3nd Nonstationary Day

March 7, 2019

Amphitheater Hermite
Institut Henri Poincaré
11 rue Pierre et Marie Curie 75231 Paris Cedex 05

Organisers: Pierre Alquier, Jennifer Denis, Paul Doukhan, Olga Klopp, Nicolas Marie, Jean-Luc Prigent, Jean Michel Zakoian

Program

9h30 Welcome participants

10h-11h
Ingo Steinwart, Stuttgart
The role of concentration inequalities for learning from (non-) i.i.d. data

11h-11h30 Pause

11h30-12h15
Benjamin Guedj, Inria & University College London
A primer on PAC-Bayesian learning

12h15-14h30 Lunch

14h30-15h15
Sébastien Fries, CREST
Path prediction of aggregated alpha-stable moving averages

15h15-16h00
Michael Neumann, Iena
Multivariate isotonic time series regression

16h-16h30 pause

16h45-17h30
Imma Curato, Ulm
Weak dependence and GMM estimation of supOU and mixed moving average processes

18h00 Cocktail

Sponsors
Labex ECODEC, ESSEC Business School, IAS University Paris-Seine, LABEX MME-DII, SFDS

Abstracts

Imma Curato and **Robert Stelzer**

Weak dependence and GMM estimation of supOU and mixed moving average processes

We consider a mixed moving average (MMA) process X driven by a Lévy basis and prove that it is weakly dependent with rates computable in terms of the moving average kernel and the characteristic quadruple of the Lévy basis. Using this property, we show conditions ensuring that sample mean and autocovariances of X have a limiting normal distribution. We extend these results to stochastic volatility models and then investigate a Generalized Method of Moments estimator for the supOU process and the supOU stochastic volatility model after choosing a suitable distribution for the mean reversion parameter. For these estimators, we analyze the asymptotic behavior in detail.

Sébastien Fries

Path prediction of aggregated alpha-stable moving averages

For (X_t) a two-sided alpha-stable moving average, this paper studies the conditional distribution of future paths given a piece of observed trajectory when the process is far from its central values. Under this framework, vectors of the form $X_t = (X_{t-m}, ..., X_t, X_{t+1}, ..., X_{t+h})$, $m \geq 0$, $h \geq 1$, are multivariate alpha-stable and the dependence between the past and future components is encoded in their spectral measures. A new representation of stable random vectors on unit cylinders -or "unit spheres" relative to adequate semi-norms- is proposed in order to describe the tail behaviour of vectors X_t when only the first m+1 components are assumed to be observed and large in norm. Not all stable vectors admit such a representation and the process (X_t) will have to be «anticipative enough» for the vector X_t to admit one. The conditional distribution of future paths during extreme events can then be explicitly derived and has a natural interpretation in terms of pattern identification. The approach extends to processes resulting from the linear combination of stable moving averages, encompassing for instance the aggregation of anticipative AR(1) proposed by Gouriéroux and Zakoïan (2017) which generates trajectories featuring explosive bubbles of different growth rates. Other bubble-generating processes such as higher-order anticipative AR and fractionally integrated processes are also encompassed.

Benjamin Guedj

A primer on PAC-Bayesian learning

Generalized Bayesian learning algorithms are increasingly popular in machine learning, due to their PAC generalization properties and flexibility. I will present a self-contained introduction on generalized Bayesian learning and the PAC-Bayes theory, and discuss their theoretical and algorithmic ins and outs (as presented in Guedj, 2019). I will then focus on the recent paper Alquier and Guedj (2018), and present how PAC-Bayesian ideas may be used to efficiently learn with dependent and/or heavy-tailed (aka hostile) data.

References:

Alquier and Guedj (2018), Simpler PAC-Bayesian Bounds for Hostile Data, Machine Learning. https://link.springer.com/

Guedj (2019), A primer on PAC-Bayesian learning, arXiv preprint. https://arxiv.org/abs/1901.

Michael Neumann

Multivariate isotonic time series regression

We consider a general monotone regression estimation where we allow for independent and dependent regressors. We propose a modification of the classical isotonic least squares estimator and establish its rate of convergence for the integrated L_1-loss function. The methodology captures the shape of the data without assuming additivity or a parametric form for the regression function. Furthermore, the degree of smoothing is chosen automatically and no auxiliary tuning is required for the theoretical analysis.

Ingo Steinwart

The role of concentration inequalities for learning from (non-) i.i.d. data

The analysis of modern machine learning algorithms require a variety of techniques from different mathematical areas. As an introduction to this field, I will therefore first provide an overview over notions, questions, and methods considered in statistical learning theory. The main part of my talk will then focus on the statistical part of the analysis. Here, I will first illustrate the main effects, different types of concentration inequalities have on the statistical analysis if the data is i.i.d. I will then show, how concentration inequalities for non-i.i.d. data can be employed in the analysis, and which difficulties need to be addressed. In the final part, I will present some examples, in which the step from i.i.d. to non-i.i.d. was either successful or not.