Style-based quantum generative adversarial networks for Monte Carlo events

C. Bravo-Prieto, J. Baglio, M. C‘e, A. Francis, D. M. Grabowska and S. Carrazza - Quantum 6, 777 (2022)

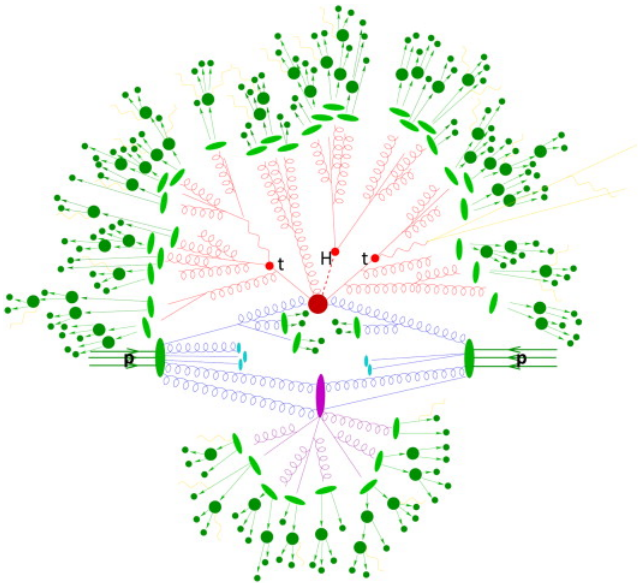
Andrea Pasquale on the behalf of Stefano Carrazza

13th October 2022

Outline

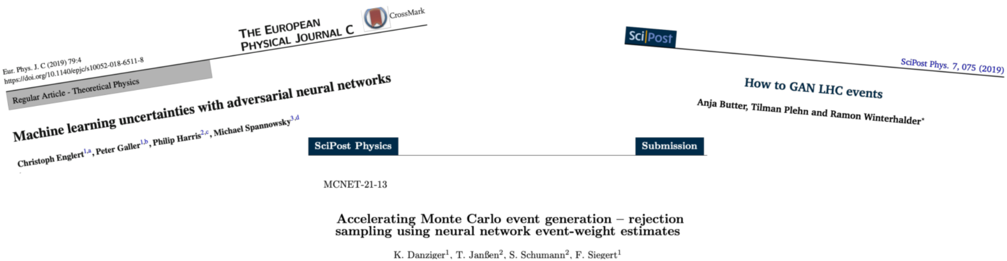
Problem: event generation at LHC

Monte Carlo event simulation is **very intensive** and requires lots of **computational power**.



Machine learning approach to event generation

Since 2018, many papers have approached event generation with machine learning techniques:



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Regular Article - Theoretical Physics

Machine learning uncertainties with adversarial neural networks

Christoph Englert[1,a], Peter Galler[1,b], Philip Harris[2,c], Michael Spannowsky[3,d]

SciPost Physics | Submission

MCNET-21-13

Accelerating Monte Carlo event generation – rejection sampling using neural network event-weight estimates

K. Danziger[1], T. Janßen[2], S. Schumann[2], F. Siegert[1]

SciPost

SciPost Phys. 7, 075 (2019)

How to GAN LHC events

Anja Butter, Tilman Plehn and Ramon Winterhalder*

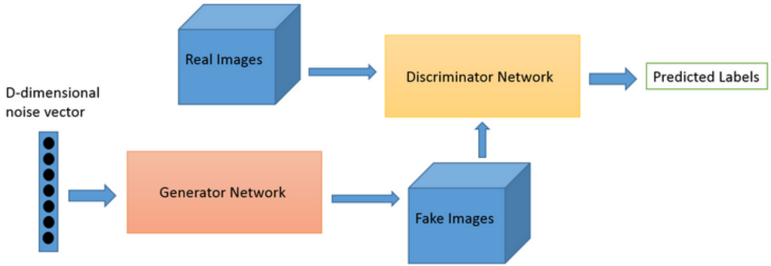
General approach:

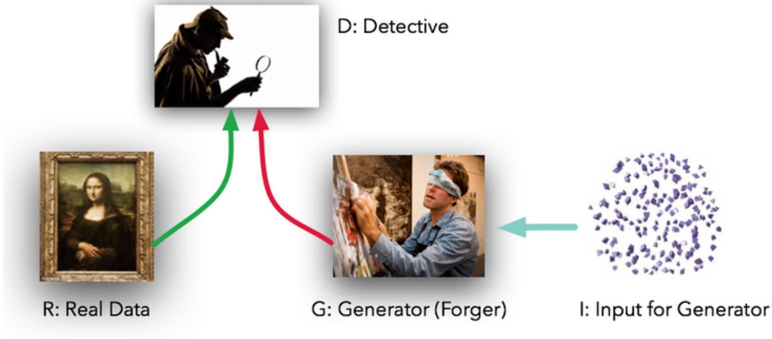
1. Train unsupervised models on **small** dataset to learn underlying pdf
2. Generate **more data** using those models $\Rightarrow$ data augmentation

Methodology

Unsupervised Learning: Generative Adversarial Networks

Two networks competing: generator produces **fake** data, while the discriminator distinguishes between **real** input data and fake data (produced by the generator).





Training: adapt alternatively the generator $G(\phi_g, z)$ and the discriminator $D(\phi_d, x)$
Metrics: binary cross-entropy for the loss functions:

- Generator loss function:

$$\mathcal{L}_G(\phi_g, \phi_d) = -\mathbb{E}_{z \sim p_{\text{prior}}(z)}[\log D(\phi_d, G(\phi_g, z))]$$

- Discriminator loss function:

$$\mathcal{L}_D(\phi_g, \phi_d) = \mathbb{E}_{x \sim p_{\text{real}}(x)}[\log D(\phi_d, x)] + \mathbb{E}_{z \sim p_{\text{prior}}(z)}[\log\big(1 - D(\phi_d, G(\phi_g, z))\big)] \,.$$

Game theory: min-max two-player game to reach Nash equilibrium

$$\min_{\phi_g} \mathcal{L}_G(\phi_g, \phi_d) \quad \max_{\phi_d} \mathcal{L}_D(\phi_g, \phi_d)$$

Machine learning with quantum computing?

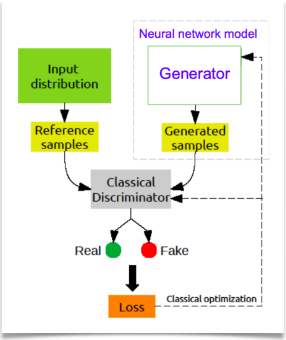
Can we develop an efficient GAN-like model for event generation using quantum hardware?

Why Quantum ML?

- Proof-of-concept, study new architectures.
    - fast inference (native representation / sampling)?
    - fast training / compact models with few parameters?
- Obtain a hardware representation (analogy with GPU and FPGA).
- Lower power consumption.

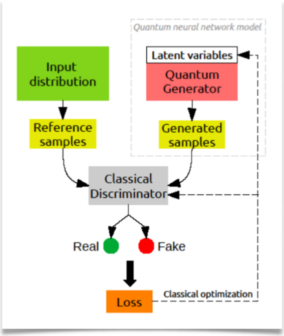
Hybrid approach

Classical setup:

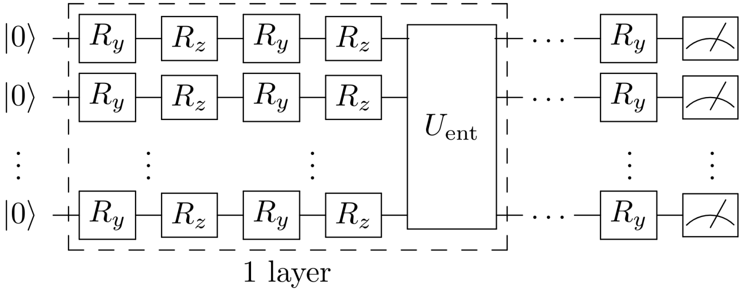


Only the generator becomes quantum

Hybrid quantum-classical setup:



Quantum generator: a series of quantum layers with rotation and entanglement gates



Style-based approach

The noise is inserted in every gate and not only in the initial quantum state

$$R^{l,m}_{y,z}(\vec{\phi}_g, \vec{z}) = R_{y,z}(\phi_g^{(l)} z^{(m)} + \phi_g^{(l-1)})$$

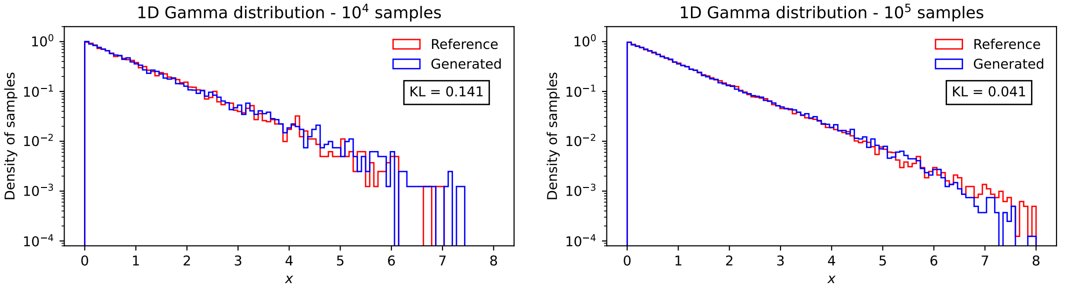
Results

Validation: 1D Gamma distribution

Assessing the validity of the approach: train and test on known toy model distribution

With 1 qubit, one layer, using 100 bins: 1D Gamma function

$$p_\gamma(x, \alpha, \beta) = x^{\alpha-1} \frac{e^{-x/\beta}}{\beta^\alpha \Gamma(\alpha)}$$



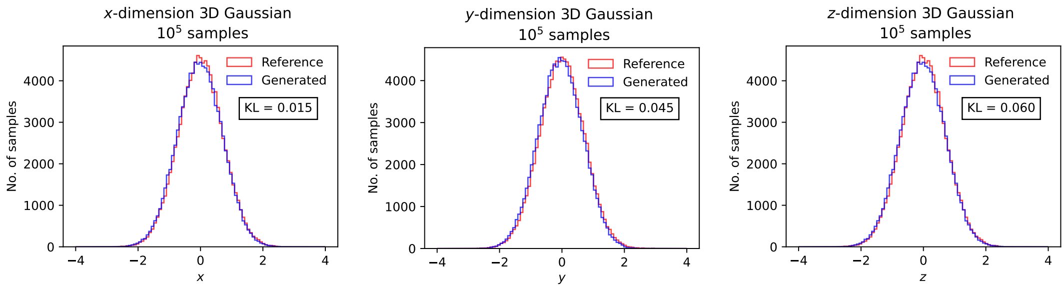
- Train on 10^4 samples until convergence is reached.
- Use generator to generate 10^4 and 10^5 samples to demonstrate data augmentation

Validation: 3D correlated Gaussian distribution

Test whether the style-qGAN captures correlations: train on 3D Gaussian distribution, with

$$p(\vec{x}) \propto \exp\left[-\frac{1}{2}(\vec{x}-\vec{\mu})^T \Sigma^{-1}(\vec{x}-\vec{\mu})\right], \quad \mu = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \quad \Sigma = \begin{pmatrix} 0.5 & 0.1 & 0.25 \\ 0.1 & 0.5 & 0.1 \\ 0.25 & 0.1 & 0.5 \end{pmatrix}.$$

Using 3 qubits, one layer, 100 bins:



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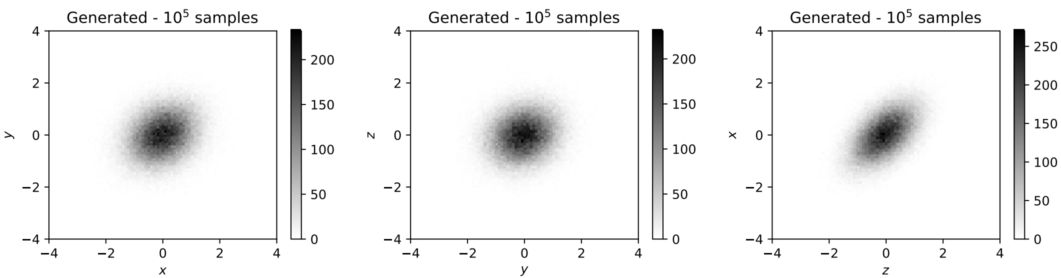

Correlations are well captured!

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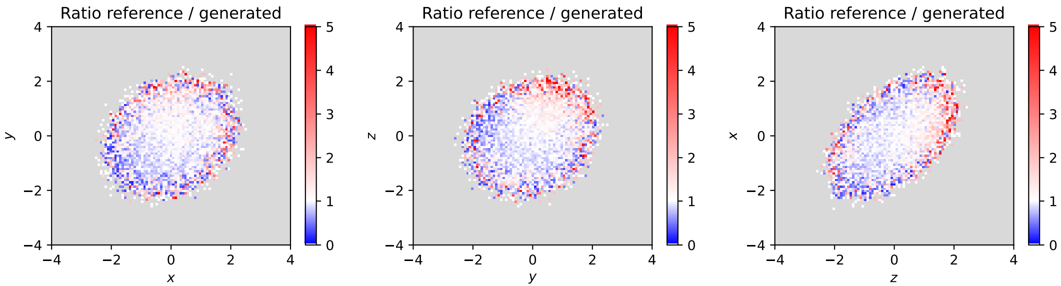
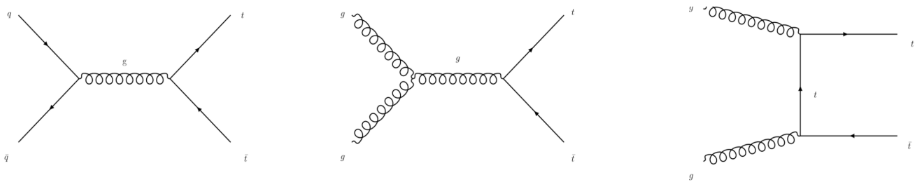


Correlations are well captured!

Testing the style-qGAN with real data: proton-proton collision $pp \to t\bar{t}$

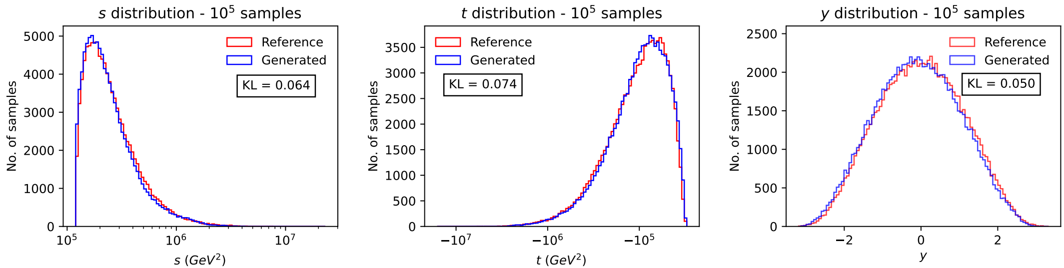


Training and reference samples generated with MadGraph5 aMC@NLO

Training set of 10^4 samples, **Mandelstam variables** (s, t) and rapidity y.

Simulation with LHC data

After training, we assess the performance with simulations: 3 qubits, 2 layers, 100 bins



Remarkable low KL divergences with data augmentation!

Simulation with LHC data

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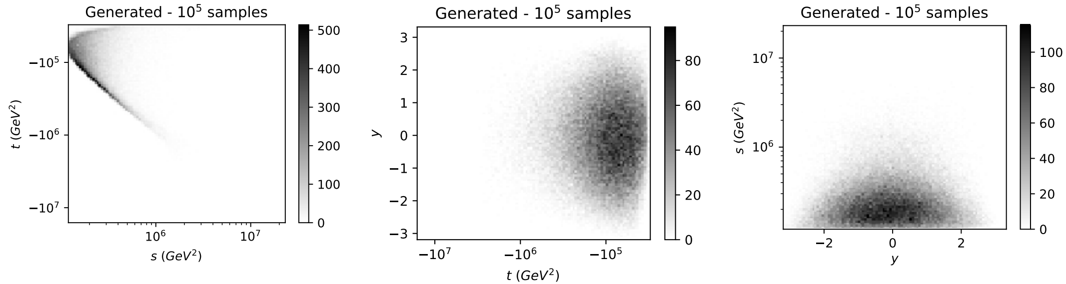

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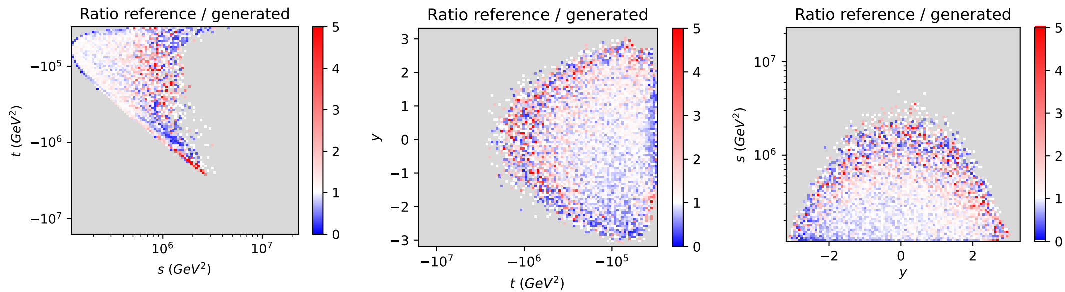
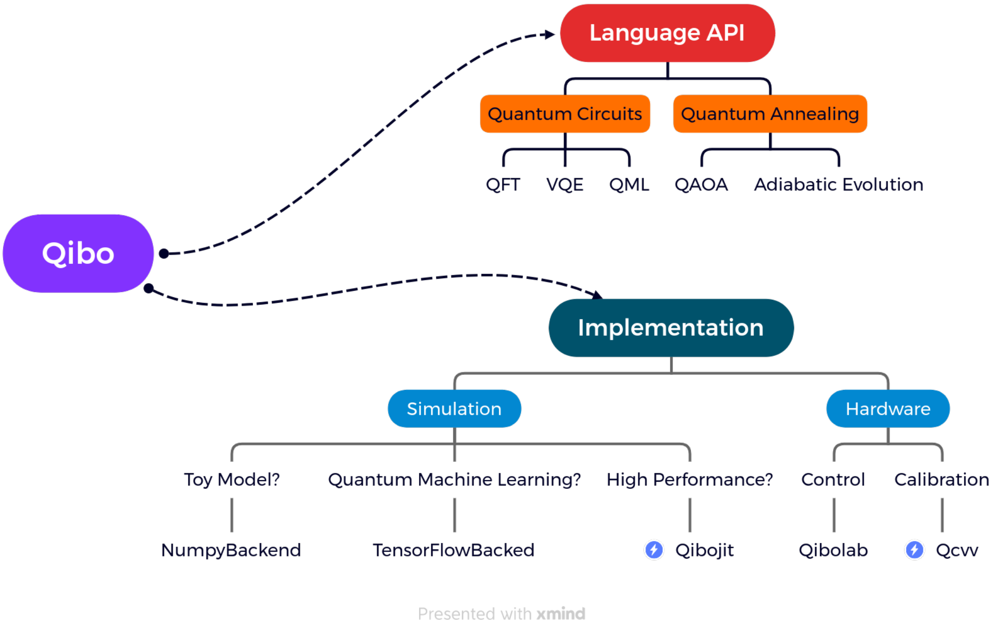
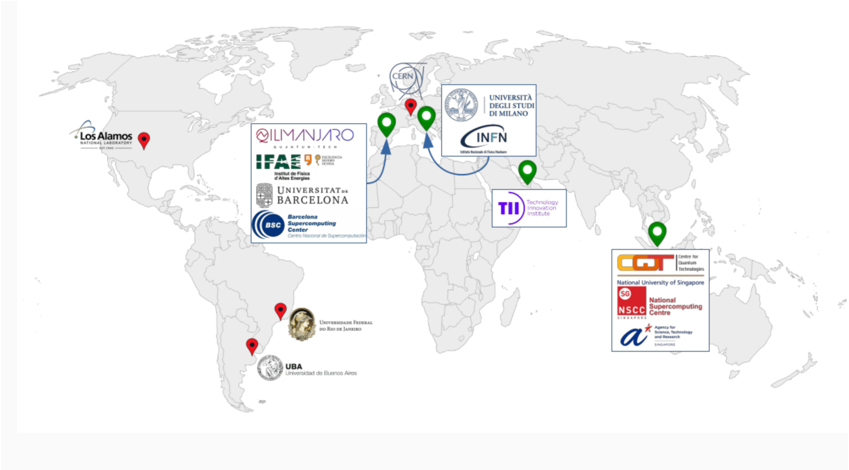


Are these results maintained on real hardware?

Qibo is an **open-source** full stack API for quantum simulation and quantum hardware control and calibration.



Qibo



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UBA
Universidad de Buenos Aires

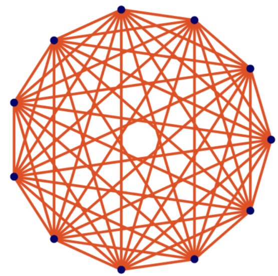
Result on Quantum Hardware

Testing different architectures

Superconducting transmon qubits: *ibmq_santiago* with 2-neighbouring site connectivity

Access via IBM Q cloud service

Trapped ion technology: *ionQ* with all-to-all connectivity

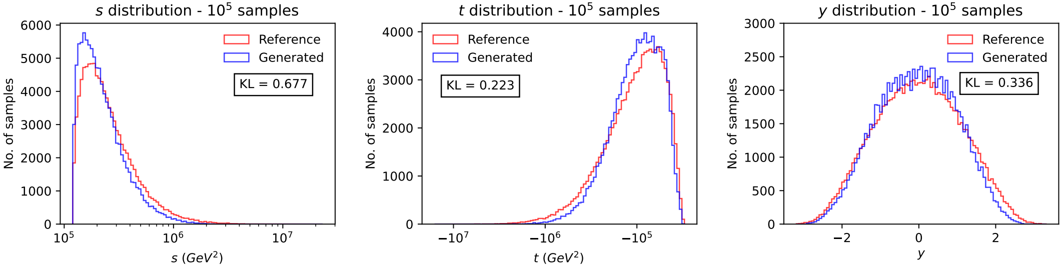


Access via Amazon Web Services

Results on IBM Q hardware

ibmq_santiago 5-qubit machine

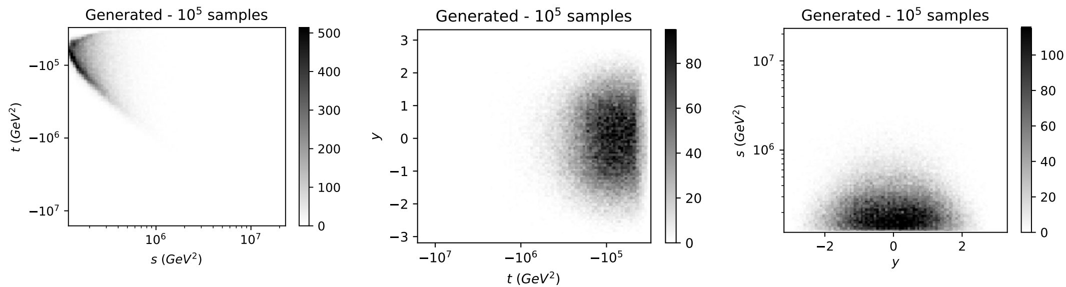
Still relatively low KL divergence!



Results on IBM Q hardware

ibmq_santiago 5-qubit machine

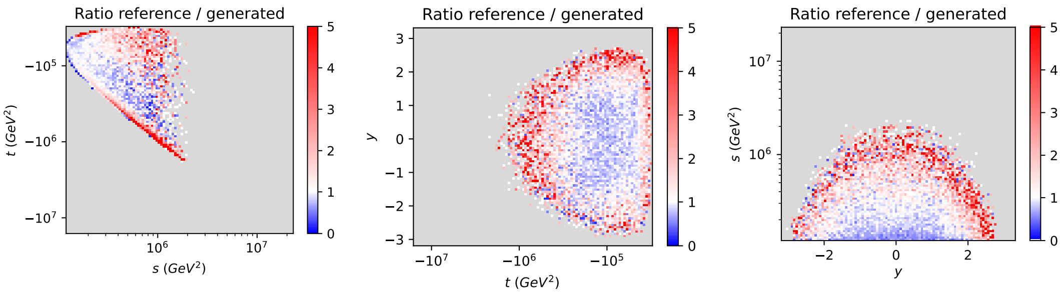
> Correlations captured on a quantum hardware!



Results on IBM Q hardware

ibmq_santiago 5-qubit machine

Still a good ratio!

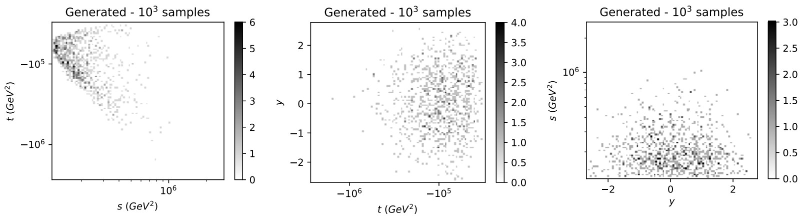


Testing different architectures

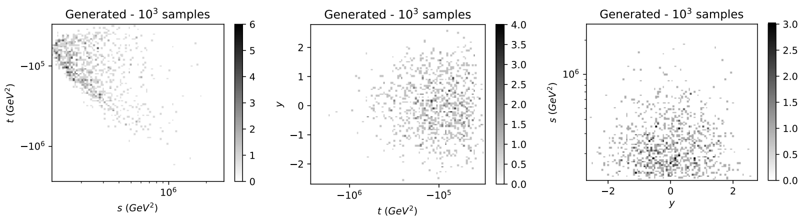
Access constraints to ionQ: test limited to 1000 samples only

> Hardware independent implementation!

IBM Q samples



ionQ samples



Outlook

Outlook

- A novel **quantum generator architecture** (style-based) has been presented.
- A test-case with real Monte Carlo event has demonstrated success: the generator has learned underlying (s, t, y) distributions and correlations for production.
- Demonstrated **data augmentation** from 10^4 training data to 10^5 generated data.
- The quantum network is **shallow**: great advantage in the current NISQ era.
- Tested on two different quantum architectures: superconducting qubits (IBM) and trapped ions (ionQ) with similar performances. The quantum generator seems quite hardware-independent.