ExU Public Online Colloquium

October 16, 2024

Quantum Algorithm and Qubit Technology Applications for Particle Physics

ICEPP, The University of Tokyo
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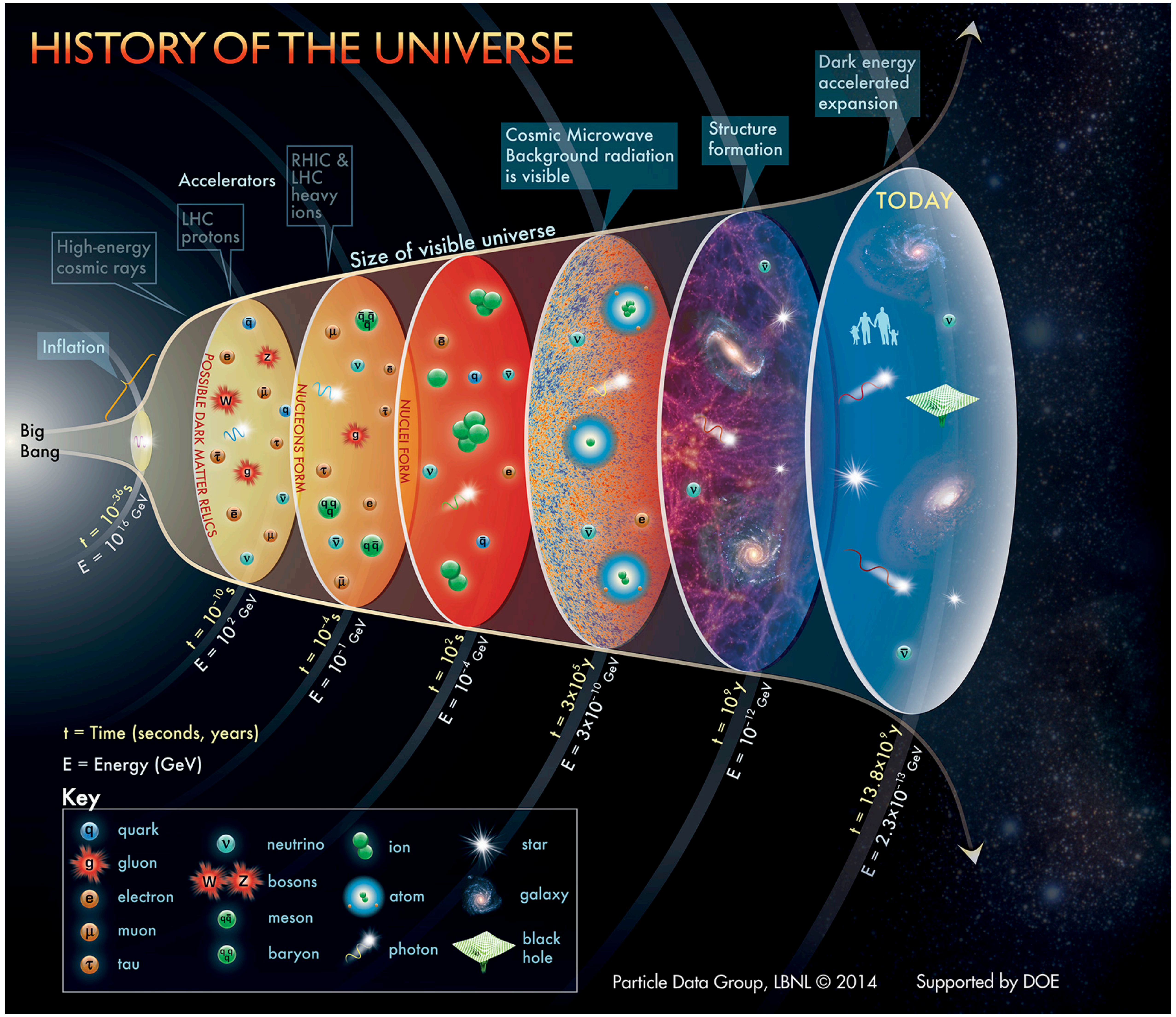
Particle Physics

Particle physics aims to answer:

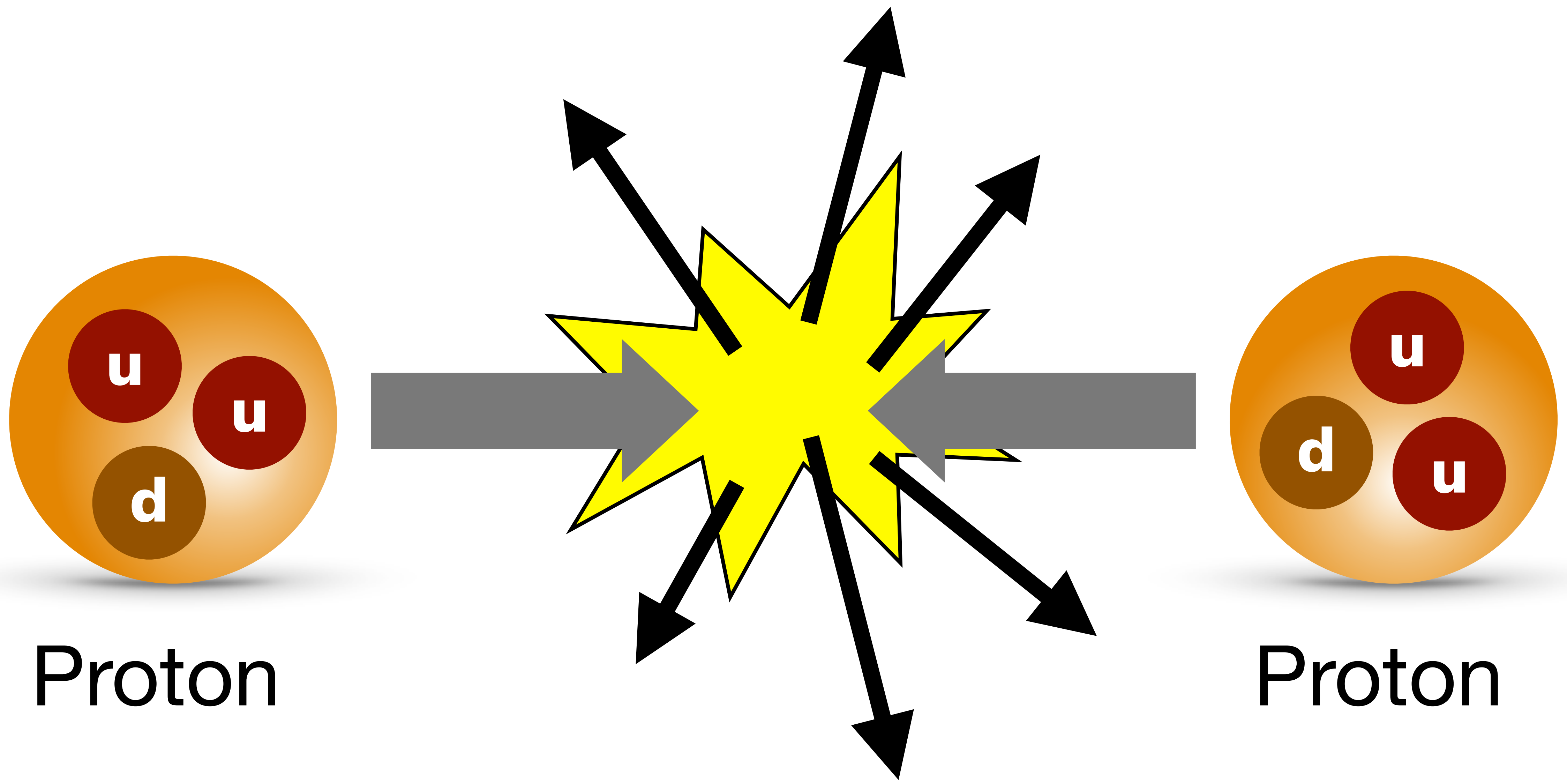
- What is the origin and future of the Universe?
- What is the nature of elementary particles?
- How do they interact?

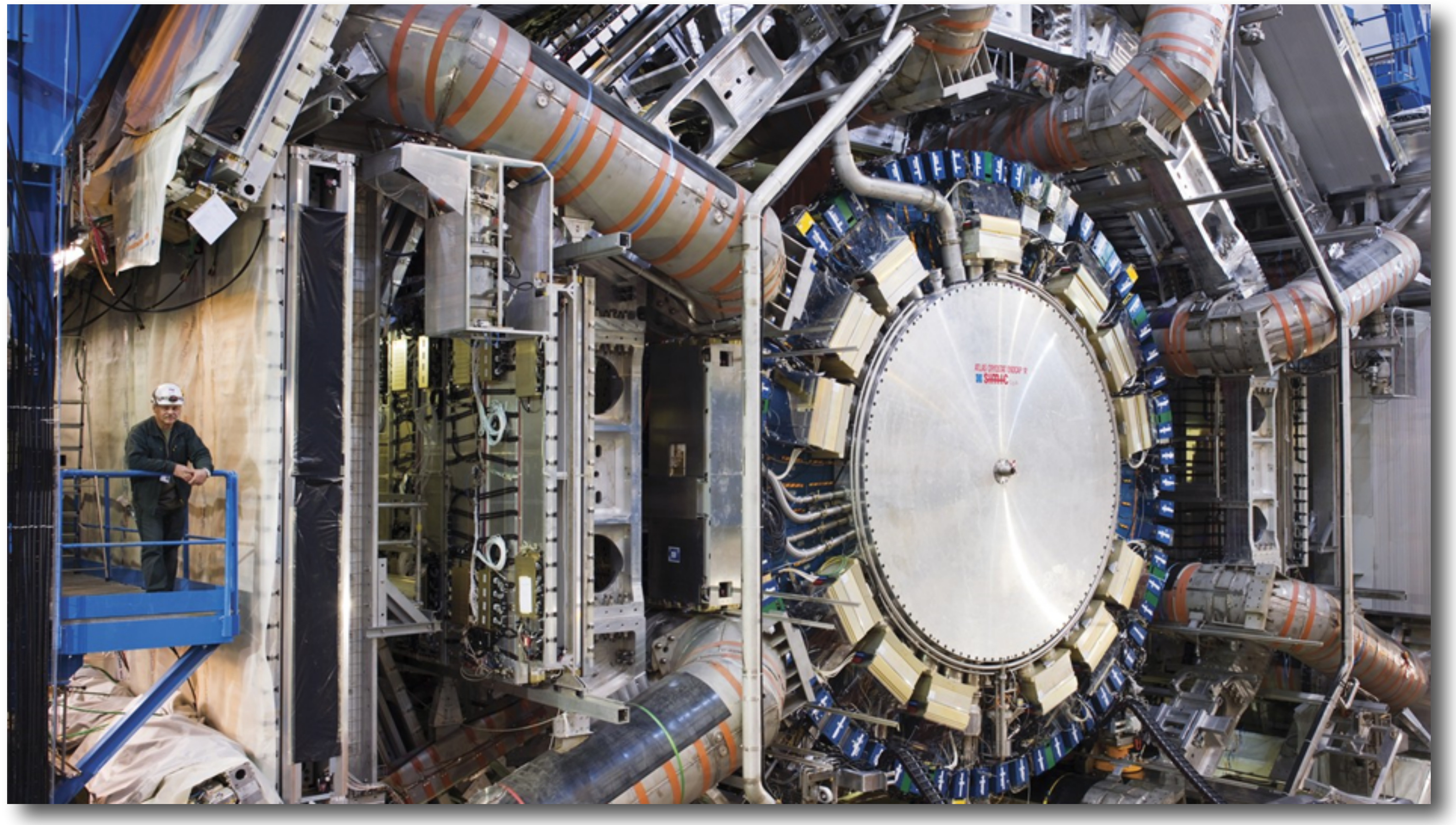
Why is the Universe like the one we see now?



How Answer to the Questions?

High-energy accelerator can directly probe fundamental constituents in nature by colliding particles



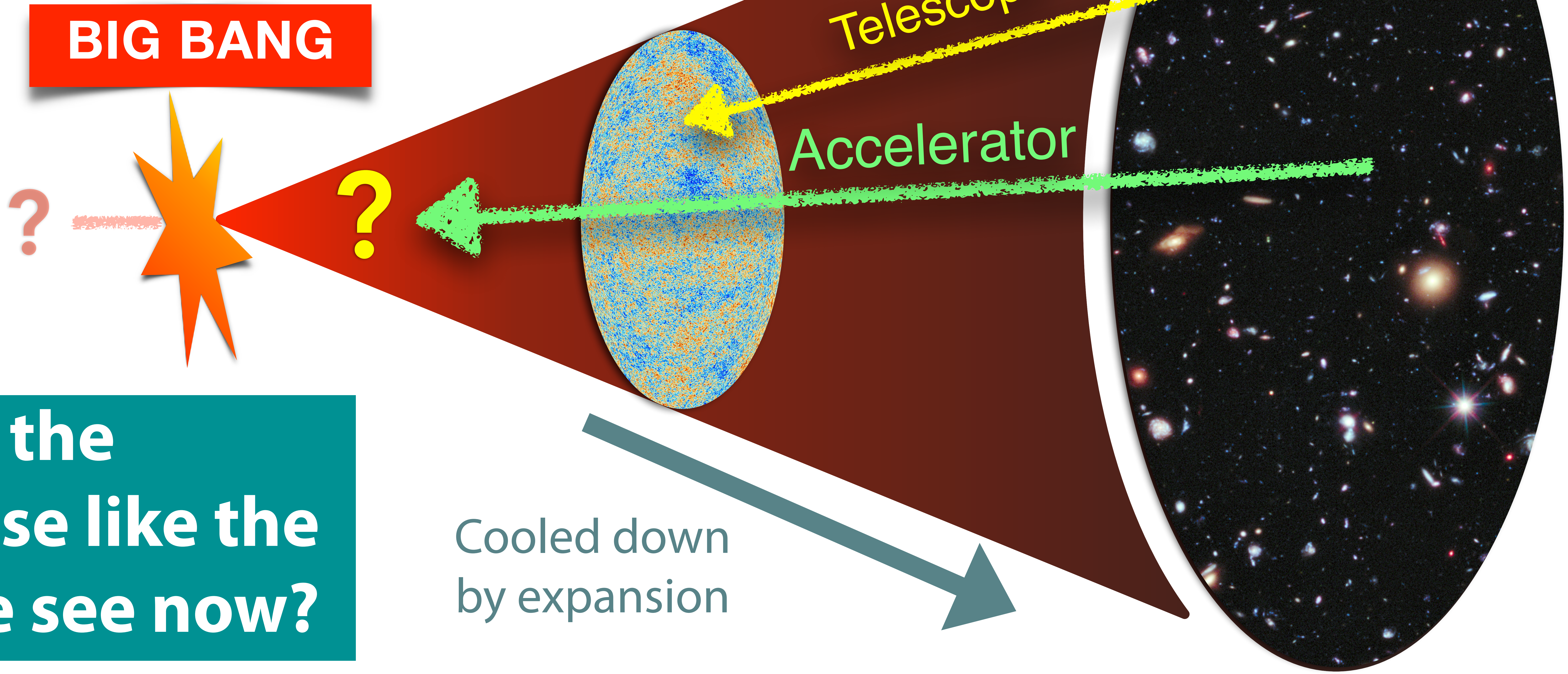


How Answer to the Questions?

Accelerator physics can probe the epoch of the birth of the Universe

Soup of elementary particles at very high temperature and density

Universe becomes visible at 3×10^5 years

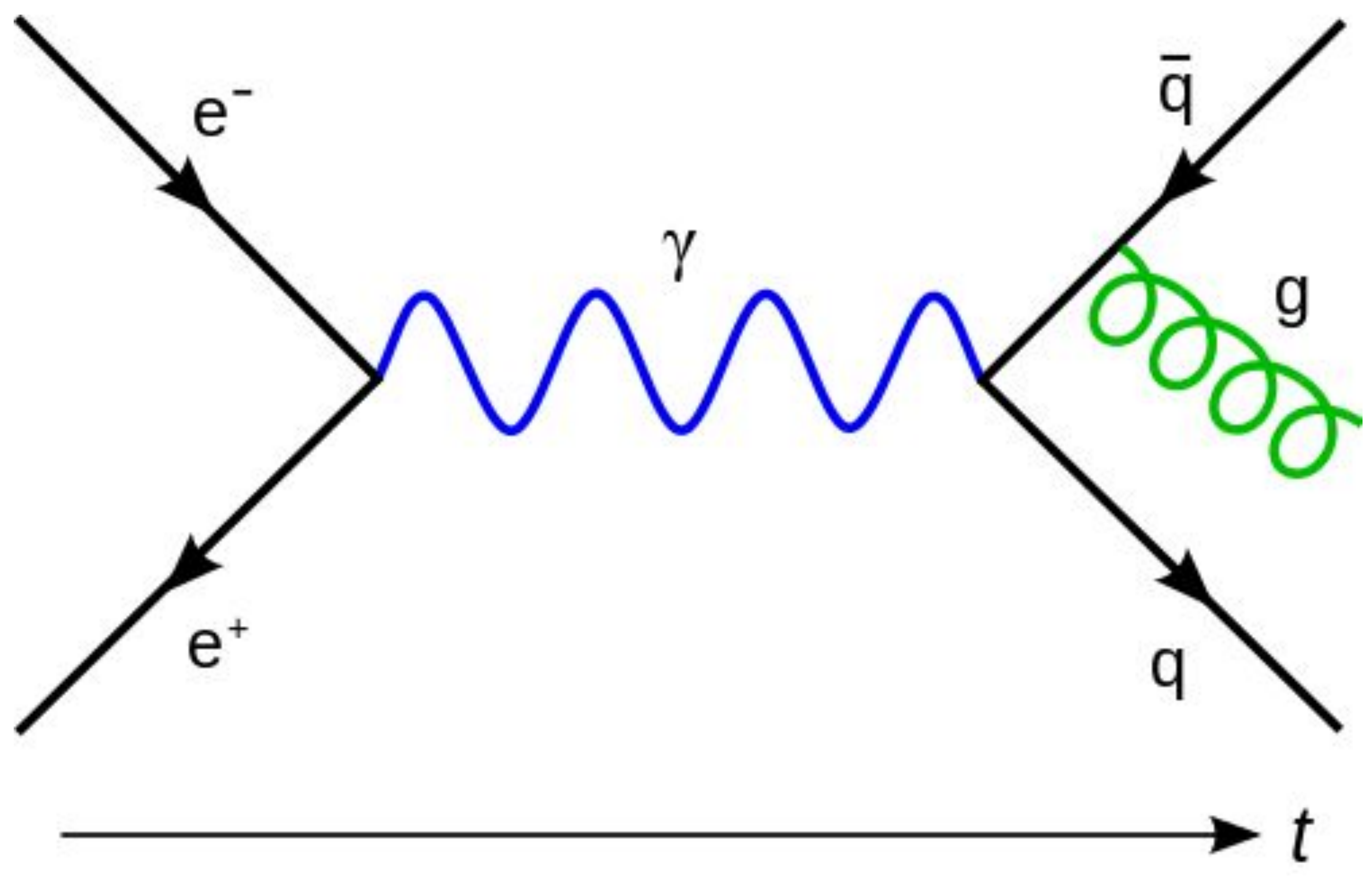


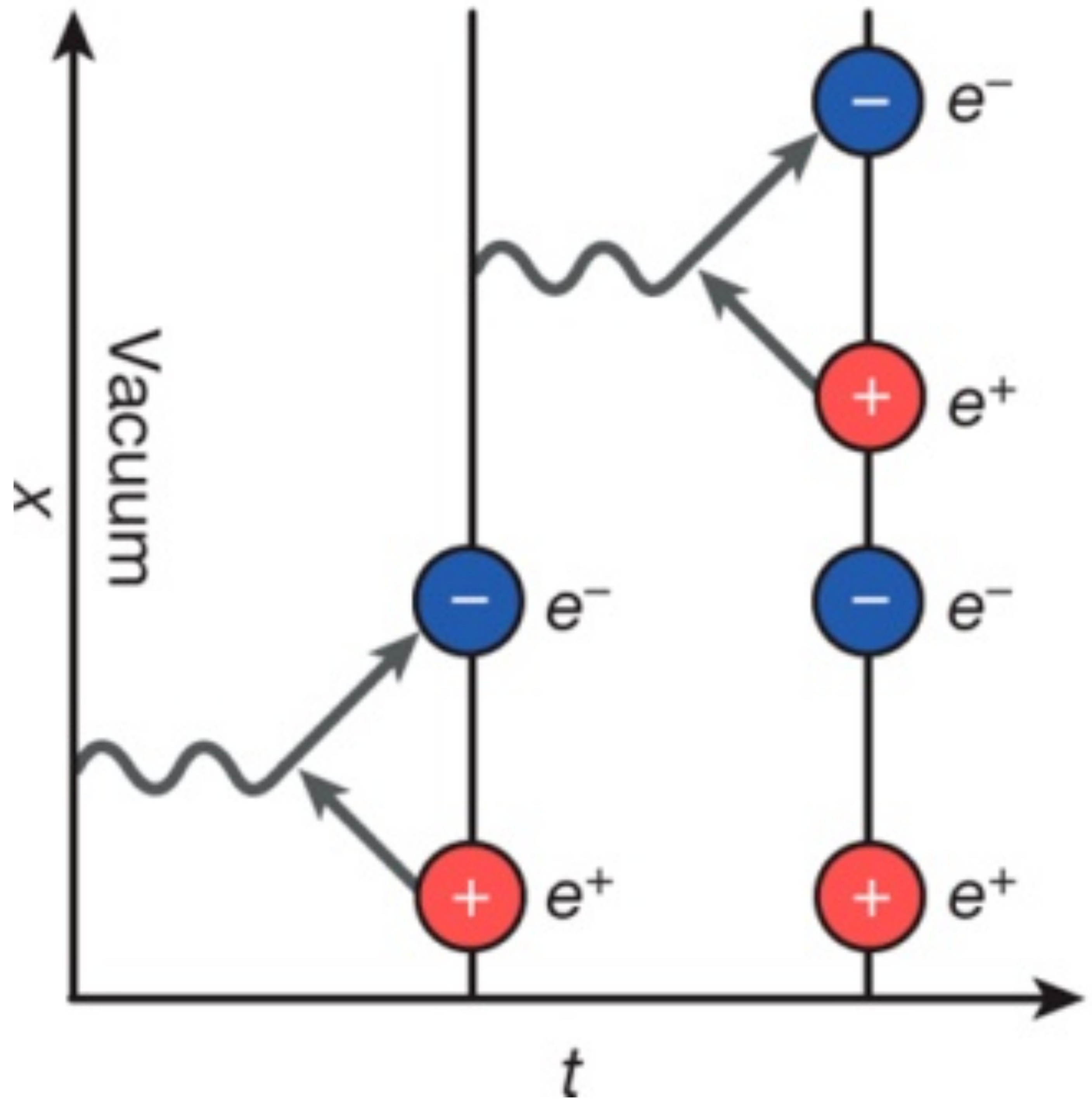
Why is the Universe like the one we see now?

Particle Physics and Quantum

Fundamental physics to understand properties/dynamics of elementary particles and nuclear matters

- Governed by $U(1) \times SU(2) \times SU(3)$ gauge theory





Quantum Field Theory (QFT) at cores in particle physics theories

Quantum mechanics as a foundation of QFT

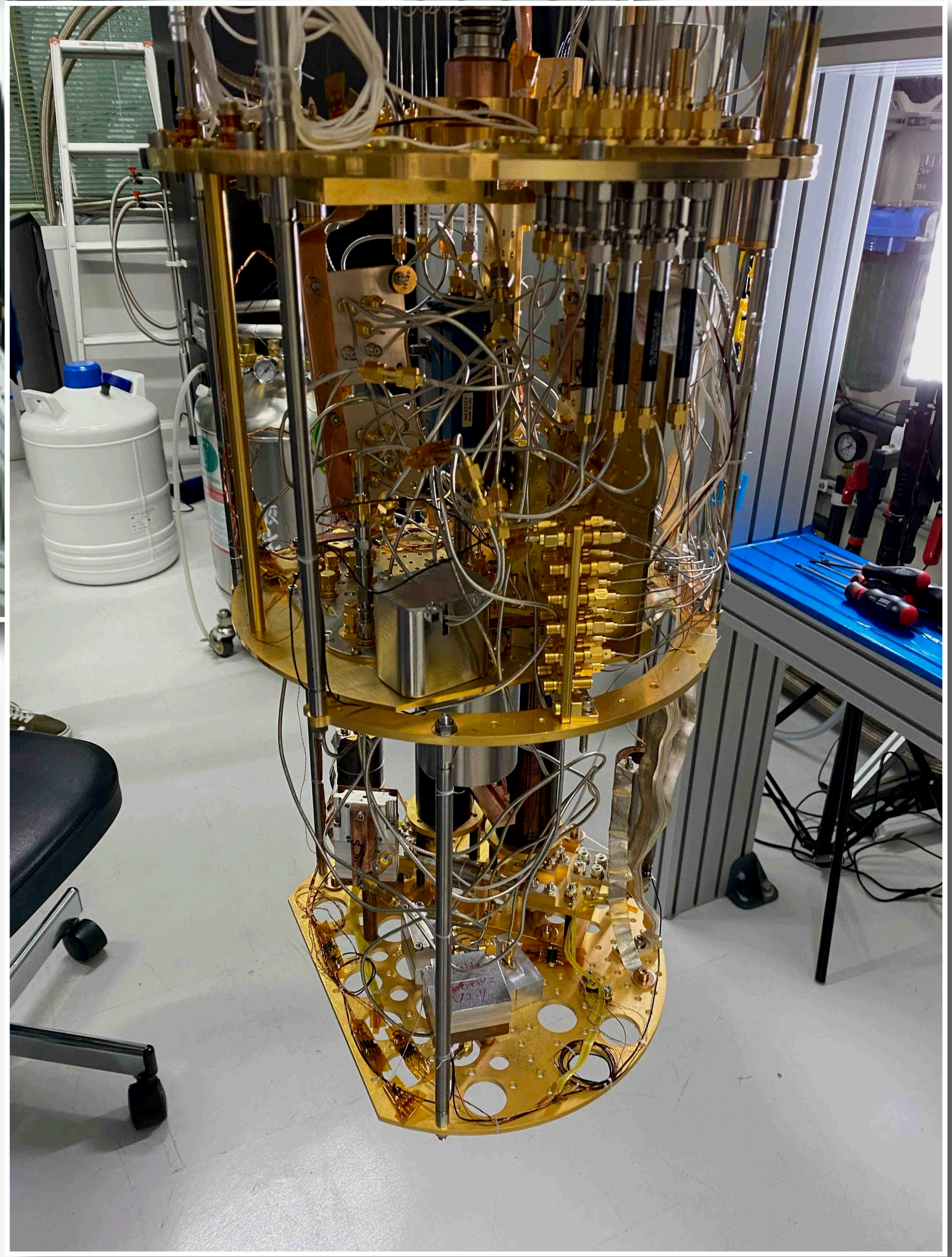
➡ Quantum computer may offer a unique opportunity to probe phenomena governed by particle physics

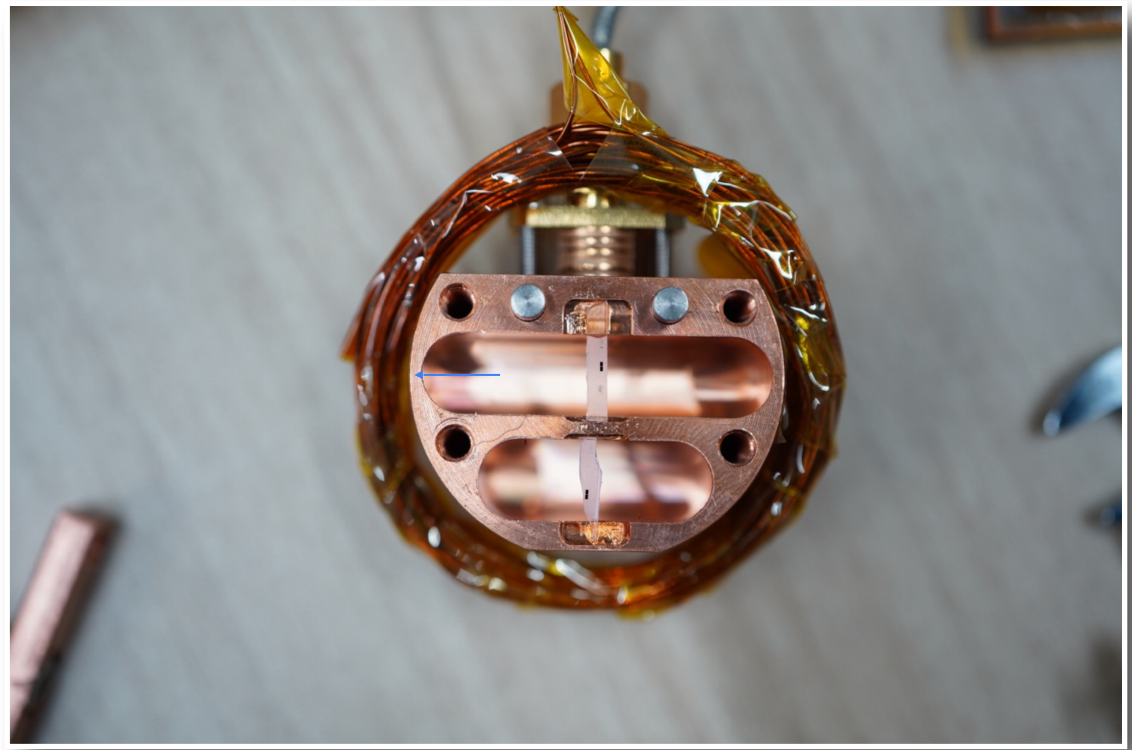
Particle Physics and Quantum

Quantum technology might be able to address the questions:

- How did the known phenomena (e.g, Higgs condensation, quark confinement) occur in early Universe?
- Can we exploit quantum resources to reach beyond conventional experimental techniques?

How did the Universe become the one we see now?





Outline

Present our recent studies at ICEPP that utilize quantum resources for the application to particle physics

Highlight a few selected results on:

- learning quantum states/processes ➡ Quantum Machine Learning
- simulating quantum dynamics in Lattice Gauge Theory ➡ Quantum Simulation
- searching for dark matter with superconducting qubits ➡ Quantum Sensing

Machine Learning of Quantum States

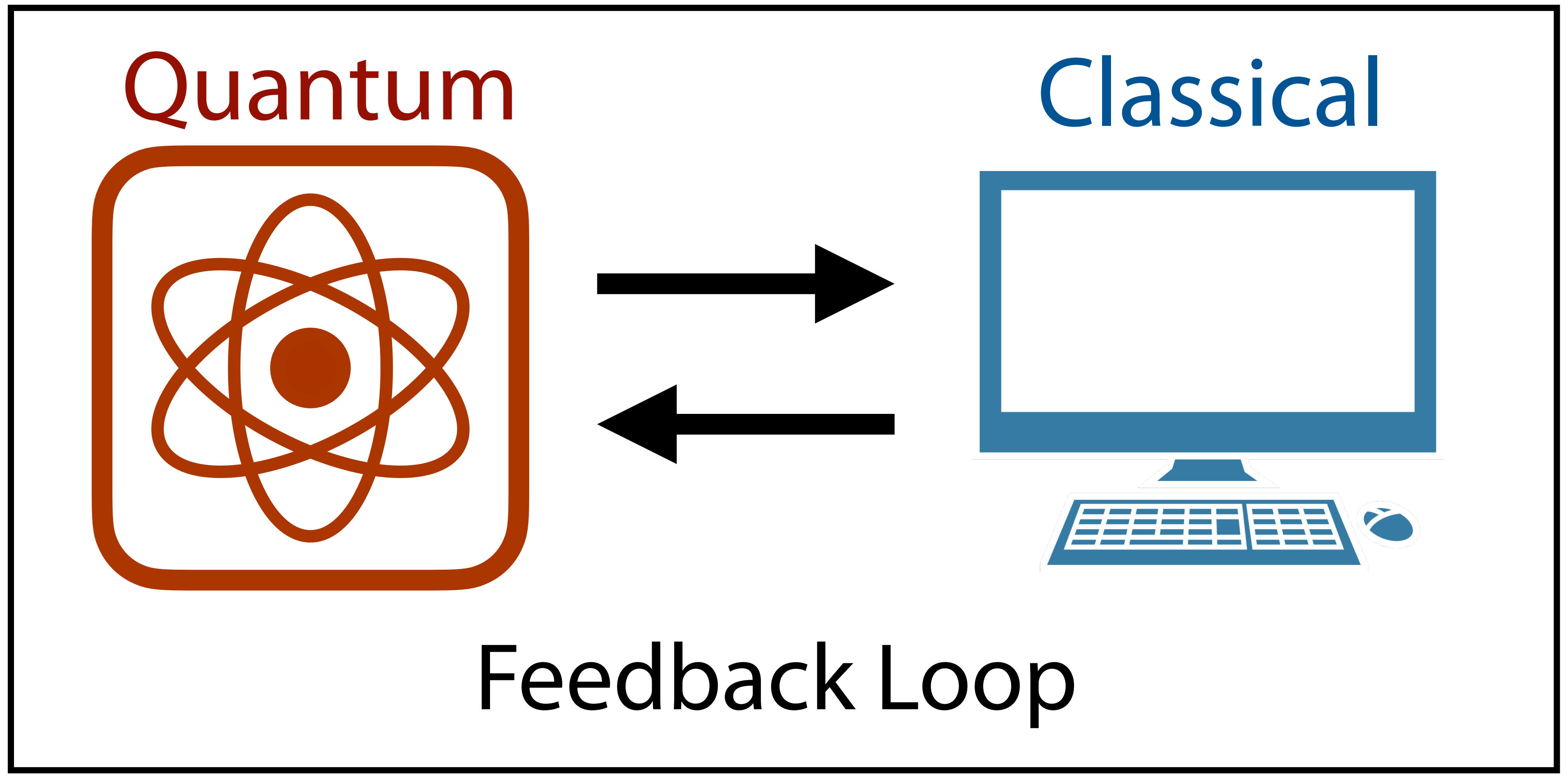
<u>Learning Task (in case of classification):</u>

- Given a dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$ (x_i = Classical or Quantum)
- Consider a hypothesis $h_{\boldsymbol{\theta}}$ which predicts the true label y_i from input x_i in D
- Define Loss function $L(y_i, h_{\boldsymbol{\theta}}(x_i))$ to quantify the difference between the label y_i and prediction $h_{\boldsymbol{\theta}}$
- Minimize the training error $\hat{R}_S(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N} L(y_i, h_{\boldsymbol{\theta}}(x_i))$ over input data in D

State preparation and optimization as key processes for learning task

Variational State Preparation and Optimization

- Prepare an input state $|\psi_{\mathrm{in}}\rangle = U(\boldsymbol{x})|\psi_0\rangle$ for classical or $|\psi_{\mathrm{in}}\rangle = |\psi_q\rangle$ for quantum
- Apply a parameterized unitary $U(\boldsymbol{\theta})$ to generate $|\psi(\boldsymbol{\theta})\rangle = U(\boldsymbol{\theta})|\psi_{\mathrm{in}}\rangle$
- Prepare the desired state by optimizing the parameter $\boldsymbol{\theta}$ with classical computer
- Calculate, e.g, expectation value of observable O with optimized parameter $\boldsymbol{\theta}^*$



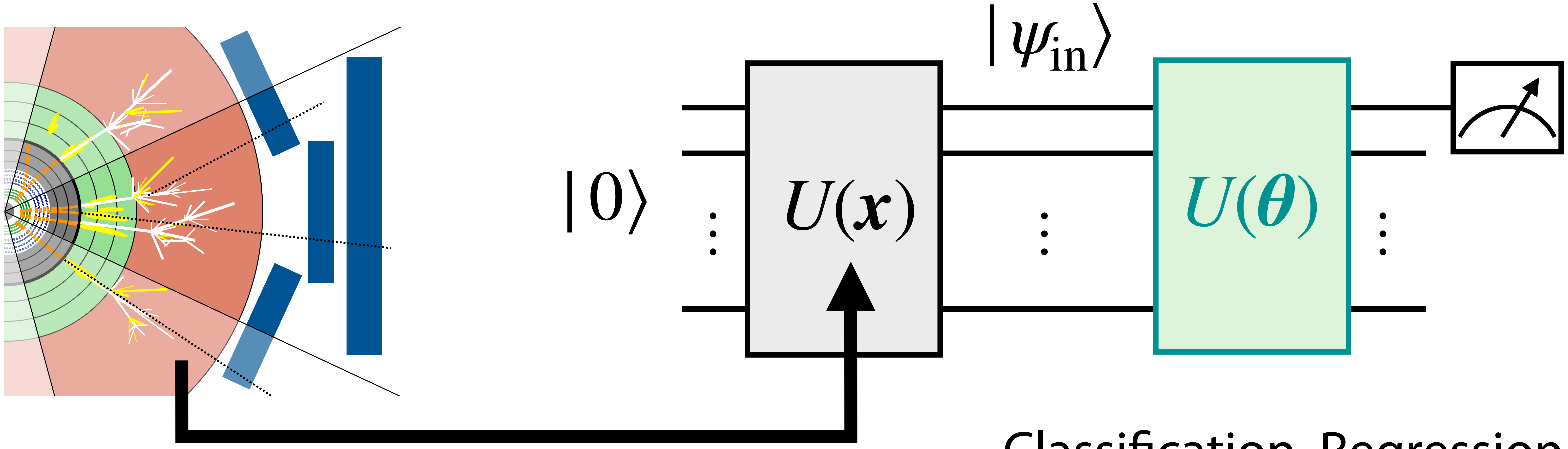
- Suitable for near-term quantum devices
- Applicable to a wide range of problems in quantum simulation (e.g, VQE), quantum machine learning

Quantum Machine Learning

Learning classical data $\boldsymbol{x}$

E.g, digitized detector signals

Quantum Neural Networks

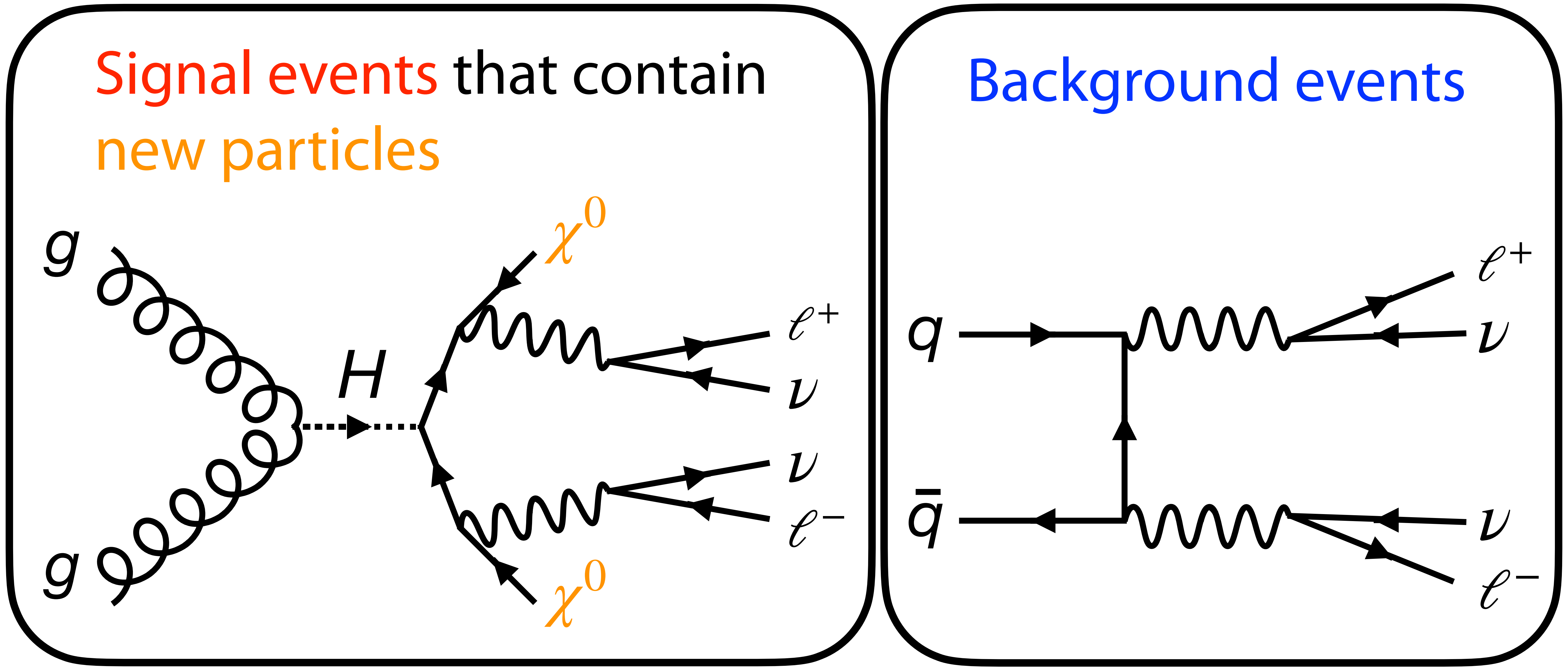


Classification, Regression

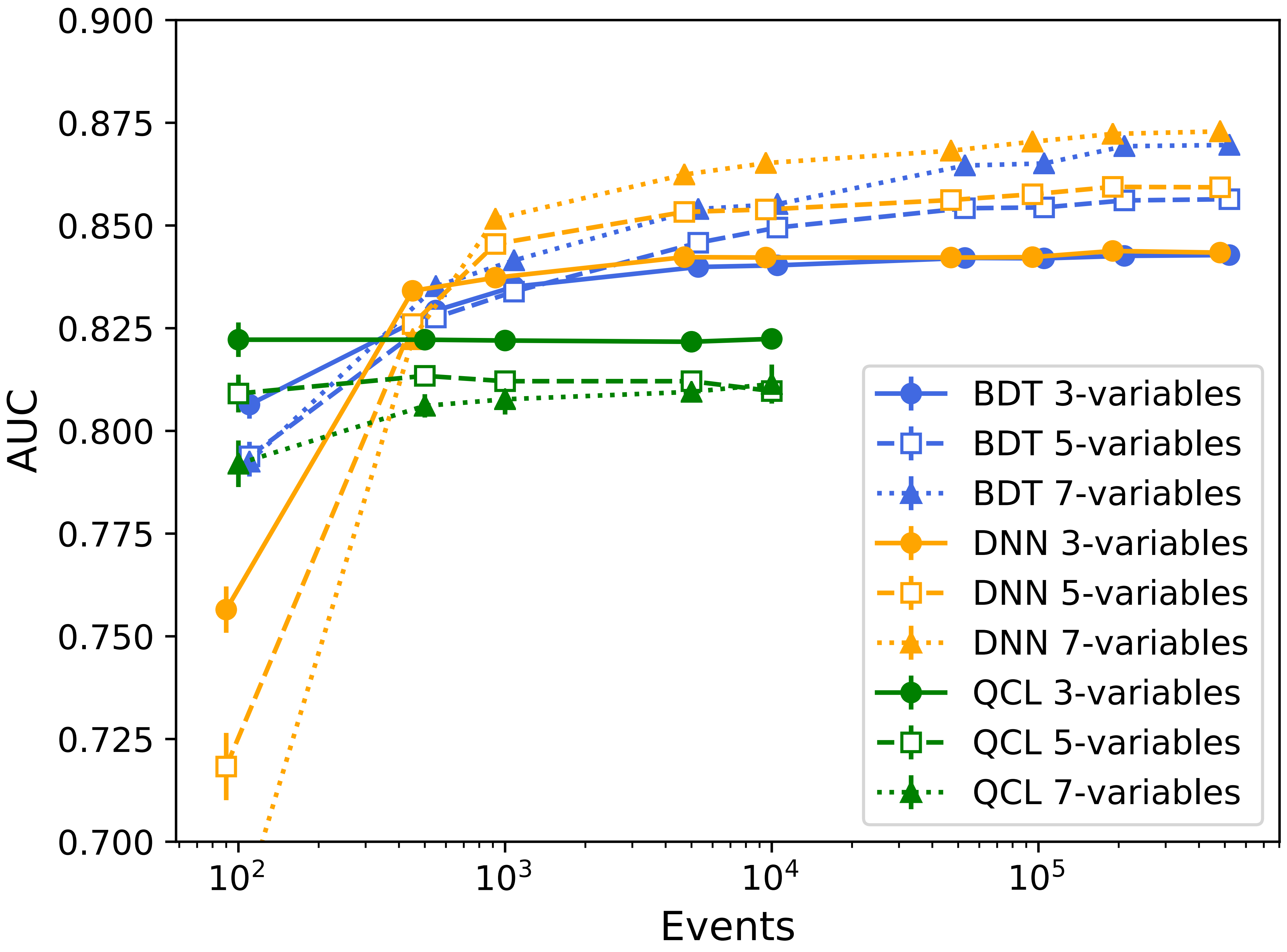
Learning HEP Data with QML

Classify new physics events from background with classical detector information

KT et al., Comput. Softw. Big Sci. 5, 2 (2021)



Simulator results



- Early attempt of QML looks encouraging with small system and dataset sizes
- Limited scalability to large-size problem (due to infamous Barren Plateau problem discussed later)

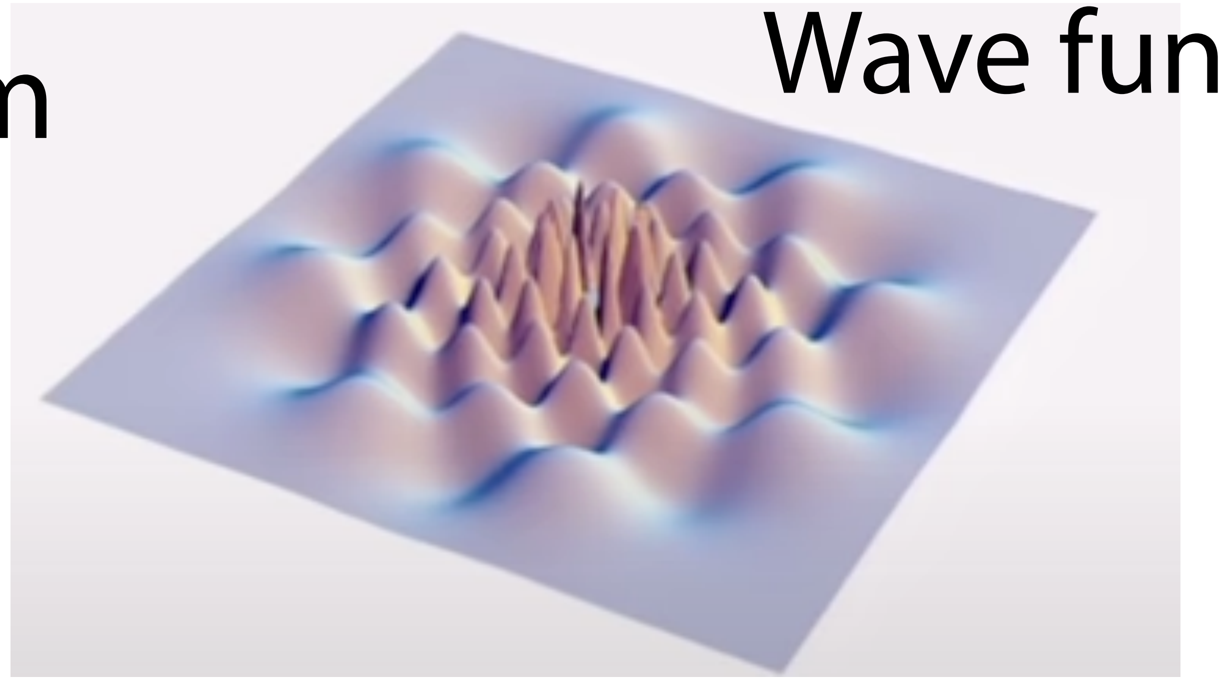
Learning Quantum Data

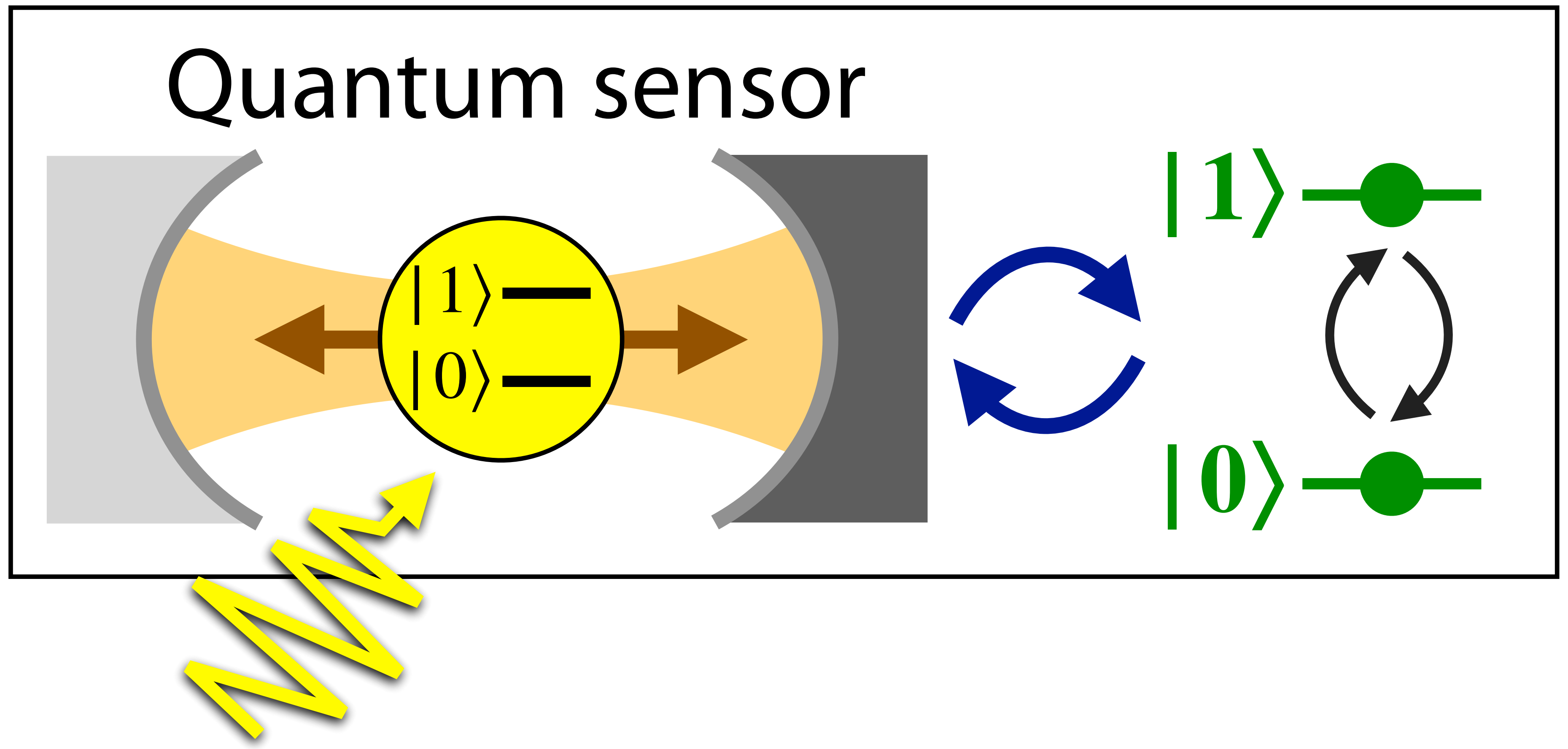
Directly learn quantum states without classical measurement, e.g, to

- Extract entanglement properties of a quantum system
- Determine classical parameters that control a physical system (e.g, Hamiltonian parameters)

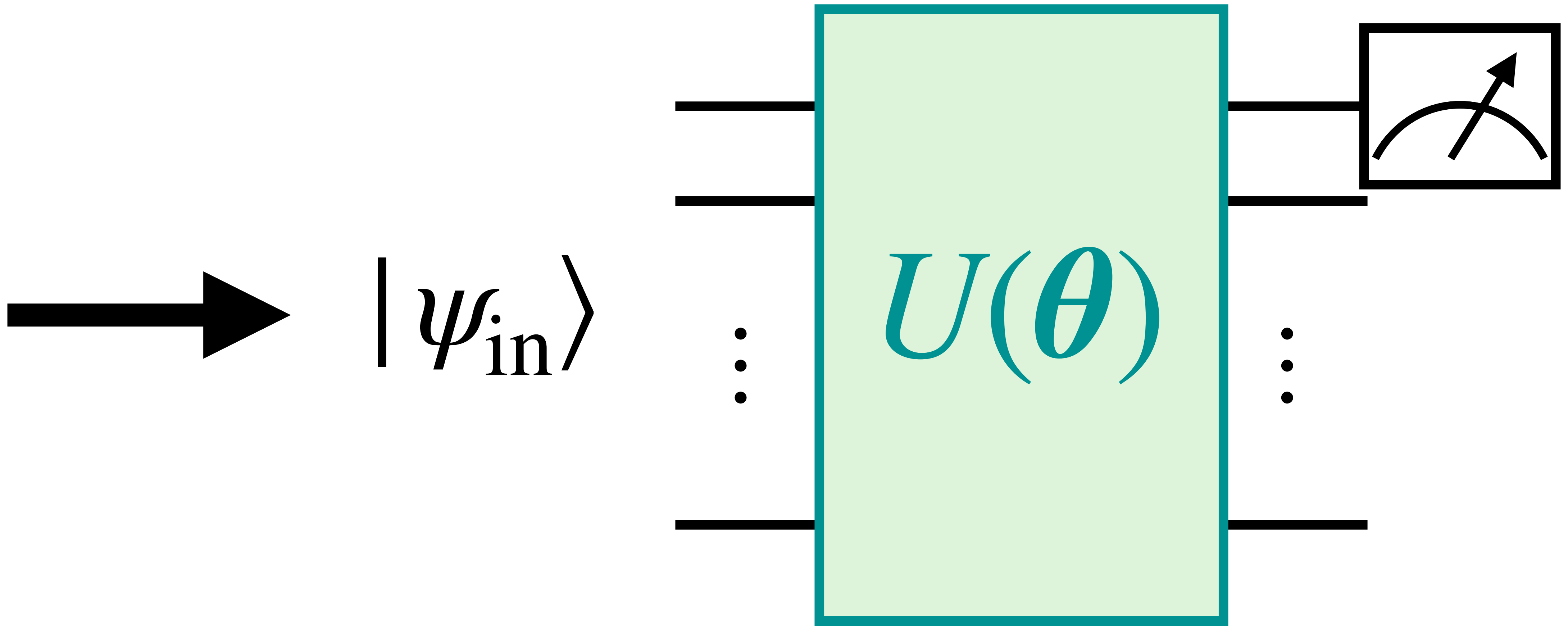
E.g, quantum state from another quantum system

Wave function





Quantum Neural Networks



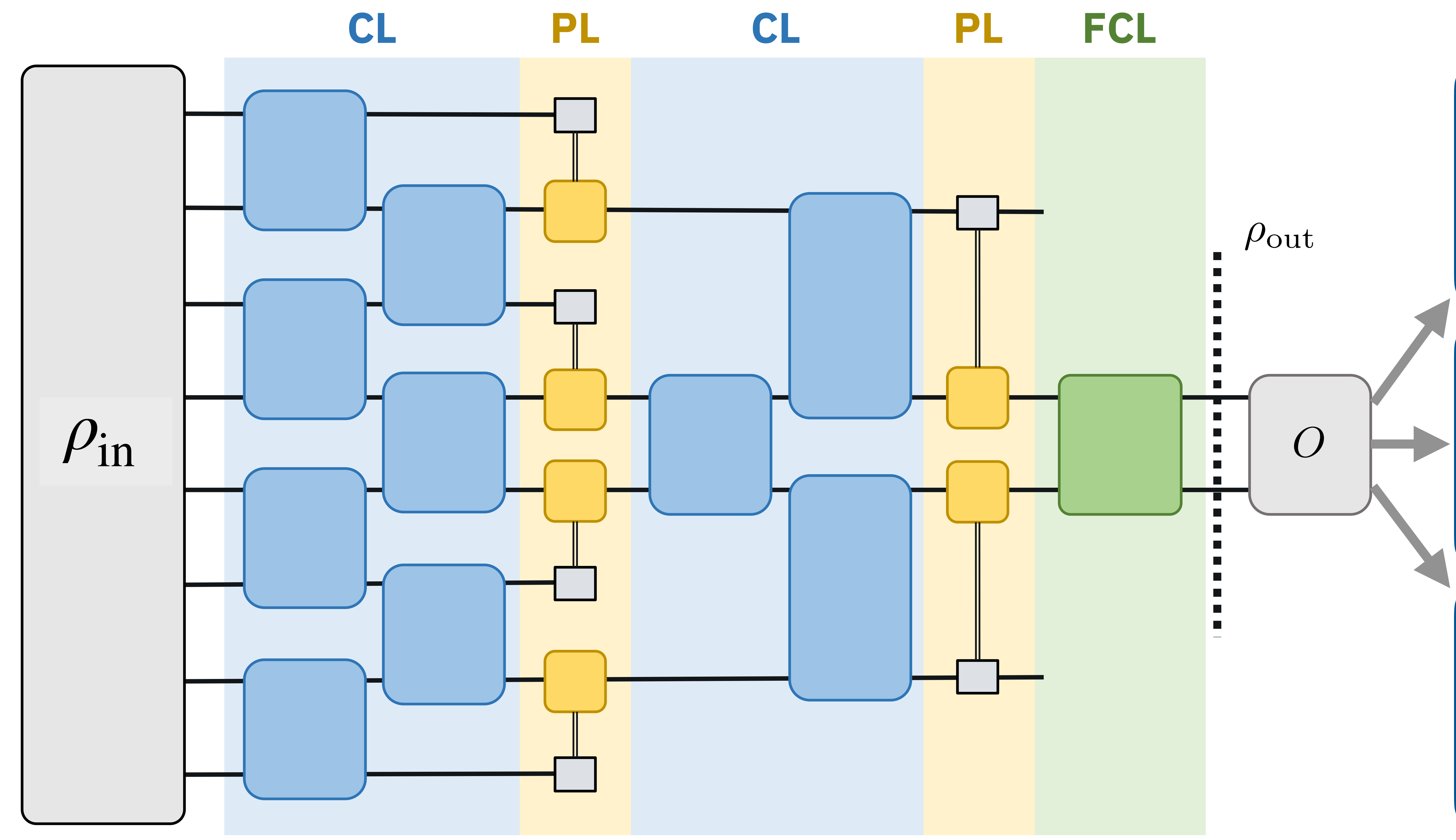
Learning Quantum Data

Learn physical properties of quantum states generated with HEP quantum simulation

Ground States
$(1+1)d$ $U(1)$
gauge theory
VQE

Time-evolved states
$(1+1)d$ $\mathbb{Z}_2$
gauge theory
time evolution

Multi-particle states
Parton shower
parton shower



Phase recognition
CT-symmetry
phases

Phase recognition
(De)confinement
phases of matter

Lagrangian parameter determination

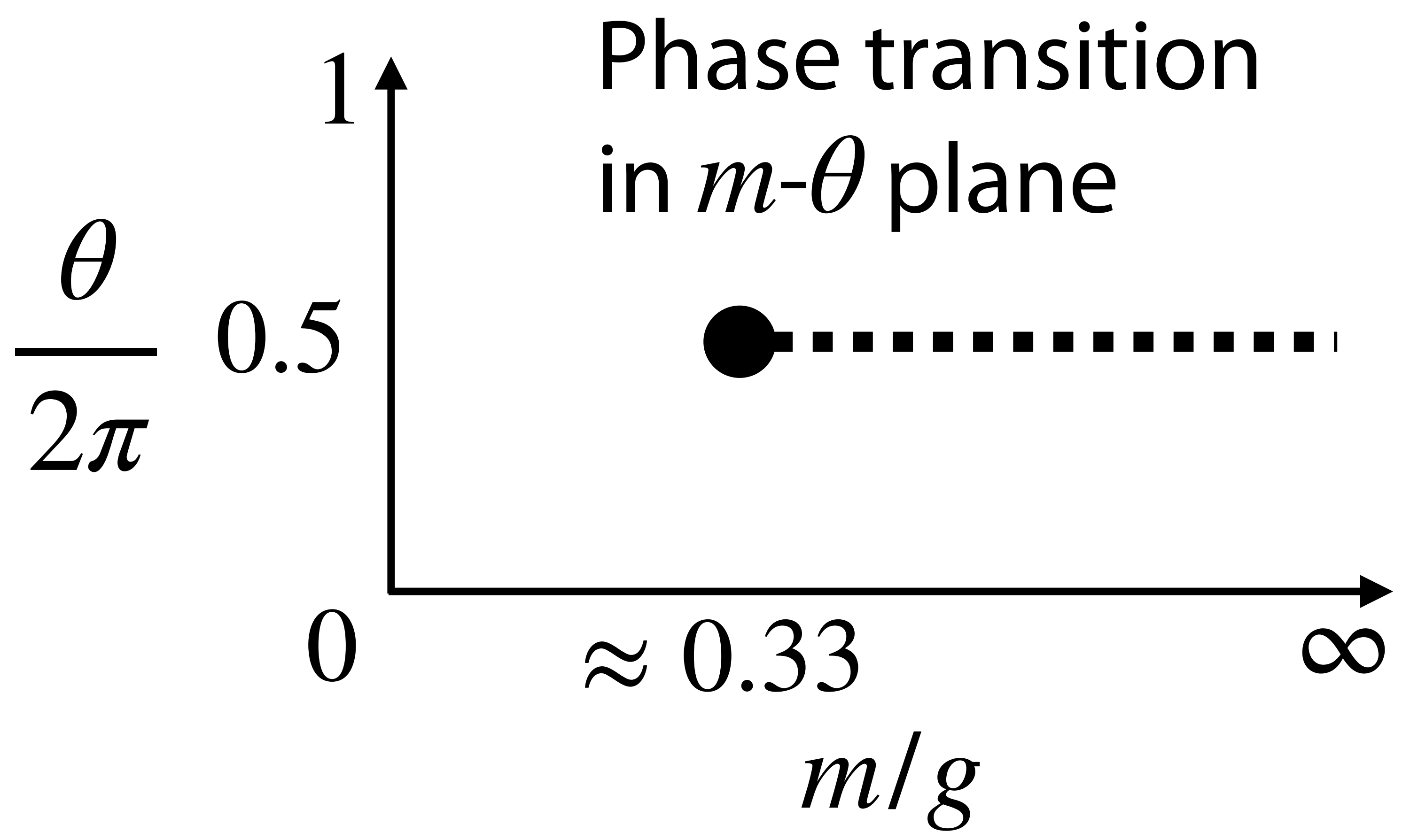
Quantum Convolutional Neural Networks

L. Nagano, KT et al., [Phys. Rev. Res. 5, 043250 (2023)]

QML to Quantum Data (I)

$(1+1)d\ U(1)$ Gauge Theory (Schwinger Model)

$$H = J\sum_{j=0}^{N_s-2}\left(\sum_{k=0}^{j}\frac{Z_k+(-1)^k}{2}+\frac{\theta}{2\pi}\right)^2+\frac{\omega}{2}\sum_{j=0}^{N_s-2}(X_jX_{j+1}+Y_jY_{j+1})+\frac{m}{2}\sum_{j=0}^{N_s-1}(-1)^jZ_j$$

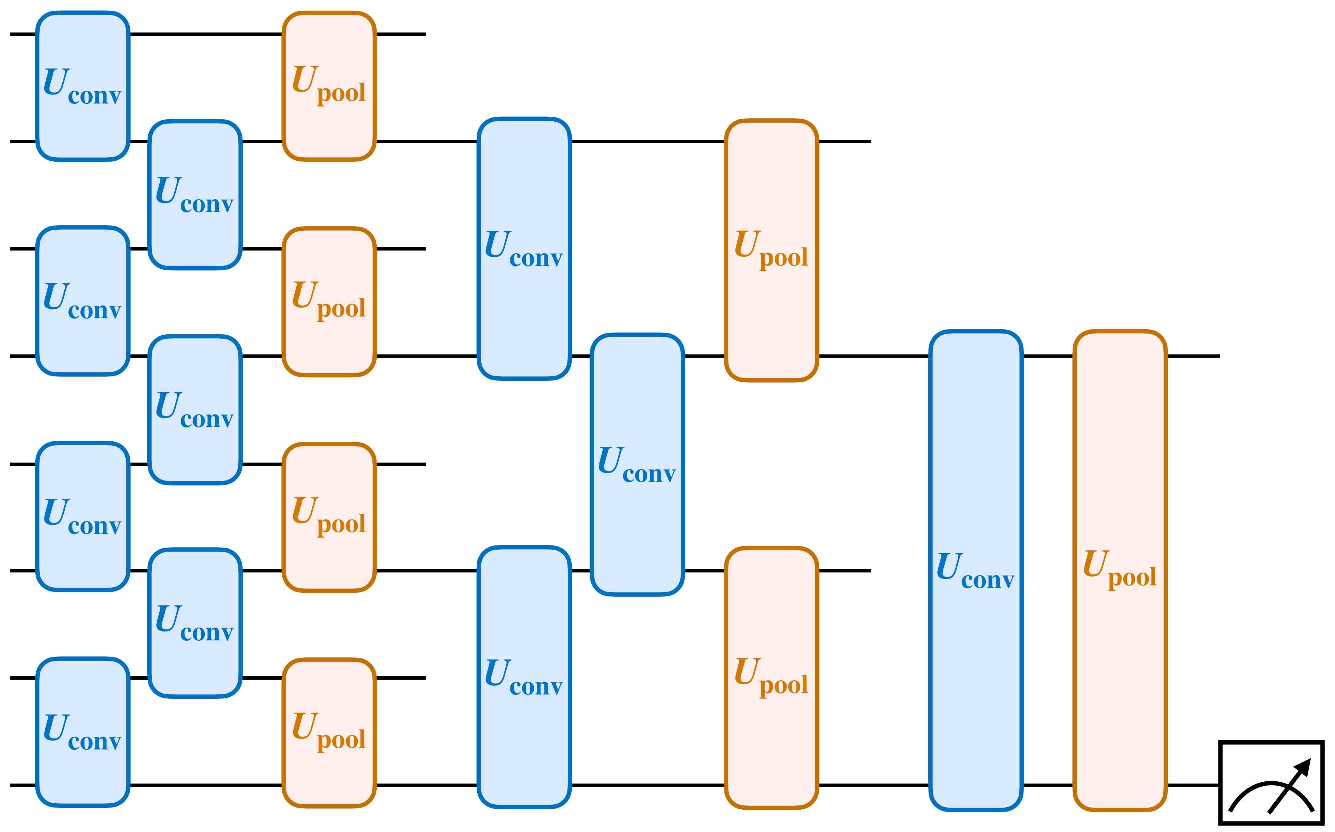


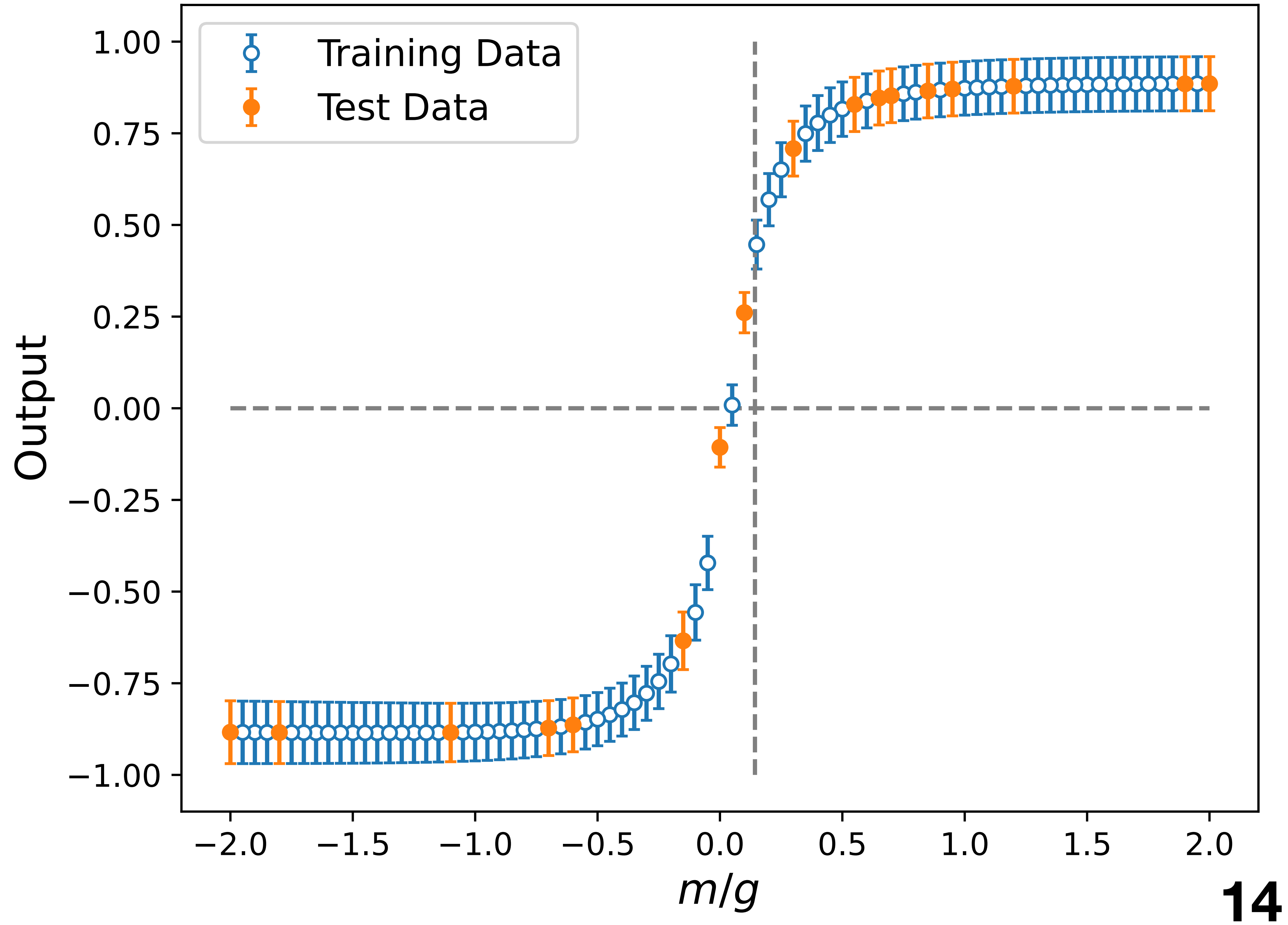
- Non-trivial properties such as chiral condensate, though the model is simple
- Phase transition at $\theta=\pi, m/g = m_c/g \approx 0.33$ due to topological θ-term

Quantum data generation and classification

- Physical parameters: $N=N_s=8, ag=2, \theta=\pi$
- Generate ground states $|\psi_{\mathrm{GS}}(m)\rangle$ using VQE within parameter range of $m/g \in [-2,2]$
- Phase recognition as a classification with label:

$$y_m = \begin{cases} +1 & (m > m_c) \\ -1 & (m < m_c) \end{cases}$$



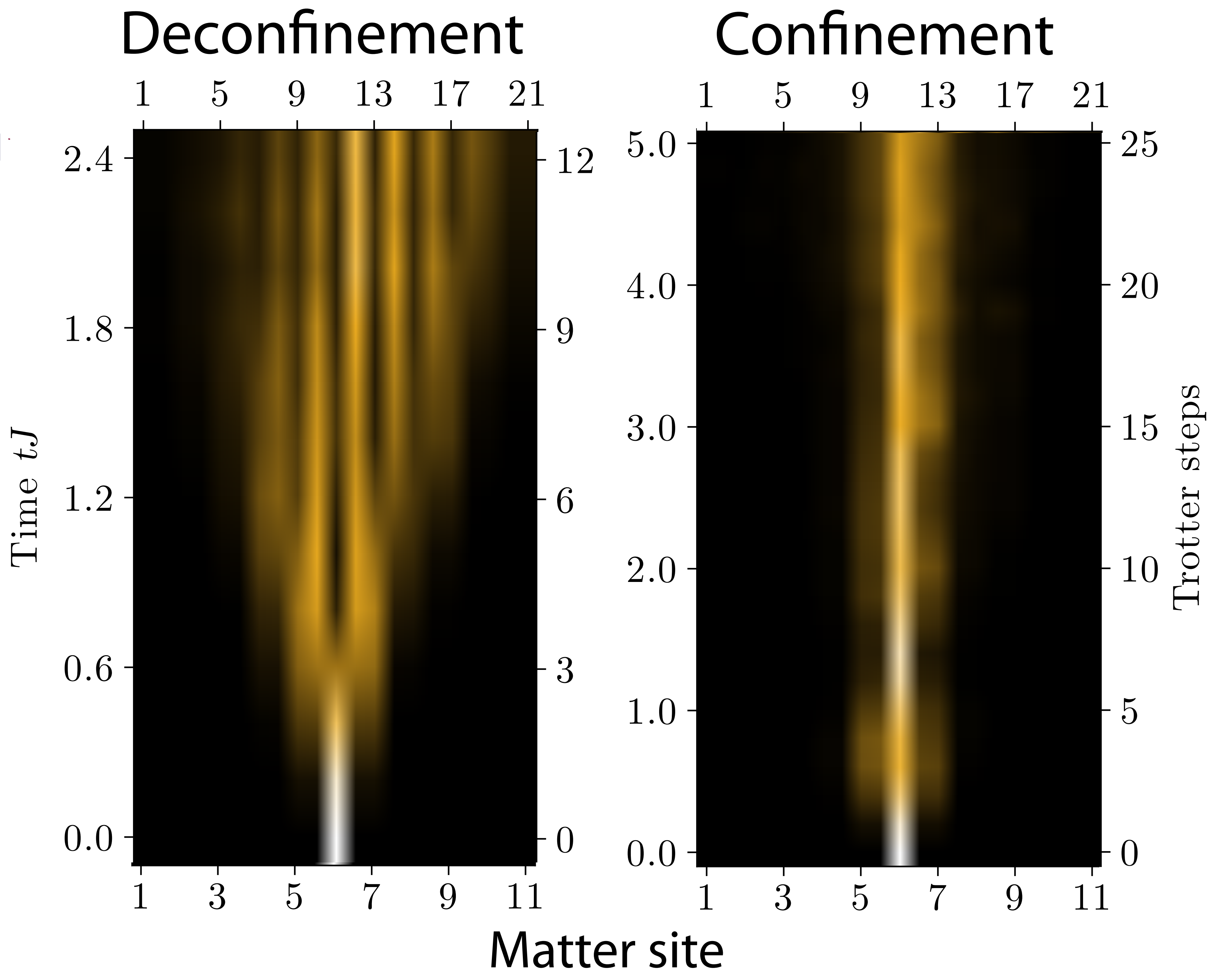


QML to Quantum Data (II)

$(1+1)d\ \mathbb{Z}_2$ Gauge Theory

$$H = -\frac{J}{2}\sum_{j=0}^{N_s-1}(X_j Z_{j,j+1}X_{j+1} + Y_j Z_{j,j+1} Y_{j+1}) - f\sum_{j=0}^{N_s-2} X_{j,j+1} + \frac{m}{2}\sum_{j=0}^{N_s-1}(-1)^j Z_j$$

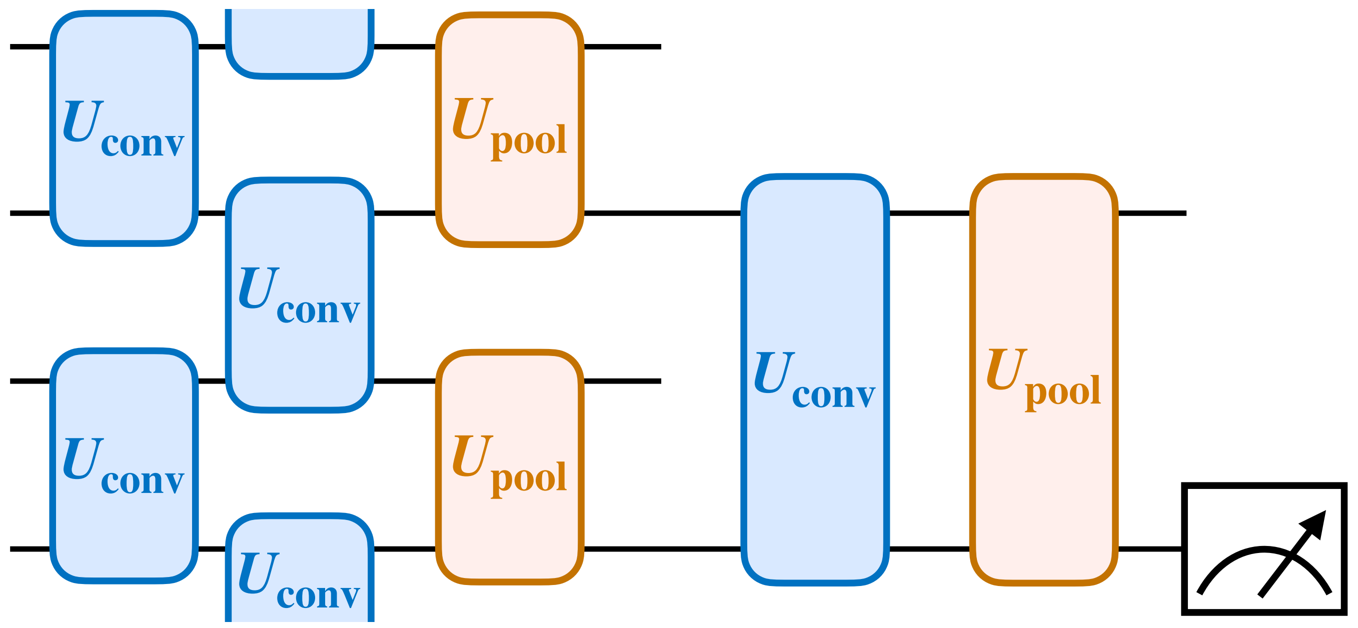
- Confinement ($f \neq 0$) and Deconfinement ($f = 0$) phases depending on the presence of background electric field

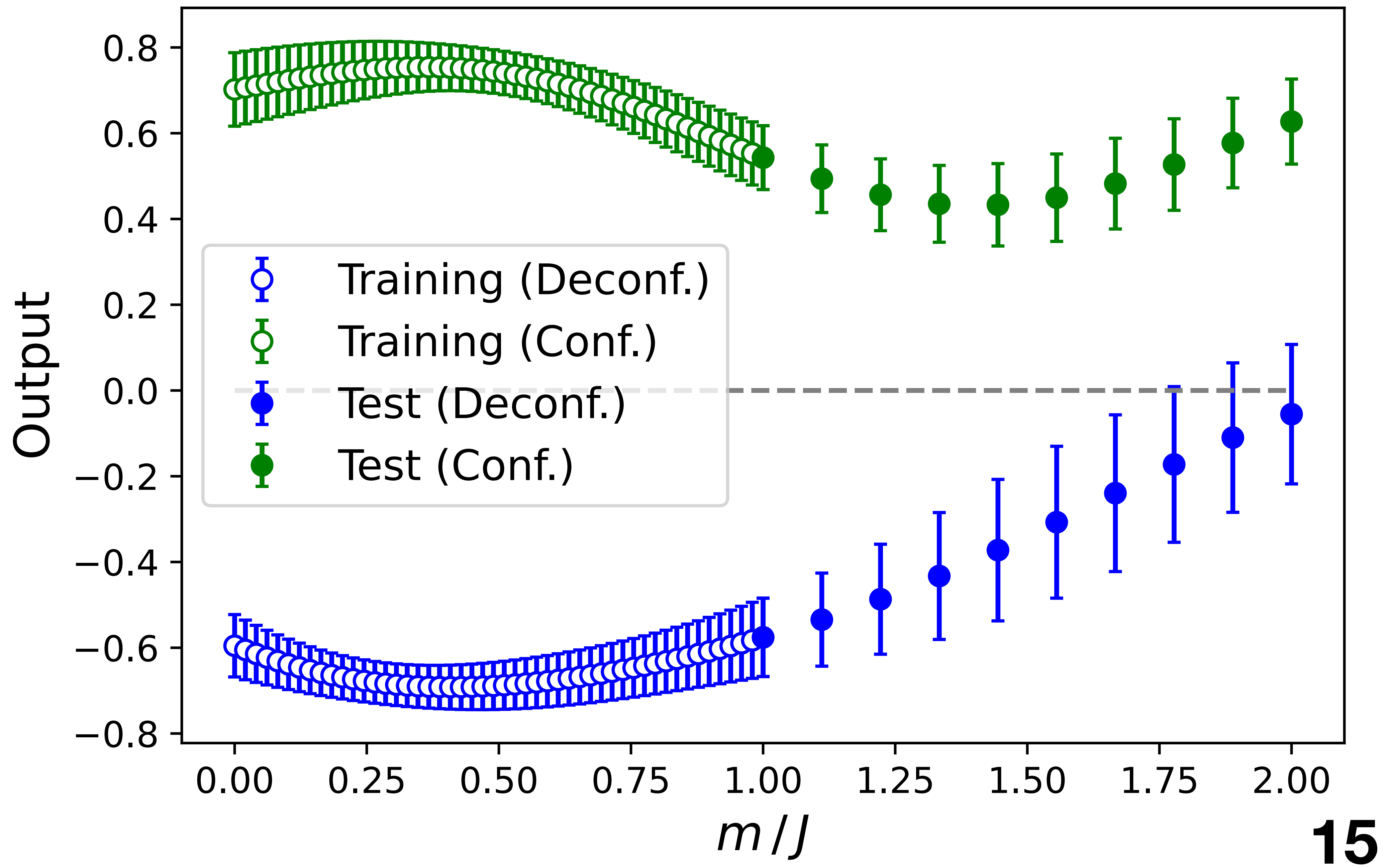


Quantum data generation and classification

- Physical parameters: $N = 2N_s = 4, J = 1, T = 2$
- Generate time-evolved states $|\psi(m,f)\rangle = e^{-iH(m,f)T}|\psi_0\rangle$ using Suzuki-Trotter decomposition within $m \in [0,2], f \in \{0,3\}$
- Phase recognition as a classification with label:

$$y_m = \begin{cases} +1 & (f \neq 0) \\ -1 & (f = 0) \end{cases}$$





Revisiting Machine Learning

Assuming that the data (x, y) has a underlying distribution P, and a dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$ is created by sampling the distribution P:

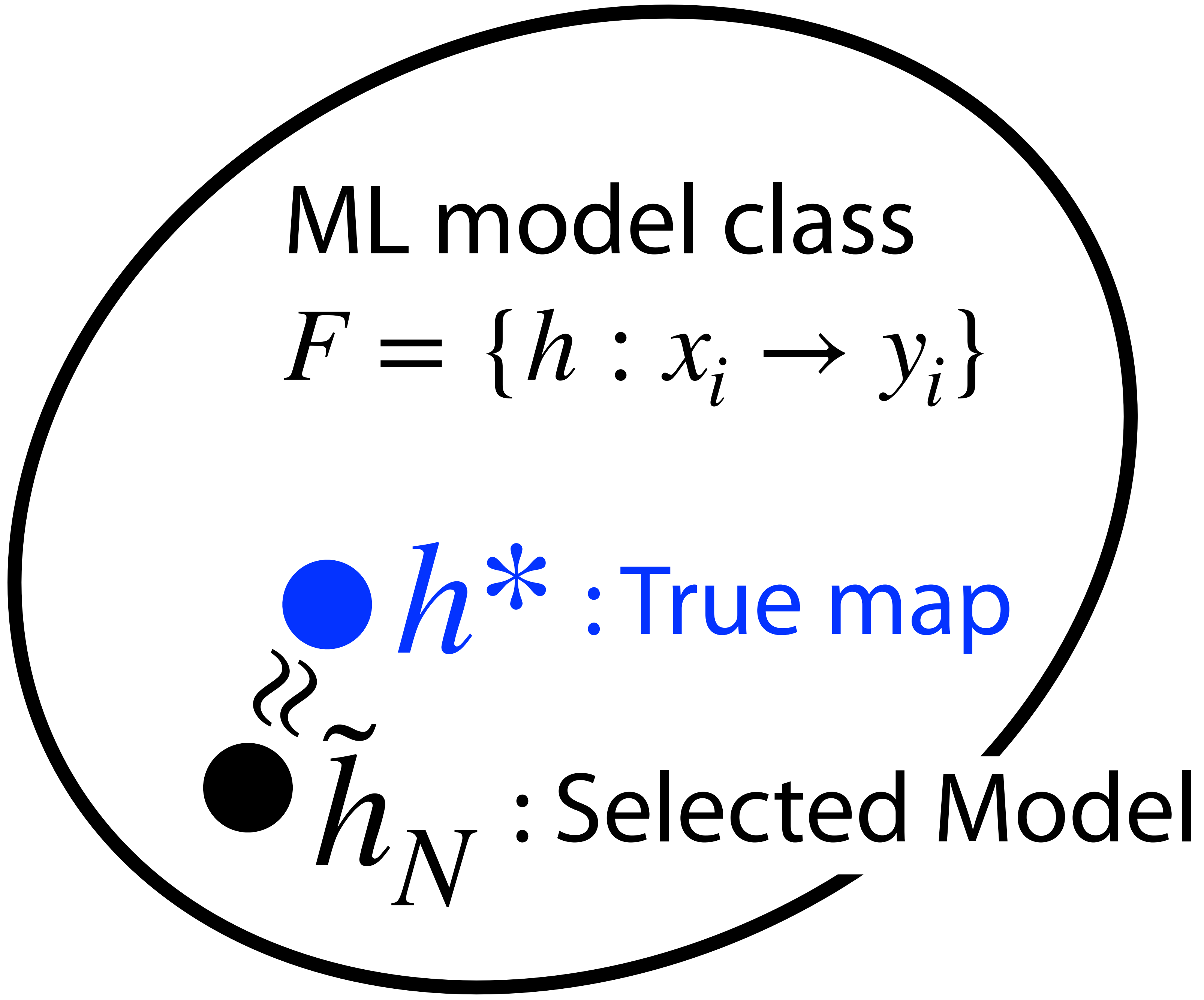
Training Error from D : $\hat{R}_S(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N} L(y_i, h_{\boldsymbol{\theta}}(x_i))$

Prediction Error (for unseen data) : $R(\boldsymbol{\theta}) = \mathbb{E}_{(x,y)\sim P}\left[L(y, h_{\boldsymbol{\theta}}(x))\right]$

Finding a hypothesis $h_{\boldsymbol{\theta}}$ that minimizes the prediction error is a goal of machine learning

Machine Learning Task and Model Class

A given ML architecture would enable certain class of models (model class)



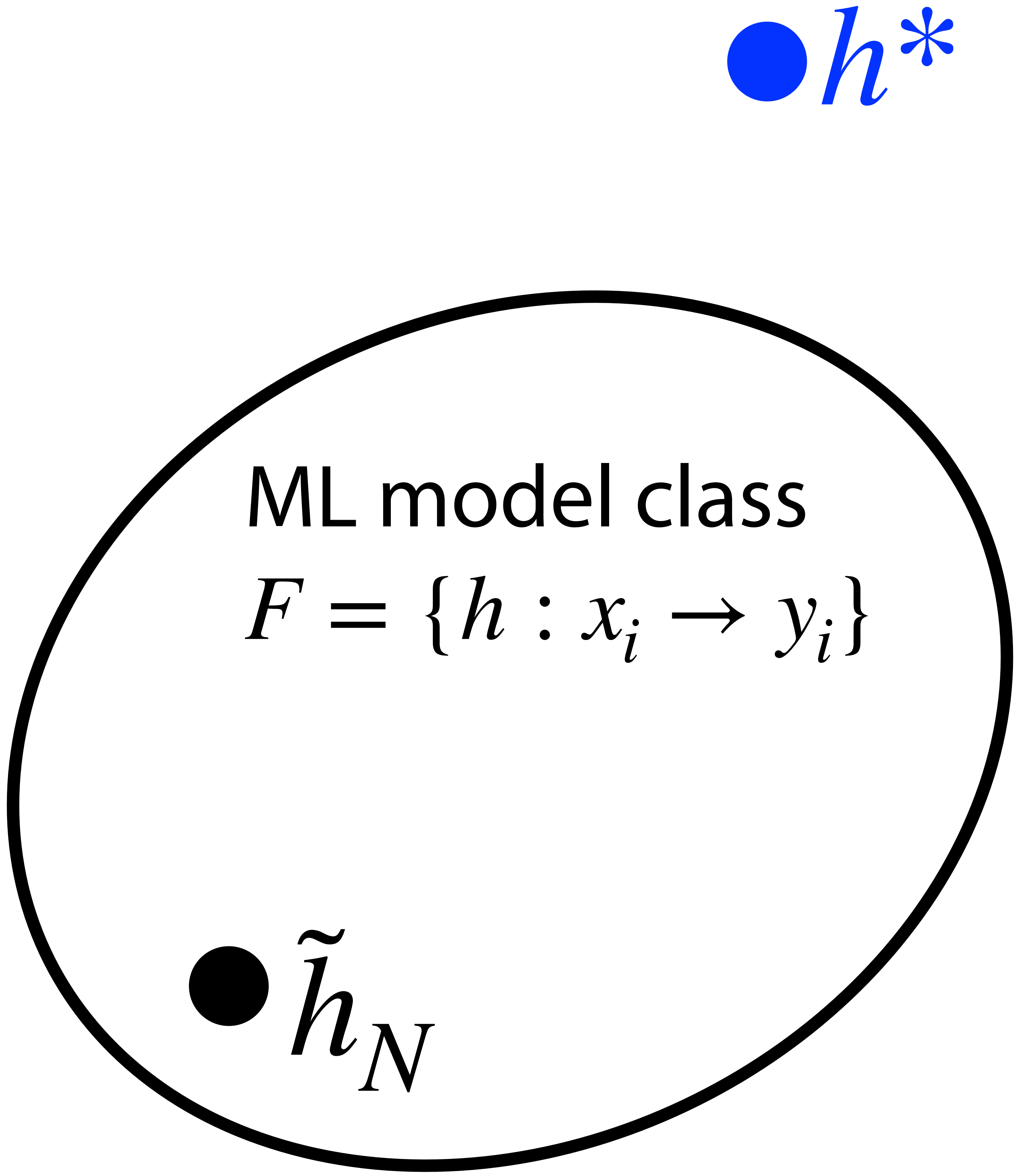
h^* : True map that faithfully outputs the true label y from an input x

Likely that the problems considered so far were simple enough, so that the true map could easily fall inside the model class :

$$\tilde{h}_N \approx h^*$$

Machine Learning Task and Model Class

True map may not necessarily reside in a given model class for more complex problems



Machine Learning Task and Model Class

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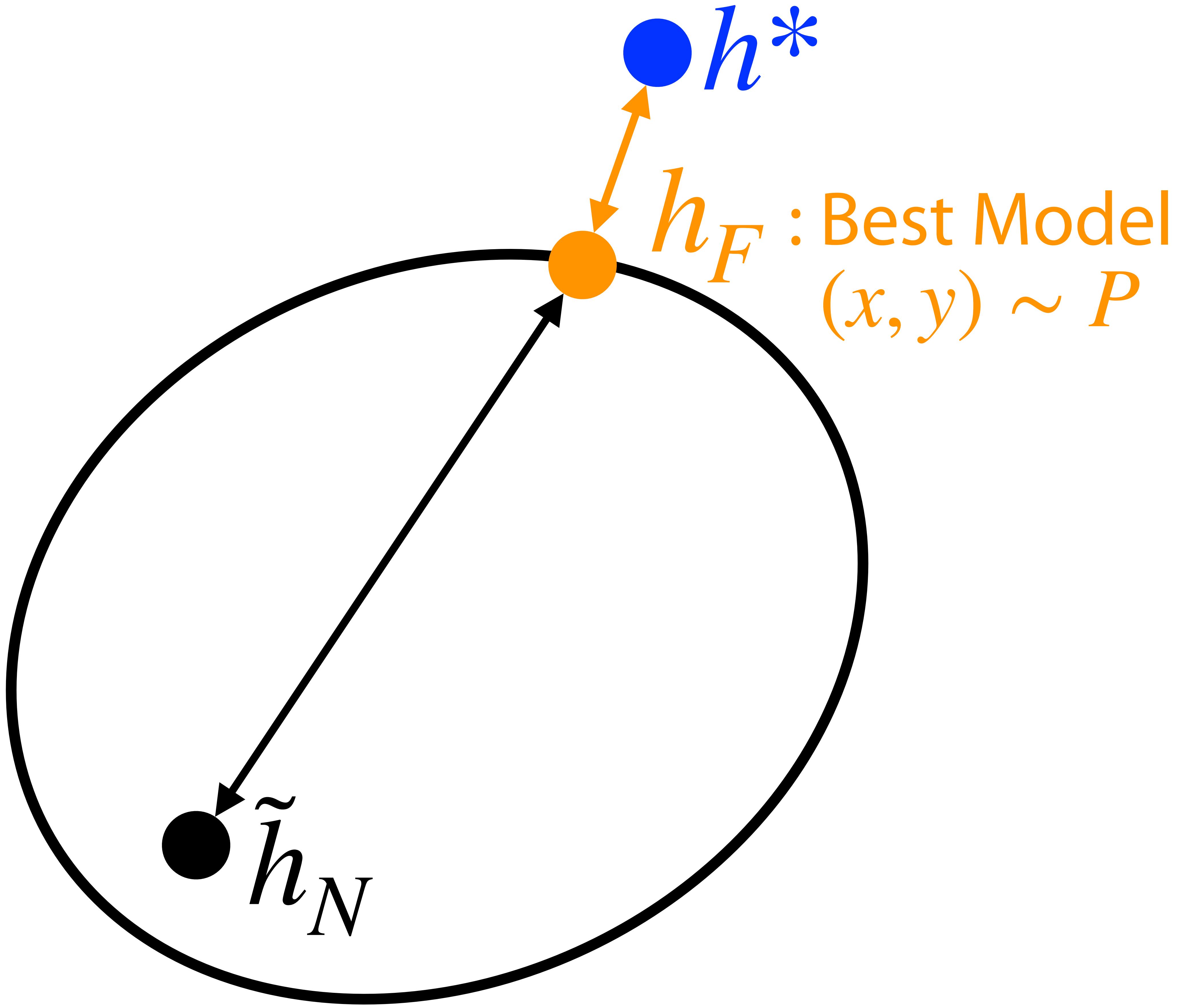
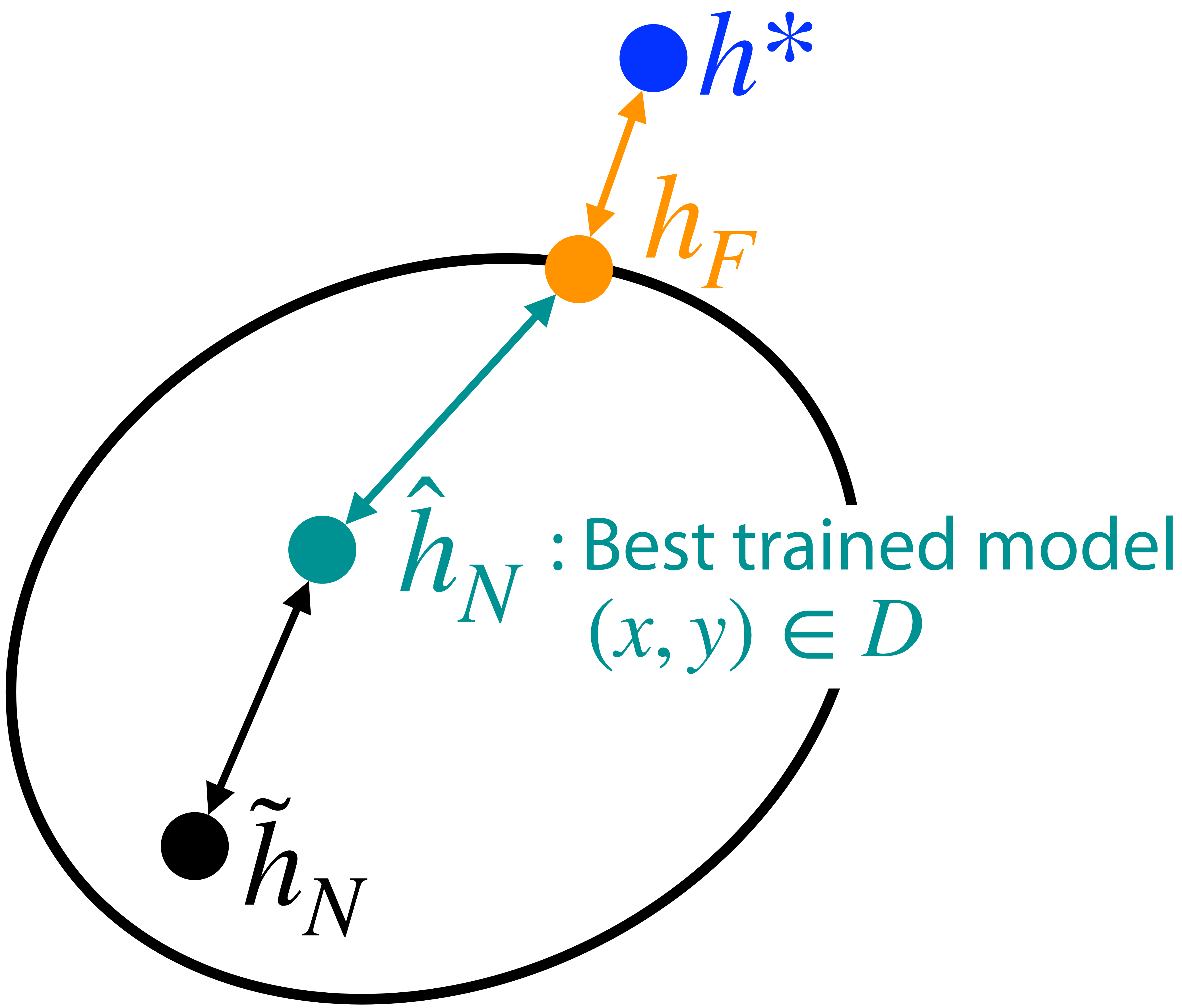


Best model within the model class may be obtained when input distribution P is directly used in the training

However, input distribution P is usually unknown

Machine Learning Task and Model Class

True map may not necessarily reside in a given model class for more complex problems



Best *trained* model is likely different from the best model because the finite dataset D is used instead of P

Different sources contribute to errors:

$R(\hat{h}_N) - R(\tilde{h}_N) =$ **Optimization Error**

$R(h_F) - R(\hat{h}_N) =$ **Estimation Error**

$R(h^*) - R(h_F) =$ **Model Error**

Optimization Errors

Insufficient training would be an important source of optimization errors

Known that the training of parameterized quantum circuit generally becomes difficult with increasing system size (*Curse of dimensionality*)

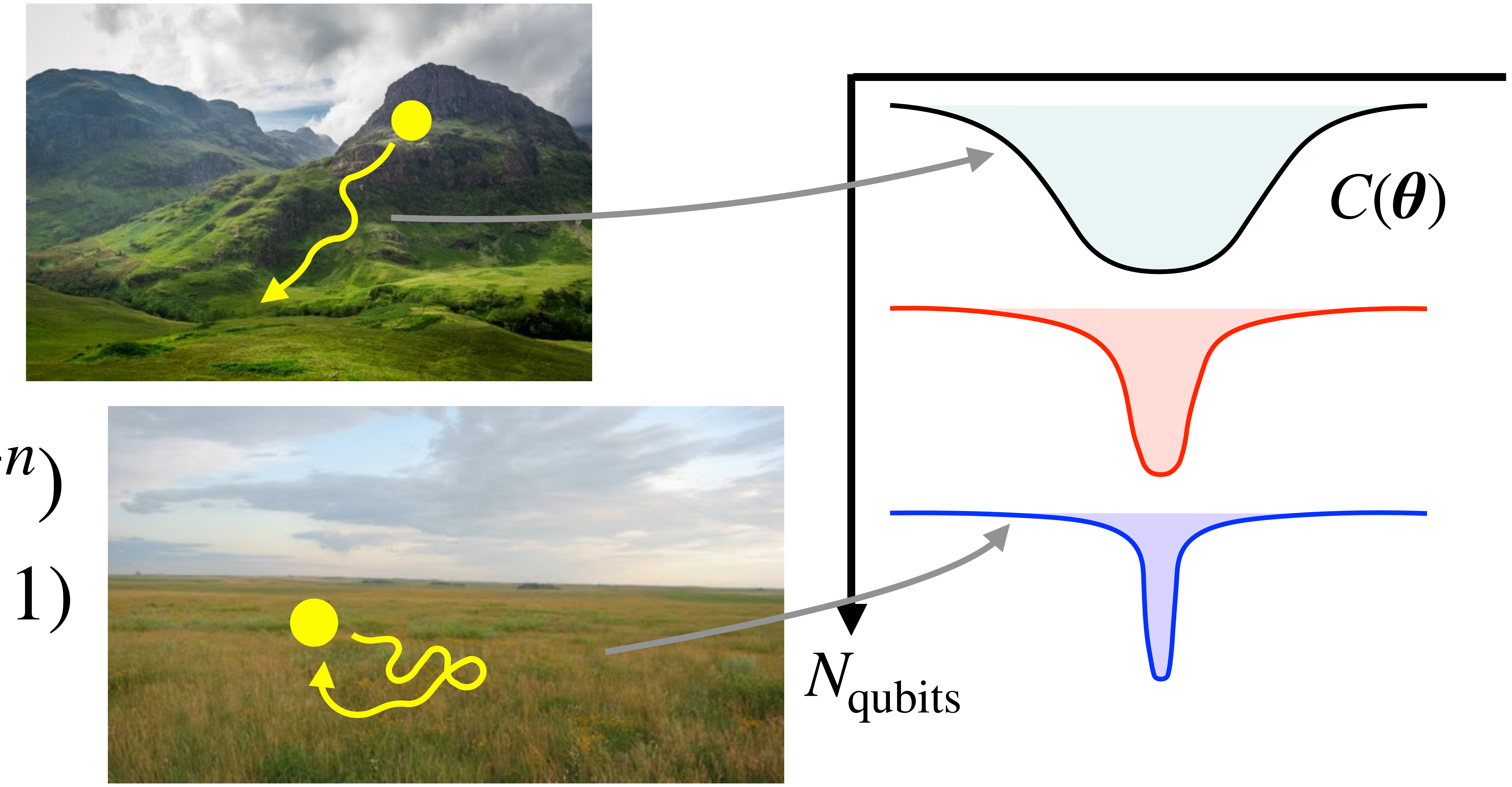
J. R. McClean et al., Nat. Commun. 9, 4812 (2018)

Cost function

$$C(\boldsymbol{\theta}) = \mathrm{Tr}[OU(\boldsymbol{\theta})\rho U^{\dagger}(\boldsymbol{\theta})]$$

$$\Rightarrow V_{\boldsymbol{\theta}\sim\mathrm{uniform}}\left[C(\boldsymbol{\theta}) \text{ or } \frac{\partial C(\boldsymbol{\theta})}{\partial \theta_i}\right] = \mathcal{O}(b^{-n}) \quad (b > 1)$$

Concentration of cost function or vanishing gradient



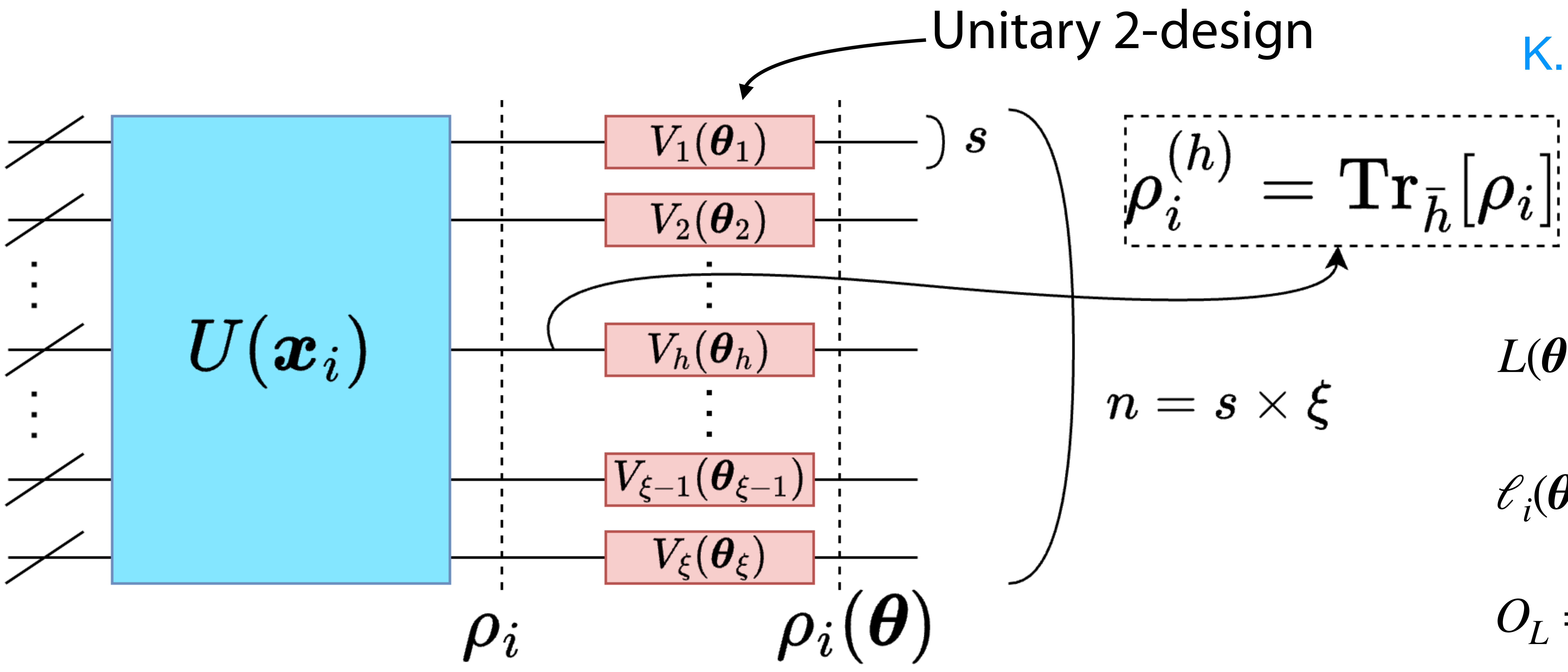
➡ **Barren Plateau** (BP) problem

Barren Plateau from Data Encoding

Learning classical data requires the data to be encoded into quantum state

➡ Examine how data-encoding unitary $U(\boldsymbol{x})$ can cause BP
(when QNN part is assumed be BP-free)

K. Kamisoyama (D1)



$$L(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N} f(y_i, \ell_i(\boldsymbol{\theta}))$$

$$\ell_i(\boldsymbol{\theta}) = \mathrm{Tr}\left[\rho_i(\boldsymbol{\theta}) O_L\right]$$

$$O_L = \frac{1}{n}\sum_{j=1}^{n} |0\rangle\langle 0|_j \otimes \mathbb{I}_{\bar{j}}$$

Barren Plateau from Data Encoding

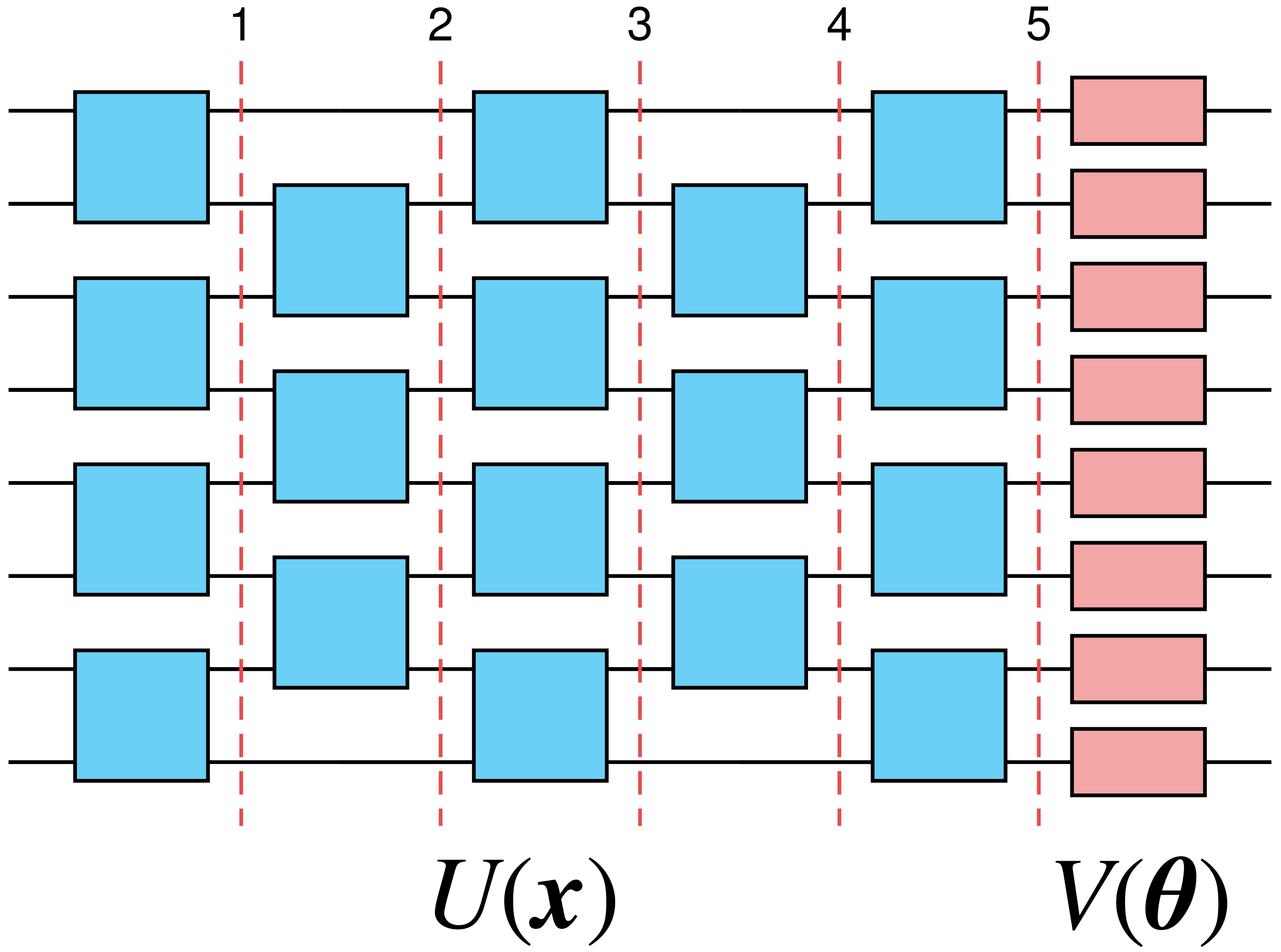
Provided a new upper bound on the variance of cost function gradient:

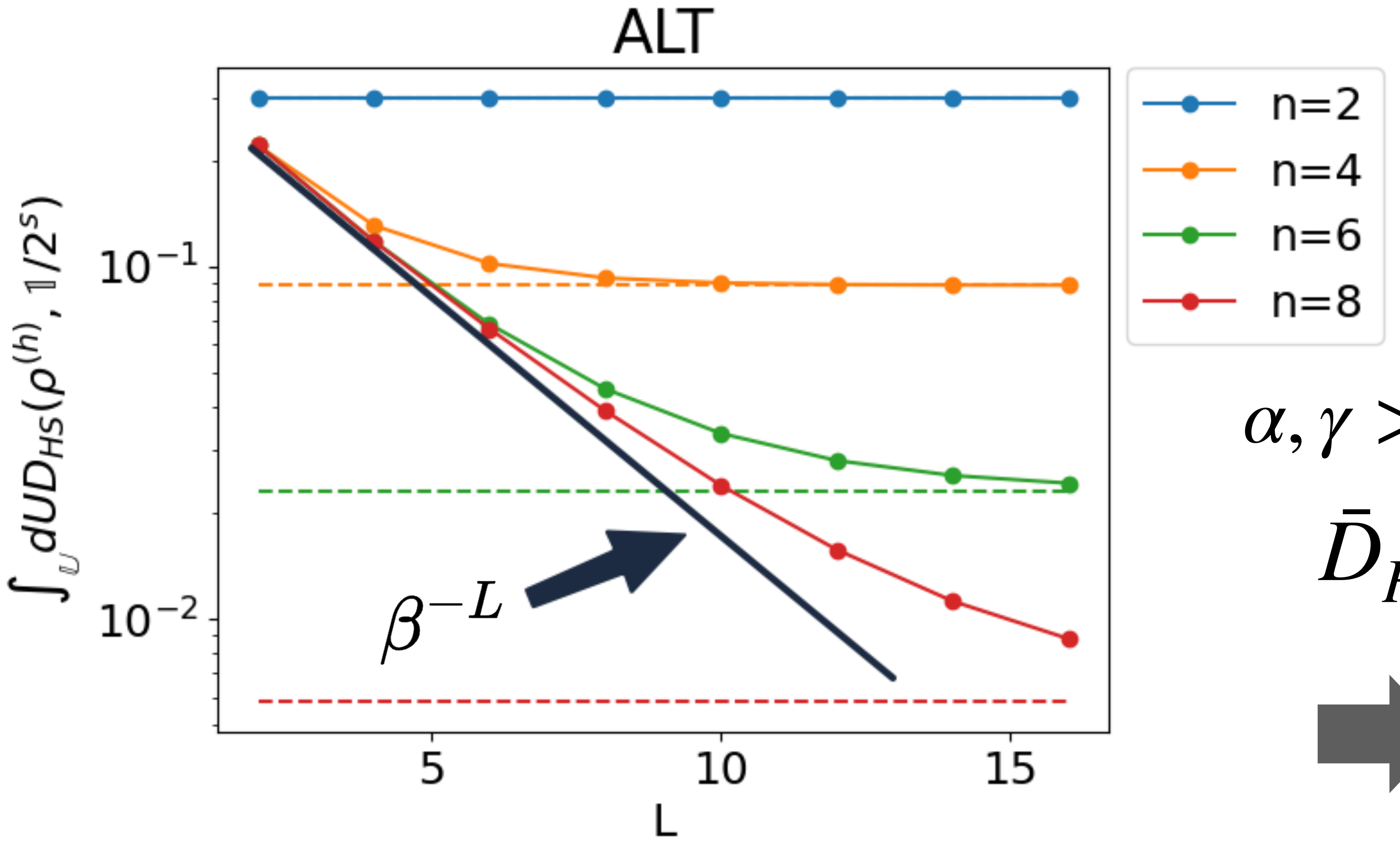
$$\mathrm{Var}_{\boldsymbol{\theta}}[\partial_{\theta_\nu}\mathscr{L}(\boldsymbol{\theta})] \leq A_f \times r_{n,s} \times \int_{\mathbb{U}_x} dU\, D_{HS}(\rho_x^{(h)}, \mathbb{I}/2^s)$$

Hilbert-Schmidt distance

Derived condition where the $\int dU\ D_{HS}$ term does not decay exponentially

(→ A necessary condition to avoid Barren Plateau)





K. Kamisoyama (D1)

$\alpha, \gamma > 0 \quad \beta > 1$

$$\bar{D}_{HS} \geq \beta^{-L} \geq n^{-\gamma}$$

$$L \leq \left(\frac{\gamma}{\log \beta}\right) \log n$$

Barren Plateau from Circuit Expressibility

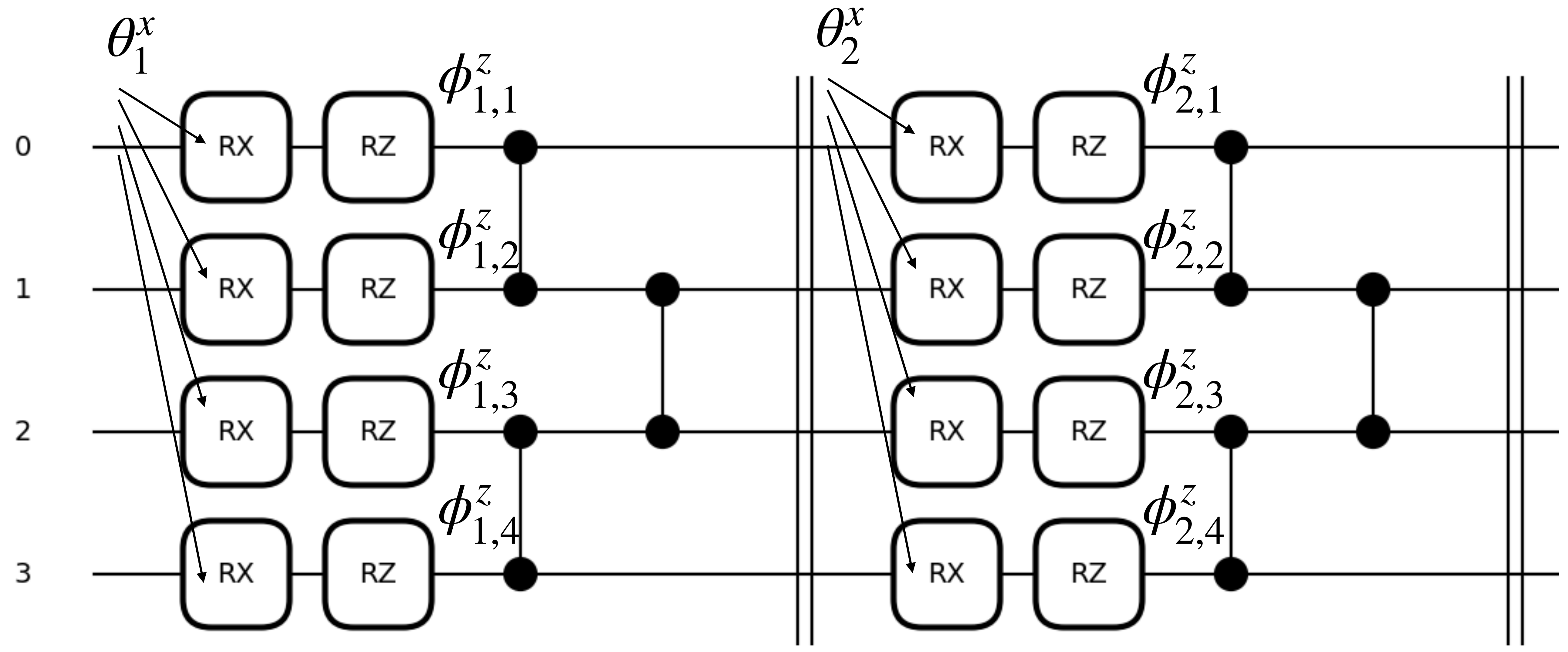
Too expressive circuit or too entangled states known to cause Barren Plateau

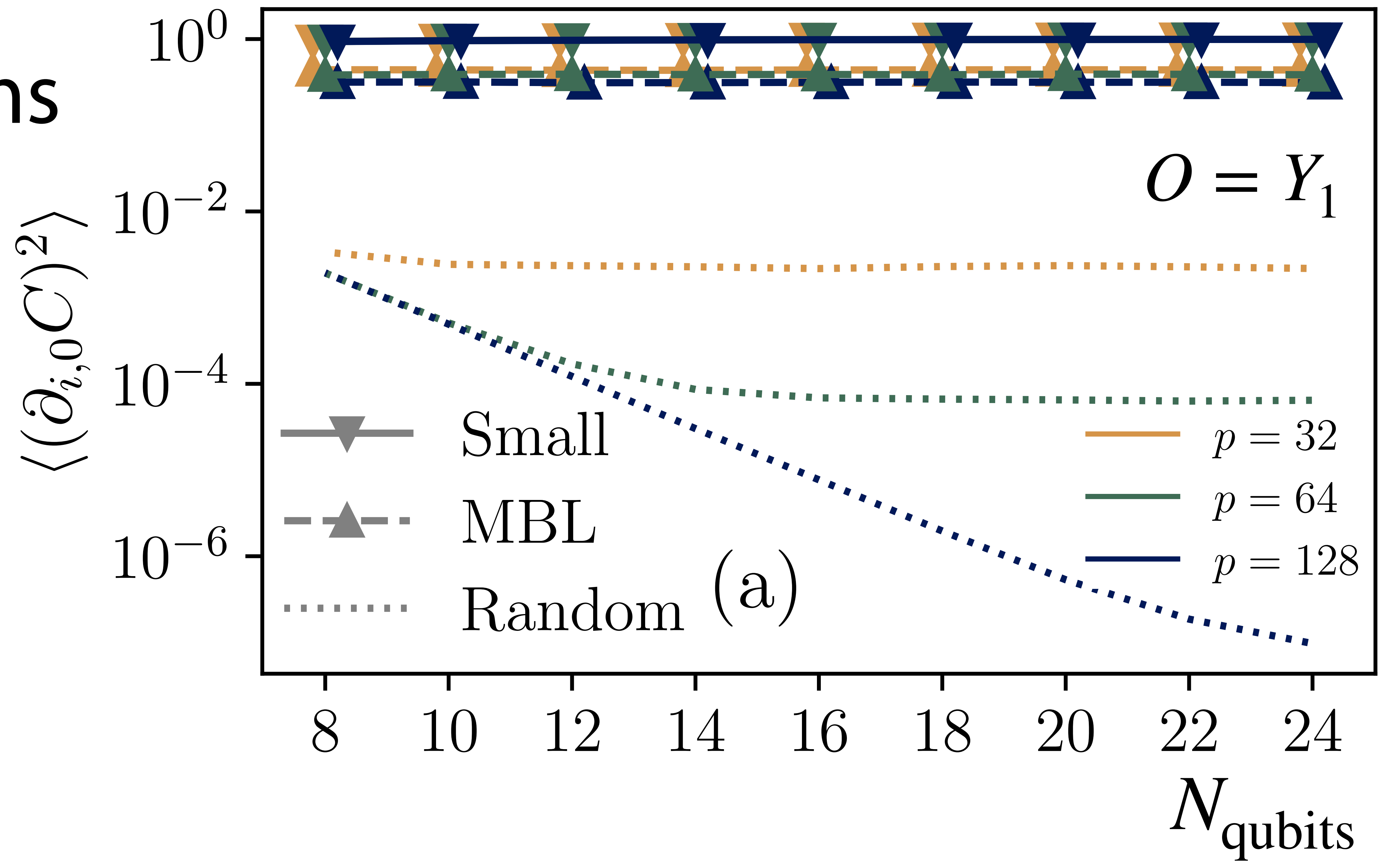
➡ Parameter initialization technique proposed as a way to avoid Barren Plateau

C.-Y. Park et al., arXiv:2403.04844

Analytically proved to have large gradient, inspired by many-body localized (MBL) systems

$$\theta_i^x \in \text{uniform}(0, 0.1) \quad \theta_i^z \in \text{uniform}(0, 2\pi)$$





Numerically confirmed that the gradient stays at large value, independently of the system size

Estimation Errors

Estimation Error $= R(h_F) - R(\hat{h}_N)$ quantifies the distance between the models that we can get with D and P

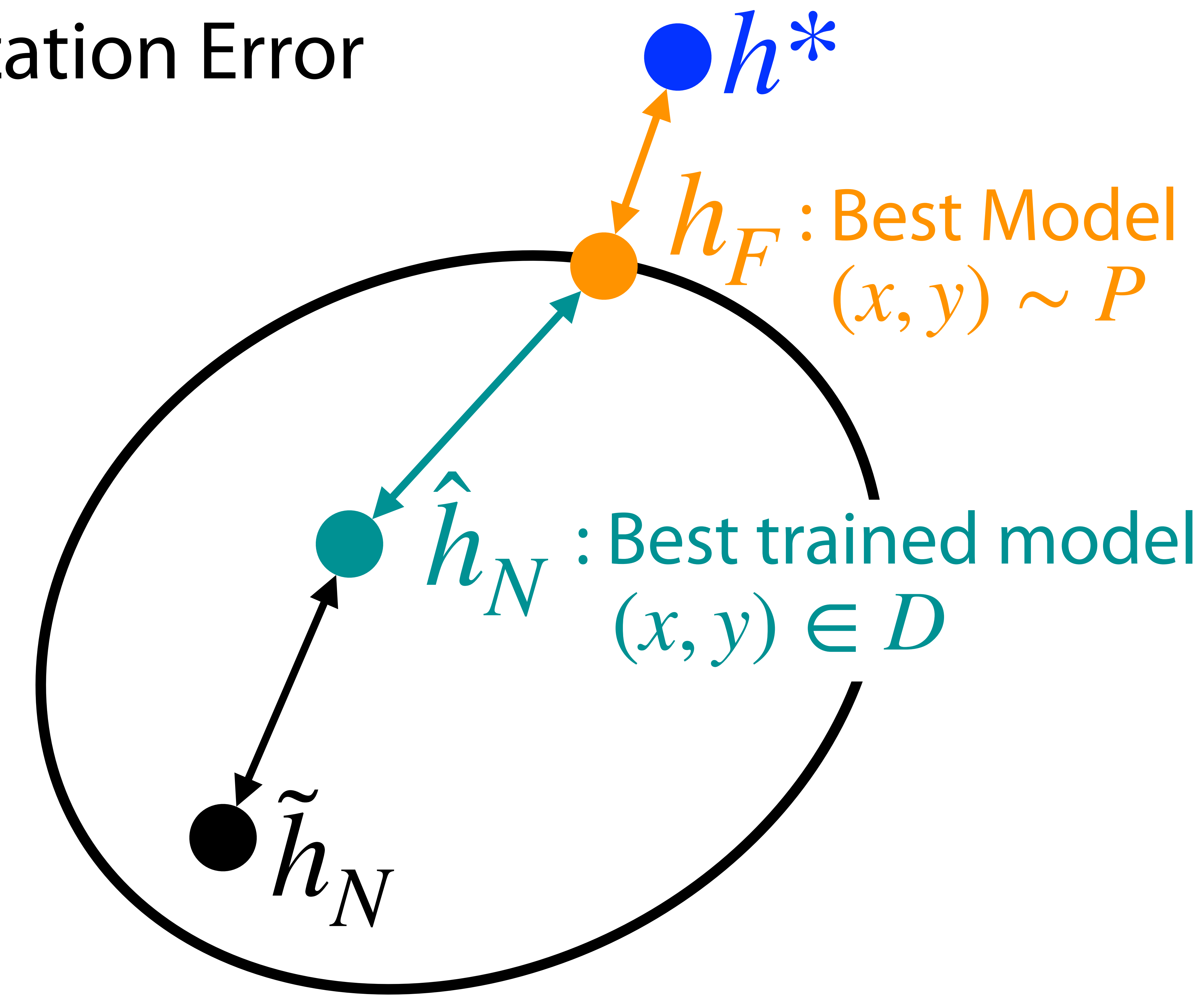
➡ Estimation error bounded using Generalization Error

$$= R(\boldsymbol{\theta}) - \hat{R}_S(\boldsymbol{\theta}):$$

How well the trained model can predict for unseen data

K. Kamisoyama (D1)

Investigating analytically how the parameter initialization can affect generalization error



Model Errors

Model Error $= R(h^*) - R(h_F)$ typically hard to quantify unless the model is very general or specific

When a *priori* knowledge of the problem is accounted for in model building, the Model Error could be reduced ➡ Inductive Bias

Symmetry of the problem at hand is a useful guide to build efficient machine learning model

Equivariant Quantum Machine Learning

Information of symmetry provides a useful resource in machine learning

- Symmetry ubiquitous in physics, e.g, Lorentz symmetry, Permutation symmetry, …
- Not obvious to incorporate general (continuous) symmetries in quantum setting

➡ Z. Li, L. Nagano, KT, Phys. Rev. Res. 6, 043028 (2024)

Investigate a generic QNN architecture to efficiently encode rotational and permutational symmetries

- Inner products as inputs (e.g, inner products of particle 4-vectors)

  → Weyl's theorem

- Twirling method to make quantum gates invariant against input permutation

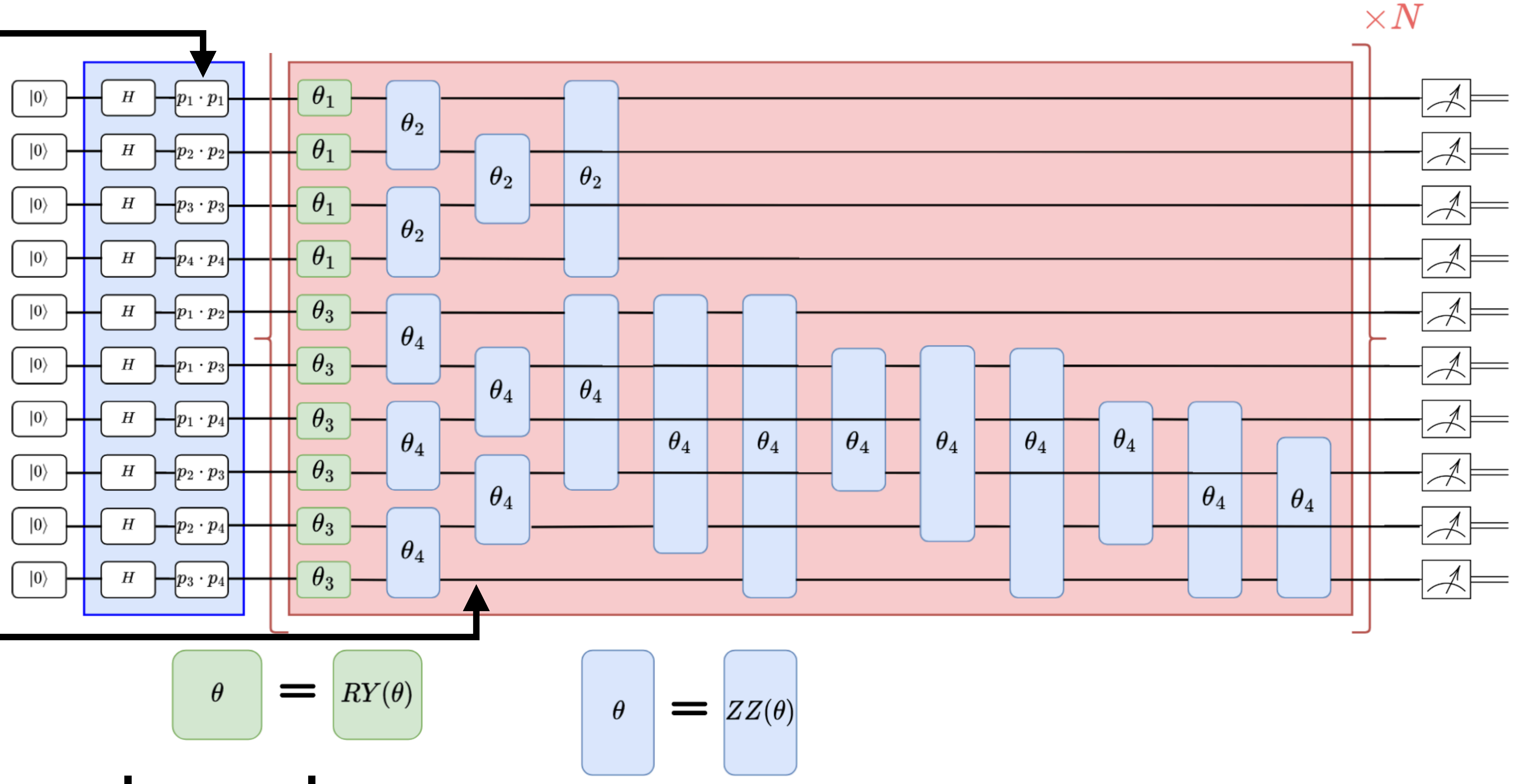
  → L. Schatzki et al., npj Quantum Inf. 10, 12 (2024)

Equivariant Quantum Machine Learning

Z. Li, L. Nagano, KT,
Phys. Rev. Res. 6, 043028 (2024)

Fully symmetric circuit

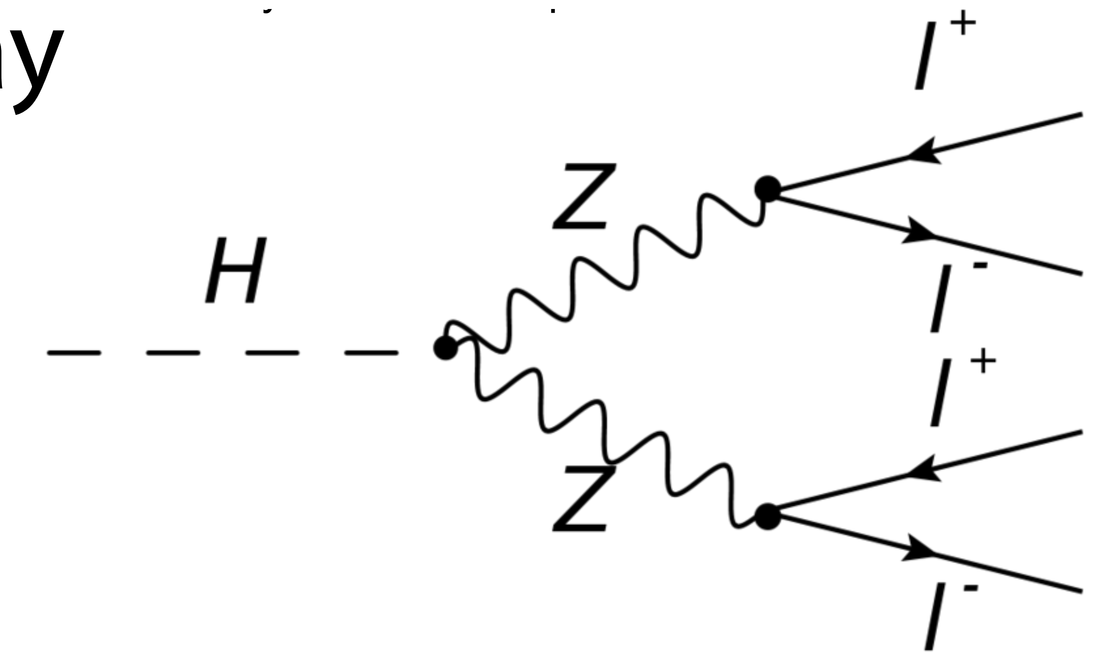
- Rotations handled by inner products
- Permutations handled by twirling

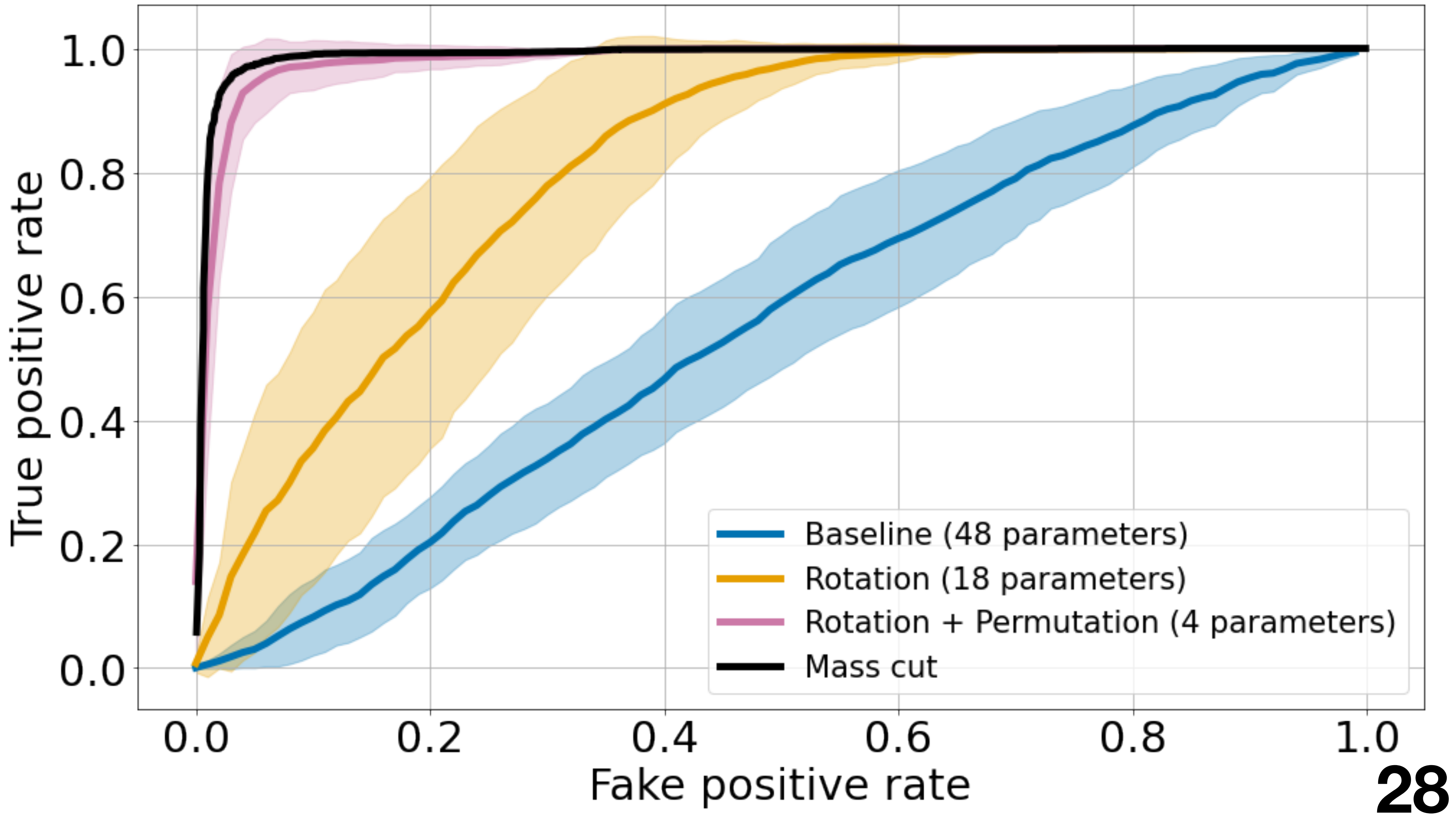


$H \to ZZ \to 4$-leptons classification as a benchmark

- Lorentz symmetry in particle decay
- Ad-hoc non-linearity added after quantum measurement:

$$L(\theta, b) = \left[-\,|f_Q(\theta) - b| - y \right]^2$$





Have demonstrated very efficient training without any indication of BP

Classical Simulability

Skepticism around variational QML approach …

QML models with provable absence of Barren Plateau in literatures can be classically simulated(?)

M. Cerezo et al., arXiv:2312.09121

Argued that operator actions in BP-free quantum circuit are likely constrained in polynomially-large subspace, hence can classically simulated

Example:

Hamiltonian Variational Ansatz (HVA) for a given H expressed as $H = \sum \alpha_i h_i$

If h_i is $\mathcal{O}(1)$-local operator, the problem class of HVA can be classically simulated

Quantum Simulation

Hamiltonian simulation as a useful computational resource with near-term QC

Lattice gauge theory for calculating non-perturbative physics

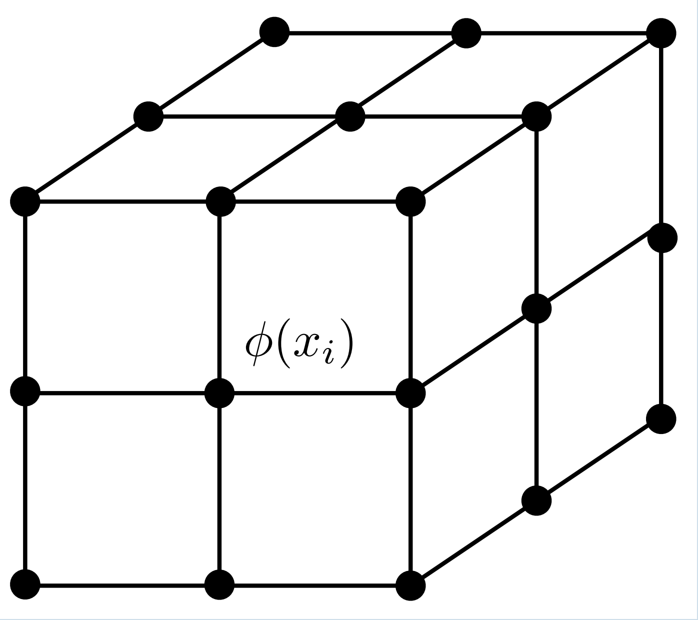
Quantum Simulation

Hamiltonian simulation as a useful computational resource with near-term QC

Lattice gauge theory for calculating non-perturbative physics

Conventional LGT simulation

- Discretize spacetime
- MC sampling for phase-space integrals of e^{-S}



Infamous sign problem with

- non-zero density, temperature
- topological term, etc.

Quantum Simulation

Hamiltonian simulation as a useful computational resource with near-term QC

Lattice gauge theory for calculating non-perturbative physics

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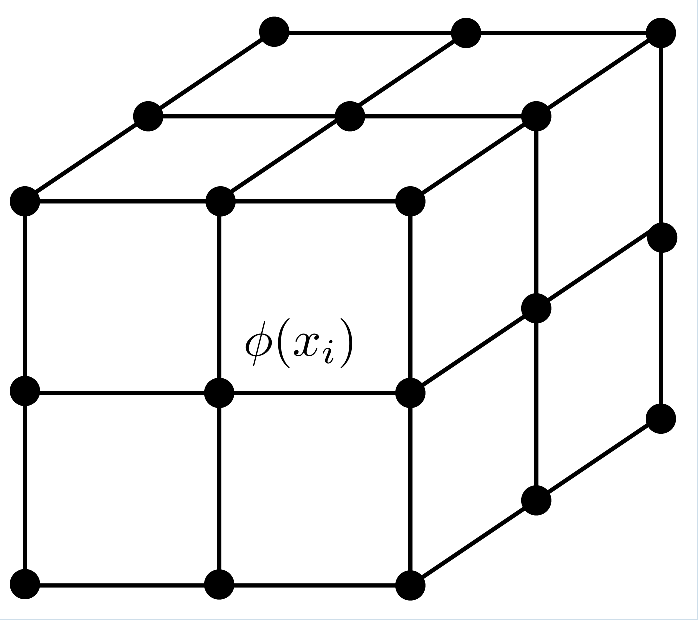
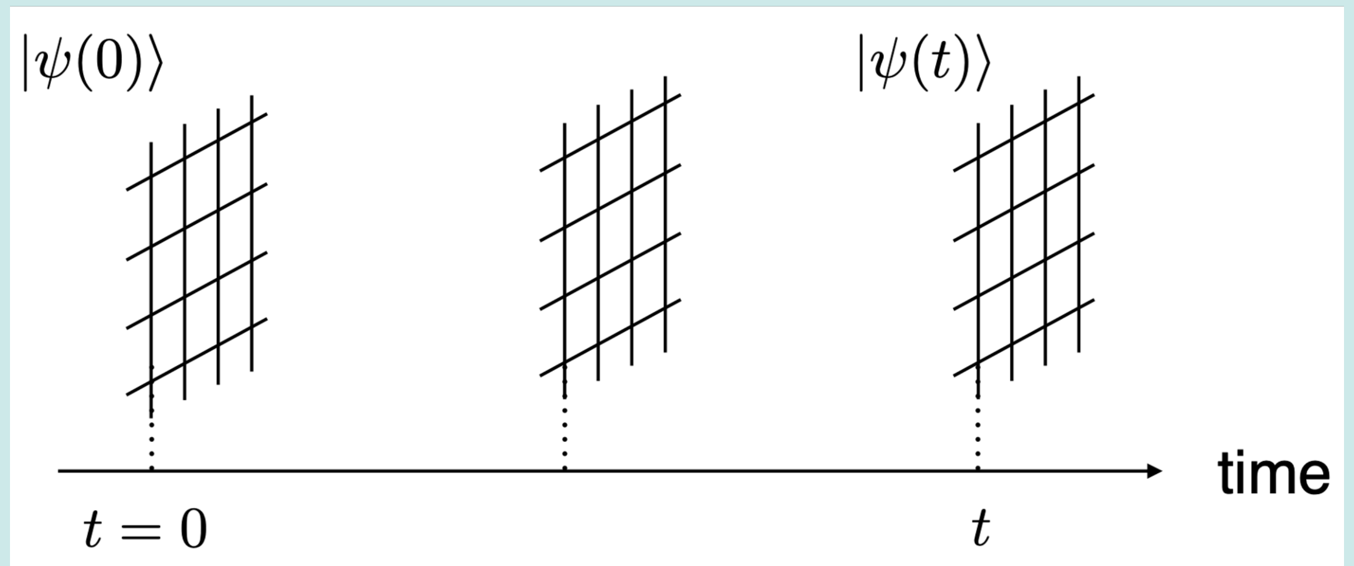


Infamous sign problem with

- non-zero density, temperature
- topological term, etc.

Hamiltonian LGT simulation

- Discretize space
- Directly simulate e^{-iHt}



No sign problem

- still need exponential resource
- infinite Hilbert spaces for gauge dof's

Quantum Simulation

Hamiltonian simulation as a useful computational resource with near-term QC

Lattice gauge theory for calculating non-perturbative physics

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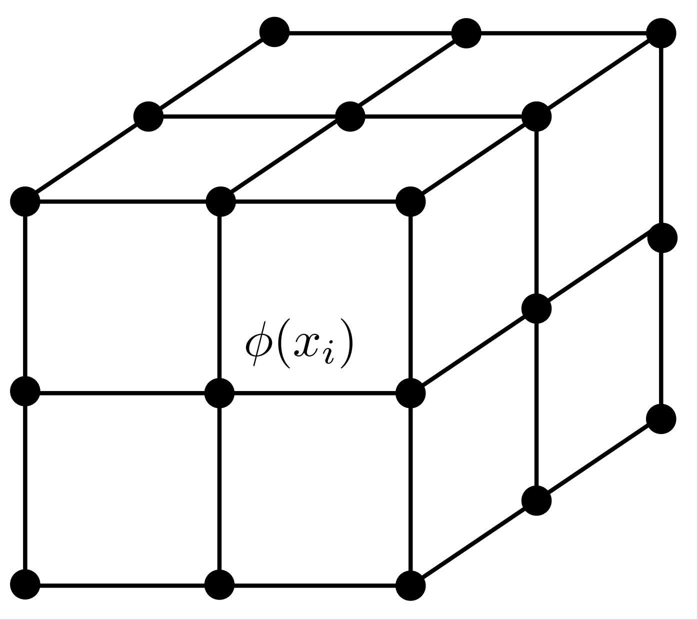

Infamous sign problem with

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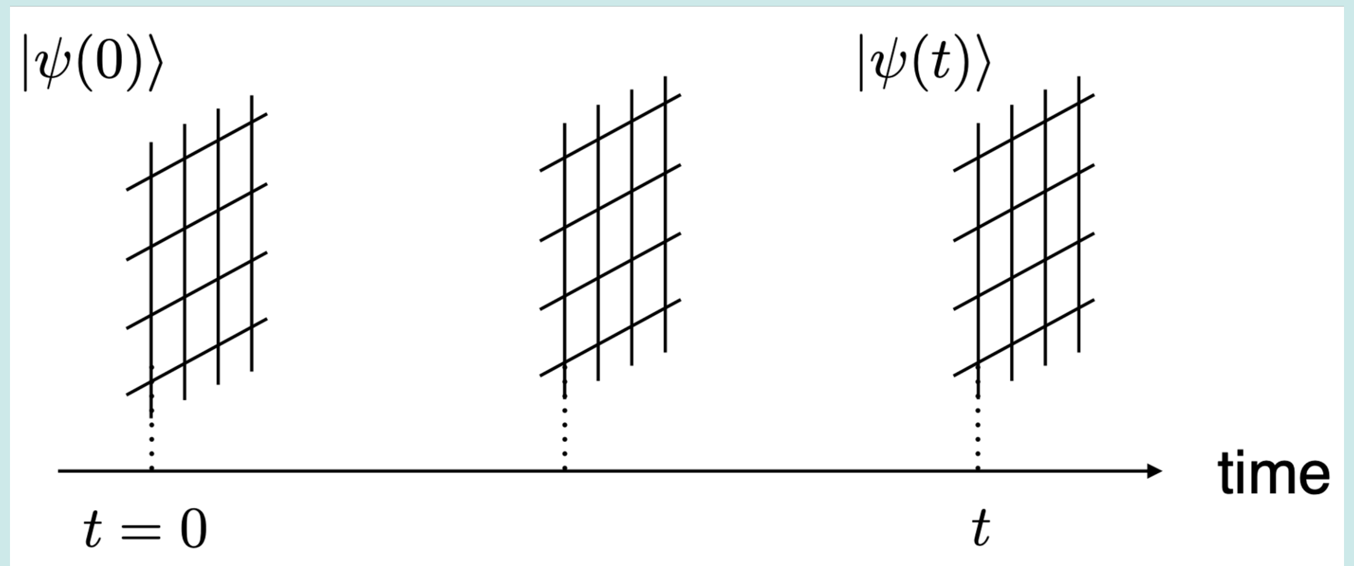
Hamiltonian LGT simulation

- Discretize space
- Directly simulate e^{-iHt}



No sign problem

- still need exponential resource
- infinite Hilbert spaces for gauge dof's

Simulation of real-time phenomena, e.g, out-of-equilibrium dynamics, particle scattering, is a promising example of quantum enhanced applications

Quantum Dynamics Simulation in Schwinger Model

Simulation of quench dynamics in $(1+1)d\ U(1)$ LGT (**Schwinger model**)

$$H = J\sum_{j=0}^{N-2}\left(\sum_{k=0}^{j}\frac{Z_k+(-1)^k}{2}+\frac{\theta}{2\pi}\right)^2+\frac{\omega}{2}\sum_{j=0}^{N-2}(X_jX_{j+1}+Y_jY_{j+1})+\frac{m}{2}\sum_{j=0}^{N-1}(-1)^jZ_j$$

Particle creation due to strong external electric field ➡ **Schwinger effect**

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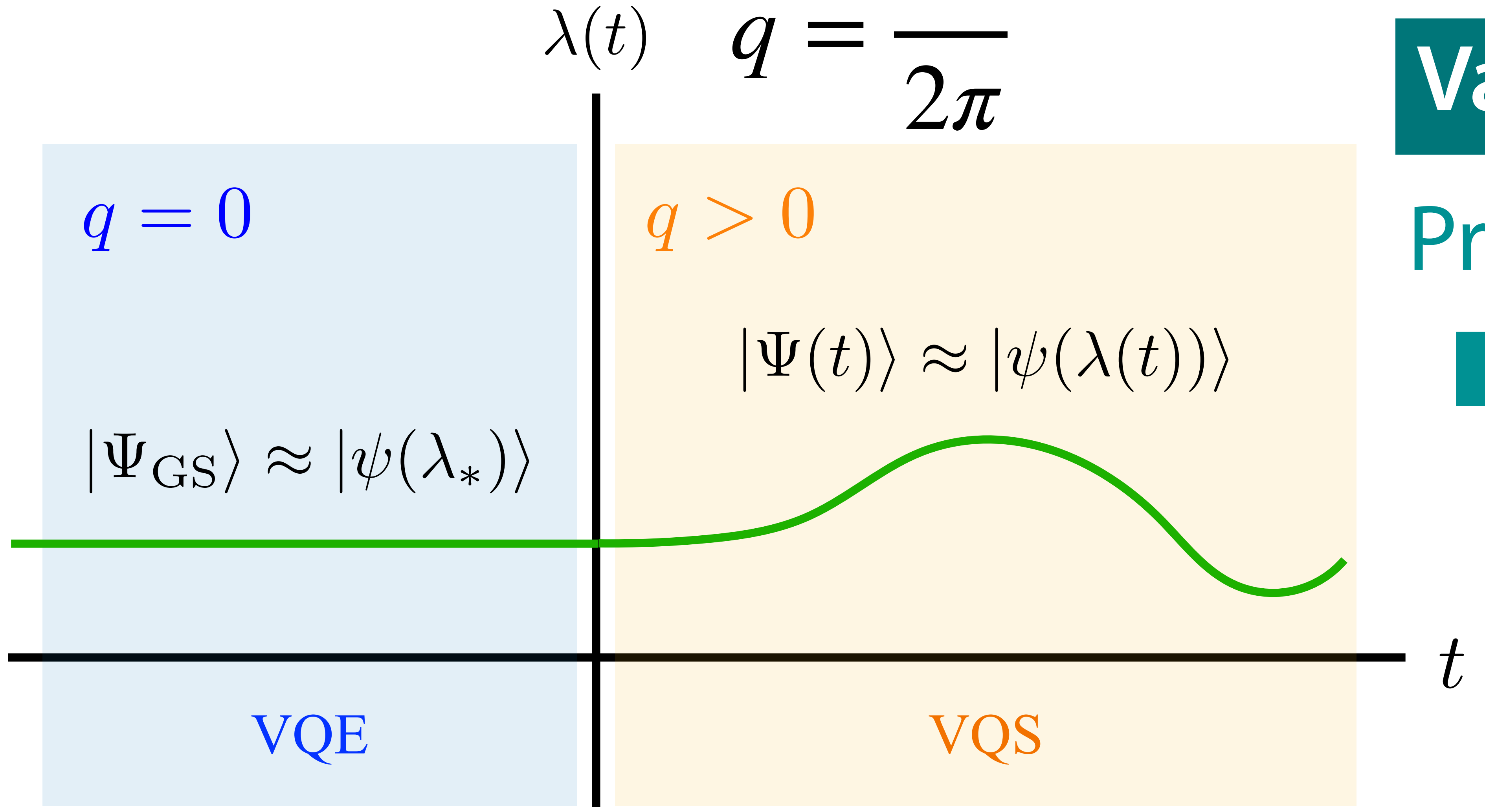
Particle creation due to strong external electric field ➡ **Schwinger effect**

L. Nagano, A. Bapat, C. W. Bauer, Phys. Rev. D 108, 034501 (2023)

$q = \frac{\theta}{2\pi}$



Ground state with VQE

Time-evolution with VQS

Variational Quantum Simulation (VQS)

Prepare quantum states using time evolution of circuit parameters

➡ Possible to simulate with fixed-depth quantum circuit

$$M_{ij} = \mathrm{Re} \frac{\partial \langle \psi(\theta) |}{\partial \theta_i} \frac{\partial | \psi(\theta) \rangle}{\partial \theta_j}$$

$$V_i = \mathrm{Im} \frac{\partial \langle \psi(\theta) |}{\partial \theta_i} H | \psi(\theta) \rangle$$

➡ Solve classically

$$\sum_j M_{ij} \dot{\theta}_j = V_i$$

Quantum Dynamics Simulation in Schwinger Model

Simulation of quench dynamics in $(1+1)d\ U(1)$ LGT (**Schwinger model**)

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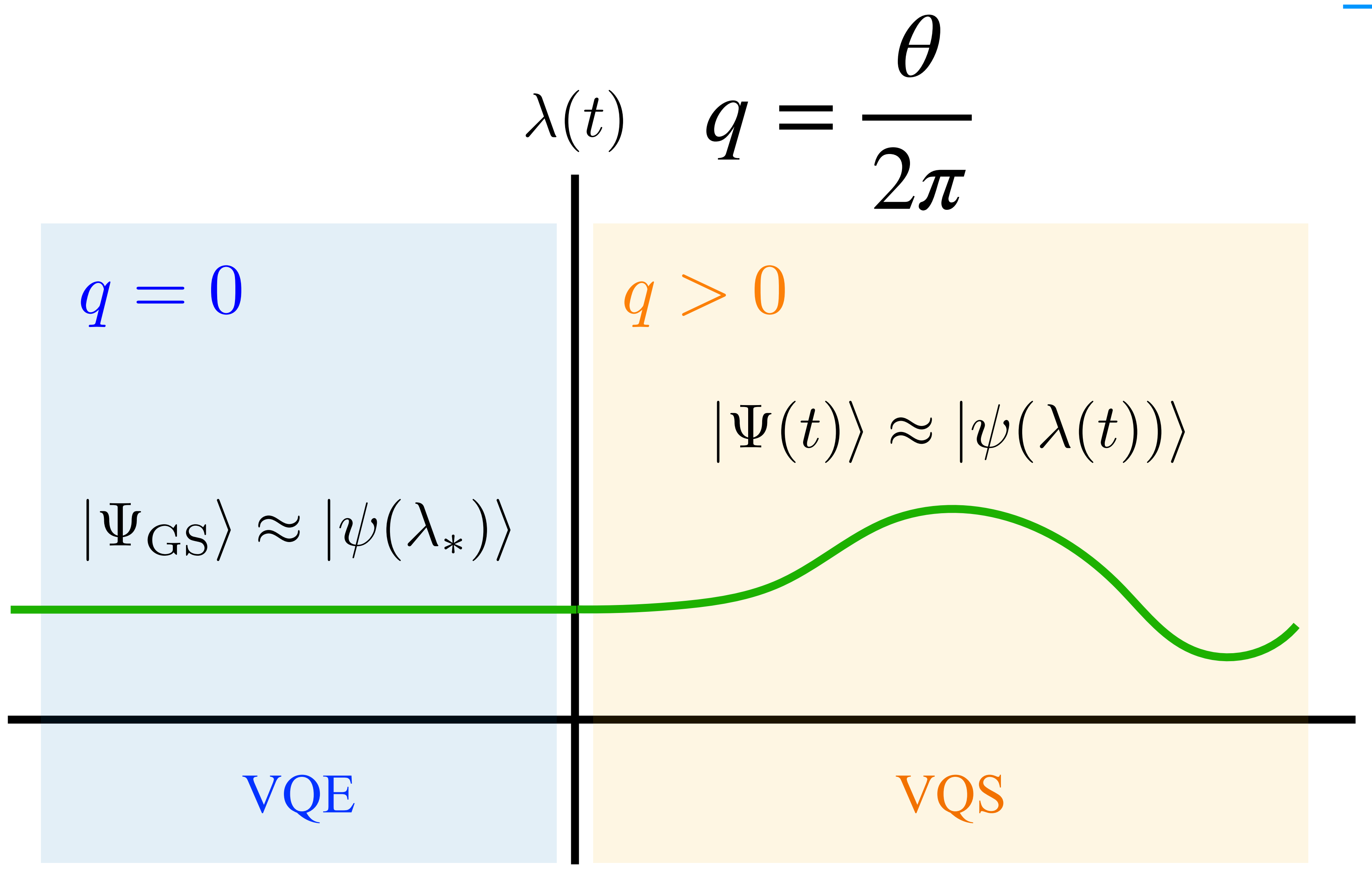
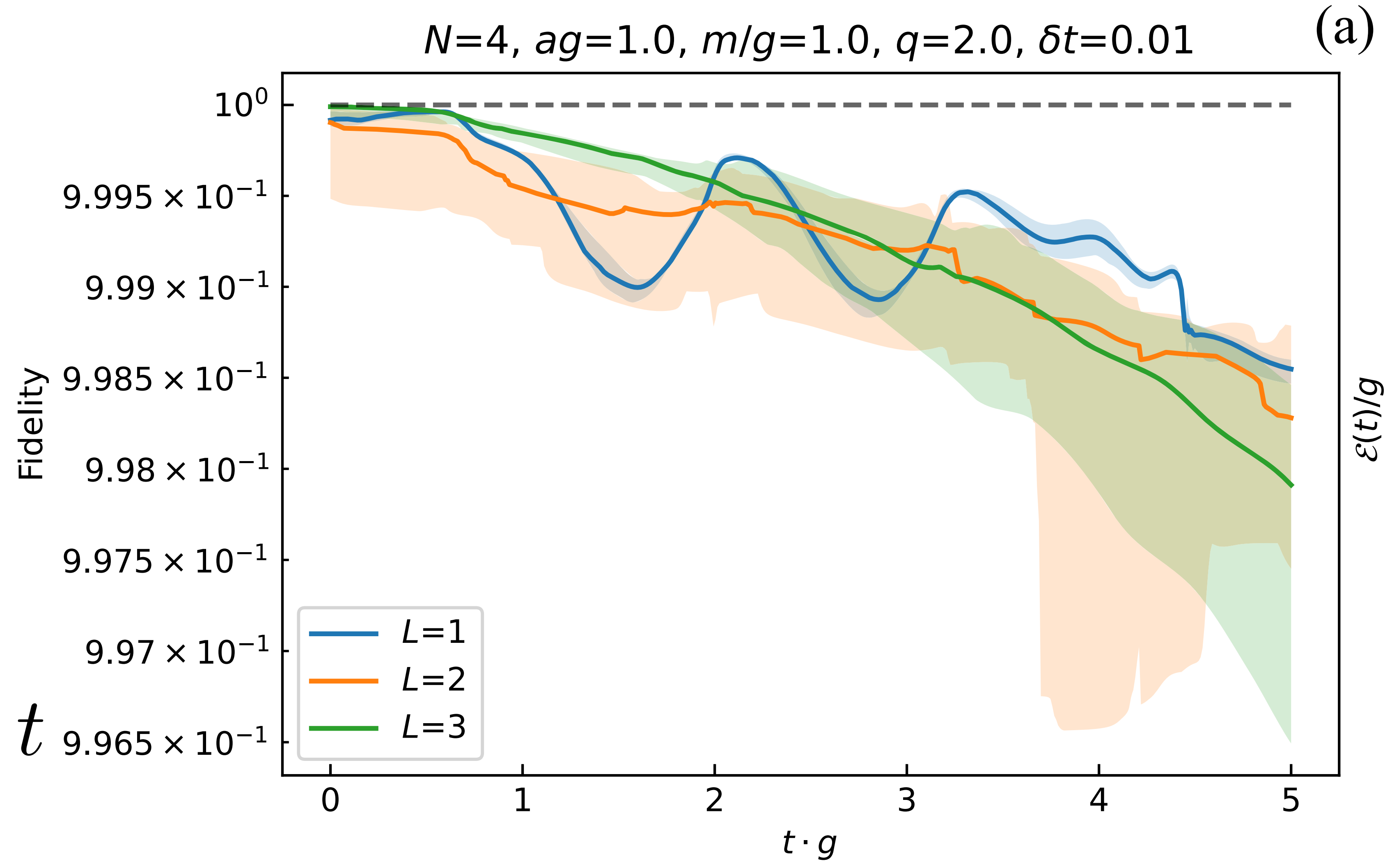
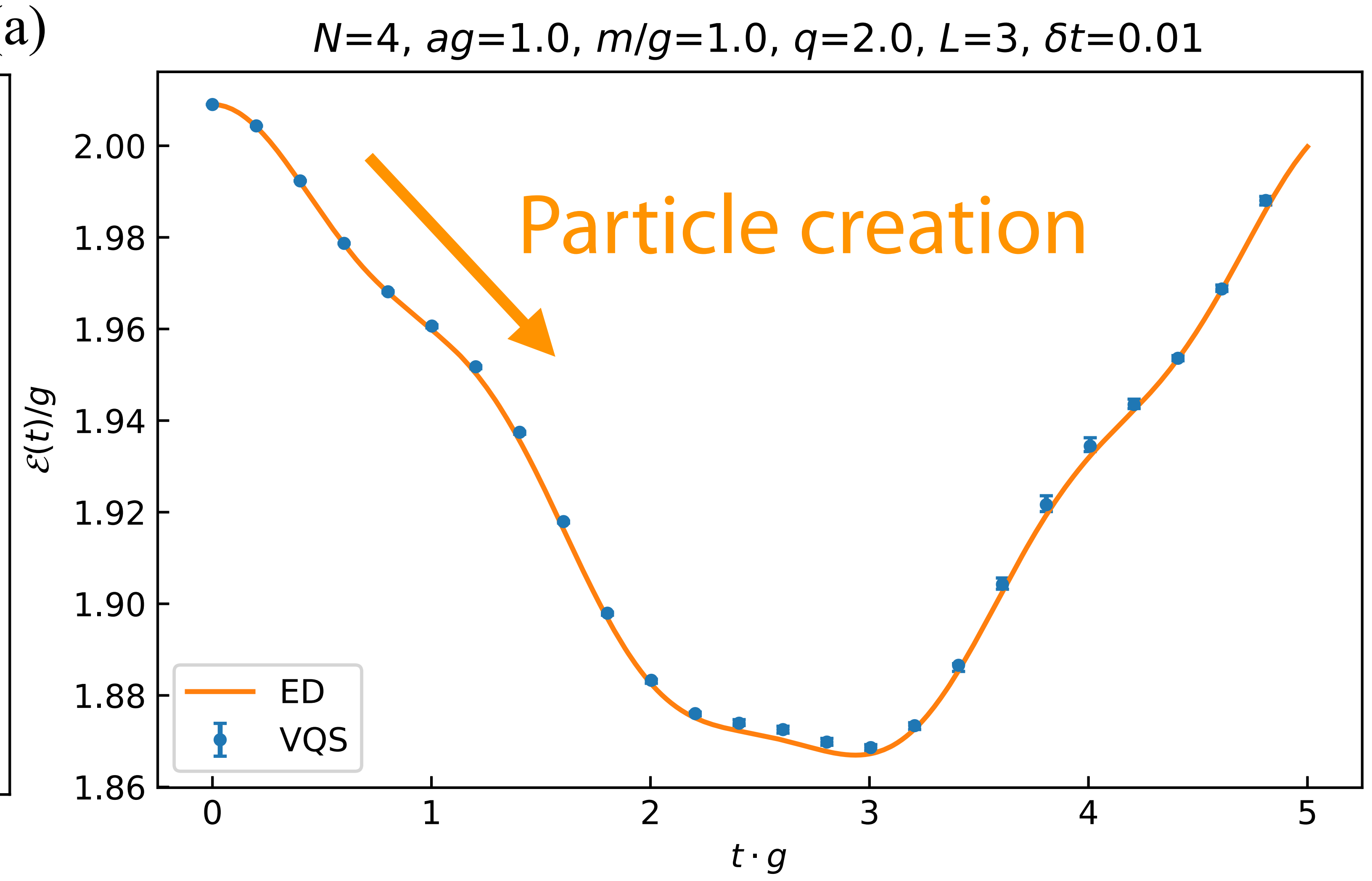


Ground state with VQE

Time-evolution with VQS

L. Nagano, A. Bapat, C. W. Bauer, Phys. Rev. D 108, 034501 (2023)





First step towards more complex, non-trivial simulation with increasing system volume

Dynamical Phase Transition in Schwinger Model

Simulation of quench dynamics in $(1+1)d\ U(1)$ LGT (**Schwinger model**)

$$H = J \sum_{j=0}^{N-2} \left(\sum_{k=0}^{j} \frac{Z_k + (-1)^k}{2} + \frac{\theta}{2\pi} \right)^2 + \frac{\omega}{2} \sum_{j=0}^{N-2} (X_j X_{j+1} + Y_j Y_{j+1}) + \frac{m}{2} \sum_{j=0}^{N-1} (-1)^j Z_j$$

Investigating topological properties through θ-term in real-time dynamics

Dynamical Phase Transition in Schwinger Model

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Investigating topological properties through θ-term in real-time dynamics

➡ Strong quenches generate dynamical phase transition

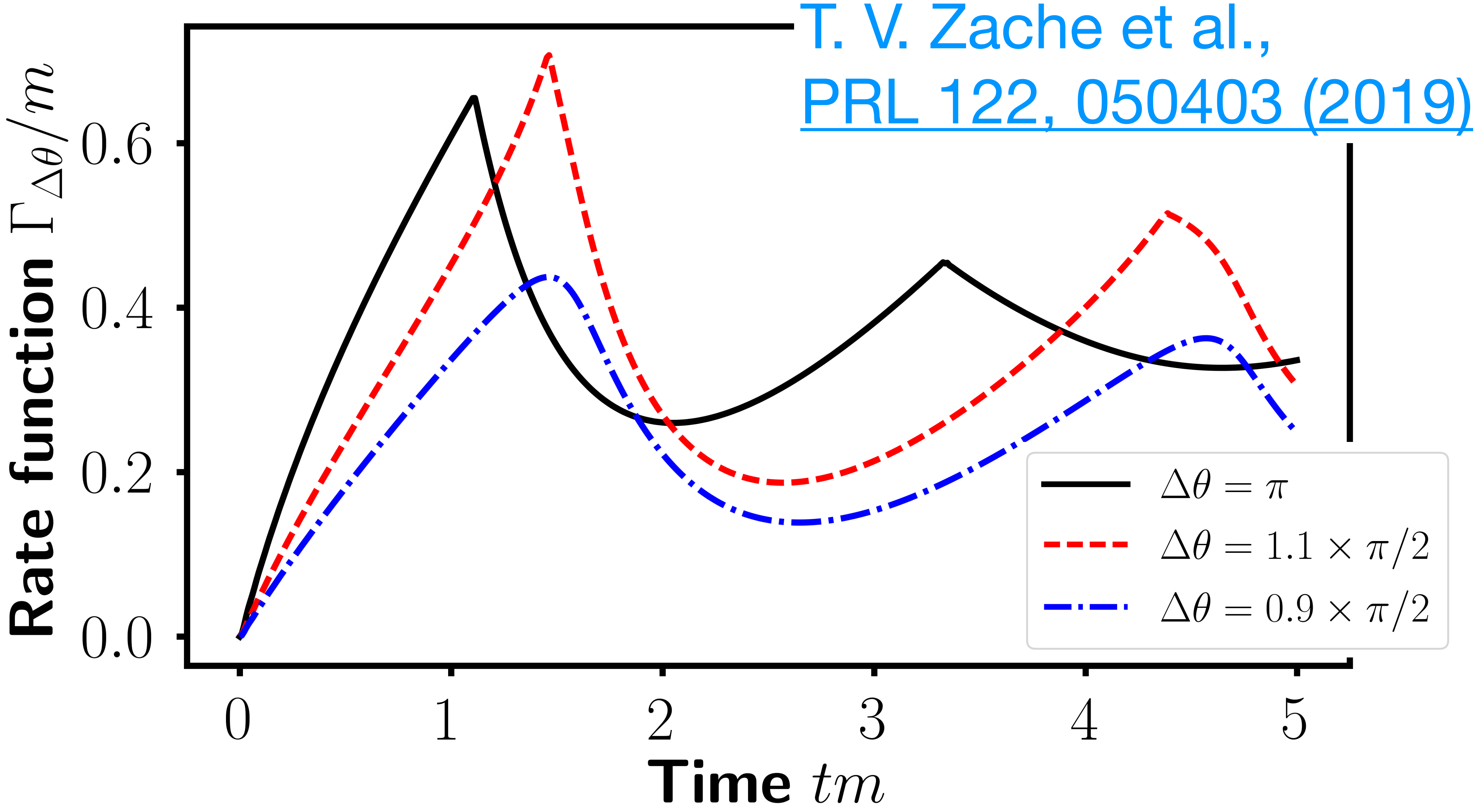
Rate function:

$$\Gamma(t) = \lim_{N\to\infty}\left\{-\frac{1}{N}\log(|L(t)|)\right\}$$

Loschmidt echo:

$L(t) = \langle\Omega|e^{-iHt}|\Omega\rangle$ with initial state $|\Omega\rangle$

T. V. Zache et al., PRL 122, 050403 (2019)



Dynamical Phase Transition in Schwinger Model

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Investigating topological properties through θ-term in real-time dynamics

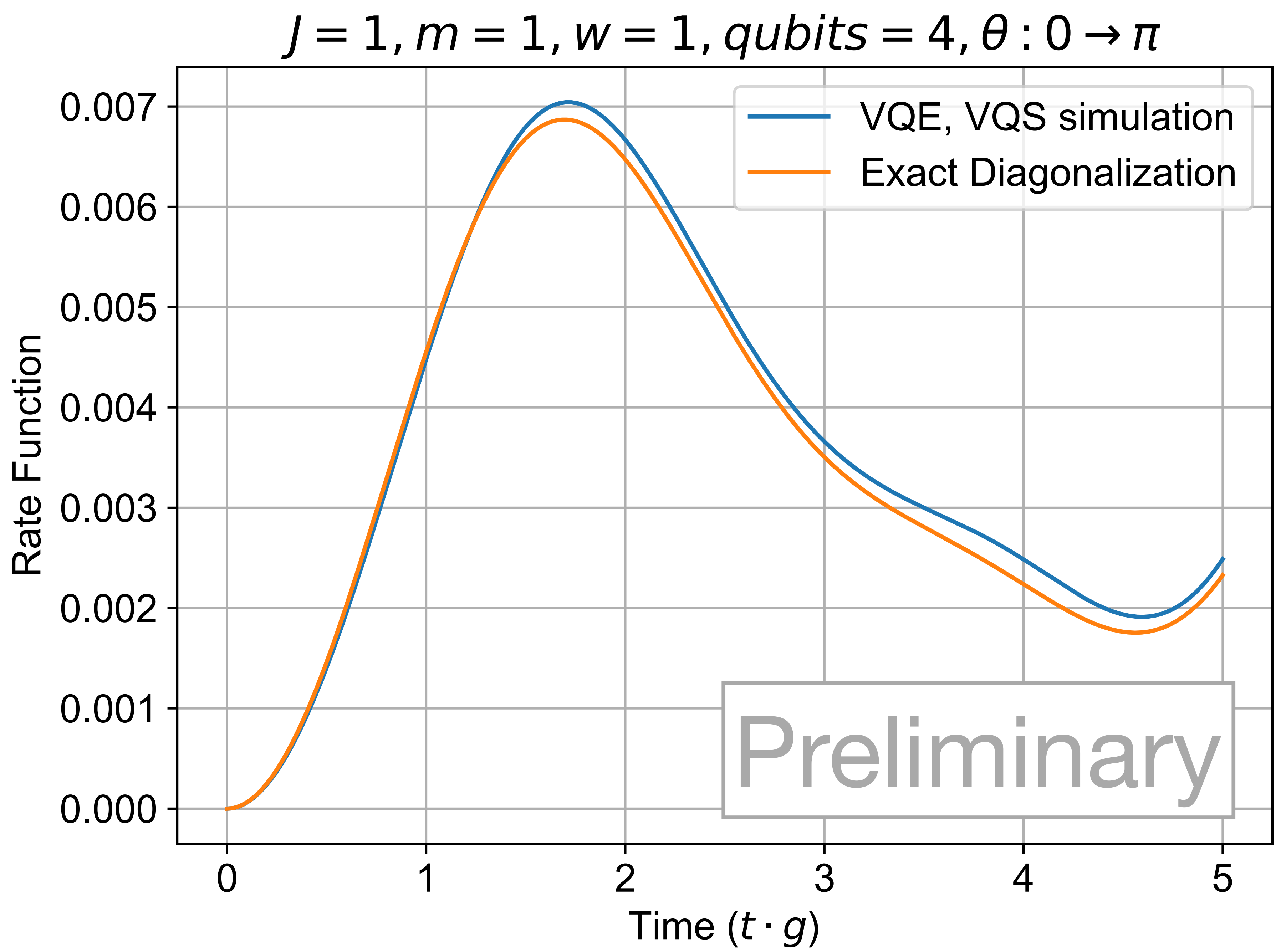
S. Ae (Internship student), L. Nagano

Adapted VQE + VQS approach to simulate dynamical phase transition

- $L(t) = \langle\Omega|e^{-iHt}|\Omega\rangle$ from

  VQS : $e^{-iHt}|\Omega\rangle \simeq U(\lambda(t))|0\rangle$,

  VQE : $|\Omega\rangle \simeq U(\lambda(0))|0\rangle$
- θ change of $0 \to 4\pi$
- Only 4 qubits so far



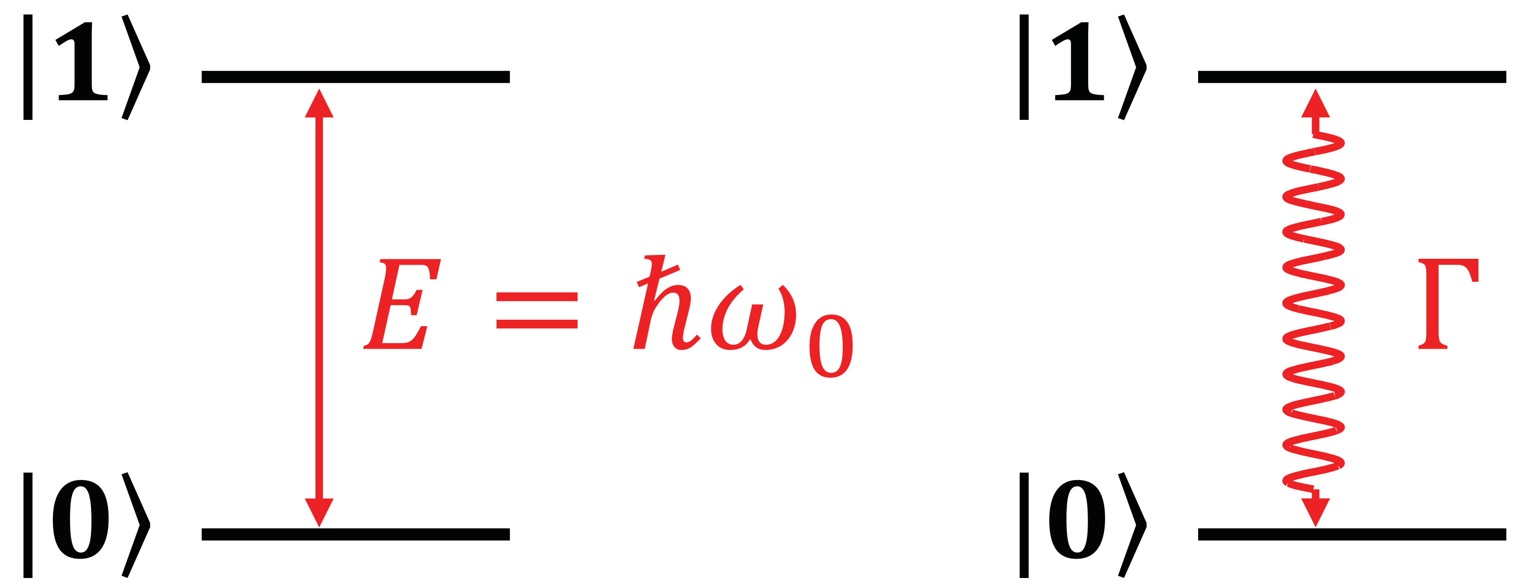
More work to do… Any interest?

Qubit Technology as a Sensor

Certain types of qubits will work as a probe to nature ➡ Quantum Sensor

<u>What quantum system can work as a quantum sensor?</u>

1. Identified, discretized energy levels (usually 2-levels)
2. Initialization and measurement
3. Coherent manipulation of state
4. **Can couple to what we want to measure (e.g, electric/magnetic field, ..)**



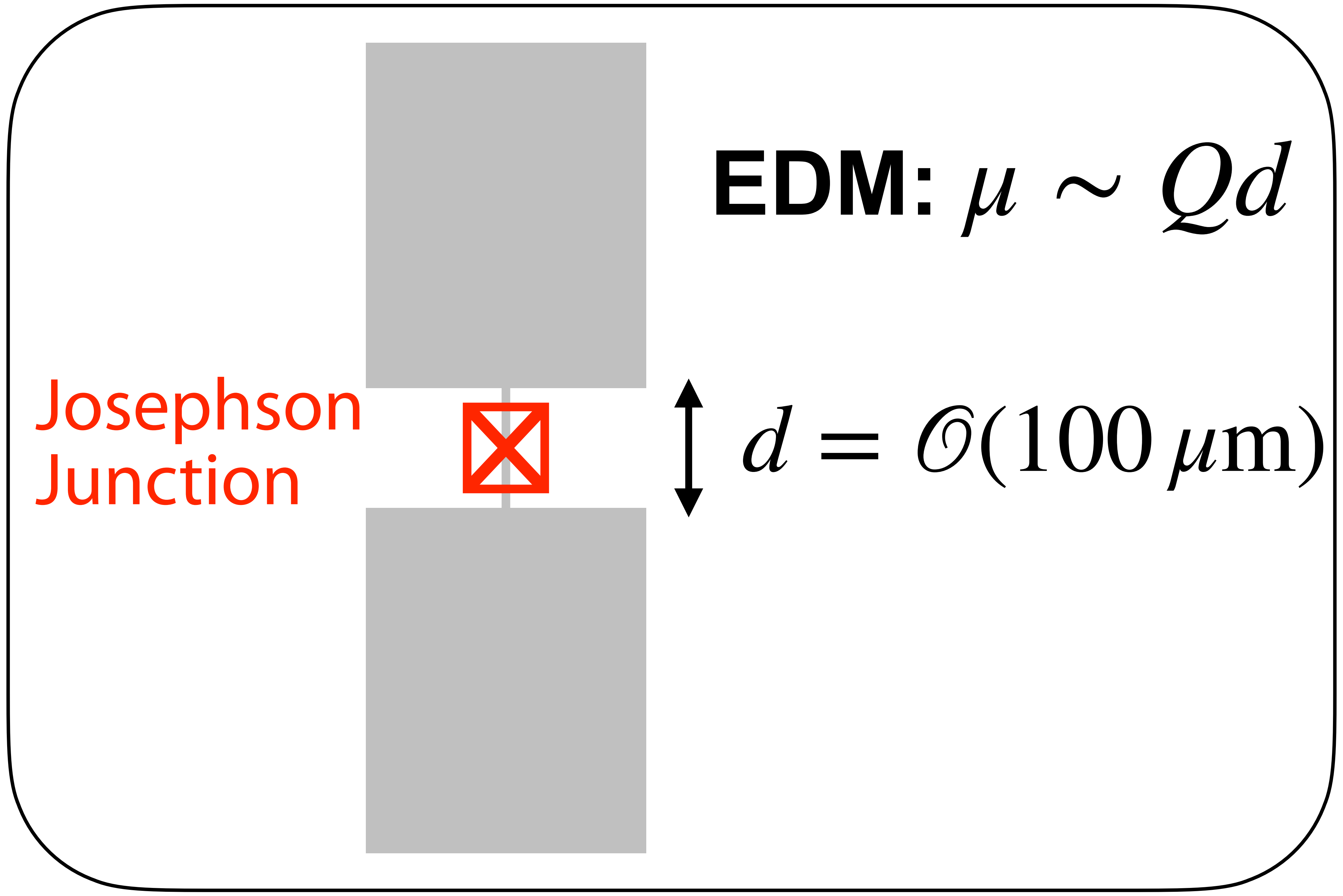
Utilizing sensor response,
e.g, qubit transition energy E or rate Γ,
to what we want to measure

Qubit technologies offer interesting opportunities to experimentally probe nature in different ways from conventional methods

Qubits as Quantum Sensor

Superconducting qubits potentially a powerful probe to nature

- Low threshold ($\sim \mu\mathrm{eV}$) at $\mathcal{O}(\mathrm{mK})$ temperature
- Coherent manipulation of states within $\mathcal{O}(100\,\mu s)$ or longer coherence time
- Robust measurement with non-demolition technique



Strong coupling to electromagnetic field

➡ $\mathcal{O}(10^6)$ stronger than single atom

Qubits as a Dark Matter Sensor

Exploring superconducting qubit technology for Dark Matter searches

Most recent results presented at 19th Patras Workshop on Axions, WIMPs and WISPs on Sep. 16-20, 2024:

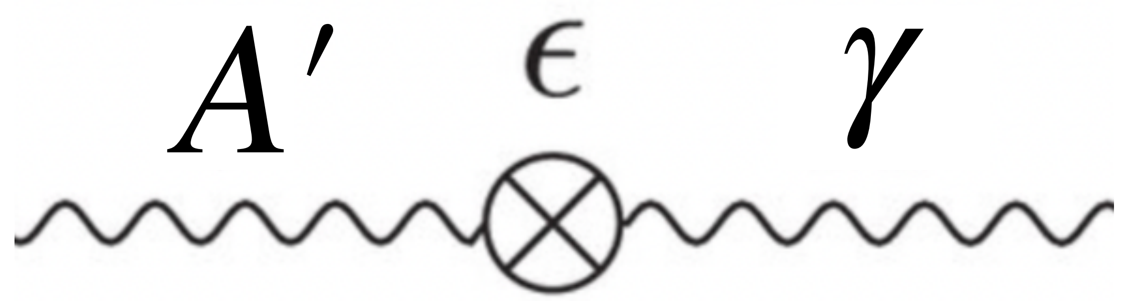
- **K. Nakazono** First results from a cavity haloscope experiment with a novel frequency tuning system using a qubit (talk)
- **K. Watanabe** Search for dark photons using direct excitations of superconducting qubits (poster)
- **T. Nitta** Towards axion searches using superconducting qubits (poster)
- **S. Chen** Search for dark photon dark matter using large-scale superconducting quantum computers as detectors (poster)

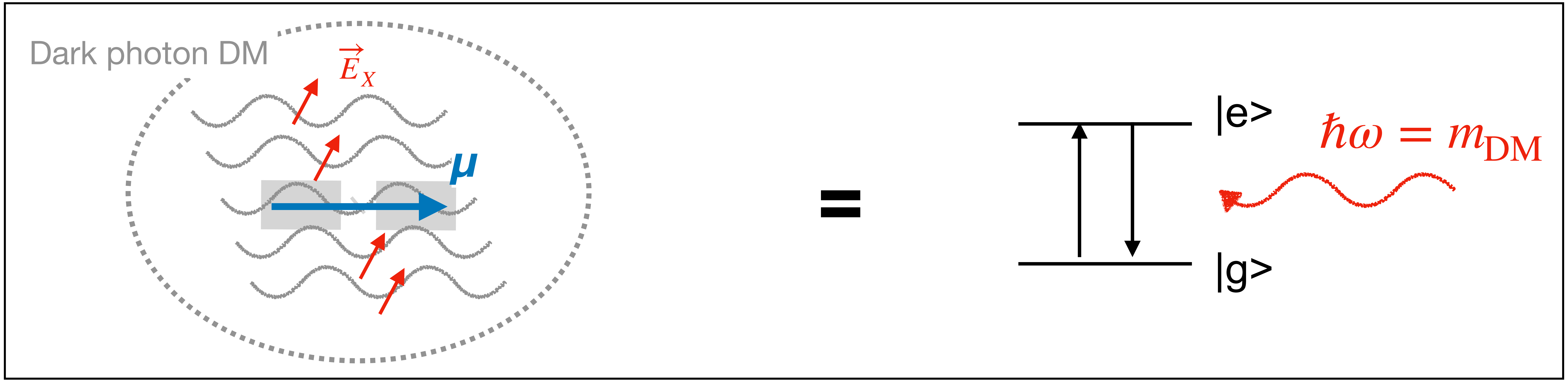
Please take a look at their talks/posters for details
Just highlight one of them today

Dark Matter Search with Direct Qubit Excitation

Wave-like DM, e.g, Axion, Dark Photon with mass $\sim \mathcal{O}(\mu\text{eV} - \text{meV})$, well motivated

- Coherent electric field generated by photons converted from DM (e.g, dark photon)
- Directly drive Qubit as a *DM-induced* microwave





S. Chen et al., PRL 131, 211001 (2023)

Superconducting qubits as an attractive probe due to

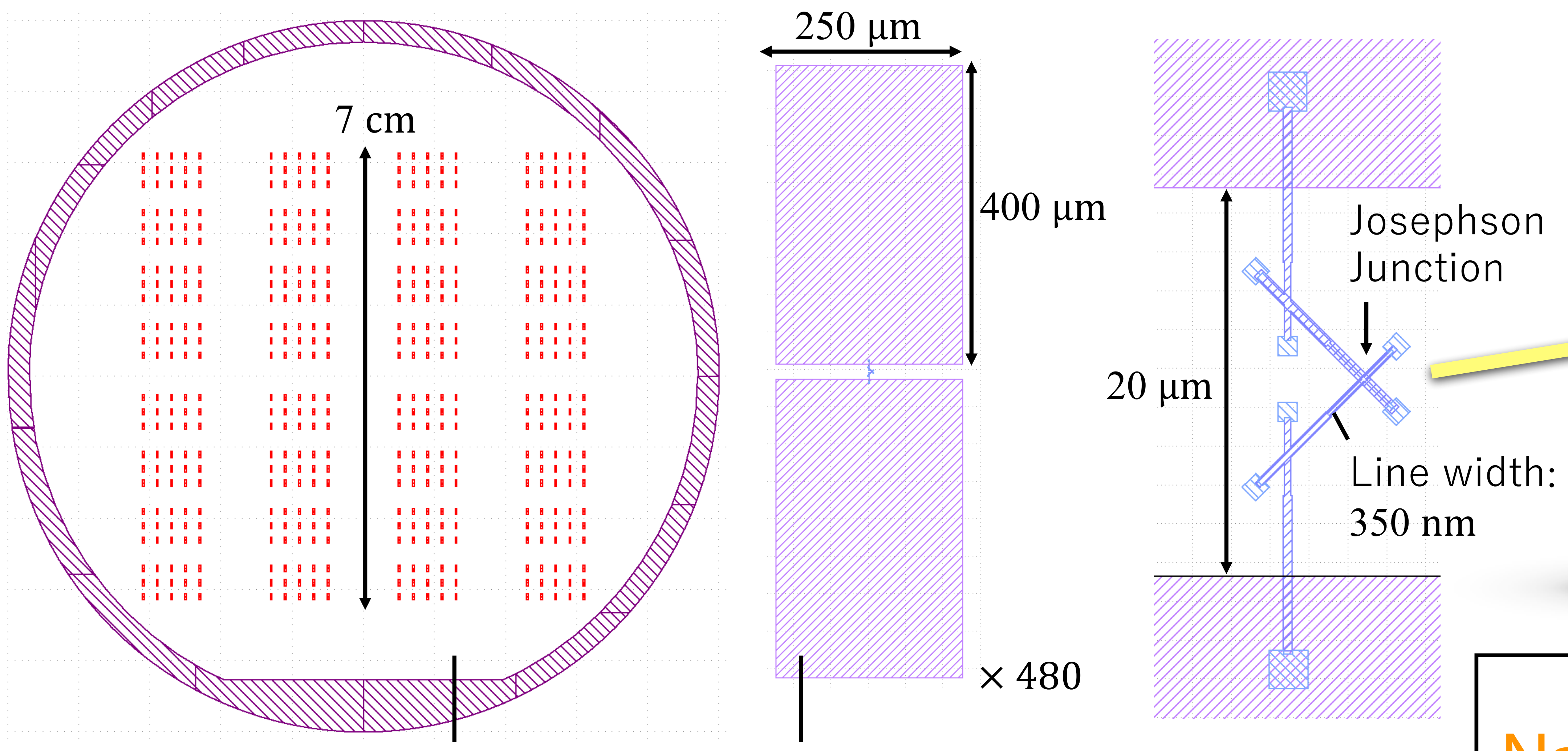
- well-motivated DM candidates in ~GHz mass range
- strong coupling of superconducting qubits to photons

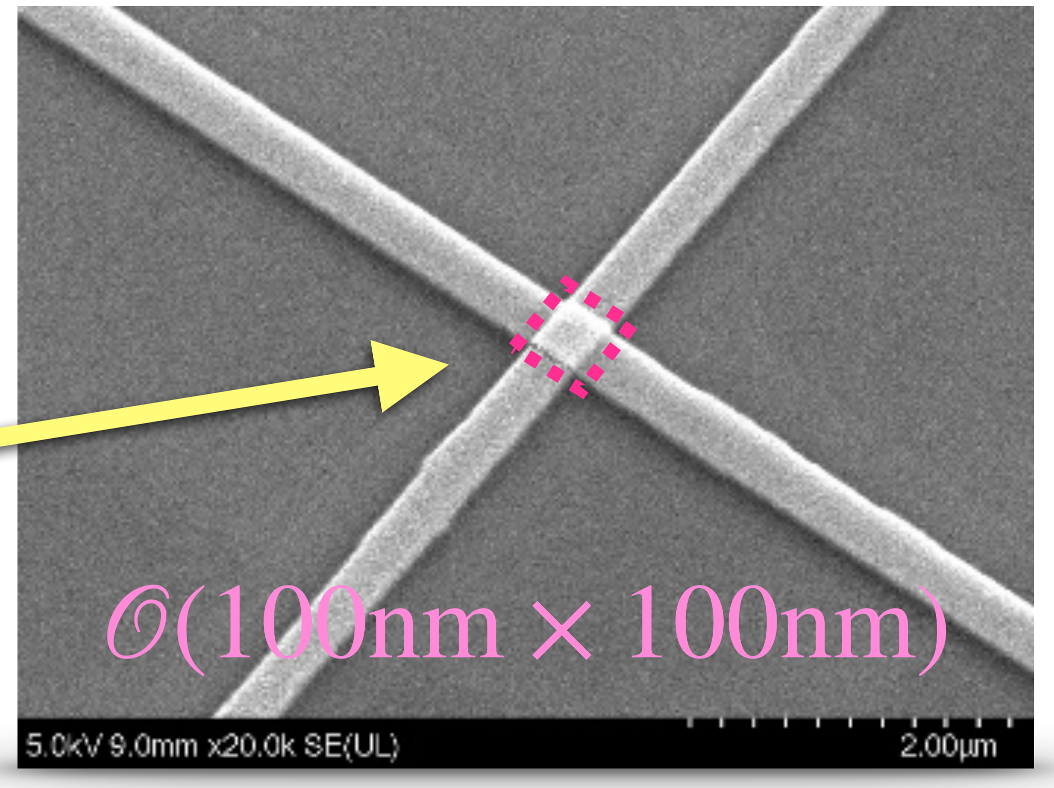
Qubit Fabrication

Create our own qubits and cavity for the experiment

K. Watanabe, K. Nakazono (M2)
T. Nitta, S. Chen, T. Inada

Fabrication of superconducting transmon

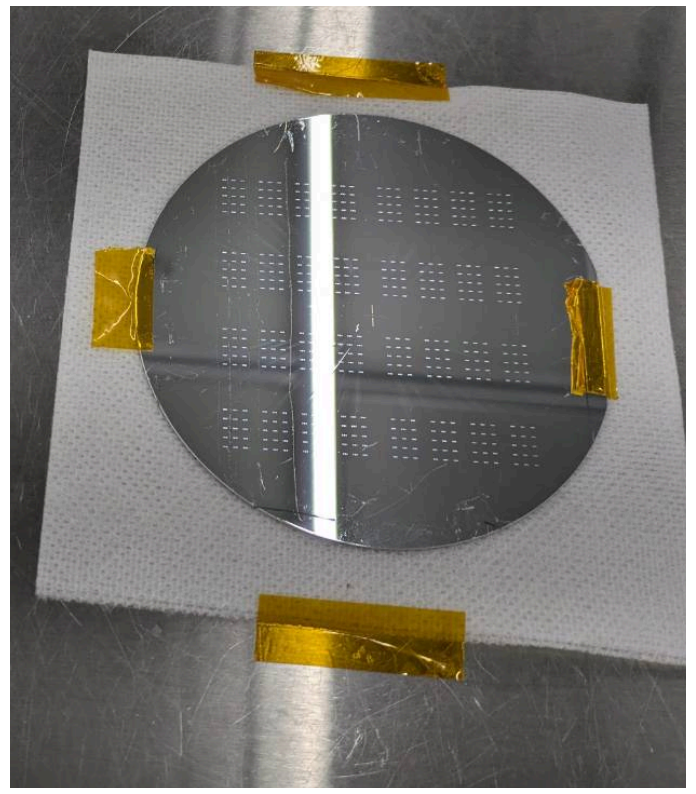




Nakazono-san (M2)

Watanabe-san (M2)

Work at Clean Room



480 qubits on Wafer

Dicing

Frequency Modulation

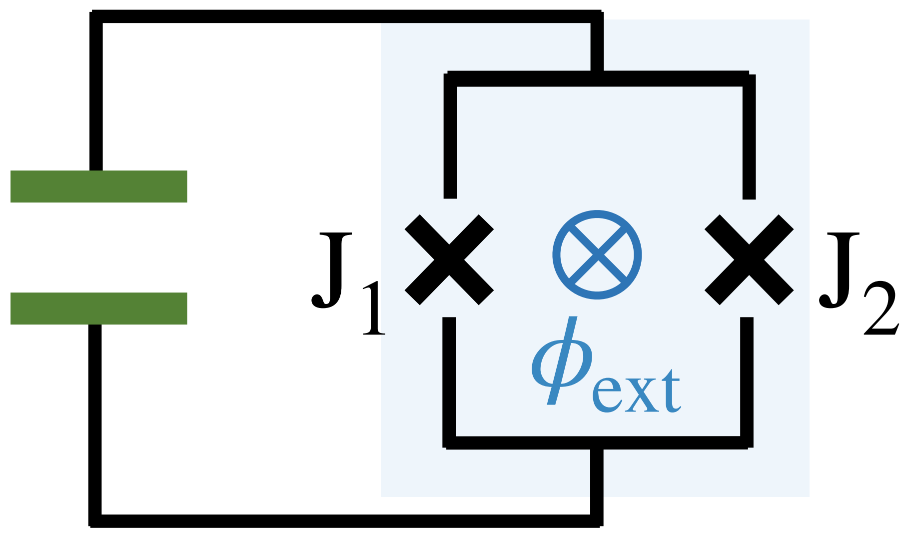
Create our own qubits and cavity for the experiment

K. Watanabe, K. Nakazono (M2)
T. Nitta, S. Chen, T. Inada

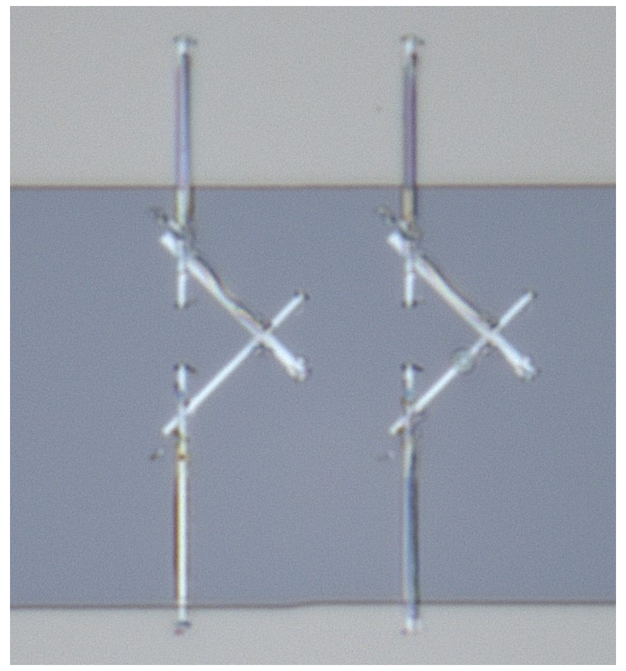
Scan DM mass by modulating qubit frequency

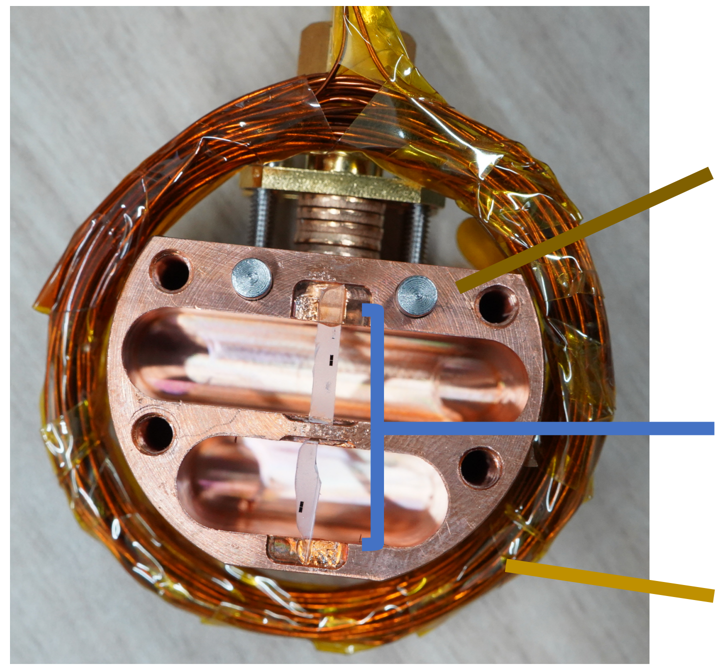
SQUID

Change qubit frequency (energy gaps) by varying magnetic flux penetrating the qubit



$$E_J^{\mathrm{eff}}(\phi_{\mathrm{ext}}) = \sqrt{E_{J1}^2 + E_{J2}^2 + 2E_{J1}E_{J2}\cos\phi_{\mathrm{ext}}}$$





Magnetic field by electric current

AC stark shift

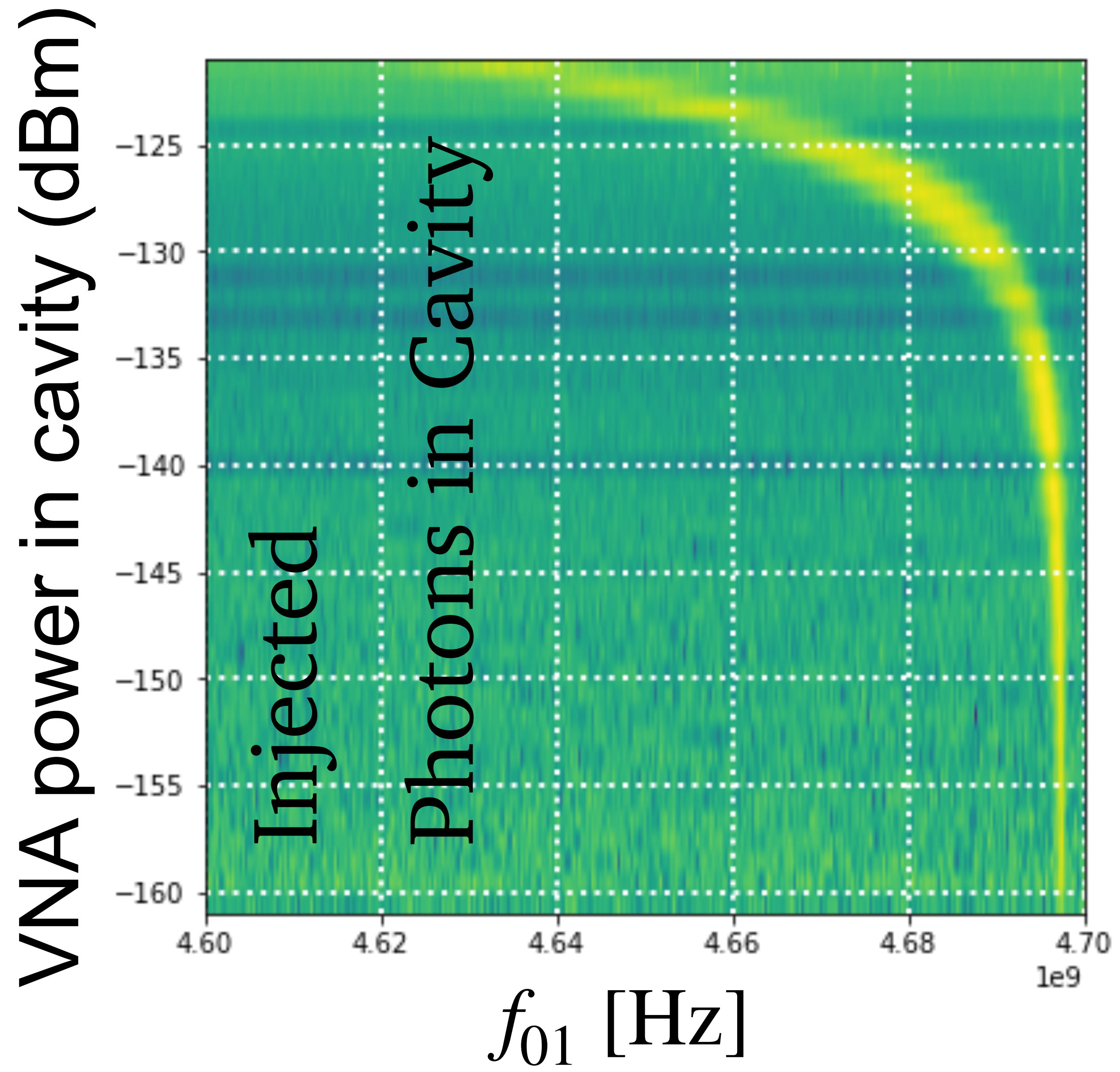
Change qubit frequency by injecting photons with off-resonant frequency in cavity

$$\Delta f_{01} = \frac{\delta_q \Omega_s^2}{2\Delta_{qs}(\delta_q + \Delta_{qs})}$$

Ω_s : amplitude of injected photons

δ_q : qubit anharmonicity

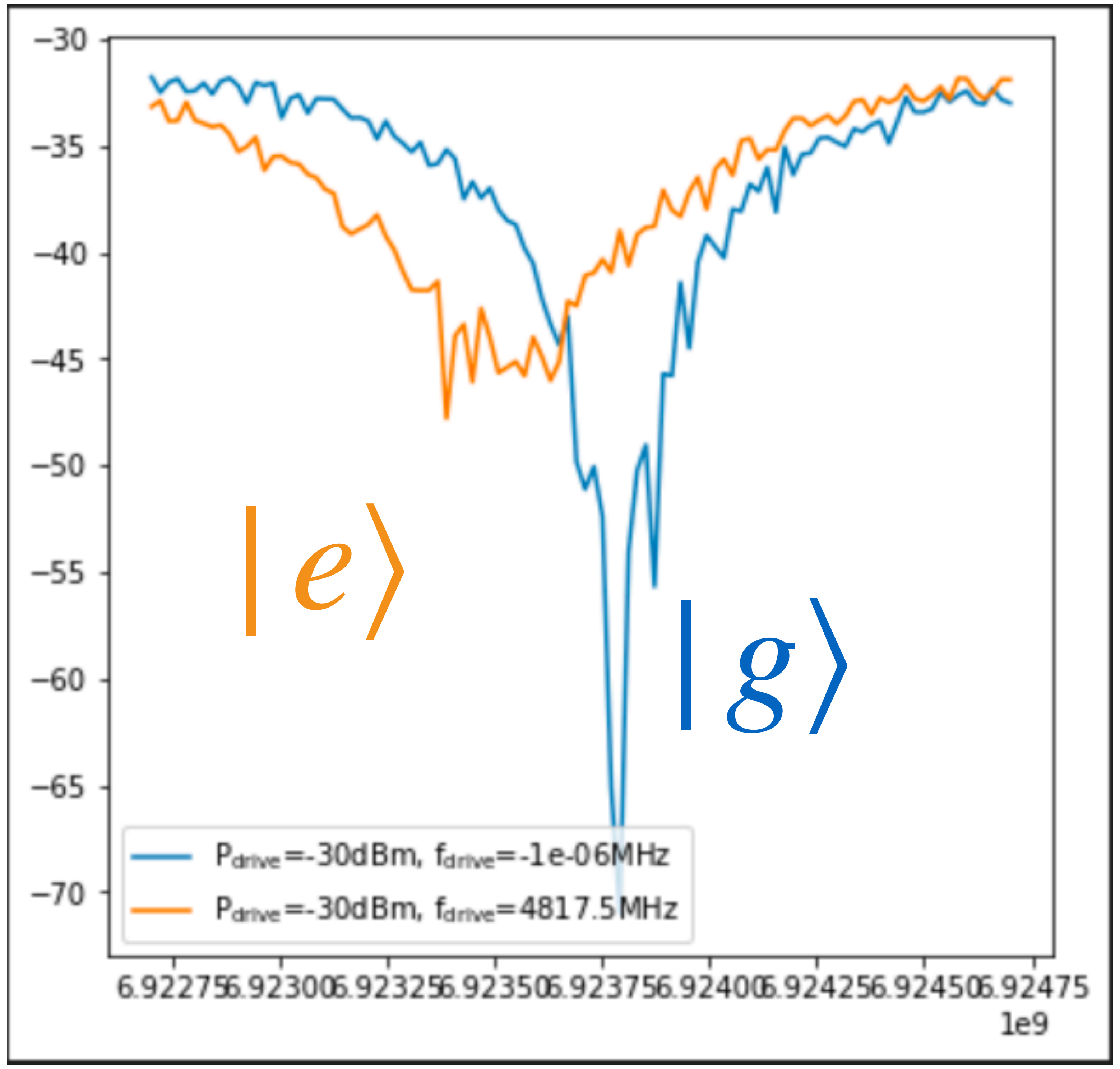
Δ_{qs} : frequency offset of injected photons wrt f_{01}



Qubit Readout and Experiment

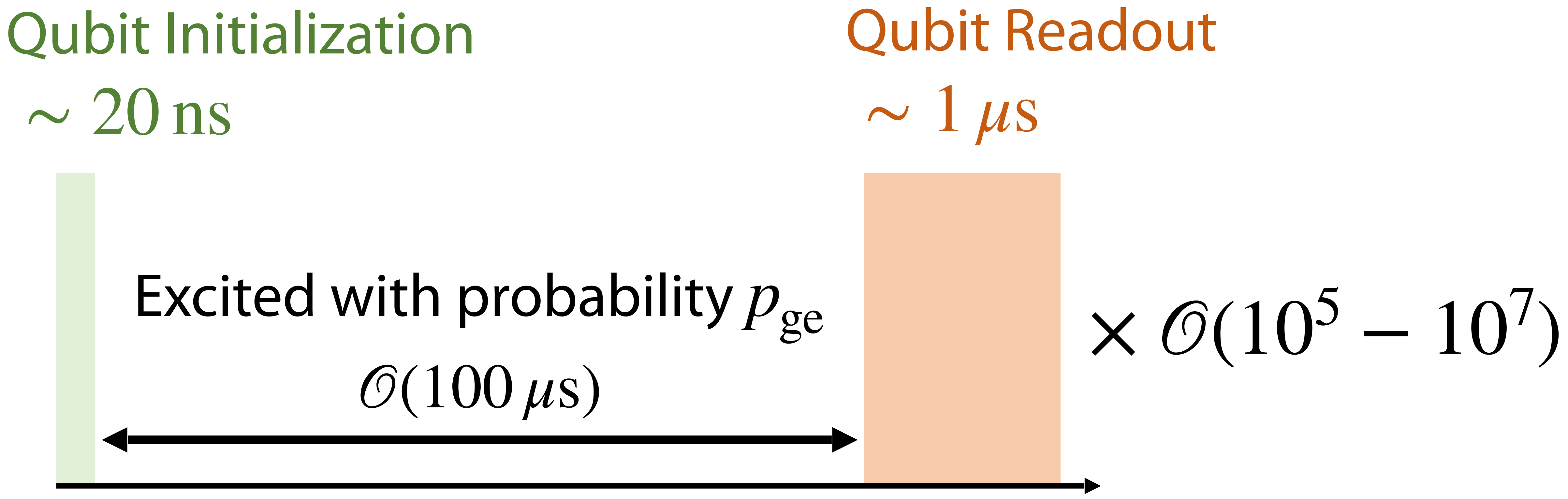
Qubit states read out through the cavity

Cavity frequency shifts depending on the qubit states (→ Dispersive readout)



Cavity Frequency

Experimental procedure for DM detection



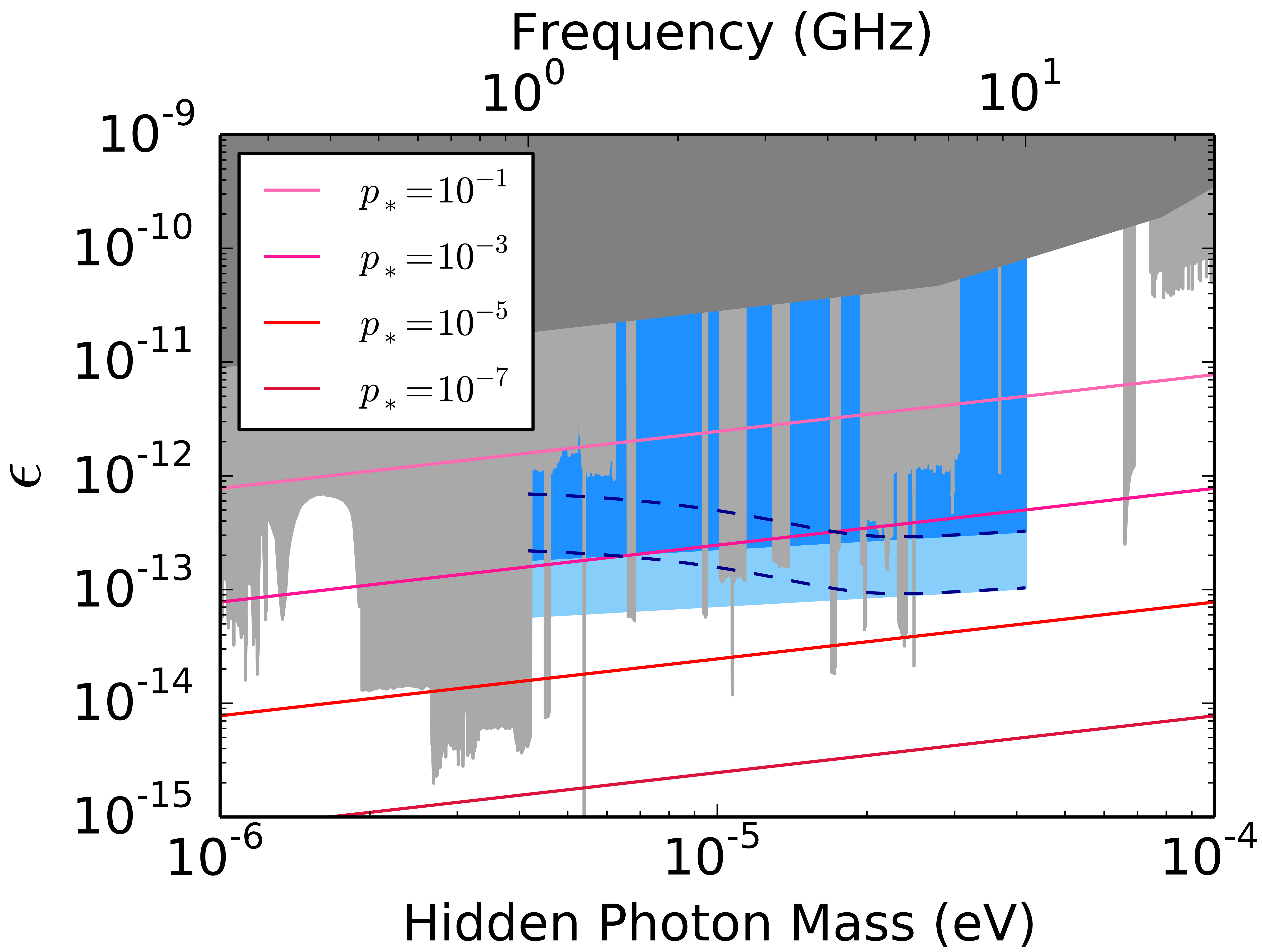
$$p_{\rm ge} \simeq 0.12 \times \kappa^2 \cos^2\Theta \left(\frac{\epsilon}{10^{-11}}\right)^2 \left(\frac{f_{01}}{1\ \rm GHz}\right) \left(\frac{\tau}{100\ \mu\rm s}\right)^2 \left(\frac{C}{0.1\ \rm pF}\right) \left(\frac{d}{100\ \mu\rm m}\right)^2 \left(\frac{\rho_{\rm DM}}{0.45\ \rm GeV/cm^3}\right)$$

Initialize qubits to $|0\rangle$, wait and measure

- Count the occurrence of $|1\rangle$ state in $\mathcal{O}(10^5 - 10^7)$ measurements

Expected Sensitivity for Direct Qubit Excitation

S. Chen et al., PRL 131, 211001 (2023)



Dark blue: $n_q = 1$ @ 1 mK / year

Light blue: $n_q = 100$ @ 1 mK / year

Dashed lines: 30 mK

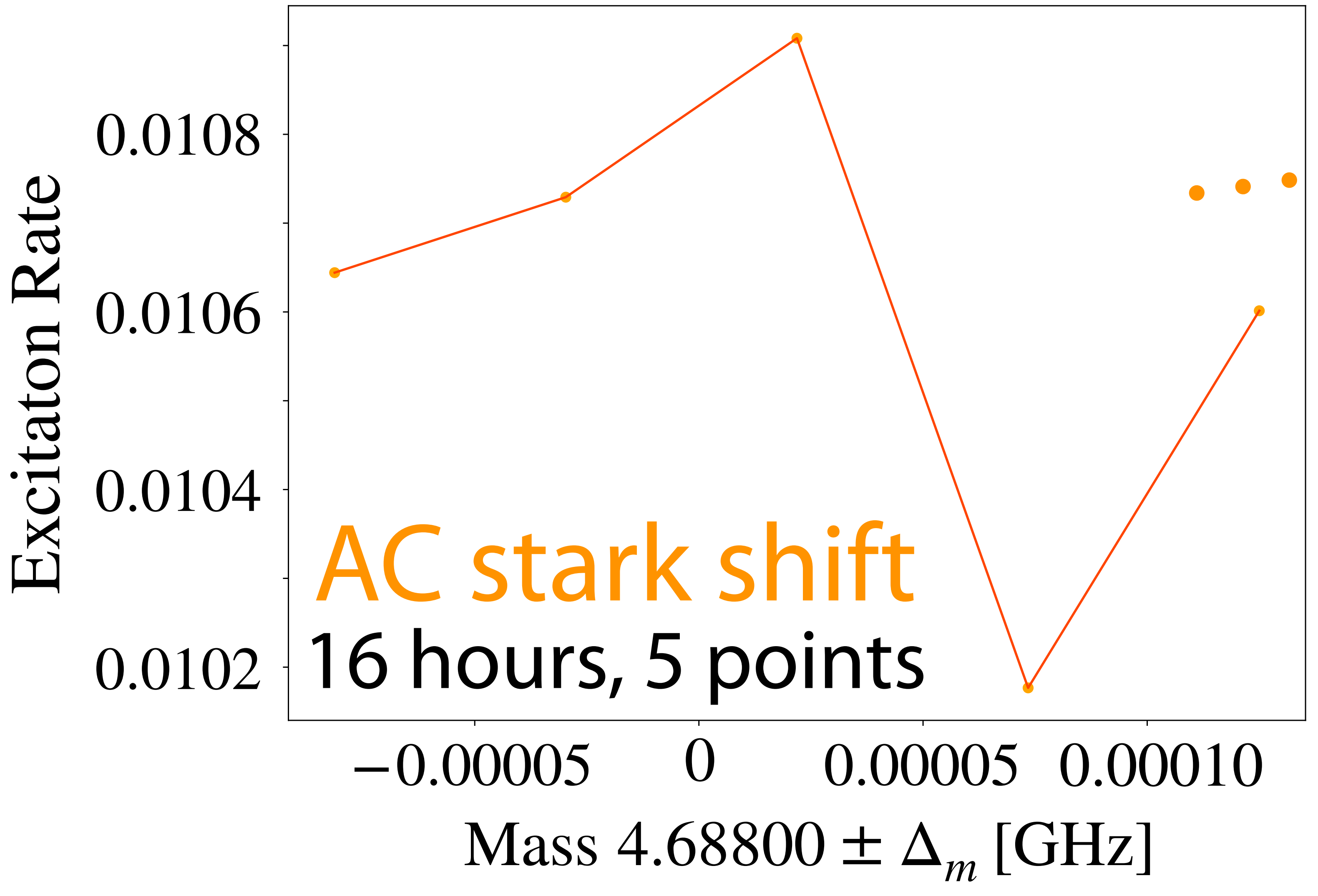
Possible to probe into unexplored region even with the excitation rate of **0.1%-10%**

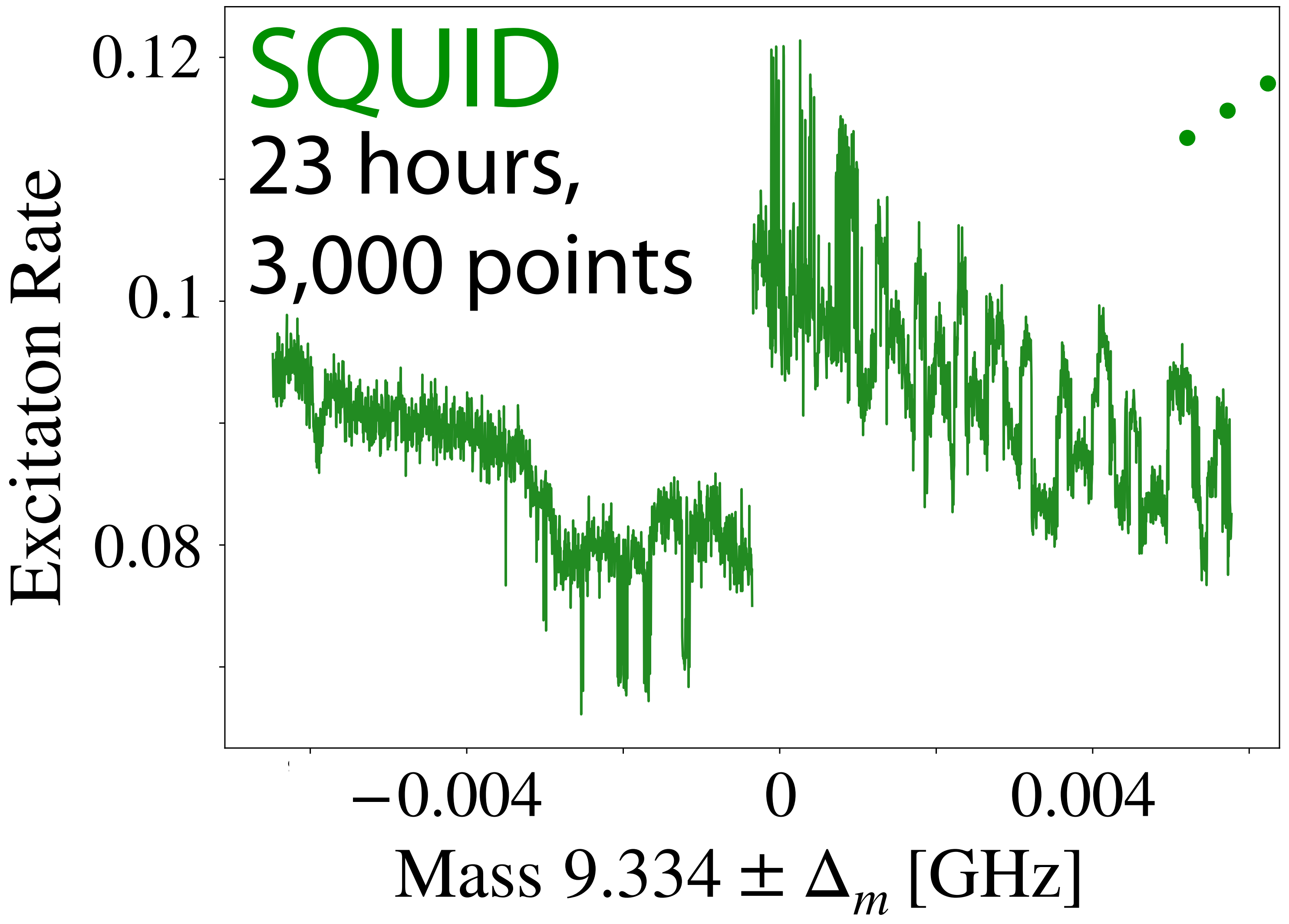
Expected noise sources of $|0\rangle \rightarrow |1\rangle$ transition

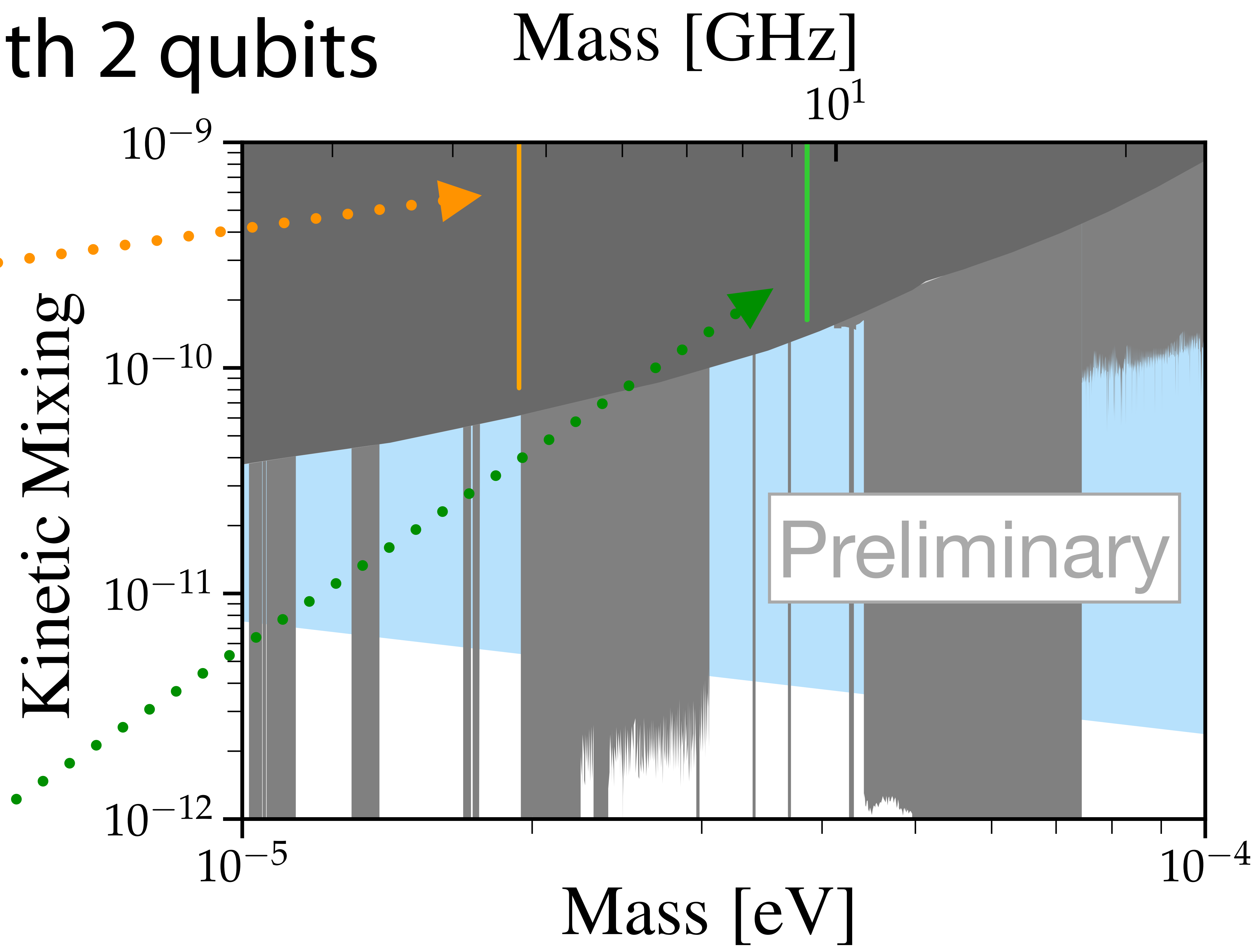
- Thermal noise:
  $p \sim e^{-\hbar\omega/k_B T} \sim 0.01\% - 1\,\%$ @ 30 mK
- Readout error : $\sim 0.1\,\%$

First Results from Direct Qubit Excitation

Performed experiments with 2 qubits







Background estimated from the baseline of observed data (mainly from thermal noise)

Expected sensitivity at $C = 0.1\,\mathrm{pF}$, $d = 100\,\mu\mathrm{m}$, $\tau = 30\,\mu\mathrm{s}$

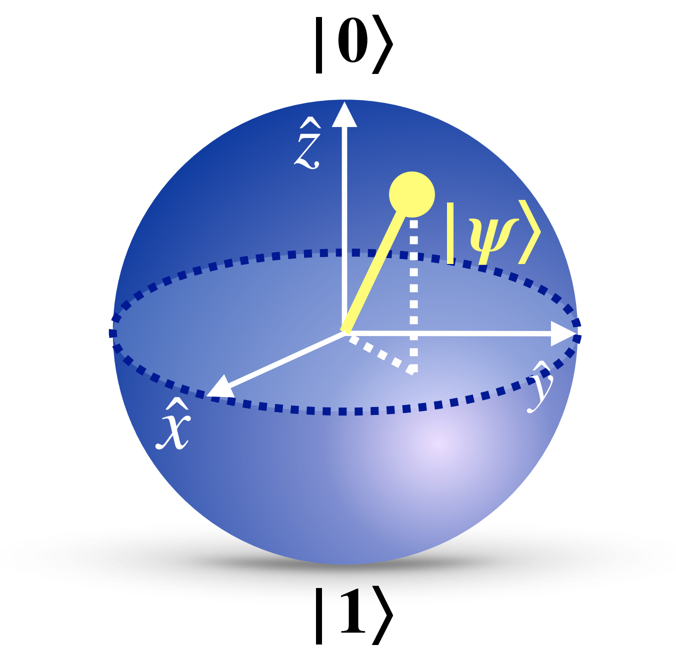
Possible future improvements:

- Qubit design optimization for larger C and d
- Sensitivity enhancement with quantum interference
  S. Chen et al., PRL 133, 021801 (2024)
- Extending to Axion search with B-field
  S. Chen et al., arXiv:2407.19755

Efforts on Quantum Computing/Sensing

ICEPP
The University of Tokyo

Application/Algorithm



Quantum machine learning:

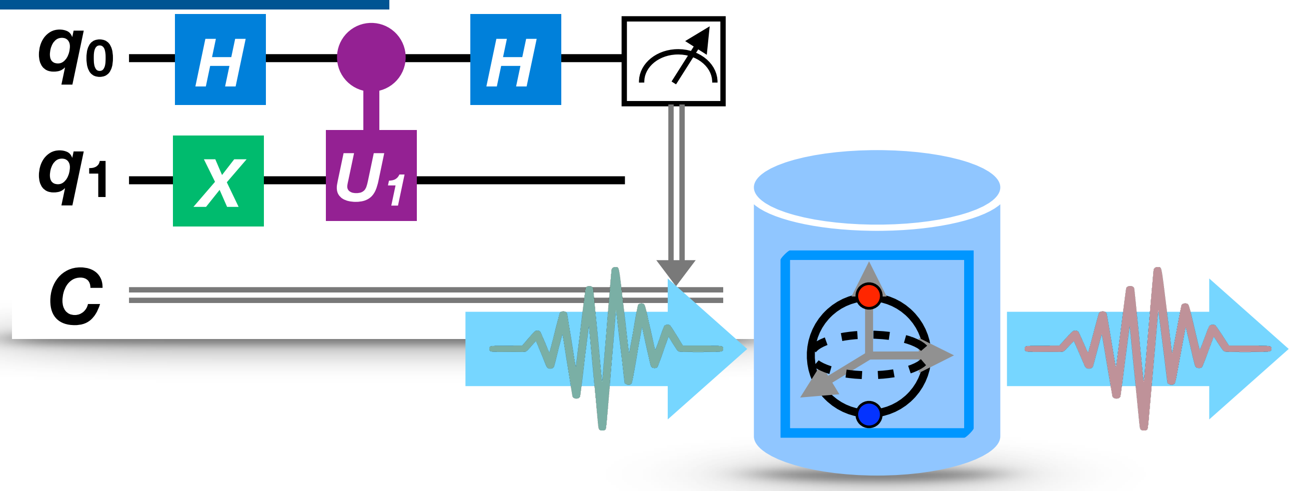
- Barren plateau, Generalization
- Learning with symmetry
- Quantum data

Quantum LGT simulation

- Low-dimensional $\mathbb{Z}_2$, SU(2) LGT
- Finite temperature/density

H. Elhag, L. Nagano et al., arXiv:2408.08701

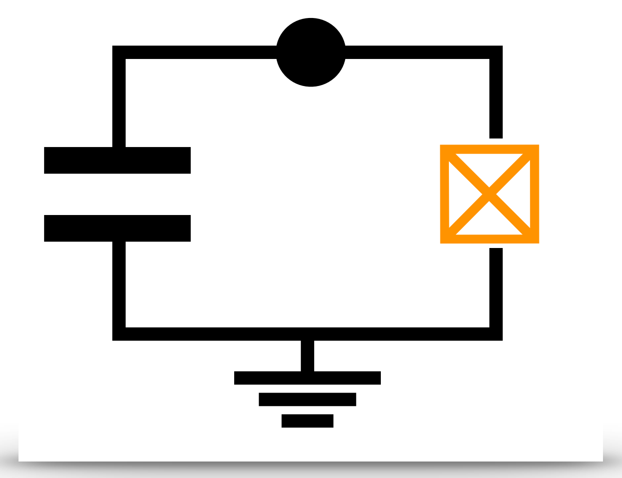
Software



- AQCEL circuit optimization
- Qutrit implementation on superconducting qubits
- Quantum error correction

Y. Iiyama, W. Jang et al., arXiv:2405.14752

Hardware



Superconducting qubits and related technology

Component for large-scale QC

- Amplifier
- Circulator/Isolator, etc.

Qubit development for DM searches

- Design optimization (e.g, larger C/d, smaller JJs)
- Magnetic field tolerance

Summary

Presented selected results at ICEPP on quantum computing and the application to particle physics:

- learning quantum states/processes
- simulating quantum dynamics in Lattice Gauge Theory
- searching for dark matter with superconducting qubits

Aiming at demonstrating quantum advantage and/or quantum as useful resources in the *computational particle physics* in future

New opportunities in technology development and scientific discovery (e.g, DM search with superconducting qubits)

Summary


Kensuke Kamisoyama


Karin Watanabe


Kan Nakazono


Toshiaki Kaji


Kirill Shulga


Zhelun Li


Lento Nagano


Kazuyuki Nakayama


Wai Yuen Chan


Tatsumi Nitta


Yutaro Iiyama


Nobuyuki Yoshioka


Toshiaki Inada


Koji Terashi


Ryu Sawada