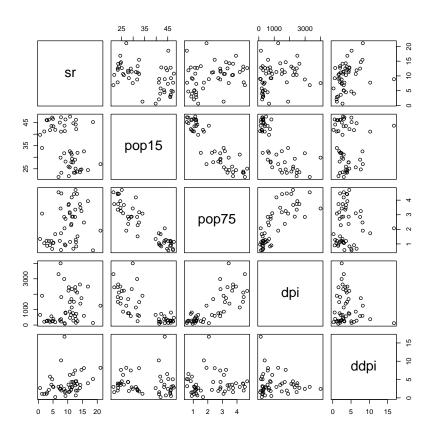
Under the life-cycle savings hypothesis as developed by Franco Modigliani, the savings ratio (aggregate personal saving divided by disposable income) is explained by per-capita disposable income, the percentage rate of change in per-capita disposable income, and two demographic variables: the percentage of population less than 15 years old and the percentage of the population over 75 years old. The data are averaged over the decade 1960-1970 to remove the business cycle or other short-term fluctuations.

```
data(LifeCycleSavings)
lcs = LifeCycleSavings
dim(lcs) # [1] 50 5
sapply(lcs, function(v) mean(is.na(v)))
#
    sr pop15 pop75
                     dpi
                          ddpi
     0
#
           0
                 0
                       0
                             0
?LifeCycleSavings
# sr
         numeric
                  aggregate personal savings
# pop15 numeric % of population under 15
# pop75 numeric % of population over 75
# dpi
         numeric real per-capita disposable income
# ddpi
         numeric % growth rate of dpi
rownames(lcs)[1:5]
#[1] "Australia" "Austria"
                             "Belgium"
                                          "Bolivia"
                                                      "Brazil"
pairs(lcs)
dev.copy(pdf, "BO6pairs.pdf"); dev.off()
```



1: Which predictors look most useful? What transformation might be worth checking? What do you see in terms of outliers (in the X and Y directions)?

```
mO = lm(sr^{-}, lcs)
summary(m0)
#Coefficients:
#
               Estimate Std. Error t value Pr(>|t|)
#(Intercept) 28.5660865 7.3545161
                                     3.884 0.000334 ***
#pop15
             -0.4611931 0.1446422 -3.189 0.002603 **
#pop75
            -1.6914977 1.0835989 -1.561 0.125530
             -0.0003369 0.0009311
#dpi
                                   -0.362 0.719173
              0.4096949 0.1961971
                                     2.088 0.042471 *
#ddpi
#Residual standard error: 3.803 on 45 degrees of freedom
#Multiple R-squared: 0.3385,
                                 Adjusted R-squared: 0.2797
```

2: Summarize what you learn from the regression results.

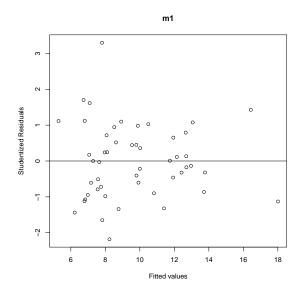
```
library(MASS) # for stepAIC()
m1 = stepAIC(lm(sr<sup>~</sup>.<sup>2</sup>,lcs))
summary(m1)
#Coefficients:
               Estimate Std. Error t value Pr(>|t|)
#
#(Intercept) 16.5287997 4.3729241 3.780 0.000459 ***
            -0.2023669 0.0981090 -2.063 0.044943 *
#pop15
#dpi
             -0.0027411 0.0011774 -2.328 0.024457 *
#ddpi
             0.0462479 0.2439993 0.190 0.850521
              0.0008171 0.0003593 2.274 0.027802 *
#dpi:ddpi
#Residual standard error: 3.698 on 45 degrees of freedom
#Multiple R-squared: 0.3745,
                                 Adjusted R-squared: 0.3189
```

3: Summarize what you learn from the new regression results.

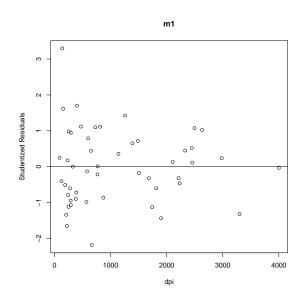
```
# A residual plotting function
rp = function(mdl, xname=NULL, fname=NULL) {
  res = rstudent(mdl)
  if (is.null(xname)) {
    x = fitted(mdl)
   xname = "Fitted values"
  } else {
    x = mdl$model[,xname]
  }
  plot(x, res, xlab=xname, ylab="Studentized Residuals",
       main = deparse(substitute(mdl)))
  abline(h=0)
  if (!is.null(fname)) {
    dev.copy(pdf, paste(fname,".pdf",sep=""))
    dev.off()
  }
  invisible(NULL)
}
```

4: Comment on the R code.

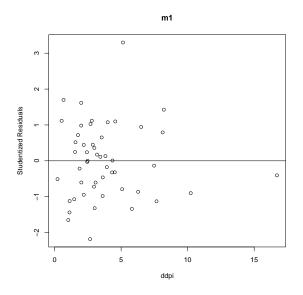
rp(m1, fname="BO6RF")



rp(m1, "dpi", "BO6Rdpi")



rp(m1, "ddpi", "BO6Rddpi")

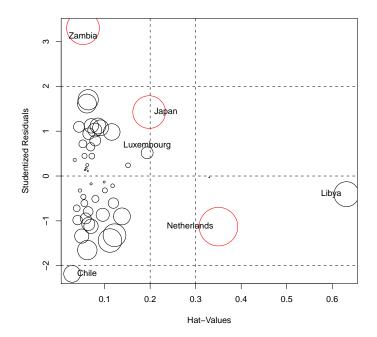


5: Comment on the residual plots

```
summary(influence.measures(m1), digits=2)
#Potentially influential observations of
          lm(formula = sr ~ ., data = lcs) :
#
#
               dfb.1_ dfb.pp15 dfb.dpi dfb.ddpi dfb.dp:d
                 0.12
                                  0.15
                                            0.07
                                                    -0.20
#Luxembourg
                         -0.14
#Netherlands
                 0.12
                         -0.15
                                  0.51
                                            0.26
                                                    -0.73
#United States
                 0.01
                         -0.01
                                 -0.02
                                            0.00
                                                     0.00
#Zambia
                -0.17
                          0.25
                                  0.06
                                            0.27
                                                    -0.13
#Libya
                 0.09
                         -0.01
                                 -0.24
                                           -0.51
                                                     0.26
#
#
              dffit cov.r cook.d hat
#Luxembourg
                0.25 1.35
                             0.01 0.19
#Netherlands
               -0.83 1.49
                             0.14 0.35
#United States -0.02 1.67
                             0.00 0.33
#Zambia
                0.78 0.39
                             0.10 0.05
               -0.53 2.98
#Libya
                             0.06 0.63
```

6: Comment on the flagged influence measures.

```
library(car) # for influencePlot()
out = influencePlot(m1) # Right click to stop identifying points
dev.copy(pdf, "BO6IP.pdf"); dev.off()
```



<pre>influence.measures(m1)\$infmat[out,] # (repeats manually deleted)</pre>									
#	dfb.1_	dfb.pp1	l5 dfb.	dpi dfb.dd	pi dfb.dp:d				
#Chile	-0.03674514	-0.0428428	33 0.03470	0.088781	91 0.01305477				
#Japan	-0.01171377	0.0291349	92 -0.44015	6044 -0.091930	93 0.53233681				
#									
#	dffit	cov.r	cook.d	hat					
#Chile	-0.3747104	0.6891229 0	0.02591532	0.02864327					
#Japan	0.7082681	1.1127700 0	0.09807518	0.19783607					

7: Comment on the additional, manually flagged influence measures

<pre>round(rbind(lcs[out,], allmean=apply(lcs,2,mean), allsd=apply(lcs,2,sd)),2)</pre>						
#	sr	pop15	pop75	dpi	ddpi	
#Chile	0.60	39.74	1.34	662.86	2.67	
#Japan	21.10	27.01	1.91	1257.28	8.21	
#Luxembourg	10.35	21.80	3.73	2449.39	1.57	
#Netherlands	14.65	24.71	3.25	1740.70	7.66	
#Zambia	18.56	45.25	0.56	138.33	5.14	
#Libya	8.89	43.69	2.07	123.58	16.71	
#allmean	9.67	35.09	2.29	1106.76	3.76	
#allsd	4.48	9.15	1.29	990.87	2.87	

8: Comment on possible actions to be taken.