Robust uncertainty sensitivity quantification.

We consider sensitivity of a generic stochastic optimization problem to model uncertainty. We take a non-parametric approach and capture model uncertainty using Wasserstein balls around the postulated model. We provide explicit formulae for the first order correction to both the value function and the optimizer and further extend our results to optimization under linear constraints. We present applications to statistics, machine learning, mathematical finance and uncertainty quantification. In particular, we prove that LASSO leads to parameter shrinkage, propose measures to quantify robustness of neural networks to adversarial examples and compute sensitivities of optimised certainty equivalents in finance. We also propose extensions of this framework to a multiperiod setting. This talk is based on joint work with Daniel Bartl, Samuel Drapeau and Jan Obloj. (Received August 28, 2020)