8.6 Singular Value Decomposition

Theorem

If A is an $n \times n$ matrix of rank k, then A can be factored as

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

where U and V are $n \times n$ orthogonal matrices and Σ is an $n \times n$ diagonal matrix whose main diagonal has k positive entires and n-k zeros.

Singular Value Decomposition of Square Matrices

Theorem

(Singular Value Decomposition of a Square Matrix) If A is an $n \times n$ matrix of rank k, then A has a singular value decomposition $A = U \Sigma V^T$ in which:

- (a) $V = [\mathbf{v}_1 \ \mathbf{v}_2 \ \cdots \ \mathbf{v}_n]$ orthogonally diagonalizes $A^T A$.
- (b) The nonzero diagonal entries of Σ are

$$\sigma_1 = \sqrt{\lambda_1}, \sigma_2 = \sqrt{\lambda_2}, \dots, \sigma_k = \sqrt{\lambda_k}$$

where $\lambda_1, \lambda_2, \dots, \lambda_k$ are the nonzero eigenvalues of A^TA corresponding to the column vectors of V.

Singular Value Decomposition of Square Matrices

(c) The column vectors of V are ordered so that $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_k > 0$.

(d)
$$\mathbf{u}_{i} = \frac{A\mathbf{v}_{i}}{\|A\mathbf{v}_{i}\|} = \frac{1}{\sigma_{i}}A\mathbf{v}_{i} \ (i = 1, 2, ..., k)$$

- (e) $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\}$ is an orthonormal basis for col(A).
- (f) $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k, \mathbf{u}_k + 1, \dots, \mathbf{u}_n\}$ is extension of $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\}$ to an orthonormal basis for \mathbb{R}^n .

Singular Value Decomposition of Square Matrices

Example

Find the singular value decomposition of the matrix

$$A = \begin{bmatrix} \sqrt{3} & 2 \\ 0 & \sqrt{3} \end{bmatrix}$$

Singular Value Decomposition of Nonsquare Matrices

Theorem

(Singular Value Decomposition of a General Matrix) If A is an $m \times n$ matrix of rank k, then A can be factored as

$$A = U\Sigma V^{T}(12)$$

in which U, Σ and V have sizes $m\times m$, $m\times n$, and $n\times n$, respectively, and in which:

Singular Value Decomposition of Nonsquare Matrices

- (a) $V = \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_n \end{bmatrix}$ orthogonally diagonalizes $A^T A$.
- (b) The nonzero diagonal entries of Σ are $\sigma_1 = \sqrt{\lambda_1}, \sigma_2 = \sqrt{\lambda_2}, \ldots, \sigma_k = \sqrt{\lambda_k}$, where $\lambda_1, \lambda_2, \ldots, \lambda_k$ are the nonzero eigenvalues of A^TA corresponding to the column vectors of V.
- (c) The column vectors of V are ordered so that $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_k > 0$.
- (d) $\mathbf{u}_{i} = \frac{A\mathbf{v}_{i}}{\|A\mathbf{v}_{i}\|} = \frac{1}{\sigma_{i}}A\mathbf{v}_{i} \ (i = 1, 2, \dots, k)$
- (e) $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\}$ is an orthonormal basis for col(A).
- (f) $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k, \mathbf{u}_k + 1, \dots, \mathbf{u}_m\}$ is extension of $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\}$ to an orthonormal basis for \mathbb{R}^m .

Singular Value Decomposition of Nonsquare Matrices

Example

Find the singular value decomposition of the matrix

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

Singular Value Decomposition And The Fundamental Spaces of A Matrix

Theorem

If A is an $m \times n$ matrix of rank k, and if $A = U \Sigma V^T$ is the singular value decomposition given in Formula (12), then:

- (a) $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\}$ is an orthonormal basis for col(A).
- (b) $\{\mathbf{u}_{k+1},\dots,\mathbf{u}_m\}$ is an orthonormal basis for $col(A)^\perp=null(A^T)$.
- (c) $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ is an orthonormal basis for row(A).
- (d) $\{\mathbf{v}_{k+1},\ldots,\mathbf{v}_n\}$ is an orthonormal basis for $row(A)^{\perp}=null(A)$.

Reduced Singular Value Decomposition

$$A = U_1 \Sigma_1 V_1^T$$

which is called a reduced singular value decomposition of A.

$$A = \sigma_1 \mathbf{u}_1 \mathbf{v}_1^T + \sigma_2 \mathbf{u}_2 \mathbf{v}_2^T + \dots + \sigma_k \mathbf{u}_k \mathbf{v}_k^T$$

which is called a reduced singular value expansion of A.