661 - accuracy: 0.7864 - 272ms/epoch - 799us/step

print(results)

##      loss  accuracy
## 0.4661362 0.7864239
```

This produced a similar test accuracy rate of 79%. Since the first model was less complex, let us revert back to that and double the nodes in each layer to see if that increases accuracy.

```
model_2 = keras_model_sequential(list(
  layer_dense(units = 40, activation = "relu"),
  layer_dense(units = 20, activation = "relu"),
  layer_dense(units = 1, activation = "sigmoid")
))

compile(model_2,
        optimizer = "rmsprop",
        loss = "binary_crossentropy",
        metrics = "accuracy")

history = fit(model_2, train_feat, train_labels,
              epochs = 50, batch_size = 500, validation_split = 0.3)

plot(history)
```

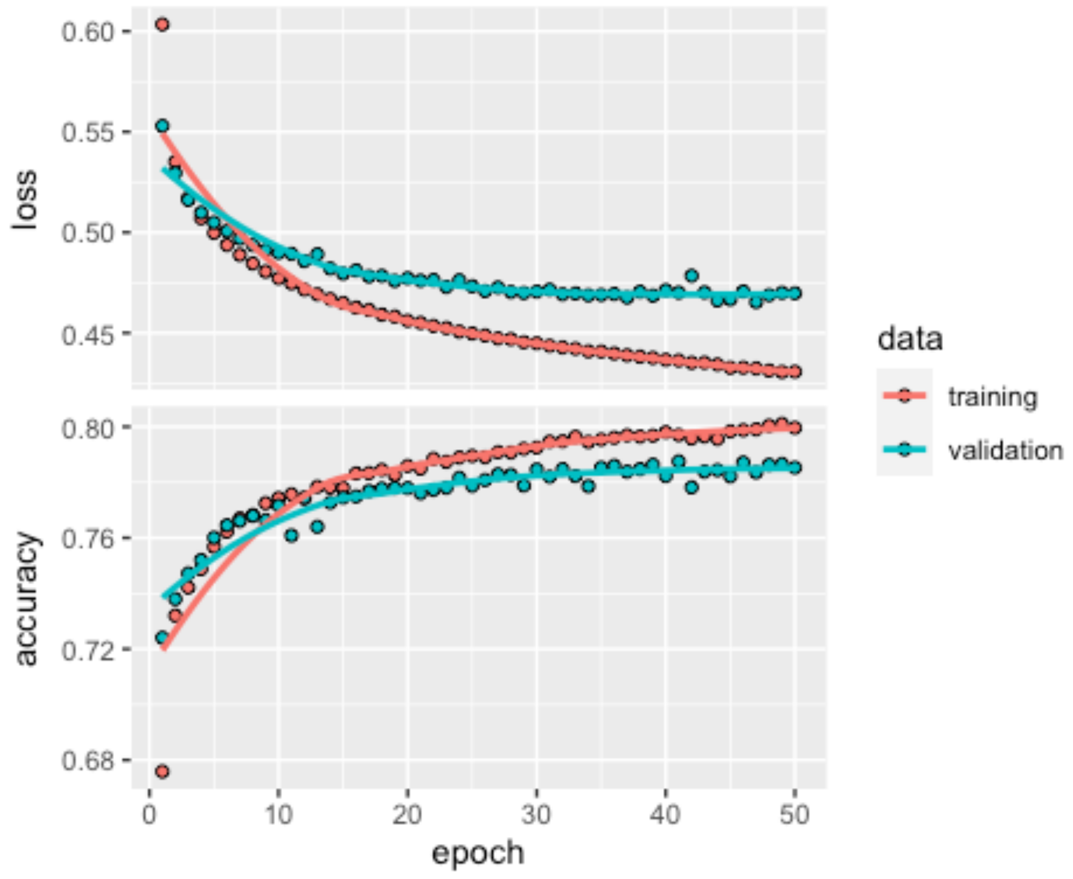


```
set.seed(123)
results = model_2 %>%
  evaluate(test_feat, test_labels)

## 340/340 - 0s - loss: 0.4594 - accuracy: 0.7924 - 268ms/epoch - 787us/step

print(results)
```

```
##      loss  accuracy
## 0.4594048 0.7924025
```

This produced a slightly better test accuracy of approximately 79%. Not much improvement. Since this model was slightly better, let us re-fit our neural network model with a decrease in batch size to see if that helps.

```
model_3 = keras_model_sequential(list(
  layer_dense(units = 40, activation = "relu"),
  layer_dense(units = 20, activation = "relu"),
  layer_dense(units = 1, activation = "sigmoid")
))

compile(model_3,
        optimizer = "rmsprop",
        loss = "binary_crossentropy",
        metrics = "accuracy")

history = fit(model_3, train_feat, train_labels,
              epochs = 50, batch_size = 250, validation_split = 0.3)

plot(history)
```



```
set.seed(123)
results = model_3 %>%
  evaluate(test_feat, test_labels)

## 340/340 - 0s - loss: 0.4548 - accuracy: 0.7927 - 293ms/epoch - 863us/step

print(results)

##      loss  accuracy
## 0.4548332 0.7926784
```

This also produced a test accuracy of about 79%.

Measure Neural Network Model

Let us use the model that had 50 epochs, 500 batch size and the three activation layers, with the final layer being our output. This is model_2 from above. Here we will measure neural network model and make assumptions on how to increase model performance. Let us use a ROC curve here to measure the model performance. Since our classification is binary, we will use 0.5 as our threshold to convert the probability from our model to predictions. If a prediction is greater than 0.5, it would belong to the canceled reservation classification. If the predictions is less than 0.5, it would belong to the non-canceled classification.

We will calculate the false positive rate (FPR) and true positive rate (TPR) for these predictions. The FPR is the percentage of incorrect predictions we make for observations that belong to the negative class. Thus, we divide the number of observations in over_threshold that belong to class 0 by the total number of observations in the test set that belong to class 0.

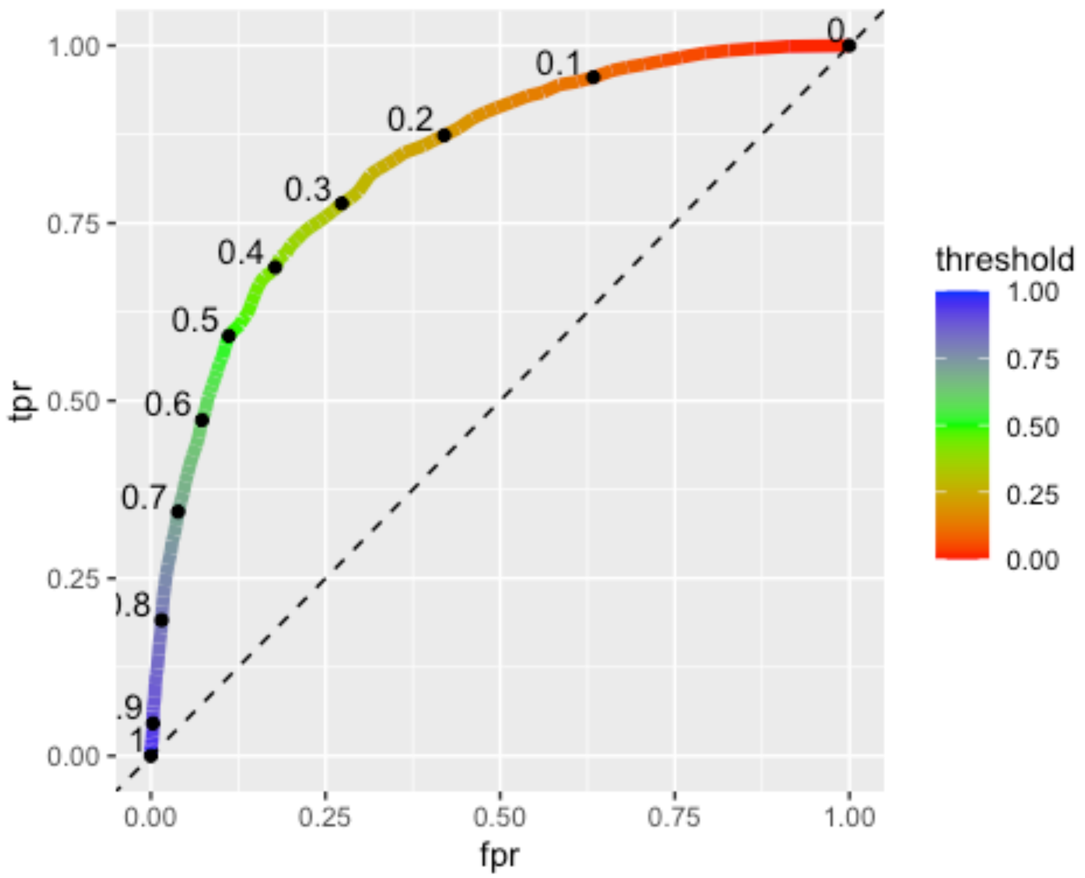
```
predictions = predict(model_2, test_feat)

## 340/340 - 0s - 317ms/epoch - 931us/step

test_df$p_prob = predictions[, 1]
head(predictions, 10)

##             [,1]
##  [1,] 0.65672284
##  [2,] 0.14577188
##  [3,] 0.05965991
##  [4,] 0.28182250
##  [5,] 0.83261532
##  [6,] 0.10673314
##  [7,] 0.89942616
##  [8,] 0.53004801
##  [9,] 0.04590573
## [10,] 0.35426077

over_threshold = test_df[test_df$p_prob >= 0.5, ]
fpr = sum(over_threshold$booking_status == 0)/sum(test_df$booking_status ==
0)
fpr

## [1] 0.1115792
```

Our model produced a false positive rate of 11%. Now, let us find the true positive rate (TPR), which is the percentage of correct predictions we make for observations that belong to the positive class (customers that actually cancel their reservation). Thus, we divide the number of observations in over_threshold that belong to class 1 by the total number of observations in the test set that belong to class 1.

```
tpr = sum(over_threshold$booking_status == 1)/sum(test_df$booking_status ==
1)
tpr

## [1] 0.5913489
```

This produced a true positive rate of 59%. Let us plot a ROC curve to show the FPR versus the TPR for different thresholds ranging form 0 to 1.

```
roc_data = data.frame(threshold=seq(1, 0, -0.01), fpr = 0, tpr = 0)
for (i in roc_data$threshold) {
  over_threshold = test_df[test_df$p_prob >= i, ]
  fpr = sum(over_threshold$booking_status == 0)/sum(test_df$booking_status ==
0)
  roc_data[roc_data$threshold == i, "fpr"] = fpr
  tpr = sum(over_threshold$booking_status == 1)/sum(test_df$booking_status ==
1)
  roc_data[roc_data$threshold == i, "tpr"] = tpr
}
ggplot() +
  geom_line(data = roc_data, aes(x = fpr, y = tpr, color = threshold), size =
2) +
  scale_color_gradientn(colors = rainbow(3)) +
  geom_abline(intercept = 0, slope = 1, lty = 2) +
  geom_point(data = roc_data[seq(1, 101, 10), ], aes(x = fpr, y = tpr)) +
  geom_text(data = roc_data[seq(1, 101, 10), ],
            aes(x = fpr, y = tpr, label = threshold, hjust = 1.2, vjust = -
0.2))

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## ℹ Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



To sum up the ROC curve with one number, we calculate the area under the ROC curve (AUC). The closer to 1 that our AUC is, the more accurate the model.

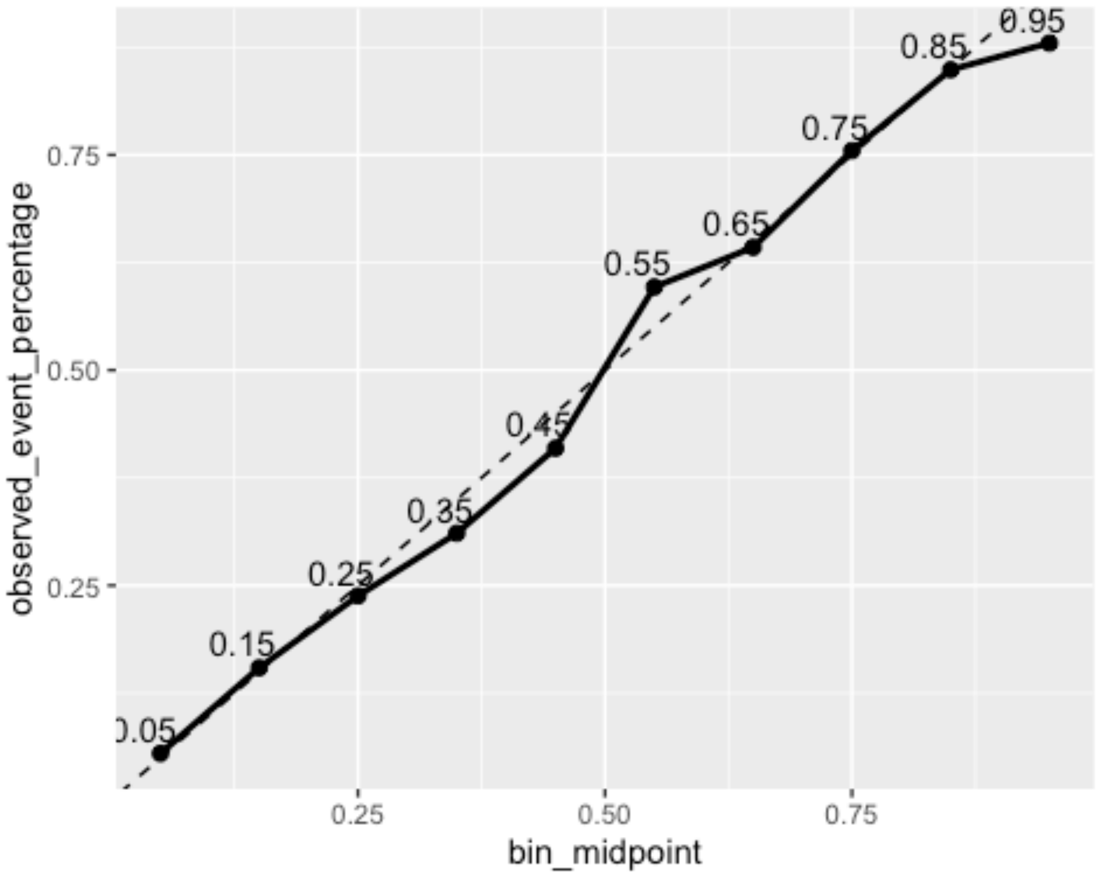
```
auc = auc(x = roc_data$fpr, y = roc_data$tpr, type = "spline")

## Warning in regularize.values(x, y, ties, missing(ties)): collapsing to
unique
## 'x' values

auc

## [1] 0.8363333
```

The AUC of our ROC is approximately 83.6.

Now, let us look at the calibration curve. The calibration curve shows the observed event percentage for any set of intervals that partition the interval (0, 1), which is the range of possible predicted probability values.

```
calibration_data = data.frame(bin_midpoint=seq(0.05, 0.95, 0.1),
                              observed_event_percentage = 0)
for (i in seq(0.05, 0.95, 0.1)) {
  in_interval = test_df[test_df$p_prob >= (i-0.05) & test_df$p_prob <=
(i+0.05), ]
```

```
  oep = nrow(in_interval[in_interval$booking_status == 1,
])/nrow(in_interval)
  calibration_data[calibration_data$bin_midpoint == i,
"observed_event_percentage"] = oep
}
ggplot(data = calibration_data, aes(x = bin_midpoint, y =
observed_event_percentage)) +
  geom_line(size = 1) +
  geom_abline(intercept = 0, slope = 1, lty = 2) +
  geom_point(size = 2) +
  geom_text(aes(label = bin_midpoint), hjust = 0.75, vjust = -0.5)
```



We want the calibration curve to lie near the dashed diagonal line, which corresponds to a well-calibrated classifier. Values that lie above the dashed diagonal line correspond to under-confident probabilities and values that lie below correspond to over-confident probabilities.

Preliminary Results Conclusion

We fit a neural network model with three activation layers. Our first layer had 40 nodes using the relu (rectified linear unit) activation function. The second layer had 20 nodes using the relu activation function. The third layer used the sigmoid activation function for our binary classification output. Using 20 epochs, a batch size of 500, and a validation split of 30%, this model produced a test label accuracy rate of approximately 79% when identifying if a customer cancelled their reservation or not. This model had a false positive rate (FPR) of approximately 11% and a true positive rate (TPR) of approximately 59%. The ROC curve did hug the upper left side of the plot when plotting FPR versus TPR. The AUC of the model's ROC was approximately 83.6%. This means that our model performed about 33.6% better than a random guessing rate of 50%. Our calibration curve did lie near the dashed diagonal line in the graph above. This corresponds to a well-calibrated classifier from our model.

Now What?

We want to see if we can fit a neural network model better than the one that we chose above. We can do this by digging deeper into our activation layers and node selections in our neural network model. We can also tune our batch size and epoch selections to see if we can produce better test predictions without overfitting the data. We will dive into this to ensure that we are selecting the best neural network mdoel possible to represent our data to help ABC hotel best identify customers who will most likely cancel their reservation. The best model will be selected for our final results.