

corresponding variances are related to the *Eigenvalues* of the *covariance matrix*. Therefore, the problem of *PCA* reduces to the following *Eigenvalue problem*,

$$\mathbf{\Sigma} \mathbf{v} = \hat{\lambda} \mathbf{v} \quad (12.2)$$

where $\mathbf{v} : \mathcal{R}^1 \mapsto \mathcal{R}^D$ is an *Eigenvector* associated with the feature vectors of interest, $\mathbf{x} : \mathcal{R}^1 \mapsto \mathcal{R}^D$, and $\mathbf{\Sigma} : \mathcal{R}^D \mapsto \mathcal{R}^D$ is the associated variance-covariance (*covariance*) matrix (see Section 6.10). $\hat{\lambda}$ is known as an *Eigenvalue* associated with *Eigenvector*, \mathbf{v} and the matrix, $\mathbf{\Sigma}$.

We may rearrange Equation 12.2 in the following form,

$$(\hat{\lambda} \mathbf{I} - \mathbf{\Sigma}) \mathbf{v} = \mathbf{0} \quad \forall \mathbf{v} \quad (12.3)$$

For any general matrix, $\mathbf{\Sigma}$, Equation 12.3 may only be true if the determinant of $\hat{\lambda} \mathbf{I} - \mathbf{\Sigma}$ is zero. There will generally be D values of $\hat{\lambda}$ (the *Eigenvalues*) for which the *determinant* can become zero, given any general matrix. $\hat{\lambda}_i, i \in \{1, 2, \dots, D\}$ are said to be the solutions to the characteristic equation,

$$\begin{aligned} |\hat{\lambda} \mathbf{I} - \mathbf{\Sigma}| &= \prod_{i=1}^D (\hat{\lambda} - \hat{\lambda}_i) \\ &= \mathbf{0} \end{aligned} \quad (12.4)$$

where $|\hat{\lambda} \mathbf{I} - \mathbf{\Sigma}|$ denotes the determinant of $\hat{\lambda} \mathbf{I} - \mathbf{\Sigma}$. Note that in general $\hat{\lambda}_i \in \mathbb{C}$.

for every *Eigenvalue*, $\hat{\lambda}_i$, Equation 12.2 must be true. There is a single *Eigenvector*, \mathbf{v}_i , associated with every $\hat{\lambda}_i$ which makes Equation 12.2 valid, namely,

$$\mathbf{\Sigma} \mathbf{v}_i = \hat{\lambda}_i \mathbf{v}_i \quad \forall i \in \{1, 2, \dots, D\} \quad (12.5)$$

Solving Equation 12.2 for all i will produce a set of D *Eigenvectors* associated with the D *Eigenvalues*, $\hat{\lambda}_i$. Let us construct a matrix, $\mathbf{V} : \mathcal{R}^D \mapsto \mathcal{R}^D$ whose columns are the *Eigenvectors*, \mathbf{v}_i , such that the first *Eigenvector* is associated with the largest *Eigenvalue* and the last one is associated with the smallest *Eigenvalue*. Also, note that Equation 12.5 may be multiplied by any constant from both sides. Therefore, the magnitude of the *Eigenvectors*, \mathbf{v}_i is arbitrary. However, in here, we assume that all \mathbf{v}_i have been normalized to have unit magnitude,

$$\|\mathbf{v}_i\|_{\ell} = 1 \quad \forall i \in \{1, 2, \dots, D\} \quad (12.6)$$

This may be simply achieved by dividing the computed *Eigenvectors* by their corresponding Euclidean norms. After applying the normalization, we will have the following relation, based on Equation 12.2,

$$\mathbf{\Sigma} \mathbf{V} = \mathbf{V} \mathbf{\Lambda} \quad (12.7)$$