

W W - DML

$$\beta : D \times M$$

$$b : D \times M = 1$$

$$z_n = b^\top \cdot x_n \quad \tilde{x}_n = b \cdot z_n \\ = b(b^\top \cdot \tilde{x}_n)$$

Reconstruction loss

$$L(z, b) = \frac{1}{N} \sum_{n=1}^N \| \tilde{x}_n - x_n \|_2^2$$

$$= \frac{1}{N} \sum_{n=1}^N \| b b^\top x_n - x_n \|_2^2$$

$$= \frac{1}{N} \sum_{n=1}^N \left(x_n^\top x_n - 2 x_n^\top b b^\top x_n + x_n^\top b b^\top b b^\top x_n \right)$$

$$= \frac{1}{N} \sum_{n=1}^N (x_n^\top x_n - x_n^\top b b^\top x_n)$$

$$= \underbrace{\frac{1}{N} \sum_{n=1}^N x_n^\top x_n}_{(2)} - b^\top \left(\frac{1}{N} \sum_{n=1}^N x_n x_n^\top \right) b$$

$$L = C - \underbrace{b^T \cdot S b}_{\text{reconnection loss}} \leftarrow$$

Variance of $\underline{z} = b^T x$

minimize \equiv maximize

$$\|b\|_2^2 = 1 \quad , \quad \begin{matrix} \text{why variance} \\ ? \end{matrix} \quad \begin{matrix} \text{=} \\ ? \end{matrix} \quad b^T S b$$

$$\begin{aligned}
 \text{Var } z &= \frac{1}{N} \sum_n z_{in}^2 \\
 &= \frac{1}{N} \sum_n (b_i^T \cdot x_n)^2 \quad z_{in} = b_i^T \cdot x_i \\
 &= \frac{1}{N} \sum_n b_i^T x_n \cdot x_n^T b_i \quad z_{in} = b_i^T \cdot x_n \\
 &= b_i^T \left[\sum_n x_n x_n^T \right] b_i
 \end{aligned}$$

$$L = C - \underbrace{b^T \cdot S b}_{\text{reconnection loss}} \leftarrow$$

Variance of $\underline{z} = b^T x$

minimize \equiv maximize

$$\|b\|_2^2 = L \quad , \quad \begin{matrix} \text{why variance} \\ ? \end{matrix} \quad \begin{matrix} \text{=} \\ ? \end{matrix} \quad b^T S b$$

$$\begin{aligned}
 \text{Var } z &= \frac{1}{N} \sum_n z_{in}^2 \\
 &= \frac{1}{N} \sum_n (b_i^T \cdot x_n)^2 \quad z_{in} = b_i^T \cdot x_i \\
 &= \frac{1}{N} \sum_n b_i^T x_n \cdot x_n^T b_i \quad z_{in} = b_i^T \cdot x_n \\
 &= b_i^T \left[\sum_n x_n x_n^T \right] b_i
 \end{aligned}$$

S

$$V = b_1^T S b_1$$

$b_1 \nearrow$

$$\max V$$

b_1

$$\left[\|b_1\|_2^2 = 1 \right]$$

equating constraint

$$\max_{b_1} V + \alpha \cdot (\|b_1\|_2^2 - 1) = F$$

b_1

$$\frac{dF}{db_1} = 0 \quad \frac{dF}{d\alpha} = 0$$

Q6, A4

$\rightarrow b_1$ eigenvector of S

α eigenvalue of S

$$J = \frac{1}{N} \sum_n \|x_n - \tilde{x}_n\|_2^2$$

$$\begin{aligned}\tilde{x}_n &= B \cdot z_n \\ &= \sum_{m=1}^M z_{mn} \cdot b_m\end{aligned}$$

$$\left\{ z_{mn} \right\}_{m=1}^M \left\{ \right\}_{n=1}^N ?$$

Given B

$$\begin{aligned}\frac{dJ}{dz_{in}} &= \frac{dJ}{dx_n}, \frac{d\tilde{x}_n}{dz_{in}} \\ &= \underbrace{\frac{d\tilde{x}_n}{dx_n}}_{\frac{1}{N}(-2)(x_n - \tilde{x}_n)} \cdot \underbrace{\frac{d\tilde{x}_n}{dz_{in}}}_{b_i^T}.\end{aligned}$$

$$= -\frac{2}{N} \cdot \left[x_n^T b_i - \tilde{x}_n^T \cdot b_i \right]$$

$$= -\frac{2}{N} \cdot \left[x_n^T b_i - \left[\sum_{m=1}^M z_{mn} b_m \right]^T b_i \right]$$

$$= -\frac{2}{N} \left[x_n^T b_i - \sum_{m=1}^M (z_{mn} \cdot \underbrace{b_m^T \cdot b_i}) \right]$$

↖

$$0 \text{ if } m \neq i$$

$$1 \text{ if } m = i$$

$$= -\frac{1}{n} \left[x_n^T b_i - z_{in} \right] = 0$$

$$\boxed{z_{in} = x_n^T b_i = b_i^T \cdot x_n}$$

z_{in} = coordinate of the

orthogonal proj onto a one-d

Subspace Spanned by $\underline{b_i}$

$$x_n = \sum_{m=1}^M z_{mn} b_m$$

$M < D$

$$\tilde{x}_n = \sum_{m=1}^M z_{mn} b_m$$

$$x_n - \tilde{x}_n = \sum_{m=M+1}^D z_{mn} b_m$$

$$= \sum_{m=M+1}^D (b_m^T \cdot x_n) b_m$$

$$J = \frac{1}{N} \sum_n \sum_{\underline{m}} (b_{\underline{m}}^T x_n b_{\underline{m}})^T b_{\underline{m}}^T x_n^T b_{\underline{m}}$$

$$= \frac{1}{N} \sum_n \sum_m b_m^T \cdot x_n x_n^T \cdot b_m$$

$$= \sum_{m=M+1}^D b_m^T \cdot S \cdot b_m$$

$$S = \frac{1}{2} X^T X$$

$X: D \times N \leftarrow$
 $\underbrace{\quad\quad\quad}_{N \times D}$

$$Sv = \lambda v$$

$$\frac{1}{2} X^T X v = \lambda v$$

of size
 $D - \text{way dimension}$

$$\frac{1}{2} \underbrace{X^T X}_{C} \underbrace{v}_{v} = \underbrace{X^T}_{M} \underbrace{\lambda v}_{\lambda v} \quad M$$

$$X \rightarrow Z \rightarrow \tilde{X}$$

$$S \cdot c = \lambda \cdot c \quad R^D \quad R^M \quad R^D$$

↓
eigenvalue of $S = N \times N$
matrix

n < D

$$S = \frac{1}{n} X^T X$$

→ same

$$S = \frac{1}{n} X^T X$$

eigenvalues

λ \vec{S} \rightarrow eigenvector of \mathcal{L} ?

$$\vec{S} \vec{C} = \lambda \vec{C}$$

$$\perp X^T X \vec{C} = \lambda \vec{C}$$

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$$\perp X \vec{X}^T X \vec{C} = X \lambda \vec{C}$$

$$\underbrace{X}_{\text{S}}$$

$$\underbrace{\vec{v}}_{\text{v}} = \lambda \cdot \vec{v}$$

$$\boxed{\vec{v} = X \cdot \vec{c}}$$

$N < D$

λ, \vec{c} eigen value + vec of \vec{S}

$$\vec{v} = X \cdot \vec{c}$$

$N > D$

λ, \vec{v} : eigen values + eigenvectors of S