

Assume cols of X have been mean-centered

PCA:

$$\hat{Cov}(z) \propto z^T z$$

if $z = XW$ then

$$\hat{Cov}(z) \propto (XW)^T XW$$

$$= W^T X^T X W$$

Goal: $\hat{Cov}(z)$ to be diag, with large elements on diag

How do we find W ?

Consider $X = UDV^T$

→ then $W^T X^T X W = W^T V \underbrace{D^T D}_I U^T U D V^T W$

$$= W^T V \underbrace{D^T D}_{\substack{\nearrow \\ D = \begin{pmatrix} D_* & 0 \end{pmatrix}}} V^T W$$

How do we make
diag?

$$D = \left[\begin{array}{c|c} D_x & 0 \\ \hline 0 & 0 \end{array} \right]$$

$$D^T D = \left[\begin{array}{c|c} D_x^2 & 0 \\ \hline 0 & 0 \end{array} \right]$$

Consider $W = V$ then $W^T V = V^T W = I$
and then

$$\hat{Cov}(z) = D^T D$$

Problem! - want W to be $p \times q$ mtr and
 V is a $P \times P$

- Want the sum of diag elements to be
as large as possible.

Solu! I can do this if I let W be
the first q cols of V

$$W = \underbrace{V_{1:q}}$$

$$\overbrace{p \times q}$$

then $W = V_{1:g}$ then

$$\hat{Cov}(z) = W^T V D^T D V^T W$$

$$= \underbrace{V_{1:g}^T V}_{\begin{bmatrix} I_g \\ 0 \end{bmatrix}} D^T D V^T V_{1:g}$$

$$\begin{bmatrix} I_g \\ 0 \end{bmatrix}$$

$$= D_{*1:g} = \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_g^2 \end{bmatrix}$$

So then sum of diag

$$\sum_{j=1}^g \sigma_j^2.$$

Pipeline: PCA

... number cols of X

① mean center cols of X

② Calc SVD of X as $X = UDV^T$

③ $W = V_{1:g}$

④ $Z = XW = XV_{1:g}$

Comments:

$$\begin{aligned} \textcircled{1} \quad z_i &= Xw_i \\ &= Xv_i \\ &= \sigma_i u_i \end{aligned}$$

$$Xv_i = \sigma_i u_i$$

notice: $\text{Var}(z_i) \propto z_i^T z_i = (\sigma_i u_i)^T (\sigma_i u_i)$

$$\begin{aligned} &= \sigma_i^2 u_i^T u_i \\ &= \sigma_i^2 \end{aligned}$$

$$\text{Var}(z_i) = \frac{1}{N-1} \sigma_i^2.$$

② Total var of Z

$$= \sum_{i=1}^q \text{Var}(z_i) = \frac{1}{N-1} \sum_{i=1}^q \sigma_i^2$$

Pct. of var. captured by first q PCs

$$= \frac{\cancel{\frac{1}{N-1}} \sum_{i=1}^q \sigma_i^2}{\cancel{\frac{1}{N-1}} \sum_{i=1}^p \sigma_i^2} \leftarrow \begin{array}{l} \text{amt. cap. var.} \\ \text{total var.} \end{array}$$

③ $z_i = \sigma_i u_i$

\nearrow kinda optional $z_i \propto u_i$

④ We first mean-centred X
 \nearrow kinda optional

If I don't then often $z_i \approx \text{mean of vars}$

Could consider:

$$\begin{aligned}
 \underbrace{X_g}_{N \times p} &= X \underbrace{P_w}_{N \times g} \\
 &= X \underbrace{V_{1:g}}_{\substack{\text{coords} \\ \text{in } g\text{-dim'l} \\ \text{subspace}}} \underbrace{V_{1:g}^T}_{\text{basis}}
 \end{aligned}$$

proj. onto $\text{Col}(W)$

$$\begin{aligned}
 &= WW^T \\
 &= V_{1:g} V_{1:g}^T
 \end{aligned}$$

$$\begin{aligned}
 P_A &= A(A^T A)^{-1} A^T \\
 &\text{(Cols of } A \text{ orthog.)} \\
 A^T A &= I, AA^T \neq I \\
 &= AA^T
 \end{aligned}$$

$$= U D V^T V_{1:g} V_{1:g}^T$$

$$\begin{bmatrix} I_g \\ 0 \end{bmatrix}$$

$g \times g$ diag upper

$$\underbrace{X_g}_{N \times p} = U_{1:g} D_g V_{1:g}^T \quad (\text{truncated SVD})$$

first g cols of U first g cols of V

X_g has rank g .

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Theorem: Eckart-Young Theorem

X_g is the best rank- g approx of X :

$$X_g = \operatorname{argmin}_{B: \operatorname{rank}(B)=g} \|X - B\|_F$$

$$\|A\|^2 = \sum_{i,j} A_{ij}^2$$
