GAN based MC event generators

Nobuo Sato

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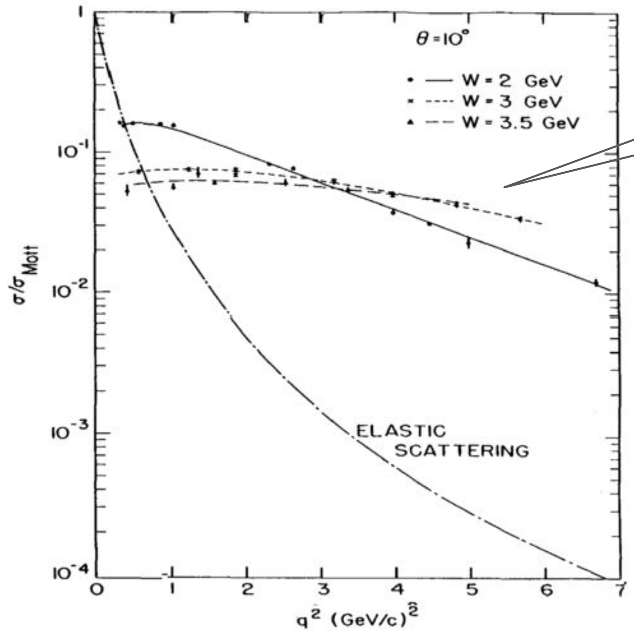
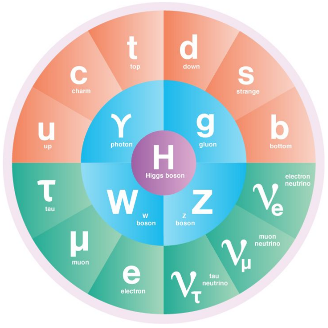
Seminar at department at Pedagogical University of Krakow - Apr 2021

Jefferson Lab

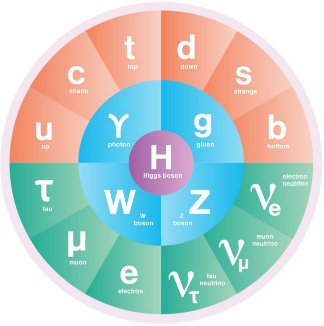


Discovery of point-like particles inside proton



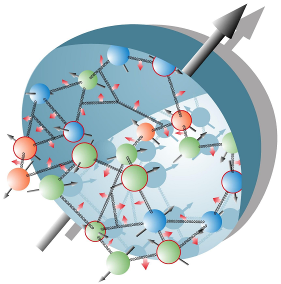
Motivations

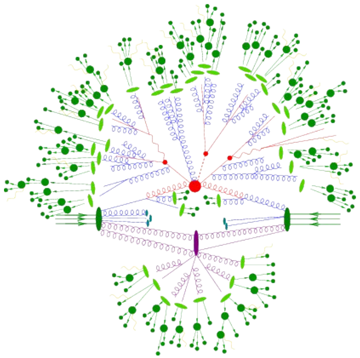
Understanding the **emergent phenomena** of QCD



parts

"In philosophy, systems theory, science, and art, emergence occurs when an ***entity is observed*** *to have properties* ***its parts*** *do not have on their own, properties or behaviors which emerge only when the parts interact in a wider whole."* Wiki





Observed entity

Hadron Structure

Hadron formation

What do we mean by "**hadron structure**" ? (1D)

$$\xi = \frac{k^+}{P^+}$$

Parton momentum fraction relative to **parent hadron**

$$f_i(\xi) = \int \frac{\mathrm{d}w^-}{4\pi} e^{-i\xi p^+ w^-} \boxed{\langle N|\bar{\psi}_i(0, w^-, \mathbf{0}_\mathrm{T})\gamma^+\psi_i(0)|N\rangle}$$

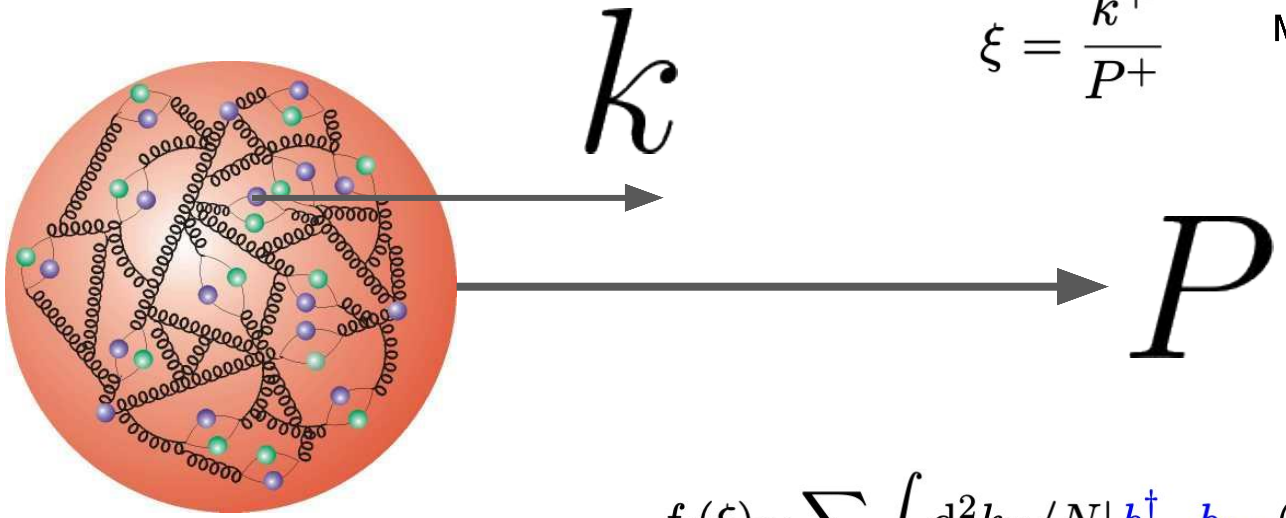
parton distribution function (PDF)

Interpretation in non-interacting QCD

$$\psi_i(x) = \sum_{k,\alpha} b_{k,\alpha}(x^+) u_{k,\alpha} e^{-ik^+x^- + ik_\mathrm{T}\cdot x_\mathrm{T}} + d^\dagger_{k,\alpha}(x^+) u_{k,-\alpha} e^{ik^+x^- - ik_\mathrm{T}\cdot x_\mathrm{T}}$$

$$f_i(\xi) \sim \sum_\alpha \int \mathrm{d}^2 k_\mathrm{T} \, \langle N| \underbrace{b^\dagger_{k,\alpha} b_{k,\alpha}(\xi p^+, k_\mathrm{T}, \alpha)}_{\text{number operator}} |N\rangle$$

How quarks and gluons are distributed?



$$\xi = \frac{k^+}{P^+}$$

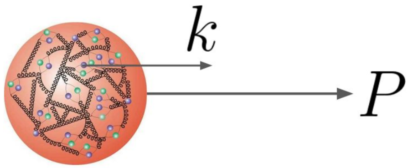
Momentum fraction

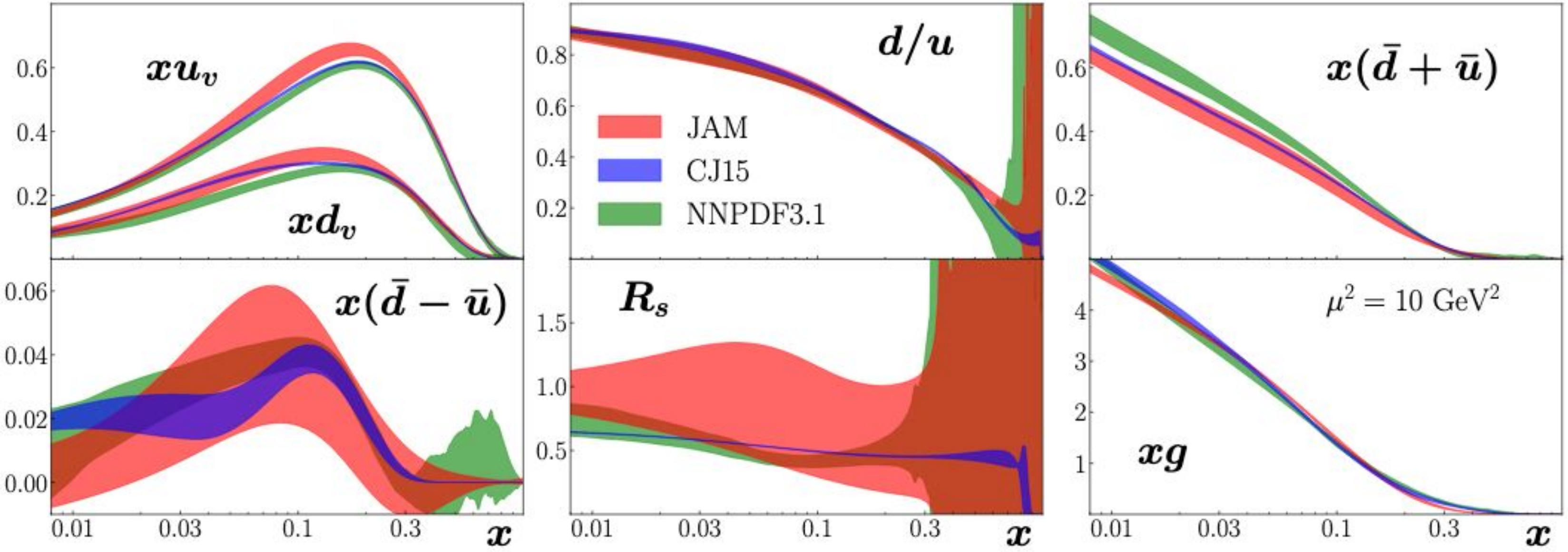
$$f_i(\xi) \sim \sum_{\alpha} \int \mathrm{d}^2 k_{\mathrm{T}} \, \langle N | \underbrace{b^{\dagger}_{k,\alpha} b_{k,\alpha}(\xi p^+, k_{\mathrm{T}}, \alpha)}_{\text{number operator}} | N \rangle$$

An example: JAM20-SIDIS

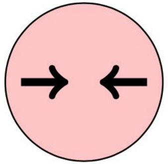
Moffat, Melnitchouk, Rogers, NS
arXiv:2101.04664

PDFs



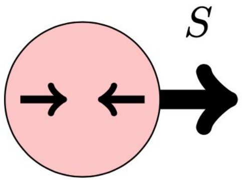


Spin structures



$$f = f_{\rightarrow} + f_{\leftarrow}$$

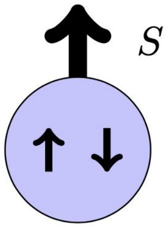
$$\langle N|\bar{\psi}_i(0, w^-, \mathbf{0}_\mathrm{T})\gamma^+\psi_i(0)|N\rangle$$



$$\Delta f = f_{\rightarrow} - f_{\leftarrow}$$

Helicity distribution

$$\langle N|\bar{\psi}_i(0, w^-, \mathbf{0}_\mathrm{T})\gamma^+\gamma_5\psi_i(0)|N\rangle$$

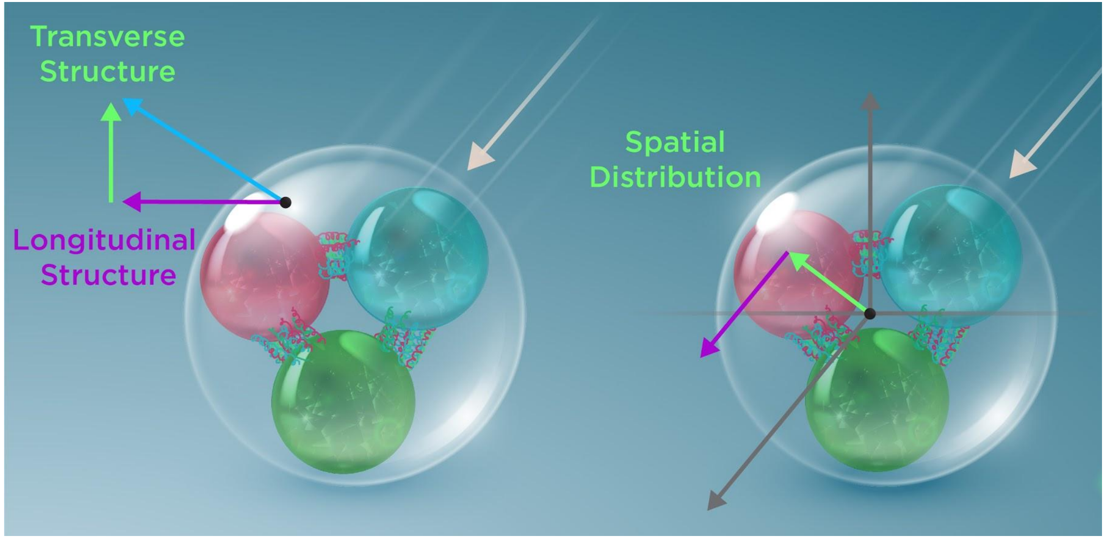


$$\delta_\mathrm{T} f = f_{\uparrow} - f_{\downarrow}$$

Transversity

$$\langle N|\bar{\psi}_i(0, w^-, \mathbf{0}_\mathrm{T})\gamma^+\gamma_\perp\gamma_5\psi_i(0)|N\rangle$$

Extensions to 3D



$$f(\xi)$$

PDFs

$$f(\xi, k_T)$$

Transverse momentum distribution -> TMDs

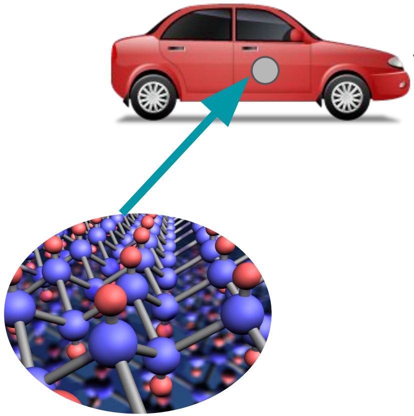
$$f(\xi, b_T)$$

Impact parameter distribution -> GPDs

So how do we get hadron structure from experimental data?

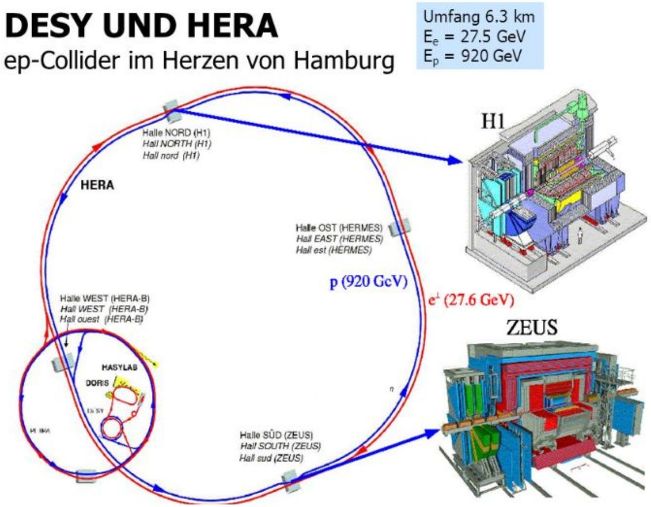
What part of this is the "internal structure"?

Want to see
internal structure



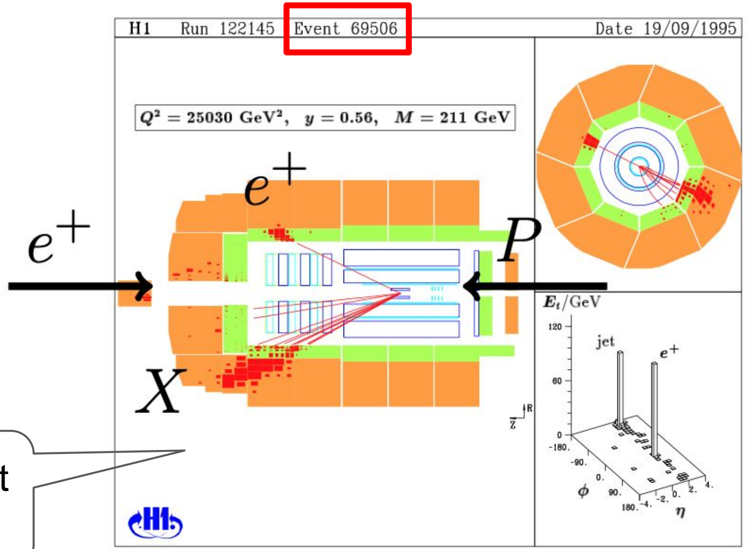
But we only see debris

A scattering event



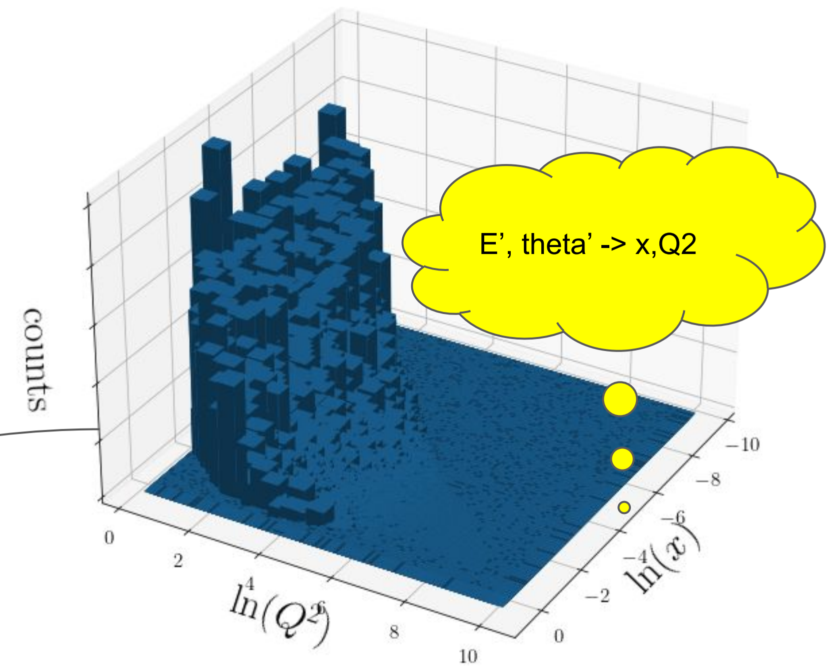
$$e^+ \; (E', \theta', \phi')$$

Measurable experimentally



Attention: this is just a single event

event	E’	theta’	phi’
1	E’_1	theta’_1	phi’_1
2	E’_2	theta’_2	phi’_2
3	E’_3	theta’_2	phi’_3
⋮	...	...	...



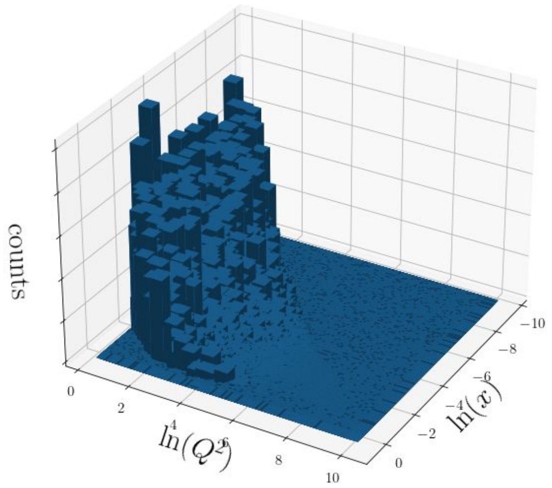
$$d\Omega = dE'\,d\theta' \quad \Leftarrow \quad \boxed{\frac{dN}{d\Omega}} = \mathcal{L}\,\boxed{\frac{d\sigma}{d\Omega}}$$

“Calculable” using QFT

Events

event	E’	theta’	phi’
1	E’_1	theta’_1	phi’_1
2	E’_2	theta’_2	phi’_2
3	E’_3	theta’_2	phi’_3
⋮	...	...	...

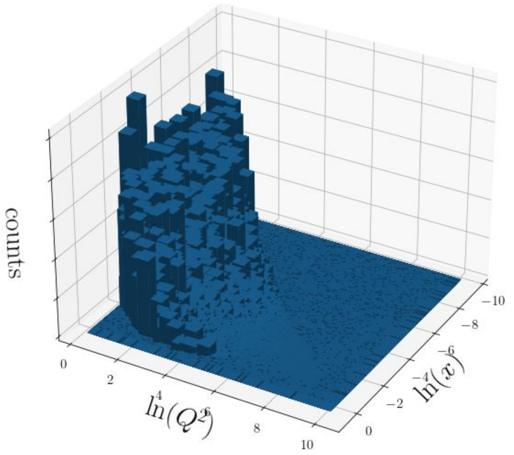
Histogram



Discretized representation of the underlying law

x	Q2	$\frac{d\sigma}{d\Omega}$	uncer.
x_1	Q2_1	rho_1	unc_1
x_2	Q2_2	rho_2	unc_2
x_3	Q2_3	rho_3	unc_3
x_4	Q2_4	rho_4	unc_4
⋮	...	...	...

Connection with hadron structure: Factorization



Collision dependent factor

Internal structure

$$\frac{d\sigma}{d\Omega} = \sum_i \int_x^1 \frac{\mathrm{d}\xi}{\xi} H_i(\xi) \, f_i\left(\frac{x}{\xi}\right) + \mathcal{O}\left(\frac{m^2}{Q^2}\right)$$

Model parameters tuned to match the data

Needs to be parametrized

Recap

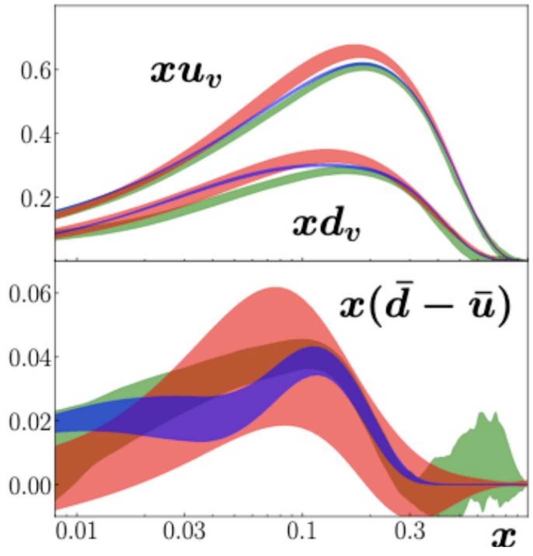
Reconstructed events from experiments

Inference on **visible** particle distributions and correlations

Inference on **invisible** partonic structures inside hadrons

event	E'	theta'	phi'
1	E'_1	theta'_1	phi'_1
2	E'_2	theta'_2	phi'_2
3	E'_3	theta'_2	phi'_3
⋮	...	...	...

x	Q2	$\frac{d\sigma}{d\Omega}$	uncer.
x_1	Q2_1	rho_1	unc_1
x_2	Q2_2	rho_2	unc_2
x_3	Q2_3	rho_3	unc_3
x_4	Q2_4	rho_4	unc_4
⋮	...	...	...



You will have to re histogram the events

What if I want to integrate over one of the variables?

Inference on **visible** particle distributions and correlations

This is a discretized representation of the underlying law

But we know the underlying law is continuous and smooth

x	Q2	$\frac{d\sigma}{d\Omega}$	uncer.
x_1	Q2_1	rho_1	unc_1
x_2	Q2_2	rho_2	unc_2
x_3	Q2_3	rho_3	unc_3
x_4	Q2_4	rho_4	unc_4
⋮	...	...	...

What if I want to change variables?

You will have to re histogram the events using the new variables

Can we parametrize the underlying law?

Machine learning ?

Statistics > Machine Learning

[Submitted on 10 Jun 2014]

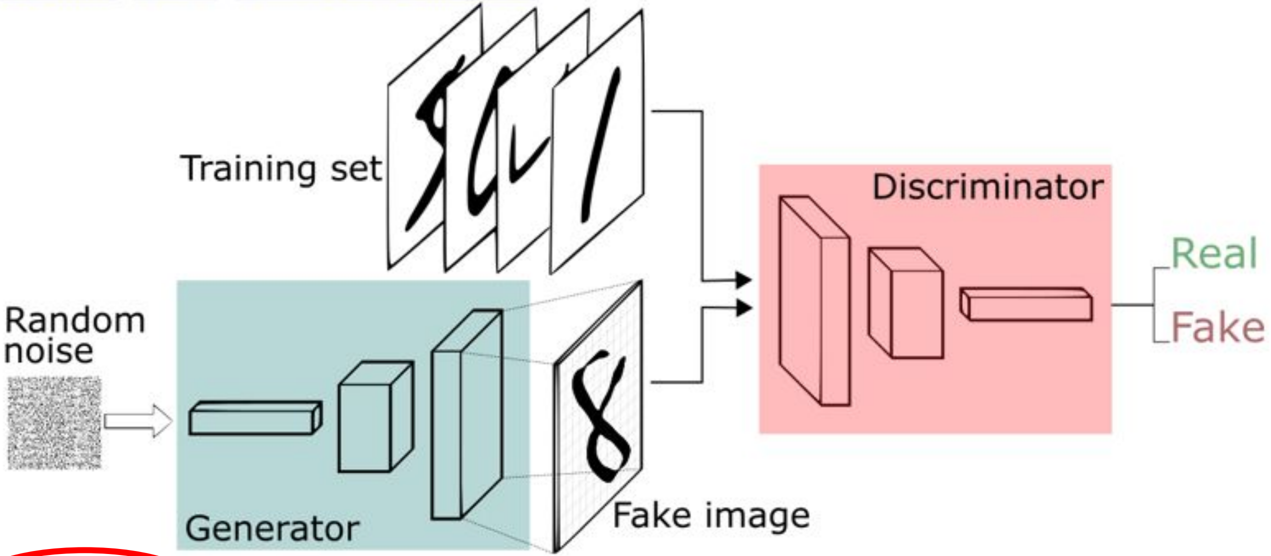
Generative Adversarial Networks

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio

Machine Learning? -> GANs

A Short Introduction to Generative Adversarial Networks

[machine-learning deep-learning representation-learning tensorflow python gans generative-models]

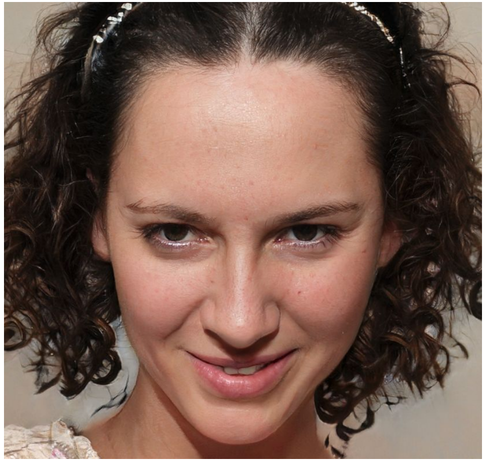


Jun 7, 2017

https://sthalles.github.io/intro-to-gans/

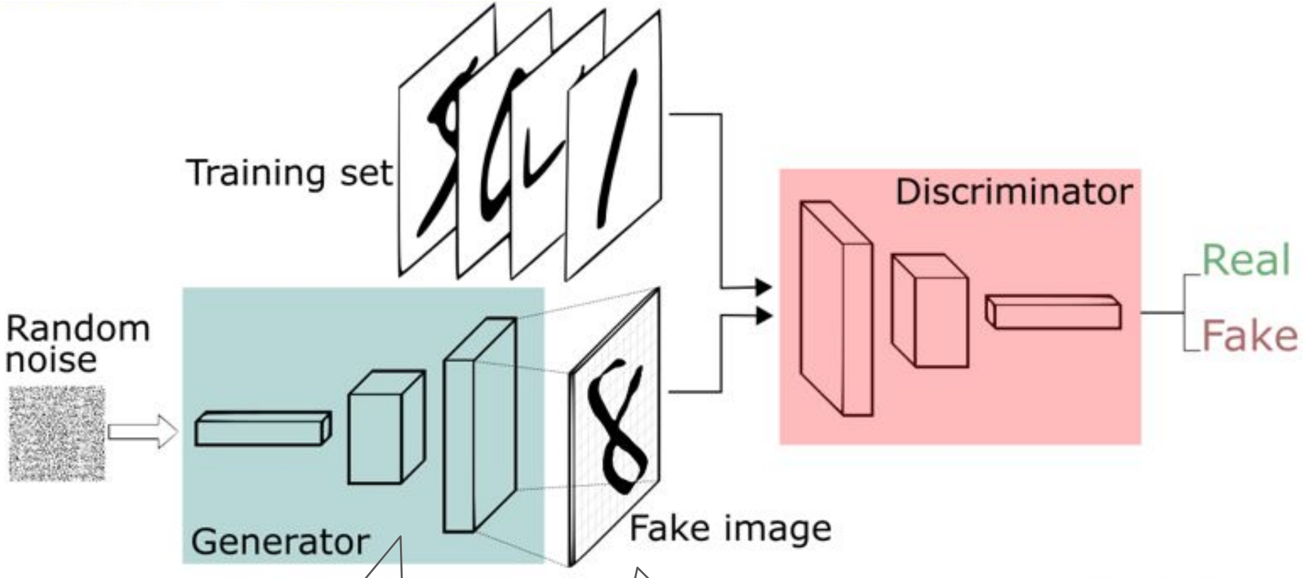






Fake people

https://thispersondoesnotexist.com

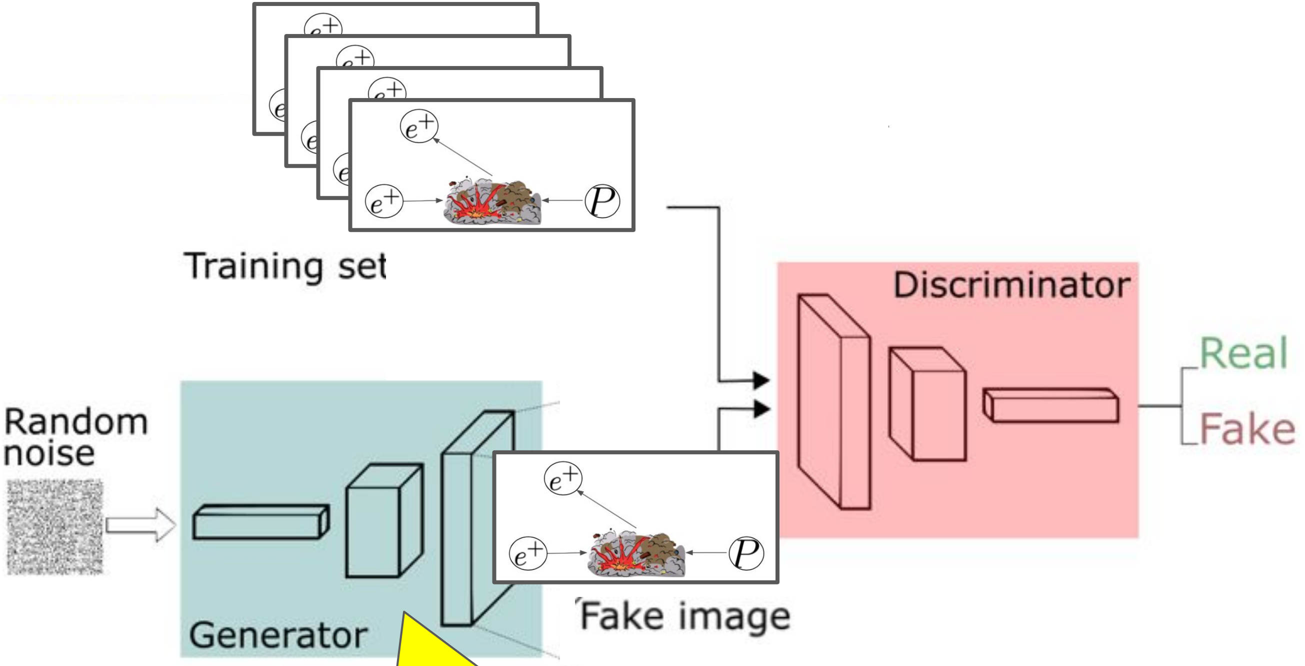


Underlying law of human faces

A random sample from underlying law

Each image is an event

Can we apply GAN for particle reactions?



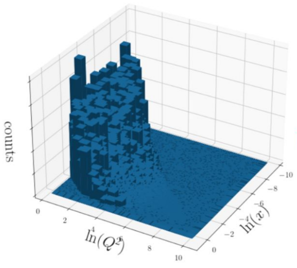
Underlying law for particle momentum distributions

Traditional approach

Events

event	E'	theta'	phi'
1	E'_1	theta'_1	phi'_1
2	E'_2	theta'_2	phi'_2
3	E'_3	theta'_2	phi'_3
⋮	...	...	...

Histogram



Discretized representation of the underlying law

x	Q2	$\frac{d\sigma}{d\Omega}$	uncer.
x_1	Q2_1	rho_1	unc_1
x_2	Q2_2	rho_2	unc_2
x_3	Q2_3	rho_3	unc_3
x_4	Q2_4	rho_4	unc_4
⋮	...	...	...

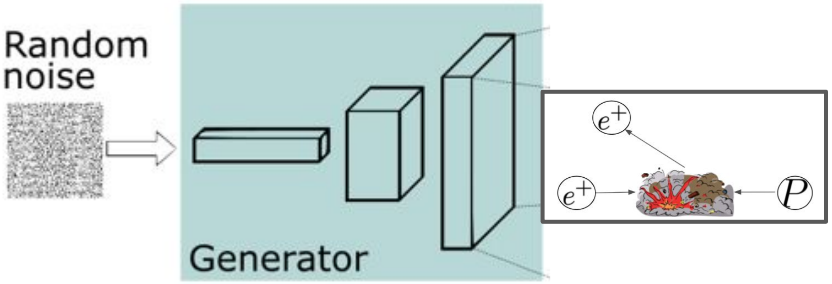
Supervised directly at the event level

GAN approach

Events

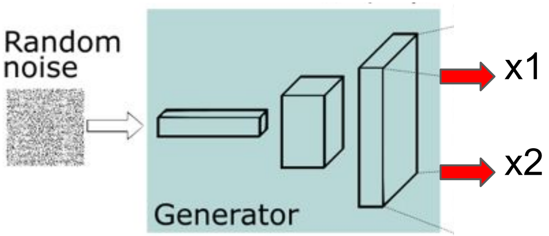
event	E'	theta'	phi'
1	E'_1	theta'_1	phi'_1
2	E'_2	theta'_2	phi'_2
3	E'_3	theta'_2	phi'_3
⋮	...	...	...

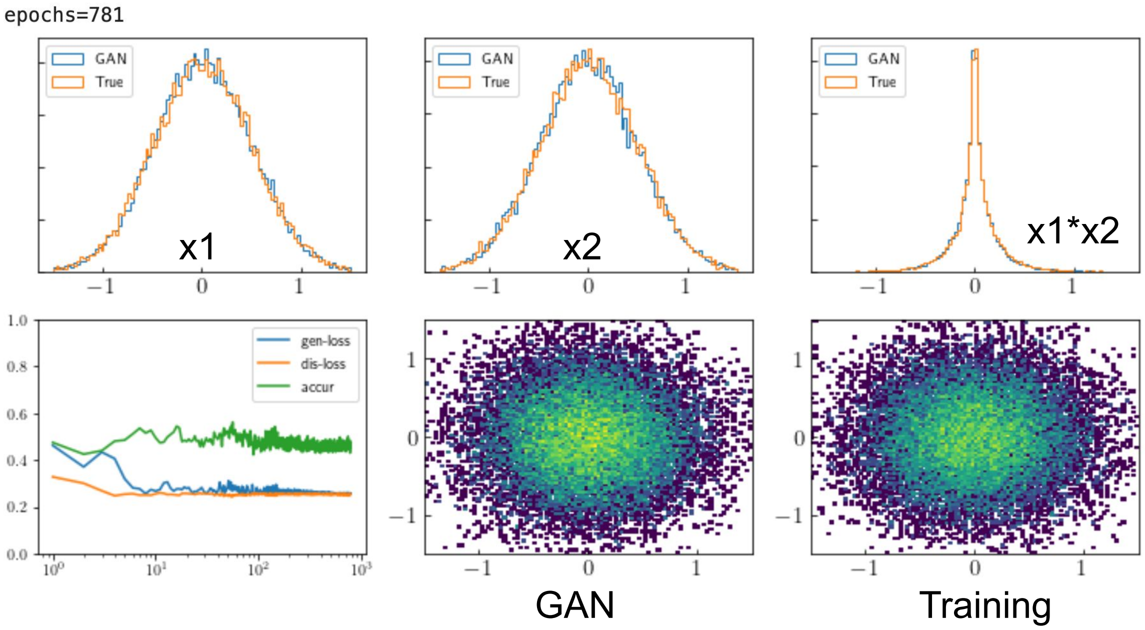
ML data representation



Toy example 2D gaussian

```
data = np.array([0, 0])+0.5*np.random.randn(20000,2)
d = data[:, 0]*data[:, 1]
d = d.reshape(-1, 1)
data = np.concatenate([data, d], axis=1)
```

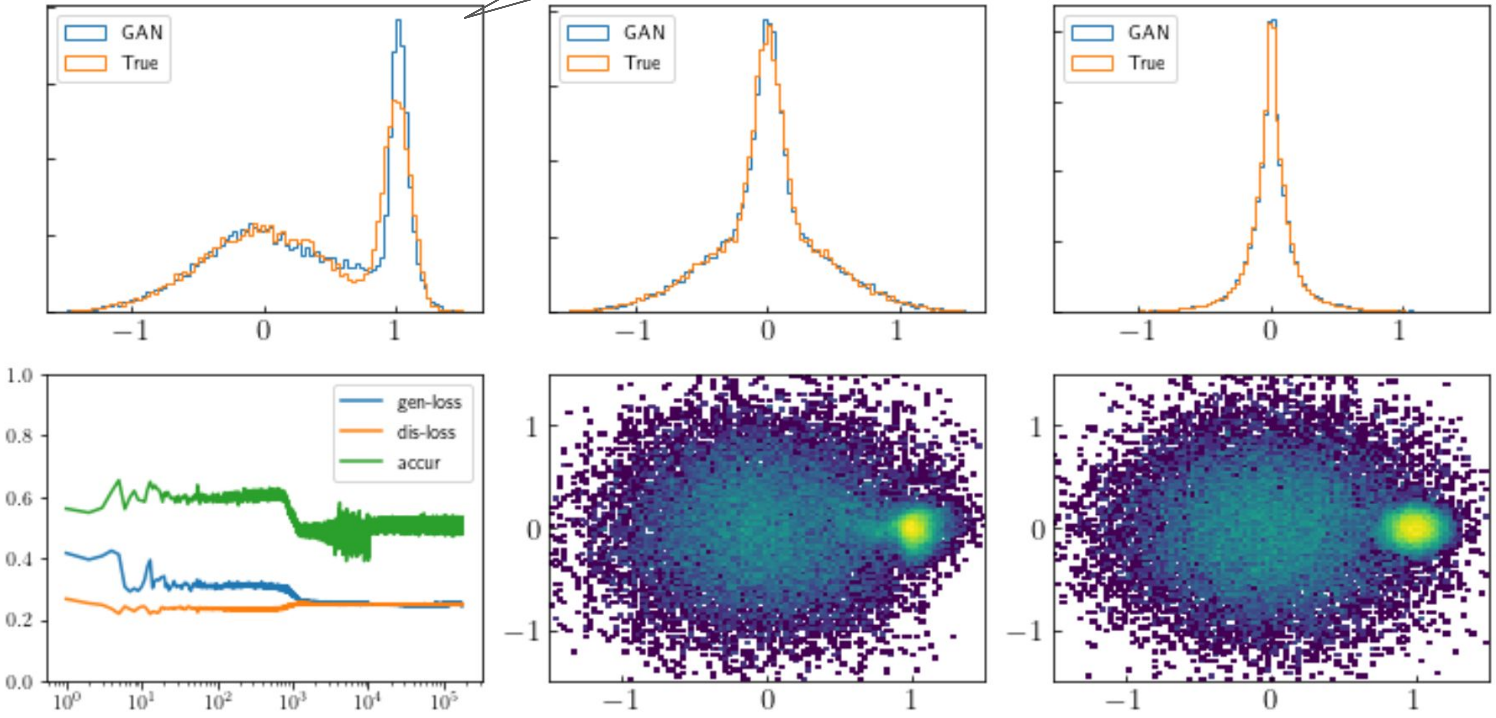




Another toy example

More tuning is needed

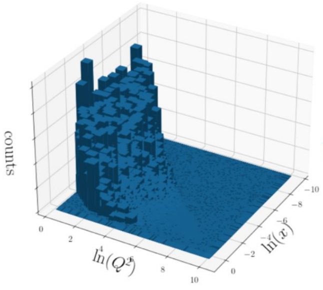
20:33:43.694020012
epochs=179205



Events

event	E'	theta'	phi'
1	E'_1	theta'_1	phi'_1
2	E'_2	theta'_2	phi'_2
3	E'_3	theta'_2	phi'_3
⋮	...	...	...

Histogram



Discretized representation of the underlying law

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x_2	Q2_2	rho_2	unc_2
x_3	Q2_3	rho_3	unc_3
x_4	Q2_4	rho_4	unc_4
⋮	...	...	...

What about GAN uncertainties?

Bootstrapping (statistics)

From Wikipedia, the free encyclopedia

For other uses, see Bootstrapping (disambiguation).

Bootstrapping is any test or metric that uses random sampling with replacement (e.g. mimicking the sampling process), and falls under the broader class of resampling methods. Bootstrapping assigns measures of accuracy (bias, variance, confidence intervals, prediction error, etc.) to sample estimates.[1][2] This technique allows estimation of the sampling distribution of almost any statistic using random sampling methods.[3][4]

High Energy Physics – Phenomenology

[Submitted on 2 Feb 2021]

A Living Review of Machine Learning for Particle Physics

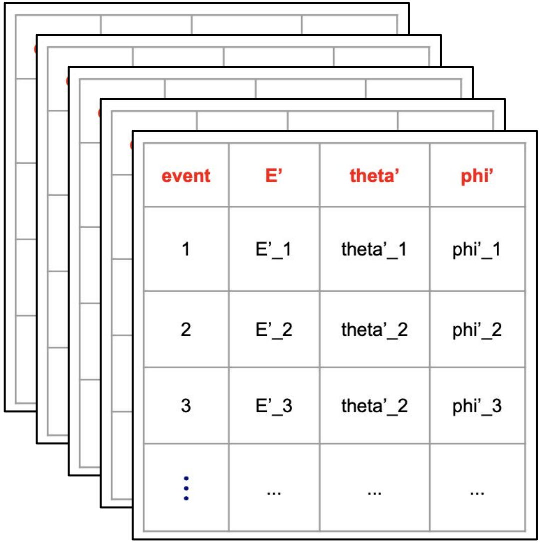
Matthew Feickert, Benjamin Nachman

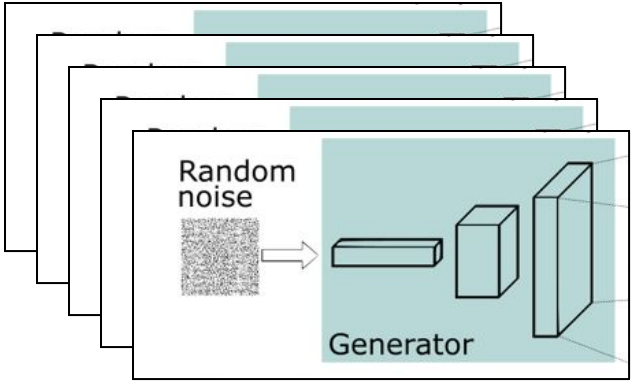
- Generative models / density estimation
  - GANs:
    - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis [DOI]
    - Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multilayer Calorimeters [DOI]
    - CaloGAN : Simulating 3D high energy particle showers in multilayer electromagnetic calorimeters with generative adversarial networks [DOI]
    - Image-based model parameter optimization using Model-Assisted Generative Adversarial Networks [DOI]
    - How to GAN Event Subtraction [DOI]
    - Particle Generative Adversarial Networks for full-event simulation at the LHC and their application to pileup description [DOI]
    - How to GAN away Detector Effects [DOI]
    - 3D convolutional GAN for fast simulation
    - Fast simulation of muons produced at the SHiP experiment using Generative Adversarial Networks [DOI]
    - Lund jet images from generative and cycle-consistent adversarial networks [DOI]
    - How to GAN LHC Events [DOI]
    - Machine Learning Templates for QCD Factorization in the Search for Physics Beyond the Standard Model [DOI]
    - DijetGAN: A Generative-Adversarial Network Approach for the Simulation of QCD Dijet Events at the LHC [DOI]
    - Generating and refining particle detector simulations using the Wasserstein distance in adversarial networks [DOI]
    - Generative models for fast cluster simulations in the TPC for the ALICE experiment
    - RICH 2018 [DOI]
    - GANs for generating EFT models [DOI]
    - Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network [DOI]
    - Reducing Autocorrelation Times in Lattice Simulations with Generative Adversarial Networks [DOI]
    - Tips and Tricks for Training GANs with Physics Constraints
    - Controlling Physical Attributes in GAN-Accelerated Simulation of Electromagnetic Calorimeters [DOI]
    - Next Generation Generative Neural Networks for HEP
    - Calorimetry with Deep Learning: Particle Classification, Energy Regression, and Simulation for High-Energy Physics
    - Calorimetry with Deep Learning: Particle Simulation and Reconstruction for Collider Physics [DOI]
    - Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed
    - AI-based Monte Carlo event generator for electron-proton scattering
    - DCTRGAN: Improving the Precision of Generative Models with Reweighting [DOI]
    - GANplifying Event Samples
    - Graph Generative Adversarial Networks for Sparse Data Generation in High Energy Physics
    - Simulating the Time Projection Chamber responses at the MPD detector using Generative Adversarial Networks
    - Explainable machine learning of the underlying physics of high-energy particle collisions

https://github.com/iml-wg/HEPML-LivingReview

GAN replicas

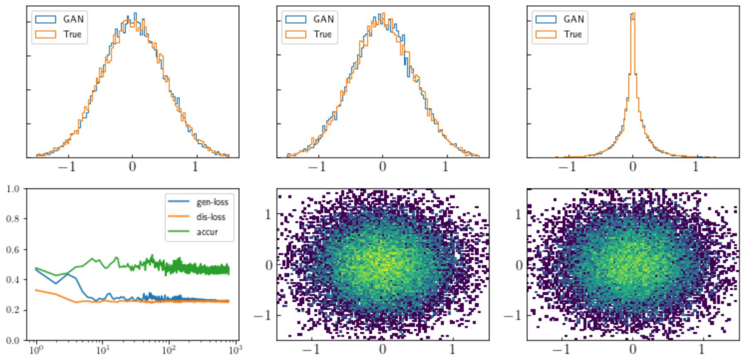
event	E’	theta’	phi’
1	E’_1	theta’_1	phi’_1
2	E’_2	theta’_2	phi’_2
3	E’_3	theta’_2	phi’_3
⋮	...	...	...

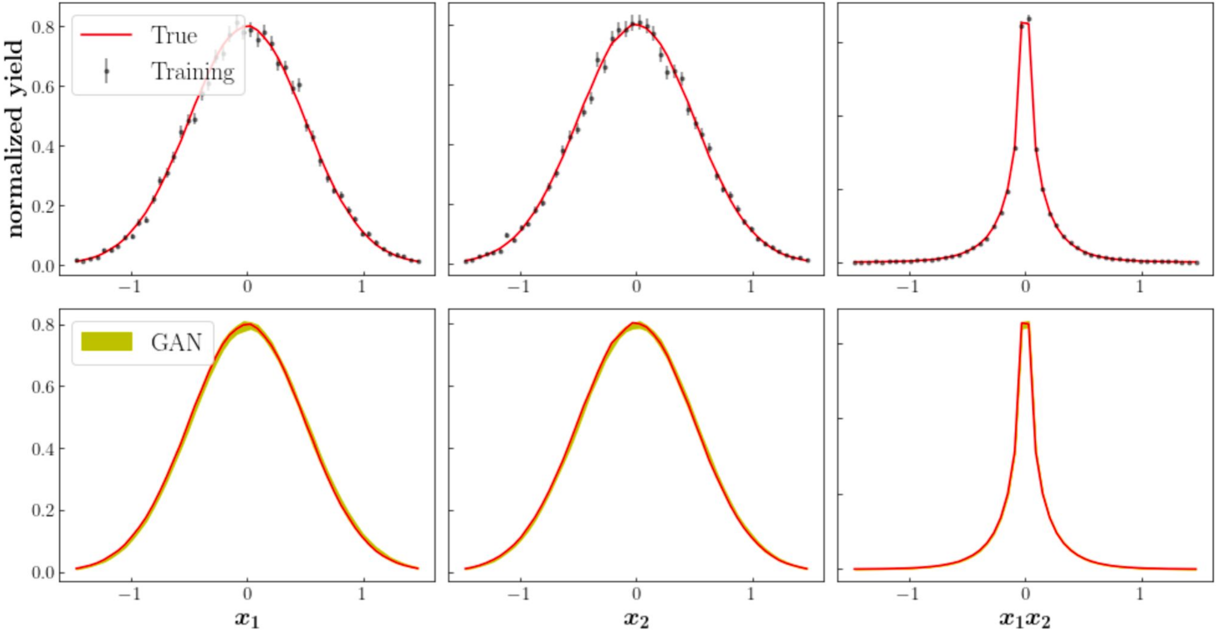


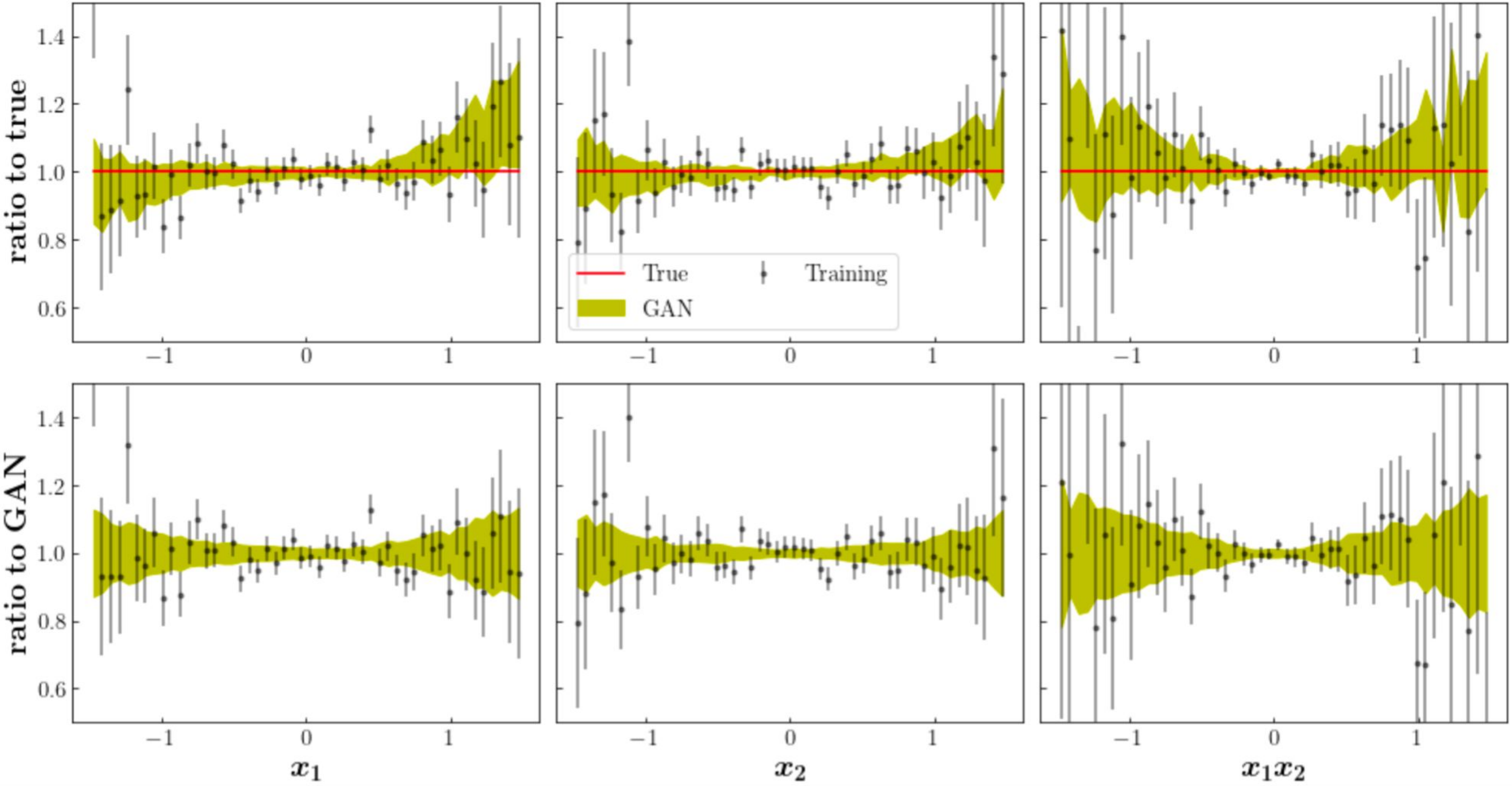


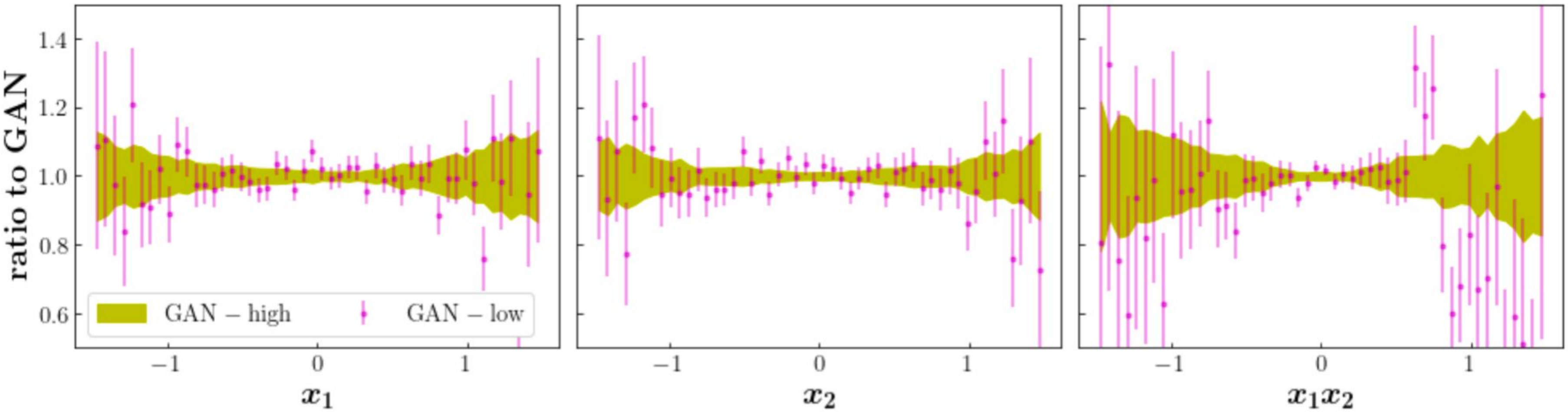
Bootstrapping

Bootstrapping toy example: 2D gaussian

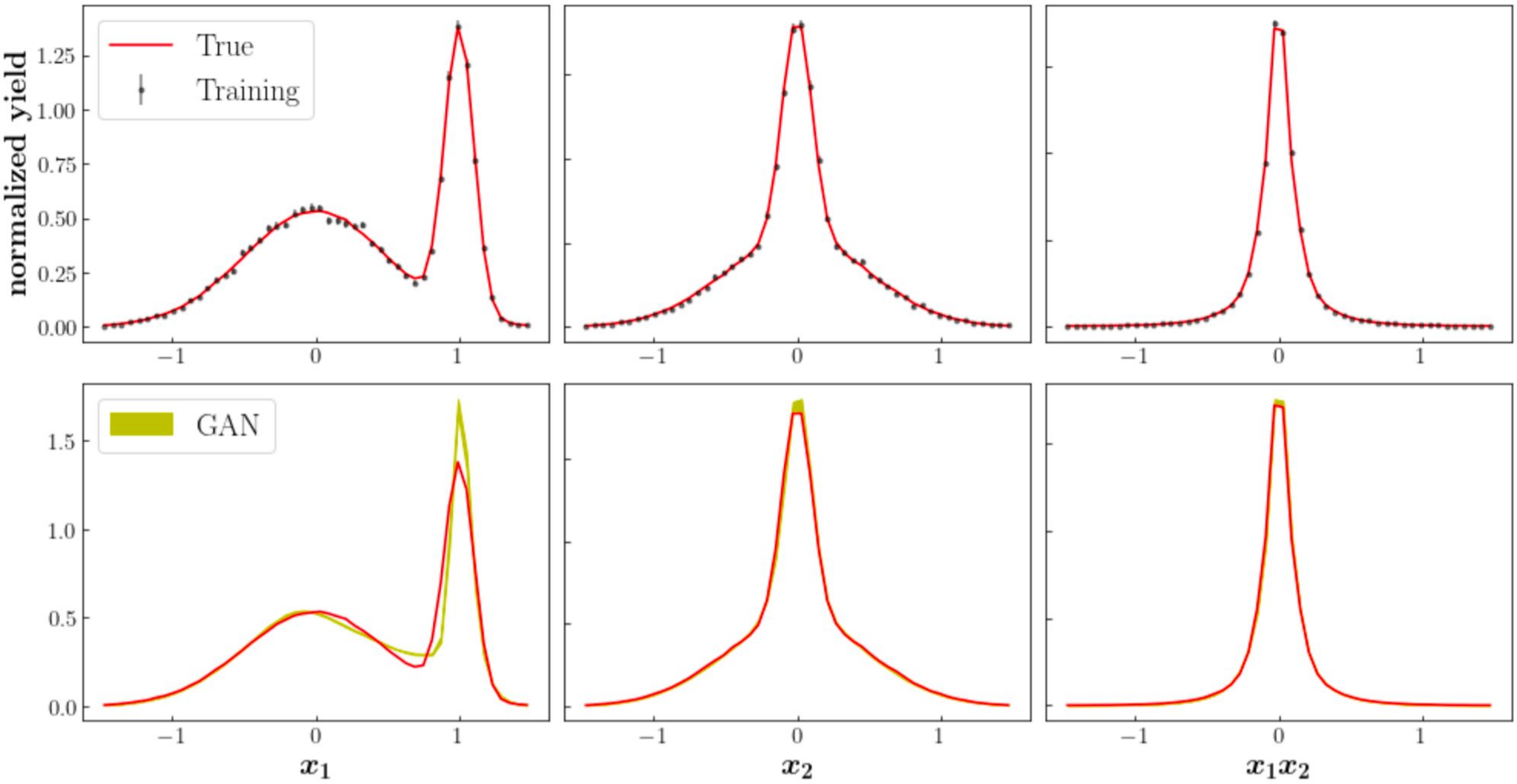




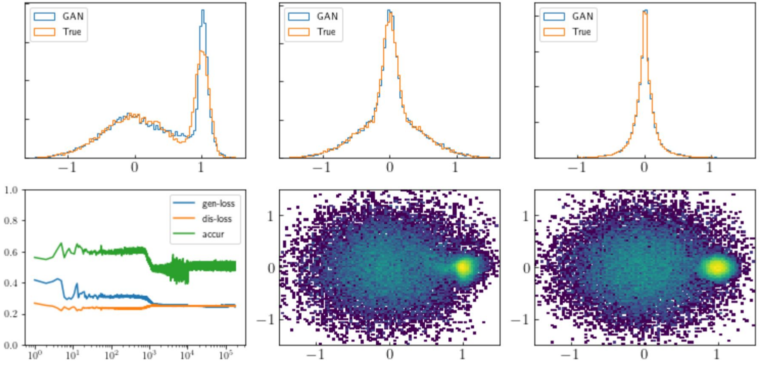

ratio to true
ratio to GAN
True
Training
GAN
x_1
x_2
$x_1 x_2$

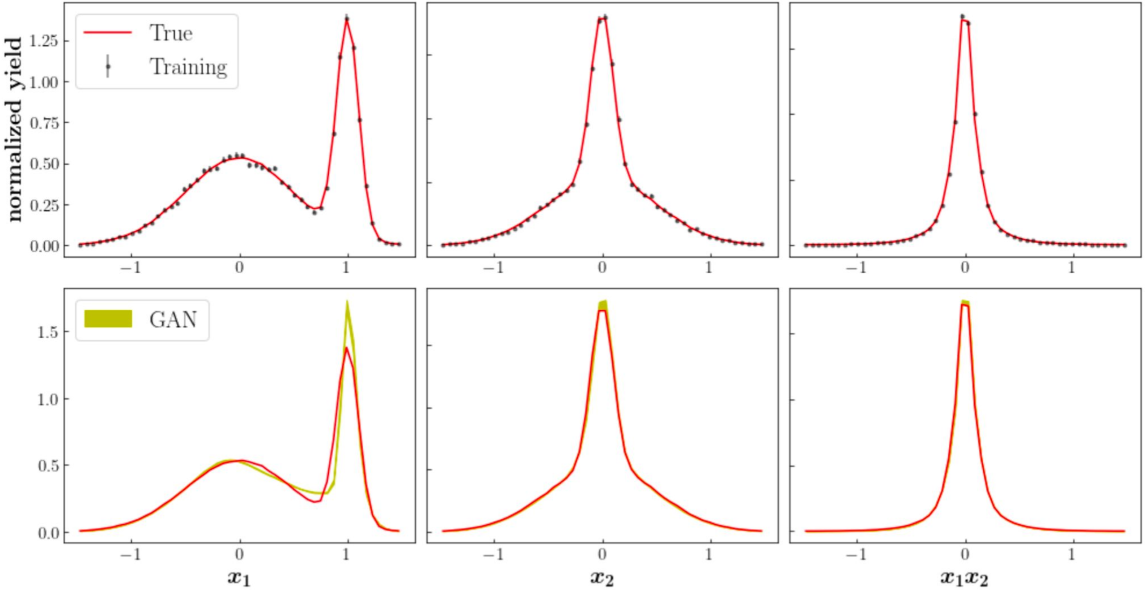


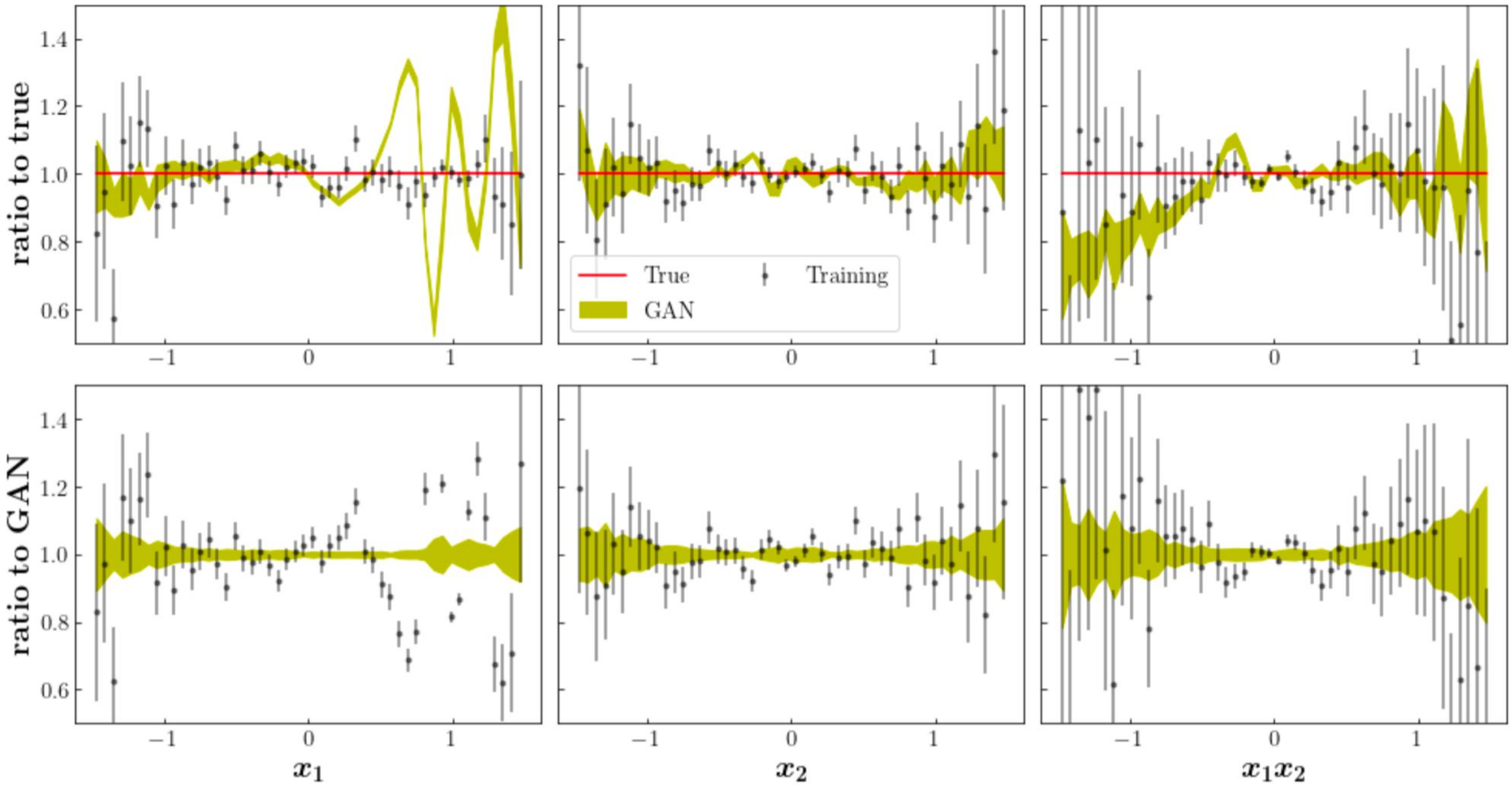
- Pink generate with the same training samples size
- Yellow combines GAN replicas each with x20 samples than original size
- Training the GAN at the event level gives higher precision of the underlying law


normalized yield
True
Training
GAN
1.25
1.00
0.75
0.50
0.25
0.00
1.5
1.0
0.5
0.0
−1
0
1
x_1
x_2
x_1x_2

Bootstrapping toy example 2

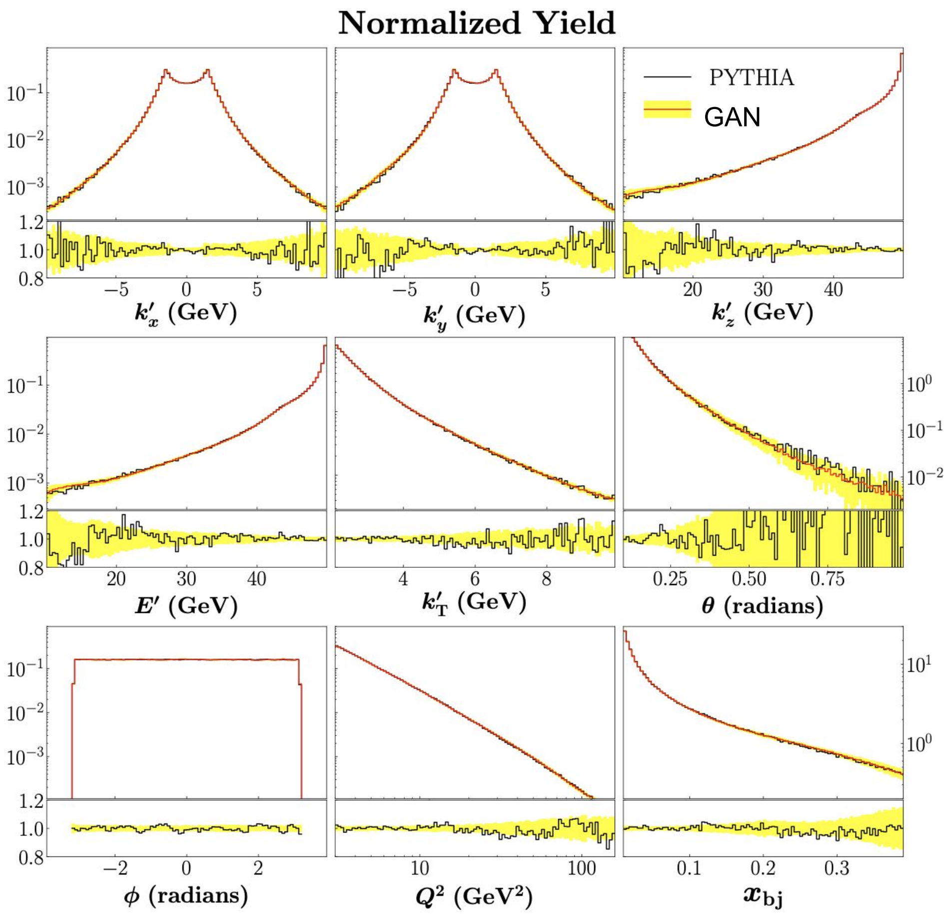






ratio to true
ratio to GAN
True
Training
GAN
x_1
x_2
x_1x_2

Real applications

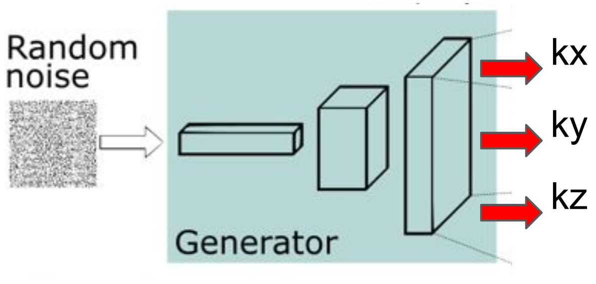


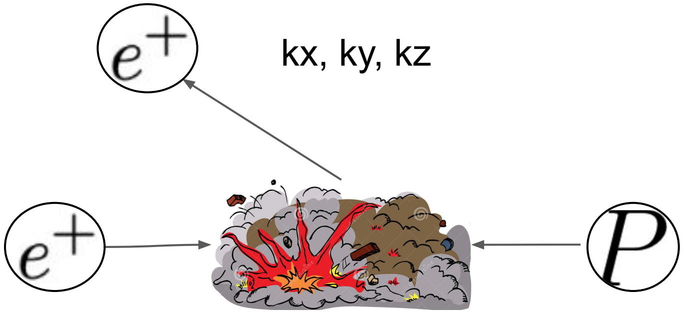
High Energy Physics – Phenomenology

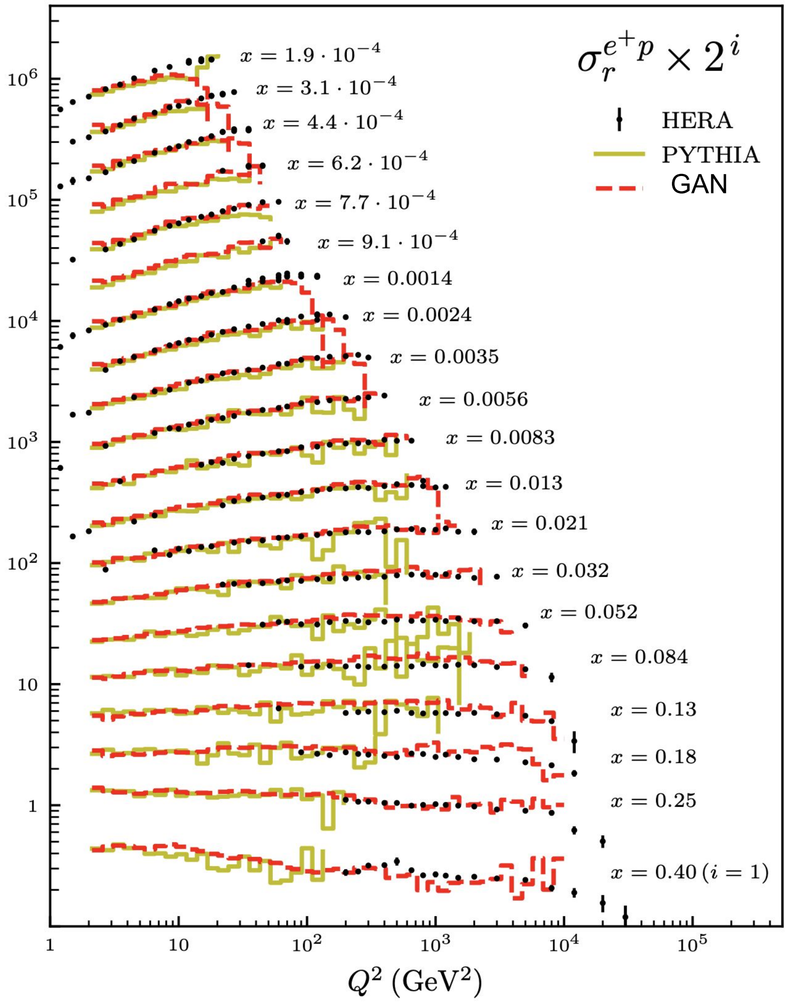
[Submitted on 6 Aug 2020]

AI-based Monte Carlo event generator for electron-proton scattering

Y. Alanazi, P. Ambrozewicz, M.P. Kuchera, Y. Li, T. Liu, R.E. McClellan, W. Melnitchouk, E. Pritchard, M. Robertson, N. Sato, R. Strauss, L. Velasco



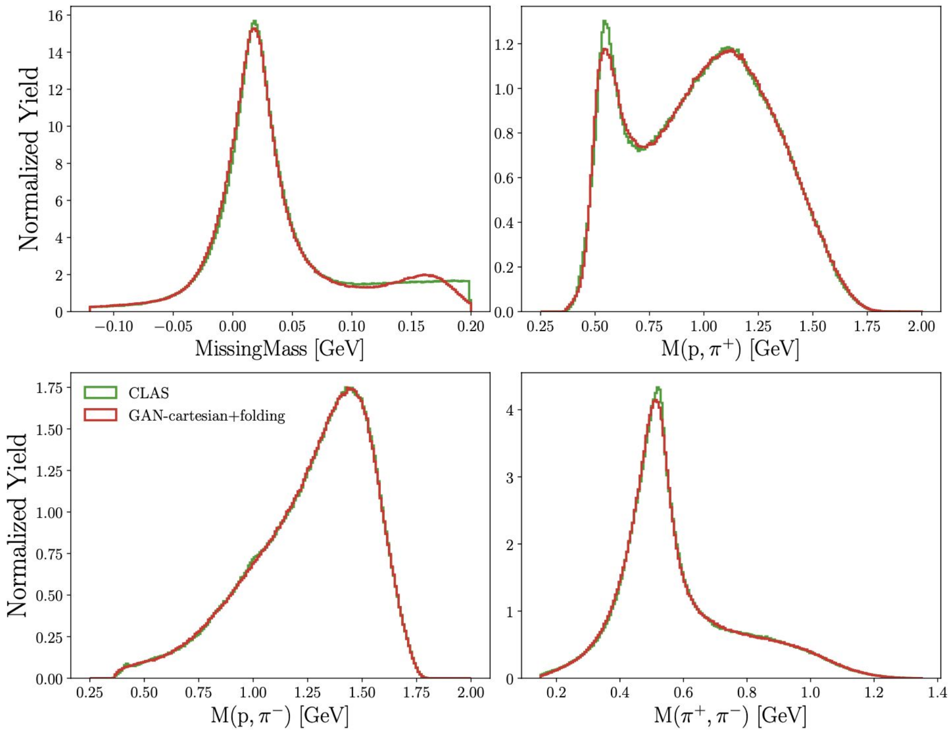


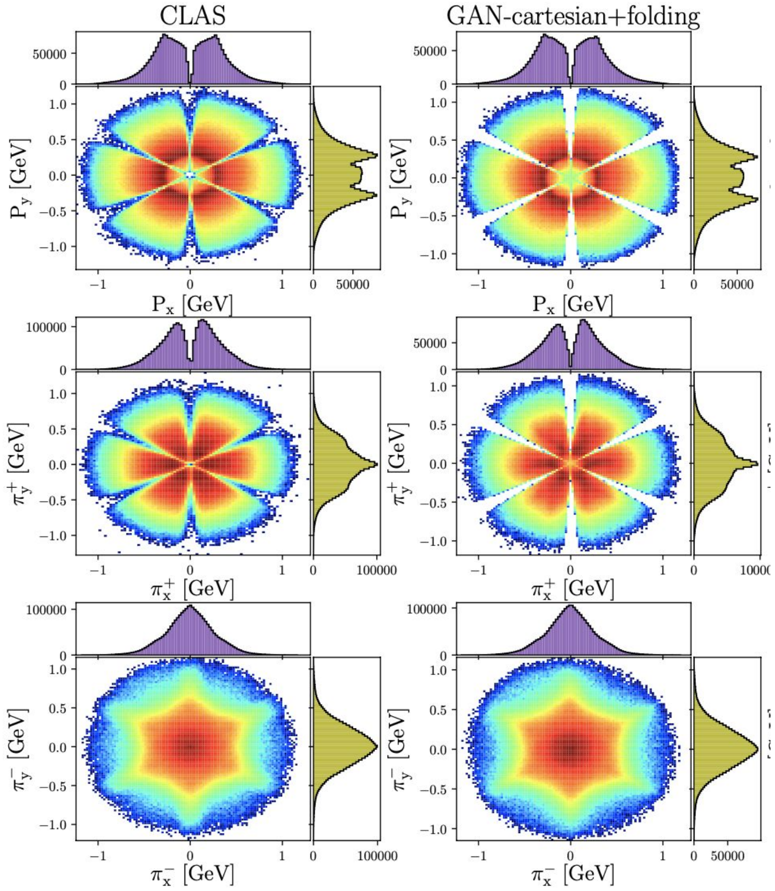


- PYTHIA has 1M events
- GAN was trained with 1M events
- GAN predictions from 100M events
- GAN has learned accurately the underlying low with lower statistics

Case study: CLAS 6 GeV data

$$\gamma + p \rightarrow p' + \pi^+ + \pi^-$$





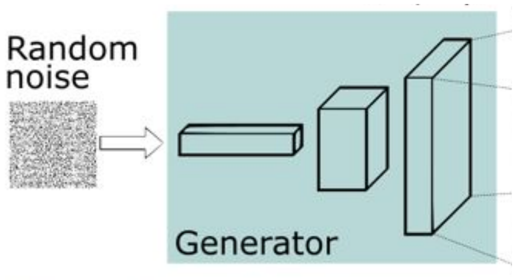
Summary and Outlook

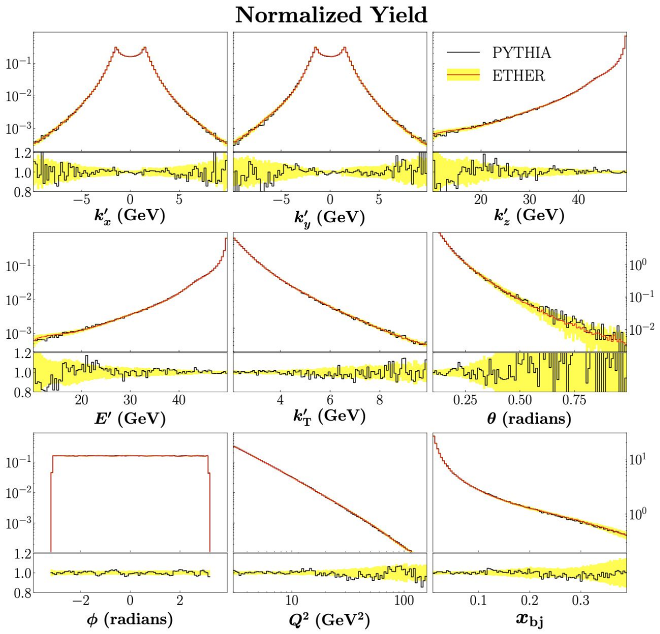
A new paradigm

- GAN offers a new way to represent experimental data in particle physics
- GANs allows to map put the underlying particle distribution using a continuous function

Near future

- Inclusion of detector effects with GANs
- Physics extraction from GANs





Backup

GAN+detector effects