High Dimensional Nonstationary Time Series

IRTG 1792
Short Course

Wei Biao Wu
On High-Dimensional Data

Lecture 1: L^2 Asymptotic Theory for High-Dimensional Data
I will present an asymptotic theory for L^2 norms of sample mean vectors of high-dimensional data. An invariance principle for the L^2 norm is derived under conditions that involve a delicate interplay between the dimension p, the sample size n and the moment condition. Under proper normalization, central and non-central limit theorems are obtained. To perform the related statistical inference, I will propose a plug-in calibration method and a re-sampling procedure to approximate the distributions of the L^2 norms. The results will be applied multiple tests and inference of covariance matrix structures.

Lecture 2: Testing for Trends in High-dimensional Time Series
We consider statistical inference for trends of high-dimensional time series. Based on a modified L2-distance between parametric and nonparametric trend estimators, we propose a de-diagonalized quadratic form test statistic for testing patterns on trends, such as linear, quadratic or parallel forms. We develop an asymptotic theory for the test statistic. A Gaussian multiplier testing procedure is proposed and it has an improved finite sample performance. Our testing procedure is applied to a spatial temporal temperature data gathered from various locations across America. A simulation study is also presented to illustrate the performance of our testing method. The work is joint with Likai Chen.

Lecture 3: Error bounds for statistical learning for time dependent data
Classical statistical learning theory primarily concerns independent data. In comparison, it has been much less investigated for time dependent data, which are commonly encountered in economics, engineering, finance, geography, physics and other fields. In this talk, we focus on concentration inequalities for suprema of empirical processes which plays a fundamental role in the statistical learning theory. We derive a Gaussian approximation and an upper bound for the tail probability of the suprema under conditions on the size of the function class, the sample size, temporal dependence and the moment conditions of the underlying time series. Due to the dependence and heavy-tailness, our tail probability bound is substantially different from those classical exponential bounds obtained under the independence assumption in that it involves an extra polynomial decaying term. We allow both short- and long-range dependent processes, where the long-range dependence case has never been previously explored. We showed our tail probability inequality is sharp up to a multiplicative constant. These bounds work as theoretical guarantees for statistical learning applications under dependence. This work is joint with Likai Chen.

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Wei Biao Wu received the Ph.D. degree in statistics in 2001 from The University of Michigan, Ann Arbor. He is currently Professor of Statistics at The University of Chicago. His research interests include probability theory, statistics, financial time series and econometrics. He is currently interested in developing asymptotic theory for high-dimensional time series. He has received the National Science Foundation Career Award (2004) and The Tjalling C. Koopmans Econometric Theory Prize (2009). His research is supported by National Science Foundation research grants.

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