

Machine Learning Exercise Sheet 10

Dimensionality Reduction & Matrix Factorization

In-class Exercises

Problem 1: In this exercise, we use proof by induction to show that the linear projection onto an M -dimensional subspace that maximizes the variance of the projected data is defined by the M eigenvectors of the data covariance matrix S , given by

$$S = \frac{1}{N} \sum_{n=1}^N (\mathbf{x}_n - \bar{\mathbf{x}})(\mathbf{x}_n - \bar{\mathbf{x}})^T \quad \bar{\mathbf{x}} = \frac{1}{N} \sum_{n=1}^N \mathbf{x}_n$$

corresponding to the M largest eigenvalues. In Section 12.1 in Bishop this result was proven for the case of $M = 1$. Now suppose the result holds for some general value of M and show that it consequently holds for dimensionality $M + 1$. To do this, first set the derivative of the variance of the projected data with respect to a vector \mathbf{u}_{M+1} defining the new direction in data space equal to zero. This should be done subject to the constraints that \mathbf{u}_{M+1} be orthogonal to the existing vectors $\mathbf{u}_1, \dots, \mathbf{u}_M$, and also that it be normalized to unit length. Use Lagrange multipliers to enforce these constraints. Then make use of the orthonormality properties of the vectors $\mathbf{u}_1, \dots, \mathbf{u}_M$ to show that the new vector \mathbf{u}_{M+1} is an eigenvector of S . Finally, show that the variance is maximized if the eigenvector is chosen to be the one corresponding to eigenvalue λ_{M+1} where the eigenvalues have been ordered in decreasing value.

Suppose that the result holds for projection spaces of dimensionality M . The $M + 1$ dimensional principal subspace will be defined by the M principal eigenvectors $\mathbf{u}_1, \dots, \mathbf{u}_M$ together with an additional direction vector \mathbf{u}_{M+1} whose value we wish to determine. We must constrain \mathbf{u}_{M+1} such that it cannot be linearly related to $\mathbf{u}_1, \dots, \mathbf{u}_M$ (otherwise it will lie in the M -dimensional projection space instead of defining an $M + 1$ independent direction). This can easily be achieved by requiring that \mathbf{u}_{M+1} be orthogonal to $\mathbf{u}_1, \dots, \mathbf{u}_M$, and these constraints can be enforced using Lagrange multipliers η_1, \dots, η_M .

Following the argument given in section 12.1.1 for \mathbf{u}_1 we see that the variance in the direction \mathbf{u}_{M+1} is given by $\mathbf{u}_{M+1}^T S \mathbf{u}_{M+1}$. We now maximize this using a Lagrange multiplier λ_{M+1} to enforce the normalization constraint $\mathbf{u}_{M+1}^T \mathbf{u}_{M+1} = 1$. Thus we seek a maximum of the function:

$$\mathbf{u}_{M+1}^T S \mathbf{u}_{M+1} + \lambda_{M+1}(1 - \mathbf{u}_{M+1}^T \mathbf{u}_{M+1}) + \sum_{i=1}^M \eta_i \mathbf{u}_{M+1}^T \mathbf{u}_i$$

with respect to \mathbf{u}_{M+1} . The stationary points occur when

$$0 = 2\mathbf{S}\mathbf{u}_{M+1} - 2\lambda_{M+1}\mathbf{u}_{M+1} + \sum_{i=1}^M \eta_i \mathbf{u}_i$$

Left multiplying with \mathbf{u}_j^T , and using the orthogonality constraints, we see that $\eta_j = 0$ for $j = 1, \dots, M$. We therefore obtain

$$\mathbf{S}\mathbf{u}_{M+1} = \lambda_{M+1}\mathbf{u}_{M+1}$$

and so \mathbf{u}_{M+1} must be an eigenvector of \mathbf{S} with eigenvalue λ_{M+1} . The variance in the direction \mathbf{u}_{M+1} is given by $\mathbf{u}_{M+1}^T \mathbf{S} \mathbf{u}_{M+1} = \lambda_{M+1}$ and so is maximized by choosing \mathbf{u}_{M+1} to be the eigenvector having the largest eigenvalue amongst those not previously selected. Thus the result holds also for projection spaces of dimensionality $M + 1$, which completes the inductive step. Since we have already shown this result explicitly for $M = 1$ it follows that the result must hold for any $M \ll D$.

Problem 2: Proof that minimizing the error is equivalent to maximizing the variance.

See Bishop chapter 12.1.2.