The A(i)DAPT program
AI for Data Analysis and Preservation

Tommaso Vittorini

on behalf of A(i)DAPT Working Group

A(i)DAPT
AI for Data Analysis and PreservaTion

- Data collected by NP/HEP experiments are (always) affected by the detector’s effects
- Before starting physics analysis the detector’s effect unfolding is required
- Traditional observables may not be adequate to extract physics in multidimensional space (multi-particles in the final state)
- At High-Intensity frontiers, data sets are large and difficult to manipulate/preserve

Should AI support NP/HEP experiments to extract physics from data in more efficient way?

A(i)DAPT

AI for Data Analysis and PreservaTion

Develop AI – supported procedures to:
- Accurately fit data in multiD space
- Unfold detector effects
- Compare synthetic (AI-generated) to experimental data
- Quantify the uncertainty (UQ)

Collaborative effort (regular meeting)
- ML experts (ODU, Jlab)
- Experimentalists (Jlab Hall-B)
- Theorists (JPAC, JAM)

The A(i)DAPT road map

- **Deploy an AI Generative Model to reproduce NP/HEP data**
  - Detector effects unfolding: smearing
  - Detector effects unfolding: acceptance
  - Extract few dimensions cross-section (PDF) (e.g. inclusive electron scattering - MC)
  - Extend the closure test to cross-sections in a mutiD phase-space (e.g. 2-pion photoproduction - MC)
  - Validate the analysis procedure extracting cross-section from data (e.g. high energy CLAS-g11 2-pion data)
  - Combine data of the same final state taken in different kinematics (e.g. low energy CLAS-g11 2-pion data)
  - Combine data from different final states (e.g. CLAS-g11 3-pion/ω data)
  - Extract cross-section and amplitudes in a 2-body reaction (e.g. ππ scattering - MC)
  - Extract amplitudes from a multi-particle exclusive channel (e.g. CLAS-g11 2-pion data)
  - Extract amplitudes in multi- coupled-channel analysis (e.g. CLAS-g11 2-pion + 3-pion/ω data)
  - Connect NN features to different physics processes (e.g. baryon and meson resonances in CLAS-g11 2-pion data)
  - …
- **Extract physics out of our data**

This Talk

- **Deploy an AI Generative Model to reproduce NP/HEP data** √
  - Detector effects unfolding: smearing √
  - Detector effects unfolding: acceptance **in progress**
  - Extract few dimensions cross-section (PDF) (e.g. inclusive electron scattering - MC) √
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  - …
- **Extract physics out of our data**

Detector unfolding

- Detector effects make measured observables (detector-level) different from the 'true' observables (vertex level)

Acceptance: Any measurement can access only a limited portion of the phase space. What can we say about these unmeasured regions?

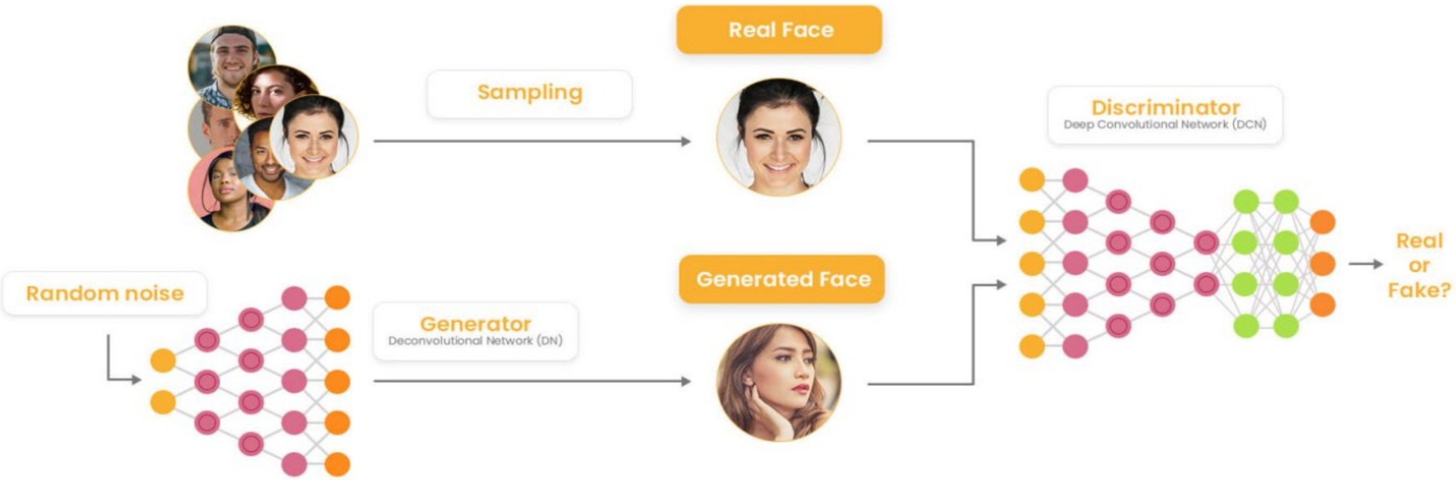
- ➢ Interpolation: deal with the holes in the phase space
- ➢ Extrapolation: extend our coverage from the borders of measured regions

Resolution: Any measurement has an experimental resolution that may modify cover up effects that we're looking for

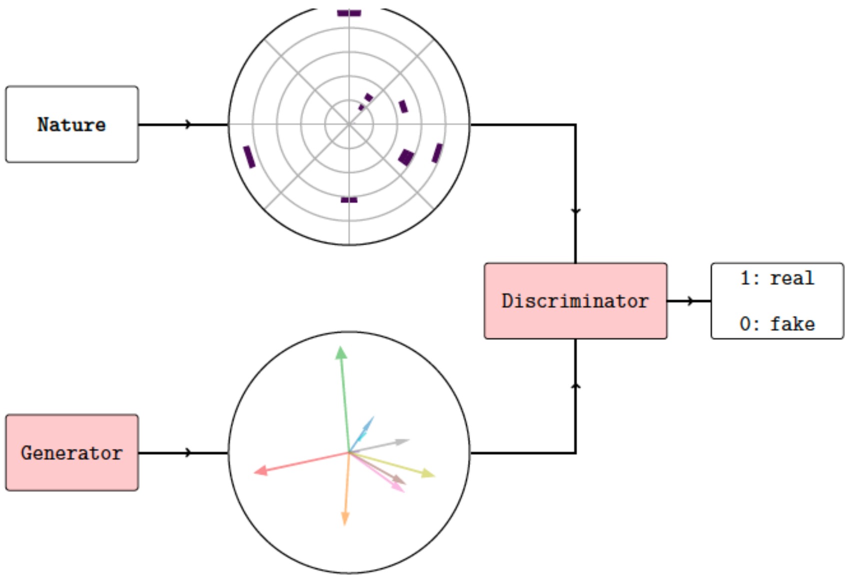
- ➢ Spikes may be concealed behind the detector resolution
- ➢ Measurements could be extended to unphysical regions

- Mitigation strategy:
  - ➢ Acceptance: 'Fiducial volumes' to exclude unmeasured regions and extend the covered measured of the phase space
  - ➢ Resolution: build and validate ML-models to unfold resolution effects

Generative Adversarial Networks (GANs)



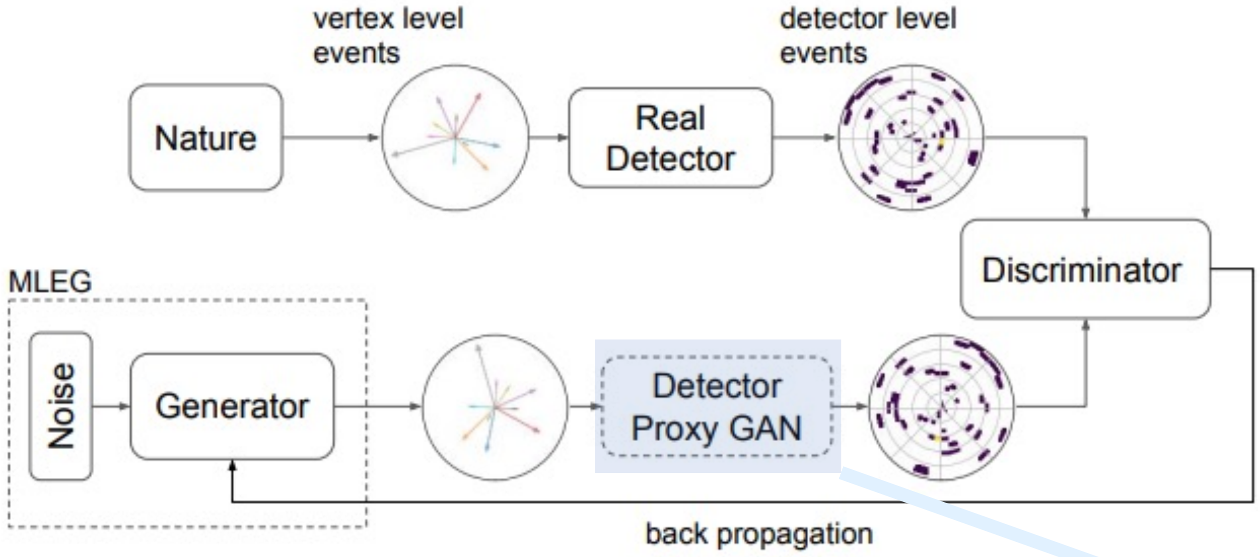
- Generative model based on the competition between two Neural Networks: Generator vs Discriminator
  - **Generator** produces synthetic data which progressively reproduce realistic data and the **Discriminator** has to distinguish between synthetic and realistic data
  - **Generator** be used to retain high dimensional correlations (detector proxies)
  - **Generator** can be used to provide highly realistic pseudo-data in an extremely fast way



A simple case study: DIS scattering

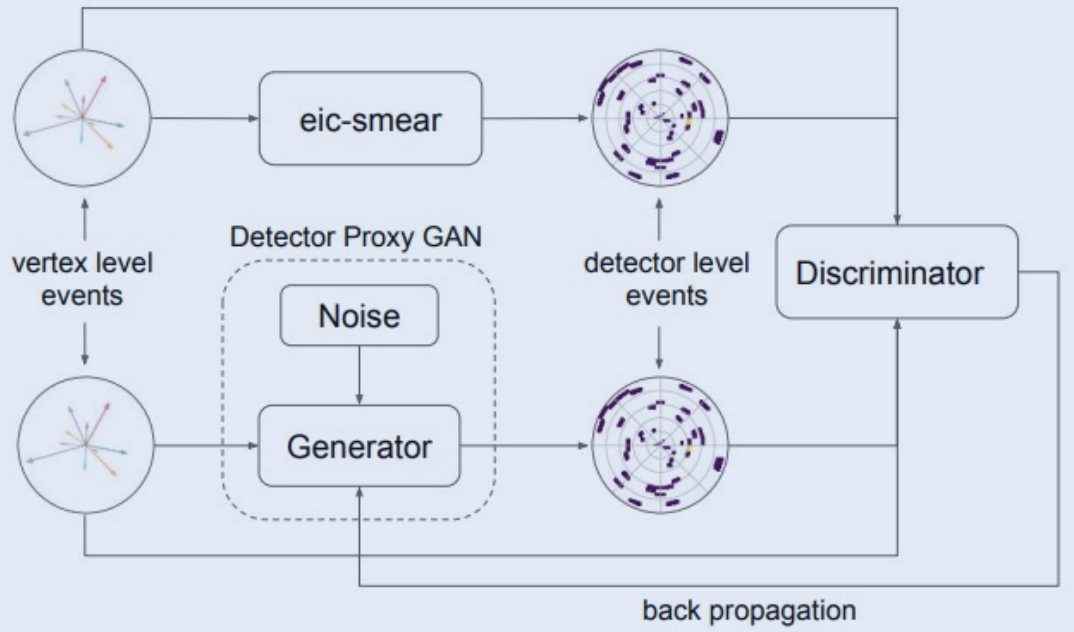
Y. Alanazi, P. Ambrozewicz, M. Battaglieri, A. N. Hiller Blin, M. P. Kuchera, Y. Li, T. Liu, R. E. McClellan, W. Melnitchouk, E. Pritchard, M. Robertson, N. Sato, R. Strauss, and L. Velasco
Phys. Rev. D **106**, 096002

ML Event Generator GAN scheme



- 100-d white noise entered at 0, unit standard dev.
- Generator: 5 hidden layers / 512 neurone per layer, ReLU activation function. Last layer connected to 2 neurons output to generate v_1 and v_2 variables
- Discriminator: same NN architecture as for the generator
- Detector proxy: similar architecture
- Least Squares GAN (LSGAN)
- Trained adversarially for 100000 epochs (pass through the training data set)
- Adam's optimizer

Detector proxy



- *eic-smear*: parametric smearing routine for the Electron Ion Collider detectors (no GEANT-based simulations)
- Parameters tuned to reproduce ZEUS/H1 detectors
- Full 4π

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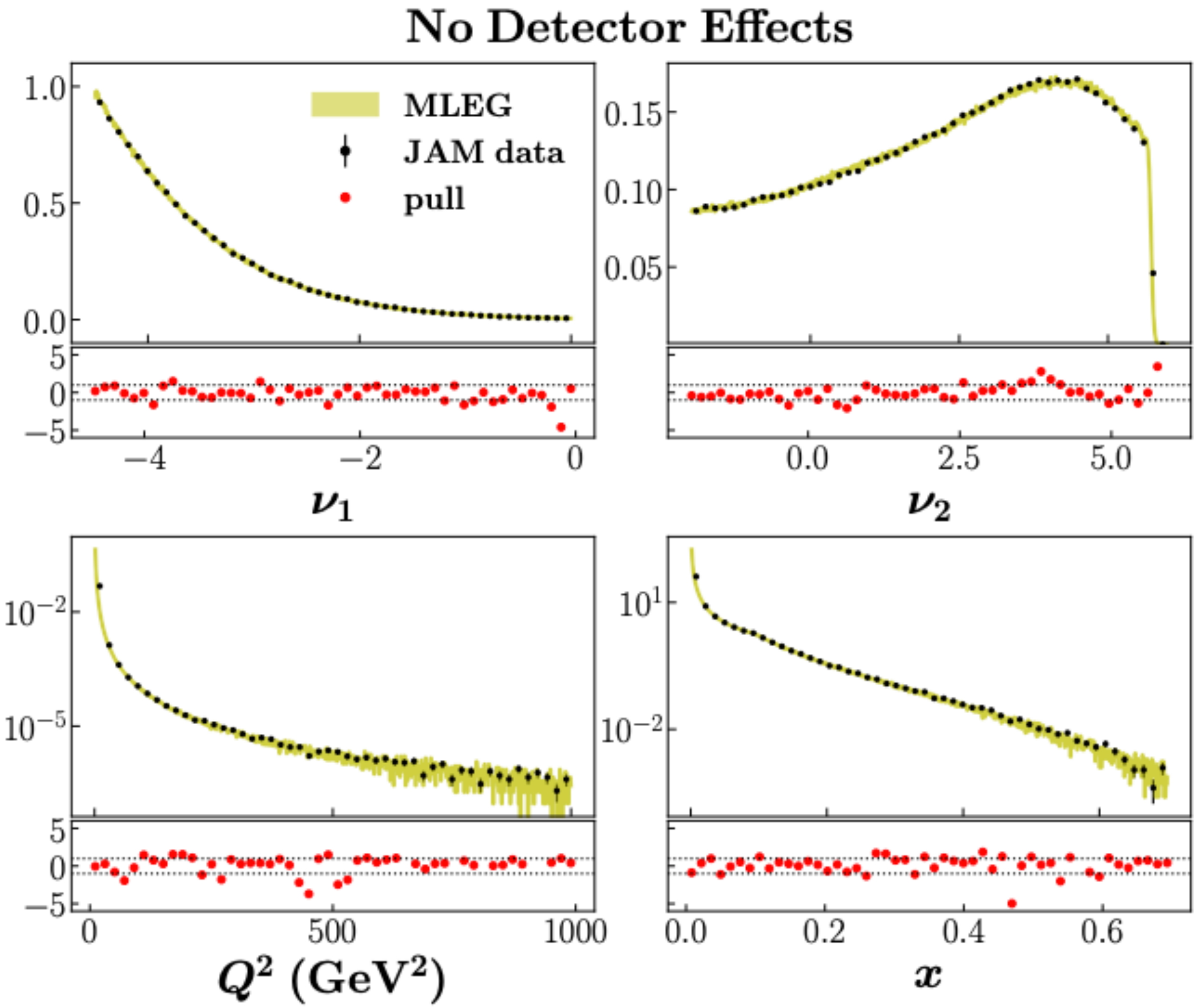
I) GAN training without detector effects

Pseudo-data sample (JAM)

- Inclusive electron DIS generated at E_{CM}=318.2 GeV (HERA kinematics)
- 2-dim differential cross section dσ/dxdQ^2
- Lorentz boosted from CM to Lab (+ uniform azimuthal angle)
- To reduce violation of momentum conservation on the edge of the phase space due to smearing effects, electron momentum is replaced by new variables:

$$\nu_1 = \ln\left((k_0' - k_z')/1\,\mathrm{GeV}\right),$$
$$\nu_2 = \ln\left((2E_e - k_0' - k_z')/1\,\mathrm{GeV}\right),$$



Uncertainty Quantification via *pull* calculation

- Metric: *pull* $$\mathrm{pull} = \frac{\mathrm{E}[\mathcal{P}(\mathcal{O}|\mathrm{bin})]_{\mathrm{GAN}} - \mathrm{E}[\mathcal{P}(\mathcal{O}|\mathrm{bin})]_{\mathrm{JAM}}}{\sqrt{\mathrm{V}[\mathcal{P}(\mathcal{O}|\mathrm{bin})]_{\mathrm{GAN}} + \mathrm{V}[\mathcal{P}(\mathcal{O}|\mathrm{bin})]_{\mathrm{JAM}}}}$$

- *Bootstrap with* 10 independently trained GANs

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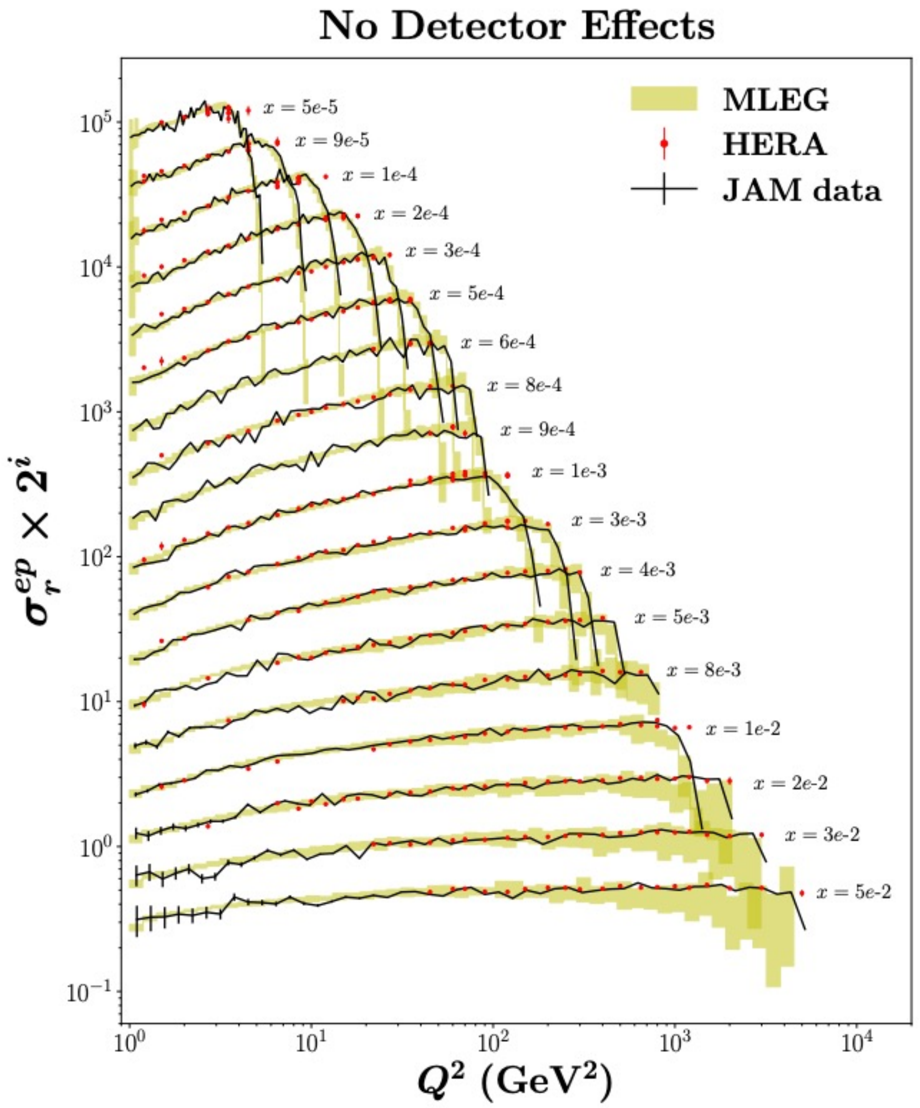

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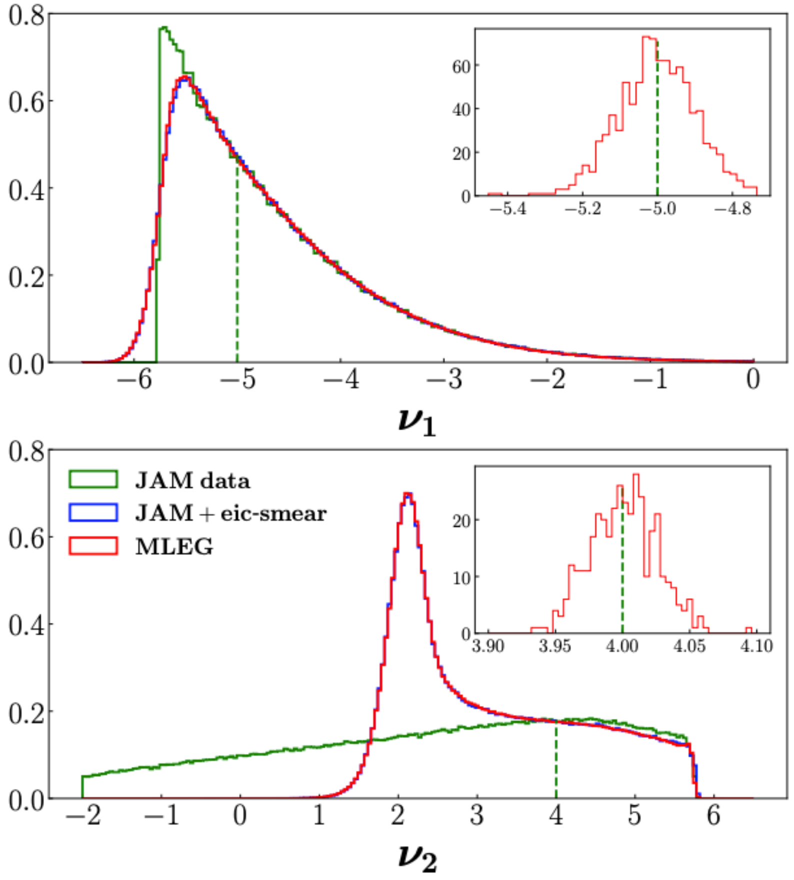
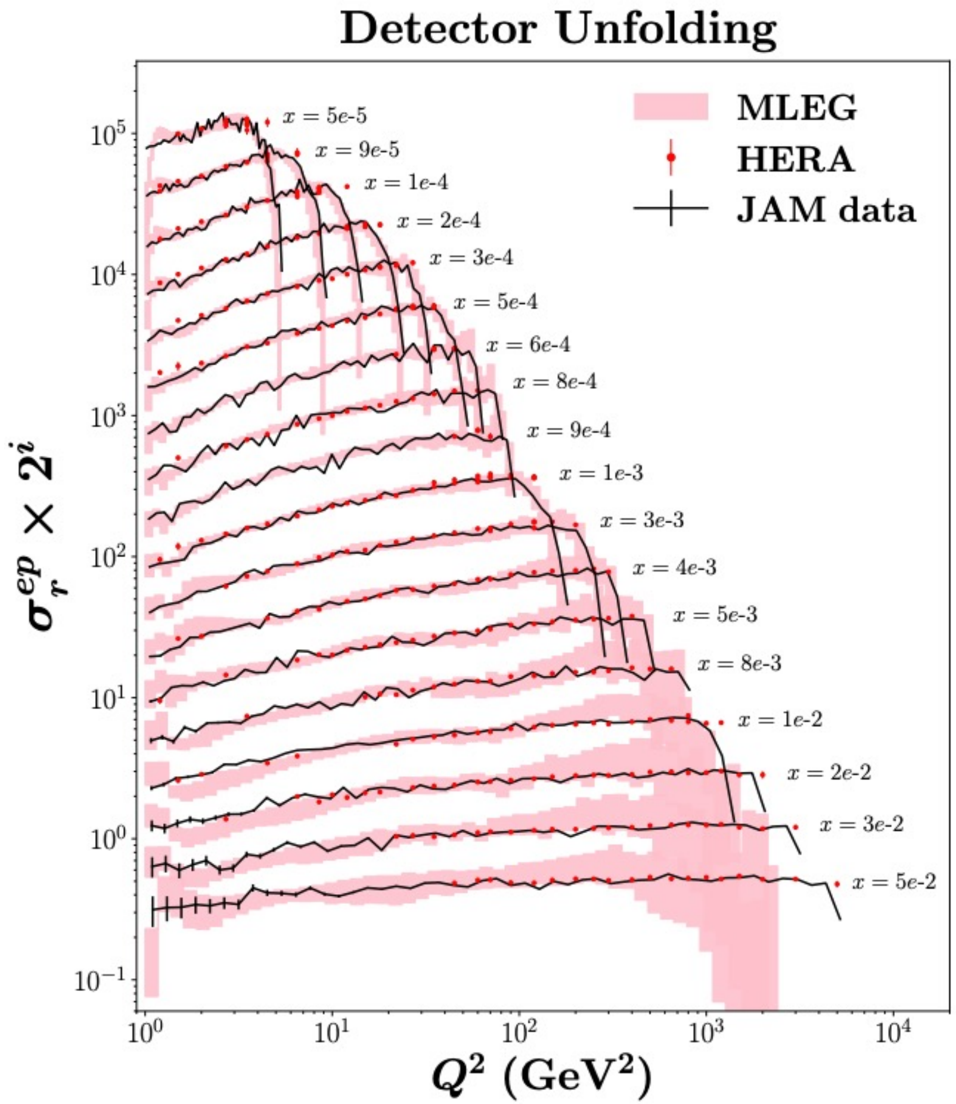
II) GAN training with detector effects

eic-smear introduces a significant distortion to the detector level event samples, in particular on ν_2





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Conclusions for the DIS case

The ‘closure test’ was successful:

- GAN generated events trained on vertex level pseudo-data are recovered
- GAN reconstructed events trained on detector-smeared pseudo-data are recovered
- GAN generated events trained on reconstructed events and unfolded with a GAN detector proxy are recovered with larger error bars, in particular on the edge of the phase space
- The PDFs are correctly recovered

Detector acceptance

- Simple 2-body process: $\gamma p \rightarrow \Delta^{+}(1232) \rightarrow \pi^{0} p$

- Simple model: Breit-Wigner amplitude with parameters m_Δ and Γ_Δ

$$\frac{d\sigma}{d\Omega} \propto \frac{p_f}{p_i\, s} \sum_{\lambda_\gamma \lambda_p \lambda'_p} \left| (-)^{\lambda_\gamma} H_{|\lambda_\gamma - \lambda_p|} \frac{d^{3/2}_{\lambda_\gamma - \lambda_p, -\lambda'_p}(\theta)}{m_\Delta^2 - s - i\Gamma_\Delta m_\Delta} \right|^2$$

$$\propto \frac{p_f}{p_i\, s} \frac{3\left|H_{3/2}\right|^2 + 5\left|H_{1/2}\right|^2 - 3\cos 2\theta \left(\left|H_{3/2}\right|^2 - \left|H_{1/2}\right|^2 \right)}{(m_\Delta^2 - s)^2 + \Gamma_\Delta^2 m_\Delta^2}$$

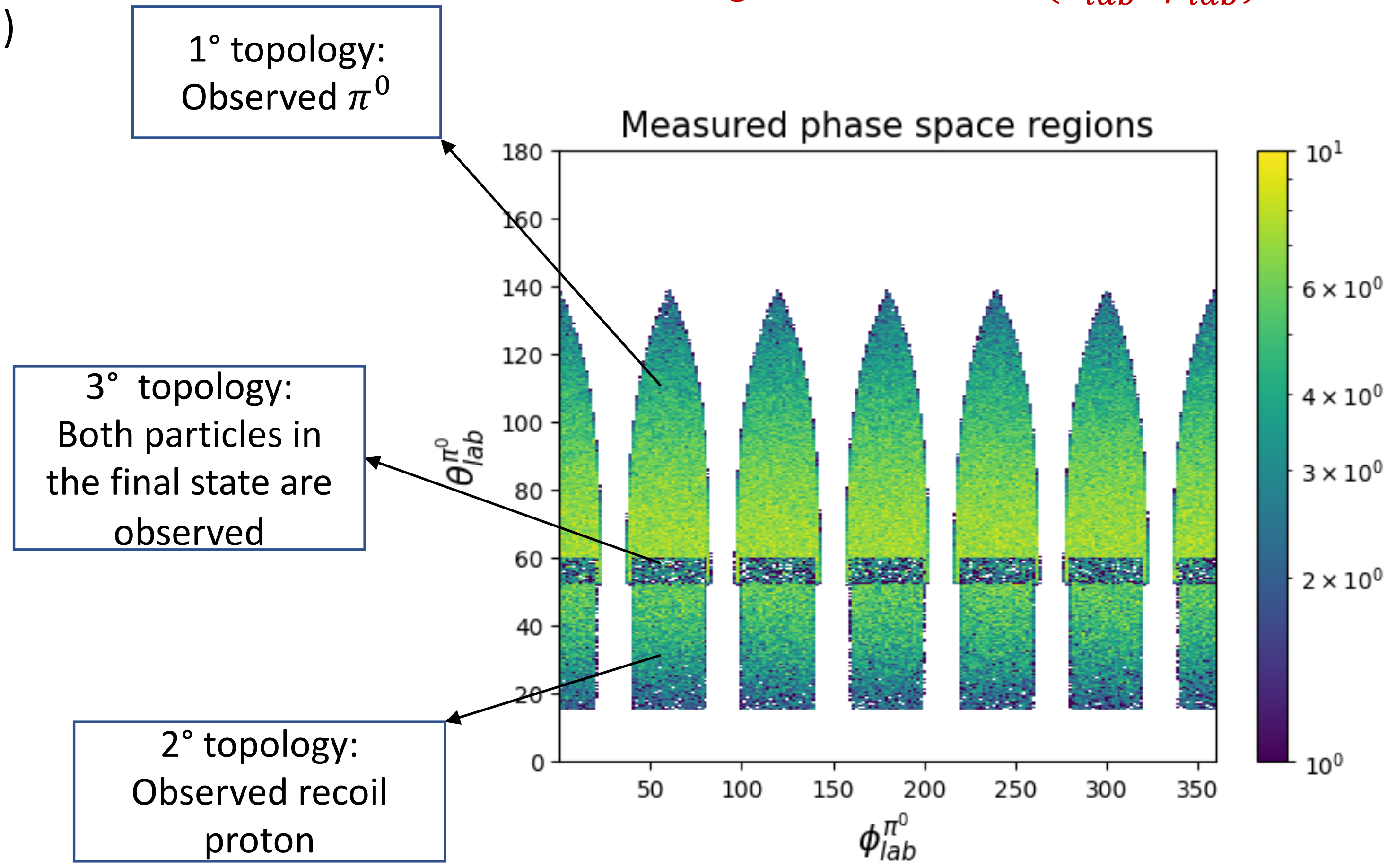
- Two independent variables for the process: We chose them to be the scattering $\theta_{lab}^{\pi^0}$ angle and the azimuthal $\phi_{lab}^{\pi^0}$ angle in the lab frame

- **Goals:**
  - ➢ Build a single GAN model which includes all the available phase space of the same reaction in order to understand if extending the range of the measured phase space would improve our knowledge of relevant observables
  - ➢ Quantify the model dependence on the unmeasured regions of the phase space

Detector acceptance

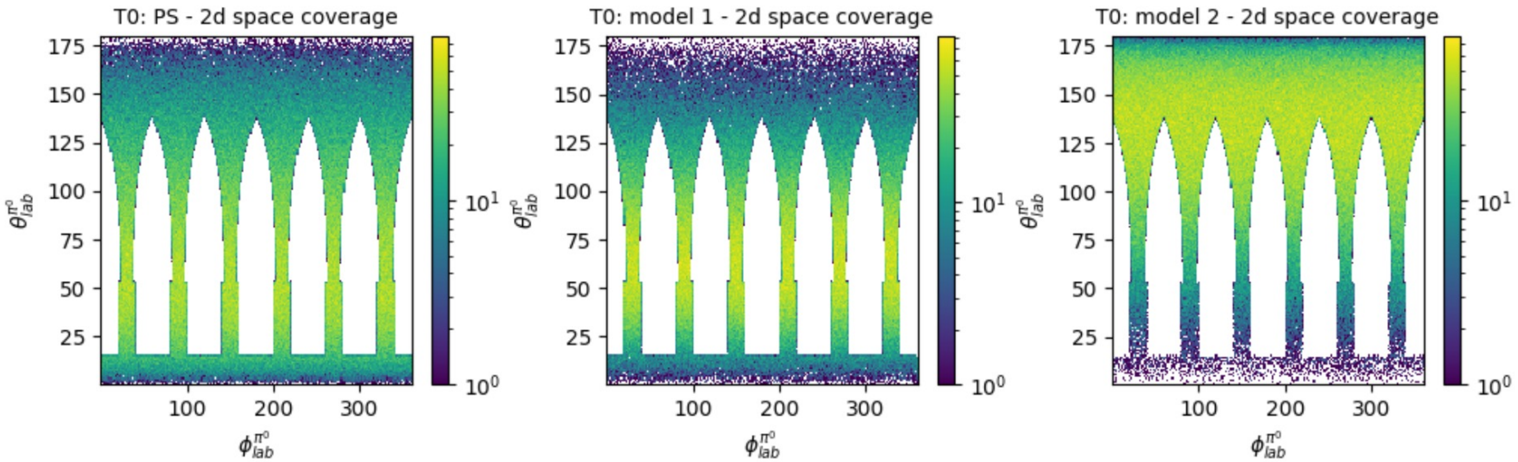
- Implementing CLAS acceptance cuts we define three different measured topologies for the reaction $\gamma p \rightarrow \pi^0 p$
  - Topology 0: $\gamma p \rightarrow (\pi^0 p)$ (Unmeasured)
  - Topology 1: $\gamma p \rightarrow \pi^0 (p)$
  - Topology 2: $\gamma p \rightarrow (\pi^0) p$
  - Topology 3: $\gamma p \rightarrow \pi^0 p$
- Build a single GAN model which includes all the measured phase space regions + different models in the unmeasured region

Combining the topologies in the lab frame looking at π^0 variables $(\theta_{lab}^{\pi^0}, \phi_{lab}^{\pi^0})$:



Detector acceptance

- Distinguish different models, built modifying the amplitudes, which will cover the unmeasured region of the phase



- Build two different datasets (PS and Model2) to train the same GAN architecture with them to check the model dependence
  - $Model1 = (M1_{meas})$ will be considered the equivalent of observed data
  - Dataset1: $(PS_{T0},\ M1_{meas})$
  - Dataset2: $(M2_{T0},\ M1_{meas})$

- Histograms considering just the measured quantities (and check that for both dataset the 'true' observed variables are recovered)
- Histogram considering **all the phase space** (measured and unmeasured) to quantify the model dependence

Summary

A(I)DAPT program aims to demonstrate a novel way to extract and interpret physics observables

We performed a positive closure test on inclusive DIS scattering:

- We demonstrated that GANs can effectively reproduce desired distributions
- We demonstrated that GANs are a viable tool to unfold detector effects (smearing) to generate a synthetic copy of data
- Preserve data in alternative compact and efficient form

We are working on:

- Quantifying the systematic error introduced by the detector acceptance
- Further verify that this procedure is well defined confronting the results obtained analysing CLAS data with traditional analysis in order to extract a 4D cross-section
- Make this procedure an efficient way to analyze CLAS12 2π data (Marco)
- Evaluating scattering amplitudes to generalize results (Gloria)

Thank you!

The A(i)DAPT program
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Marco Spreafico

on behalf of A(i)DAPT Working Group

A(i)DAPT

AI for Data Analysis and PreservaTion

Exclusive reactions: 2 → 3

$\boldsymbol{\gamma p \to \pi^+\pi^- p}$ **(unpolarized)**

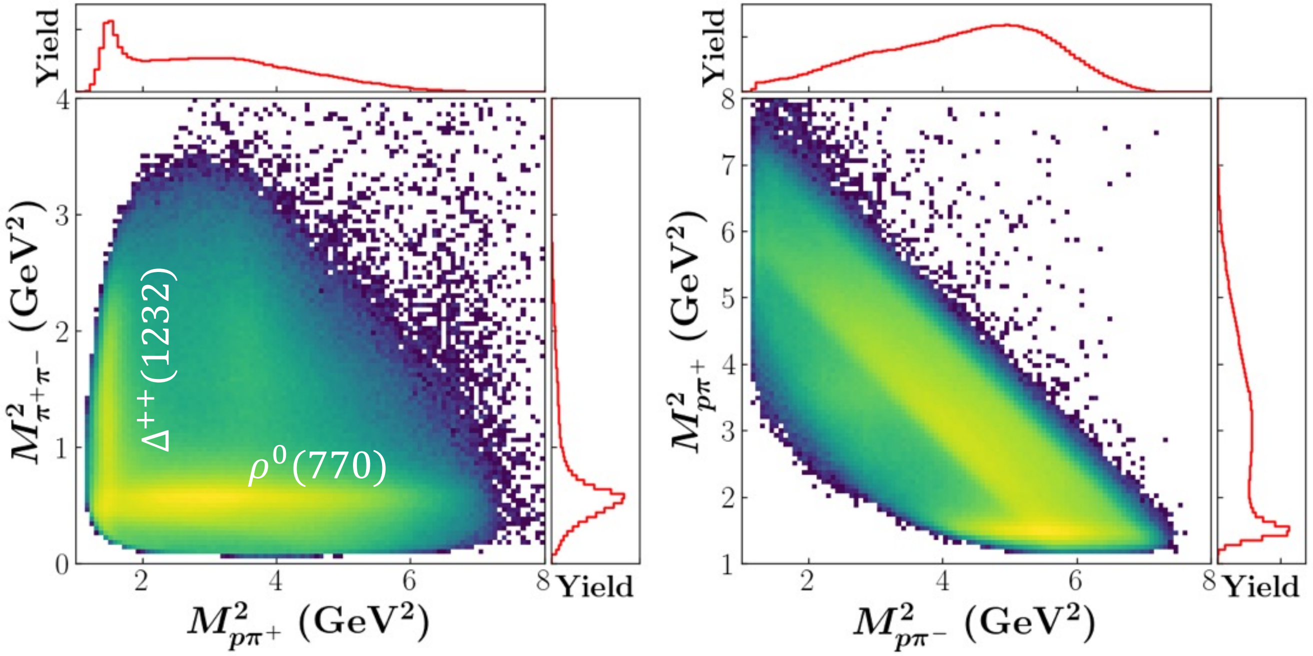
- Fully known initial state
- (3x3) – 4 = 5 Independent variables
- Possible choice: $M^2_{\pi\pi}, M^2_{p\pi}, \theta_\pi, \alpha, \phi$

CLAS g11 2π photoproduction:

- $E_\gamma = (3 - 3.8)\ GeV$
- Focus on $\gamma p \to p\pi^+(\pi^-)$
  - π^- momentum evaluated as missing momentum
  - small contamination from $\gamma p \to p\pi^+(\pi^- X)$
- Main contribution to dynamics:
  - ρ^0photoproduction
  - Δ^{++} resonance excitation

Goal: evaluate cross section in multiD phase space

$$\frac{d^5\sigma(\gamma p \to p\pi^+\pi^-)}{dM_{\pi\pi}\, dM_{p\pi}\, d\cos(\theta)\, d\alpha\, d\phi}$$



AI could provide a new way to look at data and to extract observables and physics interpretation

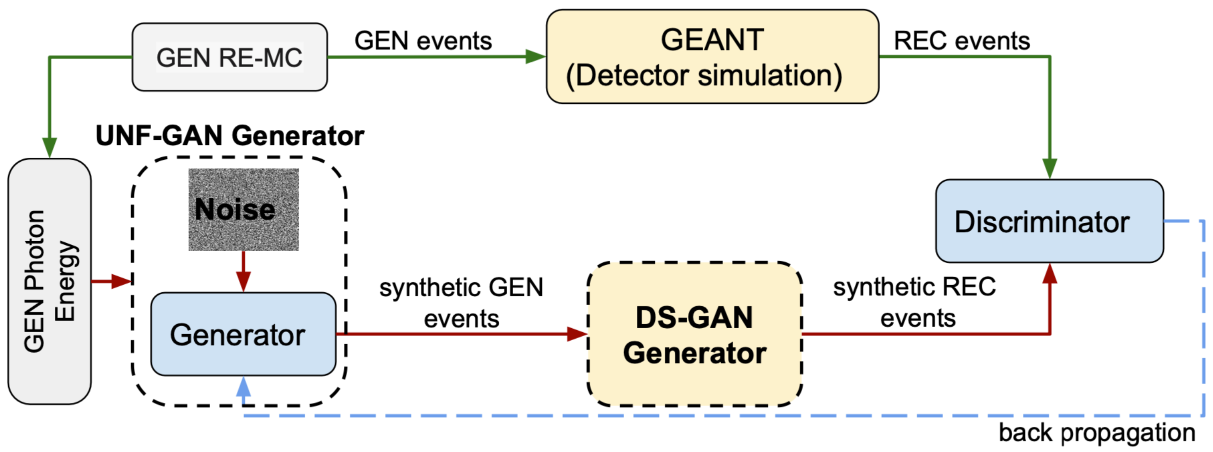
Credit: Y.Alanazi Awadh, , P.Ambrozewicz, G. Costantini A.Hiller Blin, E. Isupov, T. Jeske, Y.Li, L.Marsicano W. Menlnitchouk, V.Mokeev, N.Sato, A.Szczepaniak, T.Viducic

2π photoproduction closure test

CLOSURE TEST

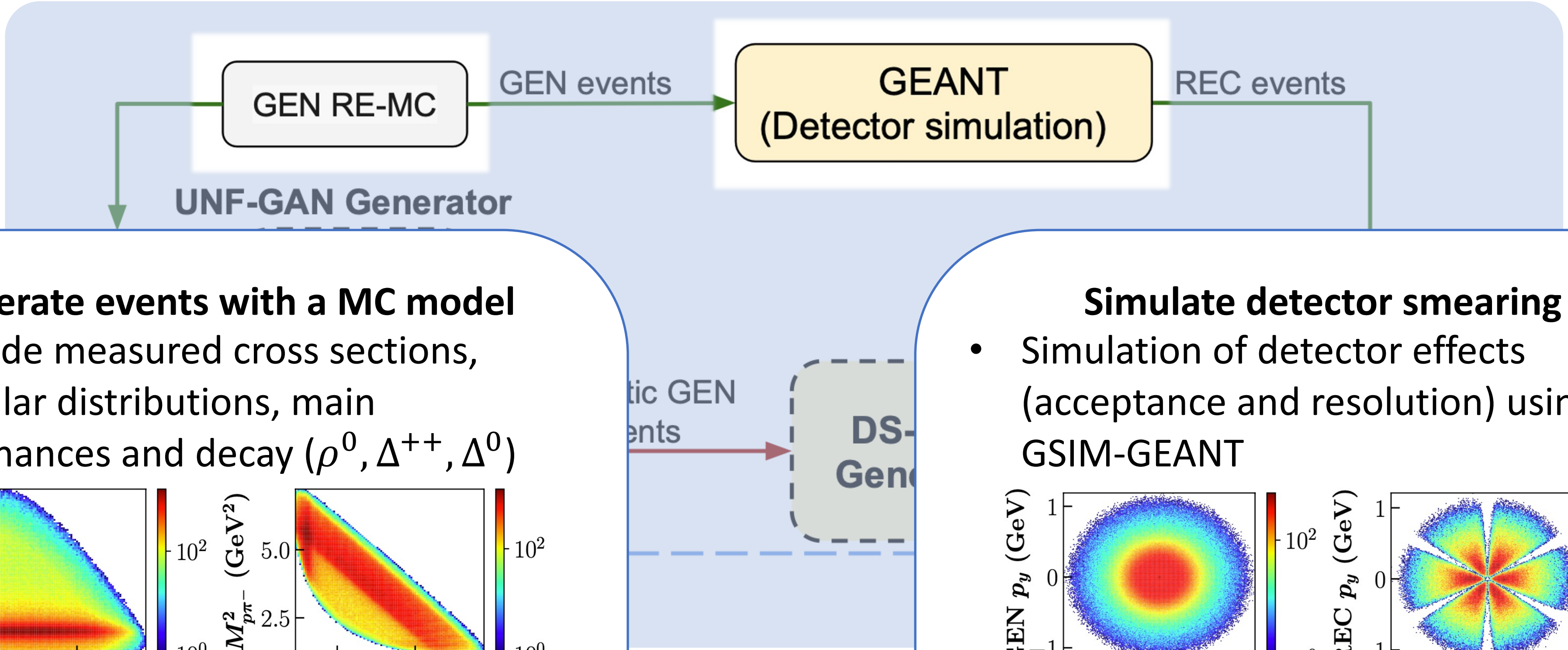
Can GANs reproduce multi dimensional correlations unfolding detector effects? How data generated by a GAN and unfolded with a GAN-based detector proxy compare to vertex-level events?

1. Generate events with a MC model
2. Simulate detector smearing using MC (GSIM-GEANT)
3. DS-GAN to simulate detector effects
   - Training on phase-space-only pseudo-data
4. UNF-GAN to generate synthetic events
   - training over MC pseudo-data
5. Compare synthetic GAN data to MC pseudo-data
6. Replace pseudo-data with CLAS data in training to unfold the vertex-level experimental distributions



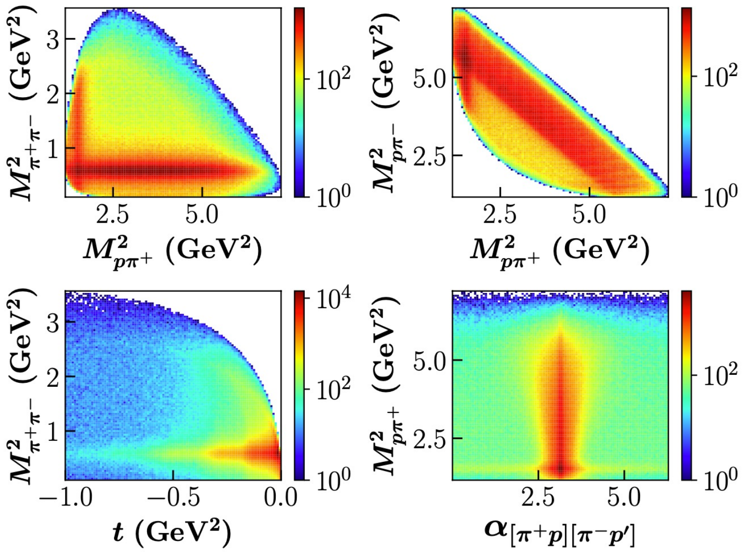
Credit: T.Alghamdi, M.Battaglieri, A.Golda, A. Hiller Blin, L.Marsicano, W.Melnitchouk, G.Montaña, E.Isupov, Y.Li, V.Mokeev, A.Pilloni, N.Sato, A.Szczepaniak, T.Vittorini, Y.Alanazi
arXiv:2307.04450

2π photoproduction closure test



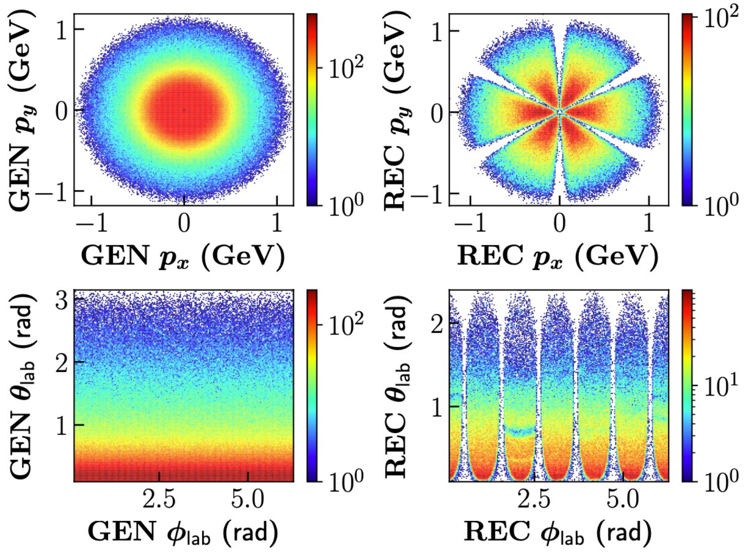
Generate events with a MC model

- Include measured cross sections, angular distributions, main resonances and decay ($\rho^0, \Delta^{++}, \Delta^0$)



Simulate detector smearing

- Simulation of detector effects (acceptance and resolution) using GSIM-GEANT



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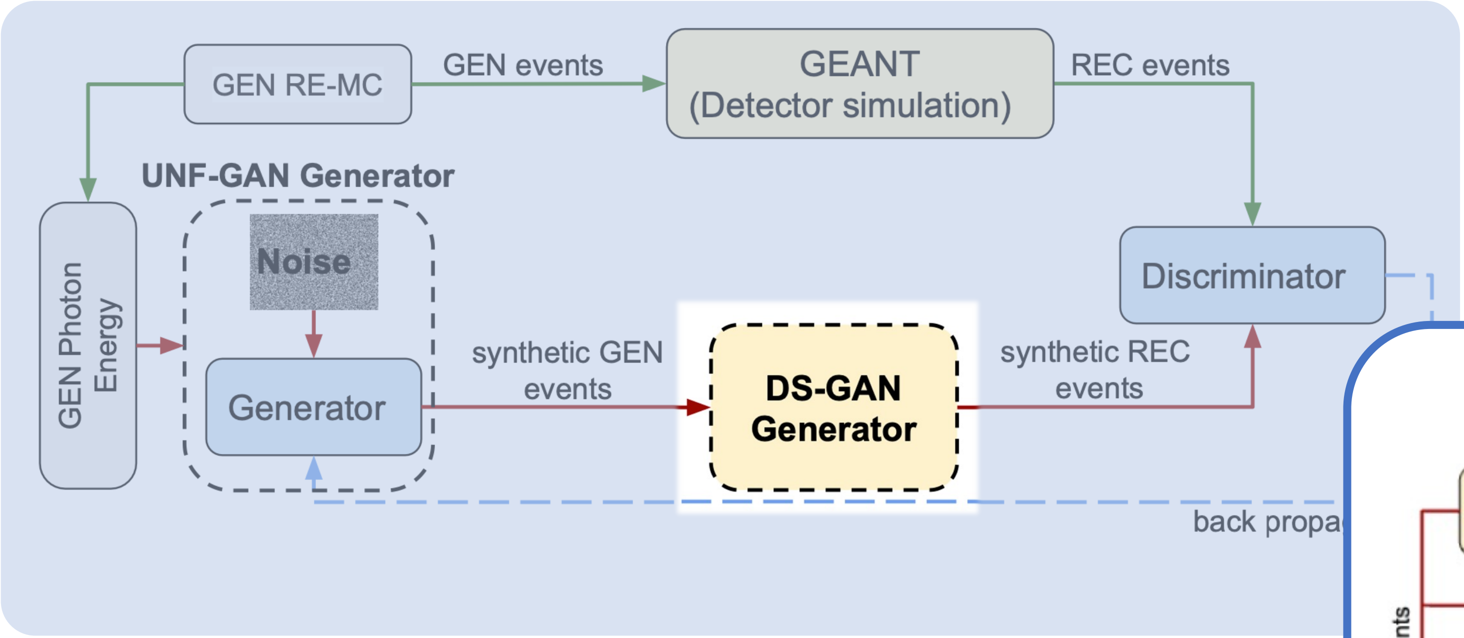
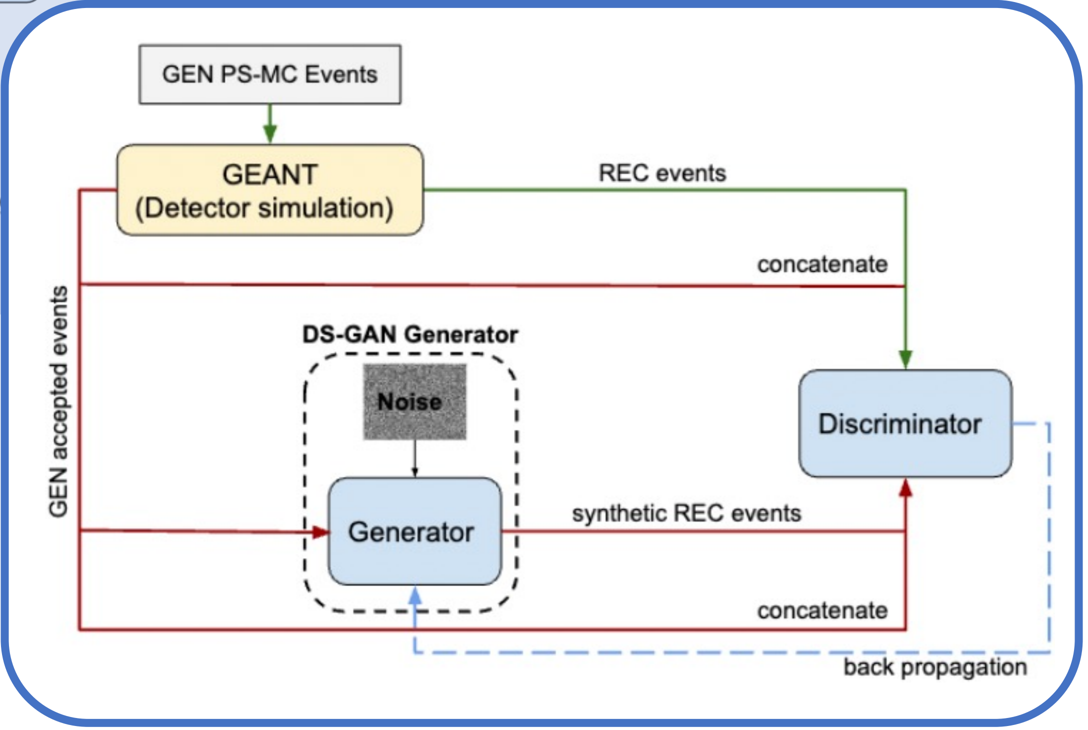
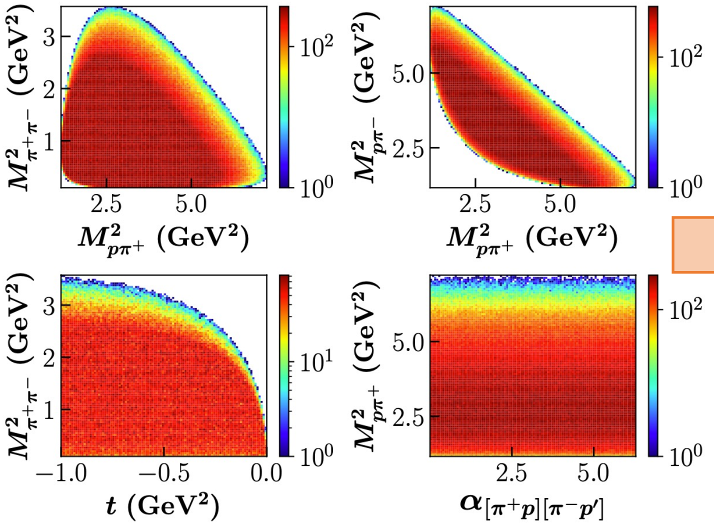
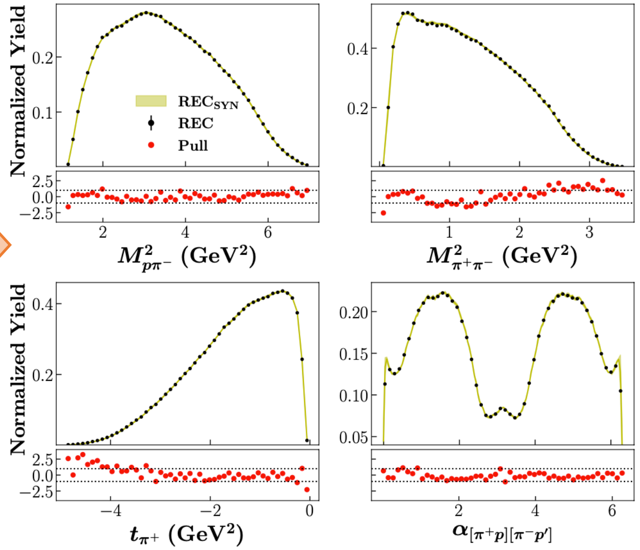


Detector simulator GAN

- Secondary GAN to learn detector effects
- Trained on phase space MC events
- Uncertainty quantification via pull calculation







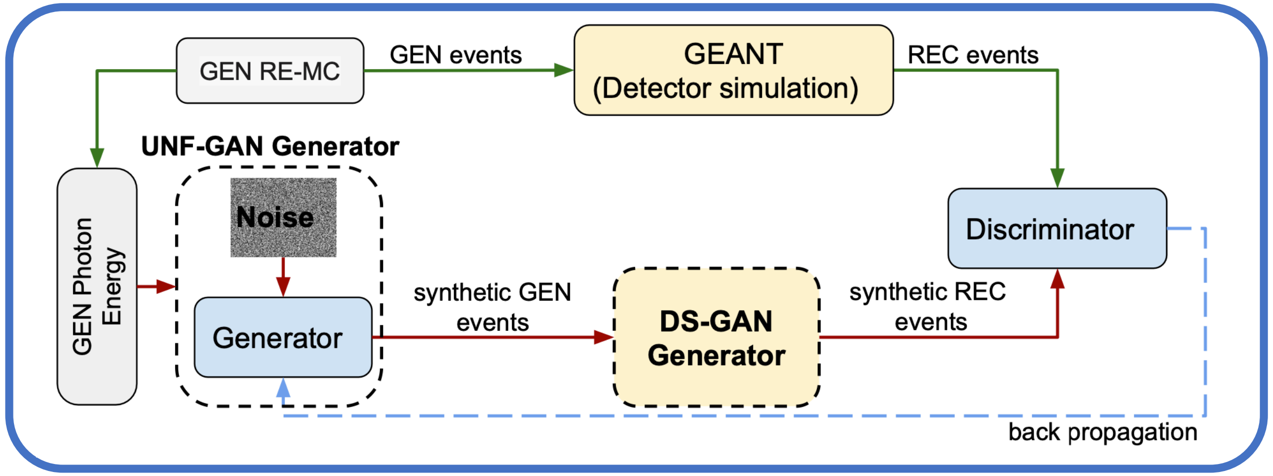
DS-GAN learned detector effects!

Credit: T.Alghamdi, M.Battaglieri, A.Golda, A. Hiller Blin, L.Marsicano, W.Melnitchouk, G.Montaña, E.Isupov, Y.Li, V.Mokeev, A.Pilloni, N.Sato, A.Szczepaniak, T.Vittorini, Y.Alanazi *arXiv:2307.04450*

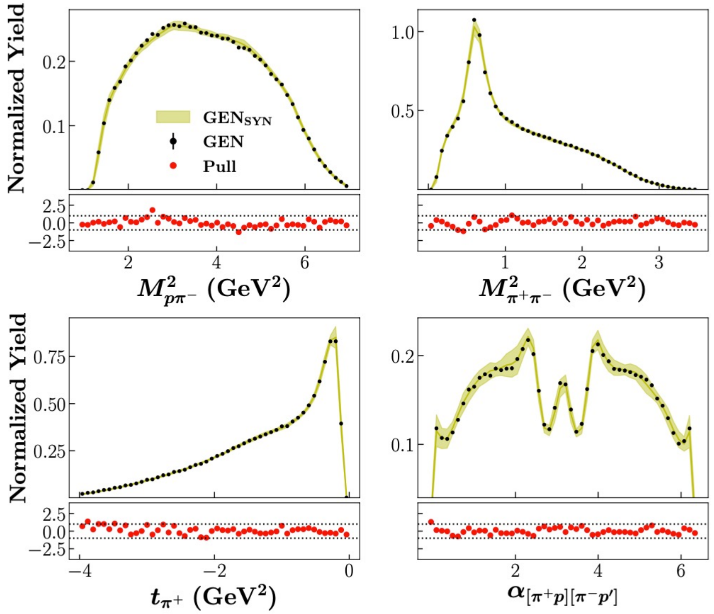
2π photoproduction closure test

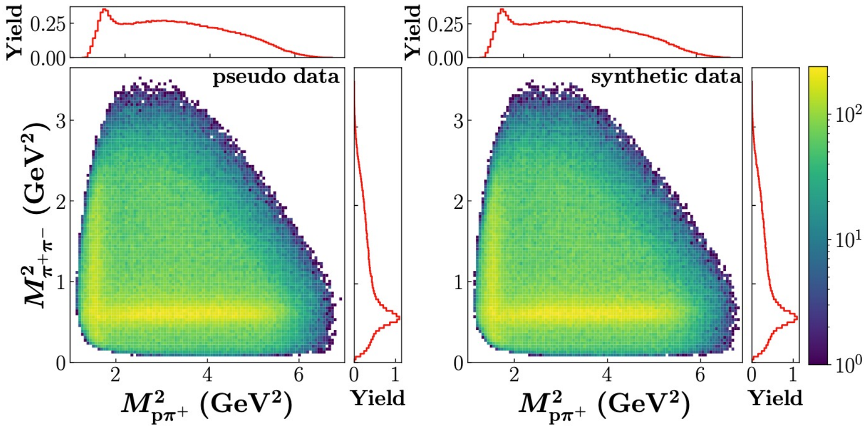
Training of the UNF-GAN with pseudo-data

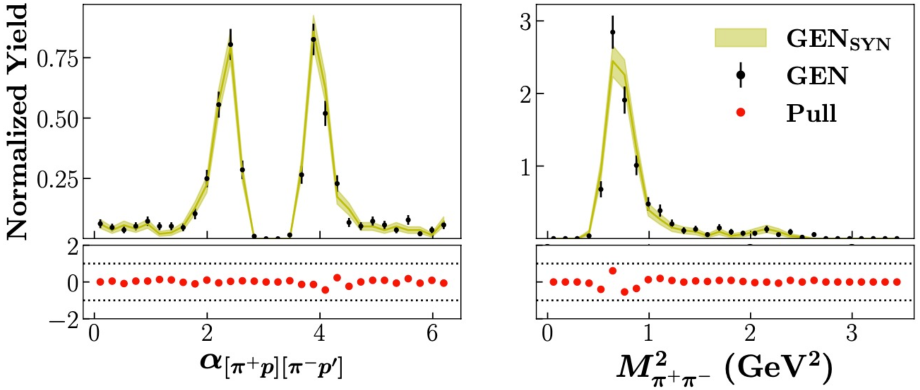
- Trained on MC pseudo-data
- Generated synthetic vertex-level data
- Detector effects applied with DS-GAN
- Uncertainty estimated with pull quantification



1D → **2D** → **4D**





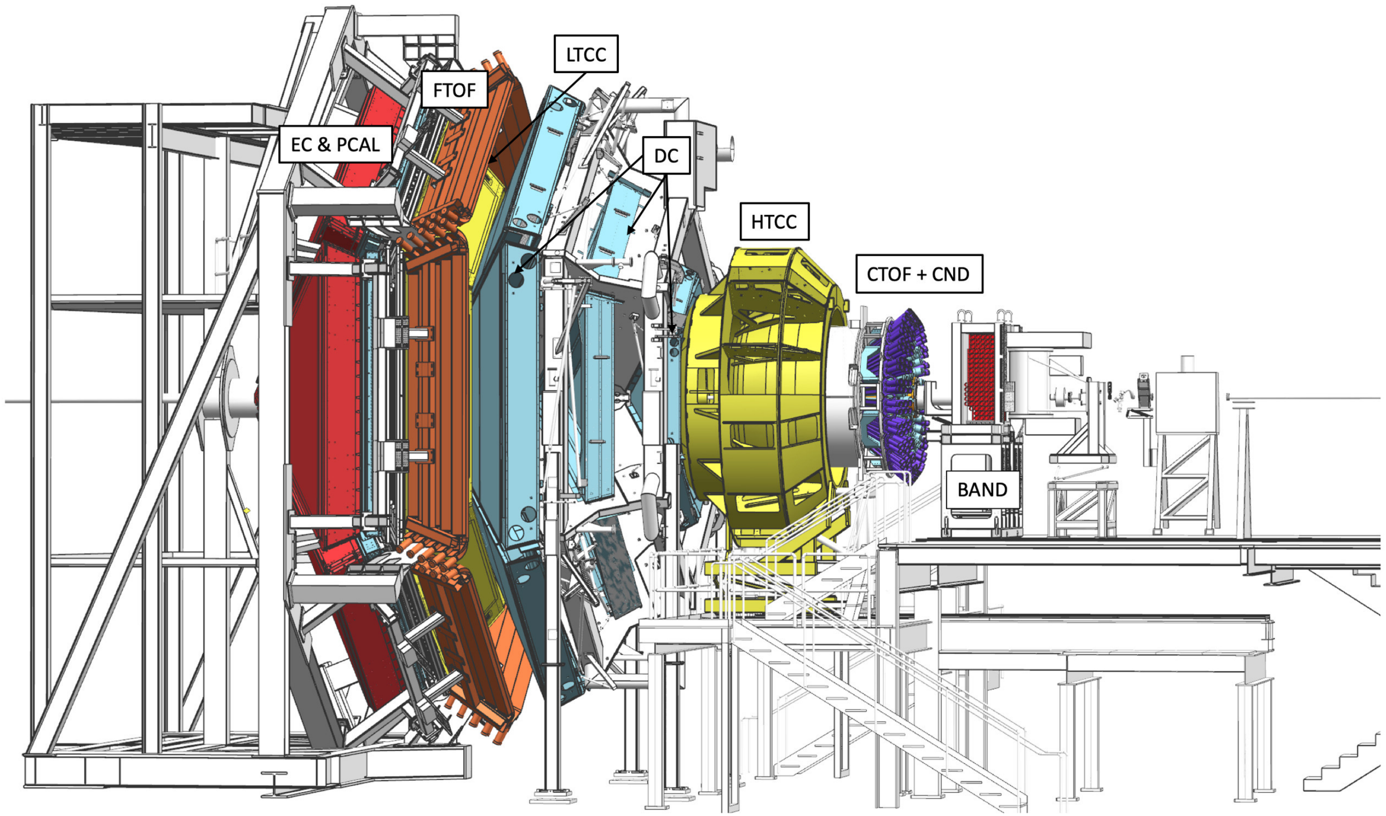


UNF-GAN can reproduce detector level pseudo-data within $\pm 1\sigma$
Correlations are preserved both in 2D and in 4D distributions within $\pm 1\sigma$

Next step

The next step to achieve A(i)DAPT goals:

- **Application to real data**
  - Train UNF-GAN using CLAS g11 data
  - Assess GAN capability to mimic real data
- **Application to CLAS12 detector and physics**
  - Train DS-GAN on CLAS12 pseudo-data
  - Apply UNF-GAN to electroproduction data
- **Extrapolation of scattering amplitudes**
  - Extract amplitudes from differential cross-sections exploiting theoretical constraints
  - Test on elastic scattering $\pi^+\pi^- \to \pi^+\pi^-$
  - Extend to multi-particle exclusive channels



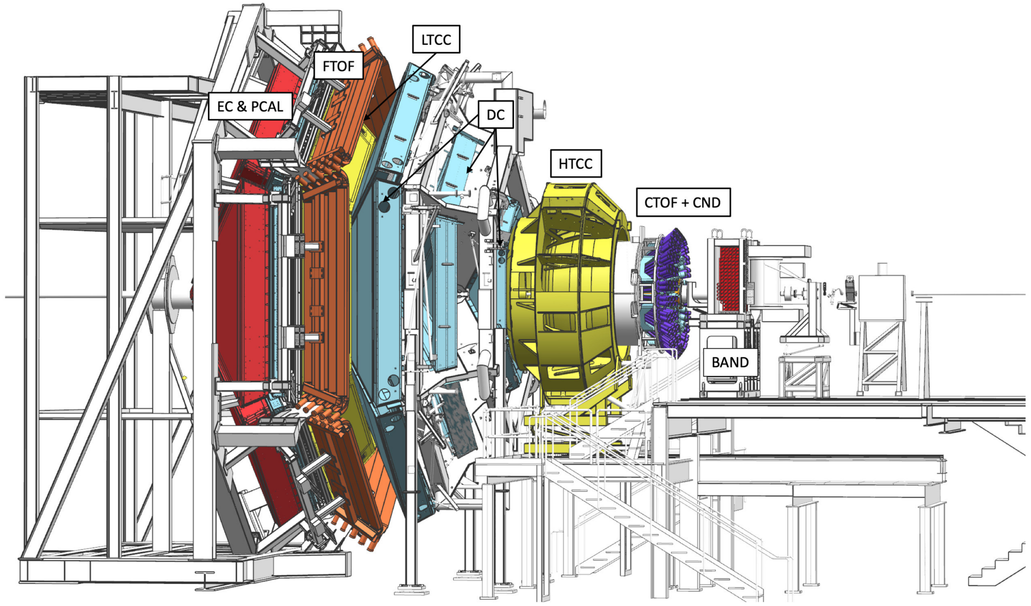
Our goal is to develop a new tool accessible to everyone and that can be used to improve any analysis

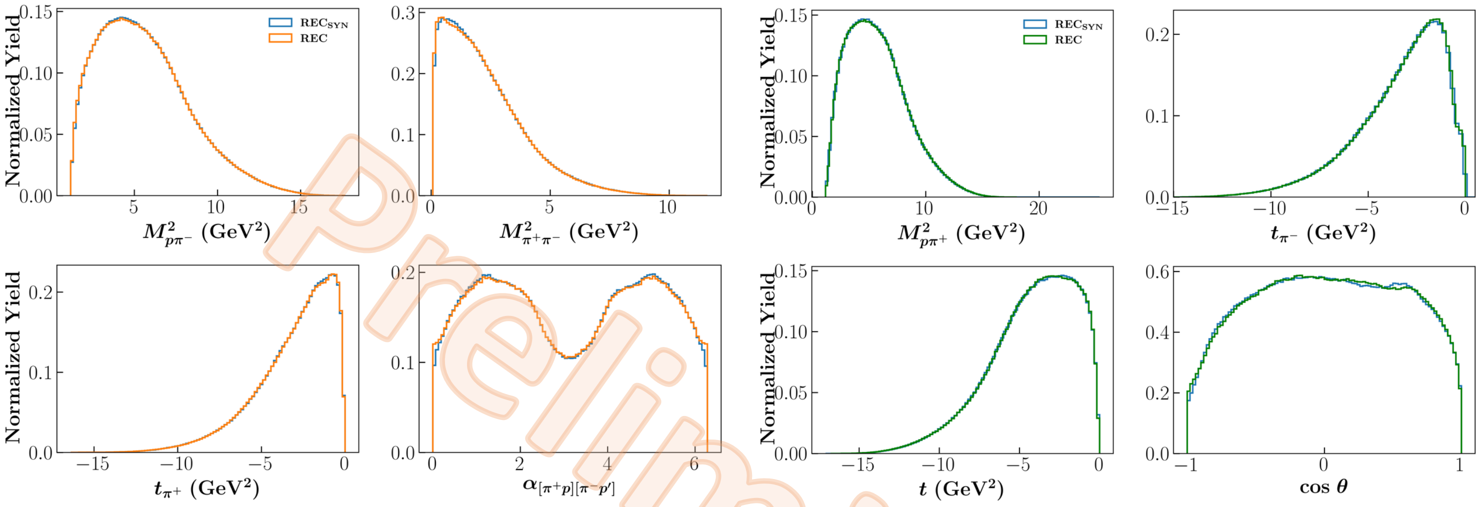
CLAS12 application

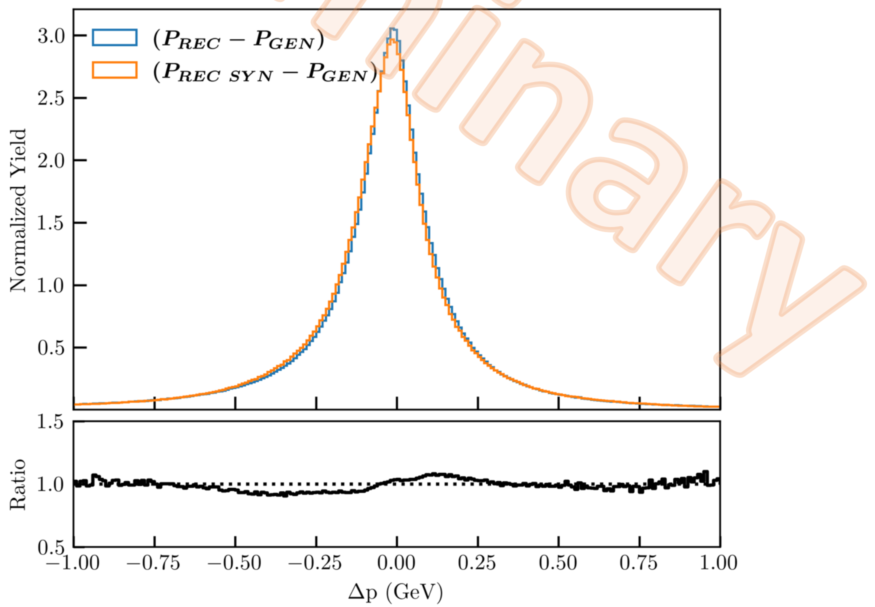
DS-GAN training on CLAS12 pseudodata

- Different detector layout
- Robustness test

The same GAN can reproduce with sufficient precision also vertex-level data for CLAS12 detector







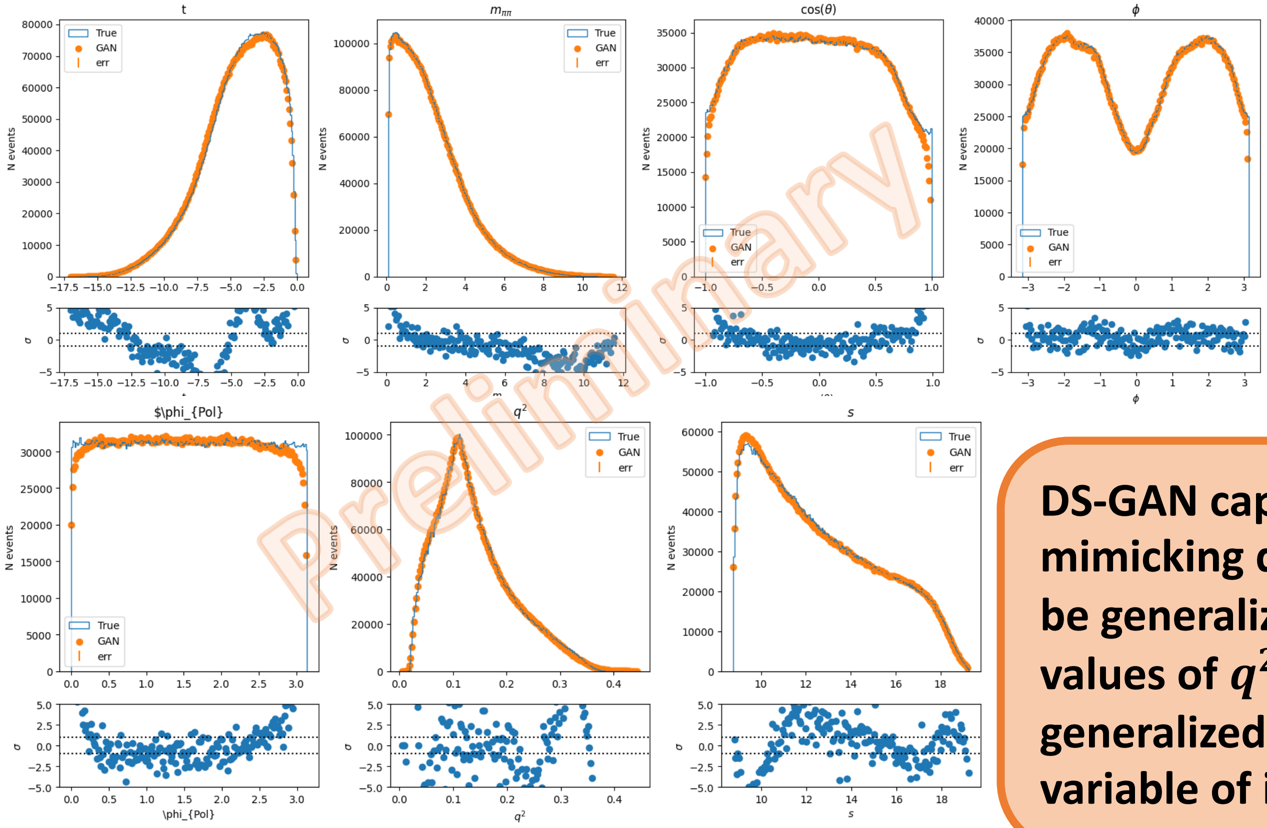
Credit: Derek Glazier, Tareq Alghamdi

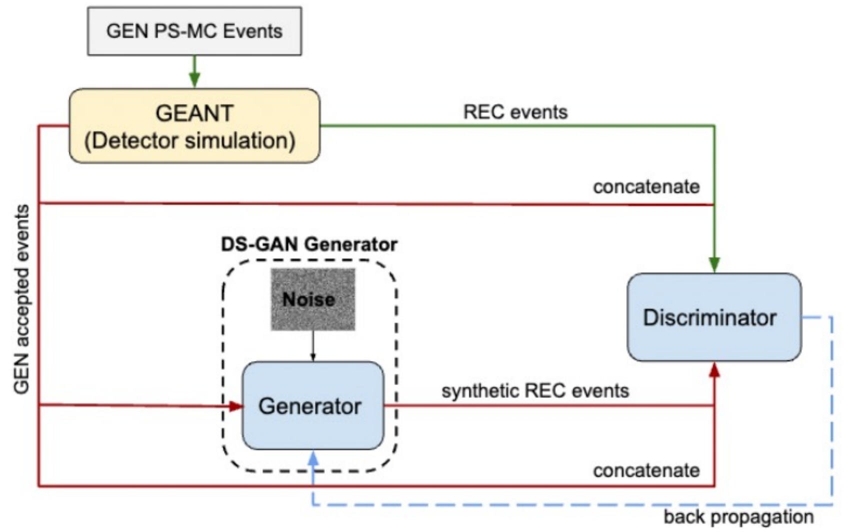
Electroproduction - $ep \to e\pi^+\pi^-p$

- 7 independent variables:

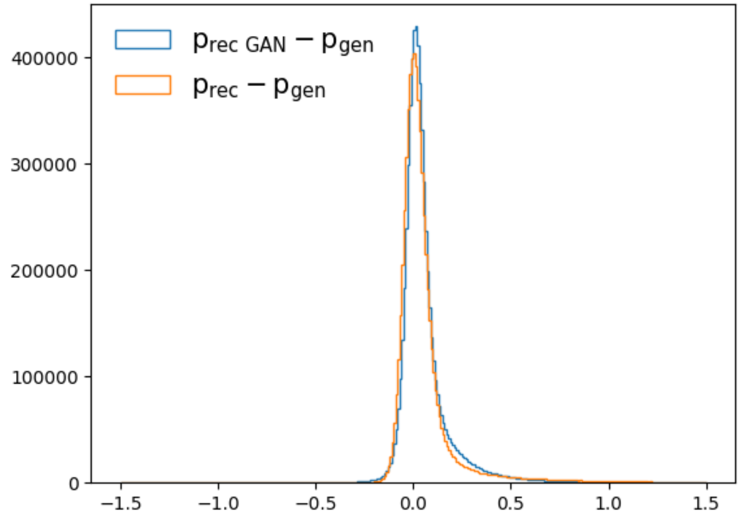
$$s = (p_\gamma + p_p)^2, t = (p_\gamma - p_{\pi\pi})^2, m_{\pi\pi}, \varphi_{POL}, \theta, \phi, q^2$$

- Increased DS-GAN output size to generate new variables





DS-GAN capability of mimicking detector effects can be generalized to different values of q^2 and can be generalized to generate any variable of interest



Summary

A(I)DAPT program aims to demonstrate a novel way to extract and interpret physics observables

- We performed a successful closure test on 2π photoproduction pseudo-data
  - GAN can reproduce detector effects on data
  - GAN can reproduce synthetic data that retain multi-dimensional correlation as “real” data

- Proven algorithm robustness:
  - Able to reproduce different detector layouts (CLAS, CLAS12)
  - Can simulate different processes (photoproduction, electroproduction)

We are working on:

- Quantification of systematic error introduced by detector acceptance (Tommaso)
- Application on real data (CLAS and CLAS12 2π data)
- Evaluation of scattering amplitude to generalize results (Gloria)

Thank you!

5th Workshop on Future Directions in Spectroscopy Analysis (FDSA2024)
Genova, January 22-24, 2024

Amplitude extraction with GANs

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Theory Center, Thomas Jefferson National Accelerator Facility

In collaboration with
A. Pilloni, Y. Li, L. Bibrzycki, M. Battaglieri and others

A(i)DAPT
AI for Data Analysis and PreservaTion

Physics model

- Elastic scattering $\pi^+\pi^- \to \pi^+\pi^-$

$$A(s,\cos\theta) = \sum_{\ell=0}^{n}(2\ell+1)f_\ell(s)P_\ell(\cos\theta)$$

- Breit-Wigner type partial waves $f_\ell(s),\ \ell = 0,1$

$$f_0(s) = \frac{m_\sigma\Gamma_\sigma}{m_\sigma^2 - s - i\Gamma_\sigma m_\sigma} \qquad m_\sigma \approx 0.475\ \text{GeV}\ ,\ \Gamma_\sigma \approx 0.55\ \text{GeV}$$

$$f_1(s) = \frac{m_\rho\Gamma_\rho}{m_\rho^2 - s - i\Gamma_\rho m_\rho} \qquad m_\rho = 0.775\ \text{GeV}\ ,\ \Gamma_\rho = 0.147\ \text{GeV}$$

$$\longrightarrow \quad A(s,\cos\theta) = f_0(s) + 3f_1(s)\cos\theta$$

- Differential cross section

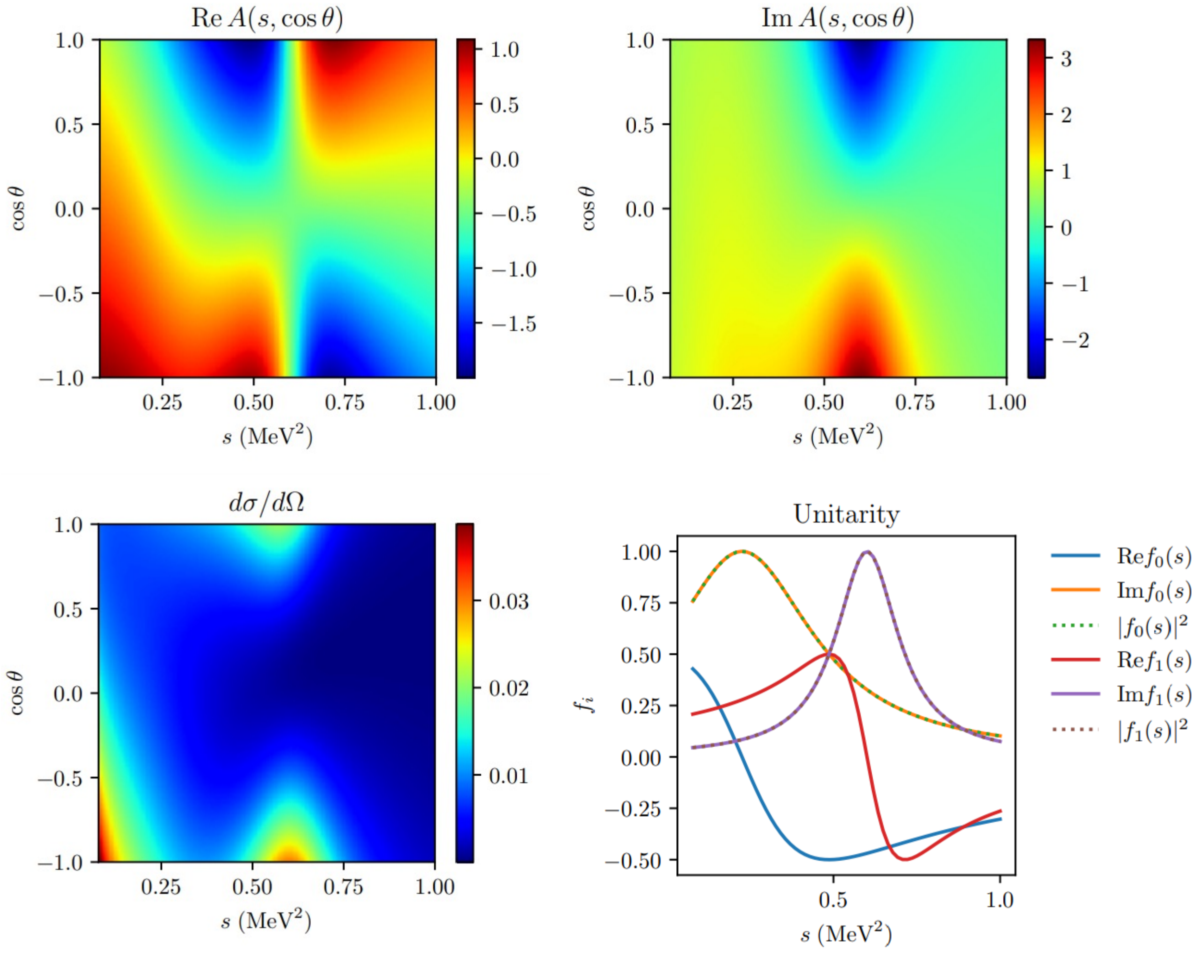
$$\frac{d\sigma}{d\Omega} = \frac{1}{64\pi^2}\frac{1}{s}|A(s,\theta)|^2$$

- Physics constraint: Unitarity of the partial waves

$$\mathrm{Im} f_0(s) = |f_0(s)|^2$$

$$\mathrm{Im} f_1(s) = |f_1(s)|^2$$

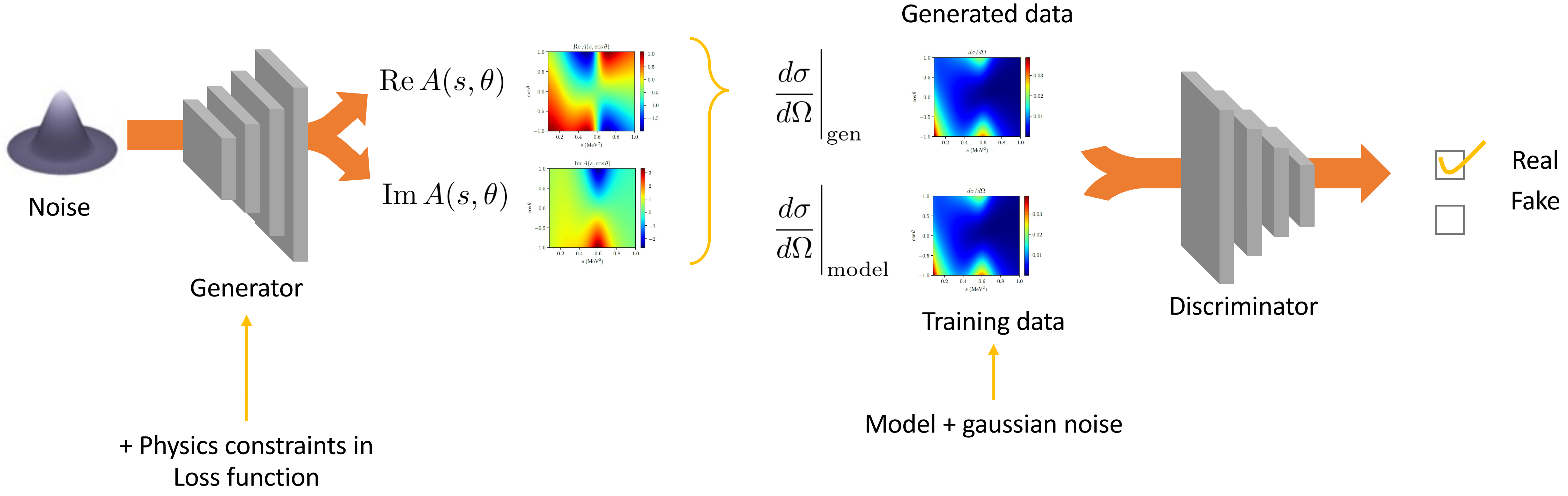
$$f_l(s) = \frac{1}{2}\int_{-1}^{+1} d(\cos\theta)P_\ell(\cos\theta)A(s,\theta)$$



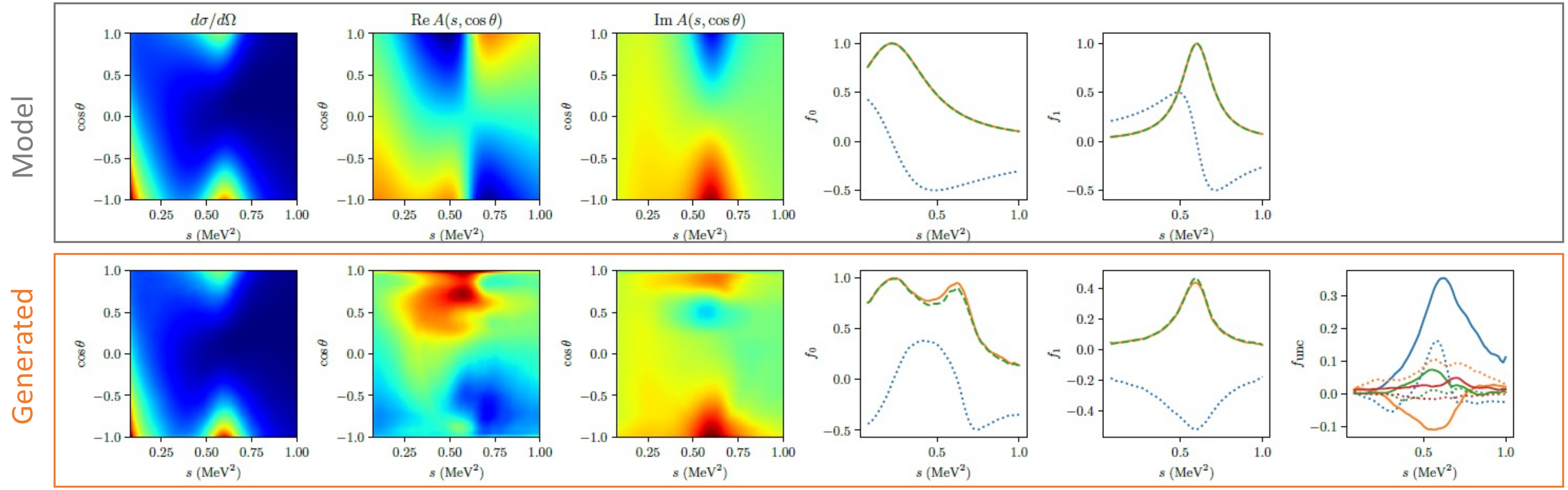
Generative Adversarial Network (GAN) with constraints

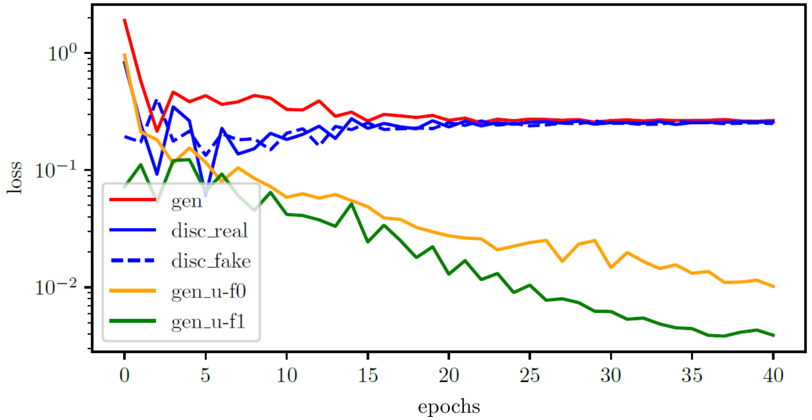
Two neural networks, the **generator** and the **discriminator**:

- The **generator** needs to capture the data distribution
- The **discriminator** estimates the probability that a sample comes from the training data rather than from the generator



Preliminary results (i)





- Cross section is reproduced qualitatively
- Unitarity constraint is satisfied
- Partial waves $\ell \geq 2$ are large

More physics constraints

- Unitarity of the partial waves $f_\ell(s),\ \ell = 0, 1$

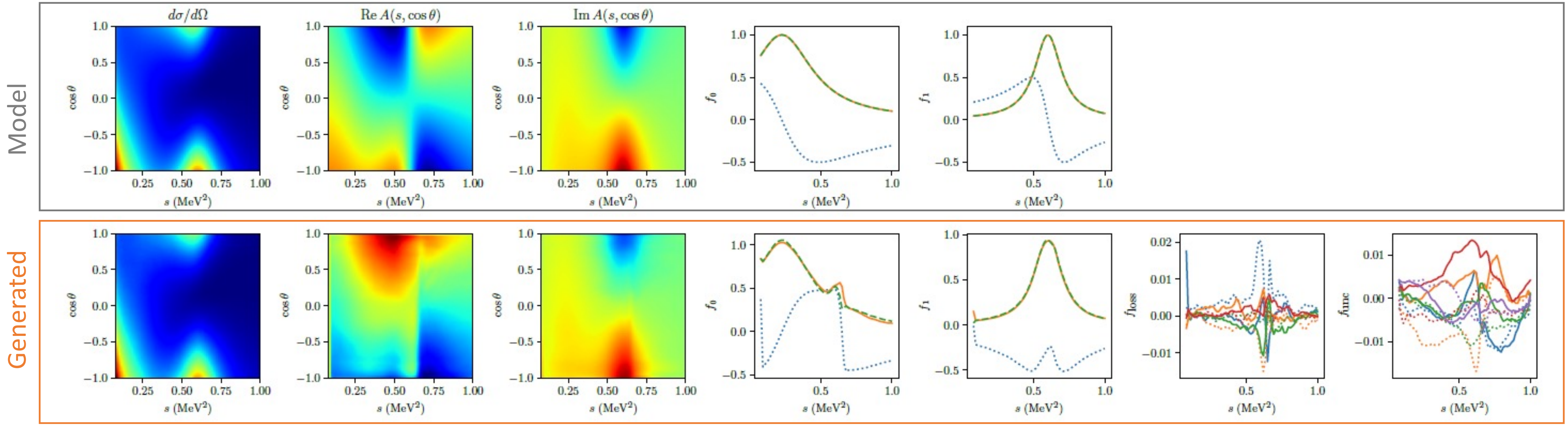
$$\mathrm{Im} f_0(s) = |f_0(s)|^2$$

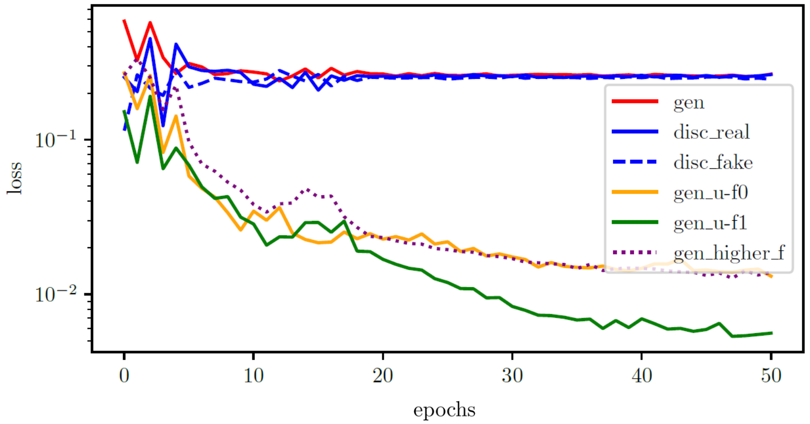
$$\mathrm{Im} f_1(s) = |f_1(s)|^2$$

- Suppression of higher partial waves

$$f_\ell(s) = 0,\ \ell \geq 2$$

Preliminary results (ii)





- Cross section is reproduced qualitatively
- Unitarity constraint is satisfied
- Partial waves $\ell \geq 2$ are suppressed
- Ambiguity in the sign of the real part

More physics constraints

- Unitarity of the partial waves $f_\ell(s),\ \ell = 0, 1$

$$\mathrm{Im} f_0(s) = |f_0(s)|^2$$

$$\mathrm{Im} f_1(s) = |f_1(s)|^2$$

- Suppression of higher partial waves

$$f_\ell(s) = 0,\ \ell \geq 2$$

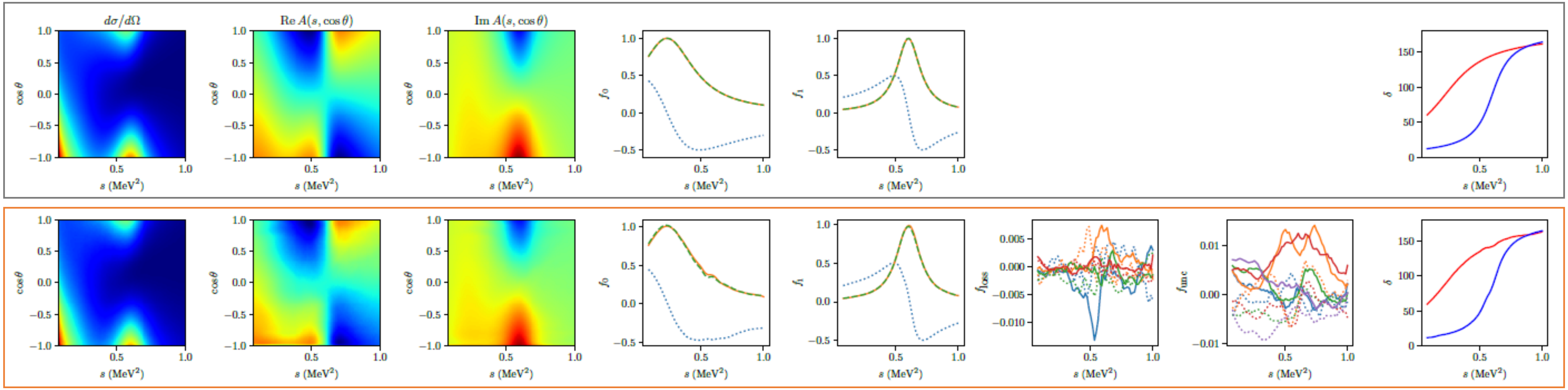
- Positive derivative of the phase shift $\delta_\ell(s) = \mathrm{atan}\left(\frac{\mathrm{Im} f_\ell(s)}{\mathrm{Re} f_\ell(s)}\right)$

$$\frac{\mathrm{d}}{\mathrm{d}s}\ \delta_0(s) \geq 0$$

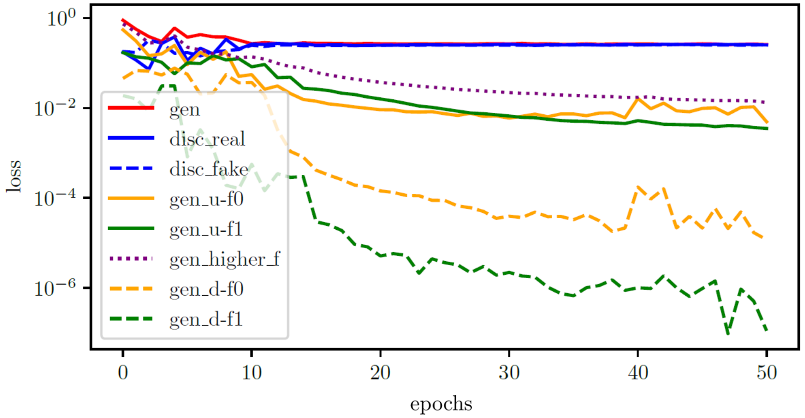
$$\frac{\mathrm{d}}{\mathrm{d}s}\ \delta_1(s) \geq 0$$

Preliminary results (iii)

Model



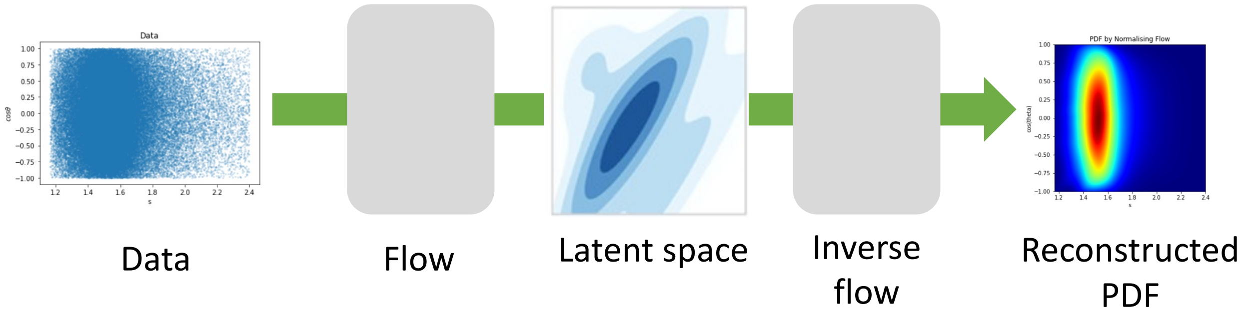
Generated



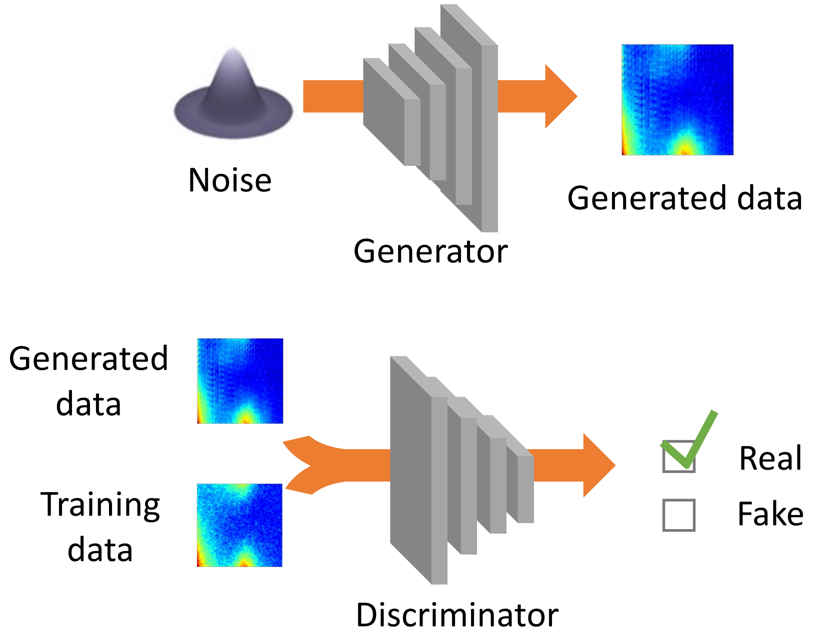
- Cross section is reproduced qualitatively
- Unitarity constraint is satisfied
- Partial waves $\ell \geq 2$ are suppressed
- The real part takes the right sign

Events → Cross section → Amplitude

A. **Normalizing Flows**: extract differential cross section (∝ Probability Density) from events distribution



B. **Generative Adversarial Networks (GANs)**: extract amplitude from differential cross sections, using unitarity



Summary and outlook

Preliminary status, but the results of using GANs to extract amplitudes from cross sections employing physics constraints are promising.

Next steps:

- Increase gaussian noise of the training pseudodata set (currently 0.1%)
- Adjust the generator and/or discriminator models and hyperparameters for convergence
- Determine quantitative agreement between generated and model

- Extension to the event level using normalizing flows

- Extension to more complicated processes
  - → Generalization of the physics constraints