Part3.

```
Code:
spam.dat<-read.table('spam.data.txt',sep=' ')</pre>
spam.dat$V58<-as.factor(spam.dat$V58)
#Part a
tree.model1<-tree(V58~.,data=spam.dat,mindev=0.0008)
cv.model <- cv.tree(tree.model1)
plot(cv.model)
size=110
size110tree<-prune.tree(tree.model1, best=size)
plot(size110tree)
plot(size110tree)
text(size110tree,cex=0.5)
summary(size110tree)
# Misclassification error rate: 0.03478 = 160 / 4600
#Part b
tree.model2<-tree(V58~.,data=spam.dat,mindev=0.005)
cv.model <- cv.tree(tree.model2)
plot(cv.model)
size=20
size20tree<-prune.tree(tree.model2, best=size)
plot(size20tree)
plot(size20tree)
text(size20tree,cex=0.5)
summary(size20tree)
# Misclassification error rate: 0.07826 = 360 / 4600
#Part c
tree.model3<-tree(V58~.,data=spam.dat,mindev=0.006)
cv.model <- cv.tree(tree.model3)
plot(cv.model)
best.size <- cv.model$size[which(cv.model$dev==min(cv.model$dev))]
best.size #[1] 18 17 16 15 14 13
bestsizetree <- prune.tree(tree.model3, best=best.size)</pre>
plot(bestsizetree)
text(bestsizetree,cex=0.8)
summary(bestsizetree)#number of terminal nodes is 13.
# Misclassification error rate: 0.08261 = 380 / 4600
Part 4.
Code:
library(boot)
spam.dat<-read.table('spam.data.txt',sep=' ')</pre>
spam.dat$V58<-as.factor(spam.dat$V58)</pre>
LR <- glm(V58~., family='binomial', data=spam.dat)
summary(LR)
cvLR<-cv.glm(spam.dat,LR,K=10)
#The cross validation error is:
cvLR[[3]]
#[1] 0.05848635 0.05832672
```

Result of Logistic Regression:

Deviance Residuals:

Min 1Q Median 3Q Max -4.127 -0.203 0.000 0.114 5.364

Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.569e+00 1.420e-01 -11.044 < 2e-16 ***
V1
        -3.895e-01 2.315e-01 -1.683 0.092388.
V2
        -1.458e-01 6.928e-02 -2.104 0.035362 *
V3
        1.141e-01 1.103e-01 1.035 0.300759
V4
        2.252e+00 1.507e+00 1.494 0.135168
V5
        5.624e-01 1.018e-01 5.524 3.31e-08 ***
V6
        8.830e-01 2.498e-01 3.534 0.000409 ***
V7
        2.279e+00 3.328e-01 6.846 7.57e-12 ***
V8
        5.696e-01 1.682e-01 3.387 0.000707 ***
V9
        7.343e-01 2.849e-01 2.577 0.009958 **
V10
         1.275e-01 7.262e-02 1.755 0.079230.
V11
        -2.557e-01 2.979e-01 -0.858 0.390655
V12
        -1.383e-01 7.405e-02 -1.868 0.061773.
V13
        -7.961e-02 2.303e-01 -0.346 0.729557
V14
         1.447e-01 1.364e-01 1.061 0.288855
V15
         1.236e+00 7.254e-01 1.704 0.088370.
         1.039e+00 1.457e-01 7.128 1.01e-12 ***
V16
V17
         9.599e-01 2.251e-01 4.264 2.01e-05 ***
V18
         1.203e-01 1.172e-01 1.027 0.304533
V19
         8.131e-02 3.505e-02 2.320 0.020334 *
         1.047e+00 5.383e-01 1.946 0.051675.
V20
         2.419e-01 5.243e-02 4.615 3.94e-06 ***
V21
V22
         2.013e-01 1.627e-01 1.238 0.215838
V23
         2.245e+00 4.714e-01 4.762 1.91e-06 ***
V24
         4.264e-01 1.621e-01 2.630 0.008535 **
V25
        -1.920e+00 3.128e-01 -6.139 8.31e-10 ***
V26
        -1.040e+00 4.396e-01 -2.366 0.017966 *
V27
        -1.177e+01 2.113e+00 -5.569 2.57e-08 ***
V28
         4.454e-01 1.991e-01 2.237 0.025255 *
V29
        -2.486e+00 1.502e+00 -1.656 0.097744.
V30
        -3.299e-01 3.137e-01 -1.052 0.292972
V31
        -1.702e-01 4.815e-01 -0.353 0.723742
V32
         2.549e+00 3.283e+00 0.776 0.437566
V33
        -7.383e-01 3.117e-01 -2.369 0.017842 *
V34
         6.679e-01 1.601e+00 0.417 0.676490
V35
        -2.055e+00 7.883e-01 -2.607 0.009124 **
         9.237e-01 3.091e-01 2.989 0.002803 **
V36
V37
         4.651e-02 1.754e-01 0.265 0.790819
V38
        -5.968e-01 4.232e-01 -1.410 0.158473
V39
        -8.650e-01 3.828e-01 -2.260 0.023844 *
V40
        -3.046e-01 3.636e-01 -0.838 0.402215
        -4.505e+01 2.660e+01 -1.694 0.090333.
V41
V42
        -2.689e+00 8.384e-01 -3.207 0.001342 **
V43
        -1.247e+00 8.064e-01 -1.547 0.121978
V44
        -1.573e+00 5.292e-01 -2.973 0.002953 **
V45
        -7.923e-01 1.556e-01 -5.091 3.56e-07 ***
```

```
V46
        -1.459e+00 2.686e-01 -5.434 5.52e-08 ***
V47
        -2.326e+00 1.659e+00 -1.402 0.160958
V48
        -4.016e+00 1.611e+00 -2.493 0.012672 *
        -1.291e+00 4.422e-01 -2.920 0.003503 **
V49
V50
        -1.881e-01 2.494e-01 -0.754 0.450663
V51
        -6.574e-01 8.383e-01 -0.784 0.432914
V52
         3.472e-01 8.926e-02 3.890 0.000100 ***
V53
         5.336e+00 7.064e-01 7.553 4.24e-14 ***
V54
         2.403e+00 1.113e+00 2.159 0.030883 *
V55
         1.199e-02 1.884e-02 0.636 0.524509
V56
         9.118e-03 2.521e-03 3.618 0.000297 ***
V57
         8.437e-04 2.251e-04 3.747 0.000179 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
```

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 6170.2 on 4600 degrees of freedom Residual deviance: 1815.8 on 4543 degrees of freedom

AIC: 1931.8

Number of Fisher Scoring iterations: 13

Part5.

Code:

library(glmnet)
spam.dat<-read.table('spam.data.txt',sep=' ')
y<-as.factor(spam.dat\$V58)
X<-model.matrix(~.,spam.dat[,1:57])
cv.myNewlogit <- cv.glmnet(X,y,alpha=1,nfolds=10,family='binomial')
plot(cv.myNewlogit,xvar="lambda")
cv.myNewlogit\$lambda.min #=0.0004034505