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FastICA

FastICA is an efficient and popular algorithm for independent component analysis invented by Aapo Hyvärinen at Helsinki University of Technology. ^{[1][2]} Like most ICA algorithms, FastICA seeks an orthogonal rotation of prewhitened data, through a fixed-point iteration scheme, that maximizes a measure of non-Gaussianity of the rotated components. Non-gaussianity serves as a proxy for statistical independence, which is a very strong condition and requires infinite data to verify. FastICA can also be alternatively derived as an approximative Newton iteration.

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Algorithm

Prewhitening the data

Let the $\mathbf{X} := (x_{ij}) \in \mathbb{R}^{N \times M}$ denote the input data matrix, M the number of columns corresponding with the number of samples of mixed signals and N the number of rows corresponding with the number of independent source signals. The input data matrix \mathbf{X} must be *prewhitened*, or centered and whitened, before applying the FastICA algorithm to it.

Centering the data entails demeaning each component of the input data X, that is,

$$x_{ij} \leftarrow x_{ij} - rac{1}{M} \sum_{j'} x_{ij'}$$

for each $i=1,\ldots,N$ and $j=1,\ldots,M$. After centering, each row of ${\bf X}$ has an expected value of ${\bf 0}$.

• Whitening the data requires a linear transformation $\mathbf{L}: \mathbb{R}^{N \times M} \to \mathbb{R}^{N \times M}$ of the centered data so that the components of $\mathbf{L}(\mathbf{X})$ are uncorrelated and have variance one. More precisely, if \mathbf{X} is a centered data matrix, the covariance of $\mathbf{L}_{\mathbf{x}} := \mathbf{L}(\mathbf{X})$ is the $(N \times N)$ -dimensional identity matrix, that is,

$$\mathrm{E}\left\{\mathbf{L}_{\mathbf{x}}\mathbf{L}_{\mathbf{x}}^{T}
ight\}=\mathbf{I}_{N}$$

A common method for whitening is by performing an eigenvalue decomposition on the covariance matrix of the centered data \mathbf{X} , $E\left\{\mathbf{X}\mathbf{X}^T\right\} = \mathbf{E}\mathbf{D}\mathbf{E}^T$, where \mathbf{E} is the matrix of eigenvectors and \mathbf{D} is the diagonal matrix of eigenvalues. The whitened data matrix is defined thus by

$$\mathbf{X} \leftarrow \mathbf{E} \mathbf{D}^{-1/2} \mathbf{E}^T \mathbf{X}$$

Single component extraction

The iterative algorithm finds the direction for the weight vector $\mathbf{w} \in \mathbb{R}^N$ that maximizes a measure of non-Gaussianity of the projection $\mathbf{w}^T \mathbf{X}$, with $\mathbf{X} \in \mathbb{R}^{N \times M}$ denoting a <u>prewhitened</u> data matrix as described above. Note that \mathbf{w} is a column vector. To measure non-Gaussianity, FastICA relies on a nonquadratic <u>nonlinear function</u> f(u), its first derivative g(u), and its second derivative g'(u). Hyvärinen states that the functions

$$f(u) = \log \cosh(u), \quad g(u) = anh(u), \quad ext{and} \quad g'(u) = 1 - anh^2(u),$$

are useful for general purposes, while

$$f(u) = -e^{-u^2/2}, \quad g(u) = ue^{-u^2/2}, \quad ext{and} \quad g'(u) = (1-u^2)e^{-u^2/2}$$

may be highly robust. [1] The steps for extracting the weight vector \mathbf{w} for single component in FastICA are the following:

- 1. Randomize the initial weight vector w
- 2. Let $\mathbf{w}^+ \leftarrow E\left\{\mathbf{X}g(\mathbf{w}^T\mathbf{X})^T\right\} E\left\{g'(\mathbf{w}^T\mathbf{X})\right\}\mathbf{w}$, where $E\left\{\dots\right\}$ means averaging over all column-vectors of matrix \mathbf{X}
- 3. Let $\mathbf{w} \leftarrow \mathbf{w}^+ / \|\mathbf{w}^+\|$
- 4. If not converged, go back to 2

Multiple component extraction

The single unit iterative algorithm estimates only one weight vector which extracts a single component. Estimating additional components that are mutually "independent" requires repeating the algorithm to obtain linearly independent projection vectors - note that the notion of $\underline{\text{independence}}$ here refers to maximizing non-Gaussianity in the estimated components. Hyvärinen provides several ways of extracting multiple components with the simplest being the following. Here, $\mathbf{1}$ is a column vector of 1's of dimension \mathbf{M} .

Algorithm FastICA

Input: C Number of desired components

Input: $\mathbf{X} \in \mathbb{R}^{N \times M}$ Prewhitened matrix, where each column represents an N-dimensional sample, where C <= N

Output: $\mathbf{W} \in \mathbb{R}^{N \times C}$ Un-mixing matrix where each column projects \mathbf{X} onto independent component.

Output: $\mathbf{S} \in \mathbb{R}^{C \times M}$ Independent components matrix, with M columns representing a sample with C dimensions.

$$\begin{aligned} & \textbf{for p in 1 to C:} \\ & \textbf{w_p} \leftarrow \textit{Random vector of length N} \\ & \textbf{while } \textbf{w_p} \text{ changes} \\ & \textbf{w_p} \leftarrow \frac{1}{M} \textbf{X} g(\textbf{w_p}^T \textbf{X})^T - \frac{1}{M} g'(\textbf{w_p}^T \textbf{X}) \textbf{1} \textbf{w_p} \\ & \textbf{w_p} \leftarrow \textbf{w_p} - (\sum_{j=1}^{p-1} \textbf{w_p}^T \textbf{w_j} \textbf{w_j}^T)^T \\ & \textbf{w_p} \leftarrow \frac{\textbf{w_p}}{\|\textbf{w_p}\|} \end{aligned}$$

Output: $\mathbf{W} = [\mathbf{w_1}, \dots, \mathbf{w_C}]$ Output: $\mathbf{S} = \mathbf{W^T} \mathbf{X}$

See also

- Unsupervised learning
- Machine learning
- The IT++ library features a FastICA implementation in C++
- Infomax

References

- 1. Hyvärinen, A.; Oja, E. (2000). "Independent component analysis: Algorithms and applications" (http://www.cs.helsinki. fi/u/ahyvarin/papers/NN00new.pdf) (PDF). Neural Networks. 13 (4–5): 411–430. doi:10.1016/S0893-6080(00)00026-5 (https://doi.org/10.1016%2FS0893-6080%2800%2900026-5). PMID 10946390 (https://www.ncbi.nlm.nih.gov/pubmed/10946390).
- 2. Hyvarinen, A. (1999). "Fast and robust fixed-point algorithms for independent component analysis" (http://www.cs.helsinki.fi/u/ahyvarin/papers/TNN99new.pdf) (PDF). *IEEE Transactions on Neural Networks.* **10** (3): 626–634. doi:10.1109/72.761722 (https://doi.org/10.1109%2F72.761722). PMID 18252563 (https://www.ncbi.nlm.nih.gov/pubmed/18252563).

External links

- FastICA package for Matlab or Octave (http://www.cis.hut.fi/projects/ica/fastica/)
- fastICA package (https://cran.r-project.org/web/packages/fastICA/index.html) in R programming language
- FastICA in Java (http://sourceforge.net/projects/fastica) on SourceForge
- FastICA in Java (http://rapid-i.com/wiki/index.php?title=Independent_Component_Analysis) in RapidMiner.

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This page was last edited on 5 March 2018, at 06:46.

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