Bayesian latent variable models for sparse representations

The problem of finding sparse representations of a "signal" given a dictionary of possibly overcomplete basis vectors is an important task in several scientific domains including signal processing, computer vision and for many application area such as signal and image compression/restoration, object recognition, etc (Olshausen and Field, 1996, 1997, 2004). Several methods have been proposed for sparse coding, for example the ones based on $l1$-norm regularized regression known as the LASSO (Tibshirani, 1996), also often referred to as Basis Pursuit (BP) (Chen et al., 1999), FOCUS (Gorodnitsky and Bhaskar, 1997), and explicitly formulated Bayesian methods for finding sparse representations (Wipf, 2006) namely l_1-norm Bayesian sparse representations (Lin, 2008) and Bayesian pursuit algorithms (Herzet and Drémeau, 2014; Drémeau and Herzet, 2011). The Bayesian inference framework for finding sparse representations offer a principled general framework for sparse coding as in many cases, cost error functions related to deterministic sparse coding approaches are particular cases for maximum a posteriori (MAP) criteria of corresponding Bayesian models. The Bayesian algorithms for sparse coding allow therefore for taking explicitly and in a principled way a prior knowledge on a formulated probabilistic model to encourage sparsity and they include namely latent data models (e.g. see (Wipf, 2006)). As a result, the problem of finding the spare representations by the Bayesian regularization approaches, consists in a statistical inference by using dedicated statistical tools such as the expectation-maximization (EM) algorithm (Dempster et al., 1977) for the case of Bayesian latent data models.

One of the fast and efficient developed approaches for sparse representations if the Predictive Sparse Decomposition (PSD) (Kavukcuoglu et al., 2008; Kavukcuoglu, 2011) which jointly learns a dictionary and approximates the sparse representations by a predictive function (rather than computing exact sparse representations). The objective of this work is first to formulate the PSD (which is non-Bayesian) into a Bayesian framework which leads to a Bayesian Predictive Sparse Decomposition (BPSD). Then, the BPSD will be reformulated as a latent variable model by integrating a mixture prior over the codes in order to control the sparsity into a probabilistic way. This may lead to a MAP criterion which may be solved by an EM-type algorithm. An experimental protocol for comparing BPSD and the latent variable version of BPSD with alternative sparse coding approaches with applications to images and/or sounds representation for recognition.

Additional Information

Supervisor: Faicel Chamroukhi http://chamroukhi.univ-tln.fr/, Maître de conférences
Location: The internship will be conducted within the LSIS laboratory UMR CNRS 7296, in Toulon
Required skills: Statistical learning, pattern recognition; *Strong skills* in Matlab or Python, *and* C; Scientific English
Desired skills: Feature learning, sparse coding, Bayesian inference
Internship gratification: 436.05 € / month for 4 to 6 months
A PhD position after the internship is possible
How to apply: Send your CV + transcripts + reference letter(s), in **A SINGLE .PDF** file, to chamroukhi@univ-tln.fr

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