

# **FIT1043 Introduction to Data Science**

Week 8: Introduction to R for data science

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# Week 7 Coverage

## Classification

## Clustering



Week	Activities	Assignments
1	Overview of data science	
2	Introduction to Python for data science	
3	Data visualisation and descriptive statistics	
4	Data sources and data wrangling	
5	Data analysis theory	Assignment 1
6	Regression analysis	
7	Classification and clustering	
8	Introduction to R for data science	Assignment 2
9	Characterising data and "big" data	
10	Big data processing	
11	Issues in data management	Assignment 3
12	Industry guest lecture	

Week 1

Overview of data science

Engineering

Weeks 9-10

Week 4

Collect

Wrangle

Analyse

Present

Week 3

Weeks 5-7

Week 11

Governance

Operationalise

Weeks 2 & 8

Tools for data science

# Week 8 Outline

- Motivation to study R
- R data types
- Essential libraries
  - Wrangling
  - Exploration and analysis
  - Visualisation

# Learning Outcomes

Week 8

**By the end of this week you should be able to:**

- Comprehend essentials for coding in R for data science
- Explain and interpret given R commands
- Apply R commands for data wrangling, visualisation, exploration and analysis

# Introduction to R for Data Science



# Data Science Programming Languages

<https://www.analyticsinsight.net/top-10-data-science-programming-languages-for-2020/>

## Python

Python holds a special place among all other programming languages. It is an object-oriented, open-source, flexible and easy to learn a programming language and has a rich set of libraries and tools designed for data science. Also, Python has a huge community base where developers and data scientists can ask their queries and answer queries of others. Data science has been using Python for a long time and it is expected to continue to be the top choice for data scientists and developers.

## R

R is a very unique language and has some really interesting features which aren't present in other languages. These features are very important for data science applications. Being a vector language, R can do many things at once, functions can be added to a single vector without putting it in a loop. As the power of R is being realized, it is finding use in a variety of other places, starting from financial studies to genetics and biology and medicine.

## SQL

SQL (Structured Query Language) is a domain-specific language used in programming and designed for managing data held in a relational database management system. As the role of a data scientist is to turn raw data into actionable insights, therefore they primarily use SQL for data retrieval. To be an effective data scientist, they must know how to wrangle and extract data from the databases using SQL language.

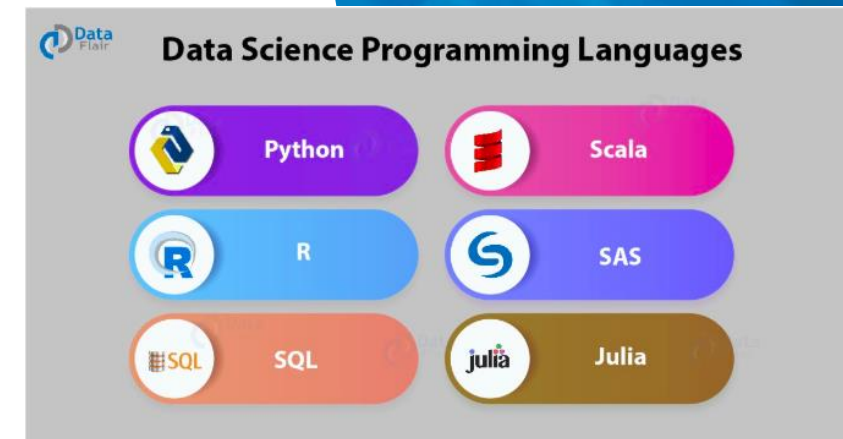


Image source: [Data Flair](https://www.dataflair.io/)



# What is R?

<https://towardsdatascience.com/top-programming-languages-for-ai-engineers-in-2020-33a9f16a80b0>

## ● R

R was created by **Ross Ihaka** and **Robert Gentleman** with the **first version being launched in 1995**. Currently being maintained by the R Development Core Team, R is the implementation of S programming language and aids in developing statistical software and data analysis.

The qualities that are making R a good fit for AI programming among developers are:

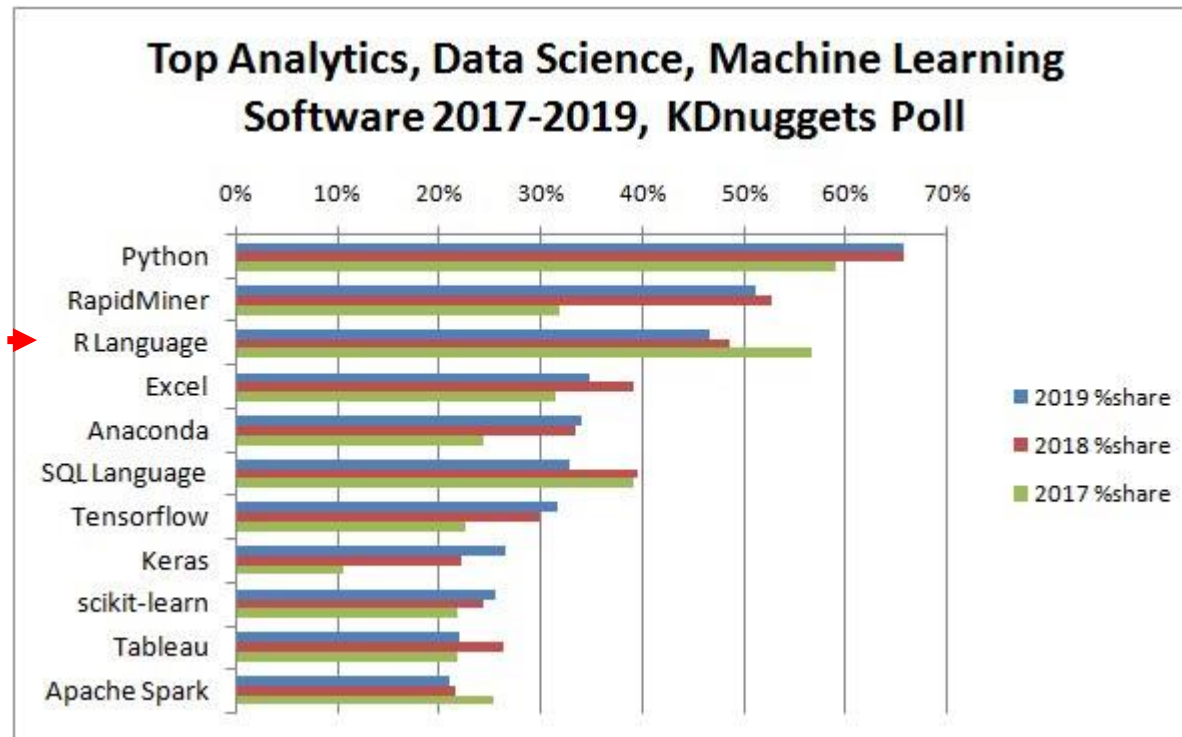
- *The fundamental feature of R being good at crunching huge numbers puts it in a better position than Python with its comparatively unrefined NumPy package.*
- *With R, you can work on various paradigms of programming such as functional programming, vectorial computation and object-oriented programming.*

# What is R?

<https://www.kdnuggets.com/2019/05/poll-top-data-science-machine-learning-platforms.html>

## A language for analysing and visualising data

- Interpreted (scripting) language, so no need to compile code
- Designed by statisticians
- Open-source
- Very popular!



# R vs Python



Parameter	R	Python
Objective	Data analysis and statistics	Deployment and production
Flexibility	Easy to use available library	Easy to construct new models from scratch
Important Packages and library	Tidyverse, ggplot2, caret, zoo	pandas, scipy, scikit-learn, TensorFlow, caret
Disadvantages	Slow, High Learning curve, Dependencies between library	Not as many specialized packages for statistical computing as R
Comparison	<ul style="list-style-type: none"><li>• Functional</li><li>• More data analysis built-in</li><li>• More statistical support in general</li></ul>	<ul style="list-style-type: none"><li>• Object Oriented</li><li>• Relies on packages</li><li>• More straightforward to do non-statistical tasks</li></ul>

**Note:** R is mainly used for statistical analysis while Python provides a more general approach to data science.

# Setting Up R Environment

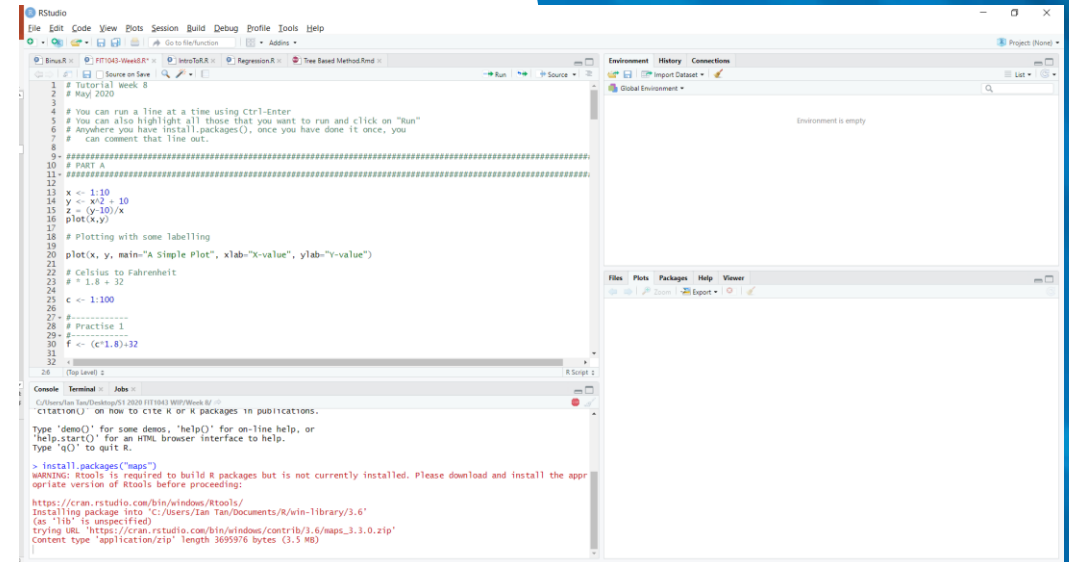
## Installing R

- Available for download from the R project
  - <https://www.r-project.org/>
- Or get the **RStudio IDE** (Integrated Development Environment) from:
  - <https://www.rstudio.com/products/rstudio/>
  - Both open source and commercial versions

- Install it from Anaconda navigator

## Running R

- Either type “R” in a shell (Linux/MacOS)
- Or start the R console or R-Studio application (Windows/MacOS)



# Setting Up R Environment

**R Studio** Products Resources Pricing About Us Blogs

## Choose Your Version of RStudio


RStudio is a set of integrated tools designed to help you be more productive with R. It includes a console, syntax-highlighting editor that supports direct code execution, and a variety of robust tools for plotting, viewing history, debugging and managing your workspace. [Learn More about RStudio features.](#)

**RStudio Team**  
RStudio's new solution for every professional data science team. RStudio Team includes RStudio Server Pro, RStudio Connect and RStudio Package Manager. [LEARN MORE](#)

	<b>RStudio Desktop</b> Open Source License	<b>RStudio Desktop</b> Commercial License	<b>RStudio Server</b> Open Source License	<b>RStudio Server Pro</b> Commercial License
	FREE	\$995 per year	FREE	\$4,975 per year (5 Named users)
	<a href="#">DOWNLOAD</a>	<a href="#">BUY</a>	<a href="#">DOWNLOAD</a>	<a href="#">BUY</a>
	<a href="#">Learn More</a>	<a href="#">Learn More</a>	<a href="#">Learn More</a>	<a href="#">Evaluation</a>   <a href="#">Learn More</a>
Integrated Tools for R	●	●	●	●
Priority Support		●		●
Access via Web Browser			●	●
Enterprise Security				●

<https://www.rstudio.com/products/rstudio/download/#download>

# Setting Up R Environment

 **Studio**

ProductsResourcesPricingAbout UsBlogs

**RStudio Desktop 1.2.1335** — Release Notes

RStudio requires R 3.0.1+. If you don't already have R, download it [here](#).

Linux users may need to import RStudio's public code-signing key prior to installation, depending on the operating system's security policy.

RStudio 1.2 requires a 64-bit operating system, and works exclusively with the 64 bit version of R. If you are on a 32 bit system or need the 32 bit version of R, you can use an older version of RStudio.

**Installers for Supported Platforms**

Installers	Size	Date	MD5
RStudio 1.2.1335 - Windows 7+ (64-bit)	126.9 MB	2019-04-08	d0e2470f1f8ef4cd35a669aa323a2136
RStudio 1.2.1335 - macOS 10.12+ (64-bit)	121.1 MB	2019-04-08	6c570b0e2144583f7c48c284ce299eef
RStudio 1.2.1335 - Ubuntu 14/Debian 8 (64-bit)	92.2 MB	2019-04-08	c1b07d0511469abfe582919b183eee83
RStudio 1.2.1335 - Ubuntu 16 (64-bit)	99.3 MB	2019-04-08	c142d69c210257fb10d18c045fff13c7
RStudio 1.2.1335 - Ubuntu 18/Debian 10 (64-bit)	100.4 MB	2019-04-08	71a8d1990c0d97939804b46cfb0aea75
RStudio 1.2.1335 - Fedora 19/RedHat 7 (64-bit)	114.1 MB	2019-04-08	296b6ef88969a91297fab6545f256a7a
RStudio 1.2.1335 - Debian 9 (64-bit)	100.6 MB	2019-04-08	1e32d4d6f6e216f086a81ca82ef65a91
RStudio 1.2.1335 - OpenSUSE 15 (64-bit)	101.6 MB	2019-04-08	2795a63c7efd8e2aa2dae86ba09a81e5
RStudio 1.2.1335 - SLES/OpenSUSE 12 (64-bit)	94.4 MB	2019-04-08	c65424b06ef6737279d982db9eefcae1

**Zip/Tarballs**

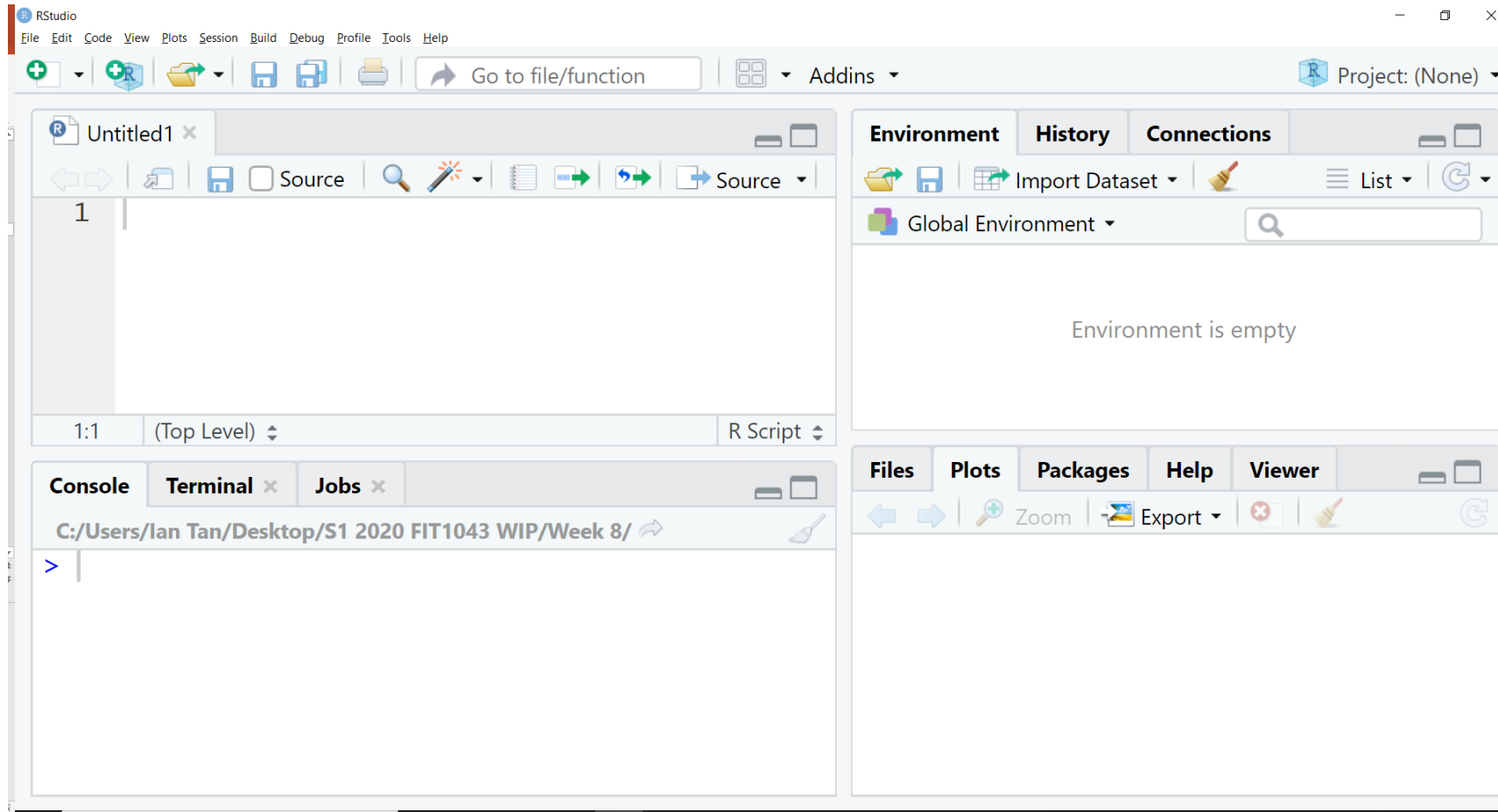
Zip/tar archives	Size	Date	MD5
RStudio 1.2.1335 - Windows 7+ (64-bit)	186.6 MB	2019-04-08	f1e013ade0c241969400507cf258e0ad
RStudio 1.2.1335 - Ubuntu 14/Debian 8 (64-bit)	137.6 MB	2019-04-08	e3e1ea2dd113fd9cfd40bc5035effdde

RStudio-1.2.1335 (1).exe105/127 MB, 1 sec left

Show all



# Setting Up R Environment



# R Basics





# Basic R Syntax

- Compute mathematical expressions:

```
> 2^3+2  
[1] 10
```

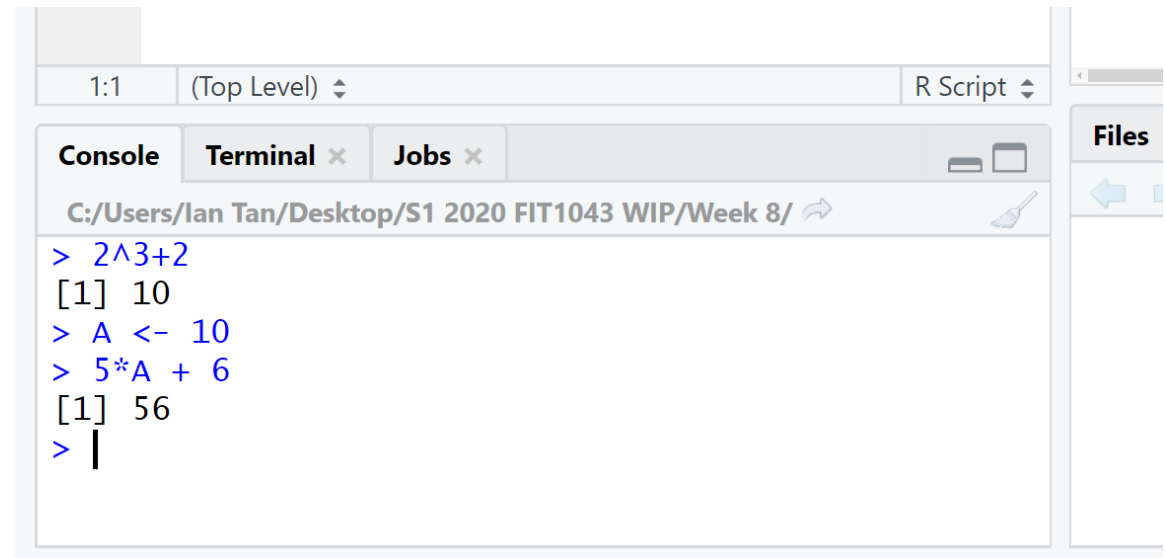
Here **>** denotes the command prompt & the output is prefixed by: **[1]**

- Define variables and assign values:

```
> A <- 10  
> 5*A + 6  
[1] 56
```

It is traditional in R to use left-arrow for assignment, but you can also use equals:

```
> A = 10
```



The screenshot shows an RStudio interface with a console window. The console displays the following R commands and their outputs:

```
1:1 (Top Level) R Script  
Console Terminal x Jobs x  
C:/Users/Ian Tan/Desktop/S1 2020 FIT1043 WIP/Week 8/  
> 2^3+2  
[1] 10  
> A <- 10  
> 5*A + 6  
[1] 56  
> |
```

# Basic Data Types

Numeric (can be integer or floating number)

```
> x <- 10.5
```

Integer

```
> x <- as.integer(10.5)
```

Complex (with real and imagery part)

```
> x <- 1+2i
```

Logical (True / False)

```
> x <- TRUE
```

Character

```
> x <- "Intro To R"
```

# Basic Data Types

- Print the class name of y

```
> y <- 8  
> class(y)  
[1] "numeric"
```

- Is y an integer?

```
> is.integer(y)  
[1] FALSE
```

- Change data type

```
> as.character(y)  
[1] "8"
```

- Getting help

```
> help(c)
```

# Operators

- Arithmetic Operators

Operator	Description
+	addition
-	subtraction
*	multiplication
/	division
^ or **	exponentiation
x %% y	modulus (x mod y) 5%%2 is 1
x %/% y	integer division 5%/%2 is 2

- Logical Operators

Operator	Description
<	less than
<=	less than or equal to
>	greater than
>=	greater than or equal to
==	exactly equal to
!=	not equal to
!x	Not x
x   y	x OR y
x & y	x AND y
isTRUE(x)	test if X is TRUE

image source: Quick\_R

# If-Else Conditions

Syntax: statement would be executed if expression is TRUE

```
if (expression)
{
    statement/s
}
```

Example:

```
> x <- 10
> if(x>0)
{
    print("This is Positive Number")
}
[1] "This is Positive number"
```

# For Loops

Syntax: statement would be executed *n*-times.

```
for(i in 1:n)
{
    statement/s
}
```

Example:

```
> for(i in 1:3)
{
    print(i^2)
}
[1] 1
[1] 4
[1] 9
```

# While Loops

Syntax:

```
while (condition)
{
    statement/s
}
```

Example:

```
> i <- 1
> while (i <=6) {
    print(i*i)
    i = i+1
}
[1] 1
[1] 4
[1] 9
```

# Break Statement

**Break:** Stop the iteration and exit the loop.

Example:

```
> x <- 1:5
> for (i in x)
{
    if (i == 3) {
        break
    }
    print(i)
}
```

[1] 1  
[1] 2



# Next Statement

**Next:** Skip one step of the loop and jumps to the next cycle.

Example:

```
> x <- 1:5
> for (i in x) {
  if (i == 3) {
    next
  }
  print(i)
}
[1] 1
[1] 2
[1] 4
[1] 5
```

# R Data Wrangling and Exploration



# Vector

R has `c()` built in function which allows to store more than one value.

Define a vector using the concatenate function:

```
> B <- c(5, 6, 3, 0)
```

```
> B
```

```
[1] 5 6 3 0
```

Concatenate function can be applied to vectors too:

```
> B <- c(B, c(1, 2))
```

```
> B
```

```
[1] 5 6 3 0 1 2
```

You **must** use the concatenate function `c()` to build a vector, just writing `(5, 6, 3, 0)` won't work!

# Accessing Vector Elements

Accessing vector elements using position

```
> x <- c("Jan", "Feb", "Mar", "April")  
> y <- x[c(1, 3, 4)]  
> print(y)  
[1] "Jan" "Mar" "April"
```

Unlike Python, the first element of an array has index 1 (not 0)

Accessing vector elements using negative indexing

```
> t <- x[c(-1, -4)]  
> print(t)  
[1] "Feb" "Mar"
```

Access range of values in vector

```
> x[1:3]  
[1] "Jan" "Feb" "Mar"
```

The colon operator **1:n** generates a vector of integers from 1 to n, **inclusive**:

# Vector Arithmetic Operations

Operations can be performed on two vectors (same length) directly and are interpreted in an element-wise fashion.

Create two vectors.

```
> v1 <- c(1,2,4,5,7,11)
> v2 <- c(12,4,3,8,1,21)
```

Vector multiplication.

```
> multi.result <- v1*v2
> print(multi.result)
[1] 12 8 12 40 7 231
```

# Data Frame

We can combine vectors together to form a table, called a “data frame”

Create the data frame

```
> names <- c("Bill", "Ted", "Henry", "Joan")  
> ages <- c(76, 82, 104, 78)  
> heights <- c(1.55, 1.69, 1.49, 1.57)  
> myTable <- data.frame(names, ages, heights)  
> print(myTable)
```

	names	ages	heights
1	Bill	76	1.55
2	Ted	82	1.69
3	Henry	104	1.49
4	Joan	78	1.57

# Rename The Columns of a Data Frame

R has `name(df)` built in function which allows you to rename data frame columns

Pass a vector of new names to the function

```
> names(myTable) <- c("Names", "Ages", "Heights")
```

```
> print(myTable)
```

	Names	Ages	Heights
1	Bill	76	1.55
2	Ted	82	1.69
3	Henry	104	1.49
4	Joan	78	1.57

# Data Frame Audit

Number of rows in data frame

```
> nrow(myTable)
```

```
[1] 4
```

Number of columns in data frame

```
> ncol(myTable)
```

```
[1] 3
```

Dimension of data frame

```
> dim(myTable)
```

```
[1] 4 3
```



# Get the Structure of the Data Frame

Display the column names and data types

```
> str(myTable)
```

```
'data.frame':      4 obs. of  3 variables:  
 $ Names   : Factor w/ 4 levels "Bill","Henry",...: 1 4 2 3  
 $ Ages    : num  76 82 104 78  
 $ Heights: num  1.55 1.69 1.49 1.57
```

# Summary Statistics

Minimum value

```
> min(myTable$Ages)
```

```
[1] 76
```

Average value

```
> mean(myTable$Heights)
```

```
[1] 1.575
```

Standard deviation

```
> sd(myTable$Heights)
```

```
[1] 0.08386497
```

# Summary of Data Frame

```
> summary(myTable)
```

names	ages	eights
Bill :1	Min. : 76.0	Min. :1.490
Henry:1	1st Qu.: 77.5	1st Qu.:1.535
Joan :1	Median : 80.0	Median :1.560
Ted :1	Mean : 85.0	Mean :1.575
	3rd Qu.: 87.5	3rd Qu.:1.600
	Max. :104.0	Max. :1.690

# Extracting Data From Data Frame

Accessing column/s by name

```
> myTable["Ages"]
```

Accessing multiple columns by name

```
> myTable[c("Names", "Ages")]
```

Accessing columns by index

```
> myTable[2]
```

Accessing multiple columns by index

```
> myTable[c(1, 2)]
```

# Extracting Data From Data Frame

Accessing first row and all the columns by appending comma

```
> myTable[1,]  
  names ages heights  
1  Bill   76    1.55
```

Strange looking syntax for selecting rows is due to fact that in R, tables are matrices that are indexed by **[row,column]** (i.e. row first)

Accessing a range of rows and all the columns

```
> myTable[2:4,]  
  names ages heights  
2   Ted   82    1.69  
3 Henry  104    1.49  
4  Joan   78    1.57
```

# Extracting Data From Data Frame

Accessing particular cells by [row,column]

```
> myTable[1,2]
```

```
[1] 76
```

```
> myTable[3:4,2:3]
```

	ages	heights
3	104	1.49
4	78	1.57

Referring to a variable (a column) by using the \$ syntax:

```
> myTable$Ages
```

```
[1] 76 82 104 78
```

```
> myTable$Ages[3]
```

```
[1] 104
```

# Sorting Data in Data Frame

Sort by ages

```
> newData <- myTable[order("Ages"),]
```

Sort by ages and heights

```
> newData <- myTable[order("Ages", "Heights"),]
```

Sort by ages (ascending) and heights (descending)

```
> newData <- mtcars[order("Ages", "Heights", decreasing = TRUE), ]
```

**\*\* Order is only for Numeric value**

# Merging Data in Data Frame

**merge()** : Used to merge two data frames by common key variable/s

Merge two data frames by ID

```
> total <- merge(dataframeA, dataframeB, by="ID")
```

**rbind()** : Used to join two data frames vertically (Must have same number of variables)

Join two data frames

```
> total <- rbind(dataframeA, dataframeB)
```



# R Working Environment



# Built-in Data Sets in R

There are several built-in data sets within the R environment

List available data set :

```
> data()
```

Load a built-in dataset

```
> data(mtcars)
```

# Aggregating Data in Data Frame

Aggregate data frame mtcars by cyl and vs, returning means for numeric variables

```
> attach(mtcars)
> aggData <- aggregate(mtcars, by=list(cyl,vs), FUN=mean, na.rm=TRUE)
> print(aggdata)
> myData <- mtcars
> detach(mtcars)
```

# Displaying Data

If a file is big, we don't want to print it all out, just to have a look at it. Instead we can inspect the first/last lines of the table:

```
> head(myData)
```

```
> tail(myData)
```

Inspect the data set

```
> head(myData, 6)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

# Getting & Setting Working Directory

Before reading/writing in R it is important to specify the location where we can find the respective file to be read/write.

Get the current working directory.

```
> getwd()  
[1] "C:/Users/username/FolderName"
```

Set current working directory.

```
> setwd("D:/FolderName")
```

# Writing CSV File

R has a `write.csv()` built in function to write data into a CSV file.

Write a data into csv file (file is in current working directory)

```
> write.csv(myData, "FileName.csv")
```

Read a csv file (file is in other location)

```
> write.csv(myData, "D:/FolderName/FileName.csv")
```

# Reading a CSV File

R has a `read.csv()` built in function to read a CSV file.

Read a csv file (file is in current working directory)

```
> newData = read.csv("FileName.csv")  
> print(newData)
```

Read a csv file (file is in other location)


```
> newData = read.csv("D:/FolderName/FileName.csv")  
> print(newData)
```

# Loading Libraries

Libraries are lists of functions that are not available in R by default.

Loading a library

```
> library(moments)
> skewness(myData$mpg)
```



The `skewness()` function is provided by the `moments` library

Before loading a library for the first time you will need to install the package on your machine:

```
> install.packages("moments")
```



# R Data Visualisation

Bar Charts  
Histograms  
Box Plots  
Scatter Plots



# Bar Chart

Compare the value for categorical data using bar chart

```
> H <- c(25,12,43,7,51)
> M <- c("Delhi","Beijing","Washington","Tokyo","Moscow")
> barplot(H, xlab="Month", ylab="Happiness Index", col="blue",
          names.arg=M, main="Happiness Index", border="red")
```

- Syntax:

- `barplot(H,xlab,ylab,main, names.arg,col)`

- Description of Parameters

**H** is a vector or matrix containing numeric values used in bar chart.

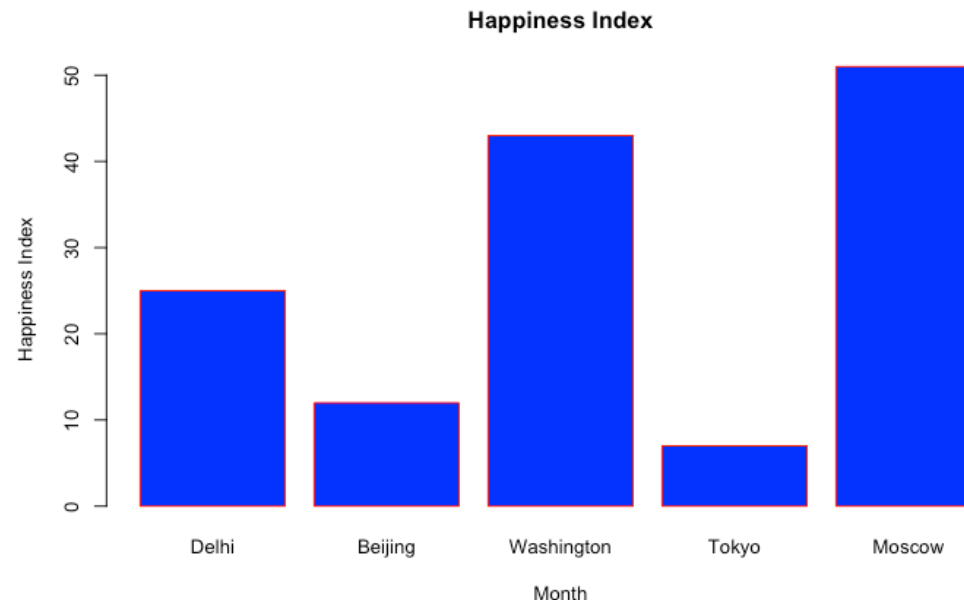
**xlab** is the label for x axis.

**ylab** is the label for y axis.

**main** is the title of the bar chart.

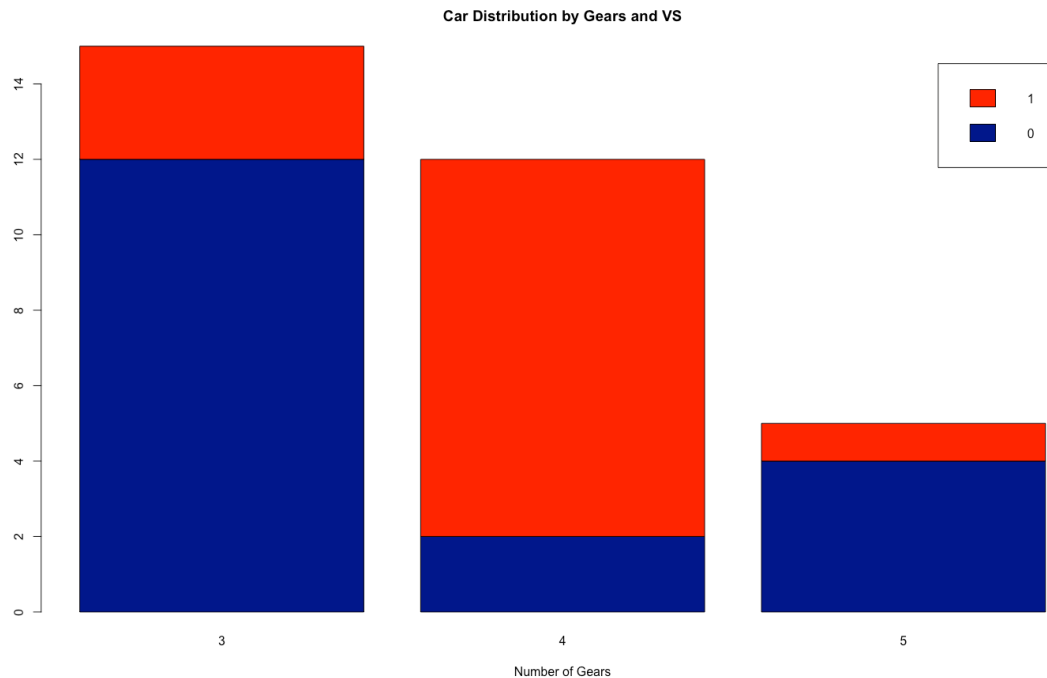
**names.arg** is a vector of names appearing under each bar.

**col** is used to give colors to the bars in the graph.



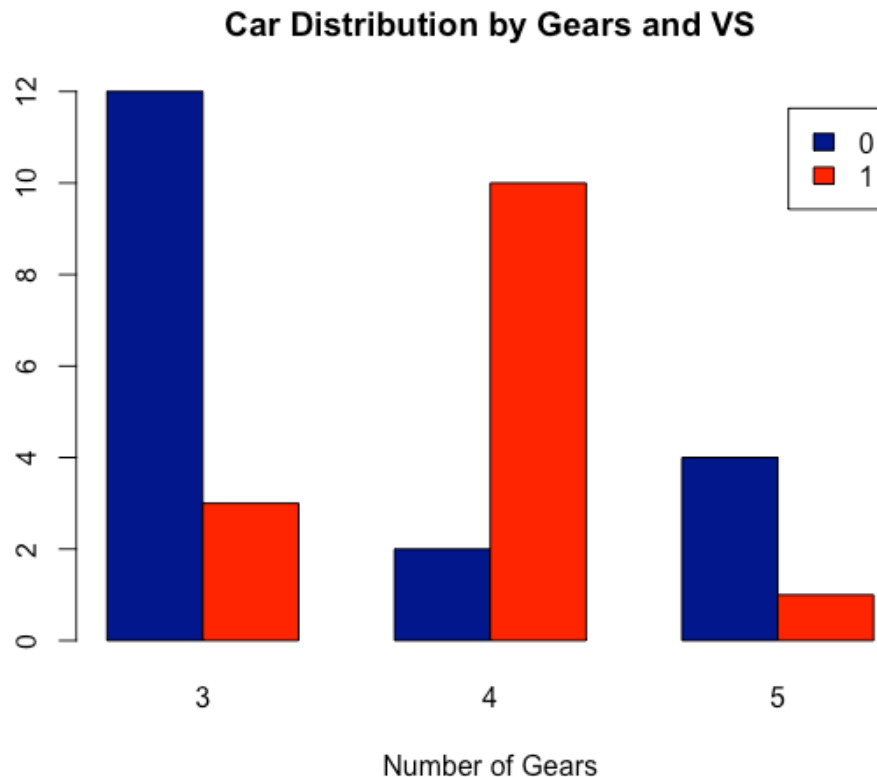
# Stacked Bar Chart

```
> counts <- table(mtcars$vs, mtcars$gear)
> barplot(counts, main="Car Distribution by Gears and VS",
          xlab="Number of Gears", col=c("darkblue", "red"),
          legend = rownames(counts))
```



# Group Bar Chart

```
> counts <- table(mtcars$vs, mtcars$gear)
> barplot(counts, main="Car Distribution by Gears and VS",
          xlab = "Number of Gears", col=c("darkblue", "red"),
          legend = rownames(counts), beside=TRUE)
```



# Histograms

Inspect the distribution of values for a particular variable by plotting it as a histogram

```
> hist(AirPassengers, main="Histogram for Air Passengers",  
      xlab = "Passengers", border = "red", col = "blue",  
      xlim = c(100, 700), breaks = 5)
```

- Syntax:
  - `hist(v, main, xlab, xlim, ylim, breaks, col, border)`

- Description of Parameters

**v** is a vector containing numeric values used in histogram.

**main** indicates title of the chart.

**xlab** is used to give description of x-axis.

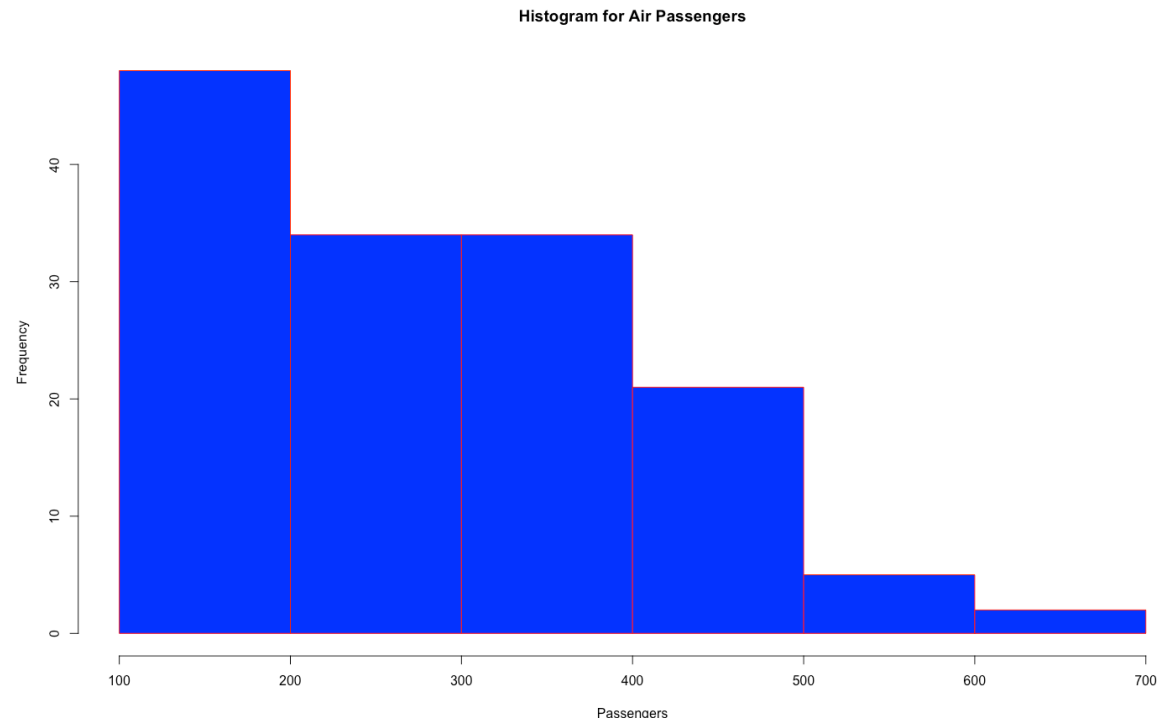
**xlim** is used to specify the range of values on the x-axis.

**ylim** is used to specify the range of values on the y-axis.

**breaks** is nothing but number of bins.

**col** is used to set color of the bars.

**border** is used to set border color of each bar.



# Boxplots

Or its summary statistics by plotting it as a boxplot

```
> boxplot(mpg ~ cyl, data=mtcars, xlab="Number of Cylinders",  
          ylab="Miles Per Gallon",main="Mileage Data")
```

- Syntax:

- `boxplot(x,data,notch,varwidth,names,main)`

- Description of Parameters

**x** is a vector or a formula.

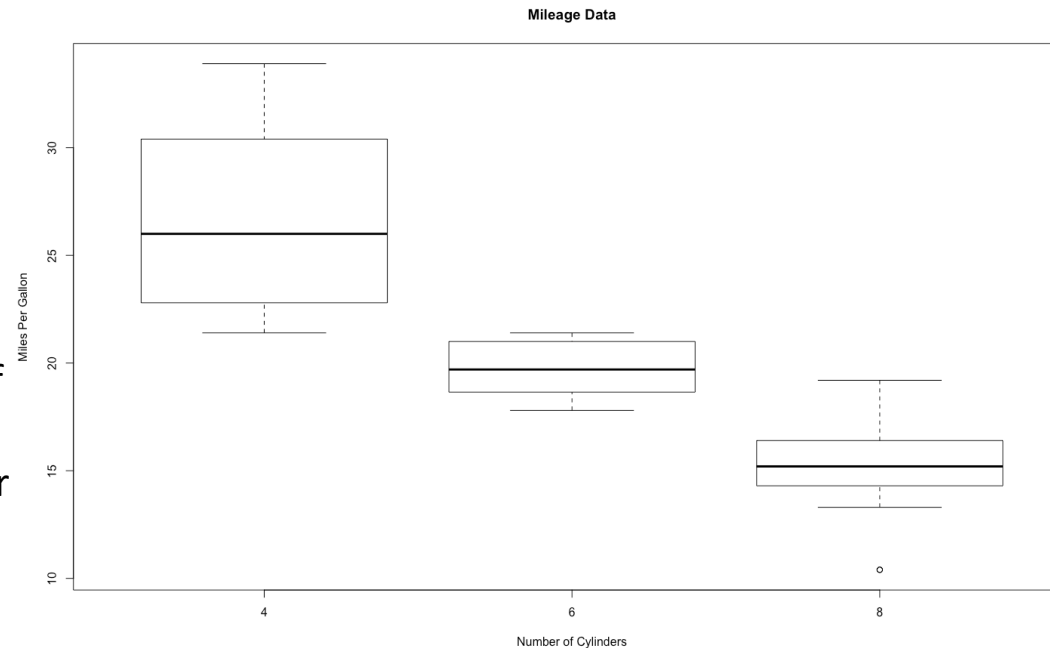
**data** is the data frame.

**notch** is a logical value. Set as TRUE to draw a notch.

**varwidth** is a logical value. Set as true to draw width of the box proportionate to the sample size.

**names** are the group labels which will be printed under each boxplot.

**main** is used to give a title to the graph.



# Boxplots

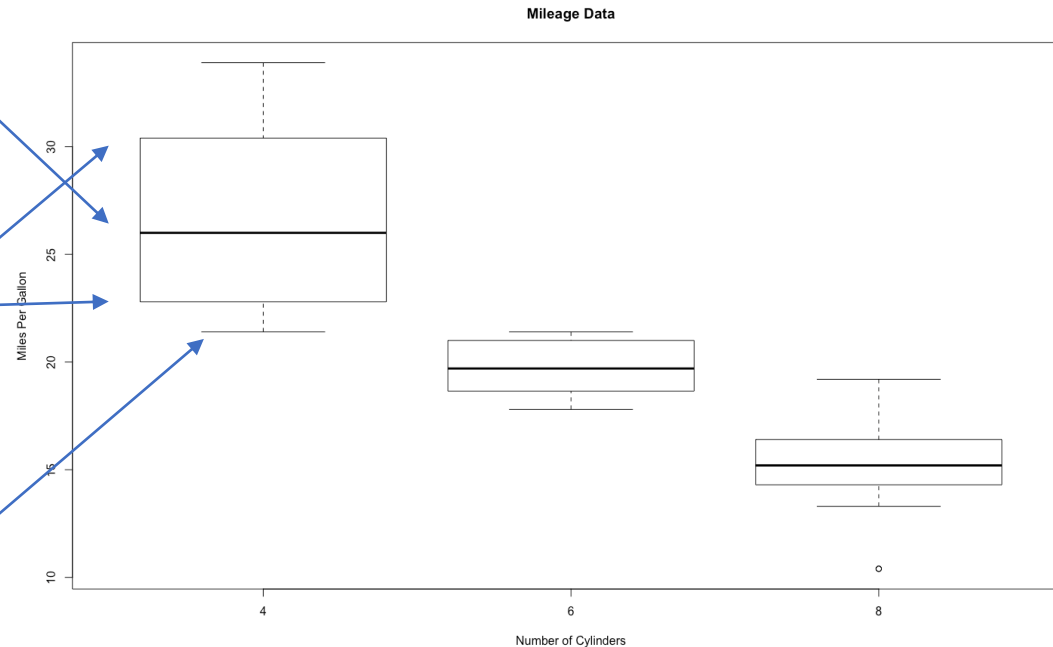
Or its summary statistics by plotting it as a boxplot

```
> boxplot(mpg ~ cyl, data=mtcars, xlab="Number of Cylinders",  
          ylab="Miles Per Gallon",main="Mileage Data")
```

**Median value** (half the data lies above and the other half below)

**Upper & lower quartiles** (25% of the data lies above/below these values and 50% between them)

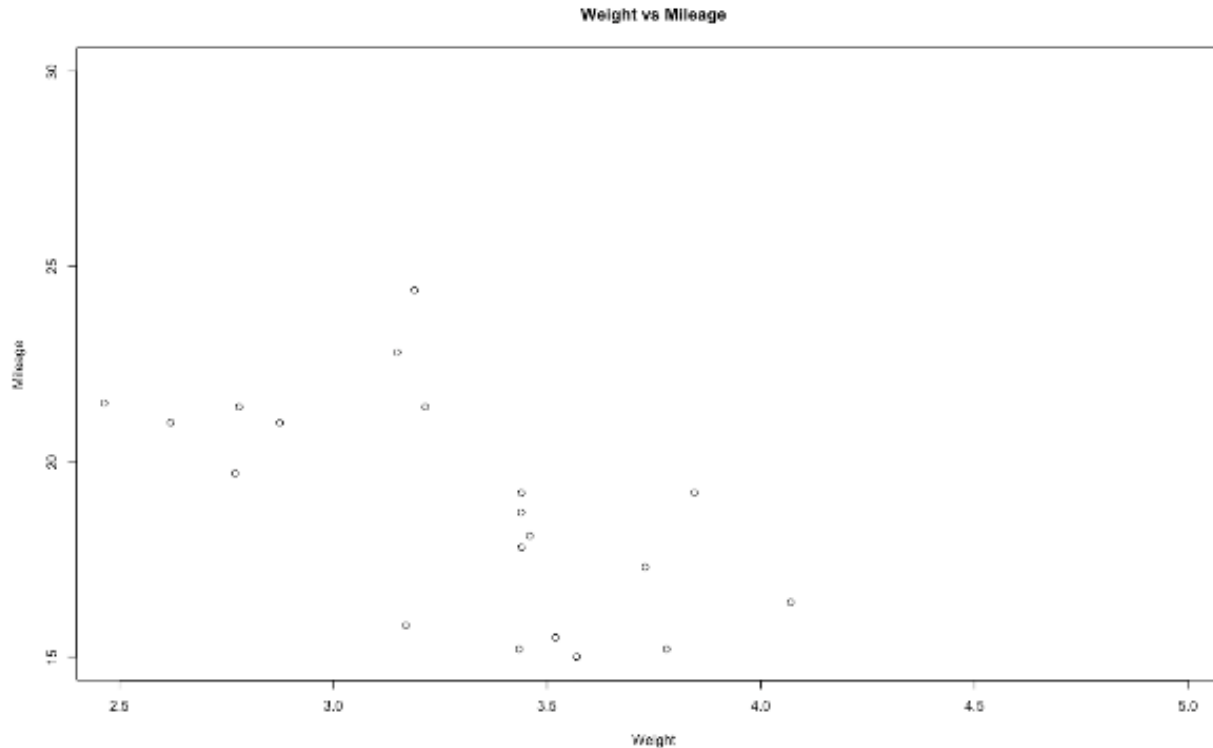
**Minimum value** (or  $1.5 \times \text{InterQuartileRange}$  below lower quartile)



# Scatter Plot

Or the variation of one variable against another by plotting data as a scatterplot

```
> input <- mtcars[,c('wt','mpg')]
> plot(x=input$wt,y=input$mpg, xlab="Weight", ylab="Mileage",
      xlim=c(2.5,5), ylim=c(15,30), main="Weight vs Mileage")
```





# Linear Regression with R



# Linear Regression

Often we'd like to see if there exists a linear trend relationship between two variables.

Creating sample Data for height and weight

```
> height <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)
> weight <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)
```

Fitting a linear model in R is very simple

```
> fit <- lm(height~weight)
> print(fit)
```

Call:

```
lm(formula = height ~ weight)
```

Coefficients:

```
(Intercept)
        61.380
```

```
weight
    1.415
```

# Linear Regression

Print out summary information regarding the fit (the slope, etc.)

```
> summary(fit)
```

Residuals:

Min	1Q	Median	3Q	Max
-6.0529	-2.4833	-0.0912	1.3774	10.0562

Coefficients:

	Estimate	Std. Error	t	value	Pr(> t )
(Intercept)	61.3803	7.2653	8.448	2.94e-05	***
weight	1.4153	0.1089	12.997	1.16e-06	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.712 on 8 degrees of freedom

Multiple R-squared: 0.9548, Adjusted R-squared: 0.9491

F-statistic: 168.9 on 1 and 8 DF, p-value: 1.164e-06

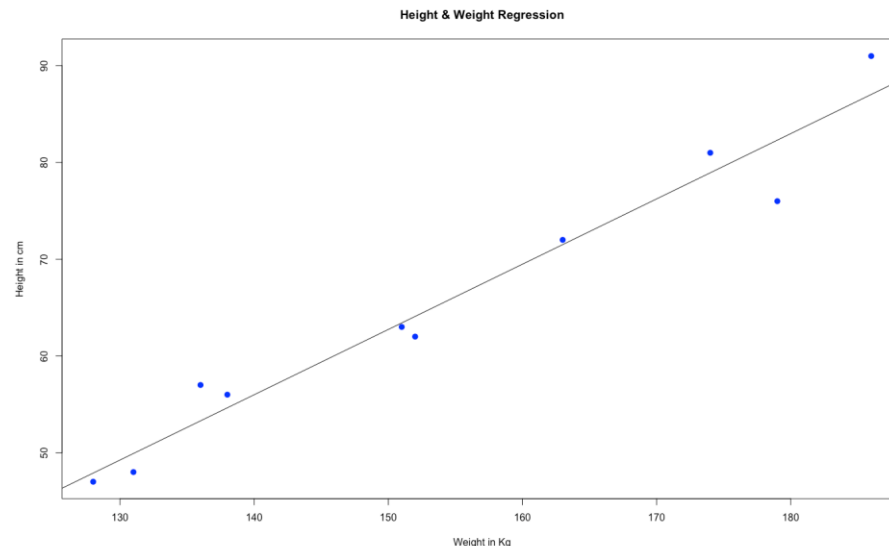
# Linear Regression Visualisation

Give the chart file a name, this will plot it to a file instead if in RStudio

```
> png(file = "linearregression.png")
```

Plot the chart

```
> plot(height, weight, col = "blue", main = "Height & Weight  
Regression", abline(lm(weight ~ height)),  
cex = 0.8, pch= 16, xlab = "Weight in Kg",  
ylab = "Height in cm")
```



# Notes

If you plot it to a file, the system will change the output automatically.

```
> png(file = "linearregression.png")
```

To reset it back, use the command

```
> dev.off()
```

You can run it a few times until you get the

```
null device
```

# Decision Trees with R



# Decision Tree

Install and load the party package.

```
> install.packages("party")  
> library(party)
```

Create the input data frame

```
> inputData <- readingSkills[c(1:105),]  
> print(inputData)
```

	nativeSpeaker	age	shoeSize	score
1	yes	5	24.83189	32.29385
2	yes	6	25.95238	36.63105
3	no	11	30.42170	49.60593
4	yes	7	28.66450	40.28456
5	yes	11	31.88207	55.46085
6	yes	10	30.07843	52.83124

# Visualise the Decision Tree

Give the chart file a name (try this after you have seen it on the RStudio bottom right pane)

```
> png(file = "decision_tree.png")
```

Create the tree.

```
> outputTree <- ctree( nativeSpeaker ~ age + shoeSize  
                        + score, data = inputData)
```

Plot the tree

```
> plot(outputTree)
```

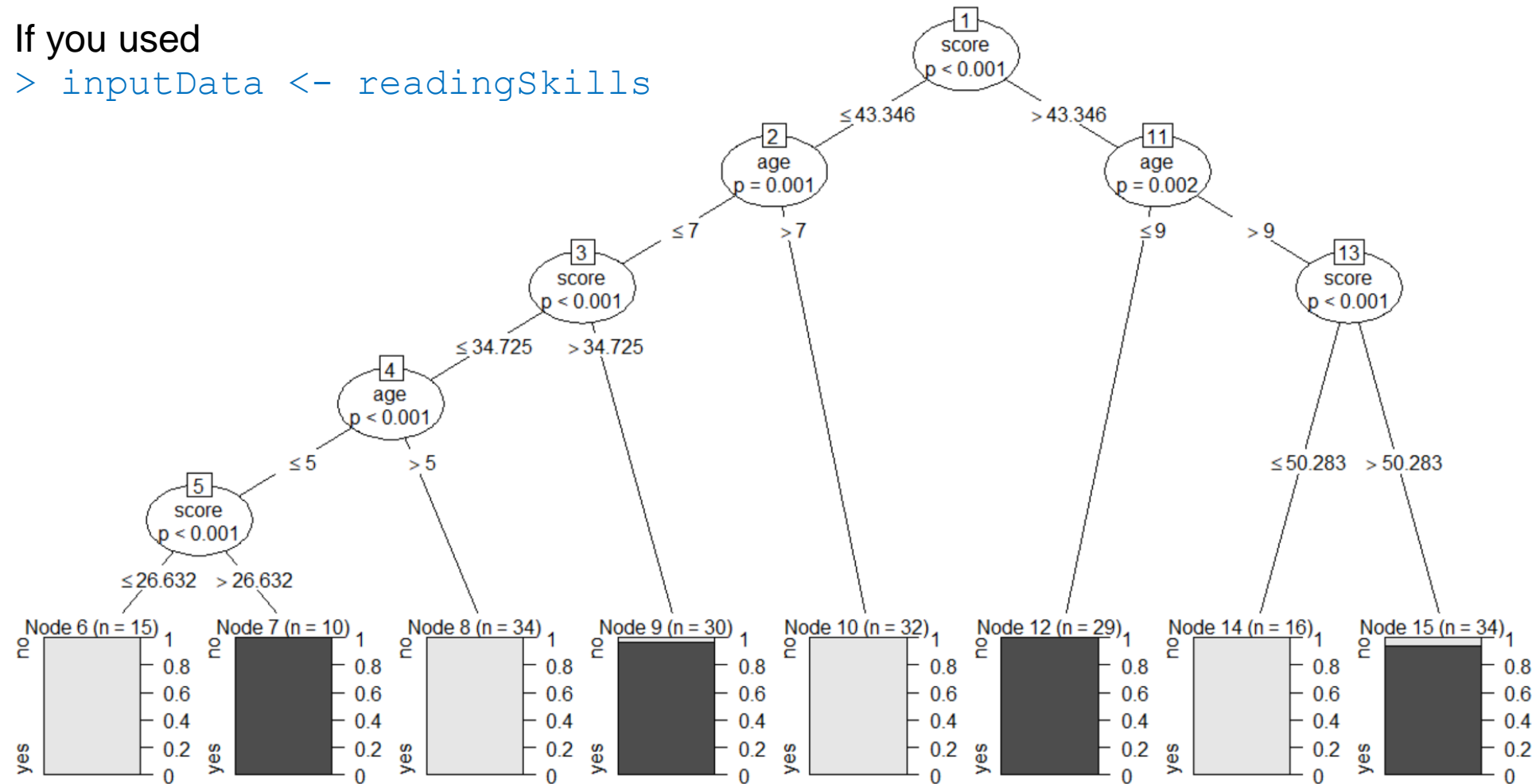


# Visualise the Decision Tree

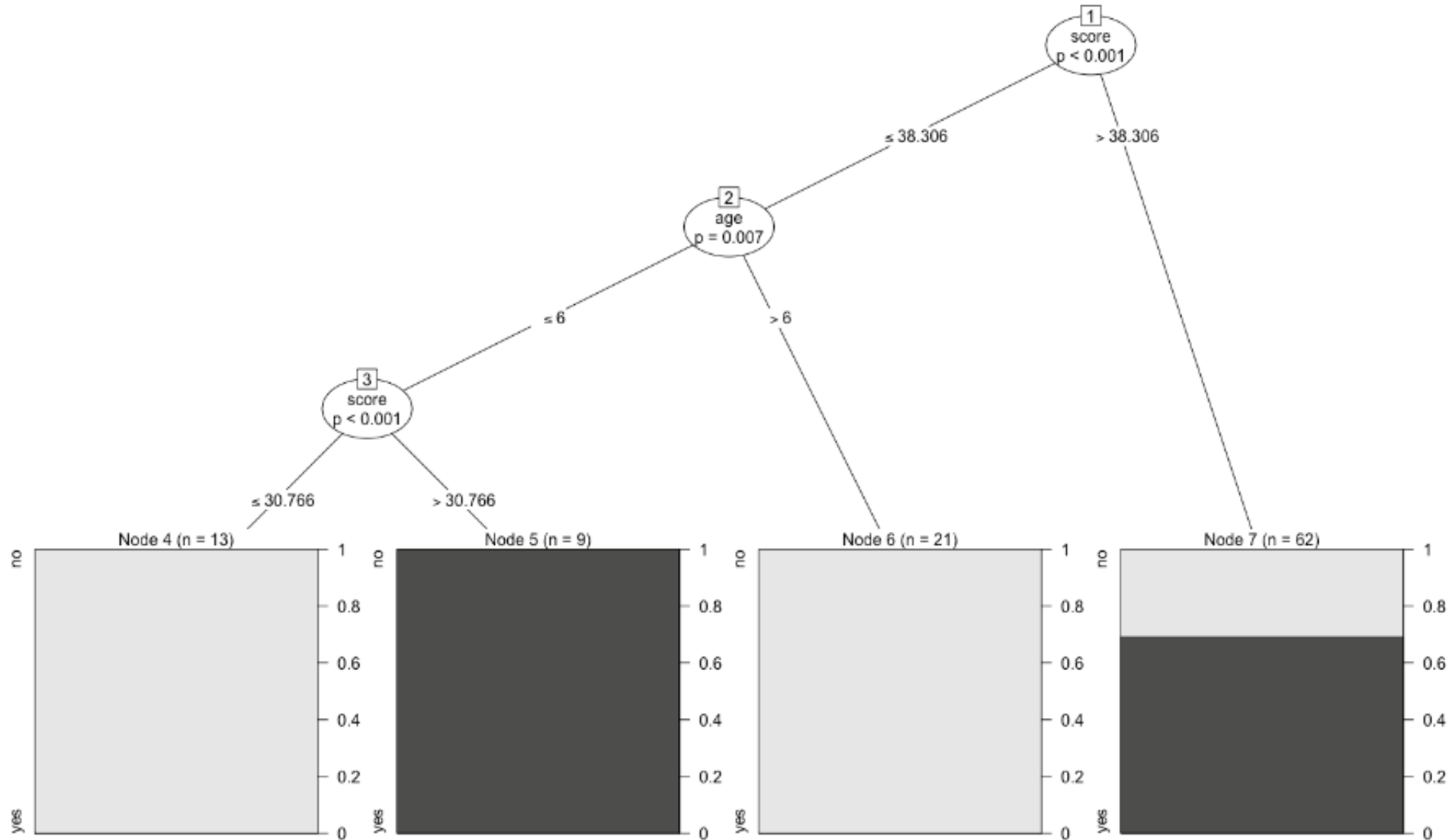
## Visualisation

If you used

```
> inputData <- readingSkills
```



# Visualise the Decision Tree



# Recap: Learning Outcomes

Week 8

**By the end of this week you should be able to:**

- Comprehend essentials for coding in R for data science
- Explain and interpret given R commands
- Apply R commands for data wrangling, visualisation, exploration and analysis

# Home Activities

Suggested Activities for the week

## Online Materials

Comprehensive courses on [Datacamp](#) to get your started, but for this Unit, just the [Introduction to R](#) would be sufficient.

## Books (Articles)

Peng, Roger D. [R programming for data science](#). Leanpub, 2016. (This is STILL free! 😊 )

Zuur, Alain, Elena N. Ieno, and Erik Meesters. [A Beginner's Guide to R](#). Springer Science & Business Media, 2009.



# Tutorials Week 8

Installation of RStudio

R walk-through