Hamilton Institute

Bayesian Inference in Kernel Learning & Gaussian Process Classification Problems

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Abstract
The integration of heterogeneous forms of informative data by inferring an optimal combination of candidate kernel matrices in classification or regression problems has been shown to be capable of providing enhanced predictive performance when compared to that obtained from kernel matrices derived from any single data source. The most significant recent work in this area of kernel learning has focused on semi-definite programming methods to induce classifiers with appropriately weighted combinations of base kernel matrices. There are many application domains where there is a paucity of data examples available to induce a classifier or infer a regression function. In such cases the adoption of Bayesian inference should prove more appropriate than estimation methods derived from maximizing likelihood.

In the first part of this talk I will develop a Bayesian hierarchical model which allows 'kernel learning' in both regression and classification problems and present hybrid Markov Chain Monte Carlo, Variational Bayes and Maximum a Posteriori methods to infer the associated model parameters. The second part of the talk will introduce a novel solution to the problem of Bayesian inference in Gaussian process classification problems where there are multiple classes. It is well known in the statistics literature that augmenting binary and polychotomous response models with Gaussian latent variables enables exact Bayesian analysis via Gibbs sampling from the parameter posterior. By adopting such a data augmentation strategy, dispensing with priors over regression coefficients in favour of Gaussian Process (GP) priors over functions, and employing variational approximations to the full posterior we obtain efficient computational methods for Gaussian Process classification in the multi-class setting. The model augmentation with additional latent variables ensures full a posteriori class coupling whilst retaining the simple a priori independent GP covariance structure from which sparse approximations, such as multi-class Informative Vector Machines (IVM), emerge in a very natural and straightforward manner.

Venue: Seminar Room, Hamilton Institute, Rye Hall,
NUI Maynooth

Time: 1.00 - 2.00pm (followed by tea/coffee)

Travel directions are available at www.hamilton.ie

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