

# Data Analysis and Visualisation using R

Vinayak Hegde

July 11, 2013

# Outline of Topics I

- 1 Introduction
  - About R
  - Workspace Basics
  - Basic functions
  - Basic Statistics functions
  - Basic Plotting Functions
  - Basic library functions
  - Resources
- 2 Data Structures
  - Vector
  - Matrix
  - Array

## Outline of Topics II

- Data Frames
- Factors
- List
- Basic datastructure functions

### 3 Working with Data

- Reading Data
- Transforming Data
- Live example

### 4 Visualisation

- Introduction
- Basic plots
- Advanced Plots

## Outline of Topics III

- Grammar of Graphics

### 5 Webapps

- Introduction to Shiny
- Features
- Architecture
- Code example

### 6 Integration with other Systems

# Outline

- 1 Introduction
- 2 Data Structures
- 3 Working with Data
- 4 Visualisation
- 5 Webapps
- 6 Integration with other Systems

# What is R ?

## Wikipedia

R is a free software programming language and a software environment for statistical computing and graphics. The R language is widely used among statisticians and data miners for developing statistical software and data analysis.

# Why use R ?

- Designed and optimised for data processing
- Lots of modules
- State of the art graphics
- Free as in freedom/beer
- Helpful community
- Very flexible and good integration

# R Studio Installation

- Go to **RStudio website**
- Download the server/desktop version
- For server - Open the browser and go to `http://127.0.0.1:8787`
- For desktop - Click on the shortcut and you are ready to go



# R Studio Basics

- The Source Editor
- The Console / Interpreter
- Workspace / History
- Plots / Packages / Help

## Basics - Starting off and getting help

- Starting the interpreter
- Getting online help - ? or help()
- Searching for help - ??
- Approximate search - apropos()

## Basics - Objects and Workspaces

- `attach(object)`
- `detach(object)`
- `rm()`
- `save.image("ExploreData.RData")`
- `load("SavedWorkspace.RData")`
- `save(data1,data2,file="SavedWorkspace.RData")`

## Basics - Using inbuilt function

- str
- summary
- head
- View
- Assignment <-
- source
- sink

## Basics - str function

```
## str function demo
str(mtcars)

## 'data.frame': 32 obs. of 11 variables:
## $ mpg : num 21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
## $ cyl : num 6 6 4 6 8 6 8 4 4 6 ...
## $ disp: num 160 160 108 258 360 ...
## $ hp : num 110 110 93 110 175 105 245 62 95 123 ...
## $ drat: num 3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
## $ wt : num 2.62 2.88 2.32 3.21 3.44 ...
## $ qsec: num 16.5 17 18.6 19.4 17 ...
## $ vs : num 0 0 1 1 0 1 0 1 1 1 ...
## $ am : num 1 1 1 0 0 0 0 0 0 0 ...
## $ gear: num 4 4 4 3 3 3 3 4 4 4 ...
## $ carb: num 4 4 1 1 2 1 4 2 2 4 ...
```

## Basics - summary function

```
## summary function demo
summary(mtcars)
```

##	mpg	cyl	displacement	hp
##	Min. :10.4	Min. :4.00	Min. : 71.1	Min. : 52.0
##	1st Qu.:15.4	1st Qu.:4.00	1st Qu.:120.8	1st Qu.: 96.5
##	Median :19.2	Median :6.00	Median :196.3	Median :123.0
##	Mean :20.1	Mean :6.19	Mean :230.7	Mean :146.7
##	3rd Qu.:22.8	3rd Qu.:8.00	3rd Qu.:326.0	3rd Qu.:180.0
##	Max. :33.9	Max. :8.00	Max. :472.0	Max. :335.0
##	drat	wt	qsec	vs
##	Min. :2.76	Min. :1.51	Min. :14.5	Min. :0.000
##	1st Qu.:3.08	1st Qu.:2.58	1st Qu.:16.9	1st Qu.:0.000
##	Median :3.69	Median :3.33	Median :17.7	Median :0.000
##	Mean :3.60	Mean :3.22	Mean :17.8	Mean :0.438
##	3rd Qu.:3.92	3rd Qu.:3.61	3rd Qu.:18.9	3rd Qu.:1.000
##	Max. :4.93	Max. :5.42	Max. :22.9	Max. :1.000

## Basics - head function

```
## head function demo  
head(mtcars)
```

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

## Basics - Inbuilt Statistics functions

- mean
- sd
- var
- median
- quantile
- hist
- plot



## Basics - Stats Functions Demo

```
set.seed(1729)
x = rnorm(25)
mean(x)

## [1] 0.1951

var(x)

## [1] 0.5624

sd(x)

## [1] 0.7499
```

## Basics - Stats Functions Demo

```
median(x)
```

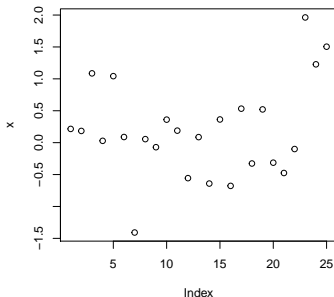
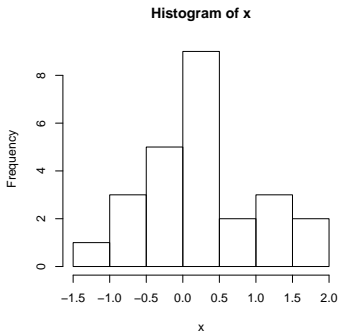
```
## [1] 0.08827
```

```
quantile(x)
```

```
##           0%          25%          50%          75%          100%  
## -1.40843 -0.31371  0.08827  0.52097  1.96241
```

# Basics - Stats Functions Demo

```
hist(x)  
plot(x)
```



## Basics - Library commands

- `install.packages("packagename")`
- `library("package")`
- `update.packages("packages")`
- `search()`
- `detach("package:packagename")`

# Install Views

- `install.views("packageGroupName")`
- `update.views("packageGroupName")`

## Package Groups

- Econometrics
- Graphics
- TimeSeries
- HighPerformanceComputing
- Optimization

# Resources

- R Project
- R Seek
- R Documentation
- R Journal
- CRAN

# Outline

- 1 Introduction
- 2 Data Structures**
- 3 Working with Data
- 4 Visualisation
- 5 Webapps
- 6 Integration with other Systems

# Vector

## Vector Datastructure

Vectors are one-dimensional arrays that can hold numeric data, character data, or logical data. Vectors can be column vectors (created with `c()`) or row vectors (can be created using the transpose function `t()`).



## Vector - Demo

```
a <- c(1, 4, 3, -1, 0, 2, 9)
b <- c("Apples", "Oranges", "Banana", "Mango")
c <- c(FALSE, TRUE, TRUE, FALSE)
a[4]

## [1] -1

b[c(2, 4)]

## [1] "Oranges" "Mango"

c[2:4]

## [1] TRUE TRUE FALSE
```

# Matrix

## Matrix Datastructure

A matrix is a two-dimensional array where each element has the same mode (numeric, character, or logical). Matrices are created with the `matrix()` function.

# Matrix - Demo 1

```
m1 <- matrix(1:20, nrow = 5, ncol = 4)
```

```
m1
```

```
##      [,1] [,2] [,3] [,4]  
## [1,]    1    6   11   16  
## [2,]    2    7   12   17  
## [3,]    3    8   13   18  
## [4,]    4    9   14   19  
## [5,]    5   10   15   20
```

## Matrix - Demo 2

```
cells <- c("A","B","C","D","E","F","G","H","I")
rnames <- c("R1", "R2", "R3")
cnames <- c("C1","C2","C3")
m2 <- matrix(cells,nrow=3,ncol=3,byrow=TRUE,
dimnames=list(rnames,cnames))
m2

##      C1  C2  C3
## R1  "A"  "B"  "C"
## R2  "D"  "E"  "F"
## R3  "G"  "H"  "I"
```

# Array

## Array Datastructure

Arrays are similar to matrices but can have more than two dimensions. They're created with an `array()` function. Like matrices, they can contain only one datatype.

## Array - Demo 1

```
arows <- c("R1", "R2")  
acols <- c("C1", "C2", "C3")  
azind <- c("Z1", "Z2")  
arr <- array(1:12, c(2, 3, 2), dimnames = list(arows, acols, azind))
```

## Array - Demo 2

```
arr

## , , Z1
##
##      C1 C2 C3
## R1   1  3  5
## R2   2  4  6
##
## , , Z2
##
##      C1 C2 C3
## R1   7  9 11
## R2   8 10 12
```

# Data Frames

## Data Frame Datastructure

A Dataframe is like a matrix but each of the columns can be a different datatype. Another way to think about it is as a bunch of different types of columns with similar keys (like a database table). A dataframe is created with the `data.frame()` function.



# Dataframe Demo 1

```
batname <- c("Sachin", "Sourav", "Rahul", "Laxman")
batttype <- c("RHB", "LHB", "RHB", "RHB")
matches <- c(198, 113, 164, 134)
batave <- c(53.86, 42.17, 52.31, 45.97)
batinfo <- data.frame(batname, batttype, matches, batave)
batinfo
```

```
##   batname batttype matches batave
## 1  Sachin      RHB      198  53.86
## 2  Sourav      LHB      113  42.17
## 3   Rahul      RHB      164  52.31
## 4  Laxman      RHB      134  45.97
```

## Dataframe Demo 2

```
batinfo$batname

## [1] Sachin Sourav Rahul  Laxman
## Levels: Laxman Rahul Sachin Sourav

batinfo$batttype

## [1] RHB LHB RHB RHB
## Levels: LHB RHB

as.numeric(batinfo$batttype)

## [1] 2 1 2 2
```

## Dataframe Demo 3

```
summary(batinfo)
```

##	batname	batttype	matches	batave
##	Laxman:1	LHB:1	Min. :113	Min. :42.2
##	Rahul :1	RHB:3	1st Qu.:129	1st Qu.:45.0
##	Sachin:1		Median :149	Median :49.1
##	Sourav:1		Mean :152	Mean :48.6
##			3rd Qu.:172	3rd Qu.:52.7
##			Max. :198	Max. :53.9

# Factors

- Factors are made of categorical data
- Factors can be ordered or unordered
- Factors are represented internally as numbers
- Assignment is by alphabetical order

## Factor - Demo 1

```
grades1 <- factor(c("Bad", "Poor", "Average", "Good", "Excellent"))
grades1

## [1] Bad      Poor      Average   Good      Excellent
## Levels: Average Bad Excellent Good Poor

as.numeric(grades1)

## [1] 2 5 1 4 3
```

## Factor - Demo 2

```
grades2 <- factor(grades1, order = TRUE, levels = grades1)
grades2

## [1] Bad      Poor      Average   Good      Excellent
## Levels: Bad < Poor < Average < Good < Excellent

as.numeric(grades2)

## [1] 1 2 3 4 5
```

# List

## List Datastructure

List is a bit of a mixed bag. A list is an ordered collection of objects. A list allows you to gather a variety of (possibly unrelated) objects under one name. A list may contain an arbitrary combination of vectors, matrices, data frames, and even other lists. You create a list using the `list()` function.

# List Demo 1

```
a <- "Hello world"
b <- c(17, 19, 23, 29)
c <- matrix(1:12, nrow = 3)
l <- list(header = a, primes = b, c)
l[[2]]

## [1] 17 19 23 29

l[["primes"]]

## [1] 17 19 23 29
```



## List Demo 2

```
1

## $header
## [1] "Hello world"
##
## $primes
## [1] 17 19 23 29
##
## [[3]]
##      [,1] [,2] [,3] [,4]
## [1,]    1    4    7   10
## [2,]    2    5    8   11
## [3,]    3    6    9   12
```

## Working with Data Structures

- concatenate `c()`
- `cbind()`
- `rbind()`
- `data.frame()`
- `mode()`
- `class()`

# Working with Data Structures

- with()
- sort()
- subset()
- select()
- transform()

# Working with Data Structures

- `names()`
- `row.names()`
- `attributes()`

# Outline

- 1 Introduction
- 2 Data Structures
- 3 Working with Data**
- 4 Visualisation
- 5 Webapps
- 6 Integration with other Systems

# Reading data from multiple Sources

- Excel files
- web pages
- csv
- databases

## Reading data in Excel files

```
library(gdata)  
read.xls("~/hacknight/All_India_Index_April3.xls", sheet = 1)
```

## Reading data from HTML tables on the web

```
library(XML)
url <- "http://en.wikipedia.org/wiki/2011_Cricket_World_Cup_statistics"
tbls <- readHTMLTable(url)
specifictbl <- readHTMLTable(url, which = 3)
```



## Reading from csv files

```
stk <- read.csv("~/stackoverflow.csv")
```

Alternatives are `read.table()`, `read.csv2()`

## Get a subset of data

### Using Subset function

```
stkjs <- subset (stk, Tag=="javascript")  
stkweb <- subset (stk, Tag=="javascript" | Tag=="html"  
| Tag=="css" | Tag=="ajax")
```

### An alternative method by column number and names

```
carsmall <- mtcars[1:10, c("mpg", "cyl", "disp", "hp", "drat")]  
carsmall <- mtcars[1:10, 1:5]  
carstrans <- t(carsmall)
```

## Filtering a set of data

```
car400plus <- mtcars[mtcars$displ > 400, ]  
carcyl6 <- mtcars[mtcars$cyl == 6, ]  
powcars <- mtcars[mtcars$cyl == 8 & mtcars$displ > 400, ]
```

## Merging Dataframes

### Merging by rows

```
car400 <- mtcars[mtcars$cyl == 8 & mtcars$disp == 400, ]  
car400plus <- mtcars[mtcars$cyl == 8 & mtcars$disp > 400, ]  
car400all <- merge(car400, car400plus, all = TRUE)
```

### Alternative Method using rbind

```
car400all <- rbind(car400, car400plus)
```

## Merging Dataframes

### Merging by columns

```
carset1 <- mtcars[1:5, c("mpg", "disp")]  
carset2 <- mtcars[1:5, c("cyl", "drat")]  
merge(carset1, carset2, all = TRUE) # Does this work ? why ?  
merge(carset1, carset2, by = "row.names", all = TRUE)
```

### Alternative Method using cbind()

```
carall <- cbind(carset1, carset2)
```

## reshape library - melt function

```
stk <- read.csv("~/stackoverflow.txt")  
head(stk)  
nrow(stk)  
stkm <- melt(stk)  
head(stkm)
```

## reshape library - cast function

```
head(stkm)
stkm$variable <- as.numeric(sub("X","",stkm$variable))
head(stkm)
names(stkm)[2] <- "YearMonth"
head(stkm)
stkc <- cast(stkm, Tag ~ YearMonth)
head(stkc)
```

## Making sense of data - A live example

Lets answer these questions

Given the Cars dataset, what is the median/mean mpg of the datapoints by number of cylinders. also what is the number of datapoints we have in each set



## Approach 1 - Manual approach - Subset and functions

```
unique(mtcars$cyl)
cyl4 <- subset(mtcars, cyl == 4)
cyl6 <- subset(mtcars, cyl == 6)
cyl8 <- subset(mtcars, cyl == 8)
nrow(cyl4)
nrow(cyl6)
nrow(cyl8)
mean(cyl6$mpg)
mean(cyl4$mpg)
mean(cyl8$mpg)
median(cyl4$mpg)
median(cyl6$mpg)
median(cyl8$mpg)
```

## Approach 2 - Get smarter - Use loops

```
ans = data.frame()
for (cylnum in unique(mtcars$cyl)) {
  tmp = subset(mtcars, mtcars$cyl == cylnum)
  count = nrow(tmp)
  mean = mean(tmp$mpg)
  median = median(tmp$mpg)
  ans = rbind(ans, data.frame(cylnum, count, mean, median))
}
```

## Approach 3 - Base R - Use \*apply functions

```
tapply(mtcars$mpg, mtcars$cyl, FUN = length)  
tapply(mtcars$mpg, mtcars$cyl, FUN = mean)  
tapply(mtcars$mpg, mtcars$cyl, FUN = median)
```

## Approach 4 - Base R - use aggregate function

```
aggregate(mpg ~ cyl, data = mtcars, FUN = "length")  
aggregate(mpg ~ cyl, data = mtcars, FUN = "mean")  
aggregate(mpg ~ cyl, data = mtcars, FUN = "median")
```

## Approach 5 - doBy Package - use summaryBy function

```
summaryBy(mpg~cyl,data=mtcars,FUN=function(x)  
  c(count=length(x), mean=mean(x), median=median(x)))
```

## Approach - ply library - use **\*\*ply** functions

```
ddply(mtcars, 'cyl', function(x)  
  c(count=nrow(x), mean=mean(x$mpg), median=median(x$mpg)),  
  .progress='text')
```

## More about the plyr module

plyr is a very useful module for applying functions to different datastructures. The functions in plyr are of the form XYply where 'X' is the Input datatype and 'Y' is the Output datatype So as in the above example, the input datatype was a dataframe and the output datatype is a dataframe. The type and their letter designations are

- a - array
- d - data.frame
- l - list
- m - matrix
- \_ - no output returned

# Outline

- 1 Introduction
- 2 Data Structures
- 3 Working with Data
- 4 Visualisation**
- 5 Webapps
- 6 Integration with other Systems



## Why Visualisation ?

- Easier to perceive differences easily (Magnitude, Range, Difference)
- Easier to see outliers, anomalies and grouping
- Easy to do exploratory analysis in R
- Easier to build narratives (Picture worth a million numbers)
- Bling !!!

# Visualisation Packages

- boxplot, pie, hist from base graphics
- specialized packages like vioplot
- Grammar of Graphics - ggplot2
- lattice

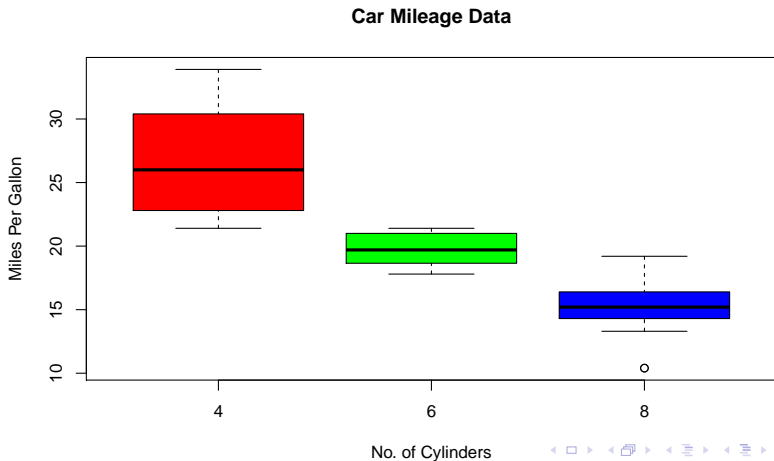
# Boxplots

- Good for individual variable or groups of variables
- Good for showing outliers and quartiles ("shape")
- take up less space than a histogram

## Boxplot example I

```
boxplot(mpg ~ cyl, data=mtcars, main="Car Mileage Data",  
        xlab="No. of Cylinders", ylab="Miles Per Gallon",  
        Notch=TRUE, col=rainbow(3))
```

## Boxplot example II



# Violin plots

- Similar to boxplots but show probability density
- Good for showing distribution
- Look like violins hence the name

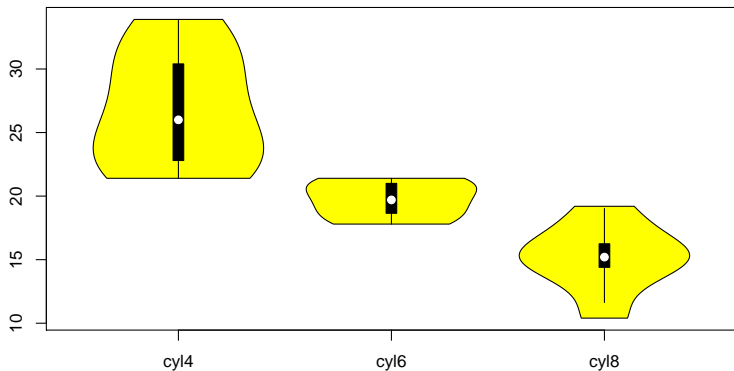
# Violin Plot Example I

```
library(vioplot)

## Loading required package:  sm
## Package 'sm', version 2.2-5:  type help(sm) for summary
information

library(sm)
cyl4 <- subset(mtcars,cyl==4)
cyl6 <- subset(mtcars,cyl==6)
cyl8 <- subset(mtcars,cyl==8)
vioplot::vioplot(cyl4$mpg,cyl6$mpg,cyl8$mpg,
names=c("cyl4","cyl6", "cyl8"), col="yellow")
```

## Violin Plot Example II





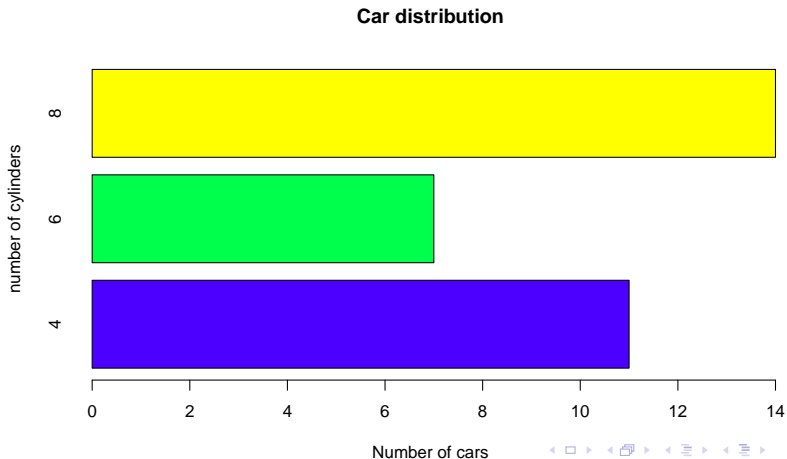
# Barplot

- Good to compare relative magnitudes
- Good to compare time series data
- Easier on the eyes

# Barplot Example I

```
barplot(table(mtcars$cyl),main="Car distribution",  
        ylab="number of cylinders",xlab="Number of cars",  
        horiz=TRUE,col=topo.colors(3))
```

## Barplot Example II

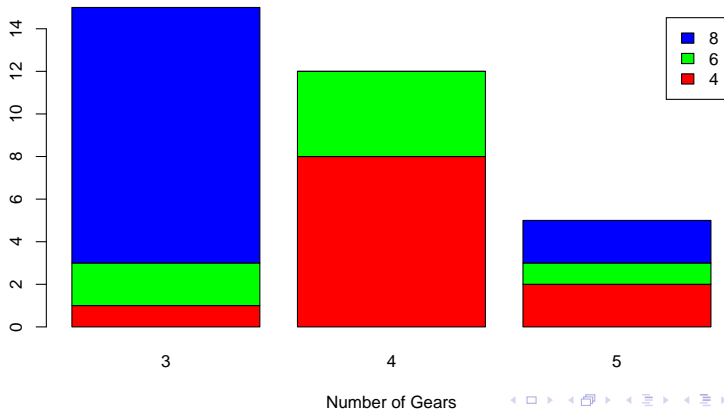


# Stacked Barplot Example I

```
counts <- table(mtcars$cyl, mtcars$gear)
barplot(counts, main="Car Distribution by Gears and CYL",
        xlab="Number of Gears", col=rainbow(3),
        legend = rownames(counts))
```

## Stacked Barplot Example II

Car Distribution by Gears and CYL



# Heatmap Example 1

```
# scale data to mean=0, sd=1 and convert to matrix
mtscaled <- as.matrix(scale(mtcars))

# create heatmap and don't reorder columns
heatmap(mtscaled, Colv = F, scale = "none")
```

## Heatmap Example 2

```
# cluster rows
hc.rows <- hclust(dist(mtscaled))
plot(hc.rows)

# transpose the matrix and cluster columns
hc.cols <- hclust(dist(t(mtscaled)))

# draw heatmap for first cluster
heatmap(mtscaled[cutree(hc.rows,k=2)==1,],
        Colv=as.dendrogram(hc.cols), scale='none')

# draw heatmap for second cluster
heatmap(mtscaled[cutree(hc.rows,k=2)==2,],
        Colv=as.dendrogram(hc.cols), scale='none')
```

# Introduction to ggplot2

- Thinking about dataviz moves away from mechanics to representation
- Allows you to layer graphics and added remove components
- Based on Leland Wilkinson's "The Grammar of Graphics" book
- Allows to compose graphs based on components
- Allows to build beautiful graphs quickly



## Components of Graphics - 1

- **Data** - The cleaned up data with all the different variables, factors. This includes the **mappings** to the aesthetic attributes of a plot.
- **Geom** - Geometric objects or geoms represent what you actually see on the screen. This includes lines, splines, points, polygons etc.
- **Stat** - Statistical transformations. These are optional. Examples include binning in a histogram or summarising a 2D relationship with a linear model.

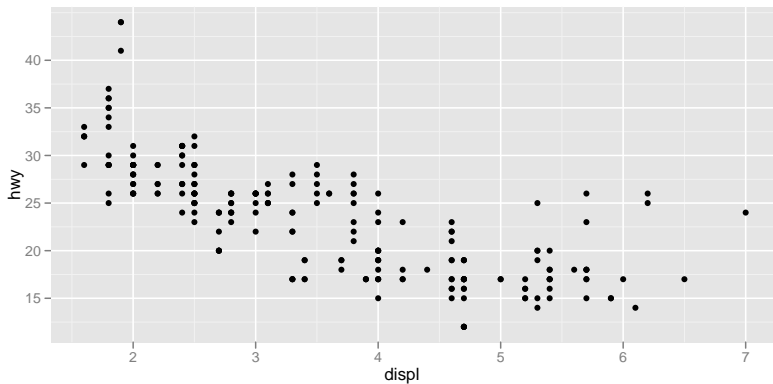
## Components of Graphics - 2

- **Scale** - Scales map values in the data into the aesthetic space such as color, size or shape. Scales draw axes and legends to represent what is seen on the screen to the actual underlying data.
- **Coord** - A coordinate systems that provides a mapping from the data onto the screen. Examples include Cartesian coordinates, map coordinates and polar coordinates.
- **Facet** - A facet gives us a method to break un the data into subsets as well as display these on the screen. Great for increasing infomation density while graphing multidimensional data.

# Scatterplot I

```
library(ggplot2)  
qplot(displ, hwy, data = mpg)
```

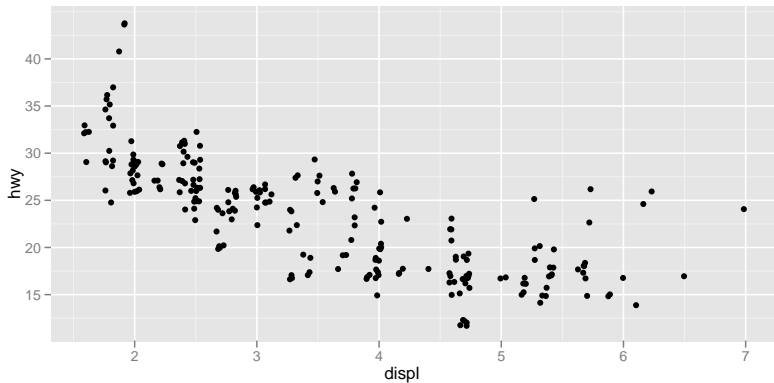
## Scatterplot II



# Scatterplot I

```
qplot(displ, hwy, data = mpg, geom = "jitter")
```

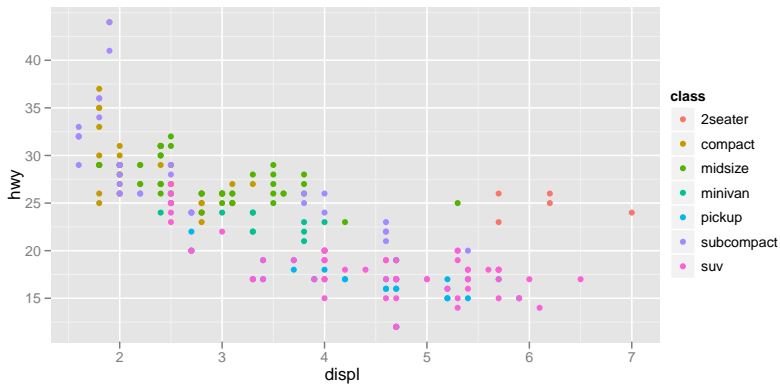
## Scatterplot II



# Scatterplot I

```
qplot(displ, hwy, data = mpg, color = class)
```

## Scatterplot II

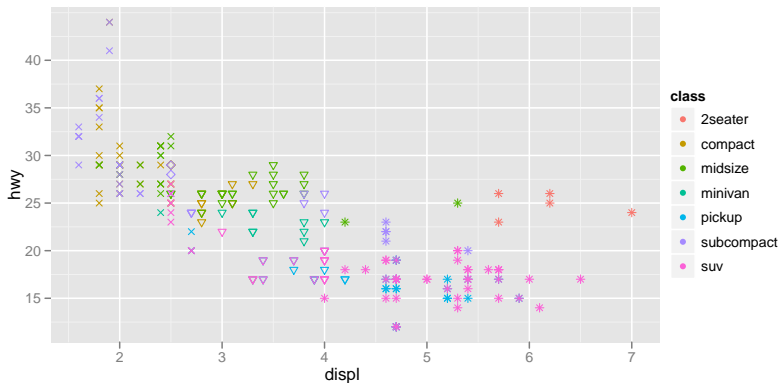




# Scatterplot I

```
qplot(displ, hwy, data = mpg, color = class, shape = cyl)
```

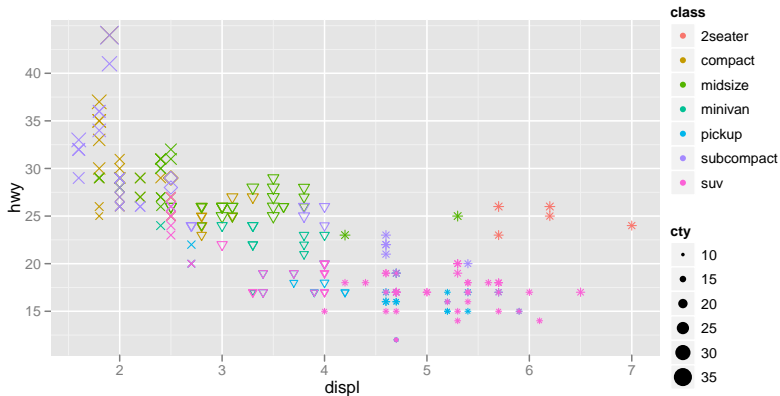
## Scatterplot II



# Scatterplot I

```
qplot(displ, hwy, data = mpg, color = class, shape = cyl, size = cty)
```

## Scatterplot II



# Scatterplot I

```
qplot(displ,hwy,data=mpg,color=class,shape=cyl,size=cty)  
+ facet_wrap (~year)
```

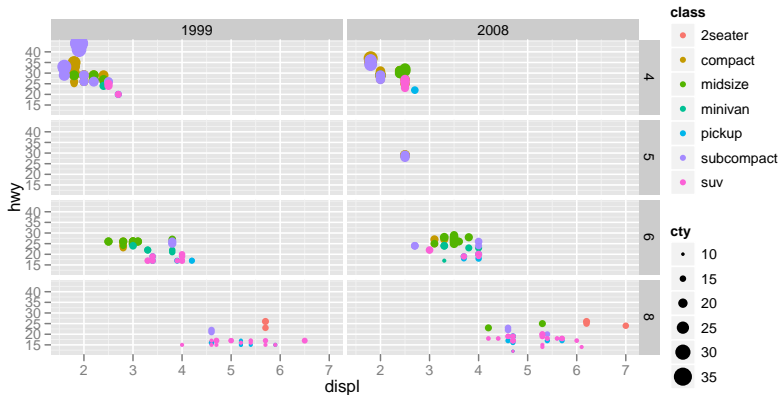
# Scatterplot I



# Scatterplot I

```
qplot(displ, hwy, data = mpg, color = class, shape = cyl, size = cty)  
+facet_wrap(~year)
```

# Scatterplot I

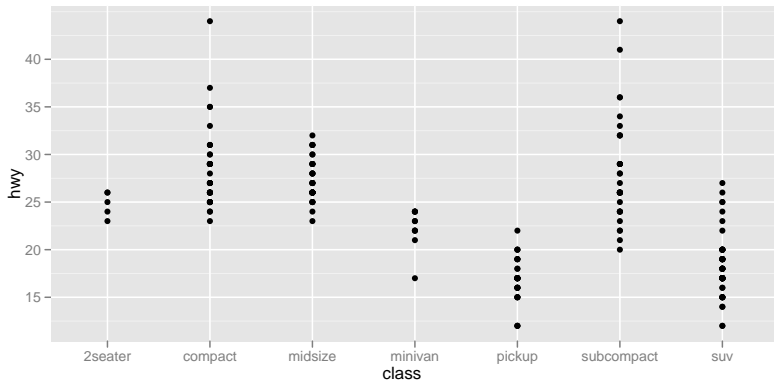




## Scatterplot 2 I

```
qplot(class, hwy, data = mpg)
```

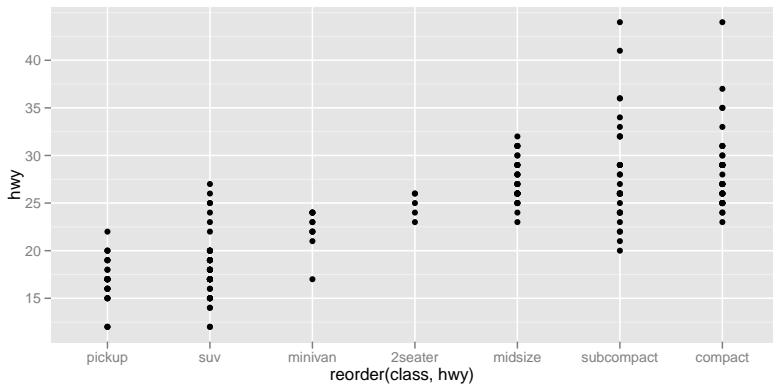
## Scatterplot 2 II



## Scatterplot 2 |

```
qplot(reorder(class, hwy), hwy, data = mpg)
```

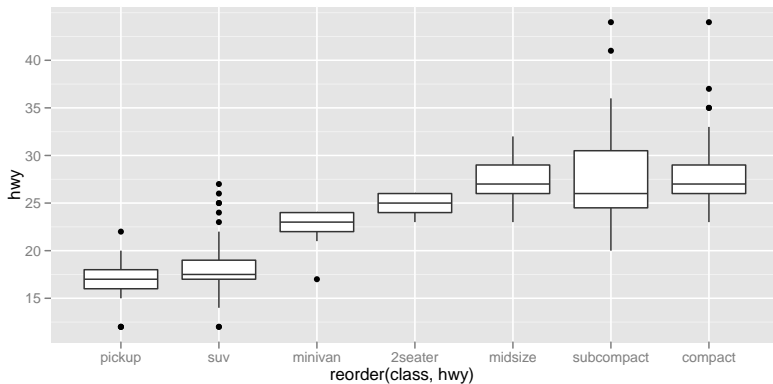
## Scatterplot 2 II



## Scatterplot 2 |

```
qplot(reorder(class, hwy), hwy, data = mpg, geom="boxplot")
```

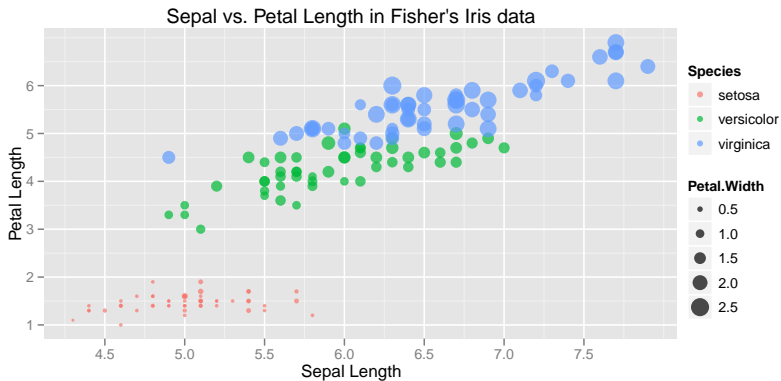
## Scatterplot 2 II



## Scatterplot 3 |

```
qplot(Sepal.Length, Petal.Length, data = iris, color = Species,  
      size = Petal.Width, alpha = I(0.7),  
      xlab = "Sepal Length", ylab = "Petal Length",  
      main = "Sepal vs. Petal Length in Fisher's Iris data")
```

## Scatterplot 3 II

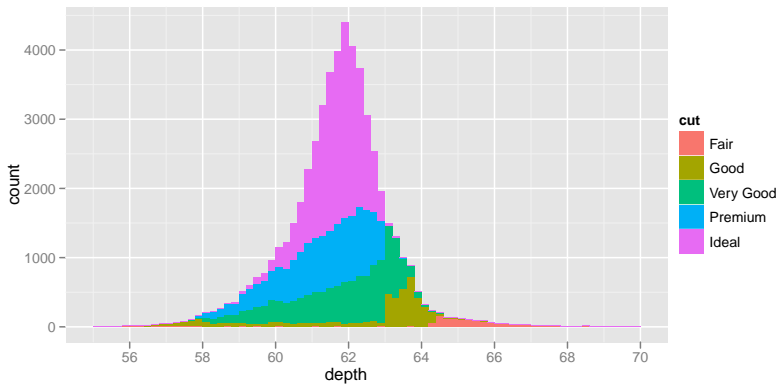




# Stackedbar Chart I

```
qplot(depth, data = diamonds, binwidth = 0.2, fill = cut) + xlim(55,70)
```

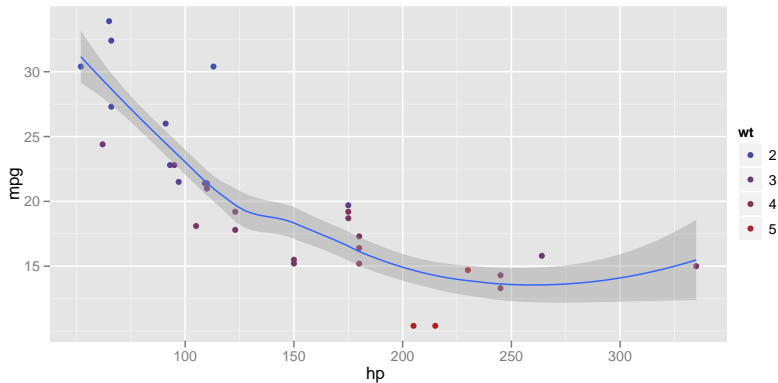
## Stackedbar Chart II



# Line plot I

```
# Scale + Layering + Aesthetic example  
plot1 <- ggplot(mtcars, aes(x=hp,y=mpg))  
plot1 + geom_point(aes(color=wt)) + geom_smooth()
```

## Line plot II



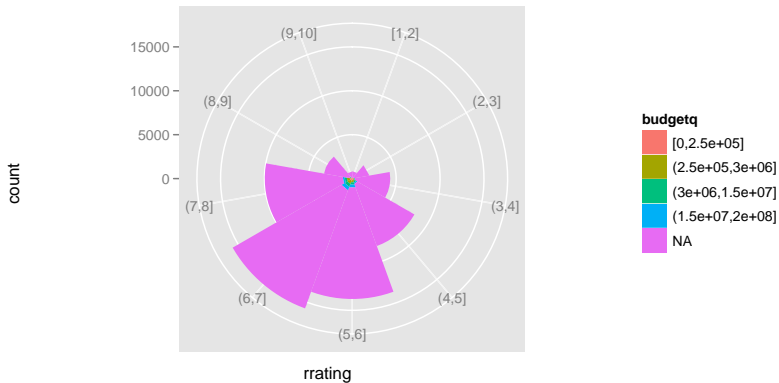
# Polar plot I

```
# from ggplot2 docs
# Windrose + doughnut plot
movies$rrating <- cut_interval(movies$rating, length = 1)
movies$budgetq <- cut_number(movies$budget, 4)

doh <- ggplot(movies, aes(x = rrating, fill = budgetq))

# Wind rose
doh + geom_bar(width = 1) + coord_polar()
```

## Polar plot II



## Cons of Grammar of Graphics

- Grammar doesn't specify finer points of graphing such as font size or background color. GGplot2 Themes tries to mitigate this)
- Great for static graphs but not good for interactivity or animation. There are workarounds for this though.

# Outline

- 1 Introduction
- 2 Data Structures
- 3 Working with Data
- 4 Visualisation
- 5 Webapps**
- 6 Integration with other Systems



# Shiny

## Shiny package from Rstudio

Shiny is a new package from RStudio that makes it incredibly easy to build interactive web applications with R.

## Features

- Build useful web applications with only a few lines of code. No JavaScript required.
- Shiny user interfaces can be built entirely using R, or integrated with HTML, CSS, and JavaScript for more flexibility.
- Works in any R environment (Console R, Rgui for Windows or Mac, ESS, StatET, RStudio, etc.)

## Features

- Pre-built output widgets for displaying plots, tables, and printed output of R objects.
- Fast bidirectional communication between the web browser and R using the websockets package.
- Uses a reactive programming model that eliminates messy event handling code, so you can focus on the code that really matters.

## Architecture and Code Layout

- Shiny applications have two components - A user-interface definition script and server script
- It follows event-based programming model - Anytime any UI component is changed such as selection or movement of slider, an event is fired to the backend to handle.
- Server and client communicate seamlessly using websockets.
- An event triggers a server response and the UI is refreshed accordingly to reflect the change.

## A live plot of mpg dataset

# Outline

- 1 Introduction
- 2 Data Structures
- 3 Working with Data
- 4 Visualisation
- 5 Webapps
- 6 Integration with other Systems**

# Packages

- hadoop - RHadoop
- c++ - RCpp
- javascript - Shiny

# Literate programming using Knitr

## Literate programming

Literate programming is an approach to programming introduced by Donald Knuth in which a program is given as an explanation of the program logic in a natural language, such as English, interspersed with snippets of macros and traditional source code, from which a compilable source code can be generated



# Knitr

- Transparent engine for dynamic report generation with R
- Implements literate programming paradigm
- Only one document to edit. Less pain to keep everything in sync
- Can output into different final outputs such as HTML, PDF etc

# Knitr features

- Faithful output
- Built-in cache
- Easy Formatting
- Flexibility in output devices

# Knitr Demo

# Thank you

- Twitter **@vinayakh**
- Email **vinayakh** at gmail