C1M6_peer_reviewed

January 15, 2022

1 Module 6: Peer Reviewed Assignment

1.0.1 Outline:

The objectives for this assignment:

1. Apply the processes of model selection with real datasets.
2. Understand why and how some problems are simpler to solve with some forms of model selection, and others are more difficult.
3. Be able to explain the balance between model power and simplicity.
4. Observe the difference between different model selection criterion.

General tips:

1. Read the questions carefully to understand what is being asked.
2. This work will be reviewed by another human, so make sure that you are clear and concise in what your explanations and answers.

[2]:
```r
# This cell loads in the necesary packages
library(tidyverse)
library(leaps)
library(ggplot2)
```

```
  Attaching packages                                        tidyverse
1.3.0

  ggplot2 3.3.0       purrr   0.3.4
  tibble  3.0.1       dplyr   0.8.5
  tidyr   1.0.2       stringr 1.4.0
  readr   1.3.1       forcats 0.5.0

  Conflicts
tidyverse_conflicts()
  dplyr::filter() masks stats::filter()
  dplyr::lag()    masks stats::lag()
```

1.1 Problem 1: We Need Concrete Evidence!

Ralphie is studying to become a civil engineer. That means she has to know everything about concrete, including what ingredients go in it and how they affect the concrete's properties. She's currently writting up a project about concrete flow, and has asked you to help her figure out which ingredients are the most important. Let's use our new model selection techniques to help Ralphie out!

Data Source: Yeh, I-Cheng, "Modeling slump flow of concrete using second-order regressions and artificial neural networks," Cement and Concrete Composites, Vol.29, No. 6, 474-480, 2007.

[3]:
```
concrete.data = read.csv("Concrete.data")

concrete.data = concrete.data[, c(-1, -9, -11)]
names(concrete.data) = c("cement", "slag", "ash", "water", "sp", "course.agg",␣
↪"fine.agg", "flow")

head(concrete.data)
```

A data.frame: 6 × 8

	cement <dbl>	slag <dbl>	ash <dbl>	water <dbl>	sp <dbl>	course.agg <dbl>	fine.agg <dbl>	flow <dbl>
1	273	82	105	210	9	904	680	62.0
2	163	149	191	180	12	843	746	20.0
3	162	148	191	179	16	840	743	20.0
4	162	148	190	179	19	838	741	21.5
5	154	112	144	220	10	923	658	64.0
6	147	89	115	202	9	860	829	55.0

1.1.1 1. (a) Initial Inspections

Sometimes, the best way to start is to just jump in and mess around with the model. So let's do that. Create a linear model with `flow` as the response and all other columns as predictors.

Just by looking at the summary for your model, is there reason to believe that our model could be simpler?

[8]:
```
# Your Code Here
lm.cement = lm(flow~., data=concrete.data)
summary(lm.cement)
```

```
Call:
lm(formula = flow ~ ., data = concrete.data)

Residuals:
    Min      1Q  Median      3Q     Max
-30.880 -10.428   1.815   9.601  22.953

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

```
(Intercept) -252.87467  350.06649  -0.722   0.4718  
cement         0.05364    0.11236   0.477   0.6342  
slag          -0.00569    0.15638  -0.036   0.9710  
ash            0.06115    0.11402   0.536   0.5930  
water          0.73180    0.35282   2.074   0.0408 *
sp             0.29833    0.66263   0.450   0.6536  
course.agg     0.07366    0.13510   0.545   0.5869  
fine.agg       0.09402    0.14191   0.663   0.5092  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.84 on 95 degrees of freedom
Multiple R-squared:  0.5022,Adjusted R-squared:  0.4656 
F-statistic: 13.69 on 7 and 95 DF,  p-value: 3.915e-12
```

Yes, none of the P-vales of the predictors are significant. This may indicate some multicollinearity. By eliminating predictors, we couild fix this issue.

1.1.2 1. (b) Backwards Selection

Our model has 7 predictors. That is not too many, so we can use backwards selection to narrow them down to the most impactful.

Perform backwards selection on your model. You don't have to automate the backwards selection process.

[9]:
```
# Your Code Here
# 'slag' has the highest p-value. So, we'll remove it.
lm.cement = update(lm.cement, .~. -slag)
summary(lm.cement)
```

```
Call:
lm(formula = flow ~ cement + ash + water + sp + course.agg + 
    fine.agg, data = concrete.data)

Residuals:
    Min      1Q  Median      3Q     Max 
-30.843 -10.451   1.771   9.589  22.939 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -265.45032   55.46193  -4.786 6.16e-06 ***
cement         0.05766    0.02088   2.761 0.006899 ** 
ash            0.06524    0.01987   3.283 0.001434 ** 
water          0.74420    0.09117   8.163 1.28e-12 ***
sp             0.31366    0.50874   0.617 0.538997    
```

```
course.agg     0.07849    0.02447   3.207 0.001820 **
fine.agg       0.09909    0.02644   3.747 0.000305 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.78 on 96 degrees of freedom
Multiple R-squared:  0.5022,Adjusted R-squared:  0.4711
F-statistic: 16.14 on 6 and 96 DF,  p-value: 9.229e-13
```

[10]:
```
#Remove 'sp'
lm.cement = update(lm.cement, .~. -sp)
summary(lm.cement)
```

```
Call:
lm(formula = flow ~ cement + ash + water + course.agg + fine.agg,
    data = concrete.data)

Residuals:
    Min      1Q  Median      3Q     Max
-31.893 -10.125   1.773   9.559  23.914

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -249.50866   48.90884  -5.102 1.67e-06 ***
cement         0.05366    0.01979   2.712 0.007909 **
ash            0.06101    0.01859   3.281 0.001436 **
water          0.72313    0.08426   8.582 1.53e-13 ***
course.agg     0.07291    0.02266   3.217 0.001760 **
fine.agg       0.09554    0.02573   3.714 0.000341 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.74 on 97 degrees of freedom
Multiple R-squared:  0.5003,Adjusted R-squared:  0.4745
F-statistic: 19.42 on 5 and 97 DF,  p-value: 2.36e-13
```

Our final model would consist of the variables `cement`, `ash`, `water`, `course.agg`, `fine.agg`

1.1.3 1. (c) Objection!

Stop right there! Think about what you just did. You just removed the “worst” features from your model. But we know that a model will become less powerful when we remove features so we should check that it’s still just as powerful as the original model. Use a test to check whether the model at the end of backward selection is significantly different than the model with all the features.

Describe why we want to balance explanatory power with simplicity.

```
[12]: # Your Code Here
      lm.cement.full = lm(flow~., data=concrete.data)
      anova(lm.cement, lm.cement.full)
```

A anova: 2 × 6

	Res.Df <dbl>	RSS <dbl>	Df <dbl>	Sum of Sq <dbl>	F <dbl>	Pr(>F) <dbl>
1	97	15733.53	NA	NA	NA	NA
2	95	15671.26	2	62.27123	0.1887457	0.8283068

In this case, we use the `anova()` function to carry out an F-test to compare the reduced model to the full model. The hypothesis test is as follows:

H_0: The reduced model is sufficient

H_1: The reduced model is not sufficient

The p-value is 0.828. We fail to reject the null hypothesis. Our reduced model is significantly different, and better, than the full model.
First, if we create our model with too much explanatory power then it could possible overfit the regresion line. This would look great when testing on the data we currently have, but terribly on data we haven't seen before. This is because the model would not capture any randomness within the dataset. On the other hand, if we have too much simplicity, then we would underfit our model. Underfitting our model would result in inaccurate predictions and explanations. It would be just as good to guess at random than to use our regression model.

1.1.4 1. (d) Checking our Model

Ralphie is nervous about her project and wants to make sure our model is correct. She's found a function called `regsubsets()` in the leaps package which allows us to see which subsets of arguments produce the best combinations. Ralphie wrote up the code for you and the documentation for the function can be found here. For each of the subsets of features, calculate the AIC, BIC and adjusted R^2. Plot the results of each criterion, with the score on the y-axis and the number of features on the x-axis.

Do all of the criterion agree on how many features make the best model? Explain why the criterion will or will not always agree on the best model.

Hint: It may help to look at the attributes stored within the regsubsets summary using `names(rs)`.

```
[13]: reg = regsubsets(flow ~ cement+slag+ash+water+sp+course.agg+fine.agg+flow,␣
       ↪data=concrete.data, nvmax=6)
      rs = summary(reg)
      rs$which

      # Your Code Here
```

```
Warning message in model.matrix.default(terms(formula, data = data), mm):
"the response appeared on the right-hand side and was dropped"
```

```
Warning message in model.matrix.default(terms(formula, data = data), mm):
"problem with term 8 in model.matrix: no columns are assigned"
```

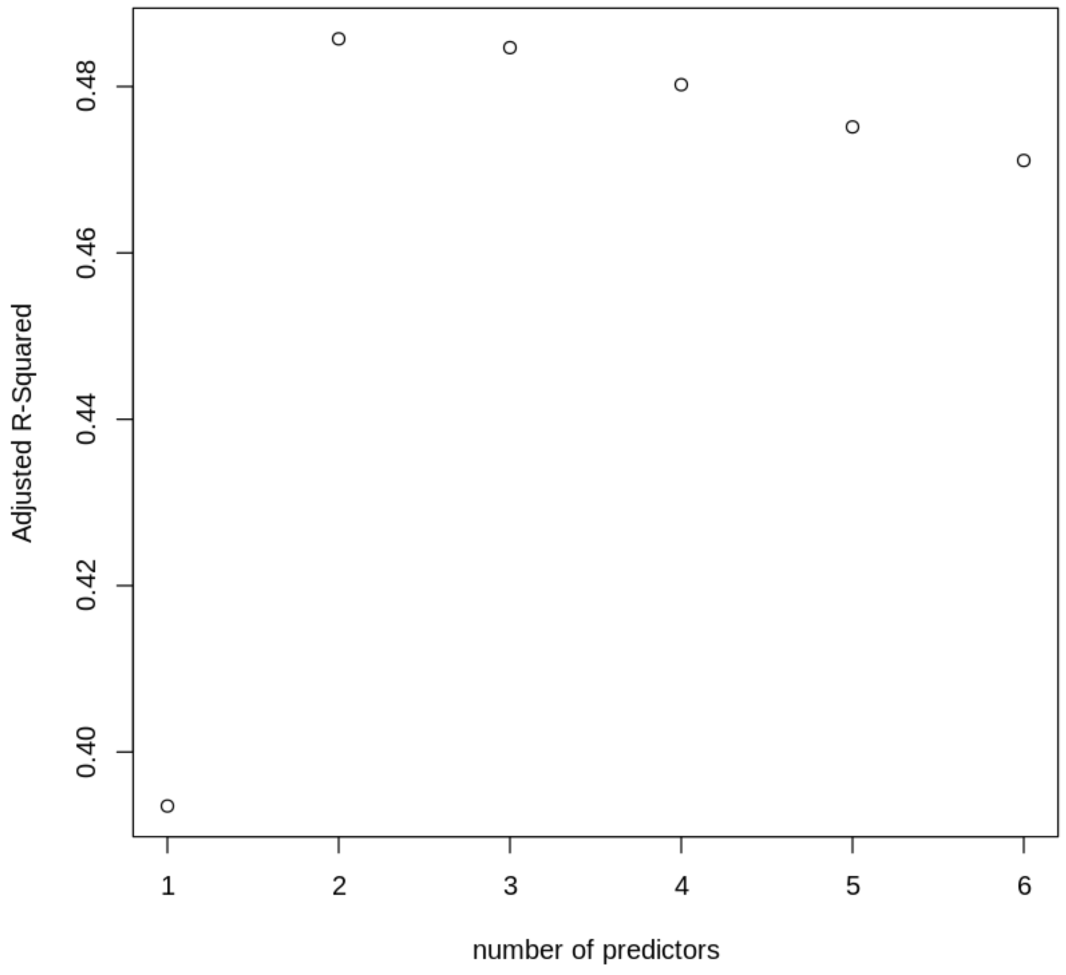
A matrix: 6 × 8 of type lgl

	(Intercept)	cement	slag	ash	water	sp	course.agg	fine.agg
1	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE
3	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	TRUE
4	TRUE	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	TRUE
5	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE
6	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE

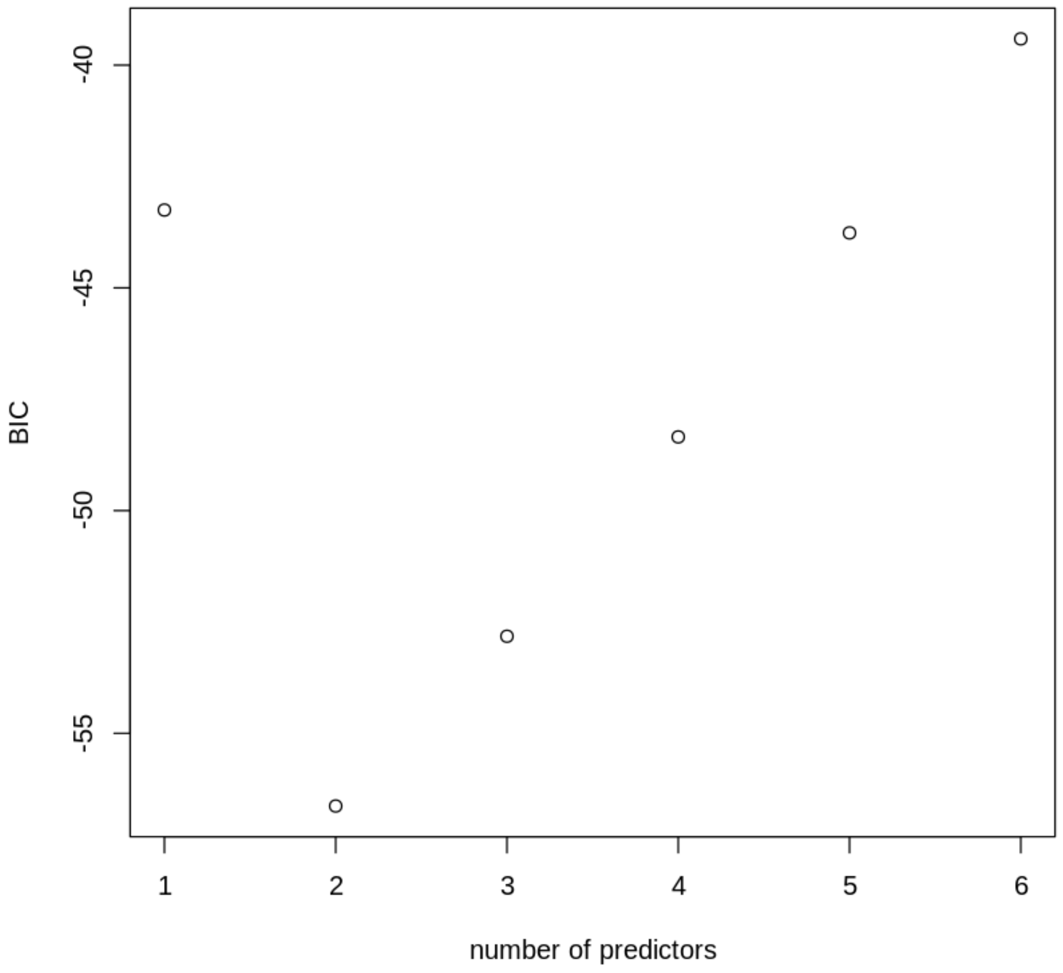
[16]:
```
names(rs)
```

1. 'which' 2. 'rsq' 3. 'rss' 4. 'adjr2' 5. 'cp' 6. 'bic' 7. 'outmat' 8. 'obj'

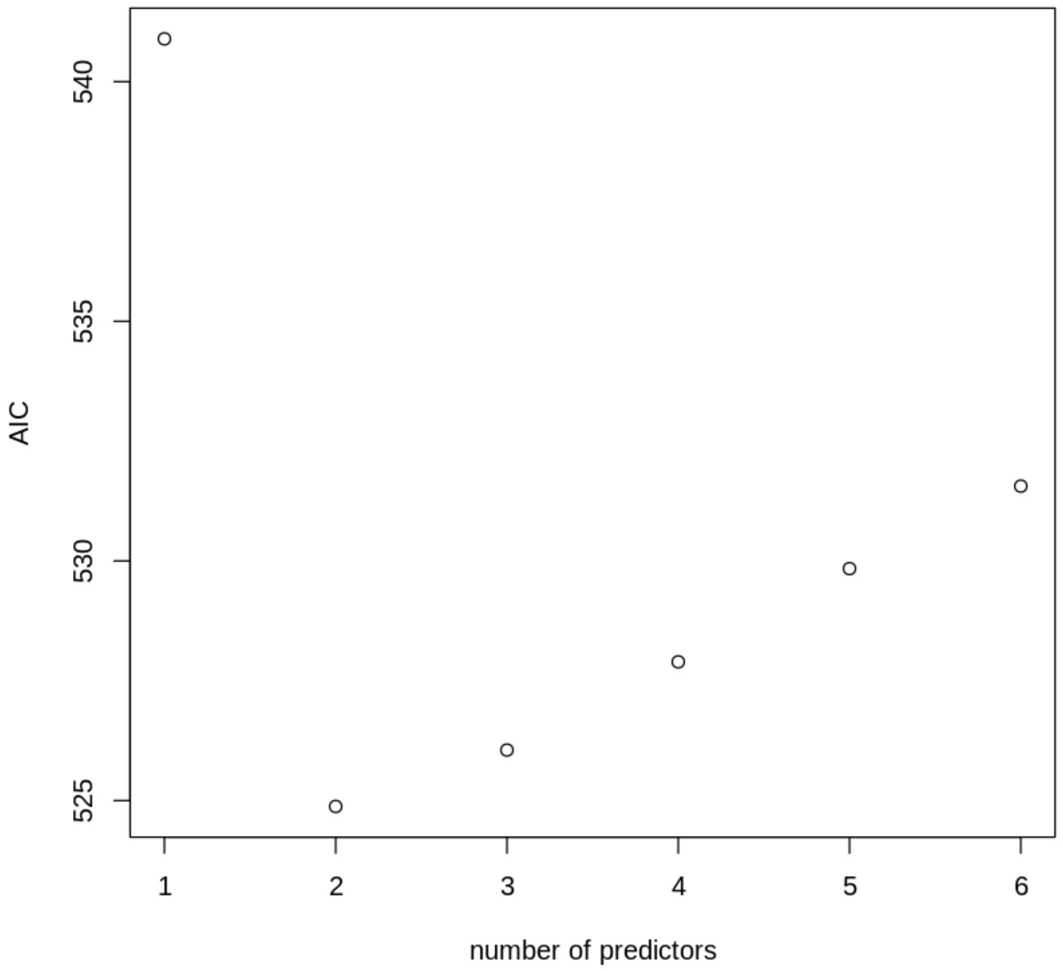
[19]:
```
cement.rsq = rs$adjr2
plot(cement.rsq ~ I(1:6), xlab="number of predictors", ylab="Adjusted␣
↪R-Squared")
```



[20]:
```
cement.bic = rs$bic
plot(cement.bic ~ I(1:6), xlab="number of predictors", ylab="BIC")
```



[21]:
```
n = dim(concrete.data)[1]
cement.aic = 2 * (2:7) + n *log(rs$rss/n)
plot(cement.aic ~ I(1:6), xlab = "number of predictors", ylab = "AIC")
```



Yes, all three plots suggest the model with 2 predictors (`slag` and `water`) is the best model. No, these plots will not always suggest the same model. First, the adjusted R-squared explains how much our regression line can explain the variability in our already **observed** data. However, AIC measures how well our model can predict data; in other words, how well we can predict unobserved data. Adding more predictors may add better explanation to our observed data, but it may hurt predictions. BIC is similar to AIC but penalizes models with more predictors.

```
[ ]:
```