

In this section we assume that we are working with a data matrix

$$A = [X_1 \quad X_2 \quad \dots \quad X_M]$$

which has been demeaned. That is $m_{X_i} = 0$, or equivalently $X_i = \tilde{X}_i$ for $i = 1, \dots, M$.

Example.

A data matrix with demeaned exam scores:

$$A = \begin{array}{c} \text{Ex 1} \quad \text{Ex 2} \quad \text{Ex 3} \\ \begin{array}{l} \text{Aly} \\ \text{Bob} \\ \text{Chen} \\ \text{Deb} \\ \text{Emma} \\ \text{Finn} \end{array} \begin{bmatrix} -24 & 1 & -40 \\ -3 & -2 & -6 \\ 29 & 5 & 17 \\ 26 & -2 & 9 \\ -43 & 5 & 30 \\ 15 & -7 & -10 \end{bmatrix} \end{array}$$

Definition

Let $A = [X_1 \dots X_M]$ be a demeaned data matrix.

- The 1st principal axis of A is a vector

$$u_1 = \begin{bmatrix} c_1 \\ \vdots \\ c_M \end{bmatrix}$$

such that $\|u_1\| = 1$ and the variance of the vector

$$Y_1 = Au_1 = c_1X_1 + \dots + c_MX_M$$

is the largest possible.

- The vector Y_1 is called the 1st principal component of A .

Computations of u_1

Take $u = \begin{bmatrix} c_1 \\ \vdots \\ c_M \end{bmatrix}$, $\|u\| = 1$, and let $Y = A \cdot u = c_1X_1 + \dots + c_MX_M$

Check: Since $X_i = \tilde{X}_i$ for $i=1, \dots, M$ thus we have $Y = \tilde{Y}$.

This gives: $\text{Var}(Y) = \frac{1}{N} Y^T Y$

$$= \frac{1}{N} (Au)^T (Au)$$

$$= \frac{1}{N} u^T A^T A u$$

$$= u^T \underbrace{\left(\frac{1}{N} A^T A \right)}_{C_A} u \leftarrow \text{the quadratic form defined by the matrix } C_A$$

C_A - the covariance matrix of A (since $A = \tilde{A}$)

Constrained optimization of quadratic forms gives:

- 1) $\text{Var}(Y)$ is the largest if u is a unit eigenvector corresponding to the largest eigenvalue λ_1 of C_A .
- 2) For this choice of u we have $\text{Var}(Y) = \lambda_1$.

Proposition

Given a demeaned data matrix $A = [X_1 \dots X_M]$ the 1st principal axis of A is a vector

$$\mathbf{u}_1 = \begin{bmatrix} c_1 \\ \vdots \\ c_M \end{bmatrix}$$

such that $\|\mathbf{u}_1\| = 1$ and \mathbf{u}_1 is an eigenvector of the covariance matrix C_A corresponding to the largest eigenvalue of this matrix.

Moreover, if $Y_1 = A\mathbf{u}_1$ is the 1st principal component of A then $\text{Var}(Y_1) = \lambda_1$ where λ_1 is the largest eigenvalue of the covariance matrix C_A .

Note:

$$\text{Var}(A) = \text{Var}(X_1) + \dots + \text{Var}(X_M) = \text{tr } C_A = \underbrace{\lambda_1 + \lambda_2 + \dots + \lambda_M}_{\substack{\text{all eigenvalues of } C_A \\ (\lambda_i \geq 0 \text{ since } C_A \\ \text{is positive semidefinite})}}$$

This gives: $0 \leq \text{Var}(Y_1) = \lambda_1 \leq \lambda_1 + \dots + \lambda_M = \text{Var}(A)$.