



Constrained LS (CLS)

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_2^2$$

$$\text{s.t. } Cx = d$$

$$A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m$$

$$C \in \mathbb{R}^{p \times n}, \quad d \in \mathbb{R}^p$$

$$C = \begin{bmatrix} C_1^T \\ C_2^T \\ \vdots \\ C_p^T \end{bmatrix} \quad \text{where } C_i^T \in \mathbb{R}^{1 \times n}$$

Construct the Lagrangian function:

$$L(x, z) = \|Ax - b\|_2^2 + z_1 (C_1^T x - d_1) + z_2 (C_2^T x - d_2) + \dots + z_p (C_p^T x - d_p)$$

where  $z = \begin{pmatrix} z_1 \\ \vdots \\ z_p \end{pmatrix} \in \mathbb{R}^p$  is a vector of Lagrange multipliers.

If  $\hat{x}$  is a solution of CLP, then there exist Lagrange multipliers  $\hat{z}$  s.t.

$$\frac{\partial L}{\partial x_i}(\hat{x}, \hat{z}) = 0 \quad \text{for } i=1, 2, \dots, n$$

} optimality conditions for CLP.

$$\frac{\partial L}{\partial z_i}(\hat{x}, \hat{z}) = 0 \quad \text{for } i=1, 2, \dots, p$$

$$\frac{\partial L}{\partial x_i}(\hat{x}, \hat{z}) = 0 \Rightarrow C_i^T \hat{x} = d_i \quad \text{for } i=1, 2, \dots, p \quad \text{(2)}$$

(constraint satisfaction by  $\hat{x}$ ).

$$\frac{\partial}{\partial x_i} L(x, z) = 2 \sum_{j=1}^n (A^T A)_{ij} x_j - 2(A^T b)_i + \sum_{j=1}^p z_j (C_j)_i$$

$$\therefore \nabla_x L(x, z) = 2(A^T A)x - 2A^T b + C^T z \quad \text{--- (1)}$$

$$\frac{\partial L}{\partial x_i}(\hat{x}, \hat{z}) = 0 \quad \& \quad \frac{\partial L}{\partial z_i}(\hat{x}, \hat{z}) = 0 \Rightarrow \begin{bmatrix} 2A^T A & C^T \\ C & 0 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{z} \end{bmatrix} = \begin{bmatrix} 2A^T b \\ d \end{bmatrix}$$

KKT conditions  
(Karush, Kuhn, Tucker)

KKT matrix  $\begin{bmatrix} 2A^T A & C^T \\ C & 0 \end{bmatrix} \in \mathbb{R}^{(n+p) \times (n+p)}$  is

invertible if and only if  $C$  has linearly independent rows and  $\begin{bmatrix} A \\ C \end{bmatrix}$  has linearly independent columns.

Let  $\begin{pmatrix} \bar{x} \\ \bar{z} \end{pmatrix}$  be a vector such that

$$\begin{bmatrix} 2A^T A & C^T \\ C & 0 \end{bmatrix} \begin{bmatrix} \bar{x} \\ \bar{z} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Rightarrow 2A^T A \bar{x} + C^T \bar{z} = 0 \quad (1)$$

$$\Rightarrow 2\bar{x}^T A^T A \bar{x} + \bar{x}^T C^T \bar{z} = 0 \Rightarrow 2\|A\bar{x}\|_2^2 + \cancel{(\bar{x})^T \bar{z}} = 0$$

Assume  $C$  has lin. indep. rows  
 $\& \begin{bmatrix} A \\ C \end{bmatrix}$  has linearly indep. cols.

To prove. KKT matrix is invertible.

$$\Rightarrow 2 \|A\bar{x}\|_2^2 = 0$$

$$\Rightarrow A\bar{x} = 0 \quad \text{and} \quad C\bar{x} = 0$$

$$\Rightarrow \begin{bmatrix} A \\ C \end{bmatrix} \bar{x} = 0$$

$$\Rightarrow \bar{x} = 0$$

From (1),  $C^T \bar{z} = 0 \Rightarrow \bar{z} = 0 \quad \therefore \text{columns of } C^T \text{ (rows of } C) \text{ are lin. indep.}$

$\Rightarrow$  KKT matrix invertible.

Converse:

$$\begin{pmatrix} \bar{x} \\ \bar{z} \end{pmatrix} = \begin{pmatrix} 2A^T A & C^T \\ C & 0 \end{pmatrix}^{-1} \begin{pmatrix} A^T b \\ d \end{pmatrix}$$

Recursive LS problem: (12.4, pg. 242, Vmls Book)

$$A = \begin{bmatrix} -a_1^T & - \\ -a_2^T & - \\ \vdots & \\ -a_k^T & - \end{bmatrix}$$

$$b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix}$$

Matrix inversion lemma:

for a matrix  $S \in \mathbb{R}^{n \times n}$

and

vectors  $u \in \mathbb{R}^{n \times 1}$ ,  
 $v \in \mathbb{R}^{1 \times n}$

$$\begin{aligned} (S + uv^T)^{-1} &= S^{-1} - S^{-1} u (1 + v^T u)^{-1} v^T \\ &= S^{-1} - \frac{(S^{-1} u) v^T}{(1 + \underbrace{v^T u})} \end{aligned}$$

$$\rightarrow \begin{matrix} (k) \\ A = \begin{bmatrix} a_1^T \\ \vdots \\ a_k^T \end{bmatrix}, \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_k \end{bmatrix} \end{matrix}$$

$$x^{(k)} = \left[ (A^{(k)})^T (A^{(k)}) \right]^{-1} (A^{(k)})^T b^{(k)}$$

$$\rightarrow \begin{matrix} (k+1) \\ A = \begin{bmatrix} a_1^T \\ a_2^T \\ \vdots \\ a_k^T \\ a_{k+1}^T \end{bmatrix} = \begin{bmatrix} A^{(k)} \\ a_{k+1}^T \end{bmatrix}, \quad b = \begin{bmatrix} b^{(k)} \\ b_{k+1} \end{bmatrix} \end{matrix}$$

$$x^{(k+1)} = \left( \begin{bmatrix} [A^{(k+1)}]^T & A^{(k+1)} \end{bmatrix} \right)^{-1} (A^{(k+1)})^T b^{(k+1)}$$

$$\begin{aligned}
 (A^{(k+1)})^T (A^{(k+1)}) &= \begin{bmatrix} A^{(k)} \\ a_{k+1}^T \end{bmatrix}^T \begin{bmatrix} A^{(k)} \\ a_{k+1}^T \end{bmatrix} \\
 &= \begin{bmatrix} (A^{(k)})^T & a_{k+1} \end{bmatrix} \begin{bmatrix} A^{(k)} \\ a_{k+1}^T \end{bmatrix} \\
 &= (A^{(k)})^T (A^{(k)}) + a_{k+1} a_{k+1}^T
 \end{aligned}$$

$$\begin{aligned}
 ((A^{(k+1)})^T A^{(k+1)})^{-1} &= ((A^{(k)})^T A^{(k)} + a_{k+1} a_{k+1}^T)^{-1} \\
 &= ((A^{(k)})^T A^{(k)})^{-1} - \frac{((A^{(k)})^T A^{(k)})^{-1} a_{k+1} a_{k+1}^T}{1 + a_{k+1} a_{k+1}^T}
 \end{aligned}$$



$$(A^{(k+1)})^T b^{(k+1)} = \begin{bmatrix} A^{(k)} \\ a_{k+1}^T \end{bmatrix}^T \begin{bmatrix} b^{(k)} \\ b_{k+1} \end{bmatrix}$$

$$= \left[ (A^{(k)})^T \quad a_{k+1} \right] \begin{bmatrix} b^{(k)} \\ b_{k+1} \end{bmatrix}$$

$$= (A^{(k)})^T b^{(k)} + a_{k+1} b_{k+1}$$

$$x^{(k+1)} = \left[ (A^{(k+1)})^T A^{(k+1)} \right]^{-1} (A^{(k+1)})^T b^{(k+1)}$$

$$x^{[k+1]} = \left\{ \left[ (A^{[k]})^T (A^{[k]}) \right]^{-1} - \frac{\left( (A^{[k]})^T A^{[k]} \right)^{-1} a_{k+1}^T a_{k+1}}{1 + a_{k+1}^T a_{k+1}} \right\}$$

$$\left\{ (A^{[k]})^T b^{[k]} + a_{k+1} b_{k+1} \right\}$$

$$x^{[k+1]} = x^{[k]} +$$