Disparity based inference proceeds by minimizing a measure of disparity between a parametric family of density functions and a kernel density estimate based on observed i.i.d. data. For a class of disparity measures, of which Hellinger distance is one of the best known, minimum disparity estimates of parameters are both robust to outliers and also statistically efficient.

This talk introduces three novel extensions of disparity methods. We develop two disparity-based approaches for nonlinear regression settings, based either on a nonparametric estimate of a conditional density, or by considering the marginal distribution of residuals. Both approaches can be shown to be both robust and efficient. Moreover, adding an $L_1$ penalty to the disparity objective function yields a robust version of the LASSO that retains its oracle properties.

We also demonstrate that disparities can be used to replace log likelihoods in Bayesian inference, allowing Monte Carlo Markov Chain methods to be applied to obtain robust posterior distributions while retaining asymptotic posterior efficiency. Combining these approaches allows any component of a Bayesian hierarchical model to be made robust to outliers by replacing part of the complete data log likelihood with a disparity. Example applications to longitudinal data analysis are given.