Fachgebiet Maschinelles Lernen Institut für Softwaretechnik und theoretische Informatik Fakultät IV, Technische Universität Berlin Prof. Dr. Klaus-Robert Müller

Email: klaus-robert.mueller@tu-berlin.de

Exercise Sheet 1

Exercise 1: Symmetries in LLE (30 P)

The Locally Linear Embedding (LLE) method takes as input a collection of data points $x_1, \ldots, x_N \in \mathbb{R}^d$ and embeds them in some low-dimensional space. LLE operates in two steps, with the first step consisting of minimizing the objective

$$\mathcal{E}(W) = \sum_{i=1}^{N} \left\| \boldsymbol{x}_i - \sum_{i} W_{ij} \boldsymbol{x}_j \right\|^2$$

where W is a collection of reconstruction weights subject to the constraint $\forall i: \sum_j W_{ij} = 1$, and where $\sum_j W_{ij} = 1$ sums over the K nearest neighbors of the data point x_i . The solution that minimizes the LLE objective can be shown to be invariant to various transformations of the data.

Show that invariance holds in particular for the following transformations:

- (a) Replacement of all x_i with αx_i , for an $\alpha \in \mathbb{R}^+ \setminus \{0\}$,
- (b) Replacement of all x_i with $x_i + v$, for a vector $v \in \mathbb{R}^d$,
- (c) Replacement of all x_i with Ux_i , where U is an orthogonal $d \times d$ matrix.

Exercise 2: Closed form for LLE (30 P)

In the following, we would like to show that the optimal weights W have an explicit analytic solution. For this, we first observe that the objective function can be decomposed as a sum of as many subobjectives as there are data points:

$$\mathcal{E}(W) = \sum_{i=1}^{N} \mathcal{E}_i(W)$$
 with $\mathcal{E}_i(W) = \left\| \boldsymbol{x}_i - \sum_{j} W_{ij} \boldsymbol{x}_j \right\|^2$

Furthermore, because each subobjective depends on different parameters, they can be optimized independently. We consider one such subobjective and for simplicity of notation, we rewrite it as:

$$\mathcal{E}_i(oldsymbol{w}) = \left\|oldsymbol{x} - \sum_{j=1}^K w_j oldsymbol{\eta}_j
ight\|^2$$

where \boldsymbol{x} is the current data point (we have dropped the index i), where $\eta = (\eta_1, \dots, \eta_K)$ is a matrix of size $K \times d$ containing the K nearest neighbors of \boldsymbol{x} , and \boldsymbol{w} is the vector of size K containing the weights to optimize and subject to the constraint $\sum_{j=1}^{K} w_j = 1$.

(a) Prove that the optimal weights for x are found by solving the following optimization problem:

$$\min_{\boldsymbol{w}} \quad \boldsymbol{w}^{\top} C \boldsymbol{w} \qquad \text{subject to} \quad \boldsymbol{w}^{\top} \mathbb{1} = 1.$$

where $C = (\mathbb{1} \boldsymbol{x}^{\top} - \eta)(\mathbb{1} \boldsymbol{x}^{\top} - \eta)^{\top}$ is the covariance matrix associated to the data point \boldsymbol{x} and $\mathbb{1}$ is a vector

(b) Show using the method of Lagrange multipliers that the minimum of the optimization problem found in (a) is given analytically as:

$$w = \frac{C^{-1} \mathbb{1}}{\mathbb{1}^{\top} C^{-1} \mathbb{1}}.$$

(c) Show that the optimal w can be equivalently found by solving the equation Cw = 1 and then rescaling wsuch that $\boldsymbol{w}^{\top} \mathbb{1} = 1$.

Exercise 3: Programming (40 P)

Download the programming files on ISIS and follow the instructions.