

Principal Components Analysis

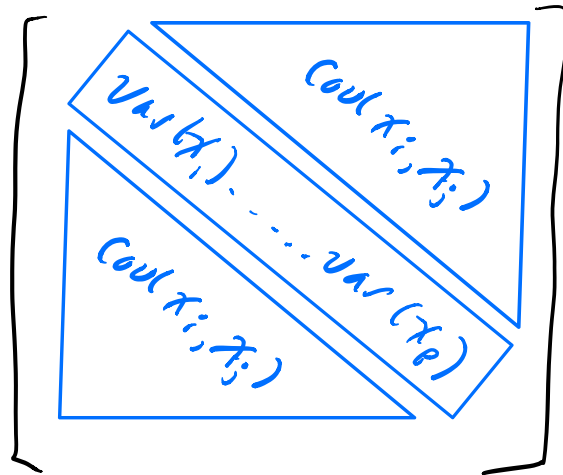
makes things easier

$$\text{col Means}(X) = 0$$

X
 $n \times p$
↑ observations ↑ predictors

Covariance Matrix

$$\text{cov}(X) = p \times p$$

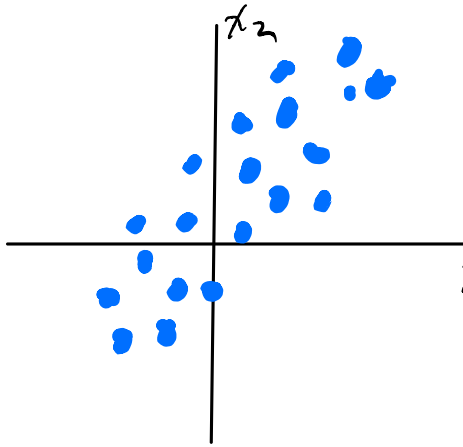


In signal $\text{cov}(X) = \frac{1}{n-1} (X - \bar{X})^T (X - \bar{X})$

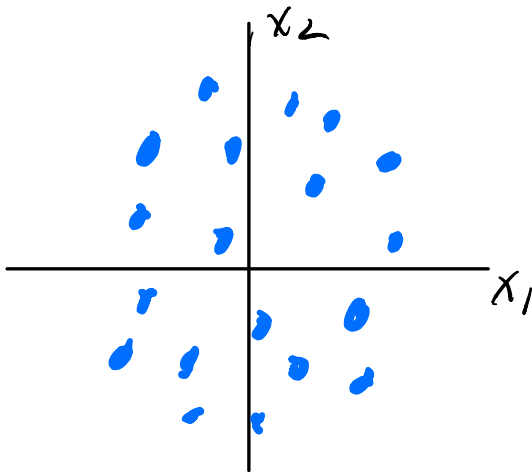
↑ $n \times p$ matrix of column means

In our case $\text{cov}(X) = \frac{1}{n-1} X^T X$

Examples



$\text{cov}(x_1, x_2) > 0$
 x_1, x_2 correlated



$\text{cov}(x_1, x_2) \approx 0$
 $x_1, x_2 \approx \text{independent}$

$$\text{SVD of } X = U \Sigma V^T \quad \text{columns}(X) = \mathcal{B}$$

$$\begin{matrix} n \times p & n \times p & p \times p & p \times p \\ U U^T = & V V^T = & I & \Sigma = \text{diag}(\sigma_1, \dots, \sigma_p) \\ p \times p & p \times p & & \sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_p \geq 0 \end{matrix}$$

Assume $\sigma_p > 0$
"full rank"

$$\text{Cov}(X) = \underset{p \times p}{X^T X}$$

$$= (U \Sigma V^T)^T (U \Sigma V^T)$$

$$= V \Sigma \underbrace{U^T U}_I \Sigma V^T$$

$$= V \Sigma^2 V^T \quad \Sigma^2 = \text{diag}(\sigma_1^2, \dots, \sigma_p^2)$$

$$V V^T = \text{id}$$

$$V = [v_1, \dots, v_p] \quad v_1, v_2, \dots, v_p$$

orthonormal basis
for \mathbb{R}^p

Change of Basis

V = Change of Basis Matrix

V -basis \rightarrow Standard basis
 v_1, v_2, \dots, v_p e_1, e_2, \dots, e_p

$$\text{i.e. if } [x]_V = \begin{bmatrix} \tilde{x}_1 \\ \vdots \\ \tilde{x}_p \end{bmatrix} \quad [x]_E = V \begin{bmatrix} \tilde{x}_1 \\ \vdots \\ \tilde{x}_p \end{bmatrix}$$

$V^{-1} = V^T$ Change of Basis Matrix

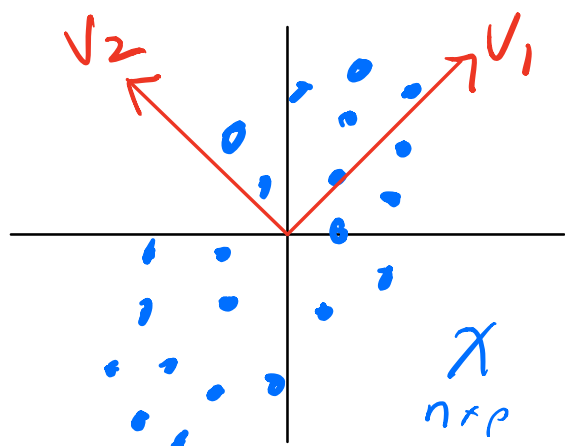
Standard basis \rightarrow V -basis
 e_1, e_2, \dots, e_p v_1, v_2, \dots, v_p

$$\text{i.e. if } [x]_E = \begin{bmatrix} x_1 \\ \vdots \\ x_p \end{bmatrix} \quad [x]_V = V^T \begin{bmatrix} x_1 \\ \vdots \\ x_p \end{bmatrix}$$

Notice X each row is observation $1 \times p$
 X^T each column is observation $p \times 1$

Change X (Standard Basis) \rightarrow \tilde{X} (V basis)
 $n \times p$ $n \times p$

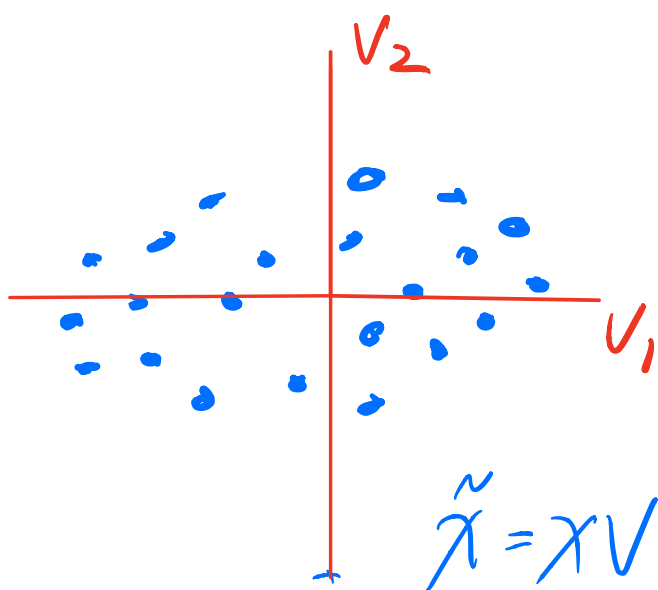
$\underbrace{X}_{n \times p} \rightarrow \underbrace{X^T}_{p \times n} \rightarrow \underbrace{V^T}_{p \times n} X^T \rightarrow \underbrace{XV}_{n \times p}$
 Data in Standard Basis Data in V Basis



Note $V_1 \perp V_2$

$V = \text{rotation}$

Change basis



$\text{Cov}(\tilde{X}) = \Sigma^2!$

diagonal
No covariances!
"decorrelated"

Check

$$\begin{aligned} \text{Cov}(\tilde{X}) &= \tilde{X}^T \tilde{X} = (XV)^T XV = V^T X^T X V \\ &= V^T V \Sigma^2 V^T V = \Sigma^2 \end{aligned}$$

$$\Sigma^2 = \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_p^2)$$

$$\underset{n \times p}{X} \longrightarrow \underset{n \times q}{\tilde{X}} = X V$$

correlated

decorrelated

Variances $\sigma_1^2 \geq \sigma_2^2 \geq \dots \geq \sigma_p^2$

Largest to smallest

$$V = [V_1 \ V_2 \ \dots \ V_p]$$

$V_i = i^{\text{th}}$ Principal Component

$\sigma_i^2 =$ Amt of Variance in i^{th}
Principal Component

In Practice

Use the first few (2, 3, 4)
Principal Components

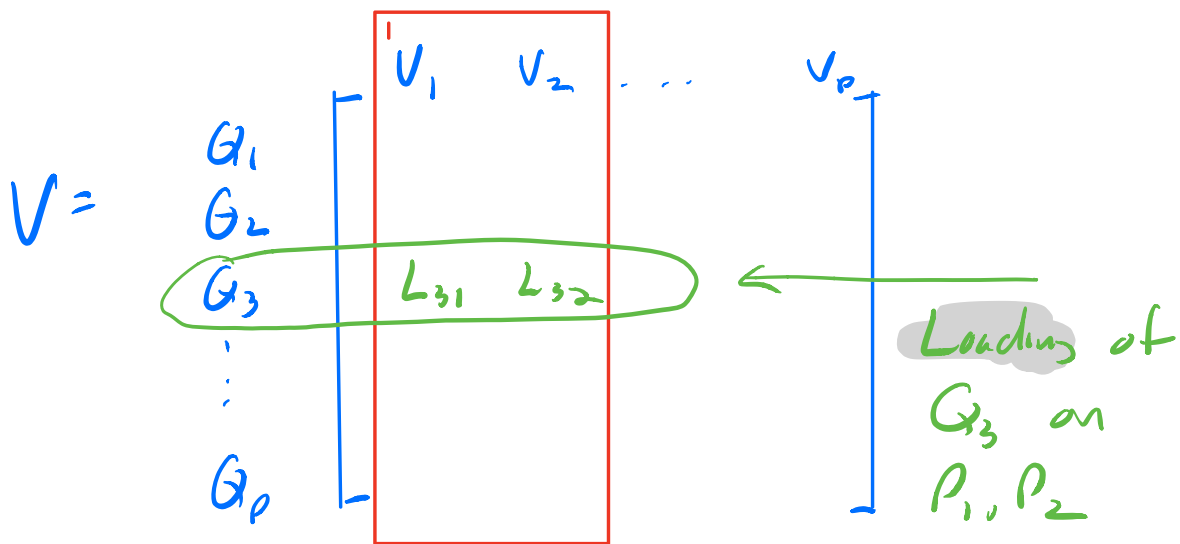
First $k = V_1, V_2, \dots, V_k$ Total Variance
 $\sigma_1^2 + \sigma_2^2 + \dots + \sigma_k^2 \leftarrow$ explained

Interpreting Principal Components

Loadings

G_1, G_2, \dots, G_p Predictors

V : Original Predictors \rightarrow Principal Comp
 G_1, G_2, \dots, G_p V_1, V_2, \dots, V_p



Use 1st 2
Principal Components

Loading: If $L_{31} \gg L_{32}$
 G_3 is heavily "loaded" on V_1

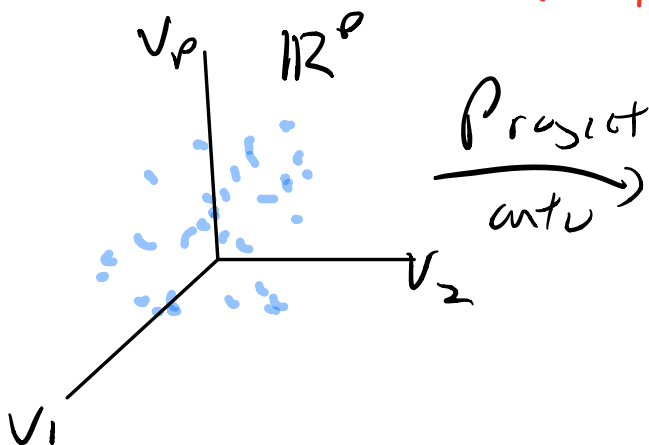
Interpreting Principal Component

Data

$$V = \begin{matrix} G_1 \\ G_2 \\ G_3 \\ \vdots \\ G_p \end{matrix} \begin{bmatrix} V_1 & V_2 & \dots & V_p \end{bmatrix}$$

Use 1st 2
Principal Components = V_{12}

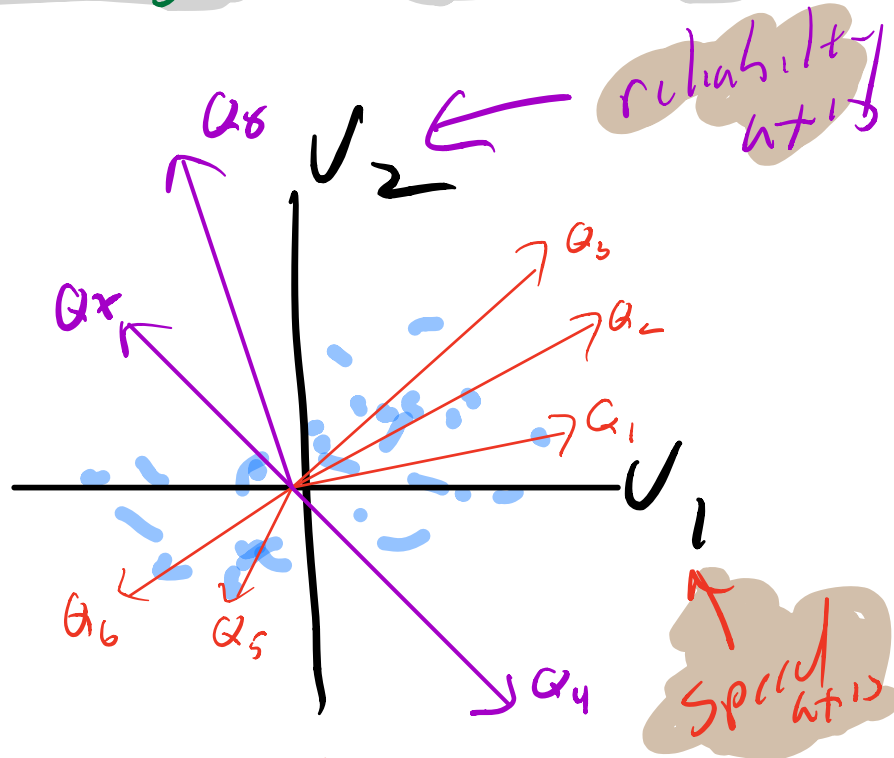
$\tilde{X}_{12} = X V_{12} \equiv$ Projection of Rotated
data in \mathbb{R}^p onto 1st
2 Principal Components



Interpreting Principal Component

Loadings

Data



$Q_1, Q_2, Q_3, Q_5, Q_6 \equiv$ Shared Qualities
"reliability"?

$Q_4, Q_7, Q_8 \equiv$ Different Shared
Quality
"speed"?

Observations near $\begin{cases} V_1 \text{ axis: Speed dominates} \\ V_2 \text{ axis: Reliability dominates} \end{cases}$