

# Nonlinear Systems

# Part II Roadmap

- Part I – Linear Algebra (units 1-12)  $Ac = b$
  - Part II – Optimization (units 13-20)
    - (units 13-16) Optimization -> **Nonlinear Equations** -> 1D roots/minima
    - (units 17-18) Computing/Avoiding Derivatives
    - (unit 19) **Hack 1.0**: "I give up"  $H = I$  and  $J$  is mostly 0 (descent methods)
    - (unit 20) **Hack 2.0**: "It's an ODE!?" (adaptive learning rate and momentum)
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graph TD; P1[Part I - Linear Algebra (units 1-12) Ac = b]; P2[Part II - Optimization (units 13-20)]; P2 -- linearize --> P1; P1 -- line search --> P2; P2 -- Theory --> NLE[Nonlinear Equations -> 1D roots/minima]; subgraph Methods; P2 -- Methods --> P2_17[units 17-18 Computing/Avoiding Derivatives]; P2 -- Methods --> P2_19[unit 19 Hack 1.0]; P2 -- Methods --> P2_20[unit 20 Hack 2.0]; end
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# Recall: Jacobian (Unit 9)

• The Jacobian of  $F(c) = \begin{pmatrix} F_1(c) \\ F_2(c) \\ \vdots \\ F_m(c) \end{pmatrix}$  has entries  $J_{ik} = \frac{\partial F_i}{\partial c_k}(c)$

• Thus, the Jacobian  $J(c) = F'(c) = \begin{pmatrix} \frac{\partial F_1}{\partial c_1}(c) & \frac{\partial F_1}{\partial c_2}(c) & \cdots & \frac{\partial F_1}{\partial c_n}(c) \\ \frac{\partial F_2}{\partial c_1}(c) & \frac{\partial F_2}{\partial c_2}(c) & \cdots & \frac{\partial F_2}{\partial c_n}(c) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial c_1}(c) & \frac{\partial F_m}{\partial c_2}(c) & \cdots & \frac{\partial F_m}{\partial c_n}(c) \end{pmatrix}$

# Linearization

- Solving a nonlinear system of equations  $F(c) = 0$  is difficult
- Linearize via the multidimensional version of the Taylor expansion:

$$F(c) \approx F(c^*) + F'(c^*) (c - c^*)$$

- More valid when  $\Delta c = c - c^*$  is small (i.e. for  $c$  close enough to  $c^*$ )
  - Alternatively written as  $F(c) - F(c^*) \approx F'(c^*)\Delta c$
- The chain rule  $\frac{dF(c)}{dt} = F'(c) \frac{dc}{dt}$  is valid for any variable  $t$ , and thus can be written in differential form as  $dF(c) = F'(c)dc$ 
    - Often referred to as the total derivative
    - Using finite size differentials leads to the approximation:  $\Delta F(c) \approx F'(c)\Delta c$
    - In 1D,  $df = f'(c)dc$  and  $\Delta f \approx f'(c)\Delta c$  are the usual  $\frac{df}{dc} = f'(c)$  and  $\frac{\Delta f}{\Delta c} \approx f'(c)$

# Newton's Method

- An iterative method: start with  $c^0$ , recursively find:  $c^1, c^2, c^3, \dots$
- Based on  $\Delta F(c) \approx F'(c)\Delta c$ , write  $F(c^{q+1}) - F(c^q) = F'(c^q)\Delta c^q$ 
  - Aiming for  $F(c) = 0$  motivates setting  $F(c^{q+1}) = 0$
  - Alternatively, set  $F(c^{q+1}) = \beta F(c^q)$  where  $0 \leq \beta < 1$  aims to slowly shrink  $F(c^q)$  towards zero
- Solve the linear system  $F'(c^q)\Delta c^q = (\beta - 1)F(c^q)$  for  $\Delta c^q$
- Use  $\Delta c^q = c^{q+1} - c^q$  to update  $c^{q+1} = c^q + \Delta c^q$

# Newton's Method

- Requires **repeatedly solving a linear system**, making robustness and efficiency for linear system solvers quite important
  - Need to consider size, rank, conditioning, symmetry, etc. of  $F'(c^q)$
- $F'(c^q)$  may be difficult to compute, since it requires every first derivative
  - Newton's Method contains linearization errors, so approximations of  $F'(c^q)$  are often valid/worthwhile (e.g. symmetric approximation, etc.)
  - More on this in units 17/18 on Computing/Avoiding Derivatives
- Generally speaking, there are no guarantees on convergence
  - May converge to any one of many roots when multiple roots exist, or not converge at all

# Solving Linear Systems (Review)

- Theory, all matrices: **SVD** (units 3, 10, 11)
- Square, full rank, dense:
  - LU factorization with pivoting (unit 2)
  - Symmetric: **Cholesky** factorization (unit 4), **Symmetric approximation** (unit 4)
- Square, full rank, sparse (iterative solvers) (unit 5):
  - SPD (sometimes SPSD): **Conjugate Gradients**
  - Nonsymmetric/Indefinite: GMRES, MINRES, BiCGSTAB (not steepest descent)
- Tall, full rank (least squares to minimize residual) (unit 8):
  - normal equations (units 9, 10), **QR**, Gram-Schmidt, **Householder** (unit 10)
- Any size/rank (minimum norm solution) (unit 11):
  - **Pseudo-Inverse**, **PCA approximation**, **Power Method** (unit 11)
  - **Levenberg-Marquardt** (iteration too), **Column Space Geometric Approach** (unit 12)

# Line Search

- Given the linearization errors in  $F'(c^q)\Delta c^q = (\beta - 1)F(c^q)$ , the resulting  $\Delta c^q$  can lead to a poor estimate for  $c^{q+1}$  via  $c^{q+1} = c^q + \Delta c^q$
- Instead,  $\Delta c^q$  is often just used as a search direction, i.e.  $c^{q+1} = c^q + \alpha^q \Delta c^q$
- The 1D (parameterized) line  $c^{q+1}(\alpha) = c^q + \alpha \Delta c^q$  is the new domain
- Find an  $\alpha$  with  $F(c^{q+1}(\alpha)) = 0$  simultaneously for all equations
- Safe Set methods restrict  $\alpha$  in various ways, e.g.  $0 \leq \alpha \leq 1$

# Line Search

- Since  $F$  is vector valued, consider  $g(\alpha) = F(c^{q+1}(\alpha))^T F(c^{q+1}(\alpha)) = 0$
- Since  $g(\alpha) \geq 0$ , solutions to  $F(c^{q+1}(\alpha)) = 0$  are minima of  $g(\alpha)$
- $g(\alpha)$  might be strictly positive (with no  $g(\alpha) = 0$ ), but minimizing  $g(\alpha)$  might still help to make progress towards an  $\alpha$  with  $F(c^{q+1}(\alpha)) = 0$
  
- Option 1: find simultaneous roots of the vector valued  $F(c^{q+1}(\alpha)) = 0$
- Option 2: find roots of or minimize  $g(\alpha) = \frac{1}{2} F^T(c^{q+1}(\alpha)) F(c^{q+1}(\alpha))$ , to find or make progress towards an  $\alpha$  with  $F(c^{q+1}(\alpha)) = 0$

# Optimization Problems

- Minimize the scalar cost function  $\hat{f}(c)$  by finding the critical points where  $\nabla \hat{f}(c) = J_{\hat{f}}^T(c) = F(c) = 0$
- $F'(c^q)\Delta c^q = (\beta - 1)F(c^q)$  gives the search direction (as usual)
- Here,  $F'(c) = J_F(c) = H_{\hat{f}}^T(c)$
- So, solve  $H_{\hat{f}}^T(c^q)\Delta c^q = (\beta - 1)J_{\hat{f}}^T(c^q)$  to find the search direction  $\Delta c^q$
- Option 1: find simultaneous roots of the vector valued  $J_{\hat{f}}^T(c^{q+1}(\alpha)) = 0$ , which are critical points of  $\hat{f}(c)$
- Option 2: find roots of or minimize  $g(\alpha) = \frac{1}{2}J_{\hat{f}}(c^{q+1}(\alpha))J_{\hat{f}}^T(c^{q+1}(\alpha))$ , to find or make progress towards critical points of  $\hat{f}(c)$
- Option 3: minimize  $\hat{f}(c^{q+1}(\alpha))$  directly