

Lab 4

Jonathan Eng

11:59PM Feb 29, 2020

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:

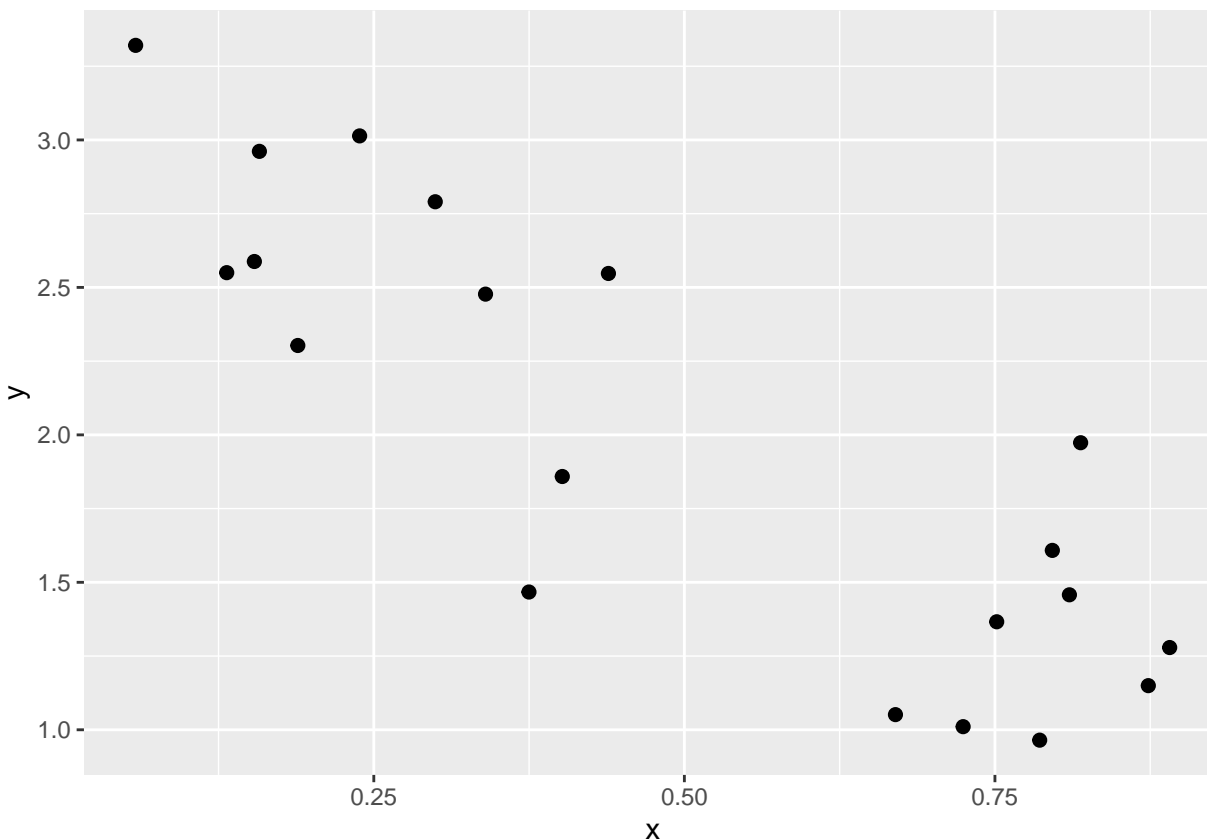
```
n = 20
x = runif(n)
beta_0 = 3
beta_1 = -2
y = beta_0 + beta_1 * x + rnorm(n, mean = 0, sd = 0.33)
```

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)
```

```

Rsq = 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 = 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 0.72439818
## [2,] 1 0.40173039
## [3,] 1 0.78603297
## [4,] 1 0.33993088
## [5,] 1 0.05827157
## [6,] 1 0.37488552
## [7,] 1 0.15385093
## [8,] 1 0.43885504
## [9,] 1 0.15789404
## [10,] 1 0.89067734
## [11,] 1 0.29945788
## [12,] 1 0.87348045
## [13,] 1 0.66992145
## [14,] 1 0.81900053
## [15,] 1 0.13158586
## [16,] 1 0.80995562
## [17,] 1 0.79622270
## [18,] 1 0.75143082
## [19,] 1 0.18882609
## [20,] 1 0.23857099

```

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 0.72439818
## 2             1 0.40173039
## 3             1 0.78603297
## 4             1 0.33993088
## 5             1 0.05827157
## 6             1 0.37488552
## 7             1 0.15385093
## 8             1 0.43885504
## 9             1 0.15789404
## 10            1 0.89067734
## 11            1 0.29945788
## 12            1 0.87348045
## 13            1 0.66992145
## 14            1 0.81900053
## 15            1 0.13158586
## 16            1 0.80995562
## 17            1 0.79622270
## 18            1 0.75143082
## 19            1 0.18882609
## 20            1 0.23857099
## 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]
## 3.080373
## x -2.207916
```

Find the hat matrix H .

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

```
##      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## [1,] 0.082228601 0.03684712 0.090897203 0.02815535 -0.011458514 0.03307153
## [2,] 0.036847117 0.05536785 0.033309356 0.05891507 0.075081965 0.05690871
## [3,] 0.090897203 0.03330936 0.101897418 0.02227974 -0.027989152 0.02851824
## [4,] 0.028155350 0.05891507 0.022279743 0.06480637 0.091656780 0.06147417
## [5,] -0.011458514 0.07508196 -0.027989152 0.09165678 0.167198660 0.08228184
## [6,] 0.033071531 0.05690871 0.028518241 0.06147417 0.082281840 0.05889189
## [7,] 0.001984208 0.06959583 -0.010930711 0.08254526 0.141563986 0.07522089
## [8,] 0.042068499 0.05323694 0.039935145 0.05537600 0.065125020 0.05416612
## [9,] 0.002552849 0.06936376 -0.010209120 0.08215983 0.140479612 0.07492220
```

```

## [10,] 0.105614869 0.02730290 0.120573728 0.01230406 -0.056055088 0.02078761
## [11,] 0.022463039 0.06123817 0.015056359 0.06866464 0.102511763 0.06446413
## [12,] 0.103196219 0.02828998 0.117504529 0.01394343 -0.051442831 0.02205803
## [13,] 0.074566744 0.03997401 0.081174517 0.03334858 0.003152309 0.03709602
## [14,] 0.095533912 0.03141706 0.107781273 0.01913697 -0.036831150 0.02608275
## [15,] -0.001147254 0.07087381 -0.014904449 0.08466777 0.147535546 0.07686572
## [16,] 0.094261795 0.03193622 0.106166992 0.01999921 -0.034405280 0.02675095
## [17,] 0.092330334 0.03272448 0.103716021 0.02130836 -0.030722069 0.02776547
## [18,] 0.086030597 0.03529548 0.095721830 0.02557834 -0.018708751 0.03107449
## [19,] 0.006903276 0.06758830 -0.004688550 0.07921110 0.132183542 0.07263708
## [20,] 0.013899627 0.06473300 0.004189626 0.07446895 0.118841810 0.06896217
##      [,7]      [,8]      [,9]      [,10]      [,11]      [,12]
## [1,] 0.001984208 0.04206850 0.002552849 0.10561487 0.022463039 0.103196219
## [2,] 0.069595827 0.05323694 0.069363758 0.02730290 0.061238168 0.028289978
## [3,] -0.010930711 0.03993515 -0.010209120 0.12057373 0.015056359 0.117504529
## [4,] 0.082545260 0.05537600 0.082159833 0.01230406 0.068664641 0.013943430
## [5,] 0.141563986 0.06512502 0.140479612 -0.05605509 0.102511763 -0.051442831
## [6,] 0.075220885 0.05416612 0.074922200 0.02078761 0.064464127 0.022058032
## [7,] 0.121536343 0.06181675 0.120689153 -0.03285783 0.091025950 -0.029254404
## [8,] 0.061816749 0.05195195 0.061676806 0.03631311 0.056776882 0.036908341
## [9,] 0.120689153 0.06167681 0.119851995 -0.03187656 0.090540088 -0.028315810
## [10,] -0.032857830 0.03631311 -0.031876561 0.14597108 0.002481200 0.141797366
## [11,] 0.091025950 0.05677688 0.090540088 0.00248120 0.073528300 0.004547758
## [12,] -0.029254404 0.03690834 -0.028315810 0.14179737 0.004547758 0.137805166
## [13,] 0.013399229 0.04395409 0.013832685 0.09239328 0.029009531 0.090549630
## [14,] -0.017838713 0.03879405 -0.017035313 0.12857501 0.011094634 0.125157836
## [15,] 0.126201753 0.06258741 0.125299311 -0.03826160 0.093701553 -0.034423165
## [16,] -0.015943449 0.03910711 -0.015162494 0.12637979 0.012181564 0.123058092
## [17,] -0.013065861 0.03958245 -0.012318985 0.12304679 0.013831855 0.119870041
## [18,] -0.003680197 0.04113282 -0.003044473 0.11217573 0.019214515 0.109471757
## [19,] 0.114207669 0.06060616 0.113447270 -0.02436930 0.086822969 -0.021135038
## [20,] 0.103784152 0.05888435 0.103147197 -0.01229614 0.080845104 -0.009586928
##      [,13]      [,14]      [,15]      [,16]      [,17]
## [1,] 0.074566744 0.095533912 -0.001147254 0.0942617946 0.092330334
## [2,] 0.039974014 0.031417058 0.070873815 0.0319362248 0.032724478
## [3,] 0.081174517 0.107781273 -0.014904449 0.1061669919 0.103716021
## [4,] 0.033348582 0.019136967 0.084667775 0.0199992121 0.021308363
## [5,] 0.003152309 -0.036831150 0.147535546 -0.0344052798 -0.030722069
## [6,] 0.037096016 0.026082753 0.076865725 0.0267509478 0.027765472
## [7,] 0.013399229 -0.017838713 0.126201753 -0.0159434491 -0.013065861
## [8,] 0.043954092 0.038794045 0.062587406 0.0391071147 0.039582450
## [9,] 0.013832685 -0.017035313 0.125299311 -0.0151624940 -0.012318985
## [10,] 0.092393283 0.128575005 -0.038261597 0.1263797929 0.123046792
## [11,] 0.029009531 0.011094634 0.093701553 0.0121815640 0.013831855
## [12,] 0.090549630 0.125157836 -0.034423165 0.1230580919 0.119870041
## [13,] 0.068726376 0.084708920 0.011012224 0.0837392290 0.082266943
## [14,] 0.084708920 0.114332209 -0.022262973 0.1125349089 0.109806060
## [15,] 0.011012224 -0.022262973 0.131171429 -0.0202441053 -0.017178849
## [16,] 0.083739229 0.112534909 -0.020244105 0.1107878216 0.108135211
## [17,] 0.082266943 0.109806060 -0.017178849 0.1081352109 0.105598353
## [18,] 0.077464873 0.100905530 -0.007181076 0.0994833417 0.097324027
## [19,] 0.017148864 -0.010888849 0.118395122 -0.0091877489 -0.006604961
## [20,] 0.022481939 -0.001004112 0.107291812 0.0004208302 0.002584327
##      [,18]      [,19]      [,20]

```

```
## [1,] 0.086030597 0.006903276 0.0138996271
## [2,] 0.035295476 0.067588296 0.0647330000
## [3,] 0.095721830 -0.004688550 0.0041896263
## [4,] 0.025578344 0.079211099 0.0744689498
## [5,] -0.018708751 0.132183542 0.1188418105
## [6,] 0.031074486 0.072637085 0.0689621650
## [7,] -0.003680197 0.114207669 0.1037841523
## [8,] 0.041132823 0.060606160 0.0588843488
## [9,] -0.003044473 0.113447270 0.1031471973
## [10,] 0.112175733 -0.024369304 -0.0122961412
## [11,] 0.019214515 0.086822969 0.0808451037
## [12,] 0.109471757 -0.021135038 -0.0095869279
## [13,] 0.077464873 0.017148864 0.0224819393
## [14,] 0.100905530 -0.010888849 -0.0010041120
## [15,] -0.007181076 0.118395122 0.1072918116
## [16,] 0.099483342 -0.009187749 0.0004208302
## [17,] 0.097324027 -0.006604961 0.0025843267
## [18,] 0.090281113 0.001819172 0.0096408798
## [19,] 0.001819172 0.107629794 0.0982741340
## [20,] 0.009640880 0.098274134 0.0904372785
```

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] 0.08222860 0.05536785 0.10189742 0.06480637 0.16719866 0.05889189
## [7] 0.12153634 0.05195195 0.11985200 0.14597108 0.07352830 0.13780517
## [13] 0.06872638 0.11433221 0.13117143 0.11078782 0.10559835 0.09028111
## [19] 0.10762979 0.09043728
```

```
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] 2.821024e-01 1.239159e-02 7.283193e-04 5.419810e-05 2.794452e-05
## [6] 6.252637e-07 3.086186e-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
## 178	68.5	66.2
## 179	68.5	66.2
## 180	68.5	66.2
## 181	68.5	66.2
## 182	68.5	66.2
## 183	68.5	66.2
## 184	68.5	66.2
## 185	68.5	66.2
## 186	68.5	66.2
## 187	68.5	66.2
## 188	68.5	66.2
## 189	68.5	66.2
## 190	68.5	66.2
## 191	68.5	66.2
## 192	68.5	66.2
## 193	68.5	66.2
## 194	68.5	66.2
## 195	68.5	66.2
## 196	68.5	66.2
## 197	68.5	66.2
## 198	67.5	66.2
## 199	67.5	66.2
## 200	67.5	66.2
## 201	67.5	66.2
## 202	67.5	66.2
## 203	67.5	66.2
## 204	67.5	66.2
## 205	67.5	66.2
## 206	67.5	66.2
## 207	67.5	66.2
## 208	67.5	66.2
## 209	67.5	66.2
## 210	67.5	66.2
## 211	67.5	66.2
## 212	67.5	66.2
## 213	67.5	66.2
## 214	67.5	66.2
## 215	67.5	66.2
## 216	67.5	66.2
## 217	67.5	66.2
## 218	67.5	66.2
## 219	67.5	66.2
## 220	67.5	66.2
## 221	67.5	66.2
## 222	67.5	66.2

##	223	67.5	66.2
##	224	67.5	66.2
##	225	67.5	66.2
##	226	67.5	66.2
##	227	67.5	66.2
##	228	67.5	66.2
##	229	67.5	66.2
##	230	67.5	66.2
##	231	67.5	66.2
##	232	67.5	66.2
##	233	67.5	66.2
##	234	66.5	66.2
##	235	66.5	66.2
##	236	66.5	66.2
##	237	66.5	66.2
##	238	66.5	66.2
##	239	66.5	66.2
##	240	66.5	66.2
##	241	66.5	66.2
##	242	66.5	66.2
##	243	66.5	66.2
##	244	66.5	66.2
##	245	66.5	66.2
##	246	66.5	66.2
##	247	66.5	66.2
##	248	66.5	66.2
##	249	66.5	66.2
##	250	66.5	66.2
##	251	65.5	66.2
##	252	65.5	66.2
##	253	65.5	66.2
##	254	65.5	66.2
##	255	65.5	66.2
##	256	65.5	66.2
##	257	65.5	66.2
##	258	65.5	66.2
##	259	65.5	66.2
##	260	65.5	66.2
##	261	65.5	66.2
##	262	64.5	66.2
##	263	64.5	66.2
##	264	64.5	66.2
##	265	64.5	66.2
##	266	64.5	66.2
##	267	64.0	66.2
##	268	64.0	66.2
##	269	71.5	67.2
##	270	71.5	67.2
##	271	71.5	67.2
##	272	71.5	67.2
##	273	70.5	67.2
##	274	70.5	67.2
##	275	70.5	67.2
##	276	69.5	67.2

## 277	69.5	67.2
## 278	69.5	67.2
## 279	69.5	67.2
## 280	69.5	67.2
## 281	69.5	67.2
## 282	69.5	67.2
## 283	69.5	67.2
## 284	69.5	67.2
## 285	69.5	67.2
## 286	69.5	67.2
## 287	69.5	67.2
## 288	69.5	67.2
## 289	69.5	67.2
## 290	69.5	67.2
## 291	69.5	67.2
## 292	69.5	67.2
## 293	69.5	67.2
## 294	69.5	67.2
## 295	69.5	67.2
## 296	69.5	67.2
## 297	69.5	67.2
## 298	69.5	67.2
## 299	69.5	67.2
## 300	69.5	67.2
## 301	69.5	67.2
## 302	69.5	67.2
## 303	68.5	67.2
## 304	68.5	67.2
## 305	68.5	67.2
## 306	68.5	67.2
## 307	68.5	67.2
## 308	68.5	67.2
## 309	68.5	67.2
## 310	68.5	67.2
## 311	68.5	67.2
## 312	68.5	67.2
## 313	68.5	67.2
## 314	68.5	67.2
## 315	68.5	67.2
## 316	68.5	67.2
## 317	68.5	67.2
## 318	68.5	67.2
## 319	68.5	67.2
## 320	68.5	67.2
## 321	68.5	67.2
## 322	68.5	67.2
## 323	68.5	67.2
## 324	68.5	67.2
## 325	68.5	67.2
## 326	68.5	67.2
## 327	68.5	67.2
## 328	68.5	67.2
## 329	68.5	67.2
## 330	68.5	67.2

##	331	68.5	67.2
##	332	68.5	67.2
##	333	68.5	67.2
##	334	67.5	67.2
##	335	67.5	67.2
##	336	67.5	67.2
##	337	67.5	67.2
##	338	67.5	67.2
##	339	67.5	67.2
##	340	67.5	67.2
##	341	67.5	67.2
##	342	67.5	67.2
##	343	67.5	67.2
##	344	67.5	67.2
##	345	67.5	67.2
##	346	67.5	67.2
##	347	67.5	67.2
##	348	67.5	67.2
##	349	67.5	67.2
##	350	67.5	67.2
##	351	67.5	67.2
##	352	67.5	67.2
##	353	67.5	67.2
##	354	67.5	67.2
##	355	67.5	67.2
##	356	67.5	67.2
##	357	67.5	67.2
##	358	67.5	67.2
##	359	67.5	67.2
##	360	67.5	67.2
##	361	67.5	67.2
##	362	67.5	67.2
##	363	67.5	67.2
##	364	67.5	67.2
##	365	67.5	67.2
##	366	67.5	67.2
##	367	67.5	67.2
##	368	67.5	67.2
##	369	67.5	67.2
##	370	67.5	67.2
##	371	67.5	67.2
##	372	66.5	67.2
##	373	66.5	67.2
##	374	66.5	67.2
##	375	66.5	67.2
##	376	66.5	67.2
##	377	66.5	67.2
##	378	66.5	67.2
##	379	66.5	67.2
##	380	66.5	67.2
##	381	66.5	67.2
##	382	66.5	67.2
##	383	66.5	67.2
##	384	66.5	67.2

##	385	66.5	67.2
##	386	66.5	67.2
##	387	66.5	67.2
##	388	66.5	67.2
##	389	65.5	67.2
##	390	65.5	67.2
##	391	65.5	67.2
##	392	65.5	67.2
##	393	65.5	67.2
##	394	65.5	67.2
##	395	65.5	67.2
##	396	65.5	67.2
##	397	65.5	67.2
##	398	65.5	67.2
##	399	65.5	67.2
##	400	64.5	67.2
##	401	64.5	67.2
##	402	64.5	67.2
##	403	64.5	67.2
##	404	64.5	67.2
##	405	64.0	67.2
##	406	64.0	67.2
##	407	72.5	68.2
##	408	71.5	68.2
##	409	71.5	68.2
##	410	71.5	68.2
##	411	70.5	68.2
##	412	70.5	68.2
##	413	70.5	68.2
##	414	70.5	68.2
##	415	70.5	68.2
##	416	70.5	68.2
##	417	70.5	68.2
##	418	70.5	68.2
##	419	70.5	68.2
##	420	70.5	68.2
##	421	70.5	68.2
##	422	70.5	68.2
##	423	69.5	68.2
##	424	69.5	68.2
##	425	69.5	68.2
##	426	69.5	68.2
##	427	69.5	68.2
##	428	69.5	68.2
##	429	69.5	68.2
##	430	69.5	68.2
##	431	69.5	68.2
##	432	69.5	68.2
##	433	69.5	68.2
##	434	69.5	68.2
##	435	69.5	68.2
##	436	69.5	68.2
##	437	69.5	68.2
##	438	69.5	68.2

##	439	69.5	68.2
##	440	69.5	68.2
##	441	69.5	68.2
##	442	69.5	68.2
##	443	68.5	68.2
##	444	68.5	68.2
##	445	68.5	68.2
##	446	68.5	68.2
##	447	68.5	68.2
##	448	68.5	68.2
##	449	68.5	68.2
##	450	68.5	68.2
##	451	68.5	68.2
##	452	68.5	68.2
##	453	68.5	68.2
##	454	68.5	68.2
##	455	68.5	68.2
##	456	68.5	68.2
##	457	68.5	68.2
##	458	68.5	68.2
##	459	68.5	68.2
##	460	68.5	68.2
##	461	68.5	68.2
##	462	68.5	68.2
##	463	68.5	68.2
##	464	68.5	68.2
##	465	68.5	68.2
##	466	68.5	68.2
##	467	68.5	68.2
##	468	68.5	68.2
##	469	68.5	68.2
##	470	68.5	68.2
##	471	68.5	68.2
##	472	68.5	68.2
##	473	68.5	68.2
##	474	68.5	68.2
##	475	68.5	68.2
##	476	68.5	68.2
##	477	67.5	68.2
##	478	67.5	68.2
##	479	67.5	68.2
##	480	67.5	68.2
##	481	67.5	68.2
##	482	67.5	68.2
##	483	67.5	68.2
##	484	67.5	68.2
##	485	67.5	68.2
##	486	67.5	68.2
##	487	67.5	68.2
##	488	67.5	68.2
##	489	67.5	68.2
##	490	67.5	68.2
##	491	67.5	68.2
##	492	67.5	68.2

## 493	67.5	68.2
## 494	67.5	68.2
## 495	67.5	68.2
## 496	67.5	68.2
## 497	67.5	68.2
## 498	67.5	68.2
## 499	67.5	68.2
## 500	67.5	68.2
## 501	67.5	68.2
## 502	67.5	68.2
## 503	67.5	68.2
## 504	67.5	68.2
## 505	66.5	68.2
## 506	66.5	68.2
## 507	66.5	68.2
## 508	66.5	68.2
## 509	66.5	68.2
## 510	66.5	68.2
## 511	66.5	68.2
## 512	66.5	68.2
## 513	66.5	68.2
## 514	66.5	68.2
## 515	66.5	68.2
## 516	66.5	68.2
## 517	66.5	68.2
## 518	66.5	68.2
## 519	65.5	68.2
## 520	65.5	68.2
## 521	65.5	68.2
## 522	65.5	68.2
## 523	65.5	68.2
## 524	65.5	68.2
## 525	65.5	68.2
## 526	64.0	68.2
## 527	72.5	69.2
## 528	72.5	69.2
## 529	71.5	69.2
## 530	71.5	69.2
## 531	71.5	69.2
## 532	71.5	69.2
## 533	71.5	69.2
## 534	70.5	69.2
## 535	70.5	69.2
## 536	70.5	69.2
## 537	70.5	69.2
## 538	70.5	69.2
## 539	70.5	69.2
## 540	70.5	69.2
## 541	70.5	69.2
## 542	70.5	69.2
## 543	70.5	69.2
## 544	70.5	69.2
## 545	70.5	69.2
## 546	70.5	69.2

##	547	70.5	69.2
##	548	70.5	69.2
##	549	70.5	69.2
##	550	70.5	69.2
##	551	70.5	69.2
##	552	69.5	69.2
##	553	69.5	69.2
##	554	69.5	69.2
##	555	69.5	69.2
##	556	69.5	69.2
##	557	69.5	69.2
##	558	69.5	69.2
##	559	69.5	69.2
##	560	69.5	69.2
##	561	69.5	69.2
##	562	69.5	69.2
##	563	69.5	69.2
##	564	69.5	69.2
##	565	69.5	69.2
##	566	69.5	69.2
##	567	69.5	69.2
##	568	69.5	69.2
##	569	69.5	69.2
##	570	69.5	69.2
##	571	69.5	69.2
##	572	69.5	69.2
##	573	69.5	69.2
##	574	69.5	69.2
##	575	69.5	69.2
##	576	69.5	69.2
##	577	69.5	69.2
##	578	69.5	69.2
##	579	69.5	69.2
##	580	69.5	69.2
##	581	69.5	69.2
##	582	69.5	69.2
##	583	69.5	69.2
##	584	69.5	69.2
##	585	68.5	69.2
##	586	68.5	69.2
##	587	68.5	69.2
##	588	68.5	69.2
##	589	68.5	69.2
##	590	68.5	69.2
##	591	68.5	69.2
##	592	68.5	69.2
##	593	68.5	69.2
##	594	68.5	69.2
##	595	68.5	69.2
##	596	68.5	69.2
##	597	68.5	69.2
##	598	68.5	69.2
##	599	68.5	69.2
##	600	68.5	69.2

##	601	68.5	69.2
##	602	68.5	69.2
##	603	68.5	69.2
##	604	68.5	69.2
##	605	68.5	69.2
##	606	68.5	69.2
##	607	68.5	69.2
##	608	68.5	69.2
##	609	68.5	69.2
##	610	68.5	69.2
##	611	68.5	69.2
##	612	68.5	69.2
##	613	68.5	69.2
##	614	68.5	69.2
##	615	68.5	69.2
##	616	68.5	69.2
##	617	68.5	69.2
##	618	68.5	69.2
##	619	68.5	69.2
##	620	68.5	69.2
##	621	68.5	69.2
##	622	68.5	69.2
##	623	68.5	69.2
##	624	68.5	69.2
##	625	68.5	69.2
##	626	68.5	69.2
##	627	68.5	69.2
##	628	68.5	69.2
##	629	68.5	69.2
##	630	68.5	69.2
##	631	68.5	69.2
##	632	68.5	69.2
##	633	67.5	69.2
##	634	67.5	69.2
##	635	67.5	69.2
##	636	67.5	69.2
##	637	67.5	69.2
##	638	67.5	69.2
##	639	67.5	69.2
##	640	67.5	69.2
##	641	67.5	69.2
##	642	67.5	69.2
##	643	67.5	69.2
##	644	67.5	69.2
##	645	67.5	69.2
##	646	67.5	69.2
##	647	67.5	69.2
##	648	67.5	69.2
##	649	67.5	69.2
##	650	67.5	69.2
##	651	67.5	69.2
##	652	67.5	69.2
##	653	67.5	69.2
##	654	67.5	69.2

##	655	67.5	69.2
##	656	67.5	69.2
##	657	67.5	69.2
##	658	67.5	69.2
##	659	67.5	69.2
##	660	67.5	69.2
##	661	67.5	69.2
##	662	67.5	69.2
##	663	67.5	69.2
##	664	67.5	69.2
##	665	67.5	69.2
##	666	67.5	69.2
##	667	67.5	69.2
##	668	67.5	69.2
##	669	67.5	69.2
##	670	67.5	69.2
##	671	66.5	69.2
##	672	66.5	69.2
##	673	66.5	69.2
##	674	66.5	69.2
##	675	66.5	69.2
##	676	66.5	69.2
##	677	66.5	69.2
##	678	66.5	69.2
##	679	66.5	69.2
##	680	66.5	69.2
##	681	66.5	69.2
##	682	66.5	69.2
##	683	66.5	69.2
##	684	65.5	69.2
##	685	65.5	69.2
##	686	65.5	69.2
##	687	65.5	69.2
##	688	65.5	69.2
##	689	65.5	69.2
##	690	65.5	69.2
##	691	64.5	69.2
##	692	64.5	69.2
##	693	64.0	69.2
##	694	72.5	70.2
##	695	71.5	70.2
##	696	71.5	70.2
##	697	71.5	70.2
##	698	71.5	70.2
##	699	71.5	70.2
##	700	71.5	70.2
##	701	71.5	70.2
##	702	71.5	70.2
##	703	71.5	70.2
##	704	71.5	70.2
##	705	70.5	70.2
##	706	70.5	70.2
##	707	70.5	70.2
##	708	70.5	70.2

##	709	70.5	70.2
##	710	70.5	70.2
##	711	70.5	70.2
##	712	70.5	70.2
##	713	70.5	70.2
##	714	70.5	70.2
##	715	70.5	70.2
##	716	70.5	70.2
##	717	70.5	70.2
##	718	70.5	70.2
##	719	69.5	70.2
##	720	69.5	70.2
##	721	69.5	70.2
##	722	69.5	70.2
##	723	69.5	70.2
##	724	69.5	70.2
##	725	69.5	70.2
##	726	69.5	70.2
##	727	69.5	70.2
##	728	69.5	70.2
##	729	69.5	70.2
##	730	69.5	70.2
##	731	69.5	70.2
##	732	69.5	70.2
##	733	69.5	70.2
##	734	69.5	70.2
##	735	69.5	70.2
##	736	69.5	70.2
##	737	69.5	70.2
##	738	69.5	70.2
##	739	69.5	70.2
##	740	69.5	70.2
##	741	69.5	70.2
##	742	69.5	70.2
##	743	69.5	70.2
##	744	68.5	70.2
##	745	68.5	70.2
##	746	68.5	70.2
##	747	68.5	70.2
##	748	68.5	70.2
##	749	68.5	70.2
##	750	68.5	70.2
##	751	68.5	70.2
##	752	68.5	70.2
##	753	68.5	70.2
##	754	68.5	70.2
##	755	68.5	70.2
##	756	68.5	70.2
##	757	68.5	70.2
##	758	68.5	70.2
##	759	68.5	70.2
##	760	68.5	70.2
##	761	68.5	70.2
##	762	68.5	70.2

## 763	68.5	70.2
## 764	68.5	70.2
## 765	67.5	70.2
## 766	67.5	70.2
## 767	67.5	70.2
## 768	67.5	70.2
## 769	67.5	70.2
## 770	67.5	70.2
## 771	67.5	70.2
## 772	67.5	70.2
## 773	67.5	70.2
## 774	67.5	70.2
## 775	67.5	70.2
## 776	67.5	70.2
## 777	67.5	70.2
## 778	67.5	70.2
## 779	67.5	70.2
## 780	67.5	70.2
## 781	67.5	70.2
## 782	67.5	70.2
## 783	67.5	70.2
## 784	66.5	70.2
## 785	66.5	70.2
## 786	66.5	70.2
## 787	66.5	70.2
## 788	65.5	70.2
## 789	65.5	70.2
## 790	65.5	70.2
## 791	65.5	70.2
## 792	65.5	70.2
## 793	72.5	71.2
## 794	72.5	71.2
## 795	71.5	71.2
## 796	71.5	71.2
## 797	71.5	71.2
## 798	71.5	71.2
## 799	70.5	71.2
## 800	70.5	71.2
## 801	70.5	71.2
## 802	70.5	71.2
## 803	70.5	71.2
## 804	70.5	71.2
## 805	70.5	71.2
## 806	69.5	71.2
## 807	69.5	71.2
## 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 .

b_0 : b_0 is the intercept. b_1 : for every unit increase in parents height the average height of the child increases by 0.6462906 (b_1) R^2 : Shows the amount of error explained in the model. Since R^2 is only ~21% the model has a lot of variance unaccounted for and is likely a bad model.

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

The model is not good because the R^2 value is only about 21%. Because of this, it is likely the model is unable to predict accurately due to the amount of variance unaccounted for.

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 is reasonable to assume that the height of the child will match the height of the parents because they pass on genetics that code for that specific height. Though the height won't be exactly equal due to other factors influencing height such as diet, it is highly unlikely the child would be a significantly different height compared to the parents due to genetics.

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?

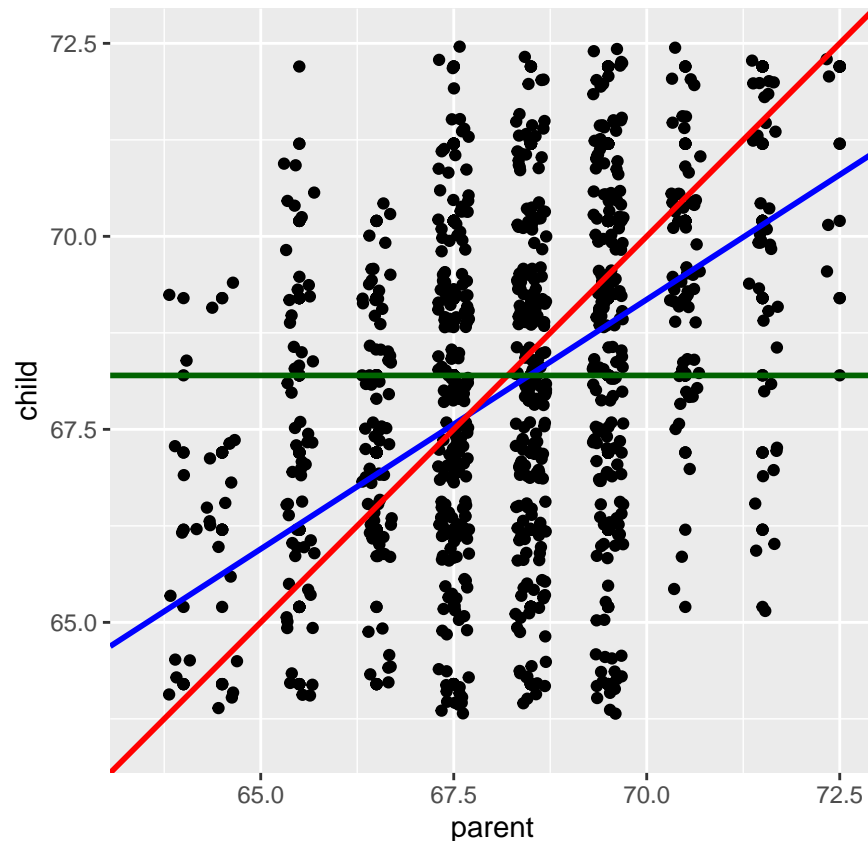
β_0 would be 0 β_1 would be 1

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



Fill in the following sentence:

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

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

The average height of the children “regressed” to the “mean” of the height of the parents. The children of taller parents ended up being shorter, averaging towards the mean height. The children of shorter parents ended up being taller, averaging towards the mean about.

Why should this effect be real?

This effect likely occurred due to sampling error. Since results are taken from children that are tall and short, the two will average out towards the mean. If taking a similar sample size from two opposing values they will always regress towards the means because their values would average each other out.

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.

It is called a regression because of Galton’s findings that the average heights of short children and tall children regressed towards the average height, coining the term “regression” and the terminology stayed. A better descriptive name for this model would be “Best Fit Line Estimator”

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

```
x = #TO DO
y = #TO DO
```

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

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 = seq(1,1000)
y = x * ((-1)^x)
```

```
lm(y~x)
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Coefficients:
## (Intercept)          x
## -1.003003      0.003003
```

```
summary(lm(y~x))
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1001.0   -500.0     1.5    500.0    998.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.003003   36.606216  -0.027   0.978
## x            0.003003    0.063356   0.047   0.962
##
## Residual standard error: 578.4 on 998 degrees of freedom
## Multiple R-squared:  2.251e-06, Adjusted R-squared:  -0.0009998
## F-statistic: 0.002247 on 1 and 998 DF,  p-value: 0.9622
```

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

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.

```
#TO-DO
```

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.

```
g0 = function(x){
  prediction = mean( (iris[iris$Species == x, ])$Petal.Length)
  prediction
}

g0("setosa")
```

```
## [1] 1.462
```

```
g0("versicolor")
```

```
## [1] 4.26
```

```
g0("virginica")
```

```
## [1] 5.552
```

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.

```
?predict()
```

```
## starting httpd help server ... done
```

```
x = iris$Species
y = iris$Petal.Length
```

```
lm(y ~ x)
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Coefficients:
## (Intercept)  xversicolor  xvirginica
##          1.462          2.798          4.090
```

```
lm(y ~ 0 + x)
```

```
##
## Call:
## lm(formula = y ~ 0 + x)
##
## Coefficients:
##      xsetosa  xversicolor  xvirginica
##      1.462      4.260      5.552
```

```
predict(lm(y ~ x))
```

```
##      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
```

```
predict(lm(y ~ 0 + x))
```

```
##      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
##    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
##    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
##    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?

```
x = iris$Species
y = iris$Petal.Length

model.matrix(y ~ x)
```

##	(Intercept)	xversicolor	xvirginica
## 1	1	0	0
## 2	1	0	0
## 3	1	0	0
## 4	1	0	0
## 5	1	0	0
## 6	1	0	0
## 7	1	0	0
## 8	1	0	0
## 9	1	0	0
## 10	1	0	0
## 11	1	0	0
## 12	1	0	0
## 13	1	0	0
## 14	1	0	0
## 15	1	0	0
## 16	1	0	0
## 17	1	0	0
## 18	1	0	0
## 19	1	0	0
## 20	1	0	0
## 21	1	0	0
## 22	1	0	0
## 23	1	0	0
## 24	1	0	0
## 25	1	0	0
## 26	1	0	0
## 27	1	0	0
## 28	1	0	0
## 29	1	0	0
## 30	1	0	0
## 31	1	0	0
## 32	1	0	0
## 33	1	0	0
## 34	1	0	0
## 35	1	0	0
## 36	1	0	0
## 37	1	0	0
## 38	1	0	0
## 39	1	0	0
## 40	1	0	0
## 41	1	0	0
## 42	1	0	0
## 43	1	0	0
## 44	1	0	0
## 45	1	0	0
## 46	1	0	0
## 47	1	0	0
## 48	1	0	0
## 49	1	0	0
## 50	1	0	0
## 51	1	1	0
## 52	1	1	0
## 53	1	1	0

## 54	1	1	0
## 55	1	1	0
## 56	1	1	0
## 57	1	1	0
## 58	1	1	0
## 59	1	1	0
## 60	1	1	0
## 61	1	1	0
## 62	1	1	0
## 63	1	1	0
## 64	1	1	0
## 65	1	1	0
## 66	1	1	0
## 67	1	1	0
## 68	1	1	0
## 69	1	1	0
## 70	1	1	0
## 71	1	1	0
## 72	1	1	0
## 73	1	1	0
## 74	1	1	0
## 75	1	1	0
## 76	1	1	0
## 77	1	1	0
## 78	1	1	0
## 79	1	1	0
## 80	1	1	0
## 81	1	1	0
## 82	1	1	0
## 83	1	1	0
## 84	1	1	0
## 85	1	1	0
## 86	1	1	0
## 87	1	1	0
## 88	1	1	0
## 89	1	1	0
## 90	1	1	0
## 91	1	1	0
## 92	1	1	0
## 93	1	1	0
## 94	1	1	0
## 95	1	1	0
## 96	1	1	0
## 97	1	1	0
## 98	1	1	0
## 99	1	1	0
## 100	1	1	0
## 101	1	0	1
## 102	1	0	1
## 103	1	0	1
## 104	1	0	1
## 105	1	0	1
## 106	1	0	1
## 107	1	0	1


```

## 108      1      0      1
## 109      1      0      1
## 110      1      0      1
## 111      1      0      1
## 112      1      0      1
## 113      1      0      1
## 114      1      0      1
## 115      1      0      1
## 116      1      0      1
## 117      1      0      1
## 118      1      0      1
## 119      1      0      1
## 120      1      0      1
## 121      1      0      1
## 122      1      0      1
## 123      1      0      1
## 124      1      0      1
## 125      1      0      1
## 126      1      0      1
## 127      1      0      1
## 128      1      0      1
## 129      1      0      1
## 130      1      0      1
## 131      1      0      1
## 132      1      0      1
## 133      1      0      1
## 134      1      0      1
## 135      1      0      1
## 136      1      0      1
## 137      1      0      1
## 138      1      0      1
## 139      1      0      1
## 140      1      0      1
## 141      1      0      1
## 142      1      0      1
## 143      1      0      1
## 144      1      0      1
## 145      1      0      1
## 146      1      0      1
## 147      1      0      1
## 148      1      0      1
## 149      1      0      1
## 150      1      0      1
## attr("assign")
## [1] 0 1 1
## attr("contrasts")
## attr("contrasts")$x
## [1] "contr.treatment"

```

```

model.matrix(y ~ 0 + x)

```

```

##      xsetosa xversicolor xvirginica
## 1      1      0      0
## 2      1      0      0

```

## 3	1	0	0
## 4	1	0	0
## 5	1	0	0
## 6	1	0	0
## 7	1	0	0
## 8	1	0	0
## 9	1	0	0
## 10	1	0	0
## 11	1	0	0
## 12	1	0	0
## 13	1	0	0
## 14	1	0	0
## 15	1	0	0
## 16	1	0	0
## 17	1	0	0
## 18	1	0	0
## 19	1	0	0
## 20	1	0	0
## 21	1	0	0
## 22	1	0	0
## 23	1	0	0
## 24	1	0	0
## 25	1	0	0
## 26	1	0	0
## 27	1	0	0
## 28	1	0	0
## 29	1	0	0
## 30	1	0	0
## 31	1	0	0
## 32	1	0	0
## 33	1	0	0
## 34	1	0	0
## 35	1	0	0
## 36	1	0	0
## 37	1	0	0
## 38	1	0	0
## 39	1	0	0
## 40	1	0	0
## 41	1	0	0
## 42	1	0	0
## 43	1	0	0
## 44	1	0	0
## 45	1	0	0
## 46	1	0	0
## 47	1	0	0
## 48	1	0	0
## 49	1	0	0
## 50	1	0	0
## 51	0	1	0
## 52	0	1	0
## 53	0	1	0
## 54	0	1	0
## 55	0	1	0
## 56	0	1	0

## 57	0	1	0
## 58	0	1	0
## 59	0	1	0
## 60	0	1	0
## 61	0	1	0
## 62	0	1	0
## 63	0	1	0
## 64	0	1	0
## 65	0	1	0
## 66	0	1	0
## 67	0	1	0
## 68	0	1	0
## 69	0	1	0
## 70	0	1	0
## 71	0	1	0
## 72	0	1	0
## 73	0	1	0
## 74	0	1	0
## 75	0	1	0
## 76	0	1	0
## 77	0	1	0
## 78	0	1	0
## 79	0	1	0
## 80	0	1	0
## 81	0	1	0
## 82	0	1	0
## 83	0	1	0
## 84	0	1	0
## 85	0	1	0
## 86	0	1	0
## 87	0	1	0
## 88	0	1	0
## 89	0	1	0
## 90	0	1	0
## 91	0	1	0
## 92	0	1	0
## 93	0	1	0
## 94	0	1	0
## 95	0	1	0
## 96	0	1	0
## 97	0	1	0
## 98	0	1	0
## 99	0	1	0
## 100	0	1	0
## 101	0	0	1
## 102	0	0	1
## 103	0	0	1
## 104	0	0	1
## 105	0	0	1
## 106	0	0	1
## 107	0	0	1
## 108	0	0	1
## 109	0	0	1
## 110	0	0	1

```

## 111      0      0      1
## 112      0      0      1
## 113      0      0      1
## 114      0      0      1
## 115      0      0      1
## 116      0      0      1
## 117      0      0      1
## 118      0      0      1
## 119      0      0      1
## 120      0      0      1
## 121      0      0      1
## 122      0      0      1
## 123      0      0      1
## 124      0      0      1
## 125      0      0      1
## 126      0      0      1
## 127      0      0      1
## 128      0      0      1
## 129      0      0      1
## 130      0      0      1
## 131      0      0      1
## 132      0      0      1
## 133      0      0      1
## 134      0      0      1
## 135      0      0      1
## 136      0      0      1
## 137      0      0      1
## 138      0      0      1
## 139      0      0      1
## 140      0      0      1
## 141      0      0      1
## 142      0      0      1
## 143      0      0      1
## 144      0      0      1
## 145      0      0      1
## 146      0      0      1
## 147      0      0      1
## 148      0      0      1
## 149      0      0      1
## 150      0      0      1
## attr("assign")
## [1] 1 1 1
## attr("contrasts")
## attr("contrasts")$x
## [1] "contr.treatment"

```

Including the intercept turned “setosa” into a reference variable, eliminating it as a category since it is now the default species and the rows added up to 1 or 2. Without the intercept there is no default species and the rows added up to 1.