Homework 3

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```
library(tidyverse)
library(tidymodels)
library(ggplot2)
library(corrplot)
library(discrim)
library(klaR)
library(yardstick)
```

```
titanic <- read_csv("titanic.csv")

titanic <- titanic %>%
  mutate(survived = as.factor(survived)) %>%
  mutate(pclass = as.factor(pclass))
```

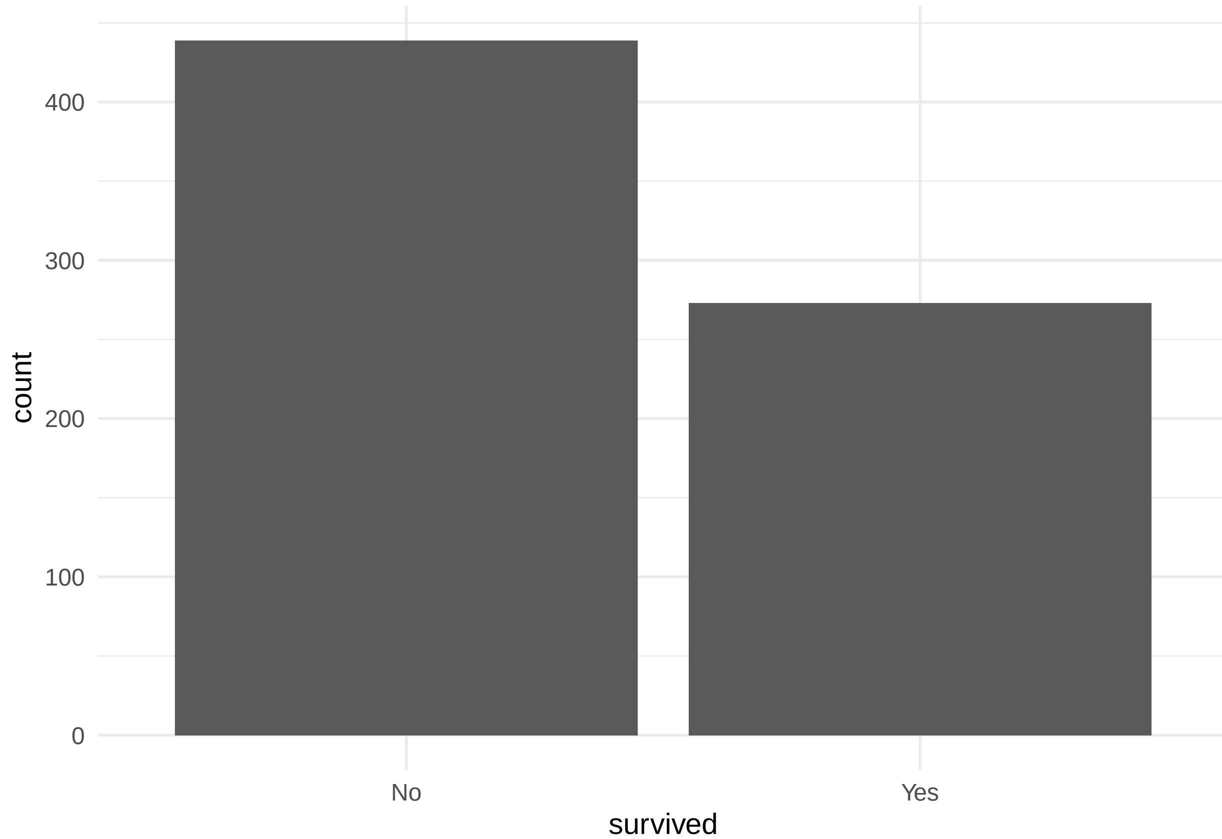
Question 1

```
set.seed(10)

titanic_split <- initial_split(titanic, prop = 0.80,
                               strata = survived)
titanic_train <- training(titanic_split)
titanic_test <- testing(titanic_split)
```

The stratification based on outcome will equate the fraction of y between training and test sample. Without using it, the fraction of y in test data could be very different from that in training data, which give us poor performance of our model.

Question 2

```
titanic_train2 <- titanic_train %>%
  mutate(survived_dummy = ifelse(survived == "Yes", 1, 0))

hist_survived <- titanic_train %>%
  ggplot(aes(survived)) +
  geom_bar() +
  theme_minimal()
plot(hist_survived)
```



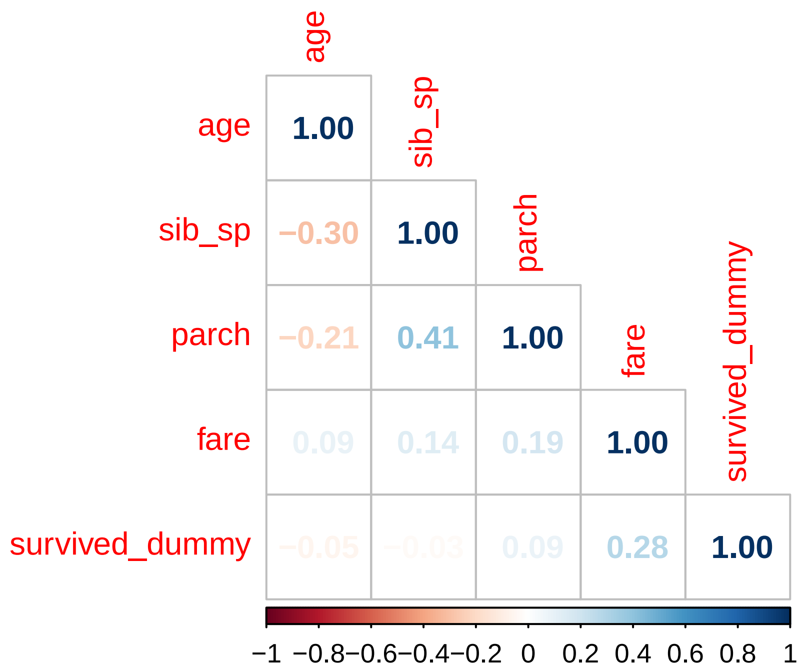

```
summary(tibble(titanic_train2$survived_dummy))
```

```
##  titanic_train2$survived_dummy
##  Min.   :0.0000
##  1st Qu.:0.0000
##  Median :0.0000
##  Mean   :0.3834
##  3rd Qu.:1.0000
##  Max.   :1.0000
```

Around 38% of passengers survived.

Question 3

```
titanic_train2 %>%
  dplyr::select(age, sib_sp, parch, fare, survived_dummy) %>%
  cor(use = "complete.obs") %>%
  corrplot(method = "number", type = "lower")
```



More expensive fare have positive correlation with survival probability. It is noteworthy that passenger age have negative correlation with # of sibling and spouse, or # of parents and children. # of sibling and spouse and # of parents and children has a positive correlation.

Question 4

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

Question 5

```
# Engine
log_reg <- logistic_reg() %>%
  set_engine("glm") %>%
  set_mode("classification")

# Workflow
log_wkflow <- workflow() %>%
  add_model(log_reg) %>%
  add_recipe(titanic_recipe)

log_fit <- fit(log_wkflow, titanic_train)
```

Question 6

```r
# Engine
lda <- discrim_linear() %>%
  set_engine("MASS") %>%
  set_mode("classification")

# Workflow
lda_wkflow <- workflow() %>%
  add_model(lda) %>%
  add_recipe(titanic_recipe)

lda_fit <- fit(lda_wkflow, titanic_train)
```

Question 7

```r
# Engine
qda <- discrim_quad() %>%
  set_engine("MASS") %>%
  set_mode("classification")

# Workflow
qda_wkflow <- workflow() %>%
  add_model(qda) %>%
  add_recipe(titanic_recipe)

qda_fit <- fit(qda_wkflow, titanic_train)
```

Question 8

```r
nb <- naive_Bayes() %>%
  set_mode("classification") %>%
  set_engine("klaR") %>%
  set_args(usekernel = FALSE)

nb_wkflow <- workflow() %>%
  add_model(nb) %>%
  add_recipe(titanic_recipe)

nb_fit <- fit(nb_wkflow, titanic_train)
```

Question 9

```r
pred_log <- predict(log_fit, new_data = titanic_train, type = "prob")
pred_lda <- predict(lda_fit, new_data = titanic_train, type = "prob")
pred_qda <- predict(qda_fit, new_data = titanic_train, type = "prob")
pred_nb <- predict(nb_fit, new_data = titanic_train, type = "prob")
```

```r
bind_cols(pred_log[,2], pred_lda[,2], pred_qda[,2], pred_nb[,2])
```

```
## New names:
## * `.pred_Yes` -> `.pred_Yes...1`
## * `.pred_Yes` -> `.pred_Yes...2`
```

```
## * `.pred_Yes` -> `.pred_Yes...3`
## * `.pred_Yes` -> `.pred_Yes...4`
```

```
## # A tibble: 712 x 4
##    .pred_Yes...1 .pred_Yes...2 .pred_Yes...3 .pred_Yes...4
##            <dbl>         <dbl>         <dbl>         <dbl>
##  1        0.0664        0.0390   0.00280        0.00839
##  2        0.0945        0.0547   0.00381        0.00858
##  3        0.334         0.263    0.0664         0.510
##  4        0.0930        0.0592   0.0000513      0.000116
##  5        0.153         0.0877   0.00632        0.00952
##  6        0.787         0.844    0.501          0.340
##  7        0.0533        0.0375   0.000000193    0.00000121
##  8        0.466         0.582    0.186          0.264
##  9        0.531         0.643    0.000360       0.00501
## 10        0.0943        0.0544   0.00376        0.00881
## # ... with 702 more rows
```

- Logistic

```
augment(log_fit, new_data = titanic_train) %>%
  conf_mat(truth = survived, estimate = .pred_class)
```

```
##           Truth
## Prediction  No Yes
##        No  391  78
##        Yes  48 195
```

*LDA

```
augment(lda_fit, new_data = titanic_train) %>%
  conf_mat(truth = survived, estimate = .pred_class)
```

```
##           Truth
## Prediction  No Yes
##        No  385  86
##        Yes  54 187
```

*QDA

```
augment(qda_fit, new_data = titanic_train) %>%
  conf_mat(truth = survived, estimate = .pred_class)
```

```
##           Truth
## Prediction  No Yes
##        No  412 126
##        Yes  27 147
```

*Naive Bayes

```
augment(nb_fit, new_data = titanic_train) %>%
  conf_mat(truth = survived, estimate = .pred_class)
```

```
##           Truth
## Prediction  No Yes
##        No  407 128
##        Yes  32 145
```

Question 10

Question 11

$$
\begin{aligned}
p &= \frac{e^z}{1+e^z} \\
&\Rightarrow p(1+e^z) = e^z \\
&\Rightarrow p = e^z(1-p) \\
&\Rightarrow e^z = \frac{p}{1-p} \\
&\Rightarrow z(p) = \ln\left(\frac{p}{1-p}\right)
\end{aligned}
$$

Question 12