Quantum Generative Adversarial Networks for $t\bar{t}H(b\bar{b})$ Process Data Generation

CERN openlab summer student Lightning talks

Togan Tlimakhov Yusuf * Andrei Voicu Tomut * Eraraya Ricardo Muten

Supervisor: Dr. Sofia Vallecorsa **Mentors:** Su Yeon Chang, Florian Rehm, Simon Schnake

07/09/2021

*presenter

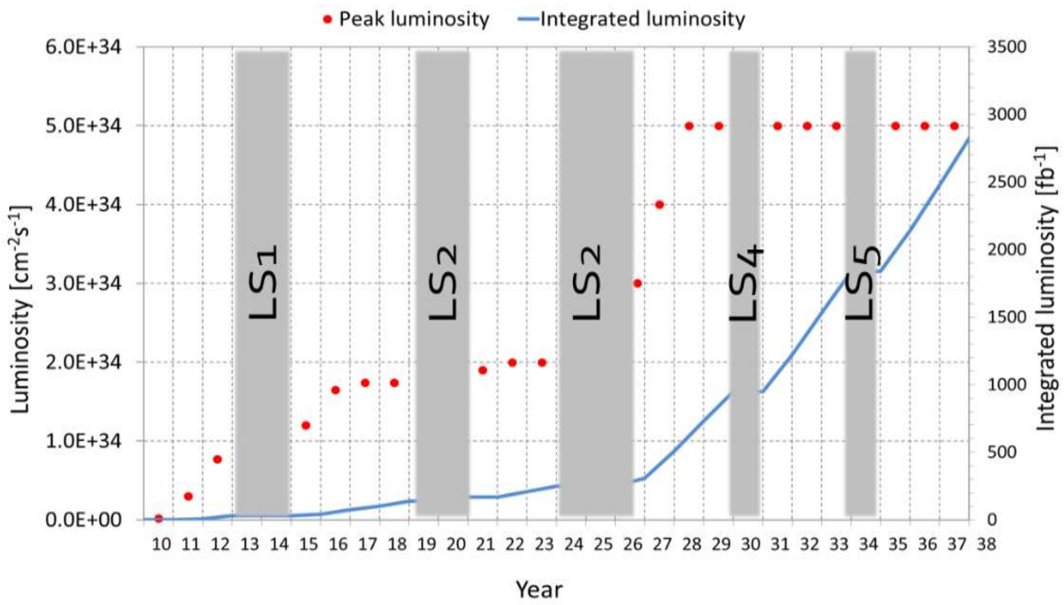
Outline

Introduction:	Background	Goals & Related Works
Dataset:	Dataset Introduction	A Closer Look Into the Dataset
Current Progress:	GAN	Classical Benchmark
Further Works:	CV Quantum Layer	CV-QGAN

Background

The upcoming HL-LHC upgrades at CERN will require ***enormous computing resources [1]***

- *Projected LHC performance through 2038 where the amount of data will increase at least 10x. More luminosity means more produced data [1]*



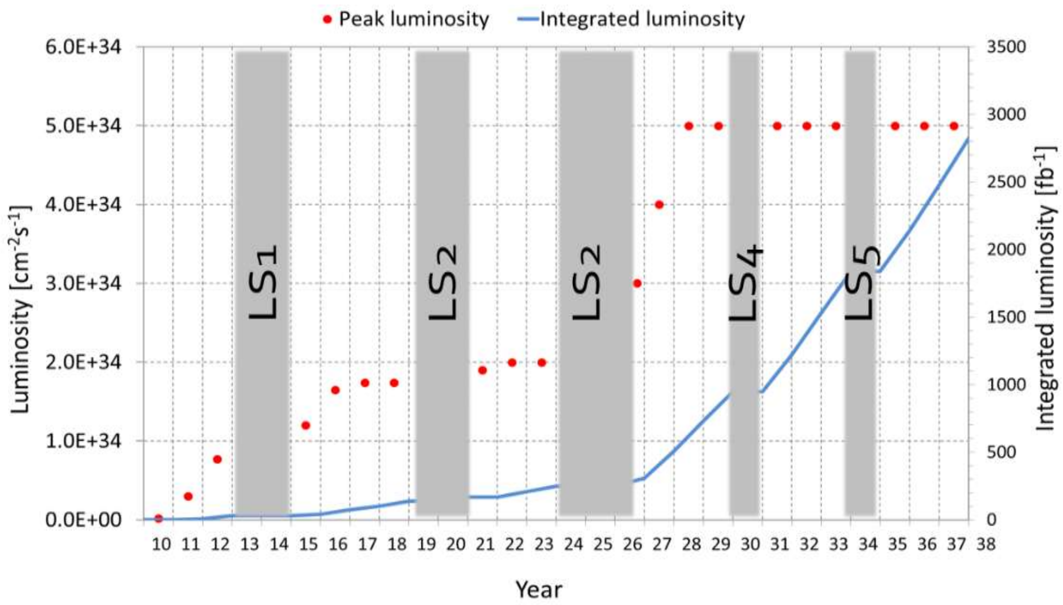
[1] Burkhard Schmidt 2016 J. Phys.: Conf. Ser. 706 022002.

Background

*The upcoming HL-LHC upgrades at CERN will require **enormous computing resources [1]***

- *Projected LHC performance through 2038 where the amount of data will increase at least 10x. More luminosity means more produced data [1]*

- *The conventional Monte Carlo based simulation required tremendous amount of time and computational resources [2]*



[1] Burkhard Schmidt 2016 J. Phys.: Conf. Ser. 706 022002.
[2] Apostolakis, J., et al. arxiv:1803.04165

CERN openlab

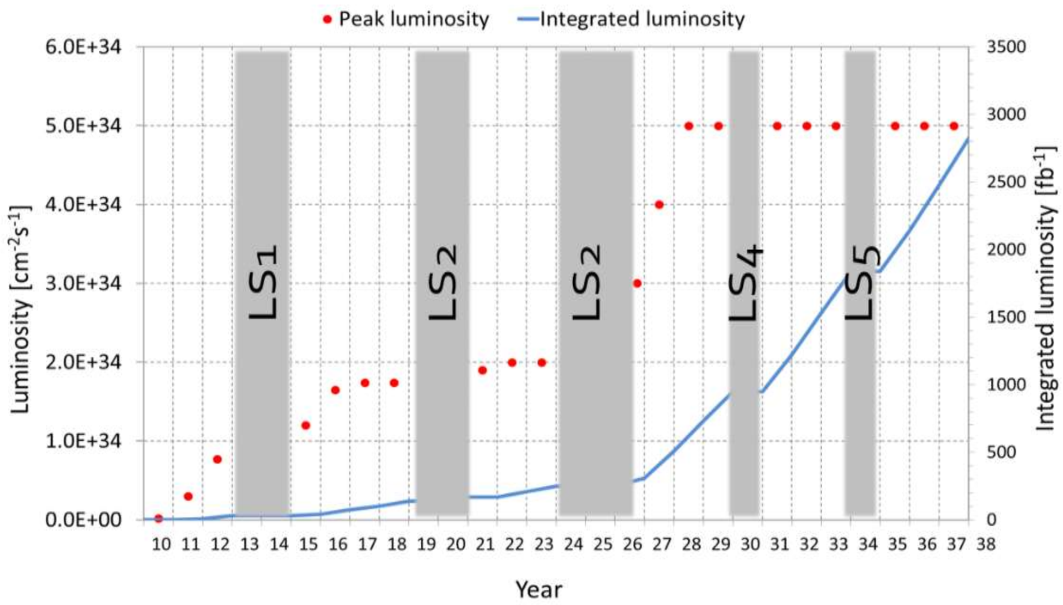
Background

The upcoming HL-LHC upgrades at CERN will require ***enormous computing resources [1]***

- *Projected LHC performance through 2038 where the amount of data will increase at least 10x. More luminosity means more produced data [1]*

- *The conventional Monte Carlo based simulation required tremendous amount of time and computational resources [2]*

✓ ***Deep Learning based generative models such as Generative Adversarial Networks present as solution***



[1] Burkhard Schmidt 2016 J. Phys.: Conf. Ser. 706 022002.
[2] Apostolakis, J., et al. arxiv:1803.04165

Goals & Related Works

The main project objectives and some related researches

- Explore the Generative Adversarial Networks and set a relatively good benchmark

CERN openlab

Goals & Related Works

The main project objectives and some related researches

- Explore the Generative Adversarial Networks and set a relatively good benchmark

- Explore the field of Quantum machine learning and particularly the different Quantum Generative Adversarial Networks (QGANs) models performance on high-energy physics data simulation

Goals & Related Works

The main project objectives and some related researches

- Explore the Generative Adversarial Networks and set a relatively good benchmark

- Explore the field of Quantum machine learning and particularly the different Quantum Generative Adversarial Networks (QGANs) models performance on high-energy physics data simulation

- Compare the classical and quantum model performances

Goals & Related Works

The main project objectives and some related researches

- Explore the Generative Adversarial Networks and set a relatively good benchmark
- Explore the field of Quantum machine learning and particularly the different Quantum Generative Adversarial Networks (QGANs) models performance on high-energy physics data simulation
- Compare the classical and quantum model performances

❖ Classical GAN to simulate LHC QCD Dijet events has been explored [3]

❖ Quantum Classifiers had been explored to classify the $t\bar{t}H(b\bar{b})$ dataset, with performance comparable to the classical counterparts (SVM, Random Forest, AdaBoost) [4]

❖ Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [5]

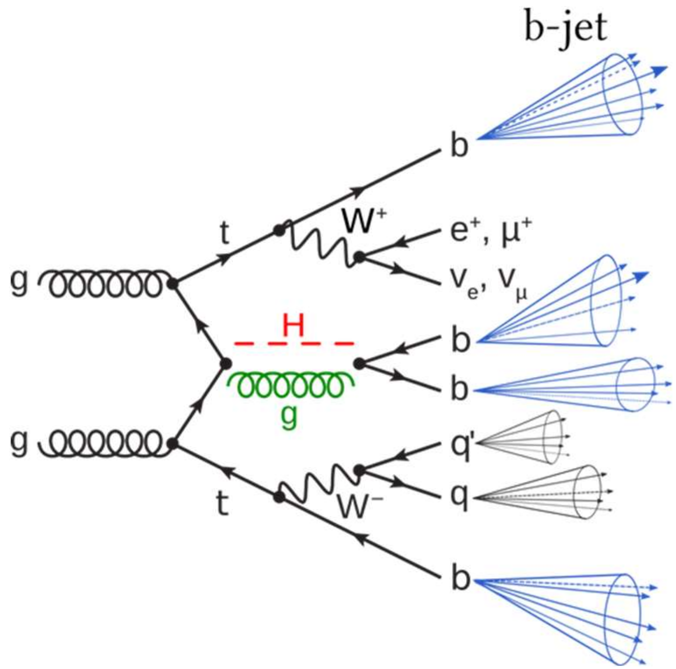
❖ Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [6]

[3] Di Sipio, R., et al. J. High Energ. Phys. 2019.
[4] Belis, V., et al. arXiv:2104.07692
[5] Chang, Su Yeon, et al. arXiv:2101.11132
[6] Chang, Su Yeon, et al. arXiv:2103.15470

Dataset Introduction

Feynman diagram of the signal process in red and the dominant background process in green

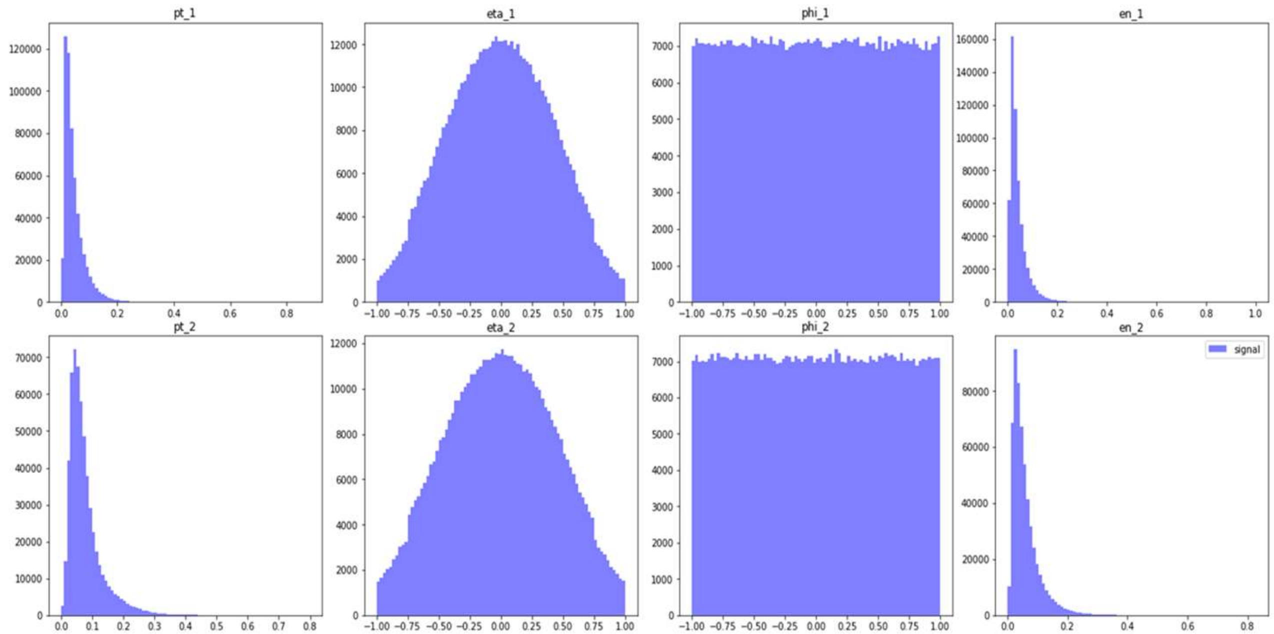
- Higgs Boson is produced in association with $t\bar{t}$ via gluon fusion and it decays to $b\bar{b}$
- We focused only on the simulation of two b-jets from the Higgs
- We also focused on simulating the Higgs event only, and not the background (gluon)



A Closer look into the Dataset

The presented dataset is from numerical Monte Carlo simulations

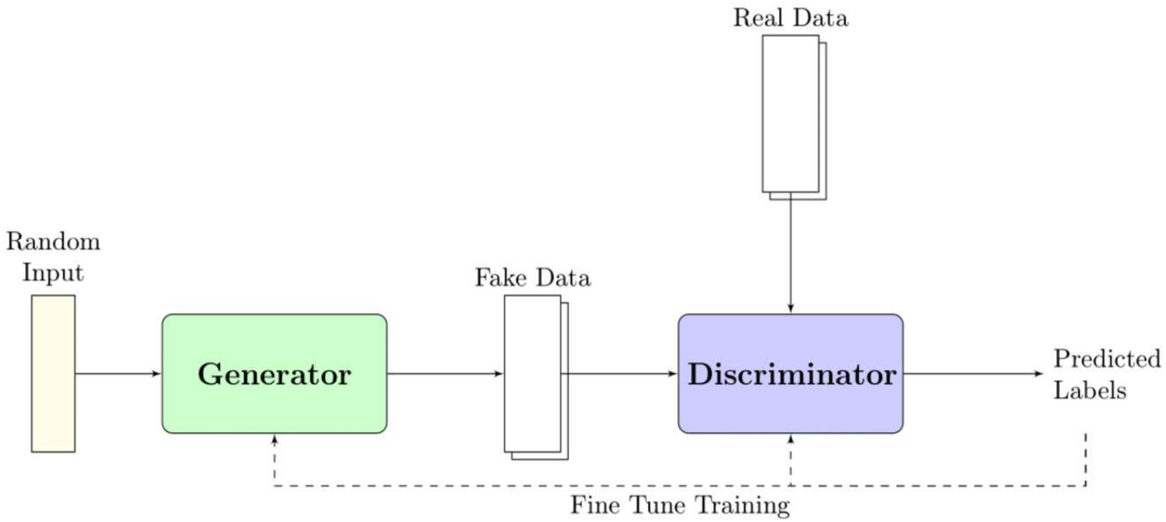
- We limit the problem to only 4 features for each b-jet (from 8)
- Normalized into either [-1, 1] or [0, 1] range
- The features that we select are:
  - Pt: Transverse momentum
  - η: Pseudo-rapidity
  - ϕ: Azimuthal angle
  - E : Energy



Generative Adversarial Networks

GANs consists of two networks, a Generator and a Discriminator competing with each other

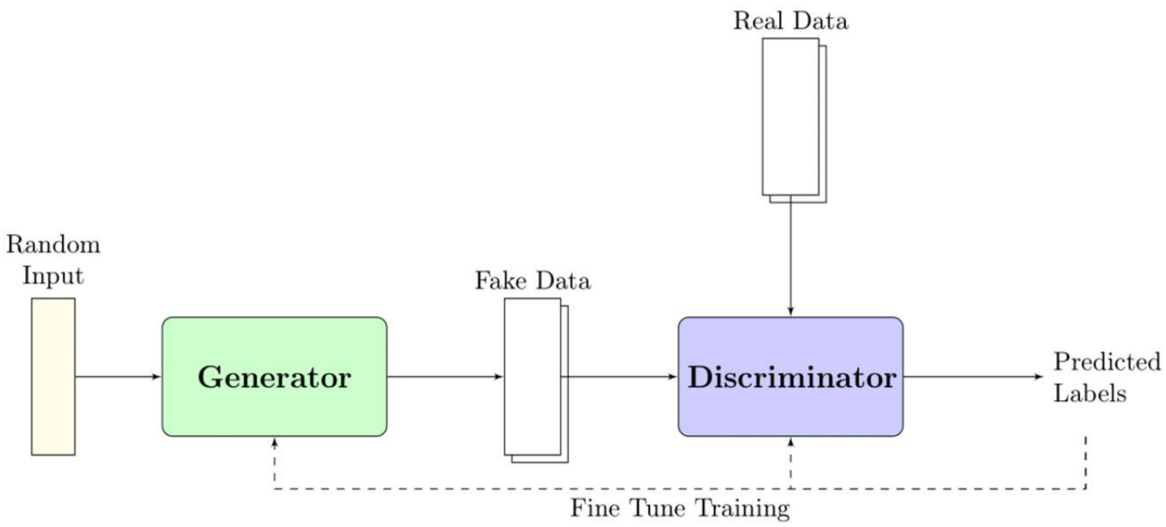
- The generative model G captures the data distribution, and the discriminative model D estimates the probability that a sample came from the training data rather than G



Generative Adversarial Networks

GANs consists of two networks, a Generator and a Discriminator competing with each other

- The generative model G captures the data distribution, and the discriminative model D estimates the probability that a sample came from the training data rather than G
- The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game [7]



[7] I. J. Goodfellow, et al., "Generative adversarial nets"

Generative Adversarial Networks

The Discriminator: *A classifier with has two classes, real and fake. Given an input x, the discriminator calculates the probabilities* p(y=real|x) and p(y=fake|x) *and classify x*

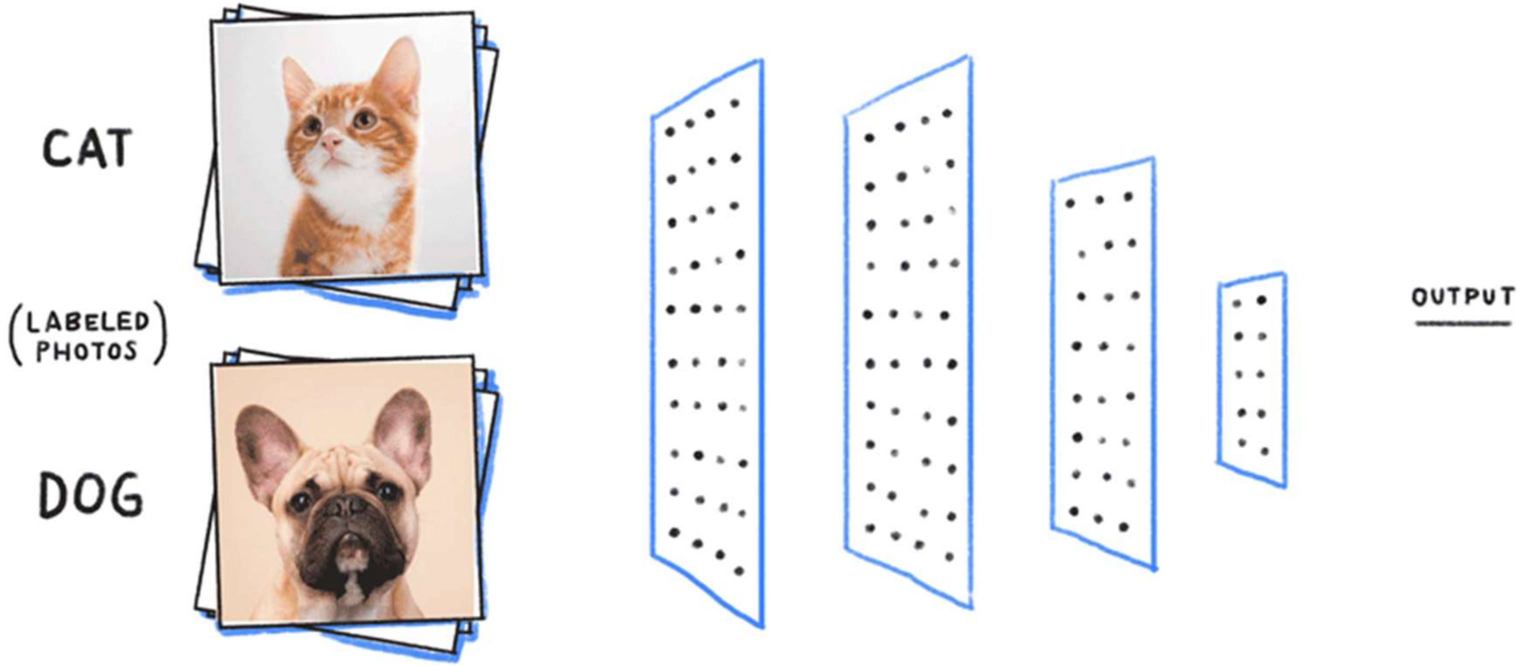


Image Credit: Google ML

CERN openlab

Generative Adversarial Networks

The Generator: *Using the feedback from the Discriminator, it tries to find all the features that represent the original input, p(x|y), which is much harder task than discrimination*

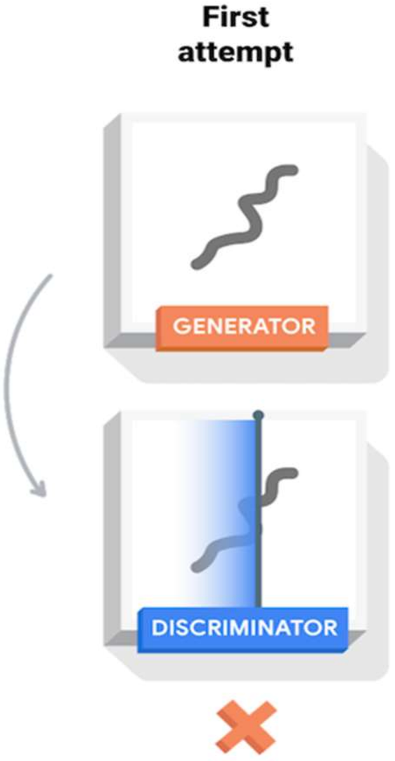


Image Credit: TensorFlow

Generative Adversarial Networks

The Generator: *Using the feedback from the Discriminator, it tries to find all the features that represent the original input, p(x|y), which is much harder task than discrimination*

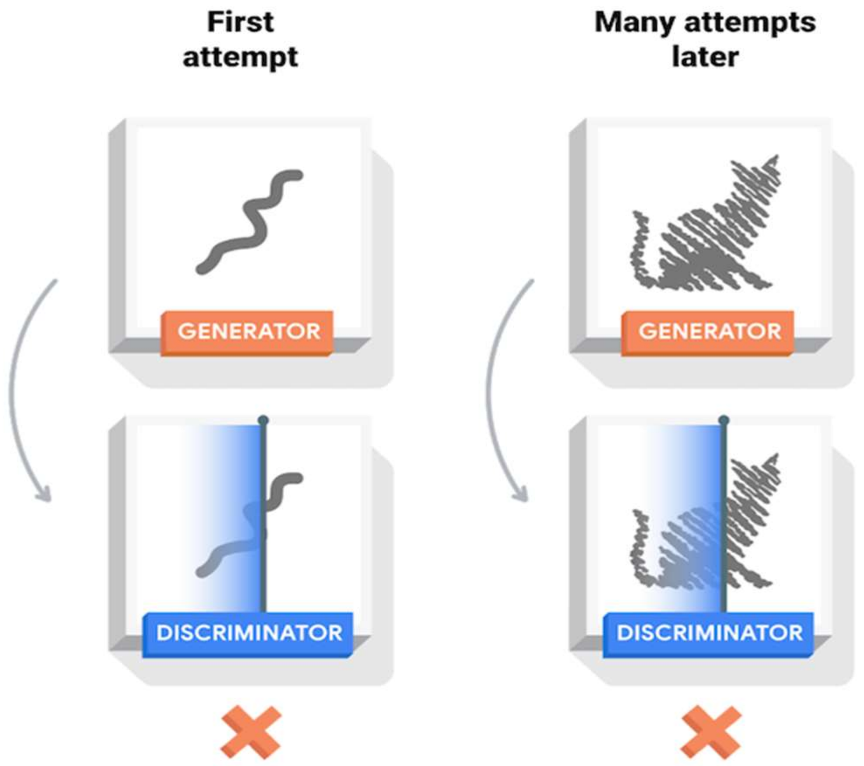


Image Credit: TensorFlow

Generative Adversarial Networks

The Generator: *Using the feedback from the Discriminator, it tries to find all the features that represent the original input, p(x|y), which is much harder task than discrimination*

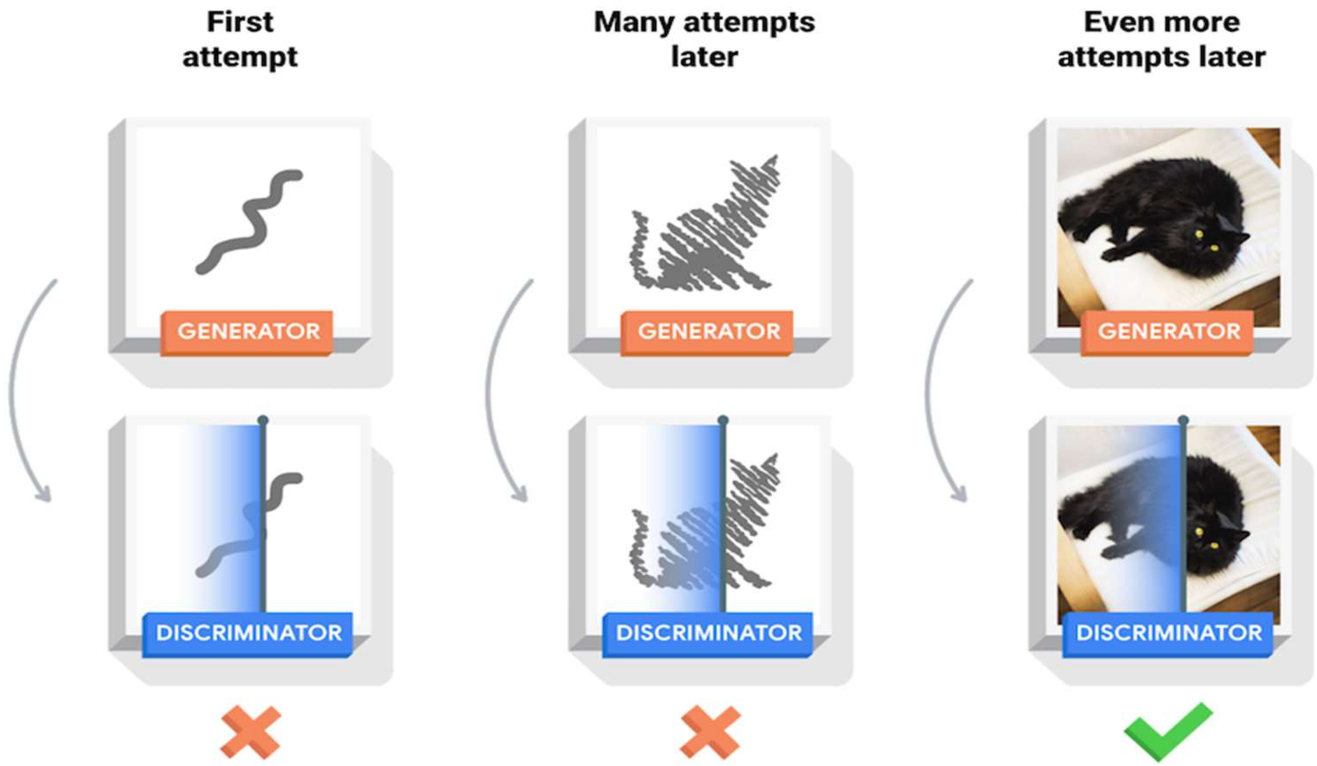
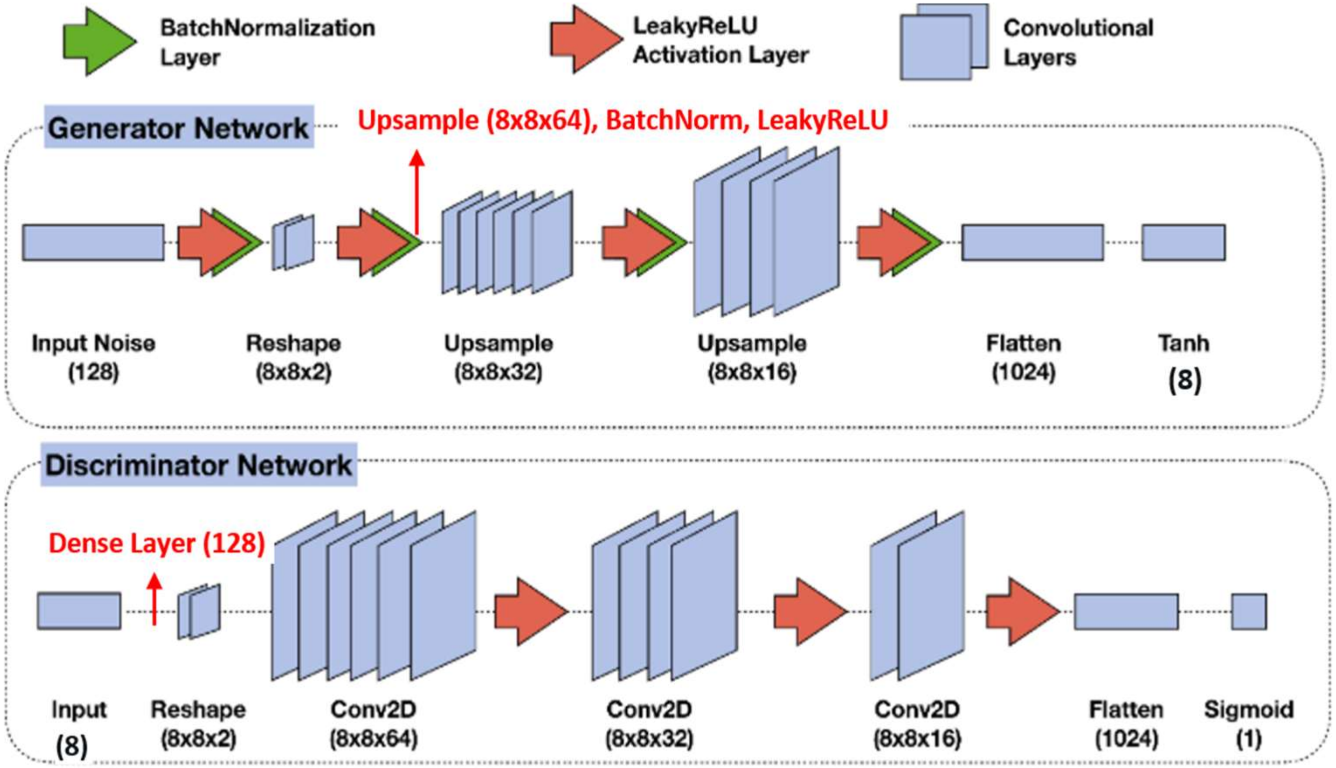


Image Credit: TensorFlow

Classical benchmark

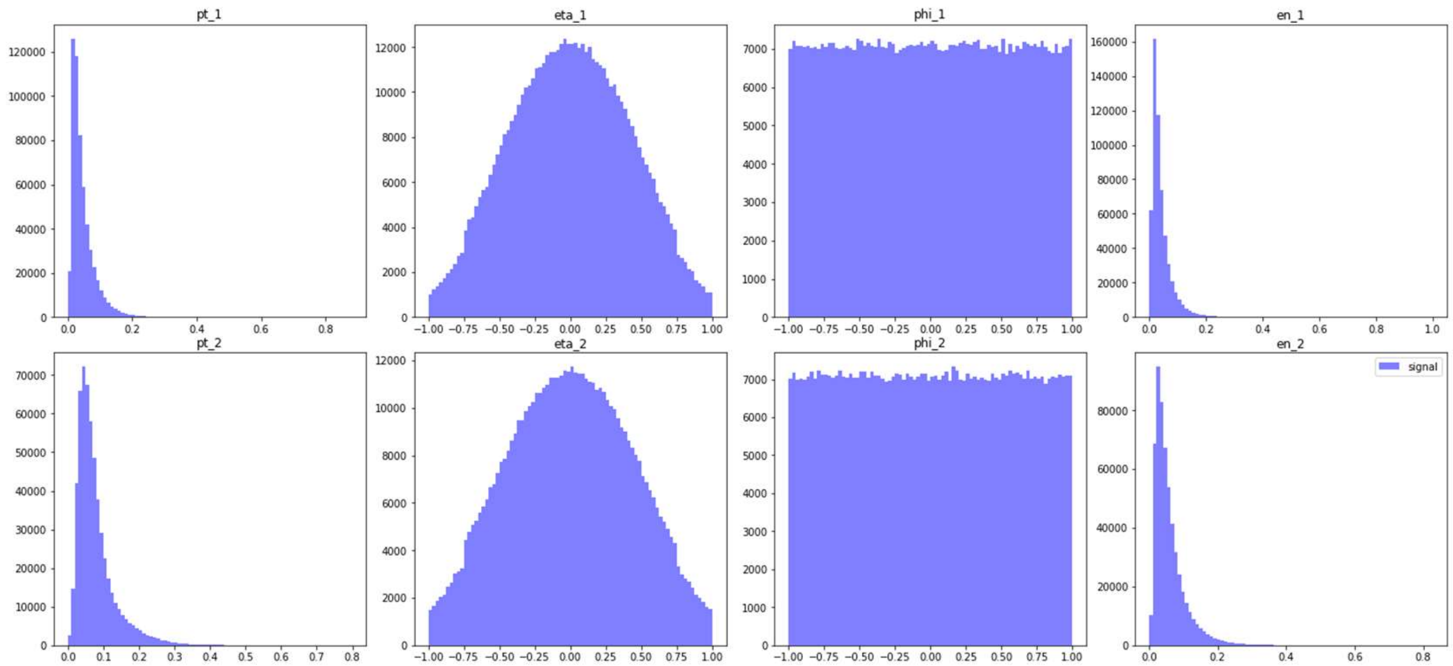
(Modified) DijetGAN: A GAN based on convolutional neural networks used to simulate the production of pairs of jets at the LHC [3]



[3] Di Sipio, R., et al. J. High Energ. Phys. 2019.

Classical benchmark

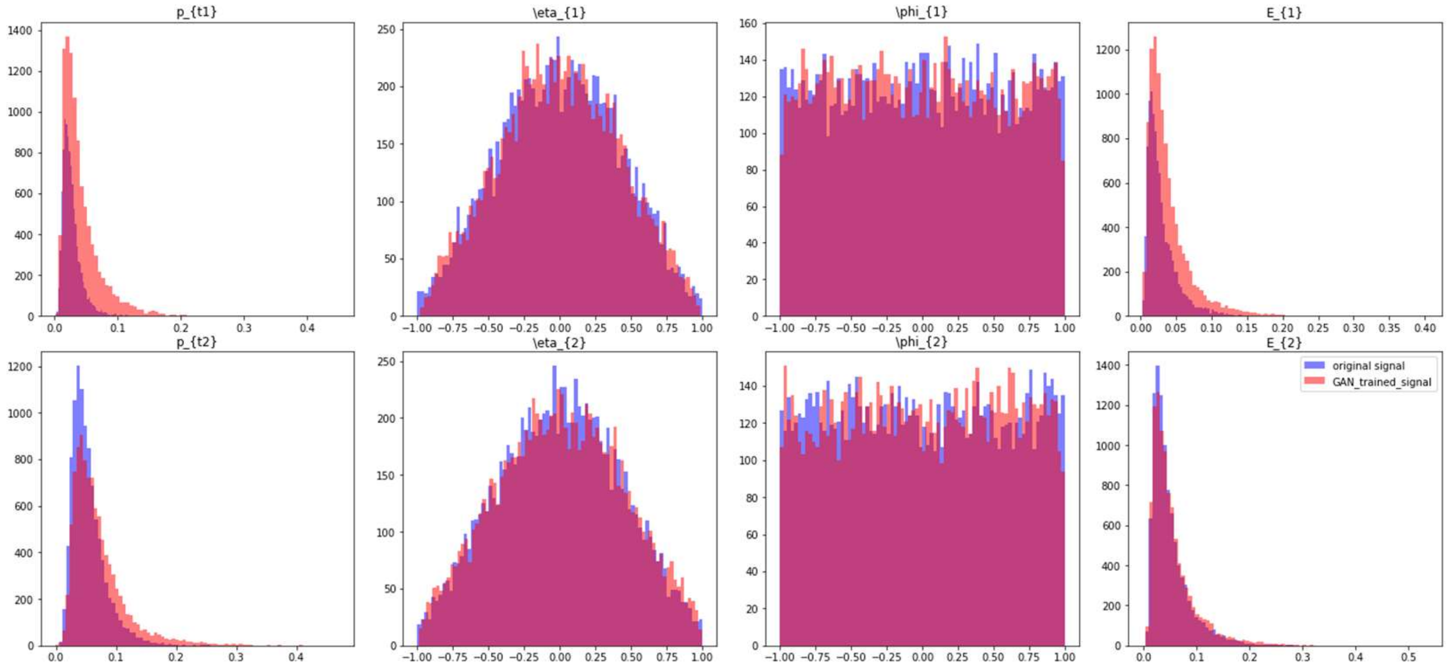
The original signals



Classical benchmark

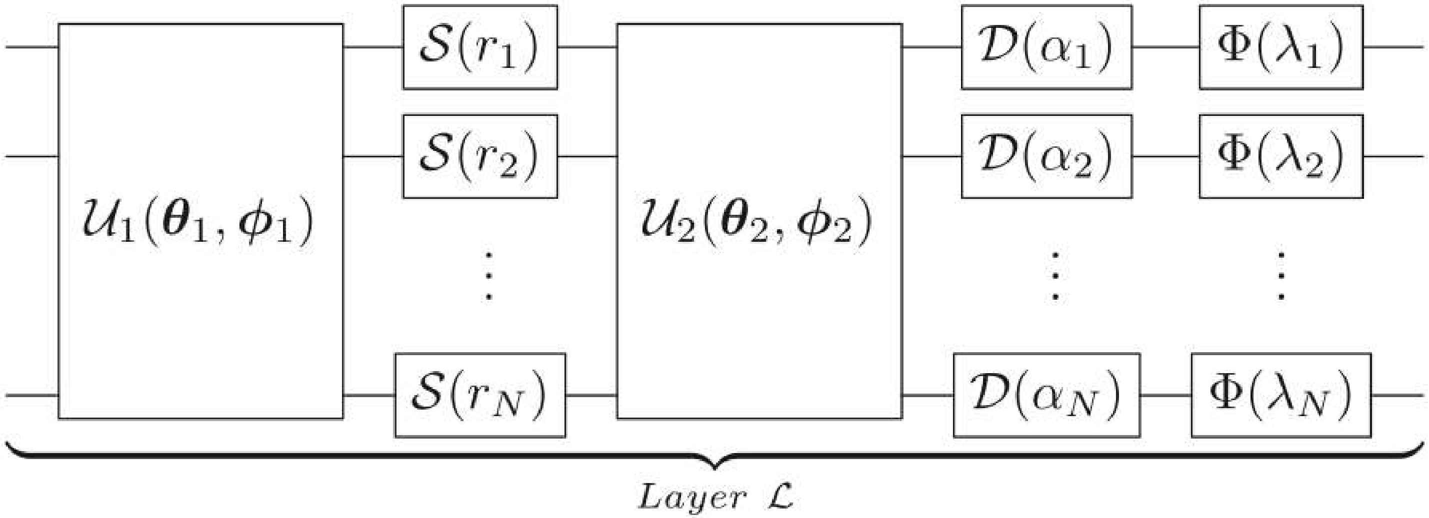
The generated signals: Best result (so far)

- Filter size for Conv2D and Upsample: 3x3, with stride 1x1
- Cross-entropy loss
- Adam with lr=10^(−5), β_1=0.5, β_2=0.9
- **Wasserstein distance: 0.0271705**



CV Quantum Layer

Quantum Circuit [8]



[8] 10.1103/PhysRevResearch.1.033063

Continuous-Variable QGAN

Continuous-Variable Gates

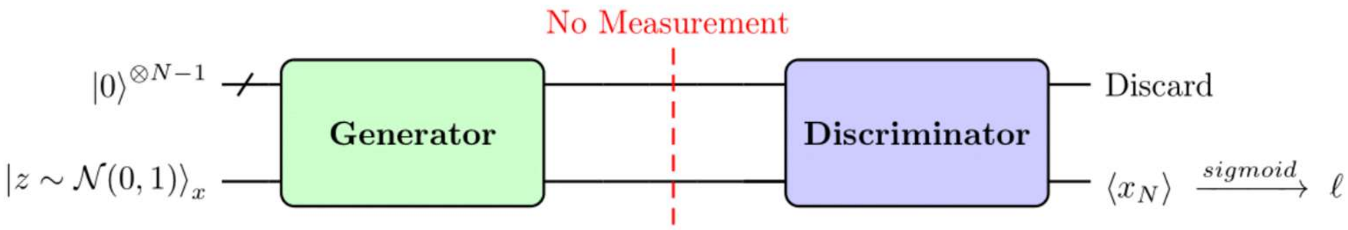
Squeezing gate

- $S(r) : \begin{pmatrix} x \\ p \end{pmatrix} = \begin{pmatrix} e^{-r} & 0 \\ 0 & e^{r} \end{pmatrix} \begin{pmatrix} x \\ p \end{pmatrix}$

Displacement gate

- $D(\alpha) : \begin{pmatrix} x \\ p \end{pmatrix} = \begin{pmatrix} x + \sqrt{2}Re(\alpha) \\ p + \sqrt{2}Im(\alpha) \end{pmatrix}$

Fully Quantum model :
Quantum Generator &
Quantum Discriminator [5]



[5] Chang, Su Yeon, et al. arXiv:2101.11132

Thank you!
Any Questions?

togan.tlimakhov@cern.ch

andrei-voicu.tomut@cern.ch

eraraya.ricardo.muten@cern.ch