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HIGH-DIMENSIONAL STATISTICAL ANALYSIS



DATE
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Dec. 11 (Fri.)-15 (Tue.), 2015

VENUE
.....

Humanities and Social Sciences Building

Academia Sinica, Taipei, Taiwan

Dec. 11 : International Conference Hall

Dec. 12-15 : 2nd Conference Room

High-Dimensional Statistical Analysis

December 11th- 15th, 2015

Institute of Statistical Science, Academia Sinica

Ministry of Science and Technology

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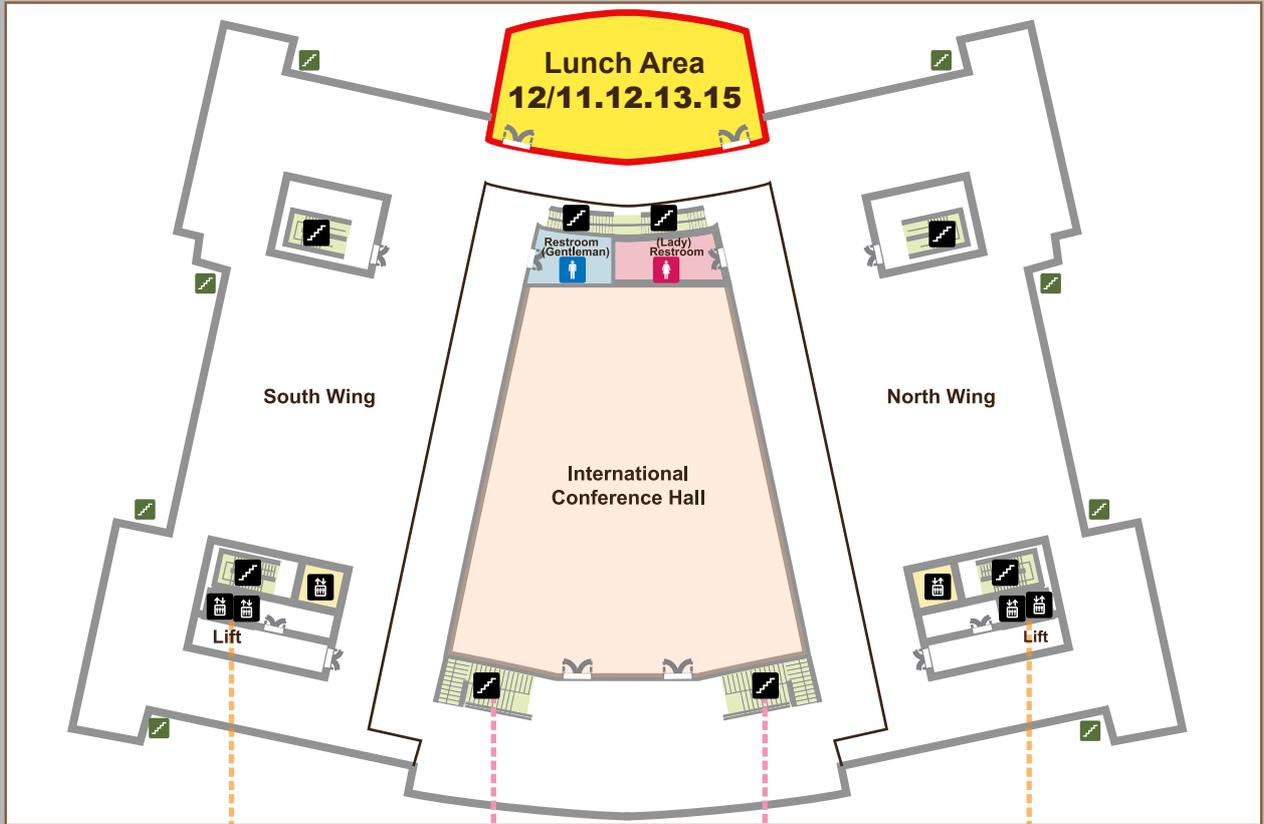
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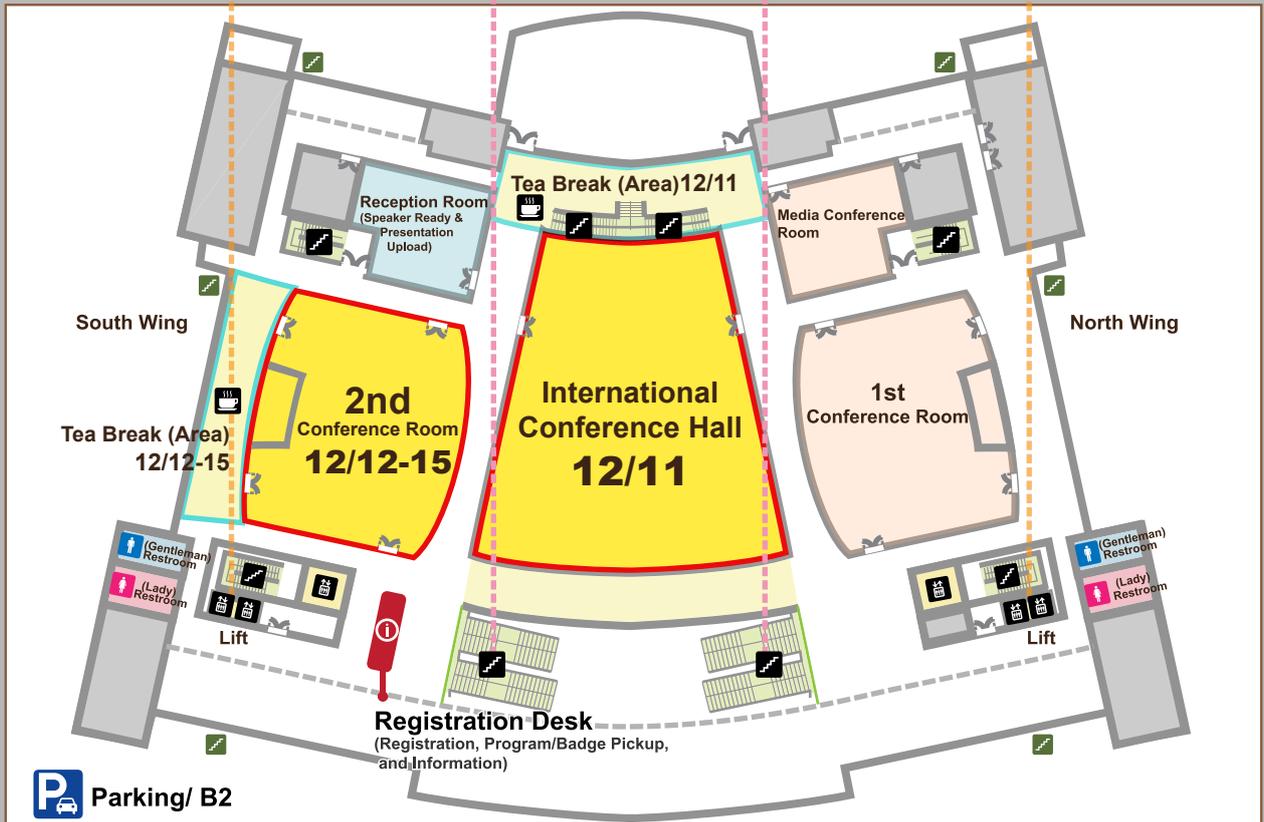
* The Institute of Mathematics, Institute of Atomic and Molecular Sciences, Institute of Astronomy and Astrophysics and some buildings belonging to the Institute of Biological Chemistry are located on the National Taiwan University campus.

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Humanities and Social Sciences Building (Level 4)



Humanities and Social Sciences Building (Level 3)



Program

Time	Dec. 11 (Fri.)	Dec. 12 (Sat.)	Dec. 13 (Sun.)	Dec. 14 (Mon.)	Dec. 15 (Tue.)
08:45-09:00	Opening				
09:00-12:00	<p>Keynote Speech (1) <u>Speaker:</u> Shinto Eguchi <u>Chair:</u> Yuan-chin Ivan Chang <i>Information geometry and spontaneous data learning (P.1)</i></p>	<p>Keynote Speech (2) <u>Speaker:</u> Yanyuan Ma <u>Chair:</u> Weijing Wang <i>1. A semiparametric approach to dimension reduction (P.5)</i> <i>2. Reviews, recent extensions and outlook on dimension reduction (P.6)</i></p>	<p>Keynote Speech (3) <u>Speaker:</u> Ker-Chau Li <u>Chair:</u> I-Liang Chern <i>A dimension reduction perspective on machine learning and multivariate statistical analysis for deep data analytics (P.10)</i></p>	<p>Keynote Speech (4) <u>Speaker:</u> Xiaotong Shen <u>Chair:</u> Dennis K.J. Lin <i>Classification with unstructured predictors with an application to sentiment analysis (P.14)</i></p>	<p>Keynote Speech (5) <u>Speaker:</u> Ruey S. Tsay <u>Chair:</u> Mei-Hui Guo <i>1. Multivariate time series analysis: brief review and recent developments (P.15)</i> <i>2. High-dimensional time series analysis (P.16)</i></p>
10:15-10:45	Tea Break	Tea Break	Tea Break	Tea Break	Tea Break
12:00-14:00	Lunch	Lunch	Lunch	<p>Local Tour (By invitation only) (Bus leaves HSS at 12:20)</p>	Lunch
14:00-14:50	<p>Session (1) <u>Speaker:</u> Su-Yun Huang <u>Chair:</u> Yuh-Jye Lee <i>A class of robust non-convex loss functions for discriminant analysis (P.2)</i></p>	<p>Session (4) <u>Speaker:</u> Kuang-Yao Lee <u>Chair:</u> Hung Chen <i>Learning causal networks via additive faithfulness (P.7)</i></p>	<p>Session (7) <u>Speaker:</u> Qiwei Yao <u>Chair:</u> Jason D. Lee <i>Principal component analysis for time series (P.11)</i></p>		<p>Session (10) <u>Speaker:</u> Ching-Kang Ing <u>Chair:</u> Nan-Jung Hsu <i>Model selection for high-dimensional time series (P.17)</i></p>

14:50-15:40	<p>Session (2) <u>Speaker:</u> Osamu Komori <u>Chair:</u> James J. Chen <i>Generalized t-statistic and AUC for binary classification (P.3)</i></p>	<p>Session (5) <u>Speaker:</u> Xin Chen <u>Chair:</u> Tso-Jung Yen <i>Testing constancy of conditional co-variance matrix in high dimension (P.8)</i></p>	<p>Session (8) <u>Speaker:</u> Hung Hung <u>Chair:</u> Henry Horng-Shing Lu <i>Sufficient dimension reduction with additional information (P.12)</i></p>		<p>Session (11) <u>Speaker:</u> Ngai Hang Chan <u>Chair:</u> Henghsiu Tsai <i>Group orthogonal greedy algorithm for structural break time series: from univariate to multivariate (P.18)</i></p>
15:40-16:10	Tea Break	Tea Break	Tea Break		
16:10-17:00	<p>Session (3) <u>Speaker:</u> Pengwen Chen <u>Chair:</u> Frederick Kin Hing Phoa <i>A revisit to maximum variance unfolding from a viewpoint of phase retrieval (P.4)</i></p>	<p>Session (6) <u>Speaker:</u> Jie Peng <u>Chair:</u> Mong-Na Lo Huang <i>Fiber orientation distribution function estimation by spherical needlets (P.9)</i></p>	<p>Session (9) <u>Speaker:</u> Ting-Li Chen <u>Chair:</u> Hua Tang <i>An ensemble algorithm for randomized singular value decomposition and randomized principal component analysis (P.13)</i></p>		
18:00-20:30	<p>Reception <i>(By invitation only)</i> (Bus leaves HSS at 17:20)</p>		<p>Banquet <i>(By invitation only)</i> (Bus leaves HSS at 17:20)</p>		

Information geometry and spontaneous data learning

Shinto Eguchi

Institute of Statistical Mathematics

Abstract

There are two parts in my talk, in which one focuses on generalized geodesic curves in a space of probability density functions; the other does a statistical application based on the geometry.

1. We introduce a class of paths or one-parameter models connecting arbitrary two probability density functions (pdf's). The path is derived by employing the Kolmogorov-Nagumo (K-N) average between the two pdf's defined by strictly increasing function φ , which we call φ -path. It gives another framework of the geometry for the space of all the pdfs. Such an information geometric insight provides understandings for probabilistic properties for statistical methods associated with the path connectedness. Here we overview a dualistic relation between statistical model and estimation, which is focused on a maximum entropy and minimum divergence. In particular, we show a close relation of φ -path, U -entropy and U -divergence. The φ -path is extended to a φ -surface, which is a maximal entropy model, on which the minimum divergence estimator is characterized by canonical statistics.

2. We discuss an approach called spontaneous data learning (SDL) to open novel explanatory paradigm connecting parametrics with nonparametrics. The statistical performance for SDL is explored from information geometric viewpoint, so that SDL gives a new perspective beyond the discussion for robustness or misspecification of parametric model. If the true distribution is exactly in the parametric model, the theory of statistical estimation has been well established, in which any minimum divergence estimator satisfies parametric consistency. We focus on a collapse of the parametric theory perturbing toward a nonparametric setting, where the true distribution may range from unimodality to multimodality; various estimators are targeted and investigated in a class of minimum divergence. In this context a selection of estimators is explored rather than model selection. Specifically we choose the power divergence class under a normal mean model, where the true distribution is, for example, a mixture of K distributions. Then we observe that the local minima of the empirical loss function for the power divergence properly suggest the K -means if they are mutually separated in the mixture distribution, and the order of power is appropriated selected. The resulting method for clustering analysis is shown to spontaneously detect the number K of clusters. Further, we observe that the normalized empirical loss function converges to the true density function if the power parameter goes to infinity. As a result the power parameter combines between the parametric and nonparametric consistency.

14:00-14:50, Dec. 11th, 2015
Session (1)

A class of robust non-convex loss functions for discriminant analysis

Su-Yun Huang

Academia Sinica

Abstract

For two-group discriminant analysis, we propose a class of non-convex loss functions. These non-convex loss functions are deformed from convex U -loss. This deformation consists of two key components: one is a diminishing weight, which can lessen and eventually reject outlier effect in pattern (or derived feature) space, and the other is a mislabel correction. Parameter estimation consistency and Bayes risk consistency will be discussed. This class of non-convex loss functions can be applied to SVM. Experimental examples will be presented.

(Based on joint work with Chia-Hsiang Yu and Shinto Eguchi)

Generalized t -statistic and AUC for binary classification

Osamu Komori

University of Fukui

Abstract

In binary classification, the Fisher linear discriminant analysis has been widely used, where the ratio of the variance between the classes to the variance within the classes is maximized to derive the linear predictor. This simple method has shown good performances in real data analyses in medical and clinical sciences; in some cases it outperforms more sophisticated methods such as machine learning methods. From this viewpoint, we proposed generalized t -statistic and AUC (area under the ROC curve) to extend the Fisher linear discriminant analysis based on a generator function U , and investigated the statistical properties in terms of estimation as well as classification accuracies. The generalized t -statistic assumes that the probability distribution of one population is homogeneous, such as a normal distribution; on the other hand, the probability distribution of the other population could be highly heterogeneous. This is the typical situation in case-control studies in clinical trials. The generalized AUC assumes heterogeneity for probability distributions for both populations. For these cases, we derived the optimal generator function U to derive the best linear predictor in terms of asymptotic variances. In order to be applicable to high dimensional data analysis, Lasso-type method is also proposed by imposing L_1 penalty on the objective function. The performances of the proposed methods are illustrated in simulation studies as well as real data analyses.

A revisit to maximum variance unfolding from a viewpoint of phase retrieval

Pengwen Chen

National Chung Hsing University

Abstract

For a set of points, multidimensional scaling recovers the spacial information (covariance matrix) from their mutual distances. Facing a set of high dimensional data sampled from a low dimensional manifold, maximum variance unfolding (MVU) estimates a low rank covariance matrix, which unveil the hidden low dimensional structure (Weinberger, Saul 2006). The computation exploits convex optimization, where the trace norm of the covariance matrix is maximized subject to a set of local-distance constraints. However, the global convergence of the desired low rank matrix in fact requires a sufficient number of local-distance constraints, as other low rank recovery problems.

As the simplest case in the low rank recovery, phase retrieval recovers a rank-one positive semidefinite matrix from a set of linear measurements. To overcome the limitation of insufficient measurements as well as the expensive computational load, nonconvex optimization methods are recently proposed to overcome the limitation of insufficient constraints, e.g., Douglas-Rachford algorithms. In addition, many spectral methods (e.g., null vector method) are proposed to generate initial guesses. In this talk, we demonstrate the application of these nonconvex methods to the maximum variance unfolding problem. In our empirical studies, MVU is applied to the lung deformation fields. If time permitted, global convergence will be discussed.

A semiparametric approach to dimension reduction

Yanyuan Ma

University of South Carolina

Abstract

We provide a novel and completely different approach to dimension-reduction problems from the existing literature. We cast the dimension reduction problem in a semiparametric estimation framework and derive estimating equations. Viewing this problem from the new angle allows us to derive a rich class of estimators, and obtain the classical dimension reduction techniques as special cases in this class. The semiparametric approach also reveals that in the inverse regression context while keeping the estimation structure intact, the common assumption of linearity and/or constant variance on the covariates can be removed at the cost of performing additional nonparametric regression. The semiparametric estimators without these common assumptions are illustrated through simulation studies and a real data example. This article has online supplementary material.

Reviews, recent extensions and outlook on dimension reduction

Yanyuan Ma

University of South Carolina

Abstract

Summarizing the effect of many covariates through a few linear combinations is an effective way of reducing covariate dimension and is the backbone of (sufficient) dimension reduction. Because the replacement of high-dimensional covariates by low-dimensional linear combinations is performed with a minimum assumption on the specific regression form, it enjoys attractive advantages as well as encounters unique challenges in comparison with the variable selection approach. We review the current literature of dimension reduction with an emphasis on the two most popular models, where the dimension reduction affects the conditional distribution and the conditional mean, respectively. We discuss various estimation and inference procedures in different levels of detail, with the intention of focusing on their underneath idea instead of technicalities. We also discuss some unsolved problems in this area for potential future research.

Learning causal networks via additive faithfulness

Kuang-Yao Lee

Yale School of Public Health

Abstract

In this work we introduce a statistical model, called additively faithful directed acyclic graph (AFDAG), for causal learning from observational data. Our approach is based on additive conditional independence (ACI), a recently proposed three-way statistical relation that shares many similarities with conditional independence. However, the nonparametric characterization of ACI does not involve multivariate kernel, so is distinct from conditional independence. Due to this special feature, AFDAG enjoys the flexibility of a nonparametric estimator but avoids the curse of dimensionality when handling high-dimensional networks. We develop an estimator for AFDAG based on a linear operator that characterizes ACI, and propose a modified PC-algorithm to implement the estimating procedures efficiently, so that their complexity is determined by the number of edges rather than the dimension of the network. We also establish the consistency and convergence rates of our estimator. Through simulation studies we show that our method outperforms existing methods when commonly assumed conditions such as Gaussian or Gaussian copula distributions do not hold. Finally, the usefulness of AFDAG formulation is demonstrated through its application to a proteomics data set.

(This is a joint work with Tianqi Liu (Yale), Bing Li (Penn State), and Hongyu Zhao (Yale).)

Key words: Additive conditional independence, additive reproducing kernel Hilbert space, directed acyclic graph, global Markov property, normalized additive conditional covariance operator, PC-algorithm.

Testing constancy of conditional co-variance matrix in high dimension

Xin Chen

National University of Singapore

Abstract

Testing constancy of conditional co-variance matrix is a crucial statistical problem especially in regression studies. It has many important applications and we shall introduce two major ones here. The first one lies in so-called inverse regression. Many sufficient dimension reduction (SDR) methods are based on the concept of inverse regression such as sliced inverse regression (SIR), sliced average variance estimation (SAVE), directional regression (DR) and so on. Two assumptions were typically imposed: the linearity for conditional expectation and constant conditional co-variance. The constant conditional variance assumption doesn't always hold in general, and it is a must to test the assumption before we apply most SDR methods. The other major application lies in multivariate linear regression (Aldrich, 2005), which assumes the response variables given the predictors follow a constant co-variance matrix. Apparently, deviation from constant conditional co-variance would result in severely inconsistent estimate. Thus, in reality, this assumption must be tested before we apply the parametric modeling. In this work, we propose a slice-based procedure to test constant conditional variance for high dimensional data which allows the number of dimensionality p grows with the sample size n , and under some mild and regular conditions, this consistency also holds when $p \gg n$. Both simulation and real data analysis favor our testing procedure. The computation is simple and fast, which can be easily implemented in several statistical software.

Fiber orientation distribution function estimation by spherical needlets

Jie Peng

University of California, Davis

Abstract

Diffusion magnetic resonance imaging (D-MRI) is an imaging technology which uses water diffusion as a proxy to probe the anatomy of biological tissues in an in-vivo and non-invasive way. D-MRI has been widely used to reconstruct white matter fiber tracts and to provide information on structure connectivity of the brain.

In D-MRI, fiber orientation distribution (FOD) function is a spherical p.d.f. that characterizes the fiber distribution at each voxel of the brain white matter. The observed diffusion weighted measurements at the corresponding voxel can be modeled as spherical convolution between FOD and a response function. We will discuss the estimation of FOD based on a spherical needlets representation. The needlets are localized both in frequency and space and form a tight frame on the space of square integrable spherical functions. Needlets representation of FOD is sparse as FOD is a smooth function with a few sharp peaks (each corresponding to a major fiber bundle). We will derive the needlets representation of FOD by an l_1 penalized regression with non-negativity constraints. Comparing with existing methods based on spherical harmonics representation, the proposed method leads to much better peak localization, particularly when the separation angles among fiber bundles are small.

(Joint work with Hao Yan from UC Davis)

09:00-12:00, Dec. 13th, 2015
Keynote Speech (3)

A dimension reduction perspective on machine learning and multivariate statistical analysis for deep data analytics

Ker-Chau Li

Academia Sinica

Abstract

As a fundamental training component in the curriculum of the emerging data science discipline, machine learning (ML) in computer science and multivariate analysis (MA) in statistics overlap substantially. In this talk, I will discuss how to exploit the commonality and uniqueness between MA and ML for deep data analytics which requires a thoughtful planning of layers and layers of analyses to maximize the outcome. Technically, I will present some salient and subtle aspects of dimension reduction involved in multiple regression, factor analysis, support vector machine and neural network.

Principal component analysis for time series

Qiwei Yao

London School of Economics

Abstract

We extend the principal component analysis (PCA) to second-order stationary vector time series in the sense that we seek for a contemporaneous linear transformation for a p -variate time series such that the transformed series is segmented into several lower-dimensional subseries, and those subseries are uncorrelated with each other both contemporaneously and serially. Therefore those lower-dimensional series can be analysed separately as far as the linear dynamic structure is concerned. Technically it boils down to an eigenanalysis for a positive definite matrix. When p is large, an additional step is required to perform a permutation in terms of either maximum cross-correlations or FDR based on multiple tests. The asymptotic theory is established for both fixed p and diverging p when the sample size n tends to infinity. Numerical experiments with both simulated and real datasets indicate that the proposed method is an effective initial step in analysing multiple time series data, which leads to substantial dimension reduction in modelling and forecasting high-dimensional linear dynamical structures. Unlike PCA for independent data, there is no guarantee that the required linear transformation exists. When it does not, the proposed method provides an approximate segmentation which leads to the advantages in, for example, forecasting for future values. The method can also be adapted to segment multiple volatility processes.

(Joint work with Jinyuan Chang and Bin Guo)

Sufficient dimension reduction with additional information

Hung Hung

National Taiwan University

Abstract

Sufficient dimension reduction is widely applied to help model building between the response Y and covariate X . In some situations, we also collect additional covariate W that has better performance in predicting Y , but has a higher obtaining cost, than X . While constructing a predictive model for Y based on (X, W) is straightforward, this strategy is not applicable since W is not available for future observations in which the constructed model is to be applied. As a result, the aim of the study is to build a predictive model for Y based on X only, where the available data is (Y, X, W) . A naive method is to conduct analysis using (Y, X) directly, but ignoring W can cause the problem of inefficiency. On the other hand, it is not trivial to utilize the information of W to infer (Y, X) , either. In this article, we propose a two-stage dimension reduction method for (Y, X) , that is able to utilize the information of W . In the breast cancer data, the risk score constructed from the two-stage method can well separate patients with different survival experiences. In the Pima data, the two-stage method requires fewer components to infer the diabetes status, while achieving higher classification accuracy than conventional method.

An ensemble algorithm for randomized singular value decomposition and randomized principal component analysis

Ting-Li Chen

Academia Sinica

Abstract

The computation of singular value decomposition (SVD) or principal component analysis (PCA) is expensive when the size of the matrix becomes large. Instead of processing the full scale of the matrix, a randomized approach is to work on a much smaller matrix which is the full scale matrix multiplied by a random matrix. In this talk, we will present an ensemble algorithm to combine the results of multiple randomized SVD. The algorithm is based on optimization on the Stiefel manifold. This ensemble SVD can be applied to solve large scale PCA. We will demonstrate the performance of the ensemble algorithm by simulation studies. We will also give theoretic results of the asymptotic behavior of the ensemble.

Classification with unstructured predictors with an application to sentiment analysis

Xiaotong Shen

University of Minnesota

Abstract

Unstructured data refers to information that lacks certain structures and cannot be organized in a predefined fashion. Unstructured data often involve words, texts, graphs, objects or multimedia types of files that are difficult to process and analyze with traditional computational tools and statistical methods. In this presentation, I will focus on ordinal classification for unstructured predictors with ordered class categories, where imprecise information concerning strengths between predictors is available for predicting class labels. However, imprecise information here is expressed in terms of a directed graph, with each node representing a predictor and a directed edge containing pairwise strengths between two nodes. Statistically, we integrate the imprecise predictor relations into linear relational constraints over classification function coefficients, where large margin ordinal classifiers are introduced, subject to many quadratically linear constraints. Moreover, the proposed classifiers are applied in sentiment analysis using binary word predictors. Finally, I will discuss some computational and theoretical aspects, in addition to an application to opinion survey.

(This work is joint with Junhui Wang, Yiwen Sun and Peiyong Qu.)

Multivariate time series analysis: brief review and recent developments

Ruey S. Tsay

University of Chicago

Abstract

We start with a brief review of multivariate time series analysis, discussing challenges, model specification, and applications of available methods. Real examples are used to demonstrate empirical analysis. We then discuss recent developments in multivariate time series analysis. The topics introduced include various factor models, modeling multivariate count data, forecasting with many predictors, and multivariate volatility modeling. Pros and cons of various models and methods are discussed. If time permits, real data are used to demonstrate the developments and to highlight the need for further improvements.

High-dimensional time series analysis

Ruey S. Tsay

University of Chicago

Abstract

Based on the discussions of the first talk, we start the talk with analysis of dependent big data. In particular, we consider the case when the dimension of the multivariate time series is increasing. We emphasize the concept of parsimony in addition to sparsity. Simple examples and simulations are used to demonstrate the limitations of the conventional methods developed for independent data or for multivariate time series analysis when the dimension is fixed. Some methods are introduced to handle dependent big data. Finally, we mention some possible directions for further research in high-dimensional time series analysis.

Model selection for high-dimensional time series

Ching-Kang Ing

Academia Sinica

Abstract

Model selection for high-dimensional regression models has been one of the most vibrant research topics in statistics and probability in the past decade. However, most of the attention has been devoted to situations where observations are independent, and hence time series data are precluded. In this talk, I shall address model selection problems for some high-dimensional time series models, including high-dimensional stochastic regression models and high-dimensional regression models with correlated errors. I shall present rates of convergence of the orthogonal greedy algorithm (OGA) under various sparsity conditions. I shall also show that when the high-dimensional information criterion (HDIC) of Ing and Lai (2011) is used in conjunction with the OGA, the resultant predictor achieves the optimal error rate.

Group orthogonal greedy algorithm for structural break time series: from univariate to multivariate

Ngai Hang Chan

Chinese University of Hong Kong

Abstract

The problem of estimating change-points in a structural break autoregressive (SBAR) model when the number of change-points m is unknown is considered in this paper. By reformulating the problem in a high-dimensional regression context, a modified high-dimensional variable selection method, namely, the so-called GOGA+HIDC+Trimming, is proposed to estimate the change-points $\{t_1, \dots, t_m\}$ and the unknown parameter m . It is further shown that these estimators are consistent and the computation can be efficiently performed. This method is further extended to the multivariate case to consider the structural break vector autoregressive (SBVAR) model. It is shown that the proposed method can be adopted to integrate the information across different components even when the change-points are relatively packed across components. Simulation studies are conducted to assess the finite sample performance.

(Joint work with Yuanbo Li and C.Y. Yau. Research supported in part by grants from HKSAR-RGC-GRF.)



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