

# Principal Component Analysis

## Linear Dimension Reduction Technique

PCA performs a linear mapping of the data to a lower-dimensional space in such a way that the variance of the data in the low-dimensional representation is maximized.

### 1 Representations of Individuals

1. For the standardized data,  $\frac{1}{n-1}\mathbf{X}^T\mathbf{X}$  is the correlation matrix.  
(If not standardized,  $\frac{1}{n-1}\mathbf{X}^T\mathbf{X}$  is the covariance matrix.)
2. **Loadings:**  $\mathbf{V}$  is the  $p \times r$  unit-norm matrix with eigenvectors of  $\frac{1}{n-1}\mathbf{X}^T\mathbf{X}$ .
  - $\frac{1}{n-1}\mathbf{X}^T\mathbf{X} = \mathbf{V}\mathbf{D}^2\mathbf{V}^T = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^T$ , where
  - Each  $\mathbf{v}_k$  reflects how much each variable  $\mathbf{X}_j$  loads in the PC  $k$ .
3. **Eigenvalues**
  - $\mathbf{D}$  is the  $r \times r$  diagonal matrix of  $\frac{1}{n-1}\mathbf{X}^T\mathbf{X}$  consisting of  $r$  positive eigenvalues (descending ordered).
  - $\mathbf{\Lambda}$  is the  $r \times r$  diagonal matrix of  $\frac{1}{n-1}\mathbf{X}^T\mathbf{X}$ , where each  $\lambda_k$  captures the projected inertia (i.e. variation) on each extracted dimension.
  - $\mathbf{\Lambda} = \mathbf{D}^2$ .
  - $r$  is the rank of  $\mathbf{X}$ .
  - When  $X$  is standardized,  $\sum_{k=1}^r \lambda_k = p$ , and the proportion of variation captured by each PC is  $\lambda_k/p$ .
4. **Scores or Principal Components:**  $\mathbf{Z}$  is the  $n \times r$  matrix in which each column is the projection of all points on that axis/ PC.
  - $\mathbf{Z} = \mathbf{X}\mathbf{V}$
  - PCs are linear combinations of the variables

## 2 Looking at Variables

1. To project the cloud of standardized variables, the projection of variable  $j$  onto an axis  $k$ , is equal to the cosine of the angle  $\theta_{jk}$ , so this criteria maximizes  $\sum_{i=1}^p \cos^2(\theta_{jk}) = \sum_{i=1}^p \text{corr}^2(\mathbf{x}_j, \mathbf{z}_k)$ .

2. **Variable Factors:**  $\mathbf{Q}$  is the  $p \times r$  matrix in which each column is a linear combination of the objects.

- Projection of variable  $j$  on axis  $H_1$  generated by vector  $\mathbf{u}_1$  is  $\mathbf{x}_j^T \mathbf{u}_1$ .
- $\mathbf{Q} = \mathbf{X}^T \mathbf{U}$

3. **Eigenvectors:**  $\mathbf{U}$  is the  $p \times k$  matrix.

- Each column  $\mathbf{u}_1$  is an eigenvector of  $\frac{1}{n-1} \mathbf{X} \mathbf{X}^T$
- $\frac{1}{n-1} \mathbf{X} \mathbf{X}^T$  is the matrix of inner products between individuals
- $\frac{1}{n-1} \mathbf{X} \mathbf{X}^T = \mathbf{U} \mathbf{\Lambda} \mathbf{U}^T = \mathbf{U} \mathbf{D}^2 \mathbf{U}^T$ .

## 3 Relationship between the representations of Individuals and Variables

1.  $\frac{1}{\sqrt{n-1}} \mathbf{X} = \mathbf{U} \mathbf{D} \mathbf{V}^T \Rightarrow \frac{1}{\sqrt{n-1}} \mathbf{X} \mathbf{V} = \mathbf{U} \mathbf{D} \mathbf{V}^T \mathbf{V} = \mathbf{U} \mathbf{D} \Rightarrow \mathbf{U} = \frac{1}{\sqrt{n-1}} \mathbf{X} \mathbf{V} \mathbf{D}^{-1}$ .  
Since  $\mathbf{Z} = \mathbf{X} \mathbf{V}$ ,  $\mathbf{U} = \frac{1}{\sqrt{n-1}} \mathbf{Z} \mathbf{D}^{-1}$

2.  $\frac{1}{\sqrt{n-1}} \mathbf{X} = \mathbf{U} \mathbf{D} \mathbf{V}^T \Rightarrow \frac{1}{\sqrt{n-1}} \mathbf{U}^T \mathbf{X} = \mathbf{U}^T \mathbf{U} \mathbf{D} \mathbf{V}^T = \mathbf{D} \mathbf{V}^T \Rightarrow$   
 $\mathbf{V} = \frac{1}{\sqrt{n-1}} \mathbf{X}^T \mathbf{U} \mathbf{D}^{-1} \Rightarrow \mathbf{V} = \frac{1}{\sqrt{n-1}} \mathbf{Q} \mathbf{D}^{-1}$ .

3.  $\mathbf{Z} = \mathbf{X} \mathbf{V} = \mathbf{X} \frac{1}{\sqrt{n-1}} \mathbf{Q} \mathbf{D}^{-1} = \frac{1}{\sqrt{n-1}} \mathbf{X} \mathbf{X}^T \mathbf{U} \mathbf{D}^{-1} = \frac{1}{\sqrt{n-1}} \mathbf{U} \mathbf{\Lambda} \mathbf{U}^T \mathbf{U} \mathbf{\Lambda}^{-1/2} =$   
 $\frac{1}{\sqrt{n-1}} \mathbf{U} \mathbf{\Lambda} \mathbf{\Lambda}^{-1/2} = \frac{1}{\sqrt{n-1}} \mathbf{U} \mathbf{\Lambda}^{1/2}$ .

## 4 Visualize PCA Results

There is a really good article providing practical guide for PCA.

You can also use the following link: <http://www.sthda.com/english/articles/31-principal-component-methods-in-r-practical-guide/112-pca-principal-component-analysis-essentials>