# Application of Generative Adversarial Networks to electron-proton scattering

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# Motivation

Any experiment requires a detailed Monte Carlo simulation for at least two reasons:

- **Before:** Assessment of capabilities of the experimental apparatus,
- **After:** Analysis of the experimental data and extraction of physics the experiment was set out to measure.

The latter proceeds through 3 main stages:

- a vertex level event generation,
- propagation through an experimental setup,
- an event reconstruction at a detector level.

# Motivation

Modern Monte Carlo event generators, based on pseudo random number generators, have some drawbacks:

- They rely on theoretical models and their assumptions,
- Parameters are tuned to suit a particular experimental task,
- Processing an event, depending on the complexity of the setup, is mostly time consuming.
- Any physics analysis operates on sets of events satisfying certain criteria, collected into histograms, so all corrections are done at the histogram level.

# Motivation

Using Deep Learning in event generation provides solutions to some of those issues. It allows to:

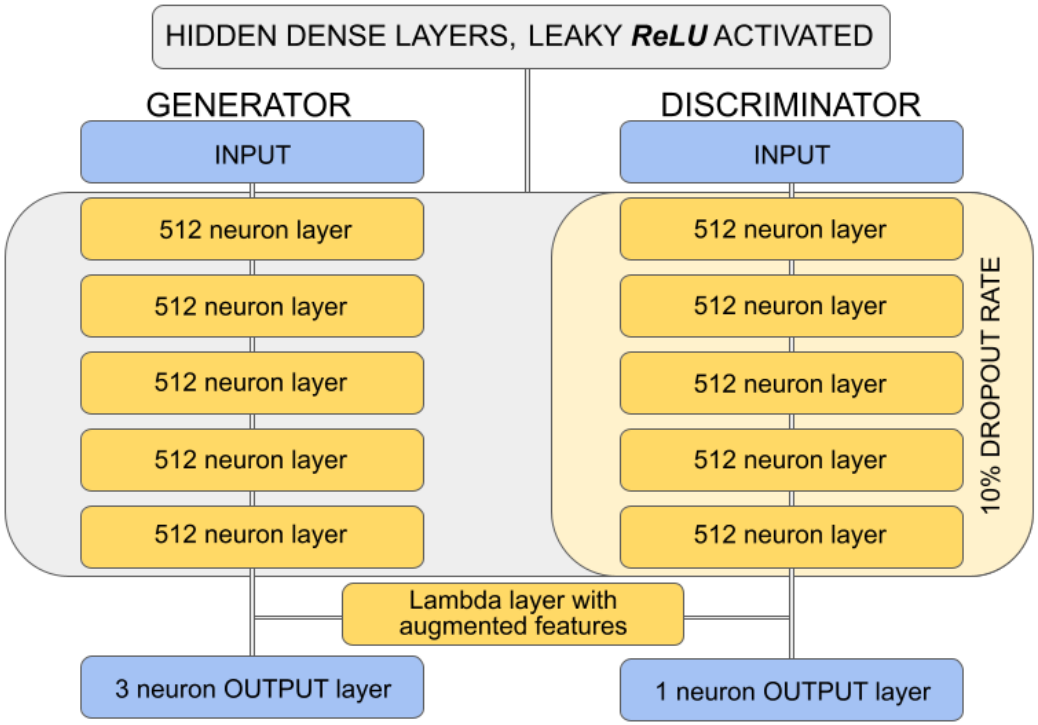
- create a theory agnostic event generator,
- generate efficiently events, although the training might be long,
- compactify experimental data - the size can be reduced from large number gigabytes to megabytes.

Most suitable approach is to use Generative Adversarial Networks (GANs), where two separate networks, a generator and a discriminator, compete against each other. The former improves the quality of fake events while the latter improves its ability to distinguish the fake from the real events.

# Architecture

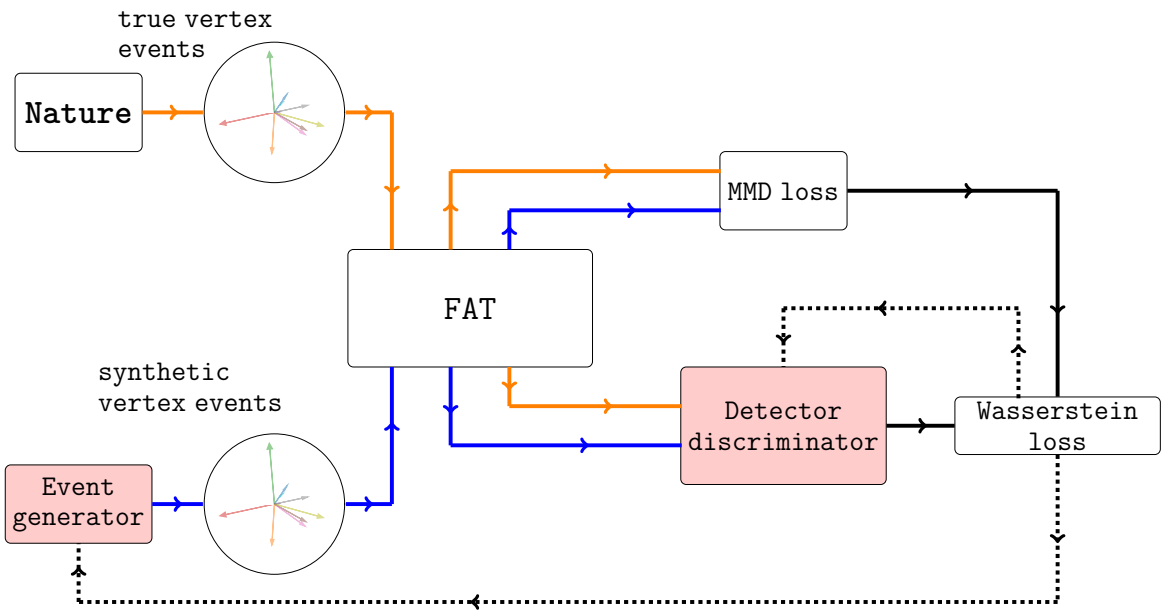
The FAT-GAN architecture consists of:

- The generator,
  *uses Wasserstein loss with gradient penalty,*
- **F**eature **A**ugmentation and **T**ransformation,
- The discriminator,
  *uses a combination of Wasserstein and Maximum Mean Discrepancy loss.*



# Architecture

## Full FAT-GAN Architecture

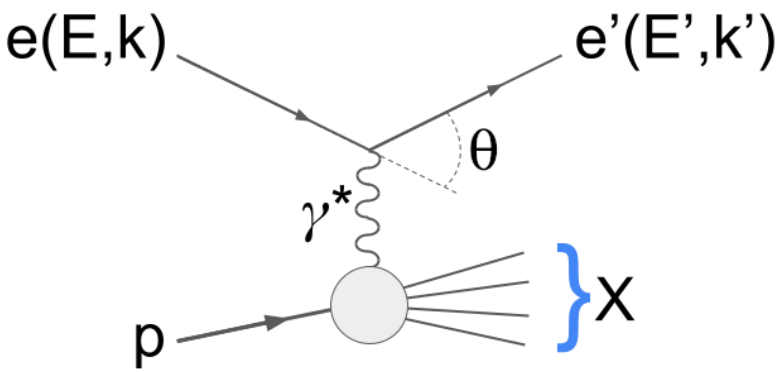



- load training samples x (real data)
- generate noise z (e.g. Gaussian)
- compute augmented features for x and z
- transform z into fake data G(z) with GAN
- evaluate real and fake data with discriminator D: D(x) and D(G(z))
- evaluate loss by subtracting the mean of the fake data discriminator from the mean of the real data discriminator
- update discriminator weights by taking the gradient of that computed loss w.r.t the previous discriminator weights

# Results

## Example: Inclusive Deep Inelastic Scattering (DIS)

Kinematics Description




Features used in the GAN training,

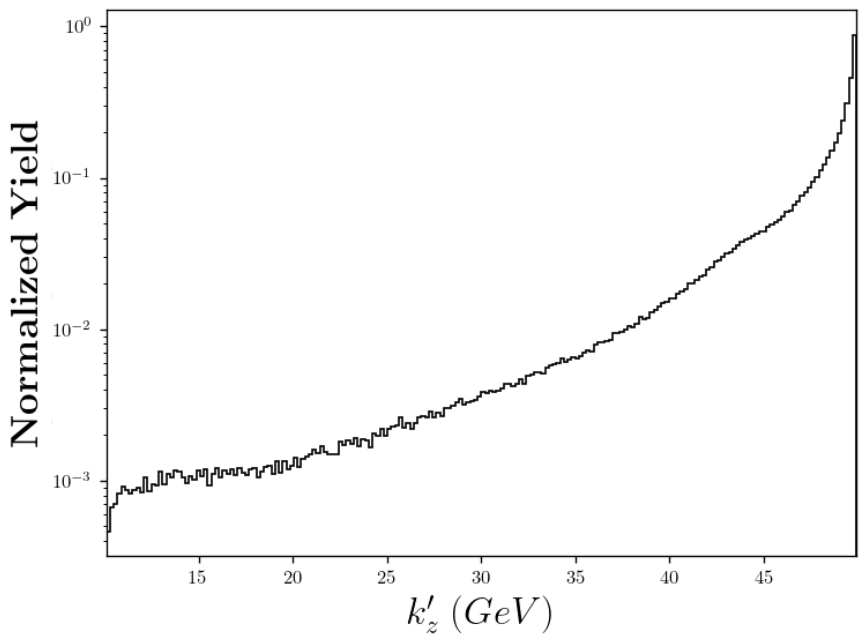
- the transverse momentum components of the scattered electron, $k'_x$, $k'_y$
- the longitudinal momentum of the scattered electron, $k'_z$, transformed to $\log(E - k'_z)$

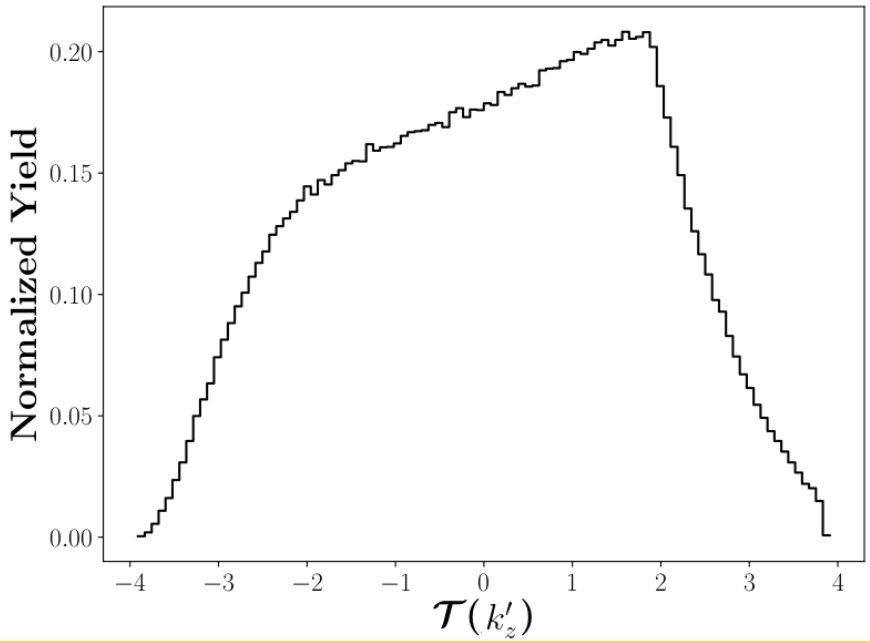
Augmented features, $E'$, $k'_T$, $k'_i \cdot k'_j$, (where $i, j = 1, 2, 3; i \neq j$) are calculated in a Lambda layer

# Results

Abrupt limits in physics variables distributions, driven by the conservation laws, resulted in poor reproduction of the DIS channel.

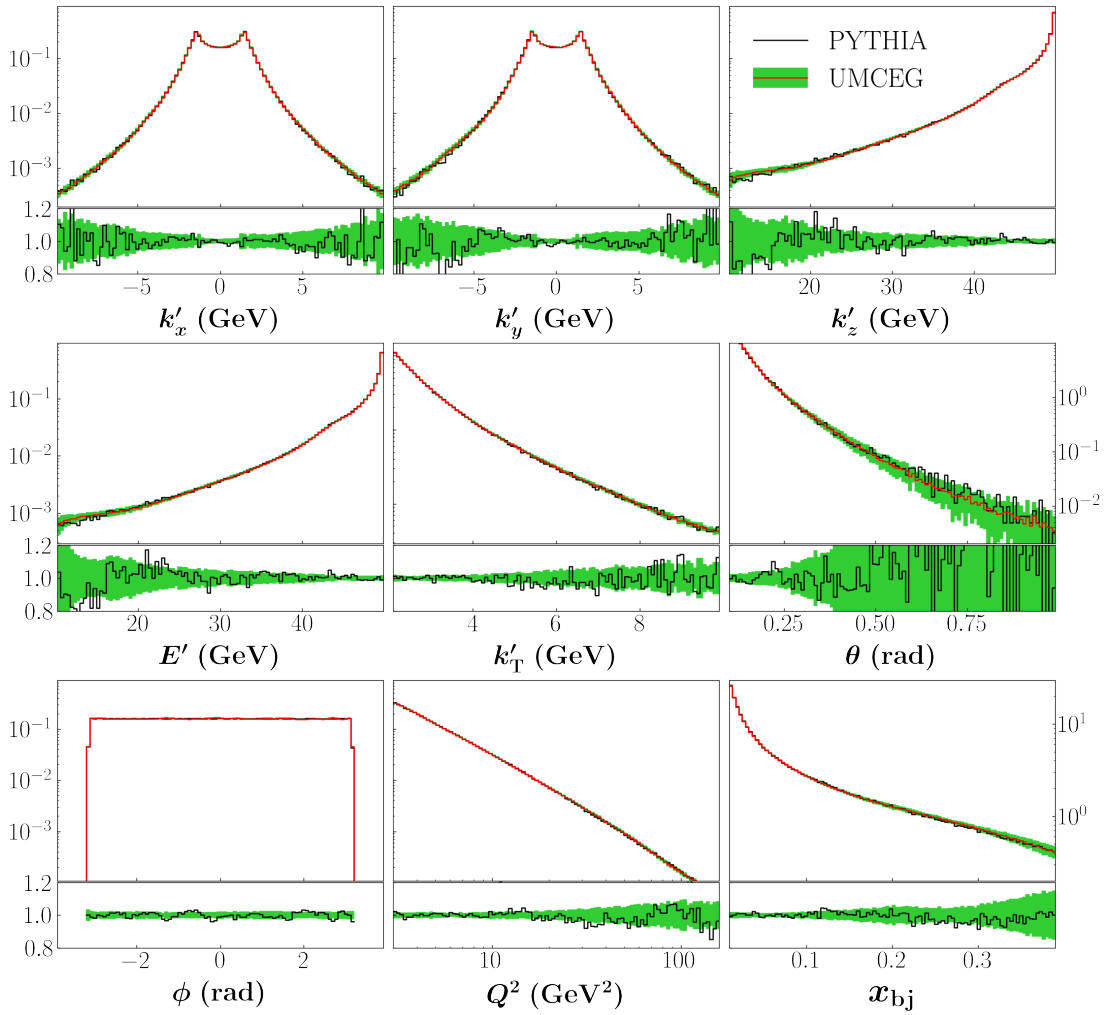
A longitudinal momentum transformation was utilized to flatten the particle distributions: $\tau(k'_z) = \log(E_{beam} - k'_z)$



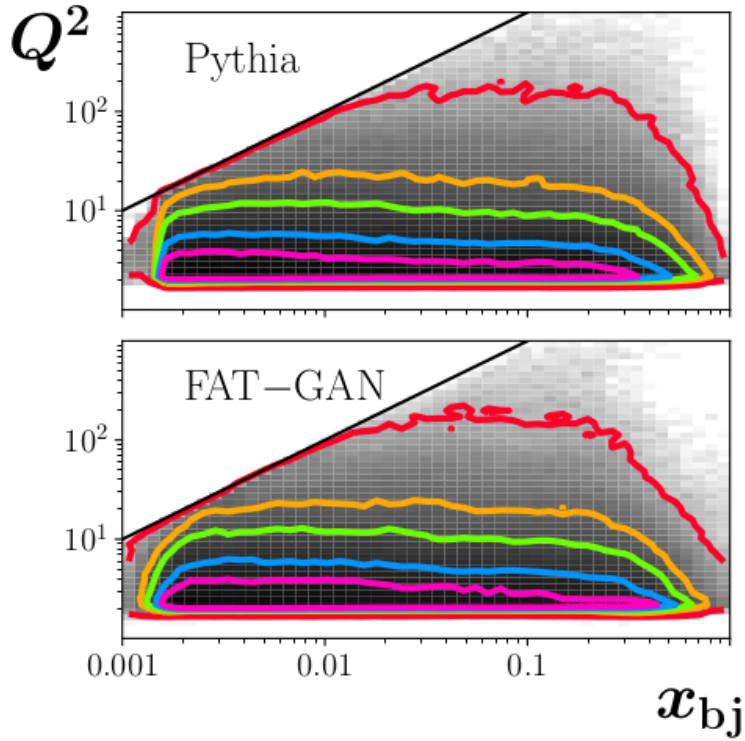



# Results

1D DISTRIBUTIONS OF FEATURES AND RECONSTRUCTED VARIABLES




2D CORRELATIONS OF RECONSTRUCTED VARIABLES



# Conclusions

In conclusion, our GAN-based Monte Carlo Event Generator

- was trained on PYTHIA data at the vertex level,
- reproduces the DIS phase space appreciably well,
- picks up correctly correlations between variables that were not used in the training,
- awaits incorporation of detector effects via a folding GAN, which will allow using experimental data in training.

**Acknowledgments**

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# Architecture

- **Loss functions:**
  - The discriminator: improved Wasserstein loss with a gradient penalty,

$$L_D = \left(\mathbb{E}[D(\widetilde{F})] - \mathbb{E}[D(F)]\right) + \lambda\, \mathbb{E}_{\widehat{F}\sim P_{\widehat{F}}}\left[(\|\nabla_{\widehat{F}} D(\widehat{F})\|_2 - 1)^2\right],$$

  - The generator: Wasserstein loss aided by a two sample test based on kernel Maximum Mean Discrepancy (MMD),

$$L_G = -\mathbb{E}[D(\widetilde{F})] + \eta\, MMD^2(F, \widetilde{F}),$$

$\mathbb{E}[\cdot]$ represents an expectation value,
$F$, $\widetilde{F}$ represent real and fake samples respectively,
$\lambda$, $\eta$ - hyperparameters optimized to improve training stability.