

# Principal Component Analysis (PCA)

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## Introduction to PCA

- PCA is used to reduce the dimensions of a given problem to encode the basic features of a multivariate data (eg. an image) by using a few appropriate variables (dimensions).
- Suitable linear transformation (change of basis).
- PCA de-correlates the original data by finding the directions (dimensions) in which the variance is maximized.

## Constructing the data matrix

Data matrix:  $X = \begin{pmatrix} | & | & & | \\ \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_n \\ | & | & & | \end{pmatrix} = \begin{pmatrix} \tilde{\mathbf{x}}_1 \\ \tilde{\mathbf{x}}_2 \\ \vdots \\ \vdots \\ \tilde{\mathbf{x}}_m \end{pmatrix}$

represents the mean subtracted data where each  $\tilde{\mathbf{x}}_k$  represents an  $m$  dimensional data point (vector) and there are  $n$  of them corresponding to  $n$  samples, and each of  $\tilde{\mathbf{x}}_k = (\tilde{x}_{k,1} \ \tilde{x}_{k,2} \ \cdots \ \tilde{x}_{k,n})$  represents the  $n$  sample observations (data points) of the  $k^{th}$  dimension.

Mean subtraction:  $\tilde{\mathbf{x}}_k \leftarrow \left( \tilde{\mathbf{x}}_k - \sum_{i=1}^n \frac{\tilde{x}_{k,i}}{n} \right).$

## Covariance matrix of the dataset

The covariance matrix of the mean subtracted data is

$$C_X = \frac{1}{n-1} X X^T = \frac{1}{n-1} \begin{pmatrix} \tilde{\mathbf{x}}_1 \tilde{\mathbf{x}}_1^T & \tilde{\mathbf{x}}_1 \tilde{\mathbf{x}}_2^T & \cdots & \tilde{\mathbf{x}}_1 \tilde{\mathbf{x}}_m^T \\ \tilde{\mathbf{x}}_2 \tilde{\mathbf{x}}_1^T & \tilde{\mathbf{x}}_2 \tilde{\mathbf{x}}_2^T & \cdots & \tilde{\mathbf{x}}_2 \tilde{\mathbf{x}}_m^T \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\mathbf{x}}_m \tilde{\mathbf{x}}_1^T & \tilde{\mathbf{x}}_m \tilde{\mathbf{x}}_2^T & \cdots & \tilde{\mathbf{x}}_m \tilde{\mathbf{x}}_m^T \end{pmatrix}. \quad (1)$$

- Optimal representation of the data should be s.t. off-diagonal terms of the covariance matrix must be zero.
- Retain those dimensions that lend themselves to exhibit the greatest variability within the data (maximal variance presents richer information). The diagonal entries of the covariance matrix in the transformed space should be as large as possible.

## Linear transformation and principal components

$X$  is transformed into a new representation  $Y$  (also  $m \times n$  matrix) by a change of basis matrix  $P$  of dimensions  $m \times m$  as follows:

$$Y = PX = \begin{pmatrix} \mathbf{p}_1 \cdot \mathbf{x}_1 & \mathbf{p}_1 \cdot \mathbf{x}_2 & \cdots & \mathbf{p}_1 \cdot \mathbf{x}_n \\ \mathbf{p}_2 \cdot \mathbf{x}_1 & \mathbf{p}_2 \cdot \mathbf{x}_2 & \cdots & \mathbf{p}_2 \cdot \mathbf{x}_n \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{p}_m \cdot \mathbf{x}_1 & \mathbf{p}_m \cdot \mathbf{x}_2 & \cdots & \mathbf{p}_m \cdot \mathbf{x}_n \end{pmatrix}. \quad (2)$$

Here  $P = \begin{pmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \vdots \\ \mathbf{p}_m \end{pmatrix}$  where  $\mathbf{p}_k$  form the new basis and are called principal components.

## How to find the change of basis matrix $P$ ?

Covariance matrix of the transformed data  $C_Y$  by

- ① maximizing the diagonal entries of  $C_Y$  (maximizing variance of every dimension), and
- ② minimizing the off-diagonal entries of  $C_Y$  (minimizing covariance between dimensions).

What does the above mean?

- Find  $P$  that makes  $C_Y$  diagonal.
- Since the columns of  $P$  must form the new basis, we must have that  $P$  is an orthonormal matrix ( $PP^T = I$ ).

Mathematically, what is P?

$$\begin{aligned}C_Y &= \frac{1}{n-1} YY^T = \frac{1}{n-1}(PX)(PX)^T = \frac{1}{n-1}(PX)(X^T P^T) \\&= \frac{1}{n-1}P(XX^T)P^T = PSP^T\end{aligned}$$

where  $S = \frac{1}{n-1}XX^T$  is an  $m \times m$  symmetric positive definite matrix and hence **diagonalizable**:  $S = EDE^T$  where  $E$  is an  $m \times m$  orthonormal matrix whose columns are the eigenvectors of  $S$  and  $D$  is a diagonal matrix with the respective eigenvalues along the diagonal.

$P = E^T$  is the desired transformation matrix!

$$C_Y = PSP^T = E^T(EDE^T)E = D \text{ because } E^TE = PP^T = I.$$

## How to find eigenvalues of S?

- By hand!
- By Singular Value Decomposition (SVD ← good idea!)

## How to recover the original data?

$$Y = PX = V^T X, \boxed{X = VY}.$$