

# Numerical Methods

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Max Turgeon

STAT 3150–Statistical Computing

# Lecture Objectives

- Describe the main differences between computer arithmetic and “normal” arithmetic.
- Apply root finding methods for one-dimensional problems.

# Motivation

- Many estimators can be defined as solutions to a given equation or optimization problem.
- For the next few weeks, we will discuss **numerical methods** and **optimization**
- This will also serve as a good introduction to using **R** as a programming language.

# Question

- Can you give examples of estimators defined by solving an equation  $f(x) = c$ ?
- Can you recall an example from the notes/assignments?

# Testing equality i

- To test for equality of integers, booleans or strings, we can use `==`.
  - `3 == 4`, `TRUE == FALSE`, `"hello" == "world"`.
- But with decimal numbers, the equality operator may behave in surprising ways

```
# Expected
```

```
(0.5 + 0.5) == 1
```

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

## Testing equality ii

```
# Unexpected
```

```
(0.1 + 0.2) == 0.3
```

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

```
# Why?
```

```
0.3 - (0.1 + 0.2)
```

```
## [1] -5.551115e-17
```

## Testing equality iii

- In computer's memory, decimal numbers are essentially represented in *binary* scientific notation.
  - Which leads to rounding errors that may be hard to predict.
- R gives us two functions to test equality more carefully:
  - `all.equal`: Tests for “near equality”, i.e. within a tolerance level
  - `identical`: Tests for whether two objects are identical (including length, attributes, etc.).

## Testing equality iv

```
all.equal(0.1 + 0.2, 0.3)
```

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

```
identical(0.1 + 0.2, 0.3)
```

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



## Testing equality v

```
# But be careful!
```

```
all.equal(1, 2)
```

```
## [1] "Mean relative difference: 1"
```

```
# Better
```

```
isTRUE(all.equal(1, 2))
```

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

## Testing equality vi

- Another approach: check whether `abs(x - y) < epsilon`, for an `epsilon` of your choice.

```
abs(0.3 - (0.2 + 0.1)) < 10^-10
```

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

# Overflow and underflow

- Another way in which computer arithmetic can be surprising: very small and very large numbers.
  - Small numbers may be rounded down to zero.
  - Large numbers will be turn into **Inf**.
- In both cases, there are two strategies that can help:
  - Simplify expressions by hand as much as you can first:
$$\frac{n!}{(n-2)!} = n(n-1).$$
  - Compute on logarithmic scale, and convert answer back to original scale with **exp**.

## Example i

- We know the Poisson mass function is

$$P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!} > 0.$$

- But when  $k$  is large, we may run into underflow issues.

```
# d is for density  
dpois(100, lambda = 1)
```

```
## [1] 3.941866e-159
```

## Example ii

```
dpois(200, lambda = 1)
```

```
## [1] 0
```

```
# Use logarithms
```

```
dpois(200, lambda = 1, log = TRUE)
```

```
## [1] -864.232
```

## Exercise

Using the properties of logarithms, evaluate

$$\frac{\Gamma\left(\frac{n-1}{2}\right)}{\Gamma\left(\frac{1}{2}\right)\Gamma\left(\frac{n-2}{2}\right)},$$

for  $n = 400$ . Use `lgamma` to evaluate the Gamma function on the logarithmic scale.

# Solution

```
n <- 400  
# With gamma  
(gamma(0.5*(n-1))/(gamma(0.5)*gamma(0.5*(n-2))))
```

```
## [1] NaN
```

```
# With lgamma  
exp(lgamma(0.5*(n-1)) - lgamma(0.5) - lgamma(0.5*(n-2)))
```

```
## [1] 7.953876
```

# Finding the roots of a function

- The first class of numerical methods we will look at our **root finding algorithms** (in one dimension).
- Assume we have a continuous function  $f(x)$  of one variable. For a given constant  $c$ , we want to find the values  $x$  such that  $f(x) = c$ .
  - Equivalent to replacing  $f(x)$  with  $f'(x) = f(x) - c$  and looking for when  $f'(x) = 0$ .
- We will look at two methods:
  - Bisection method
  - Brent's method



## Bisection method i

- Assume that we have  $f(a)$  and  $f(b)$  are nonzero and have opposite sign.
  - Exactly one is negative, the other is positive.
- Because  $f$  is continuous, the *Intermediate Value Theorem* tells us that there must be a value  $x \in (a, b)$  such that  $f(x) = 0$ .
  - It may not be unique, but there's at least one such  $x$ .

## Bisection method ii

- With the bisection method, we look at the mid-point of  $[a, b]$ :  
$$x_1 = \frac{b-a}{2} + a = \frac{b+a}{2},$$
 and we evaluate  $f(x_1)$ .
  - If  $f(a)$  and  $f(x_1)$  have the **same sign**, then the root is in the interval  $(x_1, b)$ .
  - If  $f(a)$  and  $f(x_1)$  have **opposite sign**, then the root is in the interval  $(a, x_1)$ .
- We then repeat the process on the new interval, which gives us a sequence of “guesses”  $x_1, x_2, x_3, \dots$ .
  - This sequence is **guaranteed** to converge to a root of  $f(x) = 0$ .
- We stop when we are “close enough”, i.e. when  $|f(x_n)| < \epsilon$ .

See this video: <https://youtu.be/zkd6CLfNNe8>

## Example i

- We will look at the function

$$f(x) = a^2 + x^2 + \frac{2ax}{n-1} - (n-2),$$

for  $a = 0.5$  and  $n = 20$ , on the interval  $(0, 5n)$ .

```
a <- 0.5
n <- 20
# First create a function
fun <- function(x) {
  a^2 + x^2 + 2*a*x/(n-1) - n + 2
}
```

## Example ii

```
# Check output at interval bounds
x_lb <- 0 # Lower bound
x_ub <- 5*n # Upper bound

c(fun(x_lb), fun(x_ub))

## [1] -17.750 9987.513
```

## Example iii

```
# Set up----  
x_next <- 0.5*(x_ub - x_lb) + x_lb # Midpoint  
epsilon <- 10^-10  
f_lb <- fun(x_lb)  
f_ub <- fun(x_ub)  
f_next <- fun(x_next)  
iterations <- 0
```

## Example iv

```
while(abs(f_next) > epsilon) {  
  iterations <- iterations + 1  
  if (f_ub*f_next > 0) {  
    x_ub <- x_next # same sign, move left  
    f_ub <- fun(x_ub) } else {  
    x_lb <- x_next # opposite sign, move right  
    f_lb <- fun(x_lb) }  
  x_next <- 0.5*(x_ub - x_lb) + x_lb  
  f_next <- fun(x_next)  
}
```

## Example v

```
# Our estimate the solution  $f(x) = 0$ 
```

```
x_next
```

```
## [1] 4.186841
```

```
# Number of iterations
```

```
iterations
```

```
## [1] 40
```



## Exercise

Use the bisection method to find the solution to the equation

$$\cos(x) = x^3.$$

## Solution i

- First, we can look at the solution of  $g(x) = 0$ , for  $g(x) = \cos(x) - x^3$ .
- Based on our knowledge of these two functions, we deduce that a solution, if it exists, must be positive.
- Let's look at the interval  $[0, 2]$

# First create a function

```
g_fun <- function(x) {  
  cos(x) - x^3  
}
```

## Solution ii

```
# Check output at interval bounds
x_lb <- 0 # Lower bound
x_ub <- 2 # Upper bound

c(g_fun(x_lb), g_fun(x_ub))

## [1] 1.000000 -8.416147
```

## Solution iii

```
# Set up----  
x_next <- 0.5*(x_ub - x_lb) + x_lb # Midpoint  
epsilon <- 10^-10  
g_lb <- g_fun(x_lb)  
g_ub <- g_fun(x_ub)  
g_next <- g_fun(x_next)  
iterations <- 0
```

## Solution iv

```
while(abs(g_next) > epsilon) {  
  iterations <- iterations + 1  
  if (g_ub*g_next > 0) {  
    x_ub <- x_next # same sign, move left  
    g_ub <- g_fun(x_ub) } else {  
    x_lb <- x_next # opposite sign, move right  
    g_lb <- g_fun(x_lb) }  
  x_next <- 0.5*(x_ub - x_lb) + x_lb  
  g_next <- g_fun(x_next)  
}
```

## Solution v

```
# Our estimate the solution  $g(x) = 0$ 
```

```
x_next
```

```
## [1] 0.865474
```

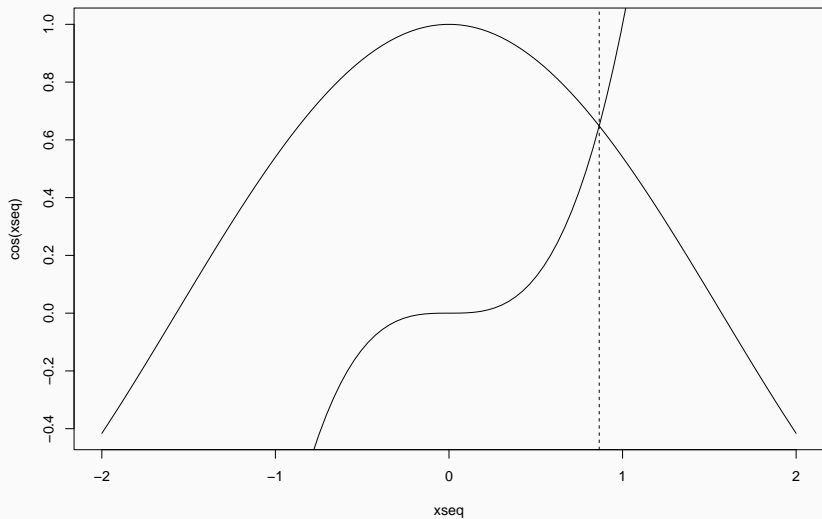
```
# Number of iterations
```

```
iterations
```

```
## [1] 34
```

```
# Plot functions to check
xseq <- seq(-2, 2, length.out = 100)
plot(xseq, cos(xseq), type = "l")
lines(xseq, xseq^3)
abline(v = x_next, lty = 2)
```

## Solution vii





# Brent's method i

- The bisection method is guaranteed to converge.
  - Intermediate Value Theorem
- But convergence can be slow...
  - For an initial interval of length  $L$ , after  $n$  step the bracketing interval has length  $L/2^n$ .
- Other methods (e.g. secant method) can converge faster, but they're not guaranteed to converge...
- **Brent's method** combines the convergence speed of these methods, but guarantees convergence by keeping the root within a shrinking interval.

- I will give a general description the algorithm, but today we will use R's implementation.
  - **Next lecture:** you will implement it.

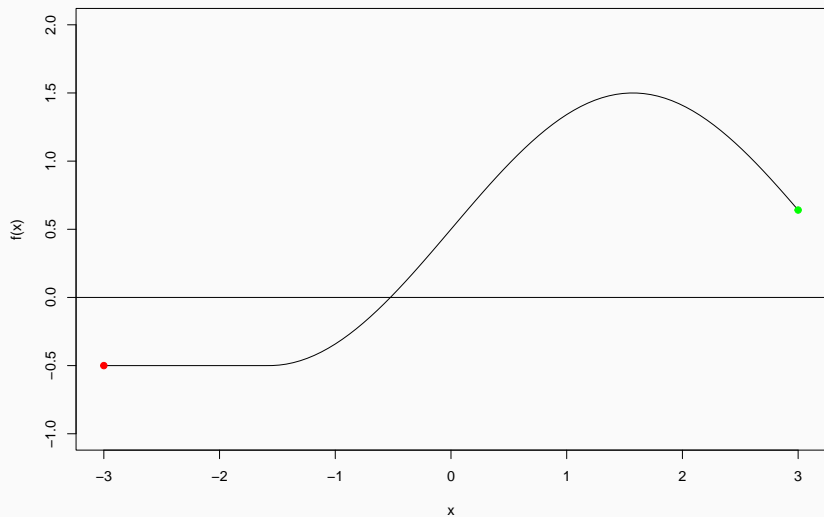
## Brent's method iii

### Algorithm

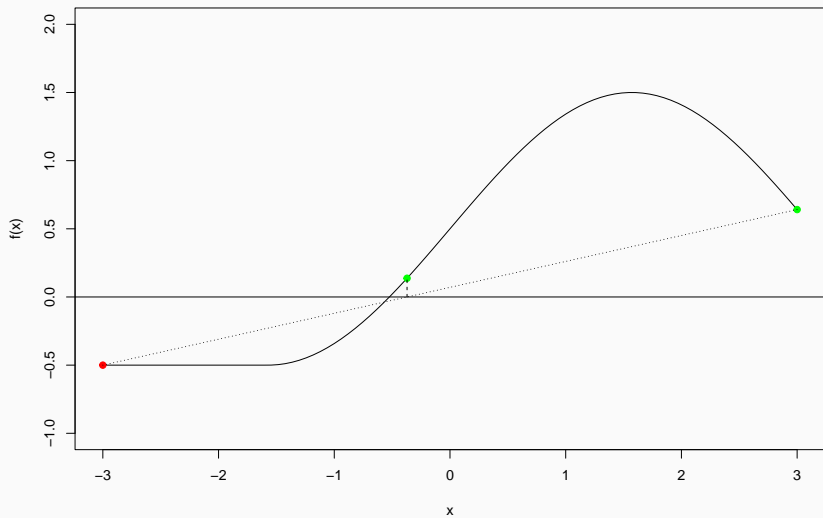
Start with interval  $[a, b]$  and continuous function  $f(x)$ . The values  $f(a)$ ,  $f(b)$  have opposite signs.

1. Define a third point  $(c, f(c))$ , where  $c$  is the value at which a linear interpolation crosses the x-axis. Depending on the sign of  $f(c)$ , we know the solution  $f(x) = 0$  falls inside the interval  $(a, c)$  or  $(c, b)$ .
2. Fit a sideways parabola to all three points, and find the intersection  $x_1$  with the x-axis. If  $x_1$  falls outside the interval from Step 1, replace  $x_1$  by the midpoint of the interval (i.e. bisection).
3. Repeat until convergence.

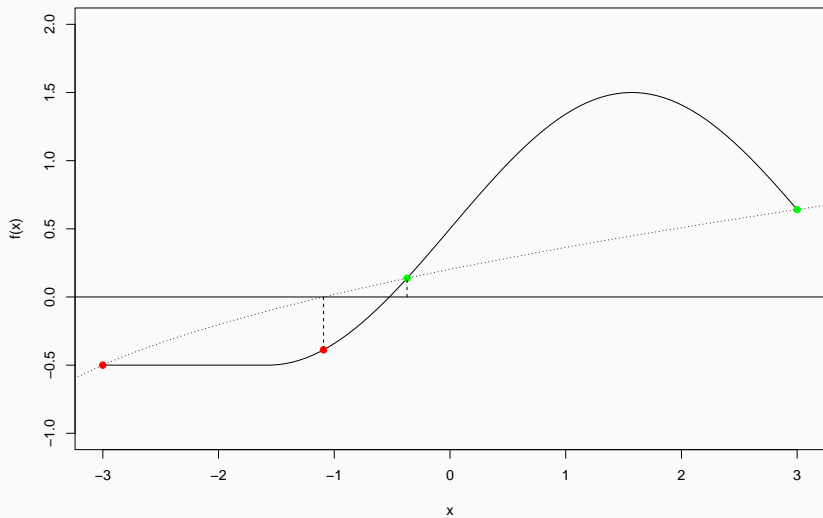
## Demo i



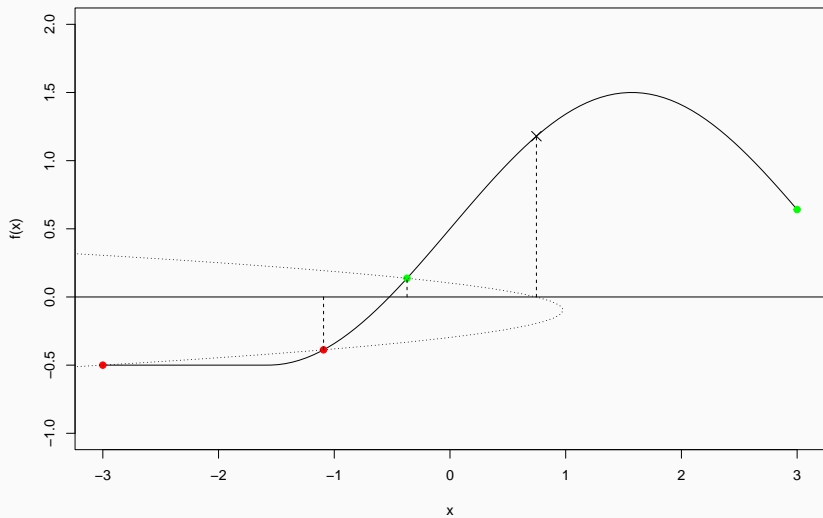
## Demo ii



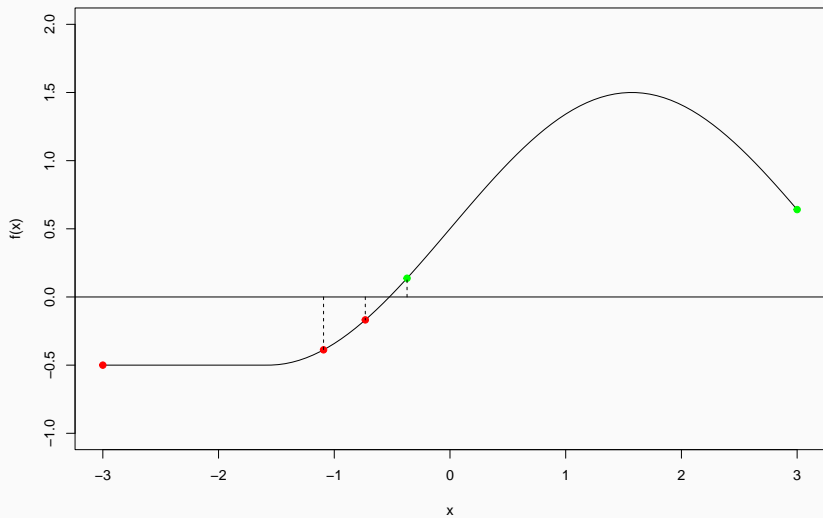
## Demo iii



## Demo iv



## Demo v





## Example i

- We will use the same example as above:

$$f(x) = a^2 + x^2 + \frac{2ax}{n-1} - (n-2),$$

for  $a = 0.5$  and  $n = 20$ , on the interval  $(0, 5n)$ .

```
a <- 0.5
n <- 20
# Create a function
fun <- function(x) {
  a^2 + x^2 + 2*a*x/(n-1) - n + 2
}
```

## Example ii

- We will use the function `uniroot` in R:
  - The first argument is the function  $f(x)$ .
  - The second argument is the interval  $[a, b]$ .
  - The argument `tol` controls the convergence.

```
output <- uniroot(f = fun,  
                  interval = c(0, 5*n),  
                  tol = 10^-10)  
names(output)
```

```
## [1] "root" "f.root" "iter" "init.it"  
"estim.prec"
```

## Example iii

```
output$root
```

```
## [1] 4.186841
```

```
output$iter
```

```
## [1] 16
```

## Exercise

Use Brent's method to find the root of

$$f(x) = e^{-x} (3.2 \sin(x) - 0.5 \cos(x)) ,$$

on the interval  $[3, 4]$ .

## Solution

```
result <- uniroot(function(x) {  
  exp(-x)*(3.2*sin(x) - 0.5*cos(x))  
}, interval = c(3, 4))
```

```
result$root
```

```
## [1] 3.296589
```

# Summary

- We discussed some important differences between computer arithmetic and “normal” arithmetic.
  - Rounding errors
  - Overflow and underflow
- We introduced two methods for finding roots  $f(x) = 0$  in one-dimension.
  - Why can't we apply these methods in higher dimensions?
- On Thursday, we will see how this can be applied to **Maximum Likelihood Estimation**.