Workshop Schedule

Day 1: June 24

Time	Event/Speaker
08:30 – 09:00	Name Badge Pickup
09:00 – 09:10	Opening Remarks by HKUST Rep.
09:10 – 10:10	Barry Nelson (Keynote)
10:10 – 10:30	Refreshment Break
10:30 – 11:00	Henry Lam
11:00 – 11:30	David Eckman
11:30 – 12:00	Russell Barton (session chair)
12:00 – 12:15	Group Photo Taking
12:15 – 14:00	Lunch at UniQue (on campus)
14:00 – 14:30	Jian-Qiang Hu
14:30 – 15:00	Yijie Peng
15:00 – 15:30	Jiaqiao Hu (session chair)
15:30 – 16:00	Refreshment Break
16:00 – 16:30	Xinyun Chen
16:30 – 17:00	Szu Hui Ng
17:00 – 17:30	Jie Xu (session chair)
18:00	Shuttle Bus from Campus to Crowne Plaza
18:30 – 21:00	Banquet at Crowne Plaza (Tseung Kwan O)

Day 2: June 25

Time	Event/Speaker
08:30 – 09:00	Name Badge Pickup
09:00 – 10:00	Sandeep Juneja (Keynote)
10:00 – 10:30	Refreshment Break
10:30 – 11:00	Raghu Pasupathy
11:00 – 11:30	Eunhye Song
11:30 – 12:00	Susan Hunter (session chair)
12:00 – 14:00	Lunch at UniQue (on campus)
14:00 – 14:30	Chang-Han Rhee
14:30 – 15:00	Karthyek Murthy
15:00 – 15:30	Xin Tong (session chair)
15:30 – 16:00	Refreshment Break
16:00 – 16:30	Siyang Gao
16:30 – 17:00	Dohyun Ahn
17:00 – 17:30	Nan Chen (session chair)

Day 3: June 26

Time	Event/Speaker
08:30 – 09:00	Name Badge Pickup
09:00 – 10:00	Jose Blanchet (Keynote)
10:00 – 10:30	Refreshment Break
10:30 – 11:00	Abhijit Gosavi
11:00 – 11:30	Xuefeng Gao
11:30 – 12:00	Zhiyuan Huang (chair)
12:00 – 14:00	Lunch at UniQue (on campus)
14:00 – 15:00	Panel Discussion (AI and Simulation Research) Panellists: Jose Blanchet, Sandeep Juneja, Henry Lam, Barry Nelson
17:30 – 20:30	Boat Trip on Victoria Harbour 17:00 Gather at HKUST Piazza 17:30 Board at HKUST Pier 20:30 Disembark at Tseung Kwan O Pier

Talk Information

Day 1: June 24

1. **Speaker**: Barry Nelson, Northwestern University

   Title: Ranking & Contextual Selection

   Abstract: We introduce ranking and contextual selection (R&CS) in which covariates provide context for data-driven decisions. R&CS optimizes over a set of covariate design points offline and then, given an actual observation of the covariate, makes an online decision based on classification, a distinctly new approach. We establish the existence of an experiment design that yields a pointwise probability of good selection guarantee and derive a post-experiment assessment of R&CS that provides an optimality-gap upper bound with guaranteed coverage for decisions with respect to future covariates. As an illustration we apply R&CS to assortment optimization using data available from Yahoo!.

2. **Speaker**: Henry Lam, Columbia University

   Title: Pseudo-Bayesian Optimization

   Abstract: Bayesian Optimization is a popular approach for optimizing expensive black-box functions. Its key idea is to use a surrogate model to approximate the objective and, importantly, quantify the associated uncertainty that allows a sequential selection of query points to balance exploitation-exploration. Gaussian process (GP) has been a common choice of surrogate model thanks to its various modeling benefits, but it also faces challenges that have spurred recent alternatives whose convergence properties are less transparent. Motivated by these, we study a framework, which we call Pseudo-Bayesian Optimization, to design optimization algorithms that are empirically superior while enjoy convergence guarantees. Our framework is based on axiomatic design principles that elicit the minimal requirements to guarantee convergence, including an understanding on the general notion of "uncertainty quantifier". We demonstrate the advantages of our approach with examples ranging from high-dimensional synthetic experiments to realistic hyperparameter tuning and robotic applications.

3. **Speaker:** David Eckman, Texas A&M University

   Title: Methods of Plausible Inference for Stochastic Simulation

Abstract: This talk will give an overview of plausible inference, a nascent mathematical framework that leverages limited simulation experiments and known or assumed functional properties of performance measures to deliver statistical inferences on the performance of unsimulated solutions. Methods of plausible inference essentially formulate and solve optimization problems at solutions of interest to determine plausible values for their performances. The results can be used to produce confidence intervals or to screen out solutions with unacceptable performance for purposes such as optimization and calibration. These inferences come with guarantees of uniform confidence and consistency and their power depends on the initial experiment design and the functional properties being exploited.

4. **Speaker:** Russell Barton, The Pennsylvania State University

   Title: Designing Experiments to Fit Inverse Metamodels

   Abstract: Many simulation-based design optimization scenarios are driven by an underlying inverse problem. Rather than iteratively exercise the (computationally expensive) simulation to find a suitable design (i.e., match a target performance vector), one might instead iteratively exercise the simulation to fit an inverse approximation, and use the approximation to indicate designs meeting multivariate performance targets. This talk examines issues in defining optimal designs for fitting inverse approximations. This is joint work with Max Morris, Iowa State.

5. **Speaker:** Jian-Qiang Hu, Fudan University

   Title: A Kernel-Based Stochastic Approximation Method for Blackbox Optimization of Co-Risk Measures

   Abstract: Co-risk measures are important for analyzing systemic risks among portfolios. Due to complexity and uncertainty of portfolios, co-risk measures are sometimes analyzed under the blackbox setting, whereby only input and random output of systems are accessible. In such a scenario, optimizing co-risk measures of portfolio losses is fairly challenging. We propose a kernel-based stochastic approximation method for blackbox optimization of co-risk measures, including CoVaR, Conditional Expected Shortfall (CoES), and marginal expected shortfall (MES). We establish the strong consistency and rate of convergence of the proposed method under appropriate conditions. Simulation experiments are presented to validate our method.

6. **Speaker:** Yijie Peng, Peking University

   Title: AlphaRank: An Artificial Intelligence Approach for Ranking and Selection Problems

Abstract: We introduce AlphaRank, an artificial intelligence approach to address the fixed-budget ranking and selection (R&S) problems. We formulate the sequential sampling decision as a Markov decision process and propose a Monte Carlo simulation-based rollout policy that utilizes classic R&S procedures as base policies for efficiently learning the value function of stochastic dynamic programming. We accelerate online sample-allocation by using deep reinforcement learning to pre-train a neural network model offline based on a given prior.We also propose a parallelizable computing framework for large-scale problems, effectively combining “divide and conquer” and “recursion” for enhanced scalability and efficiency. Numerical experiments demonstrate that the performance of AlphaRank is significantly improved over the base policies, which could be attributed to AlphaRank’s superior capability on the trade-off among mean, variance, and induced correlation overlooked by many existing policies.

7. **Speaker:** Jiaqiao Hu, Stony Brook University

   Title: Black-box Quantile Optimization via Finite Difference-based Gradient Approximation

   Abstract: We consider quantile optimization problems under a general black-box setting. We propose two new iterative multi-time scale stochastic approximation types of algorithms. The first algorithm uses an appropriately modified finite-difference-based gradient estimator that requires 2d+1 samples of the black-box function per iteration of the algorithm, where d is the number of decision variables. The second algorithm employs a simultaneous-perturbation-based gradient estimator that uses only three samples for each iteration regardless of problem dimension. We show the almost sure convergence of both algorithms and establish their rates of convergence. Numerical results are also reported to illustrate and compare the performance of the algorithms with alternative methods.

8. **Speaker:** Xinyun Chen, Chinese University of Hong Kong (Shenzhen)

   Title: Online Learning and Optimization for Queues with Unknown Arrival Rate and Service Distribution

   Abstract: We investigate an optimization problem in a queueing system where the service provider selects the optimal service fee p and service capacity μ to maximize the cumulative expected profit (the service revenue minus the capacity cost and delay penalty). The conventional predict-then-optimize (PTO) approach takes two steps: first, it estimates the model parameters (e.g., arrival rate and service-time distribution) from data; second, it optimizes a model taking these parameters as input. A major drawback of PTO is that its solution accuracy can often be highly sensitive to the parameter estimation errors because PTO is unable to effectively account for how these errors (step 1) will impact the solution quality of the downstream optimization (step 2). To remedy this issue, we develop an online learning framework that automatically incorporates the afore mentioned parameter estimation errors in the optimization process; it is an end-to-end approach that can learn the optimal solution without needing to set up the parameter estimation as a separate step as in PTO. Effectiveness of our online learning approach is substantiated by (i) theoretical results including the algorithm convergence and analysis of the regret ("cost" to pay overtime for the algorithm to learn the optimal policy), and (ii) engineering confirmation via simulation experiments of a variety of representative examples. We also provide careful comparisons between PTO and our online learning method, especially when the optimal control runs the system in heavy traffic.

9. **Speaker:** Szu Hui Ng, National University of Singapore

   Title: Trajectory-Based Bayesian Optimization for Multi-Objective Iterative Learning

   Abstract: Many real-world simulation-based applications, such as training machine learning models or monitoring the effect of drug designs, inherently involve a resource intensive and noisy iterative learning procedure that allows one to continuously observe the performance over epochs or time intervals. However, the insights gained from such a procedure typically remain under-exploited in multi-objective scenarios. Specifically, we notice that as the iterative learning proceeds, tracking the multi-objective performance of a setting generates a trajectory in the objective space that was typically overlooked in earlier studies. To this end, in this work, we propose for the first time an enhanced multi-objective optimization problem with iterative learning to capture the optimal trade-offs that may occur along the trajectories. Correspondingly, we present a novel trajectory-based multi-objective Bayesian optimization method characterized by two main features: 1) an acquisition function that measures the potential improvement made by the trajectory of any setting and 2) a multi-objective early stopping mechanism that determines when to terminate the trajectory to maximize epoch efficiency. Numerical experiments on the hyperparameter tuning for a deep neural network trained by epochs demonstrate that our algorithm outperforms the state-of-the-art multi-objective optimizers in both locating optimal trade-offs and conserving computational resources.

10. **Speaker:** Jie Xu, George Mason University

    Title: Robust Optimal Sampling for Digital Twin-based Real-time Decision Making in Manufacturing Management

    Abstract: Digital twin models facilitate real-time simulation of a system using dynamic sensor data, fostering interest in employing them to determine optimal actions based on current system states or in response to detected anomalies. For instance, in manufacturing, digital twins can aid in evaluating new production plans and selecting the best response to high-priority rush orders placed. Real-time decision-making imposes severe constraints on simulation budgets, impacting the effectiveness of state-of-the-art Ranking & Selection (R&S) algorithms like optimal computing budget allocation (OCBA). Specifically, while OCBA is asymptotically optimal, its observed algorithm performance suffers when initial replications fail to produce accurate estimates of the means and variances of all design alternatives due to insufficient sampling. To address this gap, we introduce Robust Optimal Sampling (ROS), a novel concept designed to enhance R&S algorithms' performance by balancing the simulation allocation to identify the best action and the need to improve the accuracy of parameter estimation. ROS can be applied to popular R&S algorithms like OCBA, knowledge gradient (KG), and gradient-based Complete Expected Value of Information (gCEI). We report numerical experiments that demonstrated the consistent improvement in algorithm performance when applying ROS to OCBA, KG, and gCEI, especially in scenarios with limited initial sampling budgets, such as real-time digital twin-based decision-making applications. This is joint work with Travis Goodwin (MITRE Corporation), Nurcin Celik (University of Miami), and Chun-Hung Chen (George Mason University).

Day 2: June 25

1. **Speaker:** Sandeep Juneja, Ashoka University

   Title: Selecting the Best Arm – Optimal Algorithm Based on Fluid Analysis

   Abstract: We are given finitely many unknown probability distributions that can be sampled from and our aim is, through sequential sampling, to identify the one with the largest mean. This is a classical problem in statistics, simulation and learning theory. Lately, methods have been proposed that identify a sample complexity lower bound that any algorithm providing probabilistic correctness guarantees must satisfy, and algorithms have been developed that asymptotically match these lower bounds even for general sampling distributions, as the probabilistic error guarantees converge to zero. We review these ideas and propose a novel algorithm that relies on exploiting the underlying fluid structure in the evolution of the optimal sampling process and improves upon existing asymptotically optimal algorithms.

2. **Speaker:** Raghu Pasupathy, Purdue University

   Title: Deterministic and Stochastic Frank Wolfe Recursion on Probability Spaces

   Abstract: Motivated by emergency response applications, we consider smooth optimization problems over the space of non-negative Borel measures supported on a convex compact subset of the Euclidean space. Through direct application of variational calculus, we devise a deterministic Frank-Wolfe (dFW) first-order recursion using the influence function, to generate iterates exhibiting O(ε^{-1}) convergence in function value. Importantly, the recursion we present is made possible by a simple result that expresses the solution to the infinite-dimensional

Frank-Wolfe sub-problem as the solution to a finite-dimensional optimization problem in R^d. Such a result allows writing the Frank-Wolfe recursion as a convex combination of the incumbent iterate and a Dirac measure concentrating on the minimum of the influence function at the incumbent iterate. To account for common application contexts where only Monte Carlo observations of the objective and influence function are available, we construct the stochastic Frank-Wolfe (SFW) variation that generates a sequence of random measures constructed using minima of increasingly accurate estimates of the influence function. We demonstrate that the sFW sequence exhibits O(1/k) complexity almost surely and in expectation. Furthermore, we show that an easy-to-implement fixed-step, fixed-sample version of sFW exhibits exponential convergence to ε-optimality. We end with a central limit theorem on the observed objective values at the sequence of generated random measures. We include a number of illustrative example problem classes along with exact calculations of the influence function. This is joint work with Di Yu (Purdue University) and Shane Henderson (Cornell University).

3. **Speaker:** Eunhye Song, Georgia Tech

   Title: Optimizing Input Data Collection for Ranking and Selection

   Abstract: We consider a Bayesian ranking and selection problem under input uncertainty when all solutions share the common input models. We assume that there are multiple independent input data sources from which data can be collected at a cost to reduce input uncertainty. To optimize the data collection, we first show that the most probable best (MPB)—the solution with the largest posterior probability of being optimal (posterior preference)—is a strongly consistent estimator for the true optimum. We investigate the optimal asymptotic static sampling ratios from the input data sources that maximize the convergence rate of the MPB's posterior preference. A sequential sampling rule that balances the simulation and input data collection effort is presented. We benchmark our algorithm against other state-of-the-art methods that optimizes simulation and data collection effort simultaneously and show that we indeed provide a faster empirical convergence in the probability of correct selection.

4. **Speaker:** Susan R. Hunter, Purdue University

   Title: Uniform Central Limit Theorems and Confidence Regions for Multi-Objective Stochastic Convex Quadratic Programs

   Abstract: A multi-objective stochastic convex quadratic program (MOSCQP) is a multi-objective optimization problem with convex quadratic objectives that are observed with stochastic error. This problem arises, for example, in model calibration and nonlinear system identification when a single regression model combines data from multiple distinct sources, resulting in a multi-objective least squares problem.

We consider the open problem of statistical inference for MOSCQPs, which includes estimating the efficient and Pareto sets, quantifying uncertainty through central limit theorems (CLTs), and constructing asymptotically exact confidence regions on the efficient and Pareto sets. We use parameterization to write the efficient and Pareto set estimators in closed form, which leads to a key lemma characterizing the Frechet derivatives of the efficient and Pareto sets with respect to the underlying quadratic parameters. The key lemma enables us to construct a classical delta theorem analogue for MOSCQP, resulting in uniform CLTs on the estimated efficient and Pareto sets. We also propose a direct procedure for constructing asymptotically valid confidence regions that exploits the MOSCQP problem structure. We illustrate the confidence regions through a numerical example. This is joint work with Ziyu Liu, Nan Kong, and Raghu Pasupathy (Purdue University).

5. **Speaker:** Chang-Han Rhee

   Title: Characterization and Control of Global Dynamics of Heavy-Tailed SGDs with Local Stability Analysis

   Abstract: In this talk, I will present a mathematical framework that enables precise characterization and control of global dynamics of Stochastic Gradient Descent (SGD) within the complex non-convex loss landscapes typical in deep learning. These developments build on a new (locally uniform) heavy-tailed large deviations formulation and local stability analysis framework we recently introduced. These lead to the heavy-tailed counterparts of the classical Freidlin-Wentzell and Eyring-Kramers theories. Our machinery elucidates how to manipulate heavy-tailed noises during a training phase so that SGD avoids sharp minima almost completely and hence achieves better generalization performance for the test data.

   This talk is based on the joint work with Mihail Bazhba, Jose Blanchet, Bohan Chen, Sewoong Oh, Zhe Su, Xingyu Wang, and Bert Zwart.

6. **Speaker:** Karthyek Murthy

   Title: Locally Robust Estimation for Mitigating Input Uncertainty in Minimization of Tail Risks

   Abstract: The ability to learn and control tail risks, besides being an integral part of quantitative risk management, is central to running operations requiring high service levels and cyber-physical systems with high-reliability specifications. Due to the paucity of relevant samples in the tail regions, formulations involving tail risks are almost always approached with the “estimate, then optimize” workflow involving a model estimation from data in the first step before plugging in the trained model to solve various downstream decision-making tasks via simulation. As biases due to model selection, misspecification, and overfitting to in-sample data are difficult to avoid in the first-step estimation, we construct novel locally robust estimators in which the input uncertainty due to the first-step estimation has no effect, locally, on the decisions obtained via downstream simulation. We show that this local insensitivity translates to improved out-of-sample performance freed from the first-order impact of input model uncertainty introduced in the first-step estimation.

A key ingredient in achieving this local robustness is a novel debiasing procedure that adds a non-parametric bias correction term to the objective. The debiased formulation retains convexity, and the imputation of the correction term relies only on a non-restrictive large deviations behavior conducive for transferring knowledge from representative data-rich regions to the data-scarce tail regions. The bias correction gets determined by the extent of model error in the estimation step and the specifics of the decision-making task in the optimization step, thereby serving as a scalable ”smart-correction” step bridging the disparate goals in estimation and optimization.

7. **Speaker:** Xin Tong

   Title: Stochastic Gradient Descent with Adaptive Data

   Abstract: Stochastic gradient descent (SGD) is a powerful optimization technique that is particularly useful in online learning scenarios. Its convergence analysis/effectiveness is relatively well understood under the assumption that the data samples are independent and identically distributed (iid). However, applying online learning to policy optimization problems in operations research involves a distinct challenge: the policy changes the environment and thereby affects the data used to update the policy. The adaptively generated data stream involves samples that are non-stationary, no longer independent from each other, and affected by previous decisions. The influence of previous decisions on the data-generating environment introduces estimation bias in the gradients, which presents a potential source of instability for online learning not present in the iid case. In this paper, we introduce simple criteria for the adaptively generated data stream to guarantee the convergence of SGD. We show that the convergence speed of SGD with adaptive data is largely similar to the classical iid setting, as long as the mixing time of the policy-induced dynamics is factored in. Our Lyapunov-function analysis allows one to translate existing stability analysis of systems studied in operations research into convergence rates for SGD, and we demonstrate this for queuing and inventory management problems. We also showcase how our result can be applied to study an actor-critic policy gradient algorithm.

8. **Speaker:** Siyang Gao, City University of Hong Kong

   Title: Ranking and Selection with Unknown Sampling Variances

   Abstract: We consider fixed-budget ranking and selection (R&S). This is a popular decision model in simulation optimization, with the goal of maximizing the probability of correctly selecting the best design among a finite set of alternatives within a given simulation budget. Existing R&S methods basically assume that the simulation noises of the designs follow normal distributions with known variances. We argue that the assumption of known variances is problematic, which will cause the derived sample allocation rules to underestimate the sampling uncertainty. In this research, we solve the fixed-budget R&S problem with unknown sampling variances. We follow the framework of the optimal computing budget allocation (OCBA) and establish optimality conditions, develop selection algorithms and characterize theoretical properties of the selection algorithms for this problem. In particular, Ryzhov (2016) made a conjecture about the optimality conditions of this problem. This research shows that this conjecture is partially correct, and fills in the missing parts of this conjecture.

9. **Speaker:** Dohyun Ahn, Chinese University of Hong Kong

   Title: Efficient Simulation of Polyhedral Expectations with Applications to Finance

   Abstract: We consider the problem of estimating the expectation over a convex polyhedron specified by a set of linear inequalities. This problem encompasses a multitude of financial applications including systemic risk quantification, exotic option pricing, and portfolio management. We particularly focus on the case where the target event is rare, which corresponds to extreme systemic failures, deep out-of-the-money options, and high target returns in the aforementioned applications, respectively. This rare-event setting renders the naive Monte Carlo method inefficient and requires the use of variance reduction techniques. To address this issue, we develop a novel and strongly efficient method for the computation of the said expectation in a general rare-event setting by exploiting the geometry of the target polyhedron and concentrating the sampling density almost within the polyhedron. The proposed method significantly outperforms the existing approaches in various numerical experiments in terms of accuracy and computational costs.

10. **Speaker:** Nan Chen, Chinese University of Hong Kong

    Title: Adversarial Reinforcement Learning: A Duality-Based Approach

    Abstract: When applied to stochastic control problems, deep neural networks can overlearn the data and construct non-adapted policies, and thus susceptible to generalization error. In this paper, we propose an adversarial learning approach to address this issue. It stems from the literature of information relaxation. By relaxing the adapted requirement on the control policies and incorporating a Lagrangian martingale penalty into the objective function, we reformulate the problem as a min-max game between the agent and an adversary. The algorithm aims to learn both value and policy iteratively. Numerical experiments show the effectiveness of the approach.

Day 3: June 26

1. **Speaker:** Jose Blanchet, Stanford University

   Title: On Highly Parameterized Controls and Fusion of Generative Diffusions

   Abstract: We discuss two recent simulation results in connection with two very active research areas in operations research and artificial intelligence.

   The first one involves the design of efficient gradient estimators for dynamic optimization problems based on highly parameterized controls. The motivation is the application of stochastic gradient descent for the numerical solution of stochastic control problems using neural networks. Our estimator has at least a linear speed-up in the dimension of the parameter space compared to infinitesimal perturbation analysis and it can be applied on situations in which the likelihood ratio estimator may not be applicable (e.g. If the diffusion matrix depends on the parameter of interest). We show very substantial gains in high-dimensional control problems based on experiments.

   The second result involves the development of an efficient approach for merging diffusion-based generative models. We assume the existence of several auxiliary models that have been trained with abundance of data. These models are assumed to contain features that, combined, can be useful to enhance the training of a generative diffusion model for a target distribution (with limited data). We merge the models using a Kullback-Leibler (KL) Barycenter given set of weights representing the importance of the auxiliaries. In turn, we optimize the weights to improve the overall performance of the fused model in order to fit the target. While the double optimization problem (KL Barycenter and optimizing over weights) is challenging to solve, we show that diffusion based generative modeling significantly reduce the complexity of the overall optimization problem, making the approach practical.

   The results are based on two papers, the first one (on gradient estimators) with Peter Glynn and Shengbo Wang, and the second one (on fusion) with Hao Liu, Nian Si, and Tony Ye.

2. **Speaker:** Abhijit Gosavi, Missouri University of Science and Technology

   Title: Reinforcement Learning for Remanufacturing in the World of Industry 4.0

   Abstract: The fourth industrial revolution (also called Industry 4.0) has opened opportunities for using artificial intelligence in conjunction with simulation to solve complex problems within minutes. This research focusses on a problem in a remanufacturing system where the goal is to solve a challenging problem of supplier selection in the face of rapidly changing demand. The quality and timing of arrival of the raw materials, also called cores, to the remanufacturing factory, is a source of disrupting complications in this industry due to the high variability of cores and the significant supply-demand imbalance in the markets, respectively. Using reinforcement learning, which combines paradigms from simulation and artificial intelligence, one can solve the associated complex problem of supplier selection; however, computational analyses of new algorithms, rooted in robust actor-critic learning, and appropriate tuning of algorithms, via learning rates, are needed to deliver good solutions. This talk will focus on numerical aspects of reinforcement learning under the umbrella of simulation-based optimization.

3. **Speaker:** Xuefeng Gao, Chinese University of Hong Kong

   Title: Wasserstein Convergence Guarantees for a General Class of Score-Based Generative Models

   Abstract: Score-based generative models (SGMs) is a recent class of deep generative models with state-of-the-art performance in many applications. In this paper, we establish convergence guarantees for a general class of SGMs in 2-Wasserstein distance, assuming accurate score estimates and smooth log-concave data distribution. We specialize our result to several concrete SGMs with specific choices of forward processes modelled by stochastic differential equations, and obtain an upper bound on the iteration complexity for each model, which demonstrates the impacts of different choices of the forward processes. We also provide a lower bound when the data distribution is Gaussian. Numerically, we experiment SGMs with different forward processes, some of which are newly proposed in this paper, for unconditional image generation on CIFAR-10. We find that the experimental results are in good agreement with our theoretical predictions on the iteration complexity, and the models with our newly proposed forward processes can outperform existing models.

4. **Speaker:** Zhiyuan Huang, Tongji University

   Title: Reducing Conservativeness of Data-Driven Chance Constraints via a Conformal Statistical Framework

   Abstract: Chance-constrained optimization is a popular approach to obtain decisions that balance objective performance and risk, by requiring the solution to satisfy safety constraints with a high probability. In the data-driven context, the predominant statistical framework is to attain this high-probability feasibility at a confidence level with respect to past data. Such a confidence-based guarantee, while natural, is primarily suited for decisions applied repeatedly over a long lifespan without the access to new data. However, in many operational settings where decisions are updated periodically based on recent data, this framework becomes overly conservative. In this talk, we propose an alternative statistical framework for data-driven chance-constrained optimization based on conformal prediction guarantees on the obtained decision. Our framework aims to provide less conservative and more adaptable solutions for decision-making over rolling windows. Methodologically, we demonstrate how to "conformalize" a range of approaches for data-driven chance constrained problems, including scenario generation, sampling-and-discarding, FAST, and learning-based robust optimization, which leads to smaller sample size requirements and improved objective performance for short lifespan problems than the classical framework.