

1) Given reconstruction loss function

$$L = \sum_{n=1}^N \|x^{(n)} - \hat{x}^{(n)}\|^2$$

where

$$\hat{x}^{(n)} = V(Wx^{(n)} + b) + c$$

Since we assume data is mean-centered

$$\sum_{n=1}^N x^{(n)} = 0$$

→ Simplifying this to

$$\hat{x}^{(n)} = V(Wx^{(n)})$$

$$L = \sum_{n=1}^N \|x^{(n)} - VWx^{(n)}\|^2$$

$$\frac{dL}{dV} = -2 \sum_{n=1}^N (x^{(n)} - VWx^{(n)}) x^{(n)T}$$

As $\frac{dL}{dV} = 0$, we get

$$\sum_{n=1}^N x^{(n)} x^{(n)T} = \sum_{n=1}^N VWx^{(n)} x^{(n)T}$$

$$\text{Having } \Sigma = \frac{1}{N} \sum_{n=1}^N x^{(n)} x^{(n)T}$$

$$\Sigma = VW\Sigma$$

\therefore If W is chosen optimally, the best choice is W^*

$$V = W^T$$

2) Need to show that optimal weight matrix W^* forms an orthonormal basis for the top k eigenvectors of Σ

$$h = \sum_{n=1}^N \|x^{(n)} - W^T W x^{(n)}\|^2$$

$$E[\|x - W^T W x\|^2] =$$

$$\text{tr}(\Sigma - W^T W \Sigma - \Sigma^T W^T W + W^T W \Sigma^T W^T W)$$

Since Σ is symmetric

$$E(\|x - W^T W x\|^2) = \text{tr}(\Sigma) - \text{tr}(W^T W \Sigma)$$

Minimizing this is same as
 $\text{tr}(W^T W \Sigma)$

The optimal choice of W is to pick the eigenvectors of Σ corresponding to the largest k eigenvalues as they capture maximum variance in the data.
Let $\Sigma = U \Lambda U^T$ be the eigen-decomposition where

- $U = [u_1, u_2, \dots, u_d]$ are eigenvectors of Σ
- $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_d)$ are corresponding eigenvalues

had to, planning needs to be of \therefore

\therefore Choosing W^* as top k eigenvectors

$$TW = V$$

$$W^* = [u_1, u_2, \dots, u_k]^T$$

randomly chosen vectors to be used as basis (2)

This spans the same subspace as the principal eigenvectors of Σ , completing the proof.

$$\|x - W^* W^{*T} x\|_2^2 = \sum_{i=1}^k \lambda_i^2$$

$$E[\|x - W^* W^{*T} x\|_2^2] =$$