

## Numerical Methods for Nonlinear Equations

- compute yield of a bond ( $y$ )
- compute implied volatility ( $\sigma_{imp}$ )
- compute zero rate curves from bond prices

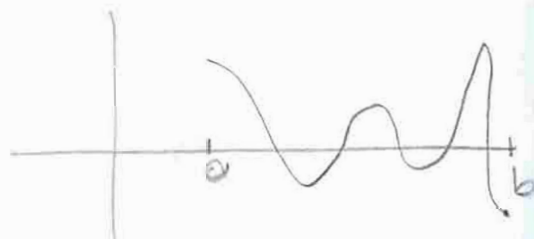
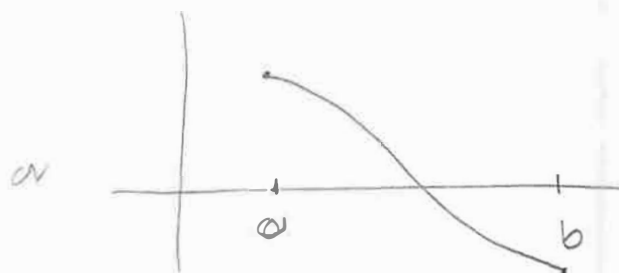
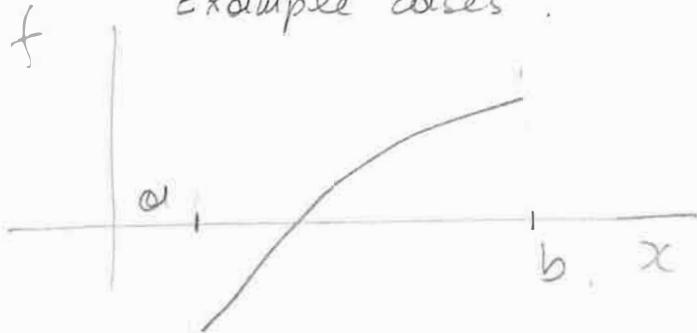
Involve solving a nonlinear equation of the form

$$f(x) = 0 \quad \text{for } x.$$

### Bisection Method

Let  $f : [a, b] \rightarrow \mathbb{R}$  such that  $f(a) = -\text{sgn}(f(b))$

Example cases.



From the intermediate value theorem there exists at least one point  $x \in (a, b)$  for which  $f(x) = 0$

There are might be more points but the bisection method finds only one i.e. it considers the case of only one point over  $[a, b]$ .

set  $c = \frac{a+b}{2}$  compute  $f(c)$

• If  $f(c) = 0$  then solution is  $x = c$

• If  $f(c)$  has different sign than  $f(a)$  then  
new  $c_{\text{new}} = \frac{c+a}{2}$  and repeat process

• If  $f(c)$  has same sign as  $f(a)$  then  
new  $c_{\text{new}} = \frac{c+b}{2}$  and repeat process for interval  $[c_{\text{new}}, b]$

Process stops when  $|f(c_{\text{new}})| < \text{toler}$ .

and interval is less than Int-tolerance.

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Theorem 8.1 If  $f : [a, b] \rightarrow \mathbb{R}$  is a continuous function and  $f(a)$  and  $f(b)$  have opposite signs, then the bisection method converges to a solution  $f(x) = 0$  for some  $x \in (a, b)$ .

### Outline of proof

At each step the interval is halved. After  $n$ -steps the active interval is

$$x_R - x_L = \frac{b-a}{2^n} \quad , \quad x_R > x_L$$

One stopping condition  $x_R - x_L \leq \text{tol-Interval}$

$$\therefore \frac{b-a}{2^n} \leq \text{tol-Interval}$$

$\Rightarrow \exists$  an  $n$  such that stopping criterion is satisfied

Assuming  $f(x)$  is differentiable i.e.  $|f'(x)| \leq C$   
 $\forall x \in [a, b]$  for some constant  $C > 0$ .

From MVT  $\exists$  a point  $\xi \in (x_L, x_R)$

$$\frac{f(x_R) - f(x_L)}{x_R - x_L} = f'(\xi)$$

$$|f(x_R) - f(x_L)| \leq |f'(5)| |x_R - x_L| \leq C |x_R - x_L|$$

ie

$$|f(x_R) - f(x_L)| \leq C \frac{(b-a)}{2^n}$$

$$\max(|f(x_R)|, |f(x_L)|) \leq |f(x_R) - f(x_L)| \leq C \frac{(b-a)}{2^n}$$

↑  
due to  $f(x_R)$  having opposite  
sign with  $f(x_L)$

∴ for large  $n$  the second stopping criterion

$$\max(|f(x_R)|, |f(x_L)|) \leq C \frac{(b-a)}{2^n} \leq f\text{-tolerance}$$

is satisfied.

Example

$$f(x) = x^4 - 5x^2 + 4 - \frac{1}{1+e^{x^3}}, \quad [-2, 3]$$

$$f(-2) = -0.9997, \quad f(3) = 40$$

$$\text{tol-Interval} = 10^{-6}, \quad \text{tol-function} = 10^{-9}$$

After 33 iterations the solution is -0.889642

Note that  $2.000028 \in [-2, 3]$  is another zero  
for  $f(x)$ .

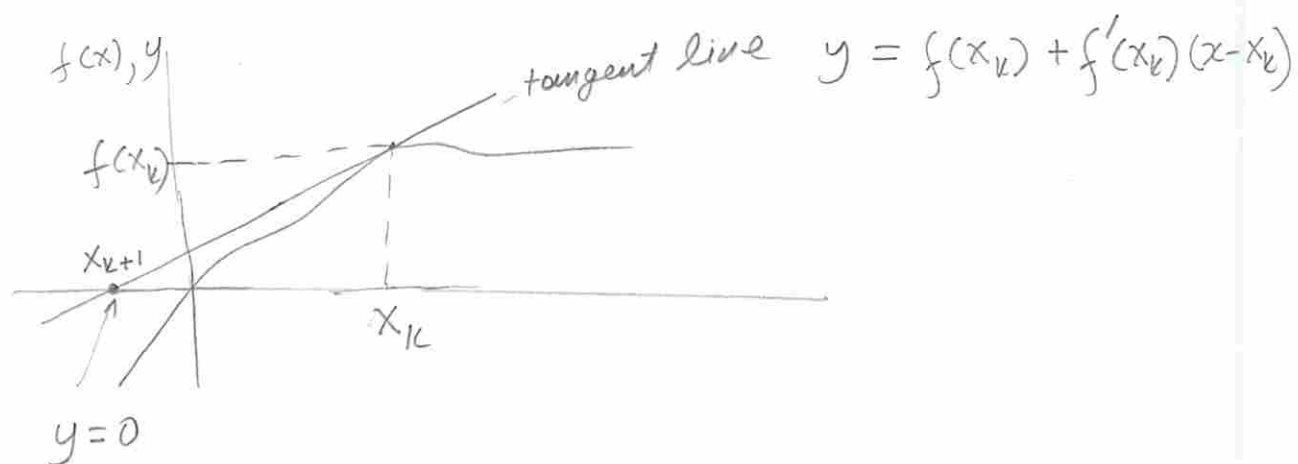
## Newton's Method

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Commonly used. It can extend to high dimensional systems.

Consider

$$f(x) = 0$$



Let  $x_k$  be an approximation of the solution  $f(x) = 0$ . The next value of  $x$  denoted by  $x_{k+1}$  is taken as the value of  $x$  which corresponds to the  $x$ -axis intercept of the tangent line  $y = f(x_k) + f'(x_k)(x - x_k)$  at the point  $x_k$ . i.e. for

$$y=0 = f(x_k) + f'(x_k)(x_{k+1} - x_k)$$

$$\Rightarrow x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

Another way of deriving the above equation is to use the Taylor expansion of  $f(x)$  around the point  $x = x_k$  :

$$f(x) \approx f(x_k) + f'(x_k)(x - x_k)$$

let  $x = x_{k+1}$  then

$$f(x_{k+1}) \approx f(x_k) + f'(x_k)(x_{k+1} - x_k)$$

$$\text{setting } f(x_{k+1}) = 0 \Rightarrow x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

Start with an initial guess  $x_0$

compute  $f(x_0)$ ,  $f'(x_0)$  then

$$x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$$

compute  $f(x_1)$ ,  $f'(x_1)$  then

$$x_2 = x_1 - \frac{f(x_1)}{f'(x_1)}$$

etc.

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Given <sup>any</sup> initial guess  $x_0$  there is no guarantee that the method will converge to an  $x$  that satisfies  $f(x)=0$ .

Speed and convergence depend on the accuracy of initial guess  $x_0$ .

In financial applications usually there is a good initial guess i.e. yield is positive within certain possible values etc.

Stopping criteria

$$|x_{N+1} - x_N| \leq \text{tol-consec.} \approx 10^{-6}$$

$$|f(x_{N+1})| \leq \text{tol-approx.} \approx 10^{-9}$$

Theorem 8.2 Let  $x^*$  be a solution of  $f(x)=0$ . Assume that  $f(x)$  is twice differentiable with  $f''(x)$  continuous. If  $f'(x^*) \neq 0$  and if  $x_0$  is close enough to  $x^*$ , then Newton's method converges quadratically i.e.  $\exists M > 0$  and a positive integer  $n_M$  such that



$$\left| \frac{x_{k+1} - x^*}{(x_k - x^*)^2} \right| < M, \quad \forall k \geq n_m$$

### Outline of proof

Let  $x^*$  be a solution of  $f(x^*) = 0$

then the recursion equation satisfies

$$\begin{aligned} x_{k+1} - x^* &= x_k - x^* - \frac{(f(x_k) - f(x^*))}{f'(x_k)} \\ &= \frac{f(x^*) - f(x_k) + (x_k - x^*) f'(x_k)}{f'(x_k)} \end{aligned}$$

From Taylor's formula

$$f(x) - P_n(x) = \frac{(x-a)^{n+1}}{(n+1)!} f^{(n+1)}(c)$$

where  $c \in (a, x)$  and

$$P_n(x) = \sum_{k=0}^n \frac{(x-a)^k}{k!} f^{(k)}(a)$$

For  $n=1$

$$f(x) - P_1(x) = f(x) - f(a) + (x-a)f'(a) = \frac{(x-a)^2}{2} f''(c)$$

Let  $x = x^*$  and  $a = x_k$



We conclude that  $\exists$  constant  $C_k$  between  $x^*$  and  $x_k$  such that

$$f(x^*) - \left( f(x_k) + (x^* - x_k) f'(x_k) \right) = \frac{(x^* - x_k)^2}{2} f''(c_k)$$

$$\therefore x_{k+1} - x^* = (x^* - x_k)^2 \frac{f''(c_k)}{2 f'(x_k)}$$

$$\Rightarrow \frac{|x_{k+1} - x^*|}{|x_k - x^*|^2} = \frac{|f''(c_k)|}{2 |f'(x_k)|}$$

Since  $f''$ ,  $f'$  are continuous and  $f'(x^*) \neq 0$  it follows that if  $x_k$  is close to  $x^*$  then  $f'(x_k) \neq 0$  by continuity.

$$\Rightarrow \frac{|f''(c_k)|}{2 |f'(x_k)|} < \infty$$

## Secant Method

For some problems  $f'(x)$  cannot be calculated as  $f(x)$  may be given in form of data and a closed form for  $f(x)$  may not be known.

In such case the Newton's method uses an approximation of  $f'(x_k)$  as

$$f'(x_k) \approx \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}}$$

$$\therefore x_{k+1} = x_k - \frac{(x_k - x_{k-1}) f(x_k)}{f(x_k) - f(x_{k-1})}, \quad \forall k \geq 0$$

Two approximate guesses  $x_{-1}$  and  $x_0$  with  $f(x_{-1}) \neq f(x_0)$  must be used to initialize the secant method.

The stopping criteria are the same as in Newton's case.

Secant method is usually slower than Newton's method.

## N-dimensional systems

$$\text{let } F: \mathbb{R}^N \rightarrow \mathbb{R}^N, \quad F = \begin{bmatrix} F_1(x) \\ F_2(x) \\ \vdots \\ F_N(x) \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

$$\text{where } F_i(x): \mathbb{R}^N \rightarrow \mathbb{R}$$

$F_i(x)$  are continuous

Solve

$$F(x) = 0 \quad \text{for } x.$$

Gradient  $DF(x)$  of  $F(x)$  is the  $N \times N$  matrix

$$DF(x) = \begin{pmatrix} \frac{\partial F_1(x)}{\partial x_1} & \frac{\partial F_1(x)}{\partial x_2} & \cdots & \frac{\partial F_1(x)}{\partial x_N} \\ \vdots & \vdots & & \vdots \\ \frac{\partial F_N}{\partial x_1} & \cdots & \cdots & \frac{\partial F_N}{\partial x_N} \end{pmatrix}$$

From Taylor expansion around  $x_k$

$$F(x) \approx F(x_k) + DF(x_k)(x - x_k)$$

$$\text{Setting } F(x_{k+1}) = 0$$

$$x_{k+1} = x_k - (DF(x_k))^{-1} F(x_k)$$

computing vector  $U_k = (DF(x_k))^{-1} F(x_k)$

is equivalent to solving the linear equation

$$DF(x_k) U_k = F(x_k)$$

More efficient numerical linear algebra methods may be used to solve for  $U_k$  for each  $k$  and then compute

$$x_{k+1} = x_k - U_k$$

Stopping criteria

$$\|F(x_{\text{new}})\| \leq \text{tol-appr.}$$

$$\|x_{\text{new}} - x_{\text{old}}\| \leq \text{tol-conseq.}$$

$\|\cdot\|$  = Euclidean norm

Theorem 8.3 Let  $x^*$  be a solution of  $F(x) = 0$  where  $F(x)$  is a function with continuous 2<sup>nd</sup> order partial derivatives. If  $DF(x^*)$  is invertible and  $x_0$  is close to  $x^*$ , then the Newton's method converges quadratically i.e.  $\exists M > 0$  and  $n_M$  pos. integer

$$\|x_{k+1} - x^*\| \leq M \|x_k - x^*\|^2 \quad \forall k \geq n_M$$

# Approximate Newton's Method

Forward finite difference approx.

$$\frac{\partial F_i(x)}{\partial x_j} \approx \Delta_j F_i(x) = \frac{F_i(x + h e_j) - F_i(x)}{h}$$

$$e_j = (0 \dots 0 \underset{\substack{\uparrow \\ j\text{th term}}}{1} 0 \dots 0)^T$$

$$\Delta F(x) = \begin{pmatrix} \Delta_1 F_1(x) & \Delta_2 F_1(x) & \dots & \Delta_N F_1(x) \\ \vdots & \vdots & & \vdots \\ \Delta_1 F_N(x) & \Delta_2 F_N(x) & \dots & \Delta_N F_N(x) \end{pmatrix}$$

$$x_{k+1} = x_k - (\Delta F(x_k))^{-1} F(x_k)$$

Another approximation (central finite differences)

$$\frac{\partial F_i(x)}{\partial x_j} \approx \frac{F_i(x + h e_j) - F_i(x - h e_j)}{2h}$$

more computations.