AI for data preservation and interpretation in hadron physics

M.Battaglieri (INFN)

on behalf of A(i)DAPT Working Group

A(i)DAPT

AI for Data Analysis and PreservaTion

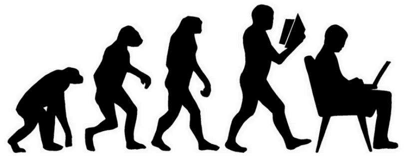
AI for NP/HEP

- Data collected by NP/HEP experiments are (always) affected by the detector's effects
- Before starting physics analysis the detector's effects unfolding are 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

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

Develop AI-supported procedures to:

- Prepare data unfolding detector effects
- Accurately fit data in multiD space
- Extract physics observables (xsec, asymmetries, …) from *synthetic* data (AI-generated)
- Interpret physics observables
- in all steps, quantifying the uncertainty (UQ)



A(i)DAPT

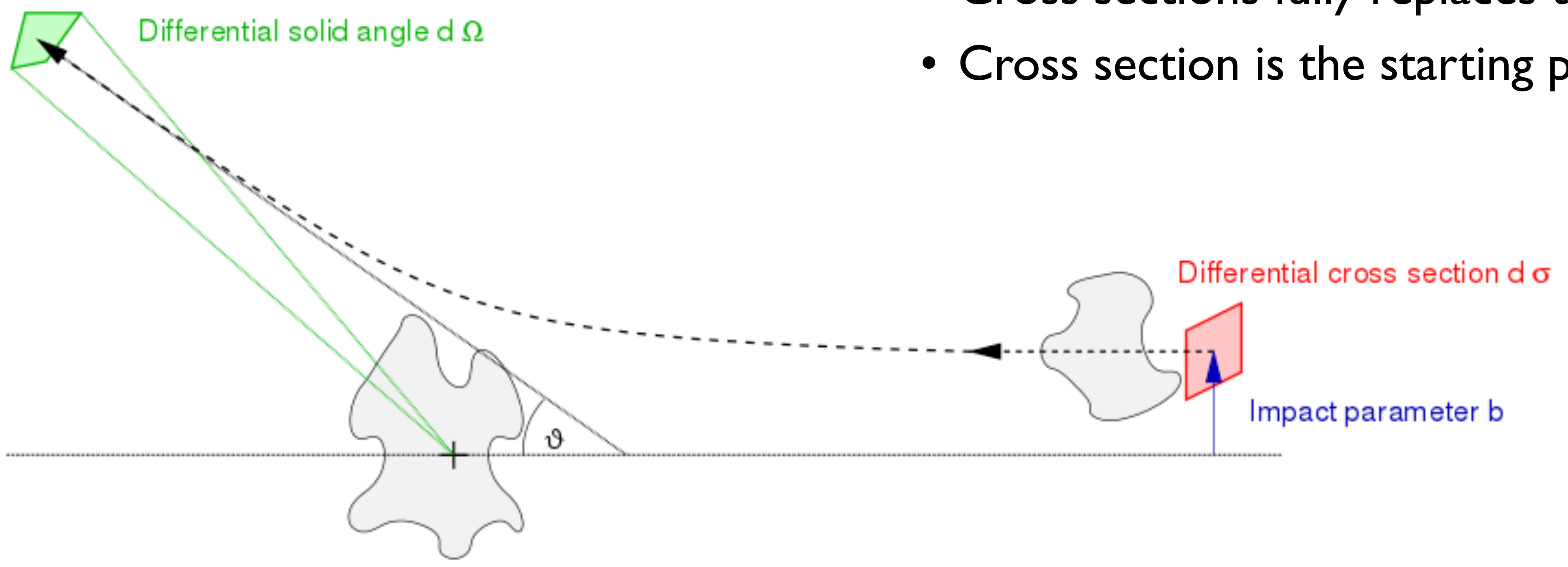
AI for Data Analysis and PreservaTion

Collaborative effort (regular meeting)

- ML experts (ODU, JLab)
- Experimentalists (JLab Hall-B)
- Theorists (JPAC, JAM)

The cross section in particle physics

$$\frac{d\sigma}{d\Omega} = (2\pi)^4 m_i m_f \frac{p_f}{p_i} |T_{fi}|^2$$



- The *cross section* is related to the transition probability between an initial to a final state
- In case of scattering, cross sections provides information about the elementary interaction
- Cross section is expressed as squared sum of scattering amplitudes (complex functions) depending on the kinematic Lorentz-invariant of the problem and embedding the interaction properties
- It is derived by measuring the momentum distributions of reaction particle (at different CM energy)
- Correlations between particles in the final state reflects the underlying dynamics
- Cross sections fully replaces the 4-mom data sample in a compact and efficient way
- Cross section is the starting point for any higher level physics analysis

- Traditional approach: particles (4-momenta) measured into the detector, extract the relevant observables, extract physics mechanisms
- Cross section **preserves** this information as replacement for the original particle-by-particle scattering information

Exclusive reactions: 2 → 2

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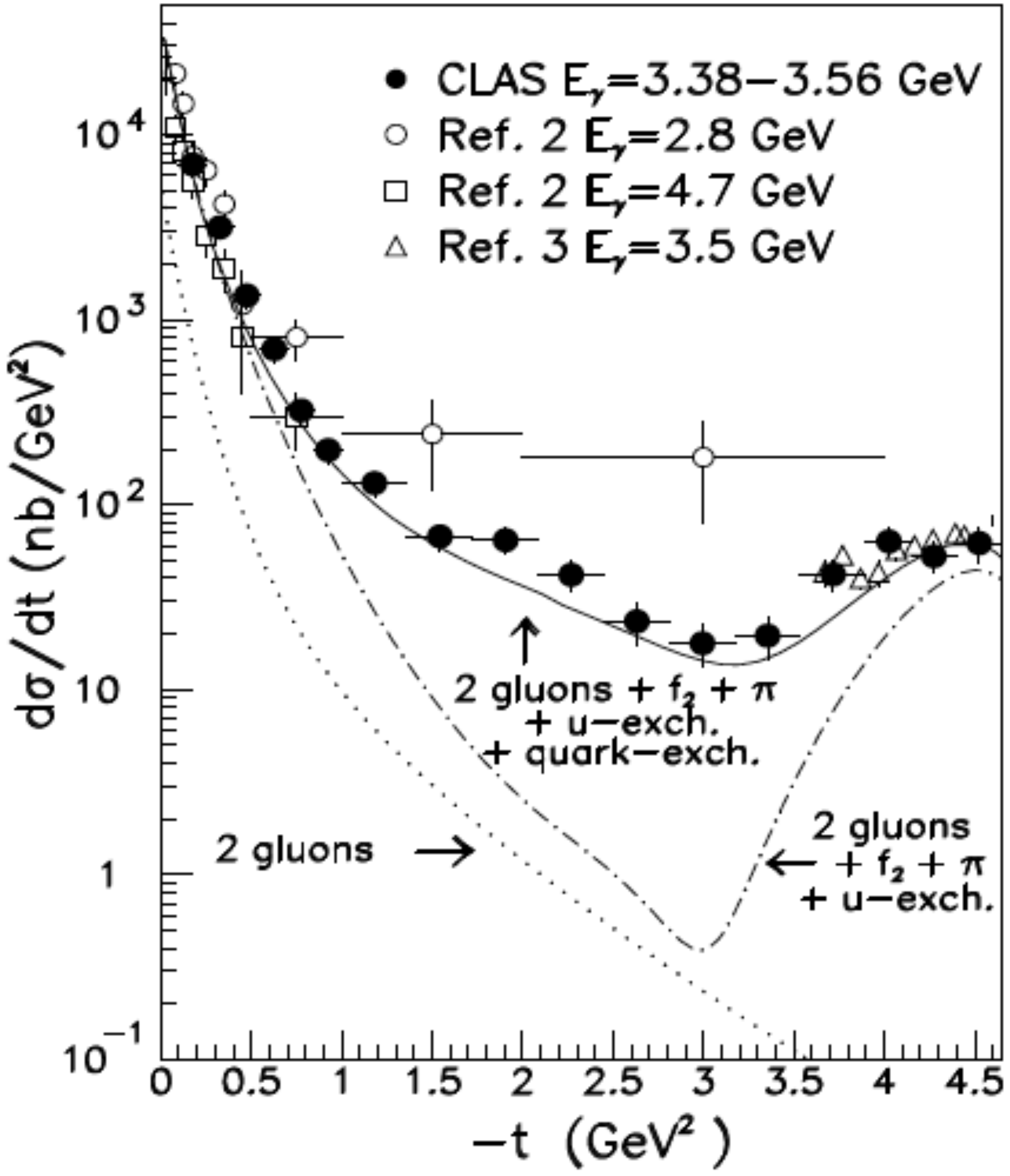
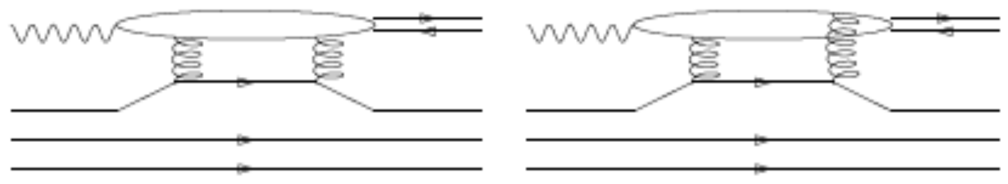
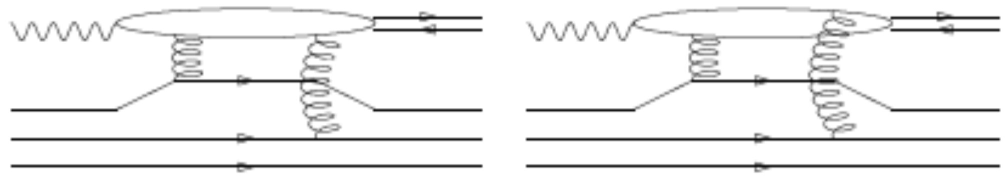


JLab-CLAS g6 ω photo production at large momentum transfer

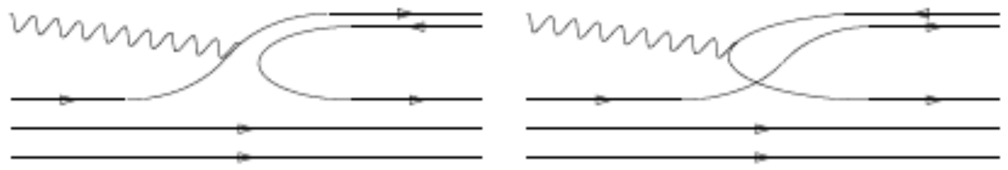
$\gamma\, p \rightarrow p\, \omega$



2-gluon exchange



Correlations



quark exchange

2 → 2 scattering (no polarisation)

- Initial state: known
- Final state: 2 x 3
- Parameters: (2 x 3) - 4 = 2
- Possible choice: -*t* and ϕ
- *the* physics depends only on one variable (-t)

- It worked (and still works!) well if limited to channels with a single variable
- Xsec, Polarization observables, angular distribution, decay matrix, …

Exclusive reactions: 2 → 3

M. Battaglieri *et al.* (CLAS Collaboration) Phys. Rev. Lett. 90, 022002

2 → 3 scattering (no polarization)
- Initial state: known
- Final state: 3 x 3
- Parameters: (3 x 3) - 4 = 5 (E_γ fixed)
- Possible choice: $M^2_{\pi\pi}$, $M^2_{p\pi}$ θ_π, α, ϕ

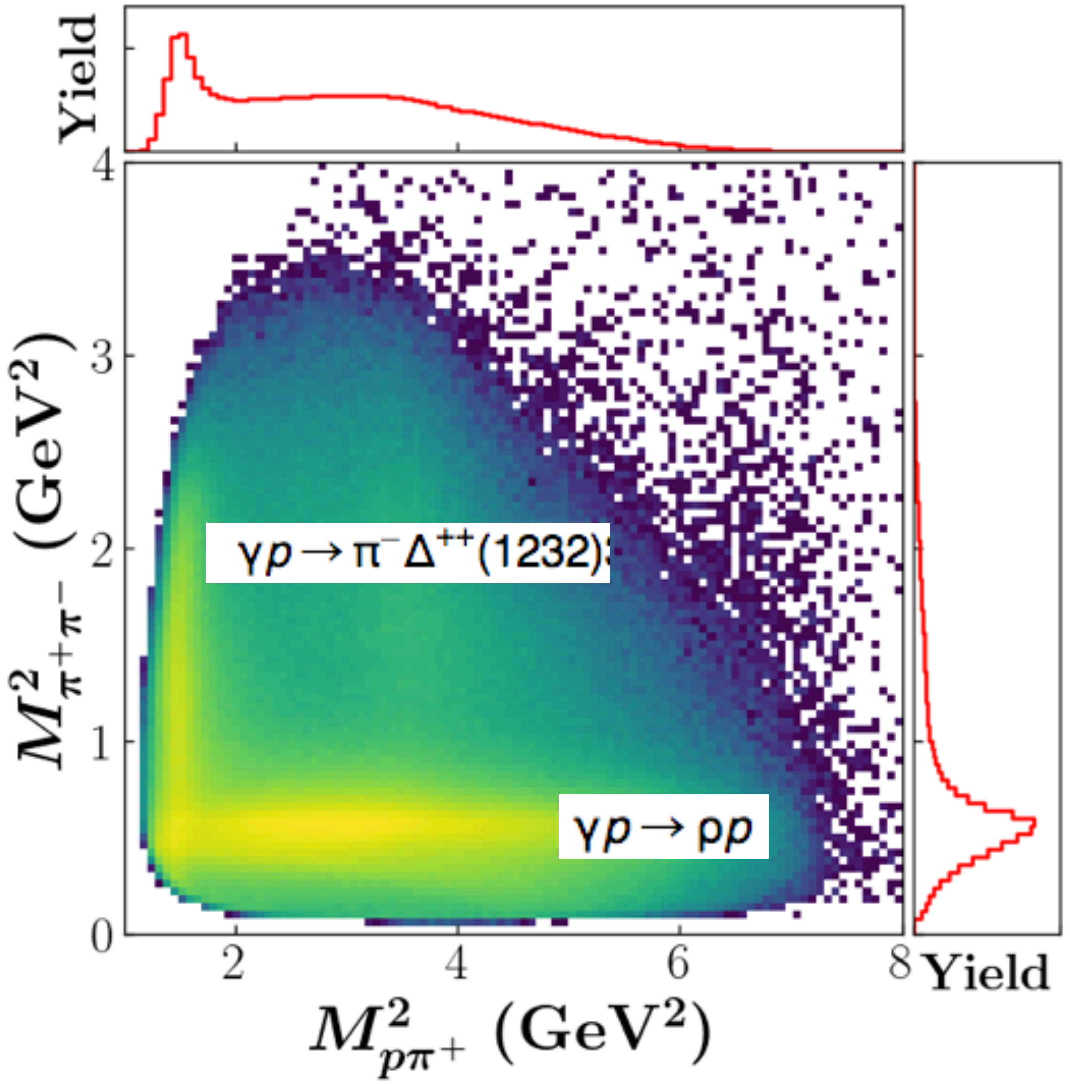
- It does not work (in practice) when you have several independent variables: multi-particle final states (spectroscopy) or multi-variable correlations (SIDIS)
- In the integration to reduce to 1-dim all correlations are lost

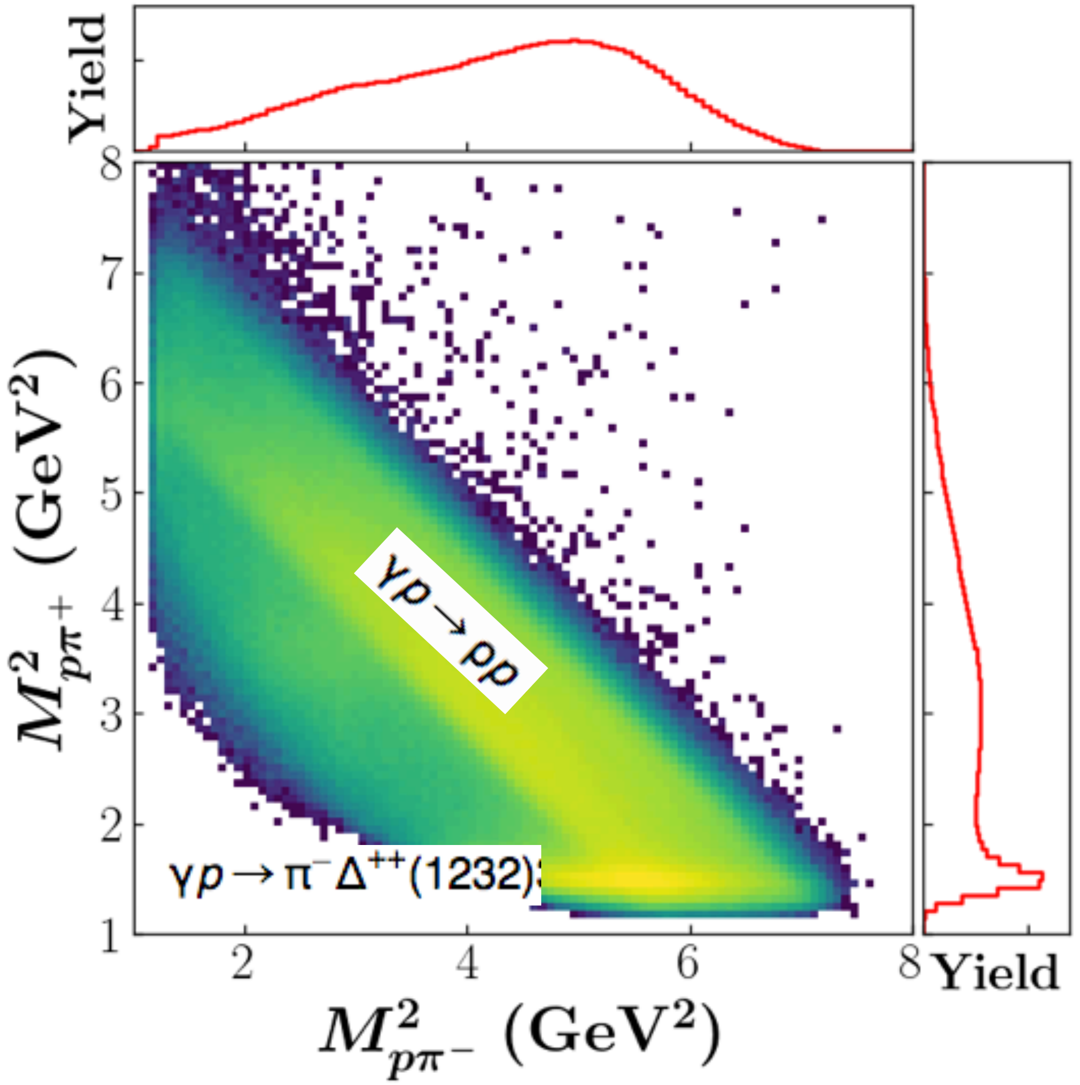
AI may provide a new way to look at data and extract observables and physics interpretation (on event by event base)

CLAS g11 2π photo production

- E_γ = (3.0 - 3.8) GeV
  $\gamma\, p \to p\, \pi^+\, \pi^-$ exclusive reaction
  - data set analyses so far $\gamma\, p \to p\, \pi^+ (\pi^-)$ + small contamination of $\gamma\, p \to p\, \pi^+$ (more than a missing π^-)
  - complicated dynamic for the overlap of (pπ) to form Δ baryon resonances and (ππ) to form meson resonances

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





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

Deploy an AI Generative Model to reproduce NP/HEP data

- **Unfold detector effects**
    - Smearing
    - Acceptance
- **Produce physics observables**
    - 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 physics out of data**
    - Extract cross-section and amplitudes in a 2-body reaction (e.g. ππ scattering - MC)
    - Extract moments of angular distributions and fit with a model (e.g. 2-pion pthotoproduction model - 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)
- …

A(i)DAPT

Deploy an AI Generative Model to reproduce NP/HEP data

This talk

- Unfold detector effects
  - Smearing ✓
  - Acceptance ✓
- **Produce physics observables**
  - 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) **in progress**
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- …

Detector unfolding

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

Resolution

- Any detector has a finite resolution that spreads the measurement
- A spike could be not resolved
- The measurement may extend in an unphysical region (e.g. negative squared missing mass)

Acceptance

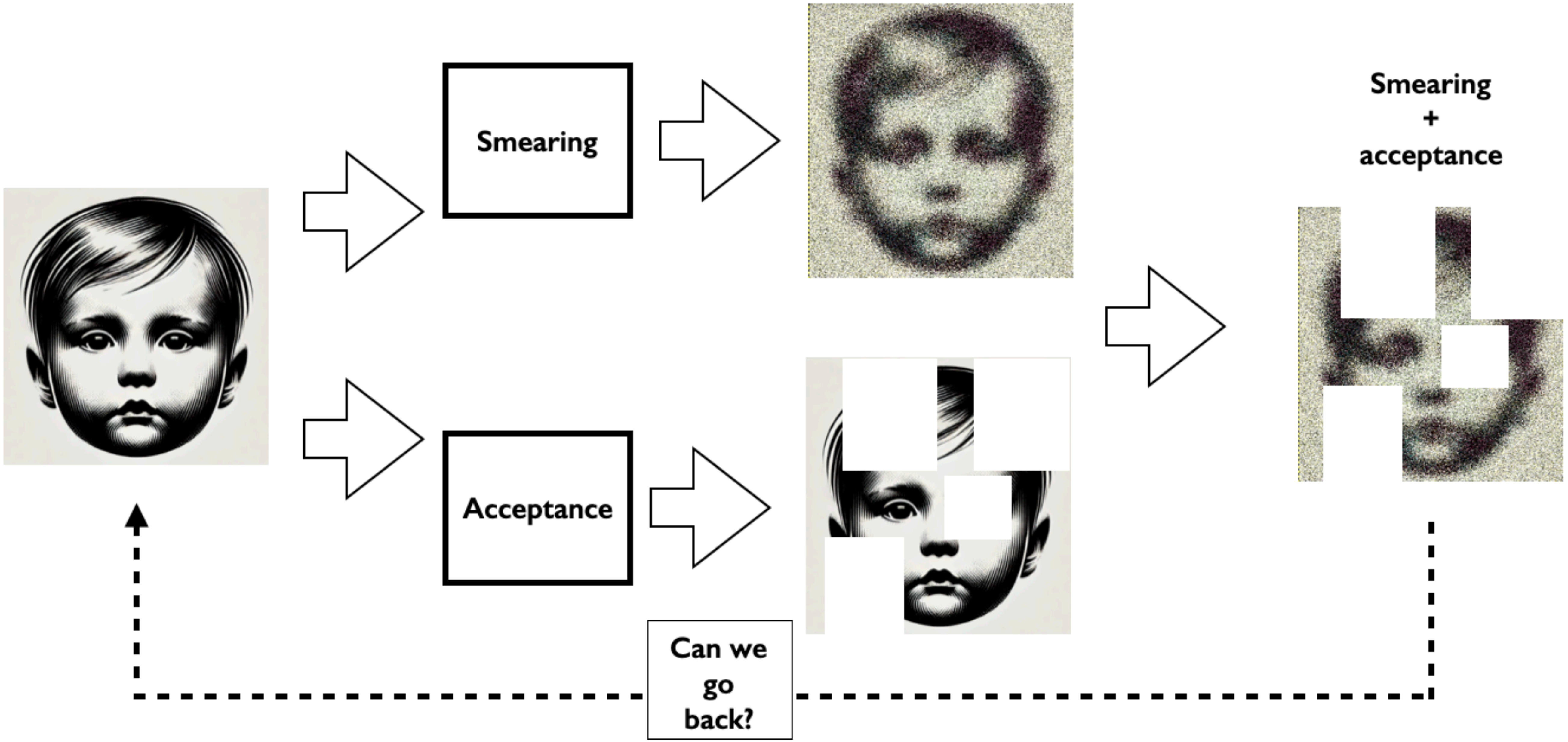
- Any measurement covers only a fraction of the reaction phase-space
- Difficulty: the cross section (Probability Density Function) can not be constrained by general rules (other than being positive) since it reflects the underlying (a-priori unknown) physics
- No model-independent extrapolation of PDF outside detector's acceptance is possible (based on measured phase space)

Use AI:

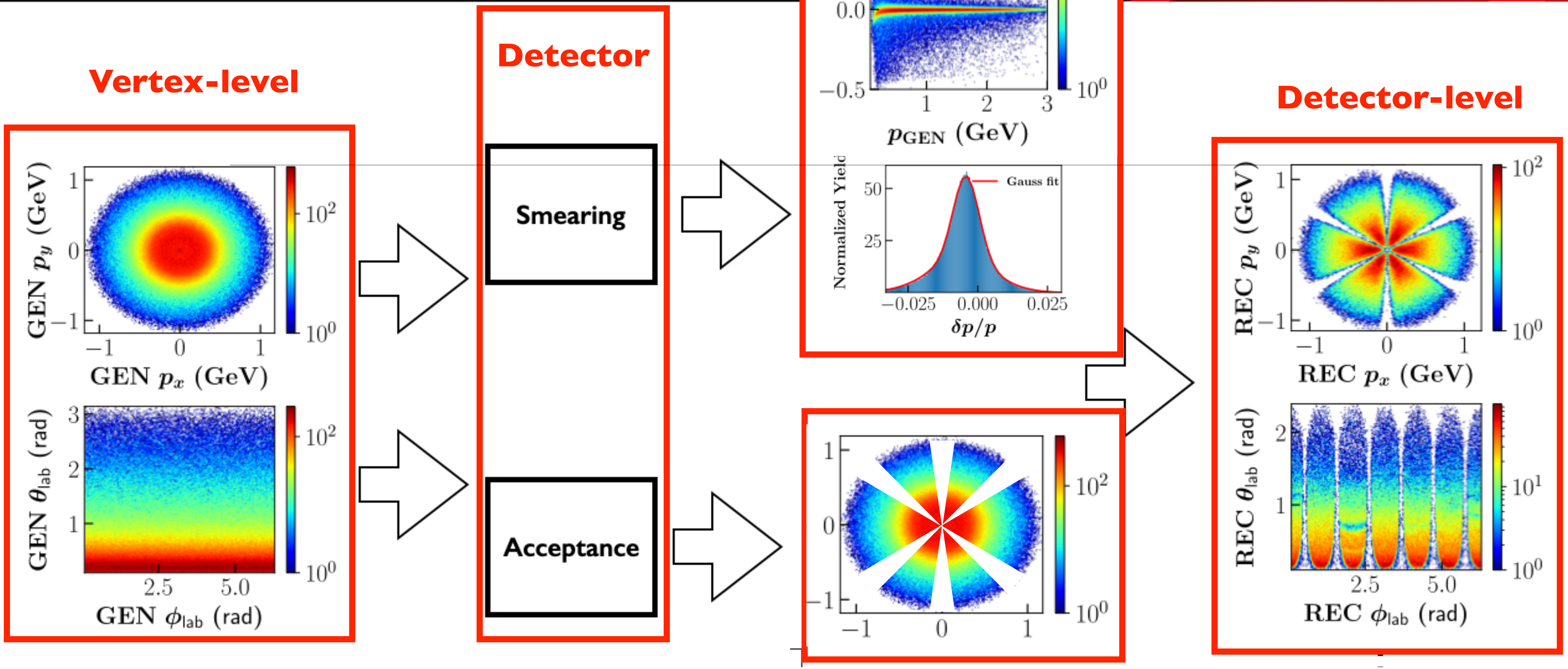
- **inside acceptance: to replace data with a synthetic replica statistically identical to the original but w/o smearing**
- **outside acceptance: to generate pseudo-data according a physics informed model**

Detector unfolding

Can we recover the original image?



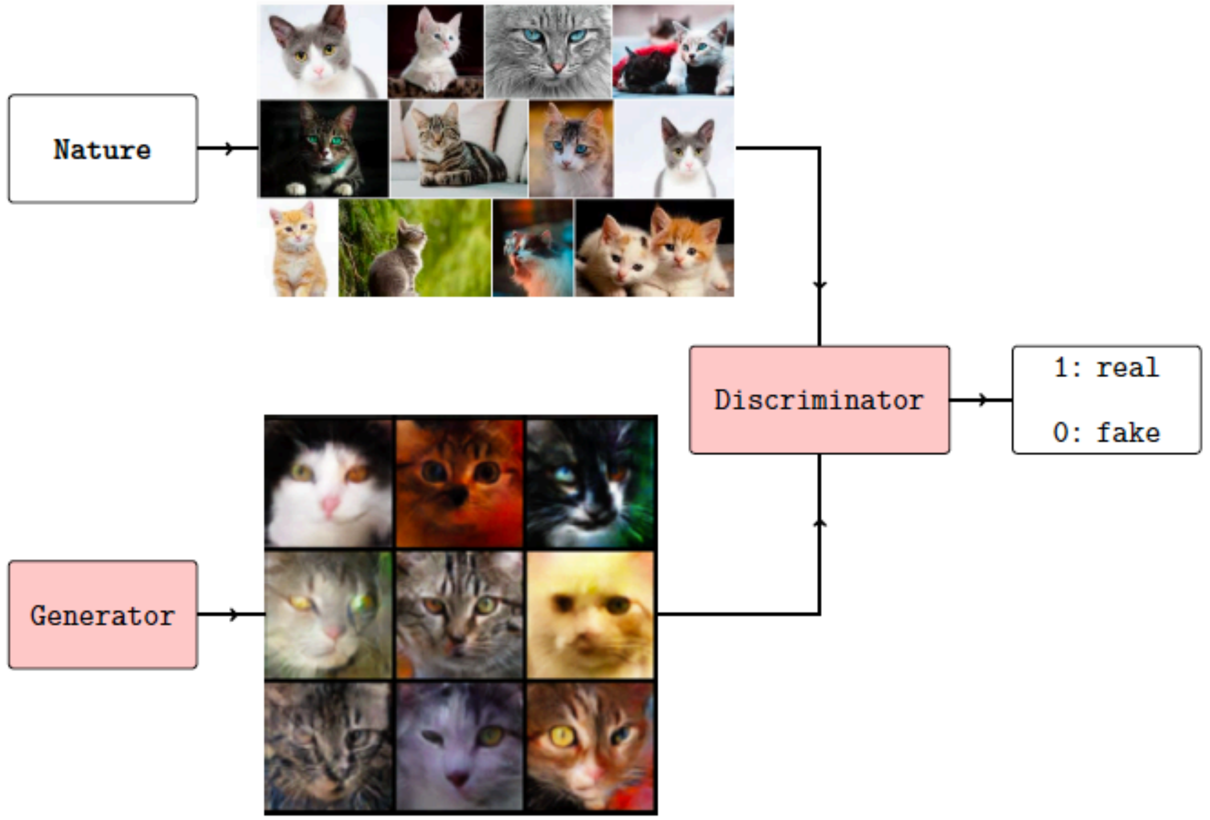
Detector unfolding

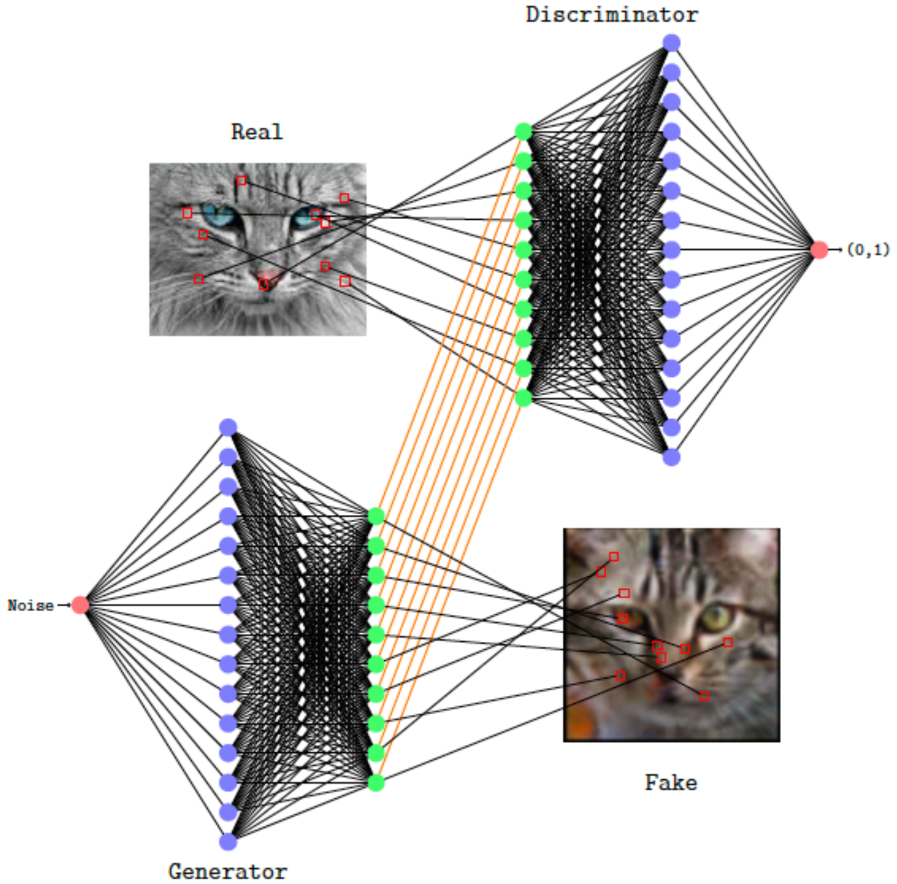


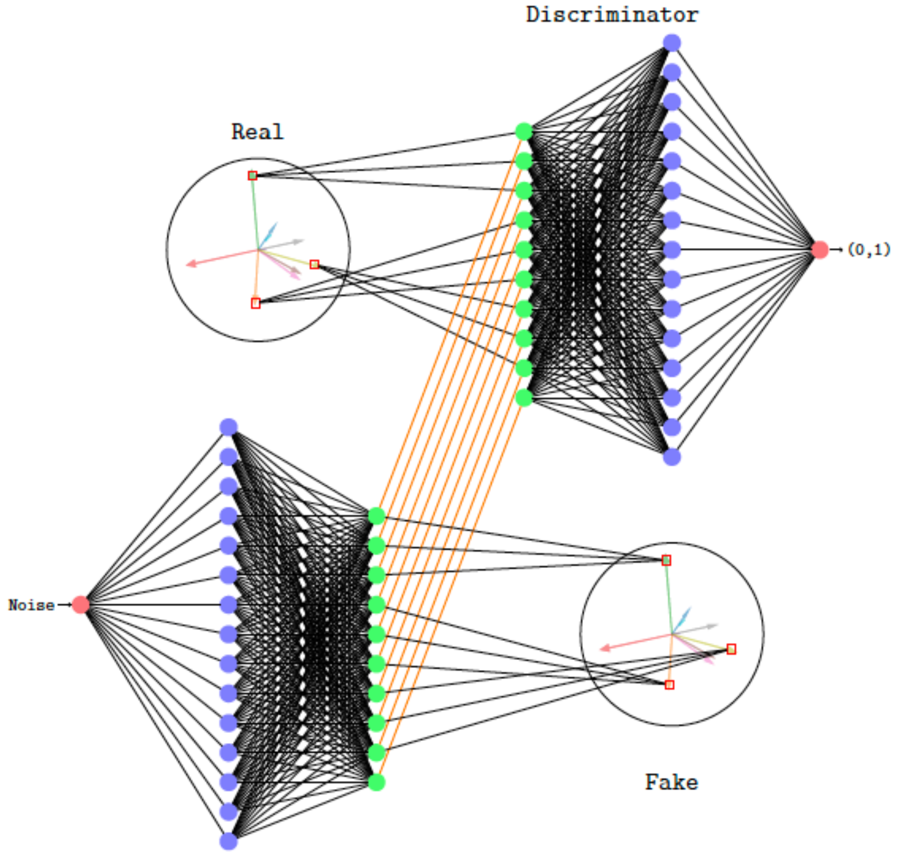
https://doi.org/10.24963/ijcai.2021/588

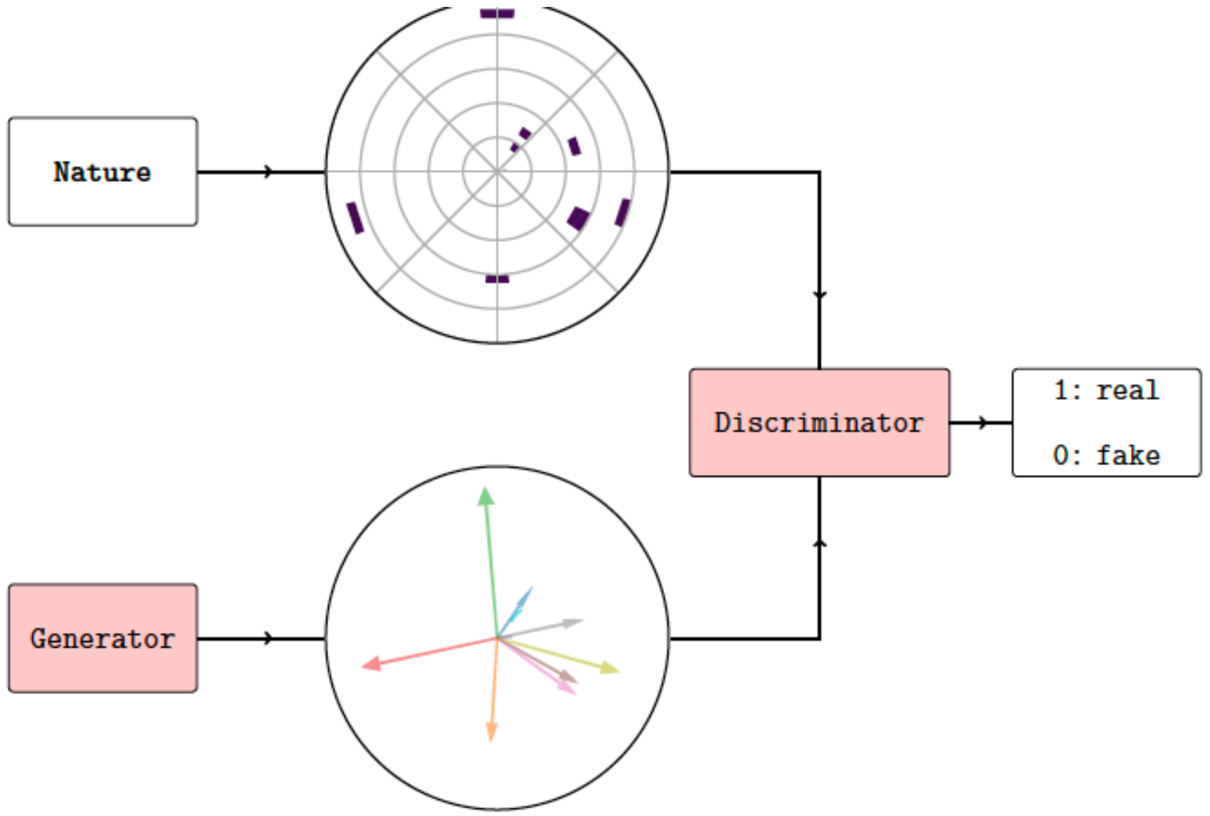
Generative Adversarial Network (GANs)

- The colored boxes are built using NNs
- Discriminator is trained to output "real" for Nature samples
- Generator is trained to fool the discriminator
- The Generator can be used as data compression tool
- Typical size for the Generator: O(MB) - to be compared to NP/HEP experiments data set O(GB/TB)
- Simple to distribute instead of events stored on tapes







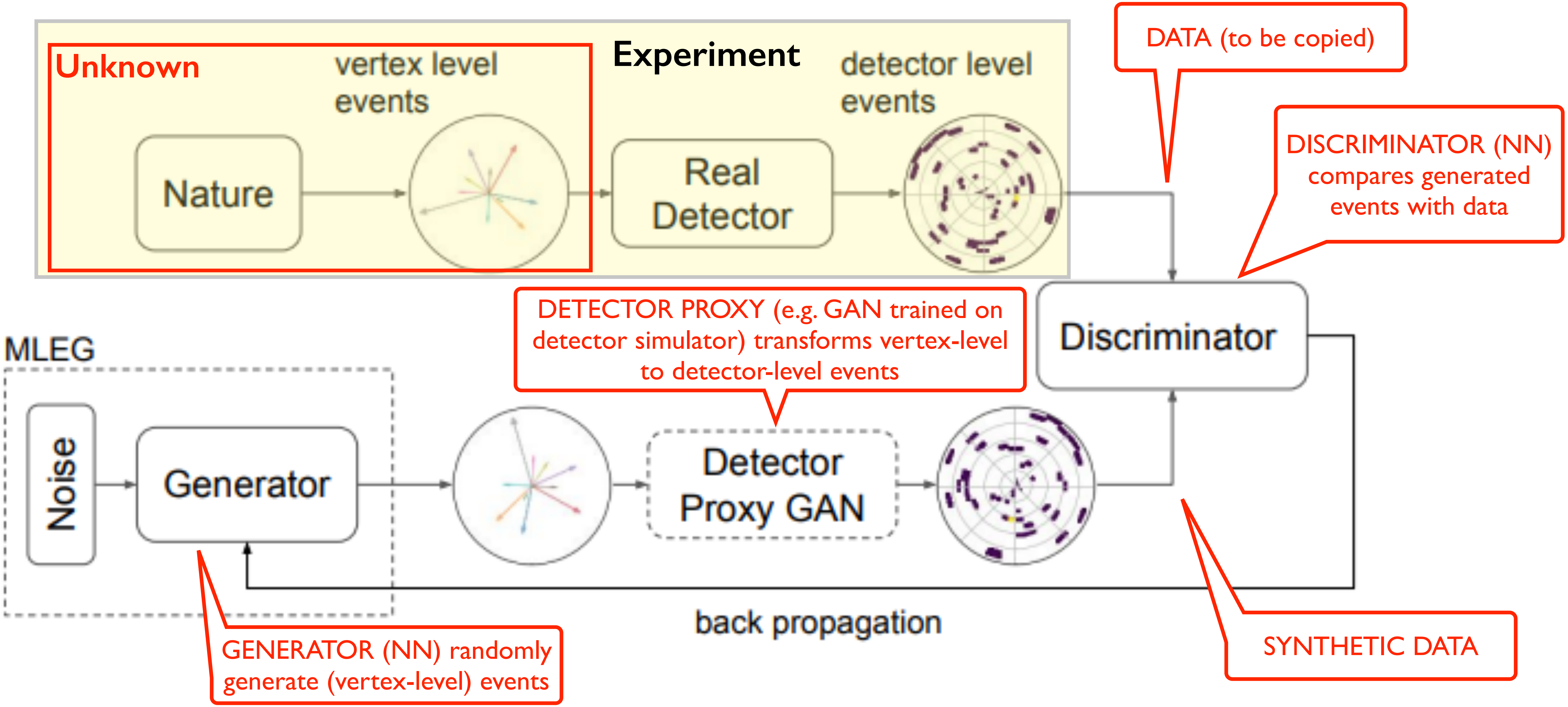


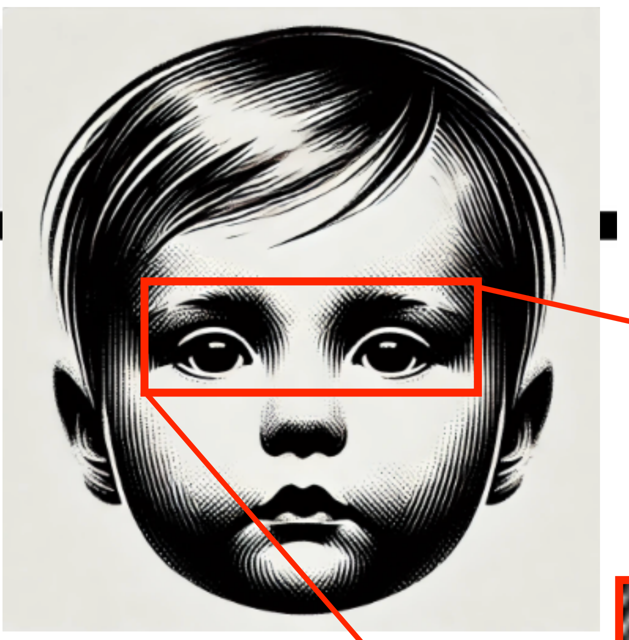
Credit: Y. Li, N.Sato

A simple study case: DIS scattering

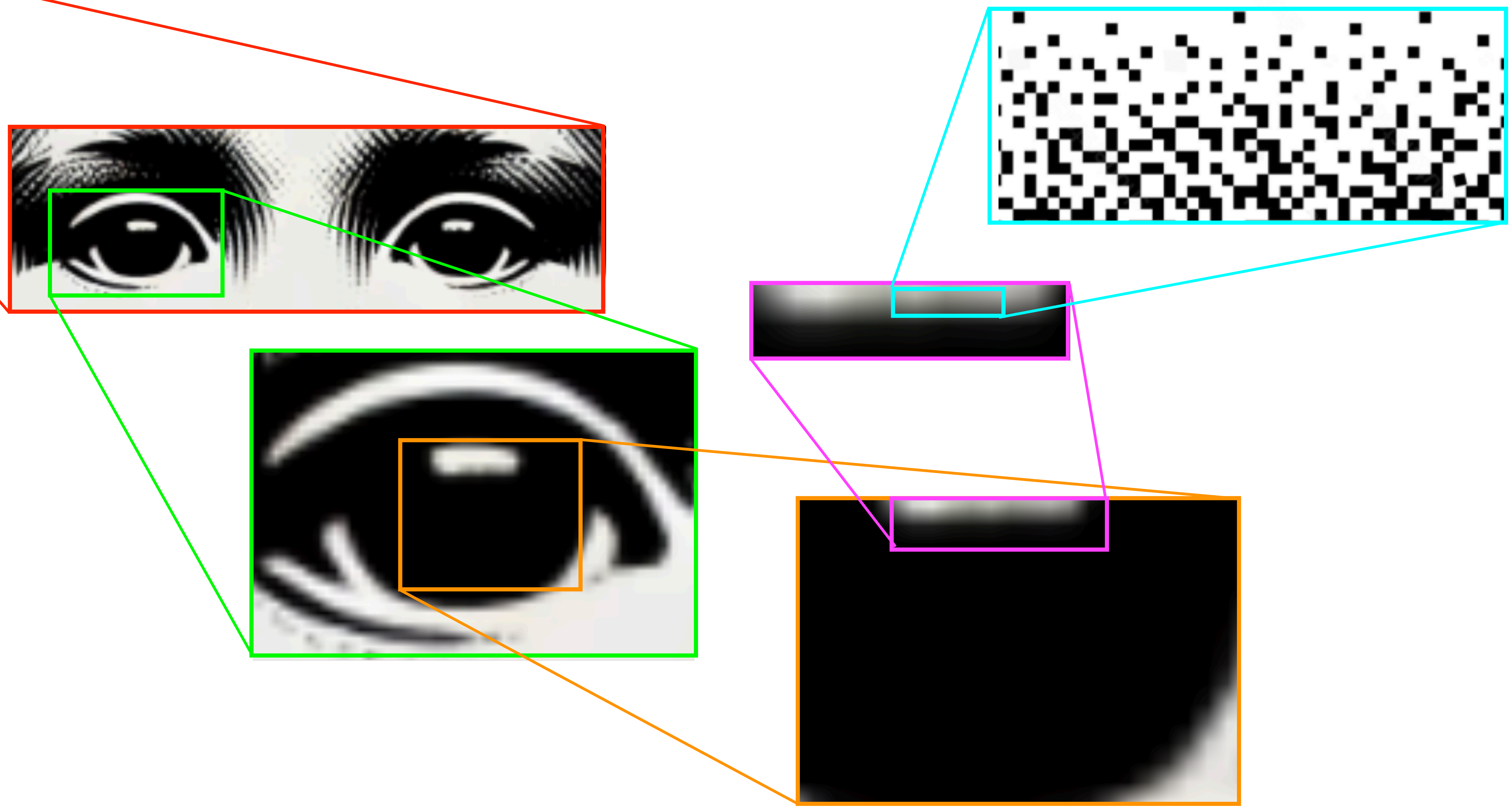
Y. Alanazi, P. Ambrozewicz, M. Battaglieri, A.N. Hiller Blin, M.P. Kuchera, Y. Li, T. Liu, R.E. McClellan, W. Melnitchouk, E. Pritchard, M. Robertson, N. Sato, R. Strauss, and L. Velasco Phys. Rev. D **106**, 096002

ML Event Generator GAN scheme





This image can be copied by randomly generating black/white pixels (GENERATOR), and at each iteration, comparing with the original (DISCRIMINATOR), adjusting the generator accordingly (TRAINING)



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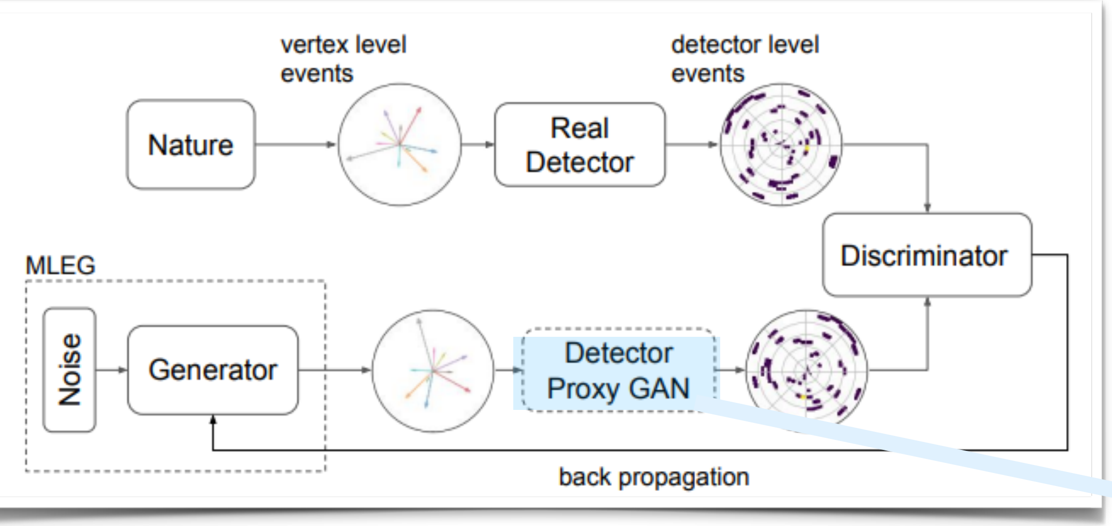

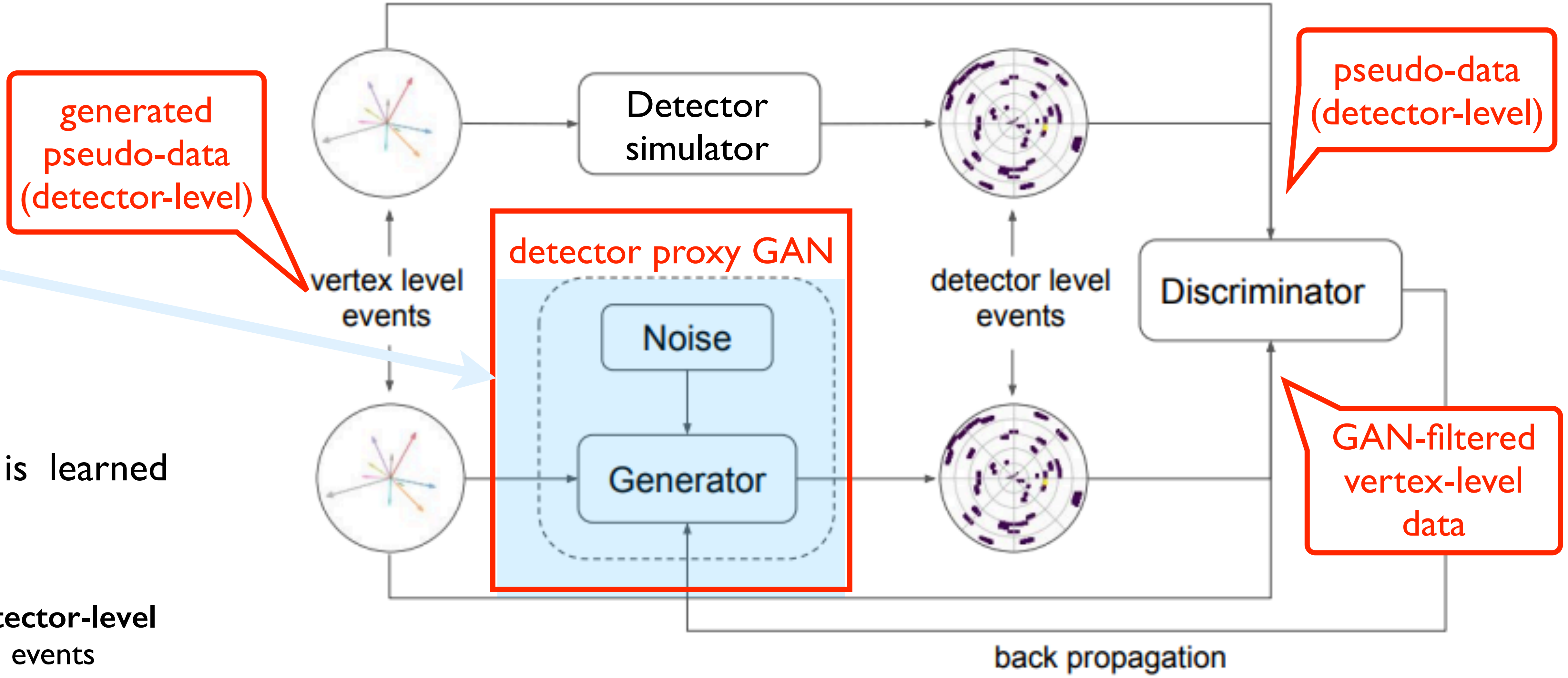

Detector Proxy

- Acts as a *filter* whose Transfer Function is learned using a model of the detector

Vertex-level events ⇨ Detector simulator/ proxy ⇨ **Detector-level** events

- parametric: e.g. a gaussian smearing on momentum and angle mimics the detector's resolution
- GEANT-like: a full simulation of detector response to detected particles
- Disclaimer: AI is not recovering inaccuracy of the detector simulator but only learning its transfer function

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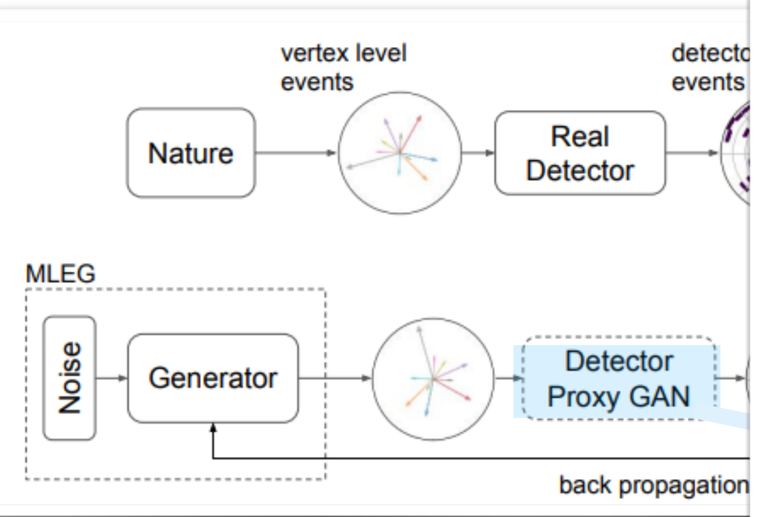


Detector Proxy

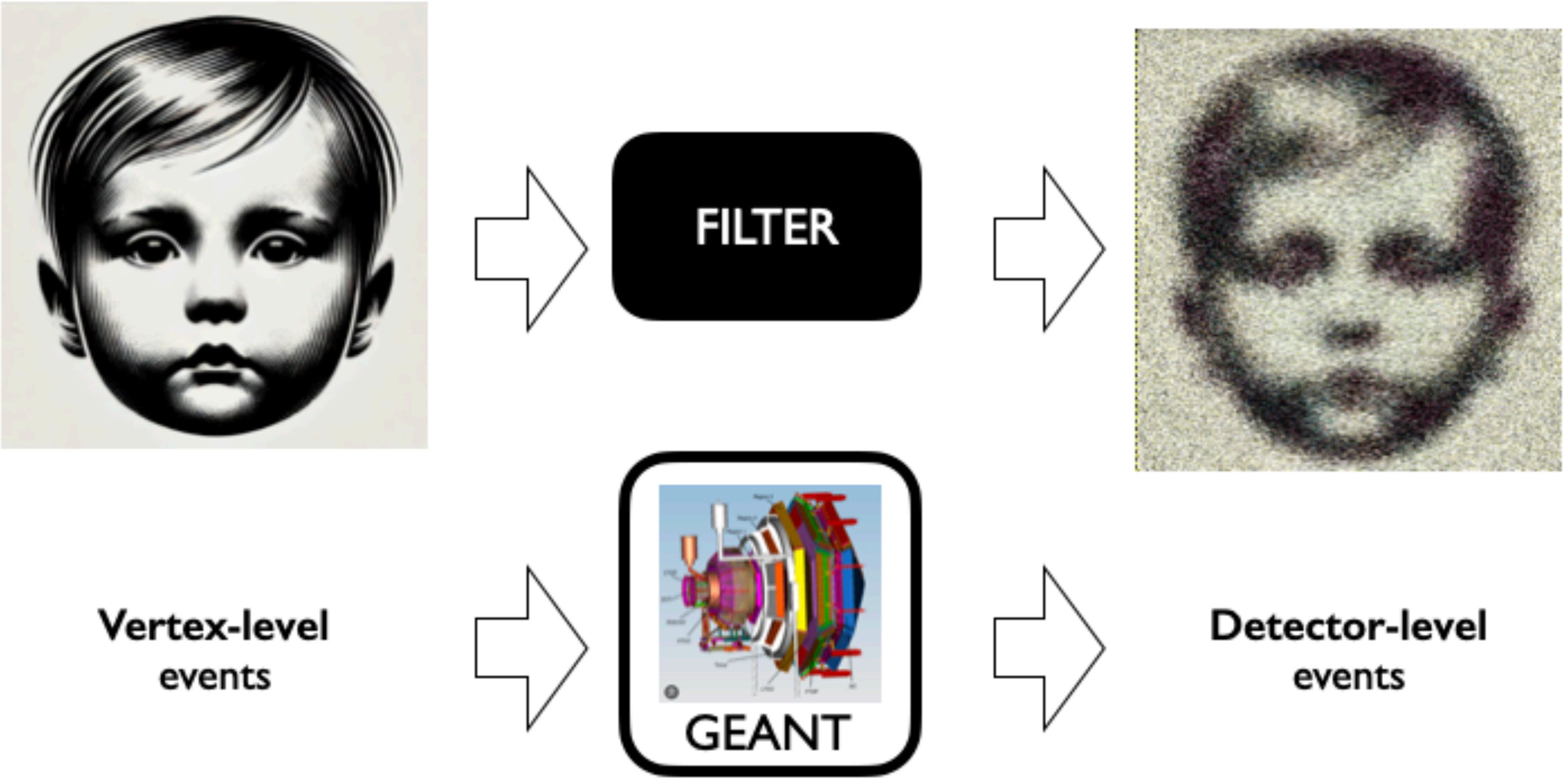
- Acts as a *filter* whose Tran

Vertex-level events

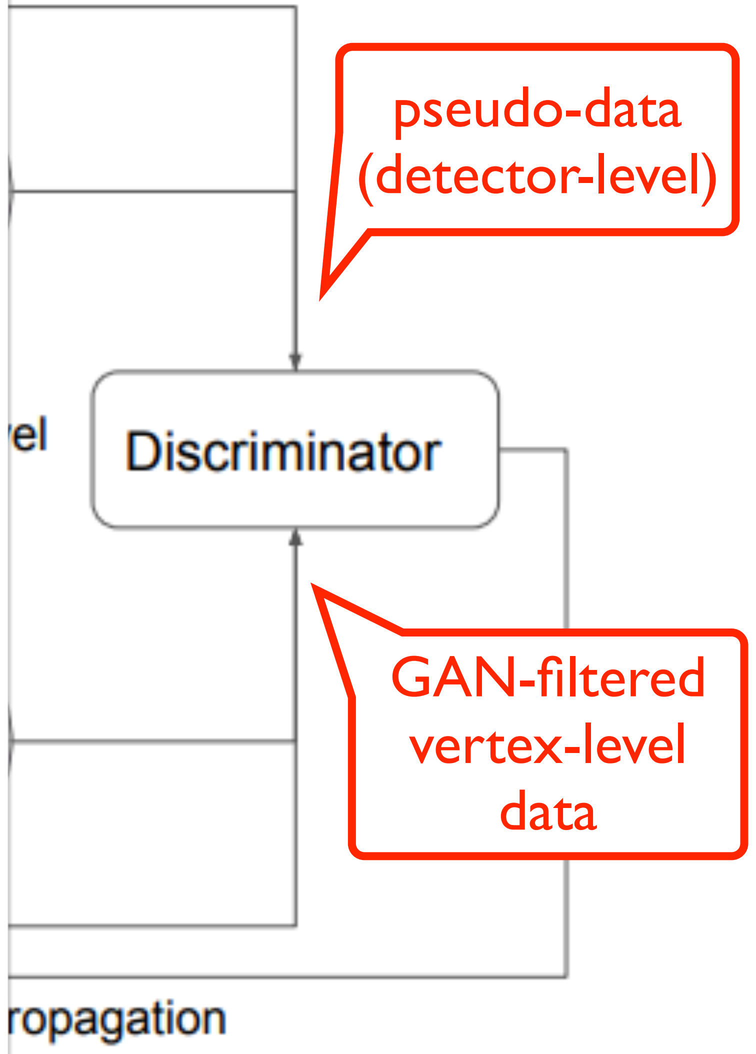
Dete simul pro

- parametric: e.g. a gaussian sr
- GEANT-like: a full simulation
- AI is not recovering inaccur

A GAN can emulate the detector proxy learning from pseudo-data passed trough a detector simulator



- Vertex-level events generated by a MC go trough a detector's proxy (e.g. GEANT) producing detector-level pseudo-data
- Pseudo-data are used to train the GAN
- At the end of the training, the GAN's generator learns how to transform vertex- to detector-level events



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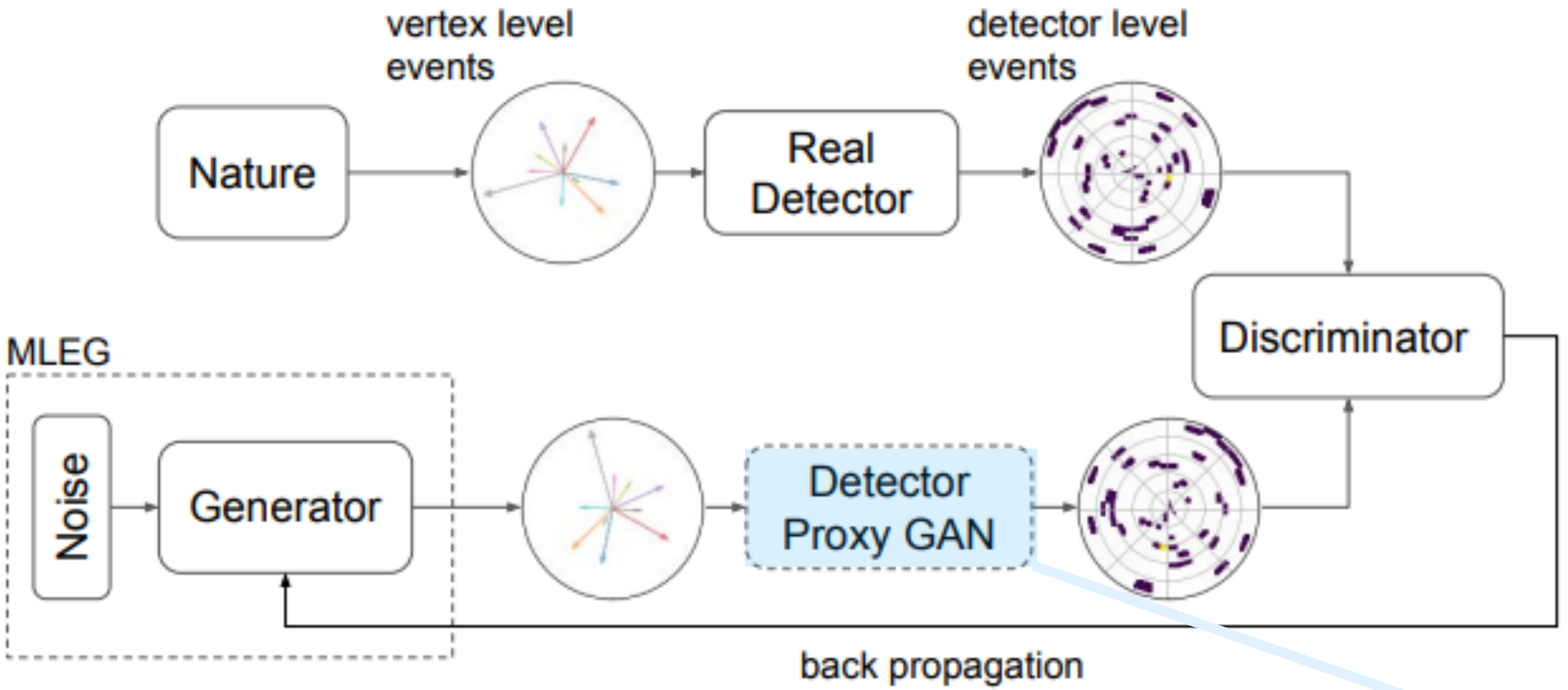
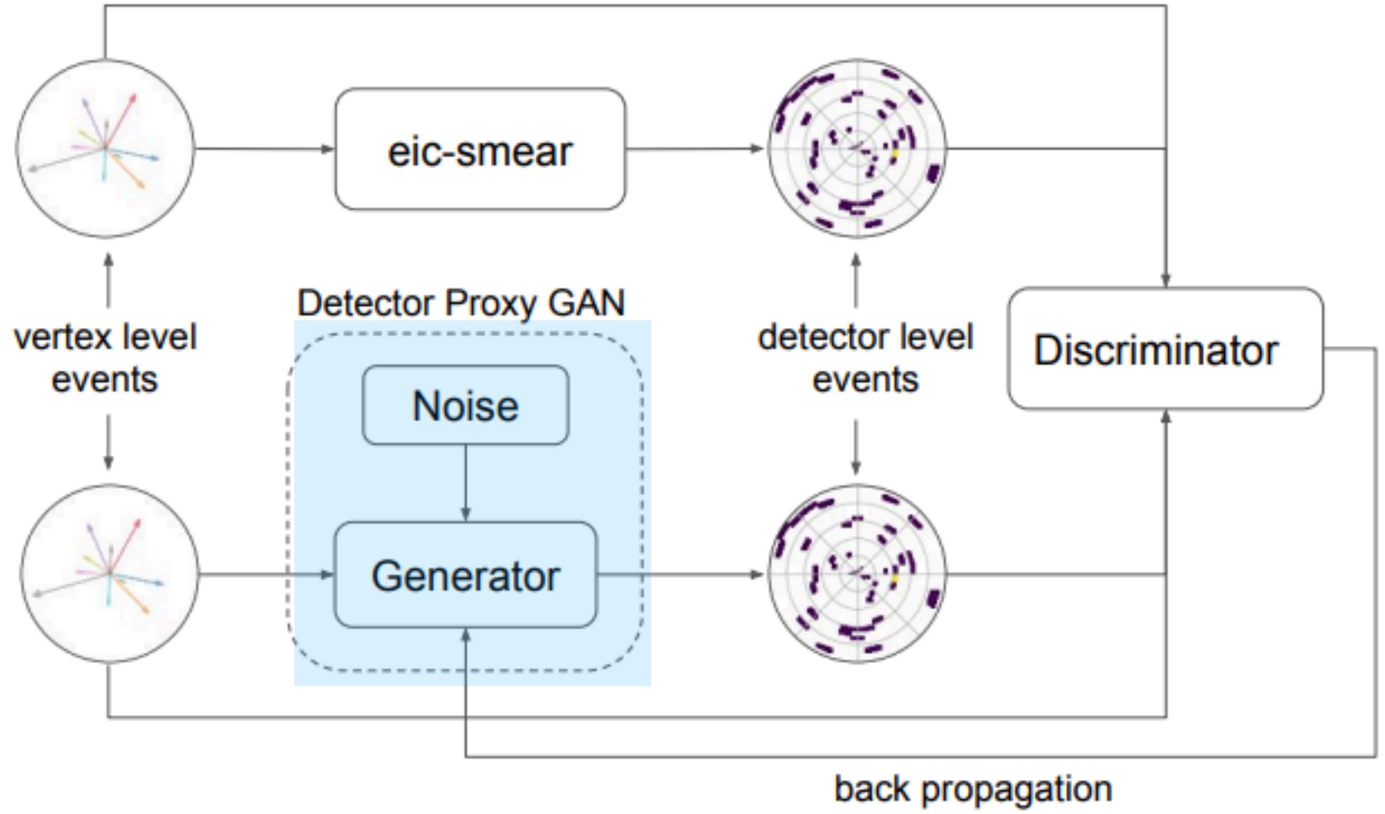


- 100-d white noise entered at 0, unit standard dev.
- Generator: 5 hidden layers / 512 neurons per layer, ReLU activation function. Last layer connected to 2 neurons output to generate v_1 and v_2 variables
- Discriminator: same NN architecture as for the generator
- Detector proxy: similar architecture
- 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 acceptance

A simple study case: DIS scattering

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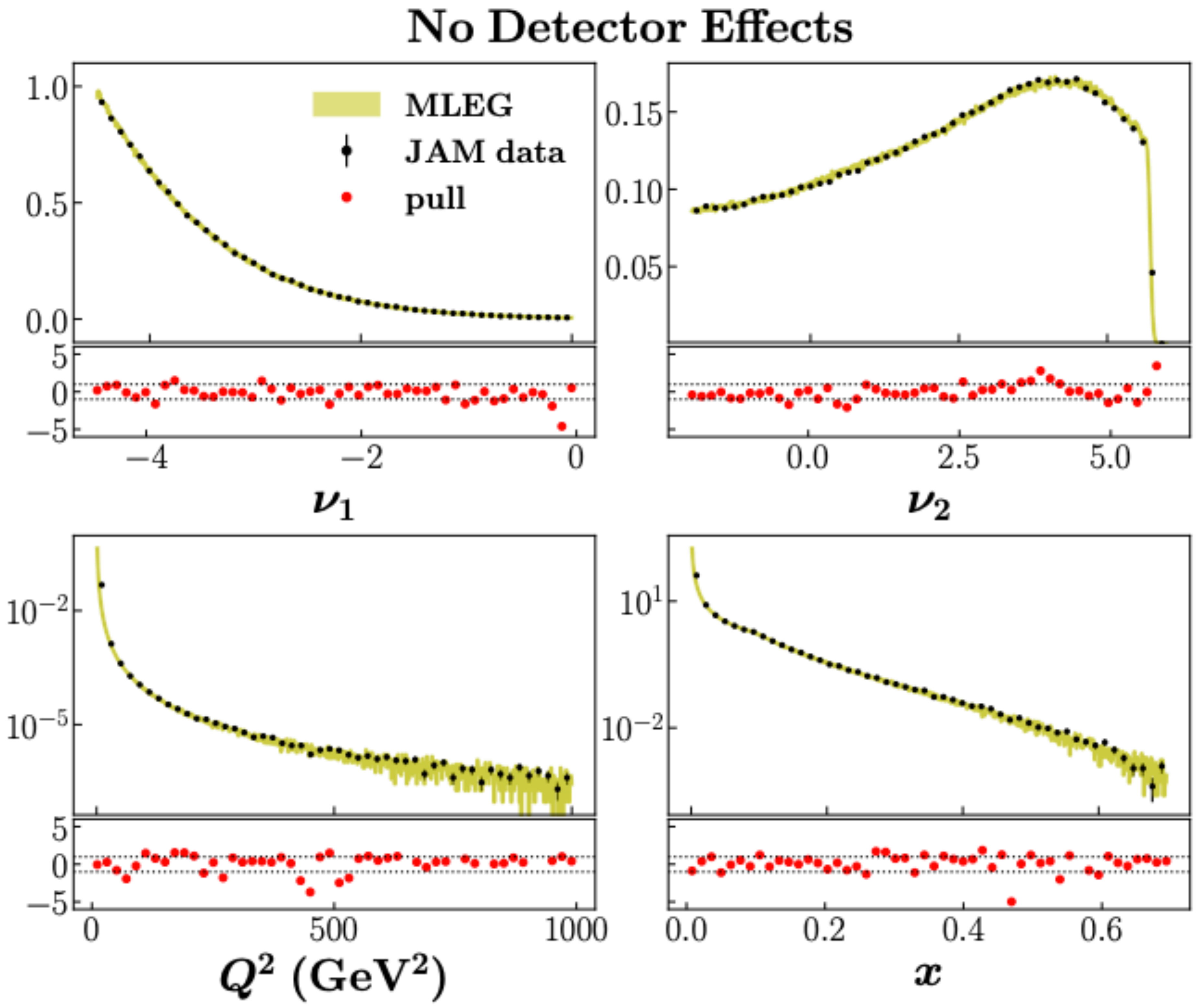
I) GAN training w/o detector effects

Pseudo-data sample (JAM)

- Inclusive electron DIS generated at E_{CM}=318.2 GeV (HERA kinematics)
- 2-dim differential cross section $d\sigma/dxdQ^2$
- 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*

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

- *Bootstrap with* 10 independently trained GANs

A simple study case: DIS scattering

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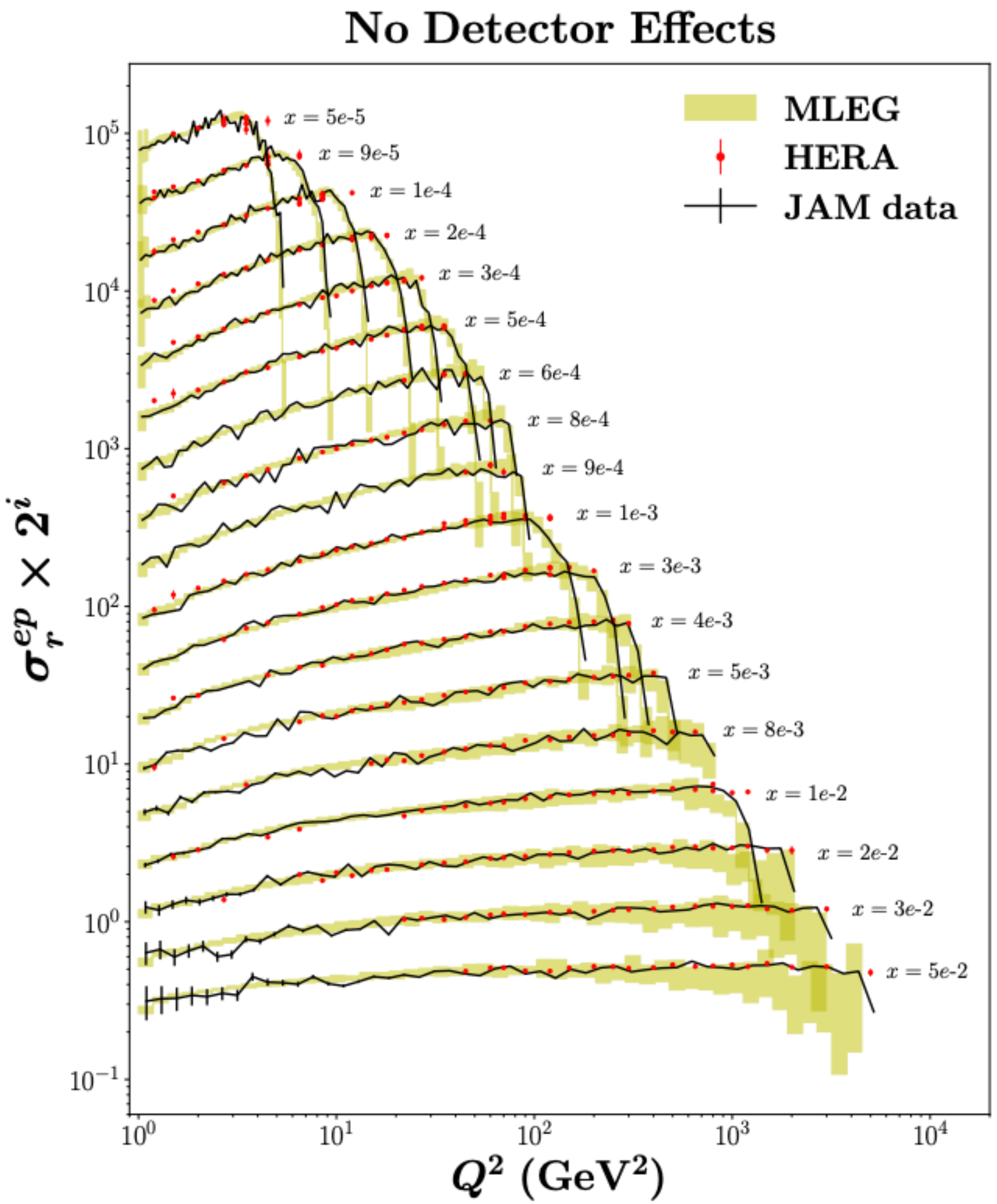

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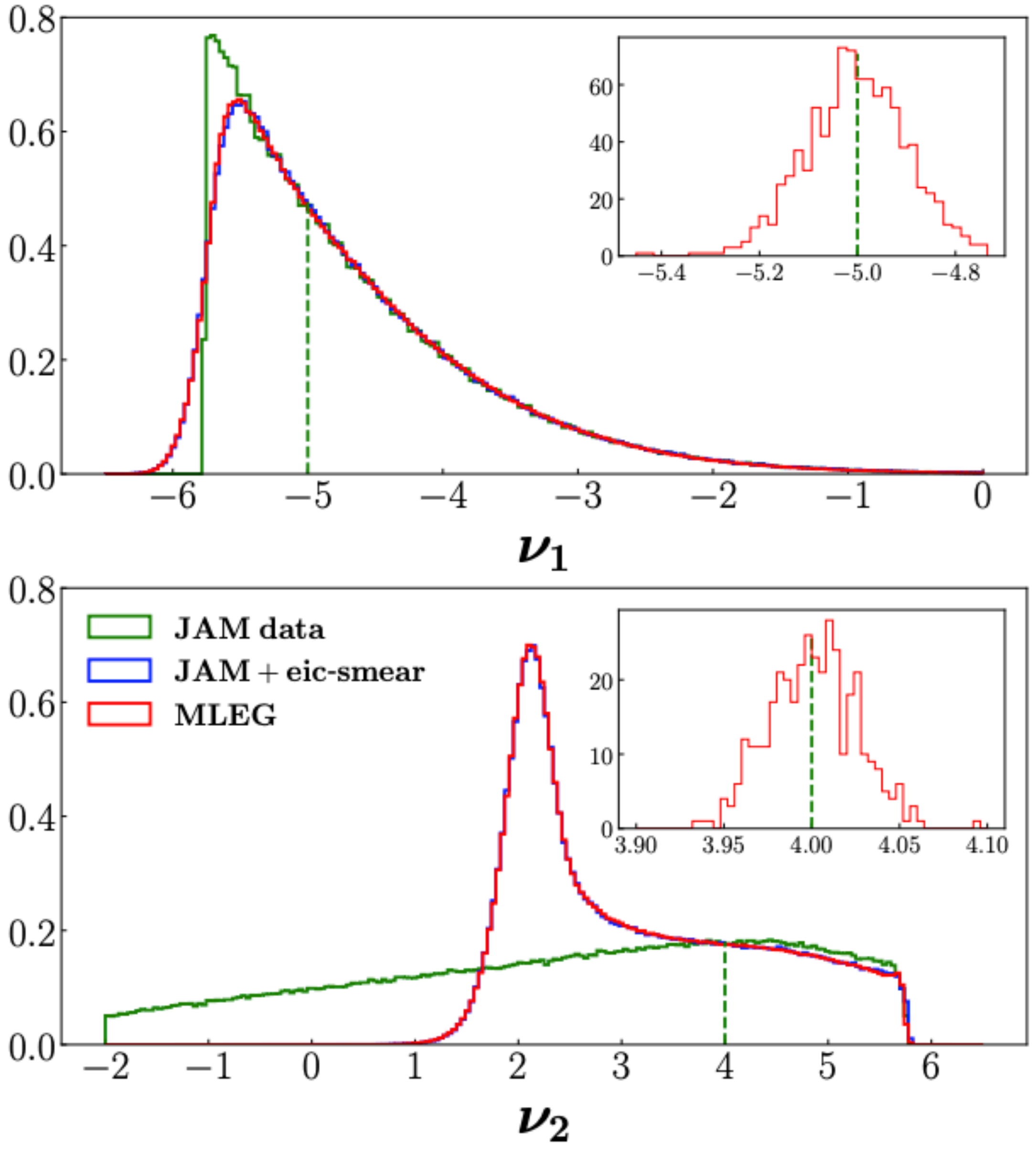
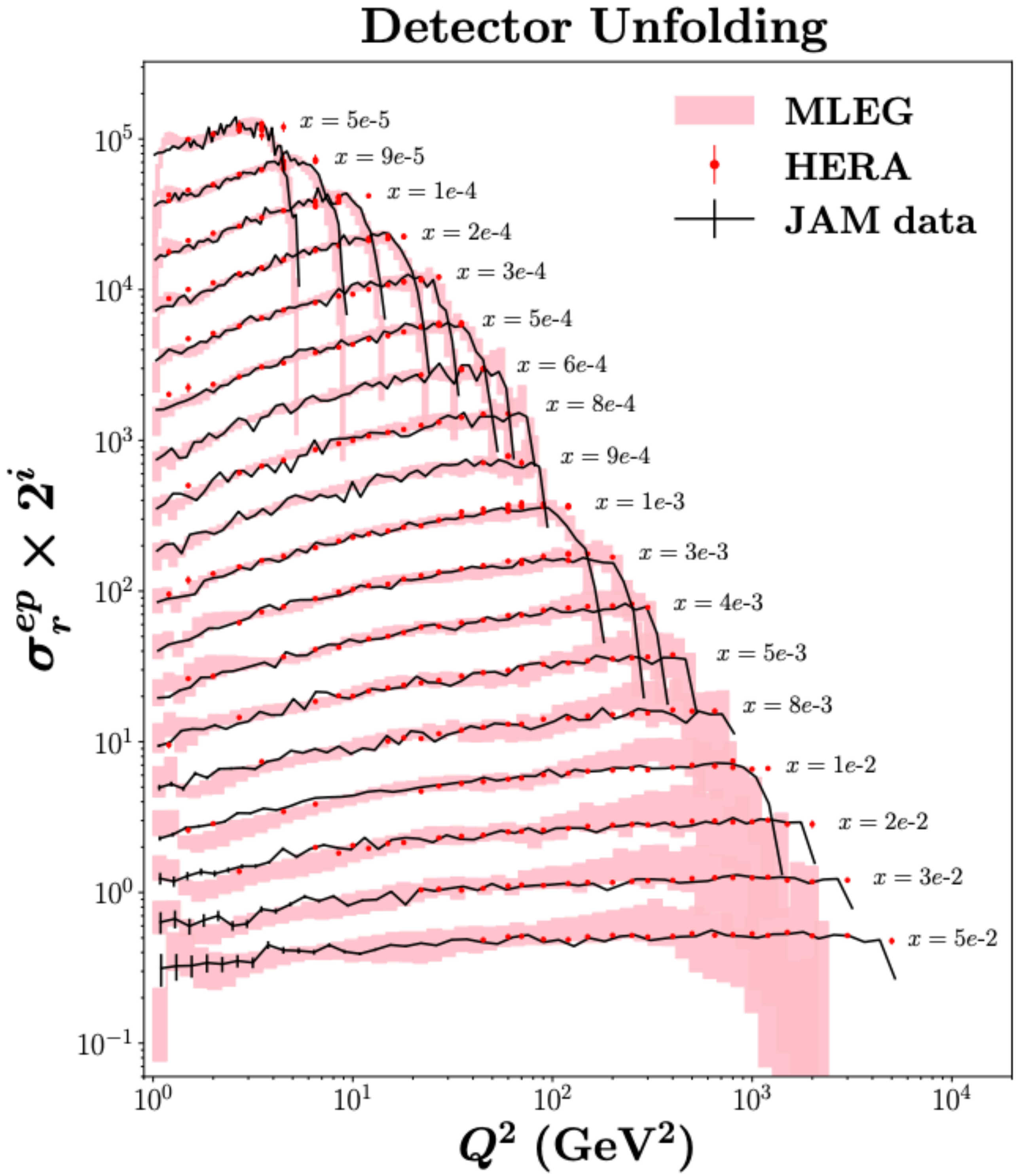
II) GAN training WITH detector effects

- eic-smear introduces significant distortions to the detector level sample in particular on ν_2



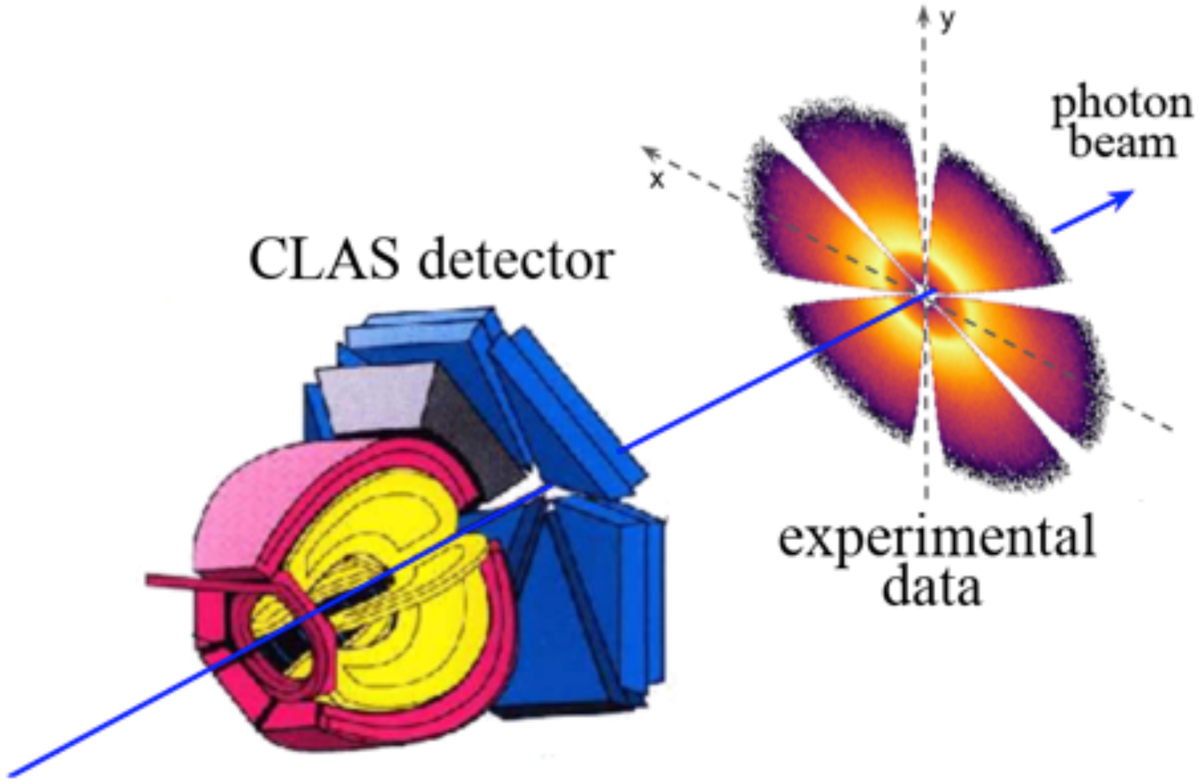


Conclusions

- The 'closure test' was successful
- 'generated' events (trained on generated)
- 'reconstructed' events (trained on reconstructed)
- 'generated' (trained on reconstructed) with larger error bars, in particular on the edge of the phase space
- The PDFs are correctly recovered

Multi-d xsec: 2π photo production

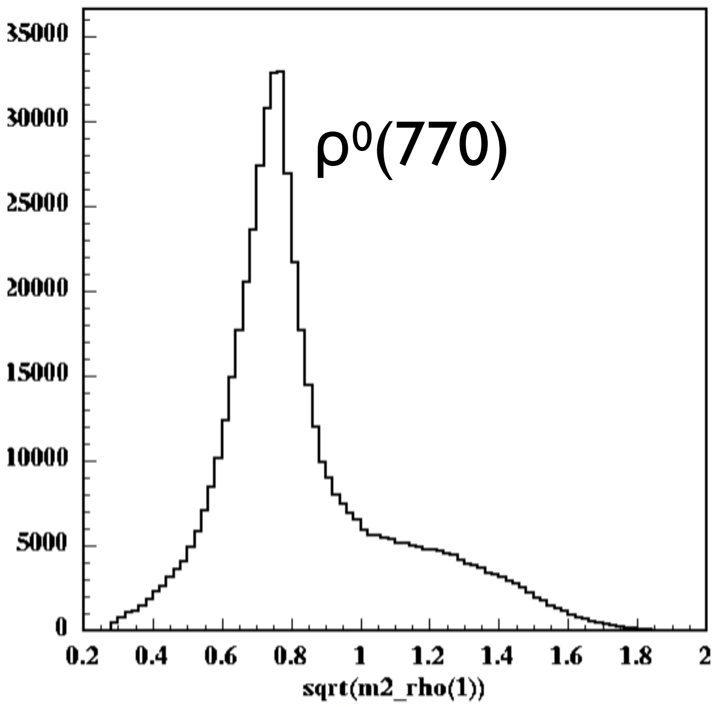
M. Battaglieri *et al.* (CLAS Collaboration) Phys. Rev. Lett. 102, 102001
M. Battaglieri *et al.* (CLAS Collaboration) Phys. Rev. D 80, 072005



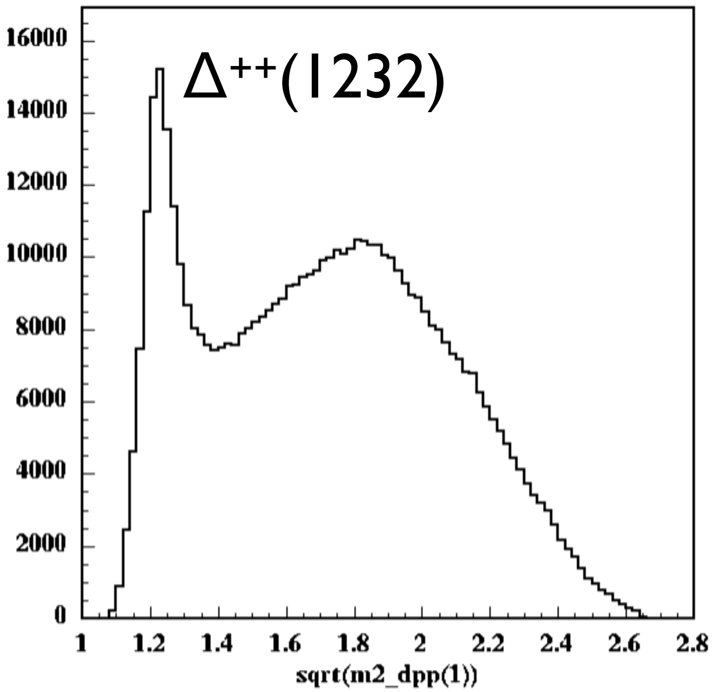
CLAS g11 kinematics

- Data set used by CLAS Collaboration for many publications
- Fiducial cuts (p, Θ, ϕ) as used in published analysis
- All four topologies are available but only focused on $\gamma\, p \rightarrow p\, \pi^+ (\pi^-)$
- Final exclusive 2π state identified by missing mass technique (variables reconstructed by energy/momentum conservation)
- Multipion background comes from $\gamma\, p \rightarrow p\, \omega^0 \rightarrow p\, \pi^+ \pi^- \pi^0$
- At E_γ=3-4 GeV reaction dynamics dominated by ρ^0 photo production ($\gamma\, p \rightarrow p\, \rho^0$) and Δ^{++} resonance excitation ($\gamma\, p \rightarrow \Delta^{++} \pi^-$)

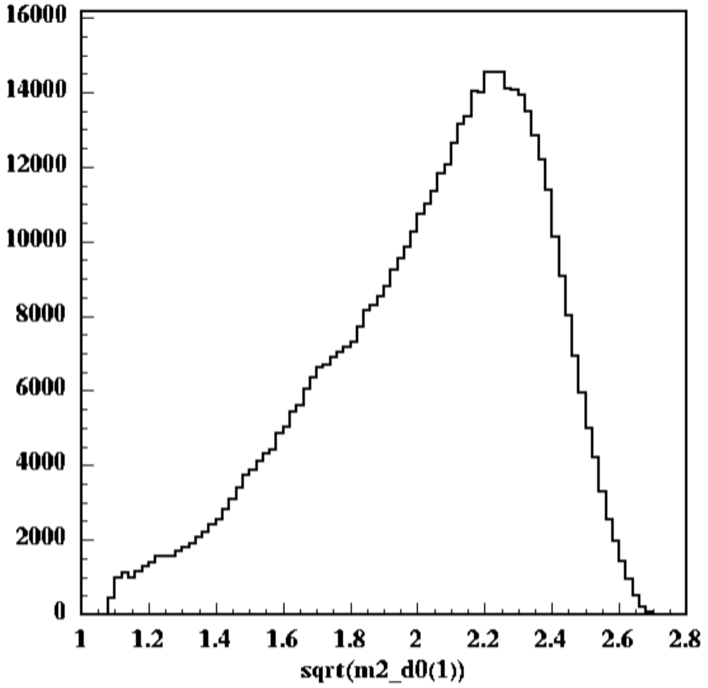
M(ππ)



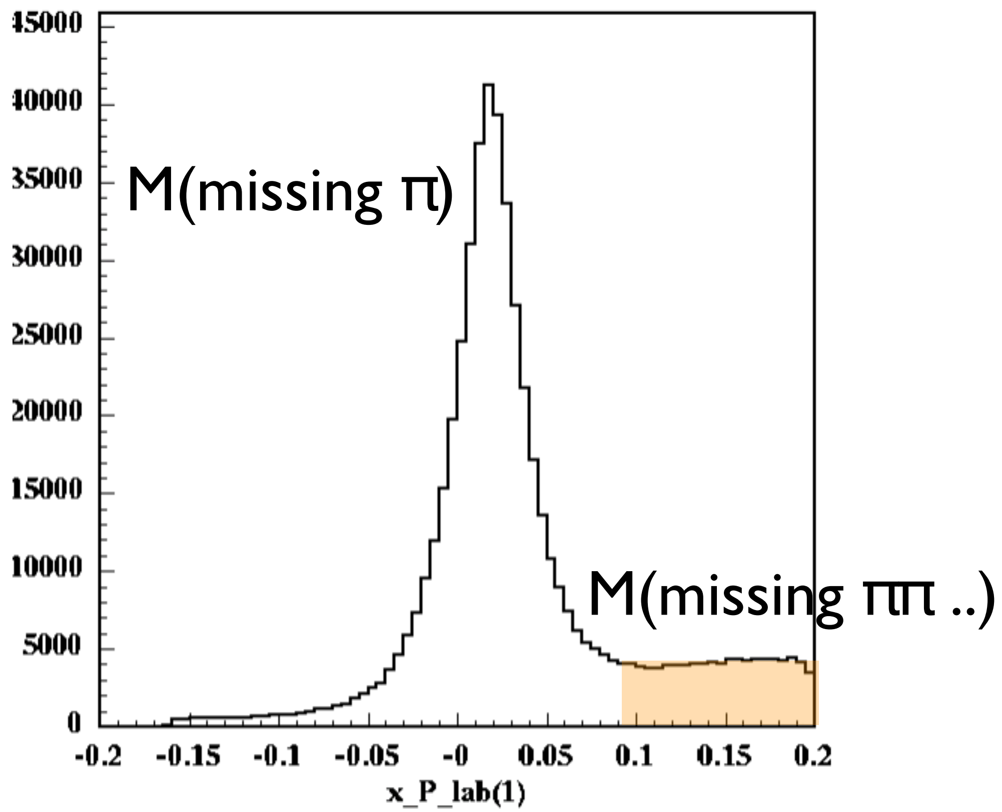
M(pπ+)



M(pπ-)



$M(\gamma\, p \rightarrow p\, \pi^+ X)$



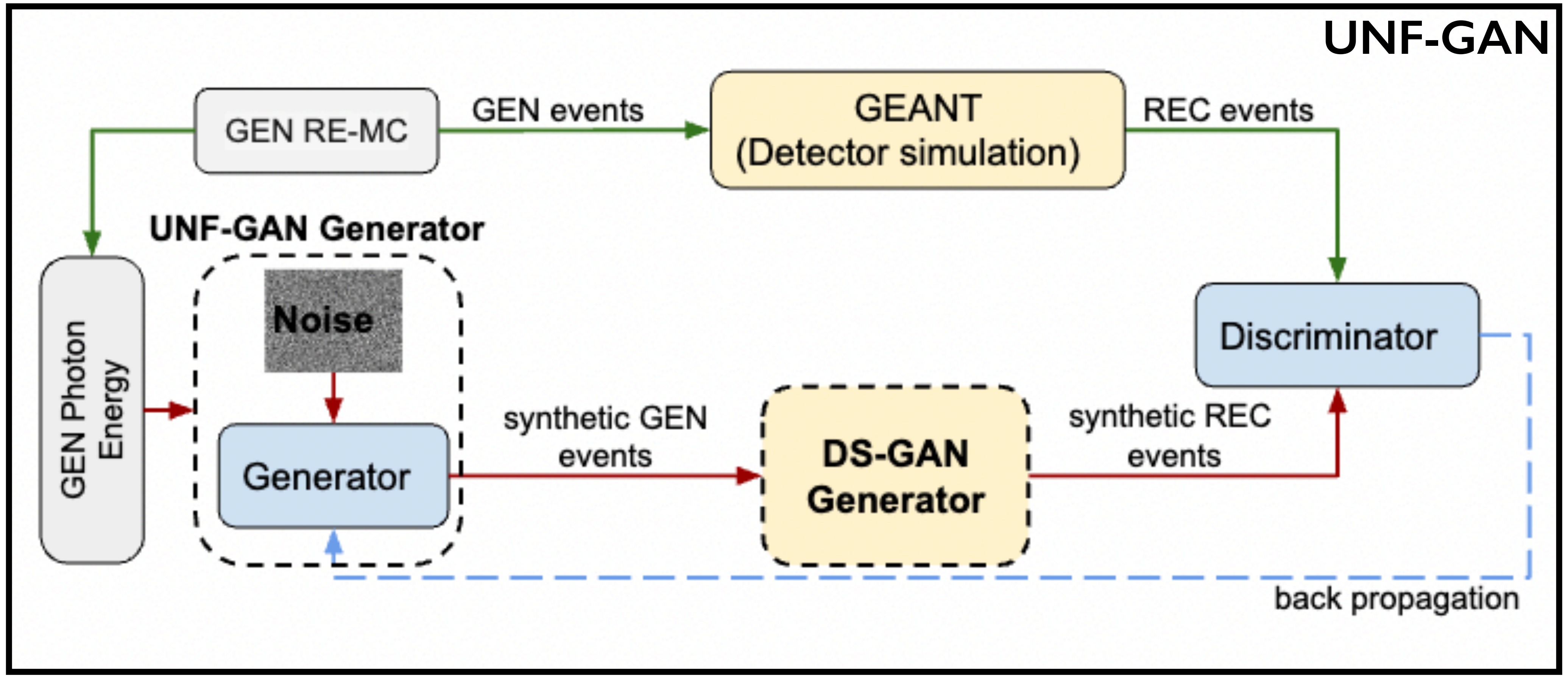
2π photo production closure test

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

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

1. Generate events with a (realistic) Monte Carlo 2π photo production 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 independent 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

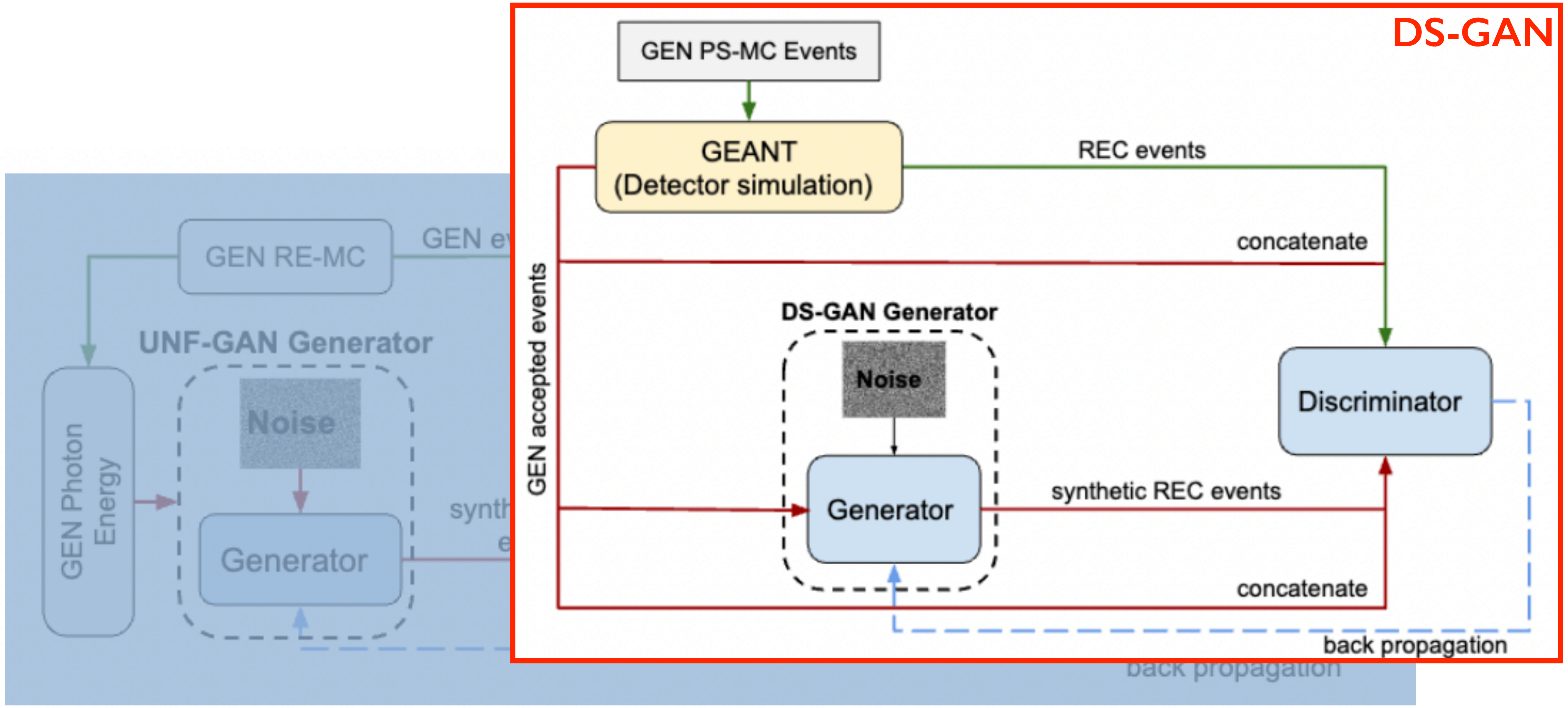
[if but works, replace RE-MC REC pseudo data with CLAS data in the training to unfold the vertex-level experimental distributions]



2π photo production closure test

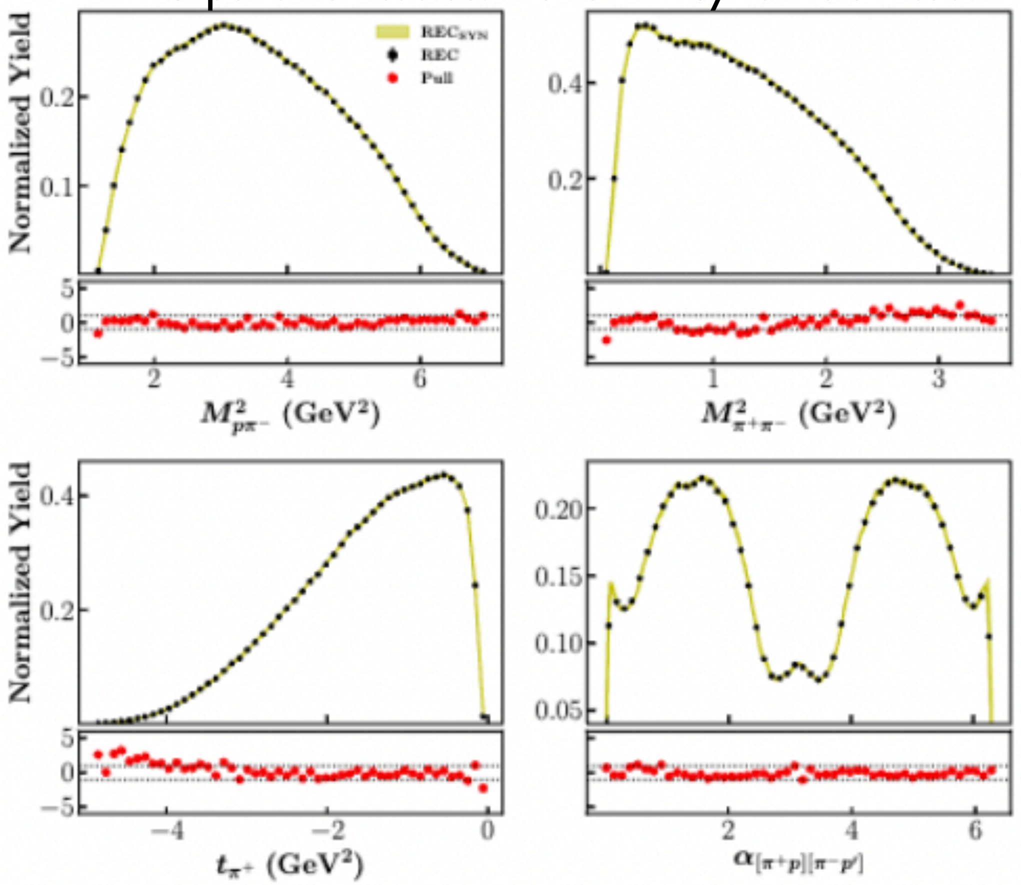
T.Alghamdi, et al. *Phys. Rev. D 108, 094030*

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

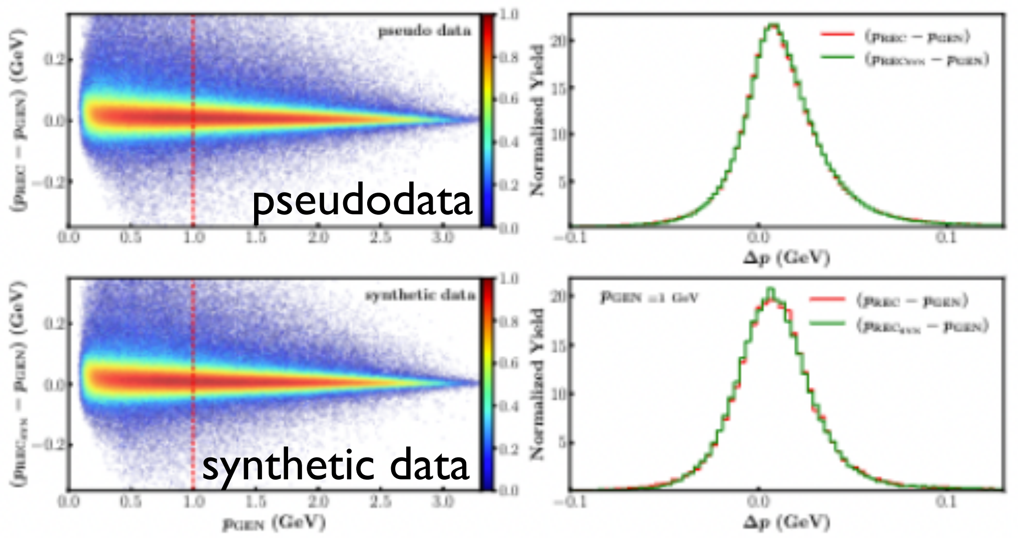


PS-MC REC events

MC pseudodata vs. DS-GAN synthetic data



CLAS resolution



Uncertainty Quantification via *pull* calculation

- *Bootstrap with* 20 independently trained GAN

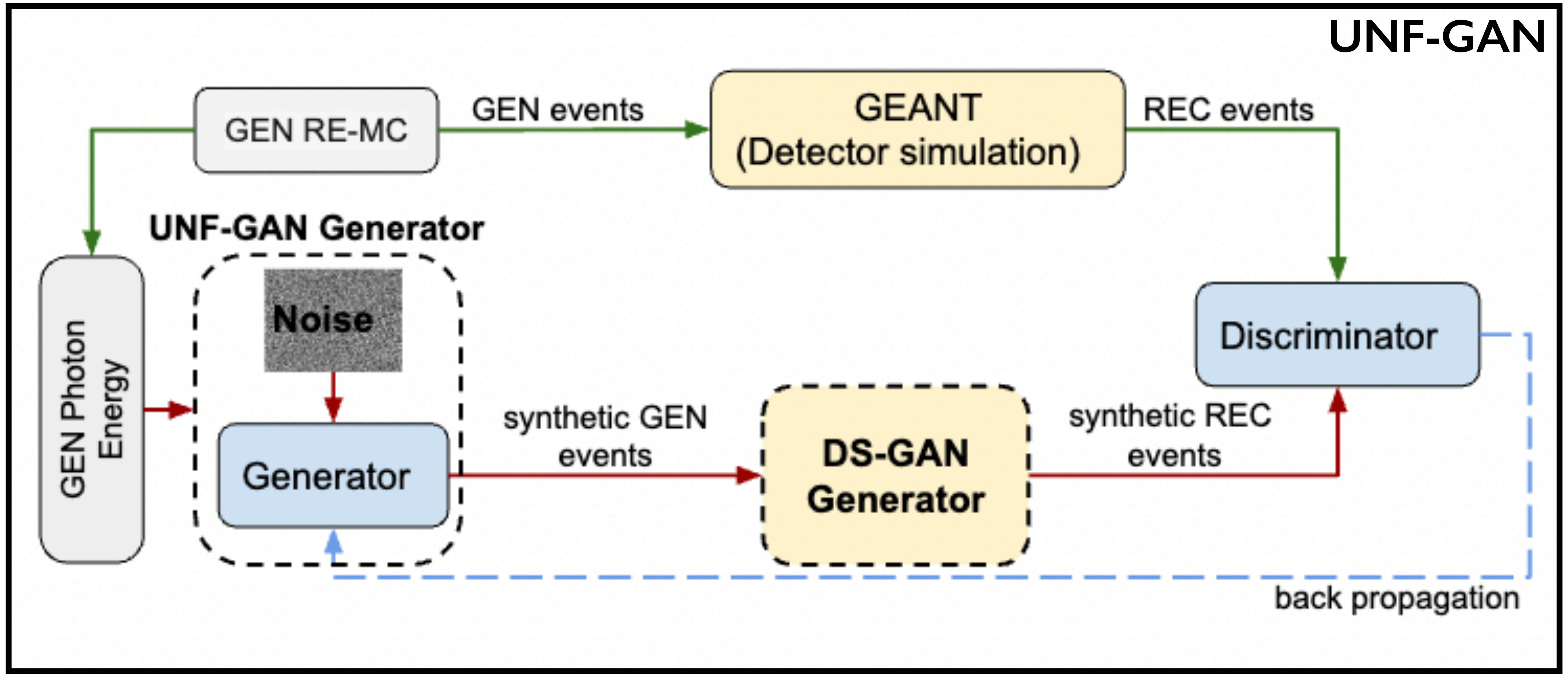
DS-GAN learned the CLAS detector effects!

2π photo production closure test

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

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

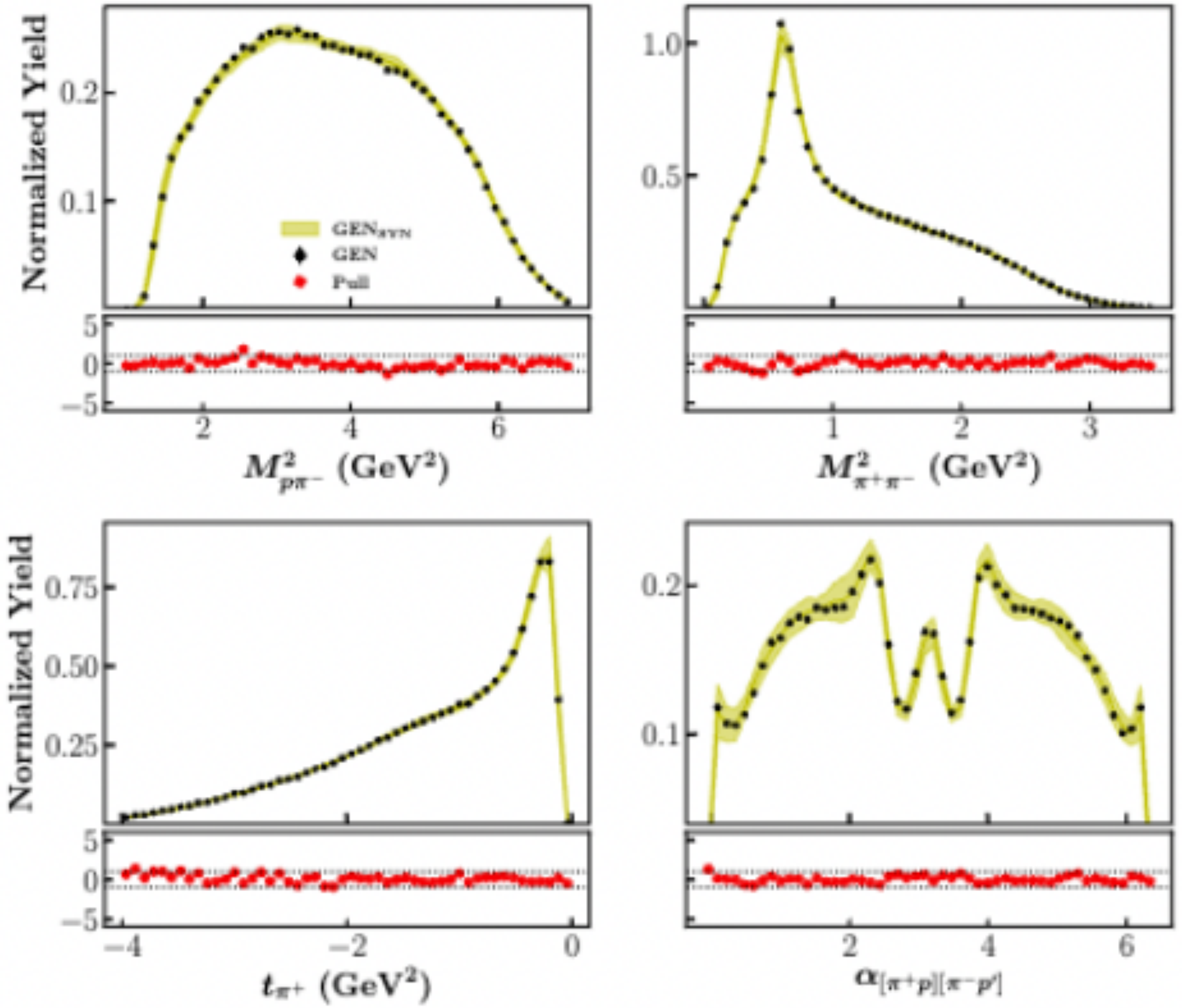
- UNF-GAN trained with RE-MC REC pseudodata (exp data proxy)
- DS-GAN used to unfold CLAS detector effects (within acceptance)



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

Good agreement (± 1σ) at vertex-level for 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 photo production closure test

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

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

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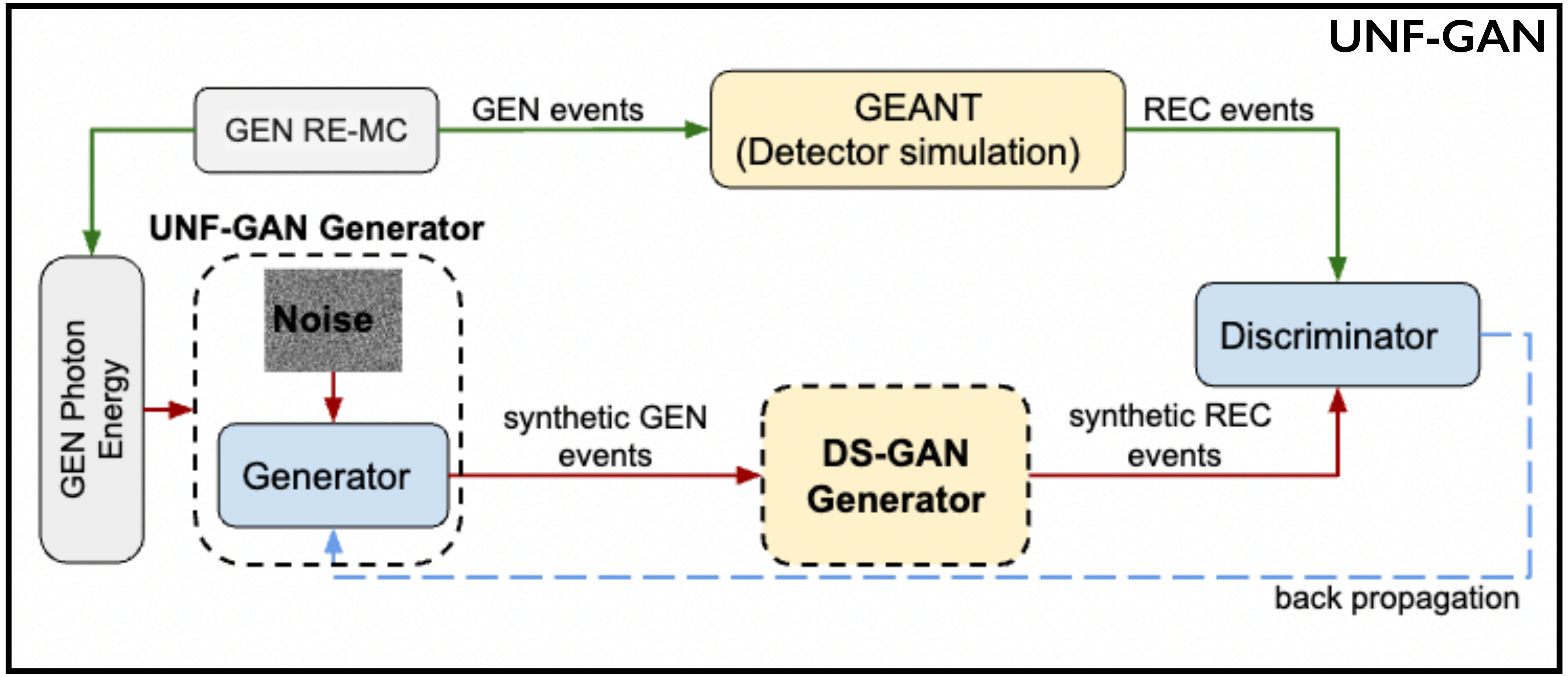
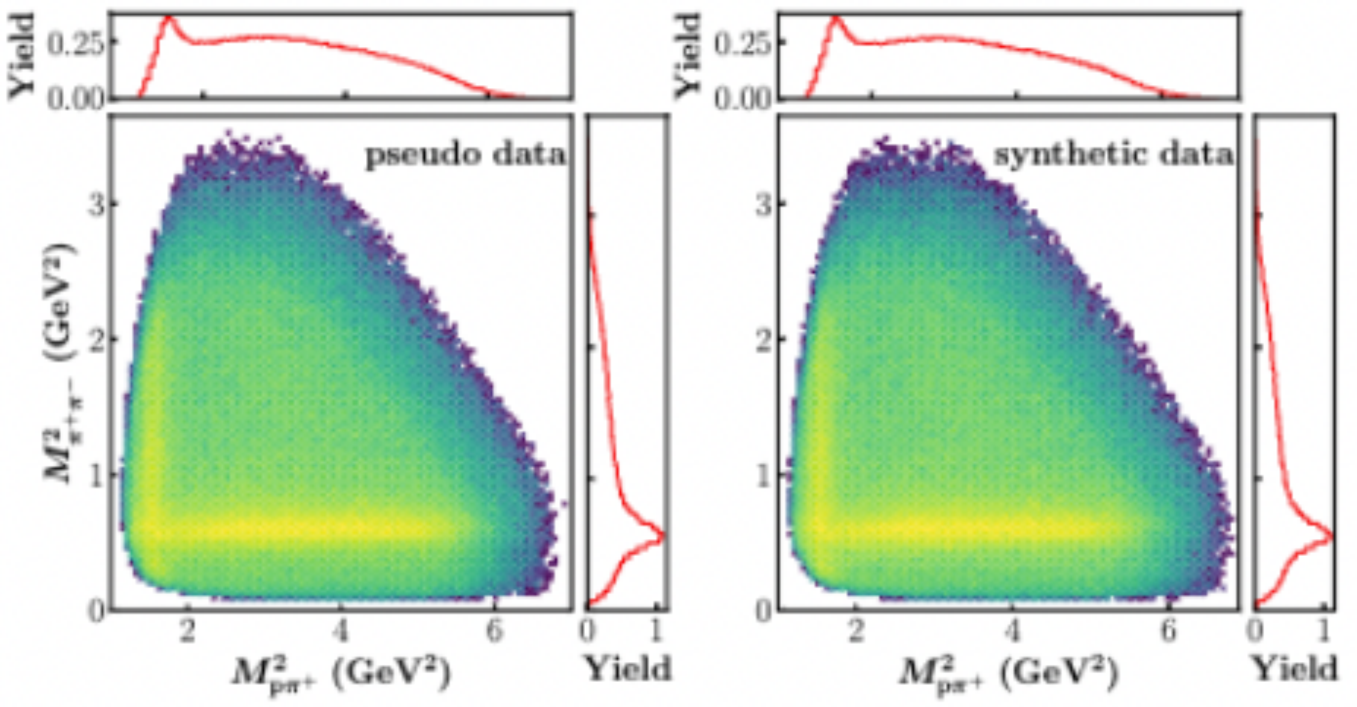


RE-MC GEN pseudodata vs. UNF-GAN SYN data



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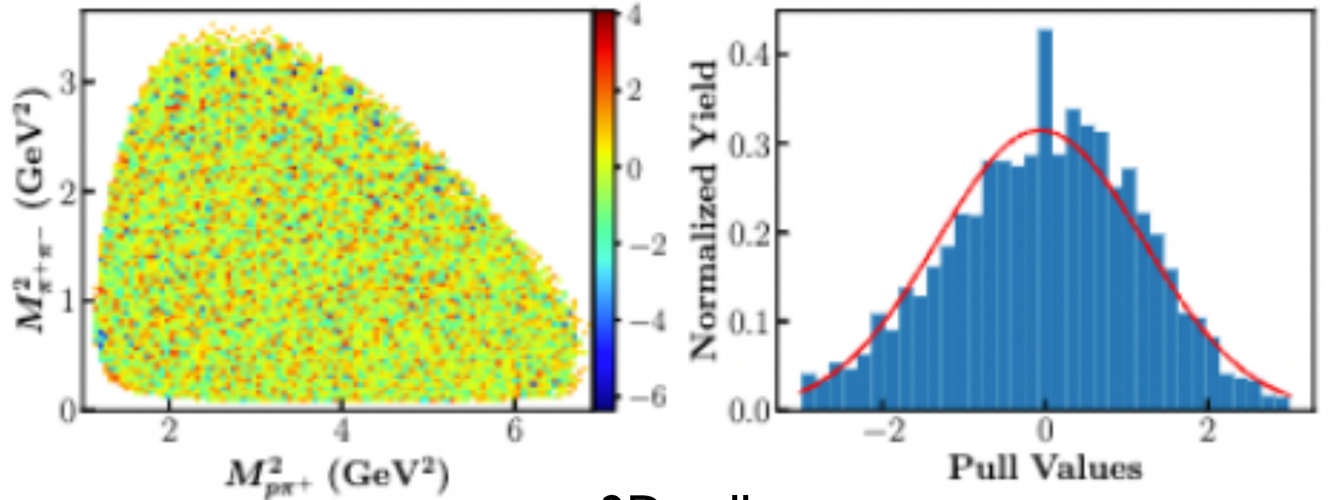


2D pulls

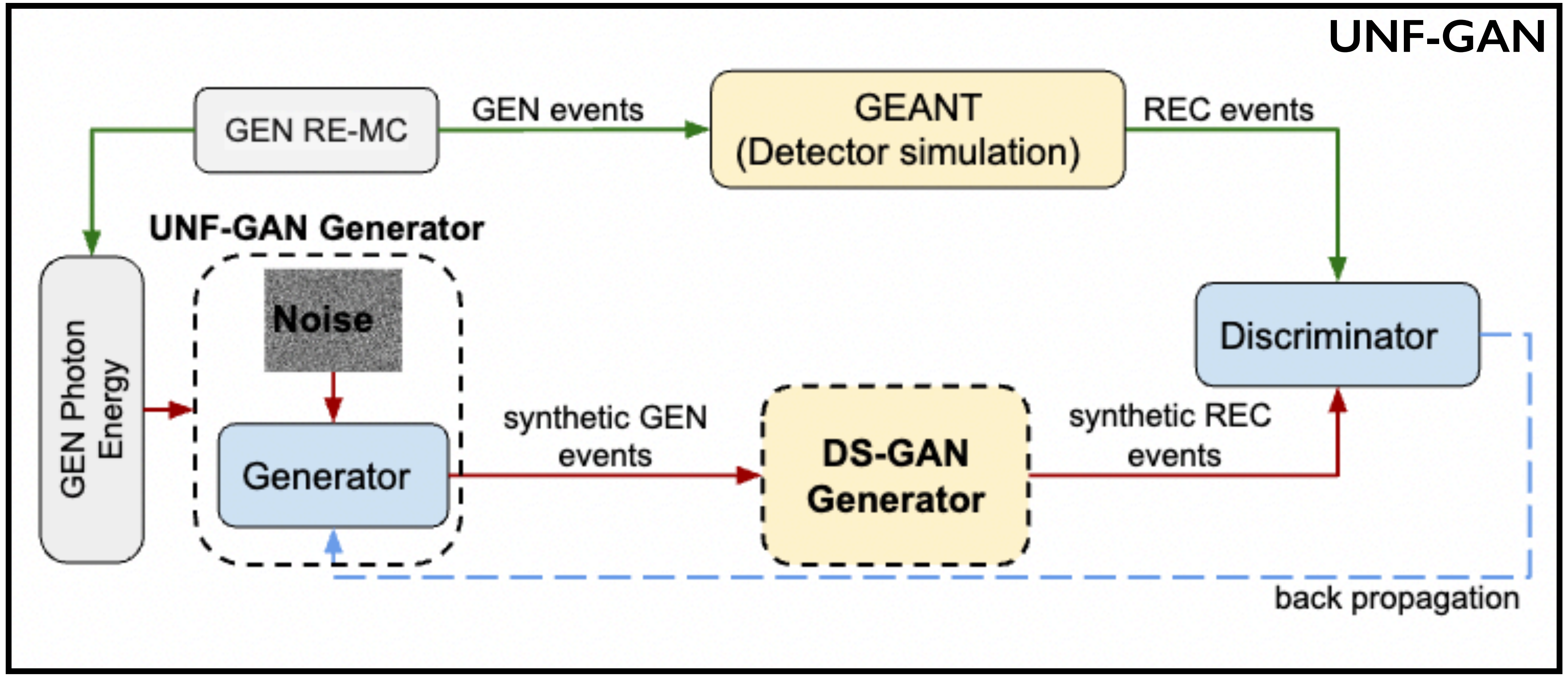
Good agreement (± 1σ) for 2D distributions (correlations)

2π photo production closure test

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

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

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

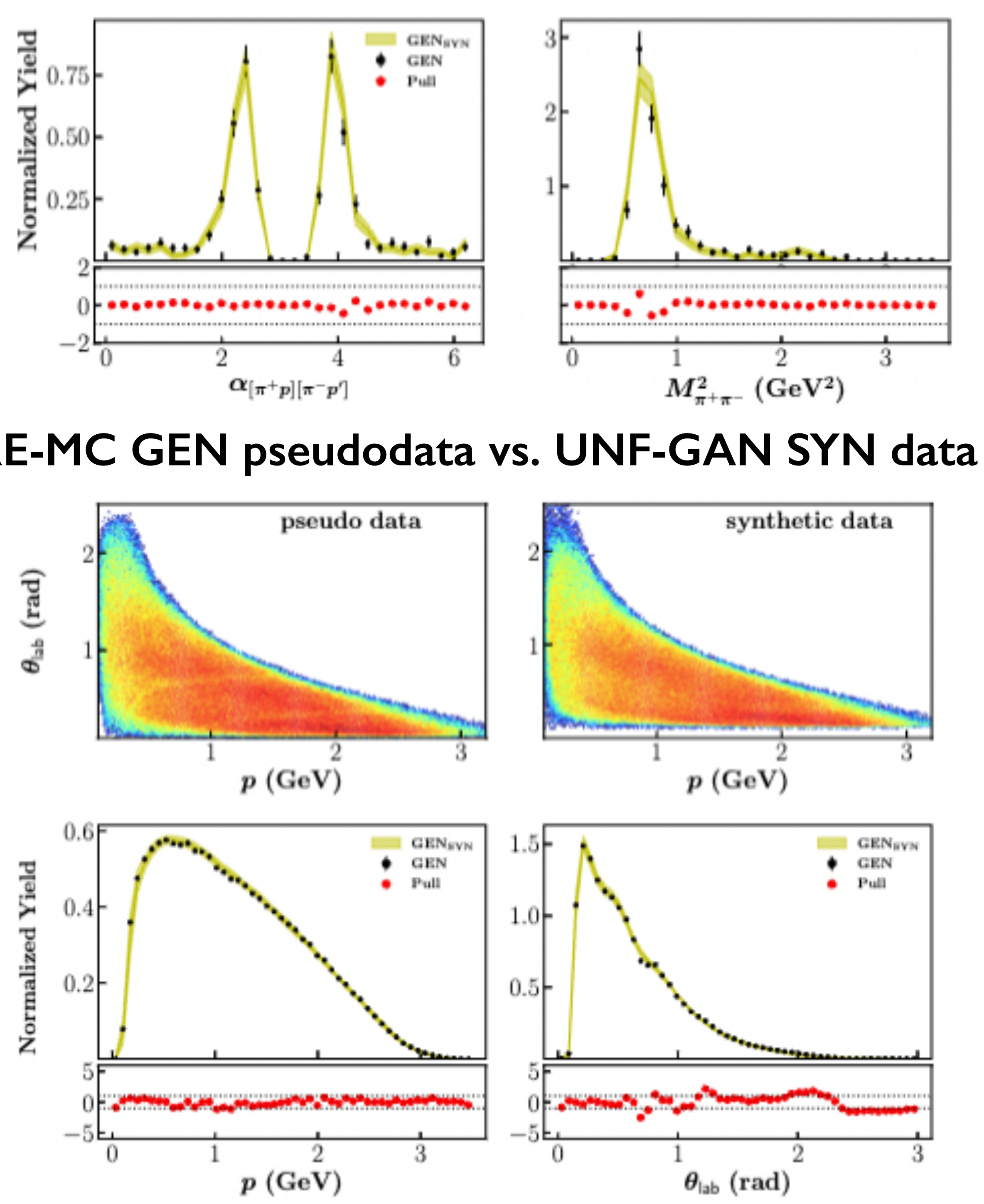


5.Compare UNF-GAN GEN SYNT data to RE-MC GEN pseudodata

Good agreement (± 1σ) for lab variables and in 4D bins

Distribution in 4D bins

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



A(i)DAPT

Deploy an AI Generative Model to reproduce NP/HEP data

We demonstrated (closure-test) that GANs:

I. reproduce detector smearing
II. unfold smearing effect
III. reproduce multi-dim distribution

- **Unfold detector effects**
  - Smearing
  - Acceptance
- **Produce physics observables**
  - 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 physics out of data**
  - Extract cross-section and amplitudes in a 2-body reaction (e.g. ππ scattering - MC)
  - Extract moments of angular distributions and fit with a model (e.g. 2-pion pthotoproduction model - 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)
- …

Unfolding detector's acceptance

Acceptance

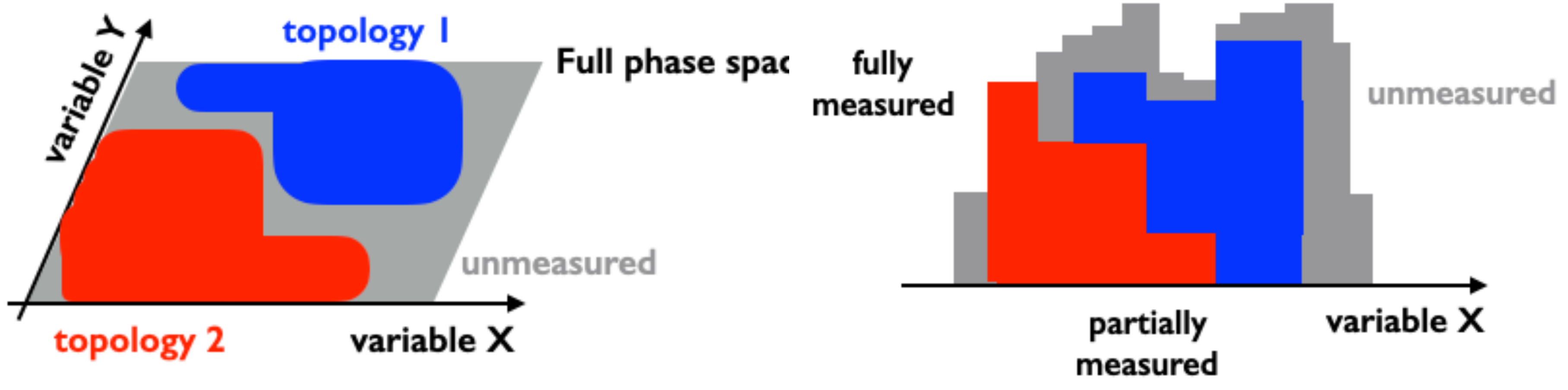
- Any measurement covers only a fraction of the reaction phase-space
- Difficulty: the cross section (Probability Density Function) can not be constrained by general rules (other than being positive) since it reflects the underlying (a-priori unknown) physics
- No model-independent extrapolation of PDF outside detector's acceptance is possible (based on measured phase space)

Use GANs to to minimize the model dependence

- extend as much as possible the measured phase space
  - combining vertex-level data from different experiments (after smearing unfolding)
  - combining measurements of different topologies measured by the same detector
- reproduce data within the detector acceptance
- use a physics model to generate pseudo-data (only) in unmeasured regions

$A + B \rightarrow C + D$

- Topology 1: $A + B \rightarrow C$ + (D undetected)
- Topology 2: $A + B \rightarrow$ (C undetected) + D

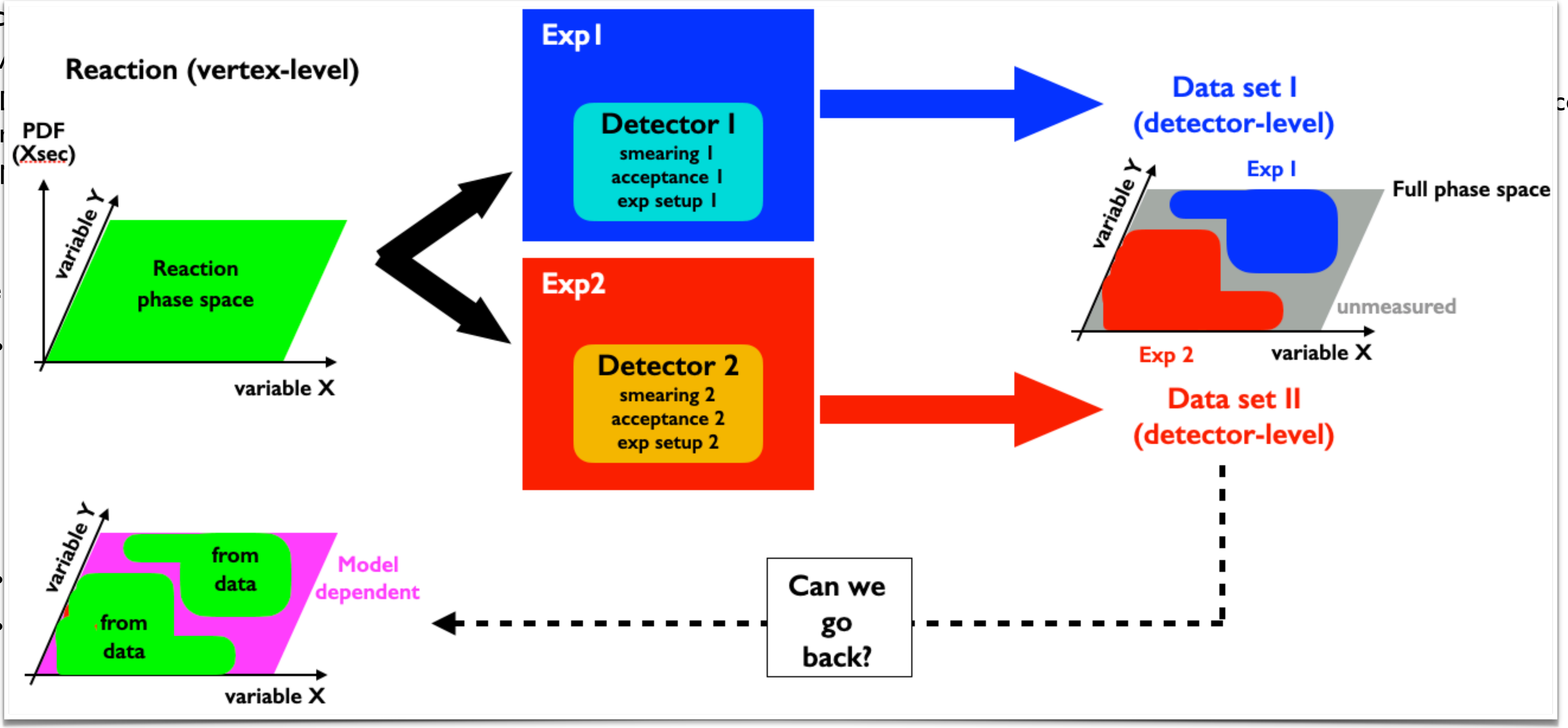


Credit: T.Vittorini ,Y.Alanazi, T.Alghamdi, Y. Li

Unfolding detector's acceptance

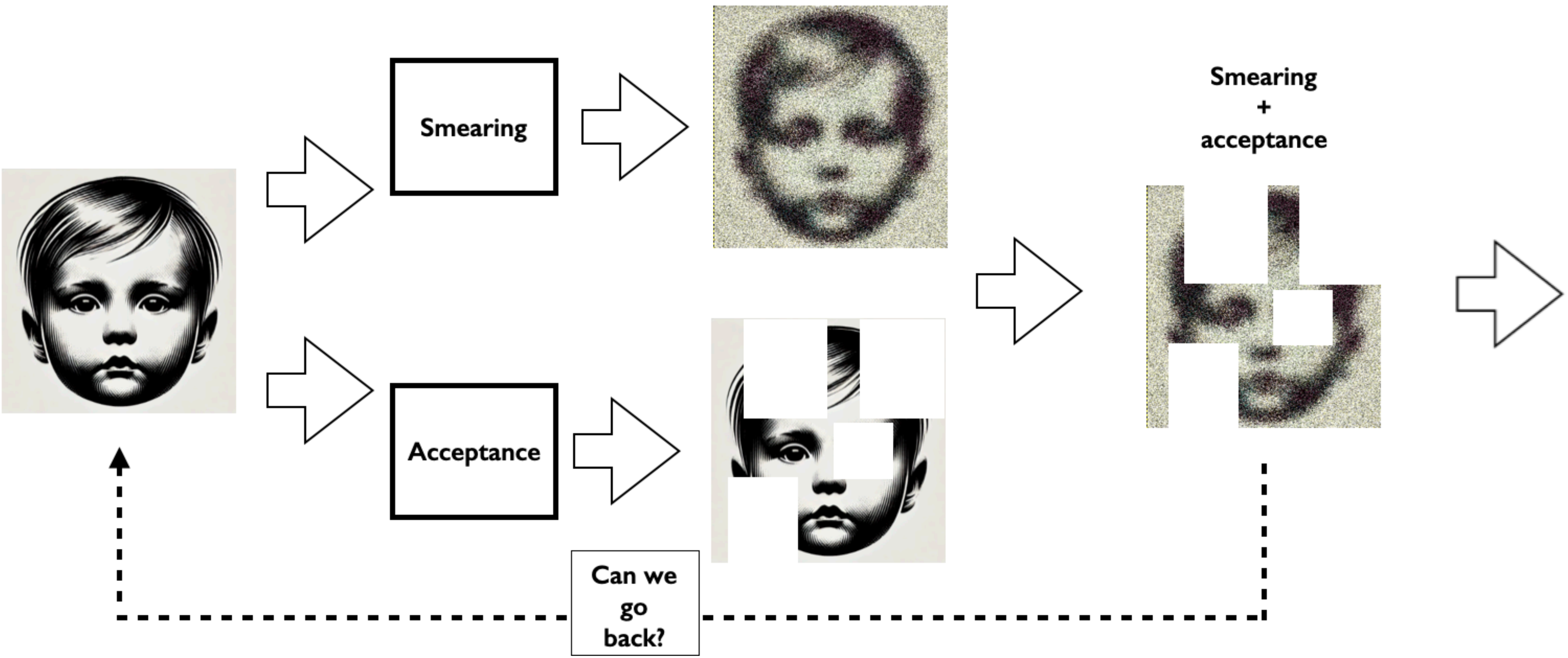
Acc

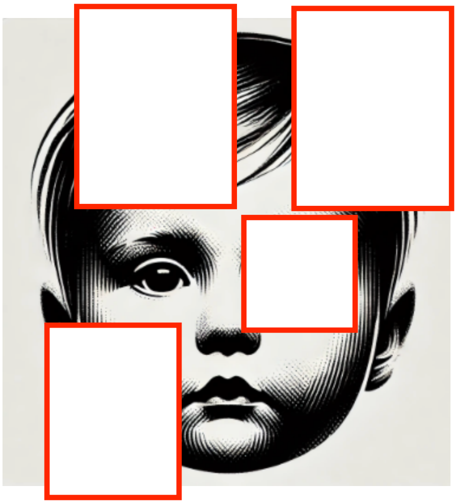
Use



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

Detector unfolding





Yes!
… but only
where we
have data …

filling gaps
(only!) with a
model

Acceptance unfolding

$$\gamma p \rightarrow \Delta^+(1232) \rightarrow \pi^0 p$$

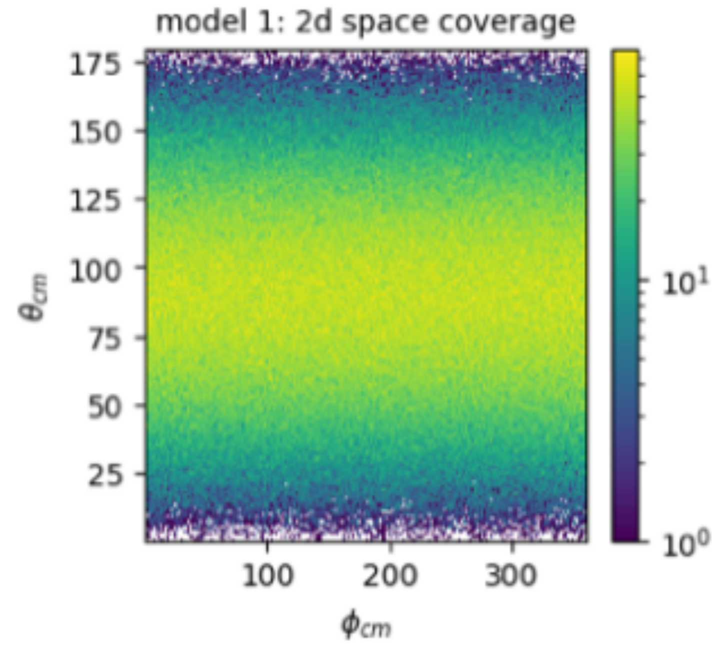
- Simple 2-body process: $\gamma p \rightarrow \Delta^+(1232) \rightarrow \pi^0 p$
- Two independent variables (at fixed E): θ_{cm} ϕ_{cm}
- Monte Carlo event generator
- Breit-Wigner with two parameters: m_Δ and Γ_Δ

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

SAID-based model

- realistic, exp data proxy

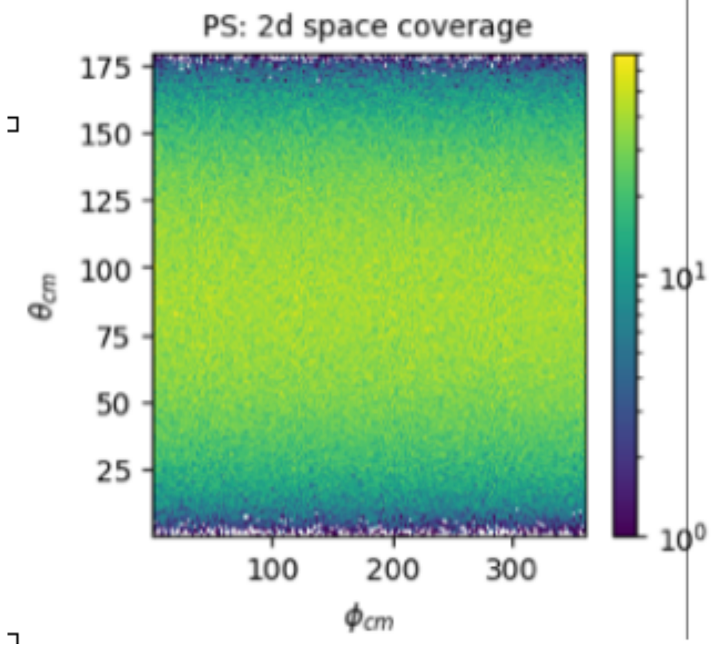
$$\frac{d\sigma}{d\Omega} = \frac{1}{64\pi^2}\frac{1}{4}\frac{p_f}{p_i\, s}\frac{3|H_{3/2}|^2+5|H_{1/2}|^2}{(m_\Delta^2-s)^2+\Gamma_\Delta^2 m_\Delta^2} - \frac{3\cos 2\theta\left(|H_{3/2}|^2-|H_{1/2}|^2\right)}{(m_\Delta^2-s)^2+\Gamma_\Delta^2 m_\Delta^2}$$



Phase-Space

- wrong physics but covers uniformly the whole ps)

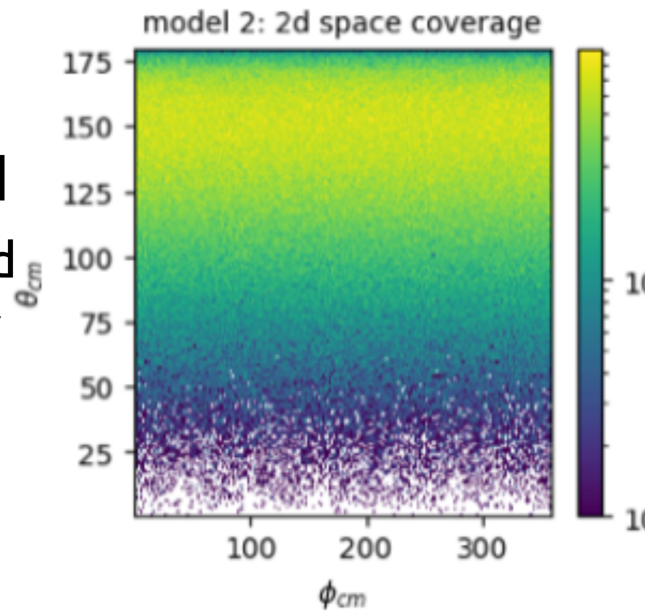
$$\frac{d\sigma}{d\Omega} = \frac{1}{64\pi^2}\frac{1}{4}\frac{p_f}{p_i\, s} * 1$$



High-E model

- extrapolated to low energy

$$\frac{d\sigma}{d\Omega} = \frac{1}{64\pi^2}\frac{1}{4}\frac{p_f}{p_i\, s}\frac{3|H_{3/2}|^2+5|H_{1/2}|^2}{(m_\Delta^2-s)^2+\Gamma_\Delta^2 m_\Delta^2} - \frac{\left(|H_{3/2}|^2-|H_{1/2}|^2\right)3e^{2\theta}}{(m_\Delta^2-s)^2+\Gamma_\Delta^2 m_\Delta^2},$$

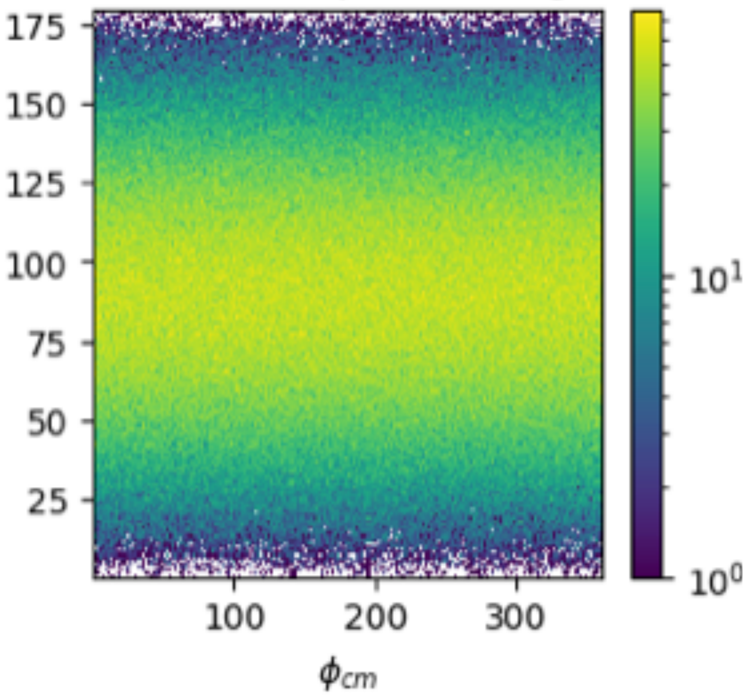


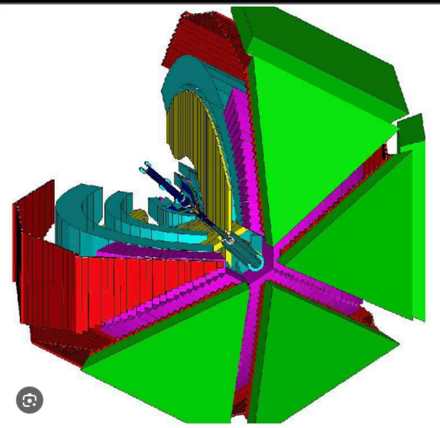
GOAL: build a MC generator that starting from ANY models, reproduces data distributions within the acceptance, and provides model-dependent pseudo data in the unmeasured regions (filling the gaps)

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

Data proxy (SAID Model)

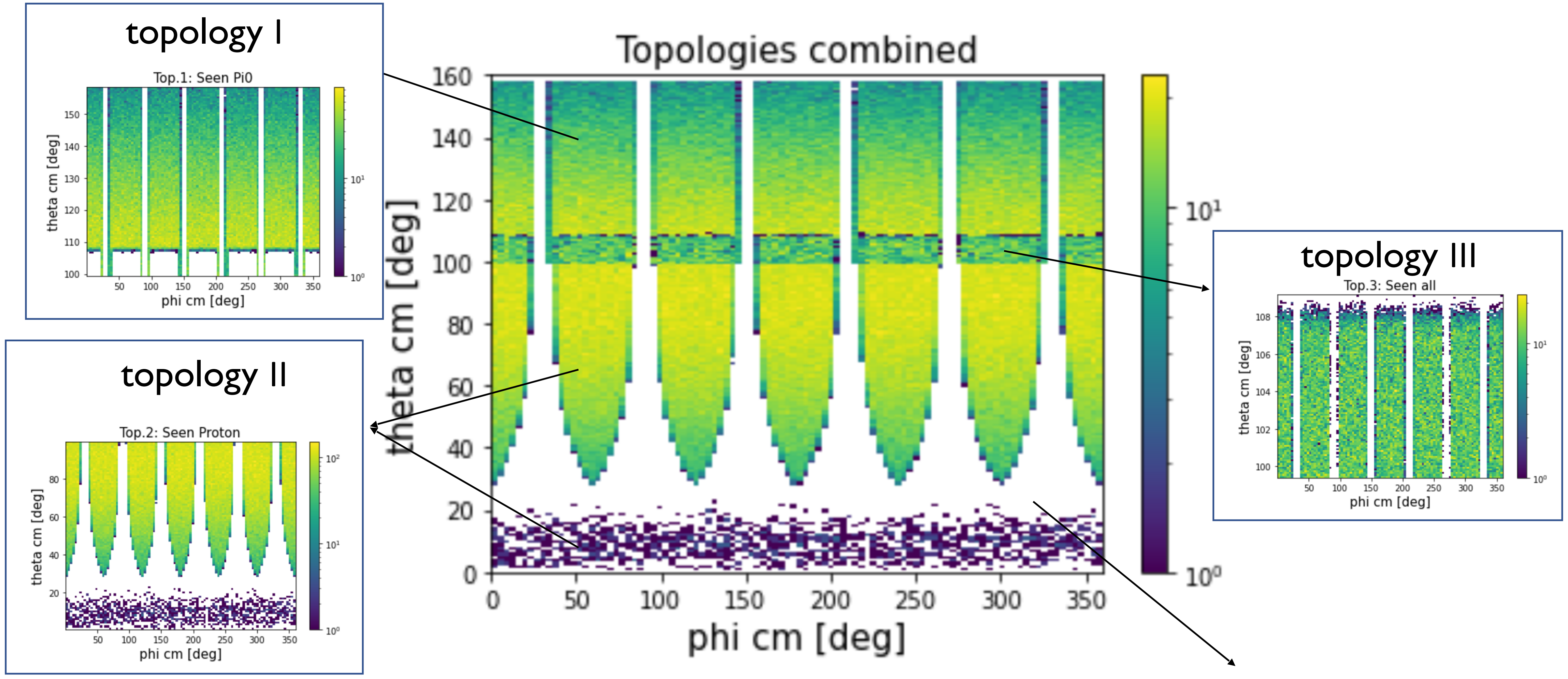
$$\gamma p \to \Delta^+(1232) \to \pi^0 p$$





CLAS detector emulator (parametric):

- fiducial cuts (coils, minimum proton momentum and angle in the lab frame)
- spread: gaussian spread applied to momenta and angles of detected particles
- simplification: we are considering the pi0 as a particle that could be detected or not (should be gammas)



topology 0: unmeasured

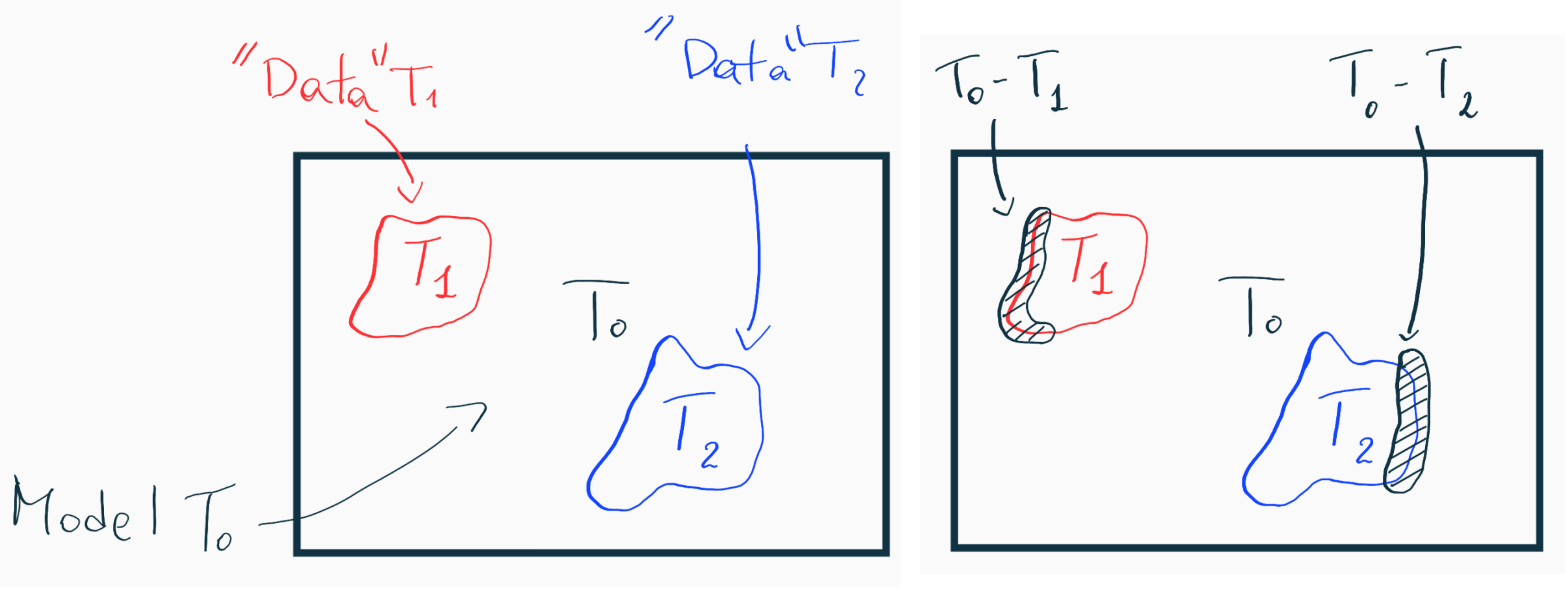
Passing SAID pseudo-data trough the date crater emulator ‘generates’ topologies

- topology I: γ p → (p) π^0 (proton missing)
- topology II: γ p → p (π^0) (π^0 missing)
- topology III: γ p → p π^0 (all detected)
- topology 0: unmeasured

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

Unfolding detector's acceptance

- Build a **single generative model** to generate vertex level events according to each topology



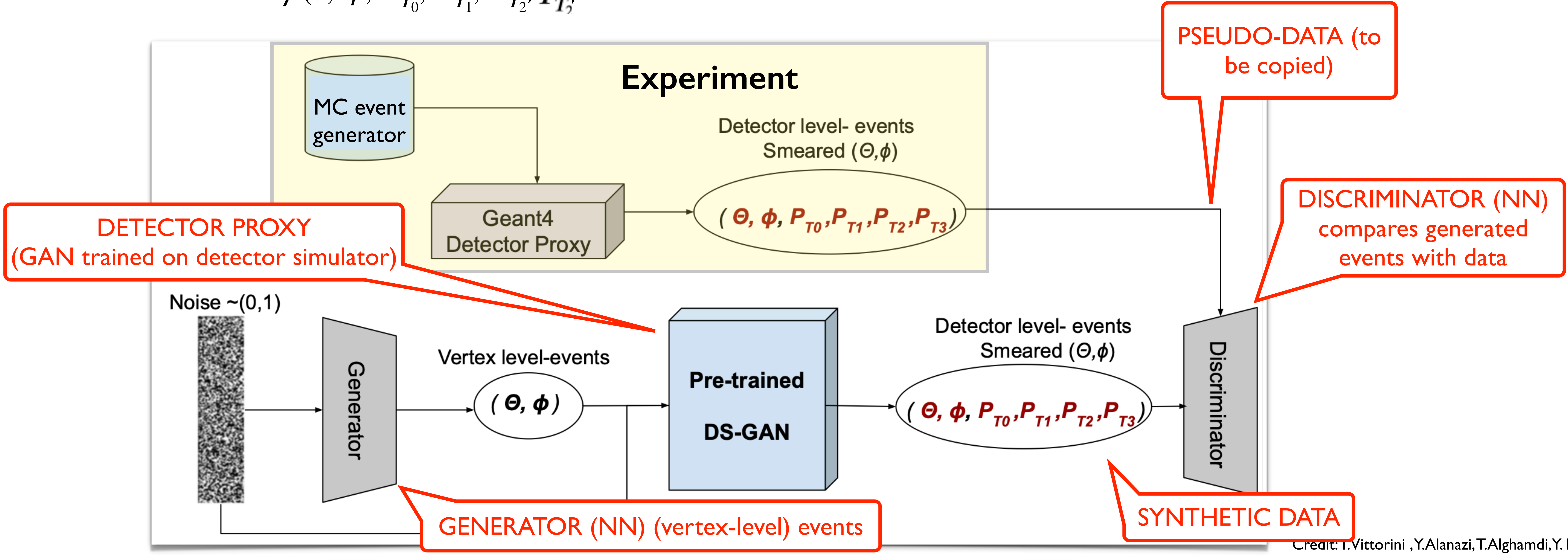
- Not each point in the ps is mapped uniquely to a given topology
- Particles have a probability in the range [0,1] to ber detected (not only 0 or 1)

GENERATOR (NN) (vertex-level) events

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

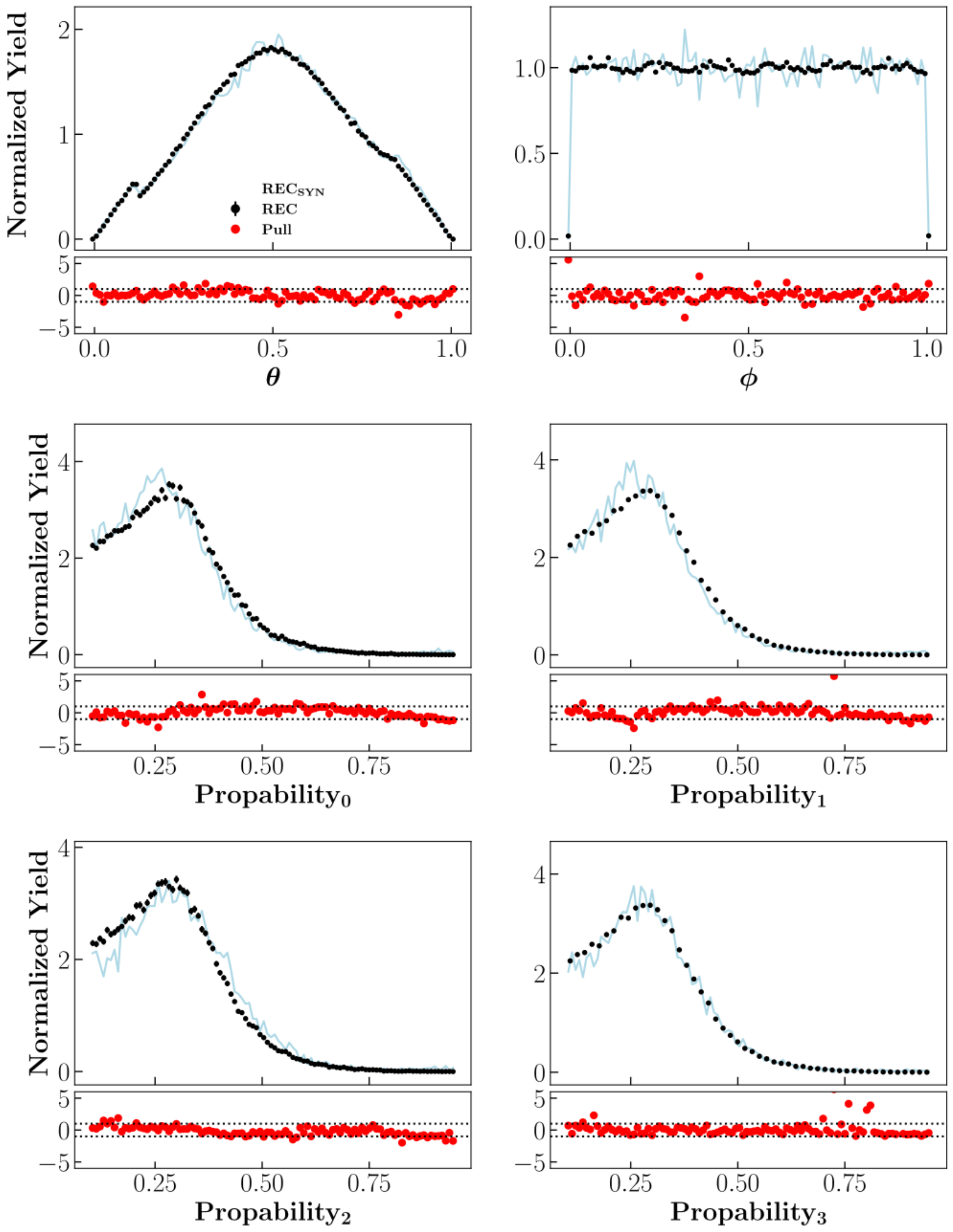
Unfolding detector's acceptance

- Build a **single generative model** to generate vertex level events according to each topology
- Pseudo-data distributed according to the correct "experimental' cross-sections inside the measured regions T_1 and T_2
- Pseudo-data according to a given model in the unmeasured region T_0
- The AI model should include $P_{detection}$ = [0,1] (not only 0 or 1 only true for orthogonal topologies)
- Each event is defined by $(\theta,\ \phi,\ P_{T_0},\ P_{T_1},\ P_{T_2}, P_{T_3})$



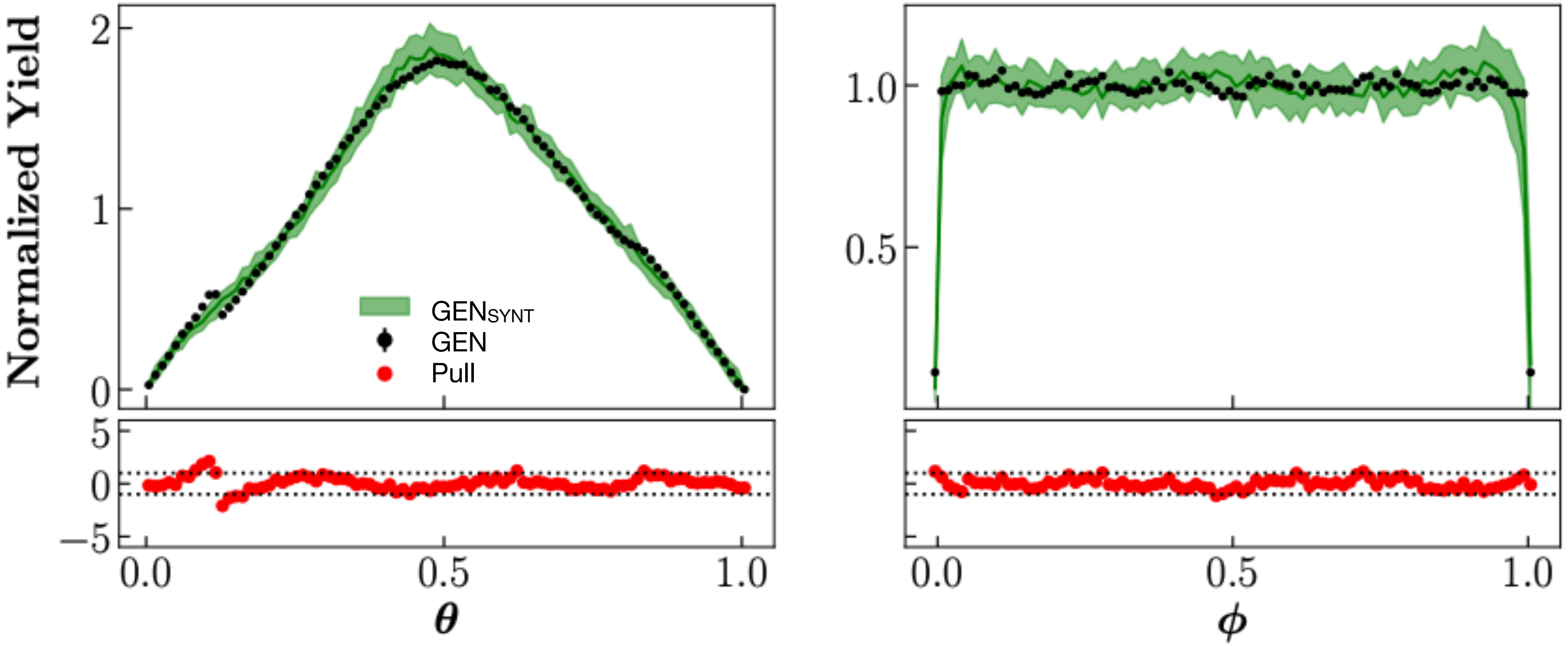
Credit: T.Vittorini ,Y.Alanazi,T.Alghamdi,Y.

Acceptance unfolding



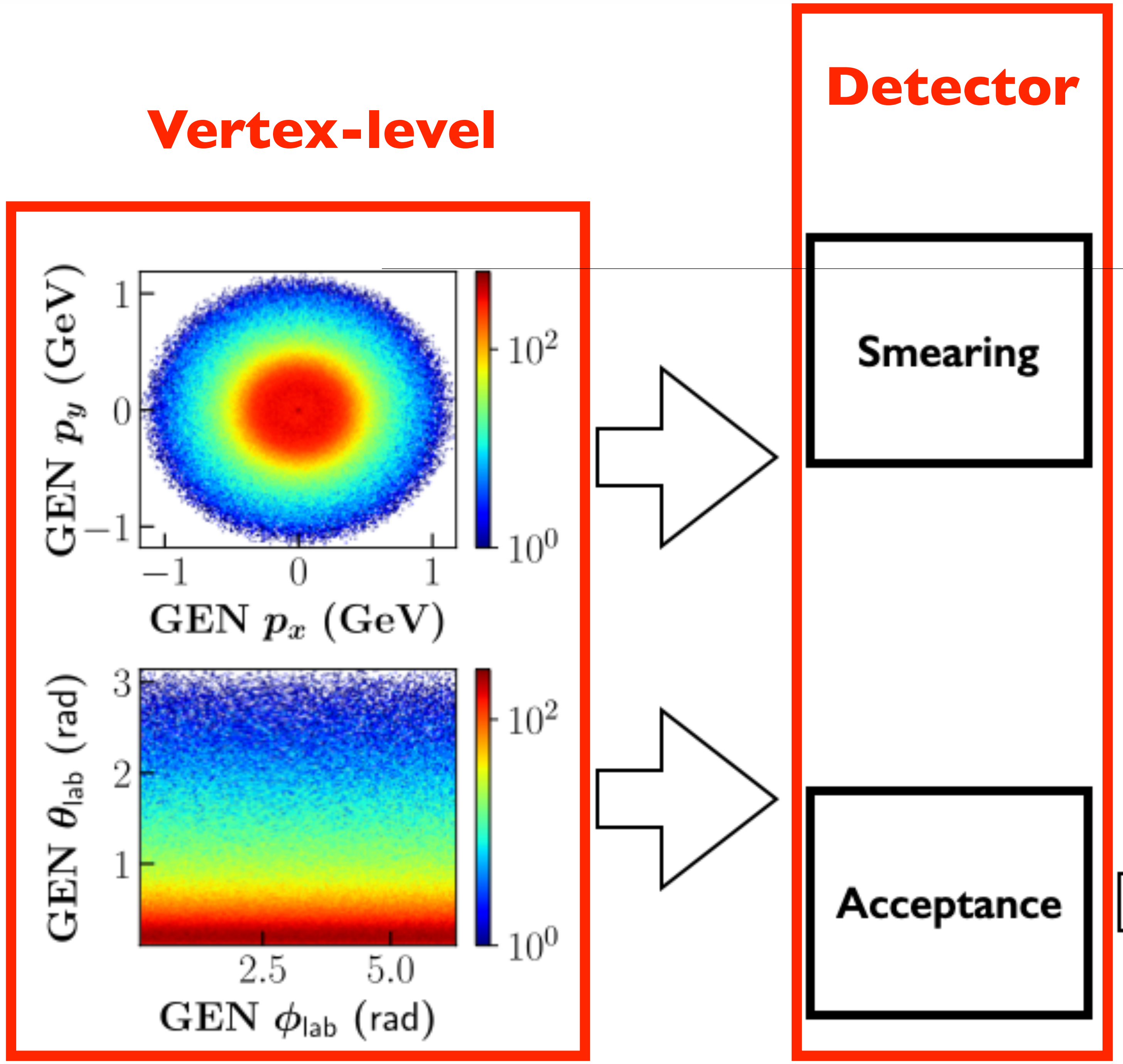
- Detector simulation GAN: REC$_{SYNT}$ vs REC pseudodata

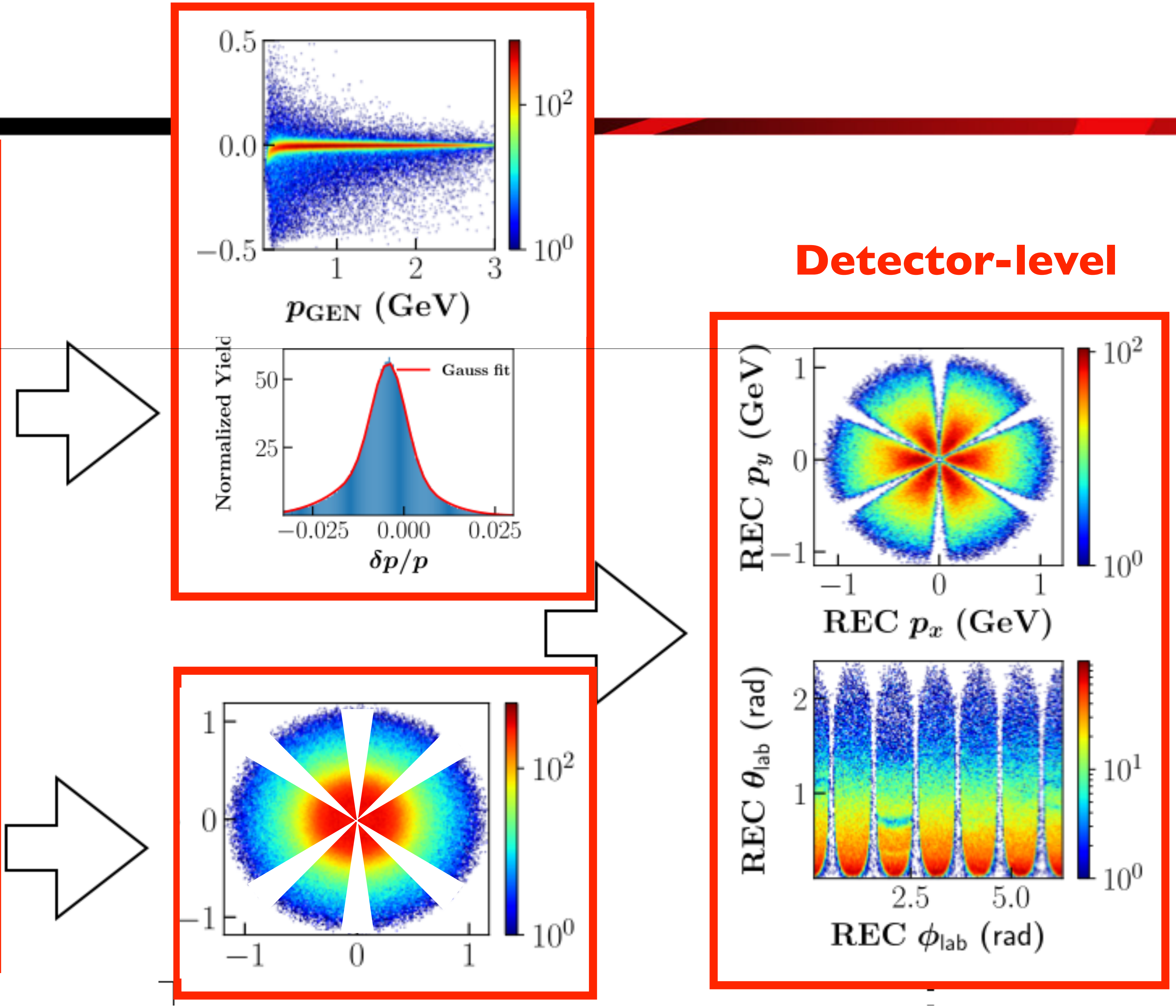
- Unfolding GAN : GEN$_{SYNT}$ vs GEN pseudodata



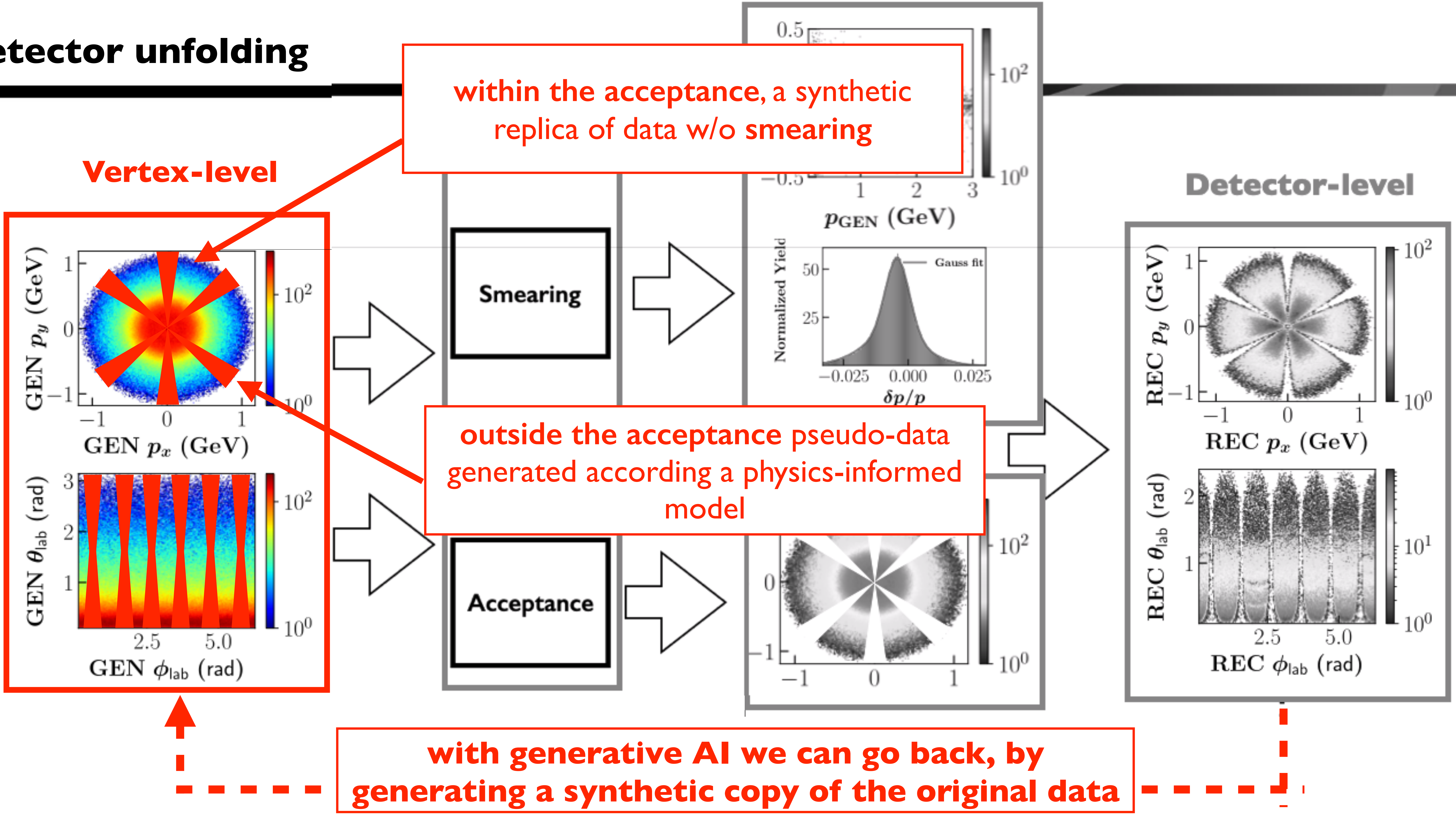
Credit: T.Vittorini ,Y.Alanazi, T.Alghamdi, Y. Li

Detector unfolding





Detector unfolding



A(i)DAPT

Deploy an AI Generative Model to reproduce NP/HEP data

We demonstrated (closure-test) that GANs:

I. unfold acceptance
II. combine raw data
III. model-dep only in unmeasured area

- **Unfold detector effects**
  - Smearing
  - Acceptance
- **Produce physics observables**
  - 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)
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  - Connect NN features to different physics processes (e.g. baryon and meson resonances in CLAS-g11 2-pion data)
- …

Unfolding detector's acceptance

Use GANs to to minimize the model dependence

- extend as much as possible the measured phase space
  - combining vertex-level data from different experiments (after smearing unfolding)
  - combining measurements of different topologies measured by the same detector
- reproduce data within the detector acceptance
- use a physics model to generate pseudo-data (only) in unmeasured regions

Model-independent

- Considering that:

$$XSec = \sum |A_i|^2 \qquad A_i = \sum \text{(Scattering amplitude for each possible process)}$$

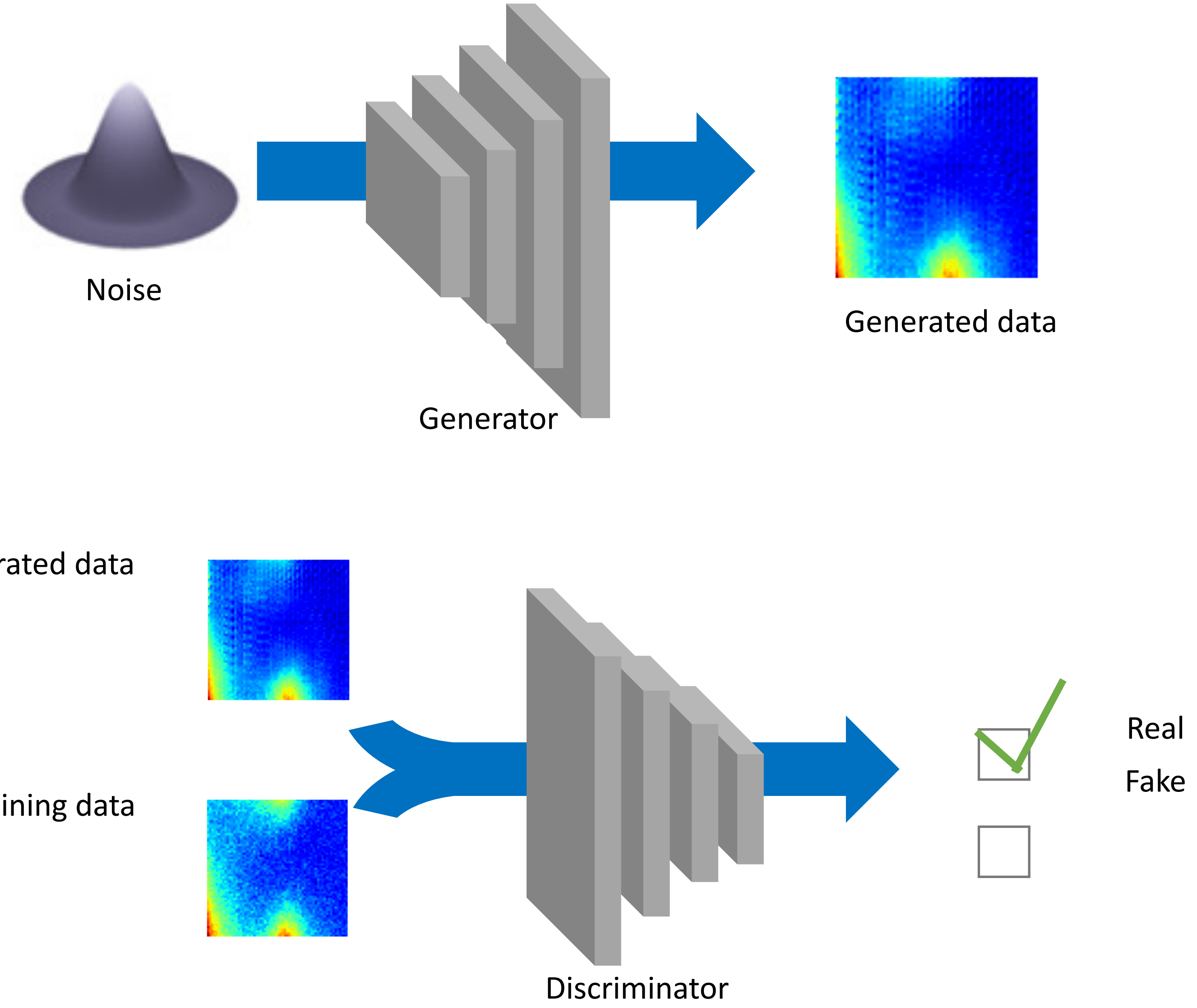
- Impose conditions to the PDF via constraints on scattering amplitudes A_i (parity conservation, analiticity, unitarity, …)
- A_i are difficult to constrain supervising on XSec
- work in progress

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

Amplitudes extraction

Goal: Train an AI model to extract amplitudes (complex numbers satisfying some physics constraints, e.g. unitarity) from events generated with Monte Carlo simulations according to a theoretical model (and eventually from experimental data)

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



Credit: G.Montaña, A.Pillioni, N.Sato

Amplitudes extraction

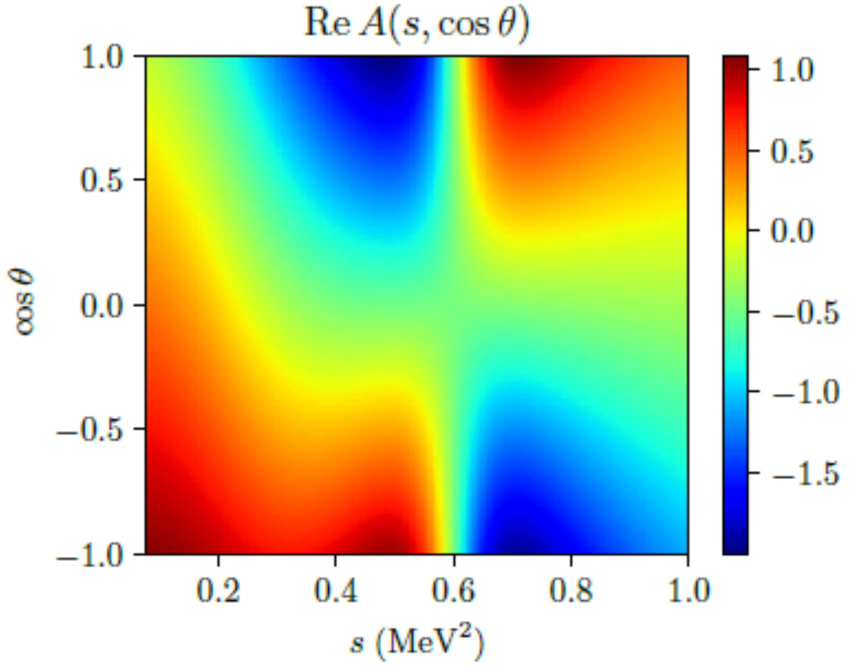
Generative Adversarial Networks (GANs):
extract amplitude from differential cross sections, using unitarity constraint

Physics model: elastic scattering $\pi^+\pi^- \to \pi^+\pi^-$

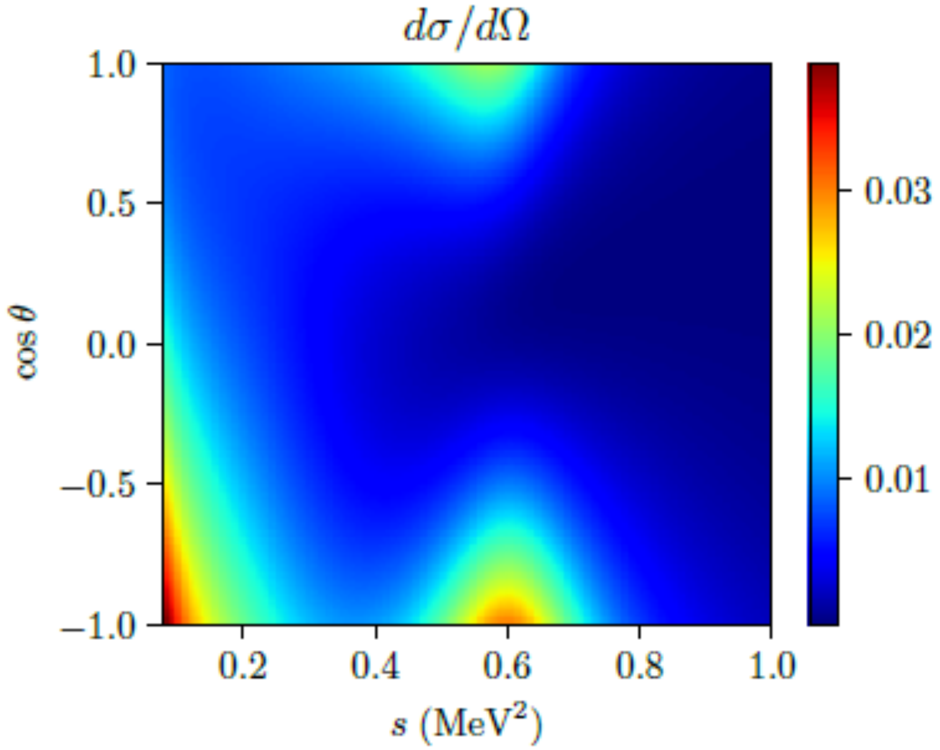
$$A(s,\cos\theta) = \sum_{\ell=0}^{n}(2\ell+1)f_\ell(s)P_\ell(\cos\theta)$$

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

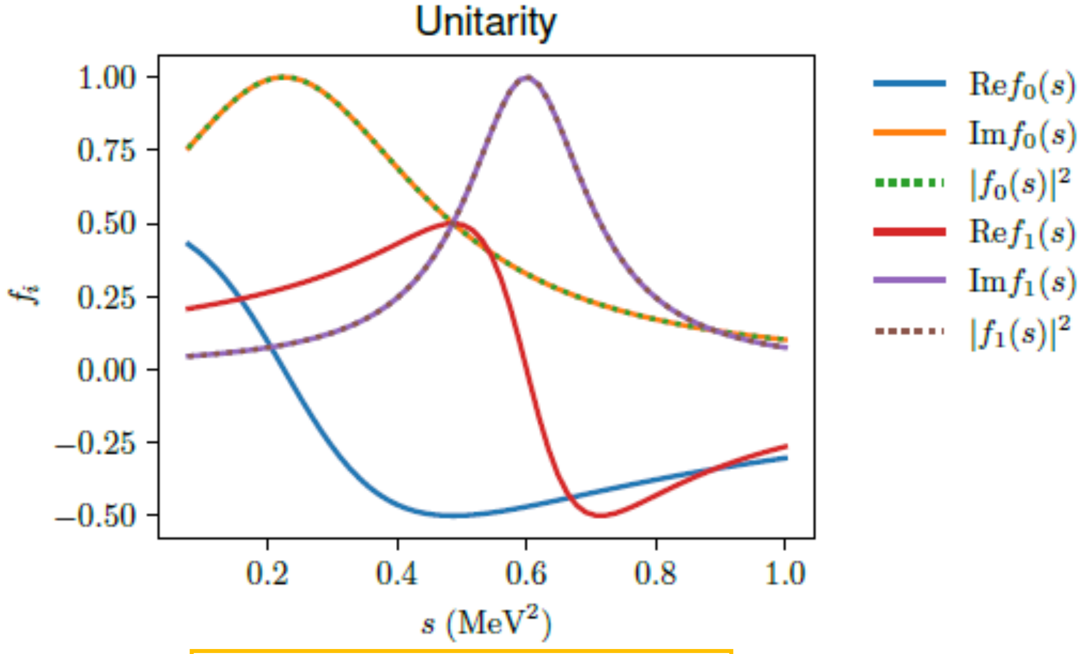
$$\begin{cases} f_0(s) = \dfrac{m_\sigma\Gamma_\sigma}{m_\sigma^2 - s - i\Gamma_\sigma m_\sigma} & m_\sigma = (0.4-0.55)\ \text{GeV}\ ,\ \Gamma_\sigma = (0.4-0.7)\ \text{GeV} \\ f_1(s) = \dfrac{m_\rho\Gamma_\rho}{m_\rho^2 - s - i\Gamma_\rho m_\rho} & m_\rho = (0.775)\ \text{GeV}\ ,\ \Gamma_\rho = (0.147)\ \text{GeV} \end{cases}$$



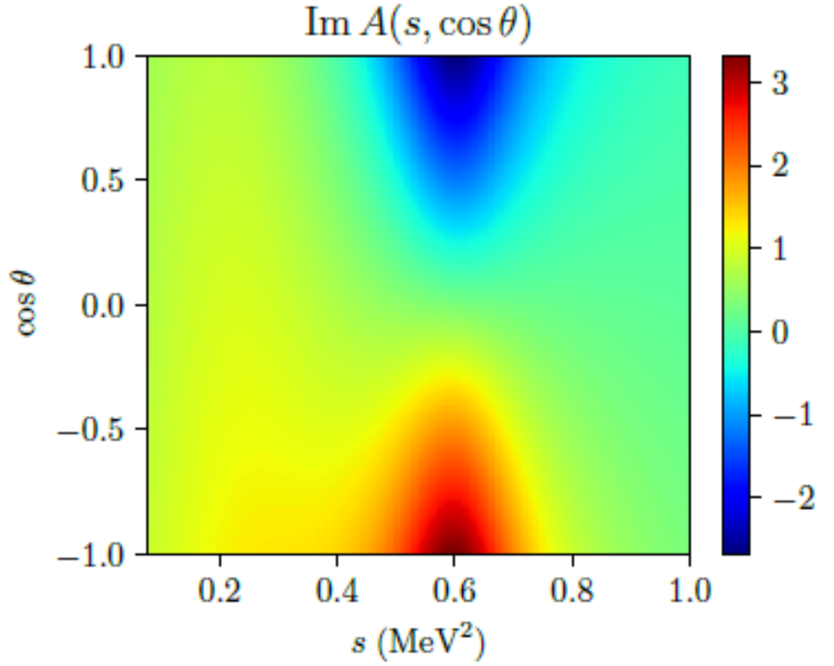
$$\frac{d\sigma}{d\Omega} = \frac{1}{64\pi^2}\frac{1}{s}|A(s,\theta)|^2$$



Partial waves satisfy the **unitarity condition**:



$$\boxed{\text{Im} f_l(s) = |f_l(s)|^2}$$

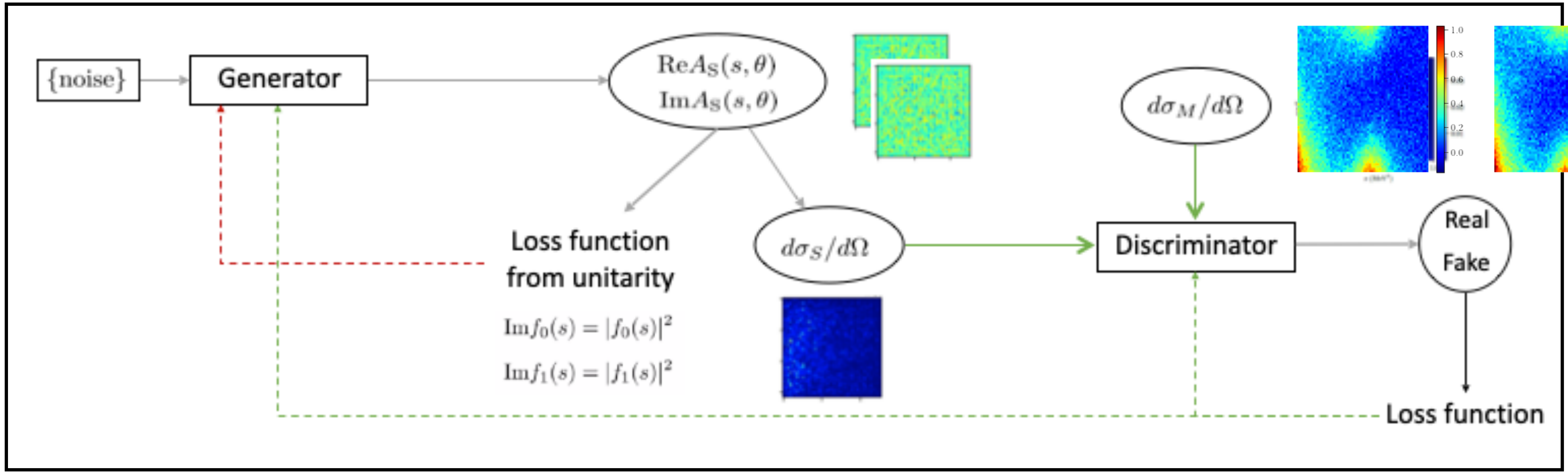


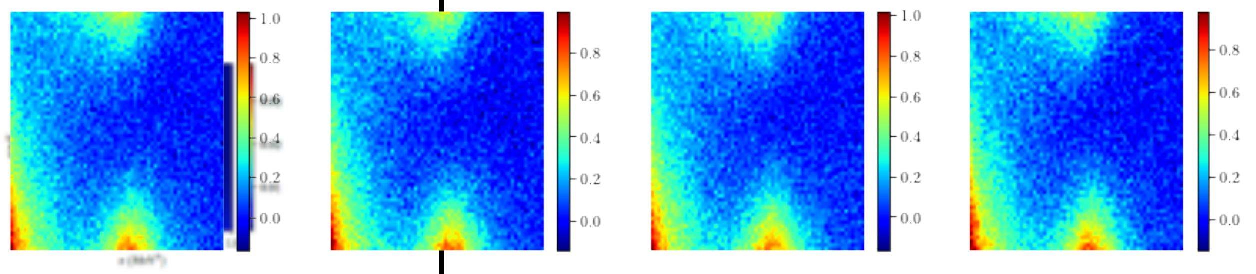
Credit: G.Montaña, A.Pillioni, N.Sato

Amplitudes extraction

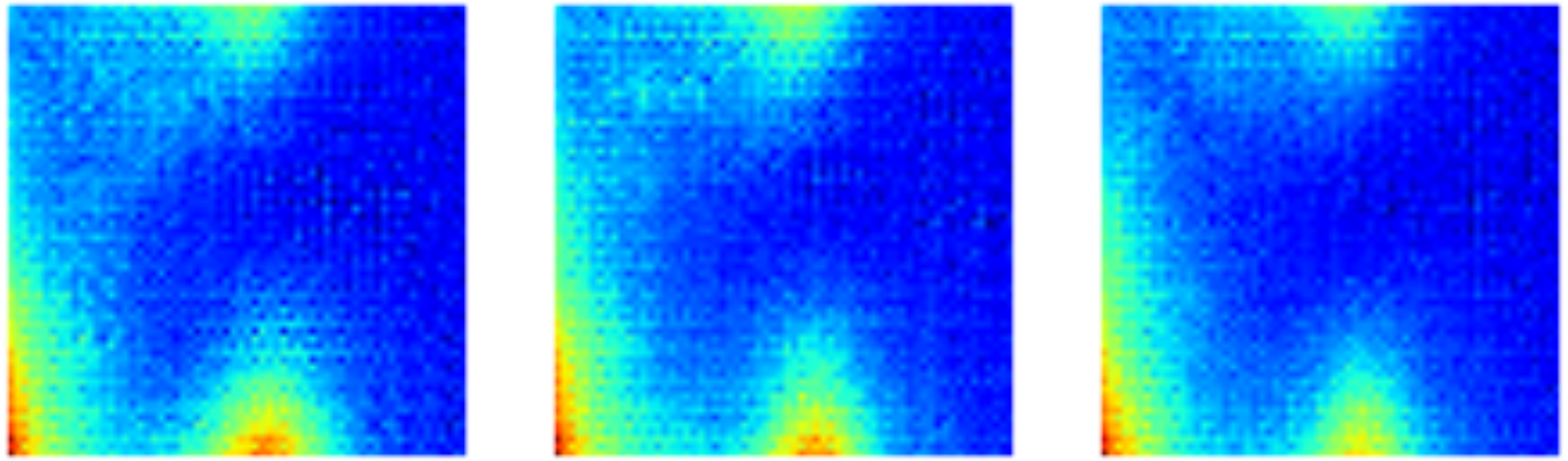
B. Generative Adversarial Networks (GANs):
extract amplitude from differential cross sections, using unitarity constraint

Training xsections generated form the model





Generated samples at the end of the training

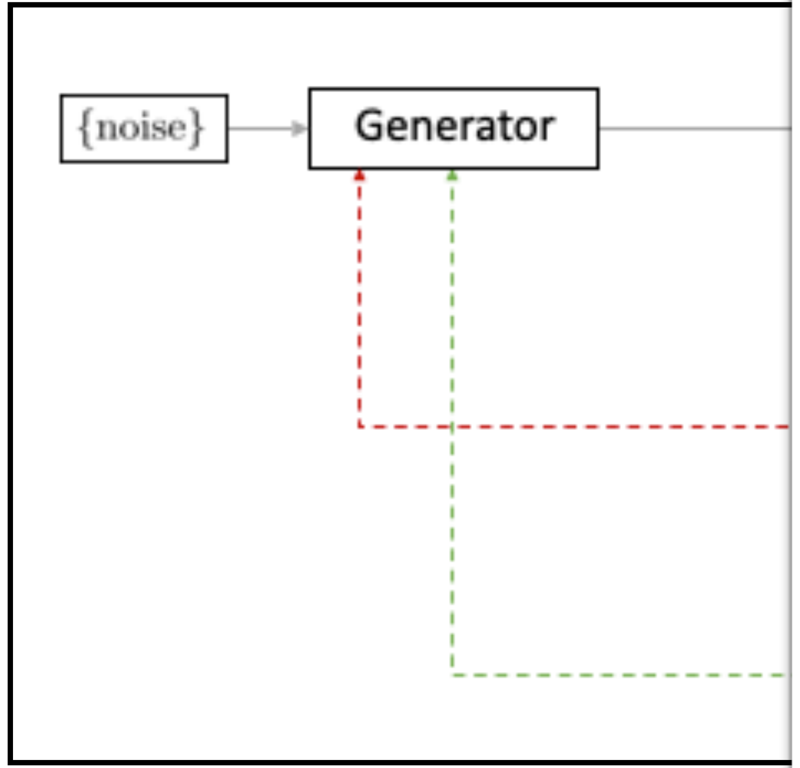


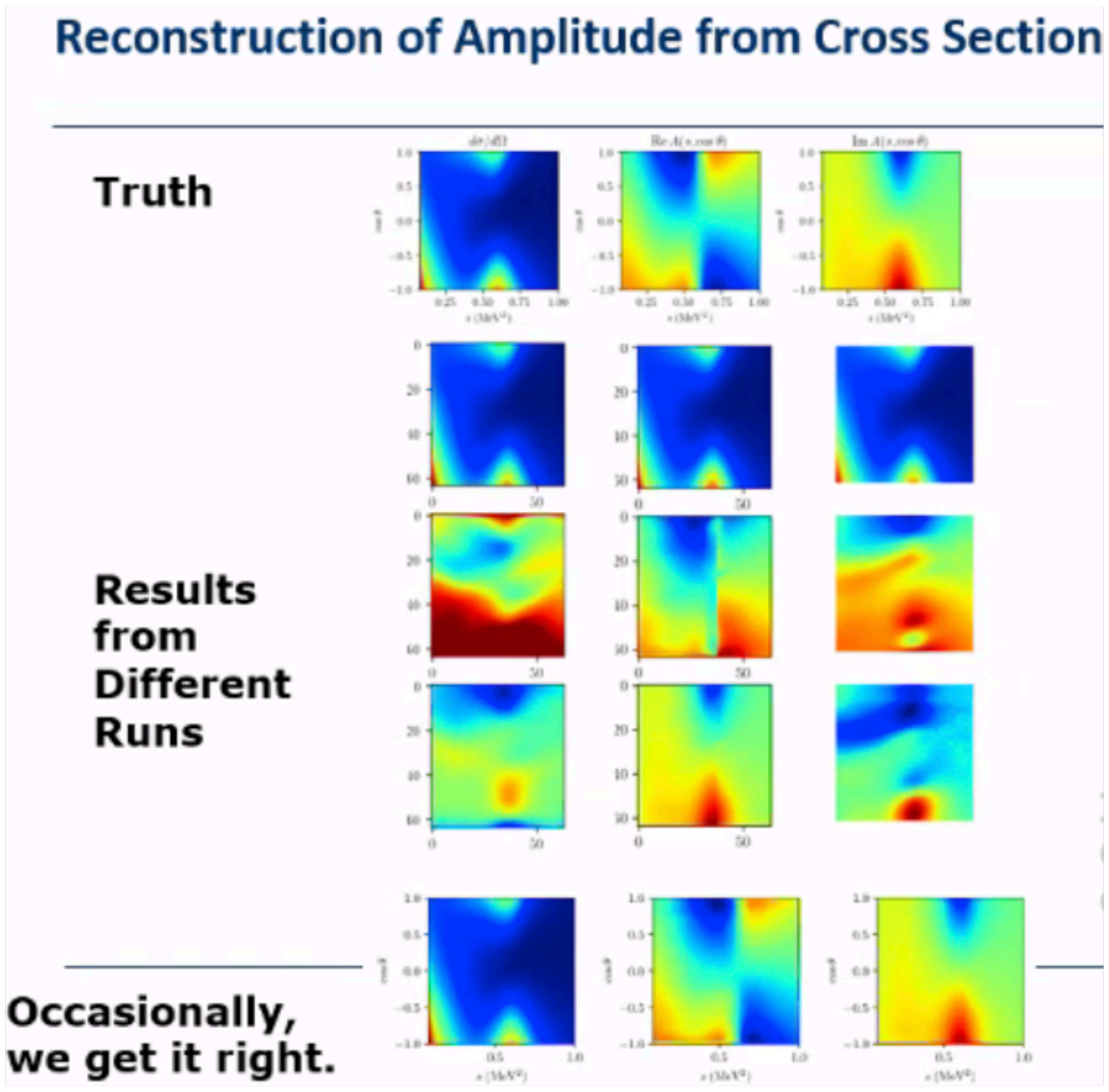
- GANs training in progress
- from preliminary results, GANs are converging

Credit: G.Montaña, A.Pillioni, N.Sato

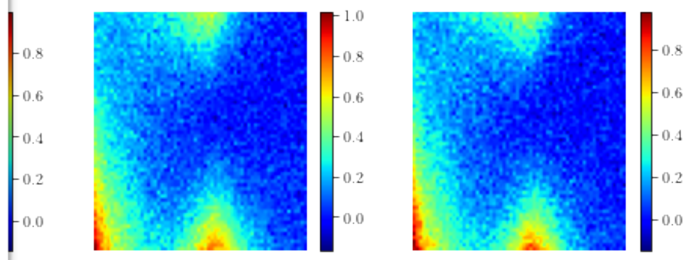
Amplitudes extraction

B. **Generative Adversarial Netw**
extract amplitude from differential cr

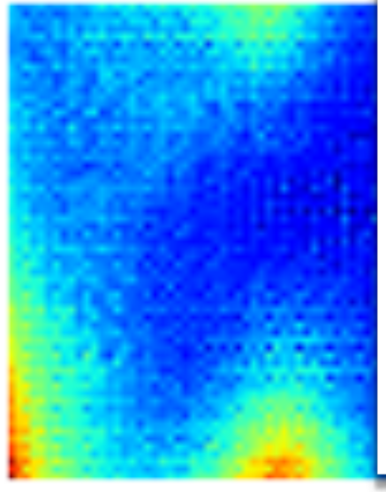




tions generated form the model



Generated samples at the end of the training



rogress
esults, GANs are converging

Credit: G.Montaña, A.Pillioni, N.Sato

Summary

Intuition:

AI has the potential to surpass traditional analysis methods in nuclear and high-energy physics (NP/HEP), offering a unique and powerful approach to extracting physics insights from data

- Unfold detector's effects to extract physics observables at vertex-level
- Embed (multiD) xsec information (correlations) in a data-trained event generators
- Preserve data in an alternative compact and efficient form
- Provide an alternative way to extract PDFs and amplitudes
- Incorporate Universality (of scattering amplitudes) training a NN with different kinematics of the same final state or different final states (coupled channels)
- Extract NN features related to the underlying physics

Where are we?

- We performed a positive closure test on inclusive electron scattering and multiD reactions (2pion photo production)
- We demonstrate that GANs are a viable tool to unfold detector effects (smearing) to generate a synthetic copy of data
- We demonstrate that original correlations are preserved
- We demonstated that the best option to address detector acceptance limitations
- The first attempt to use a model-independent procedure supervising at level of amplitudes is encouraging

Still a long way to use AI to extract physics from data in an easier and more efficient way, but, step by step, we are demonstrating this intuition is correct!