Quantum Artificial Intelligence for Experimental High-Energy Physics

2026 Workshop on New Physics and Interdisciplinary Sciences (NPhiS 2026),
May 16-18, 2026

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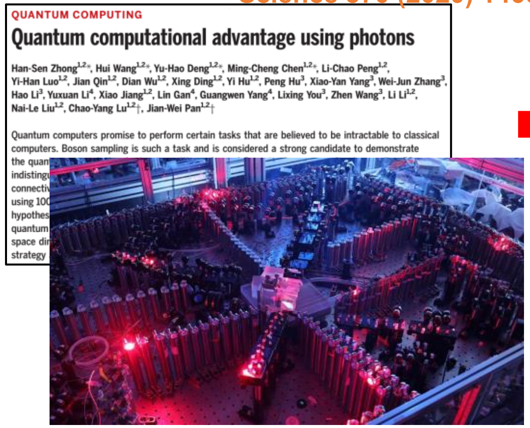
Picture credits: Qianhui Shi, Yan Liang

2nd Quantum Revolution： A New Era

Google (2019)

Jiuzhang (九章) (2020)

Science 370 (2020) 1460



Google (2024)

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

Zuchongzhi-3 (祖冲之3号) (2024)

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

Jiuzhang-4 (九章4号) (2026)

HL Liu, H Su, YH Deng *et al.* *Nature* (2026)

- **1st quantum revolution:** lasers, transistors, nuclear magnetic resonance, etc.
- **2nd quantum revolution:** Identification and control of a single quantum bit for the first time in human history. **Arrival of commercial quantum computers.**
  - First quantum supremacy for random state generation in 2019/2020.
  - Significant speed-up in Willow/Zuchongzhi-3 & surface code implementation around the end of 2024 → a milestone towards large-scale quantum computers.
  - **Yet another world record obtained by Jiuzhang-4** (a Nature article released on May 13, 2026).

3 Quantum Computing Technologies

H. Okawa (invited review), arXiv:2511.16713, accepted by MPLA

Quantum Circuits

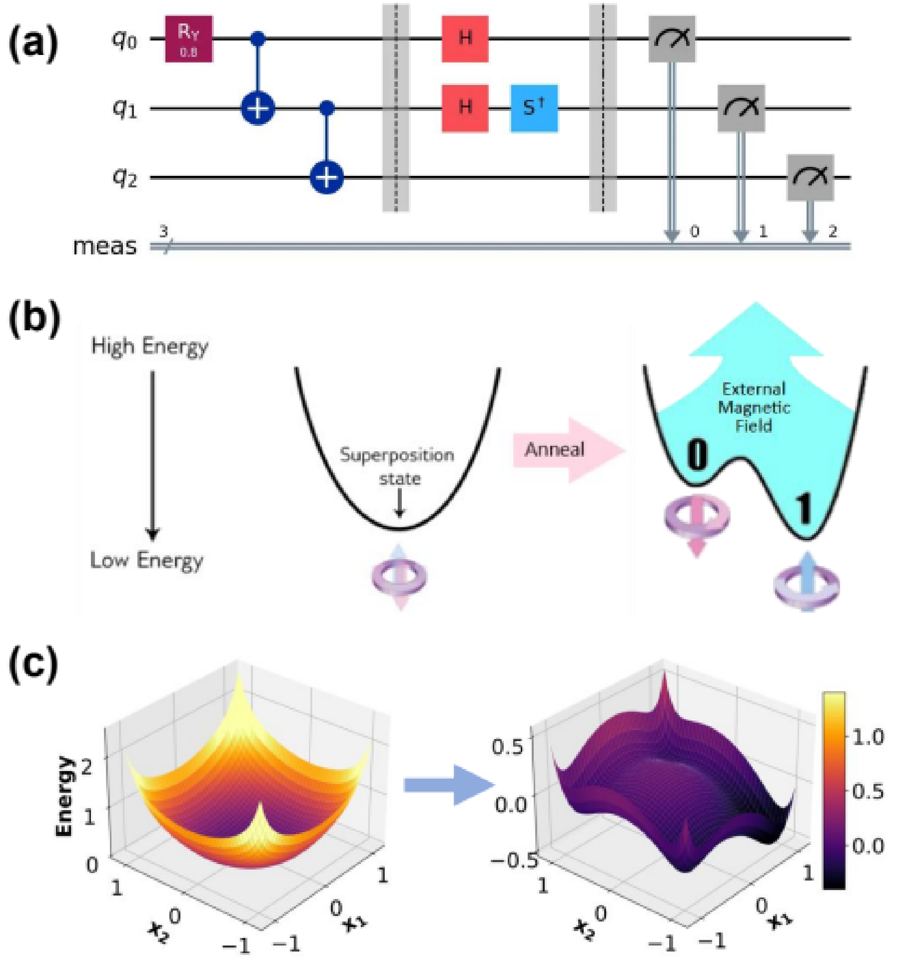
- Uses quantum logic gates. Is universal computing.
- Most quantum computers adopt this approach.

Quantum Annealing

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

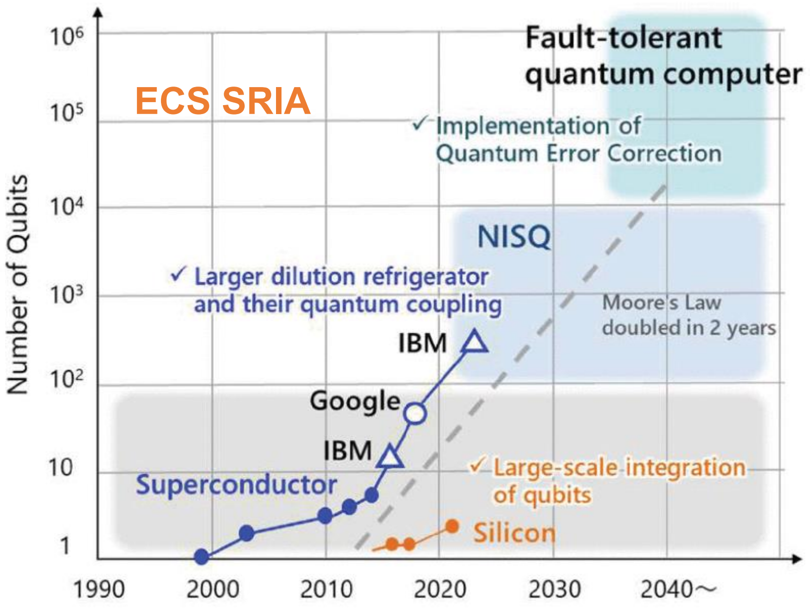
Quantum-inspired

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



* There is also analog quantum computing

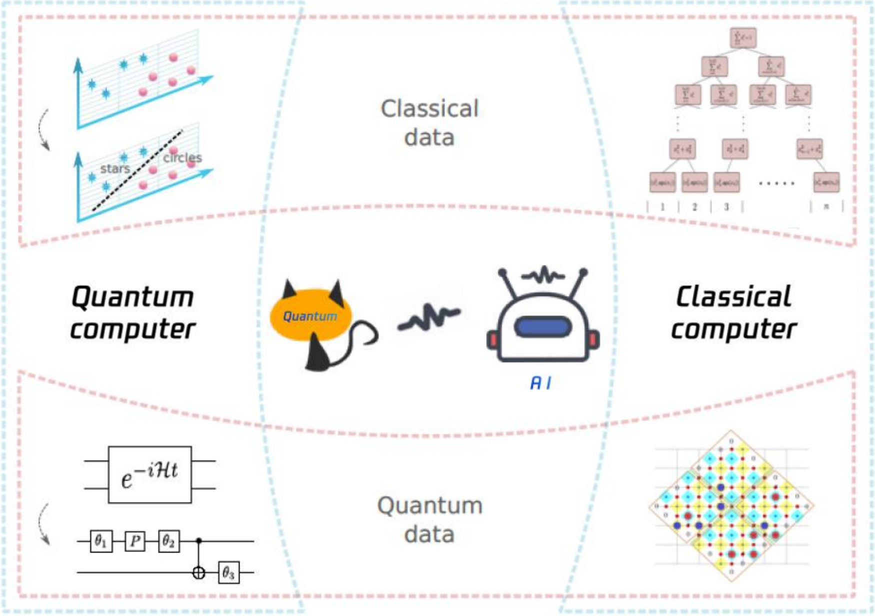
AI + Quantum



Shixin Zhang

Quantum Computing Engine for ML

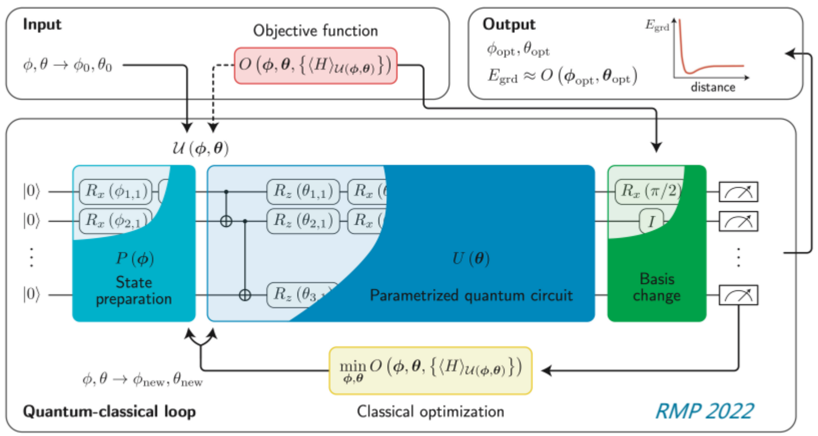
Quantum inspired ML



ML assisted quantum simulation

ML on quantum physics

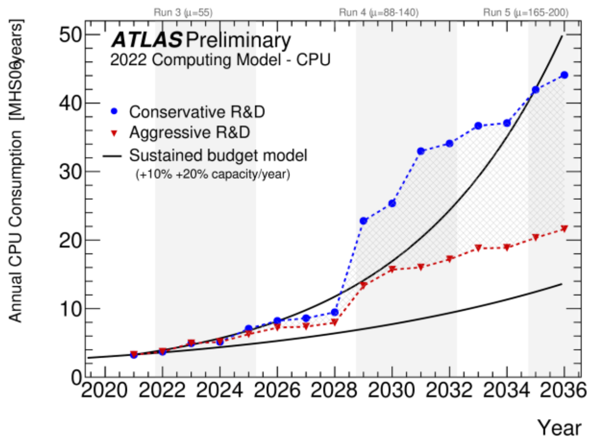
Quantum-Classical Hybrid Method

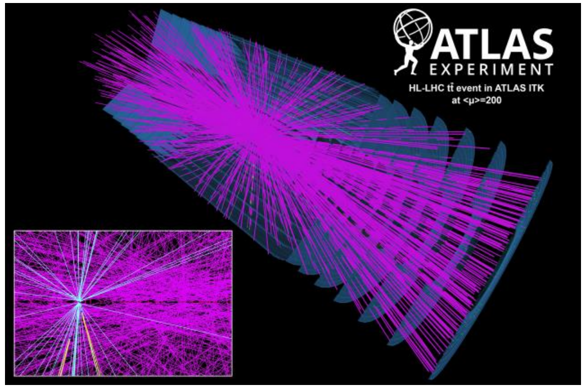


- We are still at the era of Noisy Intermediate Scale Quantum (NISQ) hardware.
- **Quantum AI studies are dominantly conducted with quantum-classical hybrid or quantum-inspired methods.**

Why Quantum AI for HEP?

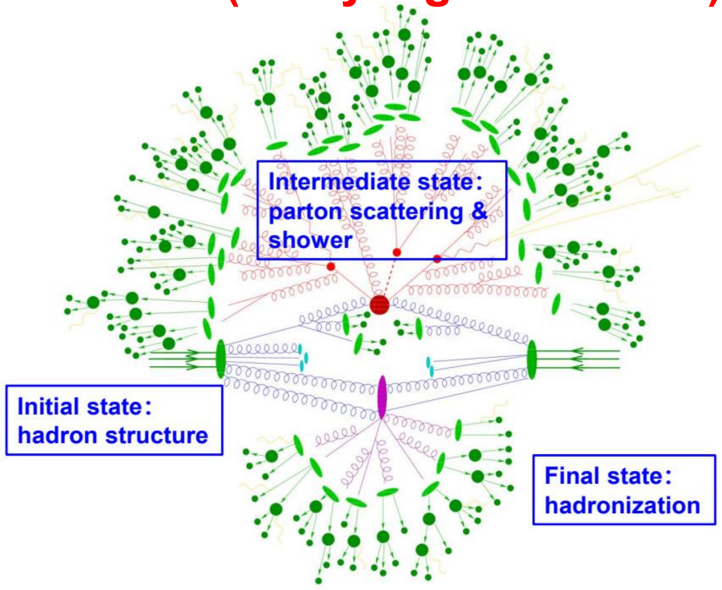
Experiments → **Quantum Machine Learning (this talk)**





- Future colliders (e.g. HL-LHC, CEPC, EIC) will enter **the EB era from the current PB-scale operation.**
- At the HL-LHC, annual computing cost will increase by a factor of 10-20. **CEPC Z-pole operation will experience similar challenges.**
- **Innovation in computing is eagerly awaited.**

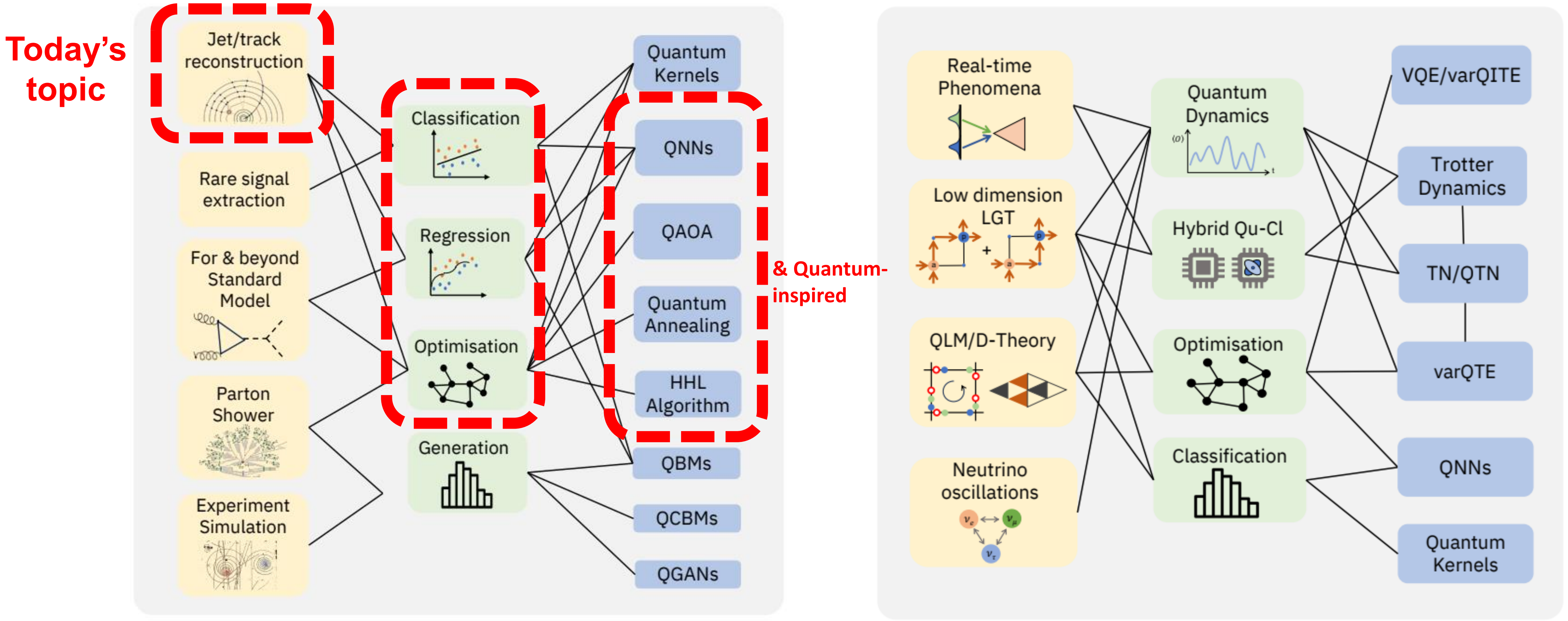
Theory → **Quantum Simulation (Wenyang Qian's talk)**



- Strong interaction dynamics is difficult to simulate classically from the first principles.
  - Non-equilibrium, non-perturbative, complexity of many-body quantum systems, quantum interference, sign problem, etc.

Quantum AI Applications in HEP

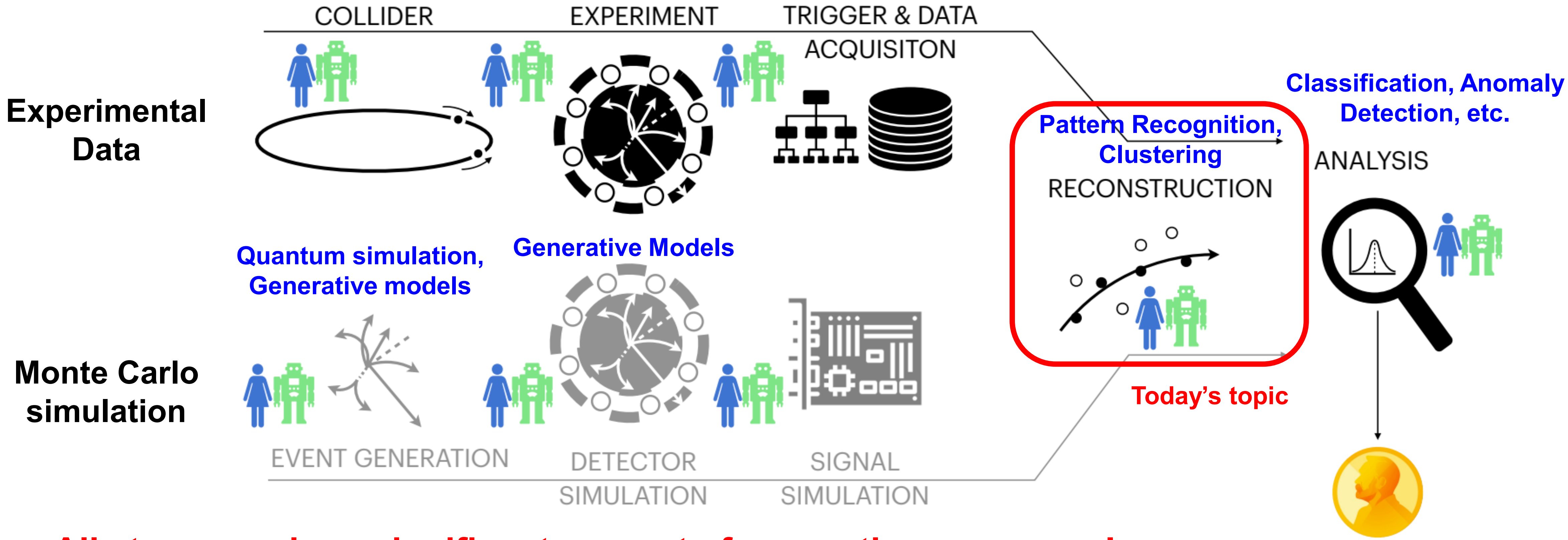
A. Di Meglio et al., PRX QUANTUM 5, 037001 (2024)



About quantum simulation, see also: C.W. Bauer et al., PRX Quantum 4 (2023) 2, 027001

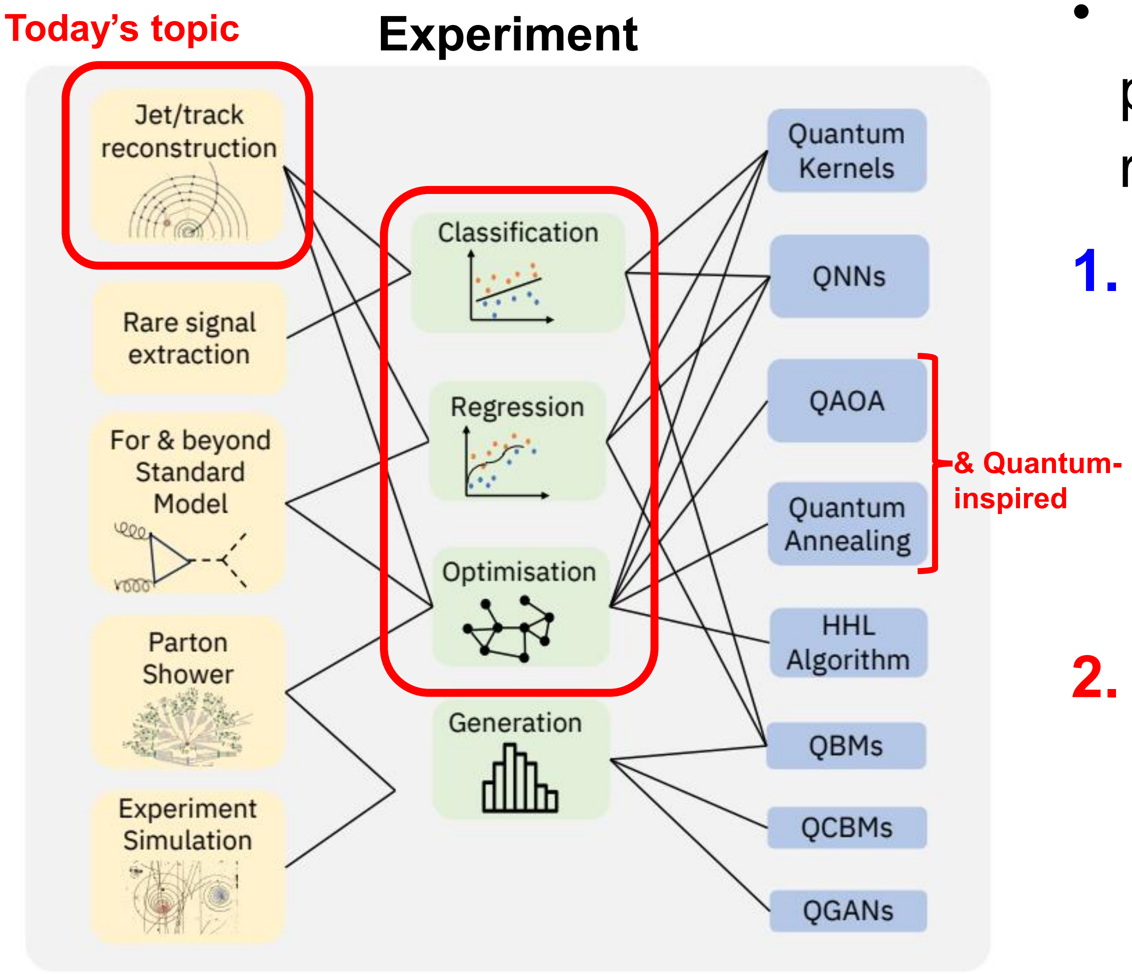
Experimental Workflow at Colliders

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 algorithms to these tasks?

Quantum AI in HEP Pattern Recognition

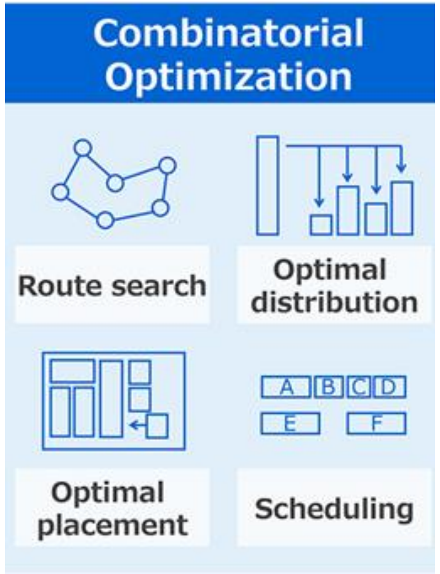


- Two classes of algorithms exist for HEP pattern recognition (e.g. track and jet reconstruction).

1. **Iterative:** e.g. Combined Kalman filter (tracking), sequential jet clustering (k_t, anti-k_t, etc.)
   - Requires quantum associative memory (QuAM; not yet available).
2. **Global:** e.g. Hough transform, XCone jet clustering
   - Global reconstruction can be formulated as combinatorial optimization (= Ising/QUBO) problems.

Optimization as Ising/QUBO Problems

Specific Problem



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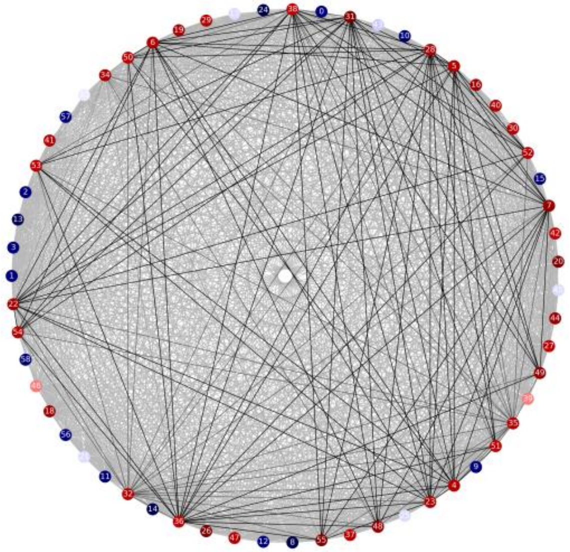
Ising/QUBO Problem Formulation

Map them to an Ising/QUBO Hamiltonian

N spins = N qubits

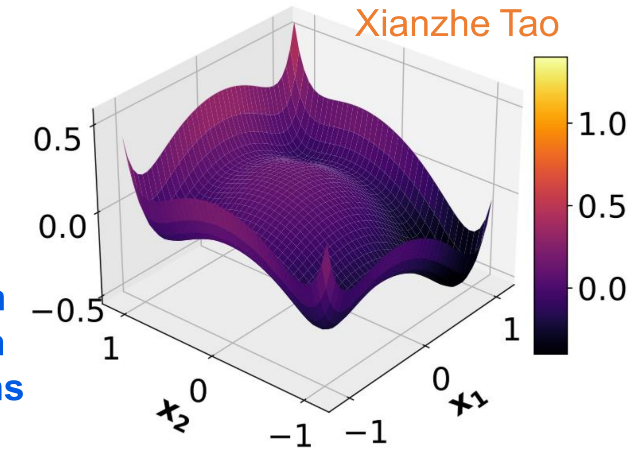


SA Abel, LA Nutricati, arXiv:2206.09956

Search the Ground State

The best spin configuration from 2^N options

Answer

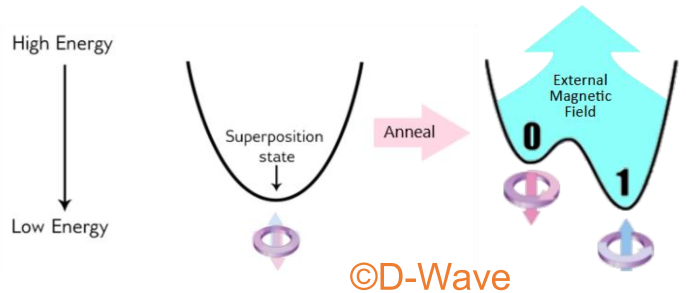


Schematic 2D Energy Landscape
→ practically N dimensional

- Many complicated problems can be formulated as Ising or QUBO Hamiltonian.
- **We design the Ising/QUBO Hamiltonian so that the ground state corresponds to the answer.**
- **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

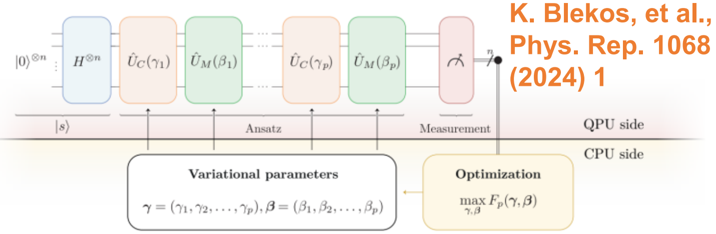
Quantum Annealing (QA)



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

- 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



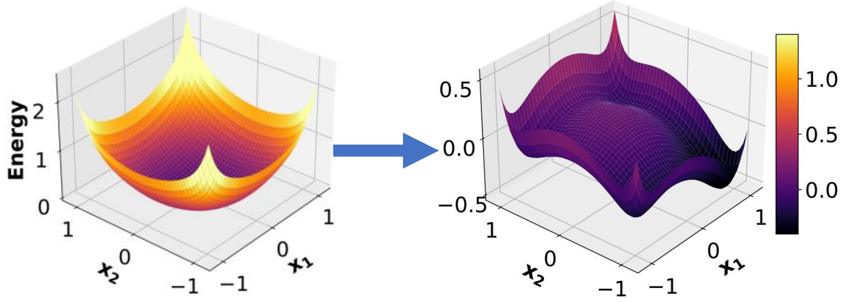
K. Blekos, et al., Phys. Rep. 1068 (2024) 1

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

- **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.

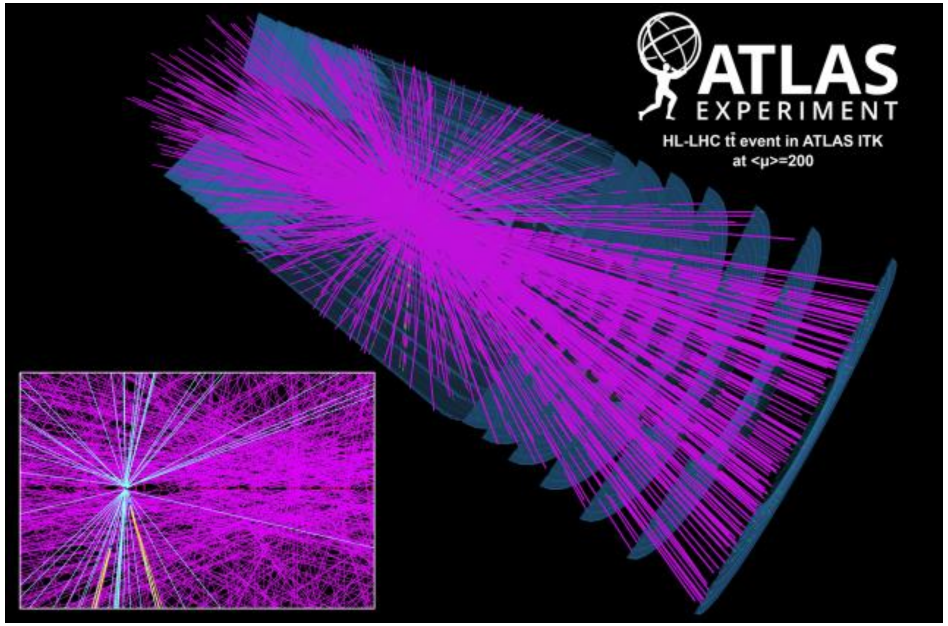
Quantum-Inspired

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.**
  - A new variant of such kind (tabu-enhanced SB) is recently developed (XZ Tao et al.).

Track Reconstruction at LHC & HL-LHC



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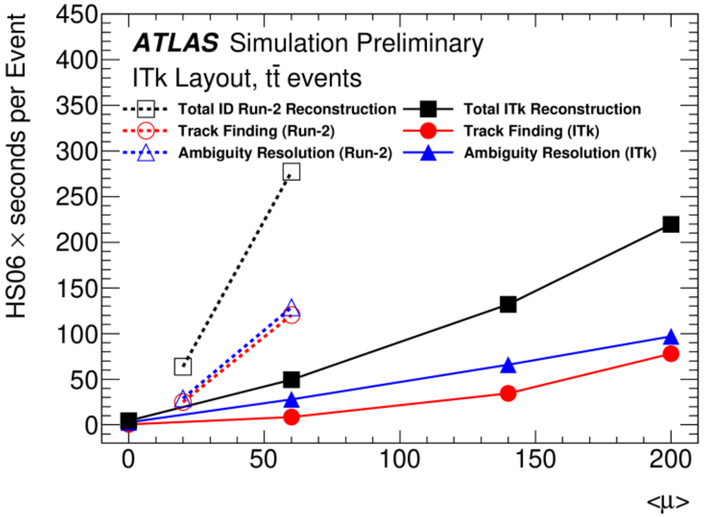
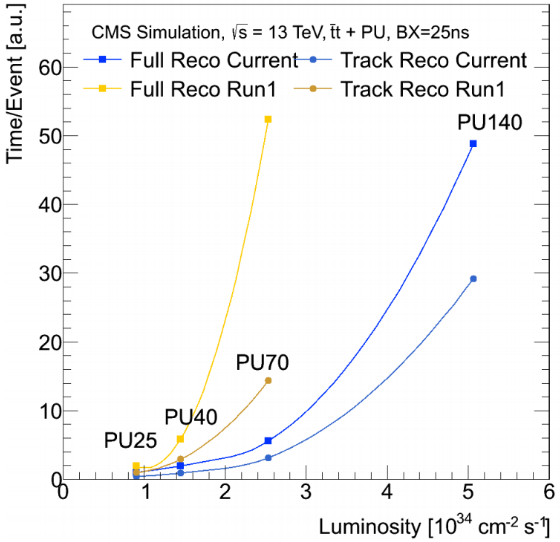


https://cds.cern.ch/record/1966040



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

- **Computing time with traditional iterative methods increases exponentially against track multiplicity.**
- **ML-based approaches are actively investigated, but quantum algorithms may play an important role.**

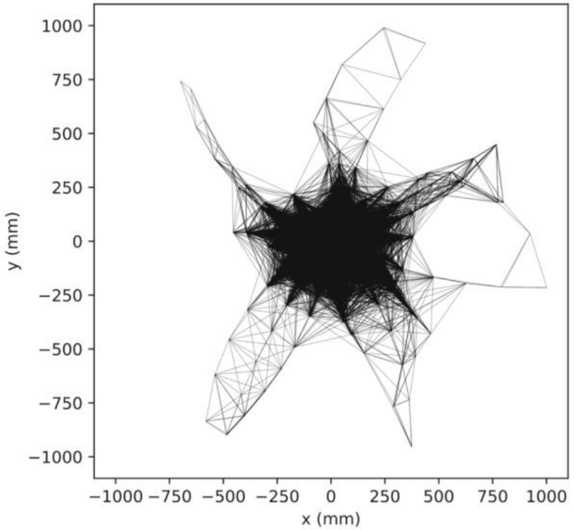
Global Track Reconstruction - Doublets

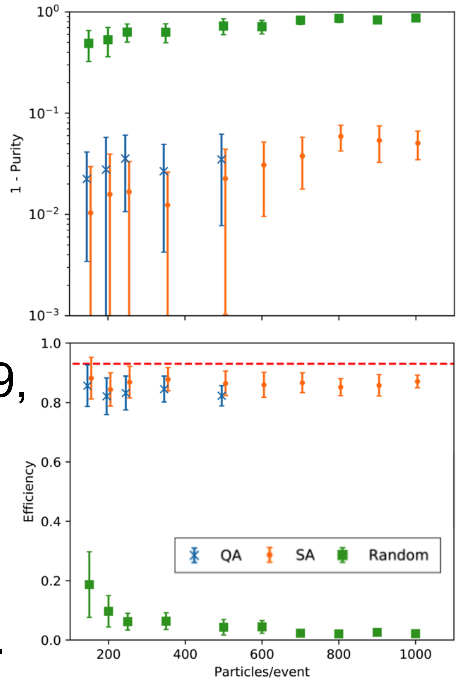
Doublet-based

A. Zlokapa et al., Quantum Mach. Intell. 3, 27 (2021)

Denby-Peterson Hamiltonian

$$E = -\sum_{a,b,c}\left(\frac{\cos^{\lambda}(\theta_{abc}) + \rho\cos^{\lambda}(\phi_{abc})}{r_{ab}+r_{bc}}\right) s_{ab}s_{bc} + \eta\sum_{a,bc}\left(z_c - \frac{z_c - z_a}{r_c - r_a} r_c\right)^{\zeta} s_{ab}s_{bc}$$
$$+\,\alpha\left(\sum_{b\neq c} s_{ab}s_{ac} + \sum_{a\neq c} s_{ab}s_{cb}\right) - \sum_{a,b}\left(\beta P(s_{ab}) - \gamma\right) s_{ab},$$

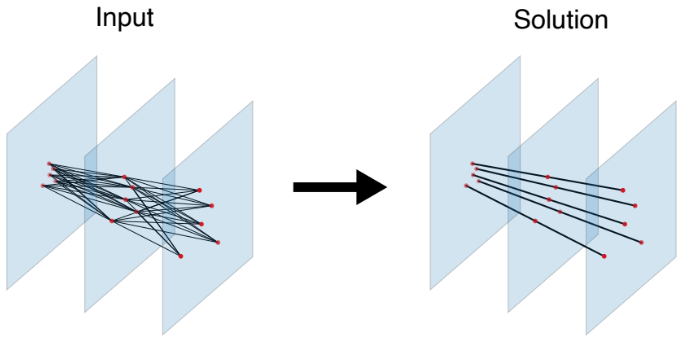




- A Denby-Peterson algorithm (1988/1989, originally used in LEP) modified for HL-LHC was tested up to 500 particles (hardware limitation) for QA.
- Comparable performance b/w QA & SA.

D. Nicotra et al., JINST 18 P11028 (2023)

LHCb



- A doublet-based Denby-Peterson Hamiltonian was also tested in LHCb with Harrow-Hassadim-Lloyd (HHL) algorithm.
- Simplified dataset up to 5 particles were adopted to run on IBM Hanoi quantum circuit hardware (27 qubits).

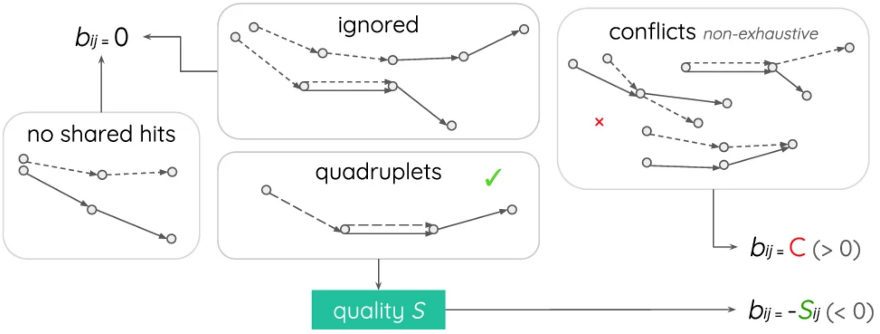
Layers	Particles	Doublets	Qubits	Depth	2-qubit gates
3	2	8	8	12 071	5 538
3	3	18	12	1 665 771	834 417
3	4	32	12	901 255	442 694
3	5	50	14	14 515 229	7 107 317
4	2	12	10	185 817	93 213
4	3	27	12	1 714 534	840 780
4	4	48	14	14 197 046	7 110 044

Global Track Reconstruction - Triplets

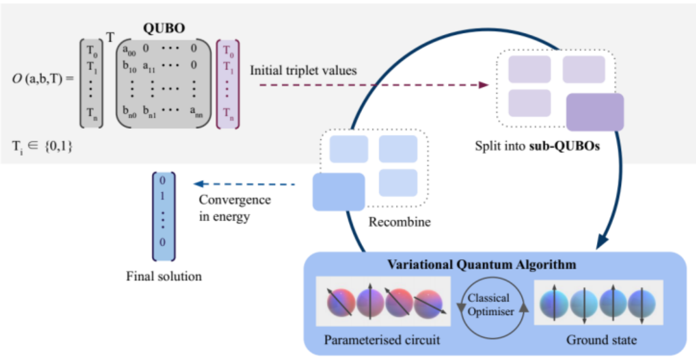
F. Bapst et al., Comput Softw Big Sci 4, 1 (2020)

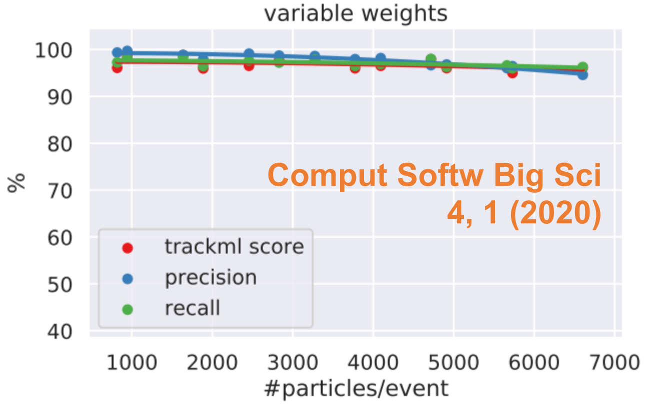
Triplet-based

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



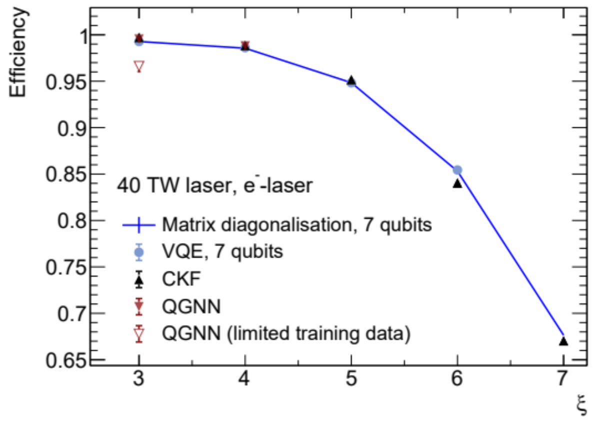
Sub-QUBO method



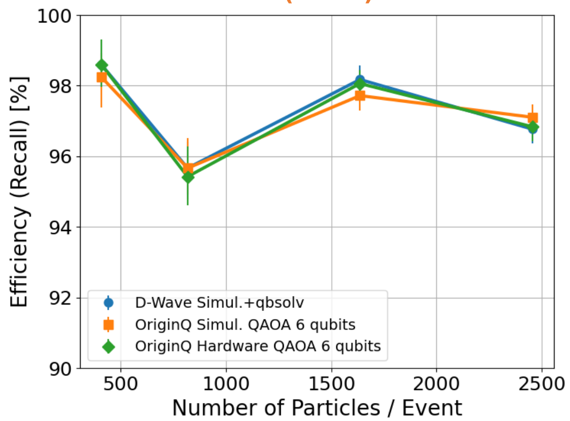


- Triplet-based approach simplifies the Hamiltonian & **reduces the number of qubits required**.
- Nevertheless, **HL-LHC conditions do not fit into near-term hardware** (needs >O(10^5) qubits). Sub-QUBO methods have been used to split the problems. → This degrades computing speed by few orders of magnitude.

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

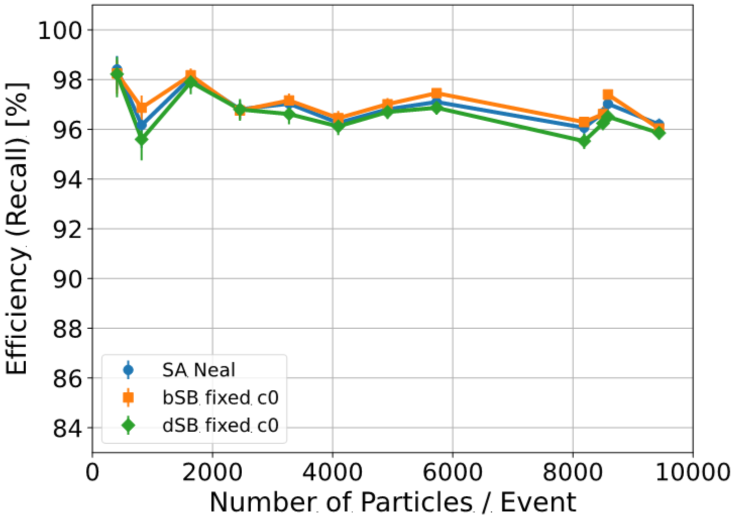


H. Okawa, Springer CCIS, 2036 (2024) 272

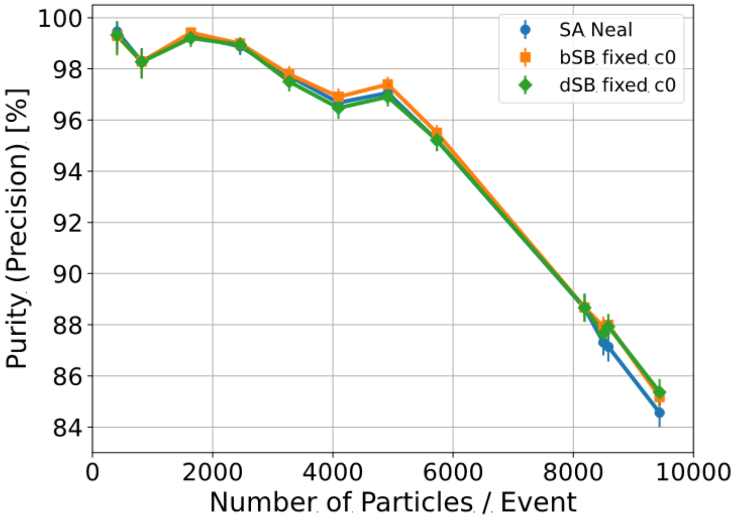


Global Track Reconstruction - Triplets

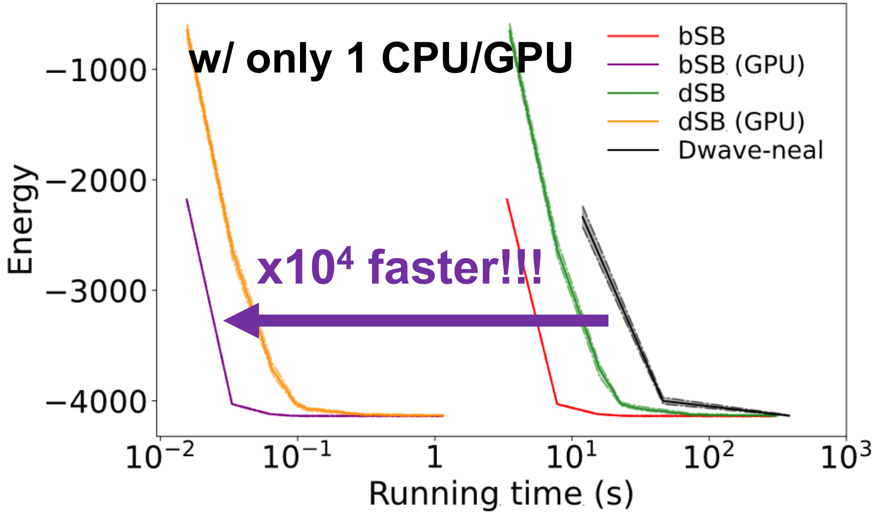
Efficiency



Purity

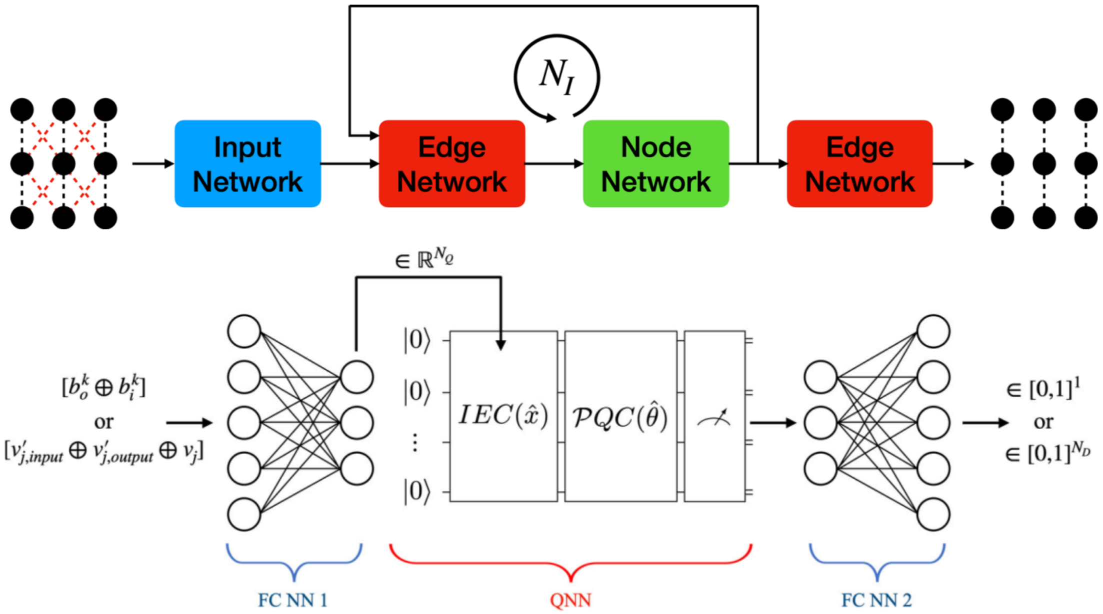


Ising Energy vs computing time

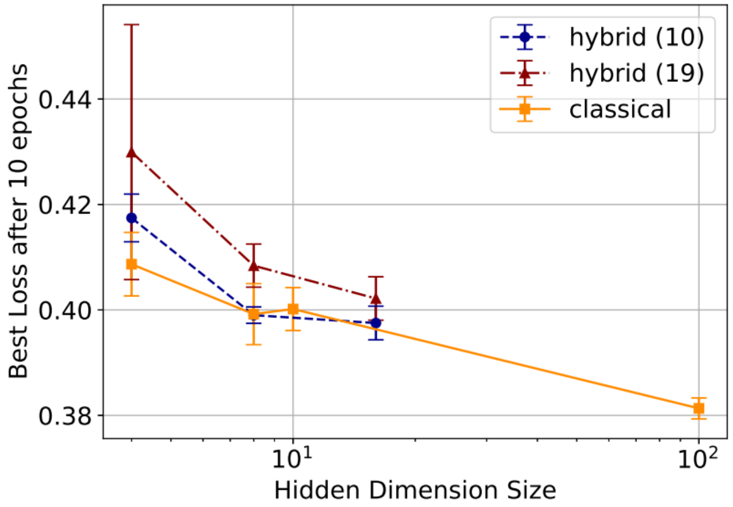


- **Quantum-inspired overcomes both hardware limitation & computing speed bottleneck.**
- **We introduced simulated bifurcation (SB) to HEP for the first time.** It provides comparable or slightly better efficiency & purity than D-Wave Neal SA.
- A SB variant, bSB provides **4 orders of magnitude speed-up (23min → 0.14s) from D-Wave Neal SA** **(cf. D-Wave hardware w/ sub-QUBO is ~2 orders of magnitude slower than Neal).**
- **SB can effectively run with multiple processing, GPU & FPGA → Perfect match with HEP!**

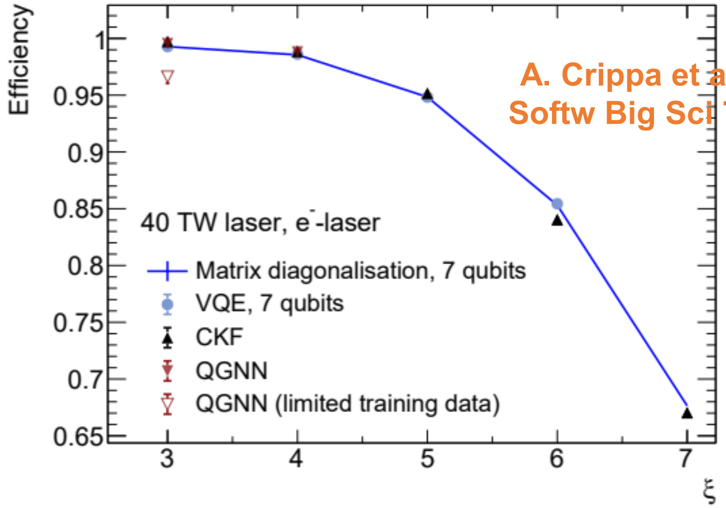
Global Track Reconstruction - QGNN



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



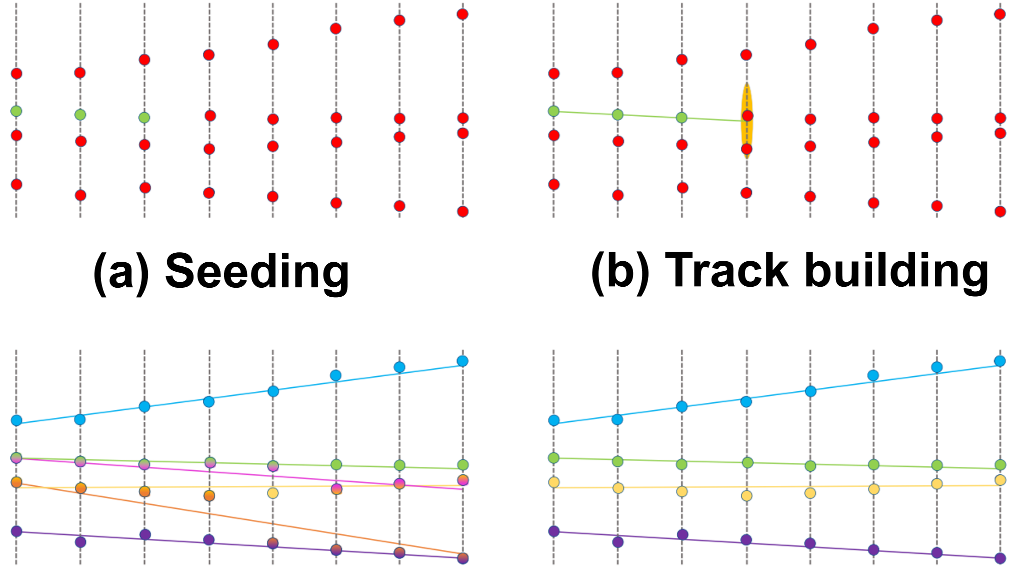
- Due to hardware limitation, only tested on quantum circuit simulator with 16 qubits (no noise).
- **Requirements of very large RAM & long training time (>1 week) are currently the limiting factor.**
- LUXE experiment also tested QGNN on low-intensity simulation data.



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

D. Magano et al., PRD 105 (2022) 7, 076012
C Brown et al., Front. Artif. Intell. 7 (2024) 1339785

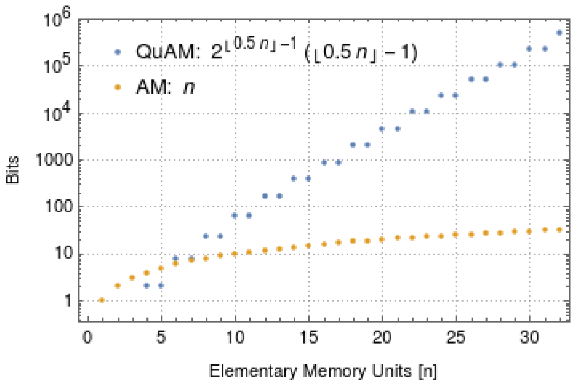
Track Reconstruction (Iterative)



(a) Seeding (b) Track building

(c) Cleaning (d) Selection

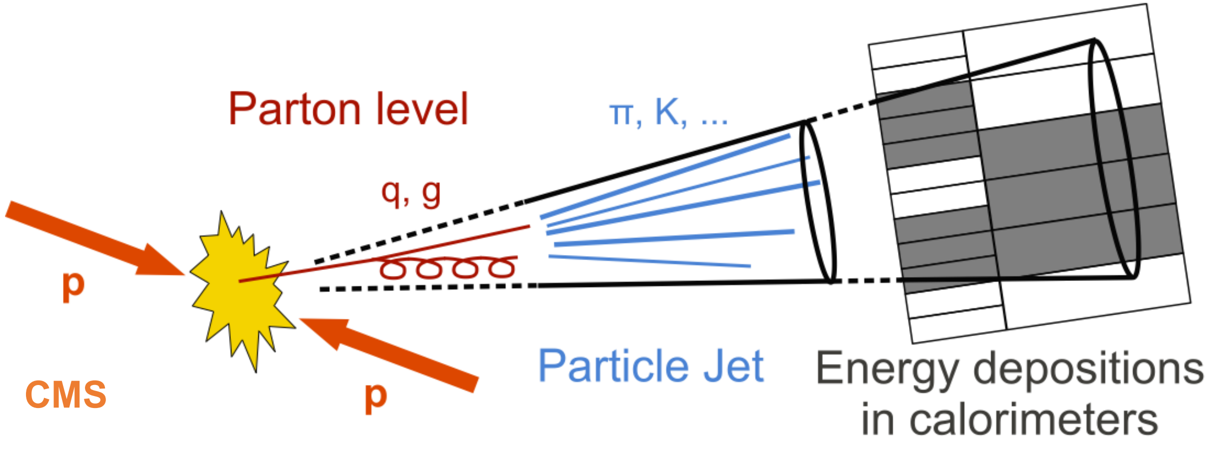
- **Iterative reconstruction requires quantum associative memory (QuAM; not yet available)**
- Conceptual complexity analyses were performed for **4 stages of reconstruction**.
- **Grover search reduces complexity of seeding & track building in square root.**
- **In summary, expected improvement is rather mild.**

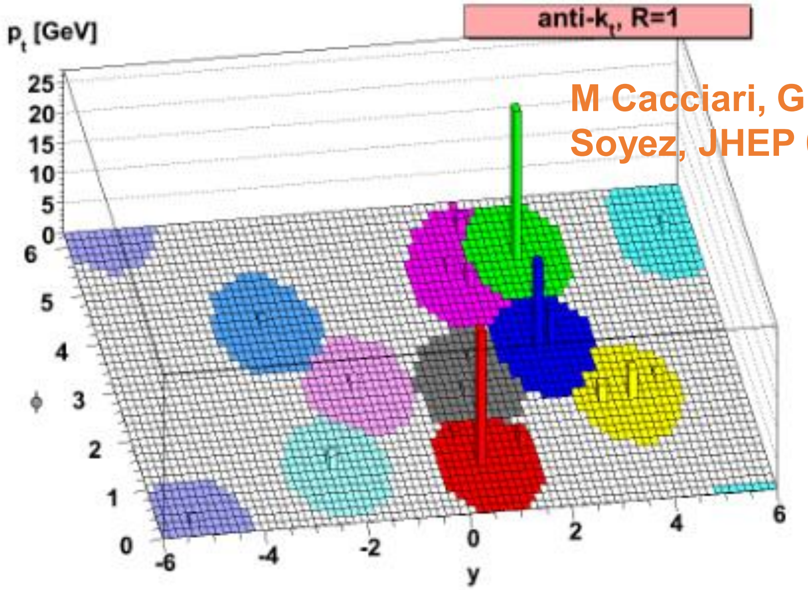


Tracking stages	Input size	Output size	Classical complexity	Quantum complexity
Seeding	$O(n)$	k_{seed}	$O(n^c)$	$\tilde{O}\left(\sqrt{k_{\text{seed}} \cdot n^c}\right)$
Track Building	$k_{\text{seed}} + O(n)$	k_{cand}	$O(k_{\text{seed}} \cdot n)$	$\tilde{O}\left(k_{\text{seed}} \cdot \sqrt{n}\right)$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

 I. Shapoval, P. Calfiura, EPJ Web of Conf. 214, 01012 (2019)

Jet Reconstruction





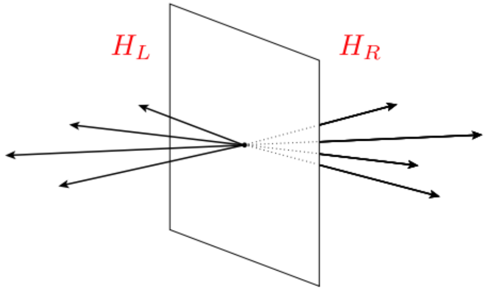
M Cacciari, GP Salam, G Soyez, JHEP 0804:063 (2008)

- Due to color confinement, gluons & quarks cannot exist on their own; they spray **collimated arrays of particles**.
- **<u>Clustering those particles as jets provides important proxies to understand the original quark/gluon kinematics</u>** but is a non-trivial & CPU-consuming task.
- **The standard jet clustering algorithms are (almost) all iterative** <u>as global clustering is way too computing intensive</u>.

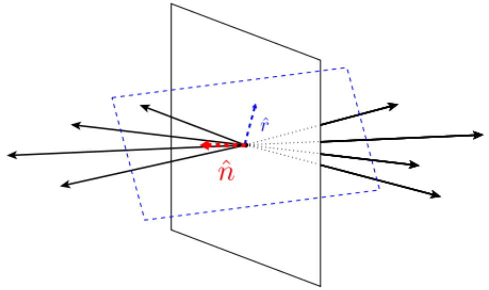
Jet Reconstruction (Iterative)

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

Thrust as partitioning (QA)



Thrust as axis finding (Grover search)

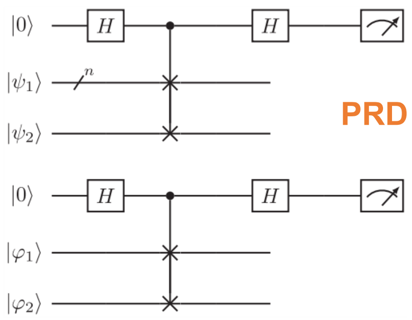


- Authors improved classical algorithm inspired by SISCone.
- **Quantum & classical algorithms scale the same, but for different reasons.**

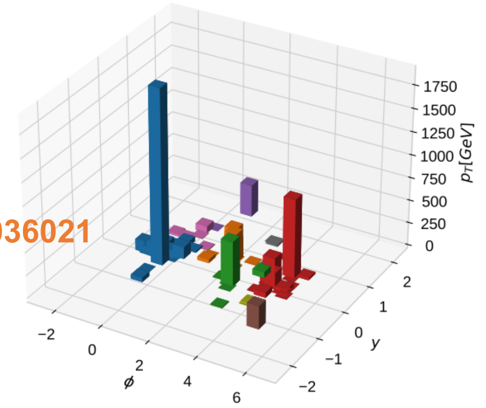
Implementation	Time Usage	Qubit Usage
Classical[124]	$O(N^3)$	—
Classical with sort inspired by SISCone[125]	$O(N^2 \log N)$	—
Classical with parallel sort	$O(N \log N)$	—
Quantum annealing	Gap dependent	$O(N)$
Quantum search: sequential model	$O(N^2)$	$O(\log N)$
Quantum search: parallel model	$O(N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

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, $p = -1$, $R = 1$, $\epsilon_c = 0.99$.

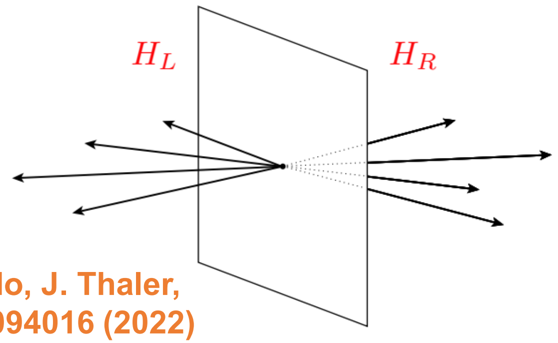
- **Quantum & classical algorithms [FastJet] scales the same for sequential clustering.**
- IBM quantum circuit simulator was also used to actually perform clustering..

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

[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)

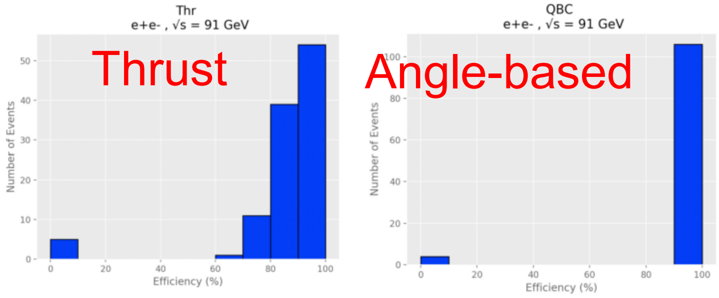
$$O_{\mathrm{QUBO}}(\{x_i\}) = \left(\sum_{i=1}^{N} |\vec{p}_i|\right)^2 T(\{x_i\})^2$$

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

- 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)



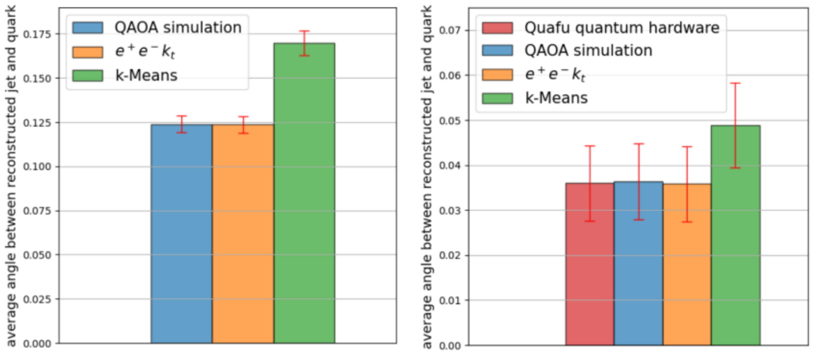
$$H = \frac{1}{2}\sum_{i,j=1}^{N} -\cos\left[\theta(\vec{p}_i, \vec{p}_j)\right] s_i s_j$$

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



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

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

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

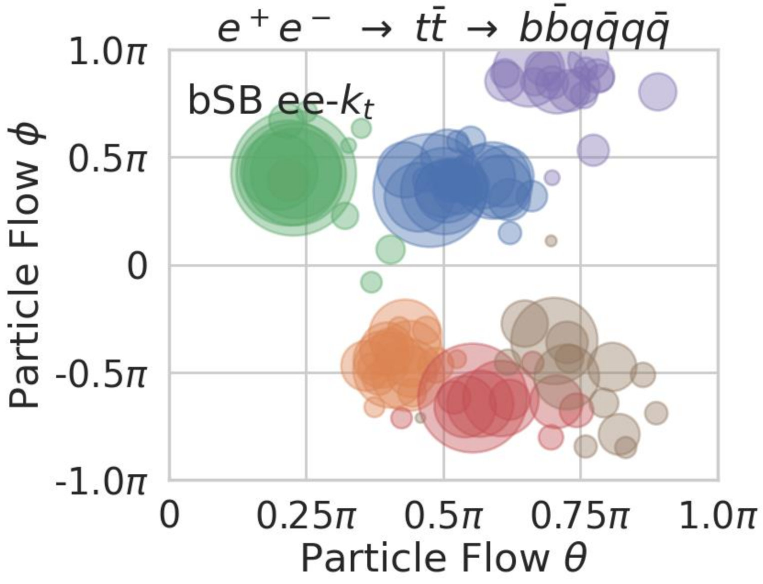
H Okawa, XZ Tao, QG Zeng, MH Yung, Phys. Lett. B, 864 (2025) 139393

Multijet Reconstruction (Global)

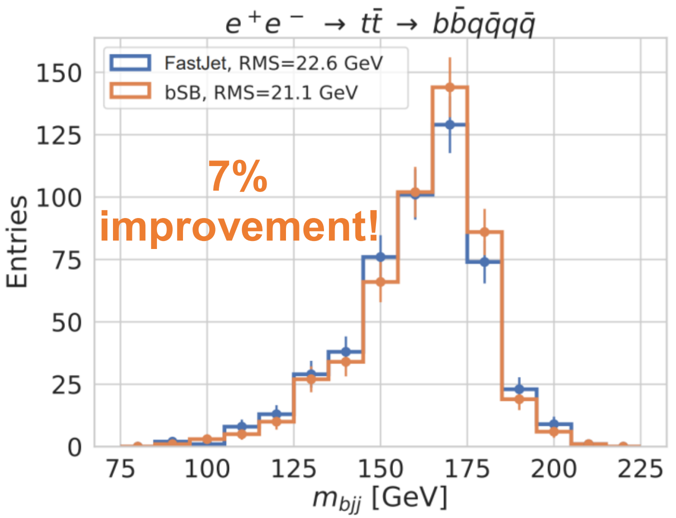
QUBO Formulation

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

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

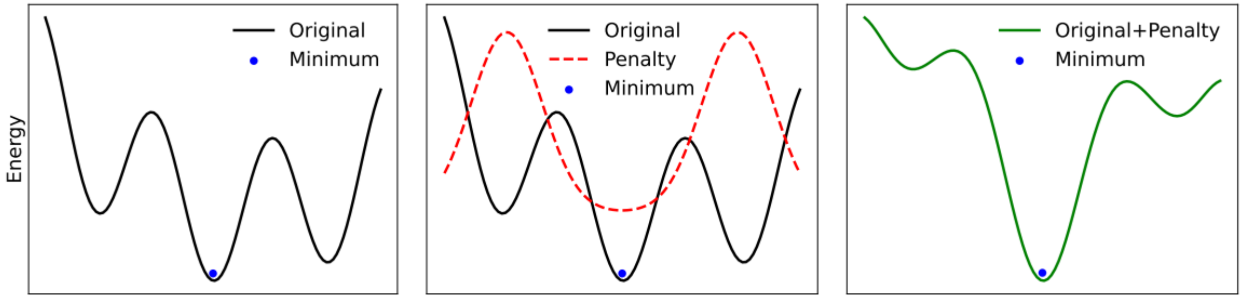


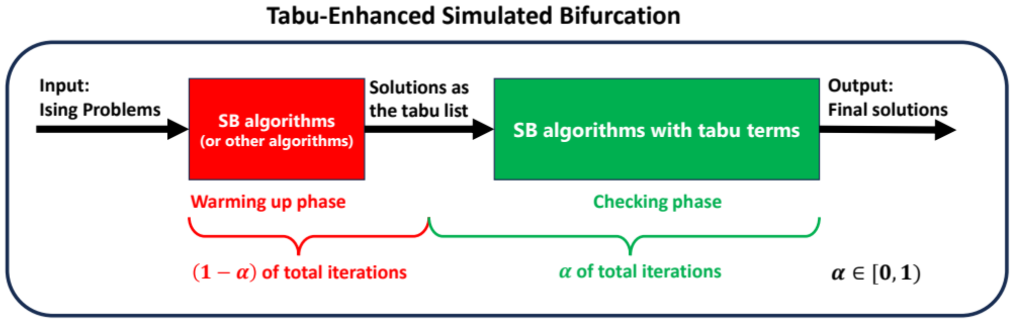
- Quantum-inspired does not suffer from qubit connectivity issues.
- **bSB quantum-inspired algorithm overcame the challenge from the one-hot encoding for multijet reconstruction.**
- **First successful global multijet clustering with a quantum algorithm→ Opened up a practical path toward global jet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



XZ Tao, QG Zeng, ZJ Huang, BW Zuo, J Zhuang, H Okawa, MH Yung, *Commun. Phys.* 9 (2026) 1, 100

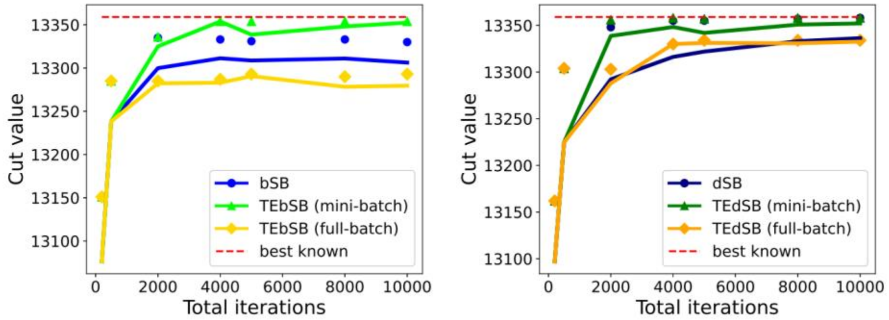
New Quantum-Inspired Algorithm





- We have developed a new variant of SB: Tabu-enhanced simulated bifurcation.
- **A penalty is applied to fill the extracted local minima during the warm-up phase.**
- **Visible improvement in <u>both minimum energy prediction & computing time</u>** for graph & TrackML benchmark datasets.
- Applications to other HEP tasks are under way.

Max-cut values from G22 instance



Minimum energy predictions from TrackML datasets

	bSB		TEbSB		dSB		TEdSB	
	Time (s)	Energy (a.u.)	Time (s)	Energy (a.u.)	Time (s)	Energy (a.u.)	Time (s)	Energy (a.u.)
ev1004 (N=109498)	8.67	-448998	7.25	**-449363**	9.02	-447488	7.43	-449349
ev1014 (N=78812)	5.06	-263353	4.27	**-263650**	5.24	-261860	4.33	-263641
ev1023 (N=80113)	5.33	-261244	4.42	-261345	5.48	-260928	4.80	**-261362**

Prospects

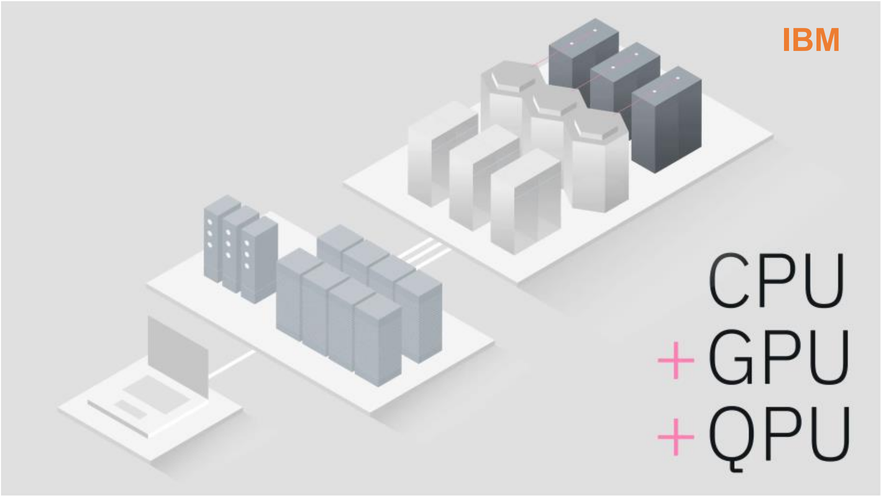
- Quantum circuits in principle accelerate some components of reconstruction but require QuAM architecture, error correction & increased # of qubits.
- For quantum annealing, increasing the connectivity will be mandatory.
- It is also to be seen what quantum-centric supercomputing can bring to HEP.
- In any case, some experimental tasks require O(10^6) qubits. Quantum-inspired techniques will likely stay valuable.

USTC Zuchongzhi-3

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

D-Wave Advantage2

Quantum-centric supercomputing



References:

- H. Okawa, CCIS 2036 (2024) 272, arXiv:2310.10255
- H. Okawa, et al., Comput. Softw. Big Sci. 8, 16 (2024)
- H. Okawa, et al., Phys. Lett. B 864 (2025) 139393
- XZ Tao et al., Commun. Phys. 9 (2026) 1, 100
- H. Okawa, arXiv:2511.16713 (invited review), accepted by MPLA

Summary

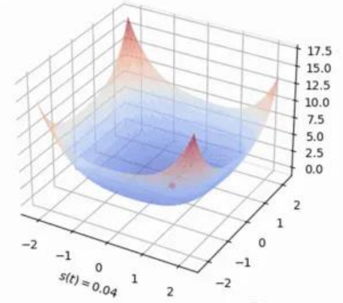
- Quantum AI application is an emerging field in high-energy physics (HEP).
- I presented recent progress in pattern recognition for HEP.
- Three quantum technologies exist: (1) universal quantum gate machines, (2) quantum annealing & (3) quantum-inspired algorithms.
- Iterative reconstruction requires QuAM, studies are mostly at the conceptual level analyzing complexity & expected speedup is rather mild.
- Global reconstruction studies are performed with all three technologies. Current quantum hardware cannot cover large datasets, whereas quantum-inspired techniques are already scalable up to ~$O(10^6)$-size problems with promising computing speed.
- Applications to other experimental tasks are currently under investigation.
- The rich program of HEP applications is likely to progress with constructive competitions among the three quantum technologies and other emerging techniques.

Picture credits: Qianhui Shi, Yan Liang

感谢倾听!

Thank you for listening!

Simulated Bifurcation (SB)



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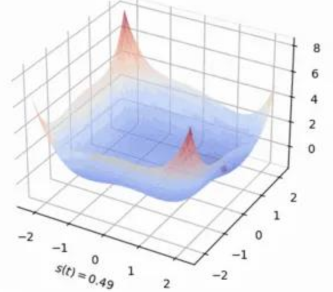
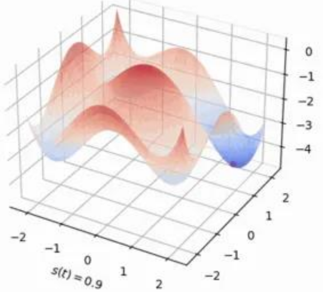




$$H_{SB}(\mathbf{x}, \mathbf{y}, t) = \sum_{i=1}^{N} \frac{\Delta}{2} y_i^2 + \sum_{i=1}^{N} [\frac{K}{4} x_i^4 + \frac{\Delta - p(t)}{2} x_i^2] - \frac{\xi_0}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} x_i x_j$$

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

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

- "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

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

adiabatic SB (aSB; original)

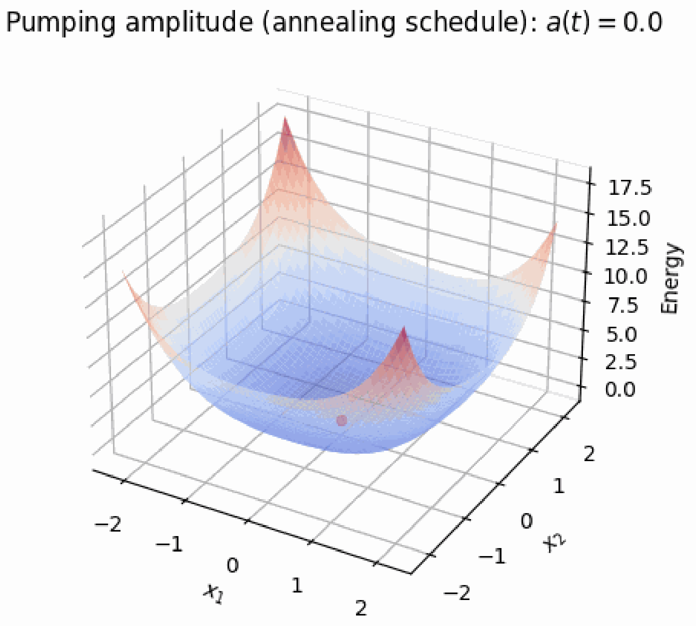
$$V_{bSB} = \begin{cases} \frac{a_0 - a(t)}{2} \sum_{i=1}^{N} x_i^2 - \frac{c_0}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} x_i x_j, & \text{if } |x_i| \le 1, \forall i \\ \infty, & \text{otherwise.} \end{cases}$$

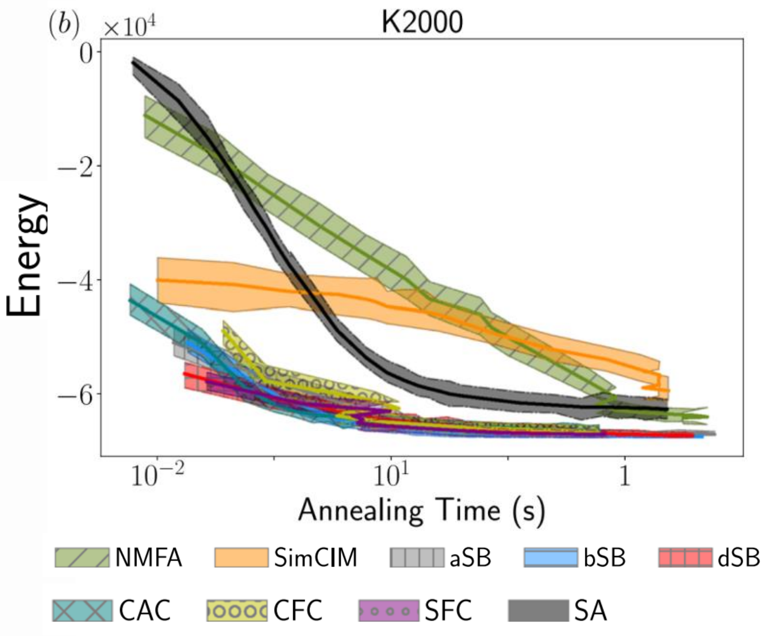
ballistic SB (bSB)

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

discrete SB (dSB)

Simulated Bifurcation (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-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.**