Thesis Title: Generalized Model Based Framework and Applications

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ABSTRACT

Real-world data involving multivariate observations exhibit skewness, correlated entries across various dimensions and non-Gaussian characteristics such as low-dimensional structures with densities that are sharply peaked and possess heavy tails. As a result, the normality assumption is violated and it is desirable to have methods to model a broader class of signals exploiting domain specific knowledge, while offering simple solutions such as available with Gaussian models.

This thesis, Generalized Model-Based Frameworks and Applications, attempts to address the problem of data modeling under model-based framework, when data exhibit correlation structure with heavy tails and skewness. The basic idea is to assume specific models for data generation, so that we can have specialized algorithms, that require less data for inference. In this work, we rely on the generalized scale mixture model, which comprises of various random and deterministic parameters. By varying distribution over random parameter, we derive a family of generalized multivariate heavy tailed distributions, which encompasses several choices of classical distributions such as Laplace, Student's t and Jeferry's prior. For inference, we develop a hybrid framework, where random parameters are estimated using Variational Bayes (VB) and deterministic parameters using Expectation Maximization (EM). To show the applicability of the proposed model, we present its utility in two different application areas.

Firstly, we consider the model-based compressed sensing framework associated with Bayesian linear model. Specifically, we address the Bayesian group sparse modeling with correlated entries and derive cSVB (correlated Sparse Variational Bayes) framework. We also propose two frameworks, viz. TSVB (Temporal Sparse Variational Bayes) and TMSVB (a low complexity version of TSVB), to solve related problems on sparse signal recovery in the multiple measurement vector (MMV) context. Next, we consider its extension to spatiotemporal data and present the Spatio-Temporal Sparse Variational Bayes (STSVB) framework. The proposed algorithm processes multi-dimensional data and is particularly helpful where we have a limited access to computational resources. We briefly discuss applications in the domains of fetal electrocardiogram (FECGs), electroencephalogram (EEG) data processing, and in the modeling of a dynamic hand dataset. We also present the utility of cSVB and STSVB frameworks for Steady-State Visual Evoked Potential (SSVEP) based EEG signals, where the task is to detect frequency components present in the data.

Next, we discuss a novel model-based clustering/classification framework using a generalized class of skewed distribution. Specifically, we present an alternative to the Gaussian Mixture Model (GMM), based on the EM framework, that is capable of handling more complex structures present in data, while offering advantages of almost similar computational complexity as that of GMM. Experimental results on five real-world datasets demonstrate the effectiveness of the model.

Finally, we explore the possible future directions in the context of model-based methods.