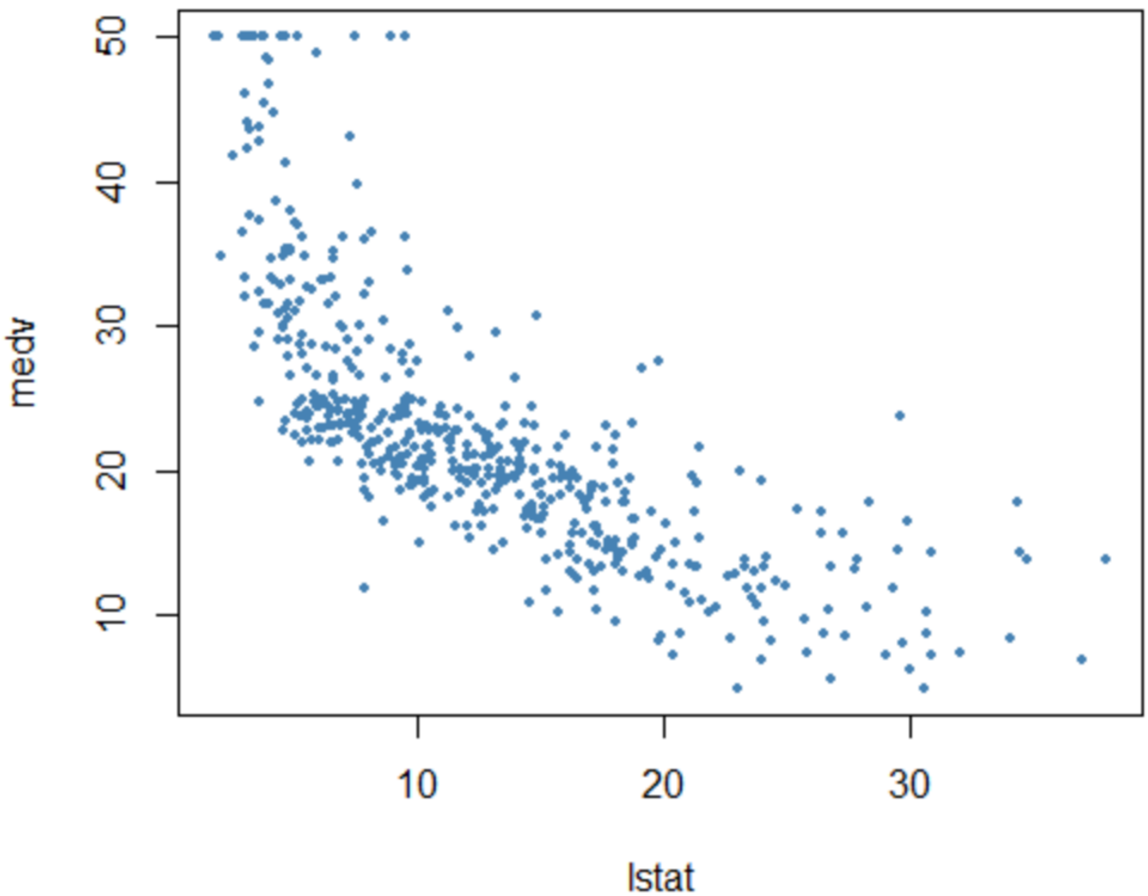
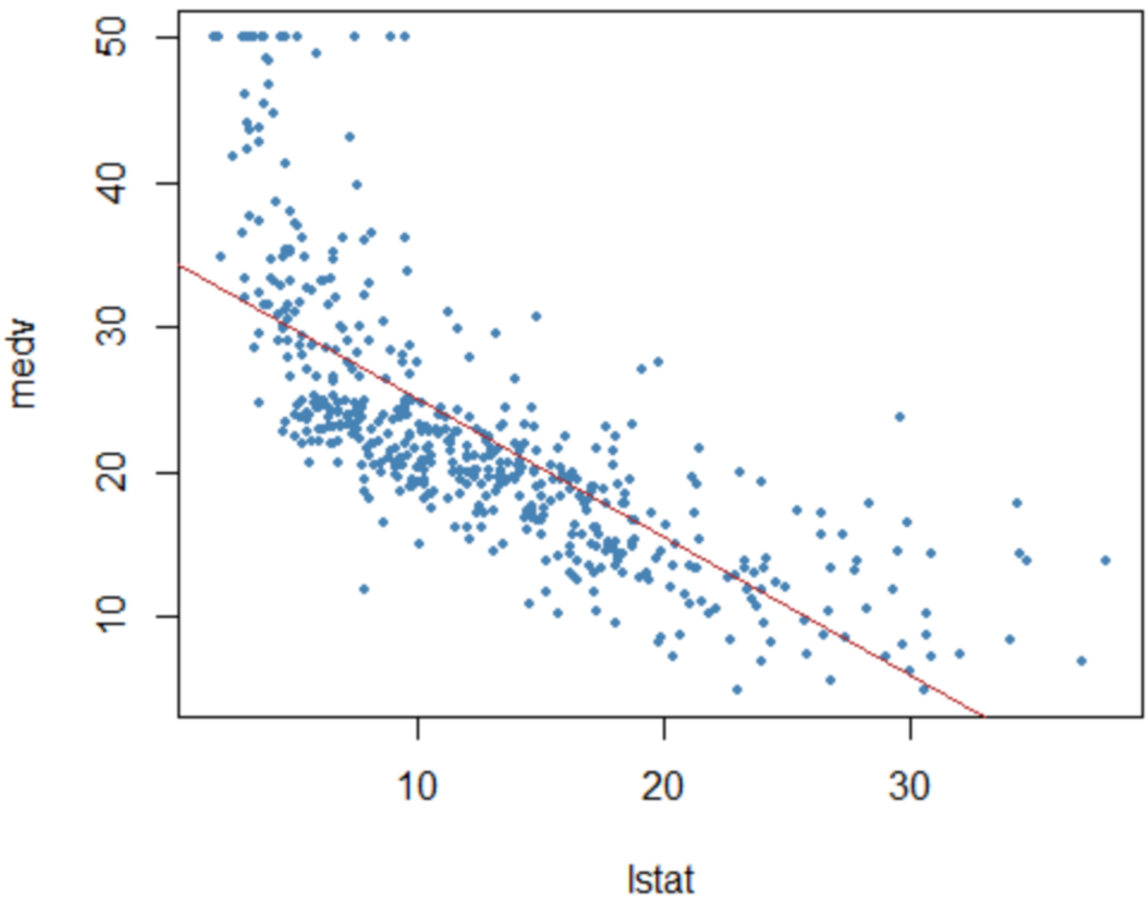
PA6323 Knowledge Mining
Assignment 6 **James Norcross**

```
> install.packages(c("easypackages","MASS","ISLR","arm"))
Error in install.packages : Updating loaded packages
> install.packages(c("easypackages", "MASS", "ISLR", "arm"))
Warning in install.packages :
  packages ‘easypackages’, ‘MASS’, ‘ISLR’, ‘arm’ are in use and will not be installed
> library(easypackages)
> libraries("arm","MASS","ISLR")
All packages loaded successfully
> ## Load datasets from MASS and ISLR packages
> attach(Boston)
The following objects are masked from Boston (pos = 5):

    age, black, chas, crim, dis, indus, lstat, medv, nox, ptratio, rad, rm, tax, zn

> ### Simple linear regression
> names(Boston)
 [1] "crim"    "zn"      "indus"   "chas"    "nox"     "rm"      "age"     "dis"     "rad"     "tax"
"ptratio"
[12] "black"   "lstat"   "medv"
> # What is the Boston dataset?
> ?Boston
> plot(medv~lstat,Boston, pch=20, cex=.8, col="steelblue")
```




```
> fit1=lm(medv~lstat,data=Boston)
> fit1

Call:
lm(formula = medv ~ lstat, data = Boston)

Coefficients:
(Intercept)        lstat
      34.55        -0.95

> summary(fit1)

Call:
lm(formula = medv ~ lstat, data = Boston)

Residuals:
```

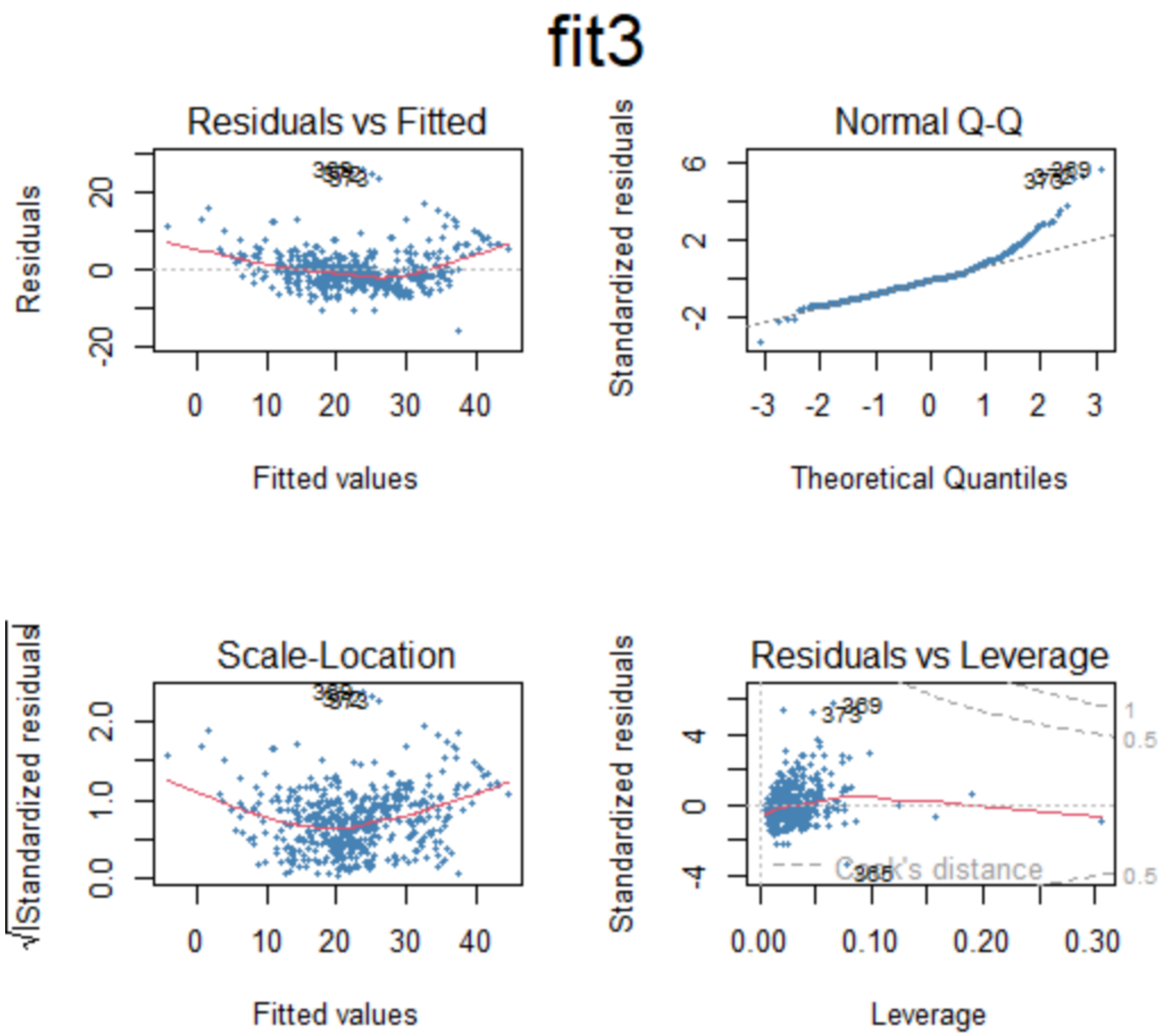
```
    Min      1Q  Median      3Q     Max 
-15.168  -3.990  -1.318   2.034  24.500 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 34.55384    0.56263   61.41   <2e-16 ***
lstat       -0.95005    0.03873  -24.53   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.216 on 504 degrees of freedom
Multiple R-squared:  0.5441,  Adjusted R-squared:  0.5432 
F-statistic: 601.6 on 1 and 504 DF,  p-value: < 2.2e-16

> abline(fit1,col="firebrick")
```




```
> names(fit1)
```

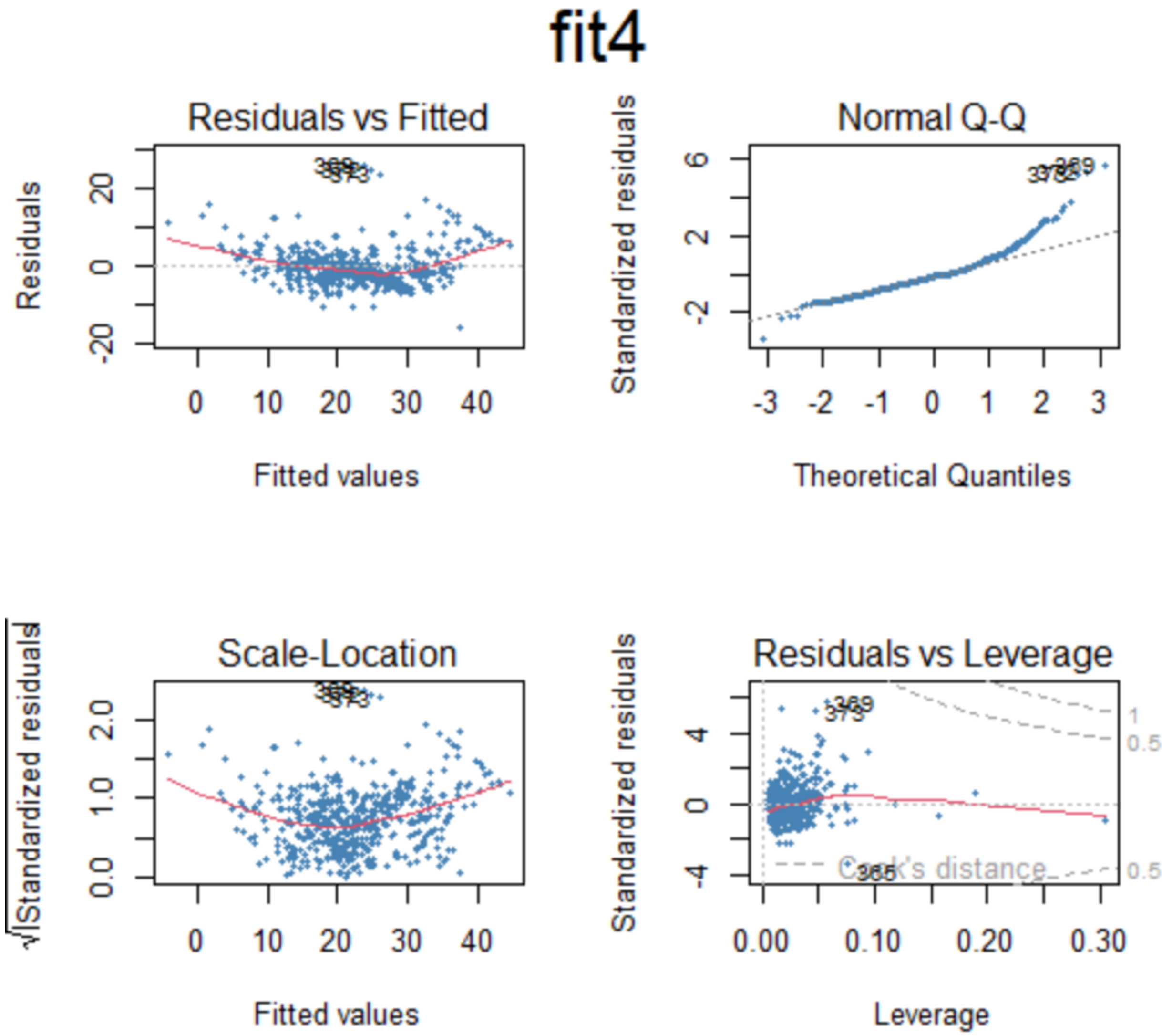
```
 [1] "coefficients"  "residuals"     "effects"       "rank"          "fitted.values" "assign"        "qr"
 [8] "df.residual"   "xlevels"       "call"          "terms"         "model"
> confint(fit1) # confidence intervals
                2.5 %     97.5 %
(Intercept) 33.448457 35.6592247
lstat       -1.026148 -0.8739505
> # Predictions using values in lstat
> predict(fit1,data.frame(lstat=c(0,5,10,15)),interval="confidence") # confidence intervals
       fit      lwr      upr
1 34.55384 33.44846 35.65922
2 29.80359 29.00741 30.59978
3 25.05335 24.47413 25.63256
4 20.30310 19.73159 20.87461
> predict(fit1,data.frame(lstat=c(0,5,10,15)),interval="prediction") # prediction intervals
       fit       lwr      upr
1 34.55384 22.291923 46.81576
2 29.80359 17.565675 42.04151
3 25.05335 12.827626 37.27907
4 20.30310  8.077742 32.52846
> ### Multiple linear regression
> fit2=lm(medv~lstat+age,data=Boston)
> summary(fit2)

Call:
lm(formula = medv ~ lstat + age, data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.981  -3.978  -1.283   1.968  23.158 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 33.22276    0.73085  45.458  < 2e-16 ***
lstat       -1.03207    0.04819 -21.416  < 2e-16 ***
age          0.03454    0.01223   2.826  0.00491 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.173 on 503 degrees of freedom
Multiple R-squared:  0.5513,  Adjusted R-squared:  0.5495 
F-statistic:   309 on 2 and 503 DF,  p-value: < 2.2e-16

> fit3=lm(medv~.,Boston)
> summary(fit3)

Call:
```

```
lm(formula = medv ~ ., data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.595  -2.730  -0.518   1.777  26.199 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.646e+01  5.103e+00   7.144 3.28e-12 ***
crim        -1.080e-01  3.286e-02  -3.287 0.001087 ** 
zn           4.642e-02  1.373e-02   3.382 0.000778 ***
indus        2.056e-02  6.150e-02   0.334 0.738288    
chas         2.687e+00  8.616e-01   3.118 0.001925 ** 
nox         -1.777e+01  3.820e+00  -4.651 4.25e-06 ***
rm           3.810e+00  4.179e-01   9.116  < 2e-16 ***
age          6.922e-04  1.321e-02   0.052 0.958229    
dis         -1.476e+00  1.995e-01  -7.398 6.01e-13 ***
rad          3.060e-01  6.635e-02   4.613 5.07e-06 ***
tax         -1.233e-02  3.760e-03  -3.280 0.001112 ** 
ptratio     -9.527e-01  1.308e-01  -7.283 1.31e-12 ***
black        9.312e-03  2.686e-03   3.467 0.000573 ***
lstat       -5.248e-01  5.072e-02 -10.347  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.745 on 492 degrees of freedom
Multiple R-squared:  0.7406,  Adjusted R-squared:  0.7338 
F-statistic: 108.1 on 13 and 492 DF,  p-value: < 2.2e-16

> par(mfrow=c(2,2))
> plot(fit3,pch=20, cex=.8, col="steelblue")
> mtext("fit3", side = 3, line = - 2, cex = 2, outer = TRUE)
```

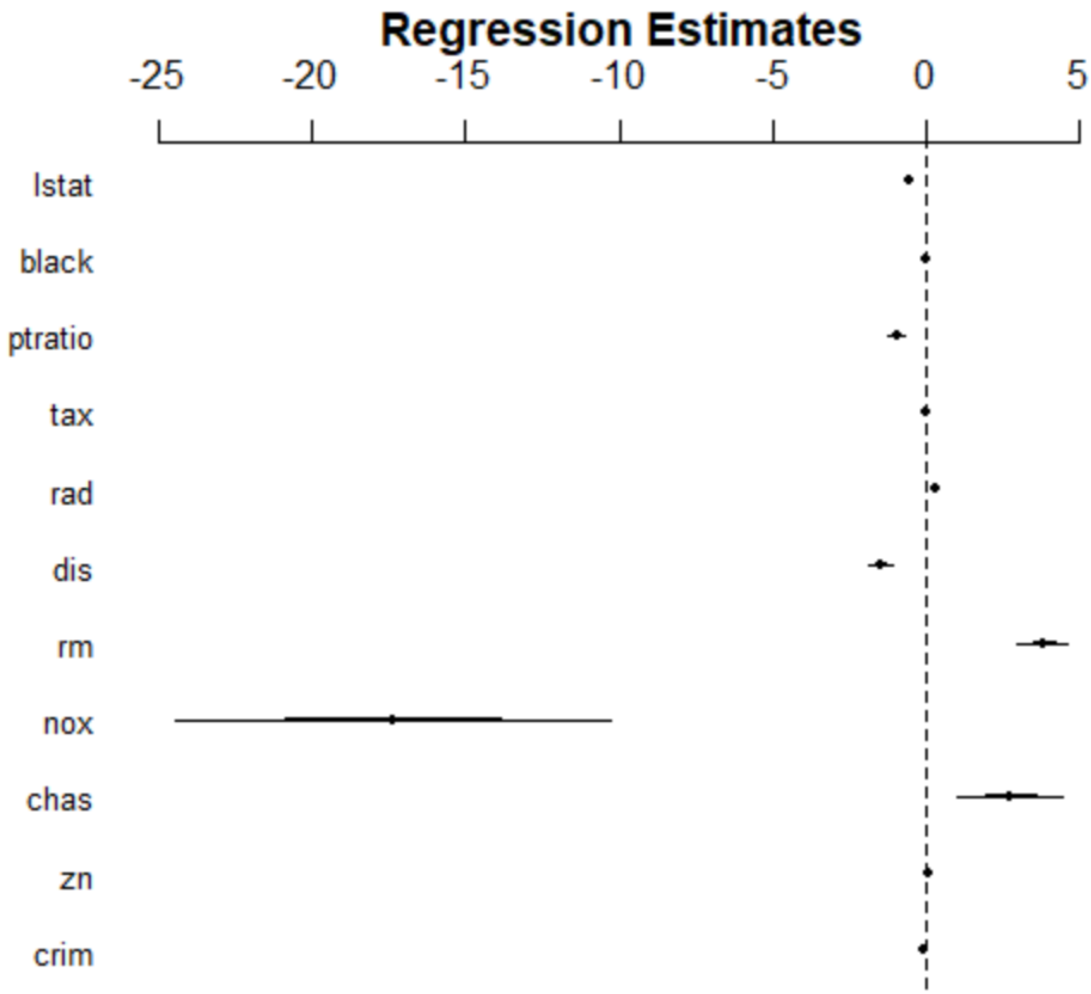



```
> # Update function to re-specify the model, i.e. include all but age and indus variables
> fit4=update(fit3,~.-age-indus)
> summary(fit4)

Call:
lm(formula = medv ~ crim + zn + chas + nox + rm + dis + rad +
    tax + ptratio + black + lstat, data = Boston)

Residuals:
     Min       1Q   Median       3Q      Max
-15.5984  -2.7386  -0.5046   1.7273  26.2373

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  36.341145   5.067492   7.171 2.73e-12 ***
crim         -0.108413   0.032779  -3.307 0.001010 **
```

```
zn            0.045845   0.013523   3.390 0.000754 ***
chas          2.718716   0.854240   3.183 0.001551 **
nox         -17.376023   3.535243  -4.915 1.21e-06 ***
rm            3.801579   0.406316   9.356  < 2e-16 ***
dis          -1.492711   0.185731  -8.037 6.84e-15 ***
rad           0.299608   0.063402   4.726 3.00e-06 ***
tax          -0.011778   0.003372  -3.493 0.000521 ***
ptratio      -0.946525   0.129066  -7.334 9.24e-13 ***
black         0.009291   0.002674   3.475 0.000557 ***
lstat        -0.522553   0.047424 -11.019  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.736 on 494 degrees of freedom
Multiple R-squared:  0.7406,  Adjusted R-squared:  0.7348
F-statistic: 128.2 on 11 and 494 DF,  p-value: < 2.2e-16

> # Set the next plot configuration
> par(mfrow=c(2,2), main="fit4")
Warning message:
In par(mfrow = c(2, 2), main = "fit4") :
  "main" is not a graphical parameter
> plot(fit4,pch=20, cex=.8, col="steelblue")
> mtext("fit4", side = 3, line = - 2, cex = 2, outer = TRUE)
```

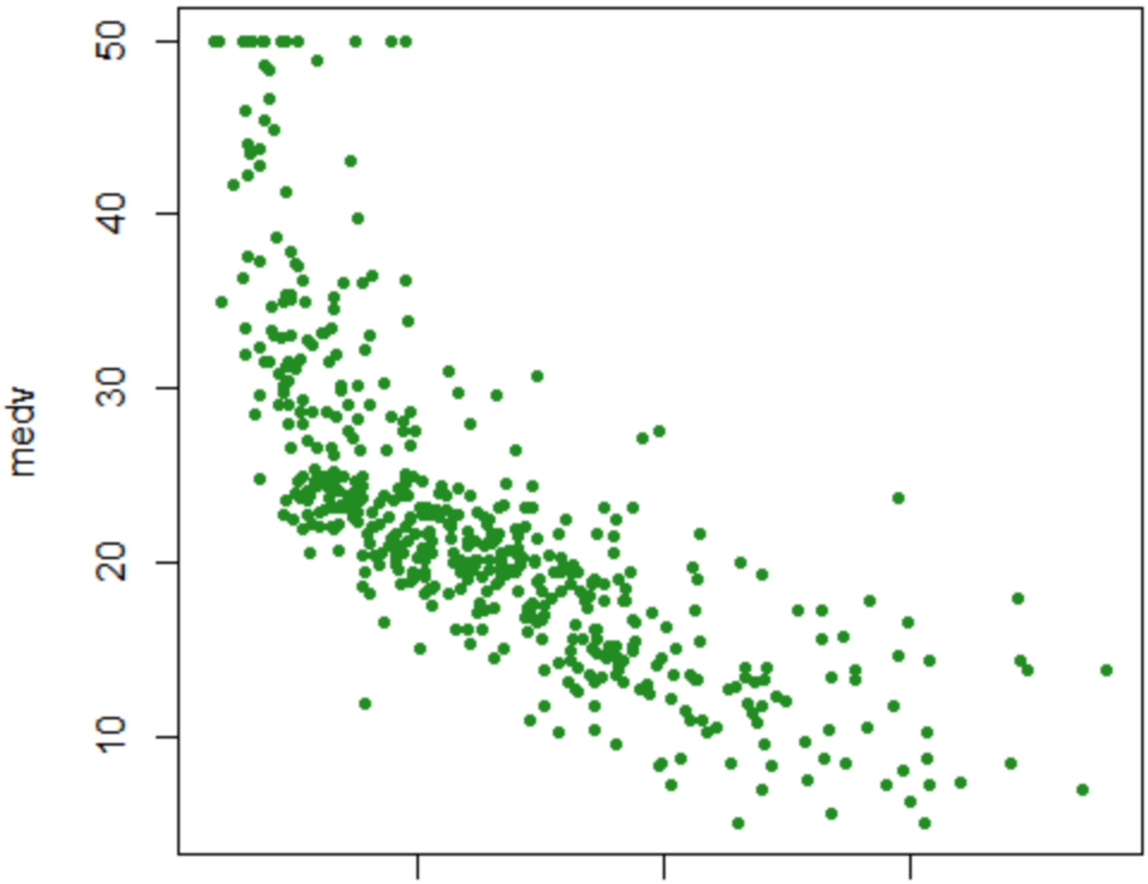


> # Uses coefplot to plot coefficients. Note the line at 0.
> par(mfrow=c(1,1))
> arm::coefplot(fit4)

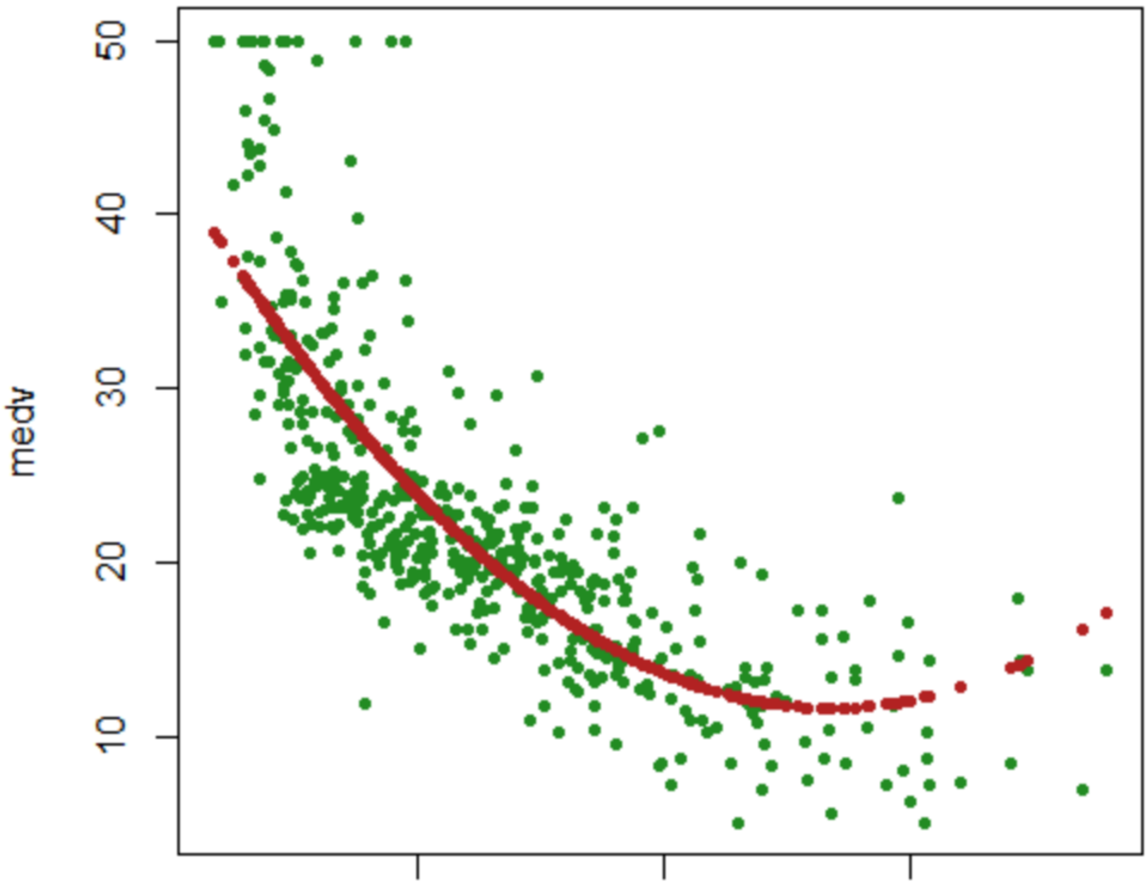



```
> ### Nonlinear terms and Interactions
> fit5=lm(medv~lstat*age,Boston) # include both variables and the interaction term x1:x2
> summary(fit5)

Call:
lm(formula = medv ~ lstat * age, data = Boston)

Residuals:
    Min      1Q  Median      3Q     Max
-15.806  -4.045  -1.333   2.085  27.552

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 36.0885359  1.4698355  24.553  < 2e-16 ***
lstat       -1.3921168  0.1674555  -8.313 8.78e-16 ***
age         -0.0007209  0.0198792  -0.036   0.9711
```

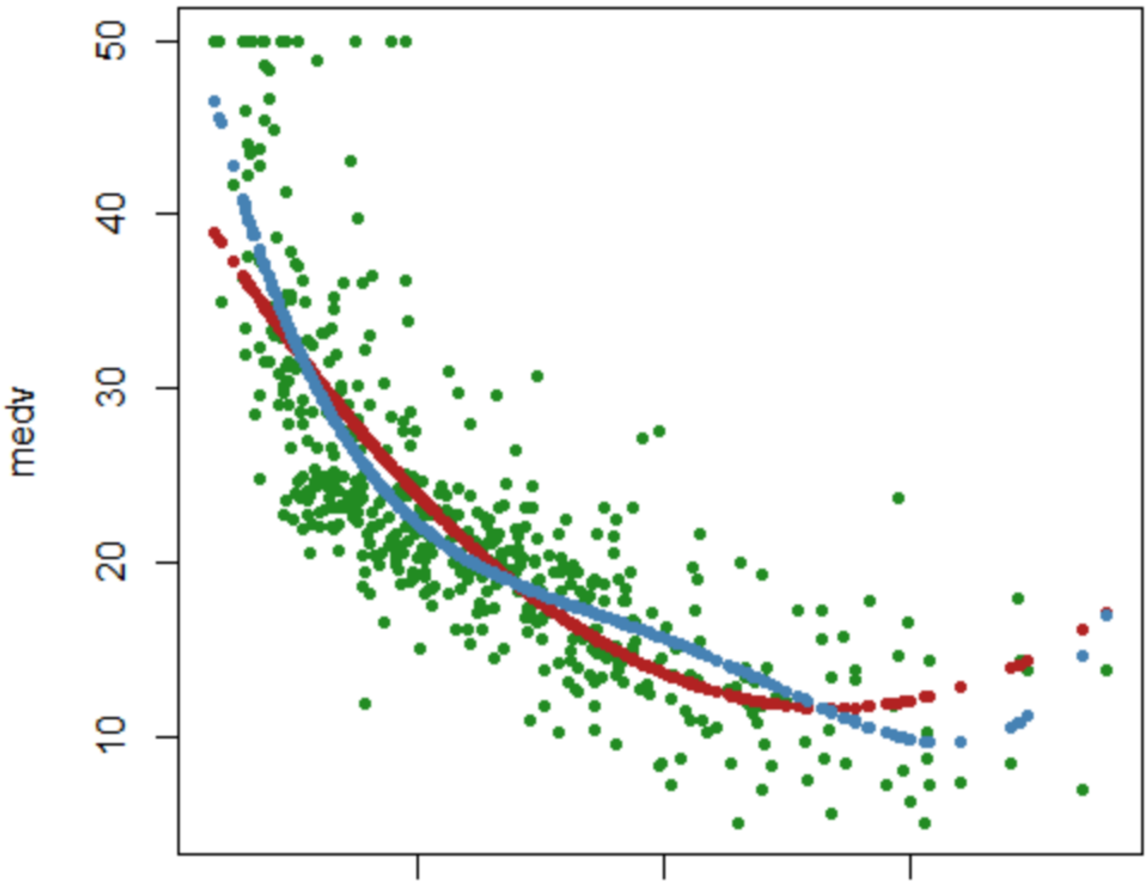
```
lstat:age    0.0041560  0.0018518   2.244   0.0252 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.149 on 502 degrees of freedom
Multiple R-squared:  0.5557,  Adjusted R-squared:  0.5531
F-statistic: 209.3 on 3 and 502 DF,  p-value: < 2.2e-16

> ## I() identity function for squared term to interpret as-is
> ## Combine two command lines with semicolon
> fit6=lm(medv~lstat +I(lstat^2),Boston); summary(fit6)

Call:
lm(formula = medv ~ lstat + I(lstat^2), data = Boston)

Residuals:
     Min       1Q   Median       3Q      Max
-15.2834  -3.8313  -0.5295   2.3095  25.4148

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 42.862007   0.872084   49.15   <2e-16 ***
lstat       -2.332821   0.123803  -18.84   <2e-16 ***
I(lstat^2)   0.043547   0.003745   11.63   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.524 on 503 degrees of freedom
Multiple R-squared:  0.6407,  Adjusted R-squared:  0.6393
F-statistic: 448.5 on 2 and 503 DF,  p-value: < 2.2e-16

> par(mfrow=c(1,1))
> plot(medv~lstat, pch=20, col="forestgreen")
```




```
> points(lstat,fitted(fit6),col="firebrick",pch=20)
```



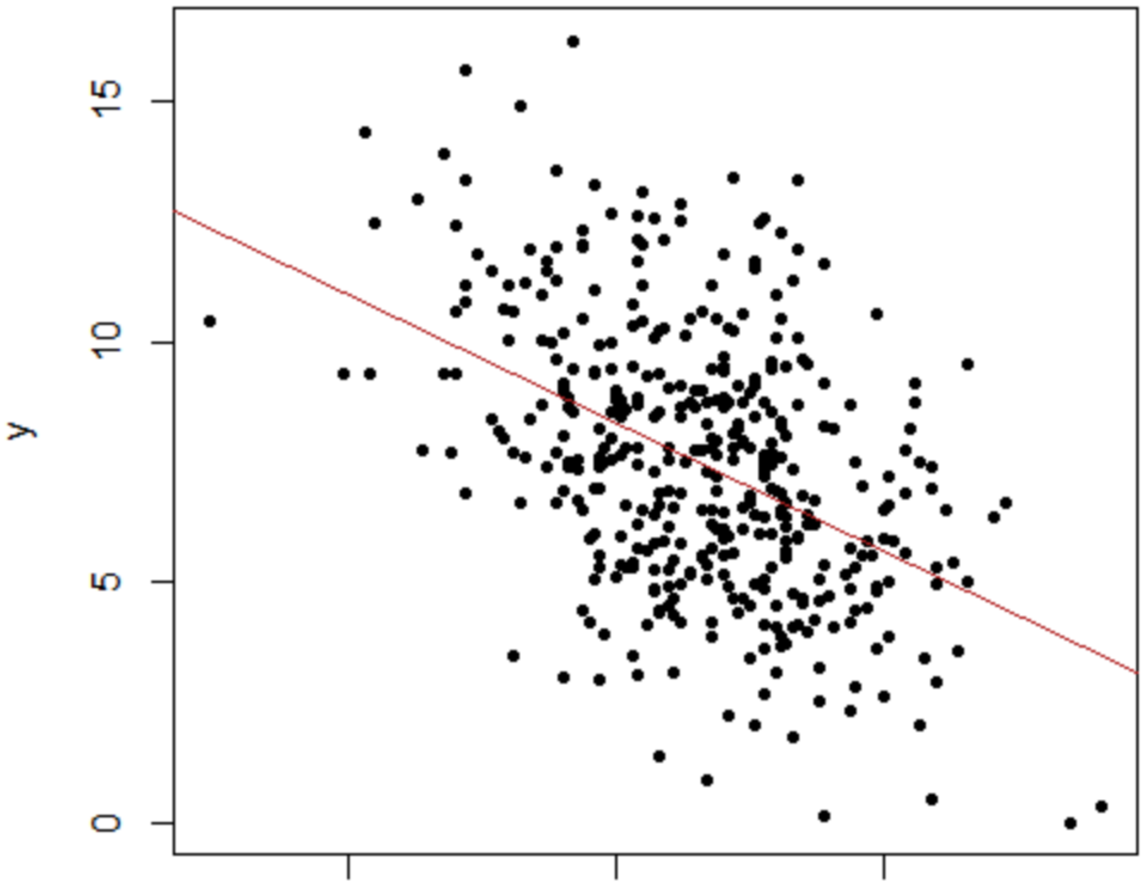
> fit7=lm(medv~poly(lstat,4))
> points(lstat,fitted(fit7),col="steelblue",pch=20)



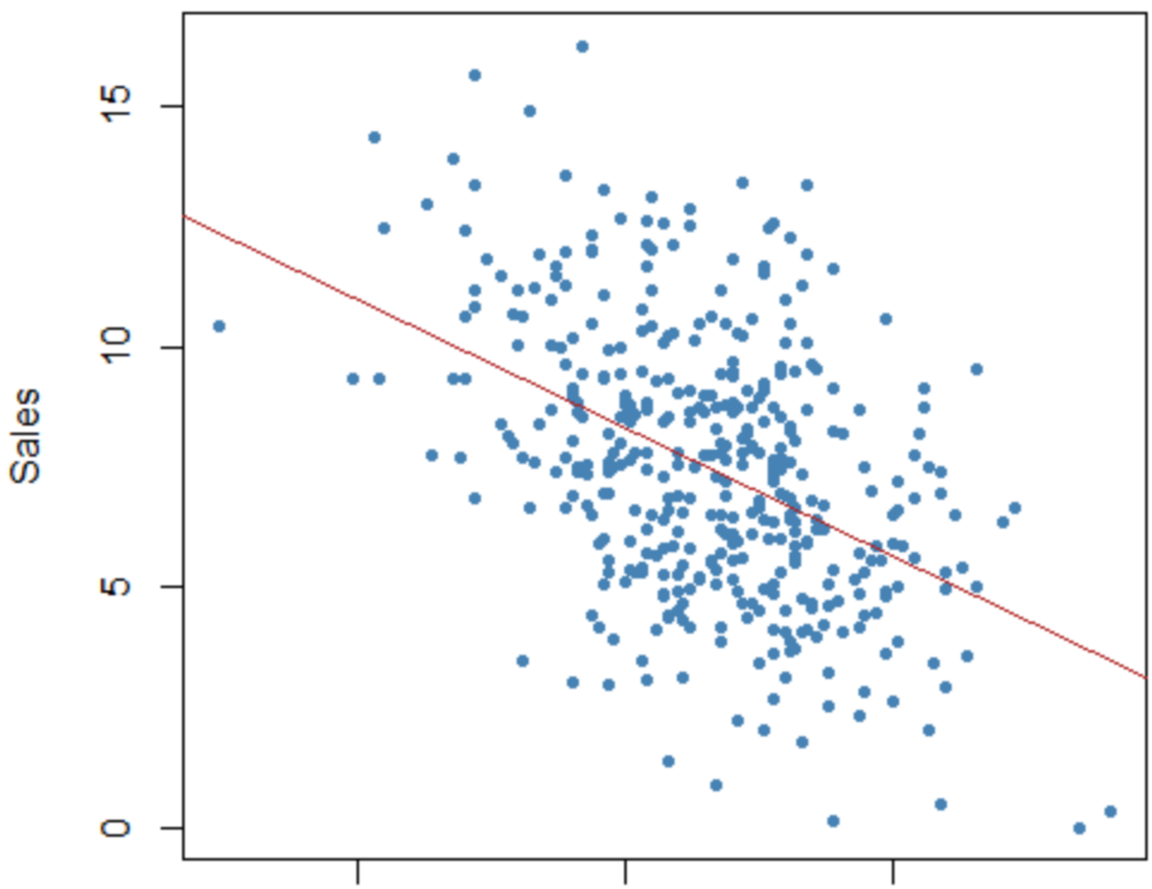

```
> ###Qualitative predictors
> names(Carseats)
 [1] "Sales"       "CompPrice"   "Income"      "Advertising" "Population"  "Price"       "ShelveLoc"  
"Age"        
 [9] "Education"   "Urban"       "US"         
> summary(Carseats)
     Sales          CompPrice       Income        Advertising       Population        Price        ShelveLoc  
 Min.   : 0.000   Min.   : 77   Min.   : 21.00   Min.   : 0.000   Min.   : 10.0   Min.   : 24.0   Bad   : 
96  
 1st Qu.: 5.390   1st Qu.:115   1st Qu.: 42.75   1st Qu.: 0.000   1st Qu.:139.0   1st Qu.:100.0   
Good  : 85  
 Median : 7.490   Median :125   Median : 69.00   Median : 5.000   Median :272.0   Median :117.0   
Medium:219  
 Mean   : 7.496   Mean   :125   Mean   : 68.66   Mean   : 6.635   Mean   :264.8   Mean   :115.8                 
 3rd Qu.: 9.320   3rd Qu.:135   3rd Qu.: 91.00   3rd Qu.:12.000   3rd Qu.:398.5   3rd Qu.:131.0                 
 Max.   :16.270   Max.   :175   Max.   :120.00   Max.   :29.000   Max.   :509.0   Max.   :191.0                 
```

```
      Age          Education    Urban       US
 Min.   :25.00   Min.   :10.0   No :118   No :142
 1st Qu.:39.75   1st Qu.:12.0   Yes:282   Yes:258
 Median :54.50   Median :14.0
 Mean   :53.32   Mean   :13.9
 3rd Qu.:66.00   3rd Qu.:16.0
 Max.   :80.00   Max.   :18.0
> fit1=lm(Sales~.+Income:Advertising+Age:Price,Carseats) # add two interaction terms
> summary(fit1)

Call:
lm(formula = Sales ~ . + Income:Advertising + Age:Price, data = Carseats)

Residuals:
    Min      1Q  Median      3Q     Max
-2.9208 -0.7503  0.0177  0.6754  3.3413

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)         6.5755654  1.0087470   6.519 2.22e-10 ***
CompPrice           0.0929371  0.0041183  22.567  < 2e-16 ***
Income              0.0108940  0.0026044   4.183 3.57e-05 ***
Advertising         0.0702462  0.0226091   3.107 0.002030 **
Population          0.0001592  0.0003679   0.433 0.665330
Price              -0.1008064  0.0074399 -13.549  < 2e-16 ***
ShelveLocGood       4.8486762  0.1528378  31.724  < 2e-16 ***
ShelveLocMedium     1.9532620  0.1257682  15.531  < 2e-16 ***
Age                -0.0579466  0.0159506  -3.633 0.000318 ***
Education          -0.0208525  0.0196131  -1.063 0.288361
UrbanYes            0.1401597  0.1124019   1.247 0.213171
USYes              -0.1575571  0.1489234  -1.058 0.290729
Income:Advertising  0.0007510  0.0002784   2.698 0.007290 **
Price:Age           0.0001068  0.0001333   0.801 0.423812
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.011 on 386 degrees of freedom
Multiple R-squared:  0.8761,  Adjusted R-squared:  0.8719
F-statistic:   210 on 13 and 386 DF,  p-value: < 2.2e-16

> attach(Carseats)
The following objects are masked from Carseats (pos = 4):

    Advertising, Age, CompPrice, Education, Income, Population, Price, Sales, ShelveLoc, Urban,
US
```

```
The following objects are masked from Carseats (pos = 5):

    Advertising, Age, CompPrice, Education, Income, Population, Price, Sales, ShelveLoc, Urban,
US

> contrasts(Carseats$ShelveLoc) # what is contrasts function?
       Good Medium
Bad       0      0
Good      1      0
Medium    0      1
> ?contrasts
> ### Writing an R function to combine the lm, plot and abline functions to
> ### create a one step regression fit plot function
> regplot=function(x,y){
+   fit=lm(y~x)
+   plot(x,y, pch=20)
+   abline(fit,col="firebrick")
+ }
> ### Writing an R function to combine the lm, plot and abline functions to
> ### create a one step regression fit plot function
> regplot=function(x,y){
+   fit=lm(y~x)
+   plot(x,y, pch=20)
+   abline(fit,col="firebrick")
+ }
> attach(Carseats)
The following objects are masked from Carseats (pos = 3):

    Advertising, Age, CompPrice, Education, Income, Population, Price, Sales, ShelveLoc, Urban,
US

The following objects are masked from Carseats (pos = 5):

    Advertising, Age, CompPrice, Education, Income, Population, Price, Sales, ShelveLoc, Urban,
US

The following objects are masked from Carseats (pos = 6):

    Advertising, Age, CompPrice, Education, Income, Population, Price, Sales, ShelveLoc, Urban,
US

> regplot(Price,Sales)
```




```
> ## Allow extra room for additional arguments/specifications
> regplot=function(x,y,...){
+   fit=lm(y~x)
+   plot(x,y,...)
+   abline(fit,col="firebrick")
+ }
> regplot(Price,Sales,xlab="Price",ylab="Sales",col="steelblue",pch=20)
```




```
> ## Additional note: try out the coefplot2 package to finetune the coefplots
> ## Additional note: try out the coefplot2 package to finetune the coefplots
> ##install.packages("coefplot2", repos="http://www.math.mcmaster.ca/bolker/R",
type="source")
>
> # Exercise
> # Exercise
> # Try other combination of interactive terms
> # Exercise
> # Try other combination of interactive terms
> # How to interpret interactive terms?
> # Exercise
> # Try other combination of interactive terms
> # How to interpret interactive terms?
> # Read: Brambor, T., Clark, W.R. and Golder, M., 2006. Understanding interaction models:
Improving empirical analyses. Political analysis, 14(1), pp.63-82.
```

```
> # Exercise
> # Try other combination of interactive terms
> # How to interpret interactive terms?
> # Read: Brambor, T., Clark, W.R. and Golder, M., 2006. Understanding interaction models: Improving empirical analyses. Political analysis, 14(1), pp.63-82.
> # What are qualitative variables?  What class should they be?
```

TEDS_2016 Data examination

```
> library(haven)
> TEDS_2016 <- read_dta("C:/Users/jsnor/OneDrive/Desktop/SCHOOL/UT-Dallas/Courses/EPPS6323/Data/TEDS_2016.dta")
> View(TEDS_2016)
> glm.vt=glm(votetsai~female, data=TEDS_2016, family=binomial)
> summary(glm.vt)

Call:
glm(formula = votetsai ~ female, family = binomial, data = TEDS_2016)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4180  -1.3889   0.9546   0.9797   0.9797

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.54971    0.08245   6.667 2.61e-11 ***
female      -0.06517    0.11644  -0.560    0.576
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1666.5  on 1260  degrees of freedom
Residual deviance: 1666.2  on 1259  degrees of freedom
  (429 observations deleted due to missingness)
AIC: 1670.2

Number of Fisher Scoring iterations: 4
```

Are female voters more likely to vote for President Tsai? Why or Why not?

While the results do not indicate a significant correlation, it does appear that 57% would not vote for President Tsai

4. **Add party ID variables (KMT, DPP) and other demographic variables (age, edu, income) to improve the model.**

What do you find? Which group of variables work better in explaining/predicting votetsai?

R-suite continued to not recognize variables in dataset unable to run further regressions

5. **Try adding the following variables**

Variables not recognized by R-suite

6. **Run the model in STATA**

```
. logit votetsai Independence Econ_worse Govt_dont_car Minnan_father Mainland_father Taiwanese KMT DPP age edu fema
> le

Iteration 0:   log likelihood =  -830.8794
Iteration 1:   log likelihood = -394.71949
Iteration 2:   log likelihood = -391.07779
Iteration 3:   log likelihood = -383.77114
Iteration 4:   log likelihood = -383.74545
Iteration 5:   log likelihood = -383.74545

Logistic regression                                     Number of obs =  1,257
                                                        LR chi2(11)   = 894.27
                                                        Prob > chi2   = 0.0000
Log likelihood = -383.74545                             Pseudo R2     = 0.5381
```

votetsai	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Independence	1.020472	.2514934	4.06	0.000	.5275539	1.51339
Econ_worse	.3029434	.1886537	1.61	0.108	-.066811	.6726979
Govt_dont_care	-.0108799	.1886126	-0.06	0.954	-.3805538	.3587941
Minnan_father	-.2508963	.2541558	-0.99	0.324	-.7490325	.2472399
Mainland_father	-1.091122	.3965396	-2.75	0.006	-1.868326	-.3139191
Taiwanese	.9053165	.1988531	4.55	0.000	.5155715	1.295061
KMT	-2.908613	.258022	-11.27	0.000	-3.414327	-2.402899
DPP	2.475992	.2751241	9.00	0.000	1.936759	3.015226
age	.0034895	.0078776	0.44	0.658	-.0119503	.0189293
edu	-.0762936	.0860751	-0.89	0.375	-.2449977	.0924106
female	-.0949213	.1897555	-0.50	0.617	-.4668353	.2769928
_cons	.0366225	.6742767	0.05	0.957	-1.284936	1.358181

With regards to the first questioned asked about female voting, it appears that approximately 62% of the female population surveyed for this study would not vote for President Tsai. Also, the logit regression on STATA is cleaner and responsive. Stata as a software, cleans the outl