## Manifold Learning models: from unsupervised data representation and classification in machines towards new insights on neural computation and biological perception rules.

Manifold Learning models usually refer to that class of unsupervised statistical problems involving tasks as: dimensionality reduction of a finite dataset, at the same time preserving or extracting the most significant features; the so-called latent factor modeling of high-dimensional observations, exploiting only a small number of underlying causes; density estimation and classification. Difficulties arise because data are in general expressed in a high-dimension space, they are intrinsically redundant, hiding coherent structure which can be revealed by the identification of strong correlations between latent factors, and lying in low-dimensional manifolds, which can be approximated by linear models only locally, but showing globally a nonlinear structure. Aim of the present work is to build a unified and comprehensive approach for the application of Manifold Learning algorithms, and in particular of the latent-factor ones, as Principal, Factor and Independent Component Analysis, and then even more useful Mixture of the same [1], together to models for Non-Linear Dimensionality Reduction and Spectral Clustering, as Isomap, Locally Linear Embedding and Laplacian Eigenmaps [2]. Applying such an approach is not only strictly important to give machines able to perform learning tasks faultlessly and faster, but also to get new perspectives on the understanding of how human perception internally works, in particular how it builds representations of an environment [3], process them and finally take decisions, in various tasks way better than any machine actually can.

References:

[1] Roweis, Ghahramani. Unifying Review of Linear Gaussian Model. Neural Computation 1999 11:2, 305-345.

[2] Roweis, Saul. Nonlinear Dimensionality Reduction by Locally Linear Embedding. Science Vol 290, 22 December 2000, 2323–2326.

[3] Seung, Lee. The Manifold Ways of Perception. Science 290 (5500), 2268-2269.