Working Group

Bayesian Inference for Quantum Correlation Functions

Wally Melnitchouk

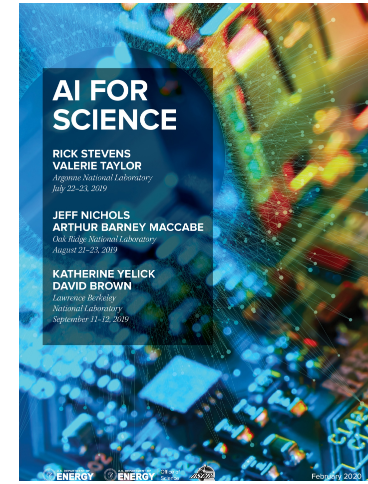
— Jefferson Lab —

Grand Challenge

- Map out nucleon's internal 3-D quark and gluon structure — "femtography"

- Quarks & gluons confined, never observed directly — "inverse problem"

- Develop next generation of QCD analysis tools to map between observables and "quantum correlation functions"
  (parton distribution functions, fragmentation functions, transverse momentum dependent distributions, generalized parton distributions, …)



2. Major (Grand) Challenges

Advances in the use of AI/ML/DL techniques in nuclear physics will be driven by the volume and complexity of new data—both from experimental facilities (as described above) and from theory and simulation. The ability to discern physical causality and discover new phenomena will require the application of new technologies to augment human understanding. We note several grand challenges for better understanding the nature of matter in this section.

Generate detailed tomography of the proton/nuclei. This 3D tomography of hadrons and nuclear structure is not directly accessible in experiments. Obtaining the quantities of interest, such as generalized and transverse momentum dependent parton distribution functions (Generalized Parton Distributions (GPDs) and Transverse Momentum Distributions (TMDs)), involves an inverse problem. This is because these objects are inferred from experimental data using theoretical frameworks such as quantum chromodynamics (QCD) factorization theorems (e.g., collinear factorization, TMD factorization). Such a procedure allows one to connect experimental data to quantum probability distributions that characterize hadron and nuclear structure and the emergence of hadrons in terms of quark and gluon degrees of freedom.

Existing techniques to extract probability distributions from data have primarily been used to obtain a 1D tomography of hadrons, provided by parton distribution and fragmentation functions. These techniques usually rely on Bayesian likelihood techniques and Monte Carlo sampling methods, which are coupled with suitable parametrizations for the distribution functions of interest (Figure 5.3).

AINP working group: **Bayesian Inference for Quantum Correlation Functions**

Wednesday, 4 March, 14:00 - 17:30

14:00 **Nobuo Sato** (JLab)
"Quantum correlations functions overview"
14:15 **Alberto Accardi** (Hampton U./JLab)
"Measuring the unobservable: quark and gluon distributions in the proton"
14:30 **Juan Rojo** (Nikhef)
"Artificial intelligence to map the proton structure"
14:45 **Andrea Signori** (Pavia U./JLab)
"Structure of TMD observables"
15:00 **Christian Weiss** (JLab)
"Generalized parton distributions overview"
15:15 **Break**

15:30 **Carlota Andres** (JLab)
"JAM multi-step strategy"
15:45 **Yiyu Zhou** (William & Mary)
"AI for jets in JAM"
16:00 **Patrick Barry** (NCSU)
"Pion PDFs and challenges in implementing threshold resummation"
16:15 **Chris Cocuzza** (Temple U.)
"Machine learning for global fits"
16:30 **Alexei Prokudin** (PSU Berks)
"The origin of spin asymmetries"
17:00 **Simonetta Liuti** (U. Virginia)
"ML-based analysis of deeply-virtual exclusive processes"
17:30 **Adjourn**

Thursday, 5 March, 14:00 - 17:30

14:00 **Nobuo Sato** (JLab)
"Universal Monte Carlo event generator"
14:15 **Tianbo Liu** (JLab)
"GAN from pseudo data to real data: inverse problem for detector effects"
14:30 **Luisa Valesco** (U. Dallas)
"GANs for ETHER"
14:45 **Yaohang Li** (ODU)
"FAT-GAN architecture for simulation of electron-proton scattering events"
15:00 **Yasir Alanazi** (ODU)
"CNN-GAN for physical event generation"
15:15 **Break**

15:30 **Nobuo Sato** (JLab)
"Next generation of QCD global analysis tools"
15:45 **Manal Alemeen** (ODU)
"Machine learning prototypes to solve the inverse problem"
16:00 **Herambeshwar Pendyala** (ODU)
"Towards an interactive web based global fitter"
16:15 **Break**

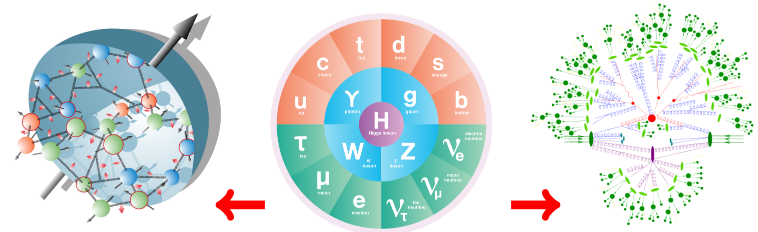
16:30 **Jake Ethier** (Nikhef)
"Nuclear PDFs with neural nets"
16:45 **Kostas Orginos** (William & Mary/JLab)
"PDFs from the lattice"
17:00 **Jake Bringewatt** (U. Maryland)
"Confronting lattice parton densities with global analysis"
17:15 **Discussion**

17:30 **Adjourn**

Statement of the problem: from observable cross sections to QCFs (inverse problem)

$\longrightarrow$ Nobuo Sato: overview

hadrons as emergent phenomena of QCD



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$\longrightarrow$ Alberto Accardi: PDFs

Inverse problem

$$\sigma_i^{\text{exp}} = \phi \otimes \hat{\sigma}_i^{\text{th}}$$

INPUT: O(5000) measurements

OUPUT: ∞–dimensional functional space

What do we mean by "**factorization**"? e.g DIS

$$F_2(x,Q) = x \sum_j e_j^2 \int_x^1 \frac{d\xi}{\xi} \boxed{C_2(\xi,\mu)} \boxed{f_j\left(\frac{x}{\xi},\mu\right)}$$

- $\boxed{C_2}$ is calculable in perturbative QCD
- $\boxed{f_j}$ cannot be solved in closed form
  $\rightarrow$ **inverse problem**

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- Statement of the problem: from observable cross sections to QCFs (inverse problem)

→ Andrea Signori: TMDs

TMD factorization

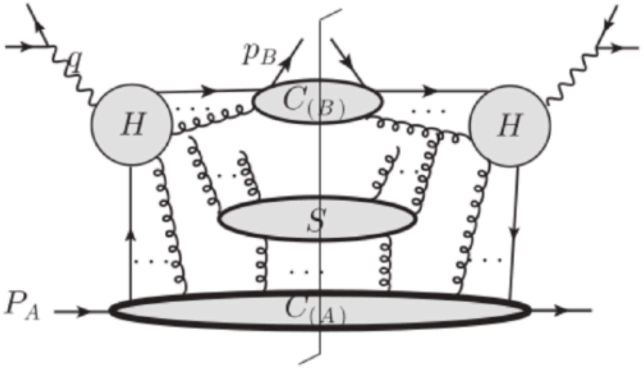
Proper separation of perturbative and non-perturbative (= structure) physics

$$F_{UU,T}(x,z,P_{hT}^2,Q^2) = \sum_a \mathcal{H}^a_{UU,T}(Q^2)$$
$$\times\, x \int d^2p_T\, d^2k_T\, \delta^{(2)}(zk_\perp + P_\perp - P_{hT})\, f_1^{a/N}(x,p_T^2,Q^2)\, D_1^{a\to h}(z,k_T^2,Q^2)$$
$$+\, Y_{UU,T}(x,z,P_{hT}^2,Q^2) + \mathcal{O}(M^2/Q^2) \approx$$

low transverse momentum

$$\approx \sum_a \mathcal{H}^a_{UU,T}(Q^2) \int_0^\infty db_T\, b_T\, J_0(b_T|P_{hT}|/z)\, \tilde{f}_1^{a/N}(x,b_T^2,Q^2)\, \tilde{D}_1^{a\to h}(z,b_T^2,Q^2)$$

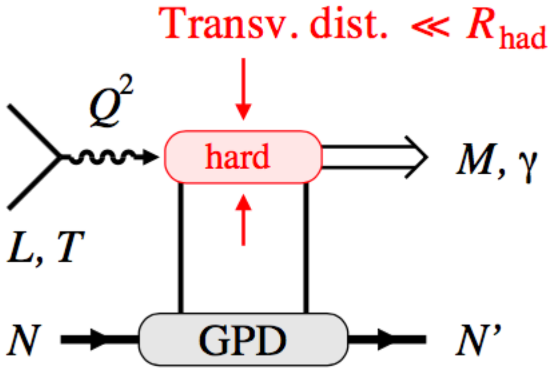
- $\mathcal{H}$: perturbative
- $\tilde{f}_1, \tilde{D}_1$: perturbative and non-perturbative



picture from Collins pQCD book

Statement of the problem: from observable cross sections to QCFs (inverse problem)

→ Christian Weiss: GPDs



GPDs: Summary

- GPDs should be regarded as "concept" more than "function"

  Synthesize information, relate various structures/measurements

  Not necessarily to be measured "point by point"

- Main limitations of GPD studies on physics side

  Relevance of asymptotic expressions for observables, power/higher-twist corrections?

  Complex structure of GPDs; connection between regions depends on dynamics

  Relation to observables through singular integrals

- Small x: Reduced complexity, successful phenomenology

- Large x: GPD extraction essentially model-dependent

  Alternative: Amplitude extraction, model-independent, reduced information

- Potential role of AI: Amplitude extraction from DVCS

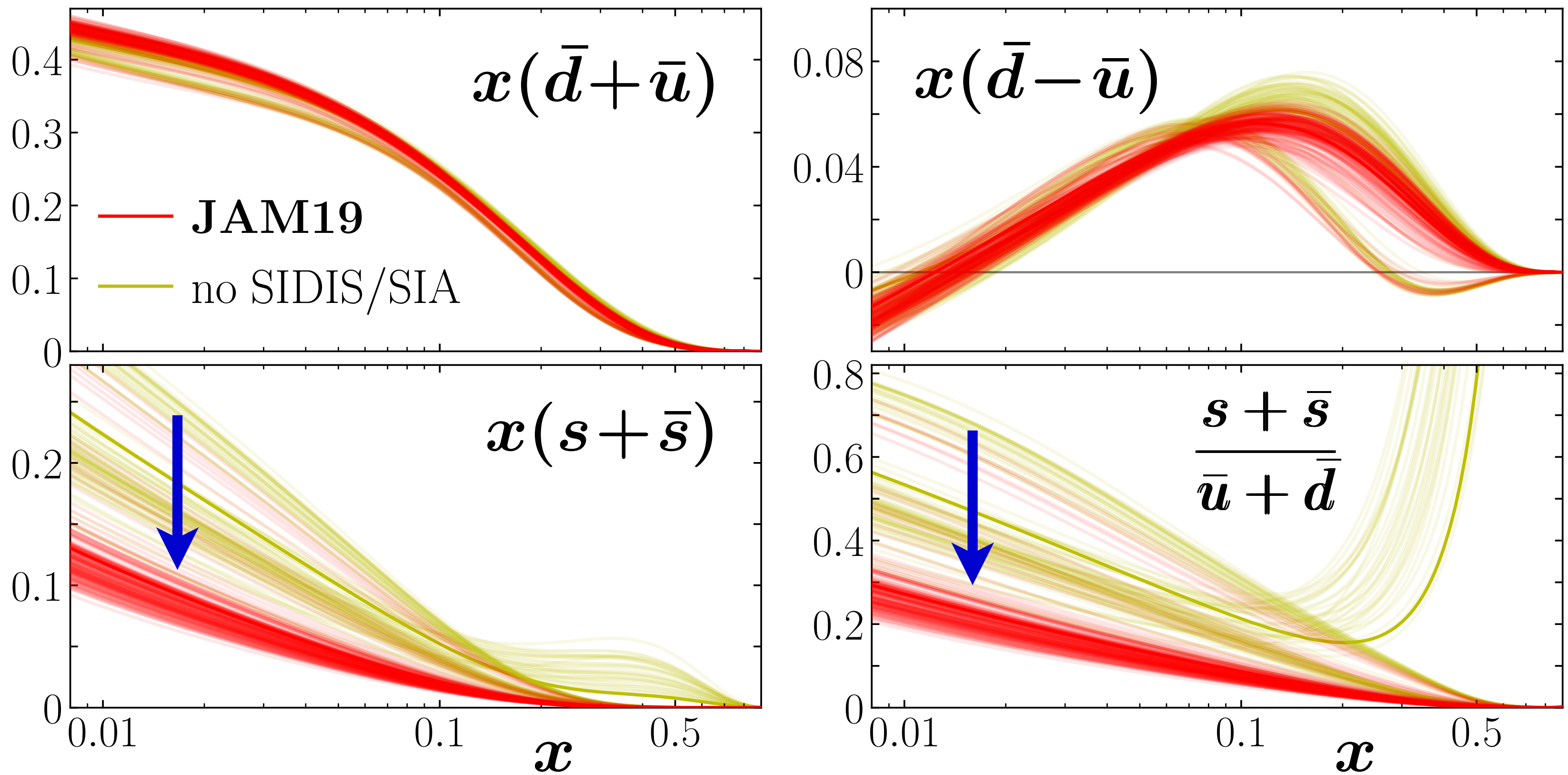
  Other applications?

State-of-the-art analysis

- → Carlota Andres: first simultaneous analysis of 1-D nucleon structure and hadronization ("JAM19")
- → Juan Rojo: neural net methodology for proton PDFs; GANs for PDFs
- → Jake Ethier: nuclear PDFs with neural nets
- → Alexei Prokudin: first universal analysis of 3-D structure (TMDs)
- → Simonetta Liuti: neural nets for GPDs
- → Jake Bringewatt, Kostas Orginos: synergies with lattice QCD

State-of-the-art analysis

→ <u>Carlota Andres</u>: first simultaneous analysis of 1-D nucleon structure and hadronization



→ vital role played by SIDIS + SIA data in constraining strange PDF

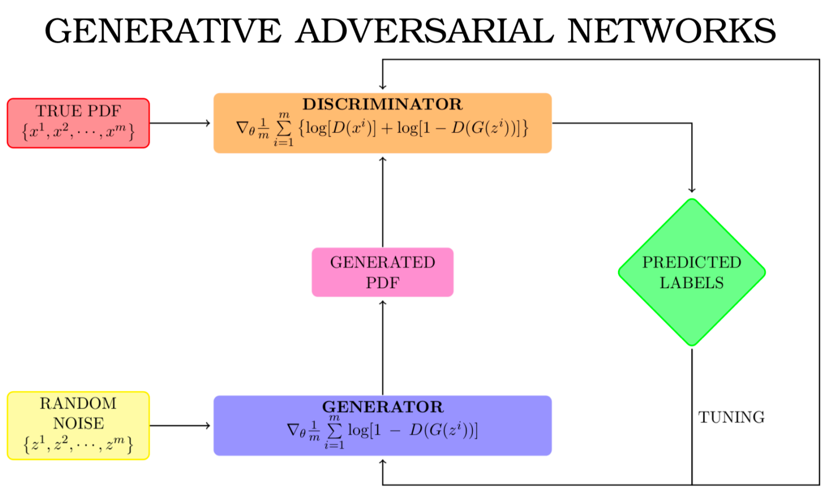
→ could not have seen this without simultaneous MC analysis

State-of-the-art analysis

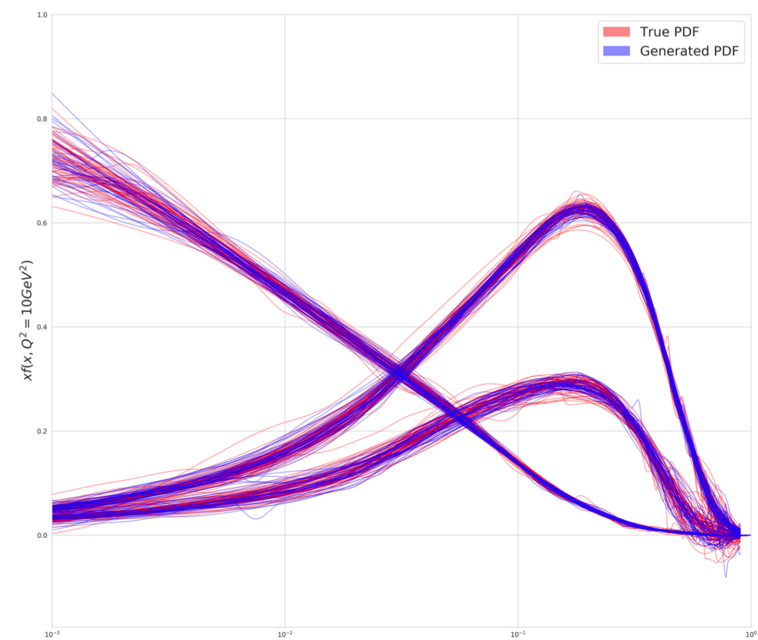
→ Juan Rojo:

GANs for PDF fits

- Even with all the n3fit speedups, producing large samples of PDF replicas still time-consuming
- Solution: produce new PDF fit replicas using **Generative Adversarial Networks**
- While no additional information is being added, such method can be applied to many cases with a very large $\mathbf{N_{rep}}$ is beneficial, such as **Bayesian reweighting studies**



n3pdf group, in preparation

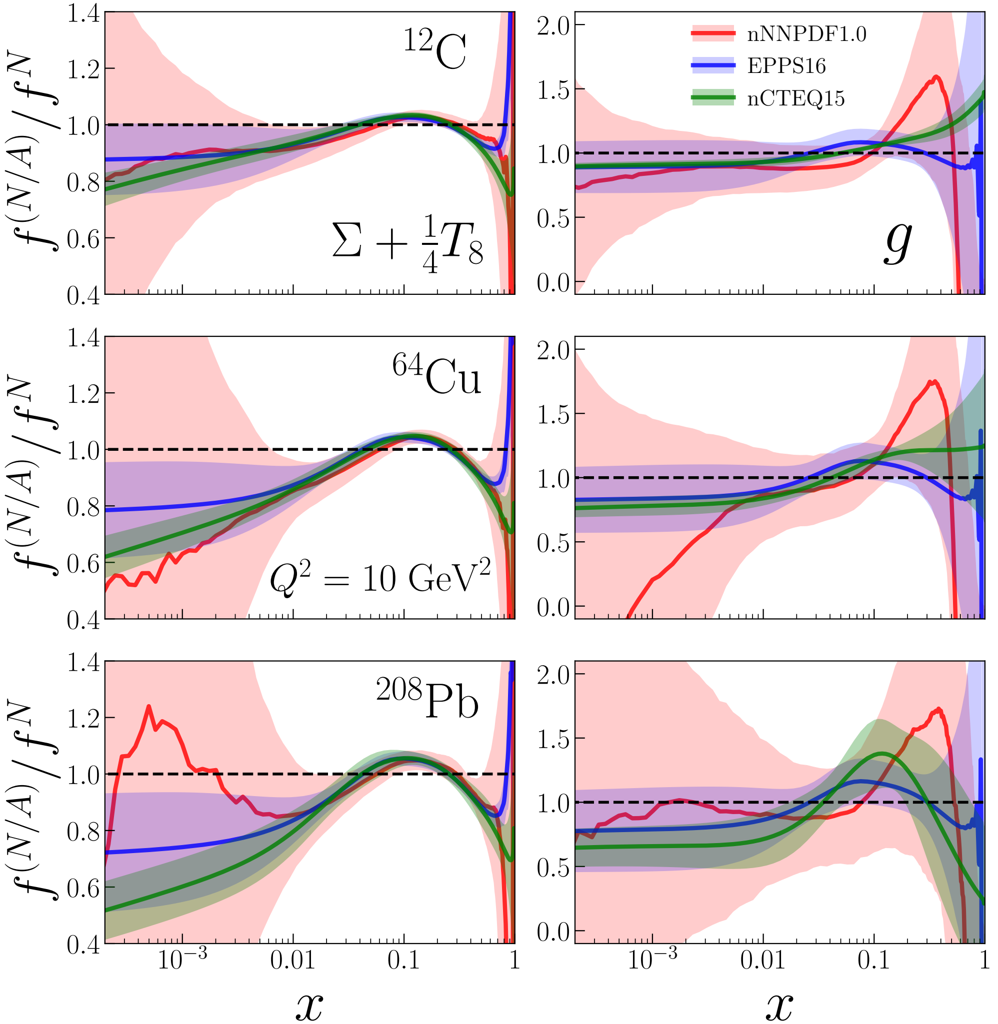


State-of-the-art analysis

→ Jake Ethier: nuclear PDFs with neural nets

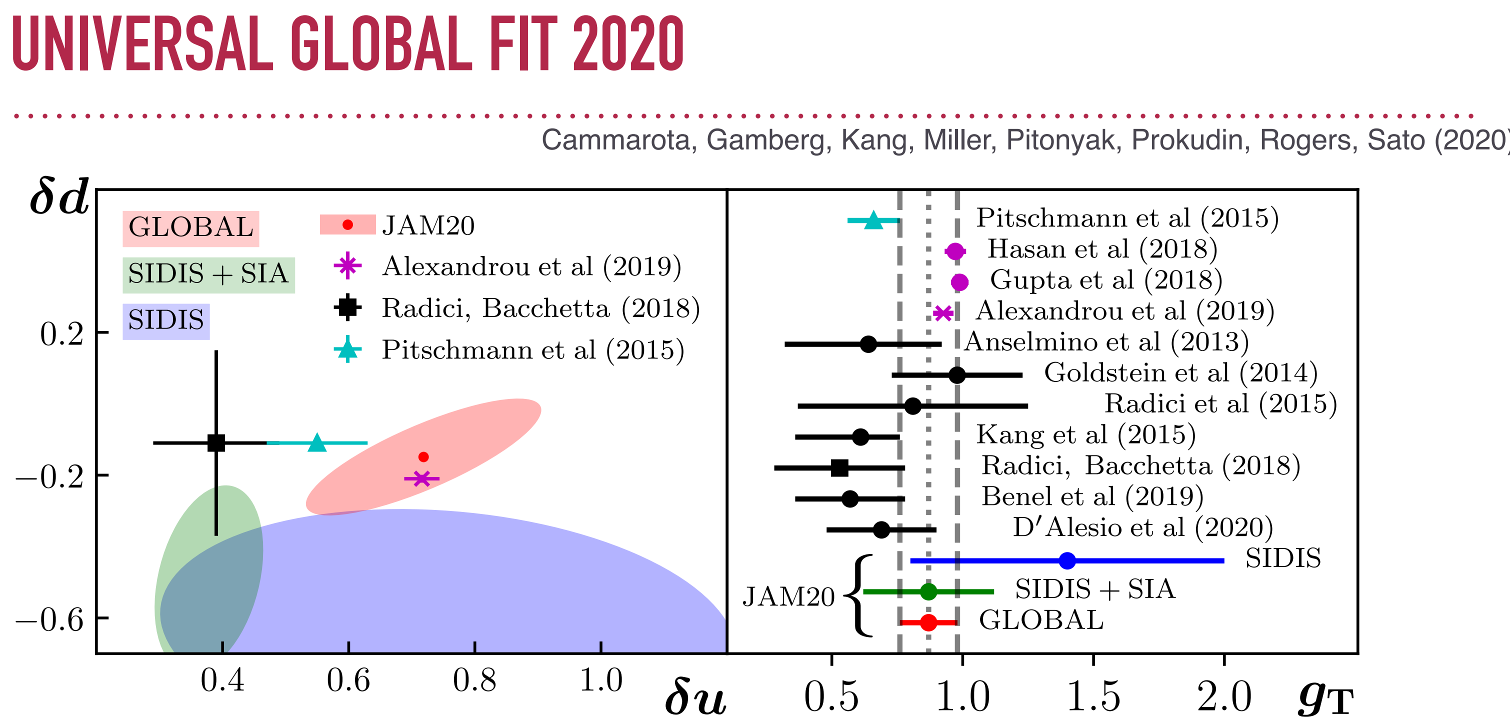
nNNPDF1.0 Results

- Distributions normalized by respective proton boundary conditions
- EPPS16 and nCTEQ15 show 90% CL ranges based on Hessian method
- Significant differences in uncertainties



State-of-the-art analysis

→ Alexei Prokudin: first universal analysis of 3-D structure



- Tensor charge from up and down quarks is constrained and compatible with lattice results
- Isovector tensor charge $g_T = \delta u - \delta d$
  gT = 0.89± 0.12 compatible with lattice results

δu and δd Q^2=4 GeV^2

δu= 0.65 ± 0.22

δd= -0.24 ± 0.2

- State-of-the-art analysis
  - → <u>Simonetta Liuti</u>: neural nets for GPDs
  - → many multi-dimensional functions

DVCS

twist two GPDs

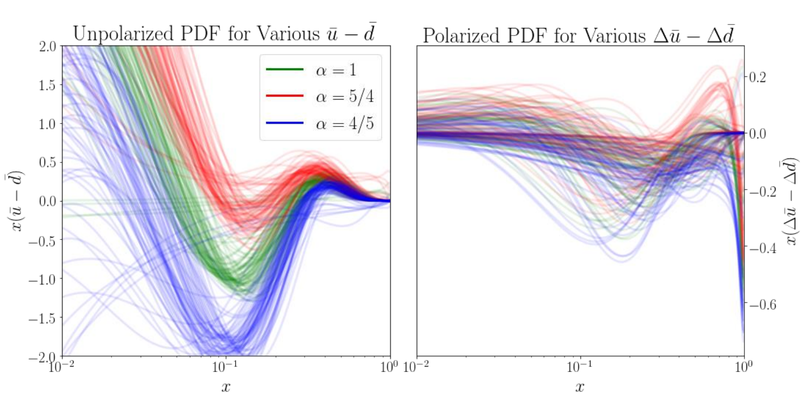
twist three GPDs

$$
\begin{aligned}
\frac{d^5\sigma_{DVCS}}{dx_{Bj}dQ^2d|t|d\phi d\phi_S} &= \frac{\alpha^3}{16\pi^2(s-M^2)^2\sqrt{1+\gamma^2}}|T_{DVCS}|^2 \\
&= \frac{\Gamma}{Q^2(1-\epsilon)}\Big\{ \Big[F_{UU,T} + \epsilon F_{UU,L} + \epsilon\cos 2\phi F_{UU}^{\cos 2\phi} \\
&+ \sqrt{\epsilon(\epsilon+1)}\,\Big[\cos\phi F_{UU}^{\cos\phi} + \cancel{\sin\phi F_{UU}^{\sin\phi}}\Big] \\
&+ \lambda_e \sqrt{2\epsilon(1-\epsilon)}\sin\phi F_{LU}^{\sin\phi}\Big] \\
&+ S_L \Big[\cancel{F_{UL}} + \sqrt{\epsilon(\epsilon+1)}\sin\phi F_{UL}^{\sin\phi} + \epsilon\sin 2\phi F_{UL}^{\sin 2\phi} \\
&+ \lambda_e \sqrt{1-\epsilon^2}F_{LL} + 2\lambda_e\sqrt{\epsilon(1-\epsilon)}\cos\phi F_{LL}^{\cos\phi}\Big] \\
&+ |S_T| \Big[\sin(\phi-\phi_S)\Big(F_{UT,T}^{\sin(\phi-\phi_S)} + \epsilon F_{UT,L}^{\sin(\phi-\phi_S)}\Big) \\
&\quad \epsilon\sin(\phi+\phi_S)F_{UT}^{\sin(\phi+\phi_S)} + \epsilon\sin(3\phi-\phi_S)F_{UT}^{\sin(3\phi-\phi_S)} \\
&\quad +\sqrt{2\epsilon(1+\epsilon)}\Big(\sin\phi_S F_{UT}^{\sin\phi_S} + \sin(2\phi-\phi_S)F_{UT}^{\sin(2\phi-\phi_S)}\Big)\Big] \\
&+ \lambda_e S_L \Big[\sqrt{1-\epsilon^2}\cos(\phi-\phi_S)F_{LT}^{\cos(\phi-\phi_S)} + \sqrt{2\epsilon(1-\epsilon)}\cos\phi_S F_{LT}^{\cos\phi_S} \\
&\quad +\sqrt{2\epsilon(1-\epsilon)}\cos(2\phi-\phi_S)F_{LT}^{\cos(2\phi-\phi_S)}\Big]\Big\}
\end{aligned}
$$

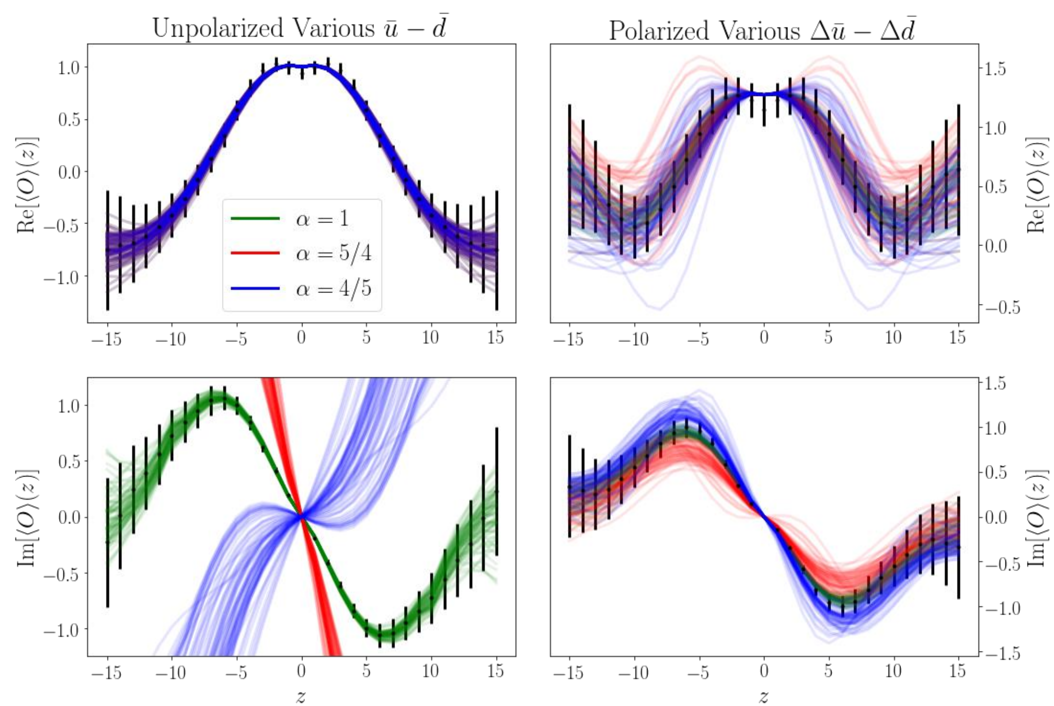
State-of-the-art analysis

→ <u>Jake Bringewatt</u>: combined analysis of experiment & lattice data

Understanding lattice data: varying $\bar{u}, \bar{d}$



$$\bar{u} \to \alpha\bar{u}$$
$$\bar{d} \to \bar{d}/\alpha$$

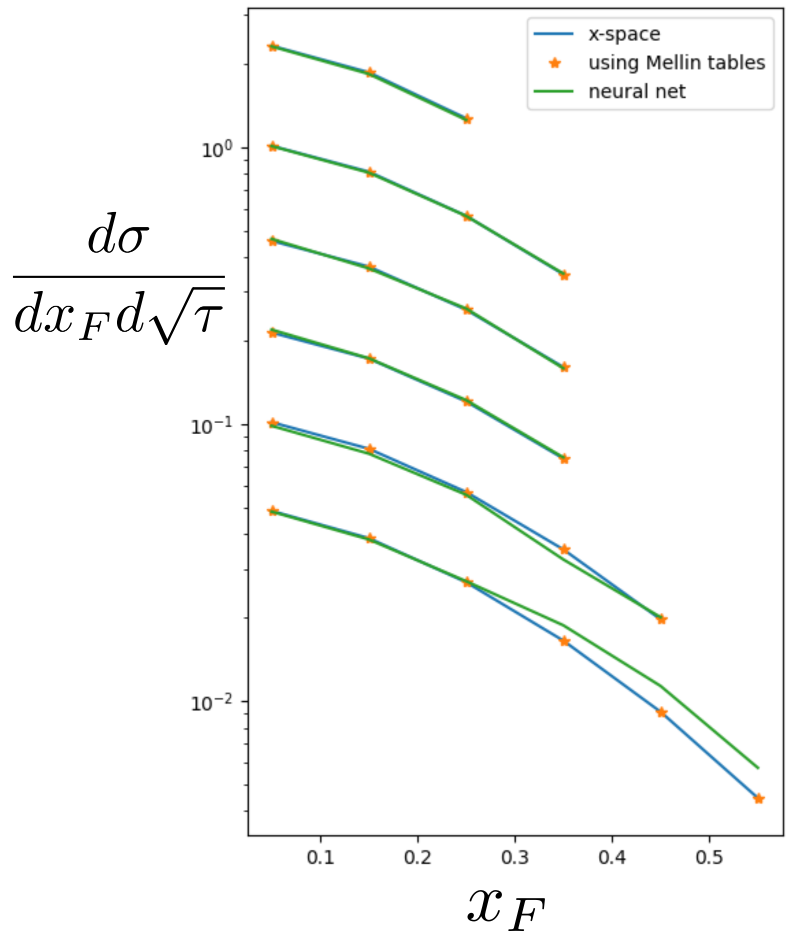


→ greater sensitivity to flavor asymmetry of the sea for unpolarized than polarized PDFs

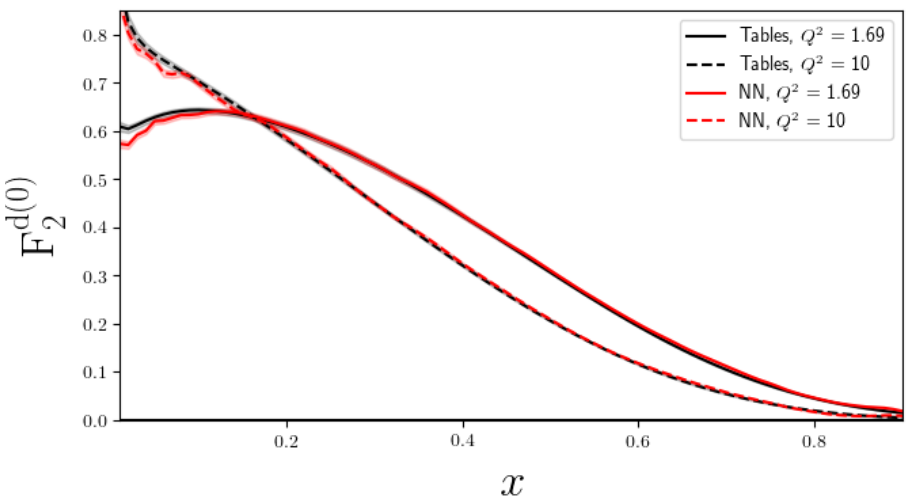
■ AI for code optimization

→ Yiyu Zhou: ML for jets

→ Patrick Barry: ML for Drell-Yan

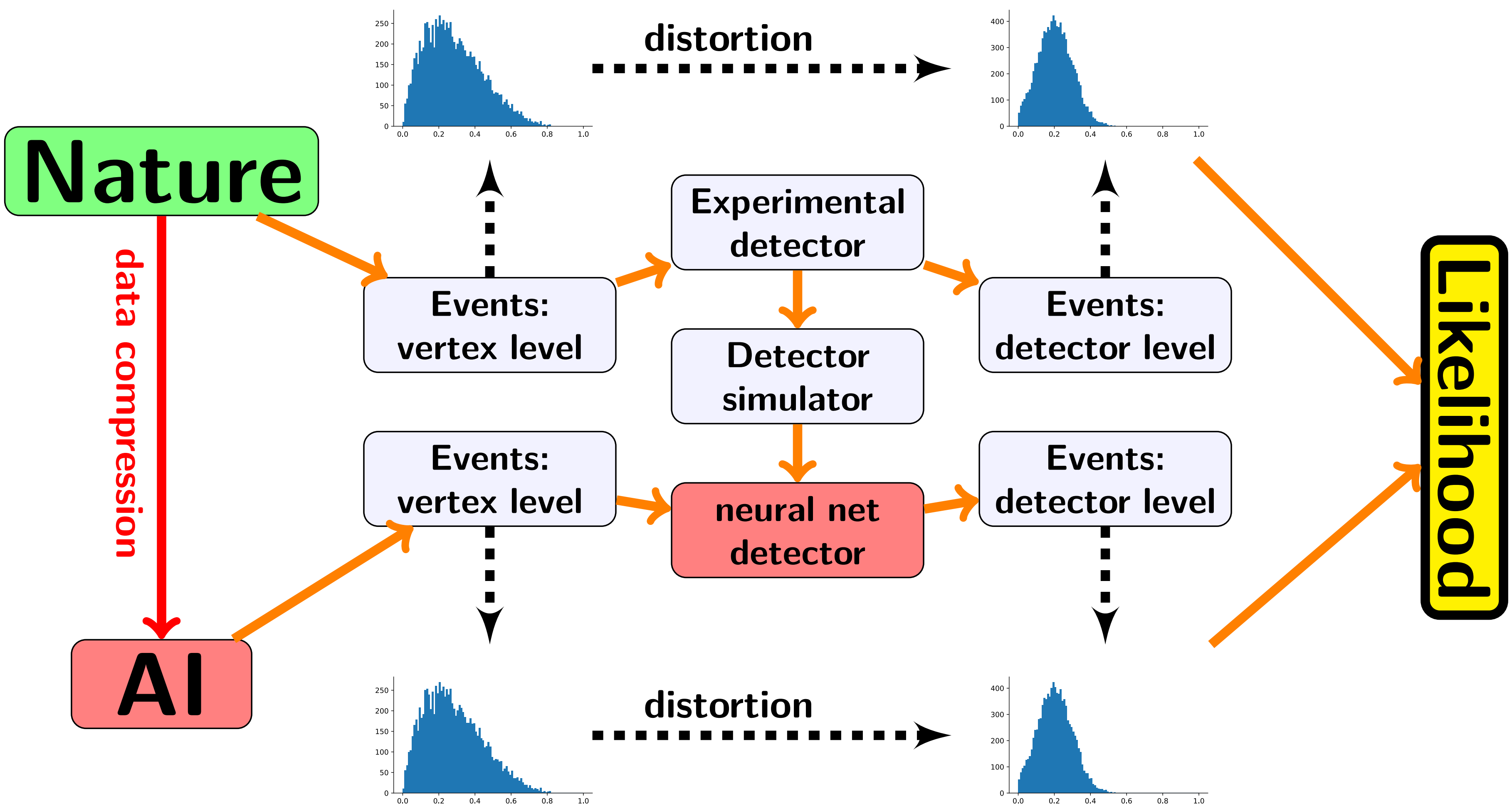


→ Chris Cocuzza: ML for nuclear DIS



AI Monte Carlo event generator

→ Nobuo Sato: Universal Monte Carlo Event Generator (UMCEG) or Empirically Trained Hadronic Event Regenerator (ETHER)



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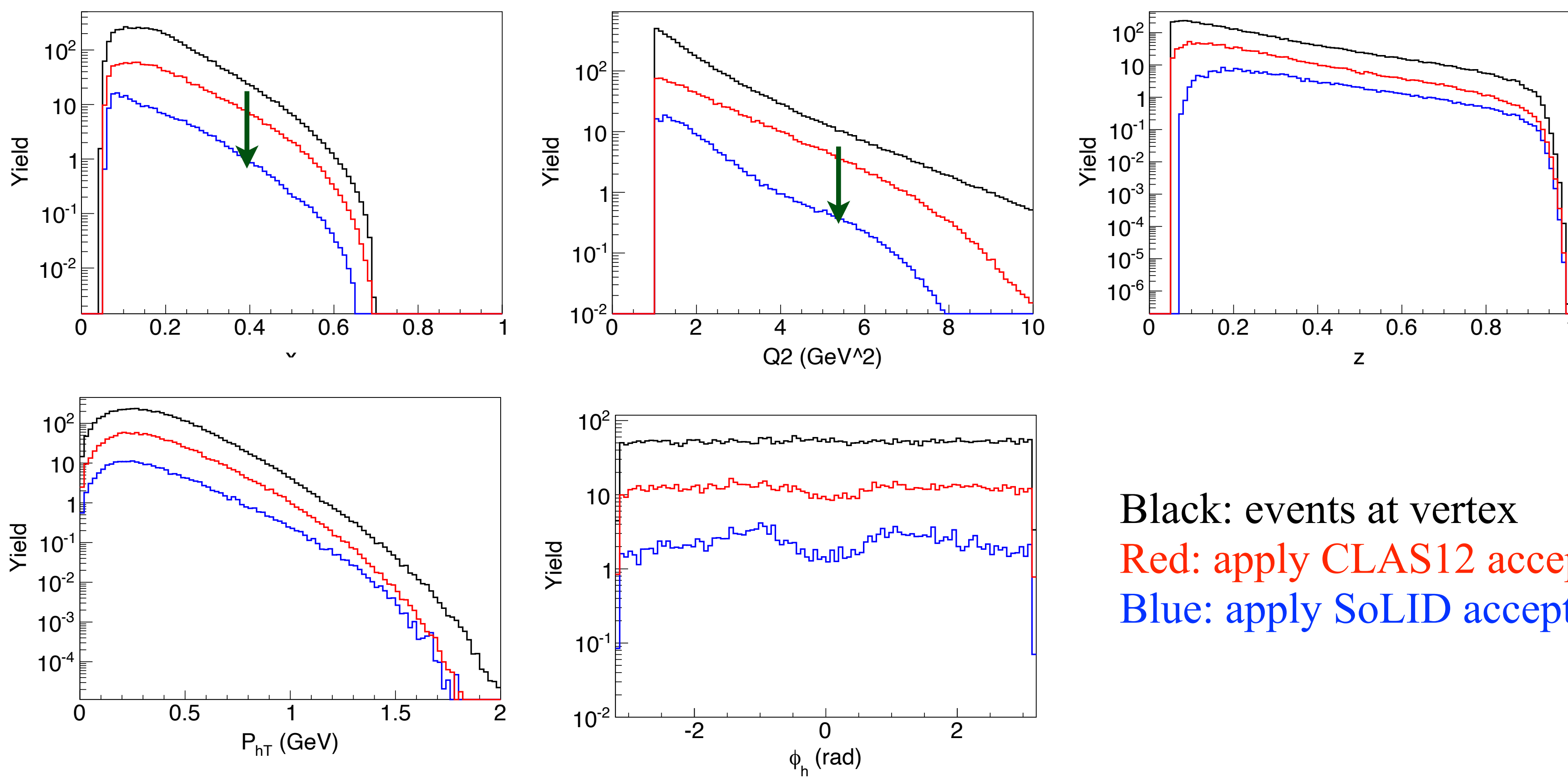
- AI Monte Carlo event generator

→ <u>Tianbo Liu</u>: complexity of detector effects

Acceptance and Efficiency

Example: (SIDIS)



Black: events at vertex

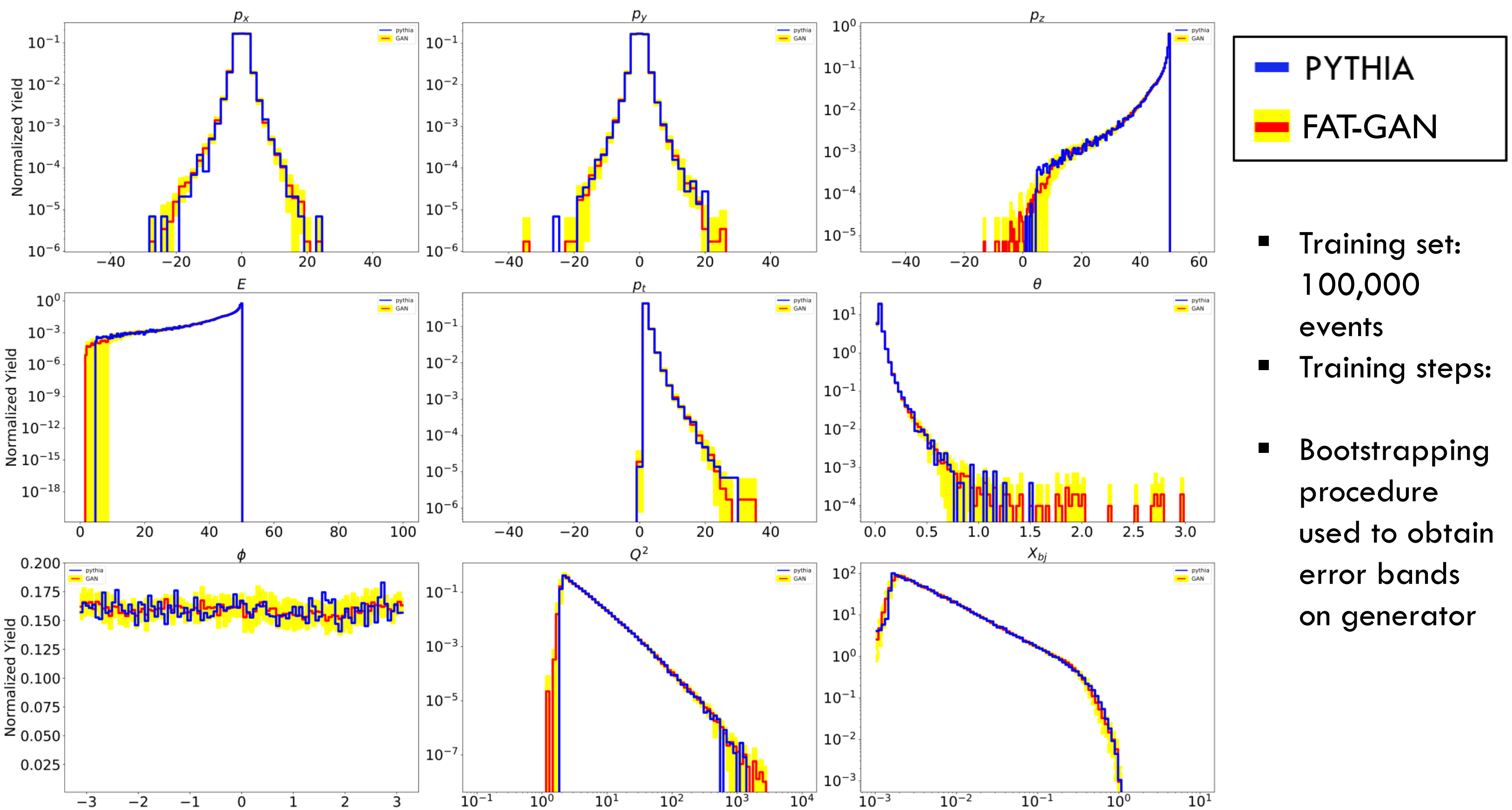
Red: apply CLAS12 acceptance

Blue: apply SoLID acceptance

AI Monte Carlo event generator

→ Luisa Velasco: GANs for ETHER

→ Yaohang Li: Feature-Augmented & Transformed (FAT) GANs

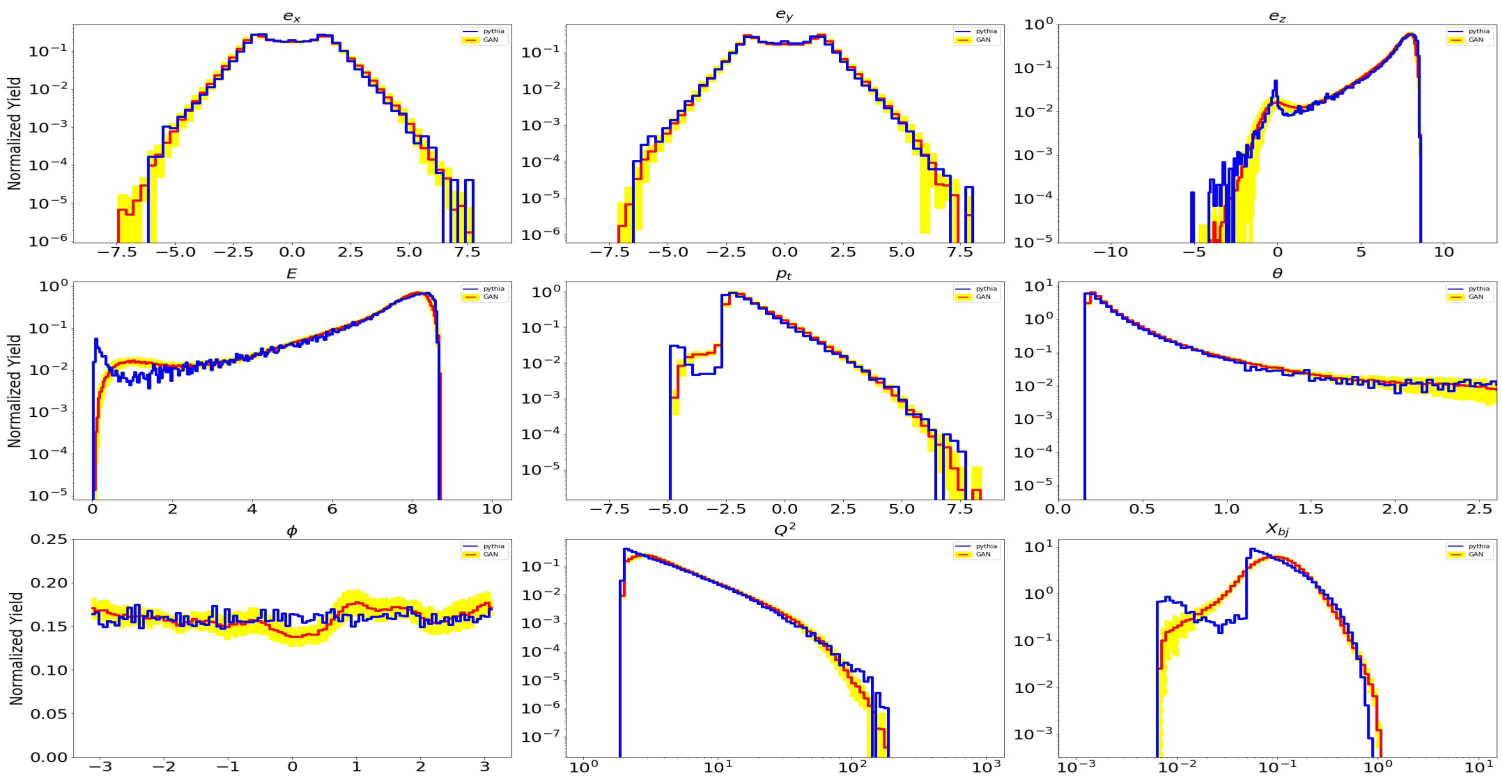


- Training set: 100,000 events
- Training steps:
- Bootstrapping procedure used to obtain error bands on generator

AI Monte Carlo event generator

→ Yasir Alanazi: CNN GANs

➢ Electron



PYTHIA

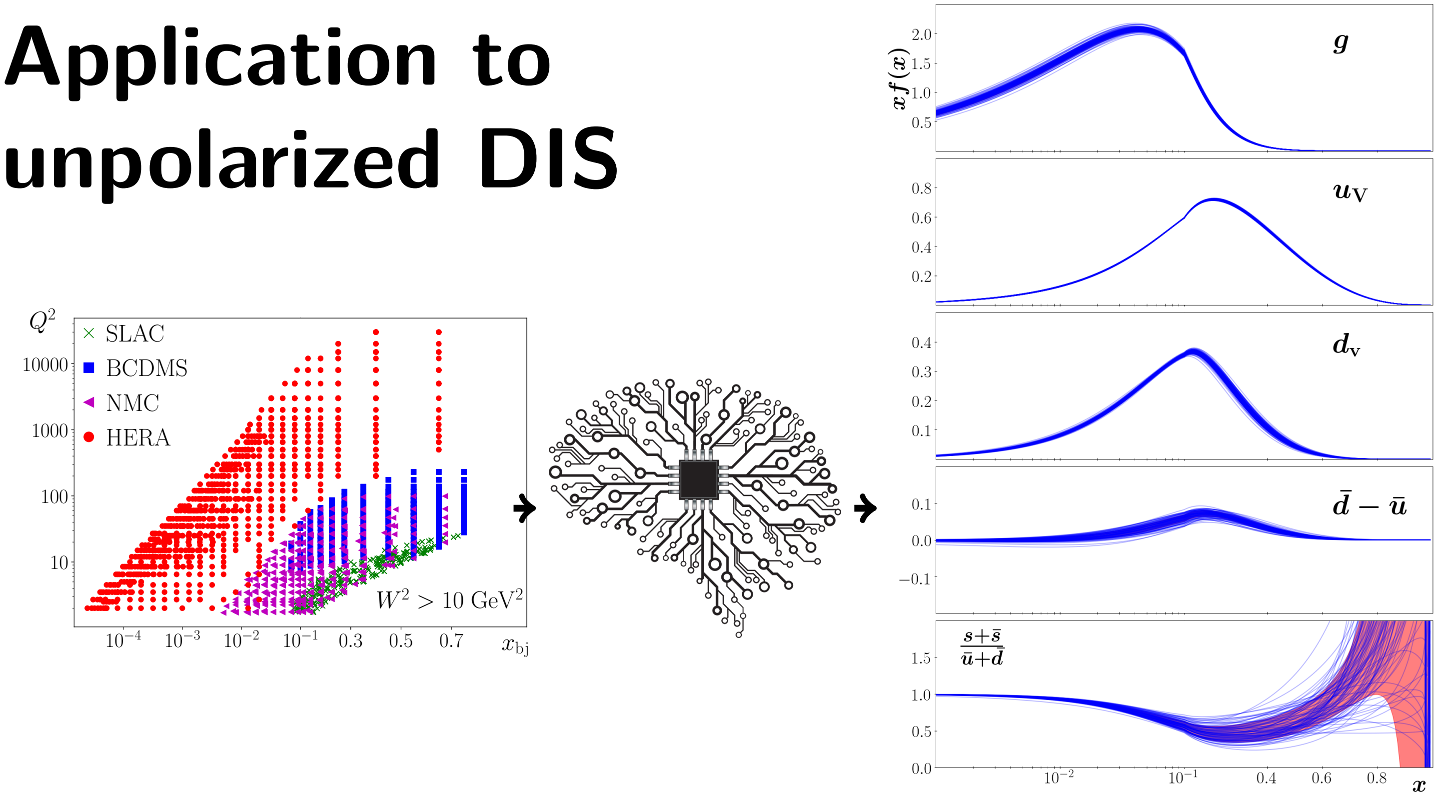
CNN-GAN

■ AI for femtographic inverse mapping

→ Nobuo Sato: next generation of global QCD analysis tools

→ Manal Alemaeen: ML for inverse mapping prototypes

Application to unpolarized DIS



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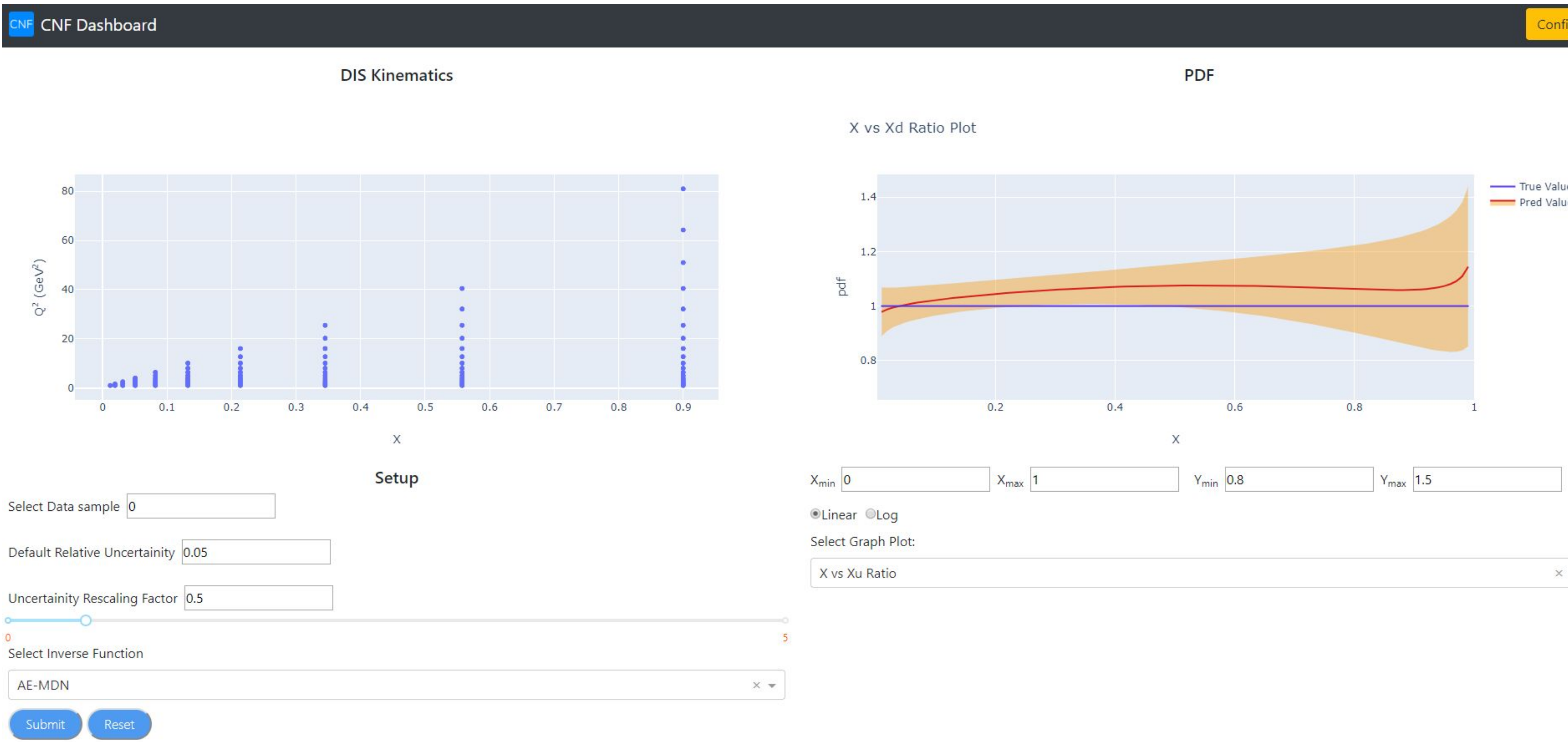
AI for femtographic inverse mapping

→ <u>Herambeshwar Pendyala</u>: interactive web-based global analysis tools



What has been learned so far?

- AI has the potential to significantly boost the science of nuclear femtography

- AI applications already identified:
  — code optimization (mapping Mellin tables)
  — inverse mappers
  — theory-independent MC event generators

- Need for ML scientists to help nuclear physicists to more efficiently implement relevant AI applications
  — consultants to assist QCD scientists for code optimization
  — collaborators to develop new strategies / prototypes for nuclear femtography

What are next steps?

- Strengthen collaboration between nuclear physicists and AI scientists

  — new initiatives (e.g. CNF)

  — regular NP–AI workshops

- Specific needs for QCD global analysis

  — improved code optimization (e.g. fully connected NNs $\longrightarrow$ CNNs)

  — inverse mappers (e.g. from discretized $\rightarrow$ continuous kinematics, remove binning dependence)

  — web-based global analysis platform

- Specific needs for MC event generators

  — GAN strategy for inverse problem with detector effects at the *event* level

Special thanks to Nobuo Sato
(Nathan Isgur Fellow)