Workshop program (titles and abstracts)

Dario AZZIMONTI

Title: *Bayesian methods for excursion set estimation*

Abstract: *In many scientific and industrial problems a system is modeled with an expensive computer experiment taking several input parameters and returning a real valued response. Practitioners are often interested in recovering the set of inputs that leads the output variable to certain values, however, when the output is expensive to compute, such sets cannot be estimated directly.*

Given few evaluations of a computer experiment, we consider the problem of estimating such excursion sets and evaluating, reducing and visualizing their uncertainty. In particular we follow classical computer-experiments literature and we emulate the expensive function with a Gaussian process (GP). We review the main methods to compute excursion set estimates from the posterior GP distribution. More specifically we focus on an efficient method to compute conservative estimates with a global confidence level. We quantify and reduce the uncertainty on such estimates with adaptive design of experiments obtained with Step-wise Uncertainty Reduction (SUR) strategies that optimally reduce the uncertainty on set estimates. Finally we discuss the profile extrema method to visualize excursion set estimates when the input space is high dimensional. Such method relies on computing constrained maxima and minima of the function to select regions inside or outside the excursion set.

Joint works with: D. Ginsbourger, C. Chevalier, J. Bect, and Y. Richet, J.Rohmer and D. Idier.

François BACHOC

Title: *Gaussian processes indexed on the symmetric group: prediction and learning*

Abstract: *In the framework of the supervised learning of a real function defined on a space X , the so called Kriging method stands on a real Gaussian field defined on X. The Euclidean case is well known and has been widely studied. In this paper, we explore the less classical case where X is the non commutative finite group of permutations. In this setting, we propose and study an harmonic analysis of the covariance operators that enables to consider Gaussian processes models and forecasting issues. Our theory is motivated by statistical ranking problems.*

Lehel CSATO

Title: *Sparse Online Gaussian Process inference in Machine Learning*

Abstract: *Gaussian process inference provides a theoretically elegant and framework for latent variable models. Observations noise other than Gaussian makes the inference process analytically intractable and one has to use approximations. In online approximations one uses a single observation to update the latent Gaussian process model. For Gaussian noise the online learning involves no approximations; it is an instance of Moore-Penrose matrix inversion formula, leads to the same result as the offline – batch – learning. For non-Gaussian observation noise, the online learning is an approximation to the true Gaussian process.*

Using a parametrisation lemma, we show that one can represent the approximation using a finite number of parameters and that the parametrisation – resembling the one by Kimeldorf-Wahba – is sufficient to describe the full Gaussian process. We show examples of how this parametrisation can be used to solve problems involving different likelihoods. When applying MLII, we illustrate the possibility to optimise model – kernel and likelihood – hyper-parameters.

Masoumeh DASHTI

Title: *MAP estimators and posterior consistency for Bayesian Inverse Problems for functions*

Abstract: *We consider the inverse problem of recovering an unknown functional parameter from noisy and indirect observations. We adopt a Bayesian approach, and show some results on characterisation of the modes of the posterior measure. We also discuss some posterior consistency results.*

This is based on joint works with S. Agapiou, M.Burger and T. Helin

Nicolas DURRANDE

Title: *Gaussian process models using banded precisions matrices*

Abstract: *Several covariance functions commonly used in Gaussian Process (GP) models can lead to sparse precision matrices. This alternative representation of GP models is usually referred to as Gaussian Markov random fields. In this work, we focus on one particular case of sparsity that is banded matrices and we show that several state of the art methods such as Maximum likelihood estimation, Hamiltonian Monte-Carlo and Variational inference can be implemented efficiently (with a complexity that is linear in the number of observation). Finally we illustrate the advantages of the proposed framework on time series and on a Gaussian process model defined over a graph structure.*

Pierre DEL MORAL

Title: *Uniform estimates for particle filters*

Abstract: *This talk is concerned with the long time behavior of particle filters and Ensemble Kalman filters. These filters can be interpreted as mean field type particle interpretation of the filtering equation and the Kalman recursion. We present a series of old and new results on the stability properties of these filters. We initiate a comparison between these particle samplers and discuss some open research questions.*

(Synthesis of join work with A. Bishop, A. Guionnet, K. Kamatani, A. Kurtzmann, L. Miclo, B. Rémillard, J. Tugaut)

Daniel HERNANDEZ-LOBATO

Title: *Approximate Inference in Multi-class and Deep Gaussian Processes by Minimizing Alpha Divergences*

Abstract: *Approximate inference in multi-class Gaussian process classification is significantly more challenging than in the binary case. The reason is that the likelihood factors are more complicated in this setting and they may even lack a closed-form analytical expression. Furthermore, instead of a single latent function, there is, typically, a latent function per each different class. Besides this, Deep Gaussian processes are very flexible models that may be very useful to alleviate the disadvantages of standard Gaussian processes, which may have problems dealing with non-stationarity or input dependent noise. Notwithstanding, approximate inference in Deep Gaussian processes is also extremely difficult. More precisely, the posterior distribution of a Gaussian process whose input is another Gaussian process is no longer a Gaussian process. Some approaches for approximate inference in these two models have been proposed in the literature. These are based on either Expectation Propagation (EP) or Variational Inference (VI), which involve the minimization of the Kullback-Leibler divergence. In this talk, I will explain how to use an alternative technique based on the minimization of alpha divergences that can be seen as a generalization of both EP and VI.*

Hugh SALIMBENI

Title: *Deep Gaussian Processes with Importance-Weighted Variational Inference*

Abstract: *Non-Gaussian densities can be constructed by passing Gaussian noise through a non-linear function. We use a deep Gaussian process (DGP) for the non-linear function as it can provide a richly expressive mapping while being robust to overfitting. This an important property as even large datasets may be sparse in regions of interest. Previous work in this model has used a variational inference with a combination sparse Gaussian processes and mean field Gaussians for the approximate posterior. We propose a novel importance weighted objective, which leverages analytic results and provides a mechanism to trade-off computation for improved accuracy. Our results demonstrate that the importance weighted objective works well in practice, and that the DGP with latent variables is an effective model on a range of practical tasks.*