The CERN Quantum Technology Initiative

Sofia Vallecorsa

CERN QTI Coordinator

QUANTUM
TECHNOLOGY
INITIATIVE

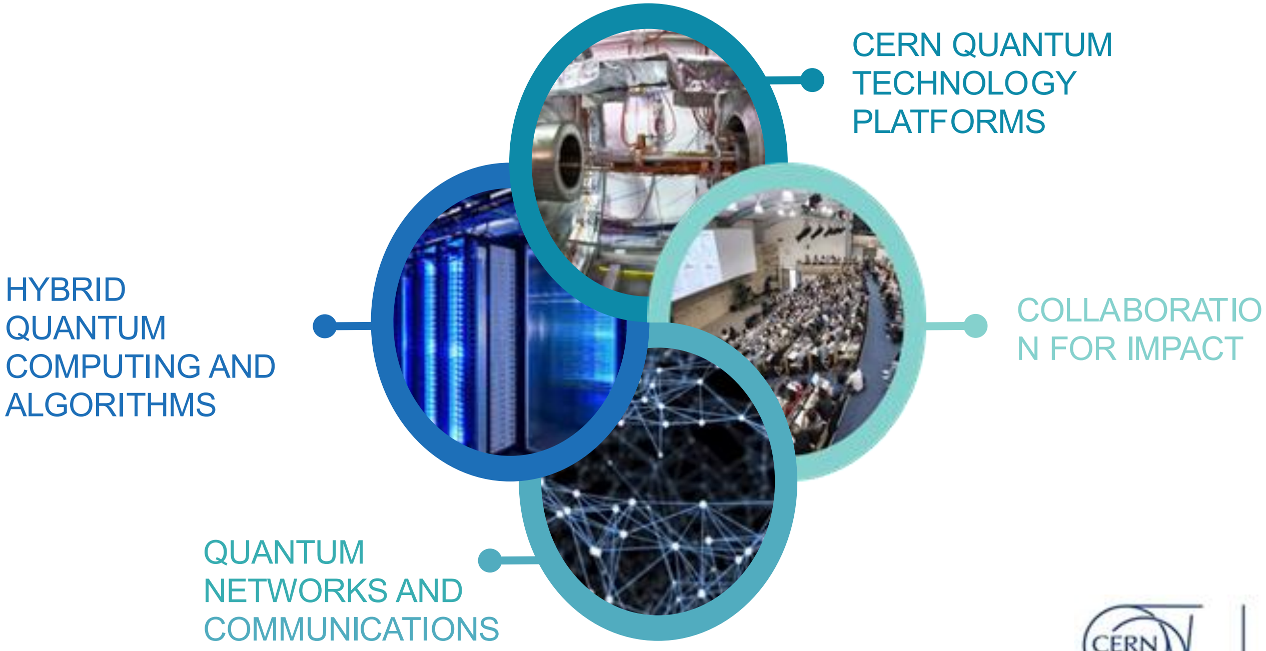
July 16th 2026

A Quantum Technology Initiative at CERN

- **A large number of quantum initiatives** in the Member States and beyond
- **QTI was approved in 2020**
- **Not competing** with existing initiatives but complementing them

A research plan organized **around four main areas**

A core team at CERN interacting with external partners



QUANTUM TECHNOLOGY INITIATIVE

An initiative grounded on existing expertise

Quantum «areas»

- Quantum Sensing ⟷ **Accelerators** Technologies and **Future Detectors** R&D
- Quantum Simulation ⟷ Theory, **Physics Beyond Colliders**
- Quantum Computing ⟷ **Scientific Computing**: Algorithms, Distributed Computing
- Quantum Communication ⟷ **Scientific Computing**: Algorithms, Distributed Computing

CERN Program

Accelerators Technologies and **Future Detectors** R&D

Theory, **Physics Beyond Colliders**

Scientific Computing: Algorithms, Distributed Computing

Two main questions

1. How can quantum technologies **contribute to CERN's scientific mission**?

2. How can CERN's technologies and expertise **contribute to the quantum development**?

A phased approach

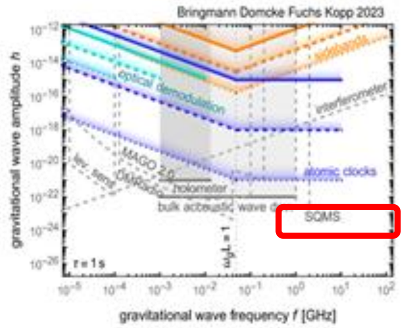
2020-2023
Exploration

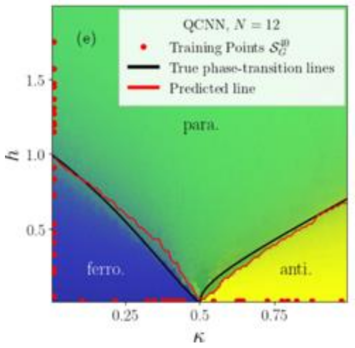
2024-2028
Consolidation

2028-…
Long term

A broad set of activities to build expertise

Bringmann, T,, et al. *Physical Review D* 108.6 (2023): L061303.



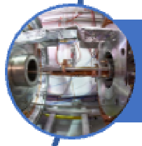


Monaco, S. et al.." *Physical Review B* 107.8 (2023): L081105.

Four main objectives drive our research today

Integrate quantum computers within HEP computing model

Make CERN a node of the future European network infrastructure



Drive the development of next generation detectors for fundamental physics

Join the broader quantum ecosystem to multiply impact

A sustainable research plan

- **Integrated**
- **Focused**
- **Impactful ..locally ☺**
- **Collaborative**
- **….**

The CERN QTI Hub collaboration framework

Integrate CERN in the ***broader quantum private/public ecosystem*** *to multiply impact*

Born 2025, managed by knowledge transfer group at CERN: more than 20 agreements already signed or in the pipeline (real projects, not MoU!)

Algorithmiq (Finland, Company)

Deutsche Telekom (Germany, Company)

Pasqal (France, Company)

Qunnect (Netherlands, Company)

Single Quantum (Netherlands, Company)

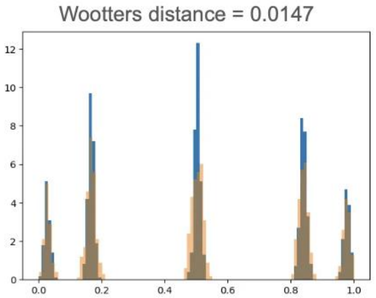
…

A prototype for collaborations at CERN!

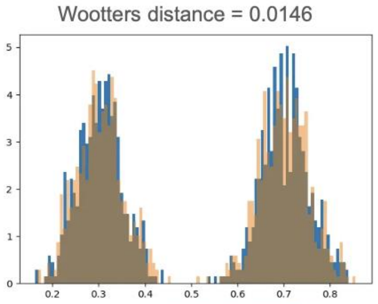
Quantum Reservoir for generative models

A. Azzam, EPS-HEP 2025

QILIMANJARO QUANTUM · TECH



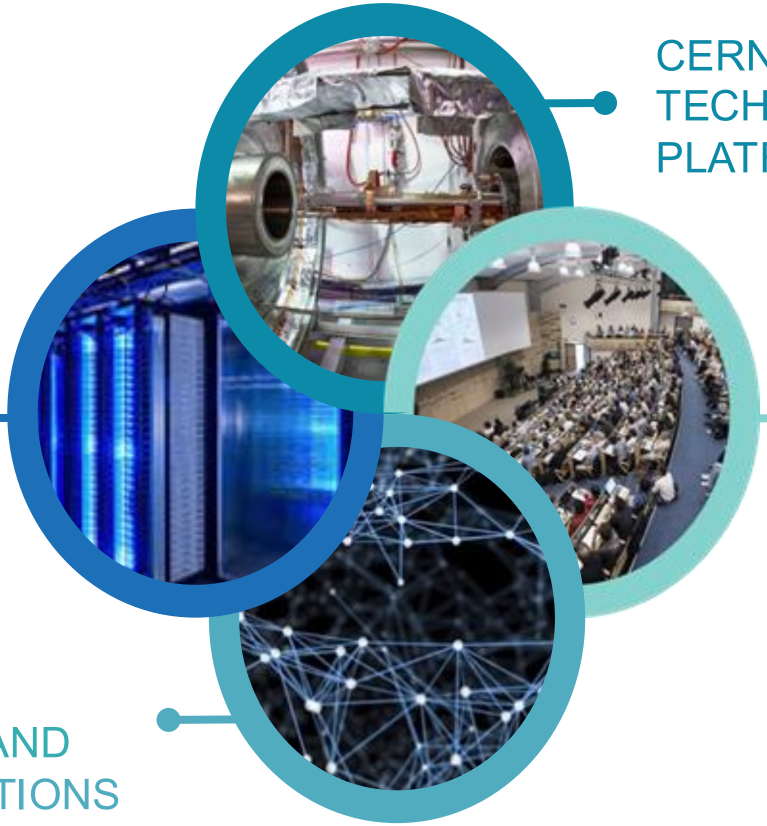
QUANTUM TECHNOLOGY INITIATIVE



IFAE Institut de Física d'Altes Energies EXCELENCIA SEVERO OCHOA

CERN QUANTUM TECHNOLOGY PLATFORMS

HYBRID QUANTUM COMPUTING AND ALGORITHMS

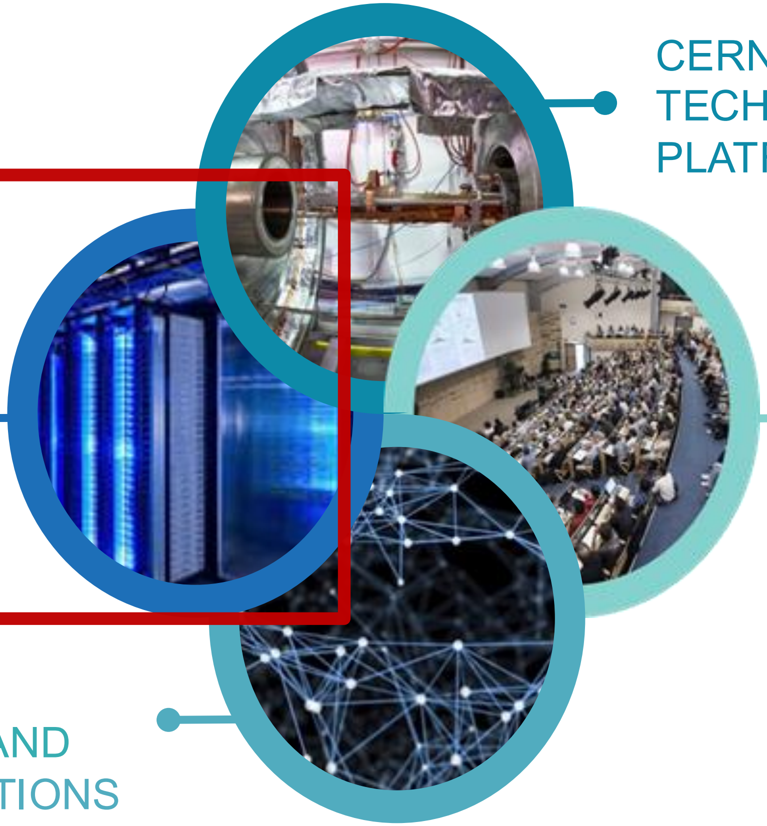


COLLABORATION FOR IMPACT

QUANTUM NETWORKS AND COMMUNICATIONS

CERN QUANTUM TECHNOLOGY PLATFORMS

HYBRID QUANTUM COMPUTING AND ALGORITHMS



COLLABORATION FOR IMPACT

QUANTUM NETWORKS AND COMMUNICATIONS

Hybrid Quantum Computing and Algorithms

Sustain ***integration of quantum computing within HEP computing model****: study near-term devices and scale to fault tolerant*

Theoretical characterization of quantum algorithms

Move beyond heuristic to formalize performance.

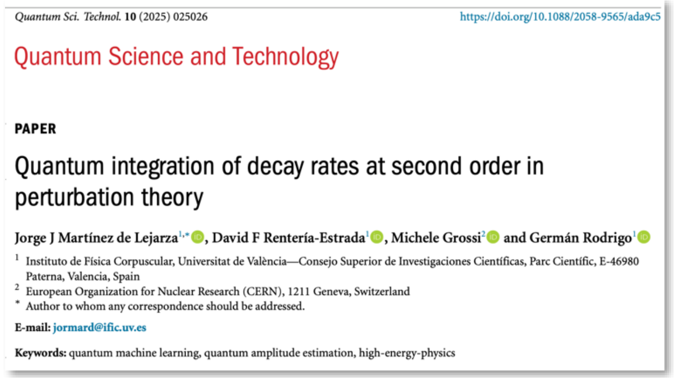
Demonstrators for HEP applications

Experimental data processing and theory

Operational feasibility of hybrid infrastructure (HPC/Cloud + QC, …)

Error correction, Kubernetes-based deployment of hybrid workloads, APIs and frameworks, ..

Pilot QC services access model for LHC experiments


Quantum Sci. Technol. **10** (2025) 025026 https://doi.org/10.1088/2058-9565/ada9c5

Quantum Science and Technology

PAPER

Quantum integration of decay rates at second order in perturbation theory

Jorge J Martínez de Lejarza[1,*], David F Rentería-Estrada[1], Michele Grossi[2] and Germán Rodrigo[1]

[1] Instituto de Física Corpuscular, Universitat de València—Consejo Superior de Investigaciones Científicas, Parc Científic, E-46980 Paterna, Valencia, Spain

[2] European Organization for Nuclear Research (CERN), 1211 Geneva, Switzerland

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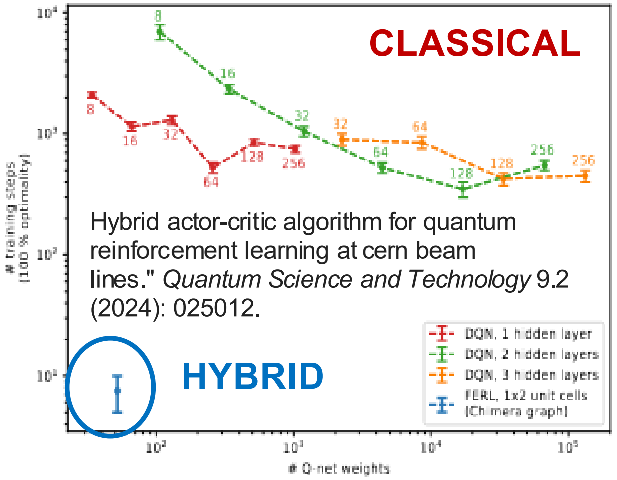
Keywords: quantum machine learning, quantum amplitude estimation, high-energy-physics



Hybrid actor-critic algorithm for quantum reinforcement learning at cern beam lines." *Quantum Science and Technology* 9.2 (2024): 025012.

Resource efficient agents for particle beam steering

Beyond heuristic results: formalization of QML

Recent examples on quantum generative models

Nov 2024

npj | quantum information — Article

Published in partnership with The University of New South Wales

https://doi.org/10.1038/s41534-024-00902-0

Trainability barriers and opportunities in quantum generative modeling

Check for updates

Manuel S. Rudolph[1,5], Sacha Lerch[1,5], Supanut Thanasilp[1,2,5], Oriel Kiss[3,4], Oxana Shaya[1], Sofia Vallecorsa[3], Michele Grossi[3] & Zoë Holmes[1]

Implicit losses for better trainability of quantum models.

Introduce quantum loss for improved data correlations modelling.

Resource bounds for universality and qubits/measurements trade-off.

Relaxed notions of universality toward quantum advantage and a practical use case.

Jul 2025

npj | quantum information — Article

Published in partnership with The University of New South Wales

https://doi.org/10.1038/s41534-025-01064-3

Parameterized quantum circuits as universal generative models for continuous multivariate distributions

Check for updates

Alice Barthe[1,2,3], Michele Grossi[1], Sofia Vallecorsa[1], Jordi Tura[2,3] & Vedran Dunjko[2,3]

Nov 2025

communications physics

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Article | Open access | Published: 29 October 2025

Expressive equivalence of classical and quantum restricted Boltzmann machines

Maria Demidik, Cenk Tüysüz, Nico Piatkowski, Michele Grossi & Karl Jansen

Communications Physics 8, Article number: 413 (2025) | Cite this article

Introduce **semi-quantum restricted Boltzmann Machines** to limit gradient computation resources

QUANTUM TECHNOLOGY INITIATIVE

Applications to HEP

Quantum kernel-based unsupervised learning for anomaly detection.

Detailed performance study up to 24 qubits implementation. Accuracy correlated to circuit entanglement.

Supervised approach study: *Machine Learning: Science and Technology*, *4*(4), 045031.

Feb 2025

Quantum Sci. Technol. **10** (2025) 025026 https://doi.org/10.1088/2058-9565/ada9c5

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Quantum integration of decay rates at second order in perturbation theory

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Keywords: quantum machine learning, quantum amplitude estimation, high-energy-physics

Higgs clssification at the LHC: classical-quantum paradigm to optimise dimensionality reduction for quantum classification.

Oct 2024

communications physics — **Article**

https://doi.org/10.1038/s42005-024-01811-6

Quantum anomaly detection in the latent space of proton collision events at the LHC

Check for updates

Vasilis Belis[1,7], Kinga Anna Woźniak[2,3,7], Ema Puljak[2,4,7], Panagiotis Barkoutsos[5], Günther Dissertori[1], Michele Grossi[2], Maurizio Pierini[2], Florentin Reiter[6], Ivano Tavernelli[5] & Sofia Vallecorsa[2]

NLO decay rates via QNN-based Fourier series decomposition. Results on simulator and hardware.

Earlier on Feynman diagrams: ***Loop Feynman integration on a quantum computer.*** *Physical Review D, 110(7), 074031 (20244)*

July 2024

MACHINE LEARNING
Science and Technology

PAPER • OPEN ACCESS

Guided quantum compression for high dimensional data classification

Vasilis Belis, Patrick Odagiu, Michele Grossi, Florentin Reiter, Günther Dissertori and Sofia Vallecorsa

Published 16 July 2024 • © 2024 The Author(s). Published by IOP Publishing Ltd

Machine Learning: Science and Technology, Volume 5, Number 3

Citation Vasilis Belis *et al* 2024 *Mach. Learn.: Sci. Technol.* **5** 035010

DOI 10.1088/2632-2153/ad5fdd

Quantum computers.. in practice

Computation of Fourier moments for nuclear effective field theory.

Advanced error suppression methods reduce noise strength by two orders of magnitude.

266 CNOT circuit on 5 qubit achieves high accuracy on IBM superconducting quantum devices

Feb 2025

OPEN ACCESS

Quantum error mitigation for Fourier moment computation

Oriel Kiss[1,2,3,*], Michele Grossi[1], and Alessandro Roggero[3,4]

Show more

Phys. Rev. D **111**, 034504 – **Published 10 February, 2025**

DOI: https://doi.org/10.1103/PhysRevD.111.034504

Oct 2025

Qiboml: towards the orchestration of quantum-classical machine learning

Matteo Robbiati,[1,2,*] Andrea Papaluca,[1,3,4,*] Andrea Pasquale,[1,3] Edoardo Pedicillo,[1,5] Renato M. S. Farias,[5] Alejandro Sopena,[5] Mattia Robbiano,[6] Ghaith Alramahi,[5,7] Simone Bordoni,[5,8] Alessandro Candido,[5] Niccolò Laurora,[1] Jogi Suda Neto,[2] Yuanzheng Paul Tan,[9] Michele Grossi,[2] and Stefano Carrazza[1,3,5]

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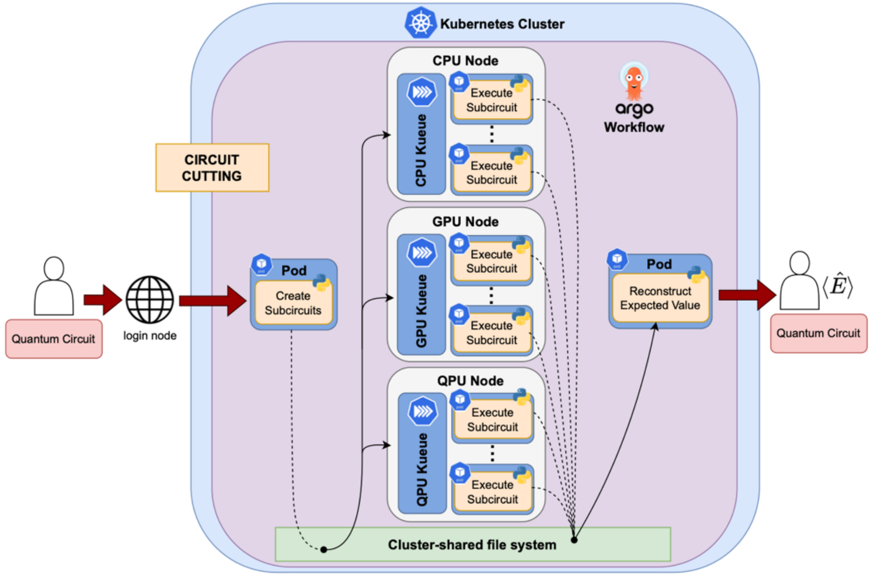
sion of Physics and Applied Physics, School of Physical and Mathematical Sciences, Nanyang Technological University, Sing

Open-source library for orchestrating hybrid machine learning workflows, fully integrated with e.g. PyTorch

A broad range of backends: multi-threaded CPUs, and multi-GPU systems for state vector or tensor network simulations; quantum processing units, on-premise and on cloud.

Kubernetes-orchestrated hybrid quantum classical workflows

Submitted to QCE2026



Some examples:

Quantum databases

Implementation protocol for variable sized **quantum databases**

Operational Framework for a Quantum Database

Carla Rieger[1,2], Michele Grossi[2], Gian Giacomo Guerreschi[3], Sofia Vallecorsa[2], and Martin Werner[1]

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[2]European Organization for Nuclear Research (CERN), Geneva 1211, Switzerland
[3]Intel Labs, Intel Corporation, 2200 Mission College Blvd, Santa Clara, CA 95054, United States of America

An Efficient Algorithm for Extending Uniform Superposition States for Time-Series Data

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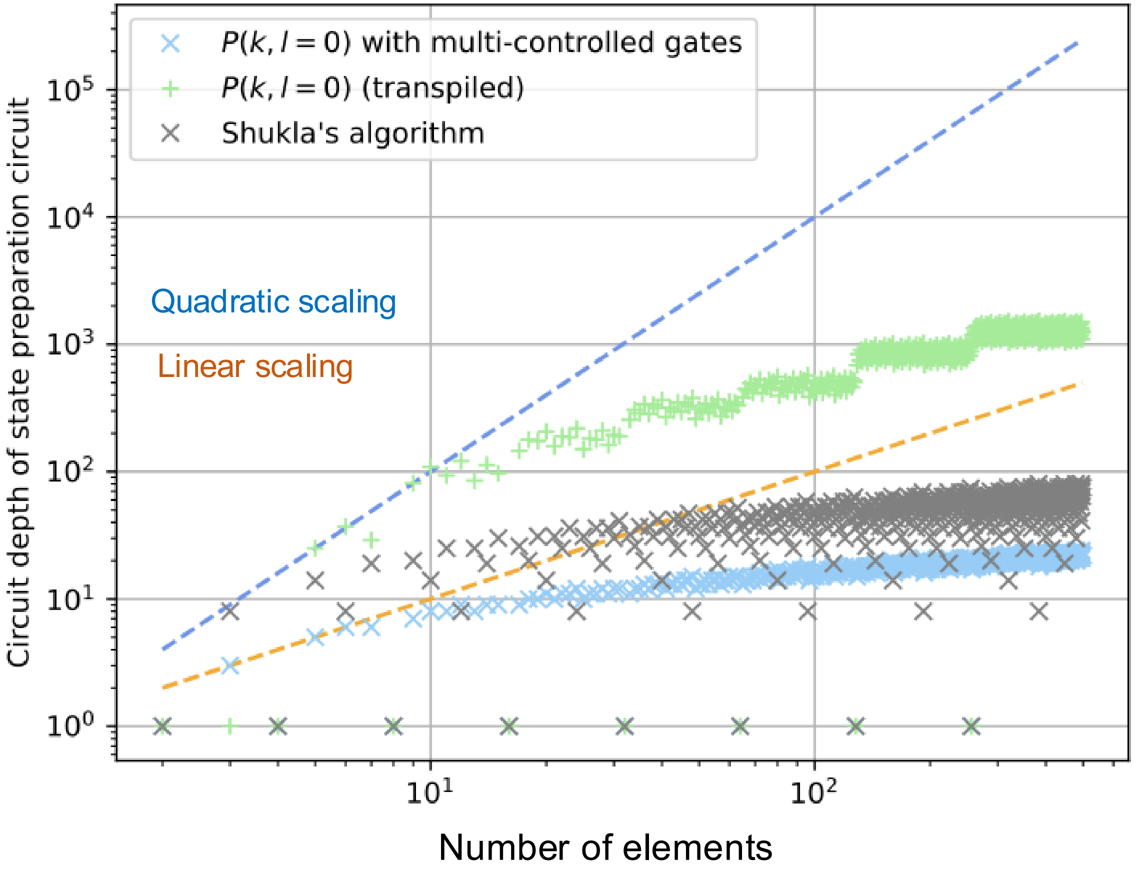
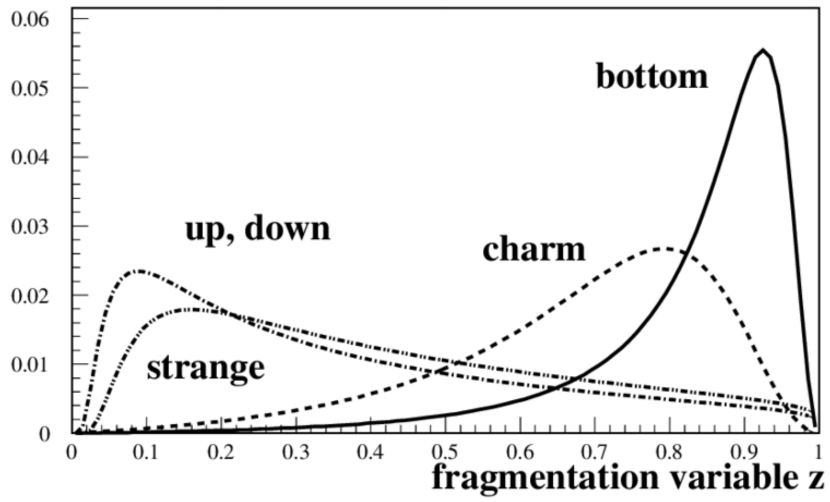
2025 IEEE International Conference on Quantum Computing and Engineering (QCE). Vol. 1. IEEE, 2025.



Fragmentation functions



From partons to hadrons:

- $D_i^h(z, Q) \propto Prob(parton(i) \rightarrow hadron(h))$

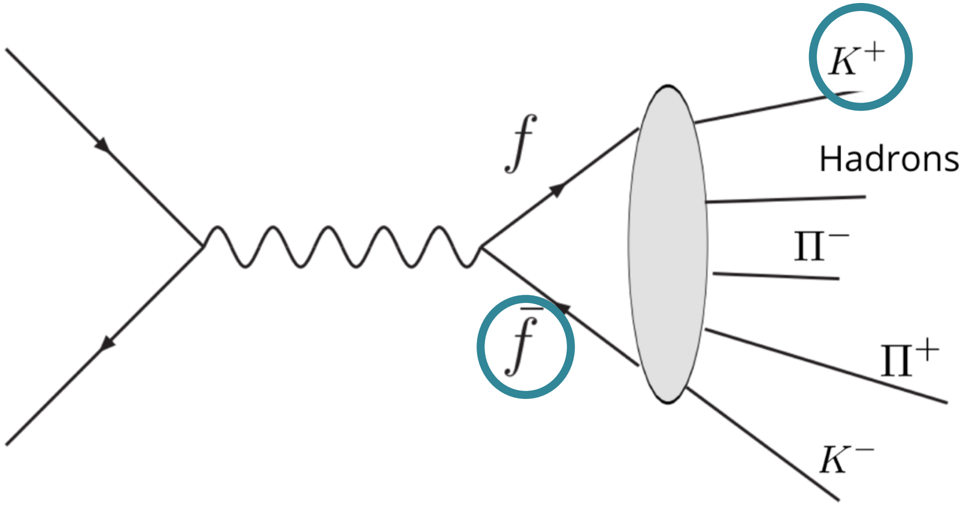
$z \equiv$ momentum fraction $\quad Q \equiv$ energy scale

Need FF to calculate e.g. cross sections (integral computation)

Primarily learned from data through statistical or ML methods

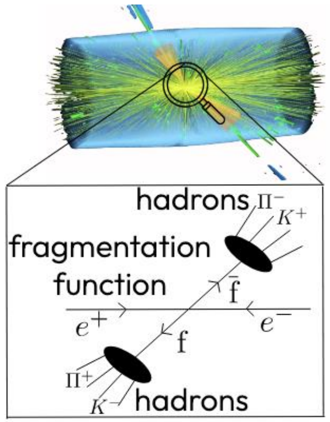
- $D_i^h(z, Q_0) \propto z^\alpha (1-z)^\beta$

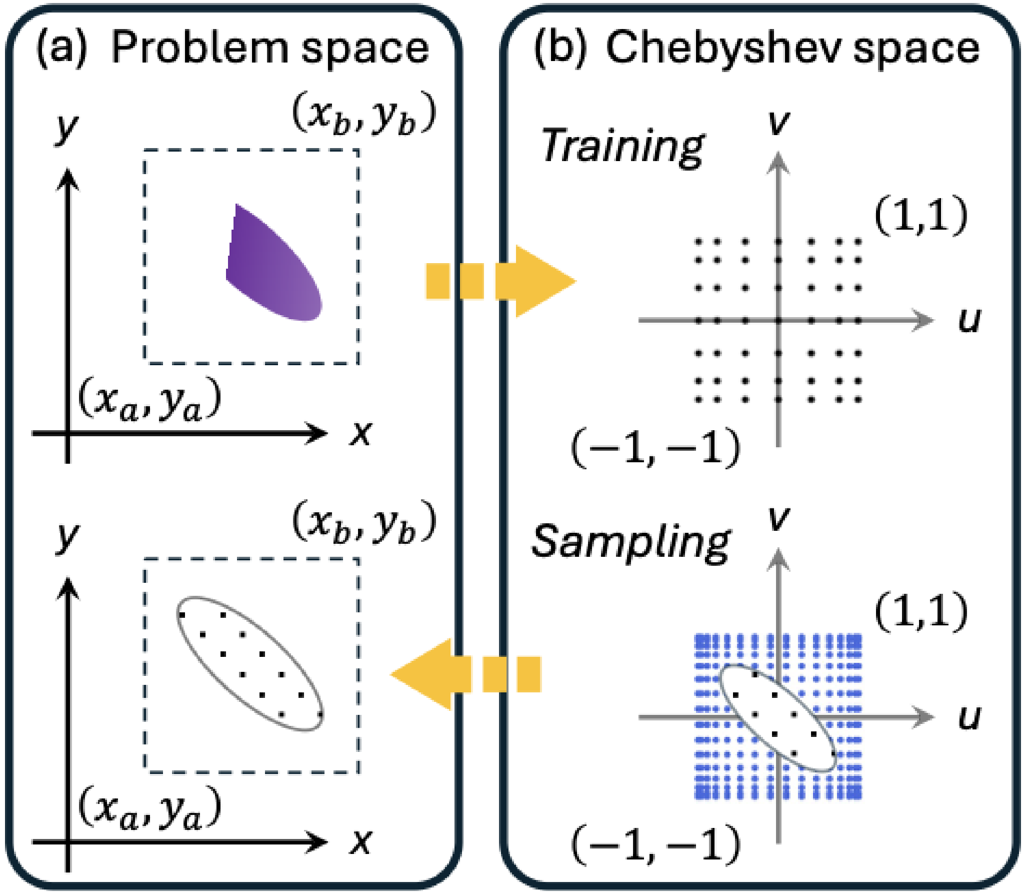
Interpolation for Q solving DGLAP evolution equations

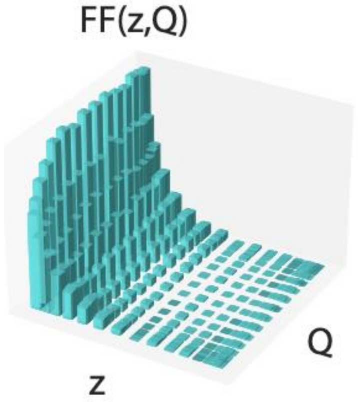


Data-driven workflow

Learn fragmentation functions from data using **quantum probabilistic models based on Chebyshev polynomials**.







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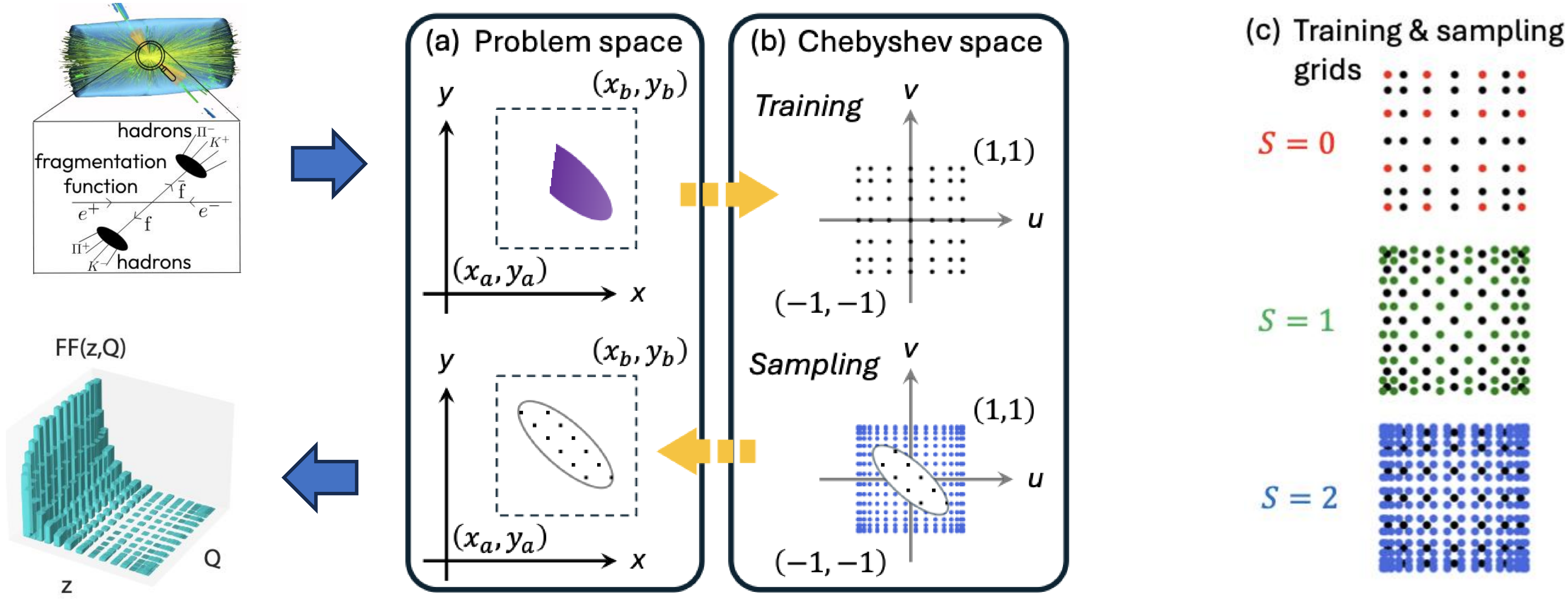


Generating Fragmentation Function

Quantum Chebyshev Probabilistic Models for Fragmentation Functions - arXiv:2503.16073

Analyze FF data:

$D^h_{u^+}, D^h_{d^++s^+}, D^h_{c^+}, D^h_{b^+}, D^h_g$

with $h = \pi^\pm, K^\pm$

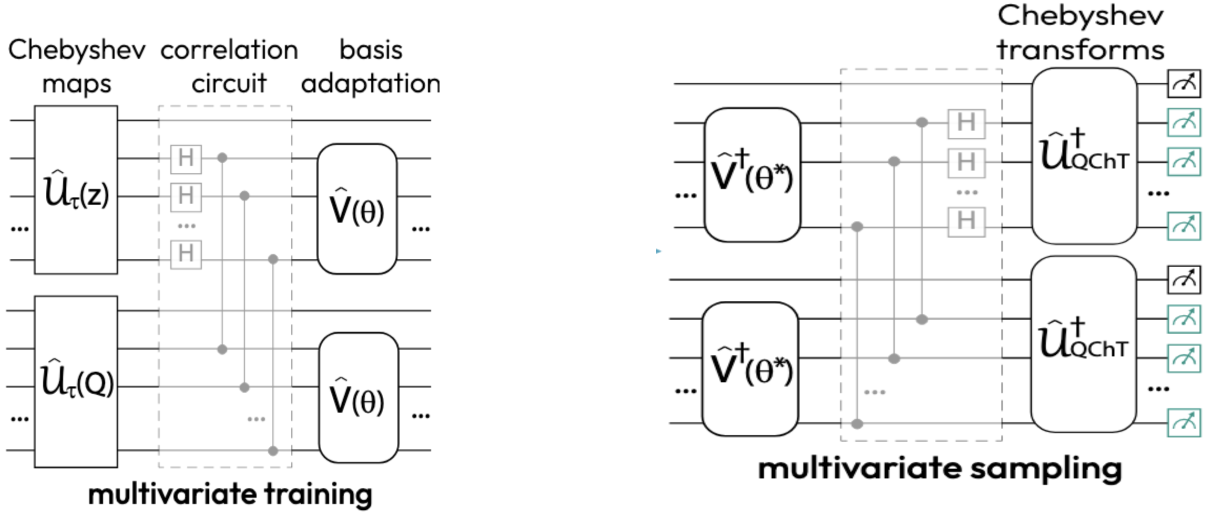
for $z \in [0.01, 1], Q \in [1, 10000]$

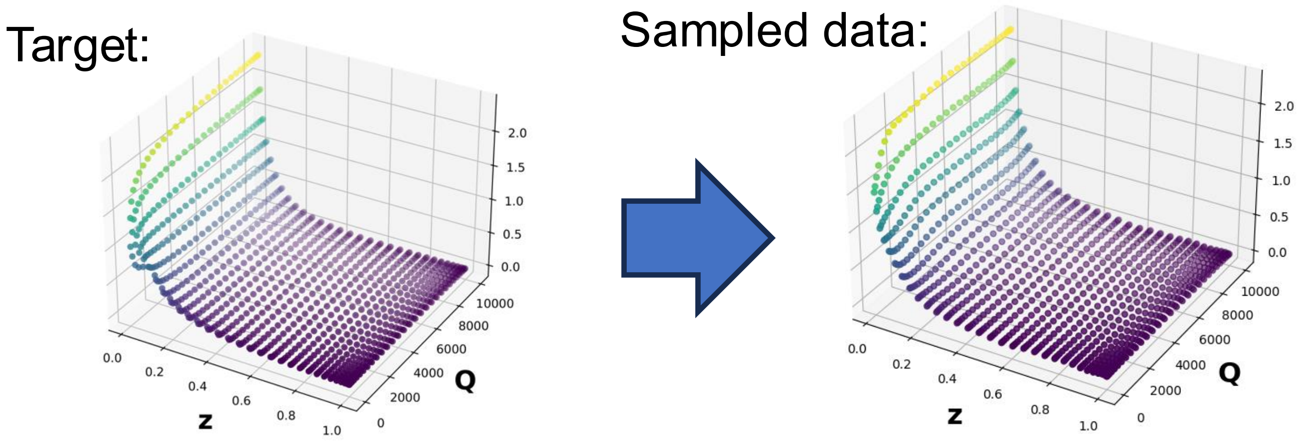
Setup quantum circuits using:

4 qubits, 3 ansatz layers →

16 parameters. (per variable)

Train for 10000 Iterations



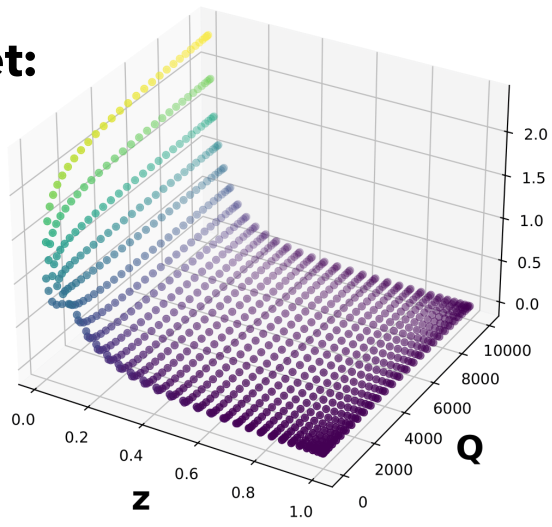


Data from http://lhapdf.hepforge.org/
(NNF10_PIsum_nnlo, NNF10_KAsum_nnlo)

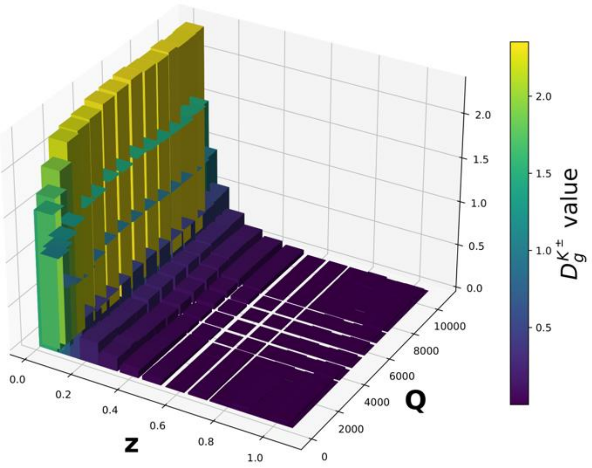
LHAPDF6: parton density access in the LHC precision era: Andy Buckley, James Ferrando, Stephen Lloyd, Karl Nordstrom, Ben Page, Martin Ruefenacht, Marek Schoenherr, Graeme Watt, *Eur.Phys.J.C* 75 (2015) 132

Interpolation and extended sampling

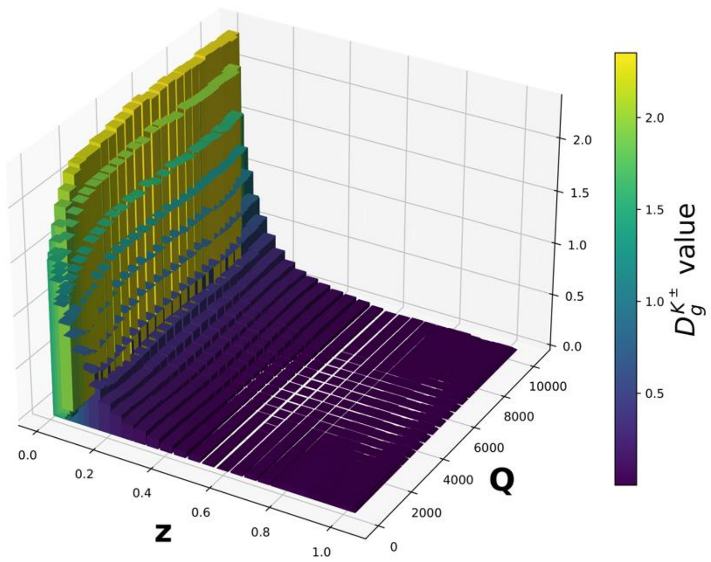
Target:



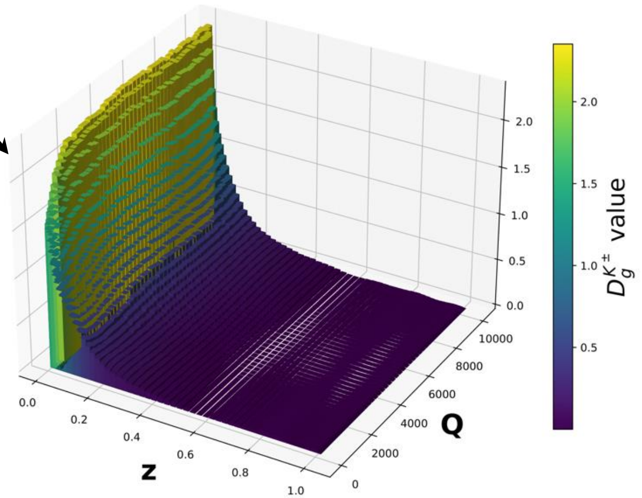
Sampling:



Extended sampling

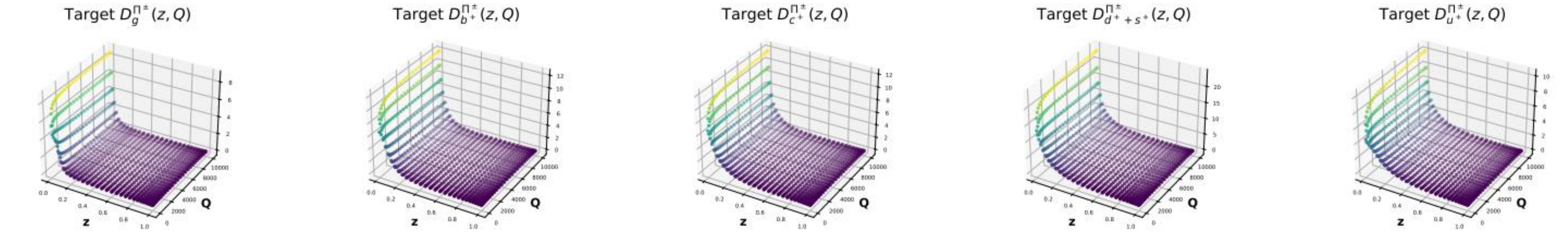


1 extra qubit per variable ($s = 1$)

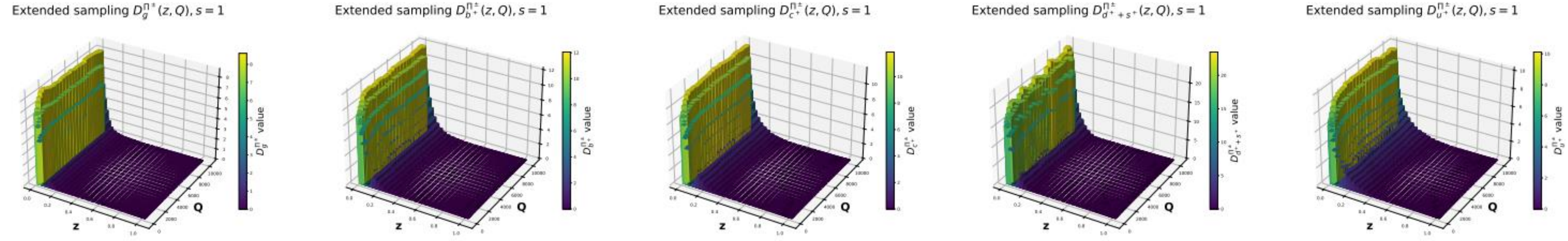


2 extra qubits per variable ($s = 2$)

$\pi^{\pm}$ Fragmentation Functions

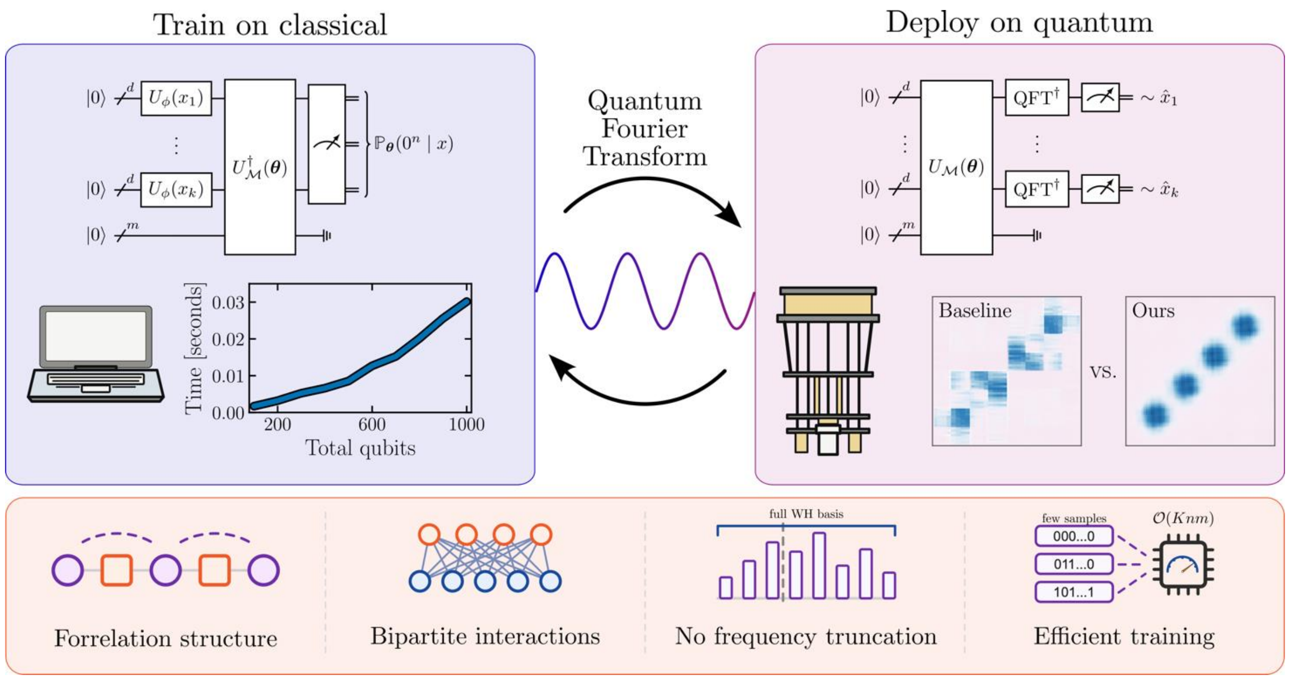


(a) Target $D_g^{\Pi\pm}$ (b) Target $D_{b+}^{\Pi\pm}$ (c) Target $D_{c+}^{\Pi\pm}$ (d) Target $D_{d^+ + s^+}^{\Pi\pm}$ (e) Target $D_{u^+}^{\Pi\pm}$

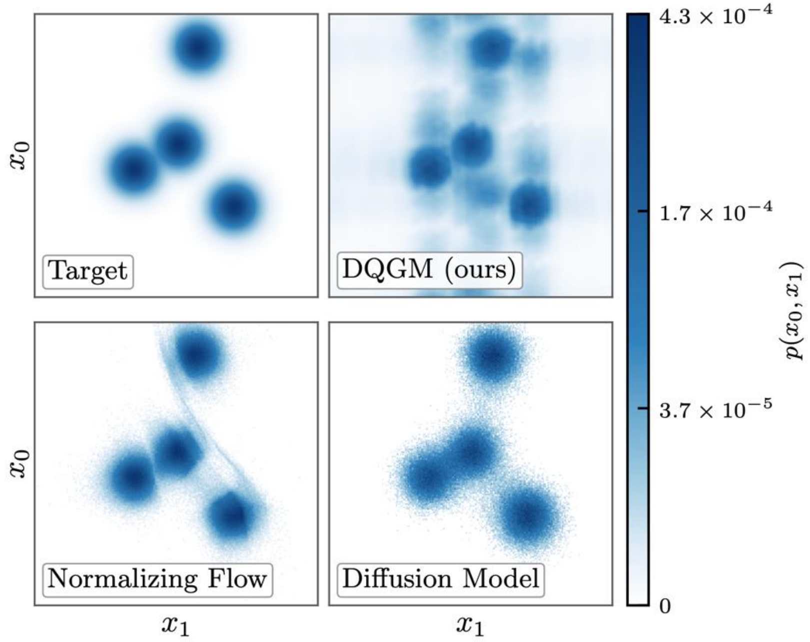


(f) Sampling $D_g^{\Pi\pm}$ (g) Sampling $D_{b+}^{\Pi\pm}$ (h) Sampling $D_{c+}^{\Pi\pm}$ (i) Sampling $D_{d^+ + s^+}^{\Pi\pm}$ (j) Sampling $D_{u^+}^{\Pi\pm}$

Quantum generative models ...at scale



- Train on GPUs O(1000) qubits Fourier-based quantum generative model
- Monte Carlo estimator on a log-likelihood loss on visible marginal probabilities
- Once trained, sample on quantum computers at rates competing with SOTA.



arXiv: 2606.28483

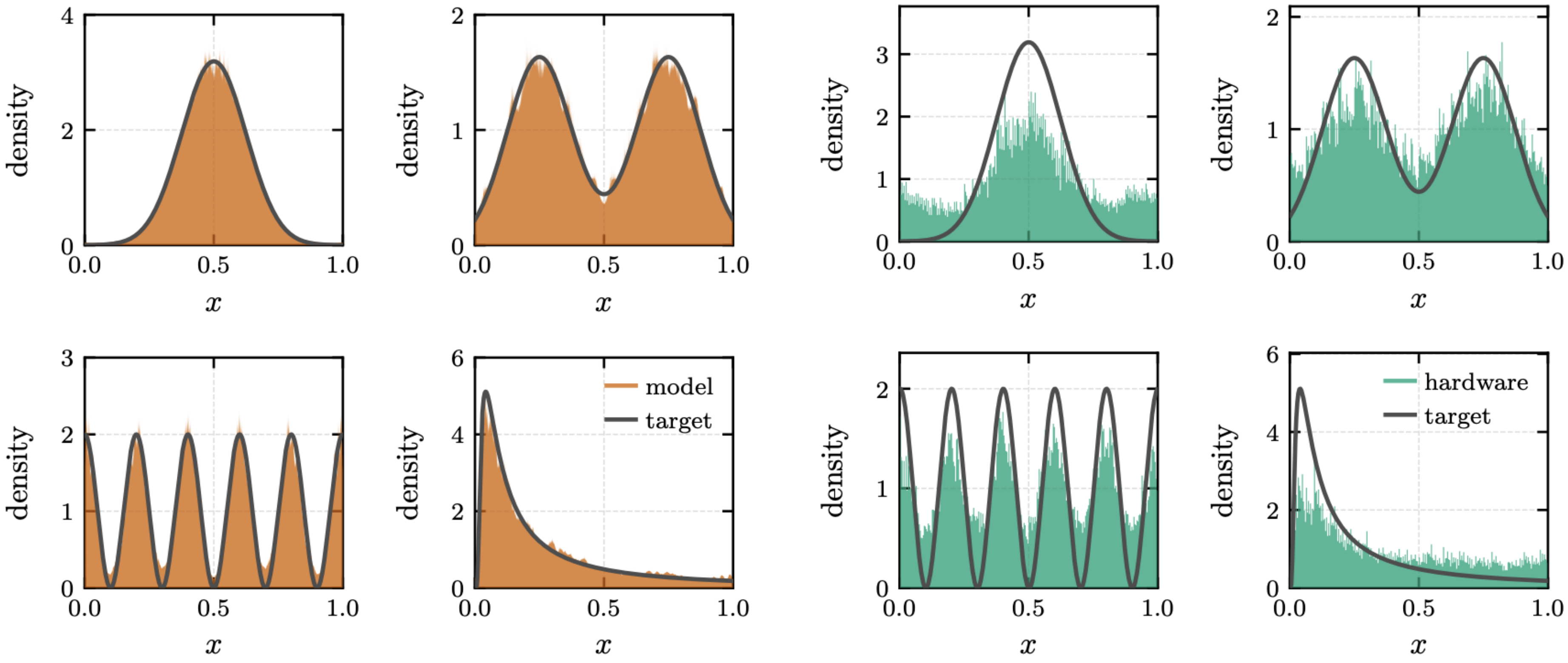
GitHub

Closing in on the performance of classical baselines on challenging tasks!

Hardware runs

Ibm_aachen

Approximate QFT^{-1}
16 qubits
4 hidden qubits
10^5 shots
30 sec hardware time



(a) Simulated results
(b) Hardware results

Sample multi-dimensional distributions

Multiple applications require sampling from complex multidimensional distributions

(e.g. Uncertainty estimation, Bayesian parameter estimation)

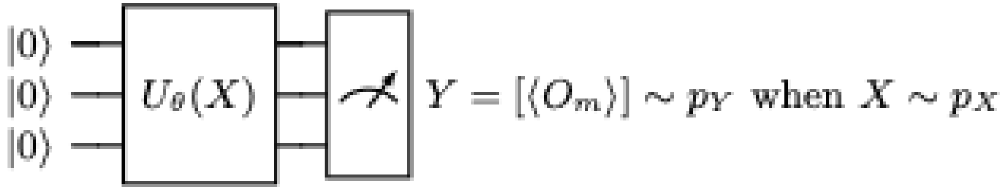
Classical methods face different challenges:

Monte Carlo sampling is accurate but often slow to converge in high-dimensional problems.

Multimodal posteriors, parameter correlations, and weight degeneracy

Quantum Expectation Value Sampler:

A trainable quantum circuit transforms the random input X to the target distribution.

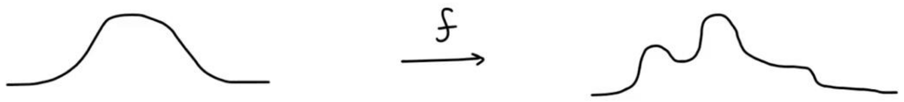


NB: Proof of universality and resources bounds Barthe, Alice, et al. npj Quantum Information 11.1 (2025): 121.

Challenge is quantum state preparation

Barthe, Alice, et al. npj Quantum Information 11.1 (2025): 121.

Universal Generative Models



$X \sim p_X$ $\quad$ $Y = f(X)$ $\quad$ $Y \sim p_Y$

Any random variable can be mapped to another of the same dimension.

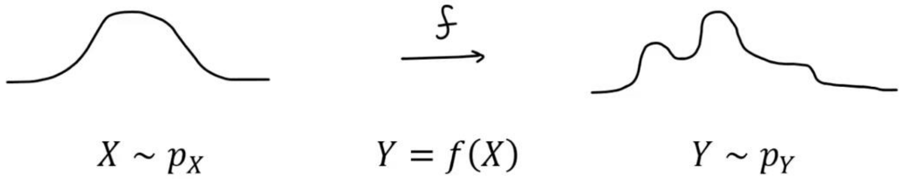
[5] Theorem 1 : To have a universal generator, it is sufficient to have:

- An absolutely continuous variable easy to sample from, $X \in \mathbb{R}^M$.
- A model of $f: \mathbb{R}^M \to \mathbb{R}^M$ mappings which is a universal approximator.

Can we learn *f(x)* ?

Barthe, Alice, et al. npj Quantum Information 11.1 (2025): 121.

Universal Generative Models



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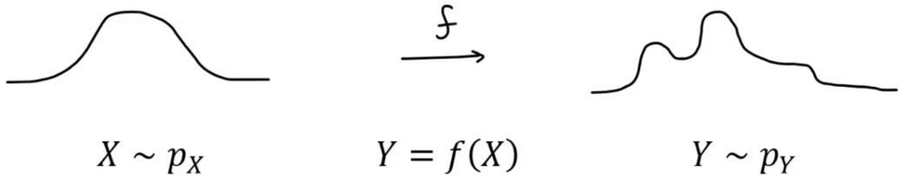
Can we learn *f(x)* ?

YES: For any target distribution **q** over a specified domain, there must exist a sequence of models whose output distributions converge to **q** under the Wasserstein-1 distance.

Barthe, Alice, et al. npj Quantum Information 11.1 (2025): 121.

Universal Generative Models



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[5] Theorem 1 : To have a universal generator, it is sufficient to have:

- An absolutely continuous variable easy to sample from, $X \in \mathbb{R}^M$.
- A model of $f: \mathbb{R}^M \rightarrow \mathbb{R}^M$ mappings which is a universal approximator.

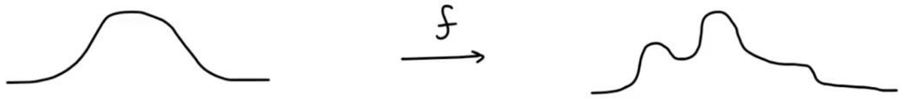
Can we learn *f(x)* ?

YES: For any target distribution **q** over a specified domain, there must exist a sequence of models whose output distributions converge to **q** under the Wasserstein-1 distance.

Can a quantum system learn *f(x)*?
What is the cost?

Barthe, Alice, et al. npj Quantum Information 11.1 (2025): 121.

Universal Generative Models



$X \sim p_X$ $\quad Y = f(X) \quad$ $Y \sim p_Y$

Any random variable can be mapped to another of the same dimension.

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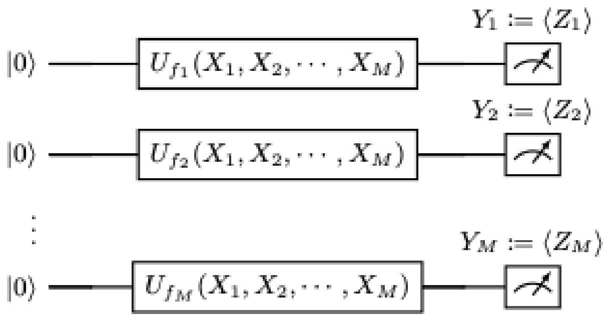
Expectation Value Samplers: Interpret expectation values of quantum observables as **natural representation of continuous multivariate distributions**

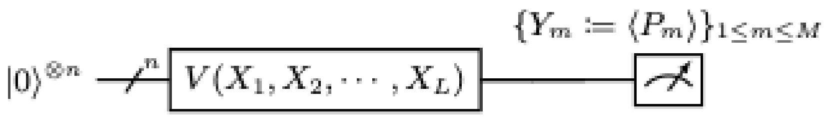
Constructing Expectation Value Samplers

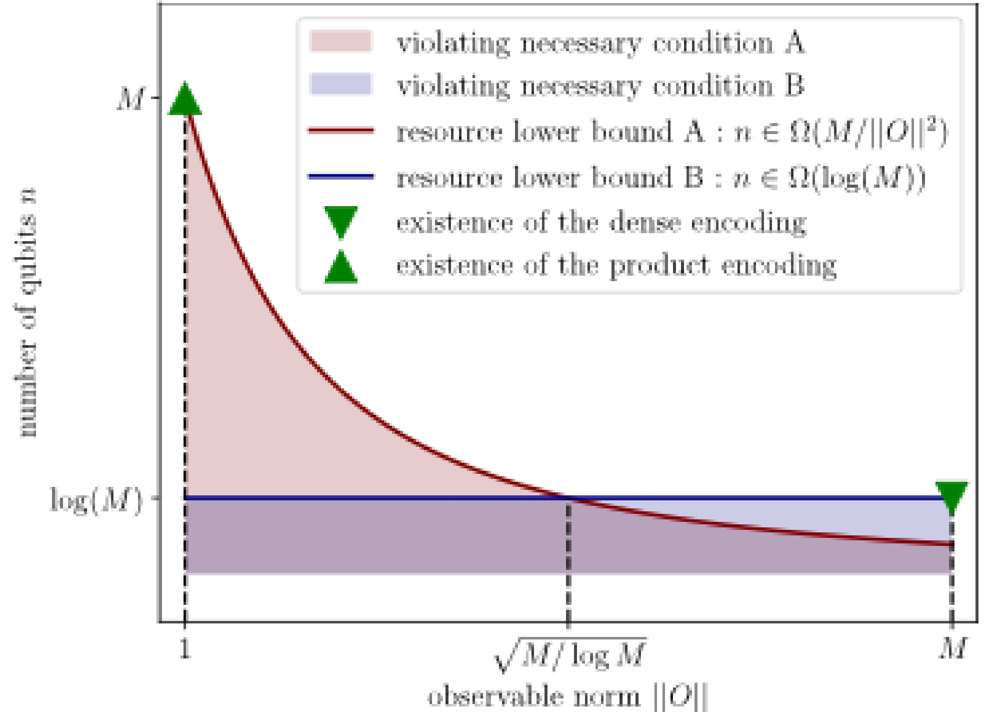
Two **universal constructions** exist:



Product encoding with M qubits and simple observables

Dense encoding model with log(M) qubits but larger observable norms.





Trade-offs between qubit count, observable spectral norms, and measurement precision

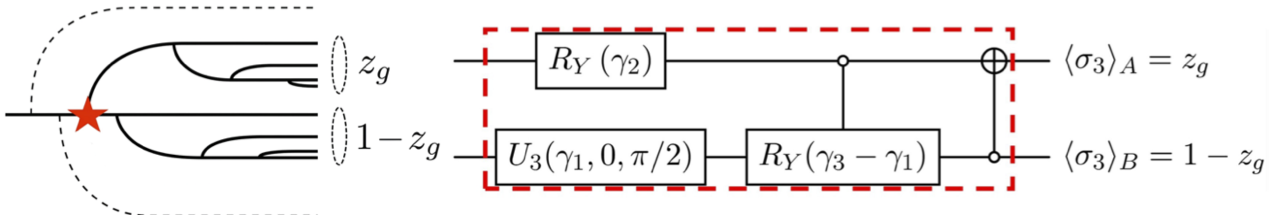
Measurement costs increase with model dimension and observable norm arxiv:2605.06789

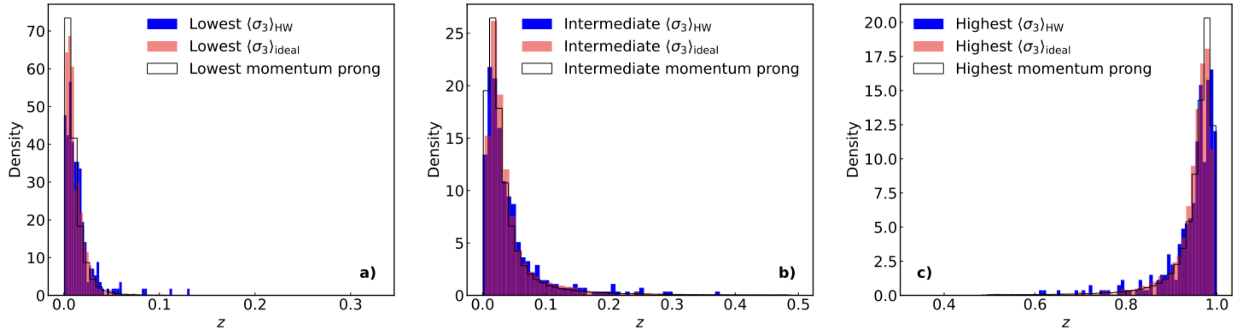
QCD Splitting functions

Define a quantum circuit primitive to model entanglements in QCD parton splitting

A building block for data –driven, physics informed event generation

1. Analytically calculate the helicity entanglement at the splitting vertex
2. Encode the momentum shared by outgoing gluons in a 2-qubit circuit (reproduces the QCD-predicted entanglement structure)
3. Calibrate to LHC jet substructure
4. Construct multi-prong momentum fraction distributions combining primitives
5. Validate 3-prongs circuit result on hardware





Summary

- The CERN Quantum Technology Initiative program is well underway.
- **Interesting results in the QTI Quantum Computing area**
  - Theoretical study of algorithms
  - Applications
  - Frameworks
- **With better quantum hardware becoming available we want to we want to strengthen the application area, focusing on real bottlenecks and demonstrating the algorithms performance in realistic settings**

Prepare for a new QTI phase, with a even stronger alignment with CERN research

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(Classical) Chebyshev Transforms

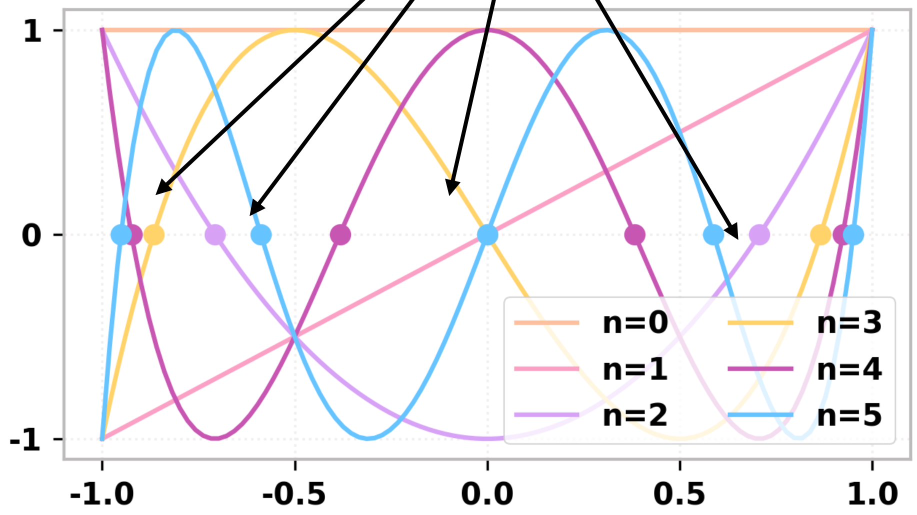
Chebyshev polynomials are a set of orthogonal polynomials, complete on [-1,1]

Used in **numerical integration** and **interpolation**

$$T_k(x) \equiv \cos\big(k \arccos(x)\big)$$

$$\begin{aligned} T_0(x) &= 1 \\ T_1(x) &= x \\ T_2(x) &= 2x^2 - 1 \\ T_3(x) &= 4x^3 - 3x \\ T_4(x) &= 8x^4 - 8x^2 + 1 \\ &\vdots \\ T_{n+1}(x) &= 2xT_n(x) - T_{n-1}(x)\,. \end{aligned}$$

$$x_k^{\mathrm{Ch}} = \cos\left(\frac{2k+1}{2n}\pi\right), \quad k = 0, \ldots, n-1$$



The discrete **Chebyshev transform**:

$$f(x_k^{\mathrm{Ch}}) = \sum_{j=0}^{N-1} a_j (-1)^j \cos\left(\frac{j\pi}{N}(k+1/2)\right)$$

Quantum Chebyshev Basis

Classical:

From the discrete **Chebyshev transform**:

$$f(x_k^{\mathrm{Ch}}) = \sum_{j=0}^{N-1} a_j (-1)^j \cos\left(\frac{j\pi}{N}(k+1/2)\right)$$

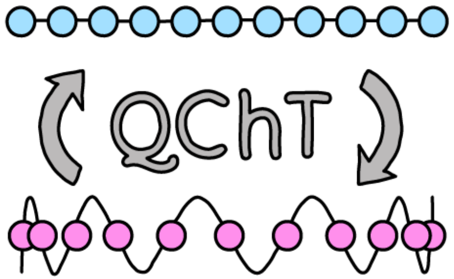
$$x_k^{\mathrm{Ch}} = \cos\left(\frac{2k+1}{2n}\pi\right), \quad k = 0, \ldots, n-1$$

Quantum:

Define the **j -th Chebyshev basis state** using N qubits as:

$$|\tau(x_j^{\mathrm{Ch}})\rangle = \frac{1}{2^{N/2}} T_0(x_j^{\mathrm{Ch}})|0\rangle + \frac{1}{2^{(N-1)/2}} \sum_{k=1}^{2^N-1} T_k(x_j^{\mathrm{Ch}})|k\rangle$$

$$\langle \tau(x_j^{\mathrm{Ch}}) | \tau(x_{j'}^{\mathrm{Ch}}) \rangle = \begin{cases} 0 & j \neq j' \\ 1 & j = j' \end{cases}$$



Basis states orthonormality ensured by Chebyshev polynomials **orthogonality and normalization**

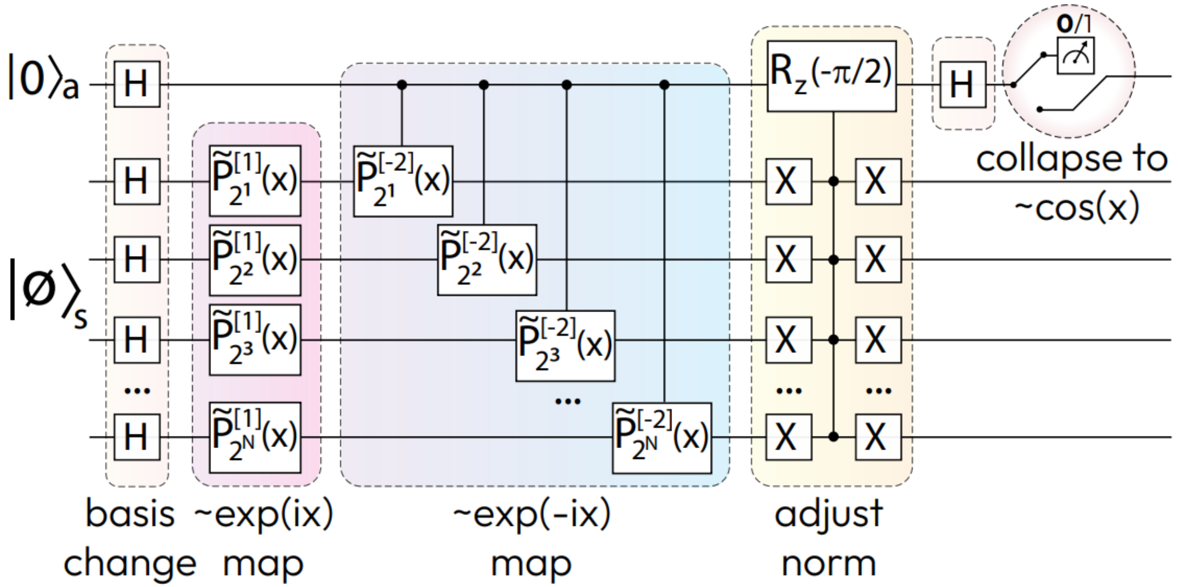
Quantum Chebyshev Feature Map and Transform

Given quantum Cheb. basis states

$$|\tau(x)\rangle = \frac{1}{2^{N/2}} T_0(x)|0\rangle + \frac{1}{2^{(N-1)/2}} \sum_{k=1}^{2^N-1} T_k(x)|k\rangle$$

The feature map is such that

$$\hat{\mathcal{U}}_\tau(x)|0\rangle = |\,\tau(x)\rangle$$



Cheb. polynomials are represented by cosines evaluated at specific grid points:

Prepare feature map using a **combination of exponents for some scaled variable x**

cos(x)= {exp(ix) + exp(−ix)}/2

Adjust interference term through ancilla qubit and normalize

Quantum Chebyshev Transform: Mapping, Embedding, Learning and Sampling Distributions: Chelsea A. Williams, Annie E. Paine, Hsin-Yu Wu, Vincent E. Elfving, Oleksandr Kyriienko, arXiv:2306.17026

Quantum Chebyshev Transform

Quantum Chebyshev Transform: Mapping, Embedding, Learning and Sampling Distributions: Chelsea A. Williams, Annie E. Paine, Hsin-Yu Wu, Vincent E. Elfving, Oleksandr Kyriienko, arXiv:2306.17026

Map between Cheb ↔ Computational bases:

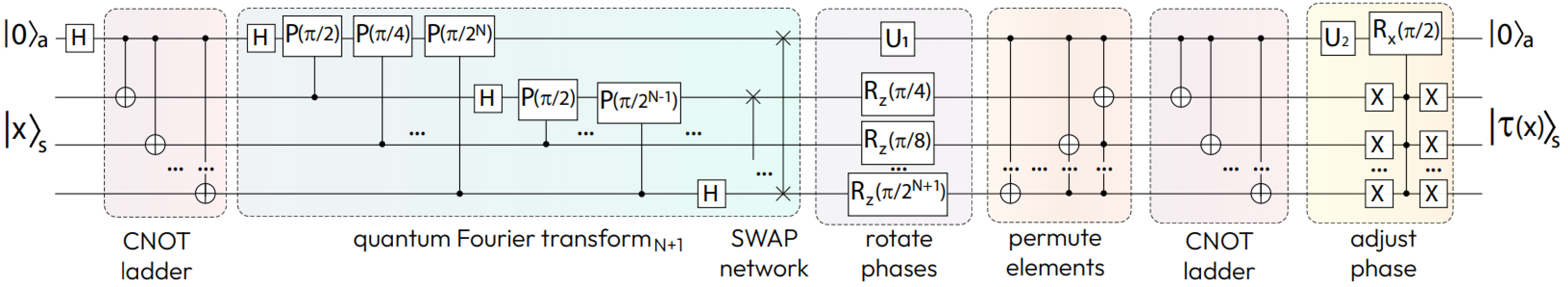
$$\hat{\mathcal{U}}_{\mathrm{QChT}} = \sum_{j=0}^{2^N-1} |\tau(x_j^{\mathrm{Ch}})\rangle\langle x_j|$$

Transform back via:

$$\hat{\mathcal{U}}_f = \hat{\mathcal{U}}^{\dagger}{}_{\mathrm{QChT}}\, \hat{\mathcal{U}}_\tau(x)$$

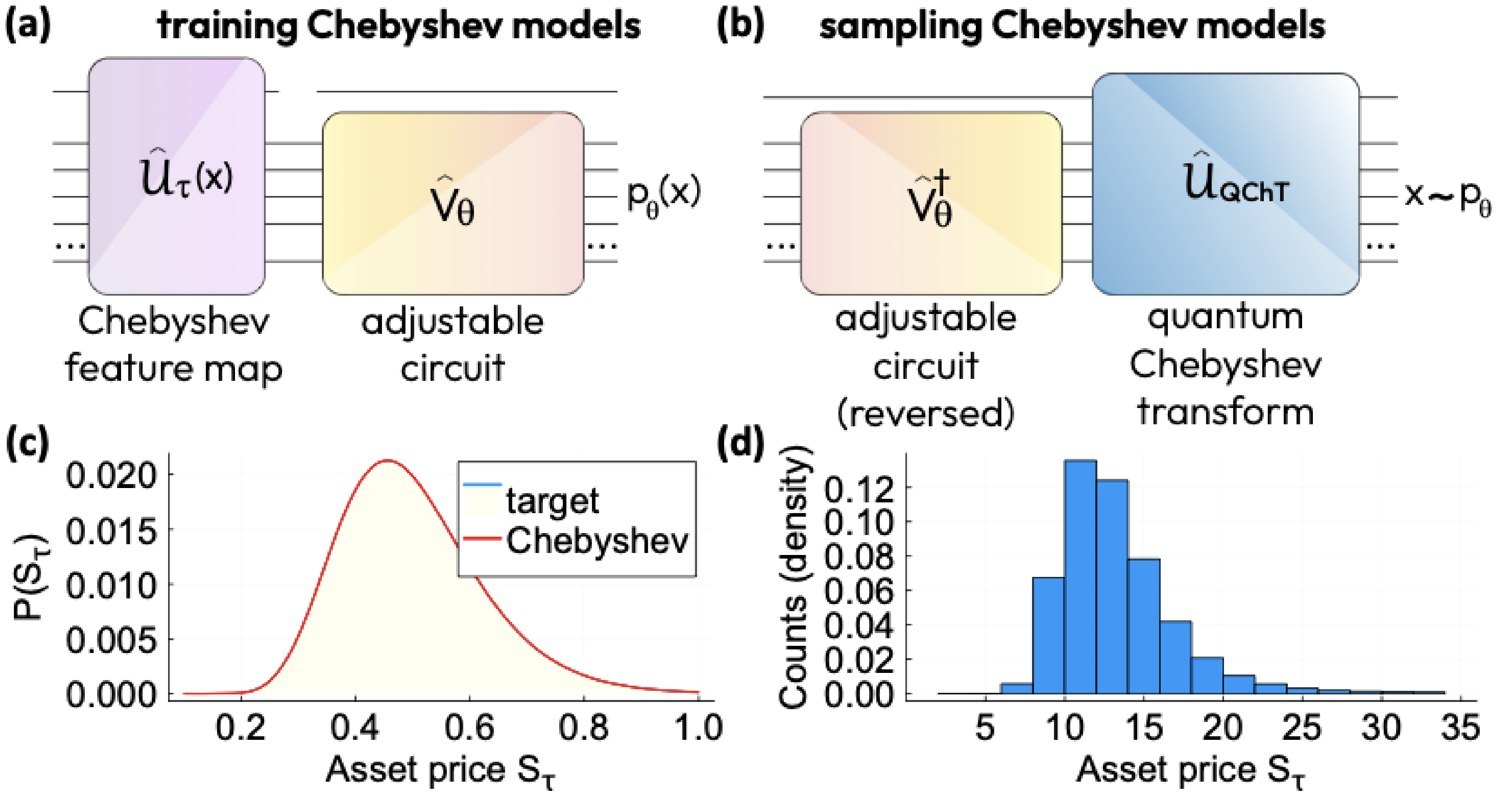
Chebyshev transform can be understood as a specific version of the cosine transform.

Can **leverage Quantum Fourier Transform** for interference and mixing

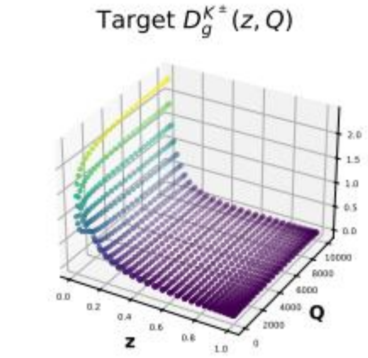


Quantum Chebyshev Transform: Mapping, Embedding, Learning and Sampling Distributions: Chelsea A. Williams, Annie E. Paine, Hsin-Yu Wu, Vincent E. Elfving, Oleksandr Kyriienko, arXiv:2306.17026

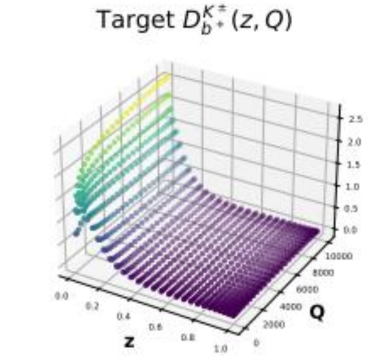
Quantum Chebyshev Generative Models



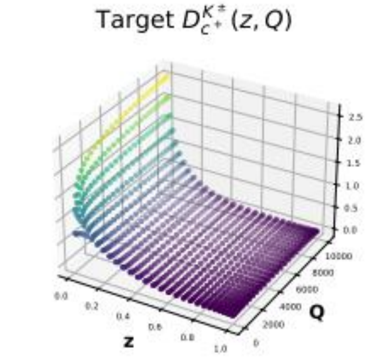
Fragmentation Functions of $K^{\pm}$



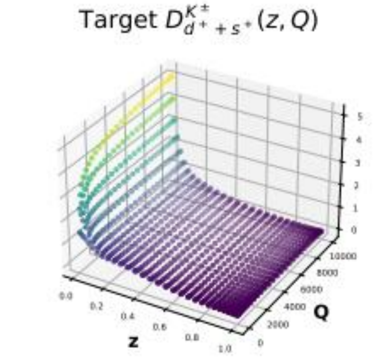
(a) Target $D_g^{K^\pm}$



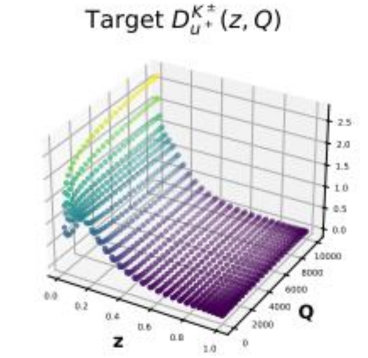
(b) Target $D_{b+}^{K^\pm}$



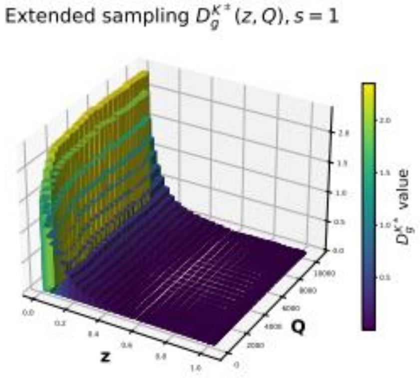
(c) Target $D_{c+}^{K^\pm}$



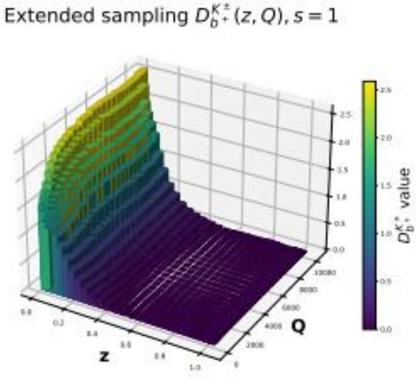
(d) Target $D_{d++s+}^{K^\pm}$



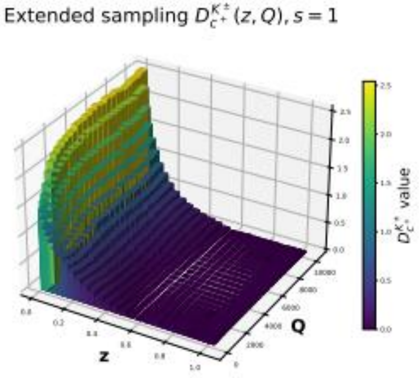
(e) Target $D_{u+}^{K^\pm}$



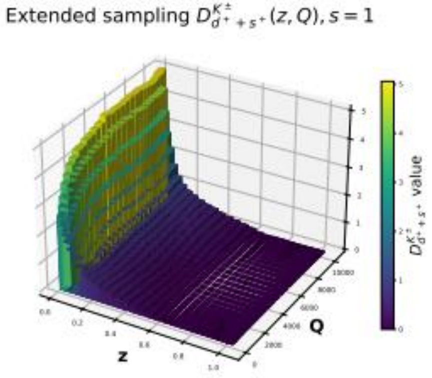
(f) Sampling $D_g^{K^\pm}$



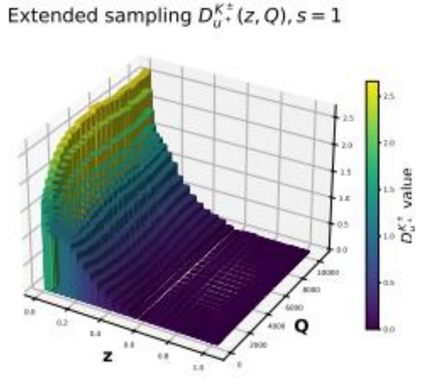
(g) Sampling $D_{b+}^{K^\pm}$



(h) Sampling $D_{c+}^{K^\pm}$



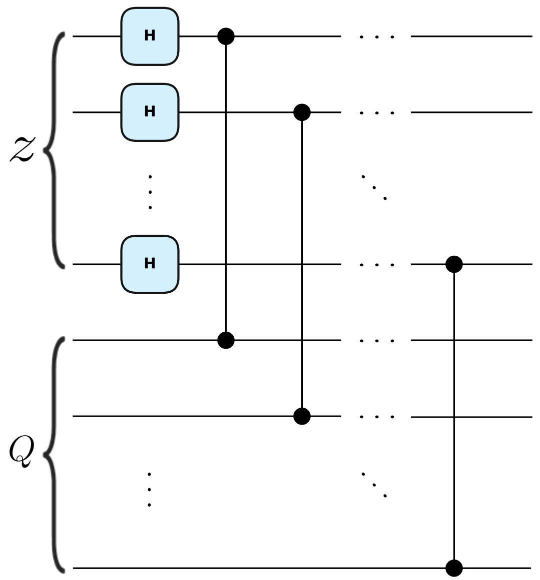
(i) Sampling $D_{d++s+}^{K^\pm}$



(j) Sampling $D_{u+}^{K^\pm}$

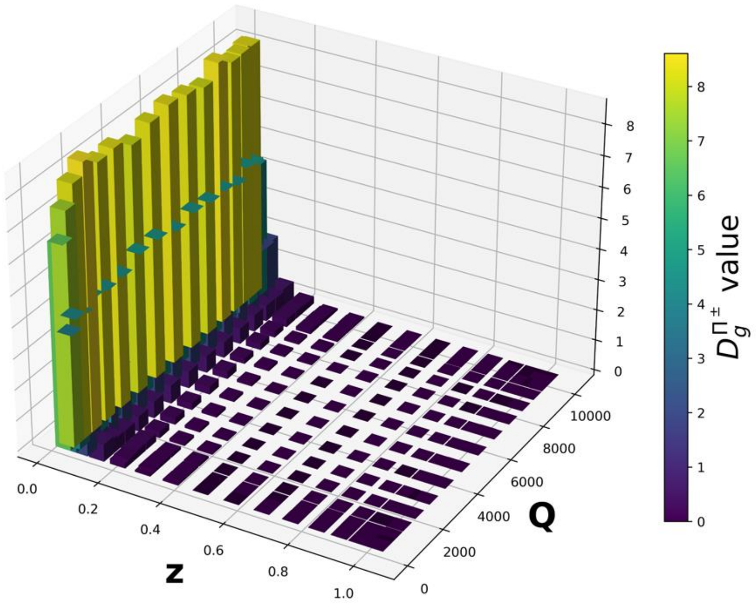
The role of Entanglement

Correlation circuit

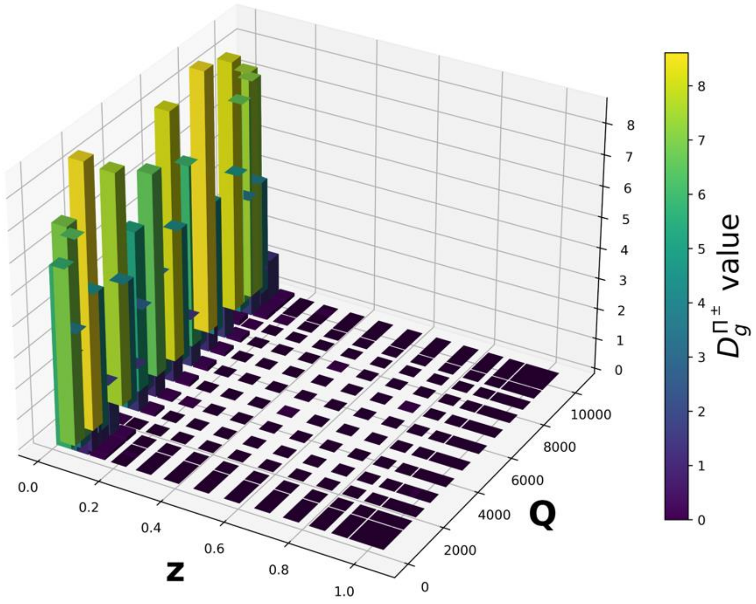


Example $D_g^{\pi^{\pm}}$: 4 qubits, 3 layers, 10000 iter., learning rate ∈ $[0.1,1]$

W/ CC: $R^2 = 0.99$

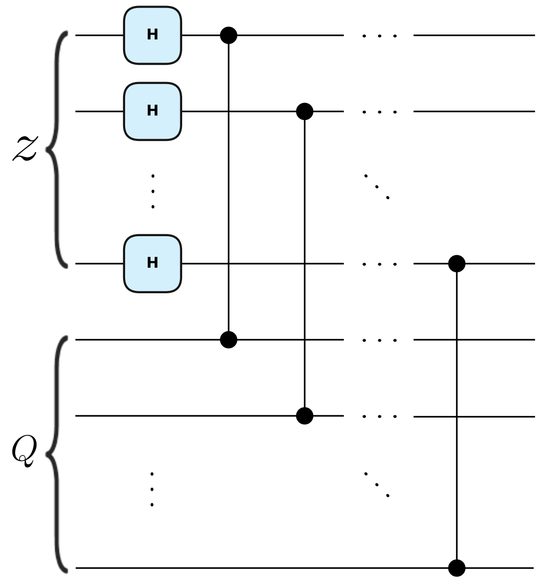


W/o CC: $R^2 = 0.85$



The role of entanglement (II)

Correlations circuit



Comparison all FF

“**Quantumness**” **help** the models to learn