Lab 3

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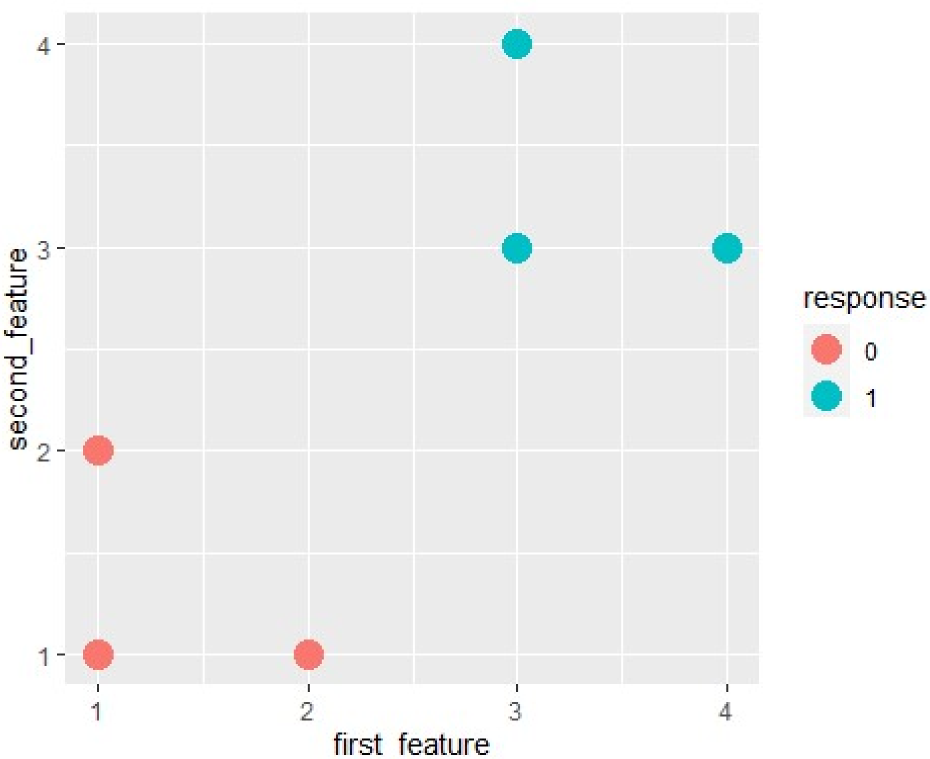
11:59PM March 4, 2021

Support Vector Machine vs. Perceptron

We recreate the data from the previous lab and visualize it:

```
pacman::p_load(ggplot2)
Xy_simple = data.frame(
 response = factor(c(0, 0, 0, 1, 1, 1)), #nominal
 first_feature = c(1, 1, 2, 3, 3, 4),     #continuous
 second_feature = c(1, 2, 1, 3, 4, 3)     #continuous
)
simple_viz_obj = ggplot(Xy_simple, aes(x = first_feature, y = second_feature,
color = response)) +
  geom_point(size = 5)
simple_viz_obj
```

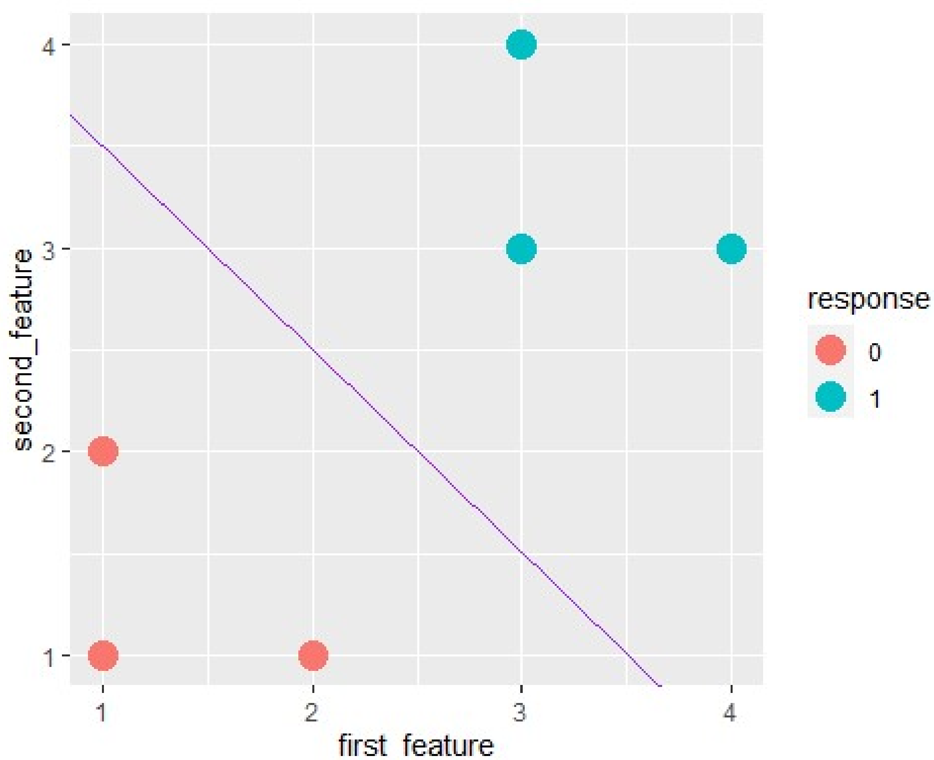


Use the `e1071` package to fit an SVM model to the simple data. Use a formula to create the model, pass in the data frame, set kernel to be `linear` for the linear SVM and don't scale the covariates. Call the model object `svm_model`. Otherwise the remaining code won't work.

```
pacman::p_load(e1071)
svm_model = svm(
  formula = Xy_simple$response ~.,
  data = Xy_simple,
  kernel = "linear",
  scale = FALSE
)
```

and then use the following code to visualize the line in purple:

```
w_vec_simple_svm = c(
  svm_model$rho, #the b term
  -t(svm_model$coefs) %*% cbind(Xy_simple$first_feature,
Xy_simple$second_feature)[svm_model$index, ] # the other terms
)
simple_svm_line = geom_abline(
    intercept = -w_vec_simple_svm[1] / w_vec_simple_svm[3],
    slope = -w_vec_simple_svm[2] / w_vec_simple_svm[3],
    color = "purple")
simple_viz_obj + simple_svm_line
```



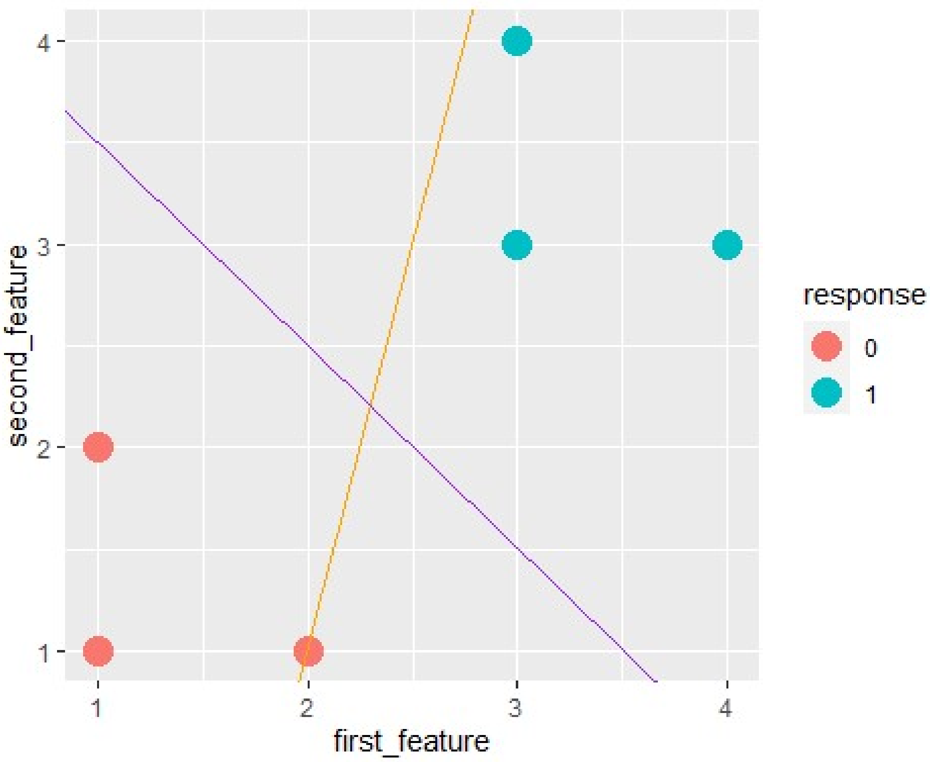
Source the `perceptron_learning_algorithm` function from lab 2. Then run the following to fit the perceptron and plot its line in orange with the SVM's line:

```
perceptron_learning_algorithm = function(Xinput, y_binary, MAX_ITER = 1000, w
= NULL){
```

```r
  Xinput = as.matrix(cbind(1,Xinput))
  p = ncol(Xinput)
  w = rep(0, p)
  r = nrow(Xinput)

  for (iter in 1 : MAX_ITER){
    for (i in 1 : r) {
      x_i = Xinput[i, ]
      yhat_i = ifelse(sum(x_i * w) > 0, 1, 0)
      y_i = y_binary[i]
      for(j in 1:p){
        w[j] = w[j] + (y_i - yhat_i) * x_i[j]
      }
    }
  }
  w
}

w_vec_simple_per = perceptron_learning_algorithm(
  cbind(Xy_simple$first_feature, Xy_simple$second_feature),
  as.numeric(Xy_simple$response == 1)
)
simple_perceptron_line = geom_abline(
    intercept = -w_vec_simple_per[1] / w_vec_simple_per[3],
    slope = -w_vec_simple_per[2] / w_vec_simple_per[3],
    color = "orange")
simple_viz_obj + simple_perceptron_line + simple_svm_line
```



Is this SVM line a better fit than the perceptron?

Yes, this SVM line is a better fit than the perecptron, it is marginally acceptable.

Now write pseuocode for your own implementation of the linear support vector machine algorithm using the Vapnik objective function we discussed.

Note there are differences between this spec and the perceptron learning algorithm spec in question #1. You should figure out a way to respect the `MAX_ITER` argument value.

```
#' Support Vector Machine
#
#' This function implements the hinge-loss + maximum margin linear support
vector machine algorithm of Vladimir Vapnik (1963).
#'
#' @param Xinput      The training data features as an n x p matrix.
#' @param y_binary    The training data responses as a vector of length n
consisting of only 0's and 1's.
#' @param MAX_ITER    The maximum number of iterations the algorithm
performs. Defaults to 5000.
#' @param lambda      A scalar hyperparameter trading off margin of the
hyperplane versus average hinge loss.
#'                    The default value is 1.
#' @return            The computed final parameter (weight) as a vector of
length p + 1
linear_svm_learning_algorithm = function(Xinput, y_binary, MAX_ITER = 5000,
lambda = 0.1){
```

```
  #Declaring the Sum of hinge error
  # SHE = 0

  #  initialize a w vector
  #  w <- () (This something like this?)

  #Iterate through the for-loop till the MAX_ITER
  #  for x in MAX_ITER{

  #Iterate through each row
  #    for i in nrow(Xinput){

           #Adding the hinge error for each i to obtain total
  #        SHE += max{0, (1/2) - (y_binary[i]-1/2)(w*Xinput[i]-b)}
  #    }
  #  }
  #  To maximize the margin
  #  argmin{(SHE/n) + lambda(distance of w)^2}

  #  Returns w (the wedge/weights?)
  #  w
}
```

If you are enrolled in 342W the following is extra credit but if you're enrolled in 650, the following is required. Write the actual code. You may want to take a look at the `optimx` package. You can feel free to define another function (a "private" function) in this chunk if you wish. R has a way to create public and private functions, but I believe you need to create a package to do that (beyond the scope of this course).

```
#' This function implements the hinge-loss + maximum margin linear support
vector machine algorithm of Vladimir Vapnik (1963).
#'
#' @param Xinput      The training data features as an n x p matrix.
#' @param y_binary    The training data responses as a vector of length n
consisting of only 0's and 1's.
#' @param MAX_ITER    The maximum number of iterations the algorithm
performs. Defaults to 5000.
#' @param lambda      A scalar hyperparameter trading off margin of the
hyperplane versus average hinge loss.
#'                    The default value is 1.
#' @return            The computed final parameter (weight) as a vector of
length p + 1
#linear_svm_learning_algorithm = function(Xinput, y_binary, MAX_ITER = 5000,
lambda = 0.1){

#}
```

If you wrote code (the extra credit), run your function using the defaults and plot it in brown vis-a-vis the previous model's line:

```
#svm_model_weights = linear_svm_learning_algorithm(Xinput, y_binary)
#my_svm_line = geom_abline(
#    intercept = svm_model_weights[1] / svm_model_weights[3],#NOTE: negative
sign removed from intercept argument here
#    slope = -svm_model_weights[2] / svm_model_weights[3],
#    color = "brown")
#simple_viz_obj  + my_svm_line
```

Is this the same as what the `e1071` implementation returned? Why or why not?

TO-DO

We now move on to simple linear modeling using the ordinary least squares algorithm.

Let's quickly recreate the sample data set from practice lecture 7:

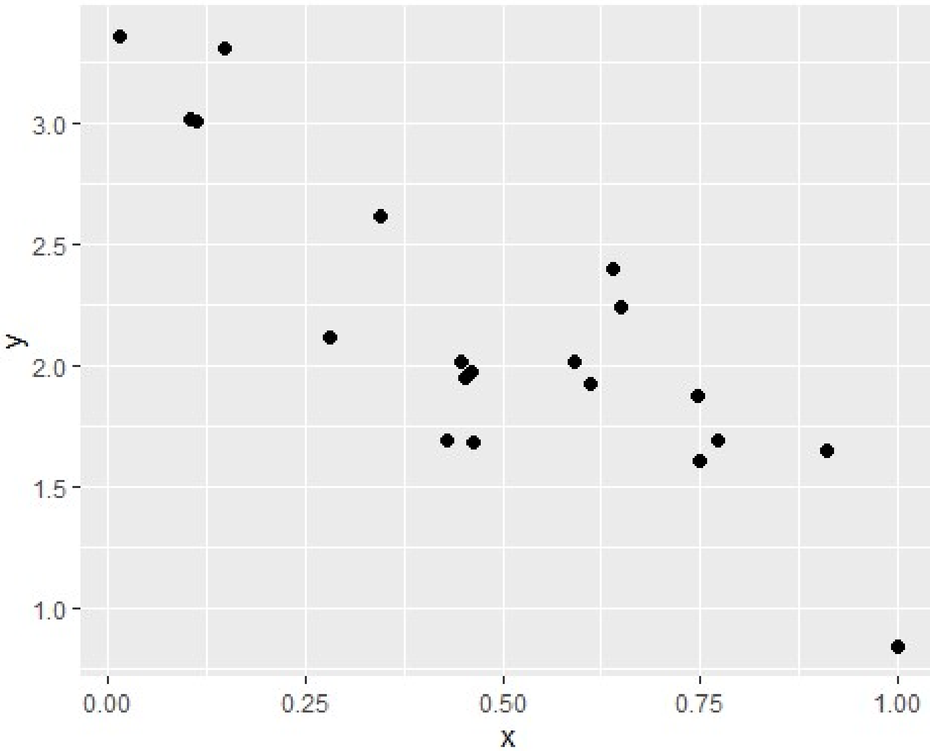
```
n = 20
x = runif(n)
beta_0 = 3
beta_1 = -2
```

Compute $h^*(x)$ as `h_star_x, then draw $\epsilon \sim N(0, 0.33^2)$ as`epsilon`, then compute $\y$.

```
h_star_x = beta_0 + beta_1 * x
epsilon = rnorm(n, 0, 0.33)
y = h_star_x + epsilon
```

Graph the data by running the following chunk:

```
pacman::p_load(ggplot2)
simple_df = data.frame(x = x, y = y)
simple_viz_obj = ggplot(simple_df, aes(x, y)) +
  geom_point(size = 2)
simple_viz_obj
```



Does this make sense given the values of $beta_0$ and $beta_1$?

yes because beta_0 in the y intercept and equals to 3 and beta_1 is the slope and equals to -2 and if you see the above graph we have something simliar to that.

Write a function `my_simple_ols` that takes in a vector `x` and vector `y` and returns a list that contains the `b_0` (intercept), `b_1` (slope), `yhat` (the predictions), `e` (the residuals), `SSE`, `SST`, `MSE`, `RMSE` and `Rsq` (for the R-squared metric). Internally, you can only use the functions `sum` and `length` and other basic arithmetic operations. You should throw errors if the inputs are non-numeric or not the same length. You should also name the class of the return value `my_simple_ols_obj` by using the `class` function as a setter. No need to create ROxygen documentation here.

```
my_simple_ols = function(x, y){
  n = length(y)

  if(n != length(x)){
    stop("x and y need to be the same length")
  }

  if(class(x) != 'numeric' && class(x) != 'integer'){
    stop("x needs to be numeric.")
  }

  if(class(y) != 'numeric' && class(y) != 'integer'){
    stop("y needs to be numeric.")
```

```
  }

  if (n <= 2){
    stop("n must be more than 2")
  }

  x_bar = sum(x) / n
  y_bar = sum(y) / n
  b_1 = (sum(x * y) - n * x_bar * y_bar)/(sum(x ^ 2)- n * x_bar ^ 2)
  b_0 = y_bar - b_1 * x_bar
  yhat = b_0 + b_1 * x
  e = y - yhat
  SSE = sum(e ^ 2)
  SST = sum ((y - y_bar) ^ 2)
  MSE = SSE / (n - 2)
  RMSE = sqrt(MSE)
  Rsqrt = 1 - (SSE/SST)

  model = list(b_0 = b_0, b_1 = b_1, yhat = yhat, e = e, SSE = SSE, SST =
SST, MSE = MSE, RMSE = RMSE, Rsqrt = Rsqrt)

  class(model) = "my_simple_ols_obj"

  model

}
```

Verify your computations are correct for the vectors x and y from the first chunk using the `lm` function in R:

```
lm_mod = lm(y ~ x)
my_simple_ols_mod = my_simple_ols(x,y)
#run the tests to ensure the function is up to spec
pacman::p_load(testthat)
expect_equal(my_simple_ols_mod$b_0, as.numeric(coef(lm_mod)[1]), tol = 1e-4)
expect_equal(my_simple_ols_mod$b_1, as.numeric(coef(lm_mod)[2]), tol = 1e-4)
expect_equal(my_simple_ols_mod$RMSE, summary(lm_mod)$sigma, tol = 1e-4)
expect_equal(my_simple_ols_mod$Rsq, summary(lm_mod)$r.squared, tol = 1e-4)
```

Verify that the average of the residuals is 0 using the `expect_equal`. Hint: use the syntax above.

```
mean(my_simple_ols_mod$e)

## [1] -1.110223e-16

expect_equal(mean(my_simple_ols_mod$e), 0)
```

Create the X matrix for this data example. Make sure it has the correct dimension.

```
X = cbind(1, x)
```

Use the `model.matrix` function to compute the matrix `X` and verify it is the same as your manual construction.

```
model.matrix(~x)
```

```
##    (Intercept)          x
## 1            1 0.65071079
## 2            1 0.44630511
## 3            1 0.61038435
## 4            1 0.14850637
## 5            1 0.90994016
## 6            1 0.99947466
## 7            1 0.34420211
## 8            1 0.28050895
## 9            1 0.64038611
## 10           1 0.45361822
## 11           1 0.77210227
## 12           1 0.10598777
## 13           1 0.43015901
## 14           1 0.46169038
## 15           1 0.46075896
## 16           1 0.74818272
## 17           1 0.11165795
## 18           1 0.59086274
## 19           1 0.74607854
## 20           1 0.01629464
## attr(,"assign")
## [1] 0 1
```

Create a prediction method `g` that takes in a vector `x_star` and `my_simple_ols_obj`, an object of type `my_simple_ols_obj` and predicts y values for each entry in `x_star`.

```
g = function(my_simple_ols_obj, x_star){
  y_star = my_simple_ols_obj$b_0 + my_simple_ols_obj$b_1 * x_star
}
```

Use this function to verify that when predicting for the average x, you get the average y.

```
expect_equal(g(my_simple_ols_mod, mean(x)), mean(y))
```

In class we spoke about error due to ignorance, misspecification error and estimation error. Show that as n grows, estimation error shrinks. Let us define an error metric that is the difference between b_0 and b_1 and β_0 and β_1. How about $h = ||b - \beta||^2$ where the quantities are now the vectors of size two. Show as n increases, this shrinks.

```
beta_0 = 3
beta_1 = -2
beta = c(beta_0, beta_1)

ns = 10 ^ (1:8)
```

```
errors_in_betas = array(NA, length(ns))

for (i in 1 : length(ns)) {
  n = ns[i]
  x = runif(n)
  h_star_x = beta_0 + beta_1 * x
  epsilon = rnorm(n, mean = 0, sd = 0.33)
  y = h_star_x + epsilon


  mod = my_simple_ols(x,y)
  b = c(mod$b_0, mod$b_1)

  errors_in_betas[i] = sum((beta - b)^2)
}

log(errors_in_betas, 10)
```

```
## [1] -0.7390252 -1.7488854 -4.1908774 -3.8096333 -5.4414950 -6.2899619 -
6.3420838
## [8] -8.1454922
```

We are now going to repeat one of the first linear model building exercises in history — that of Sir Francis Galton in 1886. First load up package `HistData`.

```
pacman::p_load(HistData)
```

In it, there is a dataset called `Galton`. Load it up.

```
data(Galton)
```

You now should have a data frame in your workspace called `Galton`. Summarize this data frame and write a few sentences about what you see. Make sure you report n, p and a bit about what the columns represent and how the data was measured. See the help file `?Galton`. p is 1 and n is 928 the number of observations

```
pacman::p_load(skimr)
skim(Galton)
```

Data summary

Name	Galton
Number of rows	928
Number of columns	2
_______________________	
Column type frequency:	
numeric	2

Group variables None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
parent	0	1	68.31	1.79	64.0	67.5	68.5	69.5	73.0	
child	0	1	68.09	2.52	61.7	66.2	68.2	70.2	73.7	

In Galton's data, I see the number of rows and columns within the data. Within the data, in the skim part. I see the parent and the child in the row, in the columns, I see the mean (parent is 68.3, child is 68.1), sd and see the percentile, 0, 25, 50, 75 and 100. n is the number of observations, p is the number of independent variable in this case it is height.

Find the average height (include both parents and children in this computation).

```
avg_height = mean(c(Galton$parent, Galton$child))
avg_height

## [1] 68.19833
```

If you were predicting the child height from the parent height and you were using null model, what would the RMSE be of this model be?

```
n =  nrow(Galton)
SST = sum((Galton$child - mean(Galton$child)) ^ 2)
sqrt(SST / (n - 1))

## [1] 2.517941
```

Note that in Math 241 you learned that the sample average is an estimate of the "mean", the population expected value of height. We will call the average the "mean" going forward since it is probably correct to the nearest tenth of an inch with this amount of data.

Run a linear model attempting to explain the childrens' height using the parents' height. Use `lm` and use the R formula notation. Compute and report b_0, b_1, RMSE and R^2.

```
mod = lm(child ~ parent, Galton)
b_0 = coef(mod)[1]
b_1 = coef(mod)[2]
summary(mod)$sigma

## [1] 2.238547

summary(mod)$r.squared

## [1] 0.2104629
```

Interpret all four quantities: b_0, b_1, RMSE and R^2. Use the correct units of these metrics in your answer.

b_0 = If x = 0, then the parent has no height that means the parent does not exist (can't have zero height, in inches) b_1 = If there is a one inch increase by the parent's height, the child average height will increases by the .64 inches. R^2 = This is about 21% variance explained which is consider low to certain standards. RMSE = This is Plus or minus 4.5 (2.23(2)) inches which makes it a 9 inches range 95% of the time

How good is this model? How well does it predict? Discuss.

This model is pretty good because it only considers one feature which is height but 9 inches can be considered a large range because the confidence interval can be almost a foot(12 inches) off of the prediction.

It is reasonable to assume that parents and their children have the same height? Explain why this is reasonable using basic biology and common sense.

Yes is it reasonable to assume that parents and their children have the same height because children inherit both their parent's height genes which would have the similar height as their parents.

If they were to have the same height and any differences were just random noise with expectation 0, what would the values of β_0 and β_1 be?

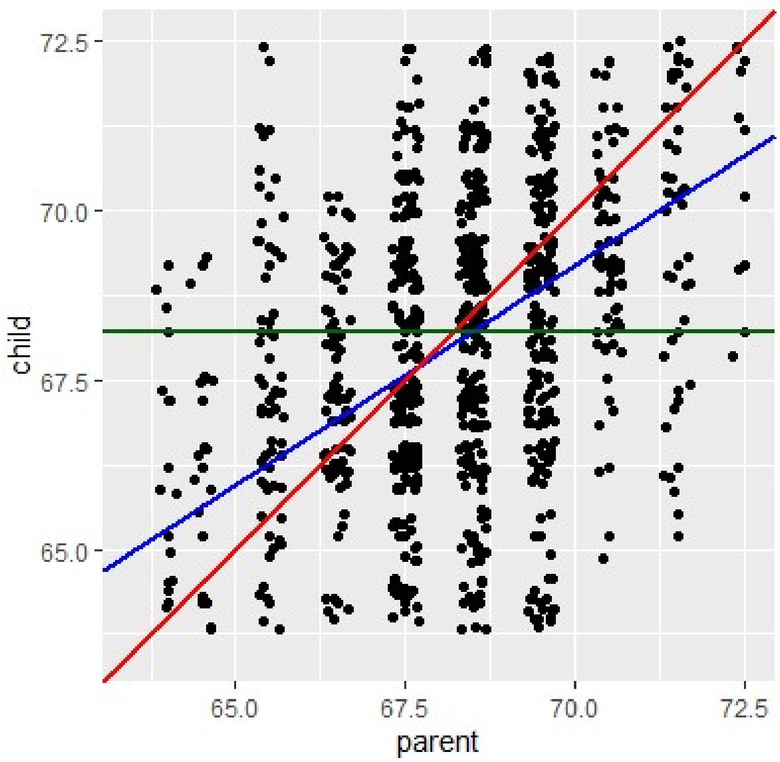
The value of beta one is 1 and value of beta zero is 0.

Let's plot (a) the data in $\mathbb{D}$ as black dots, (b) your least squares line defined by b_0 and b_1 in blue, (c) the theoretical line β_0 and β_1 if the parent-child height equality held in red and (d) the mean height in green.

```
pacman::p_load(ggplot2)
ggplot(Galton, aes(x = parent, y = child)) +
  geom_point() +
  geom_jitter() +
  geom_abline(intercept = b_0, slope = b_1, color = "blue", size = 1) +
  geom_abline(intercept = 0, slope = 1, color = "red", size = 1) +
  geom_abline(intercept = avg_height, slope = 0, color = "darkgreen", size =
1) +
  xlim(63.5, 72.5) +
  ylim(63.5, 72.5) +
  coord_equal(ratio = 1)

## Warning: Removed 76 rows containing missing values (geom_point).

## Warning: Removed 86 rows containing missing values (geom_point).
```



Fill in the following sentence:

Children of short parents became tall on average and children of tall parents became short on average.

Why did Galton call it “Regression towards mediocrity in hereditary stature” which was later shortened to “regression to the mean”?

Galton called it because if the tall parents had short children and short parents had tall parents, this led to a balance on height in the gene pool. The population by on height is regressing back to the mean.

Why should this effect be real?

This effect should be real because as time passes by, the height’s mean for the human population stays around the same point due to biology. If someone is taller or shorter than average, the population will regress to the mean.

You now have unlocked the mystery. Why is it that when modeling with y continuous, everyone calls it “regression”? Write a better, more descriptive and appropriate name for building predictive models with y continuous.

The reason why everyone calls it “regression” is because we expected the parent/child relationship to be around 1 to 1. However after running the test and viewing the results, the height average of the children seem to have regressed compared to the height average of parent. The children height average turned out to be lower than the parents height average.

You can now clear the workspace. Create a dataset $\mathbb{D}$ which we call `Xy` such that the linear model as R^2 about 50% and RMSE approximately 1.

```
x = 1:5
y = x^25
Xy = data.frame(x = x, y = y)
model = lm(x~y)
summary(model)$r.squared

## [1] 0.5028341

summary(model)$sigma

## [1] 1.28733
```

Create a dataset $\mathbb{D}$ which we call `Xy` such that the linear model as R^2 about 0% but x, y are clearly associated.

```
x = 1:400
y = x ^ 118
Xy = data.frame(x = x, y = y)
model = lm(x~y)
summary(model)$r.squared

## [1] 0.04978688
```

Extra credit: create a dataset $\mathbb{D}$ and a model that can give you R^2 arbitrarily close to 1 i.e. approximately 1 - epsilon but RMSE arbitrarily high i.e. approximately M.

```
epsilon = 0.01
M = 1000
#TO-DO
```

Write a function `my_ols` that takes in `X`, a matrix with with p columns representing the feature measurements for each of the n units, a vector of n responses `y` and returns a list that contains the `b`, the $p + 1$-sized column vector of OLS coefficients, `yhat` (the vector of n predictions), `e` (the vector of n residuals), `df` for degrees of freedom of the model, `SSE`, `SST`, `MSE`, `RMSE` and `Rsq` (for the R-squared metric). Internally, you cannot use `lm` or any other package; it must be done manually. You should throw errors if the inputs are non-numeric or not the same length. Or if `X` is not otherwise suitable. You should also name the class of the return value `my_ols` by using the `class` function as a setter. No need to create ROxygen documentation here.

```
#From Office Hours

my_ols = function(X, y){

  n = length(y)

  if (!is.numeric(X) && !is.integer(X)) {
    stop("X is not numeric")
```

```
  }

  X = cbind(rep(1, n), X)

  p = ncol(X)

  df = ncol(X)

  if (n != nrow(X)){
    stop("X rows and length of y need to be the same length.")
  }

  if(class(y) !='numeric' && class(y) !='integer'){
    stop("y needs to be numeric.")
   }

  if(n<=ncol(X)+1){
    stop("n must be more than 2.")
  }

  y_bar = sum(y) / n

  b = solve(t(X) %*% X) %*% t(X) %*% y

  yhat =  X %*% b

  e = y - yhat

  SSE = (t(e) %*% e)
  SST = t(y - y_bar) %*% (y - y_bar)
  MSE = SSE / (n- (p + 1))
  RMSE = sqrt(MSE)
  RSQ = 1 - (SSE / SST)

  model = list(b = b, yhat = yhat, df = df, e = e, SSE = SSE, SST = SST, MSE
= MSE, RMSE = RMSE, RSQ = RSQ)

  class(model) = "my_ols_obj"

  model
}
```

Verify that the OLS coefficients for the `Type` of cars in the cars dataset gives you the same results as we did in class (i.e. the ybar's within group).

```
cars = MASS::Cars93
mod = lm(Price~Type, data=cars)
my_ols(as.numeric(data.matrix(data.frame((cars$Type)))), cars$Price)
```

```
## $b
##        [,1]
##   22.871020
## X -1.001939
##
## $yhat
##           [,1]
##  [1,] 18.86327
##  [2,] 19.86520
##  [3,] 21.86908
##  [4,] 19.86520
##  [5,] 19.86520
##  [6,] 19.86520
##  [7,] 20.86714
##  [8,] 20.86714
##  [9,] 19.86520
## [10,] 20.86714
## [11,] 19.86520
## [12,] 21.86908
## [13,] 21.86908
## [14,] 17.86133
## [15,] 19.86520
## [16,] 16.85939
## [17,] 16.85939
## [18,] 20.86714
## [19,] 17.86133
## [20,] 20.86714
## [21,] 21.86908
## [22,] 20.86714
## [23,] 18.86327
## [24,] 18.86327
## [25,] 21.86908
## [26,] 16.85939
## [27,] 19.86520
## [28,] 17.86133
## [29,] 18.86327
## [30,] 20.86714
## [31,] 18.86327
## [32,] 18.86327
## [33,] 21.86908
## [34,] 17.86133
## [35,] 17.86133
## [36,] 16.85939
## [37,] 19.86520
## [38,] 20.86714
## [39,] 18.86327
## [40,] 17.86133
## [41,] 17.86133
## [42,] 18.86327
## [43,] 21.86908
```

```
## [44,] 18.86327
## [45,] 18.86327
## [46,] 17.86133
## [47,] 19.86520
## [48,] 19.86520
## [49,] 19.86520
## [50,] 19.86520
## [51,] 19.86520
## [52,] 20.86714
## [53,] 18.86327
## [54,] 18.86327
## [55,] 21.86908
## [56,] 16.85939
## [57,] 17.86133
## [58,] 21.86908
## [59,] 19.86520
## [60,] 17.86133
## [61,] 19.86520
## [62,] 18.86327
## [63,] 19.86520
## [64,] 18.86327
## [65,] 21.86908
## [66,] 16.85939
## [67,] 19.86520
## [68,] 21.86908
## [69,] 19.86520
## [70,] 16.85939
## [71,] 20.86714
## [72,] 17.86133
## [73,] 18.86327
## [74,] 21.86908
## [75,] 17.86133
## [76,] 19.86520
## [77,] 20.86714
## [78,] 21.86908
## [79,] 18.86327
## [80,] 18.86327
## [81,] 18.86327
## [82,] 21.86908
## [83,] 18.86327
## [84,] 18.86327
## [85,] 17.86133
## [86,] 19.86520
## [87,] 16.85939
## [88,] 18.86327
## [89,] 16.85939
## [90,] 21.86908
## [91,] 17.86133
## [92,] 21.86908
## [93,] 19.86520
```

```
##
## $df
## [1] 2
##
## $e
##              [,1]
##  [1,]  -2.96326531
##  [2,]  14.03479592
##  [3,]   7.23091837
##  [4,]  17.83479592
##  [5,]  10.13479592
##  [6,]  -4.16520408
##  [7,]  -0.06714286
##  [8,]   2.83285714
##  [9,]   6.43479592
## [10,]  13.83285714
## [11,]  20.23479592
## [12,]  -8.46908163
## [13,] -10.46908163
## [14,]  -2.76132653
## [15,]  -3.96520408
## [16,]  -0.55938776
## [17,]  -0.25938776
## [18,]  -2.06714286
## [19,]  20.13867347
## [20,]  -2.46714286
## [21,]  -6.06908163
## [22,]   8.63285714
## [23,]  -9.66326531
## [24,]  -7.56326531
## [25,]  -8.56908163
## [26,]   2.14061224
## [27,]  -4.26520408
## [28,]   7.93867347
## [29,]  -6.66326531
## [30,]  -1.56714286
## [31,] -11.46326531
## [32,]  -8.76326531
## [33,] -10.56908163
## [34,]  -1.96132653
## [35,]  -3.86132653
## [36,]   3.04061224
## [37,]   0.33479592
## [38,]   0.03285714
## [39,] -10.46326531
## [40,]  -5.36132653
## [41,]   1.93867347
## [42,]  -6.76326531
## [43,]  -4.36908163
## [44,] -10.86326531
```

```
## [45,]  -8.86326531
## [46,]  -7.86132653
## [47,]  -5.96520408
## [48,]  28.03479592
## [49,]   8.13479592
## [50,]  15.33479592
## [51,]  14.43479592
## [52,]  15.23285714
## [53,] -10.56326531
## [54,]  -7.26326531
## [55,]  -5.36908163
## [56,]   2.24061224
## [57,]  14.63867347
## [58,]  10.03091837
## [59,]  42.03479592
## [60,]  -3.76132653
## [61,]  -4.96520408
## [62,]  -8.56326531
## [63,]   6.23479592
## [64,]  -7.06326531
## [65,]  -6.16908163
## [66,]   2.24061224
## [67,]   1.63479592
## [68,]  -8.36908163
## [69,]  -3.56520408
## [70,]   2.64061224
## [71,]  -0.16714286
## [72,]  -3.46132653
## [73,]  -9.86326531
## [74,] -10.76908163
## [75,]  -0.16132653
## [76,]  -1.36520408
## [77,]   3.53285714
## [78,]   6.83091837
## [79,]  -7.76326531
## [80,] -10.46326531
## [81,]  -7.96326531
## [82,]  -2.36908163
## [83,] -10.26326531
## [84,]  -9.06326531
## [85,]   0.53867347
## [86,]  -1.66520408
## [87,]   5.84061224
## [88,]  -9.76326531
## [89,]   2.84061224
## [90,]  -1.86908163
## [91,]   5.43867347
## [92,]   0.83091837
## [93,]   6.83479592
##
```

```
## $SSE
##          [,1]
## [1,] 8361.872
##
## $SST
##          [,1]
## [1,] 8584.021
##
## $MSE
##          [,1]
## [1,] 92.90969
##
## $RMSE
##          [,1]
## [1,] 9.638967
##
## $RSQ
##            [,1]
## [1,] 0.02587939
##
## attr(,"class")
## [1] "my_ols_obj"
```

```
cars
```

```
##     Manufacturer          Model    Type Min.Price Price Max.Price MPG.city
## 1          Acura        Integra   Small      12.9  15.9      18.8       25
## 2          Acura         Legend Midsize      29.2  33.9      38.7       18
## 3           Audi             90 Compact      25.9  29.1      32.3       20
## 4           Audi            100 Midsize      30.8  37.7      44.6       19
## 5            BMW           535i Midsize      23.7  30.0      36.2       22
## 6          Buick        Century Midsize      14.2  15.7      17.3       22
## 7          Buick        LeSabre   Large      19.9  20.8      21.7       19
## 8          Buick     Roadmaster   Large      22.6  23.7      24.9       16
## 9          Buick        Riviera Midsize      26.3  26.3      26.3       19
## 10      Cadillac        DeVille   Large      33.0  34.7      36.3       16
## 11      Cadillac        Seville Midsize      37.5  40.1      42.7       16
## 12     Chevrolet       Cavalier Compact       8.5  13.4      18.3       25
## 13     Chevrolet        Corsica Compact      11.4  11.4      11.4       25
## 14     Chevrolet         Camaro  Sporty      13.4  15.1      16.8       19
## 15     Chevrolet         Lumina Midsize      13.4  15.9      18.4       21
## 16     Chevrolet     Lumina_APV     Van      14.7  16.3      18.0       18
## 17     Chevrolet          Astro     Van      14.7  16.6      18.6       15
## 18     Chevrolet        Caprice   Large      18.0  18.8      19.6       17
## 19     Chevrolet       Corvette  Sporty      34.6  38.0      41.5       17
## 20      Chrylser       Concorde   Large      18.4  18.4      18.4       20
## 21      Chrysler        LeBaron Compact      14.5  15.8      17.1       23
## 22      Chrysler       Imperial   Large      29.5  29.5      29.5       20
## 23         Dodge           Colt   Small       7.9   9.2      10.6       29
## 24         Dodge         Shadow   Small       8.4  11.3      14.2       23
```

```
## 25          Dodge          Spirit Compact       11.9  13.3        14.7         22
## 26          Dodge         Caravan     Van       13.6  19.0        24.4         17
## 27          Dodge         Dynasty Midsize       14.8  15.6        16.4         21
## 28          Dodge         Stealth  Sporty       18.5  25.8        33.1         18
## 29          Eagle          Summit   Small        7.9  12.2        16.5         29
## 30          Eagle          Vision   Large       17.5  19.3        21.2         20
## 31           Ford         Festiva   Small        6.9   7.4         7.9         31
## 32           Ford          Escort   Small        8.4  10.1        11.9         23
## 33           Ford           Tempo Compact       10.4  11.3        12.2         22
## 34           Ford         Mustang  Sporty       10.8  15.9        21.0         22
## 35           Ford           Probe  Sporty       12.8  14.0        15.2         24
## 36           Ford        Aerostar     Van       14.5  19.9        25.3         15
## 37           Ford          Taurus Midsize       15.6  20.2        24.8         21
## 38           Ford Crown_Victoria   Large       20.1  20.9        21.7         18
## 39            Geo           Metro   Small        6.7   8.4        10.0         46
## 40            Geo           Storm  Sporty       11.5  12.5        13.5         30
## 41          Honda         Prelude  Sporty       17.0  19.8        22.7         24
## 42          Honda           Civic   Small        8.4  12.1        15.8         42
## 43          Honda          Accord Compact       13.8  17.5        21.2         24
## 44        Hyundai           Excel   Small        6.8   8.0         9.2         29
## 45        Hyundai         Elantra   Small        9.0  10.0        11.0         22
## 46        Hyundai          Scoupe  Sporty        9.1  10.0        11.0         26
## 47        Hyundai          Sonata Midsize       12.4  13.9        15.3         20
## 48       Infiniti             Q45 Midsize       45.4  47.9        50.4         17
## 49          Lexus           ES300 Midsize       27.5  28.0        28.4         18
## 50          Lexus           SC300 Midsize       34.7  35.2        35.6         18
## 51        Lincoln     Continental Midsize       33.3  34.3        35.3         17
## 52        Lincoln        Town_Car   Large       34.4  36.1        37.8         18
## 53          Mazda             323   Small        7.4   8.3         9.1         29
## 54          Mazda         Protege   Small       10.9  11.6        12.3         28
## 55          Mazda             626 Compact       14.3  16.5        18.7         26
## 56          Mazda             MPV     Van       16.6  19.1        21.7         18
## 57          Mazda            RX-7  Sporty       32.5  32.5        32.5         17
## 58  Mercedes-Benz            190E Compact       29.0  31.9        34.9         20
## 59  Mercedes-Benz            300E Midsize       43.8  61.9        80.0         19
## 60        Mercury           Capri  Sporty       13.3  14.1        15.0         23
## 61        Mercury          Cougar Midsize       14.9  14.9        14.9         19
## 62     Mitsubishi          Mirage   Small        7.7  10.3        12.9         29
## 63     Mitsubishi        Diamante Midsize       22.4  26.1        29.9         18
## 64         Nissan          Sentra   Small        8.7  11.8        14.9         29
## 65         Nissan          Altima Compact       13.0  15.7        18.3         24
## 66         Nissan           Quest     Van       16.7  19.1        21.5         17
## 67         Nissan          Maxima Midsize       21.0  21.5        22.0         21
## 68     Oldsmobile         Achieva Compact       13.0  13.5        14.0         24
## 69     Oldsmobile   Cutlass_Ciera Midsize       14.2  16.3        18.4         23
## 70     Oldsmobile      Silhouette     Van       19.5  19.5        19.5         18
## 71     Oldsmobile     Eighty-Eight   Large       19.5  20.7        21.9         19
## 72       Plymouth           Laser  Sporty       11.4  14.4        17.4         23
## 73        Pontiac          LeMans   Small        8.2   9.0         9.9         31
## 74        Pontiac         Sunbird Compact        9.4  11.1        12.8         23
```

```
## 75       Pontiac       Firebird  Sporty      14.0  17.7       21.4         19
## 76       Pontiac     Grand_Prix Midsize      15.4  18.5       21.6         19
## 77       Pontiac     Bonneville   Large      19.4  24.4       29.4         19
## 78          Saab            900 Compact      20.3  28.7       37.1         20
## 79        Saturn             SL   Small       9.2  11.1       12.9         28
## 80        Subaru          Justy   Small       7.3   8.4        9.5         33
## 81        Subaru         Loyale   Small      10.5  10.9       11.3         25
## 82        Subaru         Legacy Compact      16.3  19.5       22.7         23
## 83        Suzuki          Swift   Small       7.3   8.6       10.0         39
## 84        Toyota         Tercel   Small       7.8   9.8       11.8         32
## 85        Toyota         Celica  Sporty      14.2  18.4       22.6         25
## 86        Toyota          Camry Midsize      15.2  18.2       21.2         22
## 87        Toyota         Previa     Van      18.9  22.7       26.6         18
## 88    Volkswagen            Fox   Small       8.7   9.1        9.5         25
## 89    Volkswagen        Eurovan     Van      16.6  19.7       22.7         17
## 90    Volkswagen         Passat Compact      17.6  20.0       22.4         21
## 91    Volkswagen        Corrado  Sporty      22.9  23.3       23.7         18
## 92         Volvo            240 Compact      21.8  22.7       23.5         21
## 93         Volvo            850 Midsize      24.8  26.7       28.5         20
##    MPG.highway            AirBags DriveTrain Cylinders EngineSize
Horsepower
## 1           31               None      Front         4        1.8
140
## 2           25 Driver & Passenger      Front         6        3.2
200
## 3           26        Driver only      Front         6        2.8
172
## 4           26 Driver & Passenger      Front         6        2.8
172
## 5           30        Driver only       Rear         4        3.5
208
## 6           31        Driver only      Front         4        2.2
110
## 7           28        Driver only      Front         6        3.8
170
## 8           25        Driver only       Rear         6        5.7
180
## 9           27        Driver only      Front         6        3.8
170
## 10          25        Driver only      Front         8        4.9
200
## 11          25 Driver & Passenger      Front         8        4.6
295
## 12          36               None      Front         4        2.2
110
## 13          34        Driver only      Front         4        2.2
110
## 14          28 Driver & Passenger       Rear         6        3.4
160
## 15          29               None      Front         4        2.2
```

```
110
## 16           23               None      Front          6        3.8
170
## 17           20               None        4WD          6        4.3
165
## 18           26        Driver only       Rear          8        5.0
170
## 19           25        Driver only       Rear          8        5.7
300
## 20           28 Driver & Passenger      Front          6        3.3
153
## 21           28 Driver & Passenger      Front          4        3.0
141
## 22           26        Driver only      Front          6        3.3
147
## 23           33               None      Front          4        1.5
92
## 24           29        Driver only      Front          4        2.2
93
## 25           27        Driver only      Front          4        2.5
100
## 26           21        Driver only        4WD          6        3.0
142
## 27           27        Driver only      Front          4        2.5
100
## 28           24        Driver only        4WD          6        3.0
300
## 29           33               None      Front          4        1.5
92
## 30           28 Driver & Passenger      Front          6        3.5
214
## 31           33               None      Front          4        1.3
63
## 32           30               None      Front          4        1.8
127
## 33           27               None      Front          4        2.3
96
## 34           29        Driver only       Rear          4        2.3
105
## 35           30        Driver only      Front          4        2.0
115
## 36           20        Driver only        4WD          6        3.0
145
## 37           30        Driver only      Front          6        3.0
140
## 38           26        Driver only       Rear          8        4.6
190
## 39           50               None      Front          3        1.0
55
## 40           36        Driver only      Front          4        1.6
```

```
90
## 41          31 Driver & Passenger      Front         4         2.3
160
## 42          46        Driver only      Front         4         1.5
102
## 43          31 Driver & Passenger      Front         4         2.2
140
## 44          33               None      Front         4         1.5
81
## 45          29               None      Front         4         1.8
124
## 46          34               None      Front         4         1.5
92
## 47          27               None      Front         4         2.0
128
## 48          22        Driver only       Rear         8         4.5
278
## 49          24        Driver only      Front         6         3.0
185
## 50          23 Driver & Passenger       Rear         6         3.0
225
## 51          26 Driver & Passenger      Front         6         3.8
160
## 52          26 Driver & Passenger       Rear         8         4.6
210
## 53          37               None      Front         4         1.6
82
## 54          36               None      Front         4         1.8
103
## 55          34        Driver only      Front         4         2.5
164
## 56          24               None        4WD         6         3.0
155
## 57          25        Driver only       Rear    rotary         1.3
255
## 58          29        Driver only       Rear         4         2.3
130
## 59          25 Driver & Passenger       Rear         6         3.2
217
## 60          26        Driver only      Front         4         1.6
100
## 61          26               None       Rear         6         3.8
140
## 62          33               None      Front         4         1.5
92
## 63          24        Driver only      Front         6         3.0
202
## 64          33        Driver only      Front         4         1.6
110
## 65          30        Driver only      Front         4         2.4
```

```
150
## 66          23               None      Front          6        3.0
151
## 67          26        Driver only      Front          6        3.0
160
## 68          31               None      Front          4        2.3
155
## 69          31        Driver only      Front          4        2.2
110
## 70          23               None      Front          6        3.8
170
## 71          28        Driver only      Front          6        3.8
170
## 72          30               None        4WD          4        1.8
92
## 73          41               None      Front          4        1.6
74
## 74          31               None      Front          4        2.0
110
## 75          28 Driver & Passenger       Rear          6        3.4
160
## 76          27               None      Front          6        3.4
200
## 77          28 Driver & Passenger      Front          6        3.8
170
## 78          26        Driver only      Front          4        2.1
140
## 79          38        Driver only      Front          4        1.9
85
## 80          37               None        4WD          3        1.2
73
## 81          30               None        4WD          4        1.8
90
## 82          30        Driver only        4WD          4        2.2
130
## 83          43               None      Front          3        1.3
70
## 84          37        Driver only      Front          4        1.5
82
## 85          32        Driver only      Front          4        2.2
135
## 86          29        Driver only      Front          4        2.2
130
## 87          22        Driver only        4WD          4        2.4
138
## 88          33               None      Front          4        1.8
81
## 89          21               None      Front          5        2.5
109
## 90          30               None      Front          4        2.0
```

```
134
## 91          25               None      Front         6        2.8
178
## 92          28        Driver only       Rear         4        2.3
114
## 93          28 Driver & Passenger      Front         5        2.4
168
##     RPM Rev.per.mile Man.trans.avail Fuel.tank.capacity Passengers Length
## 1  6300         2890             Yes               13.2          5    177
## 2  5500         2335             Yes               18.0          5    195
## 3  5500         2280             Yes               16.9          5    180
## 4  5500         2535             Yes               21.1          6    193
## 5  5700         2545             Yes               21.1          4    186
## 6  5200         2565              No               16.4          6    189
## 7  4800         1570              No               18.0          6    200
## 8  4000         1320              No               23.0          6    216
## 9  4800         1690              No               18.8          5    198
## 10 4100         1510              No               18.0          6    206
## 11 6000         1985              No               20.0          5    204
## 12 5200         2380             Yes               15.2          5    182
## 13 5200         2665             Yes               15.6          5    184
## 14 4600         1805             Yes               15.5          4    193
## 15 5200         2595              No               16.5          6    198
## 16 4800         1690              No               20.0          7    178
## 17 4000         1790              No               27.0          8    194
## 18 4200         1350              No               23.0          6    214
## 19 5000         1450             Yes               20.0          2    179
## 20 5300         1990              No               18.0          6    203
## 21 5000         2090              No               16.0          6    183
## 22 4800         1785              No               16.0          6    203
## 23 6000         3285             Yes               13.2          5    174
## 24 4800         2595             Yes               14.0          5    172
## 25 4800         2535             Yes               16.0          6    181
## 26 5000         1970              No               20.0          7    175
## 27 4800         2465              No               16.0          6    192
## 28 6000         2120             Yes               19.8          4    180
## 29 6000         2505             Yes               13.2          5    174
## 30 5800         1980              No               18.0          6    202
## 31 5000         3150             Yes               10.0          4    141
## 32 6500         2410             Yes               13.2          5    171
## 33 4200         2805             Yes               15.9          5    177
## 34 4600         2285             Yes               15.4          4    180
## 35 5500         2340             Yes               15.5          4    179
## 36 4800         2080             Yes               21.0          7    176
## 37 4800         1885              No               16.0          5    192
## 38 4200         1415              No               20.0          6    212
## 39 5700         3755             Yes               10.6          4    151
## 40 5400         3250             Yes               12.4          4    164
## 41 5800         2855             Yes               15.9          4    175
## 42 5900         2650             Yes               11.9          4    173
```

```
## 43 5600          2610            Yes               17.0          4    185
## 44 5500          2710            Yes               11.9          5    168
## 45 6000          2745            Yes               13.7          5    172
## 46 5550          2540            Yes               11.9          4    166
## 47 6000          2335            Yes               17.2          5    184
## 48 6000          1955             No               22.5          5    200
## 49 5200          2325            Yes               18.5          5    188
## 50 6000          2510            Yes               20.6          4    191
## 51 4400          1835             No               18.4          6    205
## 52 4600          1840             No               20.0          6    219
## 53 5000          2370            Yes               13.2          4    164
## 54 5500          2220            Yes               14.5          5    172
## 55 5600          2505            Yes               15.5          5    184
## 56 5000          2240             No               19.6          7    190
## 57 6500          2325            Yes               20.0          2    169
## 58 5100          2425            Yes               14.5          5    175
## 59 5500          2220             No               18.5          5    187
## 60 5750          2475            Yes               11.1          4    166
## 61 3800          1730             No               18.0          5    199
## 62 6000          2505            Yes               13.2          5    172
## 63 6000          2210             No               19.0          5    190
## 64 6000          2435            Yes               13.2          5    170
## 65 5600          2130            Yes               15.9          5    181
## 66 4800          2065             No               20.0          7    190
## 67 5200          2045             No               18.5          5    188
## 68 6000          2380             No               15.2          5    188
## 69 5200          2565             No               16.5          5    190
## 70 4800          1690             No               20.0          7    194
## 71 4800          1570             No               18.0          6    201
## 72 5000          2360            Yes               15.9          4    173
## 73 5600          3130            Yes               13.2          4    177
## 74 5200          2665            Yes               15.2          5    181
## 75 4600          1805            Yes               15.5          4    196
## 76 5000          1890            Yes               16.5          5    195
## 77 4800          1565             No               18.0          6    177
## 78 6000          2910            Yes               18.0          5    184
## 79 5000          2145            Yes               12.8          5    176
## 80 5600          2875            Yes                9.2          4    146
## 81 5200          3375            Yes               15.9          5    175
## 82 5600          2330            Yes               15.9          5    179
## 83 6000          3360            Yes               10.6          4    161
## 84 5200          3505            Yes               11.9          5    162
## 85 5400          2405            Yes               15.9          4    174
## 86 5400          2340            Yes               18.5          5    188
## 87 5000          2515            Yes               19.8          7    187
## 88 5500          2550            Yes               12.4          4    163
## 89 4500          2915            Yes               21.1          7    187
## 90 5800          2685            Yes               18.5          5    180
## 91 5800          2385            Yes               18.5          4    159
## 92 5400          2215            Yes               15.8          5    190
```

```
## 93 6200          2310            Yes              19.3         5    184
##    Wheelbase Width Turn.circle Rear.seat.room Luggage.room Weight  Origin
## 1        102    68          37           26.5           11   2705 non-USA
## 2        115    71          38           30.0           15   3560 non-USA
## 3        102    67          37           28.0           14   3375 non-USA
## 4        106    70          37           31.0           17   3405 non-USA
## 5        109    69          39           27.0           13   3640 non-USA
## 6        105    69          41           28.0           16   2880     USA
## 7        111    74          42           30.5           17   3470     USA
## 8        116    78          45           30.5           21   4105     USA
## 9        108    73          41           26.5           14   3495     USA
## 10       114    73          43           35.0           18   3620     USA
## 11       111    74          44           31.0           14   3935     USA
## 12       101    66          38           25.0           13   2490     USA
## 13       103    68          39           26.0           14   2785     USA
## 14       101    74          43           25.0           13   3240     USA
## 15       108    71          40           28.5           16   3195     USA
## 16       110    74          44           30.5           NA   3715     USA
## 17       111    78          42           33.5           NA   4025     USA
## 18       116    77          42           29.5           20   3910     USA
## 19        96    74          43             NA           NA   3380     USA
## 20       113    74          40           31.0           15   3515     USA
## 21       104    68          41           30.5           14   3085     USA
## 22       110    69          44           36.0           17   3570     USA
## 23        98    66          32           26.5           11   2270     USA
## 24        97    67          38           26.5           13   2670     USA
## 25       104    68          39           30.5           14   2970     USA
## 26       112    72          42           26.5           NA   3705     USA
## 27       105    69          42           30.5           16   3080     USA
## 28        97    72          40           20.0           11   3805     USA
## 29        98    66          36           26.5           11   2295     USA
## 30       113    74          40           30.0           15   3490     USA
## 31        90    63          33           26.0           12   1845     USA
## 32        98    67          36           28.0           12   2530     USA
## 33       100    68          39           27.5           13   2690     USA
## 34       101    68          40           24.0           12   2850     USA
## 35       103    70          38           23.0           18   2710     USA
## 36       119    72          45           30.0           NA   3735     USA
## 37       106    71          40           27.5           18   3325     USA
## 38       114    78          43           30.0           21   3950     USA
## 39        93    63          34           27.5           10   1695 non-USA
## 40        97    67          37           24.5           11   2475 non-USA
## 41       100    70          39           23.5            8   2865 non-USA
## 42       103    67          36           28.0           12   2350 non-USA
## 43       107    67          41           28.0           14   3040 non-USA
## 44        94    63          35           26.0           11   2345 non-USA
## 45        98    66          36           28.0           12   2620 non-USA
## 46        94    64          34           23.5            9   2285 non-USA
## 47       104    69          41           31.0           14   2885 non-USA
## 48       113    72          42           29.0           15   4000 non-USA
```

```
## 49         103    70           40            27.5            14   3510 non-USA
## 50         106    71           39            25.0             9   3515 non-USA
## 51         109    73           42            30.0            19   3695     USA
## 52         117    77           45            31.5            22   4055     USA
## 53          97    66           34            27.0            16   2325 non-USA
## 54          98    66           36            26.5            13   2440 non-USA
## 55         103    69           40            29.5            14   2970 non-USA
## 56         110    72           39            27.5            NA   3735 non-USA
## 57          96    69           37              NA            NA   2895 non-USA
## 58         105    67           34            26.0            12   2920 non-USA
## 59         110    69           37            27.0            15   3525 non-USA
## 60          95    65           36            19.0             6   2450     USA
## 61         113    73           38            28.0            15   3610     USA
## 62          98    67           36            26.0            11   2295 non-USA
## 63         107    70           43            27.5            14   3730 non-USA
## 64          96    66           33            26.0            12   2545 non-USA
## 65         103    67           40            28.5            14   3050 non-USA
## 66         112    74           41            27.0            NA   4100 non-USA
## 67         104    69           41            28.5            14   3200 non-USA
## 68         103    67           39            28.0            14   2910     USA
## 69         105    70           42            28.0            16   2890     USA
## 70         110    74           44            30.5            NA   3715     USA
## 71         111    74           42            31.5            17   3470     USA
## 72          97    67           39            24.5             8   2640     USA
## 73          99    66           35            25.5            17   2350     USA
## 74         101    66           39            25.0            13   2575     USA
## 75         101    75           43            25.0            13   3240     USA
## 76         108    72           41            28.5            16   3450     USA
## 77         111    74           43            30.5            18   3495     USA
## 78          99    67           37            26.5            14   2775 non-USA
## 79         102    68           40            26.5            12   2495     USA
## 80          90    60           32            23.5            10   2045 non-USA
## 81          97    65           35            27.5            15   2490 non-USA
## 82         102    67           37            27.0            14   3085 non-USA
## 83          93    63           34            27.5            10   1965 non-USA
## 84          94    65           36            24.0            11   2055 non-USA
## 85          99    69           39            23.0            13   2950 non-USA
## 86         103    70           38            28.5            15   3030 non-USA
## 87         113    71           41            35.0            NA   3785 non-USA
## 88          93    63           34            26.0            10   2240 non-USA
## 89         115    72           38            34.0            NA   3960 non-USA
## 90         103    67           35            31.5            14   2985 non-USA
## 91          97    66           36            26.0            15   2810 non-USA
## 92         104    67           37            29.5            14   2985 non-USA
## 93         105    69           38            30.0            15   3245 non-USA
##                        Make
## 1             Acura Integra
## 2              Acura Legend
## 3                   Audi 90
## 4                  Audi 100
```

```
## 5                  BMW 535i
## 6             Buick Century
## 7             Buick LeSabre
## 8          Buick Roadmaster
## 9             Buick Riviera
## 10         Cadillac DeVille
## 11         Cadillac Seville
## 12       Chevrolet Cavalier
## 13        Chevrolet Corsica
## 14         Chevrolet Camaro
## 15         Chevrolet Lumina
## 16     Chevrolet Lumina_APV
## 17          Chevrolet Astro
## 18        Chevrolet Caprice
## 19       Chevrolet Corvette
## 20        Chrylser Concorde
## 21         Chrysler LeBaron
## 22        Chrysler Imperial
## 23               Dodge Colt
## 24             Dodge Shadow
## 25             Dodge Spirit
## 26            Dodge Caravan
## 27            Dodge Dynasty
## 28            Dodge Stealth
## 29             Eagle Summit
## 30             Eagle Vision
## 31             Ford Festiva
## 32              Ford Escort
## 33               Ford Tempo
## 34             Ford Mustang
## 35               Ford Probe
## 36            Ford Aerostar
## 37              Ford Taurus
## 38      Ford Crown_Victoria
## 39                Geo Metro
## 40                Geo Storm
## 41            Honda Prelude
## 42              Honda Civic
## 43             Honda Accord
## 44            Hyundai Excel
## 45          Hyundai Elantra
## 46           Hyundai Scoupe
## 47           Hyundai Sonata
## 48             Infiniti Q45
## 49              Lexus ES300
## 50              Lexus SC300
## 51      Lincoln Continental
## 52         Lincoln Town_Car
## 53                Mazda 323
## 54            Mazda Protege
```

```
## 55                Mazda 626
## 56                Mazda MPV
## 57               Mazda RX-7
## 58        Mercedes-Benz 190E
## 59        Mercedes-Benz 300E
## 60            Mercury Capri
## 61           Mercury Cougar
## 62        Mitsubishi Mirage
## 63      Mitsubishi Diamante
## 64            Nissan Sentra
## 65            Nissan Altima
## 66             Nissan Quest
## 67            Nissan Maxima
## 68       Oldsmobile Achieva
## 69 Oldsmobile Cutlass_Ciera
## 70    Oldsmobile Silhouette
## 71  Oldsmobile Eighty-Eight
## 72           Plymouth Laser
## 73           Pontiac LeMans
## 74          Pontiac Sunbird
## 75         Pontiac Firebird
## 76       Pontiac Grand_Prix
## 77       Pontiac Bonneville
## 78                 Saab 900
## 79                Saturn SL
## 80             Subaru Justy
## 81            Subaru Loyale
## 82            Subaru Legacy
## 83             Suzuki Swift
## 84            Toyota Tercel
## 85            Toyota Celica
## 86             Toyota Camry
## 87            Toyota Previa
## 88           Volkswagen Fox
## 89       Volkswagen Eurovan
## 90        Volkswagen Passat
## 91       Volkswagen Corrado
## 92                Volvo 240
## 93                Volvo 850
```

Create a prediction method g that takes in a vector `x_star` and the dataset $\mathbb{D}$ i.e. `X` and y and returns the OLS predictions. Let `X` be a matrix with with p columns representing the feature measurements for each of the n units

```
#From Office Hours

g = function(x_star, X, y){
  b = my_ols(X, y)$b
  x_star = c(1,x_star)
  x_star %*% b
```

```
}

X = model.matrix(~Type,cars)[, 2:6]
head(X)

##   TypeLarge TypeMidsize TypeSmall TypeSporty TypeVan
## 1         0           0         1          0       0
## 2         0           1         0          0       0
## 3         0           0         0          0       0
## 4         0           1         0          0       0
## 5         0           1         0          0       0
## 6         0           1         0          0       0

g(X[1,], X, cars$Price)

##          [,1]
## [1,] 10.16667

t(c(1,X[1,])) %*% my_ols(X, cars$Price)$b

##          [,1]
## [1,] 10.16667

X[1,]

##   TypeLarge TypeMidsize   TypeSmall  TypeSporty     TypeVan
##           0           0           1           0           0

predict(mod, cars[1,])

##        1
## 10.16667
```