

R-tutorial and Introduction to R Shiny

R-Shiny by RStudio

- A web application framework for R
- No HTML, JavaScript, or CSS required
- Built on a Reactive Programming Model

Reactive Programming- programming with non parallel data streams. Programming paradigm oriented around data flows and propagation of change. If you want to learn more about this take Comp 310 or Comp 333.



Today, the following objectives will be covered:

- What consists of developing an R-Shiny applet
- Basic proficiency in R, to eventually make your own R Shiny Applet
- **We will learn a little bit of how to apply R to the following areas:**
- Areas from Statistics & Probability
- Calculus <Taking a Derivative and Integration>
- Disease Modeling in R
- Combinatorial Algorithms/Dynamic Programming

Examples of R Shiny Applets

[Long Run](#) (Category of Probability) -According to [Statistics.CalPoly.edu](#), "one..activity to help students understand change behavior is to observe the runs of consecutive heads or tails in a sequence of coin flips."

[Length/Coverage Optimal Confidence Intervals](#) ([Category of Inference](#))-According to [Statistics.CalPoly.edu](#), "In 2014 Schilling and Doi developed a binomial confidence interval that produces coverage probabilities always at least equal to the stated confidence level and has the highest possible coverage amongst all such methods."

Schilling, M., and Doi, J. (2014) 'A Coverage Probability Approach to Finding an Optimal Binomial Confidence Procedure' *The American Statistician* , 68(3), 133--145 ([Online access](#))

Schilling, M. 'The Longest Run of Heads' *The College Mathematics Journal* , 21(3), 196--207

Schilling, M. 'The Surprising Predictability of Long Runs' *Mathematics Magazine* , 85(2), 141--149

What, does an R Shiny Applet Consist of?

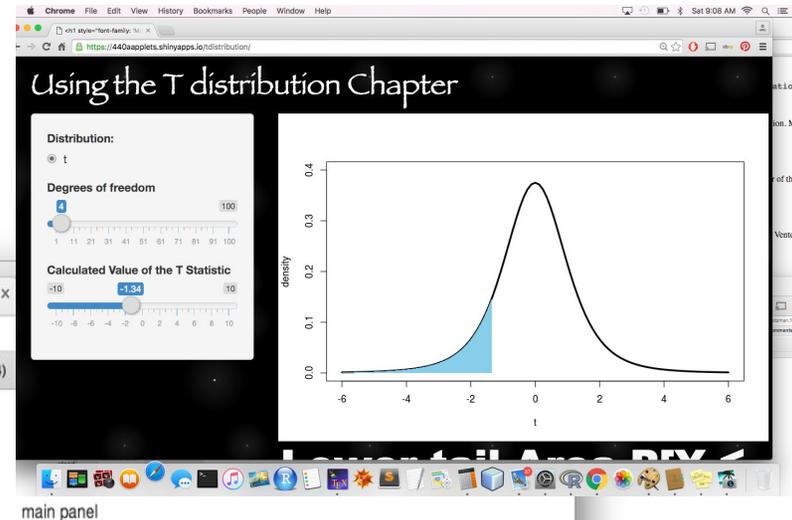
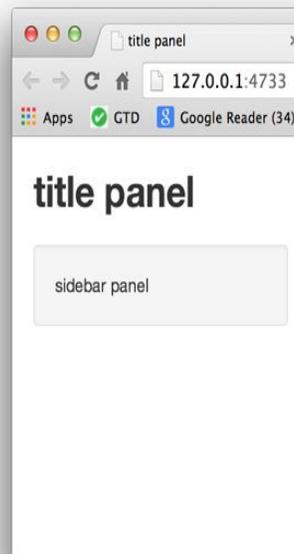
```
1 library(shiny)
2
3 shinyUI(fluidPage(
4
5   #CSS implementation from CSS
6   headerPanel(h1("Chapter 7.65 & 7.68, Using the Binomial Distribution ",
7     style = "font-family: 'Lobster', cursive;
8     font-weight: 40; line-height: 1.1;
9     color: #4d3a7d;")),
10
11
12   sidebarPanel(
13     tags$head(
14       tags$style("body {background-color: pink; }")
15     ),
16
17     radioButtons(inputId = "dist",
18       label = "Distribution:",
19       choices = c("Binomial Distribution" = "rbinom")),
20
21
22     uiOutput("n"),
23     uiOutput("p"),
24
25
26     uiOutput("a"),
27
28
29
30
31
32
33
34
35
36
37
38
39     helpText(a(href="", target="", ""))),
40
41
42
43   mainPanel(
44     plotOutput("plot", width="80%"),
45     div(paste("lower tail area P[Y ≤ Y]", textOutput("area"), paste("upper tail area P[Y >
46 Y ]"),
47     textOutput("area2"), align = "center", style="font-size:500%;
48     color: #4d3a7d;"))
49 )
50 )
51 )
```

```
1 library(shiny)
2 library(rsconnect)
3
4 shinyServer(function(input, output)
5 {
6
7
8
9
10
11   output$n = renderUI(
12     {
13       #print("n")
14       if (input$dist == "rbinom")
15       {
16         sliderInput("n",
17           "n",
18           value = 5,
19           min = 1,
20           max = 250,
21           step = 1)
22       }
23     })
24
25   output$p = renderUI(
26     {
27       #print("p")
28       if (input$dist == "rbinom")
29       {
30         sliderInput("p",
31           "p",
32           value = 0.5,
33           min = 0,
34           max = 1,
35           step = .01)
36       }
37     })
38
39
40
41
42   output$a = renderUI(
43     {
44       #print("a")
45
46       value = 1
47       min = 0
48       max = 60
49       step = 1
50     })
51 })
```

Ui.R allows you to give your applet Esthetic

```
# ui.R
```

```
shinyUI(fluidPage(  
  titlePanel("title panel"),  
  
  sidebarLayout(  
    sidebarPanel("sidebar panel"),  
    mainPanel("main panel")  
  )  
))
```



Server.R- give the applet functionality

```
51     max = 10,
52     step = 0.01)
53   })
54
55   output$plot = renderPlot(
56   {
57     #dbinom(x, size, prob, log = FALSE)
58
59     if (input$dist == "rt")
60     {
61       curve(dt(x,df=input$df,ncp=0,log=FALSE), from=-6, to=6, ylim=c(-0.0000000000000001,0.4),y="density",lwd=3,xlab="
62       x<- seq(-6, input$a,len=10000)
63       y<-dt(x,df=input$df)
64       polygon(c(x[Z], x, x[10000]), c(dt(-10, input$df), y, dt(-10, input$df)),
65             col = "sky blue", border = NA)
66     }
67
68   })
69
70   output$area = renderText(
71   {
72     #lower tail, P x<alpha, because lower.tail=TRUE, other wise, if false, you have
73     #upper tail.
74     pt(q=input$a, df=input$df, ncp=0, lower.tail = TRUE, log.p = FALSE)
75   })
76   output$area2 = renderText(
77   {
78     pt(q=input$a, df=input$df, ncp=0, lower.tail = FALSE, log.p = FALSE)
79   })
80
81 })
82
83
84
85
86
87
88
```

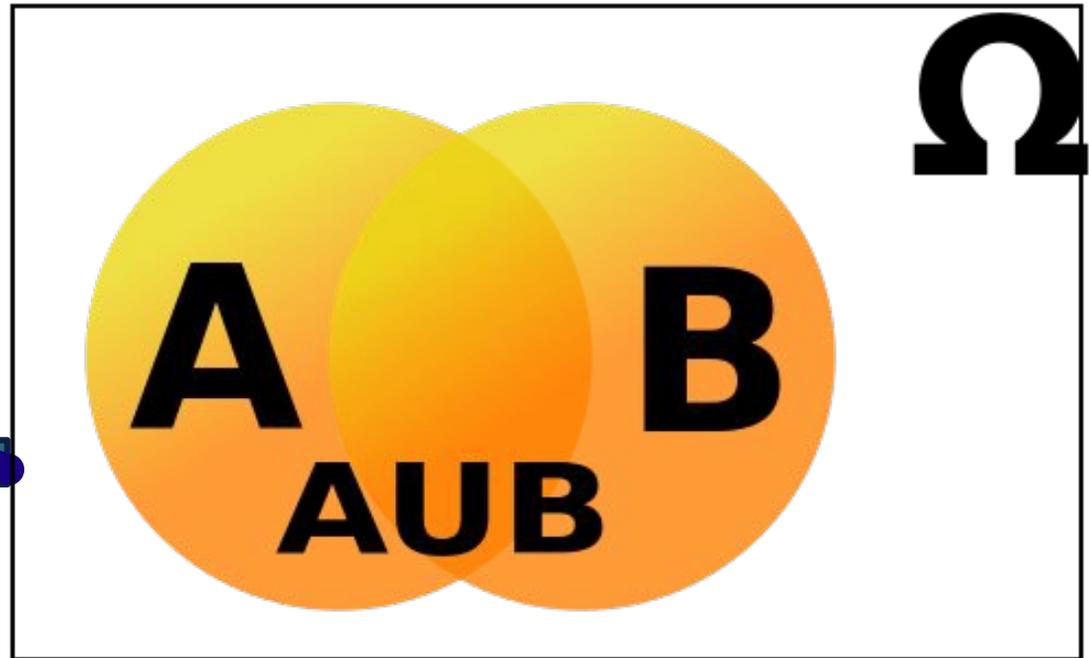
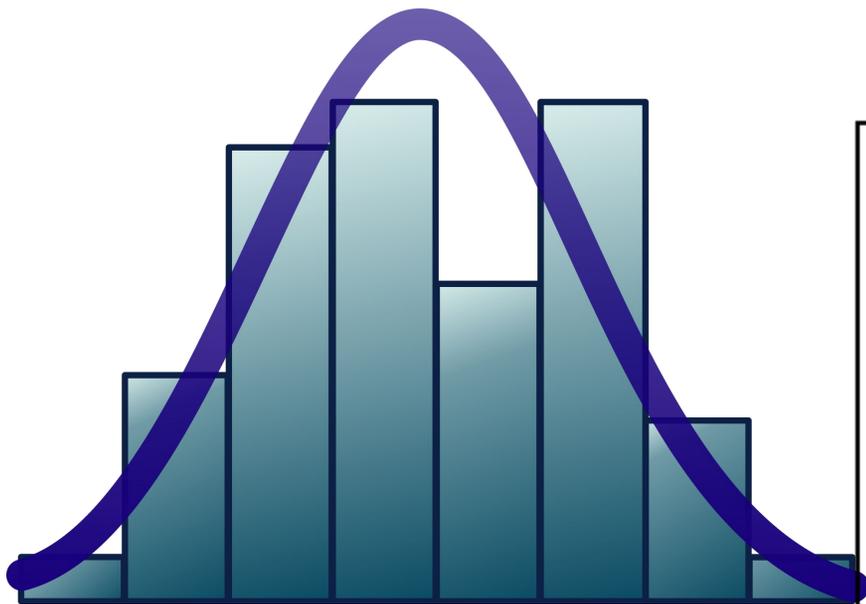
68:70 <function>(input, output) ↕ R Script

Console

Justin Romprey chiptune is god tier man. d
one
Like

relatin
study

Category: Statistics & Probability



The Basics

Computing mean

```
x <- c(x1,x2,...xn)  
mean(x)
```

Computing standard deviation

```
X <- c(x1,...xn)  
sd(X)
```

Computing the median

```
X <- c(x1....xn)  
median(X)
```

Continuation....

To determine the mode, you have to do something different.

You have to install the package, `modeest`, which provide estimators of the mode of univariate unimodal (and sometimes multimodal) data and values of the modes of usual probability distributions.

`Modeest`, allows us to return the most frequent value in a given numeric vector.

```
install.packages("modeest")
```

```
library(modeest)
```

```
mySamples <- c(x1,...xn)
```

```
mlv(mySamples, method = "mfv")
```

*mfv signifies most frequent value.

Continuation...

`factorial(num)`

We can also determine the binomial coefficient:

The number of combination of length k within n numbers (n choose k),

So you can type in :

`choose (n,k)`

Union and Intersection of numbers:

Define a function with a set of numbers,

`Function <- c(x1,.....xn)`

`Function1 <- c(x2,....xn)`

`union(Function, Function1)`

Same Approach can go for Intersection

`intersect(a:b,a:b)`

Creating histograms, stem and leaf plots, scatter plots, pie charts

Creating a histogram

Define the function vector with 5 values

```
function<- c(x1,x2,..xn)
```

```
colors = c("color1",....colorn)
```

Create a histogram for function

```
hist(function, col=colors)
```

Stem and Leaf Plot

```
x <- c(x1,x2....,xn)
```

```
stem(x,scale=?)
```

Scatter Plots

```
> library(ggplot2)
Stackoverflow is a great place to get help: http://stackoverflow.com/tags/ggplot2.
> #helps you start with the basic data you want your plot to include (x, and y variables)
> library(gridExtra)
> mtc <- mtcars
> #we are going to use the mtcars data that is available through R
> #Here is the basic syntax for a scatter plot, we give it a dataframe,mtc(data), and then in the aes statement, we give it an x and
y variable to plot.
> #basic scatter plot
> plot1 <- ggplot(mtc,aes(x=hp,y=mpg))
> # this is the base of our plot, we are going to use this as a base, and then layer everything else on top!
> #print our plot with our default data points from the mtccars, data set
> plot1+geom_point();
>
```

Pie Charts

```
# Create data for the graph.  
x <- c(x1,..xn)  
labels <- c("label1",... ,"label_n")  
  
# Give the chart file a name.  
png(file = "example.jpg")  
  
# Plot the chart.  
pie(x,labels)  
  
# Save the file.  
dev.off()
```

R functions for Probability Distributions

| Distribution | Functions | | | |
|--|-----------|-----------|-----------|-----------|
| Beta | pbeta | qbeta | dbeta | rbeta |
| Binomial | pbinom | qbinom | dbinom | rbinom |
| Cauchy | pcauchy | qcauchy | dcauchy | rcauchy |
| Chi-Square | pchisq | qchisq | dchisq | rchisq |
| Exponential | pexp | qexp | dexp | rexp |
| F | pf | qf | df | rf |
| Gamma | pgamma | qgamma | dgamma | rgamma |
| Geometric | pgeom | qgeom | dgeom | rgeom |
| Hypergeometric | phyper | qhyper | dhyper | rhyper |
| Logistic | plogis | qlogis | dlogis | rlogis |
| Log Normal | plnorm | qlnorm | dlnorm | rlnorm |
| Negative Binomial | pnbinom | qnbinom | dnbinom | rnbinom |
| Normal | pnorm | qnorm | dnorm | rnorm |
| Poisson | ppois | qpois | dpois | rpois |
| Student t | pt | qt | dt | rt |
| Studentized Range | ptukey | qtukey | dtukey | rtukey |
| Uniform | punif | qunif | dunif | runif |
| Weibull | pweibull | qweibull | dweibull | rweibull |
| Wilcoxon Rank Sum Statistic | pwilcox | qwilcox | dwilcox | rwilcox |
| Wilcoxon Signed Rank Statistic | psignrank | qsignrank | dsignrank | rsignrank |

-Every distribution that R handles has four functions. There is a root name. For example the root name for a binomial distribution is binom. This root is then prefixed by one of the following letters:

- **p for "probability", (c. d. f.)**
- **q for "quantile", the inverse c. d. f.**
- **d for "density", the density function p. d. f**
- **r for "random", a random variable having the specified distribution**

I will demonstrate with the Normal Distribution

```
starting nttpa help server ... done
- dnorm(1, mean = 0, sd = 1, log = FALSE)
[1] 0.2419707
- #dnorm function returns the height of the normal curve at some value along x axis
- dnorm(1,mean=0,sd=1,log=FALSE)
[1] 0.2419707
- #pnorm function is the cdf, it returns the area below the given value of x
- pnorm(1,mean=0,sd=1,log=FALSE)
[1] 0.8413447
- #the values for default for mean and sd are set to 0 and 1. But these values can be set to something else in the case of d norm
- #to find the area above the cutoff x, either subtract 1 or set lower.tail=FALSE
- 1-pnorm(1)
[1] 0.1586553
- pnorm(1,mean=0,sd=1,lower.tail=FALSE)
[1] 0.1586553
- #finally to get quantiles or critical values, you can use the qnorm function,
- #p=.05, one tailed (upper)
- qnorm(.95)
[1] 1.644854
- qnorm(c(.025,.975))
[1] -1.959964 1.959964
- |
```



Confidence Intervals

Confidence Interval-a range of values so defined that there is a specific probability that the value of a parameter lies within it.Interval estimate combined with a probability statement.

-We are able to compute confidence intervals from multiple simulated data sets

-To do this we can use the command `CIsim`

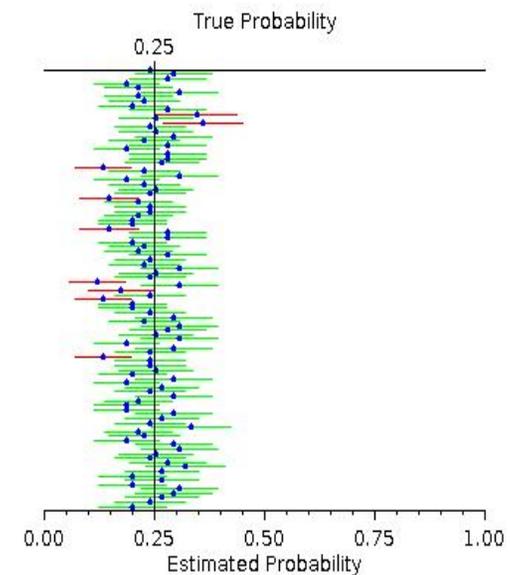
-This function automates the calculation of coverage rates for exploring the robustness of confidence interval methods

This data frame will return the following:

*A data frame with variables `lower`, `upper`, `estimate`, `cover` ('Yes' or 'No'), and `sample` is returned invisibly.

Coverage percentile will be shown on the R console

Intervals including true probability: 91 of 100 = 91.0%



| | | |
|-----------------|------------|--------------------|
| One Sample | 25 Samples | 100 Samples |
| sample size: 75 | ▼ | Conf. Coeff. .90 ▼ |

What do we need to take into consideration in order to compute this, and use the CISim command

n: size of each sample

samples: number of samples to simulate

dist: function used to draw random samples

args: arguments required by rdist

plot: one of "print", "return" or "none" describing whether a plot should be printed, returned, or no generated at all.

estimand: true value of the parameter being estimated

conf.level: confidence level for intervals.

Method- function used to compute intervals

Method.args: arguments required by method

Interval: function that computes a confidence interval from data, function should be a vector length of 2

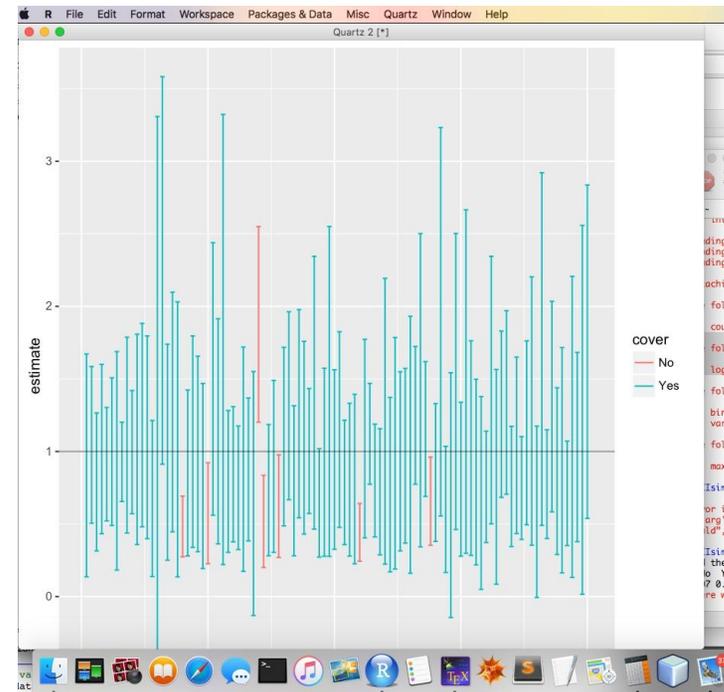
Estimate: a function that computes an estimate from data

If we want to do a Binomial

Binomial treats 1 like success, 0 like failure

```
CIsim(n=30, samples=101, rdist=rbinom, args=list(size=1, prob=.3),  
      estimand = .3, method = binom.test, method.args=list(ci = "Wald"))
```

*Every time, you put this in the console, the console will give how much of the interval did the p value cover?



```
Warning message:  
In CIsim(n=10, samples=100, rdist=rexp, estimand=1) :  
'arg' should be one of "clopper-pearson", "binom.test", "p-  
wald", "agresti-coull", "plus4"  
>  
> CIsim(n=10, samples=100, rdist=rexp, estimand=1)  
Did the interval cover?  
No Yes  
0.07 0.93  
There were 50 or more warnings (use warnings() to see the fi  
>
```

Decision Trees

Decision tree is a decision support tool that uses a tree like graph using a branching method to illustrate every possible outcome of a decision.

Examples of when Decision Trees are used:

Predicting will I pass the next Math 440B exam?

Predicting a cancer to be tumorous?

Predicting a loan to be good or bad?

Steps to develop a decision tree

```
install.packages("party")
```

The basic syntax for creating of decision tree

```
ctree(formula, data)
```

formula is a formula describing the predictor and response variables.

data name of the data set used

Predictor variable-is a variable used in regression, to predict another variable.

Response Variable-dependent variable

For our example we will use today:

We will use the famous R built in data set named **readingSkills** to create a decision tree. It describes the score of someone's readingSkills if we know the variables "age", "shoesize", "score" and whether the person is a native speaker or not.

To see the data:

```
install.packages("party")
```

```
library(party)
```

```
print(head(readingSkills))
```

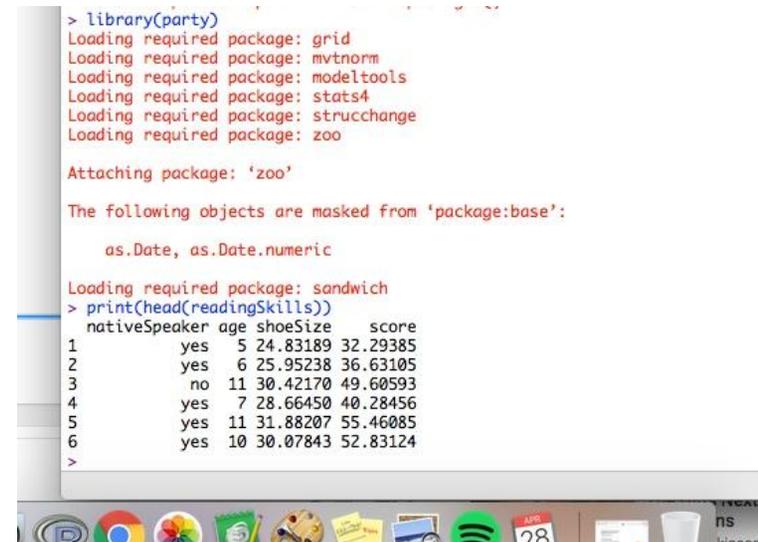
```
> library(party)
Loading required package: grid
Loading required package: mvtnorm
Loading required package: modeltools
Loading required package: stats4
Loading required package: strucchange
Loading required package: zoo

Attaching package: 'zoo'

The following objects are masked from 'package:base':

  as.Date, as.Date.numeric

Loading required package: sandwich
> print(head(readingSkills))
  nativeSpeaker age shoeSize  score
1          yes   5 24.83189 32.29385
2          yes   6 25.95238 36.63105
3          no  11 30.42170 49.60593
4          yes   7 28.66450 40.28456
5          yes  11 31.88207 55.46085
6          yes  10 30.07843 52.83124
>
```



Example of how to make a decision tree.

```
# Load the party package. It will automatically load other dependent packages.
library(party)
```

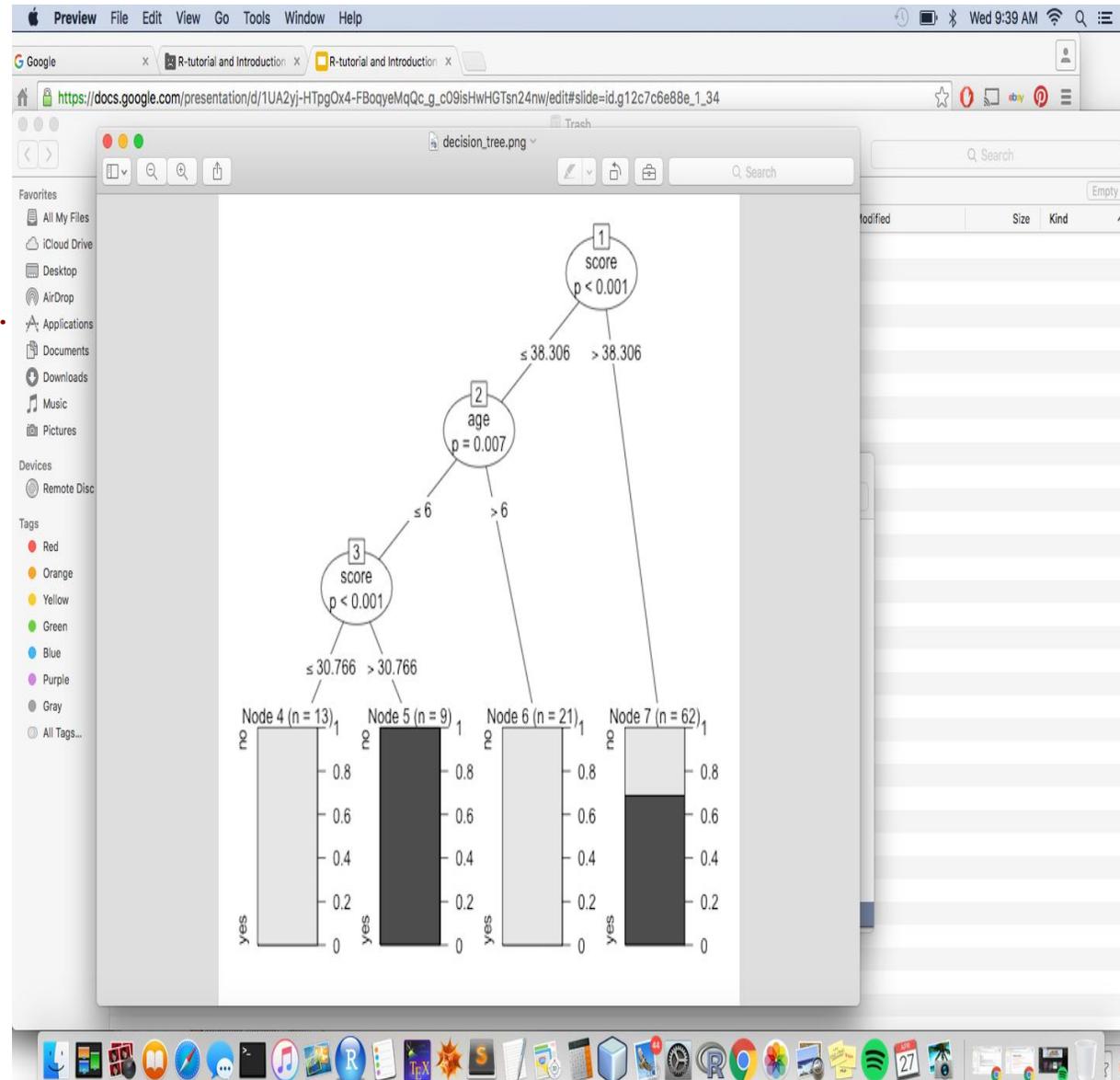
```
# Create the input data frame.
input.dat <- readingSkills[c(1:105),]
```

```
# Give the chart file a name.
png(file = "decision_tree.png")
```

```
# Create the tree.
output.tree <- ctree(
  nativeSpeaker ~ age + shoeSize + score,
  data = input.dat)
```

```
# Plot the tree.
plot(output.tree)
```

```
# Save the file.
dev.off()
```



Determining a Derivative

*This requires the mosaic library

```
library(mosaic)
```

symbolicD(function~(what you want
to take the derivative with respect to),
order=which derivative?)

```
Error: object 'd' not found
> d
Error: object 'd' not found
> d
Error: object 'd' not found
> d
Error: object 'd' not found
> library(mosaic)
> symbolicD(x^3~x, .order=1)
function (x)
3 * x^2
> symbolicD(x^3~x, .order=2)
function (x)
3 * (2 * x)
> symbolicD(x^3~x, .order=3)
function (x)
3 * 2
>
```



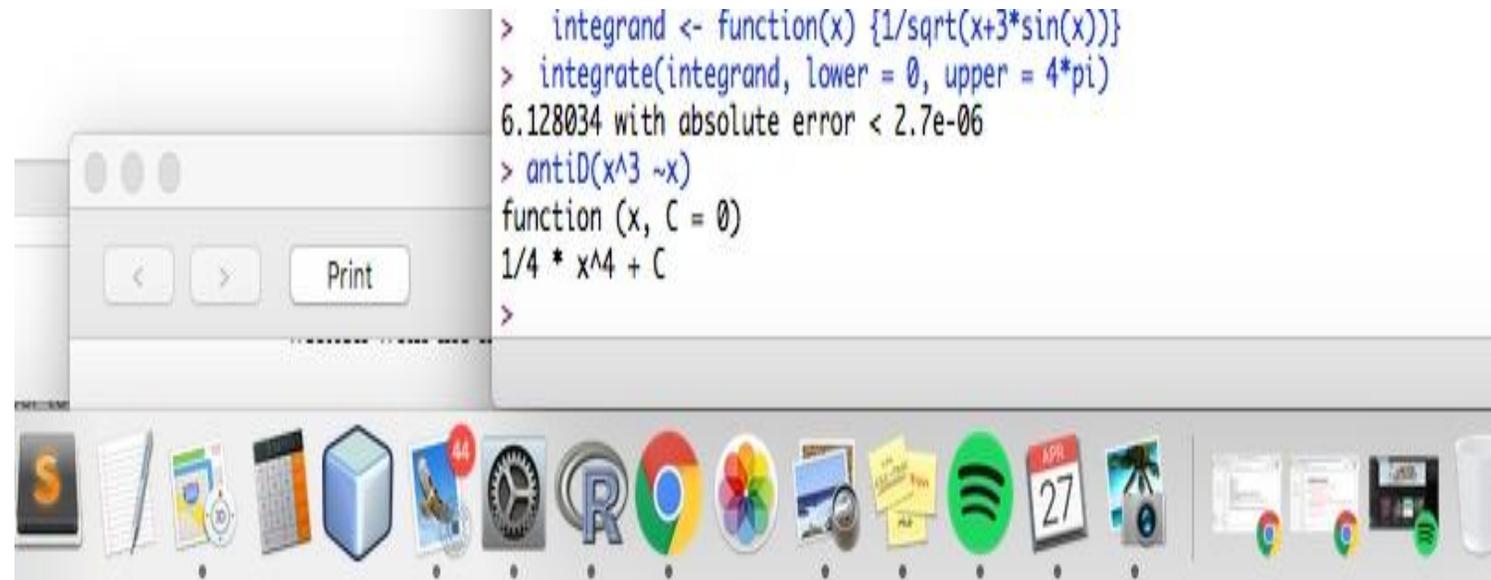
Integrals

#definite & indefinite integrals

library(stats)

integrand <- function(integrating with respect to) {function}
integrate(integrand, lower = ?, upper = ?)

antiD(function ~ integrating with respect to)



```
> integrand <- function(x) {1/sqrt(x+3*sin(x))}  
> integrate(integrand, lower = 0, upper = 4*pi)  
6.128034 with absolute error < 2.7e-06  
> antiD(x^3 ~x)  
function (x, C = 0)  
1/4 * x^4 + C  
>
```

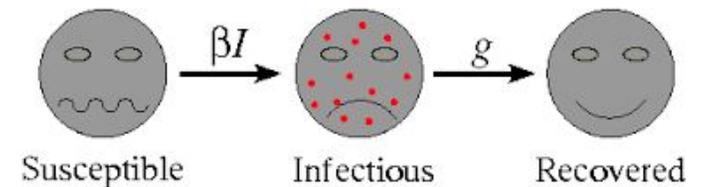
Disease Modeling in R

Applying the Simple SIR model in R

SIR model- computes the *“theoretical # of people infected with a contagious illness in a closed population over time”*

#The SIR Model is a simple model of infectious disease in a population which is broken into 3 groups:

- 1) Susceptible
- 2) Infected
- 3) Recovered



```
install.packages("deSolve")
```

```
library(deSolve)
```

```
#differential equation library
```

```
#first we need to create a function, that calls our differential equations.
```

We can do the following.

Producing the basic SIR model

#call your SIR differential equations

```
sir <- function(time, state, parameters) {
```

```
  with(as.list(c(state, parameters)), {
```

```
    dS <- -beta * S * I
```

```
    dI <- beta * S * I - gamma * I
```

```
    dR <- gamma * I
```

```
  return(list(c(dS, dI, dR)))
```

```
})
```

****To understand**

Between S and I, the transition rate is β , where β is the contact rate, which takes into account the probability of getting the disease in a contact between a susceptible and an infectious subject.

Between I and R, the transition rate is ν (simply the rate of recovery or death).

#give values to S and I and your parameters

```
init <- c(S = 1-1e-6, I = 1e-6, 0.0)
```

```
parameters <- c(beta = 1.4247, gamma = 0.14286)
```

```
times <- seq(0, 70, by = 1)
```

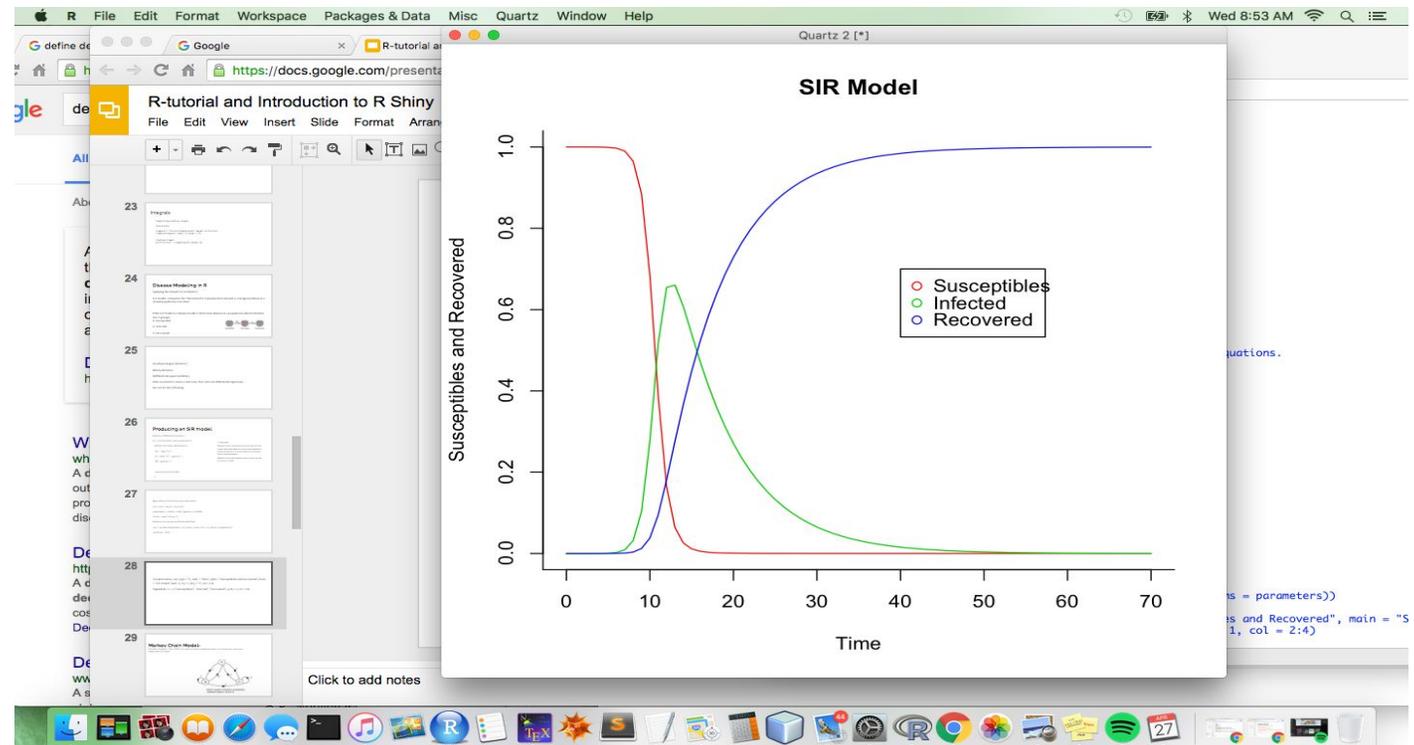
#call your d.es in a dataframe so you are able to plot them

```
out <- as.data.frame(ode(y = init, times = times, func = sir, parms = parameters))
```

```
out$time <- NULL
```

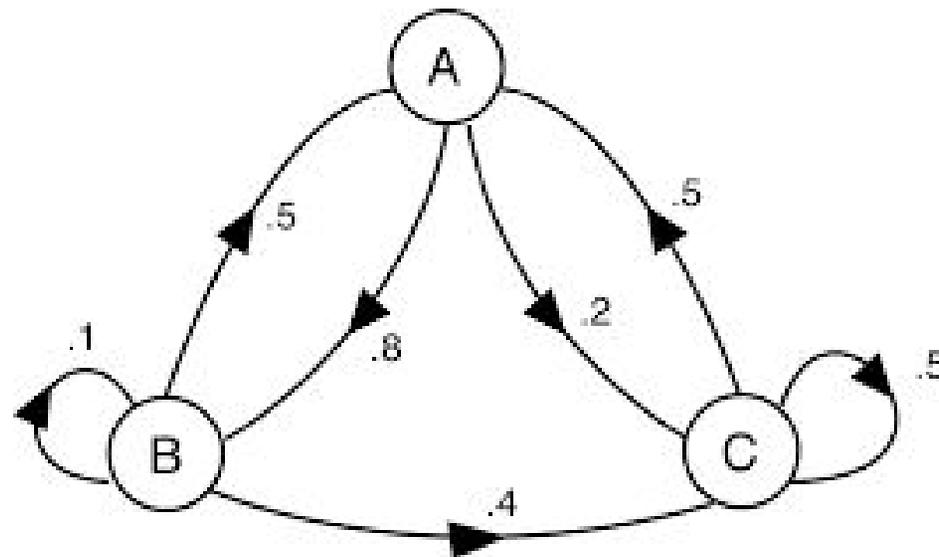
```
matplot(times, out, type = "l", xlab = "Time", ylab = "Susceptibles and Recovered",  
main = "SIR Model", lwd = 1, lty = 1, bty = "l", col = 2:4)
```

```
legend(40, 0.7, c("Susceptibles", "Infected", "Recovered"), pch = 1, col = 2:4)
```



Markov Chain Model-

A Discrete Time Markov Chain (DTMC) is a model for a random process where one or more entities can *change state* between distinct timesteps.



Markov graph of transition probabilities between states A, B and C

Developing a Markov Chain Model in R should be Simple

To Create a Markov Chain in R, we need to know the following:

- 1) Transition probabilities or the chance that an entity will move from one state to another. (Chance of getting reinfected?)**
- 2) The initial state (that is, how many entities are in each of the states at time $t=0$ to $t=3$)**
- 3) The markov chain package in R. Be sure to install markov chain before moving forward.**

Today, we will just Create a Model and model the following:

So, let's imagine the situation for our Markov Chain Model:

There is a 10% infection rate of the Zika Virus.

There is a 20% recovery rate of the Zika Virus.

This implies that 90% of the Susceptible people will remain in the Susceptible state.

80% of those who are Infected will move to the Recovered Category, between successive timesteps.

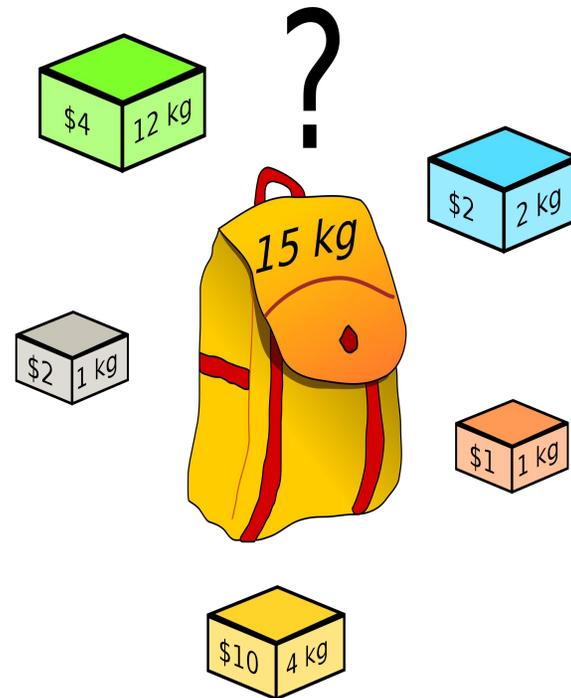
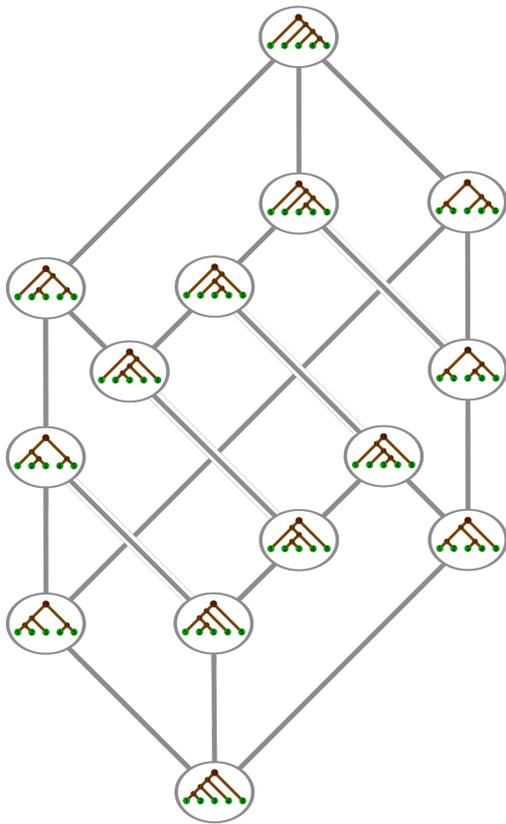
100% of those Recovered will stay recovered. None of the people who are Recovered will become Susceptible.

Let's start with a population of 200 people and only 2 is infected.

That means your initial state is that 198 are Susceptible, 2 Infected, and 2 are recovered.

Now, we can set up our Markov Chain Model.

Dynamic Programming/Combinatorial Algorithms



Longest Common Subsequence, Dynamic Programming

- We are given two sequences, and we must find the length of the longest subsequence present in both
- A subsequence is a sequence that appears in the same relative order, but not necessarily contiguous.
- "abc" & "abg" etc are subsequences of "abcdefg".
- LCS for input Sequences "ABCD" and "ABED" is ABD, length of 3

So to start in your R console download the package

```
install.packages("qualV")
```

```
library(qualV)
```

This package has “qualitative methods for certain dynamic models”.

How can we do this in R?

Let's, say if we have the following subsequences, "abcbcd" and "abcdefd"

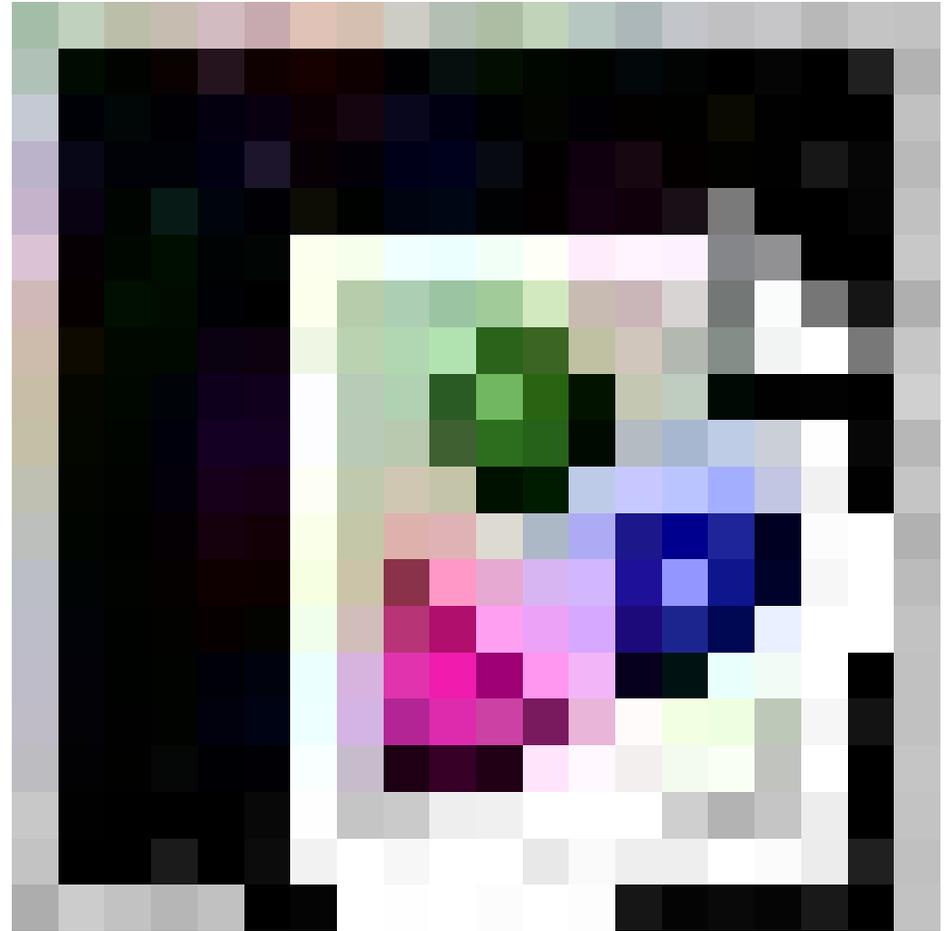
LLCS = length of LCS

LCS=longest common substring

QSI= quality similar index

va=One possible LCS vector of A

vb= One possible LCS of vector B



The Knapsack Algorithm

Description: We are given a set of items, each with a weight and value, and we must determine the number of each item to include in a collection, so that the total weight is less than or equal to given limit, and the total value is as large as possible.

This algorithm can be altered.

In the following example, we will be taking into consideration:

Retail Value & Price

The following scenario is taken from a Math 440A Lab:

A store is selling scientific equipment is having a going-out-of-business sale. its merchandise is marked down. Its merchandise is marked down to varying degrees. You are employed as a buyer for another company that sells such goods. Your assignment is to acquire objects whose total retail value is as large as possible. You can spend up to \$10,000. The available inventory is listed below. There is only one of each item available, what should you buy?

| Item | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---------------|-----|-----|-----|-----|---|-----|-----|---|---|-----|------|
| RetVal | 6.5 | 5.9 | 2.9 | 1.8 | 4 | 2.3 | 7.5 | 2 | 5 | 5.6 | 11.4 |
| Price | 3 | 2 | 1 | 1 | 1 | 1 | 2 | 1 | 3 | 2 | 4 |

So, this scenario can be applied to the idea of the KnapSack Question

most_capacity most amount of money to spend

#profit signifies Retail Price, most profit you can make out of the retail price

#indices « define how many items we have

```
> (is <-knapsack(Price,RetailValue,mostcapacity))
Error: could not find function "knapsack"
> library(adagio)
> RetailValue <- c(6.5,5.9,2.9,1.8,4,2.3,7.5,2,5.0,5.6,11.4)
> Price <- c(3,2,1,1,1,1,2,1,3,2,4)
> mostcapacity <- 10000
> (is <-knapsack(Price,RetailValue,mostcapacity))
$capacity
[1] 21

$profit
[1] 54.9

$indices
[1] 1 2 3 4 5 6 7 8 9 10 11

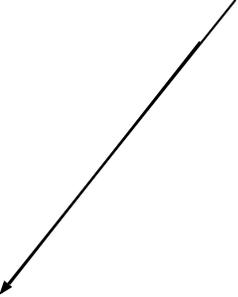
C
>
```



Stable Marriage Algorithm

It is a problem of finding a stable matching between two equally sized sets of elements given an ordering sequence. A matching is mapped from the elements of one set to the elements of the other

- The Stable Marriage Problem:
- Given n men and n women,
- where each person has ranked all members of the opposite sex in order of preference,
- marry the men and women together such that there are no two people of opposite sex who would both rather have each other than their current partners.
- When there are no such pairs of people, the set of marriages is deemed stable.



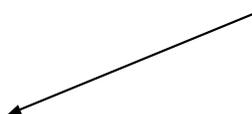
```
Propose/dispose alg
  while( $\exists$  man not engaged) {
    man proposes to his highest ranked woman who has not rejected him
    if(this woman is not engaged)
      they get engaged
    else
      woman engages the preferred man, (and rejects him)
```

This is how the Gale Shapley-Stable Marriage Algorithm Works:

Assume we have a set of given men and women and they have their preferences ranked from best to worst.

| | | | | |
|-------|-------|-------|-------|-------|
| M_1 | W_1 | W_2 | W_3 | W_4 |
| M_2 | W_2 | W_3 | W_4 | W_1 |
| M_3 | W_2 | W_3 | W_1 | W_4 |
| M_4 | W_1 | W_3 | W_2 | W_4 |

| | | | | |
|-------|-------|-------|-------|-------|
| W_1 | M_4 | M_2 | M_3 | M_1 |
| W_2 | M_4 | M_3 | M_1 | M_2 |
| W_3 | M_4 | M_2 | M_3 | M_1 |
| W_4 | M_1 | M_3 | M_4 | M_2 |



Example provided from
Professor Noga
Comp 496 ALG
Homework #1

There are a-lot of varieties of this algorithm

So, let's do the College Admissions Problem:

- In this scenario, we are taking into consideration College Admissions.
- So, we know colleges can of course accept more than one student.

#lets think of scenario, that 1000 students get matched to 400 colleges.

#Where each college has two slots. By construction 200 students will not get into any college.

#So, we draw the students and the colleges preferences.

```
install.packages("matchingR")
```

```
library(matchingR)
```

set seed, random number generator, it can be saved & restored but not altered

set.seed(1)

set number of students

nstudents = ?

set number of colleges

ncolleges = ?

generate preferences

uStudents = matrix(runif(ncolleges*nstudents), nrow = ncolleges, ncol = nstudents)

uColleges = matrix(runif(nstudents*ncolleges), nrow = nstudents, ncol = ncolleges)

student-optimal matching

results = galeShapley.collegeAdmissions(studentUtils = uStudents, collegeUtils = uColleges, slots = 2)

str(results)

check if matching is stable

galeShapley.checkStability(uStudents, uColleges, results\$matched.students, results\$matched.colleges)

End