

# INFX 573 Problem Set 8 - Prediction

Vighnesh Misal

Due: Tuesday, November 26, 2019

*Collaborators: Ashish Anand*

## *Instructions:*

Before beginning this assignment, please ensure you have access to R and RStudio.

1. Download the `problemset8.Rmd` file from Canvas. Open `problemset8.Rmd` in RStudio and supply your solutions to the assignment by editing `problemset8.Rmd`.
2. Replace the “Insert Your Name Here” text in the `author:` field with your own full name. Any collaborators must be listed on the top of your assignment.
3. Be sure to include well-documented (e.g. commented) code chunks, figures and clearly written text chunk explanations as necessary. Any figures should be clearly labeled and appropriately referenced within the text.
4. Collaboration on problem sets is acceptable, and even encouraged, but each student must turn in an individual write-up in his or her own words and his or her own work. The names of all collaborators must be listed on each assignment. Do not copy-and-paste from other students’ responses or code.
5. When you have completed the assignment and have **checked** that your code both runs in the Console and knits correctly when you click Knit PDF, rename the R Markdown file to `YourLastName_YourFirstName_ps7.Rmd`, knit a PDF and submit the PDF file on Canvas.

## *Setup:*

In this problem set you will need, at minimum, the following R packages.

```
# Load standard libraries
library(tidyverse)
library(gridExtra)
library(MASS)
library(pROC)
library(arm)
library(randomForest)
library(dplyr)
library(Metrics)
library(ROCR)
```

In this problem set we will use the `flights` and `titanic` datasets used previously in class. The `flights` dataset (via the `flights` library) contains information on flight delays and weather. `titanic.txt` file contains data about the survival of passengers aboard the Titanic. `Table` contains a description of this data.

As part of this assignment, we will evaluate the performance of several statistical learning methods. We will fit our learning models using a set of observations and measure its performance on a set of observations.

Discuss the advantages of using a training/test split when evaluating statistical models.

## Training/test split ensures that predictions are on data that is unknown. This ensures that the model can be improved upon later.

### Predictions with a continuous output variable

Load in the flights dataset. Join the flights data to the weather data based on the departure location, date, and hour of the flight. Exclude data entries which cannot be joined to weather data. Copy the joined data so we can refer to it later.

```
# Load data
library(nycflights13)

merged_columns <- c("origin", "year", "month", "day", "time_hour")
dataset1 <- merge(weather, flights, by = merged_columns)
```

From the joined data, keep only the following columns as we build our first model: departure delay, origin, departure time, temperature, wind speed, precipitation, and visibility. Omit observations that do not have all of these variables present.

```
subset1 <- subset(dataset1, select = c("dep_delay", "dep_time", "origin",
"temp", "wind_speed", "precip", "visib"))

subset1 <- subset1[complete.cases(subset1),]
```

Split your data into a train and test set based on an 80-20 split. In other words, 80% of the observations will be in the training set and 20% will be in the test set. Remember to set the random seed.

```
sample1 <- floor(0.80 * nrow(subset1))

set.seed(123)
train_independent <- sample(seq_len(nrow(subset1)), size = sample1)

train_model <- subset1[train_independent, ]
test_model <- subset1[-train_independent, ]
```

Build a linear regression model to predict departure delay using the subset of variables indicated in (3.). What is the RMSE on the training set? What is the RMSE on the test set? Which is higher and is this expected?

```
training_model1 <- lm( dep_delay ~ dep_time + precip + wind_speed,
train_model)
summary(training_model1)

##
## Call:
```

```

## lm(formula = dep_delay ~ dep_time + precip + wind_speed, data =
train_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -159.83  -18.49   -7.87    1.44 1304.61
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.768e+01  2.544e-01 -69.518  < 2e-16 ***
## dep_time     2.119e-02  1.555e-04 136.252  < 2e-16 ***
## precip       1.203e+02  2.538e+00  47.411  < 2e-16 ***
## wind_speed   1.057e-01  1.371e-02   7.708  1.28e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 38.49 on 261514 degrees of freedom
## Multiple R-squared:  0.07636,    Adjusted R-squared:  0.07635
## F-statistic: 7207 on 3 and 261514 DF,  p-value: < 2.2e-16

training_model1_y <- predict(training_model1)

RMSE_Test_set <- sqrt(mean((training_model1_y - train_model$dep_delay)^2))
RMSE_Test_set

## [1] 38.48656

testing_model1 <- lm( dep_delay ~ dep_time + precip + wind_speed, test_model)
summary(testing_model1)

##
## Call:
## lm(formula = dep_delay ~ dep_time + precip + wind_speed, data =
test_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -116.88  -18.97   -8.24    1.32 1118.60
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.710e+01  5.229e-01 -32.70  <2e-16 ***
## dep_time     2.155e-02  3.179e-04  67.80  <2e-16 ***
## precip       1.060e+02  5.222e+00  20.29  <2e-16 ***
## wind_speed   4.239e-02  2.808e-02   1.51   0.131
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.44 on 65376 degrees of freedom
## Multiple R-squared:  0.07301,    Adjusted R-squared:  0.07296
## F-statistic: 1716 on 3 and 65376 DF,  p-value: < 2.2e-16

```

Since RMSE\_test(39.44) is higher than RMSE\_training(38.48656), an assumption of model overfitting can be made.

Now, improve upon these prediction results by including additional variables in your model. Make sure you keep at least 95% of original data (i.e. about 320K observations across both the training and test datasets). Do not include the arrival time, scheduled arrival time, or the arrival delay in your model. Use the same observations as above for the training and test sets (i.e. keep the same rows but add different variables/columns at your discretion). Can you improve upon the training RMSE? Once you have a model that you feel adequately improves the training RMSE, does your model improve the test RMSE? Which variables did you include in your model?

```
training_model2 <- lm( dep_delay ~ dep_time + precip + wind_speed + temp,
train_model)
summary(training_model2)
```

```
##
## Call:
## lm(formula = dep_delay ~ dep_time + precip + wind_speed + temp,
##     data = train_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -160.03  -18.68   -8.00    1.82  1305.79
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.303e+01  3.532e-01  -65.21  <2e-16 ***
## dep_time     2.085e-02  1.562e-04  133.44  <2e-16 ***
## precip       1.197e+02  2.536e+00   47.20  <2e-16 ***
## wind_speed    1.523e-01  1.387e-02   10.99  <2e-16 ***
## temp         9.304e-02  4.266e-03   21.81  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 38.45 on 261513 degrees of freedom
## Multiple R-squared:  0.07804,    Adjusted R-squared:  0.07802
## F-statistic: 5534 on 4 and 261513 DF,  p-value: < 2.2e-16
```

```
training_model2_y <- predict(training_model2)

sqrt(mean((training_model2_y - train_model$dep_delay)^2))

## [1] 38.45161
```

```
testing_model2 <- lm( dep_delay ~ dep_time + precip + wind_speed + temp,
test_model)
summary(testing_model2)
```

```
##
## Call:
## lm(formula = dep_delay ~ dep_time + precip + wind_speed + temp,
##     data = test_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -116.31  -19.19   -8.36    1.68  1119.65
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.272e+01  7.215e-01 -31.497  < 2e-16 ***
## dep_time     2.115e-02  3.196e-04  66.181  < 2e-16 ***
## precip       1.046e+02  5.218e+00  20.054  < 2e-16 ***
## wind_speed   9.088e-02  2.838e-02   3.202  0.00136 **
## temp         9.875e-02  8.738e-03  11.301  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.4 on 65375 degrees of freedom
## Multiple R-squared:  0.07481,    Adjusted R-squared:  0.07476
## F-statistic: 1322 on 4 and 65375 DF,  p-value: < 2.2e-16

testing_model2_y <- predict(testing_model2)
sqrt(mean((testing_model2_y - test_model$dep_delay)^2))

## [1] 39.39768

training_model3 <- lm( dep_delay ~ dep_time + precip + temp, train_model)
summary(training_model3)

##
## Call:
## lm(formula = dep_delay ~ dep_time + precip + temp, data = train_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -162.73  -18.57   -8.00    1.71  1304.89
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.126e+01  3.141e-01 -67.67  <2e-16 ***
## dep_time     2.108e-02  1.548e-04  136.20  <2e-16 ***
## precip       1.206e+02  2.535e+00  47.57  <2e-16 ***
## temp         8.582e-02  4.216e-03  20.36  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 38.46 on 261514 degrees of freedom
## Multiple R-squared:  0.07761,    Adjusted R-squared:  0.0776
## F-statistic: 7335 on 3 and 261514 DF,  p-value: < 2.2e-16
```

```

training_model3_y <- predict(training_model3)

sqrt(mean((training_model3_y - train_model$dep_delay)^2))

## [1] 38.46048

testing_model3 <- lm( dep_delay ~ dep_time + precip + wind_speed + temp,
test_model)
summary(testing_model3)

##
## Call:
## lm(formula = dep_delay ~ dep_time + precip + wind_speed + temp,
##     data = test_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -116.31  -19.19   -8.36    1.68 1119.65
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.272e+01  7.215e-01 -31.497  < 2e-16 ***
## dep_time     2.115e-02  3.196e-04  66.181  < 2e-16 ***
## precip       1.046e+02  5.218e+00  20.054  < 2e-16 ***
## wind_speed   9.088e-02  2.838e-02   3.202  0.00136 **
## temp         9.875e-02  8.738e-03  11.301  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.4 on 65375 degrees of freedom
## Multiple R-squared:  0.07481,    Adjusted R-squared:  0.07476
## F-statistic: 1322 on 4 and 65375 DF,  p-value: < 2.2e-16

testing_model3_y <- predict(testing_model3)
sqrt(mean((testing_model3_y - test_model$dep_delay)^2))

## [1] 39.39768

training_model4 <- lm( dep_delay ~ dep_time + visib + origin, train_model)
summary(training_model4)

##
## Call:
## lm(formula = dep_delay ~ dep_time + visib + origin, data = train_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
##  -67.60  -18.41   -7.97    2.24 1302.81
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)

```

```

## (Intercept)  6.3585302  0.4160346  15.28  <2e-16 ***
## dep_time    0.0220997  0.0001545  143.01  <2e-16 ***
## visib       -2.2541856  0.0379704  -59.37  <2e-16 ***
## originJFK   -4.3007881  0.1808588  -23.78  <2e-16 ***
## originLGA   -3.9245684  0.1842090  -21.30  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 38.35 on 261513 degrees of freedom
## Multiple R-squared:  0.08295,    Adjusted R-squared:  0.08294
## F-statistic: 5914 on 4 and 261513 DF,  p-value: < 2.2e-16

training_model4_y <- predict(training_model4)

sqrt(mean((training_model4_y - train_model$dep_delay)^2))

## [1] 38.34902

testing_model4 <- lm( dep_delay ~ dep_time + precip + wind_speed + temp,
test_model)
summary(testing_model4)

##
## Call:
## lm(formula = dep_delay ~ dep_time + precip + wind_speed + temp,
##     data = test_model)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -116.31  -19.19   -8.36    1.68  1119.65
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.272e+01  7.215e-01 -31.497  < 2e-16 ***
## dep_time     2.115e-02  3.196e-04  66.181  < 2e-16 ***
## precip       1.046e+02  5.218e+00  20.054  < 2e-16 ***
## wind_speed    9.088e-02  2.838e-02   3.202  0.00136 **
## temp          9.875e-02  8.738e-03  11.301  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.4 on 65375 degrees of freedom
## Multiple R-squared:  0.07481,    Adjusted R-squared:  0.07476
## F-statistic: 1322 on 4 and 65375 DF,  p-value: < 2.2e-16

testing_model4_y <- predict(testing_model4)
sqrt(mean((testing_model4_y - test_model$dep_delay)^2))

## [1] 39.39768

```



## The model with the lowest observed RMSE is the best model i.e. the model with variables dep\_time + visib + origin

### Predictions with a categorical output (classification)

Load in the titanic data. Split your data into a train and test set based on an 80-20 split. In other words, 80% of the observations will be in the training set and 20% will be in the test set. Remember to set the random seed.

```
titanic_data <- read.csv('titanic.csv')

sample_size <- floor(0.80 * nrow(titanic_data))

set.seed(101)

titanic_training_data <- sample(seq_len(nrow(titanic_data)), size =
sample_size)

titanic_training <- titanic_data[titanic_training_data, ]
titanic_testing <- titanic_data[-titanic_training_data, ]
```

In this problem set our goal is to predict the survival of passengers. First, let's train a logistic regression model for survival that controls for the socioeconomic status of the passenger.

Fit the model described above (i.e. one that only takes into account socioeconomic status) using the function in R.

```
titanic_training1 <- glm(survived ~ pclass + fare, family = binomial, data =
titanic_training)

summary(titanic_training1)

##
## Call:
## glm(formula = survived ~ pclass + fare, family = binomial, data =
titanic_training)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6178  -0.7798  -0.7563   1.0568   1.6786
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.871989   0.260952   3.342 0.000833 ***
## pclass      -0.666864   0.096932  -6.880 6e-12 ***
## fare         0.002998   0.001737   1.725 0.084445 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
## Null deviance: 1379.6 on 1045 degrees of freedom
## Residual deviance: 1279.5 on 1043 degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 1285.5
##
## Number of Fisher Scoring iterations: 4

exp(coef(titanic_training1)[2])

## pclass
## 0.5133159
```

What might you conclude based on this model about the probability of survival for lower class passengers?

**It's evident from the model that lower class passengers had a lower chance of survival owing to their socio-economic status. This means that people from high class were given a preference during the evacuation.**

Next, let's consider the performance of this model.

Predict the survival of passengers for each observation in your test set using the model fit in Problem 2. Save these predictions as .

```
titanic_testing1 <- glm(survived ~ pclass + fare, family = binomial, data =
titanic_testing)
summary(titanic_testing1)

##
## Call:
## glm(formula = survived ~ pclass + fare, family = binomial, data =
titanic_testing)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6011  -0.8930  -0.8049   1.1173   1.6090
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.115042   0.644348  -0.179  0.85830
## pclass      -0.328167   0.217429  -1.509  0.13122
## fare         0.017926   0.006654   2.694  0.00705 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##      Null deviance: 357.68  on 261  degrees of freedom
## Residual deviance: 314.53  on 259  degrees of freedom
## AIC: 320.53
##
## Number of Fisher Scoring iterations: 5
```

```
yhat<- predict(titanic_testing1, titanic_testing, type="response")
```

Use a threshold of 0.5 to classify predictions. What is the number of false positives on the test data? Interpret this in your own words.

```
classify_prediction <- data.frame(titanic_testing$survived, yhat)
```

```
classify_prediction$classification <- classify_prediction$yhat > 0.5
```

```
classify_prediction
```

	titanic_testing.survived	yhat	classification
## 5	0	0.9066621	TRUE
## 12	1	0.9743069	TRUE
## 21	1	0.6222010	TRUE
## 27	1	0.7666547	TRUE
## 35	0	0.5081838	TRUE
## 41	0	0.5662772	TRUE
## 44	1	0.7159438	TRUE
## 45	1	0.8773851	TRUE
## 46	0	0.5081838	TRUE
## 50	1	0.9998401	TRUE
## 62	1	0.7251775	TRUE
## 63	0	0.6577855	TRUE
## 65	1	0.6244982	TRUE
## 66	1	0.6244982	TRUE
## 70	1	0.6324508	TRUE
## 75	0	0.6198628	TRUE
## 85	0	0.6973366	TRUE
## 96	1	0.7357936	TRUE
## 99	1	0.8122372	TRUE
## 100	1	0.5662772	TRUE
## 112	1	0.9862307	TRUE
## 114	1	0.9862307	TRUE
## 118	1	0.6404526	TRUE
## 120	1	0.8757364	TRUE
## 121	1	0.5134284	TRUE
## 122	1	0.8757364	TRUE
## 128	1	0.6244982	TRUE
## 131	1	0.6505873	TRUE
## 132	1	0.6505873	TRUE
## 136	0	0.5443872	TRUE
## 151	0	0.3909766	FALSE
## 152	1	0.7175361	TRUE
## 160	1	0.6447754	TRUE

## 165	1 0.5081838	TRUE
## 166	1 0.7631759	TRUE
## 168	1 0.7631759	TRUE
## 188	1 0.5653964	TRUE
## 190	0 0.5236285	TRUE
## 191	1 0.7219803	TRUE
## 198	0 0.6244982	TRUE
## 202	0 0.6192819	TRUE
## 205	1 0.7368812	TRUE
## 208	1 0.7631759	TRUE
## 213	0 0.5222868	TRUE
## 221	1 0.6610233	TRUE
## 225	0 0.5169172	TRUE
## 227	0 0.6793295	TRUE
## 228	1 0.6793295	TRUE
## 230	1 0.8189101	TRUE
## 231	1 0.7743281	TRUE
## 233	0 0.6198628	TRUE
## 236	1 0.5662772	TRUE
## 245	0 0.5685873	TRUE
## 250	1 0.9860777	TRUE
## 251	1 0.9860777	TRUE
## 254	1 0.9860777	TRUE
## 257	1 0.5057194	TRUE
## 274	1 0.8773851	TRUE
## 279	1 0.5258638	TRUE
## 282	1 0.6342895	TRUE
## 285	1 0.7292669	TRUE
## 289	1 0.5054021	TRUE
## 292	1 0.7280264	TRUE
## 293	1 0.6198628	TRUE
## 294	1 0.6198628	TRUE
## 300	0 0.5134284	TRUE
## 303	1 0.9998401	TRUE
## 307	0 0.7195602	TRUE
## 308	0 0.7195602	TRUE
## 314	0 0.9660469	TRUE
## 320	1 0.8773851	TRUE
## 325	1 0.4155324	FALSE
## 329	0 0.4242653	FALSE
## 349	0 0.3685757	FALSE
## 350	1 0.3685757	FALSE
## 361	1 0.4374522	FALSE
## 363	1 0.4025334	FALSE
## 368	0 0.3706642	FALSE
## 369	0 0.4242653	FALSE
## 384	0 0.3623402	FALSE
## 388	1 0.4718850	FALSE
## 403	1 0.3721637	FALSE
## 415	0 0.4025334	FALSE

## 420	0 0.3623402	FALSE
## 424	0 0.3685757	FALSE
## 429	1 0.3748555	FALSE
## 430	0 0.3685757	FALSE
## 441	1 0.5972075	TRUE
## 459	1 0.3582086	FALSE
## 464	0 0.4485100	FALSE
## 471	0 0.3658681	FALSE
## 480	1 0.4934983	FALSE
## 482	1 0.4934983	FALSE
## 484	1 0.4551700	FALSE
## 492	0 0.3771511	FALSE
## 495	1 0.4730208	FALSE
## 496	0 0.3794000	FALSE
## 505	0 0.3685757	FALSE
## 512	0 0.3548671	FALSE
## 513	0 0.4421815	FALSE
## 518	0 0.3685757	FALSE
## 519	0 0.4718850	FALSE
## 520	0 0.3706642	FALSE
## 526	0 0.3582086	FALSE
## 531	0 0.3582086	FALSE
## 533	0 0.3685757	FALSE
## 534	1 0.4025334	FALSE
## 538	0 0.3685757	FALSE
## 541	1 0.4242653	FALSE
## 544	0 0.3582086	FALSE
## 547	1 0.3685757	FALSE
## 553	0 0.3582086	FALSE
## 554	1 0.3582086	FALSE
## 561	1 0.3685757	FALSE
## 567	0 0.3771511	FALSE
## 570	0 0.5972075	TRUE
## 580	0 0.3582086	FALSE
## 583	1 0.3801211	FALSE
## 584	1 0.3801211	FALSE
## 586	0 0.4242653	FALSE
## 593	0 0.4319458	FALSE
## 596	0 0.3680544	FALSE
## 614	1 0.3180497	FALSE
## 618	0 0.2742510	FALSE
## 643	0 0.3689146	FALSE
## 644	1 0.3689146	FALSE
## 645	0 0.3689146	FALSE
## 646	1 0.2769200	FALSE
## 650	0 0.2742510	FALSE
## 652	0 0.2748758	FALSE
## 659	1 0.3198830	FALSE
## 660	1 0.3198830	FALSE
## 661	1 0.3198830	FALSE

## 664	0 0.2772791	FALSE
## 667	0 0.3014443	FALSE
## 669	0 0.2778334	FALSE
## 675	1 0.4783202	FALSE
## 677	0 0.2767556	FALSE
## 680	0 0.3044409	FALSE
## 685	0 0.3054067	FALSE
## 686	0 0.3076931	FALSE
## 687	1 0.2766659	FALSE
## 689	0 0.2742360	FALSE
## 691	0 0.2769200	FALSE
## 695	0 0.2731818	FALSE
## 697	0 0.2800418	FALSE
## 714	0 0.2766957	FALSE
## 724	0 0.2766957	FALSE
## 741	0 0.2800418	FALSE
## 745	0 0.2855255	FALSE
## 747	1 0.2767556	FALSE
## 749	0 0.3012397	FALSE
## 751	0 0.2772791	FALSE
## 755	0 0.3392544	FALSE
## 768	0 0.2772791	FALSE
## 771	0 0.2749651	FALSE
## 773	0 0.2772791	FALSE
## 775	0 0.2772791	FALSE
## 779	1 0.2940261	FALSE
## 780	0 0.2767556	FALSE
## 781	1 0.2778334	FALSE
## 790	0 0.2748758	FALSE
## 792	0 0.2748908	FALSE
## 807	0 0.3814683	FALSE
## 808	0 0.3814683	FALSE
## 811	0 0.3814683	FALSE
## 813	0 0.2767556	FALSE
## 815	0 0.2767259	FALSE
## 818	0 0.2778334	FALSE
## 830	0 0.4356607	FALSE
## 835	0 0.2789588	FALSE
## 836	0 0.2778334	FALSE
## 837	0 0.2843385	FALSE
## 844	0 0.3226521	FALSE
## 846	1 0.3067393	FALSE
## 854	0 0.2749651	FALSE
## 859	1 0.4783202	FALSE
## 860	0 0.2731818	FALSE
## 862	0 0.2773840	FALSE
## 871	1 0.2773840	FALSE
## 875	1 0.2772493	FALSE
## 884	0 0.2771297	FALSE
## 885	0 0.2771297	FALSE

## 888	1 0.2780582	FALSE
## 889	0 0.2722780	FALSE
## 896	1 0.2890584	FALSE
## 898	0 0.2768453	FALSE
## 901	0 0.3364472	FALSE
## 918	1 0.2975424	FALSE
## 922	0 0.2749651	FALSE
## 928	0 0.3014443	FALSE
## 939	0 0.2771297	FALSE
## 940	0 0.2929418	FALSE
## 943	0 0.2748758	FALSE
## 953	0 0.2768453	FALSE
## 960	0 0.2773840	FALSE
## 968	0 0.2767556	FALSE
## 975	0 0.3076931	FALSE
## 976	0 0.3076931	FALSE
## 991	0 0.2773840	FALSE
## 994	1 0.2767108	FALSE
## 998	1 0.2748758	FALSE
## 1002	1 0.3356473	FALSE
## 1004	1 0.3356473	FALSE
## 1015	0 0.2778334	FALSE
## 1019	0 0.2778334	FALSE
## 1026	1 0.2940261	FALSE
## 1028	0 0.2778334	FALSE
## 1032	0 0.2778334	FALSE
## 1034	1 0.2768453	FALSE
## 1046	0 0.2767556	FALSE
## 1048	1 0.2748758	FALSE
## 1049	1 0.3063266	FALSE
## 1051	1 0.3063266	FALSE
## 1053	0 0.2772791	FALSE
## 1058	1 0.2894579	FALSE
## 1069	0 0.2713615	FALSE
## 1071	0 0.2770399	FALSE
## 1074	0 0.2767556	FALSE
## 1079	1 0.2772195	FALSE
## 1080	1 0.2768453	FALSE
## 1085	0 0.2791092	FALSE
## 1095	1 0.2801170	FALSE
## 1100	0 0.3270094	FALSE
## 1118	0 0.2773840	FALSE
## 1122	1 0.3320922	FALSE
## 1129	0 0.2772791	FALSE
## 1137	0 0.2780582	FALSE
## 1145	0 0.3595231	FALSE
## 1147	0 0.3595231	FALSE
## 1158	0 0.3236159	FALSE
## 1160	1 0.2778334	FALSE
## 1166	0 0.2748758	FALSE

```

## 1177      0 0.5367441      TRUE
## 1184      0 0.2773840     FALSE
## 1186      0 0.3293975     FALSE
## 1187      0 0.3293975     FALSE
## 1190      1 0.3099890     FALSE
## 1191      1 0.2830787     FALSE
## 1194      0 0.2766659     FALSE
## 1200      0 0.2778334     FALSE
## 1207      0 0.3544823     FALSE
## 1215      0 0.2800418     FALSE
## 1224      1 0.2760386     FALSE
## 1228      0 0.2843082     FALSE
## 1230      0 0.2800418     FALSE
## 1235      0 0.2742510     FALSE
## 1238      0 0.2769200     FALSE
## 1241      1 0.2795151     FALSE
## 1245      1 0.2795151     FALSE
## 1248      1 0.3076931     FALSE
## 1250      0 0.2767556     FALSE
## 1256      0 0.2748908     FALSE
## 1258      1 0.3044409     FALSE
## 1259      1 0.3044409     FALSE
## 1265      0 0.3016172     FALSE
## 1276      0 0.3149957     FALSE
## 1279      0 0.2771297     FALSE
## 1288      0 0.2767556     FALSE
## 1291      1 0.2740726     FALSE
## 1297      0 0.2800418     FALSE
## 1302      0 0.2748758     FALSE

```

```

False_pos <- nrow(subset(classify_prediction, titanic_testing$survived ==0 &
classification ==1))

```

```

False_neg <- nrow(subset(classify_prediction, titanic_testing$survived ==1 &
classification ==0))

```

```

True_pos <- nrow(subset(classify_prediction, titanic_testing$survived ==1 &
classification ==1))

```

```

True_neg <- nrow(subset(classify_prediction, titanic_testing$survived ==0 &
classification ==0))

```

```

false_positive_rate = False_pos/(False_pos+True_neg)

```

```

false_positive_rate

```

```

## [1] 0.1466667

```



The model is not highly susceptible to providing false positives as it currently contains 22 false\_pos. The false positive rate is about 14.67%.

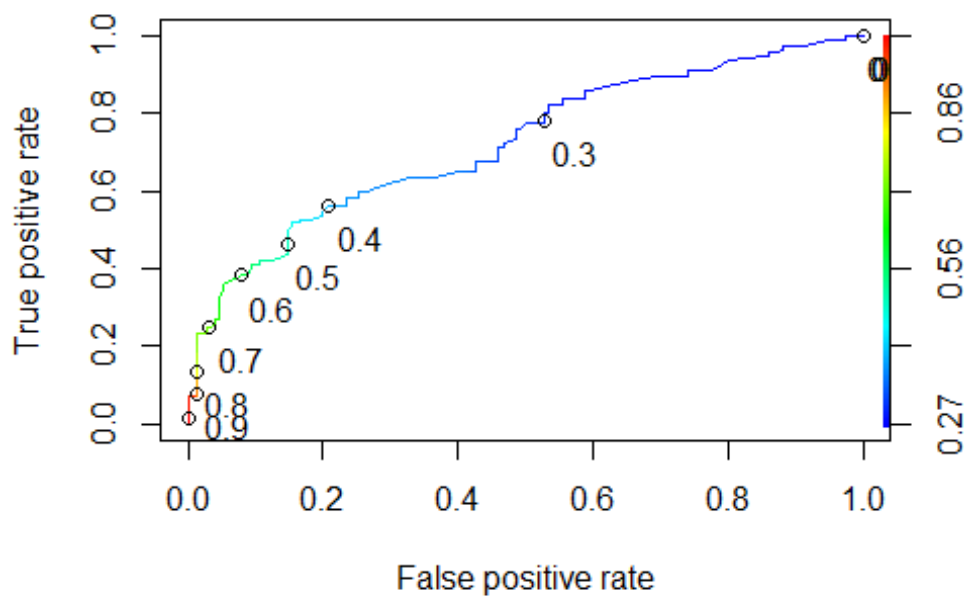
Using the function, plot the ROC curve for this model. Discuss what you find.

```
predictions_titanic <- predict(titanic_testing1, newdata=titanic_testing,
type="response")
```

```
ROCR_pred_titanic <- prediction(predictions_titanic ,
titanic_testing$survived)
```

```
ROCR_perf_titanic <- performance(ROCR_pred_titanic , measure = "tpr",
x.measure = "fpr")
```

```
plot(ROCR_perf_titanic , colorize = TRUE, text.adj = c(-0.2,1.7),
print.cutoffs.at = seq(0,1,0.1))
```



**A much lower threshold value would be more suitable as the graph with the current threshold of 0.5 doesn't give us much information.**

Suppose we use the data to construct a new predictor variable based on a passenger's listed title (i.e. Mr., Mrs., Miss., Master). Why might this be an interesting variable to help predict passenger survival?

Use the following custom function to add this predictor to your dataset.

```
# Making a feature that includes more titles
getTitles <- function(name) {
  for (title in c("Master", "Miss", "Mrs.", "Mr. ")) {
    if (grepl(title, name)) {
      return(title)
    }
  }
  return("Nothing")
}

result1 <- numeric(length(titanic_training$name))
for (i in seq_along(titanic_training$name)) {
  result1[i] <- getTitles(titanic_training$name[i])
}

title1 <- as.data.frame(result1)
title1_training <- cbind(titanic_training, title1)

result2 <- numeric(length(titanic_testing$name))
for (i in seq_along(titanic_testing$name)) {
  result2[i] <- getTitles(titanic_testing$name[i])
}

title2 <- as.data.frame(result2)
title2_testing <- cbind(titanic_testing, title2)
```

**The predictor takes into consideration the gender, age and marital status of the passengers. Generally women, elderly and children are given preference during an evacuation which can cause the survival rate to be skewed. By performing an analysis of the passenger title we can determine key characteristics of the passenger related to survival.**

Fit a second logistic regression model including this new feature. Use the function to look at the model. Did this new feature improve the model?

```
title.train <- glm(survived ~ pclass + result1 + fare, family = binomial, data = title1_training)
summary(title.train)
```

```
##
## Call:
## glm(formula = survived ~ pclass + result1 + fare, family = binomial,
##      data = title1_training)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.0931  -0.6572  -0.4132   0.6588   2.2780
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    2.75655    0.46235   5.962 2.49e-09 ***
## pclass         -1.00033    0.12042  -8.307 < 2e-16 ***
## result1Miss     0.37452    0.32544   1.151  0.24981
## result1Mr.     -2.15689    0.32119  -6.715 1.88e-11 ***
## result1Mrs.     0.71478    0.35475   2.015  0.04392 *
## result1Nothing -1.70259    0.54513  -3.123  0.00179 **
## fare           -0.00205    0.00194  -1.057  0.29058
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1379.57  on 1045  degrees of freedom
## Residual deviance:  986.35  on 1039  degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 1000.3
##
## Number of Fisher Scoring iterations: 4
```

[Comment on the overall fit of this model. For example, you might consider exploring when misclassification occurs.](#)

```
title.test2 <- glm(survived ~ pclass + result2 + fare, family = binomial,
data = title2_testing)
summary(title.test2)
```

```
##
## Call:
## glm(formula = survived ~ pclass + result2 + fare, family = binomial,
##      data = title2_testing)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.5594  -0.5985  -0.3964   0.5780   2.2727
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    2.171814    1.138679   1.907  0.05648 .
## pclass         -0.841822    0.267071  -3.152  0.00162 **
## result2Miss     1.128585    0.818425   1.379  0.16790
```

```
## result2Mr.      -2.201954    0.806780   -2.729    0.00635 **
## result2Mrs.      0.896288    0.852245    1.052    0.29295
## result2Nothing -1.811910    1.127206   -1.607    0.10796
## fare            0.006667    0.005296    1.259    0.20810
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 357.68  on 261  degrees of freedom
## Residual deviance: 217.92  on 255  degrees of freedom
## AIC: 231.92
##
## Number of Fisher Scoring iterations: 5

yhat2<- predict(title.test2, title2_testing, type="response")

classify_prediction2 <- data.frame(title2_testing$survived, yhat2)
classify_prediction2$classification <- classify_prediction2$yhat2 > 0.5
classify_prediction2

##      title2_testing.survived      yhat2 classification
## 5                          0 0.96219153          TRUE
## 12                         1 0.97686979          TRUE
## 21                         1 0.37248368          FALSE
## 27                         1 0.43420226          FALSE
## 35                         0 0.33293300          FALSE
## 41                         0 0.44573963          FALSE
## 44                         1 0.93905632          TRUE
## 45                         1 0.96627807          TRUE
## 46                         0 0.42435878          FALSE
## 50                         1 0.92715538          TRUE
## 62                         1 0.94002517          TRUE
## 63                         0 0.38601348          FALSE
## 65                         1 0.37333463          FALSE
## 66                         1 0.92958316          TRUE
## 70                         1 0.93040785          TRUE
## 75                         0 0.37162044          FALSE
## 85                         0 0.40210364          FALSE
## 96                         1 0.94114600          TRUE
## 99                         1 0.94958935          TRUE
## 100                        1 0.92345886          TRUE
## 112                        1 0.98540001          TRUE
## 114                        1 0.98540001          TRUE
## 118                        1 0.94470188          TRUE
## 120                        1 0.60088208          TRUE
## 121                        1 0.33466884          FALSE
## 122                        1 0.95760233          TRUE
## 128                        1 0.92958316          TRUE
## 131                        1 0.94555616          TRUE
```

## 132	1 0.93228347	TRUE
## 136	0 0.34503913	FALSE
## 151	0 0.29484644	FALSE
## 152	1 0.41086294	FALSE
## 160	1 0.94506645	TRUE
## 165	1 0.33293300	FALSE
## 166	1 0.43243547	FALSE
## 168	1 0.94408165	TRUE
## 188	1 0.93826964	TRUE
## 190	0 0.33806085	FALSE
## 191	1 0.95158567	TRUE
## 198	0 0.37333463	FALSE
## 202	0 0.37140639	FALSE
## 205	1 0.94126129	TRUE
## 208	1 0.95515310	TRUE
## 213	0 0.33761341	FALSE
## 221	1 0.94643465	TRUE
## 225	0 0.33582658	FALSE
## 227	0 0.39462035	FALSE
## 228	1 0.93525179	TRUE
## 230	1 0.95037342	TRUE
## 231	1 0.95614211	TRUE
## 233	0 0.37162044	FALSE
## 236	1 0.35252846	FALSE
## 245	0 0.35332780	FALSE
## 250	1 0.95602971	TRUE
## 251	1 0.98533994	TRUE
## 254	1 0.98157703	TRUE
## 257	1 0.33211912	FALSE
## 274	1 0.90262331	TRUE
## 279	1 0.43080433	FALSE
## 282	1 0.93059829	TRUE
## 285	1 0.94045598	TRUE
## 289	1 0.91676270	TRUE
## 292	1 0.94032517	TRUE
## 293	1 0.37162044	FALSE
## 294	1 0.92910158	TRUE
## 300	0 0.42626669	FALSE
## 303	1 0.99719720	TRUE
## 307	0 0.41176423	FALSE
## 308	0 0.41176423	FALSE
## 314	0 0.63137779	TRUE
## 320	1 0.96627807	TRUE
## 325	1 0.82411348	TRUE
## 329	0 0.17647162	FALSE
## 349	0 0.16422661	FALSE
## 350	1 0.84598194	TRUE
## 361	1 0.17939724	FALSE
## 363	1 0.85280404	TRUE
## 368	0 0.16468467	FALSE

## 369	0 0.17647162	FALSE
## 384	0 0.16285856	FALSE
## 388	1 0.83609768	TRUE
## 403	1 0.84672607	TRUE
## 415	0 0.17167912	FALSE
## 420	0 0.16285856	FALSE
## 424	0 0.16422661	FALSE
## 429	1 0.81474346	TRUE
## 430	0 0.16422661	FALSE
## 441	1 0.86030441	TRUE
## 459	1 0.84379764	TRUE
## 464	0 0.18186409	FALSE
## 471	0 0.16363266	FALSE
## 480	1 0.86920738	TRUE
## 482	1 0.84046227	TRUE
## 484	1 0.86256629	TRUE
## 492	0 0.16610731	FALSE
## 495	1 0.83632980	TRUE
## 496	0 0.16660049	FALSE
## 505	0 0.16422661	FALSE
## 512	0 0.16121777	FALSE
## 513	0 0.18045062	FALSE
## 518	0 0.16422661	FALSE
## 519	0 0.18713017	FALSE
## 520	0 0.16468467	FALSE
## 526	0 0.22205441	FALSE
## 531	0 0.16195164	FALSE
## 533	0 0.22494704	FALSE
## 534	1 0.85280404	TRUE
## 538	0 0.16422661	FALSE
## 541	1 0.85693960	TRUE
## 544	0 0.16195164	FALSE
## 547	1 0.22494704	FALSE
## 553	0 0.16195164	FALSE
## 554	1 0.84379764	TRUE
## 561	1 0.84598194	TRUE
## 567	0 0.16610731	FALSE
## 570	0 0.21747861	FALSE
## 580	0 0.16195164	FALSE
## 583	1 0.84835574	TRUE
## 584	1 0.81599805	TRUE
## 586	0 0.17647162	FALSE
## 593	0 0.17817365	FALSE
## 596	0 0.16411225	FALSE
## 614	1 0.08088773	FALSE
## 618	0 0.07525739	FALSE
## 643	0 0.46396582	FALSE
## 644	1 0.72794036	TRUE
## 645	0 0.08735708	FALSE
## 646	1 0.07560416	FALSE

## 650	0 0.07525739	FALSE
## 652	0 0.07533863	FALSE
## 659	1 0.71163357	TRUE
## 660	1 0.71163357	TRUE
## 661	1 0.66173466	TRUE
## 664	0 0.07565077	FALSE
## 667	0 0.65452841	TRUE
## 669	0 0.07572269	FALSE
## 675	1 0.10165761	FALSE
## 677	0 0.07558283	FALSE
## 680	0 0.70611288	TRUE
## 685	0 0.65610333	TRUE
## 686	0 0.07956559	FALSE
## 687	1 0.69560111	TRUE
## 689	0 0.07525544	FALSE
## 691	0 0.07560416	FALSE
## 695	0 0.07511831	FALSE
## 697	0 0.69692296	TRUE
## 714	0 0.07557505	FALSE
## 724	0 0.07557505	FALSE
## 741	0 0.07600900	FALSE
## 745	0 0.07671826	FALSE
## 747	1 0.07558283	FALSE
## 749	0 0.07873949	FALSE
## 751	0 0.07565077	FALSE
## 755	0 0.08358587	FALSE
## 768	0 0.07565077	FALSE
## 771	0 0.07535024	FALSE
## 773	0 0.07565077	FALSE
## 775	0 0.07565077	FALSE
## 779	1 0.70226483	TRUE
## 780	0 0.69563640	TRUE
## 781	1 0.69605972	TRUE
## 790	0 0.07533863	FALSE
## 792	0 0.07534058	FALSE
## 807	0 0.73186702	TRUE
## 808	0 0.73186702	TRUE
## 811	0 0.08895816	FALSE
## 813	0 0.07558283	FALSE
## 815	0 0.07557896	FALSE
## 818	0 0.07572269	FALSE
## 830	0 0.74793353	TRUE
## 835	0 0.07586864	FALSE
## 836	0 0.07572269	FALSE
## 837	0 0.07656492	FALSE
## 844	0 0.08147414	FALSE
## 846	1 0.65662964	TRUE
## 854	0 0.07535024	FALSE
## 859	1 0.10165761	FALSE
## 860	0 0.69422296	TRUE

## 862	0 0.69588338	TRUE
## 871	1 0.69588338	TRUE
## 875	1 0.07564690	FALSE
## 884	0 0.07563138	FALSE
## 885	0 0.07563138	FALSE
## 888	1 0.07575186	FALSE
## 889	0 0.07500065	FALSE
## 896	1 0.70039109	TRUE
## 898	0 0.07559447	FALSE
## 901	0 0.45083261	FALSE
## 918	1 0.07826524	FALSE
## 922	0 0.07535024	FALSE
## 928	0 0.07876570	FALSE
## 939	0 0.07563138	FALSE
## 940	0 0.65109690	TRUE
## 943	0 0.07533863	FALSE
## 953	0 0.07559447	FALSE
## 960	0 0.07566439	FALSE
## 968	0 0.69563640	TRUE
## 975	0 0.07956559	FALSE
## 976	0 0.65700535	TRUE
## 991	0 0.07566439	FALSE
## 994	1 0.69561876	TRUE
## 998	1 0.64355023	TRUE
## 1002	1 0.71706397	TRUE
## 1004	1 0.08312740	FALSE
## 1015	0 0.64481098	TRUE
## 1019	0 0.07572269	FALSE
## 1026	1 0.43278958	FALSE
## 1028	0 0.07572269	FALSE
## 1032	0 0.07572269	FALSE
## 1034	1 0.07559447	FALSE
## 1046	0 0.07558283	FALSE
## 1048	1 0.69489481	TRUE
## 1049	1 0.70679851	TRUE
## 1051	1 0.65646683	TRUE
## 1053	0 0.07565077	FALSE
## 1058	1 0.70054273	TRUE
## 1069	0 0.07488127	FALSE
## 1071	0 0.07561973	FALSE
## 1074	0 0.07558283	FALSE
## 1079	1 0.69581875	TRUE
## 1080	1 0.69567169	TRUE
## 1085	0 0.07588814	FALSE
## 1095	1 0.64577741	TRUE
## 1100	0 0.71411273	TRUE
## 1118	0 0.07566439	FALSE
## 1122	1 0.44903124	FALSE
## 1129	0 0.07565077	FALSE
## 1137	0 0.64490641	TRUE



## 1145	0 0.46021644	FALSE
## 1147	0 0.67629929	TRUE
## 1158	0 0.08159687	FALSE
## 1160	1 0.69605972	TRUE
## 1166	0 0.07533863	FALSE
## 1177	0 0.10988589	FALSE
## 1184	0 0.07566439	FALSE
## 1186	0 0.08233267	FALSE
## 1187	0 0.08233267	FALSE
## 1190	1 0.70812080	TRUE
## 1191	1 0.07640208	FALSE
## 1194	0 0.07557118	FALSE
## 1200	0 0.07572269	FALSE
## 1207	0 0.45818823	FALSE
## 1215	0 0.07600900	FALSE
## 1224	1 0.69535401	TRUE
## 1228	0 0.69857508	TRUE
## 1230	0 0.07600900	FALSE
## 1235	0 0.07525739	FALSE
## 1238	0 0.07560416	FALSE
## 1241	1 0.42632304	FALSE
## 1245	1 0.64552329	TRUE
## 1248	1 0.65700535	TRUE
## 1250	0 0.07558283	FALSE
## 1256	0 0.07534058	FALSE
## 1258	1 0.70611288	TRUE
## 1259	1 0.65572083	TRUE
## 1265	0 0.07878786	FALSE
## 1276	0 0.08049825	FALSE
## 1279	0 0.07563138	FALSE
## 1288	0 0.07558283	FALSE
## 1291	1 0.64320604	TRUE
## 1297	0 0.07600900	FALSE
## 1302	0 0.07533863	FALSE

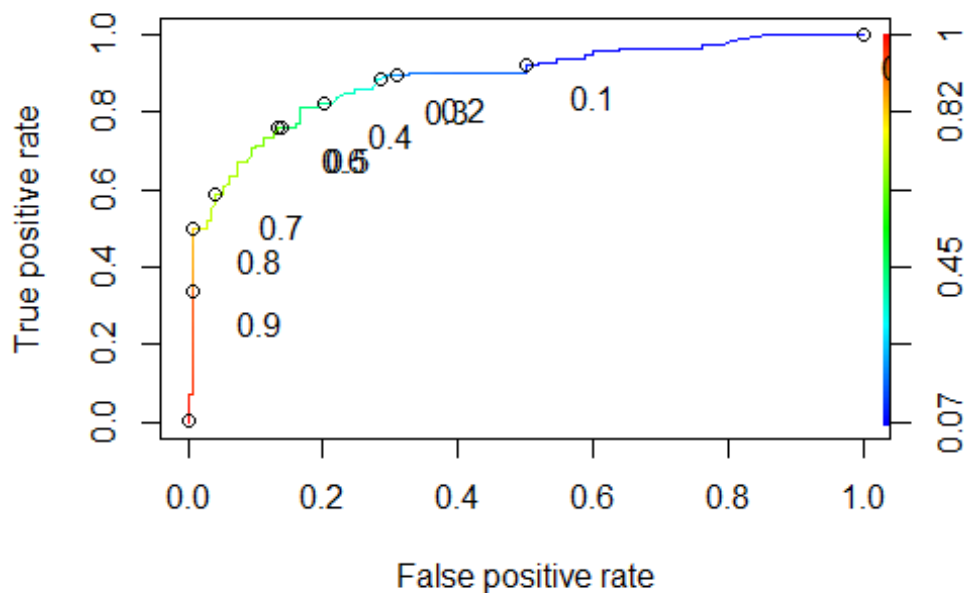
```

False_pos2 <- nrow(subset(classify_prediction2, title2_testing$survived ==0 &
classification ==1))
False_neg2 <- nrow(subset(classify_prediction2, title2_testing$survived ==1 &
classification ==0))
True_pos2 <- nrow(subset(classify_prediction2, title2_testing$survived ==1 &
classification ==1))
True_neg2 <- nrow(subset(classify_prediction2, title2_testing$survived ==0 &
classification ==0))

predictions2 <- predict(title.test2, newdata=title2_testing, type="response")
ROCR_pred_2 <- prediction(predictions2, title2_testing$survived)
ROCR_perf_2 <- performance(ROCR_pred_2, measure = "tpr", x.measure = "fpr")

plot(ROCR_perf_2, colorize = TRUE, text.adj = c(-1,1.7), print.cutoffs.at =
seq(0,1,0.1))

```



## Improved AUC signifies the overall fit for the model has improved

Predict the survival of passengers for each observation in your test data using the new model.  
Save these predictions as .

```
title.test <- glm(survived ~ pclass + result2 + fare, family = binomial, data = title2_testing)
summary(title.test)
```

```
##
## Call:
## glm(formula = survived ~ pclass + result2 + fare, family = binomial,
##      data = title2_testing)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.5594  -0.5985  -0.3964   0.5780   2.2727
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    2.171814   1.138679   1.907  0.05648 .
## pclass         -0.841822   0.267071  -3.152  0.00162 **
## result2Miss     1.128585   0.818425   1.379  0.16790
## result2Mr.     -2.201954   0.806780  -2.729  0.00635 **
## result2Mrs.     0.896288   0.852245   1.052  0.29295
## result2Nothing -1.811910   1.127206  -1.607  0.10796
```

```
## fare          0.006667    0.005296    1.259    0.20810
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 357.68  on 261  degrees of freedom
## Residual deviance: 217.92  on 255  degrees of freedom
## AIC: 231.92
##
## Number of Fisher Scoring iterations: 5

yhat2<- predict(title.test, title2_testing, type="response")
```

## Random forests

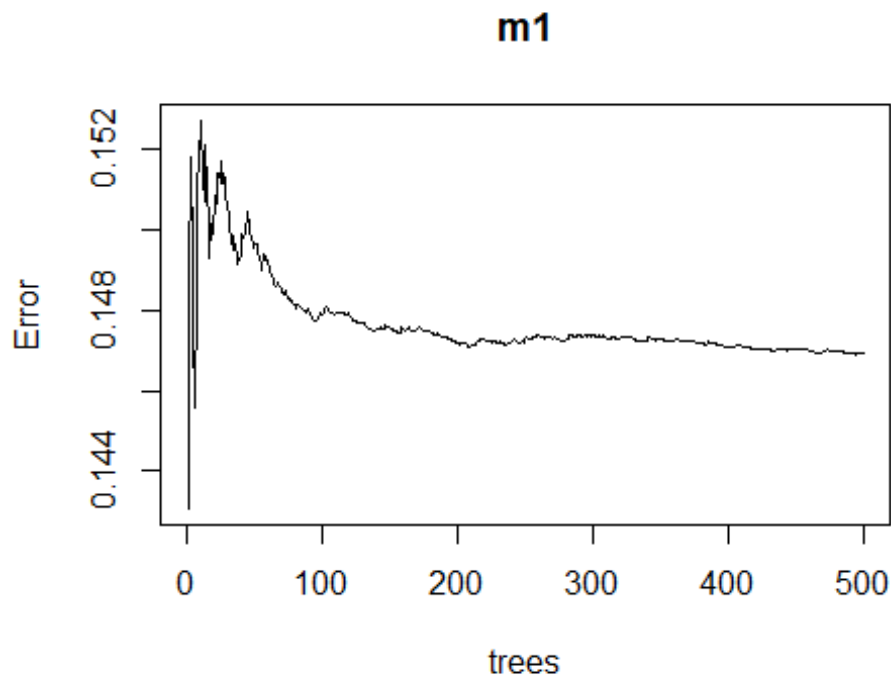
Another very popular classifier used in data science is called a .

Use the `randomForest` function to fit a random forest model with passenger class and title as predictors. Make predictions for the test set using the random forest model. Save these predictions as `result2`.  
**set.seed(171)**

```
m1 <- randomForest(formula = survived ~ pclass + result1, data =
title1_training)
```

```
## Warning in randomForest.default(m, y, ...): The response has five or fewer
## unique values. Are you sure you want to do regression?
```

```
plot(m1)
```



```
m1_test <- randomForest(formula = survived ~ pclass + result2, data =  
title2_testing)
```

```
## Warning in randomForest.default(m, y, ...): The response has five or fewer  
## unique values. Are you sure you want to do regression?
```

Develop your own random forest model (i.e. add/remove variables at your discretion), attempting to improve the model performance. Make predictions for the test set using your new random forest model. Save these predictions as .

Compare the accuracy of each of the classification models from this problem set using ROC curves. Comment on which statistical learning method works best for predicting survival of the Titanic passengers.