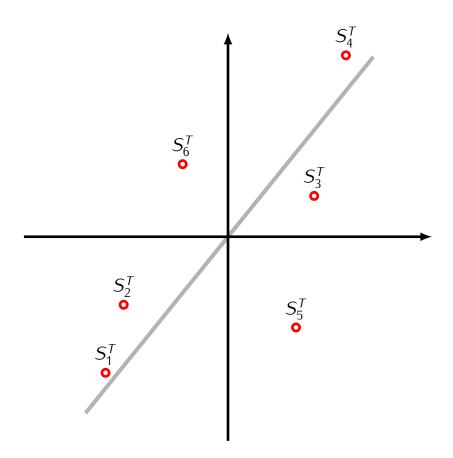
Example.

Demeaned data matrix:

$$A = \begin{bmatrix} \text{Ex 1 Ex 2} \\ \text{Aly} & \begin{bmatrix} -27 & -30 \\ -23 & -15 \\ \end{bmatrix} \\ \text{Chen} & 19 & 6 \\ \text{Deb} & 26 & 40 \\ \end{bmatrix} = \begin{bmatrix} X_1 & X_2 \\ X_1 & X_2 \end{bmatrix} = \begin{bmatrix} S_1 & S_2 & S_3 & S_4 & S_5 \\ \hline S_2 & S_3 & S_4 & S_5 \\ \hline S_5 & S_6 & S_6 \end{bmatrix}$$

Let \mathbf{u}_1 be the 1st principal axis of A, and let Y_1 be the 1st principal component of A:

$$Y_1 = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{bmatrix} = \begin{bmatrix} S_1 \mathbf{u}_1 \\ S_2 \mathbf{u}_1 \\ \vdots \\ S_N \mathbf{u}_1 \end{bmatrix}$$



The projection matrix

The difference matrix

Definition

Let A an $N \times M$ demeaned data matrix

$$A = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_N \end{bmatrix}$$

Let \mathbf{u}_1 be the 1st principal axis of A, and let Y_1 be the 1st principal component of A.

The 2^{nd} principal axis of A is the 1st principal axis of the difference matrix

$$D_1 = A - Y_1 \mathbf{u}_1^T$$

The 2^{nd} principal component Y_2 of A is the 1^{st} principal component of the matrix D_1 .

Computation of the 2^{nd} principal axis of A

Proposition

Given a demeaned data matrix A, let

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N$$

be eigenvalues of the covariance matrix C_A and let $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_N$ be orthonormal vectors such that \mathbf{u}_i is an eigenvector of C_A corresponding to the eigenvalue λ_i .

- The 2^{nd} principal axis of A is the vector \mathbf{u}_2 .
- The 2^{nd} principal component of A is the vector $Y_2 = A\mathbf{u}_2$.
- We have $Var(Y_2) = \lambda_2$.
- In addition, $Cov(Y_1, Y_2) = 0$.

The i^{th} principal component

Proposition/Definition

Given a demeaned data matrix A, let

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N$$

be eigenvalues of the covariance matrix C_A and let $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_N$ be orthonormal vectors such that \mathbf{u}_i is an eigenvector of C_A corresponding to the eigenvalue λ_i .

- The i^{th} principal axis of A is the vector \mathbf{u}_i .
- The i^{th} principal component of A is the vector $Y_i = A\mathbf{u}_i$.
- We have $Var(Y_i) = \lambda_i$.
- In addition, $Cov(Y_i, Y_j) = 0$ if $i \neq j$.