

CS475/CS675

Lecture 23: July 19, 2016

Principal Component Analysis,
Eigenfaces

Principal Component Analysis (PCA)

- Data exploration technique:
 - Dimensionality reduction
 - Principal components are axes that preserve most of the variance in the data
- Picture

Empirical Variance

- Data: X

- Empirical mean: $\mu = \frac{1}{n} \sum_{i=1}^n X_i$

- Empirical covariance:

$$C = \frac{1}{n-1} \sum_{i=1}^n [X_i - \mu][X_i - \mu]^T$$

Principal Component

- Axis v that preserves the most variance

$$\begin{aligned} \max_v \frac{1}{n-1} \sum_{i=1}^n [X_i^T v - \mu^T v]^T [X_i^T v - \mu^T v] \\ &= \max_v \frac{1}{n-1} \sum_{i=1}^n v^T [X_i - \mu][X_i - \mu]^T v \\ &= \max_v v^T \left[\frac{1}{n-1} \sum_{i=1}^n [X_i - \mu][X_i - \mu]^T \right] v \\ &= \max_v v^T C v \end{aligned}$$

When $\|v\| = 1$, then

$\max_v v^T C v$ is

v is

Principal Component Analysis

- Eigendecomposition of the empirical covariance matrix

$$C = Q\Lambda Q^T$$

- Eigenvector: dimension (or basis function)
- Eigenvalue: amount of variance preserved in that dimension

Dimensionality Reduction

- Problem: what is the smallest linear subspace (i.e., fewest dimensions) that captures 95% of the variance?
- Solution: retain eigenvectors of the k largest eigenvalues such that k is the smallest integer that satisfies

$$\frac{\sum_{i=1}^k \lambda_i}{\sum_{j=1}^n \lambda_j} \geq 0.95$$

- Picture:

Example: Eigenfaces

- Turk and Pentland (1991):
 - Image compression
 - Face detection
- Solution:
 - embed images in low dimensional eigenspace
 - Face detection: nearest neighbour in eigenspace

Principal Component Analysis

- Data: X (m pixels \times n images)
- Covariance matrix: C ($n \times n$)
- Eigendecomposition: $C = Q\Lambda Q^T$

Eigenfaces

Dataset



Mean
image

Eigenfaces



Face Detection

- Project each image in the space of eigenfaces
 - I.e., approximate each image as a linear combination of the eigenfaces

$$\tilde{v} \leftarrow Q^T v$$

- Face detection: find matching image in a database
 - Nearest neighbour in space of eigenfaces

$$w^* = \operatorname{argmin}_{\tilde{w}} \|\tilde{v} - \tilde{w}\|_2$$