Université Paris Dauphine-PSL



FUNDAMENTALS OF MACHINE LEARNING

Unsupervised learning – Project Ex 3.1

Auteurs: Elise Chin Mathide DA Cruz

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Derivation of theoretical results

Exercise 3.1 Demonstrate that the matrix of scalar products can be derived from the distance matrix via double-centering, in the case of Euclidean distance.

Given $\mathbf{x}_1,...,\mathbf{x}_n \in \mathbb{R}^m$, we define the squared distance matrix $D = [d_{ij}^2]_{ij} \in \mathbb{R}^{n \times n}$ where $d_{ij}^2 = ||\mathbf{x}_i - \mathbf{x}_j||_2^2$ and the Gram matrix $G = [g_{ij}]_{ij} \in \mathbb{R}^{n \times n}$ where $g_{ij} = x_i^T x_j$. We suppose, without loss of generality, that \mathbf{x}_i are mean-centered, i.e. $\sum_i \mathbf{x}_i = 0$. We want to prove that the Gram matrix G can be computed from the squared distance matrix D via double-centering. It is a way of transforming a rectangular matrix to the one having mean values of rows equal to zero and mean values of columns equal to zero, by multiplying the centering matrix $C = I_n - \frac{1}{n} \mathbf{1}^T \mathbf{1}^1$ to both sides of D.

In other words, we want to find a constant α such that $G = \alpha CDC$.

First, we develop the term d_{ij}^2 for any $i, j \in [1, n]$:

$$d_{ij}^{2} = ||\mathbf{x}_{i} - \mathbf{x}_{j}||_{2}^{2}$$

$$= \mathbf{x}_{i}^{T} \mathbf{x}_{i} - 2\mathbf{x}_{i}^{T} \mathbf{x}_{j} + \mathbf{x}_{j}^{T} \mathbf{x}_{j}$$

$$= g_{ii} - 2g_{ij} + g_{jj}$$
(1)

We denote that:

$$\sum_{j=1}^{n} d_{ij}^{2} = \sum_{j=1}^{n} d_{ji}^{2} = \sum_{j=1}^{n} g_{ii} - 2g_{ij} + g_{jj}$$

$$= ng_{ii} - 2\sum_{j=1}^{n} g_{ij} + Tr(G)$$

$$= ng_{ii} + Tr(G) - 2\mathbf{x}_{i}^{T}(\sum_{j=1}^{n} \mathbf{x}_{j})$$

$$= ng_{ii} + Tr(G)$$
because \mathbf{x}_{i} are mean-centered, so $\sum_{i=1}^{n} \mathbf{x}_{j} = 0$

Let $CD = [b_{ij}]_{ij}$ and $CDC = [b'_{ij}]_{ij}$. For any $i, j \in [1, n]$:

$$b_{ij} = d_{ij} - \frac{1}{n} \sum_{k=1}^{n} d_{kj}^{2}$$

$$= (g_{ii} - 2g_{ij} + g_{jj}) - \frac{1}{n} \sum_{k=1}^{n} d_{kj}^{2}$$

$$= (g_{ii} - 2g_{ij} + g_{jj}) - \frac{1}{n} (ng_{jj} + Tr(G))$$

$$= g_{ii} - 2g_{ij} - \frac{1}{n} Tr(G)$$

Thus, we obtain:

 $^{{}^{1}\}mathbf{1}^{T}\mathbf{1} \in \mathbb{R}^{n \times n}$ is a square matrix full of 1s.

$$b'_{ij} = b_{ij} - \frac{1}{n} \sum_{k=1}^{n} b_{ik}$$

$$= g_{ii} - 2g_{ij} - \frac{1}{n} Tr(G) - \frac{1}{n} \sum_{k=1}^{n} (g_{ii} - 2g_{ik} - \frac{1}{n} Tr(G))$$

$$= g_{ii} - 2g_{ij} - \frac{1}{n} Tr(G) - \frac{1}{n} (ng_{ii} - Tr(G) - 2\sum_{k=1}^{n} g_{ik})$$

$$= g_{ii} - 2g_{ij} - \frac{1}{n} Tr(G) - g_{ii} + \frac{1}{n} Tr(G)$$

$$= -2g_{ij}$$

We deduce that $CDC = -2G \iff G = -\frac{1}{2}CDC$.