

Intro to Principal Component Analysis (PCA) and Independent Component Analysis (ICA)



Similarities and Differences

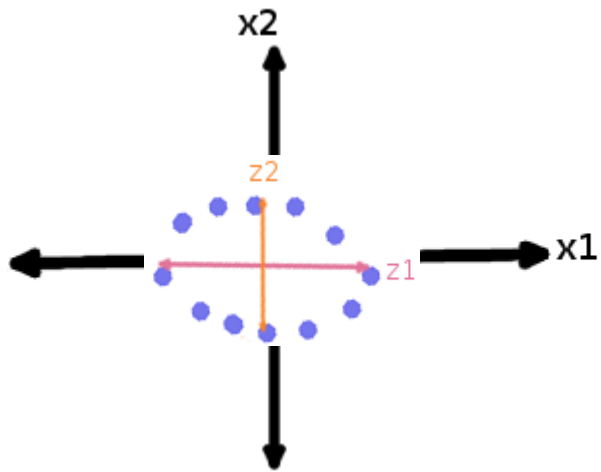
- ▶ Both are statistical transformations
 - ▶ PCA: information from second order statistics
 - ▶ ICA: information that goes up to high order statistics
- ▶ Both used in various fields:
 - ▶ Blind source separation, feature extraction, neuroscience!



PCA

- Often used prior to running machine learning algorithm
- Finds principal components of the dataset
 - Each succeeding step finds direction that explains most variance
 - Transforms data into new subspace
 - First axis corresponds to first principal component (explains greatest amount of variance in the data)

Visualizing PCA



- 2-dimensional data (x_1 and x_2)
- 2 (or less) orthogonal principal components
- Reframed data



PCA

- Principal Components = eigenvectors of covariance matrix of original dataset
 - Eigenvectors are orthogonal (covariance matrix is symmetric)
 - Principal components correspond to **direction** (in original space) with greatest variance in data
- Each eigenvector has an associated eigenvalue
 - Eigenvalue is a scalar that indicates **how much** variance there is in the data along that principal component
 - If PCA is used for dimensionality reduction, generally discard principal components with zero or near-zero eigenvalues

Algebraic Definition of Principal Components

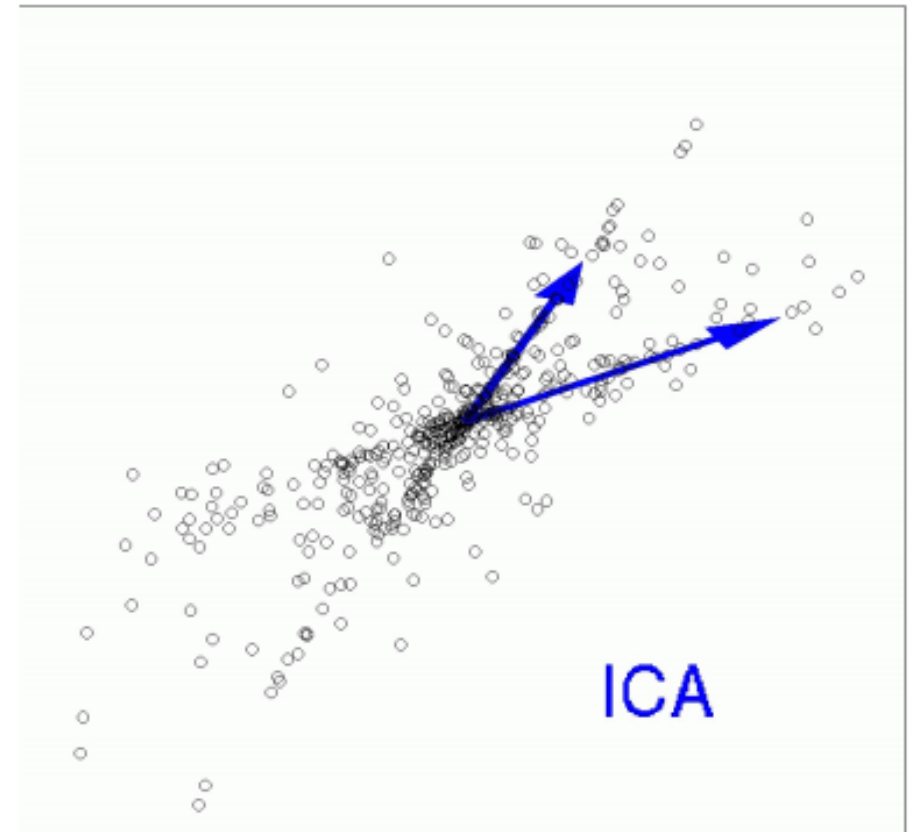
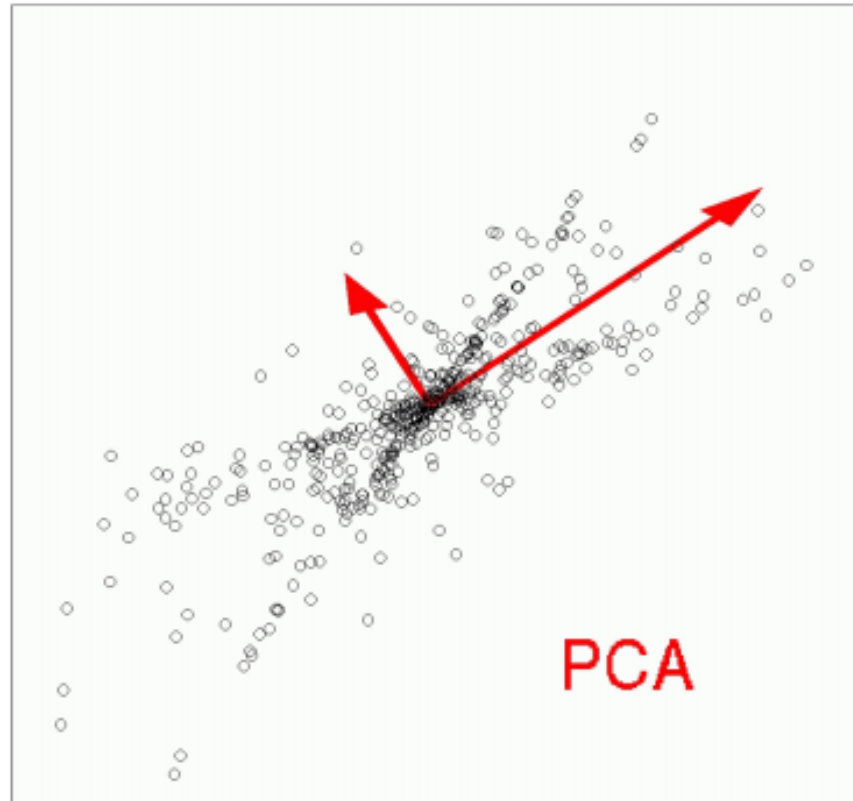
- ▶ Sample of n observations, each with p variables:
 - ▶ $x = (x_1, x_2, \dots, x_p)$
- ▶ First principal component: $z_1 \equiv a_1^T x = \sum_{i=1}^p a_{i1} x_i$
 - ▶ Where vector $a_1 = (a_{11}, a_{21}, \dots, a_{p1})$ st. $\text{var}[z_1]$ is a maximum
- ▶ k^{th} principal component: $z_k \equiv a_k^T x = \sum_{i=1}^p a_{ik} x_i$
 - ▶ Where vector $a_k = (a_{1k}, a_{2k}, \dots, a_{pk})$ st. $\text{var}[z_k]$ is a maximum
 - ▶ Subject to: $\text{cov}[z_k, z_l] = 0$ for $k > l \geq 1$
 - ▶ And to: $a_k^T a_k = 1$



Differences between ICA and PCA

- ▶ PCA removes correlations, **but not** higher order dependence
 - ▶ ICA removes correlations **and** higher order dependence
- ▶ PCA: some components are more important than others (recall eigenvalues)
 - ▶ ICA: all components are **equally important**
- ▶ PCA: vectors are orthogonal (recall eigenvectors of covariance matrix)
 - ▶ ICA vectors are **not orthogonal**

PCA vs ICA



Algebra Behind ICA

- ▶ Assume there exist independent signals: $S = [s_1(t), s_2(t), \dots, s_N(t)]$
- ▶ Linear combinations of signals: $Y(t) = A S(t)$
 - ▶ Both A and S are unknown
 - ▶ A is called the mixing matrix
- ▶ Goal of ICA: recover original signals, $S(t)$ from $Y(t)$
 - ▶ Ex. find a linear transformation, L , ideally A^{-1} st. $LY(t) = S(t)$



ICA

- Generally, preprocess data before applying ICA to remove correlation (“whitening”)
 - PCA is one way to whiten signals
- Address higher order dependence