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
- Outlook and future perspectives
- Summary

- 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)

Exlusive reactions: 2 → 3

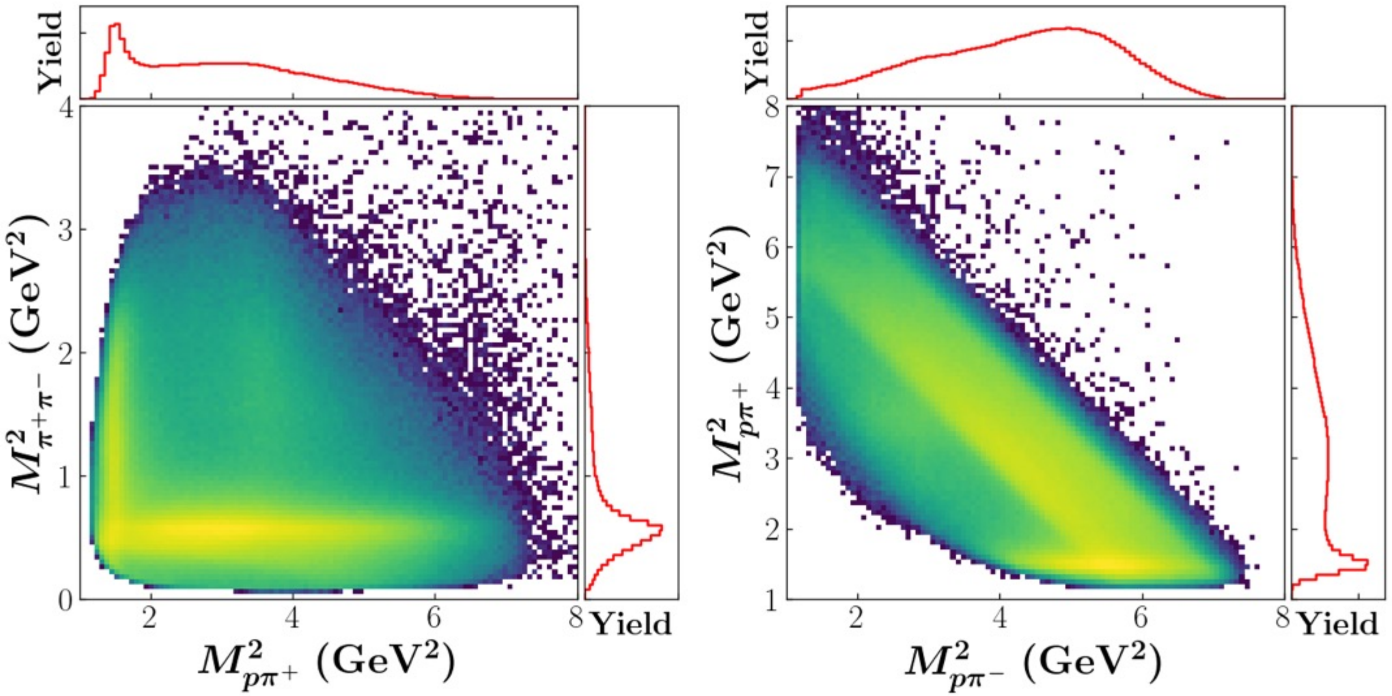
$\gamma p \to \pi^+\pi^- p$ (unpolarized)

- 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 $\gamma p \to p\pi^+(\pi^-)$ with small contamination from $\gamma p \to p\pi^+$(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

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



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

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?

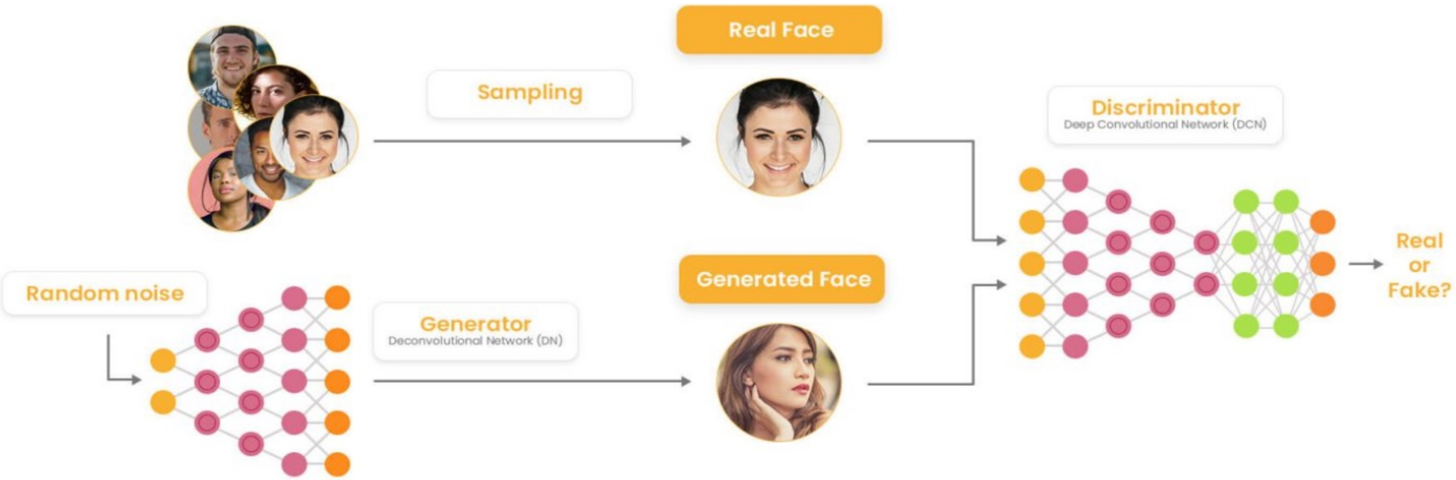
- Interpolation: deal with the holes in the phase space
- Extrapolation: extend our coverage from the borders of measured regions

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

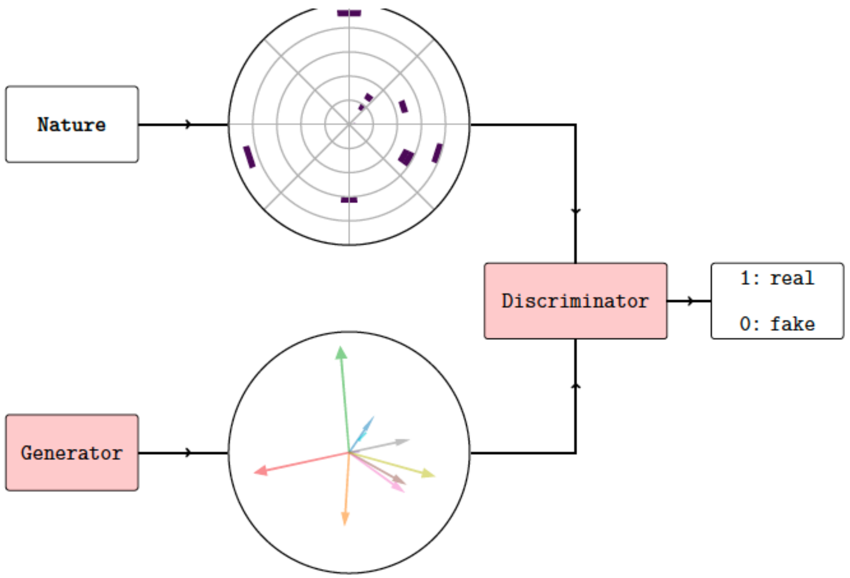
- Spikes may be concealed behind the detector resolution
- Measurements could be extended to unphysical regions

- 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)

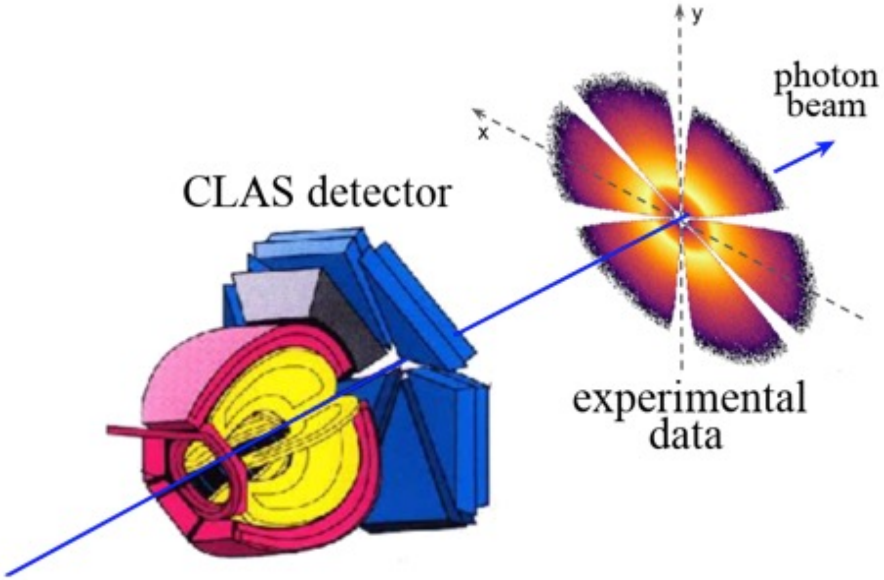


- Generative model based on the competition between two Neural Networks: Generator vs Discriminator
  - **Generator** produces synthetic data which progressively reproduce realistic data and the **Discriminator** has to distinguish between synthetic and realistic data
  - **Generator** can be used to 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

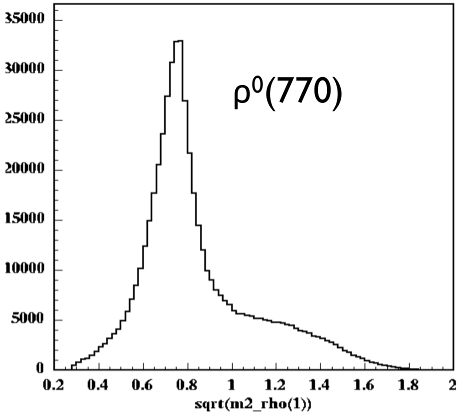
M. Battaglieri *et al.* (CLAS Collaboration)
Phys. Rev. Lett. 102, 102001
M. Battaglieri *et al.* (CLAS Collaboration)
Phys. Rev. D 80, 072005



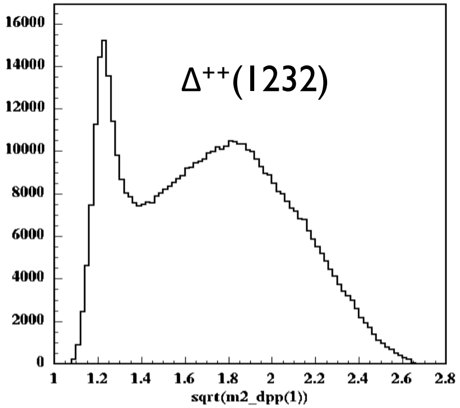
CLAS g11 kinematics

- 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 $\gamma p \rightarrow \Delta^{++}\pi^{-}$

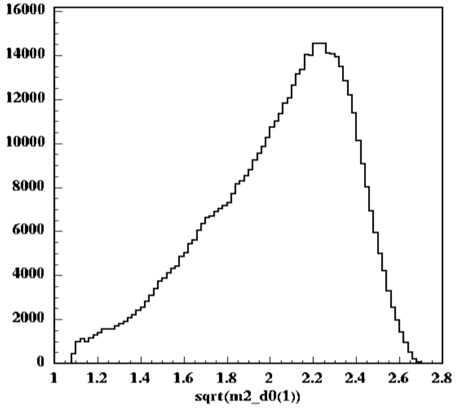
M(ππ)



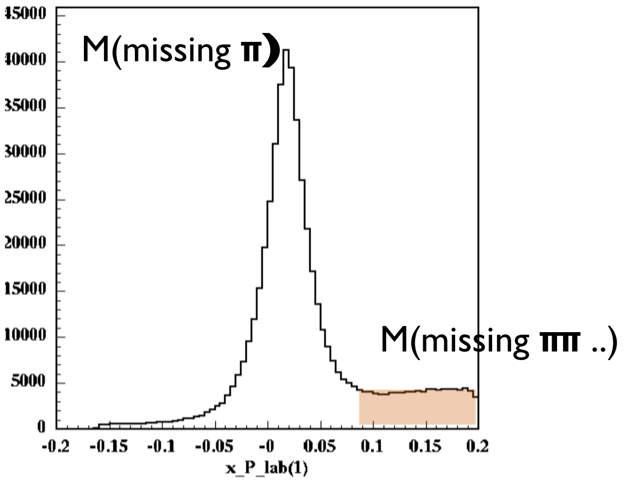
M(pπ+)



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)

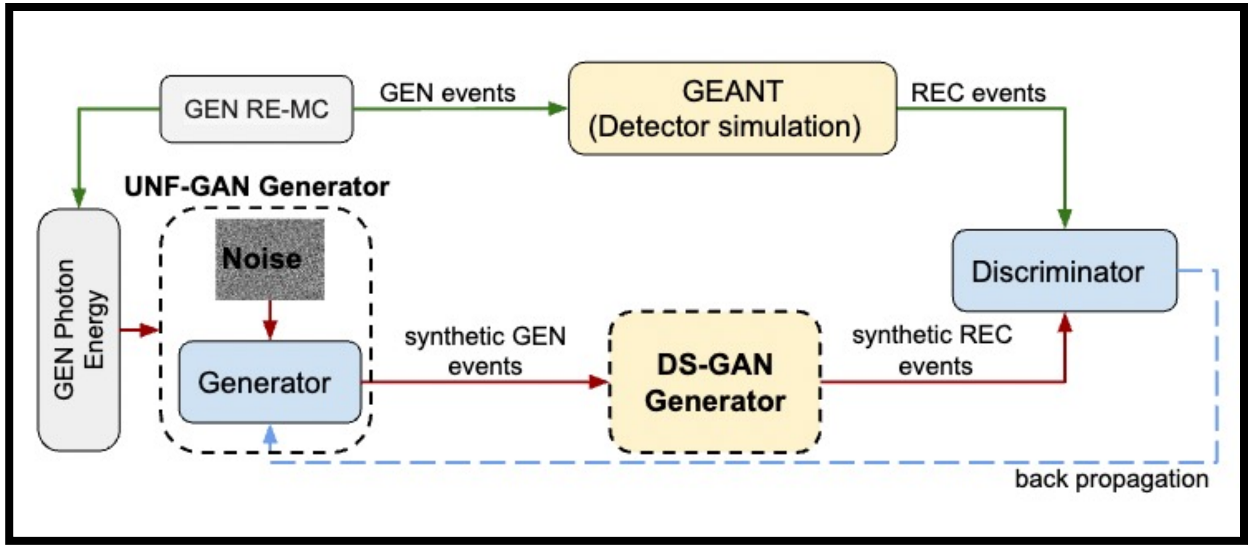
2. Apply detector effects (acceptance and resolution) via GSIM-GEANT (RE-MC REC pseudodata)

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

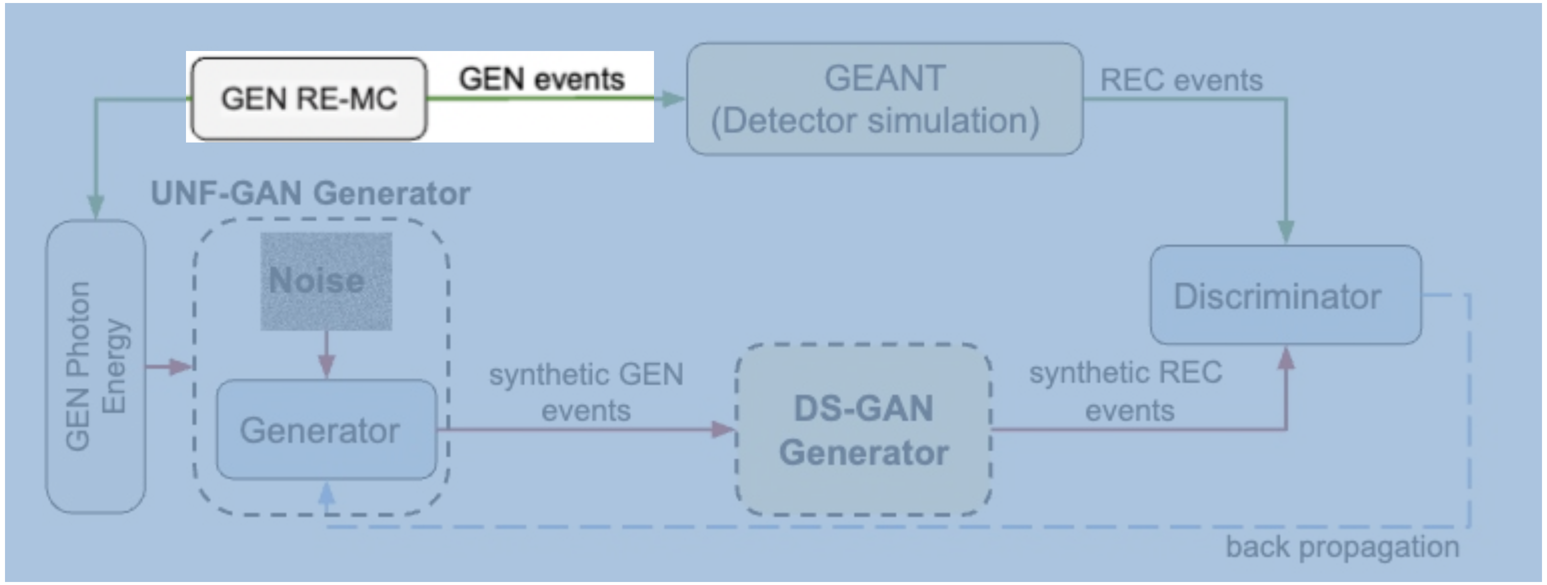


Credit: T. Alghamdi et al. Phys. Rev. D **108**, 094030

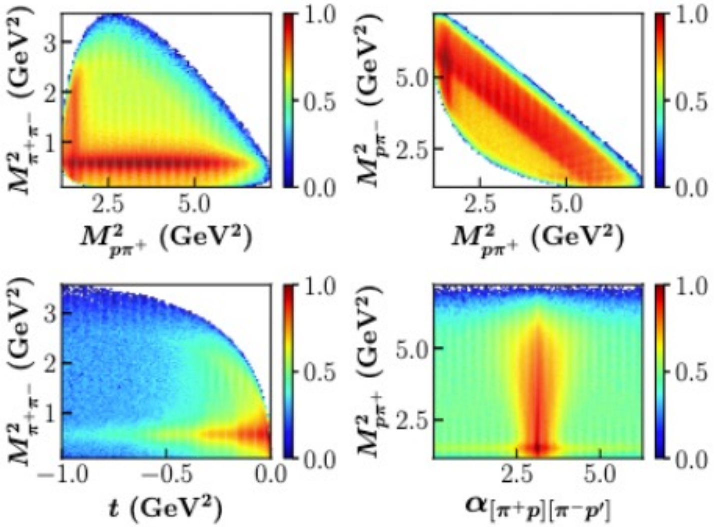
2π photoproduction closure test

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)



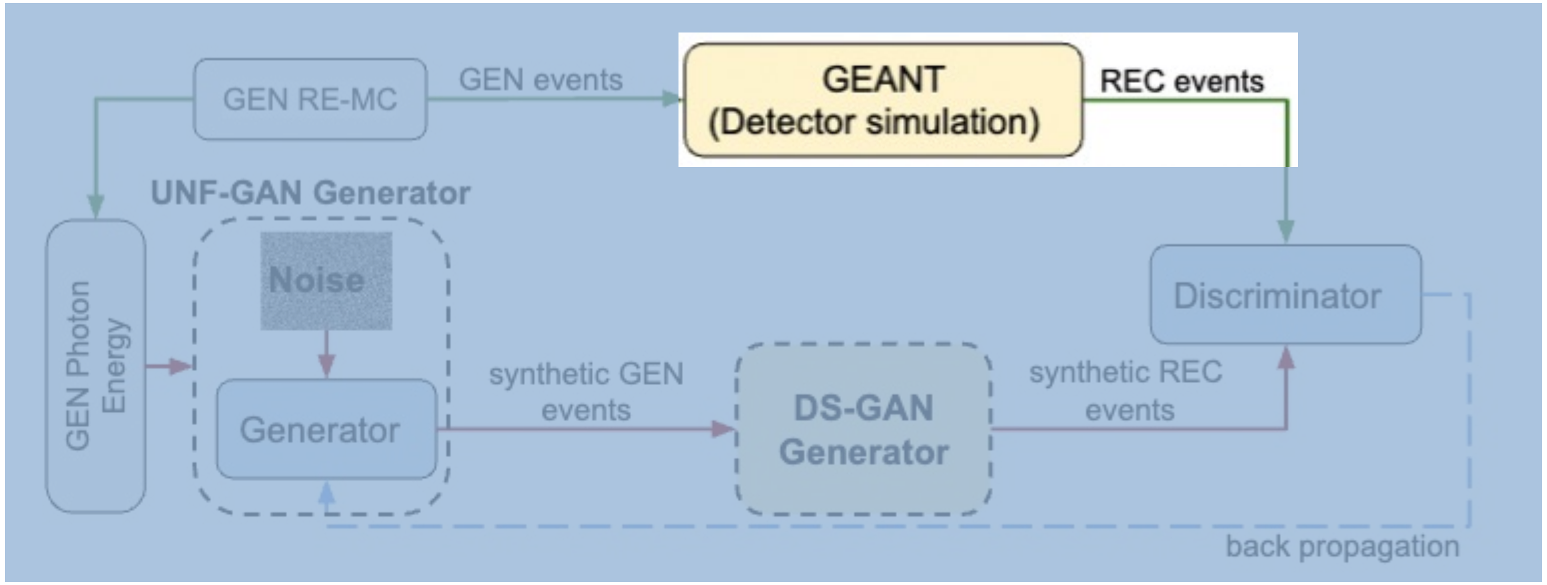
GEN events

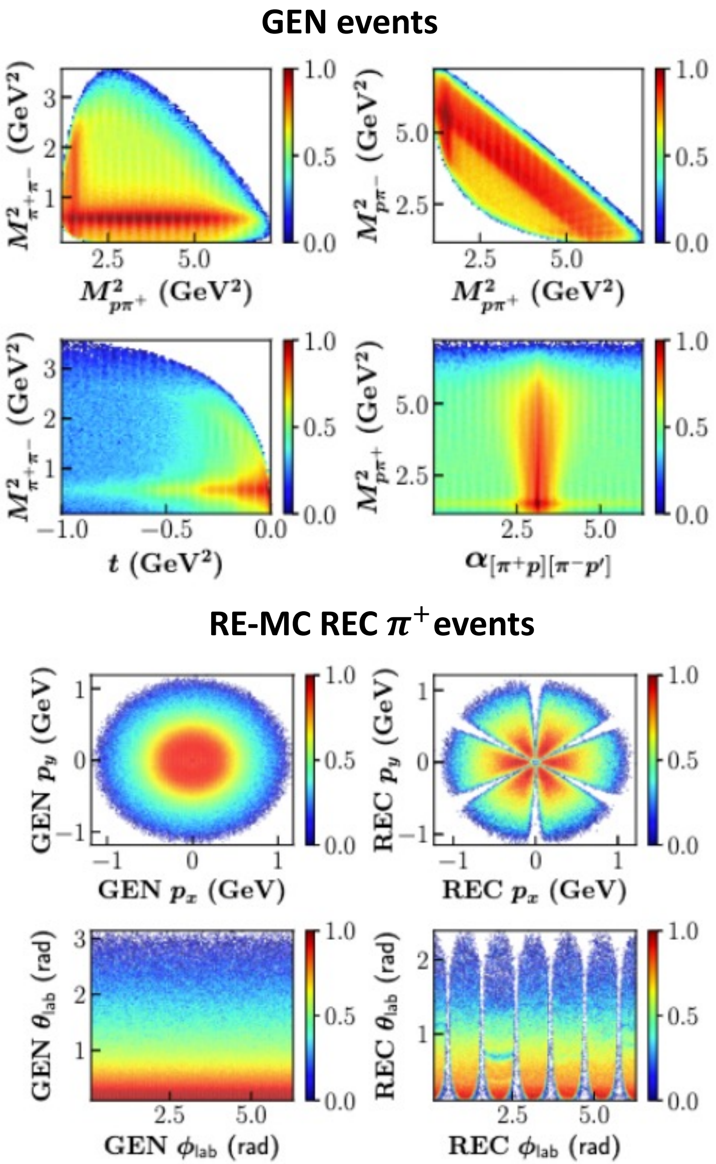


2π photoproduction closure test

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

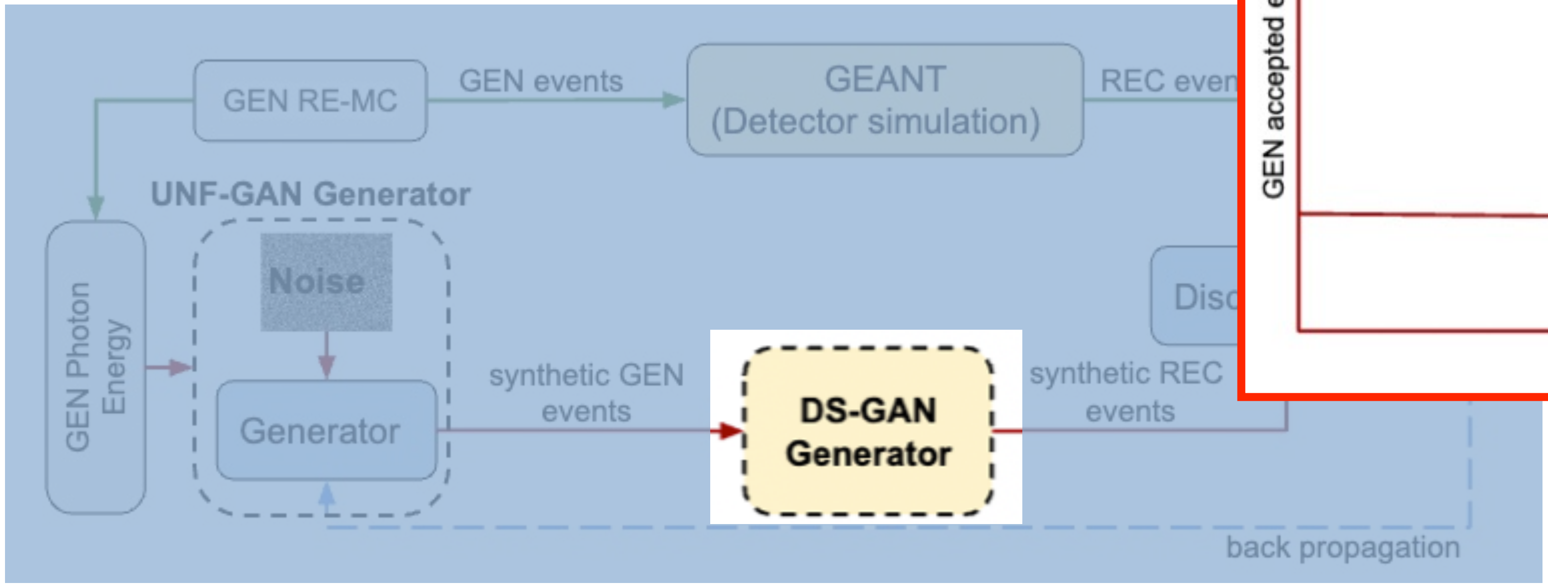
- GSIM: detector simulation package to simulate CLAS detector effects based on GEANT3

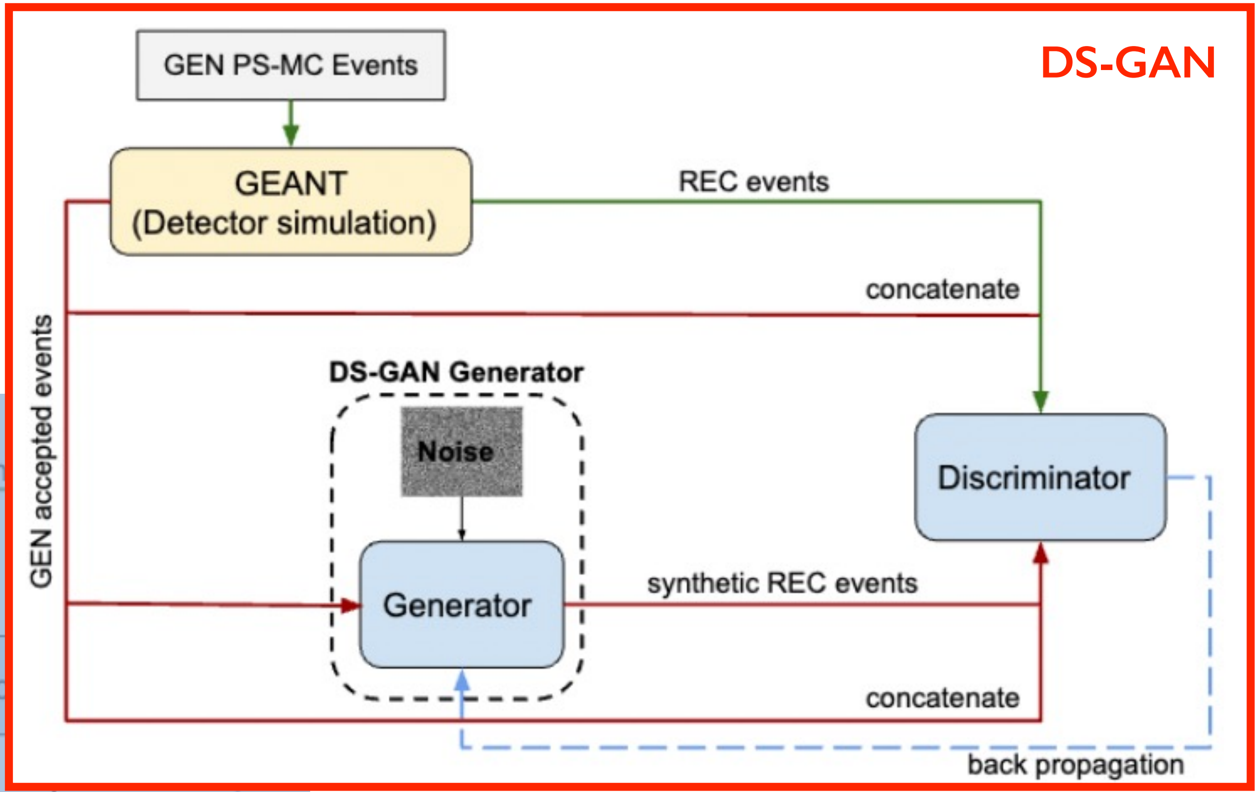




2π photoproduction closure test

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

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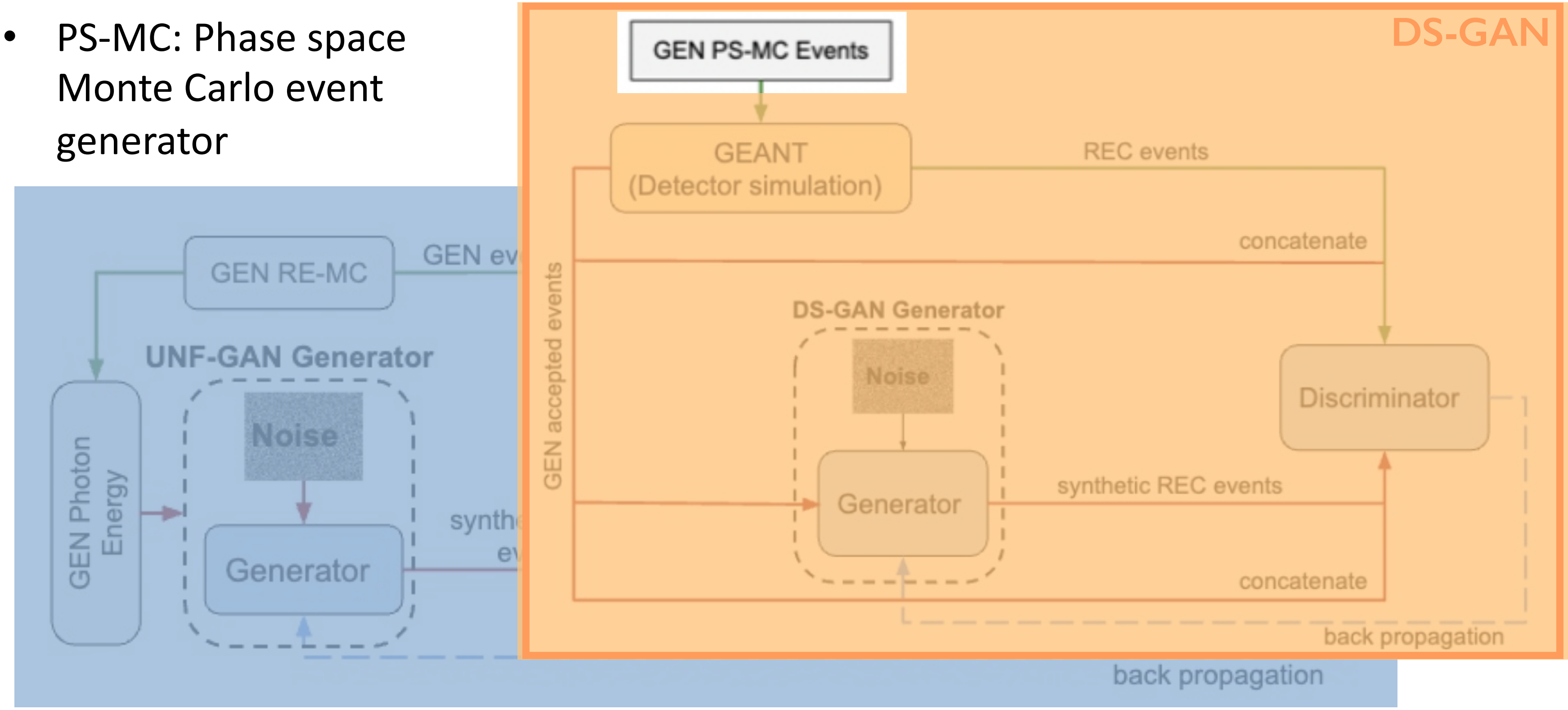
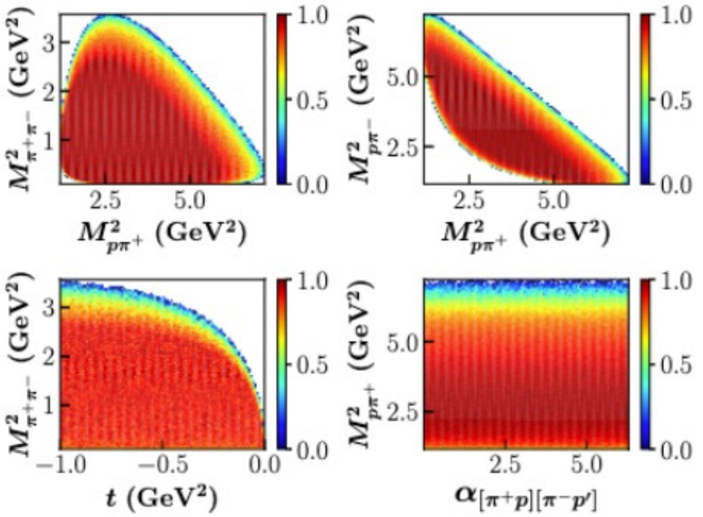
- PS-MC: Phase space Monte Carlo event generator



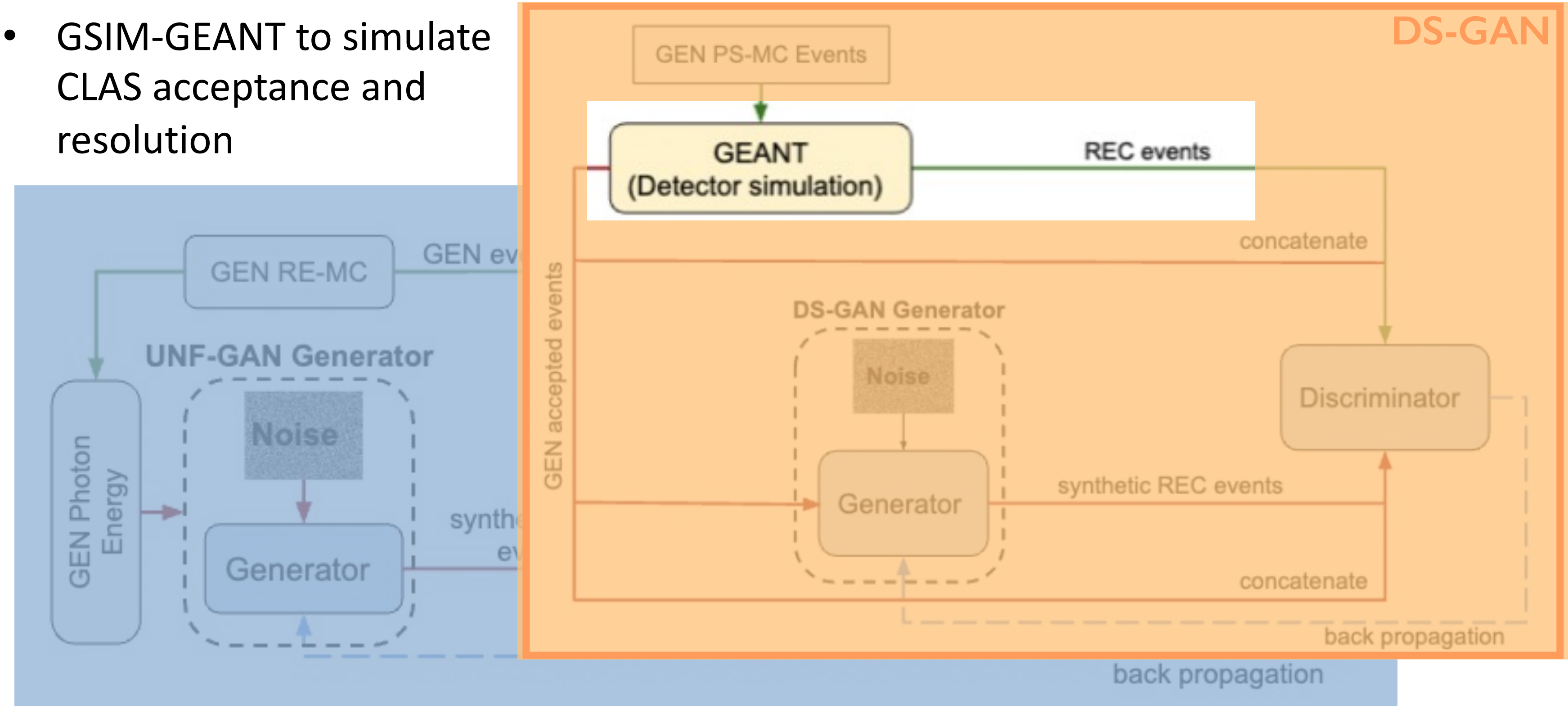
PS-MC GEN events



2π photoproduction closure test

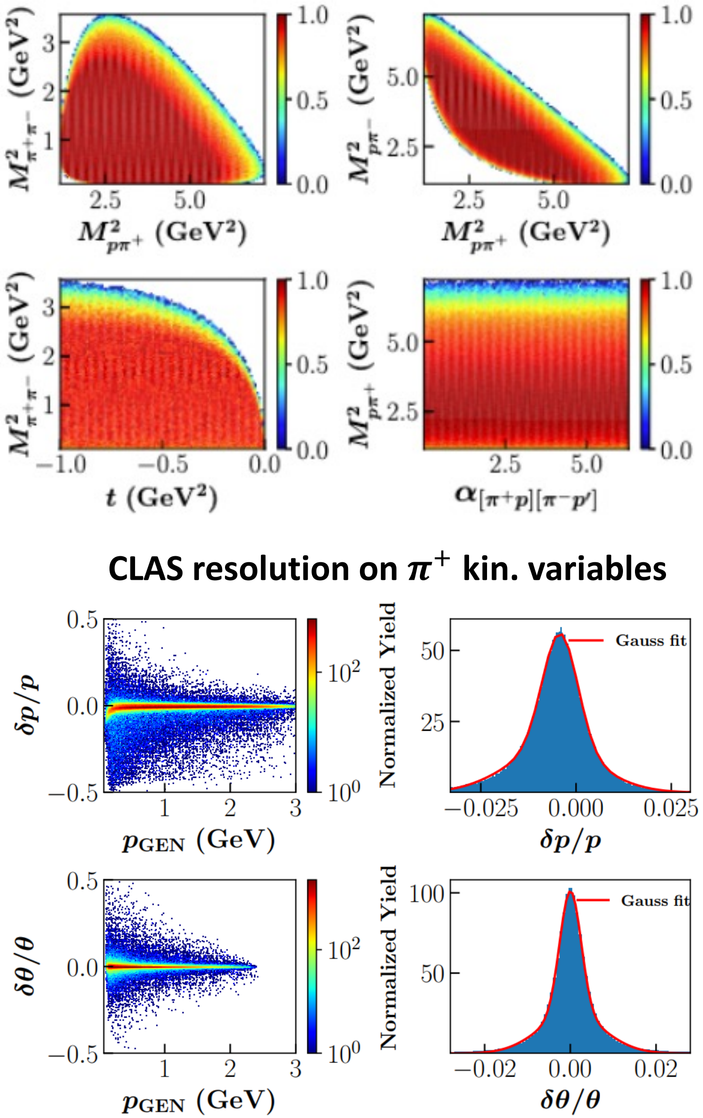
3. Deploy a secondary GAN (DS-GAN) to learn detector effects using an indipendent MC event generator (PS-MC) + GSIM-GEANT (GEN and REC pseudodata)

- GSIM-GEANT to simulate CLAS acceptance and resolution



PS-MC GEN events

CLAS resolution on π^+ kin. variables



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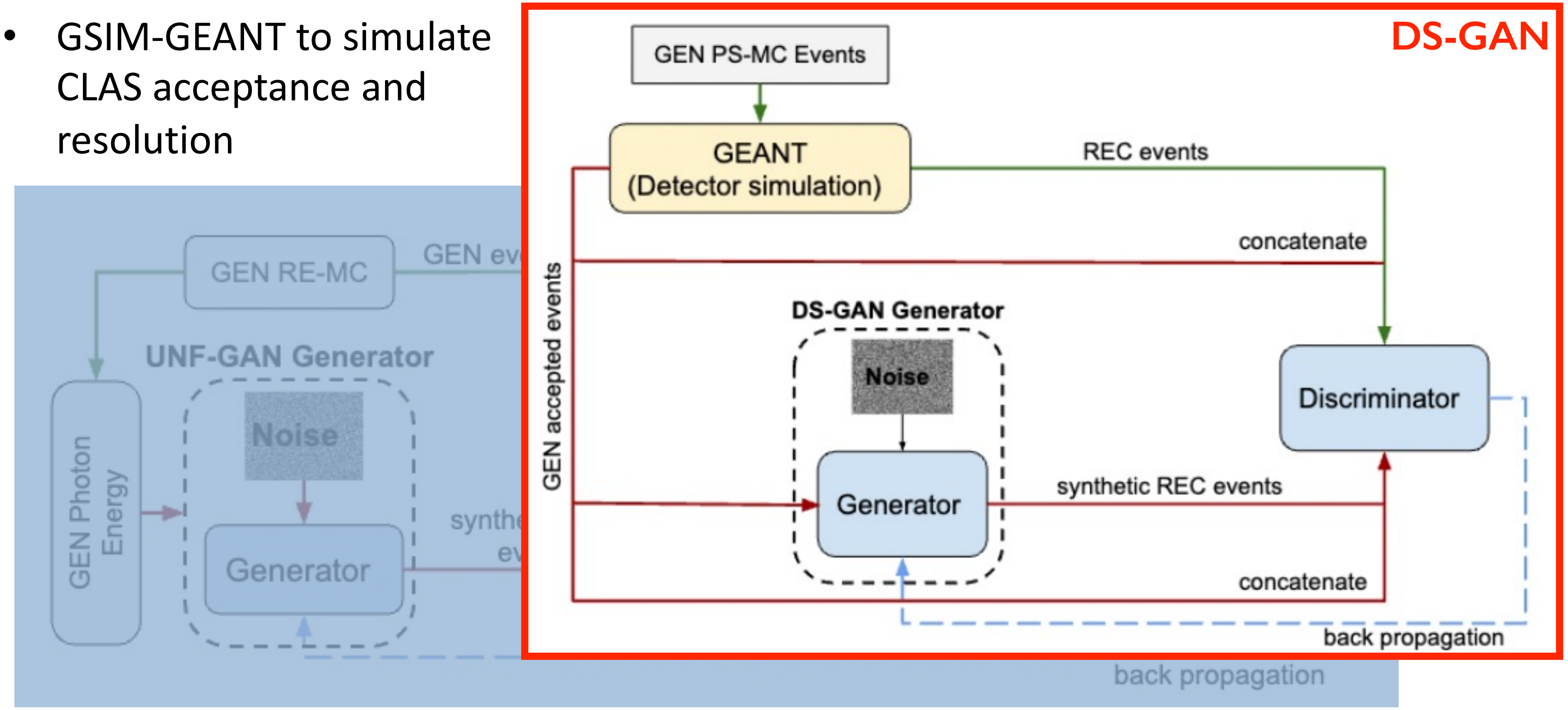
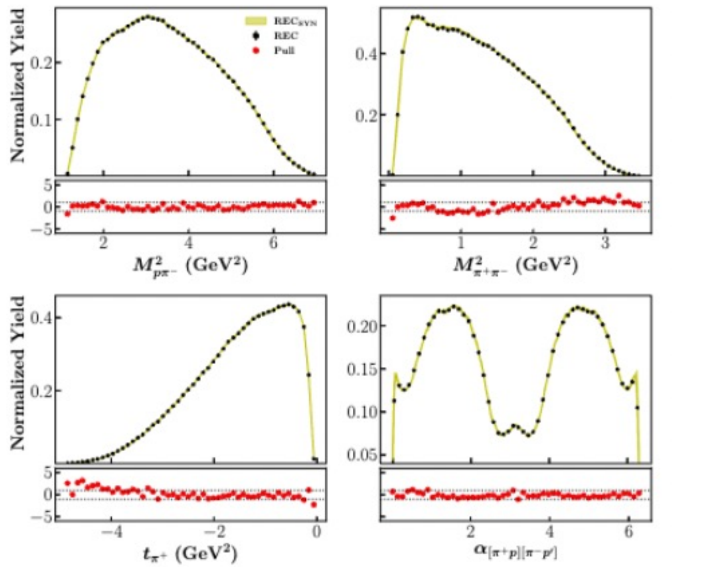
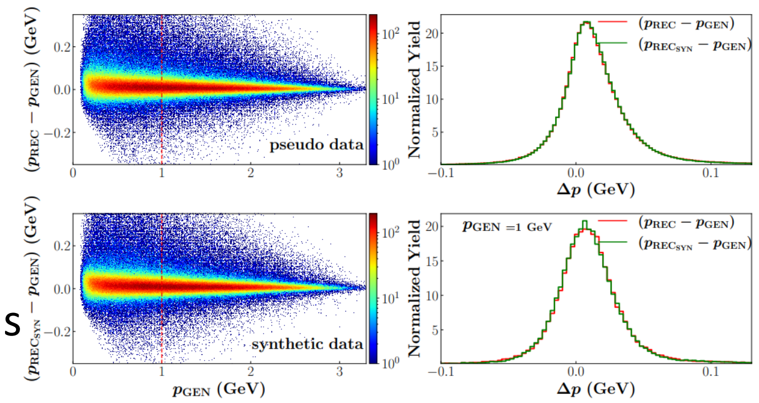


MC REC pseudodata vs. DS-GAN synthetic data



CLAS resolution

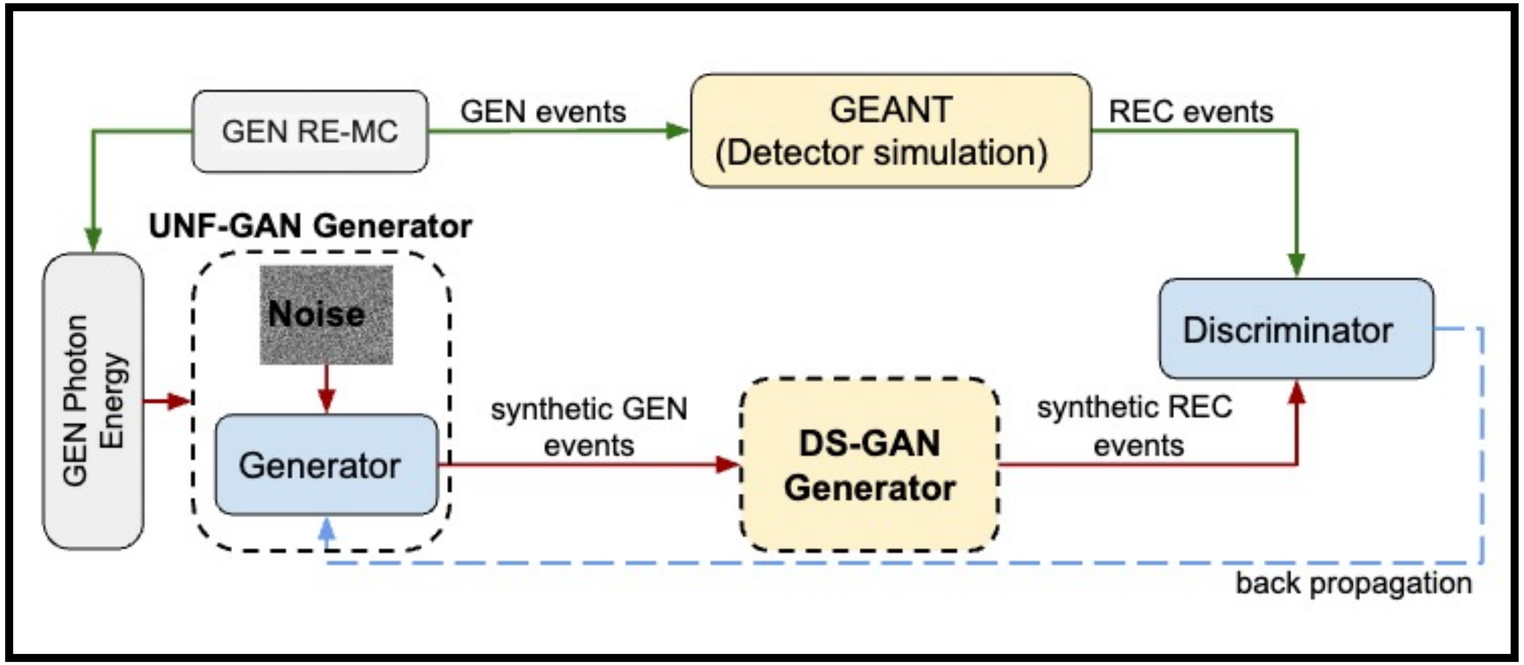


Uncertainty quantification via **pull** calculation: Bootstrap with 20 indipendently trained GANs

DS-GAN learned the CLAS detector effects!

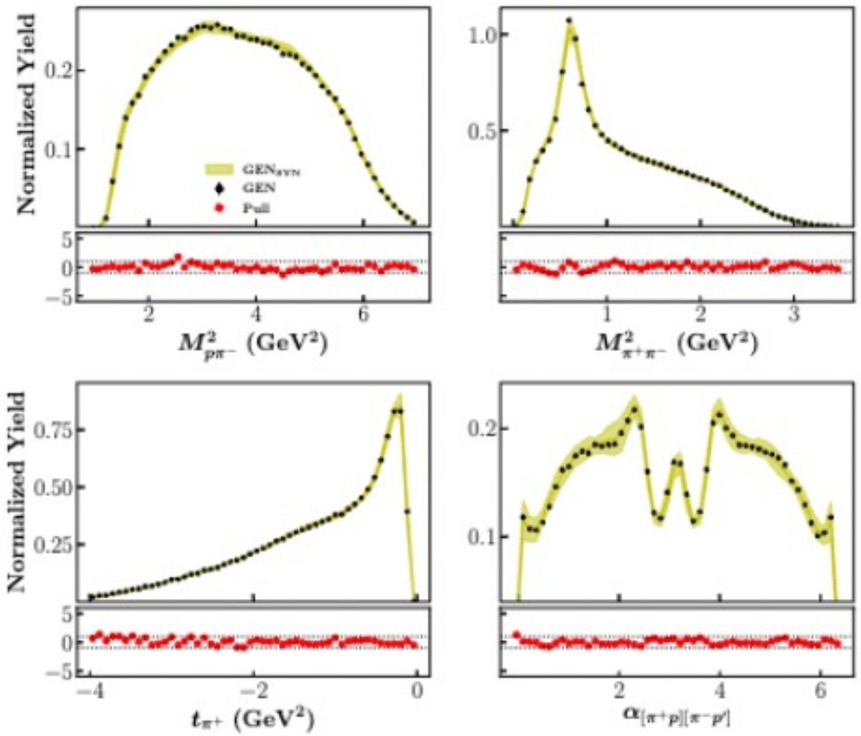
2π photoproduction closure test

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



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

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



Good agreement ($\pm1\sigma$) for vertex-level training variables!

- 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)
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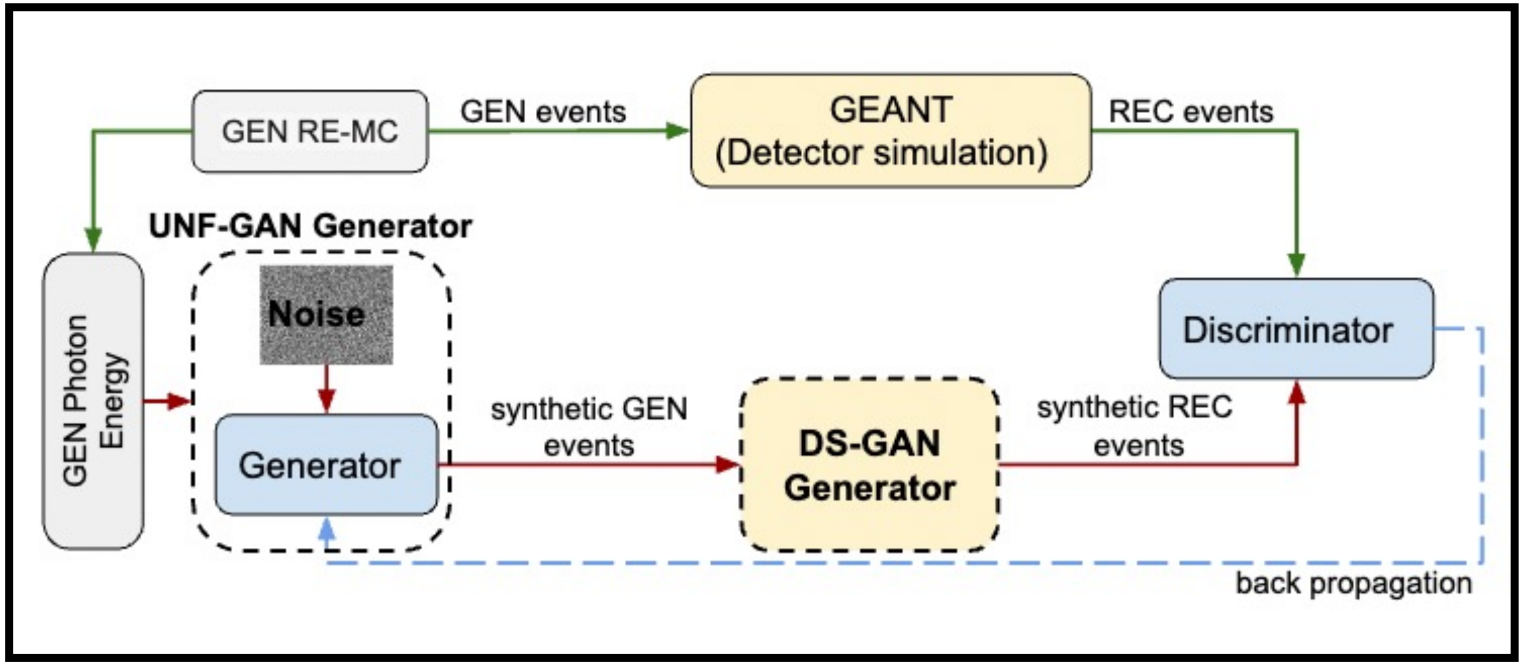
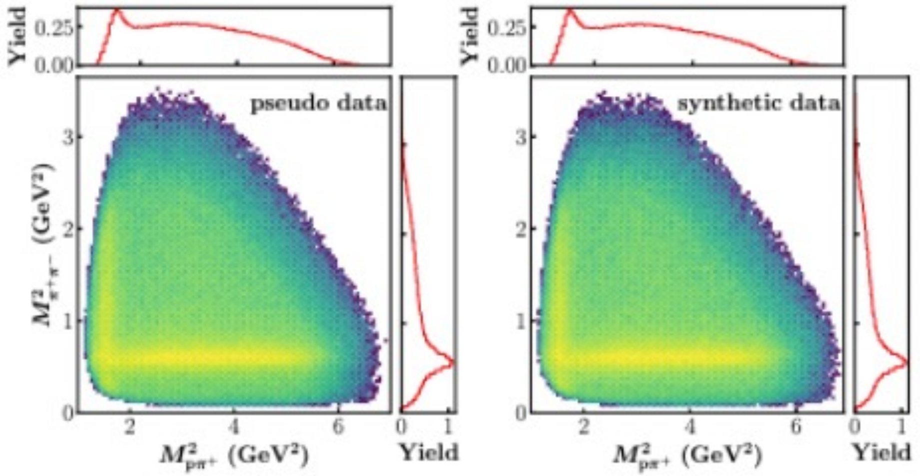


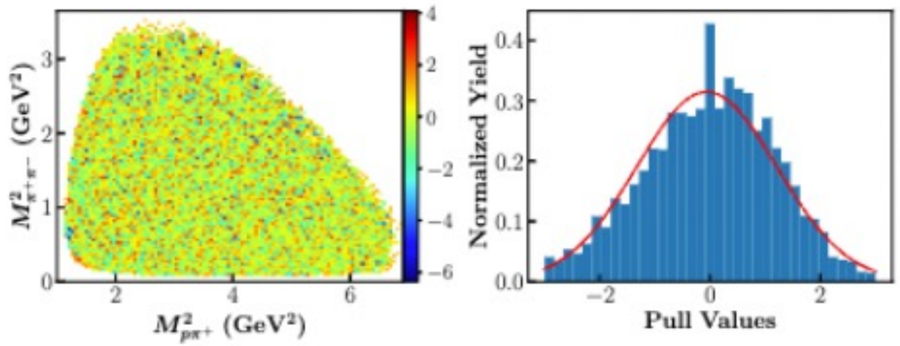
5. Compare UNF-GAN GEN SYNT to RE-MC GEN pseudodata

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

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



2D pulls



2π photoproduction closure test

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- UNF-GAN trained with REC-MC pseudodata (experimental data proxy)
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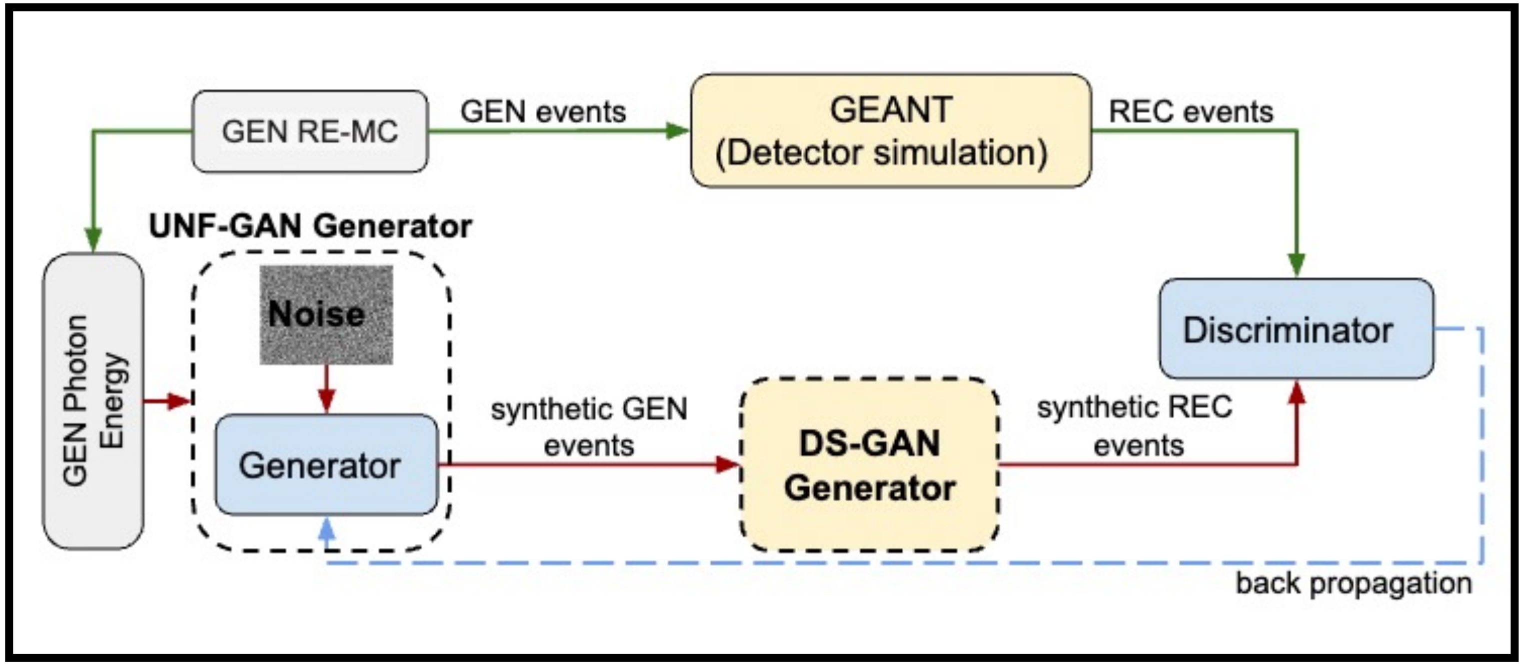
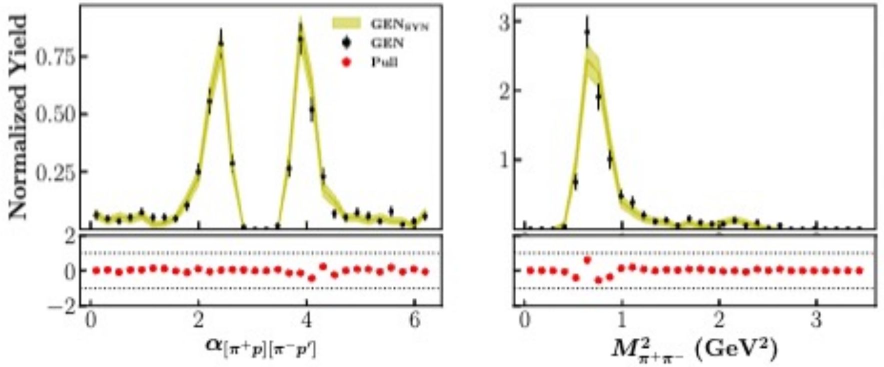


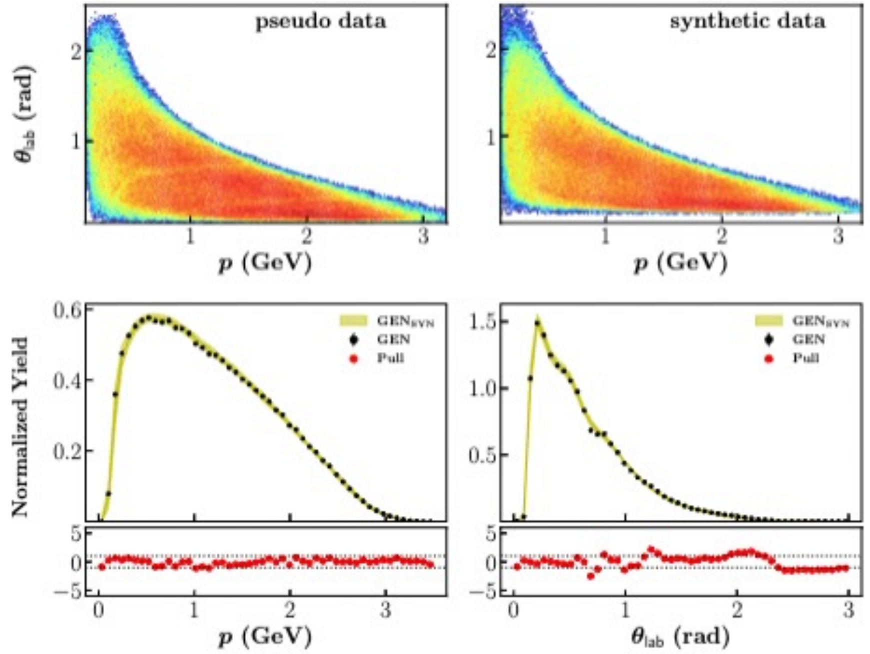
5. Compare UNF-GAN GEN SYNT to RE-MC GEN pseudodata

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



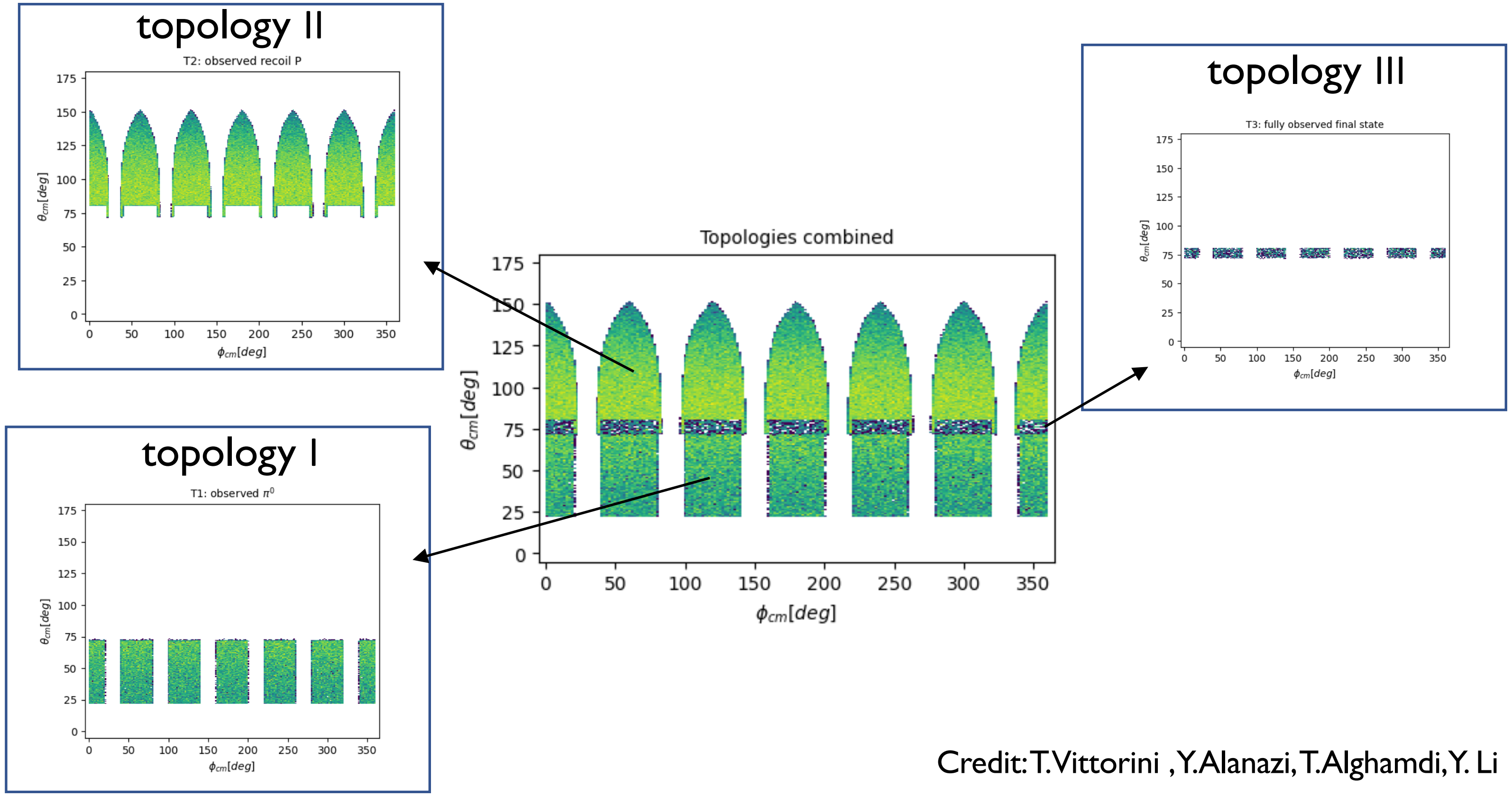
Moving forward: Acceptance

- 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

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

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

- 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 1I: γ p → p (π^0) (π^0 missing)
  - topology III: γ p → p π^0 (all detected)
  - [topology 0: unmeasured]

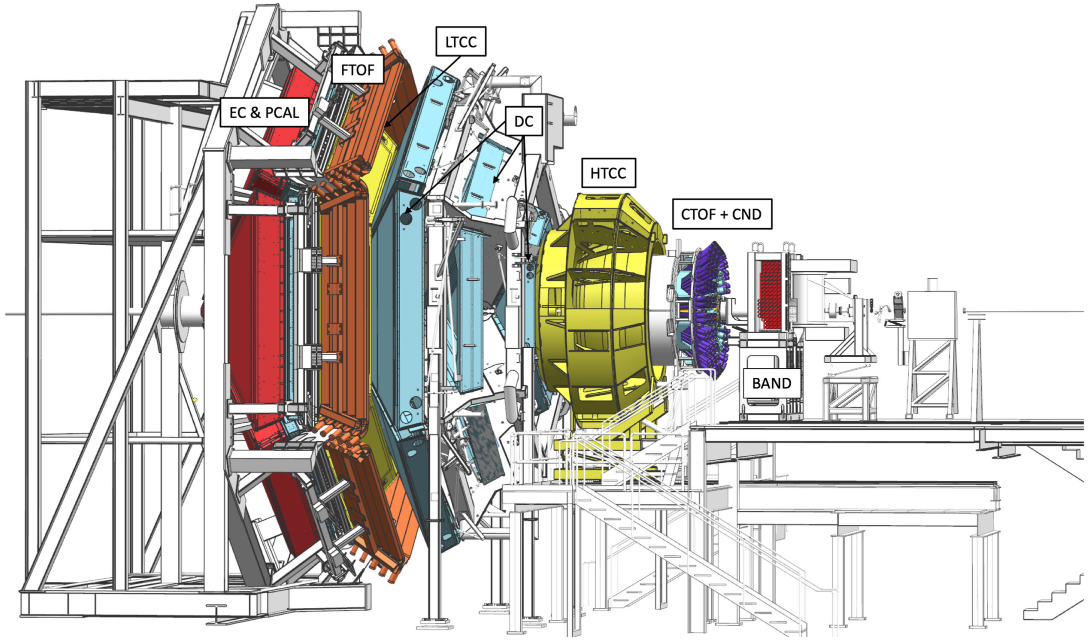


Build a single Network able to generate in the full phase space according to the correct distributions

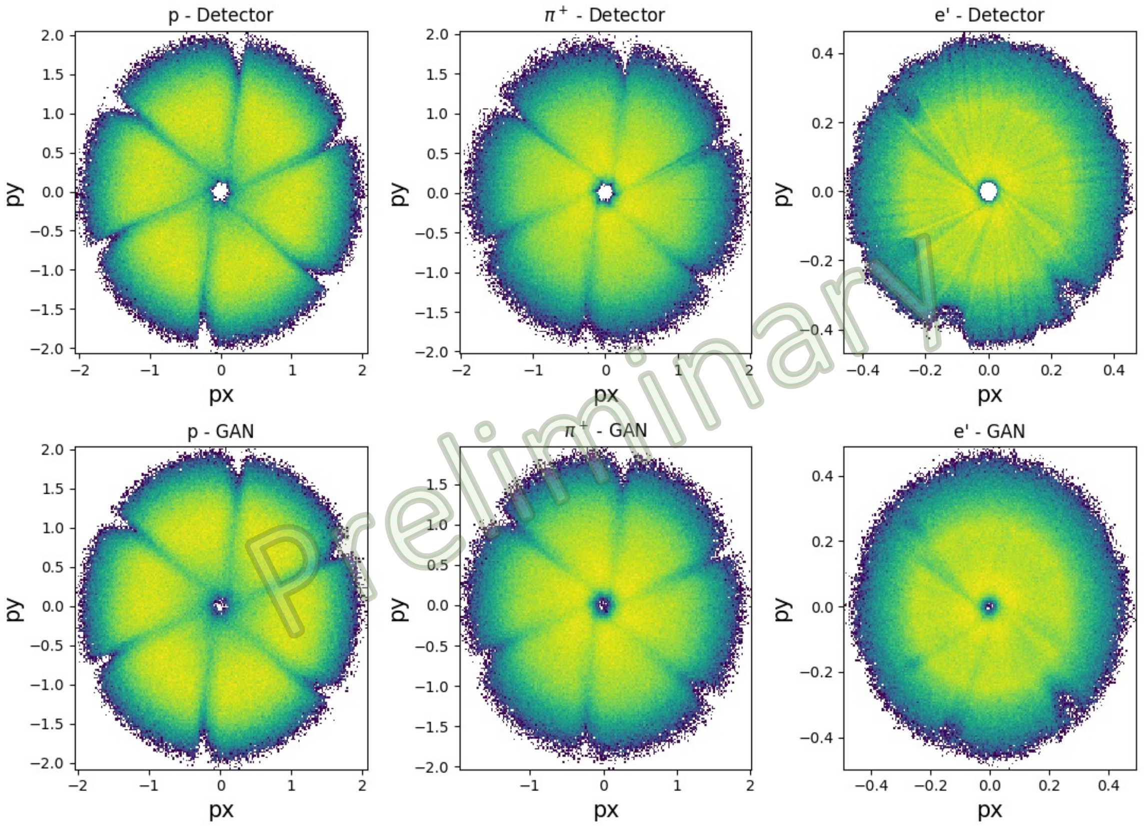
Credit: T.Vittorini , Y.Alanazi, T.Alghamdi, Y. Li

Moving forward: CLAS12 application

- Working towards the application of the developed machinery to CLAS12 pseudodata for the $ep \rightarrow e'p'\pi^+\pi^-$
- 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



DS-GAN training on the CLAS12 detector



Credit: Derek Glazier, Tareq Alghamdi, Marco 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 2pion 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 in order to extract a 4D cross-section
- 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!