How I Learned to Stop Worrying and Love the R Console

Irfan Kanat
Department of Information Systems
Arizona State University

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Outline

Who am I?

Irfan Kanat, PhD Candidate

R user since 2006

Open Source Evangelist

Before We Begin

Got R & R Studio Installed?

Get your workshop documents:

https://github.com/iekanat/rworkshop

Install caret package:

```
install.packages("caret", dependencies = c("Depends", "Suggests"))
```

What is this about?

A brief introduction to R.

- R Console
- Importing Data
- Packages
- Sample analyses
- Basic visualization
- Where to get help?

What is R?

From R project web site:

R is a language *and* an environment for statistical computing and graphics.

- Language
- Environment
- Statistics and Visualization

What is R?

All this means R is very flexible, which played a huge role in its success.

My take: Low cost, high quality, open source solution for your analysis needs.

When to Use R?

R is very strong for your classical machine learning and statistical analysis. Thousands of packages address almost all analysis needs. It is a logical first stop to start analysis.

1

When to Use R?

R is very strong for your classical machine learning and statistical analysis. Thousands of packages address almost all analysis needs. It is a logical first stop to start analysis.

Yet it's core design is starting to show its age. There are certain down sides to traditional R:

- Everything is stored in memory[1]
- R is single core[1]

[1] Except when it is not. There are packages to overcome these issues.

Best Part of R

Packages CRAN houses over 7K packages. Providing functionality way beyond what is available in commercial packages.

Community Millions of users mean, all your questions are either already answered or will be in hours.

Performance While memory and core restrictions are real, for the cost of a single user license of a commercial package, you can buy better hardware to run R. Furthermore, with the packages providing multicore and flatfile functionality, R performance is on par or better than commercial packages

Subsection 1

Familiar Examples

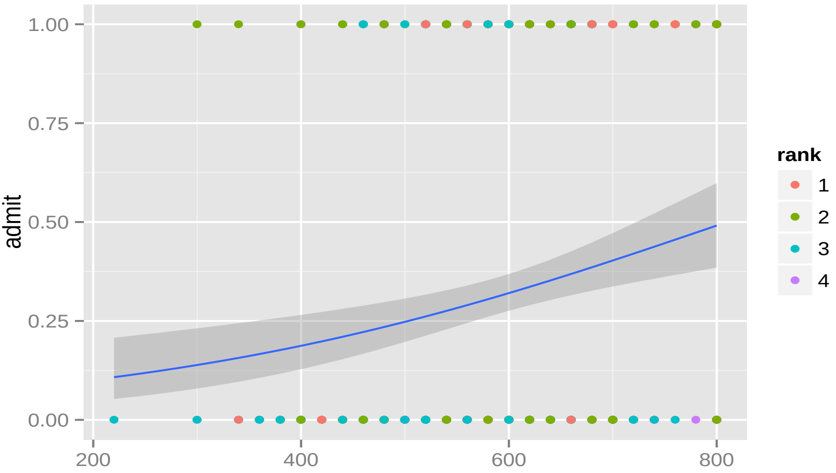
Logistic Regression

```
# Fit the model
logit_0 <- glm(admit ~ ., admitData, family = "binomial")
# Display fitted model
summary(logit_0)
```

```
##
## Call:
## glm(formula = admit ~ ., family = "binomial", data = admitData)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6268  -0.8662  -0.6388   1.1490   2.0790
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.989979   1.139951  -3.500 0.000465 ***
## gre          0.002264   0.001094   2.070 0.038465 *
## gpa          0.804038   0.331819   2.423 0.015388 *
## rank2       -0.675443   0.316490  -2.134 0.032829 *
## rank3       -1.340204   0.345306  -3.881 0.000104 ***
## rank4       -1.551464   0.417832  -3.713 0.000205 ***
## ---
```

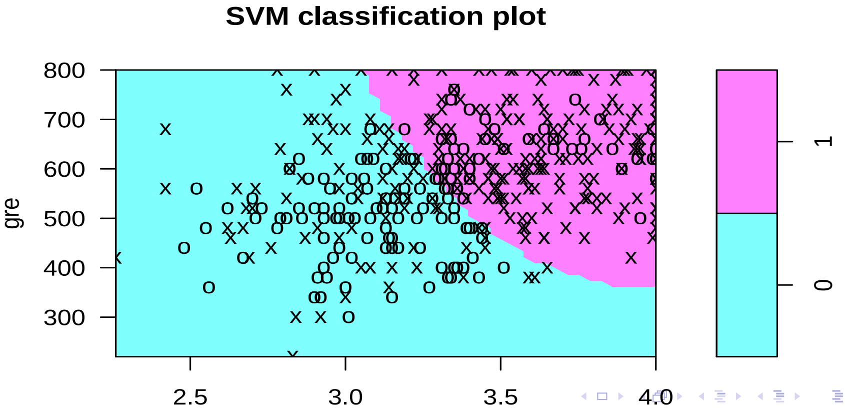
Logistic Regression

```
ggplot(admitData, aes(x = gre, y = admit)) + geom_point(aes(colour = rank)) +
    stat_smooth(method = "glm", family = "binomial", se = T)
```



Support Vector Machine

```
# Fit the model
svm_0 <- svm(admit ~ ., data = admitData, type = "C-classification")
# Plot the results
plot(svm_0, admitData, gre ~ gpa)  # Let us plot the results
```



Questions

?

Outline

Command Driven Interface

Command line may be intimidating

Power over Convenience

Consider the number of

- Functions
- Parameters
- Data sources
- Variables
- Replications

Command Driven Interface

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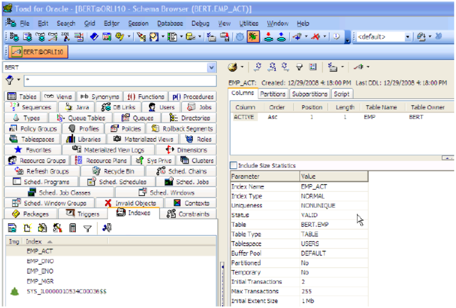
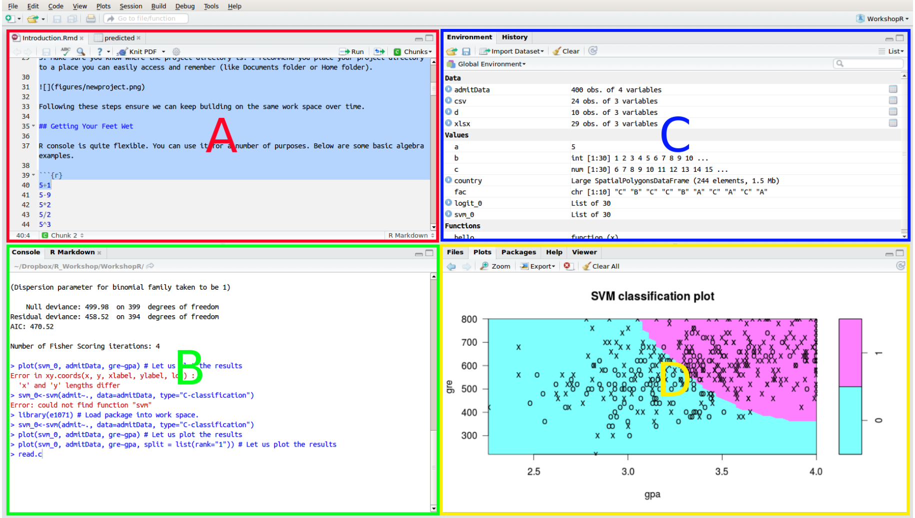


R Studio


File Edit Code View Plots Session Build Debug Tools Help
WorkshopR
Introduction.Rmd
predicted
Knit PDF
Run
Chunks
to a place you can easily access and remember (like Documents folder or Home folder).
`![](figures/newproject.png)`
Following these steps ensure we can keep building on the same work space over time.
Getting Your Feet Wet
R console is quite flexible. You can use it for a number of purposes. Below are some basic algebra examples.
```{r}
5+1
5-9
5*2
5/2
5^3
A
Environment History
Import Dataset
Clear
List
Global Environment
Data
admitData 400 obs. of 4 variables
csv 24 obs. of 3 variables
d 10 obs. of 3 variables
xlsx 29 obs. of 3 variables
Values
a 5
b int [1:30] 1 2 3 4 5 6 7 8 9 10 ...
c num [1:30] 6 7 8 9 10 11 12 13 14 15 ...
country Large SpatialPolygonsDataFrame (244 elements, 1.5 Mb)
fac chr [1:10] "C" "B" "C" "C" "B" "A" "C" "A" "C" "A"
logit_0 List of 30
svm_0 List of 30
Functions
C
Console R Markdown
~/Dropbox/R_Workshop/WorkshopR/
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 499.98 on 399 degrees of freedom
Residual deviance: 458.52 on 394 degrees of freedom
AIC: 470.52
Number of Fisher Scoring iterations: 4
> plot(svm_0, admitData, gre~gpa) # Let us plot the results
Error in xy.coords(x, y, xlabel, ylabel, log) :
'x' and 'y' lengths differ
> svm_0<-svm(admit~., data=admitData, type="C-classification")
Error: could not find function "svm"
> library(e1071) # Load package into work space.
> svm_0<-svm(admit~., data=admitData, type="C-classification")
> plot(svm_0, admitData, gre~gpa) # Let us plot the results
> plot(svm_0, admitData, gre~gpa, split = list(rank="1")) # Let us plot the results
> read.c
B
Files Plots Packages Help Viewer
Zoom
Export
Clear All
SVM classification plot
gre
gpa
D
```

New Project

File > New Project

Empty Directory > Empty Project > Directory Name: Workshop

R as a Calculator I

```
# Arithmetics
2 + 2

## [1] 4

2 * 3

## [1] 6

2^3

## [1] 8

log(100, 10)

## [1] 2
```

R as a Calculator II

```
# Logic
1 == 2

## [1] FALSE

1 != 2

## [1] TRUE

2 < 3

## [1] TRUE
```

Variables I

```
A <- 2

A

## [1] 2

a  # Case sensitive

## Error in eval(expr, envir, enclos):  object 'a' not found

"A" != "a"  # Explanation

## [1] TRUE

B <- 7

A + B

## [1] 9
```

Variables II

```r
C <- c(1, 3, 7, 9)  # A list can be in a variable
C

## [1] 1 3 7 9

C + A

## [1]  3  5  9 11

C * A

## [1]  2  6 14 18

C < 5

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

Indexes and Data Frames I

```
1:30

##  [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

C[3]

## [1] 7

C[c(2, 3)]

## [1] 3 7

C[1:3]

## [1] 1 3 7
```

Indexes and Data Frames II

```
Countries <- data.frame(names=c("US","TR","DE"), supply=c(10, 8, 7),
                        those=c(TRUE, FALSE, FALSE))

Countries

##   names supply those
## 1    US     10  TRUE
## 2    TR      8 FALSE
## 3    DE      7 FALSE
```

Indexes and Data Frames III

```
Countries[2, ]

##   names supply those
## 2    TR      8 FALSE

Countries[, 3]

## [1]  TRUE FALSE FALSE

Countries[2, 3]

## [1] FALSE

Countries[1:2, ]

##   names supply those
## 1    US     10  TRUE
## 2    TR      8 FALSE
```

Indexes and Data Frames IV

```
Countries[, "names"]

## [1] US TR DE
## Levels: DE TR US

Countries$names

## [1] US TR DE
## Levels: DE TR US

Countries$those

## [1]  TRUE FALSE FALSE
```

Loops in R

CAUTION!

R is notoriously inefficient with your classic loops

- Structure of the Data Frame
- Memory Management

Try to use an apply function instead.

Vectorize your operations.

For Loop in R

```
for (i in 1:3) print(i)

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

# Iterating through a data frame
for (i in 1:nrow(Countries)) {
    print(Countries[i, ])
}

##   names supply those
## 1    US     10  TRUE
##   names supply those
## 2    TR      8 FALSE
##   names supply those
## 3    DE      7 FALSE
```

Functions I

```
mean(C)  # Takes parameters

## [1] 5

mean(C, trim = 0.1, na.rm = T)  # Takes multiple parameters

## [1] 5

log(sum(C)/length(C))  # Can be combined

## [1] 1.609438
```

Functions II

```
HelloWorld <- function(x, y = 1) {
    for (i in 1:y) {
        print(paste("Hello", x))
    }
}

HelloWorld("MSBA")

## [1] "Hello MSBA"

HelloWorld("MSBA", 2)

## [1] "Hello MSBA"
## [1] "Hello MSBA"
```

Functions III

```
HelloWorld  # Review the source code

## function(x, y = 1) {
##     for (i in 1:y) {
##         print(paste("Hello", x))
##     }
## }

ls

## function (name, pos = -1L, envir = as.environment(pos), all.names = FALSE,
##     pattern, sorted = TRUE)
## {
##     if (!missing(name)) {
##         pos <- tryCatch(name, error = function(e) e)
##         if (inherits(pos, "error")) {
##             name <- substitute(name)
##             if (!is.character(name))
##                 name <- deparse(name)
##             warning(gettextf("%s converted to character string",
##                 sQuote(name)), domain = NA)
##             pos <- name
```

Commonly Used Functions I

```
ls()  # Get a list of objects in the workspace

## [1] "A"          "admitData"  "B"          "C"          "Countries"
## [6] "HelloWorld" "i"          "logit_0"    "svm_0"

ls(pattern = "*_0")  # partial match on object search

## [1] "logit_0" "svm_0"

rm("svm_0")  # Remove an object from the workspace

# rm(list=ls(pattern=ls())) # This would remove everything if ran
```

Commonly Used Functions II

```
mean(A)  # Mean

## [1] 2

sd(admitData[, "gre"])  # Standard Deviation

## [1] 115.5165

AIC(logit_0)

## [1] 470.5175
```

Commonly Used Functions III

```
str(Countries)  # Look at the structure of objects

## 'data.frame': 3 obs. of  3 variables:
##  $ names : Factor w/ 3 levels "DE","TR","US": 3 2 1
##  $ supply: num  10 8 7
##  $ those : logi  TRUE FALSE FALSE

summary(Countries)  # Get summary of data

##  names      supply         those
##  DE:1   Min.   : 7.000   Mode :logical
##  TR:1   1st Qu.: 7.500   FALSE:2
##  US:1   Median : 8.000   TRUE :1
##         Mean   : 8.333   NA's :0
##         3rd Qu.: 9.000
##         Max.   :10.000
```

Commonly Used Functions IV

```
summary(logit_1)  # Get summary of model

##
## Call:
## glm(formula = admit ~ gre, family = "binomial", data = admitData)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1623  -0.9052  -0.7547   1.3486   1.9879
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.901344   0.606038  -4.787 1.69e-06 ***
## gre          0.003582   0.000986   3.633  0.00028 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 499.98  on 399  degrees of freedom
## Residual deviance: 486.06  on 398  degrees of freedom
## AIC: 490.06
##
## Number of Fisher Scoring iterations: 4
```

Commonly Used Functions V

```
cor(admitData[, 1:3])  # Get correlation matrix
```

```
##           admit       gre       gpa
## admit 1.0000000 0.1844343 0.1782123
## gre   0.1844343 1.0000000 0.3842659
## gpa   0.1782123 0.3842659 1.0000000
```

Questions

?

Outline

Importing Data

R allows importing data from a wide variety of sources.

- Comma Separated Values (CSV)
- Databases
- Flat files
- Lesser statistical packages
- and more

Importing CSV Files

CSV has certain advantages that make it popular.

- Compatibility
- Flexibility
- Simplicity

Sample

"iso2", "Supply", "Those"
"AU", 20, 0
"TR", 80, 1
"US", 100, 0
"GB", 50, 0
"DE", 70, 0

We use read.csv() or read.csv2() commands to import the csv files.

```
saveData <- read.csv("PathToCSV", header = TRUE, sep = ",", quote = "\"")
```

Working with Excel Files

Much like CSV, except it lacks the simplicity, flexibility, and compatibility of CSV.

```
# Load the necessary library
library(xlsx)
# Read in the data from excel file
xlsx <- read.xlsx("country.xlsx", sheetIndex = 1)
```

Working with Databases

No speed advantage.

Data larger than memory.

Working with databases:

- Work in the database.
- Import data from database.

Working with Databases

```
# Load the necessary library
library(RMySQL)
# Establish connection to the database.
channel <- dbConnect(MySQL(), user = "uname", password = "pwd", host = "127.0.01",
    dbname = "exampledata")
# Send query and save results in R workspace
sql <- dbGetQuery(channel, "SELECT * FROM table;")
```

Lesser Statistical Packages :P

Foreign Package

Newer file formats

- sas7bdat
- readstata13

Questions

?

Outline

Packages: Source of R's Power

Encountered already

Make R extendible

Like libraries

Collection of:

- functions
- documentation
- data files

Gifts from the Community

Currently over 7000 packages

for

- Statistical Modeling
- Machine Learning
- Data Manipulation
- Visualization
- ...

from

- Economics
- Computer Science
- Statistics
- Medicine
- ...

Great but Where are My Gifts?

Comprehensive R Archive Network (CRAN)

A Group of FTP and HTML servers hosting R packages.

R has built in package management facilities.

Most of these can be achieved through the R Studio GUI. (Area D, packages pane)

Package Management

```
# Installing a package
install.packages("e1071")  # Notice the quotes around package name
# Loading package into memory
library(e1071)  # Notice the lack of quotes
# Unload package
detach("package:e1071", unload = TRUE)  # Notice the package: prepended

# Get the list of packages loaded
(.packages())
# Get list of all installed packages (output omitted)
.packages(all.available = T)
```

How to Find Packages

If you want to search a certain word in installed packages' documentation, you can always use ?? or help.search()

```
??mixed
help.search("mixed model")
```

Internet searches are a bit problematic as R can be a bit ambiguous until Google learns you are interested in the statistical computing environment.

Comprehensive R Archive Network (CRAN)

R Forge

R site search also available with command RSiteSearch()

R seek

Commonly Used Packages: Data Manipulation

data.tables Replaces traditional data.frame.

- Faster access/write
- Improved selection
- Improved subsetting
- Improved aggregation

Not a drop-in replacement as it breaks compatibility in some cases.

ddplyr

Additional functionality for:

- selection
- filtering
- aggregation

Provides efficient back-end data structures to speed things up.

Works with databases as well.

Commonly Used Packages: Statistics

Multiple Regression: Stats package, lm() (loaded by default)

Generalized Linear Models: Stats package, glm()

Traditional Econometric Models: plm package

Mixed Modeling: nlme and lme4 packages

Commonly Used Packages: Machine Learning

Most probably all you need is caret package.

Caret package is a wrapper for a host of classification and regression model training functions. It eases visualizations, data manipulation, and analytics among others. It currently supports over 150 types of models.

If you insist on using individual packages:
Classifiers: class package
Support Vector Machines: kernlab, e1071 packages
Clustering: Base package (kmeans(), hclust()), mclust package
Neural Networks: neuralnet package.

Questions

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Outline

Subsection 1

Data Manipulation

If Wishes Were Data...

We may wish for an ideal dataset, what we will invariably get is a mess.

We often need to:

- Combine datasets
- Transform variables
- Aggregate data

I am a data.tables person, but I will teach a tiny bit of dplyr for compatibility reasons.

Data I

We will investigate GDP figures from world bank and a separate dataset for continents.

```
GDP <- read.csv("GDP.csv")
head(GDP, 3)
```

```
##       Country ISO2    X2003    X2004    X2005    X2006    X2007    X2008
## 1       Aruba   AW       NA       NA       NA       NA       NA       NA
## 2     Andorra   AD       NA       NA       NA       NA       NA       NA
## 3 Afghanistan   AF 1096.756 1066.685 1145.717 1173.001 1297.821 1310.717
##      X2009    X2010     X2011    X2012
## 1       NA       NA 36016.484       NA
## 2       NA       NA        NA       NA
## 3 1547.539 1637.297  1695.153 1893.076
```

Data II

```
Continents <- read.csv("continent.csv")
head(Continents)

##   ISO2 Continent
## 1   AD        EU
## 2   AE        AS
## 3   AF        AS
## 4   AG        AN
## 5   AI        AN
## 6   AL        EU
```

Merging Dataframes I

Appending data.

```
rbind(Continents[1:3, ], Continents[231:233, ])

##     ISO2 Continent
## 1     AD        EU
## 2     AE        AS
## 3     AF        AS
## 231   UA        EU
## 232   UG        AF
## 233   UM        OC

cbind(Continents[1:3, ], Continents[231:233, ])

##   ISO2 Continent ISO2 Continent
## 1   AD        EU   UA        EU
## 2   AE        AS   UG        AF
## 3   AF        AS   UM        OC
```

Merging Dataframes II

When you want to combine two data frames by a common column

```
cData <- merge(Continents, GDP, by = "ISO2")
head(cData[, 1:6])
```

```
##   ISO2 Continent              Country      X2003      X2004      X2005
## 1   AD        EU              Andorra         NA         NA         NA
## 2   AE        AS United Arab Emirates 110549.415 111543.925 103139.799
## 3   AF        AS          Afghanistan   1096.756   1066.685   1145.717
## 4   AG        AN  Antigua and Barbuda  19566.329  20395.483  21414.230
## 5   AL        EU              Albania   6286.205   6699.225   7119.290
## 6   AM        AS              Armenia   4181.720   4635.303   5296.814
```

Subsetting I

```
library(dplyr)
# Subset of rows
filter(cData, Continent == "OC" & X2011 > 23000)

##   ISO2 Continent     Country    X2003    X2004    X2005    X2006    X2007
## 1   AU        OC   Australia 37035.05 38129.81 38840.24 39416.04 40643.45
## 2   NZ        OC New Zealand 29754.46 30355.86 30984.47 31182.26 31953.38
##      X2008    X2009    X2010    X2011    X2012
## 1 41311.94 41170.05 41329.95 41706.00 42529.87
## 2 31058.21 31398.28 31227.55 31683.45 32281.25
```

Subsetting II

```
# Subset of columns
select(cData[1:3, ], X2003:X2009)  # All columns between X2003 and X2012

##          X2003      X2004      X2005     X2006     X2007     X2008     X2009
## 1           NA         NA         NA        NA        NA        NA        NA
## 2 110549.415 111543.925 103139.799 96399.737 83655.038 73611.390 61725.280
## 3   1096.756   1066.685   1145.717  1173.001  1297.821  1310.717  1547.539

select(cData[1:3, ], -(ISO2:Country))  # All except these

##          X2003      X2004      X2005     X2006     X2007     X2008     X2009
## 1           NA         NA         NA        NA        NA        NA        NA
## 2 110549.415 111543.925 103139.799 96399.737 83655.038 73611.390 61725.280
## 3   1096.756   1066.685   1145.717  1173.001  1297.821  1310.717  1547.539
##         X2010     X2011     X2012
## 1          NA        NA        NA
## 2 57379.972 56376.770 57044.578
## 3  1637.297  1695.153  1893.076
```

Aggregating by Groups I

```
# Create grouped data
contiData <- group_by(cData, Continent)
contiData
```

```
## Source: local data frame [208 x 13]
## Groups: Continent
##
##    ISO2 Continent              Country      X2003      X2004      X2005
## 1    AD        EU              Andorra         NA         NA         NA
## 2    AE        AS United Arab Emirates 110549.415 111543.925 103139.799
## 3    AF        AS          Afghanistan   1096.756   1066.685   1145.717
## 4    AG        AN  Antigua and Barbuda  19566.329  20395.483  21414.230
## 5    AL        EU              Albania   6286.205   6699.225   7119.290
## 6    AM        AS              Armenia   4181.720   4635.303   5296.814
## 7    AO        AF               Angola   3818.663   4086.858   4667.346
## 8    AR        SA            Argentina         NA         NA         NA
## 9    AS        OC       American Samoa         NA         NA         NA
## 10   AT        EU              Austria  39732.713  40555.386  41142.303
## ..  ...       ...                  ...        ...        ...        ...
## Variables not shown: X2006 (dbl), X2007 (dbl), X2008 (dbl), X2009 (dbl),
##   X2010 (dbl), X2011 (dbl), X2012 (dbl)
```

Aggregating by Groups II

```
# Create variables on the fly
summarise(contiData, count = n(), GDP2012 = mean(X2012, na.rm = T))

## Source: local data frame [6 x 3]
##
##   Continent count   GDP2012
## 1        AF    52  5424.917
## 2        AN    31 17795.502
## 3        AS    49 24344.030
## 4        EU    46 29655.267
## 5        OC    18  9795.367
## 6        SA    12 12541.870
```

Reshape in Your Own Image

```
cDataLong <- reshape(cData, varying = 4:13, direction = "long", sep = "")
# Drop the unnecessary id column
cDataLong <- subset(cDataLong, select = -c(id, Country))
# Drop the missing observations
cDataLong <- na.exclude(cDataLong)
# Get rid of empty levels
cDataLong$ISO2 <- droplevels(cDataLong$ISO2)
# Sort based on ISO2 and Year
cDataLong <- cDataLong[order(cDataLong$ISO2, cDataLong$ISO2), ]
head(cDataLong, 3)
```

```
##        ISO2 Continent time        X
## 2.2003   AE        AS 2003 110549.4
## 2.2004   AE        AS 2004 111543.9
## 2.2005   AE        AS 2005 103139.8
```

Transforming Variables I

```
# Basic Log Transform
cData_Long$logGDP <- log(cData_Long$X)
head(cData_Long)

##         ISO2 Continent time          X   logGDP
## 2.2003   AE         AS 2003 110549.41 11.61322
## 2.2004   AE         AS 2004 111543.92 11.62217
## 2.2005   AE         AS 2005 103139.80 11.54384
## 2.2006   AE         AS 2006  96399.74 11.47626
## 2.2007   AE         AS 2007  83655.04 11.33446
## 2.2008   AE         AS 2008  73611.39 11.20656
```

```
# ASSUMING YOUR DATA IS SORTED

# More Interesting: Cumulative Sum By Groups
cData_Long$cumGDP <- ave(cData_Long$X, cData_Long$ISO2, FUN = cumsum)
```

Transforming Variables II

```
# A function, given a vector, shifts every observation by 1 and drops the
# last one.
lg <- function(x) c(NA, x[1:(length(x) - 1)])
lg(1:10)  # See how it works

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

# Run the function with group averages function
cData_Long$lagGDP <- ave(cData_Long$X, cData_Long$ISO2, FUN = lg)

## Warning in `split<-.default`(`*tmp*`, g, value = lapply(split(x, g), FUN)):
number of items to replace is not a multiple of replacement length

head(cData_Long, 3)

##        ISO2 Continent time        X   logGDP   cumGDP   lagGDP
## 2.2003   AE        AS 2003 110549.4 11.61322 110549.4       NA
## 2.2004   AE        AS 2004 111543.9 11.62217 222093.3 110549.4
## 2.2005   AE        AS 2005 103139.8 11.54384 325233.1 111543.9
```

Subsection 2

Descriptive Visualizations

Motor Trends Dataset

We will use 1974 Motor Trend dataset. It has 32 observations and 11 variables.

- mpg: Miles per gallon
- cyl: Number of cylinders
- disp: Displacement
- hp: Horse Power
- drat: Rear axle ratio
- wt: Weight
- qsec: quarter mile time
- vs: V - S
- am: 0 automatic, 1 manual
- gear: Gears
- carb: Number of carburetors

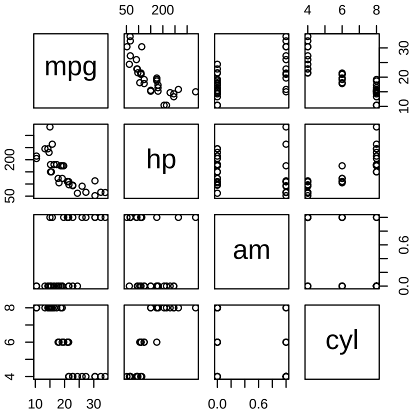
Motor Trends Dataset I

```
summary(mtcars)
```

```
##       mpg             cyl             disp             hp       
##  Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0  
##  1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5  
##  Median :19.20   Median :6.000   Median :196.3   Median :123.0  
##  Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7  
##  3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0  
##  Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0  
##       drat             wt             qsec             vs        
##  Min.   :2.760   Min.   :1.513   Min.   :14.50   Min.   :0.0000  
##  1st Qu.:3.080   1st Qu.:2.581   1st Qu.:16.89   1st Qu.:0.0000  
##  Median :3.695   Median :3.325   Median :17.71   Median :0.0000  
##  Mean   :3.597   Mean   :3.217   Mean   :17.85   Mean   :0.4375  
##  3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000  
##  Max.   :4.930   Max.   :5.424   Max.   :22.90   Max.   :1.0000  
##        am              gear            carb      
##  Min.   :0.0000   Min.   :3.000   Min.   :1.000  
##  1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:2.000  
##  Median :0.0000   Median :4.000   Median :2.000  
##  Mean   :0.4062   Mean   :3.688   Mean   :2.812  
##  3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:4.000  
##  Max.   :1.0000   Max.   :5.000   Max.   :8.000  
```

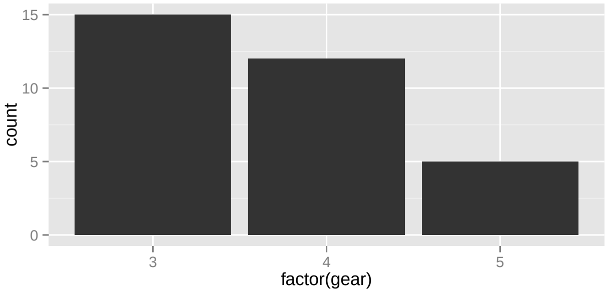
Motor Trends Dataset II

```
pairs(mtcars[, c("mpg", "hp", "am", "cyl")])  # Visualize Correlations
```



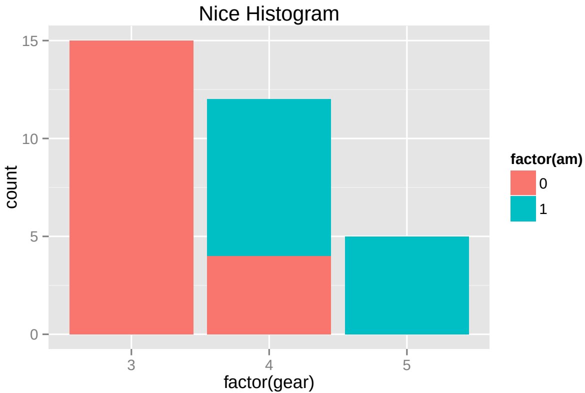
Histograms I

```r
data(mtcars)  # Load the Dataset
library(ggplot2)  # Load the ggplot package
# Nr of cars by number of gears
qplot(factor(gear), data = mtcars, geom = "bar")
```



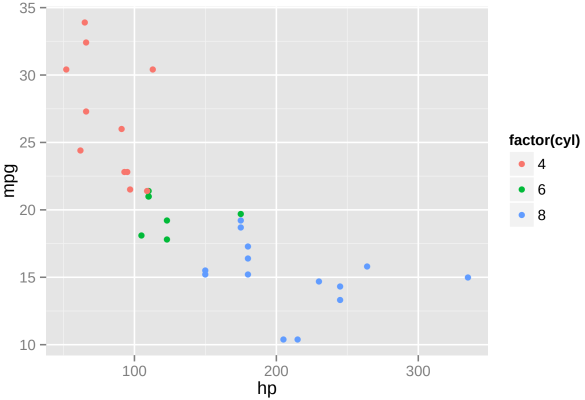
Histograms II

```
# If we are interested in a third categorical variable vs:
qplot(factor(gear), data=mtcars, geom="bar", fill=factor(am)) +
ggtitle('Nice Histogram') # This is how you add a title
```



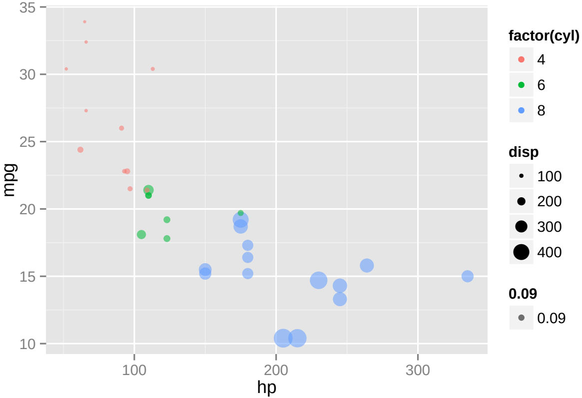
Scatter Plots I

```
# Two continuous variables
qplot(hp, mpg, data = mtcars, color = factor(cyl))
```



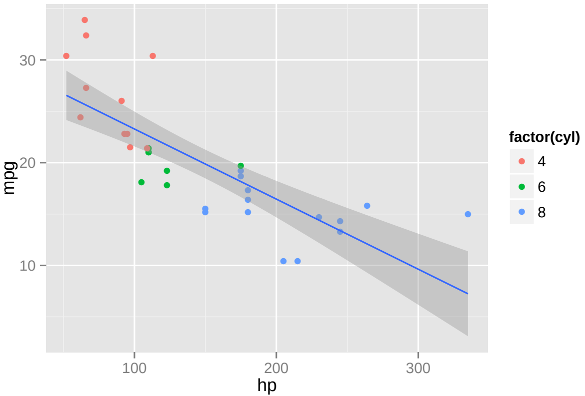
Scatter Plots II

```
# Add two more variables represented by color and size of points
qplot(hp, mpg, data = mtcars, color = factor(cyl), size = disp, alpha = 0.09)
```



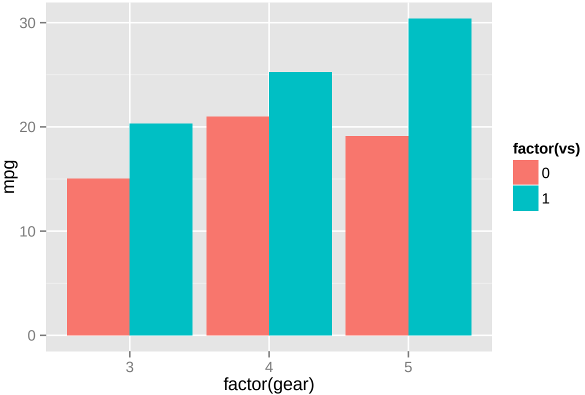
Scatter Plots III

```
ggplot(mtcars, aes(x = hp, y = mpg)) + geom_point(aes(color = factor(cyl))) +
    # Add a regression line
geom_smooth(method = lm)
```



Bar Charts I

```
ggplot(mtcars, aes(x = factor(gear), y = mpg, fill = factor(vs)), color = factor(vs
    stat_summary(fun.y = mean, position = position_dodge(), geom = "bar")
```

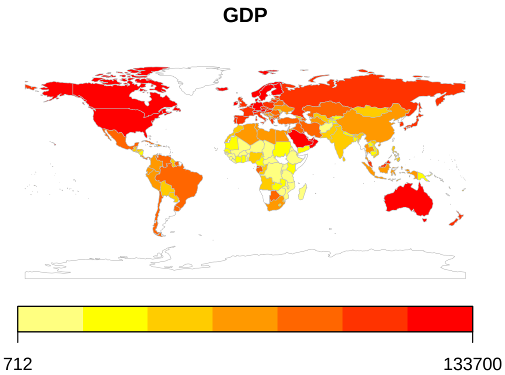


Bonus! Map Visualizations I

```r
## Display GDP Data on Map

library(rworldmap) # Install if necessary

cDataL2011 <- filter(cData_Long, time==2011)
# Rename the columns
colnames(cDataL2011)[4] <- "GDP"

# Turn into map
cDataL2011<- joinCountryData2Map(cDataL2011, joinCode = "ISO2",
                                 nameJoinColumn = 'ISO2')


## 187 codes from your data successfully matched countries in the map
## 0 codes from your data failed to match with a country code in the map
## 55 codes from the map weren't represented in your data
```

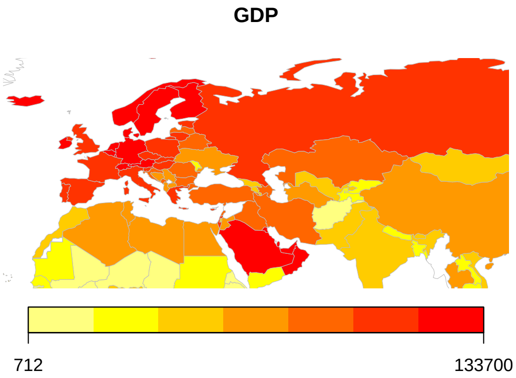
```r
mapCountryData(cDataL2011, nameColumnToPlot = "GDP")
```

Bonus! Map Visualizations II




```
mapCountryData(cDataL2011, nameColumnToPlot = "GDP", mapRegion = "eurasia")
```

Bonus! Map Visualizations III



Subsection 3

Modeling

Formula Interface

Pay close attention to how we specify the model.

R Model

$Y \sim x_1 + x_2$

This basic structure will remain constant across many R packages.

Nifty Tricks with Formula Interface

If you have lots of variables use the shortcut '.'.

mpg $\sim$.

You can do transformations on the fly, no need to create variables.

log(mpg + 1)   .

Dummy variables.

log(mpg + 1)   factor(gears)

Multiple Regression

We will keep using motor trends data set.

Formula

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

R Model

$$Y \sim x_1 + x_2$$

Regression I

```
# Let us estimate gas milage
reg_0 <- lm(mpg ~ hp + cyl + am, mtcars)
summary(reg_0)


##
## Call:
## lm(formula = mpg ~ hp + cyl + am, data = mtcars)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.864 -1.811 -0.158  1.492  6.013
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 30.88834    2.78422  11.094 9.27e-12 ***
## hp          -0.03688    0.01452  -2.540  0.01693 *
## cyl         -1.12721    0.63417  -1.777  0.08636 .
## am           3.90428    1.29659   3.011  0.00546 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.807 on 28 degrees of freedom
## Multiple R-squared:  0.8041, Adjusted R-squared:  0.7831
## F-statistic: 38.32 on 3 and 28 DF,  p-value: 4.791e-10
```

Regression II

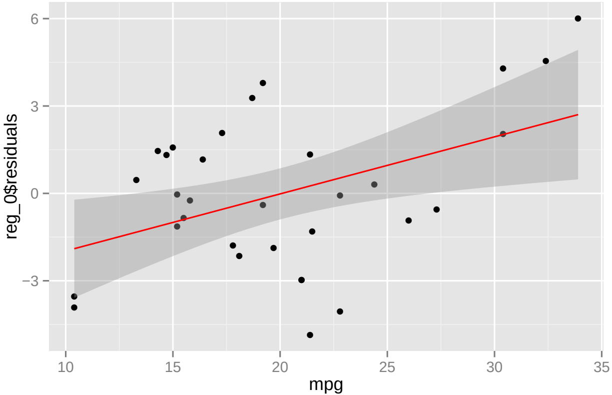
```
# Access Fitted Values View first 3 predictions
reg_0$fitted.values[1:3]

##     Mazda RX4 Mazda RX4 Wag    Datsun 710
##      23.97302      23.97302      26.85433

# Bonus: Are the residuals normally distributed
shapiro.test(reg_0$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  reg_0$residuals
## W = 0.98366, p-value = 0.8961
```

Regression III

```
# PREDICTING NEW DATA BASED ON MODEL
newCar <- mtcars[3, ]  # 3rd observation is Datsun 710
newCar$am <- 0  # What if it was automatic?
reg_0$fitted.values[3]  # Previous estimate

## Datsun 710
##   26.85433

predict(reg_0, newdata = newCar)  # Datsun with automatic transmission

## Datsun 710
##   22.95005
```

```
## Plot the residuals against observation
qplot(data=mtcars, x = mpg, y = reg_0$residuals) + #$
        stat_smooth(method = "lm", col = "red")
```

Regression IV



Regression V

```
## COMPARE MODELS
reg_1 <- lm(mpg ~ hp + cyl + am + wt, mtcars)  # add weight
anova(reg_0, reg_1)

## Analysis of Variance Table
##
## Model 1: mpg ~ hp + cyl + am
## Model 2: mpg ~ hp + cyl + am + wt
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1     28 220.55
## 2     27 170.00  1    50.555 8.0295 0.008603 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# AIC of the model
AIC(reg_0)

## [1] 162.5849

AIC(reg_1)

## [1] 156.2536
```

Logistic Regression

Dependent variable will be type (binary).

It is basically a regression with a binomial link function.

Formula

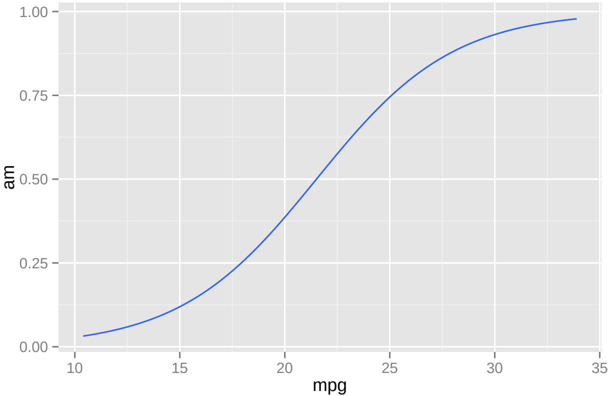
$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \epsilon$$

Logit I

```
logit_2 <- glm(am ~ mpg + drat + cyl, data = mtcars, family = "binomial")
summary(logit_2)


##
## Call:
## glm(formula = am ~ mpg + drat + cyl, family = "binomial", data = mtcars)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.58367  -0.31020  -0.03757   0.17972   1.75395
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -49.4548    24.1280  -2.050   0.0404 *
## mpg           0.6378     0.4266   1.495   0.1349
## drat          7.2595     3.2702   2.220   0.0264 *
## cyl           1.6115     1.0801   1.492   0.1357
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 43.23  on 31  degrees of freedom
## Residual deviance: 17.03  on 28  degrees of freedom
## AIC: 25.03
##
## Number of Fisher Scoring iterations: 7
```

Logit II

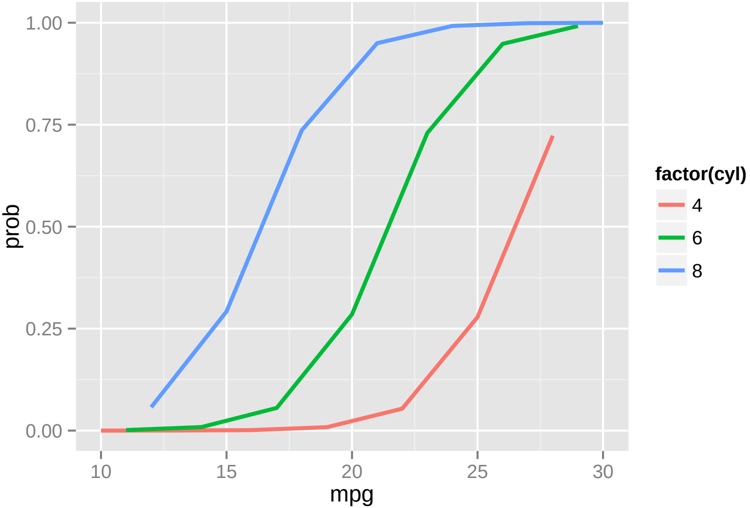
```
# VISUALIZE mpg - Transmission RELATION
ggplot(mtcars, aes(x = mpg, y = am)) +
        stat_smooth(method="glm", family="binomial", se=FALSE) #
```



Logit III

```
## VISUALIZE Mpg - Transmission FOR DIFFERENT NUMBERS OF CYLINDERS

# Create a new dataset with varying number of cylinders and other variables
# fixed at mean levels.
mtcars2 <- data.frame(mpg = rep(10:30, 3), drat = mean(mtcars$drat), disp = mean(mt
    cyl = rep(c(4, 6, 8), 21))
# Predict probability of new data
mtcars2$prob <- predict(logit_2, newdata = mtcars2, type = "response")

# Plot the results
ggplot(mtcars2, aes(x = mpg, y = prob)) + geom_line(aes(colour = factor(cyl)),
    size = 1)  # a different color for each category$
```

Logit IV



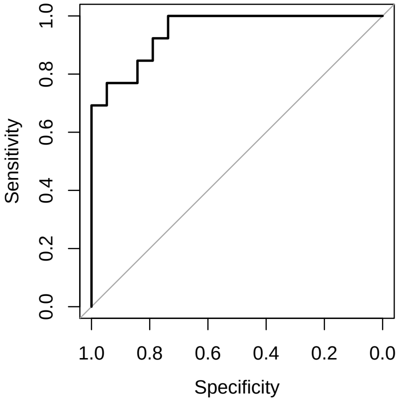
Logit V

```
## DIAGNOSTICS

# Let us compare predicted values to real values
mtcars$prob <- predict(logit_2, type = "response")
# Prevalence of Manual Transmission
mean(mtcars$am)

## [1] 0.40625

# Create predict variable
mtcars$pred <- 0
# If probability is greater than .6 (1-prevalence), set prediction to 1
mtcars[mtcars$prob > 0.6, "pred"] <- 1
```

Logit VI

```
## ROC CURVE

# Load the necessary library
library(pROC)
# Calculate the ROC curve using the predicted probability vs actual values
logit_2_roc <- roc(am ~ prob, mtcars)
# Plot ROC curve
plot(logit_2_roc)

##
## Call:
## roc.formula(formula = am ~ prob, data = mtcars)
##
## Data: prob in 19 controls (am 0) < 13 cases (am 1).
## Area under the curve: 0.9474
```

Logit VII



Logit VIII

```
library(caret)  # Needed for Confusion Matrix
confusionMatrix(table(mtcars[, c("am", "pred")]))
```

```
## Confusion Matrix and Statistics
##
##    pred
## am   0  1
##   0 18  1
##   1  3 10
##
##                Accuracy : 0.875
##                  95% CI : (0.7101, 0.9649)
##     No Information Rate : 0.6562
##     P-Value [Acc > NIR] : 0.005004
##
##                   Kappa : 0.7344
##  Mcnemar's Test P-Value : 0.617075
##
##             Sensitivity : 0.8571
##             Specificity : 0.9091
##          Pos Pred Value : 0.9474
##          Neg Pred Value : 0.7692
##              Prevalence : 0.6562
##          Detection Rate : 0.5625
##    Detection Prevalence : 0.5938
##       Balanced Accuracy : 0.8831
##
##        'Positive' Class : 0
##
```

caret Package

The Caret package is a wrapper that combines functionality from 27 R packages.

Functions Provided:

- Visualization
- Data Manipulation
- Model Training & Selection
- *Parallel Processing*

Since so many packages involved, the installation takes a while.

```
install.packages("caret", dependencies = c("Depends", "Suggests"))
```

For this part of the exercise I will focus on Caret Package, following its vignette.

What does caret Do?

Estimate model parameters

Tune variables through re-sampling strategies

Calculate performance

Classification Trees

For this exercise I will be using Kuhn's 'Predictive Modeling with R and caret Package' examples.

We will fit a classification tree on segmentationData dataset.

Dataset is of segmentation of some cell images.

The data is 2019 observations of 61 variables.

Classification Trees in R: Data I

```
# Obtain Dataset
data(segmentationData)
segmentationData <- segmentationData[, !(colnames(segmentationData) == "Cell")]  #
```

```
# Data set has a variable that separates training vs testing
Training <- segmentationData[segmentationData$Case == "Train", ]  #$ One Way
Testing <- subset(segmentationData, Case == "Test")  # Another way
Training <- Training[, !(colnames(Training) == "Case")]  # Drop Case column
Testing <- subset(Testing, select = -c(Case))  # Another way
```

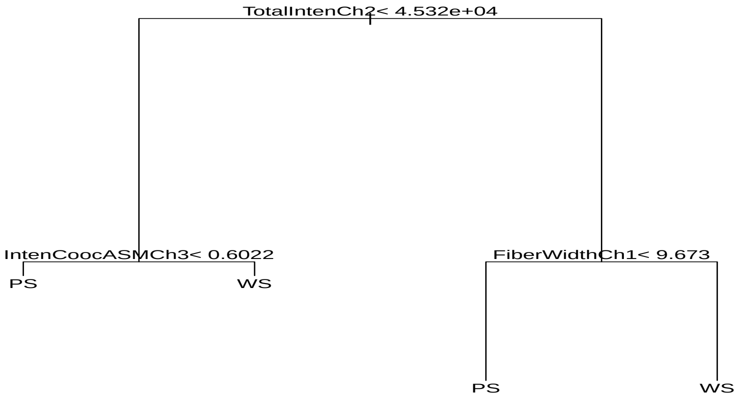
Classification Trees in R I

```
library(rpart)  # Load necessary library
rpart_1 <- rpart(Class ~ ., data = Training, control = rpart.control(maxdepth = 2))

rpart_1  # View the results


## n= 1009
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
## 1) root 1009 373 PS (0.63032706 0.36967294)
##   2) TotalIntenCh2< 45324.5 454  34 PS (0.92511013 0.07488987)
##     4) IntenCoocASMCh3< 0.6021832 447  27 PS (0.93959732 0.06040268) *
##     5) IntenCoocASMCh3>=0.6021832 7   0 WS (0.00000000 1.00000000) *
##   3) TotalIntenCh2>=45324.5 555 216 WS (0.38918919 0.61081081)
##     6) FiberWidthCh1< 9.673245 154  47 PS (0.69480519 0.30519481) *
##     7) FiberWidthCh1>=9.673245 401 109 WS (0.27182045 0.72817955) *
```

Classification Trees in R II

```r
# Visualize the Tree
plot(rpart_1)
text(rpart_1)
```

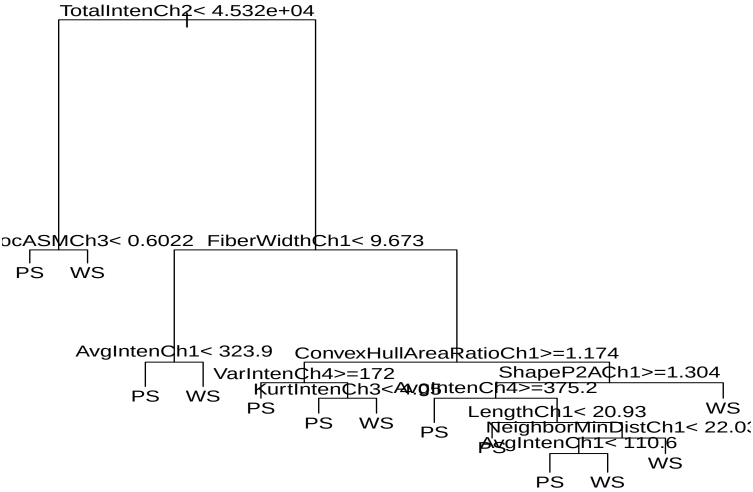
Classification Trees in R III



Classification Trees in R IV

```
# Fit a larger tree and prune it rpart does 10 fold cross validation
rpart_2 <- rpart(Class ~ ., data = Training)
plot(rpart_2)
text(rpart_2)
```

Classification Trees in R V

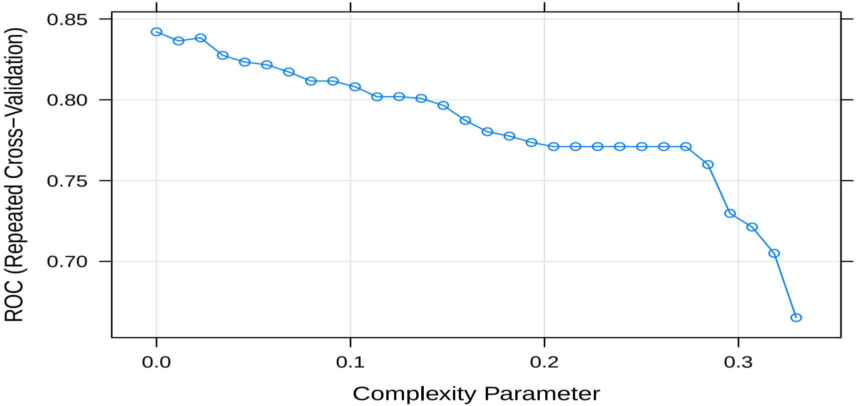


Pruning Trees with caret I

```
library(caret)
## Set Training Parameters Triple Cross Validation
cvCtrl <- trainControl(method = "repeatedcv", repeats = 3, summaryFunction = twoCla
    classProbs = TRUE)

# Use caret to fine tune the fit
CarrotTree <- train(Class ~ ., data = Training, method = "rpart", trControl = cvCtr
    metric = "ROC", tuneLength = 30)
```

```
plot(CarrotTree)
```

Pruning Trees with caret II



Pruning Trees with caret III

```
# Testing
CarrotTree_Test <- predict(CarrotTree, Testing)

confusionMatrix(CarrotTree_Test, Testing$Class)


## Confusion Matrix and Statistics
##
##           Reference
## Prediction  PS  WS
##         PS 554 104
##         WS 110 242
##
##                Accuracy : 0.7881
##                  95% CI : (0.7616, 0.8129)
##     No Information Rate : 0.6574
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.5316
##  Mcnemar's Test P-Value : 0.7325
##
##             Sensitivity : 0.8343
##             Specificity : 0.6994
##          Pos Pred Value : 0.8419
##          Neg Pred Value : 0.6875
##              Prevalence : 0.6574
##          Detection Rate : 0.5485
##    Detection Prevalence : 0.6515
##       Balanced Accuracy : 0.7669
##
##        'Positive' Class : PS
```

Discriminant Analysis with Caret

Here we will conduct a PLS DA with caret

Data Splitting I

```
## OBTAIN DATASET Dataset comes with mlbench package
library(mlbench)
# Load dataset into the current workspace
data(Sonar)
# 208 observations and 61 variables
```

```
## SPLIT THE DATA

# caret provides functionality
library(caret)
# Set random number seed for reproducibility
set.seed(107)
# Create an index of observations to be included in Training
indexTrain <- createDataPartition(y = Sonar$Class, p = 0.75, list = FALSE)

# $plit the data using the index
Train <- Sonar[indexTrain, ]
Test <- Sonar[-indexTrain, ]
```

Train a PLS Discriminant Model I

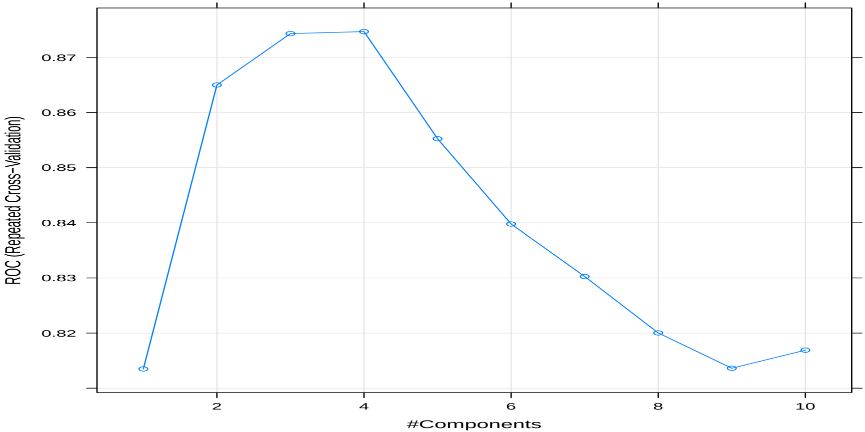
```
## Declare Tuning Control Parameters
ctrl <- trainControl(method = "repeatedcv", # K-fold cross validation
                                repeats = 3, # Repeat resampling 3 times
                     classProbs = TRUE, # Calculate predicted prob for ROC
                     summaryFunction = twoClassSummary) # Set performance metrics fo

## Train the Classifier
plsFit <- train(Class ~ ., data = Train, method = "pls",
                tuneLength = 10,   # Number of component sets to be evaluated (more
                trControl = ctrl, # Use control parameters from above
                metric = "ROC" ,  # Criteria ROC
                preProc = c("center", "scale")) # Center and scale the predictors
```

Train a PLS Discriminant Model II

```
plsFit


## Partial Least Squares
##
## 157 samples
##  60 predictors
##   2 classes: 'M', 'R'
##
## Pre-processing: centered (60), scaled (60)
## Resampling: Cross-Validated (10 fold, repeated 3 times)
## Summary of sample sizes: 142, 141, 142, 142, 142, 142, ...
## Resampling results across tuning parameters:
##
##   ncomp  ROC        Sens       Spec       ROC SD      Sens SD    Spec SD
##    1     0.8134921  0.7291667  0.7291667  0.11844879  0.1387811  0.1935289
##    2     0.8649967  0.7694444  0.8041667  0.08381907  0.1416676  0.1521373
##    3     0.8743221  0.7476852  0.8363095  0.08548836  0.1726683  0.1375303
##    4     0.8746858  0.7578704  0.7642857  0.08443793  0.1512983  0.1539276
##    5     0.8552497  0.7152778  0.7767857  0.09587112  0.1771056  0.1584577
##    6     0.8397817  0.7337963  0.7732143  0.09814150  0.1726297  0.1749730
##    7     0.8302579  0.7101852  0.7916667  0.10762747  0.1992674  0.1655561
##    8     0.8200231  0.7157407  0.7607143  0.12724476  0.1805642  0.1621515
##    9     0.8136161  0.7245370  0.7696429  0.12961432  0.1847286  0.1593987
##   10     0.8168981  0.7203704  0.7559524  0.11678705  0.1912620  0.1436503
##
## ROC was used to select the optimal model using  the largest value.
## The final value used for the model was ncomp = 4.
```

Train a PLS Discriminant Model III

```
# evaluate the performance of different number of components extracted
plot(plsFit)
```



Validate with Test Data I

```
plsPredict <- predict(plsFit, newdata = Test)  # Predict results
head(plsPredict)  # View predictions

## [1] R M M R M R
## Levels: M R

head(Test$Class)  # View actual$

## [1] R R R R R R
## Levels: M R
```

Validate with Test Data II

```
# Get confusion matrix (predicted vs actual)
confusionMatrix(data = plsPredict, Test$Class)  #$
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  M  R
##          M 17  6
##          R 10 18
##
##                Accuracy : 0.6863
##                  95% CI : (0.5411, 0.8089)
##     No Information Rate : 0.5294
##     P-Value [Acc > NIR] : 0.01674
##
##                   Kappa : 0.3761
##  Mcnemar's Test P-Value : 0.45325
##
##             Sensitivity : 0.6296
##             Specificity : 0.7500
##          Pos Pred Value : 0.7391
##          Neg Pred Value : 0.6429
##              Prevalence : 0.5294
##          Detection Rate : 0.3333
##    Detection Prevalence : 0.4510
##       Balanced Accuracy : 0.6898
##
##        'Positive' Class : M
##
```

Read caret Documentations

I provide here a brief glimpse into what caret is capable of.

Do read for yourself.

Questions

?

Outline

Professional Looking Documents

All the documentation of this workshop has been prepared in R Studio.

Look into the Rmd documents to see how this was done.

summary() function does not provide the best looking model summaries. Try the texreg package (do as I say, not as I do).

Questions

?

Outline

Quo Vadis?

8 hours is not enough!

RTFM[2]: Documentation is your friend, read the vignettes and manuals.

For tutorials: Institute For Digital Research and Education, UCLA

For questions: StackExchange[3]

- Cross Validated specializes on Statistics
- Stack Overflow for R programming

R Programming is quirky, learn about efficient R programming.

[2] Read the Friendly Manual

[3] Word of caution, pay attention to how you ask your questions. It is more important than you realize.

Questions

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