Quantum Computing for Data Analysis in High-Energy Physics

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On behalf of the whitepaper team

arXiv:2203.08805
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Hilbert space is a big place!

Carlton Caves

With 275 qubits, we can represent more basis/computational states than the number of atoms in the observable universe.

$2^{275}$

The potential to speed up certain calculations, simulate quantum mechanical systems through the manipulation of quantum mechanical properties such as entanglement.
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The potential to speed up certain calculations, simulate quantum mechanical systems through the manipulation of quantum mechanical properties such as entanglement.

Not as easy as it sounds!
Motivated by access to cloud-based processors and commercial applications.

Applications in Quantum Machine Learning (QML) spurred by the release of Xanadu’s PennyLane / Google’s Tensorflow.

Co-design:
- Algorithmic development/research is adapting to match the pace of hardware development.

Applications in quantum annealing, superconducting qubits, and continuous-variable explored.

Developed for deployment on NISQ devices.
- Few qubits,
- Noisy,
- Low gate fidelity.

Hybrid frameworks to leverage benefits of both classical and quantum computing - variational quantum circuits.
Standard Model (and beyond)

Nature

\[ L = \frac{-1}{4} F_{\mu \nu} F^{\mu \nu} + \psi \overline{\psi} + \psi D \overline{\psi} + \overline{\chi} \chi + W^3 \]
Data Analysis in High-Energy Physics

Standard Model (and beyond)

Nature

Simulation

Experiment

Detector-level observables

Analysis

See Christian Bauer’s talk on “Quantum Simulation”
Quantum-enhanced generative modeling

- GANS and QCBMs. 
- Studied in the context of data augmentation. 
- Challenges associated with the encoding of target distributions and scalable quantum error correction techniques. 
- Important for building up the “quantum pipeline” – in anomaly detection settings, intermediary encoders, etc.
Casting Data Analysis Tasks as Optimization Problems

- Reformulating clustering tasks as binary unconstrained satisfaction problems (QUBO).
- Motivated by access to D-Wave QPUs.
- Large number of available qubits, relatively easy to program.


Data Analysis in High-Energy Physics

Variational Quantum Circuits as Machine Learning Models
- Parameterized circuit training for classification tasks such as event classification, track reconstruction.
- Advanced techniques such as data-reuploading, layer wise training.
- Deployed on IBM hardware, IonQ, CV platforms.


Challenges

Quantum Annealing

- Large overhead associated with calculation of QUBO coefficients.
- Low connectivity among physical variables.
- Significant post-processing required, hyperparameter optimization.
- Problem decomposition tools lacking precision needed for HEP analysis.
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Gate-based Quantum Computing

- Limited number of qubits, low connectivity.
- High overhead in embedding classical data into quantum states.
- Training limitations associated with cloud-based access.
- Scalable error correction techniques.
★ A large number of quantum computing applications to data analysis in HEP have been developed over the last decade.

- First applications on D-Wave, followed by circuit-based applications targeted for IBM hardware, mostly.
- CV continues largely unexplored.
- Huge development in the area of QML: largest kernel-based classifier (27 qubits) and generative model (12 qubits) to-date developed for HEP applications.
A large number of quantum computing applications to data analysis in HEP have been developed over the last decade.

Quantum Machine Learning will have an important role in quantum computing for HEP in the next decade.
- Most likely not revolutionary in the analysis of classical data.
- But impactful in the analysis of quantum data, complementing quantum-enhanced searches for BSM physics and simulation of quantum systems.
Outlook

★ A large number of quantum computing applications to data analysis in HEP have been developed over the last decade.

★ Quantum Machine Learning will have an important role in quantum computing for HEP in the next decade.

★ There is still a lot of work to do.
  o Understand the role of entanglement in model trainability.
  o Scalable error correction/mitigation techniques.
  o Understanding choice of Ansatz in model expressibility.
  o How to make better use of available Hilbert space, in terms of efficient measurements, metrics.
Outlook

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★ Not covered on this talk:
  ★ Quantum-inspired models: Tensor networks as ML models.
  ★ Storing an IceCube event into quantum memory - See Jeffrey Lazar's talk at the workshop or read the whitepaper 😊
Quantum Computing for Data Analysis in High-energy Physics

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Thank you!