

1a) for $\vec{x}_i' = a \cdot \vec{x}_i$

$$\begin{aligned} \mathcal{E}(W) &= \sum_i |a \vec{x}_i - \sum_j w_{ij} \vec{x}_j|^2 \\ &= a^2 \sum_i |\vec{x}_i - \sum_j w_{ij} \vec{x}_j|^2 \\ &= a^2 \mathcal{E}(W) \end{aligned}$$

~~the~~ The optimal weights w_{ij} minimize the $\mathcal{E}(W)$, a^2 is not relevant ~~relevant~~ to the minimization of $\mathcal{E}(W)$.

1b) for $\vec{x}_i' = \vec{x}_i + \vec{v}$

$$\begin{aligned} \mathcal{E}(W) &= \sum_i |\vec{x}_i + \vec{v} - \sum_j w_{ij} \vec{x}_j + \vec{v}|^2 \\ &= \sum_i |\vec{x}_i + \vec{v} - \sum_j w_{ij} \vec{x}_j|^2 + \sum_i |\vec{v}|^2 \\ &= \sum_i |\vec{x}_i - \sum_j w_{ij} \vec{x}_j|^2 + 1 \\ &= \mathcal{E}(W) \end{aligned}$$

after translation, the minimum of \mathcal{E} is the same

1.6) for $\bar{x}_i' = W \cdot \bar{x}_i$

$$\xi(W) = \sum_i |\bar{x}_i' - \sum_j W_{ij} \bar{x}_j| ^2$$

$$\xi'(W) = \sum_i |\bar{x}_i' - \sum_j W_{ij} \bar{x}_j'| ^2$$

$$= \sum_i (\bar{x}_i' - \sum_j W_{ij} \bar{x}_j')^T (\bar{x}_i' - \sum_j W_{ij} \bar{x}_j')$$

$$= \sum_i (\bar{x}_i' - \sum_j W_{ij} \bar{x}_j')^T \underbrace{Q^T Q}_{=I} (\bar{x}_i' - \sum_j W_{ij} \bar{x}_j')$$

$$= \sum_i (\bar{x}_i' - \sum_j W_{ij} \bar{x}_j')^T (\bar{x}_i' - \sum_j W_{ij} \bar{x}_j')$$

$$= \xi(W).$$

\Rightarrow the rotation won't change the minimum of ξ .

\Rightarrow because ~~the~~ ~~after~~ rotation won't change the inner structural of the dataset. so it won't change the optimal weights that lead to minimum of ξ .

$$\min_w w^T C w$$

$$\min_w w^T (1\bar{x}^T - q)(1\bar{x}^T - q)^T w$$

2.a)

$$w^T C w$$

$$= w^T (1\bar{x}^T - q)(1\bar{x}^T - q)^T w$$

$$= ((1\bar{x} - q)^T w)^T (1\bar{x} - q) w$$

$$= \| (1\bar{x} - q)^T w \|^2$$

$$= \| \underbrace{\bar{x}^T w}_{=\sum_{j=1}^K w_j} - q^T w \|^2$$

$$= \| \sum_{j=1}^K w_j \bar{x} - q^T w \|^2$$

$$q^T = (q_1, \dots, q_K)$$

$$= \begin{pmatrix} q_{11} & q_{12} & \dots & q_{1K} \\ q_{21} & q_{22} & & \vdots \\ \vdots & \vdots & & \vdots \\ q_{K1} & q_{K2} & & q_{KK} \end{pmatrix}$$

$$w = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_K \end{pmatrix}$$

$$q^T \cdot w = \begin{pmatrix} \sum_{j=1}^K q_{1j} w_j \\ \sum_{j=1}^K q_{2j} w_j \\ \vdots \\ \sum_{j=1}^K q_{Kj} w_j \end{pmatrix} = \sum w_j q_j$$

$$\Rightarrow \| \sum_{j=1}^K w_j \bar{x} - w_j q_j \|^2$$

$$= \| \sum_{j=1}^K w_j (\bar{x} - q_j) \|^2$$

$$= \sum_{j,k} w_j w_k C_{jk}$$

$$2.b) \quad \mathcal{L}(w, \lambda) = w^T C w - \lambda(w^T \mathbf{1} - 1)$$

$$\begin{cases} \frac{\partial \mathcal{L}(w, \lambda)}{\partial w} = 2Cw - 2\lambda \mathbf{1} \stackrel{!}{=} 0 \Rightarrow Cw = \lambda \mathbf{1} \\ \frac{\partial \mathcal{L}(w, \lambda)}{\partial \lambda} = w^T \mathbf{1} - 1 = 0 \end{cases}$$

$$Cw = \lambda \mathbf{1} \Rightarrow w = \lambda C^{-1} \mathbf{1}$$

$$Cw = \lambda \mathbf{1} \Rightarrow \underbrace{\mathbf{1}^T C^{-1} C}_{=I} w = \underbrace{\mathbf{1}^T C^{-1}}_{=1} \lambda \mathbf{1} \Rightarrow \lambda = \frac{1}{\mathbf{1}^T C^{-1} \mathbf{1}} \quad \left. \begin{matrix} \\ \end{matrix} \right\} \Rightarrow w^* = \frac{C^{-1} \mathbf{1}}{\mathbf{1}^T C^{-1} \mathbf{1}}$$

$$2.c) \quad \text{solving the equation } Cw = \mathbf{1}$$

$$\Rightarrow w^* = C^{-1} \mathbf{1} \Rightarrow w^{*T} = \mathbf{1}^T C^{-1}$$

$$\text{after rescaling } w' = \frac{w^*}{w^{*T} \mathbf{1}} = \frac{C^{-1} \mathbf{1}}{\mathbf{1}^T C^{-1} \mathbf{1}}$$