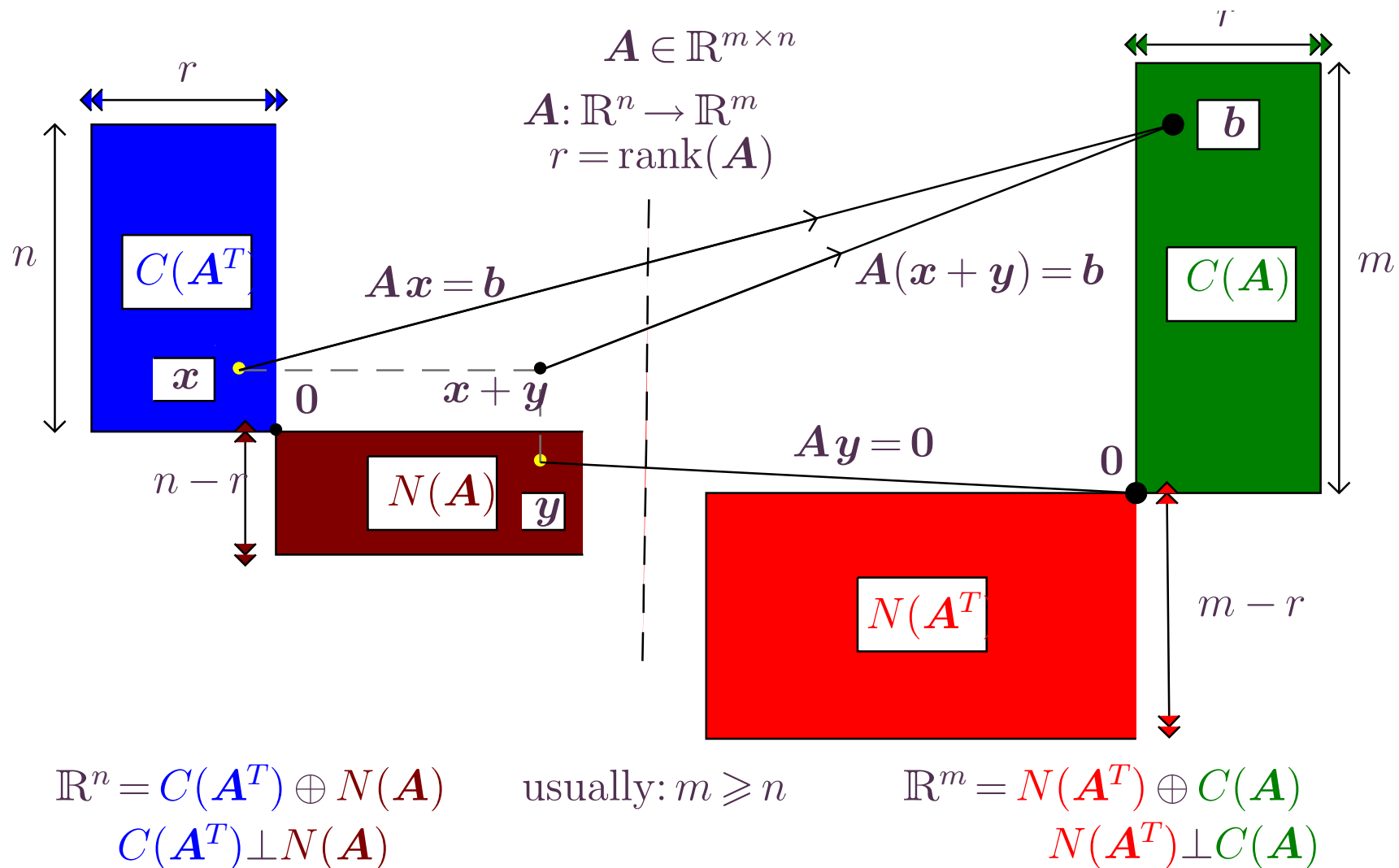




Overview

- Linear system review
- Nonlinear systems of equations
- Gradient descent methods - an introduction
- Newton and quasi-Newton methods - an introduction

- $Ax = b$, $A \in \mathbb{R}^{m \times n}$, $x \in \mathbb{R}^n$, $b \in \mathbb{R}^m$ a linear system of m equations in n unknowns. Solutions characterized by fundamental theorem of linear algebra



- No result available comparable to FTLA
- General form of a nonlinear system $\mathbf{F}: \mathbb{R}^n \rightarrow \mathbb{R}^m$, $\mathbf{F}(\mathbf{x}) = \mathbf{0}$

$$\mathbf{F}(\mathbf{x}) = \begin{bmatrix} f_1(x_1, \dots, x_n) \\ \vdots \\ f_m(x_1, \dots, x_n) \end{bmatrix} = \mathbf{0}$$

- Consider $m = n$ case. Examples:
 - 1 $x_1 + x_2 = 1$, $\tan(x_1) + \tan(x_2) = 1.10693$
 - 2 $\sin(x_1) + \sin(x_2) = 0.954061$, $e^{x_1} - e^{x_2} = 0.330294$
 - 3 $x_1^2 + x_2^2 = 0.52$, $x_1^3 + x_2^3 = 0.28$
- Approaches:
 - transform into an “easier” equivalent problem
 - introduce approximant $\mathbf{G}$ of $\mathbf{F}$, $\mathbf{F} \cong \mathbf{G}$

- To solve $\mathbf{F}(\mathbf{x}) = \mathbf{0}$ use norm properties and restate problem as $\|\mathbf{F}(\mathbf{x})\| = 0$
- Consider 2-norm and define

$$g(\mathbf{x}) = \|\mathbf{F}(\mathbf{x})\|_2^2 = \sum_{i=1}^n f_i^2(\mathbf{x})$$

- g is positive semi-definite: $\forall \mathbf{x}, g(\mathbf{x}) \geq 0$ and $g(\mathbf{x}) = 0$ iff $\mathbf{F}(\mathbf{x}) = \mathbf{0}$
- g is convex in some neighborhood of a root $\mathbf{x}$: $\exists \varepsilon > 0$ such that $\forall \mathbf{y}, \|\mathbf{x} - \mathbf{y}\| \leq \varepsilon$

$$\mathbf{H}(\mathbf{y}) = \begin{bmatrix} \frac{\partial^2 g}{\partial x_1^2} & \frac{\partial^2 g}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 g}{\partial x_1 \partial x_n} \\ \frac{\partial^2 g}{\partial x_2 \partial x_1} & \frac{\partial^2 g}{\partial x_2^2} & \cdots & \frac{\partial^2 g}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 g}{\partial x_n \partial x_1} & \frac{\partial^2 g}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 g}{\partial x_n^2} \end{bmatrix}, \mathbf{H} = \mathbf{H}^T$$

$\mathbf{H}$ is positive semi-definite, $\forall \mathbf{u} \in \mathbb{R}^n, \mathbf{u}^T \mathbf{H} \mathbf{u} \geq 0$, $\mathbf{H}$ has positive eigenvalues.

- Recall, for $g: \mathbb{R}^n \rightarrow \mathbb{R}$, $\text{grad } g = \nabla g$ is the vector indicating direction of most rapid increase of g
- Example: Rosenbrock function $g(x, y) = (1 - x)^2 + 100(y - x^2)^2$

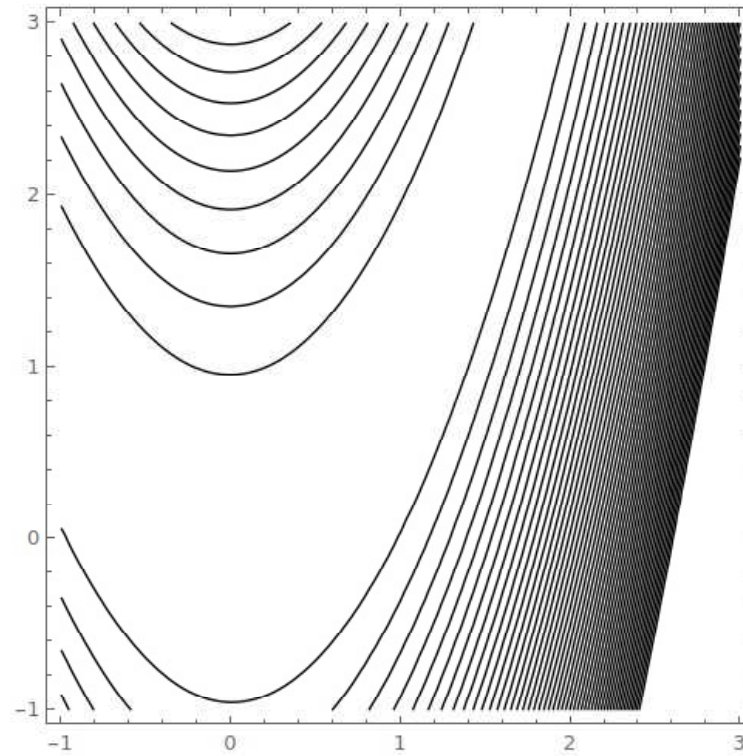


Figure 1. The Rosenbrock function

- Instead of $\mathbf{F}(\mathbf{x}) = \mathbf{0}$ solve $\mathbf{G}(\mathbf{x}) = \mathbf{0}$ with $\mathbf{F} \cong \mathbf{G}$, $\mathbf{G}$ linear approximant
- Linear approximant = Taylor polynomial of degree $m = 1$

$$\mathbf{P}(t) = \mathbf{F}(\mathbf{x}_n) + \mathbf{F}'(\mathbf{x}_n)(t - \mathbf{x}_n)$$

- Find next term in approximation sequence $\{\mathbf{x}_n\}_{n \in \mathbb{N}}$ by setting $\mathbf{P}(\mathbf{x}_{n+1}) = \mathbf{0} \Rightarrow$

$$\mathbf{F}(\mathbf{x}_n) + \mathbf{F}'(\mathbf{x}_n)(\mathbf{x}_{n+1} - \mathbf{x}_n) = \mathbf{0} \Rightarrow$$

$$\mathbf{F}'(\mathbf{x}_n)(\mathbf{x}_{n+1} - \mathbf{x}_n) = -\mathbf{F}(\mathbf{x}_n)$$

a linear system

- As in the scalar case Newton's method is second-order convergent near the root
- Difficulty: computation of Jacobian $\mathbf{F}'(\mathbf{x}_n) \in \mathbb{R}^{n \times n}$ at each iteration

- Recall that secant did not require derivatives

$$\text{replace } x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \text{ by } x_{n+1} = x_n - \frac{f(x_n)}{f(x_n) - f(x_{n-1})}(x_n - x_{n-1})$$

- Try similar approach for $\mathbf{F}: \mathbb{R}^n \rightarrow \mathbb{R}^m$, $\mathbf{F}(\mathbf{x}) = \mathbf{0}$.

$$\text{replace } \mathbf{x}_{n+1} = \mathbf{x}_n - [\mathbf{F}'(\mathbf{x}_n)]^{-1} \mathbf{F}(\mathbf{x}_n) \text{ by } \mathbf{x}_{n+1} = \mathbf{x}_n - \mathbf{B}_n^{-1} \mathbf{F}(\mathbf{x}_n)$$

- $\mathbf{B}_n$ is an approximation of the Jacobian $\mathbf{F}'(\mathbf{x}_n)$, updated at each step
- At iteration n solve $\mathbf{B}_n \mathbf{s}_n = -\mathbf{F}(\mathbf{x}_n)$, $\mathbf{s}_n = \mathbf{x}_{n+1} - \mathbf{x}_n$
- How to construct $\mathbf{B}_{n+1}$? Mimic secant property $f'(\xi)(b - a) = f(b) - f(a)$

$$\mathbf{B}_{n+1} \mathbf{s}_n = \mathbf{y}_n = \mathbf{F}(\mathbf{x}_{n+1}) - \mathbf{F}(\mathbf{x}_n) \tag{1}$$

- secant property is obtained along the direction of the most recent update
- $\mathbf{B}_{n+1}$ has n^2 components, (1) specifies only n equations

- Determine n^2 components of $\mathbf{B}_{n+1}$ by imposing it be close to $\mathbf{B}_n$

$$\min_{\mathbf{B}_{n+1}} \|\mathbf{B}_{n+1} - \mathbf{B}_n\|$$

- Choosing the 2-norm, the above minimization problem has solution

$$\mathbf{B}_{n+1} = \mathbf{B}_n + \frac{(\mathbf{y}_n - \mathbf{B}_n \mathbf{s}_n) \mathbf{s}_n^T}{\mathbf{s}_n^T \mathbf{s}_n}$$