

Lab 4

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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:

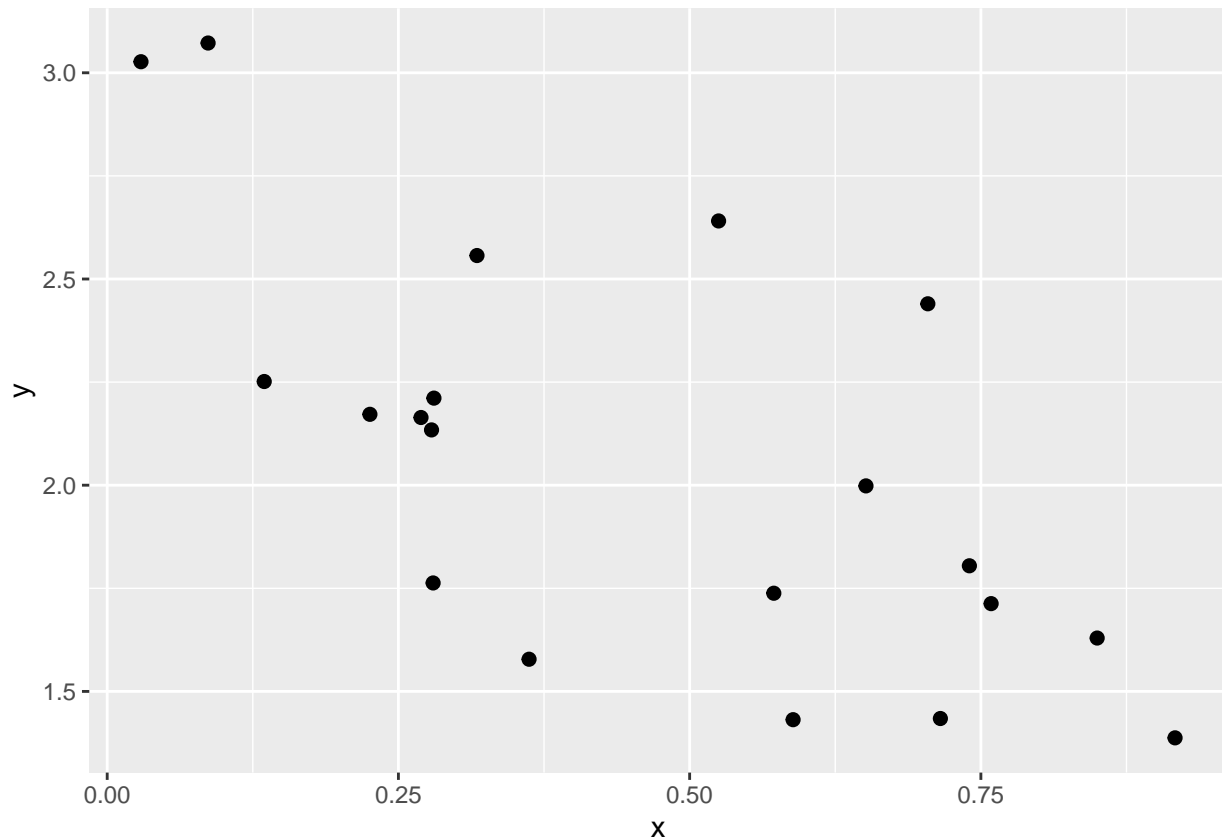
```
n = 20
x = runif(n)
beta_0 = 3
beta_1 = -2
y = beta_0 + beta_1 * x + rnorm(n, mean = 0, sd = 0.33)
```

Rewrite the computation of y so that it is $h^*(x) + \text{epsilon}$.

```
h_star_x = beta_0 + beta_1 * x
epsilon = rnorm(n, mean = 0, sd = 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 β_0 and β_1 ?

Yes.

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 `Rsqr` (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 and not the same length. You should also name the class of the return value 'my_simple_ols_obj' by using `theClass` function as a setter. No need to create ROpenSci documentation here.

```
my_simple_ols = function(x,y){
  if (class(x) != "numeric" | class(y) != "numeric") {stop("argument x or y is not numeric")}
  n = length(x)
  if (n != length(y)){stop("x and y must be same length")}

  y_bar = sum(y)/length(y)
  x_bar = sum(x)/length(x)
  s_x_squared = (1/(n-1) * sum((x - x_bar)^2))
  s_xy = (1/(n-1)) * sum((x - x_bar)*(y - y_bar))
  b1= s_xy/s_x_squared
  b0= y_bar - b1*x_bar
  y_hat = b0 + b1*x

  e = y - y_hat
  SSE = sum(e^2)
  SST = sum((y-y_bar)^2)
  Rsqr = 1 - SSE/SST # 1 - NA
  MSE = SSE / (n-2)
```

```

RMSE = sqrt(MSE)

mod = list(b_0 = b0, b_1 = b1, y_hat = y_hat, e = e, SSE = SSE, SST = SST, Rsq = Rsq, MSE = MSE, RMSE
class(mod) = "my_simple_ols_obj"
mod
}

```

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

```

Verify that the average of the residuals is 0.

```
expect_equal(mean(my_lm_mod$e), 0, tol = 1e-4)
```

Create the X matrix for this data example.

```

X = cbind(1, x)
X

```

```

##           x
## [1,] 1 0.70447080
## [2,] 1 0.65136226
## [3,] 1 0.27842115
## [4,] 1 0.28047660
## [5,] 1 0.26938924
## [6,] 1 0.57225371
## [7,] 1 0.13480810
## [8,] 1 0.52485040
## [9,] 1 0.71524499
## [10,] 1 0.02900179
## [11,] 1 0.75880682
## [12,] 1 0.22553375
## [13,] 1 0.91669713
## [14,] 1 0.31744254
## [15,] 1 0.84983519
## [16,] 1 0.27978700
## [17,] 1 0.74013728
## [18,] 1 0.08660859
## [19,] 1 0.36215297
## [20,] 1 0.58880895

```

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 0.70447080
## 2              1 0.65136226
## 3              1 0.27842115

```

```
## 4          1 0.28047660
## 5          1 0.26938924
## 6          1 0.57225371
## 7          1 0.13480810
## 8          1 0.52485040
## 9          1 0.71524499
## 10         1 0.02900179
## 11         1 0.75880682
## 12         1 0.22553375
## 13         1 0.91669713
## 14         1 0.31744254
## 15         1 0.84983519
## 16         1 0.27978700
## 17         1 0.74013728
## 18         1 0.08660859
## 19         1 0.36215297
## 20         1 0.58880895
## attr("assign")
## [1] 0 1
```

Using matrix algebra, verify the OLS estimate is the same as you computed from the `my_simple_ols` function.

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

```
##          [,1]
##      2.639744
## x -1.254370
```

Find the hat matrix H .

```
H = X %*% XtXinvX
H
```

```
##          [,1]          [,2]          [,3]          [,4]          [,5]
## [1,] 0.092019911 0.082727951 0.017477539 0.017837164 0.015897301
## [2,] 0.082727951 0.075490743 0.024669306 0.024949406 0.023438510
## [3,] 0.017477539 0.024669306 0.075171650 0.074893308 0.076394718
## [4,] 0.017837164 0.024949406 0.074893308 0.074618045 0.076102852
## [5,] 0.015897301 0.023438510 0.076394718 0.076102852 0.077677214
## [6,] 0.068886983 0.064710461 0.035381902 0.035543545 0.034671622
## [7,] -0.007649244 0.005098867 0.094619211 0.094125824 0.096787220
## [8,] 0.060593221 0.058250717 0.041801087 0.041891748 0.041402709
## [9,] 0.093904982 0.084196172 0.016018537 0.016394295 0.014367407
## [10,] -0.026161296 -0.009319573 0.108947121 0.108295300 0.111811310
## [11,] 0.101526633 0.090132429 0.010119551 0.010560538 0.008181795
## [12,] 0.008224270 0.017462234 0.082333471 0.081975936 0.083904525
## [13,] 0.129151391 0.111648461 -0.011261387 -0.010583975 -0.014238024
## [14,] 0.024304788 0.029986829 0.069887513 0.069667603 0.070853830
## [15,] 0.117453112 0.102537049 -0.002207184 -0.001629891 -0.004743885
## [16,] 0.017716511 0.024855434 0.074986691 0.074710394 0.076200772
## [17,] 0.098260179 0.087588294 0.012647713 0.013060745 0.010832798
## [18,] -0.016082313 -0.001469378 0.101146216 0.100580655 0.103631366
## [19,] 0.032127401 0.036079610 0.063832987 0.063680026 0.064505120
## [20,] 0.071783517 0.066966478 0.033140050 0.033326483 0.032320840
##          [,6]          [,7]          [,8]          [,9]          [,10]          [,11]
```

```

## [1,] 0.06888698 -0.007649244 0.06059322 0.093904982 -0.026161296 0.101526633
## [2,] 0.06471046 0.005098867 0.05825072 0.084196172 -0.009319573 0.090132429
## [3,] 0.03538190 0.094619211 0.04180109 0.016018537 0.108947121 0.010119551
## [4,] 0.03554355 0.094125824 0.04189175 0.016394295 0.108295300 0.010560538
## [5,] 0.03467162 0.096787220 0.04140271 0.014367407 0.111811310 0.008181795
## [6,] 0.05848926 0.024087991 0.05476141 0.069734279 0.015767250 0.073160036
## [7,] 0.02408799 0.129091918 0.03546662 -0.010235468 0.154489539 -0.020691997
## [8,] 0.05476141 0.035466624 0.05267055 0.061068447 0.030799735 0.062989865
## [9,] 0.06973428 -0.010235468 0.06106845 0.095874619 -0.029577996 0.103838188
## [10,] 0.01576725 0.154489539 0.03079974 -0.029577996 0.188042725 -0.043392277
## [11,] 0.07316004 -0.020691997 0.06298987 0.103838188 -0.043392277 0.113184187
## [12,] 0.03122277 0.107314240 0.03946834 0.006350153 0.125718717 -0.001227208
## [13,] 0.08557673 -0.058591802 0.06995407 0.132702231 -0.093462287 0.147058860
## [14,] 0.03845059 0.085252563 0.04352224 0.023152065 0.096572699 0.018491419
## [15,] 0.08031862 -0.042542341 0.06700493 0.120479151 -0.072259099 0.132713925
## [16,] 0.03548931 0.094291354 0.04186133 0.016268229 0.108513983 0.010412589
## [17,] 0.07169184 -0.016210583 0.06216639 0.100425196 -0.037471812 0.109178719
## [18,] 0.02029752 0.140661672 0.03334065 -0.019046856 0.169774519 -0.031032991
## [19,] 0.04196668 0.074520323 0.04549432 0.031325612 0.082394173 0.028083846
## [20,] 0.05979119 0.020114089 0.05549163 0.072760756 0.010517267 0.076711892
##      [,12]      [,13]      [,14]      [,15]      [,16]
## [1,] 0.008224270 0.129151391 0.024304788 0.117453112 0.01771651
## [2,] 0.017462234 0.111648461 0.029986829 0.102537049 0.02485543
## [3,] 0.082333471 -0.011261387 0.069887513 -0.002207184 0.07498669
## [4,] 0.081975936 -0.010583975 0.069667603 -0.001629891 0.07471039
## [5,] 0.083904525 -0.014238024 0.070853830 -0.004743885 0.07620077
## [6,] 0.031222770 0.085576729 0.038450593 0.080318622 0.03548931
## [7,] 0.107314240 -0.058591802 0.085252563 -0.042542341 0.09429135
## [8,] 0.039468338 0.069954067 0.043522236 0.067004931 0.04186133
## [9,] 0.006350153 0.132702231 0.023152065 0.120479151 0.01626823
## [10,] 0.125718717 -0.093462287 0.096572699 -0.072259099 0.10851398
## [11,] -0.001227208 0.147058860 0.018491419 0.132713925 0.01041259
## [12,] 0.091532968 -0.028691436 0.075545895 -0.017061137 0.08209589
## [13,] -0.028691436 0.199094620 0.001598855 0.177058995 -0.01081124
## [14,] 0.075545895 0.001598855 0.065712645 0.008752363 0.06974138
## [15,] -0.017061137 0.177058995 0.008752363 0.158280152 -0.00182357
## [16,] 0.082095887 -0.010811244 0.069741382 -0.001823570 0.07480309
## [17,] 0.002020265 0.140905958 0.020488859 0.127470398 0.01292217
## [18,] 0.115698303 -0.074476870 0.090409392 -0.056079655 0.10077040
## [19,] 0.067768740 0.016334031 0.060929110 0.021309735 0.06373134
## [20,] 0.028343068 0.091032826 0.036679360 0.084968328 0.03326394
##      [,17]      [,18]      [,19]      [,20]
## [1,] 0.098260179 -0.016082313 0.03212740 0.07178352
## [2,] 0.087588294 -0.001469378 0.03607961 0.06696648
## [3,] 0.012647713 0.101146216 0.06383299 0.03314005
## [4,] 0.013060745 0.100580655 0.06368003 0.03332648
## [5,] 0.010832798 0.103631366 0.06450512 0.03232084
## [6,] 0.071691840 0.020297521 0.04196668 0.05979119
## [7,] -0.016210583 0.140661672 0.07452032 0.02011409
## [8,] 0.062166392 0.033340647 0.04549432 0.05549163
## [9,] 0.100425196 -0.019046856 0.03132561 0.07276076
## [10,] -0.037471812 0.169774519 0.08239417 0.01051727
## [11,] 0.109178719 -0.031032991 0.02808385 0.07671189
## [12,] 0.002020265 0.115698303 0.06776874 0.02834307

```

```
## [13,] 0.140905958 -0.074476870 0.01633403 0.09103283
## [14,] 0.020488859 0.090409392 0.06092911 0.03667936
## [15,] 0.127470398 -0.056079655 0.02130973 0.08496833
## [16,] 0.012922174 0.100770399 0.06373134 0.03326394
## [17,] 0.105427172 -0.025896025 0.02947319 0.07501853
## [18,] -0.025896025 0.153923877 0.07810721 0.01574231
## [19,] 0.029473188 0.078107215 0.05760187 0.04073468
## [20,] 0.075018531 0.015742307 0.04073468 0.06129278
```

Verify that this specific hat matrix is symmetric.

```
expect_equal(H, t(H))
```

Using the `diag` function, find the trace of the hat matrix.

```
diag(H)
```

```
## [1] 0.09201991 0.07549074 0.07517165 0.07461804 0.07767721 0.05848926
## [7] 0.12909192 0.05267055 0.09587462 0.18804273 0.11318419 0.09153297
## [13] 0.19909462 0.06571264 0.15828015 0.07480309 0.10542717 0.15392388
## [19] 0.05760187 0.06129278
```

```
sum(diag(H))
```

```
## [1] 2
```

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

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

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

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

Create a prediction method `g` that takes in a vector `x_future` and the dataset \mathbb{D} i.e. `X` where the first column is the one vector and `y` and returns the OLS predictions.

```
g = function(x_future, X, y){
  b = solve(t(X) %*% X) %*% t(X) %*% y
  b[1] + b[2]*x_future
}
```

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.

```
ns = 10^(1:7)
errors = array(dim=length(ns))
beta = c(beta_0, beta_1)
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 = lm(y ~ x)
b = coef(mod)
errors[i] = sum((beta - b)^2)
}
errors

```

```

## [1] 4.874365e-03 7.308998e-03 1.986545e-04 9.853330e-05 8.258596e-06
## [6] 8.827203e-07 6.993816e-07

```

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

```
Galton
```

```

##      parent child
## 1      70.5  61.7
## 2      68.5  61.7
## 3      65.5  61.7
## 4      64.5  61.7
## 5      64.0  61.7
## 6      67.5  62.2
## 7      67.5  62.2
## 8      67.5  62.2
## 9      66.5  62.2
## 10     66.5  62.2
## 11     66.5  62.2
## 12     64.5  62.2
## 13     70.5  63.2
## 14     69.5  63.2
## 15     68.5  63.2
## 16     68.5  63.2
## 17     68.5  63.2
## 18     68.5  63.2
## 19     68.5  63.2
## 20     68.5  63.2
## 21     68.5  63.2
## 22     67.5  63.2
## 23     67.5  63.2
## 24     67.5  63.2
## 25     67.5  63.2
## 26     67.5  63.2
## 27     66.5  63.2
## 28     66.5  63.2
## 29     66.5  63.2
## 30     65.5  63.2
## 31     65.5  63.2
## 32     65.5  63.2

```

## 33	65.5	63.2
## 34	65.5	63.2
## 35	65.5	63.2
## 36	65.5	63.2
## 37	65.5	63.2
## 38	65.5	63.2
## 39	64.5	63.2
## 40	64.5	63.2
## 41	64.5	63.2
## 42	64.5	63.2
## 43	64.0	63.2
## 44	64.0	63.2
## 45	69.5	64.2
## 46	69.5	64.2
## 47	69.5	64.2
## 48	69.5	64.2
## 49	69.5	64.2
## 50	69.5	64.2
## 51	69.5	64.2
## 52	69.5	64.2
## 53	69.5	64.2
## 54	69.5	64.2
## 55	69.5	64.2
## 56	69.5	64.2
## 57	69.5	64.2
## 58	69.5	64.2
## 59	69.5	64.2
## 60	69.5	64.2
## 61	68.5	64.2
## 62	68.5	64.2
## 63	68.5	64.2
## 64	68.5	64.2
## 65	68.5	64.2
## 66	68.5	64.2
## 67	68.5	64.2
## 68	68.5	64.2
## 69	68.5	64.2
## 70	68.5	64.2
## 71	68.5	64.2
## 72	67.5	64.2
## 73	67.5	64.2
## 74	67.5	64.2
## 75	67.5	64.2
## 76	67.5	64.2
## 77	67.5	64.2
## 78	67.5	64.2
## 79	67.5	64.2
## 80	67.5	64.2
## 81	67.5	64.2
## 82	67.5	64.2
## 83	67.5	64.2
## 84	67.5	64.2
## 85	67.5	64.2
## 86	66.5	64.2

## 87	66.5	64.2
## 88	66.5	64.2
## 89	66.5	64.2
## 90	66.5	64.2
## 91	65.5	64.2
## 92	65.5	64.2
## 93	65.5	64.2
## 94	65.5	64.2
## 95	65.5	64.2
## 96	64.5	64.2
## 97	64.5	64.2
## 98	64.5	64.2
## 99	64.5	64.2
## 100	64.0	64.2
## 101	64.0	64.2
## 102	64.0	64.2
## 103	64.0	64.2
## 104	71.5	65.2
## 105	70.5	65.2
## 106	69.5	65.2
## 107	69.5	65.2
## 108	69.5	65.2
## 109	69.5	65.2
## 110	68.5	65.2
## 111	68.5	65.2
## 112	68.5	65.2
## 113	68.5	65.2
## 114	68.5	65.2
## 115	68.5	65.2
## 116	68.5	65.2
## 117	68.5	65.2
## 118	68.5	65.2
## 119	68.5	65.2
## 120	68.5	65.2
## 121	68.5	65.2
## 122	68.5	65.2
## 123	68.5	65.2
## 124	68.5	65.2
## 125	68.5	65.2
## 126	67.5	65.2
## 127	67.5	65.2
## 128	67.5	65.2
## 129	67.5	65.2
## 130	67.5	65.2
## 131	67.5	65.2
## 132	67.5	65.2
## 133	67.5	65.2
## 134	67.5	65.2
## 135	67.5	65.2
## 136	67.5	65.2
## 137	67.5	65.2
## 138	67.5	65.2
## 139	67.5	65.2
## 140	67.5	65.2

##	141	66.5	65.2
##	142	66.5	65.2
##	143	65.5	65.2
##	144	65.5	65.2
##	145	65.5	65.2
##	146	65.5	65.2
##	147	65.5	65.2
##	148	65.5	65.2
##	149	65.5	65.2
##	150	64.5	65.2
##	151	64.0	65.2
##	152	71.5	66.2
##	153	71.5	66.2
##	154	71.5	66.2
##	155	70.5	66.2
##	156	69.5	66.2
##	157	69.5	66.2
##	158	69.5	66.2
##	159	69.5	66.2
##	160	69.5	66.2
##	161	69.5	66.2
##	162	69.5	66.2
##	163	69.5	66.2
##	164	69.5	66.2
##	165	69.5	66.2
##	166	69.5	66.2
##	167	69.5	66.2
##	168	69.5	66.2
##	169	69.5	66.2
##	170	69.5	66.2
##	171	69.5	66.2
##	172	69.5	66.2
##	173	68.5	66.2
##	174	68.5	66.2
##	175	68.5	66.2
##	176	68.5	66.2
##	177	68.5	66.2
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## 808	69.5	71.2
## 809	69.5	71.2
## 810	69.5	71.2
## 811	69.5	71.2
## 812	69.5	71.2
## 813	69.5	71.2
## 814	69.5	71.2
## 815	69.5	71.2
## 816	69.5	71.2
## 817	69.5	71.2
## 818	69.5	71.2
## 819	69.5	71.2
## 820	69.5	71.2
## 821	69.5	71.2
## 822	69.5	71.2
## 823	69.5	71.2
## 824	69.5	71.2
## 825	69.5	71.2
## 826	68.5	71.2
## 827	68.5	71.2
## 828	68.5	71.2
## 829	68.5	71.2
## 830	68.5	71.2
## 831	68.5	71.2
## 832	68.5	71.2
## 833	68.5	71.2
## 834	68.5	71.2
## 835	68.5	71.2
## 836	68.5	71.2
## 837	68.5	71.2
## 838	68.5	71.2
## 839	68.5	71.2
## 840	68.5	71.2
## 841	68.5	71.2
## 842	68.5	71.2

## 843	68.5	71.2
## 844	67.5	71.2
## 845	67.5	71.2
## 846	67.5	71.2
## 847	67.5	71.2
## 848	67.5	71.2
## 849	67.5	71.2
## 850	67.5	71.2
## 851	67.5	71.2
## 852	67.5	71.2
## 853	67.5	71.2
## 854	67.5	71.2
## 855	65.5	71.2
## 856	65.5	71.2
## 857	73.0	72.2
## 858	72.5	72.2
## 859	72.5	72.2
## 860	72.5	72.2
## 861	72.5	72.2
## 862	72.5	72.2
## 863	72.5	72.2
## 864	72.5	72.2
## 865	71.5	72.2
## 866	71.5	72.2
## 867	71.5	72.2
## 868	71.5	72.2
## 869	71.5	72.2
## 870	71.5	72.2
## 871	71.5	72.2
## 872	71.5	72.2
## 873	71.5	72.2
## 874	70.5	72.2
## 875	70.5	72.2
## 876	70.5	72.2
## 877	70.5	72.2
## 878	69.5	72.2
## 879	69.5	72.2
## 880	69.5	72.2
## 881	69.5	72.2
## 882	69.5	72.2
## 883	69.5	72.2
## 884	69.5	72.2
## 885	69.5	72.2
## 886	69.5	72.2
## 887	69.5	72.2
## 888	69.5	72.2
## 889	68.5	72.2
## 890	68.5	72.2
## 891	68.5	72.2
## 892	68.5	72.2
## 893	67.5	72.2
## 894	67.5	72.2
## 895	67.5	72.2
## 896	67.5	72.2

```
## 897    65.5   72.2
## 898    73.0   73.2
## 899    73.0   73.2
## 900    73.0   73.2
## 901    72.5   73.2
## 902    72.5   73.2
## 903    71.5   73.2
## 904    71.5   73.2
## 905    70.5   73.2
## 906    70.5   73.2
## 907    70.5   73.2
## 908    69.5   73.2
## 909    69.5   73.2
## 910    69.5   73.2
## 911    69.5   73.2
## 912    68.5   73.2
## 913    68.5   73.2
## 914    68.5   73.2
## 915    72.5   73.7
## 916    72.5   73.7
## 917    72.5   73.7
## 918    72.5   73.7
## 919    71.5   73.7
## 920    71.5   73.7
## 921    70.5   73.7
## 922    70.5   73.7
## 923    70.5   73.7
## 924    69.5   73.7
## 925    69.5   73.7
## 926    69.5   73.7
## 927    69.5   73.7
## 928    69.5   73.7
```

TO-DO

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

```
avg_height = (mean(Galton$parent) + mean(Galton$child)) / 2
```

If you were to use the null model, what would the RMSE be of this model be?

```
rmse_null = sqrt(mean((Galton$child - avg_height) ^ 2))
```

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 . Use the correct units to report these quantities.

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

```
## (Intercept)
##      23.94153
```



```
b_1
```

```
##      parent  
## 0.6462906
```

```
summary(mod)$sigma
```

```
## [1] 2.238547
```

```
summary(mod)$r.sq
```

```
## [1] 0.2104629
```

Interpret all four quantities: b_0 , b_1 , RMSE and R^2 .

TO-DO

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

TO-DO

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.

TO-DO

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?

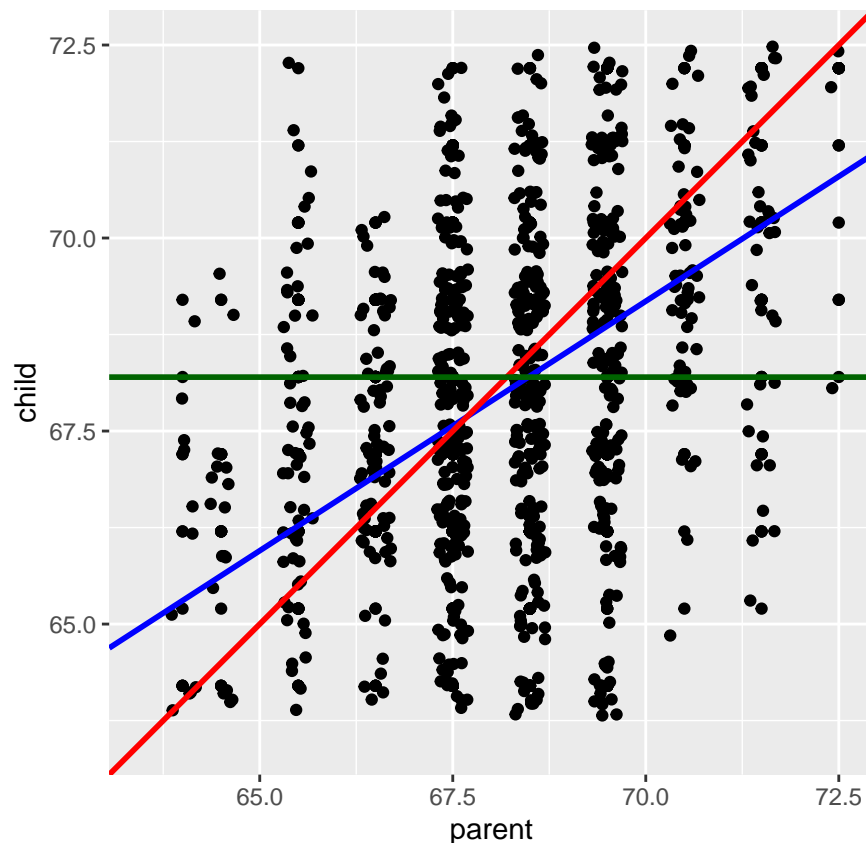
TO-DO

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 90 rows containing missing values (geom_point).
```



Fill in the following sentence:

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”?

Because children tend to move toward the mean

Why should this effect be real?

Genes?

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.

Everyone calls it regression, because of Galton's discovery of Parents and Child height moving towards the mean.

Create a dataset \mathbb{D} which we call Xy such that the linear model has R^2 about 50% and RMSE approximately 1.

```
x = c(1,2,3,4,5,6,4,1,2,3)
y = c(1,4,3,6,4,7,3,2,3,3)
Xy = data.frame(x = x, y = y)
first_model = lm(y ~ x)
summary(first_model)$r.sq
```

```
## [1] 0.6476045
```

```
summary(first_model)$sigma
```

```
## [1] 1.118483
```

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 = c(1,1,1,1)
y = c(20,40,20,40)
Xy = data.frame(x = x, y = y)
sec_model = lm(y ~ x)
summary(sec_model)$r.sq
```

```
## [1] 0
```

```
summary(sec_model)$sigma
```

```
## [1] 11.54701
```

Extra credit: create a dataset \mathbb{D} and a model (hint: not a linear model) that can give you R^2 arbitrarily close to 1 but RMSE arbitrarily high.

```
data(iris)
```

Load up the famous iris dataset. We are going to do a different prediction problem. Imagine the only input x is Species and you are trying to predict y which is Petal.Length. What would a reasonable, naive prediction be under all Species? Hint: it's what we did in class.

```
x = iris$Species
y = iris$Petal.Length
petallen_model = lm(y ~ x)
summary(petallen_model)$r.sq
```

```
## [1] 0.9413717
```

```
summary(petallen_model)$sigma
```

```
## [1] 0.4303345
```

Prove that this is the OLS model by fitting an appropriate `lm` and then using the `predict` function to verify you get the same answers as you wrote previously. Show this by doing a linear regression with and without the intercept.

```
petallen_model = lm(y ~ x)
summary(petallen_model)$r.sq
```

```
## [1] 0.9413717
```

```
summary(petallen_model)$sigma
```

```
## [1] 0.4303345
```

```
predict(petallen_model)
```

```
##      1      2      3      4      5      6      7      8      9     10     11     12     13
## 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462
## 14    15    16    17    18    19    20    21    22    23    24    25    26
## 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462
## 27    28    29    30    31    32    33    34    35    36    37    38    39
## 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462
## 40    41    42    43    44    45    46    47    48    49    50    51    52
## 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 1.462 4.260 4.260
## 53    54    55    56    57    58    59    60    61    62    63    64    65
## 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260
```

```
##      66      67      68      69      70      71      72      73      74      75      76      77      78
## 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260
##      79      80      81      82      83      84      85      86      87      88      89      90      91
## 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260
##      92      93      94      95      96      97      98      99     100     101     102     103     104
## 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 4.260 5.552 5.552 5.552 5.552
##     105     106     107     108     109     110     111     112     113     114     115     116     117
## 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552
##     118     119     120     121     122     123     124     125     126     127     128     129     130
## 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552
##     131     132     133     134     135     136     137     138     139     140     141     142     143
## 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552 5.552
##     144     145     146     147     148     149     150
## 5.552 5.552 5.552 5.552 5.552 5.552 5.552
```

Use the `model.matrix` function to compute the matrix `X` for the regression with the intercept and without the intercept. What is different?

```
model.matrix(x ~ 0,iris)
```

```
##
## 1
## 2
## 3
## 4
## 5
## 6
## 7
## 8
## 9
## 10
## 11
## 12
## 13
## 14
## 15
## 16
## 17
## 18
## 19
## 20
## 21
## 22
## 23
## 24
## 25
## 26
## 27
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## 30
## 31
## 32
## 33
## 34
```

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123
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132
133
134
135
136
137
138
139
140
141
142

```
## 143
## 144
## 145
## 146
## 147
## 148
## 149
## 150
## attr("assign")
## integer(0)
```

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

```
##      (Intercept) Sepal.Length Sepal.Width Petal.Length Petal.Width
## 1             1         5.1         3.5         1.4         0.2
## 2             1         4.9         3.0         1.4         0.2
## 3             1         4.7         3.2         1.3         0.2
## 4             1         4.6         3.1         1.5         0.2
## 5             1         5.0         3.6         1.4         0.2
## 6             1         5.4         3.9         1.7         0.4
## 7             1         4.6         3.4         1.4         0.3
## 8             1         5.0         3.4         1.5         0.2
## 9             1         4.4         2.9         1.4         0.2
## 10            1         4.9         3.1         1.5         0.1
## 11            1         5.4         3.7         1.5         0.2
## 12            1         4.8         3.4         1.6         0.2
## 13            1         4.8         3.0         1.4         0.1
## 14            1         4.3         3.0         1.1         0.1
## 15            1         5.8         4.0         1.2         0.2
## 16            1         5.7         4.4         1.5         0.4
## 17            1         5.4         3.9         1.3         0.4
## 18            1         5.1         3.5         1.4         0.3
## 19            1         5.7         3.8         1.7         0.3
## 20            1         5.1         3.8         1.5         0.3
## 21            1         5.4         3.4         1.7         0.2
## 22            1         5.1         3.7         1.5         0.4
## 23            1         4.6         3.6         1.0         0.2
## 24            1         5.1         3.3         1.7         0.5
## 25            1         4.8         3.4         1.9         0.2
## 26            1         5.0         3.0         1.6         0.2
## 27            1         5.0         3.4         1.6         0.4
## 28            1         5.2         3.5         1.5         0.2
## 29            1         5.2         3.4         1.4         0.2
## 30            1         4.7         3.2         1.6         0.2
## 31            1         4.8         3.1         1.6         0.2
## 32            1         5.4         3.4         1.5         0.4
## 33            1         5.2         4.1         1.5         0.1
## 34            1         5.5         4.2         1.4         0.2
## 35            1         4.9         3.1         1.5         0.2
## 36            1         5.0         3.2         1.2         0.2
## 37            1         5.5         3.5         1.3         0.2
## 38            1         4.9         3.6         1.4         0.1
## 39            1         4.4         3.0         1.3         0.2
## 40            1         5.1         3.4         1.5         0.2
## 41            1         5.0         3.5         1.3         0.3
```

## 42	1	4.5	2.3	1.3	0.3
## 43	1	4.4	3.2	1.3	0.2
## 44	1	5.0	3.5	1.6	0.6
## 45	1	5.1	3.8	1.9	0.4
## 46	1	4.8	3.0	1.4	0.3
## 47	1	5.1	3.8	1.6	0.2
## 48	1	4.6	3.2	1.4	0.2
## 49	1	5.3	3.7	1.5	0.2
## 50	1	5.0	3.3	1.4	0.2
## 51	1	7.0	3.2	4.7	1.4
## 52	1	6.4	3.2	4.5	1.5
## 53	1	6.9	3.1	4.9	1.5
## 54	1	5.5	2.3	4.0	1.3
## 55	1	6.5	2.8	4.6	1.5
## 56	1	5.7	2.8	4.5	1.3
## 57	1	6.3	3.3	4.7	1.6
## 58	1	4.9	2.4	3.3	1.0
## 59	1	6.6	2.9	4.6	1.3
## 60	1	5.2	2.7	3.9	1.4
## 61	1	5.0	2.0	3.5	1.0
## 62	1	5.9	3.0	4.2	1.5
## 63	1	6.0	2.2	4.0	1.0
## 64	1	6.1	2.9	4.7	1.4
## 65	1	5.6	2.9	3.6	1.3
## 66	1	6.7	3.1	4.4	1.4
## 67	1	5.6	3.0	4.5	1.5
## 68	1	5.8	2.7	4.1	1.0
## 69	1	6.2	2.2	4.5	1.5
## 70	1	5.6	2.5	3.9	1.1
## 71	1	5.9	3.2	4.8	1.8
## 72	1	6.1	2.8	4.0	1.3
## 73	1	6.3	2.5	4.9	1.5
## 74	1	6.1	2.8	4.7	1.2
## 75	1	6.4	2.9	4.3	1.3
## 76	1	6.6	3.0	4.4	1.4
## 77	1	6.8	2.8	4.8	1.4
## 78	1	6.7	3.0	5.0	1.7
## 79	1	6.0	2.9	4.5	1.5
## 80	1	5.7	2.6	3.5	1.0
## 81	1	5.5	2.4	3.8	1.1
## 82	1	5.5	2.4	3.7	1.0
## 83	1	5.8	2.7	3.9	1.2
## 84	1	6.0	2.7	5.1	1.6
## 85	1	5.4	3.0	4.5	1.5
## 86	1	6.0	3.4	4.5	1.6
## 87	1	6.7	3.1	4.7	1.5
## 88	1	6.3	2.3	4.4	1.3
## 89	1	5.6	3.0	4.1	1.3
## 90	1	5.5	2.5	4.0	1.3
## 91	1	5.5	2.6	4.4	1.2
## 92	1	6.1	3.0	4.6	1.4
## 93	1	5.8	2.6	4.0	1.2
## 94	1	5.0	2.3	3.3	1.0
## 95	1	5.6	2.7	4.2	1.3

## 96	1	5.7	3.0	4.2	1.2
## 97	1	5.7	2.9	4.2	1.3
## 98	1	6.2	2.9	4.3	1.3
## 99	1	5.1	2.5	3.0	1.1
## 100	1	5.7	2.8	4.1	1.3
## 101	1	6.3	3.3	6.0	2.5
## 102	1	5.8	2.7	5.1	1.9
## 103	1	7.1	3.0	5.9	2.1
## 104	1	6.3	2.9	5.6	1.8
## 105	1	6.5	3.0	5.8	2.2
## 106	1	7.6	3.0	6.6	2.1
## 107	1	4.9	2.5	4.5	1.7
## 108	1	7.3	2.9	6.3	1.8
## 109	1	6.7	2.5	5.8	1.8
## 110	1	7.2	3.6	6.1	2.5
## 111	1	6.5	3.2	5.1	2.0
## 112	1	6.4	2.7	5.3	1.9
## 113	1	6.8	3.0	5.5	2.1
## 114	1	5.7	2.5	5.0	2.0
## 115	1	5.8	2.8	5.1	2.4
## 116	1	6.4	3.2	5.3	2.3
## 117	1	6.5	3.0	5.5	1.8
## 118	1	7.7	3.8	6.7	2.2
## 119	1	7.7	2.6	6.9	2.3
## 120	1	6.0	2.2	5.0	1.5
## 121	1	6.9	3.2	5.7	2.3
## 122	1	5.6	2.8	4.9	2.0
## 123	1	7.7	2.8	6.7	2.0
## 124	1	6.3	2.7	4.9	1.8
## 125	1	6.7	3.3	5.7	2.1
## 126	1	7.2	3.2	6.0	1.8
## 127	1	6.2	2.8	4.8	1.8
## 128	1	6.1	3.0	4.9	1.8
## 129	1	6.4	2.8	5.6	2.1
## 130	1	7.2	3.0	5.8	1.6
## 131	1	7.4	2.8	6.1	1.9
## 132	1	7.9	3.8	6.4	2.0
## 133	1	6.4	2.8	5.6	2.2
## 134	1	6.3	2.8	5.1	1.5
## 135	1	6.1	2.6	5.6	1.4
## 136	1	7.7	3.0	6.1	2.3
## 137	1	6.3	3.4	5.6	2.4
## 138	1	6.4	3.1	5.5	1.8
## 139	1	6.0	3.0	4.8	1.8
## 140	1	6.9	3.1	5.4	2.1
## 141	1	6.7	3.1	5.6	2.4
## 142	1	6.9	3.1	5.1	2.3
## 143	1	5.8	2.7	5.1	1.9
## 144	1	6.8	3.2	5.9	2.3
## 145	1	6.7	3.3	5.7	2.5
## 146	1	6.7	3.0	5.2	2.3
## 147	1	6.3	2.5	5.0	1.9
## 148	1	6.5	3.0	5.2	2.0
## 149	1	6.2	3.4	5.4	2.3

## 150	1	5.9	3.0	5.1	1.8
##	Speciesversicolor	Speciesvirginica			
## 1	0		0		
## 2	0		0		
## 3	0		0		
## 4	0		0		
## 5	0		0		
## 6	0		0		
## 7	0		0		
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## 149          0          1
## 150          0          1
## attr("assign")
## [1] 0 1 2 3 4 5 5
## attr("contrasts")
## attr("contrasts")$Species
## [1] "contr.treatment"

```