Singular Value Decomposition

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Let $A \in \mathbb{R}^{m \times n}$.

Remark 1. If x is an eigenvector of A^tA with non-zero eigenvalue λ , then Ax is an eigenvector of AA^t with eigenvalue λ . That $(AA^t)(Ax) = \lambda Ax$ is obvious. That $Ax \neq 0$ follows from $||Ax||^2 = x^t A^t Ax = \lambda x^t x$.

If x is an eigenvector of $A^{t}A$ with eigenvalue 0, then Ax = 0.

Remark 2. Similarly if y is an eigenvalue of AA^t with non-zero eigenvalue λ then A^ty is an eigenvalue of A^tA with eigenvalue λ . If λ is zero then $A^ty = 0$.

Remark 3. It follows from the above that A^tA and AA^t have the same number of strictly positive eigenvalues.

Lemma 4. Assume A^tA has precisely k strictly positive eigenvalues $\lambda_1, \ldots, \lambda_k$. Let x_1, \ldots, x_k , be corresponding mutually orthogonal unit eigenvectors for A^tA . Define unit vectors $y_i = Ax_i/\|Ax_i\| = Ax_i/\sqrt{\lambda_i}$.

Define unit vectors $y_i = Ax_i/\|Ax_i\| = Ax_i/\sqrt{\lambda_i}$. Define $\bar{V} \in \mathbb{R}^{n \times k}$ and $\bar{U} \in \mathbb{R}^{m \times k}$ be the matrices whose columns are (x_i) and (y_i) , respectively. Let $\bar{\Sigma} = \operatorname{diag}(\sqrt{\lambda_1}, \dots, \sqrt{\lambda_k}) \in \mathbb{R}^{k \times k}$. Then

$$\bar{U}^t A \bar{V} = \bar{\Sigma}. \tag{1}$$

Proof. Let $e_i \in \mathbb{R}^k$ be the *i*th standard basis vector. Then

$$\bar{U}^t A \bar{V} e_i = \bar{U}^t A x_i = \bar{U}^t \sqrt{\lambda_i} y_i = \sqrt{\lambda_i} e_i. \tag{2}$$

Lemma 5. Complete the columns of \bar{U} and \bar{V} to $U \in \mathbb{R}^{m \times m}$ and $V \in \mathbb{R}^{n \times n}$ by adding orthonormal vectors x_i and y_i , i > k, with $A^t A x_i = 0$ and $A A^t y_i = 0$, respectively. Extend $\bar{\Sigma}$ to $\Sigma \in \mathbb{R}^{n \times m}$ by adding zeroes. I.e.,

$$U = (\bar{U} \quad U_0), V = (\bar{V} \quad V_0), \Sigma = \begin{pmatrix} \bar{\Sigma} & 0 \\ 0 & 0 \end{pmatrix}.$$
 (3)

Then

$$A = U\Sigma V^t. (4)$$

Proof. Note that U and V are orthogonal matrices. Also,

$$U^{t}AV = \begin{pmatrix} \bar{U}^{t} \\ U_{0} \end{pmatrix} A \begin{pmatrix} \bar{V} & V_{0} \end{pmatrix} = \begin{pmatrix} \bar{U}^{t}A\bar{V} & \bar{U}^{t}AV_{0} \\ U_{0}^{t}A\bar{V} & U_{0}^{t}AV_{0} \end{pmatrix}.$$
 (5)

By construction $AV_0 = 0$ and $U_0^t A = 0$. The lemma follows.

Summing up:

Theorem 6. For any $A \in \mathbb{R}^{m \times n}$, there exists orthogonal matrices $U \in \mathbb{R}^{m \times m}$ and $V \in \mathbb{R}^{n \times n}$ and a diagonal matrix $\Sigma \in \mathbb{R}^{m \times n}$ such that $A = U\Sigma V^t$.

The diagonal values of Σ are the strictly positive eigenvalues of A^tA (or equivalently AA^t) and zeroes.

Remark 7. To remember the construction of U note that

$$A^t A = V \Sigma U^t U \Sigma V = V^t \Sigma^t \Sigma V^t. \tag{6}$$

Thus if V is the matrix whose columns of eigenvectors of A^tA and $\Sigma^t\Sigma$ is the diagonal matrix of eigenvalues, then the equation is satisfied.

A similar mnemonic holds made for V.