ICEPP
The University of Tokyo

Quantum computing applications to HEP at ICEPP

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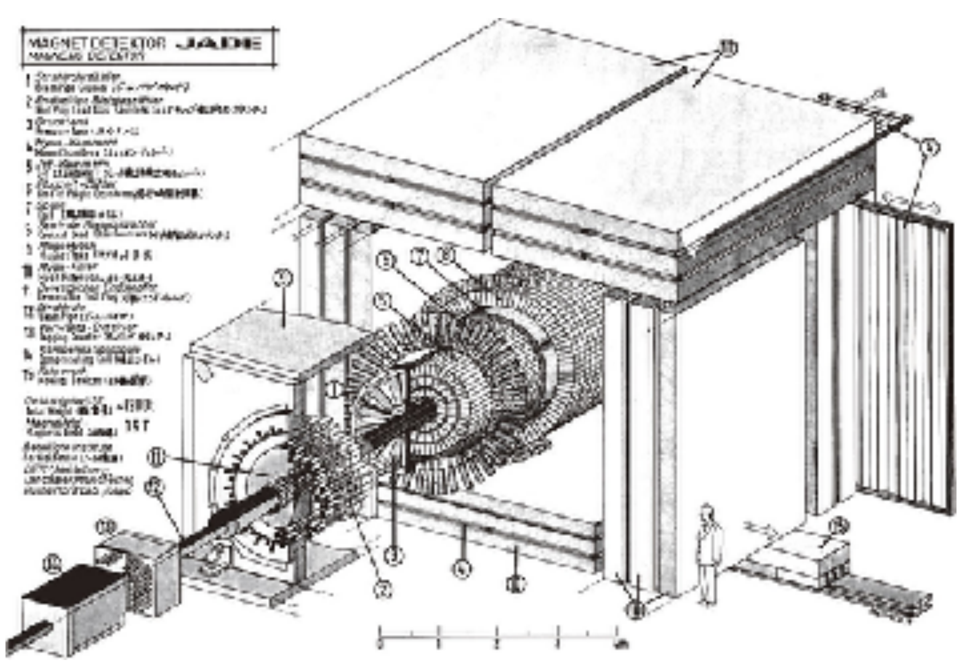
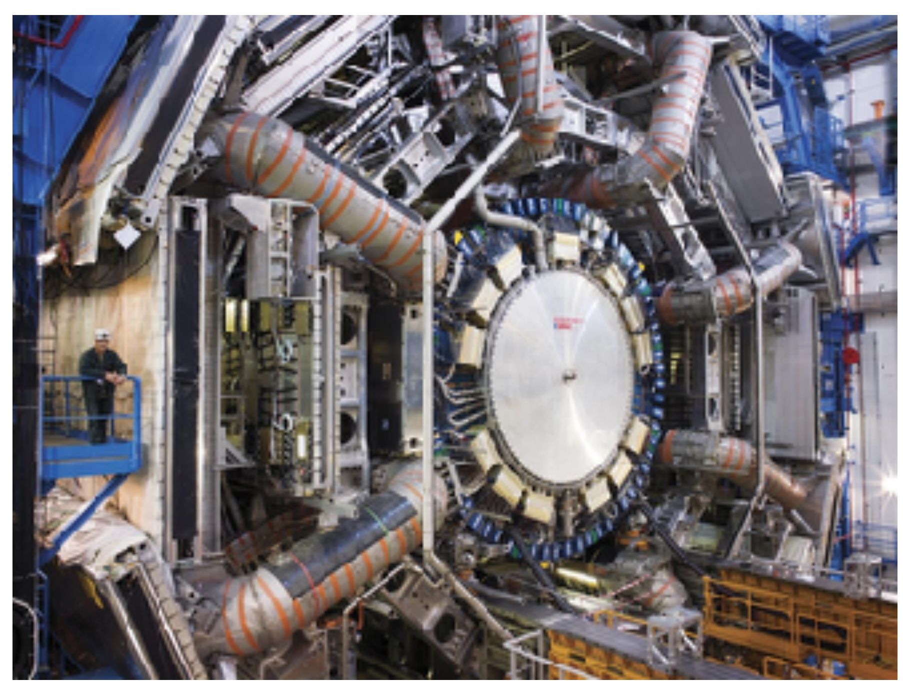
Who we are

ICEPP
The University of Tokyo

- A particle physics lab at UTokyo, established 1974
  - 10 PIs, ~20 scientific staff members, ~40 graduate students
  - ATLAS, MEG, ILC, Belle 2, smaller-scale experiments (photons, positronium, neutrons, ...)
- One of the key strengths: HEP computing & software
  - Hosts a computing grid site for ATLAS

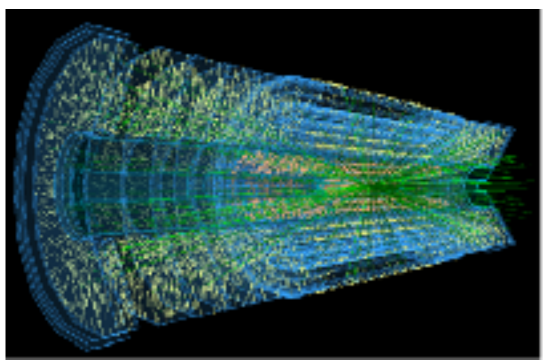


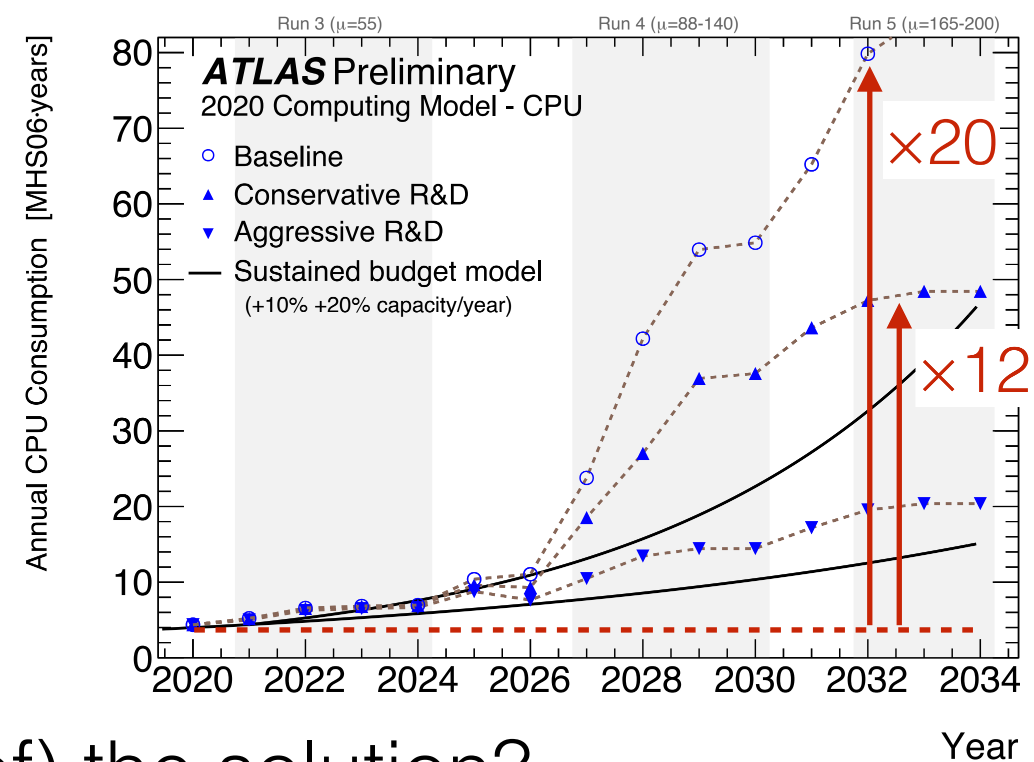


Why we are in the quantum business

Particle physics needs a computing breakthrough

- HEP research is compute-hungry
- Conventional computing cannot scale to the needs of near-future experiments





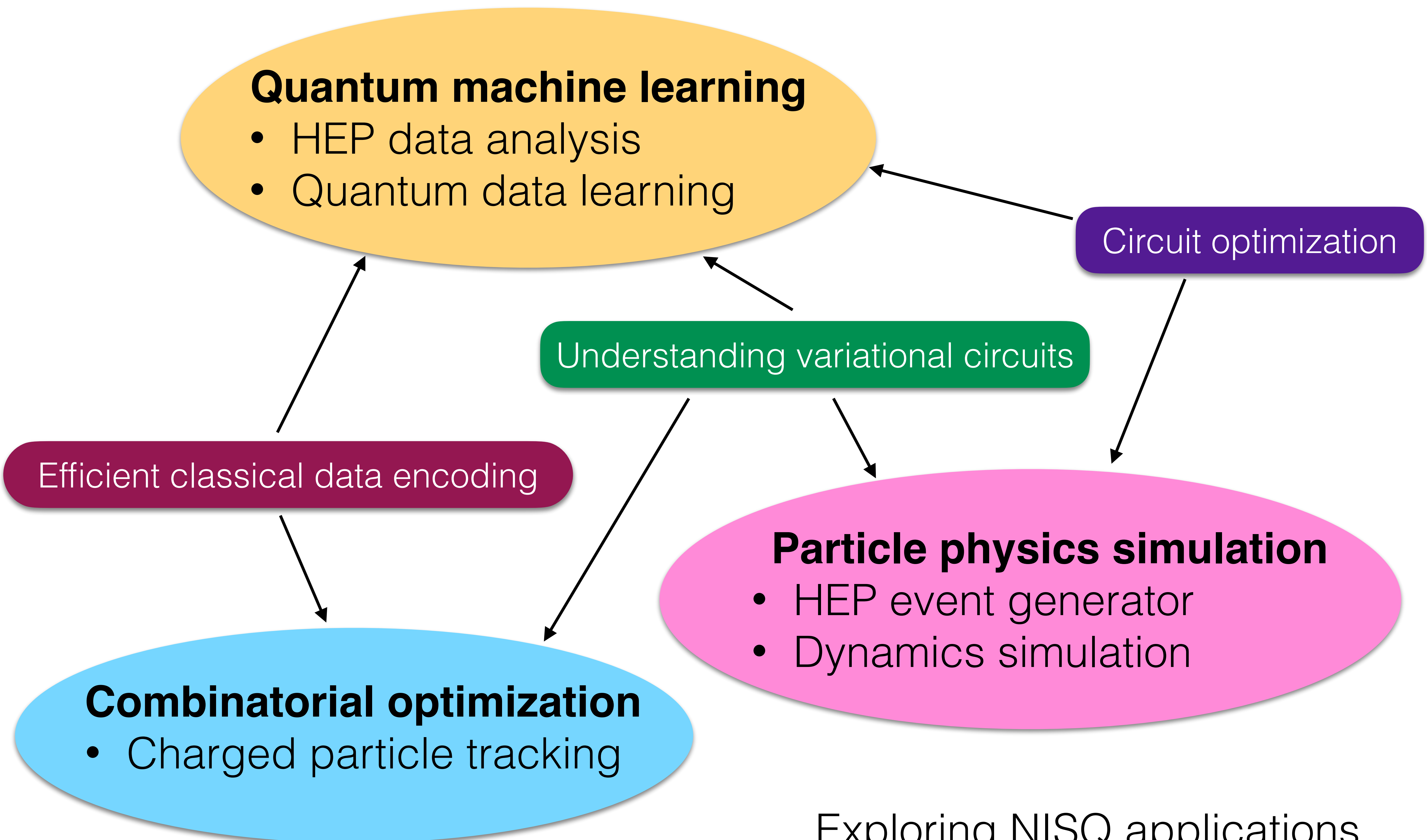
→ Can quantum computing be (a part of) the solution?

Combinatorial optimization, machine learning, physics simulation, ...

At ICEPP:

2018	2020	2021
Exploratory projects →	Launch of IBM-UTokyo Lab →	Dedicated division created
	Joined university-wide QC initiative	Full-time QC research staff added

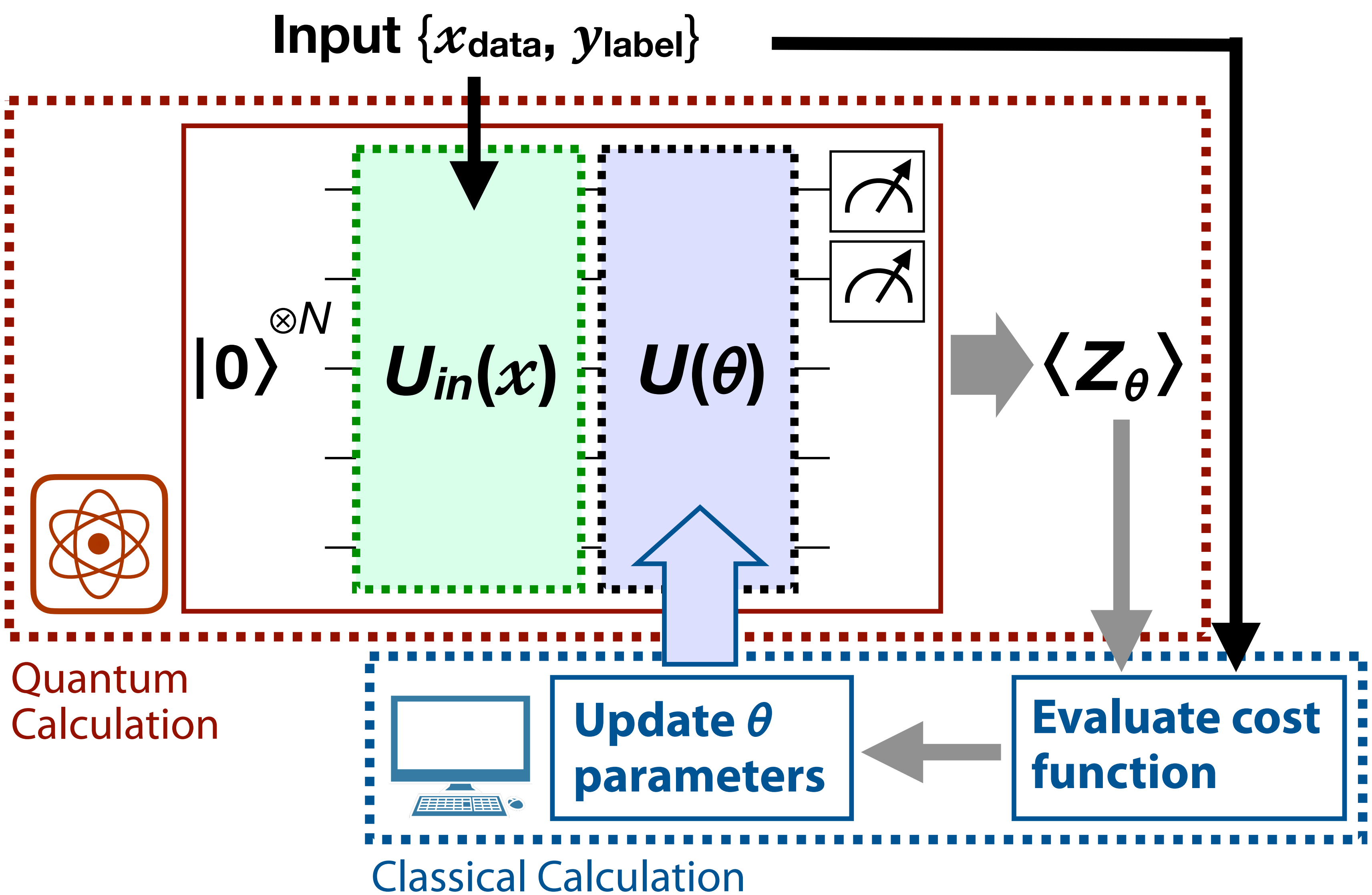
Main research thrusts



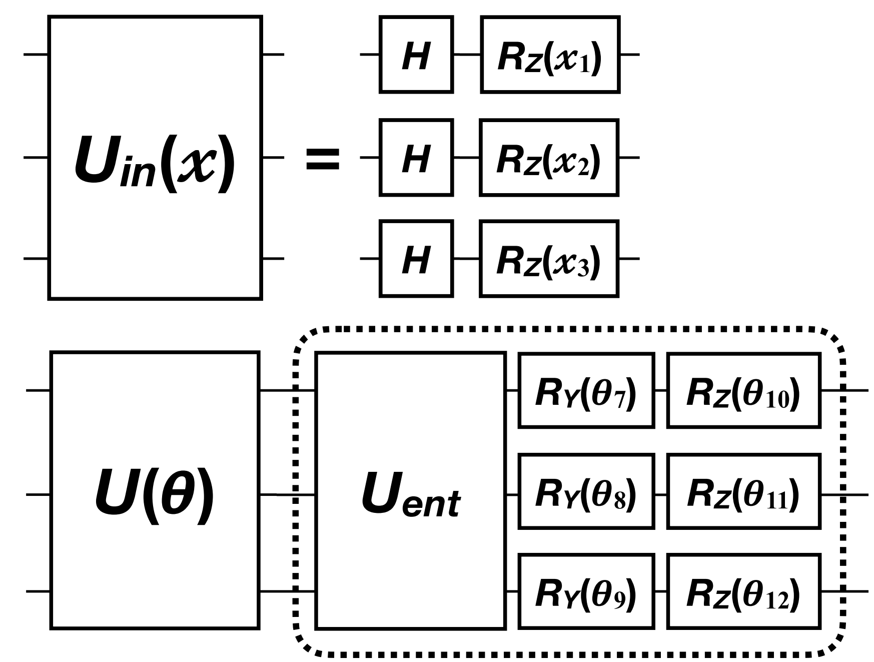
Exploring NISQ applications

Variational quantum algorithm

- Iterative quantum-classical hybrid numerical optimizer
  - Can be used for machine learning
- Considered a promising NISQ application



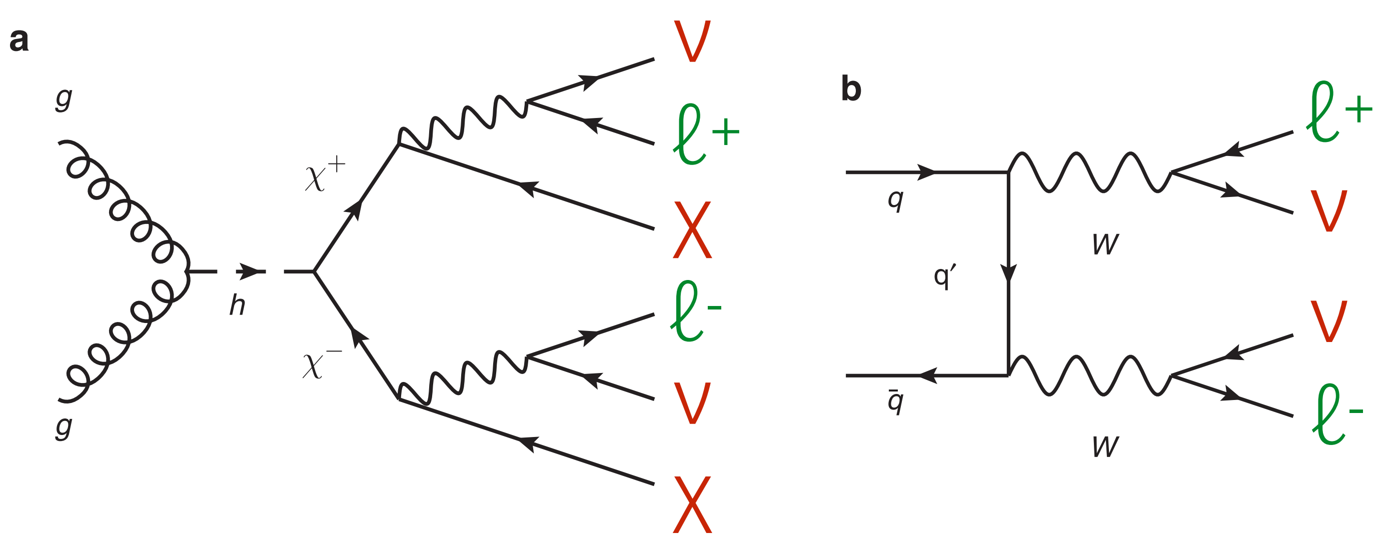
For example

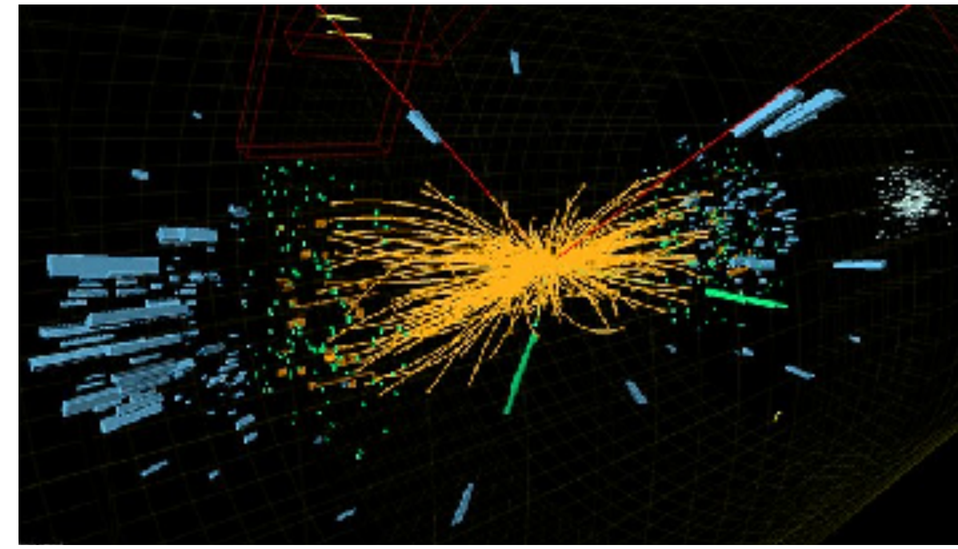


Parametric circuit = “ansatz”

HEP event classification

2002.09935



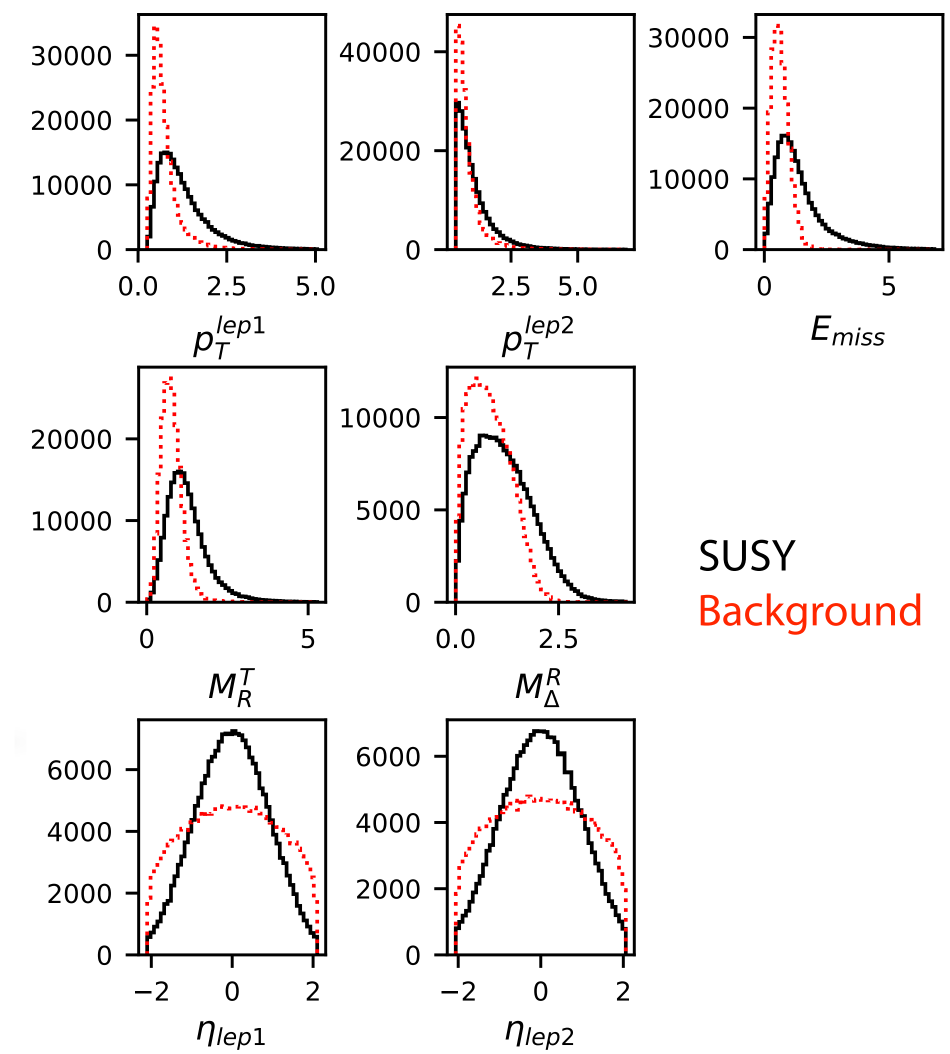


Novel particle (SUSY) signature:
2 ℓ± and large "missing energy"

Known-physics (background) signature:
2 ℓ± and large "missing energy"

→ Discrimination only through distributions in the event feature space

(Classical) ML methods able to capture the difference.
Can variational circuits too?



Variational circuit learns small problems

2002.09935

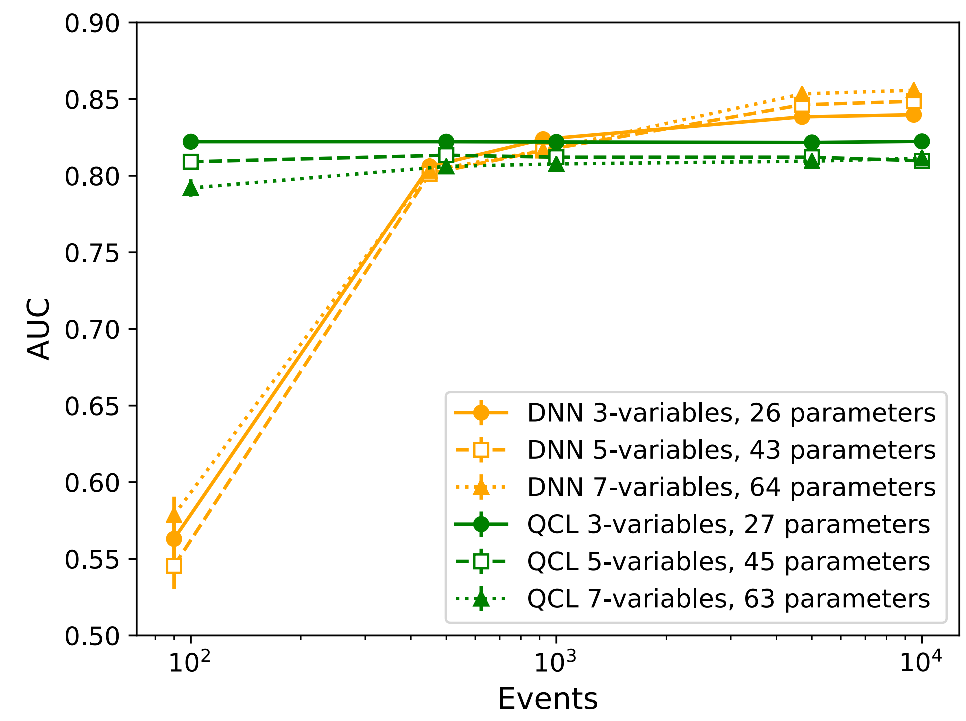
Compared algorithms:

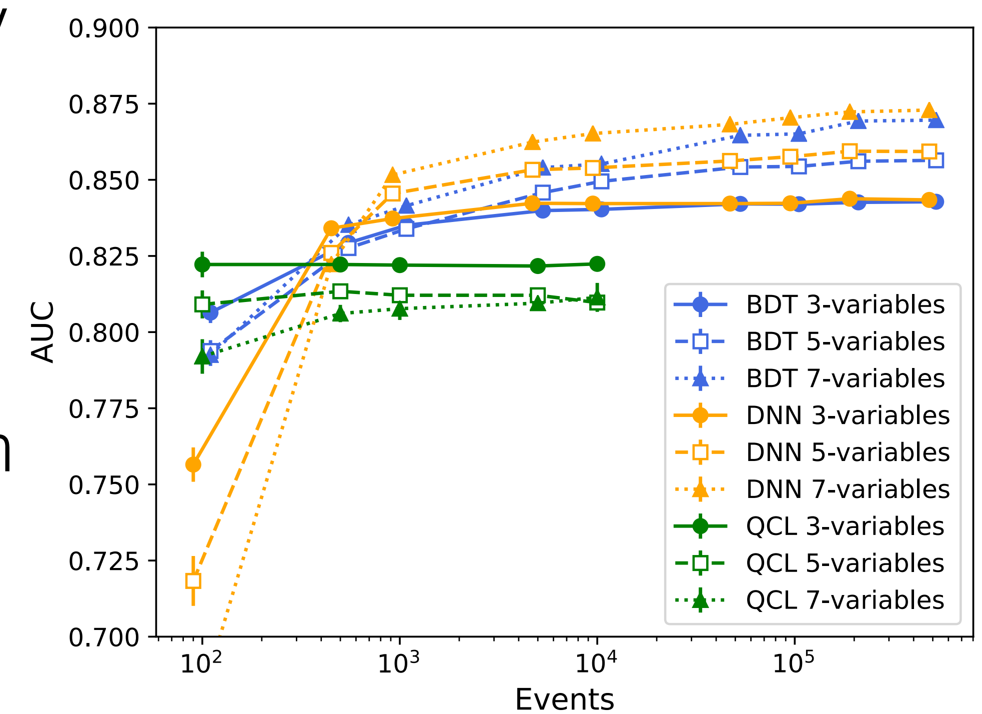
- Variational circuit (Quantum circuit learning)
  Mitarai et al. arXiv:1803.00745
- Deep neural network (DNN)
- Boosted decision tree (BDT)

Tested with 3/5/7 feature variables

Observations:

- QCL and fully trained DNN perform comparably when similar number of parameters
- QCL performance saturates with small training data set size
- Sufficiently large DNN and BDT models perform better than this particular QCL model

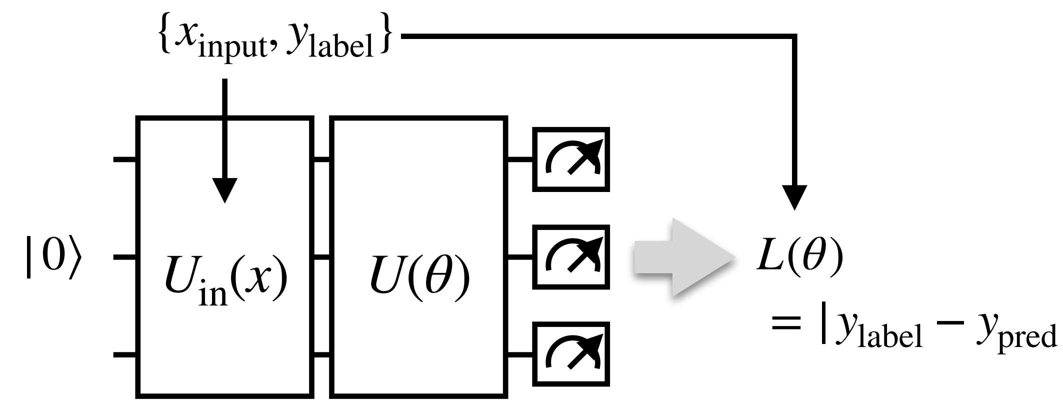




Quantum data learning

Quantum data = quantum state as input

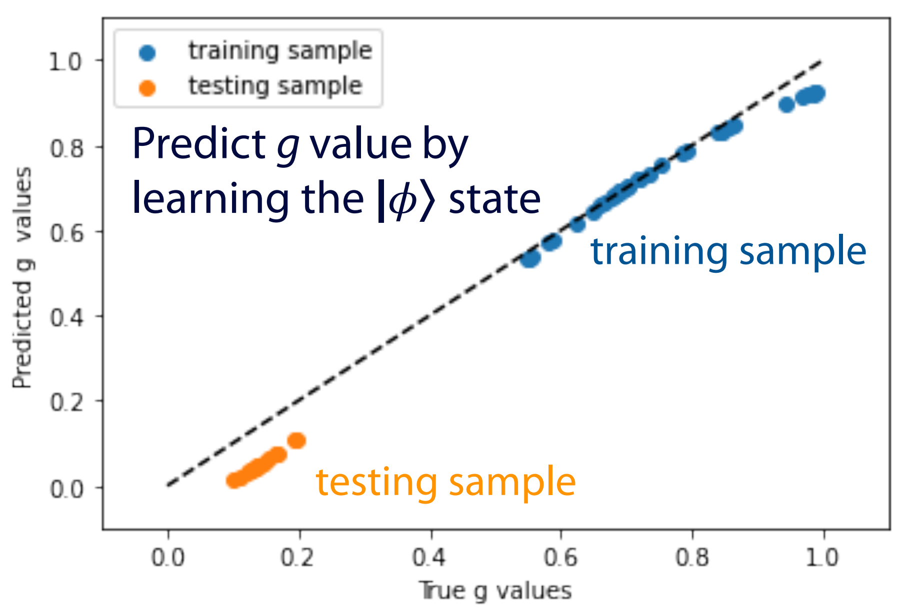
- Output of e.g. quantum sensors
- Final state of quantum simulations
- Ground state of a Hamiltonian obtained from variational quantum eigensolver[1]



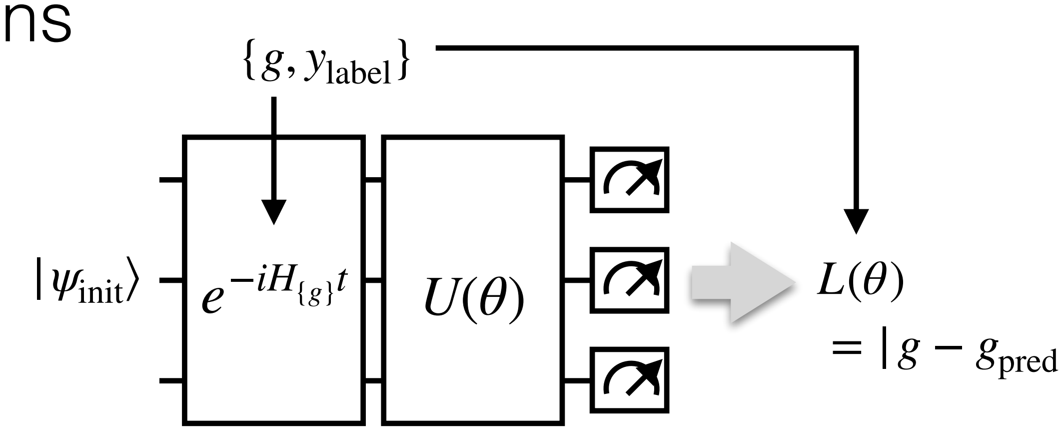
Classical data learning example

Preliminary studies indicate ability to learn & generalize

Now investigating quantum field theory questions



Predicting the coupling constant in the quantum parton shower simulation[2] given the final state

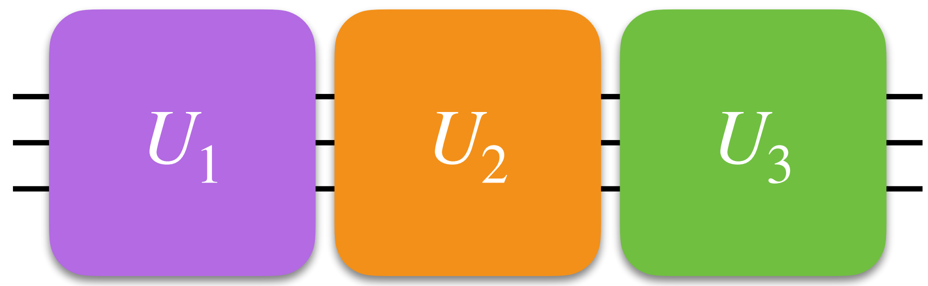


Quantum data learning example (output of dynamics simulation)

[1] Peruzzo et al. Nat. Comm. 5, 4213
[2] Bauer et al. PRL 126, 062001

Executing a long circuit on NISQ

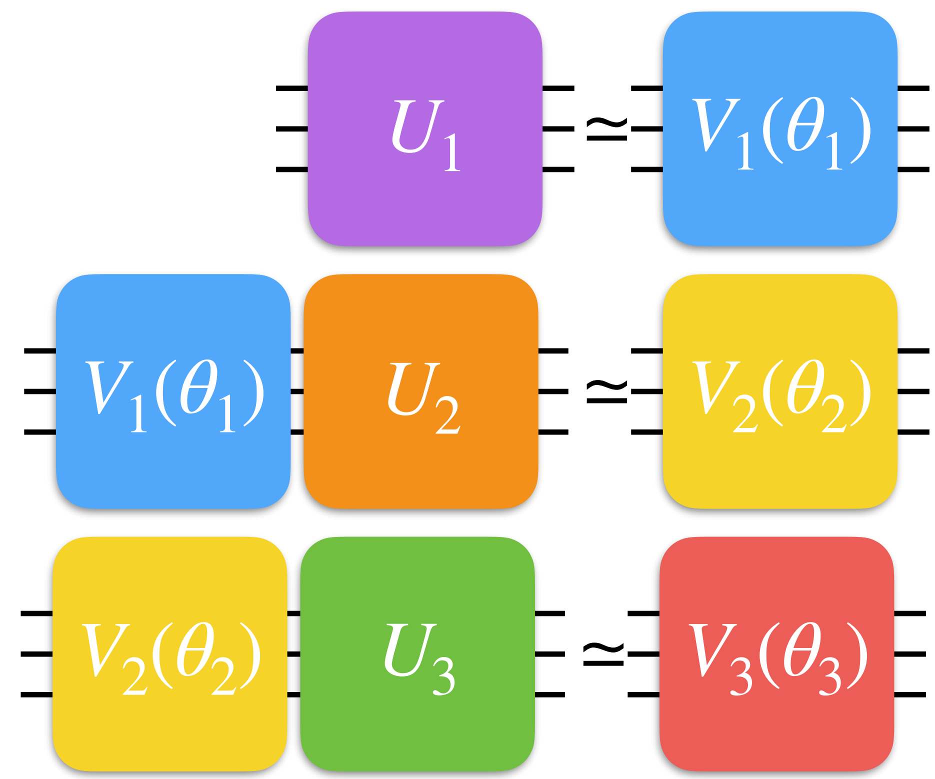
Can a circuit be executed beyond the coherence time on NISQ?



Use quantum pseudo-memory: Stop-save-resume

1. Execute U_1
2. Approximate the state with $V_1(\theta_1)$ (shorter than U_1)
3. Execute $U_2V_1(\theta_1)$
4. Approximate the state with $V_2(\theta_2)$

continue..

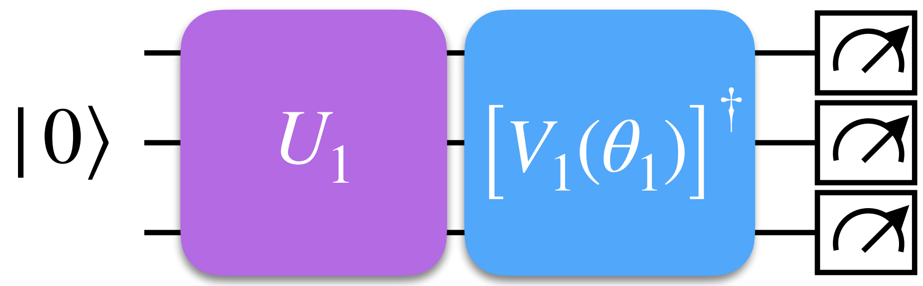


Similar ideas presented in

- Otten et al. 1910.06284 (“Restarted quantum dynamics”)
- Berthusen et al. 2112.12654 (“Variational Trotter compression”)

Approximation = “quantum compilation”

$V_n(\theta_n)$ are parametrized circuits:



$$P_0 = |\langle 0|\left[V_1(\theta_1)\right]^{\dagger} U_1 |0\rangle|^2$$

Find θ_1 that maximizes P_0

→ “Quantum-assisted quantum compiling (fixed input state)”
(Khatri et al. Quantum 3, 140)

- In principle applicable to any circuit
- In practice used for quantum dynamics simulation
  Trotter decomposition = iterative simulation
  → Valid observables from intermediate states
  → Easy to gauge the performance of the method

Simulation of the Schwinger model

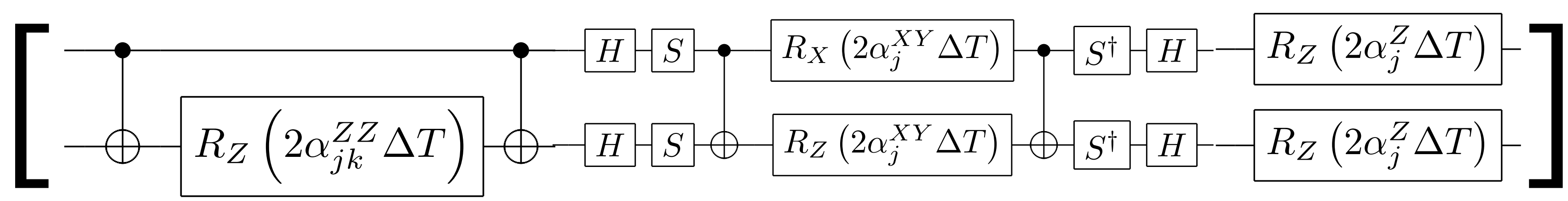
Graduate thesis, R. Okubo (2022)

Schwinger model = 1+1 dimensional quantum electrodynamics

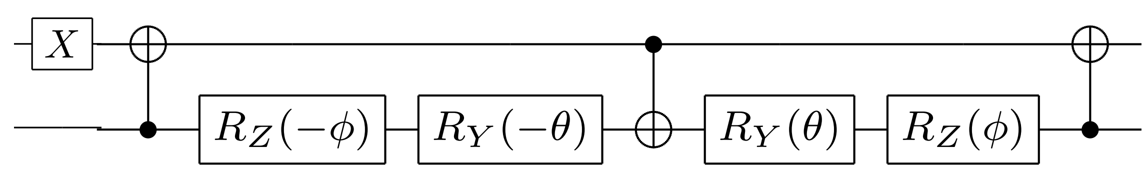
$$\mathscr{L} = -\frac{1}{4g^2}F_{\mu\nu}F^{\mu\nu} + \bar{\psi}(i\gamma^{\mu}D_{\mu} - m)\psi \quad \mu, \nu = 0,1$$

→ Qubit representation of the Hamiltonian (spatially discretized) well known[1]

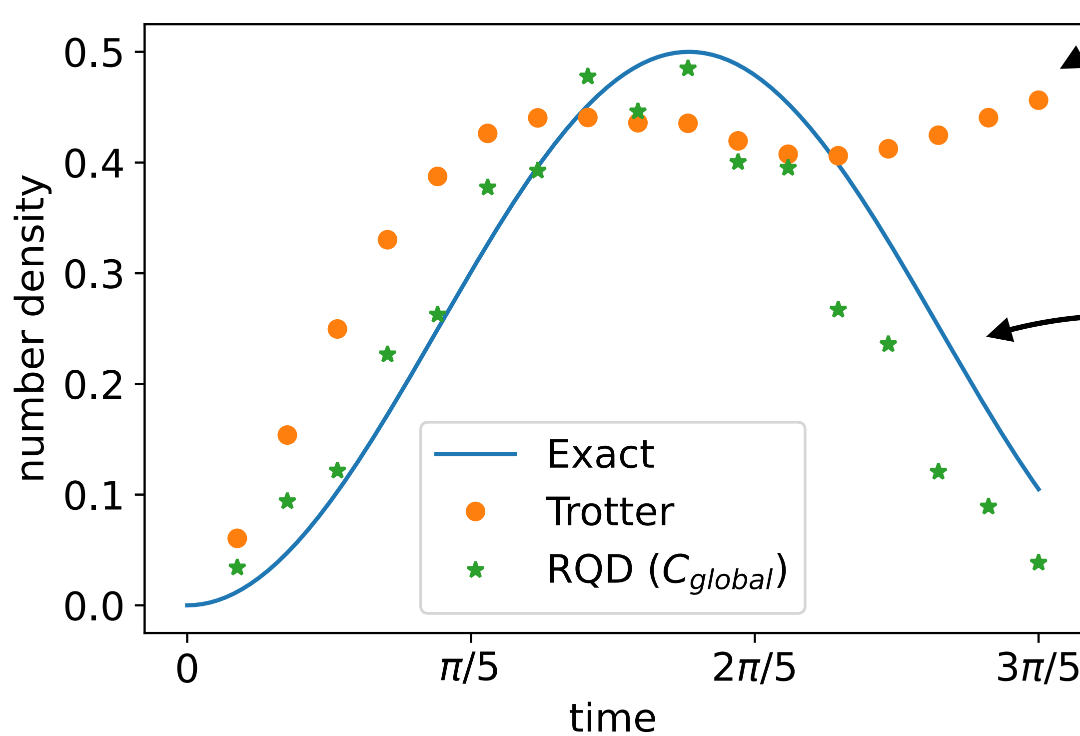
Forward circuit (U):



Approximator (V†):



Result:



Straight dynamics simulation
→ Decoheres after a few steps

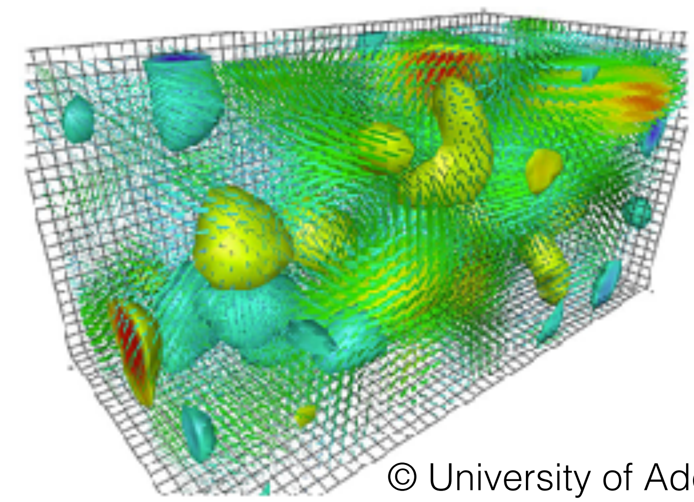
Hamiltonian diagonalization

Restarted dynamics every 3 steps

[1] Kogut et al. PRD 11, 395

HEP simulation would not be just long

The most straightforward application of QC to HEP:
Quantum field theory simulation



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Full recipe known since a while
e.g. Jordan et al. Science 336, 1130 (2012):

- Discretize space
- 1 quantum register per lattice point (field value)
  or
- 1 quantum register per momentum mode (Fock occupation number)

Is a fault-tolerant quantum computer all we need?
→ Not really; qubit requirement prohibitive

For a bosonic field,
V lattice sites, occupation number cutoff N → VlogN qubits

$$|\psi\rangle = \sum_K \beta_K |n_{K1} n_{K2} \dots n_{KV}\rangle$$

0, 1, 2, ... N-1

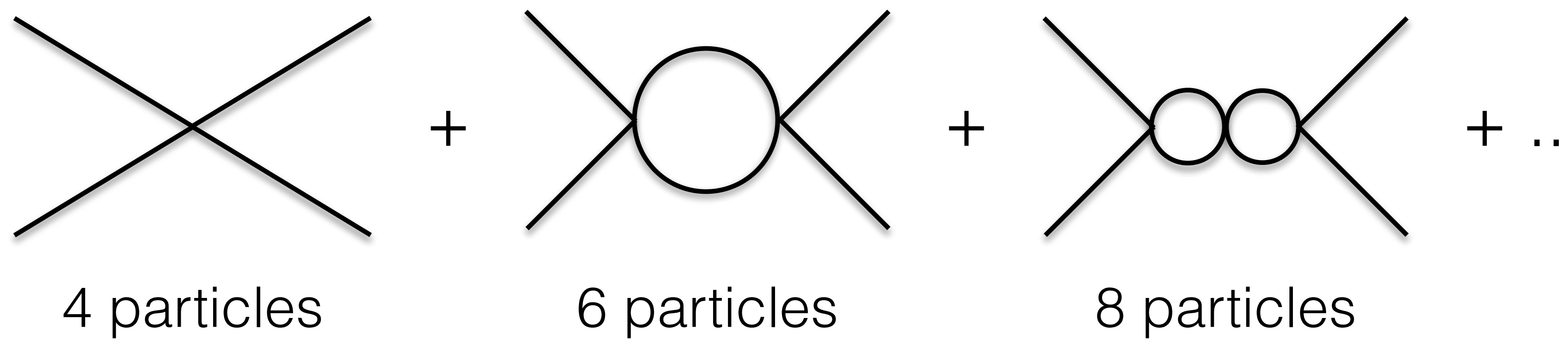
$\boxed{N=2^5,\ V=100^3 \rightarrow \text{VlogN}=5\text{M}}$

Qubit-efficient scattering simulation

In a very very early stage

What if we focus on scattering in the perturbative regime?

$$\langle p_1 p_2 | S | q_1 q_2 \rangle =$$



Regard the problem as a few-body quantum mechanics:

$$|0 \ldots \underset{i}{0\,1\,0} \ldots \underset{j}{0\,1\,0}\ldots\rangle \leftrightarrow \frac{1}{\sqrt{2}}\Big(|p_i\, p_j\rangle + |p_j\, p_i\rangle\Big)$$

Max N total particles, V possible momenta → NlogV qubits

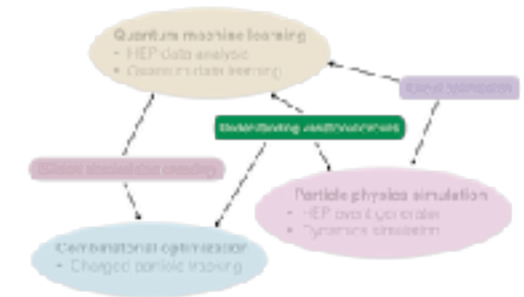
$N=2^5$, $V=100^3$ → NlogV~640

S-matrix = infinite-time evolution
→ HEP event generator from Trotter simulation?

Mode of operation:

- Initialize with incoming particles
- Run a long-time dynamics simulation
- Measure the momenta values → One N-particle final state sampled

VQA cost function landscape



Manuscript in preparation

"Barren plateau":
Gradients of sufficiently deep parametric circuits suppressed exponentially wrt number of qubits[1]

- Known to hold for most common ansatze
- Drawback for real-world applicability of NISQ

We have identified the relation between gradient suppression and

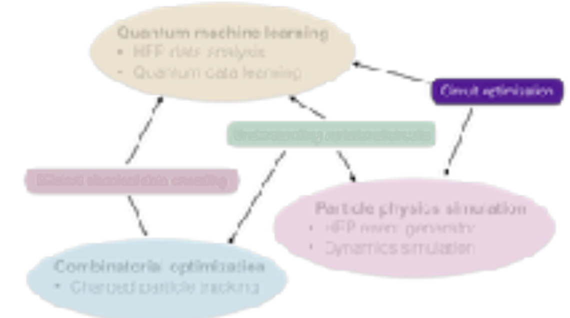
- Ansatz expressibility
- Dimensionality of the ansatz domain

→ Guides the use of VQA in all three thrusts

[1] McLean et al. Nat. Comm. 9, 4812

Circuit optimization

2102.10008



Infinitely many ways to write a circuit for a given algorithm

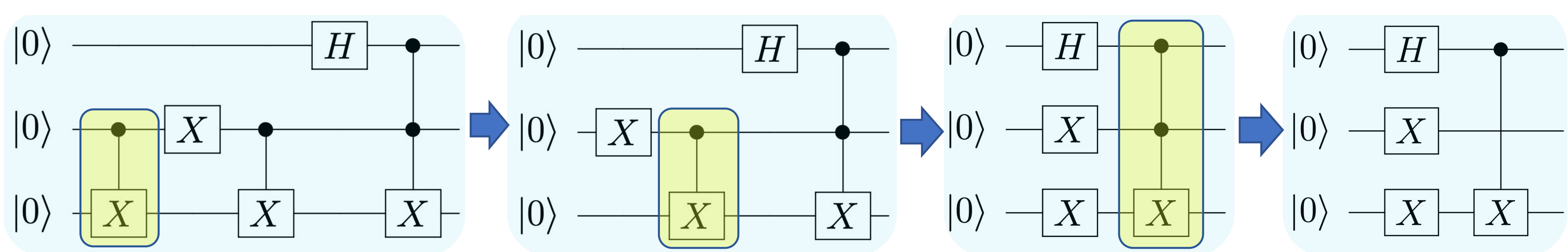
+

NISQ is coherence-time and gate-noise limited

→ Circuit optimization is a crucial technique

AQCEL (Advancing Quantum Circuit by ICEPP and LBNL)
= Initial-state dependent circuit optimization

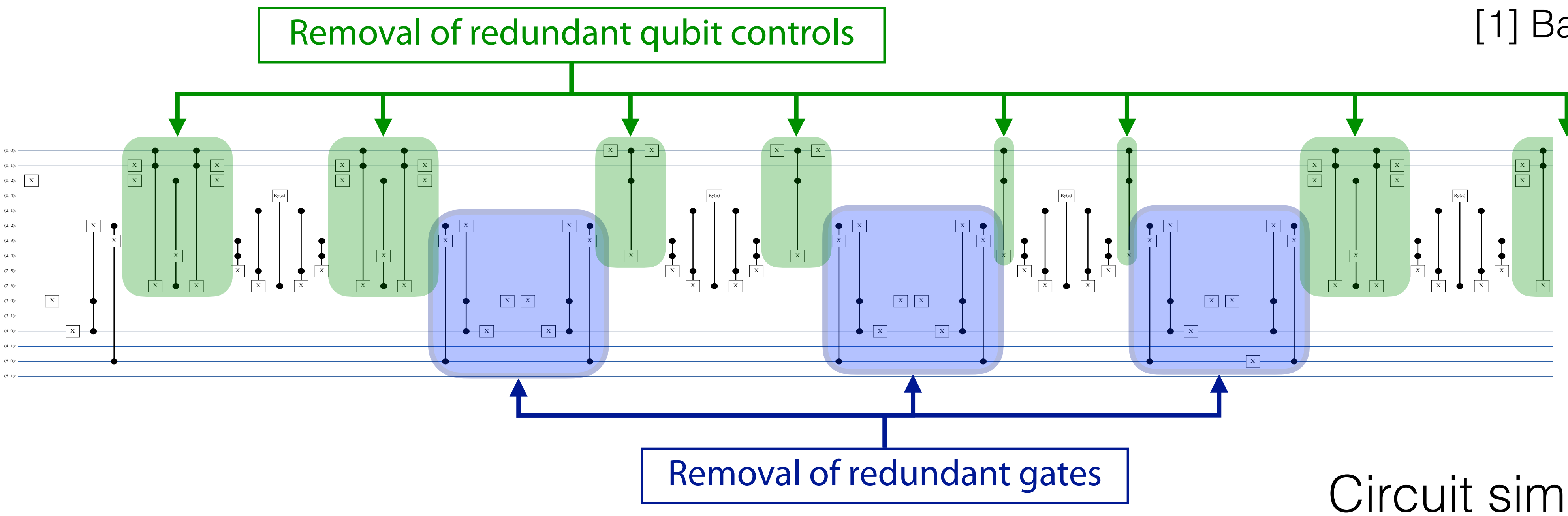
Circuits can be simplified by taking the initial state into account:



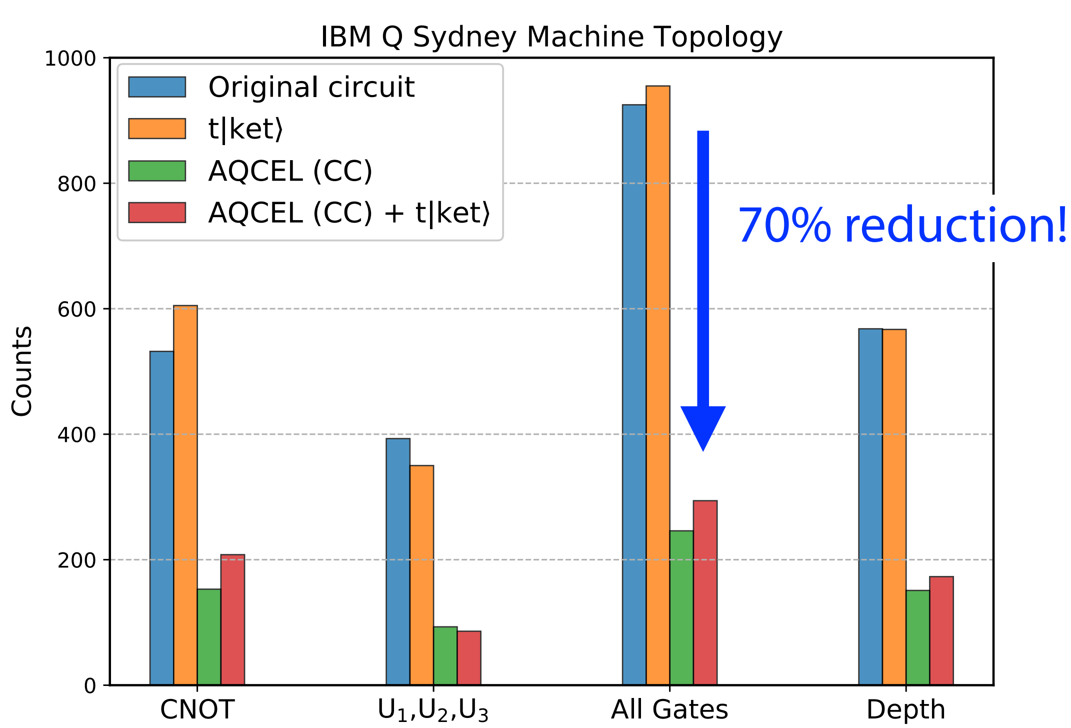
AQCEL cut gate counts by 70%

Benchmarking problem: quantum parton shower[1]

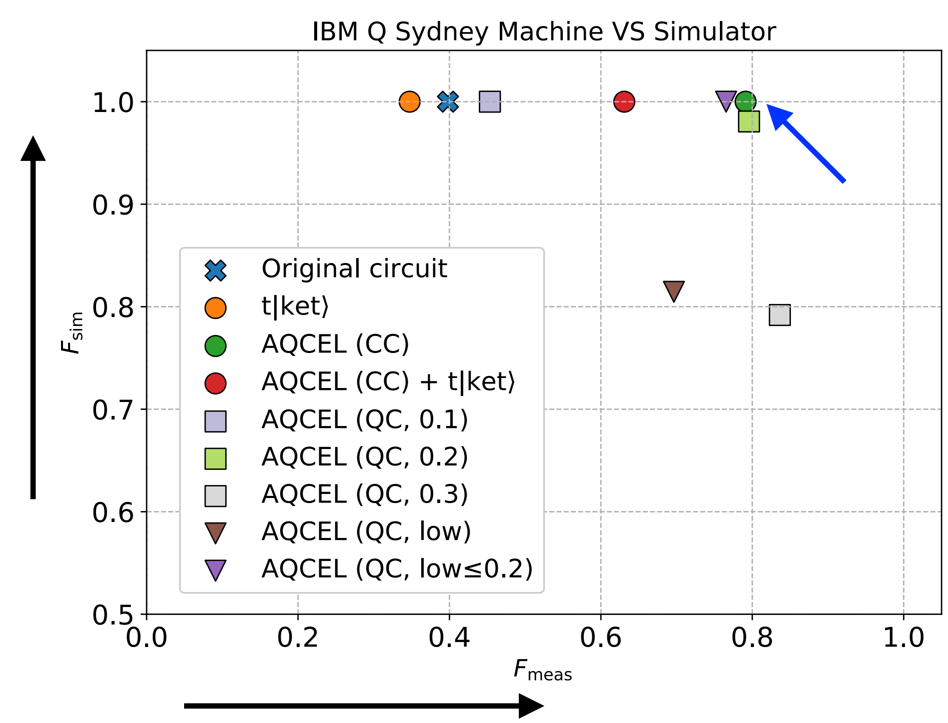
[1] Bauer et al. PRL 126, 062001



Circuit simplified while retaining algorithmic identity



Algorithmic similarity to original circuit



Fidelity of final state evaluated on IBMQ

Collaborators welcome

- We would love to work together with anyone interested in QC application to scientific / nonscientific problems
  - Particle physicist or otherwise
  - After all, why else is this workshop taking place?
- Only introduced HEP-oriented applications in this talk
  - We have a broader portfolio