Quantum Machine Learning for Collider Physics

International Workshop on New Opportunities for Particle Physics 2026
(NOPP 2026), IHEP, August 14-16, 2026

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Picture credits: Qianhui Shi, Yan Liang

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)

F. Arute et al., Nature 574 (2019) 505

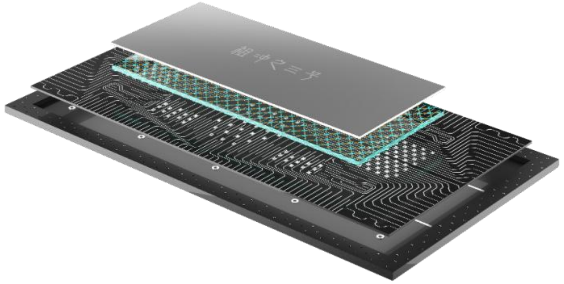
USTC Jiuzhang (2020)

Science 370 (2020) 1460

Google Willow (2024)

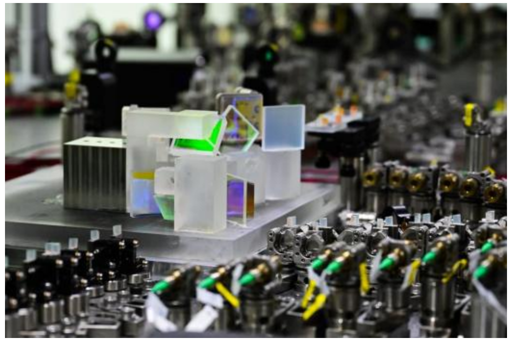
Google AI & collab., Nature 638 (2025) 920

USTC Zuchongzhi 3.0 (2024/2025)



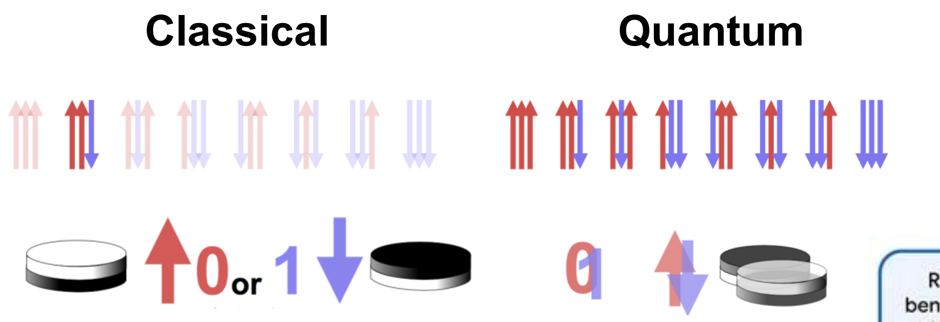
D. Gao et al., PRL 134 (2025) 090601

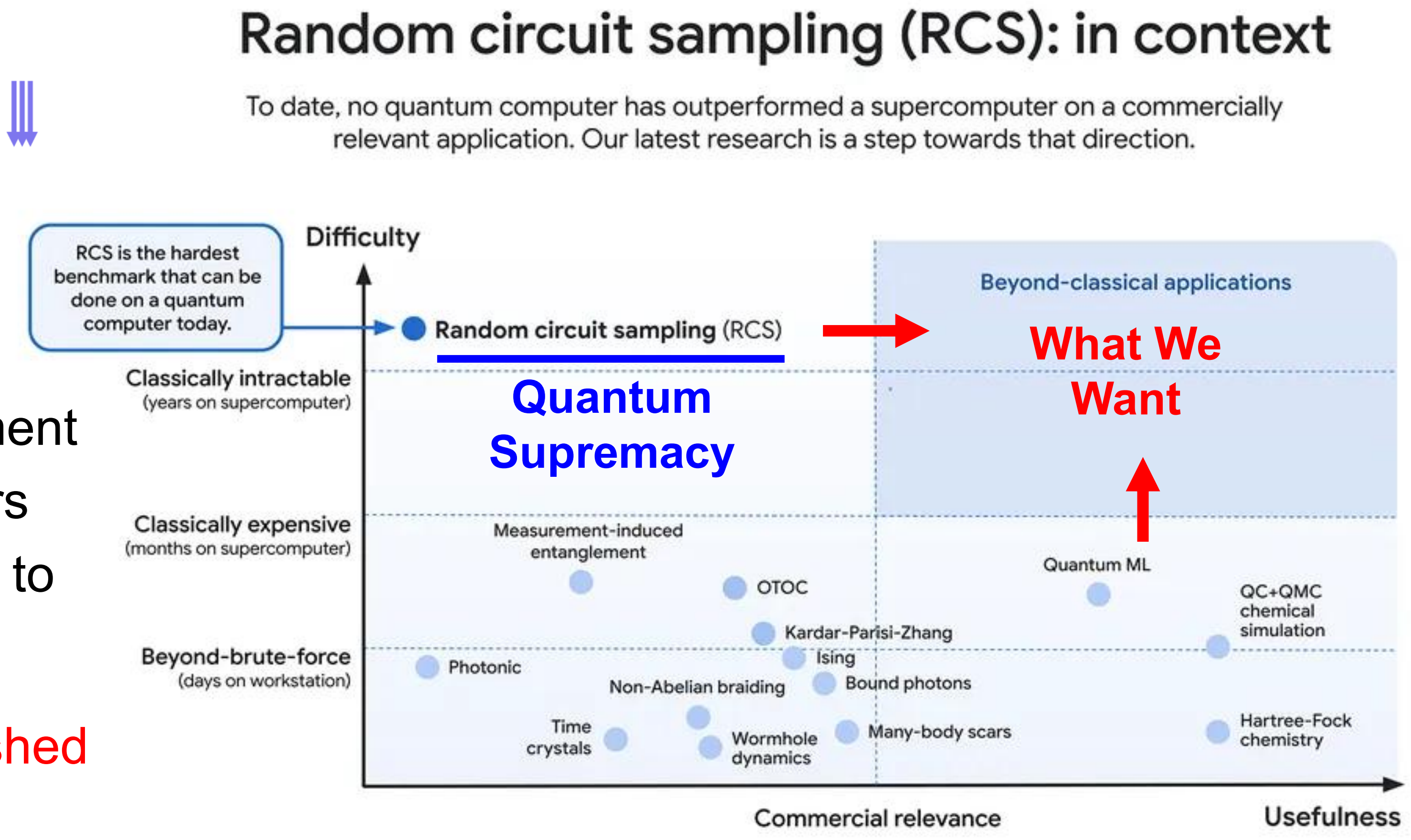
USTC Jiuzhang 4.0 (2026)



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

Quantum Supremacy & Going Beyond





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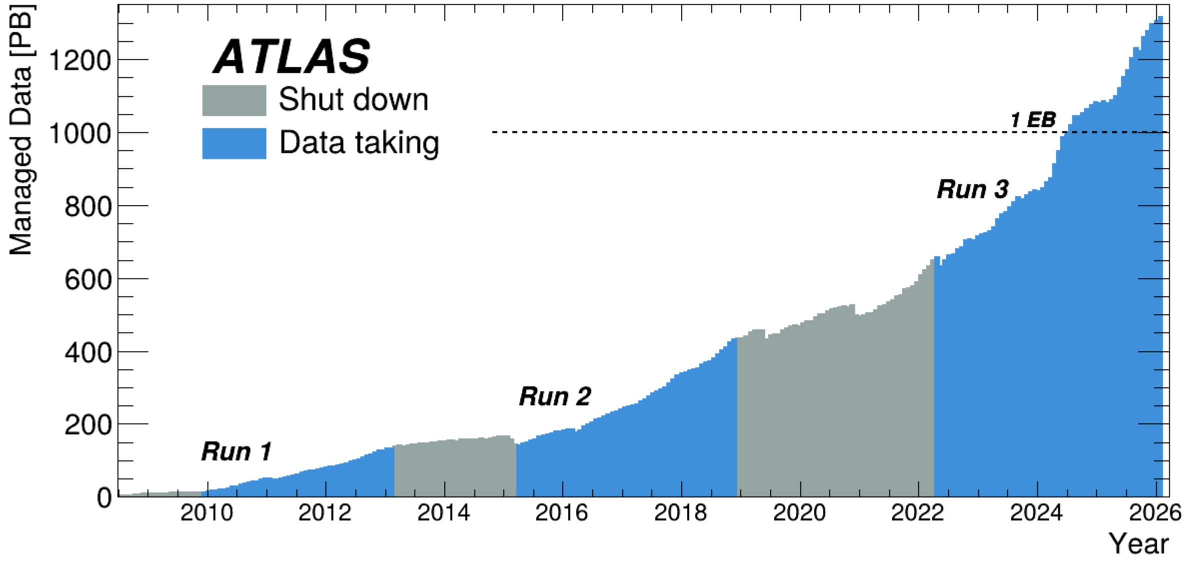
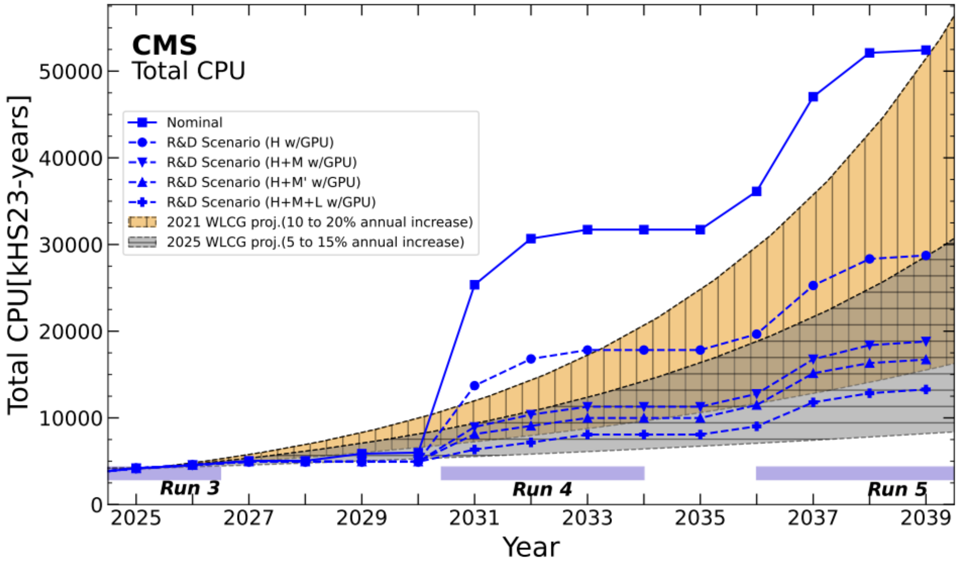
- Through superposition, entanglement & interference, quantum computers can bring in exponential speed-up to some tasks.
- However, we have not yet established practical quantum advantages.

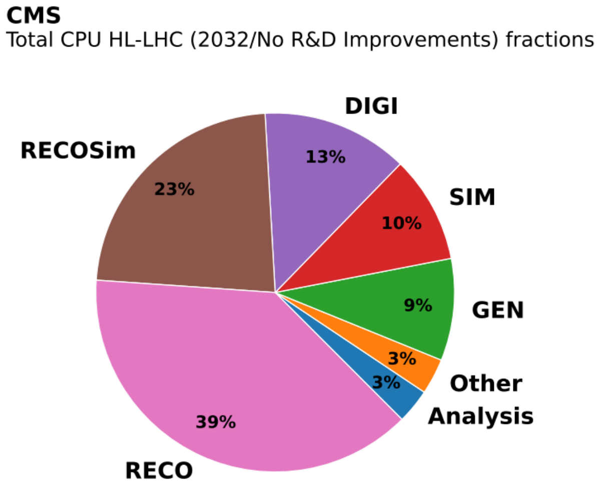
Experimental Challenges at Colliders



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

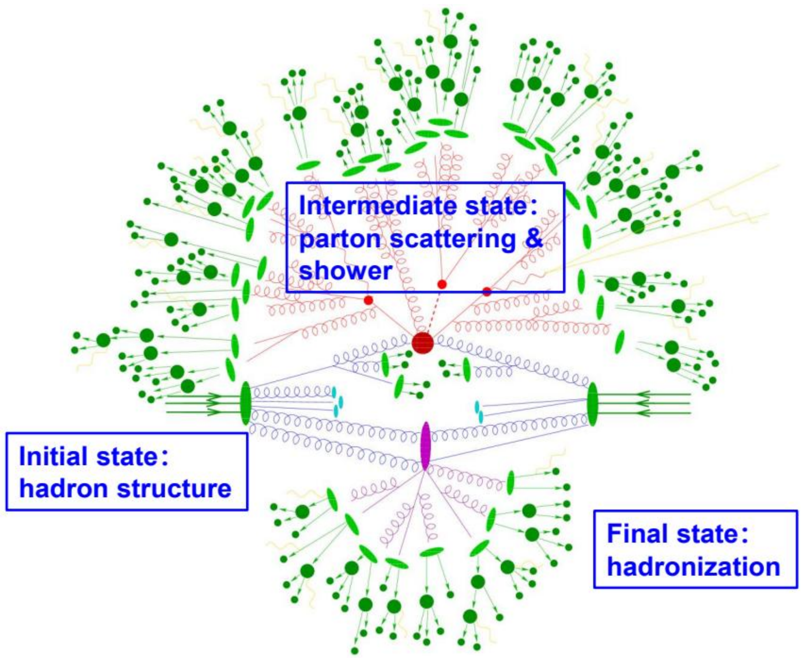


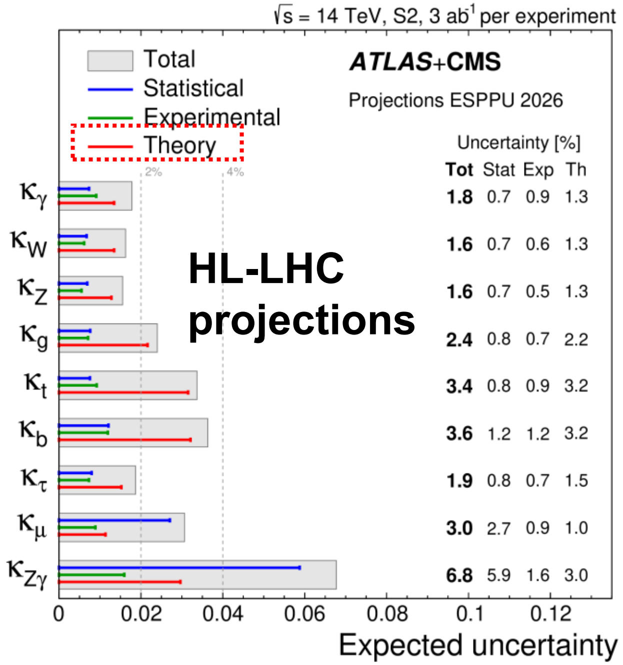
- **LHC has already entered the exabyte era!**
- Computing demands will continue to increase during the High-Luminosity LHC era (>2030). Similar challenges at CEPC, FCC-ee, EIC, etc.
- **CPU demands for reconstruction is particularly enormous.**
- Quantum computing may bring in a paradigm-shifting leap???



Parts of the slide inspired by Germán Rodrigo

Theoretical Challenges at Colliders





HL-LHC projections

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 $e^+e^- \to f\bar{f}$, initial-state radiation (ISR)	NLO, ISR logarithms up to 6th order	NNLO for $e^+e^- \to f\bar{f}$
Γ_Z (MeV)	2.3	0.004 (0.012)			
$\sin^2\theta^\ell_{\rm eff}$	1.6×10^{-4}	$1.2\ (1.2)\times10^{-6}$			
m_W (MeV)	9.9	0.18 (0.16)	lineshape of $e^+e^- \to WW$ near threshold	NLO ($e^+e^- \to 4f$ or EFT framework)	NNLO for $e^+e^- \to WW$, $W \to f\bar{f}'$ in EFT setup
HZZ coupling	–*	0.1%	cross section for $e^+e^- \to ZH$	NLO EW plus partial NNLO QCD/EW	full NNLO EW
$m_{\rm top}$ (MeV)	290	4.2 (4.9)	threshold scan $e^+e^- \to t\bar{t}$	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.

[from FSR and Freitas *et al.* arXiv:1906.05379]

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

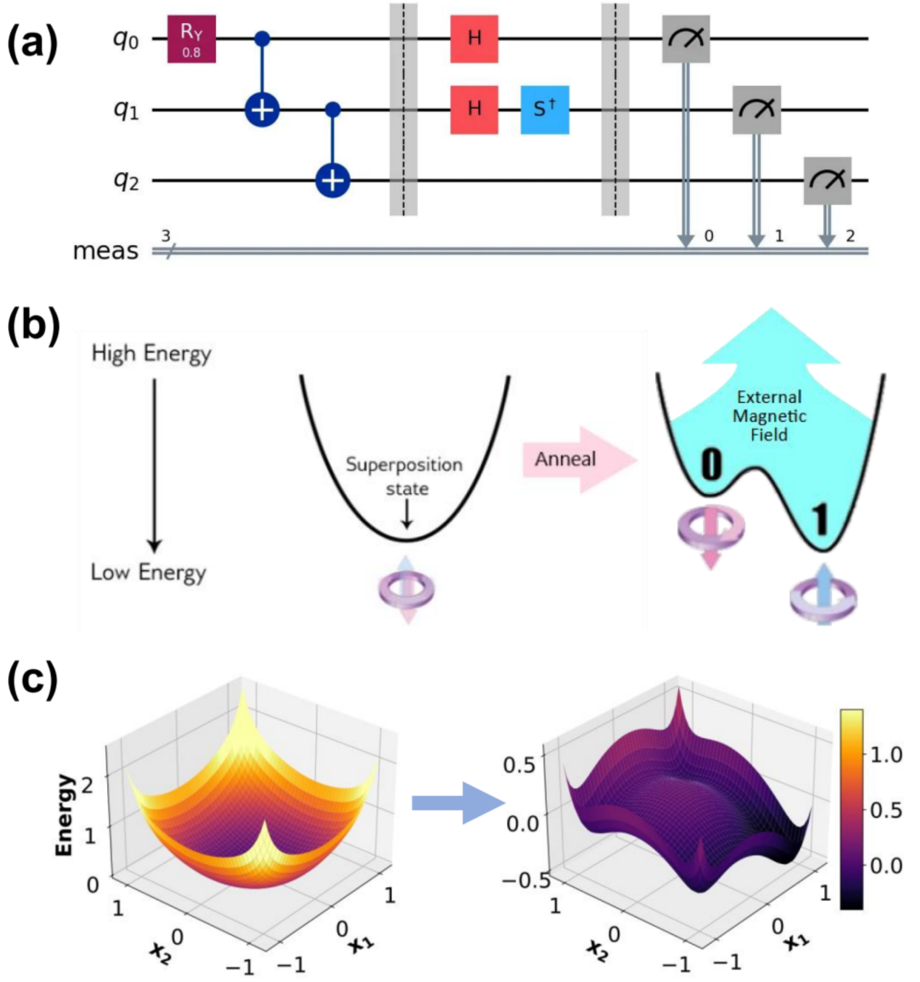
- Uses quantum logic gates. Is universal computing.
- Most quantum computers adopt this approach.

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.

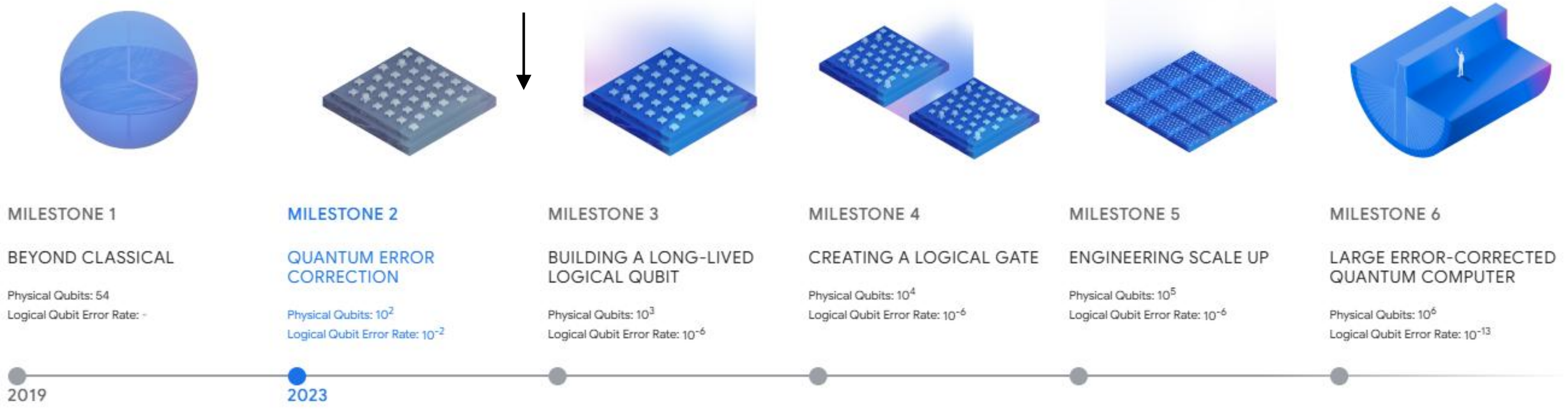


+ Analog quantum computing

Noisy Intermediate Scale Quantum

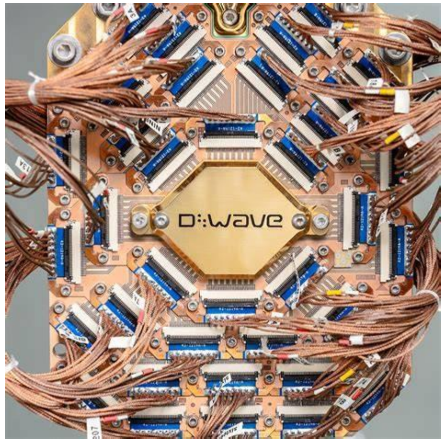
We are here now

Google Quantum AI Roadmap



USTC Zuchongzhi 3.0

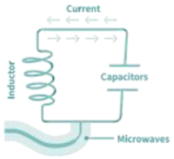
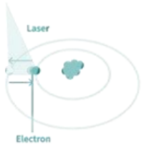
D-Wave Advantage2

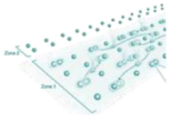
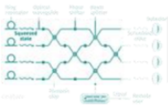
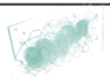


- Now is the era of **Noisy Intermediate Scale Quantum (NISQ)** hardware: **$O(10^2)$ qubits, Error rate ~ $O(10^{-2})$** for superconducting gate machines.
  - Error mitigation is introduced to various hardware. Error correction mechanisms are actively investigated.
- Newest quantum annealers (D-Wave 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
 Trapped Ion	Quantinuum	Helios	2025.11	98
	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+
 Photonic Quantum	USTC	Jiuzhang-4	2025.08	3050
	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?

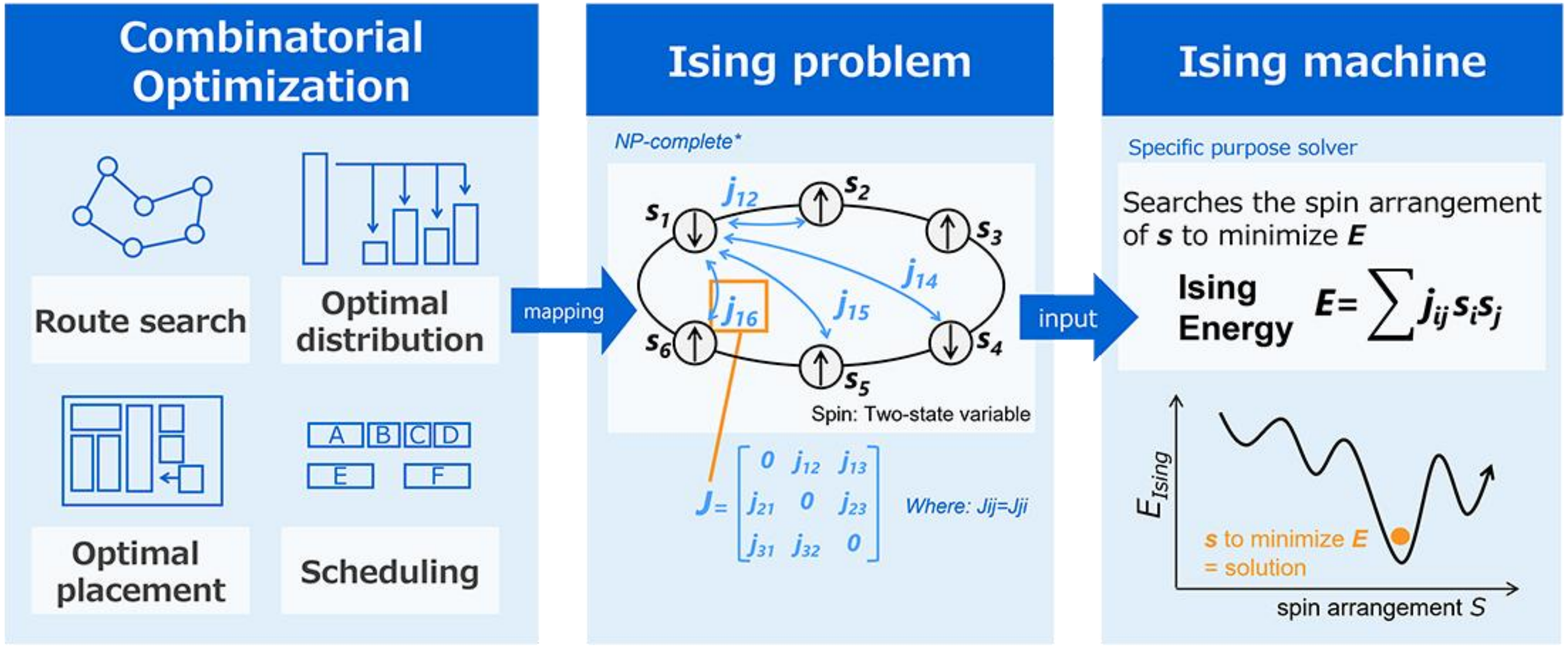
1	**SIMULATING QUANTUM SYSTEMS**	Modeling molecules and materials at the quantum level (e.g., electronic structure problems) that are intractable for classical computers.	Quantum computers naturally encode quantum states, allowing efficient simulation that scales **exponentially better.**
2	**UNSTRUCTURED 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)**	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.

→ **theoretical applications**

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

Quantum Optimization

QUBO: 0,1 binaries
Ising: ± 1 spins



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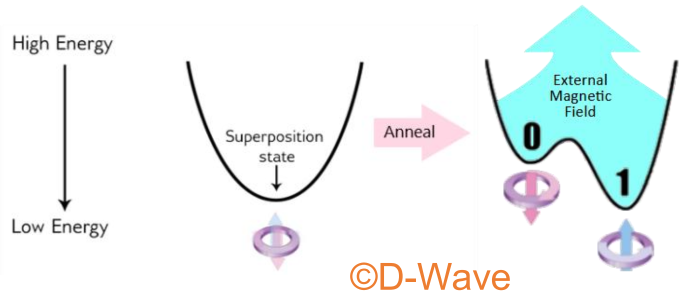
- Many complicated problems can be formulated as Ising (spin glass) or QUBO Hamiltonian.
- **We design the Hamiltonian so that the ground state corresponds to the answer.**
- **e.g. Track & jet reconstruction can also be formulated as such problems (Typical numbers of qubits required: $O(10^{5\text{-}6})$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

3 Classes of Ising Problem Solvers

Quantum Annealing (QA)

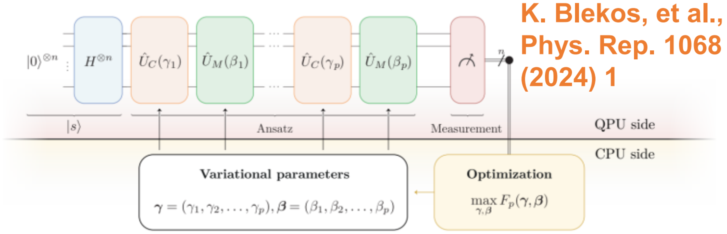


©D-Wave

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

- 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



K. Blekos, et al., Phys. Rep. 1068 (2024) 1

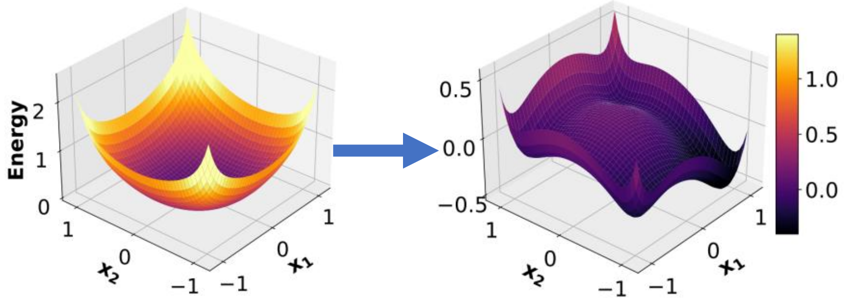
$$U \approx \prod_{n=1}^{p} e^{-iH(n\Delta t)\Delta t} = \prod_{n=1}^{p} e^{-i(1-s(n\Delta t))H_{\text{initial}}\Delta t} e^{-is(n\Delta t)H_{\text{target}}\Delta t}$$

$$= \prod_{n=1}^{p} e^{-i\beta_n H_{\text{initial}}} e^{-i\gamma_n H_{\text{target}}} = \prod_{n=1}^{p} U_M(\beta_n)U_C(\gamma_n),$$

- **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.

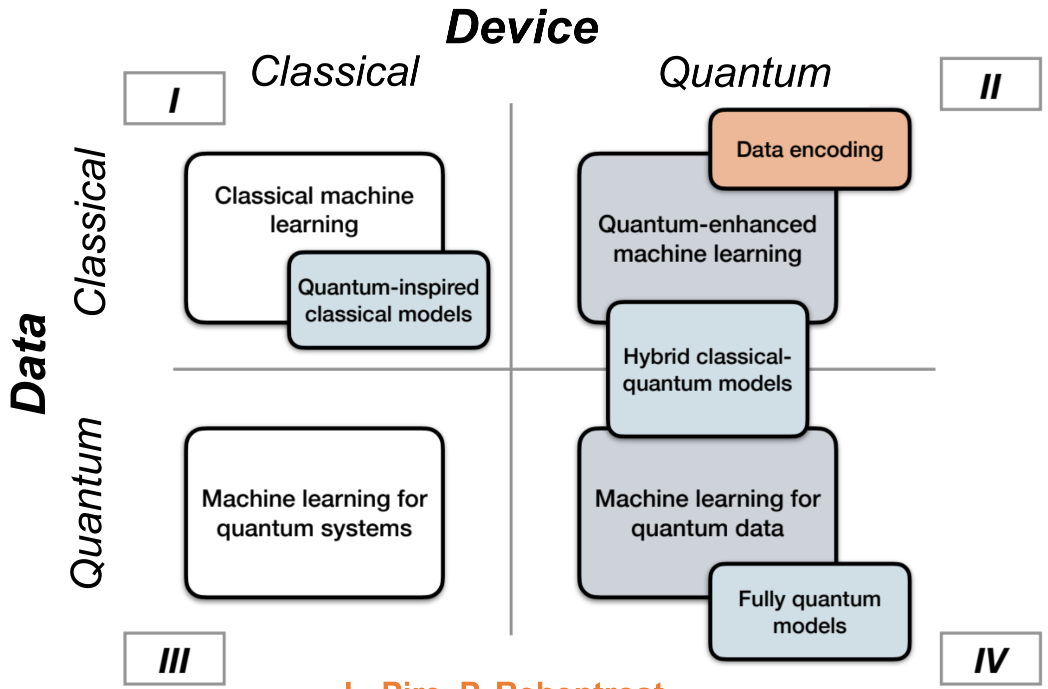
Quantum-Inspired

Xianzhe Tao

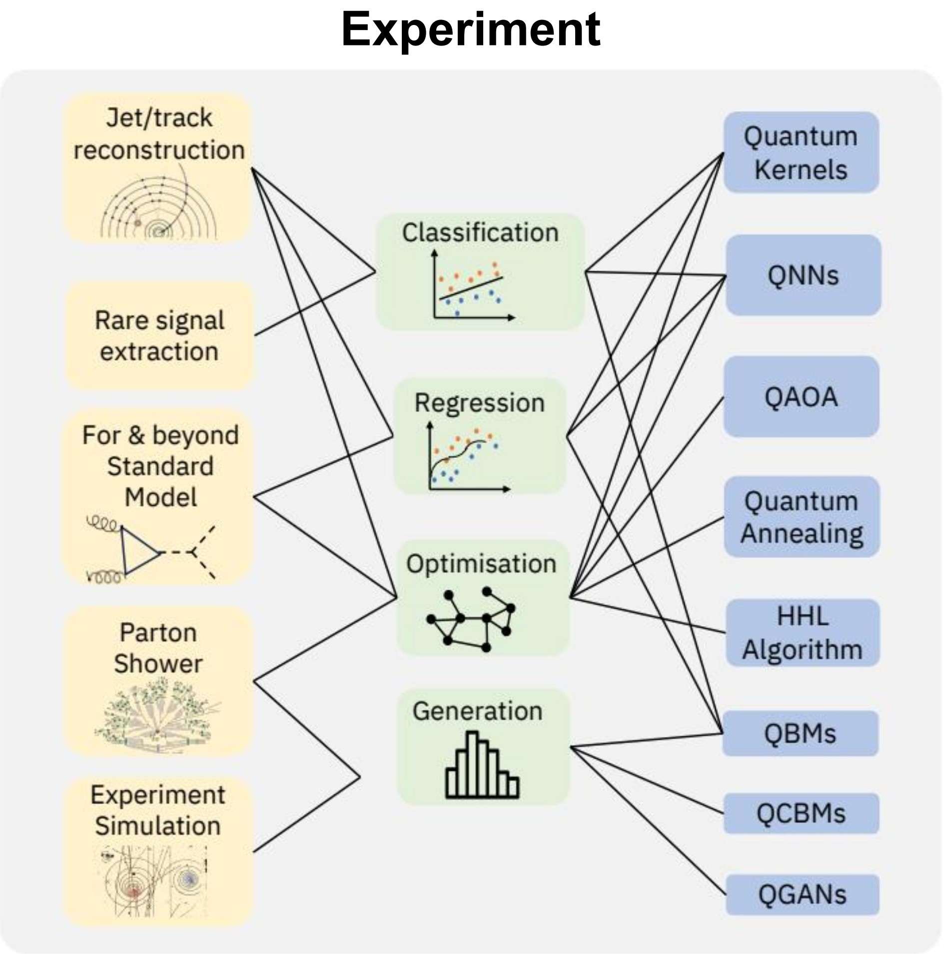


- Quantum-inspired runs on classical hardware with algorithms inspired by QC.
- **Simulated annealing (SA)** uses random moves in the solution space to search for the ground state.
- **Simulated bifurcation (SB) emulates quantum adiabatic evolution of Kerr-nonlinear parametric oscillators. It significantly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

Quantum Machine Learning & HEP



L. Pire, P. Rebentrost



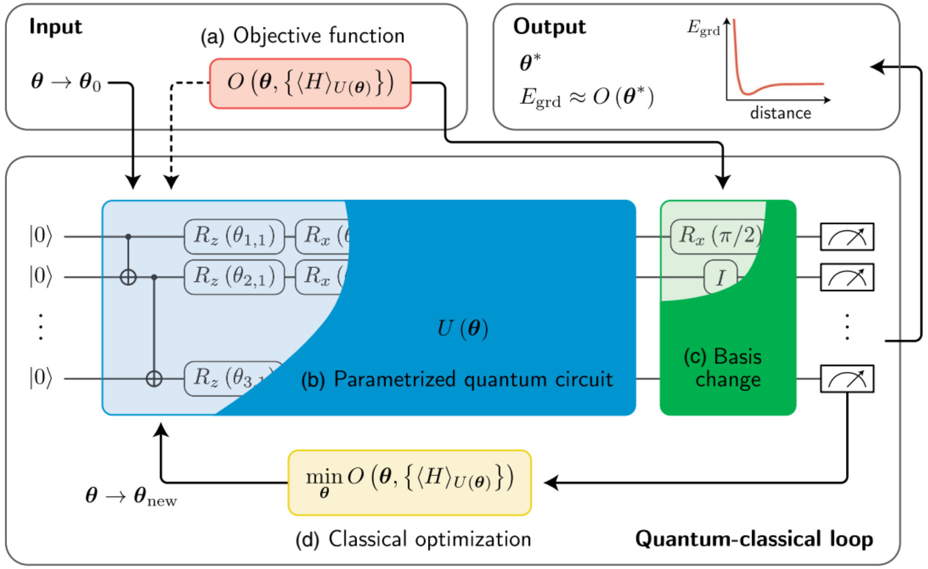
A. Di Meglio et al., PRX QUANTUM 5, 037001 (2024)

- 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)

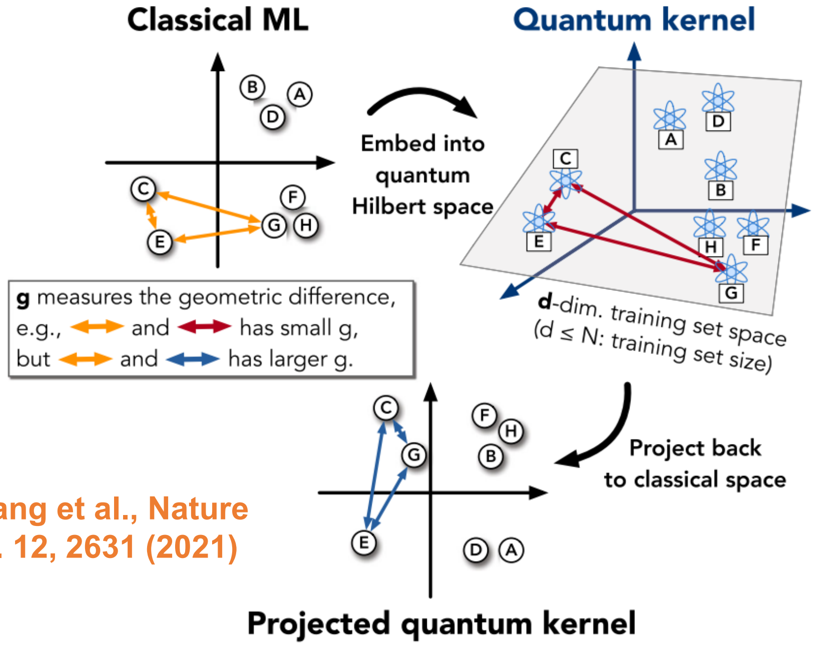
- Use variational quantum circuit, but update parameters with a classical optimizer.



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

Quantum kernel methods

- Embed feature map into quantum kernel → using rich Hilbert space

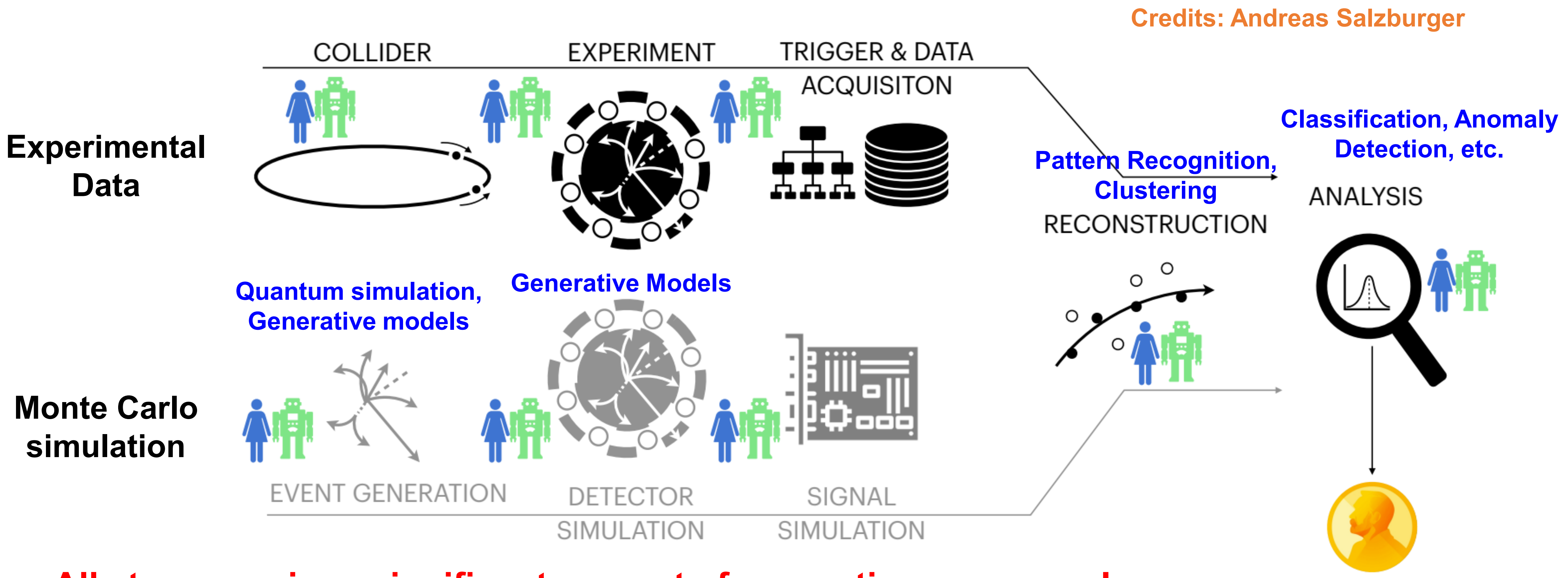


HY Huang et al., Nature Comm. 12, 2631 (2021)

Quantum-annealing-based

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

Experimental Workflow at Colliders



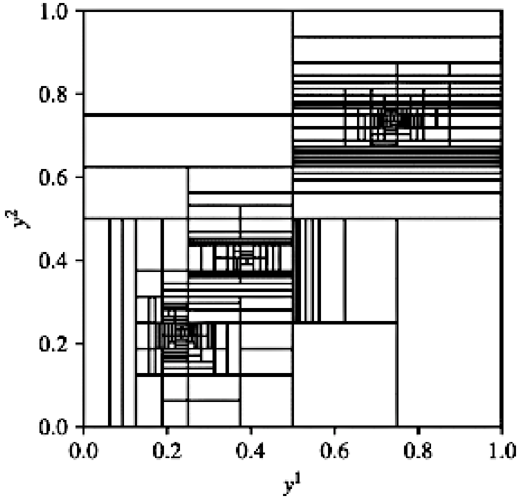
- **All steps require a significant amount of computing resources!**
- **State-of-the-art AI is currently being introduced/considered at all levels.**
- **Can we introduce quantum computing to these tasks?**

K. Pyretzidis, J. Martinez de Lejarza, G. Rodrigo, Nat. Comm. Phys. (2026), arXiv:2506.19965

Event Generation

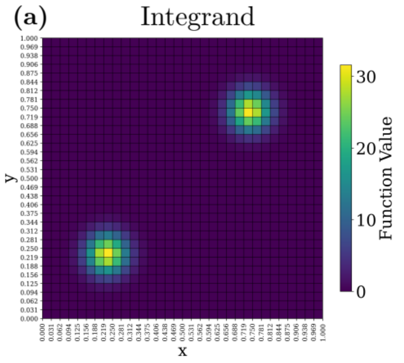
Multidimensional numerical integration is a core ingredient of calculating multiloop Feynman digrams

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

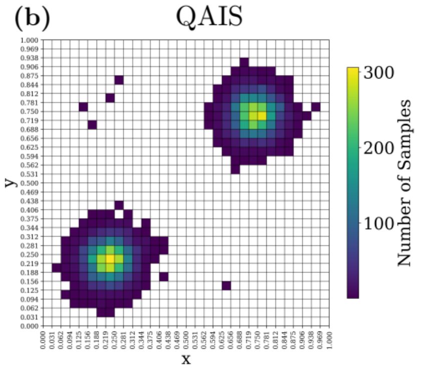


$$\int_\Omega f(x)dx \equiv \int_{[0,1]^d} J(y)f(x(y))\,dy \longrightarrow I_{\rm MC}^{\rm (VEGAS)} = \frac{1}{N}\sum_{i=1}^{N} J(y_i)f(x(y_i))$$

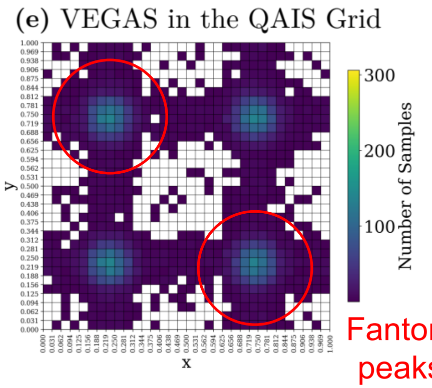
- Adaptive Importance Sampling (AIS) adapts variable-width grids to concentrate samples in regions of high variance, but suffers from phantom (fake) peaks.
- Quantum AIS (QAIS) uses PQC to encode a multidimensional PDF & can **allocate samples efficiently in the integration domain**.



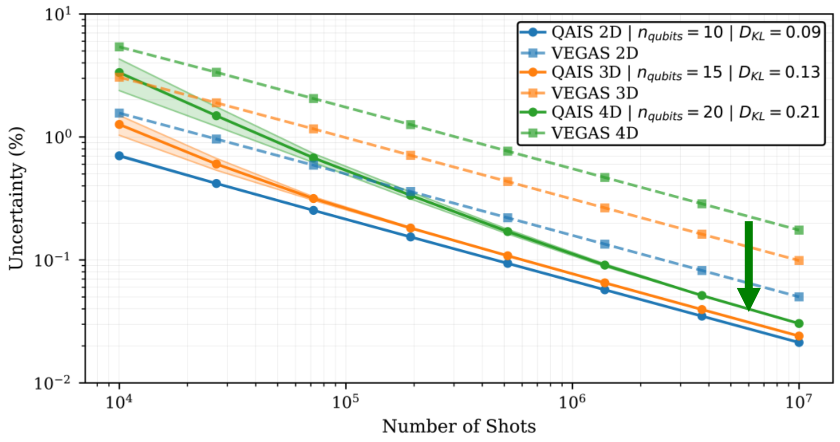
Success!



Classical AIS

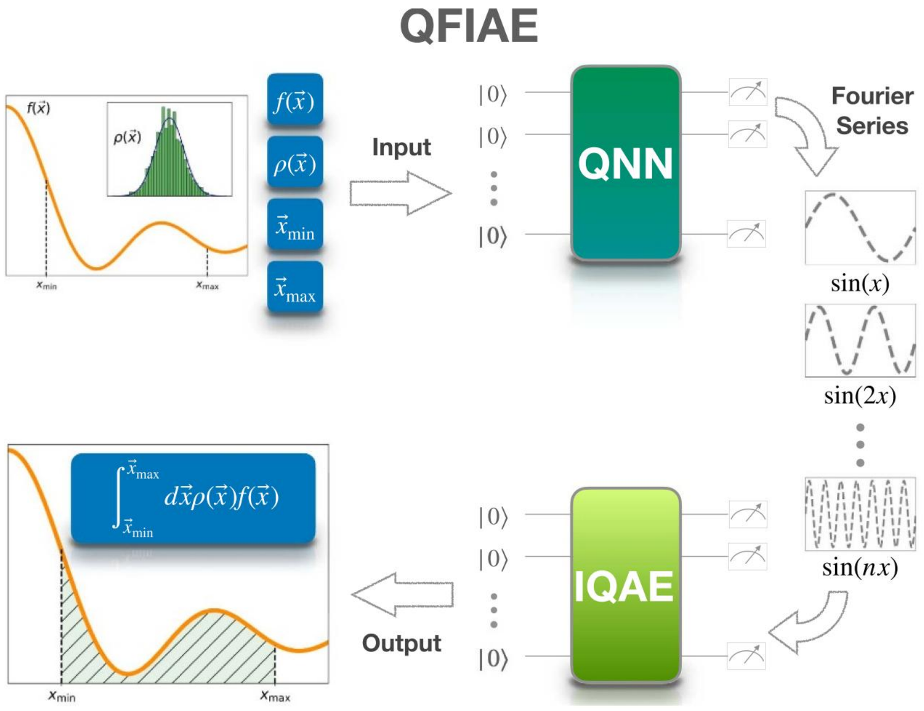


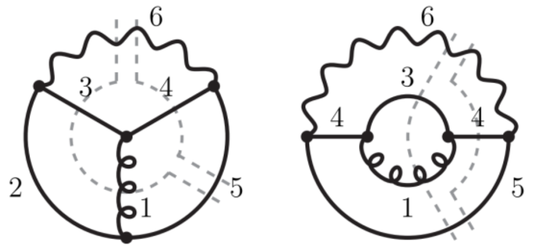
Fantom peaks

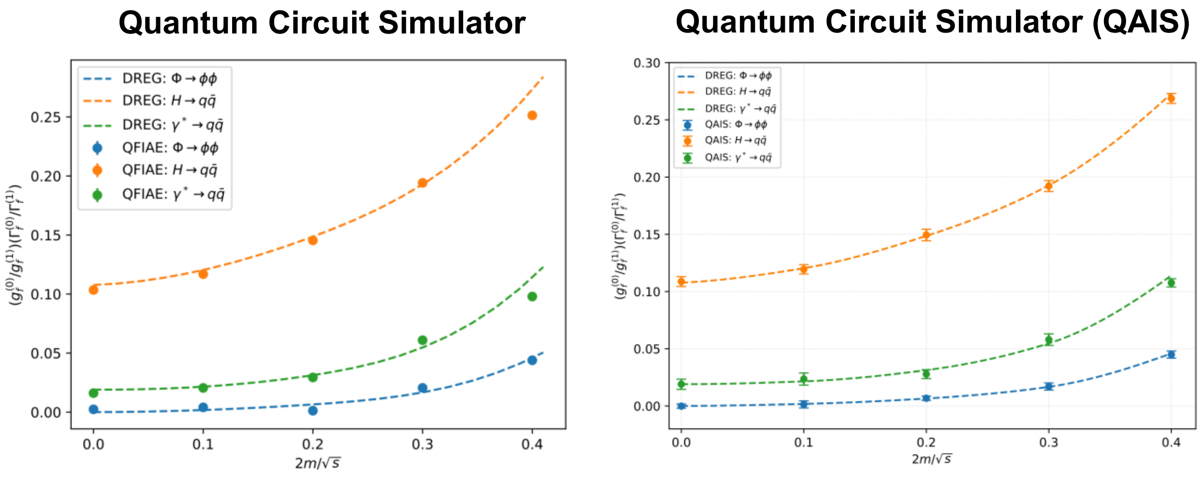


J.J. Martínez de Lejarza, D.F. Rentería Estrada, M. Grossi, G. Rodrigo, Quantum Sci. Technol. 10 (2025) 2, 025026

Decay Rates at NLO







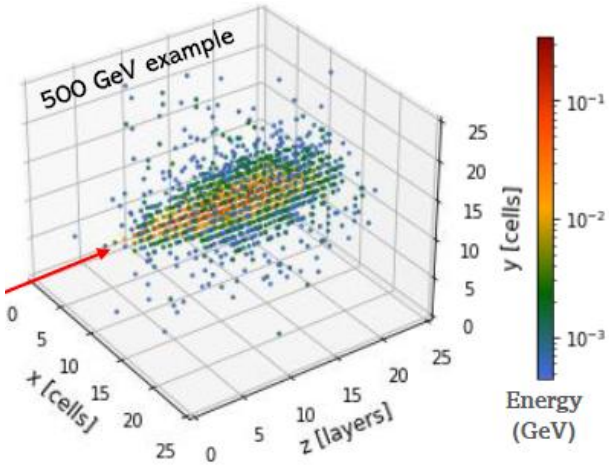
Consistent predictions as the exact analytic results

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.

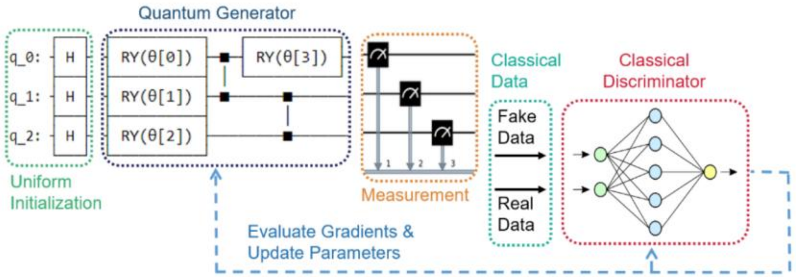
- **1st quantum computation of a total decay rate at second-order in perturbative QFT.**

Recent gate-based studies: J. Slim et al. arXiv:2608.05405, 2605.27735, 2605.16044

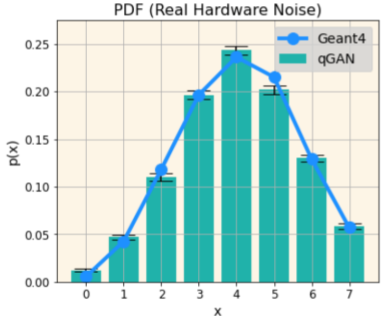
Detector Simulation



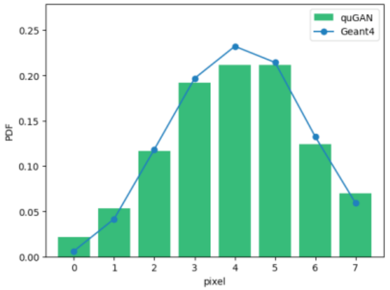
Quantum-classical hybrid GAN



IBM (F. Rehm, S. Vallecorsa, K. Borras, D. Krücker)

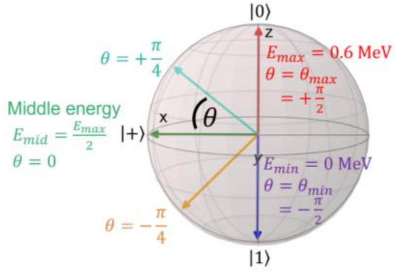


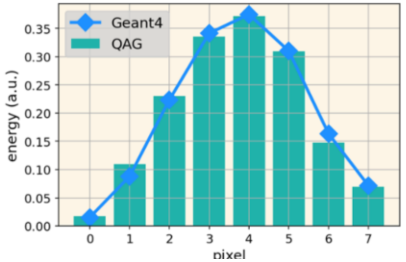
QuantumCTek (国盾) hardware (XZ Huang, WD Li)



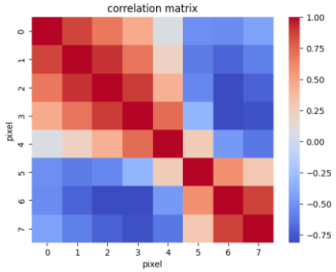
Full Quantum (e.g. QAG)

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

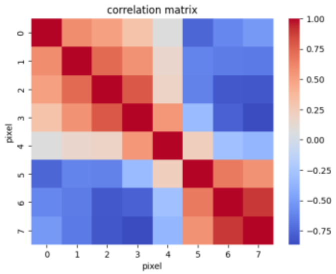




Geant4



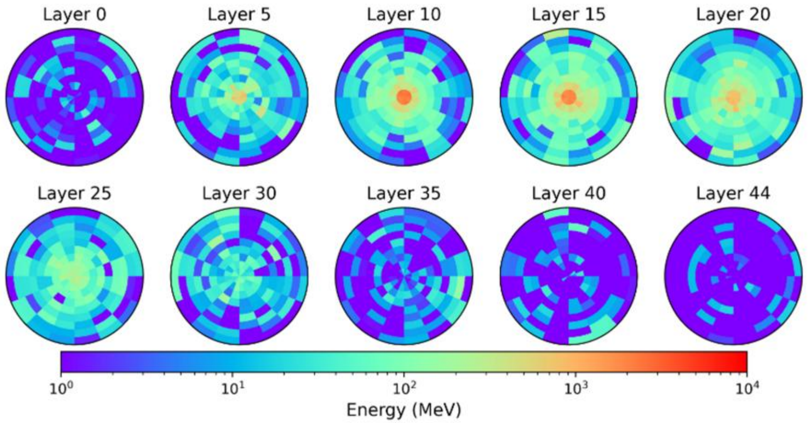
QAG

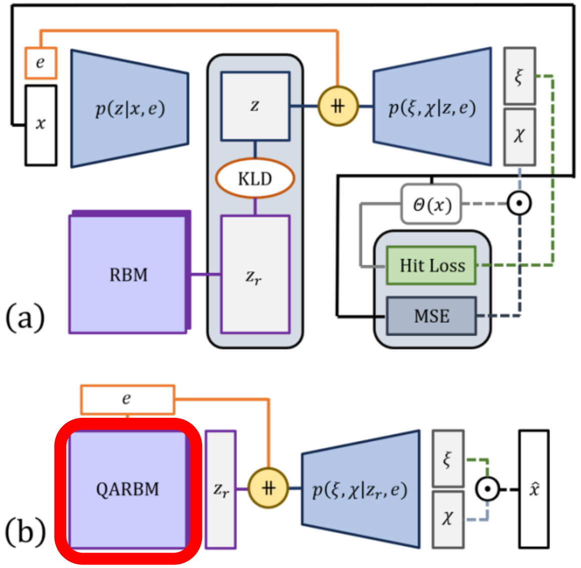


XZ Huang, WD Li

- **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

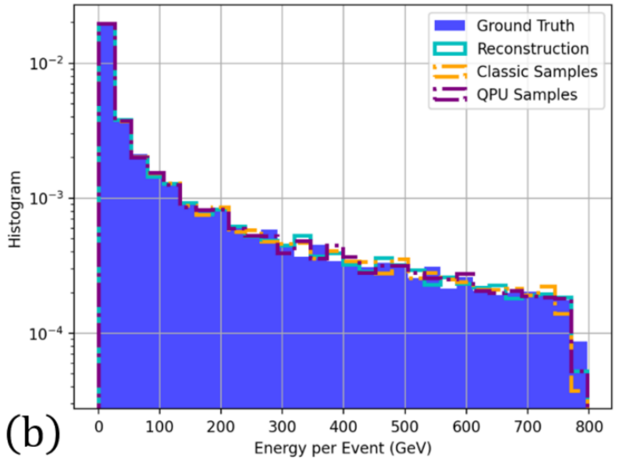


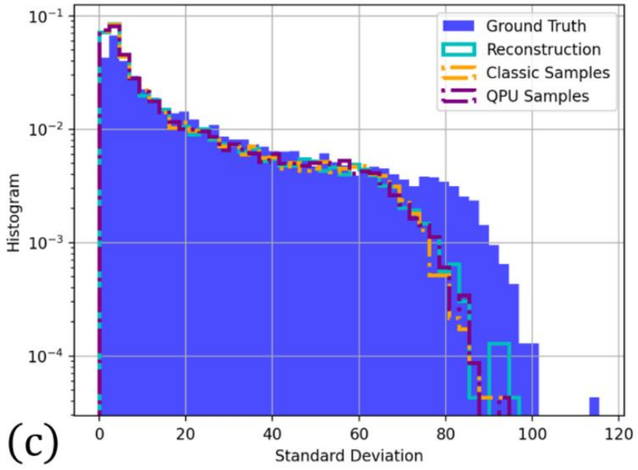


Quantum Annealing

Quantum-assisted workflow:

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

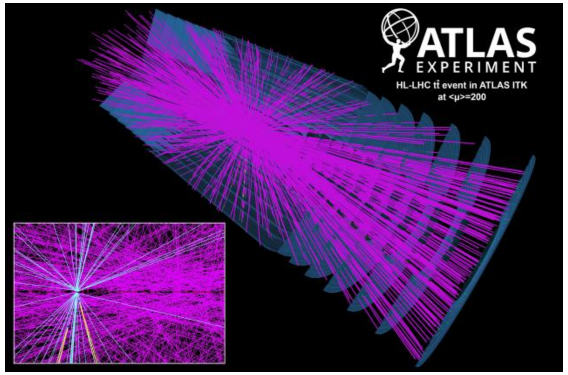


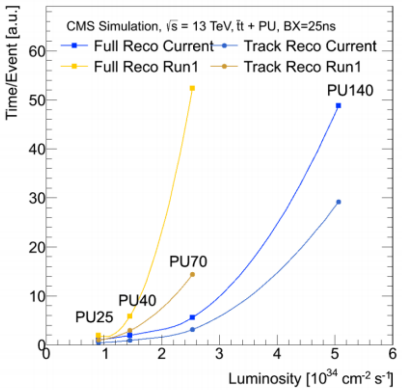


Reconstruction

Track reconstruction

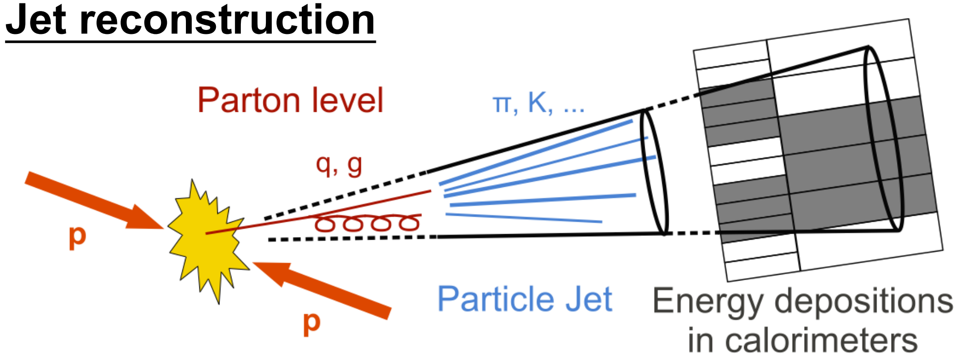
https://cds.cern.ch/record/1966040





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

Jet reconstruction

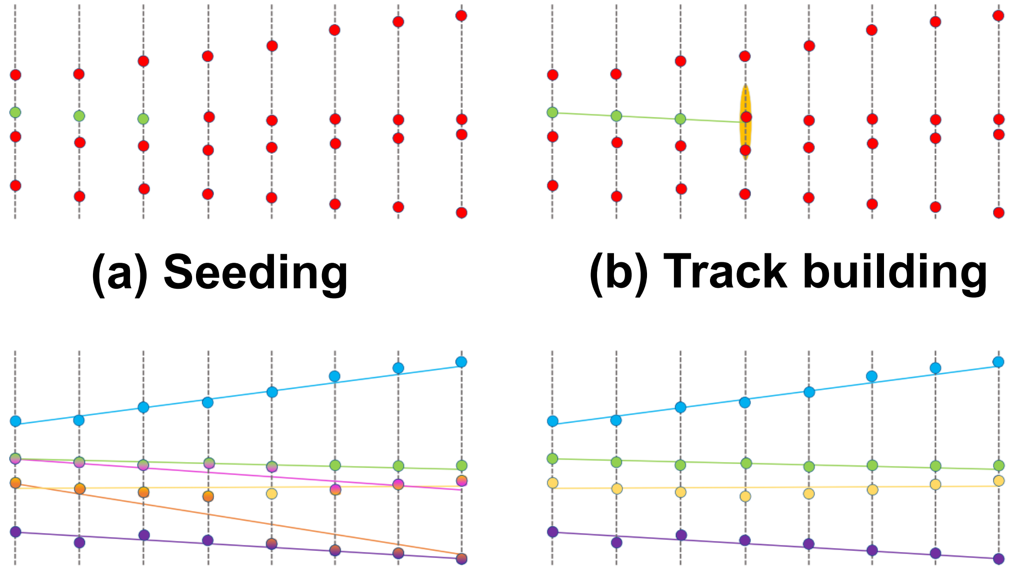


- **The most CPU-expensive task at HL-LHC.**
- Two classes of algorithms exist for both track & jet reconstruction.
- **Iterative:** e.g. Combined Kalman filter (tracking), sequential jet clustering (k_t, anti-k_t, etc.)
  - Quantum version often uses **Grover search algorithm,** which **requires quantum 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

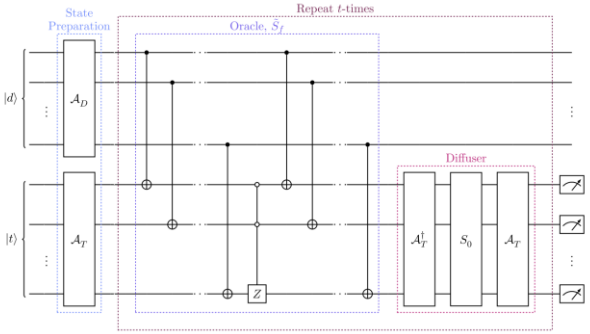


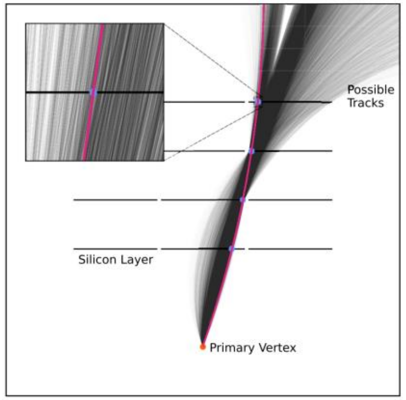
(a) Seeding (b) Track building

(c) Cleaning (d) Selection

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

Generalized Grover search
(Quantum Amplitude Amplification)

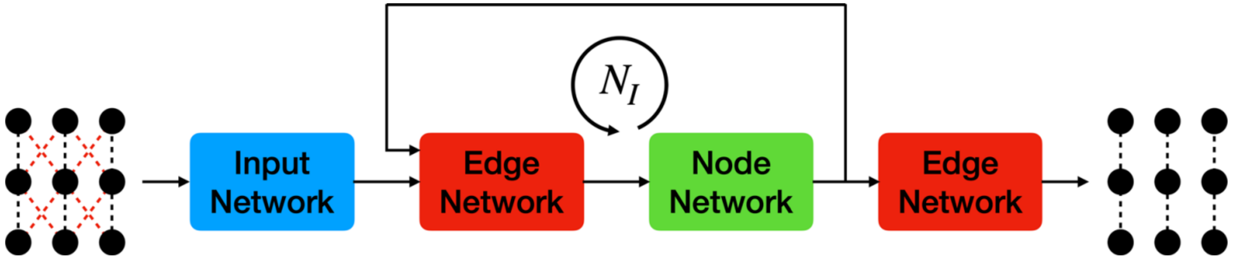


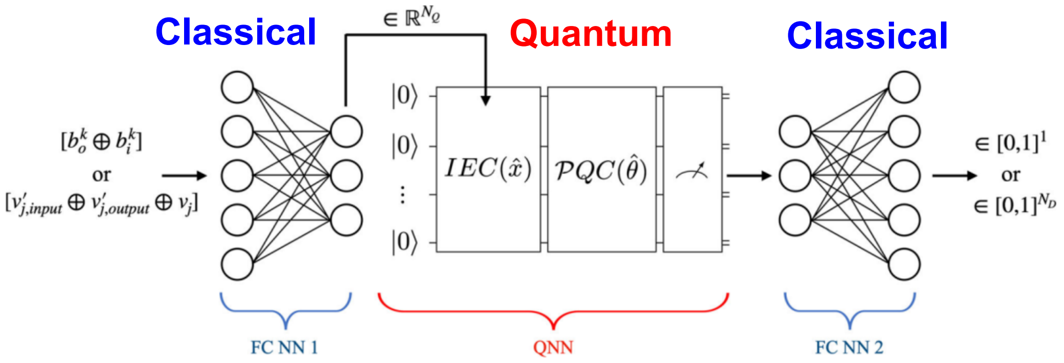


- D. Magano et al.: Due to the lack of QuAM, conceptual complexity analysis was performed. **Grover search reduces complexity of seeding & track building in square root.**
- C. Brown et al.: **a novel oracle design with a generalized Grover search** was developed & simple toy model was used for demonstration.

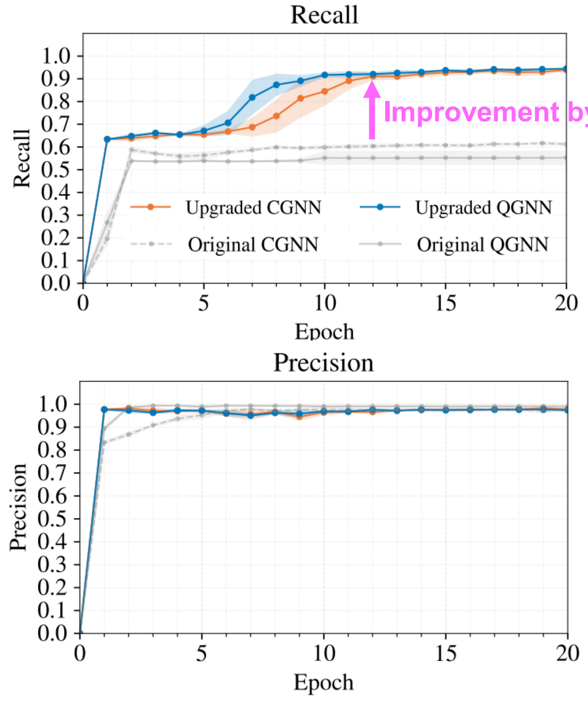
Track Reconstruction (Global): QGNN

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





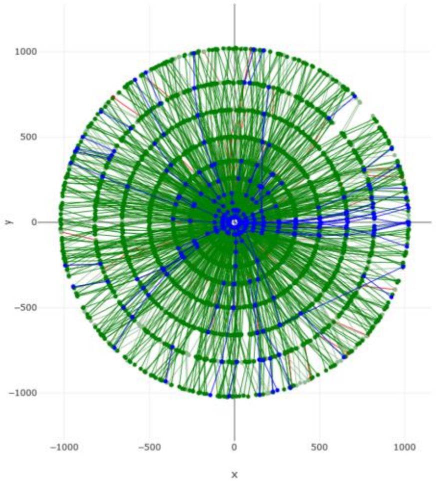
- **Hybrid classical-quantum NN** for the edge & node networks.
  → i.e. a large fraction of the network is still classical.
- **Very large RAM requirements & long training time** (originally >1 week on quantum circuit simulator, <24h in this new study).
- Running on quantum hardware is still difficult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



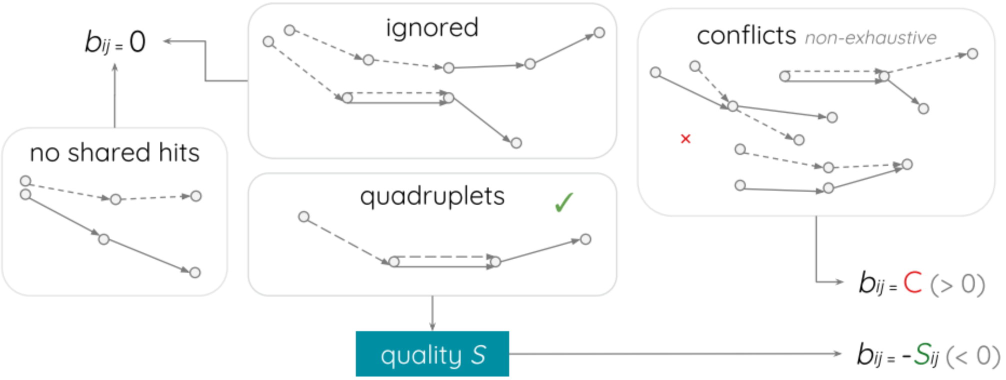
Matteo Argenton, Laura Cappelli, Concezio Bozzi, arXiv:2603.08667

See also: A. Zlokapa et al., Quantum Machine Intelligence (2021) 3:27; A.Crippa et al., Comput Softw Big Sci 7, 14 (2023); H. Okawa, Springer CCIS, 2036 (2024) 272

Track Reconstruction (Global): QUBO



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



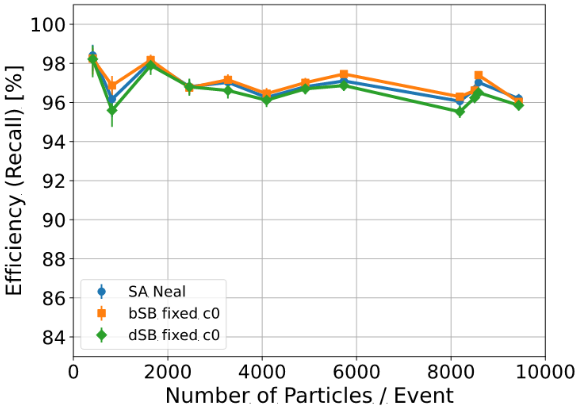
$$O(a,b,T) = \underbrace{\sum_{i=1}^{N} a_i T_i}_{\text{Quality of triplets}} + \underbrace{\sum_{i}^{N}\sum_{j<i}^{N} b_{ij} T_i T_j}_{\text{Compatibility b/w triplet pairs}}$$

$$a_i = \alpha\left(1 - e^{\frac{|d_0|}{\gamma}}\right) + \beta\left(1 - e^{\frac{|z_0|}{\lambda}}\right),$$

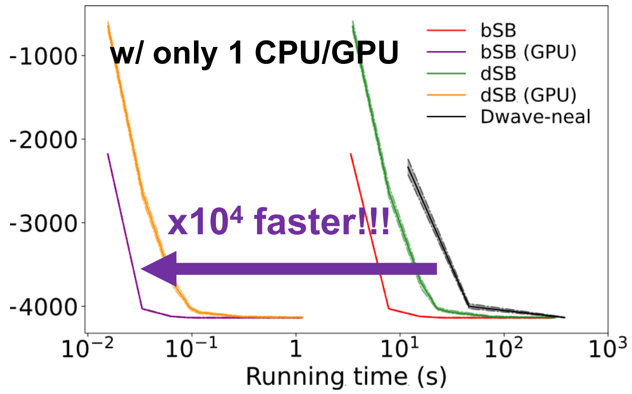
b_{ij} = 0 (if no shared hit), 1 (if conflict)
= $-S_{ij}$ (if two hits are shared)

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

Efficiency



Ising Energy vs computing time



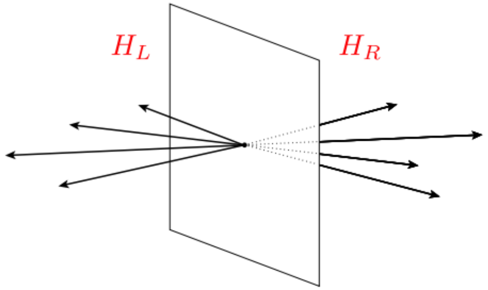
- QUBO-based approaches using quantum annealers were proposed by F. Bapst et al. & A. Zlokapa et al.
- **At the HL-LHC, the required # of qubits will reach O($10^{5\sim6}$)! Scalability is a bottleneck.**
- **Quantum-inspired algorithm (simulated bifurcation) demonstrated the first scalable approach with just 1 CPU or GPU.**

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

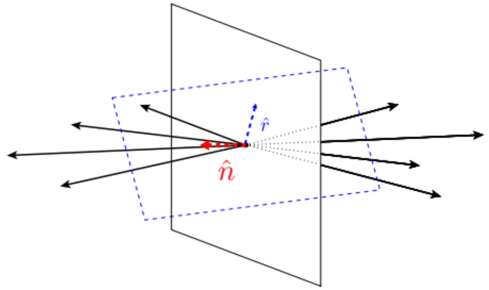
Jet Reconstruction (Iterative)

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

Thrust as partitioning (QA)



Thrust as axis finding (Grover search)

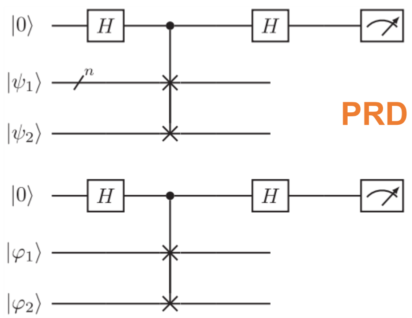


- Authors improved classical algorithm inspired by SISCone.
- **Quantum & classical algorithms scale the same, but for different reasons.**

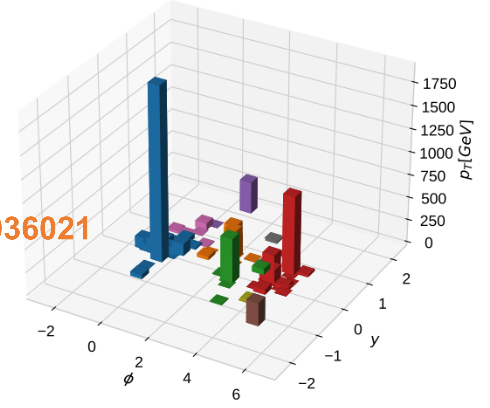
Implementation	Time Usage	Qubit Usage
Classical[124]	$O(N^3)$	—
Classical with sort inspired by SISCone[125]	$O(N^2 \log N)$	—
Classical with parallel sort	$O(N \log N)$	—
Quantum annealing	Gap dependent	$O(N)$
Quantum search: sequential model	$O(N^2)$	$O(\log N)$
Quantum search: parallel model	$O(N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

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

Quantum subroutine to compute Minkowski-based distance



PRD 106 036021



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

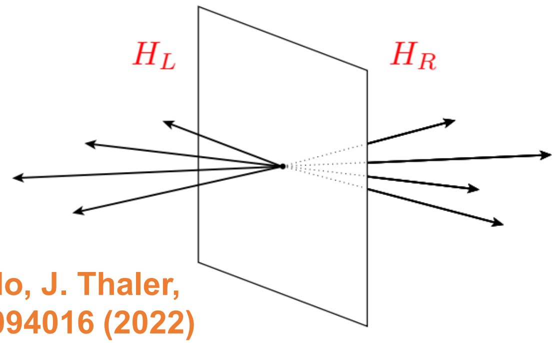
- **Quantum & classical algorithms [FastJet] scales the same for sequential clustering.**
- IBM quantum circuit simulator was also used to actually perform clustering.

Jet algorithms	Classical	Quantum
K-means	$O(NKD)$	$O(NK \log D)$,[116] $O(N \log K \log(D-1))$[127]
AP	$O(N^2TD)$	$O(N^2 T \log(D-1))$[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]

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

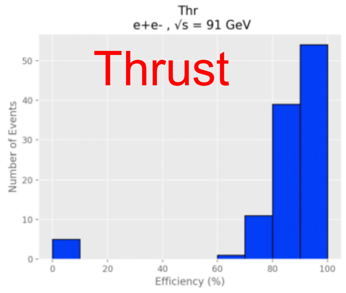
$$O_{\mathrm{QUBO}}(\{x_i\}) = \left(\sum_{i=1}^{N} |\vec{p}_i|\right)^2 T(\{x_i\})^2$$

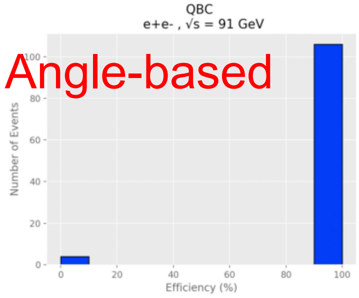
$$T(\{x_i\}) = 2\frac{\left|\sum_{i=1}^{N} x_i \vec{p}_i\right|}{\sum_{i=1}^{N} |\vec{p}_i|}$$

- 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)





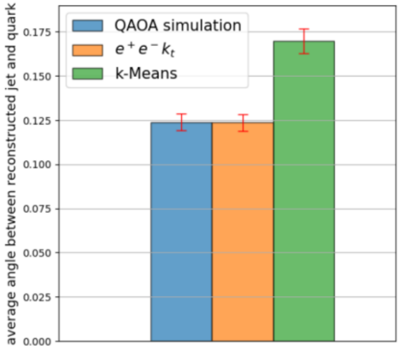
$$H = \frac{1}{2}\sum_{i,j=1}^{N} -\cos\left[\theta(\vec{p}_i, \vec{p}_j)\right] s_i s_j$$

- 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.

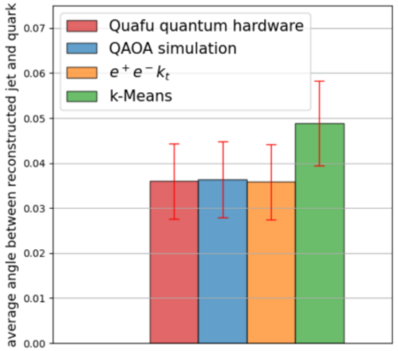
Y. Zhu et al., Sci. Bul. 70 (2025) 460

QAOA (Angle) or K-means

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



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



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

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.

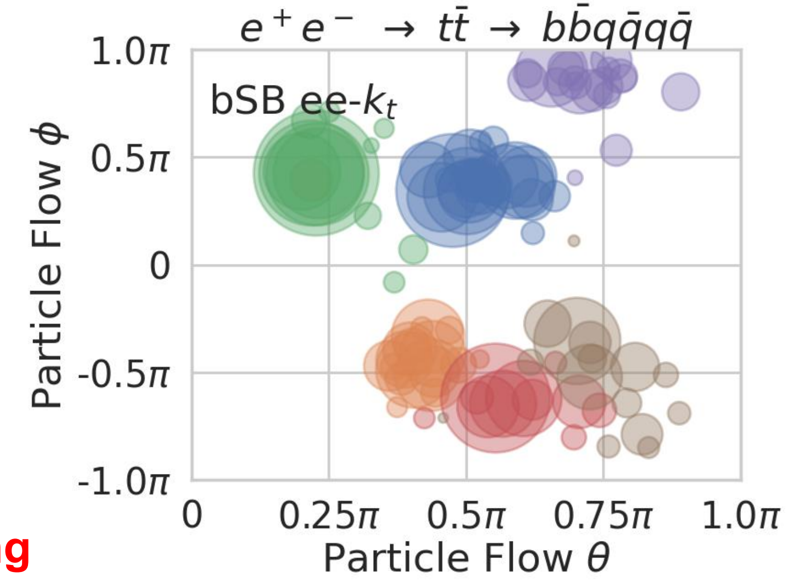
H Okawa et al., Phys. Lett. B, 864 (2025) 139393

Multijet Reconstruction (Global)

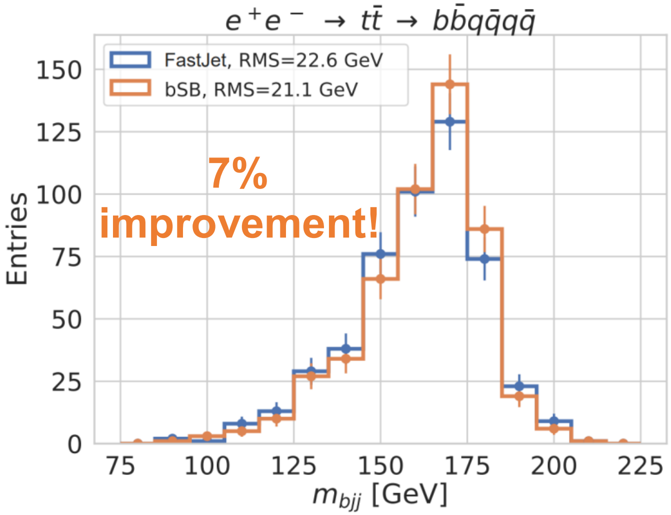
QUBO Formulation

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

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

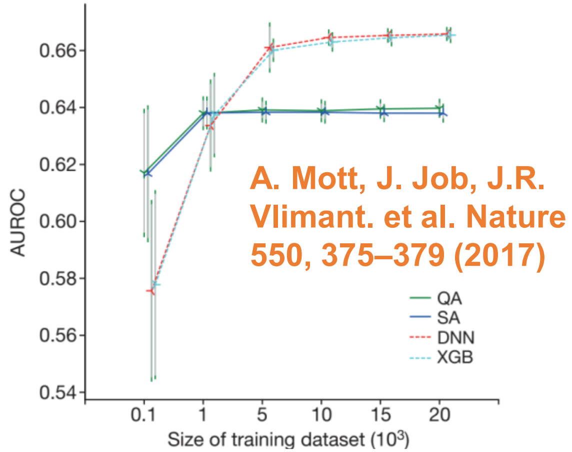


- **Quantum-hardware-driven approaches suffer from qubit-scaling & connectivity issues.** → Quantum-inspired does not
- **A quantum-inspired algorithm (bSB) overcame the challenge** for the one-hot encoding for multijet reconstruction.
- **1st successful global multijet clustering** with bSB quantum-inspired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

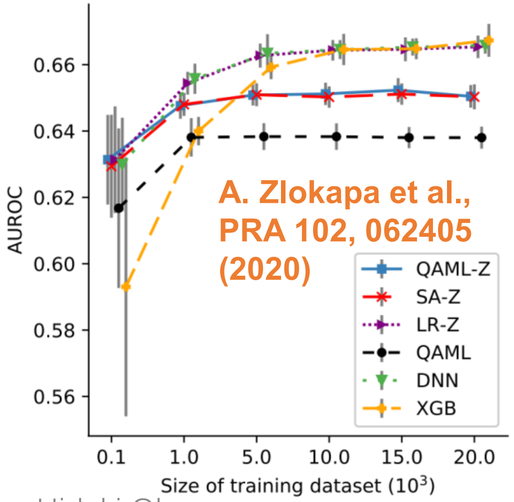


Classification

Quantum Annealing

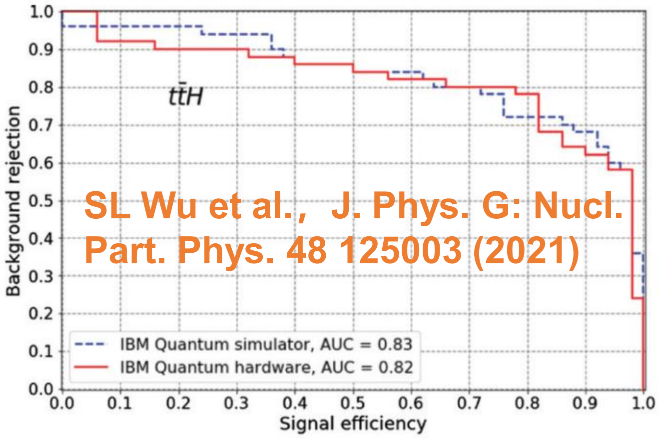


A. Mott, J. Job, J.R. Vlimant. et al. Nature 550, 375–379 (2017)



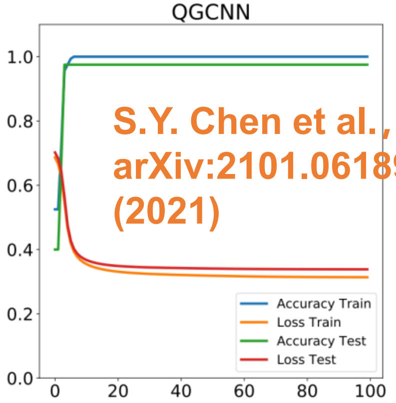
A. Zlokapa et al., PRA 102, 062405 (2020)

Quantum Gates (Variational quantum algorithms)



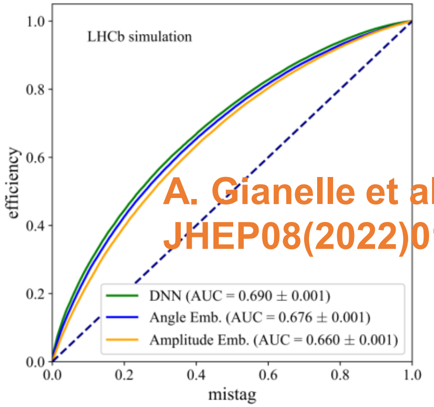
SL Wu et al., J. Phys. G: Nucl. Part. Phys. 48 125003 (2021)

QGCNN



S.Y. Chen et al., arXiv:2101.06189 (2021)

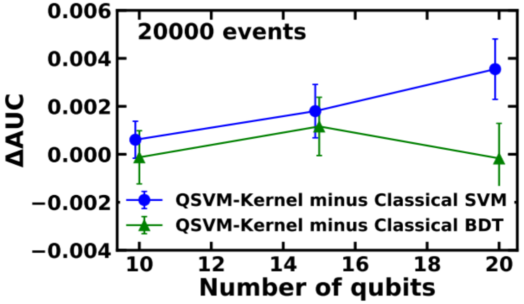
LHCb b-tag (VQC)



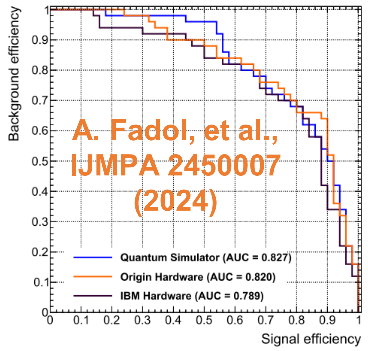
A. Gianelle et al., JHEP08(2022)014

Quantum Gates (Quantum Kernel methods)

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



CEPC event classification

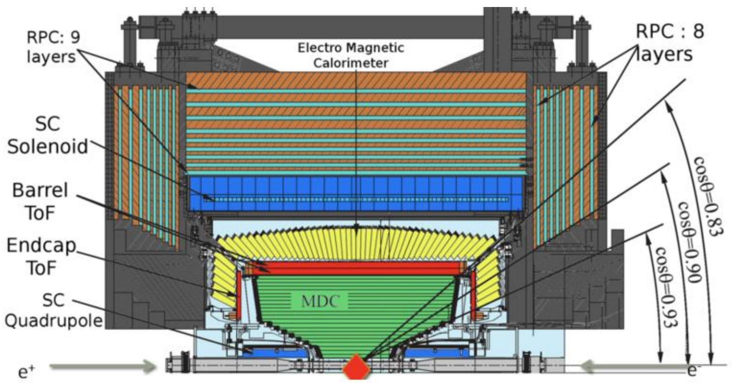


A. Fadol, et al., IJMPA 2450007 (2024)

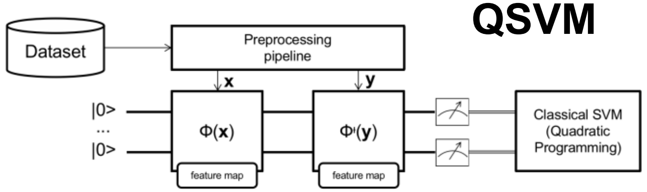
- A. Mott et al.: First QML applications in HEP using quantum annealing.
- Various QML algorithms are actively tested.

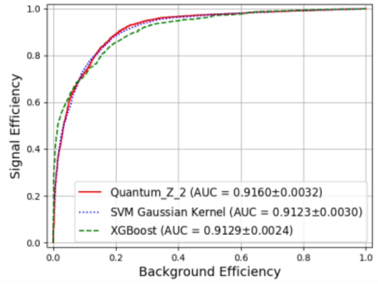
Classification

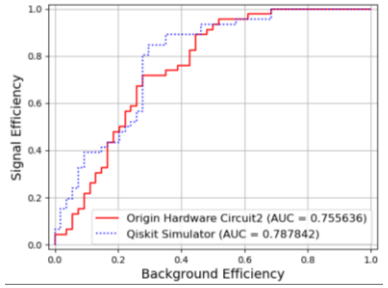
Z.P. Yao et al., EPJ Plus (2024) 139:356,
T. Li et al., J. Phys. Conf. Ser. 2438 (2023) 1, 012071



QSVM

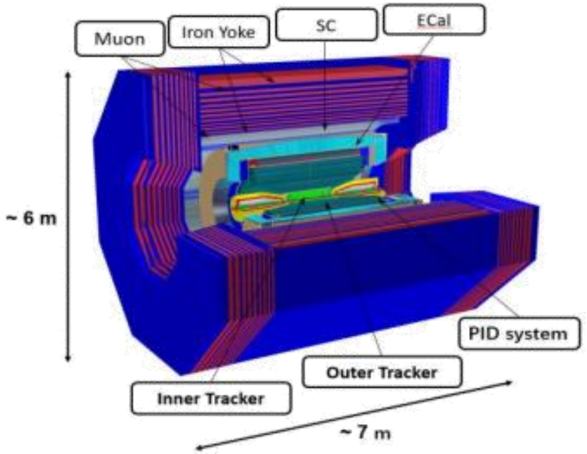


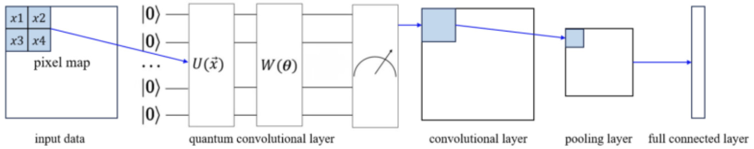




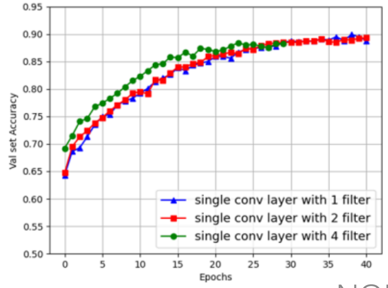
- QSVM & VQC for μ/π ID in BES3.
- Comparable QSVM performance in Origin Quantum (本源) hardware & simulator.

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

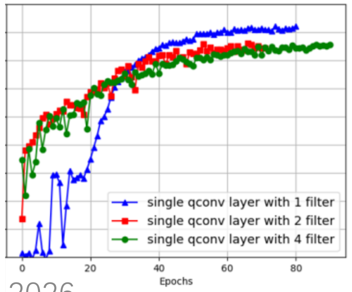




CNN



Quantum CNN

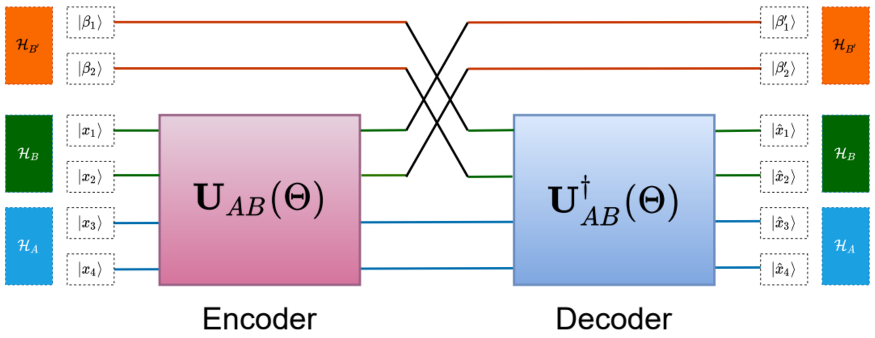


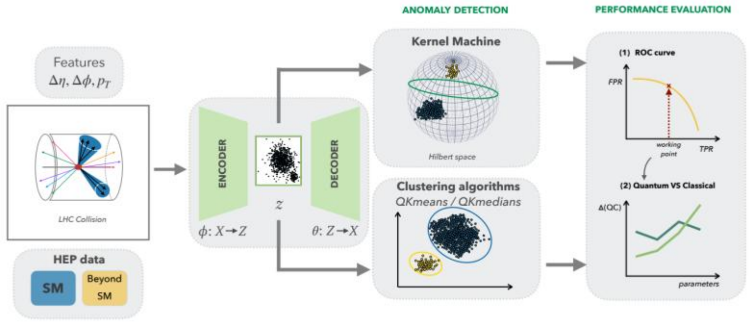
- π/K ID with QCNN in Super Tau Charm Factory (STCF) simulation.
- QCNN provides comparable performance to CNN in feature extraction and learning ability.

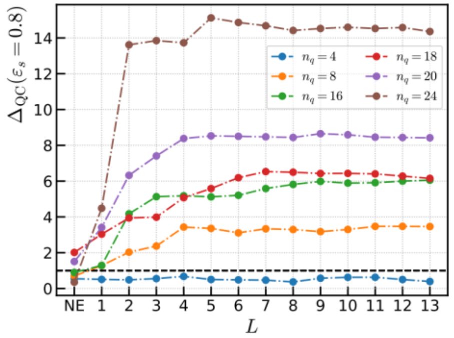
See also: S. Alvi, C.W. Bauer, B. Nachman, JHEP02(2023)220;
E. Puljak, M. Pierini, A. Garcia-Saez, Mach. Learn. Sci. Tech. 6 (2025) 4, 045001

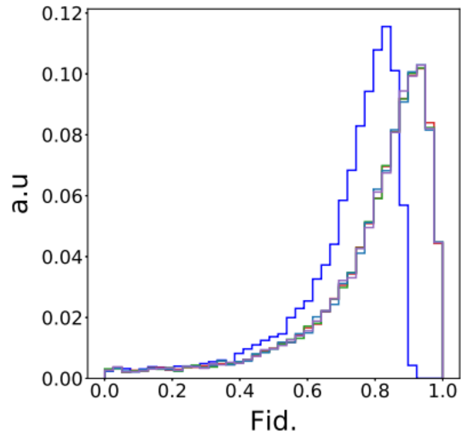
Anomaly Detection

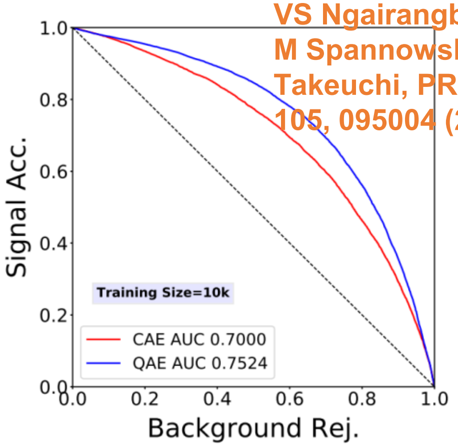
V. Belis et al., Comm. Phys. 7, 334 (2024)





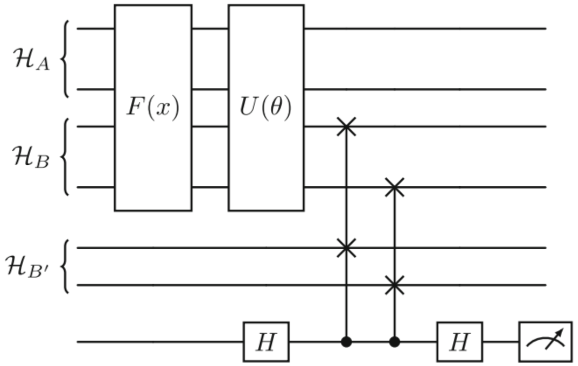


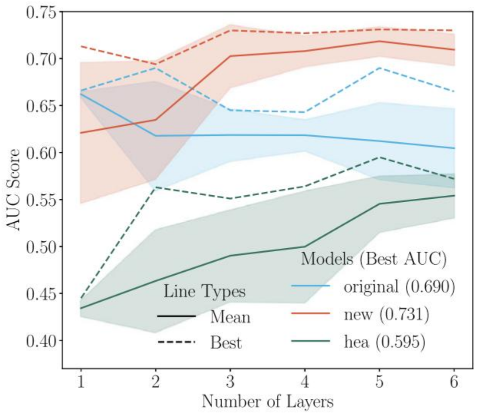




VS Ngairangbam, M Spannowsky, M Takeuchi, PRD 105, 095004 (2022)

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



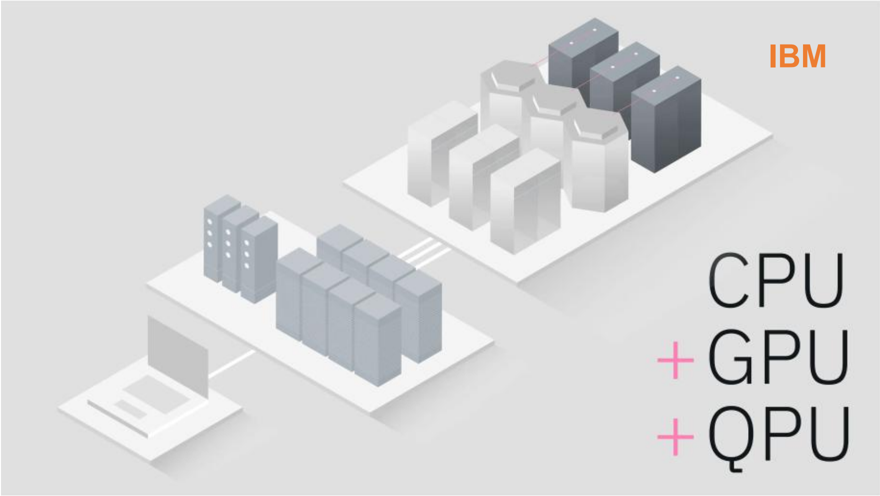


- V.S. Ngairangbam et al.: Quantum algorithm maintains performance with small datasets.
- V. Belis et al.: Performance enhances with more features & entanglement.
- C. Duffy et al.: Proposed scalable quantum circuit ansatz & demonstrated impact of ansatz design.

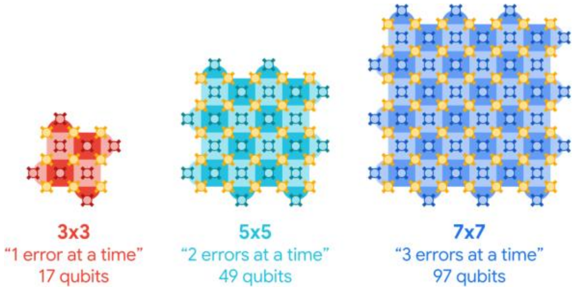
Towards Practical Applications

- Quantum computing combined with High-Performance Computing has started to operate (Quantum-centric supercomputing).
- O(~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)

H. Okawa, arXiv:2511.16713, invited review for MPLA
(dedicated for pattern recognition in HEP)

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.**

Picture credits: Qianhui Shi, Yan Liang

Thank you for listening!

Tracking as Optimization Problem

- Tracks are formed by connecting silicon detector hits: e.g. triplets (segments w/ 3 hits).
- Doublets/triplets are connected to reconstruct tracks & it can be regarded as a **quadratic unconstrained binary optimization (QUBO)/Ising** problem.

$$O(a,b,T) = \sum_{i=1}^{N} a_i T_i + \sum_{i}^{N} \sum_{j<i}^{N} b_{ij} T_i T_j$$

Quality of triplets

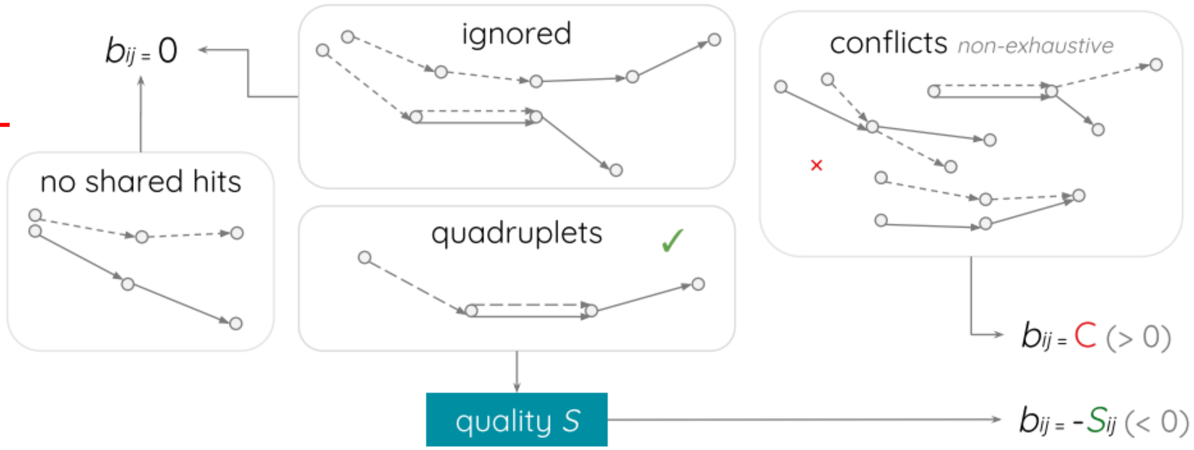
Compatibility b/w triplet pairs

$$a_i = \alpha\left(1 - e^{\frac{|d_0|}{\gamma}}\right) + \beta\left(1 - e^{\frac{|z_0|}{\lambda}}\right),$$

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

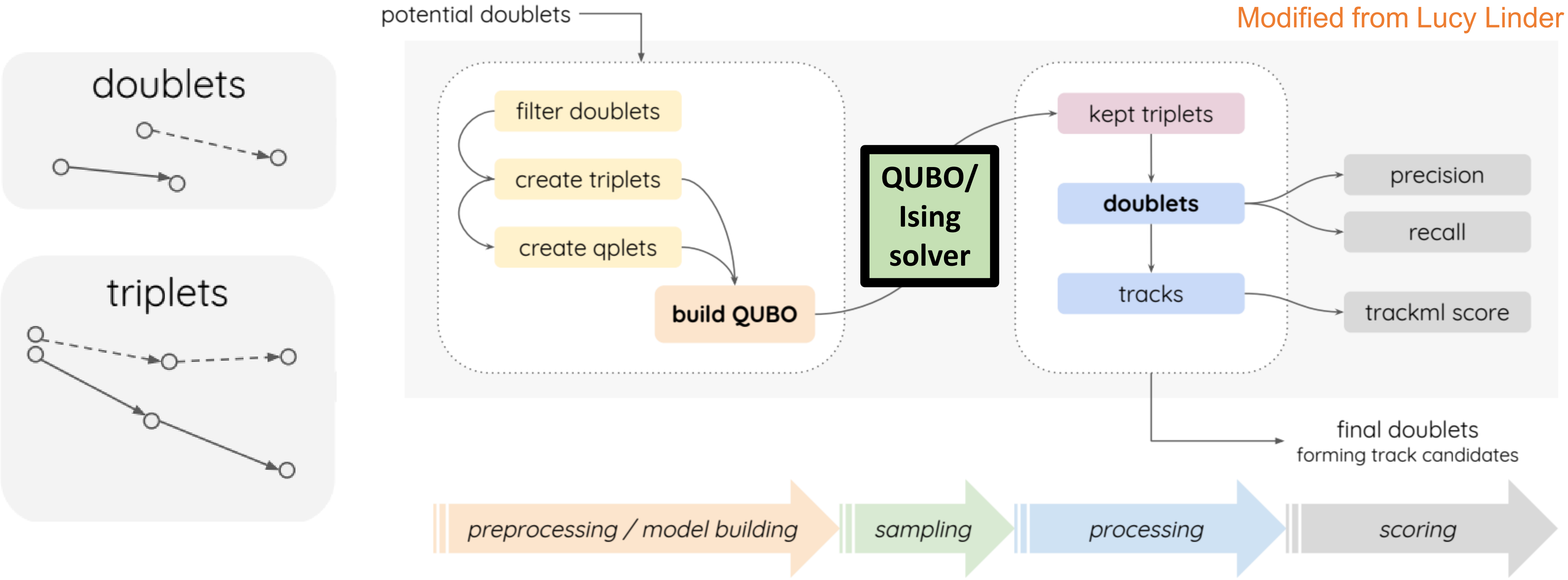
$$S_{ij} = \frac{1 - \frac{1}{2}(|\delta(q/p_{Ti}, q/p_{Tj})| + max(\delta\theta_i, \delta\theta_j))}{(1 + H_i + H_j)^2},$$

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



Minimizing QUBO is equivalent to searching for the ground state of the Hamiltonian.

Tracking Algorithm Flow w/ QUBO



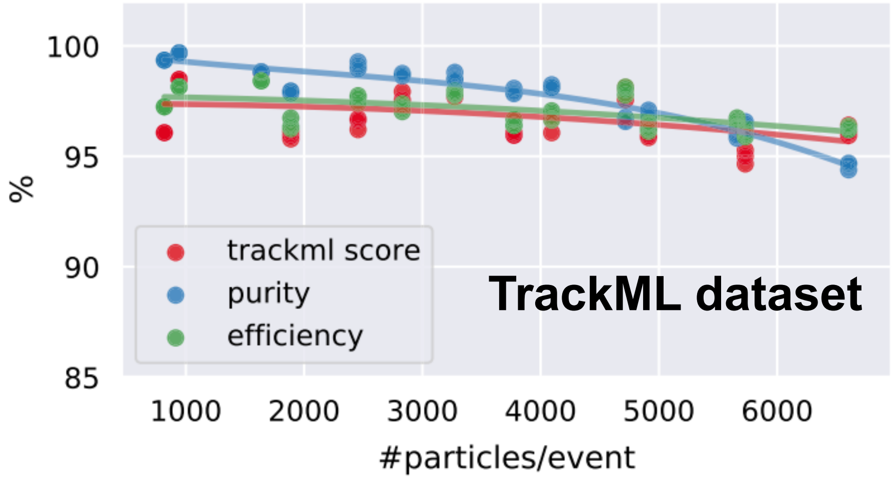
- We build QUBO on an event-by-event basis from the silicon detector hits.
- Predicted ground state will define which triplets should be kept (binary=1). Connecting the adopted triplets will give us the tracks.

See also I Shapoval, P Calafiura, EPJ Web Conf. 214 (2019) 01012; G Quiroz et al., NIM A 1010 (2021) 165557; D Magano et al., PRD 105 (2022) 076012; C Brown et al., Front. Artif. Intell. 7:1339785 (2024)

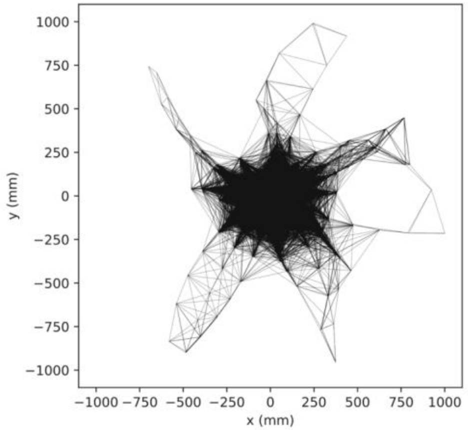
Tracking with Quantum Algorithms

Quantum annealing (w/ triplets)

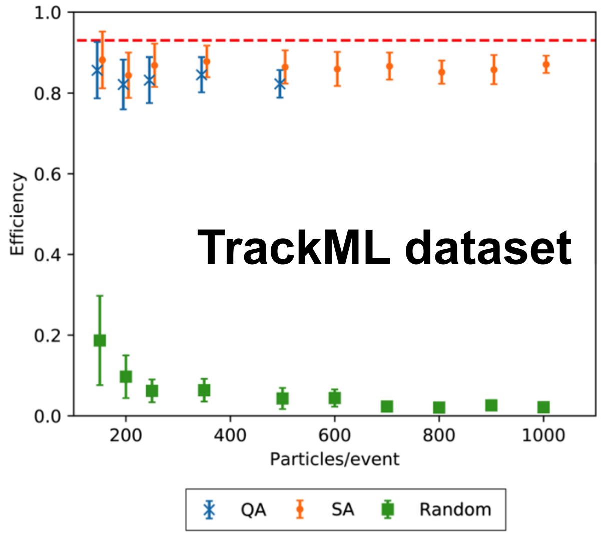
F. Bapst et al. Comp. Soft. Big Sci. 4 (2019) 1.



Quantum annealing (w/ doublets)



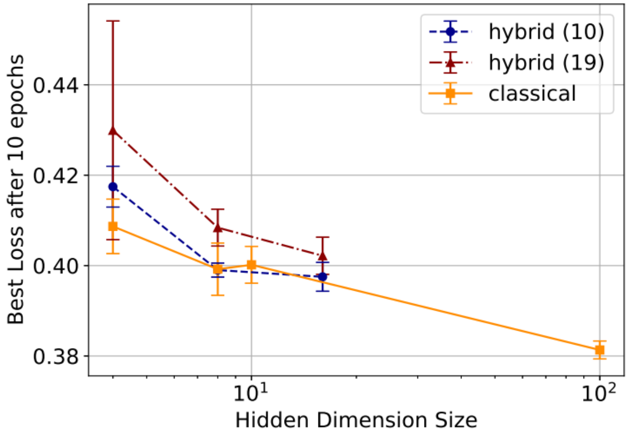
A. Zlokapa et al., Quantum Machine Intelligence (2021) 3:27



Quantum Gates (QGNN)

C. Tuysuz et al., Quantum Machine Intelligence (2021) 3:29

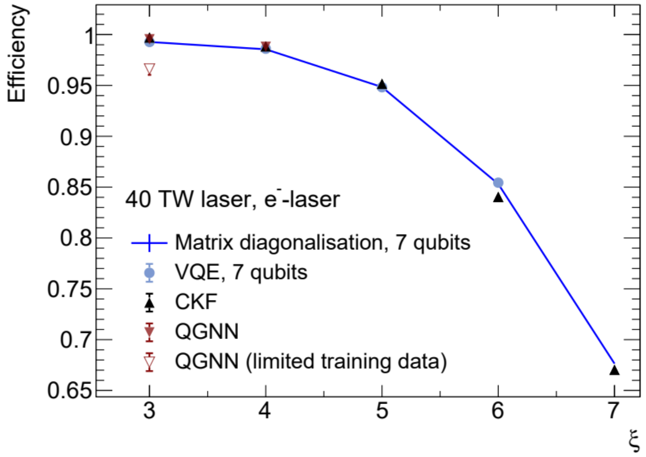
Conceptual stage



Quantum Gates (VQE w/ triplets, QGNN)

Y.C. Yap et al., PoS EPS-HEP2023 (2024) 562

DESY-LUXE simulation dataset

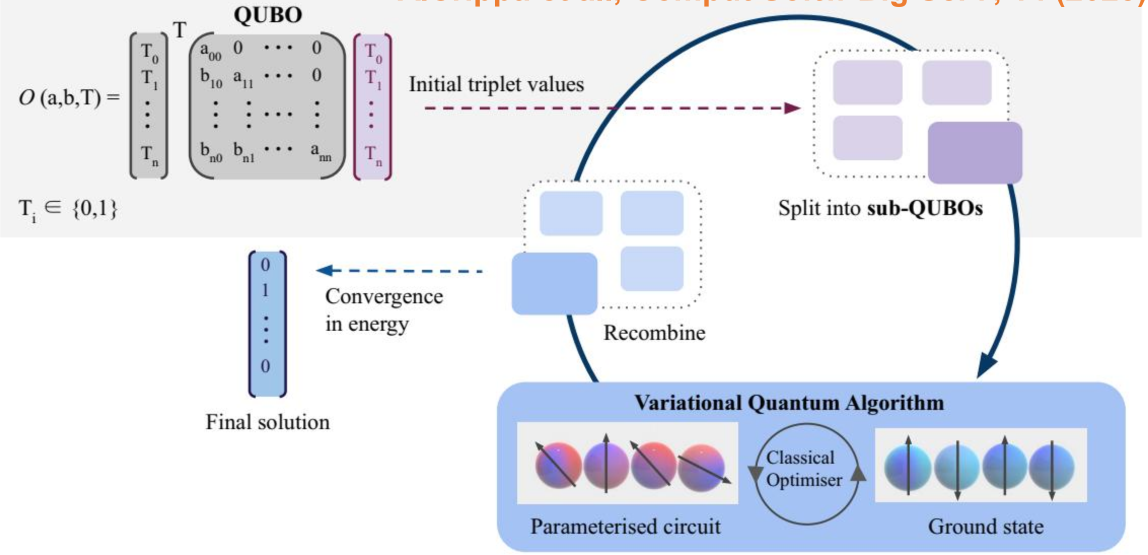


H. Okawa, Springer CCIS, 2036 (2024) 272–283, arXiv:2310.10255

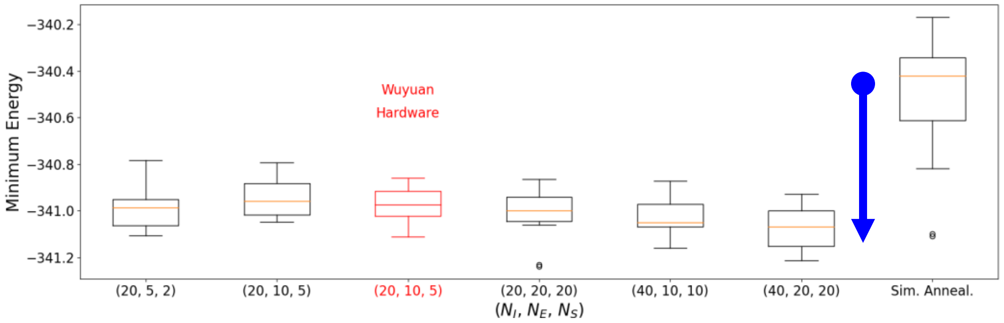
Tracking with Quantum Hardware

- # of triplet candidates determines # of qubits required → **HL-LHC conditions (~O(0.1M) qubits) do not fit into the current scale of quantum annealing & gate computers**
- **QUBO is split into sub-QUBOs.** There is no visible degradation in Ising solving precision, but **the computation speed degrades by a few orders of magnitude**.

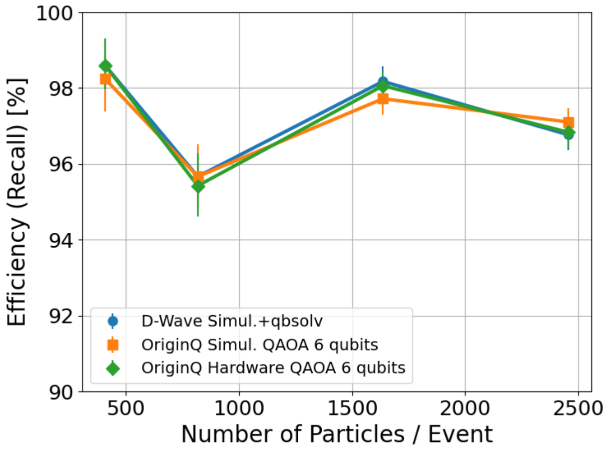
A.Crippa et al., Comput Softw Big Sci 7, 14 (2023)

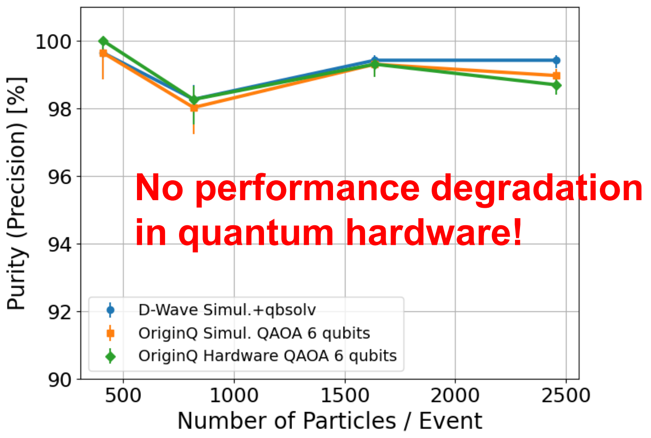


Using theoretically robust sub-QUBO algorithm (Multiple Solution Instances)



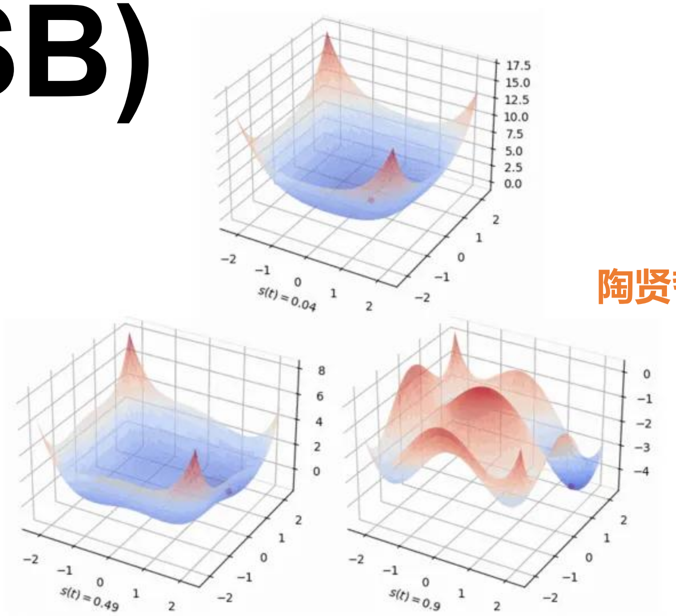
Track Finding with QAOA





Goto et al., Sci. Adv. 2019; 5: eaav2372
Goto et al., Sci. Adv. 2021; 7: eabe7953

Simulated Bifurcation (SB)



陶贤哲

$$H_{\mathrm{SB}}(\mathbf{x}, \mathbf{y}, t) = \sum_{i=1}^{N} \frac{\Delta}{2} y_i^2 + \sum_{i=1}^{N} [\frac{K}{4} x_i^4 + \frac{\Delta - p(t)}{2} x_i^2] - \frac{\xi_0}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} x_i x_j$$

$$\dot{x}_i = \frac{\partial H_{\mathrm{SB}}}{\partial y_i} = \Delta y_i$$

$$\dot{y}_i = -\frac{\partial H_{\mathrm{SB}}}{\partial x_i} = -[K x_i^2 - p(t) + \Delta] x_i + \xi_0 \sum_{j=1}^{N} J_{i,j} x_j$$

- “Quantum-annealing-inspired” algorithms search for ground state through the **classical time evolution of differential equations.**
- **Simulated bifurcation (SB) emulates quantum adiabatic evolution of Kerr-nonlinear parametric oscillators, exhibiting bifurcation phenomena.**
- Three variants exist depending on how one handles the continuous treatment of the spins (x_i): aSB, bSB, dSB

$$V_{\mathrm{aSB}} = \sum_{i=1}^{N} \left(\frac{x_i^4}{4} + \frac{a_0 - a(t)}{2} x_i^2 \right) - \frac{c_0}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} x_i x_j$$

adiabatic SB (aSB; original)

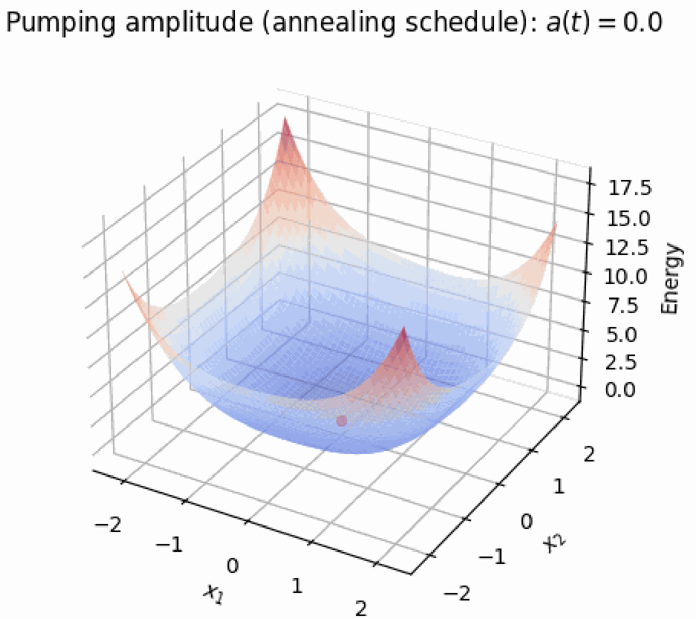
$$V_{\mathrm{bSB}} = \begin{cases} \frac{a_0 - a(t)}{2} \sum_{i=1}^{N} x_i^2 - \frac{c_0}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} x_i x_j, & \text{if } |x_i| \le 1, \forall i \\ \infty, & \text{otherwise.} \end{cases}$$

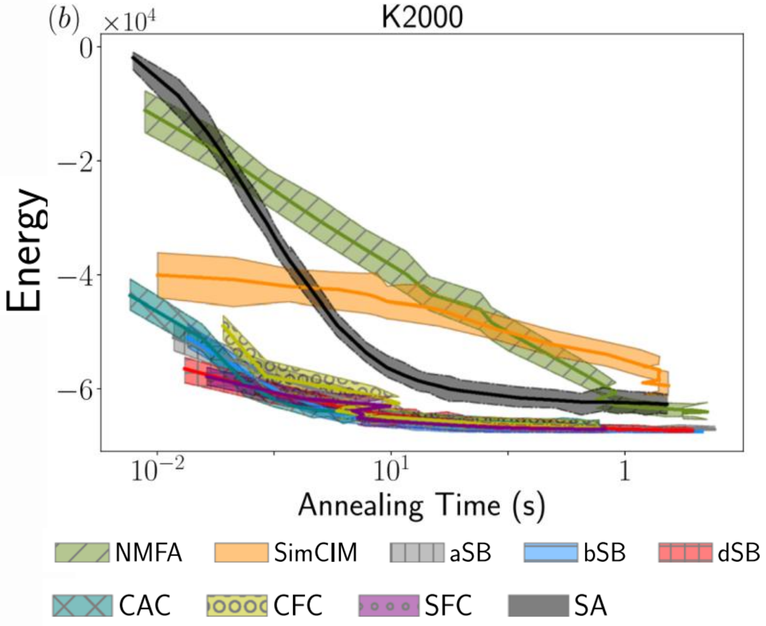
ballistic SB (bSB)

$$V_{\mathrm{dSB}} = \begin{cases} \frac{a_0 - a(t)}{2} \sum_{i=1}^{N} x_i^2 - \frac{c_0}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} x_i \operatorname{sgn}(x_j), & \text{if } |x_i| \le 1, \forall i \\ \infty, & \text{otherwise.} \end{cases}$$

discrete SB (dSB)

Quantum-Inspired Approach (SB)



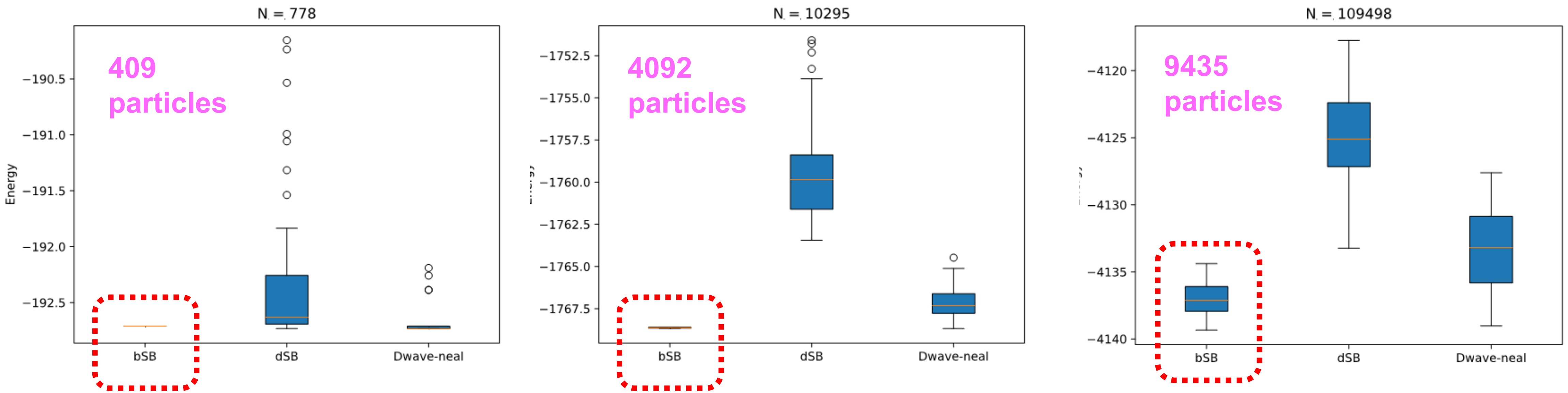


Graph size	Algorithm	Hardware	Time(s)
	TTN	CPU 1 core	5.62
	Brute-force search[46]	GPU Titan V	$>10^{48}$
4 × 4 × 8	Exact belief propagation[13]	CPU 1 core	~0.96
	QA[13]	D-Wave	~0.05
	bSB	CPU 1 core	0.12
	bSB	GPU Tesla V100	<0.001
	TTN	CPU 1 core	32400
	TTN[44]	GPU Tesla V100	84
8 × 8 × 8	Brute-force search[46]	GPU Titan V	$>10^{190}$
	Exact belief propagation[13]	CPU 1 core	~2880
	dSB	CPU 1 core	17.64
	dSB	GPU Tesla V100	<0.68

Q.G. Zeng et al., Comm. Phys. (2024) 7:249

- **SB is a powerful quantum-annealing-inspired algorithm.**
- **It can run in parallel** unlike simulated annealing. It also benefits from cutting-edge resources such as **GPUs and FPGAs**.
- **It is known to outperform other classical algorithms as well as quantum annealing (QA) for some problems.**

Minimum Ising Energy Prediction

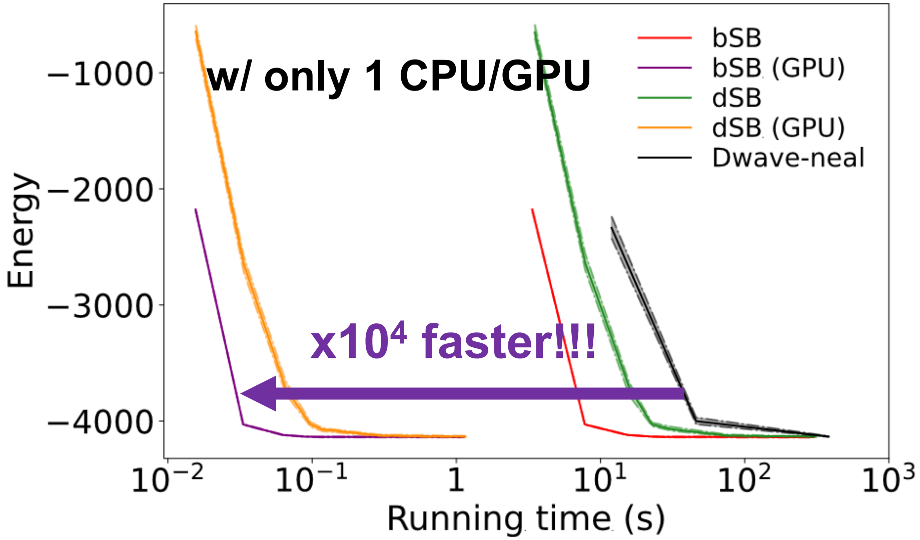


- **Ballistic simulated bifurcation (bSB) provides the best prediction of minimum energy with the least fluctuation for the tracking QUBO**.
- Discrete simulated bifurcation (dSB) is not as good as the other two, but the impact on the reconstruction performance is not significant (next slide)

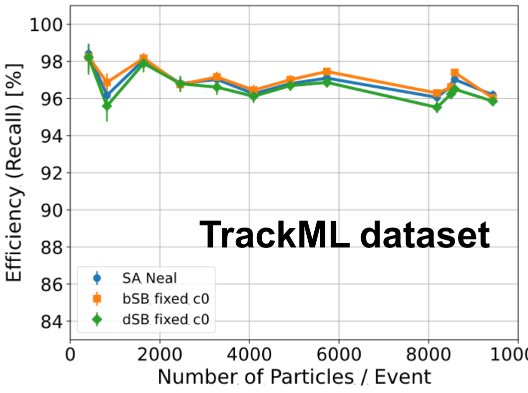
H. Okawa, Q.G. Zeng, X.Z. Tao, M.H. Yung, Springer Comput. Softw. Big Sci. 8, 16 (2024)

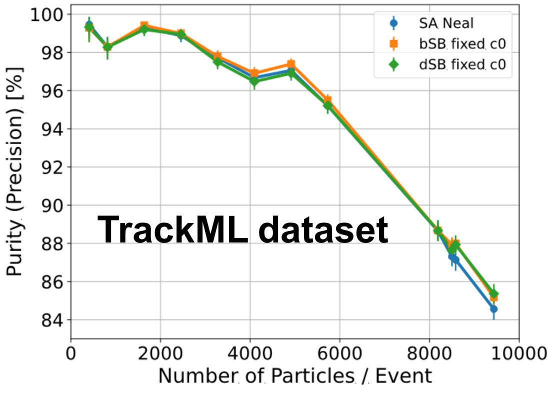
Tracking with Quantum-Inspired

- For some problems, **quantum-inspired algorithms outperform quantum annealing**.
- Ballistic simulated bifurcation (bSB) provides <u>4 orders of magnitude speed-up from D-Wave Neal simulated annealing</u> for HL-LHC data.
- **SB can effectively run <u>w/ multiple processing, GPU & FPGA.</u>**



No limitation on the problem size (up to ~million)





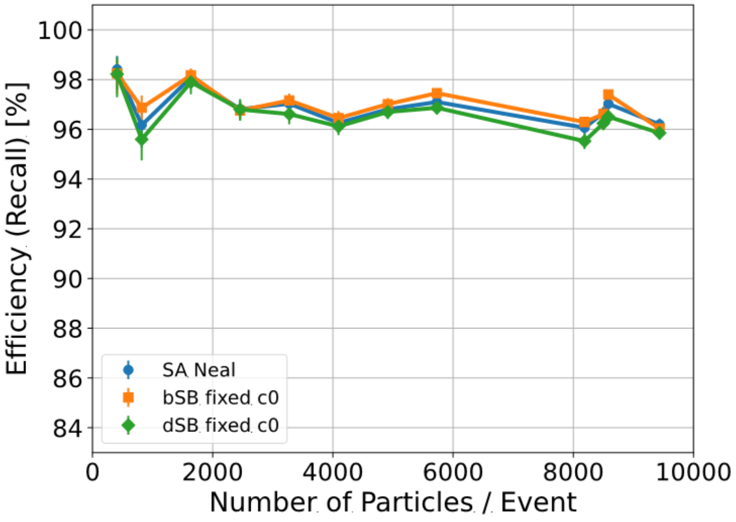
With 1 CPU or <u>1 GPU (23min → 0.13s)</u>

Data Information		Time to target [s]				
# of particles	QUBO size	bSB	bSB (GPU)	dSB	dSB (GPU)	D-Wave Neal
409	778	0.007	0.021	0.032	0.092	0.060
818	1431	0.012	0.019	0.293	0.478	0.169
1637	2904	0.012	0.019	0.293	0.478	0.169
2456	4675	0.014	0.017	–	–	0.479
3274	6945	0.032	0.022	–	–	1.229
4092	10295	0.005	0.022	0.015	0.065	0.030
4912	14855	0.027	0.016	–	–	2.165
5730	22022	0.109	0.042	–	–	3.853
8187	67570	0.488	0.028	–	–	404.297
8500	78812	1.899	0.108	–	–	785.732
8583	80113	1.321	0.067	–	–	93.782
9435	109498	3.884	0.140	–	–	1366.808

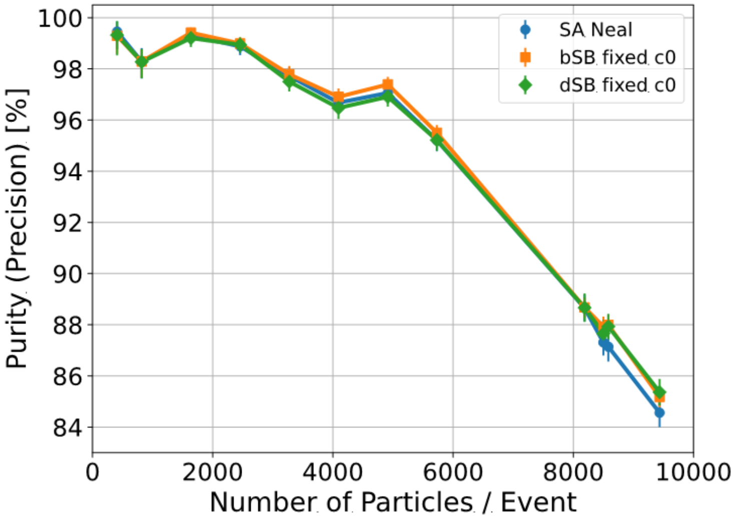
H. Okawa, Q.G. Zeng, X.Z. Tao, M.H. Yung, Springer Comput. Softw. Big Sci. 8, 16 (2024)

Quantum-Inspired Track Finding

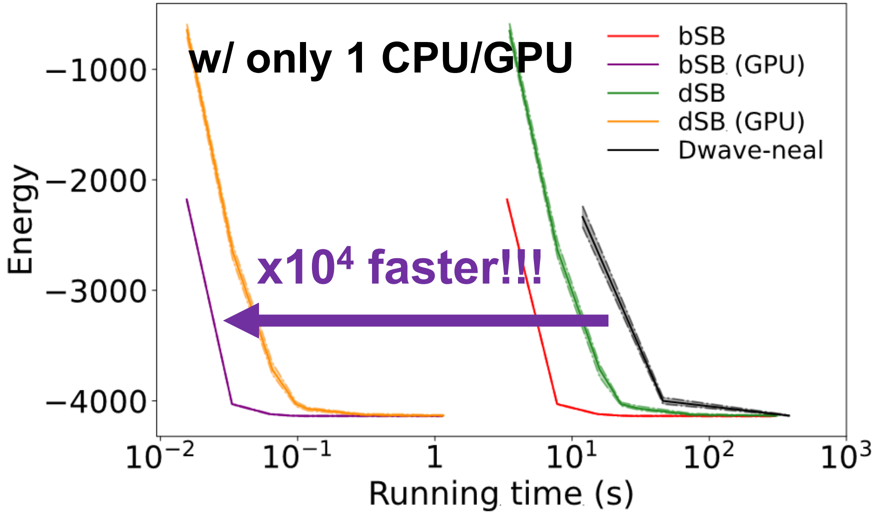
Efficiency



Purity



Ising Energy vs computing time



- **Quantum-annealing-inspired algorithm can DIRECTLY handle the HL-LHC dataset.**
- SB provides comparable or slightly better efficiency & purity than D-Wave Neal SA.
- bSB provides **4 orders of magnitude speed-up (23min → 0.14s) from D-Wave Neal** for HL-LHC data **(cf. D-Wave hardware with qbsolv is ~2 orders of magnitude slower than Neal).**
- **SB can effectively run w/ multiple processing, GPU & FPGA → Perfect match with HEP!!**

Multijet QUBO Formulation (Our Study)

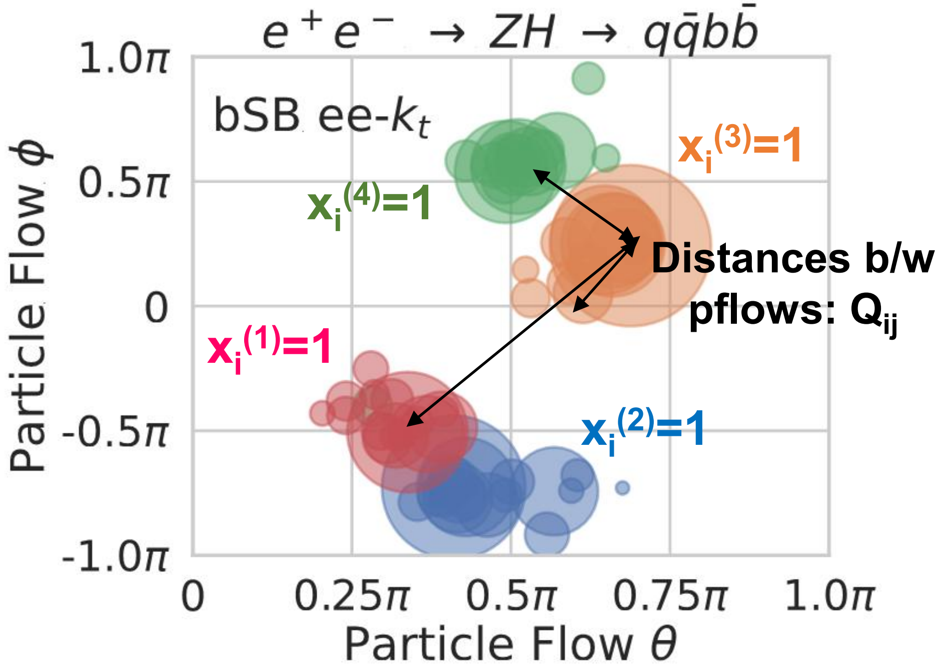
QUBO Formulation

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

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

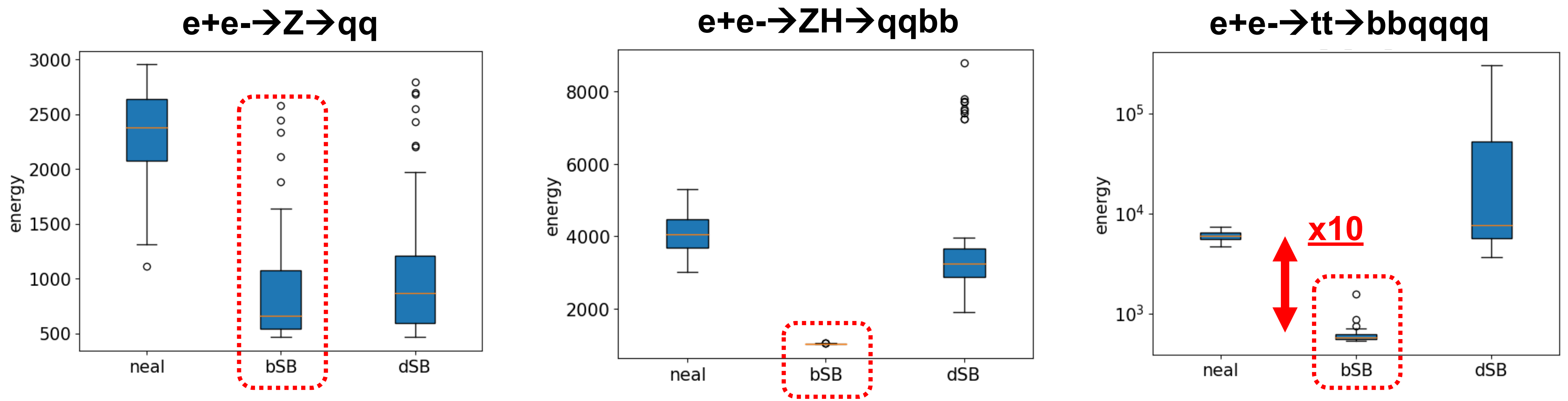
$$Q_{ij} = -\frac{1}{2}\cos\theta_{ij}$$ **[angle-based]**

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



- **Exclusive jet finding (i.e. fixed number of jets) with the ee-k_t algorithm** is the baseline at CEPC & other e+e- future Higgs factories.
- **We adopt the same distance in the QUBO formulation. QUBO is designed for general jet multiplicity beyond 2 jets.** $x_i^{(n)}=1$ means i-th constituent belongs to n-th jet.
- Performance is also compared with the angle-based method from a previous study.

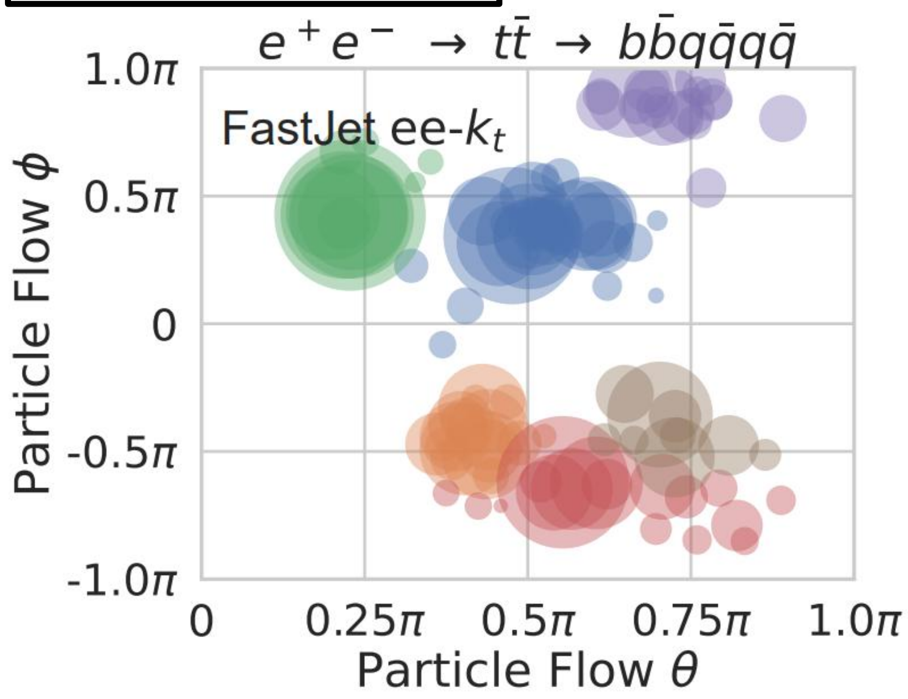
Minimum Ising Energy



- **QUBO for jet reconstruction is fully connected** unlike the track reconstruction QUBO, which is largely sparse. **Fully-connected QUBOs are difficult to solve**; it is known that quantum annealers (the real hardware) are not good at solving them.
- **bSB finds the lowest energy with the smallest fluctuation.**
- **Performance is especially outstanding for complex QUBOs → <u>bSB can find x10 lower minimum energy for the all-hadronic ttbar events!</u>**

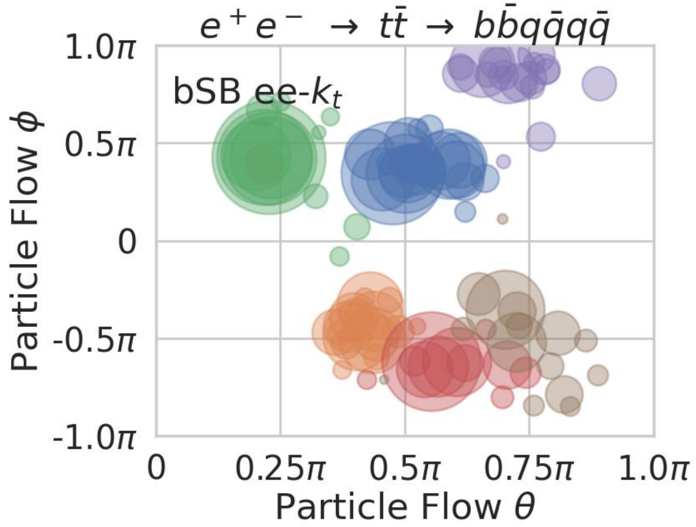
Event Displays ($t\bar{t}$)

Traditional (FastJet)

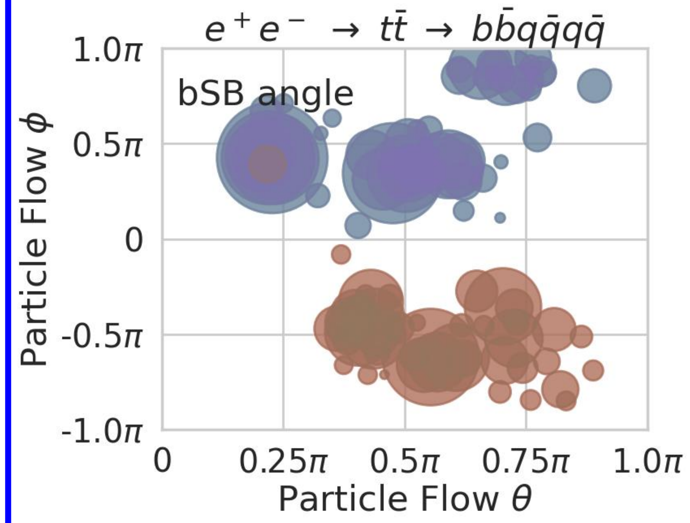


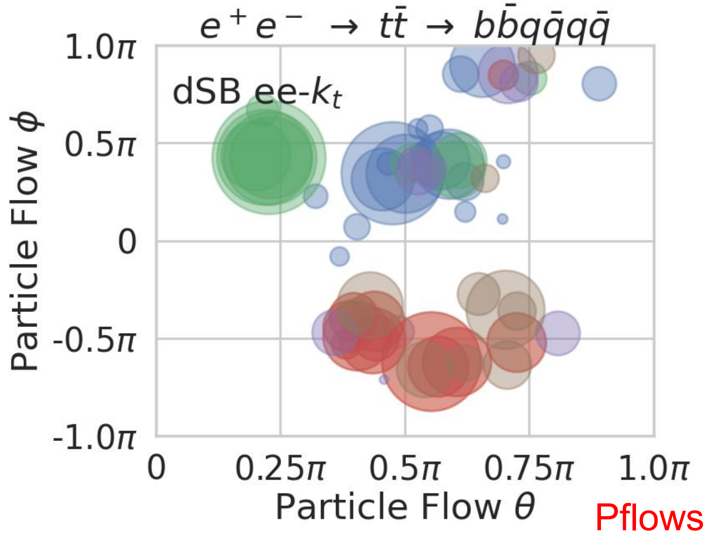
QAIAs

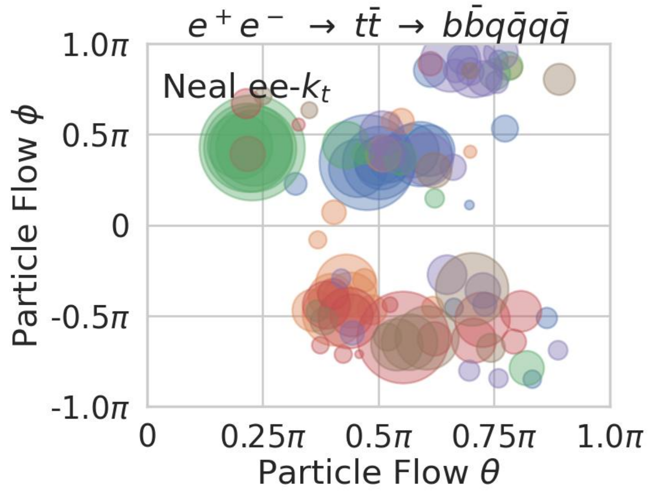
Success!



Missing some jets + double counting



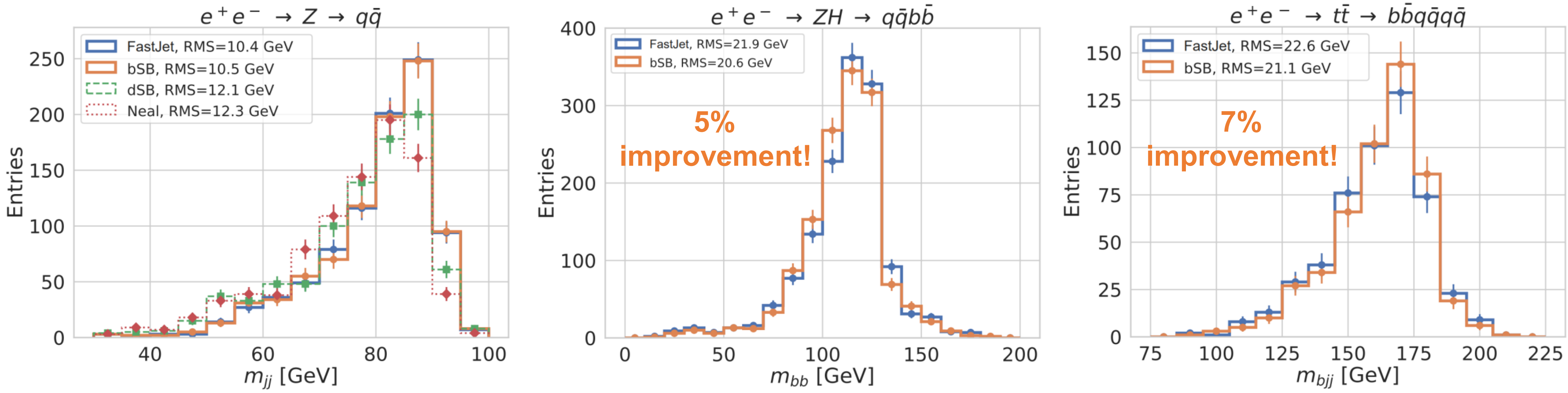




Pflows totally mixed up

- **Only bSB w/ ee-k_t QUBO model can reasonably reconstruct all jets.**
- **Angle QUBO model & other quantum-inspired algorithms miss some jets and/or PFlows are totally mixed up.**

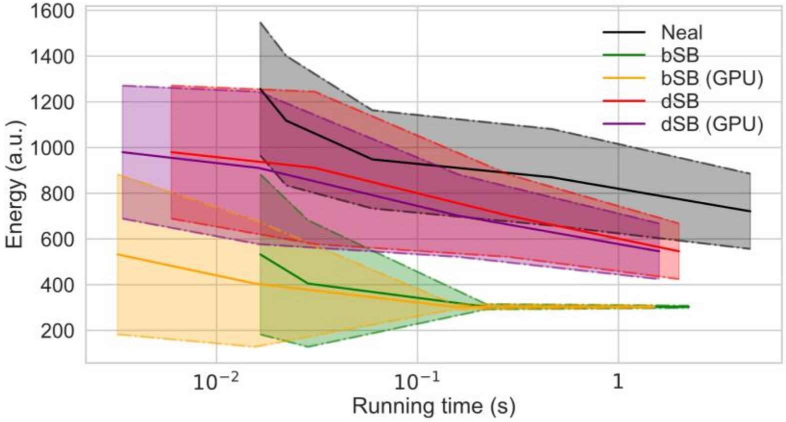
Impact on Invariant Mass



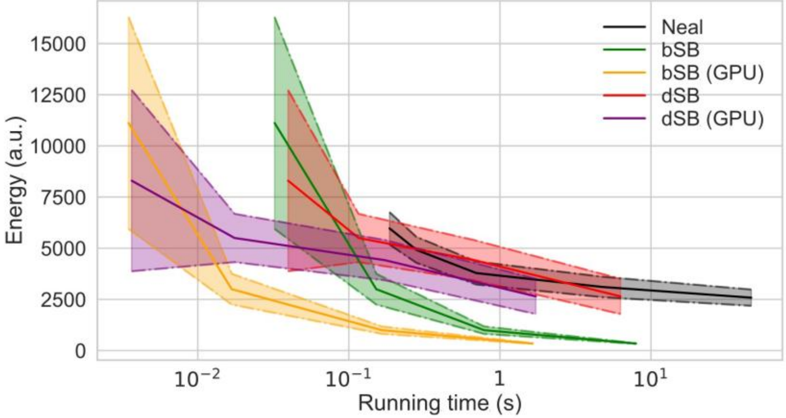
- **The clustering w/ bSB is slightly different from FastJet (see backup for quantitative comparison), <u>but it's OK</u>.** → Let's check the inv. mass resolutions.
- **<u>bSB improve mass resolution for multijet! (& comparable resolution for Z)</u>**
- Other quantum-inspired algorithms (dSB & Neal) already has ~20% degradation in Z mass resolution & unable to properly reconstruct jets in multijet events (thus not shown for ZH & $t\bar{t}$)

Computation Speed

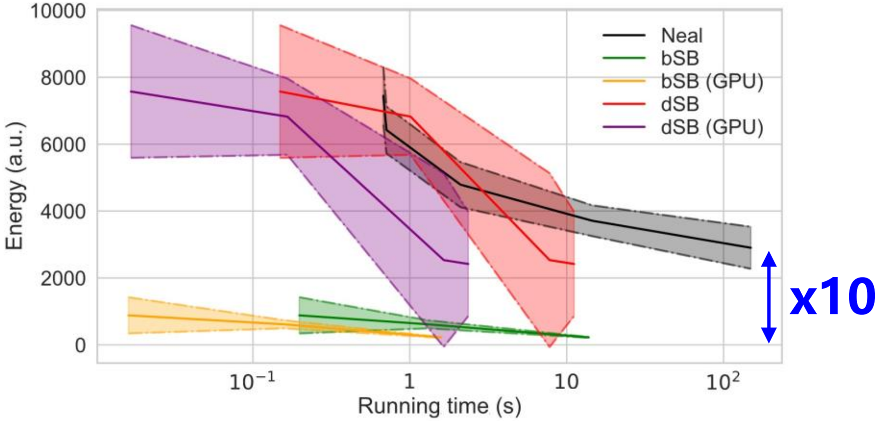
Z→qq



ZH→qqbb



$t\bar{t}$→bbqqqq



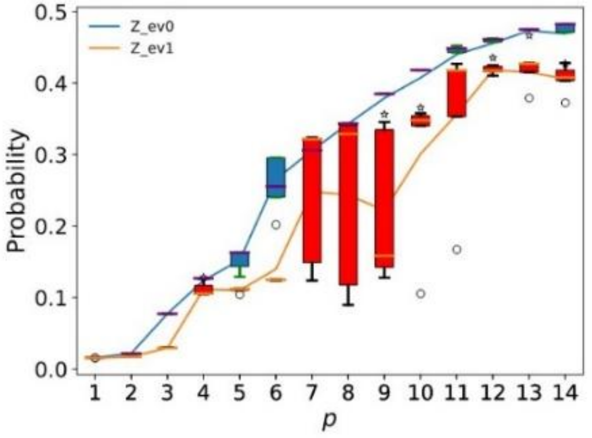
- Mean running time was evaluated for 3 processes.
- **D-Wave Neal generally cannot reach reasonable energy, regardless of the running time.**
- **dSB is slow in energy convergence & less successful than bSB for energy prediction.**
- **bSB significantly outperforms dSB & Neal.**

Data Information			Mean running time [s]	
Event	QUBO	Target eff.	bSB	bSB (GPU)
Z	64	>0.8	0.02	0.006
		>0.9	0.03	0.02
ZH	248	>0.8	3.27	0.68
		>0.9	6.35	1.32
$t\bar{t}$	444	>0.8	8.43	0.97
		>0.9	15.36	1.76

Comparison w/ QA & QAOA

- Performance was compared with two simplified datasets (12 qubits) to quantum annealing and QAOA using simulator.
- Even with such small datasets, bSB exceeds the speed of quantum annealing by about two orders of magnitude & even more for QAOA (w/ a caveat that it should run faster on real quantum hardware).

QAOA Performance



Time-to-solution for D-Wave 2000Q estimated by simulation, bSB, dSB, and QAOA on a quantum circuit simulator for two simplified $Z \to q\bar{q}$ events.

Event	D-Wave [s]	bSB [s]	dSB [s]	QAOA [s]
0	21.29	0.35	0.79	1.07×10^3
1	20.52	0.36	0.89	3.36×10^3