

$$Q1) \quad \hat{x} = VWx$$

$$\Rightarrow L = \sum \|x - \hat{x}\|^2$$

$$= (X - VWX)^T (X - VWX)$$

$$= (X^T - X^T W^T V^T)(X - VWX)$$

$$= X^T X - X^T VWX - X^T W^T V^T X + X^T W^T V^T VWX$$

$$= X^T X - 2X^T VWX + (VWX)^2$$

now we want to minimize  $L$

$$\Rightarrow \frac{dL}{dV} = 0 \quad \& \quad \frac{dL}{dW} = 0$$

$$\Rightarrow -2W^T(X - VWX)X^T = 0$$

$$\Rightarrow WV = I \quad (\text{assuming } X \text{ to be invertible})$$

assuming  $W$  to be orthonormal (ie.  $W^{-1} = W^T$ )

$$\Rightarrow \boxed{V = W^T}$$

$$Q2) \quad \text{the covariance matrix: } \Sigma = \frac{1}{N} X^T X$$

$$\Rightarrow L = N \cdot \text{tr}((I - W^T W) \Sigma (I - W^T W)^T)$$

$$= N \underbrace{\text{tr}(\Sigma)}_{\text{const.}} - N \text{tr}(\Sigma W^T W)$$

$$\Rightarrow L = -N \text{tr}(\Sigma W^T W)$$

Now use the fact that  $\Sigma$  can be decomposed as :

$$\Sigma = Q \Lambda Q^T \quad \left( \begin{array}{l} \Lambda = \text{eigen value matrix} \\ Q = \text{eigen vector matrix} \end{array} \right)$$

$$\begin{aligned} \Rightarrow \text{tr}(\Sigma W^T W) &= \text{tr}(Q \Lambda Q^T W^T W) \\ &= \text{tr}(\Lambda \underbrace{Q^T W^T W Q}_U) \quad (\text{as } \text{tr}(AB) = \text{tr}(BA)) \\ &= \text{tr}(\Lambda U) \\ &= \sum \lambda_i U_{ii} \end{aligned}$$

$\Rightarrow$  to minimize  $L$ , we need to minimize  $\sum \lambda_i U_{ii}$

$\therefore$  we need  $U_{ii} = 1$  for indices corresponding to the  $k$  largest eigen values

$\Rightarrow W^*$  (optimal  $W$ ) has rows forming an orthonormal basis for the subspace spanned by top  $k$  eigen vectors of  $\Sigma$  //