# Basic R and Basic Concepts

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## About R

- R is an object-oriented programming language
  - Data
  - Procedures
- Object's procedures can access and modify the data fields of objects.
- If you see a + means a parenthesis or bracket is open.
- R is case sensitive.
- Use / in path names. Not \.

## Using Third-party Code

- Relevant commands are: `install.packages` and `library`
- Find the appropriate packages and commands with Google and via searching in R:

```
?covariance
??covariance
install.packages("sandwich")
library(sandwich)
library("sandwich")
require(sanwich)
sanwich::vcovHC
?vcovHC
```

## Install from other sources

- If you want to install packages on GitHub:

```
require(devtools)
install_github("wch/ggplot2")
```

*This note builds on and revises material created by Aaron Zhou

- If you have a complied package downloaded on your computer (tar.gz):
- Tools -> Install Packages -> Find the location
- R cmd install *package name*

# Data types

- Character - strings
- Double / Numeric - numbers
- Logical - true/false
- Factor - unordered categorical variables

# Character

```
my.name <- "Giacomo"
paste("My","name","is","Giacomo")
```

```
## [1] "My name is Giacomo"
```

```
name.sentence <- paste0("My","name","is","Giacomo")
as.character(99)
```

```
## [1] "99"
```

```
class(my.name)
```

```
## [1] "character"
```

# Numeric

```
num <- 99.867
class(num)
```

```
## [1] "numeric"
```

```
round(num, digits=2)
```

```
## [1] 99.87
```

```
as.numeric("99") + 1
```

```
## [1] 100
```

```
pi
```

```
## [1] 3.141593
```

```
exp(1)
```

```
## [1] 2.718282
```

# Numeric

- `sin`, `exp`, `log`, `factorial`, `choose`, are some useful mathematical functions
- You probably noticed that "<-" is an assignment operator
- It lets you store objects and use them later on
- You can also use "="
- To remove something, rm(object)
- To remove everything that is stored use rm(list=ls())

# Logical

- The logical type allows us to make statements about truth

```
2 == 4
```

```
## [1] FALSE
```

```
class(2==4)
```

```
## [1] "logical"
```

```
my.name != num
```

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

```
"34" == 34
```

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

- `==`, `!=`, `>`, `<`, `>=`, `<=`, `!`, `&`, `|`, `any`, `all`, etc

# Data Structures

- There are other ways to hold data, though:
  - Vectors/Lists
  - Matrices/Dataframes
  - Array

# Vectors

- Almost everything in R is a vector.

```
as.vector(4)
```

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

```r
4
```

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

- We can combine elements in vectors with `c`, for concatenate:

```r
vec <- c("a","b","c")
vec
```

```
## [1] "a" "b" "c"
```

```r
c(2,3,vec)
```

```
## [1] "2" "3" "a" "b" "c"
```

# More Vectors

- We can index vectors in several ways

```r
vec[1]
```

```
## [1] "a"
```

```r
names(vec) <- c("first","second","third")
vec
```

```
##  first second  third
##    "a"    "b"    "c"
```

```r
vec["first"]
```

```
## first
##   "a"
```

# Creating Vectors

```r
vector1 <- 1:5
vector1
```

```
## [1] 1 2 3 4 5
```

```r
vector1 <- c(1:5,7,11)
vector1
```

```
## [1]  1  2  3  4  5  7 11
```

```r
vector2 <- seq(1, 7, 1)
vector2
```

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

# Creating Vectors

```r
cbind(vector1,vector2)
```

```
##      vector1 vector2
## [1,]       1       1
## [2,]       2       2
## [3,]       3       3
## [4,]       4       4
## [5,]       5       5
## [6,]       7       6
## [7,]      11       7
```

```r
rbind(vector1,vector2)
```

```
##         [,1] [,2] [,3] [,4] [,5] [,6] [,7]
## vector1    1    2    3    4    5    7   11
## vector2    1    2    3    4    5    6    7
```

# Missingness

```r
vec[1] <- NA
vec
```

```
##  first second  third 
##     NA    "b"    "c"
```

```r
is.na(vec)
```

```
##  first second  third 
##   TRUE  FALSE  FALSE
```

```r
vec[!is.na(vec)] # vec[complete.cases(vec)]
```

```
## second  third 
##    "b"    "c"
```

# Lists

- Lists are similar to vectors, but they allow for arbitrary mixing of types and lengths.

```r
listie <- list(first = vec, second = num)
listie
```

```
## $first
##  first second  third 
##     NA    "b"    "c" 
## 
## $second
## [1] 99.867
```

# Lists

```
listie[[1]]
```

```
##  first second  third
##     NA    "b"    "c"
```

```
listie$first
```

```
##  first second  third
##     NA    "b"    "c"
```

# Basic Functions

```
a <- c(1,2,3,4,5)
a
```

```
## [1] 1 2 3 4 5
```

```
sum(a)
```

```
## [1] 15
```

```
max(a)
```

```
## [1] 5
```

```
min(a)
```

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

# Basic Functions

```
length(a)
```

```
## [1] 5
```

```
length <- length(a)
b <- seq(from=0,to=5,by=.5)
c <- rep(10,27)
d <- runif(100)
```

More later # Matrices

- $$A = \begin{pmatrix} 1 & 3 \\ 2 & 4 \end{pmatrix}$$
- $A_{ij}$
- $A_{1,2} = 3$
- $A_{1,\cdot} = (1,3)$

```
A <- matrix(c(1,2,3,4),nrow=2,ncol=2)
A
```

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

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

```
A[1,2]
```

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

```
A[1,]
```

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

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

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

# Matrix Operations

- Its very easy to manipulate matrices:

```
solve(A) #A^{-1}
```

```
##      [,1] [,2]
## [1,]   -2  1.5
## [2,]    1 -0.5
```

```
10*A
```

```
##      [,1] [,2]
## [1,]   10   30
## [2,]   20   40
```

# Matrix Operations

```
B<-diag(c(1,2)) #Extract or replace diagonal of a matrix
B
```

```
##      [,1] [,2]
## [1,]    1    0
## [2,]    0    2
```

```
A%*%B
```

```
##      [,1] [,2]
## [1,]    1    6
## [2,]    2    8
```

# More Matrix Ops.

```
t(A) # A'
```

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

```
rbind(A,B)
```

```
##      [,1] [,2]
## [1,]    1    3
## [2,]    2    4
## [3,]    1    0
## [4,]    0    2
```

# More Matrix Ops.

```
cbind(A,B)
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    3    1    0
## [2,]    2    4    0    2
```

```
c(1,2,3)%x%c(1,1) # Kronecker Product
```

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

- How to generate the OLS estimates with $X$ and $Y$?

# Naming Things

```
rownames(A)
```

```
## NULL
```

```
rownames(A)<-c("a","b")
colnames(A)<-c("c","d")
A
```

```
##   c d
## a 1 3
## b 2 4
```

```
A[,"d"]
```

```
## a b
## 3 4
```

# Array

- An array is similar to a matrix in many ways

```
array1 <- array(c(1,2,3,4,5,6,7,8), c(2,2,2))
array1
```

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

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

```
array1[,2,]
```

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

# Dataframes

- The workhorse
- Basically just a matrix that allows mixing of types.
- R has a bunch of datasets

```
# data() gives you all the datasets
data(iris)
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

# Dataframes

- But you will generally work with your own datasets

```
getwd()
```

```
## [1] "C:/Users/giaco/Dropbox/NYU/TA Work/Quant 2 Spring 2022/Lab material/lab1"
```

```
setwd("C:/Users/giaco/Dropbox/NYU/TA Work/Quant 2 Spring 2022/Lab material/lab1")
```

- R can read any number of file types (.csv, .txt, etc.)

```
#.CSV
dat.csv <- read.csv("http://stat511.cwick.co.nz/homeworks/acs_or.csv")
```

# Dataframes

```
#STATA
require(foreign)
```

```
## Caricamento del pacchetto richiesto: foreign
```

```r
dat.data <- read.dta("https://stats.idre.ucla.edu/stat/data/test.dta")
```

# Dataframes

```r
# add variables
dat.data[, "intercept"] <- rep(1, nrow(dat.data))
# change the name of a variable
names(dat.data)[6] <- "constant"
# delete variables
dat.data <- dat.data[, -6]
# sort on one variable
dat.data <- dat.data[order(dat.data[, "mpg"]), ]


# remove all missing values
dat.data.complete <- dat.data[complete.cases(dat.data), ]
# Or similarly
dat.dat.nona <- na.omit(dat.data)

dim(dat.data.complete)
```

```
## [1] 5 5
```

```r
dim(dat.dat.nona)
```

```
## [1] 5 5
```

```r
# select a subset
dat.data.subset <- dat.data[dat.data[, "make"] == "AMC", ]
dat.data.subset <- dat.data[1:3, ]
```

# Objects

- Many functions will return objects rather than a single datatype.

```r
# Remember to always set a seed when generating random numbers
set.seed(1)

X <- 1:100
Y <- rnorm(100,X)
out.lm <- lm(Y~X)
class(out.lm)
```

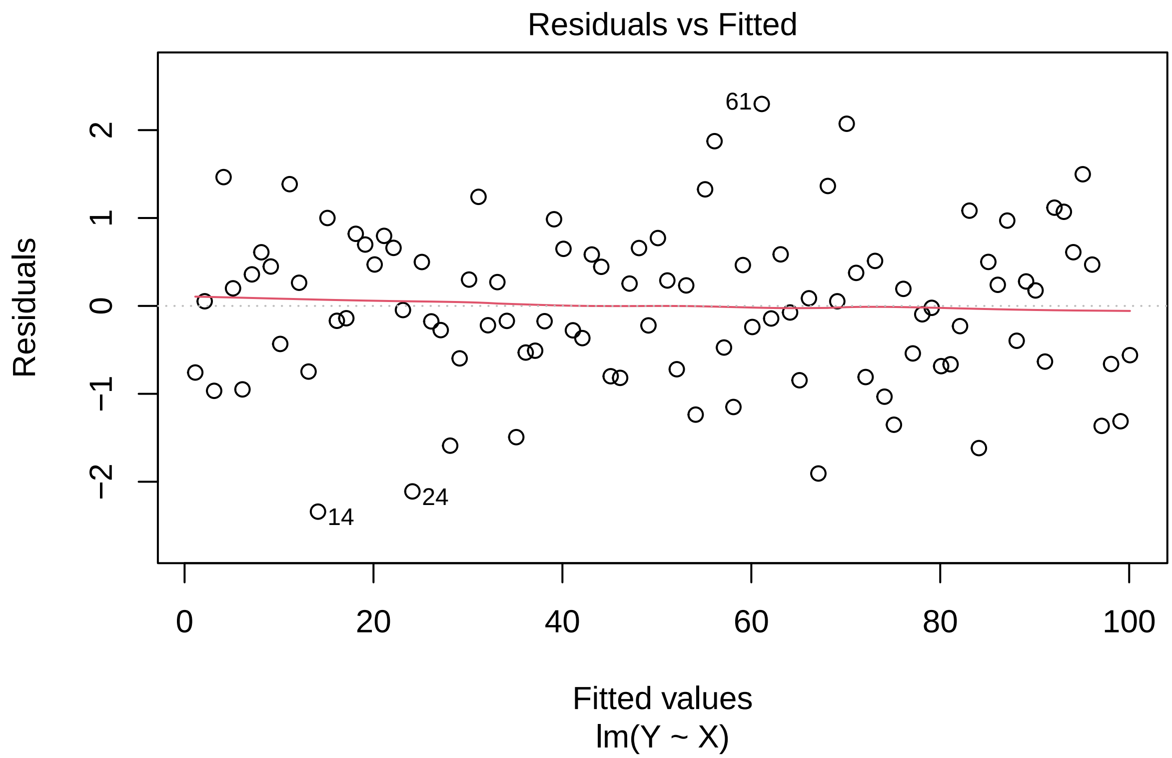
```
## [1] "lm"
```

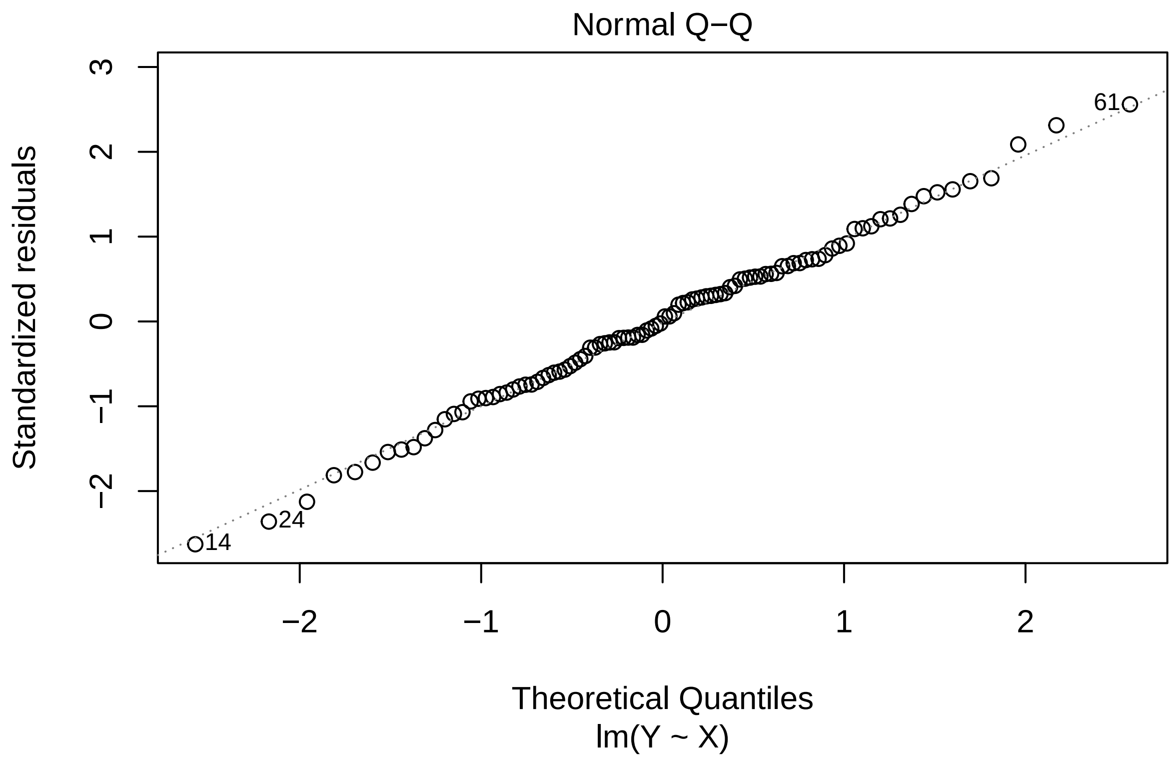
```r
predict(out.lm)
```

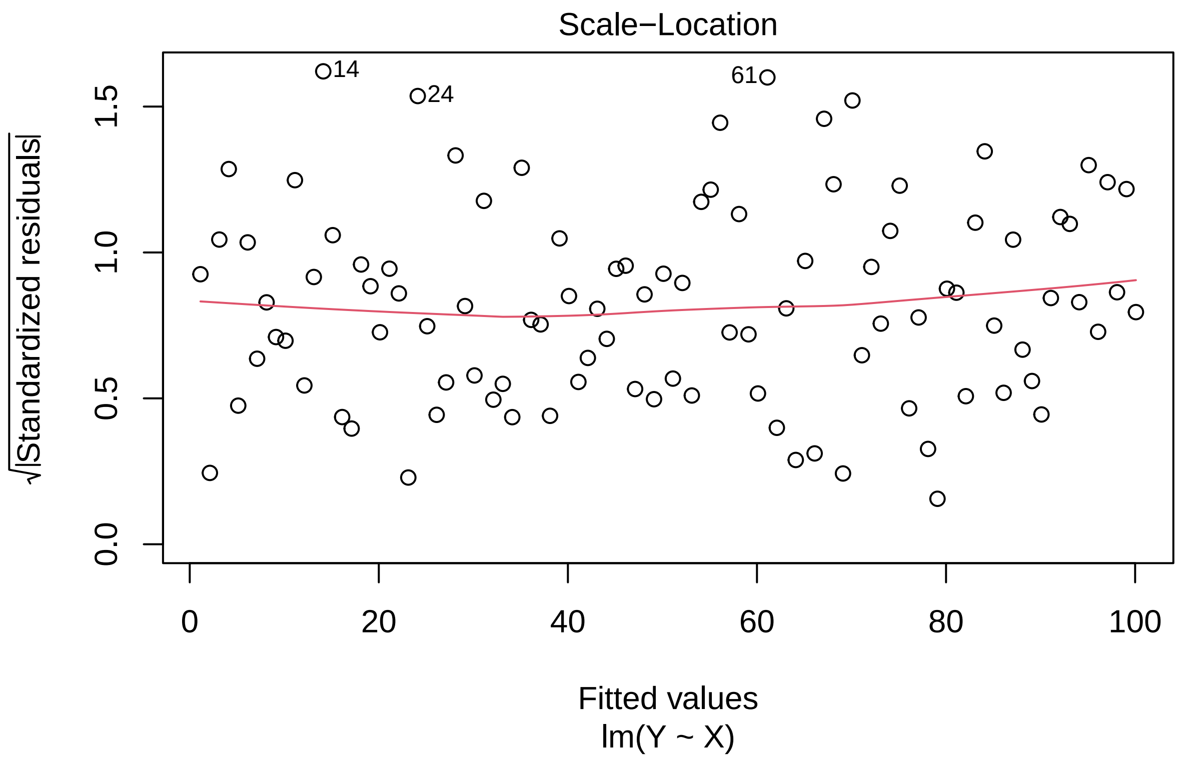
```
##         1         2         3         4         5         6         7
##  1.131215  2.130764  3.130313  4.129862  5.129410  6.128959  7.128508
##         8         9        10        11        12        13        14
##  8.128057  9.127606 10.127155 11.126704 12.126253 13.125802 14.125351
##        15        16        17        18        19        20        21
```

```
## 15.124900  16.124449  17.123998  18.123547  19.123096  20.122645  21.122194
##        22         23         24         25         26         27         28
## 22.121742  23.121291  24.120840  25.120389  26.119938  27.119487  28.119036
##        29         30         31         32         33         34         35
## 29.118585  30.118134  31.117683  32.117232  33.116781  34.116330  35.115879
##        36         37         38         39         40         41         42
## 36.115428  37.114977  38.114526  39.114075  40.113623  41.113172  42.112721
##        43         44         45         46         47         48         49
## 43.112270  44.111819  45.111368  46.110917  47.110466  48.110015  49.109564
##        50         51         52         53         54         55         56
## 50.109113  51.108662  52.108211  53.107760  54.107309  55.106858  56.106407
##        57         58         59         60         61         62         63
## 57.105955  58.105504  59.105053  60.104602  61.104151  62.103700  63.103249
##        64         65         66         67         68         69         70
## 64.102798  65.102347  66.101896  67.101445  68.100994  69.100543  70.100092
##        71         72         73         74         75         76         77
## 71.099641  72.099190  73.098739  74.098288  75.097836  76.097385  77.096934
##        78         79         80         81         82         83         84
## 78.096483  79.096032  80.095581  81.095130  82.094679  83.094228  84.093777
##        85         86         87         88         89         90         91
## 85.093326  86.092875  87.092424  88.091973  89.091522  90.091071  91.090620
##        92         93         94         95         96         97         98
## 92.090169  93.089717  94.089266  95.088815  96.088364  97.087913  98.087462
##        99        100
## 99.087011 100.086560
```

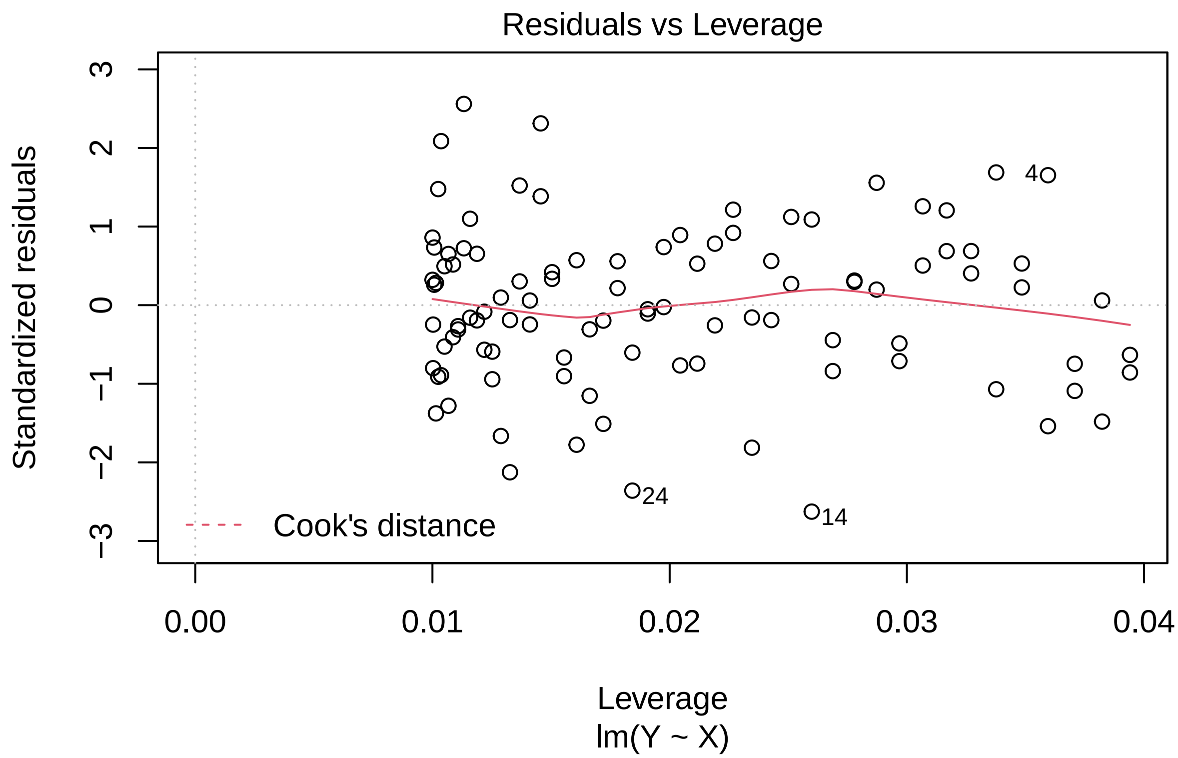
```
plot(out.lm)
```


Residuals vs Fitted
61
14
24
Residuals
2
1
0
−1
−2
0
20
40
60
80
100
Fitted values
lm(Y ~ X)


Normal Q−Q
Standardized residuals
3
2
1
0
−1
−2
61
24
14
−2
−1
0
1
2
Theoretical Quantiles
lm(Y ~ X)



Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
0
20
40
60
80
100
14
24
61
Fitted values
lm(Y ~ X)




```
summary(out.lm)
```

```
##
## Call:
## lm(formula = Y ~ X)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.34005 -0.60584  0.01551  0.58514  2.29747
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.131666   0.181897   0.724    0.471
## X           0.999549   0.003127 319.640   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9027 on 98 degrees of freedom
## Multiple R-squared:  0.999,  Adjusted R-squared:  0.999
## F-statistic: 1.022e+05 on 1 and 98 DF,  p-value: < 2.2e-16
```

- Objects can have other data embedded inside them

```
out.lm$coefficients
```

```
## (Intercept)           X
##   0.1316657   0.9995489
```

Show results properly using stargazer.

```
library(stargazer)
```

```
##
## Please cite as:

##  Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.

##  R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
```

```
stargazer(out.lm) #  This code gives you a latex code
```

```
##
## % Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harva
## % Date and time: lun, gen 31, 2022 - 10:45:55
## \begin{table}[!htbp] \centering
##   \caption{}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lc}
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{1}{c}{\textit{Dependent variable:}} \\
## \cline{2-2}
## \\[-1.8ex] & Y \\
## \hline \\[-1.8ex]
##  X & 1.000$^{***}$ \\
##   & (0.003) \\
##   & \\
##  Constant & 0.132 \\
##   & (0.182) \\
##   & \\
## \hline \\[-1.8ex]
## Observations & 100 \\
## R$^{2}$ & 0.999 \\
## Adjusted R$^{2}$ & 0.999 \\
## Residual Std. Error & 0.903 (df = 98) \\
## F Statistic & 102,169.400$^{***}$ (df = 1; 98) \\
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{1}{r}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
## \end{tabular}
## \end{table}
```

```
stargazer(out.lm, type = "text") # This gives you a table in text
```

```
##
## ===============================================
##                         Dependent variable:
##                     ---------------------------
##                                  Y
## -----------------------------------------------
## X                             1.000***
##                               (0.003)
##
## Constant                       0.132
```

```
##                              (0.182)
##
## -----------------------------------------------
## Observations                   100
## R2                            0.999
## Adjusted R2                   0.999
## Residual Std. Error       0.903 (df = 98)
## F Statistic         102,169.400*** (df = 1; 98)
## ===============================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

You can always includes latex code directly.

Table 1:

| | *Dependent variable:* |
|---|---|
| | Y |
| X | $1.000^{***}$ |
| | (0.003) |
| Constant | 0.132 |
| | (0.182) |
| Observations | 100 |
| $R^2$ | 0.999 |
| Adjusted $R^2$ | 0.999 |
| Residual Std. Error | 0.903 (df = 98) |
| F Statistic | $102{,}169.400^{***}$ (df = 1; 98) |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

# Control Flow

- loops
- if/else

# Loops

- for loops - a way to say "do this for each element of the index"
- "this" is defined in what follows the "for" expression

```
for(i in 1:5) {
  cat(i*10," ")
}
```

```
## 10  20  30  40  50
```

```r
for(i in 1:length(vec)) {
  cat(vec[i]," ")
}
```

```
## NA  b  c
```

```r
for(i in vec) {
  cat(i," ")
}
```

```
## NA  b  c
```

# If/Else

```r
if(vec[2]=="b") print("Hello World!")
```

```
## [1] "Hello World!"
```

```r
if(vec[3]=="a") {
  print("Hello World!")
} else {
  print("!dlroW olleH")
}
```

```
## [1] "!dlroW olleH"
```

```r
for(i in 2:length(vec)){
  if(vec[i]=="b") {
  print("Hello World!")
  }
  else {
  print("!dlroW olleH")
  }
}
```

```
## [1] "Hello World!"
## [1] "!dlroW olleH"
```

# Functions

- Function perform a set of operations internally and return only the output we want
- They are especially useful when we want to reiterate the same actions without copying the same lines of code forever

```r
# Simple function to estimate descriptive statistics
descr <- function(var){
  mean <- mean(var, na.rm=T)
  sd <- sd(var, na.rm=T)
  N <- length(var)
  return(round(c(mean, sd, N), 2))
}

# Apply it to our data
apply(dat.data[,c("mpg", "weight", "price")], 2, descr)
```

```
##        mpg  weight   price
## [1,] 19.20 3250.00 5058.00
## [2,]  3.11  541.62 1606.72
## [3,]  5.00    5.00    5.00
```

Since data frames are R objects, we can code our own estimators (one of the reasons people like R).

```
# Function to compute OLS coefficients
ols <- function(X, y) {
  # Input: vector or matrix X, vector y
  # Returns: coefficient vector for OLS regression (X'X)^{-1}X'y

  # Create a column for the intercept
  if ( !all(as.matrix(X)[,1] == 1) ) {X <- cbind(1, X)}
  out <- solve(t(X) %*% X) %*% t(X) %*% y
  rownames(out) <- c('Intercept', rep('', nrow(out)-1 ))
  return( t(out) )
}

# Let's estimate regression coefficients by OLS
round(ols(X, Y), 4)
```

```
##      Intercept
## [1,]    0.1317 0.9995
```

```
lm(Y ~ X)
```

```
##
## Call:
## lm(formula = Y ~ X)
##
## Coefficients:
## (Intercept)            X
##      0.1317       0.9995
```

# Simulations

- A very important tool
- Theoretical properties of estimators can be better understood by observing them in simulated data
- For empirical researchers, simulating the DGP allows to study properties of research designs such as power (especially important when designing an experiment or study)
- So, if you don't understand something, simulation is a valid option

# An example

Recall the Neyman estimator of the sampling variance of the difference in means:

$$\hat{V} = \frac{\hat{s}^2_{Y_1}}{n_1} + \frac{\hat{s}^2_{Y_0}}{n_0}$$

We have seen that, under random sampling from a super-population, this estimator is unbiased for the sampling variance of the difference in means given by both random sample variation **and** randomization within sample (Imbens and Rubin, Ch.6).

$$E[\hat{V}] = \frac{\sigma^2_{Y_1}}{n_1} + \frac{\sigma^2_{Y_0}}{n_0} = V[\bar{Y_1} - \bar{Y_0}]$$

Moreover, if there is treatment effect heterogeneity (i.e. the unit-level treatment effects are not constant), it is a (upward) biased estimator of the sampling variance of difference in means given by randomization only, for a fixed sample (Imbens and Rubin Ch.6).

$$E_D[\hat{V}|S] = V_D[\bar{Y_1} - \bar{Y_0}|S] + \frac{s^2_\rho}{n} \geq V_D[\bar{Y_1} - \bar{Y_0}|S]$$

Let's observe these properties through simulation.

```r
# Set seed
set.seed(123)

# Assume a large super population
N_pop <- 100000

# We simulate the potential outcomes for each observation
Y0 <- abs(rnorm(N_pop, mean = 5, sd = 2))
Y1 <- Y0 + rnorm(N_pop, 0, 5) + 4

# Note that the PATE is ~ 4 by construction
TE <- Y1 - Y0
(PATE <- mean(TE))
```

```
## [1] 4.026077
```

```r
# Now, we extract a random sample from this super-population
# Say, our experimental sample
Nsample <- 1000
pop <- data.frame(Y0 = Y0, Y1 = Y1, TE = TE)
sample <- pop[sample(nrow(pop), size = Nsample),]
```

```r
# What is the SATE?
(SATE <- mean(sample$TE))
```

```
## [1] 3.910847
```

```r
# Now, we can simulate the randomization distribution over this sample.
# In practice, we re-assign the treatment N times and at each iteration we compute an estimate
# for the SATE using the new **observed** values

# Number of iterations
Nboot <- 10000

# An empty vector where to store the estimates
dim <- vars <- rep(NA, Nboot)

# Start loop
for(i in 1:Nboot){
  # Treatment assignment to half units (complete randomization)
  sample$D <- 0
  sample$D[sample(Nsample, Nsample/2)] <- 1

  # Observed potential outcomes
  sample$Y <- sample$D*sample$Y1 + (1-sample$D)*sample$Y0

  # Compute simple difference in means (estimate for SATE) and store it
  dim[i] <- mean(sample$Y[sample$D==1]) - mean(sample$Y[sample$D==0])

  # Compute variance (estimate for V(SATE)) and store it
  vars[i] <- var(sample$Y[sample$D==1])/(Nsample/2) + var(sample$Y[sample$D==0])/(Nsample/2)
}


# We now have a simulated randomization distribution of differences in means
# We know this is unbiased for the SATE
mean(dim)
```

```
## [1] 3.905932
```

```r
# What is the variance of this estimator in the randomization distribution?
var(dim)
```

```
## [1] 0.03920887
```

```r
# What is the expected value of the variance estimator we computed?
mean(vars)
```

```
## [1] 0.06285642
```

```r
# Finally, let's compute the sampling variance of DIM under both randomization and sampling distributio
# Here the simulation has two levels:
# (i) we do an outer loop where we randomly draw samples from the super population
# (ii) we do an inner loop where for each sample we compute the randomization distribution, as before

# Number of sample draws to do
Nsampling <- 20
```

```r
# Matrices and vectors where to store the results
dim <- vars <- matrix(NA, Nsampling, Nboot)

# Begin loop
for(j in 1:Nsampling){
  # New random sample
  sample <- pop[sample(nrow(pop), size = Nsample),]

  # Inner loop: randomization distribution
    for(i in 1:Nboot){
      # Treatment assignment to half units (complete randomization)
      sample$D <- 0
      sample$D[sample(Nsample, Nsample/2)] <- 1

      # Observed potential outcomes
      sample$Y <- sample$D*sample$Y1 + (1-sample$D)*sample$Y0

      # Compute simple difference in means (estimate for SATE) and store it
      dim[j,i] <- mean(sample$Y[sample$D==1]) - mean(sample$Y[sample$D==0])

      # Compute variance (estimate for V(SATE)) and store it
  vars[j,i] <- var(sample$Y[sample$D==1])/(Nsample/2) + var(sample$Y[sample$D==0])/(Nsample/2)
    }
}

# We know that the DIM is unbiased also for the PATE
mean(dim)
```

```
## [1] 4.059777
```

```r
# What is the variance of this estimator in the sampling and randomization distribution?
var(as.vector(dim))
```

```
## [1] 0.06019168
```

```r
# Note that we can also compute the "true" (theoretical) value
# using the population values
var(Y1)/(Nsample/2) + var(Y0)/(Nsample/2)
```

```
## [1] 0.06595247
```

```r
# What is the expected value of the Neyman variance estimator?
mean(vars)
```

```
## [1] 0.06691493
```

Note that under sampling and randomization distribution the variance of the DIM estimator is larger! In fact, we have two sources of uncertainty (or noise) to account for. But we are able to estimate it without bias using sample quantities.