C1M6_peer_reviewed

June 7, 2023

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.

[1]:
```
# 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.

[2]:
```
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?

[3]:
```
# Your Code Here
lmod <- lm(flow ~., data = concrete.data)
summary(lmod)
```

```
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
```

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.

[6]:

```
# Your Code Here
lmod_1step <- update(lmod, ~ . - slag)
summary(lmod_1step)

lmod_2step <- update(lmod_1step, ~ . - sp)
summary(lmod_2step)
```

```
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



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
```

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.

[7]:
```
# Your Code Here
anova(best.model, lmod)
```

```
    Error in anova(best.model, lmod): object 'best.model' not found
Traceback:


    1. anova(best.model, lmod)
```

From anova, we have a p-value of 0.8283068, which means we fail to reject the null hypothesis, which means the extra parameters in the full model are not statistically significant, and therefore we do not need them and the reduced model is better than the full 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.

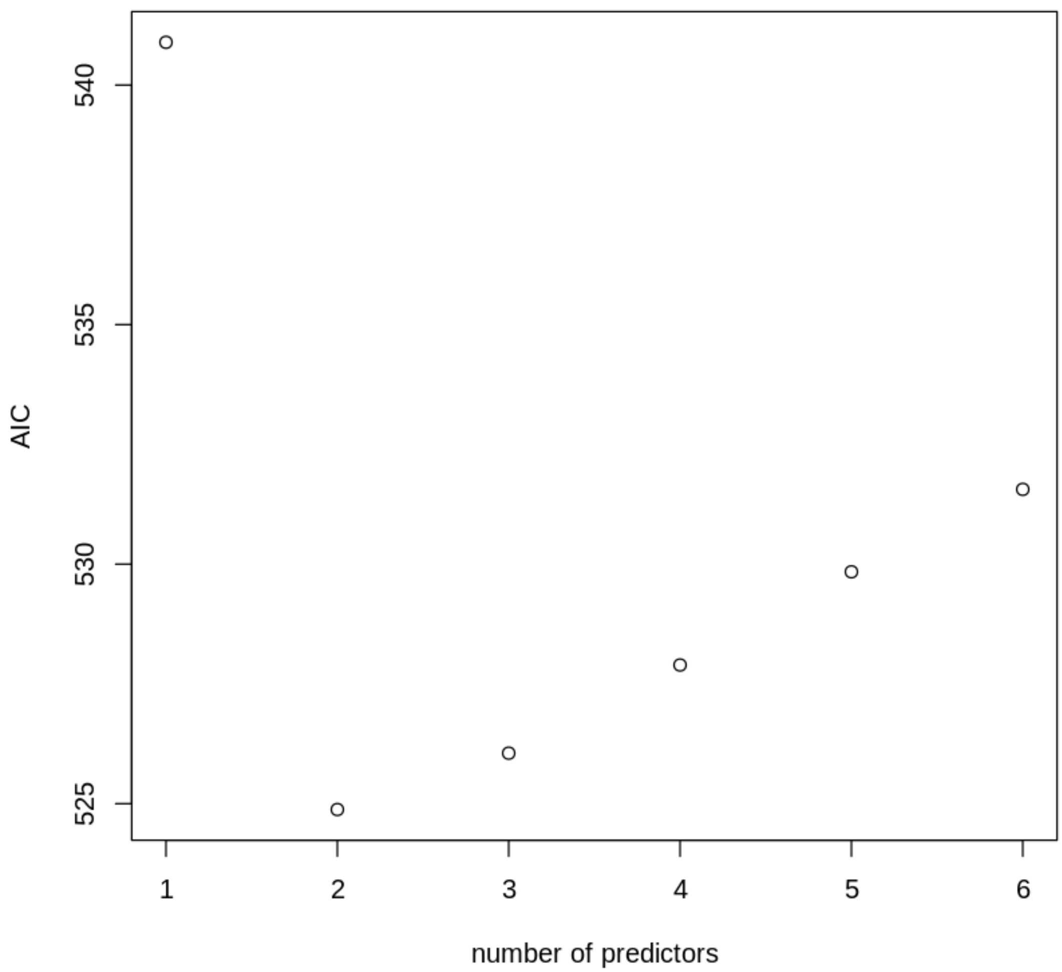
Hint: It may help to look at the attributes stored within the regsubsets summary using `names(rs)`.

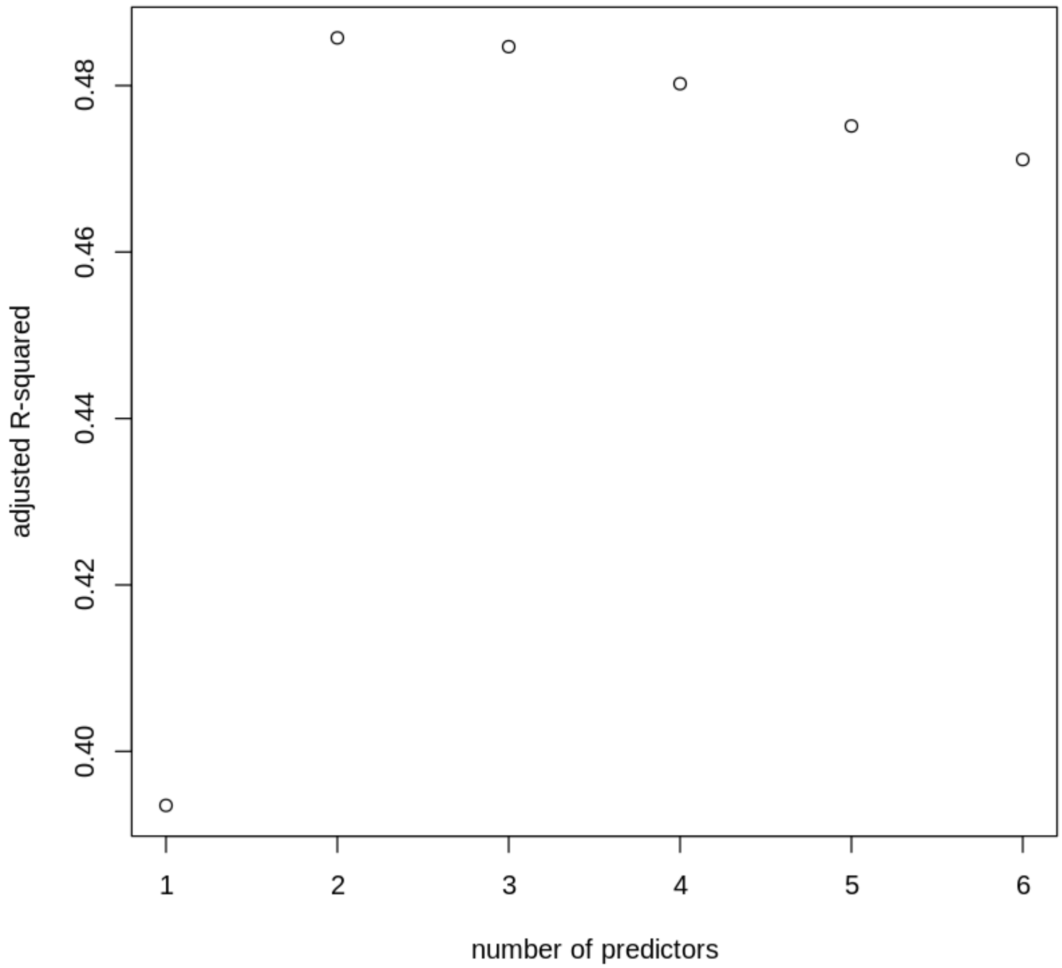
[8]:
```
reg = regsubsets(flow ~ cement+slag+ash+water+sp+course.agg+fine.agg+flow,␣
↪data=concrete.data, nvmax=6)
rs = summary(reg)
rs$which

# Your Code Here
n = dim(concrete.data)[1]

AIC = 2*(2:7) + n*log(rs$rss/n);
plot(AIC ~ I(1:6), xlab = "number of predictors", ylab = "AIC")

plot(1:6, rs$adjr2, xlab = "number of predictors", ylab = "adjusted R-squared")

BIC = log(n)*(2:7) + n*log(rs$rss/n)
plot(BIC ~ I(1:6), xlab = "number of predictors", ylab = "BIC")
```

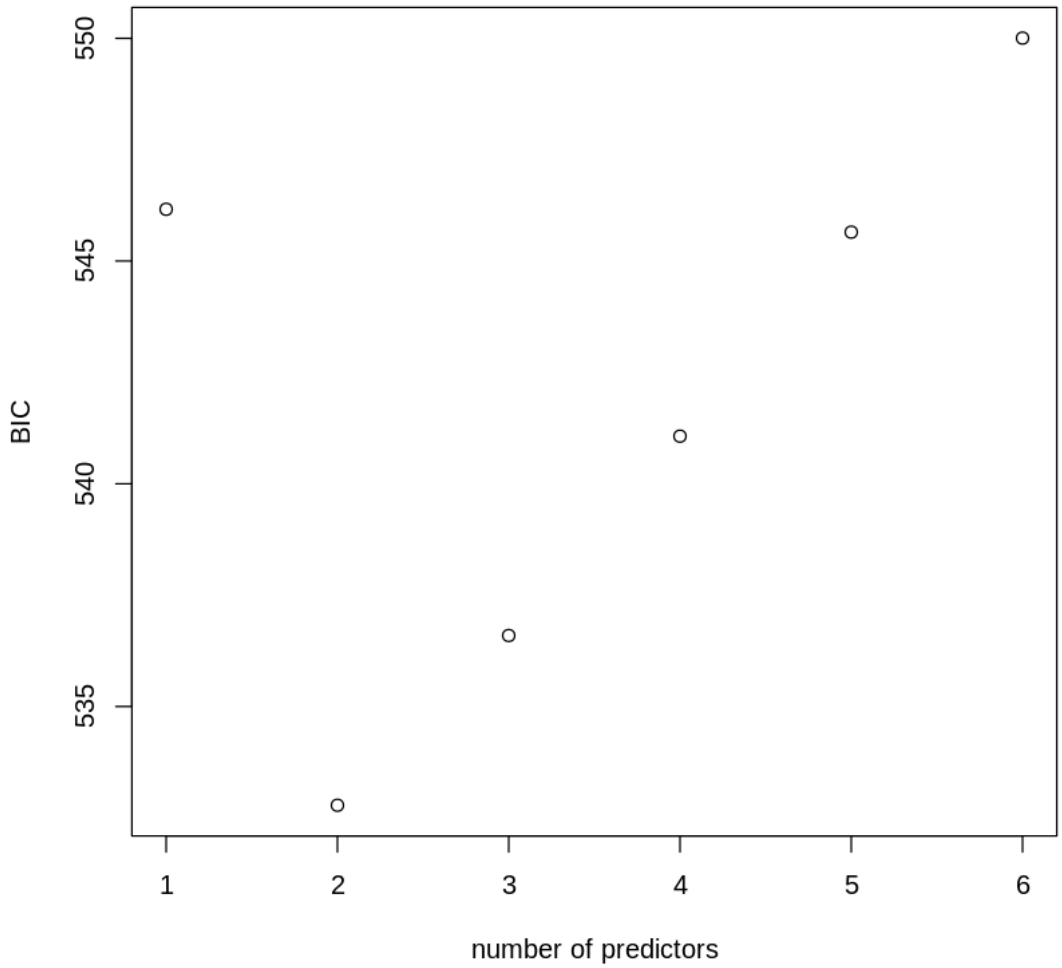
```
Warning message in model.matrix.default(terms(formula, data = data), mm):
"the response appeared on the right-hand side and was dropped"
Warning message in model.matrix.default(terms(formula, data = data), mm):
"problem with term 8 in model.matrix: no columns are assigned"
```

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




0.40
0.42
0.44
0.46
0.48
adjusted R-squared
1
2
3
4
5
6
number of predictors


550
545
540
535
BIC
1
2
3
4
5
6
number of predictors