Quantum Machine Learning Integration in the High Energy Physics Pipeline: CERN QTI perspective

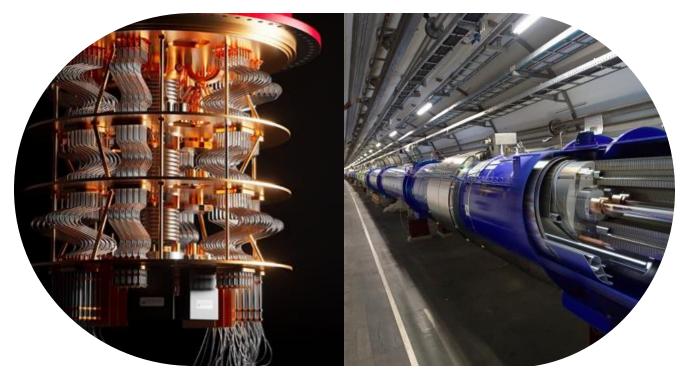


Michele Grossi

Hybrid Quantum Computing Infrastructures and Algorithms Coordinator



How does CERN engage in Quantum Technologies?



QT4HEP

Develop technologies required by the CERN scientific programme

Integrate CERN to future quantum infrastructures

Extend and share technologies available at CERN

Boost development and adoption of QT beyond CERN

HEP4QT



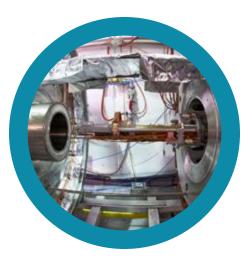
CERN QTI Phase 2

QUANTUM TECHNOLOGY

Launched January 2024







- Develop quantum sensors to provide new capabilities for particle physics research (dark matter search, axion search, gravitational wave detection...)
- Focus areas: Superconducting RF cavities, hydrogen-like Rydberg ions, and Transition Edge Sensors

CERN QUANTUM TECHNOLOGY PLATFORMS CERN's broad expertise and experimental facilities in many areas (superconducting materials, magnets, radiation effects, cryogenics, controls etc.) could be useful to support your developments.

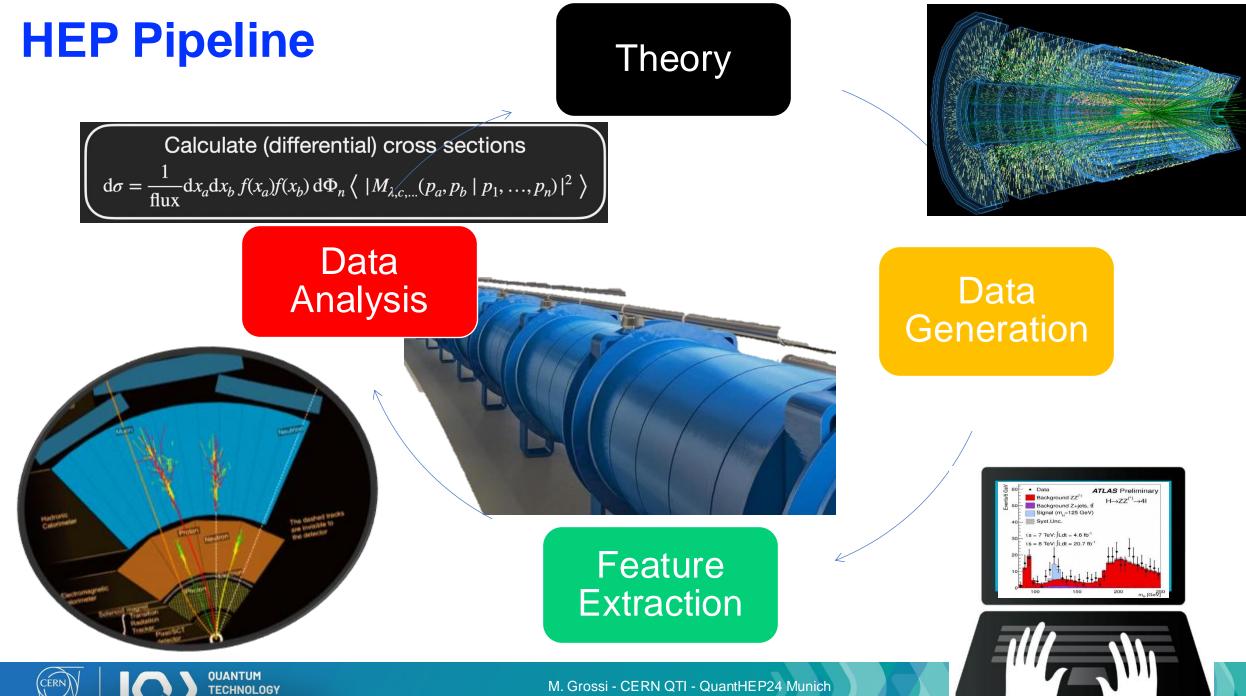




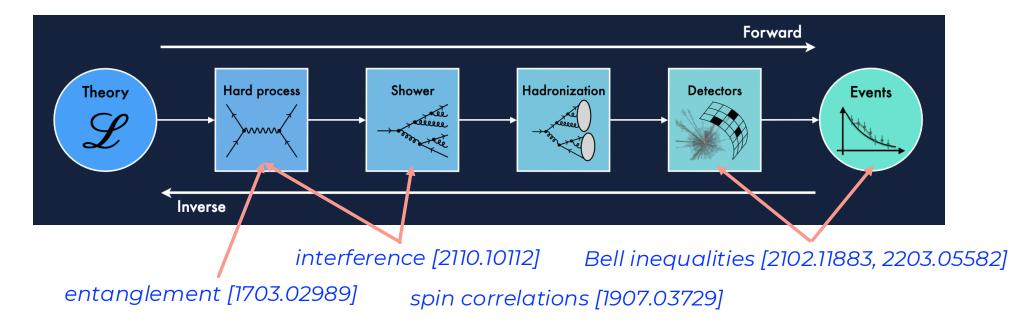
HYBRID QUANTUM COMPUTING AND ALGORITHMS

- Integration in the EU and US HPC+QCS infrastructures
- Development of hybrid classic+quantum algorithms for theoretical and experimental physics
- Lead the development of common libraries of quantum algorithms and tools for HEP and other sciences
- Simulation of high dimensional classical / quantum systems
- Software stacks for quantum devices calibration and control systems
- Investigations of distributed quantum computing, resource optimisation, green computing





Why Quantum Computing for HEP?



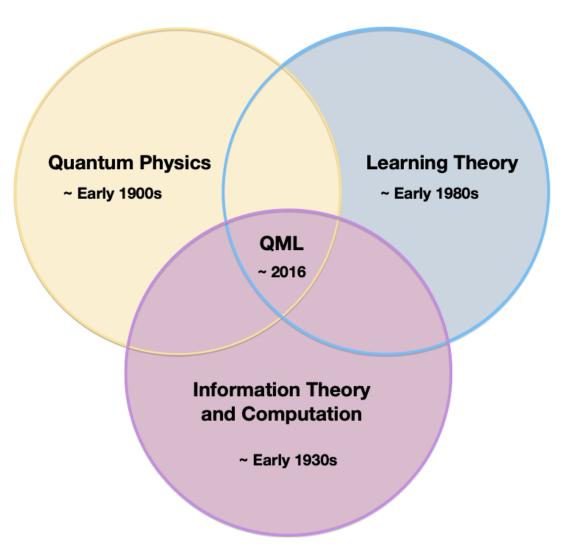
Fundamental motivation

Utilise information and correlations inherent in HEP data.

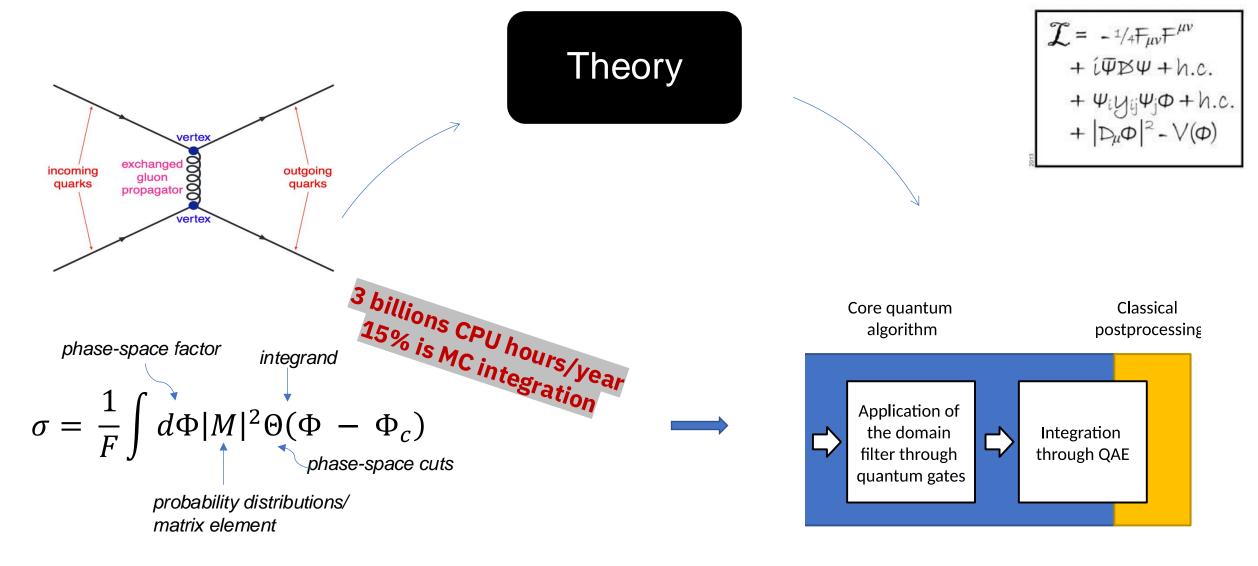
Exploit "quantum remnants" in data.



Quantum Machine Learning (QML)



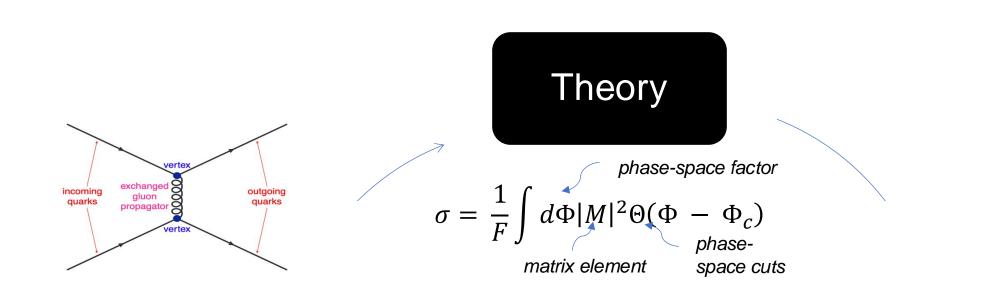


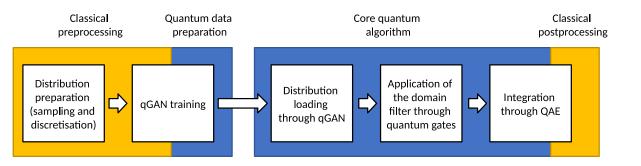


Agliardi, Grossi, Pellen, Prati "Quantum integration of elementary particle processes." <u>https://doi.org/10.1016/j.physletb.2022.137228</u>

With **QAE** the number of call to the algorithm, required to approximate I can be reduced almost quadratically beyond the MC classical bound.





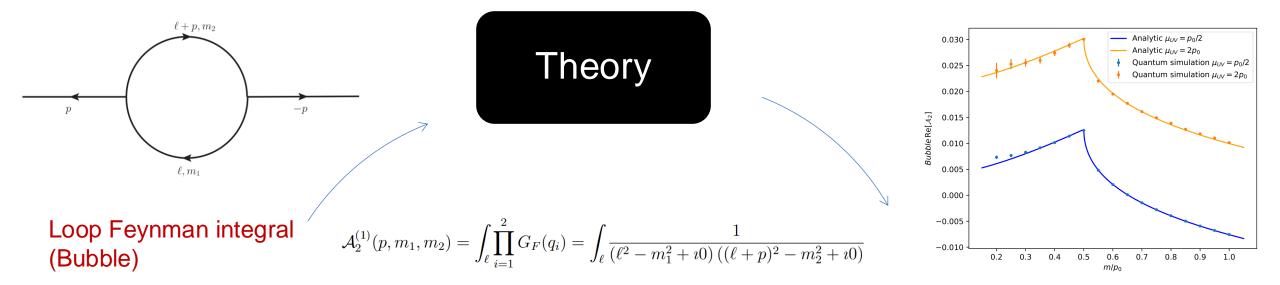


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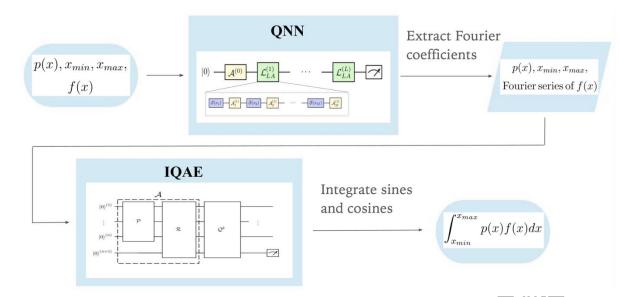
- IQAE: demonstrated speed up (Grinko, Gacon, Zoufal, Woerner <u>npj QI 7, 52 (2021))</u>
- QGAN: potential bottleneck for data/function upload
- <u>Difficult to run on real HW</u>



$$\begin{split} \mathcal{I} &= -\frac{1}{4} F_{\mu\nu} F^{\mu\nu} \\ &+ i \overline{\Psi} \mathbb{B} \Psi + h.c. \\ &+ \Psi_i \mathcal{Y} i j \Psi_j \Phi + h.c. \\ &+ |D_\mu \Phi|^2 - V(\Phi) \end{split}$$



- IQAE: demonstrated speed up (Grinko, Gacon, Zoufal, Woerner <u>npj QI 7, 52 (2021))</u>
- Integrate trigonometric functions
- QNN encoding into Fourier series
- QFIAE applicable to n-D functions
- Good result (1% error) on HW

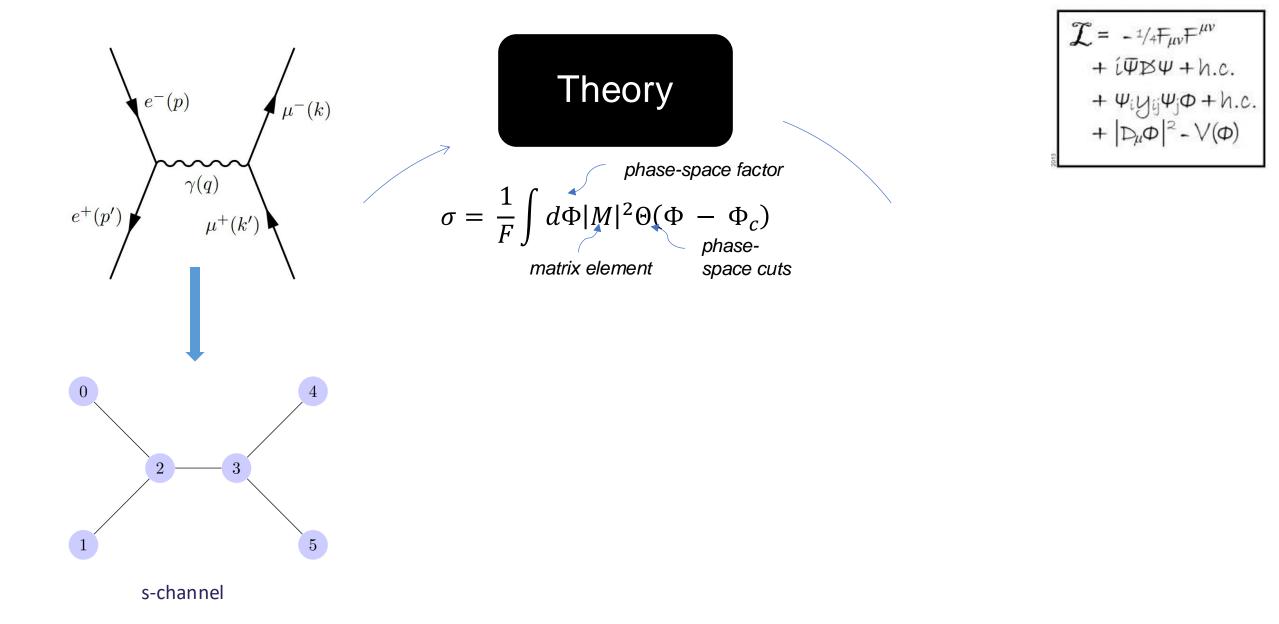


Agliardi, Grossi, Pellen, Prati "**Quantum integration of elementary particle processes**." <u>https://doi.org/10.1016/j.physletb.2022.137228</u>

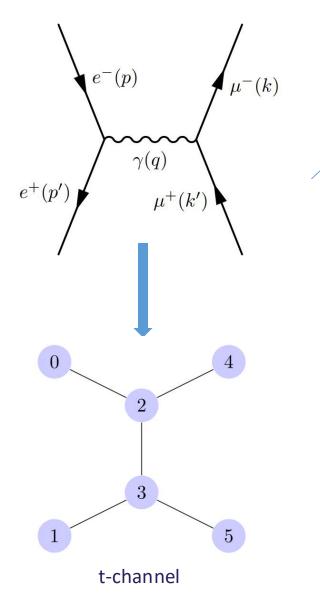
Jorge J. Martinez de Lejarza, Michele Grossi, Leandro Cieri and German Rodrigo: <u>arXiv: 2305.01686</u>

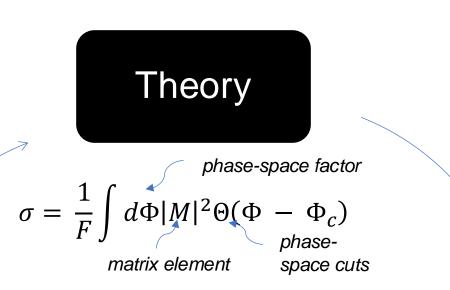












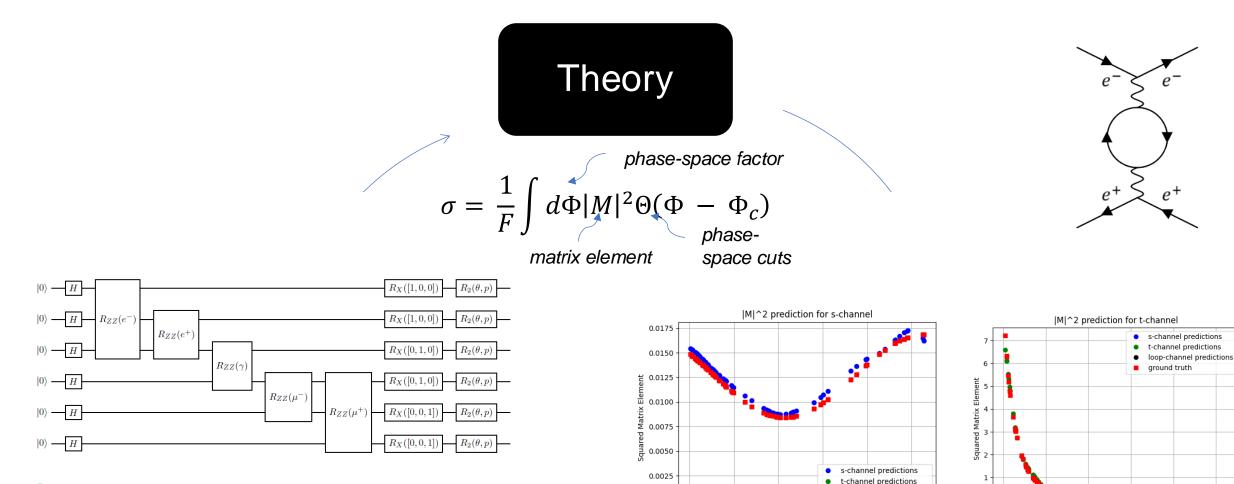
- Build a quantum supervised model that can distinguish (C) and compute (R) the scattering amplitude squared for related Feynman diagrams LO QED process
- Topology encoded in the adjacency matrix of the graph
- Particles (m,Q,S) encoded in the edges
- Time flow (initial state, interaction vertex, final state) encoded in the vertices



13

 $\mathcal{I} = -\frac{1}{4} \mathcal{F}_{\mu\nu} \mathcal{F}^{\mu\nu}$

+ $i\overline{\Psi}\mathbb{B}\Psi$ + h.c. + $\Psi_i y_{ij}\Psi_j\Phi$ + h.c. + $|D_\mu\Phi|^2$ - $V(\Phi)$



Successful training:

- Is able to learn several diagrams at the same time
- Can learn diagrams with same topology but different particles
- Task difficult with classic approaches



0.0000

0.5

1.0

1.5

2.0

Scattering Angle (rad)

loop-channel predictions

3.0

0.5

1.0

1.5

2.0

Scattering Angle (rad)

ground truth

2.5

2.5

3.0

F.Rehm et al., **Precise image generation on current noisy quantum computing devices**, *Quantum Sci. Technol.* **9** 015009

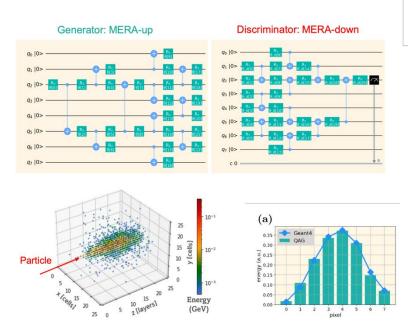
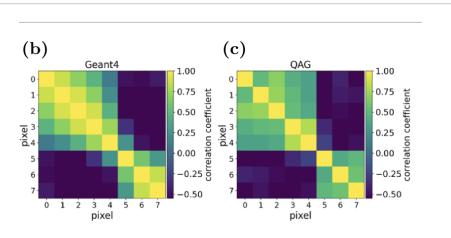
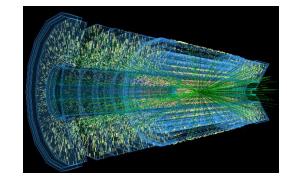


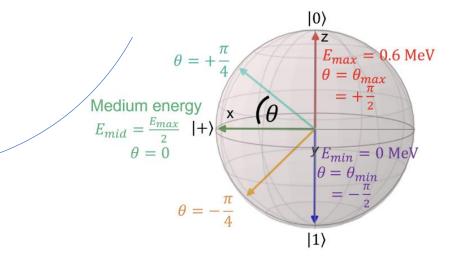
Figure 6. (a) Visualization of the average calorimeter shower shapes. The energy is given in an arbitrary unit (a.u.) due to image downsampling. The pixel-wise correlation plot for (b) Geant4 and (c) the QAG model. The correlation ranges between -1 and 1; a value of 1 indicates a perfect positive correlation.





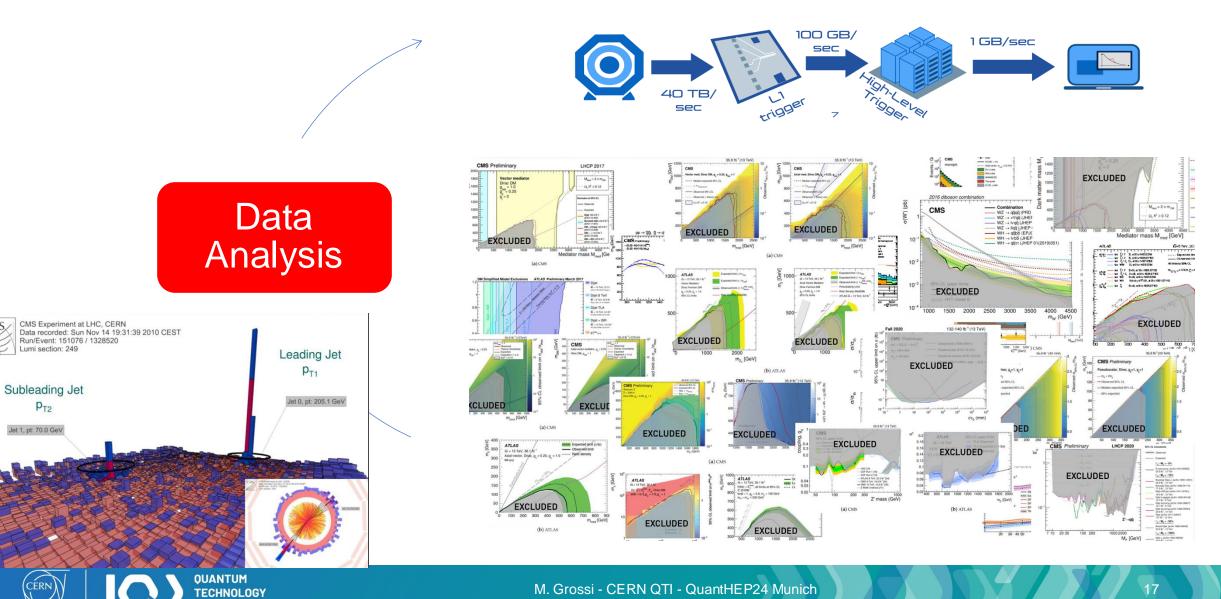
Data Generation

- Quantum angle generator (QAG): a full quantum machine learning model designed to generate accurate images on current quantum devices
- Reproduces average values, AND, complex pixel-wise correlations





Where is NEW PHYSICS? Are we using the right data?



CMS,

p_{T2}

Jet 1, pt: 70.0 GeV

CERN

Where is NEW PHYSICS? Are we using the right data?



Data Analysis

Subleading Jet

P_{T2} Jet 1, pt: 70.0 Ge Leading Jet p_{T1}

let 0. pt: 205.1 Ge

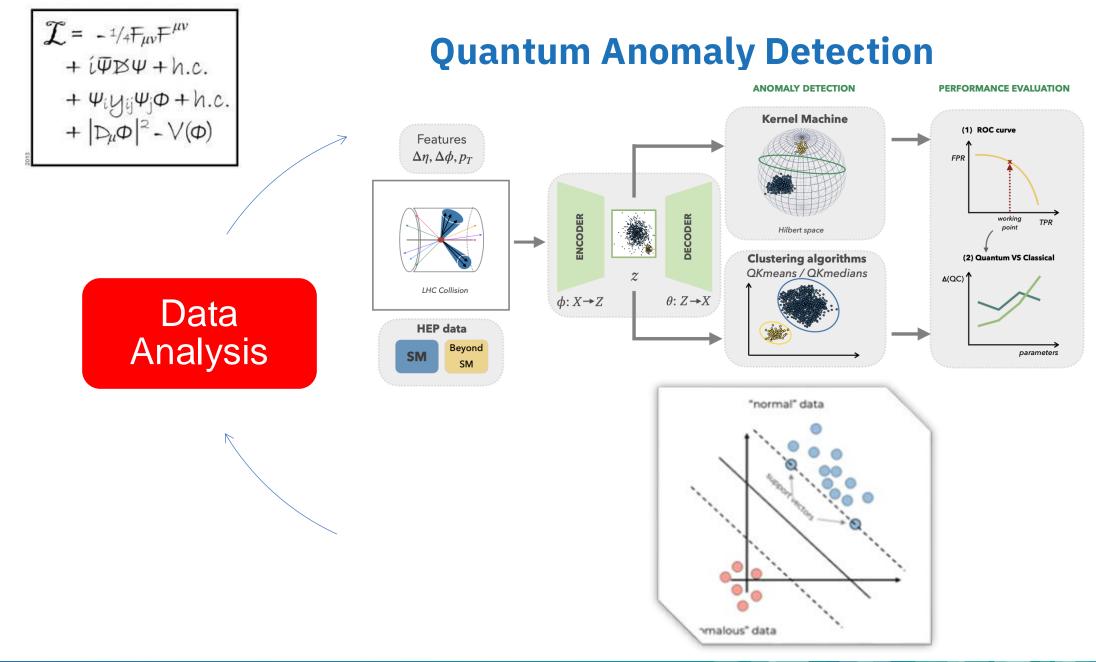
Re-embracing the scientific method: starts gathering information about nature

... our baseline is the SM (from 1970!) \rightarrow let's change the approach

Rather than specifying a signal hypothesis upfront, we could start looking at our data

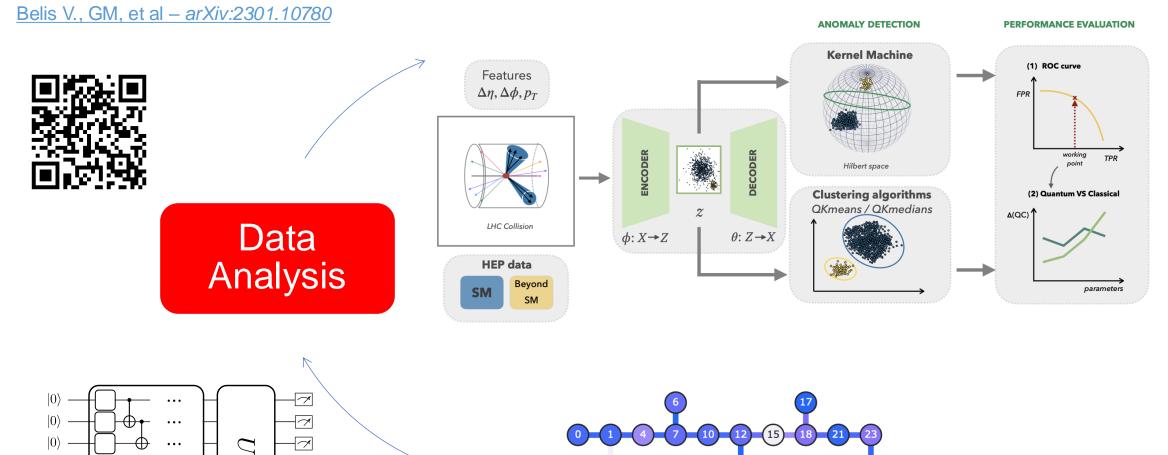
Based on what we see (e.g., clustering alike objects) we could formulate a signal hypothesis

\rightarrow QCD dijet events



CERN QUANTUM TECHNOLOGY INITIATIVE

Quantum Anomaly Detection





...

. . .

 $: U(\vec{x}_j)$

:

 $|0\rangle$

 $|0\rangle$

 $|0\rangle$

 $(\vec{x_i})$

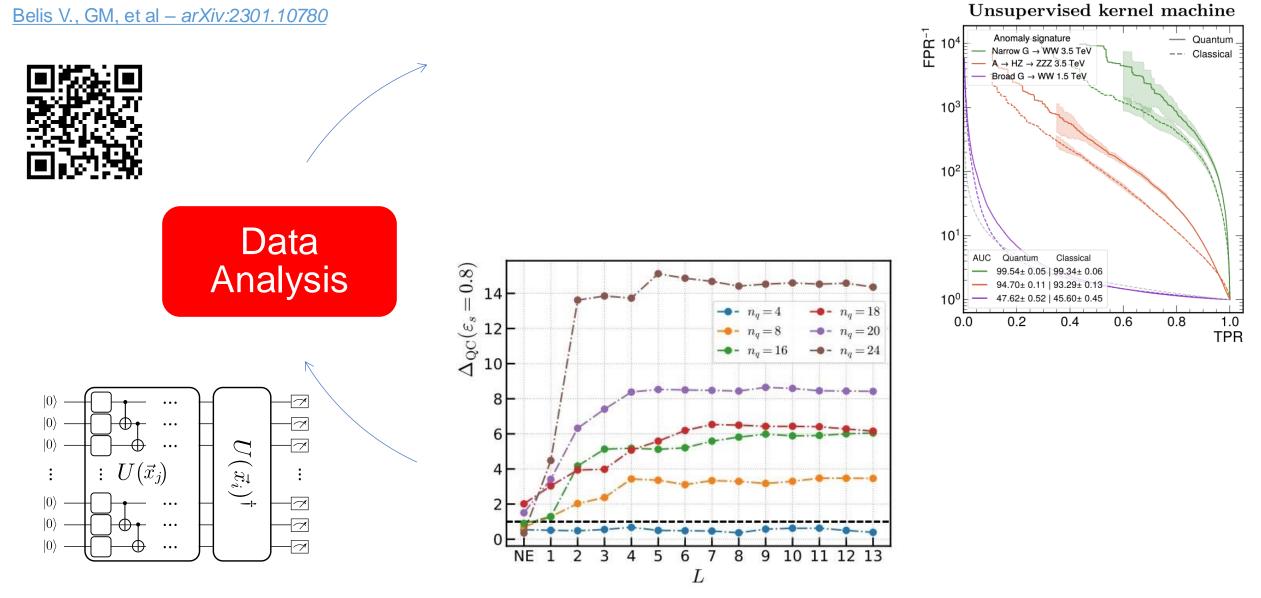
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1

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Quantum Anomaly Detection



QUANTUM TECHNOLOGY

QC research directions in HEP



PRX QUANTUM 5, 037001 (2024)

Quantum Computing for High-Energy Physics: State of the Art and Challenges

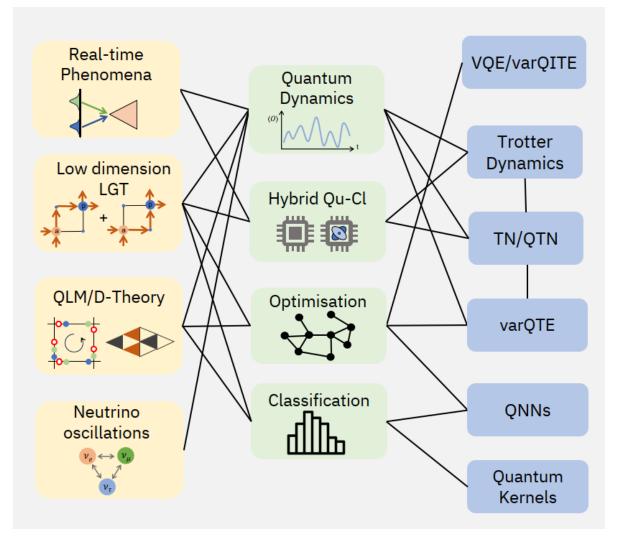
Alberto Di Meglio⁹,^{1,*} Karl Jansen,^{2,3,†} Ivano Tavernelli,^{4,‡} Constantia Alexandrou⁹,^{3,5} Srinivasan Arunachalam,⁶ Christian W. Bauer,⁷ Kerstin Borras⁶,^{8,9} Stefano Carrazza⁶,^{1,10} Arianna Crippa[®],^{2,11} Vincent Croft[®],¹² Roland de Putter,⁶ Andrea Delgado[®],¹³ Vedran Dunjko[®],¹² Daniel J. Egger[®],⁴ Elias Fernández-Combarro[®],¹⁴ Elina Fuchs[®],^{1,15,16} Lena Funcke[®],¹⁷ Daniel González-Cuadra⁰, ^{18,19} Michele Grossi⁰, ¹ Jad C. Halimeh⁰, ^{20,21} Zoë Holmes, ²² Stefan Kühn[®]² Denis Lacroix[®]²³ Randy Lewis[®]²⁴ Donatella Lucchesi[®]^{1,25} Miriam Lucio Martinez,^{26,27} Federico Meloni⁹,⁸ Antonio Mezzacapo,⁶ Simone Montangero⁹,^{1,25} Lento Nagano^{,28} Vincent R. Pascuzzi^{,6} Voica Radescu,²⁹ Enrique Rico Ortega^{,30,31,32,33} Alessandro Roggero^{1,34,35} Julian Schuhmacher^{1,4} Joao Seixas, ^{36,37,38} Pietro Silvi^{1,25} Panagiotis Spentzouris[®],³⁹ Francesco Tacchino[®],⁴ Kristan Temme,⁶ Koji Terashi[®],²⁸ Jordi Tura[®],^{12,40} Cenk Tüysüz^{2,11} Sofia Vallecorsa¹ Uwe-Jens Wiese,⁴¹ Shinjae Yoo^{43,44} and Jinglei Zhang^{43,44} European Organization for Nuclear Research (CERN), 1211 Geneva, Switzerland ²CQTA, Deutsches Elektronen-Synchrotron DESY, Platanenallee 6, 15738 Zeuthen, Germany ³Computation-based Science and Technology Research Center, The Cyprus Institute, 20 Konstantinou Kavafi Street, CY-2121 Nicosia, Cyprus ⁴IBM Research Europe — Zurich, 8803 Rüschlikon, Switzerland ⁵ Department of Physics, University of Cyprus, PO Box 20537, CY-1678 Nicosia, Cyprus ⁶IBM Quantum, IBM T.J. Watson Research Center, Yorktown Heights, NY 10598, USA ⁷ Physics Division Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Mailstop 50A5104, Berkeley, California, USA ⁸ Deutsches Elektronen-Synchrotron (DESY), Notkestraße 85, 22607 Hamburg, Germany ⁹ RWTH Aachen University, Templergraben 55, 52062 Aachen, Germany ¹⁰ TIF Lab, Dipartimento di Fisica, Università degli Studi di Milano and INFN Sezione di Milano, Milan, Italy ¹¹ Institut für Physik, Humboldt-Universität zu Berlin, Newtonstraße 15, 12489 Berlin, Germany (aOa^L) Applied Ouantum Algorithms – Leiden, Leiden, Netherlands ¹³Physics Division, Oak Ridge National Laboratory, Oak Ridge, Tennessee 37831, USA ¹⁴ Department of Computer Science, Facultad de Ciencias, University of Oviedo, 33007 Asturias, Spain ¹⁵ Institute of Theoretical Physics, Leibniz University Hannover, 30167 Hanover, Germany ¹⁶Physikalisch-Technische Bundesanstalt, 38116 Braunschweig, Germany ¹⁷ Transdisciplinary Research Area "Building Blocks of Matter and Fundamental Interactions" (TRA Matter) and Helmholtz Institute for Radiation and Nuclear Physics (HISKP), University of Bonn, Nußallee 14-16, 53115 Bonn, Germany ¹⁸ Institute for Theoretical Physics, University of Innsbruck, 6020 Innsbruck, Austria ¹⁹ Institute for Quantum Optics and Quantum Information of the Austrian Academy of Sciences, 6020 Innsbruck, Austria ²⁰ Department of Physics and Arnold Sommerfeld Center for Theoretical Physics, Ludwig-Maximilians-Universität München. Munich, Germany ²¹ Munich Center for Quantum Science and Technology, Munich, Germany ²² Institute of Physics, Ecole Polytechnique Fédérale de Lausanne, 1015 Lausanne, Switzerland ¹³ CNRS/IN2P3, IJCLab, Paris-Saclay University, 91405 Orsay, France ²⁴ Department of Physics and Astronomy, York University, Toronto, Ontario M3J 1P3, Canada ²⁵ INFN—Sezione di Padova, Via Marzolo 8, 35131 Padua, Italy ²⁶Nikhef-National Institute for Subatomic Physics, Science Park 105, 1098 XG Amsterdam, Netherlands

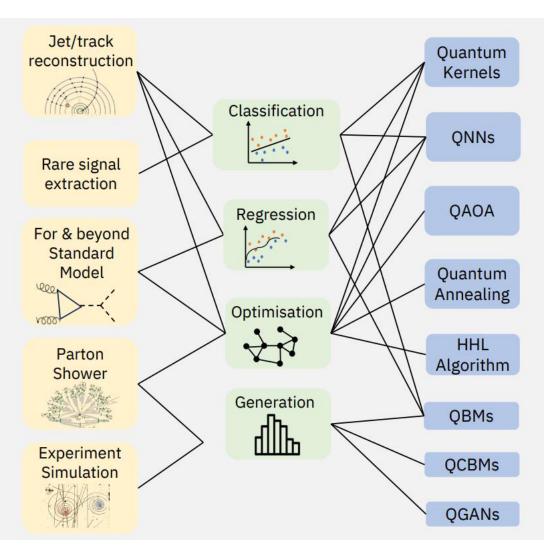
*Contact author: alberto.di.meglio@cern.ch *Contact author: karl.jansen@desy.de *Contact author: ita@zurich.ibm.com



- 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?

Methods and applications







Phase Detection with Anomaly Detection

2.0

1.5

<u>د</u> 1.0

0.5

0.0 0.0

0.25

- Quantum equivalent of an Autoencoder to learn an effective unitary operation capable of compressing all the information in the Pauli-Z expectation values of a subset of the qubits

- Minimization of the loss function
- All anomaly detection models were trained to compress the point $(\kappa, h) = (0, 0)$ of the Hamiltonian
- Training: single state selected to achieve compression
- Cost is assigned to compressed state allowing the outline of all phases

 $\mathcal{C} = \frac{1}{2} \sum_{j \in q_T} (1 - \left\langle \sigma_j^z \right\rangle),$

Numerical

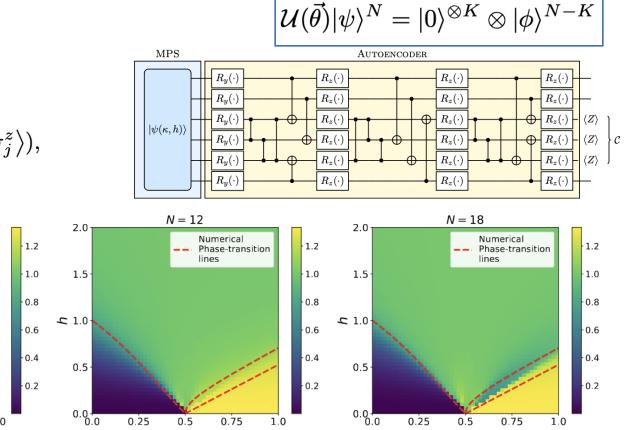
lines

Phase-transition

0.75

N = 6

0.5



0.25

0.5

0.75

1.0

Compression:

FIG. 13: Compression Scores C of the AD circuits trained on the $(\kappa, h) = (0, 0)$ point of the ANNNI model phase diagram at different system sizes N: 6 (left), 12 (middle), and 18 (right). The scores are showcased as a function of the interaction strength ratio ($\kappa = -J_2/J_1$) and the external magnetic field ($h = B/J_1$). Lower compression scores indicate better disentanglement of trash qubits from others, as defined by eq. 2.

0.5

0.75

1.0

0.25

Exploring the Phase Diagram of the quantum one-dimensional ANNNI model https://arxiv.org/abs/2402.11022



1.0

 $|\phi
angle \,\otimes |0
angle^k$

QT4HEP 2025 - save the date





