

① The singular value decomposition for a real  $m \times d$  matrix  $A$

① Let

$$\underbrace{U^T}_{d \times d} \underbrace{A^T A}_{d \times d} \underbrace{U}_{d \times d} = \Sigma^2 = \begin{bmatrix} \overset{r \times r}{\Sigma_1^2} & 0 \\ 0 & 0 \end{bmatrix} \quad (1)$$

where  $\Sigma_1^2 = \begin{bmatrix} \sigma_1^2 & & 0 \\ & \sigma_2^2 & \\ 0 & & \ddots \\ & & & \sigma_r^2 \end{bmatrix}$

i.e.  $\sigma_1^2 \geq \sigma_2^2 \geq \dots \geq \sigma_r^2 > 0$  are the positive eigenvalues of  $A^T A$  (the remaining  $d-r$  eigenvalues are 0).

$U$  is an orthogonal matrix

$$U = [\underline{u}_1 \underline{u}_2 \dots \underline{u}_d]$$

$\underline{u}_i$  is an eigenvector for the  $i$ 'th eigenvalue of  $A^T A$ . These eigenvectors are orthonormal.

(2)

② Set  $U_1 = [\underline{u}_1, \underline{u}_2, \dots, \underline{u}_r]$  a  $d \times r$  matrix with orthonormal columns, and  $U_2 = [\underline{u}_{r+1}, \dots, \underline{u}_d]$  a  $d \times (d-r)$  matrix with orthonormal columns.

$$U = [U_1, U_2]$$

③ It is easy to check from (1) that

$$U_1^T A^T A U_1 = \Sigma_1^2$$

and since  $\Sigma_1$  is invertible it follows that

$$\boxed{\Sigma_1^{-1} U_1^T A^T} \boxed{A U_1 \Sigma_1^{-1}} = I_{r \times r} \quad (2)$$

$V_1^T$                        $\ddots$  define  $V_1$

$V_1$  is an  $n \times r$  matrix, and (2) asserts that it has orthonormal columns

$$V_1 = [\underline{v}_1, \underline{v}_2, \dots, \underline{v}_r]$$

(therefore it also follows that  $r \leq n$ )

④ Using Gram-Schmidt find vectors  $\underline{v}_{r+1}, \underline{v}_{r+2}, \dots, \underline{v}_n$  so that

$\{\underline{v}_1, \underline{v}_2, \dots, \underline{v}_n\}$   
forms an orthonormal basis for  $\mathbb{R}^n$   
and define

$$V = [V_1, V_2]$$

$$\text{with } V_2 = [\underline{v}_{r+1} \dots \underline{v}_n] \quad (3)$$

⑤

We now calculate

$$\begin{aligned} V^T A U &= \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} A [u_1, u_2] \\ &= \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} [A u_1, A u_2] \end{aligned}$$

$$\begin{aligned} & \text{(cont)} \\ & = \begin{bmatrix} V_1^T A U_1 & V_1^T A U_2 \\ V_2^T A U_1 & V_2^T A U_2 \end{bmatrix} \end{aligned}$$

Since  $\underline{u}_{r+1} \dots \underline{u}_d$  are eigenvectors of  $A^T A$  corresponding to eigenvalue 0, it follows that  $A^T A \underline{u}_j = 0$   $j = r+1, \dots, d$ . Therefore  $A \underline{u}_j = 0$  for  $j = r+1, \dots, d$ . (remember  $N(A^T A) = N(A)$ ). In other words  $A U_2 = 0$  (matrix).

From the definition of  $V_1$  (2) we get that the columns of  $A U_1$  are multiples of the columns of  $V_1$ .

From the definition of  $V_2$  we have that the columns of  $V_2$  are orthogonal to those of  $V_1$ .

(5)

In other words the columns of  $AU_1$  are orthogonal to the columns of  $V_2$ , or

$$V_2^T AU_1 = 0 \text{ (matrix)}$$

(6)

We conclude that  $\swarrow$   $r \times r$

$$V^T AU = \begin{bmatrix} V_1^T AU_1 & 0 \\ 0 & 0 \end{bmatrix}$$

From (2) we see that

$$V_1^T AU_1 \Sigma_1^{-1} = I_{r \times r} \quad \text{so that}$$

$$\boxed{V_1^T AU_1 = \Sigma_1}$$

(6)

(7) In conclusion

$$V^T A U = \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\Sigma_1 = \begin{pmatrix} \sigma_1 & & 0 \\ & \sigma_2 & \\ 0 & & \sigma_r \end{pmatrix}, \quad \sigma_i > 0, \quad 1 \leq i \leq r$$

and  $V$  and  $U$  are orthogonal matrices (of dimension  $n \times n$  and  $d \times d$ , respectively).