

Introduction to Data Science for Manufacturing using



Veerasak Kritsanapraphan - Software Park Thailand

Agenda

Day 1

1. Introduction to Data Science
 - Definition
 - Sample from other industry
 - Data Science Process
2. Basic Statistics using R
 - Hypothesis Setting
 - T-Test
 - ANOVA
 - Regression
 - Design of Experiment
3. Exploratory Data Analysis
 - Exploring Times Series Data
 - Basic Statistic Chart
 - Advance Charting

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Day 2

4. Statical Quality Control using R
 - Control Chart
 - Finding outlier
5. Multivariate Data Analysis
 - Multiple Regression
 - Logistic Regression
6. Machine Learning Technique in R
 - Basic Idea
 - Training and Testing

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Day 3

7. Predictive Analytics

- Decision Tree
- Naive Bayes
- Neural Nets

8. Clustering Analytics

- K-Means
- Hierarchical Clustering

9. Other Machine Learning

- Text-Mining

10. Using Multi-Model

11. Conclusion

- Wrap-up

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About myself?

- Graduated from San Francisco State University in Master of Science in Computer Information System, 1997
- PhD. Candidate at Chulalongkorn University, research focus on Data Science, Big Data, Mobile Computing and Internet of Thing (IOT)
- Chief Technology Innovation Officer at Greenline Synergy (Subsidiary of BDMS - Bangkok Hospital Group)
- Instructor for Software Park in Data Science, Requirement Discovery and Practical Enterprise Integration
- Instructor for Chulalongkorn University in Data Mining

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Slide and Sample Data

<https://github.com/vkrit/r-programming>

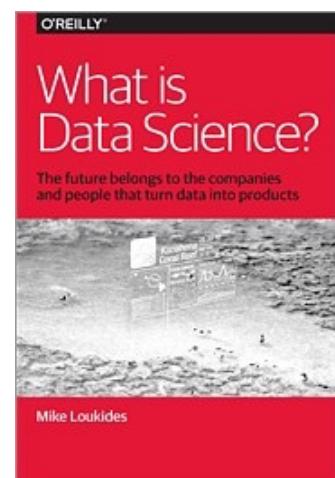


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What is Data Science?

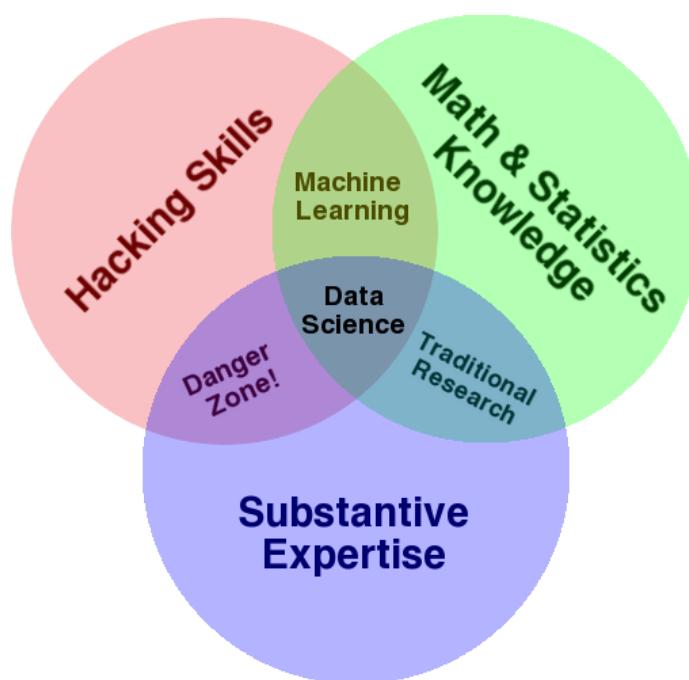
- Data Science aims to derive **knowledge** from **big data**, **efficiently** and **intelligently**
- Data Science encompasses the **set of activities, tools**, and **methods** that enable **data-driven activities** in science, business, medicine, and government



<http://www.oreilly.com/data/free/what-is-data-science.csp>

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Data Science - Drew Convey's



<http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram>

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Data Science vs. Databases

Element	Databases	Data Science
WithValue	Precious	Cheap
DataVolume	Modest	Massive
Examples	Bank records, Personnel records, Census, Medical records	Online clicks, GPS logs, Tweets, tree sensor readings
Priorities	Consistency, Error recovery, Auditability	Speed, Availability, Query richness
Structured	Strongly (Schema)	Weakly or none (Text)
Properties	Transactions, ACID ⁺	CAP * theorem (2/3), eventual consistency
Realizations	Structured Query Language (SQL)	NoSQL : Riak , Memcached , Apache Hbase , Apache River , MongoDB , Apache Cassandra , Apache CouchDB , ...

*CAP = Consistency, Availability, Partition Tolerance"

+ACID = Atomicity, Consistency, Isolation and Durability"

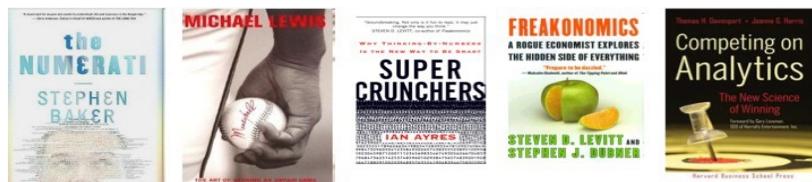
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Data Science vs. Databases

Databases	Data Science
Querying the past	Querying the future

Related – Business Analytics

- » Goal: obtain “actionable insight” in complex environments”
- » Challenge: vast amounts of disparate, unstructured data and limited time”



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Data Science vs. Traditional Machine Learning

Traditional Machine Learning	Data Science
Develop new (individual) models	Explore many models, build and tune hybrids
Prove mathematical properties of models	Understand empirical properties of models
Improve/validate on a few, relatively clean, small datasets	Develop/use tools that can handle massive datasets
Publish a paper	Take action!

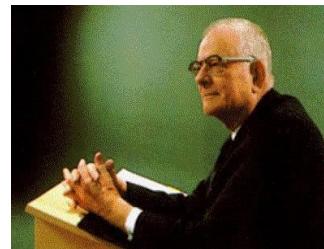
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History of Data Science

- R. A. Fisher
 - » 1935: "The Design of Experiments"
"correlation does not imply causation"



- W. E. Demming
 - » 1939: "Quality Control"

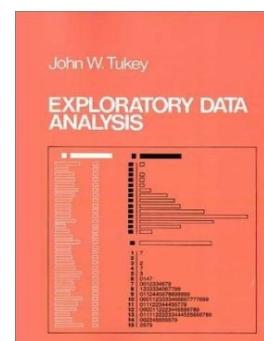


Images: <http://culturacientifica.wikispaces.com/CONTRIBUCIONES+DE+SIR+RONALD+FISHER+A+LA+ESTADISTICA+GENETICA>
http://es.wikipedia.org/wiki/William_Edwards_Deming

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Brief Data Analysis History

- Peter Luhn
 - » 1958: "A Business Intelligence System"
- John W. Tukey
 - » 1977: "Exploratory Data Analysis"
- Howard Dresner
 - » 1989: "Business Intelligence"



Images: <http://wwwbusinessintelligence.info/definiciones/business-intelligence-system-1958.html> <http://wwwbetterworldbooks.com/exploratory-data-analysis-id-0201076160.aspx>
<https://wwwflickrcom/photos/42266634@N02/4621418442>

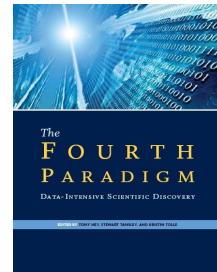
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Brief Data Analysis History

- Tom Mitchell
 - » 1997: 'Machine Learning book'
- Google
 - » 1996: 'Prototype Search Engine'
- Data-Driven Science eBook
 - » 2007: '[The Fourth Paradigm](#)'



Google



Images: <http://www.amazon.com/Machine-Learning-Tom-M-Mitchell/dp/0070428077> <http://www.google.com/about/company/history/> <http://research.microsoft.com/en-us/collaboration/fourthparadigm/>

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Brief Data Analysis History

- Peter Norvig
 - » 2009: 'The Unreasonable Effectiveness of Data'
- Exponential growth in data volume
 - » 2010: 'The Data Deluge'

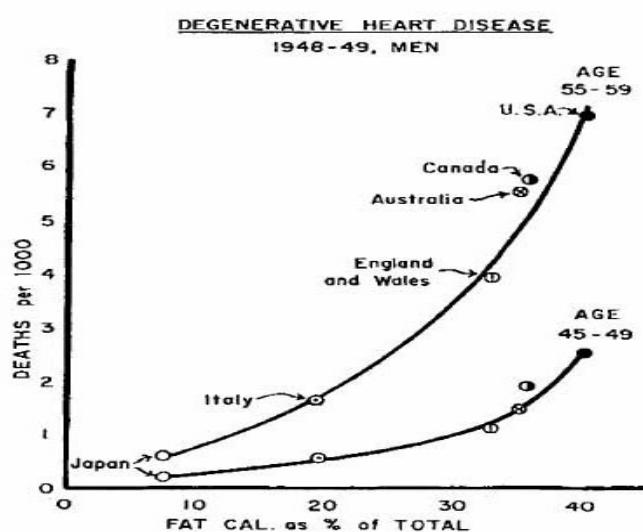


Images: http://en.wikipedia.org/wiki/Peter_Norvig
<http://www.economist.com/node/15579717>

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Data Science?

- Seven Countries Study (Ancel Keys)
 - » Started in 1958, followed 13,000 subjects total for 5-40 years

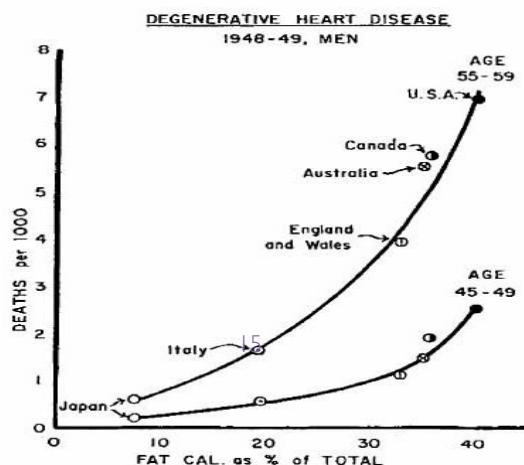


http://en.wikipedia.org/wiki/Seven_Countries_Study

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Data Science?

- Seven Countries Study (Ancel Keys)
 - » Started in 1958, followed 13,000 subjects total for 5-40 years



Significant controversy

- Only studied subset of 21 countries with data
- Failed to consider other factors (e.g., per capita annual sugar consumption in pounds)

http://en.wikipedia.org/wiki/Seven_Countries_Study

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Data Science?

- Nowcasting vs Forecasting
- Example – Google Flu Trends:
 - » February 2010 detected outbreak two weeks ahead of CDC data
 - » Initially 97% accurate but overestimated during 2011-13 including one interval in 2012-13 period where GFT was off by 2x
 - » New models are estimating which cities are most at risk for spread of the Ebola virus



<https://www.google.org/flutrends/>

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Data Science?

elections2012

Live results President | Senate | House | Governor | Choose your

Numbers nerd Nate Silver's forecasts prove all right on election night

FiveThirtyEight blogger predicted the outcome in all 50 states, assuming Barack Obama's Florida victory is confirmed

Luke Harding
guardian.co.uk, Wednesday 7 November 2012 10.45 EST



USA 2012 President ial Election

*the signal and the noise
and the noise and the noise
noise and the noise
why most noise is
predictions fail to
but some don't fail
and the noise and the
the noise and the noise
nate silver noise
and the noise*

<http://www.theguardian.com/world/2012/nov/07/nate-silver-election-forecasts-right>

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Data Science?

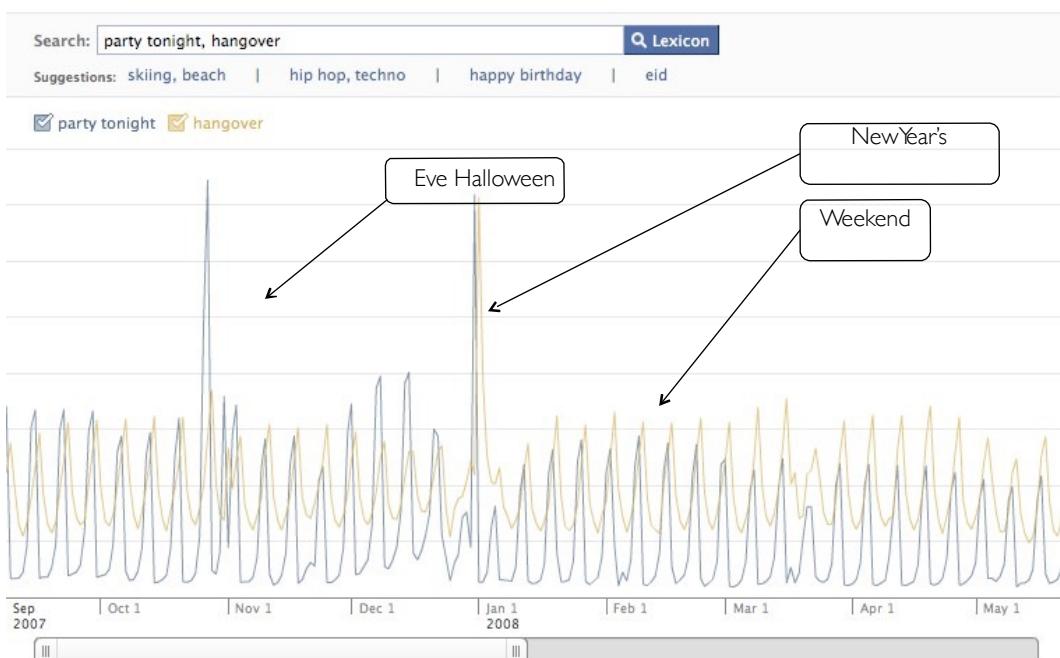
...that was just one of several ways that Mr. Obama's campaign operations, some unnoticed by Mr. Romney's aides in Boston, helped save the president's candidacy. In Chicago, the campaign recruited a team of behavioral scientists to build an extraordinarily sophisticated database

...that allowed the Obama campaign not only to alter the very nature of the electorate, making it younger and less white, but also to create a portrait of shifting voter allegiances. The power of this operation stunned Mr. Romney's aides on election night, as they saw voters they never even knew existed turn out in places like Osceola County, Fla.

[NewYorkTimes.Wed Nov 7
2012](#)

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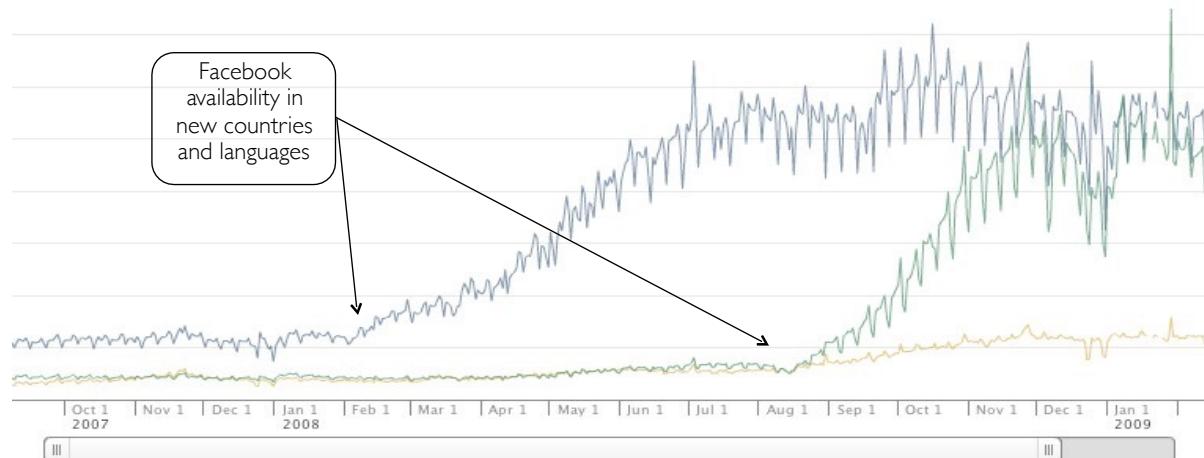
Data Science?



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Data Science?

Search: hola, salut, ciao Lexicon
Suggestions: vacation | xoxo, xoxoxo | midterm, final | party tonight, hangover
 hola salut ciao



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Data Science?

Epidemiological modeling of online social network dynamics

John Cannarella¹, Joshua A. Spechler^{1,*}

¹ Department of Mechanical and Aerospace Engineering, Princeton University, Princeton, NJ, USA

* E-mail: Corresponding spechler@princeton.edu

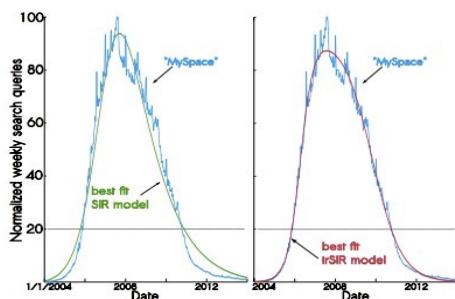
Abstract

The last decade has seen the rise of immense online social networks (OSNs) such as MySpace and Facebook. In this paper we use epidemiological models to explain user adoption and abandonment of OSNs, where adoption is analogous to infection and abandonment is analogous to recovery. We modify the traditional SIR model of disease spread by incorporating infectious recovery dynamics such that contact between a recovered and infected member of the population is required for recovery. The proposed infectious recovery SIR model (irSIR model) is validated using publicly available Google search query data for "MySpace" as a case study of an OSN that has exhibited both adoption and abandonment phases. The irSIR model is then applied to search query data for "Facebook," which is just beginning to show the onset of an abandonment phase. Extrapolating the best fit model into the future predicts a rapid decline in Facebook activity in the next few years.

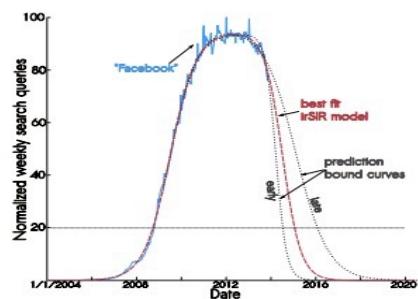
"Extrapolating the best fit model into the future predicts a rapid decline in Facebook activity in the next few years."

Data Science?

Google Trends searches for
“MySpace”



Two Figures from
the paper

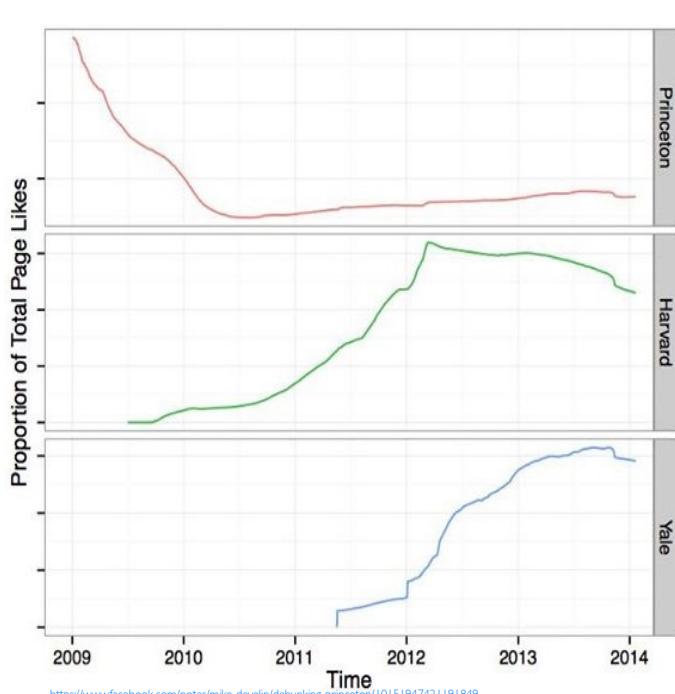


Searches for
“Facebook”

<http://arxiv.org/abs/1401.4208>

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Data Science?



In keeping with the scientific principle “**correlation equals causation**,” our research unequivocally demonstrated that Princeton may be in danger of disappearing entirely.

Princeton
Harvard
Yale

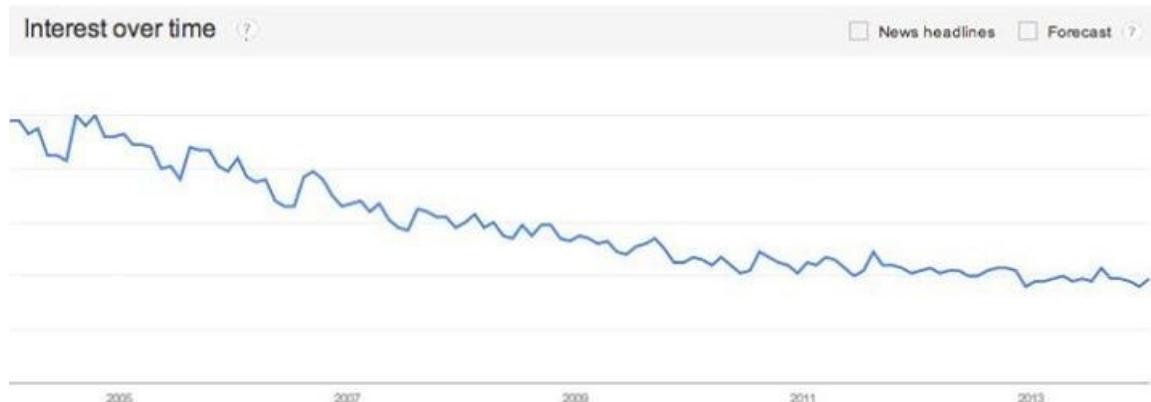
<https://www.facebook.com/notes/mike-develin/debunking-princeton/10151947421191849>

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Data Science?

... and based on Princeton search trends:

"This trend suggests that Princeton will have only half its current enrollment by 2018, and by 2021 it will have no students at all,..."

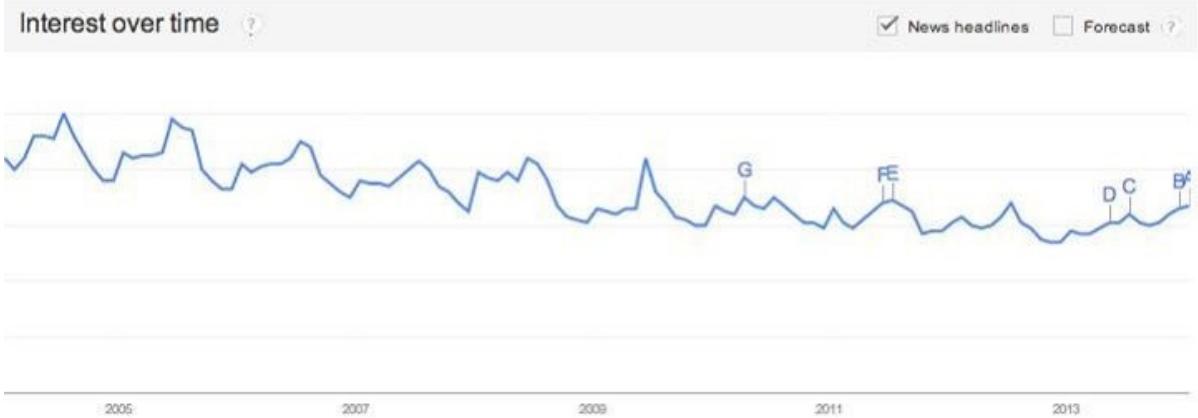


<https://www.facebook.com/notes/mike-develin/debunking-princeton/10151947421191849>

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Data Science?

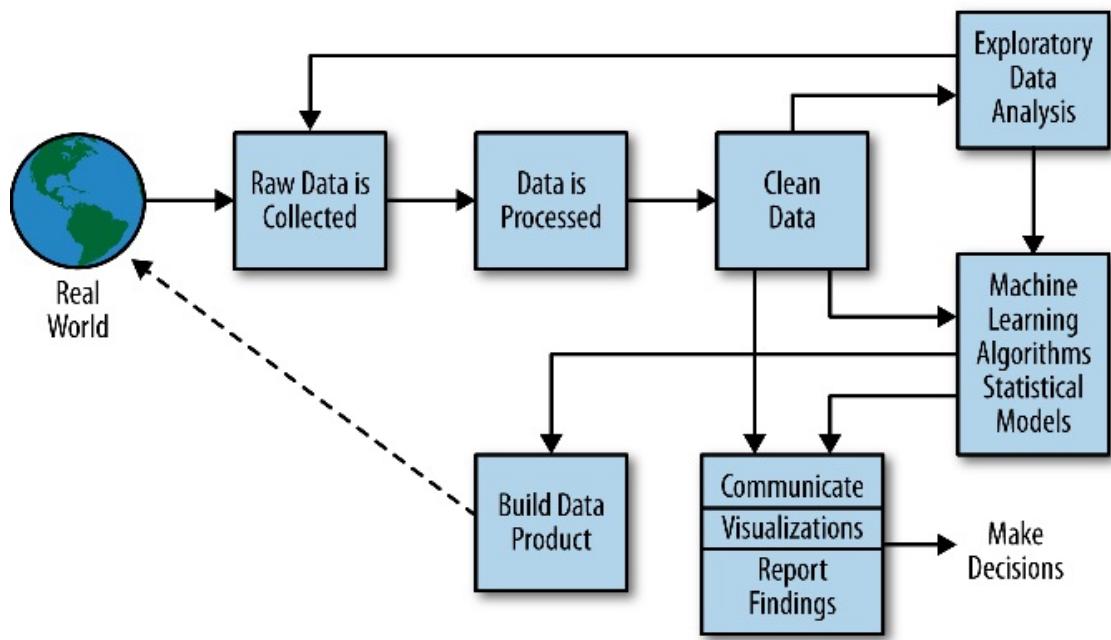
While we are concerned for Princeton University, we are even more concerned about the fate of the planet — Google Trends for “air” have also been declining steadily, and our projections show that by the year 2060 there will be no air left:



<https://www.facebook.com/notes/mike-develin/debunking-princeton/10151947421191849>

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Data Science Process



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R Programming

What is R?

- R is a system for statistical computation and graphics.
- It is heavily influenced by the **S** language
- **R** was initially written by **Ross Ihaka** and **Robert Gentleman** at the Department of Statistics of the University of Auckland in Auckland, New Zealand.
- The “**R Core Team**” maintain the source code for the software and release regular updates

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What is R?

- In addition, the R project is added to by many of its users, who write source code for many different types of analytical procedures
- Everything from analytical chemistry to epidemiology to linguistics
- Currently 6,000+ different user--written libraries available (<http://cran.r-project.org>)

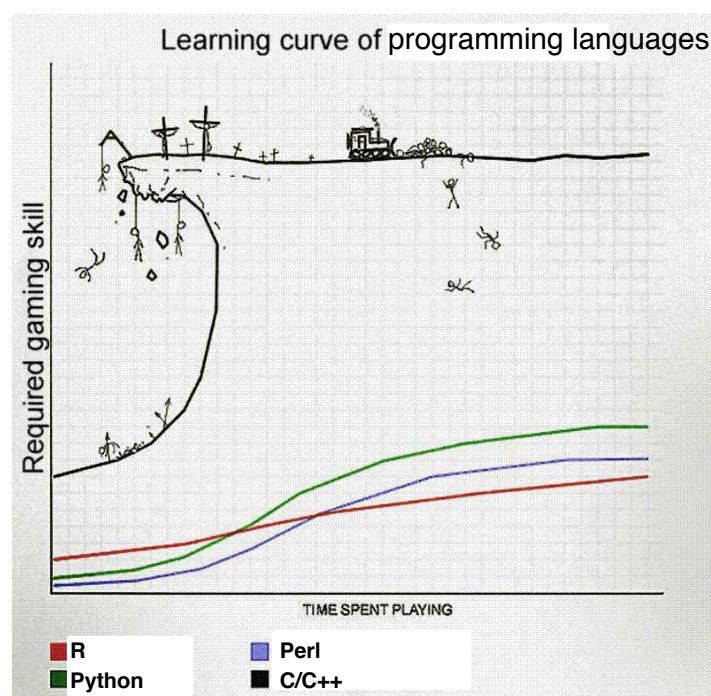
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Why use R?

- R is Open-Source Software
- Many built-in functions and installable packages that will cover nearly every possible need
- R is an interpreted language
 - Code doesn't have to be compiled
 - Interactive console makes testing and debugging easy
- Cons to using R
 - Slower than compiled languages
 - Can have runtime errors

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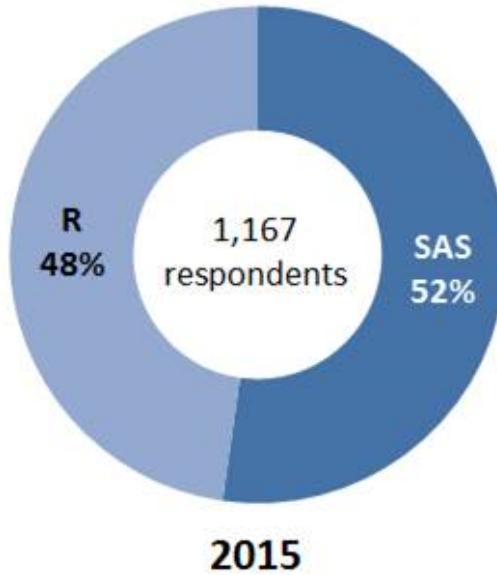
Why use R?



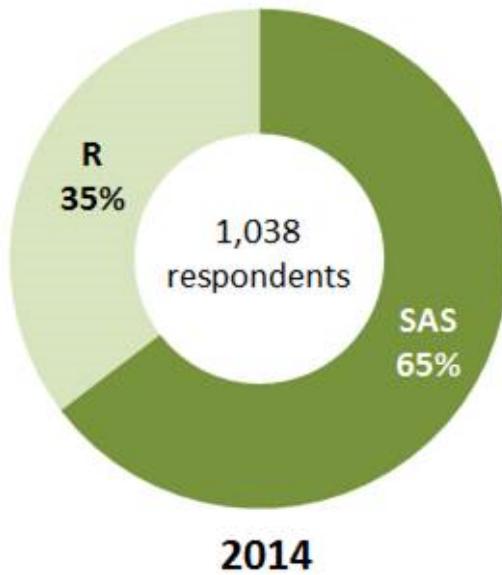
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<http://www.vayaputra.es/wordpress/wp-content/uploads/2009/02/2rmqi6o.gif>

R vs SAS



2015



2014

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Tools



R
www.r-project.org

The engine*



RStudio
www.rstudio.org

The pretty face**

* Many alternatives exist. Smallest learning curve.
** A few alternatives exist. This happens to be the easiest at the moment.

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RStudio Features

- Code completion
- Command history search
- Command history to R script / file
- Function extraction from Rscript
- Sweave and Knitr support

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Introducing R-Studio

The screenshot shows the RStudio IDE interface. On the left, the script editor displays R code for generating a diamond pricing plot. The workspace panel shows the 'diamonds' dataset and other variables. The plots panel displays a scatter plot titled 'Diamond Pricing' showing Price vs. Carat, with points colored by Clarity.

```
library(ggplot2)
source("plots/formatPlot.R")
view(diamonds)
summary(diamonds)
summary(diamonds$price)
avesize <- round(mean(diamonds$carat), 4)
clarity <- levels(diamonds$clarity)
p <- qplot(carat, price,
           data=diamonds, color=clarity,
           xlab="Carat", ylab="Price",
           main="Diamond Pricing")
```

Diamond Pricing

Clarity

- I1
- SI2
- SI1
- VS2
- VS1
- VVS2
- VVS1
- IF

Price

Carat

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RStudio Panes

Rstudio has 4 main windows ('panes'):

- **The Source pane:** create a file that you can save and run later
 - **The Console pane:** type or paste in commands to get output from R
 - **The Workspace/History pane:** see a list of variables or previous commands
 - **The Files/Plots/Packages/Help pane:** see plots, help pages, and other items in this window.

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Source and Console Panes

Source window: Create a file here, so that you can save and run it later (or turn in as homework)

Any non-command line
should start with a #

Console: Type or paste commands in here to get results from R

If you are loading a data file, you will need to be in the correct directory

> denotes that R is waiting for a command

+ denotes that R is waiting for you to finish the previous command (not shown here)

The screenshot shows an RStudio interface. The top menu bar includes 'File' (with 'hw1.R x'), 'Edit', 'Source on Save', 'Run', 'Source', and 'File'. The main workspace shows the following R code:

```
1 #  
2 # David Choi  
3 # HW 1  
4 #  
5 #  
6 # Here are the steps to accomplish problem 1:  
7 x = sqrt(5)  
8 y = sqrt(2)  
9 z = x + y  
10 z  
11
```

The status bar at the bottom indicates '11:1 f (Top Level) R Script'. Below the workspace, the 'Console' tab shows:

Console ~ /Dropbox/teaching/DataVis mini 4/homework 1/ ↵
type ~~q()~~ to quit R.

A handwritten note with a red arrow points from the 'q()' in the console to the 'q()' in the code above it. The console also displays the message '[Workspace loaded from ~/.RData]'. The command history in the console shows:

```
> setwd("~/Dropbox/teaching/DataVis mini 4/homework 1")  
> x = sqrt(5)  
> y = sqrt(2)  
> z = x + y  
> z  
[1] 3.650282  
> |
```

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Console Panes

Variables

- Save the results of a command in memory by giving it a name:

`z` uses `x` and `y`:

```
> x = 3
> y = 2
> x
[1] 3
> y
[1] 2
```

Create `x` and `y`

Values are not linked;
updating `x` doesn't
change `z`

```
> z = sqrt(x^2+y^2)
> z
[1] 3.605551
```

Redefine `z` using the new
value for `x`

```
> x = 5
> z
[1] 3.605551
```

Use " " or ' ' to distinguish
between variable names
and regular text

```
> z = sqrt(x^2+y^2)
> z
[1] 5.385165
> str = 'Hi there'
> str
[1] "Hi there"
> str2 = "It's cold outside"
> str2
[1] "It's cold outside"
```

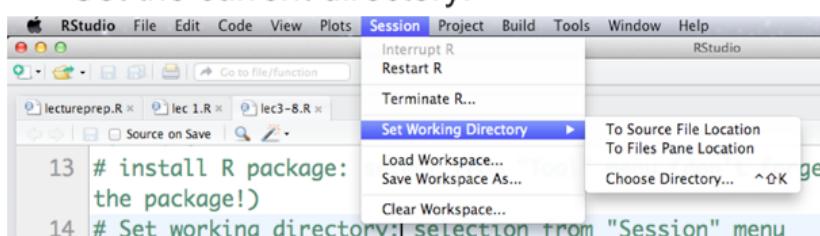
Note:
`x <- 3`: same as `x=3`

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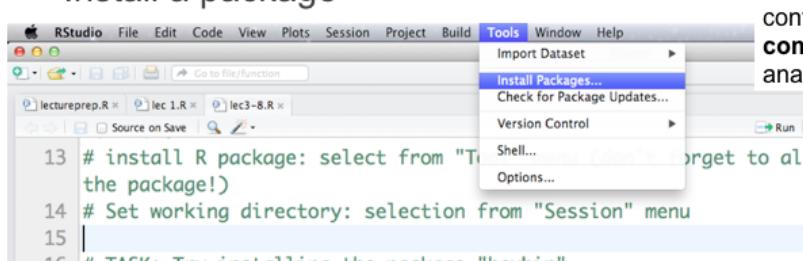
RStudio Menu

Two helpful menu items in Rstudio

- Set the current directory:



- Install a package



Packages are extensions to R, containing **new commands** for analysis or graphics

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R Markdown

```
example.Rmd x
ABC Knit HTML Chunks
1 Header 1
2 -----
3 This is an R Markdown document. Markdown is a
| simple formatting syntax for authoring web pages.
4
5 Use an asterisk mark, to provide emphasis such as
| *italics* and **bold**.
6
7 Create lists with a dash:
8 - Item 1
9 - Item 2
10 - Item 3
11
12 You can write `in-line` code with a back-tick.
13
14 ...
15 Code blocks display
16 with fixed-width font
17 ...
18
19 > Blockquotes are offset
20
```

Header 1

This is an R Markdown document. Markdown is a simple formatting syntax for authoring web pages.

Use an asterisk mark, to provide emphasis such as *italics* and **bold**.

Create lists with a dash:

- Item 1
- Item 2
- Item 3

You can write `in-line` code with a back-tick.

Code blocks display
with fixed-width font

Blockquotes are offset

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R Markdown

```
chunks.Rmd x
ABC Knit HTML Chunks
1 R Code Chunks
2 -----
3
4 With R Markdown, you can insert R code
| chunks including plots:
5
6 ````{r qplot, fig.width=4, fig.height=3,
| message=FALSE}
7 # quick summary and plot
8 library(ggplot2)
9 summary(cars)
10 qplot(speed, dist, data=cars) +
11     geom_smooth()
12 ...
13 |
```

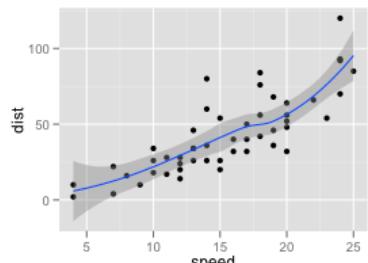
R Code Chunks

With R Markdown, you can insert R code chunks including plots:

```
# quick summary and plot
library(ggplot2)
summary(cars)
```

```
##      speed         dist
## Min.   : 4.0   Min.   : 2
## 1st Qu.:12.0   1st Qu.: 26
## Median :15.0   Median : 36
## Mean   :15.4   Mean   : 43
## 3rd Qu.:19.0   3rd Qu.: 56
## Max.   :25.0   Max.   :120
```

```
qplot(speed, dist, data = cars) + geom_smooth()
```



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Workshop 1: Hello World

Open RStudio on your machine

- File > New File > R Markdown ...
- Change summary(cars) in the first code block to print("Hello world!")
- Click Knit HTML to produce an HTML file.
- Save your Rmd file as helloworld.Rmd

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Data Types

You'll encounter different kinds of data types

- **Booleans** Direct binary values: TRUE or FALSE in R
- **Integers**: whole numbers (positive, negative or zero)
- **Characters** fixed-length blocks of bits, with special coding; strings = sequences of characters
- **Floating point numbers**: a fraction (with a finite number of bits) times an exponent, like $1.87 * 10^6$
- **Missing** or ill-defined values: NA, NaN, etc.

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Operators (Functions)

Command	Description
<code>+,-,*,\</code>	add, subtract, multiply, divide
<code>^</code>	raise to the power of
<code>%%</code>	remainder after division (ex: <code>8 %% 3 = 2</code>)
<code>()</code>	change the order of operations
<code>log(), exp()</code>	logarithms and exponents (ex: <code>log(10) = 2.302</code>)
<code>sqrt()</code>	square root
<code>round()</code>	round to the nearest whole number (ex: <code>round(2.3) = 2</code>)
<code>floor(), ceiling()</code>	round down or round up
<code>abs()</code>	absolute value

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Operators

```
7 + 5 # Addition
```

```
[1] 12
```

```
7 - 5 # Subtraction
```

```
[1] 2
```

```
7 * 5 # Multiplication
```

```
[1] 35
```

```
7 ^ 5 # Exponentiation
```

```
[1] 16807
```

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```
7 / 5 # Division
```

```
[1] 1.4
```

```
7 %% 5 # Modulus
```

```
[1] 2
```

```
7 %/% 5 # Integer division
```

```
[1] 1
```

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Operators

Comparisons are also **binary operators**; they take two objects, like numbers. and give a Boolean

```
7 > 5
```

```
[1] TRUE
```

```
7 < 5
```

```
[1] FALSE
```

```
7 >= 7
```

```
[1] TRUE
```

```
7 <= 5
```

```
[1] FALSE
```

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```
7 == 5
```

```
[1] FALSE
```

```
7 != 5
```

```
[1] TRUE
```

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Boolean Operators

Basically “and” and “or”:

```
(5 > 7) & (6*7 == 42)
```

```
[1] FALSE
```

```
(5 > 7) | (6*7 == 42)
```

```
[1] TRUE
```

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Basic Math / Basic Logic

- + addition
- subtraction
- * multiplication
- / division
- % modulus (remainder)
- ^ to the power

- ! NOT
- & bitwise AND
- | bitwise OR
- && short circuit AND
- || short circuit OR
- == equality
- != NOT equality

?Arithmetic

?Logic

Also try ?Syntax, ?Comparison

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More types

`typeof()` function returns the type

`is.foo()` functions return Booleans for whether the argument is of type foo

`as.foo()` (tries to) “cast” its argument to type foo — to translate it sensibly into a foo-type value

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```
typeof(7)
```

```
[1] "double"
```

```
is.numeric(7)
```

```
[1] TRUE
```

```
is.na(7)
```

```
[1] FALSE
```

55



```
is.character(7)
```

```
[1] FALSE
```

```
is.character("7")
```

```
[1] TRUE
```

```
is.character("seven")
```

```
[1] TRUE
```

```
is.na("seven")
```

```
[1] FALSE
```

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Variables

We can give names to data objects; these give us **variables**

A few variables are built in:

```
pi
```

```
[1] 3.141593
```

Variables can be arguments to functions or operators, just like constants:

```
pi*10
```

```
[1] 31.41593
```

```
cos(pi)
```

```
[1] -1
```

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Assignment Operator

Most variables are created with the **assignment operator**, `<-` or `=`

```
approx.pi <- 22 / 7  
approx.pi
```

```
[1] 3.142857
```

```
diameter.in.cubits = 10  
approx.pi*diameter.in.cubits
```

```
[1] 31.42857
```

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Variables

- Using names and variables makes code: easier to design, easier to debug, less prone to bugs, easier to improve, and easier for others to read
- Avoid “magic constants”; use named variables
- Use descriptive variable names
 - Good: num.students <- 35
 - Bad: ns <- 35

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Workspace

What names have you defined values for?

```
ls()
```

```
[1] "approx.pi"           "circumference.in.cubits"  
[3] "diameter.in.cubits"
```

Getting rid of variables:

```
rm("circumference.in.cubits")  
ls()
```

```
[1] "approx.pi"           "diameter.in.cubits"
```

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Data Structure : Vector

- Group related data values into one object, a **data structure**
- A **vector** is a sequence of values, all of the same type
- `c()` function returns a vector containing all its arguments in order

```
students <- c("Sean", "Louisa", "Frank", "Farhad", "Li")
midterm <- c(80, 90, 93, 82, 95)
```

- Typing the variable name at the prompt causes it to display

```
students
[1] "Sean"    "Louisa"   "Frank"    "Farhad"   "Li"
```

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Indexing Vector

- `vec[1]` is the first element, `vec[4]` is the 4th element of `vec`

```
students
[1] "Sean"    "Louisa"   "Frank"    "Farhad"   "Li"
students[4]
[1] "Farhad"
```

- `vec[-4]` is a vector containing all but the fourth element

```
students[-4]
[1] "Sean"    "Louisa"   "Frank"    "Li"
```

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Vector Arithmetic

Operators apply to vectors “pairwise” or “elementwise”:

```
final <- c(78, 84, 95, 82, 91) # Final exam scores  
midterm # Midterm exam scores  
  
[1] 80 90 93 82 95  
  
midterm + final # Sum of midterm and final scores  
  
[1] 158 174 188 164 186  
  
(midterm + final)/2 # Average exam score  
  
[1] 79 87 94 82 93  
  
course.grades <- 0.4*midterm + 0.6*final # Final course grade  
course.grades  
  
[1] 78.8 86.4 94.2 82.0 92.6
```

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Pairwise Comparison

Is the final score higher than the midterm score?

```
midterm  
  
[1] 80 90 93 82 95  
  
final  
  
[1] 78 84 95 82 91  
  
final > midterm  
  
[1] FALSE FALSE TRUE FALSE FALSE
```

Boolean operators can be applied elementwise:

```
(final < midterm) & (midterm > 80)  
  
[1] FALSE TRUE FALSE FALSE TRUE
```

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Functions on Vectors

Command	Description
sum(vec)	sums up all the elements of vec
mean(vec)	mean of vec
median(vec)	median of vec
min(vec), max(vec)	the largest or smallest element of vec
sd(vec), var(vec)	the standard deviation and variance of vec
length(vec)	the number of elements in vec
pmax(vec1, vec2), pmin(vec1, vec2)	example: pmax(quiz1, quiz2) returns the higher of quiz 1 and quiz 2 for each student
sort(vec)	returns the vec in sorted order
order(vec)	returns the index that sorts the vector vec
unique(vec)	lists the unique elements of vec
summary(vec)	gives a five-number summary
any(vec), all(vec)	useful on Boolean vectors

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Function on Vectors

```
course.grades
```

```
[1] 78.8 86.4 94.2 82.0 92.6
```

```
mean(course.grades) # mean grade
```

```
[1] 86.8
```

```
median(course.grades)
```

```
[1] 86.4
```

```
sd(course.grades) # grade standard deviation
```

```
[1] 6.625708
```

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More on Functions

```
sort(course.grades)
```

```
[1] 78.8 82.0 86.4 92.6 94.2
```

```
max(course.grades) # highest course grade
```

```
[1] 94.2
```

```
min(course.grades) # lowest course grade
```

```
[1] 78.8
```

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Referencing elements of Vectors

```
students
```

```
[1] "Sean"    "Louisa"  "Frank"   "Farhad" "Li"
```

Vector of indices:

```
students[c(2,4)]
```

```
[1] "Louisa" "Farhad"
```

Vector of negative indices

```
students[c(-1,-3)]
```

```
[1] "Louisa" "Farhad" "Li"
```

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More on Referencing

`which()` returns the TRUE indexes of a Boolean vector:

```
course.grades
```

```
[1] 78.8 86.4 94.2 82.0 92.6
```

```
a.threshold <- 90 # A grade = 90% or higher  
course.grades >= a.threshold # vector of booleans
```

```
[1] FALSE FALSE TRUE FALSE TRUE
```

```
a.students <- which(course.grades >= a.threshold) # Applying which()  
a.students
```

```
[1] 3 5
```

```
students[a.students] # Names of A students
```

```
[1] "Frank" "Li"
```

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Workshop 2

Using the same Rmarkdown file from Workshop 1, do the following:-

1) Creating sequences

: Colon operator:

```
1:10 # Numbers 1 to 10
```

```
## [1] 1 2 3 4 5 6 7 8 9 10
```

```
127:132 # Numbers 127 to 132
```

```
## [1] 127 128 129 130 131 132
```

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Workshop 2

seq function: `seq(from, to, by)`

```
seq(1,10,1) # Numbers 1 to 10
```

```
## [1] 1 2 3 4 5 6 7 8 9 10
```

```
seq(1,10,2) # Odd numbers from 1 to 10
```

```
## [1] 1 3 5 7 9
```

```
seq(2,10,2) # Even numbers from 2 to 10
```

```
## [1] 2 4 6 8 10
```

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Workshop 2 : Use RStudio to answer questions below

- (a) Use `:` to output the sequence of numbers from 3 to 12
- (b) Use `seq()` to output the sequence of numbers from 3 to 30 in increments of 3
- (c) Save the sequence from (a) as a variable `x`, and the sequence from (b) as a variable `y`. Output their product `x*y`

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Difference between = and <-

- The operators <- and = assign into the environment in which they are evaluated.
- The operator <- can be used anywhere, whereas the operator = is only allowed at the top level (e.g., in the complete expression typed at the command prompt) or as one of the subexpressions in a braced list of expressions.

```
matrix(1,nrow=2)
```

```
matrix(1,nrow<-2)
```

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Reading and Getting Data into R

Combine Command

```
c(1, 2, 3, 4)  
c(item1, item2, item3, item4)  
c("item1", "item2", "item3")
```

Scan Command

```
our.data = scan()  
  
scan(what = 'character')  
data5 = scan(sep = ',', what = 'char')  
data6 = scan(file = 'data.txt')
```

Working Directory

```
getwd()
```

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Reading Bigger Data Files

```
read.csv()  
read.csv(file, sep = ',', header = TRUE, row.names)  
fw = read.csv(file.choose())
```

```
my.ssv = read.table(file.choose(), header = TRUE)  
my.tsv = read.delim(file.choose())  
my.tsv = read.csv(file.choose(), sep = '\t')  
my.tsv = read.table(file.choose(), header = TRUE,  
sep = '\t')
```

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Importing Data

- To import tabular data into R, we use the `read.table()` command

```
1 survey <- read.table("survey_data.csv", header=TRUE, sep=",")  
2  
3
```

- Let's parse this command one component at a time
 - The data is in a file called `survey_data.csv`, which is an online file
 - The file contains a header as its first row
 - The csv format means that the data is comma-separated, so `sep=" , "`
- Could've also used `read.csv()`, which is just `read.table()` with the preset `sep=" , "`

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Exploring the Data

- R imports data into a `data.frame` object

```
class(survey)
```

```
[1] "data.frame"
```

- To view the first few rows of the data, use `head()`

```
head(survey, 3)
```

	Program	PriorExp	Rexperience	OperatingSystem	TVhours
1	MISM	Some experience	Never used	Windows	1
2	Other	Some experience	Basic competence	Windows	8
3	MISM	Extensive experience	Basic competence	Windows	4

Editor

1 Microsoft Word
2 Microsoft Word
3 Microsoft Word

- `head(data.frame, n)` returns the first n rows of the data frame
- In the Console, you can also use `View(survey)` to get a spreadsheet view

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Simple Summary

- Use the `str()` function to get a simple summary of your data set

```
str(survey)
```

```
'data.frame': 31 obs. of 6 variables:  
 $ Program      : Factor w/ 3 levels "MISM", "Other", ... : 1 2 1 3 2 3 2 1 3 3 ...  
 $ PriorExp     : Factor w/ 3 levels "Extensive experience", ... : 3 3 1 2 2 3 3 3 3 ...  
 $ Rexperience   : Factor w/ 3 levels "Basic competence", ... : 3 1 1 2 3 3 3 3 3 3 ...  
 ...  
 $ OperatingSystem: Factor w/ 2 levels "Mac OS X", "Windows": 2 2 2 2 2 1 1 2 1 2 ...  
 ...  
 $ TVhours       : int 1 8 4 5 3 10 0 10 15 4 ...  
 $ Editor        : Factor w/ 1 level "Microsoft Word": 1 1 1 1 1 1 1 1 1 1 ...
```

- This says that `TVhours` is a numeric variable, while all the rest are factors (categorical)

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Another Summary

```
summary(survey)
```

Program	PriorExp	Rexperience
MISM :10	Extensive experience : 5	Basic competence : 2
Other: 6	Never programmed before:12	Installed on machine: 7
PPM :15	Some experience :14	Never used :22

OperatingSystem	TVhours	Editor
Mac OS X:14	Min. : 0.000	Microsoft Word:31
Windows :17	1st Qu.: 1.000	
	Median : 4.000	
	Mean : 5.742	
	3rd Qu.: 9.000	
	Max. :40.000	

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Data Frames

- 2 Dimensional Objects, it has rows and columns. R treats the columns as separate samples or variables, rows represent the replicates or observations.
- To see what an R object is made up of, you can use `attributes()`

```
attributes(survey)
```

```
$names
[1] "Program"          "PriorExp"        "Rexperience"      "OperatingSystem"
[5] "TVhours"          "Editor"

$class
[1] "data.frame"

$row.names
 [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
[24] 24 25 26 27 28 29 30 31
```

An R **data frame** is a *list* whose columns you can refer to by *name* or *index*

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Data Frame dimensions

- We can use `nrow()` and `ncol` to determine the number of survey responses and the number of survey questions

```
nrow(survey) # Number of rows (responses)  
[1] 31  
  
ncol(survey) # Number of columns (questions)  
[1] 6
```

- When writing reports, you will often want to say how large your sample size was
- To do this *inline*, use the syntax:

```
`r nrow(survey)`
```

- This allows us to write “31 students responded to the survey”, and have the number displayed automatically change when `nrow(survey)` changes.

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Indexing Data Frame

- There are many different ways of indexing the same piece of a data frame

```
survey[["Program"]] # "Program" element  
[1] MISM Other MISM PPM Other PPM Other MISM PPM PPM MISM  
[12] PPM PPM PPM PPM PPM MISM MISM MISM PPM PPM  
[23] MISM Other PPM PPM MISM PPM Other Other MISM  
Levels: MISM Other PPM  
  
survey$Program # "Program" element  
[1] MISM Other MISM PPM Other PPM Other MISM PPM PPM MISM  
[12] PPM PPM PPM PPM PPM MISM MISM MISM PPM PPM  
[23] MISM Other PPM PPM MISM PPM Other Other MISM  
Levels: MISM Other PPM  
  
survey[,1] # Data from 1st column  
[1] MISM Other MISM PPM Other PPM Other MISM PPM PPM MISM  
[12] PPM PPM PPM PPM PPM MISM MISM MISM PPM PPM  
[23] MISM Other PPM PPM MISM PPM Other Other MISM  
Levels: MISM Other PPM
```

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More Indexing

- Note that single brackets and double brackets have different effects

```
survey[["Program"]]
```

```
[1] MISM Other MISM PPM Other PPM Other MISM PPM PPM MISM  
[12] PPM PPM PPM PPM PPM MISM MISM MISM PPM PPM  
[23] MISM Other PPM PPM MISM PPM Other Other MISM  
Levels: MISM Other PPM
```

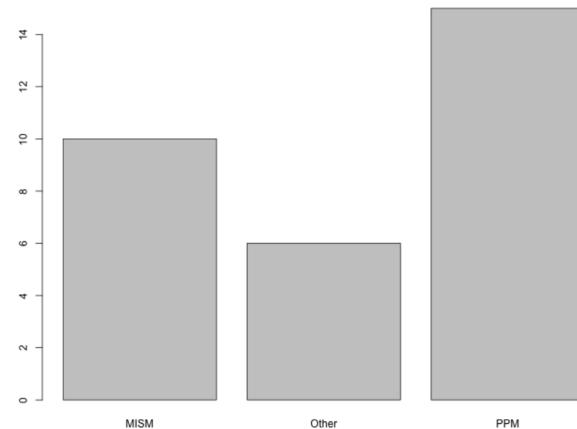
```
survey["Program"] # sub-data frame containing only "Program"
```

```
Program  
1     MISM  
2     Other  
3     MISM  
4     PPM  
5     Other  
6     PPM  
7     Other  
8     MISM  
9     PPM  
10    PPM  
11    MISM  
12    PPM  
13    PPM  
14    PPM
```

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Bar Plot (Categorical Data)

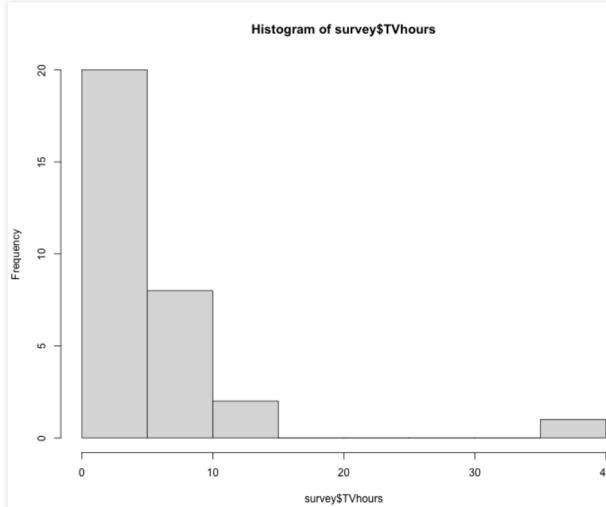
```
plot(survey[["Program"]])
```



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Histogram (Continuous Data)

```
hist(survey$TVhours, col="lightgray")
```



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Indexing Multiple Columns

```
head(survey[,c(1,5)]) # Data from 1st and 5th columns
```

```
Program TVhours
1    MISM      1
2    Other      8
3    MISM      4
4    PPM       5
5    Other      3
6    PPM      10
```

```
head(survey[c("Program", "Editor")]) # Data from "Program" and "Editor"
```

```
Program          Editor
1    MISM Microsoft Word
2    Other Microsoft Word
3    MISM Microsoft Word
4    PPM  Microsoft Word
5    Other Microsoft Word
6    PPM  Microsoft Word
```

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Indexing Row and Column

- Data frames have two dimensions to index across

```
survey[6,] # 6th row
```

```
Program      PriorExp Rexperience OperatingSystem TVhours
6      PPM Some experience    Never used        Mac OS X      10
          Editor
6 Microsoft Word
```

```
survey[6,5] # row 6, column 5
```

```
[1] 10
```

```
survey[6, "Program"] # Program of 6th survey respondent
```

```
[1] PPM
Levels: MISM Other PPM
```

```
survey[["Program"]][6] # Program of 6th survey respondent
```

```
[1] PPM
Levels: MISM Other PPM
```

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More Indexing

- We can use this operator for indexing

```
survey[1:3,] # equivalent to head(survey, 3)
```

```
Program      PriorExp      Rexperience OperatingSystem TVhours
1      MISM      Some experience    Never used        Windows      1
2      Other      Some experience Basic competence        Windows      8
3      MISM Extensive experience Basic competence        Windows      4
          Editor
1 Microsoft Word
2 Microsoft Word
3 Microsoft Word
```

```
survey[3:5, c(1,5)]
```

```
Program TVhours
3      MISM      4
4      PPM       5
5      Other      3
```

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Subsets of Data

- We are often interested in learning something a specific subset of the data

```
survey[survey$Program=="MISM",] # Data from the MISM students
```

	Program	PriorExp	Rexperience	OperatingSystem
1	MISM	Some experience	Never used	Windows
3	MISM	Extensive experience	Basic competence	Windows
8	MISM	Some experience	Never used	Windows
11	MISM	Extensive experience	Installed on machine	Mac OS X
18	MISM	Extensive experience	Never used	Mac OS X
19	MISM	Extensive experience	Never used	Windows
20	MISM	Some experience	Never used	Windows
23	MISM	Some experience	Never used	Windows
27	MISM	Some experience	Never used	Mac OS X
31	MISM	Some experience	Installed on machine	Windows
	TVhours	Editor		
1	1	Microsoft Word		
3	4	Microsoft Word		
8	10	Microsoft Word		
11	0	Microsoft Word		
18	3	Microsoft Word		
19	0	Microsoft Word		
20	1	Microsoft Word		
23	3	Microsoft Word		
27	0	Microsoft Word		
31	0	Microsoft Word		

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More subsets example

- Let's pull all of the PPM students who have never used R before

```
survey[survey$Program=="PPM" & survey$Rexperience=="Never used",]
```

	Program	PriorExp	Rexperience	OperatingSystem	TVhours
6	PPM	Some experience	Never used	Mac OS X	10
9	PPM	Never programmed before	Never used	Mac OS X	15
10	PPM	Extensive experience	Never used	Windows	4
12	PPM	Never programmed before	Never used	Windows	0
13	PPM	Some experience	Never used	Mac OS X	10
14	PPM	Never programmed before	Never used	Mac OS X	4
15	PPM	Some experience	Never used	Windows	10
16	PPM	Some experience	Never used	Mac OS X	2
22	PPM	Never programmed before	Never used	Windows	7
25	PPM	Never programmed before	Never used	Mac OS X	6
		Editor			
6	Microsoft Word				
9	Microsoft Word				
10	Microsoft Word				
12	Microsoft Word				
13	Microsoft Word				
14	Microsoft Word				
15	Microsoft Word				
16	Microsoft Word				
22	Microsoft Word				
25	Microsoft Word				

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Subset

- When the subset conditions get long or messy, it is preferable to use the `subset()` function
- Here's an example of selecting the OperatingSystem and TVhours responses from all of the students who are either in PPM or Other and who listed their R experience as "Basic competence".

```
subset(survey, select=c("OperatingSystem", "TVhours"), subset=(Program == "PPM"  
| Program == "Other") & Rexperience == "Basic competence")
```

```
OperatingSystem TVhours  
2 Windows 8
```

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Calculation from subset

```
mean(survey$TVhours[survey$Program == "PPM"]) # Average time PPM's spent watching  
TV
```

```
[1] 8.8
```

```
mean(survey$TVhours[survey$Program == "MISM"]) # Average time MISM's spent  
watching TV
```

```
[1] 2.2
```

```
mean(survey$TVhours[survey$Program == "Other"]) # Average time "Others" spent  
watching TV
```

```
[1] 4
```

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Coding Style

- Coding style (and code commenting) will become increasingly more important as we get into more advanced and involved programming tasks
- A few R “style guides” exist:
 - <http://r-pkgs.had.co.nz/style.html>
 - Google’s R Style Guide (<https://google.github.io/styleguide/Rguide.xml>)

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Example Style Guide

Assignment operator. USE `<-`

```
student.names <- c("Eric", "Hao", "Jennifer") # Good
student.names = c("Eric", "Hao", "Jennifer") # Bad
```

- Note: When specifying function arguments, only = is valid

```
sort(tv.hours, decreasing=TRUE) # Good
sort(tv.hours, decreasing<-TRUE) # Bad!!
```

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Style Guide : Variable Name

- To make code easy to read, debug, and maintain, you should use **concise** but **descriptive** variable names
- Terms in variable names should be separated by `_` or `.`

```
# Accepted
day_one    day.one   day_1    day.1    day1

# Bad
d1      DayOne   dayone

# Can be made more concise:
first.day.of.the.month
```

- Avoid using variable names that are already pre-defined in R

```
# EXTREMELY bad:
c      T      pi     sum    mean
```

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Workshop 3: Importing and Indexing data

Data practice

```
survey <- read.table("survey.csv");
```

Use command to answer these questions?

(a) How many survey respondents are from MISM or Other?

(b) What % of survey respondents are from PPM?

Index practice

(a) Use `$` notation to pull the `OperatingSystem` column from the survey data

(b) Do the same thing with `[,]` notation, referring to `OperatingSystem` by name

(c) Repeat part (b), this time referring to `OperatingSystem` by column number

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More on Data Frame

```
library(MASS)
head(Cars93, 3)
```

	Manufacturer	Model	Type	Min.Price	Price	Max.Price	MPG.city
1	Acura	Integra	Small	12.9	15.9	18.8	25
2	Acura	Legend	Midsize	29.2	33.9	38.7	18
3	Audi	90	Compact	25.9	29.1	32.3	20
	MPG.highway		AirBags	DriveTrain	Cylinders	EngineSize	
1	31		None	Front	4	1.8	
2	25	Driver & Passenger		Front	6	3.2	
3	26	Driver only		Front	6	2.8	
	Horsepower	RPM	Rev.per.mile	Man.trans.avail	Fuel.tank.capacity		
1	140	6300	2890		Yes	13.2	
2	200	5500	2335		Yes	18.0	
3	172	5500	2280		Yes	16.9	
	Passengers	Length	Wheelbase	Width	Turn.circle	Rear.seat.room	
1	5	177	102	68	37	26.5	
2	5	195	115	71	38	30.0	
3	5	180	102	67	37	28.0	
	Luggage.room	Weight	Origin		Make		
1	11	2705	non-USA	Acura	Integra		
2	15	3560	non-USA	Acura	Legend		
3	14	3375	non-USA		Audi 90		

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Add column using “Transform”

- `transform()` returns a new data frame with columns modified or added as specified by the function call

```
Cars93.metric <- transform(Cars93,
                           KMPL.city = 0.425 * MPG.city,
                           KMPL.highway = 0.425 * MPG.highway)
tail(names(Cars93.metric))
```

```
[1] "Luggage.room"   "Weight"        "Origin"        "Make"
[5] "KMPL.city"       "KMPL.highway"
```

- Our data frame has two new columns, giving the fuel consumption in km/l

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Another Approach

```
KMPL.city.2 <- 0.425 * Cars93$MPG.city  
# Add a new column called KMPL.city.2  
Cars93.metric$KMPL.city.2 <- KMPL.city.2  
tail(names(Cars93.metric))
```

```
[1] "Weight"      "Origin"       "Make"        "KMPL.city"  
[5] "KMPL.highway" "KMPL.city.2"
```

- Let's check that both approaches did the same thing

```
identical(Cars93.metric$KMPL.city, Cars93.metric$KMPL.city.2)
```

```
[1] TRUE
```

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Changing level of a factor

```
manufacturer <- Cars93$Manufacturer  
head(manufacturer, 10)
```

```
[1] Acura      Acura      Audi      Audi      BMW       Buick     Buick  
[8] Buick      Buick      Cadillac  
32 Levels: Acura Audi BMW Buick Cadillac Chevrolet Chrylser ... Volvo
```

We'll use the `mapvalues(x, from, to)` function from the `plyr` library.

```
library(plyr)  
  
# Map Chevrolet, Pontiac and Buick to GM  
manufacturer.combined <- mapvalues(manufacturer,  
                                    from = c("Chevrolet", "Pontiac", "Buick"),  
                                    to = rep("GM", 3))
```

```
head(manufacturer.combined, 10)
```

```
[1] Acura      Acura      Audi      Audi      BMW       GM        GM  
[8] GM        GM        Cadillac  
30 Levels: Acura Audi BMW GM Cadillac Chrylser Chrysler Dodge ... Volvo
```

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Another example

- A lot of data comes with integer encodings of levels
- You may want to convert the integers to more meaningful values for the purpose of your analysis
- Let's pretend that in the class survey 'Program' was coded as an integer with 1 = MISM, 2 = Other, 3 = PPM
- Here's how we would get back the program codings using the `transform()`, `as.factor()` and `mapvalues()` functions

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```
survey <- transform(survey, Program = as.factor(mapvalues(Program, c(1, 2, 3),
c("MISM", "Other", "PPM"))))
head(survey)
```

	Program	PriorExp	Rexperience	OperatingSystem
1	MISM	Some experience	Never used	Windows
2	Other	Some experience	Basic competence	Windows
3	MISM	Extensive experience	Basic competence	Windows
4	PPM	Never programmed before	Installed on machine	Windows
5	Other	Never programmed before	Never used	Windows
6	PPM	Some experience	Never used	Mac OS X
	TVhours	Editor		
1	1	Microsoft Word		
2	8	Microsoft Word		
3	4	Microsoft Word		
4	5	Microsoft Word		
5	3	Microsoft Word		
6	10	Microsoft Word		

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table() function

- The `table()` function builds **contingency tables** showing counts at each combination of factor levels

```
table(Cars93$AirBags)
```

Driver & Passenger	16	Driver only	43
		None	34

```
table(Cars93$Origin)
```

USA	non-USA
48	45

```
table(Cars93$AirBags, Cars93$Origin)
```

	USA	non-USA
Driver & Passenger	9	7
Driver only	23	20
None	16	18

- Looks like US and non-US cars had about the same distribution of AirBag types

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more table()

- When `table()` is supplied a data frame, it produces contingency tables for all combinations of factors

```
head(Cars93[c("AirBags", "Origin")], 3)
```

	AirBags	Origin
1	None	non-USA
2	Driver & Passenger	non-USA
3	Driver only	non-USA

```
table(Cars93[c("AirBags", "Origin")])
```

AirBags		Origin	
		USA	non-USA
Driver & Passenger	9	7	
Driver only	23	20	
None	16	18	

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Basic of Lists

A list is a **data structure** that can be used to store **different kinds** of data

- Recall: a vector is a data structure for storing *similar kinds of data*
- To better understand the difference, consider the following example.

```
my.vector.1 <- c("Michael", 165, TRUE) # (name, weight, is.male)
my.vector.1
[1] "Michael" "165"      "TRUE"
typeof(my.vector.1) # All the elements are now character strings!
[1] "character"
```

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List vs Vector

```
my.vector.2 <- c(FALSE, TRUE, 27) # (is.male, is.citizen, age)
typeof(my.vector.2)
[1] "double"
```

- Vectors expect elements to be all of the same type (e.g., Boolean, numeric, character)
- When data of different types are put into a vector, the R converts everything to a common type

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Lists

- To store data of different types in the same object, we use lists
- Simple way to build lists: use `list()` function

```
my.list <- list("Michael", 165, TRUE)
my.list
```

```
[[1]]
[1] "Michael"

[[2]]
[1] 165

[[3]]
[1] TRUE
```

```
sapply(my.list, typeof)
```

```
[1] "character" "double"    "logical"
```

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Named Elements

```
patient.1 <- list(name="Michael", weight=165, is.male=TRUE)
patient.1
```

```
$name
[1] "Michael"

$weight
[1] 165

$is.male
[1] TRUE
```

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Referencing element inside list

```
patient.1$name # Get "name" element (returns a string)  
[1] "Michael"  
  
patient.1[["name"]] # Get "name" element (returns a string)  
[1] "Michael"  
  
patient.1["name"] # Get "name" slice (returns a sub-list)  
  
$name  
[1] "Michael"  
  
c(typeof(patient.1$name), typeof(patient.1["name"]))  
[1] "character" "list"
```

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Function

- We have used a lot of built-in functions: `mean()`, `subset()`, `plot()`, `read.table()`...
- An important part of programming and data analysis is to write custom functions
- Functions help make code **modular**
- Functions make debugging easier
- Remember: this entire class is about applying *functions* to *data*

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what is a function?

A function is a machine that turns **input objects** (arguments) into an **output object** (return value) according to a definite rule.

- Let's look at a really simple function

```
addOne <- function(x) {  
  x + 1  
}
```

- x is the **argument** or **input**
- The function **output** is the input x incremented by 1

```
addOne(12)
```

```
[1] 13
```

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Another example

- Here's a function that returns a % given a numerator, denominator, and desired number of decimal values

```
calculatePercentage <- function(x, y, d) {  
  decimal <- x / y # Calculate decimal value  
  round(100 * decimal, d) # Convert to % and round to d digits  
}  
  
calculatePercentage(27, 80, 1)
```

```
[1] 33.8
```

- If you're calculating several %'s for your report, you should use this kind of function instead of repeatedly copying and pasting code

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Function return a list

- Here's a function that takes a person's full name (FirstName LastName), weight in lb and height in inches and converts it into a list with the person's first name, person's last name, weight in kg, height in m, and BMI.

```
createPatientRecord <- function(full.name, weight, height) {  
  name.list <- strsplit(full.name, split=" ")[[1]]  
  first.name <- name.list[1]  
  last.name <- name.list[2]  
  weight.in.kg <- weight / 2.2  
  height.in.m <- height * 0.0254  
  bmi <- weight.in.kg / (height.in.m ^ 2)  
  list(first.name=first.name, last.name=last.name, weight=weight.in.kg,  
    height=height.in.m,  
    bmi=bmi)  
}
```

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Try out function

```
createPatientRecord("Michael Smith", 185, 12 * 6 + 1)
```

```
$first.name  
[1] "Michael"  
  
$last.name  
[1] "Smith"  
  
$weight  
[1] 84.09091  
  
$height  
[1] 1.8542  
  
$bmi  
[1] 24.45884
```

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Another example

- Calculate mean, median and standard deviation

```
threeNumberSummary <- function(x) {  
  c(mean=mean(x), median=median(x), sd=sd(x))  
}  
x <- rnorm(100, mean=5, sd=2) # Vector of 100 normals with mean 5 and sd 2  
threeNumberSummary(x)
```

```
mean      median      sd  
4.926875 5.050984 1.953703
```

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If-else statement

- Oftentimes we want our code to have different effects depending on the features of the input
- Example: Calculating a student's letter grade
 - If grade ≥ 90 , assign A
 - Otherwise, if grade ≥ 80 , assign B
 - Otherwise, if grade ≥ 70 , assign C
 - In all other cases, assign F
- To code this up, we use if-else statements

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If-else example

```
calculateLetterGrade <- function(x) {  
  if(x >= 90) {  
    grade <- "A"  
  } else if(x >= 80) {  
    grade <- "B"  
  } else if(x >= 70) {  
    grade <- "C"  
  } else {  
    grade <- "F"  
  }  
  grade  
}  
  
course.grades <- c(92, 78, 87, 91, 62)  
sapply(course.grades, FUN=calculateLetterGrade)
```

```
[1] "A" "C" "B" "A" "F"
```

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return()

- In the previous examples we specified the output simply by writing the output variable as the last line of the function
- More explicitly, we can use the `return()` function

```
addOne <- function(x) {  
  return(x + 1)  
}  
  
addOne(12)
```

```
[1] 13
```

- We will generally avoid the `return()` function, but you can use it if necessary or if it makes writing a particular function easier.

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Workshop 4 : Transform

For the first two problems we'll use the Cars93 data set from the MASS library.

```
library(MASS)
```

1. Manipulating data frames

Use the **transform()** and **log()** functions to create a new data frame called Cars93.log that has MPG.highway and MPG.city replaced with log(MPG.highway) and log(MPG.city).

2. Functions, lists, and if-else

- Write a function called **isPassingGrade** whose input x is a number, and which returns FALSE if x is lower than 50 and TRUE otherwise.
- Write a function called **sendMessage** whose input x is a number, and which prints **Congratulations** if **isPassingGrade(x)** is TRUE and prints **Oh no!** if **isPassingGrade(x)** is FALSE.

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Data Wrangling and Visualization

Common Problem

- One of the most common problems you'll encounter when importing manually-entered data is inconsistent data types within columns
- For a simple example, let's look at TVhours column in a messy version of the survey data

```
survey.messy <- read.csv("survey_messy.csv", header=TRUE)  
survey.messy$TVhours
```

```
[1] 1           8h          4           5  
[5] 3           ~10         0           10  
[9] 15 (incl movies) 4           0           0  
[13] 10          4           10          2hours  
[17] 5           3           0           1  
[21] 2           7           3           10  
[25] 6.5          40          0           12  
[29] adfjalkj     3           0           0  
16 Levels: ~10 0 1 10 12 15 (incl movies) 2 2hours 3 4 40 5 6.5 7 ... adfjalkj
```

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What are the problems?

```
str(survey.messy)
```

```
'data.frame': 31 obs. of 6 variables:  
 $ Program      : Factor w/ 3 levels "MISM","Other",...: 1 2 1 3 2 3 2 1 3 3 ...  
 $ PriorExp     : Factor w/ 3 levels "Extensive experience",...: 3 3 1 2 2 3 3 3  
 2 1 ...  
 $ Rexperience   : Factor w/ 3 levels "Basic competence",...: 3 1 1 2 3 3 3 3 3 3 ...  
 ...  
 $ OperatingSystem: Factor w/ 2 levels "Mac OS X","Windows": 2 2 2 2 2 1 1 2 1 2  
 ...  
 $ TVhours       : Factor w/ 16 levels "~10","0","1",...: 3 15 10 12 9 1 2 4 6 10  
 ...  
 $ Editor        : Factor w/ 1 level "Microsoft Word": 1 1 1 1 1 1 1 1 1 1 ...
```

- Several of the entries have non-numeric values in them (they contain strings)
- As a result, TVhours is being imported as factor

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Fix the type

```
as.character(tv.hours.messy)[1:30]
```

```
[1] "1"          "8h"         "4"  
[4] "5"          "3"           "~10"  
[7] "0"          "10"          "15 (incl movies)"  
[10] "4"          "0"           "0"  
[13] "10"         "4"           "10"  
[16] "2hours"    "5"           "3"  
[19] "0"          "1"           "2"  
[22] "7"          "3"           "10"  
[25] "6.5"        "40"          "0"  
[28] "12"         "adfjalkj"   "3"
```

```
as.numeric(as.character(tv.hours.messy))[1:30]
```

```
[1] 1.0      NA     4.0    5.0    3.0    NA     0.0   10.0   NA    4.0    0.0    0.0   10.0   4.0  
[15] 10.0     NA    5.0    3.0    0.0    1.0    2.0    7.0    3.0   10.0   6.5    40.0   0.0   12.0  
[29] NA       3.0
```

```
typeof(as.numeric(as.character(tv.hours.messy))) # Success!! (Almost...)
```

```
[1] "double"
```

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A small improvement

- All the corrupted cells now appear as NA, which is R's missing indicator
- We can do a little better by cleaning up the vector once we get it to character form

```
tv.hours.strings <- as.character(tv.hours.messy)  
tv.hours.strings
```

```
[1] "1"          "8h"         "4"  
[4] "5"          "3"           "~10"  
[7] "0"          "10"          "15 (incl movies)"  
[10] "4"          "0"           "0"  
[13] "10"         "4"           "10"  
[16] "2hours"    "5"           "3"  
[19] "0"          "1"           "2"  
[22] "7"          "3"           "10"  
[25] "6.5"        "40"          "0"  
[28] "12"         "adfjalkj"   "3"  
[31] "0"
```

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Deleting non-numeric (or .) characters

```
tv.hours.strings
```

```
[1] "1"                 "8h"                "4"  
[4] "5"                 "3"                  "~10"  
[7] "0"                 "10"                "15 (incl movies)"  
[10] "4"                "0"                  "0"  
[13] "10"               "4"                  "10"  
[16] "2hours"            "5"                  "3"  
[19] "0"                 "1"                  "2"  
[22] "7"                 "3"                  "10"  
[25] "6.5"               "40"                "0"  
[28] "12"                "adfjalkj"           "3"  
[31] "0"
```

```
# Use gsub() to replace everything except digits and '.' with a blank ""  
gsub("[^0-9.]", "", tv.hours.strings)
```

```
[1] "1"    "8"    "4"    "5"    "3"    "10"   "0"    "10"   "15"   "4"    "0"  
[12] "0"   "10"   "4"    "10"   "2"    "5"    "3"    "0"    "1"    "2"    "7"  
[23] "3"   "10"   "6.5"  "40"   "0"    "12"   ""     "3"    "0"    "
```

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Redo

```
tv.hours.messy
```

```
[1] 1                 8h                4                 5  
[5] 3                 ~10               0                 10  
[9] 15 (incl movies) 4                 0                 0  
[13] 10                4                 10                2hours  
[17] 5                 3                 0                 1  
[21] 2                 7                 3                 10  
[25] 6.5               40                0                 12  
[29] adfjalkj           3                 0  
16 Levels: -10 0 1 10 12 15 (incl movies) 2 2hours 3 4 40 5 6.5 7 ... adfjalkj
```

```
tv.hours.clean <- as.numeric(gsub("[^0-9.]", "", tv.hours.strings))  
tv.hours.clean
```

```
[1] 1.0  8.0  4.0  5.0  3.0 10.0  0.0 10.0 15.0  4.0  0.0  0.0 10.0  4.0  
[15] 10.0 2.0  5.0  3.0  0.0  1.0  2.0  7.0  3.0 10.0  6.5 40.0  0.0 12.0  
[29] NA    3.0  0.0
```

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Another approach

- We can also handle this problem by setting `stringsAsFactors = FALSE` when importing our data.

```
survey.messy <- read.csv("survey_messy.csv", header=TRUE, stringsAsFactors=FALSE)
str(survey.messy)
```

```
'data.frame': 31 obs. of 6 variables:
 $ Program      : chr "MISM" "Other" "MISM" "PPM" ...
 $ PriorExp     : chr "Some experience" "Some experience" "Extensive
experience" "Never programmed before" ...
 $ Rexperience   : chr "Never used" "Basic competence" "Basic competence"
"Installed on machine" ...
 $ OperatingSystem: chr "Windows" "Windows" "Windows" "Windows" ...
 $ TVhours       : chr "1" "8h" "4" "5" ...
 $ Editor        : chr "Microsoft Word" "Microsoft Word" "Microsoft Word"
"Microsoft Word" ...
```

- Now everything is a character instead of a factor

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One-line Cleanup

- Let's clean up the `TVhours` column and cast it to numeric all in one command

```
survey <- transform(survey.messy, TVhours = as.numeric(gsub("[^0-9.]", "", 
TVhours)))
str(survey)
```

```
'data.frame': 31 obs. of 6 variables:
 $ Program      : chr "MISM" "Other" "MISM" "PPM" ...
 $ PriorExp     : chr "Some experience" "Some experience" "Extensive
experience" "Never programmed before" ...
 $ Rexperience   : chr "Never used" "Basic competence" "Basic competence"
"Installed on machine" ...
 $ OperatingSystem: chr "Windows" "Windows" "Windows" "Windows" ...
 $ TVhours       : num 1 8 4 5 3 10 0 10 15 4 ...
 $ Editor        : chr "Microsoft Word" "Microsoft Word" "Microsoft Word"
"Microsoft Word" ...
```

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What about other character column?

```
table(survey[["Program"]])
```

MISM	Other	PPM
10	6	15

```
table(as.factor(survey[["Program"]]))
```

MISM	Other	PPM
10	6	15

- Having factors coded as characters may be OK for many parts of our analysis

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Let's fix it

```
# Figure out which columns are coded as characters  
chr.indexes <- sapply(survey, FUN = is.character)  
chr.indexes
```

Program	PriorExp	Rexperience	OperatingSystem
TRUE	TRUE	TRUE	TRUE
TVhours	Editor		
FALSE	TRUE		

```
# Re-code all of the character columns to factors  
survey[chr.indexes] <- lapply(survey[chr.indexes], FUN = as.factor)
```

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Here is the outcome

```
str(survey)
```

```
'data.frame': 31 obs. of 6 variables:  
 $ Program      : Factor w/ 3 levels "MISM","Other",...: 1 2 1 3 2 3 2 1 3 3 ...  
 $ PriorExp     : Factor w/ 3 levels "Extensive experience",...: 3 3 1 2 2 3 3 3  
 2 1 ...  
 $ Rexperience   : Factor w/ 3 levels "Basic competence",...: 3 1 1 2 3 3 3 3 3 3  
 ...  
 $ OperatingSystem: Factor w/ 2 levels "Mac OS X","Windows": 2 2 2 2 2 1 1 2 1 2  
 ...  
 $ TVhours       : num  1 8 4 5 3 10 0 10 15 4 ...  
 $ Editor        : Factor w/ 1 level "Microsoft Word": 1 1 1 1 1 1 1 1 1 1 ...
```

- Success!

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Another example

- When data is entered manually, misspellings and case changes are very common
- E.g., a column showing life support mechanism may look like,

```
life.support <- as.factor(c("dialysis", "Ventilation", "Dialysis", "dialysis",  
 "none", "None", "nnone", "dyalysis", "dialysis", "ventilation", "none"))  
summary(life.support)
```

dialysis	Dialysis	dyalysis	nnone	none	None
3	1	1	1	2	1
ventilation	Ventilation				
1	1				

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```
summary(life.support)
```

dialysis	Dialysis	dyalysis	nnone	none	None
3	1	1	1	2	1
ventilation	Ventilation				
1	1				

- This factor has 8 levels even though it should have 3 (dialysis, ventilation, none)
- We can fix many of the typos by running spellcheck in Excel before importing data, or by changing the values on a case-by-case basis later

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[l/s/t]apply() functions?

- These are all efficient ways of applying a function to margins of an array or elements of a list
- Before we talk about the details of `apply()` and its relatives, we should first understand loops
- **loops** are ways of iterating over data
- The `apply()` functions can be thought of as good *alternatives* to loops

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Loop

```
for(i in 1:4) {  
  print(i)  
}
```

```
[1] 1  
[1] 2  
[1] 3  
[1] 4
```

```
phrase <- "Good Night, "  
for(word in c("and", "Good", "Luck")) {  
  phrase <- paste(phrase, word)  
  print(phrase)  
}
```

```
[1] "Good Night, and"  
[1] "Good Night, and Good"  
[1] "Good Night, and Good Luck"
```

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Loop Syntax

A **for loop** executes a chunk of code for every value of an **index variable** in an **index set**

- The basic syntax takes the form

```
for(index.variable in index.set) {  
  code to be repeated at every value of index.variable  
}
```

- The index set is often a vector of integers, but can be more general

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Example

```
index.set <- rnorm(4) # 4 random standard normal variables  
index.set
```

```
[1] -1.9912818  0.7119512  0.3999575  0.5872188
```

```
for(i in index.set) {  
  print(abs(i))  
}
```

```
[1] 1.991282  
[1] 0.7119512  
[1] 0.3999575  
[1] 0.5872188
```

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Example

```
index.set <- list(name="Michael", weight=185, is.male=TRUE) # a list  
for(i in index.set) {  
  print(c(i, typeof(i)))  
}
```

```
[1] "Michael"    "character"  
[1] "185"        "double"  
[1] "TRUE"        "logical"
```

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Example

```
fake.data <- matrix(rnorm(500), ncol=5) # create fake 100 x 5 data set
head(fake.data,2) # print first two rows
```

```
[,1]      [,2]      [,3]      [,4]      [,5]
[1,] 0.9551196 -0.3985364 -0.2338078 -1.018674 -0.684313
[2,] 0.6483192 -0.5487889  0.2091660  2.016935 -1.030668
```

```
col.sums <- numeric(ncol(fake.data)) # variable to store running column sums
for(i in 1:nrow(fake.data)) {
  col.sums <- col.sums + fake.data[i,] # add ith observation to the sum
}
print(col.sums)
```

```
[1] -12.808804 -11.552563  3.211727  4.049877 -9.901475
```

```
colSums(fake.data) # A better approach (see also colMeans())
```

```
[1] -12.808804 -11.552563  3.211727  4.049877 -9.901475
```

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While loop

- **while loops** repeat a chunk of code while the specified condition remains true

```
day <- 1
num.days <- 365
while(day <= num.days) {
  day <- day + 1
}
```

- We won't really be using while loops in this class

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Various app() function

Command	Description
apply(X, MARGIN, FUN)	Obtain a vector/array/list by applying FUN along the specified MARGIN of an array or matrix X
lapply(X, FUN)	Obtain a list by applying FUN to the elements of a list x
sapply(X, FUN)	Simplified version of lapply. Returns a vector/array instead of list.
tapply(X, INDEX, FUN)	Obtain a table by applying FUN to each combination of the factors given in INDEX

- These functions are (good!) alternatives to loops
- They are typically *more efficient* than loops (often run considerably faster on large data sets)
- Take practice to get used to, but make analysis easier to debug and less prone to error when used effectively

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Example: apply()

```
colMeans(fake.data)  
[1] -0.12808804 -0.11552563  0.03211727  0.04049877 -0.09901475  
  
apply(fake.data, MARGIN=2, FUN=mean) # MARGIN = 1 for rows, 2 for columns  
[1] -0.12808804 -0.11552563  0.03211727  0.04049877 -0.09901475  
  
# Function that calculates proportion of vector indexes that are > 0  
propPositive <- function(x) mean(x > 0)  
apply(fake.data, MARGIN=2, FUN=propPositive)  
[1] 0.51 0.47 0.51 0.51 0.46
```

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Example: lapply(), sapply()

```
lapply(survey, is.factor) # Returns a list
```

```
$Program  
[1] TRUE  
  
$PriorExp  
[1] TRUE  
  
$Rexperience  
[1] TRUE  
  
$OperatingSystem  
[1] TRUE  
  
$TVhours  
[1] FALSE  
  
$Editor  
[1] TRUE
```

```
sapply(survey, FUN = is.factor) # Returns a vector with named elements
```

Program	PriorExp	Rexperience	OperatingSystem
TRUE	TRUE	TRUE	TRUE
TVhours	Editor		
FALSE	TRUE		

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Example: apply, lapply, sapply

```
apply(cars, 2, FUN=mean) # Data frames are arrays
```

```
speed dist  
15.40 42.98
```

```
lapply(cars, FUN=mean) # Data frames are also lists
```

```
$speed  
[1] 15.4  
  
$dist  
[1] 42.98
```

```
sapply(cars, FUN=mean) # sapply() is just simplified lapply()
```

```
speed dist  
15.40 42.98
```

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tapply()

- Think of tapply() as a generalized form of the table() function

```
library(MASS)
# Get a count table, data broken down by Origin and DriveTrain
table(Cars93$Origin, Cars93$DriveTrain)
```

	4WD	Front	Rear
USA	5	34	9
non-USA	5	33	7

```
# Calculate average MPG.City, broken down by Origin and Drivetrain
tapply(Cars93$MPG.city, INDEX = Cars93[c("Origin", "DriveTrain")], FUN=mean)
```

	DriveTrain			
Origin	4WD	Front	Rear	
USA	17.6	22.14706	18.33333	
non-USA	23.4	24.93939	19.14286	

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Example: tapply()

- Let's get the average horsepower by car Origin and Type

```
tapply(Cars93[["Horsepower"]], INDEX = Cars93[c("Origin", "Type")], FUN=mean)
```

	Type						
Origin	Compact	Large	Midsize	Small	Sporty	Van	
USA	117.4286	179.4545	153.5000	89.42857	166.5000	158.40	
non-USA	141.5556	NA	189.4167	91.78571	151.6667	138.25	

- What's that NA doing there?

```
any(Cars93$Origin == "non-USA" & Cars93$type == "Large")
```

```
[1] FALSE
```

- None of the non-USA manufacturers produced Large cars!

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with()

- Thus far we've repeatedly typed out the data frame name when referencing its columns
- This is because the data variables don't exist in our working environment
- Using **with**(*data*, *expr*) lets us specify that the code in *expr* should be evaluated in an environment that contains the elements of *data* as variables

```
with(Cars93, table(Origin, Type))
```

Origin	Type					
	Compact	Large	Midsize	Small	Sporty	Van
USA	7	11	10	7	8	5
non-USA	9	0	12	14	6	4

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Example: with()

```
any(Cars93$Origin == "non-USA" & Cars93>Type == "Large")
```

```
[1] FALSE
```

```
with(Cars93, any(Origin == "non-USA" & Type == "Large")) # Same effect!
```

```
[1] FALSE
```

```
with(Cars93, tapply(Horsepower, INDEX = list(Origin, Type), FUN=mean))
```

	Compact	Large	Midsize	Small	Sporty	Van
USA	117.4286	179.4545	153.5000	89.42857	166.5000	158.40
non-USA	141.5556	NA	189.4167	91.78571	151.6667	138.25

- Using **with()** makes code simpler, easier to read, and easier to debug

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Workshop 6: Loop

Loop practice

- (a) Write a function called calculateRowMeans that uses a for loop to calculate the row means of a matrix x.
- (b) Try out your function on the random matrix fake.data defined below.
- (b) Use the apply() function to calculate the row means of the matrix fake.data
- (c) Compare this to the output of the rowMeans() function to check that your calculation is correct.

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Data Summary and Standard Graphic

Let's get started

- We're going to start by operating on the `birthwt` dataset from the MASS library
- Let's get it loaded and see what we're working with

```
library(MASS)
str(birthwt)
```

```
'data.frame': 189 obs. of 10 variables:
 $ low   : int  0 0 0 0 0 0 0 0 0 ...
 $ age   : int  19 33 20 21 18 21 22 17 29 26 ...
 $ lwt   : int  182 155 105 108 107 124 118 103 123 113 ...
 $ race  : int  2 3 1 1 1 3 1 3 1 1 ...
 $ smoke : int  0 0 1 1 1 0 0 0 1 1 ...
 $ ptl   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ ht    : int  0 0 0 0 0 0 0 0 0 0 ...
 $ ui   : int  1 0 0 1 1 0 0 0 0 0 ...
 $ ftv   : int  0 3 1 2 0 0 1 1 1 0 ...
 $ bwt   : int  2523 2551 2557 2594 2600 2622 2637 2637 2663 2665 ...
```

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Renaming columns

- The dataset doesn't come with very descriptive variable names
- Let's get better column names (use `help(birthwt)` to understand the variables and come up with better names)

```
colnames(birthwt)
```

```
[1] "low"     "age"      "lwt"      "race"     "smoke"    "ptl"      "ht"       "ui"
[9] "ftv"     "bwt"
```

```
# The default names are not very descriptive
```

```
colnames(birthwt) <- c("birthwt.below.2500", "mother.age", "mother.weight",
                      "race", "mother.smokes", "previous.prem.labor", "hypertension",
                      "uterine.irr",
                      "physician.visits", "birthwt.grams")
```

```
# Better names!
```

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Renaming the variables

- The dataset doesn't come with very descriptive variable names
- Let's get better column names (use `help(birthwt)` to understand the variables and come up with better names)

```
colnames(birthwt)  
[1] "low"     "age"      "lwt"      "race"     "smoke"    "ptl"      "ht"       "ui"  
[9] "ftv"     "bwt"  
  
# The default names are not very descriptive  
  
colnames(birthwt) <- c("birthwt.below.2500", "mother.age", "mother.weight",  
  "race", "mother.smokes", "previous.prem.labor", "hypertension",  
  "uterine.irr",  
  "physician.visits", "birthwt.grams")  
  
# Better names!
```

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Renaming the factors

- All the factors are currently represented as integers
- Let's use the `transform()` and `mapvalues()` functions to convert variables to factors and give the factors more meaningful levels

```
library(plyr)  
birthwt <- transform(birthwt,  
  race = as.factor(mapvalues(race, c(1, 2, 3),  
    c("white", "black", "other"))),  
  mother.smokes = as.factor(mapvalues(mother.smokes,  
    c(0,1), c("no", "yes"))),  
  hypertension = as.factor(mapvalues(hypertension,  
    c(0,1), c("no", "yes"))),  
  uterine.irr = as.factor(mapvalues(uterine.irr,  
    c(0,1), c("no", "yes"))),  
  birthwt.below.2500 = as.factor(mapvalues(birthwt.below.2500,  
    c(0,1), c("no", "yes"))))
```

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Summary of the data

- Now that things are coded correctly, we can look at an overall summary

```
summary(birthwt)
```

```
birthwt.below.2500    mother.age      mother.weight      race
no :130                Min. :14.00     Min.   : 80.0       black:26
yes: 59               1st Qu.:19.00    1st Qu.:110.0     other:67
                           Median :23.00     Median :121.0     white:96
                           Mean   :23.24     Mean   :129.8
                           3rd Qu.:26.00    3rd Qu.:140.0
                           Max.  :45.00     Max.  :250.0
mother.smokes previous.prem.labor hypertension uterine.irr
no :115                Min. :0.0000    no :177        no :161
yes: 74                 1st Qu.:0.0000  yes: 12       yes: 28
                           Median :0.0000
                           Mean  :0.1958
                           3rd Qu.:0.0000
                           Max.  :3.0000
physician.visits birthwt.grams
Min.  :0.0000    Min.   : 709
1st Qu.:0.0000   1st Qu.:2414
Median :0.0000    Median :2977
Mean   :0.7937    Mean   :2945
3rd Qu.:1.0000   3rd Qu.:3487
Max.   :6.0000    Max.   :4990
```

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A simple table

- Let's use the `tapply()` function to see what the average birthweight looks like when broken down by race and smoking status

```
with(birthwt, tapply(birthwt.grams, INDEX = list(race, mother.smokes), FUN =
mean))
```

	no	yes
black	2854.500	2504.000
other	2815.782	2757.167
white	3428.750	2826.846

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Output table

- Let's use the header `{r, results='asis'}`, along with the `kable()` function from the `knitr` library

```
library(knitr)
kable(with(birthwt, tapply(birthwt.grams, INDEX = list(race, mother.smokes), FUN = mean)), format = "markdown")
```

	no	yes
black	2854.500	2504.000
other	2815.782	2757.167
white	3428.750	2826.846

- `kable()` outputs the table in a way that Markdown can read and nicely display
- Note: changing the CSS changes the table appearance

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aggregate() function

- Let's first recall what `tapply()` does
- Command: `tapply(X, INDEX, FUN)`
 - Applies `FUN` to `X` grouped by factors in `INDEX`
- `aggregate()` performs a similar operation, but presents the results in a form that is at times more convenient
- There are many ways to call the `aggregate()` function
- Analog of `tapply` call: `aggregate(X, by, FUN)`
 - Here, `by` is exactly like `INDEX`

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Example: tapply vs aggregate

```
library(MASS)
with(birthwt, tapply(birthwt.grams, INDEX = list(race, mother.smokes), FUN =
mean)) # tapply
```

```
      no      yes
black 2854.500 2504.000
other 2815.782 2757.167
white 3428.750 2826.846
```

```
with(birthwt, aggregate(birthwt.grams, by = list(race, mother.smokes), FUN =
mean)) # aggregate
```

```
  Group.1 Group.2      x
1   black      no 2854.500
2   other      no 2815.782
3   white      no 3428.750
4   black     yes 2504.000
5   other     yes 2757.167
6   white     yes 2826.846
```

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Different syntax

- Here's a convenient alternative way to call aggregate
- It uses the R formula syntax, which we'll learn more about when we discuss regression

```
aggregate(birthwt.grams ~ race + mother.smokes, FUN=mean, data=birthwt)
```

```
  race mother.smokes birthwt.grams
1 black      no 2854.500
2 other      no 2815.782
3 white      no 3428.750
4 black     yes 2504.000
5 other     yes 2757.167
6 white     yes 2826.846
```

- We'll see later that aggregate output can be more convenient for plotting

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```
weight.smoke.tbl <- with(birthwt, table(birthwt.below.2500, mother.smokes))  
weight.smoke.tbl
```

```
mother.smokes  
birthwt.below.2500 no yes  
no 86 44  
yes 29 30
```

- The odds of low bwt among non-smoking mothers is

```
or.smoke.bwt <- (weight.smoke.tbl[2,2] / weight.smoke.tbl[1,2]) /  
(weight.smoke.tbl[2,1] / weight.smoke.tbl[1,1])  
or.smoke.bwt
```

```
[1] 2.021944
```

- So the odds of low birth weight are 2 times higher when the mother smokes

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- Is the mother's age correlated with birth weight?

```
with(birthwt, cor(birthwt.grams, mother.age)) # Calculate correlation  
  
[1] 0.09031781
```

- Does this change when we account for smoking status?

```
with(birthwt, cor(birthwt.grams[mother.smokes == "yes"],  
mother.age[mother.smokes == "yes"]))  
  
[1] -0.1441649  
  
with(birthwt, cor(birthwt.grams[mother.smokes == "no"], mother.age[mother.smokes  
== "no"]))  
  
[1] 0.2014558
```

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by() function

- Think of the `by(data, INDICES, FUN)` function as a `tapply()` function that operates on data frames instead of just vectors
- When using `tapply(X, INDEX, FUN)`, `X` is generally a numeric vector
- To calculate correlations, we need to allow `x` to be a data frame or matrix

```
by(data = birthwt[c("birthwt.grams", "mother.age")],
   INDICES = birthwt["mother.smokes"],
   FUN = function(x) {cor(x[,1], x[,2])})
```



```
mother.smokes: no
[1] 0.2014558
-----
mother.smokes: yes
[1] -0.1441649
```

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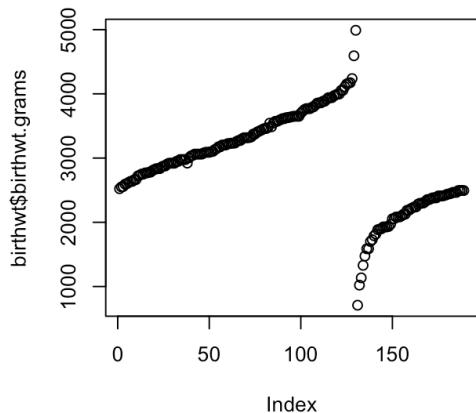
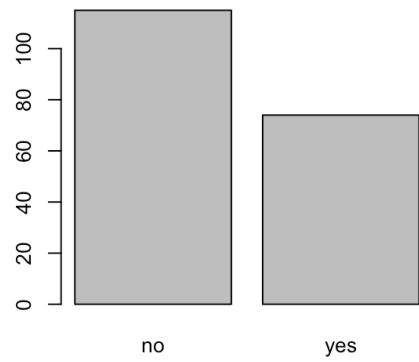
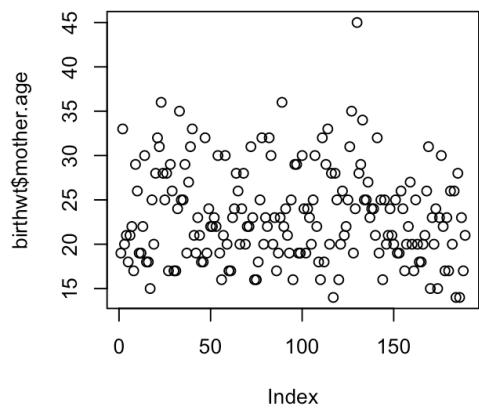
Basic single plot

Let's continue with the `birthwt` data from the `MASS` library.

Here are some basic single-variable plots.

```
par(mfrow = c(2,2)) # Display plots in a single 2 x 2 figure
plot(birthwt$mother.age)
with(birthwt, hist(mother.age))
plot(birthwt$mother.smokes)
plot(birthwt$birthwt.grams)
```

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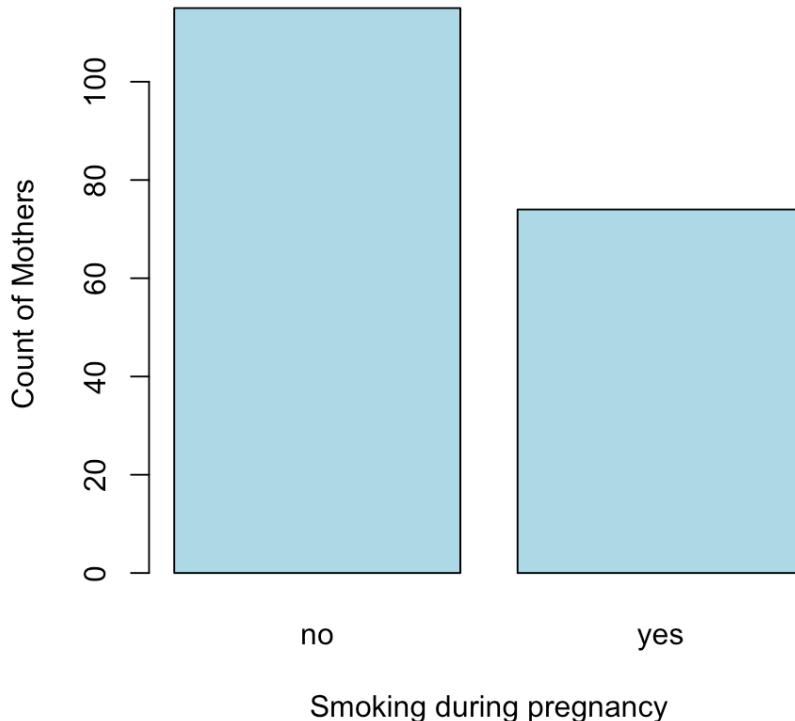


Another example

Let's add more information to the smoking bar plot, and also change the color by setting the `col` option.

```
plot(birthwt$mother.smokes,
      main = "Mothers Who Smoked In Pregnancy",
      xlab = "Smoking during pregnancy",
      ylab = "Count of Mothers",
      col = 'lightblue')
```

Mothers Who Smoked In Pregnancy



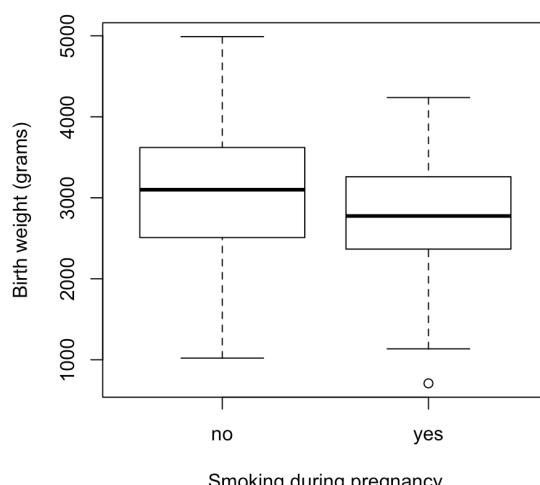
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Plots with several variables

If we call `plot(x, y, ...)` with `x` a factor and `y` numeric, R will produce boxplots of `y` at every level of `x`.

```
with(birthwt, plot(mother.smokes, birthwt.grams,
                    main = "Birth Weight by Smoking Status",
                    xlab = "Smoking during pregnancy",
                    ylab = "Birth weight (grams)"))
```

Birth Weight by Smoking Status



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More on ggplot2 demo

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Workshop 7: Plot data

Plotting the Cars93 data

- (a) Use qplot to create a scatterplot with Price on the y-axis and EngineSize on the x-axis.
- (b) Repeat part (a) using the ggplot function and geom_point() layer.
- (c) Repeat part (c), but this time specifying that the color mapping should depend on Type and the shape mapping should depend on DriveTrain.

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Other Important Packages



To load data

RODBC, RMySQL, RPostgreSQL, RSQLite - If you'd like to read in data from a database, these packages are a good place to start. Choose the package that fits your type of database.

XLConnect, xlsx - These packages help you read and write Microsoft Excel files from R. You can also just export your spreadsheets from Excel as .csv's.

foreign - Want to read a SAS data set into R? Or an SPSS data set? Foreign provides functions that help you load data files from other programs into R.

R can handle plain text files – no package required. Just use the functions `read.csv`, `read.table`, and `read.fwf..`

xlsx

```
df <- read.xlsx("<name and extension of your file>",
                 sheetIndex = 1)
```

Note that it is necessary to add a sheet name or a sheet index to this function. In the example above, the first sheet of the Excel file was assigned. If you have a bigger data set, you might get better performance when using the `read.xlsx2()` function:

```
df <- read.xlsx2("<name and extension of your file>",
                  sheetIndex = 1,
                  startRow=2,
                  colIndex = 2)
```

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```
write.xlsx(df,
           "df.xlsx",
           sheetName="Data Frame")
```

The function requires you first to specify what data frame you want to export. In the second argument, you specify the name of the file that you are outputting. If, however, you want to write the data frame to a file that already exists, you can execute the following command:

```
write.xlsx(df,
           "<name and extension of your existing file>",
           sheetName="Data Frame"
           append=TRUE)
```

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To manipulate data

dplyr - Essential shortcuts for subsetting, summarizing, rearranging, and joining together data sets. dplyr is our go to package for fast data manipulation.

tidyverse - Tools for changing the layout of your data sets. Use the gather and spread functions to convert your data into the tidy format, the layout R likes best.

stringr - Easy to learn tools for regular expressions and character strings.

lubridate - Tools that make working with dates and times easier.

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dplyr

```
install.packages("dplyr")
```

```
library(dplyr)
```

dplyr verbs

Description

`select()` select columns

`filter()` filter rows

`arrange()` re-order or arrange rows

`mutate()` create new columns

`summarise()` summarise values

`group_by()` allows for group operations in the “split-apply-combine” concept

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select

Select a set of columns: the name and the sleep_total columns.

```
sleepData <- select(msleep, name, sleep_total)  
head(sleepData)
```

```
##           name sleep_total  
## 1      Cheetah     12.1  
## 2    Owl monkey    17.0  
## 3 Mountain beaver 14.4  
## 4 Greater short-tailed shrew 14.9  
## 5          Cow     4.0  
## 6 Three-toed sloth 14.4
```

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Subtraction (-)

To select all the columns *except* a specific column, use the “-“ (subtraction) operator (also known as negative indexing)

```
head(select(msleep, -name))
```

```
##           genus vore      order conservation sleep_total sleep_rem  
## 1  Acinonyx carni Carnivora         lc     12.1       NA  
## 2      Aotus omni Primates        <NA>    17.0      1.8  
## 3   Aplodontia herbi Rodentia        nt     14.4      2.4  
## 4      Blarina omni Soricomorpha      lc     14.9      2.3  
## 5      Bos herbi Artiodactyla domesticated 4.0      0.7  
## 6   Bradypus herbi Pilosa        <NA>    14.4      2.2  
##           sleep_cycle awake brainwt bodywt  
## 1             NA  11.9      NA 50.000  
## 2             NA   7.0 0.01550  0.480  
## 3             NA   9.6      NA  1.350  
## 4  0.1333333  9.1 0.00029  0.019  
## 5  0.6666667 20.0 0.42300 600.000  
## 6  0.7666667  9.6      NA  3.850
```

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colon (:)

To select a range of columns by name, use the “:” (colon) operator

```
head(select(msleep, name:order))
```

```
##          name   genus  vore      order
## 1       Cheetah Acinonyx carni  Carnivora
## 2     Owl monkey     Aotus  omni   Primates
## 3 Mountain beaver  Aplodontia herbi Rodentia
## 4 Greater short-tailed shrew    Blarina  omni Soricomorpha
## 5            Cow        Bos herbi Artiodactyla
## 6 Three-toed sloth   Bradypus herbi   Pilosa
```

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To select all columns that start with the character string “sl”, use the function `starts_with()`

```
head(select(msleep, starts_with("sl")))
```

```
##   sleep_total sleep_rem sleep_cycle
## 1      12.1        NA        NA
## 2      17.0        1.8        NA
## 3      14.4        2.4        NA
## 4      14.9        2.3  0.1333333
## 5       4.0        0.7  0.6666667
## 6      14.4        2.2  0.7666667
```

Some additional options to select columns based on a specific criteria include

1. `ends_with()` = Select columns that end with a character string
2. `contains()` = Select columns that contain a character string
3. `matches()` = Select columns that match a regular expression
4. `one_of()` = Select columns names that are from a group of names

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filter

Filter the rows for mammals that sleep a total of more than 16 hours.

```
filter(msleep, sleep_total >= 16)
```

```
##           name   genus  vore      order conservation
## 1     Owl monkey   Aotus  omni Primates    <NA>
## 2 Long-nosed armadillo Dasypus carni Cingulata      lc
## 3 North American Opossum Didelphis  omni Didelphimorphia      lc
## 4     Big brown bat Eptesicus insecti Chiroptera      lc
## 5 Thick-tailed opossum Lutreolina carni Didelphimorphia      lc
## 6     Little brown bat   Myotis insecti Chiroptera    <NA>
## 7     Giant armadillo Priodontes insecti Cingulata      en
## 8 Arctic ground squirrel Spermophilus  herbi Rodentia      lc
##   sleep_total sleep_rem sleep_cycle awake brainwt bodywt
## 1       17.0      1.8        NA    7.0  0.01550  0.480
## 2       17.4      3.1  0.3833333    6.6  0.01080  3.500
## 3       18.0      4.9  0.3333333    6.0  0.00630  1.700
## 4       19.7      3.9  0.1166667    4.3  0.00030  0.023
## 5       19.4      6.6        NA    4.6      NA  0.370
## 6       19.9      2.0  0.2000000    4.1  0.00025  0.010
## 7       18.1      6.1        NA    5.9  0.08100 60.000
## 8       16.6      NA        NA    7.4  0.00570  0.920
```

filter with and

Filter the rows for mammals that sleep a total of more than 16 hours *and* have a body weight of greater than 1 kilogram.

```
filter(msleep, sleep_total >= 16, bodywt >= 1)
```

```
##           name   genus  vore      order conservation
## 1 Long-nosed armadillo Dasypus carni Cingulata      lc
## 2 North American Opossum Didelphis  omni Didelphimorphia      lc
## 3     Giant armadillo Priodontes insecti Cingulata      en
##   sleep_total sleep_rem sleep_cycle awake brainwt bodywt
## 1       17.4      3.1  0.3833333    6.6  0.0108     3.5
## 2       18.0      4.9  0.3333333    6.0  0.0063     1.7
## 3       18.1      6.1        NA    5.9  0.0810    60.0
```

Pipe (%>%)

```
head(select(msleep, name, sleep_total))
```

```
##           name sleep_total
## 1          Cheetah     12.1
## 2      Owl monkey    17.0
## 3 Mountain beaver   14.4
## 4 Greater short-tailed shrew 14.9
## 5          Cow       4.0
## 6 Three-toed sloth  14.4
```

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```
msleep %>%
  select(name, sleep_total) %>%
  head
```

```
##           name sleep_total
## 1          Cheetah     12.1
## 2      Owl monkey    17.0
## 3 Mountain beaver   14.4
## 4 Greater short-tailed shrew 14.9
## 5          Cow       4.0
## 6 Three-toed sloth  14.4
```

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sqldf

```
library(sqldf)
```

```
setwd()
crashes <- read.csv("crashes.csv")
roads <- read.csv("roads.csv")
head(crashes)
```

```
##   Year      Road N_Crashes Volume
## 1 1991 Interstate 65      25 40000
## 2 1992 Interstate 65      37 41000
## 3 1993 Interstate 65      45 45000
## 4 1994 Interstate 65      46 45600
## 5 1995 Interstate 65      46 49000
## 6 1996 Interstate 65      59 51000
```

```
tail(crashes)
```

```
##   Year      Road N_Crashes Volume
## 105 2007 Interstate 275      32 21900
## 106 2008 Interstate 275      21 21850
## 107 2009 Interstate 275      25 22100
## 108 2010 Interstate 275      24 21500
## 109 2011 Interstate 275      23 20300
## 110 2012 Interstate 275      22 21200
```

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```
print(roads)
```

```
##      Road      District Length
## 1 Interstate 65 Greenfield    262
## 2 Interstate 70 Vincennes   156
## 3 US-36 Crawfordsville 139
## 4 US-40 Greenfield    150
## 5 US-52 Crawfordsville 172
```

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Outer join

```
join_string <- "select
  crashes.*
, roads.District
, roads.Length
from crashes
  left join roads
    on crashes.Road = roads.Road"
```

```
crashes_join_roads <- sqldf(join_string,stringsAsFactors = FALSE)
```

```
## Loading required package: tcltk
```

```
head(crashes_join_roads)
```

```
##   Year      Road N_Crashes Volume District Length
## 1 1991 Interstate 65      25 40000 Greenfield    262
## 2 1992 Interstate 65      37 41000 Greenfield    262
## 3 1993 Interstate 65      45 45000 Greenfield    262
## 4 1994 Interstate 65      46 45600 Greenfield    262
## 5 1995 Interstate 65      46 49000 Greenfield    262
## 6 1996 Interstate 65      59 51000 Greenfield    262
```

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Inner join

By using an inner join, only matching rows will be kept.

```
join_string2 <- "select
  crashes.*
, roads.District
, roads.Length
from crashes
  inner join roads
    on crashes.Road = roads.Road"
```

```
crashes_join_roads2 <- sqldf(join_string2, stringsAsFactors = FALSE)
head(crashes_join_roads2)
```

```
##   Year      Road N_Crashes Volume District Length
## 1 1991 Interstate 65      25 40000 Greenfield    262
## 2 1992 Interstate 65      37 41000 Greenfield    262
## 3 1993 Interstate 65      45 45000 Greenfield    262
## 4 1994 Interstate 65      46 45600 Greenfield    262
## 5 1995 Interstate 65      46 49000 Greenfield    262
## 6 1996 Interstate 65      59 51000 Greenfield    262
```

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```
tail(crashes_join_roads2)
```

```
##   Year Road N_Crashes Volume      District Length
## 83 2007 US-36        49 24000 Crawfordsville    139
## 84 2008 US-36        52 24500 Crawfordsville    139
## 85 2009 US-36        55 24700 Crawfordsville    139
## 86 2010 US-36        35 23000 Crawfordsville    139
## 87 2011 US-36        33 21000 Crawfordsville    139
## 88 2012 US-36        31 20500 Crawfordsville    139
```

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Where

```
join_string2 <- "select
  crashes.*
  , roads.District
  , roads.Length
  from crashes
  inner join roads
  on crashes.Road = roads.Road
  where crashes.Road = 'US-40'"
crashes_join_roads4 <- sqldf(join_string2,stringsAsFactors = FALSE)
head(crashes_join_roads4)
```

```
##   Year Road N_Crashes Volume      District Length
## 1 1991 US-40        46 21000 Greenfield    150
## 2 1992 US-40       101 21500 Greenfield    150
## 3 1993 US-40        76 23000 Greenfield    150
## 4 1994 US-40        72 21000 Greenfield    150
## 5 1995 US-40        75 24000 Greenfield    150
## 6 1996 US-40       136 23500 Greenfield    150
```

```
tail(crashes_join_roads4)
```

```
##   Year Road N_Crashes Volume      District Length
## 17 2007 US-40        45 59500 Greenfield    150
## 18 2008 US-40        23 61000 Greenfield    150
## 19 2009 US-40        67 65000 Greenfield    150
## 20 2010 US-40       102 67000 Greenfield    150
## 21 2011 US-40        87 67500 Greenfield    150
## 22 2012 US-40        32 67500 Greenfield    150
```

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To visualize data

ggplot2 - R's famous package for making beautiful graphics. ggplot2 lets you use the grammar of graphics to build layered, customizable plots.

ggvis - Interactive, web based graphics built with the grammar of graphics.

rgl - Interactive 3D visualizations with R

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htmlwidgets - A fast way to build interactive (javascript based) visualizations with R. Packages that implement htmlwidgets include:

leaflet (maps)

dygraphs (time series)

DT (tables)

diagrammeR (diagrams)

network3D (network graphs)

threeJS (3D scatterplots and globes).

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googleVis - Let's you use Google Chart tools to visualize data in R.
Google Chart tools used to be called Gapminder, the graphing software
Hans Rosling made famous in his TED talk.

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To model data

car - car's Anova function is popular for making type II and type III Anova tables.

mgcv - Generalized Additive Models

lme4/nlme - Linear and Non-linear mixed effects models

randomForest - Random forest methods from machine learning

multcomp - Tools for multiple comparison testing

vcd - Visualization tools and tests for categorical data

glmnet - Lasso and elastic-net regression methods with cross validation

survival - Tools for survival analysis

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To report results

shiny - Easily make interactive, web apps with R. A perfect way to explore data and share findings with non-programmers.

R Markdown - The perfect workflow for reproducible reporting. Write R code in your markdown reports. When you run render, R Markdown will replace the code with its results and then export your report as an HTML, pdf, or MS Word document, or a HTML or pdf slideshow. The result?

Automated reporting. R Markdown is integrated straight into RStudio.

xtable - The xtable function takes an R object (like a data frame) and returns the latex or HTML code you need to paste a pretty version of the

195

Introduction to Shiny

- Open Sourced by RStudio November 2012
- Default widgets and settings make it easy to generate apps
- Don't need to know HTML, CSS and javascript to get started
- Twitter Bootstrap for default UI - looks good
- Web sockets for communication between client and server
- Reactive Programming model
- Works on Windows, Mac, Linux

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Introduction to Shiny

Ready to use shiny

- Install R from CRAN
- Useful to have Chrome, Firefox, Safari...
- Install Shiny using R command: `install.packages("shiny")`

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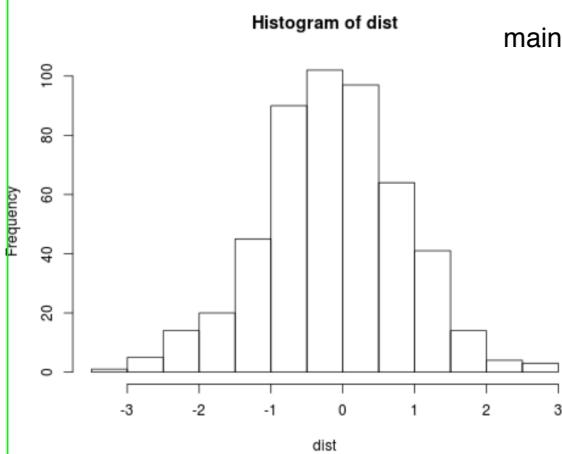
Simple Example

```
• library(shiny)  
• runExample("01_hello")
```

Hello Shiny!

headerPanel() - Title

Number of observations:
1 500 1,000



mainPanel() - Output

sidebarPanel() - Input

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ui.R :: Controls the look of the App

```
library(shiny)

# Define UI for application that draws a histogram
shinyUI(fluidPage(

  # Application title
  titlePanel("Hello Shiny!"),

  # Sidebar with a slider input for the number of bins
  sidebarLayout(
    sidebarPanel(
      sliderInput("bins",
                  "Number of bins:",
                  min = 1,
                  max = 50,
                  value = 30)
    ),

    # Show a plot of the generated distribution
    mainPanel(
      plotOutput("distPlot")
    )
  )
))
```

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server.R : Specifies what R is doing

```
library(shiny)

# Define server logic required to draw a histogram
shinyServer(function(input, output) {

  # Expression that generates a histogram. The expression is
  # wrapped in a call to renderPlot to indicate that:
  #

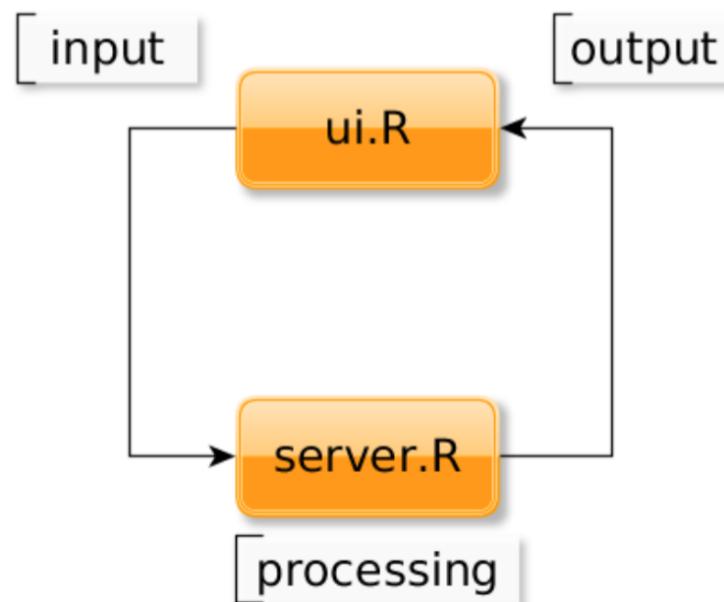
  # 1) It is "reactive" and therefore should be automatically
  #     re-executed when inputs change
  # 2) Its output type is a plot

  output$distPlot <- renderPlot({
    x      <- faithful[, 2] # Old Faithful Geyser data
    bins <- seq(min(x), max(x), length.out = input$bins + 1)

    # draw the histogram with the specified number of bins
    hist(x, breaks = bins, col = 'darkgray', border = 'white')
  })
})
```

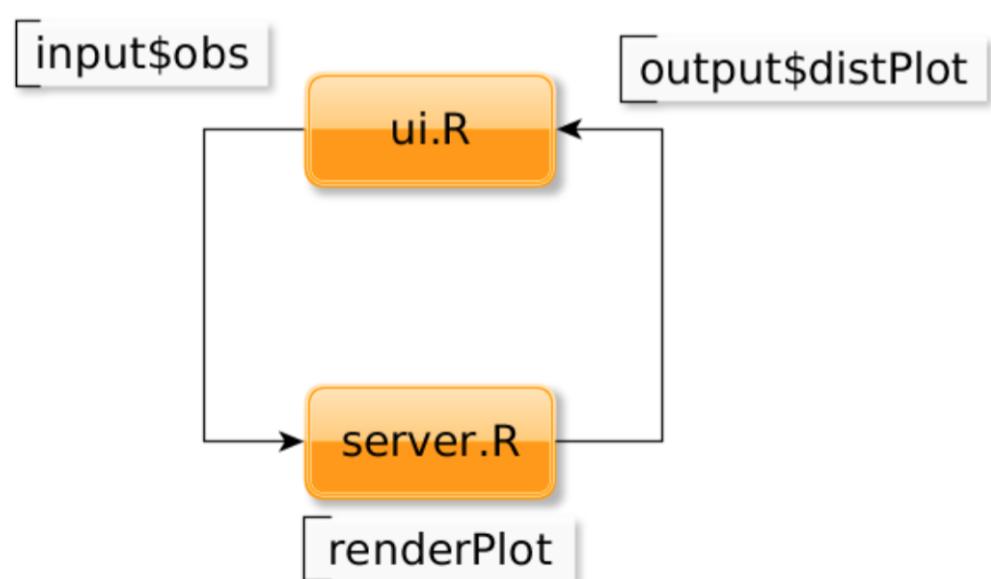
200

Relationship of ui.R and server.R



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Relationship of ui.R and server.R



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For Spatial data

sp, maptools - Tools for loading and using spatial data including shapefiles.

maps - Easy to use map polygons for plots.

ggmap - Download street maps straight from Google maps and use them as a background in your ggplots.

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To write your own R packages

devtools - An essential suite of tools for turning your code into an R package.

testthat - testthat provides an easy way to write unit tests for your code projects.

roxygen2 - A quick way to document your R packages. roxygen2 turns inline code comments into documentation pages and builds a package namespace.

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Hypothesis testing in R

Fundamental of Hypothesis Testing

There two types of **statistical inferences**, **Estimation** and **Hypothesis Testing**

Hypothesis Testing: A hypothesis is a claim (assumption) about one or more population parameters.

- Average price of a six-pack in the U.S. is $\mu = \$4.90$
- The population mean monthly cell phone bill of this city is: $\mu = \$42$
- The average number of TV sets in U.S. Homes is equal to three; $\mu = 3$



It Is always about a population parameter, not about a sample statistic

Sample evidence is used to assess the probability that the claim about the population parameter is true

A. It starts with Null Hypothesis, H_0

$$H_0: \quad =$$

1. We begin with the assumption that H_0 is true and any difference between the sample statistic and true population parameter is due to chance and not a real (systematic) difference.
2. Similar to the notion of “innocent until proven guilty”
3. That is, “innocence” is a null hypothesis.

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Null Hypo, Continued

4. Refers to the status quo
5. Always contains “=” , “≤” or “≥” sign
6. May or may not be **rejected**

B. Next we state the Alternative Hypothesis, H_1

1. Is the opposite of the null hypothesis
 1. e.g., The average number of TV sets in U.S. homes is not equal to 3 ($H_1: \mu \neq 3$)
2. Challenges the status quo
3. Never contains the “=” , “≤” or “≥” sign
4. May or may not be **proven**
5. Is generally the hypothesis that the researcher is trying to prove. Evidence is always examined with respect to H_1 , never with respect to H_0 .
6. We never “accept” H_0 , we either “reject” or “not reject” it

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Summary:

- In the process of hypothesis testing, the null hypothesis initially is assumed to be true
- Data are gathered and examined to determine whether the evidence is strong enough with respect to the alternative hypothesis to reject the assumption.
- In other words, the burden is placed on the researcher to show, using sample information, that the null hypothesis is false.
- If the sample information is sufficient enough in favor of the alternative hypothesis, then the null hypothesis is rejected. This is the same as saying if the persecutor has enough evidence of guilt, the “innocence is rejected.”
- Of course, erroneous conclusions are possible, type I and type II errors.

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Reason for Rejecting H_0

Illustration: Let say, we assume that average age in the US is 50 years ($H_0=50$). If in fact this is the true (unknown) population mean, it is unlikely that we get a sample mean of 20. So, if we have a sample that produces an average of 20, then we reject that the null hypothesis that average age is 50. (note that we are rejecting our assumption or claim). (would we get 20 if the true population mean was 50? NO. That is why we reject 50)

How Is the Test done?

We use the distribution of a Test Statistic, such as Z or t as the criteria.

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A. Rejection Region Method:

Divide the distribution into rejection and non-rejection regions

Defines the unlikely values of the sample statistic if the null hypothesis is true, the critical value(s)

Defines **rejection region** of the sampling distribution

Rejection region(s) is designated by α , (level of significance)

Typical values are .01, .05, or .10

α is selected by the researcher at the beginning

α provides the critical value(s) of the test

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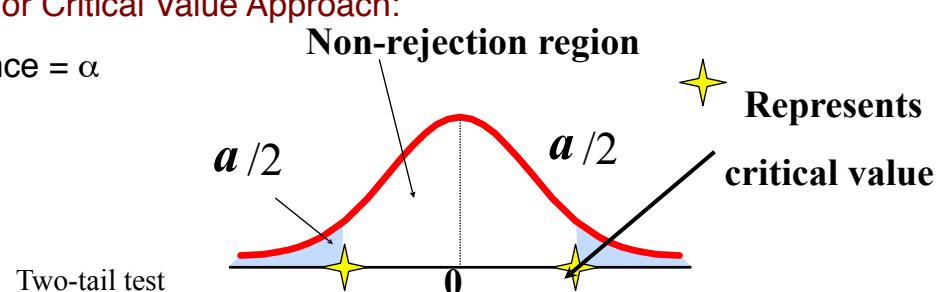


Rejection Region or Critical Value Approach:

Level of significance = α

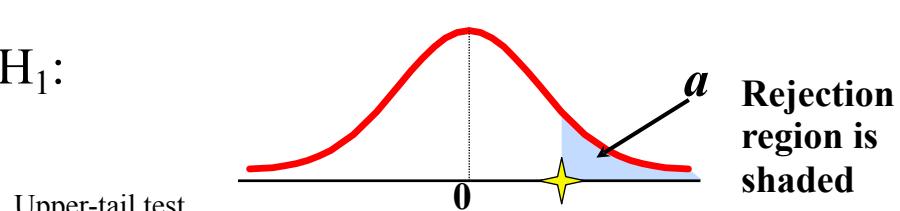
$$H_0: \mu = 12$$

$$H_1: \mu \neq 12$$



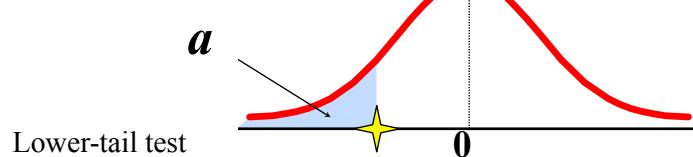
$$H_0: \mu \leq 12 \quad H_1:$$

$$\mu > 12$$



$$H_0: \mu \geq 12$$

$$H_1: \mu < 12$$



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P-Value Approach –

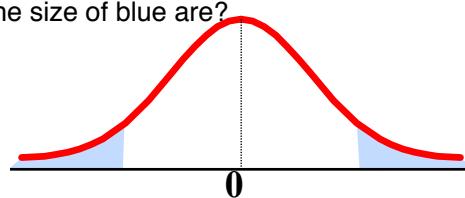
P-value=Max. Probability of (Type I Error), calculated from the sample.

Given the sample information what is the size of blue area?

$$H_0: \mu = 12$$

$$H_1: \mu \neq 12$$

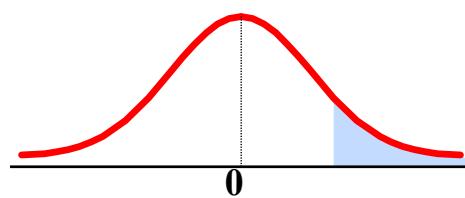
Two-tail test



$$H_0: \mu \leq 12 \quad H_1:$$

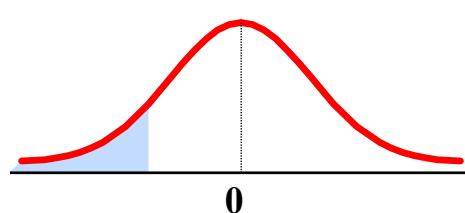
$$\mu > 12$$

Upper-tail test



$$H_0: \mu \geq 12$$

$$H_1: \mu < 12$$



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Type I and II Errors:

The size of α , the rejection region, affects the risk of making different types of incorrect decisions.

Type I Error

Rejecting a **true null hypothesis** when it should **NOT** be rejected

Considered a serious type of error

The probability of Type I Error is α

It is also called **level of significance** of the test

Type II Error

Fail to reject a **false null hypothesis** that should have been rejected

The probability of Type II Error is β

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Decision		Actual Situation		
	Hypothesis Testing			Legal System
	H ₀ True	H ₀ False	Innocence	Not innocence
Do Not Reject H ₀	No Error (1 - α)	Type II Error (β)	No Error (not guilty, found not guilty) (1 - α)	Type II Error (guilty, found not guilty) (β)
Reject H ₀	Type I Error (α)	No Error (1 - β)	Type I Error (Not guilty, found guilty) (α)	No Error (guilty, found guilty) (1 - β)

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Type I and Type II errors cannot happen at the same time

1. Type I error can only occur if H₀ is **true**
2. Type II error can only occur if H₀ is **false**
3. There is a tradeoff between type I and II errors. If the probability of type I error (α) increased, then the probability of type II error (β) declines.
4. When the difference between the hypothesized parameter and the actual true value is small, the probability of type two error (the non-rejection region) is larger.
5. Increasing the sample size, n, for a given level of α, reduces β

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B. P-Value approach to Hypothesis Testing:

1. The rejection region approach allows you to examine evidence but restrict you to not more than a certain probability (say $\alpha = 5\%$) of rejecting a true H_0 by mistake.
2. The P-value approach allows you to use the information from the sample and then calculate the **maximum probability of rejecting a true H_0 by mistake.**
3. Another way of looking at P-value is the probability of observing a sample information of “A=11.5” when the true population parameter is “12=B”. The P-value is the **maximum probability** of such mistake taking place.

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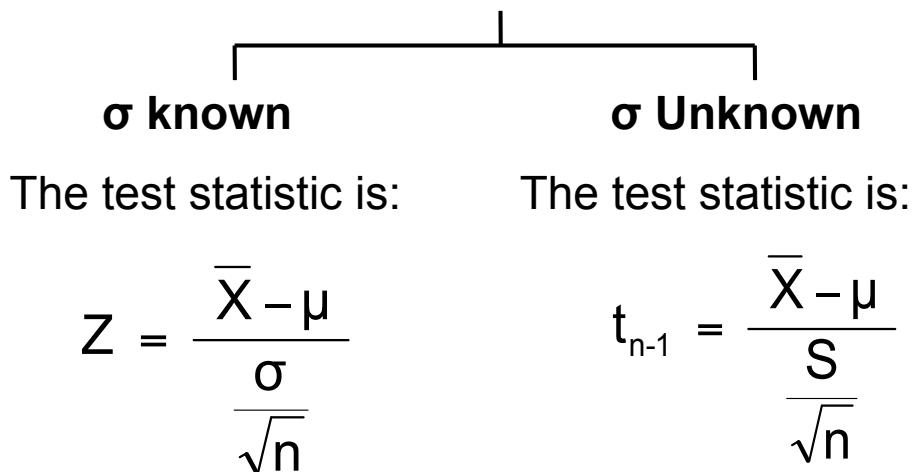
4. That is to say that P-value is the smallest value of α for which H_0 can be rejected based on the sample information
5. Convert Sample Statistic (e.g., sample mean) to Test Statistic (e.g., Z statistic)
6. Obtain the **p-value** from a table or computer
7. Compare the **p-value** with α

If $p\text{-value} < \alpha$, reject H_0

If $p\text{-value} \geq \alpha$, do not reject H_0

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Test of Hypothesis for the Mean



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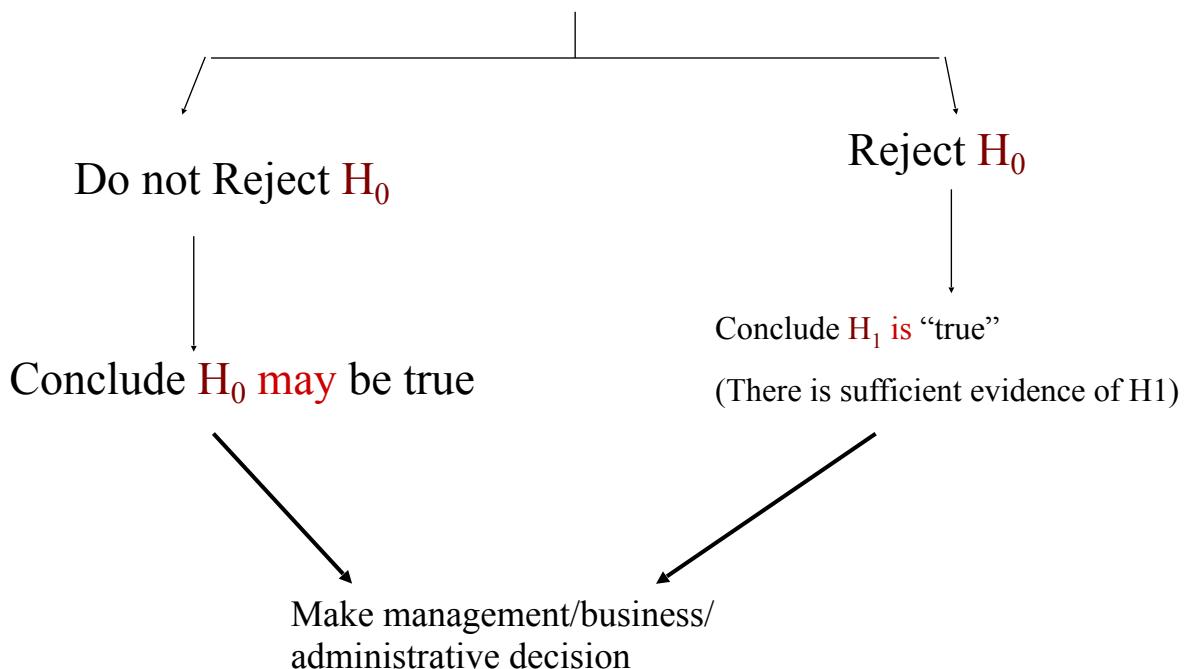
Steps to Hypothesis Testing

1. State the H_0 and H_1 clearly
2. Identify the test statistic (two-tail, one-tail, and Z or t distribution)
3. Depending on the type of risk you are willing to take, specify the level of significance,
4. Find the decision rule, critical values, and rejection regions. If –
CV < actual value (sample statistic) < +CV, then **do not reject the H_0**
5. Collect the data and do the calculation for the actual values of the test statistic from the sample

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Make statistical decision



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When do we use a two-tail test?

The answer depends on the question you are trying to answer.

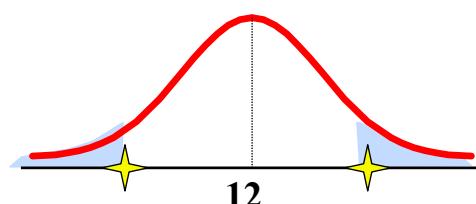
A two-tail is used when the researcher has no idea which direction the study will go, interested in both direction. (example: testing a new technique, a new product, a new theory and we don't know the direction)

A new machine is producing 12 fluid once can of soft drink. The quality control manager is concern with cans containing too much or too little.

Then, the test is a two-tailed test. That is the two rejection regions in tails is most likely (higher probability) to provide evidence of H₁.

$$H_0 : \mu = 12 \text{ oz}$$

$$H_1 : \mu \neq 12 \text{ oz}$$



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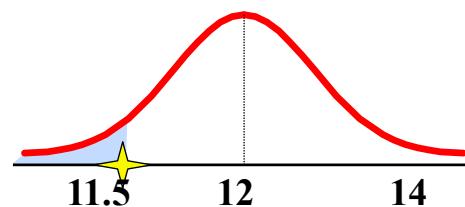
One-tail test is used when the researcher is interested in the direction.

Example: The soft-drink company puts a label on cans claiming they contain 12 oz. A consumer advocate desires to test this statement. She would assume that each can contains **at least** 12 oz and tries to find evidence to the contrary. That is, she examines the evidence for less than 12 oz.

What tail of the distribution is the most logical (higher probability) to find that evidence? The only way to reject the claim is to get evidence of less than 12 oz, left tail.

$$H_0 : \mu \geq 12 \text{ oz}$$

$$H_1 : \mu < 12 \text{ oz}$$



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Review of Hypo. Testing

What is HT?

Probability of making erroneous conclusions

Type I – only when Null Hypo is true

Type II – only when Null Hypo is false

Two Approaches

The Rejection or Critical Value Approach

The P-value Approach (we calculate the observed level of significance)

Test Statistics

Z- distribution if Population Std. Dev. is Known

t-distribution if the Population Std. Dev. is unknown

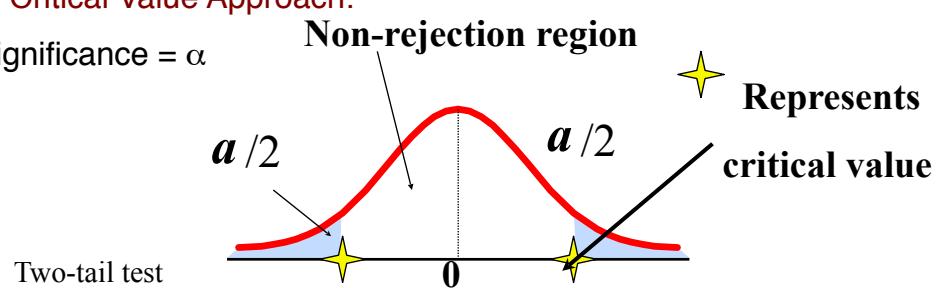
224

Rejection Region or Critical Value Approach:

The given level of significance = α

$$H_0: \mu = 12$$

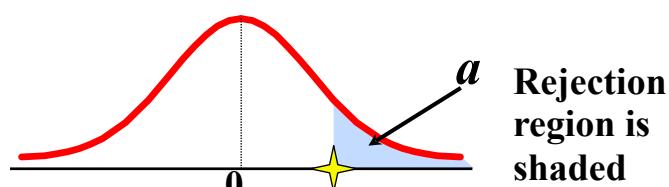
$$H_1: \mu \neq 12$$



$$H_0: \mu \leq 12 \quad H_1:$$

$$\mu > 12$$

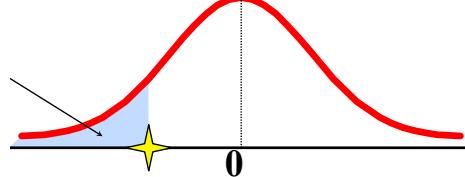
Upper-tail test



$$H_0: \mu \geq 12$$

$$H_1: \mu < 12$$

Lower-tail test



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P-Value Approach –

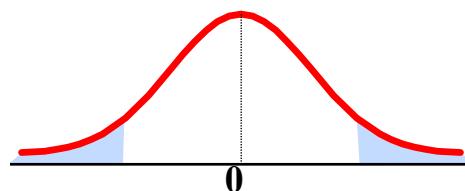
P-value=Max. Probability of (Type I Error), calculated from the sample.

Given the sample information what is the size of the blue areas? (The observed level of significance)

$$H_0: \mu = 12$$

$$H_1: \mu \neq 12$$

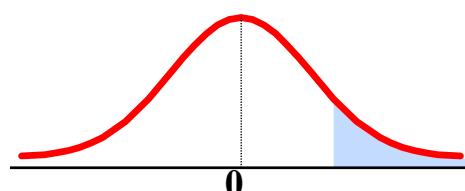
Two-tail test



$$H_0: \mu \leq 12 \quad H_1:$$

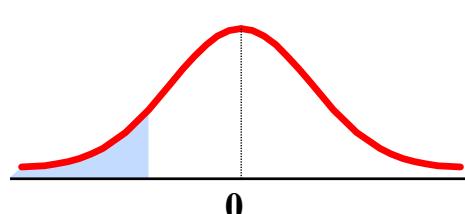
$$\mu > 12$$

Upper-tail test



$$H_0: \mu \geq 12$$

$$H_1: \mu < 12$$



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Example 1:

Let's assume a sample of 25 cans produced a sample mean of 11.5 0z and the population std dev=1 0z.

Question 1:

At a 5% level of significance (that is allowing for a maximum of 5% prob. of rejecting a true null hypo), is there evidence that the population mean is different from 12 oz?

Null Hypo is:?

Alternative Hypo is?

Can both approaches be used to answer this question?

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A: Rejection region approach: calculate the actual test statistics and compare it with the critical values

B: P-value approach: calculate the actual probability of type I error given the sample information. Then compare it with 1%, 5%, or 10% level of significance.

Interpretation of Critical Value/Rejection Region Approach:

Interpretation of P-value Approach:

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Question 2:

At a 5% level of significance (that is allowing for a maximum of 5% prob. of rejecting a true null hypo), is the evidence that the population mean is **less than 12 oz**?

Null Hypo is:?

Alternative Hypo is?

Can both approaches be used to answer this question?

Interpretation of Critical Value Approach:

Interpretation of P-value Approach:

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Question 3:

If in fact the pop. mean is 12 oz, what is the probability of obtaining a sample mean of 11.5 or less oz (sample size 25)? Null

Null Hypo is:?

Alternative Hypo is?

Question 4:

If in fact the pop. mean is 12 oz, and the sample mean is 11.5 (or less), what is the probability of erroneously rejecting the null hypo that the pop. mean is 12 oz?

Null Hypo is:?

Alternative Hypo is?

Can both approaches be used to answer these question?

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Connection to Confidence Intervals

While the confidence interval estimation and hypothesis testing serve different purposes, they are based on same concept and conclusions reached by two methods are consistent for a two-tail test.

In CI method we estimate an interval for the population mean with a degree of confidence. If the estimated interval **contains** the hypothesized value under the hypothesis testing, then this is equivalent of **not rejecting** the null hypothesis. For example: for the beer sample with mean 5.20, the confidence interval is:

$$P(4.61 \leq \mu \leq 5.78) = 95\%$$

Since this interval contains the Hypothesized mean (\$4.90), we do not (did not) reject the null hypothesis at $\alpha = .05$

Did not reject and within the interval, thus consistent results.

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Introduction to Regression Analysis

Regression analysis is used to:

Predict values of a dependent variable, Y, based on its relationship with values of at least one independent variable, X.

Explain the impact of changes in an independent variable on the dependent variable by estimating the **numerical value** of the relationship

Dependent variable: the variable we wish to explain

Independent variable: the variable used to explain the dependent variable

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Simple Linear Regression Model

Only **one** independent variable (thus, simple), X

Relationship between X and Y is described by a linear function

Changes in Y are assumed to be caused by changes in X, that is,

Change In X → **Causes** → Change in Y

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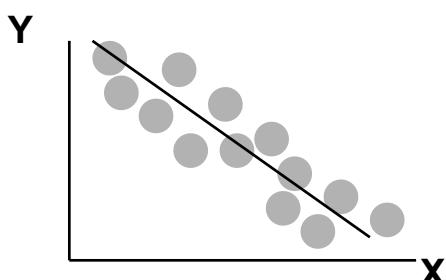
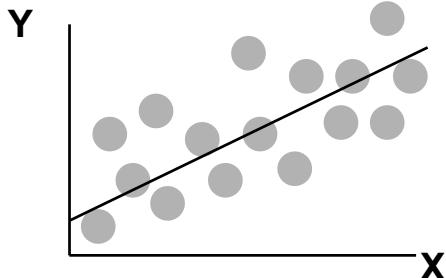
Important points before we start a regression analysis:

- The most important thing in deciding whether or not there is a relationship between X and Y is to have a systematic model that is based on logical reasons.
- Investigate the nature of the relationship between X and Y (use scatter diagram, covariance, correlation coefficient)
- Remember that regression is not an exact or deterministic mathematical equation. It is a **behavioral relationship** that is subject to randomness.
- Remember that X is not the only thing that explains the behavior of Y. There are other factor that you may not have information about.
- All you are trying to do is to have an estimate of the relationship using the **best linear fit** possible

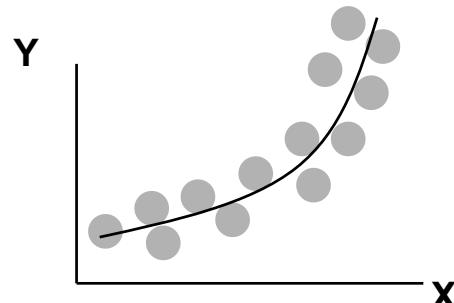
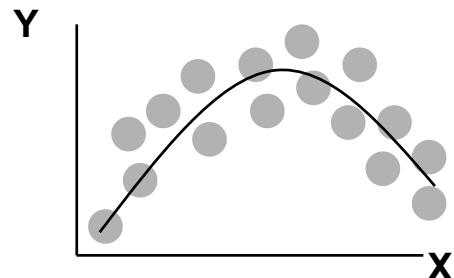
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Types of Relationships

Linear relationships



Curvilinear relationships

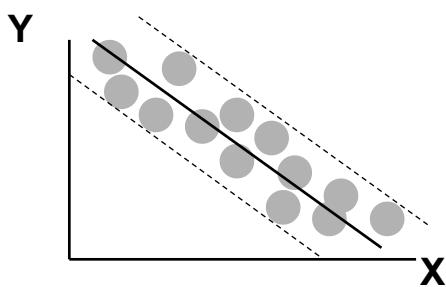
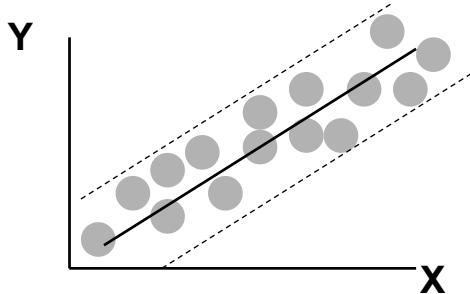


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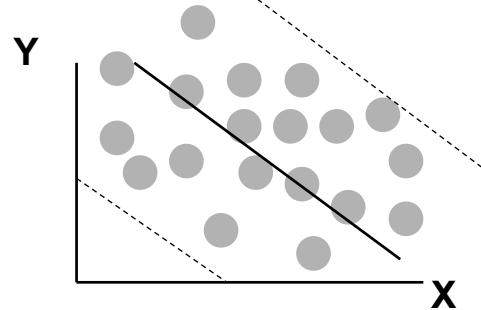
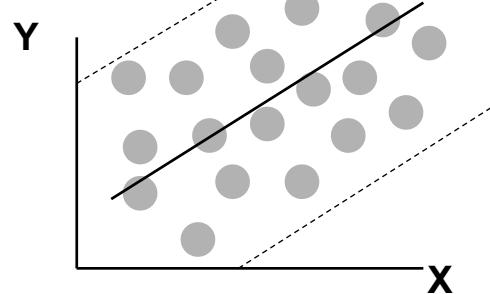
Types of Relationships

(continued)

Strong relationships



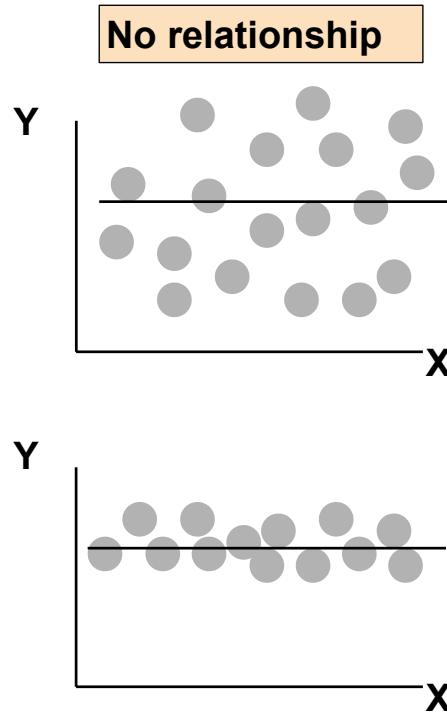
Weak relationships



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Types of Relationships

(continued)



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Simple Linear Regression Conceptual Model

The population regression model: This is a conceptual model, a hypothesis, or a postulation

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

Annotations for the equation:

- Dependent Variable: Points to Y_i
- Population Y intercept: Points to β_0
- Population Slope Coefficient: Points to β_1
- Independent Variable: Points to X_i
- Random Error term: Points to ϵ_i
- Linear component: Brackets under $\beta_0 + \beta_1 X_i$
- Random Error component: Brackets under ϵ_i

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- The model to be estimated from sample data is:

$$Y_i = b_0 + b_1 X_i + e_i$$

Residual
(random
error from
the sample)

- The actual estimated from the sample

Estimated (or predicted) Y value for observation i

Estimate of the regression intercept

Estimate of the regression slope

Value of X for observation i

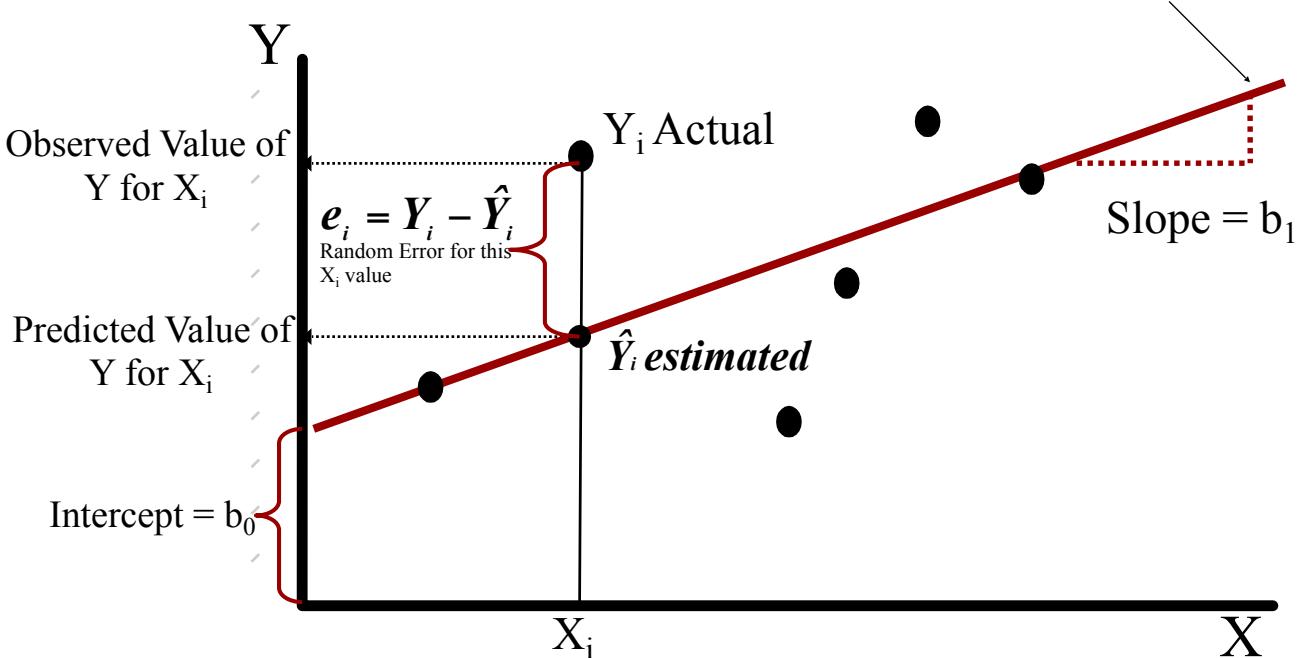
$$\hat{Y}_i = b_0 + b_1 X_i$$

– Where $e_i = Y_i - \hat{Y}_i$

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Simple Linear Regression Model

$$\hat{Y}_i = b_0 + b_1 X_i$$



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Interpretation of the slope and the intercept

$$\beta_0 = E(Y | X = 0) ; \quad \beta_1 = \Delta E(Y|X)/\Delta (X);$$

β_0 is the estimated average value of Y when the value of X is b_0 zero

β_1 is the estimated change in the average value of Y as a result of a one-unit change in X

Units of measurement of X and Y are very important for the correct interpretation of the slope and the intercept

Example: $\widehat{App\ Val} = 165.03 + 6.93 (Lot\ size)$

Predict the app. Value of a house with 10,000 s.f. lot size

$$\widehat{App\ Val} = 165.03 + 6.93 (10) = \$234,330$$

How Good is this prediction?

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How Good is the Model's prediction Power?

Total variation is made up of two parts:

$$SST = SSR + SSE$$

Total Sum of
Squares

Regression Sum
of Squares

Error Sum of
Squares

$$SST = \sum (Y_i - \bar{Y})^2 \quad SSR = \sum (\hat{Y}_i - \bar{Y})^2 \quad SSE = \sum (Y_i - \hat{Y}_i)^2$$

where:

\bar{Y} = Average value of the dependent variable

Y_i = Observed values of the dependent variable

\hat{Y}_i = Predicted value of Y for the given X_i value

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SST = total sum of squares

Measures total variation of the Y_i values around their mean

SSR = regression sum of squares (Explained)

Explained portion of total variation attributed to Y's

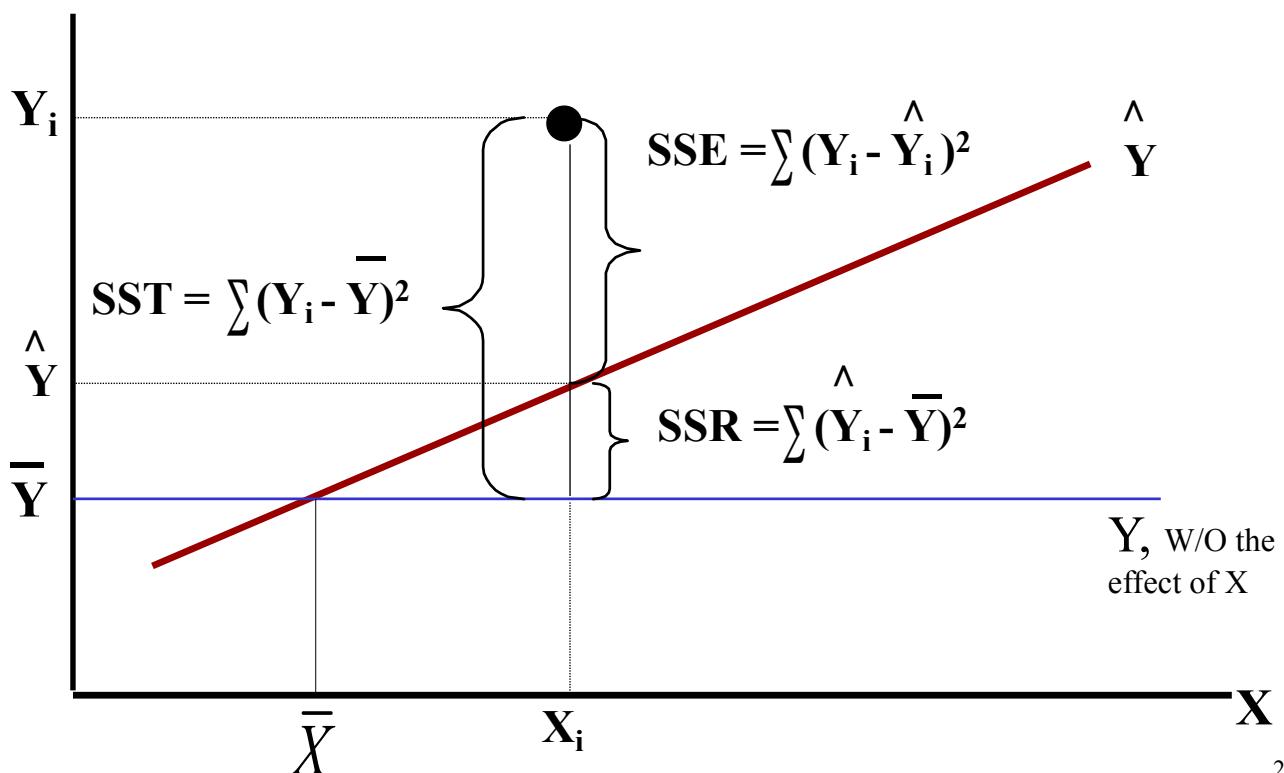
relationship with X

SSE = error sum of squares (Unexplained)

Variation of Y values attributable to other factors than its

relationship with X

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How Good is the Model's prediction Power?

The **coefficient of determination** is the portion of the total variation in the dependent variable, Y, that is explained by variation in the independent variable, X

The coefficient of determination is also called **r-squared** and is denoted as r^2

$$r^2 = \frac{SSR}{SST} = \frac{\text{regression sum of squares}}{\text{total sum of squares}}$$

$$0 \leq r^2 \leq 1$$

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Standard Error of Estimate

The standard deviation of the variation of observations **around the regression line** is estimated by

Where SSE = error sum of squares; n = sample size

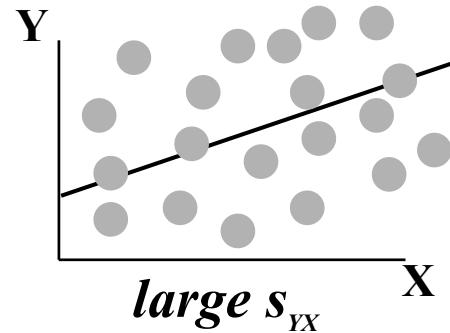
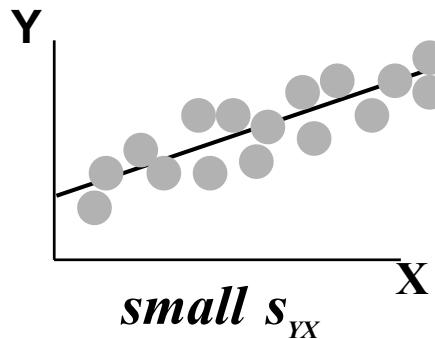
$$S_{yx} = \sqrt{\frac{SSE}{n-2}} = \sqrt{\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n-2}} = \sqrt{MSE}$$

The concept is the same as the standard deviation (average difference) around the mean of a univariate

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Comparing Standard Errors

S_{YX} is a measure of the variation of observed Y values from the regression line



The magnitude of S_{YX} should always be judged relative to the size of the Y values in the sample data

i.e., $S_{YX} = \$36.34K$ is moderately small relative to house prices in the \$200 - \$300K range (average 215K)

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Assumptions of Regression

Normality of Error

Error values (ε) are normally distributed for any given value of X

Homoscedasticity

The probability distribution of the errors has constant variance

Independence of Errors

Error values are statistically independent

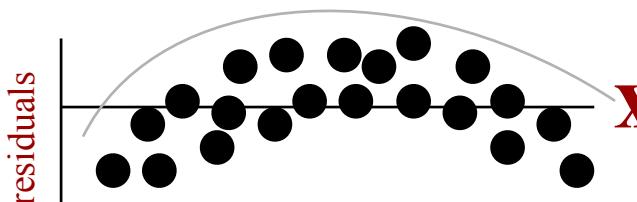
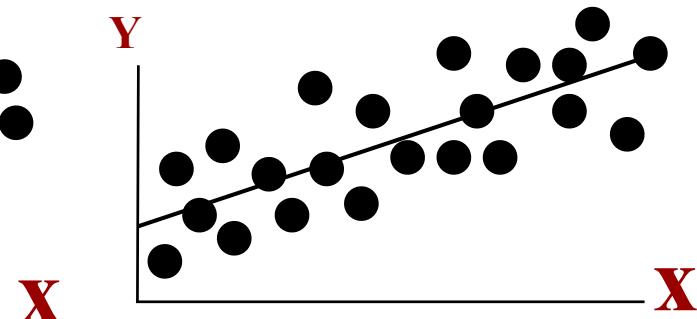
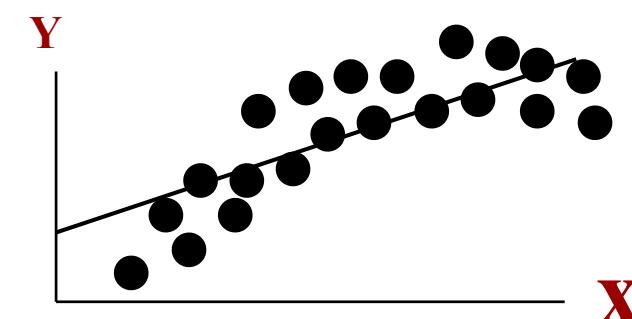
248

How to investigate the appropriateness of the fitted model

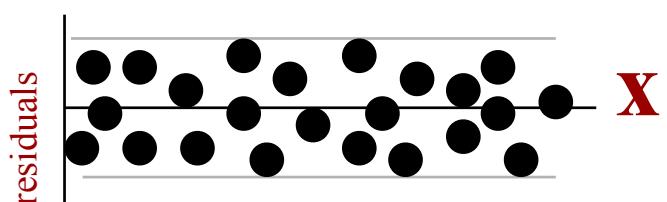
- The residual for observation i , e_i , is the difference between its observed and predicted value;
- Check the assumptions of regression by examining the residuals $e_i = Y_i - \hat{Y}_i$
 - Examine for linearity assumption
 - Examine for constant variance for all levels of X (homoscedasticity)
 - Evaluate normal distribution assumption
 - Evaluate independence assumption
- Graphical Analysis of Residuals
Can plot residuals vs. X

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Residual Analysis for Linearity



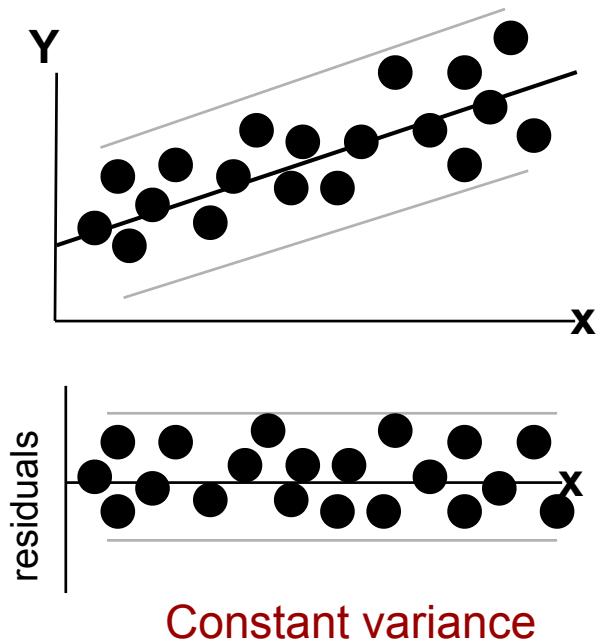
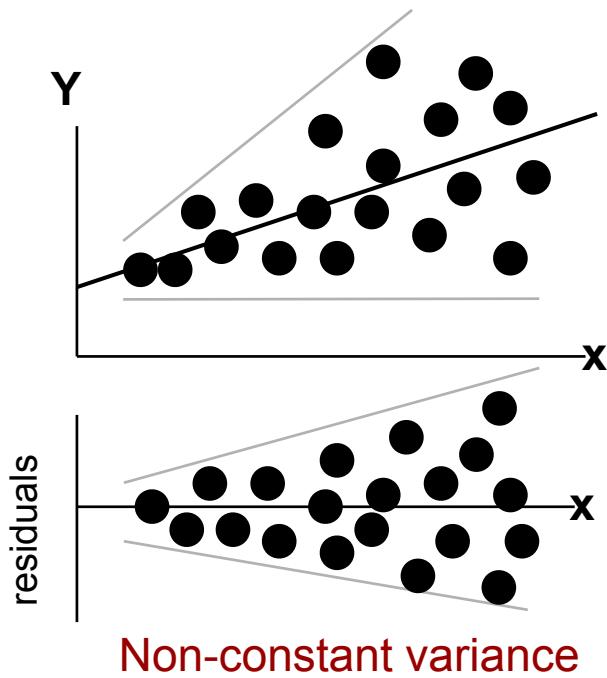
Not Linear



Linear

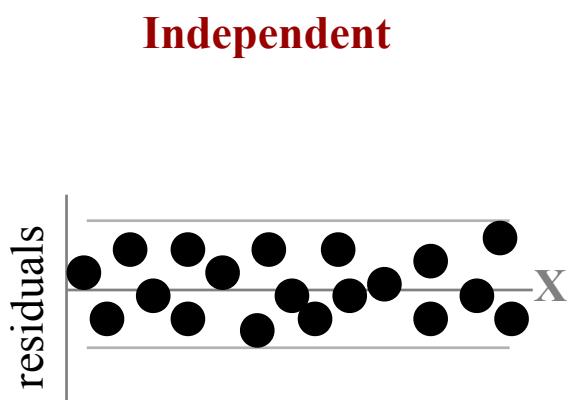
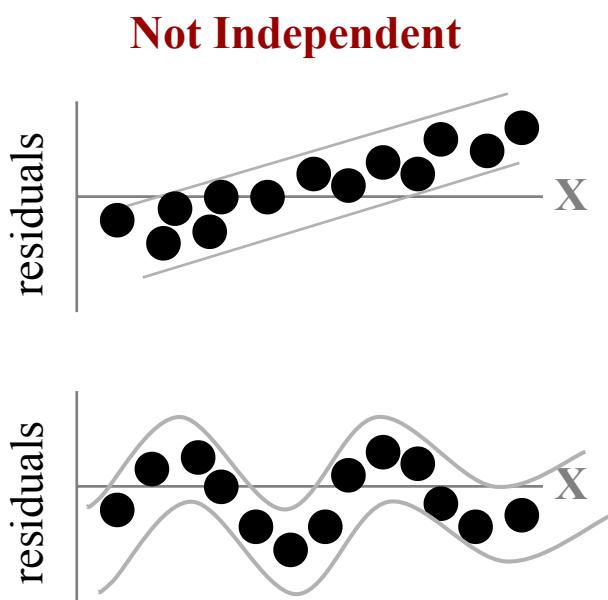
250

Residual Analysis for Homoscedasticity



251

Residual Analysis for Independence



252

Testing differences in mean between two groups

Let's begin by loading the packages we'll need to get started

```
library(MASS)
library(plyr)
library(ggplot2)
```

```
# Rename the columns to have more descriptive names
colnames(birthwt) <- c("birthwt.below.2500", "mother.age", "mother.weight",
  "race", "mother.smokes", "previous.prem.labor", "hypertension", "uterine.irr",
  "physician.visits", "birthwt.grams")

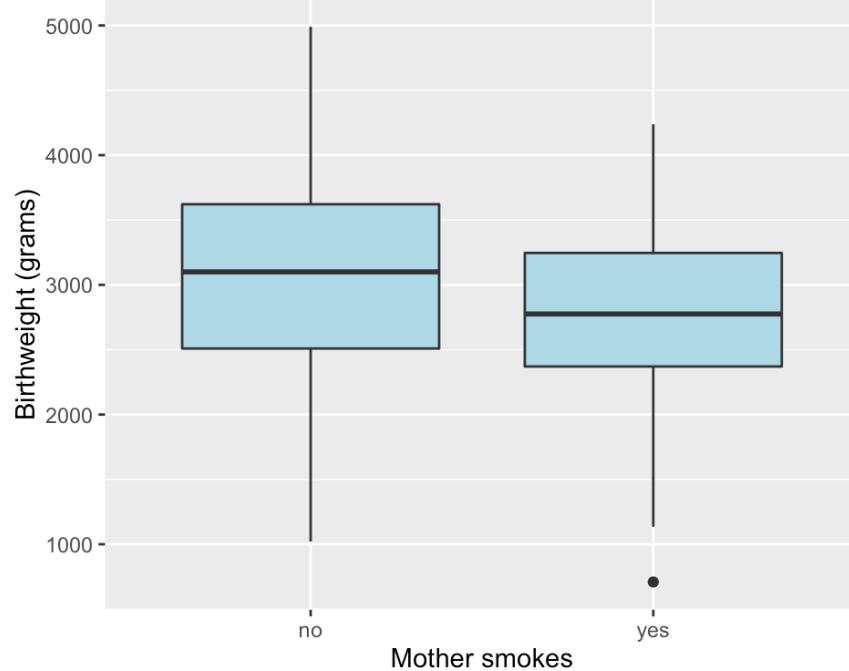
# Transform variables to factors with descriptive levels
birthwt <- transform(birthwt,
  race = as.factor(mapvalues(race, c(1, 2, 3),
    c("white", "black", "other"))),
  mother.smokes = as.factor(mapvalues(mother.smokes,
    c(0,1), c("no", "yes"))),
  hypertension = as.factor(mapvalues(hypertension,
    c(0,1), c("no", "yes"))),
  uterine.irr = as.factor(mapvalues(uterine.irr,
    c(0,1), c("no", "yes"))))
)
```

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To start, it always helps to plot things

```
# Create boxplot showing how birthwt.grams varies between
# smoking status
qplot(x = mother.smokes, y = birthwt.grams,
  geom = "boxplot", data = birthwt,
  xlab = "Mother smokes",
  ylab = "Birthweight (grams)",
  fill = I("lightblue"))
```

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This plot suggests that smoking is associated with lower birth weight.

255

How can we assess whether this difference is statistically significant?

Let's compute a summary table

```
aggregate(birthwt.grams ~ mother.smokes, data = birthwt,
          FUN = function(x) {c(mean = mean(x), sd = sd(x))})
```

	mother.smokes	birthwt.grams.mean	birthwt.grams.sd
## 1	no	3055.6957	752.6566
## 2	yes	2771.9189	659.6349

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The standard deviation is good to have, but to assess statistical significance we really want to have the standard error (which is the standard deviation adjusted by the group size).

```
aggregate(birthwt.grams ~ mother.smokes, data = birthwt,
          FUN = function(x) {c(mean = mean(x),
                                 se = sd(x) / sqrt(length(x))))})
```

```
##   mother.smokes birthwt.grams.mean birthwt.grams.se
## 1           no        3055.69565     70.18559
## 2          yes       2771.91892     76.68100
```

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t-test via t.test()

This difference is looking quite significant. To run a two-sample t-test, we can simply use the `t.test()` function.

```
birthwt.t.test <- t.test(birthwt.grams ~ mother.smokes, data = birthwt)
birthwt.t.test
```

```
##
##  Welch Two Sample t-test
##
## data: birthwt.grams by mother.smokes
## t = 2.7299, df = 170.1, p-value = 0.007003
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##    78.57486 488.97860
## sample estimates:
## mean in group no mean in group yes
##            3055.696           2771.919
```

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p-value

```
birthwt.t.test$p.value    # p-value  
  
## [1] 0.007002548  
  
birthwt.t.test$estimate   # group means  
  
## mean in group no mean in group yes  
##          3055.696           2771.919  
  
birthwt.t.test$conf.int   # confidence interval for difference  
  
## [1] 78.57486 488.97860  
## attr(,"conf.level")  
## [1] 0.95
```

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Workshop 8: t-test

Testing means between two groups

(a) Using the Cars93 data and the t.test() function, run a t-test to see if average MPG.highway is different between US and non-US vehicles.

Try doing this both using the formula style input and the x, y style input.

(b) What is the confidence interval for the difference?

(c) Repeat part (a) using the wilcox.test() function.

(d) Are your results for (a) and (c) very different?

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ANOVA and Regression



Prepare data

```
library(MASS)
library(plyr)
library(ggplot2)
library(knitr)

# Rename the columns to have more descriptive names
colnames(birthwt) <- c("birthwt.below.2500", "mother.age", "mother.weight",
"race", "mother.smokes", "previous.prem.labor", "hypertension", "uterine.irr",
"physician.visits", "birthwt.grams")

# Transform variables to factors with descriptive levels
birthwt <- transform(birthwt,
  race = as.factor(mapvalues(race, c(1, 2, 3),
    c("white", "black", "other"))),
  mother.smokes = as.factor(mapvalues(mother.smokes,
    c(0,1), c("no", "yes"))),
  hypertension = as.factor(mapvalues(hypertension,
    c(0,1), c("no", "yes"))),
  uterine.irr = as.factor(mapvalues(uterine.irr,
    c(0,1), c("no", "yes"))))
)
```

One-way ANOVA example

Question: Is there a significant association between race and birthweight?

Here's a table showing the mean and standard error of birthweight by race.

```
aggregate(birthwt.grams ~ race, data = birthwt, FUN = mean)
```

```
##   race birthwt.grams
## 1 black    2719.692
## 2 other    2805.284
## 3 white    3102.719
```

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Terminology: a k -way ANOVA is used to assess whether the mean of an outcome variable is constant across all combinations of k factors. The most common examples are 1-way ANOVA (looking at a single factor), and 2-way ANOVA (looking at two factors).

We'll use the `aov()` function. For convenience, `aov()` allows you to specify a formula.

```
summary(aov(birthwt.grams ~ race, data = birthwt))

##             Df  Sum Sq Mean Sq F value    Pr(>F)
## race          2  5015725 2507863   4.913  0.00834 ***
## Residuals   186  94953931  510505
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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Workshop 9: ANOVA

Let's form our favourite birthwt data set.

```
# Rename the columns to have more descriptive names
colnames(birthwt) <- c("birthwt.below.2500", "mother.age", "mother.weight",
  "race", "mother.smokes", "previous.prem.labor", "hypertension", "uterine.irr",
  "physician.visits", "birthwt.grams")

# Transform variables to factors with descriptive levels
birthwt <- transform(birthwt,
  race = as.factor(mapvalues(race, c(1, 2, 3),
    c("white", "black", "other"))),
  mother.smokes = as.factor(mapvalues(mother.smokes,
    c(0,1), c("no", "yes"))),
  hypertension = as.factor(mapvalues(hypertension,
    c(0,1), c("no", "yes"))),
  uterine.irr = as.factor(mapvalues(uterine.irr,
    c(0,1), c("no", "yes"))))
)
```

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- (a) Create a new factor that categorizes the number of physician visits into three levels: 0, 1, 2, 3 or more.

Hint: One way of doing this is with mapvalues, by mapping all instances of 3, 4,... etc, to “3 or more”.

- (b) Run an ANOVA to determine whether the average birth weight varies across number of physician visits.

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Quality Control using R

Use cases - Manufacturing

- Predictively model equipment failure rates
- Streamline inventory management
- Target energy-inefficient components
- Optimize factory floor space



- Sensor data to look at failures
- Quality management
- Identifying out-of-bounds manufacturing
- Visual inspection/computer vision
- Optimal run speeds
- Demand forecasting/inventory management

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Manufacturing sample

Pellets density

- Company manufacture
ceramic component which in
pellets size (g/cm³)

- Manpower
 - Receptionist
 - Recording Operator
 - Storage operators
- Materials
 - Supplier
 - Transport agency
 - Packing
- Machines
 - Compressor
 - Operation conditions
 - Machine adjustment
- Methods
 - Raw materials reception
 - Transport method
- Measurements
 - Recording method
 - Measurement apparatus

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```
cManpower <- c("Receptionist", "Record. Operator",
                 "Storage operators")
cMaterials <- c("Supplier", "Transport agency",
                 "Packing")
cMachines <- c("Compressor type",
                 "Operation conditions",
                 "Machine adjustment")
cMethods <- c("Reception", "Transport method")
cMeasurements <- c("Recording method",
                     "Measurement appraisal")
cGroups <- c("Manpower", "Materials", "Machines",
             "Methods", "Measurements")
cEffect <- "Too high density"
```

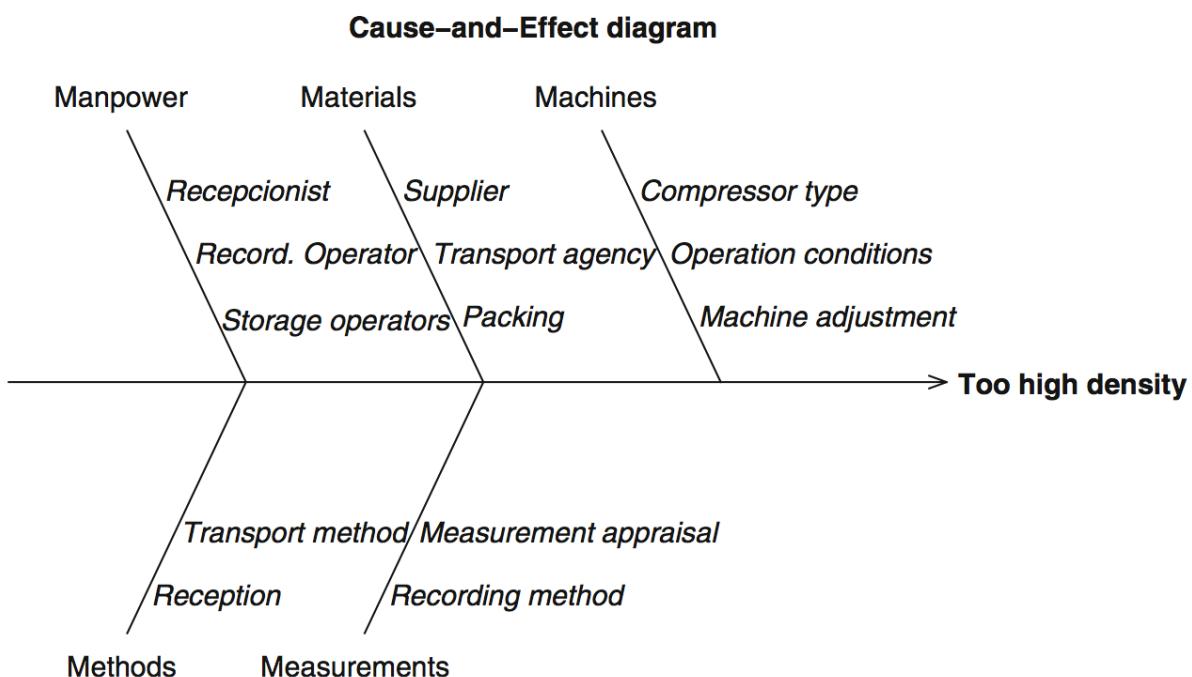
271

Ishikawa diagram, or “fishbone”

```
library(qcc)
cause.and.effect(
  cause = list(Manpower = cManpower,
               Materials = cMaterials,
               Machines = cMachines,
               Methods = cMethods,
               Measurements = cMeasurements),
  effect = cEffect)
```

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Ishikawa diagram, or “fishbone”

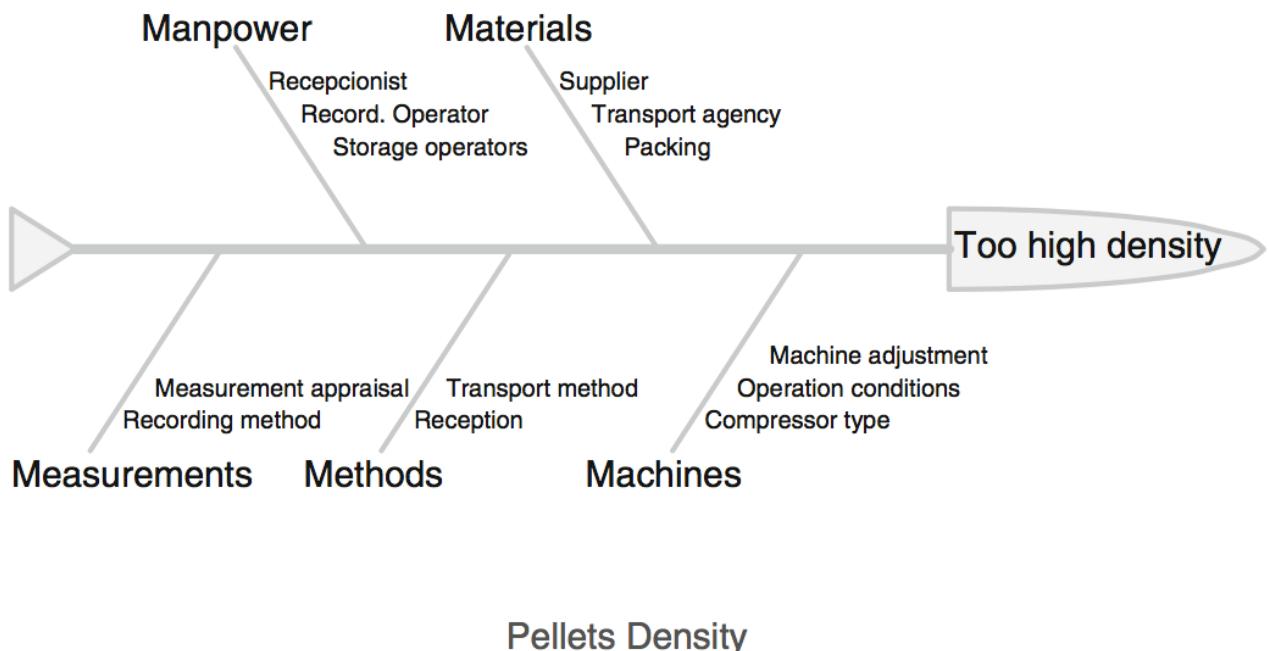


273

```
library(SixSigma)
ss.ceDiag(
  effect = cEffect,
  causes.gr <- cGroups,
  causes = list(cManpower, cMaterials, cMachines,
                cMethods, cMeasurements),
  main = "Cause-and-effect diagram",
  sub = "Pellets Density")
```

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Cause-and-effect diagram



Pellets Density

Out of control pellets density check sheet

Quality Control Department

31/01/2015

Instructions: Mark ticks for the more likely cause of the out-of-control point. Cross every four ticks to make five.

	Group	Cause	A_supplier	B_supplier	C_supplier
1	Manpower	Recepcionist	/		
2	Manpower	Record. Operator			/
3	Manpower	Storage operators		/	
4	Machines	Compressor type	/	/	
5	Machines	Operation conditions	/	/	
6	Machines	Machine adjustment		/	/
7	Materials	Supplier	/		/
8	Materials	Transport agency		/	
9	Materials	Packing		/	/
10	Methods	Reception		/	
11	Methods	Transport method	/		/
12	Measurements	Recording method			
13	Measurements	Measurement appraisal		/	/

Week

Operator

Signature

2015-03

Emilio

dt

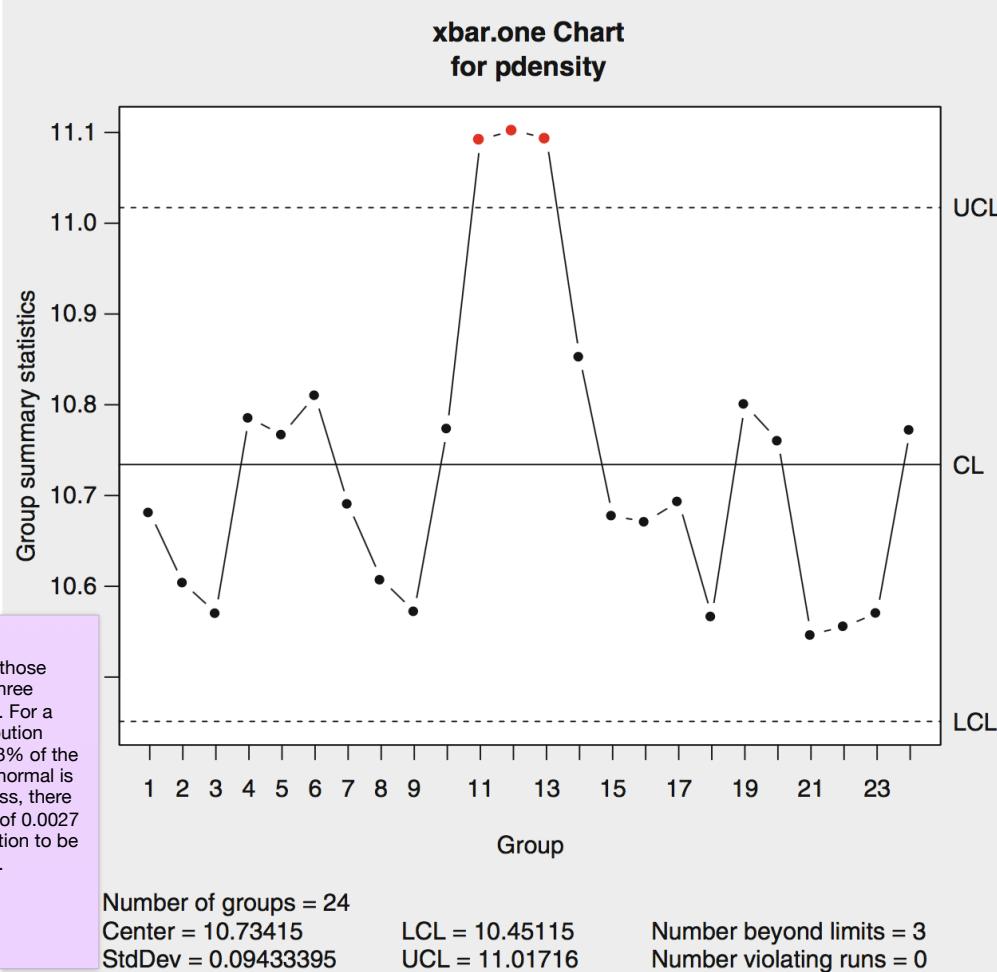
Control Chart

A control chart is a two-dimensional chart whose y-axis represents the variable we are monitoring. The x-axis of the chart is an identification of such j sample.

- Sample: We have a machine that generate a pallet with size (g/cm³) below:-

```
pdensity <- c(10.6817, 10.6040, 10.5709, 10.7858,  
             10.7668, 10.8101, 10.6905, 10.6079,  
             10.5724, 10.7736, 11.0921, 11.1023,  
             11.0934, 10.8530, 10.6774, 10.6712,  
             10.6935, 10.5669, 10.8002, 10.7607,  
             10.5470, 10.5555, 10.5705, 10.7723)
```

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Typical control limits are those between the mean and three standard deviations ('3'). For a normal probability distribution these limits include 99.73% of the data. Thus, if nothing abnormal is taking place in the process, there will only be a probability of 0.0027 for an individual observation to be outside the control limits.

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1. **Center line (CL)**: This is the central value the statistic should vary around. For example, the mean of the process;

2. **Lower control limit (LCL)**. This is the value below which it is very unlikely for the statistic to occur when the process is in control;

3. **Upper control limit (UCL)**. This is the counterpart of the LCL on the upper side of the CL. The LCL and UCL are symmetric if the probability distribution of the statistic to be monitored is symmetric (e.g., normal).

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```
myControlChart <- qcc(data = pdensity,
                      type = "xbar.one")
summary(myControlChart)

##
## Call:
## qcc(data = pdensity, type = "xbar.one")
##
## xbar.one chart for pdensity
##
## Summary of group statistics:
##      Min. 1st Qu. Median     Mean 3rd Qu.      Max.
##      10.55    10.60   10.69    10.73    10.79    11.10
##
## Group sample size:  1
## Number of groups: 24
## Center of group statistics: 10.73415
## Standard deviation: 0.09433395
##
## Control limits:
##          LCL        UCL
## 10.45115 11.01716
```

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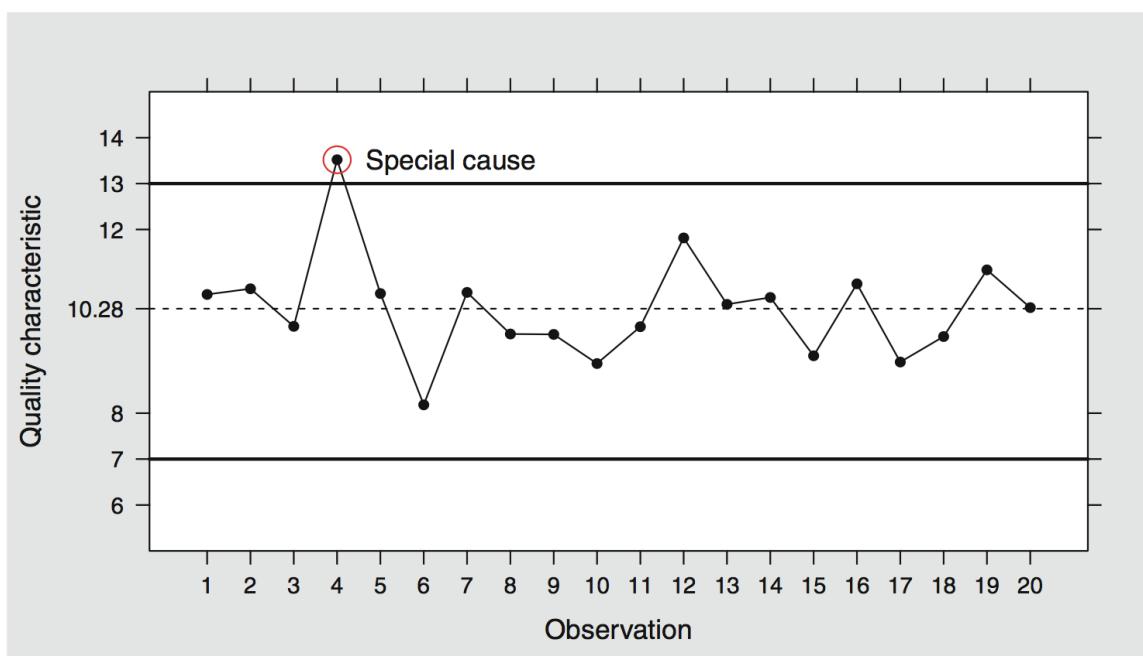


```
myControlChart$violations
```

```
## $beyond.limits  
## [1] 11 12 13  
##  
## $violating.runs  
## numeric(0)
```

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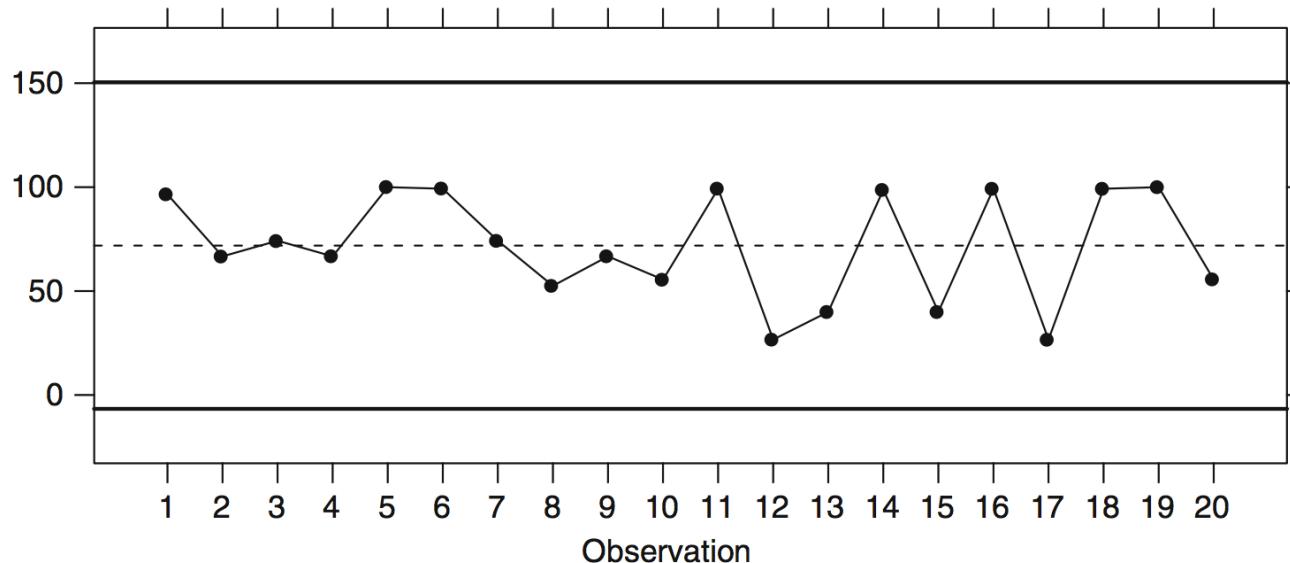
Check Special Cause



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Seasonality

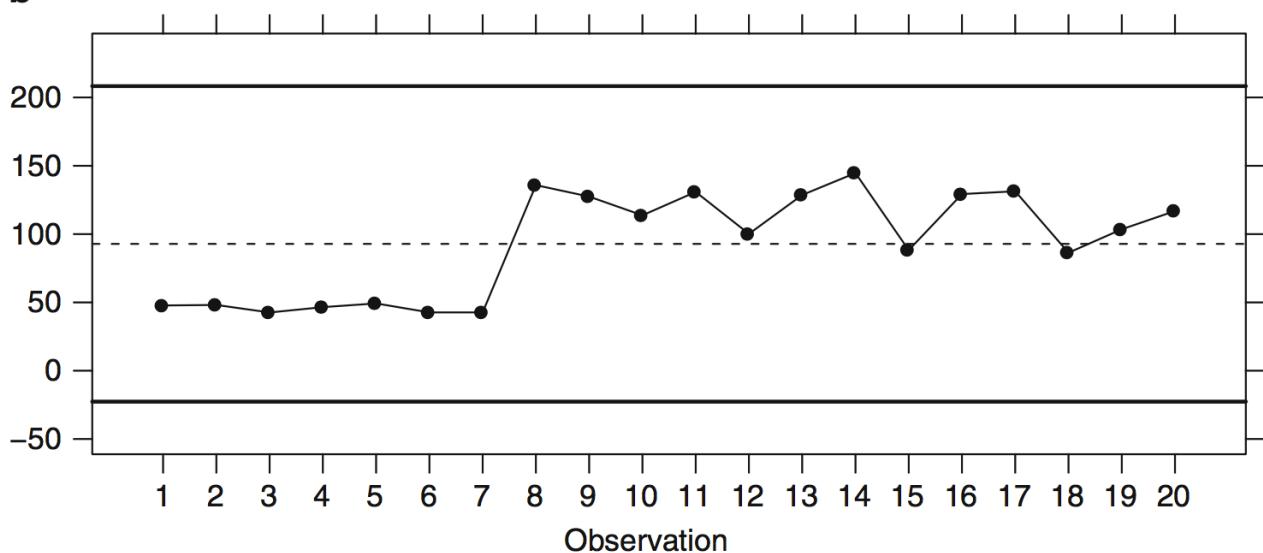
a



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Shift

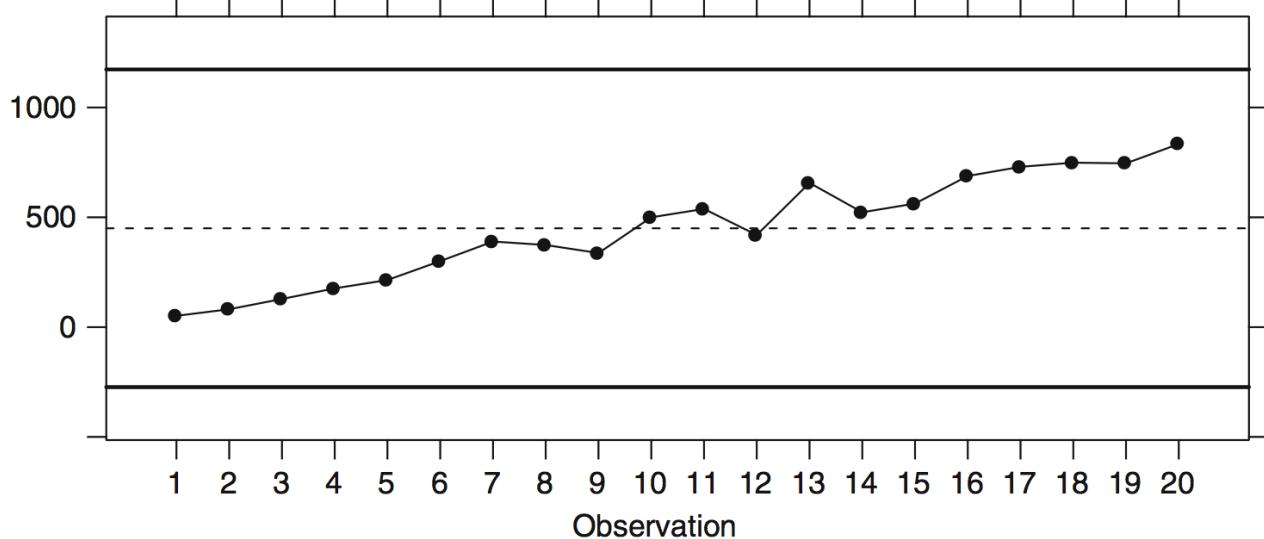
b



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Trend

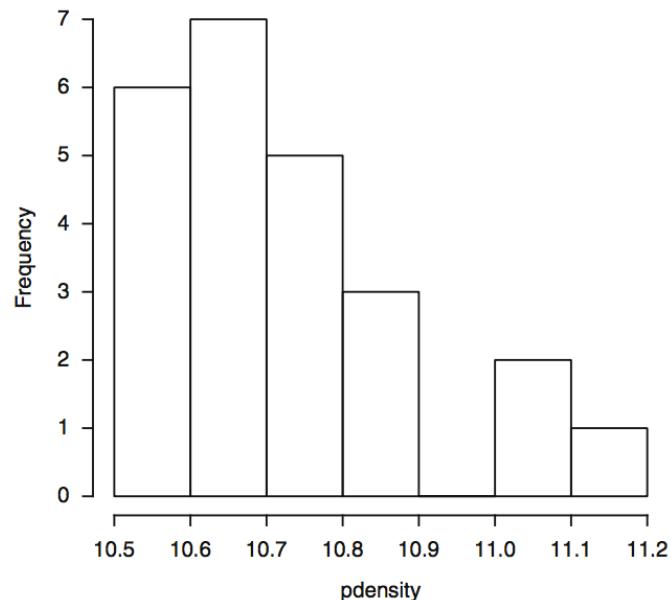
C



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`hist(pdensity)`

Histogram of pdensity

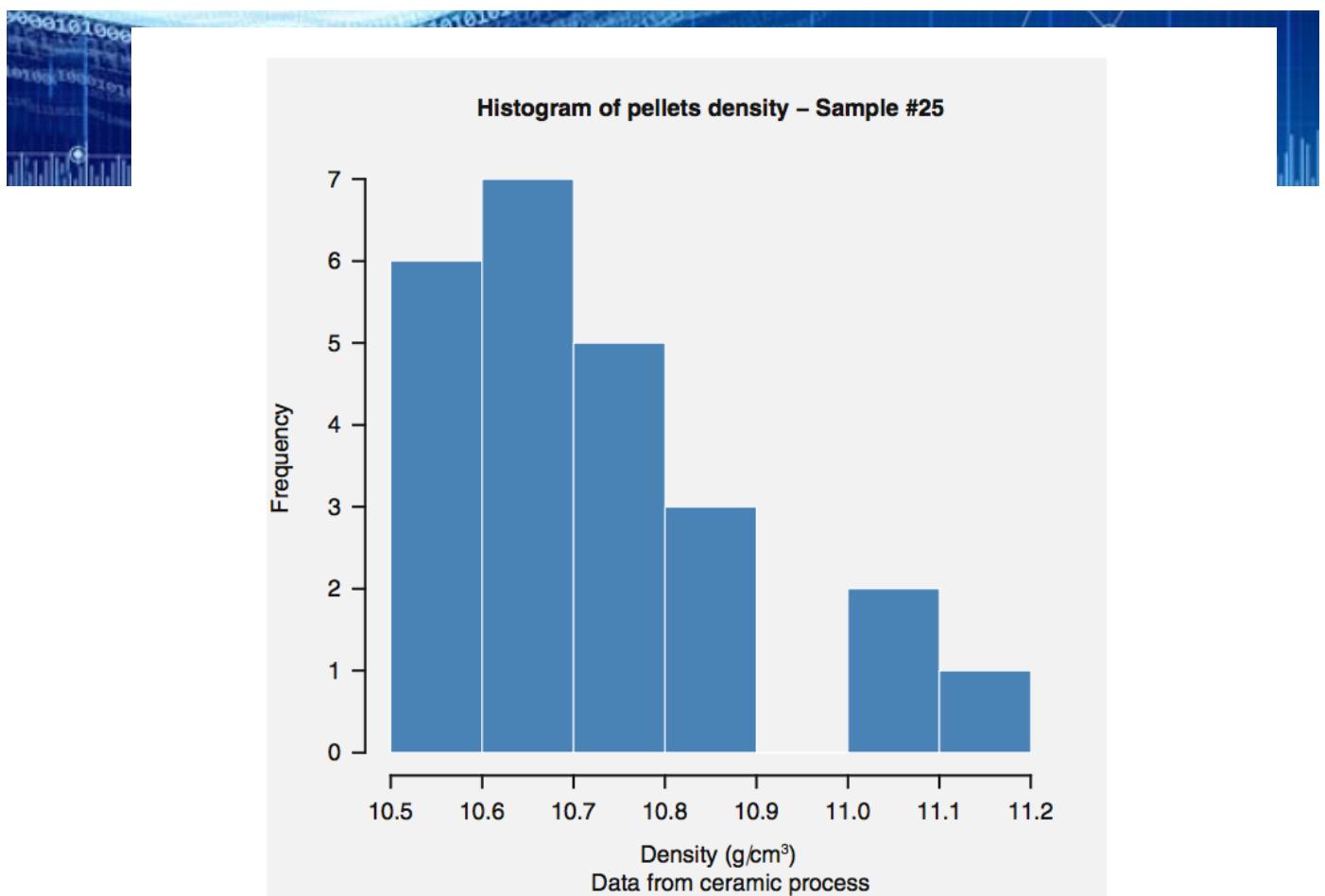


286



```
par(bg = "gray95")
hist(pdensity,
      main = "Histogram of pellets density - Sample #25",
      sub = "Data from ceramic process",
      xlab = expression("Density (g"/"cm"^{3})*") ,
      col = "steelblue",
      border = "white",
      lwd = 2,
      las = 1,
      bg = "gray")
```

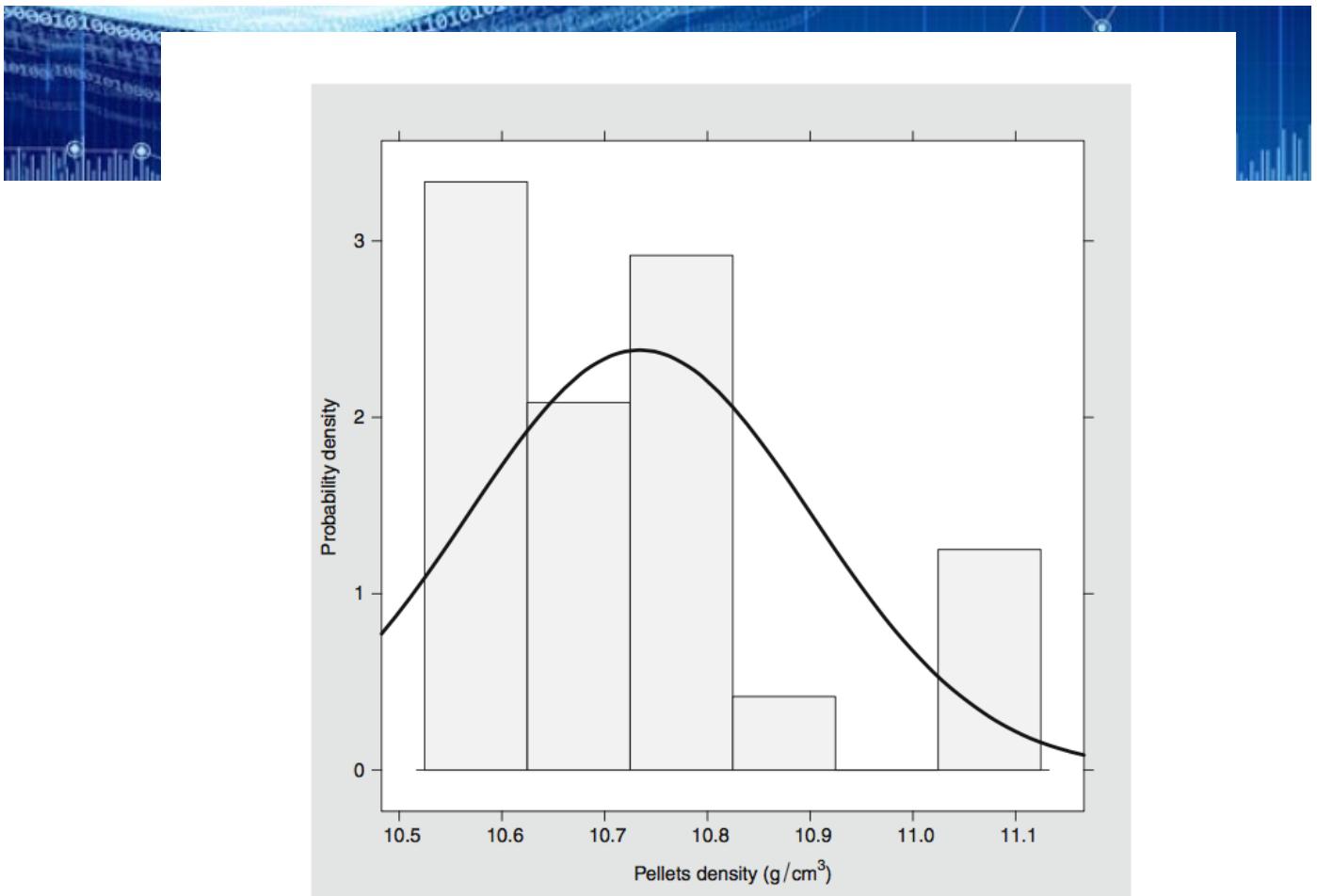
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```
library(lattice)
histogram(pdensity,
  xlab = expression("Pellets density (g/"cm"^-3* )"),
  ylab = "Probability density",
  type = "density",
  panel = function(x, ...) {
    panel.histogram(x, ...)
    panel.mathdensity(dmath = dnorm,
                      col = "black",
                      lwd = 3,
                      args = list(mean = mean(x),
                                  sd = sd(x)))
  }
)
```

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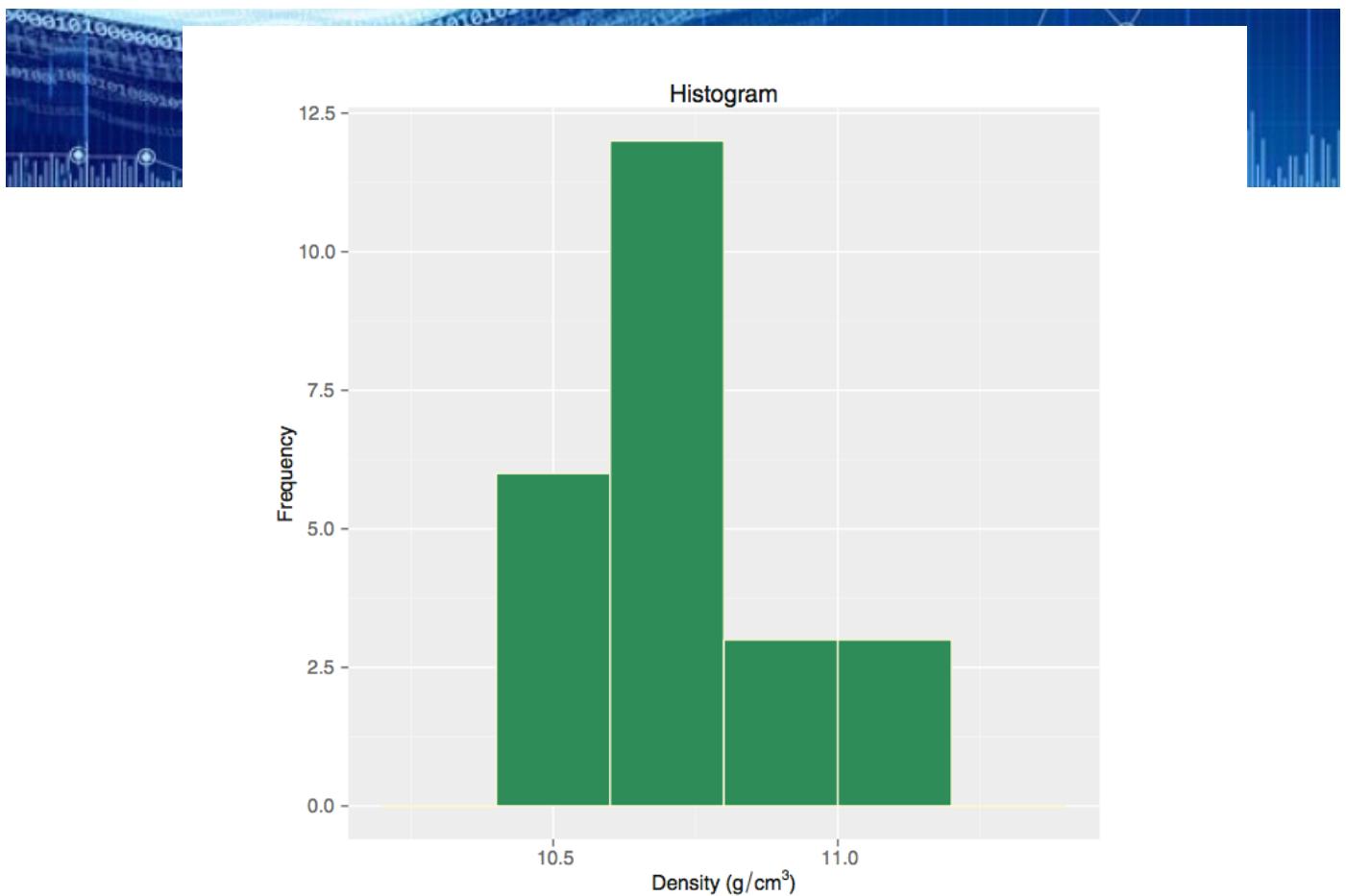


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```
library(ggplot2)
ggplot(data = data.frame(pdensity),
       aes(x = pdensity)) +
  geom_histogram(fill = "seagreen",
                 colour = "lightgoldenrodyellow",
                 binwidth = 0.2) +
  labs(title = "Histogram",
       x = expression("Density (*g/cm^3*)"),
       y = "Frequency")
```

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```

data_checkSheet$A_supplier <- c(2, 0, 0, 2, 1, 7, 1,
                                3, 6, 0, 1, 2, 0)
data_checkSheet$B_supplier <- c(0, 0, 1, 1, 2, 1, 12,
                                1, 2, 1, 0, 0, 1)
data_checkSheet$C_supplier <- c(0, 1, 0, 6, 0, 2, 2,
                                4, 3, 0, 1, 0, 2)
data_checkSheet$Total <- data_checkSheet$A_supplier +
  data_checkSheet$B_supplier +
  data_checkSheet$C_supplier

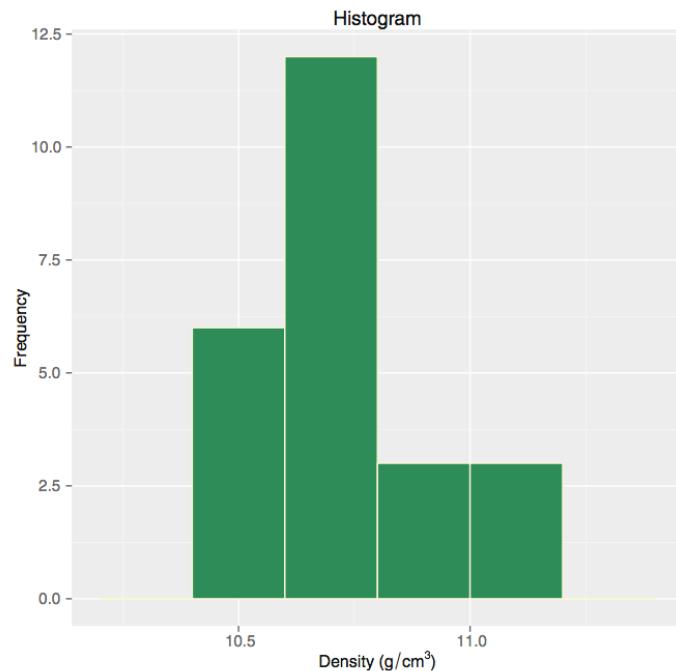
```

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data_checkSheet			
	Group	Cause	A_supplier
## 1	Manpower	Repcionist	2
## 2	Manpower	Record. Operator	0
## 3	Manpower	Storage operators	0
## 4	Machines	Compressor type	2
## 5	Machines	Operation conditions	1
## 6	Machines	Machine adjustment	7
## 7	Materials	Supplier	1
## 8	Materials	Transport agency	3
## 9	Materials	Packing	6
## 10	Methods	Reception	0
## 11	Methods	Transport method	1
## 12	Measurements	Recording method	2
## 13	Measurements	Measurement appraisal	0
	B_supplier	C_supplier	Total
## 1	0	0	2
## 2	0	1	1
## 3	1	0	1
## 4	1	6	9
## 5	2	0	3
## 6	1	2	10
## 7	12	2	15



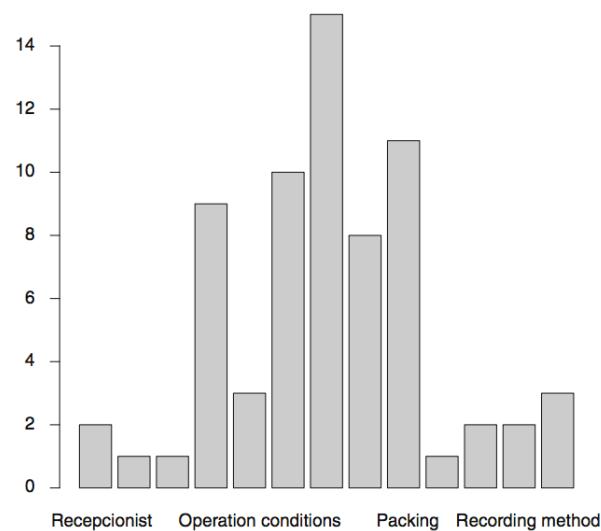
```
barplot(height = data_checkSheet$Total,  
        names.arg = data_checkSheet$Cause)
```



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```
barplot(height = data_checkSheet$Total,  
        names.arg = data_checkSheet$Cause)
```

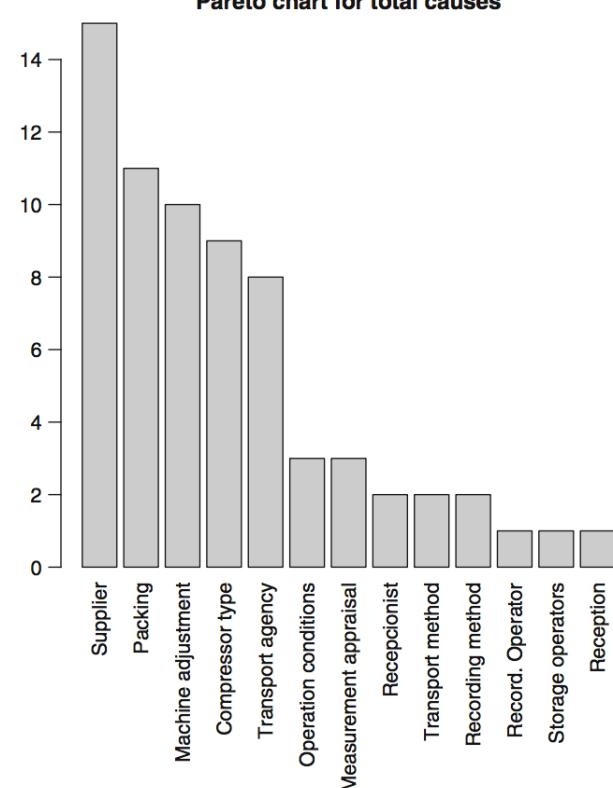


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```
data_pareto <- data_checkSheet[order(
  data_checkSheet$Total,
  decreasing = TRUE), ]
par(mar = c(8, 4, 4, 2) + 0.1)
barplot(height = data_pareto$Total,
        names.arg = data_pareto$Cause,
        las = 2,
        main = "Pareto chart for total causes")
```

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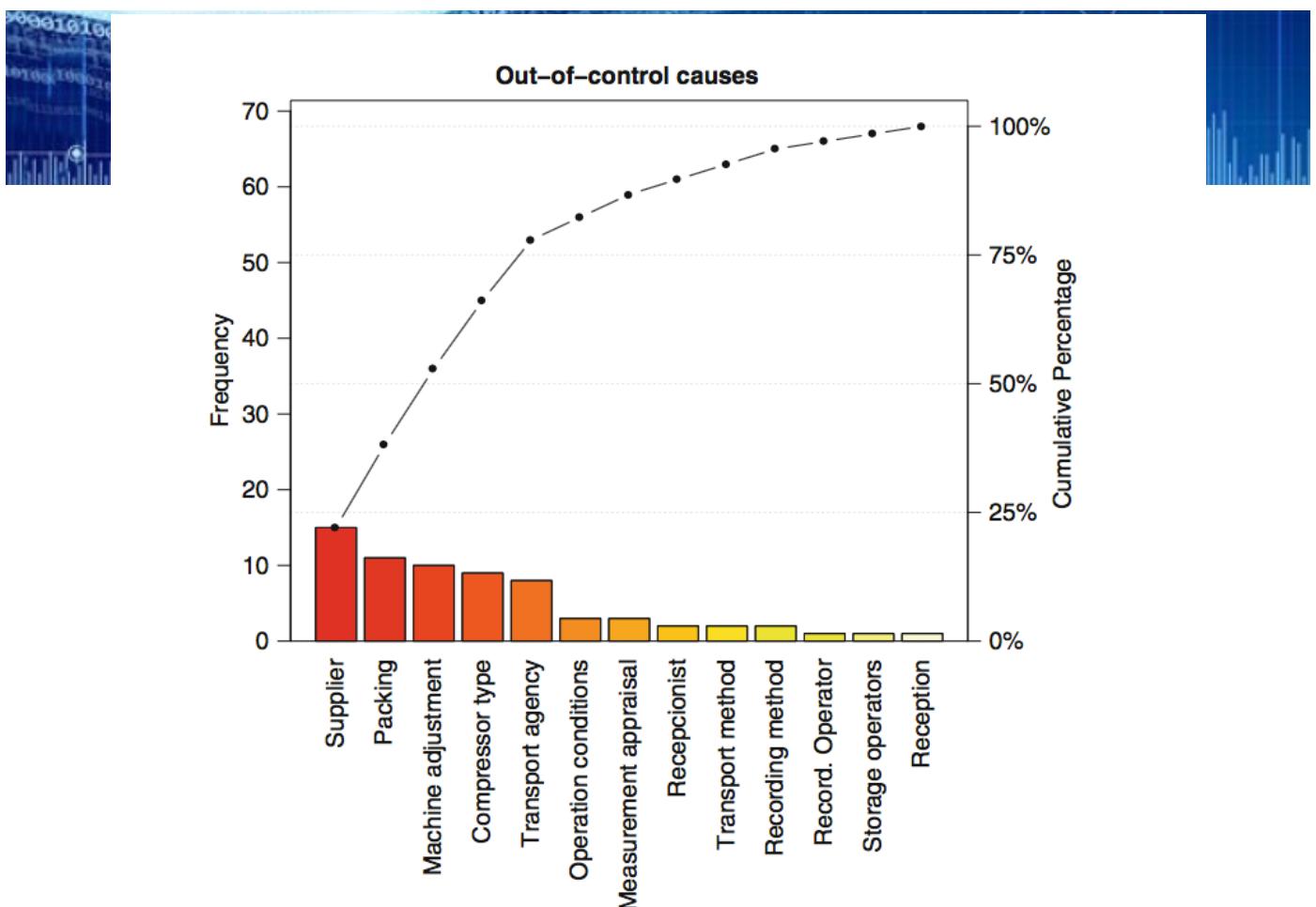


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```
library(qcc)
data_pareto2 <- data_pareto$Total
names(data_pareto2) <- data_pareto$Cause
pareto.chart(x = data_pareto2,
              main = "Out-of-control causes")
```

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300



```
##  
## Pareto chart analysis for data_pareto2  
##  
## Frequency Cum.Freq.  
## Supplier 15 15  
## Packing 11 26  
## Machine adjustment 10 36  
## Compressor type 9 45  
## Transport agency 8 53  
## Operation conditions 3 56  
## Measurement appraisal 3 59  
## Recepcionist 2 61  
## Transport method 2 63  
## Recording method 2 65  
## Record. Operator 1 66  
## Storage operators 1 67  
## Reception 1 68  
##  
## Pareto chart analysis for data_pareto2  
##  
## Percentage Cum.Percent.  
## Supplier 22.058824 22.058824  
## Packing 16.176471 38.23529  
## Machine adjustment 14.705882 52.94118  
## Compressor type 13.235294 66.17647  
## Transport agency 11.764706 77.94118  
## Operation conditions 4.411765 82.35294  
## Measurement appraisal 4.411765 86.76471  
## Recepcionist 2.941176 89.70588  
## Transport method 2.941176 92.64706  
## Recording method 2.941176 95.58824  
## Record. Operator 1.470588 97.05882  
## Storage operators 1.470588 98.52941  
## Reception 1.470588 100.00000
```

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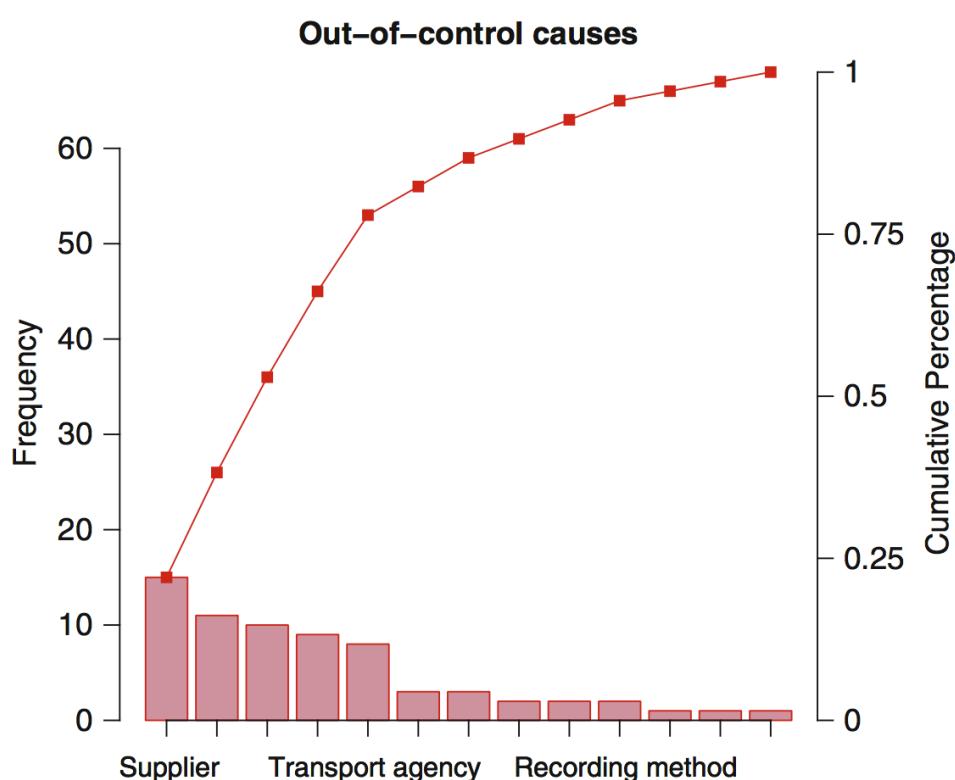
```
library(qualityTools)  
paretoChart(x = data_pareto2,  
             main = "Out-of-control causes")  
  
##  
## Frequency 15 11 10 9 8 3  
## Cum. Frequency 15 26 36 45 53 56  
## Percentage 22.1% 16.2% 14.7% 13.2% 11.8% 4.4%  
## Cum. Percentage 22.1% 38.2% 52.9% 66.2% 77.9% 82.4%
```

302



```
##  
## Frequency 3 2 2 2 1 1  
## Cum. Frequency 59 61 63 65 66 67  
## Percentage 4.4% 2.9% 2.9% 2.9% 1.5% 1.5%  
## Cum. Percentage 86.8% 89.7% 92.6% 95.6% 97.1% 98.5%  
##  
## Frequency 1  
## Cum. Frequency 68  
## Percentage 1.5%  
## Cum. Percentage 100.0%  
##  
## Frequency 15.00000 11.00000 10.00000 9.00000  
## Cum. Frequency 15.00000 26.00000 36.00000 45.00000  
## Percentage 22.05882 16.17647 14.70588 13.23529  
## Cum. Percentage 22.05882 38.23529 52.94118 66.17647  
##  
## Frequency 8.00000 3.000000 3.000000  
## Cum. Frequency 53.00000 56.000000 59.000000  
## Percentage 11.76471 4.411765 4.411765  
## Cum. Percentage 77.94118 82.352941 86.764706  
##  
## Frequency 2.000000 2.000000 2.000000  
## Cum. Frequency 61.000000 63.000000 65.000000  
## Percentage 2.941176 2.941176 2.941176  
## Cum. Percentage 89.705882 92.647059 95.588235  
##  
## Frequency 1.000000 1.000000 1.000000  
## Cum. Frequency 66.000000 67.000000 68.000000  
## Percentage 1.470588 1.470588 1.470588  
## Cum. Percentage 97.058824 98.529412 100.000000
```

303

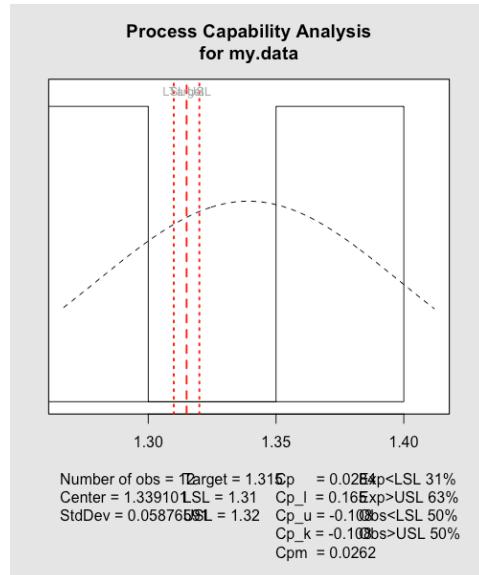


Category	Frequency	Cum. Frequency	Cum. Percentage (%)
Supplier	15	15	22
Transport agency	11	26	38
Recording method	10	36	53
Others	9	45	66
	8	53	78
	3	56	82
	3	59	87
	2	61	90
	2	63	93
	2	65	96
	1	66	97
	1	67	99
	1	68	100

304



```
lsl <- 10.85 # Fill in YOUR LSL here!
usl <- 10.95 # Fill in YOUR USL here!
process.capability(myControlChart, spec.limits=c(lsl,usl))
```



305



```
plot(pdensity ~ ptemp,
      col = "gray40",
      pch = 20,
      main = "Pellets density vs. temperature",
      xlab = "Temperature (Celsius)",
      ylab = expression("Density ("*g/cm^3*)"))
```

306

```

library(qicharts)
spreadvector <- rep(names(data_pareto2),
  times = data_pareto2)
paretochart(spreadvector)

##                                     Frequency
## Supplier                           15
## Packing                            11
## Machine adjustment                 10
## Compressor type                   9
## Transport agency                  8
## Measurement appraisal            3
## Operation conditions              3
## Receptionist                      2
## Recording method                 2
## Transport method                  2
## Reception                         1
## Record. Operator                 1
## Storage operators                1

##                                     Cumulative Frequency
## Supplier                           15
## Packing                            26
## Machine adjustment                 36
## Compressor type                  45

```

307

```
psupplier <- rep(c("A", "B", "C"), each = 8)
```

```

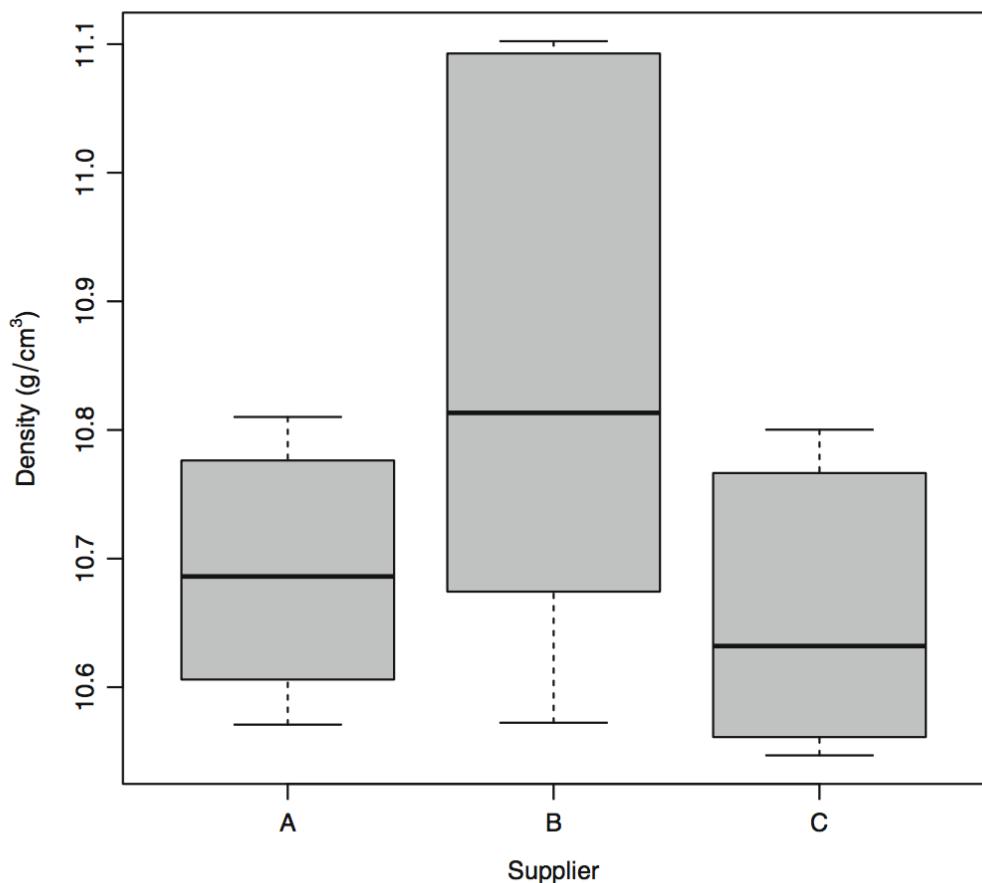
boxplot(pdensity ~ psupplier,
  col = "gray70",
  xlab = "Supplier",
  ylab = expression("Density (*g/cm^3*)"),
  main = "Box plots by supplier")

```

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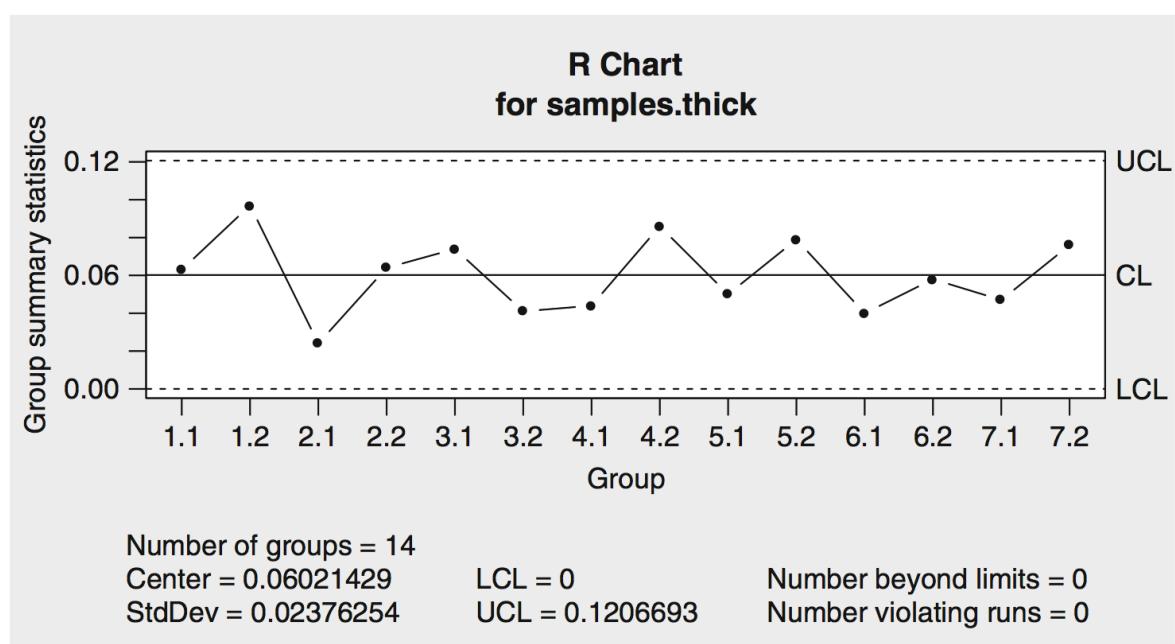
Box plots by supplier



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Range Chart

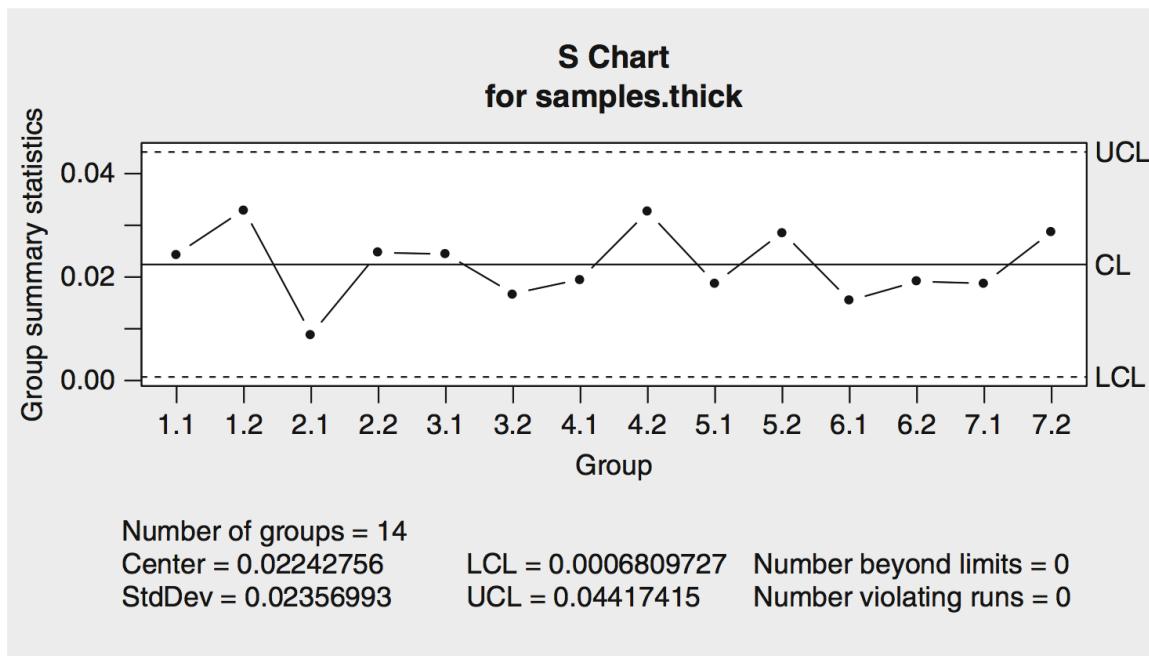
```
r.thick <- qcc(data = samples.thick, type = "R")
```



310

Standard Deviation Chart

```
r.thick <- qcc(data = samples.thick, type = "S")
```

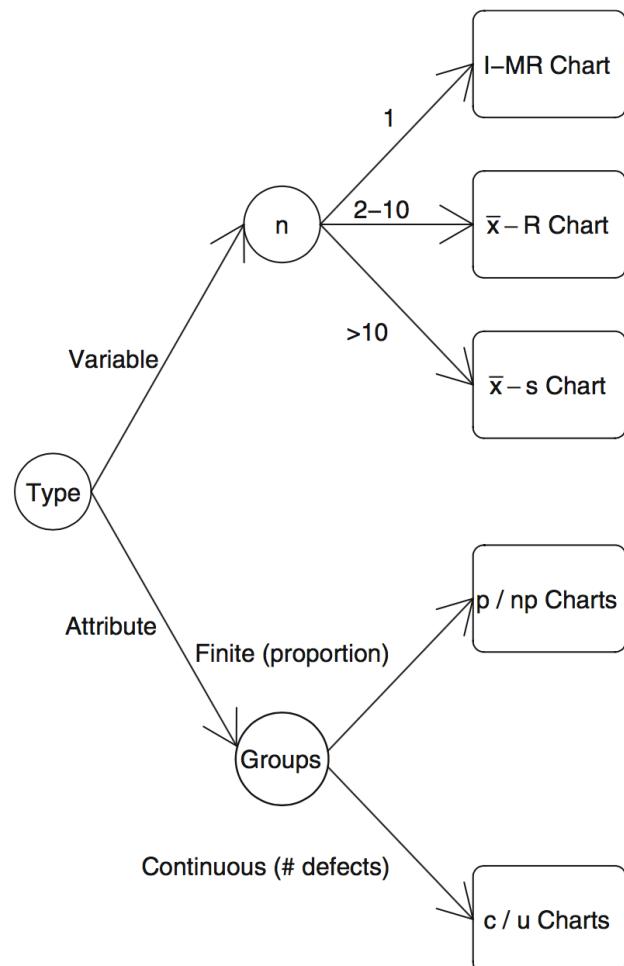


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Other QCC Chart

- Attribute Data (Discrete Data)
 - n / np QCC Chart
- Error per Interval basis
 - c Chart
- Defect per items
 - u Chart

312



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Use the data frame `ss.data.thickness2` is in the `SixSigma` package to create control chart for x -bar

314



Machine Learning for Data Science



What is Machine Learning?

- **Fundamental Question of Computer Science:**

How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?

Why machine learning?

- Learn relationships from large sets of complex data: Data mining
 - Predict clinical outcome from tests
 - Decide whether someone is a good credit risk
- Do tasks too complex to program by hand
 - Autonomous driving
- Customize programs to users/customers need
 - Recommend book/movie based on previous likes

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Why Machine Learning?

- Economically efficient
- Can consider larger data spaces and hypothesis spaces than people can
- Can formalize learning problem to explicitly identify/describe goals and criteria

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Machine Learning Paradigms

- **Supervised Learning**
 - Classification
 - Regression
- **Unsupervised Learning**
 - Clustering
- **Re-enforcement Learning**

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Supervised Learning

Approaches

- Classification (discrete predictions)
 - Regression (continuous predictions)
-
- Common considerations
 - Representation (Features)
 - Feature Selection
 - Functional form
 - Evaluation of predictive power

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Classification vs Regression

- If I want to predict whether a patient will die from a disease within six months, that is **classification**
- If I want to predict how long the patient will live, that is **regression**

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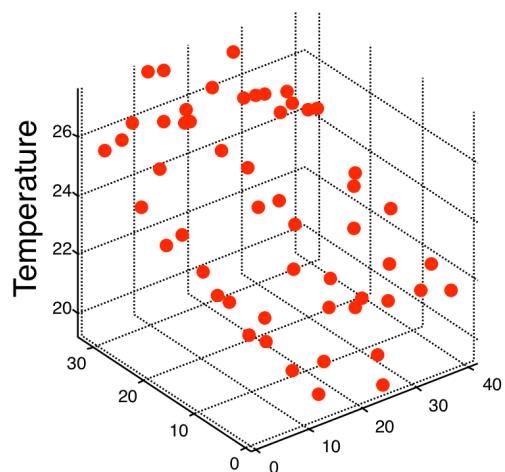
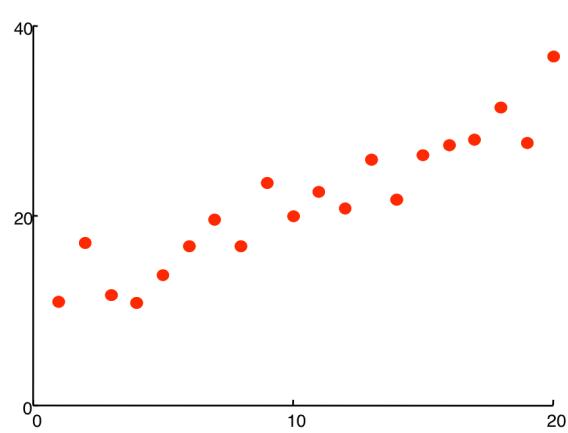
Representation

Definition of thing or things to be predicted

- Classification: classes
- Regression: regression variable
- Definition of things (instances) to make predictions for
 - Individuals
 - Families
 - Neighborhoods, etc.
- Choice of descriptors (features) to describe different aspects of instances

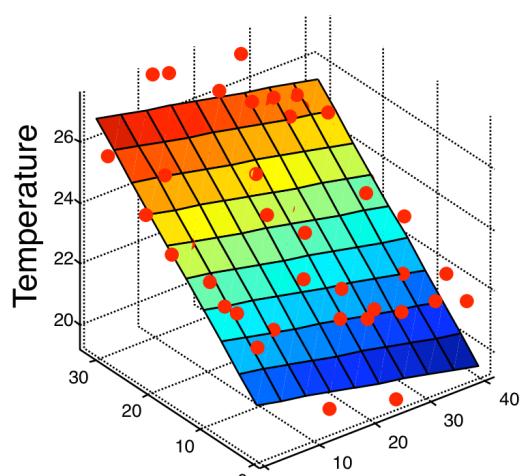
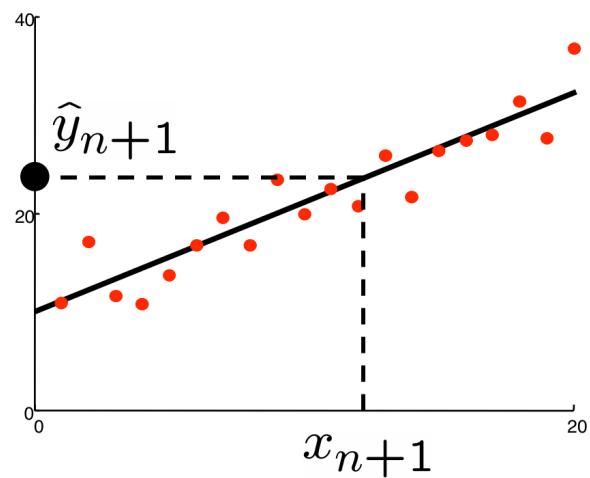
322

Linear Regression



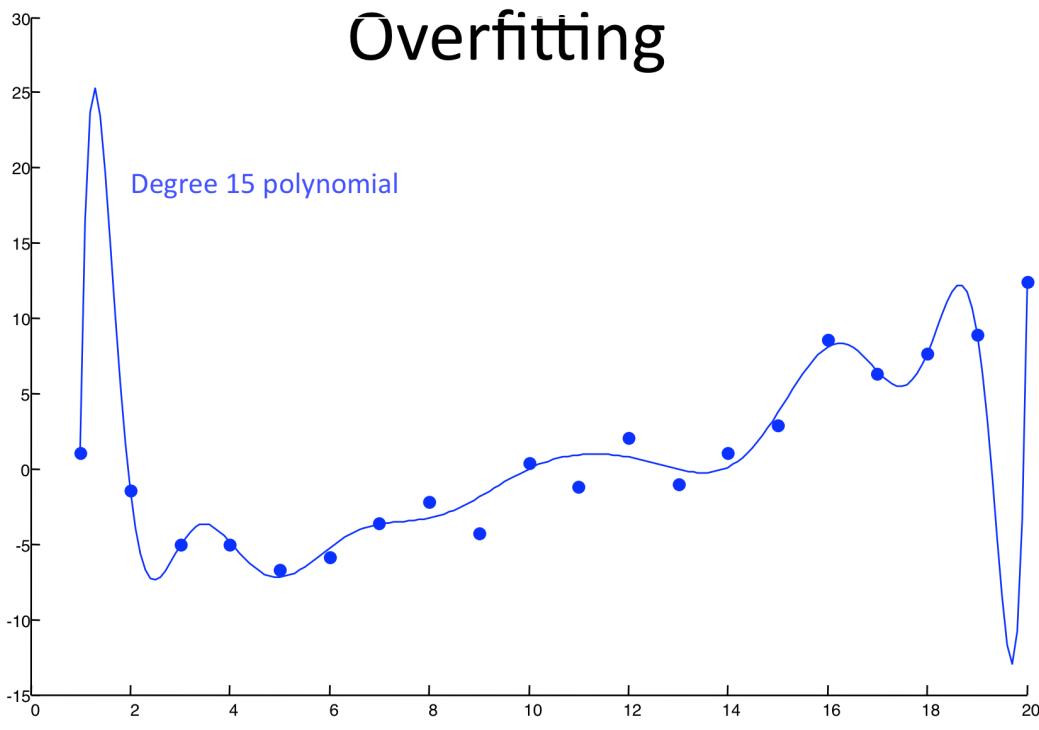
323

Linear Regression



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Overfitting



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Linear Regression

Let's first import the data set and see what we're working with.

```
# Import data set
crime <- read.table("crime_simple.txt", sep = "\t", header = TRUE)
```

The variable names that this data set comes with are very confusing, and even misleading.

R: Crime rate: # of offenses reported to police per million population

Age: The number of males of age 14-24 per 1000 population

S: Indicator variable for Southern states (0 = No, 1 = Yes)

Ed: Mean # of years of schooling x 10 for persons of age 25 or older

Ex0: 1960 per capita expenditure on police by state and local government

Ex1: 1959 per capita expenditure on police by state and local government

LF: Labor force participation rate per 1000 civilian urban males age 14-24

M: The number of males per 1000 females

N: State population size in hundred thousands

NW: The number of non-whites per 1000 population

U1: Unemployment rate of urban males per 1000 of age 14-24

U2: Unemployment rate of urban males per 1000 of age 35-39

W: Median value of transferable goods and assets or family income in tens of \$

X: The number of families per 1000 earning below 1/2 the median income

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We really need to give these variables better names

```
# Assign more meaningful variable names
colnames(crime) <- c("crime.per.million", "young.males", "is.south", "average.ed",
                      "exp.per.cap.1960", "exp.per.cap.1959", "labour.part",
                      "male.per.fem", "population", "nonwhite",
                      "unemp.youth", "unemp.adult", "median.assets", "num.low.salary")

# Convert is.south to a factor
# Divide average.ed by 10 so that the variable is actually average education
# Convert median assets to 1000's of dollars instead of 10's
crime <- transform(crime, is.south = as.factor(is.south),
                    average.ed = average.ed / 10,
                    median.assets = median.assets / 100)

# print summary of the data
summary(crime)
```

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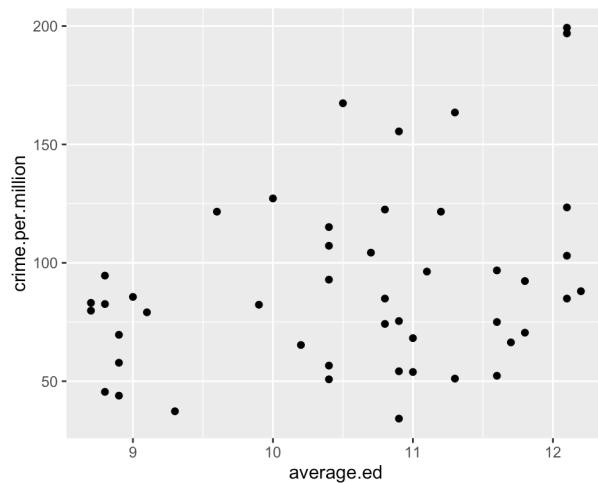


```
##   crime.per.million  young.males    is.south  average.ed
##   Min. : 34.20      Min. :119.0     0:31      Min. : 8.70
##   1st Qu.: 65.85    1st Qu.:130.0    1:16      1st Qu.: 9.75
##   Median : 83.10    Median :136.0          Median :10.80
##   Mean   : 90.51    Mean   :138.6          Mean   :10.56
##   3rd Qu.:105.75    3rd Qu.:146.0          3rd Qu.:11.45
##   Max.   :199.30    Max.   :177.0          Max.   :12.20
##   exp.per.cap.1960  exp.per.cap.1959  labour.part  male.per.fem
##   Min. : 45.0       Min. : 41.00     Min. :480.0   Min. : 934.0
##   1st Qu.: 62.5     1st Qu.: 58.50    1st Qu.:530.5  1st Qu.: 964.5
##   Median : 78.0     Median : 73.00    Median :560.0   Median : 977.0
##   Mean   : 85.0     Mean   : 80.23    Mean   :561.2   Mean   : 983.0
##   3rd Qu.:104.5    3rd Qu.: 97.00    3rd Qu.:593.0  3rd Qu.: 992.0
##   Max.   :166.0     Max.   :157.00    Max.   :641.0   Max.   :1071.0
##   population        nonwhite       unemp.youth   unemp.adult
##   Min.   : 3.00     Min.   : 2.0     Min.   : 70.00  Min.   :20.00
##   1st Qu.:10.00     1st Qu.: 24.0    1st Qu.: 80.50  1st Qu.:27.50
##   Median :25.00     Median : 76.0    Median : 92.00  Median :34.00
##   Mean   :36.62     Mean   :101.1    Mean   : 95.47  Mean   :33.98
##   3rd Qu.:41.50     3rd Qu.:132.5   3rd Qu.:104.00 3rd Qu.:38.50
##   Max.   :168.00    Max.   :423.0    Max.   :142.00  Max.   :58.00
##   median.assets    num.low.salary
##   Min.   :2.880     Min.   :126.0
##   1st Qu.:4.595     1st Qu.:165.5
##   Median :5.370     Median :176.0
##   Mean   :5.254     Mean   :194.0
##   3rd Qu.:5.915     3rd Qu.:227.5
##   Max.   :6.890     Max.   :276.0
```

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First step: some plotting and summary statistics

```
# Scatter plot of outcome (crime.per.million) against average.ed  
qplot(average.ed, crime.per.million, data = crime)
```

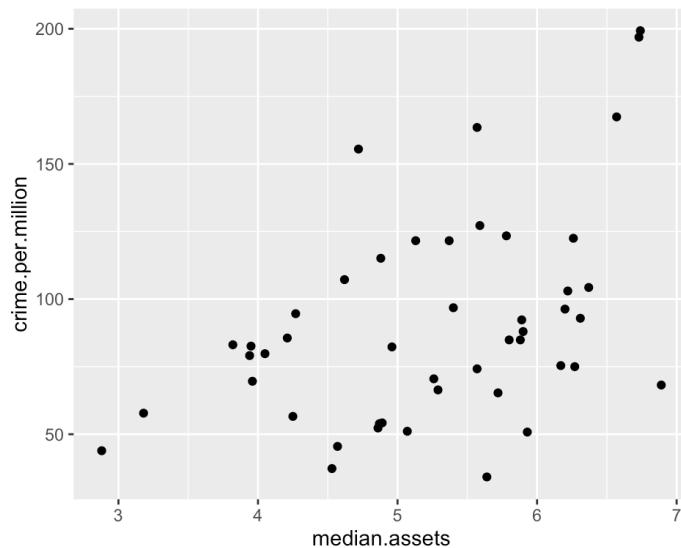


```
# correlation between education and crime  
with(crime, cor(average.ed, crime.per.million))
```

```
## [1] 0.3228349
```

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```
# Scatter plot of outcome (crime.per.million) against median.assets  
qplot(median.assets, crime.per.million, data = crime)
```

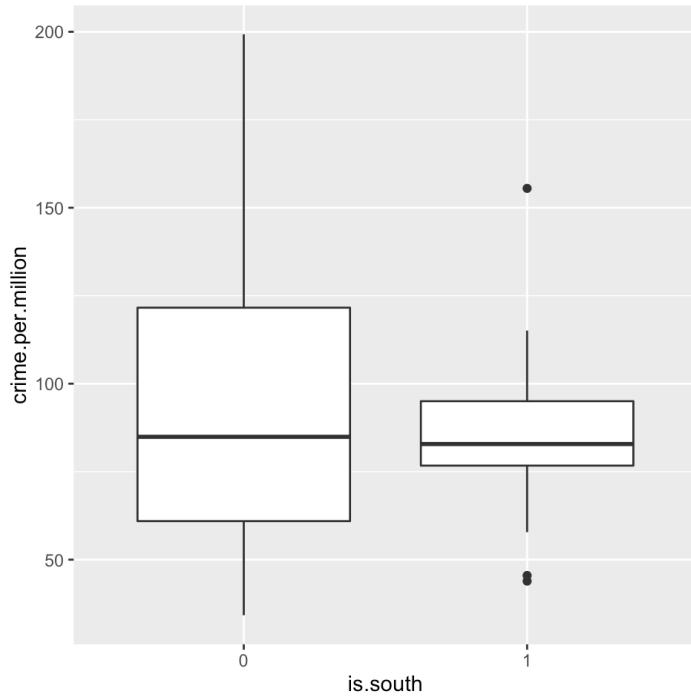


```
# correlation between education and crime  
with(crime, cor(median.assets, crime.per.million))
```

```
## [1] 0.4413199
```

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```
# Boxplots showing crime rate broken down by southern vs non-southern state
qplot(is.south, crime.per.million, geom = "boxplot", data = crime)
```



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Constructing a regression model

```
crime.lm <- lm(crime.per.million ~ ., data = crime)
# Summary of the linear regression model
crime.lm
```

```
##
## Call:
## lm(formula = crime.per.million ~ ., data = crime)
##
## Coefficients:
## (Intercept)      young.males      is.south1      average.ed
## -6.918e+02       1.040e+00      -8.308e+00      1.802e+01
## exp.per.cap.1960 exp.per.cap.1959      labour.part      male.per.fem
## 1.608e+00        -6.673e-01      -4.103e-02      1.648e-01
## population      nonwhite      unemp.youth      unemp.adult
## -4.128e-02       7.175e-03      -6.017e-01      1.792e+00
## median.assets   num.low.salary
## 1.374e+01        7.929e-01
```

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```

summary(crime.lm)

##
## Call:
## lm(formula = crime.per.million ~ ., data = crime)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -34.884 -11.923 -1.135 13.495 50.560
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)    
## (Intercept) -6.918e+02 1.559e+02 -4.438 9.56e-05 ***
## young.males  1.040e+00 4.227e-01  2.460 0.01931 *  
## is.south1    -8.308e+00 1.491e+01 -0.557 0.58117    
## average.ed   1.802e+01 6.497e+00  2.773 0.00906 ** 
## exp.per.cap.1960 1.608e+00 1.059e+00  1.519 0.13836  
## exp.per.cap.1959 -6.673e-01 1.149e+00 -0.581 0.56529  
## labour.part   -4.103e-02 1.535e-01 -0.267 0.79087  
## male.per.fem  1.648e-01 2.099e-01  0.785 0.43806  
## population    -4.128e-02 1.295e-01 -0.319 0.75196  
## nonwhite      7.175e-03 6.387e-02  0.112 0.91124  
## unemp.youth   -6.017e-01 4.372e-01 -1.376 0.17798  
## unemp.adult   1.792e+00 8.561e-01  2.093 0.04407 *  
## median.assets 1.374e+01 1.058e+01  1.298 0.20332  
## num.low.salary 7.929e-01 2.351e-01  3.373 0.00191 ** 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 21.94 on 33 degrees of freedom
## Multiple R-squared:  0.7692, Adjusted R-squared:  0.6783 
## F-statistic: 8.462 on 13 and 33 DF,  p-value: 3.686e-07

```

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```

options(scipen=4) # Set scipen = 0 to get back to default

summary(crime.lm)

##
## Call:
## lm(formula = crime.per.million ~ ., data = crime)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -34.884 -11.923 -1.135 13.495 50.560
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)    
## (Intercept) -691.837588 155.887918 -4.438 0.0000956 ***
## young.males  1.039810 0.422708  2.460 0.01931 *  
## is.south1    -8.308313 14.911588 -0.557 0.58117    
## average.ed   18.016011 6.496504  2.773 0.00906 ** 
## exp.per.cap.1960 1.607818 1.058667  1.519 0.13836  
## exp.per.cap.1959 -0.667258 1.148773 -0.581 0.56529  
## labour.part   -0.041031 0.153477 -0.267 0.79087  
## male.per.fem  0.164795 0.209932  0.785 0.43806  
## population    -0.041277 0.129516 -0.319 0.75196  
## nonwhite      0.007175 0.063867  0.112 0.91124  
## unemp.youth   -0.601675 0.437154 -1.376 0.17798  
## unemp.adult   1.792263 0.856111  2.093 0.04407 *  
## median.assets 13.735847 10.583028  1.298 0.20332  
## num.low.salary 0.792933 0.235085  3.373 0.00191 ** 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 21.94 on 33 degrees of freedom
## Multiple R-squared:  0.7692, Adjusted R-squared:  0.6783 
## F-statistic: 8.462 on 13 and 33 DF,  p-value: 0.000003686

```

Exploring the lm object

What kind of output do we get when we run a linear model (`lm`) in R?

```
# List all attributes of the linear model
attributes(crime.lm)
```

```
## $names
## [1] "coefficients"   "residuals"      "effects"       "rank"
## [5] "fitted.values"  "assign"        "qr"            "df.residual"
## [9] "contrasts"      "xlevels"       "call"          "terms"
## [13] "model"
##
## $class
## [1] "lm"
```

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```
# coefficients
crime.lm$coef
```

```
## (Intercept)    young.males     is.south1    average.ed
## -691.837587905 1.039809653 -8.308312889 18.016010601
## exp.per.cap.1960 exp.per.cap.1959 labour.part male.per.fem
## 1.607818377   -0.667258285 -0.041031047 0.164794968
## population      nonwhite      unemp.youth unemp.adult
## -0.041276887    0.007174688 -0.601675298 1.792262901
## median.assets   num.low.salary
## 13.735847285    0.792932786
```

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None of the attributes seem to give you p-values. Here's what you can do to get a table that allows you to extract p-values.

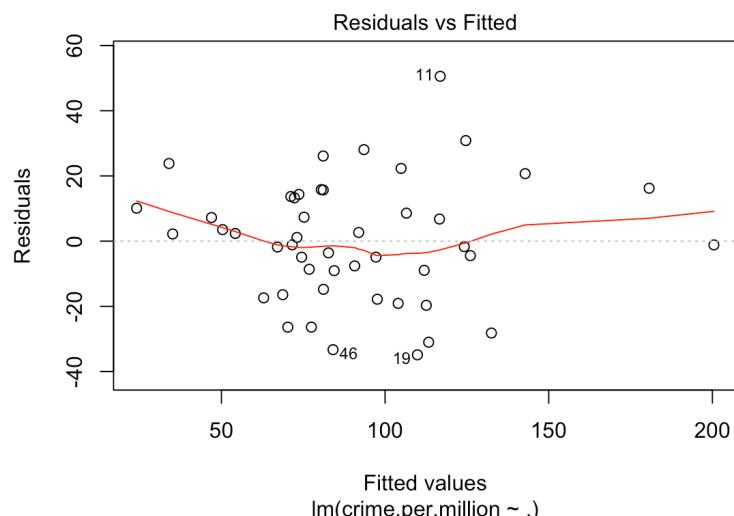
```
# Pull coefficients element from summary(lm) object
round(summary(crime.lm)$coef, 3)
```

	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	-691.838	155.888	-4.438	0.000
## young.males	1.040	0.423	2.460	0.019
## is.southl	-8.308	14.912	-0.557	0.581
## average.ed	18.016	6.497	2.773	0.009
## exp.per.cap.1960	1.608	1.059	1.519	0.138
## exp.per.cap.1959	-0.667	1.149	-0.581	0.565
## labour.part	-0.041	0.153	-0.267	0.791
## male.per.fem	0.165	0.210	0.785	0.438
## population	-0.041	0.130	-0.319	0.752
## nonwhite	0.007	0.064	0.112	0.911
## unemp.youth	-0.602	0.437	-1.376	0.178
## unemp.adult	1.792	0.856	2.093	0.044
## median.assets	13.736	10.583	1.298	0.203
## num.low.salary	0.793	0.235	3.373	0.002

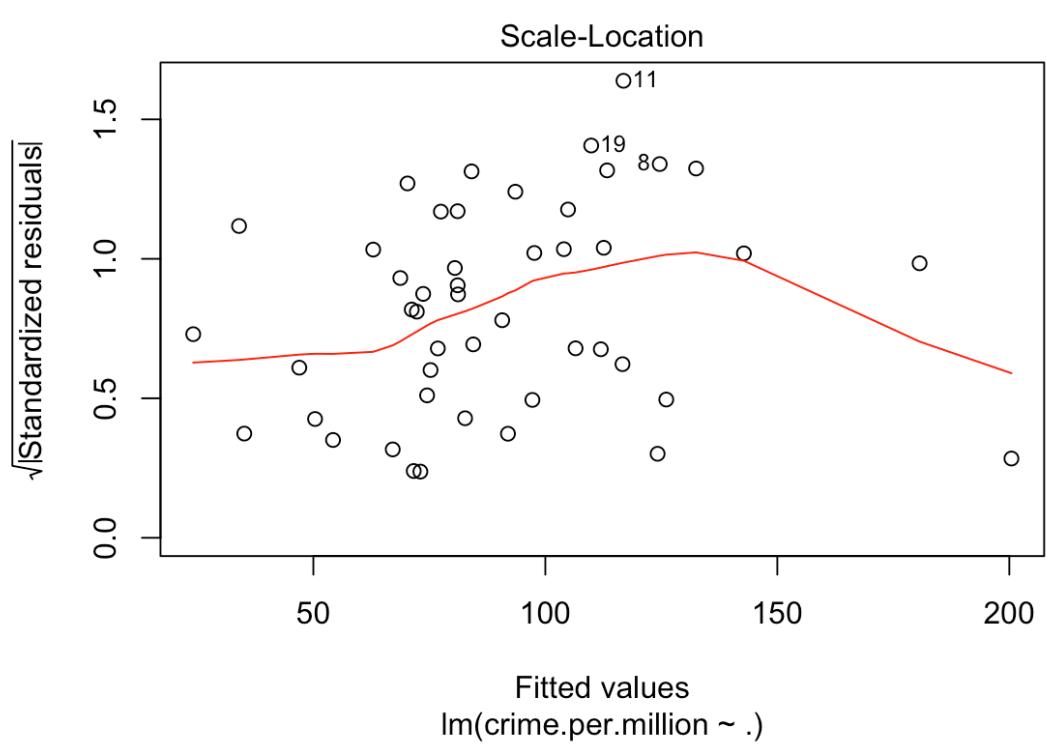
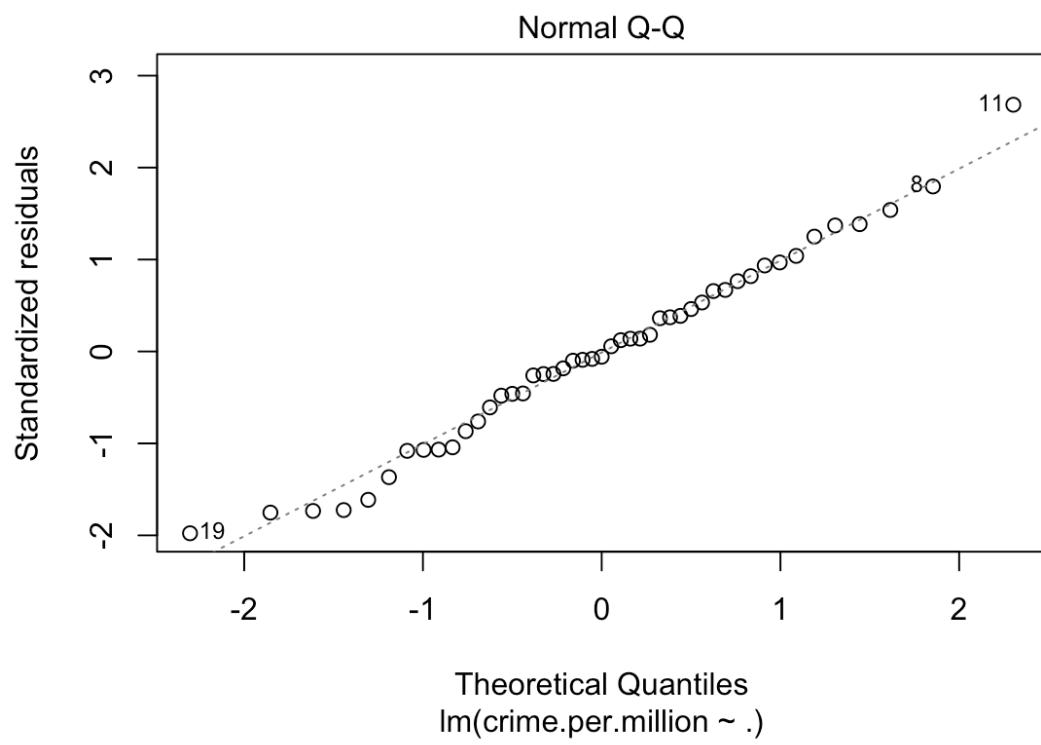
337

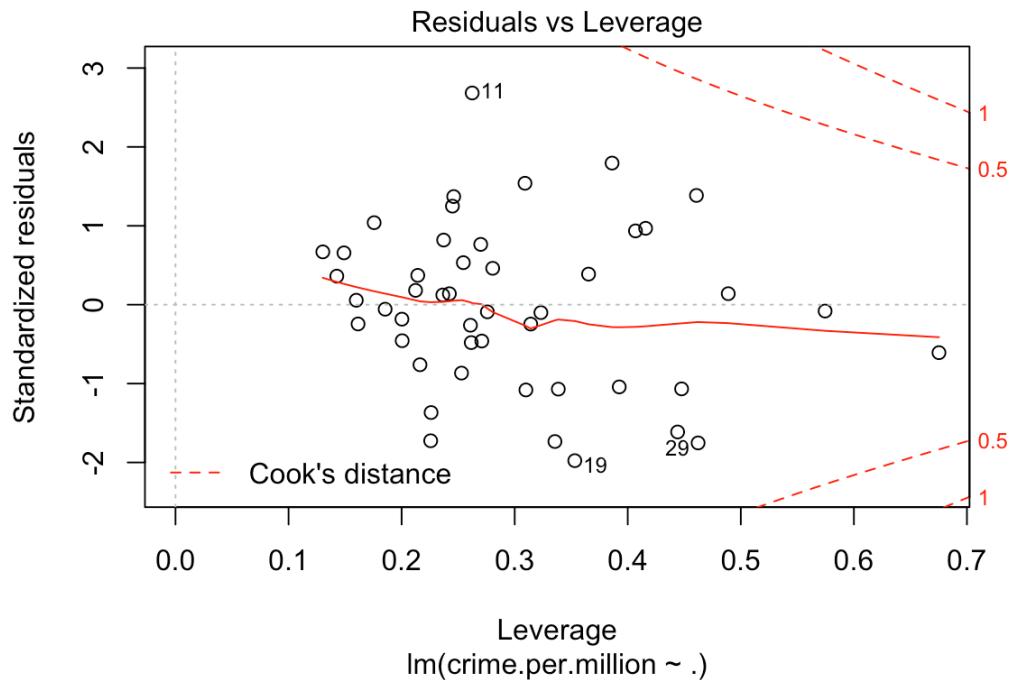
Plotting the lm object

```
plot(crime.lm)
```



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Residuals vs Fitted Plot

Residuals vs. Fitted When a linear model is appropriate, we expect

- 1 the residuals will have constant variance when plotted against fitted values; and
- 2 the residuals and fitted values will be uncorrelated.

If there are clear trends in the residual plot, or the plot looks like a funnel, these are clear indicators that the given linear model is inappropriate.

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Normal QQ Plot

Normal QQ plot You can use a linear model for prediction even if the underlying normality assumptions don't hold. However, in order for the p-values to be believable, the residuals from the regression must look approximately normally distributed.

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Scale-Location Plot

Scale-location plot This is another version of the residuals vs fitted plot. There should be no discernible trends in this plot.

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Residuals vs Leverage

Residuals vs Leverage. Leverage is a measure of how much an observation influenced the model fit. It's a one-number summary of how different the model fit would be if the given observation was excluded, compared to the model fit where the observation is included. Points with high residual (poorly described by the model) and high leverage (high influence on model fit) are outliers. They're skewing the model fit away from the rest of the data, and don't really seem to fit with the rest of the data.

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Workshop 10: Regression

We'll begin by loading some packages.

```
library(MASS)
library(plyr)
```

Interaction terms in regression

```
# Building up the familiar birthwt data...

# Rename the columns to have more descriptive names
colnames(birthwt) <- c("birthwt.below.2500", "mother.age", "mother.weight",
  "race", "mother.smokes", "previous.prem.labor", "hypertension", "uterine.irr",
  "physician.visits", "birthwt.grams")

# Transform variables to factors with descriptive levels
birthwt <- transform(birthwt,
  race = as.factor(mapvalues(race, c(1, 2, 3),
    c("white", "black", "other"))),
  mother.smokes = as.factor(mapvalues(mother.smokes,
    c(0,1), c("no", "yes"))),
  hypertension = as.factor(mapvalues(hypertension,
    c(0,1), c("no", "yes"))),
  uterine.irr = as.factor(mapvalues(uterine.irr,
    c(0,1), c("no", "yes"))))
)
```

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Workshop 10 : Regression

(a) Run a linear regression to better understand how birthweight varies with the mother's age and smoking status (do not include interaction terms).

(b) What is the coefficient of mother.age in your regression? How do you interpret this coefficient?

(c) How many coefficients are estimated for the mother's smoking status variable? How do you interpret these coefficients?

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Predictive ML

- Predictive Data Mining
- Two Phases of Processing
 - Training Phase : Learn a model from training data
 - Predicting Phase : Deploy the model to production and use that to predict the future outcome

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Data

Iris Data Set from UCI Machine Learning Repository (<https://archive.ics.uci.edu/ml/datasets/Iris>)

Attribute Information:

1. Sepal Length in cm

2. Sepal width in cm

3. Petal length in cm

4. Petal length in cm

5. Classes:

- Iris Setosa

- Iris Versicolour

- Iris Virginica



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Getting Data

```
> iris <- read.csv("iris.data.csv", header=TRUE)  
> library(datasets)  
> iris  
> colnames(iris) <- c("Sepal.Length", "Sepal.Width", "Petal.Length",  
"Petal.Width", "Species")
```

```
> 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  
> nrow(iris)  
[1] 150  
> table(iris$Species)  
  
setosa versicolor virginica  
      50        50        50
```

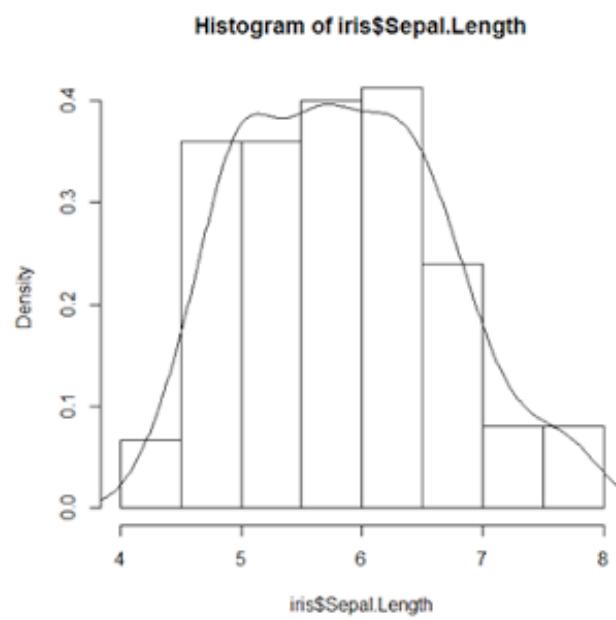
350

Data Visualization

- Visualizing existing data is a very useful way to come up with ideas about what features should be included.
- "Dataframe" in R is a common way where data samples are organized in a tabular structure.

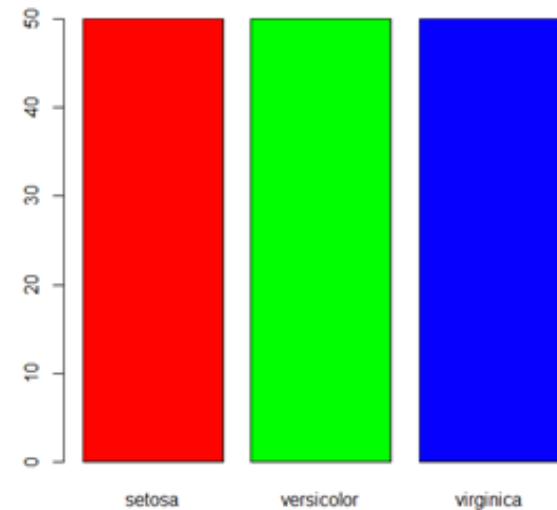
351

```
> # Plot the histogram  
> hist(iris$Sepal.Length, breaks=10, prob=T)  
> # Plot the density curve  
> lines(density(iris$Sepal.Length))  
>
```



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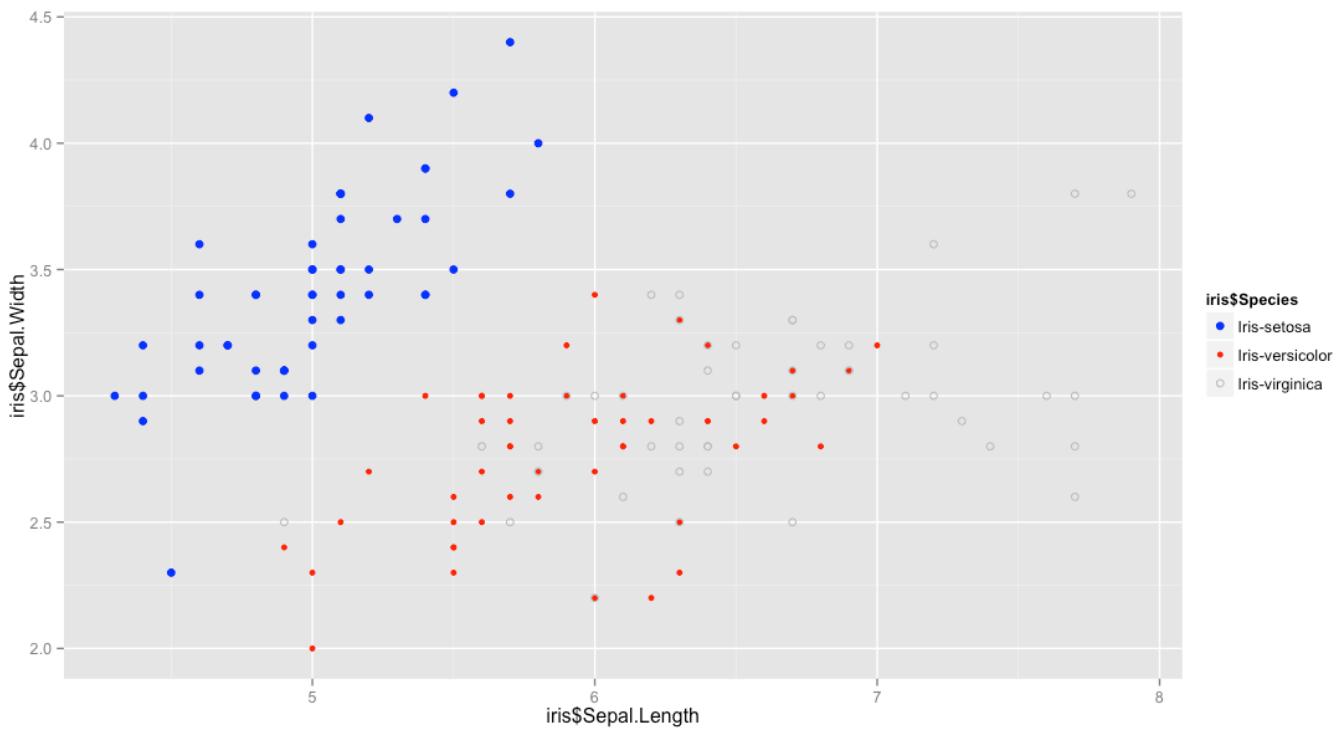
```
> categories <- table(iris$Species)
> barplot(categories, col=c('red', 'green', 'blue'))
>
```



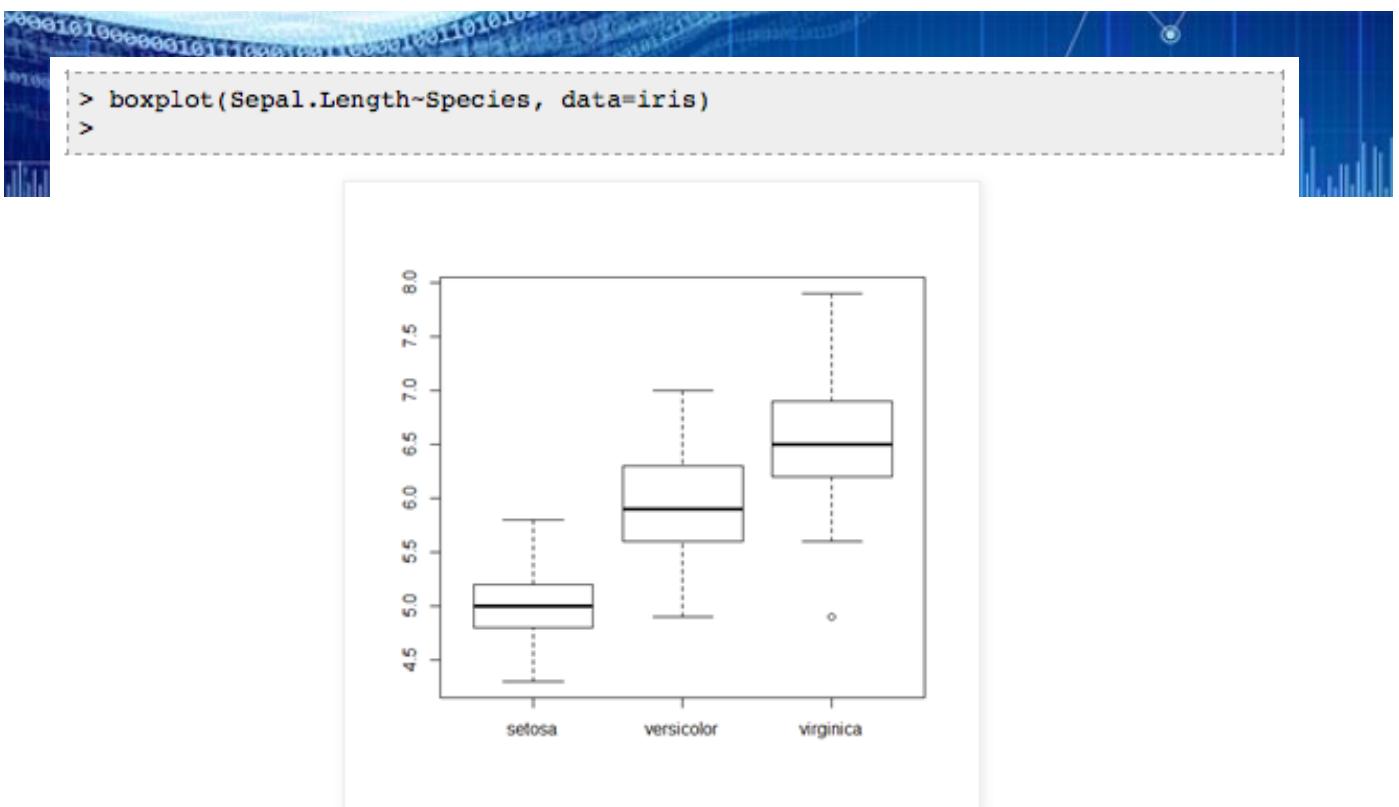
353

```
ggplot(iris, aes(x=iris$SepalLength, y=iris$SepalWidth,
group=iris$Species,shape=iris$Species)) +
geom_point(aes(colour=iris$Species)) +
scale_shape_manual(values=c(19,20,21))+
scale_colour_manual(values=c("blue", "red","gray"))
```

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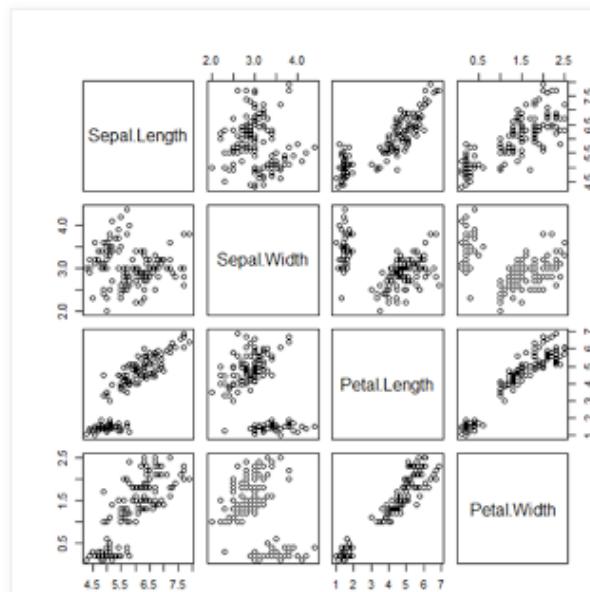


356

```

> # Scatter plot for all pairs
> pairs(iris[,c(1,2,3,4)])
> # Compute the correlation matrix
> cor(iris[,c(1,2,3,4)])
   Sepal.Length Sepal.Width Petal.Length Petal.Width
Sepal.Length    1.0000000 -0.1170695  0.8716902  0.8179410
Sepal.Width     -0.1170695  1.0000000 -0.4284401 -0.3661259
Petal.Length    0.8716902 -0.4284401  1.0000000  0.9628654
Petal.Width     0.8179410 -0.3661259  0.9628654  1.0000000
>

```

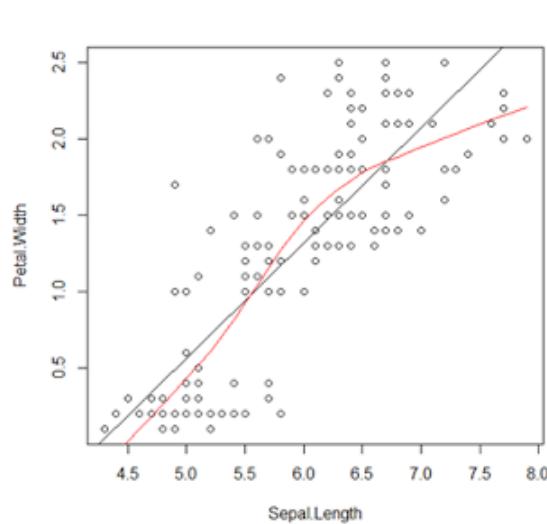


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```

> # First plot the 2 variables
> plot(Petal.Width~Sepal.Length, data=iris)
> # Learn the regression model
> model <- lm(Petal.Width~Sepal.Length, data=iris)
> # Plot the regression line
> abline(model)
> # Now learn the local linear model
> model2 <- lowess(iris$Petal.Width~iris$Sepal.Length)
> lines(model2, col="red")
>

```



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Preparing Training Data

At this step, the purpose is to transform the raw data in a form that can fit into the data mining model.

- Data sampling
- Data validation and handle missing data
- Normalize numeric value into a uniform range
- Compute aggregated value (a special case is to compute frequency counts)
- Expand categorical field to binary fields
- Discretize numeric value into categories
- Create derived fields from existing fields
- Reduce dimensionality
- Power and Log transformation

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Data Sampling

```
> # select 10 records out from iris with replacement
> index <- sample(1:nrow(iris), 10, replace=T)
> index
[1] 133  36 107 140  66  67  36   3  97  37
> irissample <- iris[index,]
> irissample
  Sepal.Length Sepal.Width Petal.Length Petal.Width   Species
133          6.4        2.8         5.6        2.2 virginica
36           5.0        3.2         1.2        0.2    setosa
107          4.9        2.5         4.5        1.7 virginica
140          6.9        3.1         5.4        2.1 virginica
66           6.7        3.1         4.4        1.4 versicolor
67           5.6        3.0         4.5        1.5 versicolor
36.1         5.0        3.2         1.2        0.2    setosa
3            4.7        3.2         1.3        0.2    setosa
97           5.7        2.9         4.2        1.3 versicolor
37           5.5        3.5         1.3        0.2    setosa
>
```

360

Impute missing data

- Discard the whole record
- Infer missing value based on the data of other record. Approach is to fill the missing data with the average or the median.

```
> # Create some missing data
> irissample[10, 1] <- NA
> irissample
   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
133         6.4        2.8        5.6        2.2 virginica
 36         5.0        3.2        1.2        0.2    setosa
107         4.9        2.5        4.5        1.7 virginica
140         6.9        3.1        5.4        2.1 virginica
 66         6.7        3.1        4.4        1.4 versicolor
 67         5.6        3.0        4.5        1.5 versicolor
36.1        5.0        3.2        1.2        0.2    setosa
 3         4.7        3.2        1.3        0.2    setosa
 97         5.7        2.9        4.2        1.3 versicolor
 37          NA        3.5        1.3        0.2    setosa
```

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```
> library(e1071)
Loading required package: class
Warning message:
package 'e1071' was built under R version 2.14.2
> fixIris1 <- impute(irissample[,1:4], what='mean')
> fixIris1
   Sepal.Length Sepal.Width Petal.Length Petal.Width
133       6.400000     2.8        5.6        2.2
 36       5.000000     3.2        1.2        0.2
107       4.900000     2.5        4.5        1.7
140       6.900000     3.1        5.4        2.1
 66       6.700000     3.1        4.4        1.4
 67       5.600000     3.0        4.5        1.5
36.1      5.000000     3.2        1.2        0.2
 3       4.700000     3.2        1.3        0.2
 97       5.700000     2.9        4.2        1.3
 37      5.655556     3.5        1.3        0.2
> fixIris2 <- impute(irissample[,1:4], what='median')
> fixIris2
   Sepal.Length Sepal.Width Petal.Length Petal.Width
133         6.4        2.8        5.6        2.2
 36         5.0        3.2        1.2        0.2
107         4.9        2.5        4.5        1.7
140         6.9        3.1        5.4        2.1
 66         6.7        3.1        4.4        1.4
 67         5.6        3.0        4.5        1.5
36.1        5.0        3.2        1.2        0.2
 3         4.7        3.2        1.3        0.2
 97         5.7        2.9        4.2        1.3
 37         5.6        3.5        1.3        0.2
>
```

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Normalize numeric value

```
> # scale the columns  
> # x-mean(x)/standard deviation  
> scaleiris <- scale(iris[, 1:4])  
> head(scaleiris)  
  Sepal.Length Sepal.Width Petal.Length Petal.Width  
[1,] -0.8976739  1.01560199 -1.335752 -1.311052  
[2,] -1.1392005 -0.13153881 -1.335752 -1.311052  
[3,] -1.3807271  0.32731751 -1.392399 -1.311052  
[4,] -1.5014904  0.09788935 -1.279104 -1.311052  
[5,] -1.0184372  1.24503015 -1.335752 -1.311052  
[6,] -0.5353840  1.93331463 -1.165809 -1.048667  
>
```

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Reduce dimensionality

There are two ways to reduce the number of input attributes.

1. Removing irrelevant input variables.
2. Removing redundant input variables.

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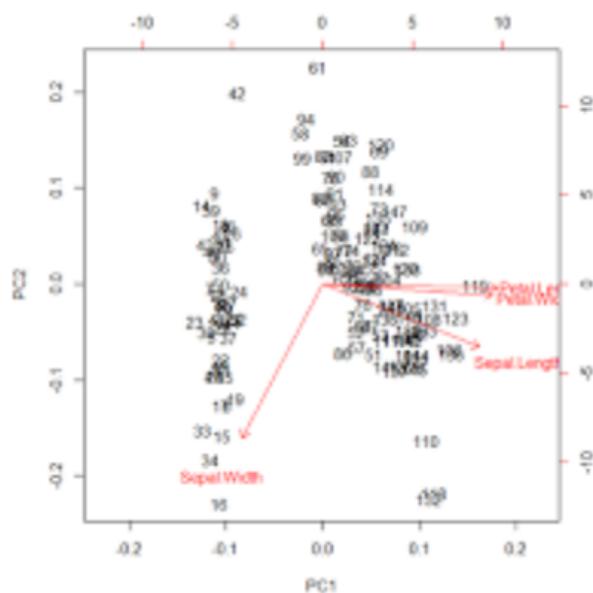
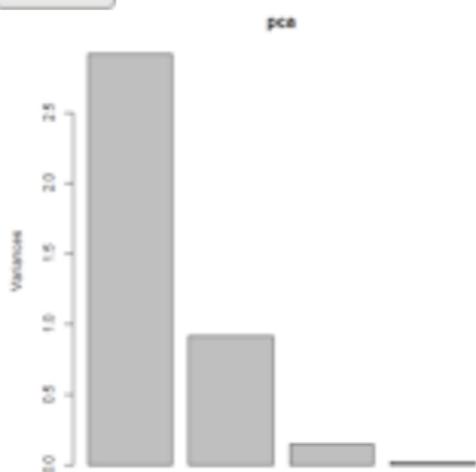
```

> # Use iris data set
> cor(iris[, -5])
      Sepal.Length Sepal.Width Petal.Length Petal.Width
Sepal.Length 1.0000000000 -0.1175697841 0.8717537759 0.8179411263
Sepal.Width -0.1175697841 1.0000000000 -0.4284401043 -0.3661259325
Petal.Length 0.8717537759 -0.4284401043 1.0000000000 0.9628654314
Petal.Width 0.8179411263 -0.3661259325 0.9628654314 1.0000000000
> # Some attributes shows high correlation, compute PCA
> pca <- prcomp(iris[, -5], scale=T)
> summary(pca)
Importance of components:
          PC1        PC2        PC3        PC4
Standard deviation 1.708361 0.9560494 0.3830886 0.1439265
Proportion of Variance 0.729620 0.2285100 0.0366900 0.0051800
Cumulative Proportion 0.729620 0.9581300 0.9948200 1.0000000
> # Notice PC1 and PC2 covers most variation
> plot(pca)
> pca$rotation
          PC1        PC2        PC3        PC4
Sepal.Length 0.5210659147 -0.37741761556 0.7195663527 0.2612862800
Sepal.Width -0.2693474425 -0.92329565954 -0.2443817795 -0.1235096196
Petal.Length 0.5804130958 -0.02449160909 -0.1421263693 -0.8014492463
Petal.Width 0.5648565358 -0.06694198697 -0.6342727371 0.5235971346
> # Project first 2 records in PCA direction
> predict(pca)[1:2,]
          PC1        PC2        PC3        PC4
[1,] -2.257141176 -0.4784238321 0.1272796237 0.02408750846
[2,] -2.074013015  0.6718826870 0.2338255167 0.10266284468
> # plot all points in top 2 PCA direction
> biplot(pca)

```

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Pinit



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Add derived attributes

```
> iris2 <- transform(iris, ratio=round(Sepal.Length/Sepal.Width, 2))
> head(iris2)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species ratio
1          5.1        3.5       1.4        0.2   setosa  1.46
2          4.9        3.0       1.4        0.2   setosa  1.63
3          4.7        3.2       1.3        0.2   setosa  1.47
4          4.6        3.1       1.5        0.2   setosa  1.48
5          5.0        3.6       1.4        0.2   setosa  1.39
6          5.4        3.9       1.7        0.4   setosa  1.38
```

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Discretize numeric value into categories

```
> # Equal width cuts
> segments <- 10
> maxL <- max(iris$Petal.Length)
> minL <- min(iris$Petal.Length)
> theBreaks <- seq(minL, maxL,
+                     by=(maxL-minL)/segments)
> cutPetalLength <- cut(iris$Petal.Length,
+                         breaks=theBreaks,
+                         include.lowest=T)
> newdata <- data.frame(orig.Petal.Len=iris$Petal.Length,
+                         cut.Petal.Len=cutPetalLength)
> head(newdata)
  orig.Petal.Len cut.Petal.Len
1          1.4      [1,1.59]
2          1.4      [1,1.59]
3          1.3      [1,1.59]
4          1.5      [1,1.59]
5          1.4      [1,1.59]
6          1.7      (1.59,2.18]
>
> # Constant frequency / height
> myBreaks <- quantile(iris$Petal.Length,
+                        probs=seq(0,1,1/segments))
> cutPetalLength2 <- cut(iris$Petal.Length,
+                         breaks=myBreaks,
+                         include.lowest=T)
> newdata2 <- data.frame(orig.Petal.Len=iris$Petal.Length,
+                         cut.Petal.Len=cutPetalLength2)
> head(newdata2)
  orig.Petal.Len cut.Petal.Len
1          1.4      [1,1.4]
2          1.4      [1,1.4]
3          1.3      [1,1.4]
4          1.5      (1.4,1.5]
5          1.4      [1,1.4]
6          1.7      (1.7,3.9]
```

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Binarize categorical attributes

```
> cat <- levels(iris$Species)
> cat
[1] "setosa"      "versicolor"   "virginica"
> binarize <- function(x) {return(iris$Species == x)}
> newcols <- sapply(cat, binarize)
> colnames(newcols) <- cat
> data <- cbind(iris[,c('Species')], newcols)
> data[45:55,]
    setosa versicolor virginica
[1,] 1       1       0       0
[2,] 1       1       0       0
[3,] 1       1       0       0
[4,] 1       1       0       0
[5,] 1       1       0       0
[6,] 1       1       0       0
[7,] 2       0       1       0
[8,] 2       0       1       0
[9,] 2       0       1       0
[10,] 2      0       1       0
[11,] 2      0       1       0
```

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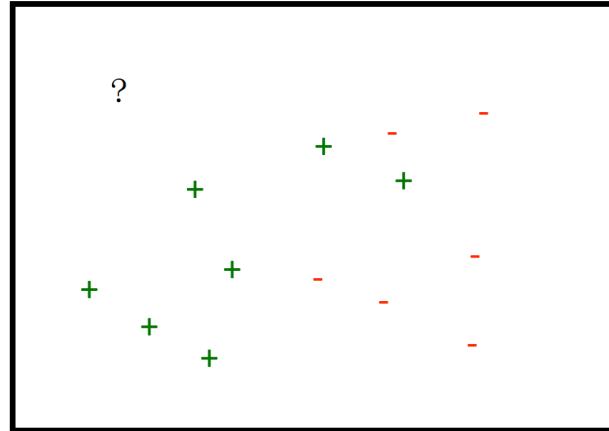
Iris Data Preparation

```
> set.seed(1234)
> ind <- sample(2, nrow(iris), replace=TRUE, prob=c(0.7, 0.3))
> trainData <- iris[ind==1,]
> testData <- iris[ind==2,]
```

370

Decision Tree

Feature #2
(e.g., roundness)



Feature #1 (e.g., 'area')

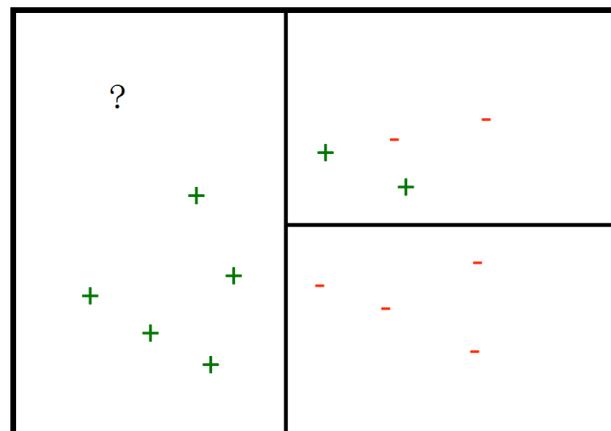
371

Decision Tree

We build tree to divide them up.

Feature #2
(e.g., roundness)

40



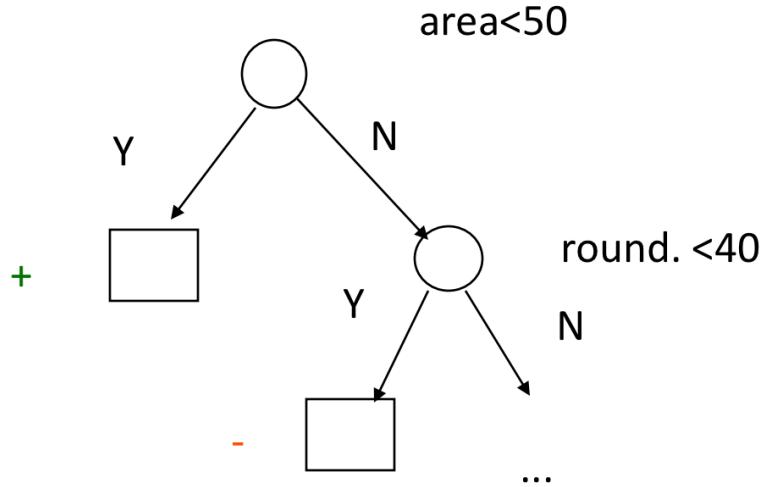
50

Feature #1 (e.g., 'area')

372

Decision Tree

Goal: split address space in (almost) homogeneous regions



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Decision Tree

Conditional Inference Trees

Description

Recursive partitioning for continuous, censored, ordered, nominal and multivariate response variables in a conditional inference framework.

Usage

```
ctree(formula, data, subset = NULL, weights = NULL,  
      controls = ctree_control(), xtrafo = ptrtafo, ytrafo = ptrafo,  
      scores = NULL)
```

Arguments

formula a symbolic description of the model to be fit. Note that symbols like : and - will not work and the tree will make use of all variables listed on the rhs of formula.
data a data frame containing the variables in the model.
subset an optional vector specifying a subset of observations to be used in the fitting process.
weights an optional vector of weights to be used in the fitting process. Only non-negative integer valued weights are allowed.
controls an object of class [TreeControl](#), which can be obtained using [ctree_control](#).
xtrafo a function to be applied to all input variables. By default, the [ptrtafo](#) function is applied.
ytrafo a function to be applied to all response variables. By default, the [ptrafo](#) function is applied.
scores an optional named list of scores to be attached to ordered factors.

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Decision Tree - Create Model

```
> library(party)
> myFormula <- Species ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width
> iris_ctree <- ctree(myFormula, data=trainData)
> # check the prediction
> table(predict(iris_ctree), trainData$Species)
```

	setosa	versicolor	virginica
setosa	40	0	0
versicolor	0	37	3
virginica	0	1	31

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```
> print(iris_ctree)

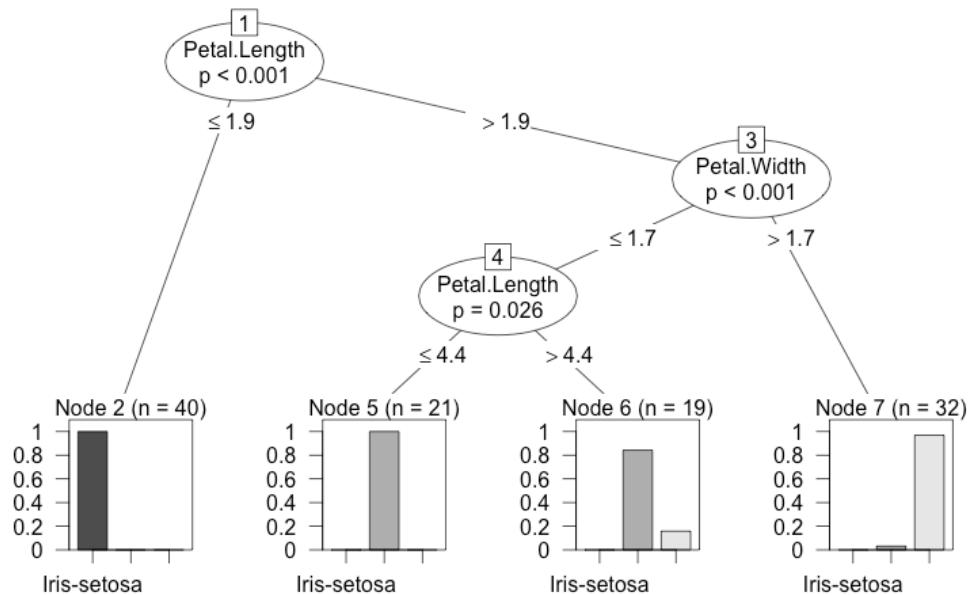
Conditional inference tree with 4 terminal nodes

Response: Species
Inputs: Sepal.Length, Sepal.Width, Petal.Length, Petal.Width
Number of observations: 112

1) Petal.Length <= 1.9; criterion = 1, statistic = 104.643
   2)* weights = 40
1) Petal.Length > 1.9
   3) Petal.Width <= 1.7; criterion = 1, statistic = 48.939
      4) Petal.Length <= 4.4; criterion = 0.974, statistic = 7.397
         5)* weights = 21
      4) Petal.Length > 4.4
         6)* weights = 19
   3) Petal.Width > 1.7
      7)* weights = 32
```

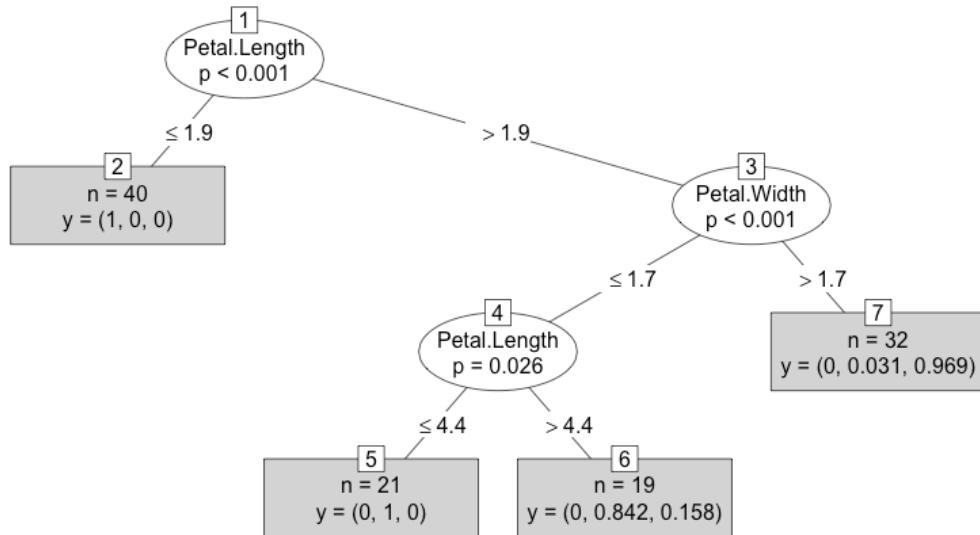
376

```
> plot(iris_ctree)
```



377

```
> plot(iris_ctree, type="simple")
```



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Decision Tree - Prediction

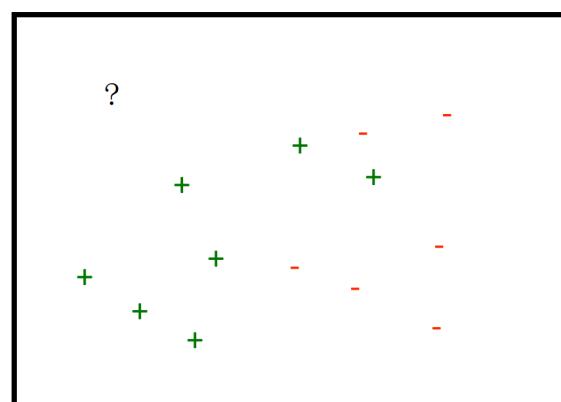
```
> # predict on test data  
> testPred <- predict(iris_ctree, newdata = testData)  
> table(testPred, testData$Species)
```

testPred	setosa	versicolor	virginica
setosa	10	0	0
versicolor	0	12	2
virginica	0	0	14

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K-Nearest Neighbor

Feature #2
(e.g., roundness)

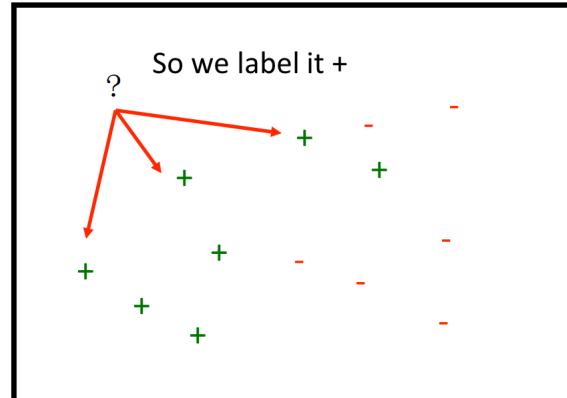


Feature #1 (e.g., 'area')

380

K-NN

Feature #2
(e.g., roundness)



for k=3,
nearest
neighbors
are

Feature #1 (e.g., 'area')

381

K-NN

k-Nearest Neighbour Classification

Description

k-nearest neighbour classification for test set from training set. For each row of the test set, the k nearest (in Euclidean distance) training set vectors are found, and the classification is decided by majority vote, with ties broken at random. If there are ties for the kth nearest vector, all candidates are included in the vote.

Usage

```
knn(train, test, cl, k = 1, l = 0, prob = FALSE, use.all = TRUE)
```

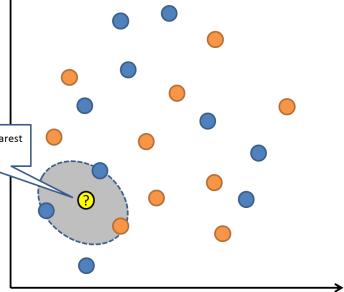
Arguments

train matrix or data frame of training set cases.
test matrix or data frame of test set cases. A vector will be interpreted as a row vector for a single case.
cl factor of true classifications of training set
k number of neighbours considered.
l minimum vote for definite decision, otherwise doubt. (More precisely, less than k-1 dissenting votes are allowed, even if k is increased by ties.)
prob If this is true, the proportion of the votes for the winning class are returned as attribute **prob**.
use.all controls handling of ties. If true, all distances equal to the kth largest are included. If false, a random selection of distances equal to the kth is chosen to use exactly k neighbours.

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K-NN

Vote by the 3 nearest neighbors



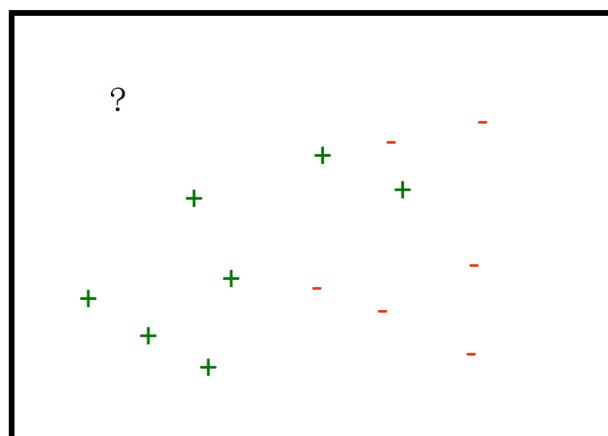
```
> library(class)
> train_input <- as.matrix(iristrain[,-5])
> train_output <- as.vector(irisstrain[,5])
> test_input <- as.matrix(iristest[,-5])
> prediction <- knn(train_input, test_input,
+                      train_output, k=5)
> table(prediction, iristest$Species)

prediction   setosa versicolor virginica
  setosa       10         0         0
  versicolor     0        10         1
  virginica      0         0         9
>
```

383

Support Vector Machines (SVMs)

Feature #2
(e.g., roundness)



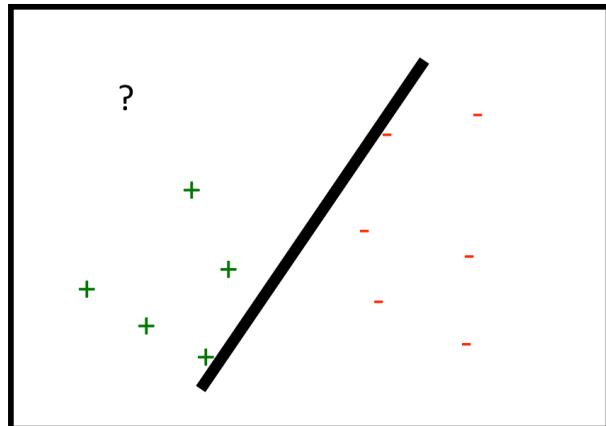
Feature #1 (e.g., 'area')

384

Support Vector Machines (SVMs)

So, we use linear line to divide them.

round.



area

385

Support Vector Machine

svm {e1071}

R Documentation

Support Vector Machines

Description

`svm` is used to train a support vector machine. It can be used to carry out general regression and classification (of nu and epsilon-type), as well as density-estimation. A formula interface is provided.

Usage

```
## S3 method for class 'formula'  
svm(formula, data = NULL, ..., subset, na.action =  
na.omit, scale = TRUE)  
## Default S3 method:  
svm(x, y = NULL, scale = TRUE, type = NULL, kernel =  
"radial", degree = 3, gamma = if (is.vector(x)) 1 else 1 / ncol(x),  
coef0 = 0, cost = 1, nu = 0.5,  
class.weights = NULL, cachesize = 40, tolerance = 0.001, epsilon = 0.1,  
shrinking = TRUE, cross = 0, probability = FALSE, fitted = TRUE,  
..., subset, na.action = na.omit)
```

Arguments

- formula** a symbolic description of the model to be fit.
- data** an optional data frame containing the variables in the model. By default the variables are taken from the environment which 'svm' is called from.
- x** a data matrix, a vector, or a sparse matrix (object of class [Matrix](#) provided by the [Matrix](#) package, or of class [matrix.csr](#) provided by the [SparseM](#) package, or of class [simple_triplet_matrix](#) provided by the [slam](#) package).
- y** a response vector with one label for each row/component of **x**. Can be either a factor (for classification tasks) or a numeric vector (for regression).

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Support Vector Machine

```
> library(e1071)
> tune <- tune.svm(Species~., data=iristrain, gamma=10^{(-6:-1)}, cost=10^{(1:4)})
> summary(tune)
Parameter tuning of 'svm':
- sampling method: 10-fold cross validation
- best parameters:
  gamma  cost
0.001 10000
- best performance: 0.03333333
> model <- svm(Species~., data=iristrain, method="C-classification",
kernel="radial", probability=T, gamma=0.001, cost=10000)
> prediction <- predict(model, iristest, probability=T)
> table(iristest$Species, prediction)
      prediction
setosa versicolor virginica
setosa       10         0         0
versicolor     0        10         0
virginica      0         3         7
>
```

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Naive Bayes

Weather	Play
Sunny	No
Overcast	Yes
Rainy	Yes
Sunny	Yes
Sunny	Yes
Overcast	Yes
Rainy	No
Rainy	No
Sunny	Yes
Rainy	Yes
Sunny	No
Overcast	Yes
Overcast	Yes
Rainy	No

Frequency Table		
Weather	No	Yes
Overcast		4
Rainy	3	2
Sunny	2	3
Grand Total	5	9

Likelihood table				
Weather	No	Yes		
Overcast		4	=4/14	0.29
Rainy	3	2	=5/14	0.36
Sunny	2	3	=5/14	0.36
All	5	9		
	=5/14	=9/14		
	0.36	0.64		

388

Naive Bayes

Naive Bayes Classifier

Description

Computes the conditional a-posterior probabilities of a categorical class variable given independent predictor variables using the Bayes rule.

Usage

```
## S3 method for class 'formula'  
naiveBayes(formula, data, laplace = 0, ..., subset, na.action = na.pass)  
## Default S3 method:  
naiveBayes(x, y, laplace = 0, ...)  
  
## S3 method for class 'naiveBayes'  
predict(object, newdata,  
       type = c("class", "raw"), threshold = 0.001, eps = 0, ...)
```

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Naive Bayes

Arguments

x	A numeric matrix, or a data frame of categorical and/or numeric variables.
y	Class vector.
formula	A formula of the form <code>class ~ x1 + x2 + ...</code> . Interactions are not allowed.
data	Either a data frame of predictors (categorical and/or numeric) or a contingency table.
laplace	positive double controlling Laplace smoothing. The default (0) disables Laplace smoothing.
...	Currently not used.
subset	For data given in a data frame, an index vector specifying the cases to be used in the training sample. (NOTE: If given, this argument must be named.)
na.action	A function to specify the action to be taken if <code>NAs</code> are found. The default action is not to count them for the computation of the probability factors. An alternative is <code>na.omit</code> , which leads to rejection of cases with missing values on any required variable. (NOTE: If given, this argument must be named.)
object	An object of class " <code>naiveBayes</code> ".
newdata	A data frame with new predictors (with possibly fewer columns than the training data). Note that the column names of <code>newdata</code> are matched against the training data ones.
type	If " <code>raw</code> ", the conditional a-posterior probabilities for each class are returned, and the class with maximal probability else.
threshold	Value replacing cells with probabilities within <code>eps</code> range.
eps	double for specifying an epsilon-range to apply laplace smoothing (to replace zero or close-zero probabilities by <code>threshold</code> .)

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Naive Bayes

```
> library(e1071)
> # Can handle both categorical and numeric input,
> # but output must be categorical
> model <- naiveBayes(Species~, data=iristrain)
> prediction <- predict(model, iristest[, -5])
> table(prediction, iristest[, 5])

prediction   setosa versicolor virginica
  setosa       10         0         0
  versicolor    0        10         2
  virginica     0         0         8
```

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Neural Network

Training of neural networks

Description

`neuralnet` is used to train neural networks using backpropagation, resilient backpropagation (RPROP) with (Riedmiller, 1994) or without weight backtracking (Riedmiller and Braun, 1993) or the modified globally convergent version (GRPROP) by Anastasiadis et al. (2005). The function allows flexible settings through custom-choice of error and activation function. Furthermore the calculation of generalized weights (Intrator O. and Intrator N., 1993) is implemented.

Usage

```
neuralnet(formula, data, hidden = 1, threshold = 0.01,
           stepmax = 1e+05, rep = 1, startweights = NULL,
           learningrate.limit = NULL,
           learningrate.factor = list(minus = 0.5, plus = 1.2),
           learningrate=NULL, lifesign = "none",
           lifesign.step = 1000, algorithm = "rprop+",
           err.fct = "sse", act.fct = "logistic",
           linear.output = TRUE, exclude = NULL,
           constant.weights = NULL, likelihood = FALSE)
```

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Neural Network

Arguments

<code>formula</code>	a symbolic description of the model to be fitted.
<code>data</code>	a data frame containing the variables specified in <code>formula</code> .
<code>hidden</code>	a vector of integers specifying the number of hidden neurons (vertices) in each layer.
<code>threshold</code>	a numeric value specifying the threshold for the partial derivatives of the error function as stopping criteria.
<code>stepmax</code>	the maximum steps for the training of the neural network. Reaching this maximum leads to a stop of the neural network's training process.
<code>rep</code>	the number of repetitions for the neural network's training.
<code>startweights</code>	a vector containing starting values for the weights. The weights will not be randomly initialized.
<code>learningrate.limit</code>	a vector or a list containing the lowest and highest limit for the learning rate. Used only for RPROP and GRPROP.
<code>learningrate.factor</code>	a vector or a list containing the multiplication factors for the upper and lower learning rate. Used only for RPROP and GRPROP.
<code>learningrate</code>	a numeric value specifying the learning rate used by traditional backpropagation. Used only for traditional backpropagation.
<code>lifesign</code>	a string specifying how much the function will print during the calculation of the neural network. 'none', 'minimal' or 'full'.

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Neural Network

<code>lifesign.step</code>	an integer specifying the stepsize to print the minimal threshold in full lifesign mode.
<code>algorithm</code>	a string containing the algorithm type to calculate the neural network. The following types are possible: 'backprop', 'rprop+', 'rprop-', 'sag', or 'slr'. 'backprop' refers to backpropagation, 'rprop+' and 'rprop-' refer to the resilient backpropagation with and without weight backtracking, while 'sag' and 'slr' induce the usage of the modified globally convergent algorithm (grprop). See Details for more information.
<code>err.fct</code>	a differentiable function that is used for the calculation of the error. Alternatively, the strings 'sse' and 'ce' which stand for the sum of squared errors and the cross-entropy can be used.
<code>act.fct</code>	a differentiable function that is used for smoothing the result of the cross product of the covariate or neurons and the weights. Additionally the strings, 'logistic' and 'tanh' are possible for the logistic function and tangent hyperbolicus.
<code>linear.output</code>	logical. If <code>act.fct</code> should not be applied to the output neurons set linear output to TRUE, otherwise to FALSE.
<code>exclude</code>	a vector or a matrix specifying the weights, that are excluded from the calculation. If given as a vector, the exact positions of the weights must be known. A matrix with n-rows and 3 columns will exclude n weights, where the first column stands for the layer, the second column for the input neuron and the third column for the output neuron of the weight.
<code>constant.weights</code>	a vector specifying the values of the weights that are excluded from the training process and treated as fix.
<code>likelihood</code>	logical. If the error function is equal to the negative log-likelihood function, the information criteria AIC and BIC will be calculated. Furthermore the usage of <code>confidence.interval</code> is meaningful.

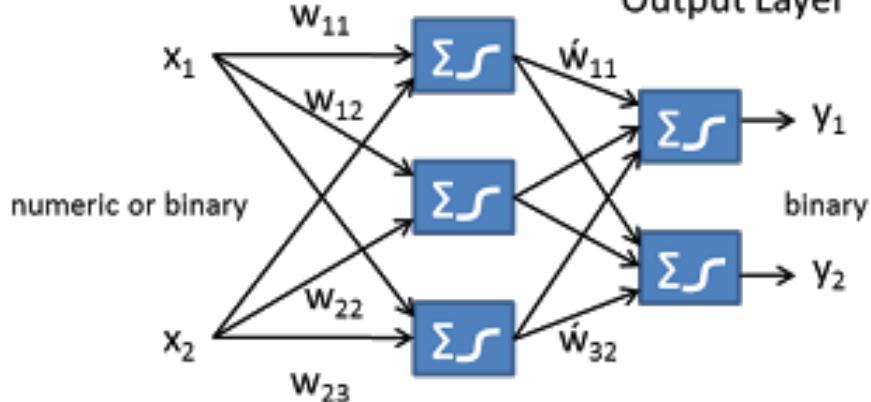
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Neural Network

Input Layer

Hidden Layer

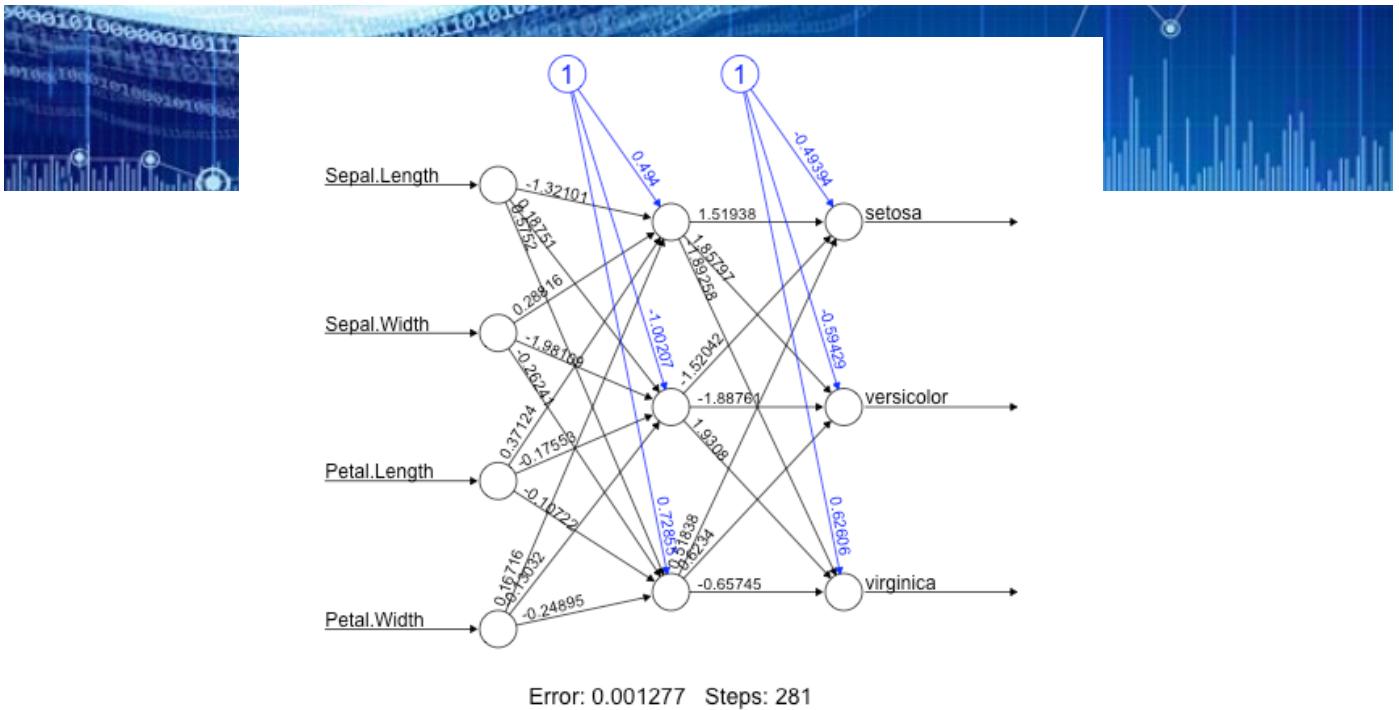
Output Layer



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```
2
3 library(neuralnet)
4 iris <- read.csv("iris.data.csv", header=TRUE)
5 # Prepare iris
6 set.seed(567)
7 ind <- sample(2, nrow(iris), replace=TRUE, prob=c(0.7, 0.3))
8 trainData <- iris[ind==1,]
9 testData <- iris[ind==2,]
10 nnet_iristrain <- trainData
11
12 #Binarize the categorical output
13 nnet_iristrain <- cbind(nnet_iristrain, trainData$Species == 'Iris-setosa')
14 nnet_iristrain <- cbind(nnet_iristrain, trainData$Species == 'Iris-versicolor')
15 nnet_iristrain <- cbind(nnet_iristrain, trainData$Species == 'Iris-virginica')
16 names(nnet_iristrain)[6] <- 'Setosa'
17 names(nnet_iristrain)[7] <- 'Versicolor'
18 names(nnet_iristrain)[8] <- 'Virginica'
19
20 nn <- neuralnet(Setosa+Versicolor+Virginica ~ Sepal.Length+Sepal.Width+Petal.Length+Petal.Width,
21                 data=nnet_iristrain, hidden=c(3))
22
23 plot(nn)
24 mypredict <- compute(nn, testData[-5])$net.result
25 # Put multiple binary output to categorical output
26 maxidx <- function(arr) {
27   return(which(arr == max(arr)))
28 }
29 idx <- apply(mypredict, c(1), maxidx)
30 prediction <- c('Iris-setosa', 'Iris-versicolor', 'Iris-virginica')[idx]
31 table(prediction, testData$Species)
32
33
```

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```
> table(prediction, testData$Species)

prediction      Iris-setosa Iris-versicolor Iris-virginica
  Iris-setosa          15            0            0
  Iris-versicolor        0           13            0
  Iris-virginica         0            0           15
> |
```

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...visualizing classifier performance

Classification

Binary classification

(Instances, Class labels): $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$

$y_i \{1, -1\}$ - valued

Classifier: provides class prediction \hat{Y} for an instance
Outcomes for a prediction:

		True class	
		1	-1
Predicted class	1	True positive (TP)	False positive (FP)
	-1	False negative (FN)	True negative (TN)

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Some basic performance measures

$P(\hat{Y} = Y)$: accuracy

$P(\hat{Y} = 1 | Y = 1)$: true positive rate

$P(\hat{Y} = 1 | Y = -1)$: false positive rate

$P(Y = 1 | \hat{Y} = 1)$: precision

		True class	
		1	-1
Predicted class	1	True positive (TP)	False positive (FP)
	-1	False negative (FN)	True negative (TN)

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Performance trade-offs

Often: Improvement in measure X →

measure Y becomes worse

Idea: Visualize trade-off in a two-dimensional plot

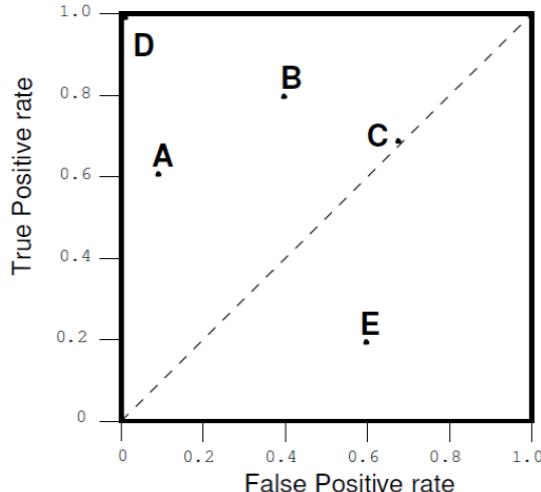
Examples:

True pos. rate vs.
false pos. rate

Precision vs. recall

Lift charts

...



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Scoring classifiers

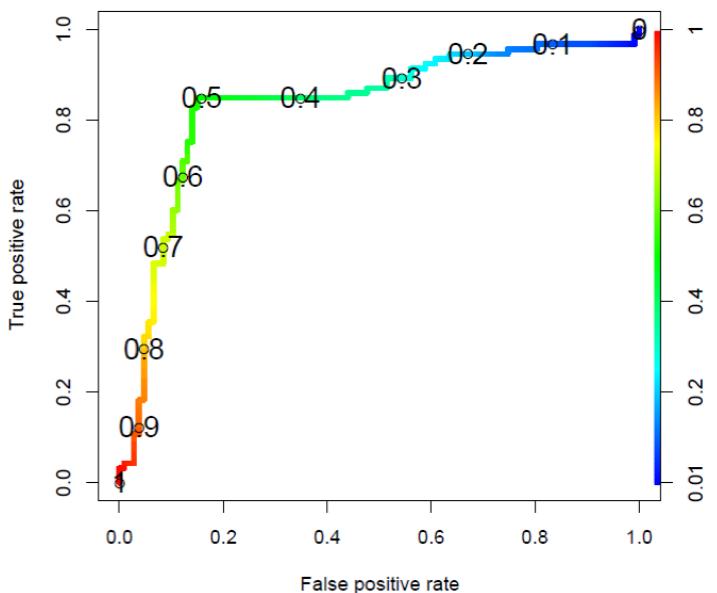
Output: continuous
(instead of actual
class prediction)
Discretized by choosing
a cut-off

$f(x) \geq c \rightarrow \text{class „1“}$

$f(x) < c \rightarrow \text{class „-1“}$

Trade-off visualizations:

cutoff-parameterized curves



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ROCR

Only three commands

```
pred <- prediction( scores, labels )
```

(pred: S4 object of class prediction)

```
perf <- performance( pred, measure.Y, measure.X )
```

(pred: S4 object of class performance)

```
plot( perf )
```

Input format

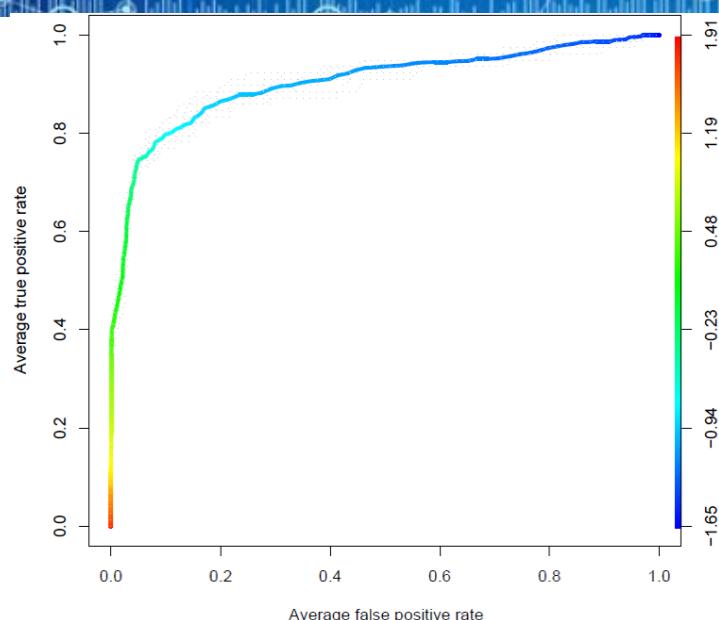
Single run:

vectors (scores: numeric; labels: anything)

Multiple runs (cross-validation, bootstrapping, ...):

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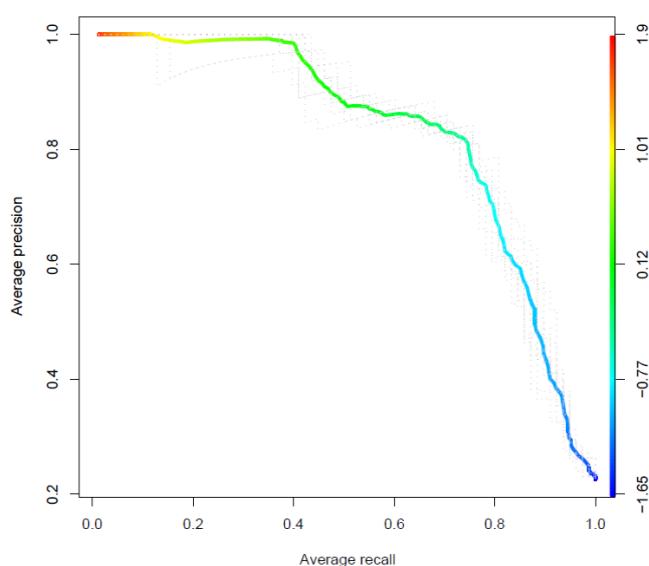
Examples (1/8): ROC curves



```
■ pred <- prediction(scores, labels)  
■ perf <- performance(pred, "tpr", "fpr")  
■ plot(perf, colorize=T)
```

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Examples (2/8): Precision/recall curves

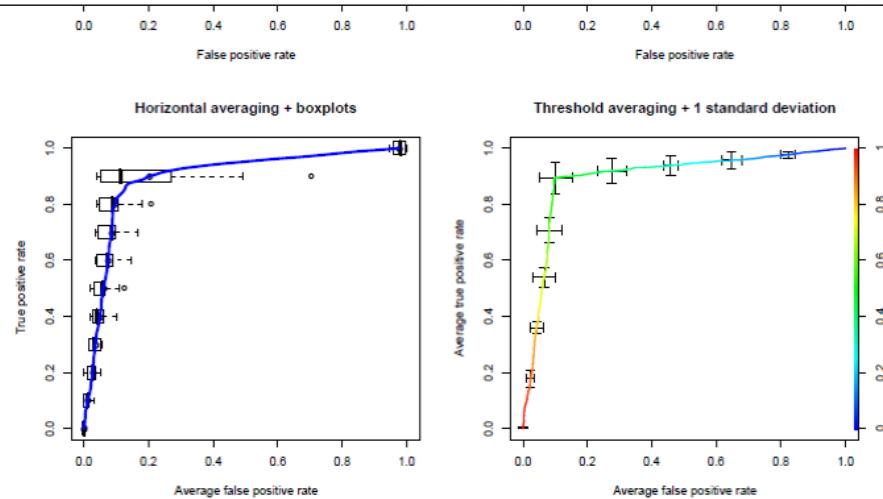


```
■ pred <- prediction(scores, labels)  
■ perf <- performance(pred, "prec", "rec")  
■ plot(perf, colorize=T)
```

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Examples (3/8): Averaging across

```
■ pred <- prediction(scores, labels)  
■ perf <- performance(pred, "tpr", "fpr")  
■ plot(perf, avg='threshold',  
      spread.estimate='stddev', colorize=T)
```



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Clustering Analysis

- Supervised learning (Classification) assumes classes are known
- Unsupervised learning (Cluster analysis) seeks to discover the classes

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Clustering

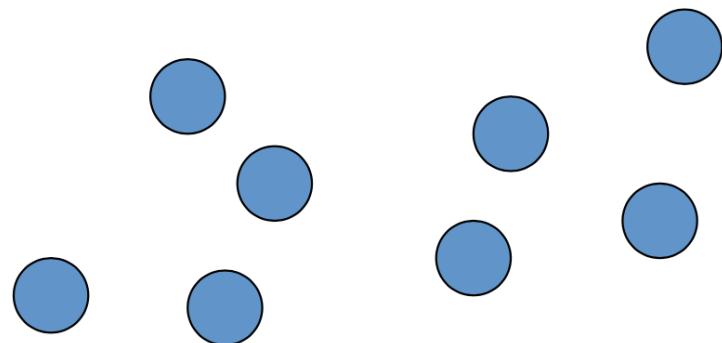
- Two most popular clustering algorithms
 1. K-Means Clustering
 2. Hierarchical Clustering
- k-means starts with k randomly chosen seed points, assigns each remaining point to the nearest seed, and repeats this until no point moves
- Hierarchical builds tree sequentially from the closest pair of points (wells/cells/probes/ conditions)

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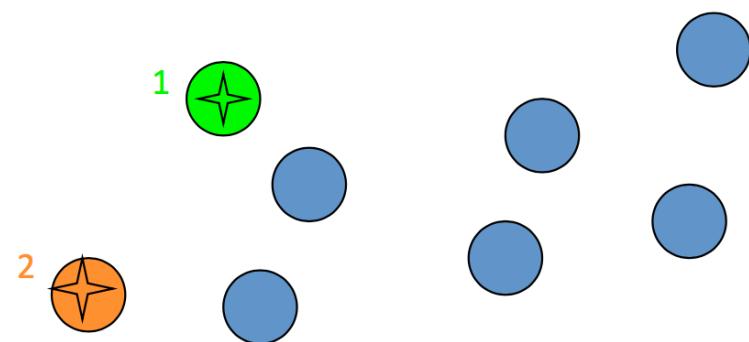
K-Means Clustering

1. Pick an initial set of K centroids (this can be random or any other means)
2. For each data point, assign it to the member of the closest centroid according to the given distance function
3. Adjust the centroid position as the mean of all its assigned member data points. Go back to (2) until the membership isn't change and centroid position is stable.
4. Output the centroids.

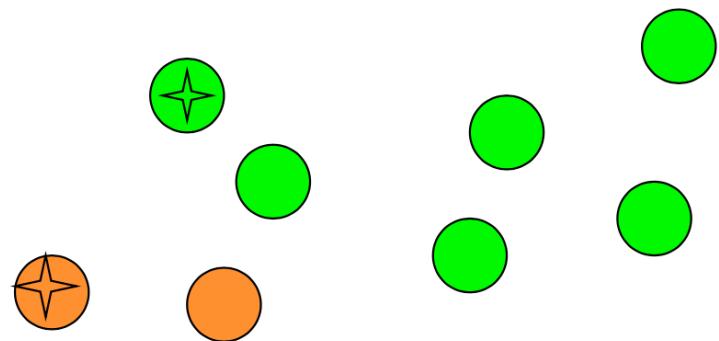
409



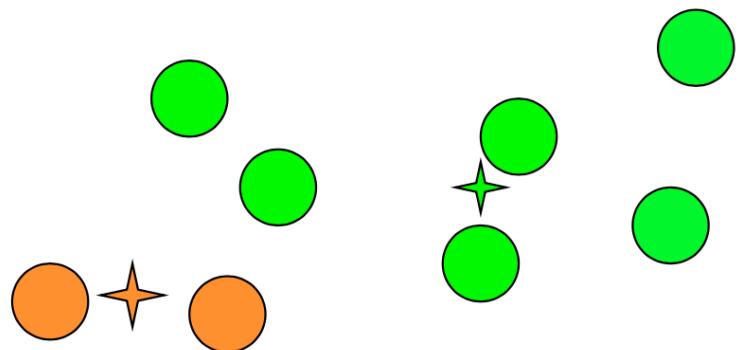
410



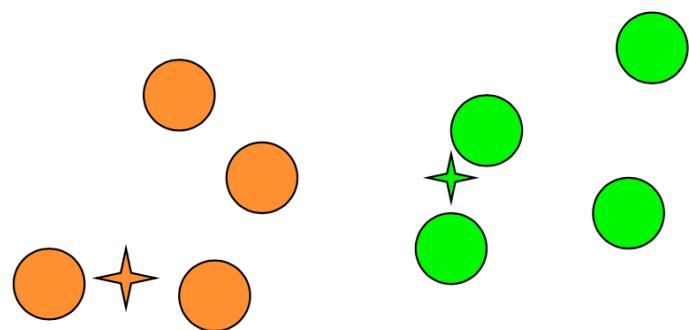
411



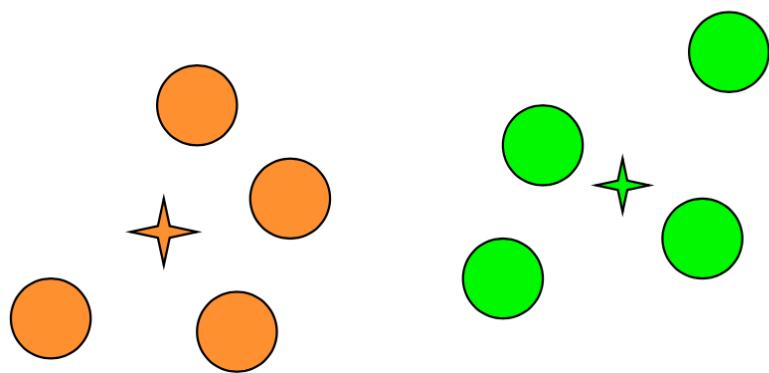
412



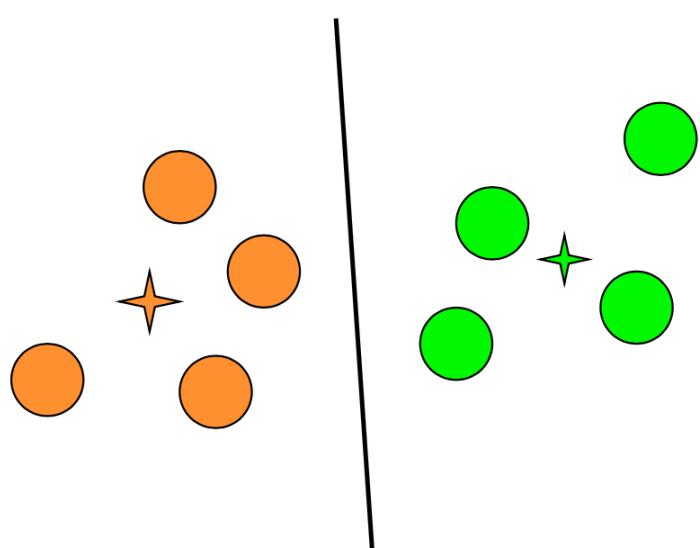
413



414



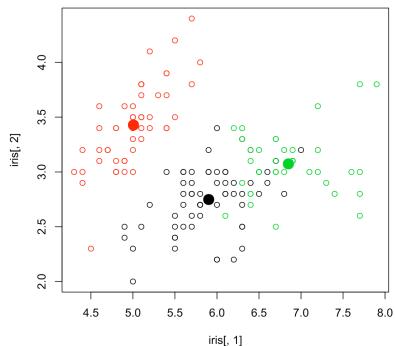
415



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```
library(stats)  
set.seed(101)  
km <- kmeans(iris[,1:4], 3)  
plot(iris[,1], iris[,2], col=km$cluster)  
points(km$centers[,c(1,2)], col=1:3, pch=19, cex=2)
```



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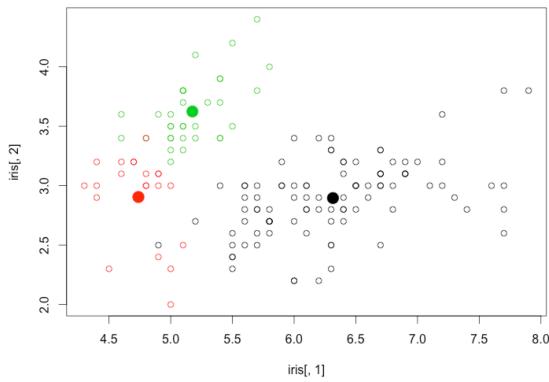
```
table(km$cluster, iris$Species)
```

	setosa	versicolor	virginica
1	0	48	14
2	50	0	0
3	0	2	36

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Another round

```
set.seed(900)  
km <- kmeans(iris[,1:4], 3)  
plot(iris[,1], iris[,2], col=km$cluster)  
points(km$centers[,c(1,2)], col=1:3, pch=19, cex=2)
```



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```
table(km$cluster, iris$Species)
```

	setosa	versicolor	virginica
1	0	46	50
2	17	4	0
3	33	0	0

420

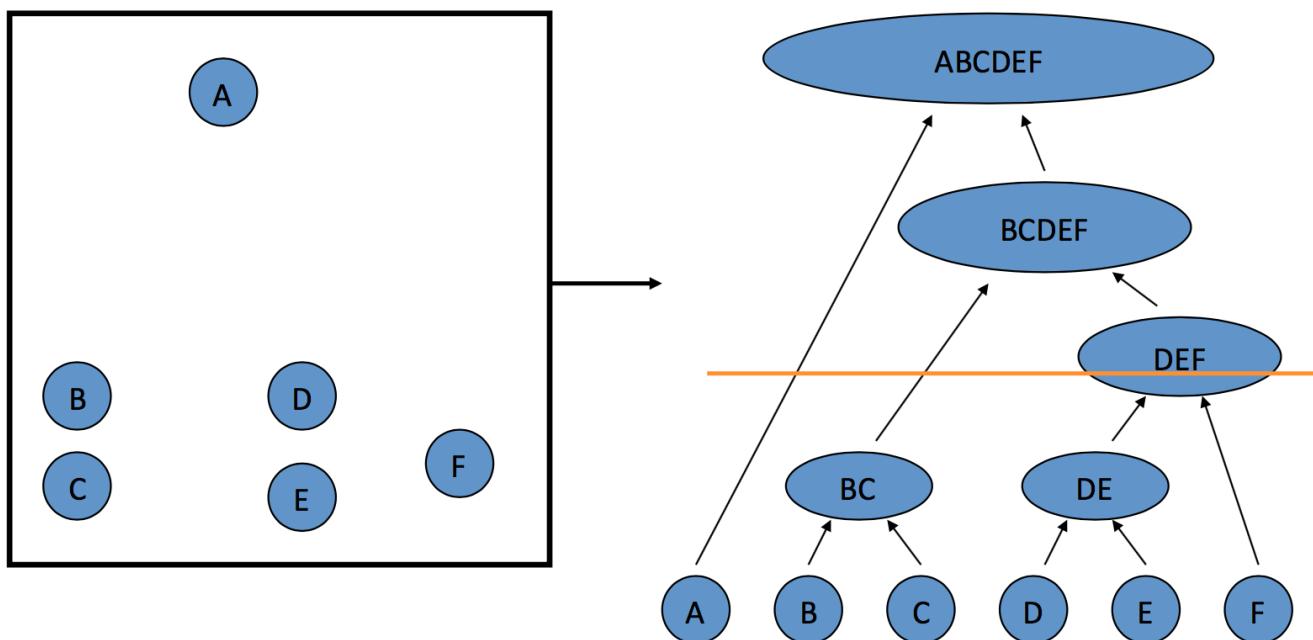
Hierarchical Clustering

Compute distance between every pairs of point/cluster.

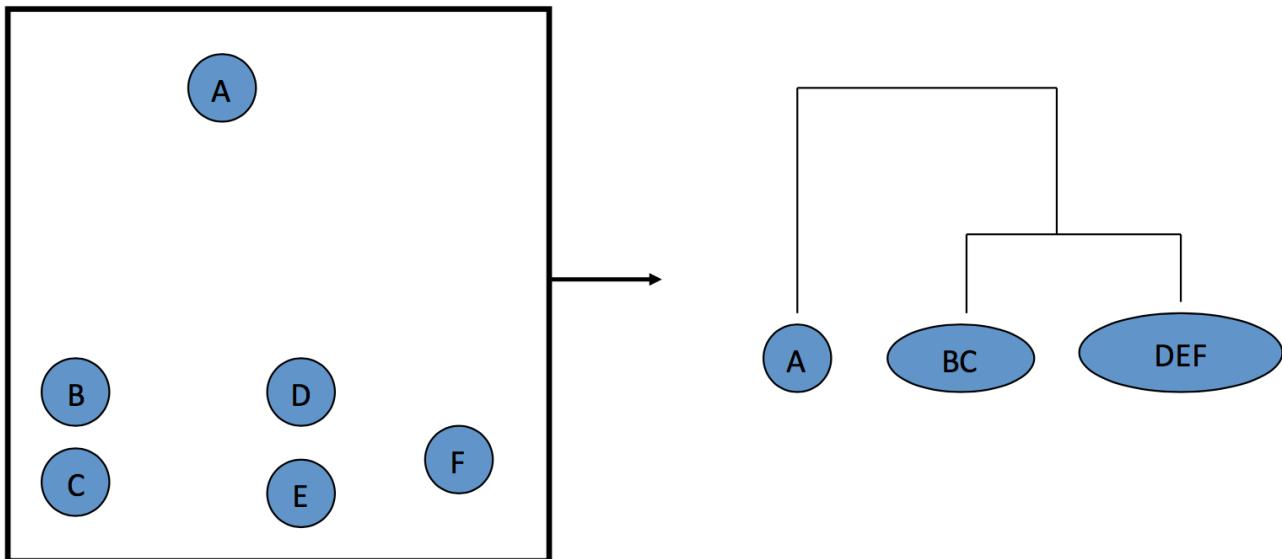
- (a) Distance between point is just using the distance function.
- (b) Compute distance between pointA to clusterB may involve many choices (such as the min/max/avg distance between the pointA and points in the clusterB).
- (c) Compute distance between clusterA to clusterB may first compute distance of all points pairs (one from clusterA and the other from clusterB) and then pick either min/max/avg of these pairs.

Combine the two closest point/cluster into a cluster. Go back to (1) until only one big cluster remains

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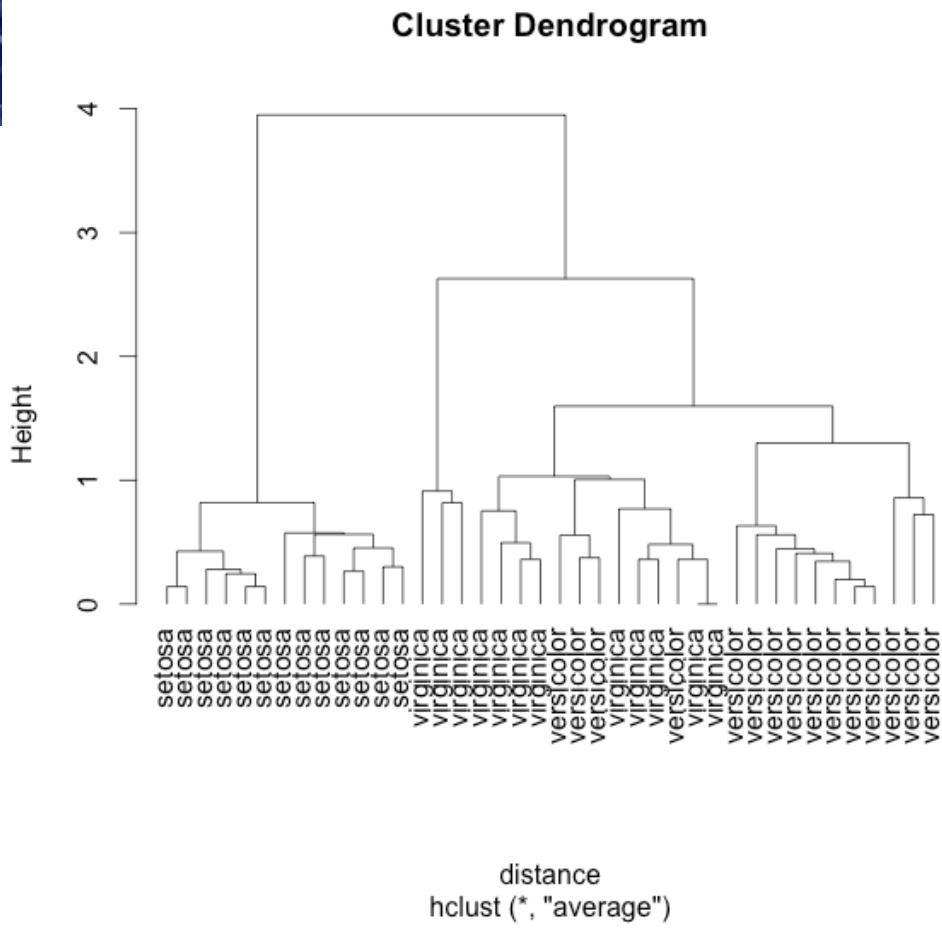


423



```
set.seed(101)
sampleiris <- iris[sample(1:150, 40),] # get samples from iris dataset
# each observation has 4 variables, ie, they are interpreted as 4-D points
distance <- dist(sampleiris[,-5], method="euclidean")
cluster <- hclust(distance, method="average")
plot(cluster, hang=-1, label=sampleiris$Species)
```

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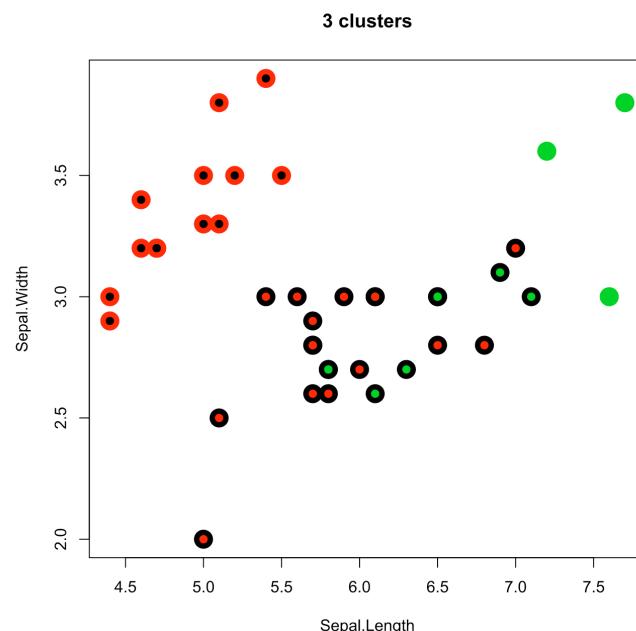
It's possible to prune the result tree.

```
par(mfrow=c(1,2))  
group.3 <- cutree(cluster, k = 3) # prune the tree by 3 clusters  
table(group.3, sampleiris$Species) # compare with known classes
```

group.3	setosa	versicolor	virginica
1	0	15	9
2	13	0	0
3	0	0	3

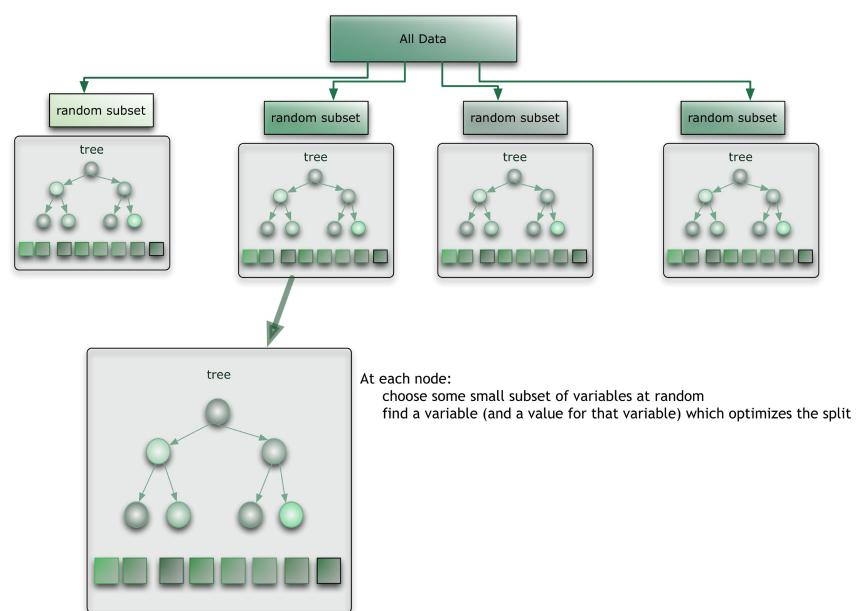


```
plot(sampleiris[,c(1,2)], col=group.3, pch=19, cex=2.5, main="3 clusters")
points(sampleiris[,c(1,2)], col=sampleiris$Species, pch=19, cex=1)
```



Ensemble : Bagging

Random Forest



Random Forest

Here is how such a system is trained; for some number of trees T:

- 1) Sample N cases at random with replacement to create a subset of the data. The subset should be about 66% of the total set.
- 2) At each node:
 - a) For some number m (see below), m predictor variables are selected at random from all the predictor variables.
 - b) The predictor variable that provides the best split, according to some objective function, is used to do a binary split on that node.
 - c) At the next node, choose another m variables at random from all predictor variables and do the same.

429

Bagging

```
> library(randomForest)
#Train 100 trees, random selected attributes
> model <- randomForest(Species~., data=iristrain, nTree=500)
#Predict using the forest
> prediction <- predict(model, newdata=iristest, type='class')
> table(prediction, iristest$Species)
> importance(model)
      MeanDecreaseGini
Sepal.Length      7.807602
Sepal.Width       1.677239
Petal.Length     31.145822
Petal.Width      38.617223
```

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Boosting

```
> library(adabag)  
> iris.adaboost <- boosting(Species~, data=iristrain, boost=TRUE,  
  mfinal=5)  
> iris.adaboost$class  
> table(iris.adaboost$class, iristrain$Species)  
> prediction <- predict(iris.adaboost, newdata=iristest)  
> table(prediction$class, iristest$Species)
```

431

Association Rules (Market Basket Analysis)

Support: The fraction of which our item set occurs in our dataset.

Confidence: probability that a rule is correct for a new transaction with items on the left.

Lift: The ratio by which the confidence of a rule exceeds the expected confidence.

Note: if the lift is 1 it indicates that the items on the left and right are independent



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Support, Confidence and Lift

There are several measures used to understand various aspects of associated products.

Let's understand the measures with the help of an example.

- In a store, there are 1000 transactions overall.
- Item A appears in 80 transactions and
- Item B occurs in 100 transactions.
- Items A and B appear in 20 transactions together.

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Support is the ratio of number of times two or more items occur together to the total number of transactions.

- **Support of A** = $\Pr(A) = 80/1000 = 8\%$ and
- **Support of B** = $\Pr(B) = 100/1000 = 10\%$.

Confidence is a conditional probability that a randomly selected transaction will include Item A given Item B.

- **Confidence of A** = $\Pr(A|B) = 20/100 = 20\%$.

Lift can be expressed as the ratio of the probability of Items A and B occurring together to the multiple of the two individual probabilities for Item A and Item B.

- **Lift** = $\Pr(A,B) / \Pr(A).\Pr(B) = (20/1000)/((80/1000)x(100/1000)) = 2.5$.

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How would you use Support, Confidence and Lift?

Support of a product or product bundle indicates the popularity of the product or product bundle in the transaction set. Higher the support, more popular is the product or product bundle. This measure can help in identifying driver of traffic to the store. Hence, if Barbie dolls have a higher support then they can be attractively priced to attract traffic to a store.

Confidence can be used for product placement strategy and increasing profitability. Place high-margin items with associated high selling (driver) items. If Market Basket Analysis indicates that customers who bought high selling Barbie dolls also bought high-margin candies, then candies should be placed near Barbie dolls.

Lift indicates the strength of an association rule over the random co-occurrence of Item A and Item B, given their individual support. Lift provides information about the change in probability of Item A in presence of Item B. Lift values greater than 1.0 indicate that transactions containing Item B tend to contain Item A more often than transactions that do not contain Item B.

435

Apriori Algorithm

?apriori

Usage

```
apriori(data, parameter = NULL, appearance = NULL, control = NULL)
```

Arguments

data object of class [transactions](#) or any data structure which can be coerced into [transactions](#) (e.g., a binary matrix or data.frame).

parameter object of class [APparameter](#) or named list. The default behavior is to mine rules with support 0.1, confidence 0.8, and maxlen 10.

appearance object of class [APappearance](#) or named list. With this argument item appearance can be restricted. By default all items can appear unrestricted.

control object of class [APcontrol](#) or named list. Controls the performance of the mining algorithm (item sorting, etc.)

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Apriori Algorithm

So lets get started by loading up our libraries and data set.

```
# Load the libraries
```

```
library(arules)
```

```
library(arulesViz)
```

```
library(datasets)
```

```
# Load the data set
```

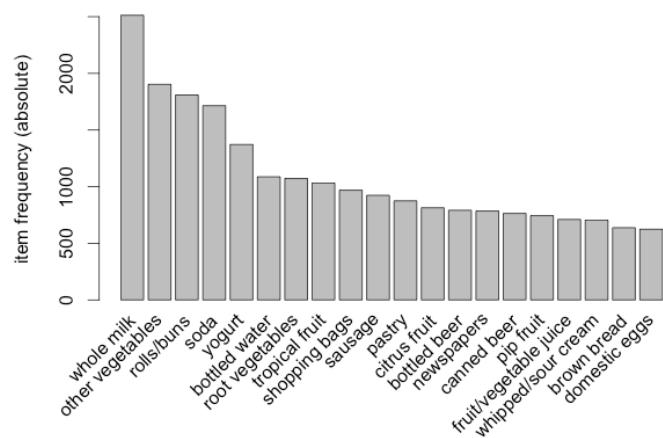
```
data(Groceries)
```

437

Explore Data

```
# Create an item frequency plot for the top 20 items
```

```
itemFrequencyPlot(Groceries, topN=20,type="absolute")
```



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```
rules <- apriori(Groceries, parameter = list(supp = 0.001, conf = 0.8))

# Show the top 5 rules, but only 2 digits
options(digits=2)

inspect(rules[1:5])
```

	lhs	rhs	support	confidence	lift
1	{liquor, red/ blush wine}	=> {bottled beer}	0.0019	0.90	11.2
2	{curd, cereals}	=> {whole milk}	0.0010	0.91	3.6
3	{yogurt, cereals}	=> {whole milk}	0.0017	0.81	3.2
4	{butter, jam}	=> {whole milk}	0.0010	0.83	3.3
5	{soups, bottled beer}	=> {whole milk}	0.0011	0.92	3.6
>					

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```
summary(rules)
```

```
set of 410 rules

rule length distribution (lhs + rhs):sizes
  3  4  5  6
 29 229 140 12

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.
      3.0    4.0    4.0    4.3    5.0    6.0

summary of quality measures:
      support      confidence      lift
      Min. :0.00102  Min. :0.80  Min. : 3.1
      1st Qu.:0.00102  1st Qu.:0.83  1st Qu.: 3.3
      Median :0.00122  Median :0.85  Median : 3.6
      Mean   :0.00125  Mean   :0.87  Mean   : 4.0
      3rd Qu.:0.00132  3rd Qu.:0.91  3rd Qu.: 4.3
      Max.   :0.00315  Max.   :1.00  Max.   :11.2

mining info:
      data ntransactions support confidence
Groceries          9835     0.001         0.8
```

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Sort Rules

```
rules<-sort(rules, by="confidence", decreasing=TRUE)
```

	lhs	rhs	support	confidence	lift
1	{rice, sugar}	=> {whole milk}	0.0012	1	3.9
2	{canned fish, hygiene articles}	=> {whole milk}	0.0011	1	3.9
3	{root vegetables, butter, rice}	=> {whole milk}	0.0010	1	3.9
4	{root vegetables, whipped/sour cream, flour}	=> {whole milk}	0.0017	1	3.9
5	{butter, soft cheese, domestic eggs}	=> {whole milk}	0.0010	1	3.9
>					

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Change to have limit association in

```
# change to have maximum of 3
```

```
rules <- apriori(Groceries, parameter = list(supp = 0.001, conf =  
0.8,maxlen=3))  
inspect(rules[1:5])
```

	lhs	rhs	support	confidence	lift
1	{liquor, red/ blush wine} => {bottled beer}	0.0019	0.90	11.2	
2	{curd, cereals}	=> {whole milk}	0.0010	0.91	3.6
3	{yogurt, cereals}	=> {whole milk}	0.0017	0.81	3.2
4	{butter, jam}	=> {whole milk}	0.0010	0.83	3.3
5	{soups, bottled beer}	=> {whole milk}	0.0011	0.92	3.6

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Rules pruned

```
subset.matrix <- is.subset(rules, rules)
subset.matrix[lower.tri(subset.matrix, diag=T)] <- NA
redundant <- colSums(subset.matrix, na.rm=T) >= 1
rules.pruned <- rules[!redundant]
rules<-rules.pruned
summary(rules)
```

set of 330 rules

rule length distribution (lhs + rhs):sizes

3	4	5	6
29	216	84	1

Min. 1st Qu. Median Mean 3rd Qu. Max.

3.0	4.0	4.0	4.2	5.0	6.0
-----	-----	-----	-----	-----	-----

summary of quality measures:

support	confidence	lift
Min. :0.00102	Min. :0.80	Min. : 3.1
1st Qu.:0.00102	1st Qu.:0.82	1st Qu.: 3.3
Median :0.00122	Median :0.85	Median : 3.6
Mean :0.00127	Mean :0.86	Mean : 3.8
3rd Qu.:0.00132	3rd Qu.:0.91	3rd Qu.: 4.3
Max. :0.00315	Max. :1.00	Max. :11.2

mining info:

data	ntransactions	support	confidence
Groceries	9835	0.001	0.8

Targeting Items

What are customers likely to buy before buying whole milk?

What are customers likely to buy if they purchase whole milk?

This essentially means we want to set either the Left Hand Side and Right Hand Side. This is not difficult to do with R!

Find whole milk's antecedents

```
rules<-apriori(data=Groceries, parameter=list(supp=0.001,conf =  
0.08), appearance = list(default="lhs",rhs="whole milk"), control =  
list(verbose=F))  
rules<-sort(rules, decreasing=TRUE,by="confidence")  
inspect(rules[1:5])
```

lhs	rhs	support	confidence	lift
1 {rice, sugar}	=> {whole milk}	0.0012	1	3.9
2 {canned fish, hygiene articles}	=> {whole milk}	0.0011	1	3.9
3 {root vegetables, butter, rice}	=> {whole milk}	0.0010	1	3.9
4 {root vegetables, whipped/sour cream, flour}	=> {whole milk}	0.0017	1	3.9
5 {butter, soft cheese, domestic eggs}	=> {whole milk}	0.0010	1	3.9
>				

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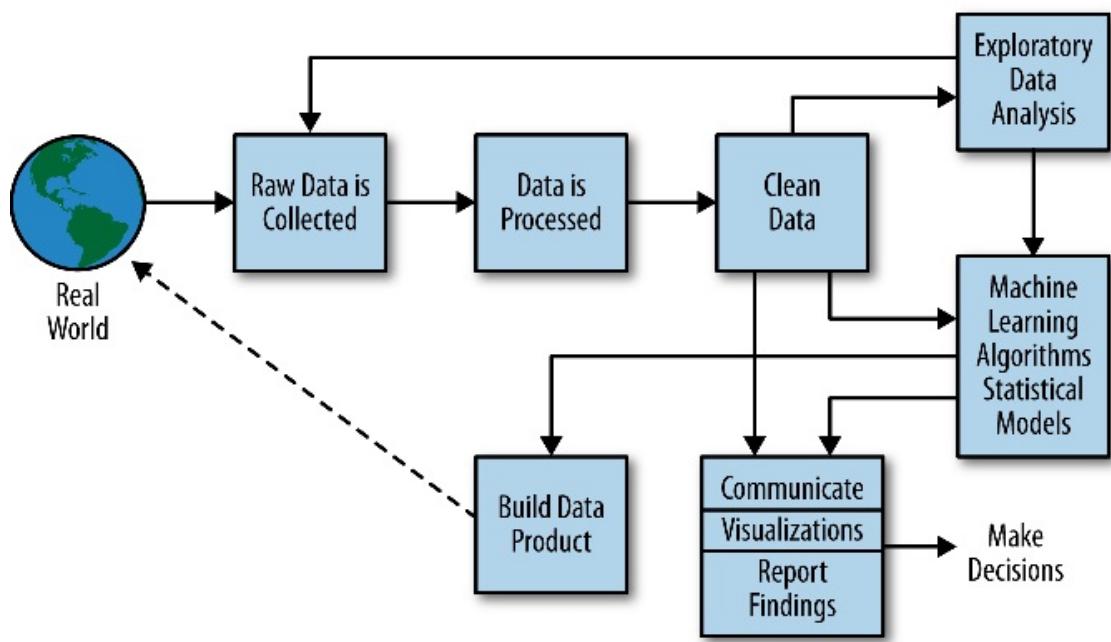
Likely to buy after buy whole milk

```
rules<-apriori(data=Groceries, parameter=list(supp=0.001,conf =  
0.15,minlen=2), appearance = list(default="rhs",lhs="whole milk"), control =  
list(verbose=F))  
rules<-sort(rules, decreasing=TRUE,by="confidence")  
inspect(rules[1:5])
```

lhs	rhs	support	confidence	lift
1 {whole milk} => {other vegetables}	0.075	0.29	1.5	
2 {whole milk} => {rolls/buns}	0.057	0.22	1.2	
3 {whole milk} => {yogurt}	0.056	0.22	1.6	
4 {whole milk} => {root vegetables}	0.049	0.19	1.8	
5 {whole milk} => {tropical fruit}	0.042	0.17	1.6	
>				

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Data Science Process



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Thank you



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