FONDAZIONE BRUNO KESSLER

ECT*
EUROPEAN CENTRE FOR THEORETICAL STUDIES IN NUCLEAR PHYSICS AND RELATED AREAS

INFN
Istituto Nazionale di Fisica Nucleare

UNIVERSITÄT BIELEFELD

WÜBBEN STIFTUNG WISSENSCHAFT

RIKEN iTHEMS
理化学研究所 数理創造研究センター
RIKEN Center for Interdisciplinary Theoretical and Mathematical Sciences

MLPhYs Foundation of "Machine Learning Physics"
Grant-in-Aid for Transformative Research Areas (A)

文部科学省 MINISTRY OF EDUCATION, CULTURE, SPORTS, SCIENCE AND TECHNOLOGY-JAPAN

UTokyo

BOOST
国家戦略分野の若手研究者及び博士後期課程学生の育成事業
次世代AI人材育成プログラム（若手研究者支援）

JST 国立研究開発法人 科学技術振興機構

BRIDGING MACHINE LEARNING AND STATISTICAL FIELD THEORY THROUGH GENERATIVE AND DIFFUSION PROCESSES

7 - 11 September 2026

ECT* - Villa Tambosi, Villazzano

ORGANIZERS

Lingxiao Wang (iTHEMS, RIKEN)

Gert Aarts (Bielefeld University)

Andreas Athenodorou (The Cyprus Institute)

Miranda Cheng (University of Amsterdam and Academia Sinica)



FONDAZIONE BRUNO KESSLER | ECT* EUROPEAN CENTRE FOR THEORETICAL STUDIES IN NUCLEAR PHYSICS AND RELATED AREAS

Bridging machine learning and statistical field theory through generative and diffusion processes

	2026/09/07(Mon)	2026/09/08(Tue)	2026/09/09(Wen)		
08:30 - 09:30	Registration				
09:30 - 09:45	Opening by ECT* Director	Anna Hasenfratz Long Talk Renormalization-group based algorithms to alleviate critical slowing down	Fernando Romero-Lopez Long T Learning the generating functior		
09:45 - 10:15	Opening (Lingxiao)				
10:15 - 11:00	Gurtej Kanwar Long Talk Combining annealing and diffusion for efficient transport in LFT	Yang-yang Tan Long Talk Generative modeling toward critical behaviors	Akio Tomiya Long Talk Self-learning Diffusion model and re developments		
11:00 - 11:30	Coffee Break	Coffee Break	Coffee Break		
11:30 - 12:15	Thomas Richard Ranner Short Talk Generalizable Equivariant Diffusion Models for LGT	Elia Cellini Short Talk Bridging Jarzynski's Equality and the Renormalization Group	Yuki Nagai Short Talk Automatic Differentiation for Latti Gauge Theory		
	Herzallah Alharazin Short Talk Reconstructing Physical Observables from Sparse Data with Generative Diffusion Models	Lorenzo Verzichelli Short Talk Fighting Topological Freezing with Stochastic Normalizing Flows	Nils Hermansson-Truedsson Short Normalizing flows for all-orders Q corrections in lattice field theor		
12:15 - 12:30	Discussion	Discussion	Discussion		
12:30 - 14:30	Lunch Break	Lunch Break	Lunch Break		
14:30 - 15:15	Mathis Gerdes Long Talk Optimizing diffusion models	Shinichi Nakajima Long Talk Data-Free Training of Diffusion Models for Lattice Simulations	Kenji Fukushima Long Talk Diffusion without fluctuation conne classical and quantum dynamic		
15:15 - 15:45	Coffee Break	Coffee Break	Coffee Break		
15:45 - 16:30	Biagio Lucini Short Talk Stochastic Path Sampler for LFT	Ankur Singha Short Talk Topological Freezing with Q-Shift and Multilevel Sampling in Lattice Gauge	Piotr Bialas/ Dawid Zapolski Short VAN based on Transformers		
	Diaa Eddin Habibi Short Talk Probing diffusion models for LFT with a configurational thermometer	Jinyang Li/Satoshi Iso Short Talk Discovering Symmetry from Energy-Based Diffusion Models	Tae-Geun Kim Short Talk Trustworthy Neural Sampler	Ouraman Hajizadeh Short Talk Sequence-Dependent Dynamics and Inverse Design	
16:30 - 17:00		Discussion	Discussion	Discussion	
17:30 - 18:30					
20:00 - 22:00				Conference Dinner	
		DM+(S)NF+More	DM+Interpretability+More	RG+Sign Probelm	AI



ECT* Generative and Diffusion
WhatsApp community

46(±2) participants

Long Talk (45 mins, w/ Q&A) **Short Talk (25 mins, w/ Q&A)**

Bridge Two Distributions

Diffusion
(Stochastic)

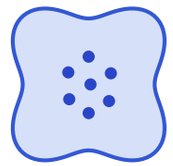
Flow Matching
(Deterministic Continuous Flow)



Simple prior
($t = 0$)





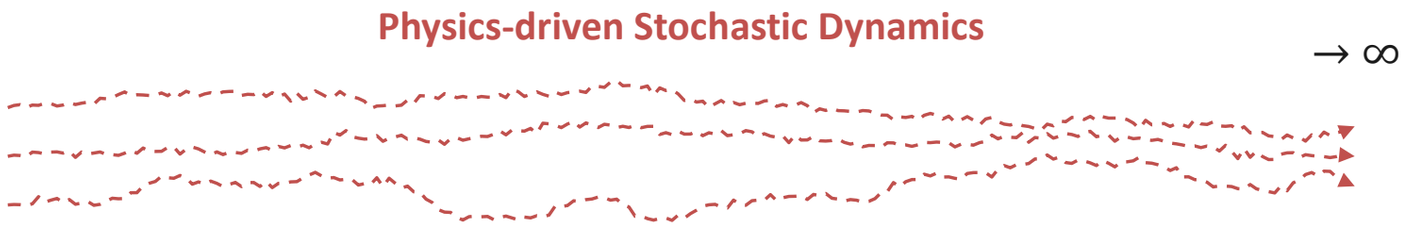


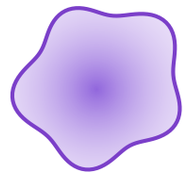
Target
($t = T$)

Stochastic *Quantization*
(Physics-driven)



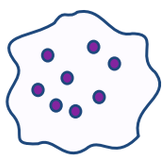
Simple prior
($t = 0$)



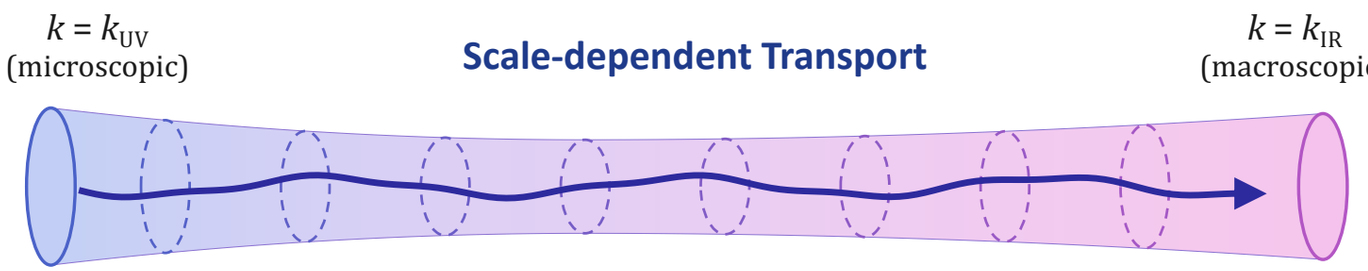


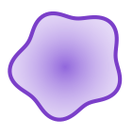
Target
($t \to \infty$)

RG Flow
(Scale-dependent Transport)



Prior (UV)



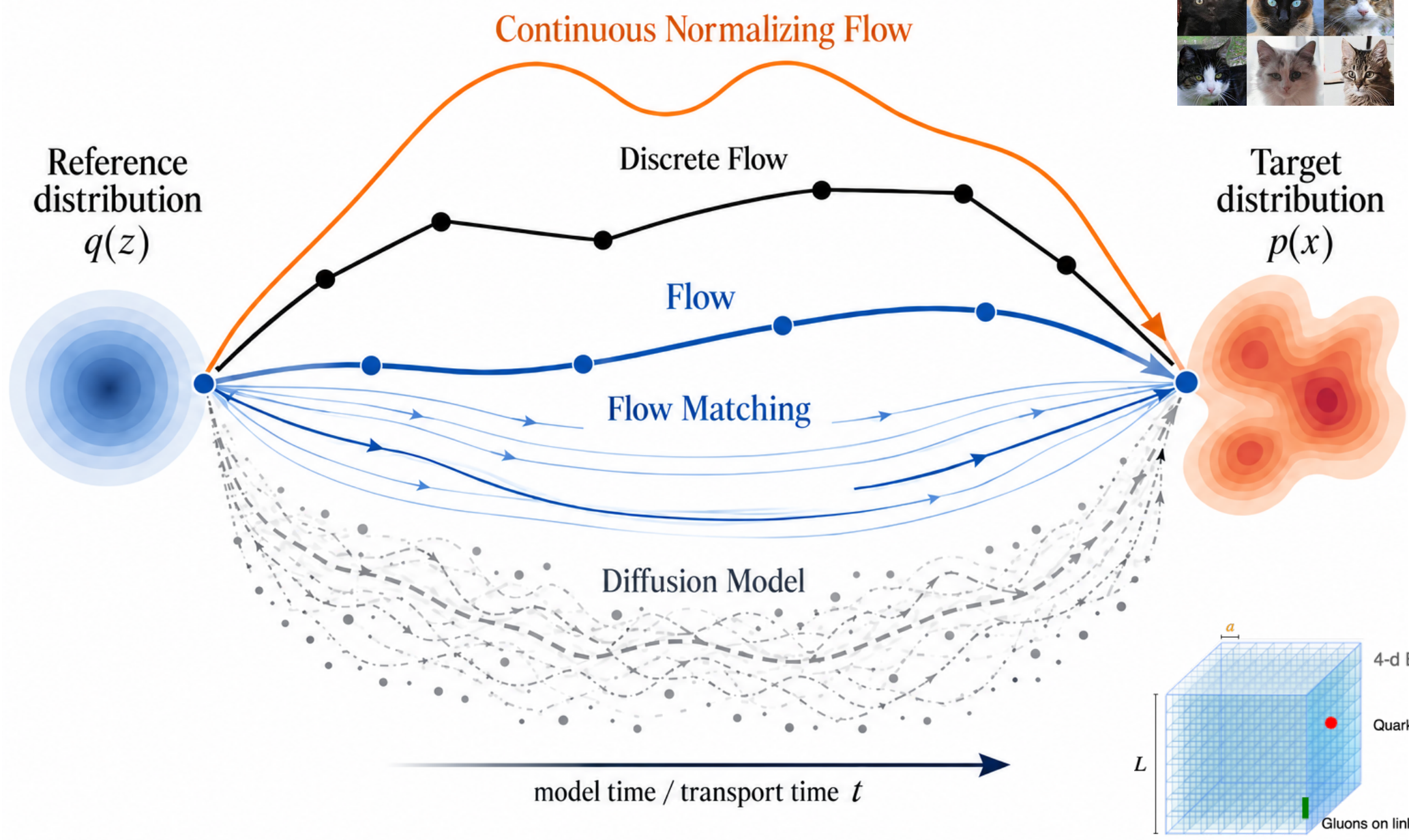


Target (IR)

$$p(\phi) = e^{-S(\phi)}/Z$$

Bridge Two Distributions





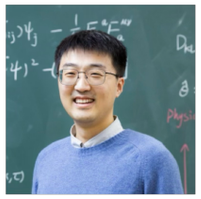
Bridge Two Distributions

Flow: RG, Stochastic, Deterministic, etc.



Stochastic

DM-QFT Collaboration



Lingxiao Wang



Yang-Yang Tan



Conglong Li



Qianteng Zhu



Wei Wang



Renzo Kapust



Jan M. Pawlowski

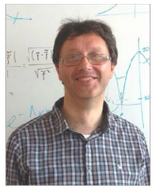
DM-QFT



Gert Aarts



Diaa E. Habibi



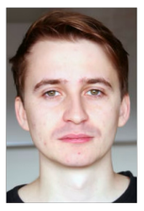
Biagio Lucini



Andreas Ipp



Thomas Richard Ranner



David Müller



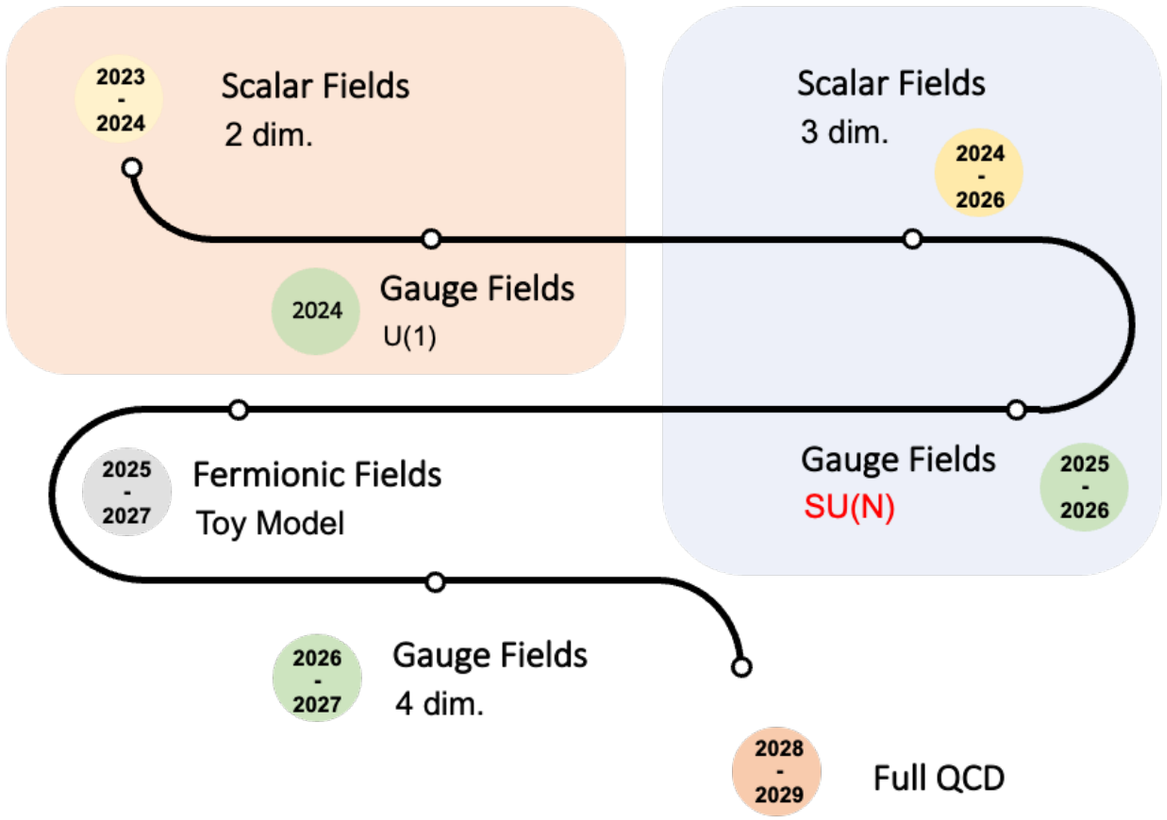
Kai Zhou

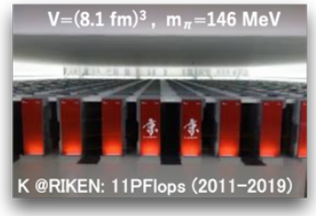
- Stochastic Quantinization: **LW**, G Aarts, K Zhou, *JHEP 05 (2024) 060* [2309.17082 [hep-lat]]; **LW**, [2607.21436 [hep-lat]].
- Physics of Diffusion Models: G Aarts, D Habibi, **LW***, K Zhou, *Mach.Learn.Sci.Tech. 6 (2025) 2, 025004* and NeurIPS 2024 ML4PS [2410.21212 [hep-lat]] (Best ‘Physics for AI’ Paper).
- Physics for Deep Models: G Aarts, K Fukushima, T Hatsuda, A Ipp, S Shi, **LW***, K Zhou, *Nature Rev.Phys. 7 (2025) 3, 154-163*, [2501.05580 [hep-lat]].
- Gauge Field Simulations: Q Zhu, G Aarts, W Wang, K Zhou, **LW***, *JHEP03(2026)111* [2502.05504 [hep-lat]] and NeurIPS 2024 ML4PS [2410.19602 [hep-lat]]; G Aarts, D Habibi, A Ipp, D, Müller, T Ranner, **LW***, W Wang, Q Zhu [2601.19552 [hep-lat]].
- Critical Behaviors: Y Tan, G Aarts, D Habibi, B Lucini, **LW*** [2607.08505 [hep-lat]].

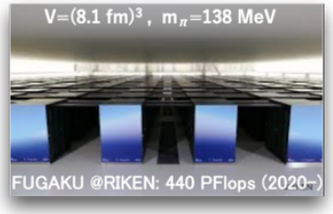
Generative Models for (Lattice) Quantum Field Theory

Sampling

- **GAN**[Zhou(2019), Pawlowski(2020), Nicoli(2021)]**, VAN**[Wu(2019), Wang(2020)]**, SLMC**[Nagai(2021)], etc.
- **Normalizing Flow(NF)**[Albergo(2019), Kanwar(2020)]**, Stochastic NF(SNF)**[Caselle(2022)]**, Continious NF(CNF)**[Gerdes(2023)], etc.
- **Diffusion Model(DM)**[Wang(2024), Zhu(2024), Aarts(2026), Vega(2026)], etc.







Simulations	**Lattice QCD**
Size	96×96×96×96
Supercomputer	Fugaku
Resource Consumption	**512 cores**
Time Consumption	**~ 1 day/configuration**

Faster and Reliable Simulation

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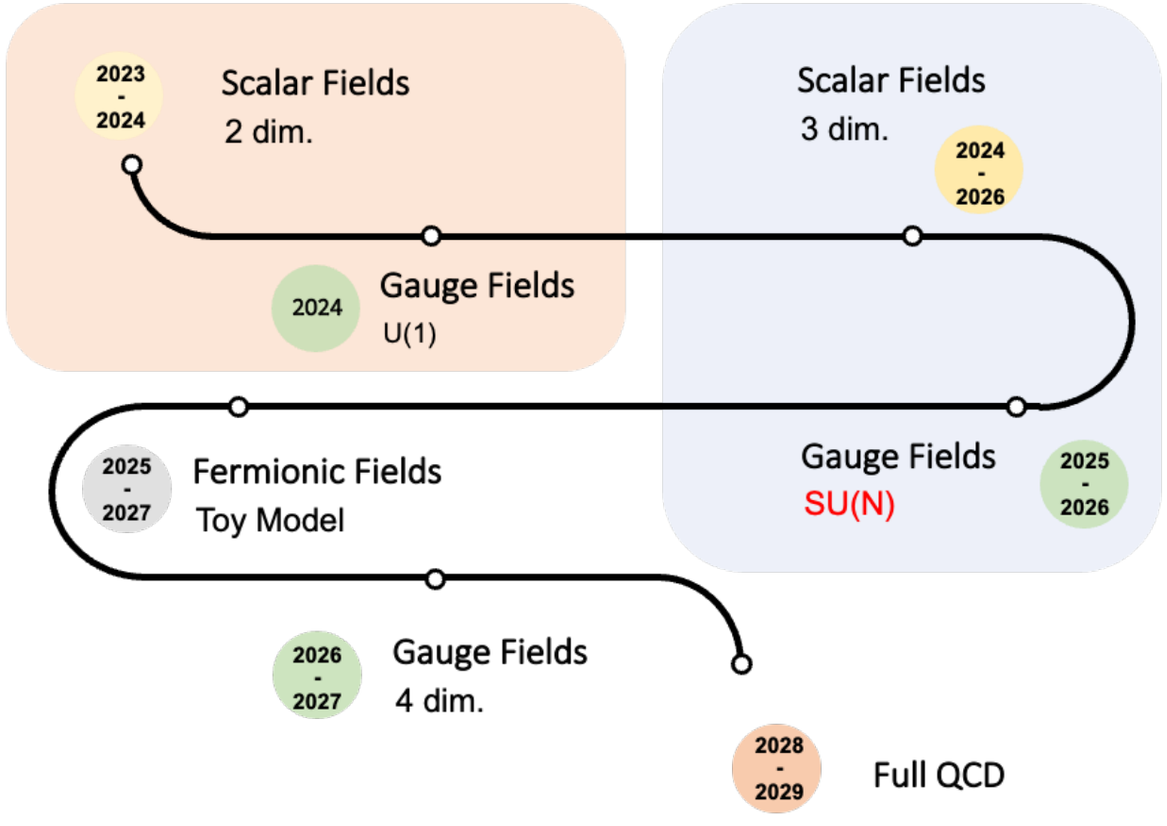

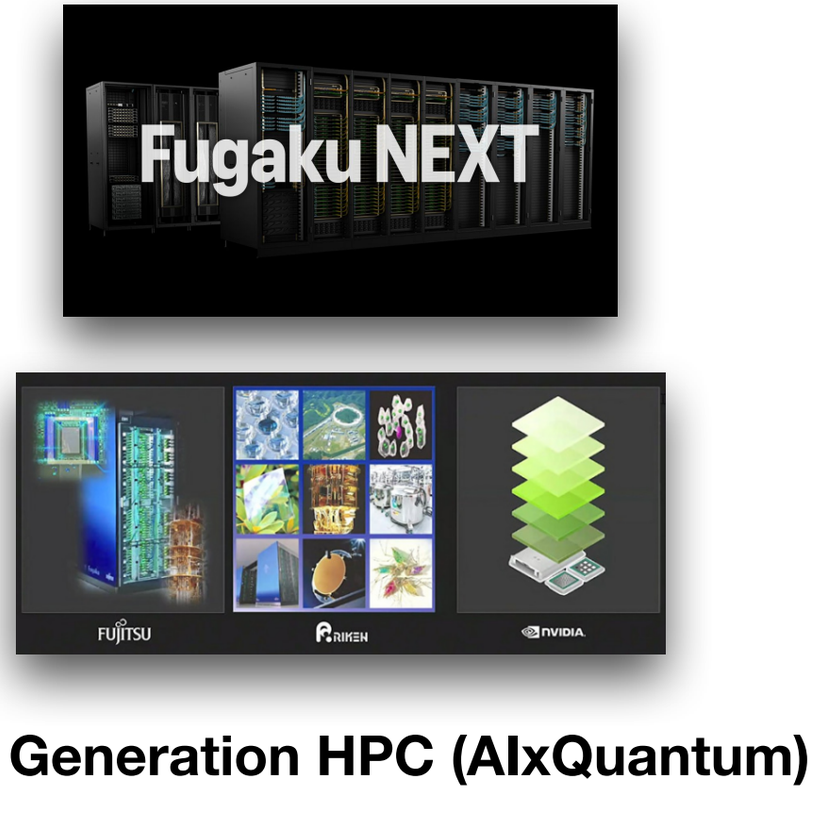

Next Generation HPC (AIxQuantum)

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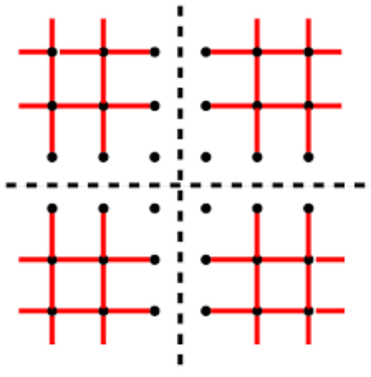
Challenging

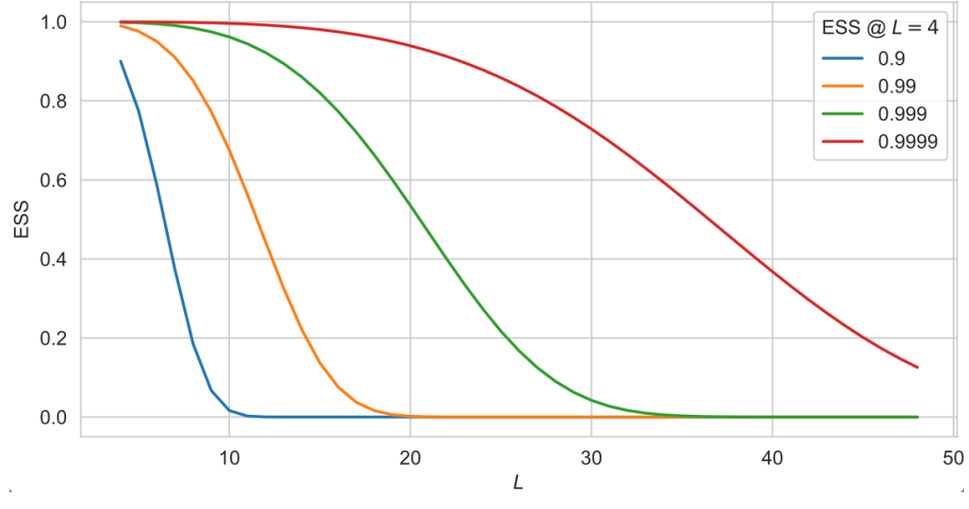
- **Volume Scaling / Topology** [Del Debbio(2021), Abbott(2023), Bonanno(2025)].
- **Dynamical Fermions** [Albergo(2021,2022,2025), Vega(2026)]





$$\mathrm{ESS}(V) \approx \mathrm{ESS}(V_0)^{V/V_0}$$

- Many caveats
- **Practical implication:** need excellent *local* modeling to do *global* reweighting



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New Opportunities

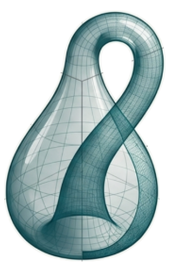
- **Real-Time** [Lawrence(2021)], **Complex Action** [Aarts(2025)]
- **Variance Reduction** [Abbott(2024), Bhattacharya(2024), Abbott(2026)]
- **Inverse RG** [Bachtis(2022), Bauer(2025), Hasenfratz(2026)]
- **Criticality** [Tan(2026)]

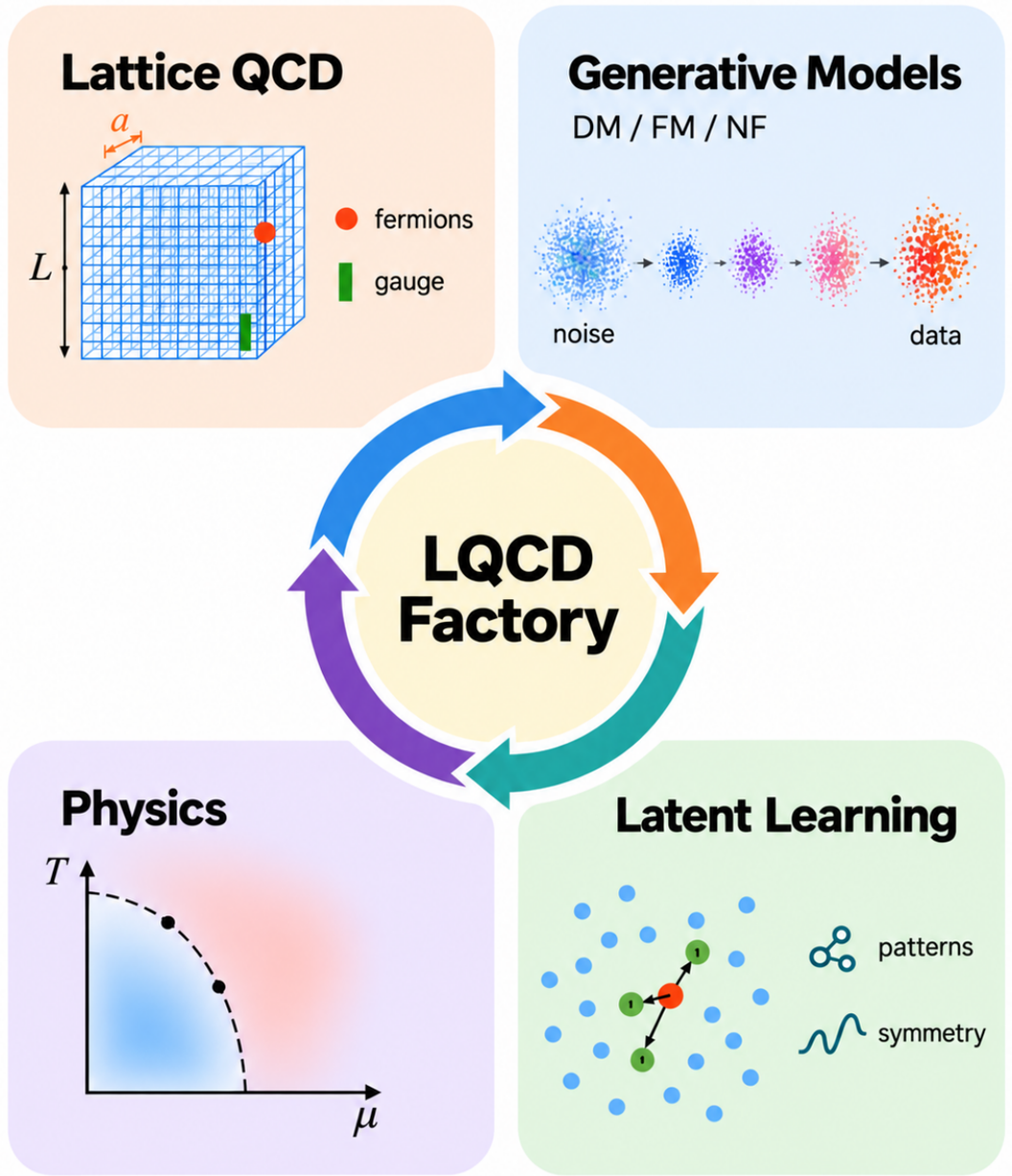
Roadmap toward full QCD

Where Shall We Go

- **Simulate LQCD/QFT**
  - NF/DM/FM, SLMC, …
- **Inverse Problem**
  - Spectral Functions
  - Physics Extraction
- **Representation Learning**
  - Learn From Configs Directly
  - Geometric Structures

Intrinsic Dimensions
[Mei(2026)]





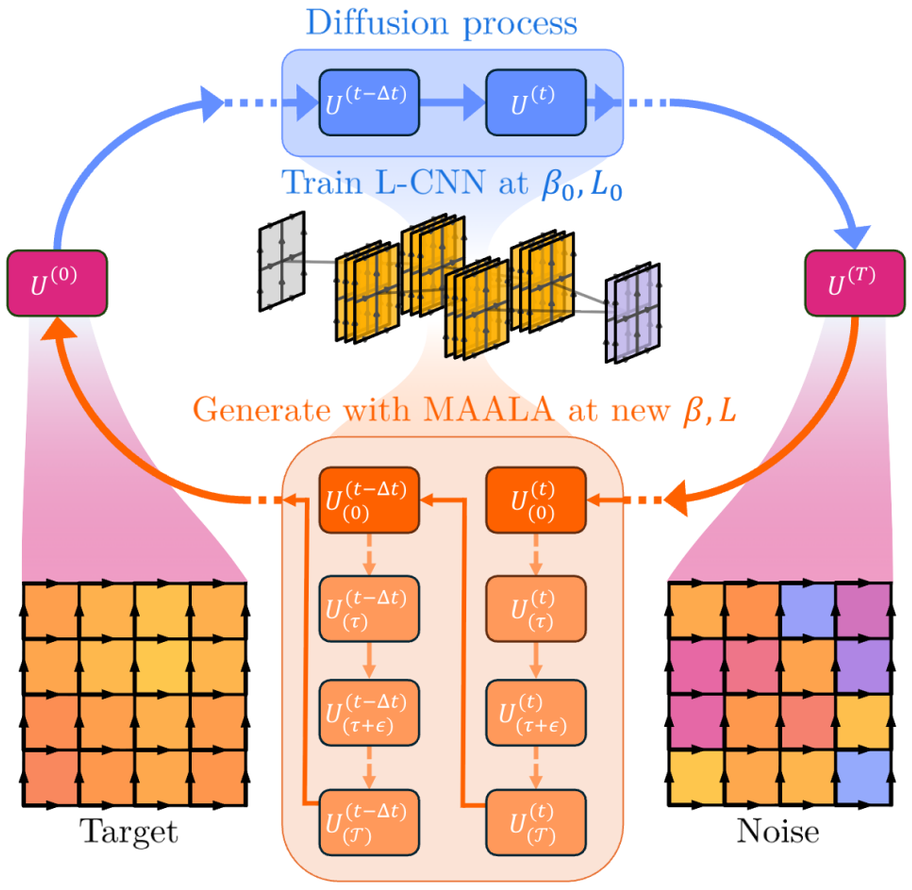
Quantum Field Theory for Generative Models

Equivariance

- **Equivariant NF** [Kanwar(2020)]
- **Equivariant DM** [Aarts(2026)]
  [Vega&Komijani(2026), Alharazin(2026)]

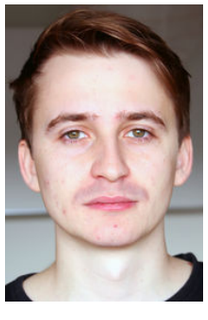
Physics Condition

- **MAALA** [Zhu(2025)]
- **Scalability** [Tan(2026), Singha(2026)]





Thomas R. Ranner



David Müller



Qianteng Zhu

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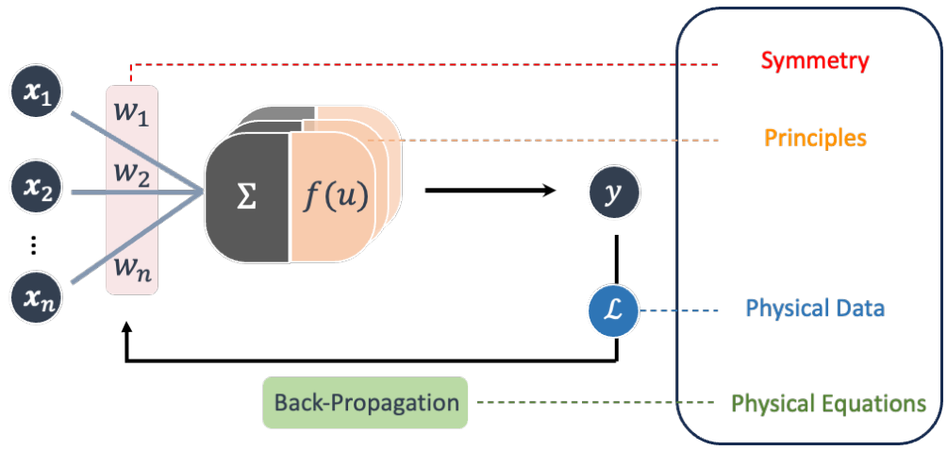

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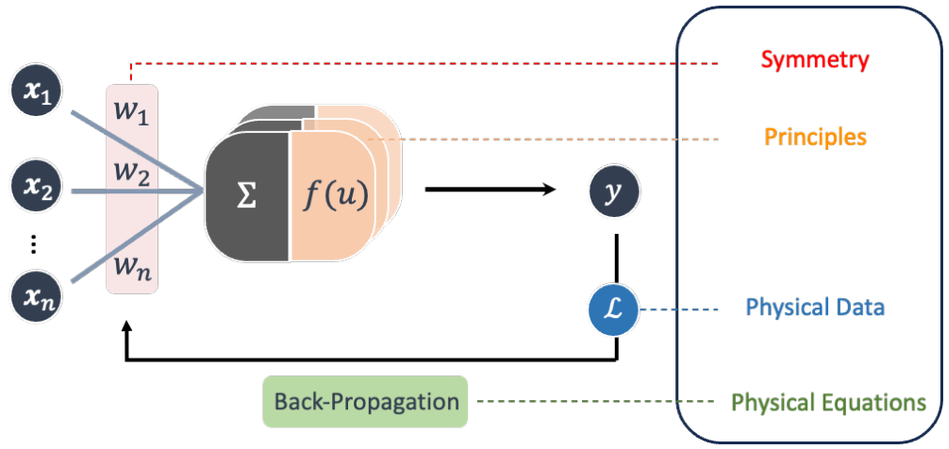

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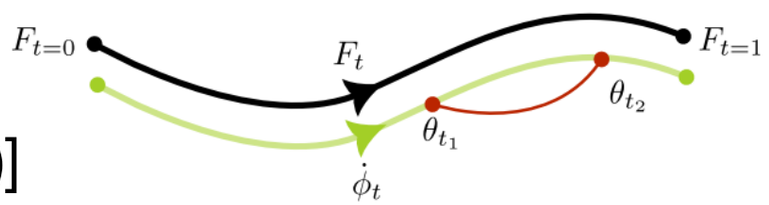
Renormalization Group

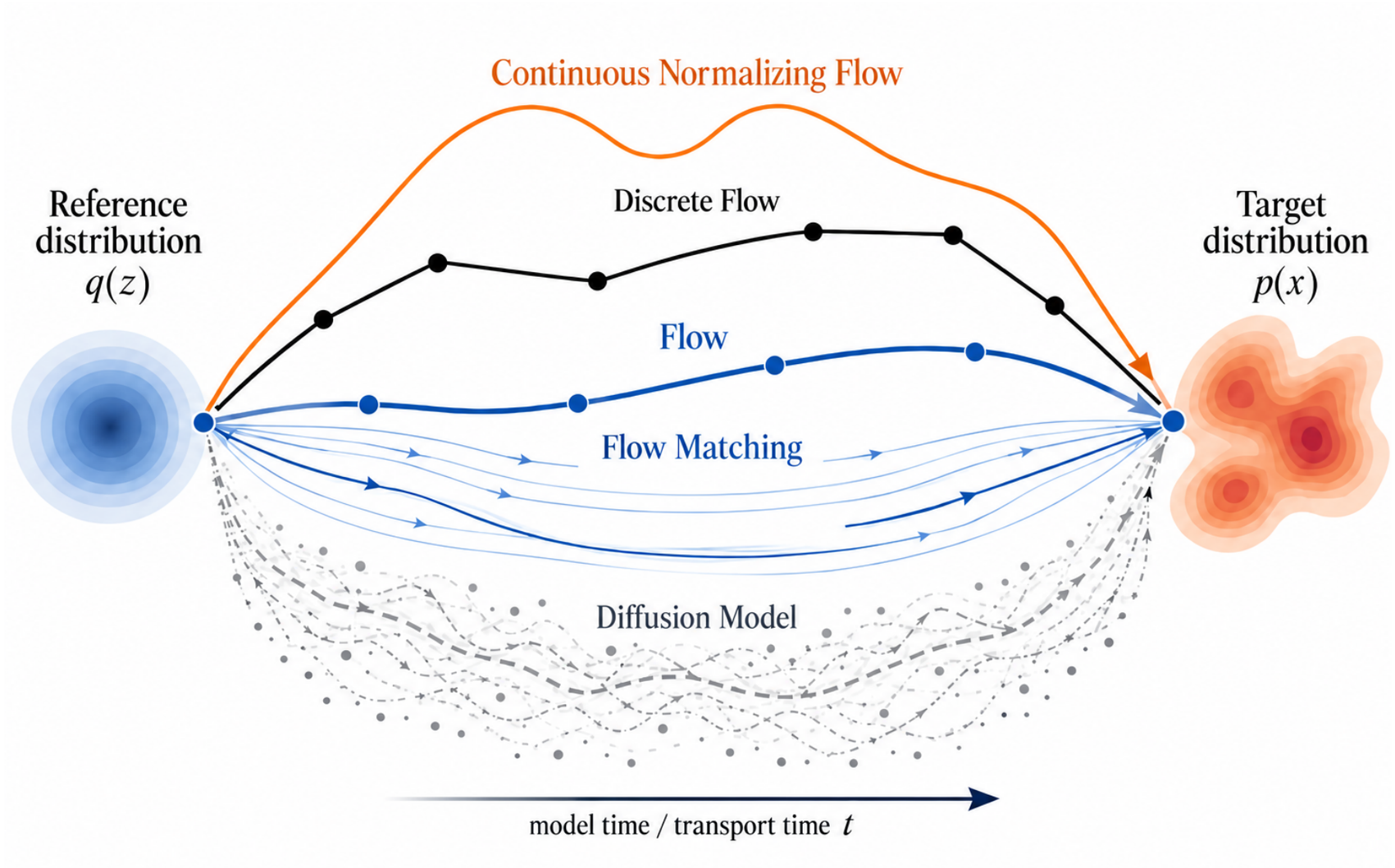
- **RG-Informed DM/FM** [Masuki(2025,2026)]
- **Physics-Informed RG** [Kapust(2025), Ihssen(2026)]



New

Where Shall We Go

- **Optimal Control**
  - How can we find the optimal Process for best sampling?



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Where Shall We Go

- **Optimal Control**
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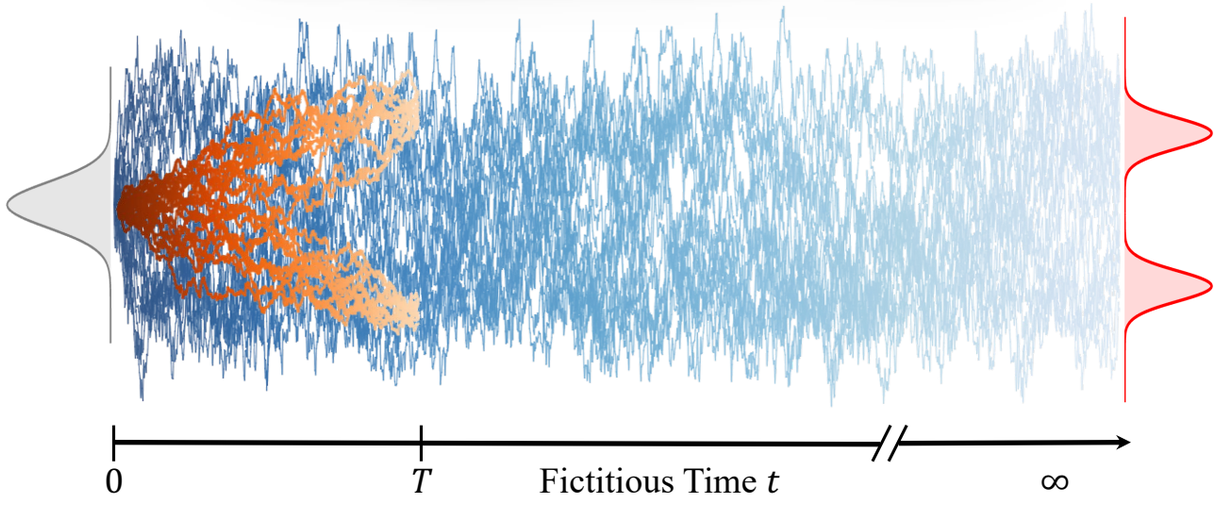
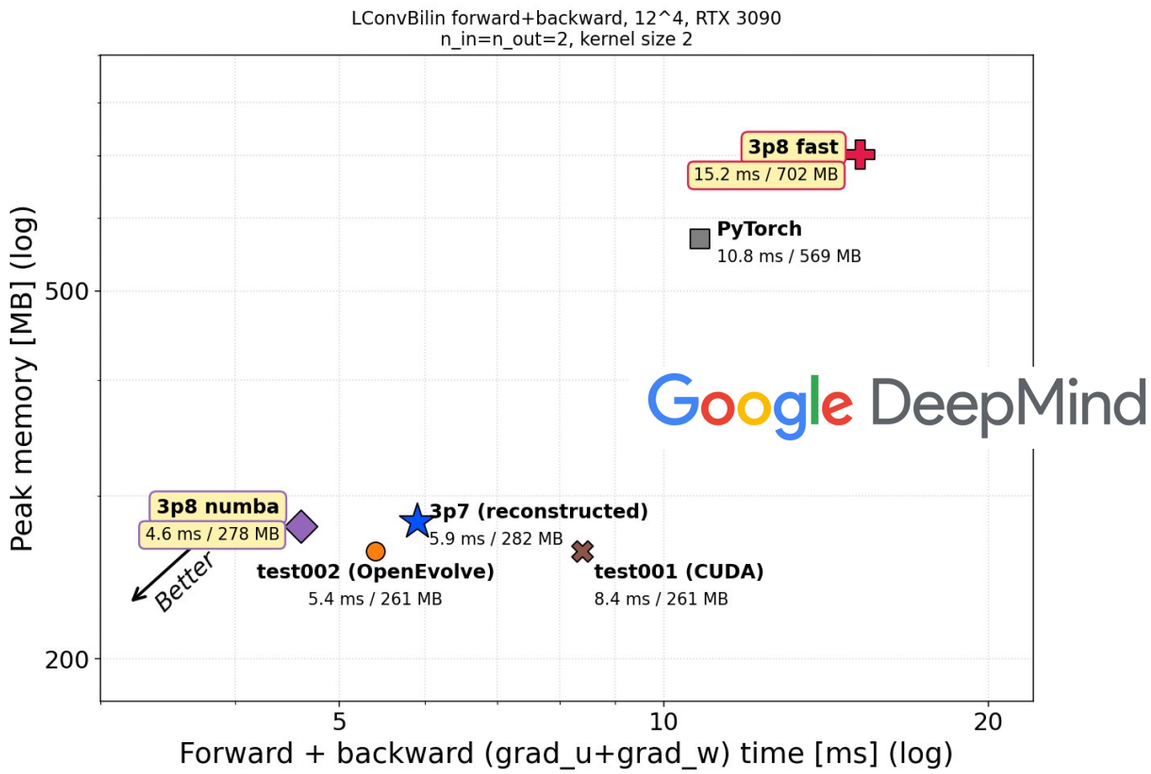
- **Information Geometry**
  - How much information should we input to the process?
  - How much information could we learn from the physics target?
- **QFT as LLMs Playground**
  - Automatic solutions [with Alenthia]
- **Benchmark**
  - Fixed computational budget!

$$d\phi_t = u_\theta(\phi_t, t)dt + g dw_t, \quad t \in [0,T]$$





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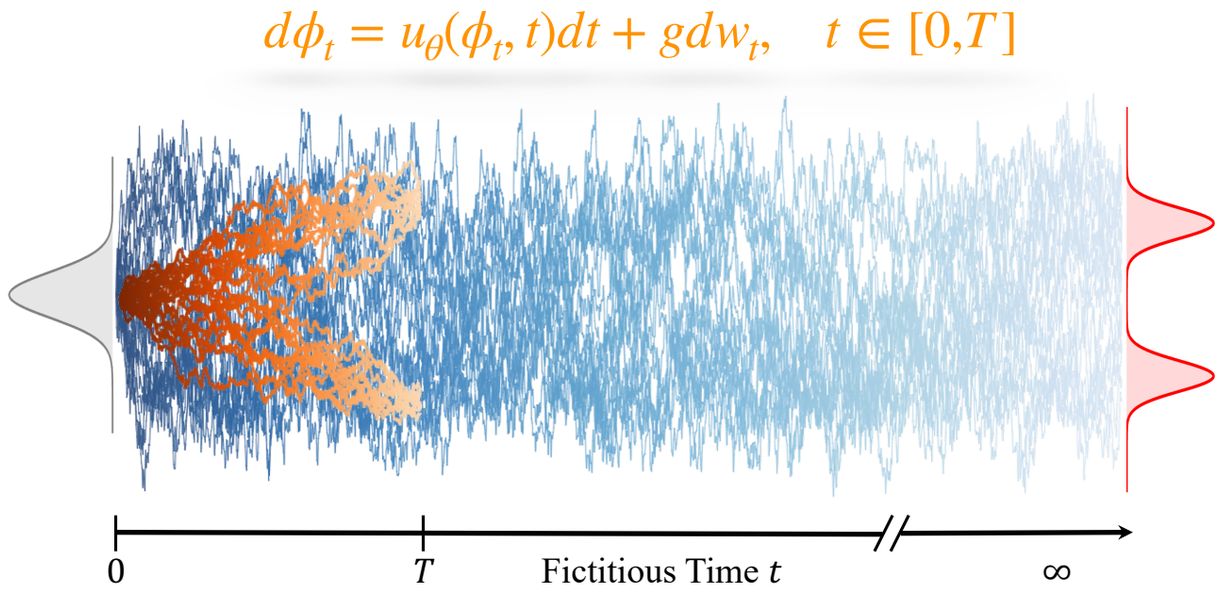



GDM Meets QFT, Opportunities and Challenges