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

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on behalf of A(i)DAPT Working Group

A(i)DAPT
AI for Data Analysis and PreservaTion

Overview

- Motivation and advantages of the deployed techniques
- Generative Adversarial Network overview
- Our approach towards reproducing experimental data
- Work in progress
- Conclusions

- 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)

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

Exlusive reactions: 2 → 3

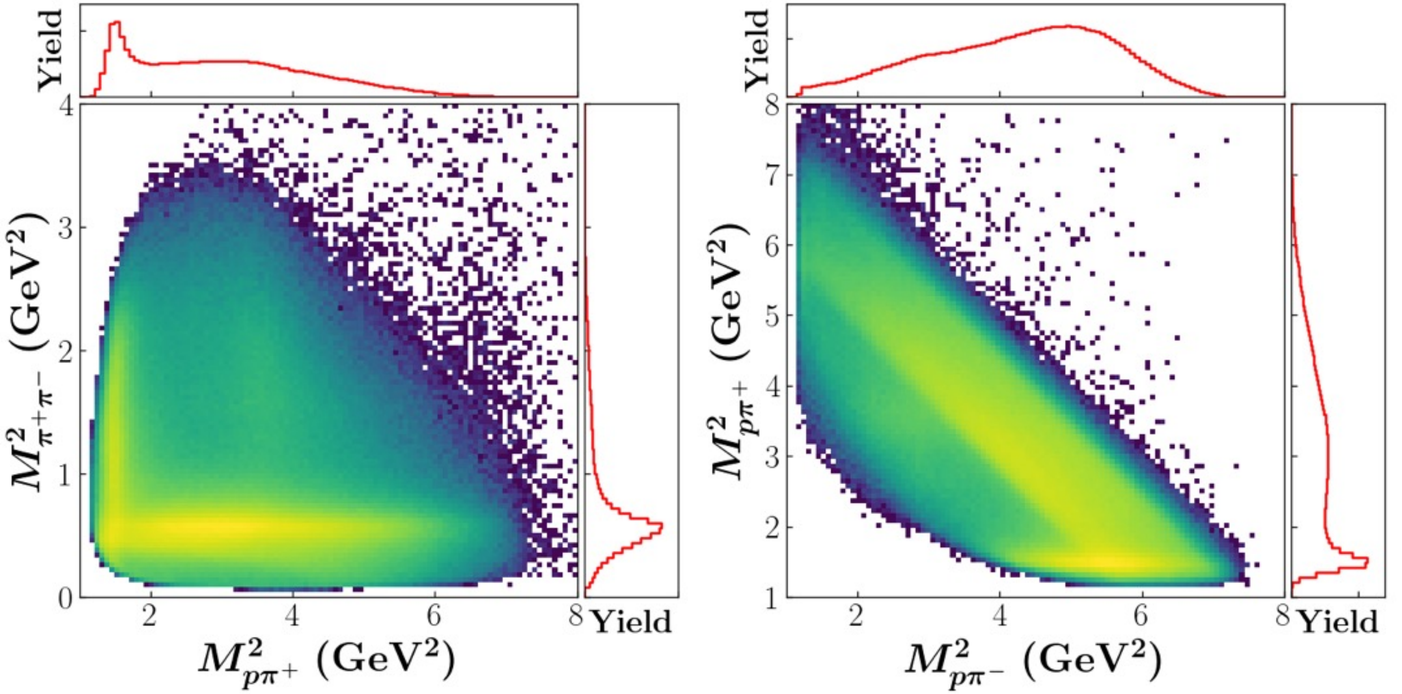
$\gamma p \rightarrow \pi^+\pi^- p$ (unpolarized)

- Initial state: Fully known
- Final state: 3x3 indipendent variables
- Indipendent variables: (3x3) – 4 = 5 (E_γ fixed)
- Many possible choices, such as $M^2_{\pi\pi}$, $M^2_{p\pi}$ θ_π, α, ϕ

CLAS g11 2π photoproduction

- $E_\gamma = (3 \ - 3.8)\ GeV$
- Dataset analyses on $\gamma p \rightarrow p\pi^+(\pi^-)$ with small contamination from $\gamma p \rightarrow p\pi^+$(more than a single missing π^-)
- Complicated dynamics due to the overlap of $(\mathrm{p}\pi)$ to form Δ baryon resnoances and $(\pi\pi)$ to form meson resonances

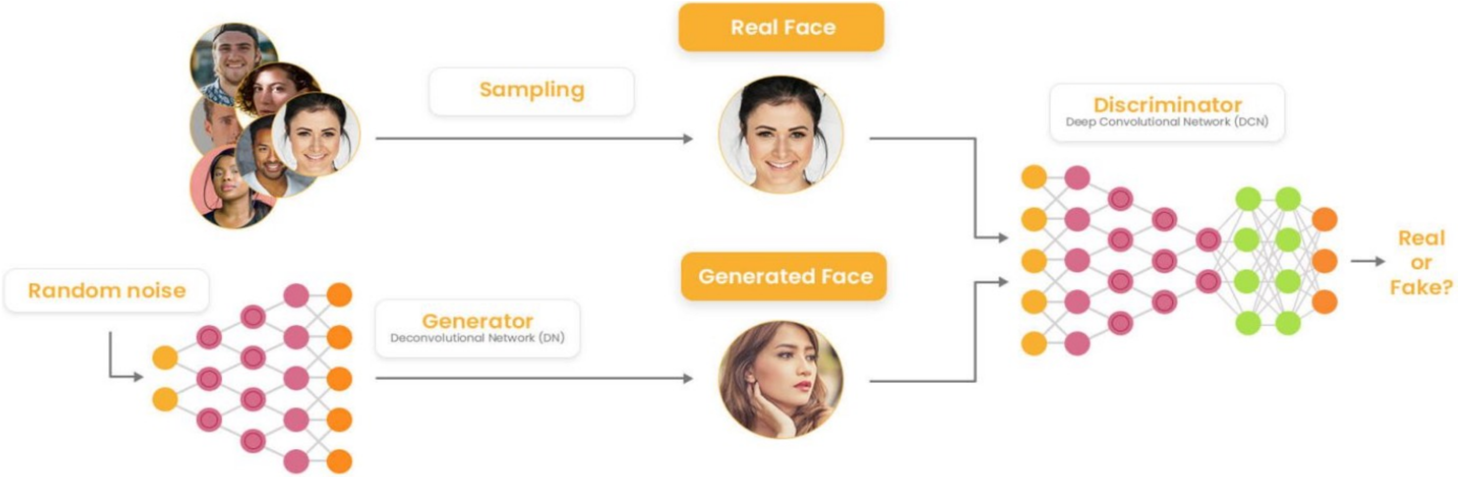
$$\frac{d\sigma\ (\gamma\ p \rightarrow p\ \pi^+\pi^-)}{dM_{\pi\pi}\ dM_{p\pi}\ d\cos(\theta_\pi\ )\ d\alpha\ d\phi}$$



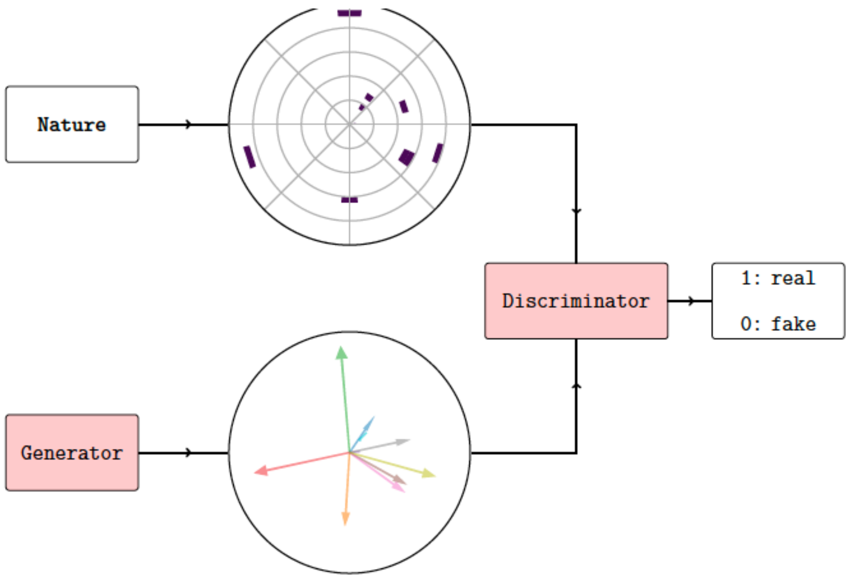
AI could provide a new way to look at data and to extract observables and physics interpretation

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

Generative Adversarial Networks (GANs)



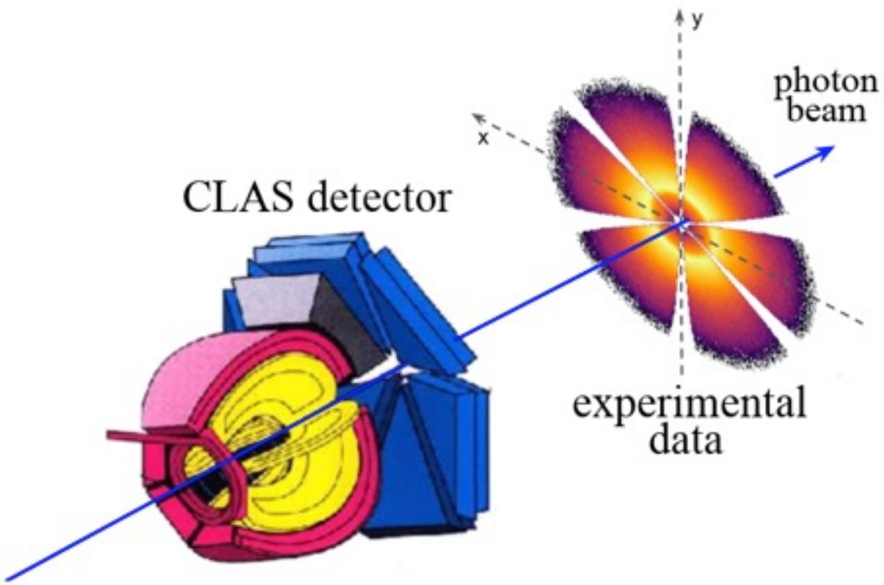
- Generative model based on the competition between two Neural Networks: Generator vs Discriminator
  - **Generator** produces synthetic data which progressively reproduce realistic data and the **Discriminator** has to distinguish between synthetic and realistic data
  - **Generator** can be used to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



Multi-d cross-section: exclusive 2π photoproduction

M. Battaglieri *et al.* (CLAS Collaboration) Phys. Rev. Lett. 102, 102001

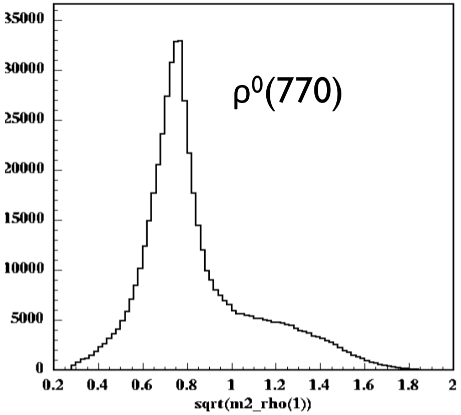
M. Battaglieri *et al.* (CLAS Collaboration) Phys. Rev. D 80, 072005



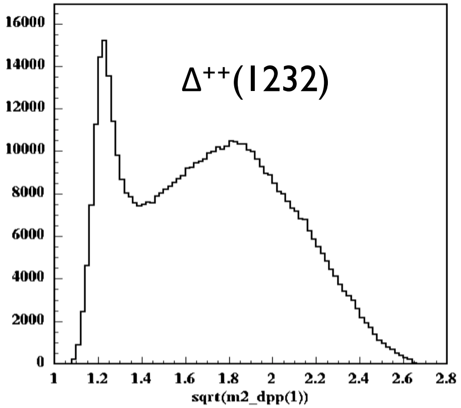
CLAS g11 kinematics

- Dataset used by CLAS Collaboration for many publications
- Fiducial cuts (p, θ, ϕ) as used in published analyses
- Focus on $\gamma p \rightarrow p\pi^+(\pi^-)$
- Final exclusive 2π state identified by missing mass technique (variables are reconstructed by energy/momentum conservation)
- Multi-pion backgound comes from $\gamma p \rightarrow p\omega^0 \rightarrow p\pi^+\pi^-\pi^0$
- At $\mathrm{E}_\gamma = (3-4)\mathrm{GeV}$ reaction dynamics are dominated by ρ^0 photproduction through $\gamma p \rightarrow p\rho^0$ and Δ^{++} resonance excitation through $\gamma p \rightarrow \Delta^{++}\pi^-$

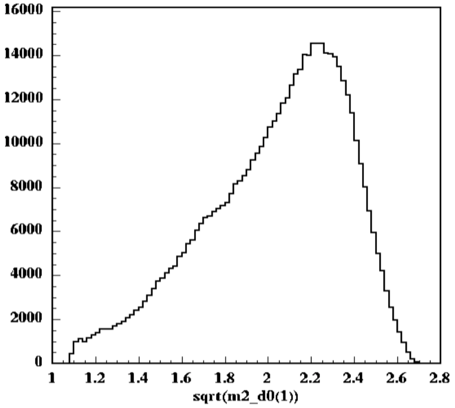
M(ππ)



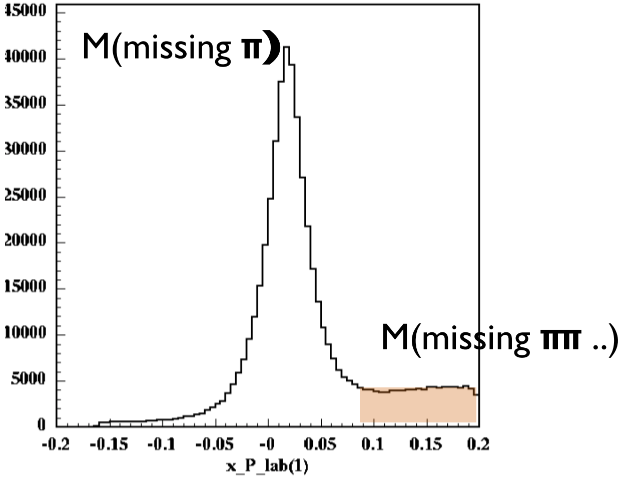
M(pπ⁺)



M(pπ⁻)



M(γ p → p π⁺ X)

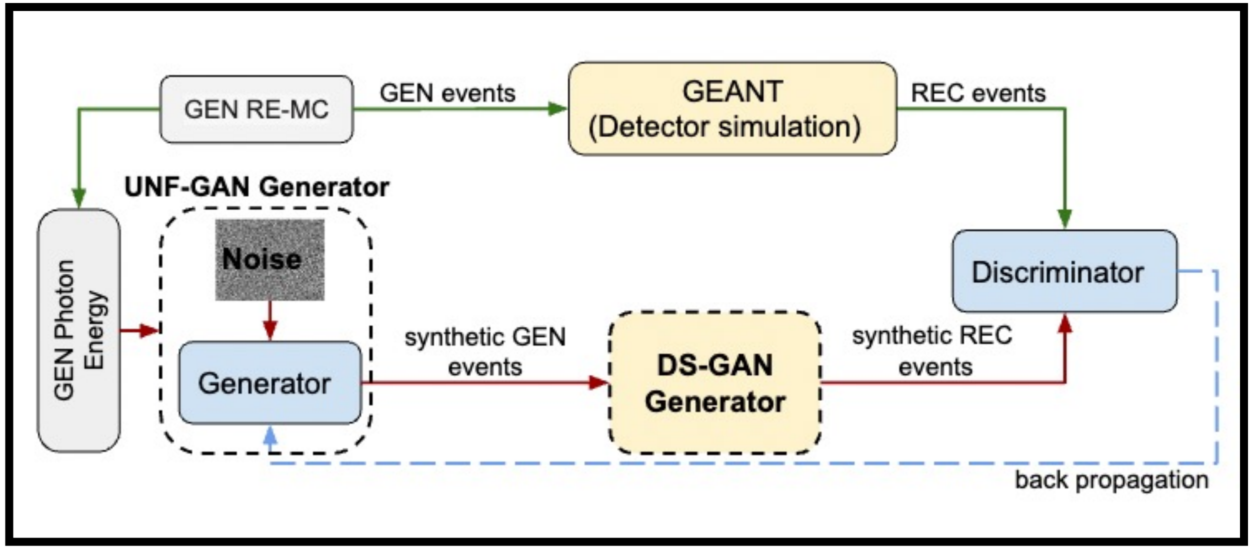


2π photoproduction closure test

- CLOSURE TEST:

  Demonstrate that GANs reproduce 'true' multi-d correlations, unfolding CLAS detector effects, comparing vertex-level (GEN) events with GAN GEN SYNT events, trained at detector-level and unfolded with a (GAN-based) detector proxy

1. Generate events with a (realistic) Monte Carlo 2π photoproduction model (RE-MC GEN pseudodata)
2. Apply detector effects (acceptance and resolution) via GSIM-GEANT (RE-MC REC pseudodata)
3. Deploy a secondary GAN (DS-GAN) to learn detector effects using an indipendent MC event generator (PS-MC) + GSIM-GEANT (GEN and REC pseudodata)
4. Deploy the unfolding GAN (UNF-GAN) that includes the DS-GAN, and train it with RE-MC REC pseudodata
5. Compare UNF-GAN GEN SYNT data to RE-MC GEN pseudodata
6. Replace RE-MC REC pseudo data with CLAS data in the training to unfold the vertex-level experimental distributions



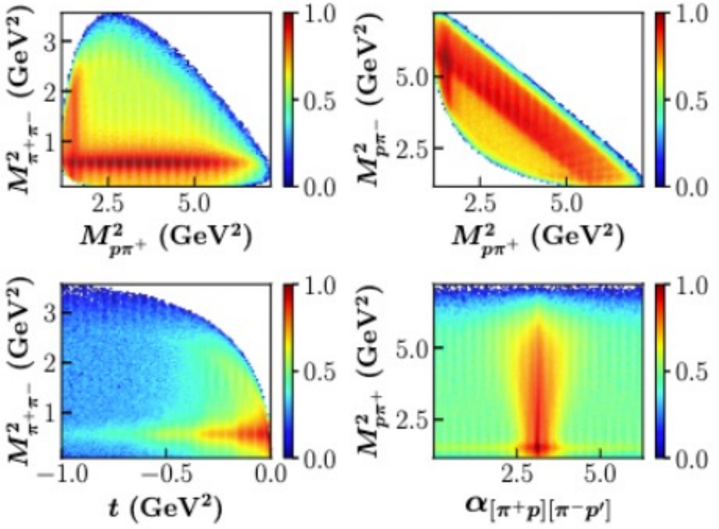
Credit: T. Alghamdi et al. Phys. Rev. D **108**, 094030

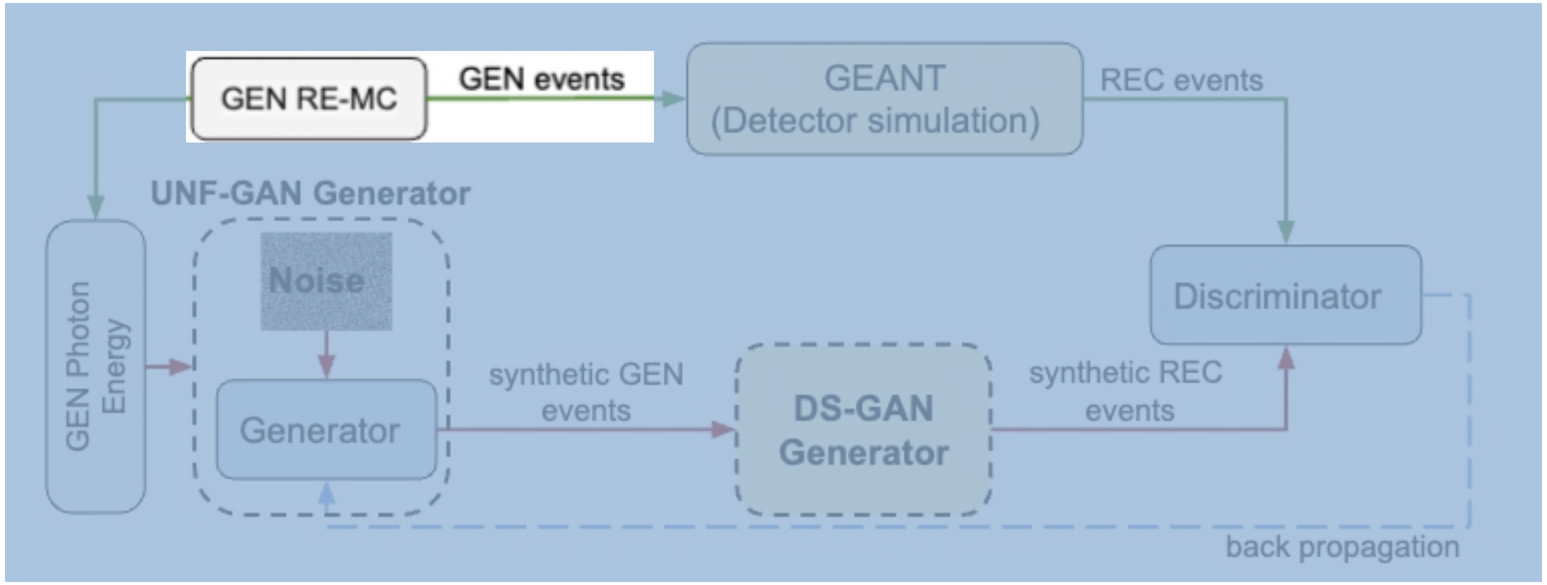
2π photoproduction closure test

1. Generate events with a (realistic) Monte Carlo 2π photoproduction model (RE-MC GEN pseudodata)

- RE-MC realistic Monte Carlo event generator to mimic real data. Includes measured cross-sections, angular distributions and decay of dominant mechanisms ($\rho^0, \Delta^{++}, \Delta^0$ + a contact term)

GEN events

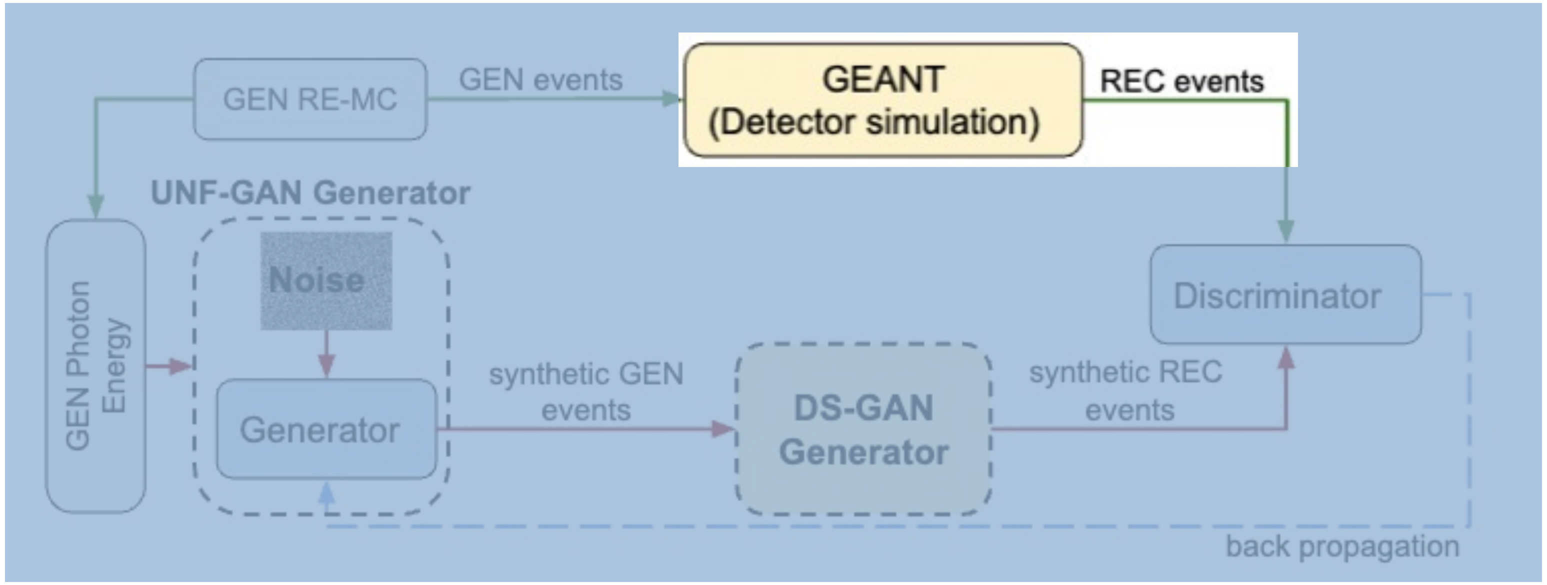




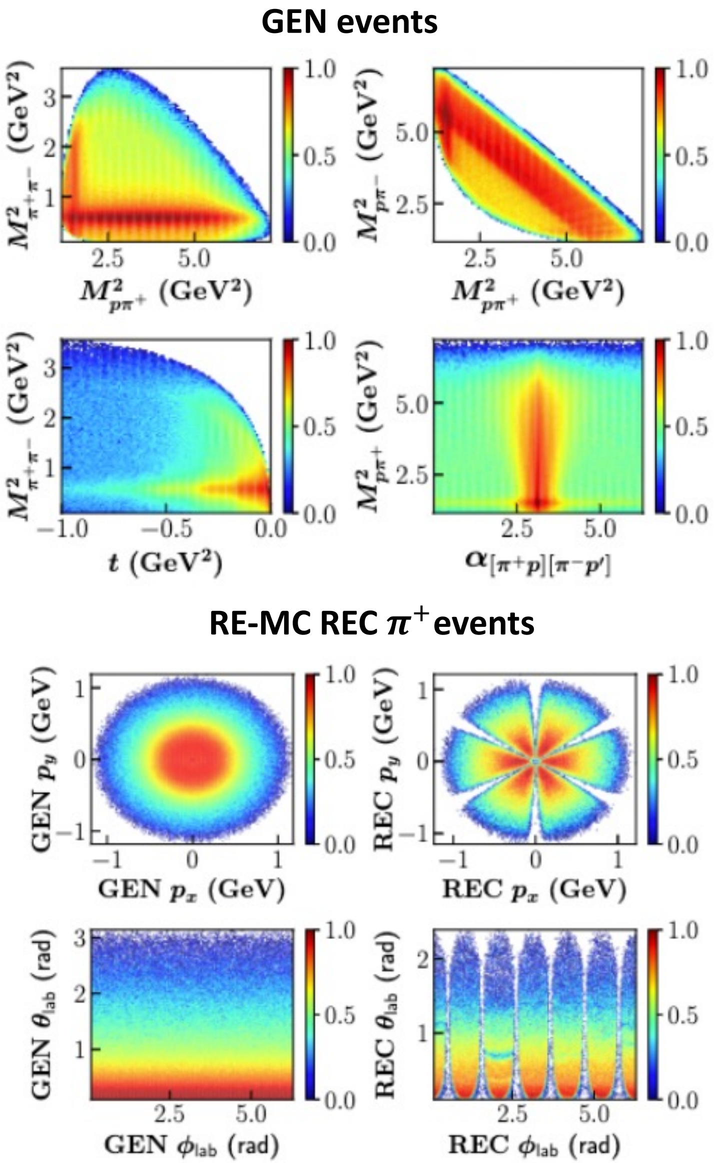
2π photoproduction closure test

2. Apply detector effects (acceptance and resolution) via GISM-GEANT (RE-MC REC pseudodata)

- GSIM: detector simulation package to simulate CLAS detector effects based on GEANT3



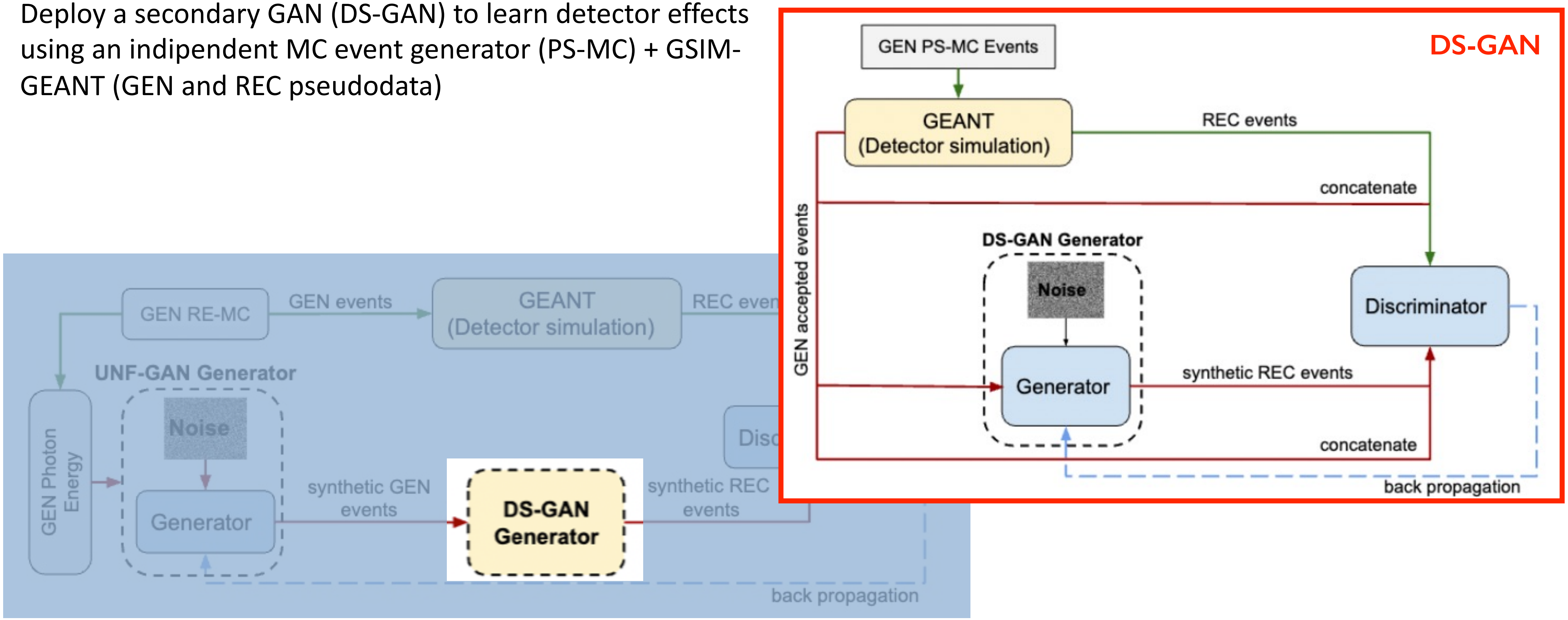
GEN events



RE-MC REC π^+ events

2π photoproduction closure test

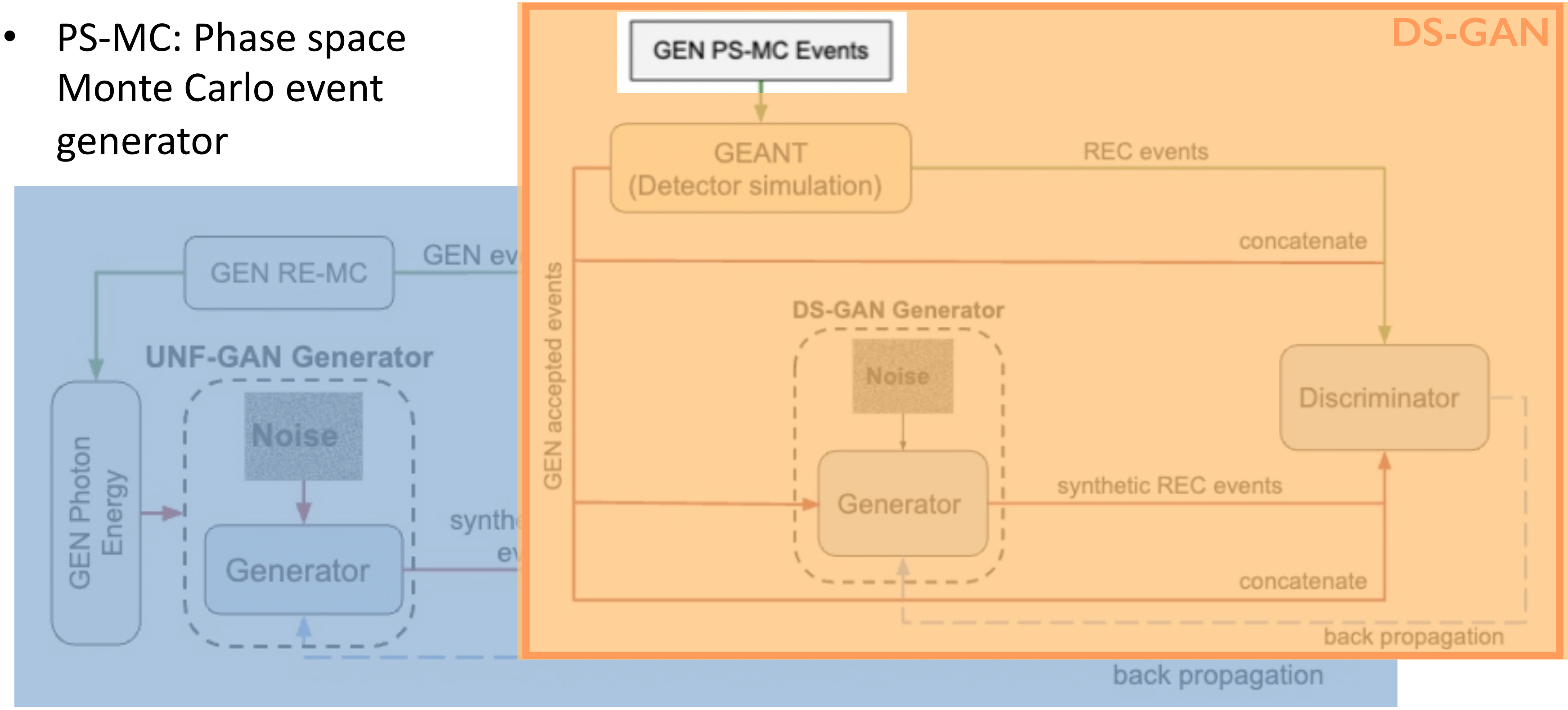
3. Deploy a secondary GAN (DS-GAN) to learn detector effects using an indipendent MC event generator (PS-MC) + GSIM-GEANT (GEN and REC pseudodata)



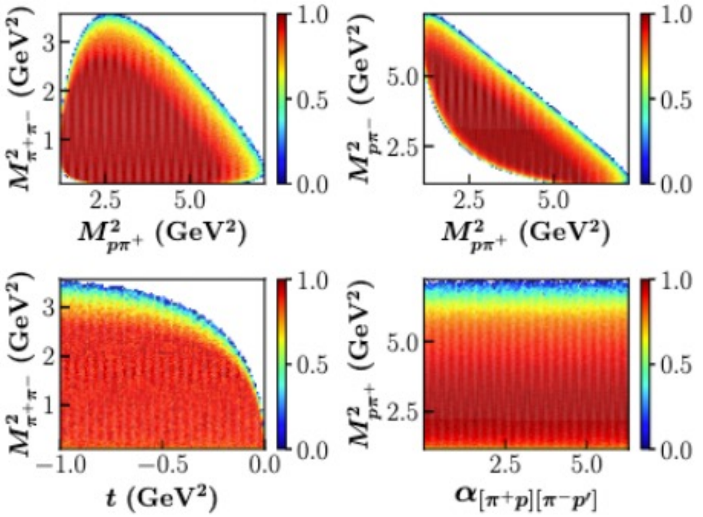
2π photoproduction closure test

3. Deploy a secondary GAN (DS-GAN) to learn detector effects using an indipendent MC event generator (PS-MC) + GSIM-GEANT (GEN and REC pseudodata)

- PS-MC: Phase space Monte Carlo event generator



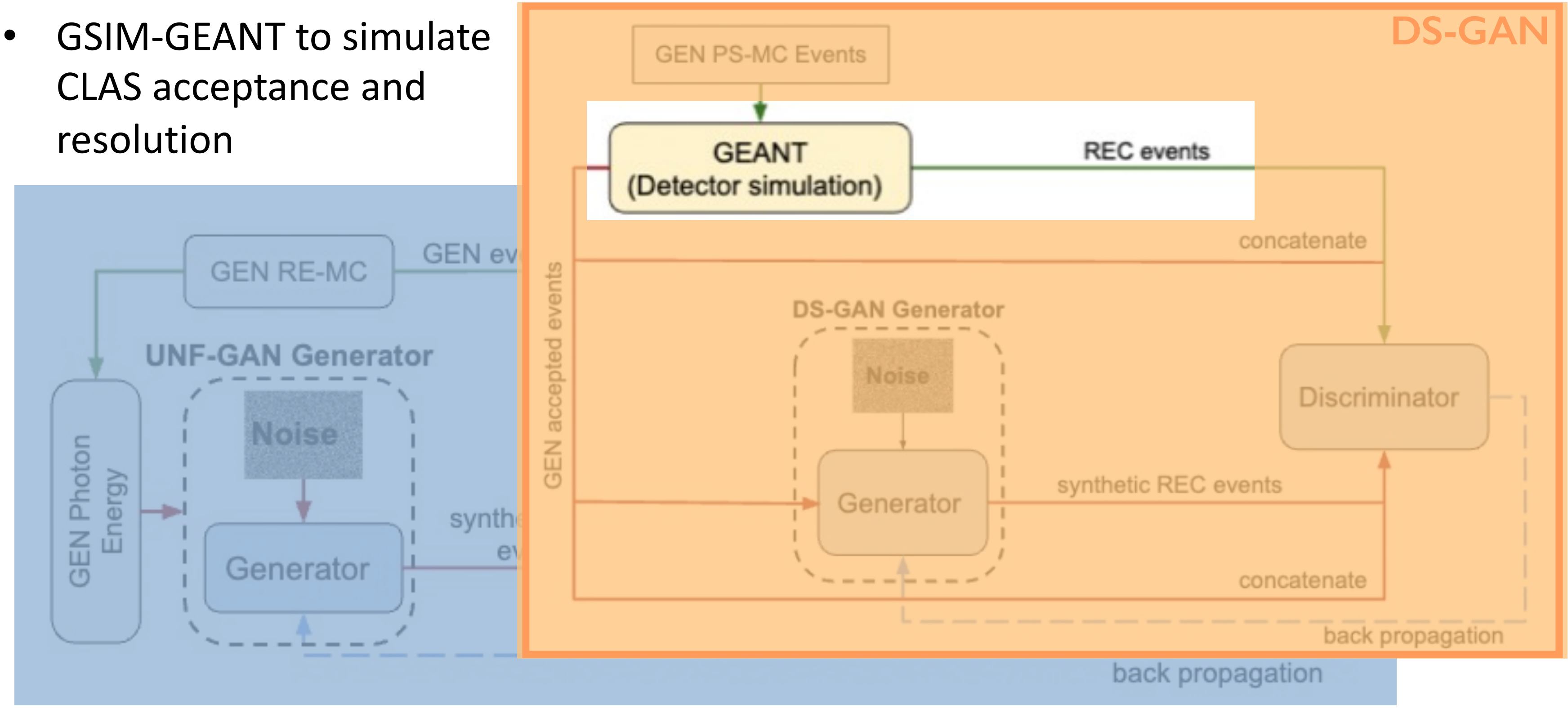
PS-MC GEN events



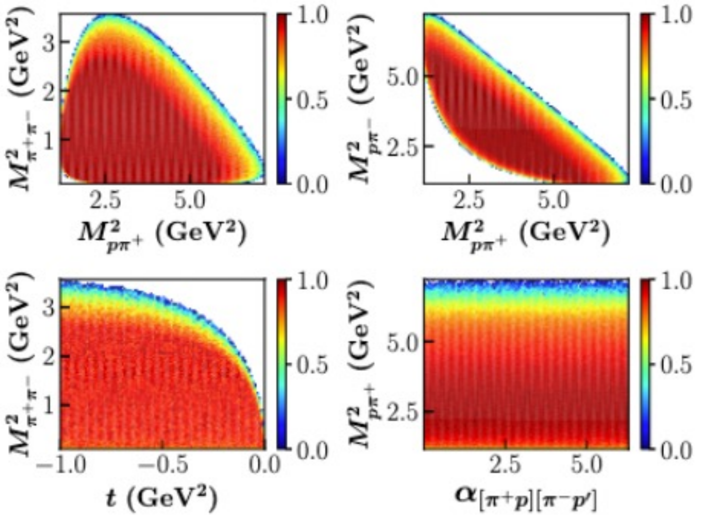
2π photoproduction closure test

3. Deploy a secondary GAN (DS-GAN) to learn detector effects using an indipendent MC event generator (PS-MC) + GSIM-GEANT (GEN and REC pseudodata)

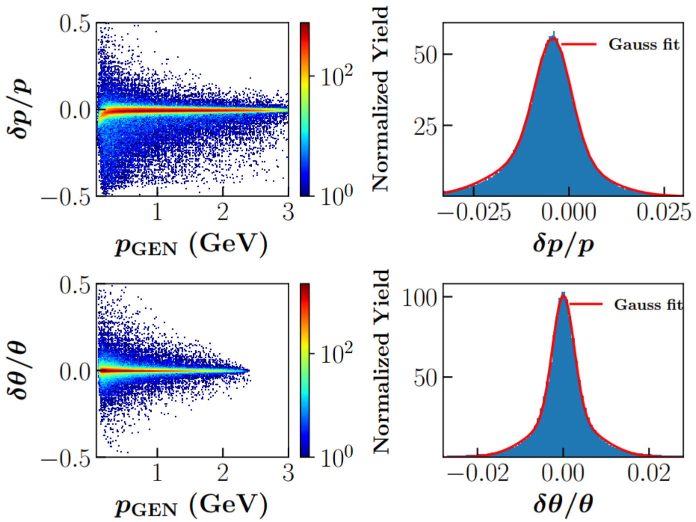
- GSIM-GEANT to simulate CLAS acceptance and resolution



PS-MC GEN events



CLAS resolution on π^+ kin. variables



2π photoproduction closure test

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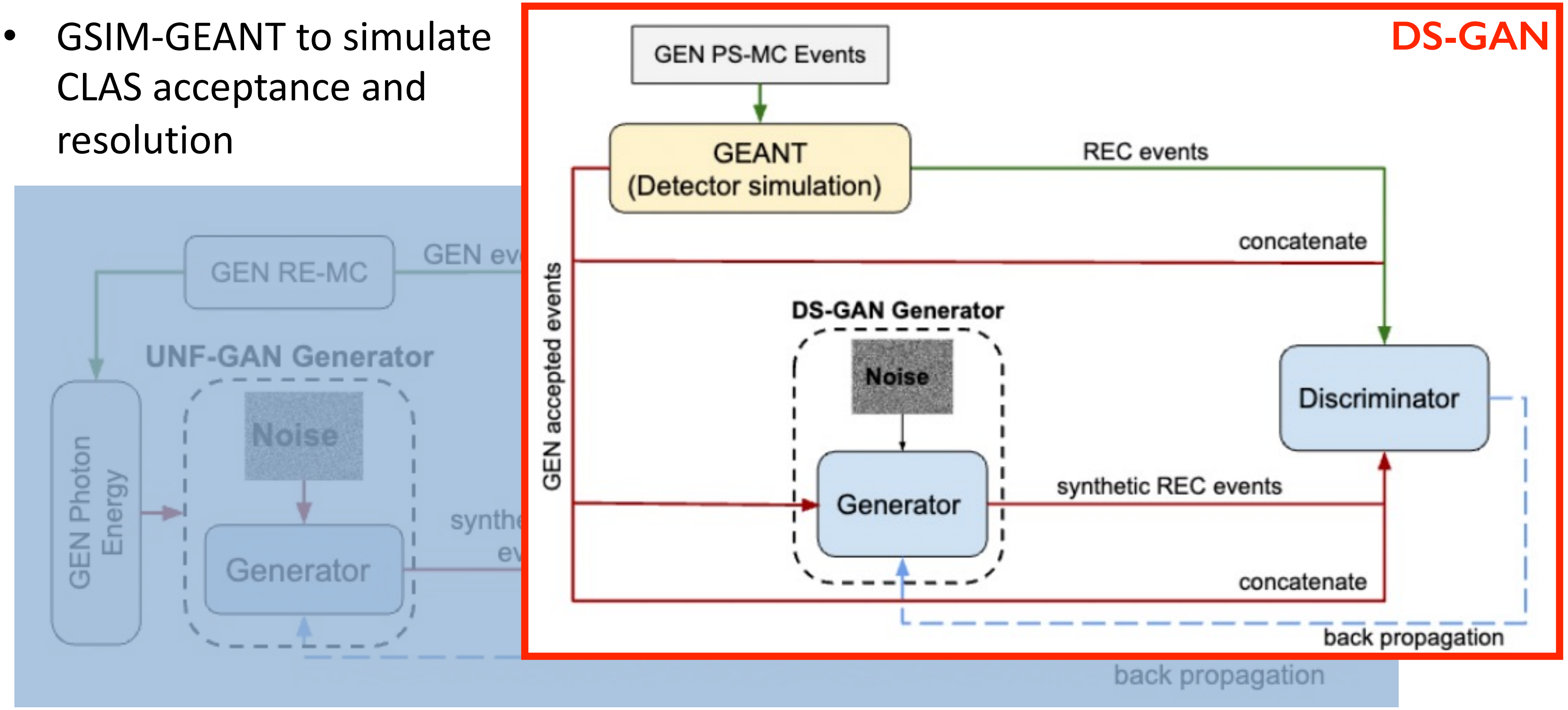
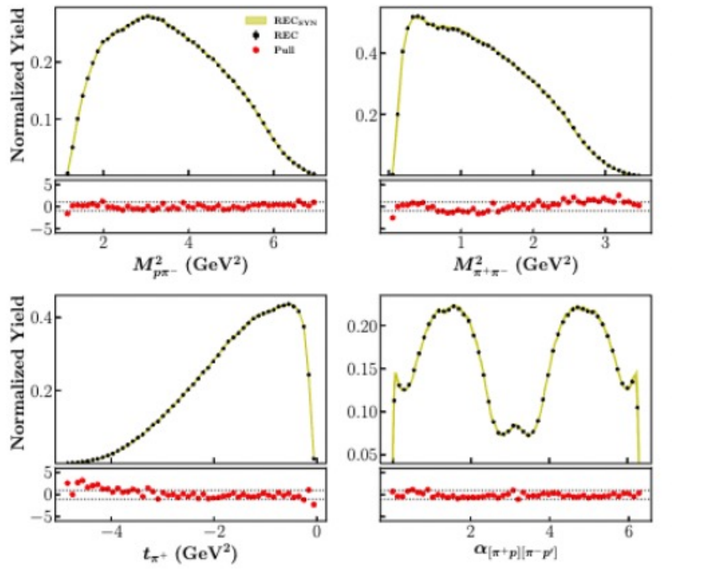
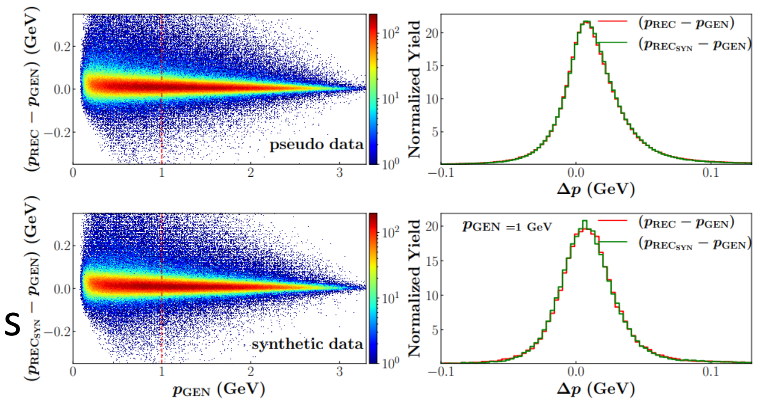


MC REC pseudodata vs. DS-GAN synthetic data



CLAS resolution

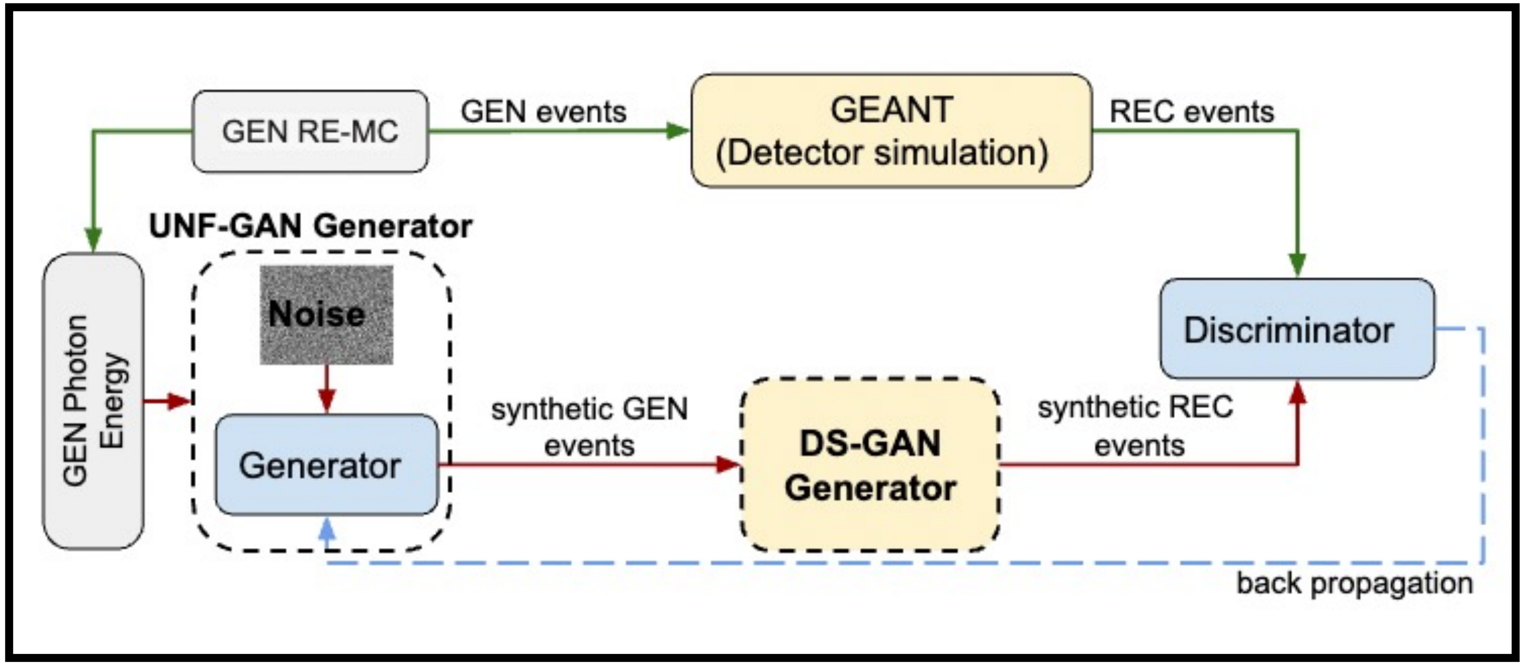


Uncertainty quantification via **pull** calculation: Bootstrap with 20 indipendently trained GANs

DS-GAN learned the CLAS detector effects!

2π photoproduction closure test

- UNF-GAN trained with REC-MC pseudodata (experimental data proxy)
- DS-GAN used to unfold CLAS detector effects (within acceptance)


GEN RE-MC

GEN events

GEANT (Detector simulation)

REC events

UNF-GAN Generator

GEN Photon Energy

Noise

Generator

synthetic GEN events

DS-GAN Generator

synthetic REC events

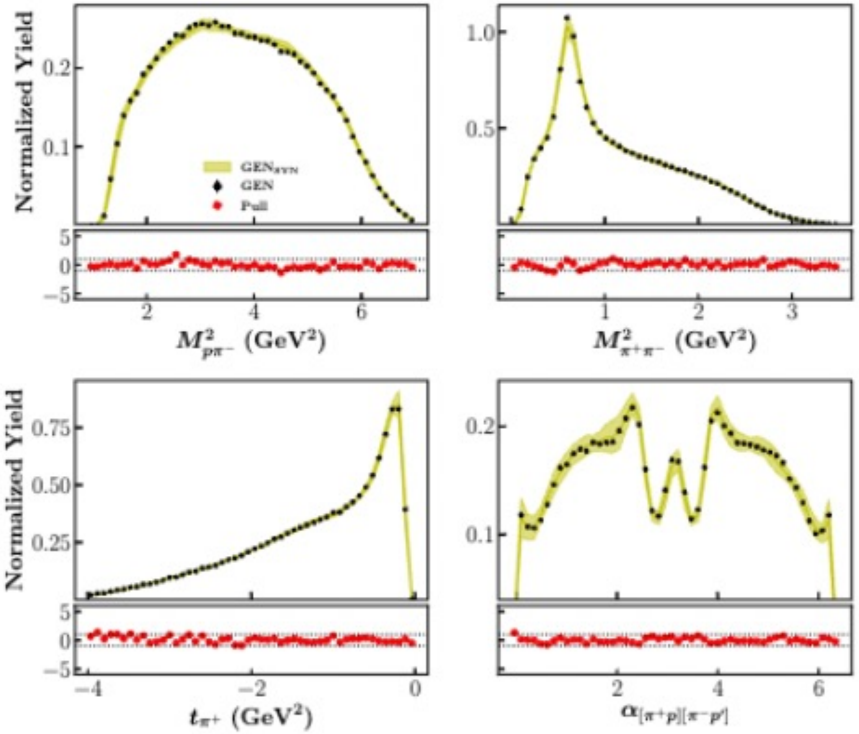
Discriminator

back propagation

5. Compare UNF-GAN GEN SYNT to RE-MC GEN pseudodata

Good agreement ($\pm 1\sigma$) for vertex-level training variables!

RE-MC GEN pseudodata vs. UNF-GAN SYN data

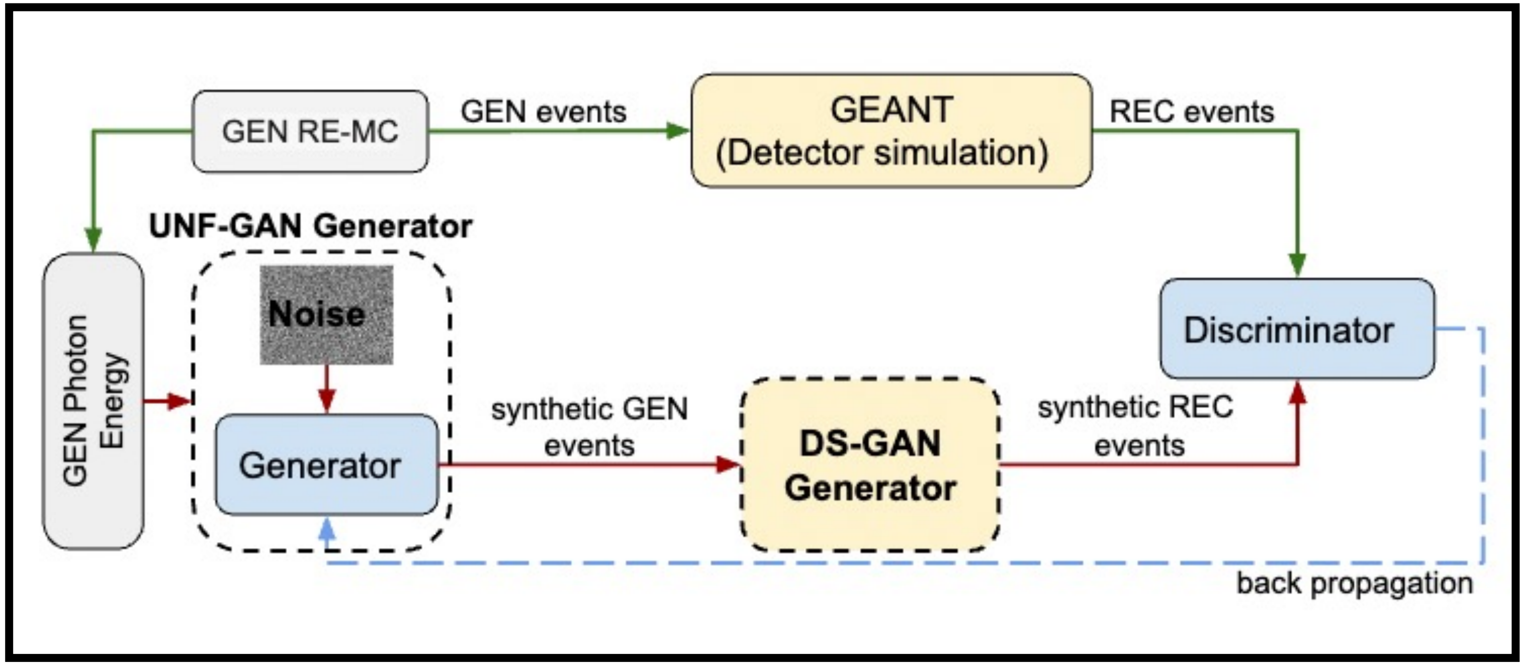


- Systematic of the full procedure (two-GANs) estimated by bootstrap with 20+20 independently trained GANs

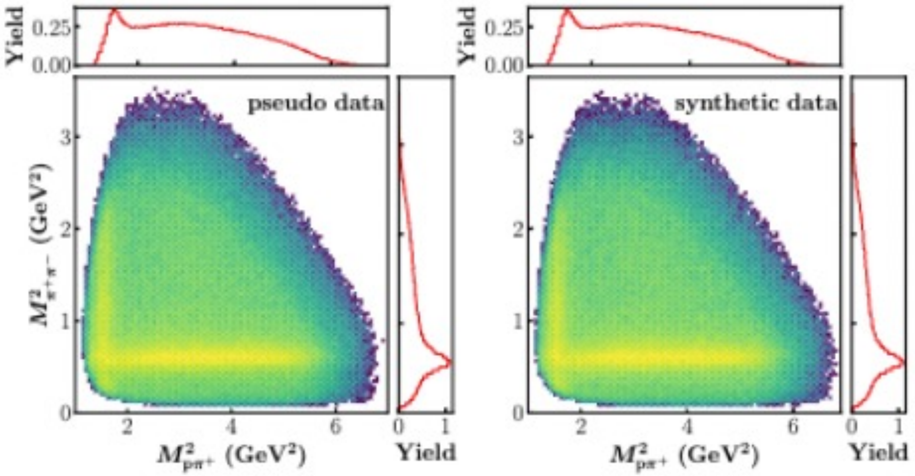
2π photoproduction closure test

4. Deploy the unfolding GAN (UNF-GAN) that includes the DS-GAN and train it with RE-MC REC pseudodata

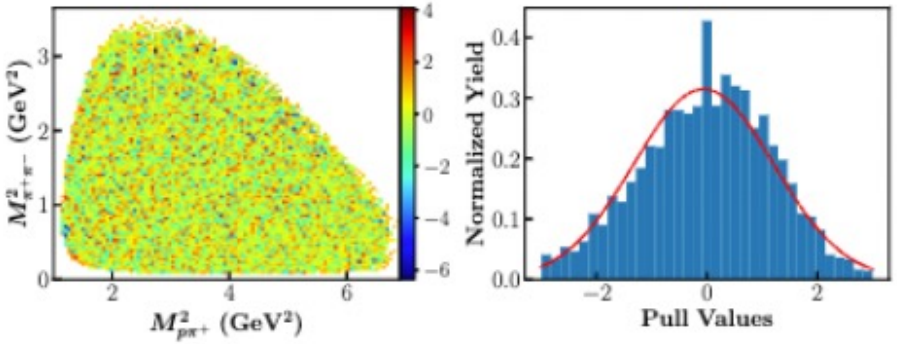
- UNF-GAN trained with REC-MC pseudodata (experimental data proxy)
- DS-GAN used to unfold CLAS detector effects (within acceptance)



RE-MC GEN pseudodata vs. UNF-GAN SYN data



2D pulls



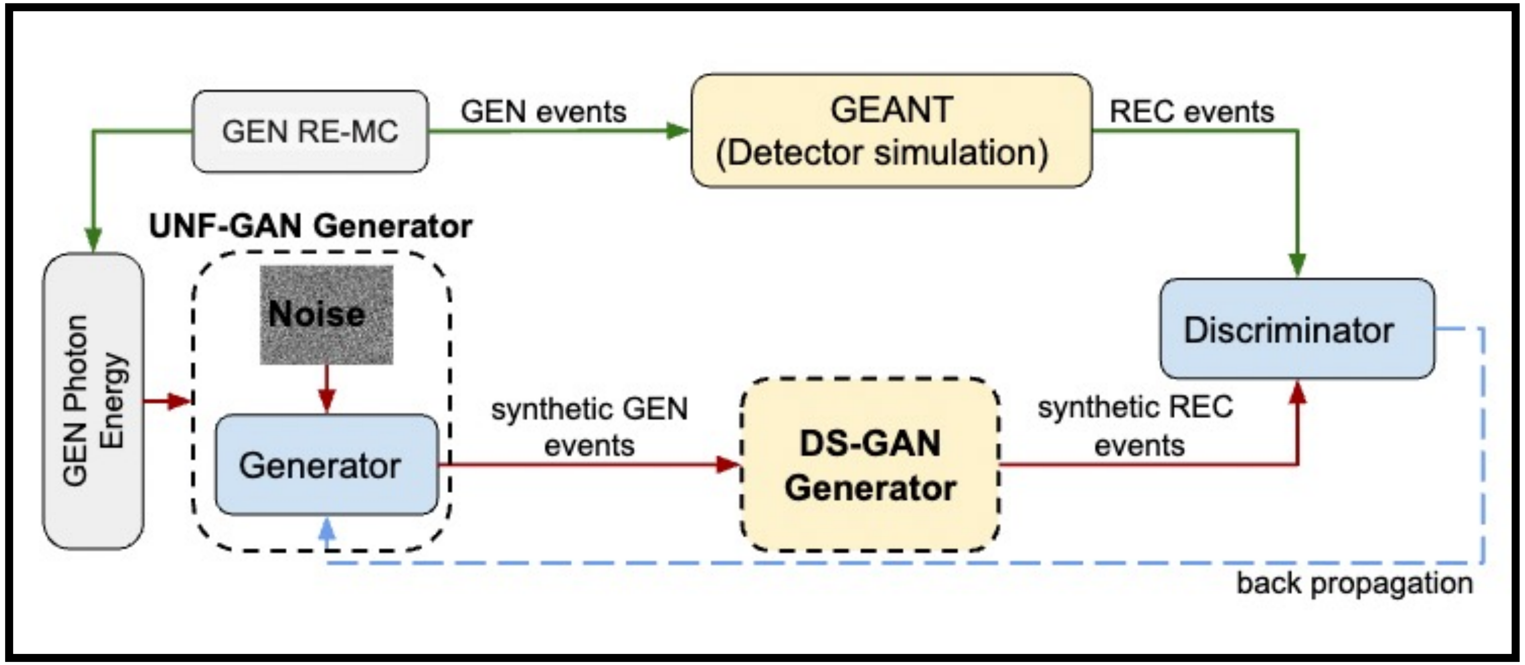
5. Compare UNF-GAN GEN SYNT to RE-MC GEN pseudodata

Good agreement ($\pm 1\sigma$) for 2D distributions (correlations)

2π photoproduction closure test

4. Deploy the unfolding GAN (UNF-GAN) that includes the DS-GAN and train it with RE-MC REC pseudodata

- UNF-GAN trained with REC-MC pseudodata (experimental data proxy)
- DS-GAN used to unfold CLAS detector effects (within acceptance)



GEN RE-MC

GEN events

GEANT (Detector simulation)

REC events

UNF-GAN Generator

GEN Photon Energy

Noise

Generator

synthetic GEN events

DS-GAN Generator

synthetic REC events

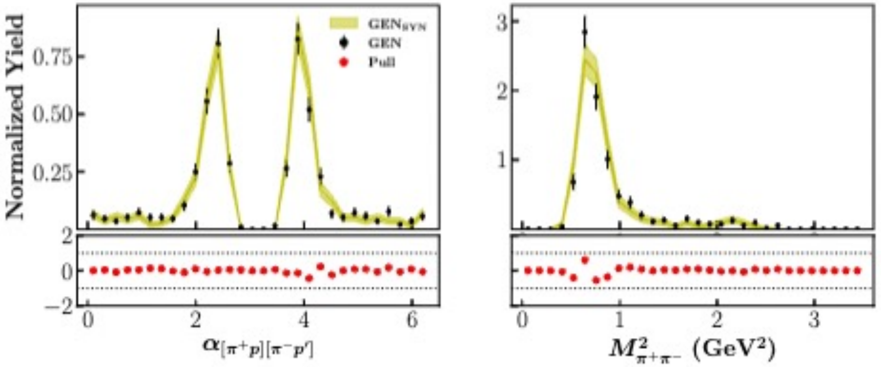
Discriminator

back propagation

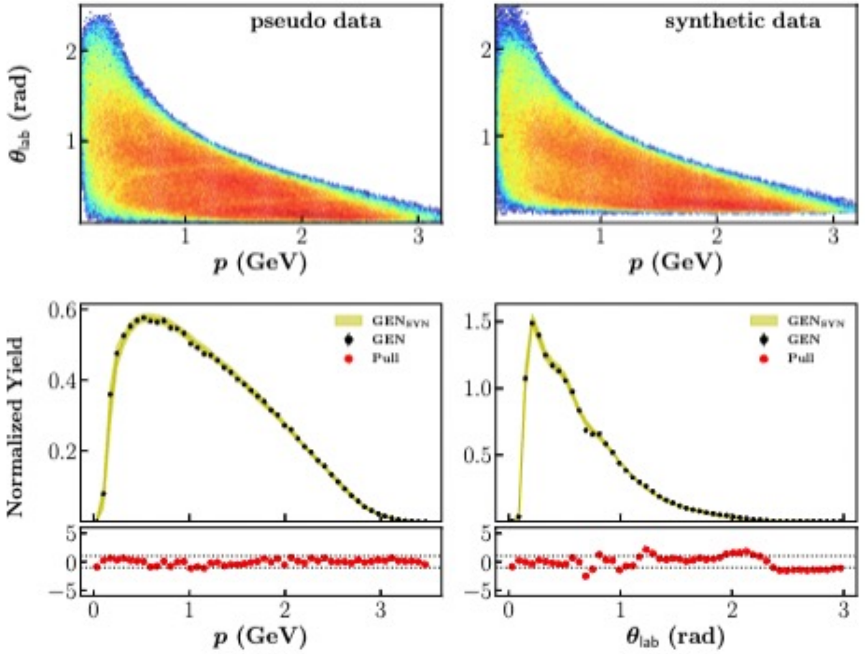
5. Compare UNF-GAN GEN SYNT to RE-MC GEN pseudodata

Good agreement ($\pm 1\sigma$) for lab variables and in 4D bins

Distribution in 4D bins



RE-MC GEN pseudodata vs. UNF-GAN SYN data



Moving forward: Acceptance

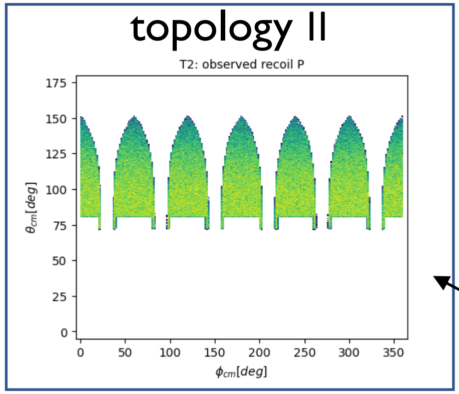
- Simple 2-body process: $\gamma p \rightarrow \Delta^+(1232) \rightarrow \pi^0 p$
- Two independent variables (at fixed energy): θ_{cm} and ϕ_{cm}
- Monte Carlo eventgenerator
- Simple model: Breit-Wigner with two parameters: m_Δ and Γ_Δ

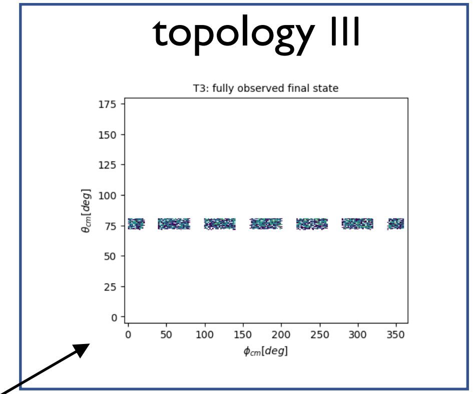
$$\frac{d\sigma}{d\Omega} \propto \frac{p_f}{p_i\, s} \sum_{\lambda_\gamma \lambda_p \lambda'_p} \left| (-)^{\lambda_\gamma} H_{|\lambda_\gamma - \lambda_p|} \frac{d^{3/2}_{\lambda_\gamma-\lambda_p,-\lambda'_p}(\theta)}{m_\Delta^2 - s - i\Gamma_\Delta m_\Delta} \right|^2$$

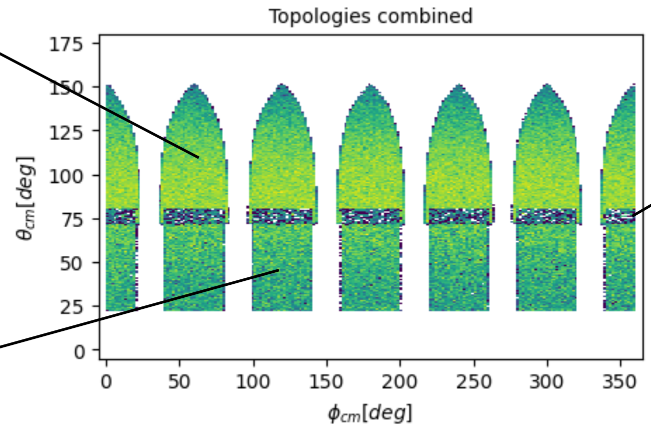
$$\propto \frac{p_f}{p_i\, s} \frac{3\left|H_{3/2}\right|^2 + 5\left|H_{1/2}\right|^2 - 3\cos 2\theta \left(\left|H_{3/2}\right|^2 - \left|H_{1/2}\right|^2\right)}{(m_\Delta^2 - s)^2 + \Gamma_\Delta^2 m_\Delta^2}$$

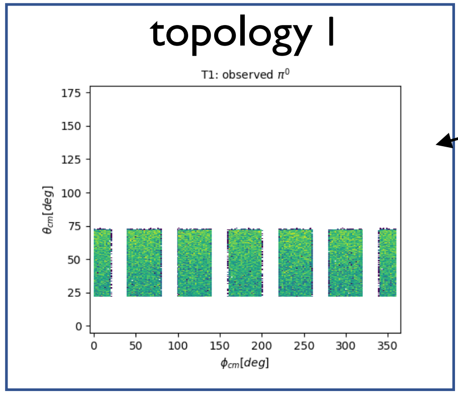
- Detector acceptance (CLAS) implemented via fiducial cuts (coils, minimum proton momentum and angle in the lab frame)
  - topology 1: γ p → (p) π^0 (proton missing)
  - topology 2: γ p → p (π^0) (π^0 missing)
  - topology 3: γ p → p π^0 (all detected)
  - [topology 0: unmeasured]

Build a single Network able to generate in the full phase space according to the correct distributions


topology II


topology III




topology I

Credit: T.Vittorini , T.Alghamdi, Y. Li

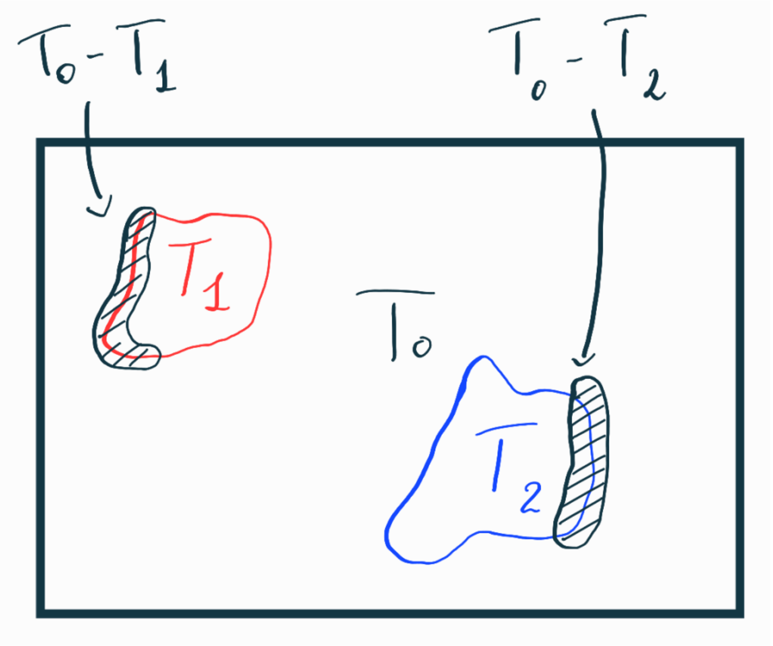
Moving forward: Detector inefficiencies

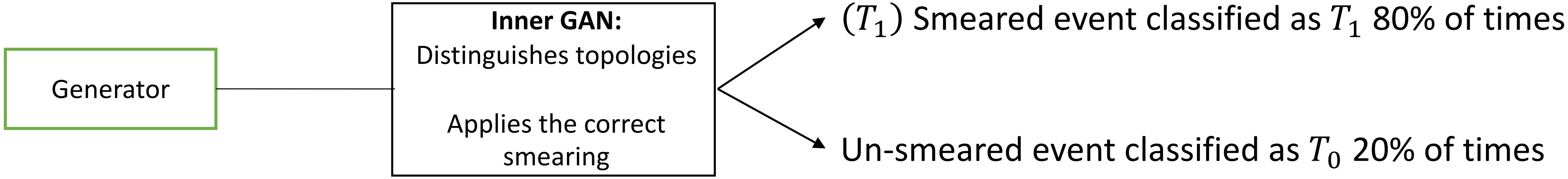
- Some evets may sometimes be classified in the wrong category:

  - Defective paddles can lead to missing events (T_1 which become T_0)

  - Reconstructed events can get missclassified (T_1 which become T_2 and viceversa)

- Existence of regions where a given generated event can go into different topologies with a given probability: Mixed events





Inner GAN:
Distinguishes topologies

Applies the correct smearing

(T_1) Smeared event classified as T_1 80% of times

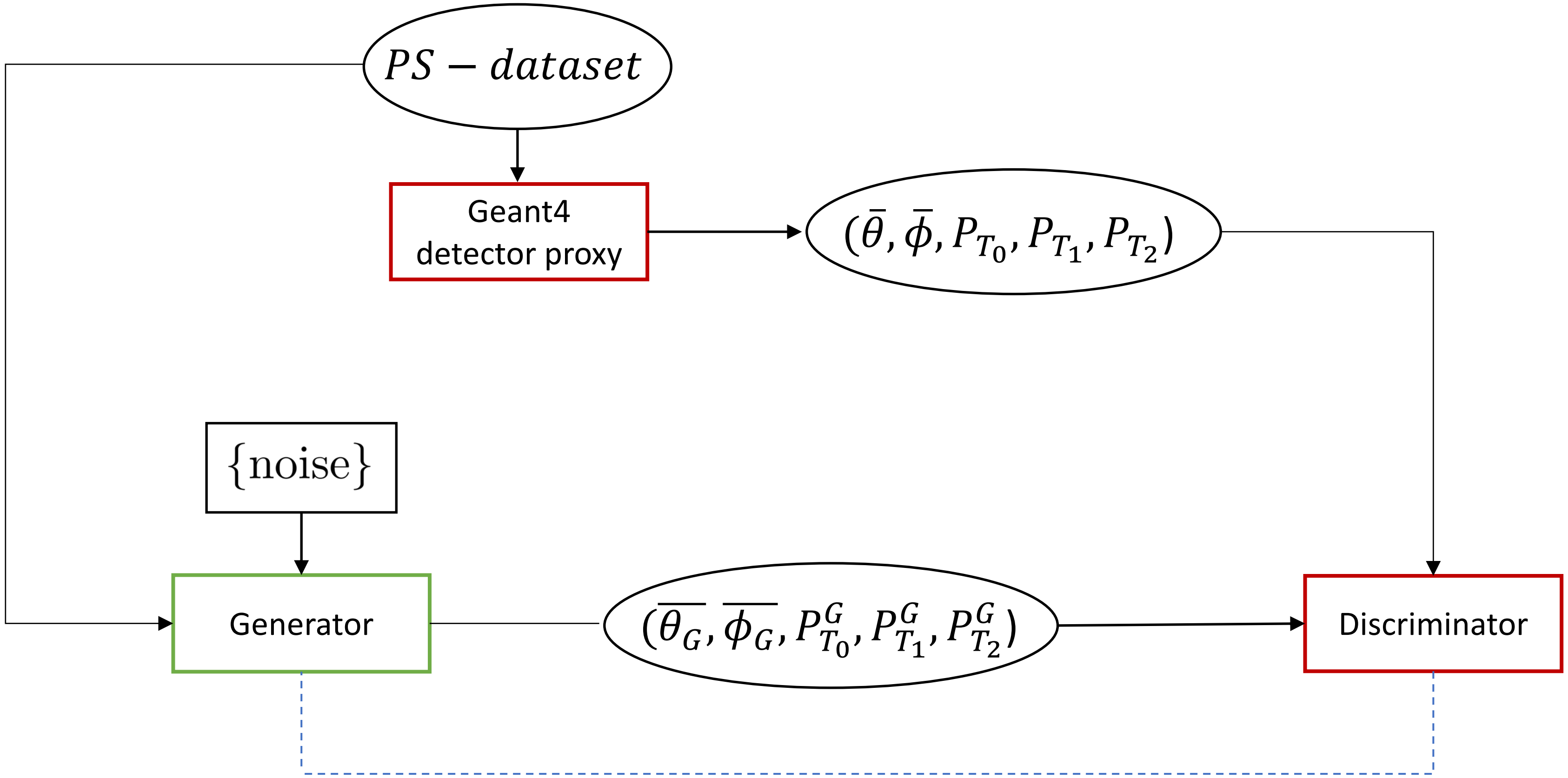
Un-smeared event classified as T_0 20% of times

Credit: T.Vittorini , T.Alghamdi, Y. Li

Moving forward: Comprehensive inner GAN

- Here we are assuming that the smearing applied to mixed events is similar: We will apply a common smearing to all the events being classified with multiple topologies

- **Inner GAN**



$PS - dataset$
Geant4 detector proxy
$(\bar{\theta}, \bar{\phi}, P_{T_0}, P_{T_1}, P_{T_2})$
{noise}
Generator
$(\overline{\theta_G}, \overline{\phi_G}, P^G_{T_0}, P^G_{T_1}, P^G_{T_2})$
Discriminator

- The process of generating training P_i will be carried out outside of the dataset training

- Each PS-event will be associated with different probabilities

- The inner GAN training dataset will consist of θ and ϕ values to identify the event + the probabilities of being classified into a given topology

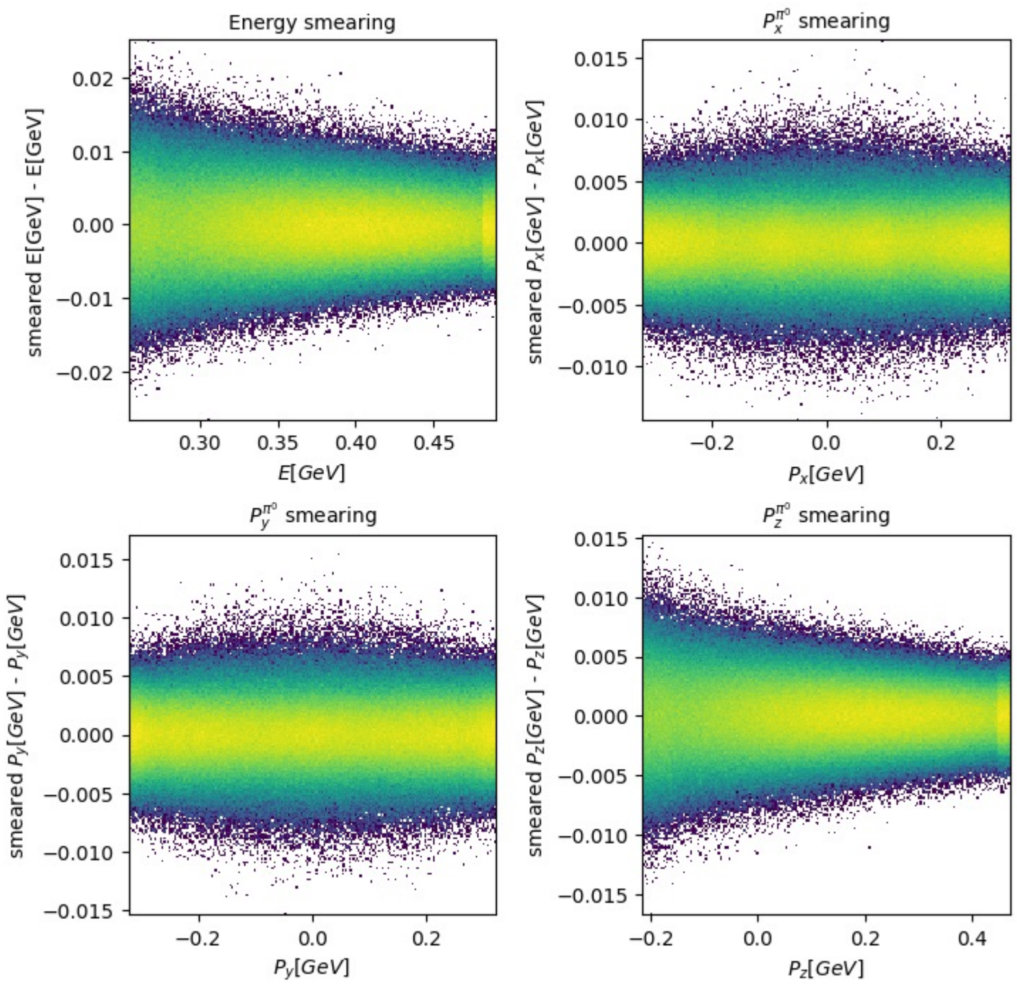
- The output of the P_i^G could be distribution peaked around the expected value

Credit: T.Vittorini , T.Alghamdi, Y. Li

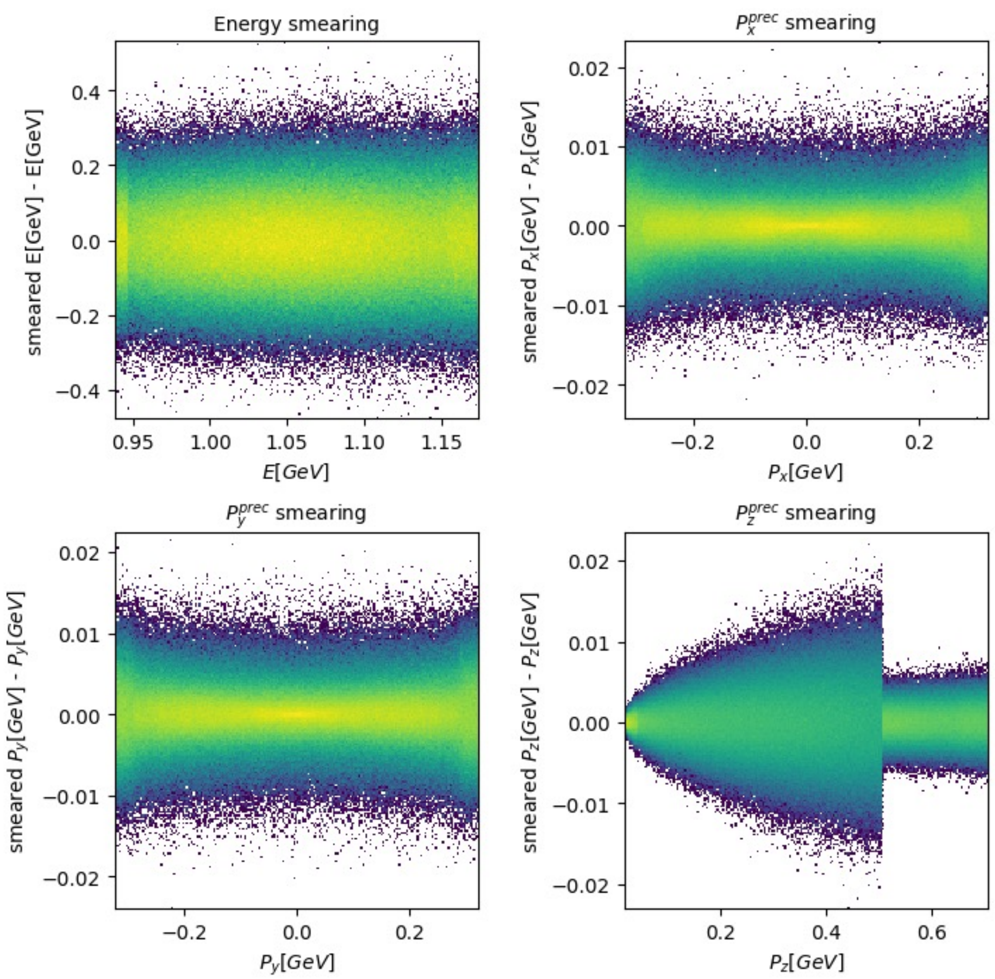
Moving forward: inner GAN results

- Reasonable smearing applied to the training variables:

π^0 4-momenta

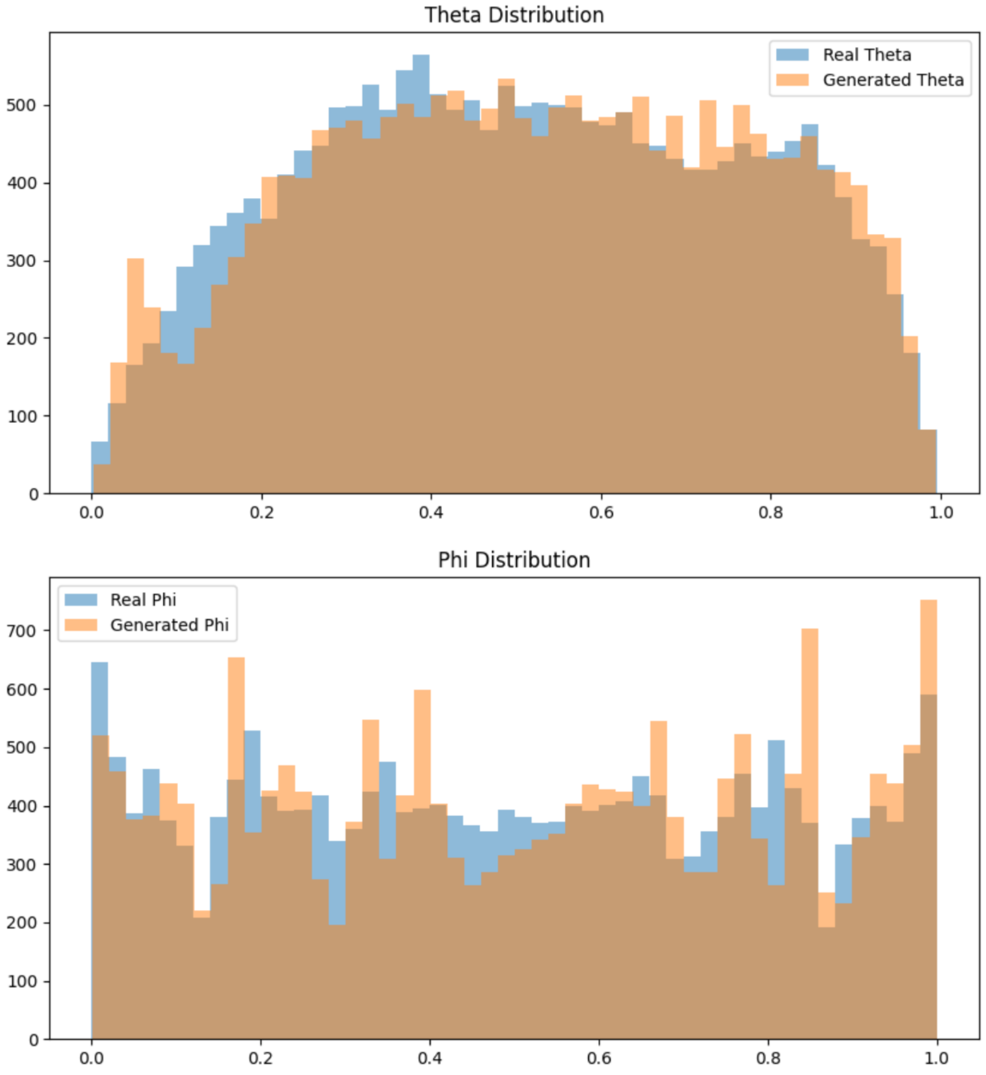


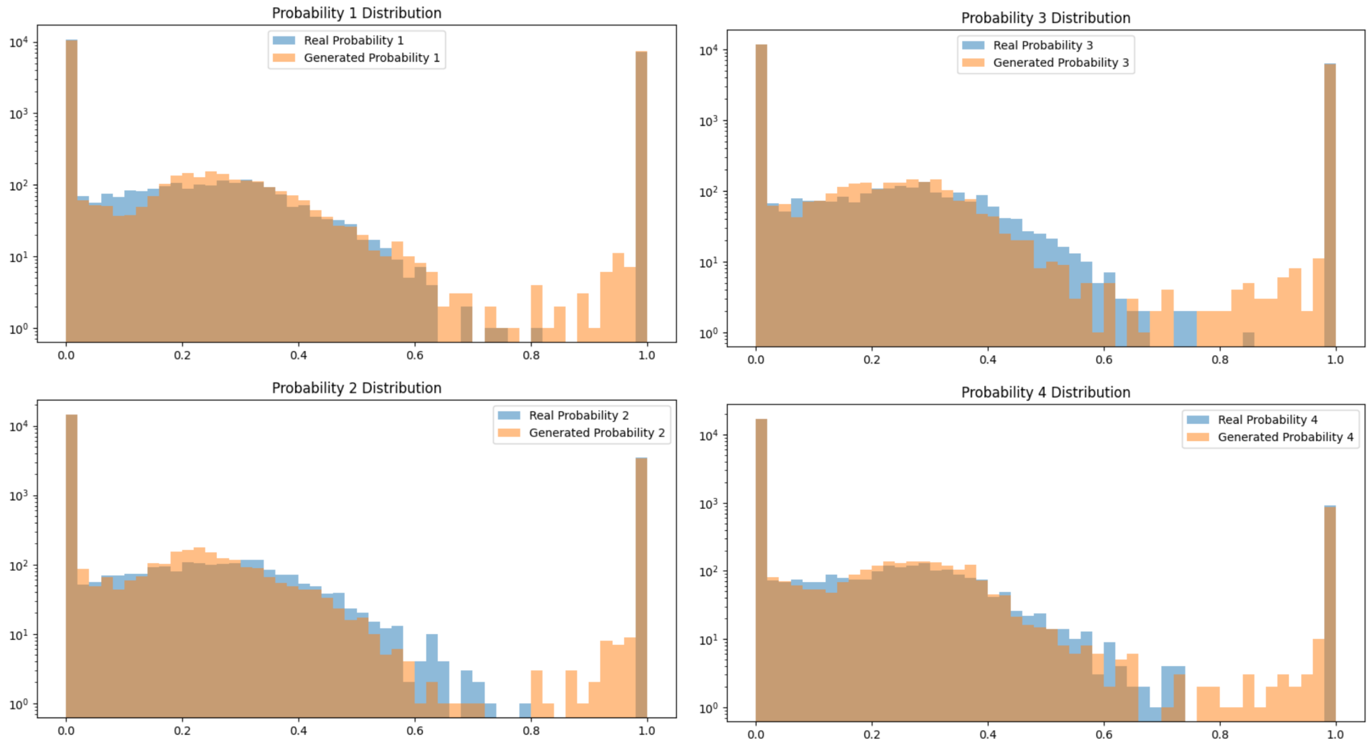
Recoil proton 4-momenta



Credit: T.Vittorini , T.Alghamdi, Y. Li

Moving forward: inner GAN results



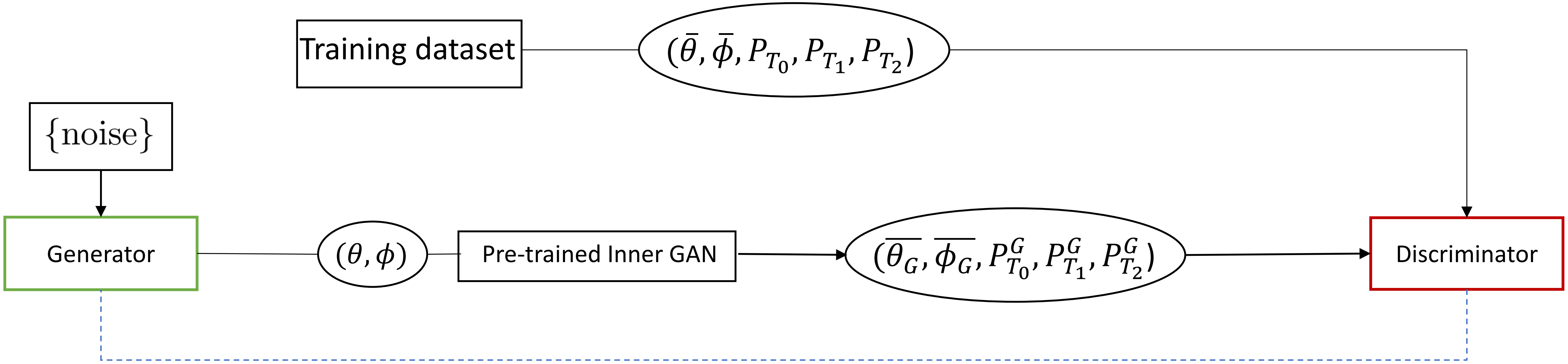


Credit: T.Vittorini , T.Alghamdi, Y. Li

Moving forward: Comprehensive outer GAN

- Here we are assuming that the smearing applied to mixed events is similar: We will apply a common smearing to all the events being classified with multiple topologies

- **Outer GAN**



Training dataset
$(\bar{\theta}, \bar{\phi}, P_{T_0}, P_{T_1}, P_{T_2})$
{noise}
Generator
(θ, ϕ)
Pre-trained Inner GAN
$(\overline{\theta_G}, \overline{\phi_G}, P^G_{T_0}, P^G_{T_1}, P^G_{T_2})$
Discriminator

- The outer GAN trained generator will be able to generate vertex level events in the full phase space, with the relative distributions derived according to experimental data (in the measured regions) and some realistic model (in the unmeasured region)

Credit: T.Vittorini , T.Alghamdi, Y. Li

Moving forward: CLAS12 application

- Working towards the application of the developed machinery to CLAS12 pseudodata

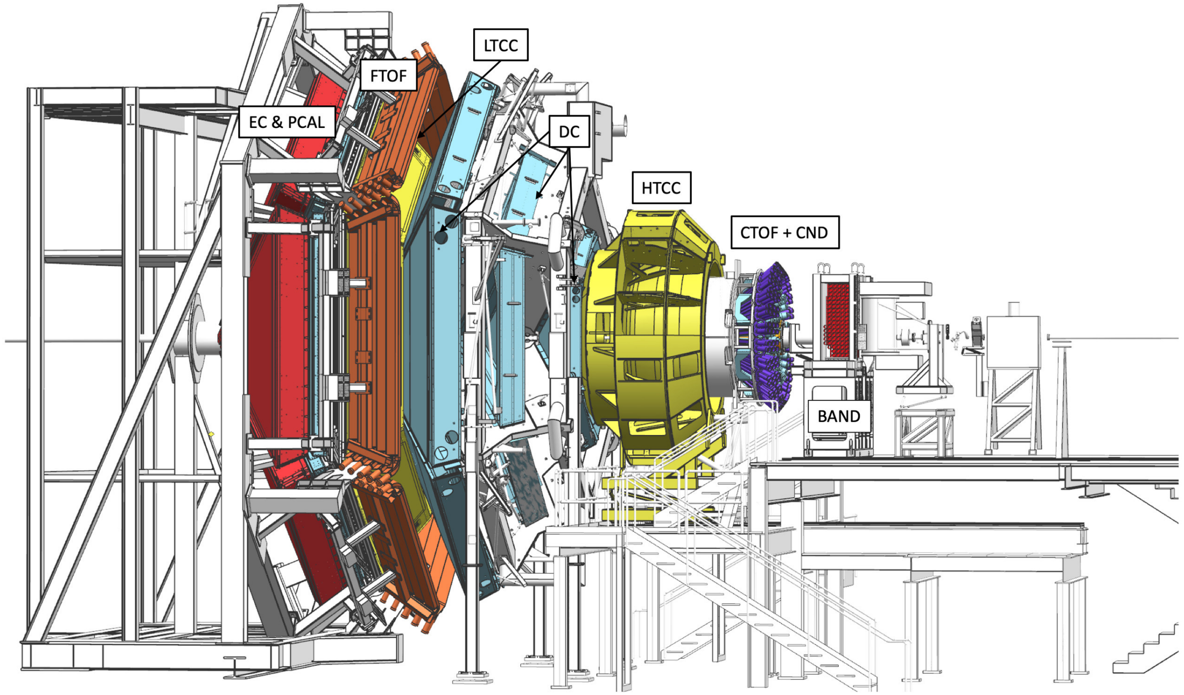
- Pseudo-data for the reaction $ep \rightarrow e'p\,\pi^+\pi^-$

- Focus on the topology with final state $e'p\,\pi^+(\pi^-)$

Test the inner – GAN architecture on CLAS12 detector

- If this procedure works well on CLAS and CLAS12 data the architecture robustness is guaranteed

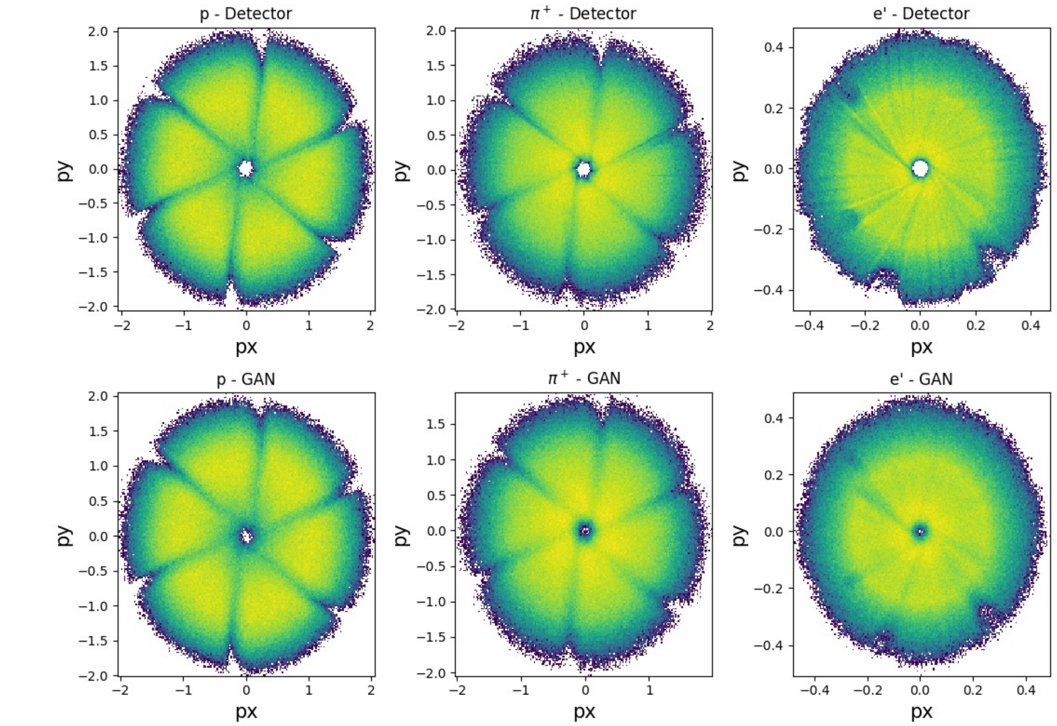
- We can put together in a coherent way information from different kinematic regions



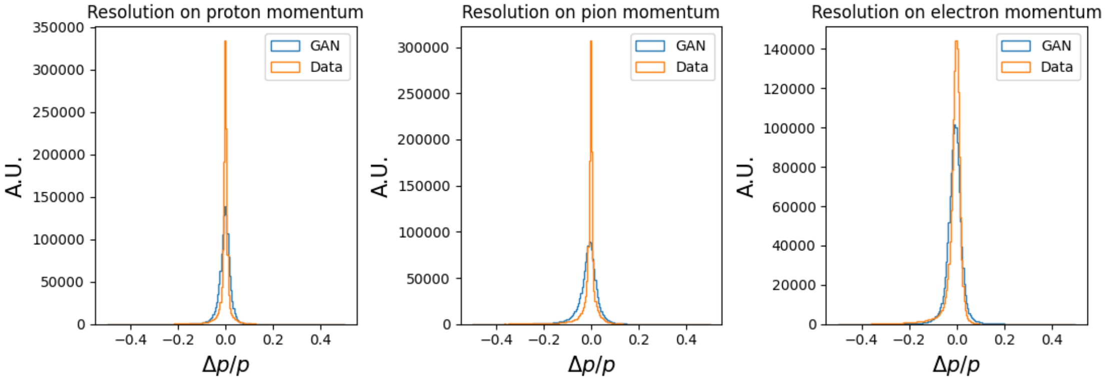
Credit: D. Glazier, T. Alghamdi, M. Spreafico

Moving forward: CLAS12 application

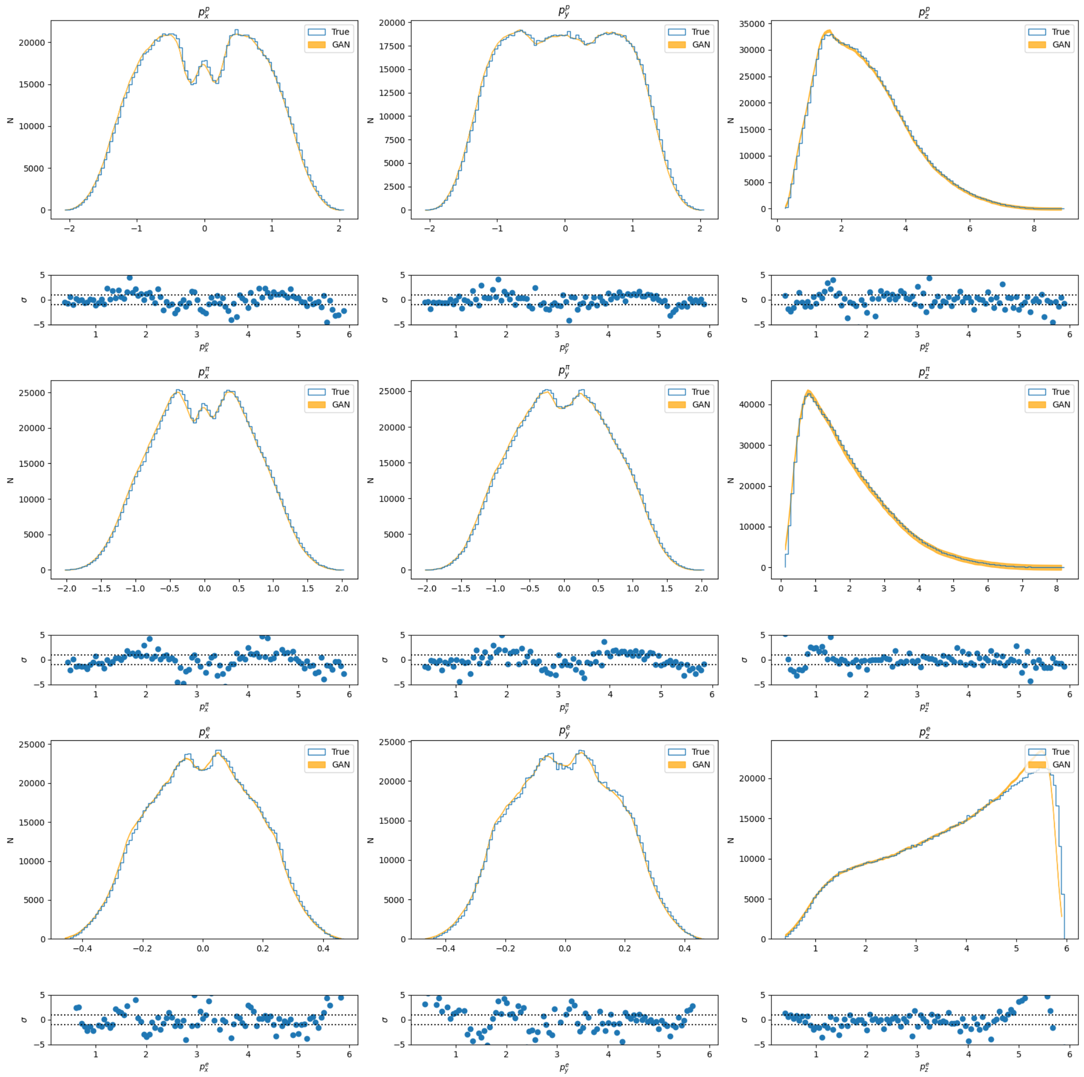
P_x vs P_y comparison



Resolution comparison



Smeared training variables comparison



Credit: D. Glazier, T. Alghamdi, M. Spreafico

Summary

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

- Multi-step program
- We performed a positive closure test on 2π photoproduction
- We demonstrated that GANs are a viable tool to unfold detector effects (smearing) to generate a synthetic copy of data
- We demonstrated that the original correlations are preserved
- Preserve data in alternative compact and efficient form

We are working on:

- Quantifying the systematic error introduced by the detector acceptance
- Implementing this architecture into jlab software in order to make it easily available to everyone
- Further verify that this procedure is well defined confronting the results obtained analysing CLAS data with traditional analysis
- Make this procedure an efficient way to analyse CLAS12 2π data

There is still a long way to go to be able to use AI to extract physics from data in an efficient way, but we are moving towards the right direction!

Thank you!

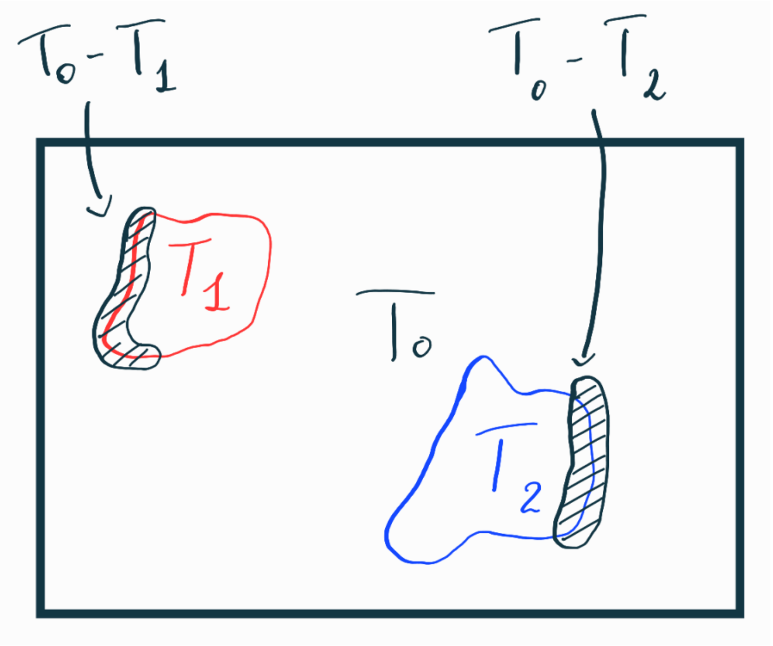
Moving forward: Detector inefficiencies

- How do we define these Mixed events?

  - We generate a dataset of vertex level events in all the phase space

  - We pass **each** event in our dataset through a realistic geant4 proxy of our detector multiple times (for example 100)

Vertex	$\#T_0$	$\#T_1$	$\#T_2$
event 0	20	80	0
…	…	…	…
event N	30	0	70



- Each event can then be defined as $(\theta, \phi, P_{T_0}, P_{T_1}, P_{T_2})$
- Event 0 would look like $(\theta, \phi, 0.2, 0.8, 0)$
- An event which always belongs to T_1 will look like this: $(\theta, \phi, 0, 1, 0)$

P_i is the probability of a given event to end up in a specific topology

Credit: T.Vittorini ,Y.Alanazi, T.Alghamdi, Y. Li