# OLS Data Analysis in R

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# Introduction to R Outline

I. Data Description
II. Data Analysis
    i. Command functions
    ii. Hand-rolling
III. OLS Diagnostics & Graphing
IV. Functions and loops
V. Moving forward

# Data Analysis: Descriptive Stats

- R has several built-in commands for describing data

- The `list()` command can output all elements of an object

```
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> #Load Libraries
> library(foreign)
>
>
> #Read in the Data
>
> data <- read.dta("Senate2002.dta")
> attach(data)
> #Descriptive Statistics - Examples
>
> list(data)
[[1]]
    repvshr income presvote pressup
1  59.52665  34135     56.0      88
2  88.14516  51571     59.0      95
3  52.55351  47203     51.0      96
4  41.20611  47381     42.0      77
5  53.46671  42433     55.0      90
6  66.68880  37572     67.0      95
7  38.65622  46590     43.0      67
8  44.69222  39469     48.0      69
9  64.67520  33672     57.0      96
10 48.29952  32566     53.0      84
11 58.43565  37240     44.0      88
12 38.46476  44667     46.0      66
13 33.58933  33024     58.0      88
14 84.97204  39250     62.0      98
15 65.04277  34133     47.8      96
16 61.21235  33400     60.0      96
17 58.66380  40916     46.5      91
18 21.57351  42090     32.0      66
19 55.13115  37082     57.0      82
20 49.92046  35282     60.0      68
21 36.88865  29696     52.0      71
22 56.77559  37892     68.0      93

>
```

# Data Analysis: Descriptive Stats

- The `summary()` command can be used to describe all variables contained within a dataframe

- The `summary()` command can also be used with individual variables

R Console

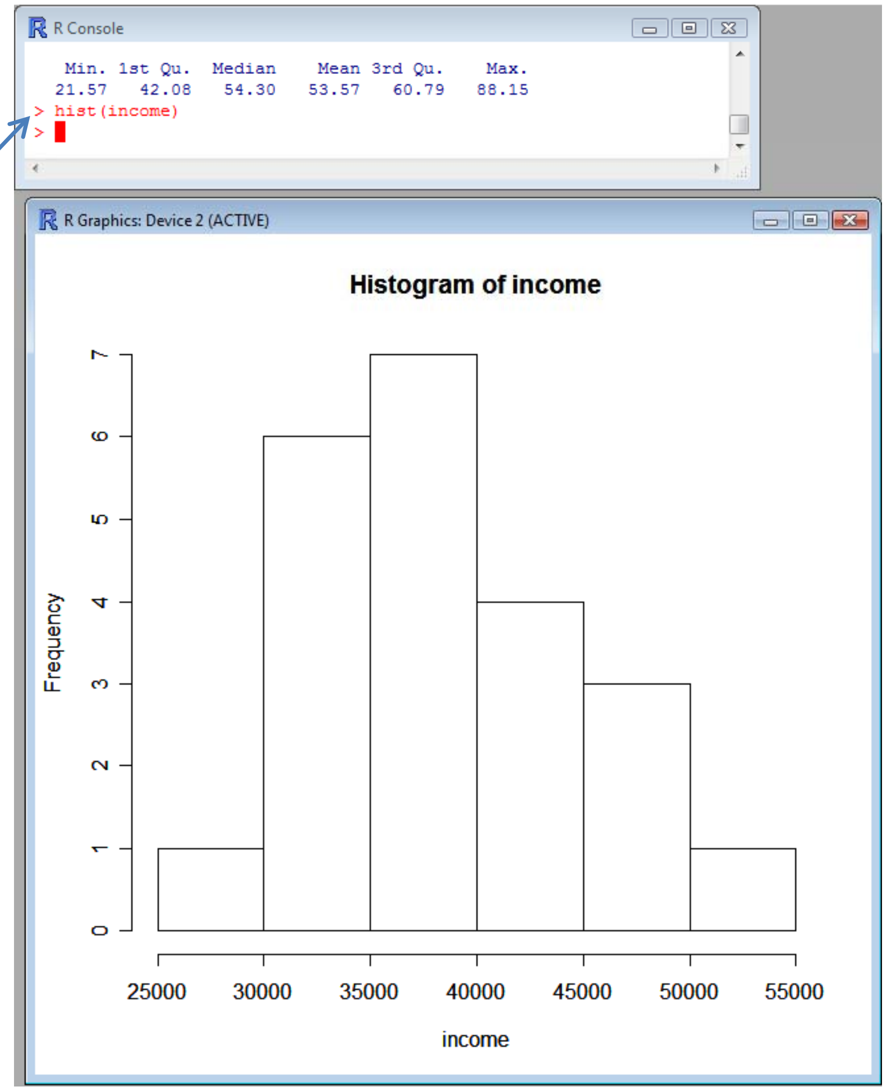
```
> #Descriptive Statistics - Examples
>
> list(data)
[[1]]
    repvshr income presvote pressup
1  59.52665  34135     56.0      88
2  88.14516  51571     59.0      95
3  52.55351  47203     51.0      96
4  41.20611  47381     42.0      77
5  53.46671  42433     55.0      90
6  66.68880  37572     67.0      95
7  38.65622  46590     43.0      67
8  44.69222  39469     48.0      69
9  64.67520  33672     57.0      96
10 48.29952  32566     53.0      84
11 58.43565  37240     44.0      88
12 38.46476  44667     46.0      66
13 33.58933  33024     58.0      88
14 84.97204  39250     62.0      98
15 65.04277  34133     47.8      96
16 61.21235  33400     60.0      96
17 58.66380  40916     46.5      91
18 21.57351  42090     32.0      66
19 55.13115  37082     57.0      82
20 49.92046  35282     60.0      68
21 36.88865  29696     52.0      71
22 56.77559  37892     68.0      93

> summary(data)
    repvshr          income          presvote         pressup
 Min.   :21.57   Min.   :29696   Min.   :32.00   Min.   :66.00
 1st Qu.:42.08   1st Qu.:34134   1st Qu.:46.82   1st Qu.:72.50
 Median :54.30   Median :37732   Median :54.00   Median :88.00
 Mean   :53.57   Mean   :38967   Mean   :52.92   Mean   :84.55
 3rd Qu.:60.79   3rd Qu.:42347   3rd Qu.:58.75   3rd Qu.:95.00
 Max.   :88.15   Max.   :51571   Max.   :68.00   Max.   :98.00
> summary(repvshr)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  21.57   42.08   54.30   53.57   60.79   88.15
>
```

# Data Analysis: Descriptive Stats

- Simple plots can also provide familiarity with the data

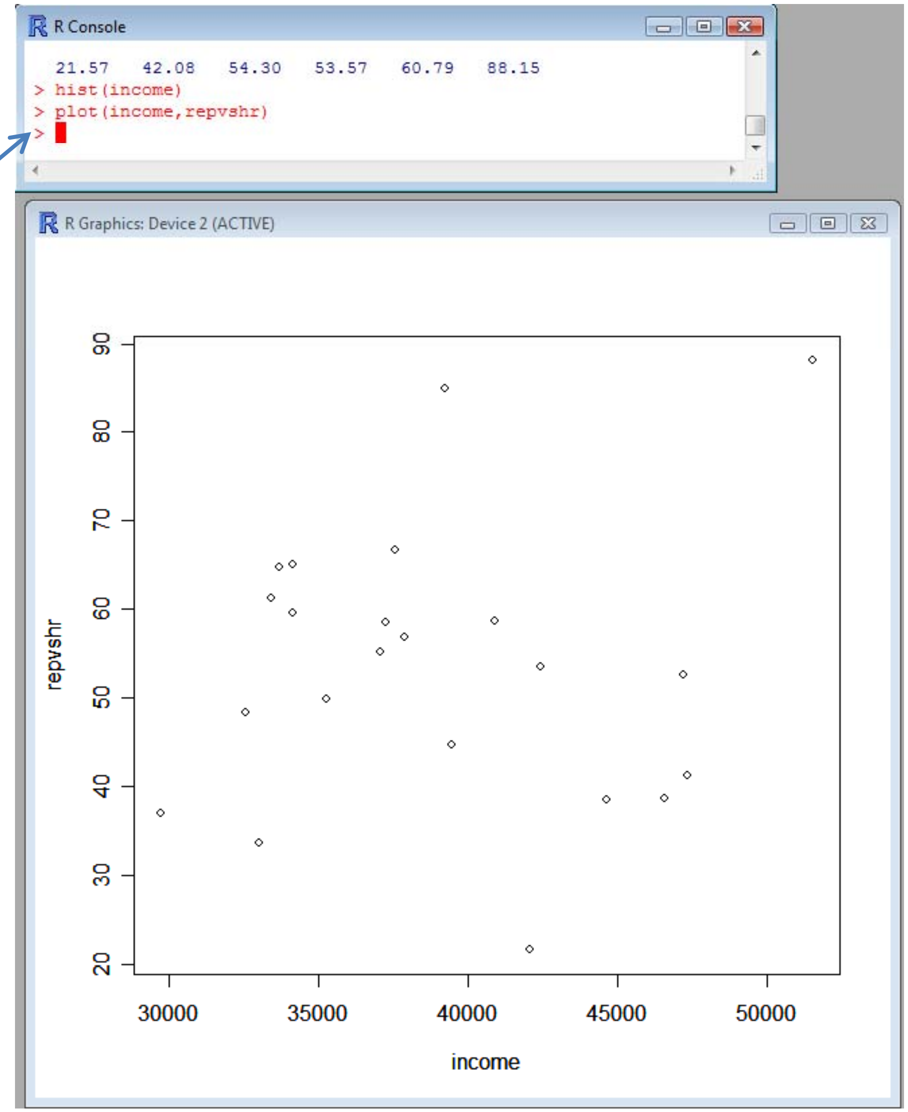
- The `hist()` command produces a histogram for any given data values



# Data Analysis: Descriptive Stats

- Simple plots can also provide familiarity with the data

- The `plot()` command can produce both univariate and bivariate plots for any given objects



# Data Analysis: Descriptive Stats

## Other Useful Commands

- `sum`
- `mean`
- `var`
- `sd`
- `range`
- `min`
- `max`
- `median`
- `cor`
- `summary`

# Data Analysis: Regression

- As mentioned above, one of the big perks of using R is flexibility.

- R comes with its own canned linear regression command: `lm(y ~ x)`

- However, we're going to use R to make our own OLS estimator. Then we will compare with the canned procedure, as well as Stata.

# Data Analysis: Regression

- First, let's take a look at our code for the hand-rolled OLS estimator
- The Holy Grail: $(X'X)^{-1}X'Y$
- We need a single matrix of independent variables
- The `cbind()` command takes the individual variable vectors and combines them into one x-variable matrix
- A "1" is included as the first element to account for the constant.

Rintro - Notepad

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```
#Hand-rolled OLS


    x<-as.matrix(cbind(int=1,income,presvote,pressup))
    y<-as.vector(repvshr)
    i<-diag(1,nrow=nrow(x),ncol=ncol(x))

    n<-length(y)
    p<-ncol(x)-1


    xy<-t(x)%*%y                  # X'Y
    xxi<-solve(t(x)%*%x)          #(X'X)^(-1)
    h<-x%*%xxi%*%t(x)             #hat matrix of x
    i<-diag(1,nrow=n,ncol=n)
    b<-as.vector(xxi%*%xy)        #estimated coefficients

    names(b)<-colnames(x)

    yhat<-as.vector(x%*%b)        #predicted values for y
    res<-y-yhat  # or (i-h)%*%y   #model residuals

    sst<-sum((y-mean(y))^2)       #Total sum of sqares
    sse<-t(res)%*%res             # or sum(res^2) which is also t(res)%*%res
    ssm<-sst-sse                  #sum of squares for model (regression)

    df.e<-(n-p-1)                 #degrees of freedom for error
    df.t<-(n-1)                   #total degrees of freedom
    df.m<-df.t-df.e               #degrees of freedom for model

    s2<-as.vector(sse/df.e) # or (t(res)%*%res)?(n-p-1)
    sigma2<-as.vector(sse/(n-p))
    r2<-1-(sse/sst)
    r2.adj<-1-((sse/df.e)/(sst/df.t))
    aic<-n*log(sse/n)+2*(p+1)
    cp<-(sse/s2)-(n-2*(p+1))
    f<-(ssm/df.m)/(sse/df.e)
    pvalue<-1-pf(f,df.m,df.e)

    b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
    b.t.statistic<-b/b.standard.errors           #t statistic for st. errors
    b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05
```

# Data Analysis: Regression

- With the **x and y matrices complete**, we can now manipulate them to produce coefficients.
- After performing the **divine multiplication**, we can observe the estimates by entering the object name (in this case “b”).

Rintro - Notepad

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```
#Hand-rolled OLS


    x<-as.matrix(cbind(int=1,income,presvote,pressup))
    y<-as.vector(repvshr)
    i<-diag(1,nrow=nrow(x),ncol=ncol(x))

    n<-length(y)
    p<-ncol(x)-1


    xy<-t(x)%*%y                # X'Y
    xxi<-solve(t(x)%*%x)        #(X'X)^(-1)
    h<-x%*%xxi%*%t(x)           #hat matrix of x
    i<-diag(1,nrow=n,ncol=n)
    b<-as.vector(xxi%*%xy)      #estimated coefficients

    names(b)<-colnames(x)

    yhat<-as.vector(x%*%b)      #predicted values for y
    res<-y-yhat  # or (i-h)%*%y #model residuals

    sst<-sum((y-mean(y))^2)     #Total sum of sqares
    sse<-t(res)%*%res           # or sum(res^2) which is also t(res)%*%res
    ssm<-sst-sse                #sum of squares for model (regression)

    df.e<-(n-p-1)               #degrees of freedom for error
    df.t<-(n-1)                 #total degrees of freedom
    df.m<-df.t-df.e             #degrees of freedom for model

    s2<-as.vector(sse/df.e) # or (t(res)%*%res)?(n-p-1)
    sigma2<-as.vector(sse/(n-p))
    r2<-1-(sse/sst)
    r2.adj<-1-((sse/df.e)/(sst/df.t))
    aic<-n*log(sse/n)+2*(p+1)
    cp<-(sse/s2)-(n-2*(p+1))
    f<-(ssm/df.m)/(sse/df.e)
    pvalue<-1-pf(f,df.m,df.e)

    b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
    b.t.statistic<-b/b.standard.errors           #t statistic for st. errors
    b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05
```

# Data Analysis: Regression

- With the x and y matrices complete, we can now manipulate them to produce coefficients.
- After performing the divine multiplication, **we can observe the estimates** by entering the object name (in this case “b”).

R Console

```
>       i<-diag(1,nrow=n,ncol=n)
>       b<-as.vector(xxi%*%xy)          #estimated coefficients
>
>       names(b)<-colnames(x)
>
>       yhat<-as.vector(x%*%b)          #predicted values for y
>       res<-y-yhat  # or (i-h)%*%y     #model residuals
>
>       sst<-sum((y-mean(y))^2)         #Total sum of sqares
>       sse<-t(res)%*%res               # or sum(res^2) which is also t($
>       ssm<-sst-sse                    #sum of squares for model (regre$
>
>       df.e<-(n-p-1)                   #degrees of freedom for error
>       df.t<-(n-1)                     #total degrees of freedom
>       df.m<-df.t-df.e                 #degrees of freedom for model
>
>       s2<-as.vector(sse/df.e) # or (t(res)%*%res)?(n-p-1)
>       sigma2<-as.vector(sse/(n-p))
>       r2<-1-(sse/sst)
>       r2.adj<-1-((sse/df.e)/(sst/df.t))
>       aic<-n*log(sse/n)+2*(p+1)
>       cp<-(sse/s2)-(n-2*(p+1))
>       f<-(ssm/df.m)/(sse/df.e)
>       pvalue<-1-pf(f,df.m,df.e)
>
>       b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient stan$
>       b.t.statistic<-b/b.standard.errors           #t statistic for $
>       b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05
> b
          int        income      presvote       pressup
-7.295361e+01  6.743087e-04  6.021832e-01  8.088049e-01
>
```

# Data Analysis: Regression

- To find the standard errors, we need to compute both the **variance of the residuals** and the cov matrix of the x's.
- The **sqrt of the diagonal elements of this var-cov matrix** will give us the standard errors.
- Other test statistics can be easily computed.
- View the standard errors.

Rintro - Notepad

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```
#Hand-rolled OLS


     x<-as.matrix(cbind(int=1,income,presvote,pressup))
     y<-as.vector(repvshr)
     i<-diag(1,nrow=nrow(x),ncol=ncol(x))

     n<-length(y)
     p<-ncol(x)-1


     xy<-t(x)%*%y                   # X'Y
     xxi<-solve(t(x)%*%x)           #(X'X)^(-1)
     h<-x%*%xxi%*%t(x)              #hat matrix of x
     i<-diag(1,nrow=n,ncol=n)
     b<-as.vector(xxi%*%xy)         #estimated coefficients

     names(b)<-colnames(x)

     yhat<-as.vector(x%*%b)         #predicted values for y
     res<-y-yhat  # or (i-h)%*%y    #model residuals

     sst<-sum((y-mean(y))^2)        #Total sum of sqares
     sse<-t(res)%*%res              # or sum(res^2) which is also t(res)%*%res
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# Data Analysis: Regression

- To find the standard errors, we need to compute both the variance of the residuals and the cov matrix of the x's.
- The sqrt of the diagonal elements of this var-cov matrix will give us the standard errors.
- **Other test statistics can be easily computed.**
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Rintro - Notepad

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     x<-as.matrix(cbind(int=1,income,presvote,pressup))
     y<-as.vector(repvshr)
     i<-diag(1,nrow=nrow(x),ncol=ncol(x))

     n<-length(y)
     p<-ncol(x)-1


     xy<-t(x)%*%y                  # X'Y
     xxi<-solve(t(x)%*%x)          #(X'X)^(-1)
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     sigma2<-as.vector(sse/(n-p))
     r2<-1-(sse/sst)
     r2.adj<-1-((sse/df.e)/(sst/df.t))
     aic<-n*log(sse/n)+2*(p+1)
     cp<-(sse/s2)-(n-2*(p+1))
     f<-(ssm/df.m)/(sse/df.e)
     pvalue<-1-pf(f,df.m,df.e)

     b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
     b.t.statistic<-b/b.standard.errors            #t statistic for st. errors
     b.t.prob<-2*(1-pt(b.t.statistic,df.e))        #alpha 0.05
```

# Data Analysis: Regression

- To find the standard errors, we need to compute both the variance of the residuals and the cov matrix of the x's.
- The sqrt of the diagonal elements of this var-cov matrix will give us the standard errors.
- Other test statistics can be easily computed.
- **View the standard errors.**

R Console

```
>       names(b)<-colnames(x)
>
>       yhat<-as.vector(x%*%b)        #predicted values for y
>       res<-y-yhat  # or (i-h)%*%y   #model residuals
>
>       sst<-sum((y-mean(y))^2)       #Total sum of sqares
>       sse<-t(res)%*%res             # or sum(res^2) which is also t($
>       ssm<-sst-sse                  #sum of squares for model (regre$
>
>       df.e<-(n-p-1)                 #degrees of freedom for error
>       df.t<-(n-1)                   #total degrees of freedom
>       df.m<-df.t-df.e               #degrees of freedom for model
>
>       s2<-as.vector(sse/df.e) # or (t(res)%*%res)?(n-p-1)
>       sigma2<-as.vector(sse/(n-p))
>       r2<-1-(sse/sst)
>       r2.adj<-1-((sse/df.e)/(sst/df.t))
>       aic<-n*log(sse/n)+2*(p+1)
>       cp<-(sse/s2)-(n-2*(p+1))
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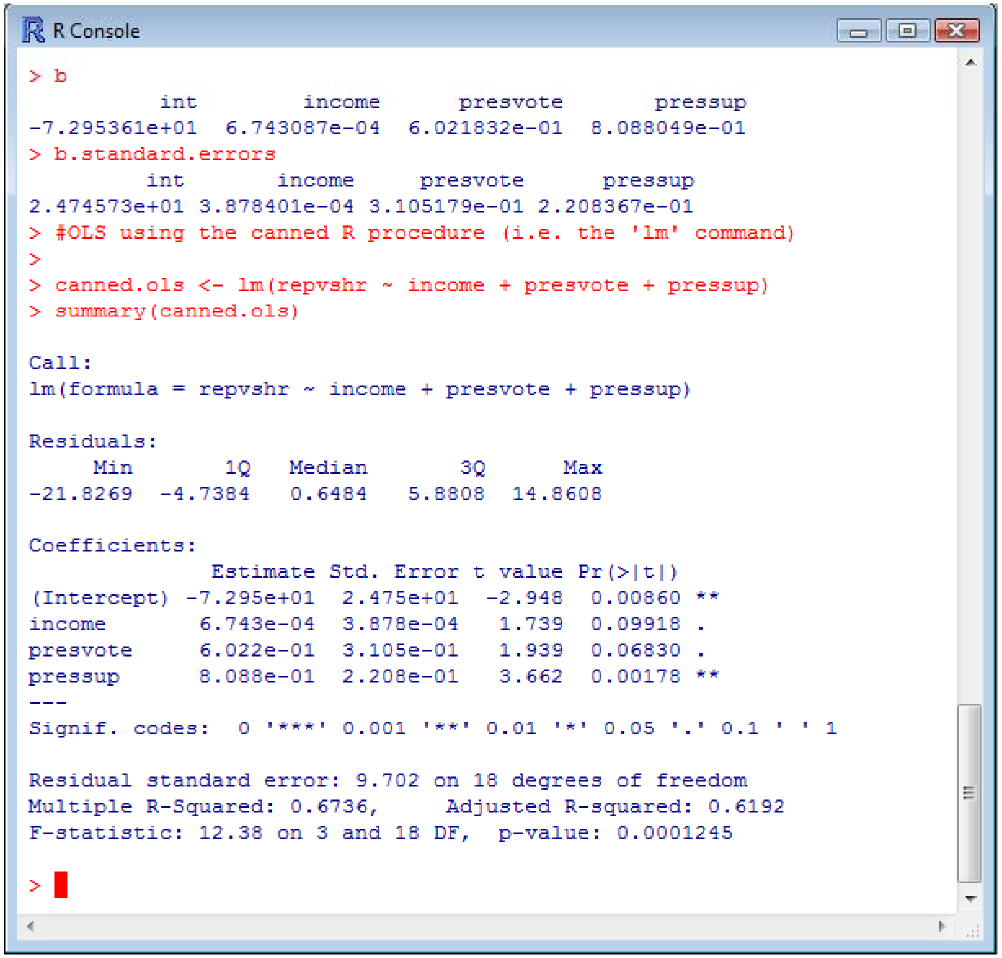
>       pvalue<-1-pf(f,df.m,df.e)
>
>       b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient stan$
>       b.t.statistic<-b/b.standard.errors           #t statistic for $
>       b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05
> b
          int        income      presvote       pressup
-7.295361e+01  6.743087e-04  6.021832e-01  8.088049e-01
> b.standard.errors
         int       income     presvote      pressup
2.474573e+01 3.878401e-04 3.105179e-01 2.208367e-01
>
```

# Data Analysis: Regression

- Time to Compare
- **Use the `lm()` command** to estimate the model using R's canned procedure
- As we can see, the estimates are very similar



```
R Console
> b
          int        income      presvote       pressup
-7.295361e+01  6.743087e-04  6.021832e-01  8.088049e-01
> b.standard.errors
         int       income     presvote      pressup
2.474573e+01 3.878401e-04 3.105179e-01 2.208367e-01
> #OLS using the canned R procedure (i.e. the 'lm' command)
>
> canned.ols <- lm(repvshr ~ income + presvote + pressup)
> summary(canned.ols)

Call:
lm(formula = repvshr ~ income + presvote + pressup)

Residuals:
     Min       1Q   Median       3Q      Max
-21.8269  -4.7384   0.6484   5.8808  14.8608

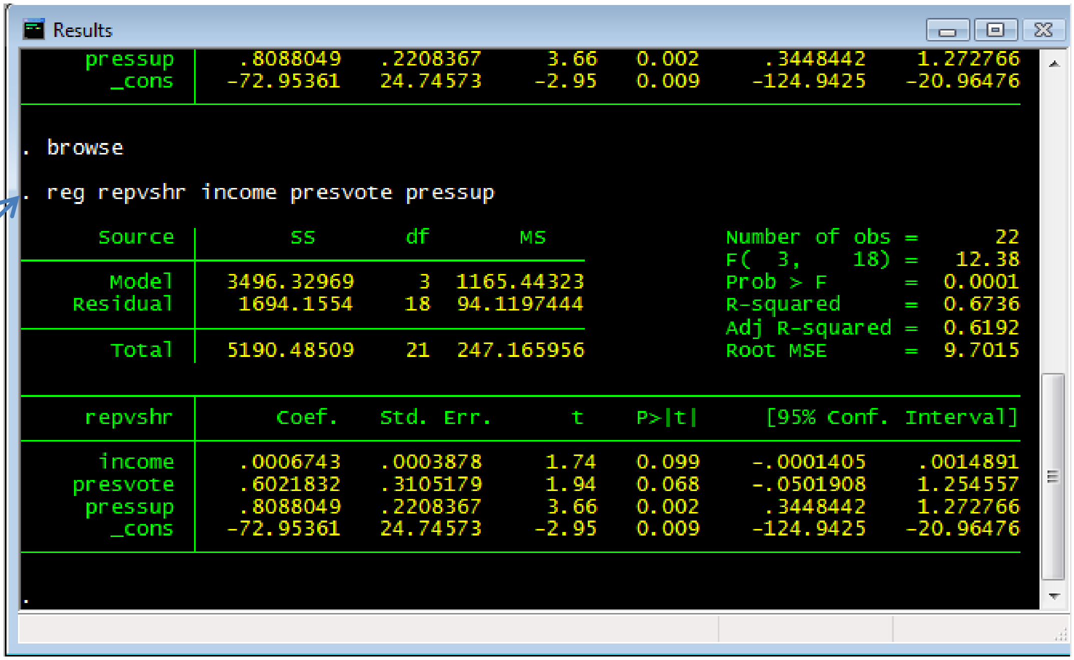
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.295e+01  2.475e+01  -2.948  0.00860 **
income       6.743e-04  3.878e-04   1.739  0.09918 .
presvote     6.022e-01  3.105e-01   1.939  0.06830 .
pressup      8.088e-01  2.208e-01   3.662  0.00178 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.702 on 18 degrees of freedom
Multiple R-Squared: 0.6736,     Adjusted R-squared: 0.6192
F-statistic: 12.38 on 3 and 18 DF,  p-value: 0.0001245

>
```

# Data Analysis: Regression

- Time to Compare
- We can also see how both the hand-rolled and canned OLS procedures stack up to Stata
- **Use the `reg` command** to estimate the model
- As we can see, the estimates are once again very similar



```
Results
     pressup |   .8088049   .2208367     3.66   0.002     .3448442    1.272766
       _cons |  -72.95361   24.74573    -2.95   0.009    -124.9425   -20.96476
------------------------------------------------------------------------------

. browse

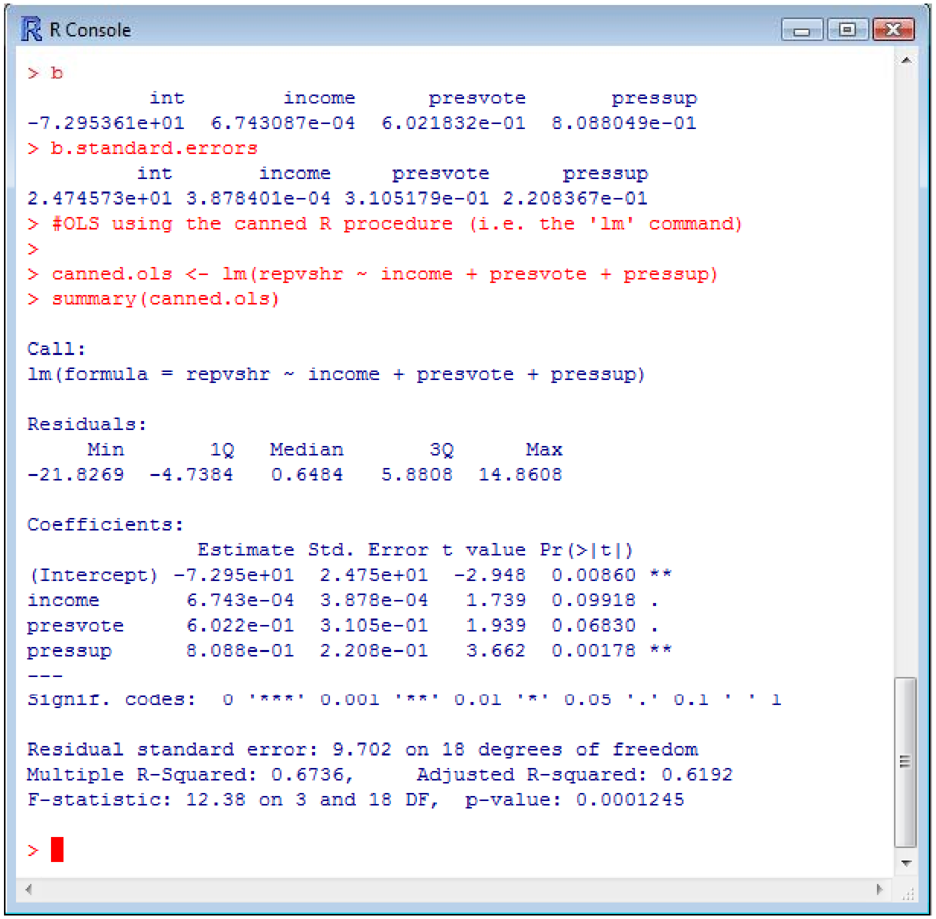
. reg repvshr income presvote pressup

      Source |       SS       df       MS              Number of obs =      22
-------------+------------------------------           F(  3,    18) =   12.38
       Model |  3496.32969     3  1165.44323           Prob > F      =  0.0001
    Residual |   1694.1554    18  94.1197444           R-squared     =  0.6736
-------------+------------------------------           Adj R-squared =  0.6192
       Total |  5190.48509    21  247.165956           Root MSE      =  9.7015

------------------------------------------------------------------------------
     repvshr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      income |   .0006743   .0003878     1.74   0.099    -.0001405    .0014891
    presvote |   .6021832   .3105179     1.94   0.068    -.0501908    1.254557
     pressup |   .8088049   .2208367     3.66   0.002     .3448442    1.272766
       _cons |  -72.95361   24.74573    -2.95   0.009    -124.9425   -20.96476
------------------------------------------------------------------------------

.
```

# Data Analysis: Regression



```
R Console
> b
          int        income      presvote       pressup
-7.295361e+01  6.743087e-04  6.021832e-01  8.088049e-01
> b.standard.errors
         int       income     presvote      pressup
2.474573e+01 3.878401e-04 3.105179e-01 2.208367e-01
> #OLS using the canned R procedure (i.e. the 'lm' command)
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> canned.ols <- lm(repvshr ~ income + presvote + pressup)
> summary(canned.ols)

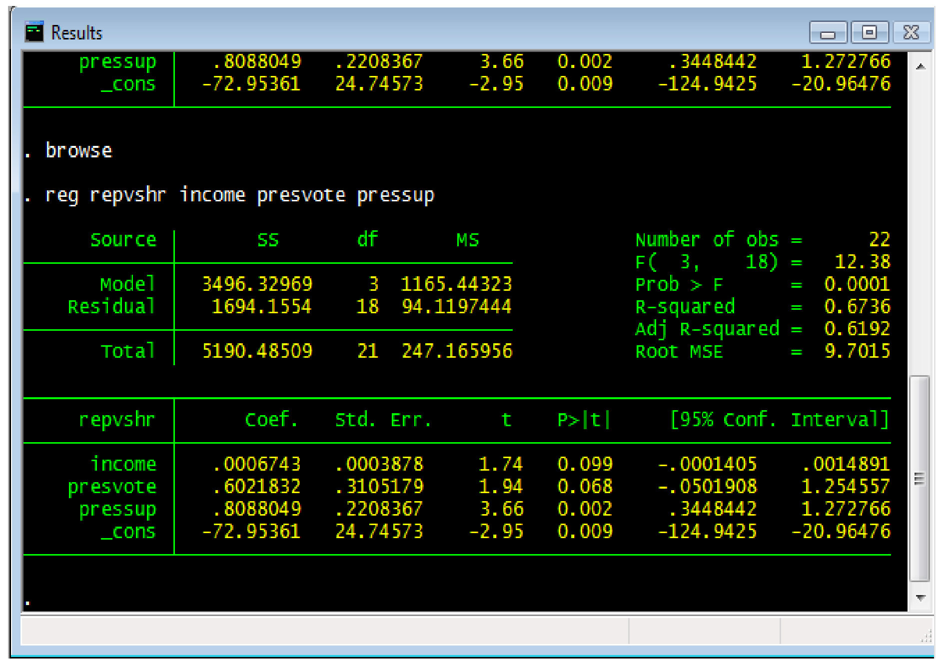
Call:
lm(formula = repvshr ~ income + presvote + pressup)

Residuals:
     Min       1Q   Median       3Q      Max
-21.8269  -4.7384   0.6484   5.8808  14.8608

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.295e+01  2.475e+01  -2.948  0.00860 **
income       6.743e-04  3.878e-04   1.739  0.09918 .
presvote     6.022e-01  3.105e-01   1.939  0.06830 .
pressup      8.088e-01  2.208e-01   3.662  0.00178 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.702 on 18 degrees of freedom
Multiple R-Squared: 0.6736,     Adjusted R-squared: 0.6192
F-statistic: 12.38 on 3 and 18 DF,  p-value: 0.0001245

>
```



```
Results
     pressup |   .8088049   .2208367     3.66   0.002     .3448442    1.272766
       _cons |  -72.95361   24.74573    -2.95   0.009    -124.9425   -20.96476
------------------------------------------------------------------------------

. browse

. reg repvshr income presvote pressup

      Source |       SS       df       MS              Number of obs =      22
-------------+------------------------------           F(  3,    18) =   12.38
       Model |  3496.32969     3  1165.44323           Prob > F      =  0.0001
    Residual |   1694.1554    18  94.1197444           R-squared     =  0.6736
-------------+------------------------------           Adj R-squared =  0.6192
       Total |  5190.48509    21  247.165956           Root MSE      =  9.7015

------------------------------------------------------------------------------
     repvshr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      income |   .0006743   .0003878     1.74   0.099    -.0001405    .0014891
    presvote |   .6021832   .3105179     1.94   0.068    -.0501908    1.254557
     pressup |   .8088049   .2208367     3.66   0.002     .3448442    1.272766
       _cons |  -72.95361   24.74573    -2.95   0.009    -124.9425   -20.96476
------------------------------------------------------------------------------

.
```

# Data Analysis: Regression

## Other Useful Commands

- **`lm`**
  - `Linear Model`
- **`lme`**
  - `Mixed Effects`
- **`anova`**
- **`glm`**
  - `General lm`
- **`multinom`**
  - `Multinomial Logit`
- **`optim`**
  - `General Optimizer`

# OLS Diagnostics in R

- Post-estimation diagnostics are key to  data analysis
  - We want to make sure we estimated the proper model
  - Besides, Irfan will hurt you if you neglect to do this
- Furthermore, diagnostics allow us the opportunity to show off some of R’s graphs
  - R’s real strength is that it has virtually unlimited graphing capabilities
  - Of course, such strengths on R’s part is dependent on your knowledge of both R and statistics
    - Still, with just some basics we can do some cool graphs

# OLS Diagnostics in R

- What could be *unjustifiably* driving our data?
  - Outlier: unusual observation
  - Leverage: ability to change the slope of the regression line
  - Influence: the combined impact of strong leverage and outlier status
    - According to John Fox, influence=leverage*outliers

# OLS Diagnostics: Leverage

- Recall our ols model
  - `ols.model1<-lm(formula = repvshr~income+presvote+pressup)`
- Our measure of leverage: is the $h_i$ or "hat value"
  - It's just the predicted values written in terms of $h_i$
  - Where, $H_{ij}$ is the contribution of observation $Y_i$ to the fitted value $Y_j$
  - If $h_{ij}$ is large, then the $i^{th}$ observation has a significant impact on the jth fitted value
  - So, skipping the formulas, we know that the larger the hat value the greater the leverage of that observation

# OLS Diagnostics: Leverage

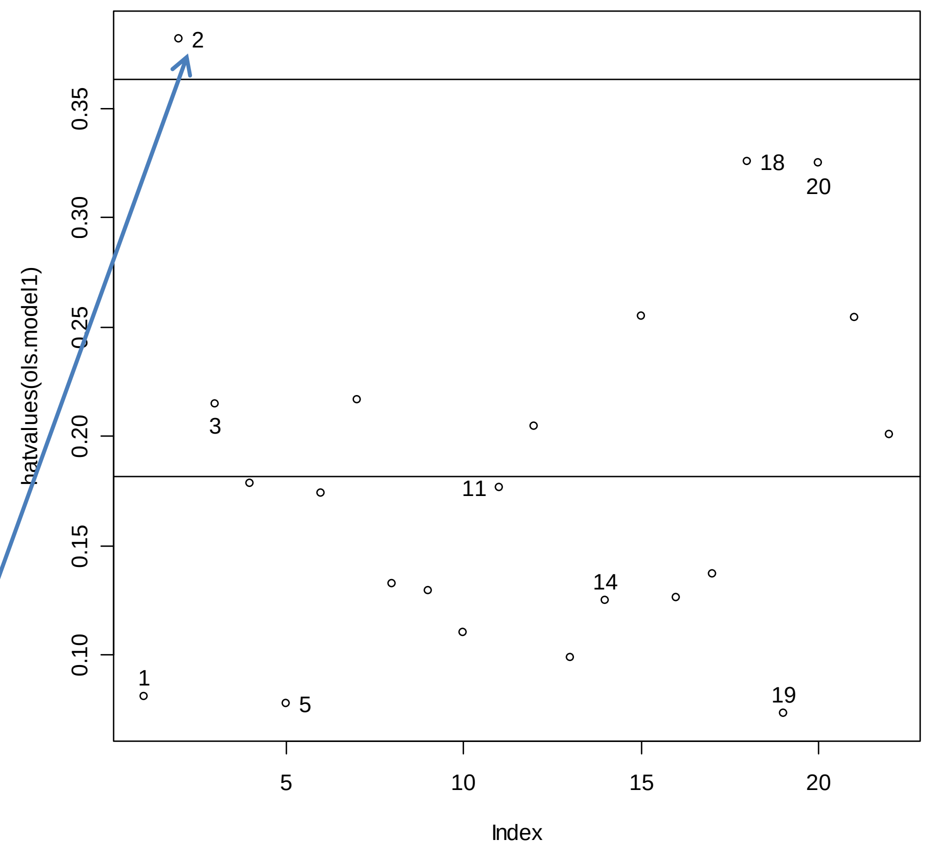
- Find the hat values
  - `hatvalues(ols.model1)`

```
> ##Leverage
> hatvalues(ols.model1)
         1          2          3          4          5          6          7 
0.08058958 0.38217510 0.21508254 0.17839298 0.07791739 0.17390212 0.21652515 
         8          9         10         11         12         13         14 
0.13240657 0.12946990 0.11013685 0.17680240 0.20482571 0.09892587 0.12505991 
        15         16         17         18         19         20         21 
0.25521188 0.12628592 0.13708349 0.32578291 0.07297085 0.32496207 0.25453795 
        22 
0.20095287 
>
> avg.mod1<-ncol(x)/nrow(x)
> avg.mod1
[1] 0.1818182
```

- Calculate the average hat value
  - `avg.mod1<-ncol(x)/nrow(x)`

# OLS Diagnostics: Leverage

- But a picture is worth a hundred numbers?
- Graph the hat values with lines for the average, twice the avg (large samples) and three times the avg (small samples) hat values
  - `plot(hatvalues(ols.model1))`
  - `abline(h=1*(ncol(x))/nrow(x))`
  - `abline(h=2*(ncol(x))/nrow(x))`
  - `abline(h=3*(ncol(x))/nrow(x))`
  - `identify(hatvalues(ols.model1))`
    - `identify` lets us select the data points in the new graph
- State #2 is over twice the avg
- Nothing above three times



# OLS Diagnostics: Outliers

- Can we find any data points that are unusual for Y given the Xs?
- Use studentized residuals

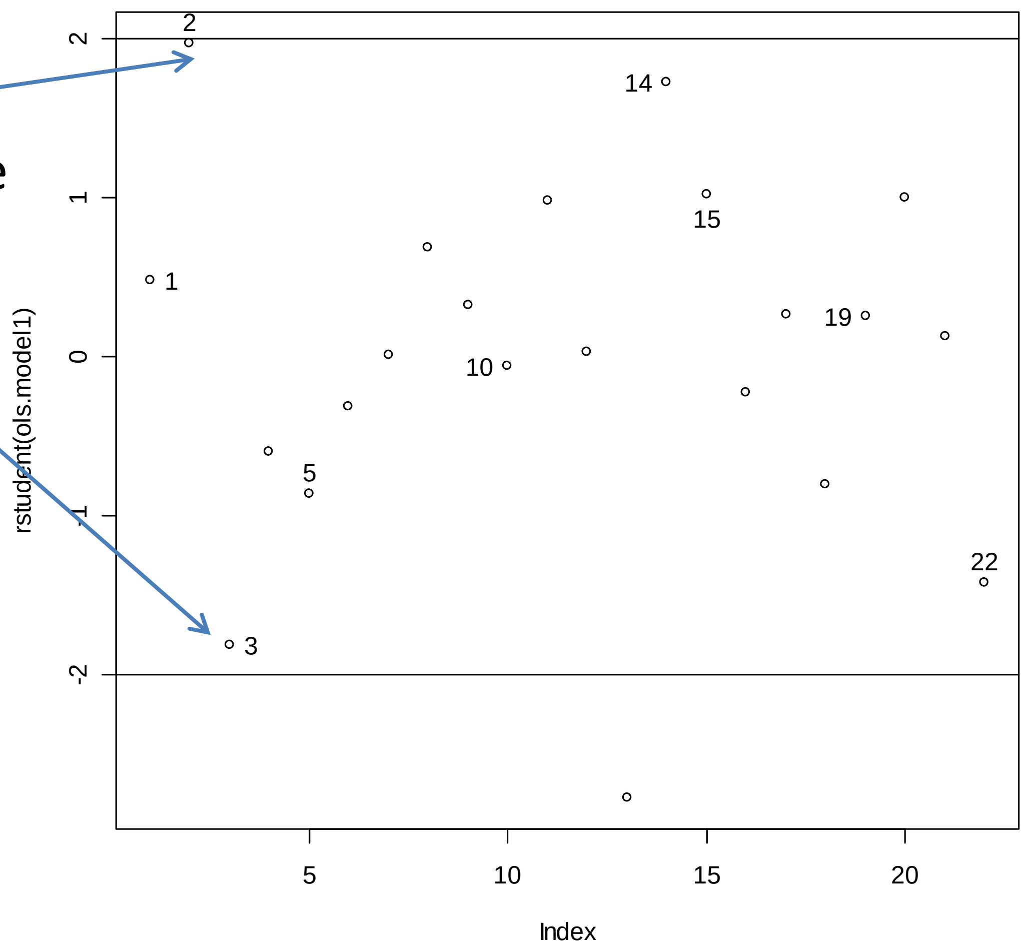
$$u_i^* = \frac{u_i}{\sigma_{u(-1)}\sqrt{1-h_i}}$$

  - We can see whether there is a significant change in the model
  - If their absolute values are larger than 2, then the corresponding observations are likely to be outliers)
  - `rstudent(ols.model1)`

```
> rstudent(ols.model1)
          1           2           3           4           5           6
 0.48019795  1.97192270 -1.81307635 -0.59849094 -0.86387841 -0.31785263
          7           8           9          10          11          12
 0.01244686  0.68902256  0.31806953 -0.05965655  0.97657494  0.02443043
         13          14          15          16          17          18
-2.77709792  1.72517421  1.02255885 -0.22885529  0.26198911 -0.80877619
         19          20          21          22
 0.25367148  0.99768167  0.12528015 -1.42108584
>
```

# OLS Diagnostics: Outliers

- Again, let's plot them with lines for 2 & -2
- States 2 and 3 appear to be outliers, or darn close
- We should definitely take a look at what makes these states unusual…
  - Perhaps there is a mistake in data entry
  - Perhaps the model is misspecified in terms of functional form (forthcoming) or omitted vars
  - Maybe you can throw out your bad observation
  - If you must include the bad observation, try robust regression

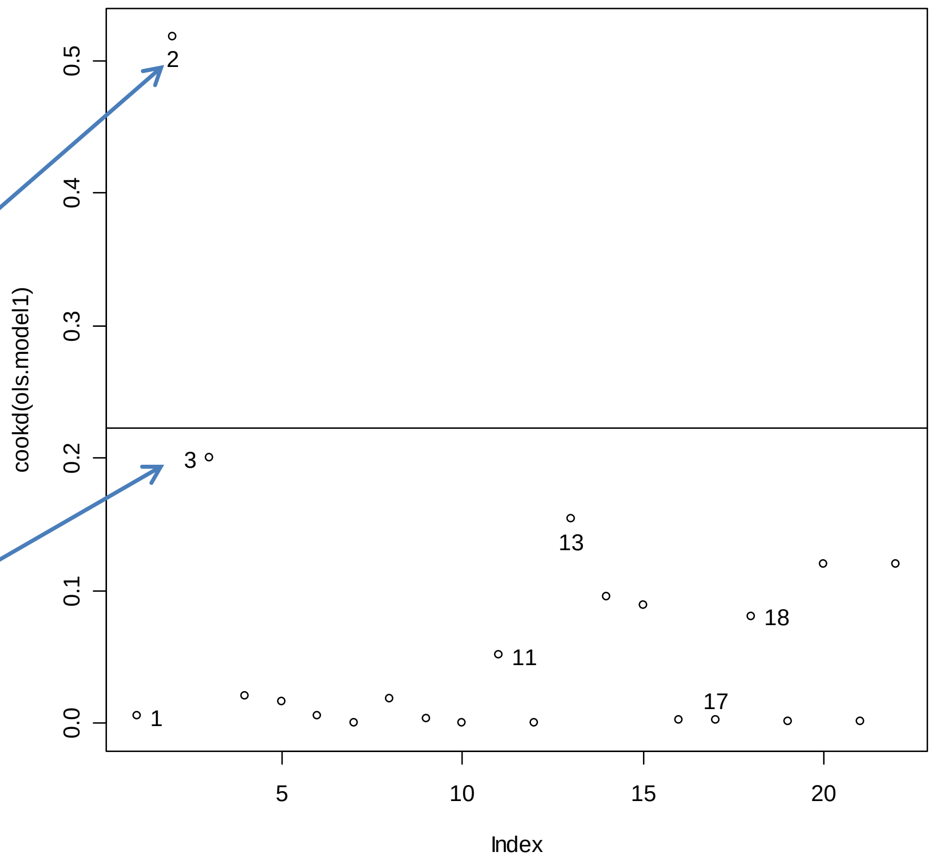


# OLS Diagnostics: Influence

- Cook's D gives a kind of summary for each observation's influence

$$D_i = \frac{u_i'^2}{k+1} * \frac{h}{1-h_i}$$

- If Cook's D is greater than 4/(n-k-1), then the observation is said to exert undue influence
- Let's just plot it
  - `plot(cookd(ols.model1))`
  - `abline(h=4/(nrow(x)-ncol(x)))`
  - `Identify(cookd(ols.model1))`
- States 2 and (maybe) 3 are in the trouble zone



# OLS Diagnostics: Influence

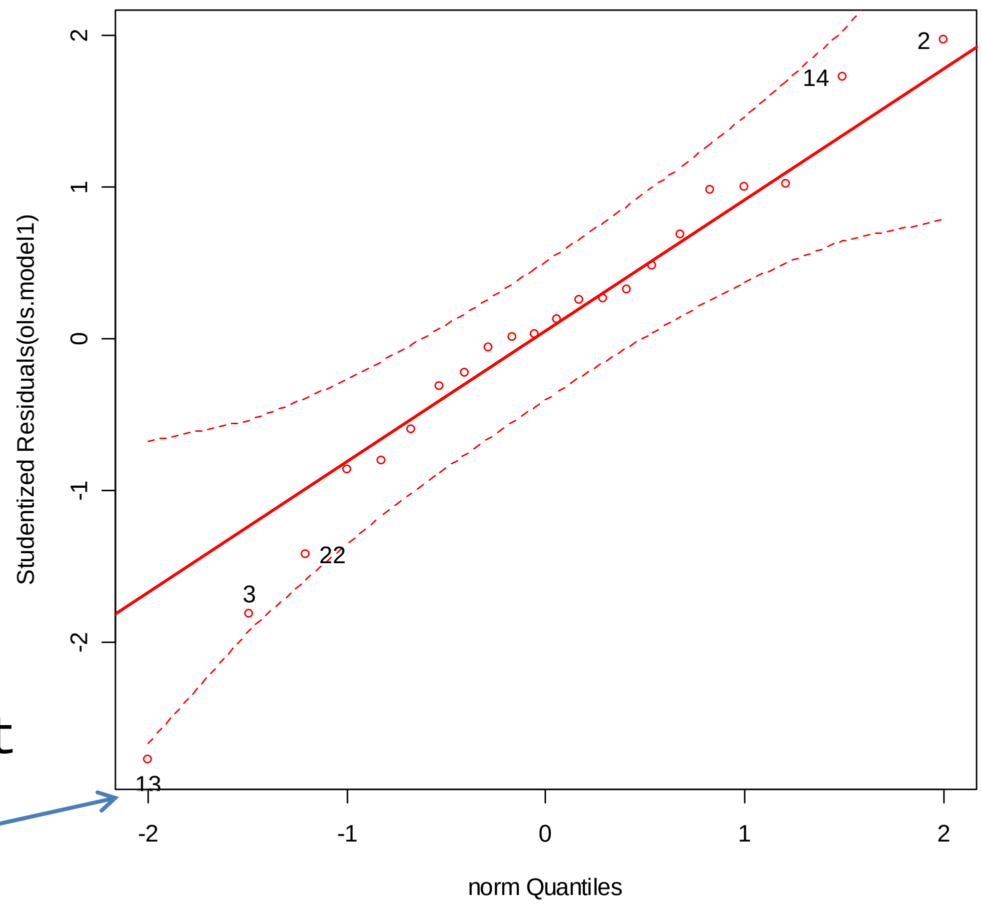
- For a host of measures of influence, including df betas and df fits
  - `influence.measures(ols.model1)`
- dfbeta gives the influence of an observation on the coefficients – or the change in iv's coefficient caused by deleting a single observation
- Simple commands for partial regression plots can be found on Fox's website…

```
> ##Other measures of influence, including df-beta and df-fit
> influence.measures(ols.model1)
Influence measures of
         lm(formula = repvshr ~ income + presvote + pressup) :

      dfb.1_ dfb.incm  dfb.prsv  dfb.prss    dffit cov.r   cook.d    hat inf
1   0.047591 -0.08463 -3.65e-03  0.020468  0.14217 1.295 5.28e-03 0.0806
2  -1.312887  1.36488  5.54e-01  0.206512  1.55092 0.892 5.18e-01 0.3822   *
3   0.589635 -0.58486  2.12e-01 -0.542793 -0.94909 0.790 2.00e-01 0.2151
4   0.018551 -0.15898  9.62e-02  0.003785 -0.27888 1.407 2.02e-02 0.1784
5   0.140077 -0.13349 -3.66e-02 -0.066607 -0.25112 1.148 1.60e-02 0.0779
6   0.074461 -0.02307 -1.05e-01  0.003705 -0.14584 1.486 5.60e-03 0.1739
7   0.000784  0.00338  6.08e-05 -0.003494  0.00654 1.604 1.13e-05 0.2165
8   0.137543  0.00171  3.56e-02 -0.197503  0.26917 1.298 1.87e-02 0.1324
9   0.012258 -0.06613 -2.85e-02  0.070448  0.12266 1.410 3.96e-03 0.1295
10 -0.013501  0.01606  4.56e-03 -0.000609 -0.02099 1.411 1.17e-04 0.1101
11  0.181001 -0.17994 -3.79e-01  0.264511  0.45258 1.227 5.13e-02 0.1768
12  0.002175  0.00537  2.43e-03 -0.008720  0.01240 1.580 4.07e-05 0.2048
13 -0.294634  0.56467 -1.25e-01 -0.026032 -0.92017 0.312 1.54e-01 0.0989   *
14 -0.398730  0.13983  2.24e-01  0.261259  0.65223 0.753 9.58e-02 0.1251
15  0.177517 -0.31912 -4.41e-01  0.439292  0.59858 1.329 8.93e-02 0.2552
16 -0.000611  0.04267 -2.17e-03 -0.037603 -0.08701 1.421 2.00e-03 0.1263
17  0.000169 -0.00028 -7.43e-02  0.072067  0.10442 1.433 2.87e-03 0.1371
18 -0.346076  0.04901  3.86e-01  0.055702 -0.56220 1.603 8.06e-02 0.3258
19  0.009685 -0.00750  3.67e-02 -0.032806  0.07117 1.335 1.34e-03 0.0730
20  0.185511 -0.04938  4.76e-01 -0.595824  0.69222 1.483 1.20e-01 0.3250
21  0.059471 -0.05104  3.78e-03 -0.037402  0.07321 1.680 1.42e-03 0.2545   *
22  0.352385 -0.14803 -5.73e-01  0.119730 -0.71266 1.004 1.20e-01 0.2010
>
```

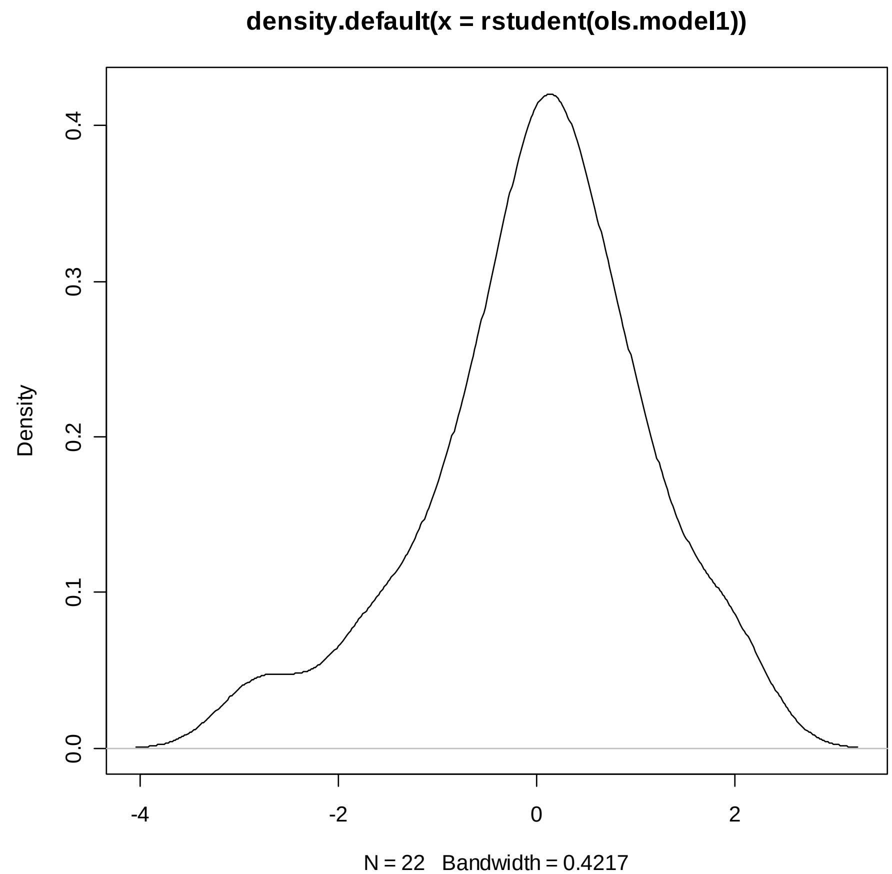
# OLS Diagnostics: Normality

- Is our data distributed normally?
- Was it correct to use a linear model?
- Use a quantile plot (qq plot) to check
  - Plots empirical quantiles of a variable against studentized residuals
  - Looking for obs on a straight line
  - In R it is simple to plot the error bands as well
  - Deviation requires us to transform our variables
- `qq.plot(ols.model1,distribution="norm")`
- The problems are again 2 and 13, with 3, 22 and 14 bordering on trouble this time around



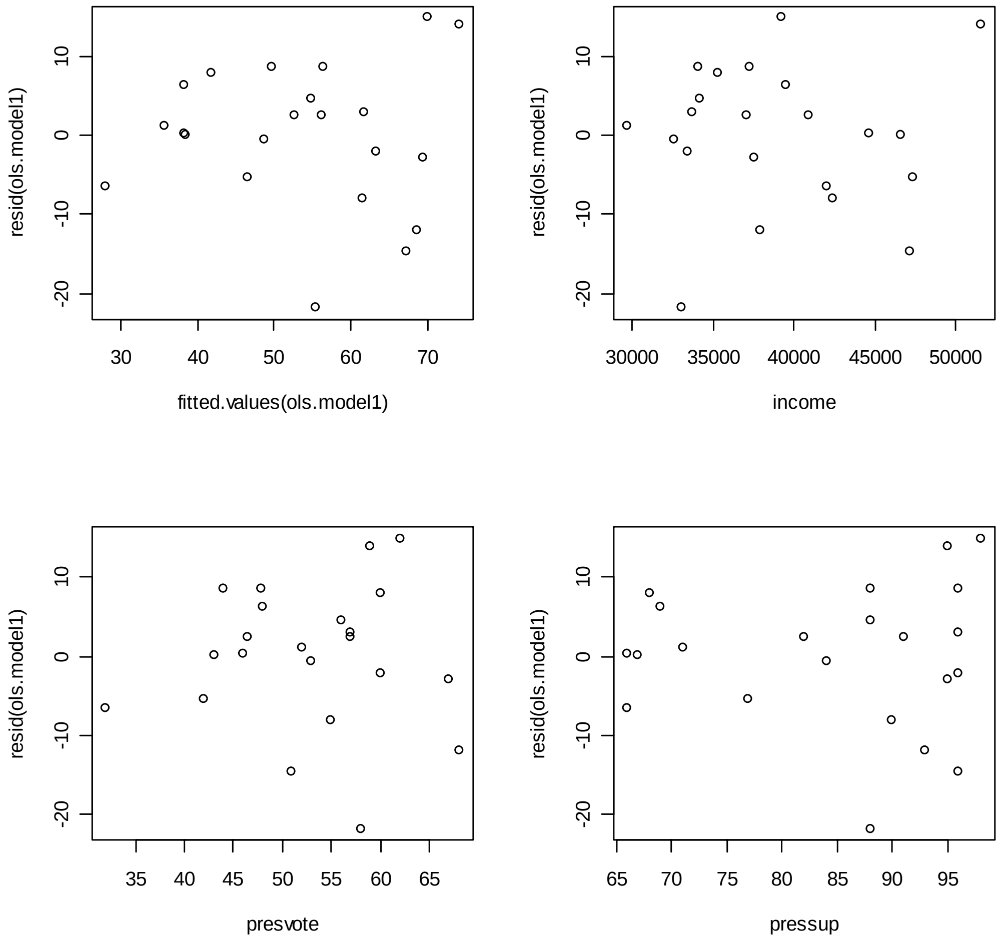
# OLS Diagnostics: Normality

- A simple density plot of the studentized residuals helps to determine the nature of our data
- The apparent deviation from the normal curve is not severe, but there certainly seems to be a slight negative skew



# OLS Diagnostics: Error Variance

- We can also easily look for heteroskedasticity
- Plotting the residuals against the fitted values and the continuous independent variables let's us examine our statistical model for the presence of unbalanced error variance
  - `par(mfrow=c(2,2))`
  - `plot(resid(ols.model1) ~fitted.values(ols.model1))`
  - `plot(resid(ols.model1) ~income)`
  - `plot(resid(ols.model1) ~presvote)`
  - `plot(resid(ols.model1) ~pressup)`



# OLS Diagnostics: Error Variance

- Formal tests for heteroskedasticity are available from the `lmtest` library
  - `library(lmtest)`
  - `bptest(ols.model1)` will give you the Breusch-Pagan test stat
  - `gqtest(ols.model1)` will give you the Goldfeld-Quandttest stat
  - `hmctest(ols.model1)` will give you the Harrison-McCabe test stat

```
> ##Breusch-Pagan, Goldfeld-Quandt, and Harrison-McCabe tests
> bptest(ols.model1)

        studentized Breusch-Pagan test

data:  ols.model1
BP = 3.2325, df = 3, p-value = 0.3571

> gqtest(ols.model1)

        Goldfeld-Quandt test

data:  ols.model1
GQ = 1.6338, df1 = 7, df2 = 7, p-value = 0.2664

> hmctest(ols.model1)

        Harrison-McCabe test

data:  ols.model1
HMC = 0.3878, p-value = 0.235
```

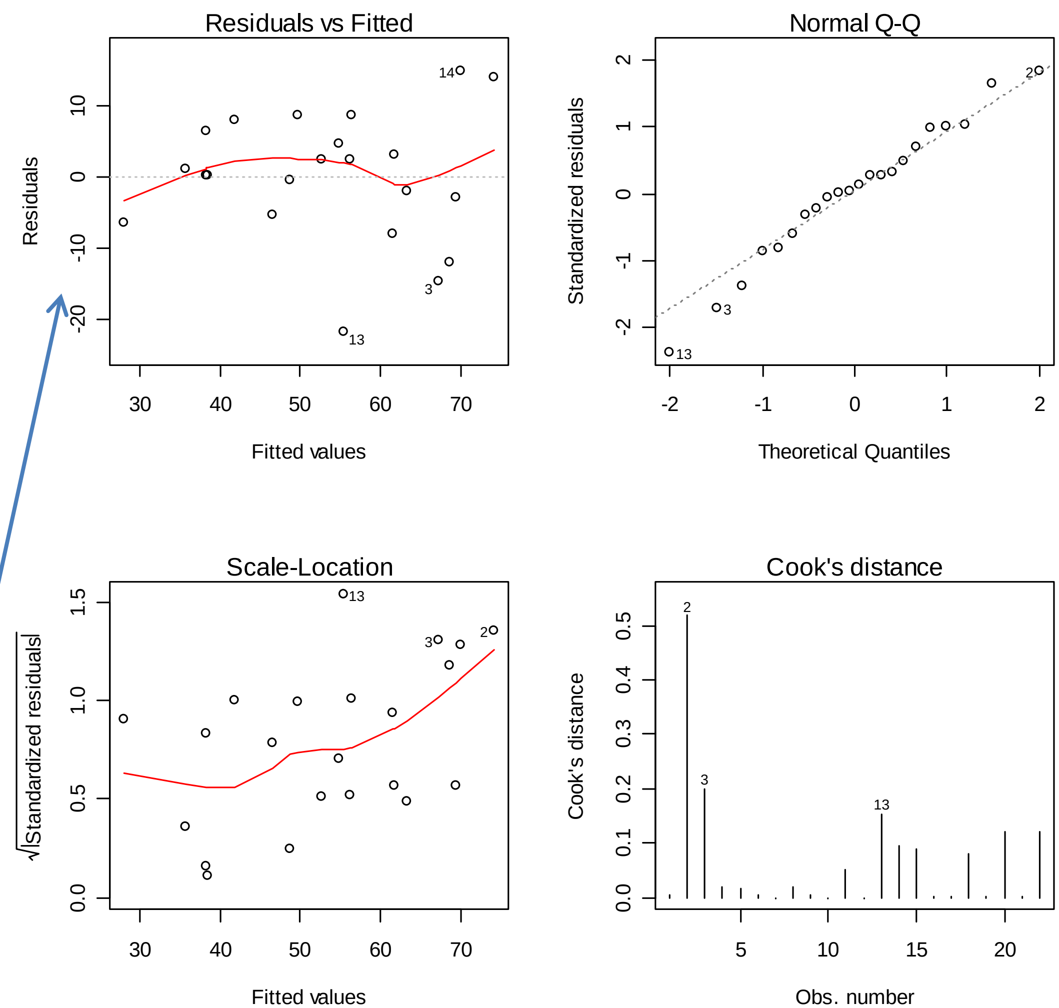
# OLS Diagnostics: Collinearity

- Finally, let’s look out for collinearity
- To get the variance inflation factors
  - `vif(ols.model1)`
- Let’s look at the condition index from the `perturb` library
  - `library(perturb)`
  - `colldiag(ols.model1)`
- Issues here  is the largest condition index
- If it is larger than 30, *Houston we have…*

```
>
> ##Variance inflation factors
> vif(ols.model1)
  income presvote  pressup
1.127017 1.636216 1.482685
>
>
> ##Obtain the condition index
> colldiag(ols.model1)
Condition
Index    Variance Decomposition Proportions
          intercept income presvote pressup
1   1.000 0.000     0.001  0.001    0.001
2  10.920 0.004     0.307  0.162    0.030
3  21.626 0.012     0.030  0.588    0.926
4  27.883 0.983     0.662  0.250    0.044
>
```

# OLS Diagnostics: Shortcut

- My favorite shortcut command to get you four essential diagnostic plots after you run your model
  - `plot(ols.model1, which=1:4)`
- Now you have no excuse not to run some diagnostics!
- Btw, look at the high residuals in the rvf plot for 14, 13 and 3 – suggesting outliers



# The Final Act: Loops and Functions

- As was mentioned above, R's biggest asset is its flexibility. Loops and functions directly utilize this asset.

- Loops can be implemented for a number of purposes, essentially when repeated actions are needed (i.e. simulations).

- Functions allow us to create our own commands. This is especially useful when a canned procedure does not exist. We will create our own OLS function with the hand-rolled code used earlier.

# Loops

- `for` loops are the most common and the only type of loop we will look at today.

- The first loop command at the right shows simple loop iteration.

R Console

```
>
>
> #Simple iteration
> for (i in 1:10) print (i)
[1] 1
[1] 2
[1] 3
[1] 4
[1] 5
[1] 6
[1] 7
[1] 8
[1] 9
[1] 10
>
>
> #Loop to calculate the mean of income
> #Create objects
> sum <- 0
> avg <- 0
>
> for (i in 1:22){
+ sum <- sum + income[i]
+ avg <- sum/i
+ }
>
> #Output
> avg
[1] 38966.55
>
> #Test against the mean command
> mean(income)
[1] 38966.55
>
```

# Loops

- However, we can also see how loops can be a little more useful.
- **The second example at right (although inefficient) calculates the mean of income**
- Note how the index accesses elements of the "income" vector.
- Loops and Monte Carlo

R Console

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[1] 1
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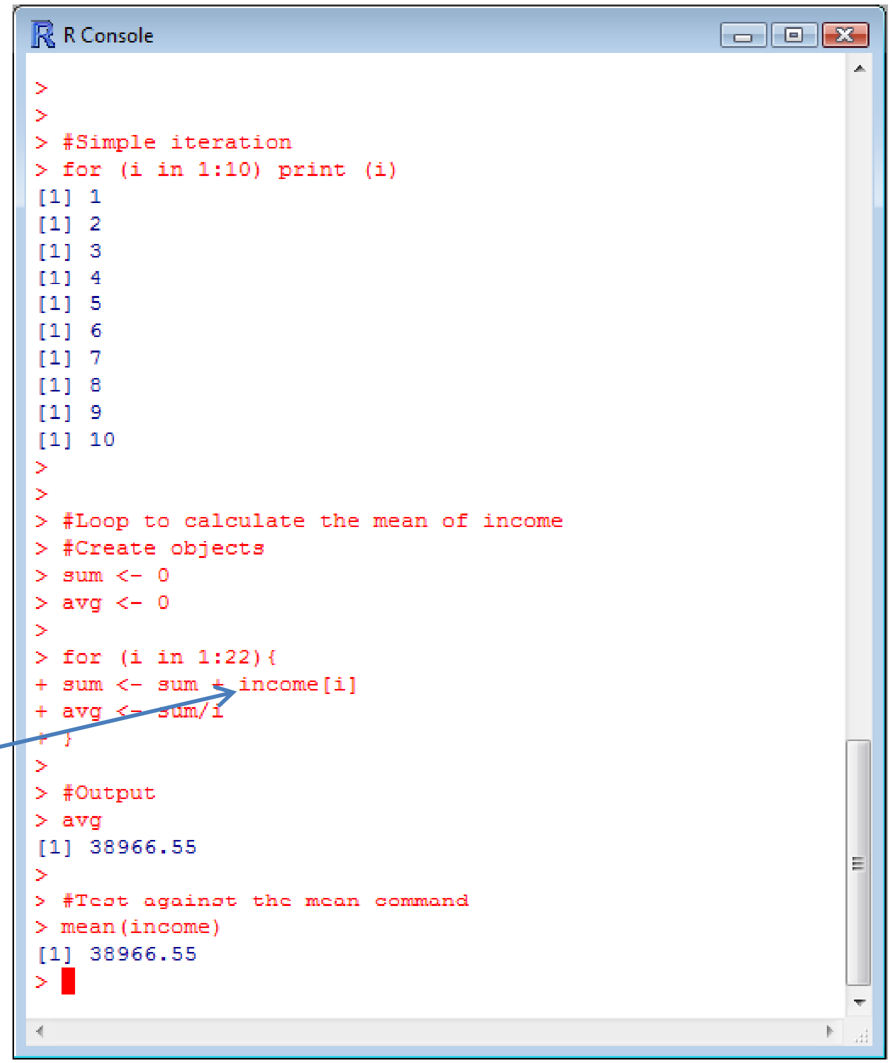

# Functions

- Now we will make our own linear regression function using our hand-rolled OLS code
- Functions require **inputs** (which are the objects to be utilized) and **arguments** (which are the commands that the function performs)
- The actual estimation procedure does not change. However, some changes are made.

Rintro - Notepad

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```
#Designing an OLS function (based on hand-rolled ols commands above)

ols<-function(y,x){



    x<-as.matrix(cbind(int=1,x))
    y<-as.vector(y)
    i<-diag(1,nrow=nrow(x),ncol=ncol(x))

    n<-length(y)
    p<-ncol(x)-1

    xy<-t(x)%*%y                   # X'Y
    xxi<-solve(t(x)%*%x)           #(X'X)^(-1)
    h<-x%*%xxi%*%t(x)              #hat matrix of x
    i<-diag(1,nrow=n,ncol=n)
    b<-as.vector(xxi%*%xy)         #estimated coefficients

    names(b)<-colnames(x)

    yhat<-as.vector(x%*%b)         #predicted values for y
    res<-y-yhat  # or (i-h)%*%y    #model residuals

    sst<-sum((y-mean(y))^2)        #Total sum of sqares
    sse<-t(res)%*%res                # or sum(res^2) which is also t(res)%*%res
    ssm<-sst-sse                   #sum of squares for model (regression)

    df.e<-(n-p-1)                  #degrees of freedom for error
    df.t<-(n-1)                    #total degrees of freedom
    df.m<-df.t-df.e                #degrees of freedom for model

    s2<-as.vector(sse/df.e) # or (t(res)%*%res)?(n-p-1)
    sigma2<-as.vector(sse/(n-p))
    r2<-1-(sse/sst)
    r2.adj<-1-((sse/df.e)/(sst/df.t))
    aic<-n*log(sse/n)+2*(p+1)
    cp<-(sse/s2)-(n-2*(p+1))
    f<-(ssm/df.m)/(sse/df.e)
    pvalue<-1-pf(f,df.m,df.e)

    b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
    b.t.statistic<-b/b.standard.errors           #t statistic for st. errors
    b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05


    b.table<-cbind(est=b,b.se=b.standard.errors,t.stat=b.t.statistic,p=b.t.prob)


  return(list(b=b.table
             ))
}
```

# Functions

- **First, we have to tell R that we are creating a function. We'll name it `ols`.**
- This lets us generalize the procedure to multiple objects.
- Second, we have to tell the function what we want "returned" or what we want the output to look like.

Rintro - Notepad

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     pvalue<-1-pf(f,df.m,df.e)

     b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
     b.t.statistic<-b/b.standard.errors           #t statistic for st. errors
     b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05


     b.table<-cbind(est=b,b.se=b.standard.errors,t.stat=b.t.statistic,p=b.t.prob)


  return(list(b=b.table
             ))
}
```

# Functions

- First, we have to tell R that we are creating a function. We'll name it `ols`.

- This lets us generalize the procedure to multiple objects.

- **Second, we have to tell the function what we want "returned" or what we want the output to look like.**

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```
#Designing an OLS function (based on hand-rolled ols commands above)

ols<-function(y,x){



     x<-as.matrix(cbind(int=1,x))
     y<-as.vector(y)
     i<-diag(1,nrow=nrow(x),ncol=ncol(x))

     n<-length(y)
     p<-ncol(x)-1

     xy<-t(x)%*%y                   # X'Y
     xxi<-solve(t(x)%*%x)           #(X'X)^(-1)
     h<-x%*%xxi%*%t(x)              #hat matrix of x
     i<-diag(1,nrow=n,ncol=n)
     b<-as.vector(xxi%*%xy)         #estimated coefficients

     names(b)<-colnames(x)

     yhat<-as.vector(x%*%b)         #predicted values for y
     res<-y-yhat  # or (i-h)%*%y    #model residuals

     sst<-sum((y-mean(y))^2)        #Total sum of sqares
     sse<-t(res)%*%res                # or sum(res^2) which is also t(res)%*%res
     ssm<-sst-sse                   #sum of squares for model (regression)

     df.e<-(n-p-1)                  #degrees of freedom for error
     df.t<-(n-1)                    #total degrees of freedom
     df.m<-df.t-df.e                #degrees of freedom for model

     s2<-as.vector(sse/df.e) # or (t(res)%*%res)?(n-p-1)
     sigma2<-as.vector(sse/(n-p))
     r2<-1-(sse/sst)
     r2.adj<-1-((sse/df.e)/(sst/df.t))
     aic<-n*log(sse/n)+2*(p+1)
     cp<-(sse/s2)-(n-2*(p+1))
     f<-(ssm/df.m)/(sse/df.e)
     pvalue<-1-pf(f,df.m,df.e)

     b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
     b.t.statistic<-b/b.standard.errors           #t statistic for st. errors
     b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05


     b.table<-cbind(est=b,b.se=b.standard.errors,t.stat=b.t.statistic,p=b.t.prob)


  return(list(b=b.table
             ))
}
```

# Functions

## OLS: Hand-rolled vs Function

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```
#Hand-rolled OLS

     x<-as.matrix(cbind(int=1,income,presvote,pressup))
     y<-as.vector(repvshr)
     i<-diag(1,nrow=nrow(x),ncol=ncol(x))

     n<-length(y)
     p<-ncol(x)-1


     xy<-t(x)%*%y                  # X'Y
     xxi<-solve(t(x)%*%x)          #(X'X)^(-1)
     h<-x%*%xxi%*%t(x)             #hat matrix of x
     i<-diag(1,nrow=n,ncol=n)
     b<-as.vector(xxi%*%xy)        #estimated coefficients

     names(b)<-colnames(x)

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     sigma2<-as.vector(sse/(n-p))
     r2<-1-(sse/sst)
     r2.adj<-1-((sse/df.e)/(sst/df.t))
     aic<-n*log(sse/n)+2*(p+1)
     cp<-(sse/s2)-(n-2*(p+1))
     f<-(ssm/df.m)/(sse/df.e)
     pvalue<-1-pf(f,df.m,df.e)

     b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)  #coefficient standard errors
     b.t.statistic<-b/b.standard.errors           #t statistic for st. errors
     b.t.prob<-2*(1-pt(b.t.statistic,df.e))       #alpha 0.05
```

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  return(list(b=b.table
              ))
}
```

# Functions

- **Implementing our new function `ols`, we get precisely the output that we asked for.**

- We can check this against the results produced by the standard `lm` function.

```
R Console
+      b.standard.errors<-sqrt(diag(xxi))*sqrt(s2)   #coeffici$
+      b.t.statistic<-b/b.standard.errors            #t statis$
+      b.t.prob<-2*(1-pt(b.t.statistic,df.e))        #alpha 0.$
+
+
+      b.table<-cbind(est=b,b.se=b.standard.errors,t.stat=b.t$
+
+
+   return(list(b=b.table
+               ))
+ }
> #Output of new ols command
> ols(repvshr, income)
$b
             est         b.se    t.stat          p
int 4.585949e+01 2.382350e+01 1.9249684 0.06857514
x   1.979220e-04 6.050306e-04 0.3271273 0.74697069

> #Compare to lm command
> lm(repvshr ~ income)

Call:
lm(formula = repvshr ~ income)

Coefficients:
(Intercept)       income
  4.586e+01    1.979e-04

>
```

# Functions

- Implementing our new function `ols`, we get precisely the output that we asked for.

- **We can check this against the results produced by the standard `lm` function.**

R Console

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> #Compare to lm command
> lm(repvshr ~ income)

Call:
lm(formula = repvshr ~ income)

Coefficients:
(Intercept)       income
  4.586e+01    1.979e-04

> 
```

# Favorite Resources

- Invaluable Resources online
  - The R manuals http://cran.r-project.org/manuals.html
  - Fox's slides http://socserv.mcmaster.ca/jfox/Courses/R-course/index.html
  - Faraway's book http://cran.r-project.org/doc/contrib/Faraway-PRA.pdf
  - Anderson's ICPSR lectures using R http://socserv.mcmaster.ca/andersen/icpsr.html
  - Arai's guide http://people.su.se/~ma/R_intro/
  - UCLA notes http://www.ats.ucla.edu/stat/SPLUS/default.htm
  - Keele's intro guide http://www.polisci.ohio-state.edu/faculty/lkeele/RIntro.pdf

- Great R books
  - Verzani's book http://www.amazon.com/Using-Introductory-Statistics-John-Verzani/dp/1584884509
  - Maindonald and Braun's book http://www.amazon.com/Data-Analysis-Graphics-Using-R/dp/0521813360