Friday, December 9, 2022 (Hong Kong Time)

08:55 – 09:00 Xinyuan Song (The Chinese University of Hong Kong)
Opening Remarks and Introduction to Guest Speakers

09:00 – 09:40 Xiao-Li Meng (Harvard University)
Statistical Learning with Low-resolution Information: There is No Free Lunch

09:40 – 10:20 Grace Yi (University of Western Ontario)
Boosting Learning of Censored Survival Data

10:20 – 11:00 Yoonkyung Lee (The Ohio State University)
Predictive Model Degrees of Freedom in Linear Regression

11:00 – 11:40 Annie Qu (University of California, Irvine)
Query-augmented Active Metric Learning

11:40 – 12:20 Jianqing Fan (Princeton University)
Factor Augmented Sparse Throughput Deep ReLU Neural Networks for High Dimensional Regression

Saturday, December 10, 2022 (Hong Kong Time)

08:55 – 09:00 Hoi Ying Wong (The Chinese University of Hong Kong)
Opening Remarks and Introduction to Guest Speakers

09:00 – 09:40 Neil Shephard (Harvard University)
Some Properties of the Sample Weighted Median of an In-fill Sequence with an Application to High Frequency Financial Econometrics

09:40 – 10:20 Alain Bensoussan (The University of Texas at Dallas)
Stochastic Control and Limited Commitment

10:20 – 11:00 Ning Cai (The Hong Kong University of Science and Technology (Guangzhou))
Sensitivity Estimates with Computable Bias Bounds

11:00 – 11:40 Chi Seng Pun (Nanyang Technological University)
Bayesian Estimation and Optimization for Learning Sequential Regularized Portfolios

11:40 – 12:20 Huyên Pham (Université Paris Cité)
Actor-Critic Learning for Mean-field Control in Continuous Time

12:20 – 12:25 Phillip Yam (The Chinese University of Hong Kong)
Closing Remarks

Contact Us

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Date: 9-10 December 2022 (Fri-Sat)
Time: 8:55am – 12:25pm (Hong Kong Time)
Mode of Delivery: Online via ZOOM

Organizing Committee
Department of Statistics
CUHK

The Symposium on Statistics and Risk Management 2022

"On the occasion of celebrating the 40th anniversary of the Department of Statistics, the symposium will be held to gather internationally renowned scholars to present their state-of-the-art research topics in statistics and risk management in order to facilitate the exchange of ideas and research collaborations."

Invited Speakers

Statistics (9 Dec)

Jianqing FAN
Princeton University

Yoonkyung LEE
The Ohio State University

Xiao-Li MENG
Harvard University

Annie QU
University of California Irvine

Grace Y. YI
University of Western Ontario

Risk Management (10 Dec)

Alain BENSOUSSAN
The University of Texas at Dallas

Ning CAI
The Hong Kong University of Science and Technology (Guangzhou)

Huyên PHAM
Université Paris Cité

Chi Seng PUN
Nanyang Technological University

Neil SHEPHARD
Harvard University

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Public Registration Link
https://cloud.itsc.cuhk.edu.hk/webform/view.php?id=13658309
Registration Deadline: 9 December 2022, 8:00am (Hong Kong Time)

Symposium website and Programmme Information
https://www.sta.cuhk.edu.hk/symposium/2022/

Jianqing FAN

Factor Augmented Sparse Throughput Deep ReLU Neural Networks for High Dimensional Regression / *Princeton University*

We introduce a Factor Augmented Sparse Throughput (FAST) model that utilizes both latent factors and sparse idiosyncratic components for nonparametric regression. The FAST model bridges factor models on one end and sparse nonparametric models on the other end. It encompasses structured nonparametric models such as factor augmented additive model and sparse low-dimensional nonparametric interaction models and covers the cases where the covariates do not admit factor structures. Via diversified projections as estimation of latent factor space, we employ truncated deep ReLU networks to nonparametric factor regression without regularization and to more general FAST model using nonconvex regularization, resulting in factor augmented regression using neural network (FAR-NN) and FAST-NN estimators respectively. We show that FAR-NN and FAST-NN estimators adapt to unknown low-dimensional structure using hierarchical composition models in nonasymptotic minimax rates. We also study statistical learning for the factor augmented sparse additive model using a more specific neural network architecture. Our results are applicable to the weak dependent cases without factor structures. In proving the main technical result for FAST-NN, we establish new a deep ReLU network approximation result that contributes to the foundation of neural network theory. Our theory and methods are further supported by simulation studies and an application to macroeconomic data.

This is a joint work with Yihong Gu.

Yoonkyung LEE

Predictive Model Degrees of Freedom in Linear Regression / *The Ohio State University*

Overparametrized interpolating models have drawn increasing attention from machine learning. Some recent studies suggest that regularized interpolating models can generalize well. This phenomenon seemingly contradicts the conventional wisdom that interpolation tends to overfit the data and may perform poorly on test data. Further, it appears to defy the bias-variance trade-off. As one of the shortcomings of the existing theory, the classical notion of model degrees of freedom fails to explain the intrinsic difference among the interpolating models since it focuses on estimation of in-sample prediction error. This motivates an alternative measure of model complexity which can differentiate those interpolating models and take different test points into account. In particular, we propose a measure with a proper adjustment based on the squared covariance between the predictions and observations. Our analysis with least squares method reveals some interesting properties of the measure, which can reconcile the "double descent" phenomenon with the classical theory. This opens doors to an extended definition of model degrees of freedom in modern predictive settings.

This is joint work with Bo Luan and Yunzhang Zhu.

Xiao-Li MENG

Statistical Learning with Low-resolution Information: There is No Free Lunch / *Harvard University*

Imprecise probabilities alleviate the need for high-resolution and unwarranted assumptions in statistical modeling and risk assessment. They present an alternative strategy to reduce irreplicable findings. However, updating imprecise models requires the user to choose among alternative updating rules. Competing rules can result in incompatible inferences, and exhibit dilation, contraction and sure loss, unsettling phenomena that cannot occur with precise probabilities and the regular Bayes rule. We revisit some famous statistical paradoxes and show that the logical fallacy stems from a set of marginally plausible yet jointly incommensurable model assumptions akin to the trio of phenomena above. Discrepancies between the generalized Bayes (B) rule, Dempster's (D) rule, and the Geometric (G) rule as competing updating rules are discussed. We note that 1) B-rule cannot contract nor induce sure loss, but is the most prone to dilation due to “overfitting” in a certain sense; 2) in absence of prior information, both B-rule and G-rule are incapable to learn from data however informative they may be; 3) D-rule and G-rule can mathematically contradict each other by contracting while the other dilating. These findings highlight the invaluable role of judicious judgment in handling low-resolution information, and the care that needs to be taken when applying updating rules to imprecise probability models.

[This talk is based on the discussion article in Statistical Science: Gong and Meng (Statist. Sci. 36(2): 169-190 (May 2021). DOI: 10.1214/19-STS765) Judicious Judgment Meets Unsettling Updating: Dilation, Sure Loss, and Simpson’s Paradox.]

Annie QU

Query-augmented Active Metric Learning / *University of California Irvine*

We propose an active metric learning method for clustering with pairwise constraints. The proposed method actively queries the label of informative instance pairs, while estimating underlying metrics by incorporating unlabeled instance pairs, which leads to a more accurate and efficient clustering process. In particular, we augment the queried constraints by generating more pairwise labels to provide additional information in learning a metric to enhance clustering performance. Furthermore, we increase the robustness of metric learning by updating the learned metric sequentially and penalizing the irrelevant features adaptively. Specifically, we propose a new active query strategy that evaluates the information gain of instance pairs more accurately by incorporating the neighborhood structure, which improves clustering efficiency without extra labeling cost. In theory, we provide a tighter error bound of the proposed metric learning method utilizing augmented queries compared with methods using existing constraints only. Furthermore, we also investigate the improvement using the active query strategy instead of random selection. Numerical studies on simulation settings and real datasets indicate that the proposed method is especially advantageous when the signal-to-noise ratio between significant features and irrelevant features is low.

Grace Y. YI

Boosting Learning of Censored Survival Data / *University of Western Ontario*

Survival data frequently arise from cancer research, biomedical studies, and clinical trials. Survival analysis has attracted extensive research interests in the past five decades. Numerous modeling strategies and inferential procedures have been developed in the literature. In this talk, I will start with a brief introductory overview of classical survival analysis which centers around statistical inference, and then discuss a boosting method which focuses on prediction. While boosting methods have been well known in the field of machine learning, they have also been broadly discussed in the statistical community for various settings, especially for cases with complete data. This talk concerns survival data which typically involve censored responses. Three adjusted loss functions are proposed to address the effects due to right-censored responses where no specific model is imposed, and an unbiased boosting estimation method is developed. Theoretical results, including consistency and convergence, are established. Numerical studies demonstrate the promising finite sample performance of the proposed method.

Alain BENSOUSSAN

Stochastic Control and Limited Commitment / *The University of Texas at Dallas*

The theory of investment and growth of firms has been an important source of stochastic control problems. The issue of CEO compensation has been addressed more recently. A seminal paper has been written by H. Ai and R. Li, with a model of CEO compensation under limited commitment. It leads to a new type of stochastic control problem, where a stochastic constraint captures the limited commitment. The authors introduce a Bellman equation, with unusual boundary conditions. Many formal arguments are used in the proof, although the amount of intuition is impressive. The objective of this work is to provide a rigorous and complete theory for this Bellman equation and to solve the corresponding stochastic control problem.

Ning CAI

Sensitivity Estimates with Computable Bias Bounds / *The Hong Kong University of Science and Technology (Guangzhou)*

The likelihood ratio method (LRM) is widely used to estimate sensitivities in risk management. Constructions of the LRM estimators depend heavily on the computations of probability density functions (and their derivatives) of the underlying models, which are usually known only through their Laplace transforms under many popular financial models. We propose a Laplace inversion based LRM with computable bias bounds under these models. By selecting the algorithm parameters appropriately, we can obtain LRM estimators with any desired bias level. In addition, some asymptotic properties of our LRM estimators are also investigated. Numerical experiments indicate that our method performs well under a broad range of popular financial models.

This is joint work with Ziyang Hao.

Huyên PHAM

Actor-Critic Learning for Mean-field Control in Continuous Time / *Université Paris Cité*

We study policy gradient for mean-field control in continuous time in a reinforcement learning setting. By considering randomised policies with entropy regularisation, we derive a gradient expectation representation of the value function, which is amenable to actor-critic type algorithms where the value functions and the policies are learnt alternately based on observations samples of the state and model-free estimation of the population state distribution. In the linear-quadratic mean-field framework, we obtain an exact parametrisation of the actor and critic functions defined on the Wasserstein space. Finally, we illustrate the results of our algorithms with some numerical experiments on concrete examples.

Chi Seng PUN

Bayesian Estimation and Optimization for Learning Sequential Regularized Portfolios / *Nanyang Technological University*

This paper incorporates Bayesian estimation and optimization into portfolio selection framework, particularly for high-dimensional portfolio in which the number of assets is larger than the number of observations. We leverage a constrained l1 minimization approach, called linear programming optimal (LPO) portfolio, to directly estimate effective parameters appearing in the optimal portfolio. We propose two refinements for the LPO strategy. First, we explore improved Bayesian estimates, instead of sample estimates, of the covariance matrix of asset returns. Second, we introduce Bayesian optimization (BO) to replace traditional grid-search cross-validation (CV) in tuning hyperparameters of the LPO strategy. We further propose modifications in the BO algorithm by (1) taking into account time-dependent nature of financial problems and (2) extending commonly used expected improvement (EI) acquisition function to include a tunable trade-off with the improvement's variance (EIVar). Allowing a general case of noisy observations, we theoretically derive the sub-linear convergence rate of BO under the newly proposed EIVar and thus our algorithm has no regret. Our empirical studies confirm that the adjusted BO result in portfolios with higher out-of-sample Sharpe ratio, certainty equivalent, and lower turnover compared to those tuned with CV. This superior performance is achieved with significant reduction in time elapsed, thus also addressing time-consuming issues of CV. Furthermore, LPO with Bayesian estimates outperform original proposal of LPO, as well as the benchmark equally weighted and plug-in strategies.

This is a joint work with Godeliva Petrina Marisu.

Neil SHEPHARD

Some Properties of the Sample Weighted Median of an In-fill Sequence with an Application to High Frequency Financial Econometrics / *Harvard University*

Using an in-fill argument, the properties of the sample median of a sequence of events are established both for the case of a fixed period of time and for a period which shrinks as the sample size grows. The results are used to study the properties of the sample median of absolute returns under stochastic volatility. This estimator is invariant, asymptotically pivotal and a 1/2 breakdown estimator. In practice it has deep robustness to jump processes even when there are jumps of α-stable type.