Homework 3

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Contents

Classification

For this assignment, we will be working with part of a Kaggle data set that was the subject of a machine learning competition and is often used for practicing ML models. The goal is classification; specifically, to predict which passengers would survive the Titanic shipwreck.

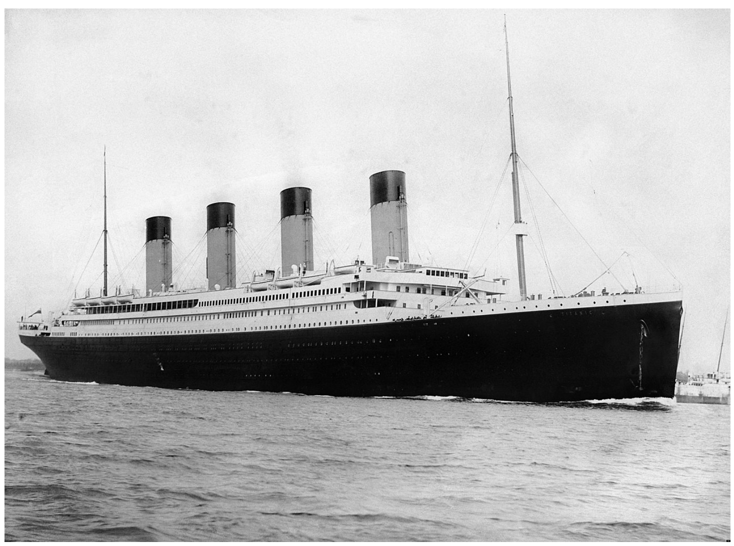


Figure 1: Fig. 1: RMS Titanic departing Southampton on April 10, 1912.

Load the data from `data/titanic.csv` into *R* and familiarize yourself with the variables it contains using the codebook (`data/titanic_codebook.txt`).

Notice that `survived` and `pclass` should be changed to factors. When changing `survived` to a factor, you may want to reorder the factor so that *"Yes"* is the first level.

Make sure you load the `tidyverse` and `tidymodels`!

```
set.seed(123)
library(tidyverse)
library(tidymodels)
titanic <- read.csv('data/titanic.csv')
titanic$survived <-factor(titanic$survived, levels=c("Yes", "No"))
```

```r
titanic$pclass <-factor(titanic$pclass)
titanic %>% head()
```

```
##   passenger_id survived pclass
## 1            1       No      3
## 2            2      Yes      1
## 3            3      Yes      3
## 4            4      Yes      1
## 5            5       No      3
## 6            6       No      3
##                                                  name    sex age sib_sp parch
## 1                             Braund, Mr. Owen Harris   male  22      1     0
## 2 Cumings, Mrs. John Bradley (Florence Briggs Thayer) female  38      1     0
## 3                              Heikkinen, Miss. Laina female  26      0     0
## 4        Futrelle, Mrs. Jacques Heath (Lily May Peel) female  35      1     0
## 5                            Allen, Mr. William Henry   male  35      0     0
## 6                                    Moran, Mr. James   male  NA      0     0
##             ticket    fare cabin embarked
## 1        A/5 21171  7.2500  <NA>        S
## 2         PC 17599 71.2833   C85        C
## 3 STON/O2. 3101282  7.9250  <NA>        S
## 4           113803 53.1000  C123        S
## 5           373450  8.0500  <NA>        S
## 6           330877  8.4583  <NA>        Q
```

Remember that you'll need to set a seed at the beginning of the document to reproduce your results.

Question 1

Split the data, stratifying on the outcome variable, `survived.` You should choose the proportions to split the data into. Verify that the training and testing data sets have the appropriate number of observations. Take a look at the training data and note any potential issues, such as missing data.

Why is it a good idea to use stratified sampling for this data?

```r
titanic_split <- initial_split(titanic, prop = 0.8,
                               strata = survived)
titanic_train <- training(titanic_split)
titanic_test <- testing(titanic_split)
nrow(titanic_train)
```

```
## [1] 712
```

```r
nrow(titanic_test)
```

```
## [1] 179
```

```r
titanic_train %>% head()
```

```
##    passenger_id survived pclass                           name  sex age sib_sp
## 5             5       No      3       Allen, Mr. William Henry male  35      0
```

```
## 6             6       No      3               Moran, Mr. James male  NA      0
## 7             7       No      1        McCarthy, Mr. Timothy J male  54      0
## 8             8       No      3 Palsson, Master. Gosta Leonard male   2      3
## 13           13       No      3 Saundercock, Mr. William Henry male  20      0
## 14           14       No      3    Andersson, Mr. Anders Johan male  39      1
##    parch    ticket    fare cabin embarked
## 5      0    373450  8.0500  <NA>        S
## 6      0    330877  8.4583  <NA>        Q
## 7      0     17463 51.8625   E46        S
## 8      1    349909 21.0750  <NA>        S
## 13     0 A/5. 2151  8.0500  <NA>        S
## 14     5    347082 31.2750  <NA>        S
```

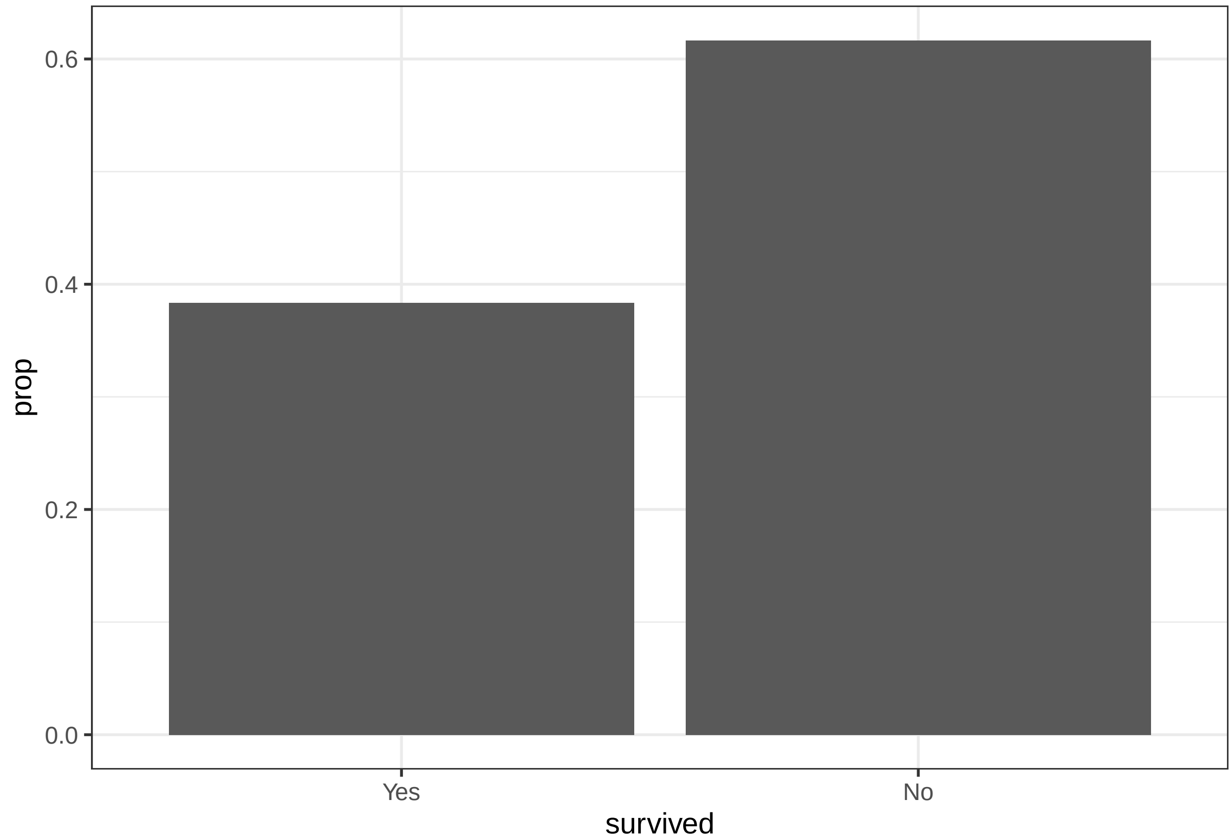
There are some issues with missing data. There are some observations that have a missing value for the age variable, while a large number of observations have missing data for the cabin variable.

It is a good idea to use stratified sampling for this data because there may be differences in the population based on whether the person survived or not.

Question 2

Using the **training** data set, explore/describe the distribution of the outcome variable `survived`.

```
titanic_train %>%
  ggplot(aes(x = survived)) +
  geom_bar(aes(y = ..prop.., group = 1)) +
  theme_bw()
```

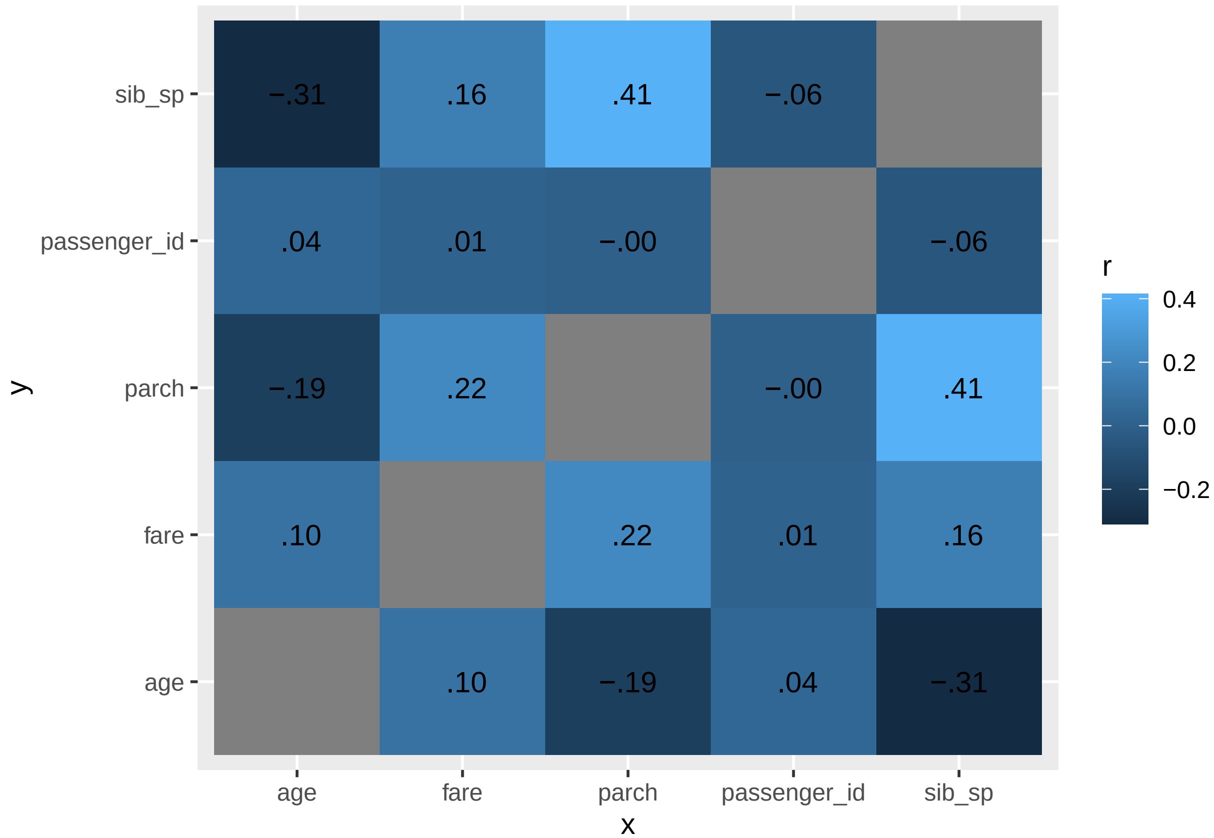


In the training data set for the titanic data, we see that there about 40% of the observations/people survived, whereas around 60% of the observations did not survive.

Question 3

Using the **training** data set, create a correlation matrix of all continuous variables. Create a visualization of the matrix, and describe any patterns you see. Are any predictors correlated with each other? Which ones, and in which direction?

```
library(corrr)
cor_titanic <- titanic %>% dplyr::select(where(is.numeric)) %>% correlate()
cor_titanic %>% stretch() %>%
  ggplot(aes(x, y, fill = r)) +
  geom_tile() +
  geom_text(aes(label = as.character(fashion(r))))
```



Most of the variables are not really correlated with each other, with the strongest correlation being between parch and sib_sp (number of parents / children aboard the Titanic and the number of siblings / spouses aboard the Titanic respectively) at 0.41. In particular, quite a few of the variable combinations have a correlation value close to 0, indicating no correlation at all between those variables.

Question 4

Using the **training** data, create a recipe predicting the outcome variable `survived`. Include the following predictors: ticket class, sex, age, number of siblings or spouses aboard, number of parents or children aboard, and passenger fare.

Recall that there were missing values for `age`. To deal with this, add an imputation step using `step_impute_linear()`. Next, use `step_dummy()` to **dummy** encode categorical predictors. Finally, include interactions between:

- Sex and passenger fare, and
- Age and passenger fare.

You'll need to investigate the `tidymodels` documentation to find the appropriate step functions to use.

```
titanic_recipe <- recipe(survived ~ pclass+sex+
                          age+sib_sp+parch+fare, data=titanic_train) %>%
                         step_impute_linear(age) %>%
                         step_dummy(all_nominal_predictors()) %>%
                         step_interact(terms = ~ starts_with("sex"):fare) %>%
                         step_interact(terms = ~ age:fare)
```

Question 5

Specify a **logistic regression** model for classification using the `"glm"` engine. Then create a workflow. Add your model and the appropriate recipe. Finally, use `fit()` to apply your workflow to the **training** data.

Hint: Make sure to store the results of `fit()`. You'll need them later on.

```
# logistic regression model using glm engine
log_reg <- logistic_reg() %>% set_engine("glm") %>% set_mode("classification")
# workflow
log_workflow <- workflow() %>% add_model(log_reg) %>% add_recipe(titanic_recipe)
# fit
log_fit <- fit(log_workflow, titanic_train)
```

Question 6

Repeat Question 5, but this time specify a linear discriminant analysis model for classification using the `"MASS"` engine.

```
library(discrim)
# linear discrimant analysis model using MASS engine
lda_model <- discrim_linear()  %>% set_mode("classification")%>% set_engine("MASS")
# workflow
lda_workflow <- workflow() %>% add_model(lda_model) %>% add_recipe(titanic_recipe)
# fit
lda_fit <- fit(lda_workflow, titanic_train)
```

Question 7

Repeat Question 5, but this time specify a quadratic discriminant analysis model for classification using the `"MASS"` engine.

```
# quadratic discriminant analysis model using MASS engine
qda_model <- discrim_quad()  %>% set_mode("classification")%>% set_engine("MASS")
# workflow
qda_workflow <- workflow() %>% add_model(qda_model) %>% add_recipe(titanic_recipe)
# fit
qda_fit <- fit(qda_workflow, titanic_train)
```

Question 8

Repeat Question 5, but this time specify a naive Bayes model for classification using the `"klaR"` engine. Set the `usekernel` argument to `FALSE`.

```
library(klaR)
# naive Bayes model using klar engine
nb_model <- naive_Bayes()  %>% set_mode("classification")%>%
            set_engine("klaR")  %>% set_args(usekernel = FALSE)
# workflow
nb_workflow <- workflow() %>% add_model(nb_model) %>% add_recipe(titanic_recipe)
# fit
nb_fit <- fit(nb_workflow, titanic_train)
```

Question 9

Now you've fit four different models to your training data.

Use `predict()` and `bind_cols()` to generate predictions using each of these 4 models and your **training** data. Then use the *accuracy* metric to assess the performance of each of the four models.

Which model achieved the highest accuracy on the training data?

```
# accessing model performance
library(dplyr)
# logistic regression
log_prediction <- bind_cols(predict(log_fit, new_data=titanic_train), titanic_train %>% dplyr::select(s
log_prediction
```

```
## # A tibble: 712 x 2
##    .pred_class survived
##    <fct>       <fct>
##  1 No          No
##  2 No          No
##  3 No          No
##  4 No          No
##  5 No          No
##  6 No          No
##  7 Yes         No
##  8 No          No
##  9 No          No
## 10 Yes         No
## # ... with 702 more rows
```

```
log_acc <- log_prediction %>%
          accuracy(truth=survived, estimate = .pred_class)
log_acc
```

```
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy binary         0.812
```

```
# LDA
lda_prediction <- bind_cols(predict(lda_fit, new_data=titanic_train), titanic_train %>% dplyr::select(s
lda_prediction
```

```
## # A tibble: 712 x 2
##    .pred_class survived
##    <fct>       <fct>
##  1 No          No
##  2 No          No
##  3 No          No
##  4 No          No
##  5 No          No
##  6 No          No
##  7 Yes         No
```

```
## 8 Yes         No
## 9 No          No
## 10 Yes         No
## # ... with 702 more rows
```

```
lda_acc <- lda_prediction %>%
          accuracy(truth=survived, estimate = .pred_class)
lda_acc
```

```
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy binary         0.805
```

```
# QDA
qda_prediction <- bind_cols(predict(qda_fit, new_data = titanic_train), titanic_train %>% dplyr::select
qda_prediction
```

```
## # A tibble: 712 x 2
##    .pred_class survived
##    <fct>       <fct>
##  1 No          No
##  2 No          No
##  3 No          No
##  4 No          No
##  5 No          No
##  6 No          No
##  7 No          No
##  8 No          No
##  9 No          No
## 10 No          No
## # ... with 702 more rows
```

```
qda_acc <- qda_prediction %>%
          accuracy(truth=survived, estimate = .pred_class)
qda_acc
```

```
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy binary         0.764
```

```
# Naive Bayes
nb_prediction <- suppressWarnings(bind_cols(predict(nb_fit, new_data = titanic_train), titanic_train %>%
nb_prediction
```

```
## # A tibble: 712 x 2
##    .pred_class survived
##    <fct>       <fct>
##  1 No          No
##  2 No          No
```

```
##   3 Yes         No
##   4 No          No
##   5 No          No
##   6 No          No
##   7 No          No
##   8 No          No
##   9 No          No
## 10 No          No
## # ... with 702 more rows
```

```
nb_acc <- nb_prediction %>%
          accuracy(truth=survived, estimate = .pred_class)
nb_acc
```

```
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy binary         0.765
```

The model with the highest training accuracy was the logistic regression model.

Question 10

Fit the model with the highest training accuracy to the **testing** data. Report the accuracy of the model on the **testing** data.

Again using the **testing** data, create a confusion matrix and visualize it. Plot an ROC curve and calculate the area under it (AUC).

How did the model perform? Compare its training and testing accuracies. If the values differ, why do you think this is so?

```
# fit testing data
bind_cols(predict(log_fit, new_data=titanic_test), titanic_test %>% dplyr::select(survived))
```

```
## # A tibble: 179 x 2
##    .pred_class survived
##    <fct>       <fct>
##   1 No          No
##   2 Yes         Yes
##   3 Yes         Yes
##   4 Yes         Yes
##   5 No          No
##   6 No          No
##   7 Yes         Yes
##   8 No          No
##   9 Yes         Yes
## 10 Yes         No
## # ... with 169 more rows
```

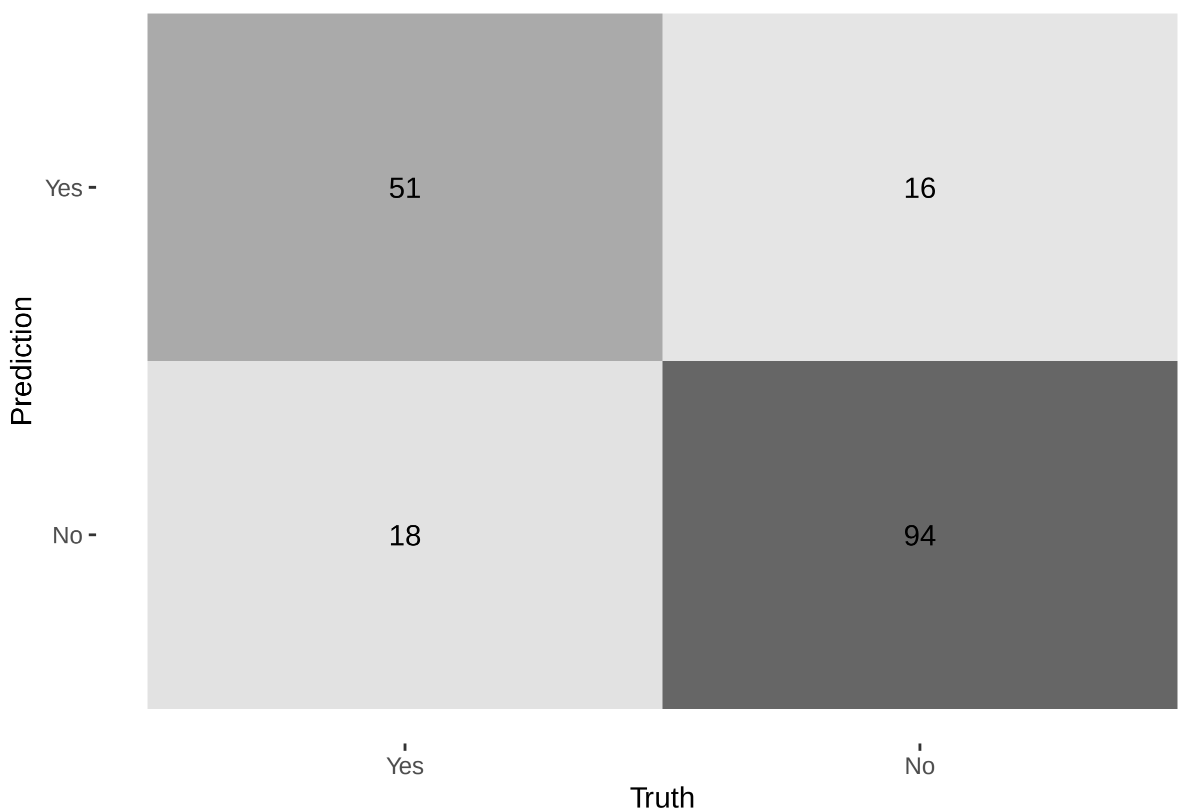
```
# accuracy
bind_cols(predict(log_fit, new_data=titanic_test), titanic_test %>% dplyr::select(survived)) %>% accura
```

```
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy binary         0.810
```

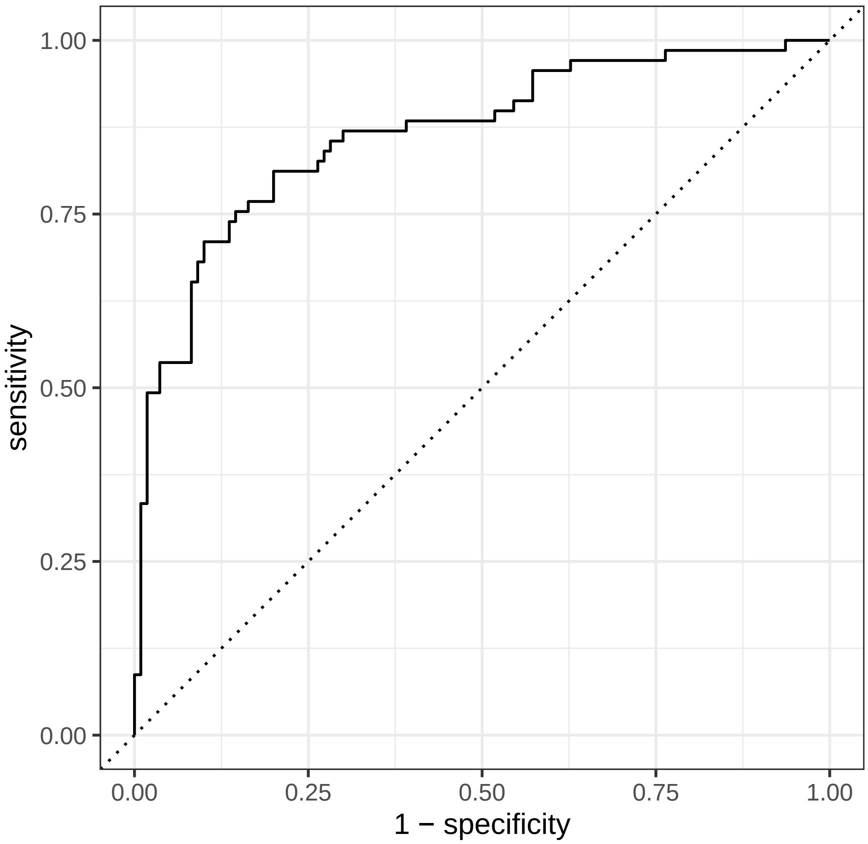
```r
# confusion matrix
augment(log_fit, new_data = titanic_test) %>%
  conf_mat(truth = survived, estimate = .pred_class)
```

```
##           Truth
## Prediction Yes No
##        Yes  51 16
##        No   18 94
```

```r
# visual
augment(log_fit, new_data = titanic_test) %>%
  conf_mat(truth = survived, estimate = .pred_class) %>% autoplot(type = "heatmap")
```




```r
# ROC curve
augment(log_fit, new_data = titanic_test) %>%
  roc_curve(survived, .pred_Yes) %>%
  autoplot()
```




```r
# AUC
pROC::auc(augment(log_fit, new_data = titanic_test)$survived, augment(log_fit, new_data = titanic_test)$
```

```
## Area under the curve: 0.8652
```

The training and testing accuracies are fairly similar (0.8117978 vs. 0.8100559), which suggests that our model is pretty good and does not have the issue of overfitting. Looking at the confusion matrix, it seems that it predicts the right outcome the majority of the time.