随机动力系统与机器学习前沿交叉研讨会

Workshop on Frontiers in the Intersection of Stochastic Dynamical Systems and Machine Learning

TY-2026-C-079

会议手册

Conference Program

召集人： Organizers：

姓名　李铁军（北京大学）

姓名　周翔（香港城市大学）

姓名　陈小丽（中国地质大学（武汉））

2026 年 9 月 6 日—12 日

September 6－12, 2026

中国・昆明

Kunming, China

天元数学国际交流中心简介

天元数学国际交流中心（以下简称“中心”）成立于2023年7月，由中国科学院、国家自然科学基金委员会、中国数学会、中国科学院数学与系统科学研究院，以及昆明市有关部门共同支持建设的数学与交叉科学交流机构。旨在搭建数学及其跨学科应用领域的学术交流平台，提升我国数学整体研究水平，成为国际一流的数学交流与合作研究中心。

中心位于昆明市宜良县柴石滩水库库区，三面环山、一面临水，环境优美，海拔约1700米。距长水国际机场约90公里（车程约1.5小时），距石林风景区约30公里，距九乡风景区约20公里。

中心总建筑面积约6000平方米，设有大报告厅（可容纳100人，配备高清LED屏）、中型会议室1间、小型会议室4间、研讨/工作室21间、图书阅览室1间、咖啡厅1间。专家楼配有56间宿舍及自助洗衣房、公共休息区等配套设施。

中心官方网站：http://tianyuan.amss.ac.cn/



Introduction to Tianyuan Mathematics Research Center（TYMRC）

The Tianyuan Mathematics Research Center (established in July 2023) is jointly supported by the Chinese Academy of Sciences, the National Natural Science Foundation of China, the Chinese Mathematical Society, the Academy of Mathematics and Systems Science of the Chinese Academy of Sciences, and relevant departments of Kunming City. It aims to build a platform for academic exchange in mathematics and interdisciplinary applications, enhance China's overall mathematical research level, and become a world-class center for mathematical exchange and collaborative research.

It is located in the national-level public welfare forest in the Chaishitan Reservoir area of Yiliang, Kunming, Yunnan Province, surrounded by mountains on three sides and facing water on one side. The center has a total land area of about 27,000 square meters, with three two-story main buildings, namely the Research Building, the Expert Building and the Logistics Building, which can accommodate nearly 200 people for academic activities, and are equipped with a library and reading room, a restaurant and a certain number of offices and guest rooms.

The center has a total construction area of approximately 6,000 square meters. It features a main lecture hall (capacity: 100 people, equipped with an HD LED screen), one medium-sized seminar room, four small meeting rooms, 21 seminar/workshop rooms, one library and reading room, and one café. The Expert Building is equipped with 56 guest rooms, as well as supporting facilities such as a self-service laundry room and a public lounge.

Official website: http://tianyuan.amss.ac.cn/

会议信息

一、研讨主题：随机动力系统与机器学习

二、活动日程：

报到：2026 年 9 月 6 日

报告：2026 年 9 月 7 日至 9 月 11 日

离会：2026 年 9 月 12 日

地点：天元数学国际交流中心（云南省昆明市宜良县柴石滩水库）

三、相关事项：

1. 本次研讨会得到天元数学国际交流中心资助，参会人员的住宿及餐饮由中心承担，其余费用（含往返交通费）由参会人员自理。
2. 中心统一安排往返昆明高铁站/长水机场及昆明市区的接送服务。请及时登录项目管理系统（http://tianyuanpm.amss.ac.cn/）登记行程信息。
3. 中心距离医院较远，建议访客适当随时携带一些必备药品。
4. **会议联系人：**

   陈小丽 （中国地质大学（武汉））：18771946918 / 13522968290

   李铁军（北京大学）：13693574010

   周翔（香港城市大学）：18813906760

Conference Information

I. Seminar Theme： Stochastic Dynamical Systems and Machine Learning

II、Program Schedule：

Check-in: Date September 6, 2026

Talks: Date September 7－ Date September 11, 2026

Departure: Date September 12, 2026

Venue: Tianyuan Mathematics Research Center (Chishitan Reservoir, Yiliang County, Kunming, Yunnan Province)

III、Practical Information：

1. This seminar is financially supported by the TYMRC. Accommodation and meals for participants will be covered by the Center. All other expenses (including round-trip transportation) shall be borne by the participants themselves.
2. The Center will arrange shuttle services to/from the following locations: Kunming High-Speed Railway Station, Kunming Changshui International Airport, and downtown Kunming. Participants are kindly requested to log in to the project management system (http://tianyuanpm.amss.ac.cn/) in a timely manner to register their travel information.
3. As the Center is located at a considerable distance from the nearest hospital, participants are advised to bring an adequate supply of essential personal medications.
4. Conference Contact:

   Xiaoli Chen: 18771946918/13522968290

   Tiejun Li：13693574010

   Xiang Zhou：18813906760

会议日程一（Schedule I）

9 月 6 日	
周日 Sunday	**报到（Registration）**
9 月 12 日	
周六 Saturday	**离会（Departure）**

9 月 7 日（周一 Monday）			
8:30-8:40	开幕式 Opening Ceremony		
时间 Time	报告人 Speaker	题目 Title of talk	主持人 Chair
8:40-9:15	Ren Kui	Generalization Properties of Adaptive Langevin Diffusion Dynamics	李铁军
9:15-10:10	董国志	从离散到连续的字典学习：反问题正则化视角之初探	李铁军
10:10-10:40	合影及讨论（Group Photo&Discussion over coffee）		
10:40-11:15	王小捷	High-dimensional non-convex sampling via solving SDEs	周翔
11:15-11:50	李筱光	A Generative Saddle Searching Method: Based on Witten-Laplacian Spectral Problem	周翔
11:50-14:00	午餐（Lunch Break）		
14:00-15:00	吴昊	Learning Stochastic Dynamics: From Coarse-Graining to Generative Models	李筱光
15:00-15:50	黄远飞	Energy Conversion and Fluctuation Relations in Levy Active Matter	李筱光
15:50-16:05	讨论（Discussion over coffee）		
16:05-16:55	周沛劼	AI 动态虚拟细胞构建理论与算法	王小捷
16:55-17:30	崔建波	Wasserstein Hamiltonian Flow and Its Structure-Preserving Numerical Scheme	王小捷

17:30-20:00	晚餐和讨论（Dinner Break and Discussion）

会议日程二（Schedule II）

9 月 8 日（周二 Tuesday）			
时间 Time	报告人 Speaker	题目 Title of talk	主持人 Chair
8:30-9:05	万林	Learning collective multicellular dynamics with interacting mean field neural SDE models	陈晓鹏
9:05-9:40	杨武岳	Learning Hidden SDEs and Mean-Field Interaction Kernels from Trajectory Data	陈晓鹏
9:40-10:15	束俊	基于 Koopman 理论的连续谱动力系统表示与预测方法	胡建宇
10:15-10:30	讨论（Discussion over coffee）		
10:30-11:05	安静	Localized Convergence of Non-Convex SGD with Dependent Data	冯灵羽
11:05-11:40	杨睿逸	Bayesian Optimization on Networks	冯灵羽
11:40-14:00	午餐（Lunch Break）		
14:00-15:00	曹语	Trajectory Sampling: From Langevin Dynamics to Quantum Stochastic Unraveling	李磊
15:00-15:50	袁胜兰	Endogenous business cycles via state-dependent saving and noise-induced metastability	李磊
15:50-16:10	讨论（Discussion over coffee）		

16:10-16:45	李磊	Deep operator learning for efficient sampling from invariant measures of stochastic differential equations	曹语
16:45-17:20	周默	Score-Based Neural ODEs for Mean-Field Control and Fokker–Planck Equations	曹语
17:20-20:00	晚餐和讨论（Dinner Break and Discussion）		

会议日程三（Schedule III）

9 月 9 日（周三 Wednesday）			
时间 Time	报告人 Speaker	题目 Title of talk	主持人 Chair
8:30-9:05	史作强	An Efficient Conditional Score-based Filter for Nonlinear Filtering Problems	汤庆
9:05-9:55	王涵	原子大模型驱动的材料设计与发现	汤庆
9:55-10:10	讨论（Discussion over coffee）		
10:10-11:00	卢裕滨	Structure-Aware Variational Learning of a Class of Generalized Diffusions	史作强
11:00-11:50	祝爱卿	非平衡耗散系统的可辨识学习	史作强
11:50-14:00	午餐（Lunch Break）		
14:00-17:00	讨论（Discussion over coffee）		
17:00-20:00	晚餐和讨论（Dinner Break and Discussion）		

会议日程四（Schedule IV）

9月10日（周四 Thursday）			
时间 Time	报告人 Speaker	题目 Title of talk	主持人 Chair
8:30-9:05	廖奇峰	A high-dimensional density estimation method and its application for solving PDEs	高婷
9:05-9:40	杨斯尧	Tensor-train density estimation and its application in free energy exploration	高婷
9:40-9:55	讨论（Discussion over coffee）		
9:55-10:30	高婷	How Mathematical Structures rise from Uncertainties: Dynamics, Geometry, and Topology	廖奇峰
10:30-11:20	胡建宇	Learning from Structured Data with Structure-Preserving Kernels	廖奇峰
11:20-11:55	巫致有	Variational Method for Transition Pathways	廖奇峰
11:55-14:00	午餐（Lunch Break）		
14:00-14:35	刘程宇	Generative Path-Finding Method for Wasserstein Gradient Flow	戴敏
14:35-15:10	汤庆	Continuous-time heterogeneous agent models with recursive utility： theory and numerical methods	戴敏
15:10-15:45	Nathanael Tepakbong	Boundary-Adapted PINNs for Elliptic Dirichlet Problems: $H^2(\Omega)$ A Priori Error Bounds with Application to Mean Escape Time Computation	刘程宇
15:45-16:00	讨论（Discussion over coffee）		

16:00-16:35	吴风艳	Transitions and Basin Stability in a Delayed FitzHugh-Nagumo Neural Model Driven by Non-Gaussian Colored Noise	刘程宇
16:35-17:10	魏崴	一类针对随机系统的量子计算方法	卢裕滨
17:10-17:45	苑罡男	MAGNet: A Differentiable Gaussian Distance Primitive for Function Approximation and Representation Disentanglement	卢裕滨
17:45-20:00	晚餐和讨论（Dinner Break and Discussion）		

会议日程五（Schedule V）

9月11日（周五 Friday）			
时间 Time	**报告人** Speaker	**题目** Title of talk	**主持人** Chair
8:30-9:05	闵含城	Transformers Learn the Optimal DDPM Denoiser for Multi-Token GMMs	胡建宇
9:05-9:40	于露	On the Limits of Latent Reuse in Diffusion Models	胡建宇
9:40-11:00	讨论（Discussion over coffee）		
11:00-14:00	午餐（Lunch Break）		
14:00-17:00	讨论（Discussion over coffee）		
17:00-20:00	晚餐和讨论（Dinner Break and Discussion）		

报告摘要（Report Abstracts）

Localized Convergence of Non-Convex SGD with Dependent Data

Jing An

Shanghai Jiao Tong University, China

Abstract: Stochastic gradient descent is widely used in machine learning, but most existing convergence theories rely on independent sampling assumptions. In this talk, we study SGD for non-convex optimization when the data arrive as a temporally dependent φ-mixing process. To mitigate the effect of dependence, we consider sampling strategies such as subsampling and mini-batching, which reduce the effective correlation between successive stochastic gradients. We investigate how the sampling design, mixing rate, and optimization dynamics jointly determine convergence. Our analysis provides a framework for understanding non-convex stochastic optimization beyond the i.i.d. setting.

Biography:安静，现为上海交通大学长聘教轨副教授，海外优青。她于2016年获得美国加州大学洛杉矶分校数学学士学位，并于2021年获得美国斯坦福大学计算与数学工程博士学位。此后，她先后在德国马普数学科学研究所(2021–2022)和美国杜克大学(2022–2025)从事博士后研究工作。她的研究方向主要聚焦于机器学习与数据科学的数学基础，尤其是利用随机分析与动理学理论刻画机器学习算法

的长时间行为；同时也长期从事演化方程的研究，包括反应–扩散方程及相关非线性偏微分方程的理论与应用。

Trajectory Sampling: From Langevin Dynamics to Quantum Stochastic Unraveling

Yu Cao

Shanghai Jiao Tong University, China

Abstract: A macroscopic dynamical system or phenomenon may be realized through a variety of microscopic dynamical systems. While this multiplicity complicates the analysis, it also offers a valuable advantage: by choosing an appropriate microscopic realization, one can achieve greater simulation efficiency. In diffusion generative models, for example, one may toggle between ODE and SDE formulations depending on the scenario. A similar situation arises in the quantum regime, where different microscopic realizations exhibit distinct fluctuation and entanglement behaviors. In this talk, we will discuss this common theme, ranging from classical Langevin dynamics to quantum stochastic unraveling.

Biography: 曹语，目前系上海交通大学副教授，杜克大学博士，纽约大学科朗数学研究所博士后。研究方向为开放物理系统的理论和计算，其中包含Lindblad方程为代表的开放量子系统、Langevin方程为代表的开放经典系统。

Wasserstein Hamiltonian Flow and Its Structure-Preserving Numerical Scheme

Jianbo Cui

The Hong Kong Polytechnic University, China

Abstract: We study discretizations of Hamiltonian systems on the probability density manifold equipped with the L^2-Wasserstein metric. For low-dimensional problems, based on discrete optimal transport theory, we derive several Wasserstein Hamiltonian flows (WHFs) on graphs, which can be viewed as spatial discretizations of the original systems. By regularizing the system with Fisher information, we propose a regularized symplectic scheme that preserves several desirable long-time behaviors. Furthermore, motivated by the coupling idea and WHF, we propose a supervised learning scheme for certain high-dimensional problems. If time permits, I will discuss further details on solving high-dimensional Hamilton-Jacobi equations via density coupling and supervised learning.

Biography: Cui Jianbo is an assistant professor at Department of Applied Mathematics, PolyU. Before that, he was a visiting assistant professor at School of Mathematics, Georgia Tech worked with Prof. Luca Dieci and Prof. Haomin Zhou. He did his PhD at Academy of Mathematics and Systems Science, CAS, where he was supervised by Prof. Jialin Hong.

从离散到连续的字典学习：反问题正则化视角之初探

Guozhi Dong

Central South University, China

Abstract: The intersection of stochastic dynamics and machine learning has rapidly emerged as a fertile ground for interdisciplinary innovation. On one hand, the mathematical paradigms of stochastic connecting orbits—particularly Schrödinger bridges and information geodesics—now serve as the rigorous theoretical backbone for modern deep generative artificial intelligence, including diffusion models and flow matching. Conversely, machine learning provides powerful, data-driven frameworks capable of solving high-dimensional stochastic optimization problems that were previously computationally intractable. In this talk, I will first provide a broad overview of the synergistic interaction between these two subjects. Following this, I will review our recent efforts to untangle the interplay between nonlinearity and uncertainty, which is known to produce metastability, long transient behavior, and abrupt transitions between qualitatively distinct dynamical regimes. Understanding these phenomena requires mathematical descriptions that connect metastable states, evolving probability distributions, and finite-time transition processes. By leveraging Onsager–Machlup action functionals, stochastic optimal transport, and dynamical Schrödinger bridges, alongside local and nonlocal Otto calculus in the Wasserstein

space, we can rigorously characterize the most probable transition pathways. Building on these connections, we introduce a unified framework of topological, probabilistic, variational, and analytical indicators. These early-warning tools are designed to detect, characterize, and anticipate impending changes in dynamical regimes. Finally, we will illustrate how these combined geometric and data-driven approaches help solve open questions of transition-path selection, demonstrating their effectiveness in anticipating critical transitions—often referred to as tipping phenomena—within neural dynamics and other complex biophysical systems.

Biography:段金桥，主要研究方向：随机动力系统的理论与应用；随机偏微分方程理论与应用；数据驱动的数学建模-分析-学习-预估；非平衡统计物理；随机现象与复杂现象的刻画与诠释；以及数学与其它学科的交叉研究。国家重大人才工程项目入选者，国家杰出青年基金B类获得者，中国科学院海外评审专家，中国科学院海外杰出学者基金获得者，中国科协海智计划专家。

How Mathematical Structures rise from Uncertainties: Dynamics, Geometry, and Topology

Ting Gao

Huazhong University of Science and Technology, China

Abstract: Uncertainty is inherent in data generation processes, whether arising from stochastic dynamics, limited samples, or complex multi-scale interactions. Understanding how structured patterns emerge from such uncertainties is a central challenge in generative modeling. This report explores this question through the lens of dynamics, geometry, and topology, with a particular focus on early warning prediction. We investigate the mechanisms underlying critical transitions in generative models, including mode collapse and vector field splitting, which manifest as topological changes across scales. Building upon the Onsager–Machlup action functional and Schrödinger bridge theory, we introduce entropy-based indicators defined in the space of probability measures to assess and anticipate such transitions. In parallel, we examine how geometric properties of latent spaces can be exploited to improve few-shot generation, where data scarcity amplifies uncertainty. By imposing geometric constraints on latent flows, we achieve more stable training and better mode coverage. Together, these perspectives—dynamical, geometrical, and topological—offer a unified framework for understanding how certainties emerge from uncertainties, and suggest new directions for building robust and interpretable generative models.

Biography:高婷，华中科技大学数学与统计学院、数学中心副教授。2015年毕业于伊利诺伊理工大学，获博士学位。研究方向：非高斯

随机动力系统与深度学习交叉，及在脑科学、信息通信与金融中的应用。在SIAM、NSR等期刊发表SCI论文40余篇。主持和骨干参与多项研究项目。

Learning from Structured Data with Structure-Preserving Kernels

Jianyu Hu

Nanyang Technological University, Singapore

Abstract: In this talk, I will present a structure-preserving kernel framework for learning from structured observations. Rather than treating physical structures as soft constraints in the loss function, the proposed approach incorporates the observation operator directly into the reproducing kernel Hilbert space formulation, leading to an explicit closed-form estimator together with strong theoretical guarantees. I will present recent results on differential reproducing properties, kernel representations, and convergence analysis, and illustrate the framework through applications to Hamiltonian systems, manifold-valued dynamics, Wasserstein Hamiltonian flows, and operator learning for partial differential equations.

Biography: Dr. Hu Jianyu is a Postdoctoral Research Fellow at the School of Physical and Mathematical Sciences, Nanyang Technological

University (NTU), Singapore. He received his Ph.D. in Mathematics from Huazhong University of Science and Technology in 2022. His research interests lie at the intersection of geometry, dynamical systems, scientific machine learnin, and stochastic dynamics, with a particular focus on structure-preserving learning theory.

Energy Conversion and Fluctuation Relations in Levy Active Matter

Yuanfei Huang

Asia Pacific Center for Theoretical Physics, South Korea

Abstract: Stochastic thermodynamics provides a unified framework to quantify energy exchange in fluctuating environments, but its standard formulation predominantly relies on continuous Gaussian noise. Here, we extend this framework to systems driven by non-Gaussian pure-jump Levy fluctuations, which naturally emerge in strongly intermittent biological and synthetic active matter. This extension reveals the fundamental relation between energy exchange mediated by active reservoirs and the maximum extractable work. By generalizing trajectory-level energetics to discontinuous dynamics, we identify two measures of active entropy production: ΔSact, first introduced in prior work (Huang et al., Phys. Rev. Lett. 136, 068302 (2026)), and 〈A〉, newly formulated here. Crucially, we show that both quantities serve as upper bounds on the extractable work fueled by nonequilibrium active fluctuations, with

distinct advantages in different regimes. Specifically, $\Delta Sact$ provides a tighter bound in near-steady-state conditions, while $\langle A \rangle$ becomes the tighter bound when the system exhibits low irreversibility, such as during short work intervals. Using a conditional path-integral approach for jump processes, we derive generalized forms of the Clausius inequality, Crooks fluctuation theorem, and Jarzynski equality. Moreover, we show that active entropy production systematically modifies the thermodynamic performance of cyclic energy converters, leading to generalized power-efficiency trade-offs and enhanced apparent efficiencies relative to passive thermal engines. These predictions are illustrated numerically using active Brownian particles driven by Poisson shot noise. Although active fluctuations have long been recognized as a potential energy resource, this work is the first to establish a rigorous mathematical framework quantifying their role in nonequilibrium energy conversion.

Biography: Yuanfei Huang is currently a Research Fellow at the Asia Pacific Center for Theoretical Physics (APCTP), Pohang, South Korea, working with Prof. Jongmin Park. Previously, he was a Postdoctoral Researcher in the Departments of Mathematics and Data Science at City University of Hong Kong, under the supervision of Prof. Xiang Zhou, and a Research Fellow in the Department of Statistics and Data Science at the National University of Singapore, working with Prof. Adrian Röllin. He received his Ph.D. in Statistics from Huazhong University of Science and

Technology in 2021, supervised by Prof. Jinqiao Duan. Dr. Huang's research focuses on stochastic dynamics, nonequilibrium statistical physics, and scientific machine learning. His work develops probability-flow formulations, transition-path theory, and score-based methods to study rare events and non-Gaussian stochastic systems. He has contributed to entropy production in active matter, Lévy-driven stochastic processes, and generative sampling algorithms for stochastic differential equations, with publications in leading journals including PRL, SINUM, SIAP, SISC, JNS, and Nonlinearity.

Deep operator learning for efficient sampling from invariant measures of stochastic differential equations

Lei Li

Shanghai Jiao Tong University, China

Abstract: We introduce an amortized neural sampler that combines operator learning with flow based sampling methods. It maps SDE coefficient functions to push-forwards from a reference measure to the invariant measures, enabling efficient sampling across families of stochastic differential equations. Different from traditional grid-based operator learning, we propose a new framework that utilizes Lagrangian trajectory sensors for the coefficient functions and a cross-attention mechanism in the architecture to handle high-dimensional problems. We

also theoretically establish the expressivity and resolution invariance of our framework.

Biography:李磊，博士毕业于美国威斯康星大学(麦迪逊)，其后在美国杜克大学数学系做博士后，于2018年加入上海交通大学。现为上海交通大学自然科学研究院、数学科学学院教授，入选了国家海外高层次人才计划(青年)，主持了国自然青年项目、面上项目、科技部重点研发计划青年科学家项目。李磊的主要研究领域为应用数学及计算数学，研究方向包括针对粒子系统及数据科学的随机模拟算法及抽样方法，迄今为止在国内外知名学术期刊上发表学术论文六十余篇。

A Generative Saddle Searching Method: Based on Witten-Laplacian Spectral Problem

Xiaoguang Li

Hunan Normal University, China

Abstract: The low-lying eigen p-forms of the Witten–Laplacian are known to localize exponentially near index-p critical points, providing a potentially powerful approach for identifying all these critical points, particularly minima (p=0) and saddles with one unstable direction (p=1). We introduce the Witten-Laplacian Generative Method, a generative framework that reformulates these eigenstates as localized probability densities to efficiently locate minima and index-1 saddles. For the 0-

forms, we derive the variational generative formulation based on the symmetrized Fokker-Planck operator to identify all minima on the energy landscape. For the 1-forms, we derive two corresponding variational problems as the lower and upper bounds of the original spectral problem of 1-forms. We rigorously prove the similar spectral gap and exponential localization, in the semi-classic limit of vanishing noise, of our new scalar-valued spectral problem to the original Witten-Laplacian. WLGM employs a normalizing flow to sample these exponentially localized probability densities, producing transport maps that converge to all local minima and index-1 saddle points. Numerical experiments demonstrate the scalability and efficiency of the proposed method.

Biography:李筱光，湖南师范大学副教授，2015年获得北京大学计算数学博士学位。获得科技部重点研究计划、国自然青年基金等科研项目资助。研究领域为结合随机方法的深度学习，成果发表于SIAM Journal on Scientific Computing, SIAM Journal on Mathematical Analysis, Multiscale Modeling and Simulation等期刊，成果被选为SIAM高影响深度学习论文。

A high-dimensional density estimation method and its application for solving PDEs

Qifeng Liao

ShanghaiTech University, China

Abstract: Probability density estimation remains an open challenging problem in computational science and engineering. By coupling the Knothe-Rosenblatt (KR) rearrangement and the flow-based generative model, we developed an invertible transport map, called KRnet, for high-dimensional density estimation. In this talk, we give an overview of KRnet and discuss its adaptive version for the Fokker-Planck equations and stochastic dynamic systems. KRnet for solving Bayesian inverse problems is also studied.

Biography:廖奇峰目前为上海科技大学信息科学与技术学院常任副教授、研究员、博士生导师，视觉与数据智能研究中心联合主任、中国数学会计算数学分会理事。于2010在英国曼彻斯特大学数学学院获得数值计算博士学位，于2006年获得四川大学数学学院学士学位。2011年1月至2012年6月，在美国马里兰大学计算机系从事博士后研究工作；2012年7月至2015年2月，在美国麻省理工学院航空航天系从事博士后研究工作；2015年3月，作为研究员加入上海科技大学信息科学与技术学院。

Generative Path-Finding Method for Wasserstein Gradient Flow

Chengyu Liu

City University of Hong Kong, China

Abstract: Wasserstein gradient flows (WGFs) describe the evolution of probability distributions in Wasserstein space as steepest descent

dynamics for a free energy functional. Computing the full path from an arbitrary initial distribution to equilibrium is challenging, especially in high dimensions. Eulerian methods suffer from the curse of dimensionality, while existing Lagrangian approaches based on particles or generative maps do not naturally improve efficiency through time step tuning. We propose GenWGP, a generative path finding framework for Wasserstein gradient paths. GenWGP learns a generative flow that transports mass from an initial density to an unknown equilibrium distribution by minimizing a path loss that encodes the full trajectory and its terminal equilibrium condition. The loss is derived from a geometric action functional motivated by Dawson Gartner large deviation theory for empirical distributions of interacting diffusion systems. We formulate both a finite horizon action under physical time parametrization and a reparameterization invariant geometric action based on Wasserstein arclength. Using normalizing flows, GenWGP computes a geometric curve toward equilibrium while enforcing approximately constant intrinsic speed between adjacent network layers, so that discretized distributions remain nearly equidistant in the Wasserstein metric along the path. This avoids delicate time stepping constraints and enables stable training that is largely independent of temporal or geometric discretization. Experiments on Fokker Planck and aggregation type problems show that GenWGP matches or exceeds high fidelity reference solutions with only about a dozen discretization points while capturing complex dynamics.

Biography:刘程宇，香港城市大学数据科学系四年级博士研究生。主要研究方向包括随机动力系统、最优输运、生成模型与稀有事件数值方法，重点关注复杂随机系统的数学建模、理论分析与数值计算，以及相关方法在科学计算和机器学习中的应用。

Structure-Aware Variational Learning of a Class of Generalized Diffusions

Yubin Lu

South China University of Technology, China

Abstract: Learning the underlying potential energy of stochastic gradient systems from partial and noisy observations is a fundamental problem arising in physics, chemistry, and data-driven modeling. Classical approaches often rely on direct regression of governing equations or velocity fields, which can be sensitive to noise and external perturbations and may fail when observations are incomplete. In this work, we propose a structure-aware, energy-based learning framework for inferring unknown potential functions in generalized diffusion processes, grounded in the energetic variational approach. Starting from the energy–dissipation law associated with the Fokker–Planck equation, we construct loss functions based on the De Giorgi dissipation functional, which

consistently couple the free energy and the dissipation mechanism of the system. This formulation avoids explicit enforcement of the governing partial differential equation and preserves the underlying variational structure of the dynamics. Through numerical experiments in one, two, and three dimensions, we demonstrate that the proposed energy-based loss exhibits enhanced robustness with respect to observation time, noise level, and the diversity and amount of available training data. These results highlight the effectiveness of energy–dissipation principles as a reliable foundation for learning stochastic diffusion dynamics from data.

Biography:卢裕滨，2017年与2022年分别于华中科技大学获得学士学位和博士学位，2022-2025年在伊利诺伊理工大学博士后。研究方向为数据驱动建模、随机动力系统、能量变分法、生成模型等。

Transformers Learn the Optimal DDPM Denoiser for Multi-Token GMMs

Hancheng Min

Shanghai Jiao Tong University, China

Abstract: Transformer-based diffusion models have demonstrated remarkable performance at generating high-quality samples. However, our theoretical understanding of the reasons for this success remains limited. For instance, existing models are typically trained by minimizing a denoising objective, which is equivalent to fitting the score function of

the training data. However, we do not know why transformer-based models can match the score function for denoising, or why gradient-based methods converge to the optimal denoising model despite the non-convex loss landscape. To the best of our knowledge, this paper provides the first convergence analysis for training transformer-based diffusion models. More specifically, we consider the population Denoising Diffusion Probabilistic Model (DDPM) objective for denoising data that follow a multi-token Gaussian mixture distribution. We theoretically quantify the required number of tokens per data point and training iterations for the global convergence towards the Bayes optimal risk of the denoising objective, thereby achieving a desired score matching error. A deeper investigation reveals that the self-attention module of the trained transformer implements a mean denoising mechanism that enables the trained model to approximate the oracle Minimum Mean Squared Error (MMSE) estimator of the injected noise in the diffusion steps. Numerical experiments validate these findings.

Biography:上海交通大学自然科学研究院/数学科学学院副教授、博士生导师。闵含城博士于2016年获上海同济大学自动化专业学士学位，2018年获美国宾夕法尼亚大学系统工程硕士学位，2023年获约翰霍普金斯大学电气与计算机工程博士学位。2023至2025年于宾夕法尼亚大学数据工程与科学创新中心(IDEAS)任博士后研究员，2025年9月加入上海交通大学。其主要研究领域为深度学习理论。

Generalization Properties of Adaptive Langevin Diffusion Dynamics

Kui Ren

Columbia University, USA

Abstract: We study how learning with an adaptive, state-dependent diffusion shapes the generalization of the trained model. Its defining feature is a decoupling, made explicit through a Girsanov-based information bound: the generalization gap is controlled by the diffusion floor alone, whereas mixing accelerates with the dynamic range of the diffusion, so noise may be inflated to explore faster at no information-theoretic generalization cost---a principle we summarize as raise the ceiling, not the floor. We turn this into a quantitative link from faster mixing to lower test error.

Biography: Professor Ren received his BS from Nanjing University in China. He obtained his PhD from the Applied Mathematics Program at Columbia University in May 2006. He moved to the University of Chicago as an L. E. Dickson instructor in 2007 and joined the University of Texas at Austin as an assistant professor in the Department of Mathematics and the Oden Institute in Fall 2008. He returned to Columbia in 2018 as a Professor of Applied Mathematics. His recent efforts include performing theoretical and numerical analysis of inverse problems for partial differential equations (for applications in various areas of imaging science), developing methods for computational optimization problems in physical systems, studying the propagation of acoustic/electromagnetic waves in complex media, characterizing emerging phenomenon in large dense random graphs and networks, as well as developing computational algorithms for simulating particle transport in heterogeneous media.

Weighted Laplacian Flow: A Deterministic Particle Flow with Provable Convergence

Zuoqiang Shi

Tsinghua University, China

Abstract: Sampling from a target probability density is a fundamental task in statistics, machine learning, and scientific computing. We introduce weighted Laplacian flow, a deterministic particle-flow method that transports samples from a tractable initial density to a target density known up to normalization. The method evolves the logarithmic density ratio between the target and the transported distribution and constructs the particle velocity by solving a weighted Poisson equation associated with the target density. We establish the global well-posedness of the proposed PDE system and prove that the transported density converges to the target density. Under a sublinear forcing condition, the method achieves exact

convergence in finite time. Numerical experiments on multimodal, heavy-tailed, and ten-dimensional targets demonstrate that weighted Laplacian flow can perform long-range mass transport, overcome energy barriers.

Biography:史作强，清华大学丘成桐数学科学中心长聘教授，北京雁栖湖应用数学研究院兼职研究员，主要研究方向为偏微分方程数值方法，图像处理和机器学习中的微分方程模型，非线性非平稳信号时频分析等，在ACHA，SIAM系列期刊，Advances in Mathematics，ARMA等国际知名学术期刊发表文章50余篇。

基于Koopman理论的连续谱动力系统表示与预测方法

Jun Shu

Xi'an Jiaotong University, China

Abstract:对高维时空混沌动力系统进行表示与预测，仍然是动力系统理论与机器学习领域中的一个基础性挑战。高维、非线性且具有连续谱结构的动力系统广泛存在于气候演化、湍流流动、复杂网络传播以及神经动力学等现实场景中。尽管目前数据驱动方法能够实现较为准确的短期预测，但在以宽频或连续谱为主导的系统中，它们往往缺乏稳定性、可解释性和可扩展性。Koopman理论为非线性动力学的表征和预测提供了一个线性化视角，但现有方法通常依赖于有限维逼近，这在高维场景下往往导致性能退化。本报告提出一种新的神经Koopman方法，通过将可逆运动与不可逆耗散分离，实

现对动力系统的结构化表示。该方法在提高长期预测精度与稳定性的同时，也有助于揭示混沌行为中哪些方面是可以被理解和学习的。

Biography: 束俊，西安交通大学数学与统计学院教授，博导。于2016年和2023年分别获西安交通大学理学学士与理学博士学位。目前从事于机器学习基础理论与方法研究；已在JMLR/TPAMI/TMLR/NSR/NeurIPS/ICML等国际顶级期刊和会议发表学术论文30余篇；ESI高被引论文2篇；单篇论文引用超1200次。主持科技部重点研发计划青年科学家项目、基金委面上项目以及多项企业横向课题等。曾获陕西省科学技术进步奖一等奖（排名第3）、教育部"基础学科拔尖学生培养计划"2.0"提问与猜想"活动特等奖优秀指导教师、"CCF博士学位论文激励计划"提名、粤港澳大湾区（黄埔）国际算法算例大赛擂台赛冠军、NeurIPS杰出审稿人奖等奖项。

Continuous-time heterogeneous agent models with recursive utility: theory and numerical methods

Qing Tang

China University of Geosciences (Wuhan), China

Abstract: We consider continuous-time heterogeneous agent models in macroeconomics with recursive utility (Epstein-Zin utility) cast as mean field games. The model leads to a system coupling a pair of Hamilton-Jacobi-Bellman equations with state constraints and Fokker-Planck-

Kolmogorov equations. We investigate the theory and numerical methods for solving these mean field games. This talk is based on two joint works with Yves Achdou (Universite Paris Cite).

Biography:汤庆，工作领域为平均场博弈论的理论与数值计算方法，以及平均场博弈方法在异质个体宏观经济模型中的应用。近期工作发表于SIAM control and optimization,M3AS,Applied Mathematics &Optimization等。

Boundary-Adapted PINNs for Elliptic Dirichlet Problems: $H^2(\Omega)$ A Priori Error Bounds with Application to Mean Escape Time Computation

Nathanael Tepakbong

City University of Hong Kong, China

Abstract: Motivated by the numerical computation of the Mean Escape Time (MET) $\tau: \Omega \to \mathbb{R}$ of a stochastic process from a bounded domain $\Omega \subseteq \mathbb{R}^d$, we study elliptic Dirichlet boundary value problems (BVPs) using boundary-enforced Physics-Informed Neural Networks (PINNs), in which the Dirichlet condition is imposed exactly by multiplying the network output with a predefined distance-to-boundary approximation ρ. Combining approximation-theoretic and statistical-learning arguments for Rectified Quadratic Unit (ReQU) and hyperbolic tangent (tanh) networks, we derive a priori error bounds that make explicit the dependence on ρ. In

particular, we show that exact boundary enforcement alone is not enough for $H^2(\Omega)$ error bounds, and that a sufficient and essentially necessary condition is for ρ to be a smooth distance approximation normalized to first order, of the kind constructed in (sukumar2022exact). We thereby identify this subclass of boundary-adapted PINNs as the appropriate neural network ansatz for solving Dirichlet BVPs. Numerical experiments support the theory, showing that appropriate choices of ρ improve accuracy and convergence, while poorly chosen distance functions can substantially degrade the solution. Our proof also yields new VC-dimension bounds for hypothesis spaces of higher-order derivatives of ReQU and tanh networks, together with new approximation bounds for shallow ReQU networks in higher-order Sobolev norms, all of which are of important independent interest.

Biography: Nathanael Tepakbong is an incoming Postdoctoral Researcher at the Department of Mathematics of City University of Hong Kong, where he also recently completed his PhD under the supervision of Prof. Xiang Zhou. He earned his bachelor's and master's degrees from ISAE-Supaéro and the University of Toulouse (France). His research interests focus on the theoretical aspects of Machine Learning and their applications to scientific problems and modern AI algorithms.

Learning collective multicellular dynamics with interacting mean field neural SDE models

Lin Wan

Chinese Academy of Sciences, China

Abstract: Time-resolved single-cell and spatial transcriptomic technologies offer unprecedented opportunities to investigate collective dynamics in heterogeneous multicellular systems. Yet many computational approaches treat cells independently or represent population effects only implicitly, limiting their ability to resolve how cell-cell interactions shape high-dimensional, nonequilibrium biological processes. In this talk, I will present scIMF and SpaMIND, two deep generative interacting-particle frameworks for learning multicellular dynamics from temporal transcriptomic data. Built on McKean–Vlasov stochastic differential equations, scIMF models each cell's dynamics through its intrinsic gene-expression state and the evolving population distribution. Cell-wise Transformer attention learns nonlocal, asymmetric, and potentially nonreciprocal interactions directly from data. SpaMIND extends this framework to time-series spatial transcriptomics by jointly modeling gene-expression and spatial-position dynamics. It combines global attention for population-wide interactions with message passing over a dynamic spatial-neighborhood graph for local interactions.

Together, these methods reconstruct collective cellular dynamics and generate interpretable hypotheses about multiscale interactions in complex biological systems.

Biography:万林，中国科学院数学与系统科学研究院研究员。2003年获南京大学物理系理学学士学位，2009年获北京大学数学科学学院理学博士学位。曾先后于美国南加州大学、美国数学生物研究所、德国马克斯·普朗克研究所等机构从事博士后或访问研究。主要研究领域为计算生物学、系统生物学、数据科学和人工智能等。

原子大模型驱动的材料设计与发现

Han Wang

Institute of Applied Physics and Computational Mathematics, China

Abstract:面向性质的材料设计受制于实验数据稀缺与分布外泛化两大困难。本报告介绍以原子大模型为核心的应对路径。理论上，我们建立局域原子环境的完备等变表示，并证明等变图神经网络的万有逼近性质。据此设计的DPA4模型在Matbench Discovery、OMat24、OMol25等基准上，以更少的参数量与推理开销达到领先精度。大规模预训练获得的原子尺度先验经微调可迁移至小数据性质预测任务，显著改善分布外泛化。以轻质因瓦合金设计为例，原子大模型与智能体驱动的干湿闭环相结合，仅需少量实验迭代即突破传统合金路线的边界，获得兼具近零膨胀与更低密度的候选合金。理论保证的

架构、大规模预训练与闭环实验反馈的结合，为稀缺数据下的材料设计提供了系统性途径。

Biography:王涵自2014年起任职于北京应用物理与计算数学研究所教授，并担任博士生导师。2011年获北京大学数学科学学院理学博士学位。2011—2014年在德国柏林自由大学数学与计算机科学系从事博士后研究。研究方向主要包括科学智能（AI for Science）、原子尺度建模与计算方法。曾获2020年戈登·贝尔奖（Gordon Bell Prize）及2024年国际基础科学大会前沿科学奖（Frontiers of Science Award）。

High-dimensional non-convex sampling via solving SDEs

Xiaojie Wang

Central South University, China

Abstract: Generating samples from a high dimensional probability distribution is a fundamental task with wide-ranging applications in the area of scientific computing, statistics and machine learning. This talk will focus on high dimensional sampling algorithms based on time discretizations of stochastic differential equations (SDEs). New algorithms and new error bounds will be then provided for high-dimensional non-convex sampling, where the convergence rate and the dimension dependence are explicitly revealed. Numerical experiments will be finally presented to corroborate the theoretical findings.

Biography:王小捷，中南大学数学与统计学院教授、博士生导师。本硕博就读于中南大学，2012年获理学博士学位。研究方向为随机微分方程数值方法、机器学习和人工智能中的高维采样算法及扩散生成模型的数学理论等，相关论文发表在 SIAM J. Numer. Anal.、Math. Comp. 、 SIAM J. Sci. Comput. 、 IMA J. Numer. Anal. 、 J. Comput. Phys.、Stoch. Proc. Appl.、Automatica等刊物以及机器学习人工智能顶会ICML。 近年来主持国家自然科学基金面上项目、湖南省自科杰出青年基金等科研项目多项。

一类针对随机系统的量子计算方法

Wei Wei

Chongqing University, China

Abstract:量子计算因其潜在的指数级加速能力而备受关注。然而，由于量子系统内在的酉演化约束，经典科学计算方法难以在保持量子优势的前提下被直接移植为量子算法。本报告将首先介绍量子计算的基本背景，随后阐述一种能高效将经典科学计算算法转化为量子算法的框架——薛定谔化方法（Schrödingerisation Method）。在此框架下，我将探讨针对线性随机微分方程的量子算法及其量子优势；此外，还将汇报近期在线性倒向随机微分方程量子算法研究上的最新进展。

Biography:魏崴，重庆大学弘深青年教师，主要研究方向为随机微分方程与量子计算方法，大偏差原理，随机系统转移现象的刻画与计算。

Transitions and Basin Stability in a Delayed FitzHugh-Nagumo Neural Model Driven by Non-Gaussian Colored Noise

Fengyan Wu

Chongqing University, China

Abstract: In this study, we investigate the state transition behaviors and basin stability of a delayed FitzHugh–Nagumo (FHN) neural model under non-Gaussian colored noise. The original time-delay stochastic system is approximated as a Markovian system for feasible dynamical analysis. We employ the mean first exit time (MFET) and first escape probability (FEP) to quantify transitions between neuronal excited and resting states, and use the stochastic basin of attraction (SBA) to evaluate regional stability. The results demonstrate that noise intensity, time delay, and non-Gaussian deviation parameter significantly affect neural dynamic behaviors. This study sheds light on how noise and time delay jointly modulate neuronal dynamical behaviors.

Biography:吴凤艳，2018年毕业于华中科技大学，毕业后入职重庆大学。主要从事随机动力系统及其应用、偏微分方程数值解、生物动力系统仿真等工作。主持完成国家自然科学基金青年科学基金、

中国博士后科学基金、重庆市自然科学基金博士后项目等，发表多篇SCI论文，获选2020年度“澳门青年学者计划”。

Learning Stochastic Dynamics: From Coarse-Graining to Generative Models

Hao Wu

Shanghai Jiao Tong University, China

Abstract:待补充

Biography: Hao Wu is a professor in the Institute of Natural Sciences at Shanghai Jiao Tong University. He earned his Bachelor's and Ph.D. degrees in Computer Science and Technology from Tsinghua University in 2002 and 2007, respectively. Dr. Wu conducted postdoctoral research at the Institute of Mathematics, Free University of Berlin, from 2007 to 2018, and later served as a faculty member in the School of Mathematical Sciences at Tongji University until 2023. During his time in Berlin, he also served as the PI of the research group on “Machine Learning for Time Series” at the Zuse Institute Berlin from 2017 to 2018. His primary research focus lies in the development of machine learning methodologies for modeling and analysis of simulation data of molecular systems.

Variational Method for Transition Pathways

Zhiyou Wu

City University of Hong Kong, China

Abstract: Rare transition events in metastable systems under noisy fluctuations are crucial to processes ranging from molecular conformational changes to nucleation and phase transformations. This talk presents variational approaches for accelerating the identification of the most probable transition pathways in high-dimensional energy landscapes. StringNET represents a continuous pathway using a neural network and employs a temperature-dependent max-flux objective to pretrain the path and accelerate subsequent geometric-action minimization, providing an effective initialization strategy. To further address the problem of finding minimum-energy paths in the low-temperature limit, a Hessian-free iterative variational method is developed within a Riemannian framework that unifies minimum-energy and minimum-free-energy paths. The consistency and convergence of the method toward generalized minimum-energy paths are established. Numerical examples involving alanine dipeptide, chignolin folding, and Barnase–Barstar association demonstrate the accuracy and efficiency of the proposed approach.

Biography: I am a PhD student in the Department of Data Science at City University of Hong Kong, supervised by Professor Xiang Zhou. My research focuses on developing methods for finding transition pathways in metastable systems.

Bayesian Optimization on Networks

Ruiyi Yang

Shanghai Jiao Tong University, China

Abstract: We study optimization on networks modeled as metric graphs. Motivated by applications where the objective function is expensive to evaluate or only available as a black box, we develop Bayesian optimization algorithms that sequentially update a Gaussian process surrogate model of the objective to guide the acquisition of query points. To ensure that the surrogates are tailored to the network's geometry, we adopt Whittle-Matérn Gaussian process prior models defined via stochastic partial differential equations on metric graphs. In addition to establishing regret bounds for optimizing sufficiently smooth objective functions, we analyze the practical case in which the smoothness of the objective is unknown and the Whittle-Matérn prior is represented using finite elements. Numerical results demonstrate the effectiveness of our algorithms for optimizing benchmark objective functions on a synthetic metric graph and for Bayesian inversion via maximum a posteriori estimation on a telecommunication network.

Biography:杨睿逸现为上海交通大学自然科学研究院和数学科学学院长聘教轨副教授。2017年本科毕业于加州大学洛杉矶分校，2022年博士毕业于芝加哥大学，随后在普林斯顿大学从事博士后研究。主要研究方向包括非欧几何场景下的贝叶斯计算方法、非参数统计理论、以及计算调和分析，为反问题和机器学习提供数学基础。学术成果发表于SIAM系列，Ann. Stat., J. Mach. Learn. Res.等期刊。

Tensor-train density estimation and its application in free energy exploration

Siyao Yang

Academy of Mathematics and Systems Science, Chinese Academy of Sciences, China

Abstract: High-dimensional probability distributions arise throughout scientific computing, yet their estimation, representation, and evaluation are often hindered by the curse of dimensionality. In this talk, I will present a tensor-train-based framework for learning high-dimensional densities from samples. The method first smooths the empirical distribution to reduce its large variance, compresses the resulting coefficient tensor using efficient tensor-train algorithms, and then applies a deconvolution step to recover a functional density estimator. The proposed method can achieve computational complexity linear in both the dimension and the number of samples. Its performance is demonstrated

on several tasks, including high-dimensional Boltzmann distribution estimation and image generation. I will then discuss an application of this framework to molecular dynamics called TT-Metadynamics. In this method, the growing sum of Gaussian bias potentials generated during metadynamics is periodically compressed into a functional tensor train. This avoids exponential grid storage and prevents the cost of evaluating the bias potential from increasing with simulation time. The method enables free-energy exploration with up to 14 collective variables and performs favorably compared with standard metadynamics in high-dimensional examples.

Biography:杨斯尧目前是中国科学院数学与系统科学研究院计算数学所副研究员。此前，于芝加哥大学计算与应用数学系担任William H. Kruskal Instructor，2020年获得新加坡国立大学应用数学博士学位，2016年获得四川大学应用数学学士学位。杨斯尧的研究兴趣主要包括开放量子系统的数值方法、稀薄气体的建模与数值模拟，以及基于张量网络的快速算法。

Learning Hidden SDEs and Mean-Field Interaction Kernels from Trajectory Data

Wuyue Yang

Beijing Institute of Mathematical Sciences and Applications (BIMSA), China

Abstract: Inferring hidden stochastic dynamics from trajectory data is a central inverse problem, yet classical approaches typically require large ensembles of trajectories. I will present a weak-form sparse-regression framework that tackles this in two settings. For a single long trajectory, we develop STWCR: ergodicity turns the trajectory into samples of the stationary distribution, whose score function is recovered in weak form; a new identity then expresses the drift through the score function and the diffusion, so both terms follow from sparse regression at low cost. The method handles non-gradient drifts, multi-scale and high-dimensional problems, and separates systems sharing a stationary distribution but differing by a curl. For interacting particle systems, we introduce WISE, which learns mean-field McKean–Vlasov interaction kernels directly from particle trajectories via Gaussian test functions and two-stage sparse optimization. Beyond polynomial, Coulomb, Cucker–Smale and Vicsek benchmarks, WISE is applied to GPS data from homing-pigeon flocks, recovering alignment strength, noise intensity and heterogeneous individual turning rates that reveal transient leadership.

Biography: Dr. Wuyue Yang is an Assistant Research Fellow at the Beijing Institute of Mathematical Sciences and Applications (BIMSA). She received her Ph.D. in Applied Mathematics from Tsinghua University's Yau Mathematical Sciences Center in 2022. Dr. Yang has published more than 20 peer-reviewed papers in journals including SIAM

Journal on Scientific Computing, Physics of Fluids, Journal of Computational Physics, npj Artificial Intelligence, and Chaos. She serves as Principal Investigator on research grants from the National Natural Science Foundation of China. She also teaches AI courses and supervises three doctoral students.

From Phase Discovery to Transition Pathways in the Landau–Brazovskii Model

Jianyuan Yin

Beijing Normal University, China

Abstract: The Landau–Brazovskii (LB) model provides a fundamental framework for describing modulated phases in systems with competing short- and long-range interactions. To identify ordered structures, a geometry-adaptive deep variational framework is developed to jointly optimize the order parameter and the computational domain. This approach enables the identification of complex 3D ordered phases without prior knowledge and the construction of the phase diagram. Transition pathways between distinct ordered phases are further explored using saddle dynamics. These results offer valuable insights into the structural transformations of modulated-phase systems.

Biography:殷鉴远，北京师范大学数学科学学院讲师，入选国家高层次人才。研究方向为鞍点和解景观的算法和应用。2017年在北京

大学获学士学位，2021年在北京大学获博士学位，2021年至2025年在新加坡国立大学从事博士后研究。2025年入职北京师范大学。

On the Limits of Latent Reuse in Diffusion Models

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Abstract: Diffusion models are often trained in low-dimensional latent spaces, which are then reused for related but shifted datasets. In this work, we study when such latent reuse remains reliable under distribution shift. We consider a source-target setting in which both datasets are approximately low-dimensional but may lie near different subspaces. We show that freezing and reusing a source latent space induces a target-domain score error governed by two quantities: the principal-angle misalignment between the source and target subspaces, and the target ambient noise amplified by the diffusion time scale. Motivated by these limits, we further study mixed source-target training and characterize how the required shared latent dimension depends on the relative geometry of the two distributions. Our results provide theoretical guidance on when latent reuse is reliable and when learning a shared representation may be necessary.

Biography:于露，现为香港城市大学数据科学系助理教授。她先后于山东大学、华盛顿大学和多伦多大学获得数学与应用数学学士、

统计学硕士和统计学博士学位，并曾在CREST/ENSAE Paris从事博士后研究。她的研究方向主要涉及机器学习、优化与统计学的交叉领域，目前主要研究抽样算法及扩散模型的理论。

MAGNet: A Differentiable Gaussian Distance Primitive for Function Approximation and Representation Disentanglement

Gangnan Yuan

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Abstract: The inner product is the nearly universal primitive of contemporary neural networks; its geometric complement, the distance to a learned prototype, was exiled from deep learning because its natural carrier, the Gaussian mixture, relied on positive-definiteness and expectation-maximization constraints that are incompatible with gradient descent. We argue that distance deserves status as a first-class neural primitive, and we make it trainable: MAGNet (Mixture of Augmented Gaussian Network) reparameterizes the Gaussian precision as , which is positive semi-definite for every real , so a valid metric is maintained automatically without EM, eigenvalue clipping, or projection, while anisotropic correlations are learned freely. We demonstrate that the distance primitive is provably complementary to projection-based units for function since the two span mutually non-inclusive function classes, so a hybrid layer is strictly more expressive than either alone. We also

show that the same module discretizes naturally into factorized codes because its responses encode proximity to a set of prototypes. We prove that, under weak factor supervision shown to be necessary, this distance-to-discrete bottleneck block-identifies the generative factors and quantizes them in a topology-preserving way, where an unconstrained linear bottleneck need not. Empirically, MAGNet matches or exceeds KAN and PINN baselines on function fitting and a Poisson equation with fewer parameters, and a plain Gaussian-Mixture autoencoder yields disentanglement competitive with or superior to variational, adversarial, and diffusion-based methods. The contribution is a primitive and a principle: distance is not an afterthought to the inner product.

Biography:苑罡男，云南大学数学与统计学院讲师，助理研究员。博士毕业于澳门大学数学系，曾在大湾区大学从事博士后工作。主要研究方向为机器学习算法设计及其应用。

Endogenous business cycles via state-dependent saving and noise-induced metastability

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Abstract: We develop a parsimonious stochastic growth model in which state-dependent saving behavior generates endogenous business-cycle-like dynamics. The model consists of three coupled equations: a Solow-

type capital accumulation equation, a linear filtering equation for the saving rate, and a bounded stochastic adjustment process. Saving is modeled as a logistic function of deviations from a balanced growth path, introducing nonlinear feedback controlled by a gain parameter. In the deterministic limit, increasing feedback strength produces a supercritical pitchfork bifurcation, splitting the balanced-growth equilibrium into two locally attracting regimes corresponding to expansion and contraction. When stochastic perturbations are introduced, these equilibria become metastable states, and the economy undergoes rare noise-induced transitions between them. The resulting dynamics exhibit persistent regimes, bimodal stationary densities, and right-skewed dwell-time distributions with approximately exponential survival tails. A discrete-time approximation is estimated using U.S. real GDP data, and Monte Carlo simulations are used to compute stationary distributions and regime persistence statistics. The results demonstrate that nonlinear state dependence, bounded multiplicative noise, and time-scale separation are sufficient to generate realistic business-cycle behavior within a low-dimensional framework.

Biography:袁胜兰，大湾区大学理学院助理教授。研究方向为随机动力系统、随机偏微分方程和统计物理。近年在SIAM Journal on Applied Dynamical Systems、Chaos等国际期刊上发表20余篇学术论文。受邀在伯努利-IMS第十一届世界概率统计大会、Oberwolfach数

学研究所、统计物理国际大会、全球年轻女士概率研究学者大会上作报告。

Score-Based Neural ODEs for Mean-Field Control and Fokker–Planck Equations

Mo Zhou

Peking University, China

Abstract: We present a score-based neural ODE framework for learning probability flows in stochastic dynamics and mean-field control. The key idea is to evolve the score function—the gradient of the logarithm of the density—along deterministic trajectories using coupled ordinary differential equations, avoiding explicit density estimation. As an important application, we reformulate the Fokker–Planck equation as a deterministic continuity equation and interpret flow matching as a mean-field control problem. The resulting score-based normalizing flow efficiently approximates the score through derivatives of the learned velocity field. Numerical experiments on Langevin dynamics, chaotic systems, and high-dimensional interacting particle systems demonstrate the accuracy and scalability of the proposed approach.

Biography:周默，北京大学数学科学学院助理教授。2018年毕业于清华大学数学科学系，2023年获美国杜克大学（Duke University）数学博士学位，随后在加州大学洛杉矶分校（UCLA）数学系担任博

士后研究员，2026年起在北京大学数学科学学院任助理教授。主要从事应用数学、科学计算与人工智能交叉领域的研究，研究方向包括随机最优控制、平均场控制与平均场博弈、深度学习与生成模型，以及高维科学计算。近年来致力于将机器学习方法与控制理论相结合，发展面向高维随机动力系统的高效算法。

AI动态虚拟细胞构建理论与算法

Peijie Zhou

Peking University, China

Abstract: 人工智能虚拟细胞（Artificial Intelligence Virtual Cell，AIVC）正日益成为生物学与人工智能交叉融合的前沿方向。其核心愿景是构建能够模拟和预测细胞状态动态演化的数字孪生，为实验设计和机制分析提供计算支撑（Cell，2024）。近年来，受大语言模型（Large Language Models，LLMs）启发的组学基础模型在多任务学习方面展现出一定潜力，但近期评测表明，在复杂生物过程建模中，其动态预测能力和机制可解释性仍存在明显局限（Nature Methods，2025）。在这一背景下，融合生物学先验与动态机制的数学建模方法重新受到关注（Cell，2025）。然而，AIVC构建所依赖的关键数据——单细胞多组学观测——普遍面临采样稀疏和高维异质性等问题。以微分方程为核心的传统建模方法在数据驱动场景下容易受到可观测性不足和维数灾难的制约，难以准确刻画高分辨率、连续的时空动态过程。针对这些问题，我们探索了一套融合生成式

人工智能方法与动力系统理论的统一建模框架。该框架将最优传输（Optimal Transport）、薛定谔桥（Schrödinger Bridge）、微分几何等数学理论，与流匹配（Flow Matching）、扩散模型等生成式人工智能技术相结合，从静态、异质的单细胞组学时序快照中推断细胞增殖、凋亡、分化、迁移以及细胞间相互作用等复杂状态转变的连续动态过程。与黑箱方法相比，该框架兼具较强的生成能力和泛化能力，同时能够更自然地引入动态约束与生物学先验，提高模型的机制可解释性。基于这一框架，可以在不同时间尺度和空间结构下生成细胞状态数据，为构建兼具可解释性、预测能力和生物学先验整合能力的动态虚拟细胞模型提供新的理论与算法基础。

Biography:周沛劼，北京大学前沿交叉学科研究院国际机器学习研究中心和定量生物学中心研究员、博士生导师，博雅青年学者，国家级青年人才。2014年和2019年在北京大学数学科学学院获得计算数学学士和博士学位，导师为李铁军教授，获北京大学优秀博士论文奖；2020-2023年任美国加州大学尔湾分校数学系访问助理教授，合作导师为聂青教授。主要从事计算系统生物学、单细胞组学动力学、复杂生物系统建模与AI for Science研究。相关成果发表在Nature正刊,大子刊(NM, NCC, NMI,NG), NC, SA, PRX, MSB, AS等重要交叉学科期刊以及ICLR, ICML, NeurIPS, AAAI等人工智能顶级会议，并担任Nature Methods, PNAS, Nature Communications, Cell Genomics, Cell Systems, SIAP等多个期刊审稿人。

非平衡耗散系统的可辨识学习

Aiqing Zhu

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Abstract:复杂耗散系统广泛存在于高分子物理、活性物质以及现代学习算法等诸多领域。这类系统通常远离热力学平衡，其动力学行为由能量耗散与时间不可逆性主导，但这些关键特征往往难以仅从观测数据中被可靠刻画。针对这一问题，本报告将介绍具有普适性和可辨识性的神经网络建模框架，其可直接从随机轨迹数据中学习耗散随机动力学。该框架在保证表达能力的同时，明确区分可逆与不可逆运动结构，识别唯一的能量景观，并支持对熵产生率的直接计算，从而为定量描述系统的不可逆性提供了严格依据。通过在高分子拉伸动力学和随机梯度朗之万动力学中的应用，结果揭示了多个非平衡特性的新规律，表明该方法能够作为一种统一的数据驱动工具，用于发现和解释复杂系统中的非平衡动力学机制。

Biography:祝爱卿，新加坡国立大学博士后。2018年本科毕业于中国科学技术大学数学系，2023年于中国科学院数学与系统科学研究院获博士学位。研究方向为动力系统的几何算法与深度学习方法，研究成果发表在SIAM系列，Nature系列，J.Comput. Phys等期刊以及ICML, ICLR等机器学习顶会上。

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