Lab Tutorial 8

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2023-12-03

Summary: This lab focuses on *Linear Regression*. The content for this lab has been copied from the textbook's worksheet on Chapter 8.

There is no assignment for this lab.

Warm-up Questions

Here are some warm-up questions on the topic of multiple regression to get you thinking before we jump into data analysis.

In multivariate k-nn regression with one outcome/target variable and two predictor variables, the predictions take the form of what shape?

A. a flat plane

B. a wiggly/flexible plane

C. A straight line

D. a wiggly/flexible line

E. a 4D hyperplane

F. a 4D wiggly/flexible hyperplane

```
#B. In multiple regression using KNN for two predictors, our predictions form a flexible p
```

In simple linear regression with one outcome/target variable and one predictor variable, the predictions take the form of what shape?

A. a flat plane

B. a wiggly/flexible plane

C. A straight line

D. a wiggly/flexible line

E. a 4D hyperplane

F. a 4D wiggly/flexible hyperplane

```
#C In simple linear regression , our predictions form a straight line since we only have 1
```

In multiple linear regression with one outcome/target variable and two predictor variables, the predictions take the form of what shape?

A. a flat plane

B. a wiggly/flexible plane

C. A straight line

D. a wiggly/flexible line

E. a 4D hyperplane

F. a 4D wiggly/flexible hyperplane

```
# A
```

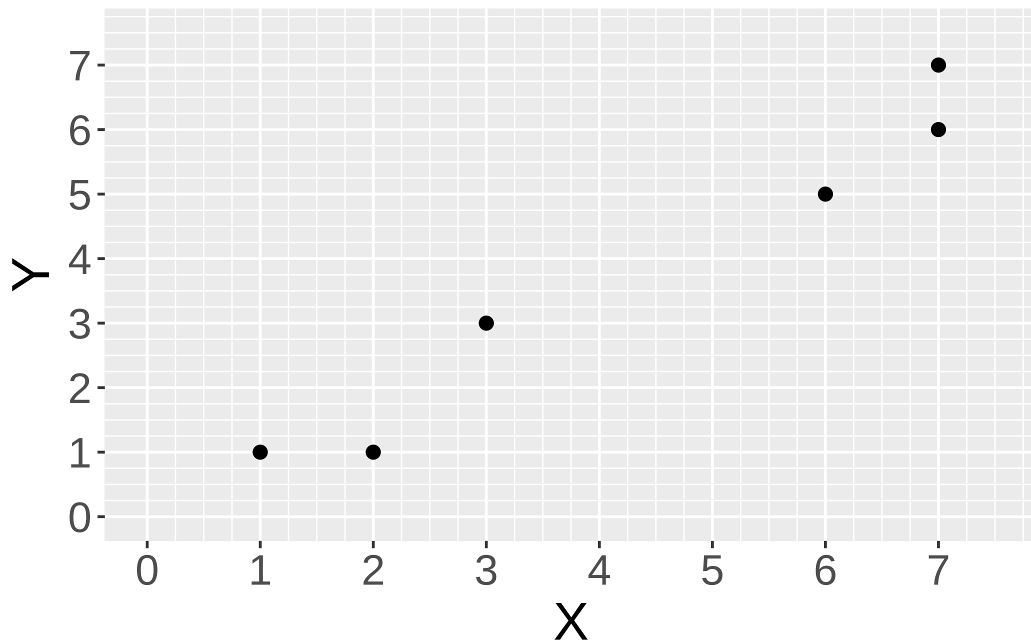
```
### Run this cell before continuing.
# run install.package("cowplot") in your console if you don't have it already
library(cowplot)
library(tidyverse)
library(repr)
library(tidymodels)
options(repr.matrix.max.rows = 6)
```

Understanding Simple Linear Regression

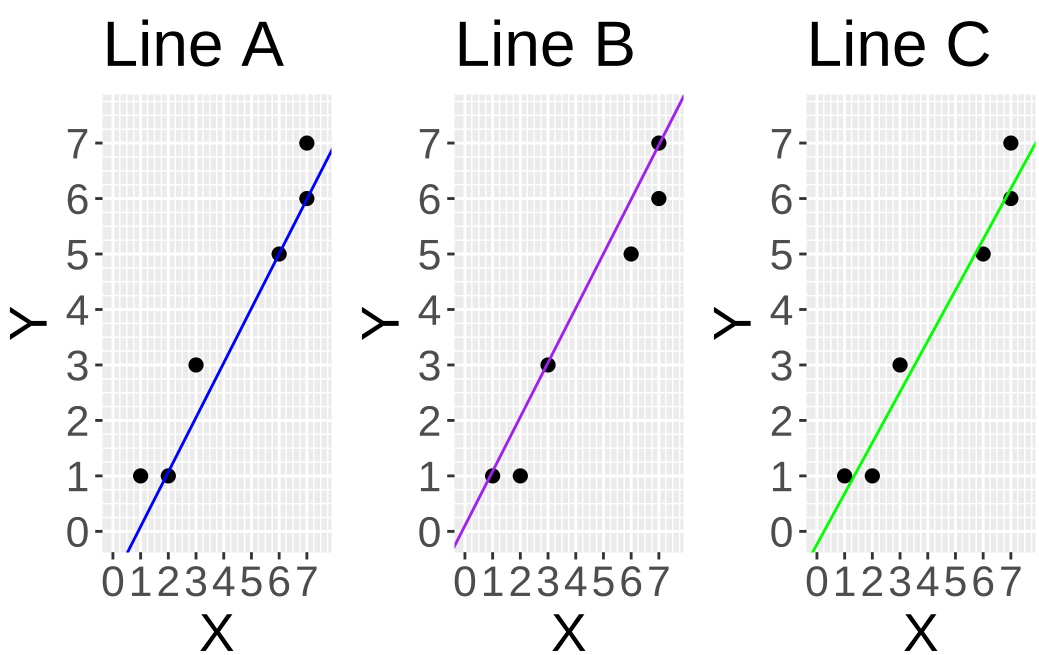
Consider this small and simple dataset:

```
simple_data  <- tibble(X = c(1, 2, 3, 6, 7, 7),
               Y = c(1, 1, 3, 5, 7, 6))
options(repr.plot.width = 5, repr.plot.height = 5)
base <- ggplot(simple_data, aes(x = X, y = Y)) +
    geom_point(size = 2) +
    scale_x_continuous(limits = c(0, 7.5), breaks = seq(0, 8), minor_breaks = seq(0, 8, 0.
    scale_y_continuous(limits = c(0, 7.5), breaks = seq(0, 8), minor_breaks = seq(0, 8, 0.
    theme(text = element_text(size = 20))
```

```
base
```

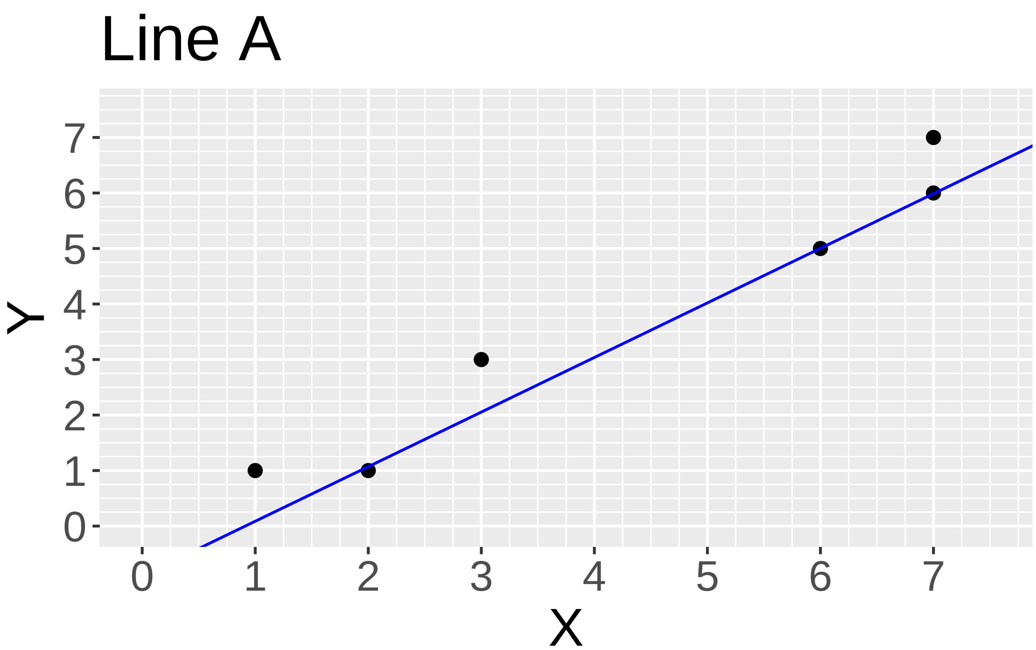


Now consider these three **potential** lines we could fit for the same dataset:



Use the graph below titled "Line A" to roughly calculate the average squared vertical distance between the points and the blue line.

```
#run this code
options(repr.plot.width = 9, repr.plot.height = 9)
line_a
```



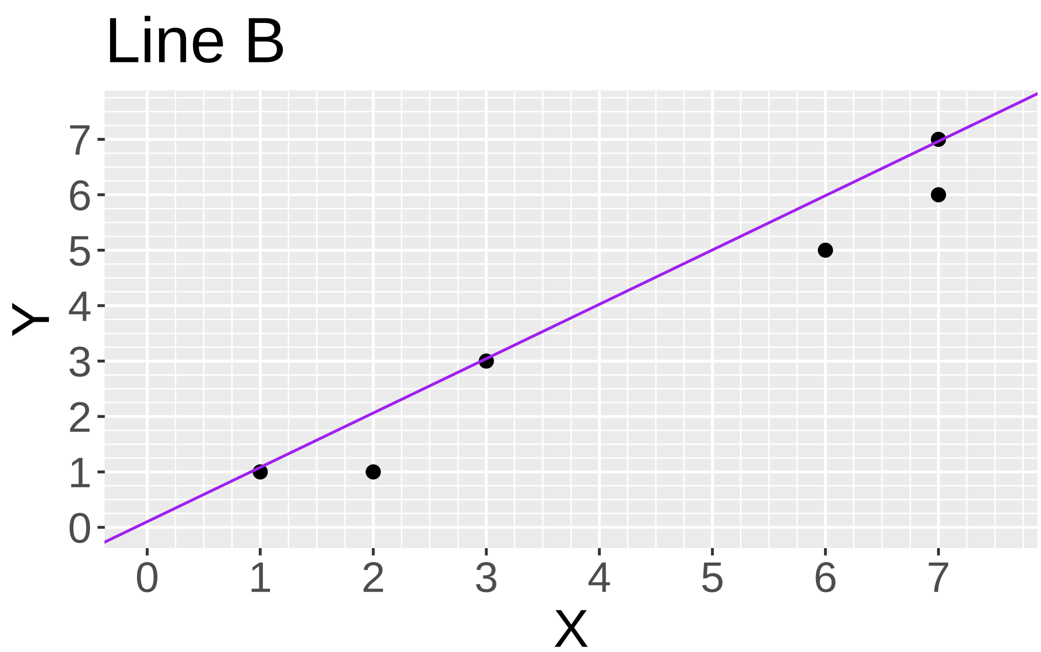

```
# we should calculate the distance between each y and predicted y (yhat) for all the datap

y <- c(1, 1, 3, 5, 7, 6)
yhat_A <- c(0,1,3,2,6,6) #looking at graph
mean((y-yhat_A)^2)
```

```
[1] 1.833333
```

Use the graph titled "Line B" to roughly calculate the average squared vertical distance between the points and the purple line.

```
options(repr.plot.width = 9, repr.plot.height = 9)
line_b
```



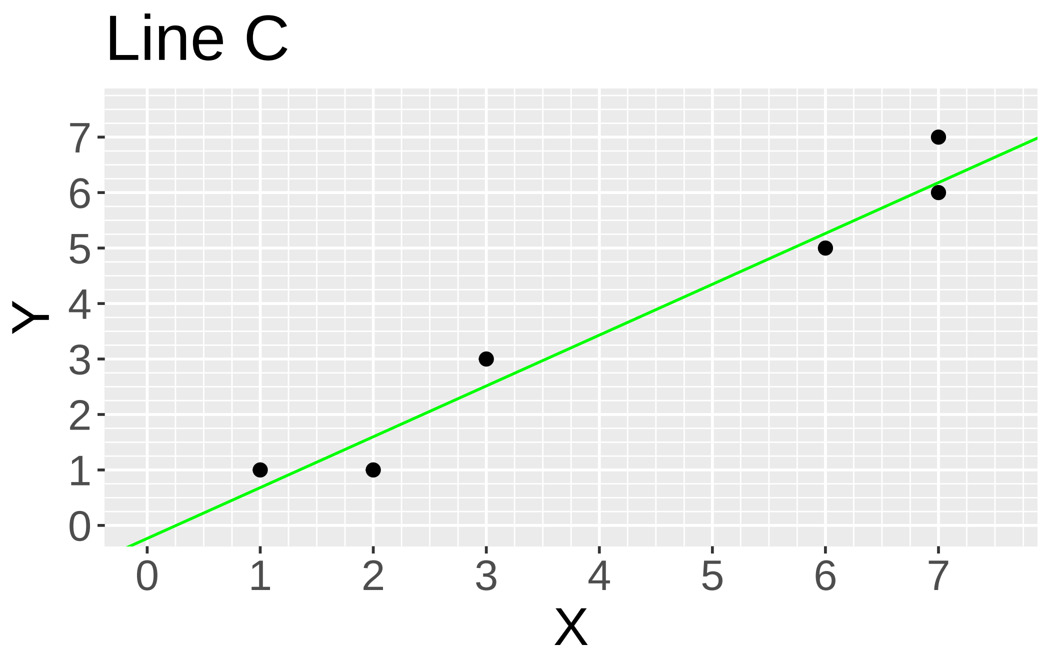

```
#Similar to the previous part

yhat_B <- c(1,2,3,6,7,7) #looking at graph
mean((y-yhat_B)^2)
```

```
[1] 0.5
```

Use the graph titled "Line C" to roughly calculate the average squared vertical distance between the points and the green line.

```
options(repr.plot.width = 9, repr.plot.height = 9)
line_c
```




```
# Read values of the graph to a precision of 0.25, we get the following values
yhat_C <- c(0.75,1.5,2.5,5.25,6.25,6.25)
mean((y-yhat_C)^2)
```

```
[1] 0.2083333
```

Based on your calculations above, which line would linear regression by ordinary least squares choose given our small and simple dataset? Line A, B or C?

```
# Ordinary least squuares find the line the has the minimum mean of squared residuals to b
```

Marathon Training Revisited with Linear Regression!

Source: https://media.giphy.com/media/BDagLpxFIm3SM/giphy.gif

Remember our question from last week: what features predict whether athletes will perform better than others? Specifically, we are interested in marathon runners, and looking at how the maximum distance ran per week during training predicts the time it takes a runner to end the race?

This time around, however, we will analyze the data using simple linear regression rather than k-nn regression. In the end, we will compare our results to what we found last week with k-nn regression.

First, load the data and assign it to an object called `marathon`.

```
marathon <- read_csv("../data/marathon.csv")
```

```
Rows: 929 Columns: 13
-- Column specification --------------------------------------------------------
Delimiter: ","
dbl (13): age, bmi, female, footwear, group, injury, mf_d, mf_di, mf_ti, max...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
#or
#marathon <- read_csv("data/marathon.csv")
```

Similar to what we have done for the last few weeks, we will first split the dataset into the training and testing datasets, using 75% of the original data as the training data. Remember, we will be putting the test dataset away in a 'lock box' that we will comeback to later after we choose our final model. In the `strata` argument of the `initial_split` function, place the variable we are trying to predict. Assign your split dataset to an object named `marathon_split`.

Assign your training dataset to an object named `marathon_training` and your testing dataset to an object named `marathon_testing`.

```
set.seed(2000) ### DO NOT CHANGE

#... <- initial_split(..., prop = ..., strata = ...)
#... <- training(...)
#... <- testing(...)
```

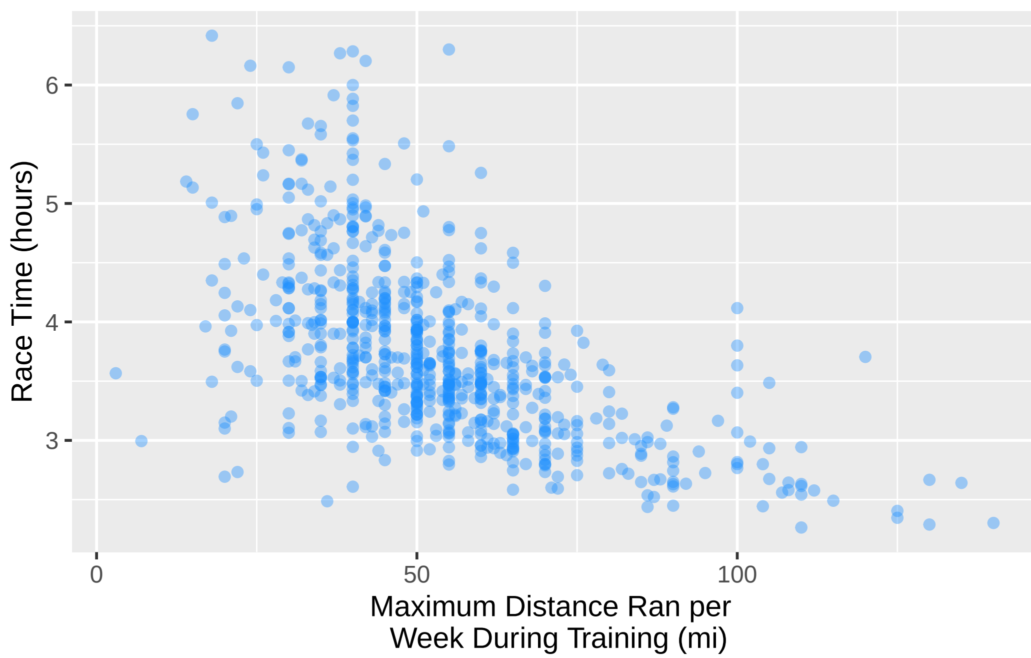
```
set.seed(2000)
marathon_split <- initial_split(marathon, prop = 0.75, strata = time_hrs)
marathon_training<- training(marathon_split)
marathon_testing<- testing(marathon_split)
```

Using only the observations in the training dataset, create a scatterplot to assess the relationship between race time (`time_hrs`) and maximum distance ran per week during training (`max`). Put `time_hrs` on the y-axis and `max` on the x-axis. Assign this plot to an object called `marathon_eda`. Remember to do whatever is necessary to make this an effective visualization.

```
# .... <- .... |>
#    ggplot(.....) +
#        geom_...() +
#        ...("Maximum Distance Ran per \n Week During Training (mi)") +
#       ...("Race Time (hours)")
```

```
marathon_eda <- marathon_training |>
    ggplot(aes(x = max, y = time_hrs)) +
        geom_point(color = 'dodgerblue', alpha = 0.4) +
        xlab("Maximum Distance Ran per \n Week During Training (mi)") +
        ylab("Race Time (hours)")

marathon_eda
```



Now that we have our training data, the next step is to build a linear regression model specification. Thankfully, building other model specifications is quite straightforward since we will still go through the same procedure (indicate the function, the engine and the mode).

Instead of using the `nearest_neighbor` function, we will be using the `linear_reg` function to let `tidymodels` know we want to perform a linear regression. In the `set_engine` function, we have typically set `"kknn"` there for k-nn. Since we are doing a linear regression here, set `"lm"` as the engine. Finally, instead of setting `"classification"` as the mode, set `"regression"` as the mode.

Assign your answer to an object named `lm_spec`.

```
#.... <- linear_reg() |>
#.....(...) |>
#set_mode(...)
```

```
lm_spec <- linear_reg() |>
  set_engine("lm") |>
  set_mode("regression")
```

After we have created our linear regression model specification, the next step is to create a recipe, establish a workflow analysis and fit our simple linear regression model.

First, create a recipe with the variables of interest (race time and max weekly training distance) using the training dataset and assign your answer to an object named `lm_recipe`.

Then, create a workflow analysis with our model specification and recipe. Remember to fit in the training dataset as well. Assign your answer to an object named `lm_fit`.

```
#... <- recipe(... ~ ..., data = ...)

#... <- workflow() |>
#       add_recipe(...) |>
#       add_model(...) |>
#       fit(...)
```

```
lm_recipe <- recipe(time_hrs ~ max, data = marathon_training)

lm_fit <- workflow() |>
  add_recipe(lm_recipe) |>
  add_model(lm_spec) |>
  fit(data = marathon_training)
lm_fit
```

```
== Workflow [trained] ==========================================================
Preprocessor: Recipe
Model: linear_reg()

-- Preprocessor ----------------------------------------------------------------
0 Recipe Steps

-- Model -----------------------------------------------------------------------
```

```
Call:
stats::lm(formula = ..y ~ ., data = data)

Coefficients:
(Intercept)          max
     4.8794      -0.0215
```

Now, let's visualize the model predictions as a straight line overlaid on the training data. Use the `predict` and `bind_cols` functions on `lm_fit` to create predictions for the `marathon_training` data. Name the resulting data frame `marathon_preds`.

Next, create a scatterplot with the marathon time (y-axis) against the maximum distance run per week (x-axis) from `marathon_preds`. Use an alpha value of 0.4 to avoid overplotting. **Plot the predictions as a black line over the data points.** Assign your plot to a variable called `lm_predictions`. Remember the fundamentals of effective visualizations such as having a human-readable axes titles.

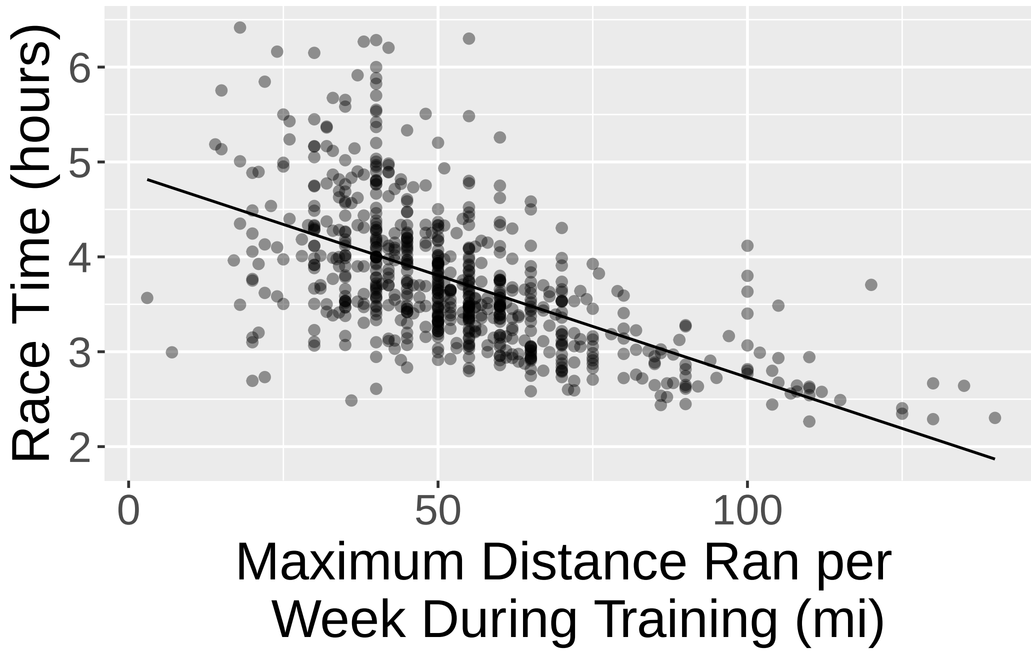
```r
options(repr.plot.width = 8, repr.plot.height = 7)

# marathon_preds <- ... |>
#   predict(...) |>
#   bind_cols(...)
#
# lm_predictions <- marathon_preds |>
#     ...(aes(x = ..., y = ...)) +
#         geom_point(... = 0.4) +
#         geom_line(
#             mapping = aes(x = ..., y = ...),
#             color = "blue") +
#         xlab("...") +
#         ylab("...") +
#         theme(text = ...(size = 20))
```

```r
marathon_preds <- lm_fit |>
  predict(marathon_training)|>
  bind_cols(marathon_training)

lm_predictions <- marathon_preds |>
     ggplot(aes(x = max, y = time_hrs)) +
        geom_point(alpha = 0.4) +
        geom_line(
```

```
                mapping = aes(x = max, y = .pred),
                color = "black") +
            xlab("Maximum Distance Ran per \n Week During Training (mi)") +
            ylab("Race Time (hours)") +
            theme(text = element_text(size = 20))
lm_predictions
```



Great! We can now see the line of best fit on the graph. Now let's calculate the $RMSPE$ using the **test data**. To get to this point, first, use the `lm_fit` to make predictions on the test data. Remember to bind the appropriate columns for the test data. Afterwards, collect the metrics and store it in an object called `lm_test_results`.

From `lm_test_results`, extract the $RMPSE$ and return a single numerical value. Assign your answer to an object named `lm_rmspe`.

```
#... <- lm_fit |>
#         predict(...) |>
#         bind_cols(...) |>
#         metrics(truth = ..., estimate = ..)

#... <- lm_test_results |>
#          filter(...) |>
```

```
#           select(...) |>
#           ...
```

```
lm_test_results <- lm_fit |>
         predict(marathon_testing) |>
         bind_cols(marathon_testing) |>
         metrics(truth = time_hrs, estimate = .pred)

lm_rmspe <- lm_test_results |>
          filter(.metric == "rmse") |>
          select(.estimate) |>
          pull()
lm_rmspe
```

```
[1] 0.5504829
```

Now, let's visualize the model predictions as a straight line overlaid on the test data. First, create a scatterplot to assess the relationship between race time (`time_hrs`) and maximum distance ran per week during training (`max`) on the **testing data.** Use and alpha value of 0.4 to avoid overplotting. Then add a line to the plot corresponding to the predictions from the fit linear regression model. Remember to do whatever is necessary to make this an effective visualization.

Assign the plot to an object called `lm_predictions_test`.

```
options(repr.plot.width = 8, repr.plot.height = 7)

# test_preds <- ...

# lm_predictions_test <- ...
```

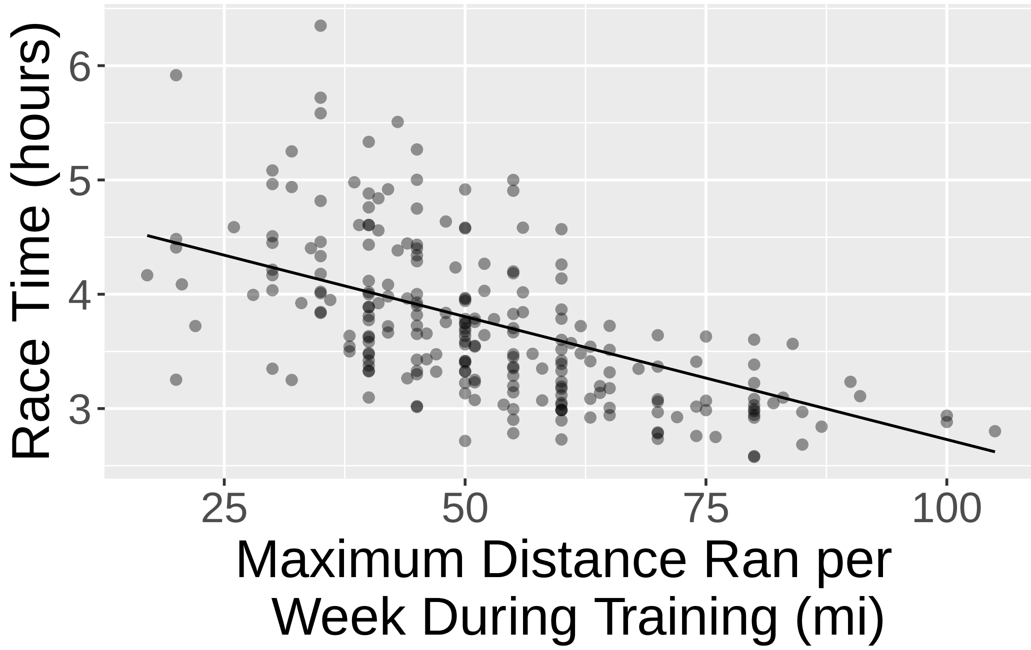
```
options(repr.plot.width = 8, repr.plot.height = 7)

test_preds <- lm_fit |>
  predict(marathon_testing) |>
  bind_cols(marathon_testing)

lm_predictions_test <- test_preds |>
     ggplot(aes(x = max, y = time_hrs)) +
        geom_point(alpha = 0.4) +
        geom_line(
```

```
            mapping = aes(x = max, y = .pred),
            color = "black") +
        xlab("Maximum Distance Ran per \n Week During Training (mi)") +
        ylab("Race Time (hours)") +
        theme(text = element_text(size = 20))

lm_predictions_test
```



Compare the test RMPSE of k-nn regression (`0.544` from last worksheet) to that of simple linear regression, which is greater?

A. *k*-nn regression has a greater RMSPE

B. Simple linear regression has a greater RMSPE

C. Neither, they are identical

```
lm_test_rmpse <- test_preds |>
  metrics(truth = time_hrs, estimate = .pred) |>
  filter(.metric == "rmse") |>
          select(.estimate) |>
          pull()
lm_test_rmpse
```

```
[1] 0.5504829
```

```
# B, SLM has slightly worse (larger) value for RMSPE
```

Which model does a better job of predicting on the test dataset?

A. k-nn regression

B. Simple linear regression

C. Neither, they are identical

```
# B, I would choose simple linear regression, even though it has sightly larger RMSE becau
```

Given that the linear regression model is a straight line, we can write our model as a mathematical equation. We can get the two numbers we need for this from the coefficients, `(Intercept)` and `time_hrs`.

```
# run this cell
lm_fit
```

```
== Workflow [trained] ==========================================================
Preprocessor: Recipe
Model: linear_reg()

-- Preprocessor ----------------------------------------------------------------
0 Recipe Steps

-- Model -----------------------------------------------------------------------

Call:
stats::lm(formula = ..y ~ ., data = data)

Coefficients:
(Intercept)          max
     4.8794      -0.0215
```

Which of the following mathematical equations represents the model based on the numbers output in the cell above?

A. $Predicted\ race\ time\ (in\ hours) = 4.88 - 0.02 * max\ (in\ miles)$

B. $Predicted\ race\ time\ (in\ hours) = -0.02 + 4.88 * max\ (in\ miles)$

C. $Predicted\ max\ (in\ miles) = 4.88 - 0.02 *\ race\ time\ (in\ hours)$

D. $Predicted\ max\ (in\ miles) = -0.02 + 4.88 *\ race\ time\ (in\ hours)$

> #A