

$$\Sigma_{m \times n} = \begin{bmatrix} \diagdown \\ \diagdown \\ \diagdown \end{bmatrix} \quad \Sigma_{n \times m}^T = \begin{bmatrix} \diagdown \\ \diagdown \\ \diagdown \end{bmatrix}$$

$A = U \Sigma V^T$

$$A v_i = \sigma_i u_i$$

$$\hookrightarrow AA^T = (U \Sigma V^T)(V \Sigma^T U^T) = U \Sigma \Sigma^T U^T$$

$$\rightarrow (AA^T) U = U \underbrace{\Sigma \Sigma^T}_{m \times m} \begin{bmatrix} \sigma_1^2 & & 0 \\ & \diagdown & \\ 0 & & \sigma_m^2 \end{bmatrix}$$

$$(AA^T) \begin{bmatrix} u_1 & \dots \\ | & \end{bmatrix} = U \begin{bmatrix} \sigma_1^2 & & \\ & \sigma_2^2 & \\ & & \ddots \\ & & & \sigma_m^2 \end{bmatrix}$$

Eigenvalue prob

Similarly $(A^T A) = (V \Sigma^T U^T)(U \Sigma V^T)$

$$(A^T A) V = V \underbrace{\Sigma^T \Sigma}_{\text{diag}(\sigma_i^2)}$$

$$\begin{bmatrix} \sigma_1^2 & & & \\ & \ddots & & \\ & & \sigma_n^2 & \\ & & & 0 \end{bmatrix} \quad n \times n.$$

Tall: $m \times n$ $A: U \Sigma V^T$ \rightarrow l. singular
 $m > n$ \rightarrow r. singular

$$\begin{bmatrix} \sigma_1^2 & & \\ & \sigma_2^2 & \\ & & \ddots \\ & & & \sigma_n^2 \end{bmatrix} \quad \uparrow n$$

$$\Sigma \Sigma^T = \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \ddots \\ & & & \text{orange circle} \end{bmatrix} \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \ddots \\ & & & \diagdown \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_n^2 \\ & & & & \ddots \\ & & & & & \ddots \\ & & & & & & \ddots \end{bmatrix} \quad \uparrow n$$

$$\Sigma^T \Sigma = \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \ddots \\ & & & \diagdown \end{bmatrix} \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \ddots \\ & & & \diagdown \end{bmatrix} = \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \ddots \\ & & & \diagdown \end{bmatrix} \quad \uparrow n$$

$\rightarrow AB = \begin{bmatrix} | & | & & | \\ Ab_1 & Ab_2 & \dots & Ab_n \\ \end{bmatrix} \rightarrow$ L.C. of cols of A

$$= \begin{bmatrix} | & & | \\ -a_1^T B & - & \\ -a_2^T B & - & \\ \vdots & & \vdots \\ -a_m^T B & - & \end{bmatrix} \quad \begin{array}{l} \text{Rows} \\ \rightarrow \text{L.C. of rows of } B \end{array}$$

$AA^T \rightarrow$ Cols are L.C. of cols of A \leftarrow

$A^T A \rightarrow$ rows are L.C. of rows of A . \leftarrow

If $\text{rank}(A) = r \Rightarrow r$ lin indep rows/cols of A .

$A, AA^T, A^T A \Rightarrow$ Have same rank r .

\Rightarrow No of singular values $= r$
 $\sqrt{\lambda_i} = \sigma_i$

By defn. : $\sigma_1^2 \geq \sigma_2^2 \geq \sigma_3^2 \dots \geq \sigma_r^2$

$$A \begin{bmatrix} v_1 & v_2 & \dots & v_r \end{bmatrix} = \begin{bmatrix} u_1 & u_2 & \dots & u_r \end{bmatrix} \begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_r & \\ & & & \ddots \end{bmatrix}$$

\downarrow \uparrow \downarrow \uparrow \downarrow \uparrow

n m r $r \times r$

$A^T = V \Sigma^T U^T$

$$A^T \begin{bmatrix} u_1 & \dots & u_r \end{bmatrix} = \begin{bmatrix} v_1 & v_2 & \dots & v_r \end{bmatrix} \begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_r & \\ & & & \ddots \end{bmatrix}$$

\uparrow \downarrow \uparrow \downarrow \uparrow \downarrow

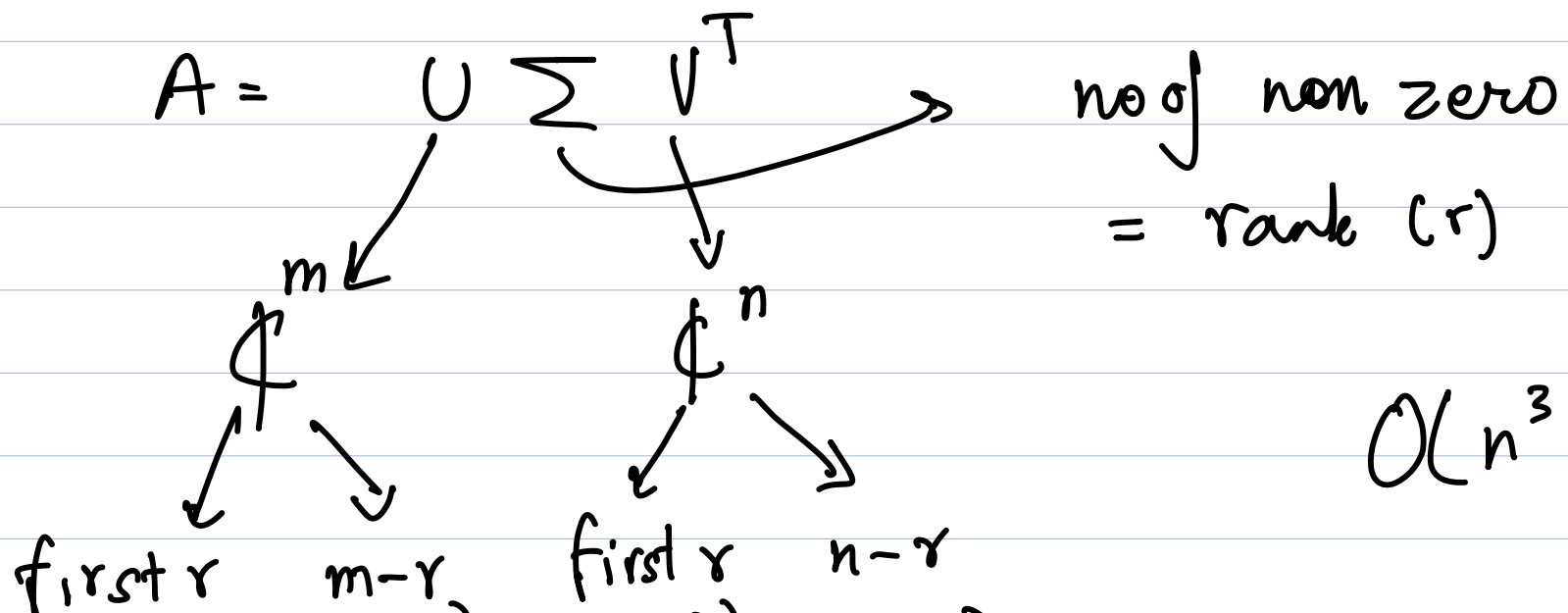
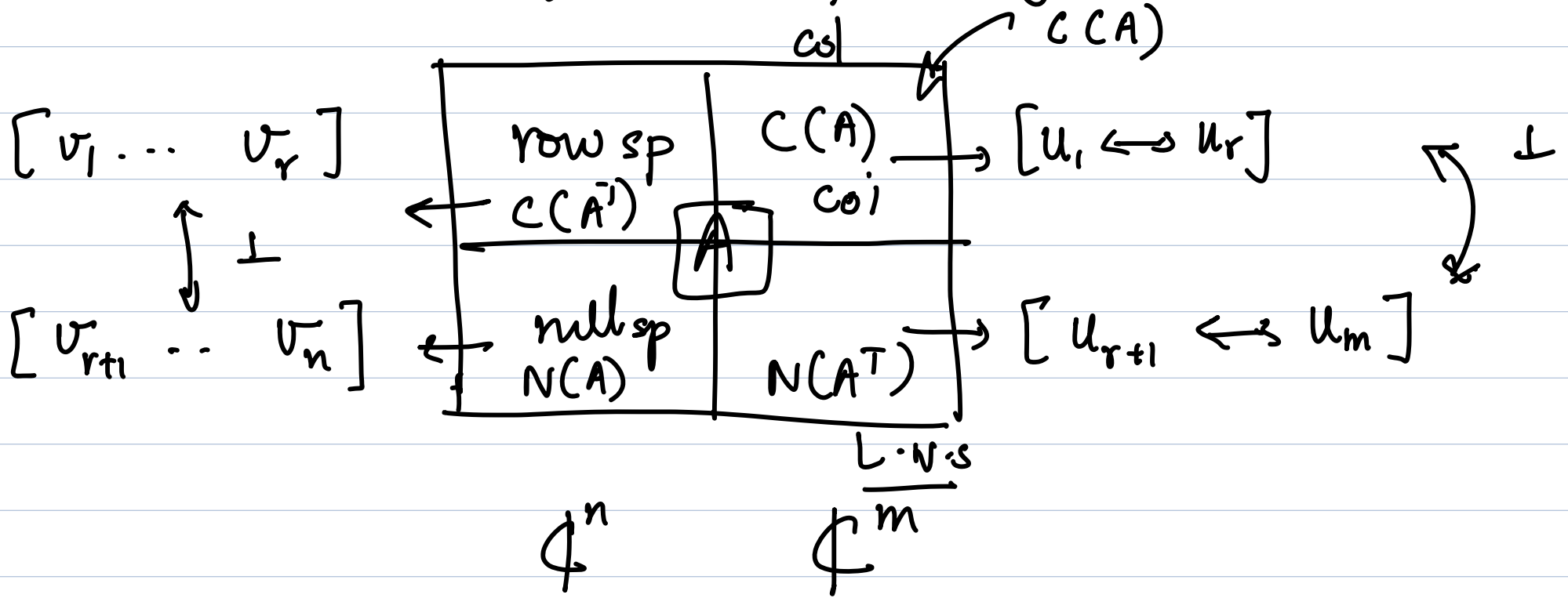
m n r $r \times r$

All are L.C.s of cols of A.

These r -linearly indep vectors form the basis of col space of A.

All are L.C.s of rows of A (cols of A^T)

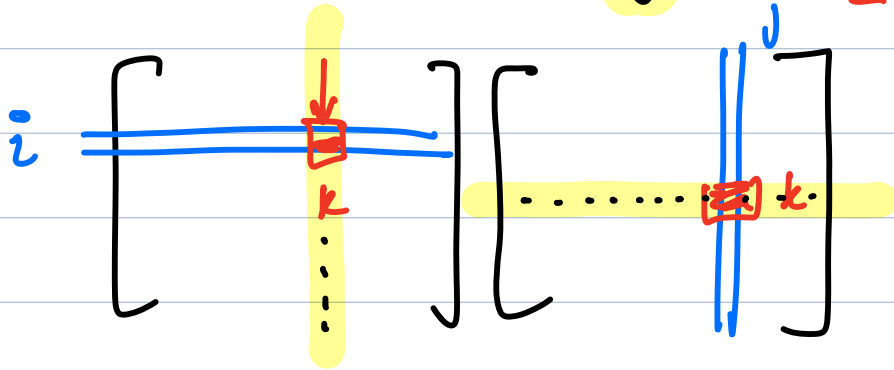
These r - linearly indepen vectors form the basis of row space of A .



$C(A)$ $N(A^T)$ $C(A^T)$ $N(A)$

Outer product notation of SVD

$$(AB)_{ij} = \sum_k A_{ik} B_{kj}$$



$$= \sum_k \begin{pmatrix} a_k & b_k^T \end{pmatrix}_{ij}$$

a_k is the k^{th} col of A
 b_k^T is the k^{th} row of B.

$$AB = \sum a_k b_k^T$$

outer product

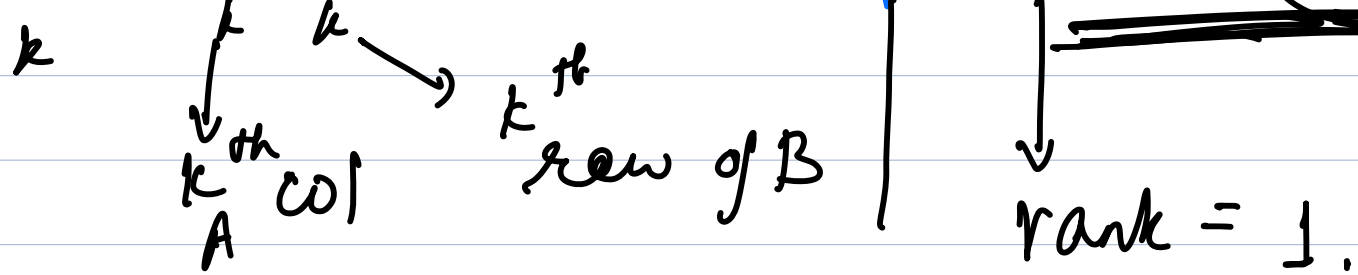
$$PQ^T = \begin{bmatrix} p_1 \\ \vdots \\ p_m \end{bmatrix} \begin{bmatrix} q_1 & \dots & q_n \end{bmatrix}$$

$$= \begin{bmatrix} p_1 q_1 & \dots & p_1 q_n \\ \vdots & & \vdots \\ p_m q_1 & \dots & p_m q_n \end{bmatrix}$$

$(PQ^T)_{ij} = p_i q_j$

$$\begin{bmatrix} | & | & | & | \end{bmatrix} \begin{bmatrix} \text{---} \\ \text{---} \\ \text{---} \end{bmatrix}$$

A B



\hookrightarrow SVD $A = U \Sigma V^T$

$m \times m$ $m \times n$
 U Σ V^T

$$= \begin{bmatrix} u_1 \sigma_1 & u_2 \sigma_2 & \dots & u_n \sigma_n \\ | & | & & \\ | & | & & \\ | & | & & \\ | & | & & \end{bmatrix} \begin{bmatrix} \text{---} u_1 \text{---} \\ \text{---} v_2 \text{---} \\ \vdots \\ \text{---} v_m \text{---} \end{bmatrix}$$

$$A = \sum_{i=1}^r \sigma_i u_i v_i^T$$

outer product

\hookrightarrow Sum of r 1-rank matrices.

e.g. 1000 x 1000 pixel image

10^6 numbers

$u \rightarrow 10^3, v \rightarrow 10^3 \rightarrow$ send only 10

$$(10^3 + 10^3) \times 10 + 10$$

$$20 \times 10^3 + 10 \approx \underline{20} \times 10^4$$

$$10^6 / 2 \times 10^4 = 50 \rightarrow$$