CERN
Quantum Technology Initiative

QUANTUM
TECHNOLOGY
INITIATIVE

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CERN QTI Coordinator
CERN

Content

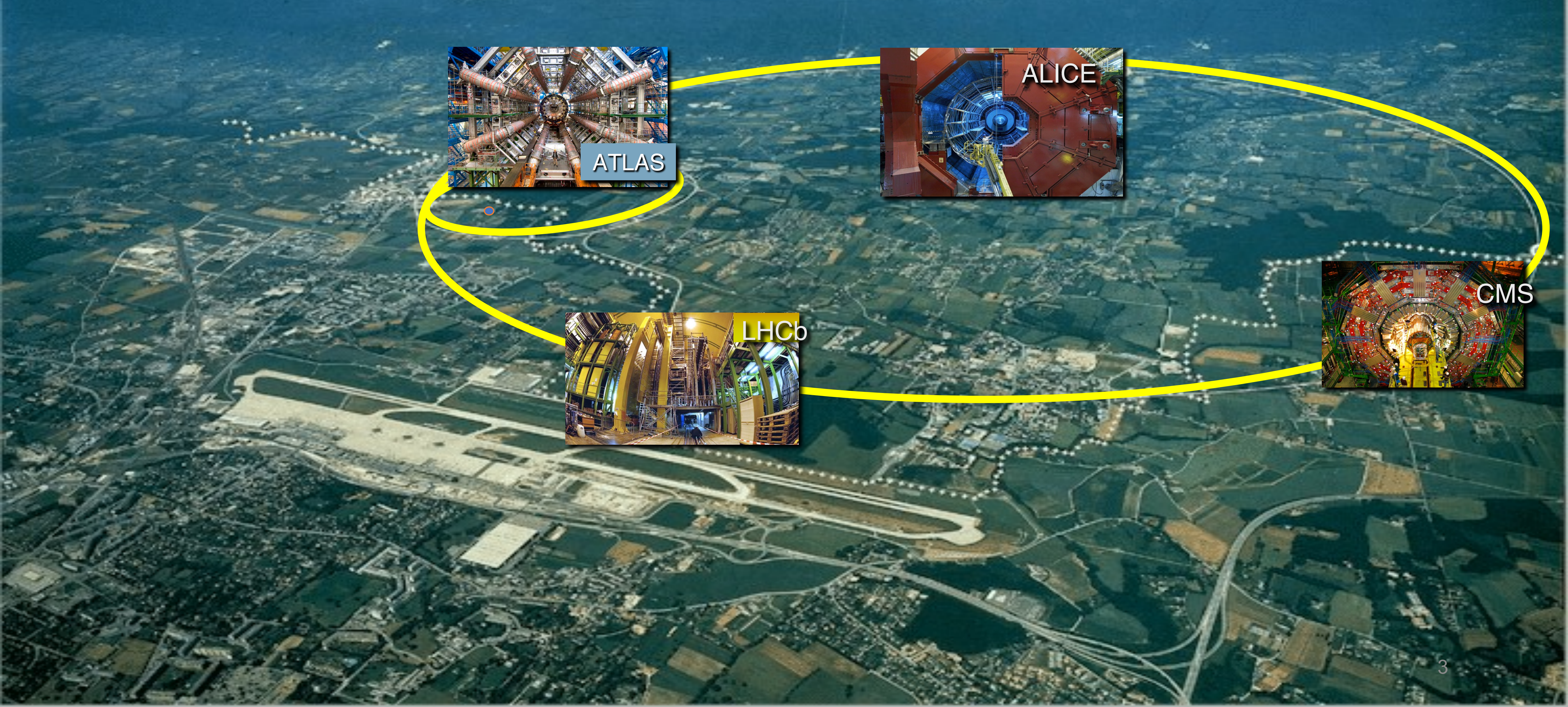
The **2020-2023 CERN Quantum Technology Initiative**

- Scope and scientific results
- Examples from Quantum Sensing, Communication and Computing

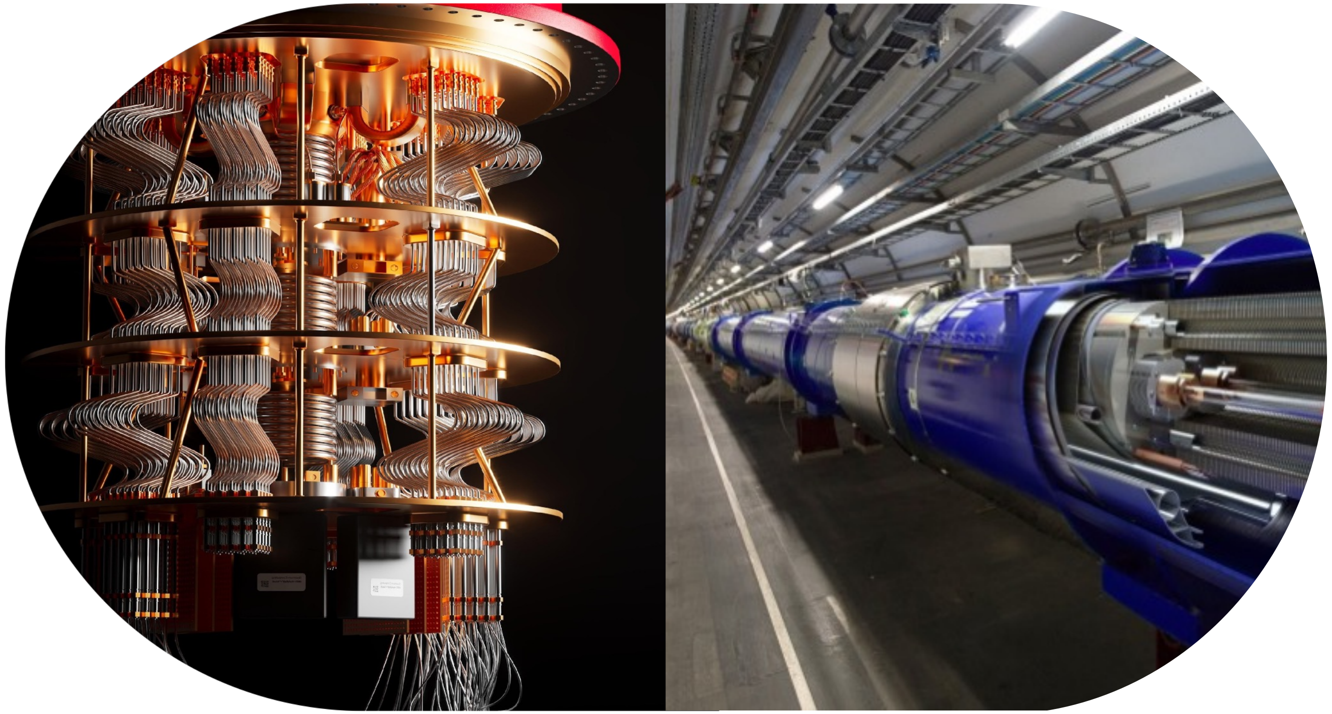
Leveraging CERN expertise for advancing Quantum Technologies

The **CERN QTI Phase2**: a new research program

CERN



How does CERN engage in Quantum Technologies?



QT4HEP

Develop technologies required by the CERN scientific programme

Integrate CERN to future quantum infrastructure

HEP4QT

Extend and share technologies available at CERN

Boost development and adoption of QT beyond CERN

The CERN QTI launched in 2020

Voir en français

CERN meets quantum technology

The CERN Quantum Technology Initiative will explore the potential of devices harnessing perplexing quantum phenomena such as entanglement to enrich and expand its challenging research programme

30 SEPTEMBER, 2020 | By Matthew Chalmers

The AEgIS 1T antimatter trap stack. CERN's AEgIS experiment is able to explore the multi-particle entangled nature of photons from positronium annihilation, and is one of several examples of existing CERN research with relevance to quantum technologies. (Image: CERN)

Main objectives

- Identify areas where **CERN can contribute to QT development**
- Evaluate **impact of quantum technology** on CERN programme
- **Align with quantum initiatives** in the CERN Member States
- **Facilitate the collaboration** across the HEP community and between HEP and the QT

QTI Roadmap: https://doi.org/10.5281/zenodo.5553774

An exploratory initiative

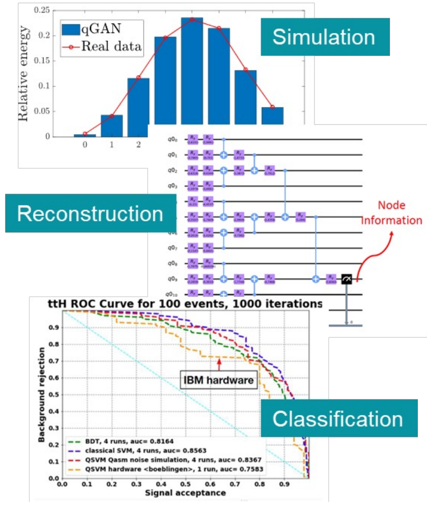
Quantum simulation and HEP theory applications

Quantum Computing

Quantum Sensing

Quantum Communication

Computing

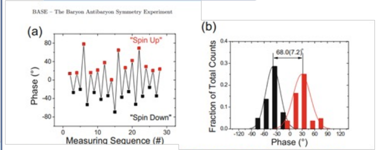


Simulation

Reconstruction

Classification

Sensing

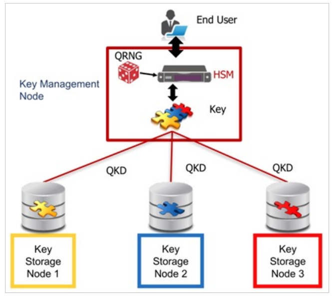


https://doi.org/10.1140/epje2015-02607-4

Low-energy experiments, quantum states measurements, nano-technologies

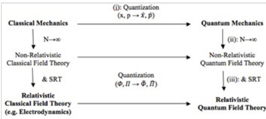
Future HEP Detectors

Communications

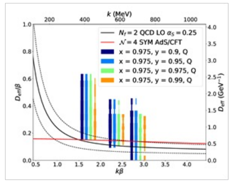


QKD infrastructures Quantum Internet

Theory



Quantum Field Theory

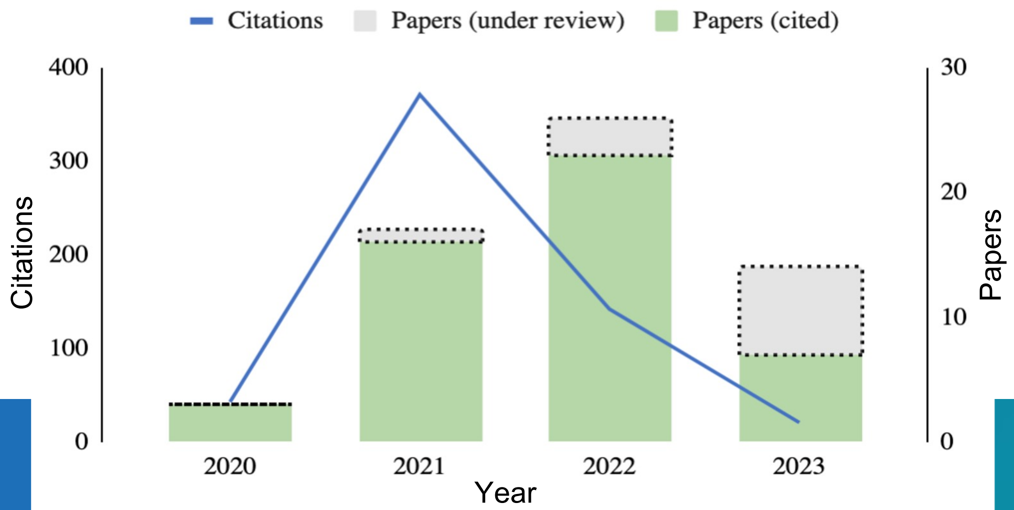


https://cds.cern.ch/record/2703396

Lattice QCD

Computing: > 60 papers with > 800 cumulative citations

(Dec 2023, Google Scholar)



Quantum Information Processing (2021) 20:214
https://doi.org/10.1007/s11128-021-03156-3

On a poset of quantum exact promise problems

Elías F. Combarro[1,2] · Sofia Vallecorsa[2] · Alberto Di Meglio[2] · Alejandro Piñera[3] · Ignacio Fernández Rúa[3]

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Abstract
Two of the most well-known quantum algorithms, those introduced by Deutsch–Jozsa and Bernstein–Vazirani, can solve promise problems with just one function query, showing an oracular separation with deterministic classical algorithms. In this work, we generalise those methods to study a family of quantum algorithms that can, with just one query, exactly solve promise problems stated over Boolean functions. We also show that these problems can be naturally ordered, inducing a partially ordered set of promise problems. We study the properties of such a poset, showing that the Deutsch–Jozsa and Bernstein–Vazirani problems are, in a certain sense, extremal problems in it, determining some of its automorphisms and proving that it is connected. We also prove that, for the problems in the poset, the corresponding classical query complexities can take any value between 1 and $2^{n-1}+1$.

Keywords Quantum algorithms · Posets · Query complexity · De
algorithm · Bernstein–Vazirani algorithm

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A report on teaching a series of online lect
computing from CERN

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Álvaro Aguilar-González[3] · José Ranilla[1] · Alberto

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Abstract
Quantum computing (QC) is one of the most promisi
Performance Computing. Its potential use in High Energy Physics has lead CERN, one of the top world users of large-scale distributed computing, to start programmes such as the Quantum Technology Initiative (QTI) to further assess and explore the applications of QC. As a part of QTI, CERN offered, in November–December 2020, a free, online series of lectures on quantum computing. In this paper, we report on the experience of designing and delivering these lectures, evaluating them in the broader context of computing education and training. Traditional textbooks and courses on QC usually focus on physical concepts and assume some knowledge of advanced mathematical and physical topics from the student. Our lectures were designed with the objective of reducing the prerequisites to the bare minimum as well as focusing on hands-on, practical aspects of programming quantum computers and not on the mathematical analysis of the algorithms. This also allowed us to include contents that are not usually covered in introductory courses, such as quantum machine learning and quantum annealing. The evaluation of the reception of the lectures shows that participants significantly increased their knowledge, validating the proposed approach not focused on mathematics and physics but on algorithmic and implementation aspects.

Keywords Quantum computing · HPC · Education · High energy physics

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Mach. Learn.: Sci. Technol. 2 (2021) 011003
https://doi.org/10.1088/2632-2153/abc17d

MACHINE LEARNING Science and Technology

TOPICAL REVIEW

Quantum machine learning in high energy physics

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Keywords: particle physics, quantum machine learning, quantum annealing, quantum circuit, quantum variational circuit

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Abstract
Machine learning has been used in high energy physics (HEP) for a long time, primarily at th
analysis level with supervised classification. Quantum computing was postulated in the early
as way to perform computations that would not be tractable with a classical computer. With
advent of noisy intermediate-scale quantum computing devices, more quantum algorithm
being developed with the aim at exploiting the capacity of the hardware for machine learn
applications. An interesting question is whether there are ways to apply quantum machin
to HEP. This paper reviews the first generation of ideas that use quantum machine learni
problems in HEP and provide an outlook on future applications.

1. Introduction

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PHYSICAL REVIEW RESEARCH 3, 033221 (2021)

Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC

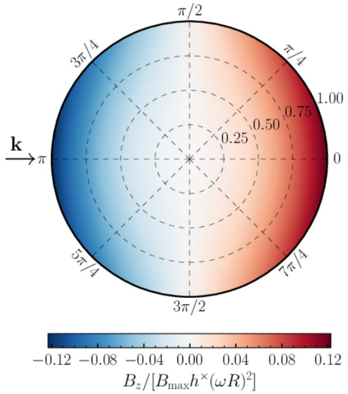
DOI: 10.1103/PhysRevResearch.3.033221

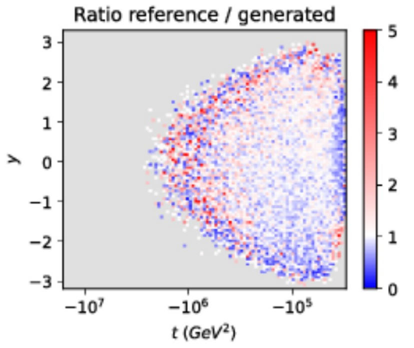
Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling

Some results from QTI1 (I)

Quantum Theory and Simulation

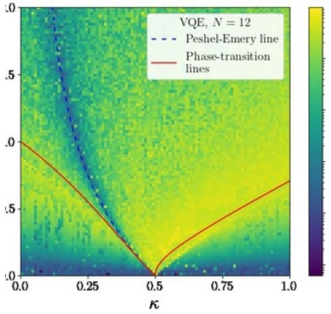
- QC applications to LQCD scalability (small lattices, long range)
- Quantum sensing for atom interferometry of GW and DM
- Atomic clocks for new physics searches

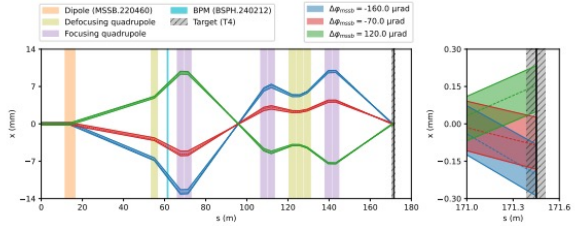




Quantum Computing and Algorithms

- Qantum algorithms for event generation, detector simulation, data processing
- Characterisation of different classes of algorithms for robustness, noise behaviour
- Quantum computing infrastructure (simulators and devices) to support all CERN projects





Some results from QTI1 (II)

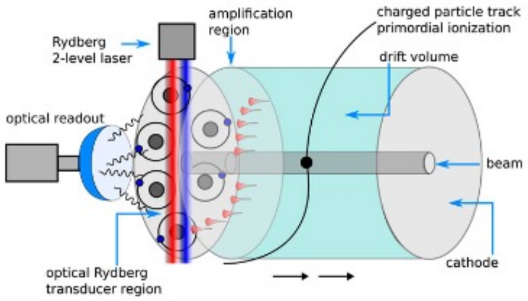
Quantum Sensing, Metrology and Materials

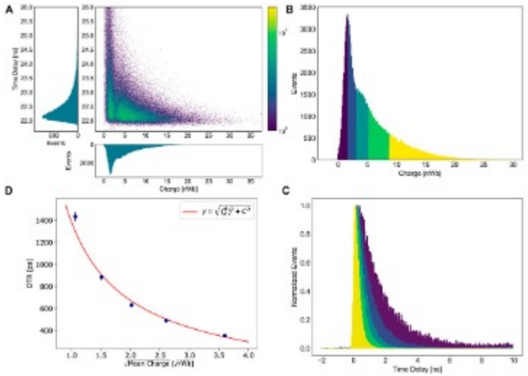
- Quantum dots with different nanomaterials and embeddings
- Procedures to transfer graphene layers nanostructures for gaseous detectors
- AMO-based DAQ and experiment control systems (AEgIS, ArtiQ) achieving dramatic speed-up in working procedures and automation

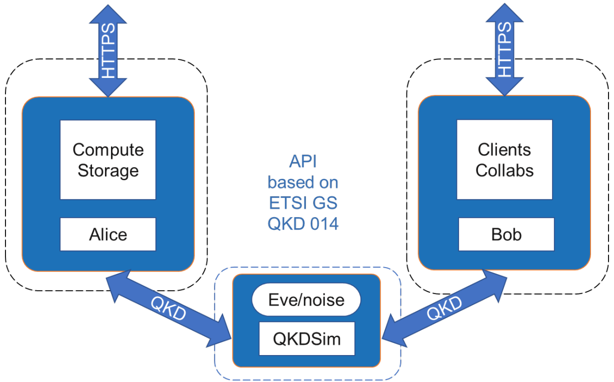
Quantum Communications and Networks

- A Quantum Key Distribution simulator with noise and attacks simulation
- Aapplications of QKD protocols to distributed data analysis with end-to-end privacy
- Tests on QKD hardware and fibre links

Figure 5





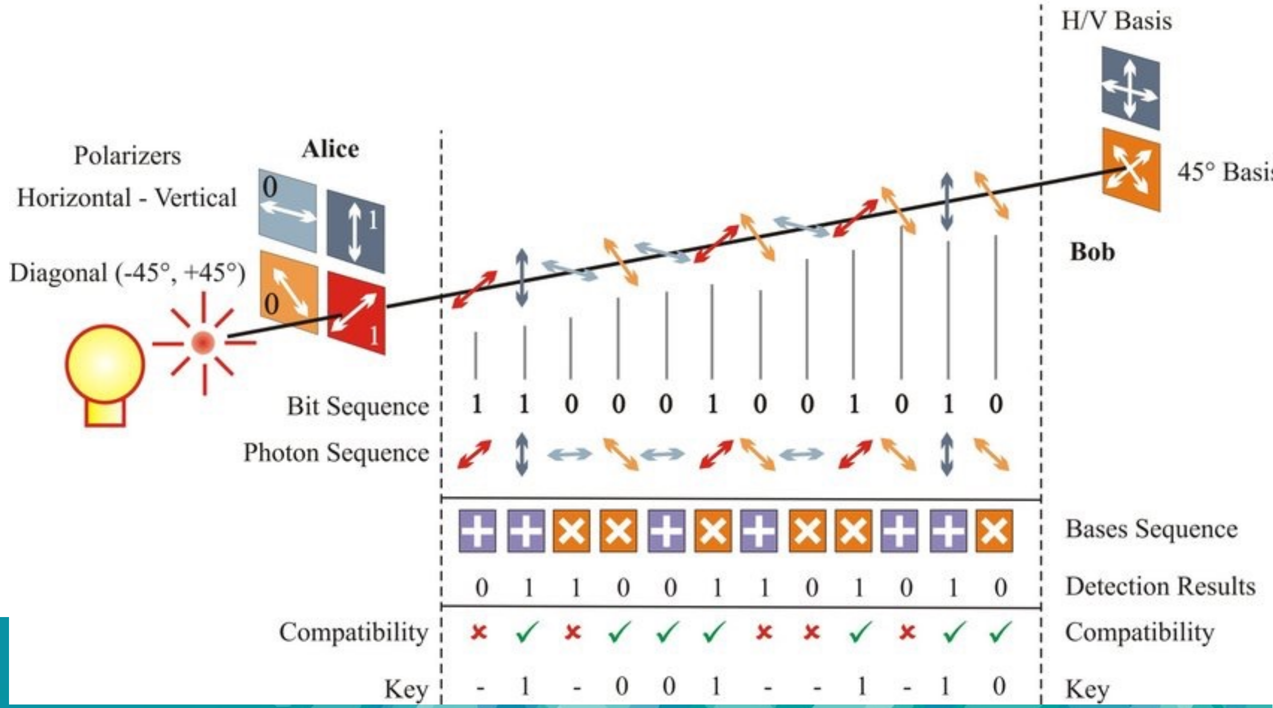


Secure Data Analytics

Quantum.Privacy

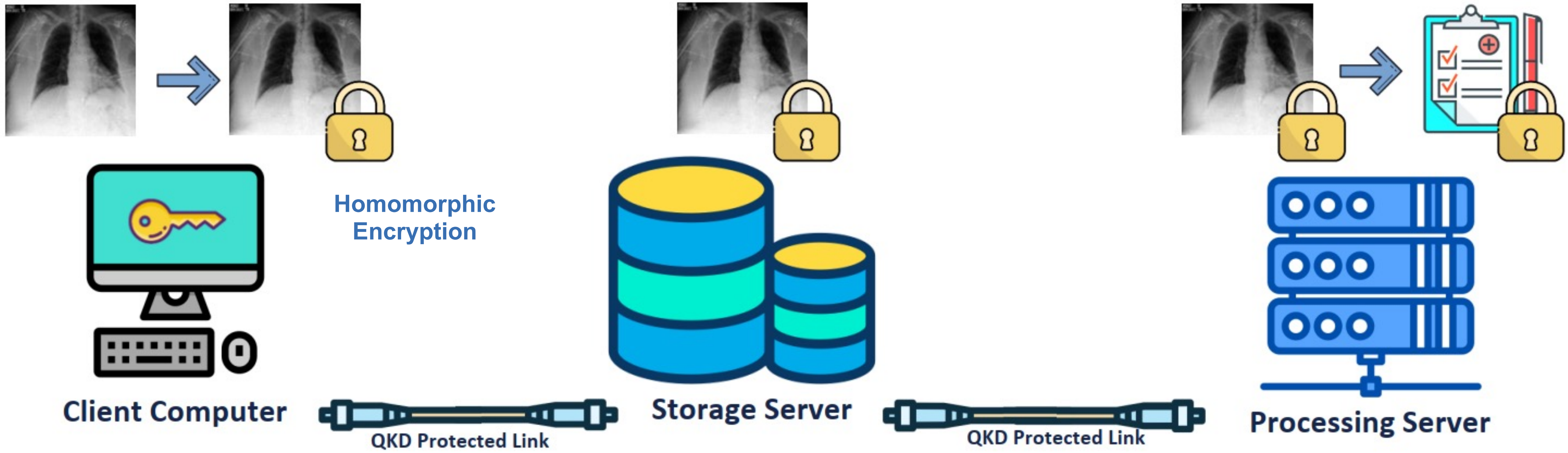
Quantumacy is a privacy-preserving data analytics platform combining the security of QKD protocols and links with state-of-the-art homomorphic encryption capabilities to execute machine-learning and deep-learning workloads across a distributed federated-learning infrastructure.

- QKD simulator including attacks
- Quantum Key Distribution (BB84 protocol)
- QKD link between CERN and the IDQ Data centre hosted by SIG in Geneva



The Quantumacy Platform

Secure Federated Learning demonstrator



Homomorphic Encryption

Client Computer

QKD Protected Link

Storage Server

QKD Protected Link

Processing Server

Example of a block chain framework to record and validate transactions across a distributed data analysis pipeline using keys generated by the QKD infrastructure and homomorphic encryption.

https://doi.org/10.5281/zenodo.7539229

Computing

Big Data @LHC?

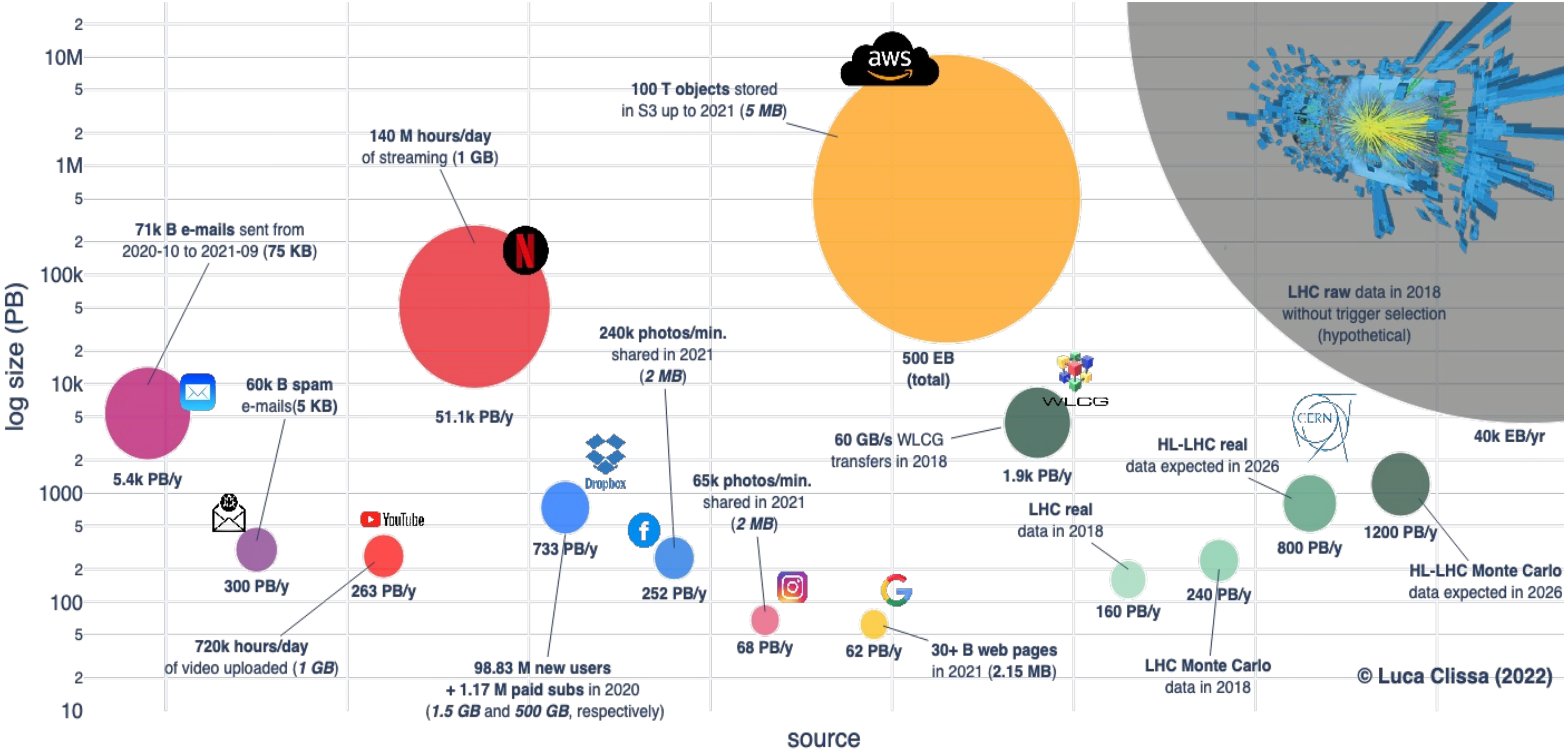
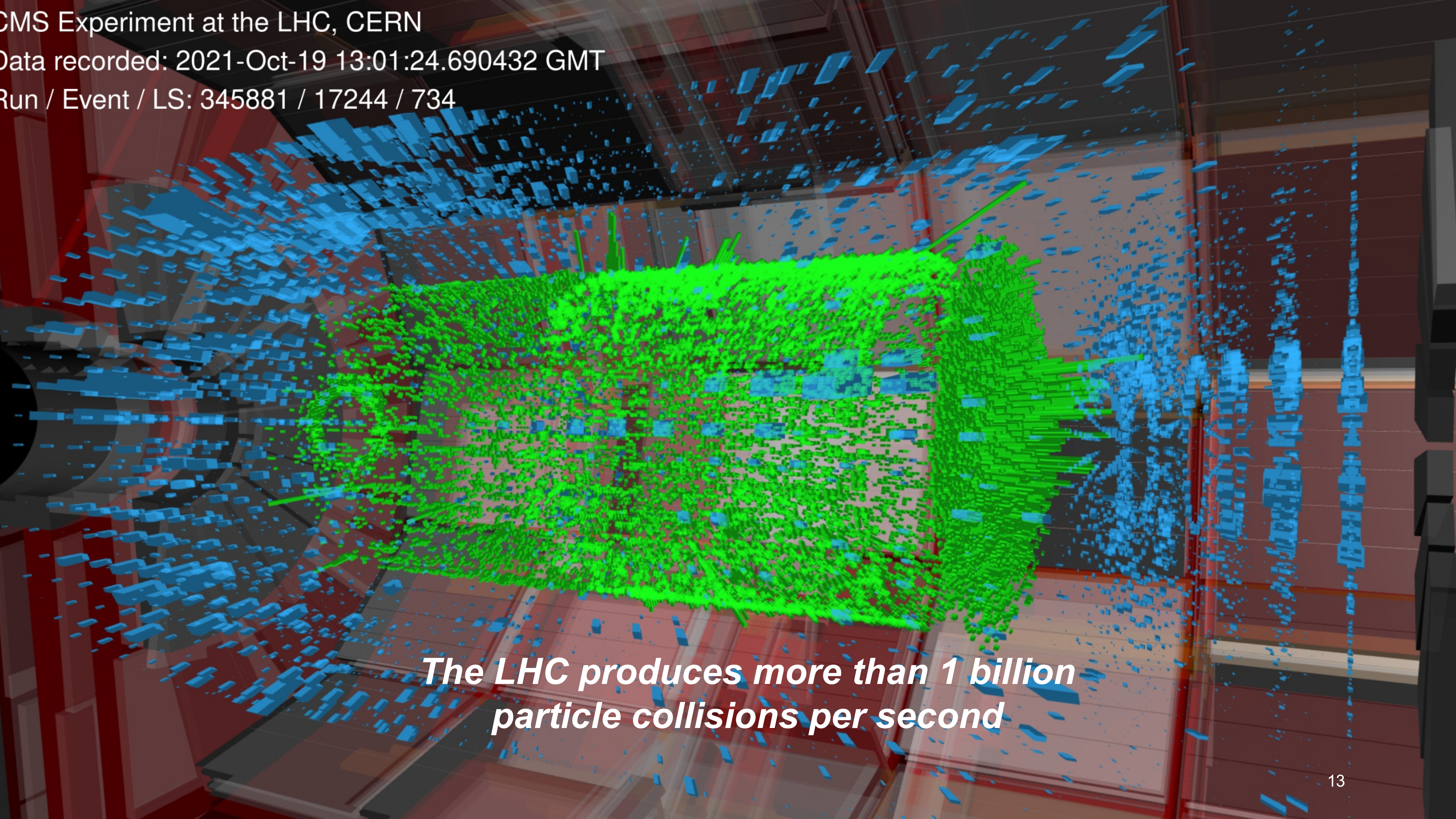


Figure 2.3: **Big Data sizes.** Bubble plot of the orders of magnitude of data produced by important big data players. The balloon areas illustrate the amount of data and the text annotations highlight the key factors considered in the estimates. Average per-unit sizes are reported in parentheses, where italic indicates measures reconstructed based on likely assumptions because no references were found.

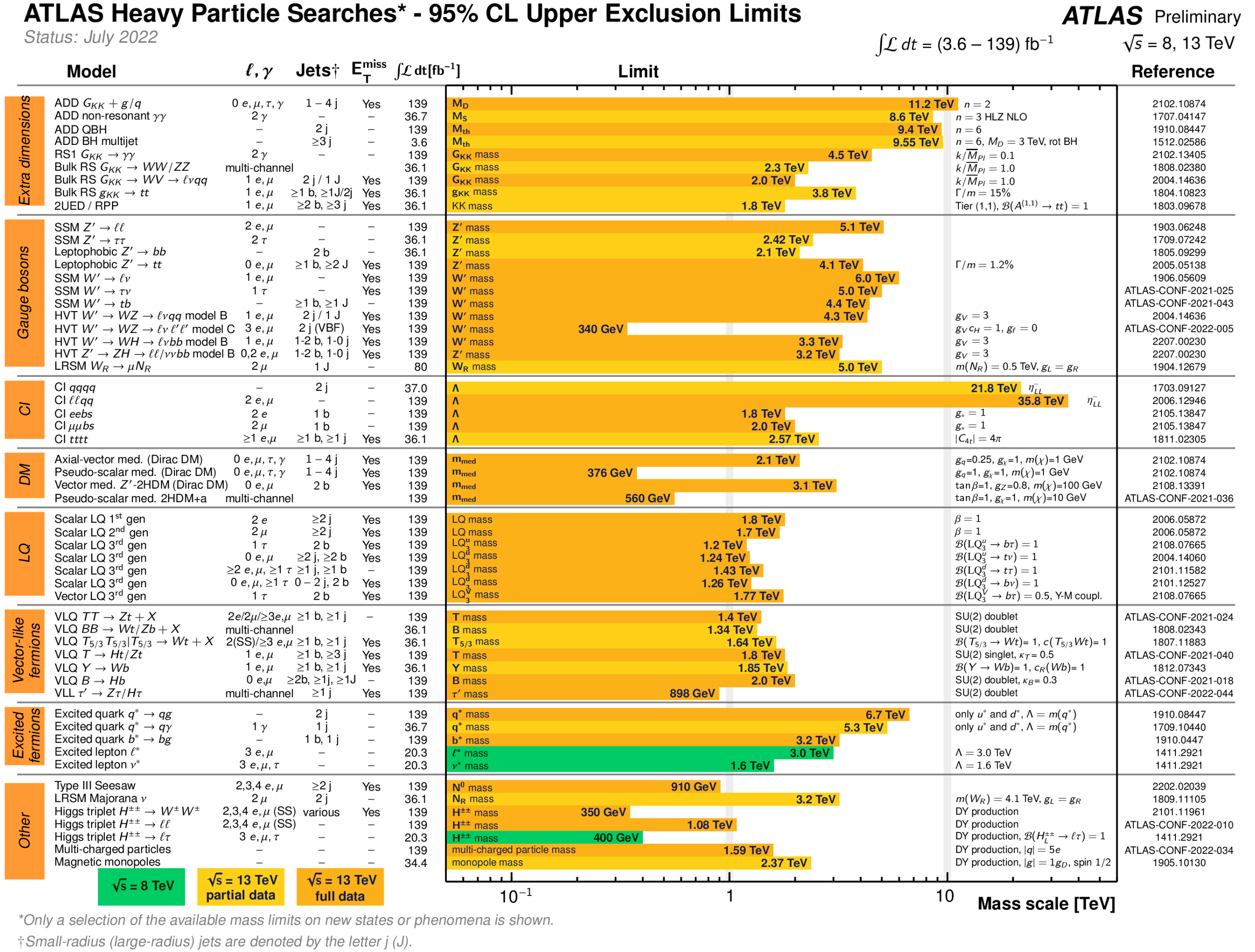
arxiv:2202.07659



The LHC produces more than 1 billion particle collisions per second

New Physics at the LHC

So far only **negative results** in **direct** (model dependent) searches



ATLAS Heavy Particle Searches* - 95% CL Upper Exclusion Limits

Status: July 2022

ATLAS Preliminary

$\int \mathcal{L}\, dt = (3.6 - 139)\ \text{fb}^{-1}$

$\sqrt{s} = 8,\ 13$ TeV

	Model	ℓ, γ	Jets†	E_T^{miss}	$\int \mathcal{L}\, dt[\text{fb}^{-1}]$	Limit			Reference
Extra dimensions	ADD $G_{KK} + g/q$	$0\ e, \mu, \tau, \gamma$	1 – 4 j	Yes	139	M_D	11.2 TeV	$n = 2$	2102.10874
	ADD non-resonant $\gamma\gamma$	$2\ \gamma$	–	–	36.7	M_S	8.6 TeV	$n = 3$ HLZ NLO	1707.04147
	ADD QBH	–	2 j	–	139	M_{th}	9.4 TeV	$n = 6$	1910.08447
	ADD BH multijet	–	≥3 j	–	3.6	M_{th}	9.55 TeV	$n = 6$, $M_D = 3$ TeV, rot BH	1512.02586
	RS1 $G_{KK} \to \gamma\gamma$	$2\ \gamma$	–	–	139	G_{KK} mass	4.5 TeV	$k/\overline{M}_{Pl} = 0.1$	2102.13405
	Bulk RS $G_{KK} \to WW/ZZ$	multi-channel			36.1	G_{KK} mass	2.3 TeV	$k/\overline{M}_{Pl} = 1.0$	1808.02380
	Bulk RS $G_{KK} \to WV \to \ell\nu qq$	$1\ e, \mu$	2 j / 1 J	Yes	139	G_{KK} mass	2.0 TeV	$k/\overline{M}_{Pl} = 1.0$	2004.14636
	Bulk RS $g_{KK} \to tt$	$1\ e, \mu$	≥1 b, ≥1J/2j	Yes	36.1	g_{KK} mass	3.8 TeV	$\Gamma/m = 15\%$	1804.10823
	2UED / RPP	$1\ e, \mu$	≥2 b, ≥3 j	Yes	36.1	KK mass	1.8 TeV	Tier (1,1), $\mathcal{B}(A^{(1,1)} \to tt) = 1$	1803.09678
Gauge bosons	SSM $Z' \to \ell\ell$	$2\ e, \mu$	–	–	139	Z' mass	5.1 TeV		1903.06248
	SSM $Z' \to \tau\tau$	$2\ \tau$	–	–	36.1	Z' mass	2.42 TeV		1709.07242
	Leptophobic $Z' \to bb$	–	2 b	–	36.1	Z' mass	2.1 TeV		1805.09299
	Leptophobic $Z' \to tt$	$0\ e, \mu$	≥1 b, ≥2 J	Yes	139	Z' mass	4.1 TeV	$\Gamma/m = 1.2\%$	2005.05138
	SSM $W' \to \ell\nu$	$1\ e, \mu$	–	Yes	139	W' mass	6.0 TeV		1906.05609
	SSM $W' \to \tau\nu$	$1\ \tau$	–	Yes	139	W' mass	5.0 TeV		ATLAS-CONF-2021-025
	SSM $W' \to tb$	–	≥1 b, ≥1 J	–	139	W' mass	4.4 TeV		ATLAS-CONF-2021-043
	HVT $W' \to WZ \to \ell\nu qq$ model B	$1\ e, \mu$	2 j / 1 J	Yes	139	W' mass	4.3 TeV	$g_V = 3$	2004.14636
	HVT $W' \to WZ \to \ell\nu\, \ell'\ell'$ model C	$3\ e, \mu$	2 j (VBF)	Yes	139	W' mass	340 GeV	$g_V c_H = 1$, $g_f = 0$	ATLAS-CONF-2022-005
	HVT $W' \to WH \to \ell\nu bb$ model B	$1\ e, \mu$	1-2 b, 1-0 j	Yes	139	W' mass	3.3 TeV	$g_V = 3$	2207.00230
	HVT $Z' \to ZH \to \ell\ell/\nu\nu bb$ model B	$0{,}2\ e, \mu$	1-2 b, 1-0 j	Yes	139	Z' mass	3.2 TeV	$g_V = 3$	2207.00230
	LRSM $W_R \to \mu N_R$	$2\ \mu$	1 J	–	80	W_R mass	5.0 TeV	$m(N_R) = 0.5$ TeV, $g_L = g_R$	1904.12679
CI	CI $qqqq$	–	2 j	–	37.0	Λ	21.8 TeV	η_{LL}^-	1703.09127
	CI $\ell\ell qq$	$2\ e, \mu$	–	–	139	Λ	35.8 TeV	η_{LL}^-	2006.12946
	CI $eebs$	$2\ e$	1 b	–	139	Λ	1.8 TeV	$g_* = 1$	2105.13847
	CI $\mu\mu bs$	$2\ \mu$	1 b	–	139	Λ	2.0 TeV	$g_* = 1$	2105.13847
	CI $tttt$	$\geq 1\ e, \mu$	≥1 b, ≥1 j	Yes	36.1	Λ	2.57 TeV	$\lvert C_{4t}\rvert = 4\pi$	1811.02305
DM	Axial-vector med. (Dirac DM)	$0\ e, \mu, \tau, \gamma$	1 – 4 j	Yes	139	m_{med}	2.1 TeV	g_q=0.25, g_χ=1, $m(\chi)$=1 GeV	2102.10874
	Pseudo-scalar med. (Dirac DM)	$0\ e, \mu, \tau, \gamma$	1 – 4 j	Yes	139	m_{med}	376 GeV	g_q=1, g_χ=1, $m(\chi)$=1 GeV	2102.10874
	Vector med. Z'-2HDM (Dirac DM)	$0\ e, \mu$	2 b	Yes	139	m_{med}	3.1 TeV	$\tan\beta$=1, g_Z=0.8, $m(\chi)$=100 GeV	2108.13391
	Pseudo-scalar med. 2HDM+a	multi-channel			139	m_{med}	560 GeV	$\tan\beta$=1, g_χ=1, $m(\chi)$=10 GeV	ATLAS-CONF-2021-036
LQ	Scalar LQ 1st gen	$2\ e$	≥2 j	Yes	139	LQ mass	1.8 TeV	$\beta = 1$	2006.05872
	Scalar LQ 2nd gen	$2\ \mu$	≥2 j	Yes	139	LQ mass	1.7 TeV	$\beta = 1$	2006.05872
	Scalar LQ 3rd gen	$1\ \tau$	2 b	Yes	139	LQ_3^u mass	1.2 TeV	$\mathcal{B}(\text{LQ}_3^u \to b\tau) = 1$	2108.07665
	Scalar LQ 3rd gen	$0\ e, \mu$	≥2 j, ≥2 b	Yes	139	LQ_3^u mass	1.24 TeV	$\mathcal{B}(\text{LQ}_3^u \to t\nu) = 1$	2004.14060
	Scalar LQ 3rd gen	$\geq 2\ e, \mu, \geq 1\ \tau$	≥1 j, ≥1 b	–	139	LQ_3^d mass	1.43 TeV	$\mathcal{B}(\text{LQ}_3^d \to t\tau) = 1$	2101.11582
	Scalar LQ 3rd gen	$0\ e, \mu, \geq 1\ \tau$	0 – 2 j, 2 b	Yes	139	LQ_3^d mass	1.26 TeV	$\mathcal{B}(\text{LQ}_3^d \to b\nu) = 1$	2101.12527
	Vector LQ 3rd gen	$1\ \tau$	2 b	Yes	139	LQ_3^V mass	1.77 TeV	$\mathcal{B}(\text{LQ}_3^V \to b\tau) = 0.5$, Y-M coupl.	2108.07665
Vector-like fermions	VLQ $TT \to Zt + X$	$2e/2\mu/\geq 3e,\mu$	≥1 b, ≥1 j	–	139	T mass	1.4 TeV	SU(2) doublet	ATLAS-CONF-2021-024
	VLQ $BB \to Wt/Zb + X$	multi-channel			36.1	B mass	1.34 TeV	SU(2) doublet	1808.02343
	VLQ $T_{5/3}T_{5/3}\vert T_{5/3} \to Wt + X$	2(SS)/$\geq 3\ e,\mu$	≥1 b, ≥1 j	Yes	36.1	$T_{5/3}$ mass	1.64 TeV	$\mathcal{B}(T_{5/3} \to Wt)$= 1, $c(T_{5/3}Wt)$= 1	1807.11883
	VLQ $T \to Ht/Zt$	$1\ e, \mu$	≥1 b, ≥3 j	Yes	139	T mass	1.8 TeV	SU(2) singlet, κ_T= 0.5	ATLAS-CONF-2021-040
	VLQ $Y \to Wb$	$1\ e, \mu$	≥1 b, ≥1 j	Yes	36.1	Y mass	1.85 TeV	$\mathcal{B}(Y \to Wb)$= 1, $c_R(Wb)$= 1	1812.07343
	VLQ $B \to Hb$	$0\ e,\mu$	≥2b, ≥1j, ≥1J	–	139	B mass	2.0 TeV	SU(2) doublet, κ_B= 0.3	ATLAS-CONF-2021-018
	VLL $\tau' \to Z\tau/H\tau$	multi-channel	≥1 j	Yes	139	τ' mass	898 GeV	SU(2) doublet	ATLAS-CONF-2022-044
Excited fermions	Excited quark $q^* \to qg$	–	2 j	–	139	q^* mass	6.7 TeV	only u^* and d^*, $\Lambda = m(q^*)$	1910.08447
	Excited quark $q^* \to q\gamma$	$1\ \gamma$	1 j	–	36.7	q^* mass	5.3 TeV	only u^* and d^*, $\Lambda = m(q^*)$	1709.10440
	Excited quark $b^* \to bg$	–	1 b, 1 j	–	139	b^* mass	3.2 TeV		1910.0447
	Excited lepton ℓ^*	$3\ e, \mu$	–	–	20.3	ℓ^* mass	3.0 TeV	$\Lambda = 3.0$ TeV	1411.2921
	Excited lepton ν^*	$3\ e, \mu, \tau$	–	–	20.3	ν^* mass	1.6 TeV	$\Lambda = 1.6$ TeV	1411.2921
Other	Type III Seesaw	$2{,}3{,}4\ e, \mu$	≥2 j	Yes	139	N^0 mass	910 GeV		2202.02039
	LRSM Majorana ν	$2\ \mu$	2 j	–	36.1	N_R mass	3.2 TeV	$m(W_R) = 4.1$ TeV, $g_L = g_R$	1809.11105
	Higgs triplet $H^{\pm\pm} \to W^\pm W^\pm$	$2{,}3{,}4\ e, \mu$ (SS)	various	Yes	139	$H^{\pm\pm}$ mass	350 GeV	DY production	2101.11961
	Higgs triplet $H^{\pm\pm} \to \ell\ell$	$2{,}3{,}4\ e, \mu$ (SS)	–	–	139	$H^{\pm\pm}$ mass	1.08 TeV	DY production	ATLAS-CONF-2022-010
	Higgs triplet $H^{\pm\pm} \to \ell\tau$	$3\ e, \mu, \tau$	–	–	20.3	$H^{\pm\pm}$ mass	400 GeV	DY production, $\mathcal{B}(H_L^{\pm\pm} \to \ell\tau) = 1$	1411.2921
	Multi-charged particles	–	–	–	139	multi-charged particle mass	1.59 TeV	DY production, $\lvert q\rvert = 5e$	ATLAS-CONF-2022-034
	Magnetic monopoles	–	–	–	34.4	monopole mass	2.37 TeV	DY production, $\lvert g\rvert = 1g_D$, spin 1/2	1905.10130

*Only a selection of the available mass limits on new states or phenomena is shown.

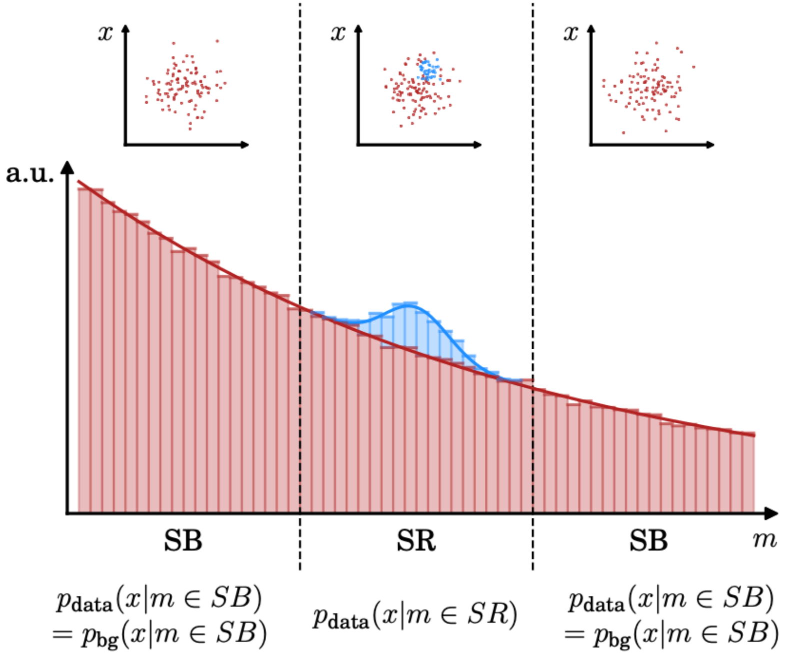
†Small-radius (large-radius) jets are denoted by the letter j (J).

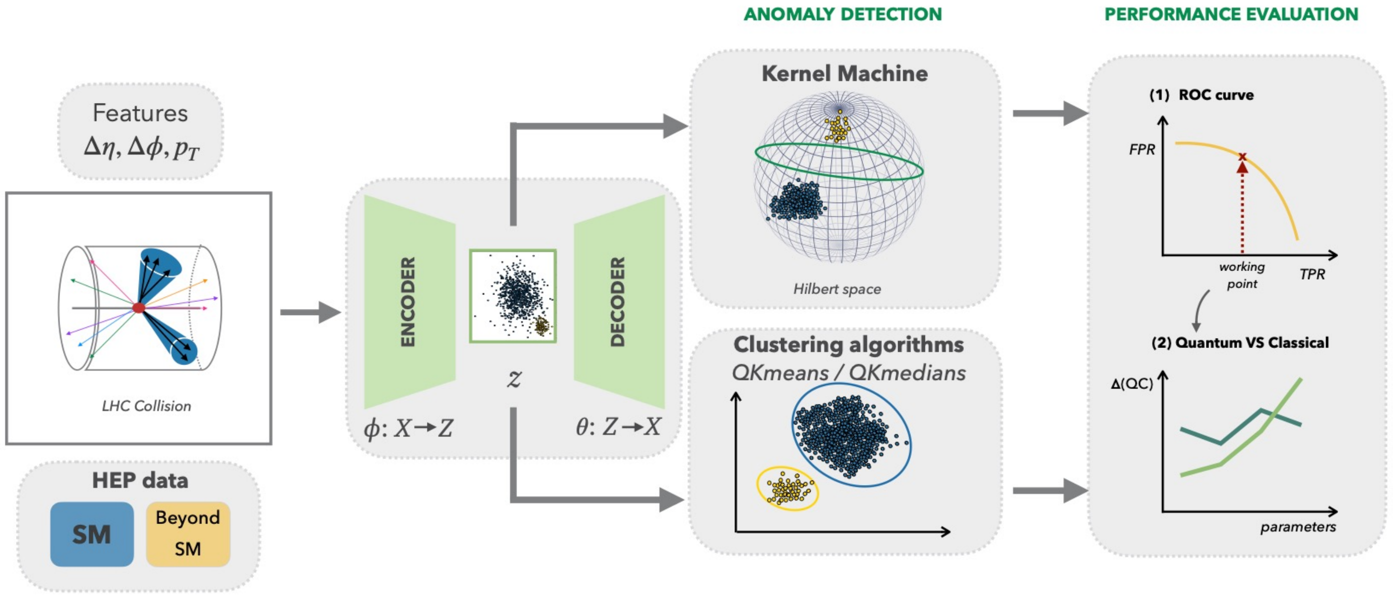
How to insure we do not miss potential discoveries?

We can design model agnostic searches!

A typical hybrid QML workflow

Paper Code





«Normal» training data

Data compression

Quantum algorithm

Output

Wózniak, Belis, Grossi, Vallecorsa et al. - https://arxiv.org/abs/2301.10780

Results

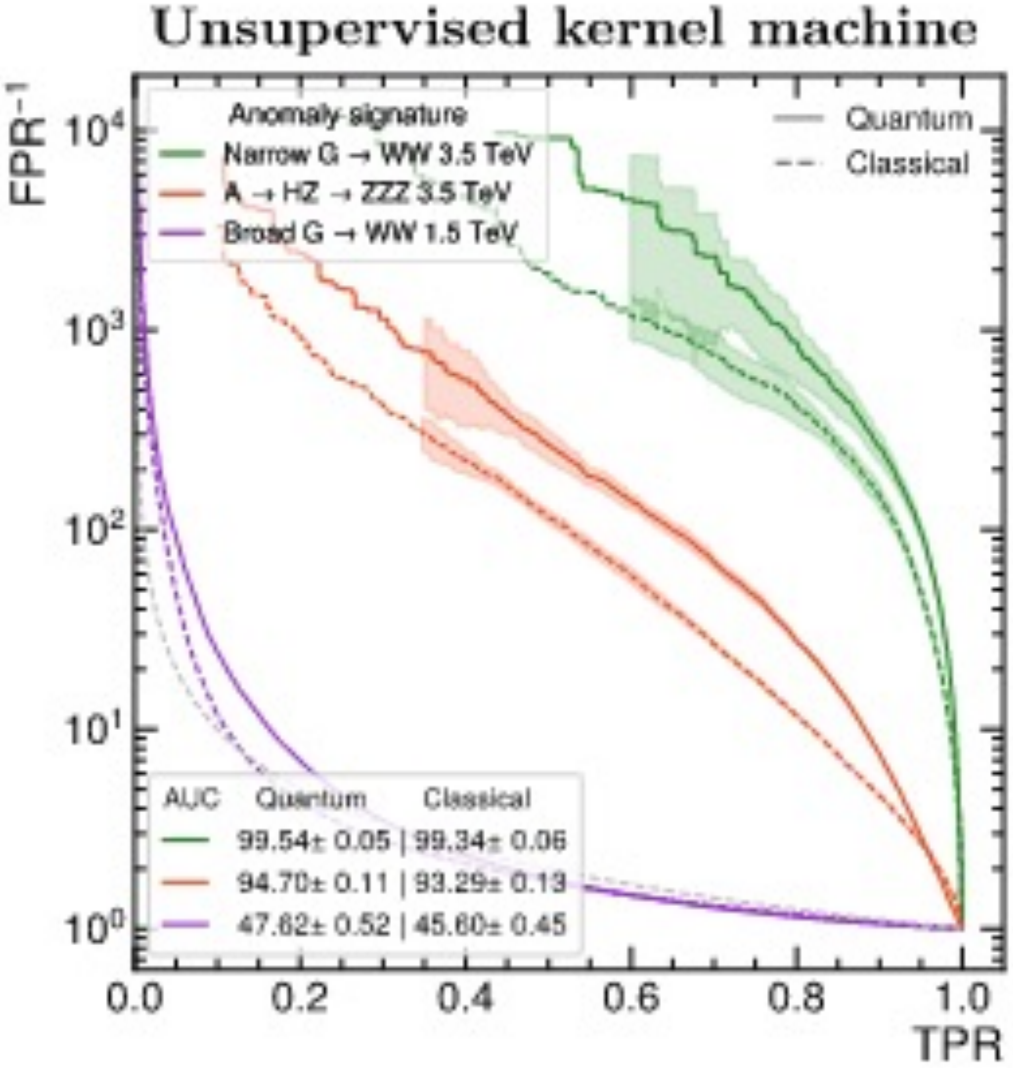
Comparison to classical algorithms:
best-performing model with similar complexity trained and tested on the same data

- RBF-based SVM

AUC shows **marginal advantage** for quantum algorithm

Evaluate performance at **typical working**, where $\varepsilon_s = 0.6, 0.8$

Quantum kernel machine works best for more complex physics



Characterizing the advantage

Higher is better

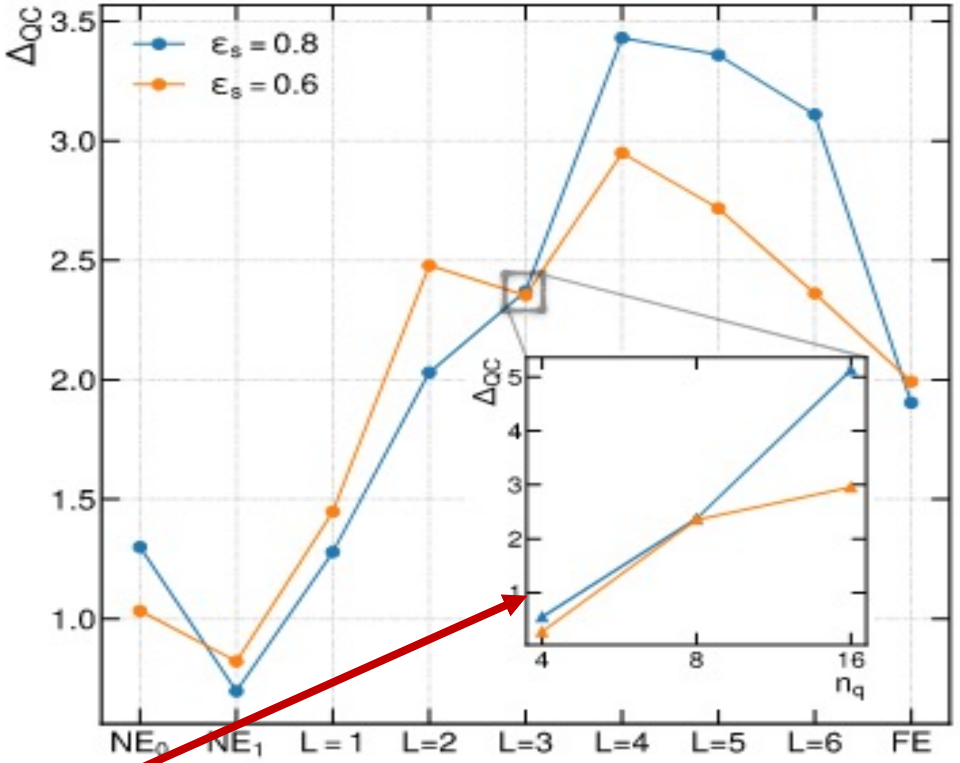
Given **signal and background efficiencies**, ε_s and ε_b respectively:

$$\Delta_{\mathrm{QC}}(\varepsilon_s) = \frac{\varepsilon_{\mathrm{b}}^{-1}(\varepsilon_s; Q)}{\varepsilon_b^{-1}(\varepsilon_s; C)}$$

Performance advantage is consistent

- Increase in the expressibility and entanglement up to L=4 improve performance, reduce it above
- **Full entanglement is not better**

Classical is better than 4 qubit QSVM
Increasing expressibility improves performance



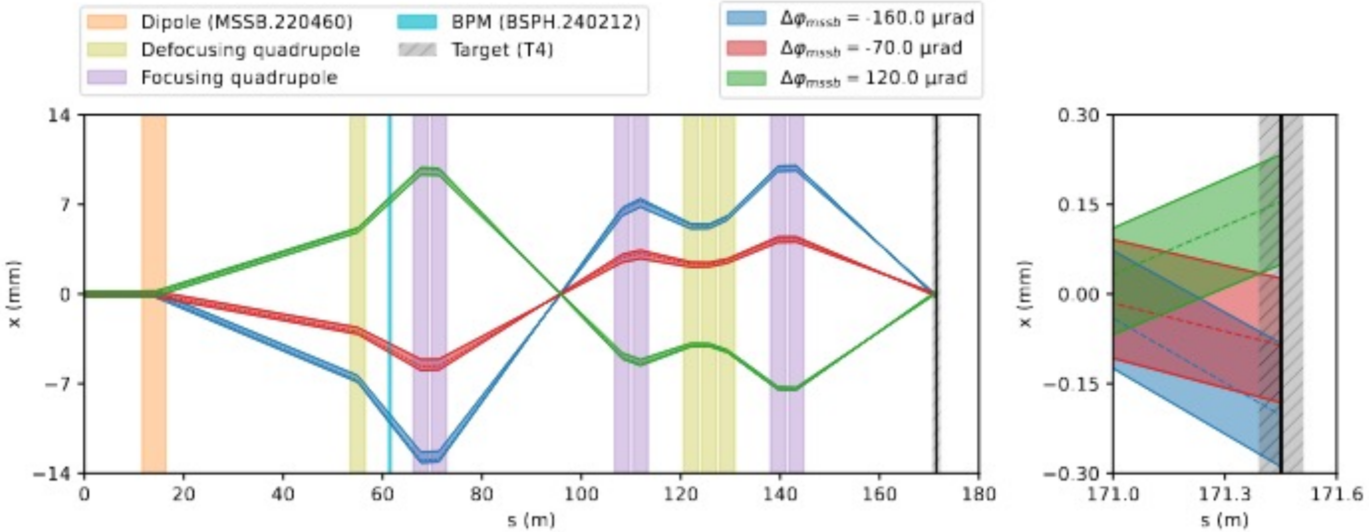
NE_0: 1 layer - No entanglement
NE_1: no entanglement

Full entanglement (all-to- all)

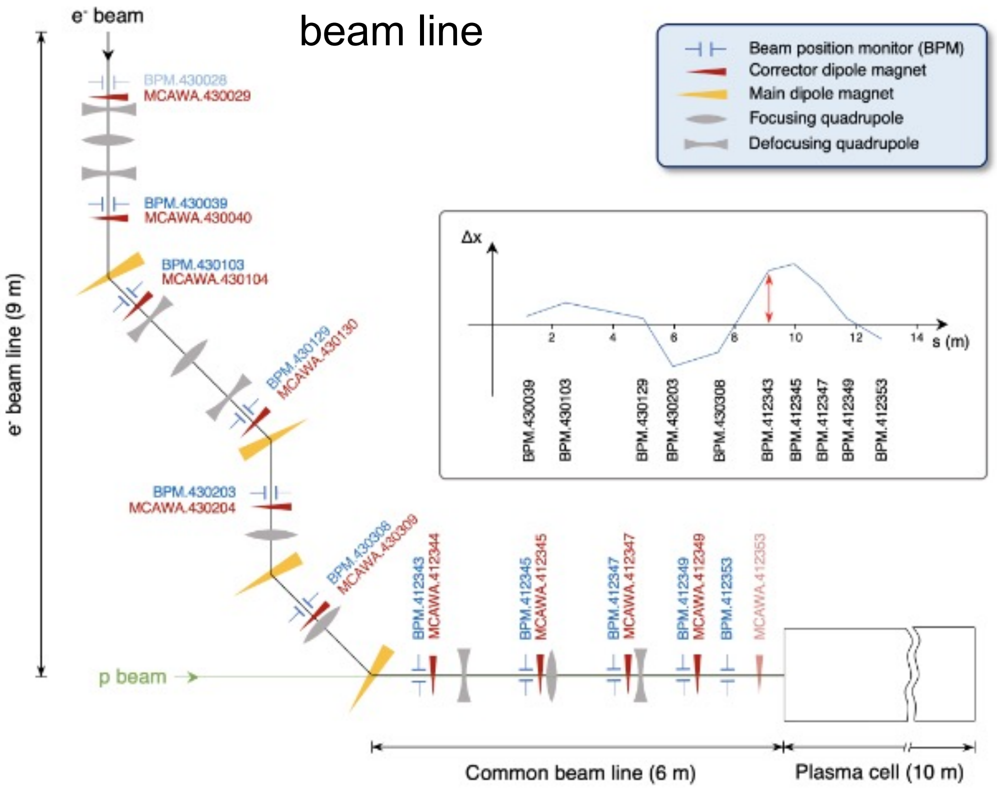
Michael Schenk et al., **Hybrid actor-critic algorithm for quantum reinforcement learning at CERN beam lines**, e-Print: 2209.11044 [quant-ph]

Beam optimisation in linear accelerators

- **Action: (discrete) deflection** angle
- **State: (continuous) BPM** position
- **Reward: integrated beam intensity on target**
- **Optimality**: fraction of states in which the agent takes the right decision



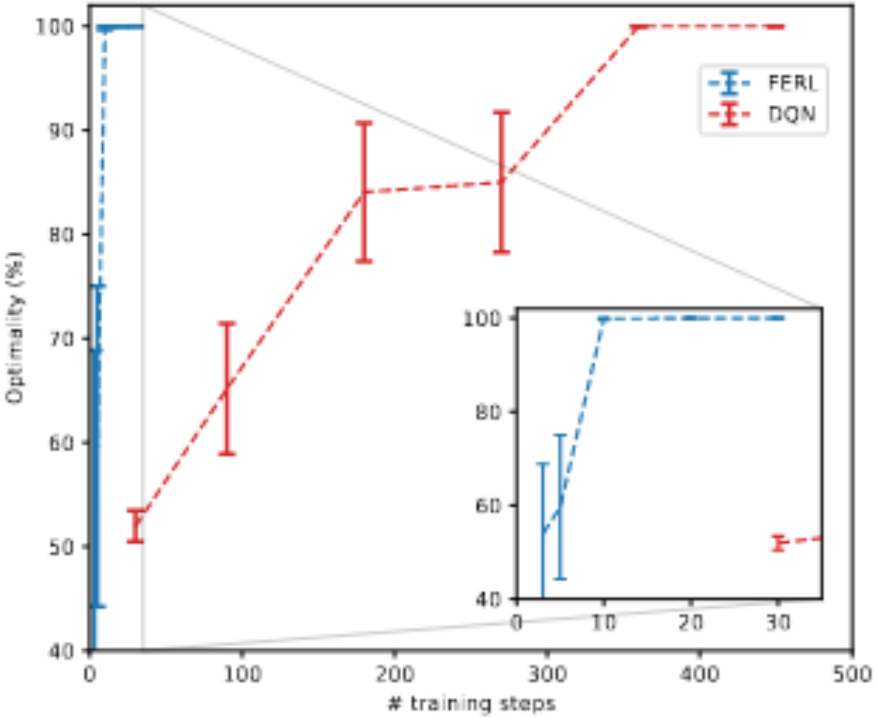
2GeV electron beam line

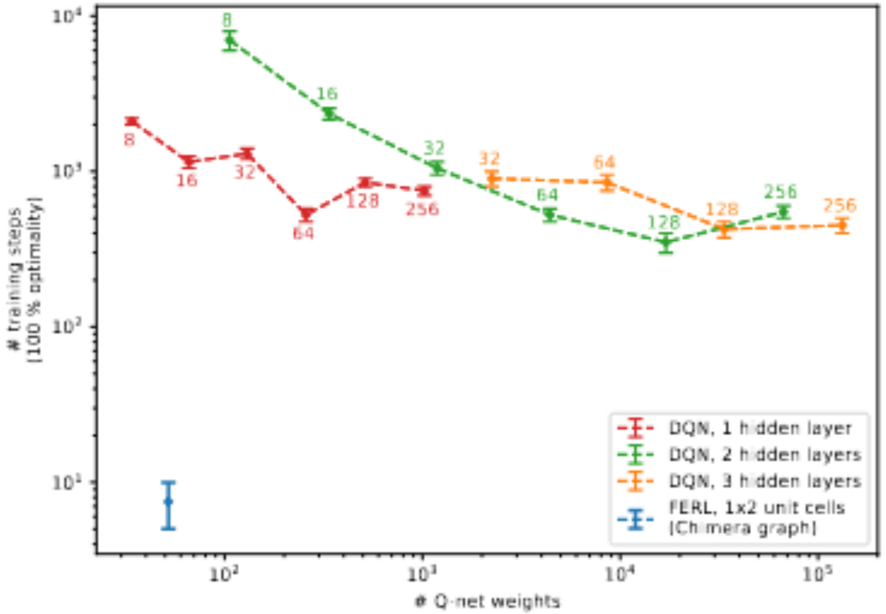


Sample complexity and representational power

- **Quantum RL massively** outperforms classical Q-learning *(8±2 vs. 320±40 steps with e. r.)*

QRL use cases confirms advantage in terms of **model size** and **training steps**





Michael Schenk, Elías F. Combarro, Michele Grossi, Verena Kain, Kevin Shing Bruce Li, Mircea-Marian Popa, Sofia Vallecorsa, **Hybrid actor-critic algorithm for quantum reinforcement learning at CERN beam lines.** arXiv:2209.11044

QC research directions in HEP

QC4HEP
working group

- Quantum computing could be **revolutionary in HEP**
- To go beyond the hype we need **concrete challenges**
    - What are the most promising applications?
    - How to **define performance metrics** and validate results?
- **Experimental data has high dimensionality**
    - Can we train **Quantum Machine Learning** algorithms effectively?
    - Can we reduce **the impact of data reduction techniques**?
- Experimental data is shaped by physics laws
    - Can we leverage them to build better algorithms?

Quantum Computing for High-Energy Physics
State of the Art and Challenges
Summary of the QC4HEP Working Group

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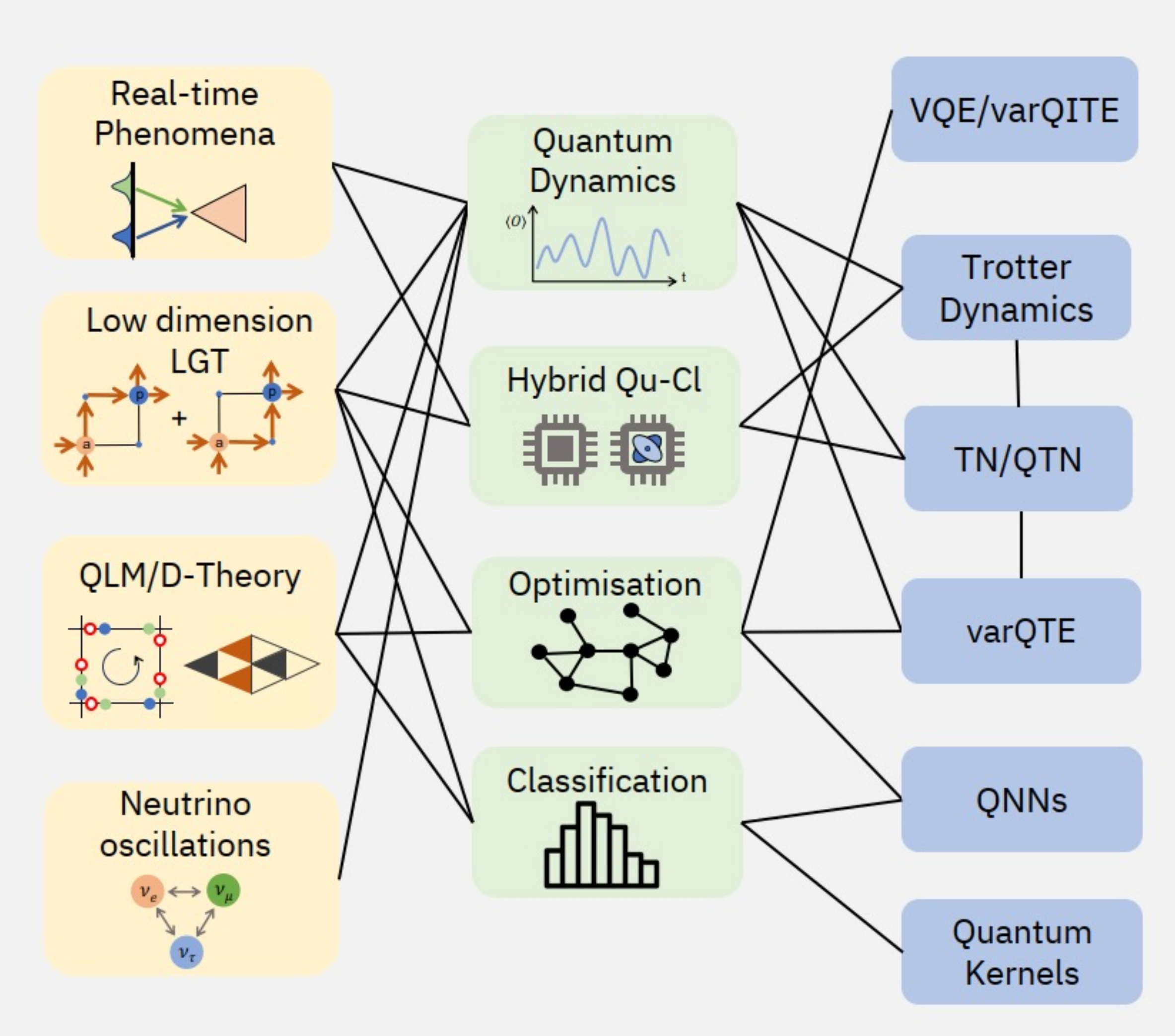
arXiv:2307.03236v1 [quant-ph] 6 Jul 2023

Methods and applications



Real-time Phenomena

Low dimension LGT

QLM/D-Theory

Neutrino oscillations

Quantum Dynamics

Hybrid Qu-Cl

Optimisation

Classification

VQE/varQITE

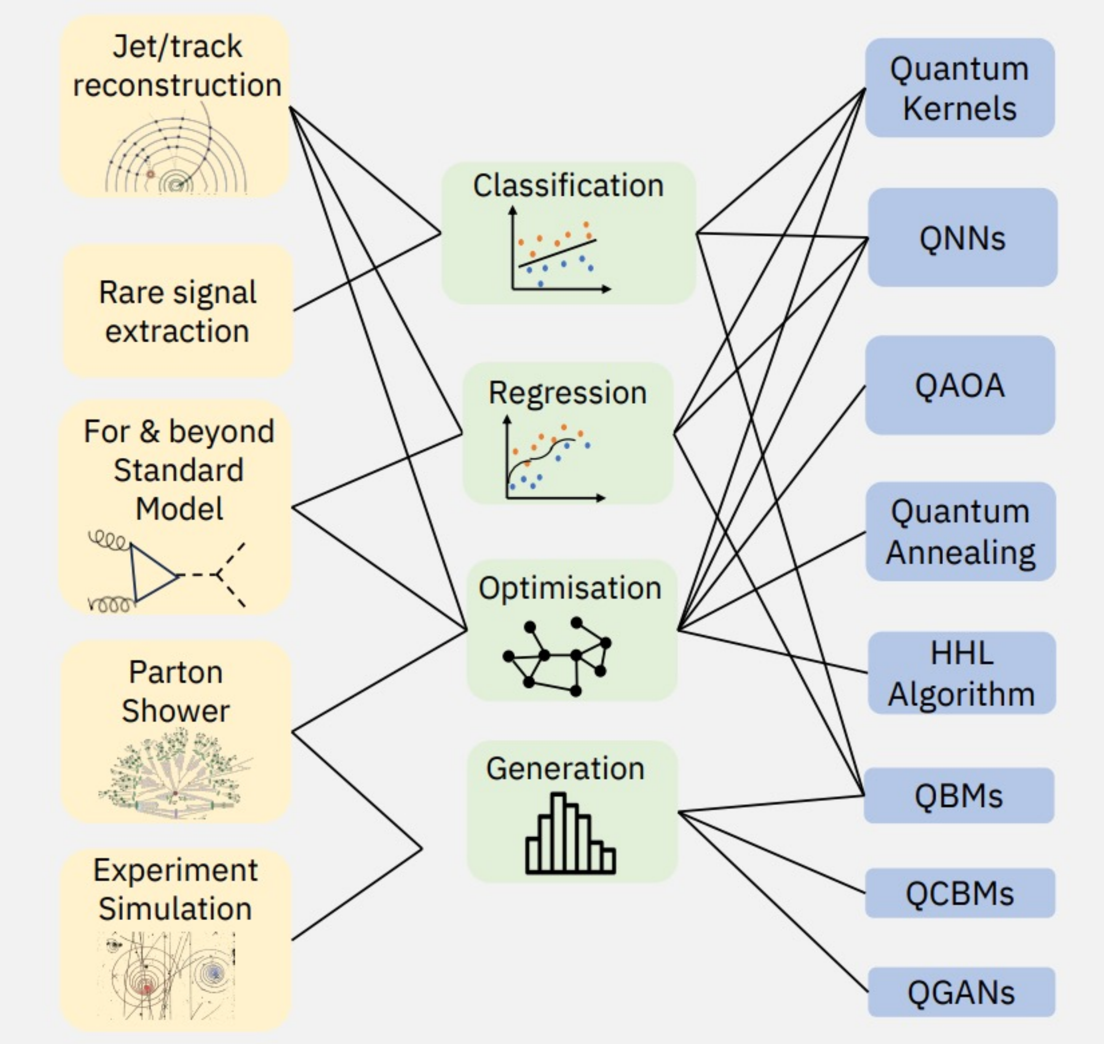
Trotter Dynamics

TN/QTN

varQTE

QNNs

Quantum Kernels



Jet/track reconstruction

Rare signal extraction

For & beyond Standard Model

Parton Shower

Experiment Simulation

Classification

Regression

Optimisation

Generation

Quantum Kernels

QNNs

QAOA

Quantum Annealing

HHL Algorithm

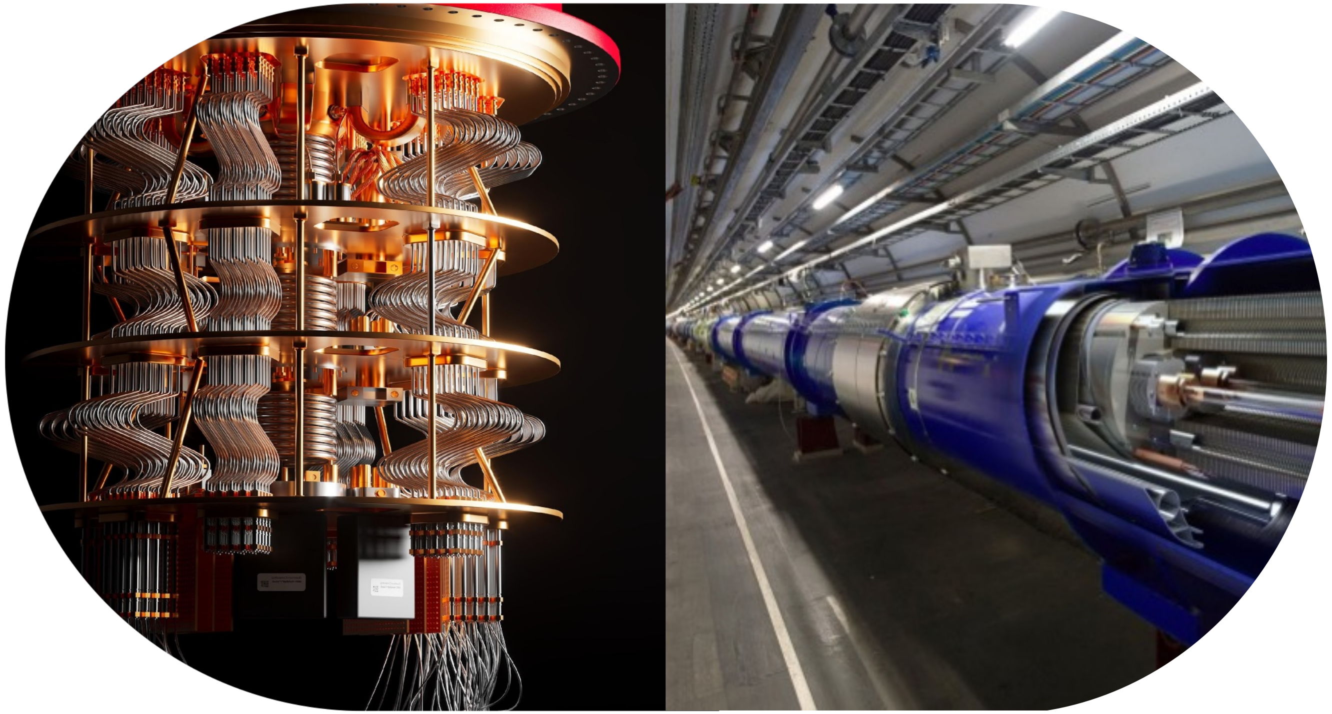
QBMs

QCBMs

QGANs

CERN QTI$_2$

How does CERN engage in Quantum Technologies?



QT4HEP

Develop technologies required by the CERN scientific programme

Integrate CERN to future quantum infrastructure

HEP4QT

Extend and share technologies available at CERN

Boost development and adoption of QT beyond CERN

Unique CERN expertise

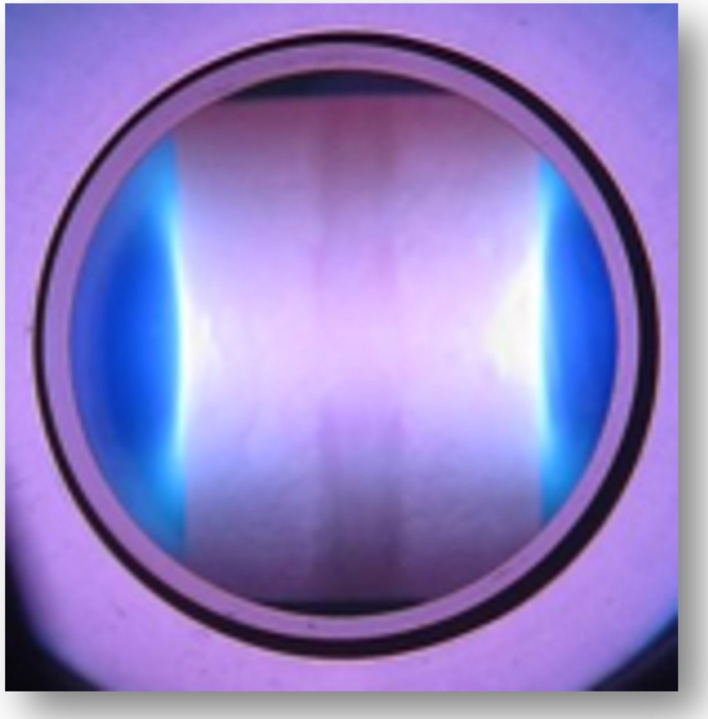
Artificial Intelligence on FPGAs (based on CERN expertise on DAQ systems)

- Error correction is one of the greatest outstanding challenges in **quantum computing**. Any error correction has to happen sufficiently fast such that it is within the lifetime of the qubit. CERN's expertise in fast inference and machine learning could be a valuable contribution to this field.
- Improved error correction on quantum computer

Superconducting Coatings for RF Cavities

Unique expertise at CERN with potential impact for both quantum computing and quantum networking

- **Quantum Computing**
  Explore SRF Cavities for bosonic quantum computers
- **Quantum Networks**
  use of SRF Cavities for quantum transducers?



White Rabbit technology for time synchronisation

Initially meant for **large physics facilities**: CERN, GSI. . .

Based on **well-established standards**

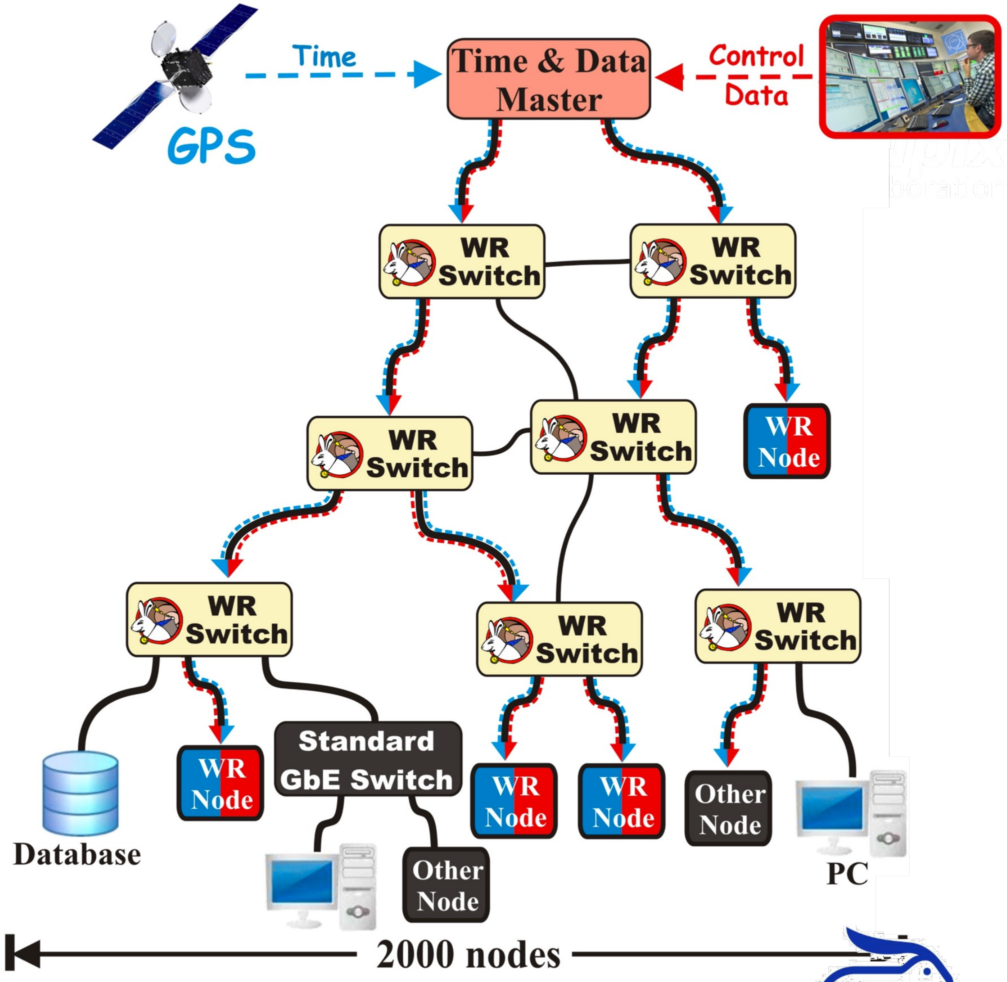
- Ethernet (IEEE 802.3), Bridged Local Area Network (IEEE 802.1Q), Precision Time Protocol (IEEE 1588)

Extends standards to meet new requirements and provides

- **Sub-ns synchronisation**
- **Deterministic data transfer**

Initial specs: links ≤10 km & ≤2000 nodes

Open Source and commercially available

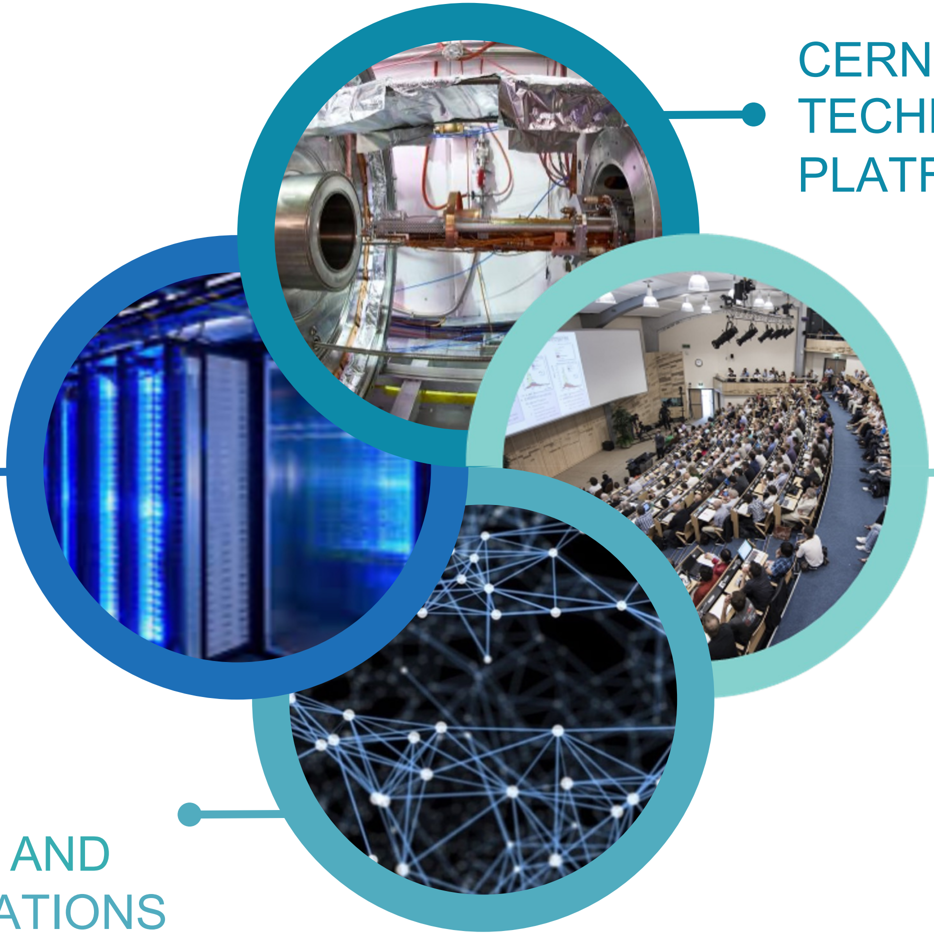


White Rabbit COLLABORATION

13th WR Workshop (21-22 March 2024 at CERN) https://ohwr.org/project/white-rabbit/wikis/mar2024meeting. and

CERN QTI Phase 2

Launched January 2024



CERN QUANTUM TECHNOLOGY PLATFORMS

HYBRID QUANTUM COMPUTING AND ALGORITHMS

COLLABORATION FOR IMPACT

QUANTUM NETWORKS AND COMMUNICATIONS

A 5 years research plan

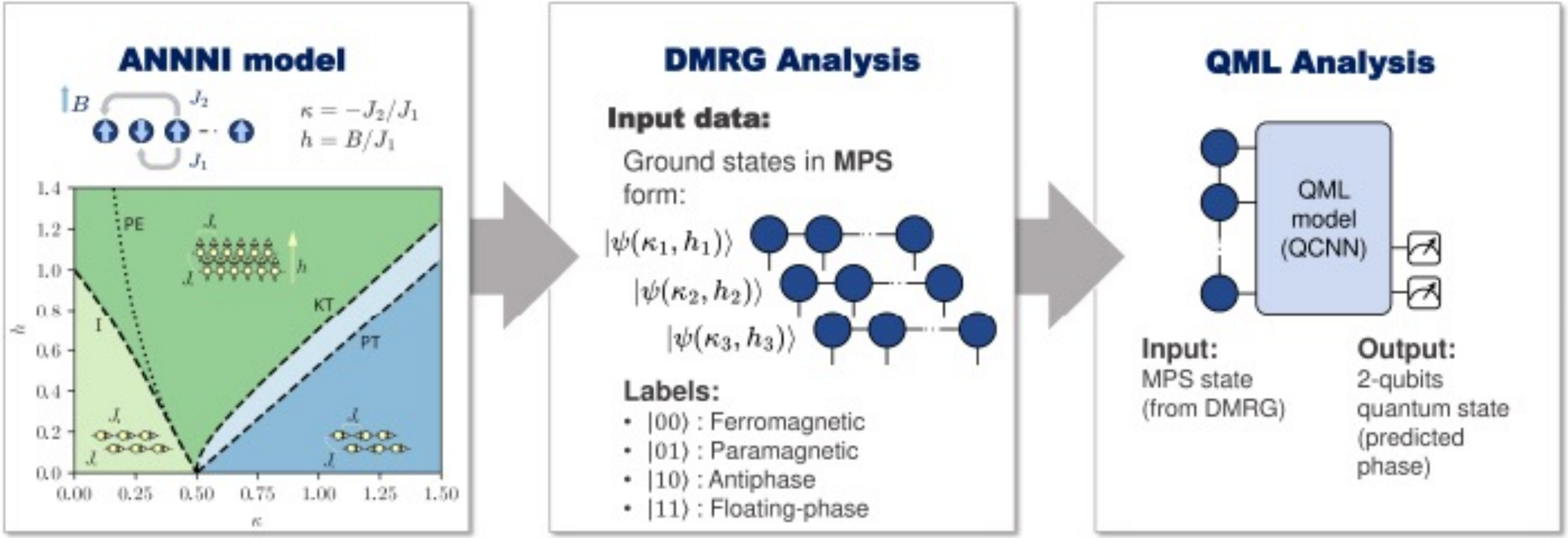
QML for quantum data: drawing phase diagrams

Cea, at al. , arxiv (2024)

Monaco, at al. Physical Review B 107.8 (2023): L081105

- **Use Tensor Networks to study phase diagram of a Ising model**
  - State-of-the-art caracterization incl. Floating Phase
  - Provide input to QML algorithm
- **(Un-)Supervised QML to classify the ground state**
- **Bottleneck from access to classical training labels**
  - Train in integrable subregions
  - Use an Anomaly Detection approach

$$H_{ANNNI} = -J_1 \sum_{i=1}^{N-1} \sigma_i^x \sigma_{i+1}^x - J_2 \sum_{i=1}^{N-2} \sigma_i^x \sigma_{i+2}^x$$



ANNNI model

DMRG Analysis

Input data:

Ground states in **MPS** form:

Labels:

- $|00\rangle$: Ferromagnetic
- $|01\rangle$: Paramagnetic
- $|10\rangle$: Antiphase
- $|11\rangle$: Floating-phase

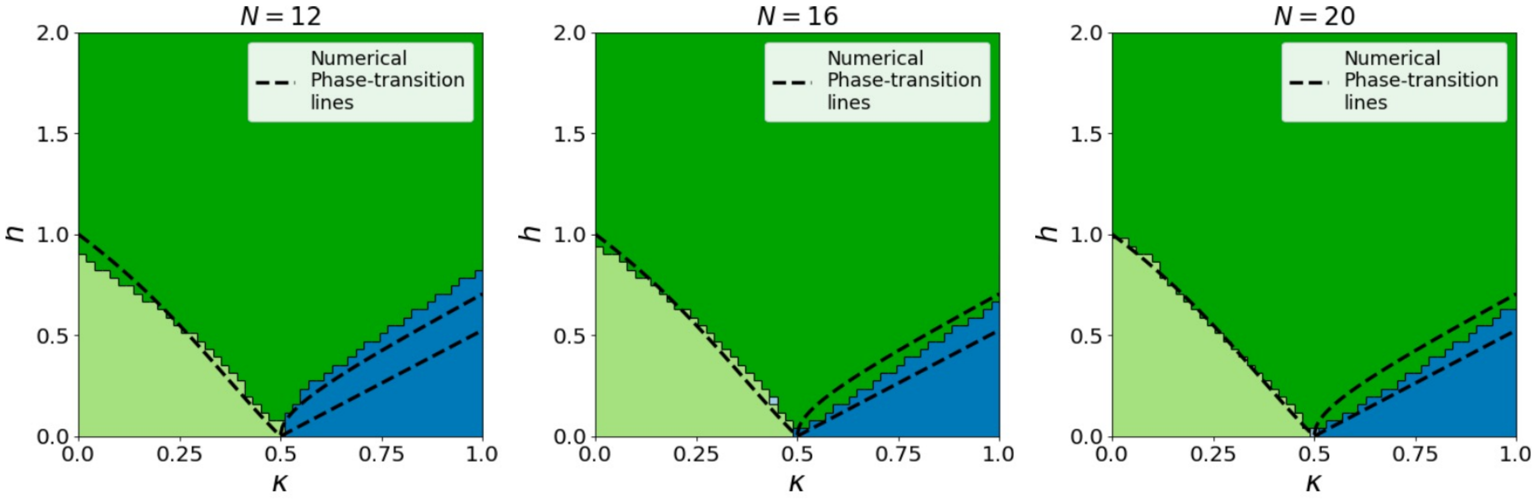
QML Analysis

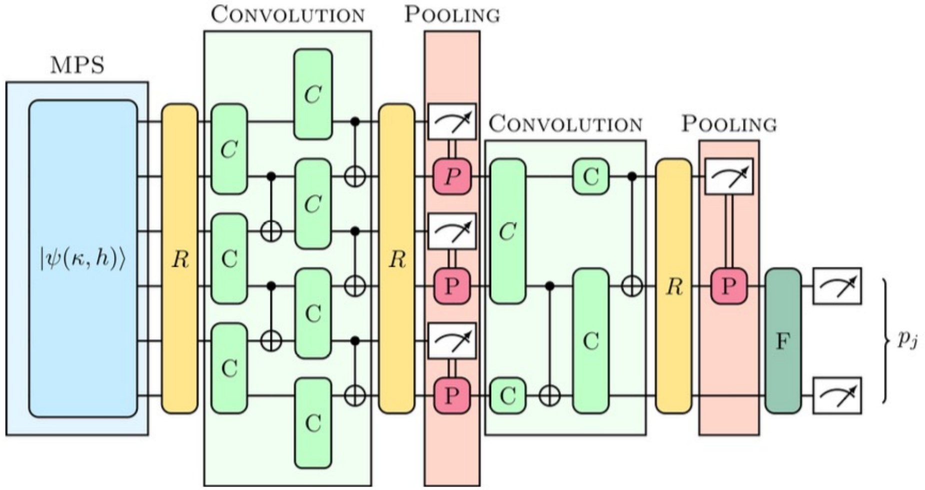
Input:
MPS state (from DMRG)

Output:
2-qubits quantum state (predicted phase)

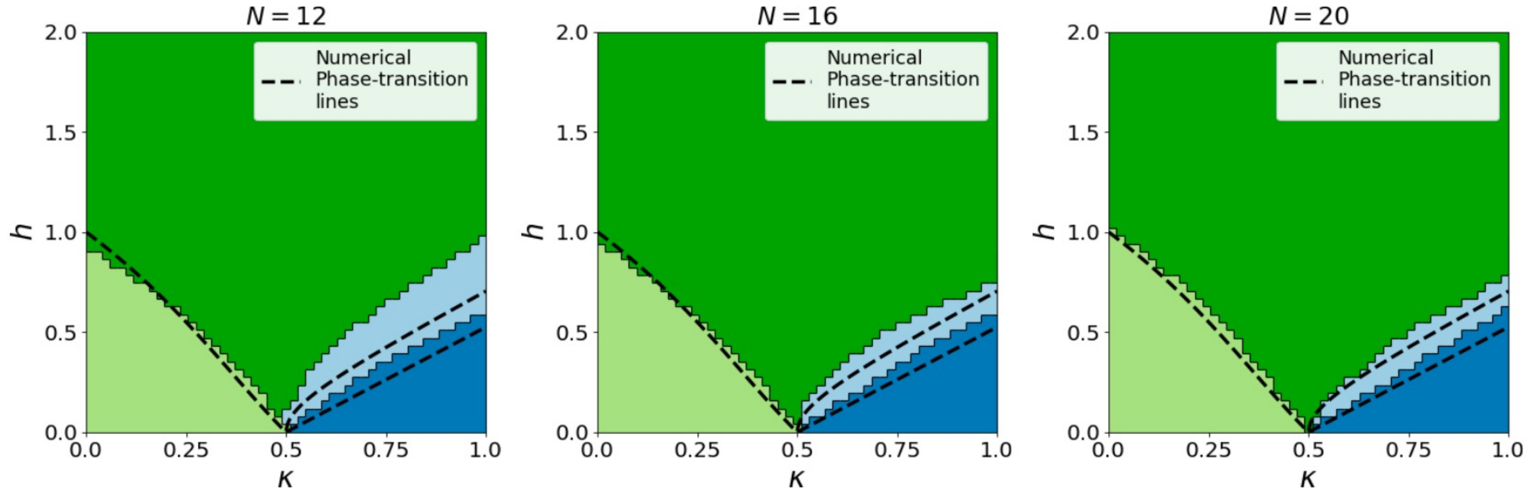
Supervised Quantum Convolutional NN

Train on analytically solvable points along the axes

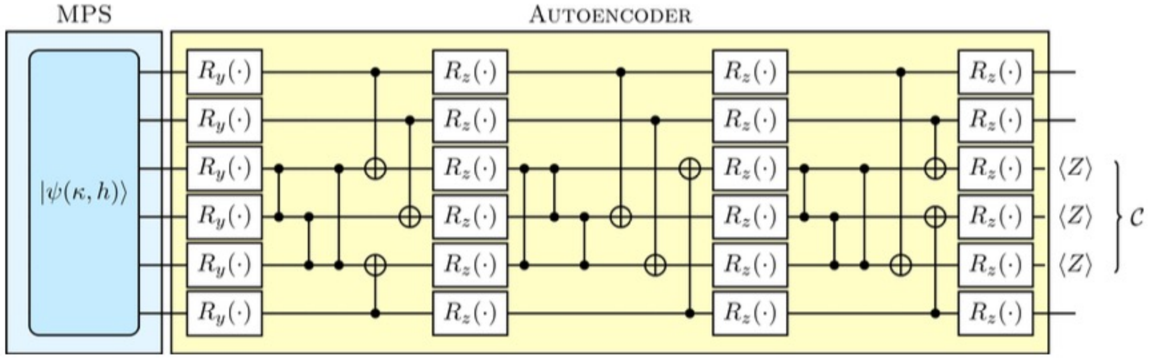




Train on all classes

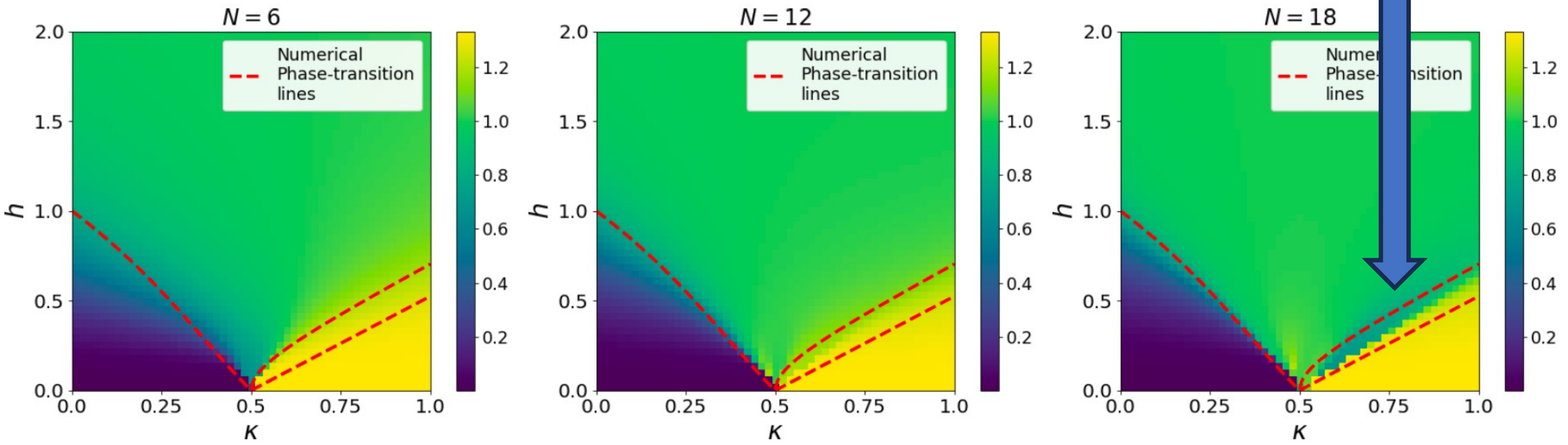


Unsupervised Quantum Auto-Encoder



Floating Phase !

Train on state at (0,0)



The DRD5 (RDq) collaboration proposal: R&D on quantum sensors

Quantum sensor R&D for particle physics

Aligned with the **2021 ECFA Detector Research and Development Roadmap**

To be **submitted to CERN** for review and approval

Soon available on quantum.cern

WP-1 : Atomic, nuclear and molecular systems and nanoparticles in traps & beams
- Exotic systems in traps and beams
- Atom Interferometry
- Networks, Signal and Clock distribution

WP-2 : Quantum materials (0-, 1- and 2-D materials)
- Application-specific
- Extended functionalities
- Simulations

WP-3: Cryogenic materials, devices and systems
WP-4: Scaling up "quantum"
WP-5 : Quantum techniques for sensing
….

Summary and Outlook

A new exciting phase of Quantum Technology research opens at CERN

- Focus continues on the **applicability of Quantum Technologies** to High Energy Physics
- Build on **CERN existing expertise to contribute to the development of Quantum Technologies**
- **Extending the network of collaborations is essential**

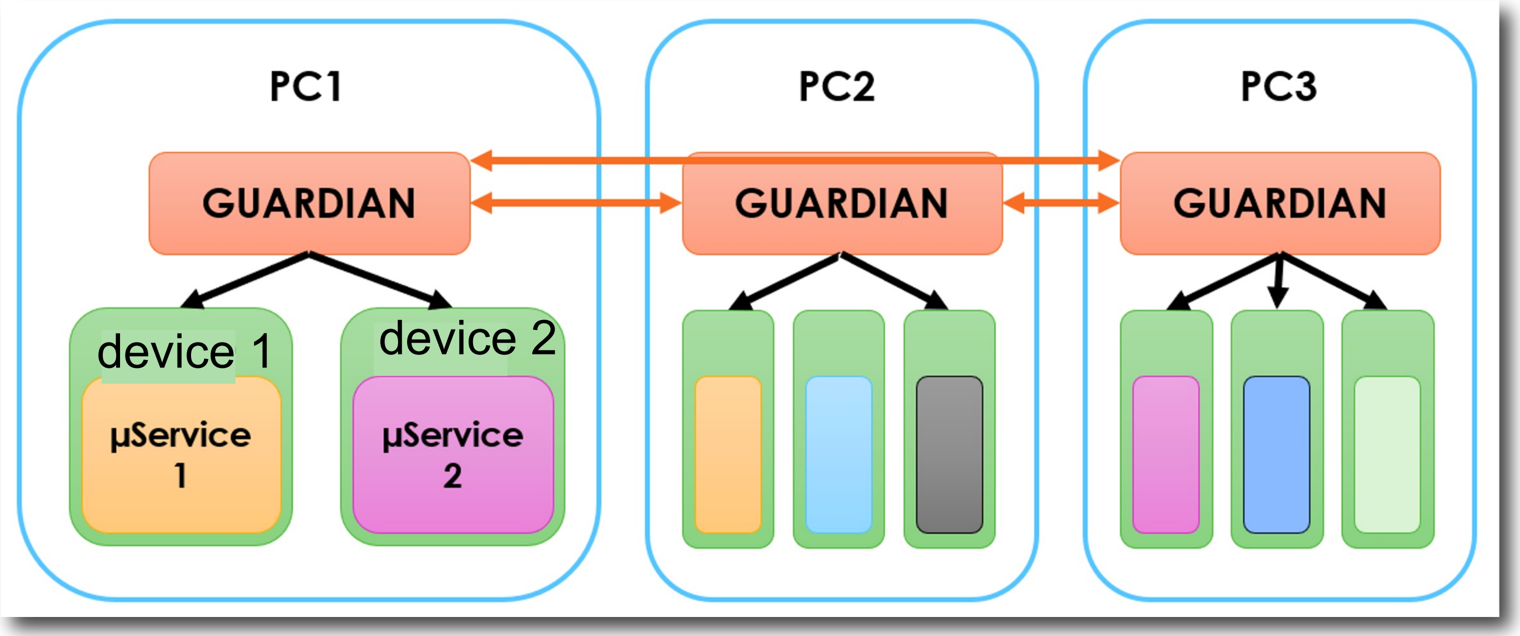
Thanks!

CERN

QUANTUM
TECHNOLOGY
INITIATIVE

Quantum optics control systems for HEP experiments

Goal: port & develop emerging quantum optics experiments standards for control of HEP experiments



Scalable, modular, high degree of automation

HW: based on emerging SINARA standard

SW: based on ARTIQ (Advanced Real Time Infrastructure for Quantum physics) standard

control: Python based

Marco Volponi
Low Energy Antimatter conference,
2023

TALOS (Total Automation of LabVIEW™ Operations for Science): autonomous unsupervised control system for complex experiments

Automated execution of many devices to 1 ns (DAC's, sequencers, pulsers, phased DAC's, digital frequency generators, …)

Already generating interest in atomic physics and trapped ion communities

S. Y. Chang *et al.*, IEEE QCE23

Geometric Quantum Machine Learning

- Given a data point $x \in \mathcal{X}$ and its label $y \in \mathcal{Y}$
- Estimate the prediction y_θ from observable O: $y_\theta(x) = \langle\psi(x)|\mathcal{U}^\dagger(\theta) O\, \mathcal{U}(\theta)\, |\psi(x)\,\rangle$
- Given a symmetry group $\mathfrak{G}$ on the data space $\mathcal{X}$
- **$\mathfrak{G}$ – Invariance** : For all $x \in \mathcal{X}$ and $g \in \mathfrak{G}$

$$y_\theta(g[x]) = y_\theta(x)$$

- **Final prediction y_θ is invariant if:**

Equivariant data embedding:

For feature map $\psi: \mathcal{X} \to \mathcal{H}$

$$|\psi(g[x])\rangle = V_s[g]|\psi(x)0\rangle$$

$V_s[g]$ = **Representation** of g on $\mathcal{H}$ induced by ψ

Equivariant ansatz:

For operators generated by a fixed generator G as $R_G(\theta) = \exp(-i\theta G)$:

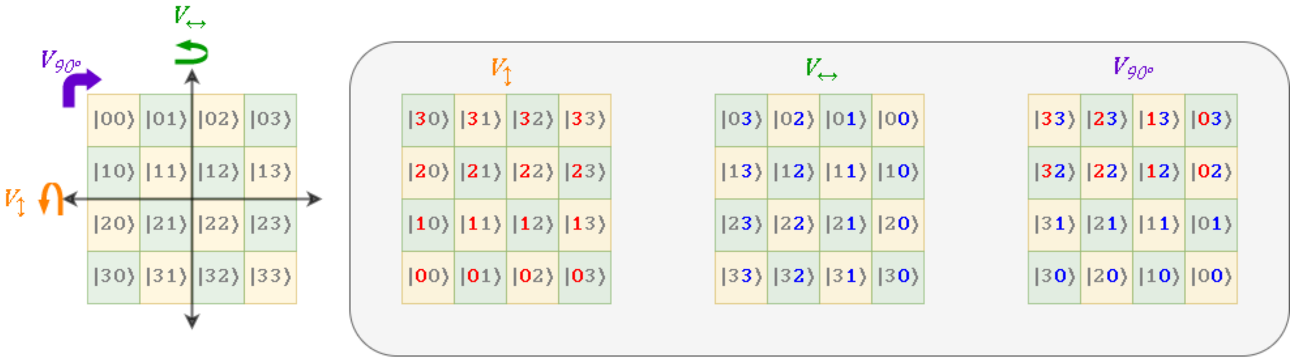
$$[R_G(\theta), V_s[g]] = 0 \;\leftrightarrow\; [G, V_s[g]] = 0$$

Invariant Measurement:

$$V_s^\dagger[g] O V_s[g] = O$$

Equivariant Quantum CNN

- Construct **equivariant** quantum CNN **under rotational & reflectional symmetry (p4m)**
- Improved generalization power



$\|00\rangle$	$\|01\rangle$	$\|02\rangle$	$\|03\rangle$
$\|10\rangle$	$\|11\rangle$	$\|12\rangle$	$\|13\rangle$
$\|20\rangle$	$\|21\rangle$	$\|22\rangle$	$\|23\rangle$
$\|30\rangle$	$\|31\rangle$	$\|32\rangle$	$\|33\rangle$

$V_{\updownarrow}$

$\|30\rangle$	$\|31\rangle$	$\|32\rangle$	$\|33\rangle$
$\|20\rangle$	$\|21\rangle$	$\|22\rangle$	$\|23\rangle$
$\|10\rangle$	$\|11\rangle$	$\|12\rangle$	$\|13\rangle$
$\|00\rangle$	$\|01\rangle$	$\|02\rangle$	$\|03\rangle$

$V_{\leftrightarrow}$

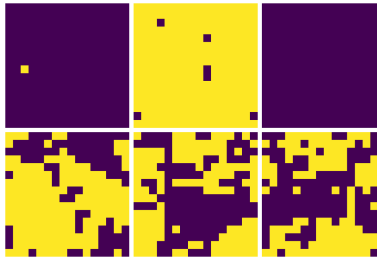
$\|03\rangle$	$\|02\rangle$	$\|01\rangle$	$\|00\rangle$
$\|13\rangle$	$\|12\rangle$	$\|11\rangle$	$\|10\rangle$
$\|23\rangle$	$\|22\rangle$	$\|21\rangle$	$\|20\rangle$
$\|33\rangle$	$\|32\rangle$	$\|31\rangle$	$\|30\rangle$

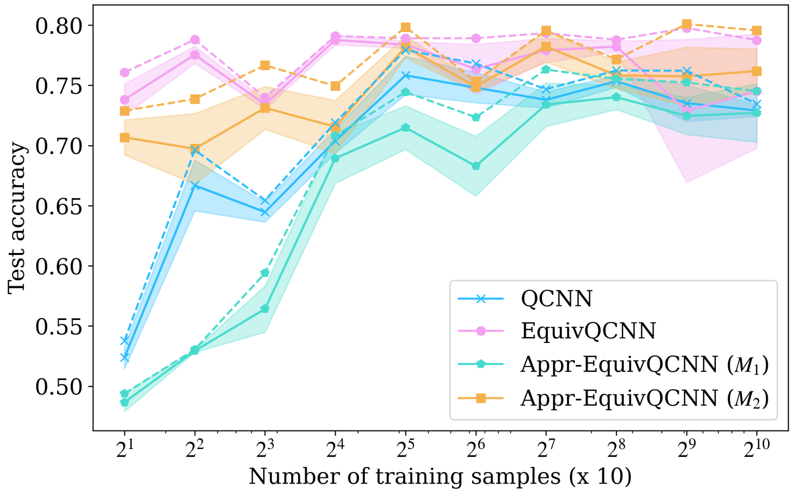
V_{90°

$\|33\rangle$	$\|23\rangle$	$\|13\rangle$	$\|03\rangle$
$\|32\rangle$	$\|22\rangle$	$\|12\rangle$	$\|02\rangle$
$\|31\rangle$	$\|21\rangle$	$\|11\rangle$	$\|01\rangle$
$\|30\rangle$	$\|20\rangle$	$\|10\rangle$	$\|00\rangle$

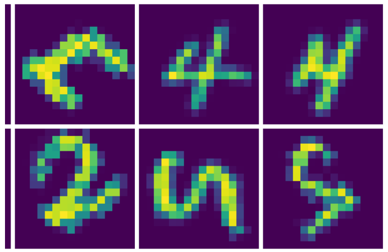
$$\mathcal{H} = -J \sum_{\langle ij \rangle} \sigma_i \sigma_j$$

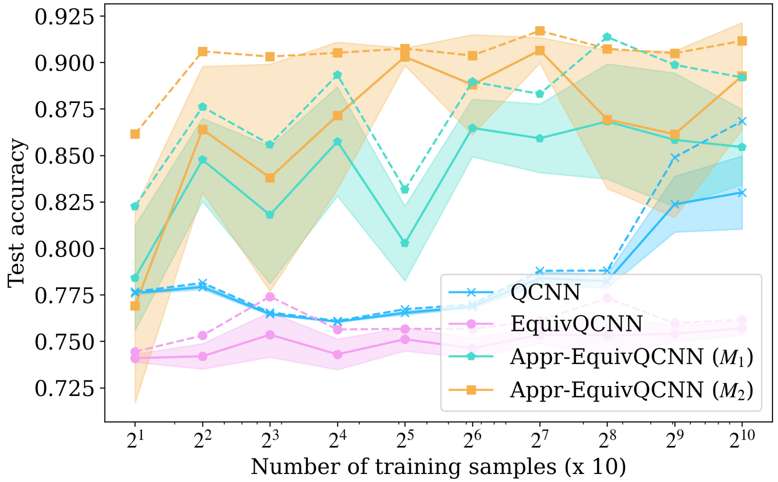
Ising spins phase classification :





Extended MNIST
Image classification:
(digits 4,5)





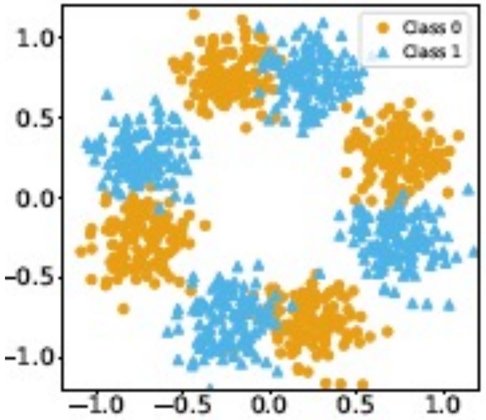
Tüysüz, Cenk, et al. "Symmetry breaking in geometric quantum machine learning in the presence of noise." *arXiv preprint arXiv:2401.10293* (2024).

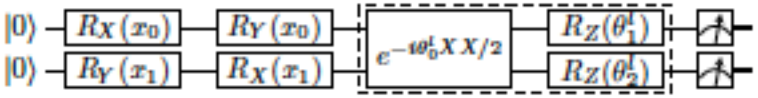
Noise induced symmetry breaking

Noise effects on **EQNN** wrt discrete symmetry groups e.g.

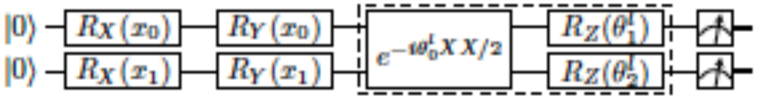
$\mathbb{Z}_2$: $R(\sigma)\cdot(x_i) = -x_i$

Bit Flip, Depolarizing (Pauli) and **Amplitude Damping channels**





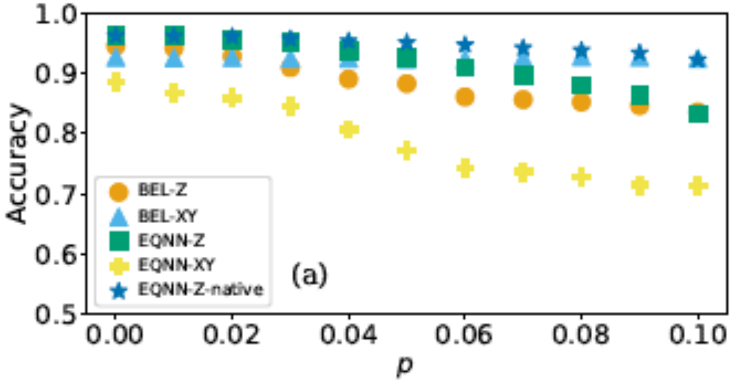
(a) EQNN-Z



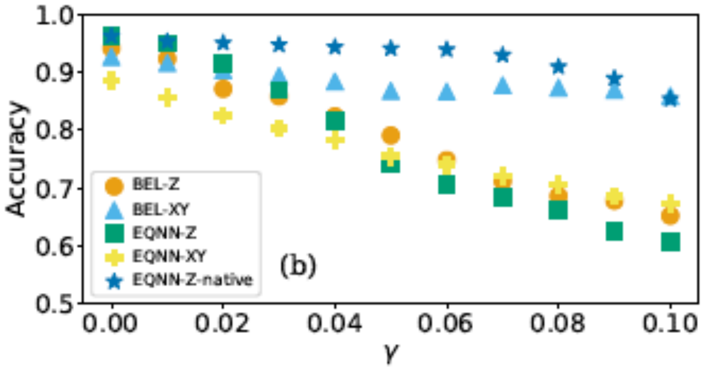
(b) EQNN-XY

(d) BEL

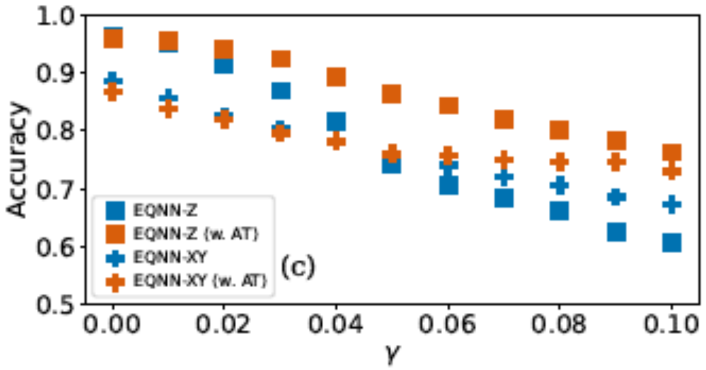
DP should not affect symmetry



EQNN performance drops with AD



Adaptive threshold classification

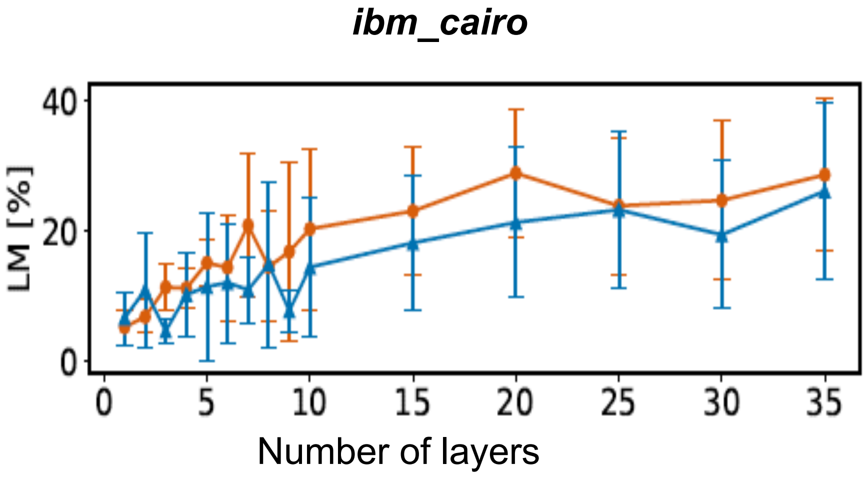


EQNN-Z native: Z_0Z_1 commutes with the AD channel generator, but native gate set is limited on hardware!

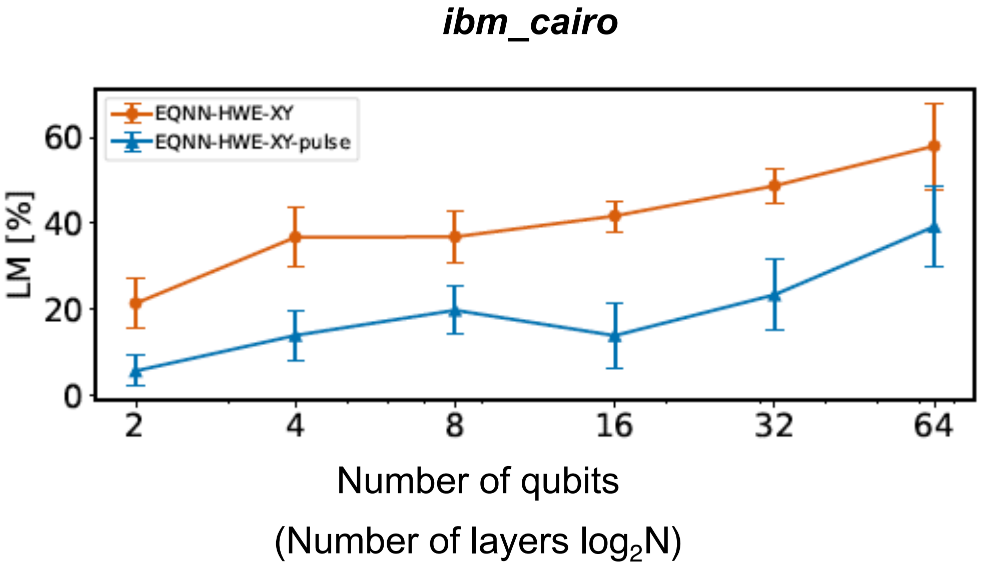
Symmetry breaking on hardware

$$LM = \frac{1}{M} \sum_{i=1}^{M} \frac{(\tau(\hat{y}_i) - \tau(\hat{y}_j))^2}{\tau(\hat{y}_i) + \tau(\hat{y}_j)}$$

Label Misassignment uses adaptive thresholds

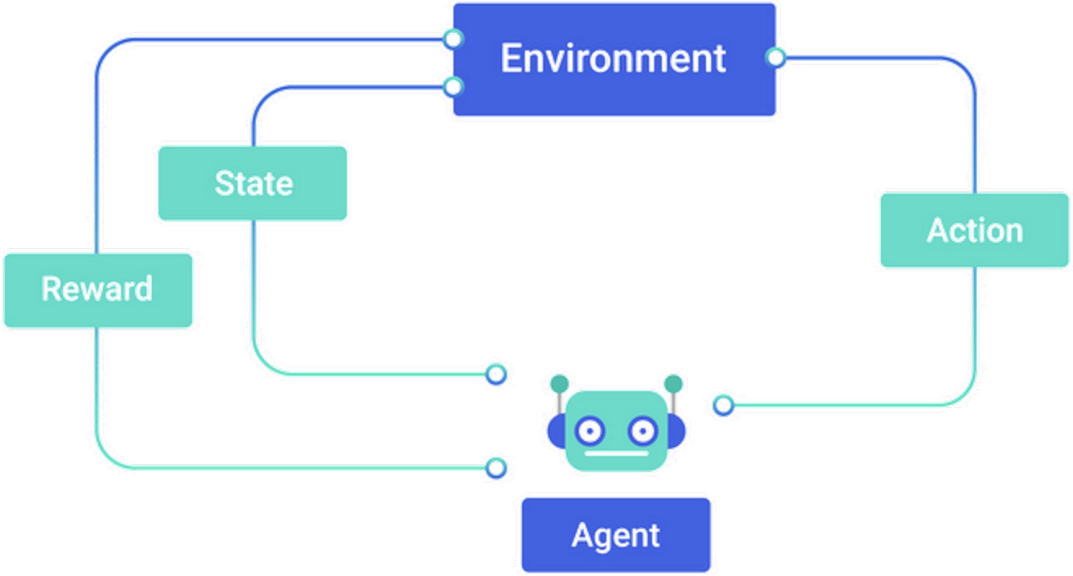


- Tests on *ibm_cairo*
  - Confirms AD channel is dominant
  - **Symmetry breaking is linear in the number of layers**
- Tests on *ibm_cusco* using **hardware efficient ansatz** and **pulse efficient gate** implementation
  - create $R_{ZX}(\theta)$ gates by controlling pulses in a continuous way
- **LM reaches 50% (random) at around 50 qubits**



Michael Schenk et al., **Hybrid actor-critic algorithm for quantum reinforcement learning at CERN beam lines.** arXiv:2209.11044

Quantum Reinforcement Learning



Agent interacts with environment

- Follow **policy**
- Find policy that **maximizes**

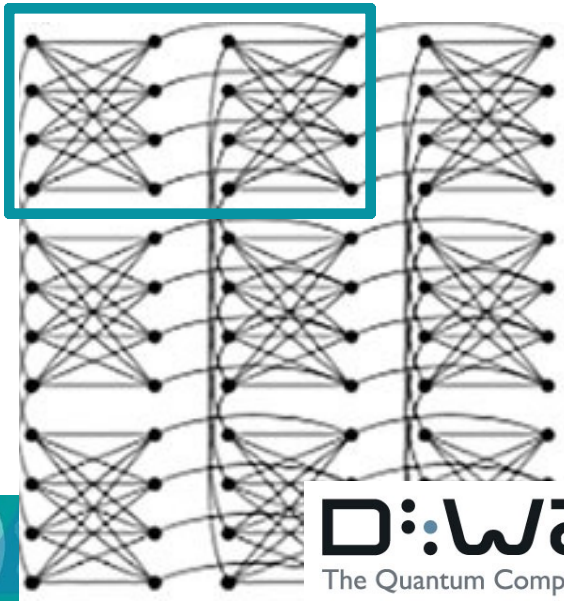
Expected reward is estimated by ***value function*** $\boldsymbol{Q}(\boldsymbol{s}, \boldsymbol{a})$

- **DQN:** Deep Q-learning *(NN-based)*
- **FERL:** Free energy-based RL *(clamped Quantum Boltzmann Machine)*

Implement the **quantum NN on a set of qubits**

Quantum computer calculates the **reward as the energy** of the qubit system

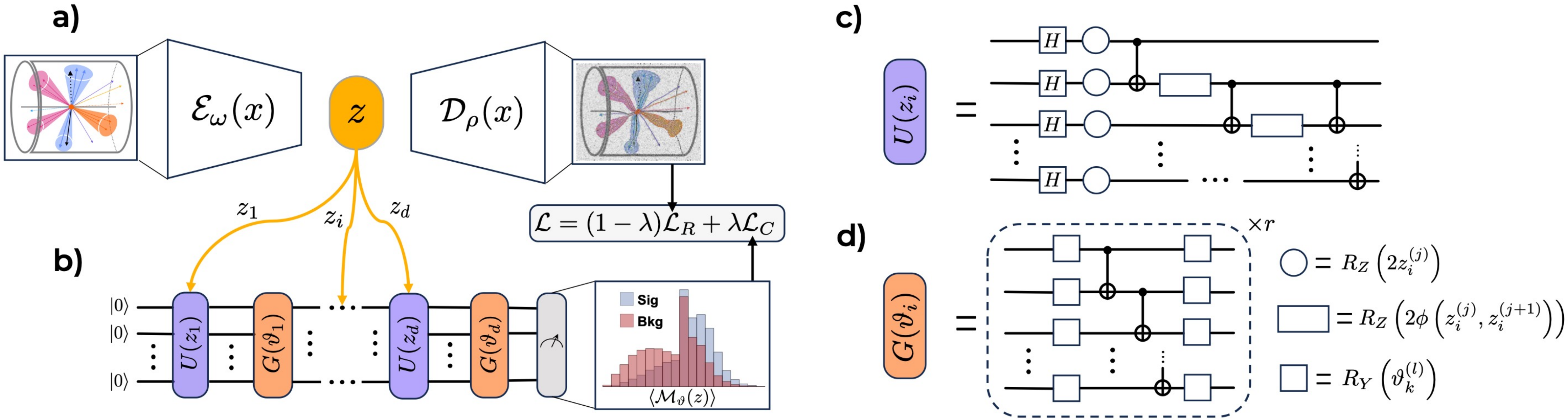
In this framework the **agent is classical**



D:wave The Quantum Computing Company™

V. Belis *et al.*, arxiv: 2402.0952

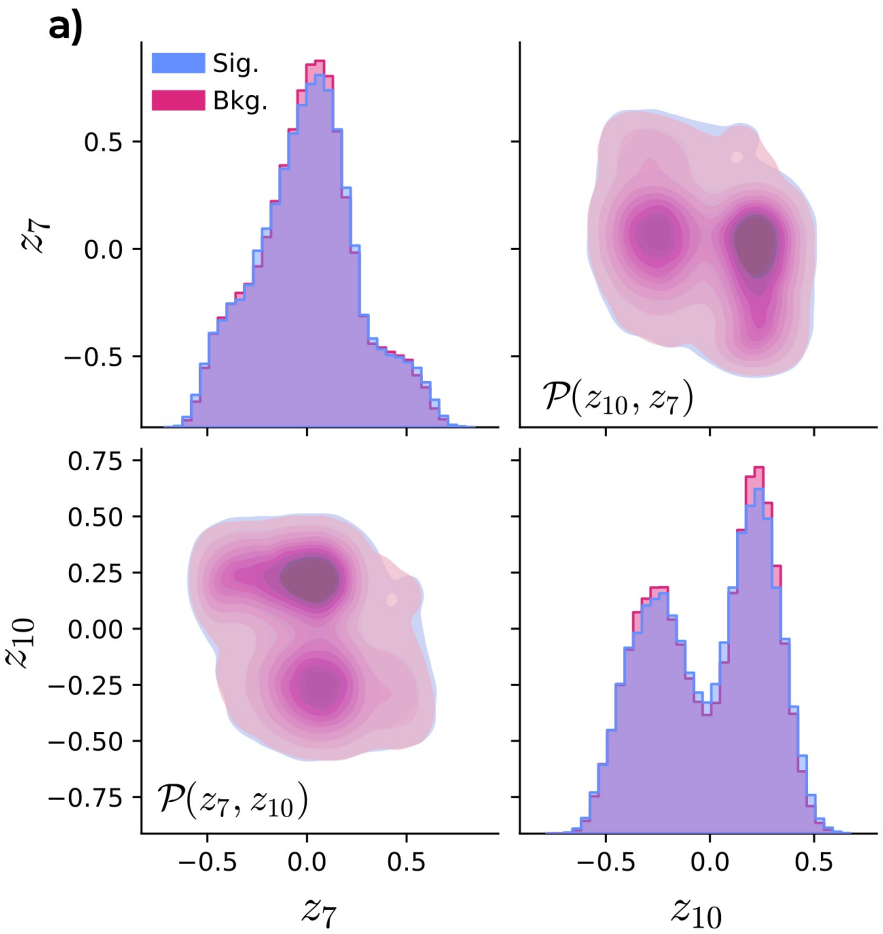
Guided Quantum Compression



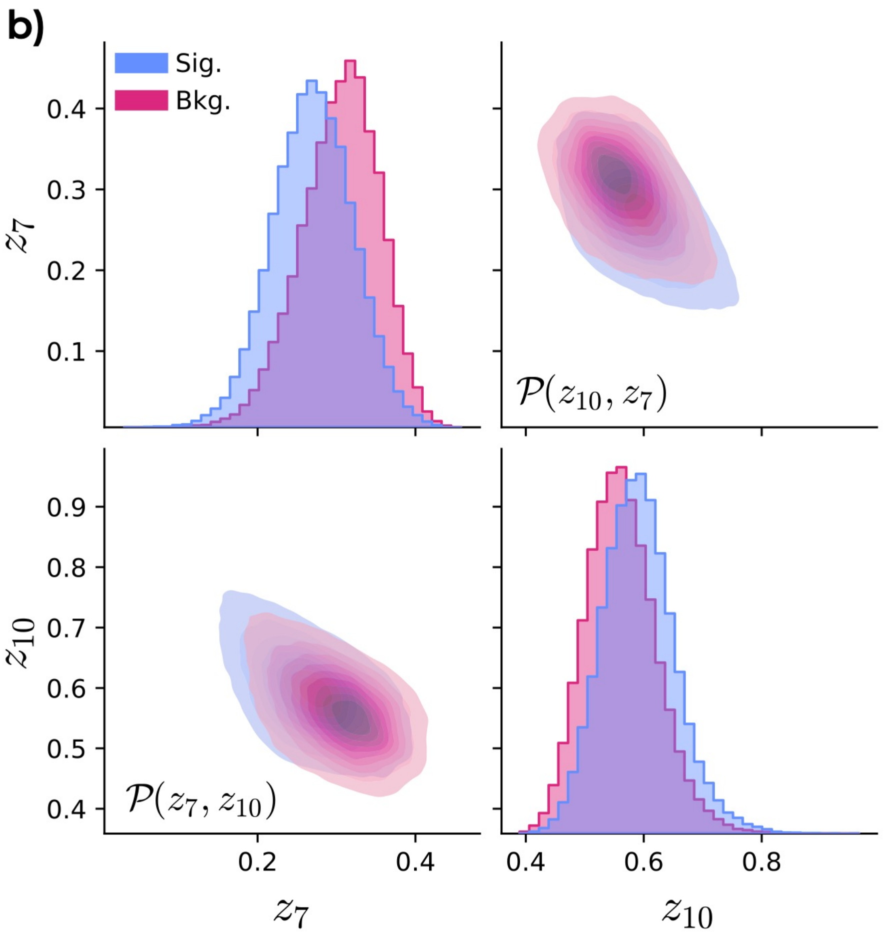
Two hybrid quantum-classical strategies:
GQC: Joint training
2Steps: The data compression step is independently trained

Latent Space Representation

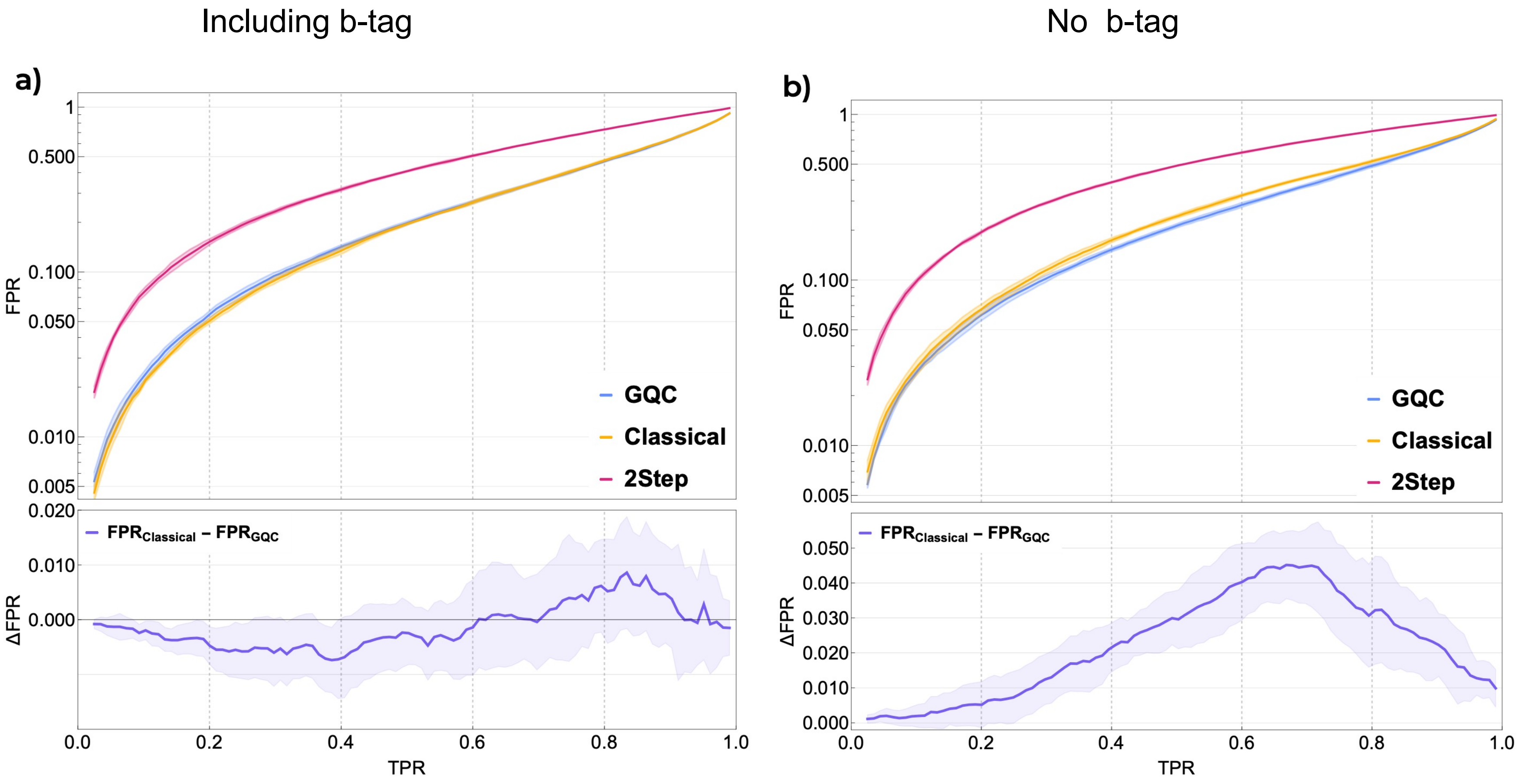
2 Steps



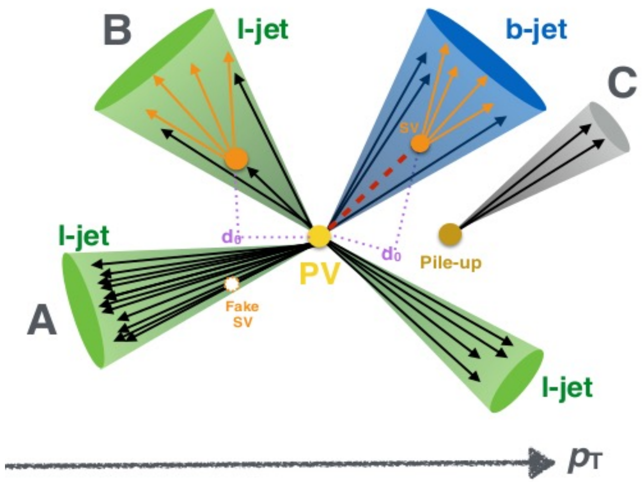
GQC



Results


Including b-tag

No b-tag



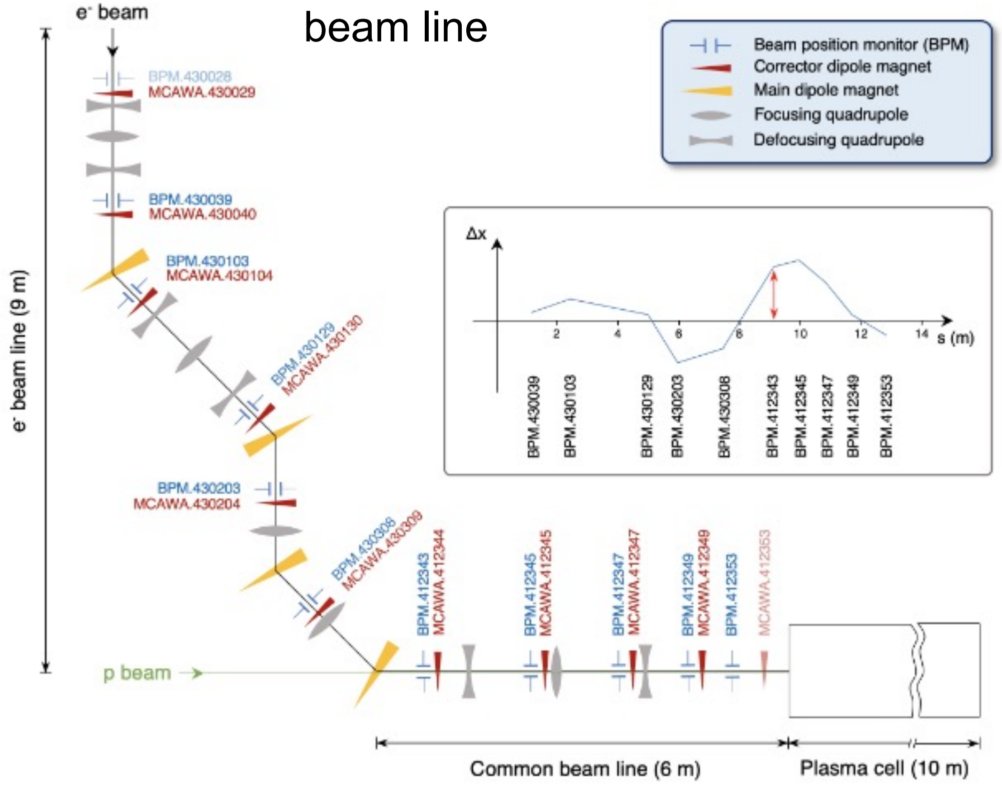
b-tag features are high level features containing information about the quark content

compression method has significant impact on the classifier performance.

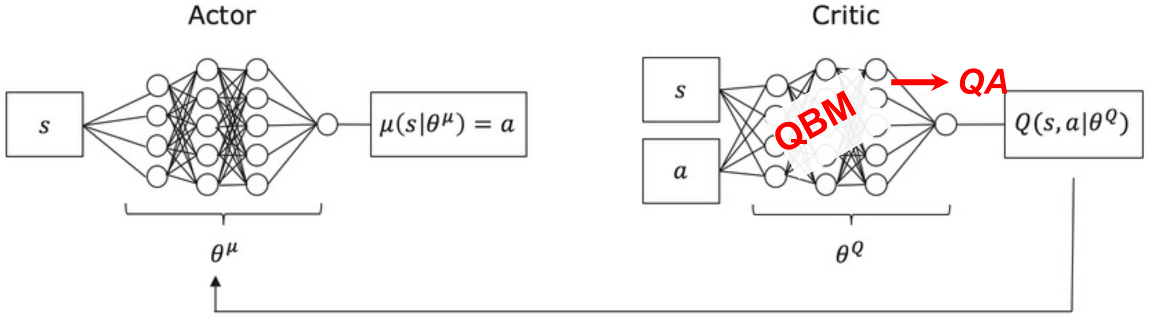
CHALLENGE: DATA COMPRESSION

CERN AWAKE facility

2GeV electron beam line



Michael Schenk et al., **Hybrid actor-critic algorithm for quantum reinforcement learning at CERN beam lines**, e-Print: 2209.11044 [quant-ph]



Policy Gradient: $\nabla_{\theta^\mu}\mu = \mathbb{E}_\mu[\nabla_{\theta^\mu} Q(s,\mu(s|\theta^\mu)|\theta^Q)] = \mathbb{E}_\mu[\nabla_a Q(s,a|\theta^Q)\cdot\nabla_{\theta^\mu}\mu(s|\theta^\mu)]$

Actor-Critic Q-learning training D-Wave Advantage

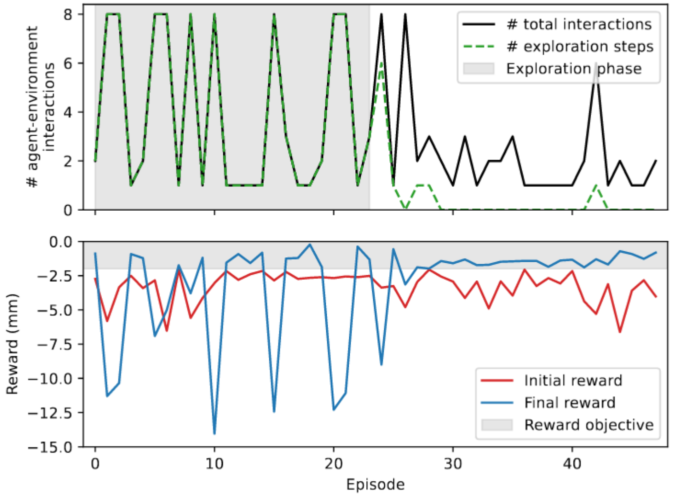
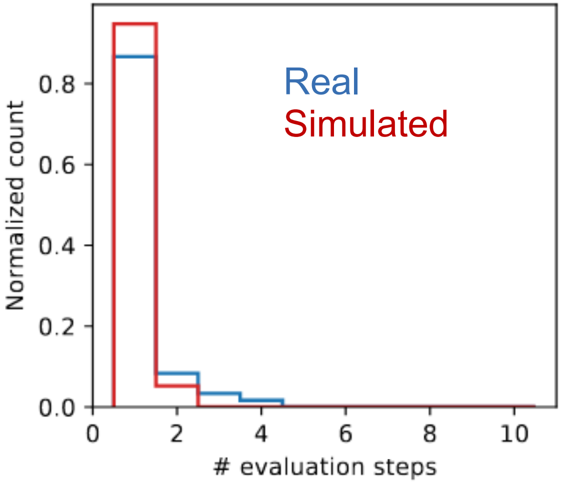


Figure 11: Single RL agent training evolution on D-Wave Advantage Systems using the simulated AWAKE environment with a reward objective of -2 mm.

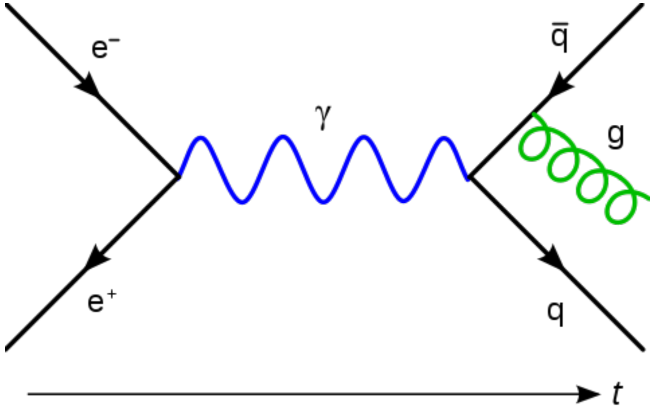
Successful evaluation on the real beam-line

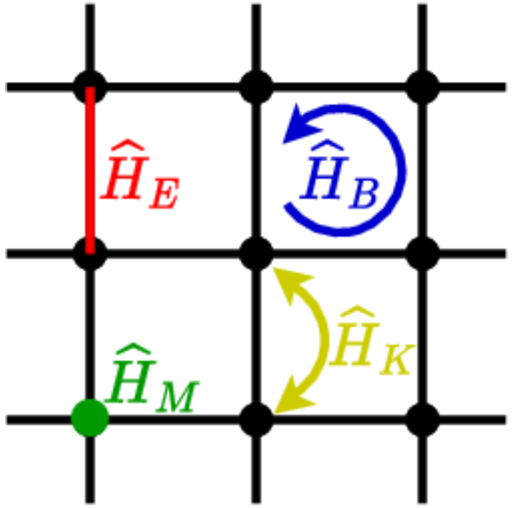


Example 1: Simulation of Real-Time Phenomena

Challenge

Theoretical predictions of scattering processes have limitations which make them applicable in regimes accessible via perturbation theory mainly capturing equilibrium properties (e.g. Monte Carlo methods). The “sign problem” and the complexity of numerical integration make real-time simulations challenging.





Chen, Zhuo et al. *ArXiv* abs/2212.06835 (2022)

Goals

Use the Hamiltonian formalism by discretising the space dimensions in square/cubic lattices and keeping time as a continuous variable.

Ex: Kogut-Susskind formulation of (2+1)D QED

$$H_{tot} = H_E + H_B + H_m + H_{kin}$$

Quantum methods

The Hamiltonian can be encoded on a quantum computer using various ansatz, the ground-state energy can be found using methods like VQE, SSVQE, or VQD

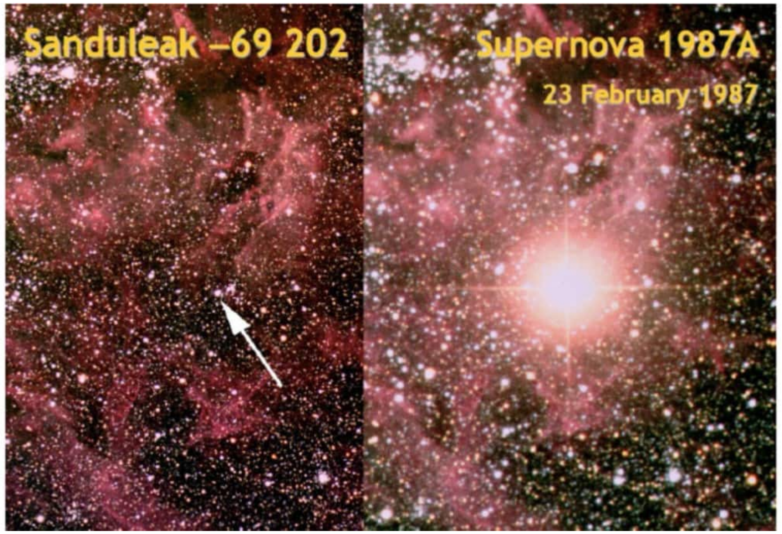
Analog quantum devices can also be used to approximate the time evolution of the target H.

Tensor Networks are interesting at equilibrium and out-of-equilibrium (for low entanglement production)

Example 2: Collective Neutrino Oscillations

Challenge

Neutrinos play a central role in extreme astrophysical events (supernovae or neutron star). Neutrino clouds are a strongly coupled many-body system, direct solution of the flavor evolution equations can be exponentially hard with classical simulations.



(Image: IIT Guwahati)

Goals

Study the flavor evolution of a homogeneous gas of neutrinos both at fixed density and at different local conditions (e.g. within the emitting neutron stars and as they travel in space) using a Hamiltonian formulation

$$H = \sum_{i=1}^{N} \boldsymbol{b_i} \cdot \boldsymbol{\sigma_i} + \lambda_e \sum_{i=1}^{N} \sigma_i^z + \frac{\mu}{2N} \sum_{i<j}^{N} \left(1 - \cos\theta_{1j}\right) \boldsymbol{\sigma_i} \cdot \boldsymbol{\sigma_j}$$

Quantum methods

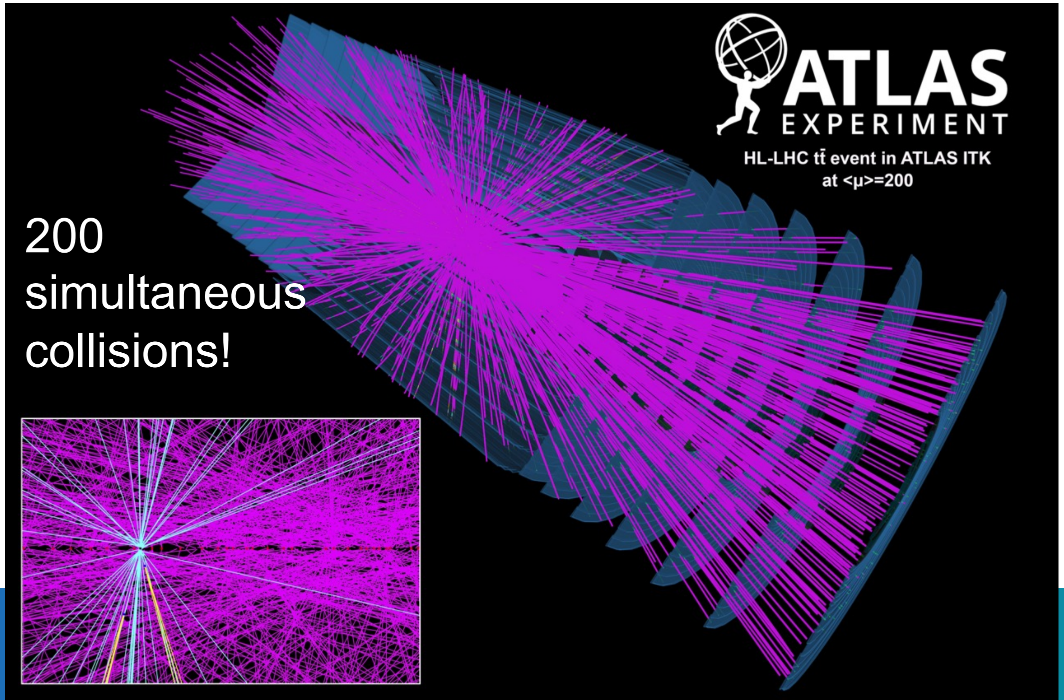
The Hamiltonian can be encoded on a quantum computer using 1 qubit per neutrino, which so far restricts the simulation to small N numbers.

Evolution of the method involves scaling to higher N → more qubits, and more sophisticated initial conditions than simple wave-functions of non-correlated neutrinos.

Example 3: Particle Jets and Trajectory reconstruction

Challenge

Reconstruction of high-level physics features (ex. trajectories) from detector output is a complex task due to the high granularity geometry of detectors.
At next generation hadronic collider detectors, the dimensionality of the problem will increase by orders of magnitude.



HL-LHC $t\bar{t}$ event in ATLAS ITK
at $<\mu>=200$

200 simultaneous collisions!

Goals

Reduce time to solution. Pattern recognition tasks are formulated as multi-step processes. The goal is achieved by accelerating individual steps or designing new end-to-end approaches beyond today's estimation algorithms.

Quantum methods

The problem can be formulated as **QML,** as a **energy minimisation problem** (using both quantum annealers and digial computers) or as **a search problem (using quantum associative memories)** (ex. Quantum Associative Memory (annealer based **or** digital)

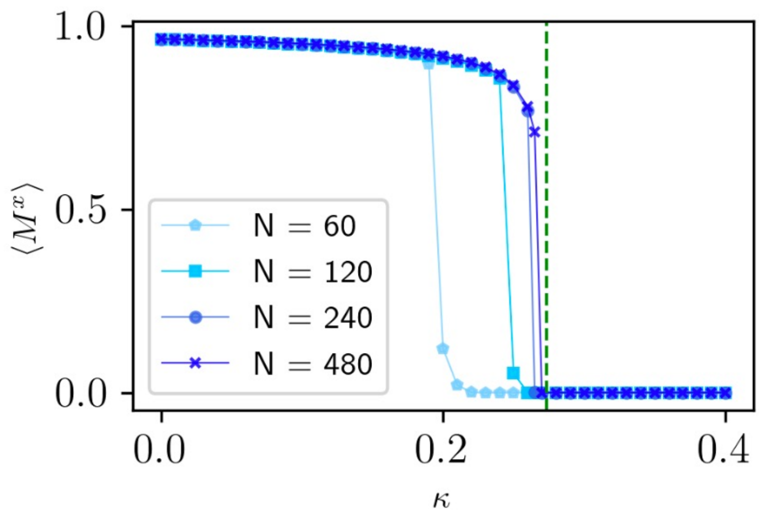
The ANNNI Phase Diagram

$$H_{ANNNI} = -J_1 \sum_{i=1}^{N-1} \sigma_i^x \sigma_{i+1}^x - J_2 \sum_{i=1}^{N-2} \sigma_i^x \sigma_{i+2}^x - B \sum_{i=1}^{N} \sigma_i^z,$$

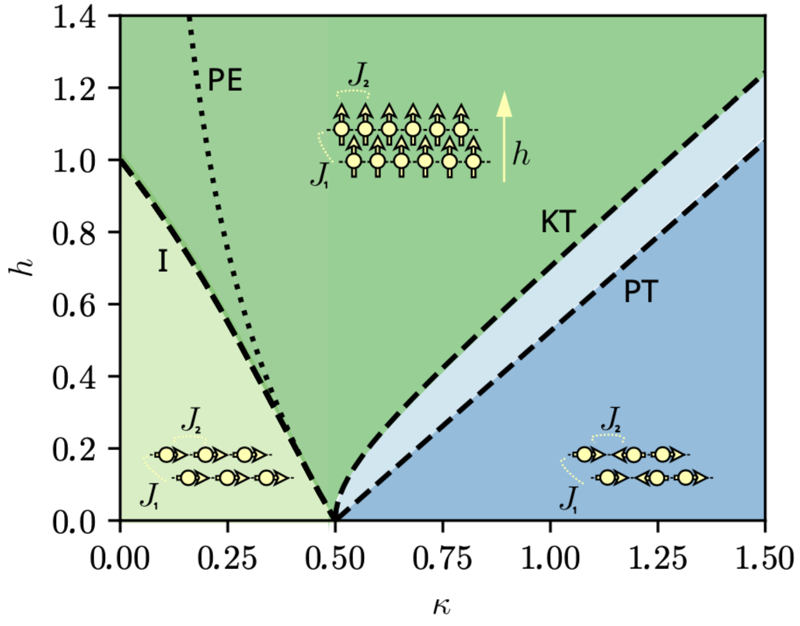
Use MPS representation of ANNNI model

- DMRG to analyse phase diagram of finite size systems (up to 480 sites)
- Detailed properties study

Generate wave function (up to 20 spins) as input to the QML analysis



$\kappa = -J_2/J_1$ and $h = B/J_1$



Study correlation range by fixing the transverse field and varying the frustration parameter: