

The results below are generated from an R script.

```
# Assignment: ASSIGNMENT 6
# Name: Jordan, Andrew
# Date: 2022-05-11

## Set the working directory to the root of your DSC 520 directory
setwd("/Users/Andrew/StatClass/dsc520/")

## Load the 'data/r4ds/heights.csv' to
heights_df <- read.csv("data/r4ds/heights.csv")
heights_df

##      earn  height  sex ed age    race
## 1  50000 74.42444  male 16  45   white
## 2  60000 65.53754 female 16  58   white
## 3  30000 63.62920 female 16  29   white
## 4  50000 63.10856 female 16  91  other
## 5  51000 63.40248 female 17  39   white
## 6   9000 64.39951 female 15  26   white
## 7  29000 61.65633 female 12  49   white
## 8  32000 72.69854  male 17  46   white
## 9   2000 72.03947  male 15  21 hispanic
## 10 27000 72.23493  male 12  26   white
## 11   6530 69.51215  male 16  65   white
## 12 30000 68.03161  male 11  34   white
## 13 12000 67.55693  male 12  27   white
## 14 12000 65.43059 female 12  51   white
## 15 22000 65.66285 female 16  35   white
## 16 17000 67.75877  male 12  58   white
## 17 40000 68.35184 female 14  29   white
## 18 44000 69.60957  male 13  44   white
## 19   7000 64.18457 female 12  55  black
## 20 53000 73.07461  male 13  35  black
## 21   5000 62.37553 female 13  51   white
## 22 14000 63.02393 female 14  21   white
## 23   5500 67.22990  male 14  22   white
## 24 40000 65.55111 female 12  41   white
## 25 34000 72.07965  male 12  45   white
## 26 10000 63.09113 female 12  35  black
## 27 27000 64.32355 female 16  60   white
## 28 50000 71.64285  male 16  38   white
## 29 41000 76.79309  male 16  33   white
## 30 15000 63.89391 female 14  25   white
## 31 25000 63.80262 female 12  33   white
## 32 75000 71.59223  male 17  39   white
## 33 27000 67.52196  male 17  31   white
## 34 12000 64.39435 female 12  26   white
## 35   7500 61.17822 female 14  78   white
## 36 30000 66.98388 female 14  31  black
## 37 21000 65.31646 female 12  57   white
## 38 27000 63.57419 female 14  26   white
## 39   3000 66.61100 female 15  65   white
## 40 25000 64.91176 female 12  30   white
## 41 24000 64.78968 female 12  41   white
```

## 42	32000	66.93769	female	18	29	white
## 43	10000	68.17281	female	17	30	white
## 44	11000	60.45066	female	12	21	hispanic
## 45	18700	64.79325	female	13	32	white
## 46	20000	61.81492	female	12	29	white
## 47	3500	71.57215	male	10	18	white
## 48	13000	67.31441	male	8	56	black
## 49	25000	69.89987	male	12	65	white
## 50	21000	69.76170	male	17	41	white
## 51	34000	67.74647	female	17	49	white
## 52	6000	60.19022	female	12	65	white
## 53	17000	71.00650	male	12	28	white
## 54	35000	71.16680	male	12	32	white
## 55	4000	72.73563	male	13	18	white
## 56	14000	68.13822	female	14	55	white
## 57	10000	66.37981	female	12	57	white
## 58	25000	69.23278	male	16	29	white
## 59	16000	63.27394	female	14	27	white
## 60	16000	61.82776	male	14	28	hispanic
## 61	16500	64.22121	female	14	43	white
## 62	4000	63.84127	female	9	68	white
## 63	3840	66.97477	female	9	52	white
## 64	22000	71.45149	male	12	39	white
## 65	200	59.61265	female	16	53	white
## 66	26000	65.79939	female	16	27	white
## 67	2500	66.45804	female	15	21	white
## 68	17000	64.60288	female	14	39	white
## 69	8000	70.44048	female	13	22	white
## 70	12000	65.92281	female	13	68	white
## 71	10000	61.85683	female	12	47	white
## 72	10000	65.78444	female	15	67	white
## 73	15000	71.83128	male	12	39	white
## 74	2400	67.04533	female	8	39	hispanic
## 75	30000	68.30551	male	12	32	hispanic
## 76	30000	70.02546	male	12	33	white
## 77	10000	61.81039	female	12	38	white
## 78	5000	62.95107	female	13	26	white
## 79	12000	65.82114	female	13	63	white
## 80	20000	70.39755	female	10	61	white
## 81	20000	68.37778	female	12	36	white
## 82	20000	69.93270	male	14	23	white
## 83	1200	66.17181	female	12	20	white
## 84	700	68.45636	female	16	32	white
## 85	20000	69.90386	male	16	27	white
## 86	10000	61.14966	female	12	22	hispanic
## 87	30000	63.36335	female	12	73	white
## 88	40000	64.14708	female	14	56	white
## 89	25000	67.31839	male	12	89	white
## 90	10000	60.67494	female	17	79	white
## 91	60000	68.84090	female	18	63	white
## 92	18000	67.68273	female	12	66	white
## 93	16040	64.49677	female	12	33	white
## 94	15000	66.81240	female	14	30	black
## 95	10000	68.74644	male	17	23	white

##	96	33000	67.06765	female	13	43	white
##	97	18000	68.13799	female	12	30	white
##	98	15000	63.34290	female	12	37	white
##	99	21000	71.38667	male	12	22	white
##	100	21000	63.98834	female	17	43	black
##	101	37000	68.48639	male	11	37	white
##	102	38000	67.51614	female	17	44	white
##	103	17000	65.60084	female	14	43	hispanic
##	104	32000	76.80019	male	16	30	white
##	105	27500	67.10538	female	12	58	white
##	106	16500	62.15164	female	12	44	white
##	107	25000	66.86762	female	18	35	white
##	108	27000	61.04220	female	18	43	white
##	109	5000	64.12329	female	12	28	white
##	110	70000	61.54482	female	16	38	white
##	111	5000	62.55624	female	12	40	white
##	112	5000	68.16377	male	16	24	white
##	113	20000	63.65513	female	15	26	white
##	114	4000	72.37352	male	15	21	white
##	115	60000	64.14708	female	16	35	white
##	116	5000	61.32670	female	13	31	white
##	117	30000	74.36640	male	12	38	white
##	118	70000	70.21016	male	14	35	white
##	119	50000	71.10619	male	16	41	white
##	120	44000	62.59484	female	12	39	white
##	121	30000	64.05496	female	14	43	white
##	122	10000	61.57362	female	16	40	white
##	123	23000	70.48020	female	17	42	white
##	124	45000	71.18591	male	17	62	white
##	125	15000	71.43364	male	14	31	white
##	126	4000	70.22885	female	14	71	white
##	127	17000	67.28086	male	14	31	white
##	128	30000	63.75869	female	12	32	white
##	129	27500	67.08652	female	12	30	white
##	130	5688	61.67960	female	8	69	white
##	131	18000	62.28600	female	13	56	hispanic
##	132	43000	68.29248	male	13	44	black
##	133	32000	61.58948	female	14	44	black
##	134	10000	68.41774	female	18	56	black
##	135	60000	73.99126	male	13	45	white
##	136	21000	67.56107	female	12	50	other
##	137	2400	62.33793	female	16	22	white
##	138	1000	66.24001	female	15	28	white
##	139	27000	68.09847	male	12	27	white
##	140	6600	59.77087	female	14	28	hispanic
##	141	16000	68.06338	male	8	43	white
##	142	90000	71.68015	male	12	26	white
##	143	8000	66.35971	female	12	42	white
##	144	20000	68.35626	male	10	32	white
##	145	15000	68.45654	female	12	18	white
##	146	12000	68.78610	female	12	60	white
##	147	24000	64.10224	female	16	46	white
##	148	20000	65.11349	female	14	39	white
##	149	19000	60.64919	female	12	46	white

```

## 150 10000 72.12570   male 12  49   white
## 151 40000 65.51073 female 16  34   white
## 152 25000 67.93190   male 14  64   white
## 153 25000 70.44492   male 12  24   white
## 154 25000 71.36585   male 14  32   white
## 155 19000 71.12507   male 16  61   white
## 156 44000 68.16014   male 16  48   white
## 157 15000 60.11333 female 14  49   white
## 158 17000 62.78820 female 12  36   white
## 159 24000 68.07772   male 12  56   white
## 160 23000 64.05084 female 12  37   white
## 161 13000 69.71580   male 12  74   white
## 162 65000 68.22067   male 16  46   white
## 163  7000 60.88386 female 12  63   white
## 164 40000 68.40754   male 18  63   white
## 165 15000 66.00198 female 17  43   white
## 166 20000 69.79789   male 16  25   white
## [ reached 'max' / getOption("max.print") -- omitted 1026 rows ]

## Load the ggplot2 library
library(ggplot2)

## Fit a linear model using the 'age' variable as the predictor and 'earn' as the outcome
age_lm <- lm(earn~age, data = heights_df)

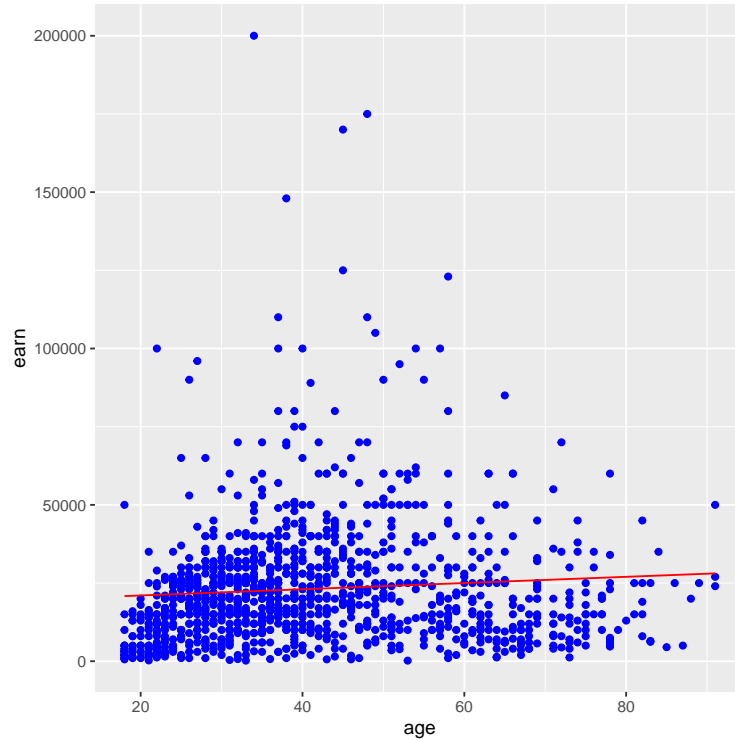
## View the summary of your model using 'summary()'
summary(age_lm)

##
## Call:
## lm(formula = earn ~ age, data = heights_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -25098 -12622  -3667   6883 177579
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 19041.53    1571.26  12.119  < 2e-16 ***
## age          99.41       35.46   2.804  0.00514 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19420 on 1190 degrees of freedom
## Multiple R-squared:  0.006561, Adjusted R-squared:  0.005727
## F-statistic:  7.86 on 1 and 1190 DF,  p-value: 0.005137

## Creating predictions using 'predict()'
age_predict_df <- data.frame(earn = predict(age_lm, heights_df), age=heights_df$age)

## Plot the predictions against the original data
ggplot(data = heights_df, aes(y = earn, x = age)) +
  geom_point(color='blue') +
  geom_line(color='red', data = age_predict_df, aes(y=earn, x=age))

```



```

mean_earn <- mean(heights_df$earn)
## Corrected Sum of Squares Total
sst <- sum((mean_earn - heights_df$earn)^2)
## Corrected Sum of Squares for Model
ssm <- sum((mean_earn - age_predict_df$earn)^2)
## Residuals
residuals <- heights_df$earn - age_predict_df$earn
## Sum of Squares for Error
sse <- sum(residuals^2)
## R Squared  $R^2 = SSM/SST$ 
r_squared <- ssm/sst

## Number of observations
n <- sum(complete.cases(heights_df))
## Number of regression parameters
p <- 2
## Corrected Degrees of Freedom for Model ( $p-1$ )
dfm <- p-1
## Degrees of Freedom for Error ( $n-p$ )
dfe <- n-p
## Corrected Degrees of Freedom Total:  $DFT = n - 1$ 
dft <- n-1

## Mean of Squares for Model:  $MSM = SSM / DFM$ 
msm <- ssm/dfm
## Mean of Squares for Error:  $MSE = SSE / DFE$ 
mse <- sse/dfe
## Mean of Squares Total:  $MST = SST / DFT$ 
mst <- sst/dft

```

```
## F Statistic  $F = \text{MSM}/\text{MSE}$ 
f_score <- msm/mse

## Adjusted R Squared  $R^2 = 1 - (1 - R^2)(n - 1) / (n - p)$ 
adjusted_r_squared <- 1-(1-r_squared)*(n-1)/(n-p)

## Calculate the p-value from the F distribution
p_value <- pf(f_score, dfm, dft, lower.tail=F)
```

The R session information (including the OS info, R version and all packages used):

```
sessionInfo()

## R version 4.2.0 (2022-04-22 ucrt)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 19044)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_United States.utf8  LC_CTYPE=English_United States.utf8
## [3] LC_MONETARY=English_United States.utf8 LC_NUMERIC=C
## [5] LC_TIME=English_United States.utf8
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods    base
##
## other attached packages:
## [1] car_3.0-13      carData_3.0-5 lm.beta_1.6-2 ggplot2_3.3.6 readxl_1.4.0
##
## loaded via a namespace (and not attached):
## [1] highr_0.9          cellranger_1.1.0 pillar_1.7.0      compiler_4.2.0    tools_4.2.0
## [6] digest_0.6.29      evaluate_0.15     lifecycle_1.0.1   tibble_3.1.7      gtable_0.3.0
## [11] pkgconfig_2.0.3    rlang_1.0.2       cli_3.3.0         yaml_2.3.5        xfun_0.30
## [16] fastmap_1.1.0      stringr_1.4.0     withr_2.5.0       dplyr_1.0.9       knitr_1.39
## [21] generics_0.1.2     vctrs_0.4.1       grid_4.2.0        tidyselect_1.1.2  glue_1.6.2
## [26] R6_2.5.1           fansi_1.0.3       rmarkdown_2.14    farver_2.1.0      purrr_0.3.4
## [31] magrittr_2.0.3     scales_1.2.0      ellipsis_0.3.2    htmltools_0.5.2   abind_1.4-5
## [36] colorspace_2.0-3   labeling_0.4.2    utf8_1.2.2        stringi_1.7.6     munsell_0.5.0
## [41] crayon_1.5.1

Sys.time()

## [1] "2022-05-15 13:01:12 EDT"
```