MS8: Recent Advances in Statistical Learning Theory

Functional Linear Regression Using Gaussian Kernel

Jun Fan, *University of Wisconsin-Madison*

Functional data analysis is a branch of data science that analyzes infinite dimensional data such as curves or images. In this talk, we will introduce a reproducing kernel Hilbert space approach to functional linear regression. The algorithm is generated from Tikhonov regularization scheme associated with Gaussian kernel. We show that the convergence rate for prediction risk is minimax-optimal up to a logarithmic factor, whatever the smoothness level of the slope function.

Analysis of Some Online Learning Algorithms with Kernels

Yiming Ying, *University at Albany, State University of New York*

Many machine learning tasks can be formulated as a regularization framework associated with a loss function and a regularization term in a reproducing kernel Hilbert space (RKHS). The main difficulty in obtaining optimal solutions of such formulations is the volume of the data, where there are many observations (large n). Online algorithms such as stochastic gradient descent which pass over the data only once, are widely used in practice. In this talk, I will give an overview of our theoretical contribution in this research direction. In particular, for standard pointwise learning problems I will present convergence results of online learning algorithms for both regularized and un-regularized formulations. For pairwise learning problems such as ranking and metric/kernel learning, I will describe our recently proposed algorithm called Opera and present its convergence rates.

A Refined Algorithm of Sliced Inverse Regression

Ning Zhang, *Middle Tennessee State University*

Sliced inverse regression is a statistical method for dimension reduction. We proposed a refined implementation by allowing overlapping slices. Simulation studies show that the refined algorithm is able to estimate the effective dimension reduction space more accurately and more stably.