How I Learned to Stop Worrying and Love the R Console

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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

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

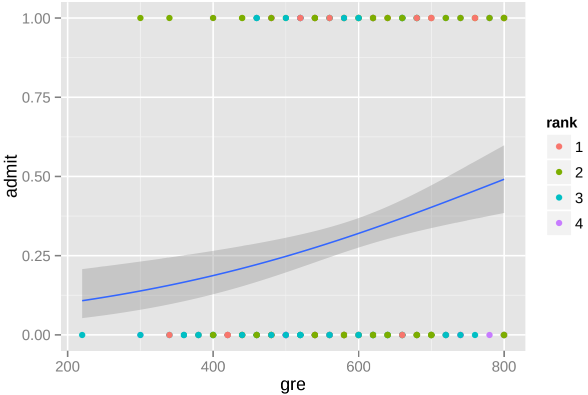
Logistic Regression

```
# 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 ***
## ---
```

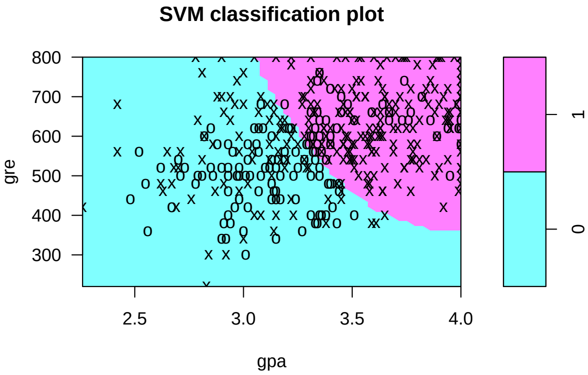
Logistic Regression

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



Support Vector Machine

```
# 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

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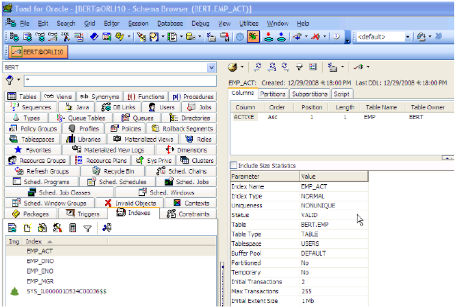
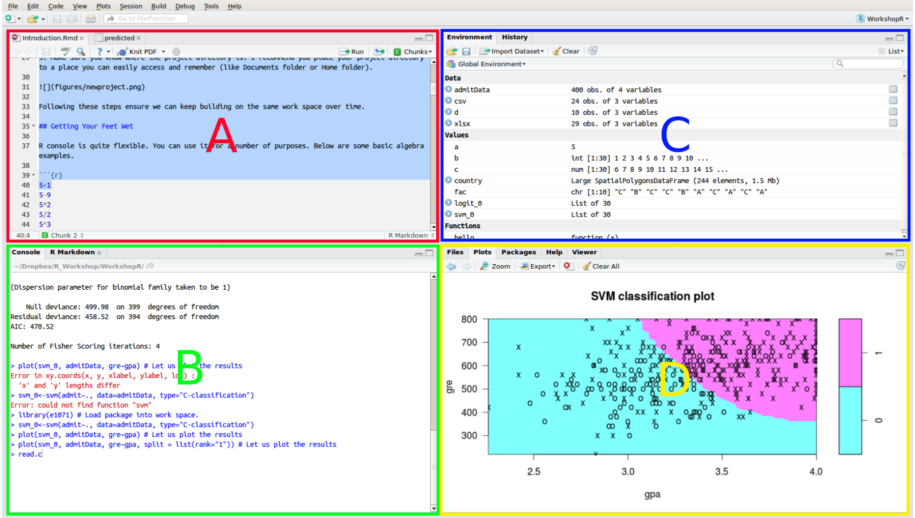


R Studio



A
B
C
D
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
Environment
History
Import Dataset
Clear
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
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
Files
Plots
Packages
Help
Viewer
Zoom
Export
Clear All
SVM classification plot
gre
gpa
```

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

```r
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

```
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

```r
# 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

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

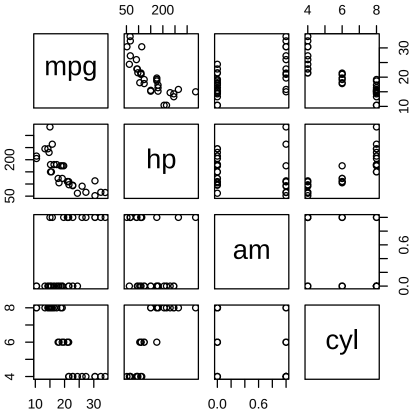
Motor Trends Dataset I

```
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  
```

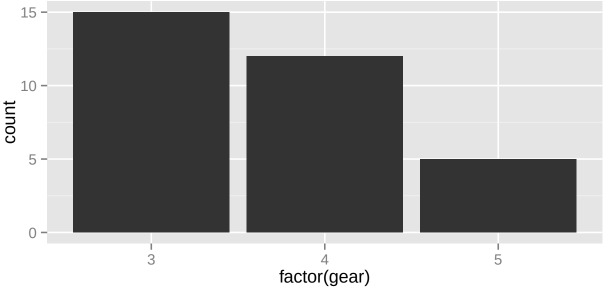
Motor Trends Dataset II

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



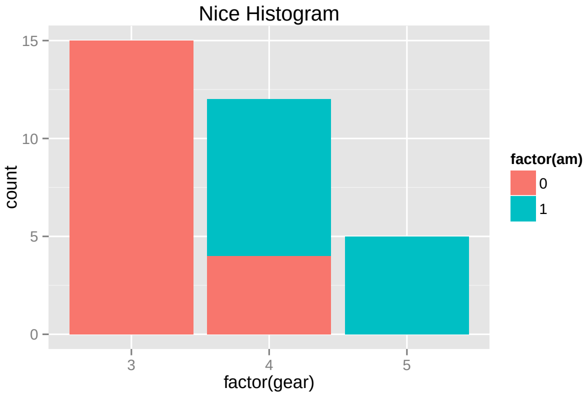
Histograms I

```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")
```



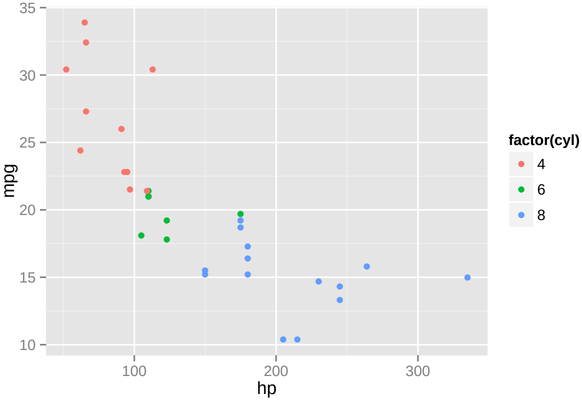
Histograms II

```
# 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
```



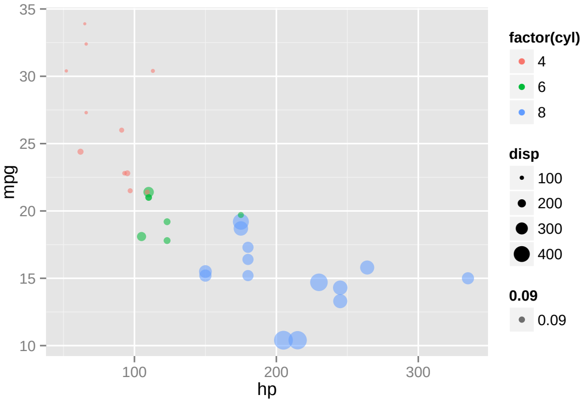
Scatter Plots I

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



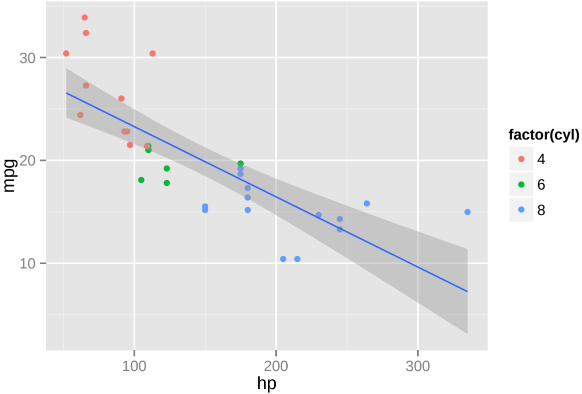
Scatter Plots II

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



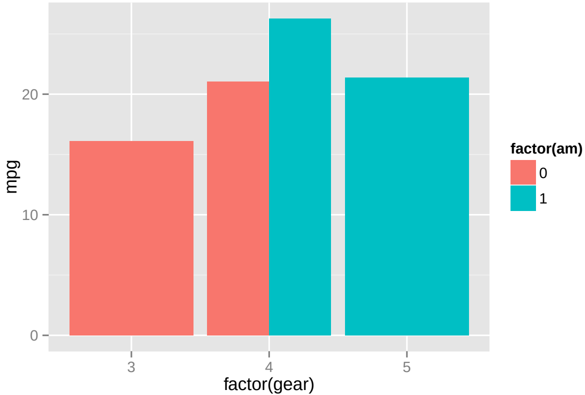
Scatter Plots III

```
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(am)), color = factor(am
    stat_summary(fun.y = mean, position = position_dodge(), geom = "bar")
```



Multiple 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.

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

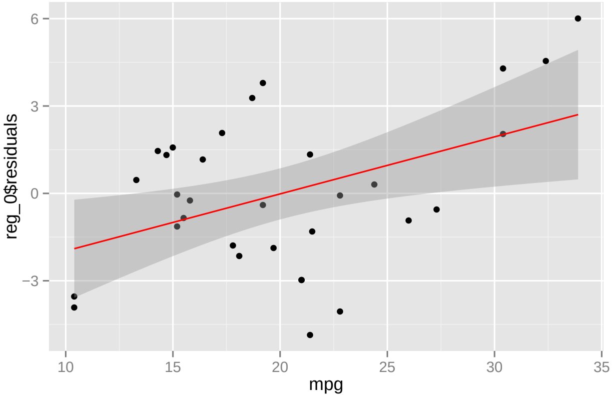
```
# Access Fitted Values View first 3 predictions
reg_0$fitted.values[1:3]

##     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

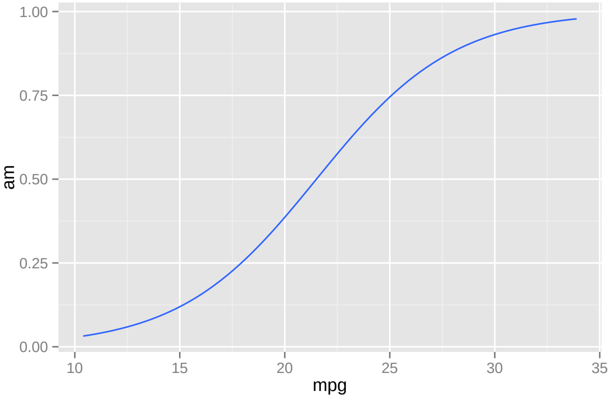
$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \epsilon$$

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

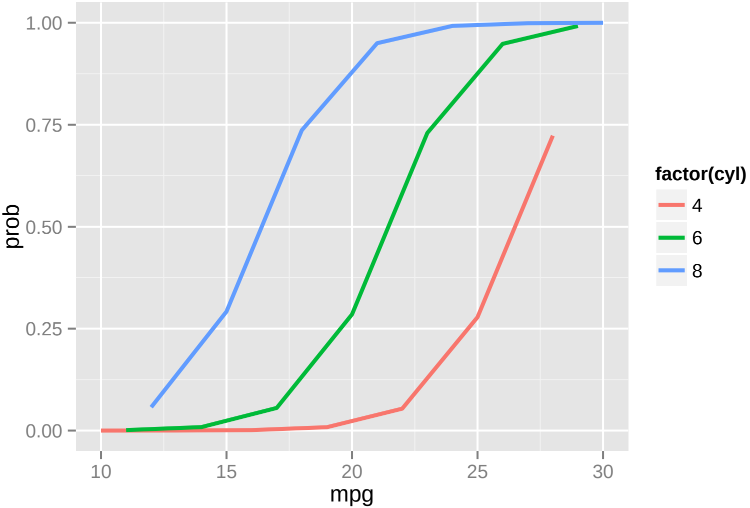
```
# VISUALIZE mpg - Transmission RELATION
ggplot(mtcars, aes(x = mpg, y = am)) +
       stat_smooth(method="glm", family="binomial", se=FALSE) #
```



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



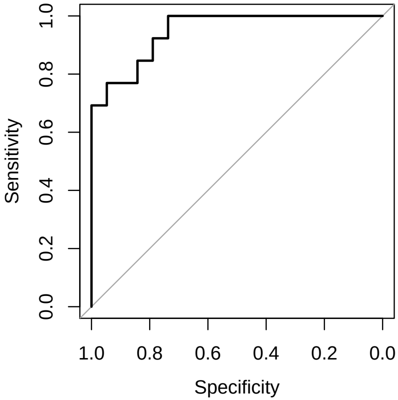
Logit V

```
## 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.

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

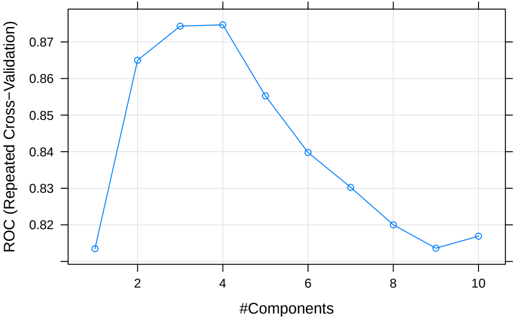
```
## Declare Tuning Control Parameters
ctrl <- trainControl(method = "repeatedcv", # K-fold cross validation
                              repeats = 3, # Repeat resampling 3 times
                    classProbs = TRUE, # Calculate predicted prob for ROC
                    summaryFunction = twoClassSummary)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

Questions

?

Outline

Questions

?

Outline