Lab 3

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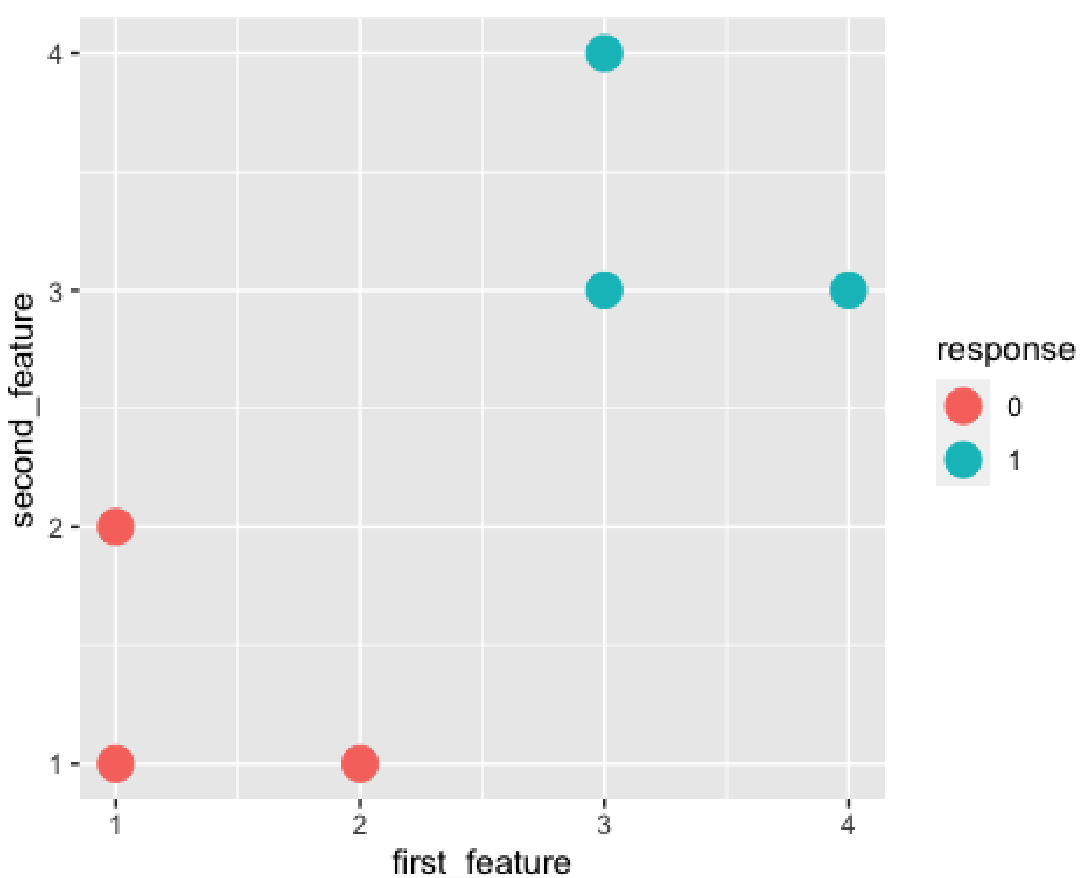
Support Vector Machine vs. Perceptron

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

```
#svm model
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
```



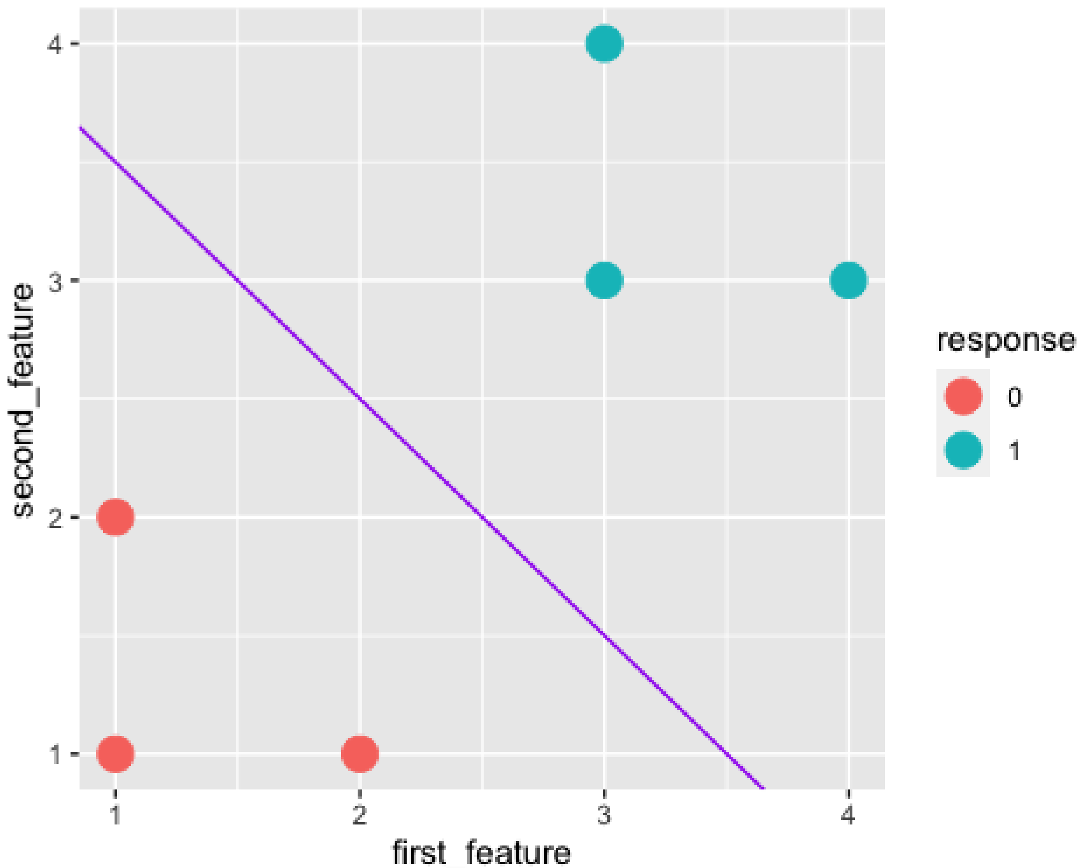
Use the `e1071` package to fit an SVM model to the simple data. Use a formula to create the model, pass in the data frame, set kernel to be `linear` for the linear SVM and don't scale the covariates. Call the model object `svm_model`. Otherwise the remaining code won't work.

```
pacman::p_load(e1071)
svm_model = svm(
  formula = Xy_simple$response~.,#TO-DO, a symbolic description of the model to be fit
    data = Xy_simple,#TO-DO, fdata fram rom the previous example
    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){

    #Add 1 column to matrix making P + 1 size
  Xinput = as.matrix(cbind(1,Xinput))

  w = rep(0, ncol(Xinput))

  for (i in 1 : MAX_ITER){
    for (j in 1 : nrow(Xinput)) {

        #Get tuple
      x = Xinput[j, ]

      #Compute y hat
      y_hat = if(sum(x * w) >= 0) 1 else 0

      #Generate new weights
      for(k in 1:ncol(Xinput)){
        w[k] = w[k] + (y_binary[j] - y_hat) * x[k]
```

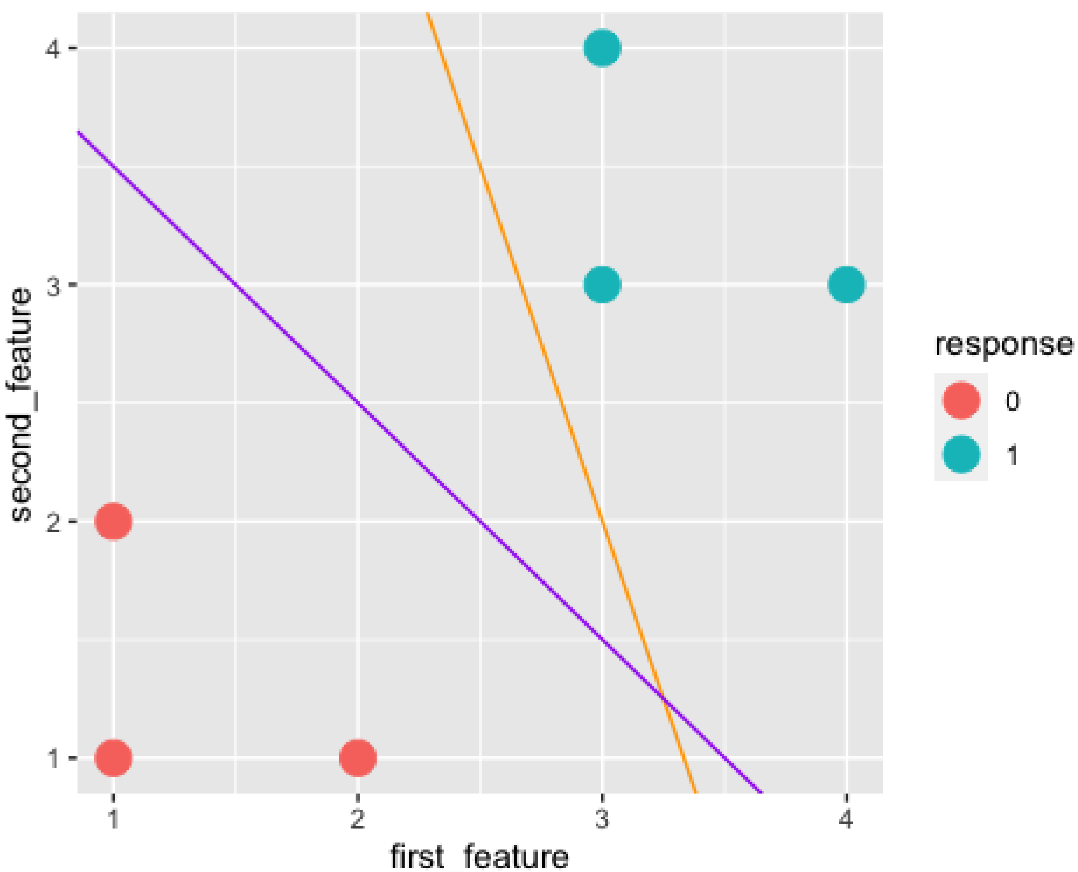
```
      }
    }
  }

  return(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, by the maximum support hyperplane

TO-DO

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

takin in param w vector and b minimize distrance error add lamda times the mmaximum w for all ws in the w vector then return the argmin

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){
  #TO-DO: write pseudo code in comments
  #
  # Intilize a w vector
  # for ( i in 1 : MAX_ITER){
  #  for (j in 1 : nrow(Xinput)){
  #    loop for max margin
  #  using argin{1/n she +lamda }
  #    if margin[i]>margin[j]
  #    then max margin= margin[i]
  #   }
  #  }
  # return 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).
#'
```

```r
#' @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){
  #TO-DO
}
```

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:

```r
#svm_model_weights = linear_svm_learning_algorithm(X_simple_feature_matrix,
y_binary)
#
#   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:

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

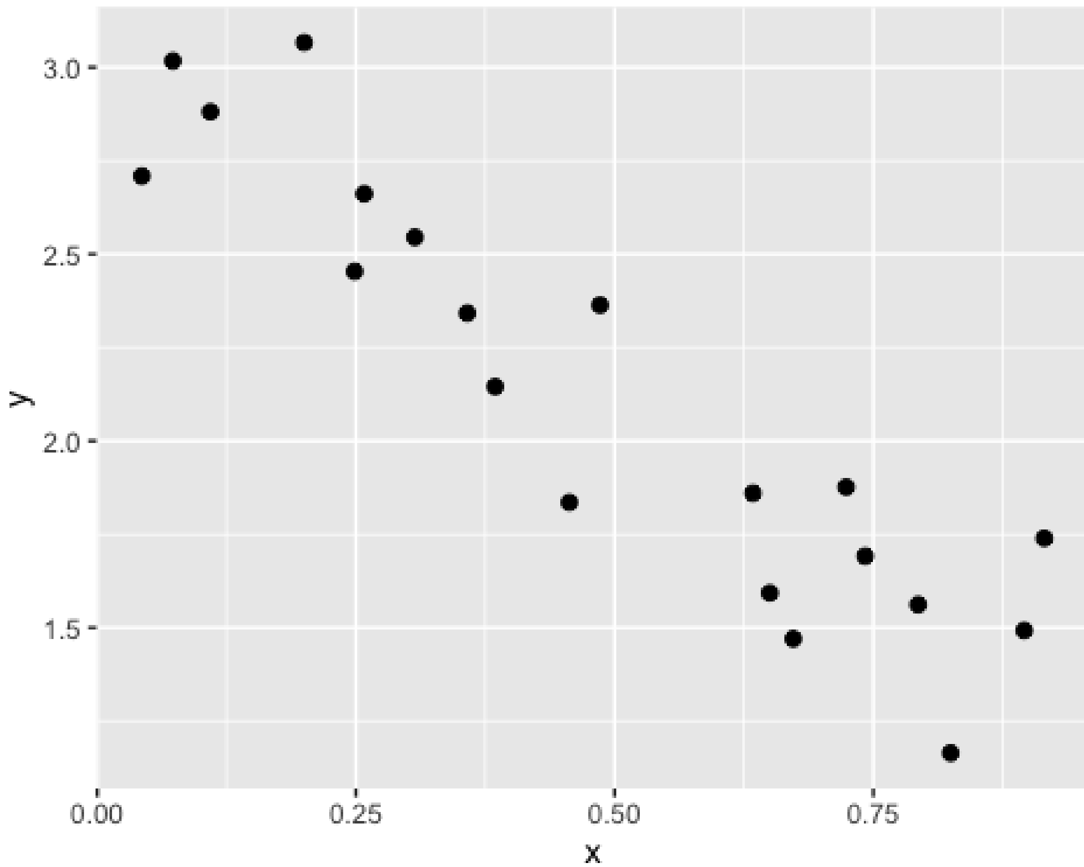
Compute $h^*(x)$ as `h_star_x`, then draw $\epsilon \sim N(0, 0.33^2)$ as `epsilon`, then compute $\y$.

```r
h_star_x = beta_0 +beta_1*x  #optinal line
  epsilon =    rnorm(n, 0, 0.33)             #do u miss error and things you
cant see
  y = h_star_x + epsilon
```

Graph the data by running the following chunk:

```r
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 it makes sense because b_0 =3 which is the intercept and b_1= -2 and the graph is going downward

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.

```
class(x)

## [1] "numeric"

class(y)

## [1] "numeric"
```

```
is.numeric(x)

## [1] TRUE

x

##  [1] 0.38459512 0.82485169 0.72385164 0.45631771 0.07307958 0.63370822
##  [7] 0.91533595 0.20000530 0.74214662 0.30696256 0.04304941 0.79336849
## [13] 0.67274127 0.48596955 0.65003893 0.35766766 0.25800682 0.10939092
## [19] 0.24868208 0.89591499

y

##  [1] 2.145299 1.164972 1.876675 1.835707 3.016890 1.860386 1.739696
3.066272
##  [9] 1.691856 2.545291 2.709181 1.561910 1.470540 2.363526 1.593065
2.342021
## [17] 2.661619 2.880730 2.453795 1.492694

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

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

  if(class(x) != 'numeric' && class(x) != 'integer'){
    stop("x needs to me  a numeric")
  }
  if(class(y) != 'numeric' && class(y) != 'integer'){
    stop("y needs to me  a numeric")
  }

  if(n<=2){
    stop("n needs to be greater 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)
  Rsq = 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, Rsq = Rsq)
  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)

#it works there fore we have duplicated the linear model
```

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] -1.109749e-17

expect_equal(mean(my_simple_ols_mod$e),0, tol = 1e-4) # should not do this in
the real world because it could be numerically zero but not actually zero we
need a tolerance ie: error tolerance
```

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

```
#it would be the one vector then the x vector, two vectors togther, col bind
them
cbind(1,x)

##                  x
##  [1,] 1 0.38459512
##  [2,] 1 0.82485169
##  [3,] 1 0.72385164
##  [4,] 1 0.45631771
##  [5,] 1 0.07307958
##  [6,] 1 0.63370822
##  [7,] 1 0.91533595
##  [8,] 1 0.20000530
##  [9,] 1 0.74214662
## [10,] 1 0.30696256
```

```
## [11,] 1 0.04304941
## [12,] 1 0.79336849
## [13,] 1 0.67274127
## [14,] 1 0.48596955
## [15,] 1 0.65003893
## [16,] 1 0.35766766
## [17,] 1 0.25800682
## [18,] 1 0.10939092
## [19,] 1 0.24868208
## [20,] 1 0.89591499

# bind a sclar to a vector it reps the 1's rep(n, length(x))
```

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

```
#TO-DO
model.matrix(~x)

##    (Intercept)          x
## 1            1 0.38459512
## 2            1 0.82485169
## 3            1 0.72385164
## 4            1 0.45631771
## 5            1 0.07307958
## 6            1 0.63370822
## 7            1 0.91533595
## 8            1 0.20000530
## 9            1 0.74214662
## 10           1 0.30696256
## 11           1 0.04304941
## 12           1 0.79336849
## 13           1 0.67274127
## 14           1 0.48596955
## 15           1 0.65003893
## 16           1 0.35766766
## 17           1 0.25800682
## 18           1 0.10939092
## 19           1 0.24868208
## 20           1 0.89591499
## 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){
  #TO-DO
  y_star = my_simple_ols_obj$b_0 +my_simple_ols_mod$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)
#if ns get very large bs converge to it's actual param (beta)

ns = 10^(1:7)
  error_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)
  error_in_betas[i] = sum((beta - b)^2)
}
log(error_in_betas,10)

## [1] -0.2985566 -1.3002695 -4.5249939 -4.3219707 -4.4175853 -6.9990530 -
6.4030230
```

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	▁▃▇▇▂

TO-DO

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

```
#TO-DO

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

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

```
#TO-DO
n= nrow(Galton)
#sse_0 == sst
SSE= sum((Galton$child -mean(Galton$child))^2)
RMSE=sqrt(SSE/(n-2))
RMSE

## [1] 2.519301

#only fitting one pram
#RMSE = standard divination of y
```

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

R_Squared =summary(mod)$r.square # very low it's not fitting the var



#b_0
#b_1
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. The R^e is very low thus it model is not very accurate

How good is this model? How well does it predict? Discuss. It's okay it predicts better near the mean while it regresses at the ends

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.

it reasonable to assume the average height of a child while the model

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?

b_0 which is equal to the y interecept would be equal to 0 because the random noise could be ignored from the data and the b_1

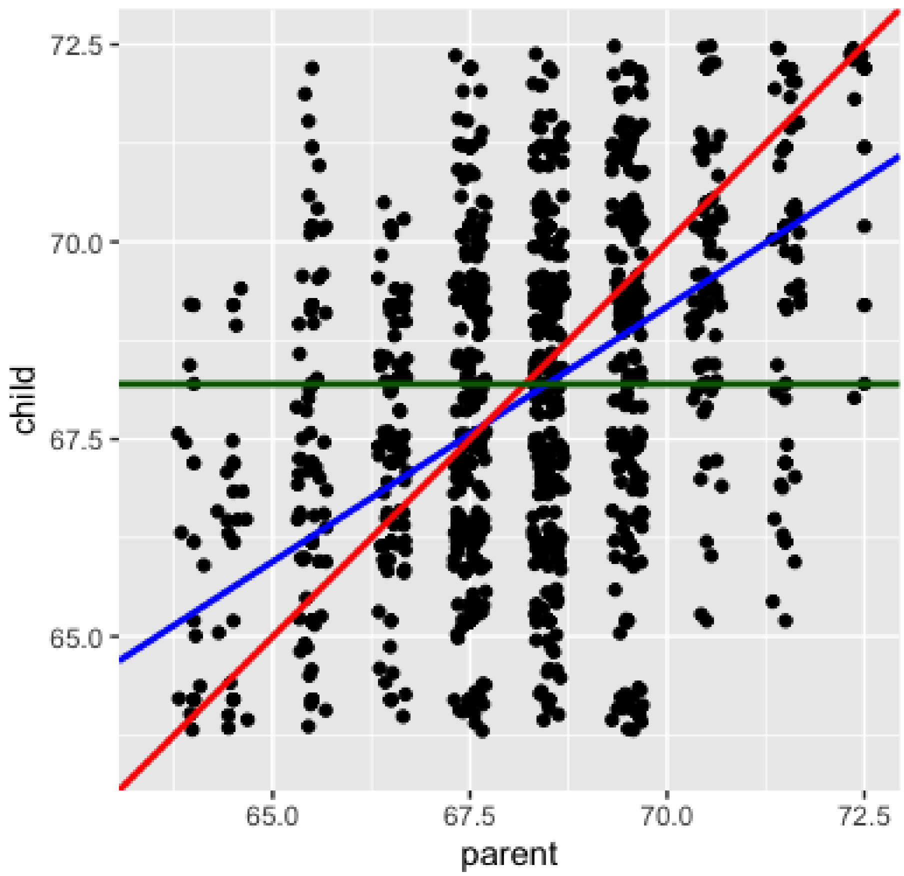
Let's plot (a) the data in $\mathbb{D}$ as black dots, (b) your least squares line defined by b_0 and b_1 in blue, (c) the theoretical line β_0 and β_1 if the parent-child height equality held in red and (d) the mean height in green.

```
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:

TO-DO: Children of short parents became taller on average and children of tall parents became shorter on average.

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

TO-DO he said this because the child’s right would lean towards the average heights there for if a parent’s height was bellow the mean the child’s height was taller and if the parent’s heights were above the mean the child heights would inversely lean towards the average height.

Why should this effect be real?

this sould be real because the causal drivers of height and how much the human body grows is not well understood therefore we have a regression to the mean. which also means that most people over all are average.

TO-DO

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. Continuous Regression Prediction of a Child’s height TO-DO

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 = summary(mod)$r.squared
y = summary(mod)$sigma

Xy = data.frame(x = x, y = y)
Xy

##           x        y
## 1 0.2104629 2.238547
```

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 = #TO-DO
y = #TO-DO
Xy = data.frame(x = x, y = y)
```

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.

```
  my_ols = function(X, y){
  n = length(y)
   #p = ncol(X)
```

```
  if (!is.numeric(X) && !is.integer(X)) {
    stop("X is not numeric")
  }
  X = cbind(rep(1, n), X)

  p = ncol(X)
  df = p+1

  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 = sum(t(e) %*% e)
  SST = sum((y - y_bar)^2)
  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] 3
##
## $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] 8361.872
##
## $SST
## [1] 8584.021
##
## $MSE
## [1] 92.90969
##
## $RMSE
## [1] 9.638967
##
## $Rsq
## [1] 0.02587939
##
## attr(,"class")
## [1] "my_ols_obj"
```

```
#cars
```

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

```
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]

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

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

```
predict(mod, cars[1,])
```

```
##        1
## 10.16667
```