

Polar and Singular-Value Decompositions

POLAR DECOMPOSITION

Let \mathbf{A} be a real $N \times M$ matrix, where $N \geq M$ (*i.e.*, mapping from an M -dimensional source vector space to a larger N -dimensional target vector space). Then, there exists a column-wise orthogonal matrix \mathbf{S} ($\in \mathfrak{R}^{N \times M}$ and) such that

$$\mathbf{A} = \mathbf{S}\mathbf{J}, \quad (1)$$

$$\mathbf{S}^T \mathbf{S} = \mathbf{I}^{M \times M}, \quad (2)$$

where $\mathbf{I}^{M \times M}$ is the identity matrix and the unique nonnegative matrix \mathbf{J} is

$$\mathbf{J} = \sqrt{\mathbf{A}^T \mathbf{A}} \in \mathfrak{R}^{M \times M}. \quad (3)$$

(Proof)

Consider a spectral (or eigen) decomposition of \mathbf{J} :

$$\mathbf{J} = \sum_{i=1}^M \lambda_i |i\rangle \langle i|, \quad (4)$$

where $\lambda_i (\geq 0)$ is the i -th eigenvalue and $\{|i\rangle \mid i = 1, \dots, M\}$ is an orthonormal set of eigenvectors. Define

$$|\psi_i\rangle = \mathbf{A}|i\rangle (\in \mathfrak{R}^N), \quad (5)$$

then

$$\langle \psi_i | \psi_i \rangle = \langle i | \mathbf{A}^T \mathbf{A} | i \rangle = \langle i | \mathbf{J}^2 | i \rangle = \lambda_i^2. \quad (6)$$

For those eigenvectors with $\lambda_i \neq 0$, define

$$|e_i\rangle = |\psi_i\rangle / \lambda_i (\in \mathfrak{R}^N), \quad (7)$$

so that these vectors are orthonormal. For those eigenvectors with $\lambda_i = 0$, we use the Gram-Schmidt procedure to construct an orthonormal basis set and append it to the above basis set. Define a column-wise orthogonal matrix,

$$\mathbf{U} = \sum_{i=1}^M |e_i\rangle \langle i| \in \mathfrak{R}^{N \times M}. \quad (8)$$

When $\lambda_i \neq 0$, we have

$$\mathbf{U}\mathbf{J}|i\rangle = \sum_{j=1}^M |e_j\rangle \lambda_i \underbrace{\langle j|i\rangle}_{\delta_{ji}} = \lambda_i |e_i\rangle = |\psi_i\rangle = \mathbf{A}|i\rangle. \quad (9)$$

When $\lambda_i = 0$,

$$\mathbf{U}\mathbf{J}|i\rangle = \sum_{j=1}^M |e_j\rangle \underbrace{\lambda_i}_{0} \underbrace{\langle j|i\rangle}_{\delta_{ji}} = 0 |e_i\rangle = 0 = |\psi_i\rangle = \mathbf{A}|i\rangle. \quad (10)$$

Namely, $\mathbf{U}\mathbf{J}$ is identical to \mathbf{A} as a mapping for the entire M -dimensional source vector space. //

SINGULAR VALUE DECOMPOSITION (SVD)

Let \mathbf{A} be a real $N \times M$ matrix, where $N \geq M$ as above. Then, there exists column-wise orthogonal matrices \mathbf{U} ($\in \mathfrak{R}^{N \times M}$) and \mathbf{V} ($\in \mathfrak{R}^{M \times M}$), such that

$$\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^T, \quad (11)$$

$$\mathbf{U}^T \mathbf{U} = \mathbf{V}^T \mathbf{V} = \mathbf{I}^{M \times M}, \quad (12)$$

where \mathbf{D} ($\in \mathfrak{R}^{M \times M}$) is a nonnegative diagonal matrix.

(Proof)

Consider the polar decomposition, $\mathbf{A} = \mathbf{S}\mathbf{J}$, in Eq. (1). We perform the eigen-decomposition of \mathbf{J} as

$$\mathbf{J} = \mathbf{V}\mathbf{D}\mathbf{V}^T, \quad (13)$$

where \mathbf{D} is the diagonal matrix such that its matrix elements are

$$D_{ij} = \lambda_i \delta_{ij}, \quad (14)$$

and $\mathbf{V} (\in \mathfrak{R}^{M \times M})$ is an orthogonal matrix, *i.e.*, $\mathbf{V}^T \mathbf{V} = \mathbf{I}^{M \times M}$. Substituting Eq. (13) in Eq. (1), we have

$$\mathbf{A} = \mathbf{S}\mathbf{V}\mathbf{D}\mathbf{V}^T \equiv \mathbf{U}\mathbf{D}\mathbf{V}^T, \quad (13)$$

Note that $\mathbf{U} = \mathbf{S}\mathbf{V} (\in \mathfrak{R}^{N \times M})$ is a column-wise orthogonal, since

$$\mathbf{U}^T \mathbf{U} = \mathbf{V}^T \mathbf{S}^T \mathbf{S} \mathbf{V} = \mathbf{V}^T \underbrace{\mathbf{S}^T \mathbf{S}}_{\mathbf{I} \in \mathfrak{I}^{M \times M}} \mathbf{V} = \mathbf{V}^T \mathbf{V} = \mathbf{I}^{M \times M}. //$$