

# Linear Regression Lab

This is the R Notebook version of the Linear Regression lab. This version of the document allows for R code and text to coexist in the same script. The R script version of this file, which is how we operated the labs, is also available in canvas. You can learn more about R Notebook at this tutorial if you would like to utilize this functionality: [https://rmarkdown.rstudio.com/r\\_notebooks.html](https://rmarkdown.rstudio.com/r_notebooks.html)

The first task when we open RStudio is to set our working directory. As covered in both of the optional labs, and in the documentation, navigate in the files window (bottom right) to your documents folder for this class. In “More”, click “Set as Working Directory”.

Now let’s load in the dataset. You can either open it from your working directory (if you’ve saved it there) or pull it up with the below command. Change the file path to make sure it matches yours.

```
calschooldist <- read.csv("calschooldist.csv")
View(calschooldist)
```

We can rename our dataset as an object. You can name this whatever you want, but I recommend calschool because it will be in line with the code below.

```
calschool <- calschooldist
```

We need to load “packages” in R which include commands and functions that we can leverage. These packages will vary based on the lab. Today we are going to be using the below for the assignment. You only need to do this once:

Activate these packages: You need to do this every time you open R. We’ve only installed them, now we need to activate them for this instance.

```
library(car)
```

```
## Warning: package 'car' was built under R version 3.4.3
```

```
library(psych)
```

```
##
## Attaching package: 'psych'
## The following object is masked from 'package:car':
##
##      logit
```

If you’re having trouble installing the car package, try the following code:

To see our numbers (particularly the p values) more clearly, we can remove scientific notation. We need to repeat this every time we open R.

```
options(scipen=999)
```

Now that our working directory is set, our packages are loaded, we can begin the steps outlined in the prompt.

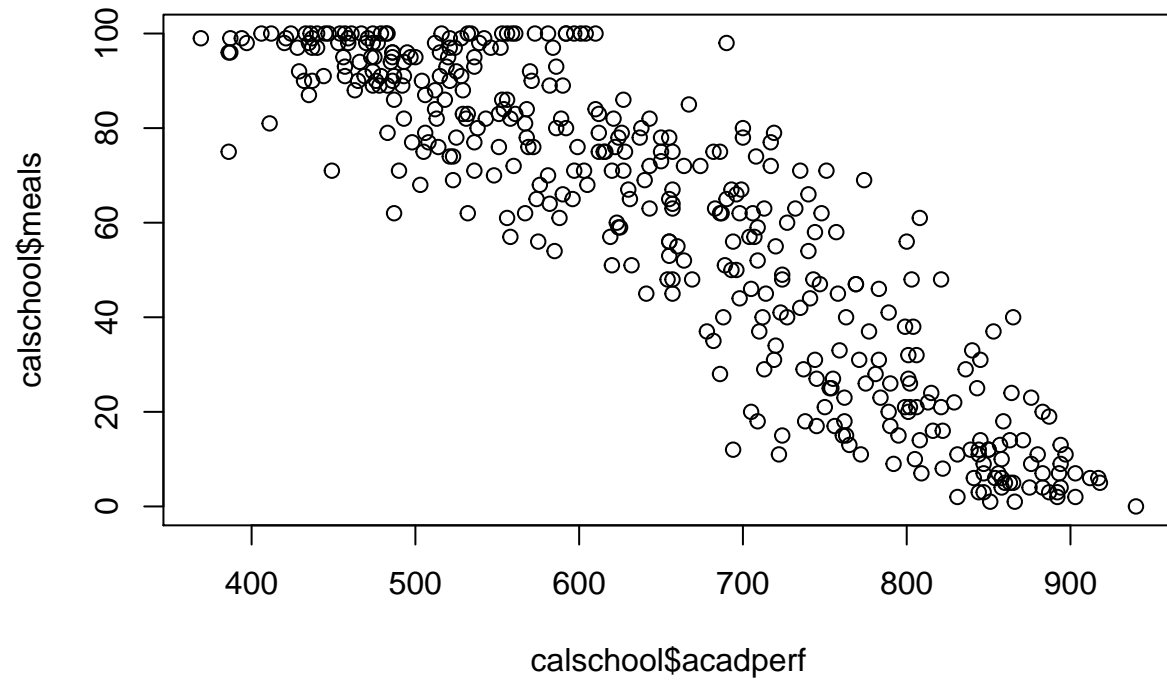
STEP 1: no R code to complete this

STEP 2: no R code to complete this

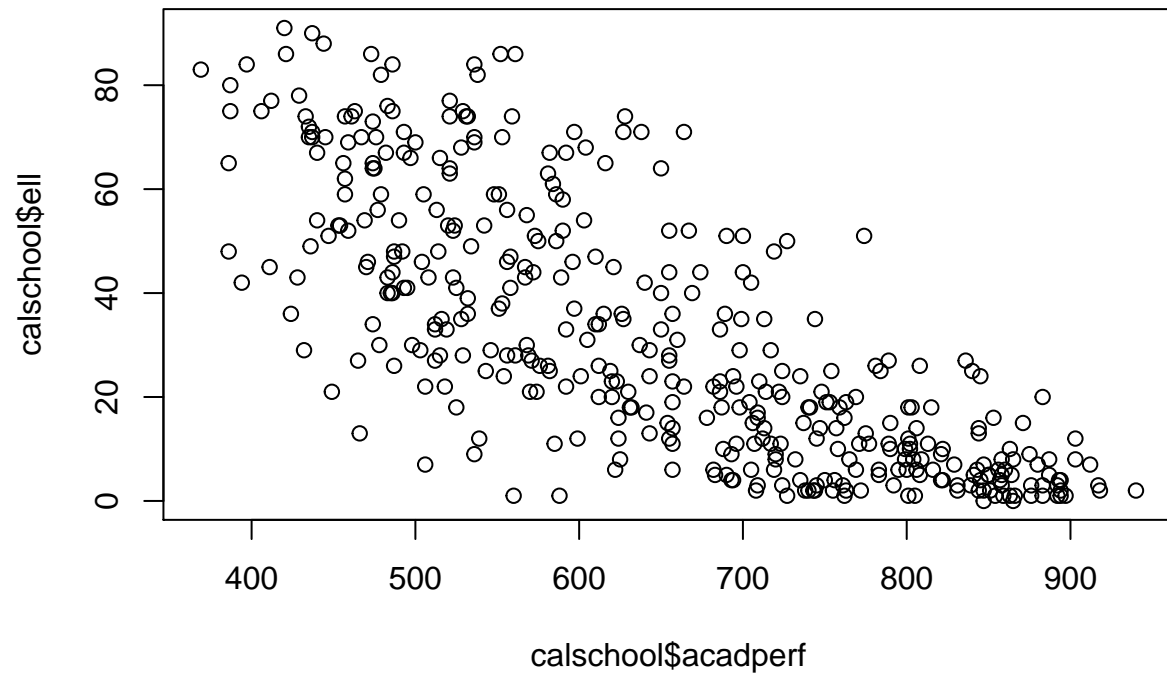
STEP 3: no R code to complete this

STEP 4: Perform basic checks of the candidate variables. Do you have any missing value or out of range data problems? If so, what did you do to resolve them, if anything? First, let’s look at plots to get a feel for the data. In R, we can just use “plot” to create a scatterplot of two variables. We have to define those two items. Let’s plot our dependent variable, acadperf, against some of the independent variables.

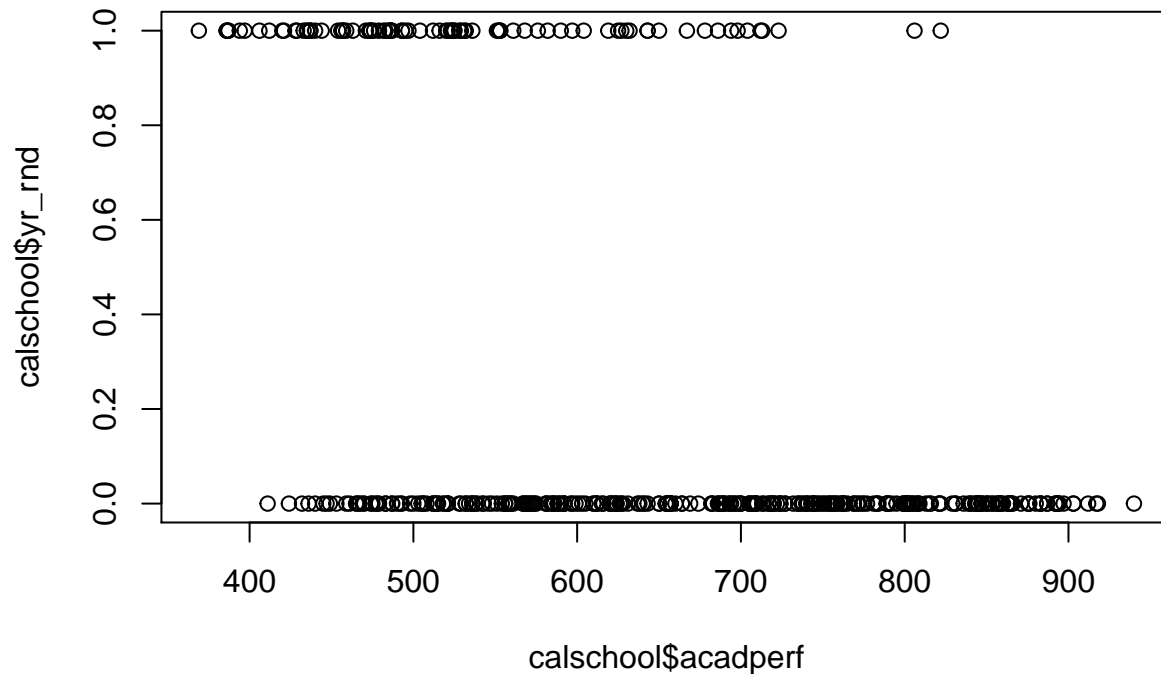
```
plot(calschool$acadperf, calschool$meals)
```



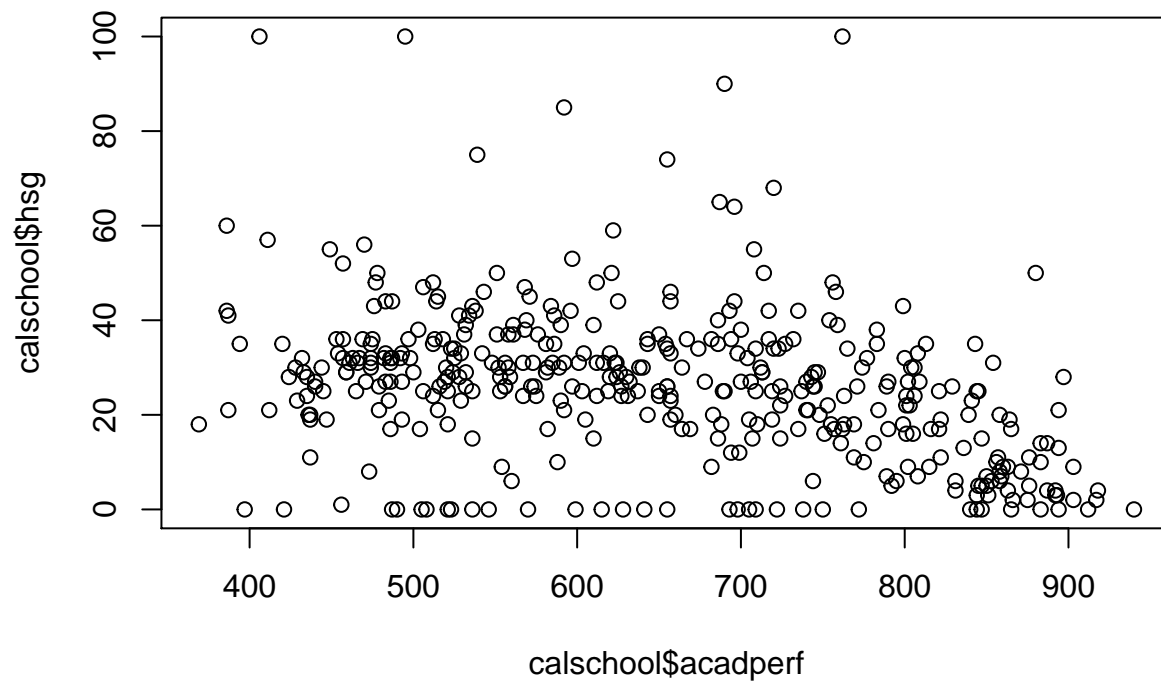
```
plot(calschool$acadperf, calschool$ell)
```



```
plot(calschool$acadperf, calschool$yr_rnd)
```



```
plot(calschool$acadperf, calschool$hsg)
```



Have you noticed that any have a strong correlation? What does the graph of `acadperf` vs `ell` tell us about the `ell` data? Confirm this with the str code we completed in the lab. We can try a new function here, called “describe”. This will give us new statistics that are a little different than “summary”.

```
describe(calschool)
```

```
##      vars    n   mean      sd median trimmed   mad min  max range
## snum      1 400 2866.81 1543.81 3007.5 2880.86 1894.02  58 6072 6014
## dnum      2 400  457.74  184.82  401.0  468.53  284.66  41  796  755
## acadperf   3 400  647.62  142.25  643.0  645.79  177.17 369  940  571
```

```
## meals      4 400 60.31 31.91 67.5 62.18 37.81 0 100 100
## ell        5 400 31.45 24.84 25.0 29.39 28.17 0 91 91
## yr_rnd     6 400 0.23 0.42 0.0 0.16 0.00 0 1 1
## mobility   7 399 18.25 7.48 17.0 17.66 5.93 2 47 45
## acs        8 398 19.16 1.37 19.0 19.21 1.48 14 25 11
## not_hsg    9 400 21.25 20.68 14.0 18.65 19.27 0 100 100
## hsg       10 400 26.02 16.33 26.0 25.29 13.34 0 100 100
## some_col   11 400 19.71 11.34 19.0 19.65 11.86 0 67 67
## col_grad   12 400 19.70 16.47 16.0 18.12 16.31 0 100 100
## grad_sch   13 400 8.64 12.13 4.0 5.85 5.93 0 67 67
## full       14 400 84.55 14.95 88.0 86.60 14.83 37 100 63
## emer       15 400 12.66 11.75 10.0 11.14 10.38 0 59 59
## enroll     16 400 483.46 226.45 435.0 459.41 202.37 130 1570 1440
## mealcat    17 400 2.02 0.82 2.0 2.02 1.48 1 3 2
##           skew kurtosis se
## snum      -0.01 -1.03 77.19
## dnum      -0.35 -0.78 9.24
## acadperf  0.10 -1.13 7.11
## meals     -0.41 -1.20 1.60
## ell       0.57 -0.87 1.24
## yr_rnd    1.28 -0.37 0.02
## mobility  0.83 1.14 0.37
## acs       -0.23 1.64 0.07
## not_hsg   0.99 0.44 1.03
## hsg       0.95 3.08 0.82
## some_col  0.25 0.13 0.57
## col_grad  1.47 4.32 0.82
## grad_sch  2.16 4.72 0.61
## full     -0.97 0.17 0.75
## emer      1.06 0.76 0.59
## enroll    1.34 3.02 11.32
## mealcat  -0.03 -1.51 0.04
```

Here we can see missing values, ranges, measures of central tendency, and standard deviation. What are your inferences about these values? I can see that most variables include 400 total entries, but mobility and acs have less than 400. I have to remove the nulls with the following code:

```
calschooldist2=na.omit(calschooldist)
describe(calschooldist2)
```

```
##      vars  n   mean    sd median trimmed   mad min  max range
## snum     1 398 2869.53 1539.25 3007.5 2881.53 1892.54 58 6072 6014
## dnum     2 398 457.71 184.90 401.0 468.07 284.66 41 796 755
## acadperf 3 398 648.47 142.08 643.0 646.85 176.43 369 940 571
## meals    4 398 60.16 31.91 67.0 61.96 38.55 0 100 100
## ell      5 398 31.29 24.80 25.0 29.22 28.17 0 91 91
## yr_rnd   6 398 0.23 0.42 0.0 0.17 0.00 0 1 1
## mobility 7 398 18.26 7.49 17.0 17.67 5.93 2 47 45
## acs      8 398 19.16 1.37 19.0 19.21 1.48 14 25 11
## not_hsg  9 398 21.19 20.70 14.0 18.59 19.27 0 100 100
## hsg     10 398 25.99 16.37 26.0 25.24 13.34 0 100 100
## some_col 11 398 19.71 11.36 19.0 19.64 11.86 0 67 67
## col_grad 12 398 19.74 16.50 16.0 18.18 16.31 0 100 100
## grad_sch 13 398 8.66 12.16 4.0 5.92 5.93 0 67 67
## full     14 398 84.63 14.86 88.0 86.63 14.83 37 100 63
```

```
## emer      15 398    12.62    11.67    10.0    11.14    10.38    0   59    59
## enroll    16 398   483.21   226.98   433.0   459.19   203.12  130 1570  1440
## mealcat   17 398     2.01     0.82     2.0     2.01     1.48    1    3     2
##           skew kurtosis    se
## snum      -0.01    -1.02  77.16
## dnum      -0.35    -0.78   9.27
## acadperf   0.09    -1.13   7.12
## meals     -0.41    -1.21   1.60
## ell        0.59    -0.84   1.24
## yr_rnd     1.27    -0.39   0.02
## mobility   0.83     1.13   0.38
## acs        -0.23     1.64   0.07
## not_hsg    0.99     0.45   1.04
## hsg        0.95     3.06   0.82
## some_col   0.25     0.12   0.57
## col_grad   1.47     4.29   0.83
## grad_sch   2.15     4.68   0.61
## full       -0.97     0.18   0.74
## emer       1.06     0.80   0.58
## enroll     1.34     3.00  11.38
## mealcat    -0.02    -1.51   0.04
```

Now `calschooldist2` does not include any null values. Lets replace `calschool` so we don't have these NA values.

```
calschool <- calschooldist2
```

Step 5: What did your check of the correlation matrix find? Did you add any variables to the end of you list based on it? Does it look like you need to worry about multicollinearity? Do you remember this from the lab? This is a function that gives us not only our Pearson's Coefficients, but also gives us our p-values too! This function will be loaded into R, then when we run `cor.prob` with our data, we'll get the output. When looking at output generated by `cor.prob`, remember, p values are above and coefficients are below the diagonal line.

```
cor.prob <- function(X, dfr = nrow(X) - 2) {
  R <- cor(X, use="pairwise.complete.obs")
  above <- row(R) < col(R)
  r2 <- R[above]^2
  Fstat <- r2 * dfr/(1 - r2)
  R[above] <- 1 - pf(Fstat, 1, dfr)
  R[row(R) == col(R)] <- NA
  R
}
```

Now that we have added the function, let's run it

```
correlation_table_calschool <- cor.prob(calschool)
View(correlation_table_calschool)
```

You can save this table to your working directory with the following code:

```
write.csv(correlation_table_calschool, file = "Correlation Matrix California Schools.csv")
```

Are there any noteworthy correlations that might help you build your model? Which variables have the strongest relationships with academic performance? Would these variables be good to include in a regression analysis?

STEP 6: no R code to complete this

STEP 7: REGRESSION! Add your first independent variable. Show your bivariate / unadjusted model. Did

it accord with your expectations? Now we'll see a new command, "lm". This will fit a simple regression model to the data. The format for this code is `lm(y~x, data)` where y is the response (dependent variable), x is the predictor (independent variable), and the data is `calschool`.

Give it a try with your first variable, but YOU MUST CHANGE the variable name where I have [your first variable]:

This is what it would look like if "meals" was your first variable:

```
regression_1 <- lm(acadperf ~ meals, data = calschool)
```

Let's review the summary of this regression:

```
summary(regression_1)
```

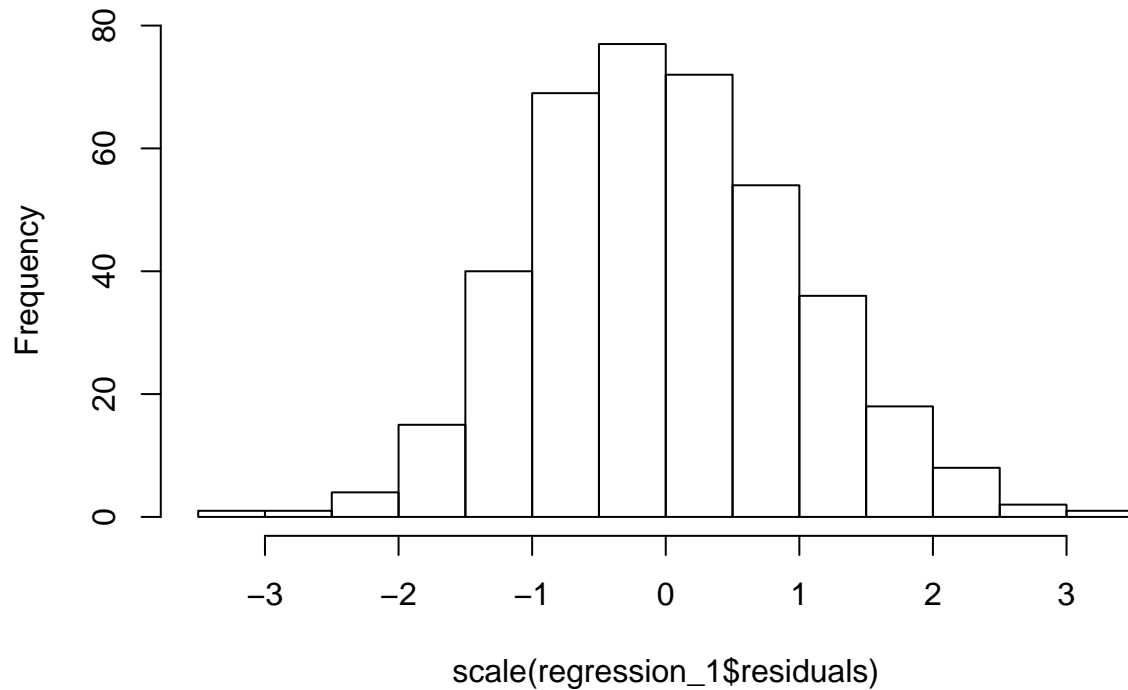
```
##
## Call:
## lm(formula = acadperf ~ meals, data = calschool)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -202.99  -41.22   -3.45   44.30  193.19
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  889.60032     6.63315   134.11 <0.0000000000000002 ***
## meals        -4.00810     0.09743   -41.14 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 61.95 on 396 degrees of freedom
## Multiple R-squared:  0.8104, Adjusted R-squared:  0.8099
## F-statistic: 1692 on 1 and 396 DF, p-value: < 0.00000000000000022
```

This tells us the results of our regression. Is it in line with your expectations?

STEP 8: Check for regression violations for this bivariate mode. Did you find any major violations? To analyze residuals and test assumptions, we can explore some graphs. We'll start with a histogram of the residuals.

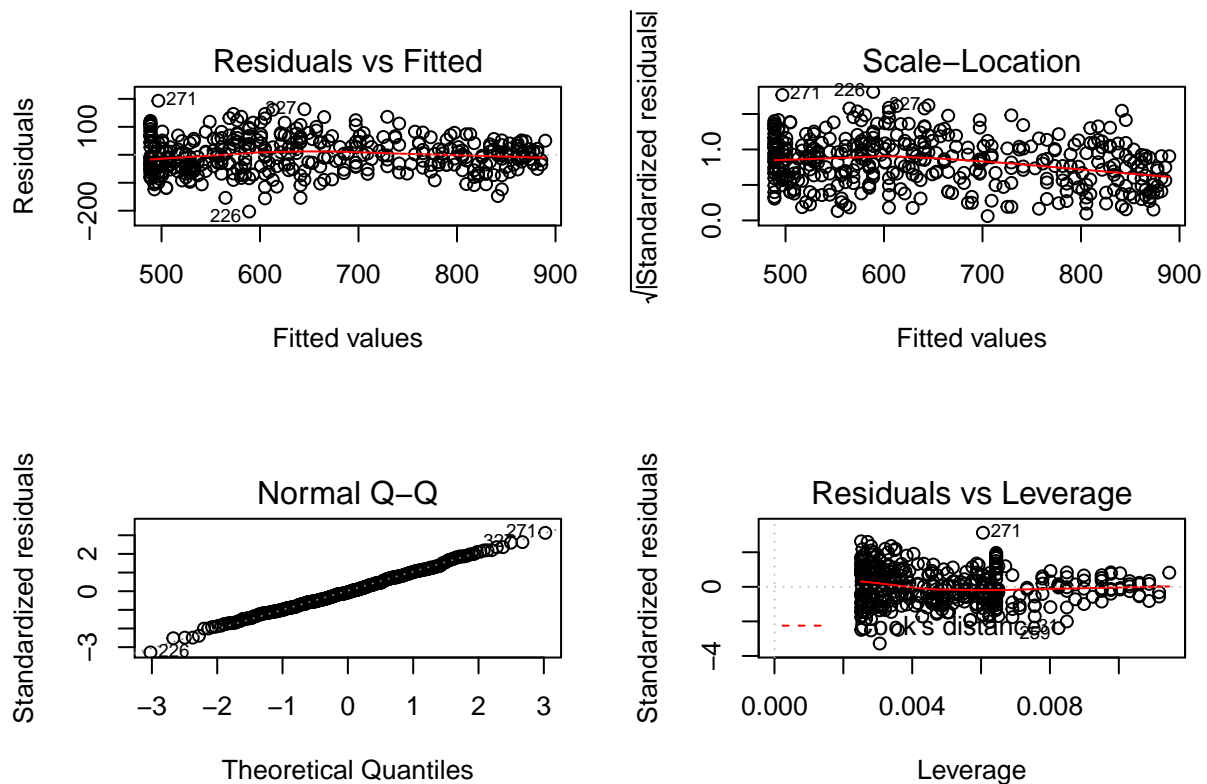
```
hist(scale(regression_1$residuals))
```

## Histogram of scale(regression\_1\$residuals)



Let's tell R to layout our graphs in a matrix so we can easily view 4 graphs at once. The `plot()` function graphs 4 helpful plots for us.

```
layout(matrix(c(1,2,3,4),2,2))
plot(regression_1)
```



What if we want standardized coefficients? R is a little difficult in that it doesn't give them as part of the standard output. By using "scale" in our lm function, we can standardize the unit of analysis to compare coefficients. Input your first variable.

Mine will look like this:

```
lm(scale(acadperf) ~ scale(meals), data = calschool)
```

```
##
## Call:
## lm(formula = scale(acadperf) ~ scale(meals), data = calschool)
##
## Coefficients:
##              (Intercept)              scale(meals)
## -0.0000000000000003511  -0.9002098779509647430
```

How can the standardized coefficient be interpreted? How about standardized residuals? We'll start by viewing all residuals. R has a function "names()" so we can learn more about what information is available.

```
names(regression_1)
```

```
## [1] "coefficients" "residuals"      "effects"        "rank"
## [5] "fitted.values" "assign"          "qr"             "df.residual"
## [9] "xlevels"      "call"           "terms"          "model"
```

You can see that we have access to the coefficients and residuals of this regression. This can be an easy way to look only at the relevant data.

```
coefficients(regression_1)
```

```
## (Intercept)      meals
##  889.600316   -4.008099
```

We can also specify the entire set of residuals of each point (residual = predicted value - actual value)

```
regression_1$residuals
```

```
##          1          2          3          4          5
##  71.9423263  49.1448047  45.1853004  42.1286064 -54.8794927
##          6          7          8          9         10
##   8.4806754  48.4401797 -50.5841177  -9.5598203 -36.3654410
##         11         12         13         14         15
## -34.5922168 -69.0252772 -30.5760186 -72.4950272 -52.5436220
##         16         17         18         19         20
##  11.5778651  -5.5436220 -17.2763505 -44.5193246 -63.3006479
##         21         22         23         24         25
## -42.1386651 -60.3654410  42.8613349 -90.0414755  25.9261280
##         26         27         28         29         30
## -70.0009798 -72.0009798 -108.4545315 -83.9928806 -55.4545315
##         31         32         33         34         35
## -123.5112255  -2.0252772  35.9423263  -0.2277556 -35.3978375
##         36         37         38         39         40
## -115.0252772 -15.2439539  53.6021625  134.8532357  19.5049728
##         41         42         43         44         45
##  75.9099297  66.7074513  70.5940633  50.3996840 -61.5274237
##         46         47         48         49         50
##   9.4239814 -10.3897384  -3.4707298   0.5697659  -9.4707298
##         51         52         53         54         55
##   8.0962099  97.0071194 -89.9604841  -8.4383332 -36.3978375
```



##	56	57	58	59	60
##	41.4563780	-34.7904022	-48.7904022	2.1529039	-40.9199884
##	61	62	63	64	65
##	4.1448047	-42.8713936	-91.8713936	-41.7904022	-26.9037901
##	66	67	68	69	70
##	-9.7904022	-64.7904022	19.1529039	39.0071194	21.9747228
##	71	72	73	74	75
##	-33.0738720	62.9828220	-10.1467643	27.0071194	-30.9523849
##	76	77	78	79	80
##	77.8856323	-35.5355229	69.0476151	-28.0333763	-13.4140358
##	81	82	83	84	86
##	37.5130719	-74.0981694	-65.1872599	-68.4788289	46.4482788
##	87	88	89	90	91
##	21.4563780	2.4968737	34.4887745	20.4320806	-15.5679194
##	92	93	94	95	96
##	-14.5436220	115.2095978	64.2095978	23.9180289	-40.8794927
##	97	98	99	100	101
##	131.0476151	57.1205073	35.6993521	118.0881108	67.7803435
##	102	103	104	105	106
##	73.0314168	72.2095978	4.0719125	108.2095978	15.0800116
##	107	108	109	110	111
##	60.0314168	-57.1062686	123.7884426	70.2095978	3.8046409
##	112	113	114	115	116
##	49.2014987	82.6669556	60.0638133	-37.8632944	44.9018306
##	117	118	119	120	121
##	-73.8875918	-52.8713936	15.5697659	-76.7904022	-98.7985013
##	122	123	124	125	126
##	21.5940633	28.8532357	-55.7904022	-41.0171780	-12.9847815
##	127	128	129	130	131
##	-12.0495746	-26.3816393	-33.8308979	11.1691021	-82.7904022
##	132	133	134	135	136
##	-21.7985013	-17.1791608	-67.8632944	83.1853004	129.9747228
##	137	138	139	140	141
##	-44.9766824	5.6507573	-5.7904022	-117.8227987	61.0071194
##	142	143	144	145	146
##	-21.7904022	-61.0333763	-65.4626306	-60.8146996	92.2095978
##	147	148	149	150	151
##	10.1772013	51.4482788	19.9099297	-2.2682513	-66.9604841
##	152	153	154	155	156
##	-15.9847815	-46.8389970	-9.1548634	27.1691021	-18.8227987
##	157	158	159	160	161
##	-43.8066005	45.9099297	-33.7985013	-52.8308979	55.0719125
##	162	163	164	165	166
##	-105.7985013	-76.8066005	-9.8227987	51.1853004	-21.3492427
##	167	168	169	170	171
##	-19.8066005	-58.8794927	70.9342271	103.2095978	52.9909211
##	172	173	174	175	176
##	-123.7985013	-55.7985013	-33.9847815	-91.8551953	-61.8066005
##	177	178	179	180	181
##	45.7803435	-24.8875918	-22.8066005	8.4968737	-5.9280875
##	182	183	184	185	186
##	-6.7904022	45.2095978	-34.8956910	11.0962099	-31.7904022
##	187	188	189	190	191
##	-11.8308979	146.0395159	49.1205073	-18.8227987	28.2014987

##	192	193	194	195	196
##	-118.8227987	-99.8066005	1.9261280	-72.8146996	56.5049728
##	197	198	199	200	201
##	-71.7985013	23.1853004	43.2095978	72.9828220	28.0638133
##	202	203	204	205	206
##	-63.8146996	115.9828220	17.0476151	-26.8066005	-14.7904022
##	207	208	209	210	211
##	77.9423263	68.0071194	1.6669556	-67.9361867	111.6993521
##	212	213	214	215	216
##	-19.5922168	-52.2358548	8.4968737	31.4563780	-76.4626306
##	217	218	219	220	221
##	-46.3492427	77.7722444	26.0071194	-45.8632944	-66.4788289
##	222	223	224	225	226
##	-28.2115574	14.4239814	-35.0657729	-70.9847815	-202.9928806
##	227	228	229	230	231
##	-153.9442858	160.9585245	-1.5112255	-82.9766824	-29.1224668
##	232	233	234	235	236
##	-96.8713936	-105.8956910	-156.0252772	-105.4788289	40.4725763
##	237	238	239	240	241
##	14.0152185	-72.9766824	51.4887745	-59.8470961	-51.0819711
##	242	243	244	245	246
##	21.4158823	-6.5598203	-33.5760186	-7.5517212	-3.4302341
##	247	248	249	250	251
##	1.4320806	50.8451366	-49.8794927	6.8046409	60.9261280
##	252	253	254	255	256
##	136.0233176	45.9018306	-26.1143677	-41.2763505	5.9099297
##	257	258	259	260	261
##	-55.0738720	-53.1872599	-147.5031263	-109.0981694	-40.2115574
##	262	263	264	265	266
##	-104.4383332	48.7641452	-89.1062686	-37.8066005	84.2095978
##	267	268	269	270	271
##	45.8613349	103.2095978	30.7965418	27.5778651	193.1933995
##	272	273	274	275	276
##	121.2095978	35.2014987	-88.1629625	41.5454685	94.9099297
##	277	278	279	280	281
##	-6.4302341	11.5130719	-11.5517212	4.6102616	-2.5031263
##	282	283	284	285	286
##	3.8127401	-24.5517212	-19.8389970	82.0638133	56.9018306
##	287	288	289	290	291
##	-22.8308979	23.0071194	8.9423263	-51.9685832	-27.8389970
##	292	293	294	295	296
##	-46.8551953	20.1853004	39.6588564	55.8775332	62.6345590
##	297	298	299	300	301
##	67.7803435	64.9018306	78.0314168	79.6507573	63.7317487
##	303	304	305	306	307
##	114.9990202	145.9747228	-27.7904022	99.8694340	135.7236495
##	308	309	310	311	312
##	2.0557142	106.9018306	39.0395159	-8.8308979	66.8370375
##	313	314	315	316	317
##	114.9342271	9.4320806	61.7074513	73.5535676	-31.8632944
##	318	319	320	321	322
##	69.1529039	53.0395159	3.1367056	27.7560461	14.9747228
##	323	324	325	326	327
##	105.7884426	-10.1467643	-8.0252772	-20.4383332	162.8937314

```
##          328          329          330          331          332
## -24.9280875 -114.0495746 -22.1710617  3.6264599 -25.4869281
##          333          334          335          336          337
##  41.9828220 123.0314168 -2.9361867 -34.4788289 -67.3168462
##          338          339          340          341          342
##  93.0071194 10.4158823 22.4725763 -31.4626306 -103.1386651
##          343          344          345          346          347
## -90.1467643 -91.3735401 -31.3006479 -154.0981694 -35.4140358
##          348          349          350          351          352
##  19.6183607 26.9585245 112.2095978 47.0314168 29.5130719
##          353          354          355          356          357
##  27.8208392 73.5616668 33.7236495 -2.2763505 -8.9685832
##          358          359          360          361          362
##  45.7884426 26.7884426 -14.5112255 78.5859642 67.2095978
##          363          364          365          366          367
## -6.5274237 37.0152185 -29.9361867 -7.8713936 -35.8308979
##          368          369          370          371          372
## -7.8875918 44.6588564 86.8694340 -80.8632944 4.7641452
##          373          374          375          376          377
## -4.5598203 -68.2358548 -73.5112255 -55.4302341 -79.4545315
##          378          379          380          381          382
## -27.9280875 1.0800116 -24.8713936 23.0476151 82.0962099
##          383          384          385          386          387
## -28.1224668 -52.7904022 -57.9037901 57.0800116 27.2095978
##          388          389          390          391          392
## -63.8713936 -43.2115574 13.7398478 -41.0495746 -55.8632944
##          393          394          395          396          397
## -9.8632944 -17.9361867 17.6507573 -36.3816393 -33.3249453
##          398          399          400
##  16.6102616 42.1933995 15.1933995
```

Next, we'll create a component of our regression to store our standardized residuals. We'll use the standardized residuals to determine if any have an absolute value greater than 2.

```
regression_1$standardized.residuals <- rstandard(regression_1)
regression_1$large_residual <- regression_1$standardized.residuals >2 | regression_1$standardized.residuals <-2
sum(regression_1$large_residual)
```

```
## [1] 18
```

What is your interpretation of the results? Let's calculate the Durban-Watson statistic.

```
dwt(regression_1)
```

```
## lag Autocorrelation D-W Statistic p-value
## 1 0.2756506 1.445141 0
## Alternative hypothesis: rho != 0
```

STEP 9: Sequentially build up the model adding variables in the order you specified (don't check reg. assumptions at each stage) To build variables into your model, continue to use the `lm()` function, and add the variable on the back side of the `~`. You should update the name of the model so you can save each iteration in R. The form is below. Don't forget to replace with your variables in the order that you defined.

As an example, this is the form:

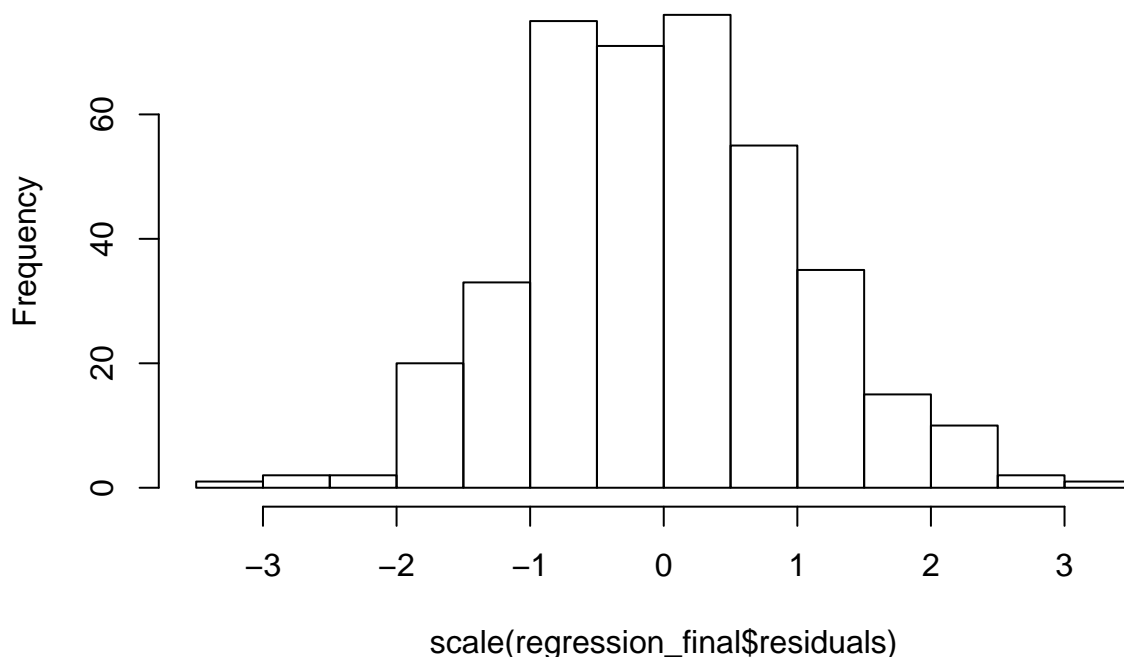
```
regression_final <- lm(acadperf ~ meals + hsg + some_col, data = calschool)
summary(regression_final)
```

```
##
## Call:
## lm(formula = acadperf ~ meals + hsg + some_col, data = calschool)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -204.996  -42.817   -1.903   41.940  183.493
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  868.789886    9.595132  90.545 < 0.0000000000000002 ***
## meals        -3.939685    0.109528 -35.970 < 0.0000000000000002 ***
## hsg          -0.007379    0.208689  -0.035     0.97181
## some_col      0.856806    0.281680   3.042     0.00251 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 61.37 on 394 degrees of freedom
## Multiple R-squared:  0.8148, Adjusted R-squared:  0.8134
## F-statistic: 577.9 on 3 and 394 DF,  p-value: < 0.00000000000000022
```

STEP 10: Recheck model assumptions Once we have our final model, let's check assumptions through residual analysis as we did earlier.

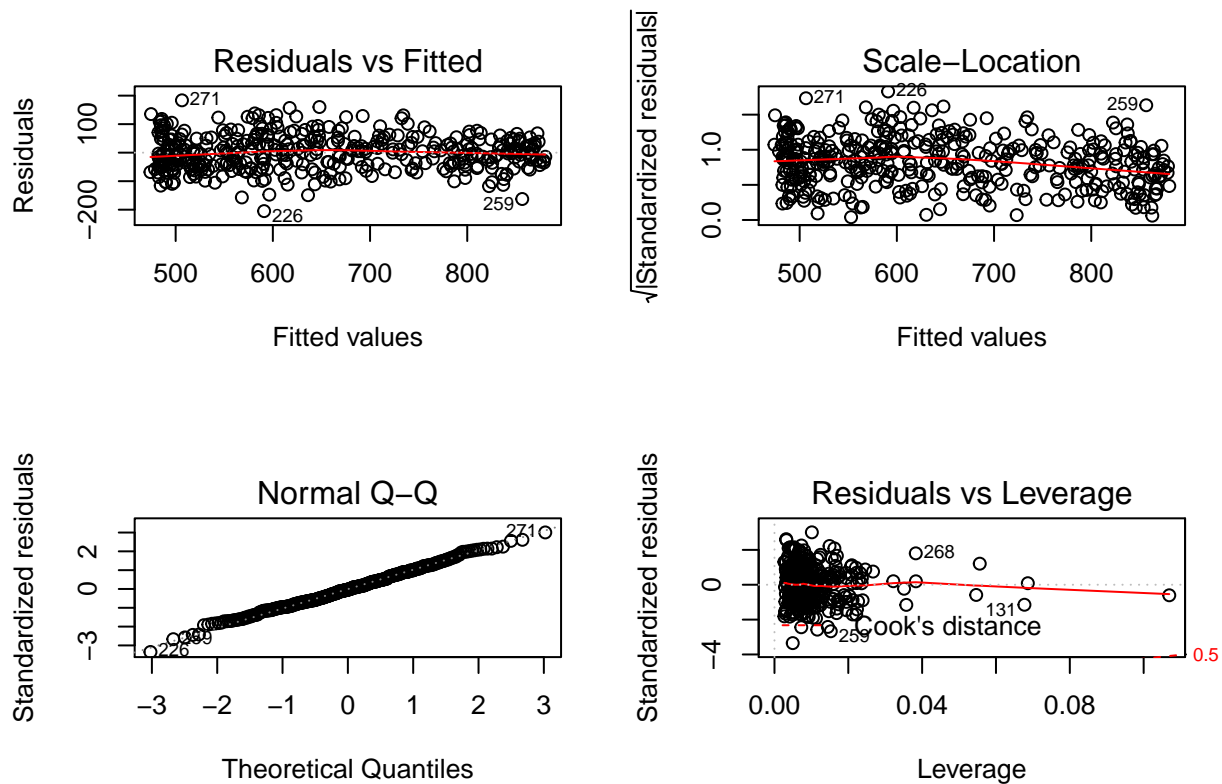
```
hist(scale(regression_final$residuals))
```

### Histogram of scale(regression\_final\$residuals)



View all plots at once

```
layout(matrix(c(1,2,3,4),2,2))
plot(regression_final)
```



Standardized residual analysis (how many residuals are more than two deviations away)

```
regression_final$standardized.residuals <- rstandard(regression_final)
regression_final$large_residual <- regression_final$standardized.residuals > 2 | regression_final$standardized.residuals < -2
sum(regression_final$large_residual)
```

```
## [1] 18
```

Calculate the standardized coefficients as we did prior.

Mine will look like this:

```
lm(scale(acadperf) ~ scale(meals) + scale(hsg) + scale(some_col), data = calschool)
```

```
##
## Call:
## lm(formula = scale(acadperf) ~ scale(meals) + scale(hsg) + scale(some_col),
##     data = calschool)
##
## Coefficients:
##             (Intercept)             scale(meals)             scale(hsg)
## -0.00000000000000003583  -0.8848443174696255520  -0.0008499628631633799
##             scale(some_col)
## 0.0684972185835148323
```

You may have more (or fewer) variables in your model in comparison to my examples and that is okay. Just make sure all your variables in your final model are in standardized coefficients. Now that we have multiple terms in the model, let's include the multicollinearity test as well as Durbin-Watson.

```
vif(regression_final)
```

```
##      meals      hsg some_col
```

```
## 1.287600 1.229519 1.078979
```

```
dwt(regression_final)
```

```
## lag Autocorrelation D-W Statistic p-value  
## 1 0.2624994 1.469487 0  
## Alternative hypothesis: rho != 0
```

Discuss these results in your report and/or technical appendix. Don't forget to include an advanced extension, in a different file.