

$$\begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{n-1} \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

$\sim nx1$        $\sim mx1$

$$y = x_0 + x_1 t$$

$m \times n$

$\sim mx1$

(m)      (n)

$b \notin \text{range}(A) \Rightarrow$

$$A x \approx b$$

$\sim nx1$

$$\min_x \|Ax - b\|_2$$

Normal Equations

A is full rank

$n \times m$

$$A^T A x = A^T b$$

$\sim nxm$        $\sim mx1$

rank deficient  $\rightarrow$  SVD (no longer unique)

$$A = U_R \Sigma_R V^T$$

$A$  is  $m \times n$ ,  $U_R$  is  $m \times n$ ,  $\Sigma_R$  is  $n \times n$ , and  $V^T$  is  $n \times n$ .

$\tilde{x}$  solution

$$\min_x \|Ax - b\|_2^2$$

+

$$\min_x \|x\|_2$$

$$\tilde{x} = V \Sigma_R^+ (U_R^T b)$$

$\tilde{x}$  is  $n \times 1$ ,  $V$  is  $n \times n$ ,  $\Sigma_R^+$  is  $n \times n$ ,  $U_R^T$  is  $n \times m$ , and  $b$  is  $m \times 1$ .

full rank  
 $\Sigma_R^+ = \Sigma_R^{-1}$

# Example:

Consider solving the least squares problem  $Ax \cong b$ , where the singular value decomposition of the matrix  $A = U \Sigma V^T$  is:

$$\begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 14 & 0 & 0 \\ 0 & 14 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \cong \begin{bmatrix} 12 \\ 9 \\ 9 \\ 10 \end{bmatrix}$$

Determine  $\|b - Ax\|_2$

$$r = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 9 \end{bmatrix}$$

Diagram showing the residual vector  $r$  with components 1 and 9, and arrows pointing to 10 and 9.

$$\|r\| = \sqrt{10^2 + 9^2} = \sqrt{181}$$

$$r = Ax - b = (U \Sigma V^T x - b)$$

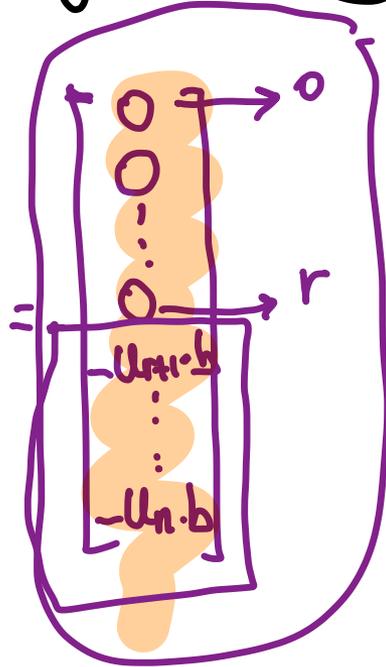
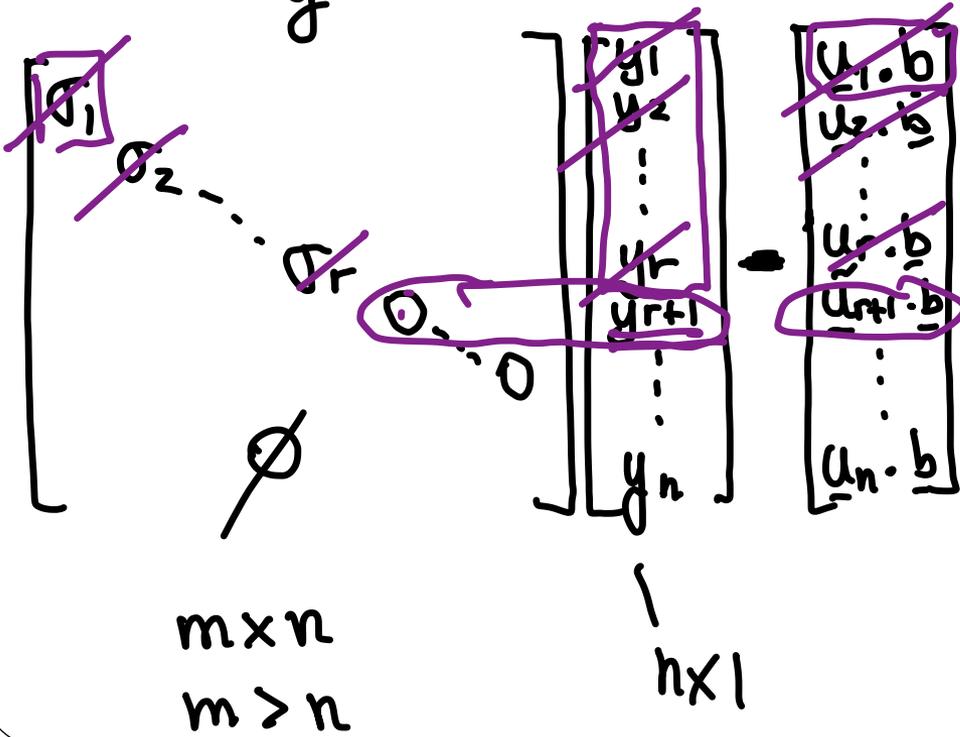
$$\|r\| \rightarrow \|U^T (U \Sigma V^T x - b)\|$$

$m \times m$     $m \times n$     $n \times n$     $n \times 1$     $m \times 1$

$$y_i = \frac{u_i \cdot b}{\sigma_i}$$

$\sigma_i \neq 0$

$$\| \underbrace{\Sigma V^T x}_y - U^T b \| = \| \Sigma y - \underbrace{U^T b}_{y} \|$$



$$\|r\| = \text{la.norm}()$$

$(U^T b)[r+1:]$   
 not Python not.

$$\text{score} = w_1 \text{rough} + w_2 \text{size} + w_3 t$$

