



Quantum Machine Learning for Collider Physics

Quantum Computing and Machine Learning Workshop 2026,
Shenzhen, August 17-19, 2026

Hideki Okawa (大川英希)

Institute of High Energy Physics, Chinese Academy of Sciences

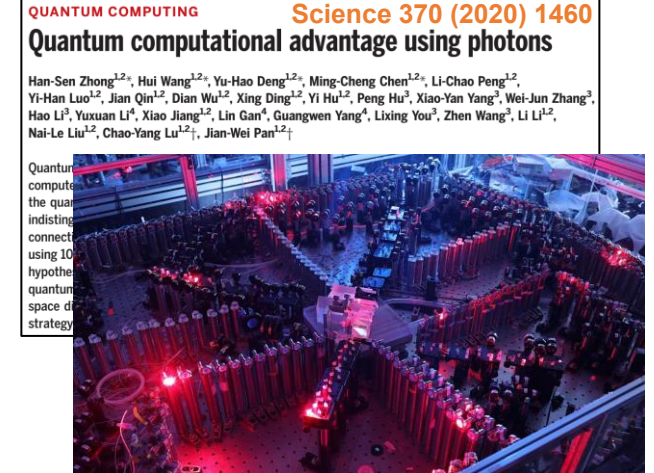
Quantum Supremacy

- 2nd quantum revolution led to the arrival of commercial quantum computers.
- Quantum supremacy was achieved for random state generation in 2019/2020.
- Recent significant speed-up in Willow/Zuchongzhi-3 & surface code implementation → a milestone towards large-scale fault-tolerant quantum computers.
- 2026: Jiuzhang 4.0 achieved significant performance improvement.

Google Sycamore (2019)

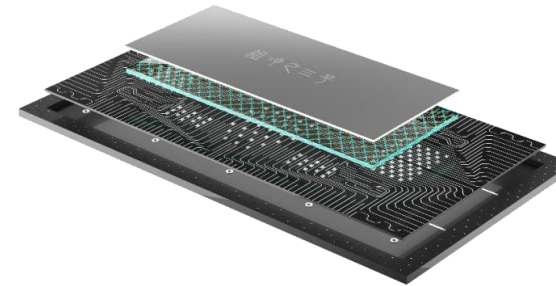


USTC Jiuzhang (2020)

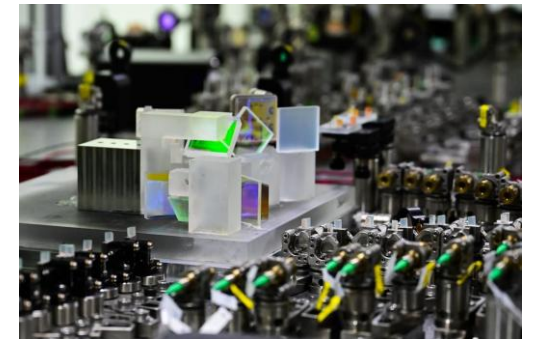


Google AI & collab., Nature 638 (2025) 920

USTC Zuchongzhi 3.0 (2024/2025)



D. Gao et al., PRL 134 (2025) 090601



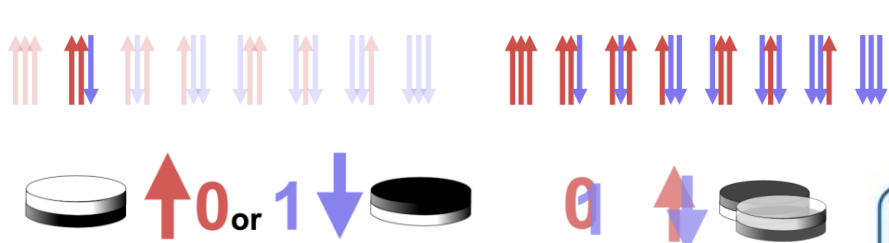
H.-L. Liu et al., Nature 653, 687 (2026)

Quantum Supremacy & Going Beyond

©QunaSys

Classical

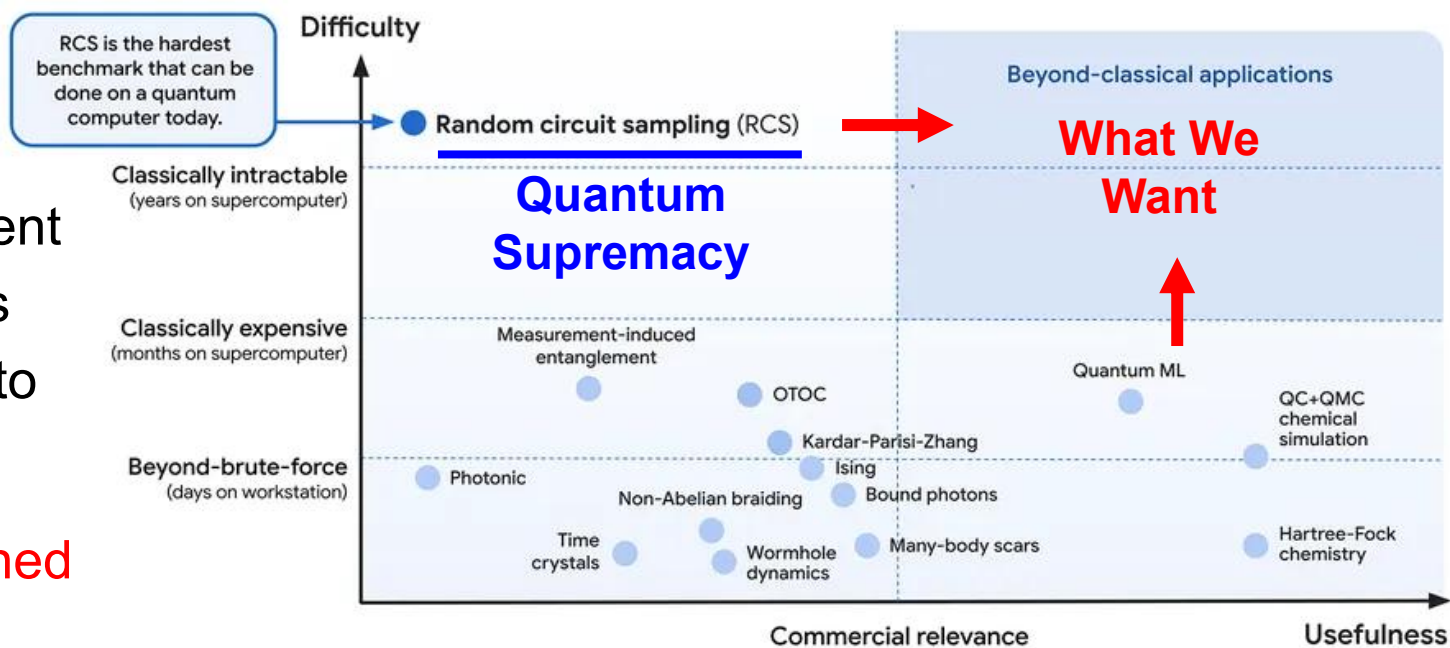
Quantum



Random circuit sampling (RCS): in context

To date, no quantum computer has outperformed a supercomputer on a commercially relevant application. Our latest research is a step towards that direction.

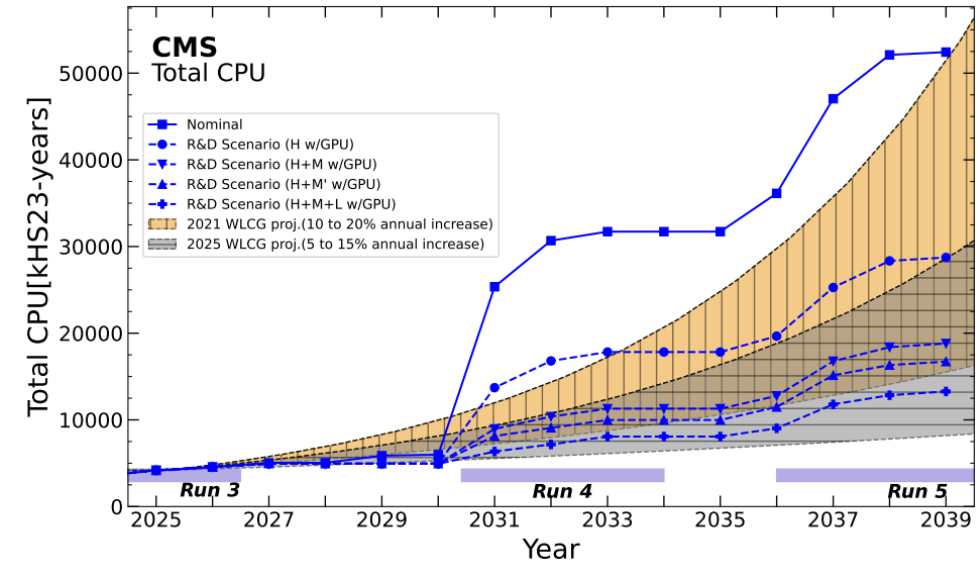
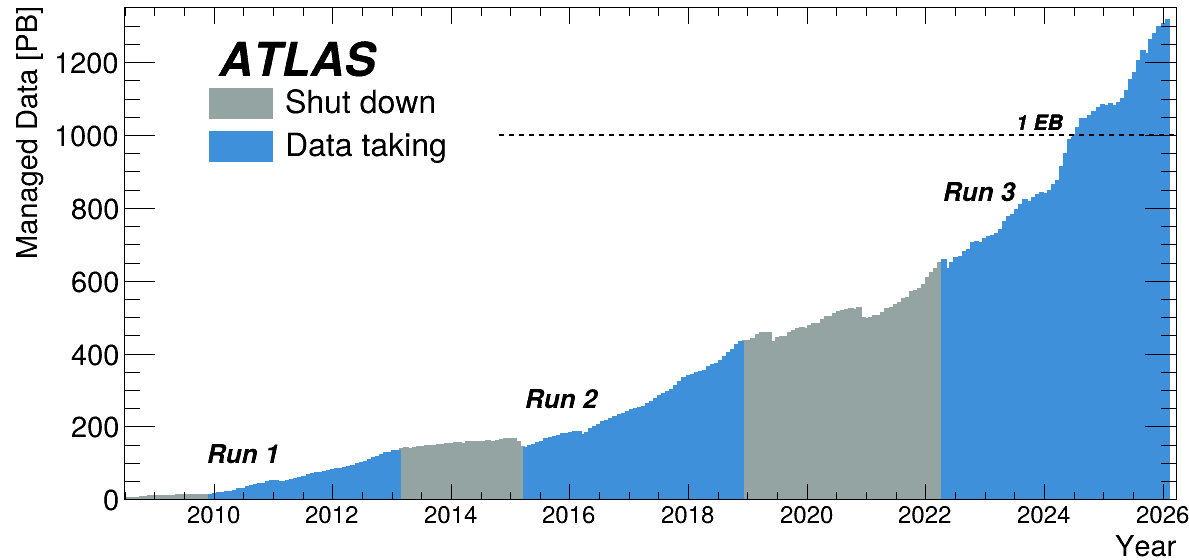
- Through superposition, entanglement & interference, quantum computers can bring in exponential speed-up to some tasks.
- However, we have not yet established practical quantum advantages.



©Google

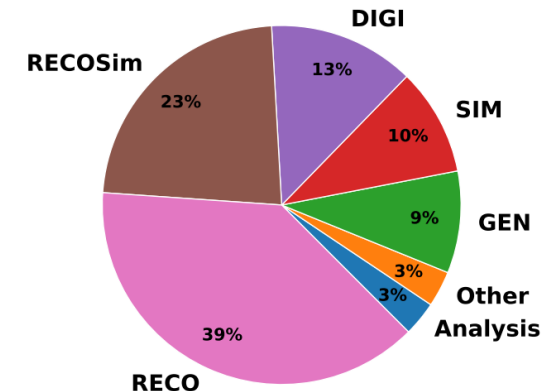
Experimental Challenges at Colliders

CMS, HL-LHC Software/Computing CDR, CERN-LHCC-2026-003 (2026)

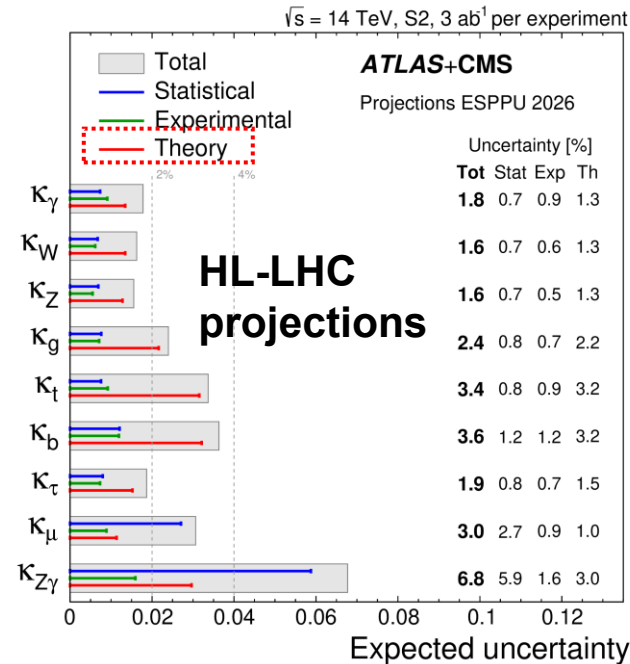
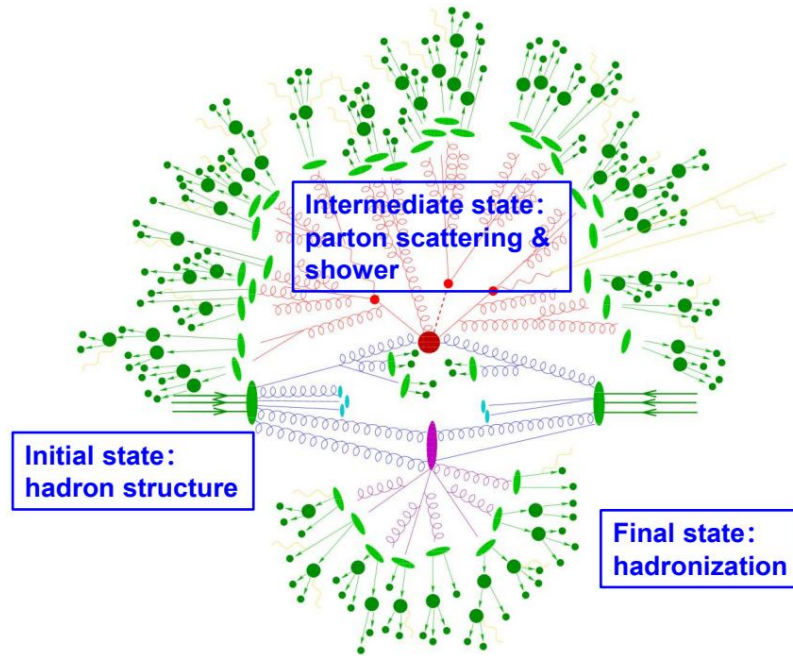


- **LHC has already entered the exabyte era!**
- Computing demands will continue to increase during the High-Luminosity LHC era (>2030). Similar challenges at CEPC, FCC-ee, EIC, etc.
- **CPU demands for reconstruction is particularly enormous.**
- Quantum computing may bring in a paradigm-shifting leap???

CMS
Total CPU HL-LHC (2032/No R&D Improvements) fractions



Theoretical Challenges at Colliders



FCC-ee theoretical requirements

e.g. theoretical work needed to enable extraction of EWPO from measurements (additional work needed for making predictions)

Quantity	Current precision	FCC-ee stat. (syst.) precision	Required theory input	Theory status as of today	Needed theory improvement [†]
m_Z (MeV)	2.0	0.004 (0.1)	non-resonant $e^+e^- \rightarrow f\bar{f}$, initial-state radiation (ISR)	NLO, ISR logarithms up to 6 th order	NNLO for $e^+e^- \rightarrow f\bar{f}$
Γ_Z (MeV)	2.3	0.004 (0.012)			
$\sin^2 \theta_{\text{eff}}^{\ell}$	1.6×10^{-4}	$1.2 (1.2) \times 10^{-6}$			
m_W (MeV)	9.9	0.18 (0.16)	lineshape of $e^+e^- \rightarrow WW$ near threshold	NLO ($e^+e^- \rightarrow 4f$ or EFT framework)	NNLO for $e^+e^- \rightarrow WW$, $W \rightarrow f\bar{f}'$ in EFT setup
HZZ coupling	— *	0.1%	cross section for $e^+e^- \rightarrow ZH$	NLO EW plus partial NNLO QCD/EW	full NNLO EW
m_{top} (MeV)	290	4.2 (4.9)	threshold scan $e^+e^- \rightarrow t\bar{t}$	N ³ LO QCD, NNLO EW, resummations up to NNLL, $\mathcal{O}(30 \text{ MeV})$ scale uncert.	Matching fixed orders with resummations, merging with MC, α_S (input)

[†] The necessary theory calculations mentioned are a minimum baseline; additional partial higher-order contributions may also be required.

* No absolute value for the HZZ coupling can be extracted from the LHC data without additional assumptions.

Guy Wilkinson (LIII IMFP 2026)

- Strong interaction dynamics** is difficult to simulate classically from the first principles: due to non-equilibrium, non-perturbativity, complexity of many-body quantum systems, quantum interference, sign problem, etc.
- Furthermore, we need **higher order calculations for future collider measurements (HL-LHC, CEPC, FCC-ee)**.

Quantum Computing Technologies

H. Okawa, arXiv:2511.16713, invited review for MPLA

Quantum Circuits / Gate-based

- Uses quantum logic gates. Is universal computing.
- Most quantum computers adopt this approach.

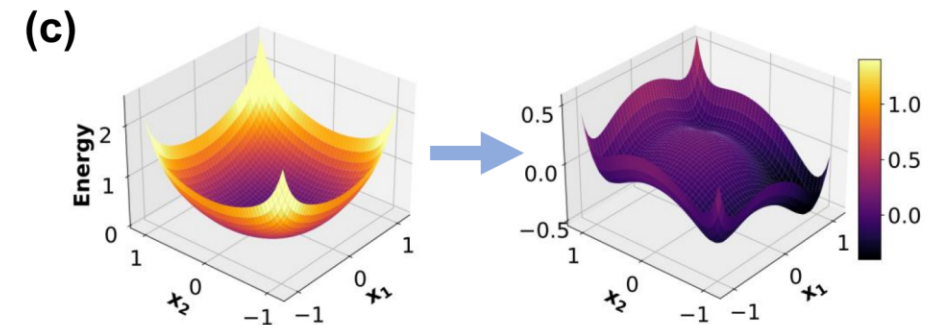
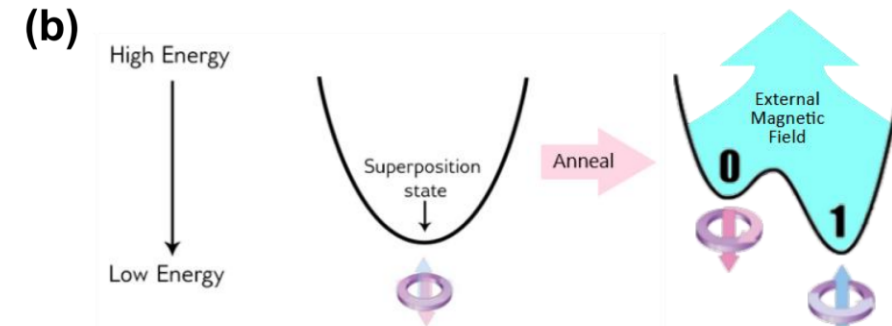
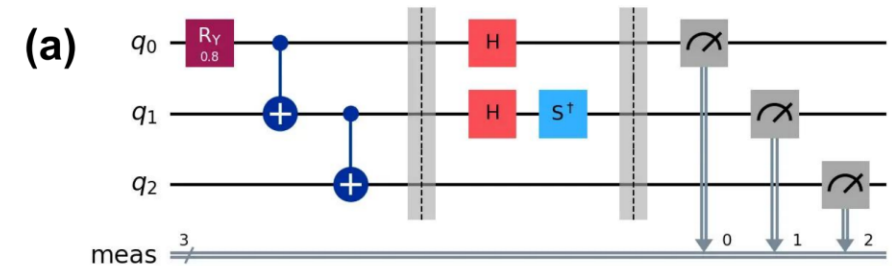
Quantum Annealing

- Uses the adiabatic theorem to seek Hamiltonian ground states.
- Is non-universal, only applicable to optimization problems.

Quantum-inspired

- Classical algorithms inspired by quantum computing concepts: Simulated annealing, simulated bifurcation, tensor networks, etc.

+ Analog quantum computing



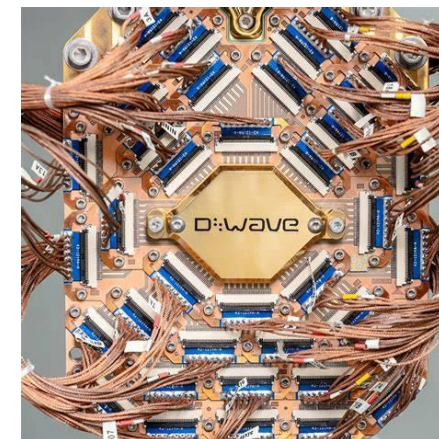
Noisy Intermediate Scale Quantum



USTC Zuchongzhi 3.0



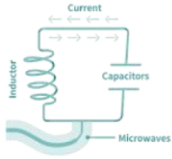
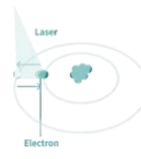
D-Wave Advantage2

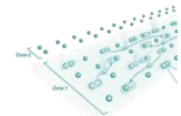
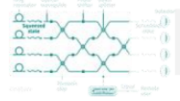


- Now is the era of **Noisy Intermediate Scale Quantum (NISQ)** hardware: **$O(10^2)$ qubits, Error rate $\sim O(10^{-2})$** for superconducting gate machines.
 - Error mitigation is introduced to various hardware. Error correction mechanisms are actively investigated.
- Newest quantum annealers (D-Wave Advantage2) have 4400+ qubits with 20-way connectivity.

World-wide Quantum Computers

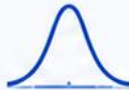
iCV TA&K (Feb. 2026)

Technical Route	Institution	Model	Release Date	Qubit Count / Number of Modes
 Superconducting	IBM	Nighthawk	2025.11	120
	Google	Willow	2024.12	105
	Rigetti Computing	Cepheus-1-36Q	2025.07	36
	QuantWare	Tenor	2023.02	64
	IQM	Crystal 150	2025.11	150
	OQC	OQC Toshiko Gen 1	2023.11	32
	Alice & Bob	Helium 2	2025.09	12
	RIKEN	-	2025.04	256
	USTC, China Telecom Quantum Group, QuantumCTek	Zuchongzhi 3	2024.12	105
	USTC, China Telecom Quantum Group, QuantumCTek	Tianyan 287	2025.11	287
	BAQIS	Yunmeng	2024.04	156
	Origin Quantum	Origin Wukong	2024.01	72
	IOP,CAS、BAQIS	Zhuangzi	2023.08	43
	SpinQ	Shaowei	2025.11	103
	Quantinuum	Helios	2025.11	98
 Trapped Ion	IonQ	Tempo	2025.9	100
	AQT	PINE	2023.02	30
	HYQ	HYQ-B100	2024	100
	Unitary Quantum	UQM1	2024.09	30

 Neutral Atom	QuEra Computing	Gemini	2025.12	260
	Atom Computing	AC1000	2023.01	1200+
	Pasqal	Orion Gamma	2025	140+
	CAS COLD ATOM	Hanyuan-1	2024.06	100+
	USTC	Jiuzhang-4	2025.08	3050
 Photonic Quantum	Xanadu	Aurora	2025.1	12
	QCi	Dirac-3	2024.03	949(Number of Variables)
	QC82	-	2021	40
	Silicon Extreme	-	2024.02	32
	PsiQuantum	Omega	2025.2	-
	ORCA Computing	ORCA PT 2	2024.10	90
	TuringQ	TuringQ Gen2	2025.06	-
 Semiconductor	Quantum Motion	-	2025.9	-
	Intel	Tunnel Falls	2023.6	12
	Equal1	UnityQ	2025	6
	Silicon Quantum Computing	--	2025.11-	11
 Topology	Microsoft	Majorana 1	2025.2	8

$O(10^2)$ -qubit hardware is emerging with various technologies across the globe.

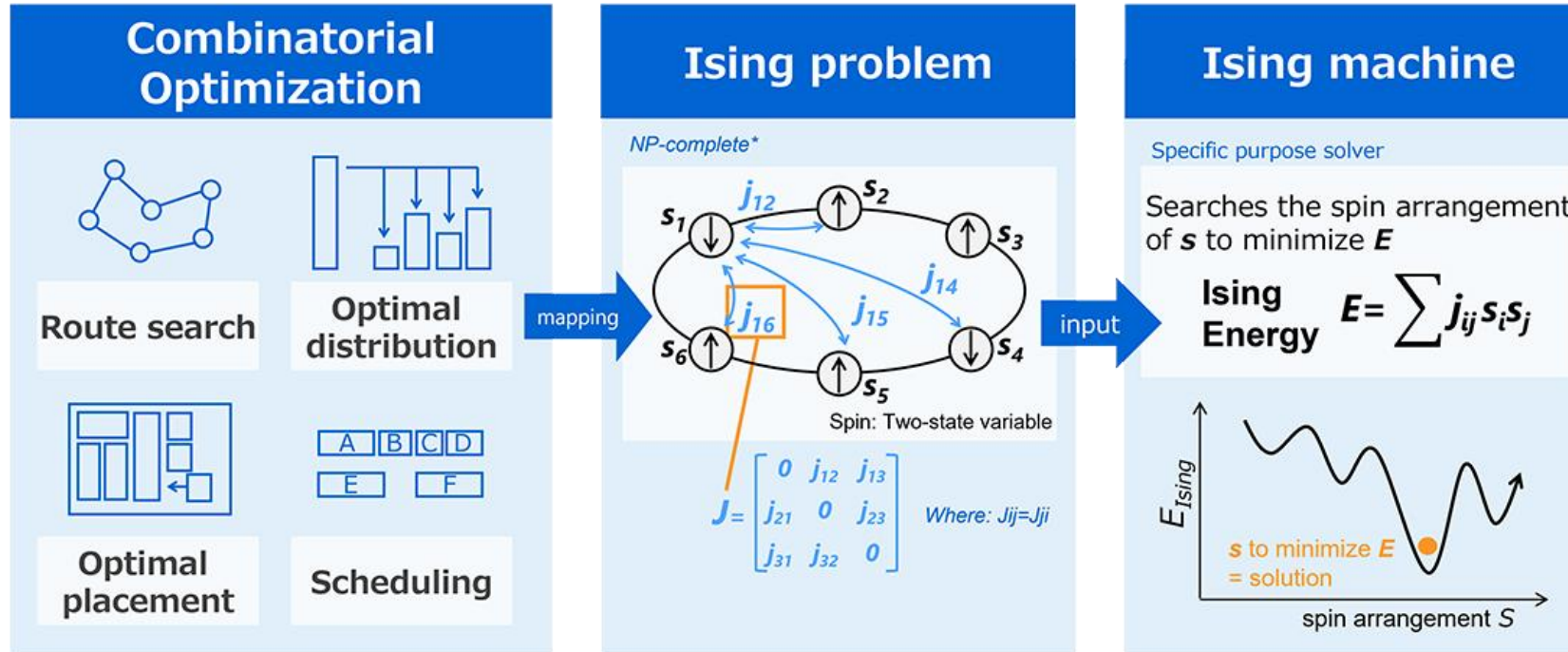
What is Quantum Computing Good At?

1	SIMULATING QUANTUM SYSTEMS		Modeling molecules and materials at the quantum level (e.g., electronic structure problems) that are intractable for classical computers.	 Quantum computers naturally encode quantum states, allowing efficient simulation that scales exponentially better .	→ theoretical applications
2	UNSTRUCTURED SEARCH (Grover's Algorithm)		Searching an unsorted database of N items.	 Finds a solution in $O(\sqrt{N})$ queries vs. $O(N)$ classically (quadratic speedup).	
3	QUANTUM OPTIMIZATION		Solving hard optimization problems (e.g., scheduling, routing, portfolio optimization, Max-Cut).	 Quantum algorithms and heuristics can explore solution spaces more efficiently and escape local optima.	
4	SOLVING LINEAR ALGEBRA PROBLEMS (HHL Algorithm)	$\begin{bmatrix} 1 & 0 & \dots \\ 0 & 1 & \dots \\ \vdots & \dots & \dots \end{bmatrix}$	Solving linear systems $Ax = b$ of equations, a core subroutine in many scientific and machine learning applications.	$Ax = b$ HHL and related algorithms can solve certain linear systems exponentially faster (in ideal cases) than classical methods.	
5	SAMPLING		Sampling from complex probability distributions that are hard to sample from classically.	 Quantum computers can sample from certain distributions more efficiently , with applications in physics, machine learning, and statistics.	

Excluding items irrelevant to HEP (e.g. encryption)

Quantum Optimization

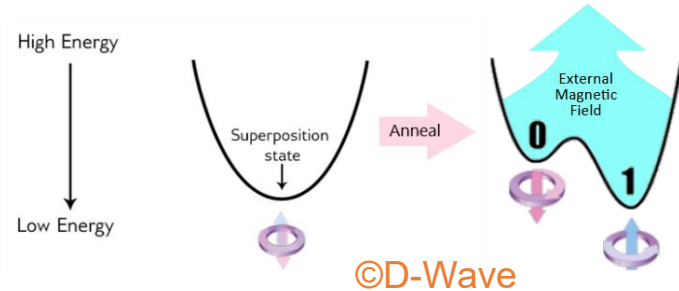
QUBO: 0,1 binaries
Ising: ± 1 spins



- Many complicated problems can be formulated as Ising (spin glass) or QUBO Hamiltonian.
- We design the Hamiltonian so that the ground state corresponds to the answer.
- e.g. Track & jet reconstruction can also be formulated as such problems (Typical numbers of qubits required: $O(10^{5-6})$ [track], $O(10^{2-3})$ [jet]).

3 Classes of Ising Problem Solvers

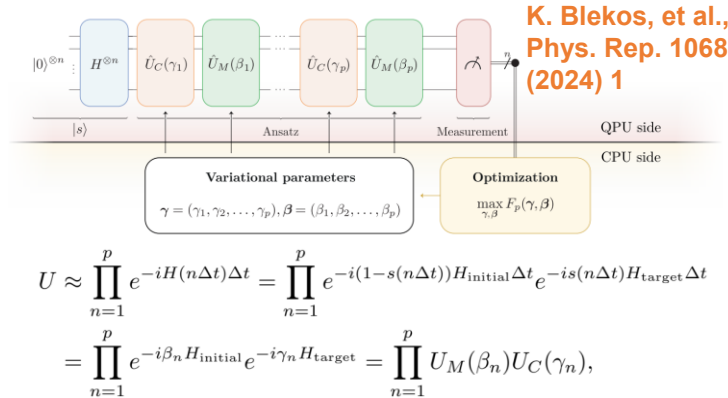
Quantum Annealing (QA)



$$H(s) = A(s)H_{\text{initial}} + B(s)H_{\text{target}}$$

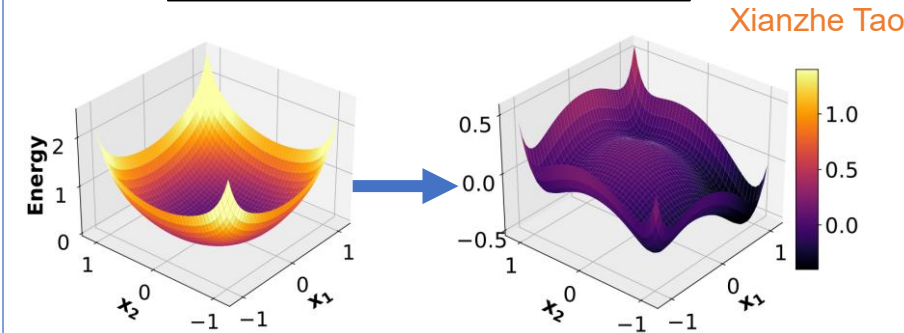
- Hamiltonian is slowly modified from a symmetric initial form to the target Hamiltonian describing the Ising problem.
- Quantum adiabatic theorem supports the success of obtaining the ground state.
- **Quantum tunneling** helps avoid local minima.

Quantum Circuits



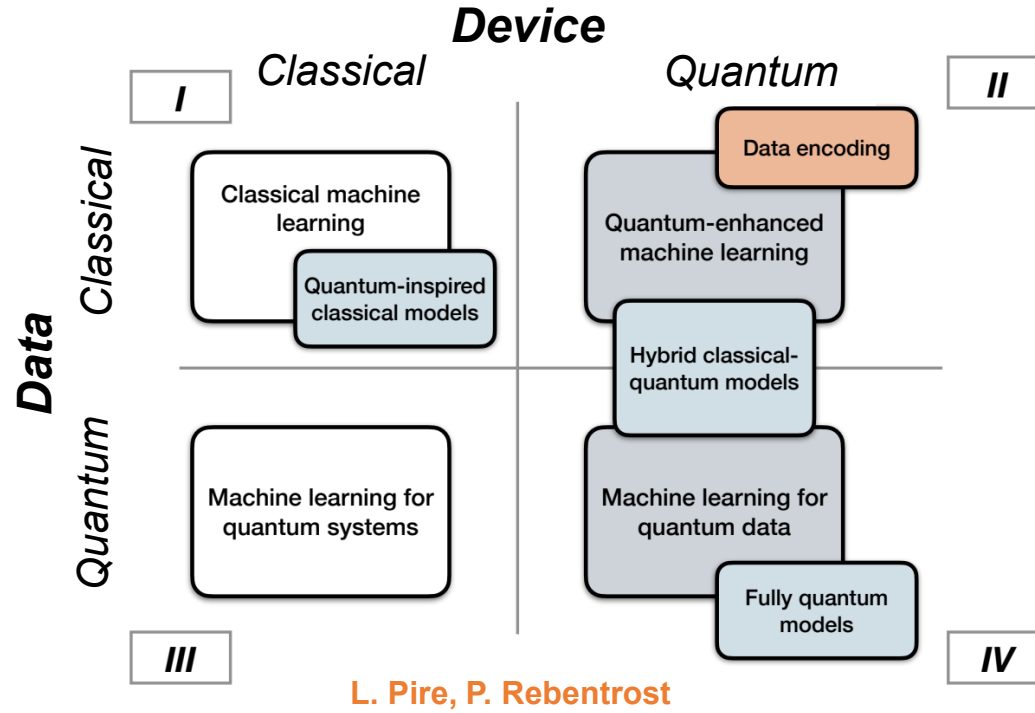
- **Quantum Approximate Optimization Algorithm (QAOA)** mimics quantum annealing with Trotterization.
- Imaginary Hamiltonian variational ansatz (iHVA) & Imaginary Time Evolution-Mimicking Circuit (ITEMC) overcome some known bottlenecks of QAOA.

Quantum-Inspired

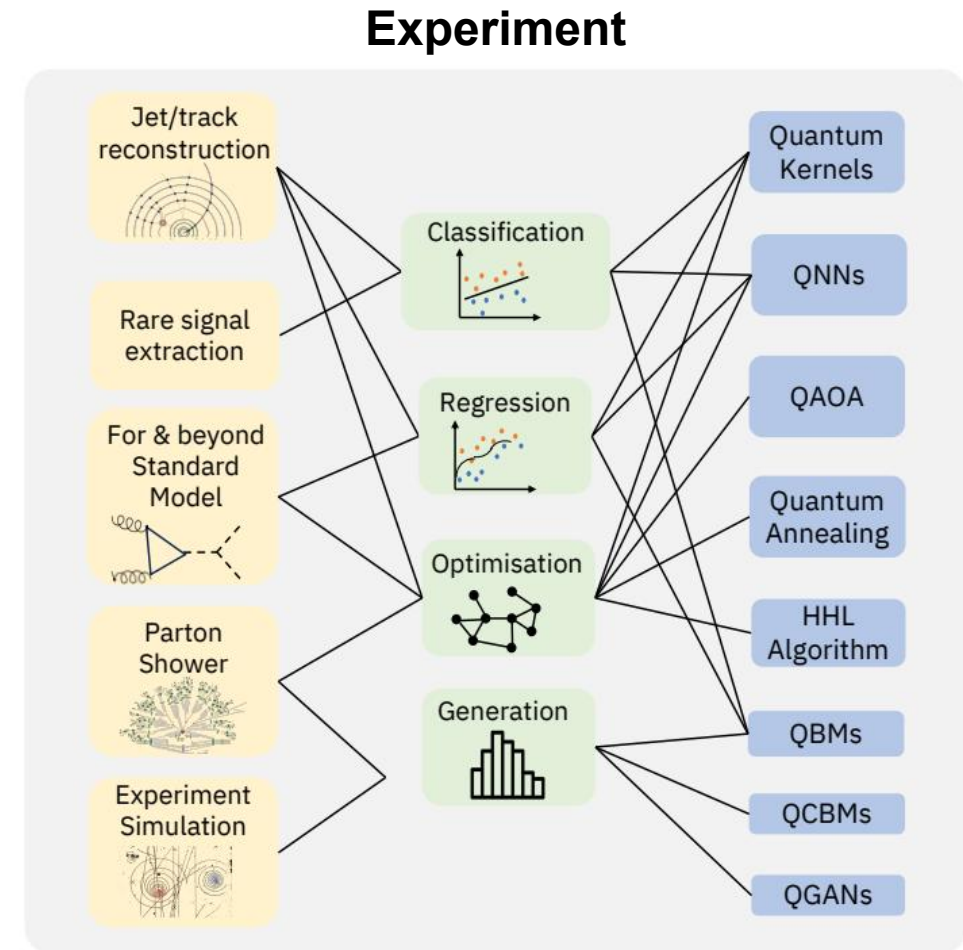


- Quantum-inspired runs on classical hardware with algorithms inspired by QC.
- **Simulated annealing (SA)** uses random moves in the solution space to search for the ground state.
- **Simulated bifurcation (SB) emulates quantum adiabatic evolution of Kerr-nonlinear parametric oscillators. It significantly outperforms SA.**

Quantum Machine Learning & HEP



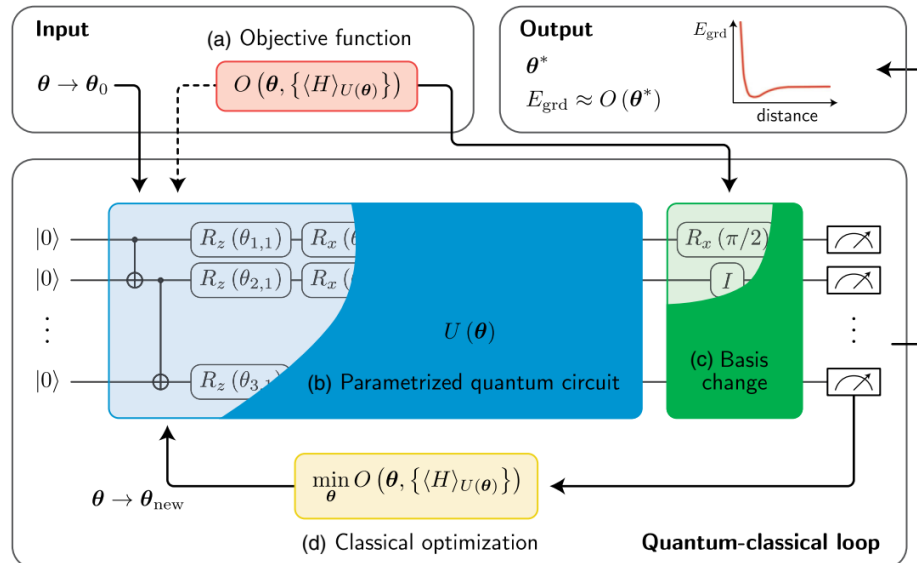
- Applications of quantum machine learning have been investigated for all components of experimental workflow with various quantum technologies (i.e. quantum gates, quantum annealing, quantum-inspired, etc.)



Quantum Supervised Learning

Variational quantum algorithms (hybrid)

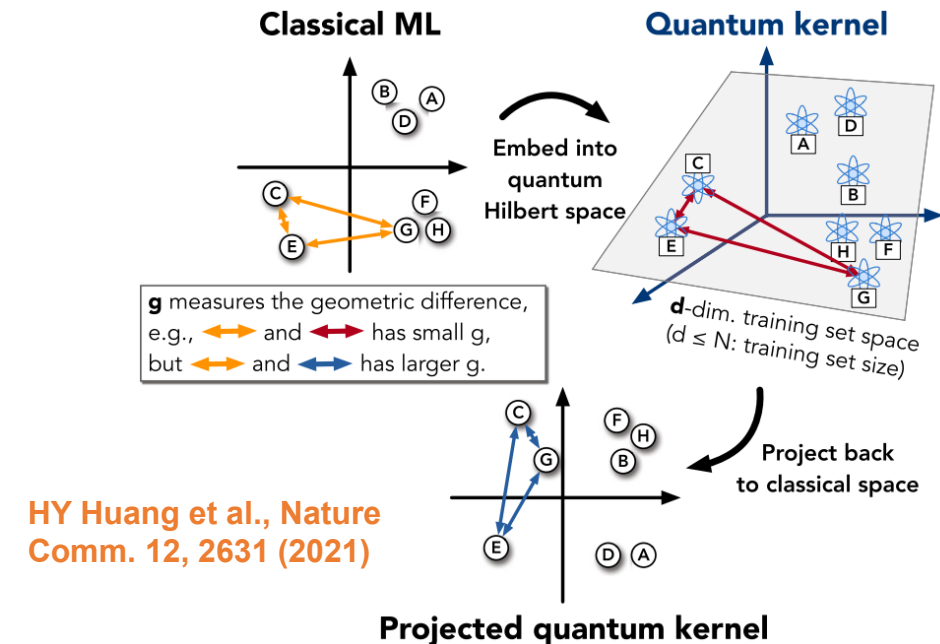
- Use variational quantum circuit, but update parameters with a classical optimizer.



K. Bharti et al., Rev. Mod. Phys. 94, 015004 (2022)

Quantum kernel methods

- Embed feature map into quantum kernel $\rightarrow$ using rich Hilbert space

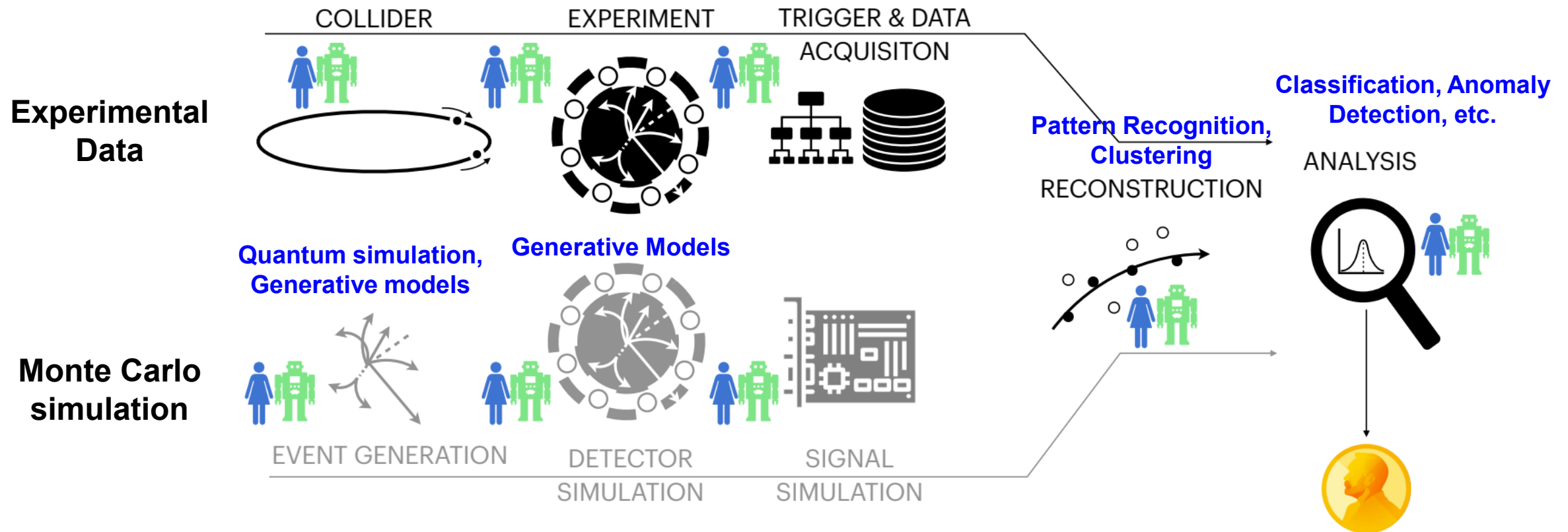


Quantum-annealing-based

- Map machine learning into optimization problems (QBoost, QAML, QAML-Z etc.)

Experimental Workflow at Colliders

Credits: Andreas Salzburger

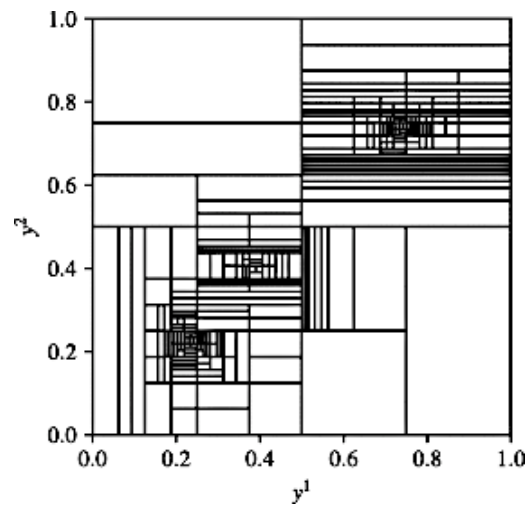


- **All steps require a significant amount of computing resources!**
- **State-of-the-art AI is currently being introduced/considered at all levels.**
- **Can we introduce quantum computing to these tasks?**

Event Generation

Multidimensional numerical integration is a core ingredient of calculating multiloop Feynman digrams

Lepage, J. Comput. Phys. 27 (1978) 192 Lepage, J. Comput. Phys. 439 (2021) 110386

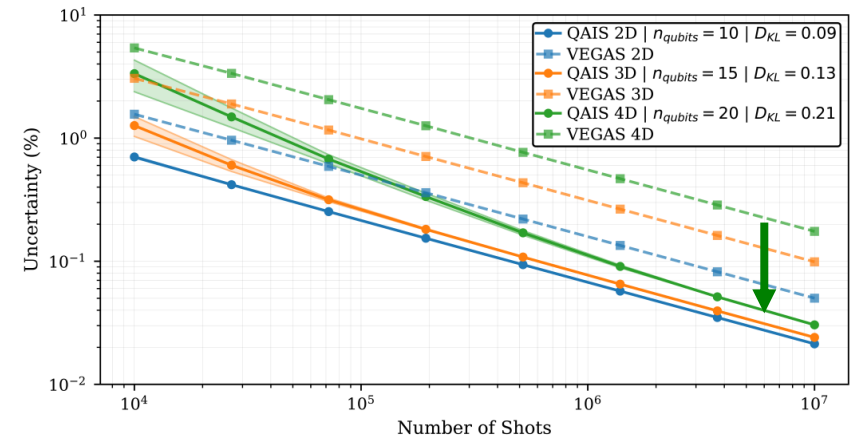
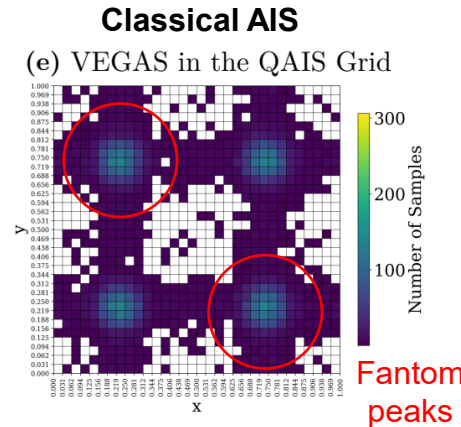
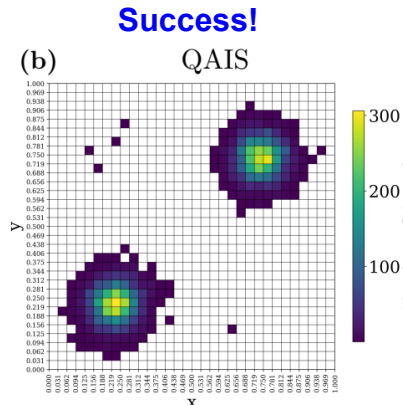
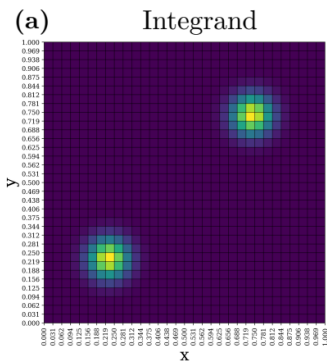


$$\int_{\Omega} f(x) dx \equiv \int_{[0,1]^d} J(y) f(x(y)) dy$$

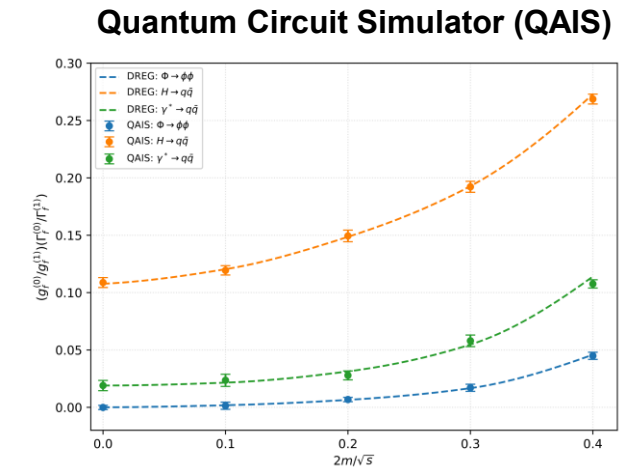
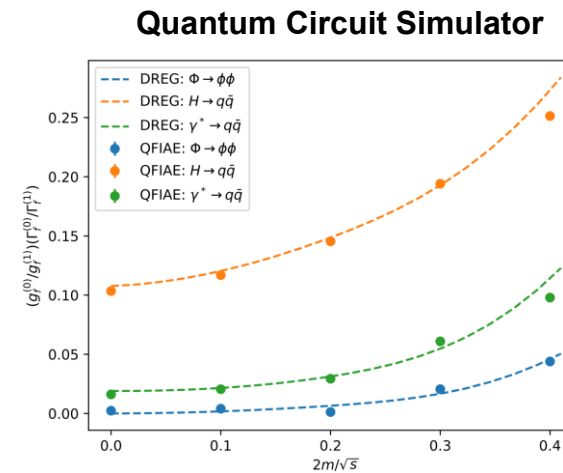
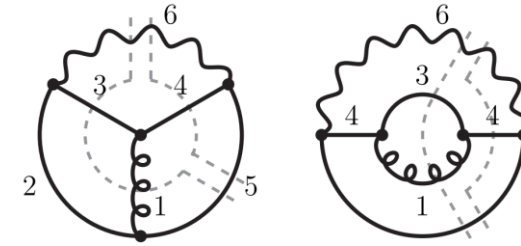
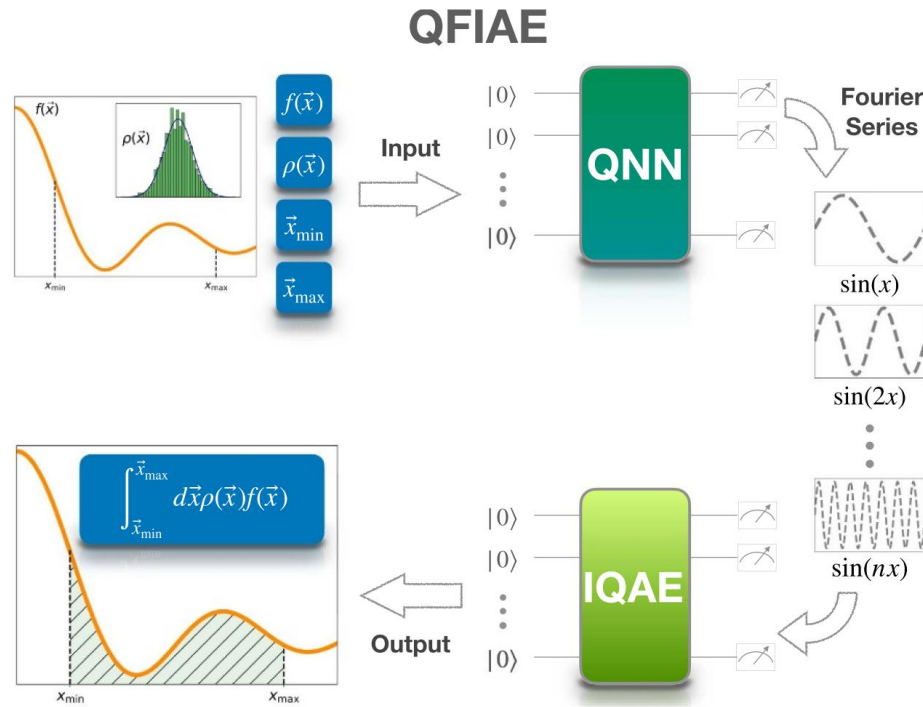
→

$$I_{MC}^{(VEGAS)} = \frac{1}{N} \sum_{i=1}^N J(y_i) f(x(y_i))$$

- Adaptive Importance Sampling (AIS) adapts variable-width grids to concentrate samples in regions of high variance, but suffers from phantom (fake) peaks.
- Quantum AIS (QAIS) uses PQC to encode a multidimensional PDF & can **allocate samples efficiently in the integration domain.**



Decay Rates at NLO

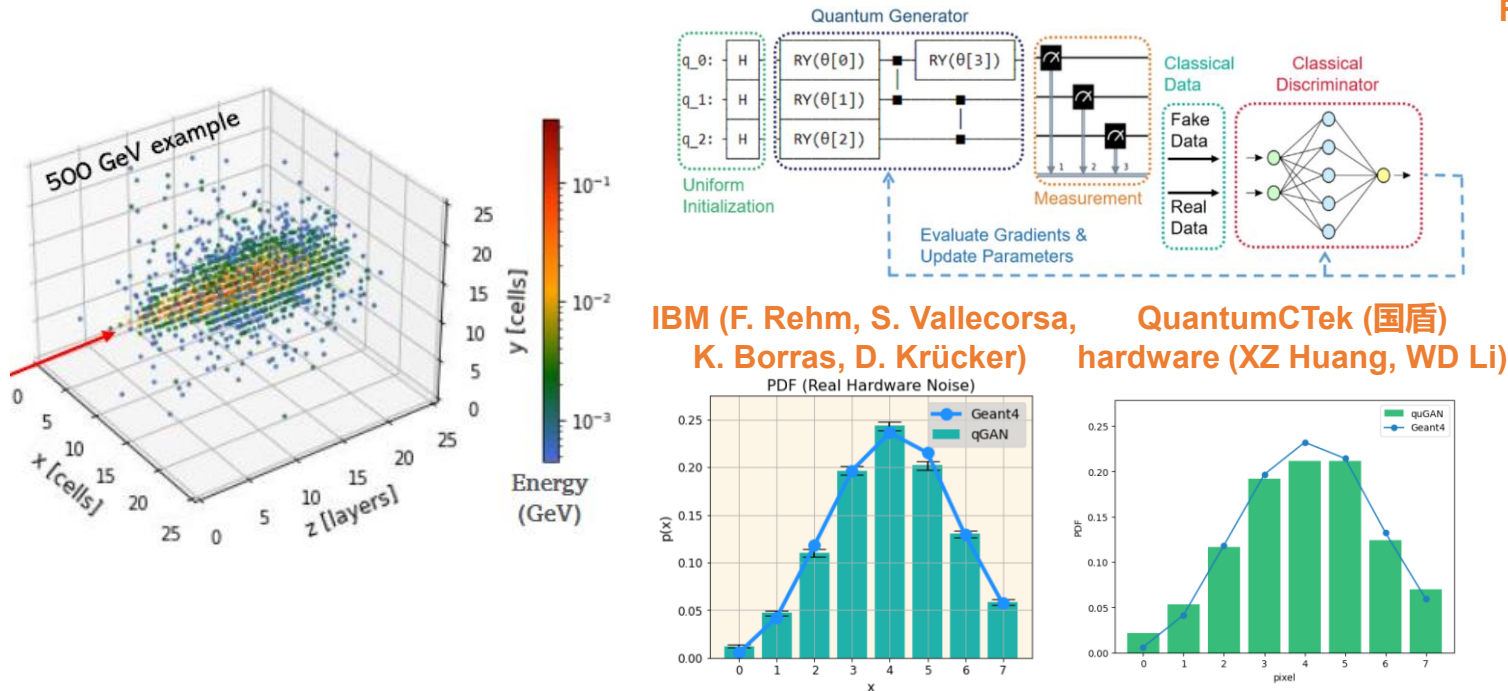


Consistent predictions as the exact analytic results

1. QFIAE: QNN decomposes the target function into Fourier series, then quantum integration follows.
 2. Loop-Tree Duality (LTD) causal unitary enables a unified treatment of loop and tree-level contributions.
- **1st quantum computation of a total decay rate at second-order in perturbative QFT.**

Detector Simulation

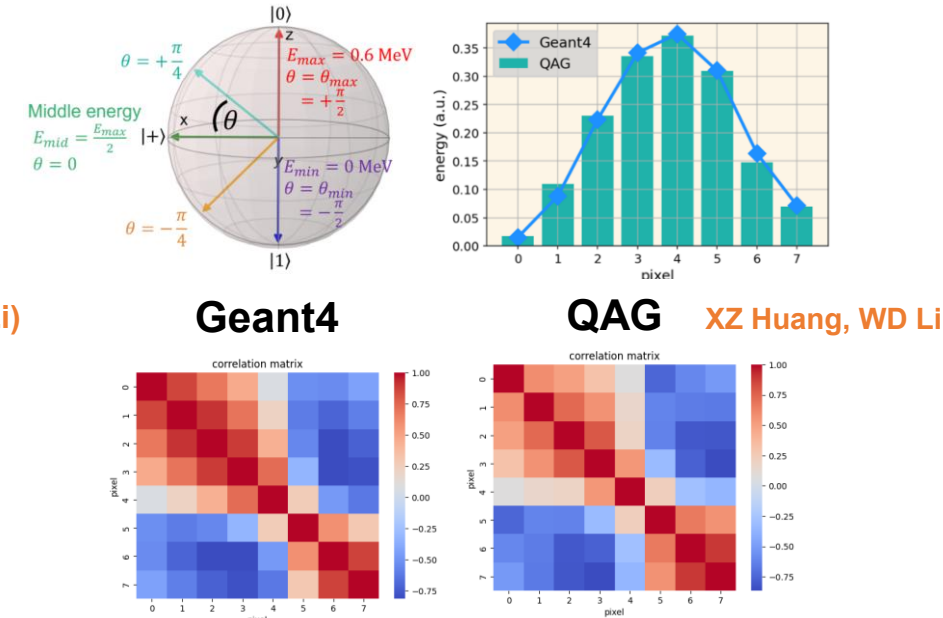
Quantum-classical hybrid GAN



IBM (F. Rehm, S. Vallecorsa, K. Borras, D. Krücker) QuantumCTek (国盾) hardware (XZ Huang, WD Li)

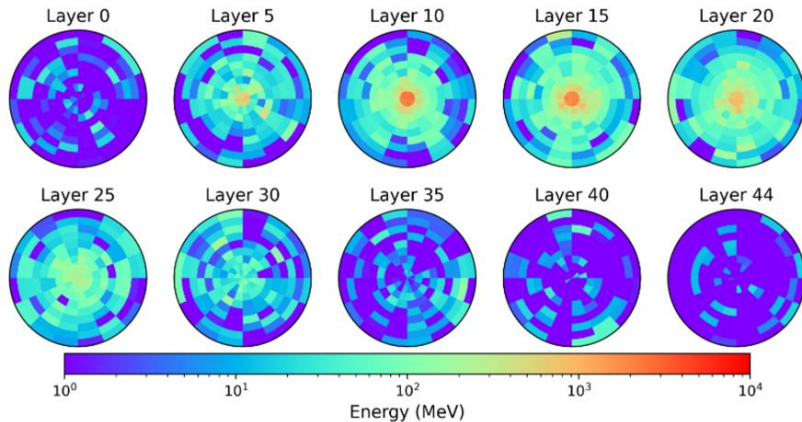
Full Quantum (e.g. QAG)

F Rehm et al., Quantum Sci. Technol. 9 015009 (2023)



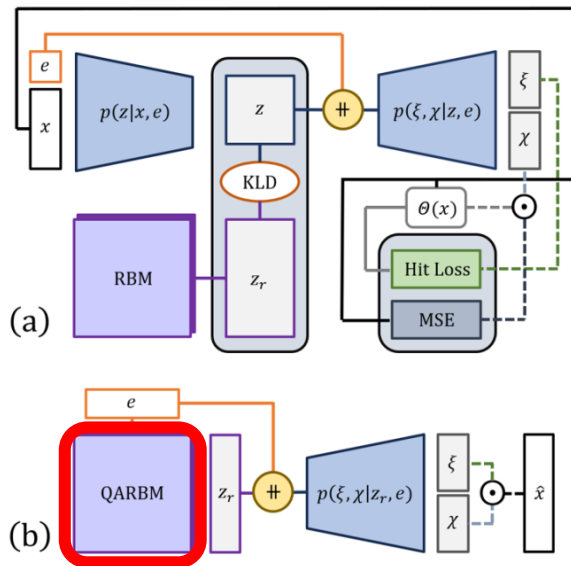
- **Simulating particle shower development in calorimeter is very CPU-consuming.** Classical generative AI has been intensively introduced (GAN, VAE, diffusion etc.)
- Two strategies: (1) quantum-classical hybrid / quantum-assisted, (2) fully quantum.

Quantum-Annealing-Assisted VAE



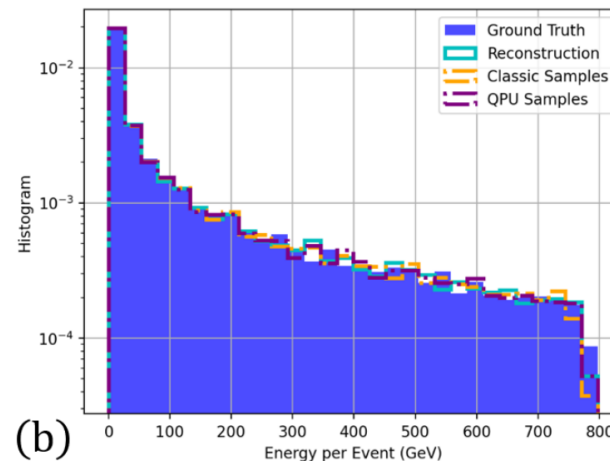
Quantum-assisted workflow:

1. **[Classical]** Conditioned Restricted Boltzmann Machine (RBM) is trained to learn the representations compressed by the encoder.
2. **[Quantum]** Classically trained RBM is loaded onto D-Wave Advantage quantum annealer.
3. **[Classical]** Decoder generates events from quantum-annealing RBM sampling.



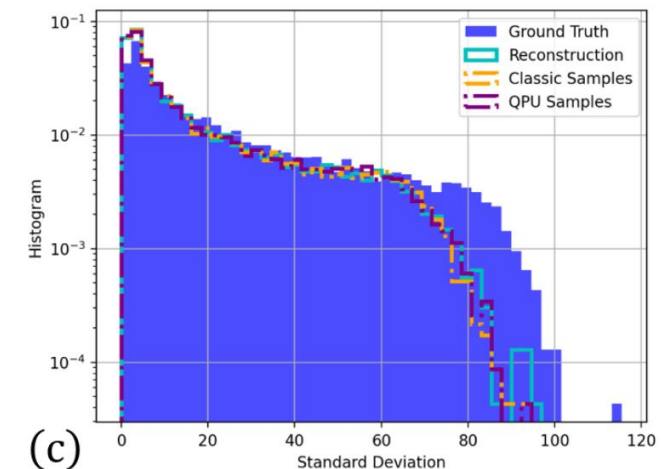
Quantum Annealing

Hideki Okawa



(b)

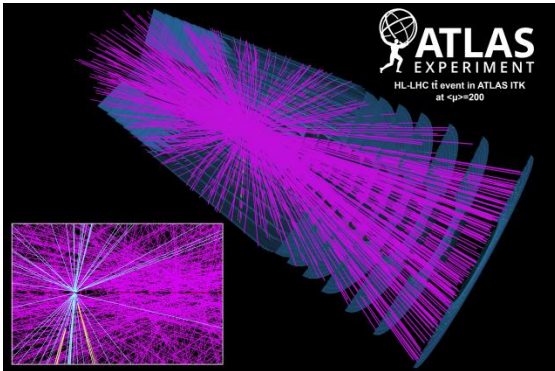
QCML Workshop 2026



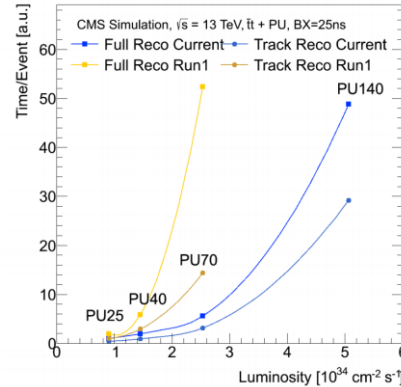
(c)

Reconstruction

Track reconstruction

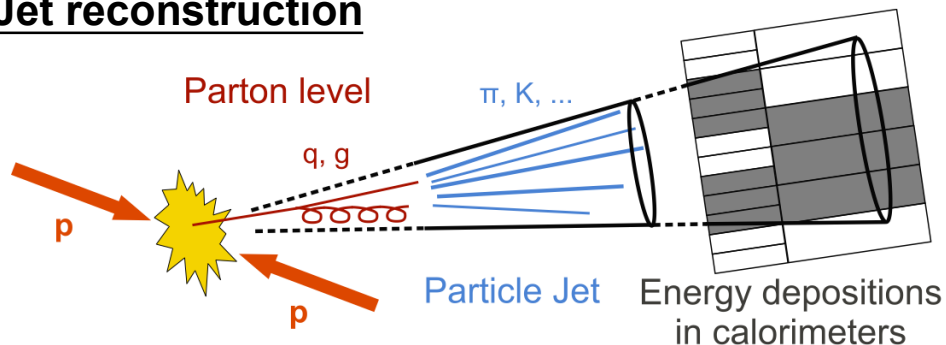


<https://cds.cern.ch/record/1966040>



	Run 1	Run 2	HL-LHC
μ	21	40	150-200
Tracks	~280	~600	~7-10k

Jet reconstruction

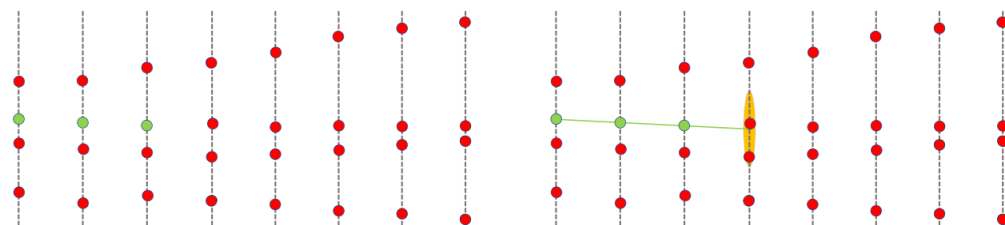


- The most CPU-expensive task at HL-LHC.
- Two classes of algorithms exist for both track & jet reconstruction.
- **Iterative:** e.g. Combined Kalman filter (tracking), sequential jet clustering (k_t , anti- k_t , etc.)
 - Quantum version often uses **Grover search algorithm**, which **requires quantum associative memory (QuAM)**.
- **Global:** e.g. Hough transform, XCone jet clustering
 - Quantum versions can be defined as **combinatorial optimization (= Ising/QUBO) problems**.

Track Reconstruction (Iterative)

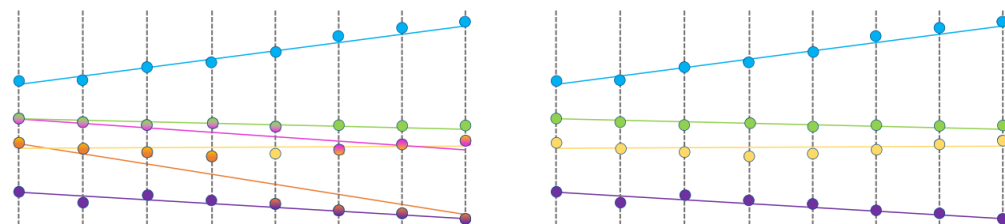
D. Magano et al., PRD 105 (2022) 7, 076012

C Brown et al., Front. Artif. Intell. 7 (2024) 1339785



(a) Seeding

(b) Track building

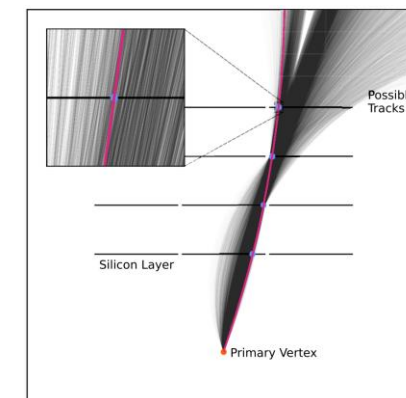
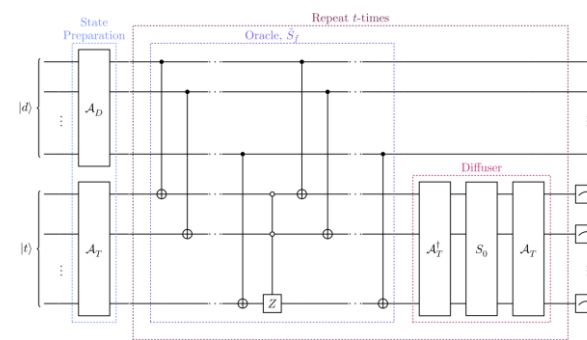


(c) Cleaning

(d) Selection

Tracking stages	Input size	Output size	Classical complexity	Quantum complexity
Seeding	$O(n)$	k_{seed}	$O(n^c)$	$\tilde{O}(\sqrt{k_{\text{seed}} \cdot n^c})$
Track Building	$k_{\text{seed}} + O(n)$	k_{cand}	$O(k_{\text{seed}} \cdot n)$	$\tilde{O}(k_{\text{seed}} \cdot \sqrt{n})$
Cleaning (original)	k_{cand}	$O(k_{\text{cand}})$	$O(k_{\text{cand}}^2)$	—
Cleaning (improved)	k_{cand}	$O(k_{\text{cand}})$	$\tilde{O}(k_{\text{cand}})$	—
Selection	$O(k_{\text{cand}})$	$O(k_{\text{cand}})$	$O(k_{\text{cand}})$	—
Full Reconstruction	n	$O(n^c)$	$O(n^{c+1})$	$\tilde{O}(n^{c+0.5})$
Full Reconstruction with $O(n)$ reconstructed tracks	n	$O(n)$	$O(n^{c+1})$	$\tilde{O}(n^{(c+3)/2})$

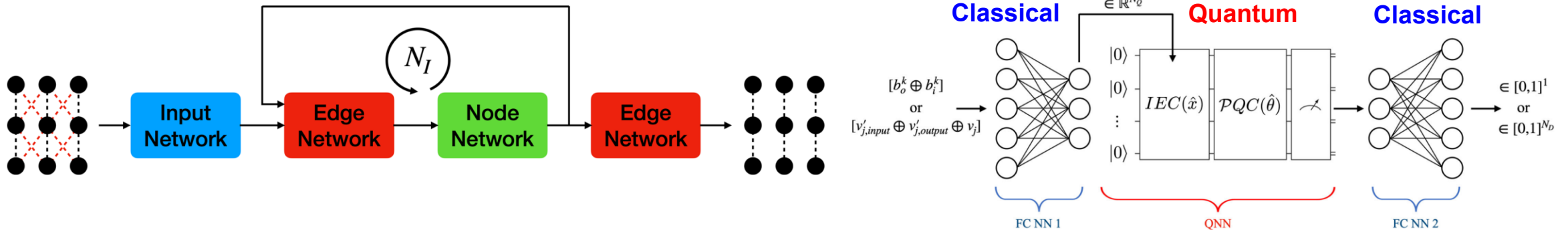
Generalized Grover search
(Quantum Amplitude Amplification)



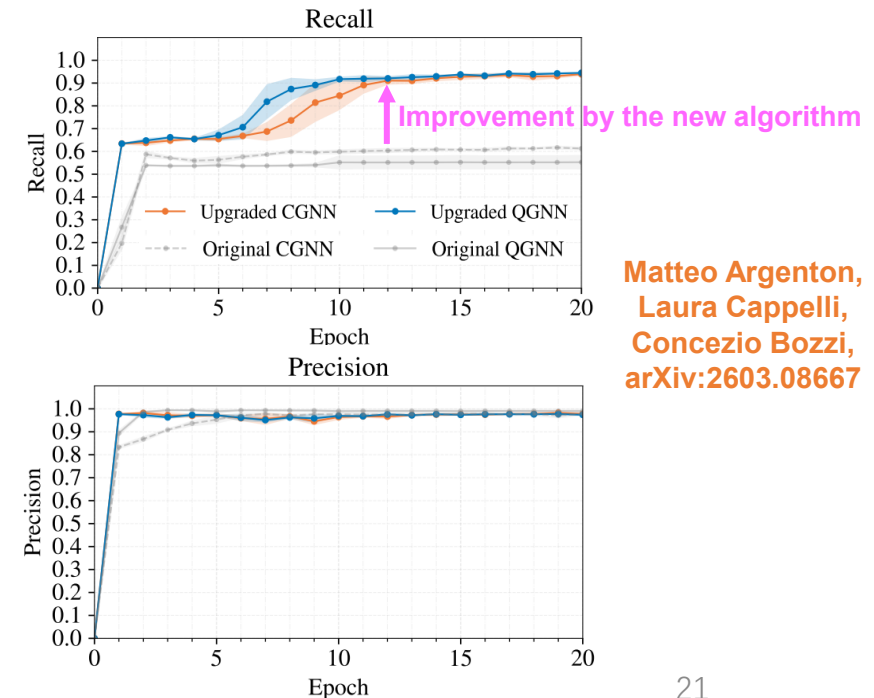
- D. Magano et al.: Due to the lack of QuAM, conceptual complexity analysis was performed. **Grover search reduces complexity of seeding & track building in square root.**
- C. Brown et al.: **a novel oracle design with a generalized Grover search** was developed & simple toy model was used for demonstration.

Track Reconstruction (Global): QGNN

C. Tüysüz et al., Quantum Mach. Intell. 3, 29 (2021)

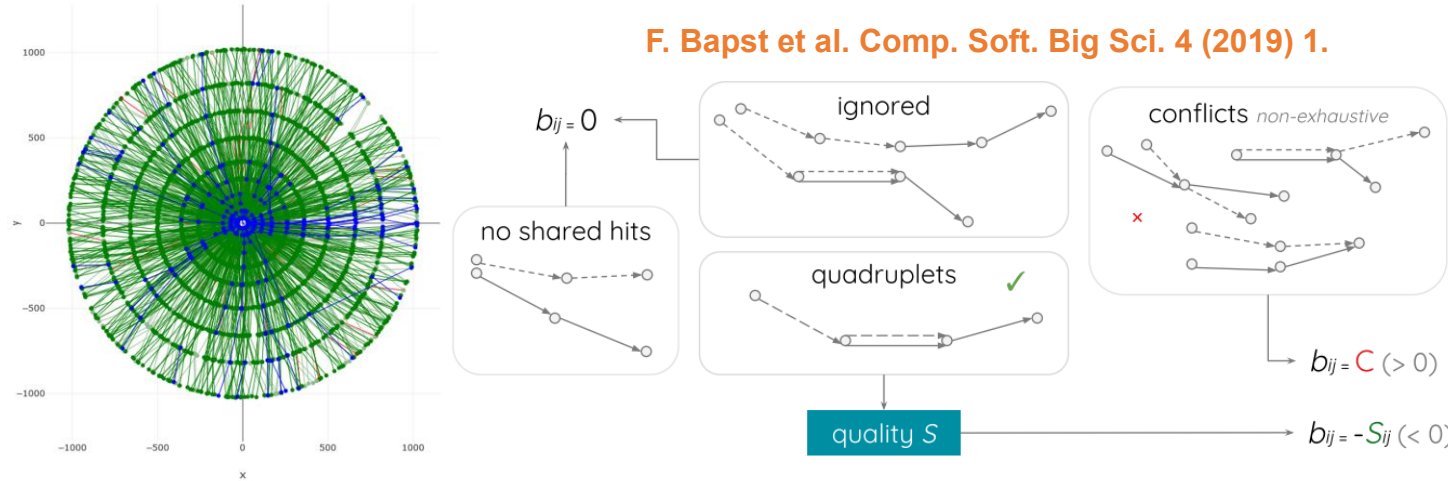


- **Hybrid classical-quantum NN** for the edge & node networks.
→ i.e. a large fraction of the network is still classical.
- **Very large RAM requirements & long training time** (originally >1 week on quantum circuit simulator, <24h in this new study).
- Running on quantum hardware is still difficult for its high queuing time & limited access.
- Hybrid QGNN tracking shows earlier convergence than the classical GNN but no demonstration of quantum advantage yet.



Track Reconstruction (Global): QUBO

F. Bapst et al. Comp. Soft. Big Sci. 4 (2019) 1.



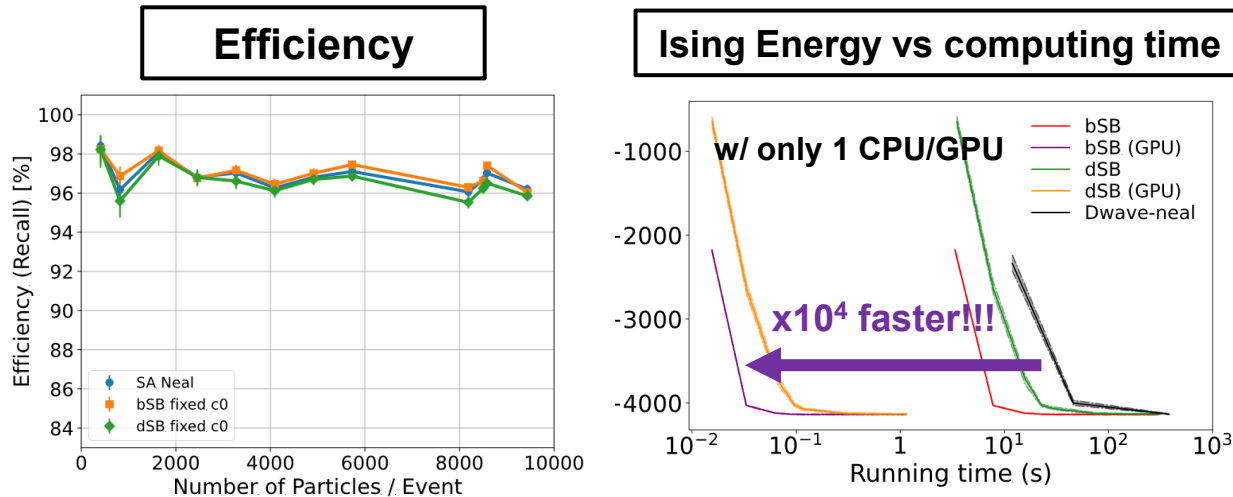
$$O(a, b, T) = \underbrace{\sum_{i=1}^N a_i T_i}_{\text{Quality of triplets}} + \underbrace{\sum_i^N \sum_{j<i}^N b_{ij} T_i T_j}_{\text{Compatibility b/w triplet pairs}}$$

Quality of triplets
Compatibility b/w triplet pairs

$$a_i = \alpha \left(1 - e^{-\frac{|d_{0i}|}{\gamma}} \right) + \beta \left(1 - e^{-\frac{|z_{0i}|}{\lambda}} \right),$$

$$b_{ij} = 0 \text{ (if no shared hit), } 1 \text{ (if conflict)} \\ = -S_{ij} \text{ (if two hits are shared)}$$

H. Okawa et al., Comput. Softw. Big Sci. 8, 16 (2024)



Hideki Okawa

QCML Workshop 2026

- QUBO-based approaches using quantum annealers were proposed by F. Bapst et al. & A. Zlokapa et al.
- At the HL-LHC, the required # of qubits will reach $O(10^5 \sim 10^6)$! **Scalability is a bottleneck.**
- Quantum-inspired algorithm (simulated bifurcation) demonstrated the first scalable approach with just 1 CPU or GPU.

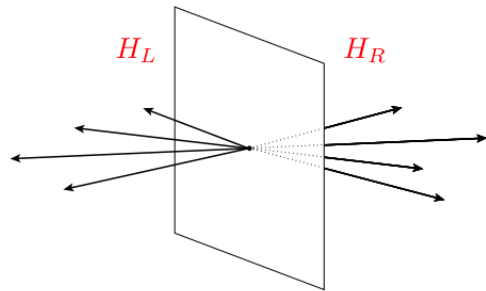
→ Further computational improvement in
XZ Tao et al., Nat. Commun. Phys. 9 (2026) 1, 100

22

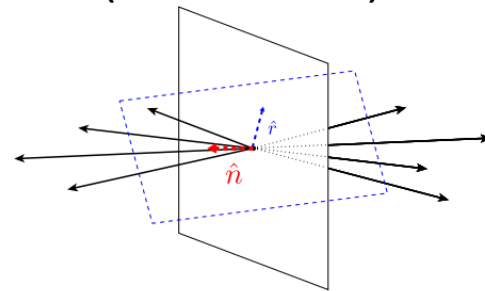
Jet Reconstruction (Iterative)

Iterative jet reconstruction also requires QuAM, so studies are mostly on complexity analyses.

Thrust as partitioning (QA)



Thrust as axis finding (Grover search)



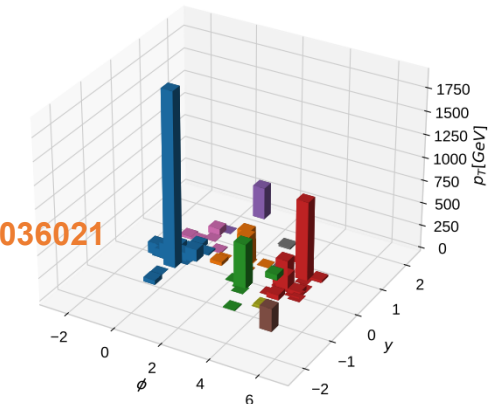
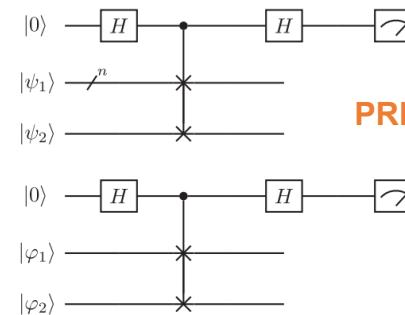
- Authors improved classical algorithm inspired by SISCone.
- **Quantum & classical algorithms scale the same, but for different reasons.**

Implementation	Time Usage	Qubit Usage
Classical ¹²⁴	$O(N^3)$	—
Classical with sort inspired by SISCone ¹²⁵	$O(N^2 \log N)$	—
Classical with parallel sort	$O(N \log N)$	—
Quantum annealing	Gap dependent	$O(N)$
Quantum search: sequential model	$O(N^2)$	$O(\log N)$
Quantum search: parallel model	$O(N \log N)$	$O(N \log N)$

A. Wei, P. Naik, A.W. Harrow, J. Thaler, PRD 101, 094015 (2020),

Hideki Okawa

Quantum subroutine to compute Minkowski-based distance



(b) Quantum anti- k_T , $p = -1$, $R = 1$, $\epsilon_c = 0.99$.

- **Quantum & classical algorithms [FastJet] scales the same for sequential clustering.**
- IBM quantum circuit simulator was also used to actually perform clustering.

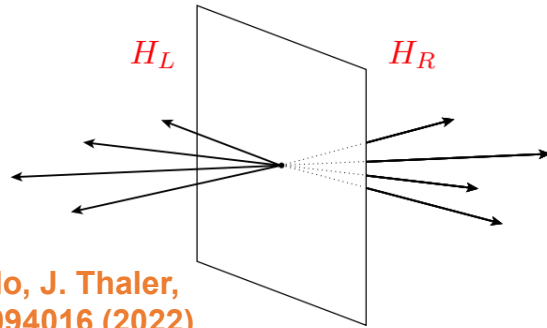
Jet algorithms	Classical	Quantum
K-means	$O(NKD)$	$O(NK \log D)$, ¹¹⁶ $O(N \log K \log(D-1))$ ¹²⁷
AP	$O(N^2TD)$	$O(N^2T \log(D-1))$ ¹²⁷
k_t , C/A, anti- k_t	$O(N^3)$ [suboptimal]	$O(N^2 \log N)$ ¹²⁷
	$O(N \log N)$ [FastJet] ^{132, 133}	$O(N \log N)$ ¹²⁷

¹¹⁶D. Pires, P. Bargassa, J. Seixas, Y. Omar, arXiv:2101.05618 (2021)

¹²⁷J.J. Martinez de Lejarza, L. Cieri, G. Rodrigo, PRD 106 036021 (2022)

Dijet Reconstruction (Global)

Quantum Annealing (Thrust)



A. Delgado, J. Thaler,
PRD 106, 094016 (2022)

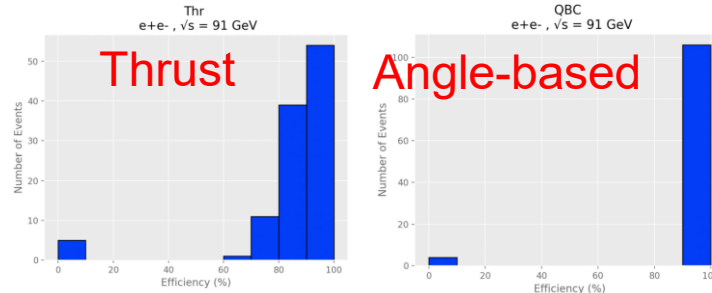
$$O_{\text{QUBO}}(\{x_i\}) = \left(\sum_{i=1}^N |\vec{p}_i| \right)^2 T(\{x_i\})^2$$

$$T(\{x_i\}) = 2 \frac{\left| \sum_{i=1}^N x_i \vec{p}_i \right|}{\sum_{i=1}^N |\vec{p}_i|}$$

- Quantum annealing with tuned annealing parameters & hybrid quantum/classical approach without tuned parameters exhibit similar performance to exact classical approaches.

D. Pires, Y. Omar, J. Seixas, PLB 843 (2023) 138000

Quantum Annealing (Angle)



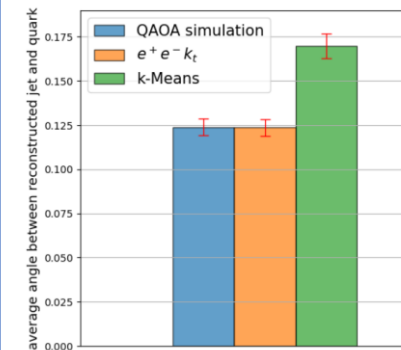
$$H = \frac{1}{2} \sum_{i,j=1}^N -\cos[\theta(\vec{p}_i, \vec{p}_j)] s_i s_j$$

- Angle-based approach shows more compatible clustering as ee- k_t for dijet events.
- However, **the same approach did not work for multijet events.** → Usage of multiple qubits for one hot encoding is prone to errors.

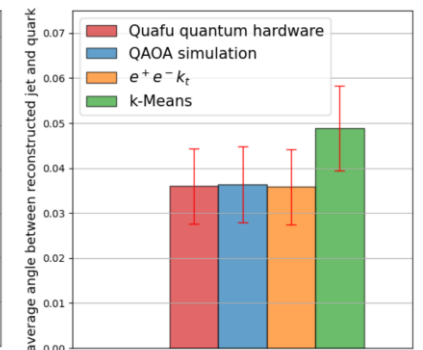
Y. Zhu et al., Sci. Bul. 70 (2025) 460

QAOA (Angle) or K-means

30-particle data
($e^+e^- \rightarrow ZH \rightarrow \nu\nu ss$)



6-particle data
($e^+e^- \rightarrow ZH \rightarrow \nu\nu ss$)



$$\hat{H}_C = \frac{1}{2} \sum_{(i,j) \in E} W_{ij} (I - \sigma_i^z \sigma_j^z)$$

W_{ij} : angle b/w particles i & j

- Used simplified/small-sized (6- or 30-particle) dijet events.
- Evaluated average angle with QAOA or K-means on Quafu hardware/simulator.

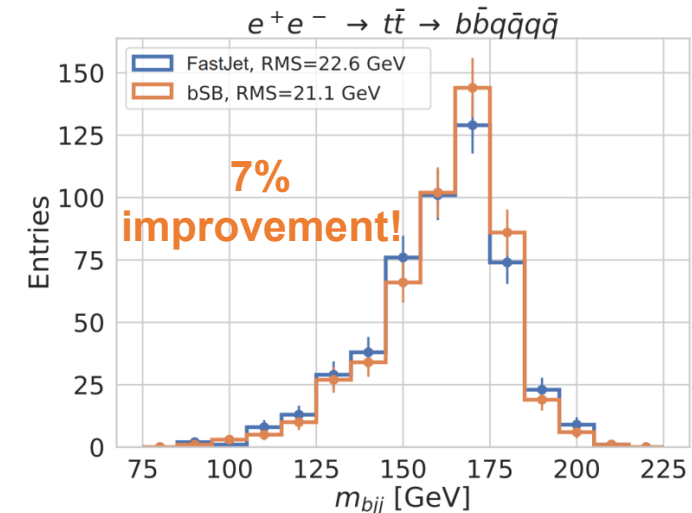
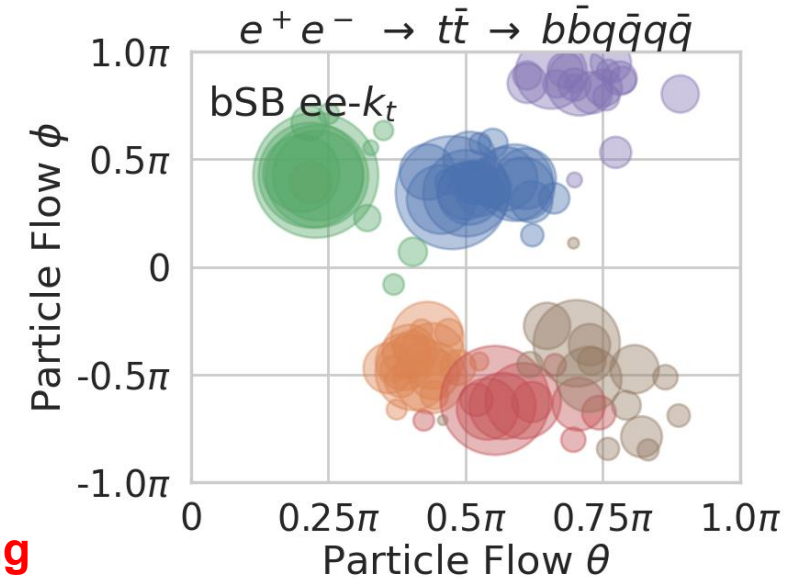
Multijet Reconstruction (Global)

QUBO Formulation

$$O_{\text{QUBO}}^{\text{multijet}}(x_i) = \underbrace{\sum_{n=1}^{n_{\text{jet}}} \sum_{i,j=1}^{N_{\text{input}}} Q_{ij} x_i^{(n)} x_j^{(n)}}_{\text{Defines distances b/w particle flow candidates}} + \lambda \underbrace{\sum_{i=1}^{N_{\text{input}}} \left(1 - \sum_{n=1}^{n_{\text{jet}}} x_i^{(n)}\right)^2}_{\text{Avoids double/none-assignment of particle flow candidates}},$$

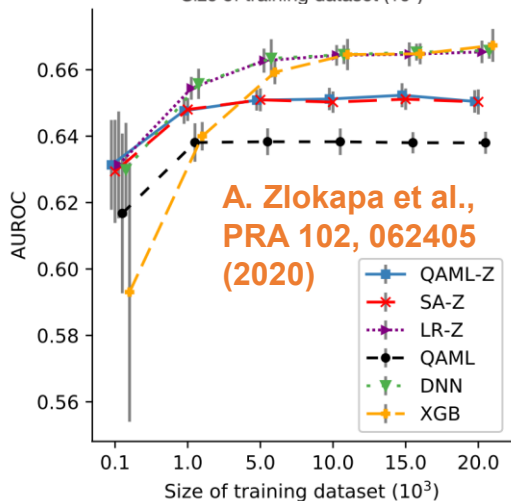
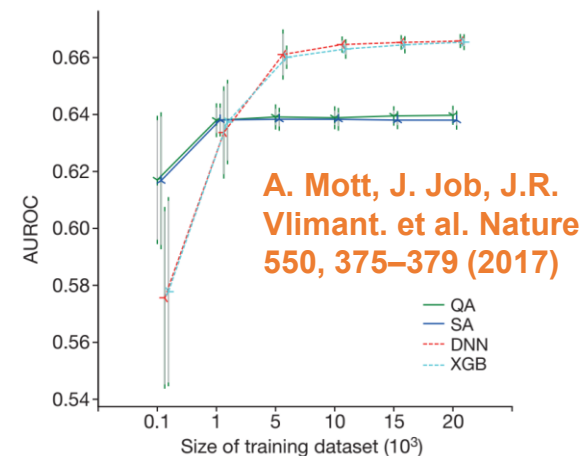
$$Q_{ij} = 2\min(E_i^2, E_j^2)(1 - \cos \theta_{ij}). \quad [\text{ee-}k_t \text{ distance}]$$

- **Quantum-hardware-driven approaches suffer from qubit-scaling & connectivity issues.** → Quantum-inspired does not
- **A quantum-inspired algorithm (bSB) overcame the challenge** for the one-hot encoding for multijet reconstruction.
- **1st successful global multijet clustering** with bSB quantum-inspired algorithm. → Opened up a practical path toward global jet reconstruction
- **Invariant mass resolution improves by 6~7%** for Higgs bosons/top-quarks.



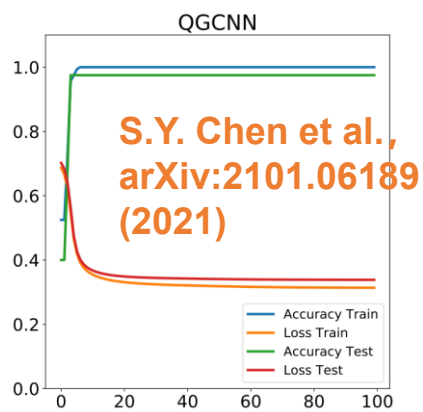
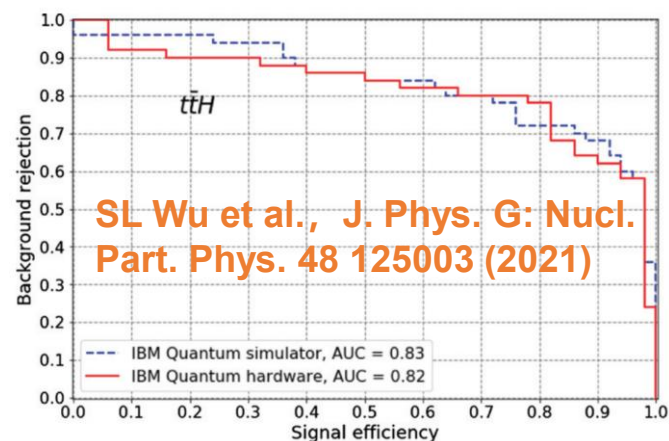
Classification

Quantum Annealing

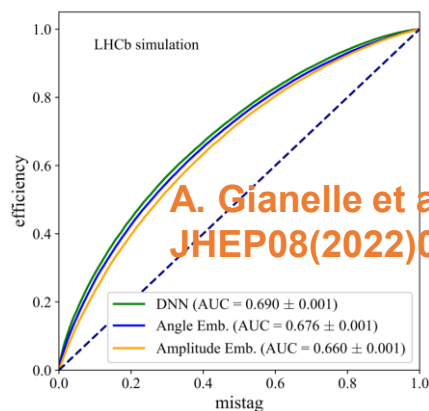


Hideki Okawa

Quantum Gates (Variational quantum algorithms)



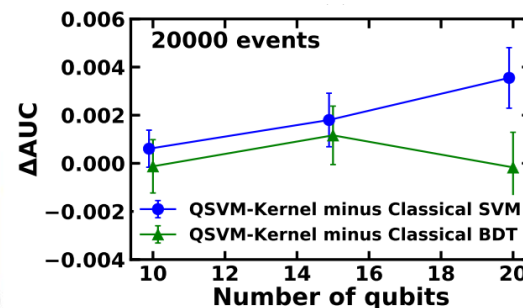
LHCb b-tag (VQC)



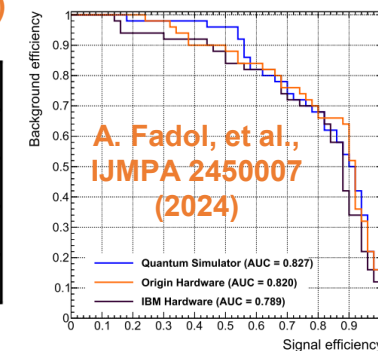
QCML Workshop 2026

Quantum Gates (Quantum Kernel methods)

SL Wu et al., Phys. Rev. Research 3, 033221 (2021)



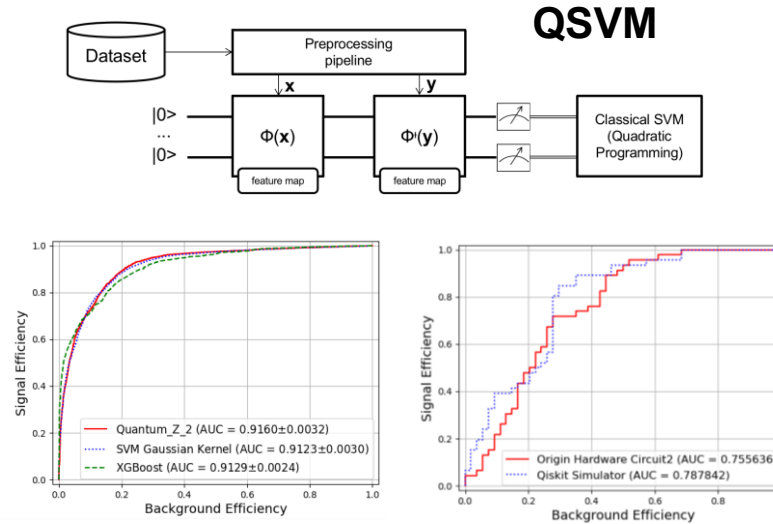
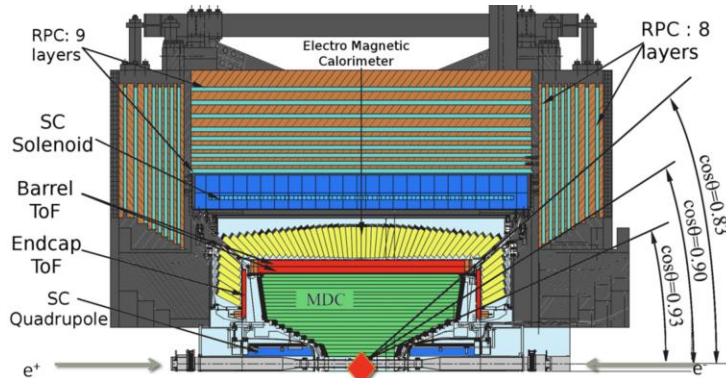
CEPC event classification



- A. Mott et al.: First QML applications in HEP using quantum annealing.
- Various QML algorithms are actively tested.

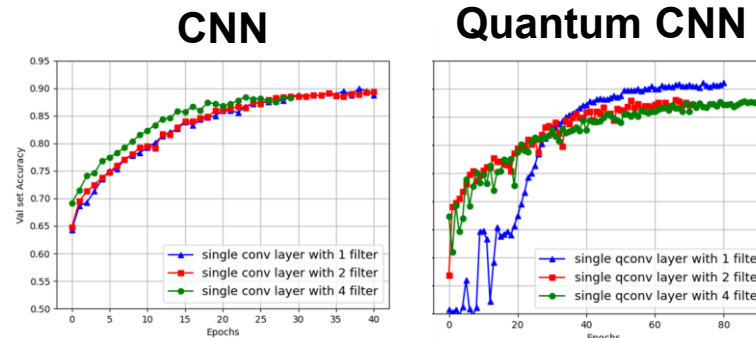
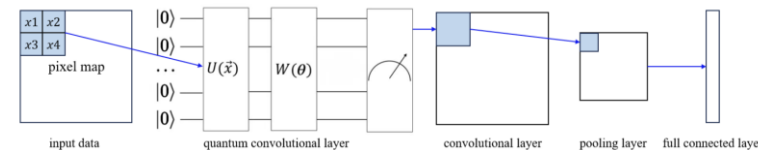
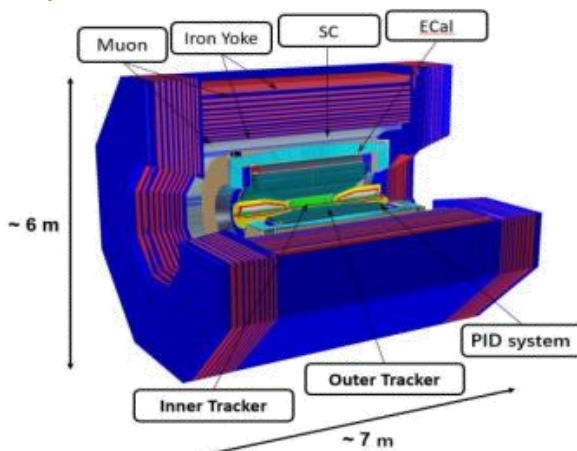
Classification

Z.P. Yao et al., EPJ Plus (2024) 139:356,
T. Li et al., J. Phys. Conf. Ser. 2438 (2023) 1, 012071



- QSVM & VQC for μ/π ID in BES3.
- Comparable QSVM performance in Origin Quantum (本源) hardware & simulator.

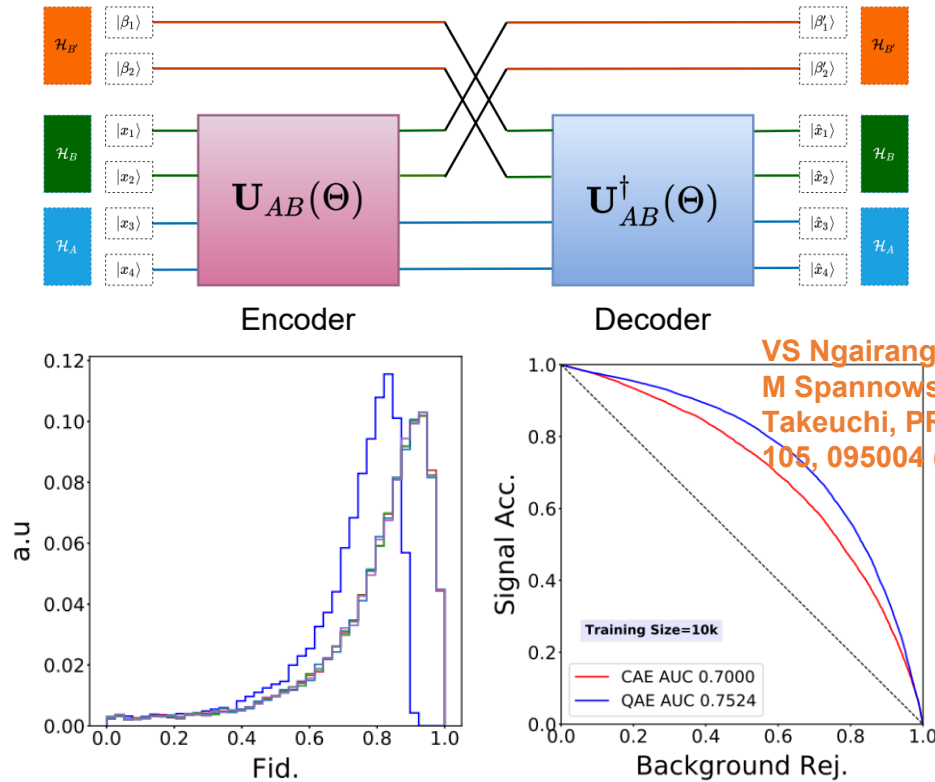
Z.P. Yao, T. Li, X.T. Huang, EPJ Web Conf. 295 (2024) 09030



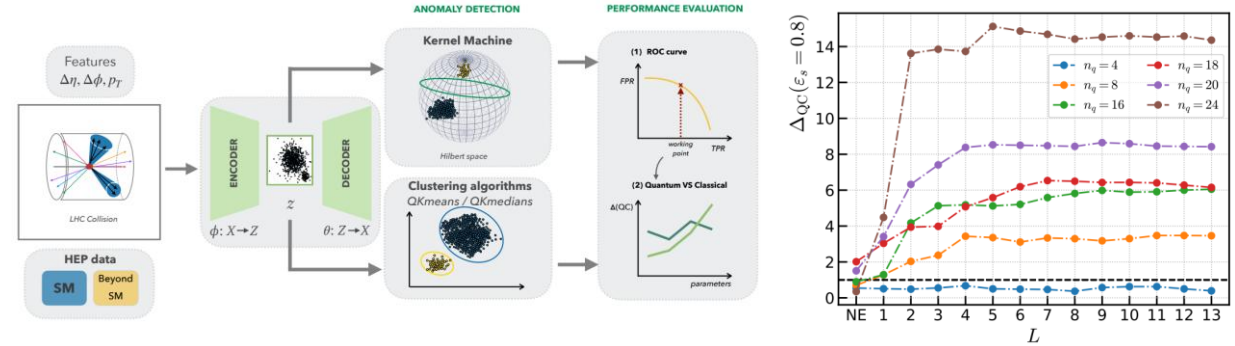
- π/K ID with QCNN in Super Tau Charm Factory (STCF) simulation.
- QCNN provides comparable performance to CNN in feature extraction and learning ability.

Anomaly Detection

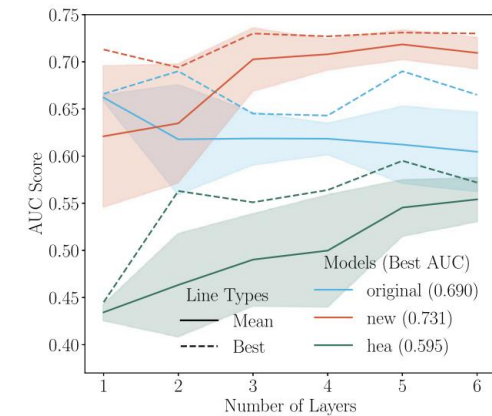
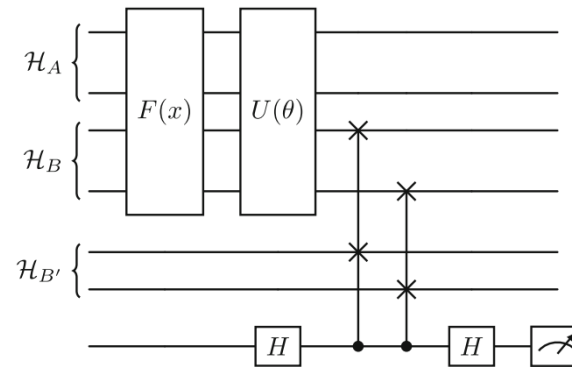
V. Belis et al., Comm. Phys. 7, 334 (2024)



VS Ngairangbam,
M Spannowsky, M
Takeuchi, PRD
105, 095004 (2022)



C. Duffy, et al. Quantum Mach. Intell. (2025) 7:41

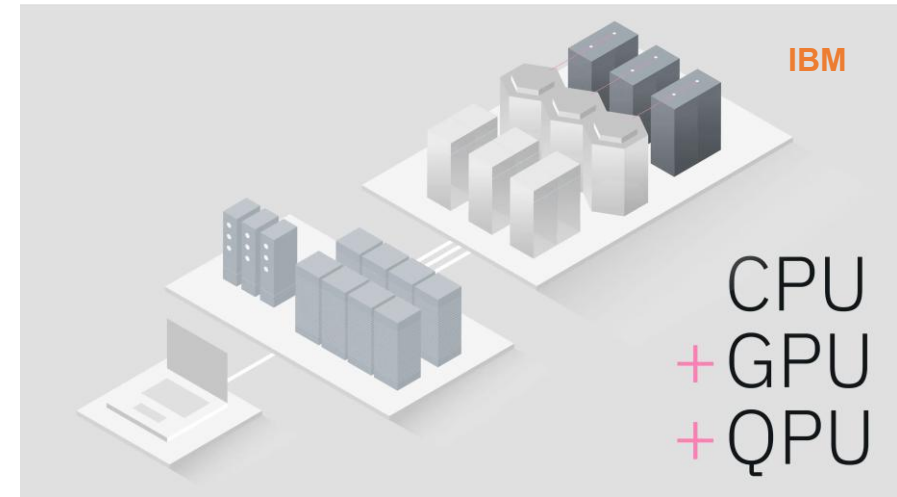


- V.S. Ngairangbam et al.: Quantum algorithm maintains performance with small datasets.
- V. Belis et al.: Performance enhances with more features & entanglement.
- C. Duffy et al.: Proposed scalable quantum circuit ansatz & demonstrated impact of ansatz design.

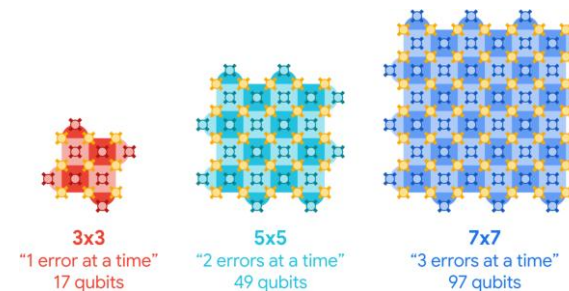
Towards Practical Applications

- Quantum computing combined with High-Performance Computing has started to operate (Quantum-centric supercomputing).
- $O(\sim 10^2)$ -qubit level fault-tolerant quantum computers will likely to show up around 2030.
 - IBM aims for fault-tolerant quantum computers by 2029 (100M gates, 200 logical qubits)
- In any case, some components of HEP experimental workflow require $O(10^6)$ qubits.
- Quantum-inspired techniques are also likely to stay valuable.

Quantum-centric supercomputing



Surface code logical qubits



Google Quantum AI



QuantumCtek (国盾量子)

Summary

- Quantum computing applications are an emerging field in high-energy physics.
- Quantum machine learning is actively investigated for experimental tasks.
- Three major quantum technologies exist: (1) universal quantum gate machines, (2) quantum annealing & (3) quantum-inspired algorithms.
- Each approach has its pros/cons and appropriate use cases.
- With the rapid development of quantum hardware and quantum-inspired algorithms, **it would be really exciting to see how all of our efforts converge in the end & understand how practical quantum advantages can be realized in high-energy physics.**



Thank you for listening!