

(2)

"pure" methods for finding x_* such that

$$f(x_*) = 0, \quad f: \mathbb{R}^1 \rightarrow \mathbb{R}^1$$

- Bisection \sim v -linear convergence; 1-function eval./iter.
- Newton's method \sim 2-quadratic local convergence
1-function eval./iter. + 1- f' eval./iter.
- Secant \sim 2-order $\frac{1+\sqrt{5}}{2}$ local convergence
1-function eval./iter.

For secant method can also show

Suppose: f is continuously differentiable near x_*
such that $f(x_*) = 0, f'(x_*) \neq 0$

Suppose that:

$$|f'(x) - f'(x_*)| \leq L |x - x_*|$$

If x_0, x_- are sufficiently near x_* , then secant
iterates $\{x_k\}$ converges to x_* with

$$|x_{k+1} - x_*| \leq \gamma |x_k - x_*| |x_{k-1} - x_*|$$

for some that

$$|x_{k+1} - x_*| \leq c_k |x_k - x_*|$$

for $c_k = \gamma |x_{k-1} - x_*| \rightarrow 0$ (superlinear
convergence)

Can also show $\exists \gamma \in (0,1)$ such that

$$|x_k - x_*| \leq \gamma^{r^k} \text{ where } r = \frac{1+\sqrt{5}}{2}$$

since $\gamma^{r^k} \rightarrow 0$ with 2 order $\frac{1+\sqrt{5}}{2}$ follows that

$$x_k \rightarrow x_* \text{ with } r \text{ order } \frac{1+\sqrt{5}}{2}$$

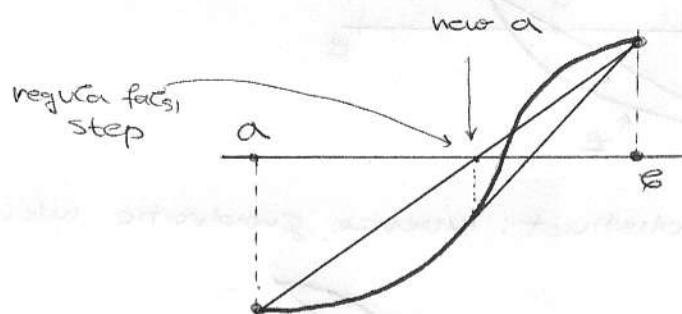
see Ralston & Rabinowitz

Practical "hybrid" methods

Idea: combine features of different "pure" methods
To retain advantages, avoid disadvantages

classical: regula falsi (false position)

suppose have $f(a) \cdot f(b) < 0$



Often works well but not always



More effective idea: Brent's algorithm
(from work of Dekker (1969) & Brent (1973))

Operation:

Begins with

i) a, b such that $f(a) \cdot f(b) < 0$

ii) tolerance δ (algorithm returns approximate solution with 2δ of a solution)

Maintains at each iteration a, b, c (initially $c=a$)
such that:

i) $f(a) \cdot f(c) \leq 0$

ii) $|f(b)| \leq |f(c)| \Rightarrow c$ is current approximate solution

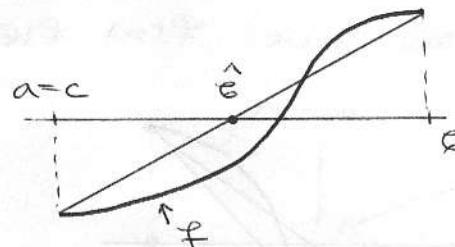
iii) either a is distinct from b and c ,
or $a=c$ and is immediate past value
of b

Iteration :

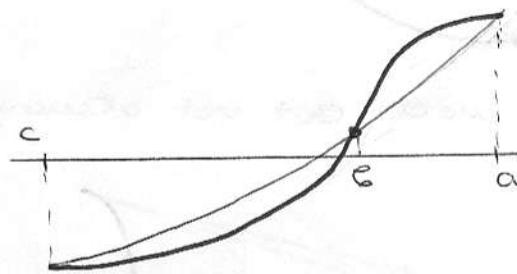
1) If $|b-a| < \delta$, return $\hat{e} \approx x_*$

2) else, determine a trial \hat{e} :

i) $a=c$: linear interpolation



ii) a, b, c distinct: inverse quadratic interpolation



Have a, b, c and $f(a), f(b), f(c)$

Determine:

$$p(y) = x + sy + ty^2$$

such that

$$p(f(a)) = a \quad p(f(b)) = b \quad ; \quad p(f(c)) = c$$

Then take $\hat{e} = p(0) = x$

iii) obtain final \hat{e} by adjusting \hat{e} if necessary so it's neither too conge nor too stout (and occasionally force a bisection step)

iv) use a, b, c and final \hat{e} to choose new a, b, c according to complicated rules

good ref: Forsythe, Maccorm, Moler

MATLAB ex:

```
fzero(@(x) 4*x+tan(x), 2*pi+.01)
```

ans: pi/2

```
options = optimset ('Display', 'iter')
```

Newton's method for systems

Consider a general system problem

find x_* such that $F(x_*) = 0$

Here: $F: \mathbb{R}^n \rightarrow \mathbb{R}^m$ (usually $m=n$)

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \in \mathbb{R}^n \quad F(x) = \begin{pmatrix} F_1(x) \\ \vdots \\ F_m(x) \end{pmatrix} \in \mathbb{R}^m$$

example: $x_1^2 + x_1 x_2^3 = g$

$$3x_1^2 x_2 - x_2^3 = h$$

here: $x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \quad F(x) = \begin{pmatrix} x_1^2 + x_1 x_2^3 - g \\ 3x_1^2 x_2 - x_2^3 - h \end{pmatrix}$

Preliminaries:

$$\mathbb{R}^n = \left\{ x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} : x_i \in \mathbb{R}^1, \text{ for } 1 \leq i \leq n \right\}$$

$$\mathbb{R}^{m \times n} = \left\{ A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \dots & a_{mn} \end{pmatrix} : a_{ij} \in \mathbb{R}^1, \text{ for } \begin{array}{l} 1 \leq i \leq m \\ 1 \leq j \leq n \end{array} \right\}$$

These are vector spaces under usual vector and matrix addition and scalar multiplication

Def: A norm $\| \cdot \|$ is a non-negative function such that for all vectors v, u and scalar α

i) $\|v\| > 0$, with $\|v\| = 0 \Leftrightarrow v = 0$

ii) $\|\alpha v\| = |\alpha| \|v\|$

iii) $\|v+u\| \leq \|v\| + \|u\|$ (triangle inequality)

Examples: on \mathbb{R}^n , $v = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}$

$$\text{i)} \|v\|_1 = \sum_{i=1}^n |v_i|$$

$$\text{ii)} \|v\|_\infty = \max \{|v_i|, 1 \leq i \leq n\}$$

$$\text{iii)} \|v\|_p = \left[\sum_i |v_i|^p \right]^{1/p}$$

$p=2 \Rightarrow$ Euclidean norm

Any norm $\|\cdot\|$ on \mathbb{R}^n induces a norm $\|\cdot\|$ on $\mathbb{R}^{m \times n}$ by:

$$\|A\| = \max_{\|v\|=1} \|Av\| = \max_{v \neq 0} \frac{\|Av\|}{\|v\|}$$

Note: If $A \in \mathbb{R}^{m \times p}$, $B \in \mathbb{R}^{p \times n}$ then

$$\|AB\| \leq \|A\| + \|B\|$$

Examples:

i) $\|\cdot\|_1$ on \mathbb{R}^n defines

$$\|A\|_1 = \max_j \sum_{i=1}^n |a_{ij}|$$

ii) $\|\cdot\|_\infty$ on \mathbb{R}^n defines

$$\|A\|_\infty = \max_i \sum_{j=1}^n |a_{ij}|$$

Not all matrix norms are induced

Ex: Frobenius norm

$$\|A\|_F = \left\{ \sum_{i,j} |a_{ij}|^2 \right\}^{1/2} = \left\{ \text{trace} \{AA^T\} \right\}^{1/2}$$

Note: this comes from the inner product on $\mathbb{R}^{m \times n}$

$$\langle A, B \rangle_F = \text{trace} \{AB^T\} = \sum_{i,j} a_{ij} b_{ij}$$

Fact: Any two norms on a finite-dimensional vector space (such as \mathbb{R}^n or $\mathbb{R}^{m \times n}$) are equivalent, i.e. if $\|\cdot\|$ and $\|\cdot\|'$ are any two norms, then $\exists c_1 > 0$ and $c_2 > 0$ such that

$$c_1 \|\cdot\| \leq \|\cdot\|' \leq c_2 \|\cdot\| \quad \text{for all } \omega$$

Def: $\{x_k\}$ converges to x_* if $\|x_k - x_*\| \rightarrow 0$

On a finite dimension space, by norm-equivalence convergence in any norm implies convergence in every norm. Convergence is norm-independent.

Rate of convergence:

Say $x_k \rightarrow x_*$

▽ ϱ -linearity if $\exists \lambda \in (0,1)$ such that

$$\|x_k - x_*\| \leq \lambda \|x_k - x_*\|$$

▽ ϱ -superlinearity if

$$\|x_{k+1} - x_*\| \leq c_k \|x_k - x_*\|, \quad c_k \rightarrow 0$$

▽ ϱ -order p , $1 < p < \infty$ if

$$\|x_{k+1} - x_k\| \leq \gamma \|x_k - x_*\|^p$$

Can show: ϱ -superlinearity and ϱ -order p ($1 < p < \infty$) convergence are norm independent
but ϱ -linear convergence is norm dependent

Say $x_k \rightarrow x_*$ r -linearity (r -superlinearity, r -order p)

if $\|x_k - x_*\| \leq \gamma_k$, where $\gamma_k \rightarrow 0$

ϱ -linearity (ϱ -superlinearity, ϱ -order p)

Suppose X, Y are vector spaces with norms

$$\| \cdot \|_X, \| \cdot \|_Y$$

Then $F: X \rightarrow Y$ is continuous at $x \in X$ if for every $\epsilon > 0$, $\exists \delta > 0$ such that

$$\|y - x\|_X < \delta \Rightarrow \|F(y) - F(x)\|_Y < \epsilon$$

Continuity can be subtle

ex: $F: \mathbb{R}^2 \rightarrow \mathbb{R}$

$$F(x) = \begin{cases} \frac{x_1 x_2}{x_1^2 + x_2^2}, & x \neq 0 \\ 0, & x = 0 \end{cases}$$

continuous
everywhere
except at 0

Along any ray $x = r \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$ with $\cos \theta \sin \theta \neq 0$

$$F(x) = \cos \theta \sin \theta \rightarrow F(0) = 0$$

But if either x_1 or x_2 is fixed, $F(x)$ is continuous in the other

Def: $F: X \rightarrow Y$ is Lipschitz continuous at x if

$\exists L$ such that

$$\|F(y) - F(x)\|_Y \leq L \|y - x\|_X$$

see: Lipschitz continuity \Rightarrow continuity

Suppose: $F: \mathbb{R}^n \rightarrow \mathbb{R}^m$ given by

$$F(x) = \begin{pmatrix} f_1(x) \\ \vdots \\ f_m(x) \end{pmatrix}$$

If $\frac{\partial f_i}{\partial x_j}$ exists for each i, j finite

$$F'(x) = \begin{pmatrix} \frac{\partial F_1}{\partial x_1} & \dots & \frac{\partial F_1}{\partial x_n} \\ \vdots \\ \frac{\partial F_m}{\partial x_1} & \dots & \frac{\partial F_m}{\partial x_n} \end{pmatrix}$$

Jacobian matrix
Sometimes denote
by $J(x)$

If $F'(x)$ exists and $F(y) = F(x) + F'(x)(y-x) + \theta(y-x)$

then F is (Frechet) differentiable at x and
 $F'(x)$ is the (Frechet) derivative of F at x

Here $\frac{\theta(y-x)}{\|y-x\|} \rightarrow 0$ as $y \rightarrow x$

Recall: If $m=n=1$ then $F'(x)$ exist \Leftrightarrow
 F is differentiable

Jacobian matrix can exist without function being
differentiable

Note: F differentiable at $x \Rightarrow F$ continuous at x

Ex: (i) $F(x) = \frac{x_1 x_2}{x_1^2 + x_2^2}$ see $F'(0) = (0,0)$

But F not even continuous at $x = (0,0)$

$$(ii) F(x) = \frac{x_1 x_2}{\sqrt{x_1^2 + x_2^2}}$$

continuous at $x = (0,0)$ and $F'(0) = (0,0)$

But on a ray $x = r \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$ with
 $\cos \theta \sin \theta \neq 0$

$F(x) = r \cos \theta \sin \theta \sim \theta(x)$ but not $\theta(x)$

\Rightarrow not differentiable at $x = (0,0)$

Note: F differentiable at $x \Rightarrow F$ Lipschitz
continuous at x

Newton's method

(assume $m=u$)

Suppose F continuously differentiable near x_* such that

$$F(x_*) = 0$$

Then

$$0 = F(x_*) = F(x) + F'(x)(x_* - x) + \mathcal{O}(x_* - x)$$

$$\Rightarrow x_* = x - F'(x)^{-1} F(x) - \underbrace{F'(x)^{-1} \mathcal{O}(x_* - x)}_{\mathcal{O}(x - x_*)}$$

provided $F'(x)$ is invertible

so have

$$x_* \approx x_* \equiv x - F'(x)^{-1} F(x)$$

and

$$\frac{\|x_* - x_*\|}{\|x - x_*\|} \rightarrow 0 \quad \text{as } x \rightarrow x_*$$

approximation
gets
better and
better

given initial x

until termination do

$$x \leftarrow x - F'(x)^{-1} F(x) \quad \dots \quad (*)$$

Remarks:

(1) (*) is better phrased as

$$\text{solve } F'(x) \cdot s = -F(x)$$

$$\text{update } x \leftarrow x + s$$

(2) method breaks down if $F'(x)$ is singular
- numerical difficulties may occur if $F'(x)$
is ill-conditioned

(3) solving $F'(x) \cdot s = -F(x)$ takes up to $\mathcal{O}(n^3)$
arithmetic operations in general

(4) evaluating $F'(x)$ requires up to n^2 scalar function evaluations

(5) "until termination" much as before:
Termination criteria

$$\|F(x)\| \leq tol_F$$

$$\|x_t - x\| \leq tol_X$$

$$it.\text{ number} \geq ITMAX$$

as before must choose tol_F and tol_X with eye toward scales of F and x

(6) new complication: different components of F and x may have different scales
Might want to use diagonal scaling matrices D_F , D_x and use

$$\|D_F F(x)\| \leq tol_F$$

$$\|D_x x\| \leq tol_X$$

(7) convergence issues are much as before
Iterates may diverge in general but usually converge rapidly (typically quadratic) if initial guess is near solution

$$x_1^2 + x_1 x_2^3 = 9$$

$$3x_1^2 x_2 + x_2^3 = 4$$