

# A Survey of Dimensionality Reduction Techniques

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This note set gives a short summary of a collection of commonly-used linear and non-linear dimensionality reduction techniques.

## Contents

<b>1</b>	<b>Linear Dimensionality Reduction (LDR) Techniques</b>	<b>2</b>
1.1	Principal Component Analysis (PCA) . . . . .	2

# 1 Linear Dimensionality Reduction (LDR) Techniques

## 1.1 Principal Component Analysis (PCA)

PCA is a tool used to describe a data set in terms of its directions of highest covariance. Given a data set  $X = \{x^{(i)}\}_{i=1}^m \in \mathbb{R}^n$  with mean  $\mu_X = (\mu_1, \dots, \mu_n)$  and  $\mu_k = (1/m) \sum_{i=1}^m x_k^{(i)}$ , the general sequence of steps is as follows:

- (1) Compute the covariance matrix  $\Sigma$  associated to the data set  $X$ , where  $\Sigma_{ij} = \text{cov}(x^{(i)}, x^{(j)}) = (1/n) \sum_{k=1}^n (x_k^{(i)} - \mu_i)(x_k^{(j)} - \mu_j)$ .
- (2) Diagonalize  $\Sigma$  via the matrices  $\Phi$  and  $\Lambda$ , where  $\Phi$  is orthogonal and  $\Lambda$  is diagonal. The matrix  $\Phi$  has columns that form the orthonormal basis of eigenvectors of  $\Sigma$ ,  $\Lambda$  gives the corresponding eigenvalues, and the equation  $\Sigma = \Phi \Lambda \Phi^T$  holds. This is always possible since  $\Sigma$  is real and symmetric.
- (3) The magnitude of the eigenvalues in  $\Lambda$  provide insight into the number of dimensions along which the data is organized.

(source: <https://stat.duke.edu/~sayan/Sta613/2015/lec/IDAPILecture15.pdf>)

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