

STATISTICAL LEARNING SYSTEMS

LECTURE 9: FINDING STRUCTURE IN DATA - contd.

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Independent component analysis (ICA)

We start with the model

$$\mathbf{x} = \mathbf{\Delta}\mathbf{z} + \mathbf{e},$$

where we not only assume that the data are centered, but also that the $x^{(i)}$, $i = 1, \dots, p$, have unit variance and are uncorrelated. Moreover, for simplicity, we assume that $\mathbf{\Delta}$ is a $p \times p$ matrix, $\mathbf{e} = \mathbf{0}$ and none of the $x^{(i)}$ has normal distribution. In fact, therefore, our model is:

$$\mathbf{x} = \mathbf{\Delta}\mathbf{z}. \quad (1)$$

The task is to find such $\mathbf{\Delta}$ that the $z^{(i)}$ are mutually independent ($\mathbf{\Delta}$ is nonestimable if at least 2 of the $z^{(i)}$ are normal). Clearly, since we assume that the data are spherical, $\mathbf{\Delta}$ is orthogonal, and hence, once found, we have

$$\mathbf{z} = \mathbf{\Delta}'\mathbf{x}. \quad (2)$$



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Independent component analysis (ICA)

Recall that the **entropy** of a random p -vector \mathbf{z} with joint density $f(\mathbf{z})$ is (for convenience, we assume that \mathbf{z} has continuous distribution):

$$H(\mathbf{z}) = - \int_{-\infty}^{\infty} f(\mathbf{z}) \log f(\mathbf{z}) d\mathbf{z}.$$

Mutual information between the $z^{(i)}$, $i = 1, \dots, p$, and \mathbf{z} is:

$$I(z^{(1)}, \dots, z^{(p)}) = \sum_{i=1}^p H(z^{(i)}) - H(\mathbf{z}).$$

It is zero if and only if the $z^{(i)}$ are mutually independent. It is also equal to the **Kullback-Leibler divergence** (or **Kullback-Leibler distance**) of $f(\mathbf{z})$ from

$$f_1(z^{(1)}) f_2(z^{(2)}) \cdots f_p(z^{(p)}).$$

Independent component analysis (ICA)

This last fact readily follows from the definition of the Kullback-Leibler divergence of density $g_1(\mathbf{v})$ from density $g_2(\mathbf{v})$ on R^p :

$$\delta(g_1, g_2) = \int_{-\infty}^{\infty} g_1(\mathbf{v}) \log \frac{g_1(\mathbf{v})}{g_2(\mathbf{v})} d\mathbf{v}.$$

It is zero if and only if the two densities are equal. Moreover,

$$\int_{-\infty}^{\infty} |g_1(\mathbf{v}) - g_2(\mathbf{v})| d\mathbf{v} \leq \sqrt{2\delta(g_1, g_2)}.$$



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Independent component analysis (ICA)

Let us return to (2). Orthogonality of matrix $\mathbf{\Delta}'$ implies that the mutual information between the $z^{(i)}$ satisfies the following equality

$$I(z^{(1)}, \dots, z^{(p)}) = \sum_{i=1}^p H(z^{(i)}) - H(\mathbf{z}) = \sum_{i=1}^p H(z^{(i)}) - H(\mathbf{x}) - \log |\det \mathbf{\Delta}'|. \quad (3)$$

Minimizing (3) w.r.t. $\mathbf{\Delta}'$ is equivalent to finding such a transformation of the original data that the new features $z^{(i)}$ are as close to mutual independence as possible. Note also that minimizing (3) amounts to minimizing the sum of entropies $H(z^{(i)})$, i.e. to maximizing the distance (when measured by entropy) between the distributions of the $z^{(i)}$, $i = 1, \dots, p$ and a normal distribution (with the same covariance).



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Independent component analysis (ICA)

This last fact is of crucial importance: Most of the algorithms designed to perform ICA, i.e., to find matrix $\mathbf{\Delta}$, are based on maximizing the distance (however understood) between the latent variables $z^{(i)}$ and a normal distribution; e.g., classical algorithms seek the maximum absolute value of kurtosis of the $z^{(i)}$. Generally speaking, such algorithms always rest on the ideas from nonlinear programming, in particular gradient or Newton-like algorithms.

An interesting non-classical algorithm, in which the problem of maximizing (3) is directly addressed, has been proposed in [HTF].



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Dissimilarity and similarity measures

Dissimilarity measure does not need to be a metric (triangle inequality does not need to be satisfied).

For vectors in R^p : any metric on R^p may be considered; for quantitative features on different scales weighted Euclidean distance is appropriate

$$d(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^p w_i^2 (x_i - y_i)^2 \right)^{1/2}$$

where w_i

is either (standard deviation of i^{th} variable) $^{-1}$ or (range) $^{-1}$.

Dissimilarity and similarity measures

For vectors with binary (0 and 1) coordinates: $x = (x_1, x_2, \dots, x_p)$,
 $y = (y_1, y_2, \dots, y_p)$ we define

$$\begin{aligned} a &= \#\{x_i = 1 \& y_i = 1\}, & b &= \#\{x_i = 0 \& y_i = 1\}; \\ c &= \#\{x_i = 1 \& y_i = 0\}, & d &= \#\{x_i = 0 \& y_i = 0\}. \end{aligned}$$

Dissimilarity measures for binary data:

- Normalized Hamming distance: $\frac{b+c}{a+b+c+d}$
- Jacquard: $\frac{b+c}{a+b+c}$
(lack of occurrence of a feature does not make objects more similar)
- Czekanowski: $1 - \frac{2a}{2a+b+c}$



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Dissimilarity and similarity measures

For qualitative vectors having more than two levels:

$$1 - \frac{\# \text{coordinates having the same value}}{\# \text{coordinates}}$$

Gower coefficients for mixed variables:

We assume that the coefficient is normalized, i.e., its values are from the $[0, 1]$ interval, and we start with (partial) similarities s_{ijk} between the i -th and j -th element in the sample calculated coordinatewise for each k -th feature (coordinate), $k = 1, \dots, p$. The s_{ijk} are assumed to be normalized too and they are related to the corresponding (partial) dissimilarities d_{ijk} between the i -th and j -th element along the k -th feature (coordinate) by equation

$$s_{ijk} = 1 - d_{ijk}.$$



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Dissimilarity and similarity measures

We allow that the comparison between a pair of elements along one or more coordinates is impossible. Accordingly, we define coefficient δ_{ijk} and, if the comparison between the i -th and j -th elements along the k -th coordinate is impossible, we set $\delta_{ijk} = 0$ (s_{ijk} is then unknown, but for reasons that will prove obvious we set $s_{ijk} = 0$); otherwise, $\delta_{ijk} = 1$.



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Dissimilarity and similarity measures

We define

$$s_{ij} = \frac{\sum_{k=1}^p s_{ijk}}{\sum_{k=1}^p \delta_{ijk}}, \quad d_{ij} = 1 - s_{ij}, \quad (4)$$

where

$$s_{ijk} = 1 - \frac{|x_i^{(k)} - x_j^{(k)}|}{\text{range of } k\text{-th variable}},$$

for quantitative variables,

$$s_{ijk} = \begin{cases} 1, & \text{if } x_i^{(k)} = x_j^{(k)} \\ 0, & \text{otherwise} \end{cases}$$

for qualitative variables, and

	k-th variable's value			
i-th observation	1	1	0	0
j-th observation	1	0	1	0
s_{ijk}	1	0	0	0
δ_{ijk}	1	1	1	0

for binary variables.

Multidimensional scaling (MDS)

Let d_{ij} , $i, j = 1, \dots, n$, be Euclidean distances between observations \mathbf{x}_i and \mathbf{x}_j in R^p . Let our task consist in finding a subspace R^r of a fixed dimension r , $r < p$, such that the distances \hat{d}_{ij} between the projections of \mathbf{x}_i and \mathbf{x}_j on this subspace make the following sum minimal

$$V = \sum_{i=1}^n \sum_{j=1}^n (d_{ij}^2 - \hat{d}_{ij}^2). \quad (5)$$

Interestingly, the R^r sought is given by the first r principal components for \mathbf{x}_i , $i = 1, \dots, n$. Actually the task described is the task of the so-called **multidimensional scaling** in the particular case when distances are Euclidean. **In general, the task of (metric) multidimensional scaling is the same, albeit for any given dissimilarity matrix.**

Remark: Note that, in fact, in all generality we even do not have to know the \mathbf{x}_i , but only the dissimilarities between them.

Multidimensional scaling (MDS)

In whatever way we have acquired dissimilarity matrix $[d_{ij}]$, $i, j = 1, \dots, n$, a question worth an answer is the following:

given dissimilarity matrix $[d_{ij}]$, is it possible to find R^s of some dimension s and a set of n points in this space such that Euclidean distances between these points, \tilde{d}_{ij} , $i, j = 1, \dots, n$, form matrix $[d_{ij}]$, i.e., $\tilde{d}_{ij} = d_{ij}$, $i, j = 1, \dots, n$?

If yes, given the space R^s with the given property, is it possible, for any natural number u , $u < s$, to find a set of n points in R^u such that Euclidean distances between these points, \hat{d}_{ij} , minimize V defined by (5)?



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Multidimensional scaling (MDS)

During the lecture, we shall briefly discuss these issues (not forgetting about a discussion on how to verify results obtained [e.g., by properly using a **minimum spanning tree** of the original data]).

We shall also mention the problem of **nonmetric** MDS.



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