AI GOES MAD^2

Advancing Quantum Control and Information Retrieval with Machine Learning Technique

Xi Chen

Instituto de Ciencia de Materiales de Madrid – CSIC

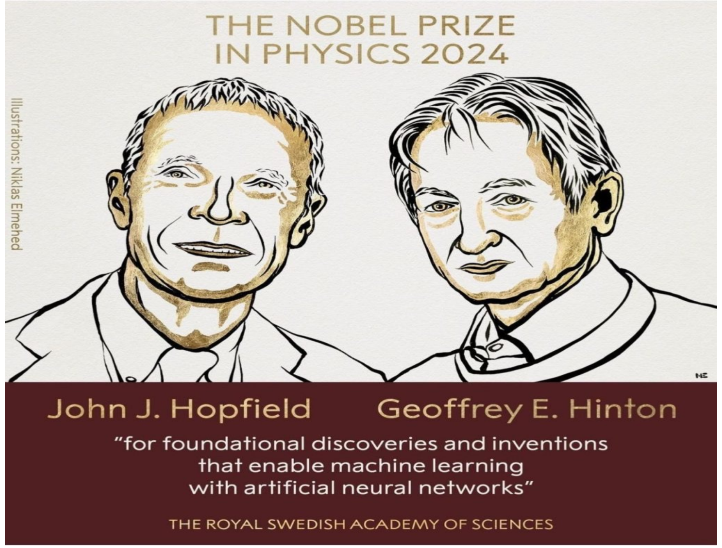
October 16th, 2024

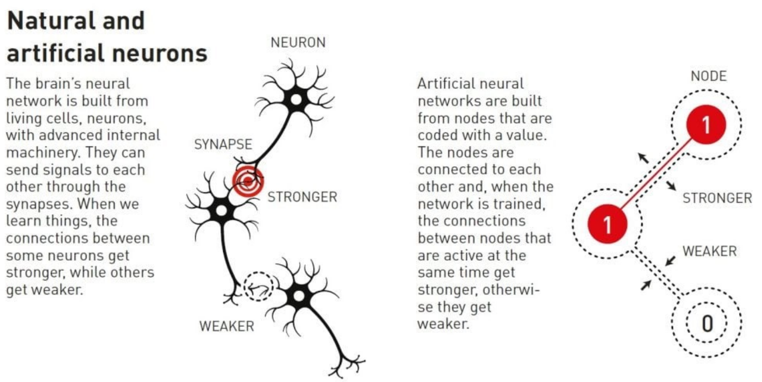
OUTLINE

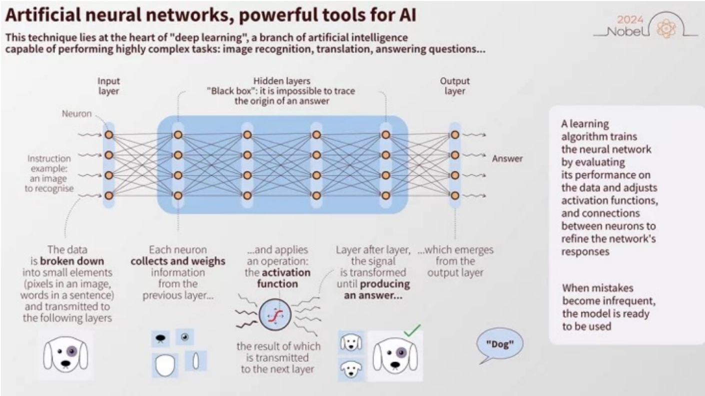
1. Introduction
2. Machine learning for quantum optimal control
3. Active learning for quantum information retrival
4. Conclusion

Nobel Prize in Physics 2024： Machine learning with ANN

Nobel Prize in Chemistry 2024： Computational and ML protein design

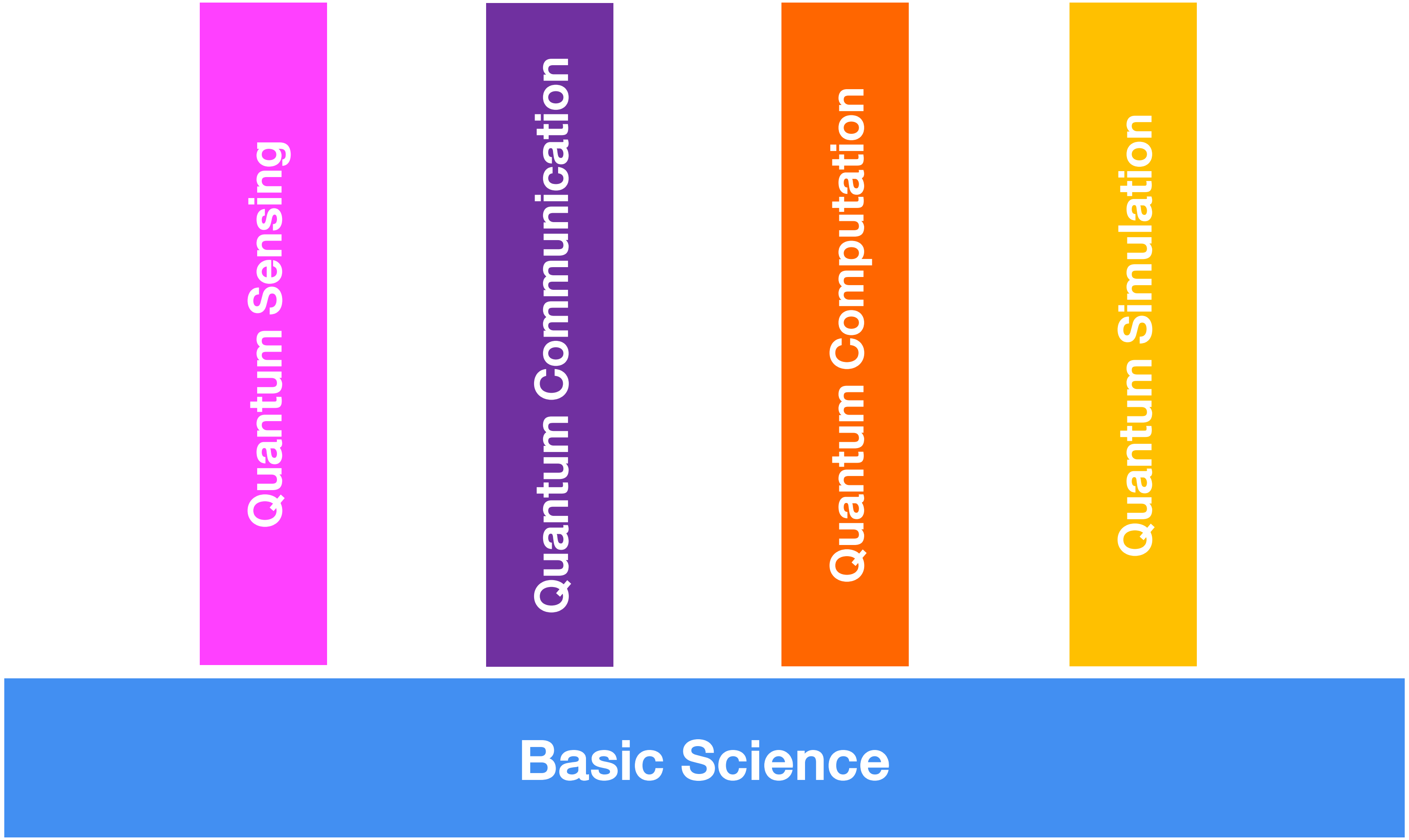




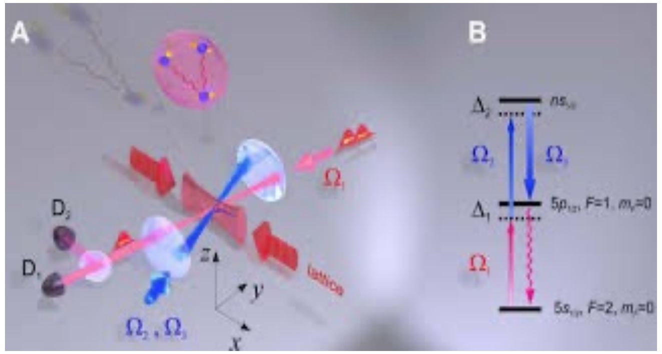


The **Second Quantum Revolution** refers to

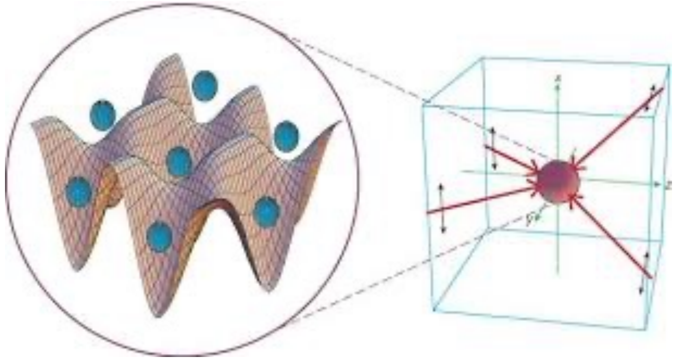
a contemporary wave of advancements and breakthroughs in the field of quantum physics



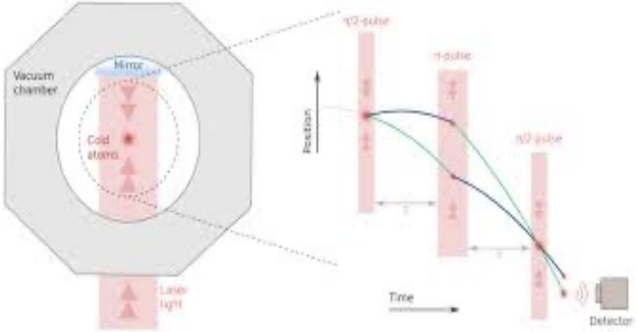
Quantum Information Processing



Quantum Simulation

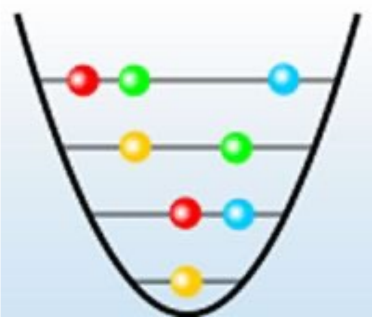


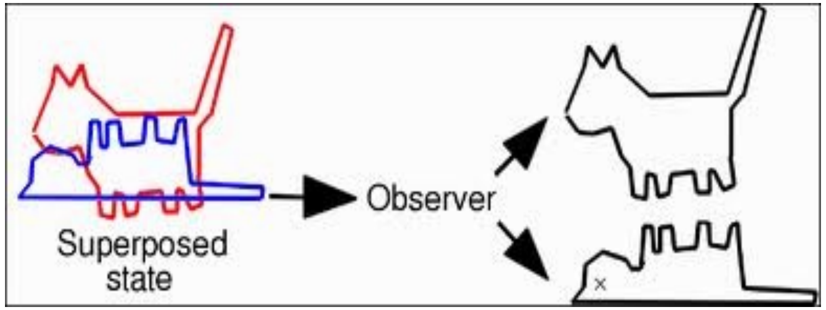
Quantum Metrology

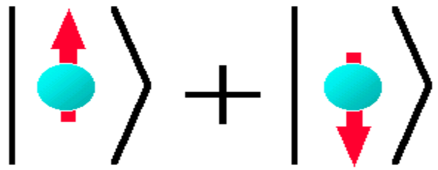


Essential: Preparation, control and manipulation of quantum states with high-fidelity and in a fast and robust way

Superposition | **Coherence** | **Entanglement**



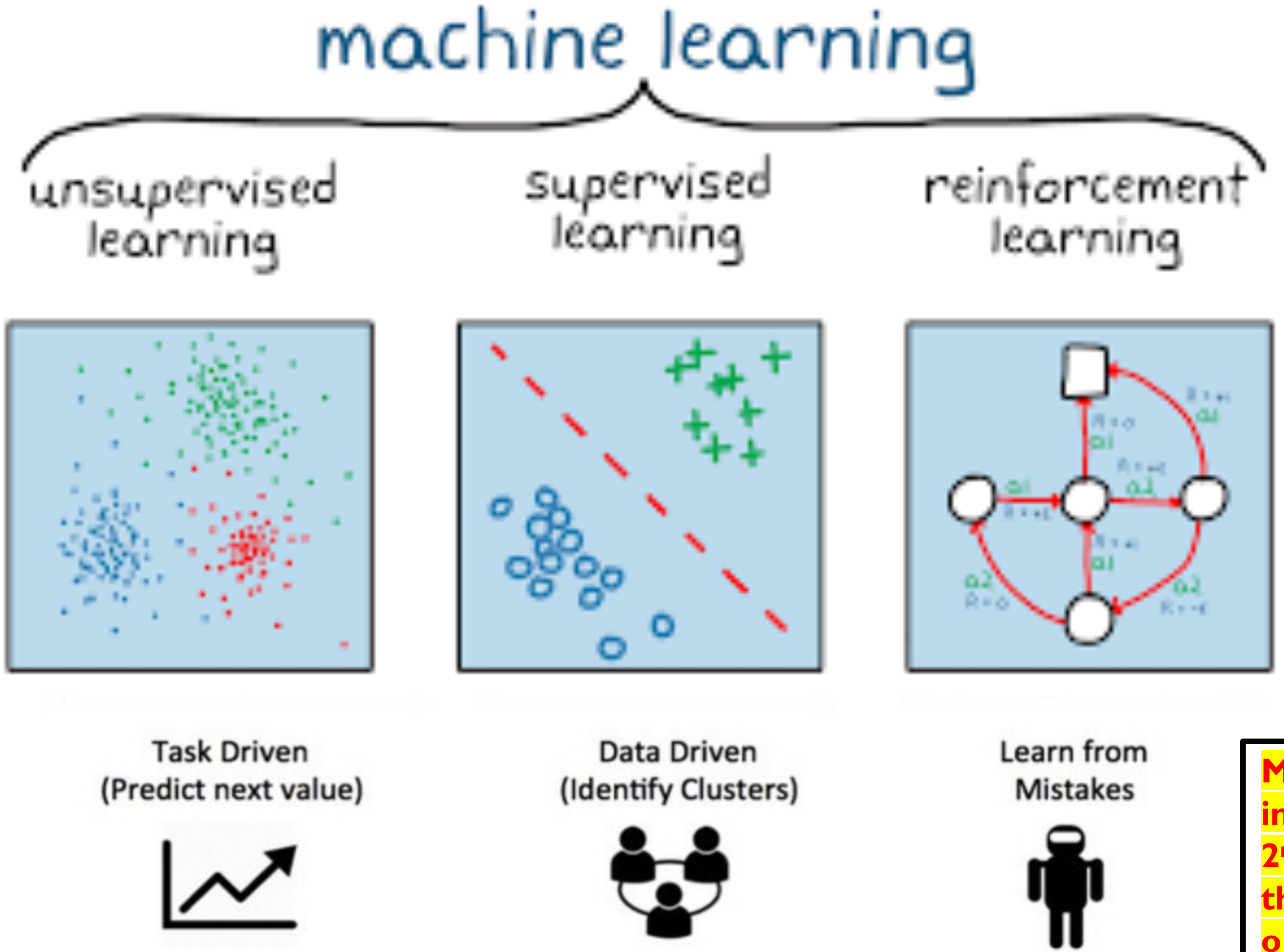




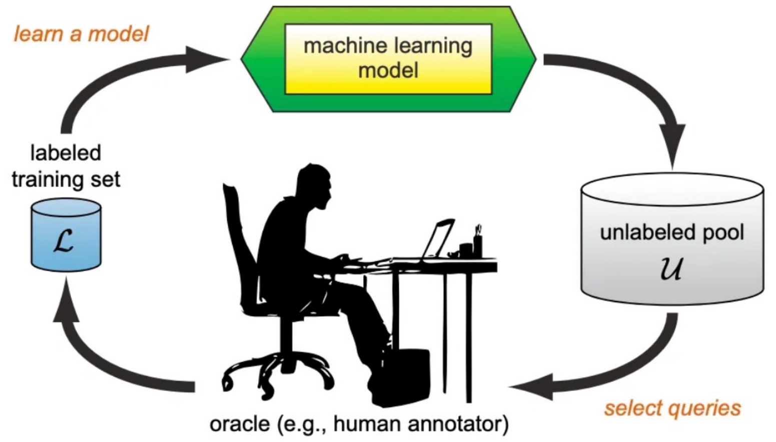
$$\frac{1}{\sqrt{2}}\left(|0\rangle_A \otimes |1\rangle_B - |1\rangle_A \otimes |0\rangle_B\right)$$

Quantum information exploits quantum mechanical properties to enable more efficient information processing.

Types of Machine Learning – Supervised, Unsupervised, Reinforcement

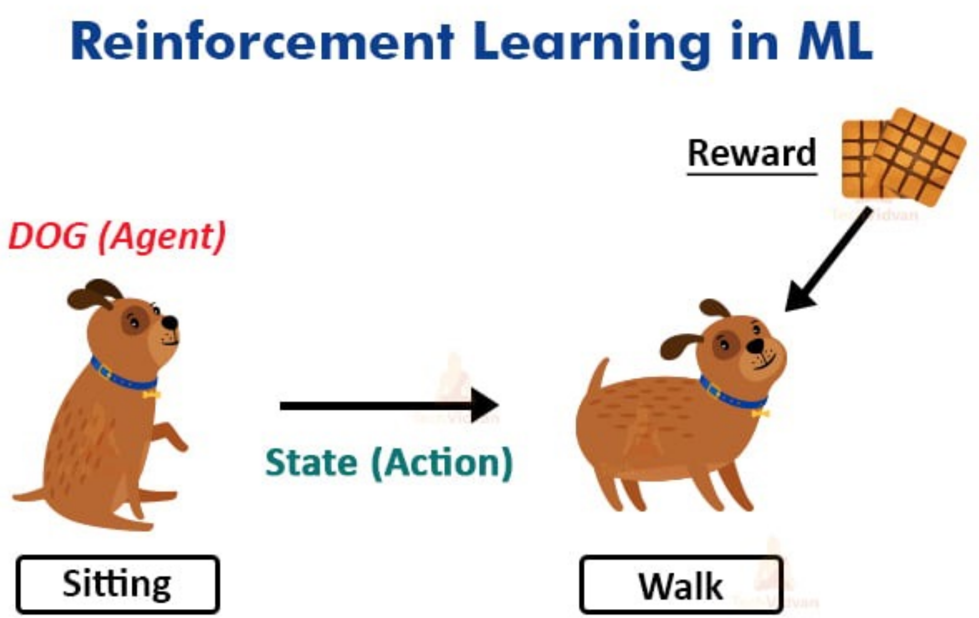


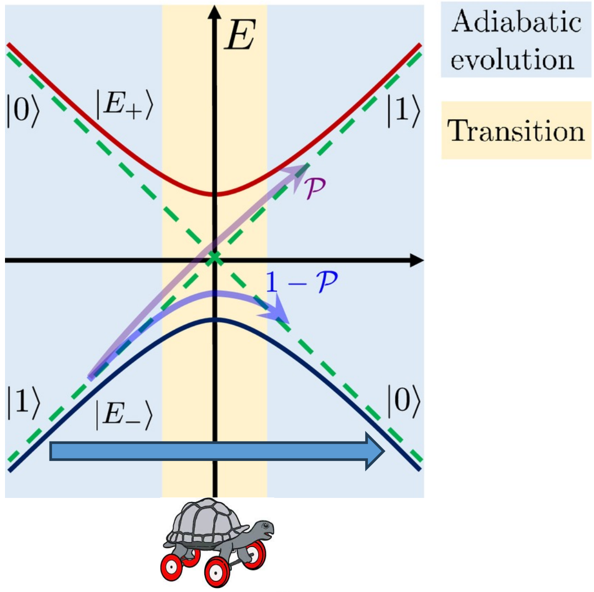
Active Learning

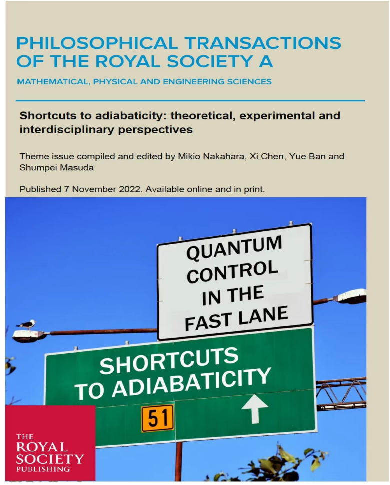


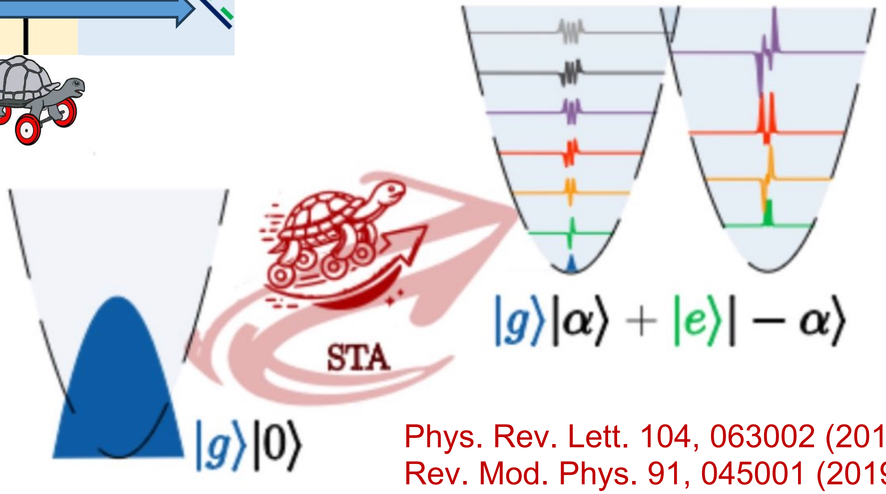
ML can be combined with quantum control and quantum information, embodying the interdisciplinary spirit of the 2nd quantum revolution. This integration not only drives the advancement of QST but also fosters the development of new paradigms in high-performance CS and AI.

Reinforcement Learning for Quantum Optimal Control









Phys. Rev. A 103, L040401 (2021).

Sci. China Phys. Mech. Astron. 65, 250312 (2022).

Phys. Rev. Lett. 104, 063002 (2010)
Rev. Mod. Phys. 91, 045001 (2019)

Physical Model – single qubit control

Landau–Zener type

We consider two-level system, which is described by $H(t) = \frac{\hbar}{2}[\Omega\sigma_x + \Delta(t)\sigma_z],$

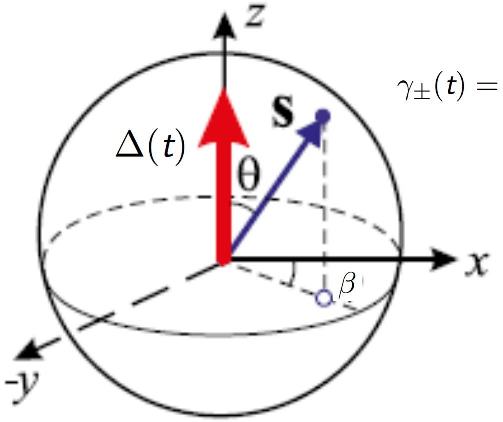
The corresponding Lewis-Riesenfeld invariant is given by $I(t) = \frac{\hbar}{2}\Omega_0 \sum_{\pm} |\phi_\pm(t)\rangle\langle\phi_\pm(t)|,$

and its eigenstates are $|\phi_+(t)\rangle = \left(\cos\frac{\theta}{2}e^{-i\frac{\beta}{2}}, \sin\frac{\theta}{2}e^{i\frac{\beta}{2}}\right)^T, \; |\phi_-(t)\rangle = \left(\sin\frac{\theta}{2}e^{-i\frac{\beta}{2}}, -\cos\frac{\theta}{2}e^{i\frac{\beta}{2}}\right)^T.$

The condition $dI(t)/dt \equiv \partial I(t)/\partial t + (1/i\hbar)[I(t), H(t)] = 0$

gives

$$\Delta(t) = -\frac{\ddot{\theta}}{\Omega\sqrt{1-\left(\frac{\dot{\theta}}{\Omega}\right)^2}} + \Omega\cot\theta\sqrt{1-\left(\frac{\dot{\theta}}{\Omega}\right)^2}.$$



$$\gamma_\pm(t) = \pm\frac{1}{2}\int_0^t \left(\frac{\dot{\theta}\cot\beta}{\sin\theta}\right) dt'.$$

$$|\Psi(t)\rangle = \sum_{\pm} c_\pm \exp(i\gamma_\pm)|\phi_\pm(t)\rangle,$$

Shortcuts-to-adiabaticity Protocol

The ansantz $$\theta(t) = \frac{\Omega T}{a}\left[as - \frac{\pi^2}{2}(1-s)^2 + \frac{\pi^2}{3}(1-s)^3 + \cos(\pi s) + A\right]$$

where $$s = t/T,\ \ A = \pi^2/6 - 1,\ \ T = -\pi a/[(2 - a - \pi^2/6)\Omega].\ \ a > 2 - \pi^2/6$$

Considering the systematic errors in Rabi frequency and detuning, e.g.

$$\Omega \to \Omega(1+\delta_\Omega) \qquad\qquad \Delta(t) \to \Delta(t) + \delta_\Delta$$

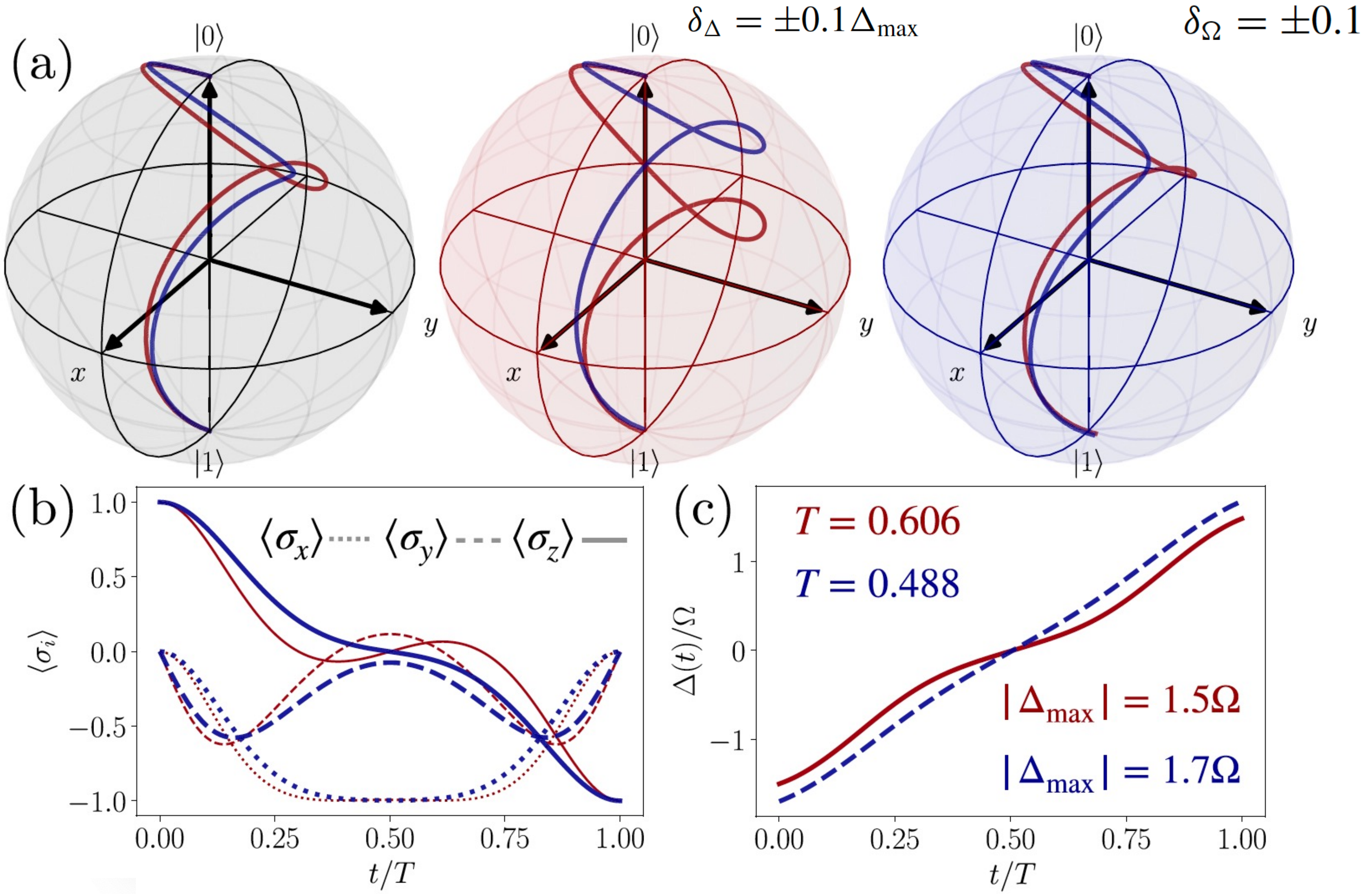
We find the error sensitivity, using time-dependent perturbation theory,

$$\left|\int_0^T dt e^{i\eta(t)}\left(\delta_\Delta \sin\theta - i2\delta_\Omega\dot{\theta}\sin^2\theta\right)\right| = 0,\ \ \eta(t) = 2\gamma_+(t)$$

$$\eta(t) = 2\theta + \alpha_1\sin(2\theta) + \alpha_2\sin(4\theta) + \cdots + \alpha_n\sin(2n\theta)$$

Rabi $\alpha_1 = -1$

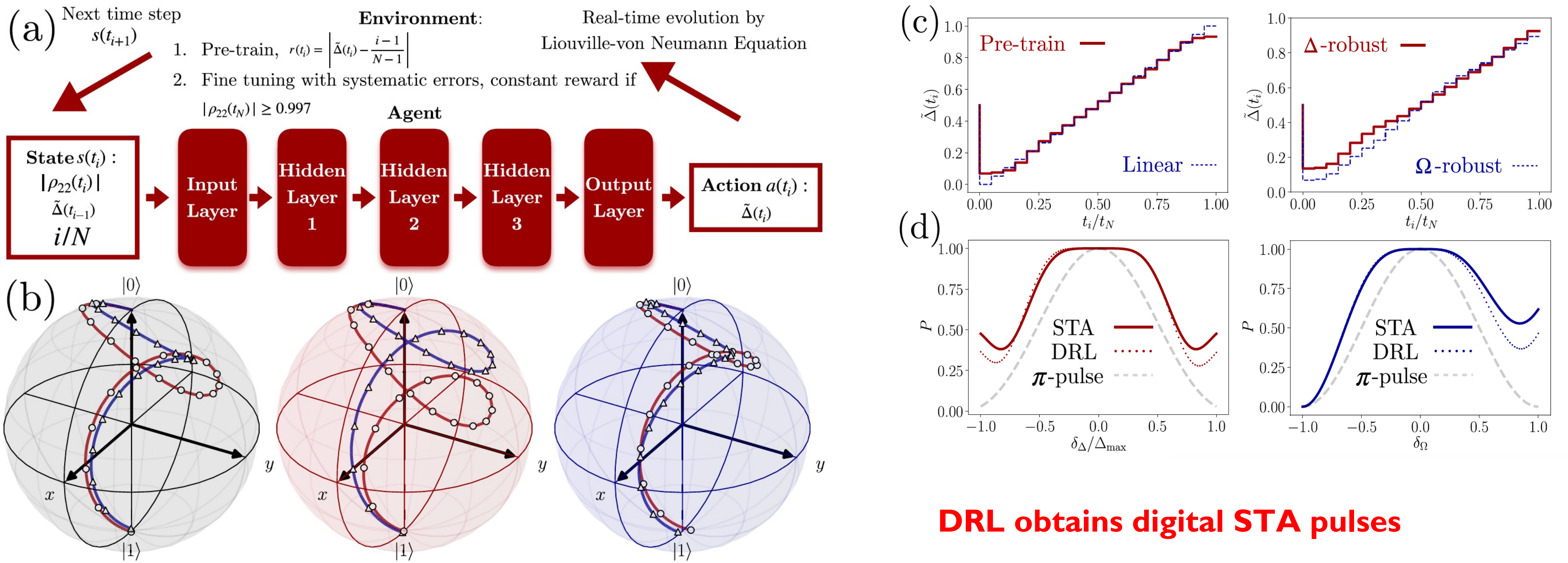
detuning $\alpha_1 = -1.74$



$\Omega = 20 \times 2\pi$ MHz

$a = 0.604$ (red curve) and 0.728 (blue curve)

Breaking adiabatic quantum control with deep learning



Agent: Deep Artificial Neural Network (ANN)

Input Layer Nodes: encoded state

Output Layer Nodes: encoded action

A deep ANN can effectively approximate an (unknown) optimal map

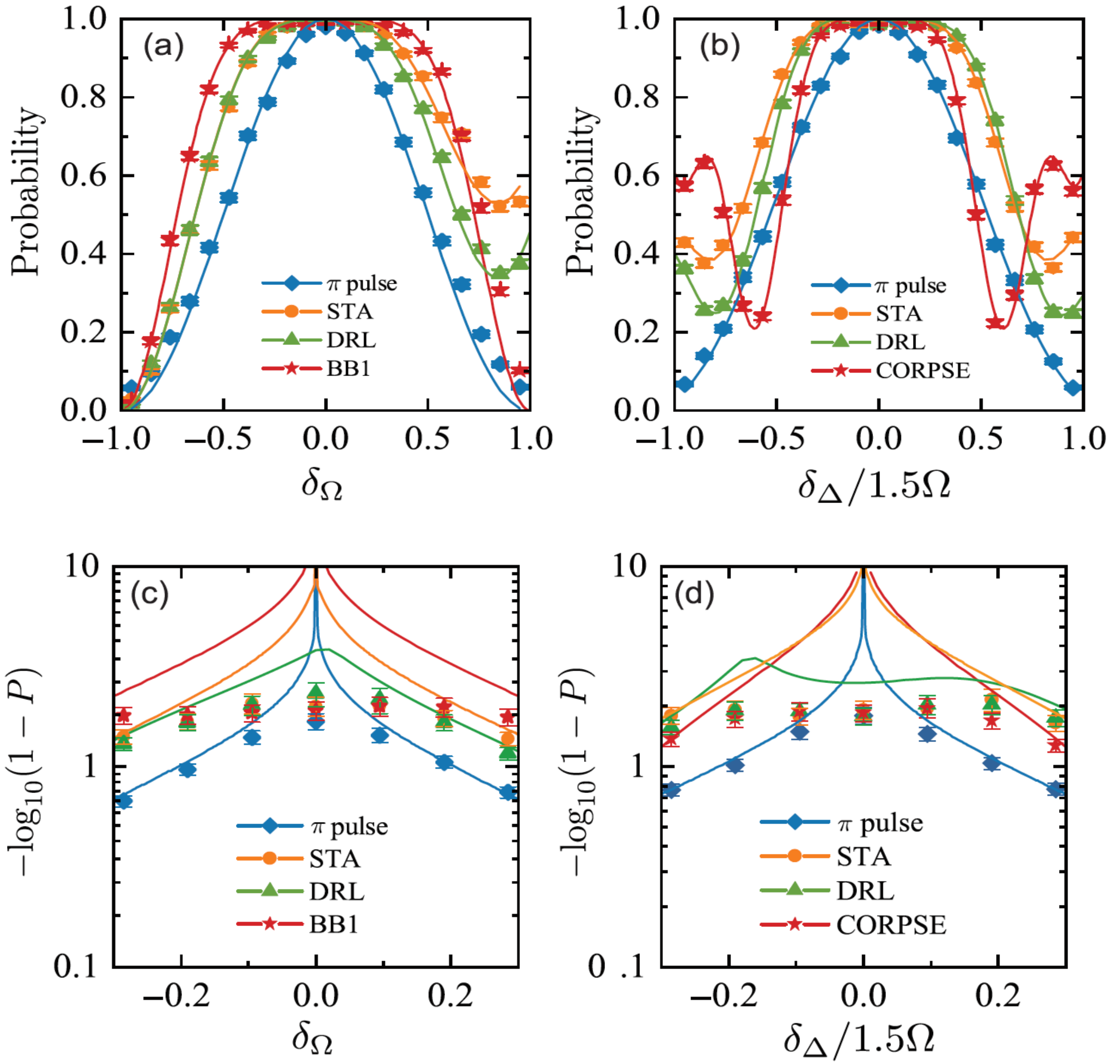
DRL obtains digital STA pulses

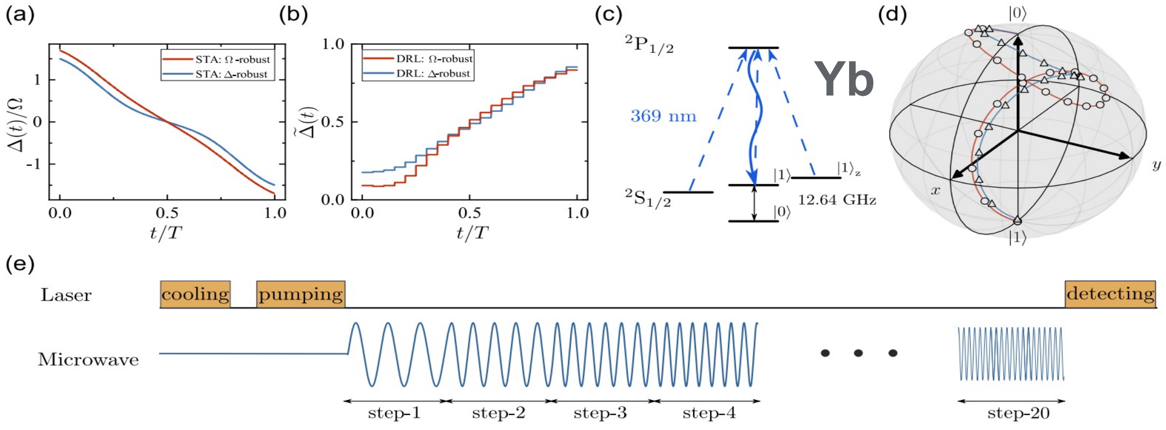
STA educates DRL agent well

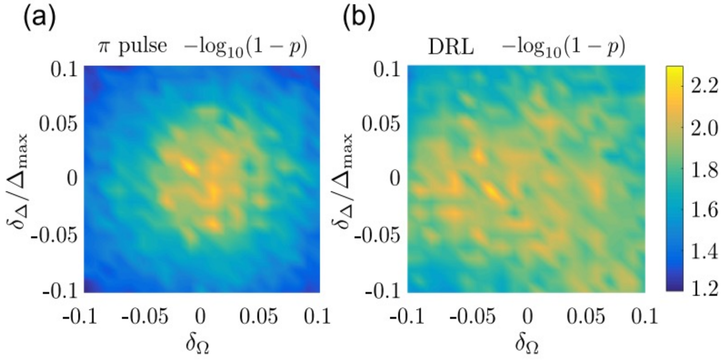
DRL explores protocols independently

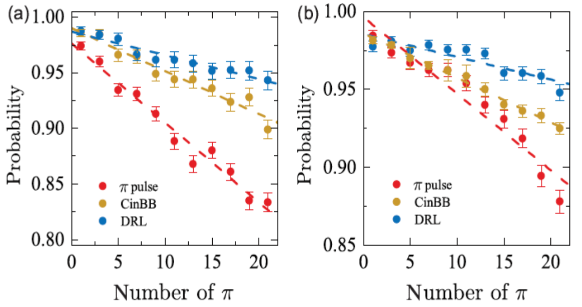
Proximal Policy Optimization

USTC's experiment on ion trap systems



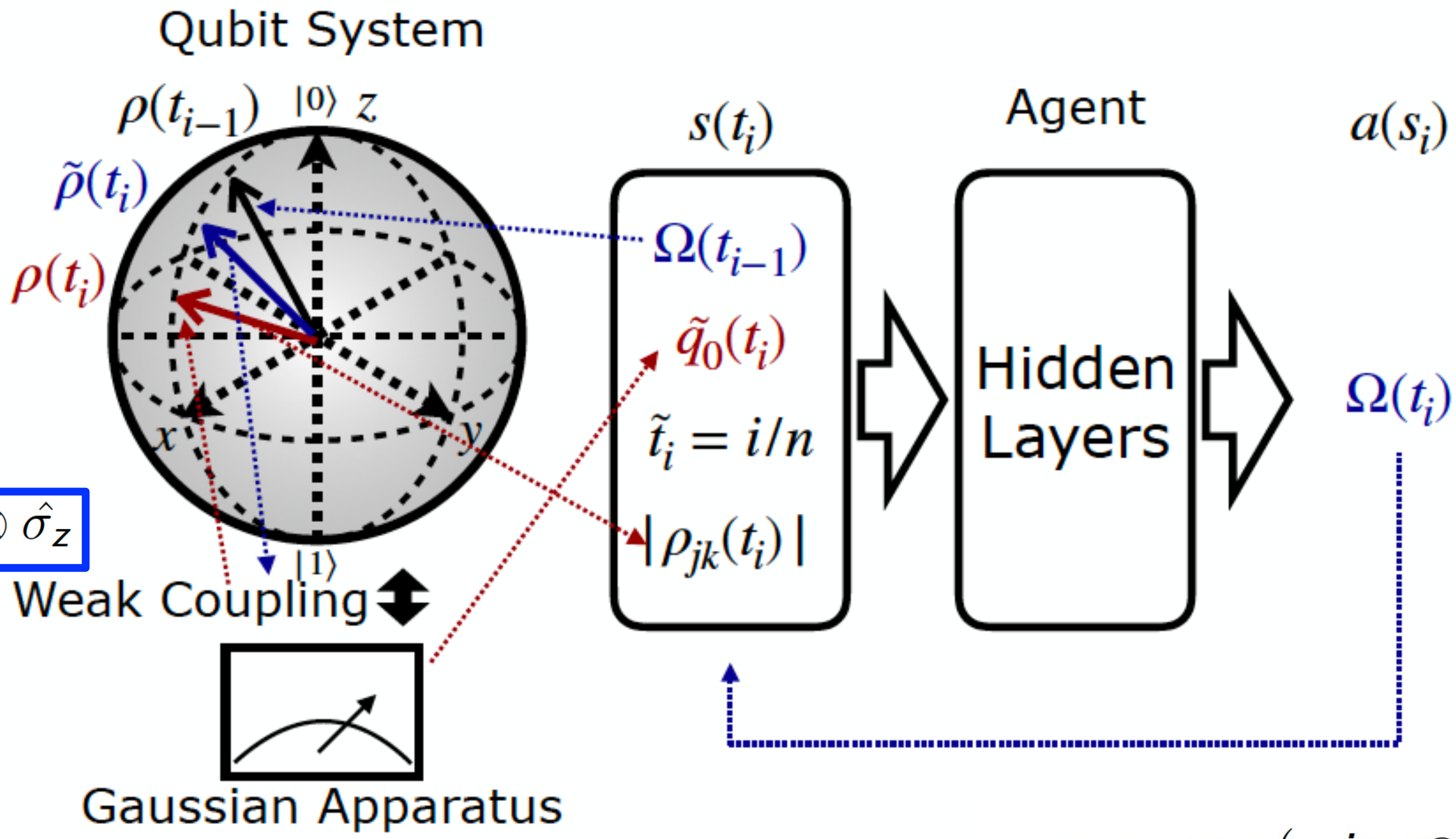






DL works for mixed errors and has noise-resilience feature even when the system lacks an analytical solution

Closed-loop control with weak-value feedback



$$H_{int} = g\delta(t - t')p \otimes \hat{\sigma}_z$$

$$\rho_{ini} = \rho_p \otimes \rho$$

$$\rho_{fin} = \exp(-igp \otimes \hat{\sigma}_z)\rho_{ini}\exp(igp \otimes \hat{\sigma}_z)$$

Lindblad

$$\dot{\rho}(t) = -\frac{i}{\hbar}[H(t), \rho(t)] + \sum_n \frac{1}{2}\left[2C_n\rho(t)C_n^\dagger - \rho(t)C_n^\dagger C_n - C_n^\dagger C_n\rho(t)\right]$$

Mach. Learn.: Sci. Technol. 4, 025020 (2022)

Weak measurement

In this way, we can obtain <A> of the qubit by measuring the ancilla's position q with an arbitrary uncertainty, since weak measurement protocol requires σ ≫ maxj (a_j).

The probability distribution of the ancilla's. position gives

The probability can be approximated by

$$P(q) \approx \frac{1}{(2\pi\sigma^2)^{\frac{1}{2}}} \exp\left[-\frac{(q-\cos\alpha)^2}{2\sigma^2}\right].$$

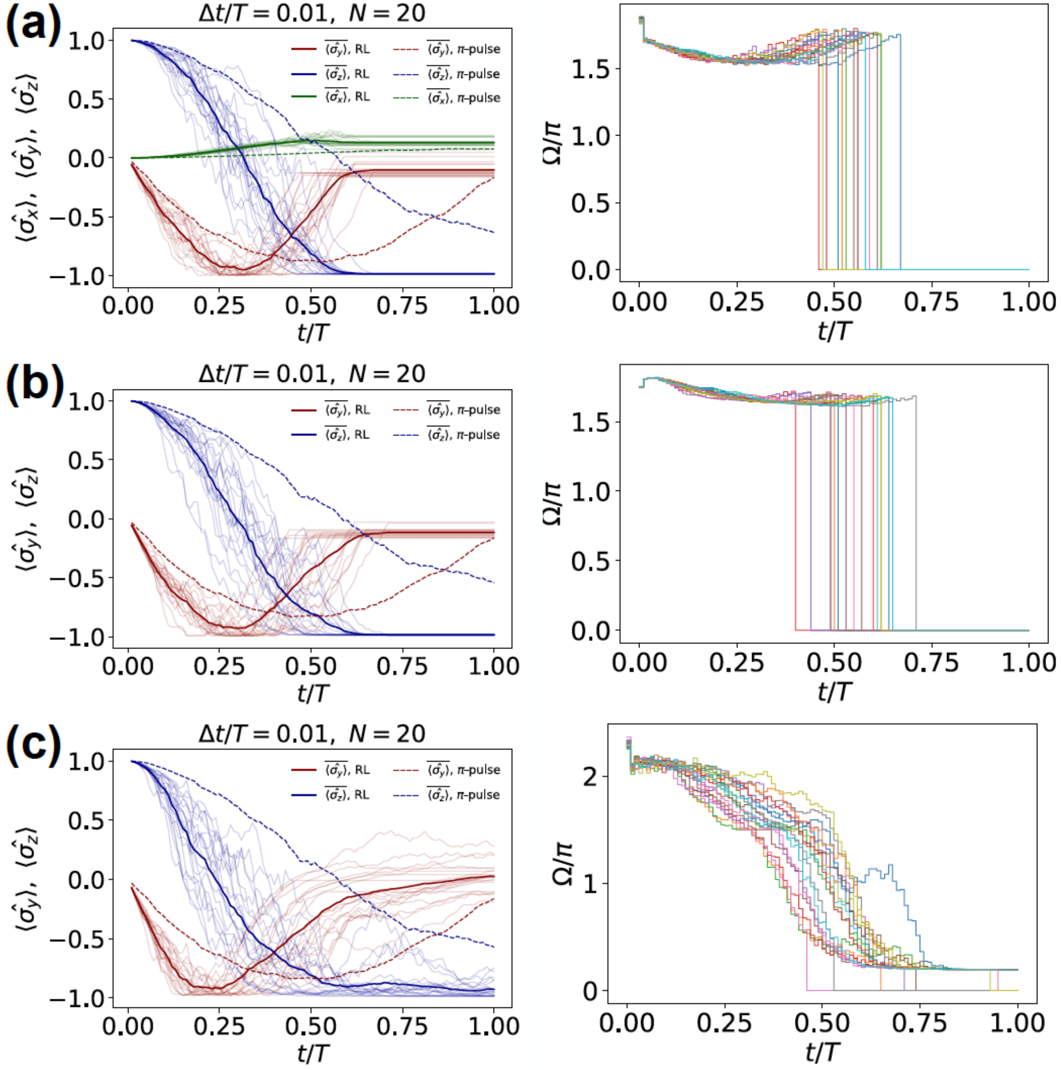
$$P(q) = (2\pi\sigma^2)^{-\frac{1}{2}}\left[\cos^2\frac{\alpha}{2}\exp\left(-\frac{(q-a_1)^2}{2\sigma^2}\right) + \sin^2\frac{\alpha}{2}\exp\left(-\frac{(q-a_2)^2}{2\sigma^2}\right)\right].$$

If we perform a weak measurement on the Z direction of the qubit, which leads to |a1⟩ = |0⟩, |a2⟩ = |1⟩, and a2, a1 = ∓ 1 ,

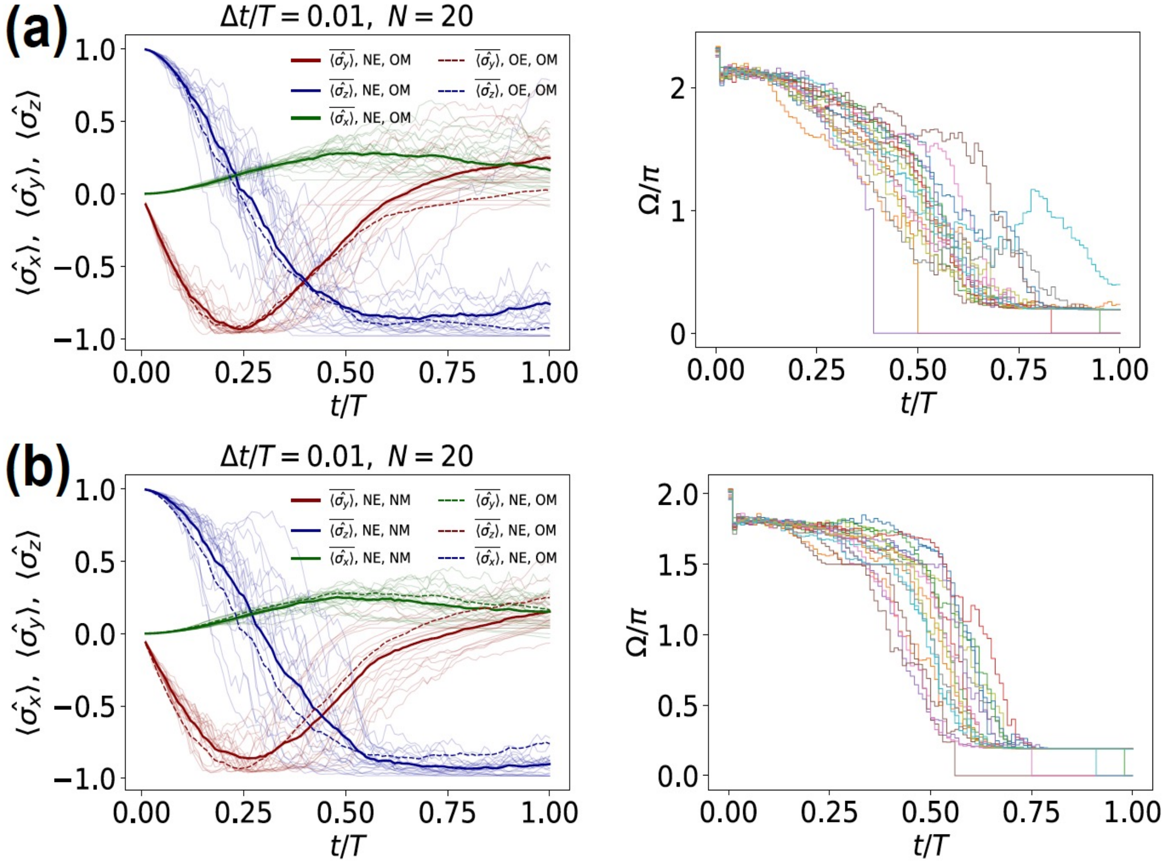
A normalized wave function of the system after a quantum measurement on the apparatus is

$$|\Psi_f\rangle \propto \frac{1}{(2\pi\sigma^2)^{\frac{1}{4}}}\left\{\cos\frac{\alpha}{2}\exp\left[-\frac{(q_0-1)^2}{4\sigma^2}\right]|0\rangle + \sin\frac{\alpha}{2}\exp\left[-\frac{(q_0+1)^2}{4\sigma^2}\right]|1\rangle\right\},$$

the measurement feedback of the apparatus position

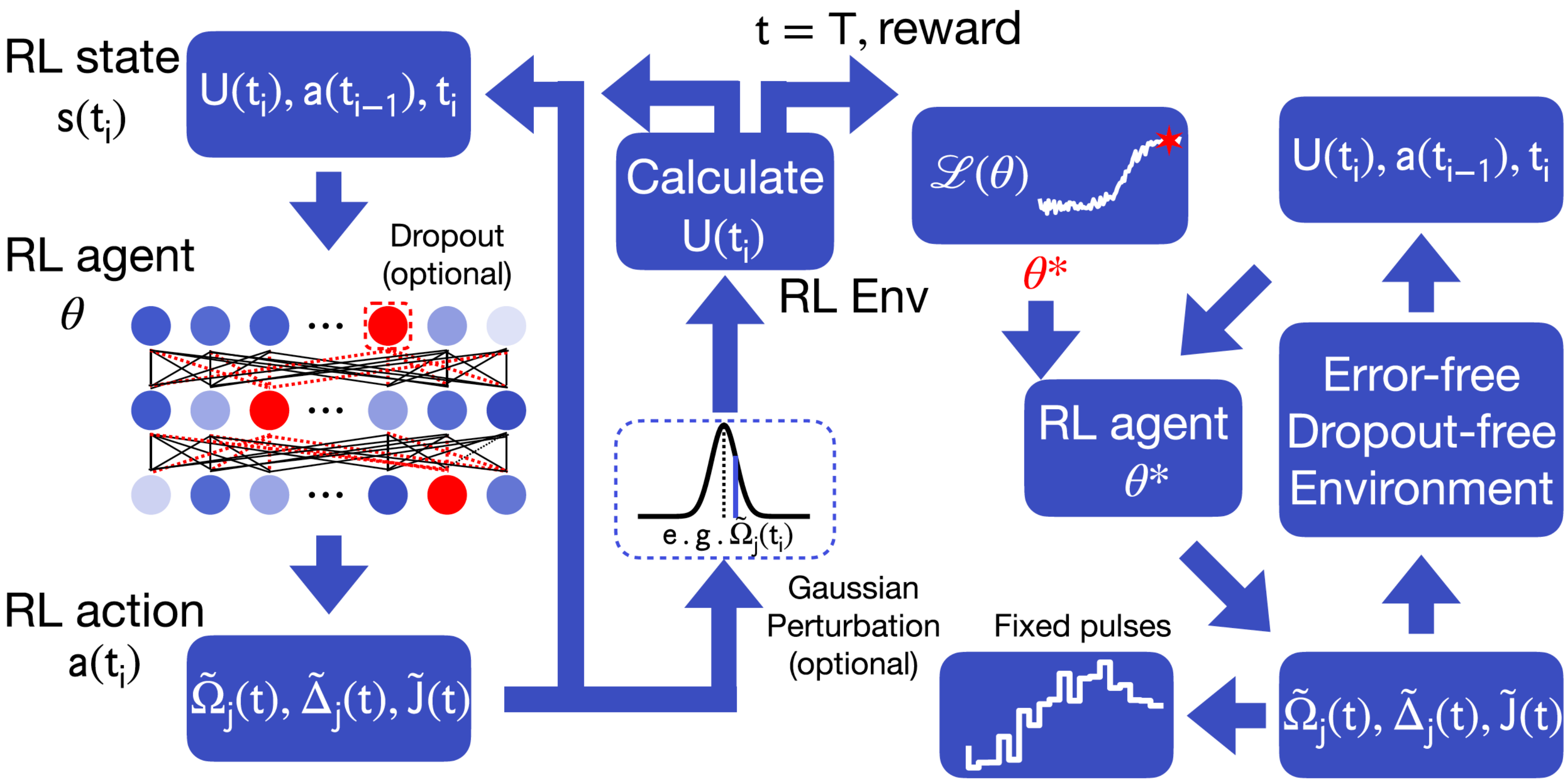


(a) detuning, (b) dephasing, and (c) σx relaxation



This combination of closed-loop control and transfer learning can thus enhance the system's resilience and adaptability, providing a dynamic way to maintain quantum coherence and improve control fidelity under varying conditions.

Dropout is all you need - robust two-qubit gate



Gaussian perturbation on the action and dropout in the ANN are used to obtain robustness against systematic errors

Phys. Rev. A 110, 032614 (2024)

The general Hamiltonian appears in the study of Josephson charge qubits or liquid-state NMR

$$H = H_1 \otimes I_2 + I_1 \otimes H_2 + \frac{J}{2} Z_1 \otimes Z_2,$$

$$H_{1,2} = \tfrac{1}{2}[\Omega_{1,2}\cos(\omega t)X_{1,2} + \Omega_{1,2}\sin(\omega t)Y_{1,2} + \Delta Z_{1,2}]$$

we simplify the two-qubit Hamiltonian into two parts

$$H^{\pm}(t) = \frac{1}{2}[\Omega\cos(\omega t)G_x^{\pm} + \Omega\sin(\omega t)G_y^{\pm} + \Delta^{\pm}G_z^{\pm}],$$

where $G_i^{\pm} = (I_1 \pm Z_1)/2 \otimes (i \in \{X, Y, Z\})$ **and** $\Delta^{\pm} = \Delta \pm J$

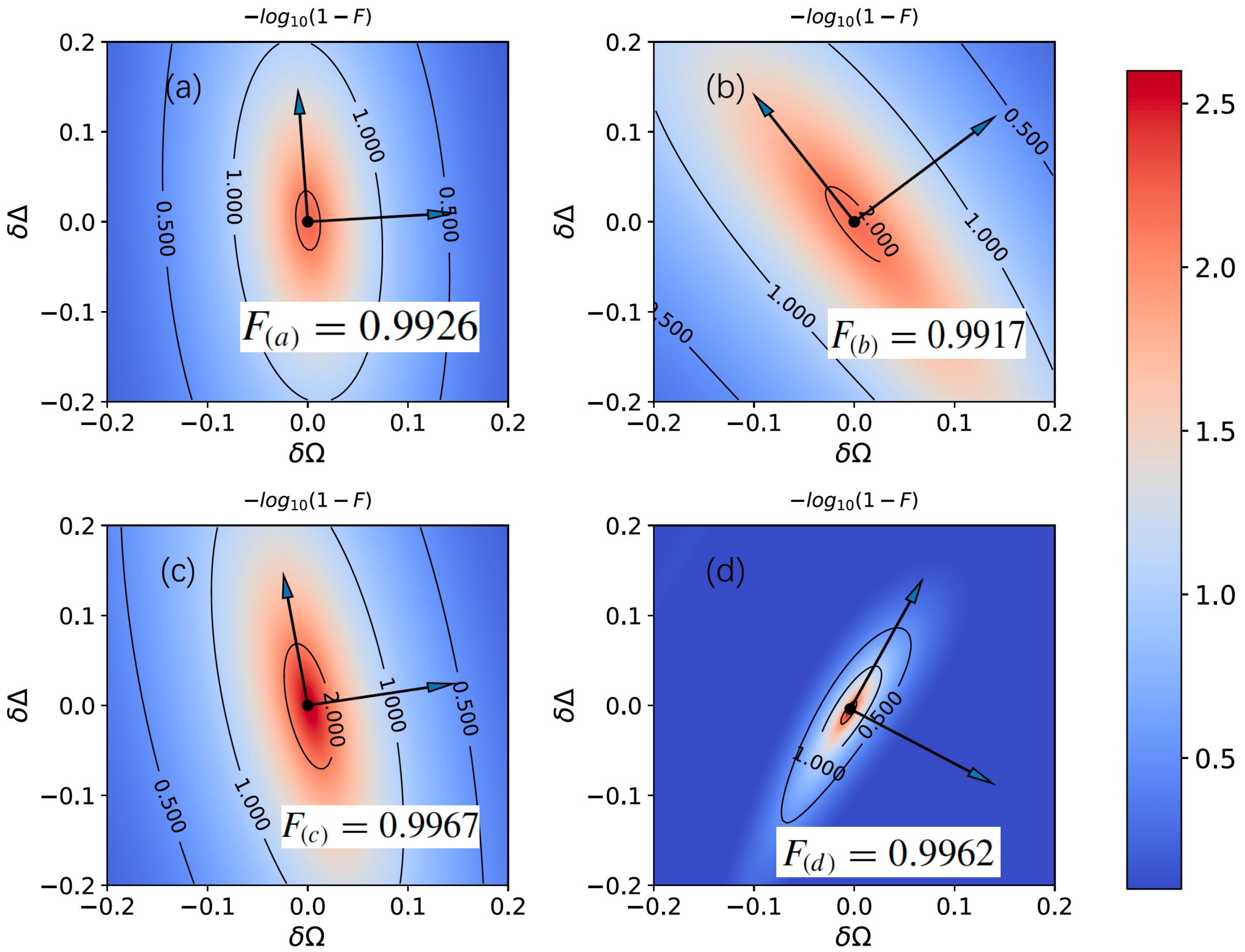
The dynamical invariant of H is then given by $I^{\pm}(t) = \Omega\cos(\omega t)G_x^{\pm} + \Omega\sin(\omega t)G_y^{\pm} + (\Delta^{\pm} - \omega)G_z^{\pm}.$

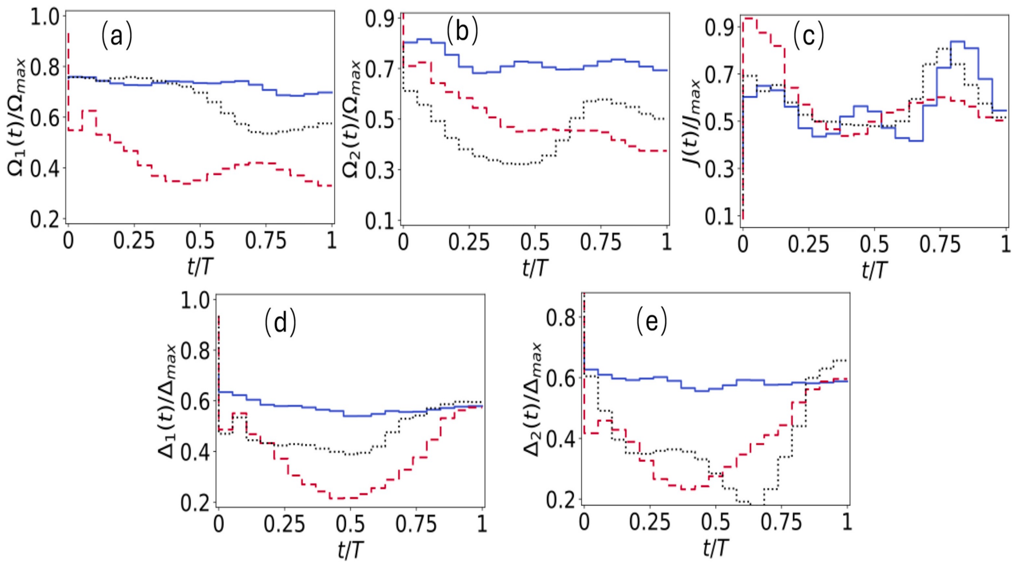
$$H_{\mathrm{DRL}} = \sum_{j=1}^{2} H_j + \frac{J(t)}{2} Z_1 \otimes Z_2,$$

where $H_j = \Omega_j(t)\cos(\omega t)X_j + \Omega_j(t)\sin(\omega t)Y_j + \Delta_j(t)Z_j,$

$$U(t_i, t_0) = \mathcal{T}\prod_{j=0}^{i-1} U(t_{j+1}, t_j) = \mathcal{T}\prod_{j=0}^{i-1} \exp[-iH_{\mathrm{DRL}}(j\delta T)\delta T] \Rightarrow \exp(-i\pi Y_1 \otimes Y_2)$$

Robustness of the entangling gate R_{YY} ($\pi/4$) against errors





(a) standard batch method

(b) Gaussian perturbation

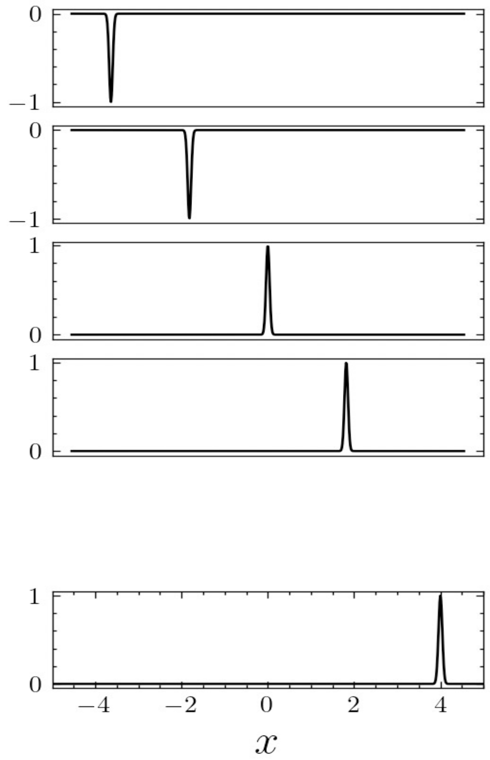
(c) dropout

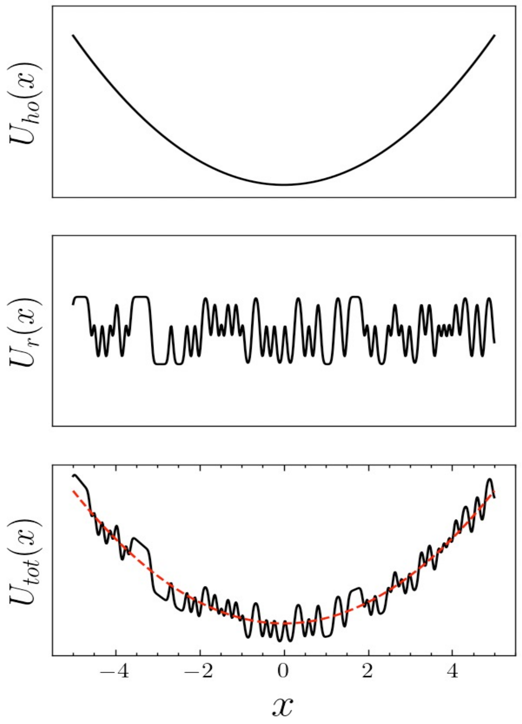
(d) analytical nonadiabatic geometric gate

ML-enhanced quantum control in random environment

$$H(t) = \frac{p^2}{2} + \frac{1}{2}\omega^2(t)x^2 + U_r(x)$$

random potential





$$U_r(x) = U_0 \sum_{i=0}^{\mathcal{N}-1} s_j f(x - x_j)$$

$$j \in [0, \mathcal{N})$$

$$S[j] = [1, -1, 1, 1, -1, \ldots, 1],$$

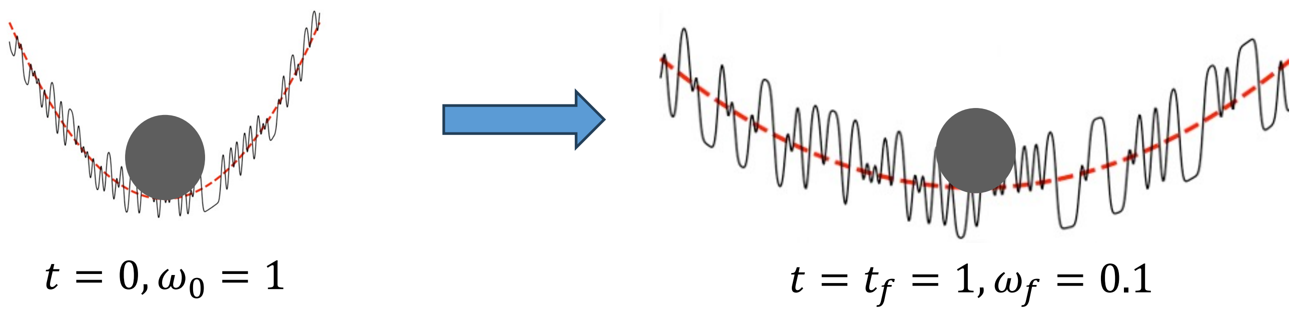
$$\langle S \rangle = 0, \langle U_r \rangle = 0$$

Disorder realizations $\sim 2^{\mathcal{N}}$

$\mathcal{N}$: *impurity number*

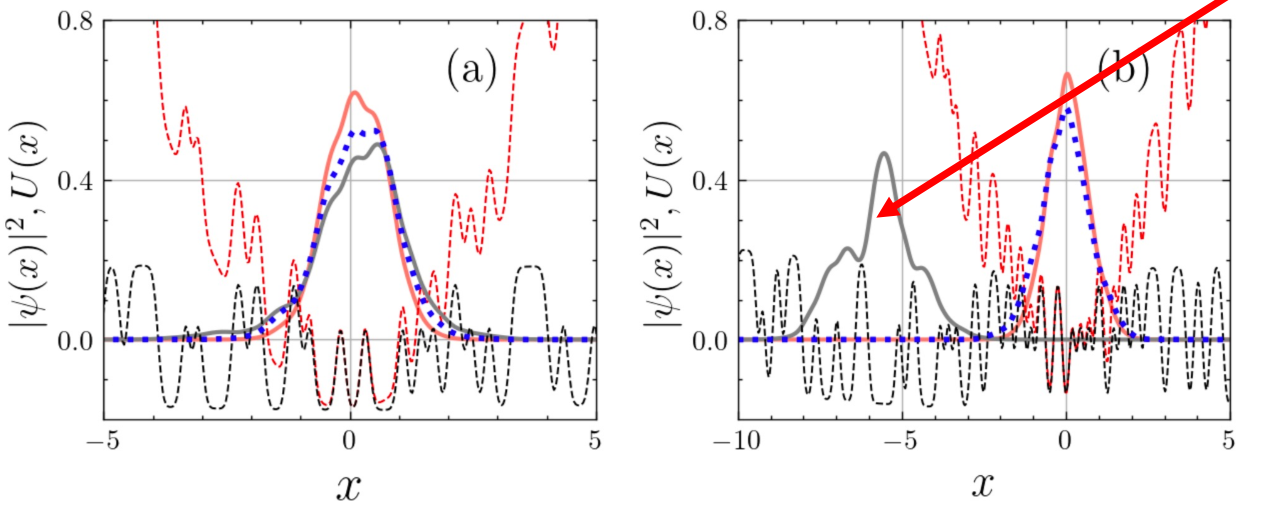
Phys. Rev. Applied 17, 024040 (2022)

Expansion of quantum particle in presence of random potential



Two realizations are exemplified to illustrate the consequence of disorder

the ground state can be positioned far away from the origin



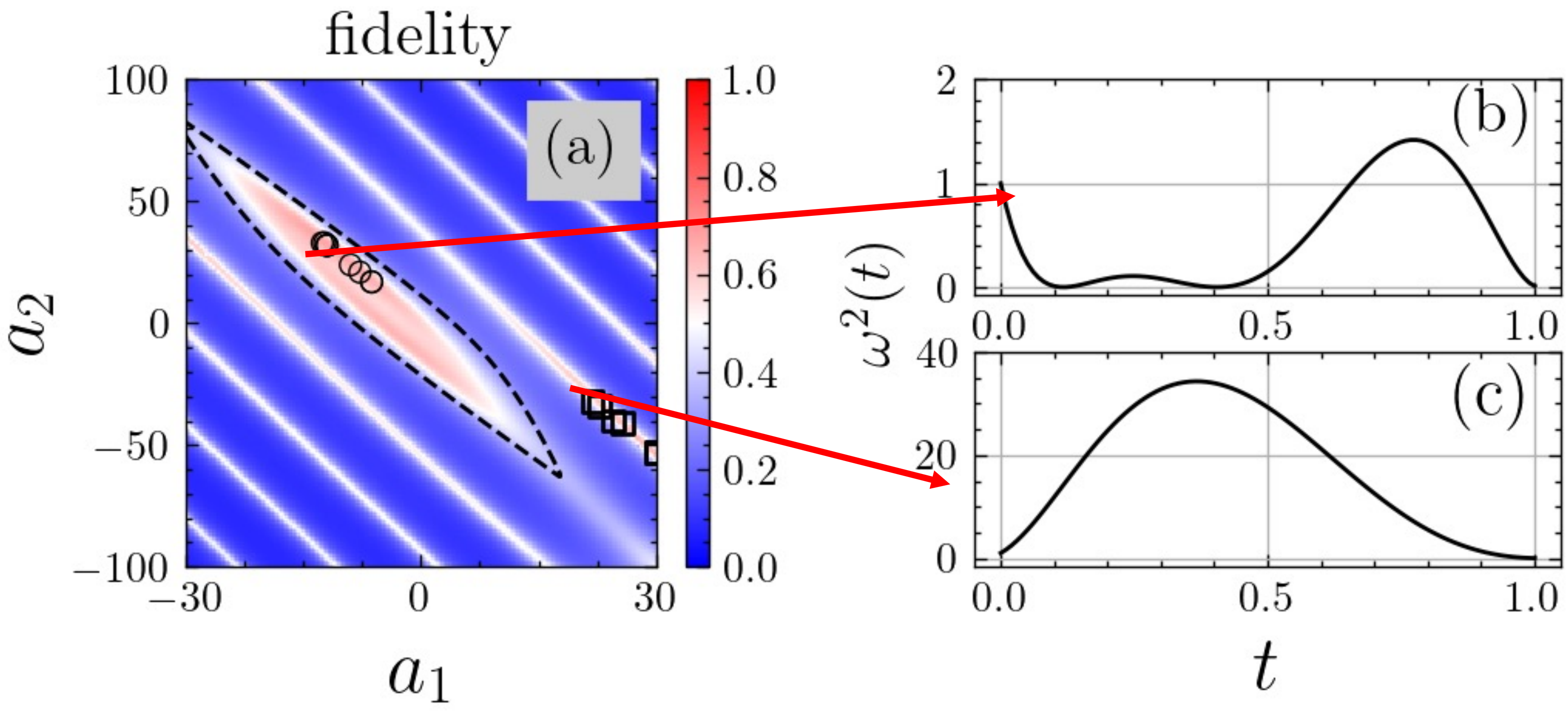
initial ground state (red solid line)

final ground state (black solid line)

final state (blue dotted) by our protocol

Parameters: $U_0 = 1, \omega_0 = 1$, and $\omega_f = 0.1$.

The fidelity on the control policy $A = \{a_1, a_2\}$.

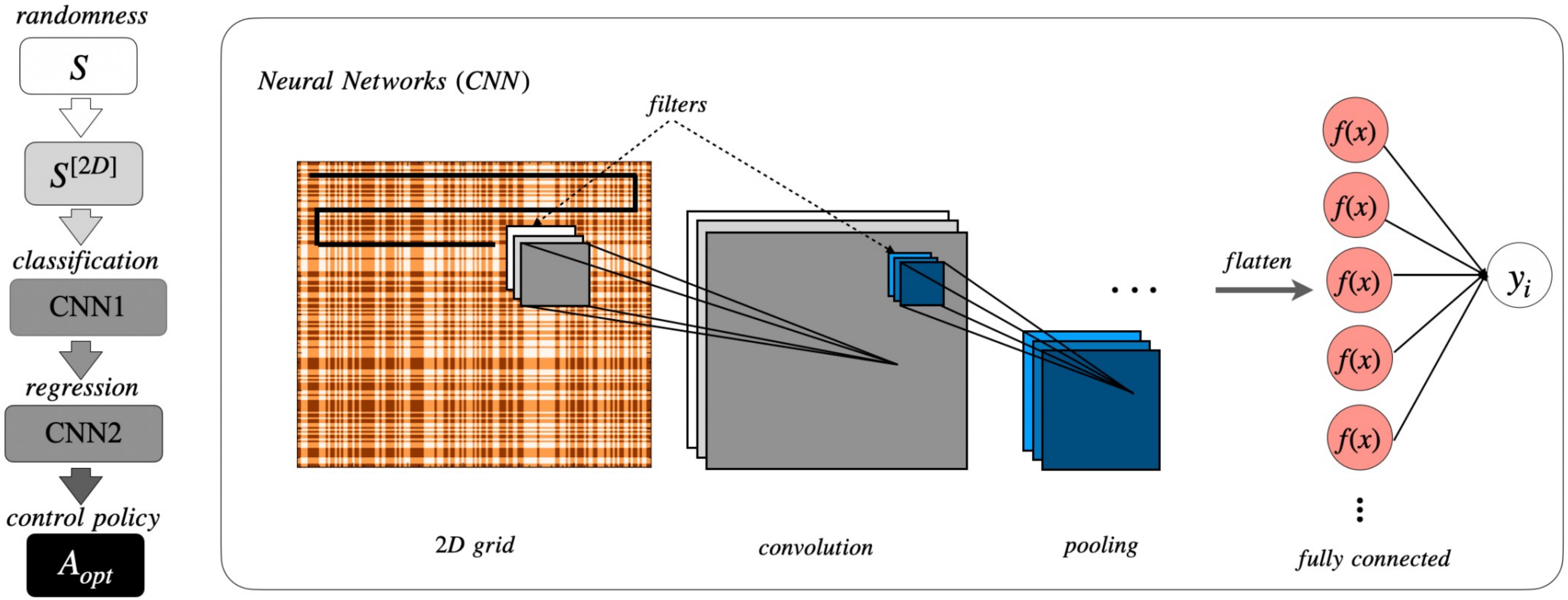


Control Ansatz

$$\omega(t) = a_0 + a_1 t + a_2 t^2 + a_3 t \quad \begin{cases} a_0 = \omega_0 \\ a_3 = [\omega_f - (\omega_0 + a_1 t_f + a_2 t_f^2)]/t_f^3. \end{cases}$$

Random sequence → Optimal control policy: $A_{opt} = \{a_1^{opt}, a_2^{opt}\}$.

Supervised learning for randomness recognition and regression

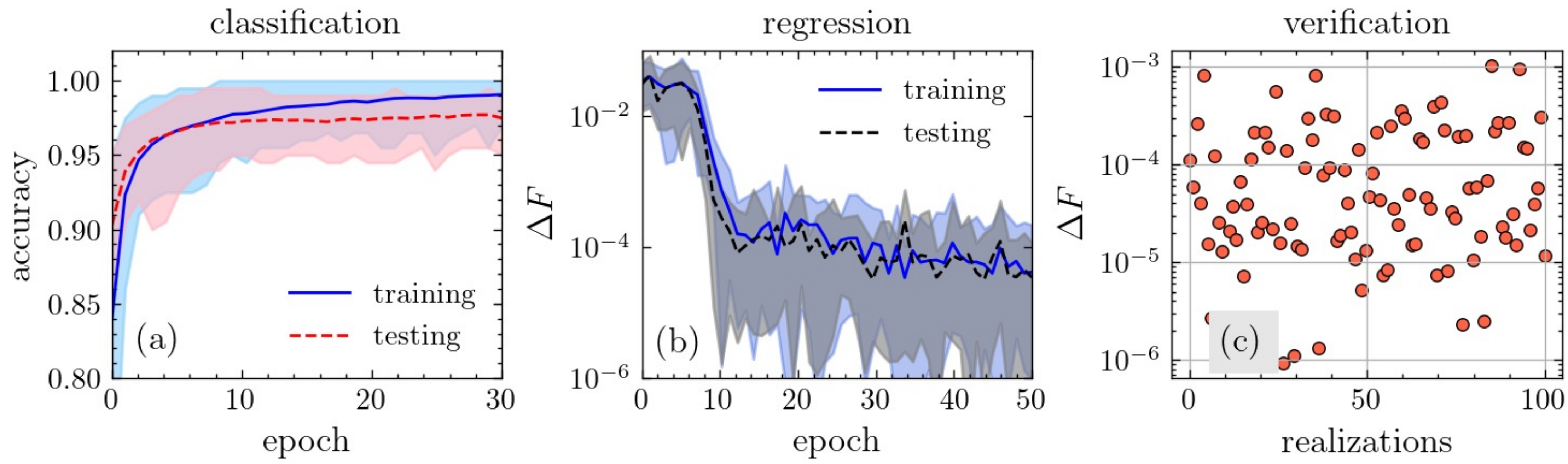


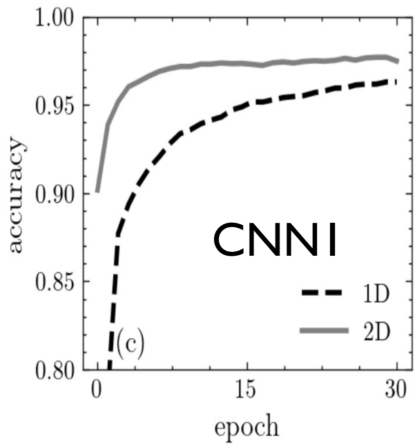
$$S_i[j] = \{1,1,-1,1,\ldots,-1,1\} \quad 1\times 160$$

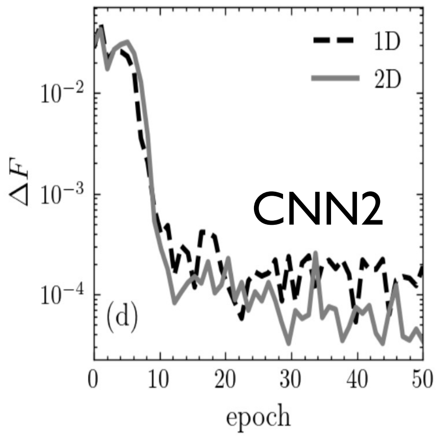
$$S_i^{[2D]}[j_1,j_2] = S_i[j_1] + S_i[j_2] \quad 160\times 160$$

conversion from 1D S_i to 2D grid $S_i^{[2D]}[j_1,j_2]$

convolution and pooling layers, fully-connected layer with the activation function $f(x)$ and the output y_i.







The outputs from two trained CNNs (red crosses)

compared with the numerical results (black circles) for 100 testing realizations

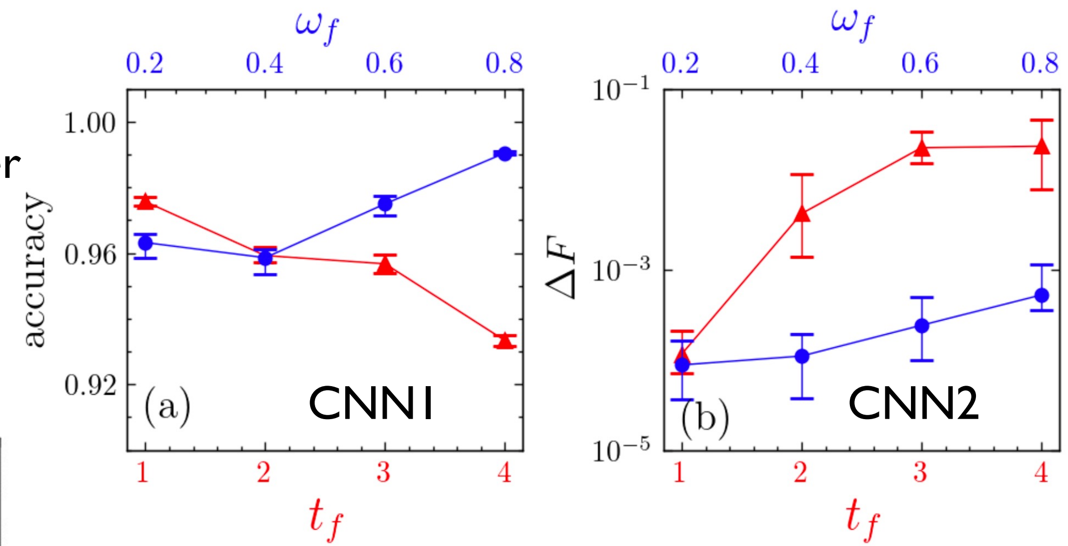
The performances by using 2D input date outperform!

Results:

Stationary state and dynamics rely on the disorder realizations

Choosing various ansatz forms would not modify the effect of disorder

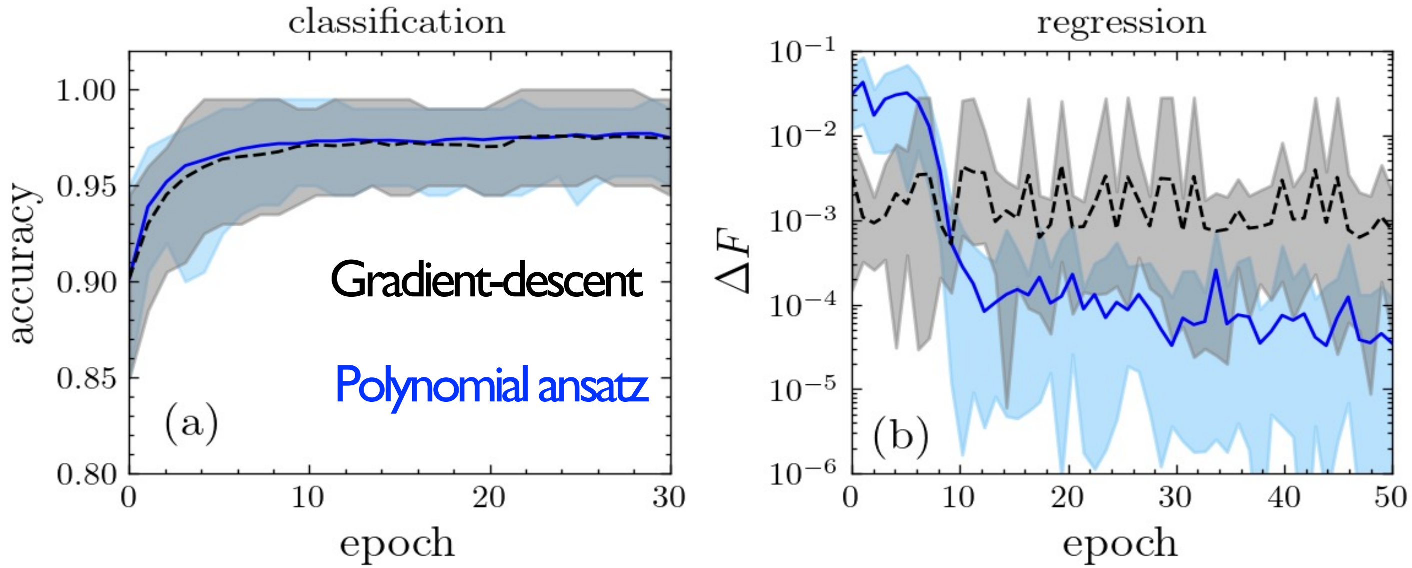
Our methods are applicable to other the robust optimal control



The combined effects of the trapping potential and

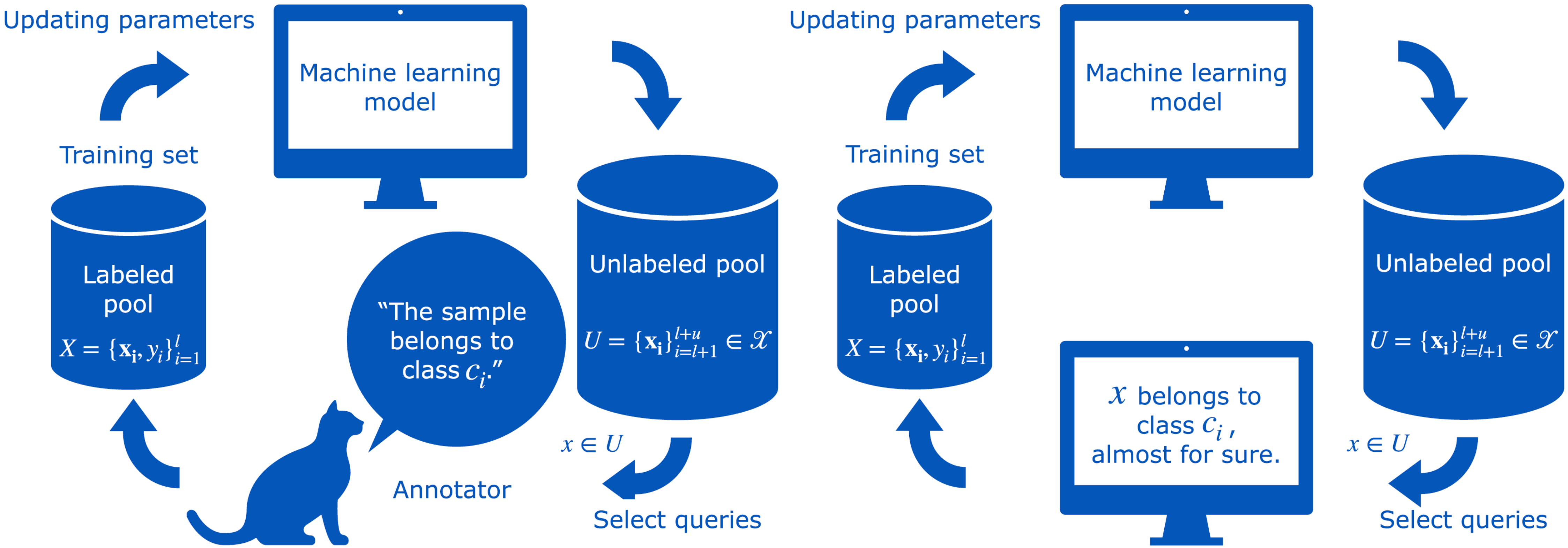
disorder plays an important role in dynamical control,

characterized by the fidelity and the required energy cost.



Hint: the fidelity depends on the localization induced by random potential rather than on the control strategy

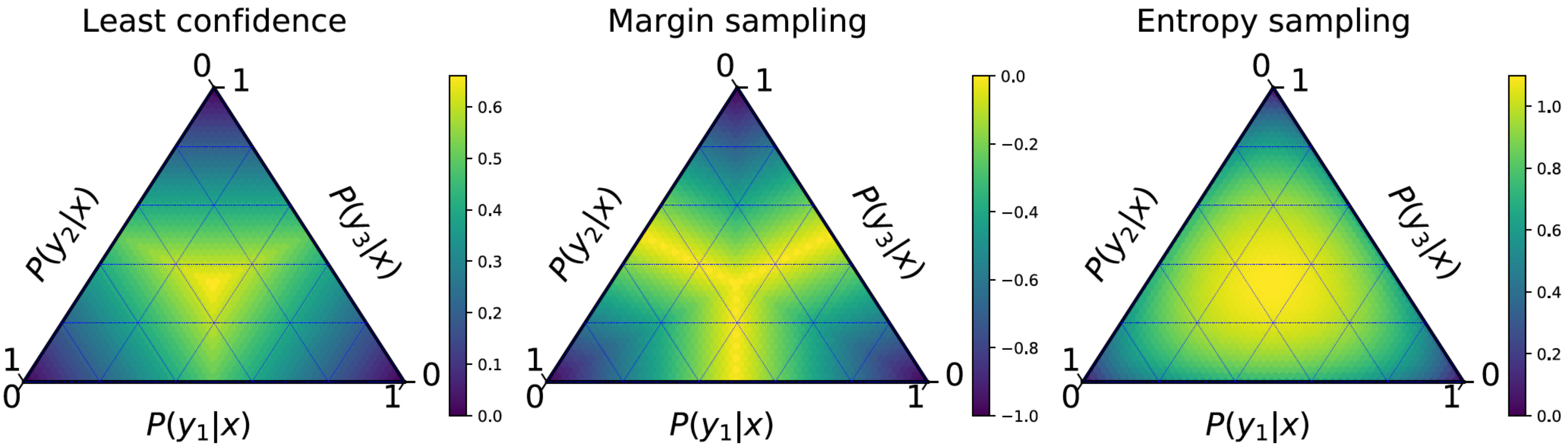
Retrieving Quantum Information with Active Learning



Phys. Rev. Lett. 124, 140504 (2020)

Adv. Quantum Technol. 2300208 (2023)

Quantum Active Learning, see arXiv: 2405.18230



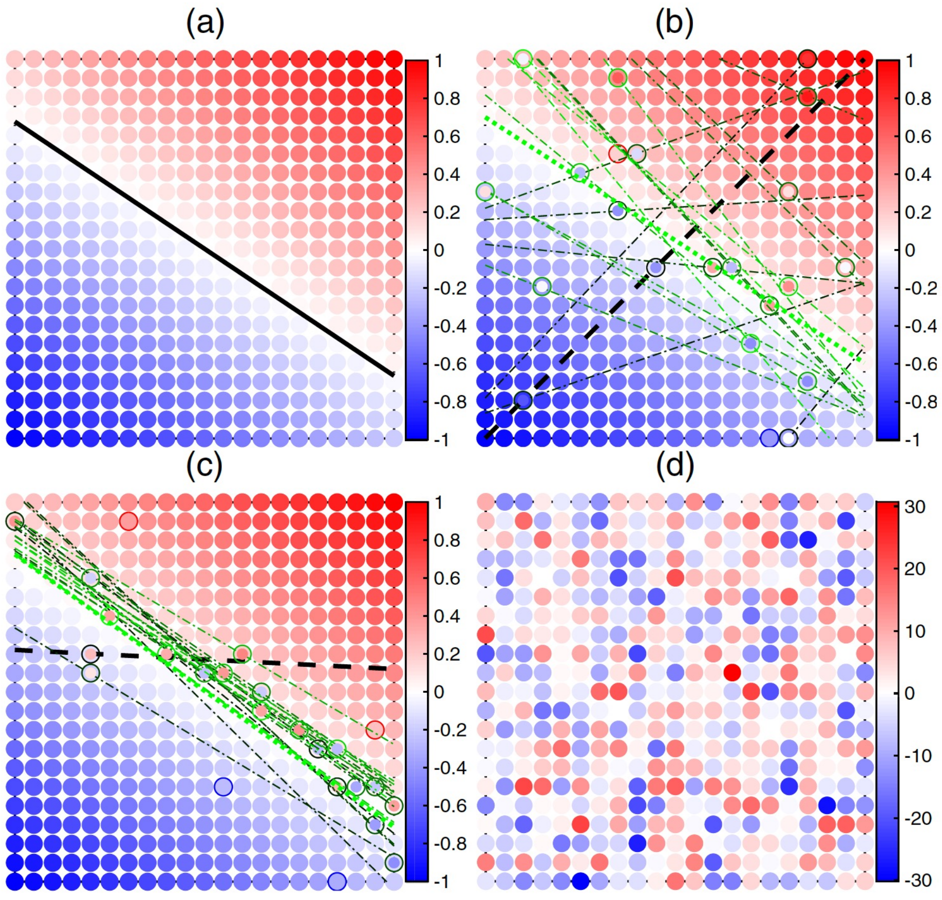
least confidence **margin sampling** **entropy-based USAMP**

$$x_{LC} = \underset{x}{\text{argmax}} \left[1 - P_\theta(\hat{y}|x)\right], \quad \hat{y} = \underset{y}{\text{argmax}} \left[P_\theta(y|x)\right].$$

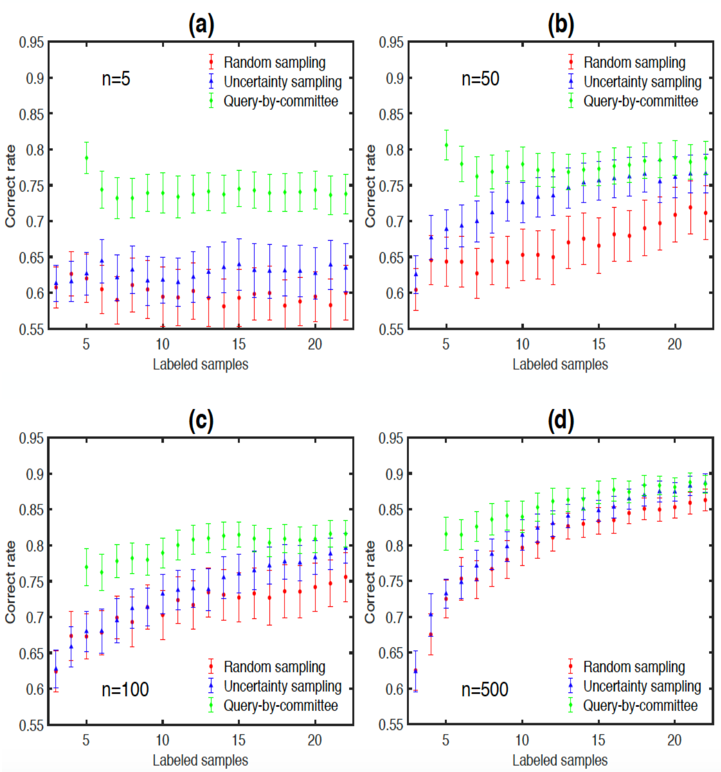
$$x_M = \underset{x}{\text{argmin}} \left[P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x)\right].$$

$$x_E = \underset{x}{\text{argmax}} \left[-\sum_i P_\theta(\hat{y}_i|x) \log P_\theta(\hat{y}_i|x)\right].$$

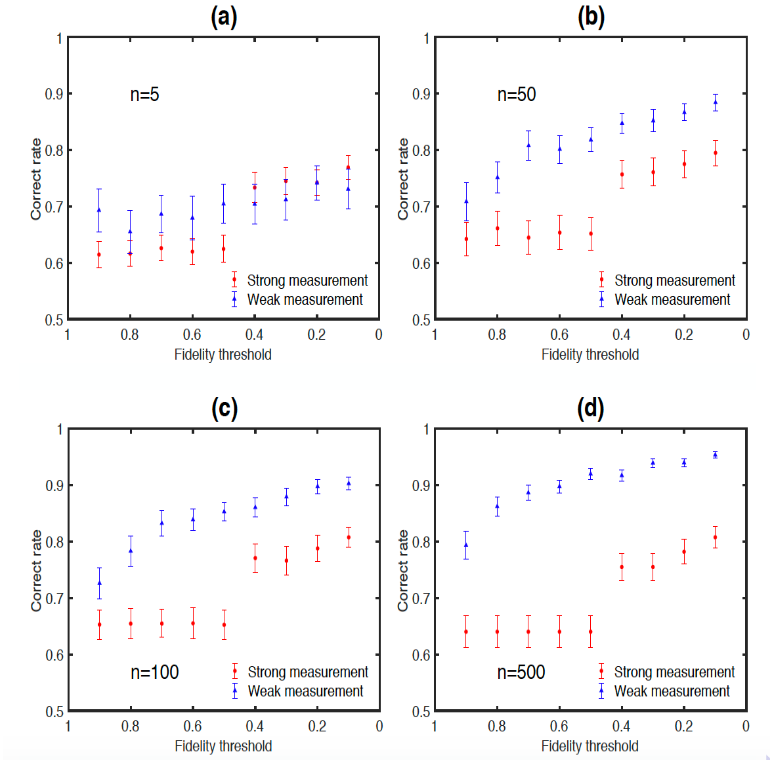
Game between Alice and Bob



Gaming strategy: active learning



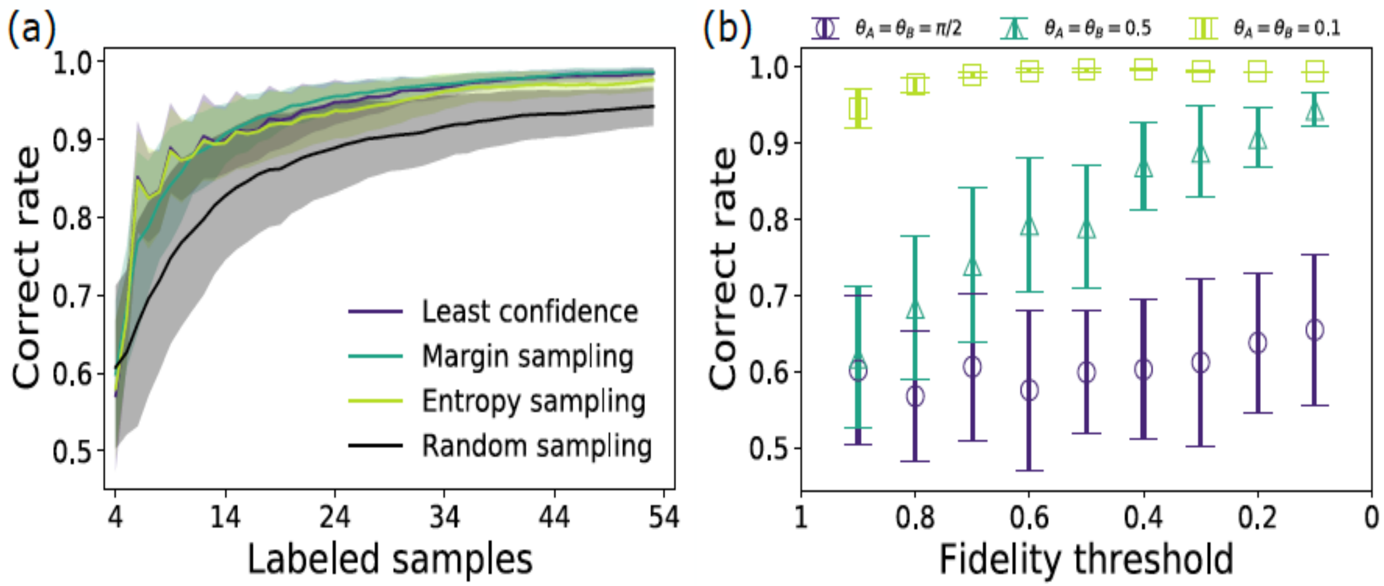
Weak-to-strong measurement

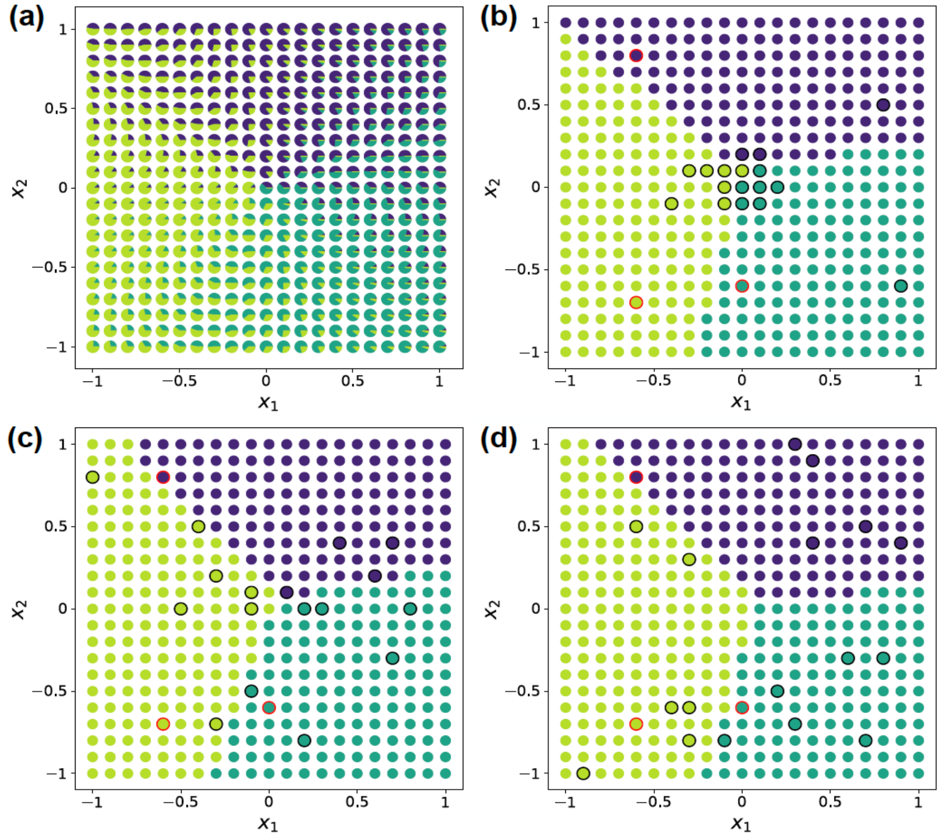


Voting entropy for query-by-committee

$$x_{\mathrm{VE}} = \underset{x}{\operatorname{argmax}} \left(-\sum_i \frac{V(y_i)}{C} \log \frac{V(y_i)}{C} \right).$$

Multinomial classification qutrit system

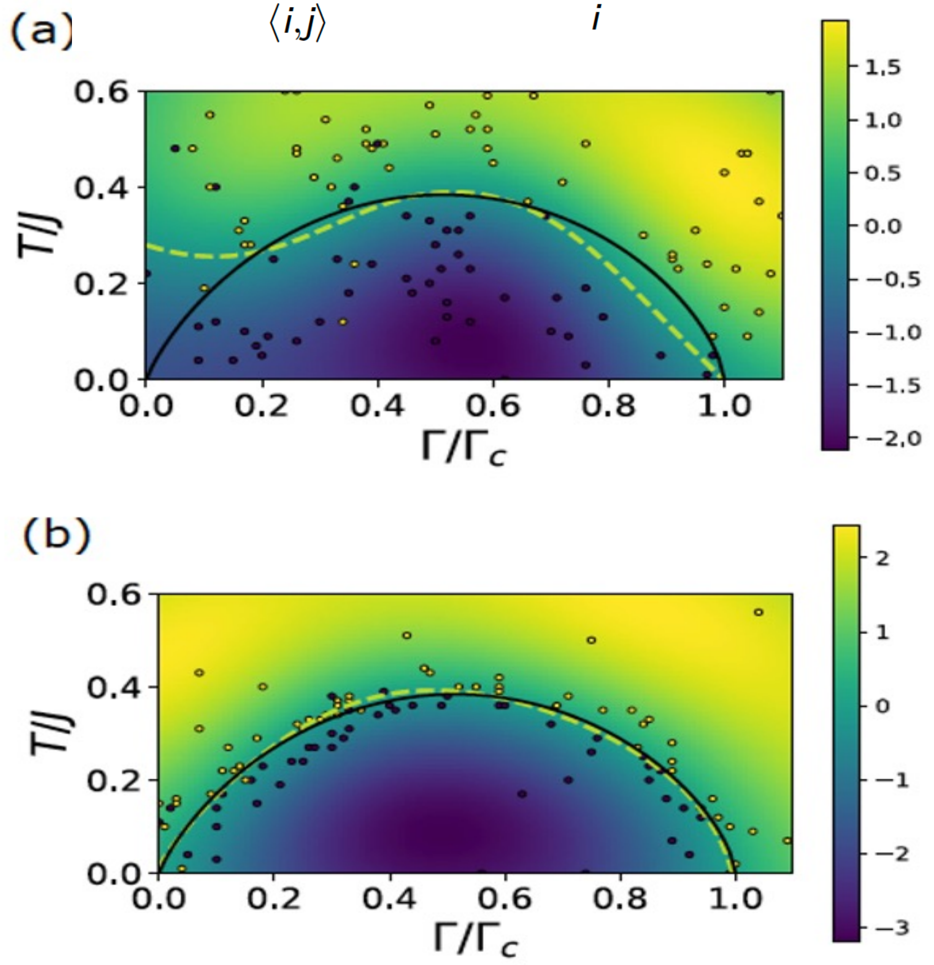


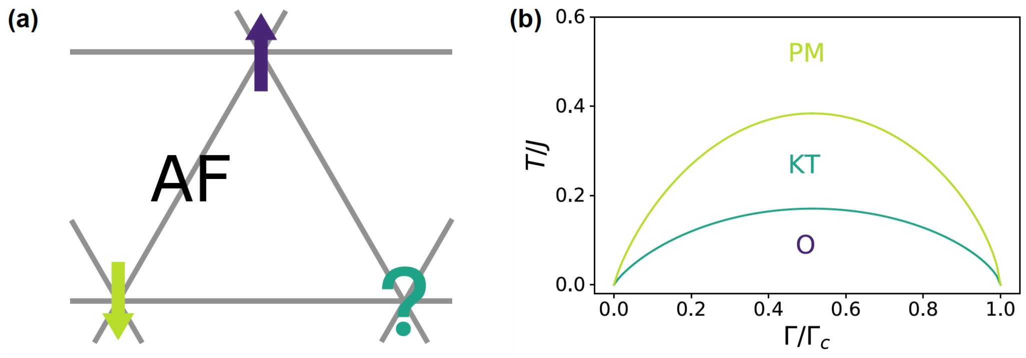


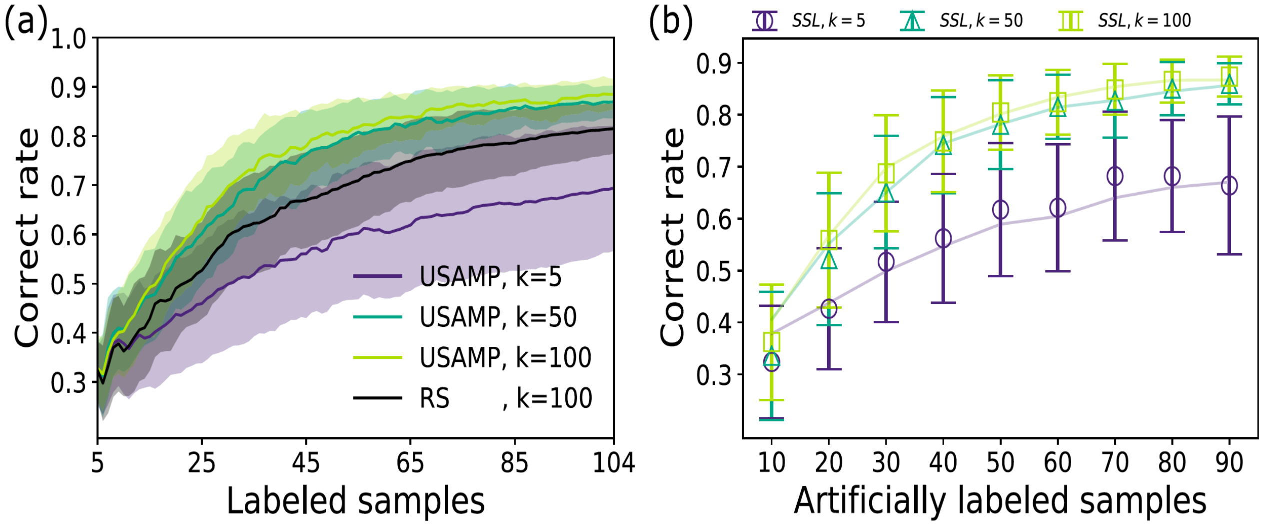
Phys. Rev. Research 4, 013213 (2022)

Phase boundary prediction in geometrically frustrated system

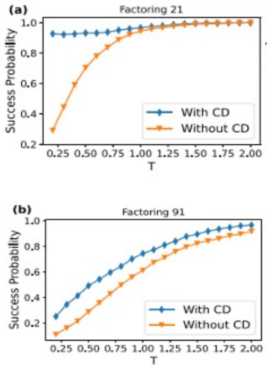
$$H = J\sum_{\langle i,j\rangle} \sigma_i^z \sigma_j^z - \Gamma \sum_i \sigma_i^x$$



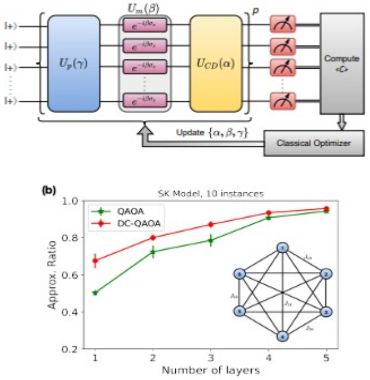




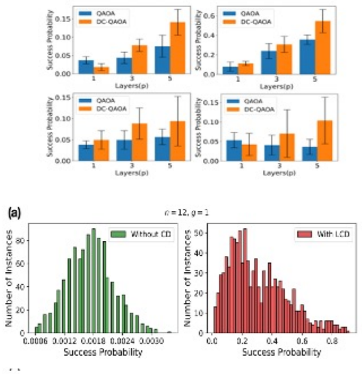
Summary



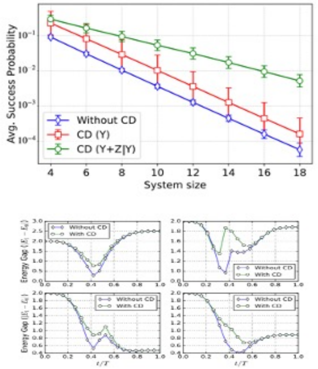
PRA 104, L050403 (2021)



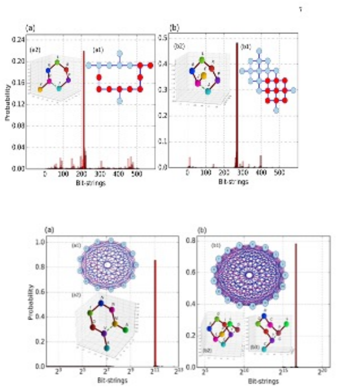
PRR 4, 013141 (2022)



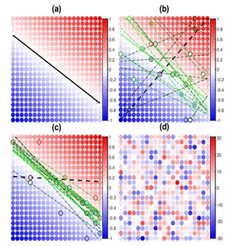
PRR 4, 043204 (2022)



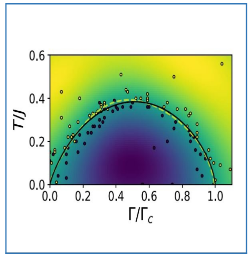
PRR 4, L042030 (2022)



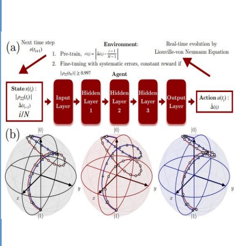
PR Applied 20, 014024 (2023)



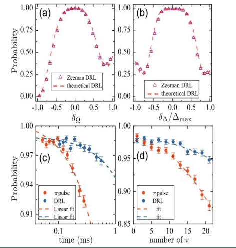
PRL 124, 140504 (2020)



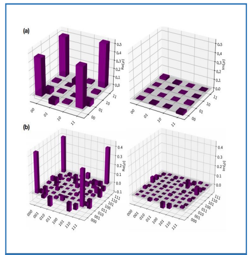
PRR 4, 013213 (2022)



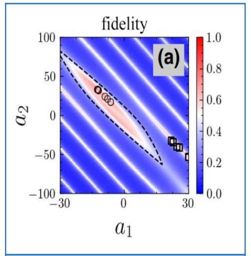
PRA 101, L040401 (2021)



SCPMA 65, 250312 (2022)



PR Applied 15, 024038 (2021)



PR Applied 17, 024040 (2022)

Thanks to the main collaborators

Yongcheng Ding (SHU)

Jose Martin-Guerrero (UV)

Yue Ban (U3M)

Tangyou Huang (CTH)

Jorge Casanova (UPV/EHU)

Mikel Sanz (UPV/EHU)

…

Thank You for Your Attention!