How I Learned to Stop Worrying and Love the R Console

Irfan Kanat
Department of Information Systems
Arizona State University

November 3, 2015

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

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

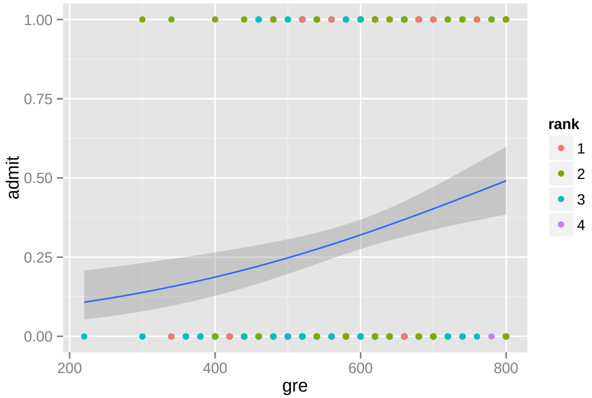
Outline

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 ***
## ---
```

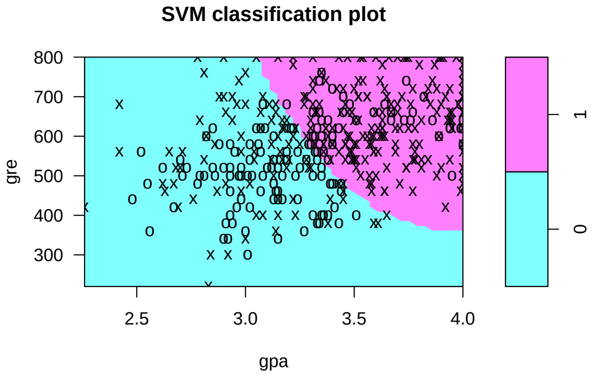
Logistic Regression

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



Support Vector Machine

```r
# 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

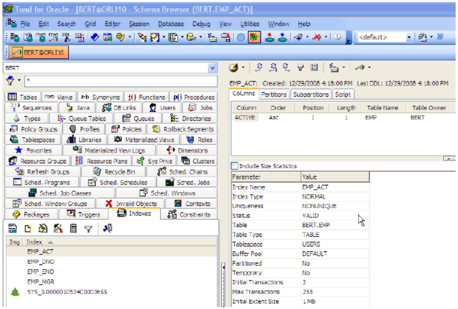
Command Driven Interface

Command line may be intimidating

Power over Convenience

Consider the number of

- Functions
- Parameters
- Data sources
- Variables
- Replications


Toad for Oracle - [BERT@ORLI10 - Schema Browser (BERT.EMP_ACT)]
File Edit Search Grid Editor Session Database Debug View Utilities Window Help
<default>
BERT@ORLI10
BERT
Tables Views Synonyms Functions Procedures
Sequences Java DB Links Users Jobs
Types Queue Tables Queues Directories
Policy Groups Profiles Policies Rollback Segments
Tablespaces Libraries Materialized Views Roles
Favorites Materialized View Logs Dimensions
Resource Groups Resource Plans Sys Privs Clusters
Refresh Groups Recycle Bin Sched. Chains
Sched. Programs Sched. Schedules Sched. Jobs
Sched. Job Classes Sched. Windows
Sched. Window Groups Invalid Objects Contexts
Packages Triggers Indexes Constraints
Columns Partitions Subpartitions Script
Include Size Statistics

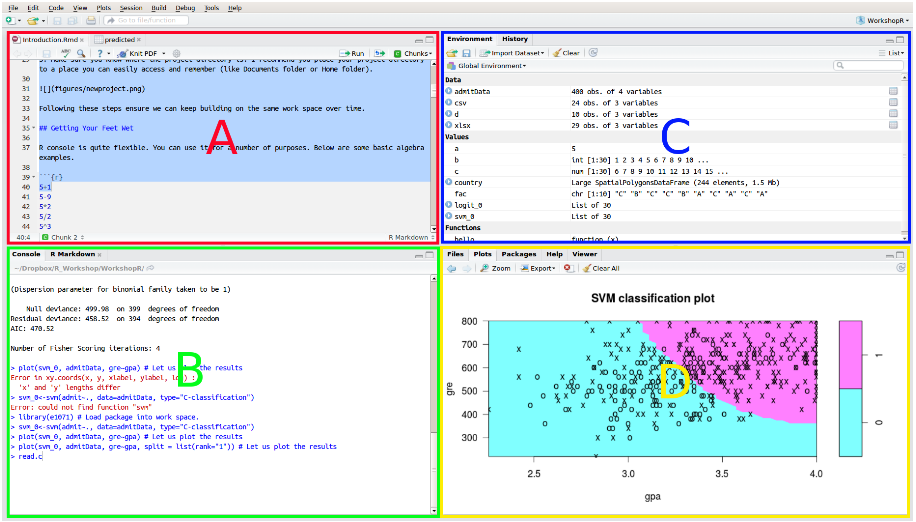
Img	Index
	EMP_ACT
	EMP_DNO
	EMP_ENO
	EMP_MGR
	SYS_IL0000010534C00036$$

EMP_ACT: Created: 12/29/2008 4:18:00 PM Last DDL: 12/29/2008 4:18:00 PM

Column	Order	Position	Length	Table Name	Table Owner
ACTIVE	Asc	1	1	EMP	BERT

Parameter	Value
Index Name	EMP_ACT
Index Type	NORMAL
Uniqueness	NONUNIQUE
Status	VALID
Table	BERT.EMP
Table Type	TABLE
Tablespace	USERS
Buffer Pool	DEFAULT
Partitioned	No
Temporary	No
Initial Transactions	2
Max Transactions	255
Initial Extent Size	1 Mb

R Studio



~~~
3. Make sure you know where the project directory is. I recommend you place your project directory
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
~~~

40:4   Chunk 2   R Markdown

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 [illegible] the results
Error in xy.coords(x, y, xlabel, ylabel, lo[illegible]) :
  '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
```

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	
hello	function (x)

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

```
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

```
ls()  # List the contents of the environment

##  [1] "A"           "admitData"   "B"           "c"           "C"
##  [6] "Countries"   "HelloWorld"  "i"           "lmvreg_0"    "logit_0"
## [11] "logit_1"     "logit_2"     "mtcars"      "mvreg_0"     "mvreg_0_fit"
## [16] "mvreg_0_res" "pima2"       "Pima.tr"     "Sonar"       "svm_0"

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"           "C"
##  [6] "Countries"   "HelloWorld"  "i"           "lmvreg_0"    "logit_0"
## [11] "logit_1"     "logit_2"     "mtcars"      "mvreg_0"     "mvreg_0_fit"
## [16] "mvreg_0_res" "pima2"       "Pima.tr"     "Sonar"       "svm_0"

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

## [1] "lmvreg_0"    "logit_0"     "mvreg_0"     "mvreg_0_fit" "mvreg_0_res"
## [6] "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.

```r
# 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())

##  [1] "mlbench"   "MASS"      "e1071"     "ggplot2"   "knitr"
##  [6] "stats"     "graphics"  "grDevices" "utils"     "datasets"
## [11] "methods"   "base"

# Get list of all installed packages (part of output omitted)
.packages(all.available = T)

##   [1] "acepack"            "AER"                "AGD"
##   [4] "akima"              "alabama"            "ape"
##   [7] "assertthat"         "bbmle"              "bdsmatrix"
##  [10] "betareg"            "BH"                 "biglm"
```

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

Multivariate 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

?

Outline

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

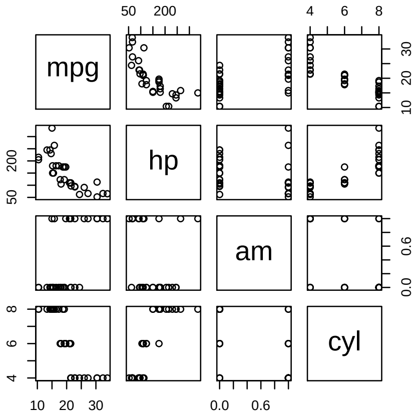
Motor Trends Dataset I

```
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  
```

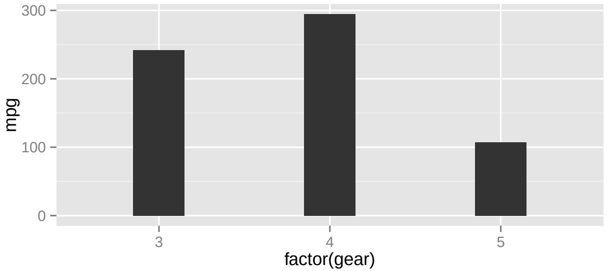
Motor Trends Dataset II

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



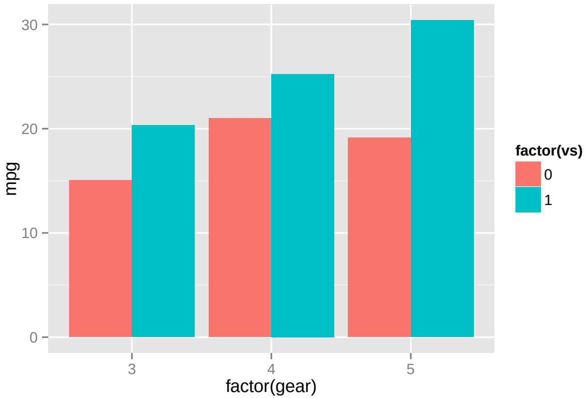
Bar Charts I

```r
# Load the Dataset
data(mtcars)
## ggplot2 package is already loaded, else library(ggplot2)

## Simple plot of just the means Initialize the plot with variables of
## interest
ggplot(mtcars, aes(x = factor(gear), y = mpg)) + # Instruct ggplot to plot bars of
geom_bar(stat = "identity", width = 0.3)
```



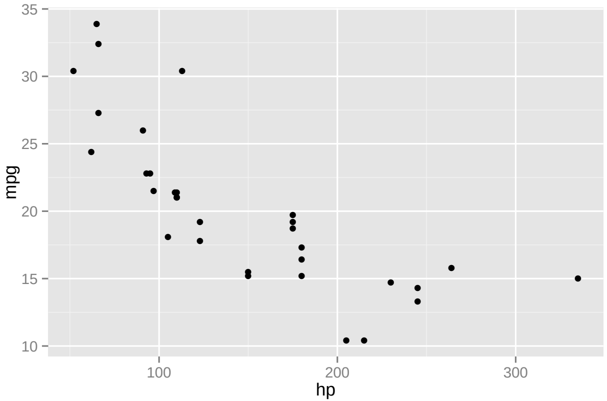
Bar Charts II

```
# If we are interested in a third categorical variable vs:
ggplot(mtcars, aes(x = factor(gear), y = mpg, fill = factor(vs)), color = factor(vs
    stat_summary(fun.y = mean, position = position_dodge(), geom = "bar")
```



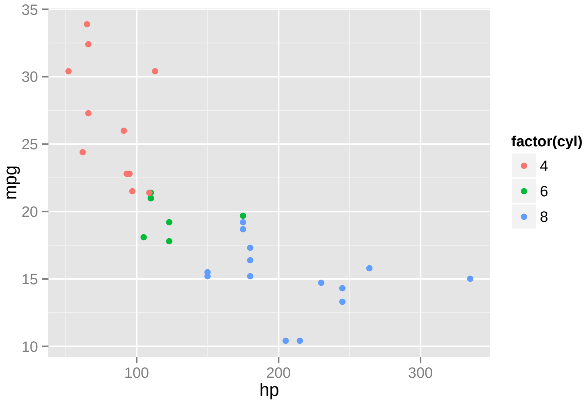
Scatter Plots I

```
# Initialize Plot
ggplot(mtcars, aes(x = hp, y = mpg)) + # Instruct points to be plotted
geom_point()
```



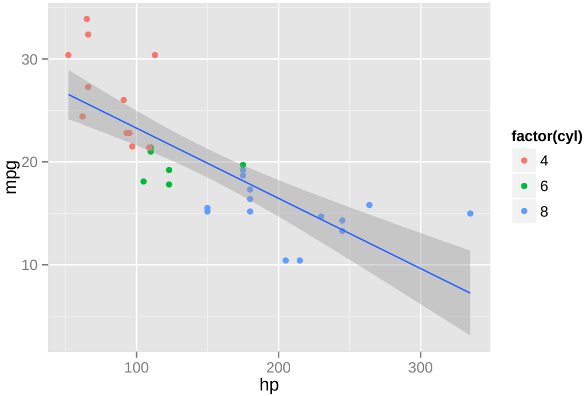
Scatter Plots II

```
ggplot(mtcars, aes(x = hp, y = mpg)) + # Put some color in those points
geom_point(aes(color = factor(cyl)))
```



Scatter Plots III

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



Multivariate Regression

We will keep using motor trends data set.

Pay close attention to how we specify the model.

Formula

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

R Model

$$Y \sim x_1 + x_2$$

This basic structure will remain constant across many R packages.

MV Regression I

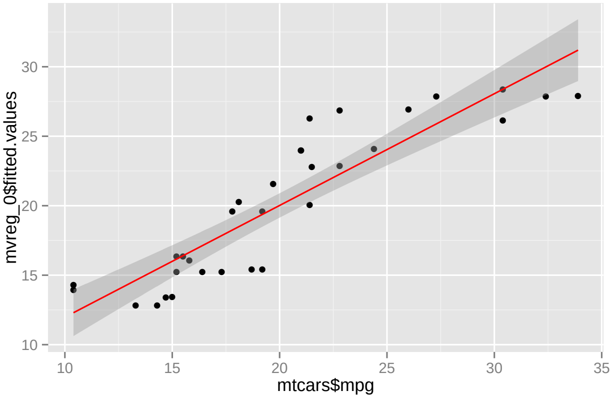
```
# Let us estimate body weight index
mvreg_0 <- lmvreg_0 <- lm(mpg ~ hp + cyl + am, mtcars)
summary(mvreg_0)


##
## 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
```

MV Regression II

```
# Access Fitted Values View first 3 predictions
mvreg_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(mvreg_0$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  mvreg_0$residuals
## W = 0.98366, p-value = 0.8961

# AIC of the model
AIC(mvreg_0)

## [1] 162.5849
```

MV Regression III

```
# Plot the fitted values against real values
ggplot(mtcars, aes(x = mtcars$mpg, y = mvreg_0$fitted.values)) + geom_point() +
    stat_smooth(method = "lm", col = "red")
```



Logistic Regression

We will use a well established dataset on Diabetes among Pima Indians During Pregnancy.

Variables are:

- npreg: Number of times pregnant
- glu: Plasma glucose concentration
- bp: Diastolic blood pressure (mm Hg)
- skin: Triceps skin fold thickness (mm)
- bmi: Body mass index (weight in kg/(height in m)^2)
- ped: Diabetes pedigree function
- age: Age (years)
- type: Diabetic (yes, no)

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

```
library(MASS) # data file is part of MASS package

data(Pima.tr) # Load data file

??Pima.tr # Help on data file

head(Pima.tr, 3) # Top 3 rows

##   npreg glu bp skin  bmi   ped age type
## 1     5  86 68   28 30.2 0.364  24   No
## 2     7 195 70   33 25.1 0.163  55  Yes
## 3     5  77 82   41 35.8 0.156  35   No
```

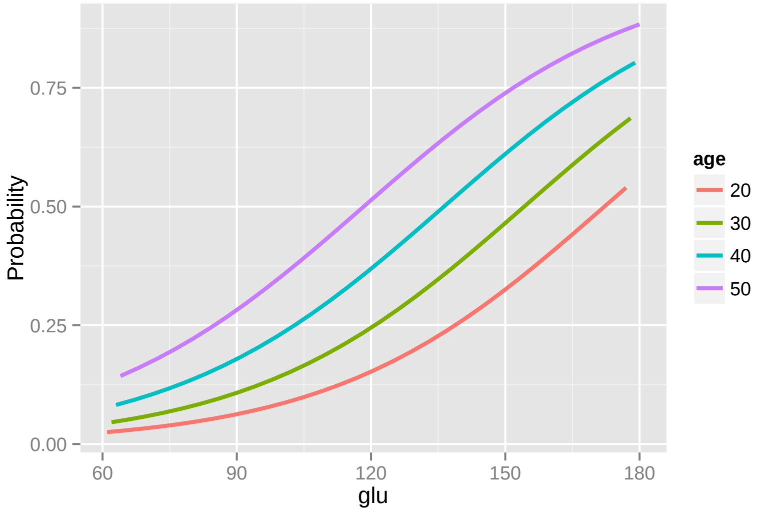
Logit II

```
logit_2 <- glm(type ~ glu + ped + age, Pima.tr, family = "binomial")
summary(logit_2)


##
## Call:
## glm(formula = type ~ glu + ped + age, family = "binomial", data = Pima.tr)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0755  -0.7169  -0.4236   0.7078   2.3526
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -7.706001   1.082177  -7.121 1.07e-12 ***
## glu          0.032903   0.006617   4.973 6.60e-07 ***
## ped          1.869117   0.626096   2.985  0.00283 **
## age          0.059003   0.017505   3.371  0.00075 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 256.41  on 199  degrees of freedom
## Residual deviance: 187.10  on 196  degrees of freedom
## AIC: 195.1
##
## Number of Fisher Scoring iterations: 4
```

Logit III

```
## Let us create a simulated dataset to predict effect of age Create a
## dataset
pima2 <- data.frame(glu = 61:180, ped = mean(Pima.tr$ped), age = rep(c(20, 30,
    40, 50), 30))
# Get the predicted probabilities to plot
pima2$pred <- predict(logit_2, newdata = pima2, type = "response")
# Declare age as categorical
pima2$age <- as.factor(pima2$age)


## Plot the results, with categorical age as lines o.  Initialize the plot
## with probability on y axis and glucose on x
ggplot(pima2, aes(x = glu, y = (pred))) + # Colored lines for each age category
geom_line(aes(colour = age), size = 1) + # Rename the y axis label
ylab("Probability")
```

Logit IV


Probability
0.75
0.50
0.25
0.00
60
90
120
150
180
glu
age
20
30
40
50

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.

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

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

Data Splitting I

Let us obtain our dataset

```r
# Dataset comes with mlbench package
library(mlbench)
# Load dataset into the current workspace
data(Sonar)
```

208 observations and 61 variables

Split the data into training and testing datasets, conserving the dependent variables' distribution.

Data Splitting II

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

## Error in eval(expr, envir, enclos):  could not find function
"createDataPartition"

# $plit the data
Train <- Sonar[indexTrain, ]

## Error in `[.data.frame`(Sonar, indexTrain, ):  object 'indexTrain' not found

Test <- Sonar[-indexTrain, ]

## Error in `[.data.frame`(Sonar, -indexTrain, ):  object 'indexTrain' not found
```

Train a PLS Discriminant Model

```
plsFit <- train(Class ~ ., data = Train, method = "pls",
                # Center and scale the predictors
                preProc = c("center", "scale"))

## Error in eval(expr, envir, enclos):  could not find function "train"
```

Questions

?

Outline

Questions

?

Outline