

# Abstracts

7<sup>èmes</sup> Journées Statistiques du Sud, Barcelona, June 9–11, 2014

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## Monday 9

**9:30-10:00** Welcoming / Registration

**10:00-11:15** Luc Devroye (I)

**11:15-11:45** Coffee break

**11:45-12:30** Catherine Matias

**12:30-13:15** Pierre Alquier

**13:15-15:00** Lunch

**15:00-16:15** Martin Wainwright (I)

**16:15-17:00** Pedro Delicado

## Tuesday 10

**10:00-11:15** Francis Bach (I)

**11:15-11:45** Coffee break

**11:45-12:30** Aurélien Garivier

**12:30-13:15** Alejandra Cabaña

**13:15-15:00** Lunch

**15:00-16:15** Martin Wainwright (II)

**16:15-17:00** Gersende Fort

**21:00** Conference Dinner

## Wednesday 11

**10:00-11:15** Luc Devroye (II)

**11:15-11:45** Coffee break

**11:45-13:00** Francis Bach (II)

**13:00-15:00** Lunch

Pierre ALQUIER (University College Dublin)  
**Bayesian estimation of low-rank matrices**

The problem of low-rank matrix estimation recently received an increased attention due to several challenging applications. Many algorithms were proposed, based either on fitting various criterion with a convex penalty, or on Bayesian statistics. While the theoretical performances of the penalized methods is now well understood, not much has been done on the theoretical analysis of the Bayesian methods. In this talk, we review the different type of priors considered on low-rank matrices. We also prove that the Bayesian estimators, under suitable assumptions, enjoy almost the same optimality properties as the ones based on penalization.

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Francis BACH (INRIA - École Normale Supérieure)  
**Beyond stochastic gradient descent for large-scale machine learning**

Many machine learning and signal processing problems are traditionally cast as convex optimization problems. A common difficulty in solving these problems is the size of the data, where there are many observations ("large  $n$ ") and each of these is large ("large  $p$ "). In this setting, online algorithms such as stochastic gradient descent which pass over the data only once, are usually preferred over batch algorithms, which require multiple passes over the data. In this talk, I will show how the smoothness of loss functions may be used to design novel algorithms with improved behavior, both in theory and practice: in the ideal infinite-data setting, an efficient novel Newton-based stochastic approximation algorithm leads to a convergence rate of  $\mathcal{O}(1/n)$  without strong convexity assumptions, while in the practical finite-data setting, an appropriate combination of batch and online algorithms leads to unexpected behaviors, such as a linear convergence rate for strongly convex problems, with an iteration cost similar to stochastic gradient descent.

Joint work with Nicolas Le Roux, Eric Moulines and Mark Schmidt.

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Alejandra CABAÑA (Universitat Autònoma de Barcelona)  
**Modeling stationary data by classes of generalized Ornstein-Uhlenbeck processes**

Consider the complex Ornstein-Uhlenbeck operator defined by  $\text{OU}_\kappa y(t) = \int_{-\infty}^t e^{-\kappa(t-s)}$ ,  $\kappa \in \mathbf{C}, \Re(\kappa) > 0$  provided that the integral makes sense. In particular, when  $y$  is replaced by a Levy process  $\Lambda$  on  $R$ ,  $x(t) = \text{OU}_\kappa \Lambda(t)$ , is Levy-driven Ornstein-Uhlenbeck process.

New stationary processes can be constructed by iterating the application of OU to Levy processes, in particular, to the Wiener process  $w$ . We denote by  $\text{OU}(p)$  the families of processes obtained by applying successively  $p$  OU operators  $\text{OU}_{\kappa_j}$ ,  $j = 1, 2, \dots, p$  to  $\Lambda$ . These processes can be used as models for stationary continuous parameter processes, and their discretized version, for stationary time series.

We show in particular that the series  $x(0), x(1), \dots, x(n)$  obtained from  $x = \prod_{j=1}^p \text{OU}_{\kappa_j}(\Lambda)$  has the same second order moments of an ARMA( $p, p-1$ ) model hence, it is an ARMA when the driving process is a Wiener process.

We present an empirical comparison of the abilities of OU and ARMA models to fit stationary data. In particular, we show examples of processes with long dependence where the fitting of the empirical autocorrelations is improved by using OU process rather than ARMA models, and with fewer parameters in the former case.

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Pedro DELICADO (Universitat Politècnica de Catalunya)

**Optimal representation of bivariate density functions by level sets**

In bivariate density representation there is an extensive literature on level set estimation when the level is fixed, but this is not so much the case when choosing which level is (or which levels are) of most interest. This is an important practical question which depends on the kind of problem one has to deal with as well as the kind of feature one wishes to highlight in the density, the answer to which requires both the definition of what the optimal level is and the construction of a method for finding it. We consider two scenarios for this problem. The first one corresponds to situations in which one has just a single density function to be represented. However, as a result of the technical progress in data collecting, problems are emerging in which one has to deal with a sample of densities. In these situations, the need arises to develop joint representation for all these densities, and this is the second scenario considered in this paper. For each case, we provide consistency results for the estimated levels and present wide Monte Carlo simulated experiments illustrating the interest and feasibility of the proposed method.

Joint work with Philippe Vieu (Université Toulouse III - Paul Sabatier).

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Luc DEVROYE (McGill University)

TBA.

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Gersende FORT (CNRS - Télécom ParisTech)

**Sampling multimodal densities on large dimensional space**

Classical Markov chain Monte Carlo methods are known to be inefficient when sampling multimodal densities on large dimensional space. Different strategies were proposed in the literature to overcome this weakness. In this talk, I will present two different strategies namely the Equi-Energy sampler and the Wang-Landau sampler. The first one is based on interacting Markov chains and the second one can be seen as an adaptive Importance Sampling sampler. The convergence properties of these samplers will be also discussed: we will see that the main tools to address this convergence are convergence results of controlled Markov chains and convergence results of Stochastic Approximation algorithms with Markovian dynamics.

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Aurélien GARIVIER (Université Toulouse III - Paul Sabatier)

**Empirical Likelihood Upper-Confidence Bounds For Bandit Algorithms**

The classical Upper-Confidence Bound policies are known to have some nice optimality properties in simple bandit models. In more general contexts, however, they appear to be quite unsatisfying, because of the too rudimentary estimation procedure they rely on. In this talk, I will explain how the Empirical Likelihood method may be adapted to address this issue. A central requirement of the bandit context is the necessity to obtain non-asymptotic confidence bounds, while most results on the Empirical Likelihood method are asymptotic.

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Catherine MATIAS (CNRS - Université d'Évry Val d'Essonne)

**Modelling heterogeneity in random graphs through the stochastic block model**

The stochastic block model is used to analyse graphs structures from a clustering point of view. It may handle binary as well as weighted graphs. I will discuss these models, their properties and various extensions.

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Martin WAINWRIGHT (University of California at Berkeley)

**Statistical minimax with constraints**

The classical minimax framework characterizes the performance of optimal estimators without any constraints. Modern applications of statistics frequently involve constraints on estimators, whether computational, communication-based or involving privacy. In these two lectures, we provide an overview on an evolving line of work on statistical minimax theory with constraints. We discuss in detail the effect of privacy constraints on minimax rates, as well as techniques for obtaining lower bounds on communication-constrained estimators in distributed settings.

Based on joint works with John Duchi, Michael Jordan and Yuchen Zhang. Overview: [http://www.eecs.berkeley.edu/~wainwrig/Barcelona14/Wainwright\\_ICM14.pdf](http://www.eecs.berkeley.edu/~wainwrig/Barcelona14/Wainwright_ICM14.pdf)