

# Numerical Methods I: Newton and nonlinear least squares

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Newton's method to solve  $F(\boldsymbol{x}) = \mathbf{0}$ ,  $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$

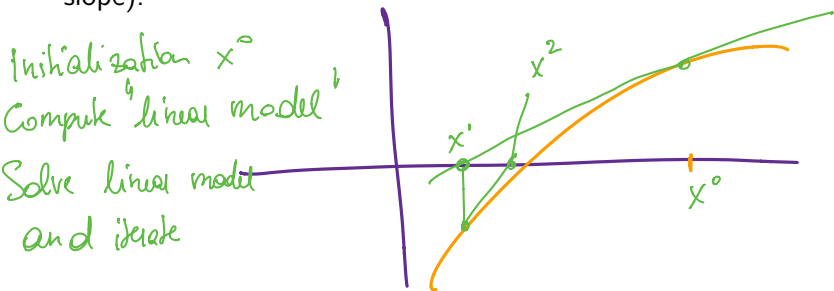
# Newton's method: Example

In one dimension, solve  $f(x) = 0$  with  $f : \mathbb{R} \rightarrow \mathbb{R}$ :

Start with  $x_0$ , and compute  $x_1, x_2, \dots$  from

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}, \quad k = 0, 1, \dots$$

Requires  $f'(x_k) \neq 0$  to be well-defined (i.e., tangent has nonzero slope).



# Newton's method

Let  $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ ,  $n \geq 1$  and solve

$$F(\mathbf{x}) = 0.$$

Taylor expansion about starting point  $\mathbf{x}^0$ :

$$F(\mathbf{x}) = F(\mathbf{x}^0) + F'(\mathbf{x}^0)(\mathbf{x} - \mathbf{x}^0) + o(|\mathbf{x} - \mathbf{x}^0|) \quad \text{for } \mathbf{x} \rightarrow \mathbf{x}^0.$$

Hence:

$$\mathbf{x}^1 = \mathbf{x}^0 - \overbrace{F'(\mathbf{x}^0)^{-1}F(\mathbf{x}^0)}^{\Delta \mathbf{x} \text{ Newton step/increment}}$$

**Newton iteration:** Start with  $\mathbf{x}^0 \in \mathbb{R}^n$ , and for  $k = 0, 1, \dots$  compute

$$F'(\mathbf{x}^k)\Delta \mathbf{x}^k = -F(\mathbf{x}^k), \quad \mathbf{x}^{k+1} = \mathbf{x}^k + \Delta \mathbf{x}^k$$

Requires that  $F'(\mathbf{x}^k) \in \mathbb{R}^{n \times n}$  is invertible.

Terminate iteration when  $\|F(\mathbf{x}^k)\| < \epsilon$  or  $\frac{\|F(\mathbf{x}^k)\|}{\|F(\mathbf{x}^0)\|} < \tilde{\epsilon}$

# Newton's method

**Newton iteration:** Start with  $\mathbf{x}^0 \in \mathbb{R}^n$ , and for  $k = 0, 1, \dots$   
compute

$$F'(\mathbf{x}^k) \Delta \mathbf{x}^k = -F(\mathbf{x}^k), \quad \mathbf{x}^{k+1} = \mathbf{x}^k + \Delta \mathbf{x}^k$$

Equivalently:

$$\mathbf{x}^{k+1} = \mathbf{x}^k - F'(\mathbf{x}^k)^{-1} F(\mathbf{x}^k)$$

Newton's method is **affine invariant**, that is, the sequence is invariant to affine transformations:

Instead of solving  $F(\mathbf{x}) = 0$  solve  $AF(\mathbf{x}) = G(\mathbf{x}) = 0$   
Newton iteration for  $G(\mathbf{x}) = 0$ :  $A \in \mathbb{R}^{n \times n}, \det(A) \neq 0$

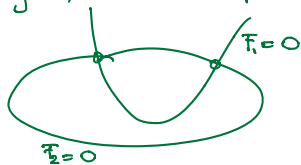
$$\begin{aligned} \Delta \mathbf{x} &= -G'(\mathbf{x}^k)^{-1} G(\mathbf{x}^k) = (AF'(\mathbf{x}^k))^{-1} AF(\mathbf{x}^k) \\ &= F'(\mathbf{x}^k)^{-1} \cancel{A^{-1}A} F(\mathbf{x}^k) = F'(\mathbf{x}^k)^{-1} F(\mathbf{x}^k) = \text{Newton step computed using } F \end{aligned}$$

# Newton's method

Intersection point between  $F_1(x,y) = y - x^2 + x = 0$  parabola

$F_2(x,y) = \frac{x^2}{16} + y^2 - 1 = 0$  ellipse

$$F(x,y) = \begin{pmatrix} F_1(x,y) \\ F_2(x,y) \end{pmatrix} = \begin{pmatrix} y - x^2 + x \\ \frac{x^2}{16} + y^2 - 1 \end{pmatrix}, \quad F: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$



$$F'(x,y) = \begin{pmatrix} \frac{\partial F_1(x,y)}{\partial x} & \frac{\partial F_1(x,y)}{\partial y} \\ \frac{\partial F_2(x,y)}{\partial x} & \frac{\partial F_2(x,y)}{\partial y} \end{pmatrix} = \begin{pmatrix} -2x+1 & 1 \\ \frac{x}{8} & 2y \end{pmatrix}$$

Newton iterations

$$x^0 = \begin{pmatrix} 1 \\ 0 \end{pmatrix},$$

Solve

$$\begin{pmatrix} -1 & 1 \\ \frac{1}{8} & 0 \end{pmatrix} \Delta x = -F(x^0)$$

$\rightarrow x^1 = x^0 + \Delta x$  repeat, stop if  $\|F(x^k)\| < \epsilon$

## Convergence of Newton's method

**Assumptions on  $F$ :**  $D \subset \mathbb{R}^n$  open and convex,  $F : D \rightarrow \mathbb{R}^n$  continuously differentiable with  $F'(\mathbf{x})$  is invertible for all  $\mathbf{x}$ , and there exists  $\omega \geq 0$  such that

$$\|F'(\mathbf{x})^{-1}(F'(\mathbf{x} + s\mathbf{v}) - F'(\mathbf{x}))\mathbf{v}\| \leq s\omega\|\mathbf{v}\|^2$$

for all  $s \in [0, 1]$ ,  $\mathbf{x} \in D$ ,  $\mathbf{v} \in \mathbb{R}^n$  with  $\mathbf{x} + \mathbf{v} \in D$ .

**Assumptions on  $\mathbf{x}^*$  and  $\mathbf{x}^0$ :** There exists a solution  $\mathbf{x}^* \in D$  and a starting point  $\mathbf{x}^0 \in D$  such that

$$\rho := \|\mathbf{x}^* - \mathbf{x}^0\| \leq \frac{2}{\omega} \text{ and } B_\rho(\mathbf{x}^*) \subset D$$

**Theorem:** Then, the Newton sequence  $\mathbf{x}^k$  stays in  $B_\rho(\mathbf{x}^*)$  and  $\lim_{k \rightarrow \infty} \mathbf{x}^k = \mathbf{x}^*$ , and

$$\|\mathbf{x}^{k+1} - \mathbf{x}^*\| \leq \frac{\omega}{2} \|\mathbf{x}^k - \mathbf{x}^*\|^2$$

# Convergence of Newton's method

$$x, y \in \mathcal{D}$$

Mean theorem for integrals:

$$F(y) - F(x) - F'(x)(y-x) = \int_0^1 (F'(x+s(y-x)) - F'(x))(y-x) ds$$

take norms:

$$\|F'(x)^{-1} \left[ \int \dots \right]\| \leq \int_{s=0}^1 s \omega \|y-x\|^2 ds = \frac{\omega}{2} \|y-x\|^2$$

$$\|F'(x)^{-1} (F(y) - F(x) - F'(x)(y-x))\| \leq \frac{\omega}{2} \|y-x\|^2 \quad (1)$$

$$\begin{aligned} x^{k+1} - x^* &= x^k - F'(x^k)^{-1} F(x^k) - x^* \\ &= x^k - x^* - F'(x^k)^{-1} (F(x^k) - F(x^*)) \\ &= F'(x^k)^{-1} [F(x^*) - F(x^k) - F'(x^k)(x^* - x^k)] \end{aligned} \quad (2)$$

$$\stackrel{(1)+(2)}{\implies} \|x^{k+1} - x^*\| \leq \frac{\omega}{2} \|x^k - x^*\|^2 \longrightarrow \text{quadratic convergence}$$



# Convergence of Newton's method

$$0 < \|x^k - x^*\| \leq \rho$$

$$\|x^{k+1} - x^*\| \leq \underbrace{\frac{L}{2} \|x^k - x^*\|}_{\leq \frac{L}{2} \rho \leq 1} \|x^k - x^*\|$$

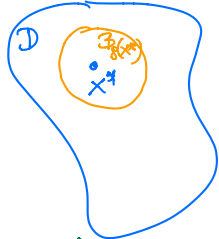
$\Rightarrow$  I'm staying in  $\mathcal{B}_\rho(x^*)$  if  $x^k$  is in  $\mathcal{B}_\rho(x^*)$

Uniqueness:  $x^*$ ,  $x^{**}$  solutions

$$\|x^* - x^{**}\| \leq \underbrace{\frac{L}{2} \|x^* - x^{**}\|}_{\leq 1} \|x^* - x^{**}\|$$

$$\Rightarrow \|x^* - x^{**}\| < \|x^* - x^{**}\|$$

$$\rightarrow x^* = x^{**}$$



(first general result  
on previous  
page)

□.

# Newton's method—when does convergence theorem apply?

- ▶ Example 1:  $f(x) = x^3$

$$x^* = 0 \text{ solution}$$

$$f'(x^*) = 0$$

1, x: 0.666666666667  
2, x: 0.444444444444  
3, x: 0.296296296296  
...  
17, x: 0.001014959227  
18, x: 0.000676639485  
19, x: 0.000451092990  
20, x: 0.000300728660

- ▶ Example 2:  $f(x) = x^{3/2}$

$$x^* = 0 \text{ solution}$$

$$f'(x^*) = 0$$

1, x: 0.333333333333  
2, x: 0.111111111111  
3, x: 0.037037037037  
4, x: 0.012345679012  
...  
16, x: 0.000000023231  
17, x: 0.00000007744  
18, x: 0.00000002581  
19, x: 0.00000000860  
20, x: 0.00000000287

# Newton's method

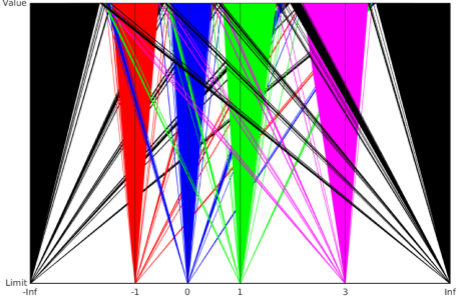
## Role of initialization

Choice of **initialization**  $x^0$  is critical. Depending on the initialization, the Newton iteration might

- ▶ not converge (it could “blow up” or “oscillate” between two points)
- ▶ converge to different solutions
- ▶ fail cause it hits a point where the Jacobian is not invertible (this cannot happen if the conditions of the convergence theorem are satisfied)
- ▶ ...

# Global Behavior of Newton Method

Start Value



Limit

$-\infty$

$-1$

$0$

$1$

$3$

$\infty$

# Newton's method

## Convergence of Newton's method

- ▶ The “more nonlinear” a problem, the harder it is to solve.

$$\|F'(\mathbf{x})^{-1}(F'(\mathbf{x} + s\mathbf{v}) - F'(\mathbf{x}))\mathbf{v}\| \leq s\omega\|\mathbf{v}\|^2$$

very nonlinear  $\rightarrow F'(\mathbf{x})$  changes  
a lot  
 $\rightarrow \omega$  large

- ▶ **Computation of Jacobian**  $F'(\mathbf{x}^k)$  can be costly/complicated

(sometimes approximations of  $F'(\mathbf{x}^k)$  are used)

# Newton's method

## Convergence of Newton's method

- ▶ There's **no reliable black-box solver** for nonlinear problems; at least for higher-dimensional problems, the structure of the problem must be taken into account.
  
- ▶ Sometimes, **continuation ideas** must be used to find good initializations: Solve simpler problems first and use solution as starting point for harder problems.

**Monotonicity test** (affine invariant):

$$\|F'(\mathbf{x}^k)^{-1}F(\mathbf{x}^{k+1})\| \leq \bar{\Theta} \|F'(\mathbf{x}^k)^{-1}F(\mathbf{x}^k)\|, \quad \bar{\Theta} < 1$$

**Damping:**

$$\mathbf{x}^{k+1} = \mathbf{x}^k + \lambda_k \Delta \mathbf{x}^k, \quad 0 < \lambda_k \leq 1$$

For difficult problems, start with small  $\lambda_k$  and increase later in the iteration (close to the solution  $\lambda_k$  should be 1).

**Approximative Jacobians:** Use approximative Jacobians  $\tilde{F}'(\mathbf{x}^k)$ , e.g., computed through finite differences.

# Nonlinear versus linear problems

“Classification of mathematical problems as linear and nonlinear is like classification of the Universe as bananas and non-bananas.”

or (according to Stanislav Ulam):

Using a term like nonlinear science is like referring to the bulk of zoology as the study of non-elephant animals.



## Nonlinear least squares—Gauss-Newton

# Nonlinear least-squares problems

Assume a least squares problem, where the parameters  $\mathbf{x}$  do *not* enter linearly into the model. Instead of

$$\min_{\mathbf{x} \in \mathbb{R}^n} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2,$$

we have with  $F : D \rightarrow \mathbb{R}^m$ ,  $D \subset \mathbb{R}^n$ :

$$\min_{\mathbf{x} \in \mathbb{R}^n} g(\mathbf{x}) := \frac{1}{2} \|F(\mathbf{x})\|^2, \quad \text{where } F(\mathbf{x})_i = \varphi(t_i, \mathbf{x}) - b_i, 1 \leq i \leq m$$

The (local) minimum  $\mathbf{x}^*$  of this optimization problem satisfies:

$$g'(\mathbf{x}) = 0, \quad g''(\mathbf{x}) \text{ is positive definite.}$$

# Nonlinear least-squares problems

$$g(\mathbf{x}) = \frac{1}{2} \|F(\mathbf{x})\|^2$$

The **derivative** of  $g(\cdot)$  is

$$G(\mathbf{x}) := g'(\mathbf{x}) = \underbrace{F'(\mathbf{x})^T}_{\text{row vector}} \underbrace{F(\mathbf{x})}_{\text{column vector}}$$

This is a nonlinear system in  $\mathbf{x}$ ,  $G : D \rightarrow \mathbb{R}^n$ . Let's try to solve it using Newton's method:

$$G'(\mathbf{x}^k) \Delta \mathbf{x}^k = -G(\mathbf{x}^k), \quad \mathbf{x}^{k+1} = \mathbf{x}^k + \Delta \mathbf{x}^k$$

where

$$G'(\mathbf{x}) = \underbrace{F'(\mathbf{x})^T}_{\text{row vector}} \underbrace{F'(\mathbf{x})}_{\text{row vector}} + \underbrace{F''^T(\mathbf{x})}_{\text{tensor}} \underbrace{F(\mathbf{x})}_{\text{column vector}}$$

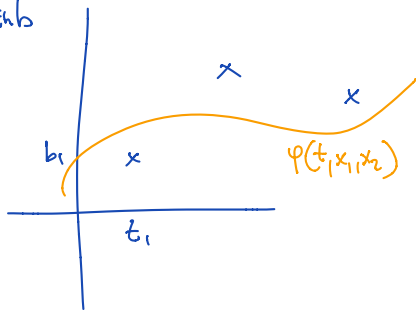
# Nonlinear least-squares problems: Example

$(t_i, b_i)$   $i = 1, 2, 3$  data points

$$\varphi(t; x_1, x_2) = \exp(x_1) t^2 + x_2^2 \sin(t)$$

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

↑ ↑  
nonlinear in  $x$



$$F(x) = \begin{bmatrix} \varphi(t_1; x_1, x_2) - b_1 \\ \varphi(t_2 \dots) - b_2 \\ \varphi(t_3 \dots) - b_3 \end{bmatrix}$$

$$\min_{x_1, x_2} \frac{1}{2} \|F(x)\|^2 = \frac{1}{2} \left\| \begin{bmatrix} \exp(x_1) t_1^2 + x_2^2 \sin(t_1) - b_1 \\ \text{---} t_2 \text{ ---} t_2 - b_2 \\ \text{---} t_3 \text{ ---} t_3 - b_3 \end{bmatrix} \right\|^2$$

# Nonlinear least-squares problems: Example

$$G(x) = F'(x)^T F(x) = \begin{array}{|c|} \hline \text{Jacobian} \\ \hline \in \mathbb{R}^{2 \times 3} \\ \hline \end{array} \begin{array}{|c|} \hline \\ \hline \end{array}$$

Gauss-Newton method

$$F'(x^k)^T F'(x^k) \Delta x = -F'(x^k)^T F(x^k)$$
$$x^{k+1} = x^k + \Delta x$$

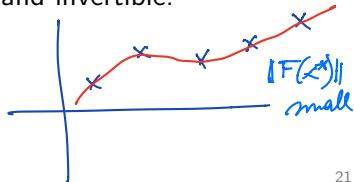
linear least squares:  $A^T A x = -A^T b$

# Nonlinear least-squares problems

$F''(\mathbf{x})$  is a tensor. It is often neglected due to the following reasons:

- ▶ It's difficult to compute and we can use an approximate Jacobian in Newton's method.
- ▶ If the data is compatible with the model, then  $F(\mathbf{x}^*) = 0$  and the term involving  $F''(\mathbf{x})$  drops out. If  $\|F(\mathbf{x}^*)\|$  is small, neglecting that term might not make the convergence much slower.
- ▶ We know that  $g''(\mathbf{x}^*)$  must be positive. If  $F'(\mathbf{x}^k)$  has full rank, then  $F'(\mathbf{x})^T F'(\mathbf{x})$  is positive and invertible.

We neglect  $F''(\mathbf{x}) F(\mathbf{x})$  | compatible :



# Nonlinear least-squares problems—Gauss-Newton

The resulting Newton method for the nonlinear least squares problem is called **Gauss-Newton method**: Initialize  $\mathbf{x}^0$  and for  $k = 0, 1, \dots$  solve

$$F'(\mathbf{x}^k)^T F'(\mathbf{x}^k) \Delta \mathbf{x}^k = -F'(\mathbf{x}^k)^T F(\mathbf{x}^k) \quad (\text{solve})$$

$$\mathbf{x}^{k+1} = \mathbf{x}^k + \Delta \mathbf{x}^k. \quad (\text{update step})$$

# Nonlinear least-squares problems—Gauss-Newton

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$$\mathbf{x}^{k+1} = \mathbf{x}^k + \Delta \mathbf{x}^k. \quad (\text{update step})$$

The solve step is the normal equation for the linear least squares problem

$$\min_{\Delta \mathbf{x}} \|F'(\mathbf{x}^k) \Delta \mathbf{x}^k + F(\mathbf{x}^k)\|.$$



# Convergence of Gauss-Newton method

**Assumptions on  $F$ :**  $D \subset \mathbb{R}^n$  open and convex,  $F : D \rightarrow \mathbb{R}^m$ ,  $m \geq n$  continuously differentiable with  $F'(\mathbf{x})$  has full rank for all  $\mathbf{x}$ , and let  $\omega \geq 0, 0 \leq \kappa^* < 1$  such that

$$\|F'(\mathbf{x})^+(F'(\mathbf{x} + s\mathbf{v}) - F'(\mathbf{x}))\mathbf{v}\| \leq s\omega\|\mathbf{v}\|^2$$

for all  $s \in [0, 1]$ ,  $\mathbf{x} \in D$ ,  $\mathbf{v} \in \mathbb{R}^n$  with  $\mathbf{x} + \mathbf{v} \in D$ .

**Assumptions on  $\mathbf{x}^*$  and  $\mathbf{x}^0$ :** Assume there exists a solution  $\mathbf{x}^* \in D$  of the least squares problem and a starting point  $\mathbf{x}^0 \in D$  such that

$$\|F'(\mathbf{x})^+F(\mathbf{x}^*)\| \leq \kappa^*\|\mathbf{x} - \mathbf{x}^*\|$$

$$\rho := \|\mathbf{x}^* - \mathbf{x}^0\| \leq \frac{2(1 - \kappa^*)}{\omega} := \sigma$$

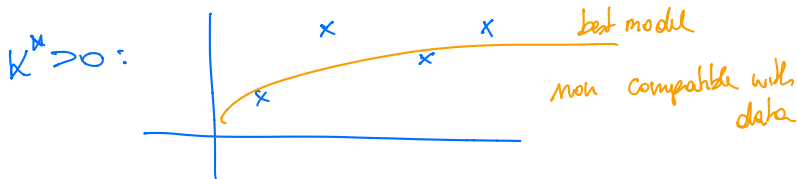
**Theorem:** Then, the sequence  $\mathbf{x}^k$  stays in  $B_\rho(\mathbf{x}^*)$  and  $\lim_{k \rightarrow \infty} \mathbf{x}^k = \mathbf{x}^*$ , and

$$\|\mathbf{x}^{k+1} - \mathbf{x}^*\| \leq \frac{\omega}{2}\|\mathbf{x}^k - \mathbf{x}^*\|^2 + \kappa^*\|\mathbf{x}^k - \mathbf{x}^*\|$$

# Convergence of Gauss-Newton method

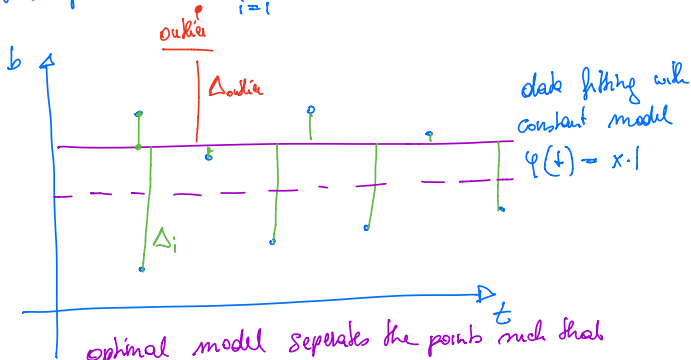
- ▶ Role of  $\kappa^*$ : Represents omission of  $F''(x)$ 
  - ▶  $\kappa^*$  can be chosen as 0  $\Rightarrow$  local quadratic convergence
  - ▶  $\kappa^* > 0$  linear convergence (thus we require  $\kappa^* < 1$ ).

model curve  
can fit  
data  
exactly



- ▶ Damping strategy as before (better: linesearch to make guaranteed progress in minimization problem)
- ▶ There can, in principle, be multiple solutions.

Why do outliers in data not matter when using the functional  $\sum_{i=1}^m |\Delta_i|$  ?



optimal model separates the points such that the same number of points is on both sides, so outliers have (almost) no influence

If I minimize  $\sum_{i=1}^m \Delta_i^2$ , outliers have a big influence as we minimize the squares.