

A. Definition for a Matrix $\mathbf{X} \in \mathbb{R}^{n \times p}$

First Definition (Maximizing Variance)¹

The first principal component, defined by maximizing variance ($\mathbf{PC}_1^{\text{var}}$), is the unit vector \mathbf{w} that maximizes the sum of squared projections of the data points (\mathbf{x}_i) onto it. This can be expressed as:

$$\begin{aligned}\mathbf{PC}_1^{\text{var}} &= \arg \max_{\substack{\mathbf{w} \in \mathbb{R}^p \\ \|\mathbf{w}\|_2=1}} \sum_{i=1}^n (\mathbf{w}^T \mathbf{x}_i)^2 \\ &= \arg \max_{\substack{\mathbf{w} \in \mathbb{R}^p \\ \|\mathbf{w}\|_2=1}} \|\mathbf{X}\mathbf{w}\|_2^2 \\ &= \arg \max_{\substack{\mathbf{w} \in \mathbb{R}^p \\ \|\mathbf{w}\|_2=1}} \mathbf{w}^T \mathbf{X}^T \mathbf{X} \mathbf{w}\end{aligned}$$

Note: The notation $\|\mathbf{w}\| = 1$ typically implies the Euclidean norm, $\|\mathbf{w}\|_2 = 1$.

Second Definition (Minimizing Least Squares Error)

The first principal component, defined by minimizing the least squares reconstruction error ($\mathbf{PC}_1^{\text{LS}}$), is the unit vector \mathbf{w} that minimizes the sum of squared distances between the data points (\mathbf{x}_i) and their projections onto the line defined by \mathbf{w} . This is given by:

$$\mathbf{PC}_1^{\text{LS}} = \arg \min_{\substack{\mathbf{w} \in \mathbb{R}^p \\ \|\mathbf{w}\|_2=1}} \sum_{i=1}^n \text{dist}(\mathbf{x}_i, \mathbf{w})^2$$

where:

$$\text{dist}(\mathbf{x}_i, \mathbf{w}) = \|\mathbf{x}_i - P_{\mathbf{w}}(\mathbf{x}_i)\|_2$$

and $P_{\mathbf{w}}(\mathbf{x}_i)$ is the orthonormal projection of the point \mathbf{x}_i onto the one-dimensional subspace spanned by the vector \mathbf{w} . Specifically, $P_{\mathbf{w}}(\mathbf{x}_i) = (\mathbf{w}^T \mathbf{x}_i) \mathbf{w}$ since $\|\mathbf{w}\|_2 = 1$.

Exercise. Assume that the eigenvalues of the matrix $\mathbf{X}^T \mathbf{X}$ satisfy $\lambda_1 > \lambda_2 > \dots > \lambda_p \geq 0$. Show that $\mathbf{PC}_1^{\text{var}}$ corresponds to \mathbf{v}_1 , the first column vector (eigenvector corresponding to λ_1) of \mathbf{U} in the spectral decomposition of $\mathbf{X}^T \mathbf{X}$:

$$\mathbf{X}^T \mathbf{X} = \mathbf{U} \mathbf{\Lambda} \mathbf{U}^T$$

(Where \mathbf{U} is the orthogonal matrix whose columns are the eigenvectors \mathbf{v}_i , and $\mathbf{\Lambda}$ is the diagonal matrix of eigenvalues λ_i).

¹ The superscript '1' might refer to a footnote or citation in the original source document.