education_data

February 20, 2021

[2]:

```
library(ISLR)
library(dplyr)
library(lmridge)
library(leaps)
library(glmnet)
library(DAAG)
library(lmvar)
library(MASS)
```

Importing GEORGIA education data…

[3]:

```
# Import
k_read = read.csv("kread.csv")
```

[4]:

```
#convert Farm to binary
k_read = cbind(k_read, 'FARM_BIN' = as.integer(k_read[,'FARM']=='Y'))
k_read = subset(k_read, select = -c(FARM))
```

0.1 Fill in missing values somehow

We need to fill in missing values, so let's clean the NA values from the data first.

[5]:

```
cleaned_read = k_read[complete.cases(k_read),]
cleaned_read = subset(cleaned_read, select = -c(ID.))

##get rows which correspond to NA vals

R_na = subset(k_read,is.na(R.SCORE))
L_na = subset(k_read,is.na(L.SCORE))

#drop columsn with NAs to create test set

R_test = subset(R_na, select= -c(R.SCORE,ID.))
L_test = subset(L_na, select = -c(L.SCORE,ID.))

##Use R Score, DIEBLS, INP, FARM_BIN to predict L Score
##Use L Score, DIEBELS, INP, FARM_BIN to predict R score
```

Create a train/test set since we want to figure out if an lm model will be any good in predicting

L.SCORE/R.SCORE. We are doing this since we don't have any actualy groundtruth labels for the NA values, and want to see how good this model is.

[6]:
```
num_rows = c(1:nrow(cleaned_read)) ##CONSTANT
set.seed(0)
sampled = sample(num_rows)
test_size = .20*nrow(cleaned_read) ##CONSTANT
train_size = nrow(cleaned_read)-test_size ##CONSTANT
train_index = sampled[1:train_size] ##CONSTANT
test_index = sampled[(train_size + 1): nrow(cleaned_read)] ##CONSTANT

train_set = cleaned_read[train_index,]
test_set = cleaned_read[test_index,]
```

[7]:
```
train_set
```

A data.frame: 136 × 5

	R.SCORE	L.SCORE	DIEBLS	INP	FARM_BIN
	<int>	<int>	<int>	<int>	<int>
157	14	18	33	0	1
78	17	18	16	0	0
182	20	21	42	0	0
144	18	20	30	0	1
177	20	20	38	0	0
50	14	10	8	1	1
15	9	11	0	1	0
61	14	9	12	1	0
97	16	21	20	0	0
22	16	13	0	1	0
118	15	19	24	0	1
85	12	13	18	0	0
8	14	8	0	1	1
84	19	21	17	0	0
90	15	17	19	0	1
44	16	14	6	1	1
117	21	17	24	0	0
124	17	16	26	0	0
41	16	17	4	1	0
175	20	16	38	0	0
141	17	16	30	0	1
101	20	19	21	0	0
40	12	14	4	1	1
96	20	20	20	0	0
81	15	16	17	0	1
174	20	20	37	0	0
49	13	8	8	1	1
125	16	17	26	0	1
21	13	13	0	1	1
51	11	11	8	1	1
...	...	...	...	...	...
183	19	19	44	0	0
168	20	20	35	0	1
7	19	7	0	1	1
110	19	21	22	0	1
62	16	13	12	1	0
48	12	16	7	1	0
170	18	20	36	0	0
53	14	13	8	1	0
58	14	18	10	1	1
3	7	5	0	1	1
73	15	13	15	0	0
184	19	20	50	0	0
173	19	19	37	0	1
67	15	14	13	1	0
134	15	19	28	0	0
156	20	21	32	0	0
92	16	18	19	0	0
55	0	16	8	1	1
28	18	20	0	1	1
98	10	13	21	0	1

Fit the models on the train set using all variables other than R.Score/L.Score. This is probably not best practice because were are trying to predict DIEBELS with R.Score/L.Score

[8]:
```
model_R = lm(R.SCORE~.,train_set, x = TRUE,y= TRUE)
model_L =lm(L.SCORE~.,train_set, x= TRUE, y= TRUE)
```

Creating custom scoring metrics for the cross validations

[9]:
```
rsqd = function(object, y, X){
    preds = predict(object, as.data.frame(X))
    tss = sum((y-mean(y))%*%(y-mean(y)))
    rss = sum((y-preds)%*%(y-preds))
    rsq = 1 - (rss/tss)
    return(rsq)
    }
rse = function(object,y,X){
    preds = predict(object, as.data.frame(X))
    rss = sum((y-preds)%*%(y-preds))
    rse = sqrt(rss/(length(y)-(length(coefficients(object)-1))))
    return(rse)
}
```

Run 5 fold CV on built-in metrics as well as rsqd custom metric

[10]:
```
cv_R_rsq = cv.lm(object = model_R, k = 5, fun = rsqd, seed = 24)
cv_L_rsq = cv.lm(object = model_L, k =5, fun = rsqd, seed = 24)
```

[11]:
```
cv_R_rsq
```

```
Mean absolute error        :  2.335835
Sample standard deviation  :  0.3632365

Mean squared error         :  10.20601
Sample standard deviation  :  3.343929

Root mean squared error    :  3.159387
Sample standard deviation  :  0.5294868

User supplied function     :  0.3890505
Sample standard deviation  :  0.197561
```

[12]:
```
cv_L_rsq
```

```
Mean absolute error        :  2.369548
Sample standard deviation  :  0.3360425

Mean squared error         :  9.654316
Sample standard deviation  :  3.038032
```

```
Root mean squared error    :  3.073806
Sample standard deviation  :  0.507485

User supplied function     :  0.4191553
Sample standard deviation  :  0.1789954
```

Rsquard test statistic is around .4 for all models. Rsqared is low, so there isn't too much of a linear relationship here. Shouldn't expect much during testing. Figure out rse below.

[13]:
```
cv_R_rse = cv.lm(object = model_R, k = 5, fun = rsqd, seed = 24)
cv_L_rse = cv.lm(object = model_L, k =5, fun = rse, seed = 24)
```

Below, RSE is around 3 for both models, which isn't that bad.

[14]:
```
cv_R_rse
```

```
Mean absolute error        :  2.335835
Sample standard deviation  :  0.3632365

Mean squared error         :  10.20601
Sample standard deviation  :  3.343929

Root mean squared error    :  3.159387
Sample standard deviation  :  0.5294868

User supplied function     :  0.3890505
Sample standard deviation  :  0.197561
```

[15]:
```
cv_L_rse
```

```
Mean absolute error        :  2.369548
Sample standard deviation  :  0.3360425

Mean squared error         :  9.654316
Sample standard deviation  :  3.038032

Root mean squared error    :  3.073806
Sample standard deviation  :  0.507485

User supplied function     :  3.405234
Sample standard deviation  :  0.5622038
```

[16]:
```
test_preds_R = predict(model_R, subset(test_set,select = -c(R.SCORE)))
test_preds_L = predict(model_L, subset(test_set,select = -c(L.SCORE)))
```

Compute the RSE and R^2 statistics.

[17]:

```
y_R = test_set[,'R.SCORE']
y_L = test_set[,'L.SCORE']
rss_R = sum((test_preds_R -y_R)%*%(test_preds_R-y_R))
rss_L = sum((test_preds_L-y_L)%*%(test_preds_L-y_L))
tss_R = sum((y_R -mean(y_R))%*%(y_R-mean(y_R)))
tss_L = sum((y_L-mean(y_L))%*%(y_L-mean(y_L)))

rsq_R = 1 - rss_R/tss_R
rsq_L = 1 - rss_L/tss_L

rse_R = sqrt(rss_R/(length(y_L)-2))
rse_L = sqrt(rss_L/(length(y_L)-2))
```

[18]:

```
c(rsq_R,rsq_L,rse_R,rse_L)
```

1. 0.358059616325482 2. 0.637019820218491 3. 4.10994481278894 4. 2.71121416750214

We replace NA values with our predictions.

[19]:

```
R_score_pred = predict(model_R, subset(R_na, select = -c(R.SCORE, ID.)) )
L_score_pred = predict(model_L, subset(L_na, select = -c(L.SCORE, ID.)))

##insert predicted values
R_na[,'R.SCORE'] = round(R_score_pred)
L_na[,'L.SCORE'] = round(L_score_pred)
#reset cleaned data variable
cleaned_read = k_read[complete.cases(k_read),]
#combine data frames
filled_read = rbind(cleaned_read, R_na)
filled_read = rbind(filled_read, L_na)
```

[20]:

```
filled_read
```

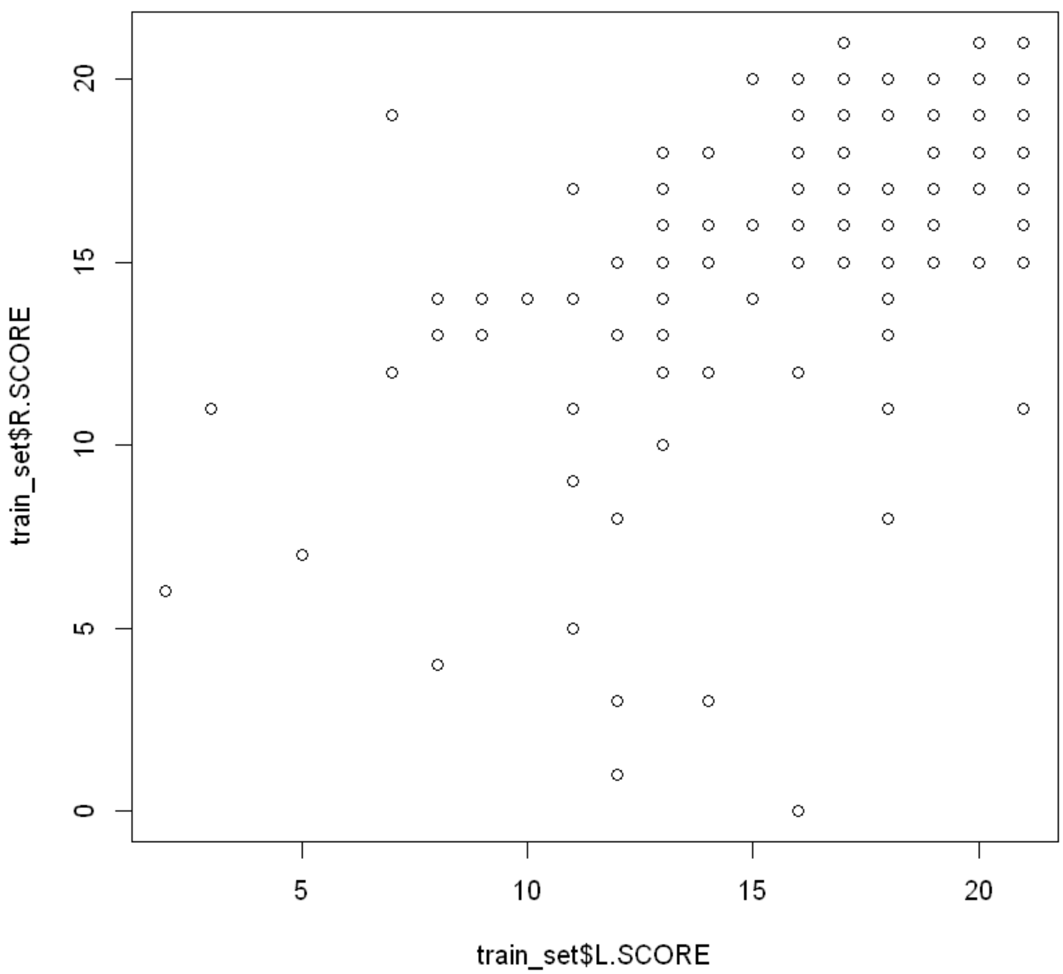
A data.frame: 185 × 6

	ID.	R.SCORE	L.SCORE	DIEBLS	INP	FARM_BIN
	<int>	<dbl>	<dbl>	<int>	<int>	<int>
1	1	6	2	0	1	1
2	2	11	3	0	1	1
3	3	7	5	0	1	1
4	4	10	5	0	1	1
6	6	0	7	0	1	1
7	7	19	7	0	1	1
8	8	14	8	0	1	1
9	9	14	8	0	1	1
10	10	12	9	0	1	1
11	11	13	9	0	1	1
12	12	13	9	0	1	0
13	13	0	10	0	1	1
14	14	5	11	0	1	1
15	15	9	11	0	1	0
16	16	14	11	0	1	1
17	17	17	11	0	1	1
18	18	1	12	0	1	1
19	19	3	12	0	1	1
20	20	8	12	0	1	0
21	21	13	13	0	1	1
22	22	16	13	0	1	0
23	23	16	13	0	1	0
24	24	17	13	0	1	0
25	25	3	14	0	1	1
26	26	8	18	0	1	1
27	27	16	19	0	1	1
28	28	18	20	0	1	1
29	29	11	21	0	1	1
35	35	4	8	2	1	1
36	36	21	15	3	1	1
...	...	...	...	...	...	...
171	171	20	20	36	0	0
172	172	16	19	37	0	1
173	173	19	19	37	0	1
174	174	20	20	37	0	0
175	175	20	16	38	0	0
176	176	20	17	38	0	0
177	177	20	20	38	0	0
178	178	21	20	39	0	0
179	179	17	16	40	0	0
180	180	19	18	41	0	1
181	181	18	21	41	0	0
182	182	20	21	42	0	0
183	183	19	19	44	0	0
184	184	19	20	50	0	0
185	185	20	20	52	0	1
5	5	9	6	0	1	1
54	54	13	15	8	1	1
57	57	12	13	9	1	1
91	91	16	17	19	0	1
119	119	19	21	24	0	0

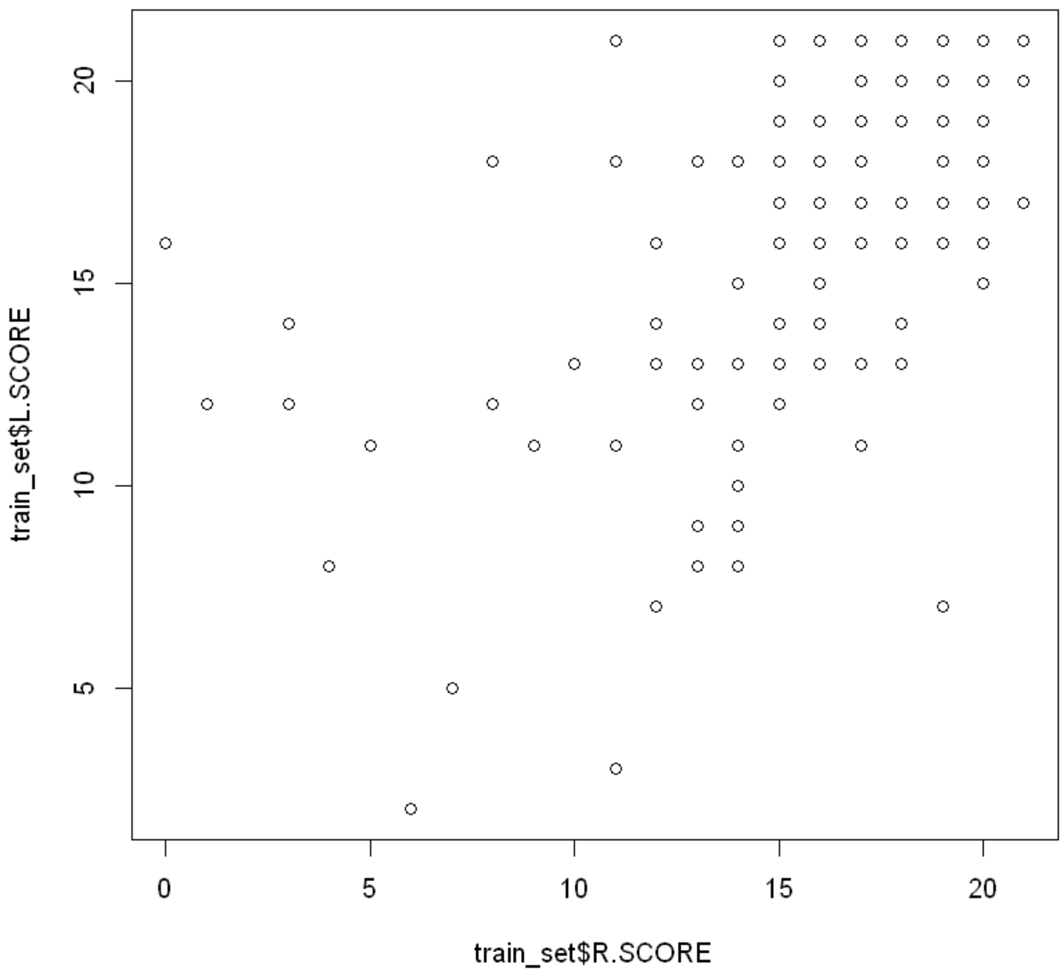
[21]:
```
#reset row names
rownames(filled_read) <- 1:nrow(filled_read)
```

This isn't good pracice though, maybe a better thing to do would just be to regress R.Score on L.Score. Let's see if there is some natural relationship between R.Score and L.Score. The graph below is less than exciting,but still shows a linear trend. Let's use R.Score to predict L.Score, and throug this relationship, we can determine R.Score through the coefficients by working backwards.

[22]:
```
plot(train_set$L.SCORE, train_set$R.SCORE)
```



[23]:
```
plot(train_set$R.SCORE, train_set$L.SCORE)
```



Fit the model and run CV validation on model_R_new

[24]:
```
model_R_new =lm(R.SCORE~L.SCORE, train_set, x = TRUE,y= TRUE)
model_L_new = lm(L.SCORE~R.SCORE, train_set, x = TRUE, y= TRUE)
```

[25]:
```
cv_R_new_rsqd = cv.lm(object = model_R_new, k = 5, fun = rsqd, seed = 24)
cv_R_new_rse = cv.lm(object = model_R_new, k = 5, fun = rse, seed = 24)
```

[26]:
```
cv_R_new_rsqd ##considerably worse than before
```

```
Mean absolute error        :  2.476237
Sample standard deviation  :  0.3516305

Mean squared error         :  12.37
```

```
Sample standard deviation  :  4.007563

Root mean squared error    :  3.476131
Sample standard deviation  :  0.5984562

User supplied function     :  0.2781961
Sample standard deviation  :  0.1640992
```

[27]:
```
cv_R_new_rse
```

```
Mean absolute error        :  2.476237
Sample standard deviation  :  0.3516305

Mean squared error         :  12.37
Sample standard deviation  :  4.007563

Root mean squared error    :  3.476131
Sample standard deviation  :  0.5984562

User supplied function     :  3.612501
Sample standard deviation  :  0.6219339
```

[28]:
```
model_R_new$coefficients
model_L_new$coefficients ##get coefficients, since it is probably better to use
 ↪a model whose covariate does not include diebls
```

(Intercept)	5.50149566257854	**L.SCORE**	0.626034499950144
(Intercept)	7.14186792869685	**R.SCORE**	0.584053302945383

[29]:
```
test_preds_R_new = predict(model_R_new, subset(test_set,select = -c(R.SCORE)))
```

Test scores

[30]:
```
rss_R_new = sum((test_preds_R_new -y_R)%*%(test_preds_R_new-y_R))
tss_R_new = sum((y_R -mean(y_R))%*%(y_R-mean(y_R)))
rsq_R_new = 1 - rss_R_new/tss_R_new
rse_R_new = sqrt(rss_R_new/(length(y_R)-2))
```

[31]:
```
c(rss_R_new,tss_R_new,rsq_R_new,rse_R_new)
```

1. 505.14149615482 2. 842.029411764706 3. 0.400090437344515 4. 3.97311864343844

Get rss_R for comparison

[32]:
```
RSS_r_new = sum((model_R_new$residuals)^2)
RSS_r = sum((model_R$residuals)^2)
```

[33]:
```
RSS_r_new
```

1604.54526872071

[34]:
```
RSS_r
```

1263.21423558875

Let's quickly do a model comparison between model_R_new and model_R. We have $\frac{(RSS_0 - RSS_1)/(p-p_0)}{RSS_1/(n-p-1)} \sim F_{p-p_0,n-p-1}$, where the 0 subscripts refer to model_R_new.

We have rss_R_new $= RSS_0 =$ 1604.54526872071 and rss_R =1263.21423558875 $= RSS_1$. We also have $p_0 = 1$, $p = 4$ and $n = 136$. Computing our test stat, we have $\frac{(1604.54526872071 - 1263.21423558875)/(3)}{1263.21423558875/(136-4-1)} = -.6328$. We have $F_{3,29}$, so we compute the test stat with $\alpha = 0.05$.

[35]:
```
f_stat = ((RSS_r_new - RSS_r)/3)/(RSS_r/131)
```

[36]:
```
f_stat
```

11.7990979097978

[37]:
```
pf(11.799,3,29,lower = FALSE)
```

3.17290704084422e-05

We therefore reject the null, and believe that the relationship is better explained with the alternative model. Of course, I don't think we should use the alternative model. We will use the other one.

Let's get our predictions and replace the NA vals with them.

[38]:
```
R_new_preds = predict(model_R_new, subset(R_na, select = -c(R.SCORE, ID.)) )
L_new_preds = predict(model_L_new, subset(L_na, select = -c(L.SCORE, ID.)))

##insert predicted values
R_na[,'R.SCORE'] = round(R_new_preds)
L_na[,'L.SCORE'] = round(L_new_preds)
#reset cleaned data variable
cleaned_read = k_read[complete.cases(k_read),]
#combine data frames
filled_read = rbind(cleaned_read, R_na)
filled_read = rbind(filled_read, L_na)
rownames(filled_read) <- 1:nrow(filled_read)
```

Alright, we'll use this one. I don't know how bad of practice it is to regress two variables on eachother, but this is better I believe than attempting to use DIEBLS to predict R.SCORE/L.SCORE."filled_read" is our new data frame with non-na values.

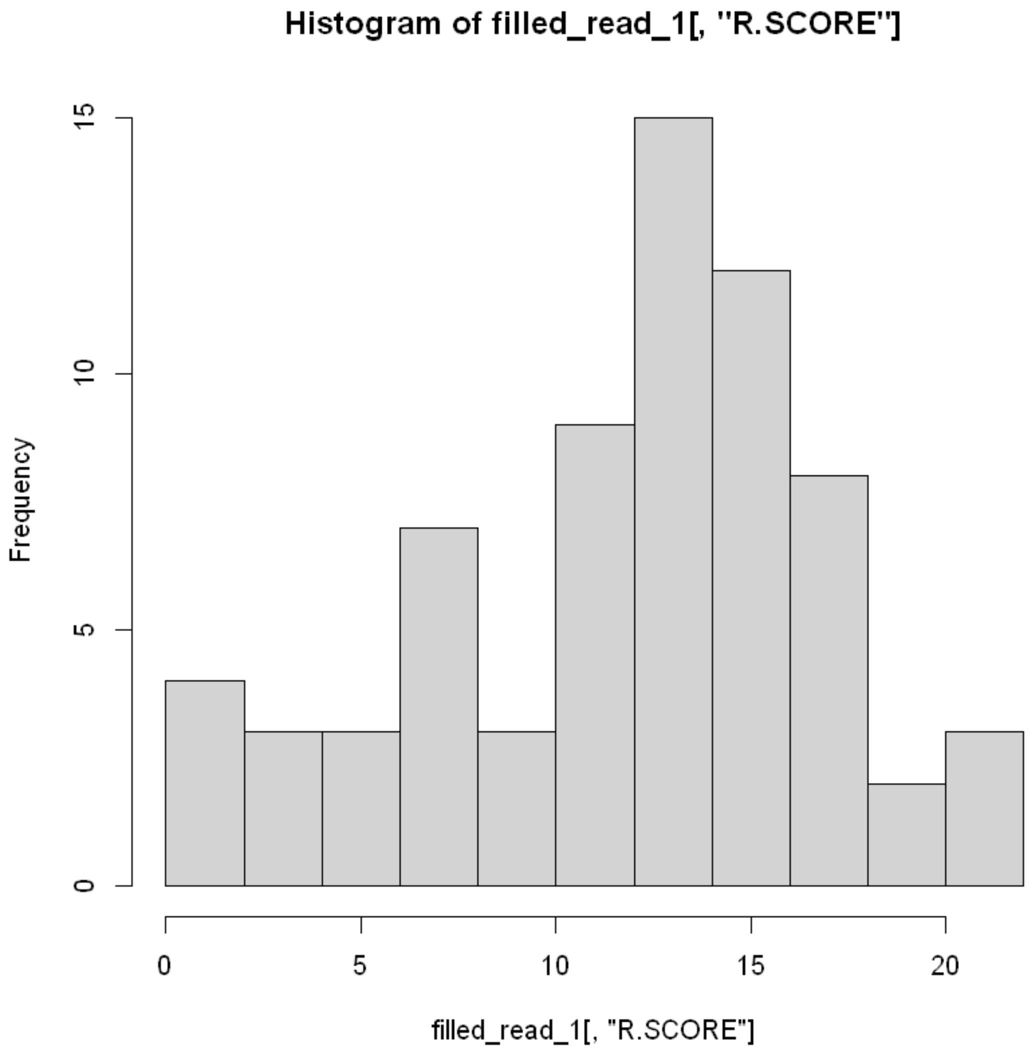
[39]:
```
head(filled_read)
```

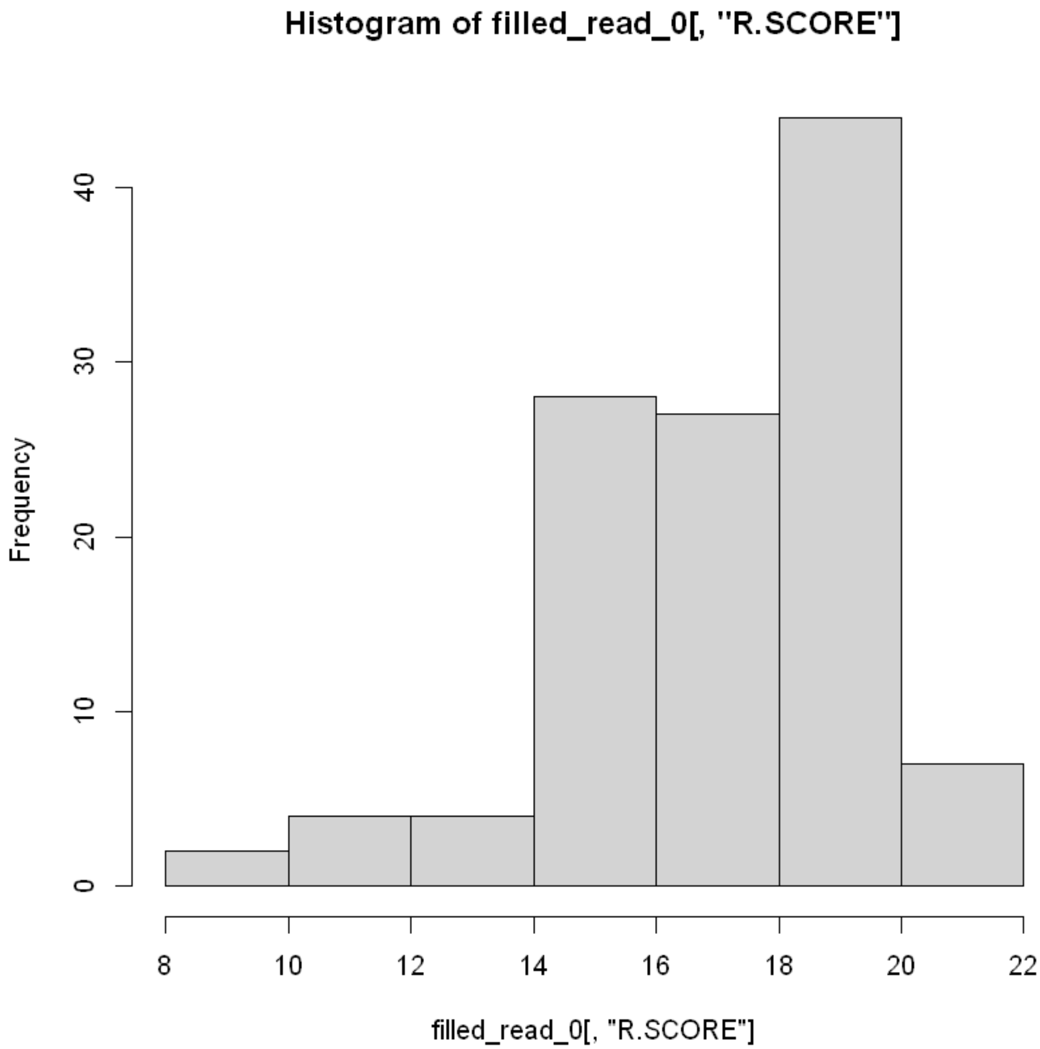
A data.frame: 6 × 6

	ID.	R.SCORE	L.SCORE	DIEBLS	INP	FARM_BIN
	<int>	<dbl>	<dbl>	<int>	<int>	<int>
1	1	6	2	0	1	1
2	2	11	3	0	1	1
3	3	7	5	0	1	1
4	4	10	5	0	1	1
5	6	0	7	0	1	1
6	7	19	7	0	1	1

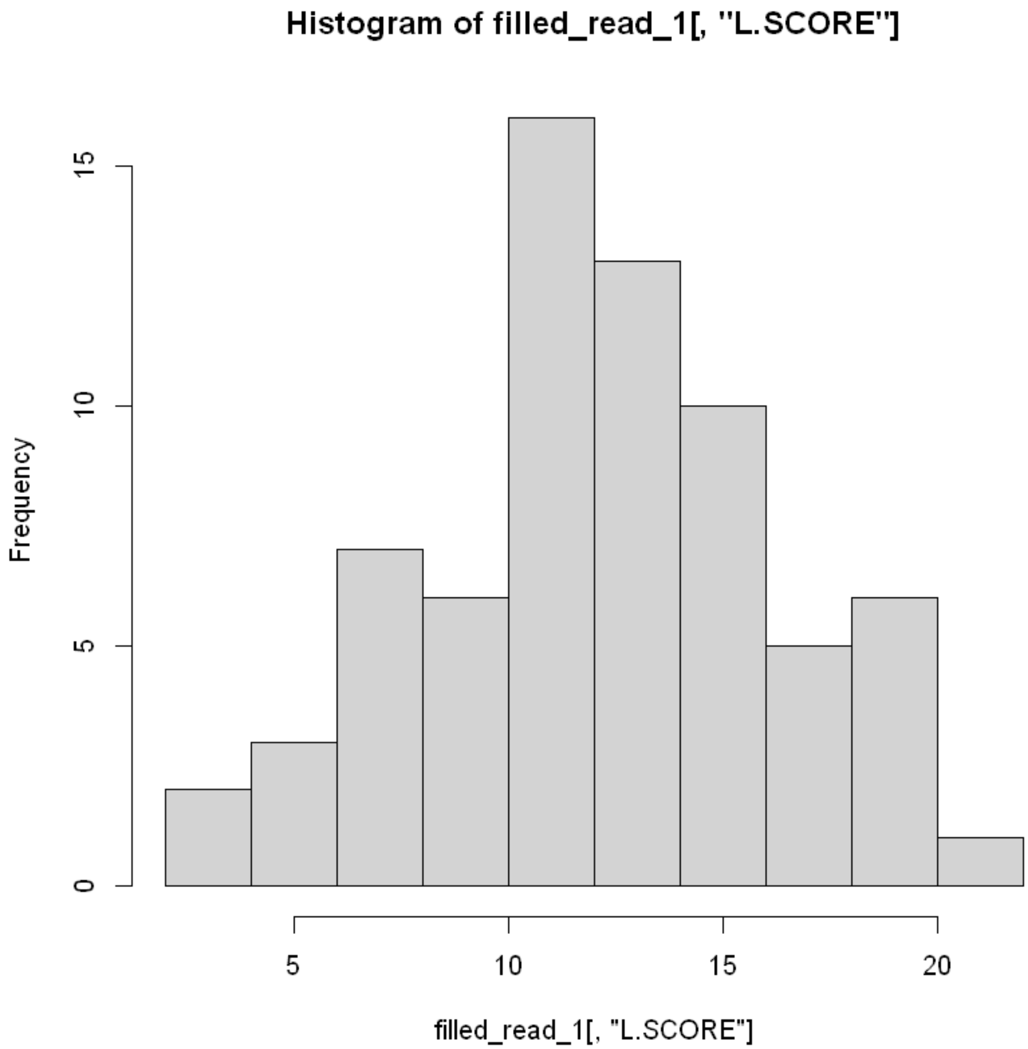
0.2 Check if there is any statistical difference between RScore LScore by group

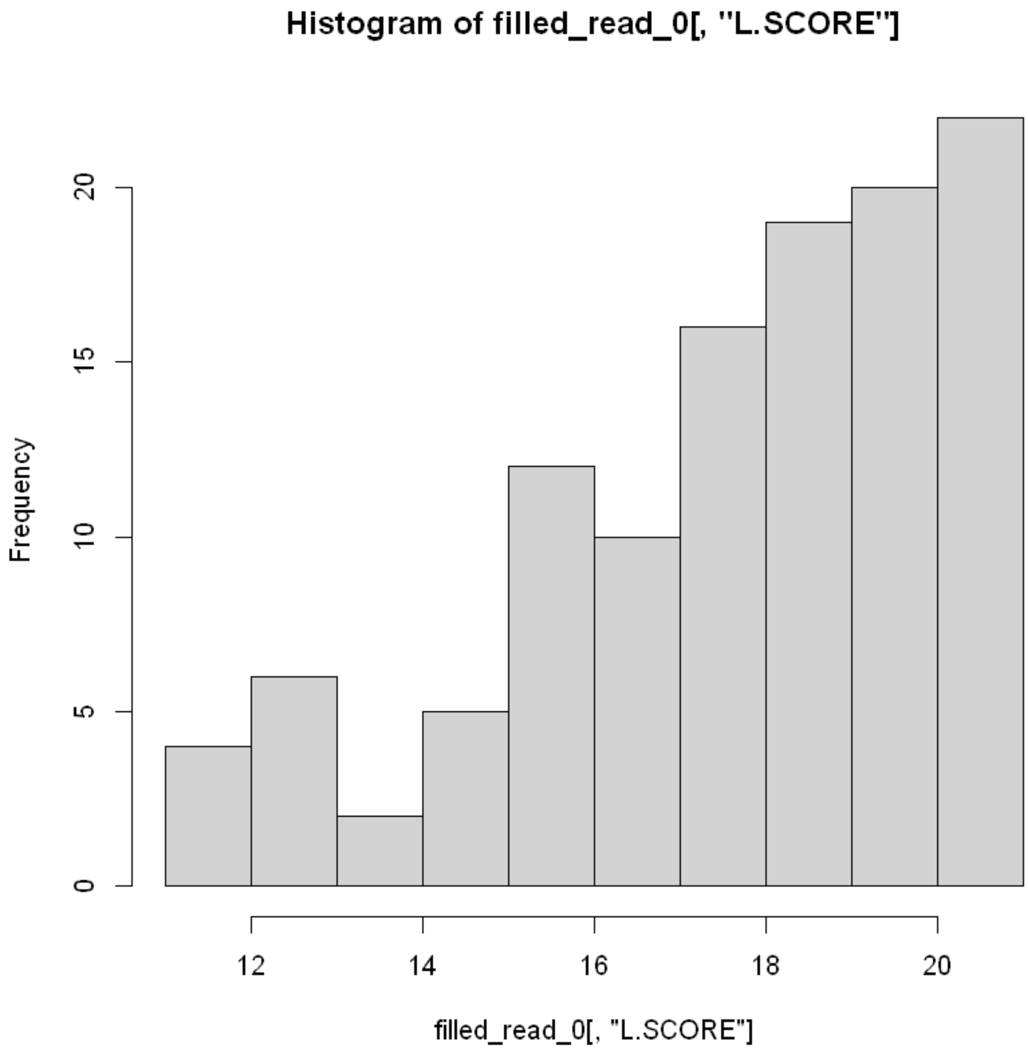
[40]:
```
##using filled_read

filled_read_1 = filled_read[filled_read['INP']==1,]
filled_read_0 = filled_read[filled_read['INP']==0,]

##check normality

hist(filled_read_1[,'R.SCORE'])
hist(filled_read_0[,'R.SCORE'])
hist(filled_read_1[,'L.SCORE'])
hist(filled_read_0[,'L.SCORE'])
```


Histogram of filled_read_1[, "R.SCORE"]
Frequency
0
5
10
15
0
5
10
15
20
filled_read_1[, "R.SCORE"]



Histogram of filled_read_0[, "R.SCORE"]
Frequency
0
10
20
30
40
8
10
12
14
16
18
20
22
filled_read_0[, "R.SCORE"]


Histogram of filled_read_1[, "L.SCORE"]
Frequency
0
5
10
15
5
10
15
20
filled_read_1[, "L.SCORE"]



All of these look approximately normal, except the last histogram. While it might be bad practice to run t-tests on the last one it's not a crazy assumption to believe that the reading scores of a pre-kindergarten population will be asymptotically normal

For the t-tests below, we have natural assumption that those with greater reading score belong in the group that don't find placement

[41]:
```
t.test(filled_read_0[,'R.SCORE'],filled_read_1[,'R.SCORE'], alternative =␣
 ↪'greater')
t.test(filled_read_0[,'L.SCORE'], filled_read_1[,'L.SCORE'], alternative =␣
 ↪'greater')
```

```
        Welch Two Sample t-test
```

```
data:  filled_read_0[, "R.SCORE"] and filled_read_1[, "R.SCORE"]
t = 7.9135, df = 87.474, p-value = 3.597e-12
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 4.136328      Inf
sample estimates:
mean of x mean of y
 17.48276  12.24638



        Welch Two Sample t-test

data:  filled_read_0[, "L.SCORE"] and filled_read_1[, "L.SCORE"]
t = 9.8546, df = 97.967, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 4.563974      Inf
sample estimates:
mean of x mean of y
 18.11207  12.62319
```

With a 95% confidence level, in both, we have p-values which are **significantly** less than 0.05. We should expect good predictive power using R.SCORE and L.SCORE to predict DIEBLS.

[42]:
```
wilcox.test(filled_read_0[,'R.SCORE'], y = filled_read_1[,'R.SCORE'],␣
↪alternative = 'greater')
```

```
        Wilcoxon rank sum test with continuity correction

data:  filled_read_0[, "R.SCORE"] and filled_read_1[, "R.SCORE"]
W = 6671.5, p-value = 1.332e-14
alternative hypothesis: true location shift is greater than 0
```

[43]:
```
wilcox.test(filled_read_0[,'L.SCORE'], filled_read_1[,'L.SCORE'],alternative =␣
↪'greater')
```

```
        Wilcoxon rank sum test with continuity correction

data:  filled_read_0[, "L.SCORE"] and filled_read_1[, "L.SCORE"]
W = 6933.5, p-value < 2.2e-16
alternative hypothesis: true location shift is greater than 0
```

[44]:
```
length(filled_read_0[,'R.SCORE'])
```

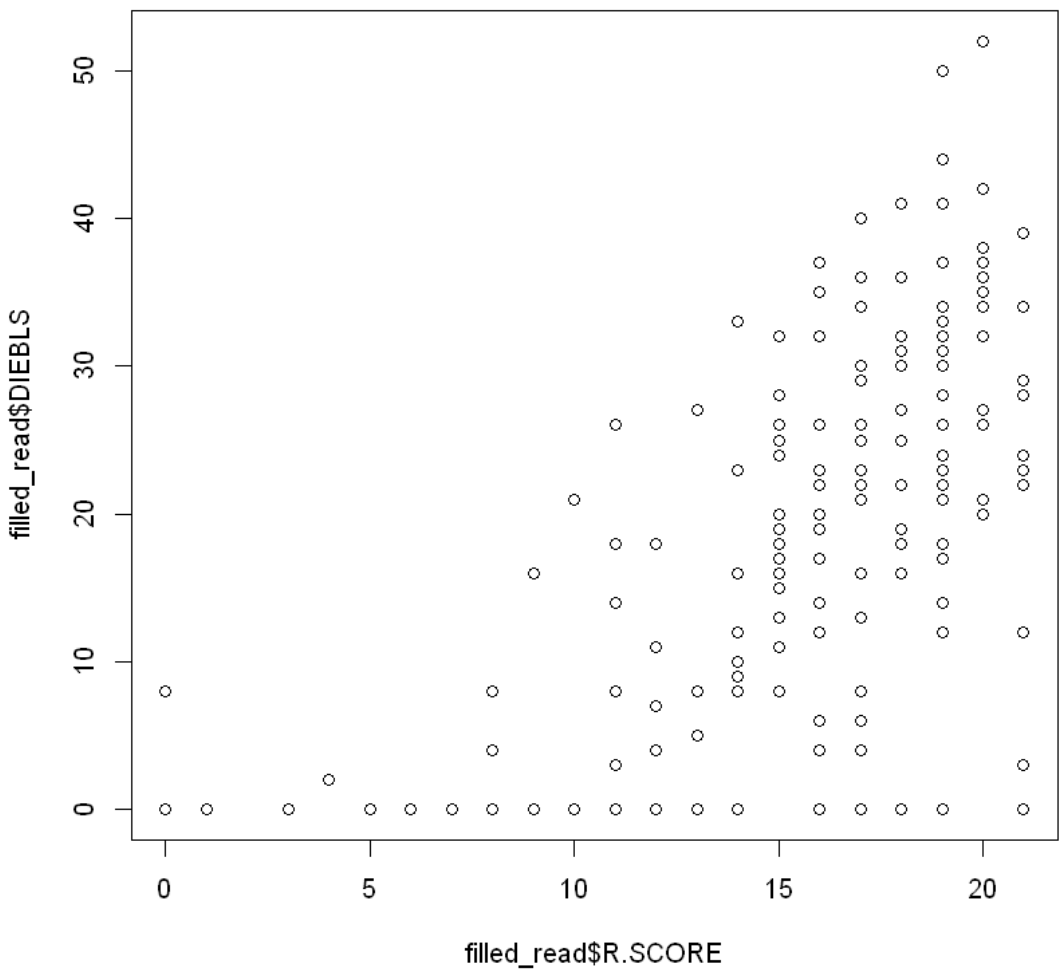
116

[45]:
```
length(filled_read_1[,'R.SCORE'])
```

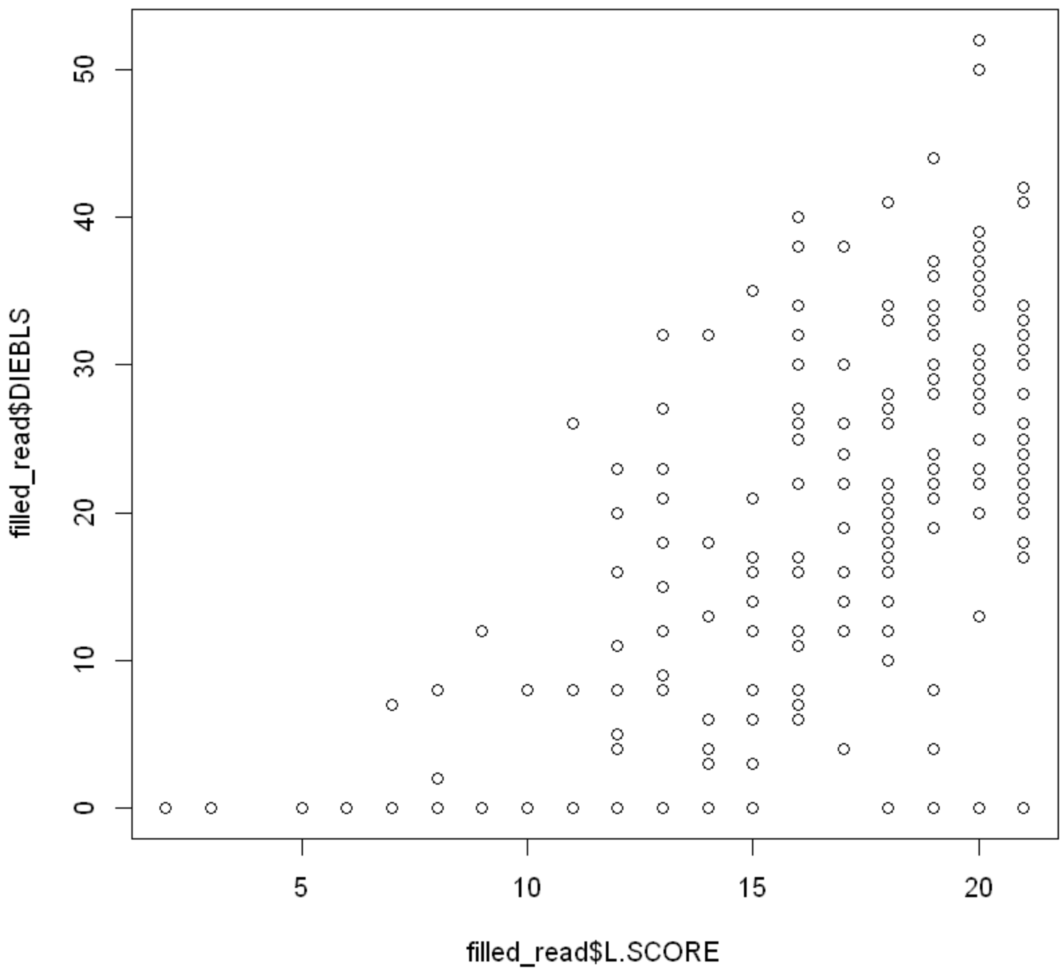
69

0.3 Model Selection

[46]:
```
plot(filled_read$R.SCORE, filled_read$DIEBLS) #weak positive linear trend␣
↪except for all the 0's
```



[47]:
```
plot(filled_read$L.SCORE, filled_read$DIEBLS) #weak positive linear trend␣
↪except for the Os
```



0.3.1 Full model

Let's fit the full model first, using R.SCORE, L.SCORE, INP, and FARM_BIN, and see how good of covariates these are. Here, we are using "filled_read". First, remove the ID column and call this "features_full".

[48]:
```
features_full= subset(filled_read, select = -c(ID.,INP)) ##create features␣
↪matrix from filled_read
```

[49]:
```
INP = filled_read$INP
```

We use the constants from earlier for the indices/sizes. We'll set a different seed though.

[50]:
```
invisible(num_rows) ##CONSTANT
set.seed(1) #different seed
sampled_fill = sample(num_rows)
invisible(test_size) ##CONSTANT
invisible(train_size) ##CONSTANT
train_index_fill = sampled_fill[1:train_size]
test_index_fill = sampled_fill[(train_size + 1): nrow(cleaned_read)] ##CONSTANT

train_set_fill = features_full[train_index_fill,]  #train and test sets
test_set_fill = features_full[test_index_fill,]
```

[51]:
```
filled_read[test_index_fill,]$INP
```

1. 0 2. 0 3. 0 4. 0 5. 1 6. 1 7. 0 8. 0 9. 0 10. 0 11. 1 12. 0 13. 1 14. 1 15. 0 16. 0 17. 0 18. 1 19. 0 20. 1 21. 0 22. 1 23. 1 24. 0 25. 1 26. 0 27. 1 28. 0 29. 1 30. 0 31. 0 32. 0 33. 0 34. 0

[53]:
```
INP_train = filled_read[train_index_fill,]$INP
INP_test = filled_read[test_index_fill,]$INP
```

We have separated our train/test sets, so let's use CV to determine the validation errors of a full model first. We'll feed in both RSS and RSE as scoring metrics, setting a seed to maintain that we're getting the same folds.

[54]:
```
full_fit = lm(DIEBLS~., train_set_fill, x = TRUE, y = TRUE)
```

[55]:
```
cv_full_rsqd = cv.lm(full_fit, k = 5, fun = rsqd, seed = 23) ##set different␣
↪seed
```

[56]:
```
cv_full_rse = cv.lm(full_fit,  k = 5, fun = rse, seed = 23)
```

[57]:
```
##Mean R^2 is 45%! Not much variance explained.
cv_full_rsqd
```

```
Mean absolute error        :  7.717329
Sample standard deviation  :  0.8457575

Mean squared error         :  91.45073
Sample standard deviation  :  18.81876

Root mean squared error    :  9.522736
Sample standard deviation  :  0.9799461

User supplied function     :  0.4528572
Sample standard deviation  :  0.112877
```

[58]:
```
##Mean RS is 9. Note great.
cv_full_rse
```

```
Mean absolute error          :  7.717329
Sample standard deviation    :  0.8457575

Mean squared error           :  91.45073
Sample standard deviation    :  18.81876

Root mean squared error      :  9.522736
Sample standard deviation    :  0.9799461

User supplied function       :  10.31762
Sample standard deviation    :  1.061745
```

Let's predict on our test test, compute R^2, RSS, RSE, MSE, and TSS.

[59]:
```
preds_full = predict(full_fit, subset(test_set_fill, select = -c(DIEBLS)))
RSS_full = (preds_full -␣
 ↪test_set_fill$DIEBLS)%*%(preds_full-test_set_fill$DIEBLS)
TSS_full = (test_set_fill$DIEBLS -␣
 ↪mean(test_set_fill$DIEBLS))%*%(test_set_fill$DIEBLS-␣
 ↪mean(test_set_fill$DIEBLS))
R2_full = 1 - RSS_full/TSS_full
RSE_full = sqrt(RSS_full/(length(preds_full) -␣
 ↪length(coefficients(full_fit)-1)))
MSE_full = RSS_full/length(preds_full)
```

[60]:
```
full_fit_coef = coef(full_fit)
```

[61]:
```
full_fit_coef
```

(Intercept) -18.9131905525481 **R.SCORE** 1.15634799931682 **L.SCORE** 1.23235286333114 **FARM_BIN** 0.0171337679086991

[62]:
```
full_stats = c(RSS_full, TSS_full, R2_full, RSE_full, MSE_full)
```

[63]:
```
full_stats ##R^2 on test set is 50%
```

1. 2860.47471980569 2. 5824.5 3. 0.50888922314264 4. 9.76468931030867 5. 84.1316094060498

After making our predictions, we now check if we accurately predicted the INP for students.

[151]:
```
sum(as.integer(preds_full <= 13)) #how many did we enroll in extra help
```

7

[160]:
```
inp_pred = as.integer(preds_full <= 13) ##assign the binary vector of INP
```

[161]:
```
INP_test #check the actual INP assignments
```

1. 0 2. 0 3. 0 4. 0 5. 1 6. 1 7. 0 8. 0 9. 0 10. 0 11. 1 12. 0 13. 1 14. 1 15. 0 16. 0 17. 0 18. 1 19. 0 20. 1 21. 0 22. 1 23. 1 24. 0 25. 1 26. 0 27. 1 28. 0 29. 1 30. 0 31. 0 32. 0 33. 0 34. 0

[162]:
```
sum(as.integer(inp_pred == INP_test)) #how many did we assign correctly?
```

29

[163]:
```
29/34 #what is our percentage?
```

0.852941176470588

[136]:
```
preds_full
```

92 24.0245538790094 **146** 26.4132547416574 **112** 24.0245538790094 **62** 25.2569067423406 **11** 7.21050920855075 **57** 15.6849695238401 **66** 22.8682058796926 **130** 27.7216124690029 **97** 26.565264469686 **91** 22.7750672477696 **30** 23.8725441509808 **114** 28.9368315644253 **8** 7.15163811244513 **9** 6.07129497714263 **128** 25.3329116063549 **155** 26.5481307017773 **157** 23.0202156077213 **5** -10.2695867413215 **95** 24.1765636070381 **32** 15.5500935637201 **96** 28.8019556043054 **50** 9.76835356713604 **12** -6.57252815132806 **88** 22.9442107437069 **4** -1.17081247481555 **94** 23.0202156077213 **38** 19.2300183858048 **63** 14.4526166605089 **56** 21.7878627443901 **170** 28.8779604683197 **117** 21.6358530163615 **71** 19.3060232498192 **136** 16.8413175231569 **152** 18.0908041543967

0.3.2 Ridge

Next, let's use lasso and ridge models to penalize some of the covariates. First, ridge.

[166]:
```
lambdas = 10^seq(6, -6, by = -.1)
set.seed(0)
ridge_cv = cv.glmnet(as.matrix(subset(train_set_fill, select = -c(DIEBLS))), as.
↪matrix(train_set_fill$DIEBLS), alpha = 0, lambda  = lambdas)
```

[167]:
```
ridge_cv$lambda.min
```

1

[168]:
```
set.seed(0)
ridge_fit <- glmnet(as.matrix(subset(train_set_fill, select = -c(DIEBLS))),as.
↪matrix(train_set_fill$DIEBLS), alpha = 0, lambda = ridge_cv$lambda.min)
```

[169]:
```
#Get RSS
```

[170]:
```
rid_fit_coef = coef(ridge_fit)
```

Let's compute R^2, RSS, RSE, MSE, TSS.

[171]:
```
preds_ridge = predict(ridge_fit, as.matrix(subset(test_set_fill, select =␣
↪-c(DIEBLS))))
```

```
RSS_rid = (as.vector(preds_ridge) - test_set_fill$DIEBLS)%*%(as.
 ↪vector(preds_ridge)-test_set_fill$DIEBLS)
TSS_rid = (test_set_fill$DIEBLS -␣
 ↪mean(test_set_fill$DIEBLS))%*%(test_set_fill$DIEBLS-␣
 ↪mean(test_set_fill$DIEBLS))
R2_rid = 1 - RSS_rid/TSS_rid
RSE_rid = sqrt(RSS_rid/(length(preds_ridge)-length(coefficients(ridge_fit)-1)))
MSE_rid = RSS_rid/length(preds_ridge)
```

[172]:
```
ridge_stats = c(RSS_rid, TSS_rid, R2_rid, RSE_rid, MSE_rid)
```

[173]:
```
ridge_stats ##R^2 51%
```

1. 2853.04153276127 2. 5824.5 3. 0.510165416299893 4. 9.75199386922366 5. 83.9129862576845

[178]:
```
sum(as.integer(preds_ridge <= 13))
```

7

[180]:
```
inp_pred_ridge = as.integer(preds_ridge <= 13) #assign binary vector for INP
```

[183]:
```
sum(as.integer(inp_pred_ridge == INP_test)) #how many did we get correct
```

29

[182]:
```
29/34 #correct percentage
```

0.852941176470588

[184]:
```
as.integer(preds_ridge <= 13) == as.integer(preds_full <= 13) ##same␣
 ↪predictions as the full model
```

1. TRUE 2. TRUE 3. TRUE 4. TRUE 5. TRUE 6. TRUE 7. TRUE 8. TRUE 9. TRUE 10. TRUE 11. TRUE 12. TRUE 13. TRUE 14. TRUE 15. TRUE 16. TRUE 17. TRUE 18. TRUE 19. TRUE 20. TRUE 21. TRUE 22. TRUE 23. TRUE 24. TRUE 25. TRUE 26. TRUE 27. TRUE 28. TRUE 29. TRUE 30. TRUE 31. TRUE 32. TRUE 33. TRUE 34. TRUE

[186]:
```
preds_ridge #our DIEBLS predictions
```

A matrix: 34 × 1 of type dbl

	s0
92	23.6559324
146	25.9229901
112	23.6559324
62	24.8271193
11	7.9730247
57	16.0207005
66	22.5600617
130	27.1694930
97	26.0736223
91	22.7465573
30	23.5053002
114	28.6024916
8	7.6358969
9	6.6153422
128	24.9024354
155	26.3354340
157	22.7106939
5	-8.8774806
95	23.8065646
32	15.6082566
96	28.1900477
50	10.1289028
12	-5.3639201
88	22.6353778
4	-0.2611468
94	22.7106939
38	19.3836289
63	14.8495137
56	21.5395070
170	28.2653638
117	21.3888748
71	19.4589450
136	17.1165713
152	18.0259464

0.3.3 LASSO

Let's run a LASSO model. It will be interesting to see if it reduces FARM to 0 for later analysis when we do model accuracy tests.

[187]:
```
lambdas = 10^seq(6, -6, by = -.1) ##same lambdas
set.seed(0) ##same seed
lasso_cv = cv.glmnet(as.matrix(subset(train_set_fill, select = -c(DIEBLS))), as.
↪matrix(train_set_fill$DIEBLS), alpha = 1, lambda  = lambdas)
```

[188]:
```
lasso_cv$lambda.min
```

0.398107170553497

[189]:
```
set.seed(0)
lasso_fit =  glmnet(as.matrix(subset(train_set_fill, select = -c(DIEBLS))),as.
↪matrix(train_set_fill$DIEBLS), alpha = 1, lambda = lasso_cv$lambda.min)
```

[190]:
```
## GEt RSS/RSE
```

[191]:
```
lass_fit_coef =  coef(lasso_fit)
```

[192]:
```
lass_fit_coef #FARM reduced to 0
```

```
4 x 1 sparse Matrix of class "dgCMatrix"
                    s0
(Intercept) -17.022647
R.SCORE       1.098742
L.SCORE       1.172488
FARM_BIN      .
```

[193]:
```
preds_lasso = predict(lasso_fit, as.matrix(subset(test_set_fill, select =␣
↪-c(DIEBLS))))
RSS_las = (as.vector(preds_lasso) - test_set_fill$DIEBLS)%*%(as.
↪vector(preds_lasso)-test_set_fill$DIEBLS)
TSS_las = (test_set_fill$DIEBLS -␣
↪mean(test_set_fill$DIEBLS))%*%(test_set_fill$DIEBLS-␣
↪mean(test_set_fill$DIEBLS))
R2_las= 1 - RSS_las/TSS_las
RSE_las = sqrt(RSS_las/(length(preds_lasso)-length(coefficients(lasso_fit)-1)))
MSE_las = RSS_las/length(preds_lasso)
```

[194]:
```
lasso_stats = c(RSS_las, TSS_las, R2_las, RSE_las, MSE_las)
```

[195]:
```
lasso_stats ##R2 still around 51%
```

1. 2851.53438818623 2. 5824.5 3. 0.510424175777109 4. 9.74941774019733 5. 83.8686584760656

0.3.4 Test Results

Create a results data frame for all test scores

[196]:
```
results = data.frame(full_stats, ridge_stats, lasso_stats)
```

[197]:
```
rownames(results) <- c("RSS", "TSS", "R2", "RSE", "MSE")
```

[198]:
```
results ##super similar (TSS is obviously the same for all), although the R2,␣
↪MSE, RSS, RSE are just marginally better
```

A data.frame: 5 × 3

	full_stats <dbl>	ridge_stats <dbl>	lasso_stats <dbl>
RSS	2860.4747198	2853.0415328	2851.5343882
TSS	5824.5000000	5824.5000000	5824.5000000
R2	0.5088892	0.5101654	0.5104242
RSE	9.7646893	9.7519939	9.7494177
MSE	84.1316094	83.9129863	83.8686585

Create data frame with all coefficients

[199]:
```
results = data.frame(as.vector(full_fit_coef), as.vector(rid_fit_coef), as.
↪vector(lass_fit_coef))
```

colnames(results) = c("full", "ridge","lasso") rownames(results) = c("Int", "RSCORE", 'LSCORE', 'FARMBIN')

[200]:
```
results
```

A data.frame: 4 × 3

as.vector.full_fit_coef. <dbl>	as.vector.rid_fit_coef. <dbl>	as.vector.lass_fit_coef. <dbl>
-18.91319055	-16.8139770	-17.022647
1.15634800	1.0958708	1.098742
1.23235286	1.1711869	1.172488
0.01713377	-0.2618117	0.000000

0.3.5 Testing on Marginal Effect/Model Accuracy for FARM

We already know LASSO reduced FARM to 0. Our test on marginal effect can be found in summary tables. We can then compared accuracy between models within full/ridge. If we were to compute marginal manually for both models, our hypotheses are as follows:

$H_0 : \beta_{FARM} = 0$ versus $H_1 : \beta_{FARM} \neq 0$.

For full model, we have $\hat{\sigma} = RSE_{full} = 9.4546198$ and for ridge model, we have $\hat{\sigma} = RSE_{ridge} = 9.4423275$. In both cases, we need to compute $\sqrt{\nu_j}$ which is the third diagonal entry in $(X^TX)^{-1}$, our train features matrix with added intercept.Our test statistic for both models will be $t = \frac{\hat{\beta}_{FARM}}{\sqrt{\nu_{FARM}}RSE} \sim t_{n-p-1} = t_{136-3-1} = t_{132}$. But instead of doing this for the full, we can use summary.

[201]:
```
summary(full_fit)
```

```
Call:
lm(formula = DIEBLS ~ ., data = train_set_fill, x = TRUE, y = TRUE)

Residuals:
     Min       1Q   Median       3Q      Max
-26.5653  -6.3297   0.4297   6.5737  22.2955

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept) -18.91319    4.01468  -4.711 6.16e-06 ***
R.SCORE       1.15635    0.23264   4.971 2.03e-06 ***
L.SCORE       1.23235    0.23597   5.223 6.69e-07 ***
FARM_BIN      0.01713    1.70673   0.010    0.992
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.342 on 132 degrees of freedom
Multiple R-squared:  0.496,	Adjusted R-squared:  0.4846
F-statistic: 43.31 on 3 and 132 DF,  p-value: < 2.2e-16
```

Since .992 > .05 we fail the reject the hypothesis that FARMBIN is 0. Let's now compute the test stat for ridge.

[202]:
```
features = subset(train_set_fill, select = -c(DIEBLS))
```

[203]:
```
features_inter = cbind(intercept = rep(1,136), features)
```

[204]:
```
solve(as.matrix(t(features_inter))%*%as.matrix(features_inter))
```

A matrix: 4 × 4 of type dbl

	intercept	R.SCORE	L.SCORE	FARM_BIN
intercept	0.184664153	-0.0045825060	-0.0051293269	-0.0397955442
R.SCORE	-0.004582506	0.0006200687	-0.0003491395	0.0010932296
L.SCORE	-0.005129327	-0.0003491395	0.0006379494	0.0002767817
FARM_BIN	-0.039795544	0.0010932296	0.0002767817	0.0333741279

We retrieve the 3rd diagonal (0-3 indexing). And so we have $\nu_{FARM} = 0.0333741279$.

For the ridge model:

[207]:
```
t = (-0.2618117)/(sqrt(0.0333741279)*RSE_rid)
```

[208]:
```
pt(-.153224, 132)
```

0.439227809270612

We fail to reject the hypothesis that FARM is 0.

0.3.6 Next we compare accuracy of models on training using F-test.

Really, we should only do this for the full model, since both ridge and lasso penalize coefficients to reduce error. We already have the full model (full_fit). Let's train another model without using FARM.

[162]:
```
fit_no_farm = lm(DIEBLS~., subset(train_set_fill, select = -c(FARM_BIN)), x =
 ↪TRUE, y = TRUE)
```

[163]:
```
rss_no_farm = sum((residuals(fit_no_farm))^2)
```

[164]:
```
rss_no_farm
```

11521.0642338322

[180]:
```
fit_full = lm(DIEBLS~., train_set_fill, x = TRUE, y = TRUE)
```

[181]:
```
rss_full = sum((residuals(fit_full))^2)
```

[182]:
```
rss_full
```

11521.0554376173

[183]:
```
# follows f_(p-po,n-p-1) = f_(1,132) distribution
F = (rss_no_farm - rss_full)/(rss_full/(132))
```

[185]:
```
qf(.025,1,132, lower = TRUE)
```

0.000985799773244089

We keep FARM BIN and REJECT the null, since .0001 < .000985.

[186]:
```
anova(fit_no_farm, fit_full)
```

A anova: 2 × 6

	Res.Df <dbl>	RSS <dbl>	Df <dbl>	Sum of Sq <dbl>	F <dbl>	Pr(>F) <dbl>
1	133	11521.06	NA	NA	NA	NA
2	132	11521.06	1	0.008796215	0.0001007807	0.9920054