

5) Instead of projecting  $\mathbf{z}_i$  onto a single  $\bar{\mathbf{e}}$ , let's project it onto two  $\bar{\mathbf{e}}_a$  &  $\bar{\mathbf{e}}_b$ 's - both are orthonormal to each other.  
(Here  $\mathbf{z}_i = \mathbf{x}_i - \bar{\mathbf{x}}_i$ )

Consider,

$$\hat{\mathbf{z}}_i = (\mathbf{z}_i \cdot \mathbf{e}_a) \mathbf{e}_a + (\mathbf{e}_b \cdot \mathbf{z}_i) \mathbf{e}_b$$

Our goal is to find the  $\hat{\mathbf{z}}_i$  that minimizes the MSE.

$$\text{MSE} = \sum_{i=1}^N \|\mathbf{z}_i - \hat{\mathbf{z}}_i\|^2 \times \frac{1}{N-1} \quad (\text{let there be } N \text{ samples \& let } \mathbf{z}_i \in \mathbb{R}^d)$$

$$\text{MSE} = \frac{1}{N-1} \sum_{i=1}^N (\mathbf{z}_i - (\mathbf{z}_i \cdot \mathbf{e}_a) \mathbf{e}_a - (\mathbf{z}_i \cdot \mathbf{e}_b) \mathbf{e}_b) \cdot (\mathbf{z}_i - (\mathbf{z}_i \cdot \mathbf{e}_a) \mathbf{e}_a - (\mathbf{z}_i \cdot \mathbf{e}_b) \mathbf{e}_b)$$

$$= \frac{1}{N-1} \sum_{i=1}^N \|\mathbf{z}_i\|^2 - (\mathbf{z}_i \cdot \mathbf{e}_a)^2 - (\mathbf{z}_i \cdot \mathbf{e}_b)^2$$

$$= \left( \frac{1}{N-1} \sum_{i=1}^N \|\mathbf{z}_i\|^2 \right) - \left( \frac{1}{N-1} \sum_{i=1}^N (\mathbf{z}_i \cdot \mathbf{e}_a)^2 \right) - \frac{1}{N-1} \left( \sum_{i=1}^N (\mathbf{z}_i \cdot \mathbf{e}_b)^2 \right)$$

$$= \frac{1}{N-1} \sum_{i=1}^N \|\mathbf{z}_i\|^2 - \frac{1}{N-1} (\mathbf{e}_a^T \mathbf{Z} \mathbf{Z}^T \mathbf{e}_a) - \frac{1}{N-1} (\mathbf{e}_b^T \mathbf{Z} \mathbf{Z}^T \mathbf{e}_b)$$

For minimizing MSE, we need to maximise

$$\mathbf{e}_a^T \left( \frac{\mathbf{Z} \mathbf{Z}^T}{N-1} \right) \mathbf{e}_a + \frac{\mathbf{e}_b^T (\mathbf{Z} \mathbf{Z}^T) \mathbf{e}_b}{N-1}$$

$$= \underbrace{\mathbf{e}_a^T (\mathbf{C}) \mathbf{e}_a}_{\lambda_1} + \underbrace{\mathbf{e}_b^T (\mathbf{C}) \mathbf{e}_b}_{\lambda_2}$$

Because each of the terms is independent, we need to maximize them separately.

$$T_1 = e_a^T C e_a, \quad T_2 = e_b^T C e_b$$

We could like to impose restrictions like  $\|e_a\| = 1$  &  $\|e_b\| = 1$   
 So, we can use the Lagrange multiplier method

$$L_1(e_a, \lambda) = T_1 - \lambda_1 (e_a^T e_a - 1)$$

$$[e_a^T e_a = \|e_a\|^2 = 1]$$

is the constraint

$$L_2(e_b, \lambda) = T_2 - \lambda_2 (e_b^T e_b - 1)$$

$$[e_b^T e_b = \|e_b\|^2 = 1]$$

is the constraint

$$\frac{\partial L_1}{\partial \lambda_1} = -(e_a^T e_a - 1)$$

$$\frac{\partial L_2}{\partial \lambda_2} = -(e_b^T e_b - 1)$$

$$\frac{\partial L_1}{\partial e_a} = 2C e_a - 2\lambda_1 e_a$$

$$\frac{\partial L_2}{\partial e_b} = 2C e_b - 2\lambda_2 e_b$$

$$\Rightarrow e_a^T e_a = \|e_a\|^2 = 1$$

$$e_b^T e_b = \|e_b\|^2 = 1$$

$$C e_a = \lambda_1 e_a$$

$$C e_b = \lambda_2 e_b$$

So,  $e_a$  &  $e_b$  are both eigen vectors of 'C' matrix

$$T_1 = \lambda_1 (e_a^T e_a) \\ = \lambda_1$$

$$T_2 = \lambda_2 (e_b^T e_b) \\ = \lambda_2$$

So, if we want to maximize  $T_1 + T_2$ , we need to choose  $\lambda_1$  &  $\lambda_2$  values in such a way they are the largest two eigen values.

Hence, the question  $\nabla$  will be the eigen vector with the second highest eigen value