

Ex2 Show that $\bar{\mathbf{X}} = \mathbf{X}(\mathbf{I} - \frac{1}{n}\mathbf{e}\mathbf{e}^T)$ (here \mathbf{e} = vector of all ones). What does the projector $(\mathbf{I} - \frac{1}{n}\mathbf{e}\mathbf{e}^T)$ do?

Solution: Each column of $\bar{\mathbf{X}}$ is $\bar{\mathbf{x}} = \mathbf{x} - \boldsymbol{\mu}$ so that $\bar{\mathbf{X}} = \mathbf{X} - \boldsymbol{\mu}\mathbf{e}^T$, where $\boldsymbol{\mu}$ is the sample mean. But we have $\boldsymbol{\mu} = \frac{1}{n} \sum \mathbf{x}_i = \frac{1}{n}\mathbf{X}\mathbf{e}$ and so,

$$\bar{\mathbf{X}} = \mathbf{X} - \frac{1}{n}\mathbf{X}\mathbf{e}\mathbf{e}^T = \mathbf{X}[\mathbf{I} - \frac{1}{n}\mathbf{e}\mathbf{e}^T]$$

The matrix $(\mathbf{I} - \frac{1}{n}\mathbf{e}\mathbf{e}^T)$ represents a projector that centers the data so the mean is zero.

Ex3 Show that solution \mathbf{V} also minimizes ‘reconstruction error’ ..

Solution: The main property that is exploited in the proof is the fact that $\text{Tr}(\mathbf{ABC}) = \text{Tr}(\mathbf{BCA})$ (when dimensions are compatible). First we note that $\sum_i \|\bar{\mathbf{x}}_i - \mathbf{V}\mathbf{V}^T\bar{\mathbf{x}}_i\|^2 = \|(\mathbf{I} - \mathbf{V}\mathbf{V}^T)\mathbf{X}\mathbf{F}\|^2$. We will call \mathbf{P} the projector $\mathbf{P} = \mathbf{V}\mathbf{V}^T$. Then:

$$\begin{aligned}
\|(I - VV^T)X\|_F^2 &= \text{Tr}(I - P)XX^T(I - P) \\
&= \text{Tr}(XX^T - PXX^T)(I - P) \\
&= \text{Tr}(XX^T) - \text{Tr}(PXX^T) - \text{Tr}(XX^T P) + \text{Tr}(PXX^T P) \\
&= \text{Tr}(XX^T) - \text{Tr}(PXX^T) - \text{Tr}(XX^T P) + \text{Tr}(XX^T P^2) \\
&= \text{Tr}(XX^T) - \text{Tr}(PXX^T) - \text{Tr}(XX^T P) + \text{Tr}(XX^T P) \\
&= \text{Tr}(XX^T) - \text{Tr}(PXX^T) \\
&= \text{Tr}(XX^T) - \text{Tr}(VV^T XX^T) \\
&= \text{Tr}(XX^T) - \text{Tr}(V^T XX^T V)
\end{aligned}$$

The first term is a constant, therefore the minimum is reached when the maximum of the second term is reached. \square