

$$x = A^{-1}b$$

$$Ax = b \longrightarrow \text{full rank.}$$

$$\text{LM by } A^T \rightarrow \boxed{A^T A x = A^T b}$$

$$x^T (A^T A) x \quad \text{P.D.}$$

$$= \|Ax\|^2 = 0 \quad \text{only when } x = 0$$

Conjugate Gradient Method. (CGM)

1)
$$p_k = -r_k + \beta_k p_{k-1}$$

2)
$$p_0 = -r_0$$

Scalar factor $(Ax_k - b)$

Conjugacy $\rightarrow p_i^T A p_j = 0 \quad i \neq j$

LM $\rightarrow p_{k-1}^T A p_k = -p_{k-1}^T A r_k + \beta_k p_{k-1}^T A p_{k-1}$

I want conjugacy.

$$\Rightarrow \beta_k = \frac{P_{k-1}^T A \gamma_k}{P_{k-1}^T A P_{k-1}}$$

$$x_{k+1} = x_k + \alpha_k P_k, \quad \alpha_k = \frac{-\gamma_k P_k^T}{P_k^T A P_k}$$

$$\begin{bmatrix} 2vv, 1mv \\ 2vv, 2mv \end{bmatrix}$$

Some more algebra.

$$\gamma_{k+1} - \gamma_k = A(x_{k+1} - x_k) = \alpha_k A P_k.$$

1 mv
2 vv

Final:

$$\alpha_k = \frac{\gamma_k^T \gamma_k}{p_k^T A p_k}, \quad \beta_k = \frac{\gamma_k^T \gamma_k}{\gamma_{k-1}^T \gamma_{k-1}}$$

To store $p_k = -\gamma_k + \beta_k p_{k-1}$

to get: $\gamma_k, p_{k-1}, \gamma_{k-1}$

→ Linear rate of convergence

A has eigenvalues: $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$

$$\text{Cond no } \kappa = \frac{\lambda_n}{\lambda_1}$$

1) If I know the eigenvalues of A

$$\|x_{k+1} - x^*\| \leq \left[\frac{\lambda_{n-k} - \lambda_1}{\lambda_{n-k} + \lambda_1} \right] \|x_0 - x^*\|$$

$$n=10$$

$$k=1$$

$$\|x_2 - x^*\|$$

$$k=5$$

$$(\lambda_9 - \lambda_1) / \|x_6 - x^*\| \rightarrow (\lambda_5 - \lambda_1)$$

2) If I don't know eigenvalues of A

$\rightarrow k$

$$\|x_{k+1} - x^*\| \leq 2 \left(\frac{\sqrt{k} - 1}{\sqrt{k} + 1} \right)^k \|x_0 - x^*\|$$

In SD $\cdot \sqrt{k} \rightarrow k$ ✓

CGM

1) $r_k^T r_i = 0$ for $i = 0, 1, \dots, k-1$

EST $\rightarrow r_k^T P_i = 0$ for $i \in [0, k-1]$

$$P_i = -\gamma_i + \beta_i P_{i-1}$$
$$\gamma_k^T \underbrace{(\downarrow)}_{P_i} = \cancel{\gamma_k^T P_i} = -\gamma_k^T \gamma_i + \beta_i \cancel{\gamma_k^T P_{i-1}}$$

$\Rightarrow \gamma_k^T \gamma_i = 0, \quad i \in [0, k-1]$