CW2_13128128_N_Katz.rmd

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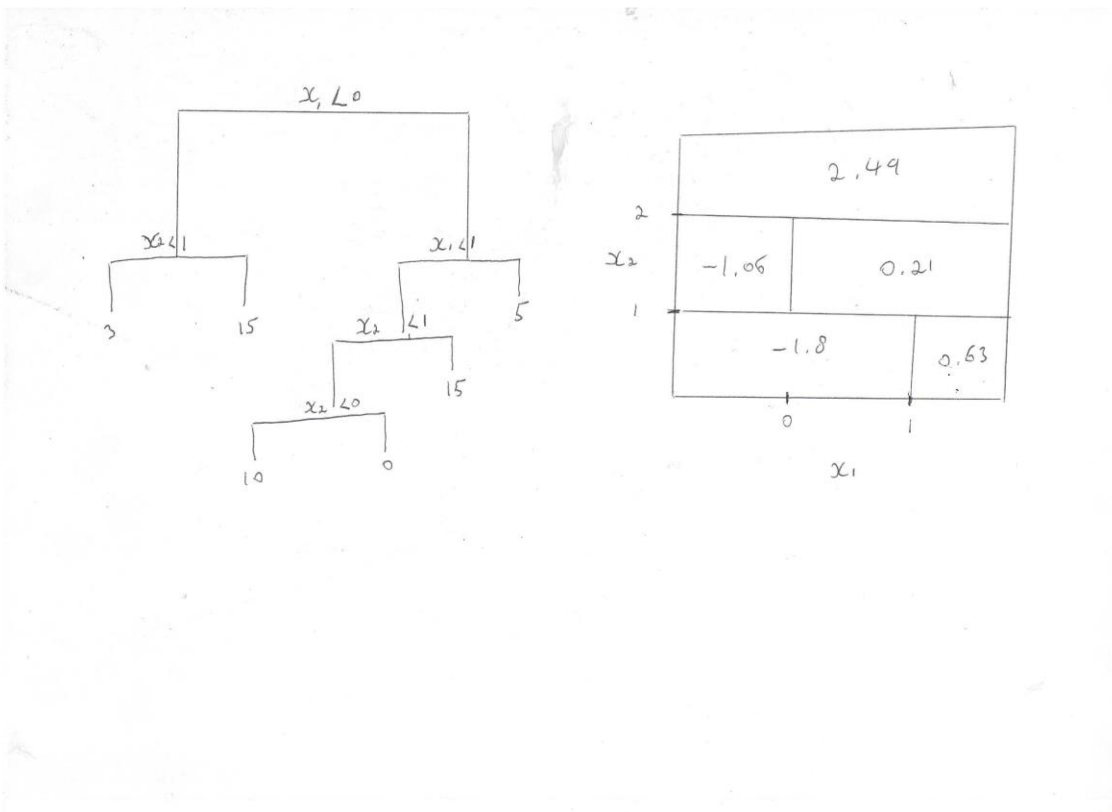
6 January 2019

1 Decision trees

```r
knitr::include_graphics('./treeScatch.jpg')
```



2. Regression Trees

a) and b)

```r
library(ISLR)
data(Carseats)
head(Carseats)
```

```
##   Sales CompPrice Income Advertising Population Price ShelveLoc Age
## 1  9.50       138     73          11        276   120       Bad  42
## 2 11.22       111     48          16        260    83      Good  65
## 3 10.06       113     35          10        269    80    Medium  59
## 4  7.40       117    100           4        466    97    Medium  55
## 5  4.15       141     64           3        340   128       Bad  38
## 6 10.81       124    113          13        501    72       Bad  78
```

```
##   Education Urban  US
## 1        17   Yes Yes
## 2        10   Yes Yes
## 3        12   Yes Yes
## 4        14   Yes Yes
## 5        13   Yes  No
## 6        16    No Yes
```

```
library(tree)
```

```
## Warning: package 'tree' was built under R version 3.5.2
```

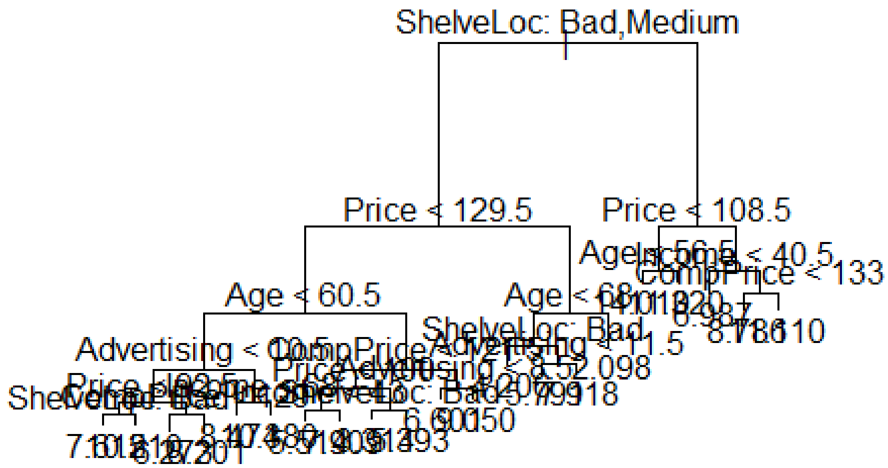
```
nrow(Carseats)
```

```
## [1] 400
```

```
set.seed(7)
carseat.train<-sample(1:nrow(Carseats),200)
carseat.test<-Carseats[-carseat.train,]

#creating tree
tree.carseat.train<- tree(Carseats$Sales ~ .,Carseats, subset=carseat.train)
View(Carseats)
summary(tree.carseat.train)
```

```
##
## Regression tree:
## tree(formula = Carseats$Sales ~ ., data = Carseats, subset =
carseat.train)
## Variables actually used in tree construction:
## [1] "ShelveLoc"   "Price"       "Age"         "Advertising" "CompPrice"
## [6] "Income"
## Number of terminal nodes:  21
## Residual mean deviance:  1.85 = 331.2 / 179
## Distribution of residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -3.67600 -0.85430 -0.06197  0.00000  0.87880  3.14400
```

```
plot(tree.carseat.train)
text(tree.carseat.train, pretty=0)
```




```
#calculating MSE for unpruned tree
carseat.yhat<-predict(tree.carseat.train, newdata = Carseats[-
carseat.train,])
carseat.test.trueSales<-Carseats[-carseat.train,"Sales"]
print(carseat.testMSE.sales.unpruned<-mean((carseat.yhat-
carseat.test.trueSales)^2))

## [1] 4.83821

sqrt(carseat.testMSE.sales.unpruned)

## [1] 2.199593

#* The price and the quality of the shelving location where the carseats are
sold
#(which I guess mean either how they're 'visually' presented to the customer,
#or the actual physical conditions under which they're kept/stored until
sale)
#- seem to be of biggest importance.
#* That if shelveLoc was good, advertising was not anymore a factor.
#* That the highest sales were made when shelveloc was good, the price was
more than a 100,
#community level was higher than 40.5K, but the competitors price was more
than 130

#21 terminal nodes. 6 predictors are used.
#The test MSE is  4.83821 and its square root  2.199593,
```

```
#which means that the model leads to a prediction which are within around
2.2K of the true sales of carseats at the 400 locations.




#c) calculating cv the check wether to prune
set.seed(8)
cv.tree.carseat.train<-cv.tree(tree.carseat.train)
cv.tree.carseat.train

## $size
##  [1] 21 20 19 18 17 16 15 14 12 11 10  8  7  6  5  4  3  2  1
##
## $dev
##  [1] 1029.463 1055.227 1048.794 1070.248 1075.000 1067.051 1074.142
##  [8] 1083.777 1115.698 1135.104 1115.885 1084.262 1068.703 1096.376
## [15] 1104.488 1086.615 1129.119 1236.911 1549.416
##
## $k
##  [1]      -Inf  16.69862  17.24085  18.00964  18.42218  19.12008  21.61897
##  [8]  22.49100  26.97919  32.27733  33.39821  37.74202  39.43387  60.02008
## [15]  61.36933  85.90284 106.87019 167.30725 352.05311
##
## $method
## [1] "deviance"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"

prune.carseat.tree.train<-prune.tree(tree.carseat.train, best=21)
summary(prune.carseat.tree.train)

##
## Regression tree:
## tree(formula = Carseats$Sales ~ ., data = Carseats, subset =
carseat.train)
## Variables actually used in tree construction:
## [1] "ShelveLoc"   "Price"       "Age"         "Advertising" "CompPrice"
## [6] "Income"
## Number of terminal nodes:  21
## Residual mean deviance:  1.85 = 331.2 / 179
## Distribution of residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -3.67600 -0.85430 -0.06197  0.00000  0.87880  3.14400

#calculating MSE for pruned tree
pruned.carseat.yhat<-predict(prune.carseat.tree.train, newdata = Carseats[-
carseat.train,])
```

```r
print(carseat.testMSE.sales.pruned<-mean((pruned.carseat.yhat-
carseat.test.trueSales)^2))

## [1] 4.83821

sqrt(carseat.testMSE.sales.pruned)

## [1] 2.199593

#Pruning the tree isn't needed as the tree is already split on 21 terminal
nodes, which according to the cv test produce the best MSE.

#d)
library(MASS)
library(randomForest)

## Warning: package 'randomForest' was built under R version 3.5.2

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

set.seed(1)
bag.sales.carseats<-randomForest(Sales~., data=Carseats, subset =
carseat.train, mtry=10,  importance=TRUE)
bag.sales.carseats

##
## Call:
##  randomForest(formula = Sales ~ ., data = Carseats, mtry = 10,
importance = TRUE, subset = carseat.train)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 10
##
##           Mean of squared residuals: 2.646289
##                     % Var explained: 65.47

#calculating MSE for bagging
yhat.carseat.bagged<-predict(bag.sales.carseats, newdata = Carseats[-
carseat.train,])
print(carseat.testMSE.sales.bagged<-mean((yhat.carseat.bagged-
carseat.test.trueSales)^2))

## [1] 2.646667

sqrt(carseat.testMSE.sales.bagged)

## [1] 1.626858

importance(bag.sales.carseats)
```

```
##                %IncMSE IncNodePurity
## CompPrice   27.4390584    164.077437
## Income      10.0957705     90.944867
## Advertising 18.2365333    151.700051
## Population   0.3942538     49.646314
## Price       50.0568235    410.931673
## ShelveLoc   53.2097815    410.482922
## Age         19.1148237    161.216522
## Education   -0.2807402     38.677414
## Urban       -0.4987723     12.265129
## US           3.2916492      5.267416

#We do get a better MSE as an sqrt(MSE) of 1.630 is better than 2.200. Also,
the Variance explained is 65.5
# * The Var is best best explained when all 10 variables are considered for
each split of the trees.
# * importance() confirms that shelveloc and price carry the most importance,
and they coincide for both, bagging and the following (random forest).

#d) calculate mse on mtry=10 floor 3
rf3.bag.sales.carseats<-randomForest(Sales~., data=Carseats, subset =
carseat.train, mtry=3,  importance=TRUE)
rf.yhat.carseat.bagged<-predict(rf3.bag.sales.carseats, newdata = Carseats[-
carseat.train,])
print(carseat.testMSE.sales.bagged<-mean((rf.yhat.carseat.bagged-
carseat.test.trueSales)^2))

## [1] 3.159781

sqrt(carseat.testMSE.sales.bagged)

## [1] 1.777577

importance(rf3.bag.sales.carseats)

##                %IncMSE IncNodePurity
## CompPrice   14.2544522     164.46739
## Income       5.7995929     119.38034
## Advertising 13.5730392     152.90169
## Population  -1.2232437      89.34527
## Price       32.9267632     326.59118
## ShelveLoc   36.2625605     311.00154
## Age         12.6141528     167.86985
## Education    0.5978316      64.94182
## Urban        1.8521890      16.38307
## US           5.0639390      27.17933

#calculate mse on mtry=10 ceiling-division 3
rf4.bag.sales.carseats<-randomForest(Sales~., data=Carseats, subset =
carseat.train, mtry=4,  importance=TRUE)
rf.yhat.carseat.bagged<-predict(rf4.bag.sales.carseats, newdata = Carseats[-
```

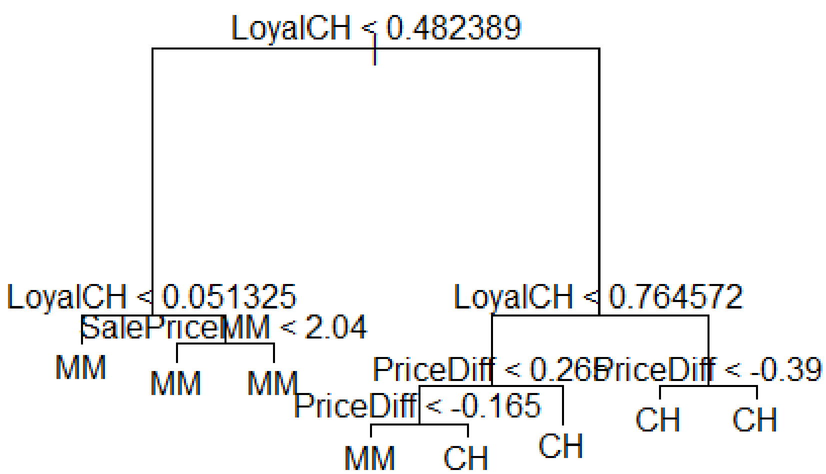
```
carseat.train,])
print(rf.carseat.testMSE.sales.bagged<-mean((rf.yhat.carseat.bagged-
carseat.test.trueSales)^2))

## [1] 2.913912

sqrt(rf.carseat.testMSE.sales.bagged)

## [1] 1.707018

importance(rf3.bag.sales.carseats)

##                %IncMSE IncNodePurity
## CompPrice   14.2544522     164.46739
## Income       5.7995929     119.38034
## Advertising 13.5730392     152.90169
## Population  -1.2232437      89.34527
## Price       32.9267632     326.59118
## ShelveLoc   36.2625605     311.00154
## Age         12.6141528     167.86985
## Education    0.5978316      64.94182
## Urban        1.8521890      16.38307
## US           5.0639390      27.17933

#This is not better than when all m is used, however using 4 is obviously
bettern than using 3.
```

3. Classification trees

```
#a)
library(ISLR)
library(tree)
data(OJ)
head(OJ)

##   Purchase WeekofPurchase StoreID PriceCH PriceMM DiscCH DiscMM SpecialCH
## 1       CH            237       1    1.75    1.99   0.00    0.0         0
## 2       CH            239       1    1.75    1.99   0.00    0.3         0
## 3       CH            245       1    1.86    2.09   0.17    0.0         0
## 4       MM            227       1    1.69    1.69   0.00    0.0         0
## 5       CH            228       7    1.69    1.69   0.00    0.0         0
## 6       CH            230       7    1.69    1.99   0.00    0.0         0
##   SpecialMM  LoyalCH SalePriceMM SalePriceCH PriceDiff Store7 PctDiscMM
## 1         0 0.500000        1.99        1.75      0.24     No  0.000000
## 2         1 0.600000        1.69        1.75     -0.06     No  0.150754
## 3         0 0.680000        2.09        1.69      0.40     No  0.000000
## 4         0 0.400000        1.69        1.69      0.00     No  0.000000
## 5         0 0.956535        1.69        1.69      0.00    Yes  0.000000
## 6         1 0.965228        1.99        1.69      0.30    Yes  0.000000
##   PctDiscCH ListPriceDiff STORE
## 1  0.000000          0.24     1
## 2  0.000000          0.24     1
```

```
## 3  0.091398          0.23     1
## 4  0.000000          0.00     1
## 5  0.000000          0.00     0
## 6  0.000000          0.30     0

purchase01= as.factor(OJ$Purchase)
OJ<-data.frame(OJ, purchase01)
nrow(OJ)

## [1] 1070

set.seed(7)
oj.train<-sample(1:nrow(OJ),800)
oj.test<-OJ[-oj.train,]
nrow(oj.train)

## NULL

purchase01.test<-OJ$purchase01[-oj.train]

#B)
tree.oj<-tree(purchase01 ~.- Purchase, OJ, subset=oj.train)
summary(tree.oj)

##
## Classification tree:
## tree(formula = purchase01 ~ . - Purchase, data = OJ, subset = oj.train)
## Variables actually used in tree construction:
## [1] "LoyalCH"     "SalePriceMM" "PriceDiff"
## Number of terminal nodes:  8
## Residual mean deviance:  0.7597 = 601.6 / 792
## Misclassification error rate: 0.1788 = 143 / 800

#The tree has 8 terminal nodes. The training error rate is 18%. The loyalty,
the price of the product and the diff in price
#between the two products are what's important.

#C) and d)
tree.oj

## node), split, n, deviance, yval, (yprob)
##       * denotes terminal node
##
##  1) root 800 1073.00 CH ( 0.60625 0.39375 )
##    2) LoyalCH < 0.482389 303  334.60 MM ( 0.24092 0.75908 )
##      4) LoyalCH < 0.051325 62   10.24 MM ( 0.01613 0.98387 ) *
##      5) LoyalCH > 0.051325 241  293.90 MM ( 0.29876 0.70124 )
##       10) SalePriceMM < 2.04 137  133.10 MM ( 0.18978 0.81022 ) *
##       11) SalePriceMM > 2.04 104  142.80 MM ( 0.44231 0.55769 ) *
##    3) LoyalCH > 0.482389 497  454.80 CH ( 0.82897 0.17103 )
##      6) LoyalCH < 0.764572 250  308.70 CH ( 0.69200 0.30800 )
```

```
##        12) PriceDiff < 0.265 157  215.30 CH ( 0.56051 0.43949 )
##          24) PriceDiff < -0.165 39   48.14 MM ( 0.30769 0.69231 ) *
##          25) PriceDiff > -0.165 118  153.60 CH ( 0.64407 0.35593 ) *
##        13) PriceDiff > 0.265 93   54.54 CH ( 0.91398 0.08602 ) *
##       7) LoyalCH > 0.764572 247   70.62 CH ( 0.96761 0.03239 )
##        14) PriceDiff < -0.39 8   10.59 CH ( 0.62500 0.37500 ) *
##        15) PriceDiff > -0.39 239   48.56 CH ( 0.97908 0.02092 ) *

plot(tree.oj)
text(tree.oj, pretty=0)
```




```
#If loyalty to CH is more than 48%,  then the only way people would go for mm
was if the the price difference is less than 17 cent (line no 24, upon
getting a detailed text output). Else, if their loyalty is less, they'd
always go for mm, no matter the difference in price.
# So as an example, interperting line 24, when typing the name of the tree to
get detailed text output: For a loyalty score of less than 48%, if price of
MM less of CH is less than 16.5 cent, based on 39 observations (with a
smallest sum of squares for this node summed as 48.14 - though this has no
meaning here since this is a classification and not regression tree), an 'MM
purchase' is the overall prediction for this branch with a probebility of 69%
.

#e)
tree.pred.oj.test<-predict(tree.oj, oj.test, type ="class")
table(tree.pred.oj.test, purchase01.test)
```

```
##                    purchase01.test
## tree.pred.oj.test  CH  MM
##                 CH 147  18
##                 MM  21  84
```

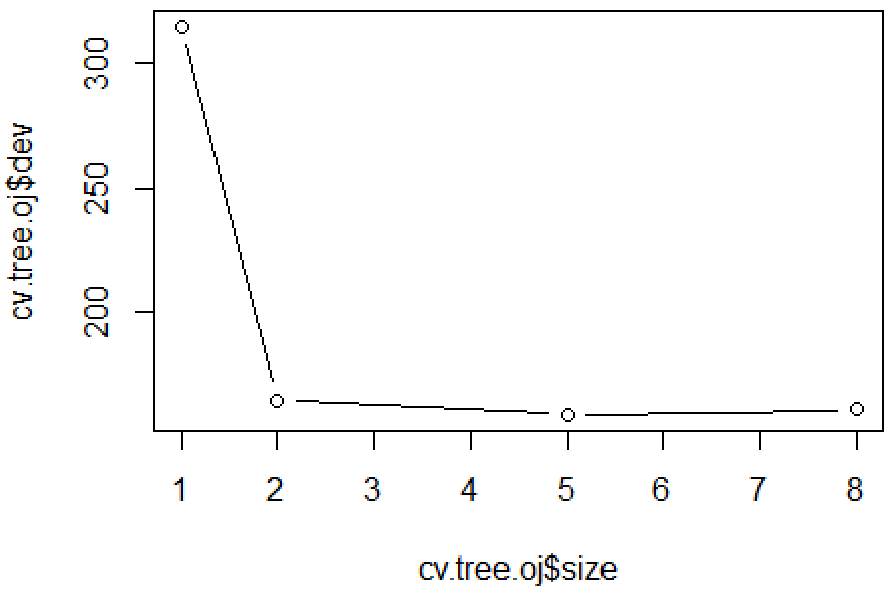
```r
print((18+21)/270)
```

```
## [1] 0.1444444
```

```r
# Test error rate is 14%, bettern than before

#f), g), h) and i)
set.seed(3)
cv.tree.oj<- cv.tree(tree.oj, FUN=prune.misclass)
cv.tree.oj
```

```
## $size
## [1] 8 5 2 1
##
## $dev
## [1] 161 159 165 315
##
## $k
## [1] -Inf    0    5  157
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```r
plot(cv.tree.oj$size,cv.tree.oj$dev,type='b')
```




```
prune.tree.oj <- prune.misclass(tree.oj,best=5)
prune.tree.pred.oj.test<-predict(prune.tree.oj, oj.test, type ="class")
table(prune.tree.pred.oj.test, purchase01.test)

##                          purchase01.test
## prune.tree.pred.oj.test  CH  MM
##                       CH 147  18
##                       MM  21  84

#cv shows that prunning the tree with 5 is best but when pruned, the error
rates aren't actually make any difference

#j) and k)
summary(prune.tree.oj)

##
## Classification tree:
## snip.tree(tree = tree.oj, nodes = c(2L, 7L))
## Variables actually used in tree construction:
## [1] "LoyalCH"   "PriceDiff"
## Number of terminal nodes:  5
## Residual mean deviance:  0.8321 = 661.5 / 795
## Misclassification error rate: 0.1788 = 143 / 800

# the  training error for both are the same and the test error for both are
the same
```

4 SVM

```r
#a)

library(e1071)

## Warning: package 'e1071' was built under R version 3.5.2

library(ISLR)
data(Auto)
median(Auto$mpg)

## [1] 22.75

milAbvMedn<-c(ifelse(Auto$mpg<median(Auto$mpg),0,1))
auto.dat<-data.frame(x=Auto,  y= as.factor(milAbvMedn))

#b)
#Cost=1
svmfit.linear.higmil.c1 <- svm(y ~ ., data=auto.dat, kernel="linear",
cost=1)
svmfit.linear.higmil.c1

##
## Call:
## svm(formula = y ~ ., data = auto.dat, kernel = "linear", cost = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##       gamma:  0.003205128
##
## Number of Support Vectors:  56

summary(svmfit.linear.higmil.c1)

##
## Call:
## svm(formula = y ~ ., data = auto.dat, kernel = "linear", cost = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##       gamma:  0.003205128
##
## Number of Support Vectors:  56
##
```

```
##  ( 26 30 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

```r
#There are 56 support vectotrs; 26 from side y=0 and 30 from side y=1.

#Cost=0.01
svmfit.linear.higmil.c001 <- svm(y ~ ., data=auto.dat, kernel="linear",
cost=0.01)
svmfit.linear.higmil.c001
```

```
##
## Call:
## svm(formula = y ~ ., data = auto.dat, kernel = "linear", cost = 0.01)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.01
##       gamma:  0.003205128
##
## Number of Support Vectors:  150
```

```r
summary(svmfit.linear.higmil.c001)
```

```
##
## Call:
## svm(formula = y ~ ., data = auto.dat, kernel = "linear", cost = 0.01)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.01
##       gamma:  0.003205128
##
## Number of Support Vectors:  150
##
##  ( 74 76 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

```r
#There are 150 support vectotrs; 74 from side y=0 and 76 from side y=1, as
smaller cost
#means many more support vectors involved in determining the margins (or
hyperplanein this case).

#Cost=100,000
svmfit.linear.higmil.c100000 <- svm(y ~ ., data=auto.dat, kernel="linear",
cost=1e5)
svmfit.linear.higmil.c100000

##
## Call:
## svm(formula = y ~ ., data = auto.dat, kernel = "linear", cost = 1e+05)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1e+05
##       gamma:  0.003205128
##
## Number of Support Vectors:  35

summary(svmfit.linear.higmil.c100000)

##
## Call:
## svm(formula = y ~ ., data = auto.dat, kernel = "linear", cost = 1e+05)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1e+05
##       gamma:  0.003205128
##
## Number of Support Vectors:  35
##
##  ( 21 14 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1

#There are 35 support vectotrs; 21 from side y=0 and 14 from side y=1.

#Perform cross validation on different values of cost
set.seed(9)
tune.out.lin<-tune(svm, y ~., data = auto.dat, kernel="linear", ranges =
```

```r
list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100, 1000, 10000, 1e5)))
summary(tune.out.lin)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost
##     1
##
## - best performance: 0.01282051
##
## - Detailed performance results:
##     cost      error dispersion
## 1  1e-03 0.09217949 0.05450084
## 2  1e-02 0.07679487 0.04850079
## 3  1e-01 0.05121795 0.03203768
## 4  1e+00 0.01282051 0.02179068
## 5  5e+00 0.02044872 0.02354784
## 6  1e+01 0.02301282 0.02244393
## 7  1e+02 0.03326923 0.03211170
## 8  1e+03 0.03326923 0.03211170
## 9  1e+04 0.03326923 0.03211170
## 10 1e+05 0.03326923 0.03211170
```

```r
summary(tune.out.lin$best.model)
```

```
##
## Call:
## best.tune(method = svm, train.x = y ~ ., data = auto.dat, ranges =
list(cost = c(0.001,
##     0.01, 0.1, 1, 5, 10, 100, 1000, 10000, 1e+05)), kernel = "linear")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##       gamma:  0.003205128
##
## Number of Support Vectors:  56
##
##  ( 26 30 )
##
##
## Number of Classes:  2
##
```

```
## Levels:
##  0 1

#Best performence of the cv is a training error of 0.01282051  which is when
cost = to 10^0 which is =1.
#i.e. the best balance between having a high cost, narrow margins/fewer
violations but high overfitting
#and therefor high variance vs lower cost, wide margins/more violations and
more bias but a better generlized model
#with less variance each time it is applied.


#c)
set.seed(8)
tune.out.poly<-tune(svm, y ~., data = auto.dat, kernel="polynomial", ranges =
list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100, 1000, 10000, 1e5)),gamma =
c(0.5,1,2,3,4), degree=c(0,1,2,3,4,5))
summary(tune.out.poly)

##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##  0.001
##
## - best performance: 0.5305769
##
## - Detailed performance results:
##     cost     error dispersion
## 1  1e-03 0.5305769 0.02184519
## 2  1e-02 0.5305769 0.02184519
## 3  1e-01 0.5305769 0.02184519
## 4  1e+00 0.5305769 0.02184519
## 5  5e+00 0.5305769 0.02184519
## 6  1e+01 0.5305769 0.02184519
## 7  1e+02 0.5305769 0.02184519
## 8  1e+03 0.5305769 0.02184519
## 9  1e+04 0.5305769 0.02184519
## 10 1e+05 0.5305769 0.02184519

summary(tune.out.poly$best.model)

##
## Call:
## best.tune(method = svm, train.x = y ~ ., data = auto.dat, ranges =
list(cost = c(0.001,
##     0.01, 0.1, 1, 5, 10, 100, 1000, 10000, 1e+05)), kernel = "polynomial",
##     gamma = c(0.5, 1, 2, 3, 4), degree = c(0, 1, 2, 3, 4, 5))
```

```
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  polynomial
##        cost:  0.001
##      degree:  0 1 2 3 4 5
##       gamma:  0.5 1 2 3 4
##      coef.0:  0
##
## Number of Support Vectors:  392
##
##  ( 196 196 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

```
#Not good at all as  training error of 0.5305769  no matter which cost so
clearly not good model.



set.seed(7)
tune.out.radial <- tune(svm,y ~ .,data = auto.dat,  kernel = "radial", ranges
= list(cost = c(0.1,1,10,100,1000), gamma = c(0.5,1,2,3,4)))
summary(tune.out.radial)
```

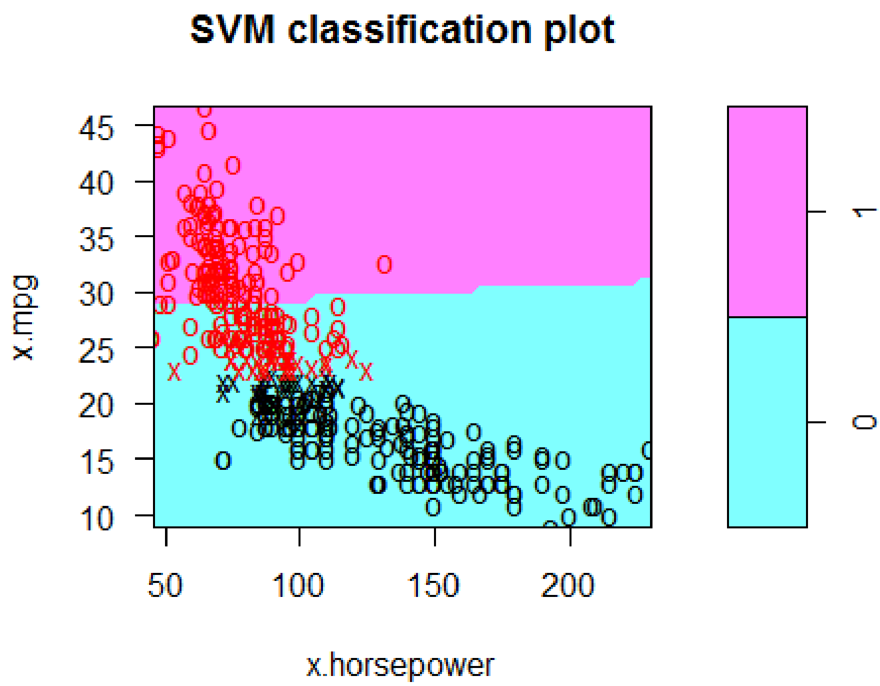
```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost gamma
##    10   0.5
##
## - best performance: 0.04057692
##
## - Detailed performance results:
##     cost gamma      error dispersion
## 1  1e-01   0.5 0.08391026 0.04247619
## 2  1e+00   0.5 0.04307692 0.04917112
## 3  1e+01   0.5 0.04057692 0.05249461
## 4  1e+02   0.5 0.04057692 0.05249461
## 5  1e+03   0.5 0.04057692 0.05249461
## 6  1e-01   1.0 0.56647436 0.06705049
## 7  1e+00   1.0 0.06352564 0.04649727
```

```
## 8  1e+01   1.0 0.05333333 0.05132281
## 9  1e+02   1.0 0.05333333 0.05132281
## 10 1e+03   1.0 0.05333333 0.05132281
## 11 1e-01   2.0 0.56647436 0.06705049
## 12 1e+00   2.0 0.12756410 0.09126708
## 13 1e+01   2.0 0.11730769 0.08118533
## 14 1e+02   2.0 0.11730769 0.08118533
## 15 1e+03   2.0 0.11730769 0.08118533
## 16 1e-01   3.0 0.56647436 0.06705049
## 17 1e+00   3.0 0.41051282 0.16471773
## 18 1e+01   3.0 0.39256410 0.16697298
## 19 1e+02   3.0 0.39256410 0.16697298
## 20 1e+03   3.0 0.39256410 0.16697298
## 21 1e-01   4.0 0.56647436 0.06705049
## 22 1e+00   4.0 0.49487179 0.09105724
## 23 1e+01   4.0 0.47948718 0.10995495
## 24 1e+02   4.0 0.47948718 0.10995495
## 25 1e+03   4.0 0.47948718 0.10995495
```

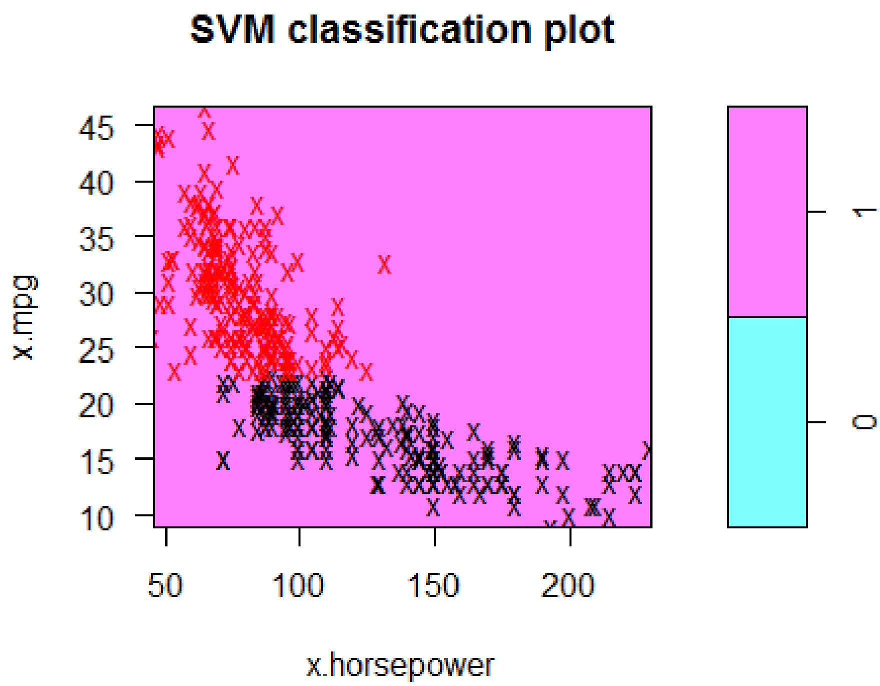
```
summary(tune.out.radial$best.model)
```

```
##
## Call:
## best.tune(method = svm, train.x = y ~ ., data = auto.dat, ranges =
list(cost = c(0.1,
##     1, 10, 100, 1000), gamma = c(0.5, 1, 2, 3, 4)), kernel = "radial")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  10
##       gamma:  0.5
##
## Number of Support Vectors:  259
##
##  ( 127 132 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

```
#Also not as good as linear as error is training error is still bigger,
0.04057692, cost=10 and gamma=0.5.


#d)
plot(tune.out.lin$best.model, auto.dat, x.mpg~x.horsepower)
```



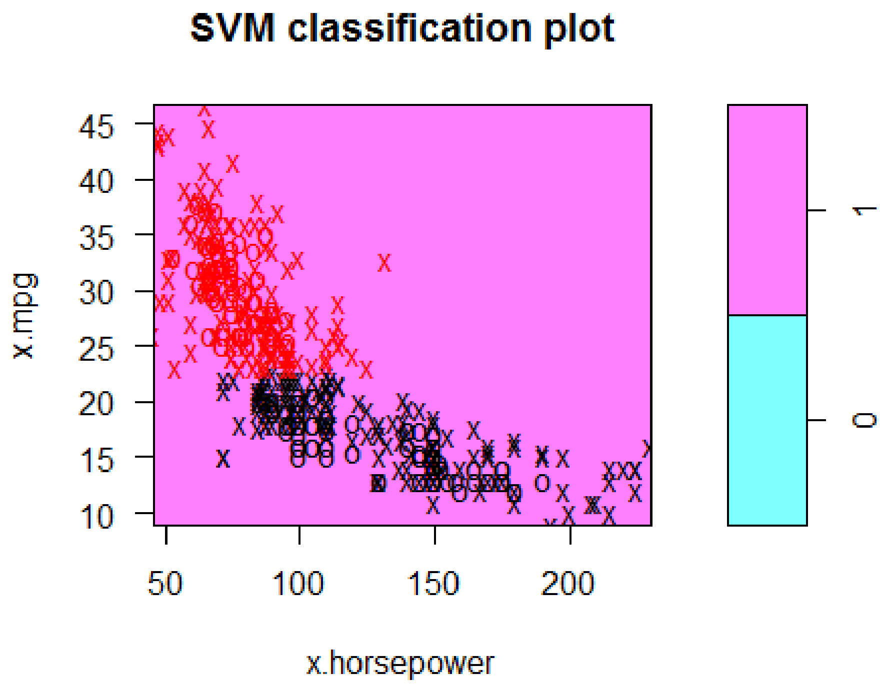

```
tune.out.lin$best.model$index

##  [1]  16  18  46  61  77  78  80 109 110 112 119 178 190 191 193 208 240
## [18] 241 242 258 269 275 279 281 359 384  15  22  49  57  59  82 101 118
## [35] 122 131 146 148 167 169 170 172 176 177 192 233 270 271 272 297 299
## [52] 314 332 338 358 369

plot(tune.out.poly$best.model, auto.dat, x.mpg~x.horsepower)
```




```
tune.out.poly$best.model$index
```

```
##   [1]   1   2   3   4   5   6   7   8   9  10  11  12  13  14  16  17  18
##  [18]  25  26  27  28  29  33  34  35  36  37  38  39  40  41  42  43  44
##  [35]  45  46  47  48  60  61  62  63  64  65  66  67  68  69  70  71  72
##  [52]  73  74  75  76  77  78  80  85  86  87  88  89  90  91  92  93  94
##  [69]  95  96  97  98  99 100 103 104 105 106 107 108 109 110 111 112 113
##  [86] 115 116 119 120 121 123 124 125 126 127 132 133 134 135 136 137 138
## [103] 139 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 168
## [120] 173 175 178 186 187 188 189 190 191 193 198 199 200 201 206 207 208
## [137] 209 210 211 212 213 214 220 221 222 223 224 225 226 227 228 229 230
## [154] 231 240 241 242 248 249 250 251 252 253 255 256 257 258 259 260 261
## [171] 262 263 264 269 273 274 275 276 279 280 281 282 283 284 285 286 287
## [188] 288 289 290 291 315 359 361 362 384  15  19  20  21  22  23  24  30
## [205]  31  32  49  50  51  52  53  54  55  56  57  58  59  79  81  82  83
## [222]  84 101 102 114 117 118 122 128 129 130 131 140 141 142 143 144 145
## [239] 146 147 148 149 150 166 167 169 170 171 172 174 176 177 179 180 181
## [256] 182 183 184 185 192 194 195 196 197 202 203 204 205 215 216 217 218
## [273] 219 232 233 234 235 236 237 238 239 243 244 245 246 247 254 265 266
## [290] 267 268 270 271 272 277 278 292 293 294 295 296 297 298 299 300 301
## [307] 302 303 304 305 306 307 308 309 310 311 312 313 314 316 317 318 319
## [324] 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336
## [341] 337 338 339 340 341 342 343 344 345 346 347 348 349 350 351 352 353
## [358] 354 355 356 357 358 360 363 364 365 366 367 368 369 370 371 372 373
## [375] 374 375 376 377 378 379 380 381 382 383 385 386 387 388 389 390 391
## [392] 392
```

```r
plot(tune.out.radial$best.model, auto.dat, x.mpg~x.horsepower)
```




```r
tune.out.radial$best.model$index

##   [1]   1   2   3   4   5   6   7   8   9  10  11  12  13  14  16  18  25
##  [18]  26  27  28  29  33  36  40  41  42  43  44  45  46  48  61  67  71
##  [35]  73  74  76  77  78  80  88  90  91  94  95 100 103 104 108 109 110
##  [52] 111 112 113 116 119 120 121 123 124 125 136 138 139 153 154 155 157
##  [69] 158 159 163 164 165 168 173 178 190 191 193 199 206 208 209 210 211
##  [86] 212 221 223 228 229 230 231 240 241 242 248 249 250 251 252 253 258
## [103] 261 262 263 269 273 274 275 276 279 280 281 282 284 285 286 287 288
## [120] 289 290 291 315 359 361 362 384  15  19  20  21  22  23  24  31  49
## [137]  51  53  54  55  56  57  58  59  79  81  82  83  84 101 102 117 118
## [154] 122 128 130 131 143 146 147 148 149 167 169 170 172 176 177 179 180
## [171] 183 192 194 195 202 217 233 234 243 244 245 246 254 267 270 271 272
## [188] 294 296 297 298 299 300 302 305 306 307 308 309 313 314 317 319 321
## [205] 322 323 324 325 326 327 328 330 331 332 336 337 338 339 340 341 342
## [222] 344 347 348 349 353 354 355 356 357 358 360 363 364 365 368 369 370
## [239] 371 372 373 374 375 376 377 378 379 380 381 382 383 385 386 387 388
## [256] 389 390 391 392
```

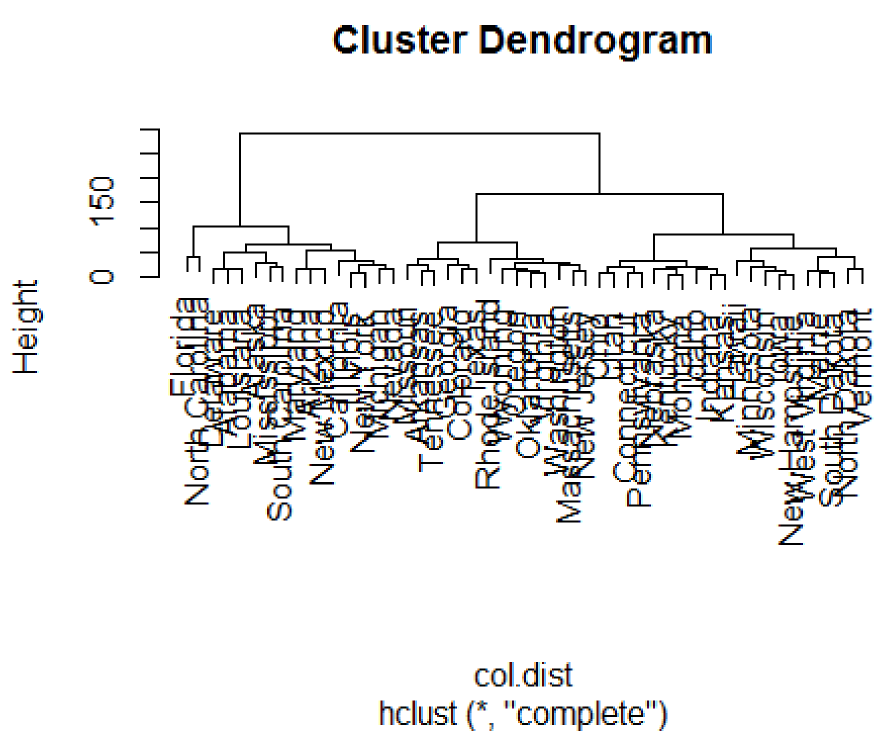
6. Hierarchical clustering

```r
data("USArrests")
#a) Calculate distance of each vector to each, using uclidean method, and
cluster the the States
col.dist<-dist(USArrests)
clustrd.states<-hclust(col.dist,method="complete")
```

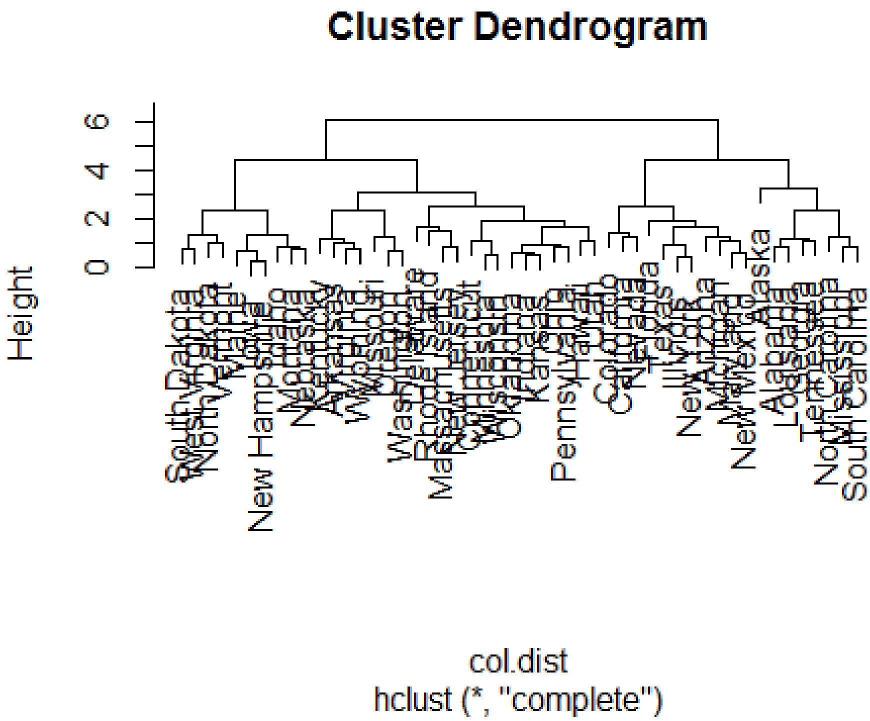
```r
#b)
cutree(clustrd.states,3)
```

```
##        Alabama         Alaska        Arizona       Arkansas     California 
##              1              1              1              2              1 
##       Colorado    Connecticut       Delaware        Florida        Georgia 
##              2              3              1              1              2 
##         Hawaii          Idaho       Illinois        Indiana           Iowa 
##              3              3              1              3              3 
##         Kansas       Kentucky      Louisiana          Maine       Maryland 
##              3              3              1              3              1 
##  Massachusetts       Michigan      Minnesota    Mississippi       Missouri 
##              2              1              3              1              2 
##        Montana       Nebraska         Nevada  New Hampshire     New Jersey 
##              3              3              1              3              2 
##     New Mexico       New York North Carolina   North Dakota           Ohio 
##              1              1              1              3              3 
##       Oklahoma         Oregon   Pennsylvania   Rhode Island South Carolina 
##              2              2              3              2              1 
##   South Dakota      Tennessee          Texas           Utah        Vermont 
##              3              2              2              3              3 
##       Virginia     Washington  West Virginia      Wisconsin        Wyoming 
##              2              2              3              3              2
```

```r
plot(clustrd.states)
```



```r
#Executing cutree() gives us a list of the states with the cluster number
associated to them

#c)
#?scale
#scale(USArrests, center = TRUE, scale = TRUE)
col.dist<-dist(scale(USArrests, center = TRUE, scale = TRUE))
clustrd.states.scaled<-hclust(col.dist,method="complete")
cutree(clustrd.states.scaled,3)

##        Alabama         Alaska        Arizona       Arkansas     California
##              1              1              2              3              2
##       Colorado    Connecticut       Delaware        Florida        Georgia
##              2              3              3              2              1
##         Hawaii          Idaho       Illinois        Indiana           Iowa
##              3              3              2              3              3
##         Kansas       Kentucky      Louisiana          Maine       Maryland
##              3              3              1              3              2
##  Massachusetts       Michigan      Minnesota    Mississippi       Missouri
##              3              2              3              1              3
##        Montana       Nebraska         Nevada  New Hampshire     New Jersey
##              3              3              2              3              3
##     New Mexico       New York North Carolina   North Dakota           Ohio
##              2              2              1              3              3
##       Oklahoma         Oregon   Pennsylvania   Rhode Island South Carolina
##              3              3              3              3              1
##   South Dakota      Tennessee          Texas           Utah        Vermont
##              3              1              2              3              3
##       Virginia     Washington  West Virginia      Wisconsin        Wyoming
##              3              3              3              3              3

plot(clustrd.states.scaled)
```




```
#d) It divides the data into 4 to 5 clusters. My opinion is they should be scaled
#as looking at the data, UrbanPop values are on a larger scaling than Rape and Murder respectively and the values in Assult are even larger.
```