Statistical Methods for Bioinformatics $[I0U31a] \\ Assignment~05 - Chapter~7$

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7.9.10

```
(a)
```

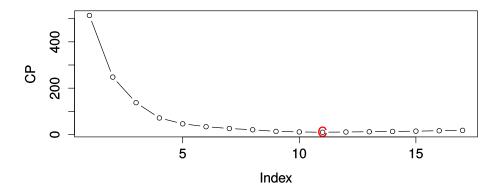


Figure 1: CP plot

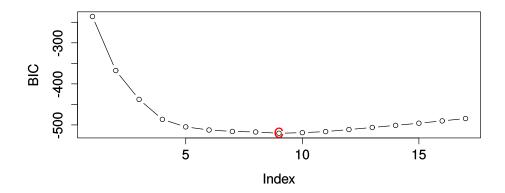


Figure 2: BIC plot

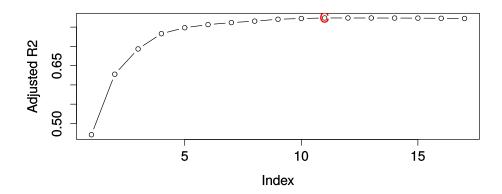
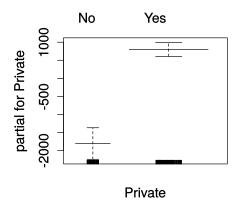


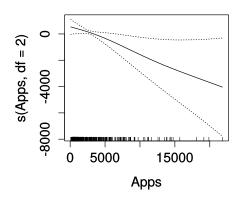
Figure 3: Adjusted \mathbb{R}^2

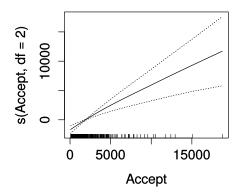
Minimum CP and also maximum adjusted \mathbb{R}^2 correspond to the model with 11 variables. But minimum BIC corresponds to the model with 9 variables. So we fit a model with this 11 variables:

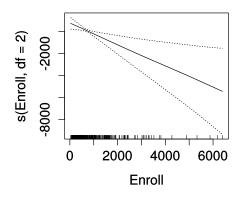
```
> coef(fwd.college, id = 11)
```

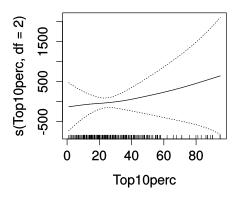
```
(Intercept)
                     PrivateYes
                                              Apps
                                                             Accept
       Enroll
-2266.1474174
                  2591.6010582
                                       -0.2576897
                                                         0.8452096
     -1.0789110
     Top10perc
                     {\bf Room\,.\,Board}
                                         Personal
                                                          Terminal
                                                                        perc.
         alumni
    17.3710739
                       0.7653948
                                       -0.3793180
                                                        27.0520396
        37.8893471
        Expend
                      \operatorname{Grad}.\operatorname{Rate}
     0.2642780
                     28.2822643
lm.\,\texttt{college} \, \longleftarrow \, lm(\,\texttt{Outstate}^{\, \sim} \,\, \texttt{Private} \,\, + \,\, \texttt{Apps} \,\, + \,\, \texttt{Accept} \,\, + \,\, \texttt{Enroll}
                     + Top10perc + Room.Board + Personal + Terminal
                     + perc.alumni + Expend + Grad.Rate,
                     data= College , subset = train )
yhat.lm <- predict(lm.college, newdata = College[-train,])</pre>
> min((yhat.lm - College[-train, "Outstate"])^2)
[1] 0.1008338
(b)
library (gam)
gam.college <- gam(Outstate Private + s(Apps, df=2) + s(Accept,
      \mathbf{df} = 2
                       + s(Enroll, df=2) + s(Top10perc, df=2)
                       + s(Room.Board, df=2) + s(Personal, df=2)
                       + s(Terminal, df=2) + s(perc.alumni, df=2)
                       + s(Expend, df=2) + s(Grad.Rate, df=2), data=
                             College, subset = train)
> plot(gam.college, se=TRUE)
```

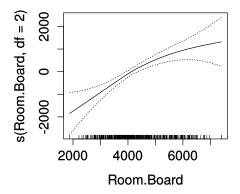


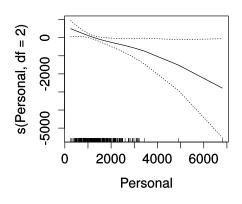


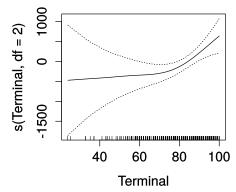


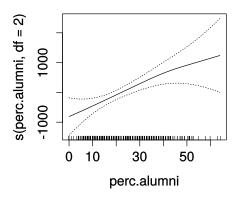


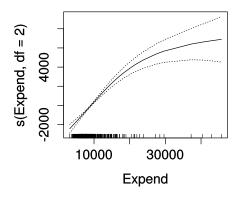


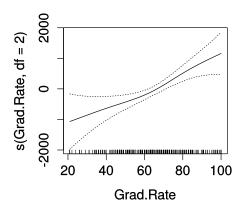












(c)

$[1] \ 1.739645\,\mathrm{e}{-05}$

Test error for the GAM fit is very small, which shows that it's a good fit.

Vervij Data

```
library(tree)
\#dummy \ coding : DM->1 , NODM->0
phenotype = ifelse(data$meta == "DM", 1, 0)
vijver \leftarrow cbind (phenotype, data[, -1])
vijver$phenotype <- as.factor(vijver$phenotype)</pre>
\#train/test
train <- sample(1:nrow(vijver), nrow(vijver)/2)
vijver.test <- vijver[-train, "phenotype"]</pre>
\#building\ a\ tree
vijver.tree <- tree(phenotype~., data = vijver[train,])</pre>
> summary(vijver.tree)
Classification tree:
\texttt{tree} \, ( \, \textbf{formula} \, = \, \texttt{phenotype} \, \, \tilde{} \, \, \, . \, \, , \, \, \, \textbf{data} \, = \, \texttt{vijver} \, [ \, \texttt{train} \, \, , \, \, \, ] \, )
Variables actually used in tree construction:
[1] "NM_003981"
                          "M27749"
                                               "NM_017443"
                                                                    "NM_{-}
    016109"
[5] "Contig42615_RC"
Number of terminal nodes: 6
Residual mean deviance: 0.1633 = 14.37 / 88
Misclassification error rate: 0.04255 = 4 / 94
tree.pred <- predict(vijver.tree, newdata = vijver[-train,],</pre>
    type = 'class')
> table(tree.pred, vijver.test)
           vijver.test
tree.pred 0 1
          0 \ 40 \ 23
          1 14 17
```

