# Linear Constraints

**CPSC 406 – Computational Optimization** 

## Linear constraints

- underdetermined linear systems
- reduced-gradient methods

## Linearly-constrained optimization

$$\min_{x\in \mathbb{R}^n} \ \set{f(x) \mid Ax = b}$$

- $f: \mathbb{R}^n 
  ightarrow \mathbb{R}$  is a smooth function
- A is m imes n, b is an m-vector, m < n (underdetermined)
- assume throughout that A has full row rank
- feasible set

$$\mathcal{F} = \{x \in \mathbb{R}^n \mid Ax = b\}$$



## **Eliminating constraints**

• equivalent representation of the feasible set

$$\mathcal{F} = \{x \in \mathbb{R}^n \mid Ax = b\} = \{ar{x} + Zp \mid p \in \mathbb{R}^{n-m}\}$$

- $ar{x}$  is a particular solution, ie,  $Aar{x}=b$
- Z is a basis for the null space of A, ie, AZ=0
- reduced problem is unconstrained in n-m variables

 $\min_{p\in \mathbb{R}^{n-m}} \; f(ar{x}+Zp)$ 

- apply any unconstrained optimization method to solve to obtain solution  $p^st$
- then a solution  $x^* = ar{x} + Zp^*$  is the solution to the original problem

## Example (in class)

$$\min_{x\in \mathbb{R}^2} \; ig\{ rac{1}{2} (x_1^2 + x_2^2) \mid x_1 + x_2 = 1 ig\}$$

## **Optimality conditions**

- define **reduced** objective for any particular solution  $ar{x}$  and basis Z

$$f_Z(p) = f(\bar{x} + Zp)$$

 $abla f_Z(p) = Z^T 
abla f(ar x + Zp) \quad ( ext{reduced gradient})$ 

- let  $p^*$  be a solution to the reduced problem and set  $x^* = ar{x} + Z p^*$ 

$$abla f_Z(p^*) = 0 \quad \Longleftrightarrow \quad Z^T 
abla f(x^*) = 0 \quad \Longleftrightarrow \quad 
abla f(x^*) \in \mathbf{null}(Z^T)$$

• funadamental subspaces of A and Z are orthogonal complements

$$\mathbf{null}(A) \equiv \mathbf{range}(Z) \iff \mathbf{null}(Z^T) \equiv \mathbf{range}(A^T)$$

• thus,

$$abla f(x^*) \in \mathbf{null}(Z^T) \quad \Longleftrightarrow \quad 
abla f(x^*) \in \mathbf{range}(A^T) \quad \Longleftrightarrow \quad \exists y \operatorname{st} 
abla f(x^*) = A^T y$$

### **First-order necessary conditions**

A point  $x^*$  is a local minimizer of the linearly-constrained problem **only if** 

$$\exists \ y \in \mathbb{R}^m ext{ st } 
abla f(x^*) = A^T y \qquad ext{[optimality]}$$

$$Ax^* = b$$
 [feasibility]

• optimality condition is equivalent to

$$Z^T 
abla f(x^*) = 0 \quad \Longleftrightarrow \quad 
abla f(x^*)^\intercal p = 0 \quad orall p \in \mathbf{null}(A)$$

• the *m*-vector *y* contains the Lagrange multipliers

$$abla f(x^*) = A^T y = \sum_{i=1}^m y_i a_i$$



#### **Second-order optimality**

 $f_Z(p):=f(ar{x}+Zp) \qquad 
abla f_Z(p):=Z^T
abla f(ar{x}+Zp) \qquad 
abla^2 f_Z(p):=Z^T
abla^2 f(ar{x}+Zp)Z$ 

**Necessary** 2nd-order optimality:  $x^*$  is a local minimizer **only if** 

$$egin{array}{c} Ax^* = b \ Z^T 
abla f(x^*) = 0 \ Z^T 
abla^2 f(x^*) Z \succeq 0 \end{array} ightarrow \left\{ egin{array}{c} Ax^* = b \ 
abla f(x^*) = A^T y \ p^T 
abla^2 f_Z(p^*) p \geq 0 \end{array} ightarrow p \in {f null}(A) \end{array} 
ight.$$
 for some  $y$ 

Necessary and sufficient 2nd-order optimality:  $x^*$  is a local minimizer if and only if

$$egin{array}{c} Ax^* = b \ Z^T 
abla f(x^*) = 0 \ Z^T 
abla^2 f(x^*) Z \succ 0 \end{array} iggrightarrow i$$

### **Example: Least norm solutions**

$$\min_{x\in \mathbb{R}^n} \left\{ \; \|x\| \mid Ax = b \; 
ight\}$$

Take  $f(x) = rac{1}{2} \|x\|^2$  and apply first-order optimality conditions

$$egin{array}{ccc} x = A^T y & ext{for some } y \ Ax = b \end{array} & & egin{array}{ccc} -I & A^T \ A & 0 \end{bmatrix} egin{array}{ccc} x \ y \end{bmatrix} = egin{array}{ccc} 0 \ b \end{bmatrix}$$

A possible solution approach: - observe that multiplier y satisfies

$$AA^Ty = b$$

- factor  $A^T = QR$  (thin QR factorization)
- multipliers:  $y = R^{-1}R^{-T}b$
- solution:  $x = A^T y = (QR)(R^{-1}R^{-T}b) = QR^{-T}b$



Find a minimimal norm solution to the linear system

$$\sum_{i=1}^n \xi_i = 1$$

If n=5 and  $x=(\xi_1,\xi_2,\xi_3,\xi_4,\xi_5)$ , which of the following is a minimal norm solution?

a.  $x = 1/5 \cdot (1, 1, 1, 1, 1)$ b.  $x = 5 \cdot (5, 5, 5, 5, 5)$ c. x = (1, 1, 1, 1, 1)d. x = (1, 2, 3, 4, 5)

## Question

What are the lagrange multipliers for the minimum-norm problem

$$\min_{x\in \mathbb{R}^n} \left\{ \; \|x\|^2 \mid Ax = b \; 
ight\}$$

where

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$
 and  $b = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ 

## **Reduced gradient method**

$$\min_{x\in \mathbb{R}^n} \ \{f(x) \mid Ax = b\}$$

- choose  $x^0$  and Z such that  $Ax^0 = b$  and AZ = 0
- for  $k=0,1,2,\ldots$ 
  - compute gradient  $g^k = 
    abla f(x^k)$
  - STOP if  $\|Z^Tg^k\|$  small
  - compute Hessian approximation  $H^k pprox 
    abla^2 f(x^k)$  ,  $H^k \succ 0$
  - solve  $Z^T H^k Z p^k = -Z^T g^k$
  - linesearch on  $f(x^k + \alpha Z p^k)$

## **Obtaining a null-space basis**

• assume variables (columns of A) permuted so that

 $A = \begin{bmatrix} B & N \end{bmatrix}$  where B nonsingular

• feasibility requires

$$b = Ax = Bx_B + Nx_N$$

- basic  $(x_B)$  and nonbasic  $(x_N)$  variables:
  - $x_N$  are "free"
  - $x_B = B^{-1}b B^{-1}Nx_N$  uniquely determined by  $x_N$
- constructing a null-space matrix

$$Z = \begin{bmatrix} -B^{-1}N \\ I \end{bmatrix} \implies AZ = \begin{bmatrix} B & N \end{bmatrix} \begin{bmatrix} -B^{-1}N \\ I \end{bmatrix} = 0$$