Homework 2

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PSTAT 131/231 Statistical Machine Learning - Fall 2022

Linear Regression

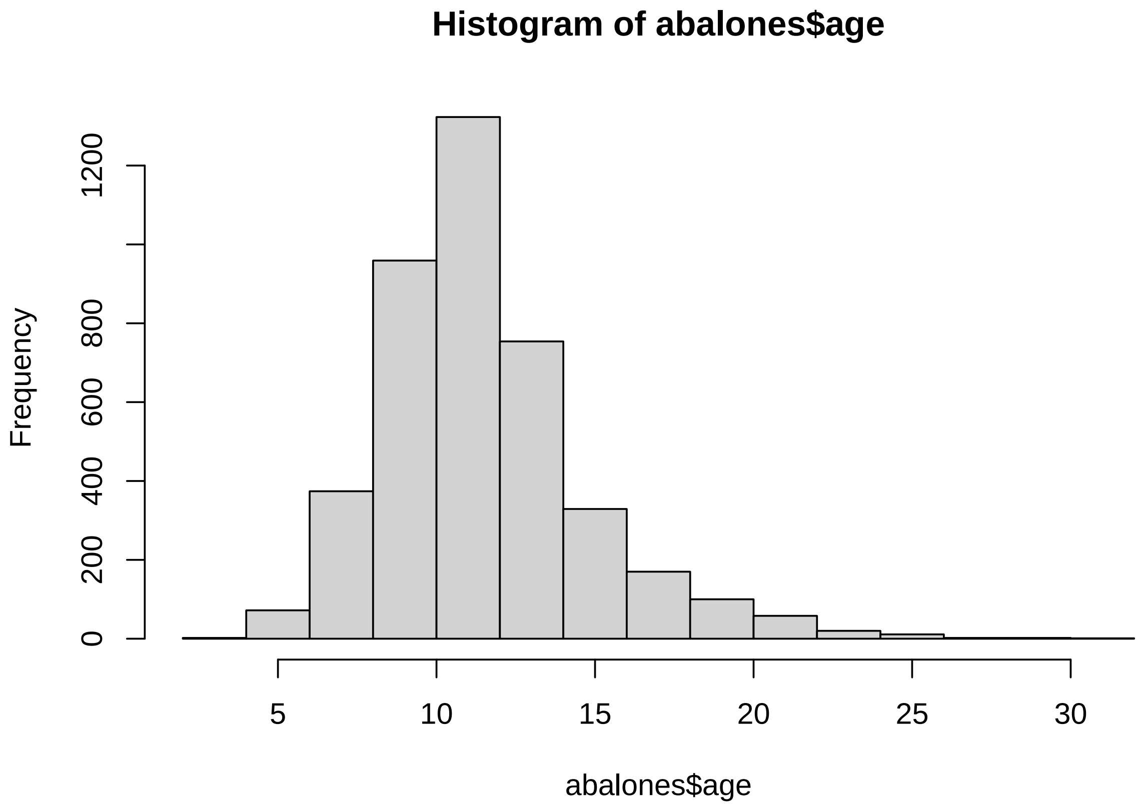
Question 1

```
# Adding the age variable as a column to the Abalone data frame
abalones <- aba_data %>%
  mutate(age = rings + 1.5)

# Checking to see it was correctly added
head(abalones)
```

```
##   type longest_shell diameter height whole_weight shucked_weight viscera_weight
## 1    M         0.455    0.365  0.095       0.5140         0.2245         0.1010
## 2    M         0.350    0.265  0.090       0.2255         0.0995         0.0485
## 3    F         0.530    0.420  0.135       0.6770         0.2565         0.1415
## 4    M         0.440    0.365  0.125       0.5160         0.2155         0.1140
## 5    I         0.330    0.255  0.080       0.2050         0.0895         0.0395
## 6    I         0.425    0.300  0.095       0.3515         0.1410         0.0775
##   shell_weight rings  age
## 1        0.150    15 16.5
## 2        0.070     7  8.5
## 3        0.210     9 10.5
## 4        0.155    10 11.5
## 5        0.055     7  8.5
## 6        0.120     8  9.5
```

```
# Making a histogram of the age in order to asses the distribution
hist(abalones$age)
```



Using a histogram, we can see that the age of the abalones is normally distributed and skewed right, with an average age of about 11 years old. While there are more outliers that are older in age, most abalones tend to live between 5 and 15 years.

Question 2

```
set.seed(8488)

abalones_split <- initial_split(abalones, prop=0.80, strata=age)

abalones_train <- training(abalones_split)
abalones_test <- testing(abalones_split)
```

Question 3

We shouldn't include *rings* in the recipe to predict *age* since the *age* variable was calculated and added to the abalones dataset using the *rings* variable. As done in Question 1, we copied the *rings* column and added 1.5 in order to create the *age* column.

```
abalone_recipe <- recipe(age ~ ., data=abalones_train) %>%
  # removing rings variable
  step_rm(rings) %>%
  # Step 1: dummy code categorical predictors
  step_dummy(all_nominal_predictors()) %>%
  # Step 2: creating interactions
  step_interact(terms = ~ starts_with("type"):shucked_weight +
                  longest_shell:diameter + shucked_weight:shell_weight) %>%
  # Step 3 & 4: centering and scaling predictors
  step_normalize(all_predictors())

abalone_recipe
```

Question 4

Creating and storing a linear regression object using the "lm" engine.

```
lm_model <- linear_reg() %>%
  set_engine("lm")
```

Question 5

Setting up an empty workflow, adding the model we created in Question 4, and adding the recipe that we created in Question 3.

```
lm_wflow <- workflow() %>%
  add_model(lm_model) %>%
  add_recipe(abalone_recipe)
```

Question 6

```
# fitting our model using the training data
lm_fit <- fit(lm_wflow, abalones_train)

lm_fit %>%
  # This returns the parsnip object:
  extract_fit_parsnip() %>%
  # Now tidy the linear model object:
  tidy()
```

```
## # A tibble: 14 x 5
##    term                          estimate std.error statistic  p.value
##    <chr>                            <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)                    11.4       0.0370   309.    0
##  2 longest_shell                   0.448     0.283      1.59  1.13e- 1
##  3 diameter                        2.10      0.311      6.77  1.53e-11
##  4 height                          0.273     0.0691     3.96  7.71e- 5
##  5 whole_weight                    5.27      0.395     13.3   1.50e-39
##  6 shucked_weight                 -4.56      0.256    -17.8   6.11e-68
##  7 viscera_weight                 -0.942     0.158     -5.97  2.65e- 9
##  8 shell_weight                    1.50      0.212      7.08  1.74e-12
##  9 type_I                         -1.04      0.116     -8.99  4.18e-19
## 10 type_M                         -0.297     0.103     -2.89  3.89e- 3
## 11 type_I_x_shucked_weight          0.602     0.0871     6.91  5.73e-12
## 12 type_M_x_shucked_weight          0.371     0.109      3.41  6.51e- 4
## 13 longest_shell_x_diameter       -2.80      0.397     -7.05  2.21e-12
## 14 shucked_weight_x_shell_weight  -0.0378    0.200     -0.189 8.50e- 1
```

```
# making a tibble for a hypothetical female abalone
new_aba <- tibble(type = "F", longest_shell = 0.50, diameter = 0.10,
                  height = 0.30, whole_weight = 4, shucked_weight = 1,
                  viscera_weight = 2, shell_weight = 1, rings = 0)

# using predict() and fit() to predict its age based on the above data
hypo_abalone <- predict(lm_fit, new_data = new_aba)
hypo_abalone
```

```
## # A tibble: 1 x 1
##   .pred
##   <dbl>
## 1  24.5
```

The age of the hypothetical female abalone with all the above characteristics would be approximately 24.45 years old.

Question 7

Now, we assess our model's performance.

```
library(yardstick)

# tibble using predict()
abalone_train_res <- predict(lm_fit, new_data = abalones_train %>% select(-age))
abalone_train_res %>%
  head()
```

```
## # A tibble: 6 x 1
##   .pred
##   <dbl>
## 1  8.07
## 2  9.74
## 3 10.5
## 4 10.1
## 5  6.28
## 6  5.80
```

```
# tibble using bind_cols()
abalone_train_res <- bind_cols(abalone_train_res, abalones_train %>% select(age))
abalone_train_res %>%
  head()
```

```
## # A tibble: 6 x 2
##   .pred   age
##   <dbl> <dbl>
## 1  8.07   8.5
## 2  9.74   8.5
## 3 10.5    8.5
## 4 10.1    9.5
## 5  6.28   6.5
## 6  5.80   6.5
```

```
# creating a metric set including R2, RMSE, and MAE
abalone_metrics <- metric_set(rmse, rsq, mae)
# applying the metric to the tibble
abalone_metrics(abalone_train_res, truth = age,
                estimate = .pred)
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       2.14
## 2 rsq     standard       0.569
## 3 mae     standard       1.54
```

After applying the metric set to the tibble, the results are a R2 value of 0.5693, a RMSE value of 2.1365, and a MAE value of 1.5406. With a R2 value of 0.5693, it can be said that about 57% of the variability observed in the age variable is explained by the linear regression model.