

Principal Component Analysis

Proof: Left Singular Vector is the First Principal Component

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Let $\mathbf{A} = [\mathbf{a}_1 \ \mathbf{a}_2 \ \cdots \ \mathbf{a}_M]$ be an N -by- M ($N \geq M$) matrix with columns \mathbf{a}_i . The expression $\mathbf{f}^T \mathbf{A} \mathbf{A}^T \mathbf{f}$ represents the sum of squares of the elements of the vector $\mathbf{A}^T \mathbf{f}$, whose elements are the inner product between \mathbf{f} and each column of \mathbf{A} . The solution to the problem

$$\max_{\|\mathbf{f}\|_2^2=1} \sum_{i=1}^M |\mathbf{f}^T \mathbf{a}_i|^2 = \max_{\|\mathbf{f}\|_2^2=1} \mathbf{f}^T \mathbf{A} \mathbf{A}^T \mathbf{f}$$

gives the direction \mathbf{f} containing the maximum variability or variance across the columns of \mathbf{A} , that is, the direction that best fits the set of vectors $\mathbf{a}_i, i = 1, 2, \dots, M$. The vector \mathbf{f} is called the first principal component of the data $\mathbf{a}_i, i = 1, 2, \dots, M$. Let the \mathbf{A} have singular value decomposition $\mathbf{U} \mathbf{\Sigma} \mathbf{V}^T$ where \mathbf{U}, \mathbf{V} are square matrices, that is, the full singular value decomposition.

Theorem:

$$\max_{\|\mathbf{f}\|_2^2=1} \mathbf{f}^T \mathbf{A} \mathbf{A}^T \mathbf{f} = \sigma_1^2$$

is obtained by setting $\mathbf{f} = \mathbf{u}_1$, the left singular vector corresponding to the largest singular value.

Proof: Substitute the singular value decomposition for $\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T$ to write

$$\mathbf{f}^T \mathbf{A} \mathbf{A}^T \mathbf{f} = \mathbf{f}^T \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T \mathbf{V} \mathbf{\Sigma} \mathbf{U}^T \mathbf{f} = \mathbf{f}^T \mathbf{U} \mathbf{\Sigma}^2 \mathbf{U}^T \mathbf{f}$$

where the second equality follows from the orthonormality of the columns of \mathbf{V} : $\mathbf{V}^T \mathbf{V} = \mathbf{I}$. Now let $\mathbf{z} = \mathbf{U}^T \mathbf{f}$ and note that $\|\mathbf{z}\|_2^2 = \mathbf{f}^T \mathbf{U} \mathbf{U}^T \mathbf{f} = \mathbf{f}^T \mathbf{f} = \|\mathbf{f}\|_2^2$ because the right singular vectors in \mathbf{U} are orthonormal. That is, $\mathbf{U} \mathbf{U}^T = \mathbf{U}^T \mathbf{U} = \mathbf{I}$. Hence we may rewrite the maximization problem as

$$\max_{\|\mathbf{z}\|_2^2=1} \mathbf{z}^T \mathbf{\Sigma}^2 \mathbf{z} = \max_{\sum_{i=1}^M z_i^2=1} \sum_{j=1}^M \sigma_j^2 z_j^2$$

where z_i is the i^{th} element of \mathbf{z} .

The unit norm constraint on \mathbf{z} implies that an increase in the magnitude of any one element z_k must be offset by a decrease in the magnitudes of the other elements of \mathbf{z} . Since $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_p > 0$, the best strategy is to allocate all of the unit energy in \mathbf{z} to z_1 . To see this, consider the case where $M = 2$ and $\sigma_1 > \sigma_2$. In this case we require $z_2^2 = 1 - z_1^2$ and

$$\sum_{i=1}^M \sigma_i^2 z_i^2 = \sigma_1^2 z_1^2 + \sigma_2^2 (1 - z_1^2) = z_1^2 (\sigma_1^2 - \sigma_2^2) + \sigma_2^2$$

Since $\sigma_1^2 - \sigma_2^2 > 0$, this quantity is maximized by choosing z_1^2 to be as large or possible, that is, $z_1^2 = 1$. Any energy allocated to z_2 is multiplied by σ_2^2 , which results in a lower value than had that same energy been allocated to z_1 because $\sigma_1 > \sigma_2$. A similar argument applies to the case $M > 2$. The strategy that maximizes $\sum_{i=1}^p \sigma_i^2 z_i^2$ allocates all of the unit energy in \mathbf{z} to z_1 , so $\mathbf{z} = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}$. The orthonormality of the columns of \mathbf{U} thus imply that $\mathbf{f} = \mathbf{U}^T \mathbf{z}$ or $\mathbf{f} = \mathbf{u}_1$ where \mathbf{u}_1 is the first column of \mathbf{U} , the first left singular vector of \mathbf{A} .