

## Ch 10.2: Newton's method for systems

Tuesday, September 23, 2025

2:18 PM

Let  $F(\vec{x}) = \begin{bmatrix} f_1(\vec{x}) \\ \vdots \\ f_n(\vec{x}) \end{bmatrix}$ ,  $F: \mathbb{R}^n \rightarrow \mathbb{R}^n$ . Look for a solution  $F(\vec{x}) = \vec{0}$ .  
 $n$  equations,  $n$  variables  
For now, these must match

Multi-dim. Taylor Series:

$$F(\vec{x}) = \underbrace{F(\vec{x}^{(k)}) + \overset{\text{Jacobian}}{J_F(\vec{x}^{(k)})} \cdot (\vec{x} - \vec{x}^{(k)})}_{\text{this is our model } m(\vec{x})} + \dots \text{higher order terms that we'll neglect } \dots$$

Solve for a root of our simple model

Find  $\vec{x}$  st.

$$0 = F(\vec{x}^{(k)}) + J_F(\vec{x}^{(k)}) \cdot (\vec{x} - \vec{x}^{(k)})$$

Recall the Jacobian

$$(J_F(\vec{x}))_{ij} = \frac{\partial f_i}{\partial x_j}(\vec{x})$$

$$\text{i.e. } J_F(\vec{x}) = \begin{bmatrix} -\nabla f_1(\vec{x})^T \\ \vdots \\ -\nabla f_n(\vec{x})^T \end{bmatrix}$$

i.e. NEWTON'S METHOD

$$\vec{x}^{(k+1)} = \vec{x}^{(k)} - J_F(\vec{x}^{(k)})^{-1} \cdot F(\vec{x}^{(k)})$$

$$\begin{bmatrix} \end{bmatrix} = \begin{bmatrix} \end{bmatrix} - \begin{bmatrix} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \end{bmatrix}$$

use LU factorization  
or backslash (Matlab)  
or np.linalg.solve (J, F)

NOT inverse.

generalizes 1D case

$$x^{(k+1)} = x^{(k)} - \frac{f(x^{(k)})}{f'(x^{(k)})}$$

- Like 1D case,
- ① need not converge  $\begin{matrix} \nearrow \text{diverge} \\ \text{or} \\ \searrow f'(x)=0 \text{ or } J(\vec{x}) \text{ is singular} \end{matrix}$
  - ② for nice problems, if started close enough, converges quadratically.
  - ③ computing derivatives (Jacobian) is annoying  
... autodiff helps...

Unlike 1D case,

- Solving  $J_F(\vec{x}^{(k)})^{-1} F(\vec{x}^{(k)})$  costs  $O(n^3)$  flops  
in general... it gets worse as dimension  $n$  increases  
So it's rare to use Newton in very high dimension
- Often approximately solve, eg. via a Krylov Subspace method  
we'll see later... and use Jacobian-vector-products from  
your autodiff software.

## Ch 10.2, p. 2: Affine Invariance of Newton's method

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2:23 PM

Affine change-of-variables won't affect convergence rate  
( $\Rightarrow$  Newton is impervious to some types of ill-conditioning)

$$F(\vec{x}) = \vec{0}, \text{ Newton is } \vec{x} \leftarrow \vec{x} - J_F(\vec{x})^{-1} F(\vec{x})$$

try  $\tilde{F}(\vec{y}) = \vec{0}$ ,  $\tilde{F}(\vec{y}) := F(\underbrace{A\vec{y} + \vec{b}}_{\substack{\text{invertible} \\ \text{affine transformation of } \vec{y}}})$

This is an equivalent problem, in this sense

$$\left. \begin{array}{l} \tilde{F}(\vec{y}) = \vec{0} \Rightarrow \vec{x} = A\vec{y} + \vec{b} \text{ is a root of } F \\ F(\vec{x}) = \vec{0} \Rightarrow \vec{y} = A^{-1}(\vec{x} - \vec{b}) \text{ is a root of } \tilde{F} \end{array} \right\}$$

run Newton on  $\tilde{F}$ :

$$\vec{y} \leftarrow \vec{y} - J_{\tilde{F}}(\vec{y})^{-1} \tilde{F}(\vec{y})$$

$$J_{\tilde{F}}(\vec{y}) = J_F(A\vec{y} + \vec{b}) \cdot A \quad \text{via chain rule}$$

$$\vec{y} \leftarrow \vec{y} - (J_F(A\vec{y} + \vec{b}) A)^{-1} F(A\vec{y} + \vec{b})$$

$$\vec{y} \leftarrow \vec{y} - A^{-1} J_F(A\vec{y} + \vec{b})^{-1} F(A\vec{y} + \vec{b})$$

$$A\vec{y} \leftarrow A\vec{y} - J_F(A\vec{y} + \vec{b})^{-1} F(A\vec{y} + \vec{b})$$

$$A\vec{y} + \vec{b} \leftarrow A\vec{y} + \vec{b} - J_F(A\vec{y} + \vec{b})^{-1} F(A\vec{y} + \vec{b})$$

$$\vec{x} \leftarrow \vec{x} - J_F(\vec{x})^{-1} F(\vec{x}) \quad \vec{x} := A\vec{y} + \vec{b}$$

which is our original Newton iteration