Jose Bento: Learning Stochastic Differential Equations – Fundamental limits and efficient algorithms

Models based on stochastic differential equations (SDEs) play a crucial role in several domains of science and technology, ranging from chemistry to finance.

In this talk I consider the problem of learning the drift coefficient of a p-dimensional stochastic differential equation from a sample path of length T. I assume that the drift is parametrized by a high dimensional vector, and study the support recovery problem in the case where p is allowed to grow with T.

In particular, I describe a general lower bound on the sample-complexity T by using a characterization of mutual information as time integral of conditional variance, due to Kadota, Zakai, and Ziv. For linear stochastic differential equations, the drift coefficient is parametrized by a p by p matrix which describes which degrees of freedom interact under the dynamics. In this case, I analyze an L1-regularized least-squares estimator and describe an upper bound on T that nearly matches the lower bound on specific classes of sparse matrices.

I describe how this same algorithm can be used to learn non-linear SDEs and in addition show by means of a numerical experiment why one should expect the sample-complexity to be of the same order as that for linear SDEs.