

Assignment 4

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Q2) Given a set of N vectors $X = \{x_1, x_2, \dots, x_N\}$ each in \mathbb{R}^d , with $\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$. Direction \underline{e} such that $\sum_{i=1}^N \|x_i - \bar{x} - (e \cdot (x_i - \bar{x}))e\|^2$ is minimized is obtained by maximizing $e^T C e$, with C is the covariance matrix of vectors in X , is the eigenvector e with the highest eigenvalue. Considering another direction f such that $f^T C f$ is maximised is, using the loss function (f is \perp to e),

$$\begin{aligned} J(e, f) &= \sum_{i=1}^N \|x_i - \bar{x} - (e^T(x_i - \bar{x}))e - (f^T(x_i - \bar{x}))f\|^2 \\ &= \|x_i - \bar{x}\|^2 + \|e^T(x_i - \bar{x})e\|^2 + \|f^T(x_i - \bar{x})f\|^2 \\ &\quad - 2 \sum_{i=1}^N \{ (e^T(x_i - \bar{x}))e^T(x_i - \bar{x}) + (f^T(x_i - \bar{x}))f^T(x_i - \bar{x}) \} \end{aligned}$$

$$J(e, f) = -(e^T S e + f^T S f) + \sum_{i=1}^N \|x_i - \bar{x}\|^2 - 2(e^T(x_i - \bar{x}))e^T f (f^T(x_i - \bar{x}))$$

Now, maximising

(derivation similar as e & f are perpendicular to each other to that done in class)

$\tilde{J}(e, f) = e^T S e + f^T S f$ with constraints $e^T e = 1$ & $f^T f = 1$ and using Lagrange multipliers

$$\tilde{J}(e, f) = e^T S e + f^T S f - \lambda(e^T e - 1) - \mu(f^T f - 1)$$

taking derivatives w.r.t \underline{e} & \underline{f} we get,

$$\frac{d\tilde{J}}{de} = 2Se - 2\lambda e = 0 \quad \& \quad \frac{d\tilde{J}}{df} = 2Sf - 2\mu f = 0$$

$$\Rightarrow \underline{Se = \lambda e} \quad \& \quad \underline{Sf = \mu f}$$

$$\Rightarrow \underline{e^T S e = \lambda} \quad \& \quad \underline{f^T S f = \mu} \quad \text{as } S = (N-1)C, \text{ it is a symmetric, positive semi-definite matrix is}$$

Thus using as e & f are orthonormal &

$\lambda \neq \mu$. Thus to maximise $\tilde{J}(e, f)$, \underline{e} corresponds to the eigenvalue which is the largest & \underline{f} corresponds to the 2nd largest eigenvalue of C .

And due to C being symmetric and f being \perp to $e \Rightarrow \lambda \neq \mu$ & $\lambda > \mu$.