

Nonlinear Algebraic Equations Example

Continuous Stirred Tank Reactor (CSTR).

Look for steady state concentrations & temperature.

In: N_s species with concentrations $c_i^{(in)}$,

heat capacities $c_{p,i}^{(in)}$ and temperature $T^{(in)}$

Inside: N_r reactions with stoichiometric coefficients $\sigma_{\alpha,i}$
and reaction constants r_α .

Out: N_s species with concentrations $c_i^{(in)}$

(c-s may be equal to zero),

heat capacities $c_{p,i}$ and temperature T .

Nonlinear Algebraic Equations Example

$$(F/V) \left[c_i^{(\text{in})} - c_i \right] + \sum_{\alpha=1}^{N_r} \sigma_{\alpha,i} r_{\alpha} = 0 \quad i = 1, 2, \dots, N_s$$

Mass balance for species 1, 2, ..., N_s

$$(F/V) \sum_{i=1}^{N_s} \left[c_i^{(\text{in})} c_{p,i}^{(\text{in})} T^{(\text{in})} - c_i c_{p,i} T \right] - \sum_{\alpha=1}^{N_r} \Delta H_{\alpha} r_{\alpha} = 0$$

Energy balance

Column of unknown variables : $\mathbf{x} = [c_1, c_2, \dots, c_{N_s}, T]^T$

Nonlinear Algebraic Equations Example

Each of the above equations may be written in the general form:

$$f_i(x_1, x_2, \dots, x_N) = 0:$$

$$f_1(x_1, x_2, \dots, x_N) = 0$$

$$f_2(x_1, x_2, \dots, x_N) = 0$$

...

$$f_N(x_1, x_2, \dots, x_N) = 0$$

In vector form:

$$f(\mathbf{x})=0$$

$$f(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) \\ f_2(\mathbf{x}) \\ \dots \\ f_N(\mathbf{x}) \end{bmatrix}$$

Let $\hat{\mathbf{x}}$ be the solution staisfying $f(\mathbf{x})=0$.

We do not know $\hat{\mathbf{x}}$ and take $\mathbf{x}^{[0]}$ as initial guess.

Nonlinear Algebraic Equations

We need to form a sequence of estimates to the solution:

$x^{[1]}, x^{[2]}, x^{[3]}, \dots$ that will hopefully converge to \hat{x} .

Thus we want: $\lim_{m \rightarrow \infty} x^{[m]} = \hat{x}$

$$\lim_{m \rightarrow \infty} \left\| \hat{x} - x^{[m]} \right\| = 0$$

Unlike with linear equations, we can't say much about existence or uniqueness of solutions, even for a single equation.

Single Nonlinear Equation

We assume $f(x)$ is infinitely differentiable at the solution \hat{x} .

Then $f(x)$ may be Taylor expanded around \hat{x} :

$$f(x) = f(\hat{x}) + (x - \hat{x})f'(\hat{x}) + \frac{1}{2}(x - \hat{x})^2 f''(\hat{x}) + \frac{1}{3!}(x - \hat{x})^3 f'''(\hat{x}) + \dots$$

Assume $x^{[0]}$ being close to \hat{x} so that the series may be truncated:

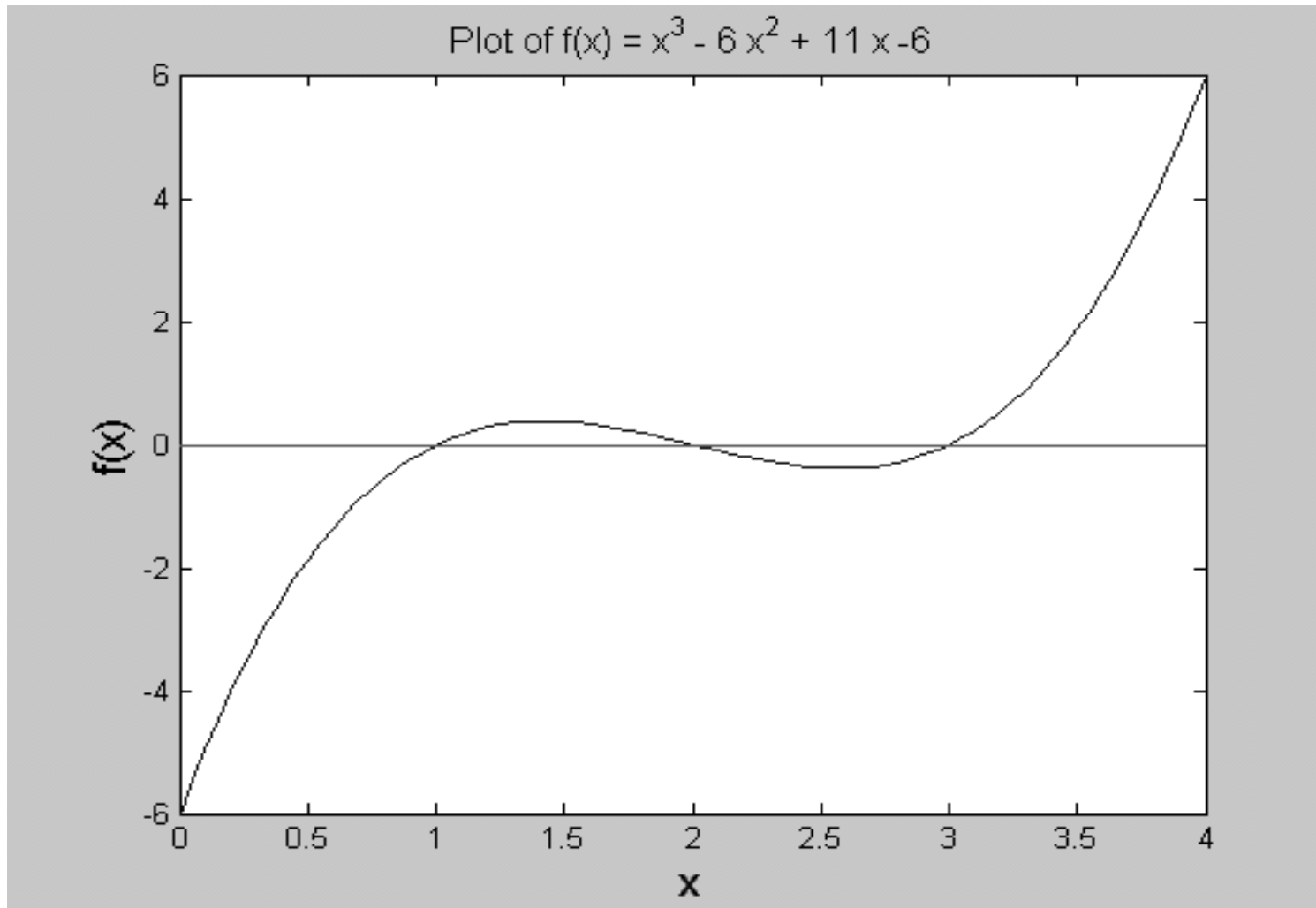
$$f(x^{[0]}) \approx (x^{[0]} - \hat{x})f'(\hat{x}), \quad \text{or}$$

$$f(x^{[0]}) \approx (x^{[0]} - x^{[1]})f'(x^{[0]}) \quad x^{[1]} = x^{[0]} - \frac{f(x^{[0]})}{f'(x^{[0]})}$$

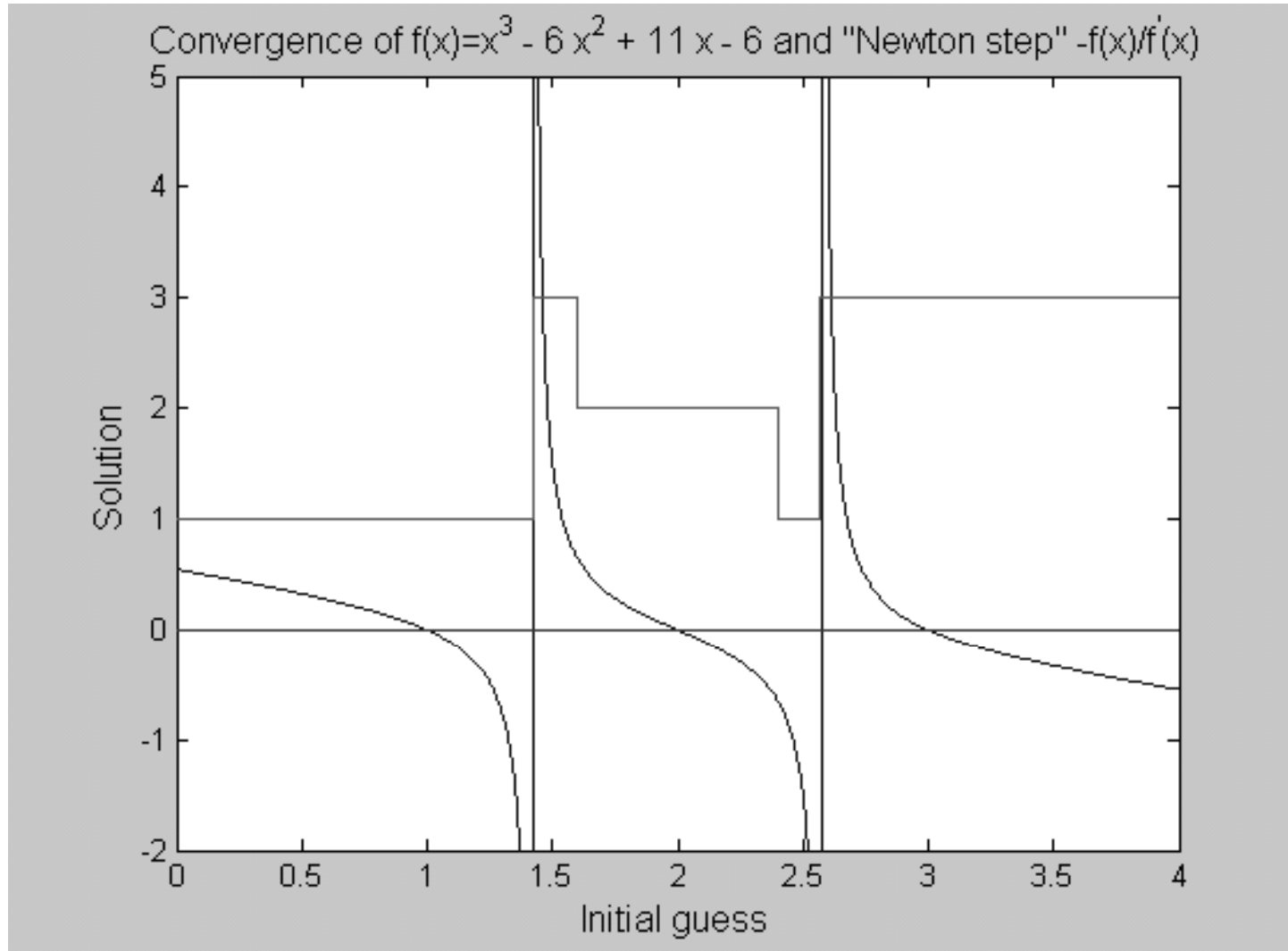
– Newton's method

Example : $f(x) = (x - 3)(x - 2)(x - 1) = x^3 - 6x^2 + 11x - 6$

Single Nonlinear Equation



Single Nonlinear Equation



Single Nonlinear Equation

For $f(x)=(x-3)(x-2)(x-1)=x^3-6x^2+11x+6=0$, we see that Newton's method converges to the root at $x=2$ only if $1.6 < x^{[0]} < 2.4$.

We may look at the direction of the first step and see why:

$$x^{[1]} - x^{[0]} = -f(x^{[0]}) / f'(x^{[0]}).$$

So, we have 2 “easy” roots: $x=1$, $x=3$ and a more difficult one.

We may “factorize out” the roots we already know.

Single Nonlinear Equation

Introduce $g(x) = \frac{f(x)}{(x-3)(x-1)}$

$$g'(x) = \frac{f'(x)}{(x-3)(x-1)} - \frac{f(x)}{(x-3)(x-1)} \left(\frac{1}{(x-3)} + \frac{1}{(x-1)} \right)$$

We now use Newton's method to find the roots of $g(x)$:

$$x^{[i+1]} = x^{[i]} - \frac{g(x)}{g'(x)} \rightarrow \text{get } x = 2.$$

Systems of Nonlinear Equations

Let's extend the method to multiple equations:

$$f_1(x_1, x_2, x, \dots, x_N) = 0$$

$$f_2(x_1, x_2, x, \dots, x_N) = 0 \quad \Rightarrow \quad f(x) = 0$$

.....

$$f_N(x_1, x_2, x, \dots, x_N) = 0$$

Start from initial guess $x^{[0]}$

As before expand each equation at the solution \hat{x} with $f(\hat{x}) = 0$:

$$f_i(x) = f_i(\hat{x}) + \sum_{j=1}^N (x_j - \hat{x}_j) \frac{\partial f_i(\hat{x})}{\partial x_j} + \frac{1}{2} \sum_{j=1}^N \sum_{k=1}^N (x_j - \hat{x}_j) \frac{\partial^2 f_i(\hat{x})}{\partial x_j \partial x_k} (x_k - \hat{x}_k) + \dots$$

Assume $x^{[0]}$ is close to \hat{x} and discard quadratic terms:

$$f_i(x) \approx \sum_{j=1}^N (x_j - \hat{x}_j) \frac{\partial f_i(\hat{x})}{\partial x_j}$$

Systems of Nonlinear Equations

Let's define the Jacobian matrix $J(\hat{\mathbf{x}})$ with the elements:

$$J_{ij}(\hat{\mathbf{x}}) = \frac{\partial f_i(\hat{\mathbf{x}})}{\partial x_j}$$

Then our approximate expansion may be written as:

$$f_i(\mathbf{x}) \approx \sum_{j=1}^N J_{ij}(\hat{\mathbf{x}})(x_j - \hat{x}_j) = \left(J(\hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}}) \right)_i$$

This gives us the linear system:

$$\mathbf{f}(\mathbf{x}) \approx J(\hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}})$$

Systems of Nonlinear Equations

$$\mathbf{f}(\mathbf{x}^{[i]}) = \mathbf{J}(\mathbf{x}^{[i]})(\mathbf{x}^{[i]} - \mathbf{x}^{[i+1]}) = \left(\mathbf{J}(\hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}}) \right)_i$$

Note, Jacobian is evaluated at the position of an old iteration, not at an unknown solution

Defining $\Delta\mathbf{x}^{[i]} = \mathbf{x}^{[i+1]} - \mathbf{x}^{[i]}$, we rewrite the equation as

$$\mathbf{J}(\mathbf{x}^{[i]})\Delta\mathbf{x}^{[i]} = -\mathbf{f}(\mathbf{x}^{[i]}) \quad \text{or just} \quad \mathbf{J}^{[i]}\Delta\mathbf{x}^{[i]} = -\mathbf{f}^{[i]}$$

The iterations are continued until some convergence criteria are met:

$$\text{relative error} \quad \|\mathbf{f}^{[i]}\| \leq \delta_{\text{rel}} \|\mathbf{f}^{[0]}\|$$

$$\text{absolute error} \quad \|\mathbf{f}^{[i]}\| \leq \delta_{\text{abs}}$$

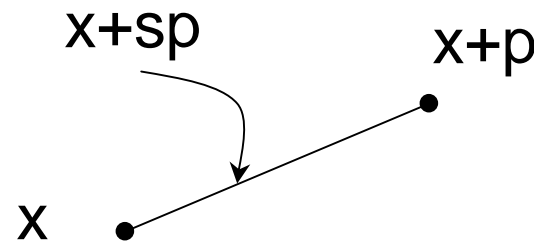
Systems of Nonlinear Equations

Newton's method does not always converge. If it does, can we estimate the error?

Let our function $f(x)$ be continuously differentiable in the vicinity of x and the vector connecting x and $x + p$ all lies inside this vicinity.

$$J(x + sp) = \left. \frac{\partial f}{\partial x^T} \right|_{x+sp}$$

$$f(x + p) = f(x) + \int_0^1 J(x + sp) p \, ds$$



– use path integral along the line $x - x+p$, parametrized by s .

Systems of Nonlinear Equations

Add and subtract $J(x)p$ to RHS:

$$\underbrace{f(x+p) - f(x) - J(x)p}_{\text{error}} = \int_0^1 [J(x+sp) - J(x)] p ds$$

In Newton's method we ignore the integral term and choose p to estimate $f(x+p)$. Thus the error in this case is:

$$\int_0^1 [J(x+sp) - J(x)] p ds = \text{error}$$

What is the upper bound on this error?

$f(x)$ and $J(x)$ are continuous:

$$\|J(x+sp) - J(x)\| \rightarrow 0 \text{ as } p \rightarrow 0 \text{ for all } 0 \leq s \leq 1.$$

Systems of Nonlinear Equations

The norm of the matrix is defined as: $\|A\| = \max_{v \neq 0} \frac{\|Av\|}{\|v\|}$,

so for any y $\|A\| \geq \frac{\|Ay\|}{\|y\|}$, or $\|Ay\| \leq \|A\| \|y\|$, therefore

$$\left\| \int_0^1 [J(x+sp) - J(x)] p ds \right\| \leq \left\| \int_0^1 [J(x+sp) - J(x)] ds \right\| \|p\|$$

The error goes down at least as fast as $\|p\|$ because for a continuous Jacobian $\|J(x+sp) - J(x)\| \rightarrow 0$ as $p \rightarrow 0$.

Systems of Nonlinear Equations

If we suggest that there exist some $L > 0$ such that

$$\|J(y) - J(z)\| \leq L \|y - z\|$$

or there is some upper bound on the "stretching" effect of J .

$$\|f(x + sp)\| = \left\| \int_0^1 [J(x + sp) - J(x)] p \, ds \right\| \leq \left\| \int_0^1 [J(x + sp) - J(x)] \, ds \right\| \|p\|$$

and $\left\| \int_0^1 [J(x + sp) - J(x)] \, ds \right\| \leq L |s| \|p\|$, so in this case

$$\begin{aligned} \|f(x + sp)\| &= \left\| \int_0^1 [J(x + sp) - J(x)] p \, ds \right\| \leq (L |s| \|p\|) \|p\| \\ &\leq (L |s|) \|p\|^2 = O(\|p\|^2) \end{aligned}$$

Systems of Nonlinear Equations

Thus if we are at distance p from the solution, our error scales as $\|p\|^2$.

What about convergence? How the error scales with the number of iterations?

The answer is:

$$\left\| \mathbf{x}^{[i+1]} - \hat{\mathbf{x}} \right\| = O\left(\left\| \mathbf{x}^{[i]} - \hat{\mathbf{x}} \right\|^2 \right) - \text{local quadratic convergence,}$$

a very fast one! Works when you are close enough to the solution.

Systems of Nonlinear Equations

$$\left\| \mathbf{x}^{[i]} - \hat{\mathbf{x}} \right\| \sim 0.1 = 10^{-1}$$

$$\left\| \mathbf{x}^{[i+1]} - \hat{\mathbf{x}} \right\| \sim 0.01 = 10^{-2}$$

$$\left\| \mathbf{x}^{[i+2]} - \hat{\mathbf{x}} \right\| \sim 0.00001 = 10^{-4}$$

$$\left\| \mathbf{x}^{[i+3]} - \hat{\mathbf{x}} \right\| \sim 0.000000001 = 10^{-8}$$

Works if we are close enough to an isolated

(non-singular) solution: $\det \left[\mathbf{J}(\hat{\mathbf{x}}) \right] \neq 0$.

Systems of Nonlinear Equations, Example

Let's examine how Newton's method works for a simple system:

$$\begin{aligned} f_1 &= 3x_1^3 + 4x_2^2 - 145 = 0 \\ f_2 &= 4x_1^2 - x_2^3 + 28 = 0 \end{aligned} \quad \hat{\mathbf{x}} = \begin{bmatrix} 3 \\ 4 \end{bmatrix}$$

The Jacobian is:

$$\mathbf{J} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 9x_1^2 & 8x_2 \\ 8x_1 & -3x_2^2 \end{bmatrix}$$

Systems of Nonlinear Equations, Example

At each step we have the following system to solve :

$$\mathbf{J}^{[i]} = \begin{bmatrix} 9(x_1^{[i]})^2 & 8x_2^{[i]} \\ 8x_1^{[i]} & -3(x_2^{[i]})^2 \end{bmatrix}$$

$$\mathbf{f}^{[i]} = \begin{bmatrix} 3(x_1^{[i]})^3 + 4(x_2^{[i]})^2 - 145 \\ 4(x_1^{[i]})^2 - (x_2^{[i]})^3 + 28 \end{bmatrix}$$

$$\mathbf{J}^{[i]} \Delta \mathbf{x}^{[i]} = -\mathbf{f}^{[i]} \quad \mathbf{x}^{[i+1]} = \mathbf{x}^{[i]} + \Delta \mathbf{x}^{[i]}$$

Systems of Nonlinear Equations, Example

Let us examine performance of
Newton's method with the convergence
criterion $\|f\| = \max\{|f_1|, |f_2|\} < \delta_{\text{abs}}$

$$\delta_{\text{bs}} = 10^{-10}$$

Newton's Method

Newton's method works well close to the solution, but otherwise takes large erratic steps, shows poor performance and reliability.

Let's try to avoid such large steps: employ reduced step Newton's algorithm.

“Full” Newton's step gives $x^{[i+1]} = x^{[i]} + p^{[i]}$. We'll use only fraction of of the step: $x^{[i+1]} = x^{[i]} + \lambda_i p^{[i]}$, $0 < \lambda_i < 1$.

Newton's Method

How do we choose λ_i ?

Simplest way - weak line search:

- start with $\lambda_i = 2^{-m}$ for $m=0,1,2,\dots$

As we reduce the value of λ_i by a factor of 2 at each step, we accept the first one that satisfies a

descent criterion:
$$\|f(\mathbf{x}^{[i]} + \lambda_i \mathbf{p}^{[i]})\| < \|f(\mathbf{x}^{[i]})\|$$

It can be proven that if the Jacobian is not singular, the correct solution will be found by the reduced step Newton's algorithm.