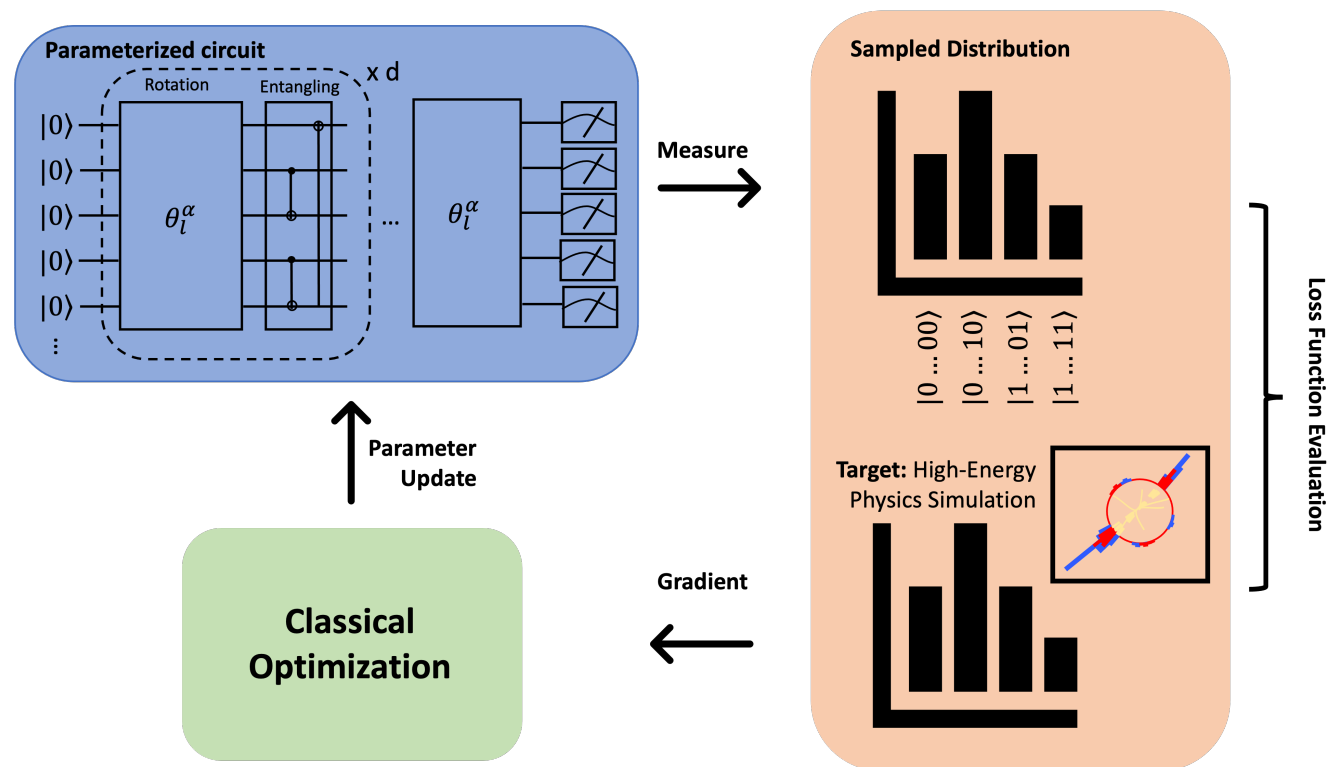


# Unsupervised Quantum Circuit Learning in High Energy Physics

**Andrea Delgado**, Physics Division, PSD

**Kathleen E. Hamilton**, Quantum Computing Group, CSED

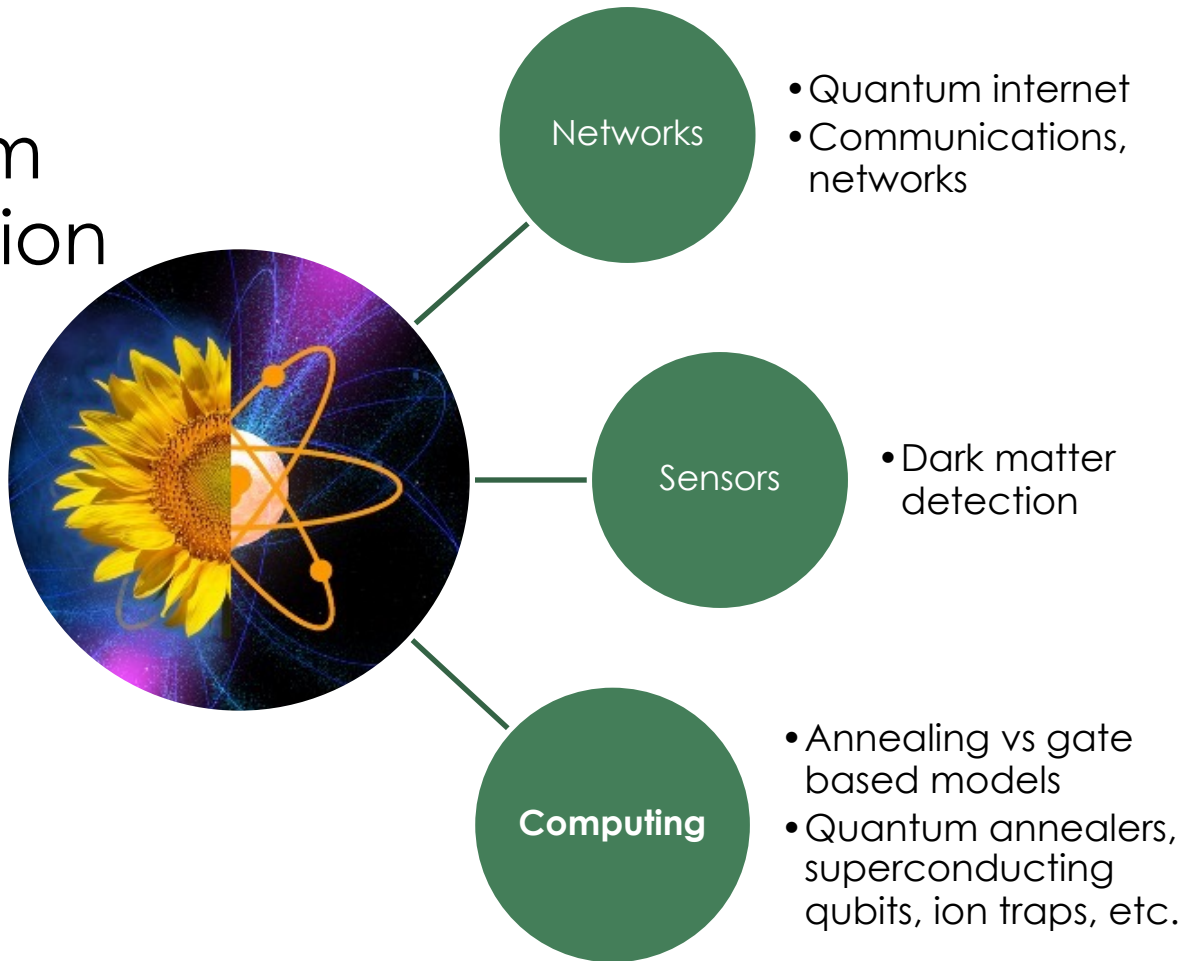
# The topic of this talk...



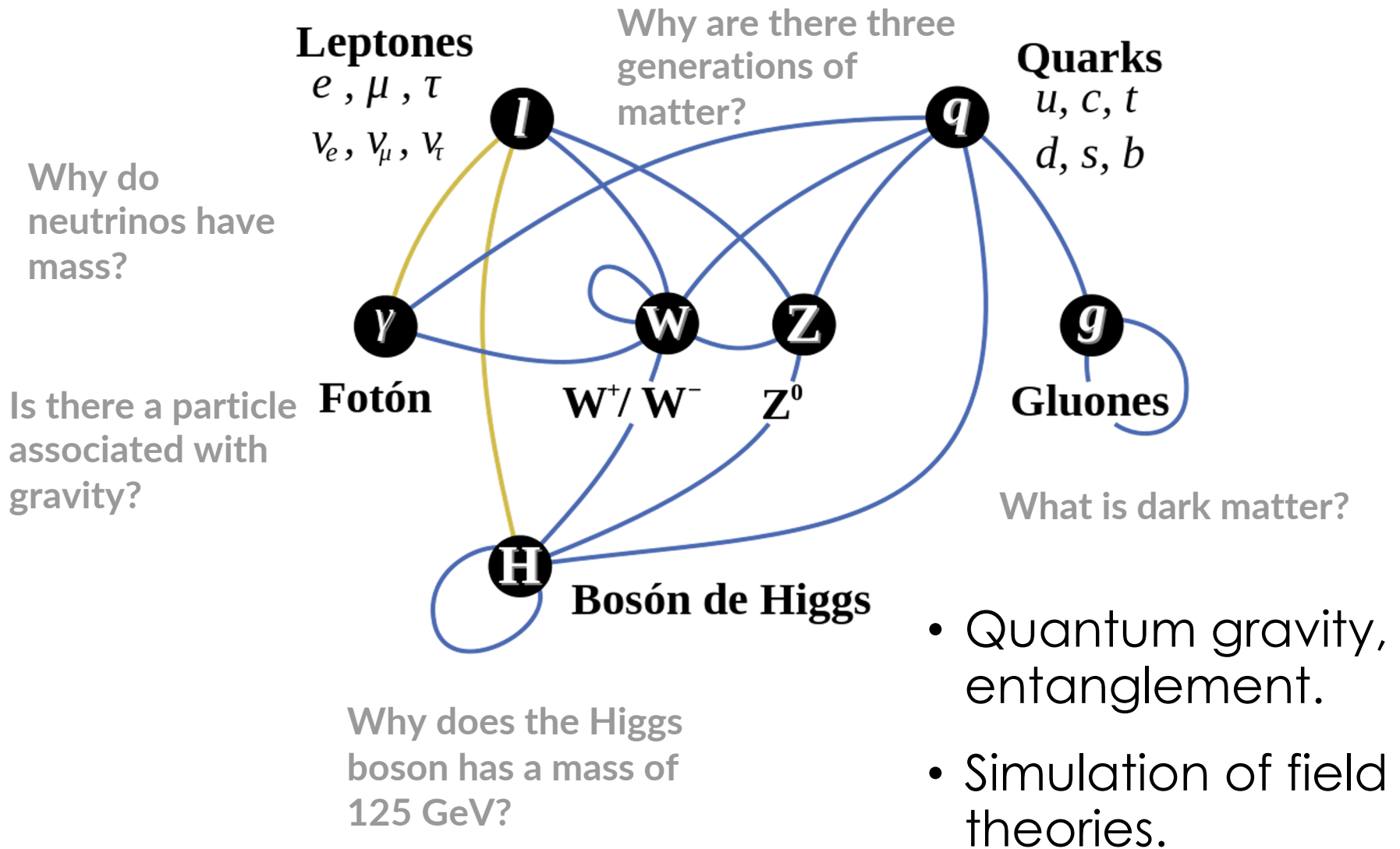
- We use non-adversarial, gradient-based training of quantum circuit Born machines (QCBM) to generate joint distributions over 2 and 3 variables.
- The goal is to provide a quantum alternative to traditional MC methods for detector response simulation in HEP.

# The Second Quantum Revolution

## Quantum Information Science



# Quantum Computing Applications in High-Energy Physics

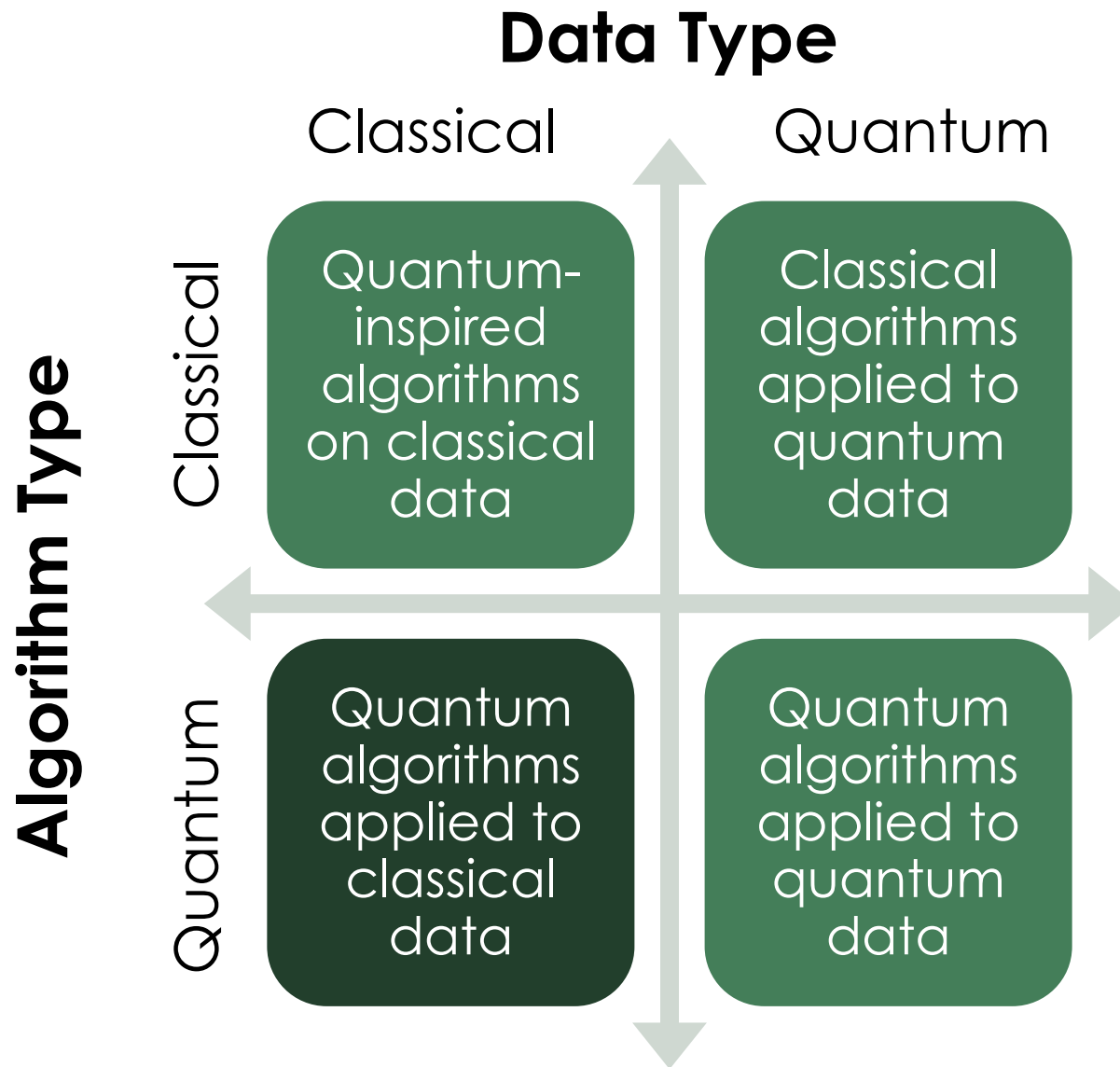


- Quantum gravity, entanglement.
- Simulation of field theories.

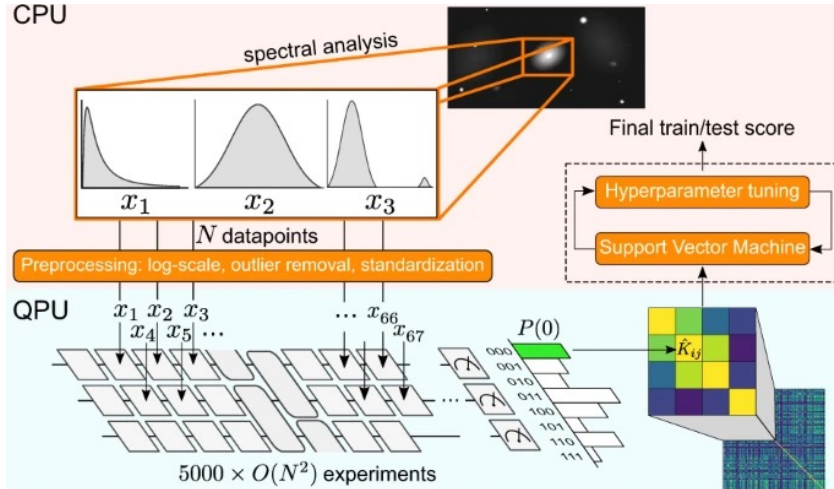
- **Data analysis**

**Snowmass Workshop on QC for HEP:**  
<https://indico.phy.ornl.gov/event/144/>

# The many faces of Quantum Machine Learning



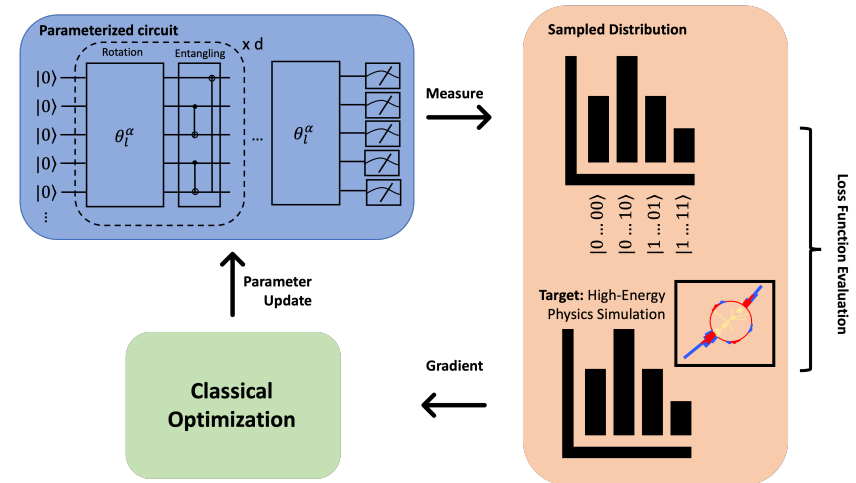
# Promising QML Applications in HEP



## Supervised Learning

- Classification based on kernel methods

Peters, E., Caldeira, J., Ho, A. *et al.* **Machine learning of high dimensional data on a noisy quantum processor.** *npj Quantum Inf* **7**, 161 (2021).



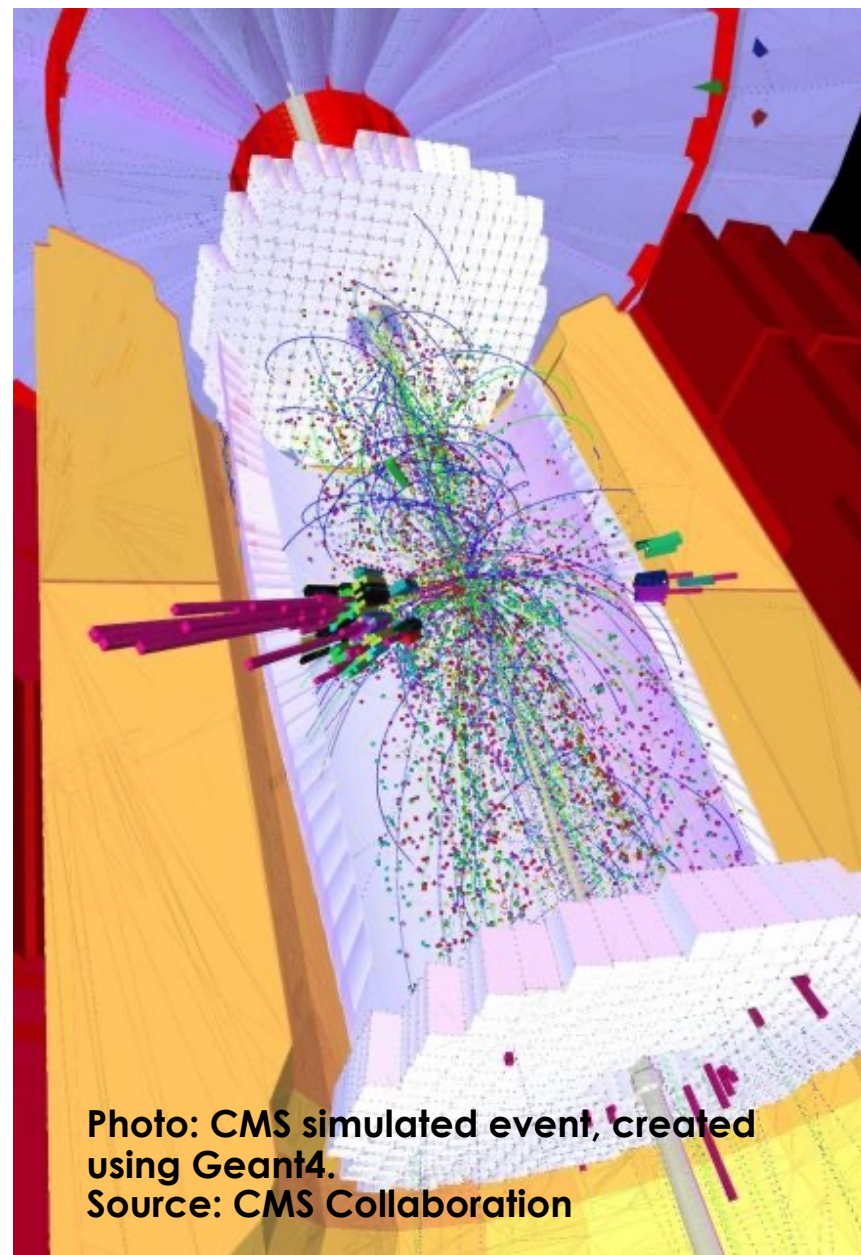
## Unsupervised Learning

- Generative modeling tasks

This work in progress, A. Delgado, K. E. Hamilton

# Simulation in the 21<sup>st</sup> century

- The HEP community relies heavily on accurate simulation of the physics processes under study, as well as the interaction with the detector.
- Existing frameworks based on MC techniques provide a remarkable agreement between data and simulation.
  - They are also very demanding in terms of computational resources.
- Several alternatives have been explored
  - Including fast simulation, ML-assisted techniques, quantum computing!

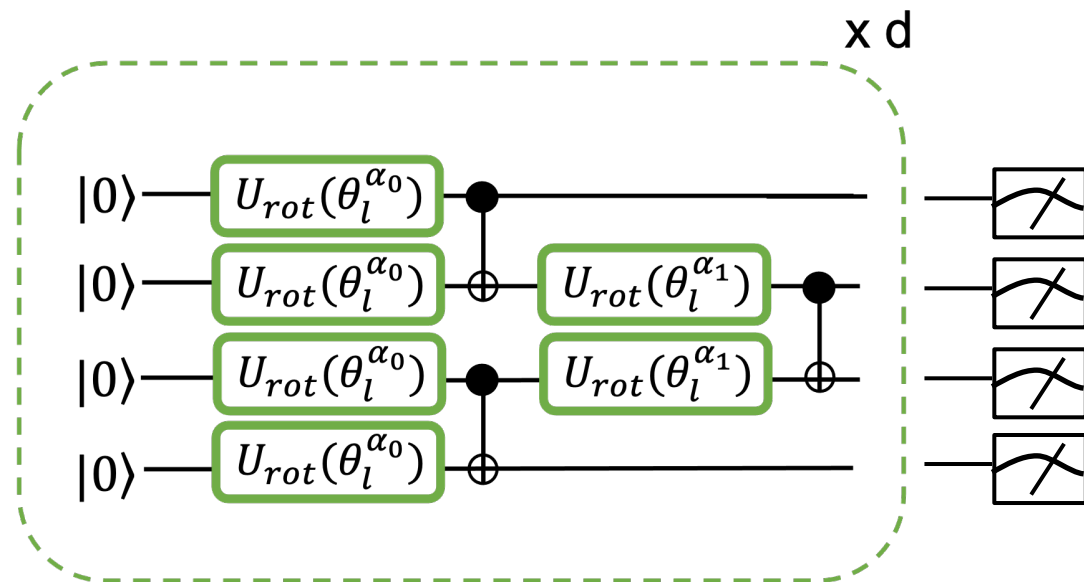


**Photo: CMS simulated event, created using Geant4.  
Source: CMS Collaboration**

# Unsupervised Quantum Circuit Learning

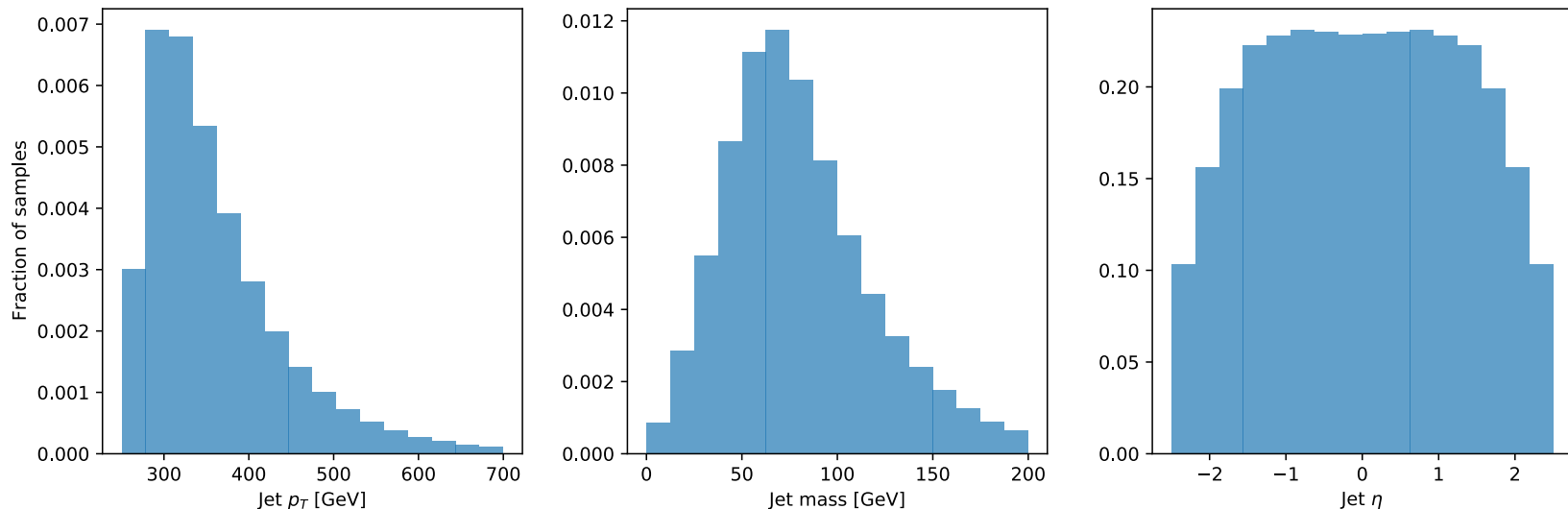
We use non-adversarial, gradient-based training of quantum circuit Born machines (QCBM) to generate joint distributions over 2 and 3 variables.

- QCBMs are parameterized quantum circuits used with the objective of preparing a target distribution with high-fidelity.
- A quantum state is prepared by a parameterized ansatz which takes the initial qubit register from the all-zero state to a final state.
- QCBMs are constructed by alternating layers of rotation gates with layers of two-qubit entangling operations

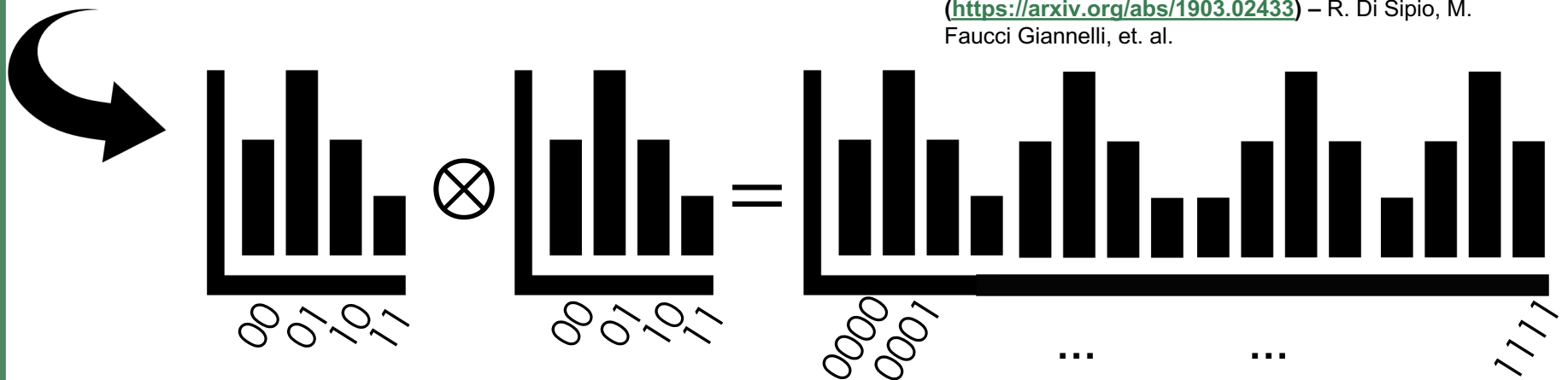


# Unsupervised Quantum Circuit Learning

We use non-adversarial, gradient-based training of quantum circuit Born machines (QCBM) to generate joint distributions over 2 and 3 variables.



DijetGAN: A Generative-Adversarial Network Approach for the Simulation of QCD Dijet Events at the LHC (<https://arxiv.org/abs/1903.02433>) – R. Di Sipio, M. Fauci Giannelli, et. al.

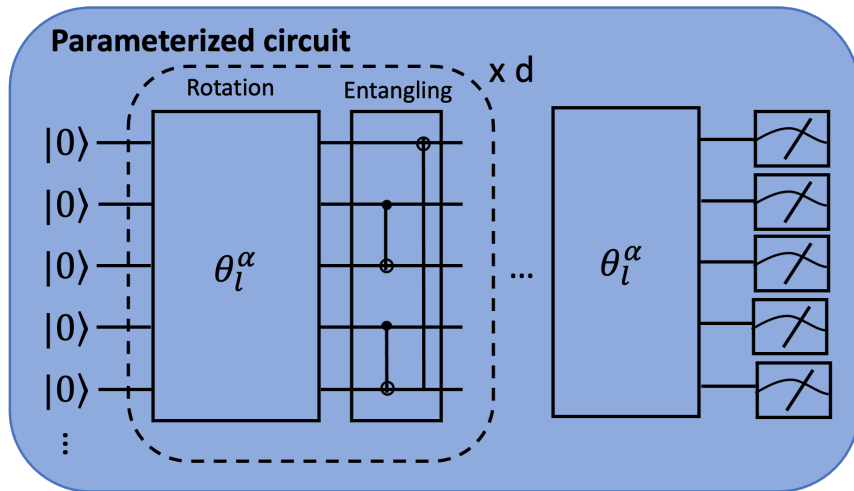


# Unsupervised Quantum Circuit Learning

The training consists of a hybrid workflow:

Initialize ansatz parameters  
(angles of rotation gates)

Run the quantum  
circuit with  $m$  shots



Measure

Update the angles by  
using a gradient-based  
classical optimizer  
(Adam ( $lr = 0.01$ ))

Parameter  
Update

Classical  
Optimization

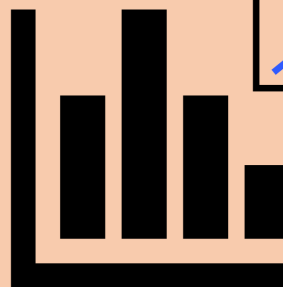
Gradient

Sampled Distribution



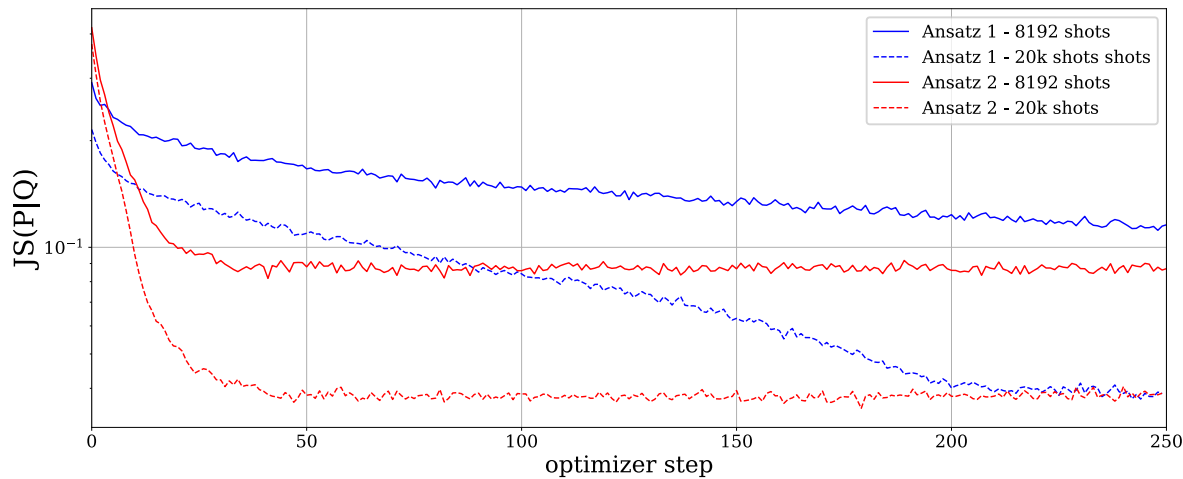
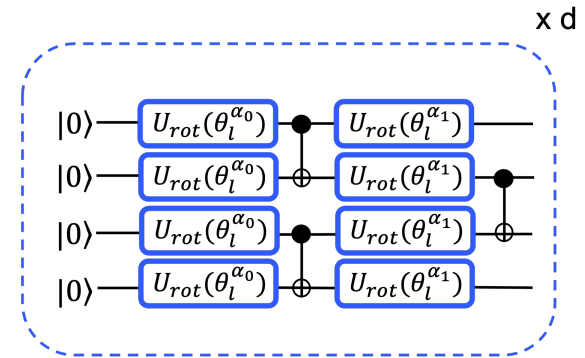
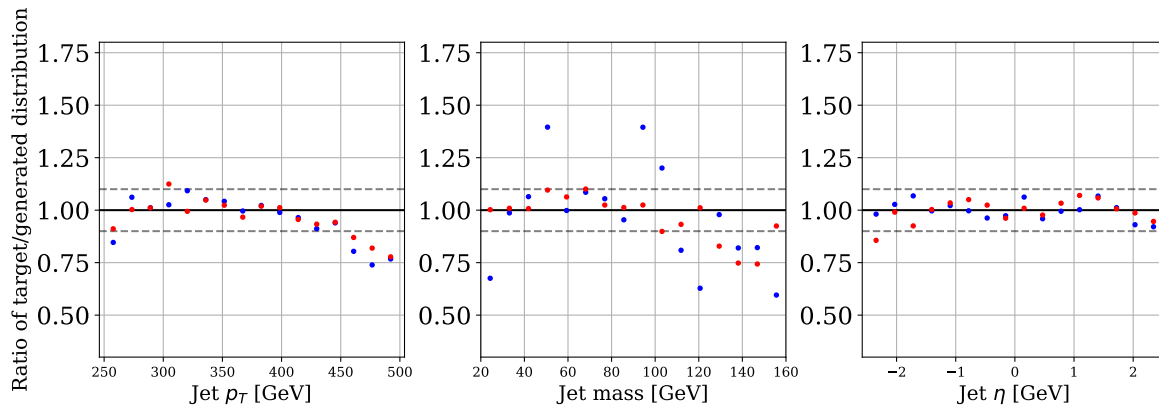
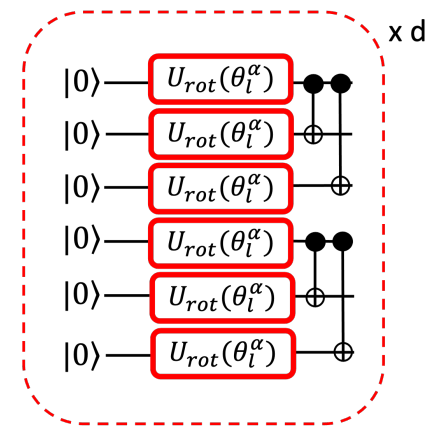
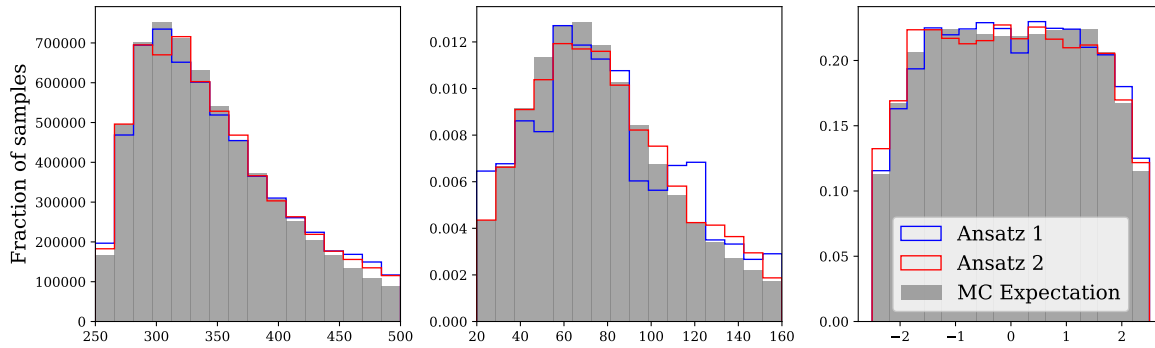
Calculate the  
Jensen-Shannon  
divergence  
between the  
sampled and  
target distribution

Target: High-Energy  
Physics Simulation



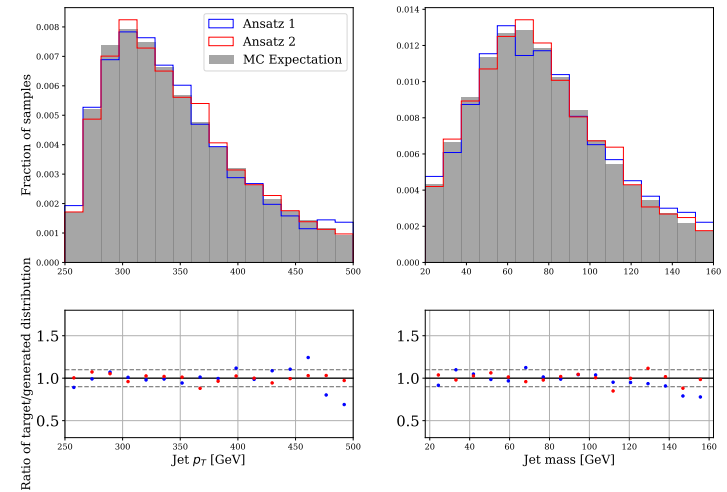
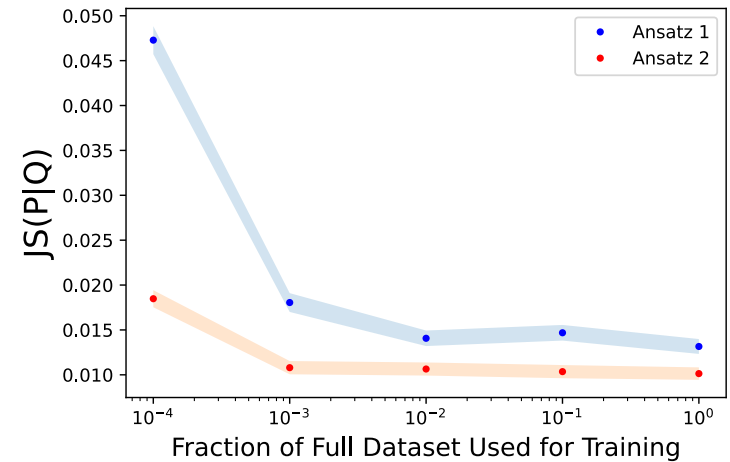
Loss Function Evaluation

# Results for 3D Joint Distributions



# Summary

- This work is the first demonstration of a large-scale generative model that was successfully trained and deployed in hardware!
- There are still many things we don't fully understand.
- As an HEP application, it is a promising alternative to MC-based methods.



# Thank you!