Homework 2

PSTAT 131/231

Contents

Linear Regression

For this lab, we will be working with a data set from the UCI (University of California, Irvine) Machine Learning repository (see website here). The full data set consists of $4,177$ observations of abalone in Tasmania. (Fun fact: Tasmania supplies about 25% of the yearly world abalone harvest.)

The age of an abalone is typically determined by cutting the shell open and counting the number of rings with a microscope. The purpose of this data set is to determine whether abalone age (**number of rings + 1.5**) can be accurately predicted using other, easier-to-obtain information about the abalone.

The full abalone data set is located in the `\data` subdirectory. Read it into *R* using `read_csv()`. Take a moment to read through the codebook (`abalone_codebook.txt`) and familiarize yourself with the variable definitions.

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

Question 1

Your goal is to predict abalone age, which is calculated as the number of rings plus 1.5. Notice there currently is no `age` variable in the data set. Add `age` to the data set.

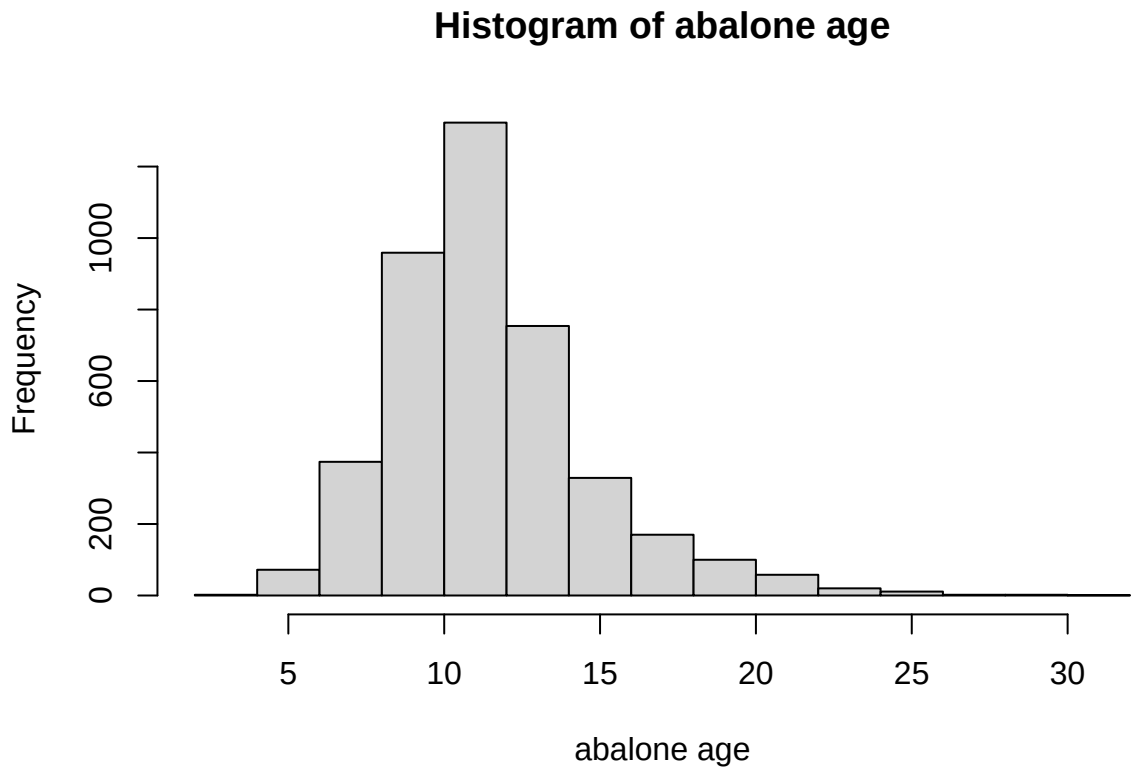
Assess and describe the distribution of `age`.

```
library(tidyverse)
library(tidymodels)

# read in the data
abalone <- read_csv("C:/Users/cupca/OneDrive/Documents/UCSB/Fall2022/PSTAT131/homework-2/data/abalone.cs

# add age as a variable
abalone_w_age <- abalone %>% mutate(age = rings + 1.5)
abalone_w_age
```

```
## # A tibble: 4,177 x 10
##    type  longest_sh~1 diame~2 height whole~3 shuck~4 visce~5 shell~6 rings   age
##    <chr>        <dbl>   <dbl>  <dbl>   <dbl>   <dbl>   <dbl>   <dbl> <dbl> <dbl>
##  1 M            0.455   0.365  0.095   0.514  0.224   0.101    0.15     15  16.5
##  2 M            0.35    0.265  0.09    0.226  0.0995  0.0485   0.07      7   8.5
##  3 F            0.53    0.42   0.135   0.677  0.256   0.142    0.21      9  10.5
```

```
##  4 M           0.44    0.365  0.125   0.516  0.216   0.114    0.155    10  11.5
##  5 I           0.33    0.255  0.08    0.205  0.0895  0.0395   0.055     7   8.5
##  6 I           0.425   0.3    0.095   0.352  0.141   0.0775   0.12      8   9.5
##  7 F           0.53    0.415  0.15    0.778  0.237   0.142    0.33     20  21.5
##  8 F           0.545   0.425  0.125   0.768  0.294   0.150    0.26     16  17.5
##  9 M           0.475   0.37   0.125   0.509  0.216   0.112    0.165     9  10.5
## 10 F           0.55    0.44   0.15    0.894  0.314   0.151    0.32     19  20.5
## # ... with 4,167 more rows, and abbreviated variable names 1: longest_shell,
## #   2: diameter, 3: whole_weight, 4: shucked_weight, 5: viscera_weight,
## #   6: shell_weight
```

```r
# simple histogram of abalone age
hist(abalone_w_age$age,
     xlab = "abalone age",
     main = "Histogram of abalone age")
```



Answer: After making a histogram of the abalone age variable, it seems that age is approximately normally distributed, showing a bell-shaped curve.

Question 2

Split the abalone data into a training set and a testing set. Use stratified sampling. You should decide on appropriate percentages for splitting the data.

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

```
set.seed(3435)

# preparing data for splitting
abalone_w_age <- abalone_w_age %>%
  select(-rings) %>% # remove rings variable
  mutate(type=as.factor(type)) # convert type variable to factor type

# split into training/testing sets
abalone_split <- initial_split(abalone_w_age, prop = 0.80,
                               strata = age)
abalone_train <- training(abalone_split)
abalone_test <- testing(abalone_split)
```

Question 3

Using the **training** data, create a recipe predicting the outcome variable, `age`, with all other predictor variables. Note that you should not include `rings` to predict `age`. Explain why you shouldn't use `rings` to predict `age`.

Steps for your recipe: 1. dummy code any categorical predictors

2. create interactions between
    - `type` and `shucked_weight`,
    - `longest_shell` and `diameter`,
    - `shucked_weight` and `shell_weight`
3. center all predictors, and
4. scale all predictors.

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

```
# recipe (do not include rings)
abalone_recipe <- recipe(age~., data = abalone_train) %>%
  step_dummy(all_nominal_predictors()) %>% # dummy code categorical predictors
  step_interact(terms = ~ starts_with("type"):shucked_weight) %>% # create interactions
  step_interact(terms = ~ longest_shell:diameter) %>%
  step_interact(terms = ~ shucked_weight:shell_weight) %>%
  step_center(all_predictors()) %>% # center predictors
  step_scale(all_predictors()) # scale predictors
```

Answer: We should not include rings to predict age because age is calculated based on rings (rings + 1.5). If we used rings, it would be like using a scaled version of the outcome as a predictor to help predict the outcome, which doesn't make much sense.

Question 4

Create and store a linear regression object using the `"lm"` engine.

```
# create model, store linear regression object
lm_model <- linear_reg() %>%
  set_engine("lm")
```

Question 5

Now: 1. set up an empty workflow, 2. add the model you created in Question 4, and 3. add the recipe that you created in Question 3.

```
lm_wflow <- workflow() %>% # empty workflow
  add_model(lm_model) %>%  # add model
  add_recipe(abalone_recipe) # add recipe

lm_fit <- fit(lm_wflow, abalone_train) # see how our fitted model did

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        0.0375  305.     0
##  2 longest_shell                   0.591      0.286     2.07   3.86e- 2
##  3 diameter                        2.06       0.313     6.61   4.59e-11
##  4 height                          0.236      0.0696    3.39   7.10e- 4
##  5 whole_weight                    4.29       0.387    11.1    4.66e-28
##  6 shucked_weight                 -4.06       0.250   -16.2    5.35e-57
##  7 viscera_weight                 -0.792      0.158    -5.00   6.12e- 7
##  8 shell_weight                    1.74       0.212     8.20   3.32e-16
##  9 type_I                         -0.942      0.117    -8.07   9.36e-16
## 10 type_M                         -0.239      0.104    -2.29   2.21e- 2
## 11 type_I_x_shucked_weight         0.525      0.0876    5.99   2.26e- 9
## 12 type_M_x_shucked_weight         0.293      0.109     2.68   7.41e- 3
## 13 longest_shell_x_diameter       -2.75       0.396    -6.95   4.32e-12
## 14 shucked_weight_x_shell_weight -0.00330    0.205    -0.0161 9.87e- 1
```

Question 6

Use your `fit()` object to predict the age of a hypothetical female abalone with longest_shell = 0.50, diameter = 0.10, height = 0.30, whole_weight = 4, shucked_weight = 1, viscera_weight = 2, shell_weight = 1.

```
# new observation to predict
new_abalone <- data.frame(type=as.factor("F"),
                          longest_shell=0.50,
                          diameter=0.10,
                          height=0.30,
                          whole_weight=4,
                          shucked_weight=1,
```

```
                          viscera_weight=2,
                          shell_weight=1)
new_abalone <- as_tibble(new_abalone) # convert to tibble

abalone_train_res <- predict(lm_fit, new_data = new_abalone) # use model to predict
abalone_train_res
```

```
## # A tibble: 1 x 1
##   .pred
##   <dbl>
## 1  23.7
```

Question 7

Now you want to assess your model's performance. To do this, use the `yardstick` package:

1. Create a metric set that includes R^2, RMSE (root mean squared error), and MAE (mean absolute error).
2. Use `predict()` and `bind_cols()` to create a tibble of your model's predicted values from the **training data** along with the actual observed ages (these are needed to assess your model's performance).
3. Finally, apply your metric set to the tibble, report the results, and interpret the R^2 value.

```
# metric set
abalone_metrics <- metric_set(rmse, rsq, mae)

# tibble of predicted values
abalone_train_res <- predict(lm_fit, new_data = abalone_train %>% select(-age))
abalone_train_res %>%
  head()
```

```
## # A tibble: 6 x 1
##   .pred
##   <dbl>
## 1  8.03
## 2  9.68
## 3 10.4
## 4 10.1
## 5 10.9
## 6  6.26
```

```
# add actual observed ages
abalone_train_res <- bind_cols(abalone_train_res, abalone_train %>% select(age))
abalone_train_res %>%
  head()
```

```
## # A tibble: 6 x 2
##   .pred   age
##   <dbl> <dbl>
## 1  8.03   8.5
## 2  9.68   8.5
## 3 10.4    8.5
```

```
## 4 10.1    9.5
## 5 10.9    9.5
## 6  6.26   6.5
```

```
# apply metric set to tibble
abalone_metrics(abalone_train_res, truth = age,
                estimate = .pred)
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       2.16
## 2 rsq     standard       0.551
## 3 mae     standard       1.55
```

Answer: R^2 measures the proportion of variability in the outcome Y (age of the abalone), that can be explained through the predictor X (longest_shell, diameter, height, whole_weight, shucked_weight, viscera_weight, and shell_weight). So according to the metric set, it seems that there is about 0.55 variability in abalone age that can be accounted for by our predictors.