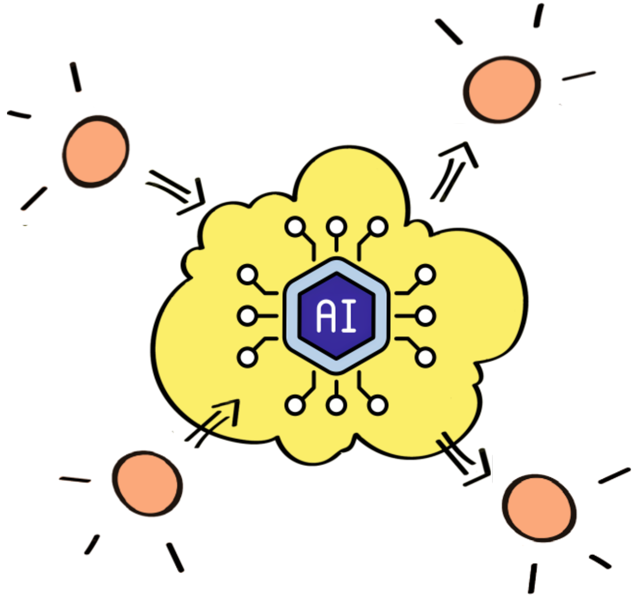
Generative AI for Amplitude Analysis



Glòria Montaña

Theory Center - Thomas Jefferson National Accelerator Facility

gmontana@jlab.org

2025 JLUO Annual Meeting

Jefferson Lab JSA A SURA Company

A(i)DAPT
AI for Data Analysis and PreservaTion

JPAC

EXOHAD
EXOTIC HADRONS TOPICAL COLLABORATION

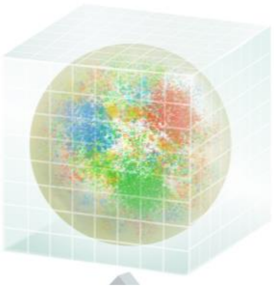
Inverse problems in QCD

Forward problem

Known input ⟶ Operator ⟶ Predict output

Inverse problem

Estimate input ⟵ Operator ⟵ Observed output

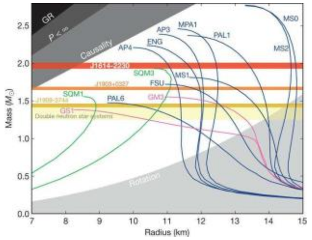


Lattice QCD correlators

▼

Hadron spectrum

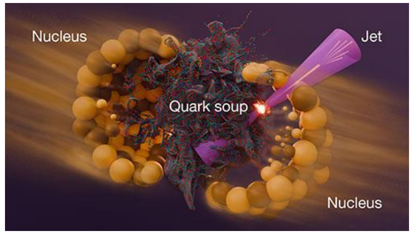
Interaction potentials



Observations of masses and radii of neutron stars

▼

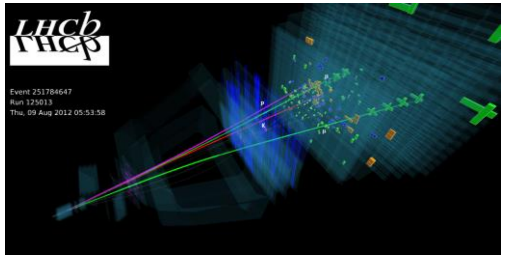
Equation of state (EoS) of dense matter



Heavy-ion collision experiments

▼

Properties of the quark-gluon plasma



Event-level data from accelerators

▼

Hadron spectrum

Scattering amplitudes

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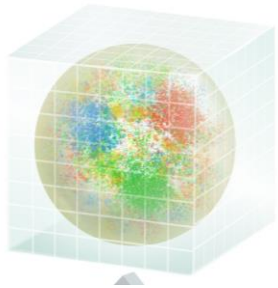

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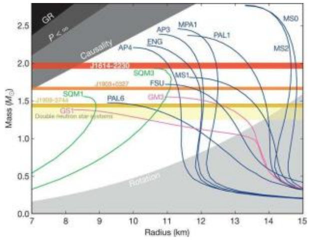

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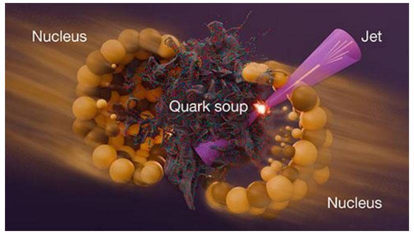

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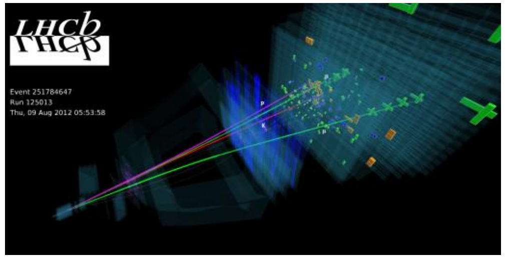

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Inverse problems are ill-posed and hard!

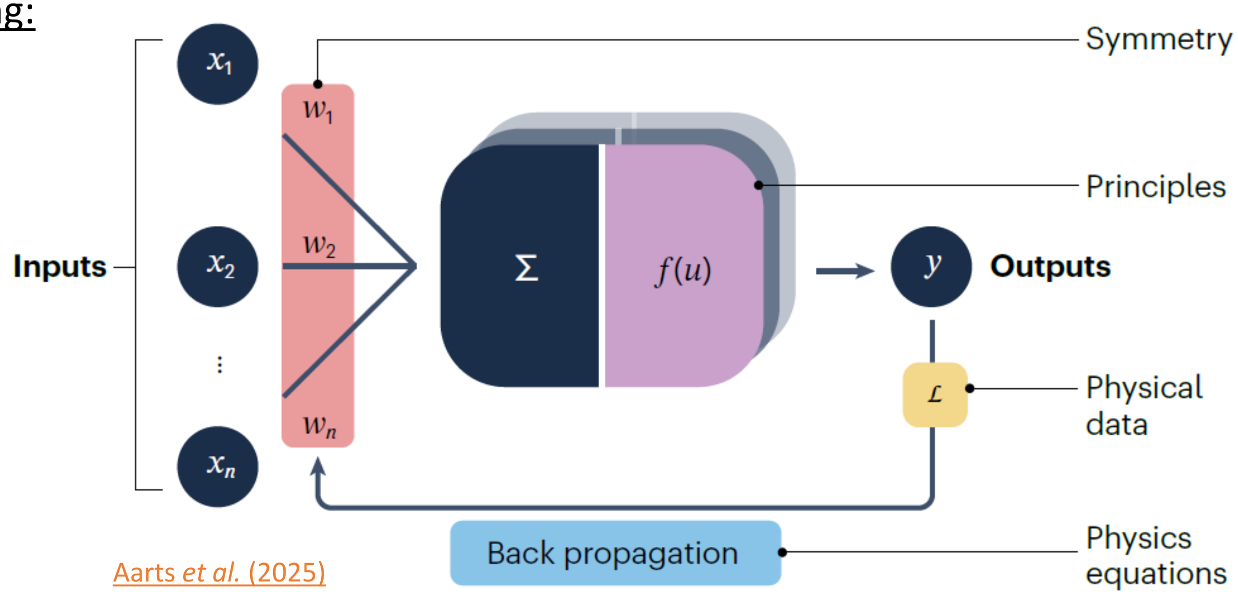
- **Noisy and incomplete data:** Limited experimental resolution
- **Loss of information**: Observables are integrated over variables
- **Ambiguities**: Multiple parameter sets can describe the same data
- **Model dependence**: Assumptions that can introduce biases

Can we use Machine Learning techniques to solve Inverse Problems?

Yes! Benefits:

- ☑ **Data-driven:** Learn patterns directly from experimental data, reduce model assumptions
- ☑ **Introduce prior knowledge:** Incorporate constraints to ensure physically meaningful solutions
- ☑ **High-dimensional efficiency:** Handle complex datasets
- ☑ **Scan large parameter spaces:** Find solutions that traditional methods miss

Physics-informed deep learning:



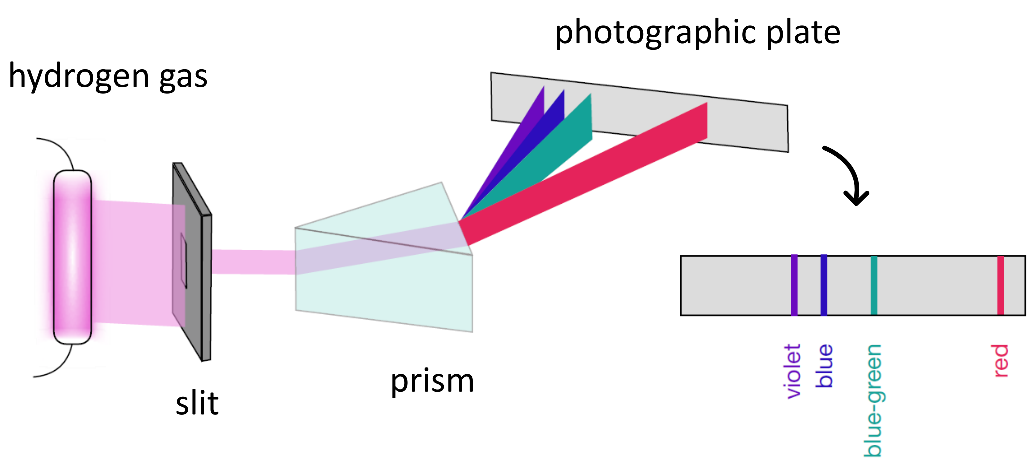
Aarts *et al.* (2025)

Why is Spectroscopy important?

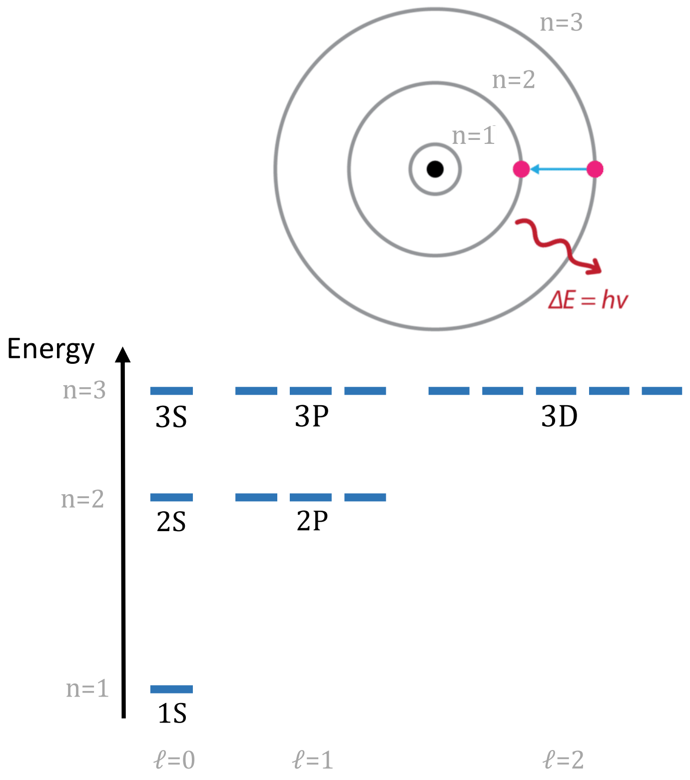
Spectroscopy provides fundamental insights into physical phenomena

- The hydrogen atom led to the discovery of **Quantum Mechanics**
- Precision spectroscopy helped establish **Quantum Electrodynamics** (QED)

Spectral lines of atomic hydrogen



Orbital energy levels of the hydrogen atom



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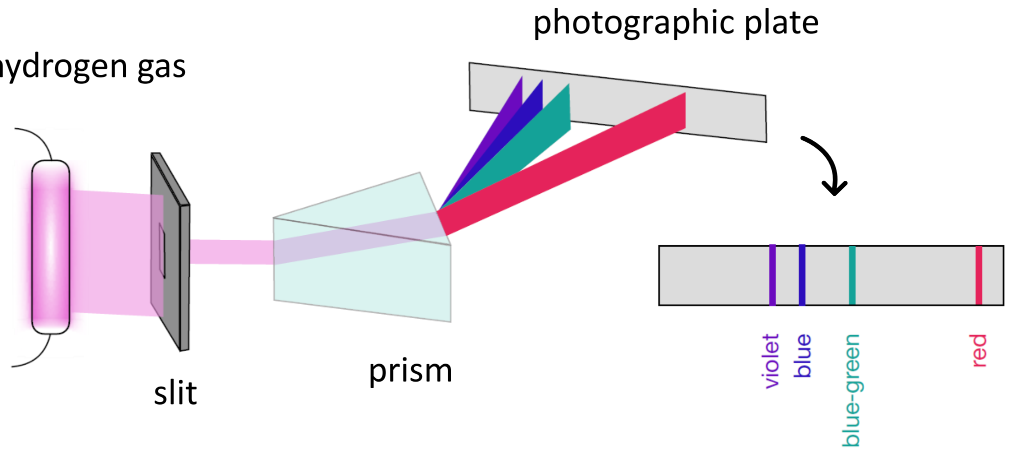

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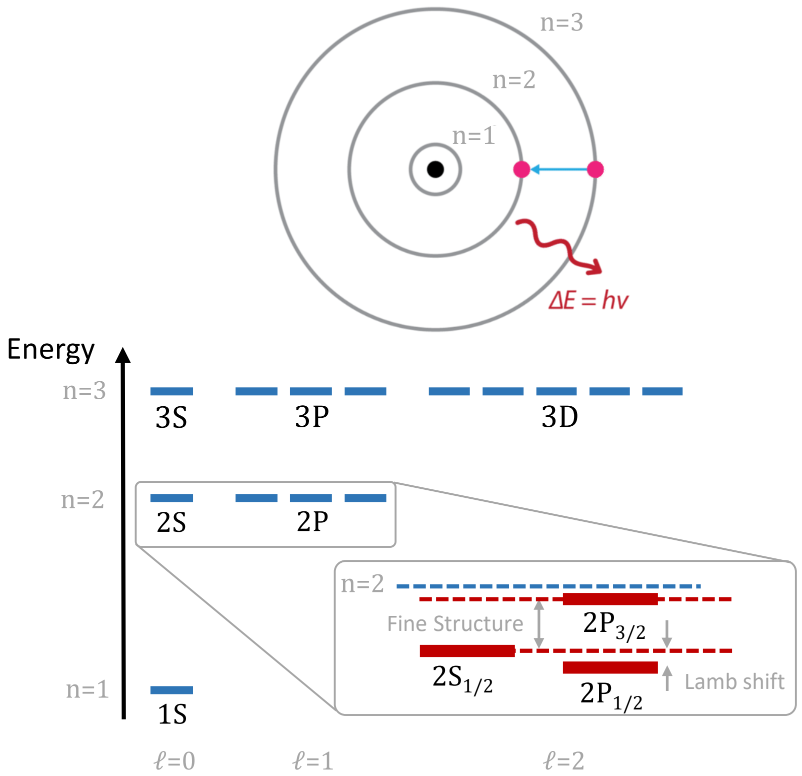


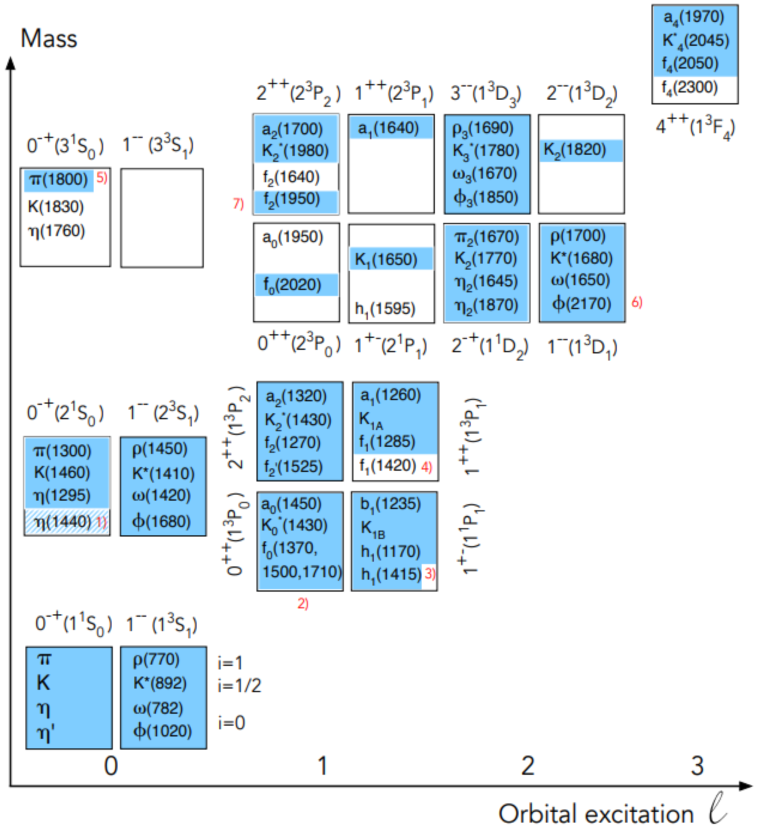
Why is Hadron Spectroscopy important?

baryons mesons

Hadron spectroscopy provides fundamental insights into **Quantum Chromodynamics** (QCD)

- Hadrons are classified by quantum numbers:
  - → spin (J), parity (P), charge conjugation (C), isospin (I), strangeness (S), …
- The constituent quark model explains the gross structure of the hadron spectrum
- A rich spectrum of excited states and exotic hadrons revealed through particle accelerators and lattice QCD

Light mesons organized in $J^{PC}(n^{2s+1}l_j)$ (PDG)



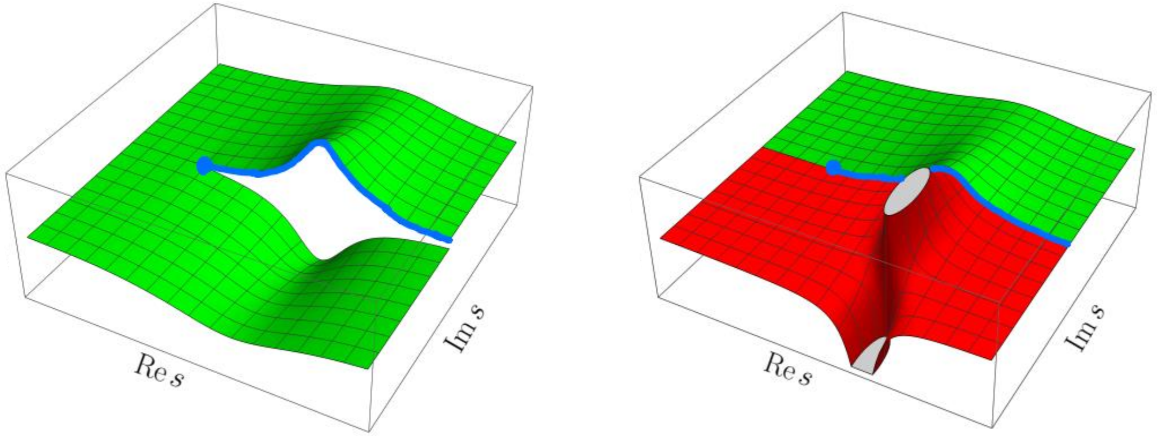
CEBAF accelerator

Spectroscopy of hadrons is important to learn about their composition (quarks and gluons), structure, and dynamics (strong force)!

Challenges in Hadron Spectroscopy with traditional techniques

Most hadrons are resonances, sometimes observed as bumps in the cross section.

Resonances are poles of the scattering amplitude in the complex energy plane



Pole parameters

$$\sqrt{s_{\mathrm{R}}} = M_{\mathrm{R}} - i\frac{\Gamma_{\mathrm{R}}}{2}$$

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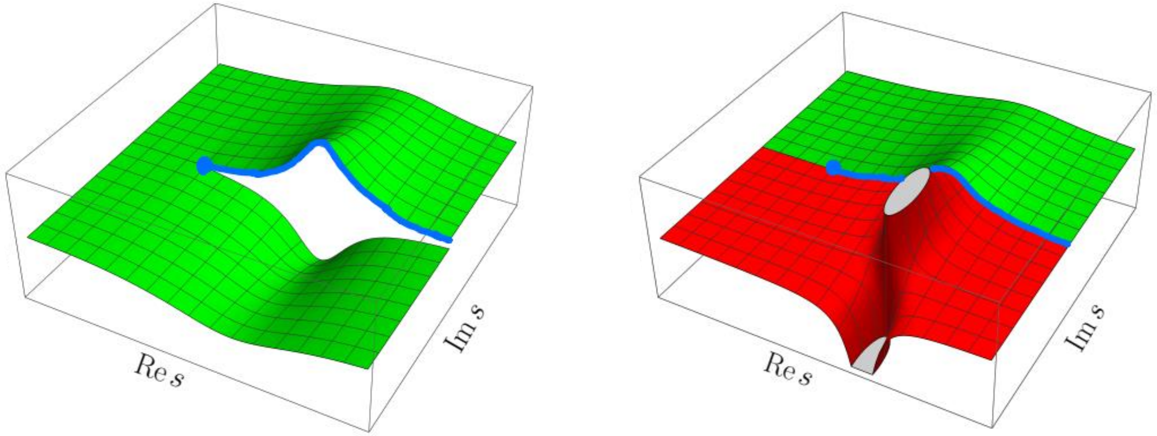
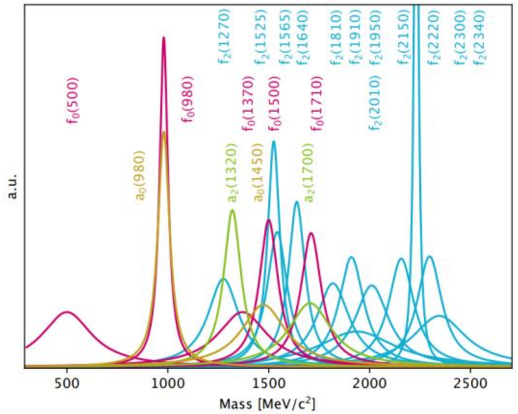


Pole parameters

$$\sqrt{s_R} = M_R - i\frac{\Gamma_R}{2}$$

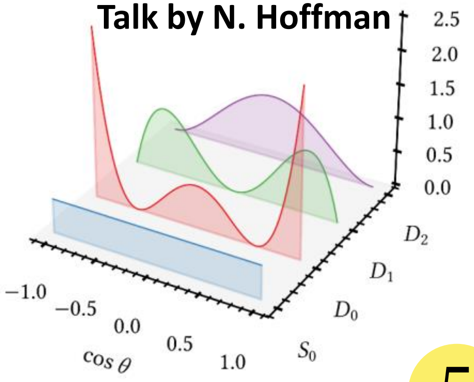
Talk by M. Küßner



Challenges in identifying and characterizing resonances

- Overlapping and broad states
- Partial wave analyses techniques are complicated and often require theoretical input
- Determining pole positions requires amplitude analyses with theoretical assumptions
- Assigning quantum numbers and internal structure (e.g. molecule vs tetraquark) is often model dependent

Talk by N. Hoffman



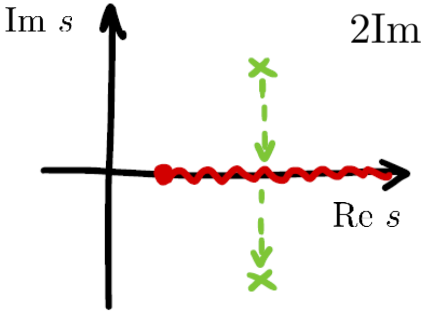
See Hadron Spectroscopy talks on Wed, June 25

Principles of Scattering Theory

Scattering amplitudes satisfy

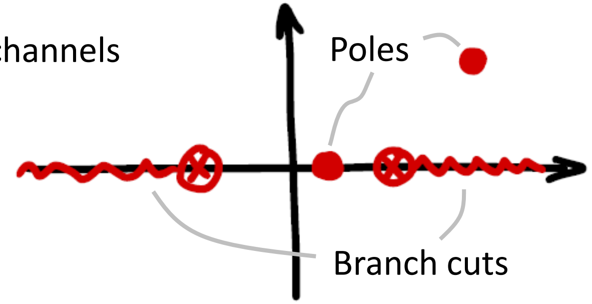
- **Unitarity:** probability conservation (all possible outcomes must add up to 100%)
- **Analyticity:** causality (outcome cannot happen before interaction, smooth dependence on energy)
- **Crossing symmetry:** swapping particles and anti-particles (the mathematical description remains the same)

Discontinuity over the unitarity cut

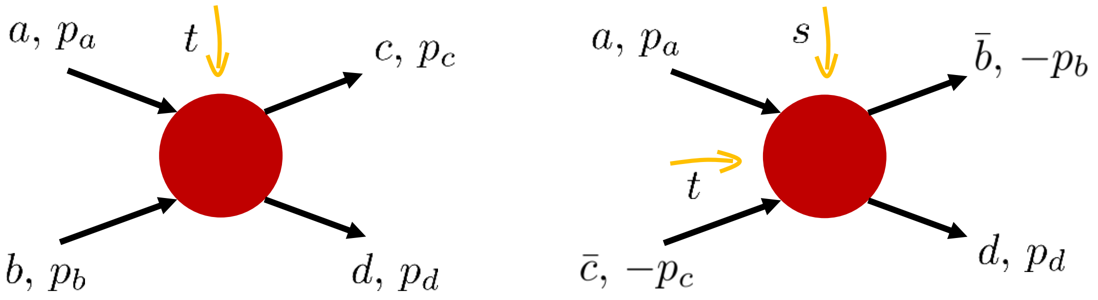


$$2\text{Im}\, A_{i\to f} \propto \sum_n A_{i\to n} A^\dagger_{n\to f}$$

Sum over all intermediate channels



$a + b \to c + d$ $\qquad$ $a + \bar{c} \to \bar{b} + d$

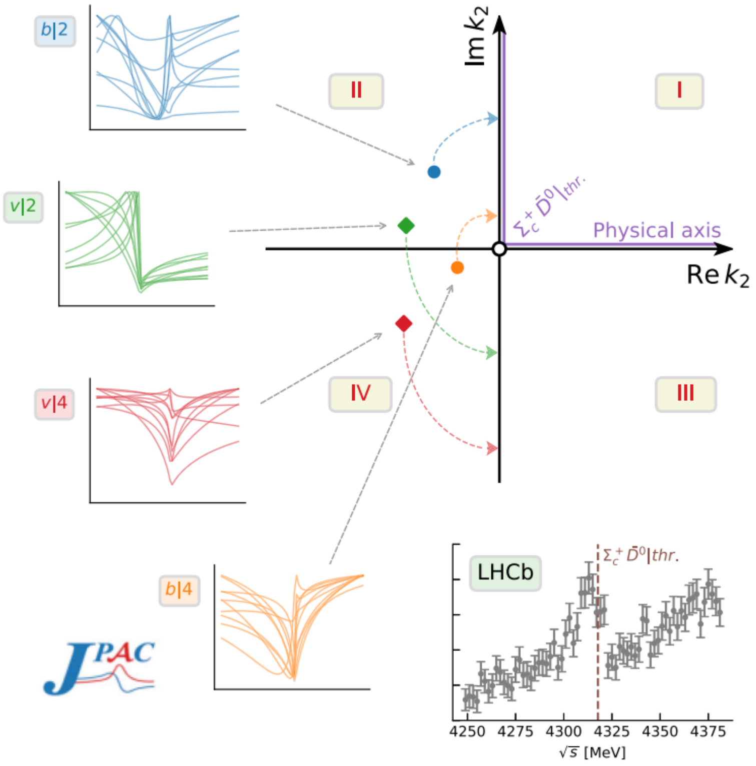


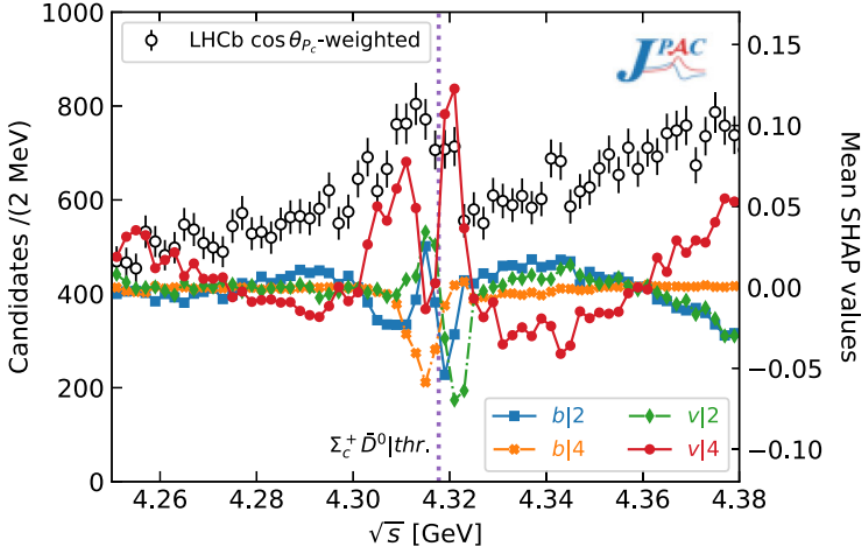
$$A_{ab\to cd}(s,t,u) = A_{a\bar{c}\to\bar{b}d}(t,s,u)$$

Deep Neural Networks as Classifiers for Hadron Spectroscopy

D.L.B. Sombillo et al. (2021)

L. Ng et al. (JPAC) (2022) → DNN to determine the nature of the $P_c(4312)$ pentaquark





Only valid for near-threshold resonances.

Results the interpretation of the $P_c(4312)$ pentaquark as a virtual state.

Work in progress to extend the method for larger class of resonances, and determine their nature and the pole position, $a_0(980)/f_0(980)$ or other resonances located near thresholds

NN analysis of pion-pion scattering data

W. Smith, A. Rodas, A. Pilloni, G. Foti, A. Fulci, M. Filippini

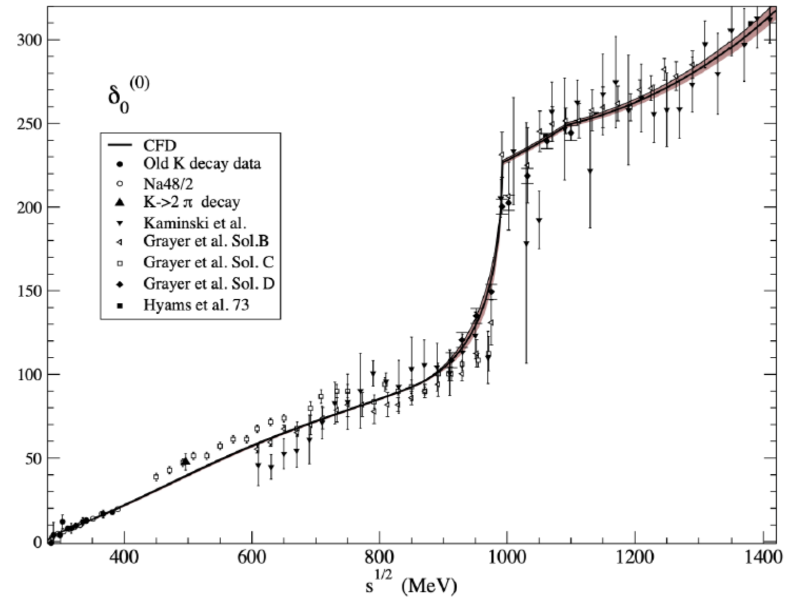
Problem: Experimental data is old, data sets are incompatible, and errors are likely underestimated!

Previous effort to parametrize ππ data:

- Select compatible data, perform unconstrained fit, slowly turn on unitarity constraints (Roy eq.)

The pion-pion scattering amplitude. IV: Improved analysis with once subtracted Roy-like equations up to 1100 MeV

R. García-Martín[a], R. Kamiński[b], J. R. Peláez[a], J. Ruiz de Elvira[a] and F. J. Ynduráin[c,*]

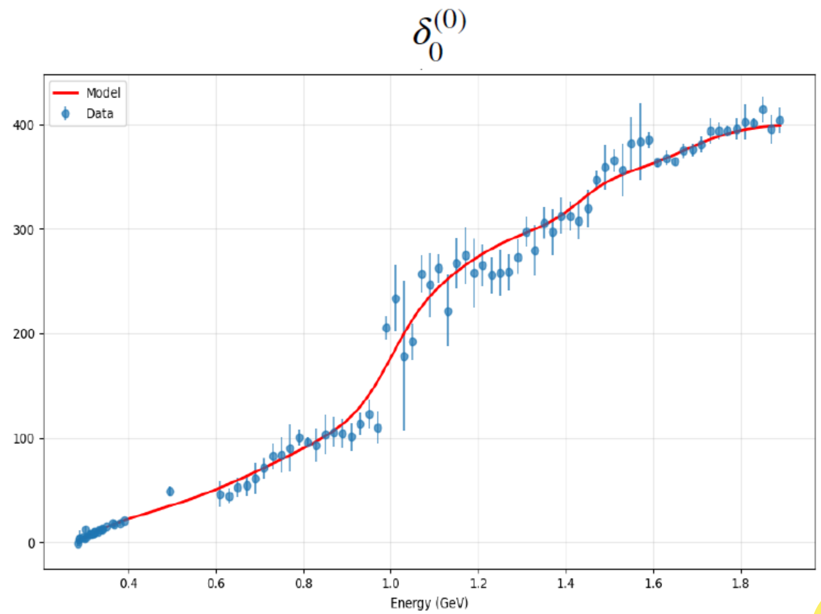


NN strategy

- Use a NN instead of a complicated model
- Train many NNs on resampled data
- Physics content enforced by carefully constructed loss function

$$\mathcal{L} = \text{MSE} + \lambda_{\text{Roy}}\mathcal{L}_{\text{Roy}} + \lambda_{\text{Regge}}\text{MSE}_{\text{Regge}}$$

Preliminary fit with MSE only



Autoencoders for Partial Wave Analyses

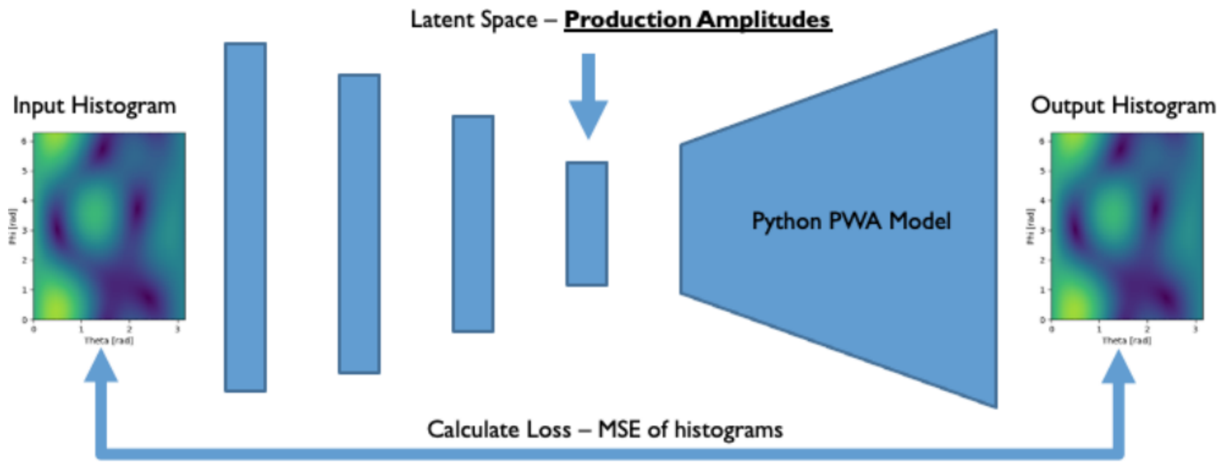
W. Phelps, C. Salgado, L. Guo, T. Reed and others

PyPWA

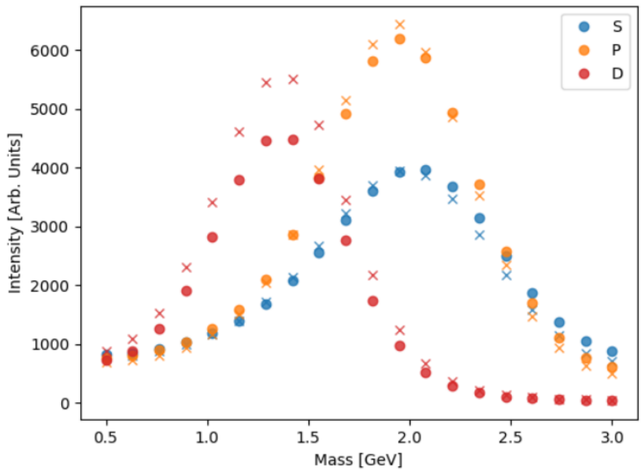
M. Jones et al. (2024)

- Uncertainty Quantification
- Wave Selection
- Mass Dependent

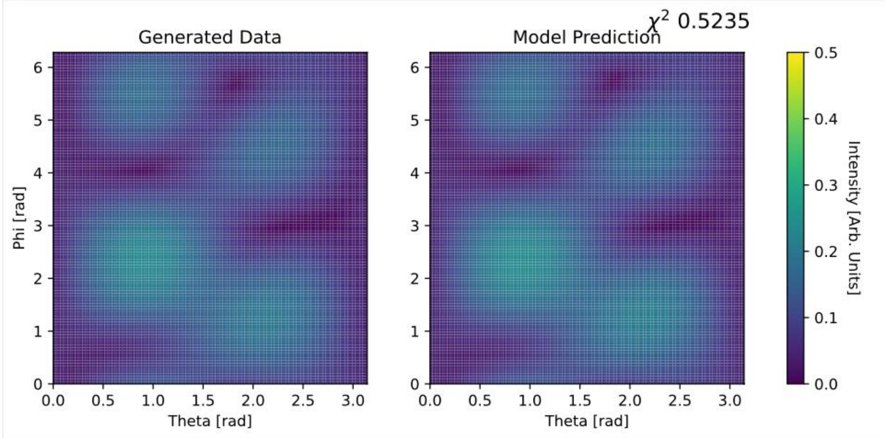
$$I(\Omega) = \sum_{\epsilon_R} \sum_{l,|m|,l',|m'|} Y_l^{\epsilon_R,|m|}(\Omega)\, V_{l,|m|}^{\epsilon_R}\, V_{l',|m'|}^{\epsilon_R *}\, Y_{l'}^{\epsilon_R,|m'|*}(\Omega)$$

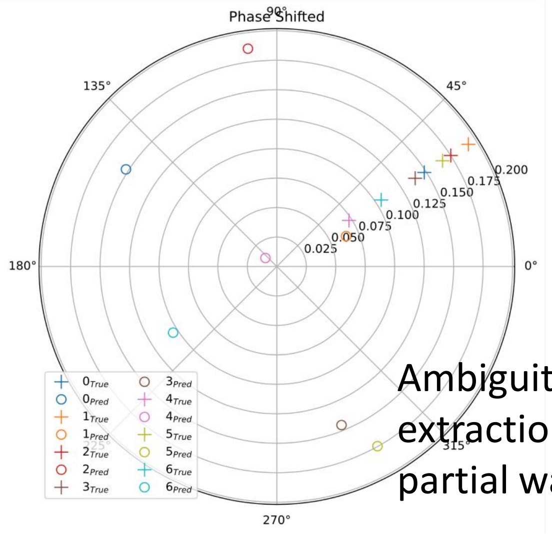


Generated vs Inferred Resonances



Generated vs Model Intensities





Ambiguities in the extraction of the partial waves

T. Reed (talk at AI for Hadron Spectroscopy at JLab 2025)

W. Phelps (talk at Nstar 2024)

The A(i)DAPT collaborative effort

A(i)DAPT
AI for Data Analysis and PreservaTion

- Experimentalists
- Theorists
- ML experts

M. Battaglieri, Y. Li, A. Pilloni, N. Sato, A. Szczepaniak, T. Alghamdi, T. Vittorini, D. Glazier, L. Bibrzycki, D. Lersch, T. Reed, G. Montana, G. Foti, M. Spreafico, and others

- Experimental data are inherently distorted by detector effects

- Detector effects must be unfolded before extracting meaningful physics

- Traditional observables may not be adequate in multidimensional space (multi-particles final states)

- High-intensity experiments produce large datasets, which can be difficult to manipulate/preserve

→ Develop generative AI methods to:

- Accurately fit data in multiD space
- Unfold detector effects
- Compare synthetic (AI-generated) to experimental data
- Quantify the uncertainties
- Move from cross sections to amplitudes

AI to reproduce experimental data

ML Event Generator with GANs

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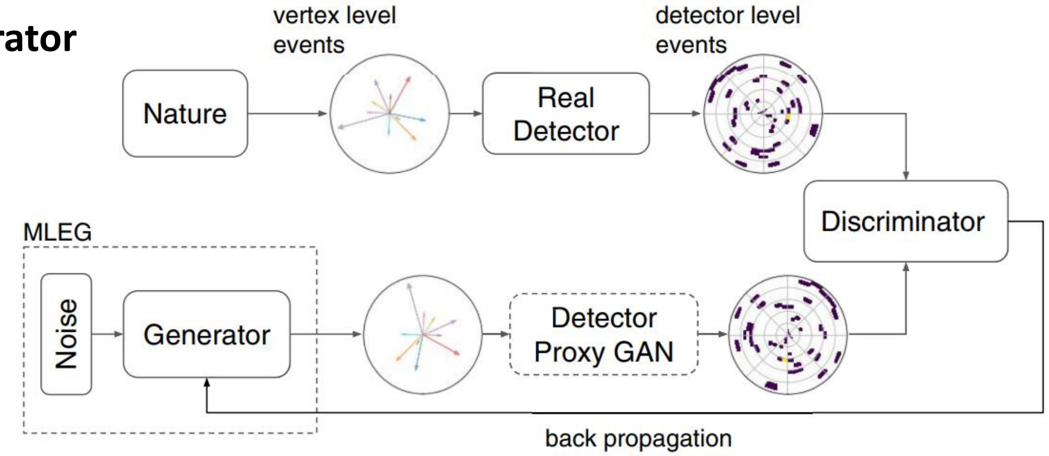

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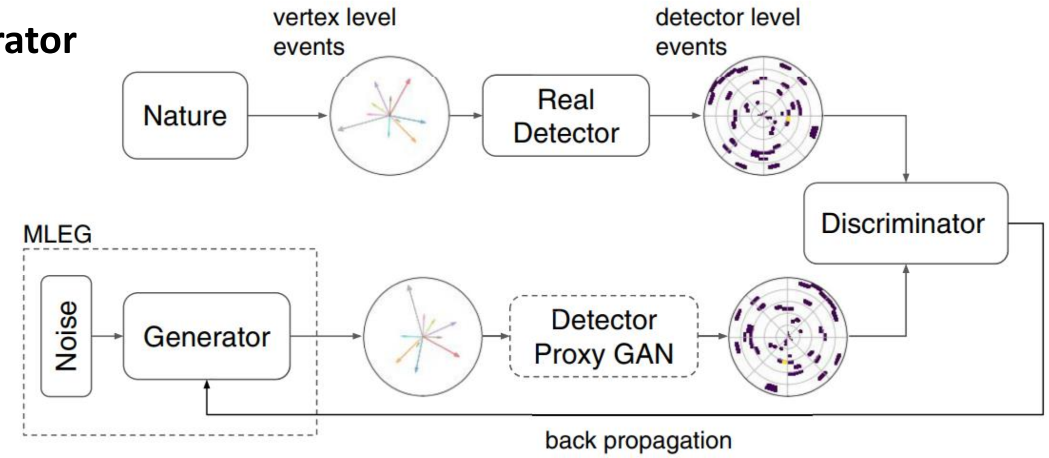
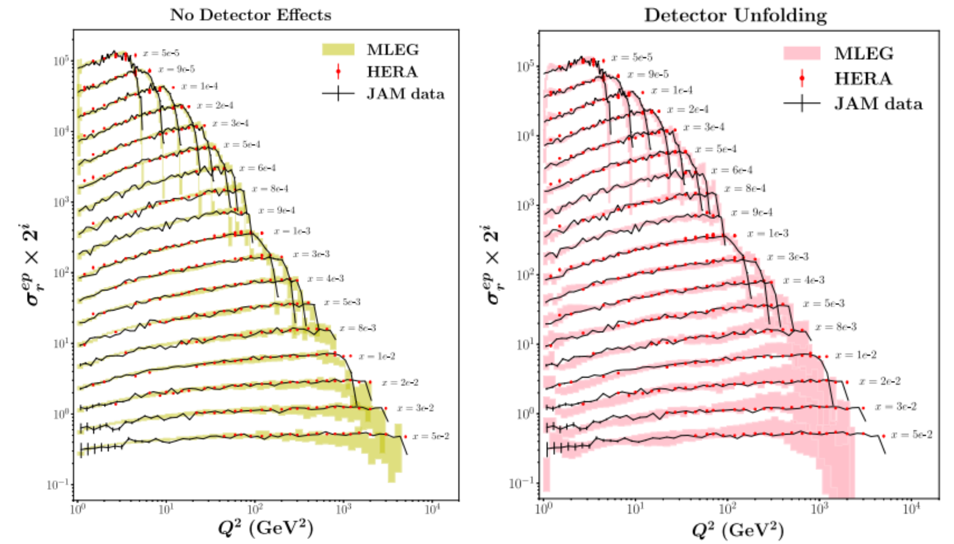


Tested and validated on simulated data of inclusive DIS

Alanazi et al. (2022)



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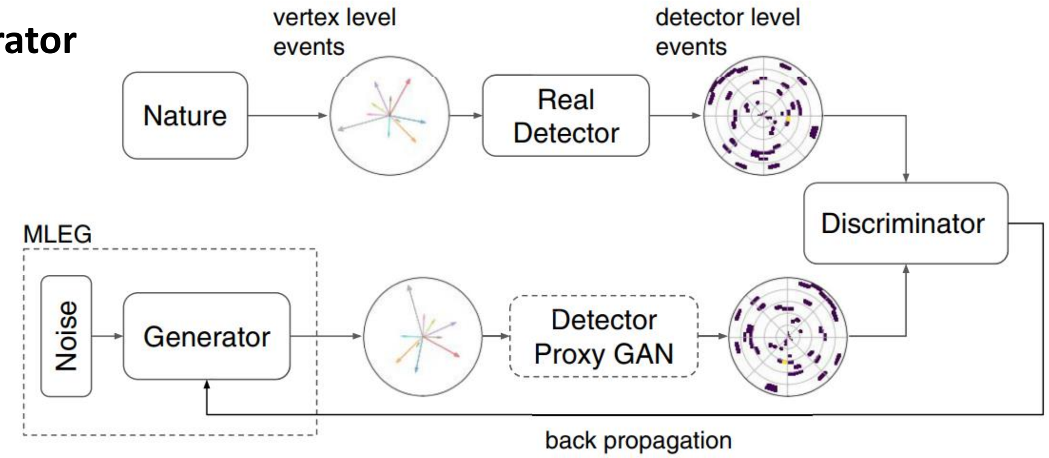

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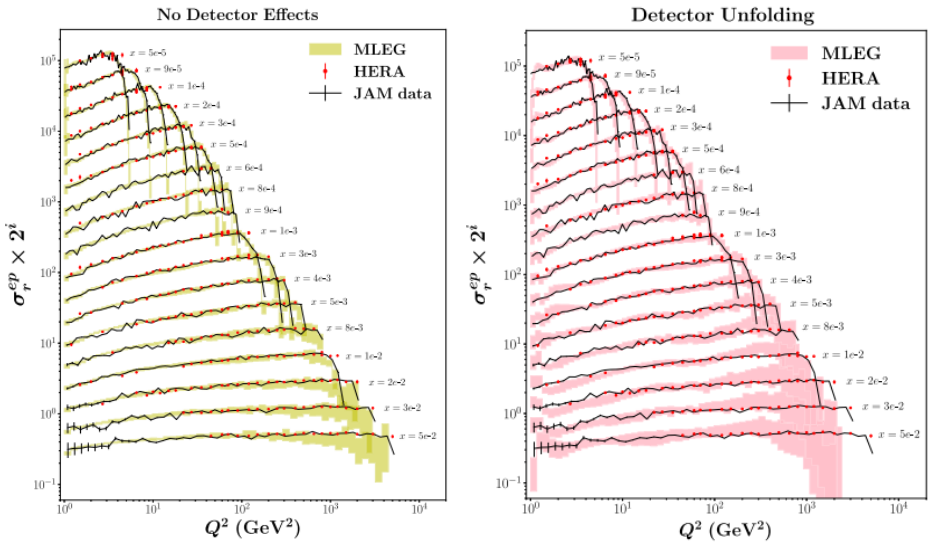
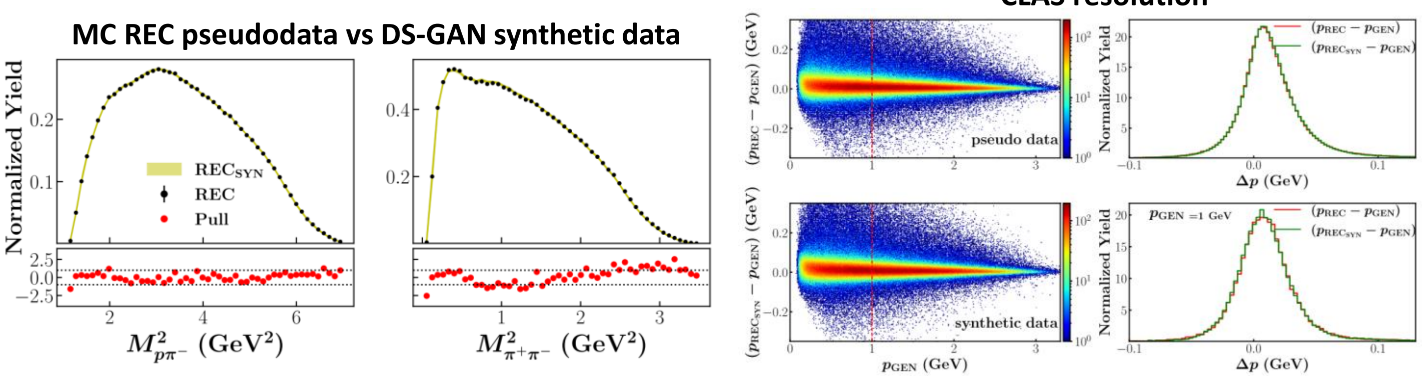


Closure test on pseudodata of CLAS exclusive 2π photoproduction

Alghamdi et al. (2024)

MC REC pseudodata vs DS-GAN synthetic data

CLAS resolution



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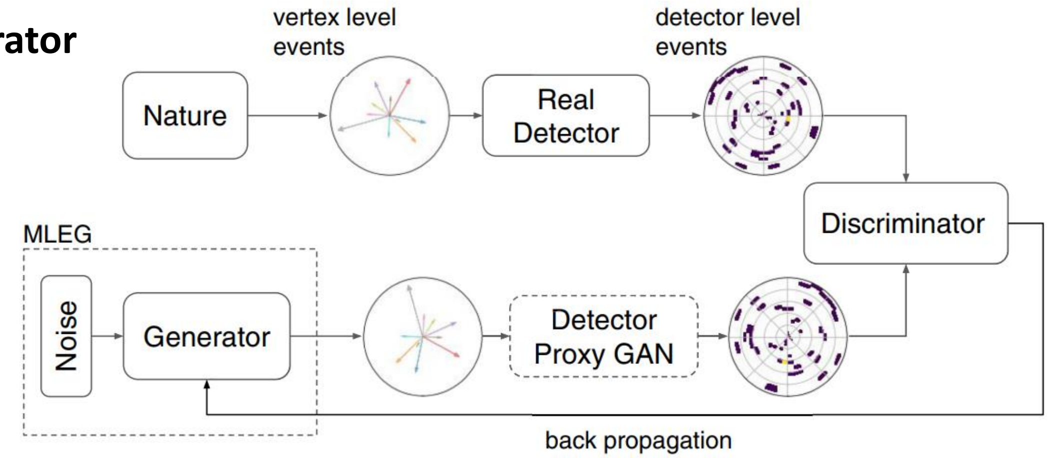

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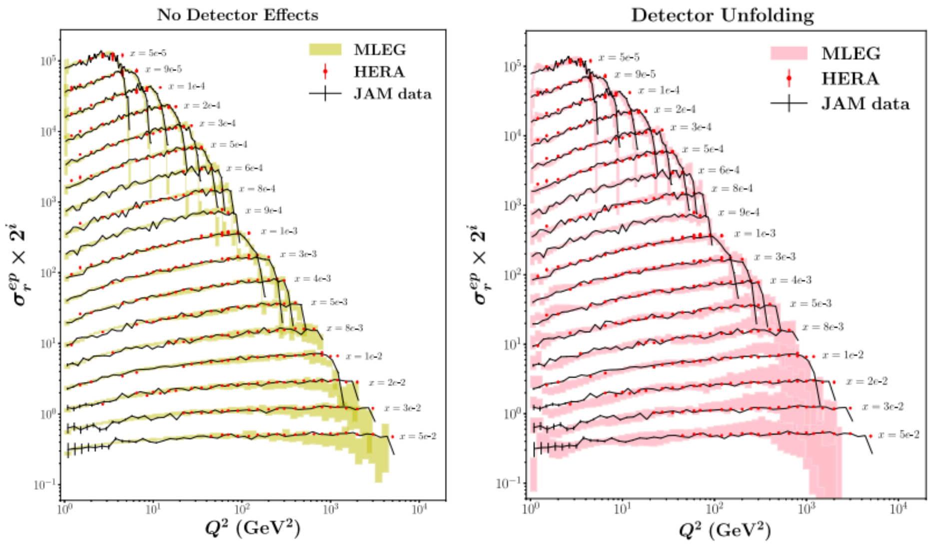

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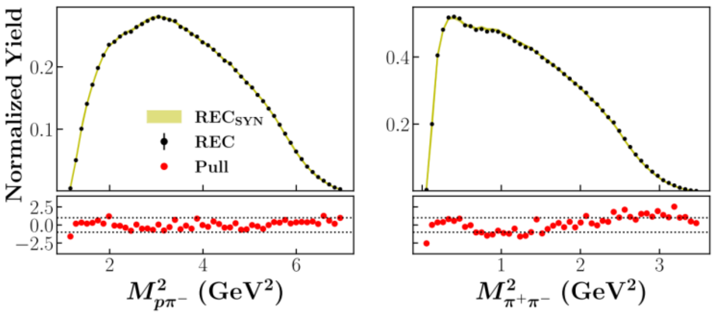

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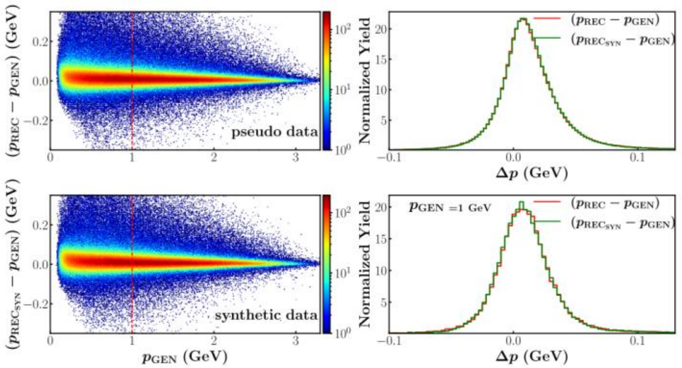
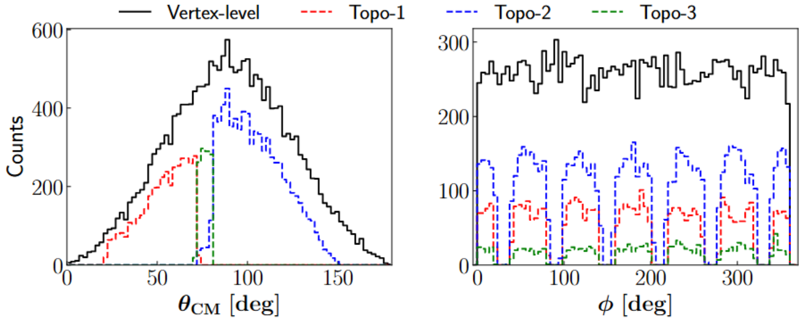


Smearing and acceptance of CLAS detector in $\gamma p \to \pi^0 p$

Alghamdi et al. (in preparation)



See poster by T. Vittorini

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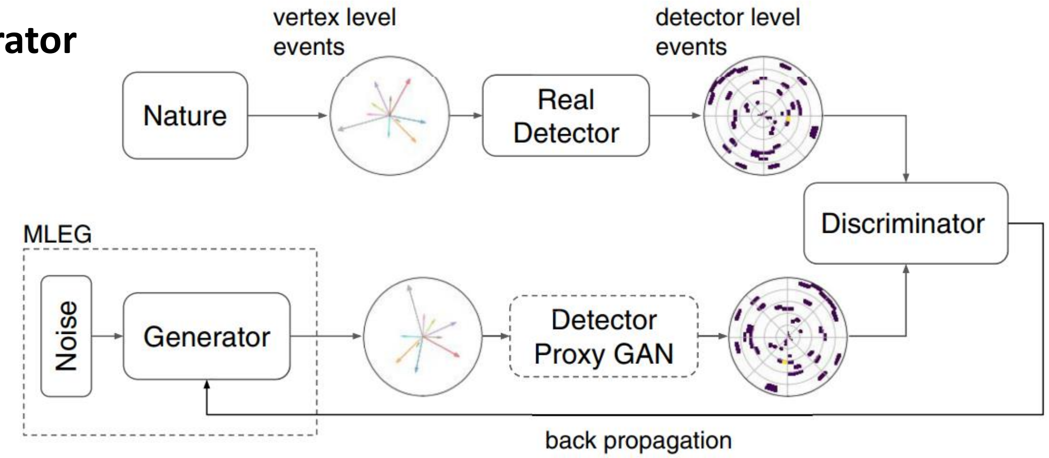

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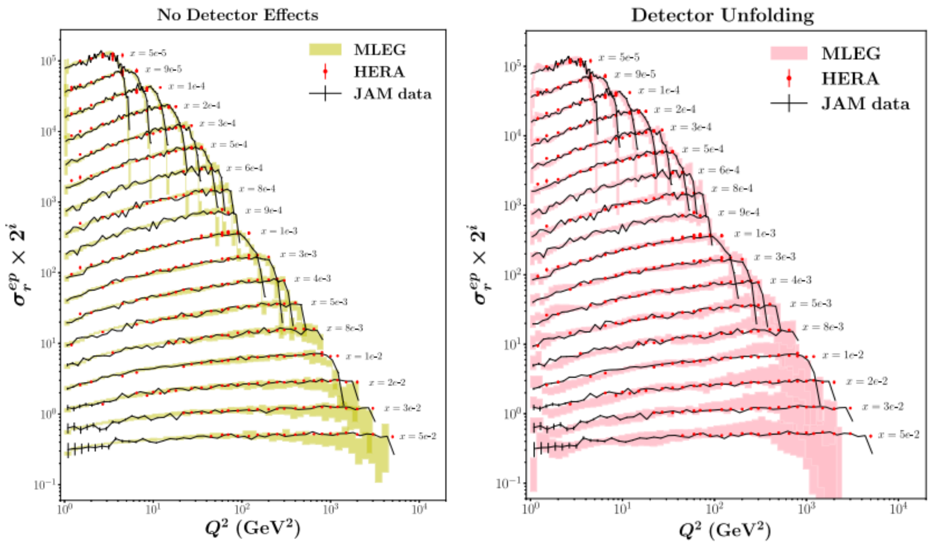

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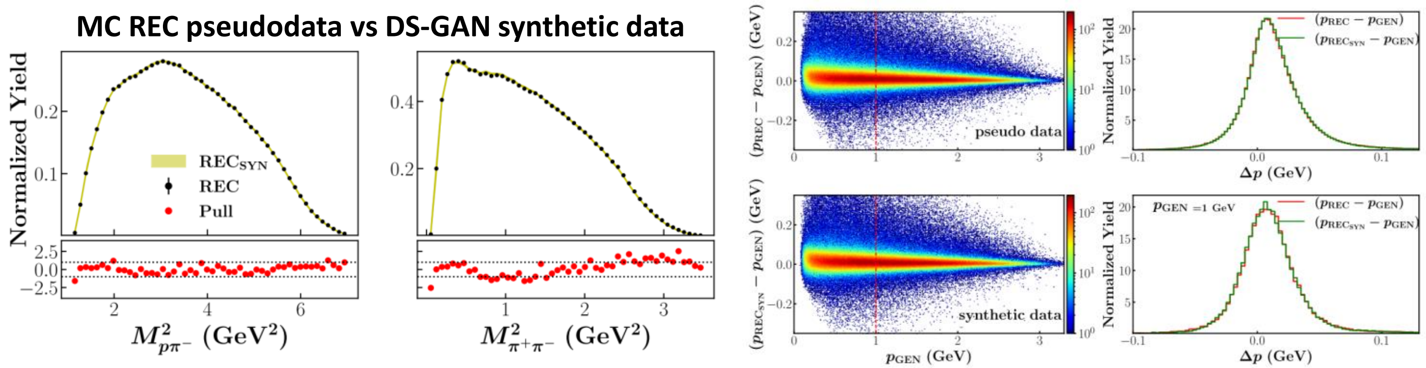

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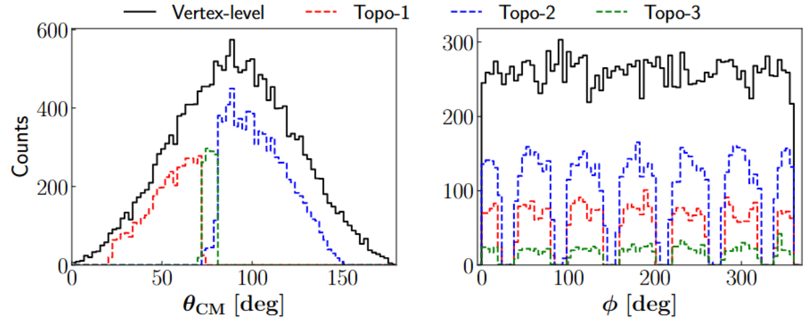

See poster by T. Vittorini

Diffusion Model for CLAS detector effects unfolding in photoproduction of π+π- photoproduction

CLAS moments: Battaglieri et al. (2009)
JPAC model: Bibrzycki et al. (2025)

AI to extract scattering amplitudes

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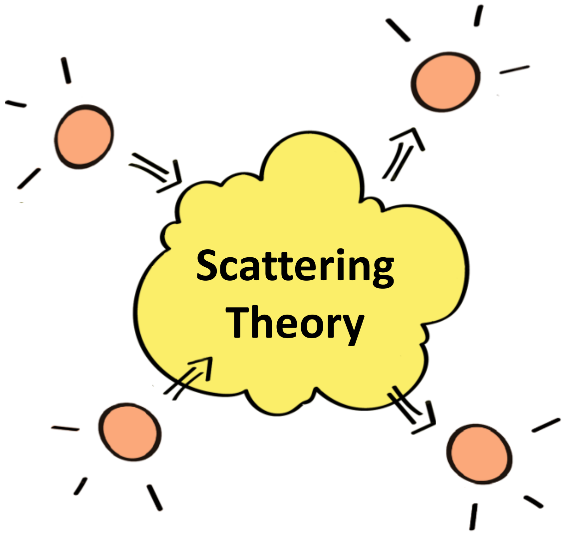
AI for Data Analysis and PreservaTion

The **scattering amplitude** $\mathcal{A}$ is the fundamental quantity of interest in hadron reactions:

- Encodes the underlying dynamics of the interaction
- Crucial for understanding resonance production, decays…
- Is a complex quantity: magnitude + phase



The **cross section** σ is an experimentally observable quantity:

- Related to $|\mathcal{A}|^2$
- The information about the phase is lost

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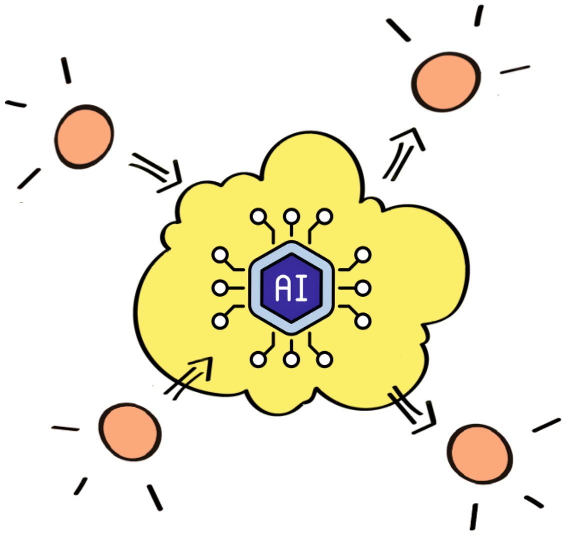

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Physics-informed generative models

- ✓ Learn distributions and patterns of the (pseudo) data
- ✓ Incorporate physics constraints, e.g. unitarity

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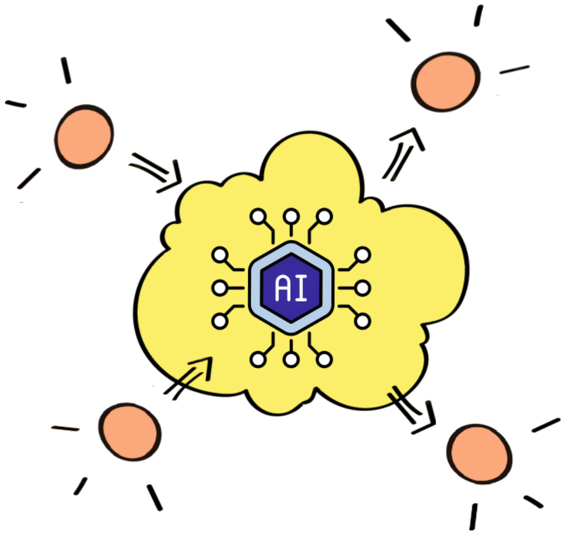

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Physics-informed generative models

- ✓ Learn distributions and patterns of the (pseudo) data
- ✓ Incorporate physics constraints, e.g. unitarity

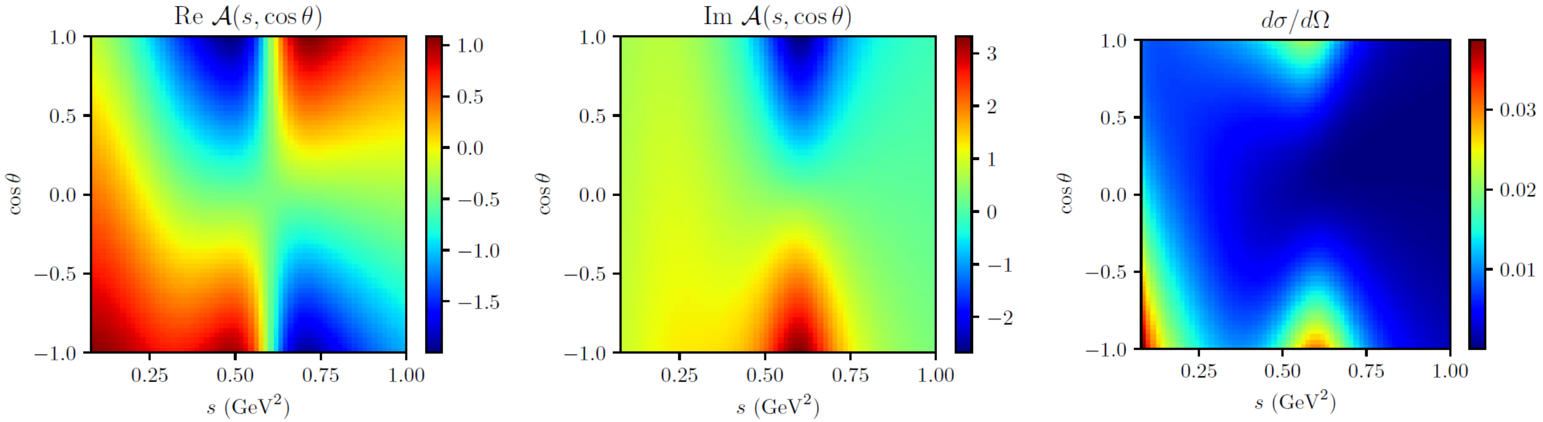
Input model for closure test

Elastic scattering $\pi^+\pi^- \to \pi^+\pi^-$ dominated by $f_0(500)$ and $\rho(770)$ resonance

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

$$f_\ell = \frac{m_\ell \Gamma_\ell}{m_\ell^2 - s - i m_\ell \Gamma_\ell}$$

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

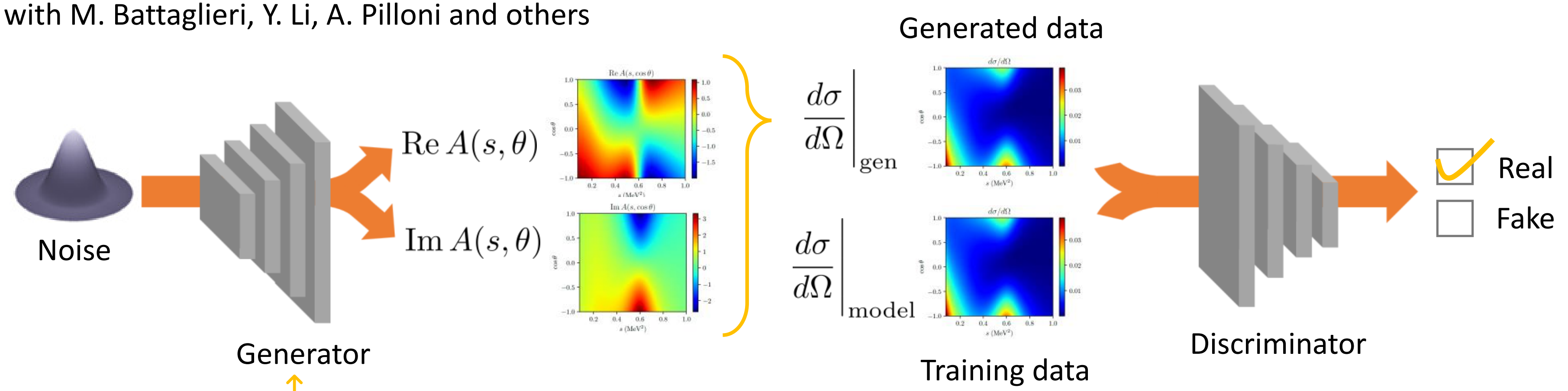


AI to extract scattering amplitudes

A(i)DAPT
AI for Data Analysis and PreservaTion

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

Physics-constrained GAN



+ Physics constraints in loss function

$$\mathcal{L} = \mathcal{L}_{\text{GAN}} + \lambda_{\text{u}}\mathcal{L}_{\text{u}} + \lambda_{\delta}\mathcal{L}_{\delta}$$

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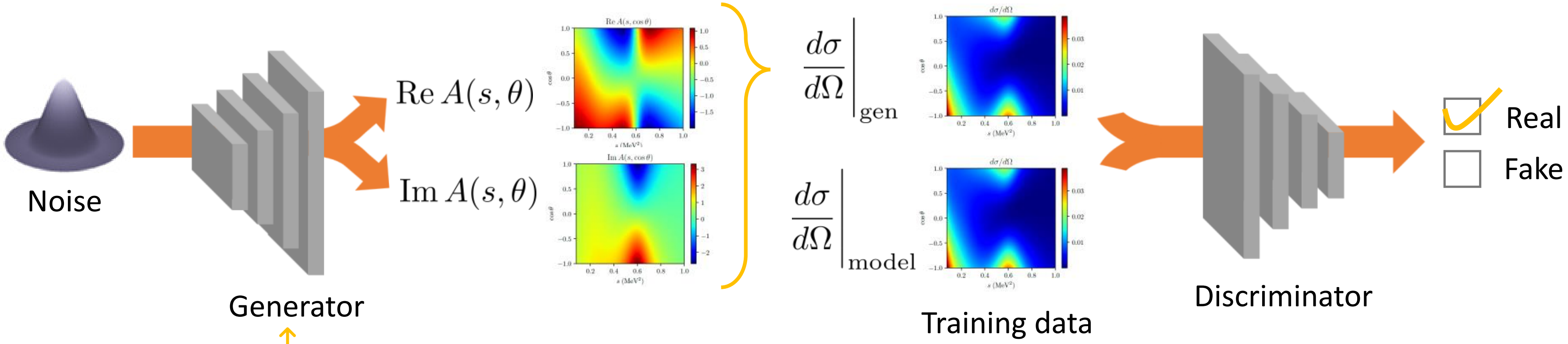

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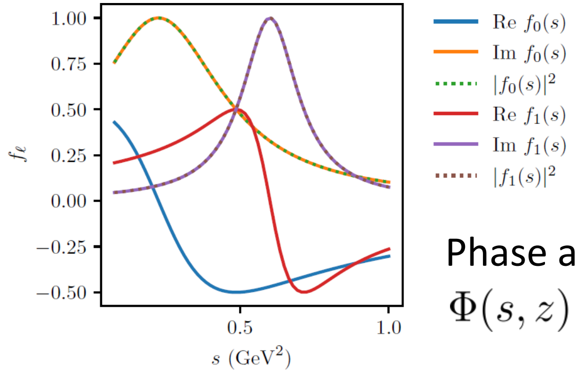
$$\text{Im } f_\ell(s) = |f_\ell(s)|^2$$



Phase ambiguity:

$$\Phi(s,z) \to \pi - \Phi(s,z)$$

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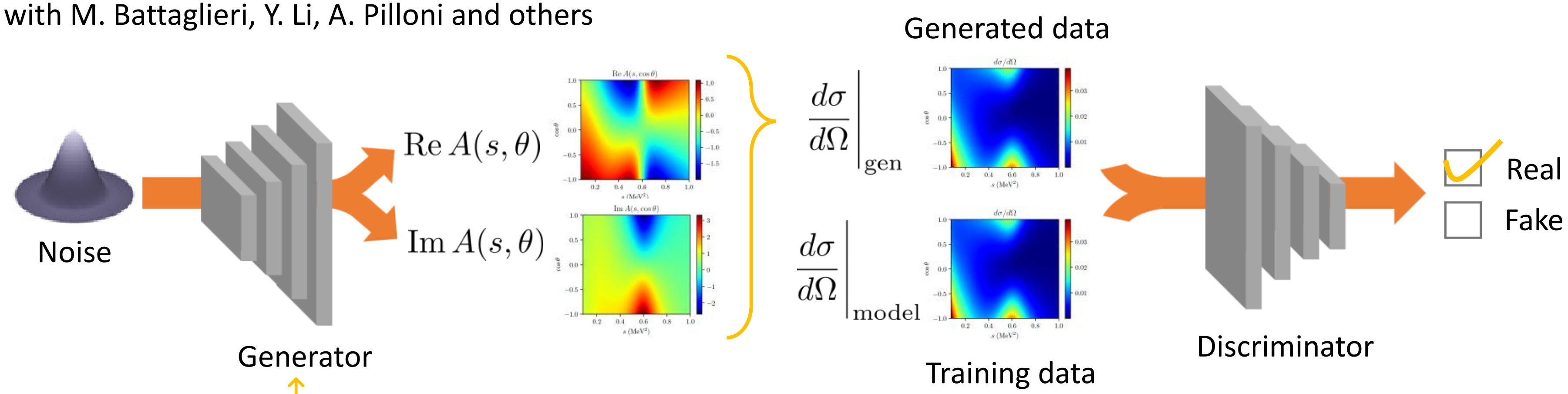

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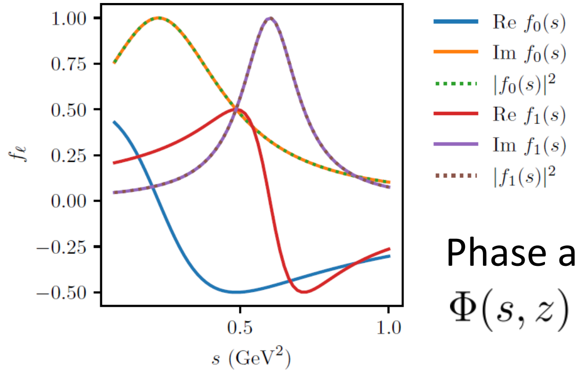
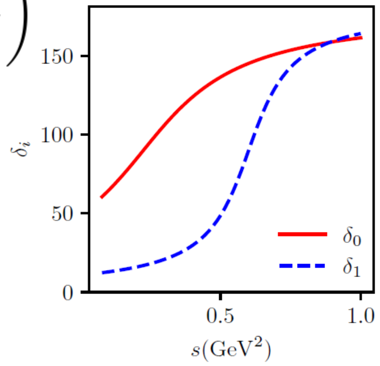


2 Positive derivative of the phase shifts

$$\delta_\ell = \text{atan}\left(\frac{\text{Im } f_\ell(s)}{\text{Re } f_\ell(s)}\right)$$



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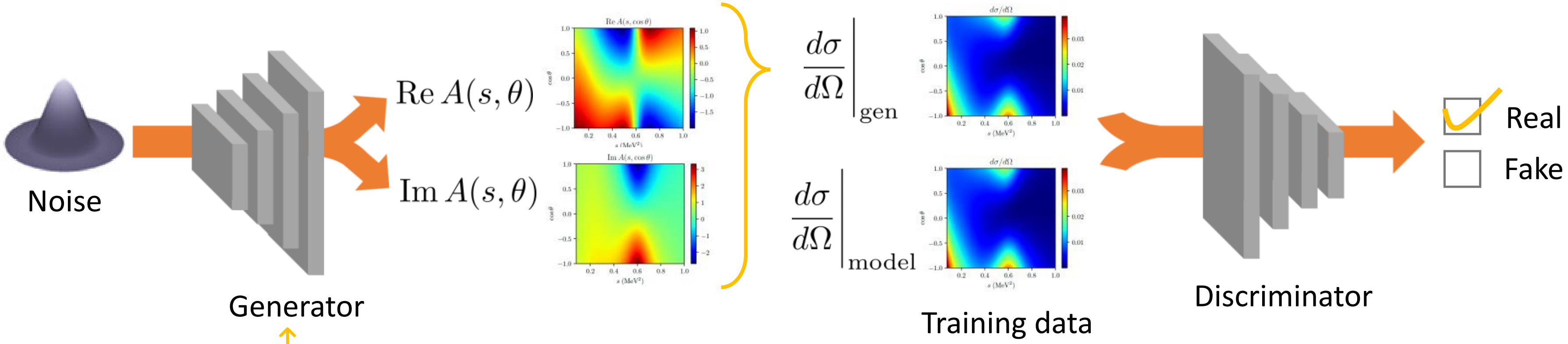

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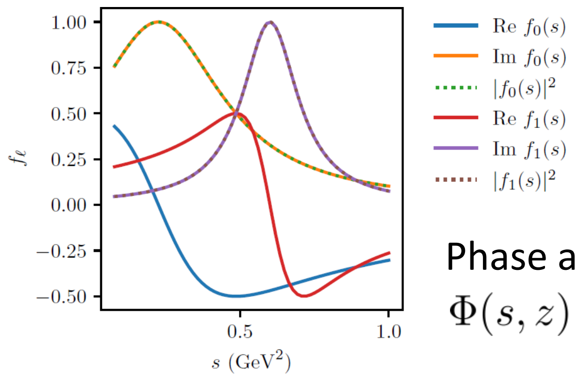

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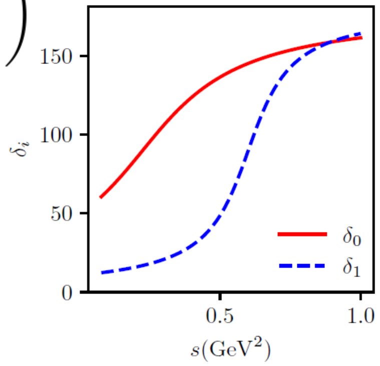

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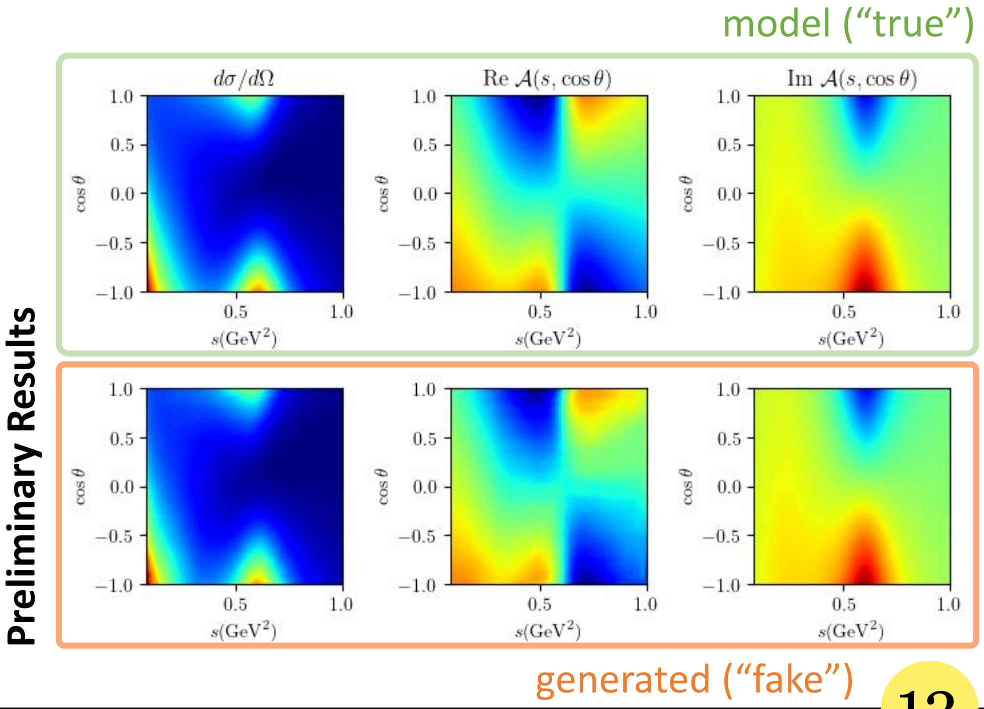
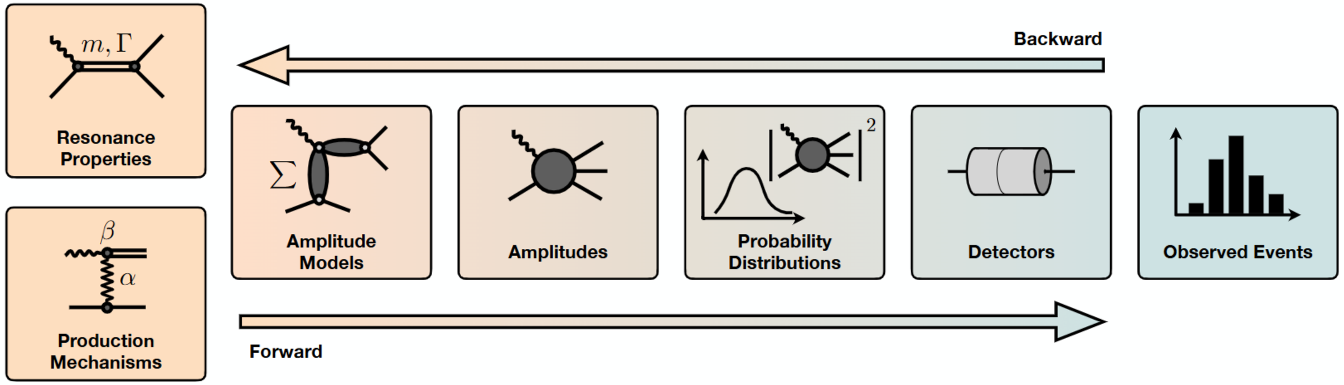


Building the future for AI-driven hadron spectroscopy at JLab

DOE FOA Proposal – FY25 Submission

- Funding Opportunity: *Artificial Intelligence and Machine Learning Applied to Nuclear Science and Technology* (DE-FOA-0003458, DOE Office of Nuclear Physics)
- Proposal Title: *Generative AI for Low Multiplicity Inclusive and Exclusive Reactions at Jefferson Lab*
- Participants: UVA, JLab, Argonne, LBNL, W&M, IU, ODU + unfunded international institutions



1. Theory development
2. Event level detector unfolding
3. Amplitude level unfolding
4. Full unfolding to amplitudes

Workshop organization:

- Digital Twins for Nuclear and Particle physics - NPTwins 2024 (Dec 16-18, 2024, Genova)
- AI for Hadron Spectroscopy at JLab (June 4-5, 2025, Jefferson Lab)
- Digital Twins for Nuclear and Particle physics - NPTwins 2025 (Oct 6-8, 2025, Messina)

Summary and Outlook

- The application of AI, particularly generative models, to amplitude analyses and hadron spectroscopy is a relatively recent but rapidly advancing effort
- Significant progress has been made in identifying key challenges and demonstrating the value of AI-enhanced approaches
- Collaboration across disciplines, combining expertise from experiment, theory, and data science, has been essential to this progress
- Generative AI models, when combined with physics-informed constraints, showing strong potential to overcome limitations of traditional amplitude analysis techniques and the extraction of physics insights from data
- Future efforts will focus on uncertainty quantification, integrating physics knowledge more deeply, scaling models to higher-dimensional data, and improving interpretability
- First steps toward Simulation Based Inference have been achieved, which will ultimately enable the direct extraction of physical quantities (e.g. pole positions, couplings) directly from experimental data, beyond the reach of traditional techniques
- This is a rapidly evolving and exciting research area. As AI tools continue to evolve, they will unlock new opportunities in hadron spectroscopy and amplitude analyses that we have not yet imagined