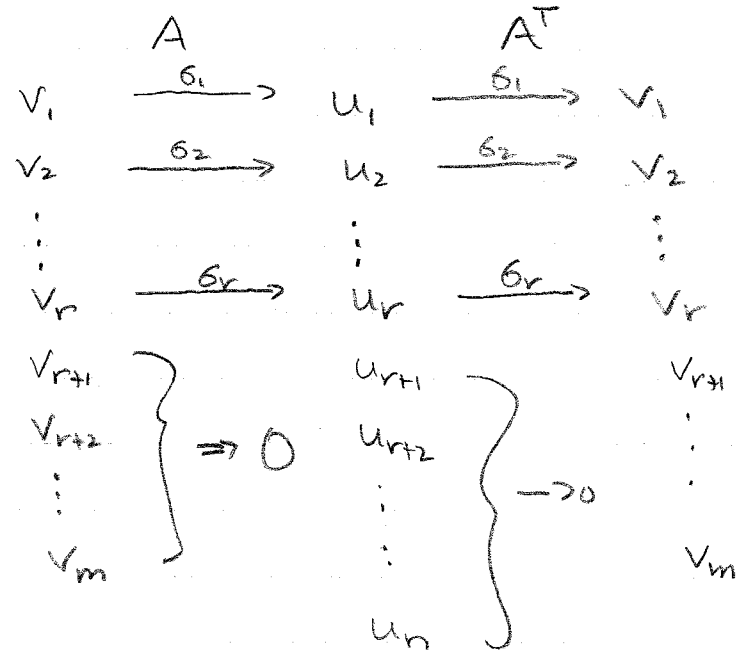


SVD & E-values / E-vectors of $A^T A$ & $A A^T$

There is a nice relationship between the SVD for $A \in \mathbb{R}^{n \times m}$ and E-values / E-vectors of the matrices $A^T A \in \mathbb{R}^{m \times m}$ and $A A^T \in \mathbb{R}^{n \times n}$

Recall the Picture: (Still assuming $\text{rank}(A) = r$)



For the SVD of A :

$$A v_i = \begin{cases} \sigma_i u_i, & i=1, 2, \dots, r \\ 0, & i=r+1, \dots, m \end{cases} \quad \text{and} \quad A^T u_i = \begin{cases} \sigma_i v_i, & i=1, 2, \dots, r \\ 0, & i=r+1, r+2, \dots, n \end{cases}$$

So for $i=1, 2, \dots, r$

$$A^T A v_i = A^T (\sigma_i u_i) = \sigma_i A^T u_i = \sigma_i (\sigma_i v_i) = \sigma_i^2 v_i$$

Hence, for $i=1, 2, \dots, r$, the squares of the singular values, σ_i^2 , are e-values of $A^T A$ with corresponding e-vectors v_i .

Similarly,

$$AA^T u_i = A(\sigma_i v_i) = \sigma_i A v_i = \sigma_i (\sigma_i u_i) = \sigma_i^2 u_i$$

So, for $i=1, 2, \dots, r$, the squares of the singular values, σ_i^2 , are e-values of AA^T with corresponding e-vectors u_i .

In addition,

- $N(A^T A) = N(A)$ and $N(AA^T) = N(A^T)$
- $\text{rank}(A^T A) = \text{rank}(A) = \text{rank}(A^T) = \text{rank}(AA^T) = r$

• So, the SVD of A identifies the range spaces $R(AA^T)$ and $R(A^T A)$ along with $N(AA^T)$ and $N(A^T A)$.

• This also shows us that the e-values of AA^T and $A^T A$, are all non-negative. In particular, each of AA^T and $A^T A$ have exactly r positive e-values. The multiplicity of the e-value $\lambda=0$ depends on the value of r , related to m and n .

$A^T A \in \mathbb{R}^{m \times m}$, so $A^T A$ has a zero eigenvalue of multiplicity $m-r$.

$AA^T \in \mathbb{R}^{n \times n}$, so AA^T has a zero eigenvalue of multiplicity $n-r$.

Two Disclaimers:

- 1. σ_i 's are uniquely determined, but just as eigenvectors of length 1 are not unique because we can always multiply the vector by -1 and get another e-vector of length 1, we can do the same for right + left singular vectors v_i 's and u_i 's.
- 2. I've tacitly assumed that I can always find a linearly independent set of right + left singular vectors (ie. e-vectors), but if we have repeated eigenvalues / singular values, then this can be messy!

Finally, an EXAMPLE!

- There are many ways to compute an SVD - here will compute AA^T just to connect it with previous discussion.

$$A = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 0 & 2 \end{bmatrix}$$

$A^T A \in \mathbb{R}^{3 \times 3}$ and $AA^T \in \mathbb{R}^{2 \times 2}$, so we use AA^T

$$AA^T = \begin{bmatrix} 5 & 2 \\ 2 & 8 \end{bmatrix}$$

$$p(\lambda) = (5-\lambda)(8-\lambda) - 4 = 0$$

$$\lambda^2 - 13\lambda + 36 = 0$$

$$\lambda = \frac{13 \pm \sqrt{169 - 4(36)}}{2} = \frac{13 \pm 5}{2}$$

E-values of AA^T are : $\lambda_1 = 9, \lambda_2 = 4$

Singular Values of A are: $\sigma_1 = 3, \sigma_2 = 2$
 (Note: $\text{rank}(A) = 2$ so that $r = 2$ here)

Left Singular Vectors of A : These are e-vectors of AA^T

$\lambda_1 = 9$ Let $u_1 = \begin{bmatrix} x \\ y \end{bmatrix}$ and find u_1 so that $\|u_1\| = 1$ and

$$AA^T u_1 = 9u_1 \quad (\text{i.e. } [AA^T - 9I]u_1 = \vec{0})$$

$$\left(\begin{bmatrix} 5 & 2 \\ 2 & 8 \end{bmatrix} - \begin{bmatrix} 9 & 0 \\ 0 & 9 \end{bmatrix} \right) u_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\left. \begin{array}{l} -4x + 2y = 0 \\ 2x - y = 0 \end{array} \right\} \begin{array}{l} \text{These eqns should} \\ \text{give the same info} \end{array}$$

$$\Rightarrow y = 2x$$

$$\text{Choose } u_1 = \frac{\begin{bmatrix} 1 \\ 2 \end{bmatrix}}{\| \begin{bmatrix} 1 \\ 2 \end{bmatrix} \|} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$\lambda_2 = 4$ Let $u_2 = \begin{bmatrix} x \\ y \end{bmatrix}$ and find u_2 so that $\|u_2\| = 1$

$$\text{and } [AA^T - 4I]u_2 = \vec{0}$$

$$\Rightarrow \left(\begin{bmatrix} 5 & 2 \\ 2 & 8 \end{bmatrix} - \begin{bmatrix} 4 & 0 \\ 0 & 4 \end{bmatrix} \right) \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\left. \begin{array}{l} x + 2y = 0 \\ 2x + 4y = 0 \end{array} \right\} \Rightarrow x = -2y \text{ or } y = -\frac{1}{2}x$$

$$\text{Choose } u_2 = \frac{\begin{bmatrix} 2 \\ -1 \end{bmatrix}}{\| \begin{bmatrix} 2 \\ -1 \end{bmatrix} \|} = \frac{1}{\sqrt{5}} \begin{bmatrix} 2 \\ -1 \end{bmatrix}$$

Observe that $u_1 \perp u_2$ - according to theory, they must be!

Right Singular Vectors of A:

- We could compute $A^T A$ and find its e-vectors to get the Right Singular vectors v_1, v_2, v_3 . But, an easier, more efficient way to do this is to use the relationship stated in the SVD theorem that is $A^T u_i = \sigma_i v_i, i=1, \dots, r$

i.e. $v_i = \frac{1}{\sigma_i} A^T u_i$ for $i=1, 2$ in this case

$$v_1 = \frac{1}{3} \begin{bmatrix} 1 & 2 \\ 2 & 0 \\ 0 & 2 \end{bmatrix} \left(\frac{1}{\sqrt{5}}\right) \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \text{and} \quad v_2 = \frac{1}{2} \begin{bmatrix} 1 & 2 \\ 2 & 0 \\ 0 & 2 \end{bmatrix} \left(\frac{1}{\sqrt{3}}\right) \begin{bmatrix} 2 \\ -1 \end{bmatrix}$$

$$v_1 = \frac{1}{3\sqrt{5}} \begin{bmatrix} 5 \\ 2 \\ 4 \end{bmatrix} \quad v_2 = \frac{1}{2\sqrt{3}} \begin{bmatrix} 0 \\ 4 \\ -2 \end{bmatrix} = \frac{1}{\sqrt{3}} \begin{bmatrix} 0 \\ 2 \\ -1 \end{bmatrix}$$

To obtain v_3 , we can use the relationship from the SVD Thm that $Av_3 = 0$, or we could apply Gram-Schmidt using v_1, v_2 - and then normalize to get v_3 :

Gram-Schmidt

$$\phi_1 = v_1$$

$$\phi_2 = v_2$$

$$\phi_3 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \frac{\langle v_1, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \rangle}{\|v_1\|} v_1 - \frac{\langle v_2, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \rangle}{\|v_2\|} v_2$$

$$= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \frac{\frac{1}{3\sqrt{5}}(11)}{1} \cdot \left(\frac{1}{3\sqrt{5}}\right) \begin{bmatrix} 5 \\ 2 \\ 4 \end{bmatrix} - \frac{\frac{1}{\sqrt{3}}(1)}{1} \cdot \left(\frac{1}{\sqrt{3}}\right) \begin{bmatrix} 0 \\ 2 \\ -1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \frac{11}{45} \begin{bmatrix} 5 \\ 2 \\ 4 \end{bmatrix} - \frac{1}{5} \begin{bmatrix} 0 \\ 2 \\ -1 \end{bmatrix}$$

$$= \frac{1}{9} \begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}$$

$$\text{So, } v_3 = \frac{\phi_3}{\|\phi_3\|} \rightarrow$$

Choose this vector so that it's Lin. Ind. with v_1, v_2

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Normalizing $v_3 = \frac{\frac{1}{9} \begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}}{\|\frac{1}{9} \begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}\|} = \frac{\begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}}{3} = \frac{1}{3} \begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}$

Putting it all together:

$$U = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 2 \\ 2 & -1 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} 3 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad V = \frac{1}{3\sqrt{5}} \begin{bmatrix} 5 & 0 & -2\sqrt{5} \\ 2 & 6 & \sqrt{5} \\ 4 & -3 & 2\sqrt{5} \end{bmatrix}$$

- Check that $A = U \Sigma V^T$
- Note that $A^T = V \Sigma U^T$
- Also observe that $A^T A$ and $A A^T$ have e-values that are non-negative. This agrees with other items from linear algebra theory.

1. $A^T A$ and $A A^T$ are positive semidefinite.
That is, $x^T (A^T A) x \geq 0 \quad \forall x \neq 0$ and
 $x^T (A A^T) x \geq 0 \quad \forall x \neq 0$

Why? $x^T A^T A x = (Ax)^T (Ax) = \langle Ax, Ax \rangle = \|Ax\|^2 \geq 0$
 $\forall x \neq 0.$

(Similarly for $A A^T$)

2. All e-values of $A A^T$ & $A^T A$ are non-negative
(See your homework for this one)