Abdoulaye Niamou Data mining Homework4

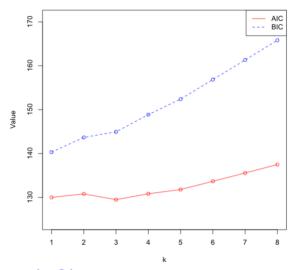
1.

AIC, BIC and Linear Regression

Selection Algorithm: exhaustive

		lcavol	lweight	age	lbph	svi	lcp	gleason	pgg45	lpsa
1	(1)		" "	"*"	" "	" "	" "		" "	" "
2	(1)	" "	" "	" "	" "	" "	" "	"*"	"*"	" "
3	(1)	" "	" "	"*"	" "	" "	" "	"*"	"*"	" "
4	(1)	" "	" "	"*"	" "	" "	"*"	"*"	"*"	" "
5	(1)	" "	" "	"*"	"*"	" "	"*"	"*"	"*"	" "
6	(1)	" "	"*"	"*"	"*"	" "	"*"	"*"	"*"	" "
7	(1)	" "	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "
8	(1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "

AIC & BIC



> aic_list

[1] 130.0186 130.7968 129.5066 130.8388 131.8057 133.6803 135.5732 137.4892 > bic_list

> errors_lm [1] 0.2059847 0.2034065 0.1966227 0.1952737 0.1932049 0.1929553 0.1927423 [8] 0.1925755

Selection Algorithm: exhaustive

```
lcavol lweight age lbph svi lcp gleason pgg45 lpsa
                       "*" " "
                                . . . . . . .
                                                      " "
  (1)
1
                                                "*"
  (1)""
2
 (1)
3
  (1)
4
                                                11 🕸 11
5
  (1)
                                                "*"
                                                      "*"
6
  (1)
  (1)""
                                                      "*"
7
               " "
                       "*" "*"
                                                "*"
  (1)"*"
```

> test_errors_5fold

[1] 0.1636624 0.1791347 0.1634921 0.1645180 0.1744424 0.1753804 0.1709710 [8] 0.1728674

Selection Algorithm: exhaustive

```
lcavol lweight age lbph svi lcp gleason pgg45 lpsa
                     "*" " "
                              . . . . . . .
                                                  . .
  (1)""
1
2 (1)""
3 (1)""
                                            "*"
4 (1)""
                                            "*"
5 (1)""
             " "
                                            "*"
 (1)""
                                            "*"
                                                  "*"
6
  (1)"*"
              " "
                                            "*"
                                                  "*"
7
8 (1) "*"
                                            *"
                                                  "*"
```

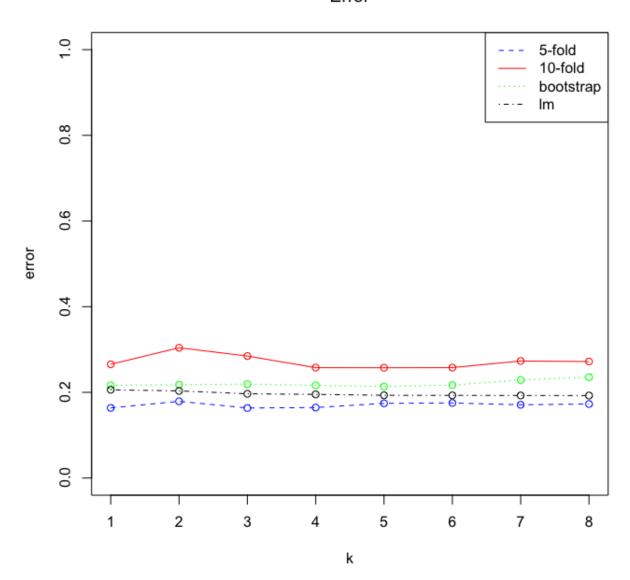
> test_errors_10fold

- [1] 0.2655908 0.3040962 0.2847995 0.2577092 0.2575082 0.2577841 0.2732500
- [8] 0.2719529

> errors_boot

[1] 0.2162353 0.2178410 0.2192147 0.2162492 0.2137146 0.2170170 0.2288264 [8] 0.2355435

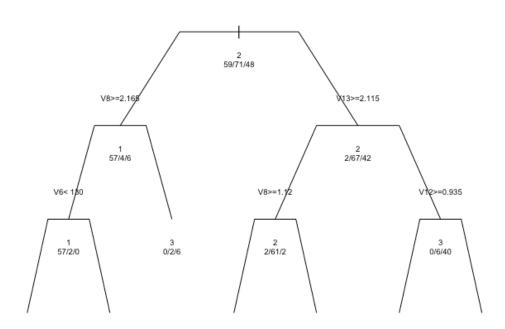




we can see that 5-fold across validations and linear model have lower errors and therefore perform better than the other two methods. For the 5-fold across validations, k = 3 performs best.

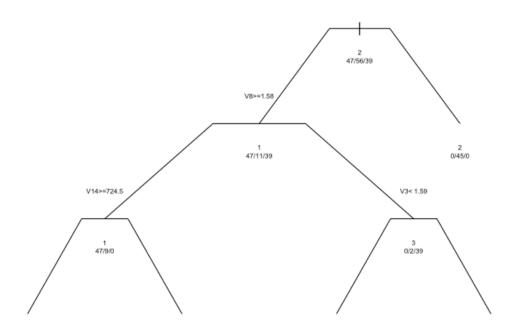
We have 57 cases of Class1 wine, 2 cases of Class2 wine and 0 case of Class3 wine were classified under the first node. 2 cases of Class2 wine and 6 cases of Class3 wine were classified under the second node. 2 cases of Class1 wine, 61 cases of Class2 wine

Tree for Full Dataset



and 2 case2 of Class3 wine were classified under the third node. 0 case of Class1 wine, 6 cases of Class2 wine and 40 cases of Class3 wine were classified under the forth node.

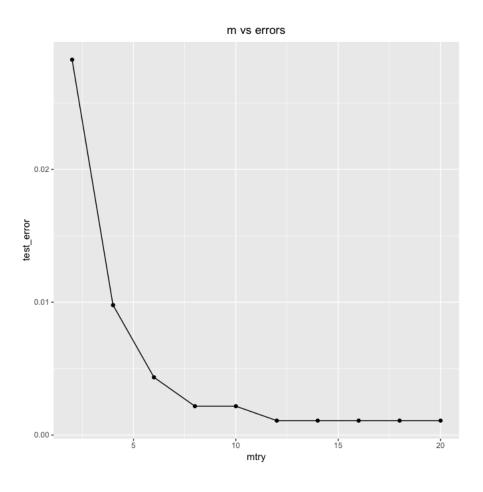
Pruned Tree



From the pruned tree we see that 47 case4 of Class1 wine, 9 cases of Class2 wine and 0 case of Class3 wine were classified under the first node; 0 case of Class1 wine, 2 cases of Class2 wine and 39 cases of Class3 wine were classified under the second node; 0 case of Class1 wine, 45 cases of Class2 wine and 0 case of Class3 wine were classified under the third node.

From those results we can see that the pruned tree performs well.

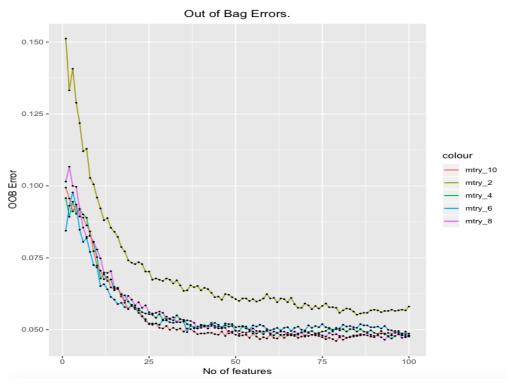
```
tree_pred
    1 2 3
1 12 0 0
2 0 14 1 > mean(tree_pred != wine_test_data$V1)
3 0 2 7 [1] 0.08333333
```



> cbind(m, TestErrors)

- m TestErrors
- [1,] 2 0.028260869565
- [2,] 4 0.009782608696
- [3,] 6 0.004347826087
- [4,] 8 0.002173913043
- [5,] 10 0.002173913043
- [6,] 12 0.001086956522
- [7,] 14 0.001086956522
- [8,] 16 0.001086956522
- [9,] 18 0.001086956522
- [10,] 20 0.001086956522

The following figure shows the relationship between m vs OBB errors. The OBB errors have the same trending with the test errors. The OBB errors will decrease with the increase of the number of features (m). And the error of $mtry_2$ (where m=2) is consistently more out of all the curves which approve this pattern again.



A random forest randomly selects observations and specific variables to build multiple decision trees, Then averages the results. After the of trees are built, each tree chooses the class, and the class chosen the most by simple majority is the or predicted class. It is random because we do not know the predicted class.