Challenge 3.

Challenges in Model Discrepancy

Decision making in physical, social, environmental, biological and health sciences is commonly informed by model predictions. It is common to use statistical methods to quantify the uncertainty in these predictions due to the uncertainty in model inputs. However, methods for quantifying uncertainty due to inadequacy in model structure are less developed. This inadequacy, referred to as model discrepancy, can be thought of as the difference between a model run at its true input and the true value of the output quantity. In other words, model discrepancy arises as a result of the gap between a model of reality and reality itself.

“Essentially all models are wrong, but some are useful.” is one of the most common quotations in science. The reasons why models are imperfect representations of the systems they are meant to describe include the incomplete understanding of the system and simplifications made in favour of making computation feasible. Although these reasons are widely recognised, quantifying model discrepancy is challenging since it requires judgements about a model's ability to represent a complex real life decision process faithfully. Solving this problem is of the utmost importance since quantifying this inevitable source of uncertainty will provide a principled method of compensating for over-confident predictions.

Some of the challenges that will be discussed in this section include, but are not limited to: How to represent model discrepancy in a meaningful, informative way? How to include relevant prior information provided by experts? How to use model discrepancy to learn about model parameters and aide calibration? What are the risks for decision making associated with ignoring model discrepancy? How can this risk be mitigated?

Panel Speakers

Dr Richard Ahlfeld is a Royal Academy of Engineering Fellow at Imperial College London. His research interests focus on finding new opportunities for artificial intelligence methods in Aerospace Engineering. Richard is also the co-founder and CEO of UQuant; a spin-off from the Imperial College London Uncertainty Quantification Lab. UQuant seeks to develop hybrid approaches between data analytics, machine learning and physical engineering simulations (CAE).

Dr. Jenny Brynjarsdóttir is an assistant professor at the Department of Mathematics, Applied Mathematics and Statistics at Case Western Reserve University, USA. Her research interests include Bayesian statitics, environmental statistics, dimension reduction in space-time modelling and uncertainty quantification.

Prof. Michael Goldstein a Professor in Statistics at Durham University. Michaels' research interests include the foundations, methodology and applications of Bayesian/subjectivist approaches to statistics; particularly for problems which are sufficiently large and complex to make the usual Bayesian modelling and analysis extremely difficult. Much of his work concerns the synthesis of expert judgements and experimental data under partial prior belief specification, and comes together under the general structure of Bayes Linear Methodology.

Dr. Edward Wheatcroft is a research officer at the London School of Economics where he works on understanding of the effect of climate change on Ecosystems within protected areas in Europe. He also works at designing systems to recycle heat streams in urban environments. His research interests include probabilistic forecasting, forecast evaluation and data assimilation.

Session Chairs

Prof. Peter Challenor (University of Exeter)
Dr. Alejandro Diaz (University of Liverpool)