

→ SPNS - Lecture 10 (B) - 5/12/2015

$$\begin{aligned} & \text{minimize} && \|Ax - B\| \\ & \text{subject to} && Cx = D \end{aligned}$$

→ for a variable x
⇒ least-norm problem

$$\begin{aligned} \min & & (1/2) \|Ax - B\|^2 \\ \text{s.t.} & & Cx = D \end{aligned}$$

$$x = (A^T A)^{-1} (A^T B - C^T (C (A^T A)^{-1} C^T)^{-1} \dots)$$

~~$(C (A^T A)^{-1} A^T B - D)$~~

→ Lagrangian

$$\begin{aligned} L(x, \lambda) &= \frac{1}{2} \|Ax - B\|^2 + \lambda^T (Cx - D) \\ &= (1/2) x^T A^T A x - B^T A x + (1/2) (B^T B) + \dots \\ & \quad \lambda^T C x - \lambda^T D \end{aligned}$$

OPTIMALITY CONDITIONS ARE:

$$\nabla_x L = A^T A x - A^T B + C^T \lambda = 0$$

and $\nabla_\lambda L = Cx - D = 0$

WRITE THIS in block matrix form as:

$$\begin{bmatrix} A^T A & C^T \\ e & 0 \end{bmatrix} \begin{bmatrix} x \\ \lambda \end{bmatrix} = \begin{bmatrix} A^T B \\ D \end{bmatrix}$$

If the Block matrix is invertible:

$$\begin{bmatrix} X \\ \lambda \end{bmatrix} = \begin{bmatrix} A^T A & C^T \\ C & 0 \end{bmatrix}^{-1} \begin{bmatrix} A^T B \\ D \end{bmatrix}$$

Now if $A^T A$ is invertible we can derive a more explicit formula for x

$$X = (A^T A)^{-1} (A^T B - C^T \lambda)$$

If we substitute $CX = D$

↓

$$C (A^T A)^{-1} (A^T B - C^T \lambda) = D$$

$$\text{So } \lambda = \left(C (A^T A)^{-1} C^T \right)^{-1} \left(C (A^T A)^{-1} (A^T B) - D \right)$$