Titanic - Machine Learning Kaggle Competition

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Abstract

The purpose of our final project is to enter Kaggle's "Titanic - Machine Learning from Disaster" competition. The goal is to predict as accurately as possible which passengers aboard the Titanic survived the shipwreck. We chose this challenge as our final project because it is the culmination of all the skills and methodologies we learned during this semester. This project will use several techniques for the classification of each passenger as someone who either died or survived, including logistic regression and random forest modeling. A logistic regression model ended up producing the best results, outperforming or random forest models. Our best model received a score of 0.77511

Background and Challenge Description

"The sinking of the Titanic is one of the most infamous shipwrecks in history.

On April 15, 1912, during her maiden voyage, the widely considered "unsinkable" RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren't enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.

While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

In this challenge, we ask you to build a predictive model that answers the question: "what sorts of people were more likely to survive?" using passenger data (i.e. name, age, gender, socio-economic class, etc.)."(https://www.kaggle.com/c/titanic)

Literature Review

Below is a list of articles that helped us in determining our approach to this competition.

https://towardsdatascience.com/kaggles-titanic-competition-in-10-minutes-part-i-e6d18e59dbce

https://medium.datadriveninvestor.com/start-with-kaggle-a-comprehensive-guide-to-solve-the-titanic-challenge-8ac5815b0473

https://python.plainenglish.io/what-happened-when-i-used-stacking-on-the-kaggle-titanic-competition-7914b1b02d6c

https://datatricks.co.uk/80-in-kaggles-titanic-competition-in-50-lines-of-r-code https://towardsdatascience.com/predicting-titanic-survivors-a-kaggle-competition-625405f5031e

These articles provide a good overview of the current state-of-the-art for solving the Titanic Kaggle competition. While several articles describe examples in python, they provide good examples of different strategies that can be used even our project will be done in R. Several of the articles suggest imputation of the Age values that are missing, as there are many missing values in this column.

The literature also suggests that feature engineering is also a key to solving this problem. Most of the articles mention designing new variables around the title information that can be extracted from the "Name" column. In our case, we decided to go a step further than the literature and classify various types of titles, such as military, royal, and others. Some articles in the literature suggested using a decision tree algorithm, but we opted for logistic regression and random forest.

Methodology

Our methodology consisted of a 5-step process. The data was provided by Kaggle and was pre-separated into training and testing sets. The competition called for the "test" dataset to be used for model evaluation. Our process included the following: • Data Exploration: summary statistics and simple visualizations were created to search for relationships between the variables.

- Data Preparation: null values were imputed and new features were engineered.

- Logistic Regression Modeling: A binomial logistic regression model was used as an initial comparison for the following model that was simplified using stepwise regression.

- Random Forest Modeling: two different random forest functions were used from different packages to be sure we had the best version.

- Evaluation: the test data was then cleaned and run through the models and their performance was evaluated. Additional tweaks to the models were made in attempt to improve performance.

Variable Descriptions

Variable	Description
survival	Survival (0 = No; 1 = Yes)
pclass	Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
name	Name
sex	Sex
age	Age
sibsp	Number of Siblings/Spouses Aboard
parch	Number of Parents/Children Aboard
ticket	Ticket Number
fare	Passenger Fare
cabin	Cabin
embarked	Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

Experimentation and Results

Data Exploration

First, we loaded the data and examined the structure. The data has 5 factor, 5 discrete, and 2 continuous variables. There will need to be further exploration to see if any of the columns are missing data.

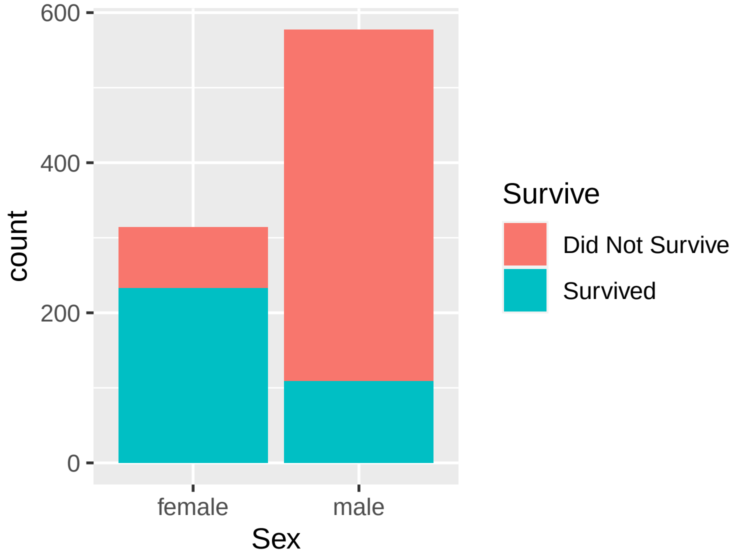
```
## Rows: 891
## Columns: 12
## $ PassengerId <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,~
## $ Survived    <int> 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1~
## $ Pclass      <int> 3, 1, 3, 1, 3, 3, 1, 3, 3, 2, 3, 1, 3, 3, 3, 2, 3, 2, 3, 3~
## $ Name        <chr> "Braund, Mr. Owen Harris", "Cumings, Mrs. John Bradley (Fl~
## $ Sex         <chr> "male", "female", "female", "female", "male", "male", "mal~
## $ Age         <dbl> 22, 38, 26, 35, 35, NA, 54, 2, 27, 14, 4, 58, 20, 39, 14, ~
```

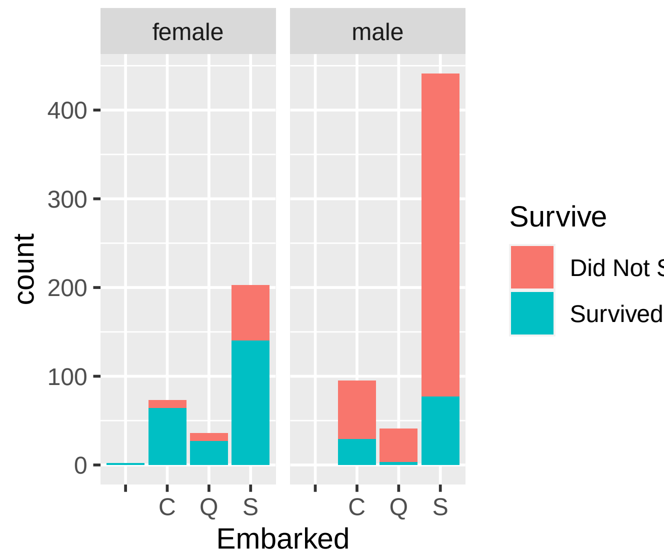
```
## $ SibSp       <int> 1, 1, 0, 1, 0, 0, 0, 3, 0, 1, 1, 0, 0, 1, 0, 0, 4, 0, 1, 0~
## $ Parch       <int> 0, 0, 0, 0, 0, 0, 0, 1, 2, 0, 1, 0, 0, 5, 0, 0, 1, 0, 0, 0~
## $ Ticket      <chr> "A/5 21171", "PC 17599", "STON/O2. 3101282", "113803", "37~
## $ Fare        <dbl> 7.2500, 71.2833, 7.9250, 53.1000, 8.0500, 8.4583, 51.8625,~
## $ Cabin       <chr> "", "C85", "", "C123", "", "", "E46", "", "", "", "G6", "C~
## $ Embarked    <chr> "S", "C", "S", "S", "S", "Q", "S", "S", "S", "C", "S", "S"~
```

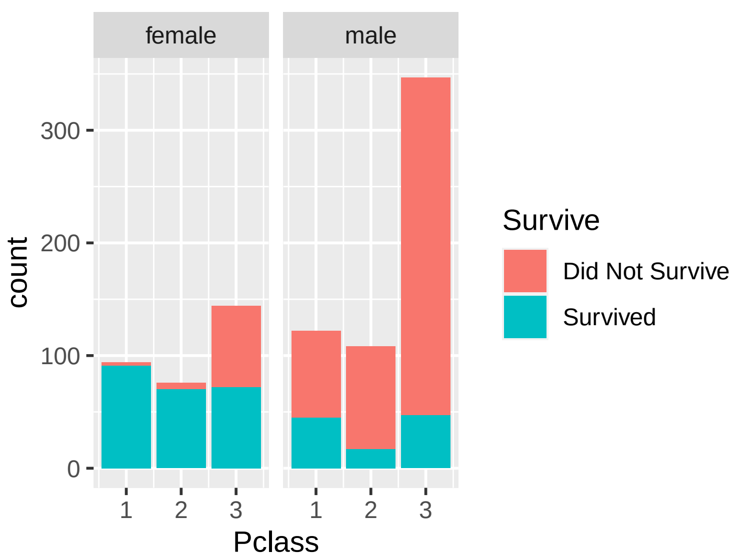
From the summary above, the first thing that caught my eye is there are NAs, AKA missing values. Before we can make any statistical model, we will need to deal with them first.

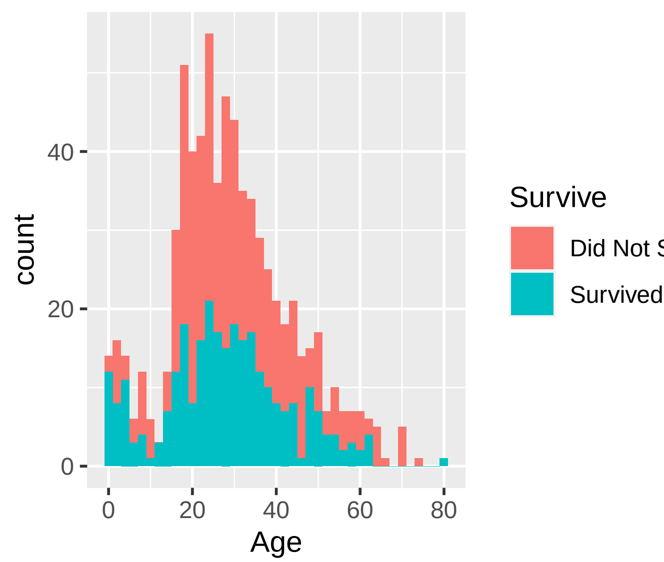
The Cabin column has 687 empty values, imputing that data may not be the best choice since we're filling in more than 50% of the empty values. On the other hand Embarked only has 2 empty values, so we can fill in those empty values without major impact.

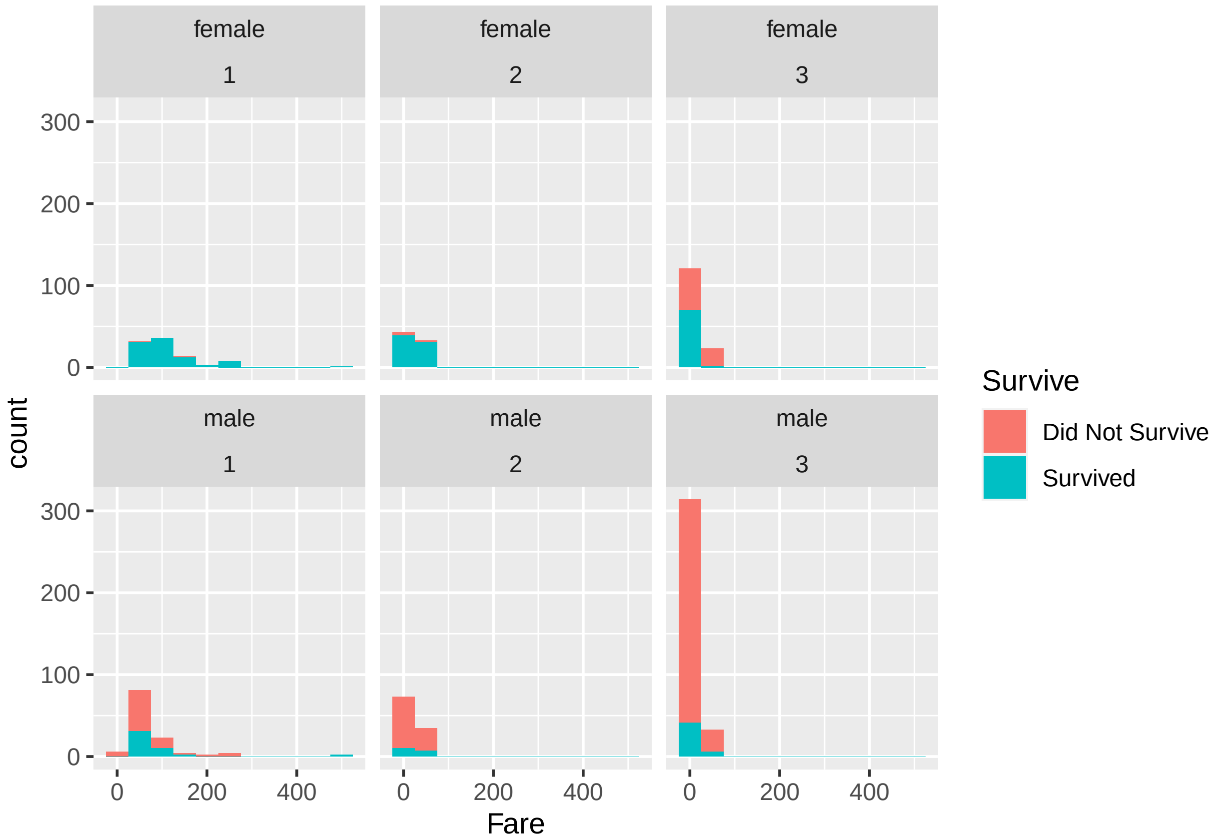
Visualization Below are several visualizations to help us see how survivors are distributed amongst certain variables.





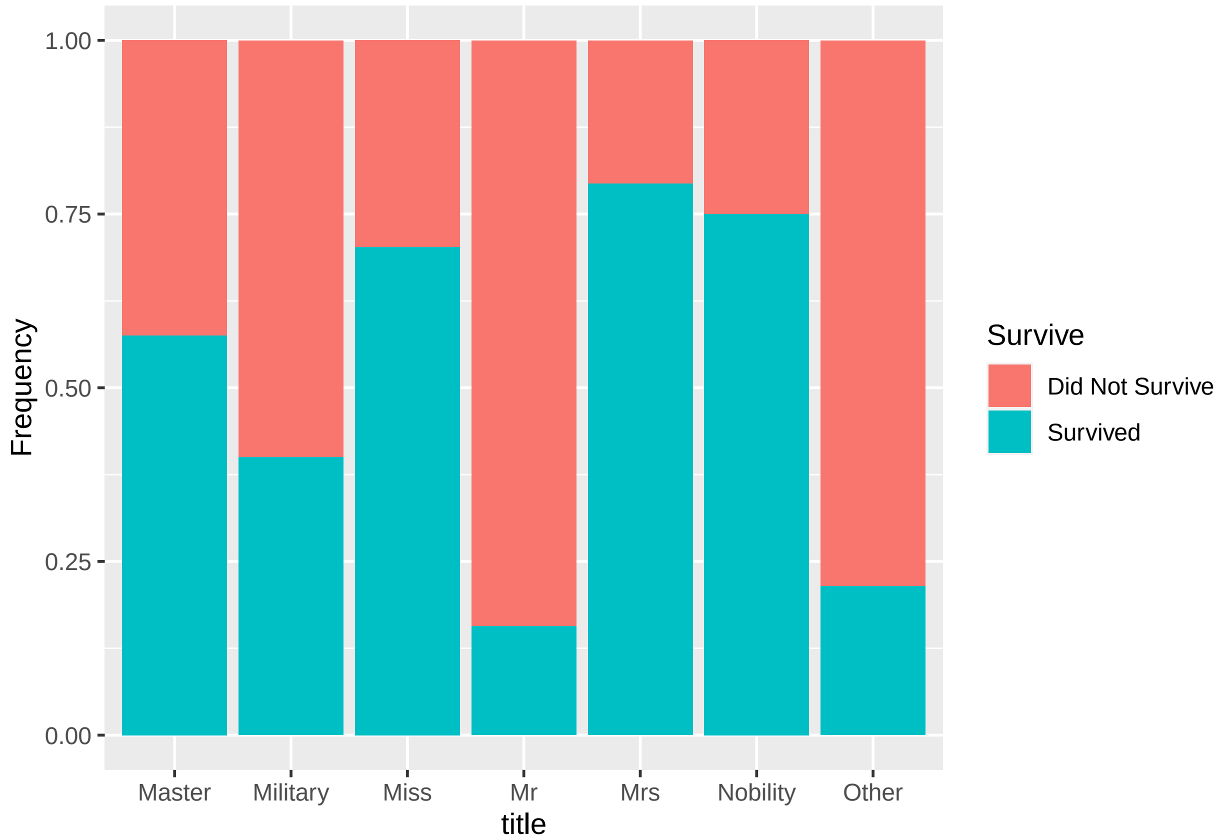






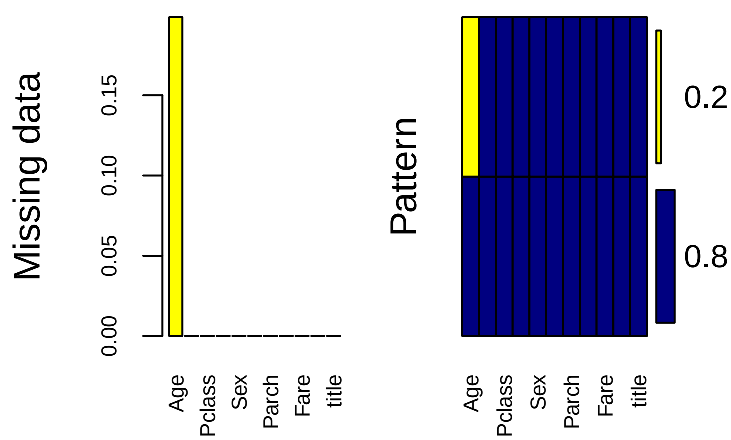
From the plots above, we can conclude that:

- If a passenger is from upper class, he has a much higher chance to survive than middle or lower class.
- Female passengers have a better chance to survive than male, which is as expected.
- The Fare plot suggests that survived people paid more than the deceased. we notice that people paid as high as $500 for the ticket. So I suspect this kind of ticket is group ticket. Family members or friends are likely to buy tickets like these.
- The distribution of Age variable seems quite similar for different passenger fate. But we know that when the Titanic sank, "women and children first" rule was carried out. This is a very important information for the project, so I will keep Age variable in the model anyway.



Data Preparation

There are three variables with missing or empty values based on our exploration of the data and visualizations: Embark, Cabin, and Age. Only passengers 62 and 830 are missing their embark ports. We randomly assigned them a value of "C". The column Cabin had too many missing values to impute or fill, so we dropped the Cabin column from the training data set.



```
##
##  Variables sorted by number of missings:
##  Variable     Count
##       Age 0.1986532
##  Survived 0.0000000
##    Pclass 0.0000000
##      Name 0.0000000
##       Sex 0.0000000
##     SibSp 0.0000000
##     Parch 0.0000000
##    Ticket 0.0000000
##      Fare 0.0000000
##  Embarked 0.0000000
##     title 0.0000000
```

From the plot and table, we can see that there are 263 NAs (roughly 20%) in Age variable, We can see that Age was missing nearly 20% of its values. This data was imputed using the rpart function.

Modeling

After exploring the patterns and creating new features, now I will build statistical models to predict the fate of the passengers in the test data set.

Three machine learning methods are used in this project:

- Binomial with logit link function (w/ Imputed data)
- Stepwise regression
- Random Forest

Model 1: Binomial with logit link function (w/ Imputed data)

This model is used when the data have binary outcomes. We fit a generalized linear model (binomial with logit link function) with Pclass, Sex, title, Embarked, Fare, Age, SibSp and Parch, as predictors of the number of survived passenger. we can see that Pclass, Sex, Age and SibSp are all significant variables.

```
##
## Call:
## glm(formula = Survived ~ Pclass + Sex + title + Embarked + Fare +
##     Age + SibSp + Parch, family = binomial(link = "logit"), data = train3)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4068  -0.5433  -0.3760   0.5370   2.5761
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    20.721916 481.641207   0.043  0.96568
## Pclass         -1.140275   0.161793  -7.048 1.82e-12 ***
## Sexmale       -15.092293 481.640636  -0.031  0.97500
## titleMilitary  -2.779350   1.133695  -2.452  0.01422 *
## titleMiss     -15.629763 481.640884  -0.032  0.97411
## titleMr        -3.405782   0.548291  -6.212 5.24e-10 ***
```

```
## titleMrs      -14.742217 481.640937  -0.031  0.97558
## titleNobility  -2.728641   1.529793  -1.784  0.07448 .
## titleOther     -3.995306   0.979950  -4.077 4.56e-05 ***
## EmbarkedQ      -0.103967   0.397173  -0.262  0.79350
## EmbarkedS      -0.414950   0.248222  -1.672  0.09459 .
## Fare            0.003291   0.002608   1.262  0.20689
## Age            -0.031319   0.009698  -3.229  0.00124 **
## SibSp          -0.569119   0.127482  -4.464 8.03e-06 ***
## Parch          -0.365867   0.136334  -2.684  0.00728 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1186.66  on 890  degrees of freedom
## Residual deviance:  722.12  on 876  degrees of freedom
## AIC: 752.12
##
## Number of Fisher Scoring iterations: 13
```

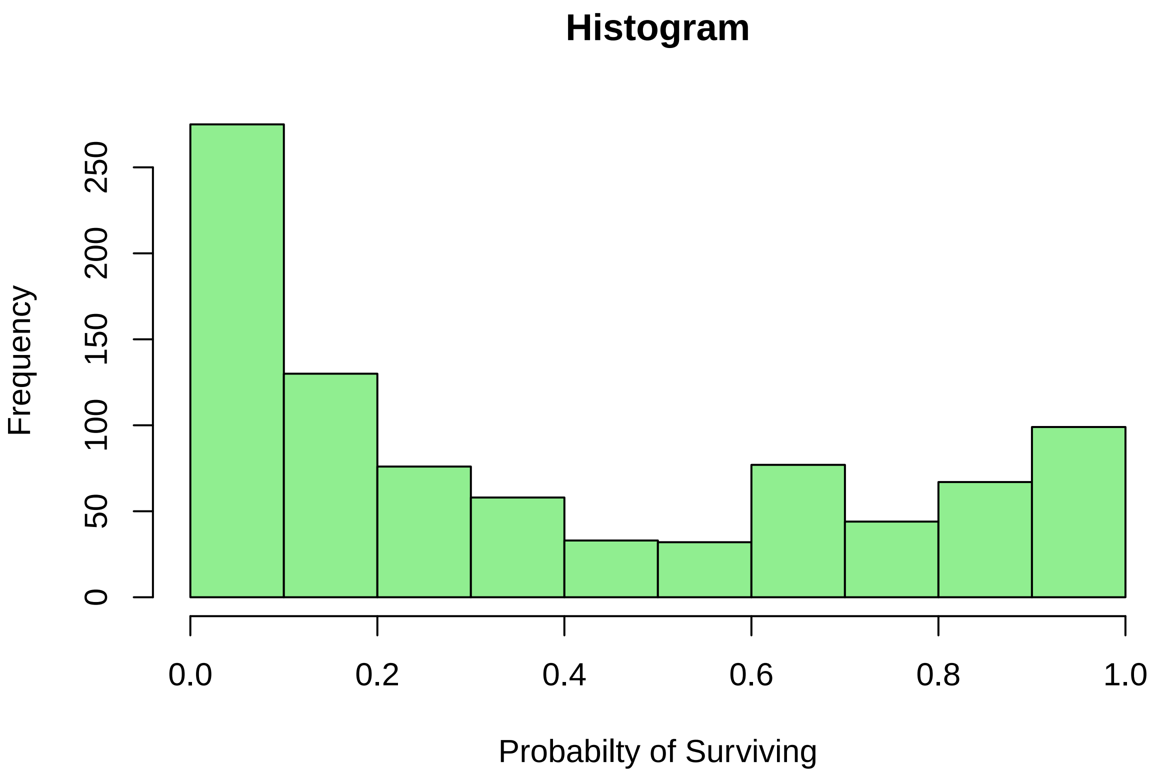
Model 2: Stepwise

```
## Start:  AIC=752.12
## Survived ~ Pclass + Sex + title + Embarked + Fare + Age + SibSp +
##     Parch
##
##            Df Deviance    AIC
## - Embarked  2   725.41 751.41
## - Fare      1   723.92 751.92
## <none>          722.12 752.12
## - Sex       1   726.54 754.54
## - Parch     1   729.88 757.88
## - Age       1   733.03 761.03
## - SibSp     1   747.11 775.11
## - title     6   780.25 798.25
## - Pclass    1   772.73 800.73
##
## Step:  AIC=751.41
## Survived ~ Pclass + Sex + title + Fare + Age + SibSp + Parch
##
##          Df Deviance    AIC
## <none>        725.41 751.41
## - Fare    1   728.49 752.49
## - Sex     1   729.60 753.60
## - Parch   1   733.84 757.84
## - Age     1   736.90 760.90
## - SibSp   1   753.19 777.19
## - title   6   783.55 797.55
## - Pclass  1   777.98 801.98
```

The AIC listed on the far right is what the model would have if we drop the variable in question. Lower AIC values are still better, The lowest AIC possible, can be selected as the best model

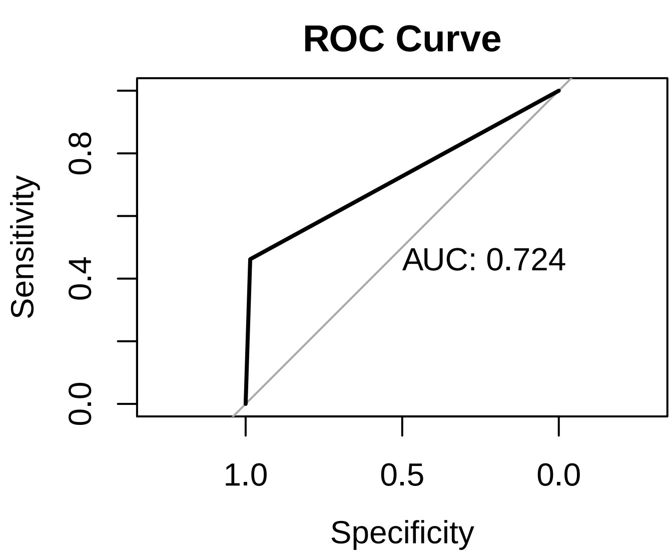
```
##
```

```
## Call:
## glm(formula = Survived ~ Pclass + Sex + title + Fare + Age +
##     SibSp + Parch, family = binomial(link = "logit"), data = train3)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4747  -0.5493  -0.3854   0.5225   2.6670
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    20.321420 481.372829   0.042 0.966327
## Pclass         -1.132427   0.157823  -7.175 7.21e-13 ***
## Sexmale       -14.986038 481.372309  -0.031 0.975164
## titleMilitary  -2.813948   1.128833  -2.493 0.012674 *
## titleMiss     -15.516876 481.372559  -0.032 0.974285
## titleMr        -3.444979   0.545960  -6.310 2.79e-10 ***
## titleMrs      -14.666556 481.372612  -0.030 0.975694
## titleNobility  -2.640764   1.543909  -1.710 0.087185 .
## titleOther     -3.920256   0.965141  -4.062 4.87e-05 ***
## Fare            0.004198   0.002594   1.618 0.105608
## Age            -0.031856   0.009633  -3.307 0.000943 ***
## SibSp          -0.591944   0.126686  -4.673 2.97e-06 ***
## Parch          -0.378039   0.135425  -2.791 0.005247 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1186.66  on 890  degrees of freedom
## Residual deviance:  725.41  on 878  degrees of freedom
## AIC: 751.41
##
## Number of Fisher Scoring iterations: 13
```




```
##      res.deviance  df         p
## [1,]     725.4096 878 0.9999434

##            Actual
## Predictions   0   1
##           0 541 184
##           1   8 158
```



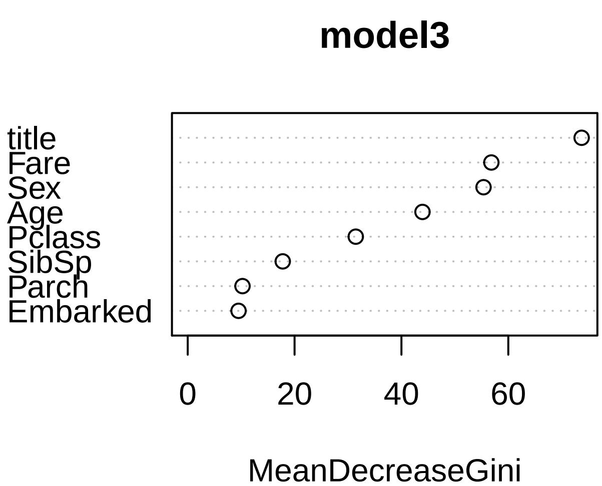
Model 3: Random Forest

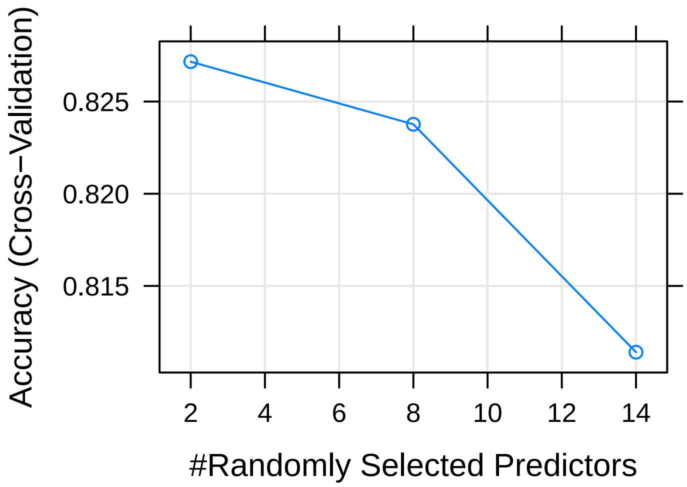
Random Forest is our favorite machine learning algorithm so far. We will use the randomForest function from the randomForest package.

```
## Random Forest
##
## 891 samples
##   8 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 802, 801, 802, 802, 801, 803, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.8271624  0.6270858
##    8    0.8237652  0.6230913
##   14    0.8114053  0.5968540
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

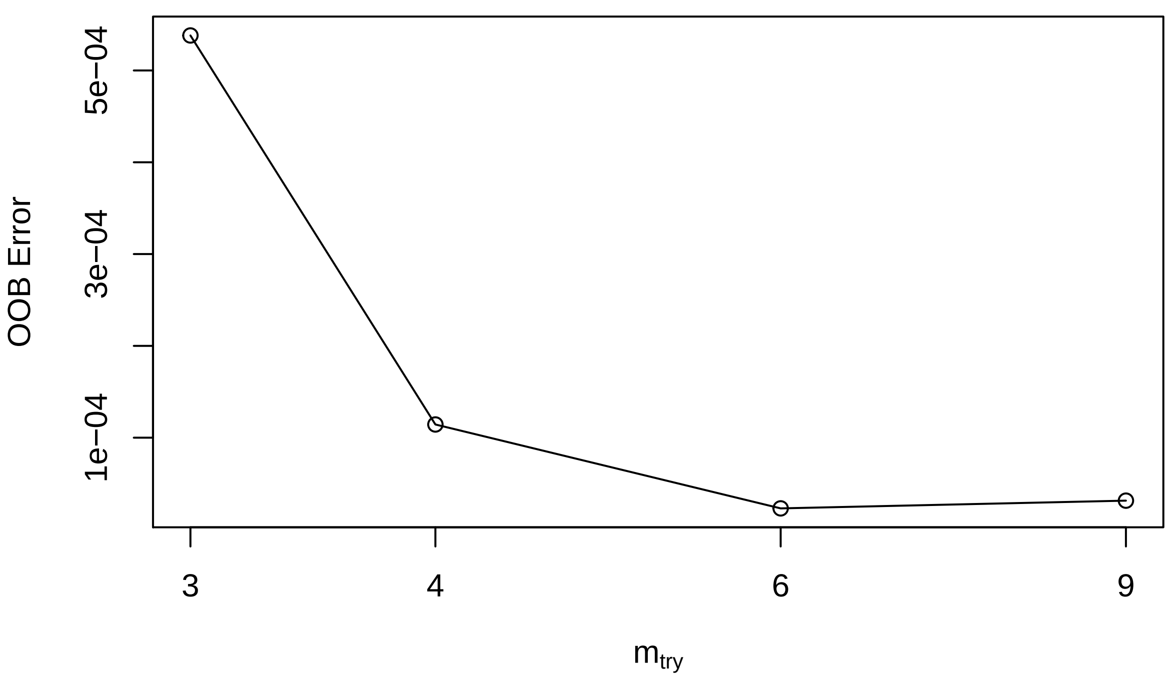
```
## integer(0)
```

The plot below shows the importance of the variables judged by the mean decrease accuracy. A variable is considered the most important if the accuracy of the model without it decreased the most compared to the full model.



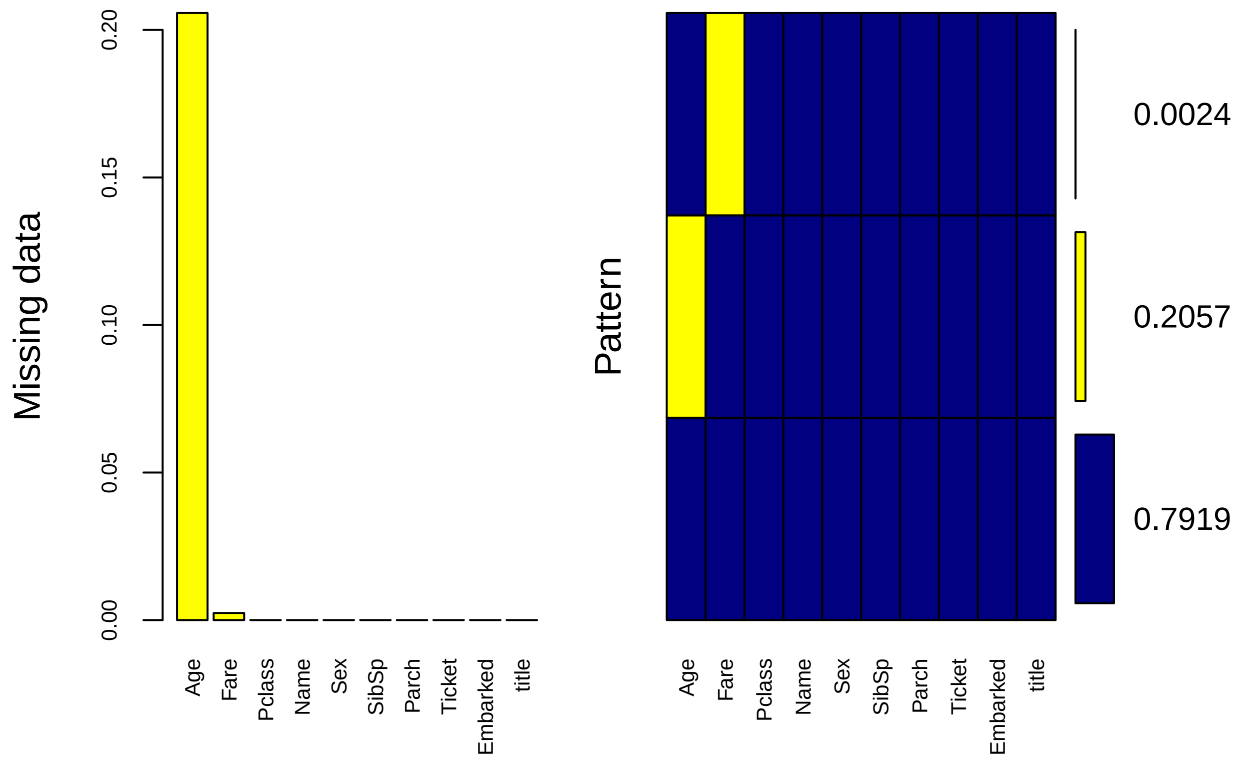



```
## -3.704311 0.01
## 0.7988898 0.01
## -0.3660311 0.01
```



Test Models

The same data cleaning steps were repeated for the test data as the training data.The null values were imputed and the title categories were created




```
##
##  Variables sorted by number of missings:
##  Variable       Count
##       Age 0.205741627
##      Fare 0.002392344
##    Pclass 0.000000000
##      Name 0.000000000
##       Sex 0.000000000
##     SibSp 0.000000000
##     Parch 0.000000000
##    Ticket 0.000000000
##  Embarked 0.000000000
##     title 0.000000000
```

Interestingly, Fare is missing values as well as Age in the test dataset. In the training data set, only Age had a significant amount of missing values. We imputed these values in Rpart as well as age.

Running the Models on the Test Set In this stage, we will save our predictions as a csv file to submit to Kaggle competition for grading then we will evaluate the performance of each model.

Select Model

The model with the most accurate result is model 2. Tweaking the thresholds changed final results on kaggle but changing the threshold to 0.75 seemed to be optimal (produced score of 0.77511), while the random forest models produced scores of 0.75358.

Discussion and conclusion

The models might see greater accuracy testing different methods of imputation. The age column saw the greatest amount of missing values, focusing on creating accurate age values will most likely improve the models. Aslo, because of the nature of Kaggle competitions, the test data we were provided with did not contain a reference column. Thus when we ran our predictions, the predictions were outputed to a new csv file and submitted to Kaggle for grading. The grading helped us as well on selecting the model who performed better.

Appendix

```
library(corrplot)
library(tidyverse)
library(Hmisc)
library(PerformanceAnalytics)
library(mice)
library(gt)
library(caret)
library(bnstruct)
library(VIM)
library(corrr)
library(kableExtra)
library(rpart)
library(gtsummary)
library(reshape)
library(pROC)
library(randomForest)
library(pscl)
#Import the training and testing data sets:
train <- read.csv("https://raw.githubusercontent.com/aaitelmouden/DATA621/master/Final%20Project/train.c
test <- read.csv("https://raw.githubusercontent.com/aaitelmouden/DATA621/master/Final%20Project/test.csv
glimpse(train)
summary(train)
train_visual <- train%>%mutate(Survive = case_when(Survived==1~"Survived", Survived==0~"Did Not Survive
# Examine the survival rate for the overall population
prop.table(table(train_visual$Survive))
train_visual%>%ggplot(aes(Sex,fill=Survive))+geom_bar()
train_visual%>%ggplot(aes(Embarked,fill=Survive))+geom_bar()+facet_wrap(~Sex)
train_visual%>%ggplot(aes(Pclass, fill=Survive)) + geom_bar()+facet_wrap(~Sex)
train_visual%>%ggplot(aes(Age, fill=Survive)) + geom_histogram(binwidth = 2)
train_visual %>% ggplot(aes(Fare, fill=Survive))+geom_histogram(binwidth = 50)+facet_wrap(Sex~Pclass)
#Create a new column with all the different titles
train$title <- gsub('(.*, )|(\\..*)', '', train$Name)
table(train$Sex, train$title)
military_title <-c('Capt', 'Col', 'Major')
royal_title <-c('the Countess', 'Jonkheer', 'Sir', 'Lady')
the_rest <- c('Dr', 'Don', 'Rev')
the_master <- c('Master')
train$title[train$title=='Mlle']<-'Miss'
train$title[train$title=='Ms']<- 'Miss'
train$title[train$title=='Mme']<-'Mrs'
train$title[train$title %in% the_master] <- 'Master'
train$title[train$title %in% military_title] <- 'Military'
train$title[train$title %in% royal_title] <- 'Nobility'
train$title[train$title %in% the_rest] <- 'Other'
table(train$Sex, train$title)
train$title <- as.factor(train$title)
train_visual$title <- train$title
train_visual%>%ggplot(aes(title, fill=Survive)) + geom_bar(position = 'fill') + ylab('Frequency')
#Localization of the empty values for Embark
train$Embarked[train$Embarked == ""] <- NA
train[(which(is.na(train$Embarked))), 1]
# Only passengers 62 and 830 are missing their embark ports. We will randomly assign them "C".
```

```
train$Embarked[c(62, 830)] <- 'C'
train2 <- subset(train, select = -c(Cabin, PassengerId))
aggr(train2, col=c('navyblue','yellow'),
numbers=TRUE, sortVars=TRUE,
labels=names(train2), cex.axis=.7,
gap=3, ylab=c("Missing data","Pattern"))
#We can impute the age date using the rpart function.
#source: https://cran.r-project.org/web/packages/rpart/vignettes/longintro.pdf
train3 <- train2
predicted_age <- rpart(Age ~ Pclass + Sex + SibSp + Parch + Fare + Embarked + title,
                       data = train3[!is.na(train3$Age),], method = "anova")
train3$Age[is.na(train3$Age)] <- predict(predicted_age, train3[is.na(train3$Age),])

#### Model 1: Binomial with logit link function (w/ Imputed data)
model1 <- glm(Survived ~ Pclass + Sex + title + Embarked + Fare + Age + SibSp + Parch, family = binomial
summary(model1)
## Model 2
model2 <- step(model1)
summary(model2)
hist(model2$fitted.values, main="Histogram", xlab="Probabilty of Surviving", col="light green")
with(model2, cbind(res.deviance = deviance, df = df.residual,  p = pchisq(deviance, df.residual, lower.
train4 <- train3
probabilities <- predict(model2, train4, type = "response")
predicted.classes <- ifelse(probabilities > 0.8, 1, 0)
train4$pred.class <- predicted.classes
table("Predictions" = train4$pred.class, "Actual" = train4$Survived)
confusionMatrix(as.factor(predicted.classes), as.factor(train4$Survived), positive = '1')
curve <- roc(response = train4$Survived,
    predictor = predicted.classes,
    plot = TRUE,
    print.auc = TRUE,
    main = "ROC Curve")
#### Model 3: Random Forest
set.seed(51)
#model3 <- randomForest(factor(Survived) ~ Pclass + title + Sex + Fare + SibSp + Parch + Age + Embarked
model3.1 <- train(factor(Survived) ~ Pclass + title + Sex + Fare + SibSp + Parch + Age + Embarked,
                  data = train3,
                  method = 'rf',
                  trControl = trainControl(method = 'cv',
                                           number = 10))
model3.1
which.min(model3$mse)
varImpPlot(model3)
plot(model3.1)
model_tuned <- tuneRF(
               x=train3[,c(-3, -8)], #define predictor variables
               y=train3$Survived, #define response variable
               ntreeTry=500,
               mtryStart=4,
               stepFactor=1.5,
               improve=0.01,
               trace=FALSE #don't show real-time progress
               )
# Repeating the same data cleaning steps for the test data as the training data.
```

```
summary(test)
test$title <- gsub('(.*, )|(\\..*)', '', test$Name)
table(test$Sex, test$title)
military_title <-c('Capt', 'Col', 'Major')
royal_title <-c('the Countess', 'Jonkheer', 'Sir', 'Lady')
the_rest <- c('Dr', 'Don', 'Rev', 'Dona')
the_master <- c('Master')
test$title[test$title=='Mlle']<-'Miss'
test$title[test$title=='Ms']<- 'Miss'
test$title[test$title=='Mme']<-'Mrs'
test$title[test$title %in% the_master] <- 'Master'
test$title[test$title %in% military_title] <- 'Military'
test$title[test$title %in% royal_title] <- 'Nobility'
test$title[test$title %in% the_rest] <- 'Other'
table(test$Sex, test$title)
test$title <- as.factor(test$title)
#Checking for Embarked missing passengers, which there are none.
test$Embarked[test$Embarked == ""] <- NA
test[(which(is.na(test$Embarked))), 1]
test2 <- subset(test, select = -c(Cabin, PassengerId))
aggr(test2, col=c('navyblue','yellow'),
numbers=TRUE, sortVars=TRUE,
labels=names(test2), cex.axis=.7,
gap=3, ylab=c("Missing data","Pattern"))
test3 <- test2
predicted_age_test <- rpart(Age ~ Pclass + Sex + SibSp + Parch + Fare + Embarked + title,
                       data = test3[!is.na(test3$Age),], method = "anova")
test3$Age[is.na(test3$Age)] <- predict(predicted_age_test, test3[is.na(test3$Age),])
predicted_fare_test <- rpart(Fare ~ Pclass + Sex + SibSp + Parch + Age + Embarked + title,
                       data = test3[!is.na(test3$Fare),], method = "anova")
test3$Fare[is.na(test3$Fare)] <- predict(predicted_fare_test, test3[is.na(test3$Fare),])
#Second Model Predictions
test4 <- test3
pred.test2 <- predict(model2, test4, type = "response")
predtest.classes <- ifelse(pred.test2 > 0.75, 1, 0)
test4$pred.class <- predtest.classes
sub1 <- data.frame(test$PassengerId, test4$pred.class)
colnames(sub1) = c("PassengerId", "Survived")
#Third Model Predictions
#source: https://stackoverflow.com/questions/24829674/r-random-forest-error-type-of-predictors-in-new-da
xtest <- rbind(train3[1,-1], test3)
xtest <- xtest[-1,]
#Random Forest with train method
pred.test3.1 <- predict(model3.1, newdata=xtest, type="raw")
sub2 <- data.frame(test$PassengerId, pred.test3.1)
colnames(sub2) = c("PassengerId", "Survived")
#Random Forest with randomForest function
pred.test3 <- predict(model3, newdata = xtest, type = "response")
sub3 <- data.frame(test$PassengerId, pred.test3)
colnames(sub3) = c("PassengerId", "Survived")
```