# PCA under An Optimization Lens

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# **PCA** IN THE MATRIX FORMAT

#### Maximization of variance

In PCA, we want to find the M leading principal components by solving

$$\max_{\boldsymbol{b}_{j}} \boldsymbol{b}_{j}^{\mathsf{T}} \boldsymbol{S} \boldsymbol{b}_{j} \quad \text{for } j = 1, \cdots, M$$
  
subject to  $\boldsymbol{b}_{j}^{\mathsf{T}} \boldsymbol{b}_{k} = \begin{cases} 1 & \text{if } j = k \\ 0 & \text{if } j \neq k. \end{cases}$  (1)

• Show that  $\operatorname{tr}(\boldsymbol{B}^{\top}\boldsymbol{S}\boldsymbol{B}) = \sum_{j=1}^{M} \boldsymbol{b}_{j}^{\top}\boldsymbol{S}\boldsymbol{b}_{j}$  if  $\boldsymbol{B} = (\boldsymbol{b}_{1}, \dots, \boldsymbol{b}_{M}) \in \mathbb{R}^{D \times M}$ .

■ We can rewrite Eq. (1) as

$$\max_{\boldsymbol{B}} \operatorname{tr}(\boldsymbol{B}^{ op} \boldsymbol{S} \boldsymbol{B})$$
subject to  $\boldsymbol{B}^{ op} \boldsymbol{B} = \boldsymbol{I}_{M imes M}$ 

Alternatively, in PCA, we want to find projection of the data onto an M dimensional subspace spanned by B = (b<sub>1</sub>, ..., b<sub>M</sub>) such that the reconstruction error is minimized

$$\min_{\boldsymbol{B}} \sum_{n=1}^{N} \|\boldsymbol{x}_n - \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}} \boldsymbol{x}_n\|^2$$
subject to  $\boldsymbol{B}^{\mathsf{T}} \boldsymbol{B} = \boldsymbol{I}_{M \times M}$ 
(2)

• We can show that for 
$$\boldsymbol{X} = (\boldsymbol{x}_1, \cdots, \boldsymbol{x}_N)^\top \in \mathbb{R}^{N \times D}$$

$$\sum_{n=1}^{N} \left\| \boldsymbol{x}_{n} - \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{x}_{n} \right\|^{2} = \operatorname{tr}((\boldsymbol{X}^{\mathsf{T}} - \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}})^{\mathsf{T}}(\boldsymbol{X}^{\mathsf{T}} - \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}}))$$
$$= \left\| \boldsymbol{X}^{\mathsf{T}} - \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}} \right\|_{F}^{2}$$

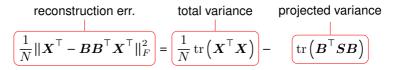
■ Here  $|| \cdot ||_F$  is the Frobenius matrix norm. The Frobenius norm of an  $m \times n$  matrix  $\mathbf{A} = (a_{ij})$ , denoted  $|| \cdot ||_F$ , is defined by

$$\|\mathbf{A}\|_F \equiv \sqrt{\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2} = \sqrt{\operatorname{tr}(\mathbf{A}^\top \mathbf{A})}$$

Thus we can rewrite Eq. (2) as

$$\min_{\boldsymbol{B}} \frac{1}{N} \| \boldsymbol{X}^{\top} - \boldsymbol{B} \boldsymbol{B}^{\top} \boldsymbol{X}^{\top} \|_{F}^{2} \equiv \frac{1}{N} \| \boldsymbol{X} - \boldsymbol{X} \boldsymbol{B} \boldsymbol{B}^{\top} \|_{F}^{2}$$
  
subject to  $\boldsymbol{B}^{\top} \boldsymbol{B} = \boldsymbol{I}_{M \times M}$ 

We can also show that



Proof

$$\frac{1}{N} \left\| \boldsymbol{X}^{\mathsf{T}} - \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}} \right\|_{F}^{2} = \frac{1}{N} \left\| \boldsymbol{X} - \boldsymbol{X}\boldsymbol{B}\boldsymbol{B}^{\mathsf{T}} \right\|_{F}^{2}$$

$$= \frac{1}{N} \operatorname{tr} \left( \left( \boldsymbol{X} - \boldsymbol{X}\boldsymbol{B}\boldsymbol{B}^{\mathsf{T}} \right)^{\mathsf{T}} \left( \boldsymbol{X} - \boldsymbol{X}\boldsymbol{B}\boldsymbol{B}^{\mathsf{T}} \right) \right)$$

$$= \frac{1}{N} \operatorname{tr} \left( \boldsymbol{X}^{\mathsf{T}}\boldsymbol{X} \right) - \frac{2}{N} \operatorname{tr} \left( \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}}\boldsymbol{X} \right)$$

$$+ \frac{1}{N} \operatorname{tr} \left( \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}}\boldsymbol{X} \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}} \right)$$

$$= \frac{1}{N} \operatorname{tr} \left( \boldsymbol{X}^{\mathsf{T}}\boldsymbol{X} \right) - \frac{2}{N} \operatorname{tr} \left( \boldsymbol{B}\boldsymbol{B}^{\mathsf{T}}\boldsymbol{X}^{\mathsf{T}}\boldsymbol{X} \right)$$

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$$= \frac{1}{N} \operatorname{tr} \left( \boldsymbol{X}^{\mathsf{T}}\boldsymbol{X} \right) - \operatorname{tr} \left( \boldsymbol{B}^{\mathsf{T}}\boldsymbol{S}\boldsymbol{B} \right)$$