ETICS 2017

École Thématique sur les Incertitudes en Calcul Scientifique
Research School on Uncertainty in Scientific Computing

October 1-6 2017

Centre IGESA de Porquerolles

https://www.igesa.fr/les-catalogues-igesa/groupes-et-seminaires-2016/

Objectives

The goal of this school is to develop the skills of researchers and engineers in the domain of uncertainty management of computer codes. Some of the lectures will be followed by practical computer works. Collaborative works, round tables and poster sessions will promote exchanges between participants. The prerequisites to possess are the mathematical bases of the uncertainty quantification science.

Lecturers

Max Gunzburger (Florida State University, USA): Multifidelity approaches to UQ and Optimal Multilevel Multifidelity Monte Carlo methods

Luc Pronzato (CNRS - Sophia Antipolis, Nice, France): Optimal Design of Experiments

Sébastien Destercke (Université de Technologie de Compiègne, France): Imprecise probabilities: why, when, how?

Pierre-Henri Wuillemin (Université Pierre et Marie Curie, Paris, France): Applications of probabilistic graphical models

Nicolas Bousquet (EDF R&D, Chatou): Stochastic prior modelling for uncertain inputs

Organization

CEA DAM

EDF R&D

CMLA - ENS Cachan

Under the scientific labeling of the GdR MASCOT-NUM

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Registration fees: 900€ - Link: https://www.azur-colloque.fr/DR01/inscription/inscription/85/fr

Tentative Schedule

Sunday, October, 1th: Shuttle from Toulon TGV (18:20) and Hyeres airport (18:50) to La Tour Fondue harbor (19:10), and boat to Porquerolles before 19:30 (last hour permitted)

Monday, October, 2d:

9:00 - 9:30	Opening and Welcome speech	Jean Giorla and Bertrand Iooss
9:30 – 12:30	Multifidelity approaches to UQ and Multilevel Multifidelity Monte Carlo	Max Gunzburger
14:00 – 17:30	Probabilistic Graphical Models	Pierre-Henri Wuillemin

Tuesday, October, 3th:

9:00 – 12:30	Multifidelity approaches to UQ and Multilevel Multifidelity Monte Carlo	Max Gunzburger
14:00 – 17:30	Applications of Probabilistic Graphical Models	Pierre-Henri Wuillemin

Wednesday, October, 4th:

9:00 – 12:30	Introduction to Imprecise Probabilities	Sébastien Destercke
14:00 – 18:30	Social event at Porquerolles Island	All
18:30- 20:00	Poster session	All

Thursday, October, 5th:

9:00 – 12:30	Design of experiments in nonlinear models	Luc Pronzato
14:00 – 17:30	Stochastic prior modelling for uncertain inputs	Nicolas Bousquet

Friday, October, 6th:

9:15 – 12:15	Design of computer experiments	Luc Pronzato

Boat from Porquerolles (12:30) and Shuttle to Hyeres airport and Toulon TGV (before 14:30)

ABSTRACTS

Max Gunzburger (Department of Scientific Computing, Florida State University, USA)
http://people.sc.fsu.edu/~mgunzburger

Multifidelity approaches to UQ and Optimal Multilevel Multifidelity Monte Carlo methods

In the first part of the lecturer, I will present surrogates for high-fidelity, high-cost approximate solutions of PDEs with random inputs, including recent advances in interpolant, reduced-order, compressed sensing, and other approximations. This would also include very brief reviews of polynomial chaos and sparse grid approaches, mainly to establish a basis for discussing the recent advances.

The second part will be devoted to multi-level and multi-fidelity methods for reducing the cost of obtaining high-fidelity, approximate solutions of PDEs with random inputs.

Luc Pronzato (CNRS - Sophia Antipolis, Nice, France)
http://www.i3s.unice.fr/~pronzato/

Optimal Design of Experiments

Lecture 1: Design of experiments in nonlinear models

The objective of the course is to present an overview of the design of optimal experiments for parameter estimation in nonlinear models. The course will be based on the volume "Designs of Experiments in Nonlinear Models -- Asymptotic Normality, Optimality Criteria and Small-Sample Properties", Springer, 2013, by L. Pronzato and A. Pazman.

The first part will be devoted to an introduction to optimal design based on the asymptotic normality of the estimator of the model parameters, including a presentation of the main algorithmic procedures for the construction of optimal experiments.

The second part will concern the specific difficulties raised by nonlinear models: (i) the normality assumption may be strongly invalidated for small sample sizes, (ii) the optimal experiment depends on the (unknown) value of the parameters to be estimated. Different approaches to circumvent those difficulties will be presented.

Lecture 2: Design of computer experiments.

We shall consider the situation where observations are deterministic and correspond to the results of numerical simulations, and no parametric model of the simulator response is available. When the objective is to predict the model response over a predefined domain for the input variables, a reasonable computer experiment should spread the design points (the choice of inputs for the simulations to be performed) at best over this domain in order to observe "everywhere". The quality of the distribution of these design points can be measured in different ways, which correspond to different optimality criteria. One of the main objective of the course is to show the connections that exist between the multitude of design approaches for computer experiments.

The first part will concern model-free approaches, where the choice of the distribution of points will be based on geometrical properties, or will rely on criteria measuring uniformity (entropy, discrepancy).

In the second part we shall consider optimal design for Gaussian-process models and kriging: when a prediction model is specified, its associated mean-squared prediction error yields natural criteria for designing optimal experiments, as it is the case for parametric models.

Sébastien Destercke (Université de technologie de Compiègne, France)

https://www.hds.utc.fr/~sdesterc/dokuwiki/start/

Imprecise probabilities: why, when, how?

Imprecise probability theories (understood in a large sense) have emerged in the past decades as an answer to the criticisms made to probabistic modelling, pointing out its potential inability to model lack of knowledge or imprecision. These interrelated theories have expanded both set (interval) and probabilistic calculi in different ways. This means that they present technical discrepancies (as frequentist and Bayesian view do), but more importantly, they also share a number of unifying features. Those theories can address the cases where probabilities are ill-defined, or where the use of probabilities as a golden standard is questionable.

In this lecture, I will mainly answer different questions one may have about these theories, such as: Why and when not using probabilities? What are the alternatives, how are they connected and how are they different? How to model (and propagate) uncertainties in practice with these alternatives? What can I make of the resulting propagation? I will illustrate these points with basic example, inspired from risk analysis problems.

Some references:

Representation, propagation, and decision issues in risk analysis under incomplete probabilistic information. D Dubois - Risk analysis, 2010 - Wiley Online Library.

Statistical reasoning with set-valued information: Ontic vs. epistemic views. I Couso, D Dubois - International Journal of Approximate Reasoning, 2014 – Elsevier.

Other uncertainty theories based on capacities. S Destercke, D Dubois - Introduction to Imprecise Probabilities, 2014.

Formal representations of uncertainty. D Dubois, H Prade - Decision-Making Process: Concepts and Methods, 2009.

Pierre-Henri Wuillemin (Université Pierre et Marie Curie, Paris, France)
https://www.lip6.fr/actualite/personnes-fiche.php?ident=P67
Applications of probabilistic graphical models

This lecture is a general presentation of the different domains of Bayesian networks, including models, inference, learning and applications. Practical computer works will be proposed with the library pyAgrum (http://agrum.gitlab.io).

Nicolas Bousquet (EDF R&D, Dpt. of Industrial Risk Management, Chatou, France)

http://nbousque.free.fr/research.php.html

Stochastic prior modelling for uncertain inputs

The uncertainty affecting inputs of computer models, most often, is traduced by random variables. Probabilistic information, required to select which distributions should be used for their modelling, should ideally arise from observations. But in many situations, information has to be interpreted as the deconvolution of prior knowledge (for instance proposed by experts, old databases, meta-analysis…). In such cases, Bayesian elicitation principles can be used to limit the influence of subjectivity in the modelling. The aim of this course is to give a view of the state of the art and some research avenues in this field. The course will make a tour of several main modelling principles, including theoretical basis (e.g., Cox-Jaynes theorem), a focus on information invariance requirements and Haar measures, critics of usual choices made in situations of low information (e.g., maximum entropy distributions), links with decision theory and representation methods (e.g., histogram methods) submitted to several forms of bias. While nonparametric method will be examined, a focus will be made on virtual data posterior priors as good choices for parametric modelling and sensitivity analysis. Prior compatibility principles will be evoked as requirements for input modelling selection in this latter framework. The course will besides examine several arguments, still discussed, that may be in favor of stochastic approaches of uncertainty modelling, and works-in-progress in this field, including robust Bayesian modelling. Examples will be picked up from industrial and environmental worlds.

Some references:

Wolfson, L.J. and Bousquet, N. (2016). Elicitation. Wiley StatRef (Encylopedia of Statistics).

O'Hagan, A. et al. (2006). Uncertain Judgements: Eliciting Expert's Probabilities

Low-Choy, S. et al. (2009). Elicitation by design in ecology: using expert opinion to inform priors for Bayesian statistical models

Jaynes, E.T. (2003). Probability theory: the logic of science.