Input vector: $\mathbf{x} \in \mathbb{R}^D$

Transformation matrix:
$$\mathbf{A} = egin{bmatrix} | & & | \\ \boldsymbol{lpha_1} & \dots & \boldsymbol{lpha_M} \\ | & & | \end{bmatrix} \in \Re^{D imes M}$$

Finding 1st PCA dimension $\alpha_1 \in \mathbb{R}^D$

We would like to find $\alpha_1 \in \mathbb{R}^D$ that maximizes the variance:

$$Var\{\boldsymbol{\alpha}_1^T\mathbf{x}\} = \boldsymbol{\alpha}_1^T\boldsymbol{\Sigma}\boldsymbol{\alpha}_1$$

where Σ is the covariance of the data $\{x_1, \dots, x_N\}$.

Constrained optimization problem:

$$\max \boldsymbol{\alpha}_{1}^{T} \boldsymbol{\Sigma} \boldsymbol{\alpha}_{1}$$
, s.t. $\boldsymbol{\alpha}_{1}^{T} \boldsymbol{\alpha}_{1} = 1$

Lagrange optimization:

$$L = \boldsymbol{\alpha}_{1}^{T} \boldsymbol{\Sigma} \boldsymbol{\alpha}_{1} - \lambda (\boldsymbol{\alpha}_{1}^{T} \boldsymbol{\alpha}_{1} - 1)$$

$$\Rightarrow \frac{\theta L}{\theta \boldsymbol{\alpha}_{1}} = 0 \Rightarrow \boldsymbol{\Sigma} \boldsymbol{\alpha}_{1} - \lambda \boldsymbol{\alpha}_{1} = 0 \Rightarrow \lambda \boldsymbol{\alpha}_{1} = \boldsymbol{\Sigma} \boldsymbol{\alpha}_{1}$$

This is the eigenvector equation! We choose the eigenvector with the largest eigenvalue: $\Sigma \alpha_1$ is the projection of Σ onto the eigenvector α_1 , The largest this projection, the more variance vector α_1 will represent, therefore we have to choose the eigenvector with the largest eigenvalue.

Finding 2nd PCA dimension $\alpha_{\mathbf{2}} \in \mathbb{R}^D$

We would like to find $\alpha_2 \in \mathbb{R}^D$ that maximizes the variance $Var\{\alpha_2^T \mathbf{x}\}$, so that α_2 is *orthogonal* to α_1 .

Constrained optimization problem:

$$\max \boldsymbol{\alpha}_{2}^{T} \boldsymbol{\Sigma} \boldsymbol{\alpha}_{2}$$
, s.t. $\boldsymbol{\alpha}_{2}^{T} \boldsymbol{\alpha}_{2} = 1$ and $\boldsymbol{\alpha}_{2}^{T} \boldsymbol{\alpha}_{1} = 0$

Lagrange optimization:

$$L = \boldsymbol{\alpha}_{2}^{T} \boldsymbol{\Sigma} \boldsymbol{\alpha}_{2} - \lambda (\boldsymbol{\alpha}_{2}^{T} \boldsymbol{\alpha}_{2} - 1) - \phi \boldsymbol{\alpha}_{2}^{T} \boldsymbol{\alpha}_{1}$$

$$\Rightarrow \frac{\theta L}{\theta \boldsymbol{\alpha}_{2}} = 0 \Rightarrow \boldsymbol{\Sigma} \boldsymbol{\alpha}_{2} - \lambda \boldsymbol{\alpha}_{2} - \phi \boldsymbol{\alpha}_{1} = 0$$

If we right-multiply α_1 in the above expression:

$$\Sigma \alpha_2 \alpha_1^T - \lambda \alpha_2 \alpha_1^T - \phi \alpha_1 \alpha_1^T = 0 \Rightarrow \phi = 0$$

When $\phi = 0$, we get $\lambda \alpha_2 = \Sigma \alpha_2$. This corresponds to another eigenvalue equation and we choose the eigenvector with the second largest eigenvalue.