Chapter 2: Statistical Learning

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```
# Libraries
library(MASS)
library(ISLR)
```

```
# Basic Commands

x <- c(1,3,2,5)
x
```

```
## [1] 1 3 2 5
```

```
x = c(1,6,2)
x
```

```
## [1] 1 6 2
```

```
y = c(1,4,3)
length(x)
```

```
## [1] 3
```

```
length(y)
```

```
## [1] 3
```

```
x+y
```

```
## [1]  2 10  5
```

```
ls()
```

```
## [1] "x" "y"
```

```
rm(x,y)
ls()
```

```
## character(0)
```

```
rm(list=ls())
?matrix
```

```
## starting httpd help server ... done
```

```
x=matrix(data=c(1,2,3,4), nrow=2, ncol=2)
x
```

```
##      [,1] [,2]
## [1,]    1    3
## [2,]    2    4
```

```
x=matrix(c(1,2,3,4),2,2)
matrix(c(1,2,3,4),2,2,byrow=TRUE)
```

```
##      [,1] [,2]
## [1,]    1    2
```

```
## [2,]    3    4
```

```r
sqrt(x)
```

```
##          [,1]     [,2]
## [1,] 1.000000 1.732051
## [2,] 1.414214 2.000000
```

```r
x^2
```

```
##      [,1] [,2]
## [1,]    1    9
## [2,]    4   16
```

```r
x=rnorm(50)
y=x+rnorm(50,mean=50,sd=.1)
cor(x,y)
```

```
## [1] 0.9939653
```

```r
set.seed(1303)
rnorm(50)
```

```
##  [1] -1.1439763145  1.3421293656  2.1853904757  0.5363925179  0.0631929665
##  [6]  0.5022344825 -0.0004167247  0.5658198405 -0.5725226890 -1.1102250073
## [11] -0.0486871234 -0.6956562176  0.8289174803  0.2066528551 -0.2356745091
## [16] -0.5563104914 -0.3647543571  0.8623550343 -0.6307715354  0.3136021252
## [21] -0.9314953177  0.8238676185  0.5233707021  0.7069214120  0.4202043256
## [26] -0.2690521547 -1.5103172999 -0.6902124766 -0.1434719524 -1.0135274099
## [31]  1.5732737361  0.0127465055  0.8726470499  0.4220661905 -0.0188157917
## [36]  2.6157489689 -0.6931401748 -0.2663217810 -0.7206364412  1.3677342065
## [41]  0.2640073322  0.6321868074 -1.3306509858  0.0268888182  1.0406363208
## [46]  1.3120237985 -0.0300020767 -0.2500257125  0.0234144857  1.6598706557
```

```r
set.seed(3)
y=rnorm(100)
mean(y)
```

```
## [1] 0.01103557
```

```r
var(y)
```

```
## [1] 0.7328675
```

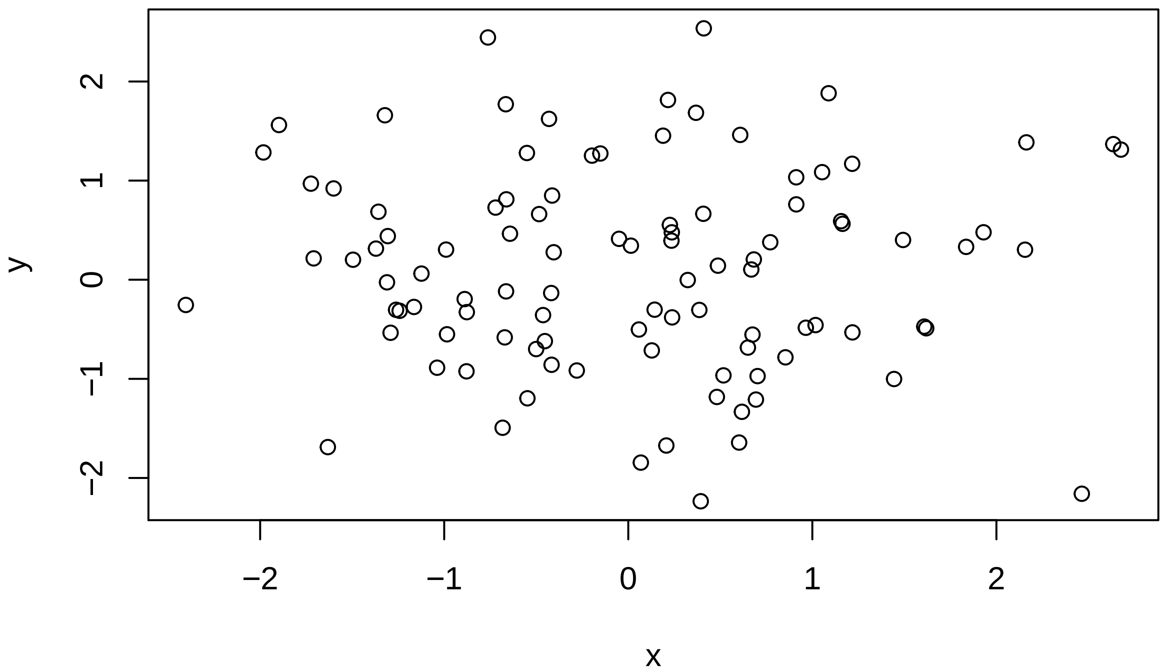
```r
sqrt(var(y))
```

```
## [1] 0.8560768
```

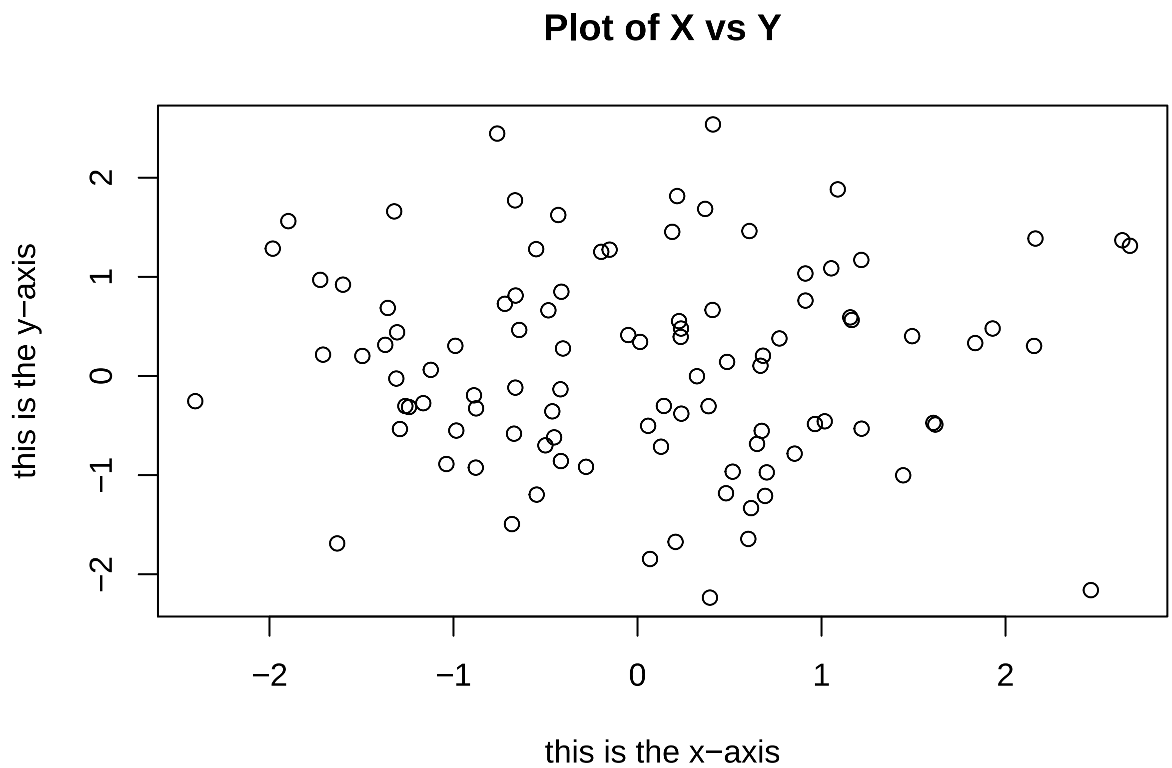
```r
sd(y)
```

```
## [1] 0.8560768
```

```r
# Graphics

x=rnorm(100)
y=rnorm(100)
plot(x,y)
```




```
plot(x,y,xlab="this is the x-axis",ylab="this is the y-axis",main="Plot of X vs Y")
```




```
pdf("Figure.pdf")
plot(x,y,col="green")
dev.off()
```

```
## pdf
##   2
```

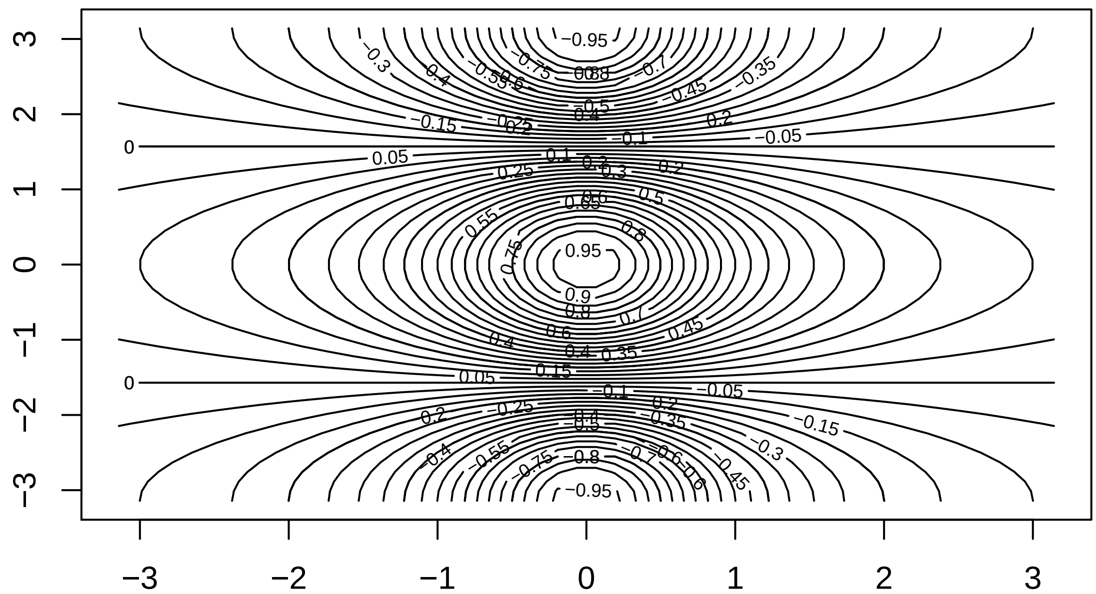
```
x=seq(1,10)
x
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

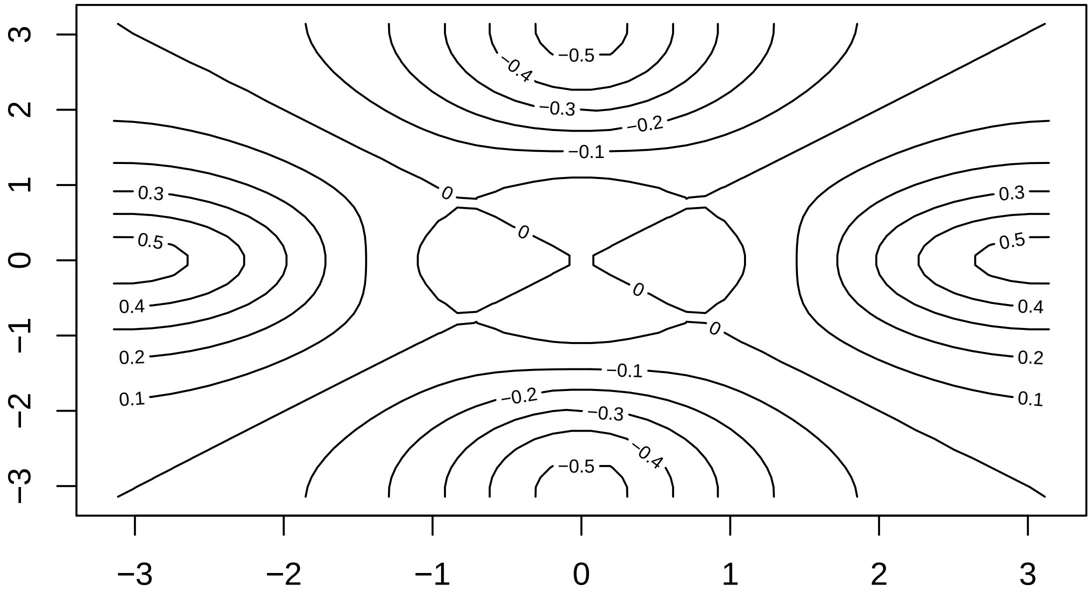
```
x=1:10
x
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

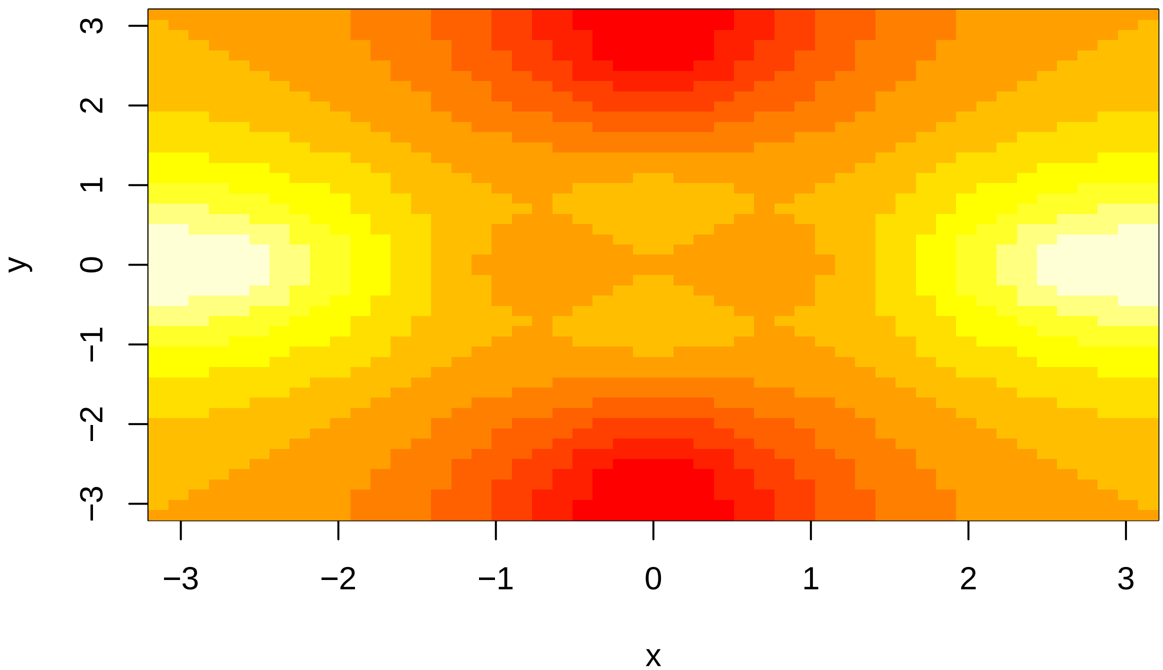
```
x=seq(-pi,pi,length=50)
y=x
f=outer(x,y,function(x,y)cos(y)/(1+x^2))
contour(x,y,f)
contour(x,y,f,nlevels=45,add=T)
```



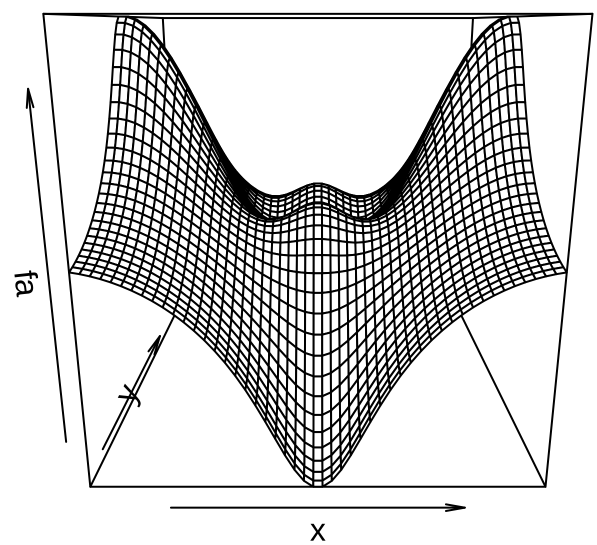
```
fa=(f-t(f))/2
contour(x,y,fa,nlevels=15)
```



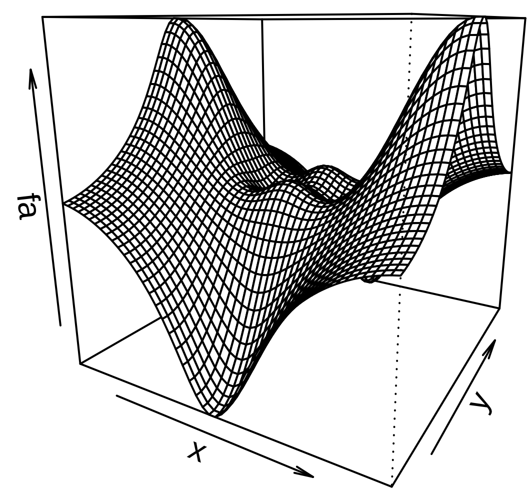

```r
image(x,y,fa)
```



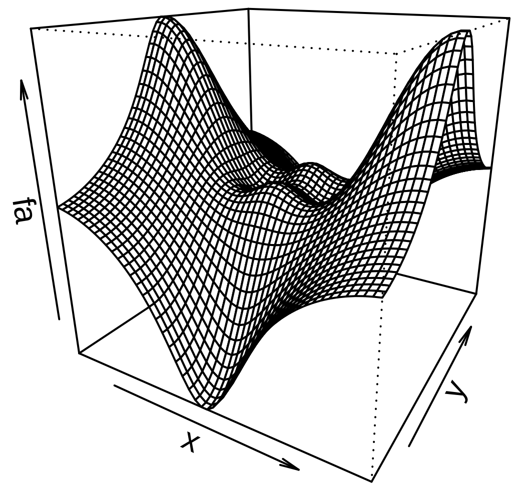

```r
persp(x,y,fa)
```



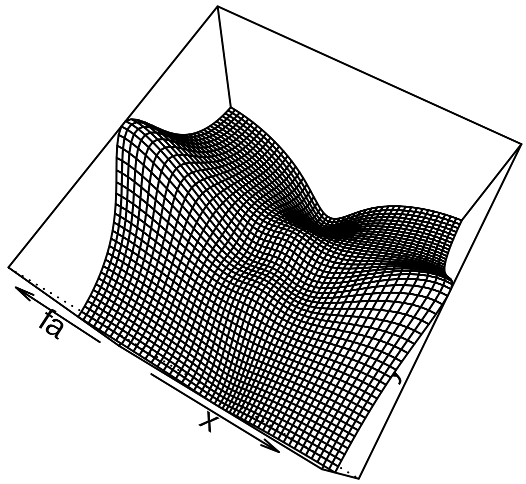

```r
persp(x,y,fa,theta=30)
```



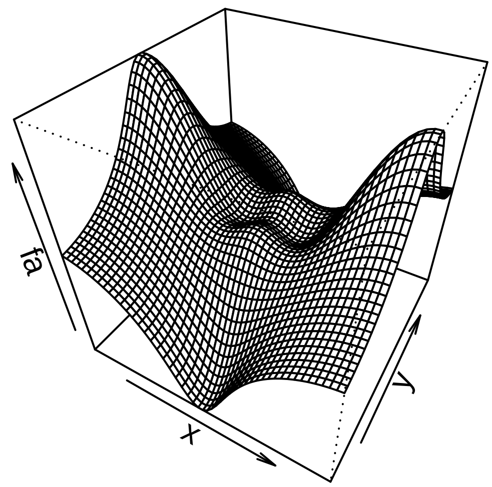

```r
persp(x,y,fa,theta=30,phi=20)
```




```
persp(x,y,fa,theta=30,phi=70)
```




```r
persp(x,y,fa,theta=30,phi=40)
```




```
# Indexing Data

A=matrix(1:16,4,4)
A
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    5    9   13
## [2,]    2    6   10   14
## [3,]    3    7   11   15
## [4,]    4    8   12   16
```

```
A[2,3]
```

```
## [1] 10
```

```
A[c(1,3),c(2,4)]
```

```
##      [,1] [,2]
## [1,]    5   13
## [2,]    7   15
```

```
A[1:3,2:4]
```

```
##      [,1] [,2] [,3]
## [1,]    5    9   13
## [2,]    6   10   14
## [3,]    7   11   15
```

```r
A[1:2,]
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    5    9   13
## [2,]    2    6   10   14
```

```r
A[,1:2]
```

```
##      [,1] [,2]
## [1,]    1    5
## [2,]    2    6
## [3,]    3    7
## [4,]    4    8
```

```r
A[1,]
```

```
## [1]  1  5  9 13
```

```r
A[-c(1,3),]
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    2    6   10   14
## [2,]    4    8   12   16
```

```r
A[-c(1,3),-c(1,3,4)]
```

```
## [1] 6 8
```

```r
dim(A)
```

```
## [1] 4 4
```

```r
# Loading Data

fix(Auto)
dim(Auto)
```

```
## [1] 392   9
```

```r
Auto[1:4,]
```

```
##   mpg cylinders displacement horsepower weight acceleration year origin
## 1  18         8          307        130   3504         12.0   70      1
## 2  15         8          350        165   3693         11.5   70      1
## 3  18         8          318        150   3436         11.0   70      1
## 4  16         8          304        150   3433         12.0   70      1
##                        name
## 1 chevrolet chevelle malibu
## 2         buick skylark 320
## 3        plymouth satellite
## 4             amc rebel sst
```

```r
Auto=na.omit(Auto)
dim(Auto)
```

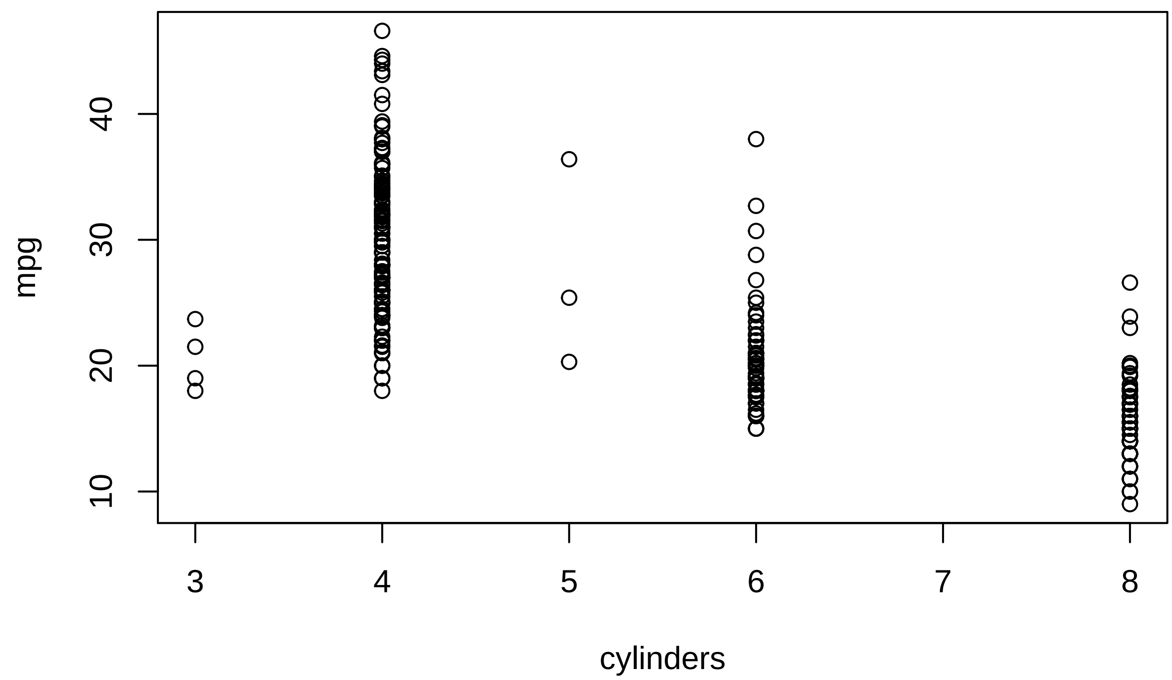
```
## [1] 392   9
```

```r
names(Auto)
```

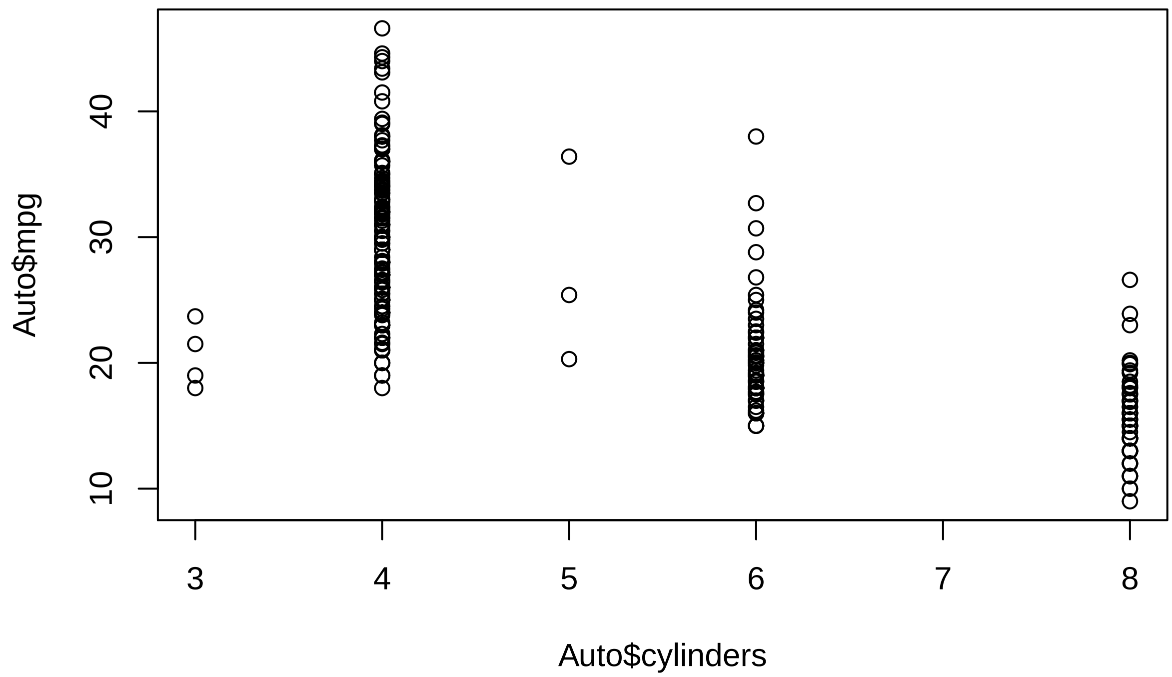
```
## [1] "mpg"          "cylinders"    "displacement" "horsepower"
## [5] "weight"       "acceleration" "year"         "origin"
```

```
## [9] "name"
```

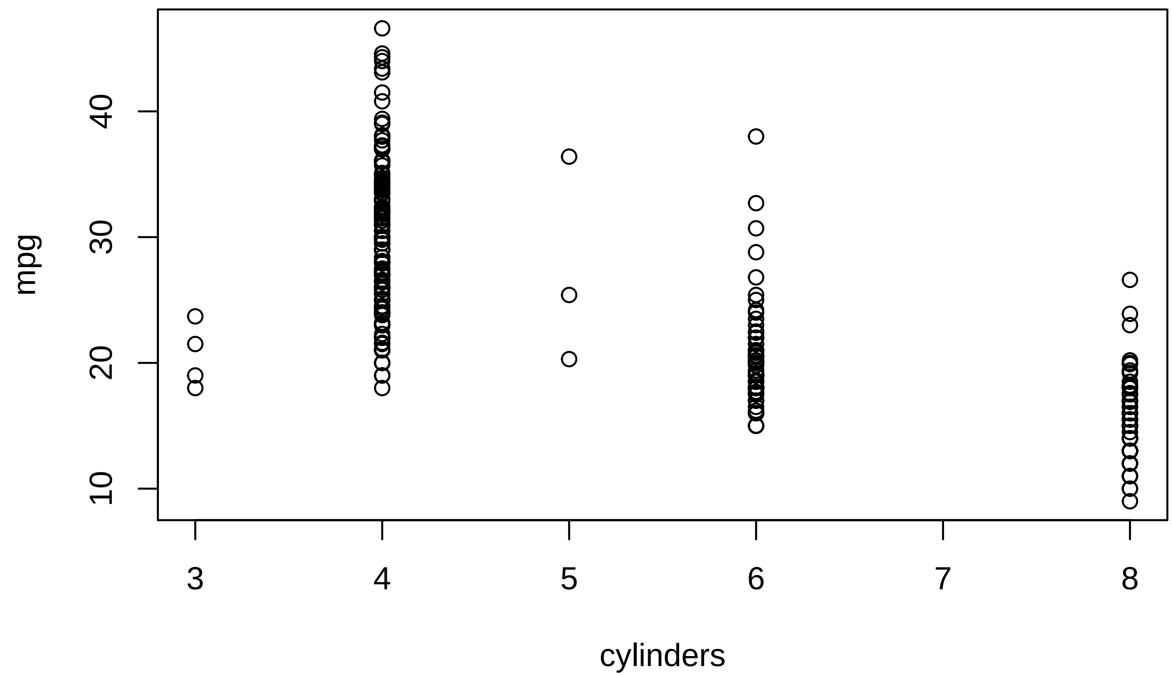
```r
# Additional Graphical and Numerical Summaries

attach(Auto)
plot(cylinders, mpg)
```



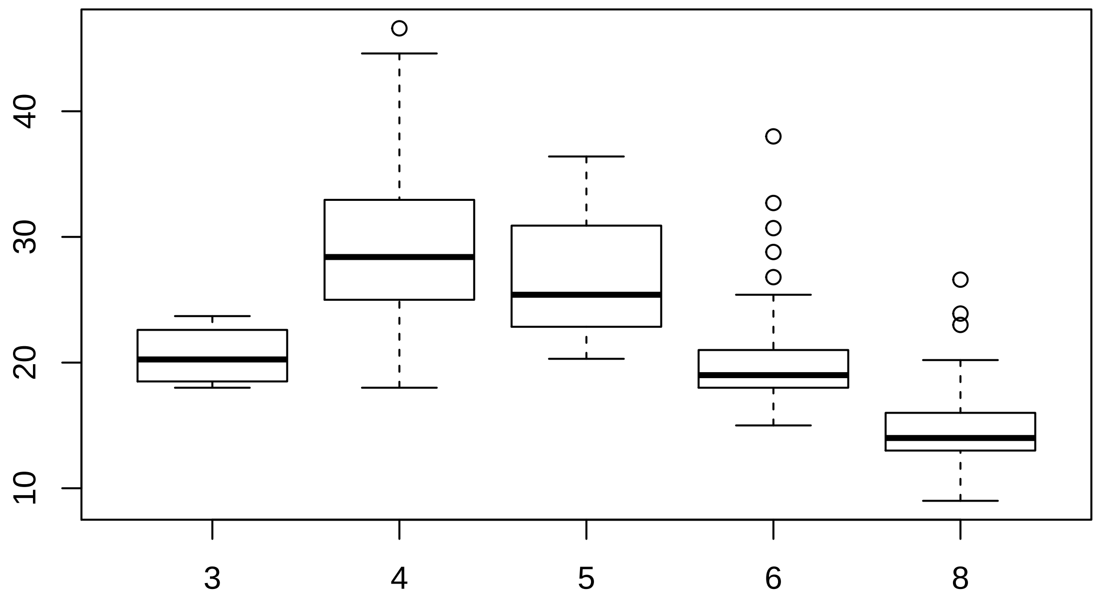

```r
plot(Auto$cylinders, Auto$mpg)
```



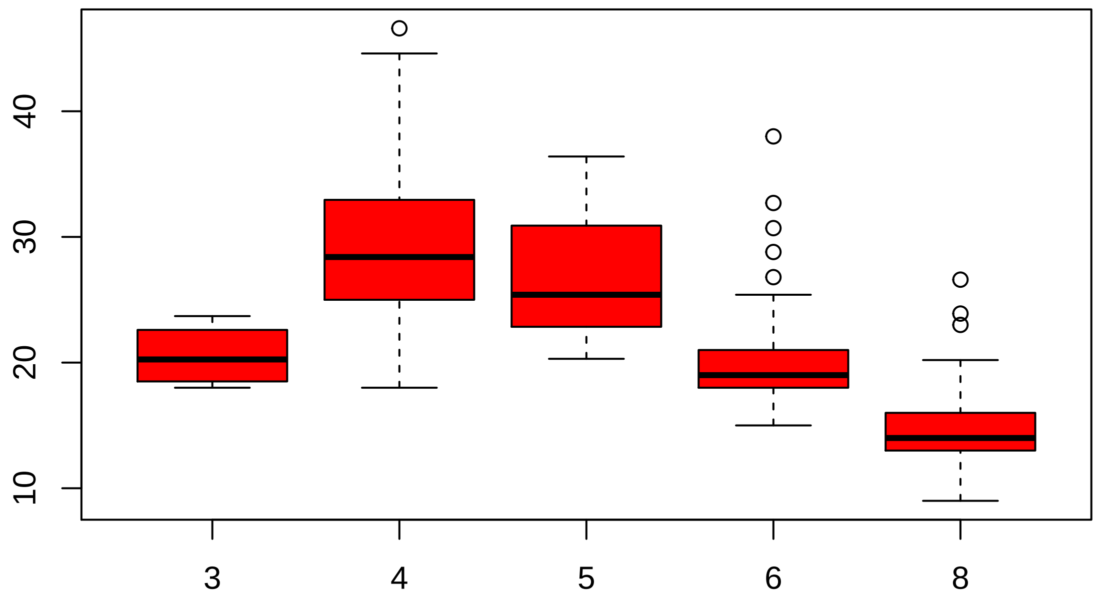

```r
plot(cylinders, mpg)
```



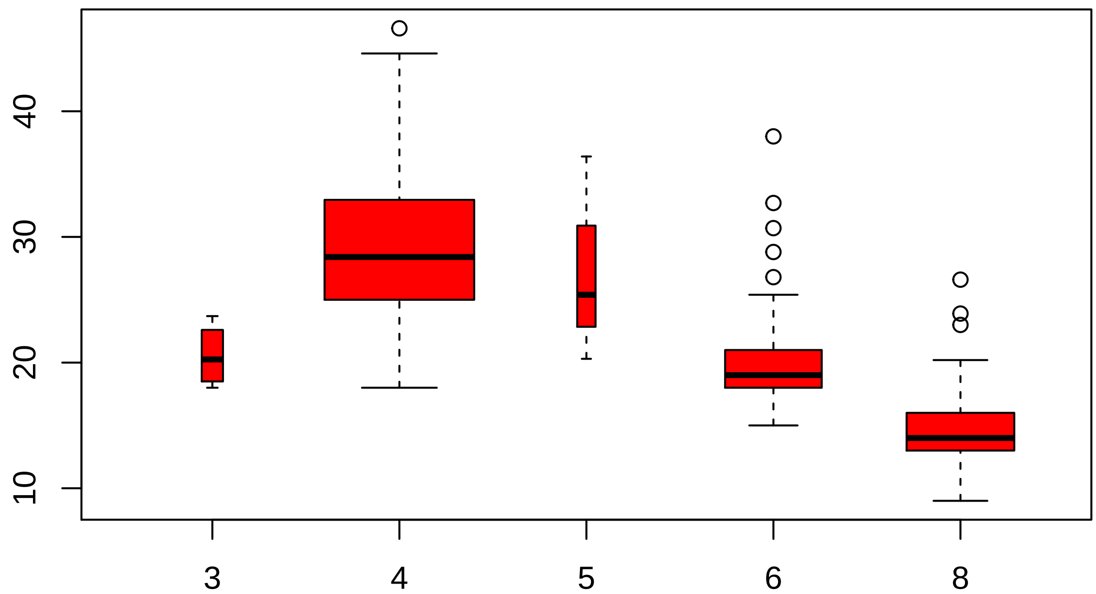

```r
cylinders=as.factor(cylinders)
plot(cylinders, mpg)
```



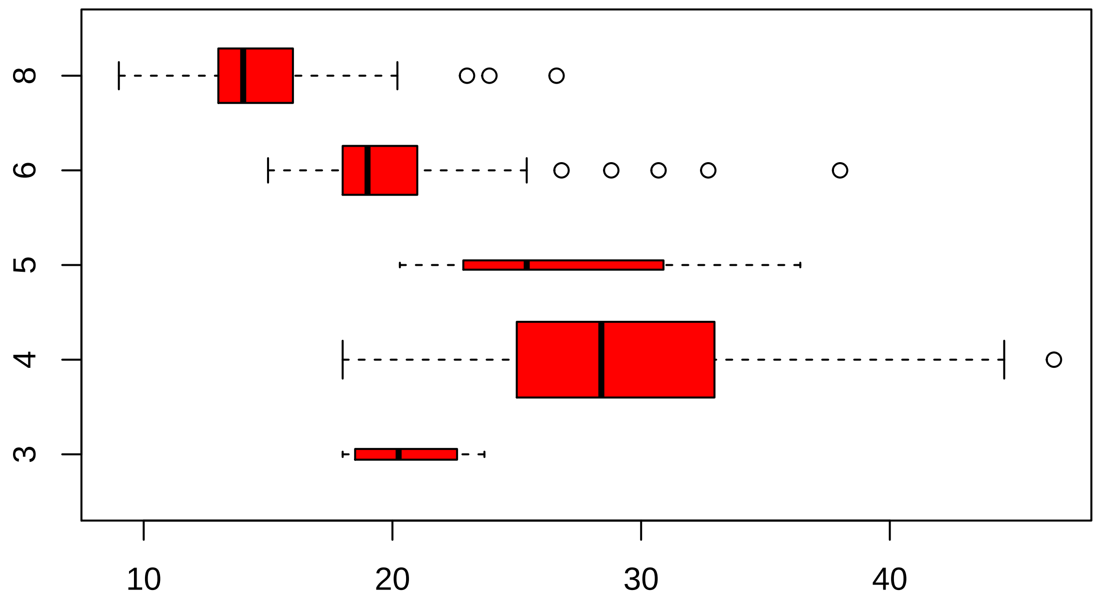

```r
plot(cylinders, mpg, col="red")
```



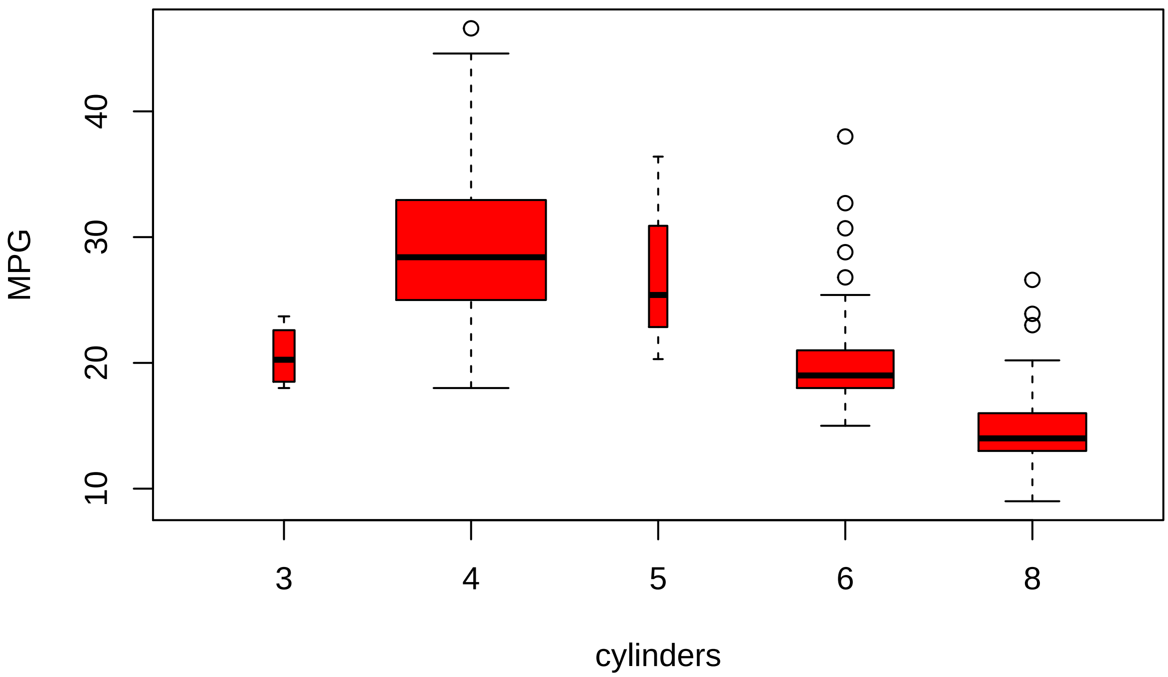

```
plot(cylinders, mpg, col="red", varwidth=T)
```



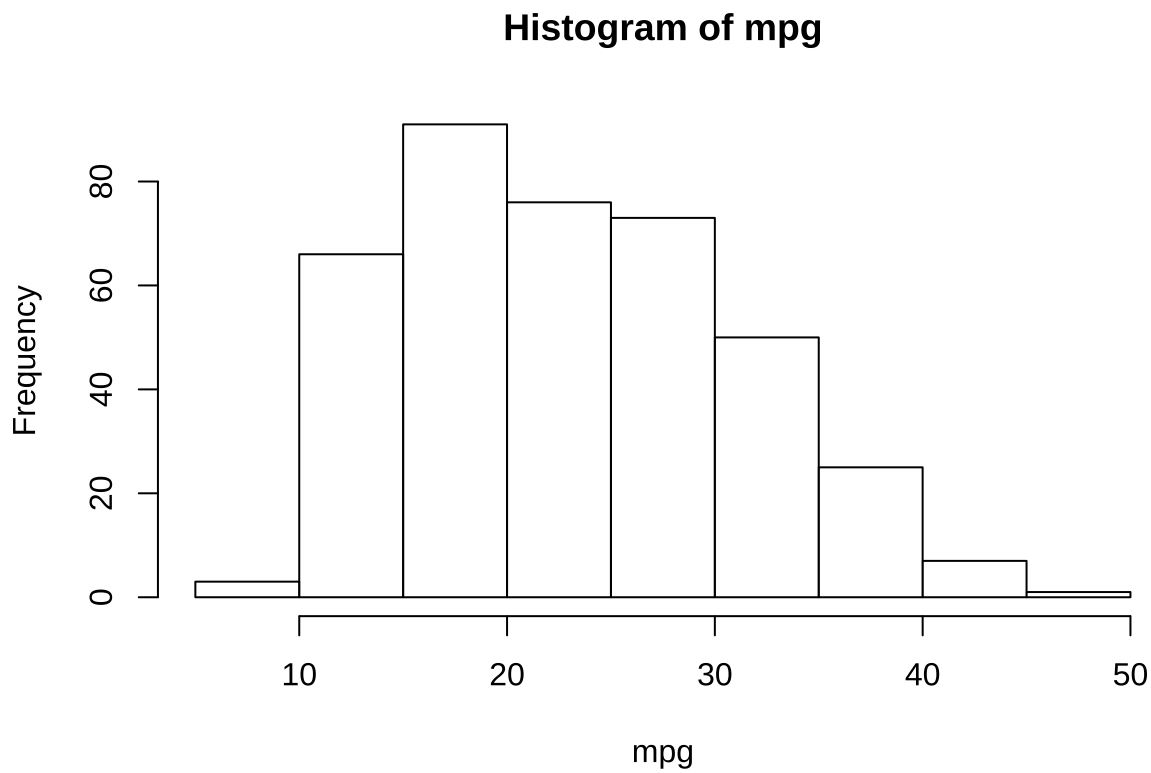

```r
plot(cylinders, mpg, col="red", varwidth=T,horizontal=T)
```



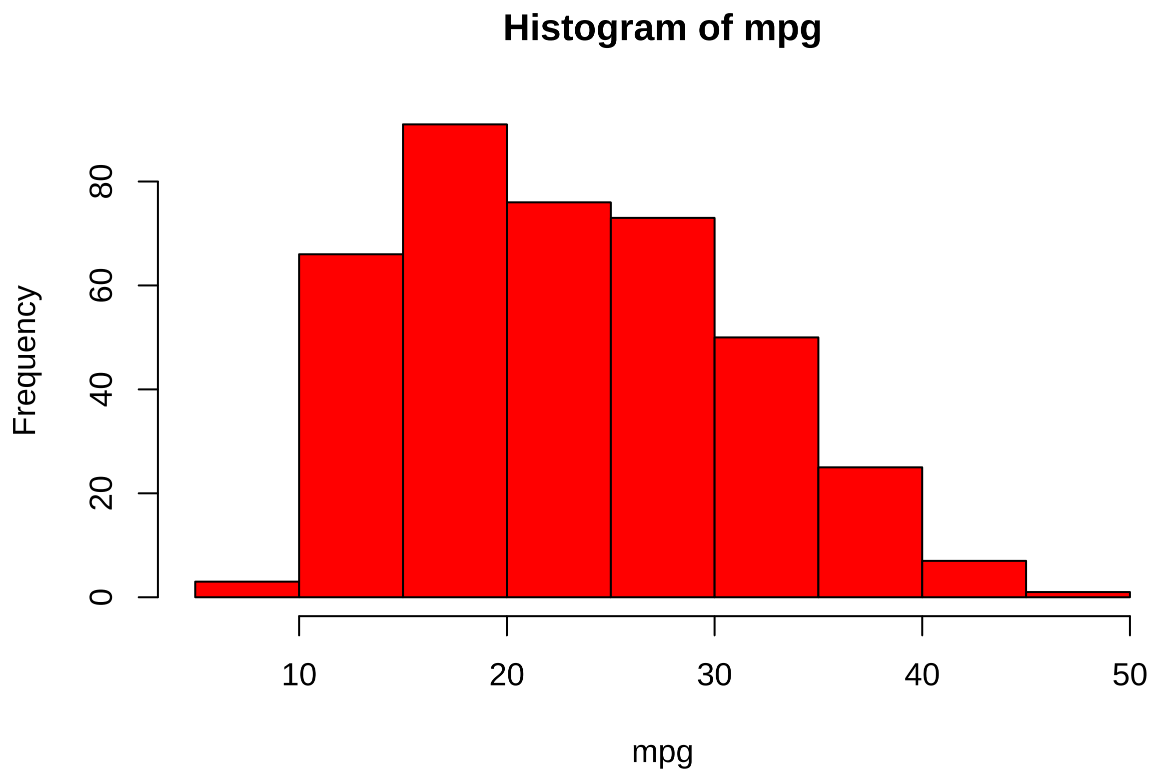

```r
plot(cylinders, mpg, col="red", varwidth=T, xlab="cylinders", ylab="MPG")
```



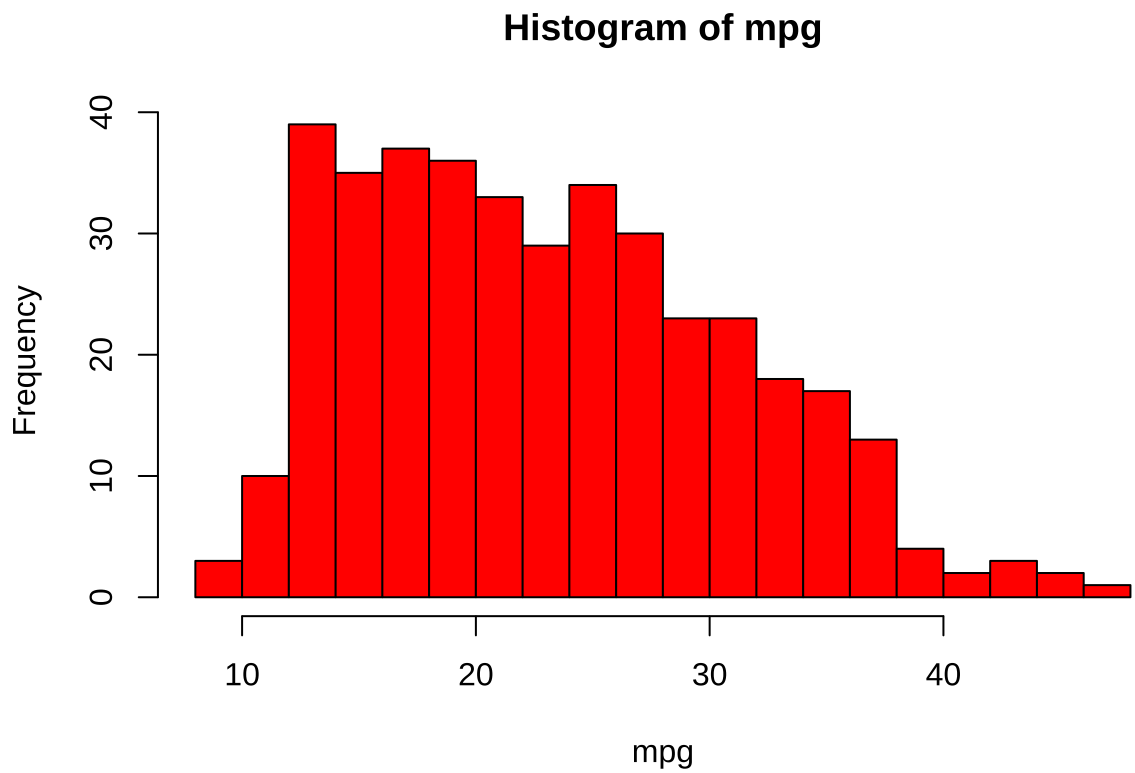

```
hist(mpg)
```



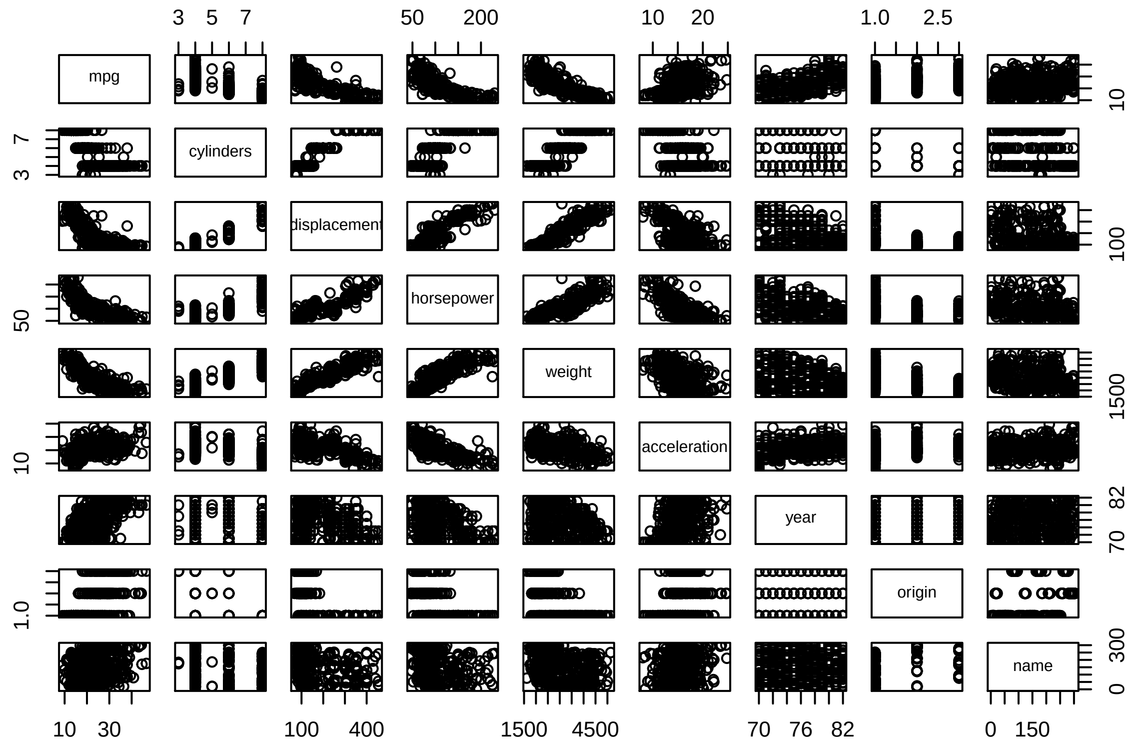

```r
hist(mpg,col=2)
```



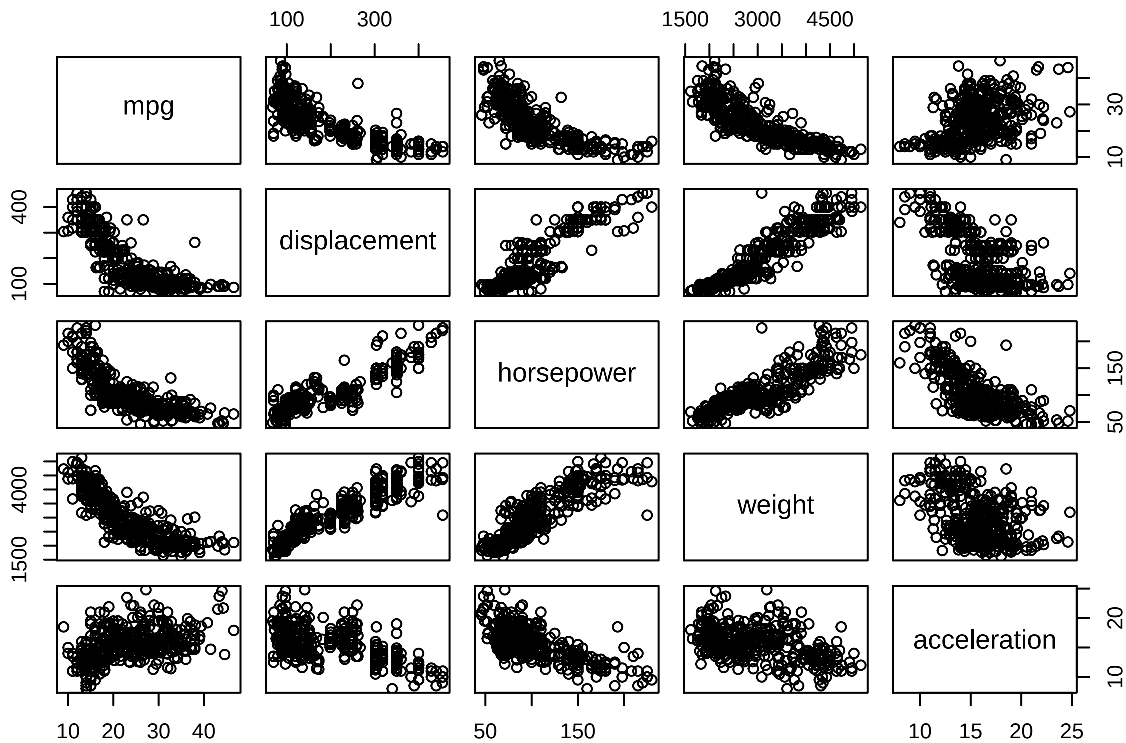

```r
hist(mpg,col=2,breaks=15)
```



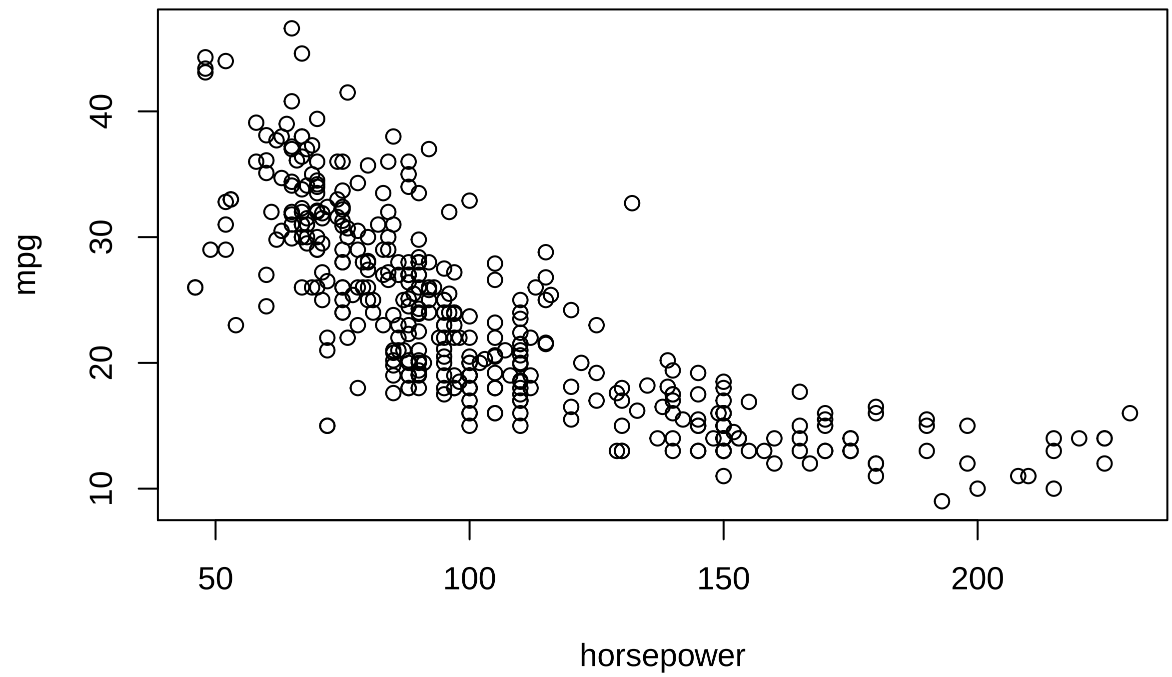

```
pairs(Auto)
```




```r
pairs(~ mpg + displacement + horsepower + weight + acceleration, Auto)
```




```r
plot(horsepower,mpg)
identify(horsepower,mpg,name)
```




```
## integer(0)
```

```
summary(Auto)
```

```
##       mpg          cylinders      displacement     horsepower
##  Min.   : 9.00   Min.   :3.000   Min.   : 68.0   Min.   : 46.0
##  1st Qu.:17.00   1st Qu.:4.000   1st Qu.:105.0   1st Qu.: 75.0
##  Median :22.75   Median :4.000   Median :151.0   Median : 93.5
##  Mean   :23.45   Mean   :5.472   Mean   :194.4   Mean   :104.5
##  3rd Qu.:29.00   3rd Qu.:8.000   3rd Qu.:275.8   3rd Qu.:126.0
##  Max.   :46.60   Max.   :8.000   Max.   :455.0   Max.   :230.0
##
##      weight      acceleration        year           origin
##  Min.   :1613   Min.   : 8.00   Min.   :70.00   Min.   :1.000
##  1st Qu.:2225   1st Qu.:13.78   1st Qu.:73.00   1st Qu.:1.000
##  Median :2804   Median :15.50   Median :76.00   Median :1.000
##  Mean   :2978   Mean   :15.54   Mean   :75.98   Mean   :1.577
##  3rd Qu.:3615   3rd Qu.:17.02   3rd Qu.:79.00   3rd Qu.:2.000
##  Max.   :5140   Max.   :24.80   Max.   :82.00   Max.   :3.000
##
##                  name
##  amc matador       :  5
##  ford pinto        :  5
##  toyota corolla    :  5
##  amc gremlin       :  4
##  amc hornet        :  4
##  chevrolet chevette:  4
```

```
##  (Other)            :365
```

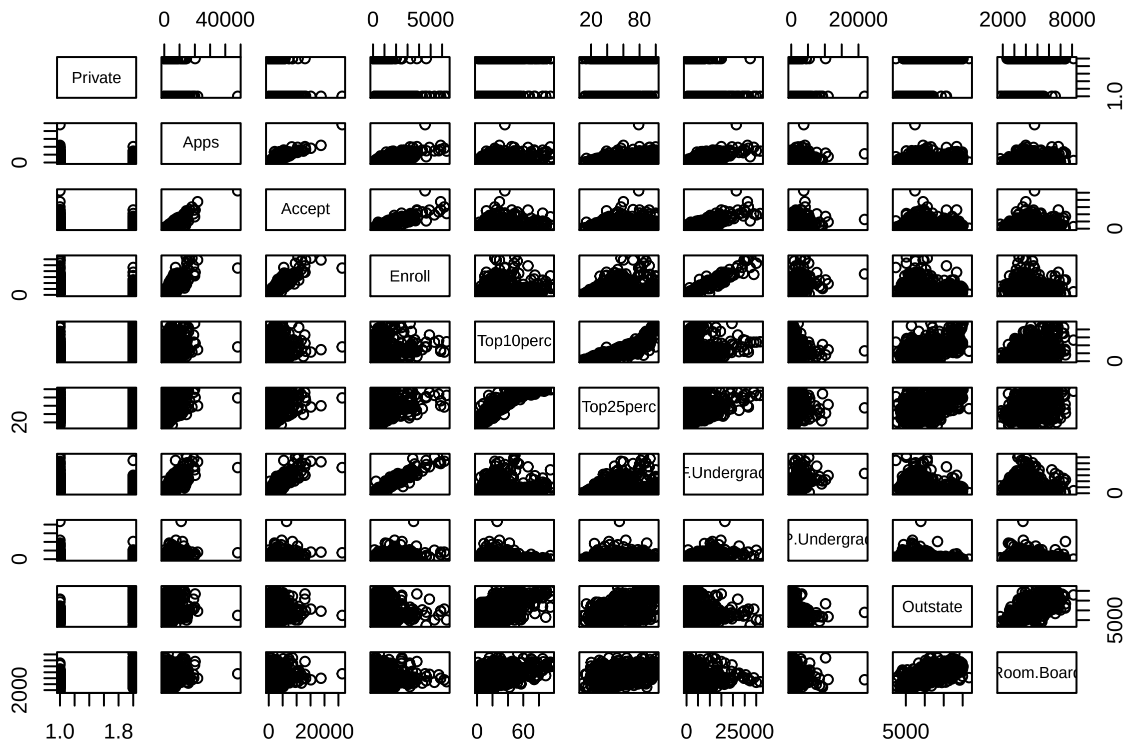
```r
summary(mpg)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    9.00   17.00   22.75   23.45   29.00   46.60
```

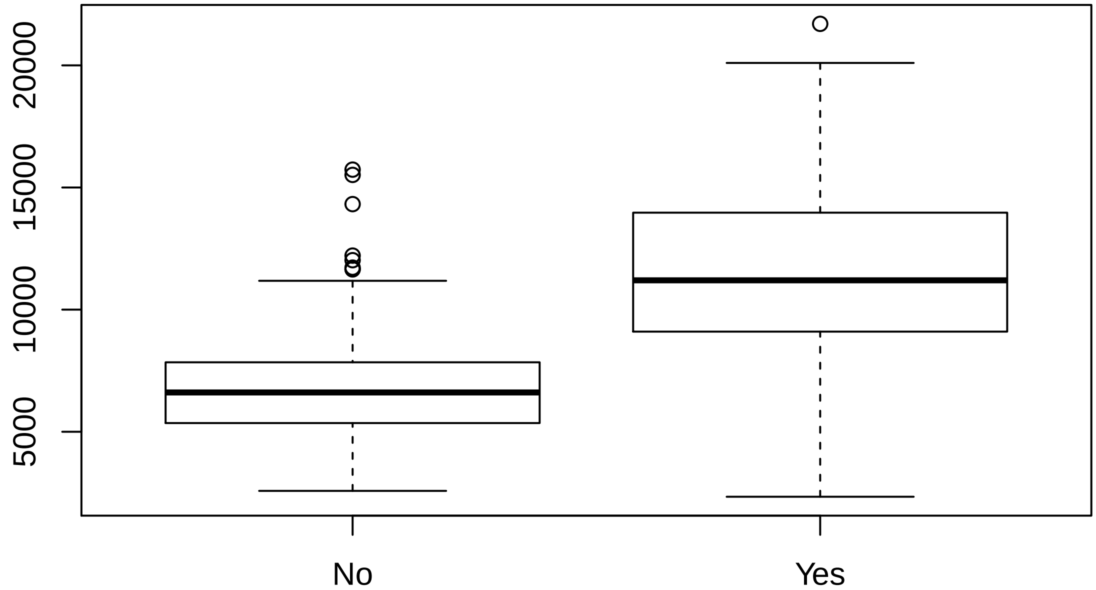
```r
# 8. (a)
college = College
# 8. (b)
#fix(college)
#rownames(college) = college[,1]
#college = college[,-1]
#fix(college)
# 8. (c)
# i.
summary(college)
```

```
##  Private        Apps           Accept          Enroll       Top10perc
##  No :212   Min.   :   81   Min.   :   72   Min.   :  35   Min.   : 1.00
##  Yes:565   1st Qu.:  776   1st Qu.:  604   1st Qu.: 242   1st Qu.:15.00
##            Median : 1558   Median : 1110   Median : 434   Median :23.00
##            Mean   : 3002   Mean   : 2019   Mean   : 780   Mean   :27.56
##            3rd Qu.: 3624   3rd Qu.: 2424   3rd Qu.: 902   3rd Qu.:35.00
##            Max.   :48094   Max.   :26330   Max.   :6392   Max.   :96.00
##    Top25perc      F.Undergrad     P.Undergrad         Outstate
##  Min.   :  9.0   Min.   :  139   Min.   :    1.0   Min.   : 2340
##  1st Qu.: 41.0   1st Qu.:  992   1st Qu.:   95.0   1st Qu.: 7320
##  Median : 54.0   Median : 1707   Median :  353.0   Median : 9990
##  Mean   : 55.8   Mean   : 3700   Mean   :  855.3   Mean   :10441
##  3rd Qu.: 69.0   3rd Qu.: 4005   3rd Qu.:  967.0   3rd Qu.:12925
##  Max.   :100.0   Max.   :31643   Max.   :21836.0   Max.   :21700
##    Room.Board       Books           Personal         PhD
##  Min.   :1780   Min.   :  96.0   Min.   : 250   Min.   :  8.00
##  1st Qu.:3597   1st Qu.: 470.0   1st Qu.: 850   1st Qu.: 62.00
##  Median :4200   Median : 500.0   Median :1200   Median : 75.00
##  Mean   :4358   Mean   : 549.4   Mean   :1341   Mean   : 72.66
##  3rd Qu.:5050   3rd Qu.: 600.0   3rd Qu.:1700   3rd Qu.: 85.00
##  Max.   :8124   Max.   :2340.0   Max.   :6800   Max.   :103.00
##     Terminal       S.F.Ratio      perc.alumni        Expend
##  Min.   : 24.0   Min.   : 2.50   Min.   : 0.00   Min.   : 3186
##  1st Qu.: 71.0   1st Qu.:11.50   1st Qu.:13.00   1st Qu.: 6751
##  Median : 82.0   Median :13.60   Median :21.00   Median : 8377
##  Mean   : 79.7   Mean   :14.09   Mean   :22.74   Mean   : 9660
##  3rd Qu.: 92.0   3rd Qu.:16.50   3rd Qu.:31.00   3rd Qu.:10830
##  Max.   :100.0   Max.   :39.80   Max.   :64.00   Max.   :56233
##    Grad.Rate
##  Min.   : 10.00
##  1st Qu.: 53.00
##  Median : 65.00
##  Mean   : 65.46
##  3rd Qu.: 78.00
##  Max.   :118.00
```

```r
# ii.
pairs(college[,1:10])
```



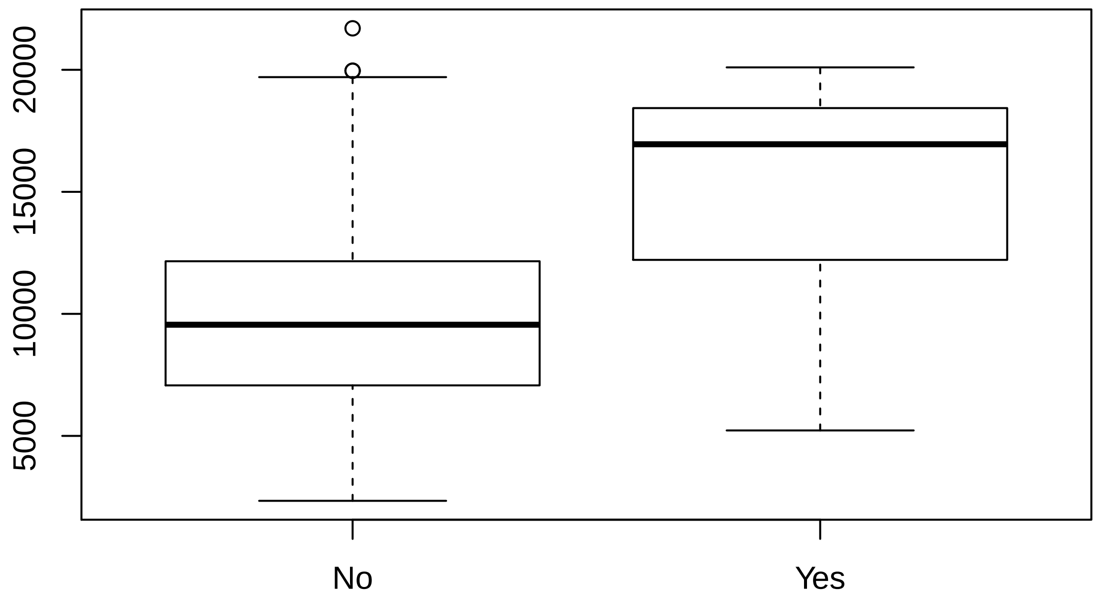

```r
# iii.
plot(college$Private, college$Outstate)
```



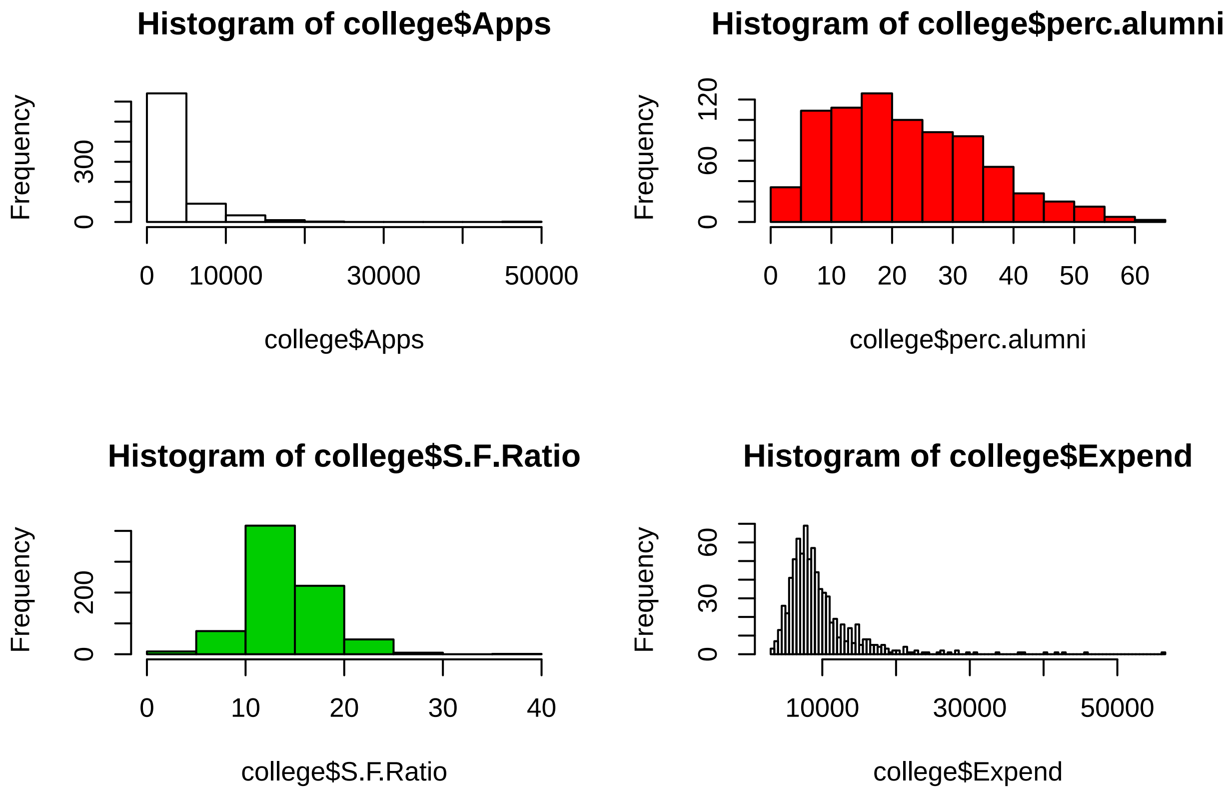

```r
# iv.
Elite = rep("No", nrow(college))
Elite[college$Top10perc>50] = "Yes"
Elite = as.factor(Elite)
college = data.frame(college, Elite)
summary(college$Elite)
```

```
##  No Yes
## 699  78
```

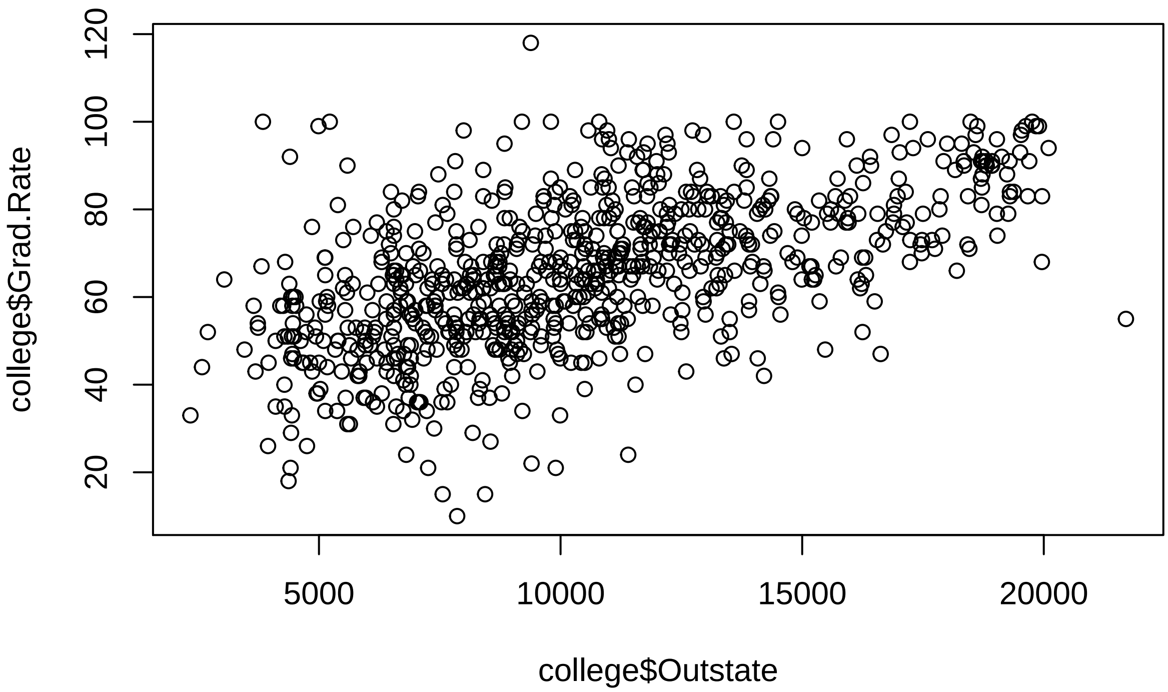
```r
plot(college$Elite, college$Outstate)
```



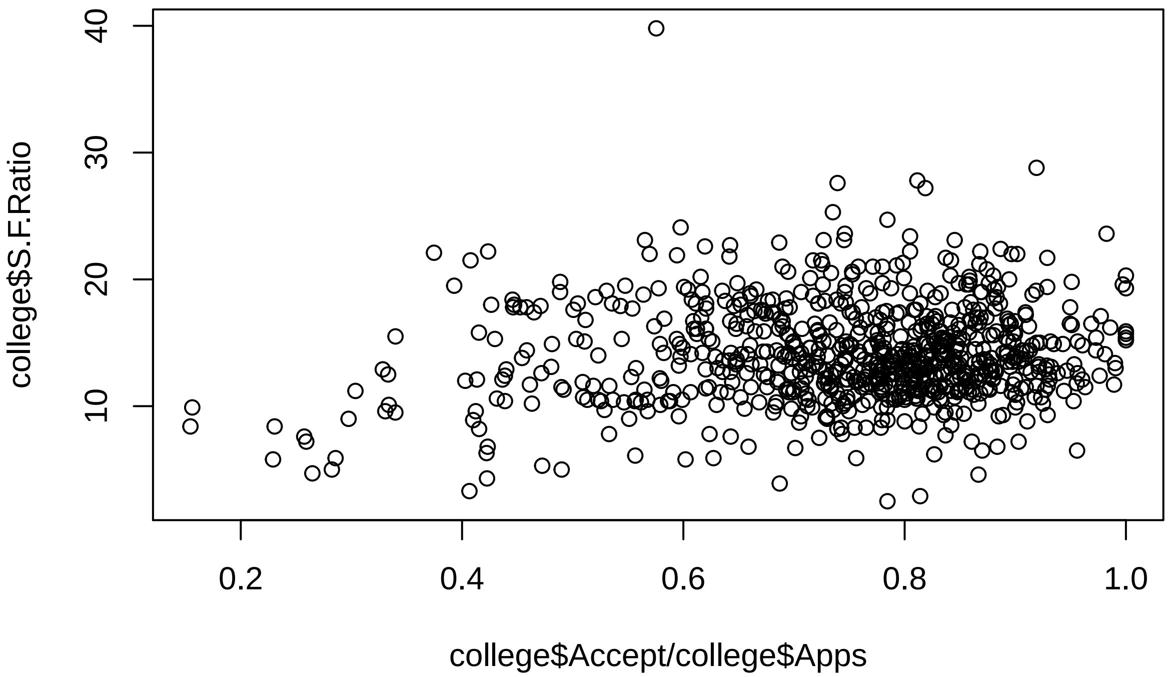

```
# v.
par(mfrow=c(2,2))
hist(college$Apps)
hist(college$perc.alumni, col=2)
hist(college$S.F.Ratio, col=3, breaks=10)
hist(college$Expend, breaks=100)
```



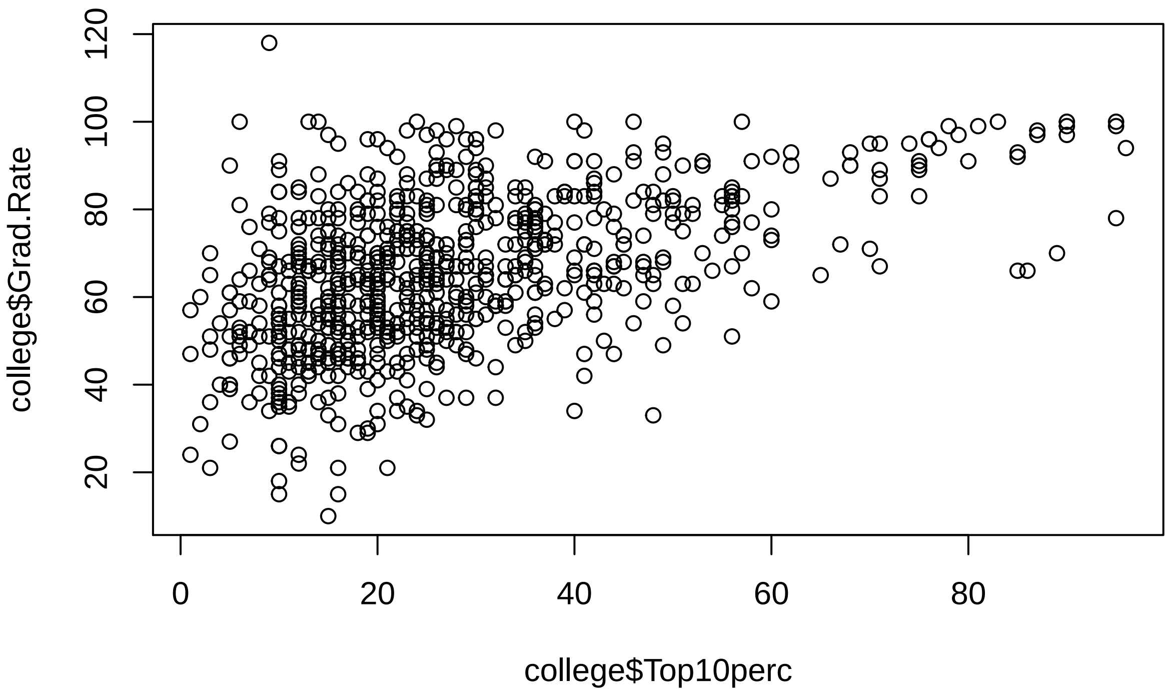

```
# vi.
par(mfrow=c(1,1))
plot(college$Outstate, college$Grad.Rate)
```




```
# High tuition correlates to high graduation rate.
plot(college$Accept / college$Apps, college$S.F.Ratio)
```




```r
# Colleges with low acceptance rate tend to have low S:F ratio.
plot(college$Top10perc, college$Grad.Rate)
```




```r
# Colleges with the most students from top 10% perc don't necessarily have
# the highest graduation rate. Also, rate > 100 is erroneous!
```

```r
# 9.
Auto = Auto
Auto = na.omit(Auto)
dim(Auto)
```

```
## [1] 392   9
```

```r
summary(Auto)
```

```
##       mpg          cylinders      displacement     horsepower
##  Min.   : 9.00   Min.   :3.000   Min.   : 68.0   Min.   : 46.0
##  1st Qu.:17.00   1st Qu.:4.000   1st Qu.:105.0   1st Qu.: 75.0
##  Median :22.75   Median :4.000   Median :151.0   Median : 93.5
##  Mean   :23.45   Mean   :5.472   Mean   :194.4   Mean   :104.5
##  3rd Qu.:29.00   3rd Qu.:8.000   3rd Qu.:275.8   3rd Qu.:126.0
##  Max.   :46.60   Max.   :8.000   Max.   :455.0   Max.   :230.0
##
##      weight      acceleration        year           origin
##  Min.   :1613   Min.   : 8.00   Min.   :70.00   Min.   :1.000
##  1st Qu.:2225   1st Qu.:13.78   1st Qu.:73.00   1st Qu.:1.000
##  Median :2804   Median :15.50   Median :76.00   Median :1.000
##  Mean   :2978   Mean   :15.54   Mean   :75.98   Mean   :1.577
##  3rd Qu.:3615   3rd Qu.:17.02   3rd Qu.:79.00   3rd Qu.:2.000
##  Max.   :5140   Max.   :24.80   Max.   :82.00   Max.   :3.000
##
```

```
##                  name
##  amc matador       :  5
##  ford pinto        :  5
##  toyota corolla    :  5
##  amc gremlin       :  4
##  amc hornet        :  4
##  chevrolet chevette:  4
##  (Other)           :365
```

```r
# (a)
# quantitative: mpg, cylinders, displacement, horsepower, weight,
# acceleration, year
# qualitative: name, origin

# (b)
# apply the range function to the first seven columns of Auto
sapply(Auto[, 1:7], range)
```

```
##       mpg cylinders displacement horsepower weight acceleration year
## [1,]  9.0         3           68         46   1613          8.0   70
## [2,] 46.6         8          455        230   5140         24.8   82
```

```r
#       mpg cylinders displacement horsepower weight acceleration year
# [1,]  9.0         3           68         46   1613          8.0   70
# [2,] 46.6         8          455        230   5140         24.8   82

# (c)
sapply(Auto[, 1:7], mean)
```

```
##          mpg    cylinders displacement   horsepower       weight
##    23.445918     5.471939   194.411990   104.469388  2977.584184
## acceleration         year
##    15.541327    75.979592
```

```r
#          mpg    cylinders displacement   horsepower       weight acceleration
#    23.445918     5.471939   194.411990   104.469388  2977.584184    15.541327
#         year
#    75.979592

sapply(Auto[, 1:7], sd)
```

```
##          mpg    cylinders displacement   horsepower       weight
##     7.805007     1.705783   104.644004    38.491160   849.402560
## acceleration         year
##     2.758864     3.683737
```

```r
#          mpg    cylinders displacement   horsepower       weight acceleration
#     7.805007     1.705783   104.644004    38.491160   849.402560     2.758864
#         year
#     3.683737

# (d)
newAuto = Auto[-(10:85),]
dim(newAuto) == dim(Auto) - c(76,0)
```

```
## [1] TRUE TRUE
```

```r
newAuto[9,] == Auto[9,]
```

```
##    mpg cylinders displacement horsepower weight acceleration year origin
## 9 TRUE      TRUE         TRUE       TRUE   TRUE         TRUE TRUE   TRUE
##   name
## 9 TRUE
```

```r
newAuto[10,] == Auto[86,]
```

```
##     mpg cylinders displacement horsepower weight acceleration year origin
## 87 TRUE      TRUE         TRUE       TRUE   TRUE         TRUE TRUE   TRUE
##    name
## 87 TRUE
```

```r
sapply(newAuto[, 1:7], range)
```

```
##       mpg cylinders displacement horsepower weight acceleration year
## [1,] 11.0         3           68         46   1649          8.5   70
## [2,] 46.6         8          455        230   4997         24.8   82
```

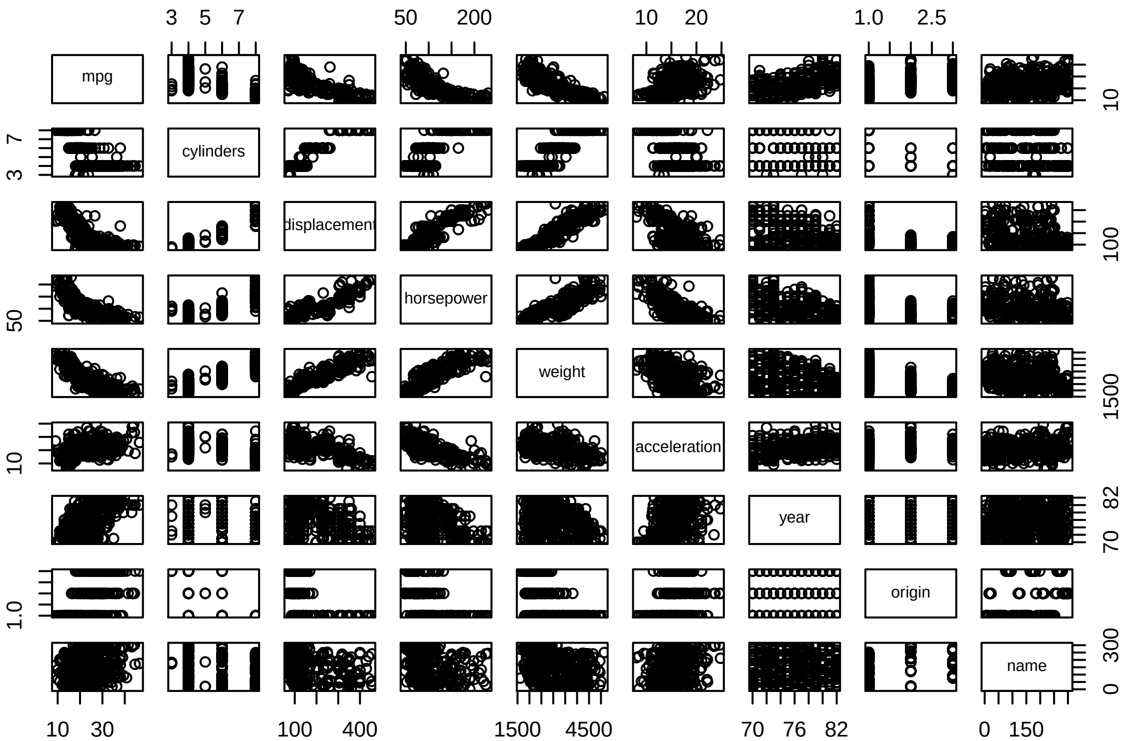
```r
#       mpg cylinders displacement horsepower weight acceleration year
# [1,] 11.0         3           68         46   1649          8.5   70
# [2,] 46.6         8          455        230   4997         24.8   82
sapply(newAuto[, 1:7], mean)
```

```
##          mpg    cylinders displacement   horsepower       weight
##    24.404430     5.373418   187.240506   100.721519  2935.971519
## acceleration         year
##    15.726899    77.145570
```

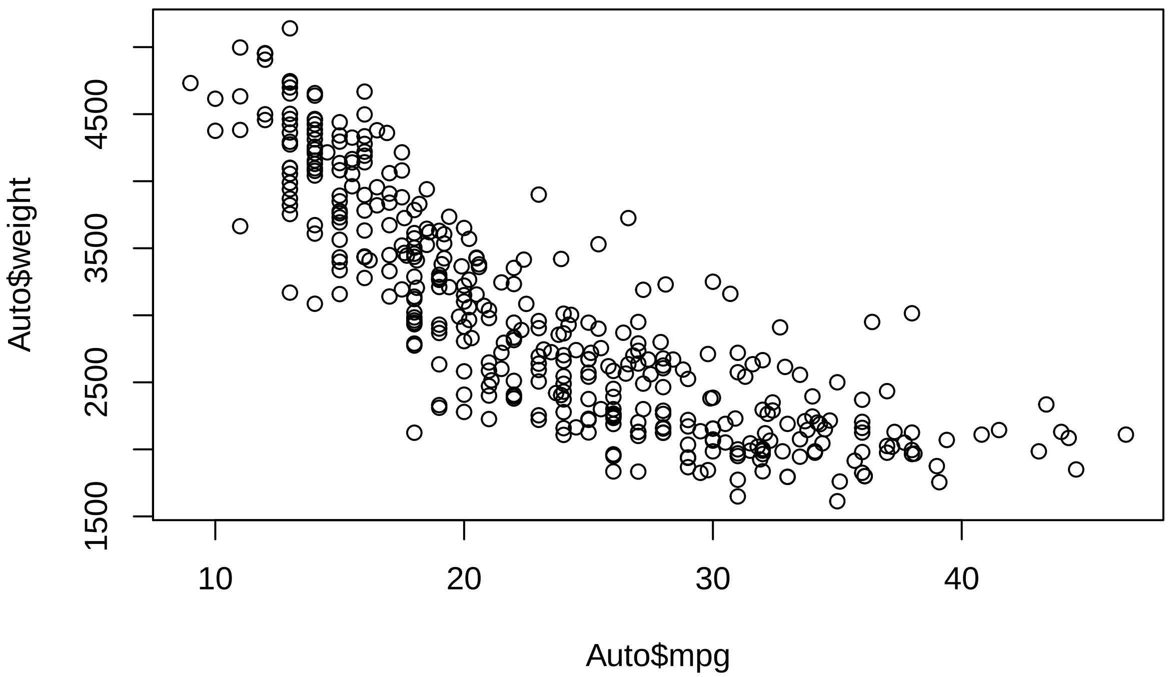
```r
#          mpg    cylinders displacement   horsepower       weight acceleration
#    24.404430     5.373418   187.240506   100.721519  2935.971519    15.726899
#         year
#    77.145570
sapply(newAuto[, 1:7], sd)
```

```
##          mpg    cylinders displacement   horsepower       weight
##     7.867283     1.654179    99.678367    35.708853   811.300208
## acceleration         year
##     2.693721     3.106217
```

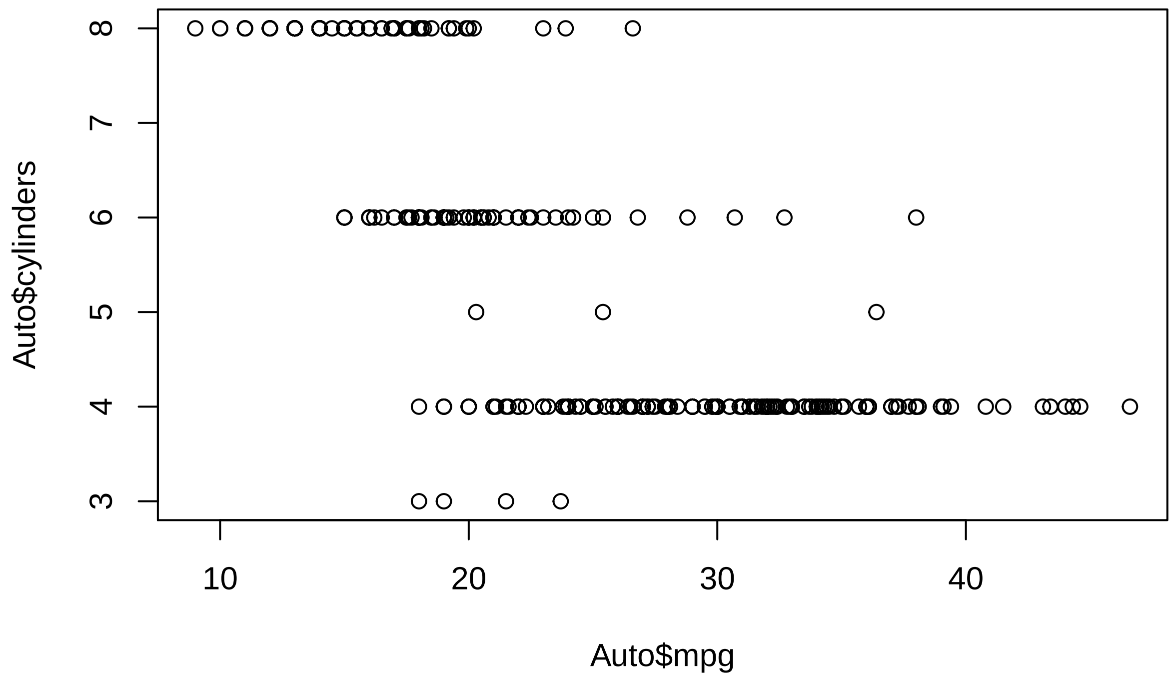
```r
#          mpg    cylinders displacement   horsepower       weight acceleration
#     7.867283     1.654179    99.678367    35.708853   811.300208     2.693721
#         year
#     3.106217

# (e)
pairs(Auto)
```



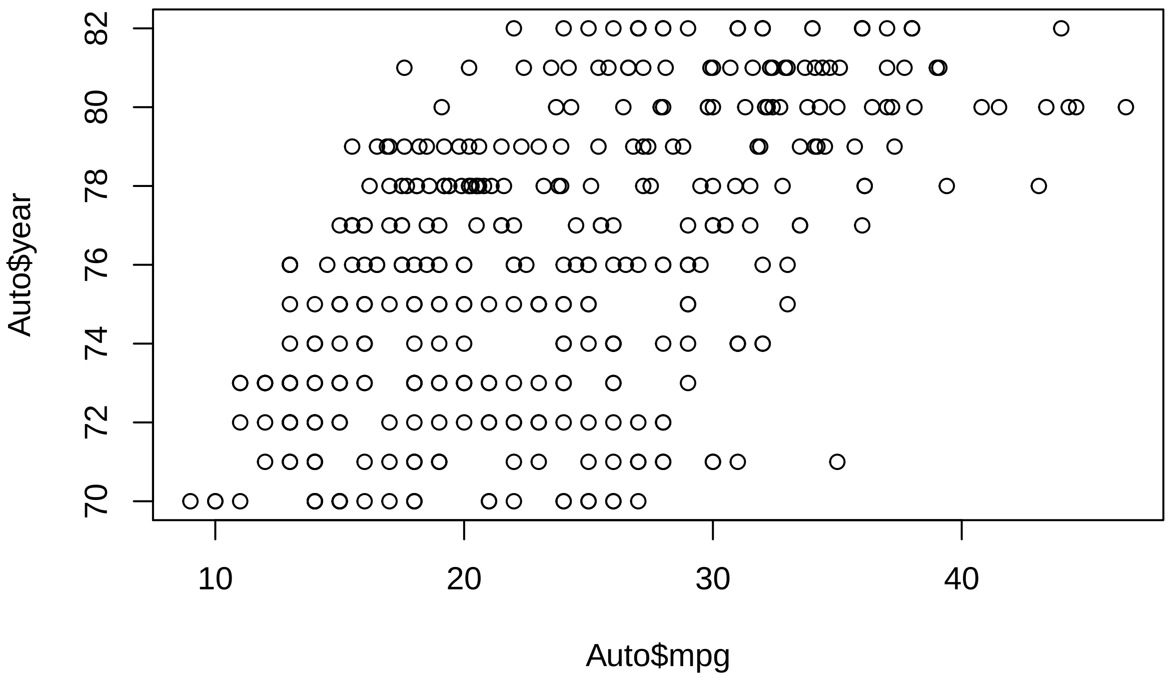

```r
plot(Auto$mpg, Auto$weight)
```



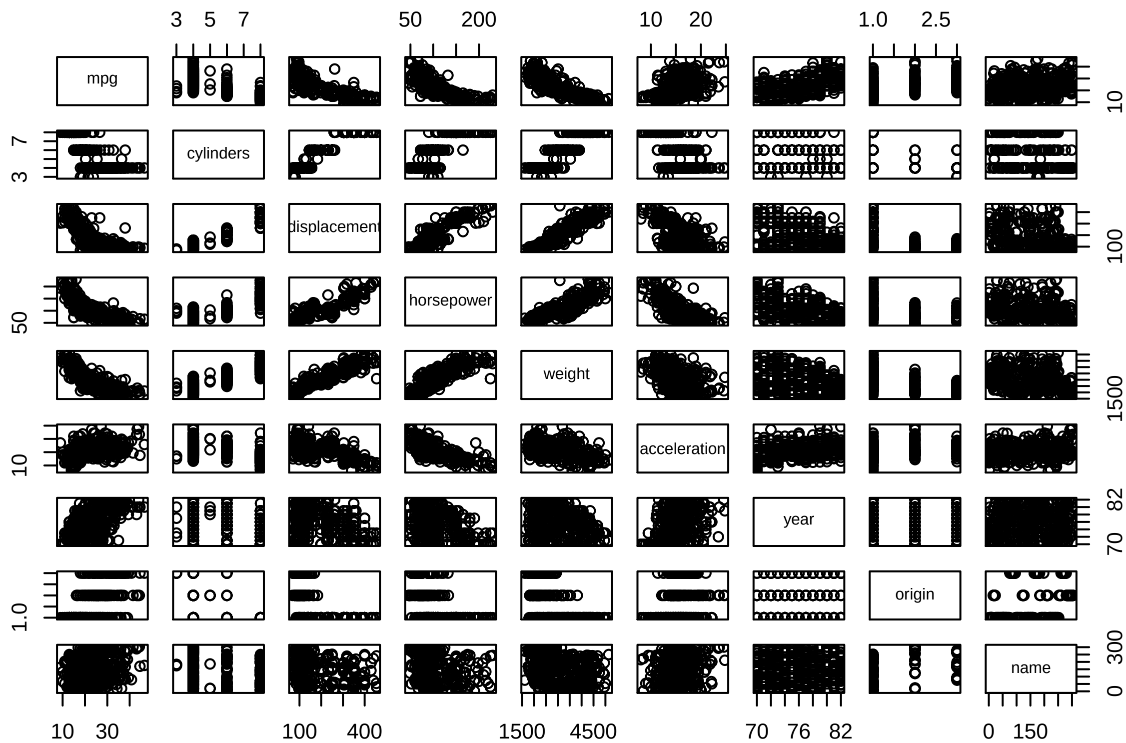

```
# Heavier weight correlates with lower mpg.
plot(Auto$mpg, Auto$cylinders)
```




```r
# More cylinders, less mpg.
plot(Auto$mpg, Auto$year)
```




```r
# Cars become more efficient over time.

# (f)
pairs(Auto)
```

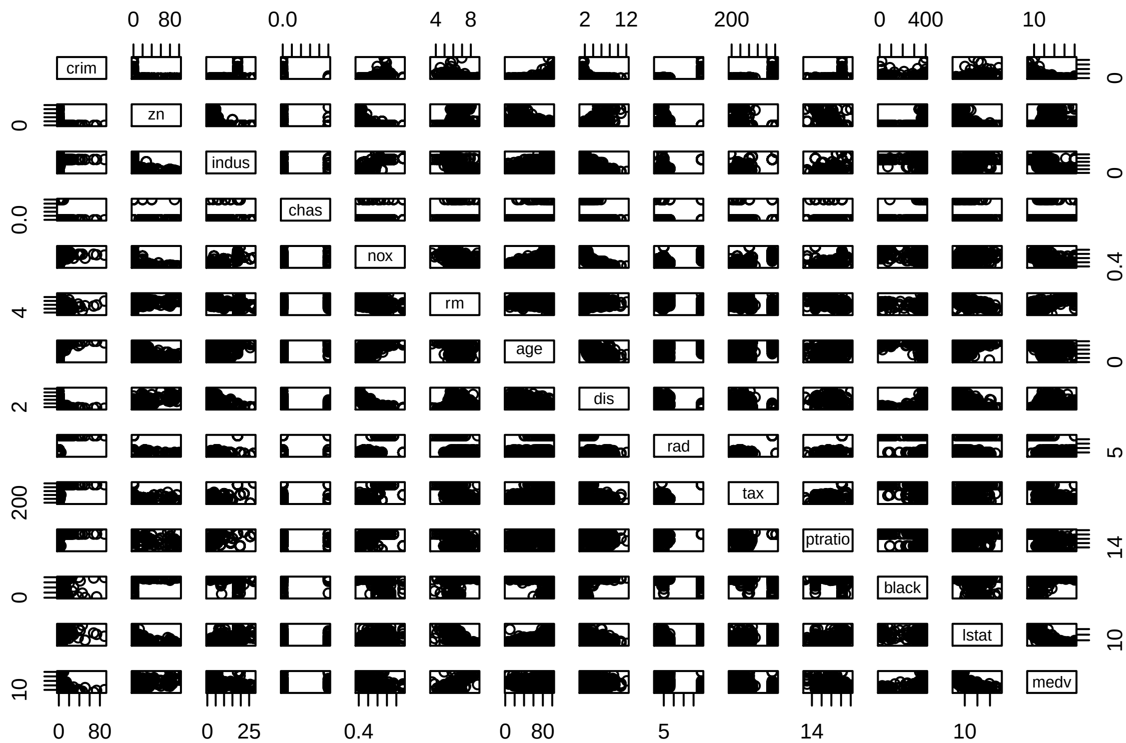



```r
# See descriptions of plots in (e).
# All of the predictors show some correlation with mpg. The name predictor has
# too little observations per name though, so using this as a predictor is
# likely to result in overfitting the data and will not generalize well.
```

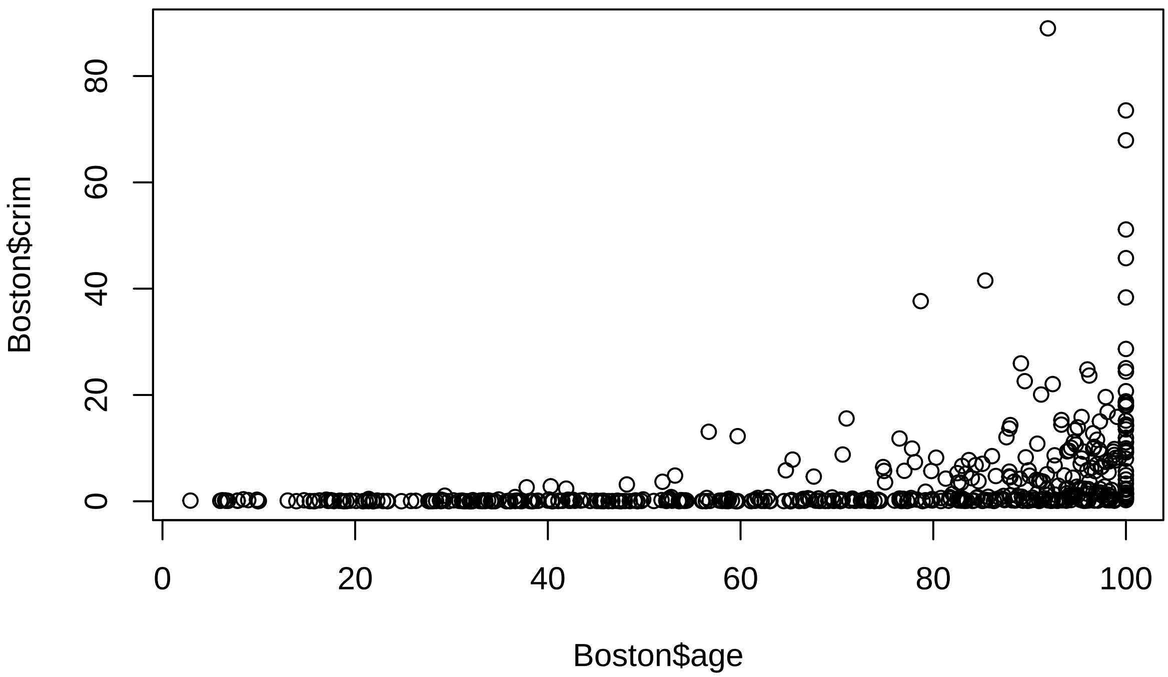
```r
# 10.
# (a)
library(MASS)
?Boston
dim(Boston)
```

```
## [1] 506  14
```

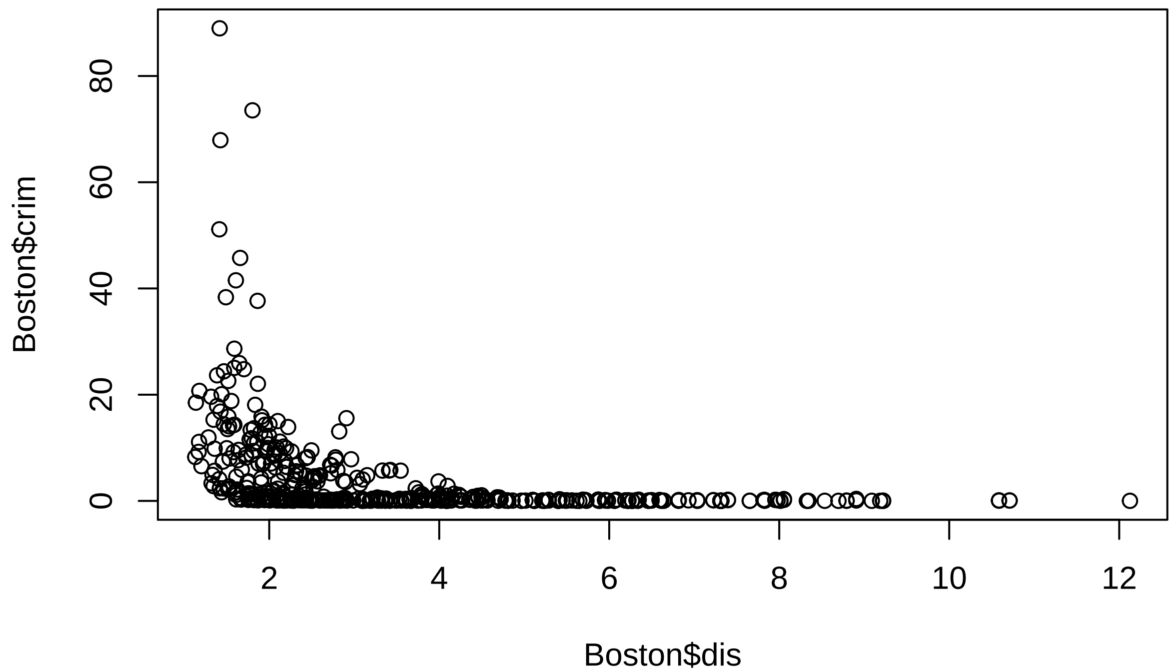
```r
# 506 rows, 14 columns
# 14 features, 506 housing values in Boston suburbs


# (b)
pairs(Boston)
```



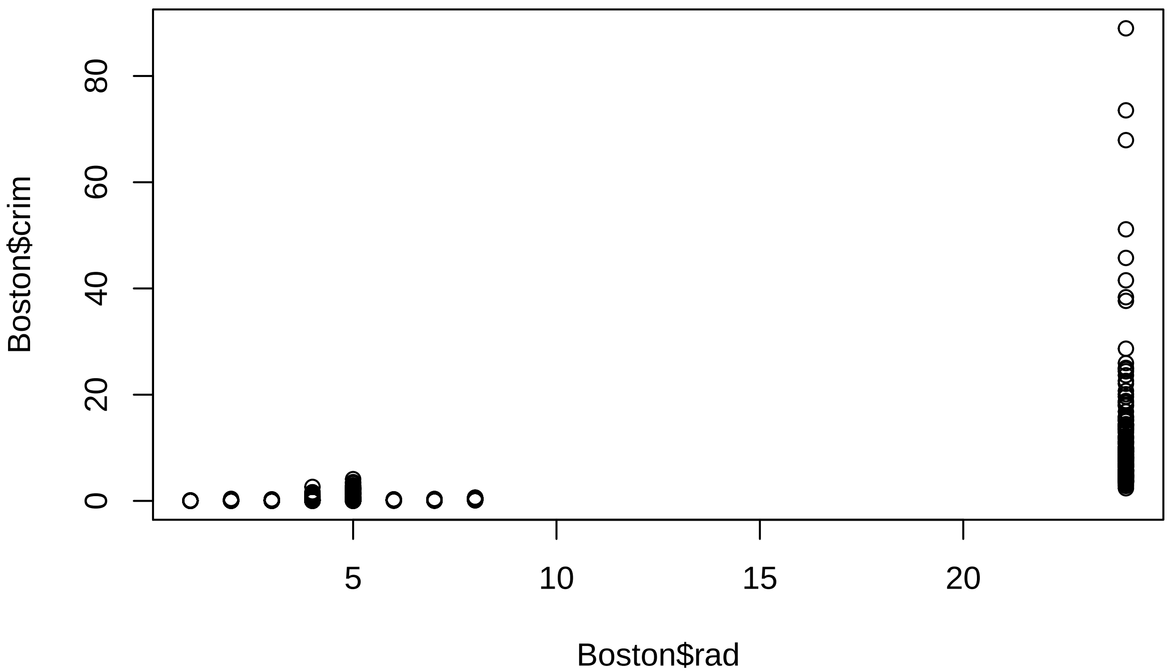

```r
# X correlates with: a, b, c
# crim: age, dis, rad, tax, ptratio
# zn: indus, nox, age, lstat
# indus: age, dis
# nox: age, dis
# dis: lstat
# lstat: medv

# (c)
plot(Boston$age, Boston$crim)
```



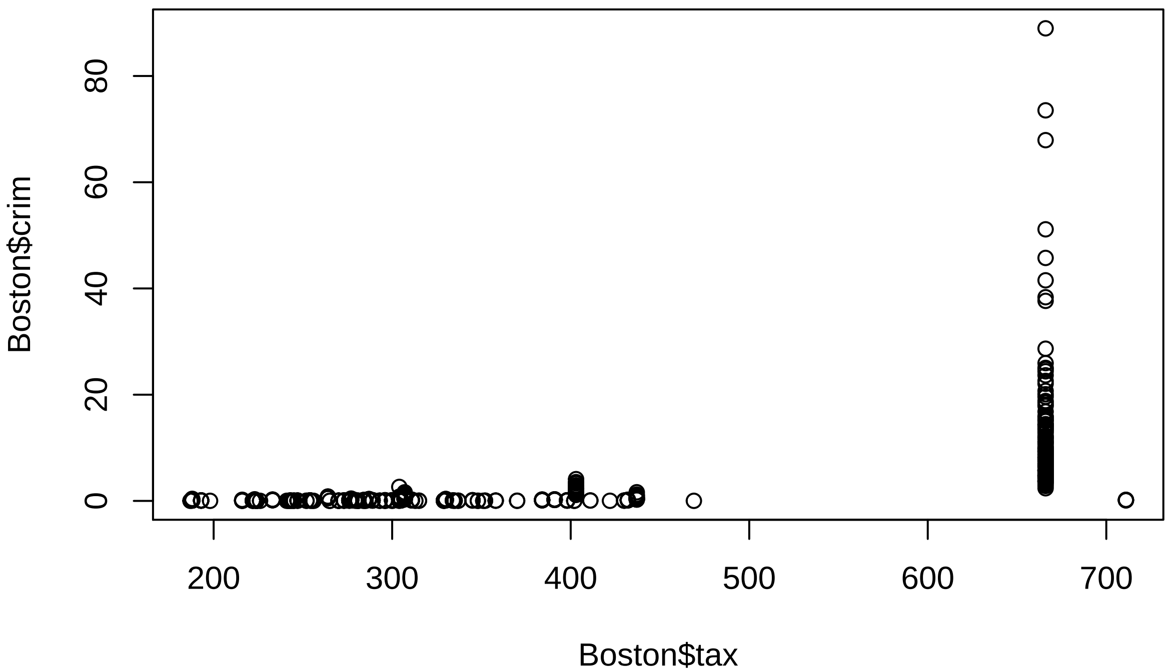

```r
# Older homes, more crime
plot(Boston$dis, Boston$crim)
```



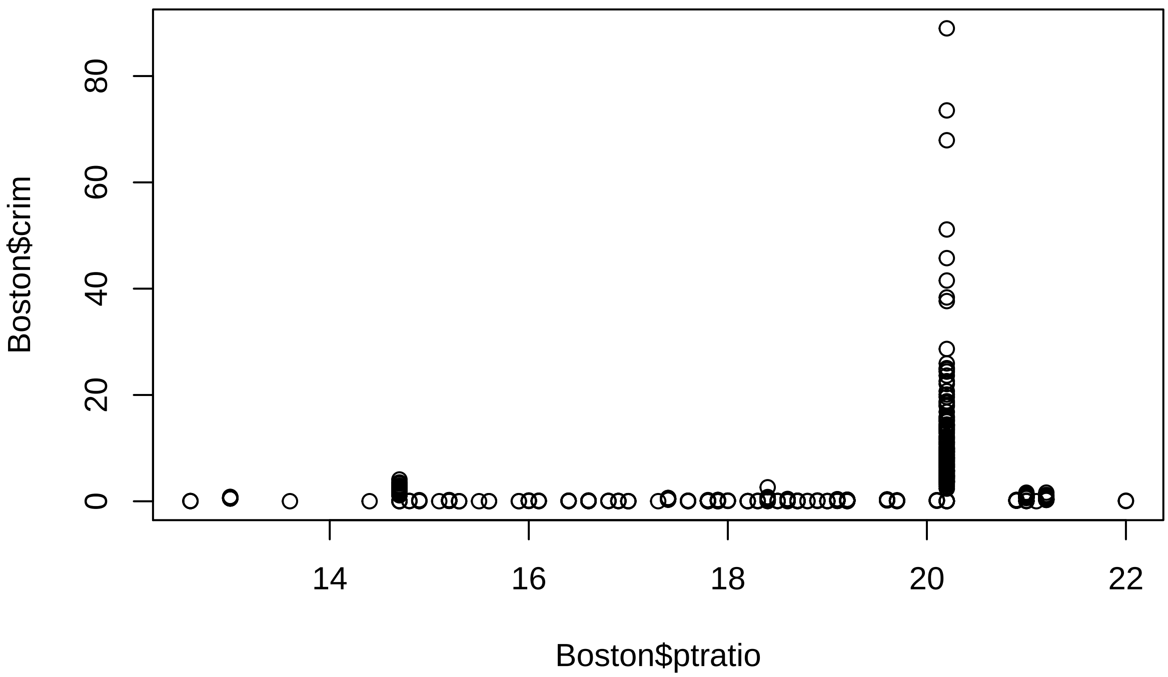

```r
# Closer to work-area, more crime
plot(Boston$rad, Boston$crim)
```



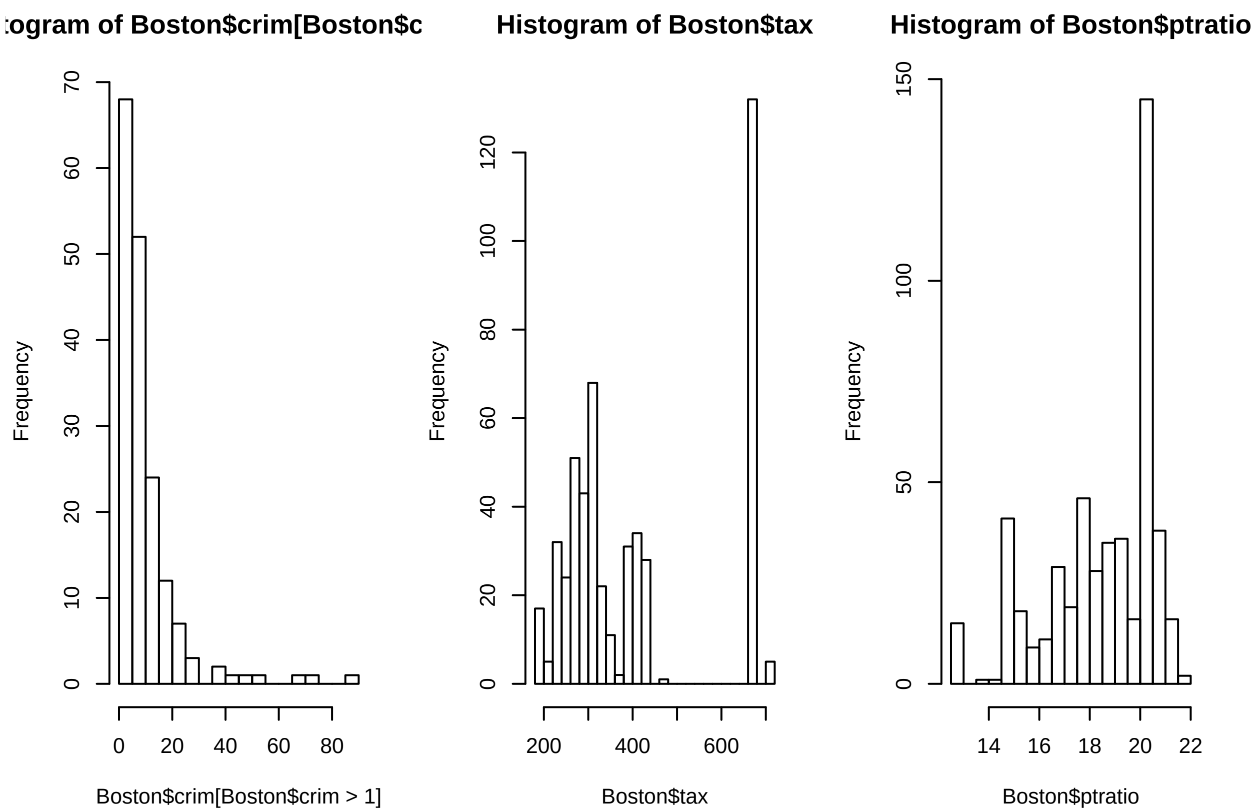

```r
# Higher index of accessibility to radial highways, more crime
plot(Boston$tax, Boston$crim)
```




```r
# Higher tax rate, more crime
plot(Boston$ptratio, Boston$crim)
```




```r
# Higher pupil:teacher ratio, more crime

# (d)
par(mfrow=c(1,3))
hist(Boston$crim[Boston$crim>1], breaks=25)
# most cities have low crime rates, but there is a long tail: 18 suburbs appear
# to have a crime rate > 20, reaching to above 80
hist(Boston$tax, breaks=25)
# there is a large divide between suburbs with low tax rates and a peak at 660-680
hist(Boston$ptratio, breaks=25)
```




```r
# a skew towards high ratios, but no particularly high ratios

# (e)
dim(subset(Boston, chas == 1))
```

```
## [1] 35 14
```

```r
# 35 suburbs

# (f)
median(Boston$ptratio)
```

```
## [1] 19.05
```

```r
# 19.05

# (g)
(subset(Boston, medv == min(Boston$medv)))
```

```
##        crim zn indus chas   nox    rm age    dis rad tax ptratio  black
## 399 38.3518  0  18.1    0 0.693 5.453 100 1.4896  24 666    20.2 396.90
## 406 67.9208  0  18.1    0 0.693 5.683 100 1.4254  24 666    20.2 384.97
##     lstat medv
## 399 30.59    5
## 406 22.98    5
```

```r
#               399      406
# crim      38.3518  67.9208 above 3rd quartile
# zn         0.0000   0.0000 at min
```

```r
# indus    18.1000  18.1000 at 3rd quartile
# chas      0.0000   0.0000 not bounded by river
# nox       0.6930   0.6930 above 3rd quartile
# rm        5.4530   5.6830 below 1st quartile
# age     100.0000 100.0000 at max
# dis       1.4896   1.4254 below 1st quartile
# rad      24.0000  24.0000 at max
# tax     666.0000 666.0000 at 3rd quartile
# ptratio  20.2000  20.2000 at 3rd quartile
# black   396.9000 384.9700 at max; above 1st quartile
# lstat    30.5900  22.9800 above 3rd quartile
# medv      5.0000   5.0000 at min
summary(Boston)
```

```
##       crim                zn             indus            chas
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000
##  1st Qu.: 0.08204   1st Qu.:  0.00   1st Qu.: 5.19   1st Qu.:0.00000
##  Median : 0.25651   Median :  0.00   Median : 9.69   Median :0.00000
##  Mean   : 3.61352   Mean   : 11.36   Mean   :11.14   Mean   :0.06917
##  3rd Qu.: 3.67708   3rd Qu.: 12.50   3rd Qu.:18.10   3rd Qu.:0.00000
##  Max.   :88.97620   Max.   :100.00   Max.   :27.74   Max.   :1.00000
##       nox               rm             age              dis
##  Min.   :0.3850   Min.   :3.561   Min.   :  2.90   Min.   : 1.130
##  1st Qu.:0.4490   1st Qu.:5.886   1st Qu.: 45.02   1st Qu.: 2.100
##  Median :0.5380   Median :6.208   Median : 77.50   Median : 3.207
##  Mean   :0.5547   Mean   :6.285   Mean   : 68.57   Mean   : 3.795
##  3rd Qu.:0.6240   3rd Qu.:6.623   3rd Qu.: 94.08   3rd Qu.: 5.188
##  Max.   :0.8710   Max.   :8.780   Max.   :100.00   Max.   :12.127
##       rad              tax           ptratio          black
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   :  0.32
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.:375.38
##  Median : 5.000   Median :330.0   Median :19.05   Median :391.44
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :356.67
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:396.23
##  Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :396.90
##      lstat            medv
##  Min.   : 1.73   Min.   : 5.00
##  1st Qu.: 6.95   1st Qu.:17.02
##  Median :11.36   Median :21.20
##  Mean   :12.65   Mean   :22.53
##  3rd Qu.:16.95   3rd Qu.:25.00
##  Max.   :37.97   Max.   :50.00
```

```r
# Not the best place to live, but certainly not the worst.

# (h)
dim(subset(Boston, rm > 7))
```

```
## [1] 64 14
```

```r
# 64
dim(subset(Boston, rm > 8))
```

```
## [1] 13 14
```

```r
# 13
summary(subset(Boston, rm > 8))
```

```
##       crim               zn            indus             chas       
##  Min.   :0.02009   Min.   : 0.00   Min.   : 2.680   Min.   :0.0000  
##  1st Qu.:0.33147   1st Qu.: 0.00   1st Qu.: 3.970   1st Qu.:0.0000  
##  Median :0.52014   Median : 0.00   Median : 6.200   Median :0.0000  
##  Mean   :0.71879   Mean   :13.62   Mean   : 7.078   Mean   :0.1538  
##  3rd Qu.:0.57834   3rd Qu.:20.00   3rd Qu.: 6.200   3rd Qu.:0.0000  
##  Max.   :3.47428   Max.   :95.00   Max.   :19.580   Max.   :1.0000  
##       nox               rm             age             dis       
##  Min.   :0.4161   Min.   :8.034   Min.   : 8.40   Min.   :1.801  
##  1st Qu.:0.5040   1st Qu.:8.247   1st Qu.:70.40   1st Qu.:2.288  
##  Median :0.5070   Median :8.297   Median :78.30   Median :2.894  
##  Mean   :0.5392   Mean   :8.349   Mean   :71.54   Mean   :3.430  
##  3rd Qu.:0.6050   3rd Qu.:8.398   3rd Qu.:86.50   3rd Qu.:3.652  
##  Max.   :0.7180   Max.   :8.780   Max.   :93.90   Max.   :8.907  
##       rad              tax           ptratio          black      
##  Min.   : 2.000   Min.   :224.0   Min.   :13.00   Min.   :354.6  
##  1st Qu.: 5.000   1st Qu.:264.0   1st Qu.:14.70   1st Qu.:384.5  
##  Median : 7.000   Median :307.0   Median :17.40   Median :386.9  
##  Mean   : 7.462   Mean   :325.1   Mean   :16.36   Mean   :385.2  
##  3rd Qu.: 8.000   3rd Qu.:307.0   3rd Qu.:17.40   3rd Qu.:389.7  
##  Max.   :24.000   Max.   :666.0   Max.   :20.20   Max.   :396.9  
##      lstat           medv     
##  Min.   :2.47   Min.   :21.9  
##  1st Qu.:3.32   1st Qu.:41.7  
##  Median :4.14   Median :48.3  
##  Mean   :4.31   Mean   :44.2  
##  3rd Qu.:5.12   3rd Qu.:50.0  
##  Max.   :7.44   Max.   :50.0
```

```r
summary(Boston)
```

```
##       crim                zn             indus            chas        
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000  
##  1st Qu.: 0.08204   1st Qu.:  0.00   1st Qu.: 5.19   1st Qu.:0.00000  
##  Median : 0.25651   Median :  0.00   Median : 9.69   Median :0.00000  
##  Mean   : 3.61352   Mean   : 11.36   Mean   :11.14   Mean   :0.06917  
##  3rd Qu.: 3.67708   3rd Qu.: 12.50   3rd Qu.:18.10   3rd Qu.:0.00000  
##  Max.   :88.97620   Max.   :100.00   Max.   :27.74   Max.   :1.00000  
##       nox               rm             age              dis        
##  Min.   :0.3850   Min.   :3.561   Min.   :  2.90   Min.   : 1.130  
##  1st Qu.:0.4490   1st Qu.:5.886   1st Qu.: 45.02   1st Qu.: 2.100  
##  Median :0.5380   Median :6.208   Median : 77.50   Median : 3.207  
##  Mean   :0.5547   Mean   :6.285   Mean   : 68.57   Mean   : 3.795  
##  3rd Qu.:0.6240   3rd Qu.:6.623   3rd Qu.: 94.08   3rd Qu.: 5.188  
##  Max.   :0.8710   Max.   :8.780   Max.   :100.00   Max.   :12.127  
##       rad              tax           ptratio          black       
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   :  0.32  
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.:375.38  
##  Median : 5.000   Median :330.0   Median :19.05   Median :391.44  
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :356.67  
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:396.23
```

```
## Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :396.90
##      lstat            medv
## Min.   : 1.73   Min.   : 5.00
## 1st Qu.: 6.95   1st Qu.:17.02
## Median :11.36   Median :21.20
## Mean   :12.65   Mean   :22.53
## 3rd Qu.:16.95   3rd Qu.:25.00
## Max.   :37.97   Max.   :50.00
```

```r
# relatively lower crime (comparing range), lower lstat (comparing range)
```