Title: Machine Learning Meets Quantum Science

Speakers: Di Luo

Series: Machine Learning Initiative

Date: April 06, 2023 - 3:00 PM

URL: https://pirsa.org/23040078

Abstract: The recent advancement of machine learning provides new opportunities for tackling challenges in quantum science, ranging from condensed matter physics, high energy physics to quantum information science. In this talk, I will first discuss a class of anti-symmetric wave functions based on neural network backflow, which is efficient for simulating strongly-correlated lattice models and artificial quantum materials. Next, I will talk about recent progress of simulating continuum quantum field theories with neural quantum field state, and lattice gauge theories such as 2+1D quantum electrodynamics with finite density dynamical fermions using gauge symmetric neural networks. I will further discuss neural network representation based on positive-value-operator and phase space measurements for quantum dynamics simulations. Finally, I will present applications of machine learning in quantum control, quantum optimization and quantum machine learning.

Zoom link: https://pitp.zoom.us/j/93834456412?pwd=R0hxdEpxanFFRnZmTHlqZTBXRi82QT09

Machine Learning Meets Quantum Science

Di Luo
IAIFI Fellow, MIT

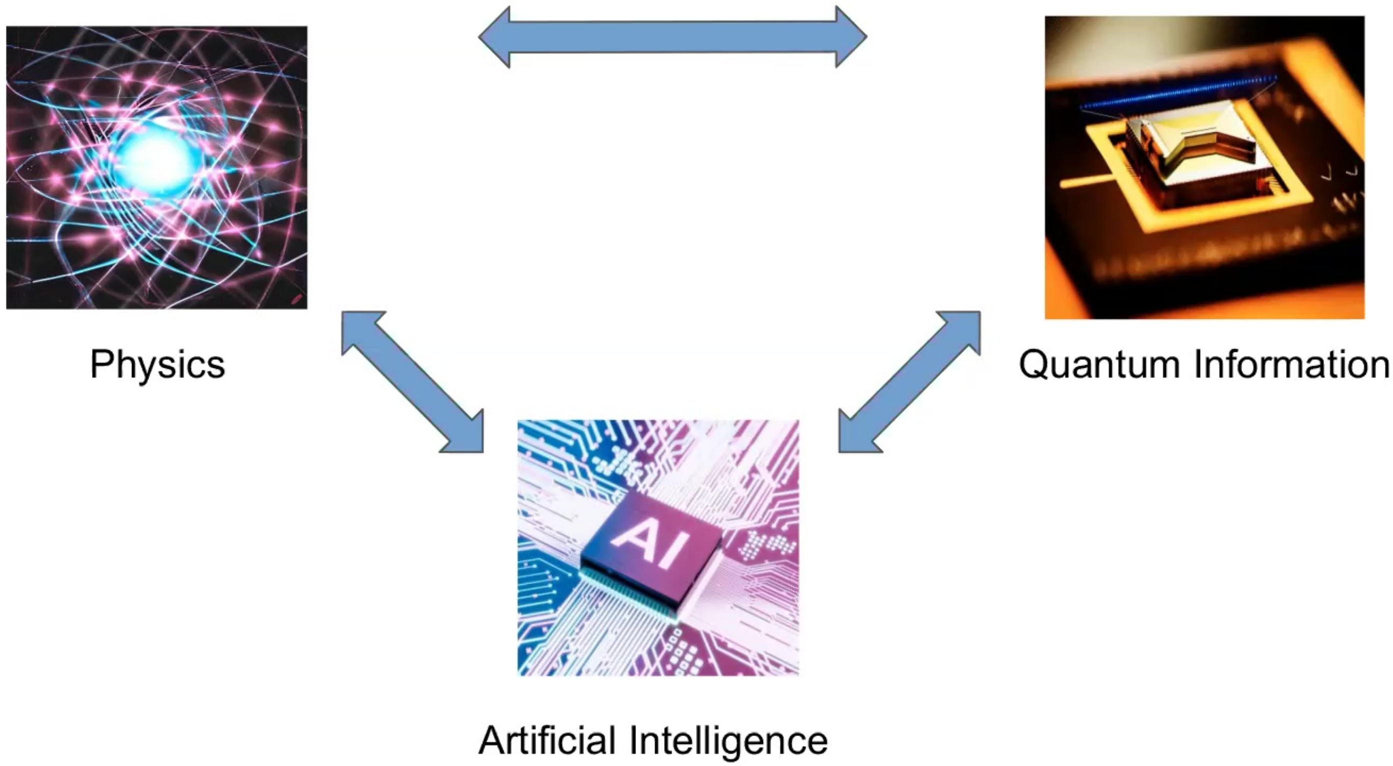
AI for Quantum Many-body Physics & Quantum Information Science

IAIFI: The NSF AI Institute for Artificial Intelligence and Fundamental Interactions

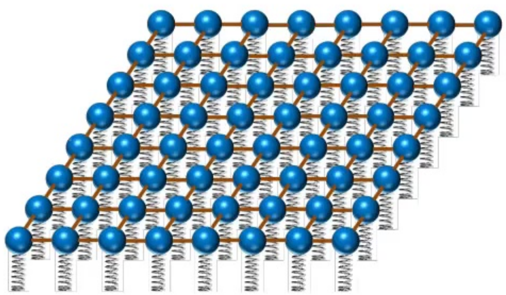
Quantum Many-body Simulation & Quantum Information Science

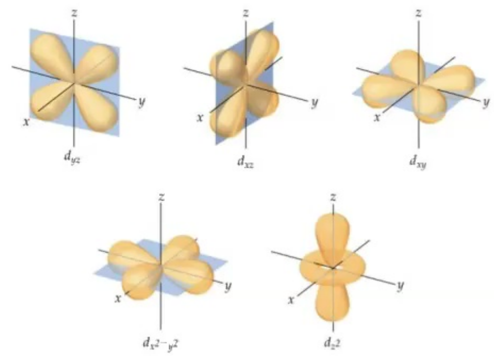
C2QA: Co-design Center for Quantum Advantage

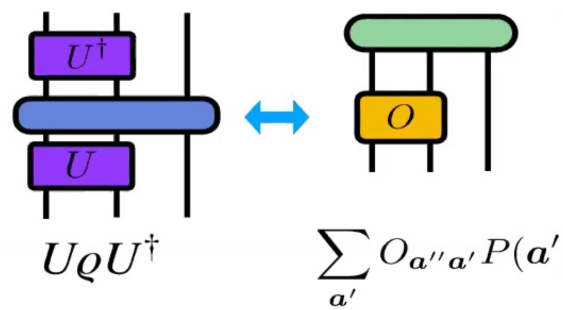
Artificial Intelligence, Quantum Information and Physics



AI for Quantum Science







High energy physics

Phys. Rev. Lett. 127, 276402

arxiv: 2101.07243

arxiv: 2202.03530

arxiv. 2101.07243

arxiv. 2212.06835

Condensed matter physics

Phys. Rev. Lett. 122, 226401

arxiv: 2112.00723

arxiv. 2212.00782

Nano Lett. 2020, 20, 5, 3369–3377
arxiv.2304.01996

Quantum information science

Phys. Rev. Lett. 128, 090501

Phys. Rev. A 104, 032610

PRX Quantum 2, 020332

arxiv. 2211.01365

Physics for AI

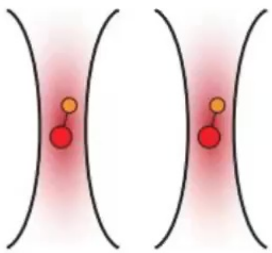
Geometry of contact: contact planning for multi-legged robots via spin models duality

Baxi Chong*[1], Di Luo*[2 3 4], Tianyu Wang[1 5], Gabriel B. Margolis[6], Juntao He[1 5], Pulkit Agrawal[2 6], Marin Soljačić[7], and Daniel I. Goldman[1 5]

GENPHYS: FROM PHYSICAL PROCESSES TO GENERATIVE MODELS

Ziming Liu, Di Luo, Yilun Xu, Tommi Jaakkola, Max Tegmark
Massachusetts Institute of Technology
{zmliu,diluo,ylxu,jaakkola,tegmark}@mit.edu

QI for Physics: Quantum Simulations and Quantum Information Science

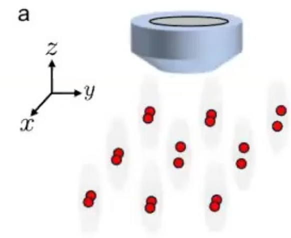


Dipolar molecule

Framework for simulating gauge theories with dipolar spin systems, Phys. Rev. A 102, 032617 (2020)

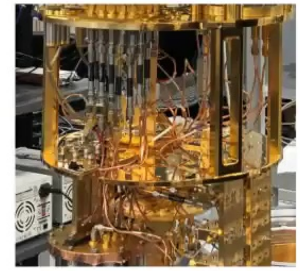
Rydberg atoms

Simulating Quantum Mechanics with a θ-term and an 't Hooft Anomaly on a Synthetic Dimension, Phys. Rev. D 105, 074505 (2022)



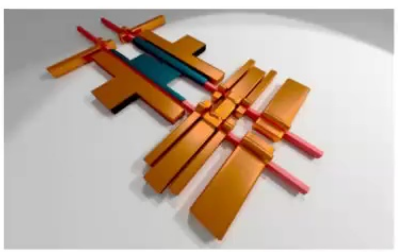
Fermion Pair

Quantum Computation and Simulation using Fermion-Pair Registers



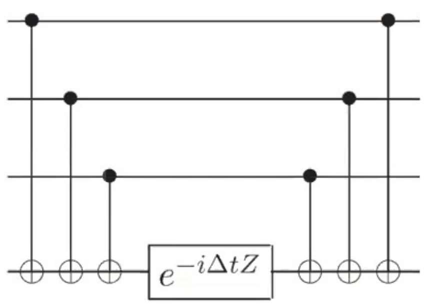
Bosonic mode

Bosonic Mode Quantum Simulations for Many-body Physics



Topological braiding

PRX Quantum 2, 020332



Digital circuit

Quantum tomography
Quantum simulations

arxiv.2110.02965
arxiv.2211.01365

....

Quantum Many-body Physics Simulation

Spectrum calculation

$$H|\psi> = E|\psi>$$

Eg. phase diagram, excited states, steady states

Real time evolution

$$H(t)\,|\,\psi(t)\rangle = i\hbar\frac{d}{dt}\,|\,\psi(t)\rangle$$

Eg. quantum chaos, quantum circuit simulation, dynamics of gauge theories

Challenges:

- Sign problem: non-positive real number / complex number
- high dimensionality: Hilbert space scales exponentially with particles

ChatGPT: Large Language Model

OpenAI

ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response.

Motivations

AU

Challenges of Quantum Many-body Physics Simulation

Quantum many-body physics simulation involves simulating the behavior of a large number of interacting quantum systems. This is a challenging task due to the exponential growth of the dimensionality of the Hilbert space with the number of particles in the system. This makes it difficult to simulate systems with a large number of particles using classical computers. Additionally, the complexity of the interactions between the particles, such as those described by the Coulomb force, also makes simulation difficult. Other challenges include dealing with decoherence and the need for efficient algorithms for manipulating and measuring large quantum states.

Ongoing Efforts: Quantum Monte Carlo

Quantum monte carlo: sample high dimension objects

$$e^{-\tau H}|\psi\rangle \approx \prod^{N}(I - \frac{\tau}{N}H)|\psi\rangle$$

↓

Transition probability with signs

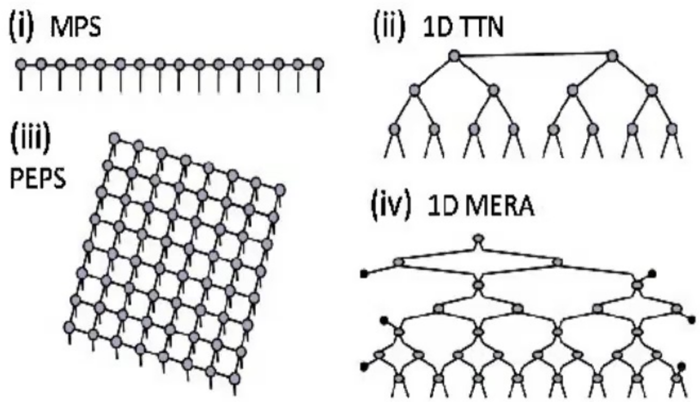
- Draw samples according to $|\psi|^2$, apply transition probability kernel
- Due to sign problem, the relative variance of the sign scales exponentially

Ongoing Efforts: Tensor Network

Tensor network: tensor decomposition of high dimensional objects

High rank tensor

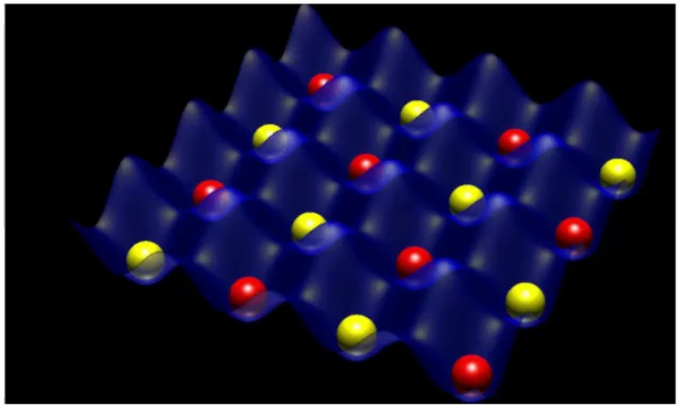
$$T_{i,j,k,l} =$$



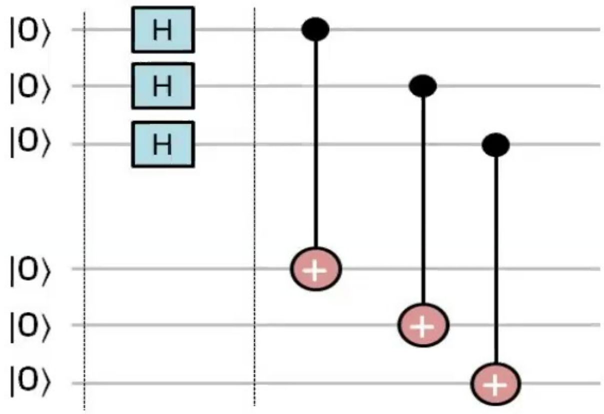
- Efficient for 1 dimensional system due to area law
- Challenges exist for two or three dimensional physics system

Ongoing Efforts: Quantum Computation

Quantum computation: naturally represents and operates on quantum objects



Analog quantum computation



Digital quantum computation

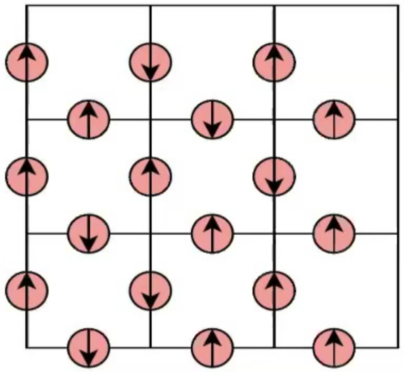
- Natural for quantum dynamics, could be used for ground state problems
- Challenges exist under current technology

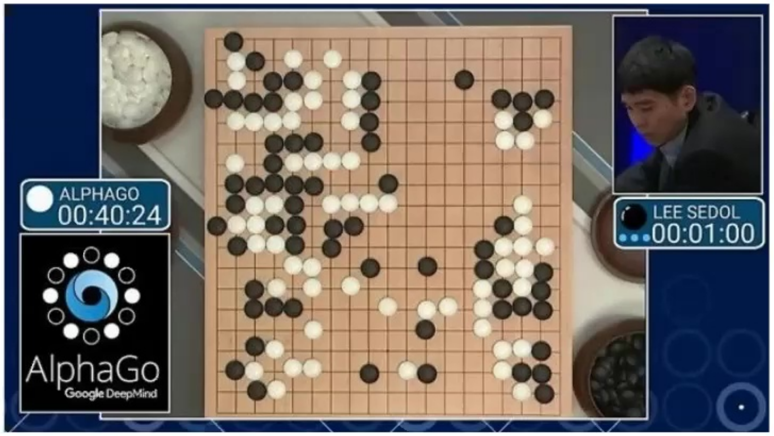
Neural Quantum States

For a n-particle (spin ½) system:

2^n x 2^n hermitian matrix ← $H|\psi> = E|\psi>$

2^n vector



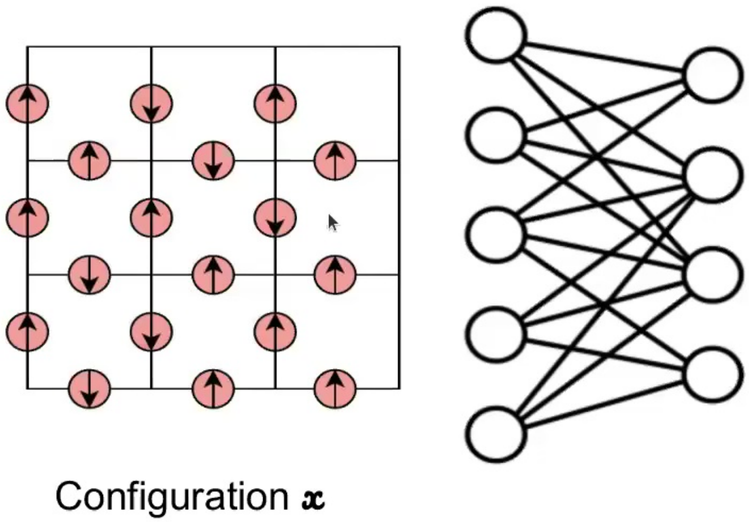


Superposition of 2^n configurations!

Q: Can machine learning help to find the best superposition of configurations?

Neural Quantum States

Neural network: low dimensional representation of high dimensional objects



Universal Approximation Theorem [Cybenko]

$$\longrightarrow \Psi(x)$$

Wave function amplitude [Carleo]

Variational Monte Carlo

Variational principle: $$E = \frac{\langle\psi|H|\psi\rangle}{\langle\psi|\psi\rangle} \geq E_0$$

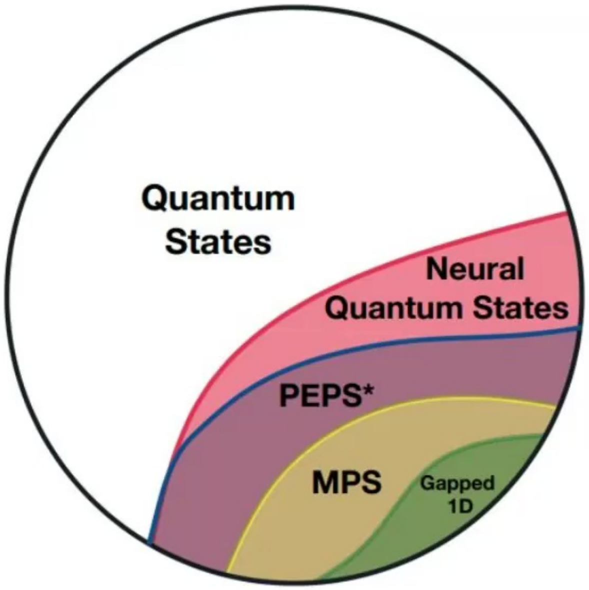
$$\partial_\theta E(\theta) = \frac{1}{N} \sum_{x \sim |\psi_\theta(x)|^2} [(E_L(x) - \langle E_L \rangle) \nabla_\theta log \psi_\theta(x)]$$

Sampling without sign problem

Parameterized wave function

Local energy $$E_L(x) = \frac{H\psi_\theta(x)}{\psi_\theta(x)}$$

Neural Quantum States



Or Sharir, Amnon Shashua, Giuseppe Carleo
https://arxiv.org/abs/2103.10293

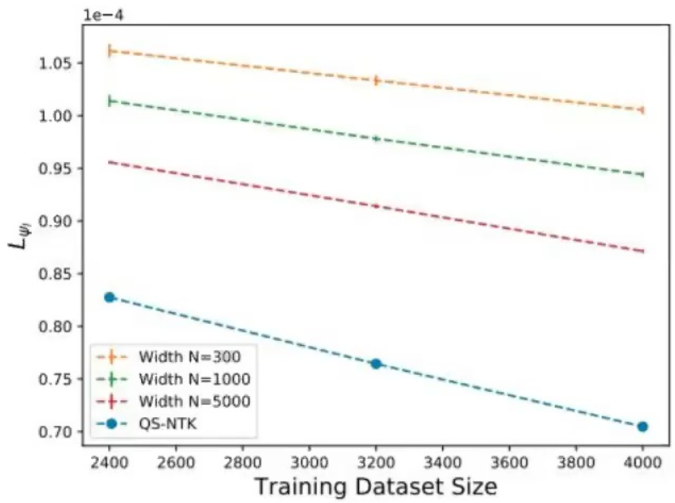
Neural Network Quantum State:

- It is able to represent volume law state
- Exact representation for Jastrow, stabilizer states
- Variational simulation for theories with sign problems

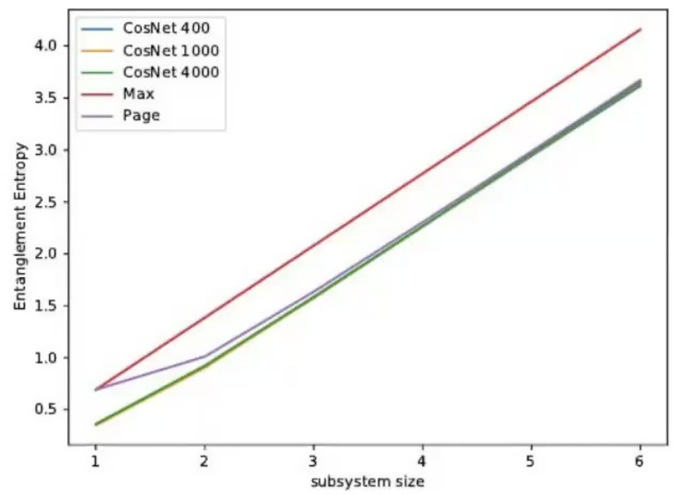
Neural Quantum States

Di Luo, James Halverson, arxiv: 2112.00723

Infinite Neural Network Quantum State: Entanglement and Training Dynamics



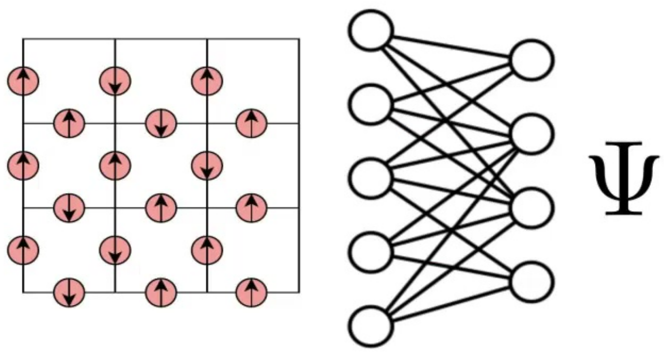
Quantum State Neural Tangent Kernel



Theorem. Quantum state supervised learning training is guaranteed to converge in infinite width limit.

Volume law entanglement engineering of CosNet

Neural Quantum States



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RESEARCH ARTICLES | PHYSICS

Solving the quantum many-body problem with artificial neural networks

Giuseppe Carleo[1,*], Matthias Troyer[1,2]

Efficient representation of quantum many-body states with deep neural networks

Xun Gao & Lu-Ming Duan

Nature Communications **8**, Article number: 662 (2017) | Cite this article

Quantum Entanglement in Neural Network States

Dong-Ling Deng, Xiaopeng Li, and S. Das Sarma
Phys. Rev. X **7**, 021021 – Published 11 May 2017

Neural-network quantum state tomography

Giacomo Torlai, Guglielmo Mazzola, Juan Carrasquilla, Matthias Troyer, Roger Melko & Giuseppe Carleo

Nature Physics **14**, 447–450 (2018) | Cite this article

18

AI for Quantum: Quantum Many-body Physics

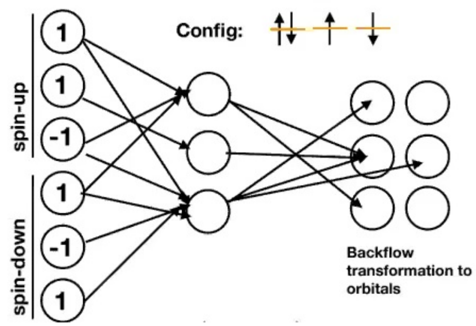
I. Strongly Correlated Systems

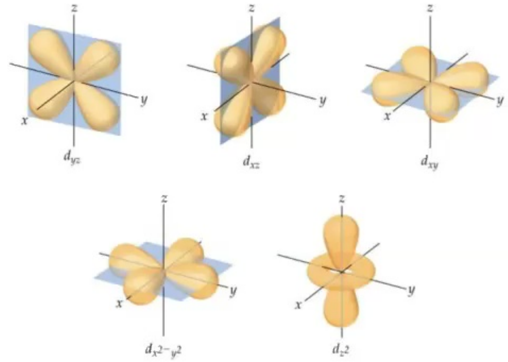
Di Luo, Bryan Clark, Phys. Rev. Lett. 122, 226401

Backflow Transformations via Neural Networks for Quantum Many-Body Wave-Functions

--- Develop anti-symmetry neural network for fermionic simulations

$$\Psi(\cdots, x_i, \cdots, x_j, \cdots) = -\Psi(\cdots, x_j, \cdots, x_i, \cdots)$$





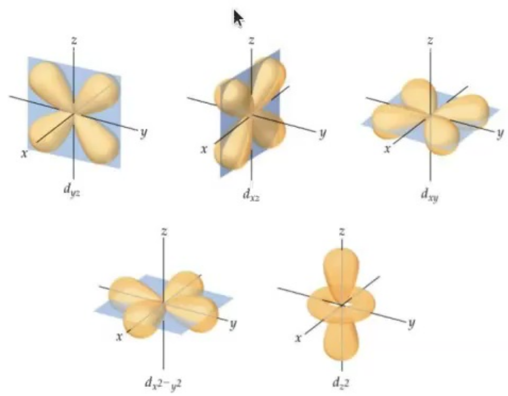
Di Luo, Bryan Clark, Phys. Rev. Lett. 122, 226401

Neural Network Backflow

Jastrow

+

Backflow
Slater Determinant



Pro: include correlation effect

Con: hard to figure out good configuration dependent orbitals

Backflow transformation

[Feynman], [Sorella]

General form of backflow?

Configuration dependent orbitals

r → Determinant →

Mean field solution

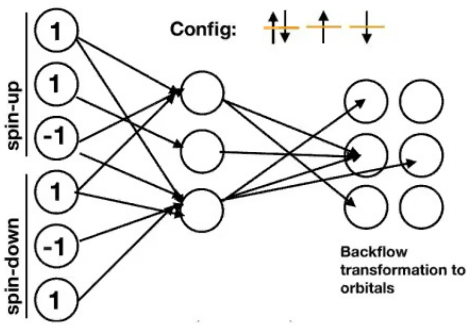
$$\Psi(\mathbf{r}) = det([\phi_{k\sigma}(r_{i,\sigma})])$$

?

$$\Psi(\mathbf{r}) = det([\phi^b_{k\sigma}(r_{i,\sigma};\mathbf{r})])$$

Di Luo, Bryan Clark, Phys. Rev. Lett. 122, 226401

Neural Network Backflow



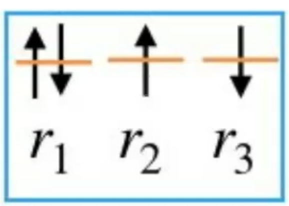
Neural network interacting orbitals

Mean field orbital

Neural network backflow output

$$\phi^b_{k\sigma}(r_{i,\sigma};\boldsymbol{r}) = \phi_{k\sigma}(r_{i,\sigma}) + a^{NN}_{ki,\sigma}(\boldsymbol{r})$$

- Configuration dependent many-particle orbital
- Allow neural network to work with fermion and change sign structure directly
- Generalization of backflow to arbitrary system



Input configuration ***r***

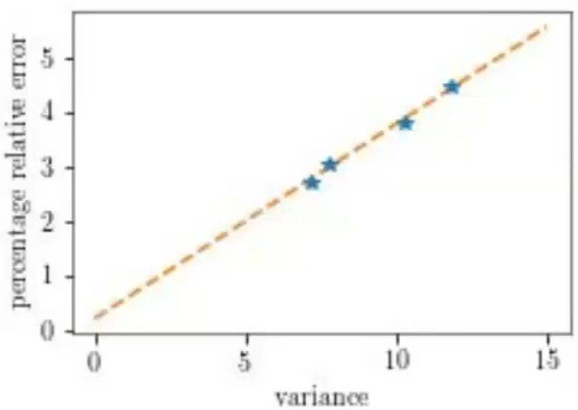
Determinant

$$\Psi(\mathbf{r}) = det([\phi^b_{k\sigma}(r_{i,\sigma};\mathbf{r})])$$

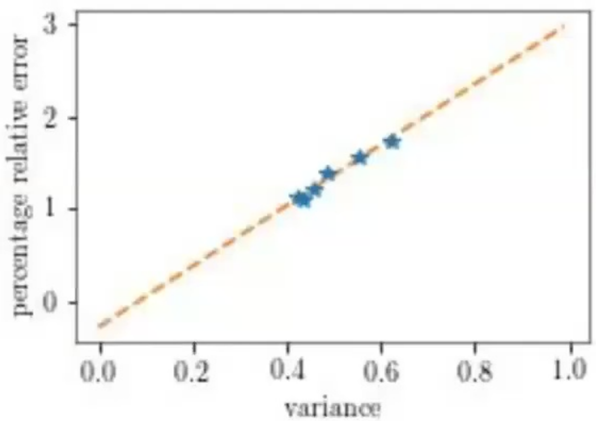
Di Luo, Bryan Clark, Phys. Rev. Lett. 122, 226401

Neural Network Backflow

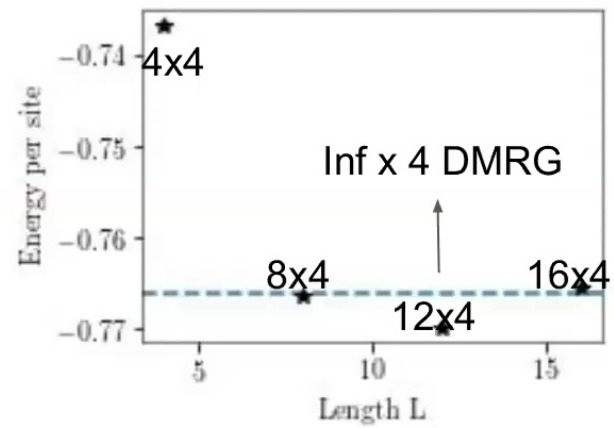
Generalization of backflow to arbitrary lattice systems with complicated sign structure.



16x4 Hubbard, U/t=8, n=0.875
Variance extrapolation
error=0.209%



4x4x3 Kagome
Variance extrapolation
error=0.286%



Hubbard model,
U/t=8, n=0.875,
finite size study

Di Luo, Bryan Clark, Phys. Rev. Lett. 122, 226401

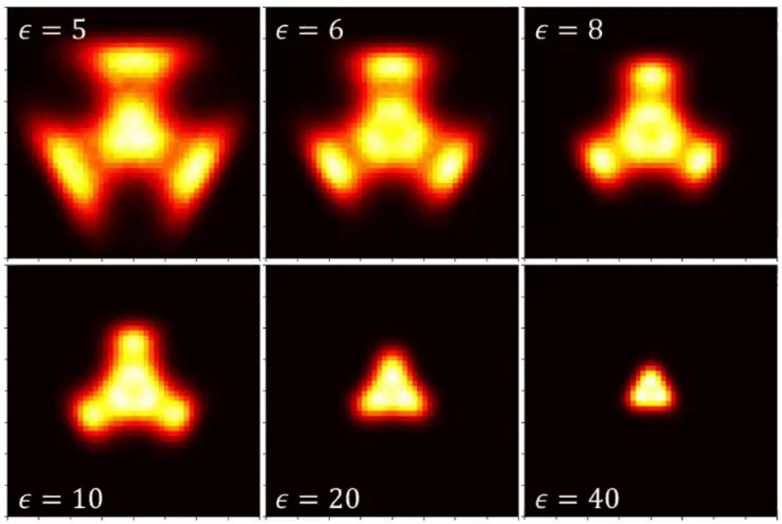
Neural Network Backflow

- Anti-symmetric neural network
- Change sign structure directly and generalization to arbitrary lattices
- Theoretically exact and lower bound for existing backflow methods, generalization of Slater-Jastrow-Backflow hierarchy
- Generalization to Autoregressive Neural TensorNet (arxiv.2304.01996)
- Further advancement in quantum chemistry: FermiNet, PauliNet

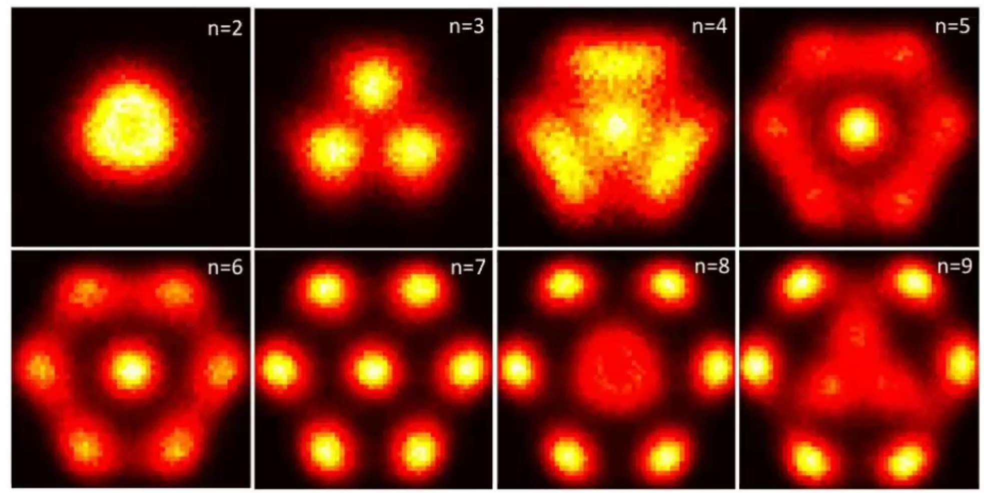
Di Luo, Aidan P. Reddy, Trithep Devakul, Liang Fu, arxiv.2303.08162

Neural Network Backflow

Artificial intelligence for artificial materials: moiré atom

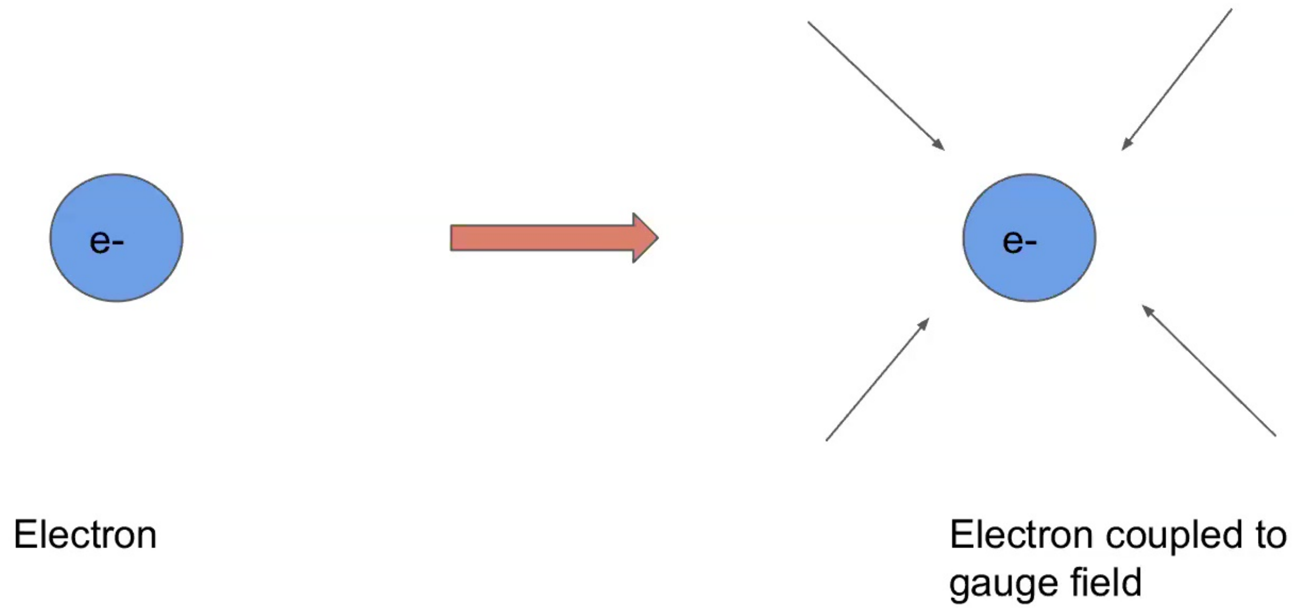


From Schrödinger atom to Wigner molecule

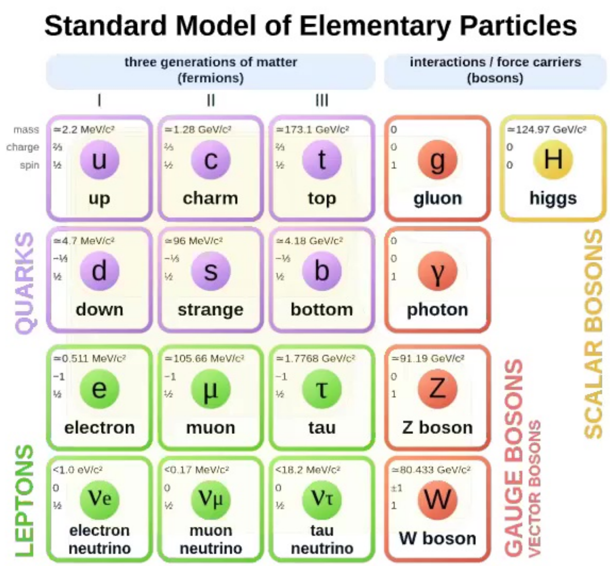


Effect of crystal field on charge distribution

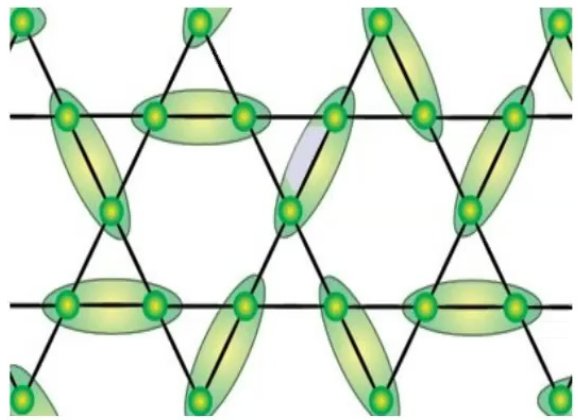
Motivations: Simulation of Gauge Theory



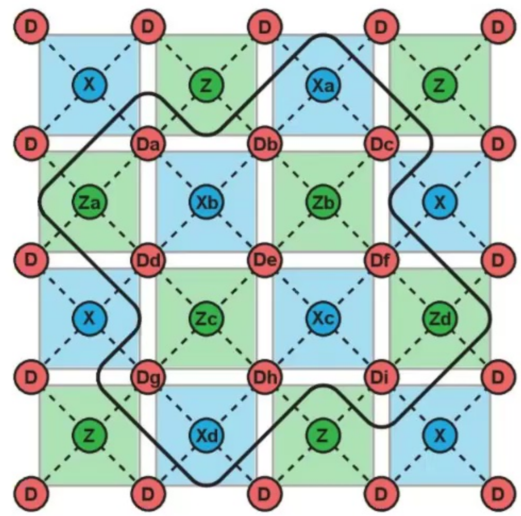
Motivations: Simulation of Gauge Theory



High energy



Condensed matter



Quantum error correction

Challenges: Simulation of Gauge Theory

- *High dimension Hilbert space*
- *Sign problems*
- *Gauge symmetries*
- *Continuous field variables*
- *Continuous limit*

New Exploration

- Gauge Equivariant Neural Network

  (Phys. Rev. Lett. 127, 276402, arxiv. 2211.03198)

- Gauge-Fermion FlowNet for 2+1D QED at Finite Density

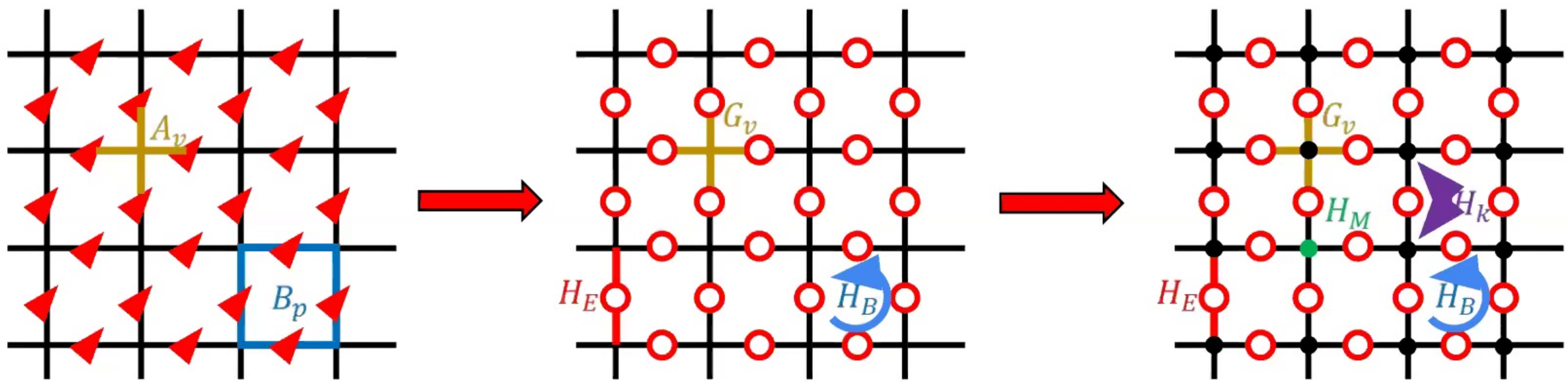
  (Phys. Rev. Lett. 122, 226401, arxiv.2101.07243, arxiv. 2212.06835)

- Neural Quantum Field State for continuum Quantum Field Theories

  (arxiv. 2212.00782)

Motivations: Simulation of Quantum Field Theories

$\mathbb{Z}_2$ toric code model | U(1) pure gauge theory | U(1) gauge theory with fermions



$\mathbb{Z}_2$ gauge theory
A_v: Gauss's law

Continuous gauge theory
Infinite degree of freedom

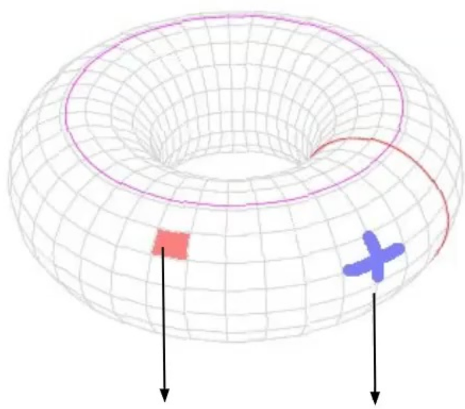
Gauge field fermion interaction
Fermionic sign problem

Di Luo, Giuseppe Carleo, Bryan Clark, James Stokes. Phys. Rev. Lett. 127, 276402

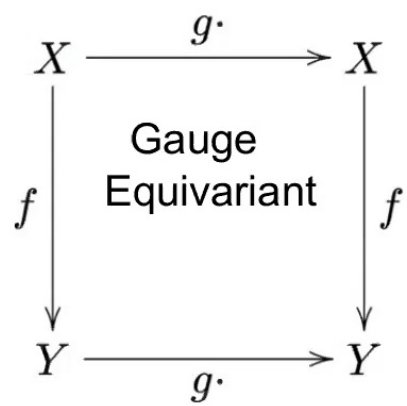
Gauge Equivariant Neural Network for Quantum Lattice Gauge Theories

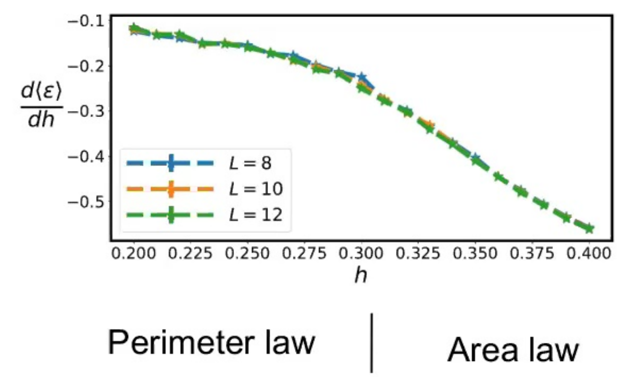
--- Develop gauge equivariant neural network for simulating quantum lattice gauge models

$$\mathcal{H}_{\text{gauge}} = \{|\psi\rangle \in \mathcal{H} : G_v|\psi\rangle = |\psi\rangle \ \forall v \in V\} \qquad \psi(G_v x) = \psi(x)$$



$$W_f := \prod_{e \in f} Z_e \qquad G_v := \prod_{e \ni v} X_e$$





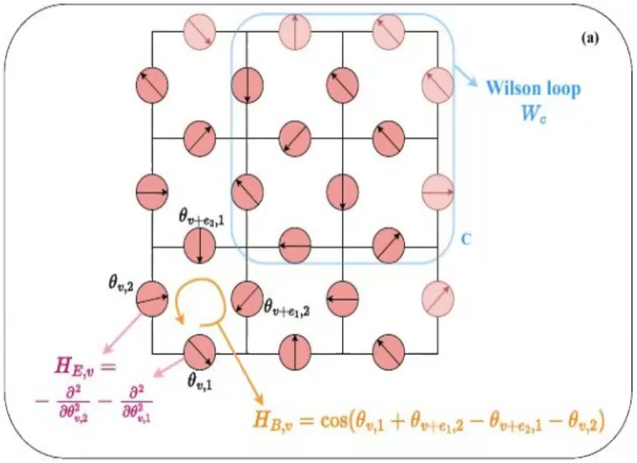
32

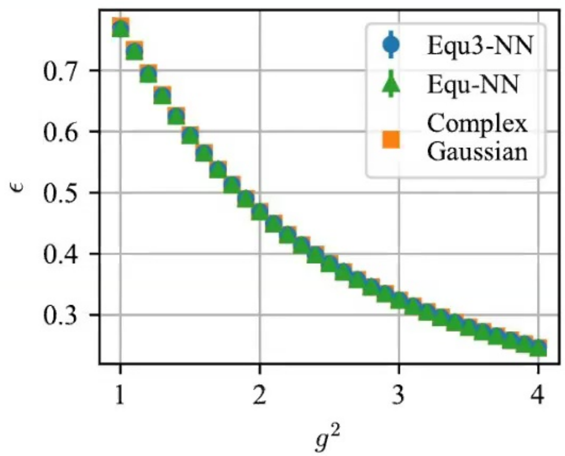
Di Luo†, Shunyue Yuan†, James Stokes, Bryan Clark. arxiv. 2211.03198

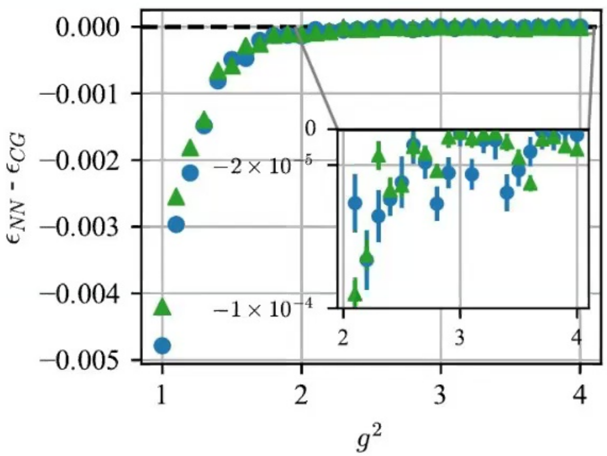
Gauge Equivariant Neural Network for 2+1D U(1) Gauge Theory Simulations in Hamiltonian Formulation

--- Develop gauge equivariant neural network for simulating continuous-variable quantum lattice gauge models

$$\Psi(\cdots, \theta_{v,\delta}, \cdots) = \Psi(\cdots, \theta_{v,\delta} + \alpha_{v+e_\delta} - \alpha_v, \cdots)$$





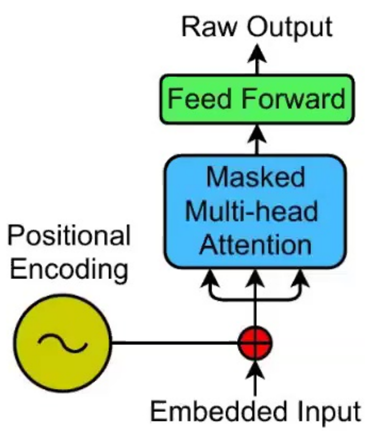


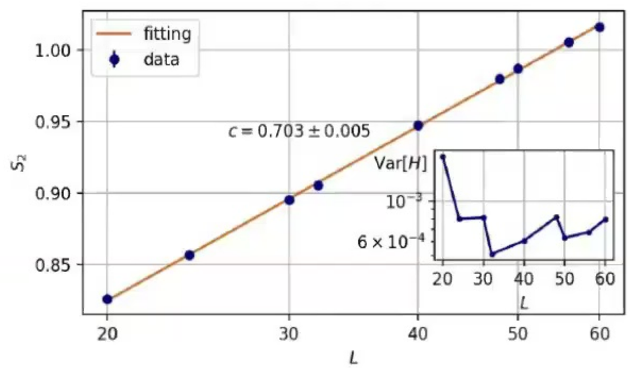
Di Luo†, Zhuo Chen†, Kaiwen Hu, Zhizhen Zhao, Vera Hu, Bryan Clark. arxiv: 2012.05232

Gauge Invariant and Anyonic Symmetric Autoregressive Neural Network for Quantum Lattice Models

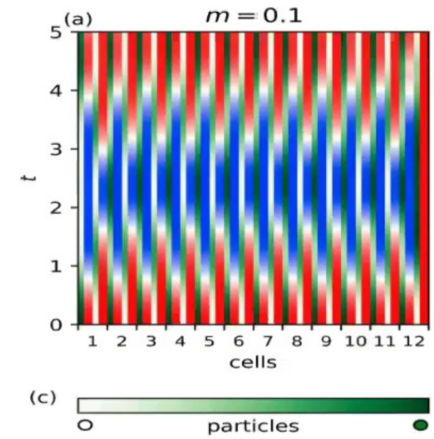
--- Develop autoregressive neural network that satisfies gauge constraints and algebraic constraints with applications to quantum link models, toric codes, Fracton, anyonic models

$$f(x_1, x_2, ..., x_n) = \prod_i^n f(x_i | x_{i<})$$





Anyon central charge



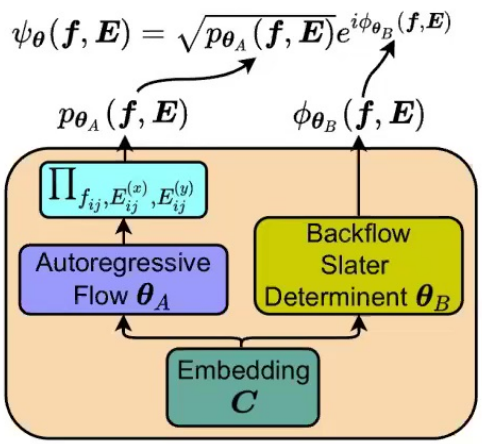
1+1-D QED dynamics

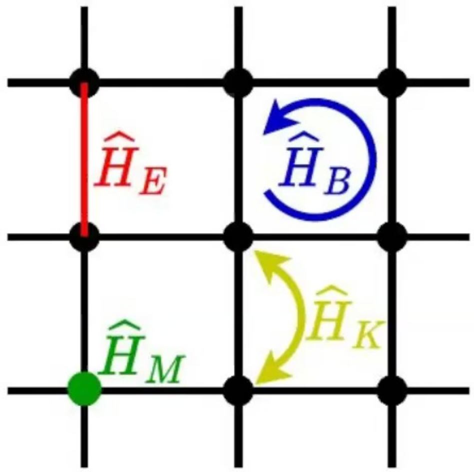
Zhuo Chen†, Di Luo†, Kaiwen Hu, Bryan Clark. arxiv. 2212.06835

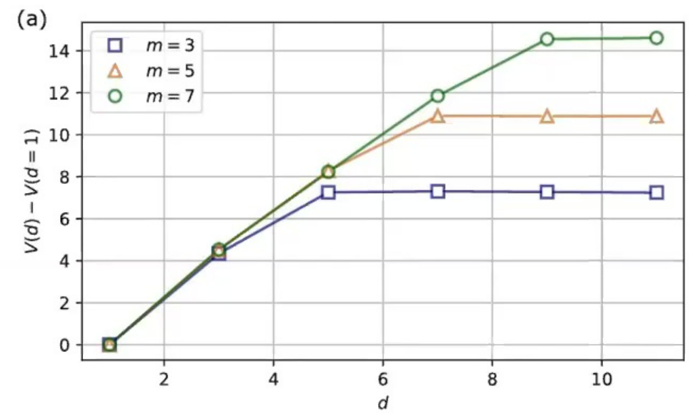
Simulating 2+1D Lattice Quantum Electrodynamics at Finite Density with Neural Flow Wavefunctions

--- Develop Gauge-Fermion FlowNet, which represents U(1) gauge field without cutoff, obey Gauss's law, samples without auto-correlation time and variationally simulates model with sign problems.

--- Simulate 2+1D QED at finite density to study string breaking, charge crystal phase transition and magnetic phase transition.





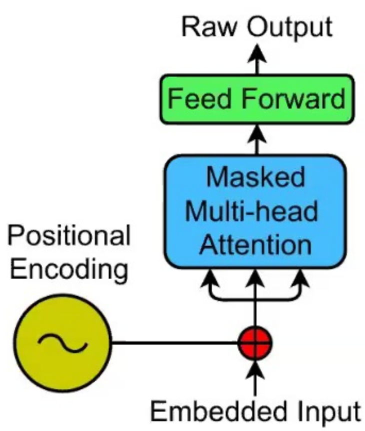


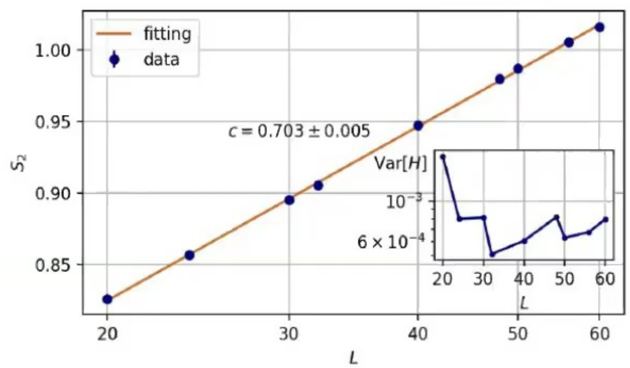
Di Luo†, Zhuo Chen†, Kaiwen Hu, Zhizhen Zhao, Vera Hu, Bryan Clark. arxiv: 2012.05232

Gauge Invariant and Anyonic Symmetric Autoregressive Neural Network for Quantum Lattice Models

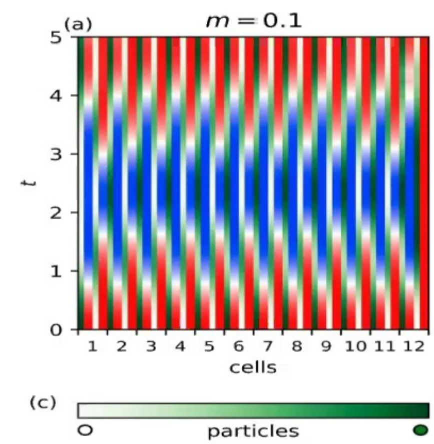
--- Develop autoregressive neural network that satisfies gauge constraints and algebraic constraints with applications to quantum link models, toric codes, Fracton, anyonic models

$$f(x_1, x_2, ..., x_n) = \prod_{i}^{n} f(x_i | x_{i<})$$





Anyon central charge



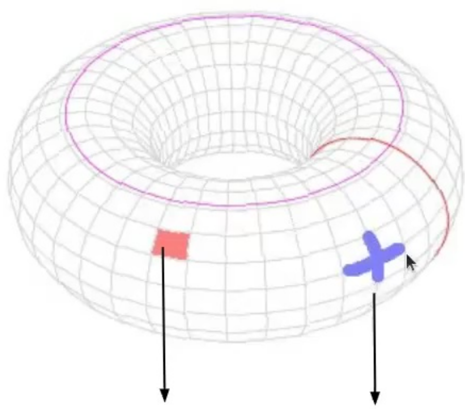
1+1-D QED dynamics

Di Luo, Giuseppe Carleo, Bryan Clark, James Stokes. Phys. Rev. Lett. 127, 276402

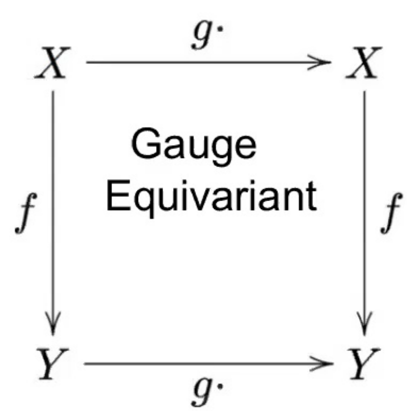
Gauge Equivariant Neural Network for Quantum Lattice Gauge Theories

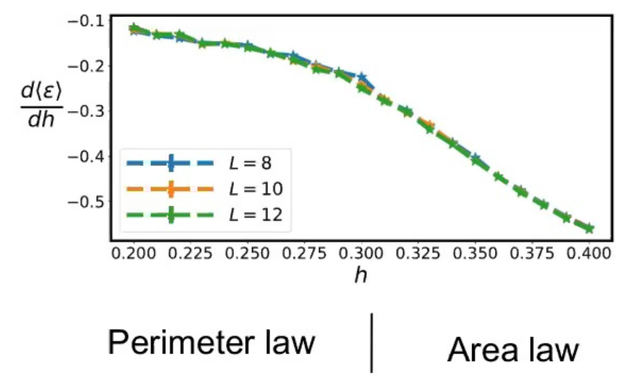
--- Develop gauge equivariant neural network for simulating quantum lattice gauge models

$$\mathcal{H}_{\text{gauge}} = \{|\psi\rangle \in \mathcal{H} : G_v|\psi\rangle = |\psi\rangle \;\; \forall v \in V\} \qquad \psi(G_v x) = \psi(x)$$



$W_f := \prod_{e \in f} Z_e \qquad G_v := \prod_{e \ni v} X_e$





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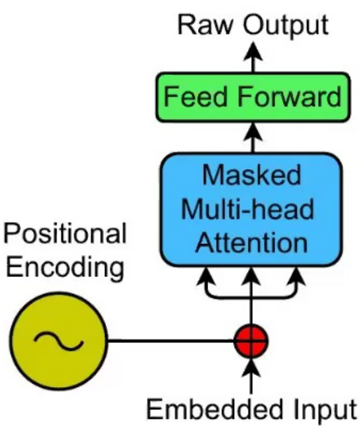

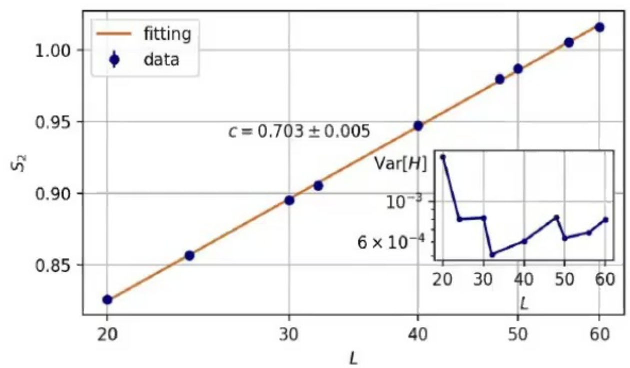

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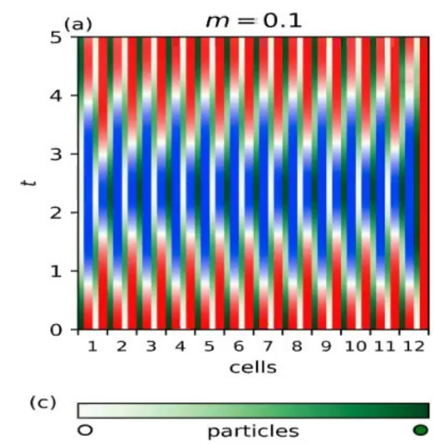

1+1-D QED dynamics

Zhuo Chen†, Di Luo†, Kaiwen Hu, Bryan Clark. arxiv. 2212.06835

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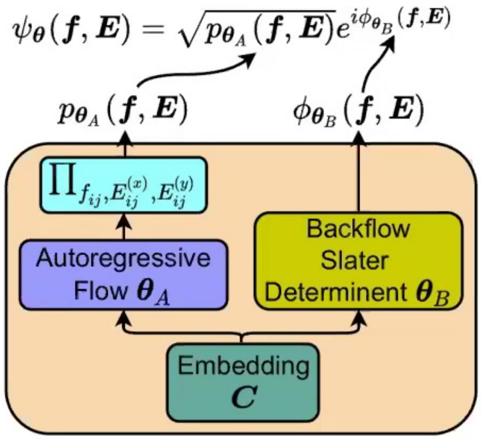
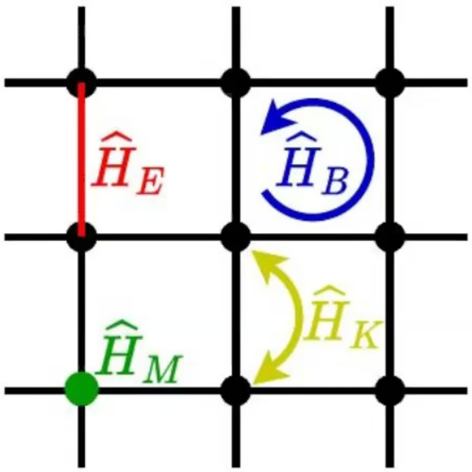
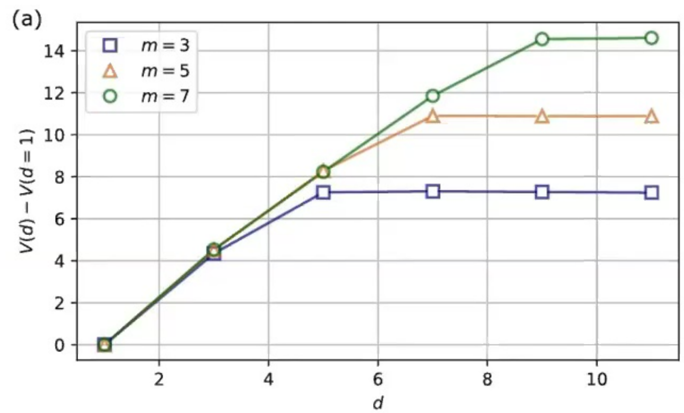




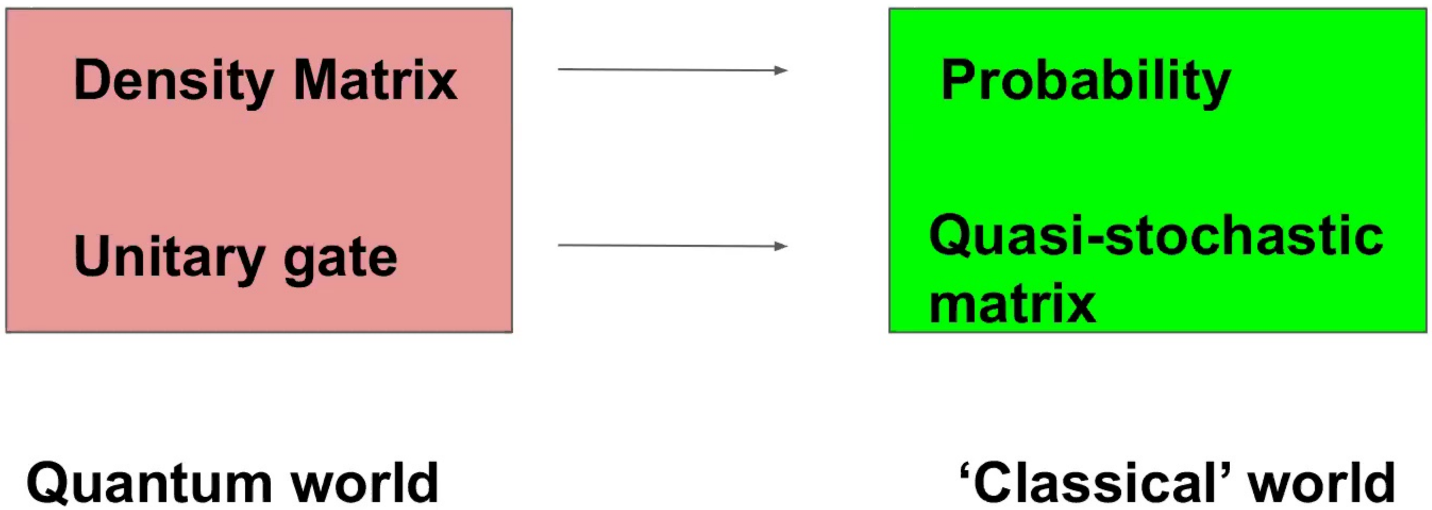


AI for Quantum: Quantum Many-body Physics

III. Real-time Quantum Dynamics

Neural POVM Simulation of Quantum Dynamics

Q: What is the connection of the quantum world and the classical world?

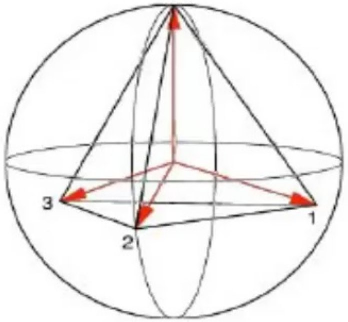


Neural POVM Simulation

Positive Operator-Valued Measurement (POVM)

Tetrahedral POVM:

$$P_{(i)} = \mathrm{tr}(\rho M_{(i)})$$



Quantum tomography

$$M_{(i)} = \frac{1}{4}(\mathbb{1} + v_{(i)} \cdot \sigma)$$

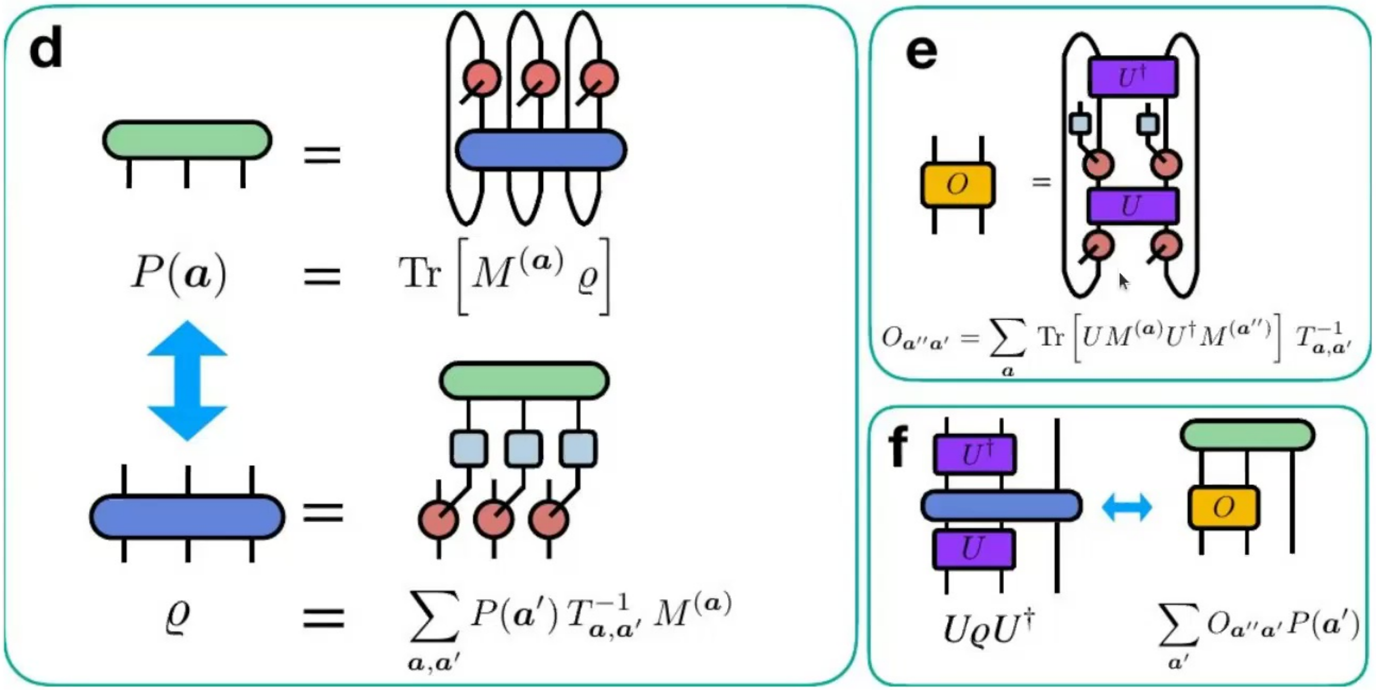
$$v_{(1)} = (1, 1, 1) \quad v_{(2)} = (1, -1, -1)$$

$$v_{(3)} = (-1, 1, -1) \quad v_{(4)} = (-1, -1, 1)$$

Juan Carrasquilla, Di Luo, et al. Phys. Rev. A 104, 032610

Neural POVM Simulation: Quantum Circuits

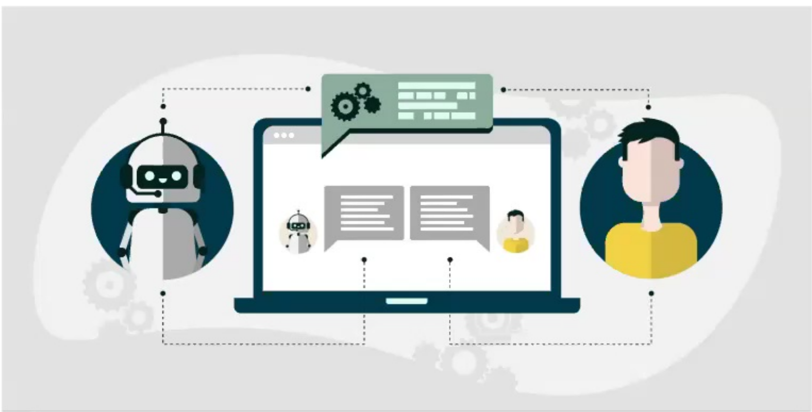
POVM simulation of quantum circuit



Juan Carrasquilla, Di Luo, et al. Phys. Rev. A 104, 032610

Neural POVM Simulation: Quantum Circuits

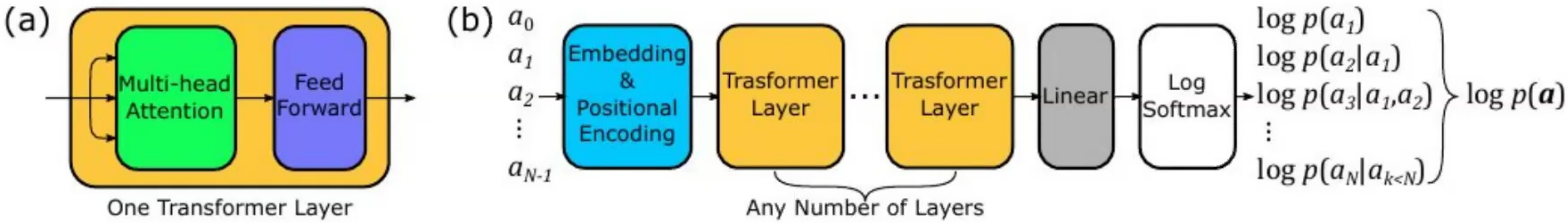
qubits as language: high dimensional distribution with long range correlation



Juan Carrasquilla, Di Luo, et al. Phys. Rev. A 104, 032610

Neural POVM Simulation: Transformer Representation

$$P_\theta(a_1, \ldots, a_N) = \prod^{N} P_\theta(a_k | a_{<k}),$$



Attention is All You Need
(https://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf)

Conditional probability for exact sampling and inference

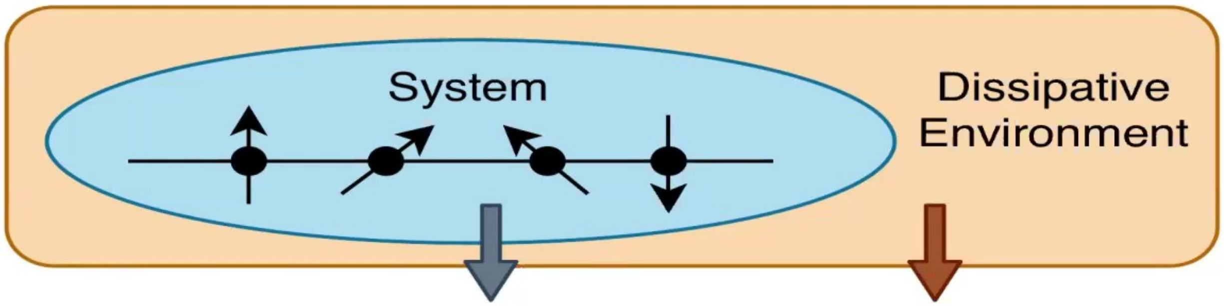
Compact representation for high dimensional distribution

Di Luo†, Zhuo Chen†, Juan Carrasquilla, Bryan K. Clark, Phys. Rev. Lett. 128, 090501

Neural POVM Simulation: Open System Dynamics

Quantum formulation:

$$\dot{\rho} = \mathcal{L}\rho \equiv -i[H,\rho] + \sum_k \frac{\gamma_k}{2}\left(2\Gamma_k \rho \Gamma_k^\dagger - \{\rho, \Gamma_k^\dagger \Gamma_k\}\right)$$



$$\boldsymbol{L} = -\boldsymbol{h}\boldsymbol{H} + \boldsymbol{\gamma}\boldsymbol{\Gamma}$$

POVM formulation:

$$\dot{p}(\boldsymbol{a}) = \sum_{\boldsymbol{b}} p(\boldsymbol{b}) L_{\boldsymbol{a}}^{\boldsymbol{b}} = \sum_{\boldsymbol{b}} p(\boldsymbol{b}) \left(A_{\boldsymbol{a}}^{\boldsymbol{b}} + B_{\boldsymbol{a}}^{\boldsymbol{b}}\right)$$

$$A_{\boldsymbol{a}}^{\boldsymbol{b}} = -i\,\mathrm{Tr}\left(H[N^{(\boldsymbol{b})}, M_{(\boldsymbol{a})}]\right); \qquad B_{\boldsymbol{a}}^{\boldsymbol{b}} = \sum_k \frac{\gamma_k}{2}\,\mathrm{Tr}\left(2\Gamma_k N^{(\boldsymbol{b})}\Gamma_k^\dagger M_{(\boldsymbol{a})} - \Gamma_k^\dagger \Gamma_k \{N^{(\boldsymbol{b})}, M_{(\boldsymbol{a})}\}\right).$$

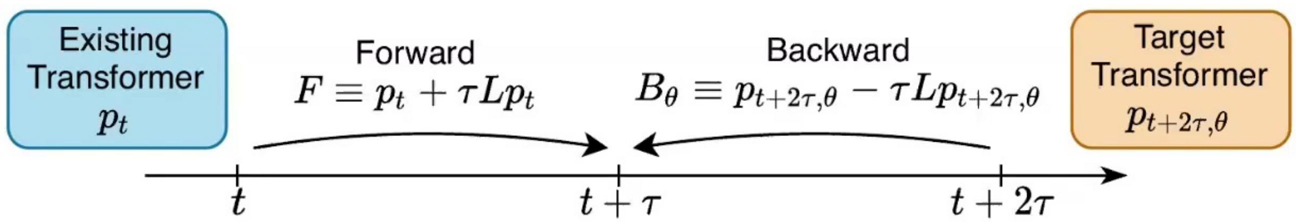
Di Luo†, Zhuo Chen†, Juan Carrasquilla, Bryan K. Clark, Phys. Rev. Lett. 128, 090501

Neural POVM Simulation: Optimization

$$\dot{p}(\boldsymbol{a}) = \sum_{\boldsymbol{b}} p(\boldsymbol{b}) L_{\boldsymbol{a}}^{\boldsymbol{b}} = \sum_{\boldsymbol{b}} p(\boldsymbol{b}) \left(A_{\boldsymbol{a}}^{\boldsymbol{b}} + B_{\boldsymbol{a}}^{\boldsymbol{b}} \right)$$

Dynamics:

$$\theta = \arg\min E_{a \sim p_{t+2\tau}} \left[\frac{1}{p_{t+2\tau}(a)} |B_\theta(a) - F(a)| \right]$$



Steady state: minimize the derivative to be zero

$$\|\dot{p_\theta}\|_1 = \sum_{\boldsymbol{a}} \left| \sum_{\boldsymbol{b}} p_\theta(\boldsymbol{b}) L_{\boldsymbol{a}}^{\boldsymbol{b}} \right| = \frac{1}{N_s} \sum_{\boldsymbol{a} \sim p_\theta}^{N_s} \frac{\left| \sum_{\boldsymbol{b}} p_\theta(\boldsymbol{b}) L_{\boldsymbol{a}}^{\boldsymbol{b}} \right|}{p_\theta(\boldsymbol{a})}$$

Di Luo†, Zhuo Chen†, Juan Carrasquilla, Bryan K. Clark, Phys. Rev. Lett. 128, 090501

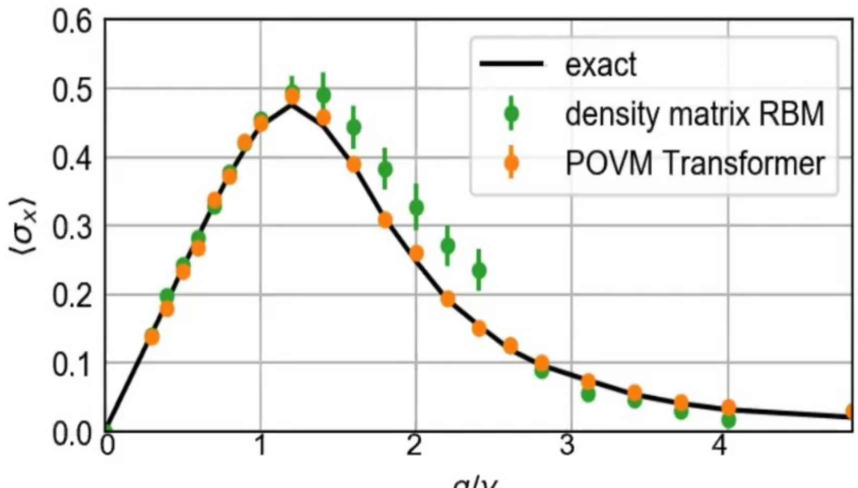
Neural POVM Simulation: Open System Dynamics

1D Dissipative Transverse Ising Chain $H = \frac{V}{4} \sum_{\langle i,j \rangle} \sigma_i^{(z)} \sigma_j^{(z)} + \frac{g}{2} \sum_k \sigma_k^{(x)}$

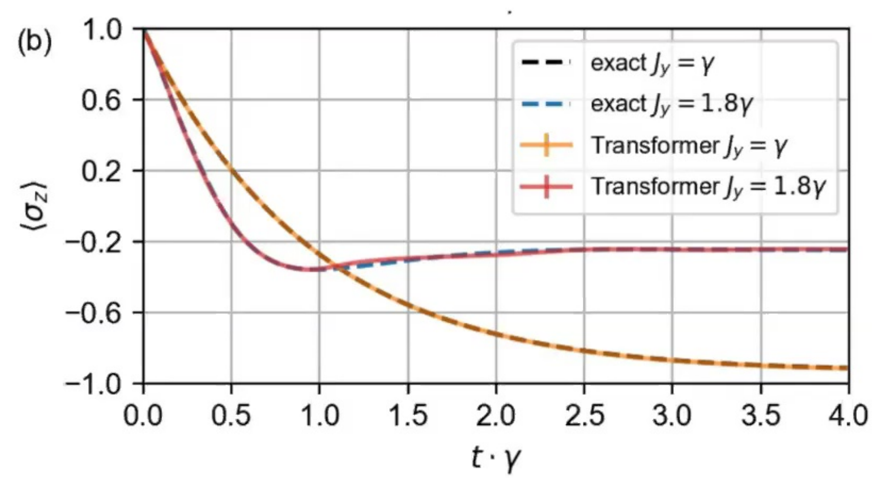
Dissipative Heisenberg Chain $H = \sum_{\langle i,j \rangle} \sum_{w=x,y,z} J_w \sigma_i^{(w)} \sigma_j^{(w)} + B \sum_k \sigma_k^{(z)}$

$$\Gamma_k = \sigma_k^{(-)} = \frac{1}{2}(\sigma_k^{(x)} - i\sigma_k^{(y)})$$

RBM data: Phys. Rev. Lett. 122, 250503



1D steady state

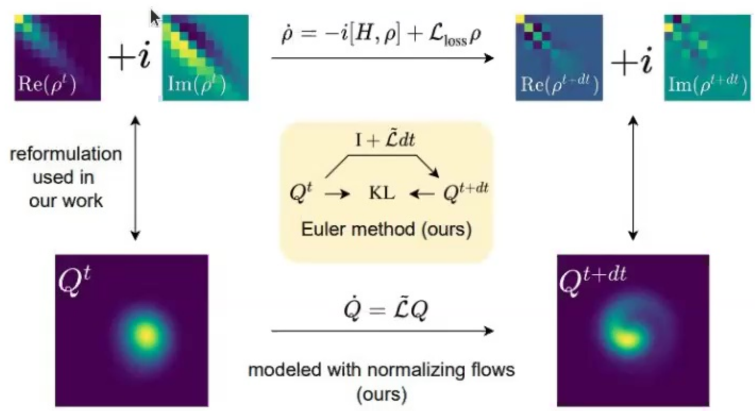


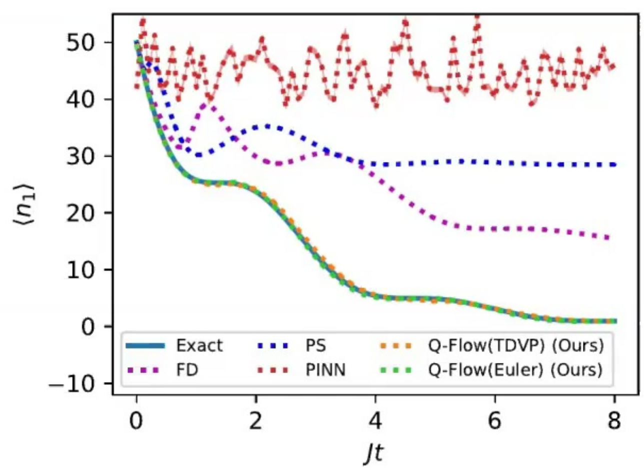
2D dynamics

Owen Dugan, Peter Y. Lu, Rumen Dangovski, Di Luo, Marin Soljačić, arxiv.2302.12235

QFlow: Generative Modeling for Differential Equations of Open Quantum Dynamics with Normalizing Flows

--- Develop flow-based models with Q function for continuous variable open quantum dynamics simulations using stochastic Euler methods and time dependent variational principle





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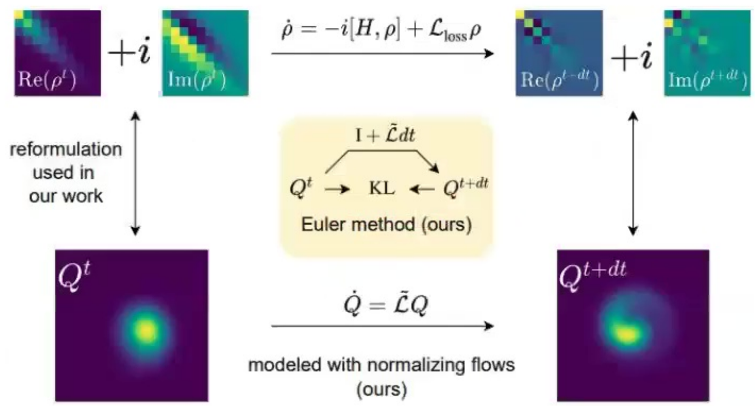
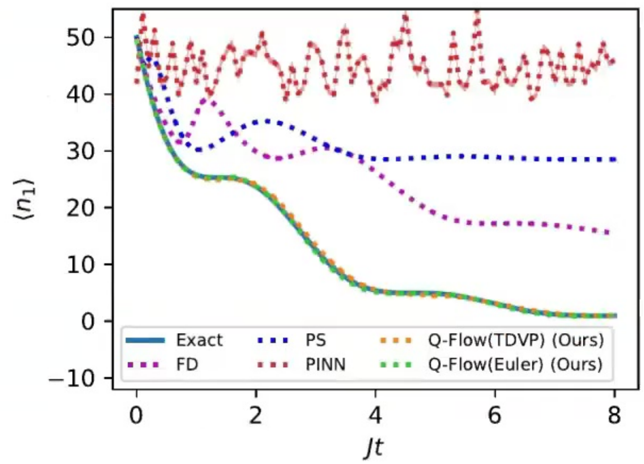
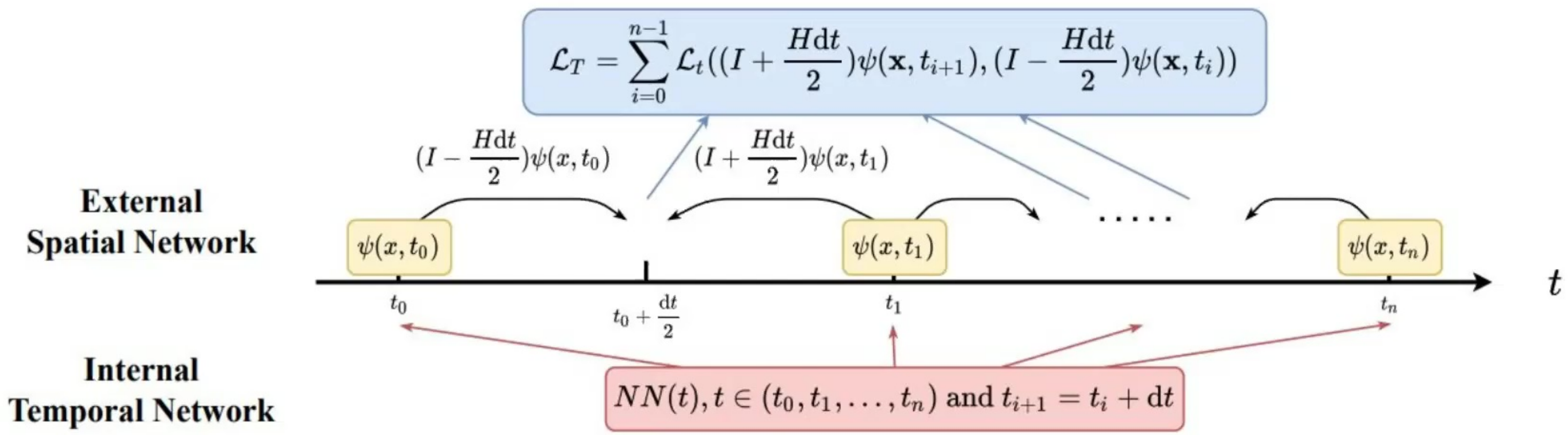




Jiangran Wang, Zhuo Chen, Di Luo, Zhizhen Zhao, Vera Mikyoung Hur, Bryan K. Clark, arxiv.2108.02200

Spacetime Neural Network for High Dimensional Quantum Dynamics

--- Develop space time neural network that is able to all all the time steps dynamics simultaneously

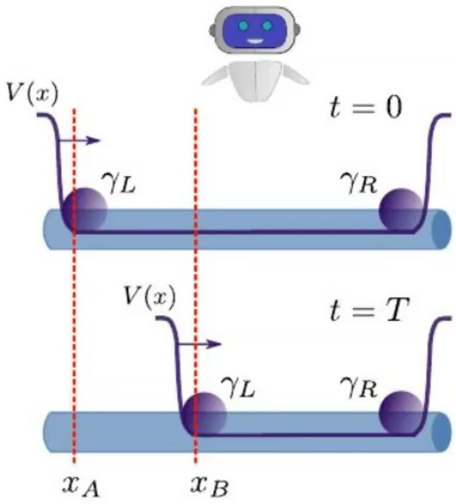


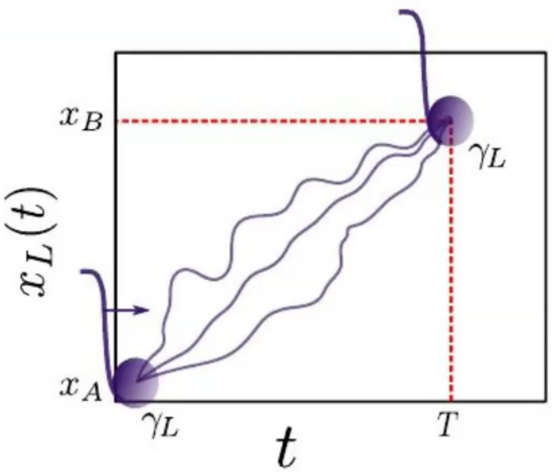
49

PRX Quantum 2, 020332

Protocol Discovery for the Quantum Control of Majoranas by Differentiable Programming and Natural Evolution Strategies

Luuk Coopmans†, Di Luo†, Graham Kells, Bryan K. Clark, Juan Carrasquilla





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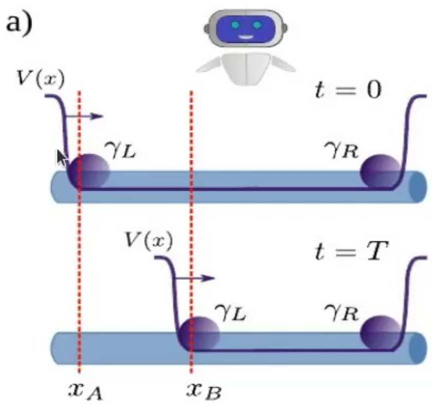
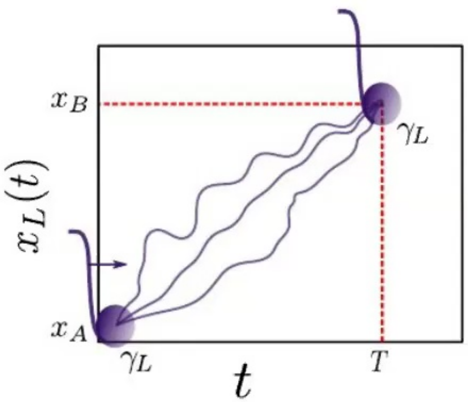
Differentiable Programming for Quantum Control

PRX Quantum 2, 020332





Control: V(x,t)

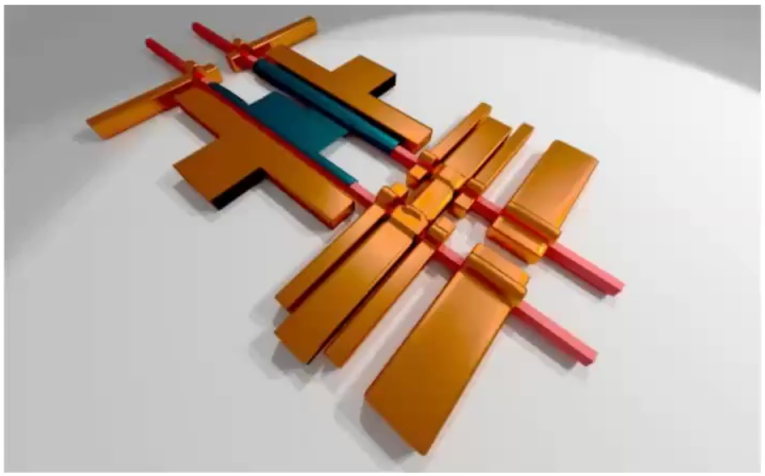
$$\mathcal{H}(t) = -\sum_{x=1}^{N}[\mu(x) - V(x,t)](c_x^\dagger c_x - 1/2) - w\sum_{x=1}^{N-1}(c_x^\dagger c_{x+1} + h.c) + \Delta\sum_{x=1}^{N-1}(c_x^\dagger c_{x+1}^\dagger + h.c.),$$

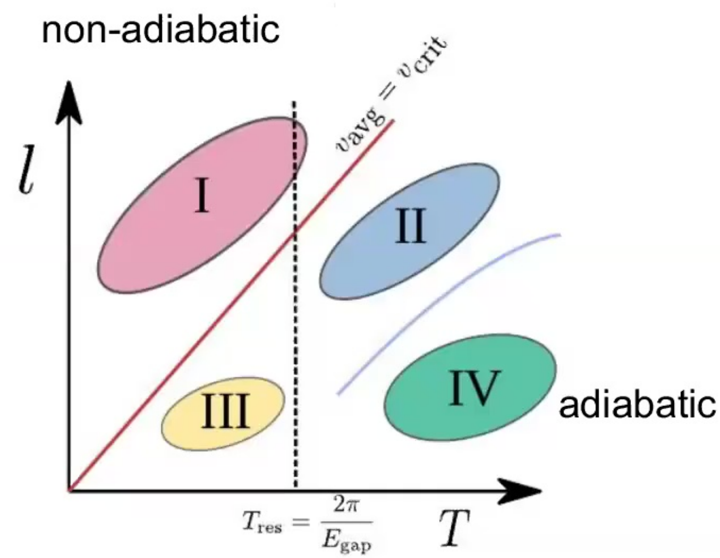
Goal: minimize

$$\mathcal{I}(T) = 1 - |\langle\psi_B|\mathcal{T}e^{-i\int_0^T \mathcal{H}(t)dt}|\psi_A\rangle|^2 \equiv 1 - \mathcal{F}(T)$$

PRX Quantum 2, 020332

Differentiable Programming for Quantum Control

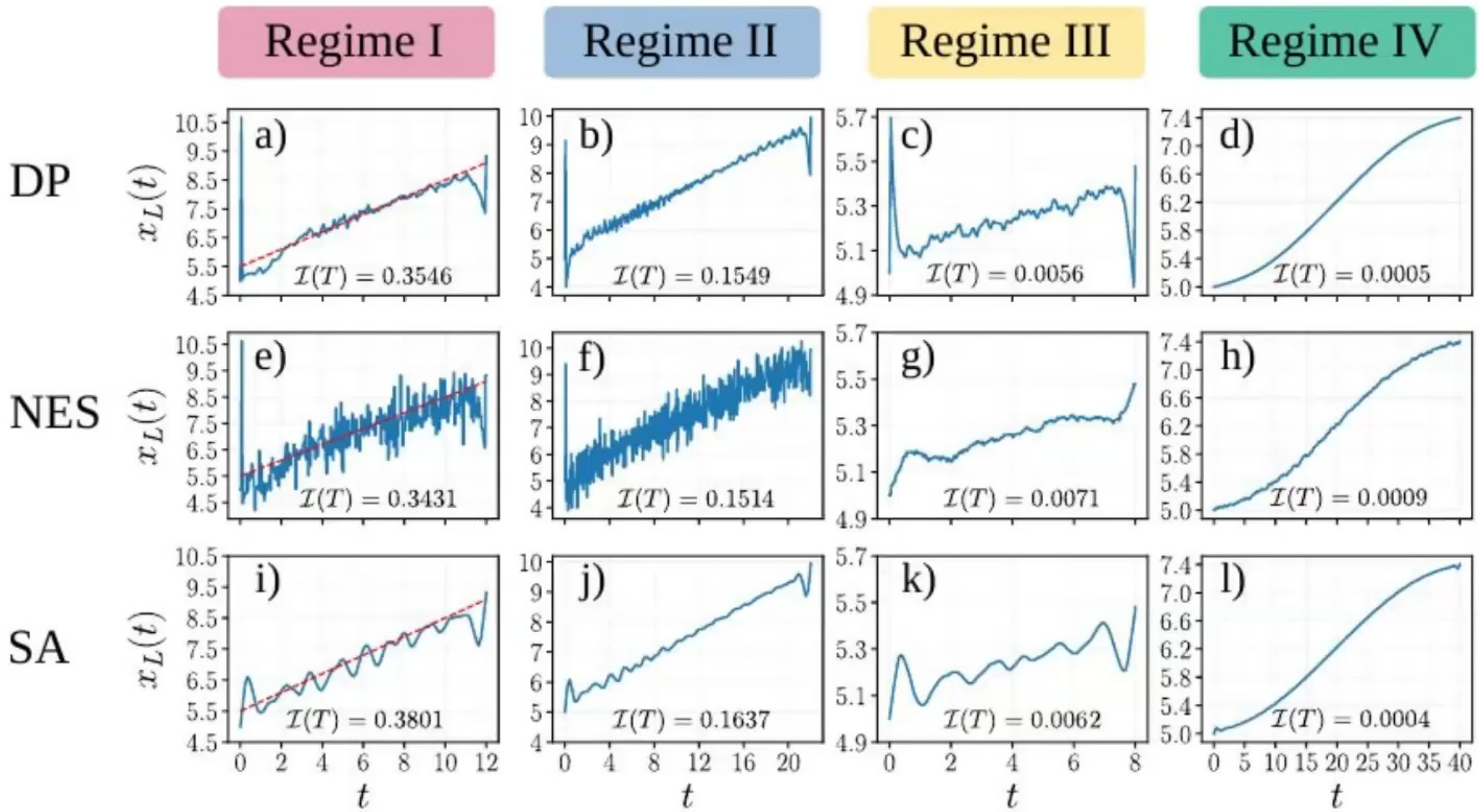




Topological quantum computation and majorana braiding

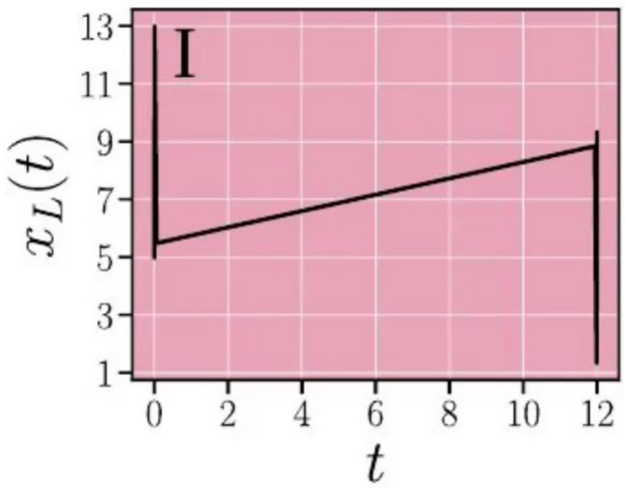
PRX Quantum 2, 020332

Differentiable Programming for Quantum Control

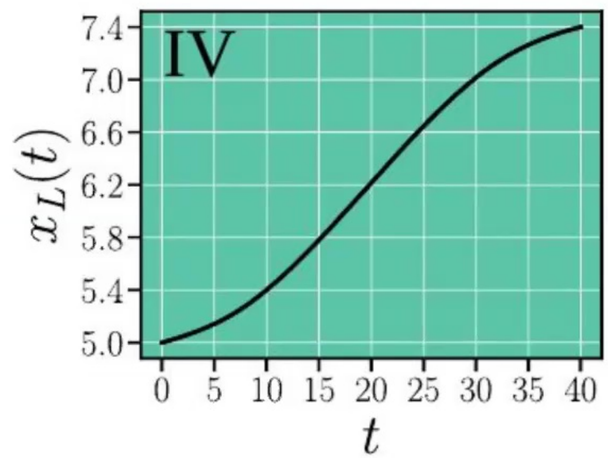


Differentiable Programming for Quantum Control

PRX Quantum 2, 020332



New Jump-move-jump protocol discovered
(later justified by moving frame analysis)



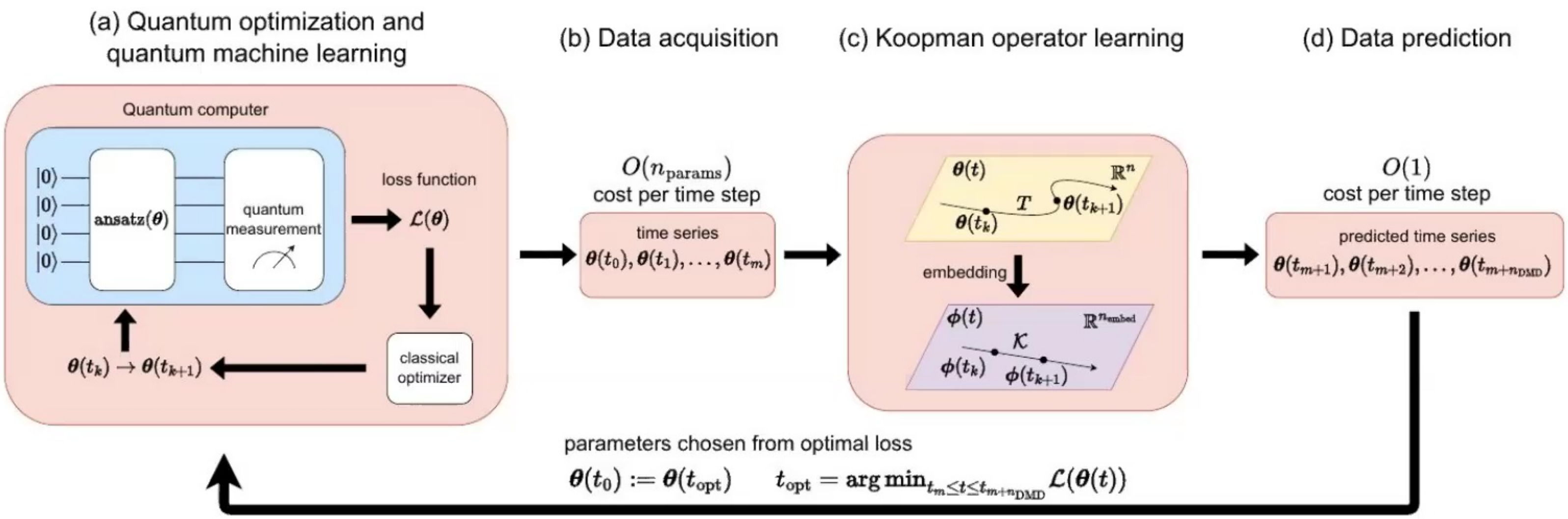
Rediscover of ramp-up ramp down
adiabatic protocol

56

arxiv. 2211.01365

Koopman Operator learning for Accelerating Quantum Optimization and Machine Learning

Di Luo†, Jiayu Shen†, Rumen Dangovski, Marin Soljačić



1 57

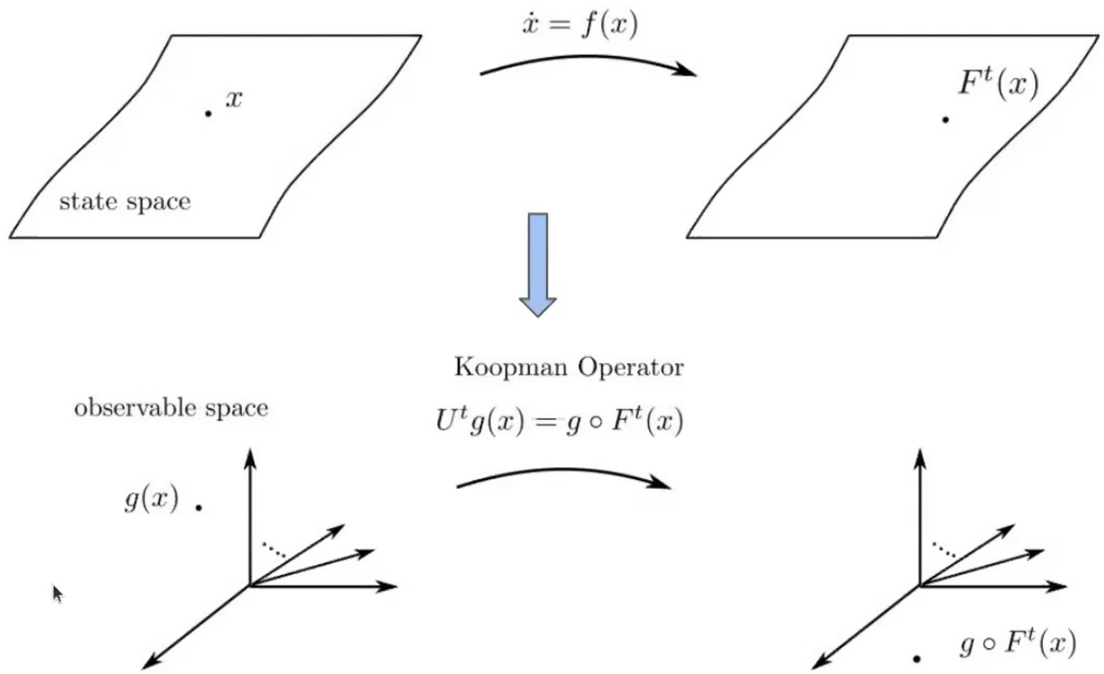
Koopman Operator Theory for Quantum

arxiv. 2211.01365

Predict quantum gradient as dynamical equation using Koopman Operator theory

Classical variable

Quantum observable embedding

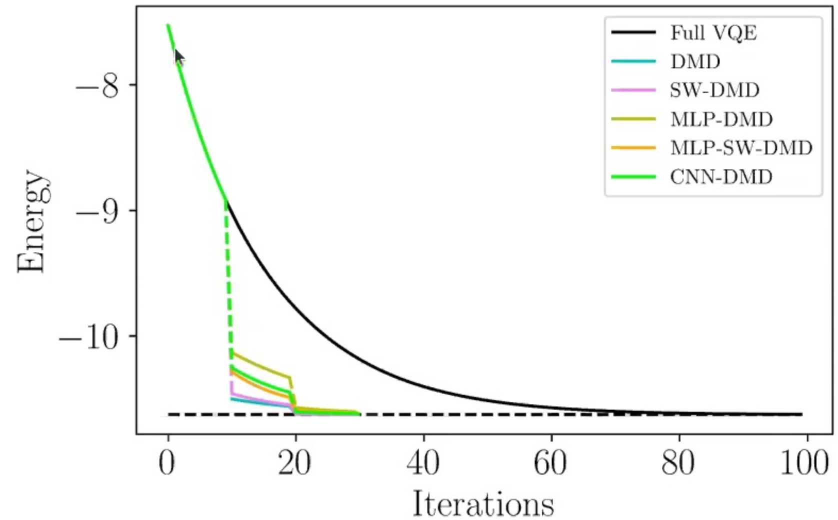


1 58

Koopman Operator Theory for Quantum

arxiv. 2211.01365

	Classical ML	VQA
Data Type	Classical	Classical or Quantum
Typical Model	Classical Neural Net	Parametrized Quantum Circuit
Forward Propagation Cost per Step	$O(1)$	$O(n_{\text{shots}})$
Backward Propagation Cost per Step	$O(1)$	$O(n_{\text{params}} \cdot n_{\text{shots}})$
QuACK Gradient Cost per Step	$O(1)$	$O(n_{\text{shots}})$



10-qubit quantum Ising model
with quantum natural gradient

Summary and Outlook

- New opportunities from machine learning for simulating quantum many-body physics and quantum information science
- Open questions to handle fermionic symmetry, gauge symmetries, continuous fields, open quantum dynamics
- Study ground state phase diagram, finite temperature physics, and real-time dynamics of quantum many-body systems