#### TDT4127 Programming and Numerics Week 42

Newton's method in multiple dimensions



# Learning goals

- Goals
  - Solving nonlinear systems of equations
  - Algorithm:
    - Newton's method for systems
- Curriculum
  - Exercise set 7
  - Programming for Computations Python
    - Ch. 6.6





#### Newton's method

• Week 38-39: Newton's method for scalar equations:

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

- There is a natural extension to multiple dimensions
   Topic of this week's lecture
- Will only cover the formulation of it, not theory around



### **Systems of equations**

• A system of (nonlinear) equations:

$$f_0(x_0, x_1, ..., x_n) = 0$$
  

$$f_1(x_0, x_1, ..., x_n) = 0$$
  
:  

$$f_n(x_0, x_1, ..., x_n) = 0$$

- Unlike linear systems, we **cannot** say more about the structure of the  $f_i$ , and can't write it in matrix-vector form.
- We can write the system more compactly with vectors:

$$\boldsymbol{x} = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}, \qquad \boldsymbol{f}(\boldsymbol{x}) = \begin{bmatrix} f_0(\boldsymbol{x}) \\ f_1(\boldsymbol{x}) \\ \vdots \\ f_n(\boldsymbol{x}) \end{bmatrix} = \boldsymbol{0}$$



- We want to solve the nonlinear system of equations f(x) = 0
- What is the trick we've been using all along?
   That's right linearization!
- Idea: Exchange the nonlinear system of equations with a linear system, and solve

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

• Step 1: Find an approximate linear system g(x)



### Linear approximation

In the 1D case, Taylor's theorem gives a linear approximation:

 $f(\mathbf{x}) \approx f(\mathbf{x}^k) + f'(\mathbf{x}^k)(\mathbf{x} - \mathbf{x}^k)$ 

• In several dimensions, Taylor's theorem also gives a linear approximation, using partial derivatives:

• 
$$f_j(\mathbf{x}) \approx f_j(\mathbf{x}^k) + \frac{\partial f_j}{\partial x_0}(\mathbf{x}^k)(\mathbf{x}_0 - \mathbf{x}_0^k)$$
  
  $+ \frac{\partial f_j}{\partial x_1}(\mathbf{x}^k)(\mathbf{x}_1 - \mathbf{x}_1^k) + \dots + \frac{\partial f_j}{\partial x_n}(\mathbf{x}^k)(\mathbf{x}_n - \mathbf{x}_n^k)$ 



#### Linear approximation

- So, each equation is approximated by
- $g_{0}(\mathbf{x}) = b_{0} + a_{00}(x_{0} x_{0}^{k}) + a_{01}(x_{1} x_{1}^{k}) + \dots + a_{0n}(x_{n} x_{n}^{k})$   $g_{1}(\mathbf{x}) = b_{1} + a_{10}(x_{0} x_{0}^{k}) + a_{11}(x_{1} x_{1}^{k}) + \dots + a_{1n}(x_{n} x_{n}^{k})$   $\vdots$   $g_{n}(\mathbf{x}) = b_{n} + a_{n0}(x_{0} x_{0}^{k}) + a_{n1}(x_{1} x_{1}^{k}) + \dots + a_{nn}(x_{n} x_{n}^{k})$ where

$$b_j = f_j(x^k), \qquad a_{jl} = \frac{\partial f_j}{\partial x_l}(x^k)$$

• This is a linear system!

$$\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{b} + A\big(\boldsymbol{x} - \boldsymbol{x}^k\big)$$



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$$\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{b} + A\big(\boldsymbol{x} - \boldsymbol{x}^k\big)$$

• The matrix A is called the Jacobian of f and is often written  $J_f(x^k)$ . In general:

$$J_{f}(y) = \begin{bmatrix} \frac{\partial f_{0}}{\partial x_{0}}(y) & \frac{\partial f_{0}}{\partial x_{1}}(y) & \cdots & \frac{\partial f_{0}}{\partial x_{n}}(y) \\ \frac{\partial f_{1}}{\partial x_{0}}(y) & \frac{\partial f_{1}}{\partial x_{1}}(y) & \cdots & \frac{\partial f_{1}}{\partial x_{n}}(y) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_{n}}{\partial x_{0}}(y) & \frac{\partial f_{n}}{\partial x_{1}}(y) & \cdots & \frac{\partial f_{n}}{\partial x_{n}}(y) \end{bmatrix}$$



• This is a linear system!

$$\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{b} + A\big(\boldsymbol{x} - \boldsymbol{x}^k\big)$$

- Note also that  $b = f(x^k)$  so we have, more precisely:  $g(x) = f(x^k) + J_f(x^k)(x - x^k)$
- We solve g(x) = 0 in two steps:
- 1. Solve the linear system  $J_f(x^k)y = -f(x^k)$
- 2. Compute  $x = x^k + y$



• We could also directly solve

$$f(x^k) + J_f(x^k)(x - x^k) = 0$$

by writing

$$\boldsymbol{x} = \boldsymbol{x}^k - J_f(\boldsymbol{x}^k)^{-1} f(\boldsymbol{x}^k)$$

• This formulation is a bit misleading, though – we don't want to actually compute  $J_f(x^k)^{-1}$ , just solve the linear system! Hence the two-step formulation from last slide.



Solving g(x) = 0 does not give us the exact solution since g only approximates f, but we get a method from it:

$$x^{k+1} = x^k - J_f(x^k)^{-1} f(x^k)$$

• Note the similarities with 1D-Newton:

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

• As with 1D-Newton, we require stopping conditions



## **Stopping conditions**

• 1D Newton's method: Stop when

$$|x^{k+1}-x^k| < \delta$$
, or  $|f(x^{k+1})| < \epsilon$ .

... or a combination of the two

Here: stop on reaching one or more of the following:
 |x<sub>i</sub><sup>k+1</sup> − x<sub>i</sub><sup>k</sup>| < δ for all j</li>

$$-\sqrt{(x_0^{k+1}-x_0^k)^2 + (x_1^{k+1}-x_1^k)^2 + \dots + (x_n^{k+1}-x_n^k)^2} < \delta$$

$$- |f_j(\mathbf{x^{k+1}})| < \epsilon \text{ for all } j$$

 $-\sqrt{f_0(x^{k+1})^2 + f_1(x^{k+1})^2 + \dots + f_n(x^{k+1})^2} < \epsilon$ 

• We can pick and choose stopping conditions based on what seems reasonable for the problem.



### **Programming Newton's for systems**

- 1. Write code for evaluating  $J_f(x^k)$  and  $f(x^k)$
- 2. Choose an initial guess  $x^0$
- 3. Iterate until stopping condition is met:
  - 1. Solve the linear system  $J_f(x^k)y = -f(x^k)$
  - 2. Compute  $x^{k+1} = x^k + y$

**Demonstration:** newtonSkeleton.py



## Summary

- We can generalize Newton's method to higherdimensional equations
  - Relies on a linearization of the problem
  - Uses the Jacobian of the function we want to find a root of
- Newton's method for systems requires vectors and matrices, and each step requires solution of a linear system
- Implementation is best done using several subfunctions



# Questions?

