Summer Institute on Wigner Imaging and Femtography

Simonetta Liuti
University of Virginia

CNF Symposium

August 12-13, 2019

SURA Headquarters, Washington DC

Summer Institute for Wigner Imaging and Femtography


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Matthias Burkardt
Co Principle Investigator
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Co Principle Investigator
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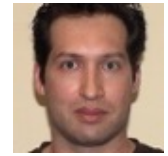
Dustin Keller
Co Principle Investigator
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Olivier Pfister
Co Principle Investigator
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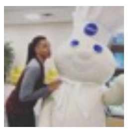
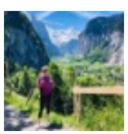
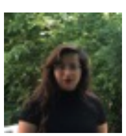
Wigner Theory


Librado Anglero
University of Virginia
Physics


Fatma Aslan
New Mexico State University
PhD

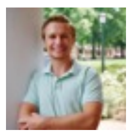

Kyle-Thomas Pressler
University of Virginia
Physics

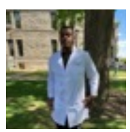

Emma Yeats
University of Virginia
Physics


Fernanda Yepez-Lopez
University of Virginia
Mathematics

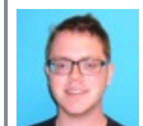
Machine Learning

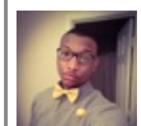

Jake Grigsby
Machine Learning Group Leader
University of Virginia
Computer Science and Mathematics

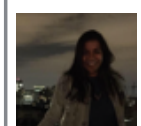

Evan Anders Magnusson
University of Virginia
Computer Engineering and
Computer Science

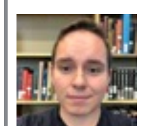

Christopher Thompson
Virginia Union University
Physics and Engineering

Observables

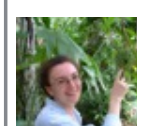

Brandon Kriesten
University of Virginia
Observables Group Leader


Krisean D Allen
Virginia Union University
Physics

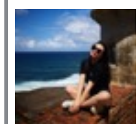

Meg Graham
University of Virginia
Computer Science


Andrew Meyer
University of Virginia

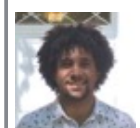
William A Oliver
Virginia Commonwealth University

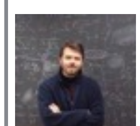

Yelena Prok
Virginia Commonwealth University
Assistant Professor

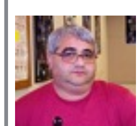
Data Management/ Communication

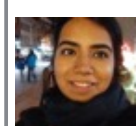

Yao(Grace) Tong
University of Virginia
Mathematics and Economics

Consultant


Carlos Gonzalez Arciniegas
University of Virginia


Timothy John Hobbs
Southern Methodist University
EIC Center at Jefferson Lab


Gabriel Niculescu
James Madison University


Abha Rajan
University of Virginia

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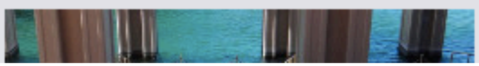
Red: Undergraduate
Blue: Graduate

Our project was characterized from the very beginning by a great response from students and young researchers:

HOME > CONFERENCE EXPERIENCE FOR UNDERGRADUATES (CEU)

Conference Experience for Undergraduates (CEU)

https://www.uwlax.edu/ceu/current/

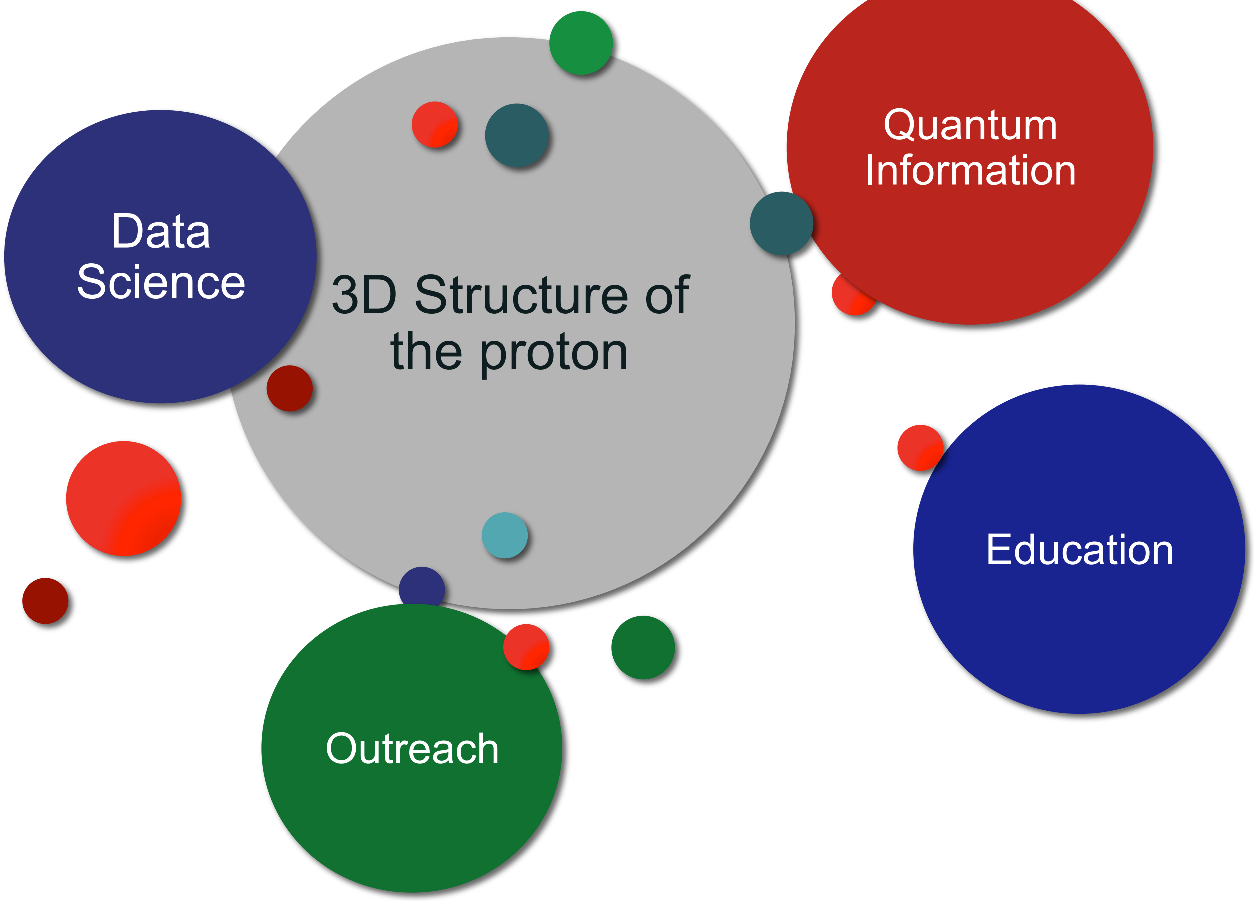


The goal of Conference Experience for Undergraduates (CEU) is to provide a capstone conference experience for undergraduate students who have conducted research in nuclear science by providing them the opportunity to present their research to the larger professional community and to one another. Additionally, it enables the students to converse with faculty and senior scientists from graduate institutions about graduate school opportunities.

2019 - Crystal City

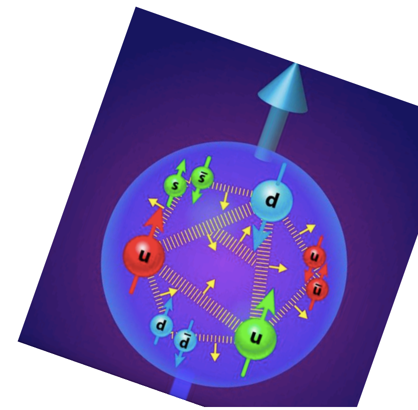
3 contributions submitted to CEU@ Annual Fall Meeting of DNP!

A truly interdisciplinary effort

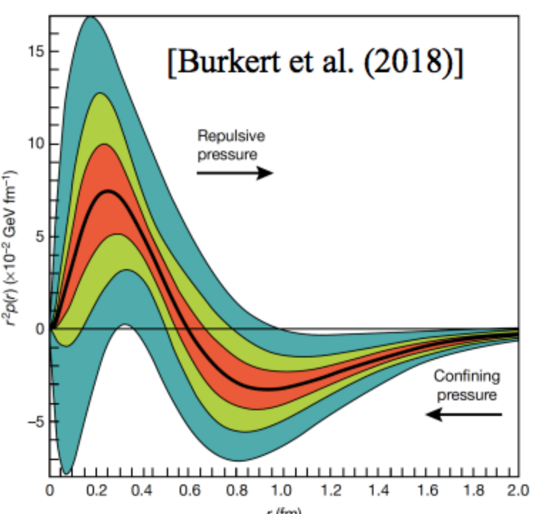


Main Questions we want to answer

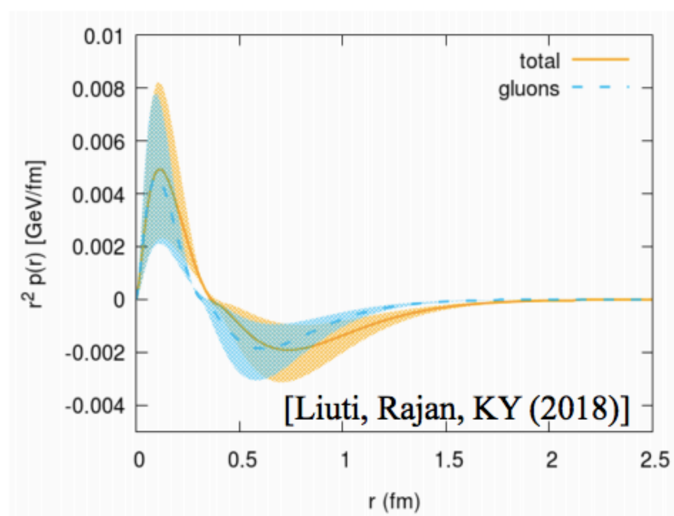
- What are the necessary steps for an unbiased extraction of the 3D structure and mechanical properties of the proton?
- GPDs and Compton Form Factors are the observables
- Probing nuclear physics with gravitational waves

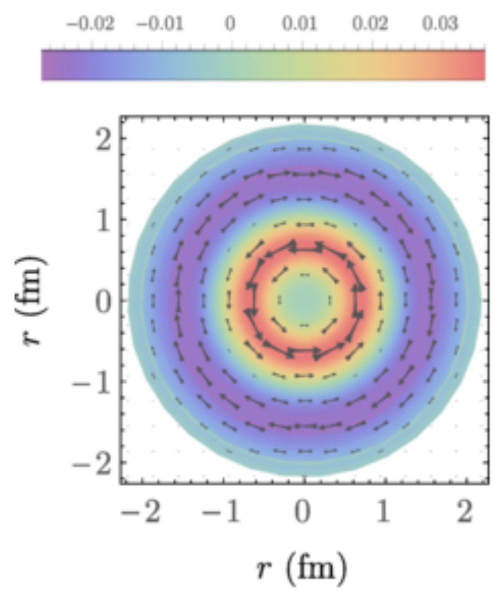


J-Lab Hall B



based on lattice simulations





Wigner Theory

- Modeling the Wigner Function
- Exploring issues in common with Atomic Physics

Data Analysis

- Modeling the Cross Section
- Extracting Observables from Data
- Error Analysis

Visualization

- Outreach/ pedagogical
- Research Tool

Communication

- Data Management
- Dissemination
- Webpage/github
- Code sharing opensourcing

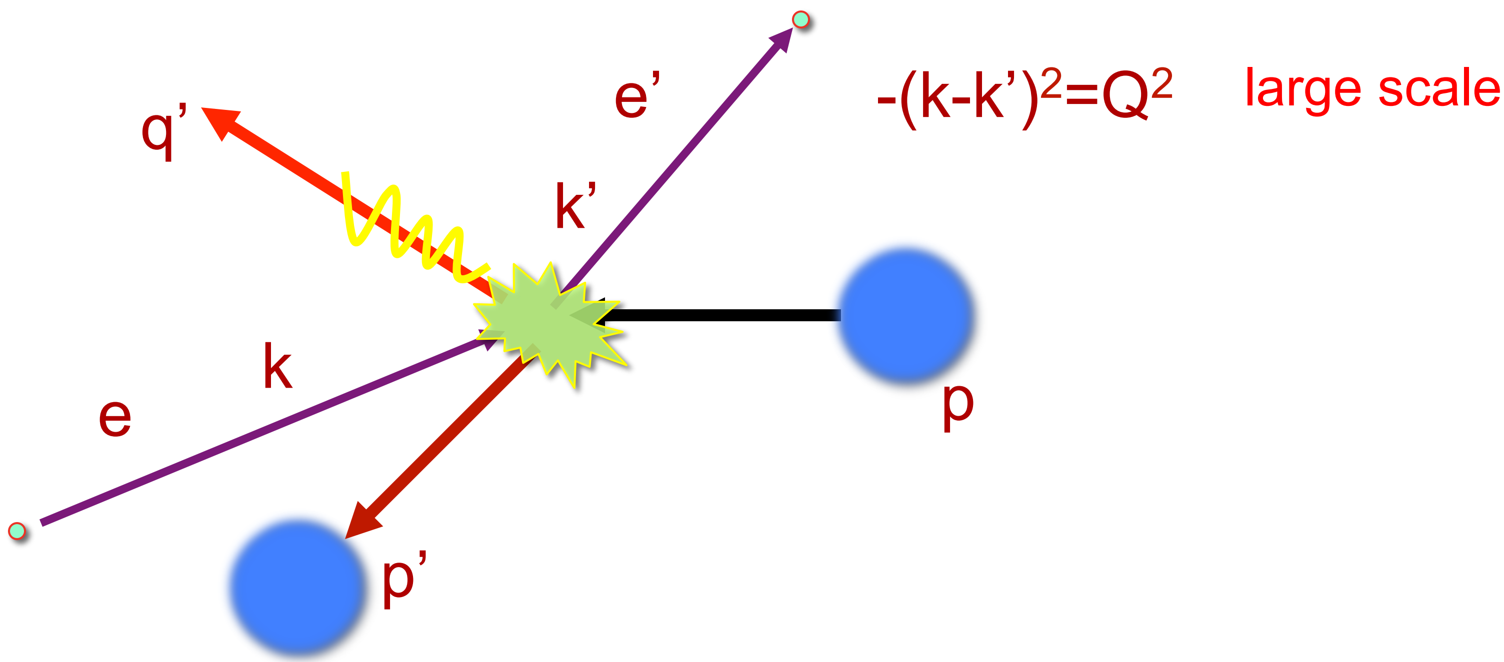
Wigner Theory

Modeling the Wigner Function

Exploring issues in common with Atomic Physics

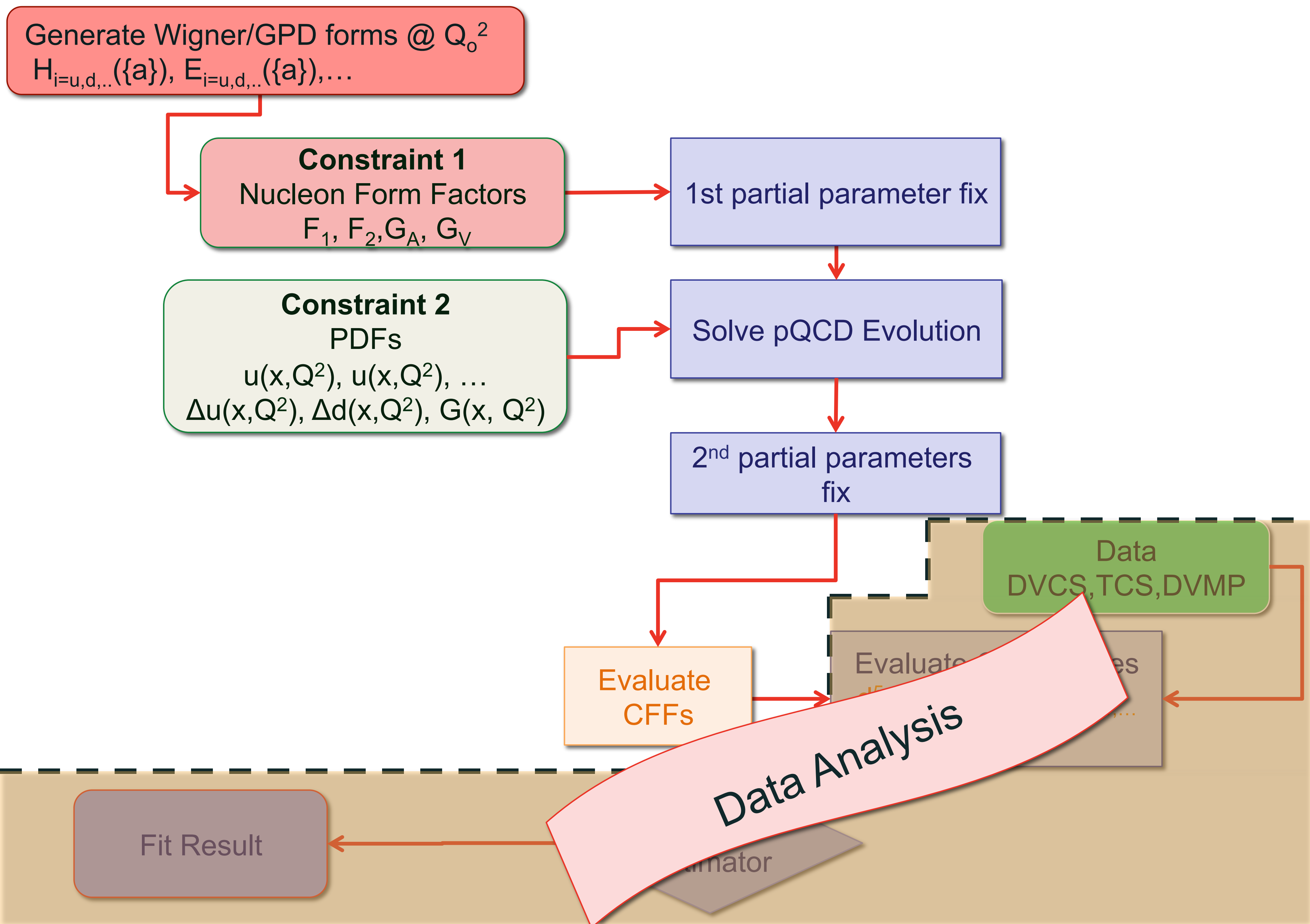
Deeply Virtual Compton Scattering

$$ep \to e'\gamma' p'$$



- We focus on GPDs (one projection of the Wigner distribution which is directly observable in DVCS)
- The observables are the Compton Form Factors which are convolutions of GPDs with known kernels

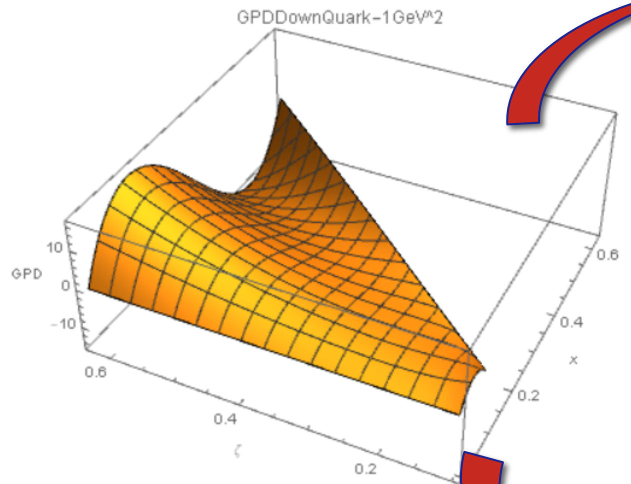
Flowchart/roadmap from data/observables to GPDs

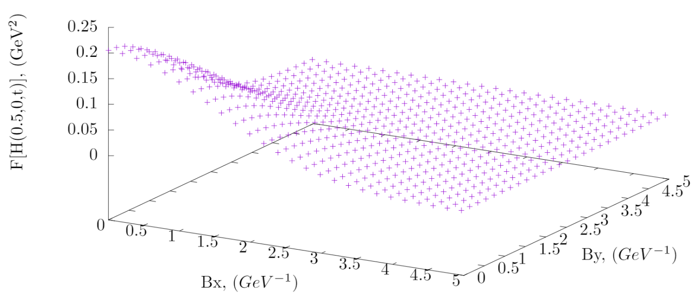


u,d quarks and gluon GPDs

from PQCD evolved GPD H(x,0,t)

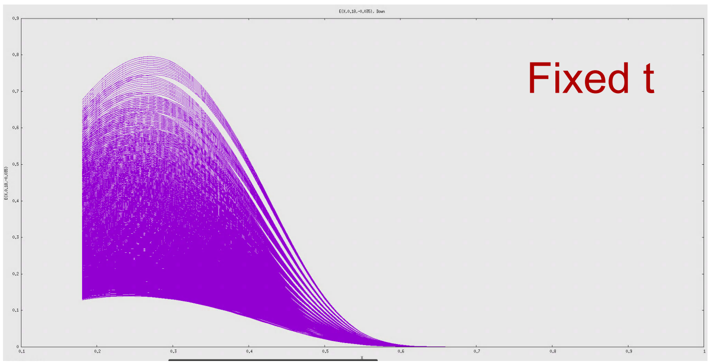
…to Fourier transform: H(x,b)





parameter variations used for input for Data Analysis

H(x,0,t)



x

$$H_{i=u,d,\ldots}(x,\xi,t) = \mathcal{N} G_{\{a\}}(x,\xi,t)\, R_{\{\beta\}}(x,\xi,t)$$

$$\{a\} = M_X, m, M_\Lambda$$

$$\{\beta\} = \alpha, \alpha', p$$

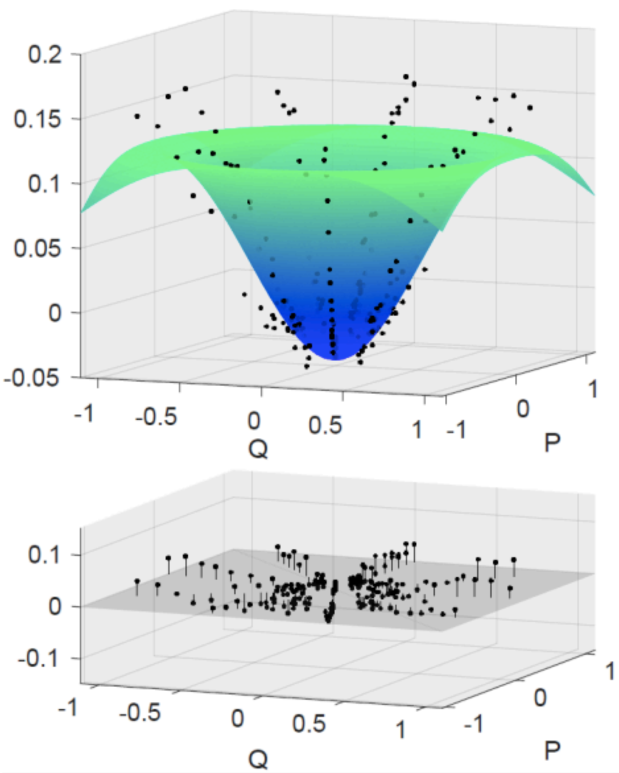
(parametrization from J. O. Gonzalez et al., arXiv:1206.1876, PRC88(2013))

Working on Connection with Atomic Physics/Quantum Information

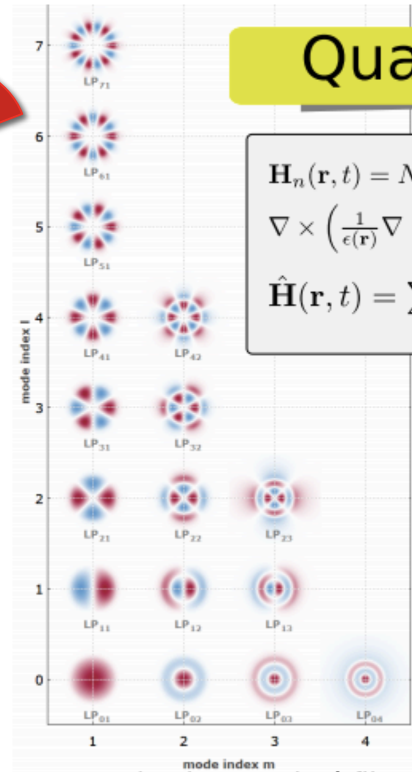
with O. Pfister and C. Gonzalez Arciniegas

Quantum Optics

Experimental Results from UVA



Nehra et. al. arXiv:1906.02093 [quant-ph] (2019)



Modes in a optical fiber
https://www.rp-photonics.com/modes.html

$$\mathbf{H}_n(\mathbf{r},t) = N_m \mathbf{h}_n(\mathbf{r}) e^{-i\omega_n t}$$

$$\nabla \times \left(\frac{1}{\epsilon(\mathbf{r})} \nabla \times \mathbf{h}_n(\mathbf{r})\right) = \left(\frac{\omega_n}{c}\right)^2 \mathbf{h}_n(\mathbf{r})$$

$$\hat{\mathbf{H}}(\mathbf{r},t) = \sum_n N_m \left(\hat{a}_n(t)\mathbf{h}_n(\mathbf{r}) + \hat{a}_n^\dagger(t)\mathbf{h}_n^*(\mathbf{r})\right)$$

Modes of the EMF

$$\hat{\mathcal{H}} = \sum_n \hbar\omega_n \tfrac{1}{2}\left(\hat{a}_n(t)\hat{a}_n^\dagger(t) + \hat{a}_n^\dagger(t)\hat{a}_n(t)\right)$$
$$= \sum_n \hbar\omega_n \tfrac{1}{2}\left(\hat{q}_n(t)^2 + \hat{p}_n(t)^2\right)$$

$$\hat{a} = \frac{1}{\sqrt{2}}(\hat{q} + i\hat{p}) \qquad [\hat{q}, \hat{p}] = i$$

q AND p ARE EQUIVALENT TO POSITION AND MOMENTUM (dimesionlees) OF A ONE DIMENTIONAL PARTICLE

C. Gonzalez Arciniegas
https://pages.shanti.virginia.edu/Femtography/files/2019/06/Seminar.pdf

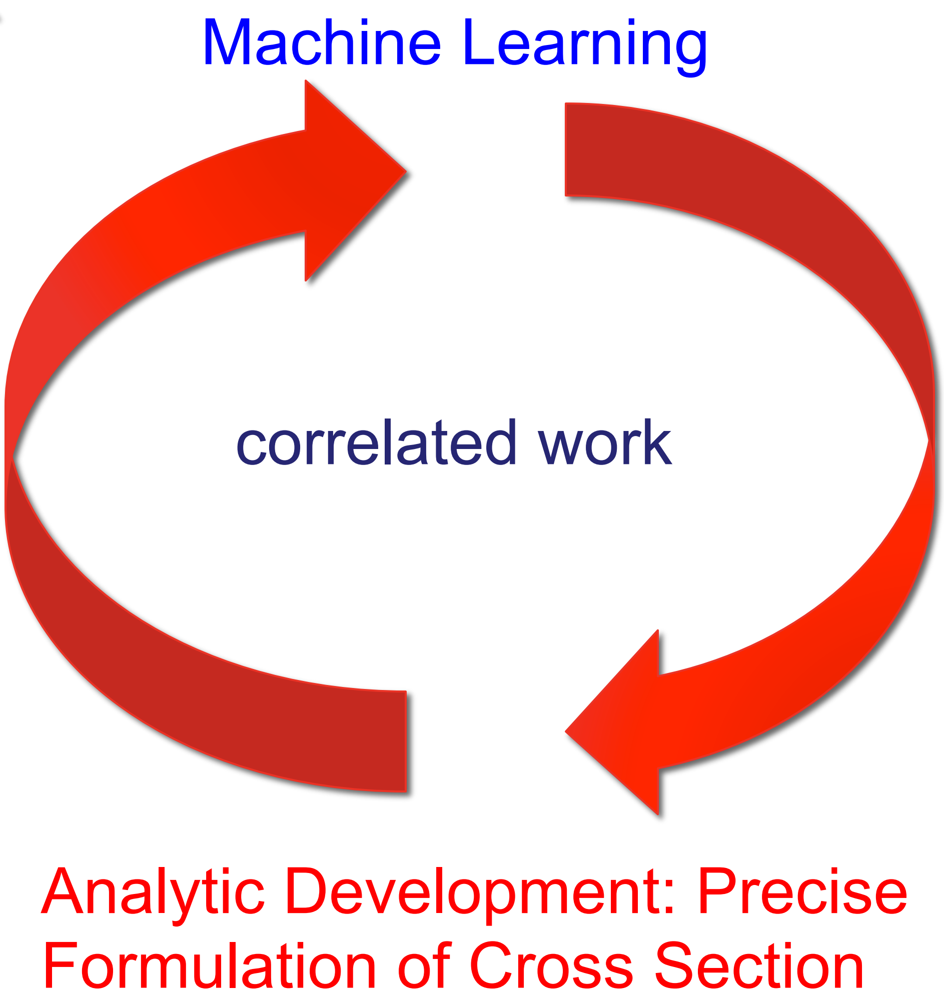
Data Analysis

Modeling the Cross Section

Extracting Observables from Data

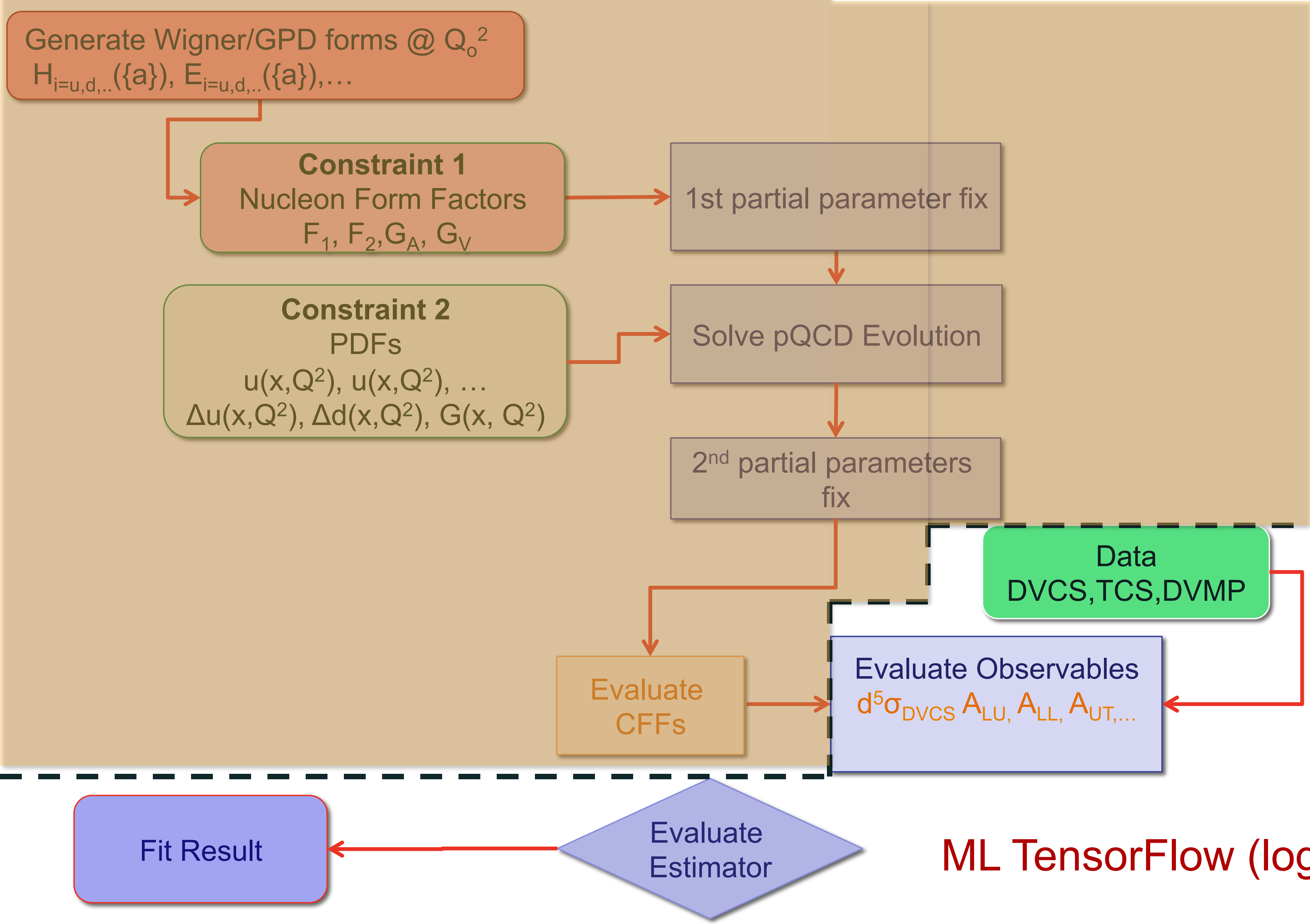
Error Analysis

Interdisciplinary effort with data science



- What physics questions drive our choice?
- What type of Machine Learning?
- What kinematical domains are sensitive to which GPDs/Compton Form Factors
- With what uncertainty?

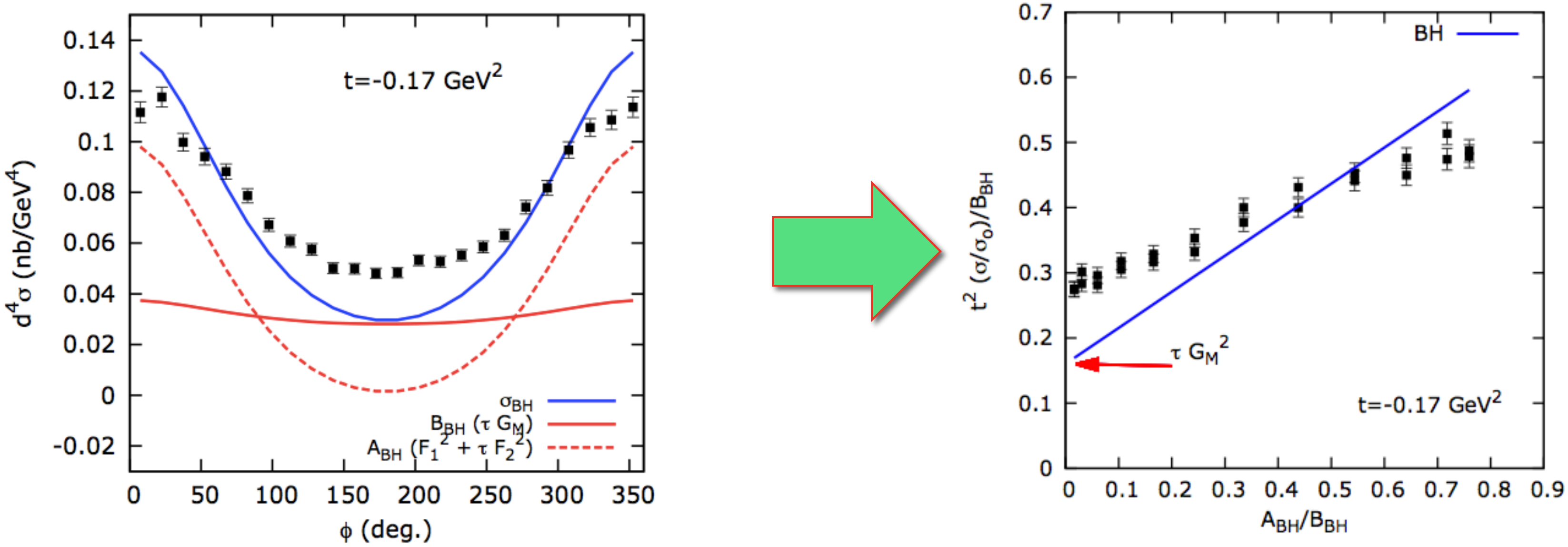
Flowchart/roadmap from data/observables to GPDs



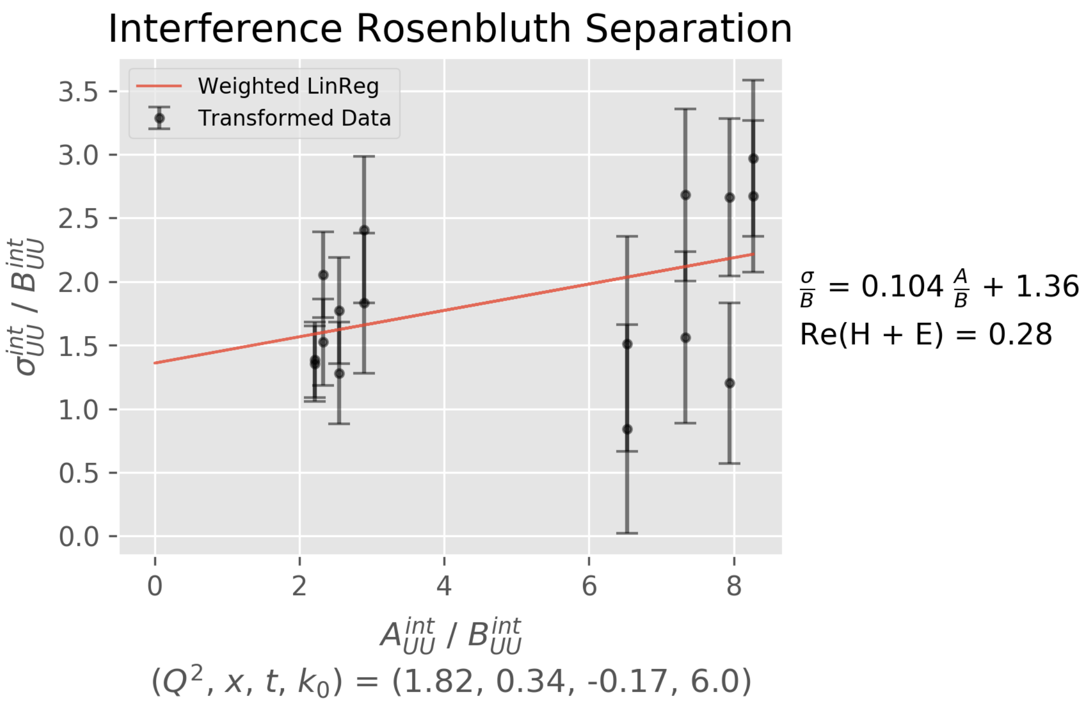
Modeling the Cross Section

Introducing the complete formalism where all kinematical dependences are precisely known and approximations are under control

Rosenbluth separation for Bethe-Heitler contribution



$$\frac{d^5\sigma^{BH}_{unpol}}{dx_{Bj}dQ^2d|t|d\phi d\phi_S} = \frac{\Gamma}{t^2}\left[A_{BH}\left(F_1^2+\tau F_2^2\right)+B_{BH}\tau G_M^2(t)\right]$$



G_E^2 G_M^2 $G_M\,G_A$

$$\frac{d^5\sigma^{\mathcal{I}}_{unpol}}{dx_{Bj}dQ^2d|t|d\phi d\phi_S} = \frac{\Gamma}{Q^2(-t)}\left[A_{\mathcal{I}}\left(F_1\Re e\mathcal{H} + \tau F_2\Re e\mathcal{E}\right) + B_{\mathcal{I}}G_M\,\Re e(\mathcal{H}+\mathcal{E}) + C_{\mathcal{I}}G_M\,\Re e\widetilde{\mathcal{H}}\right]$$

Extracting Observables from Data/Error Analysis

The goal is to single out what measurements have the greatest impact on determining the Compton Form Factors.

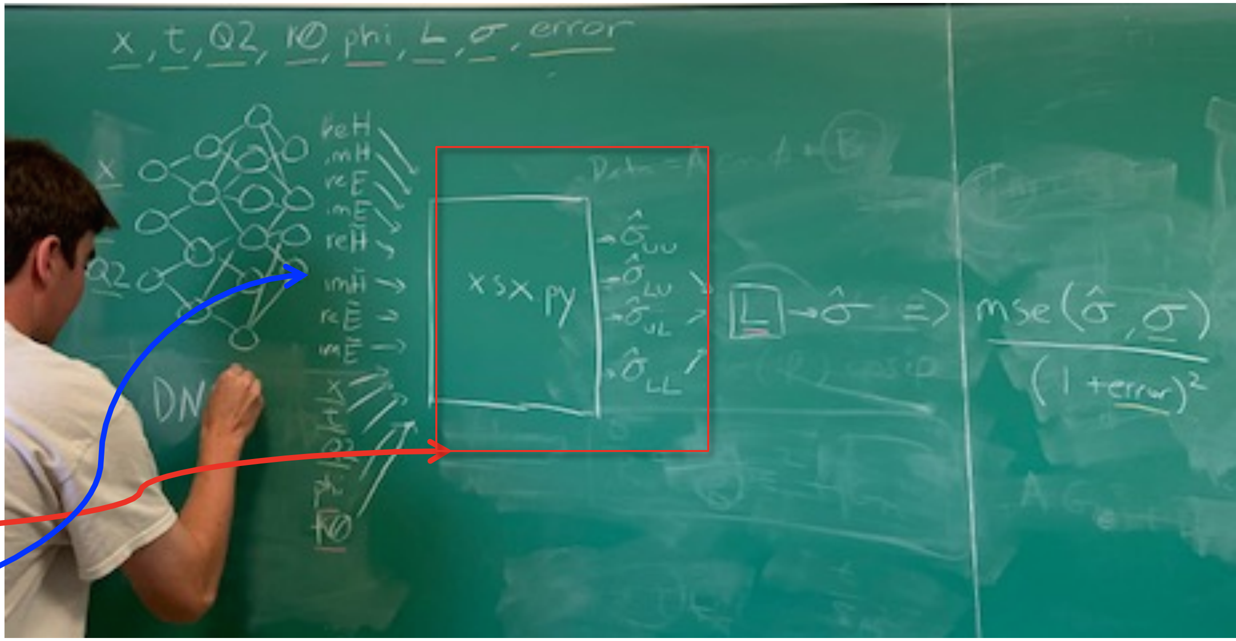
To address this challenge we present two analysis methods to identify both the type of experiments (beam/target polarization) and the kinematical domain providing the best constraints.

Based on Supervised Learning…

Femtography Imaging with Neural Networks (FINN)

Strategy:

1. A fully connected neural network maps input kinematic data to a vector of eight form factors (see diagram).
2. Use a code developed by our Data Analysis Team to evaluate the cross sections and in terms of the CFFs.

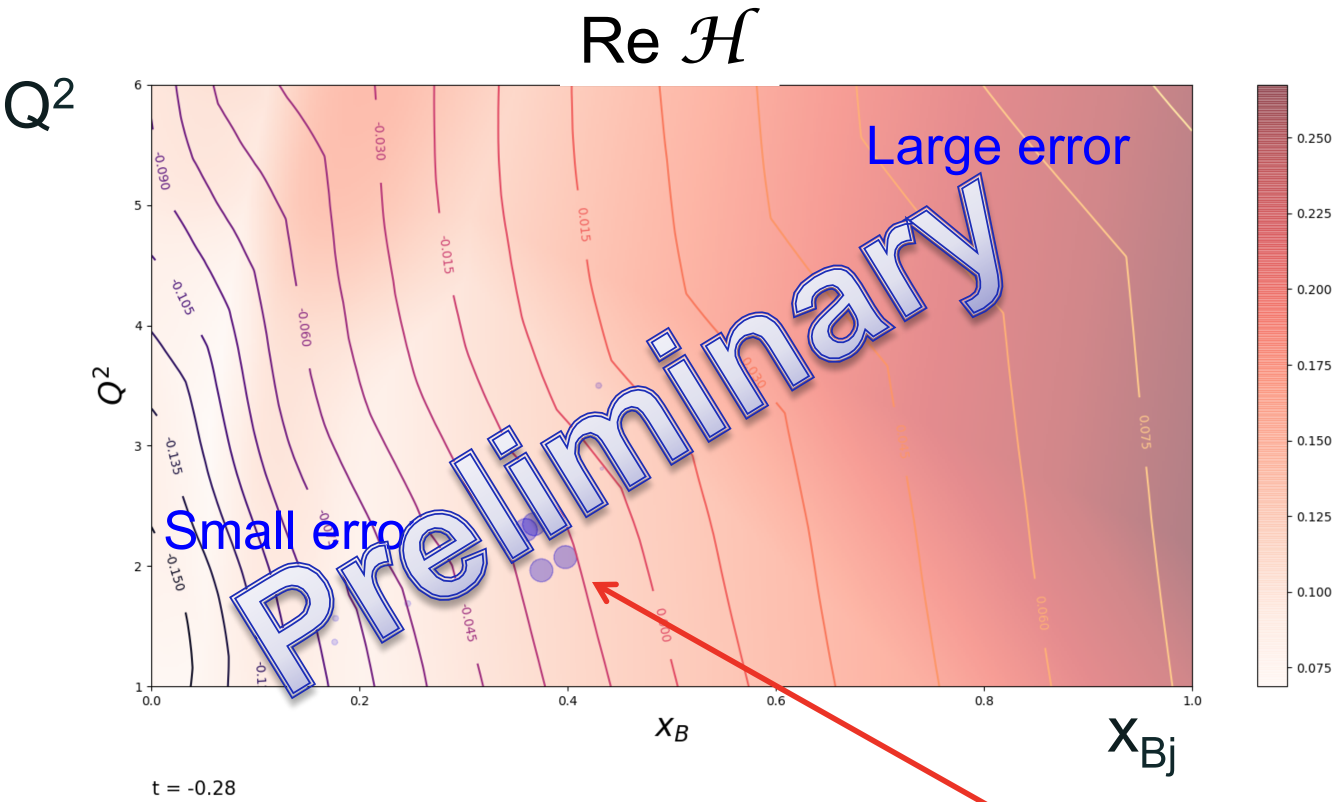


We translate the x-sec. code into TensorFlow

→ Automatically differentiable

→ At variance with other efforts we can train CFF extraction network with backpropagation and variants of stochastic gradient descent.

Understanding the Error/Systematic bias: example



present data kinematical coverage

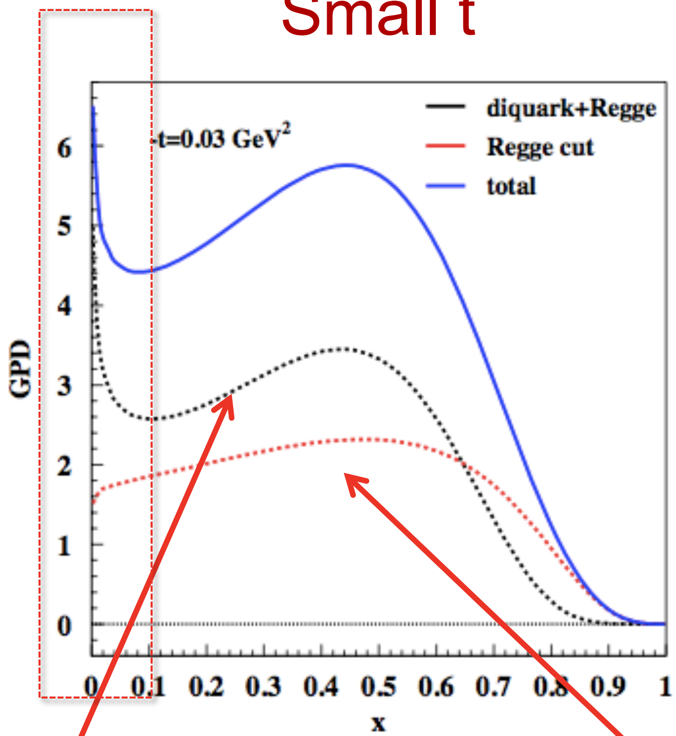
The biggest challenge we have is limited data, which we can solve with a combination of regularization, Monte Carlo generation and interpolation between phi values for each kinematic range.

Larger datasets from future DVCS/TCS experiments will ease these engineering challenges.

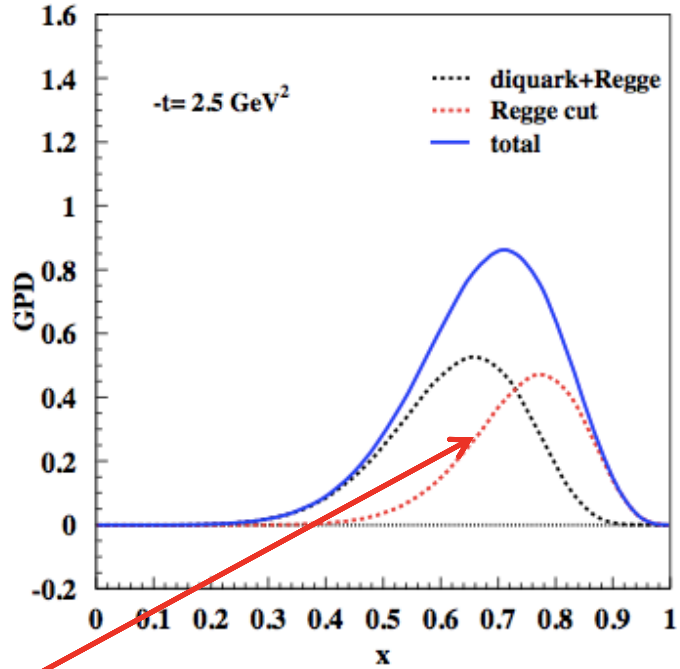
Based on unsupervised learning….

Ultimately, we want to understand features of the GPDs behavior

Small t



Large t



diquark correlations

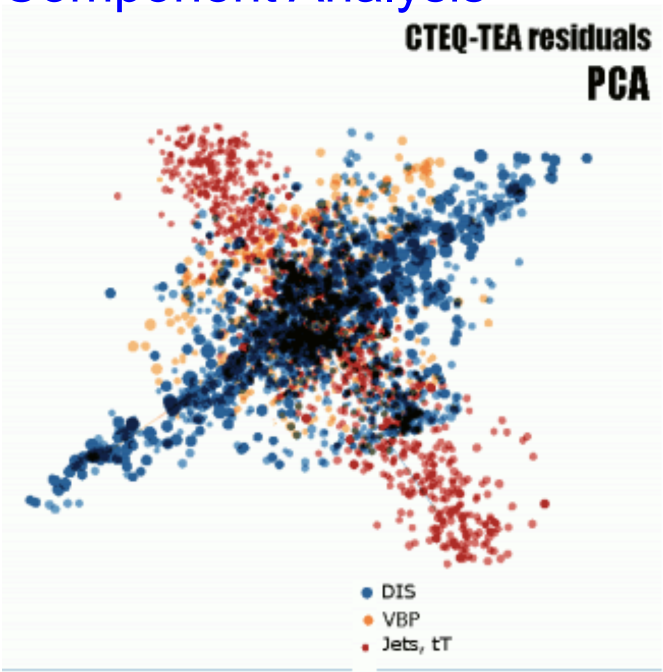
Reggeized diquark model

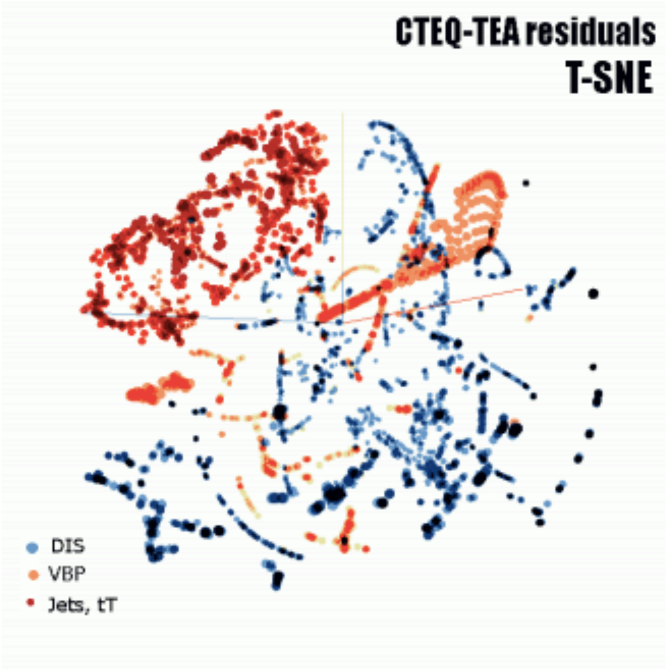
Using UMAP (Uniform Manifold Approximation and Projection) to cluster GPDs from the Wigner Theory team into 2D

Can be extended to 3D for virtual reality!

… similarities with CTEQ analysis

Principal Component Analysis





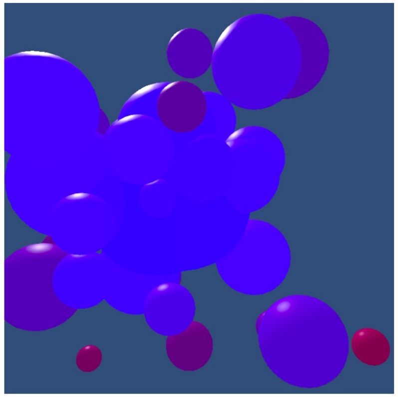
https://arxiv.org/pdf/1803.02777.pdf

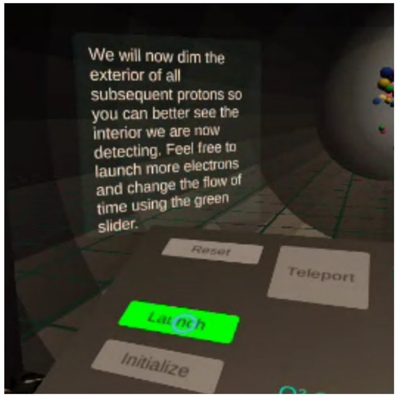
Visualization

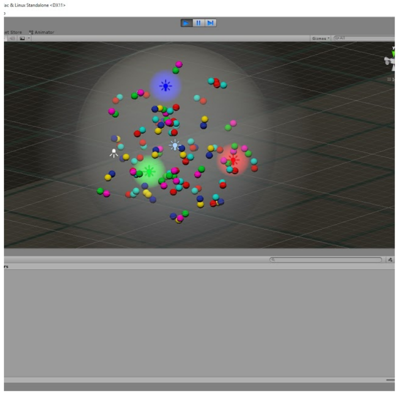
Outreach/ pedagogical

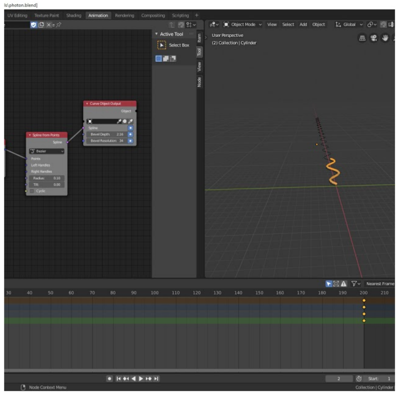
Research Tool

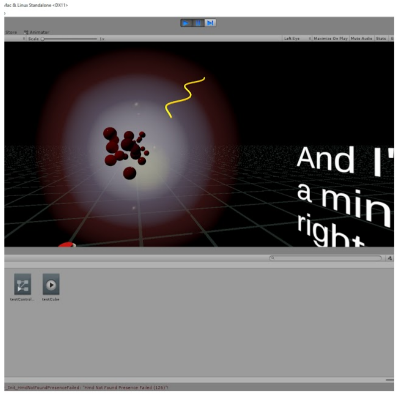
Outreach tool



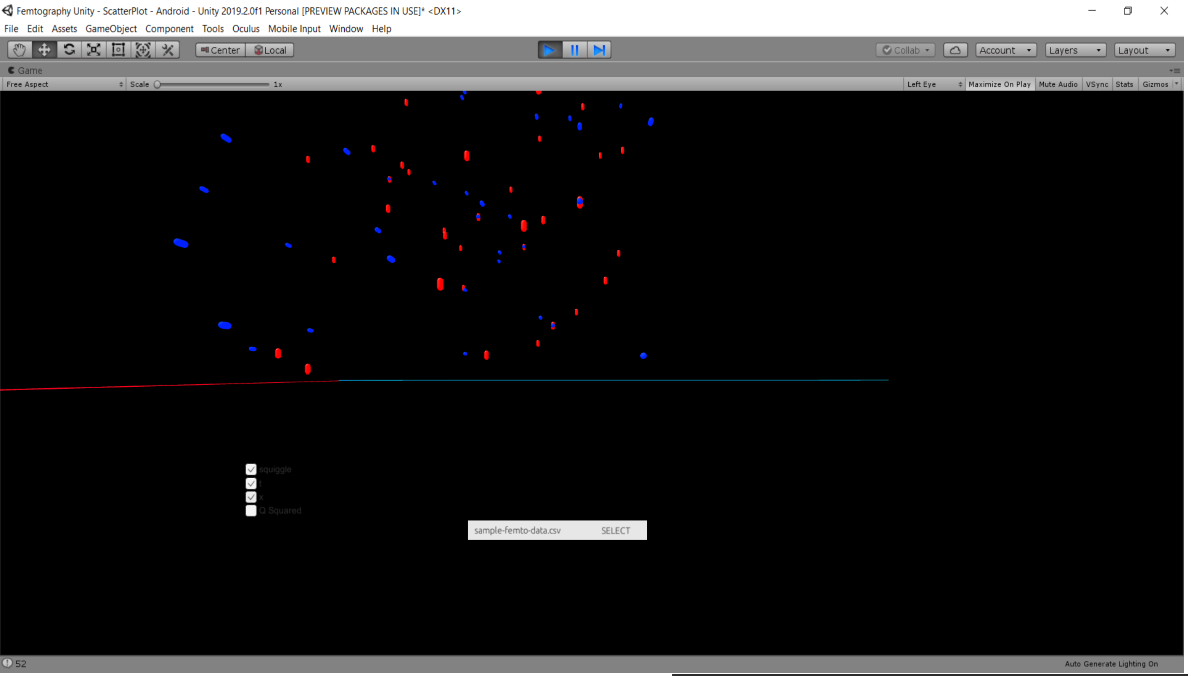


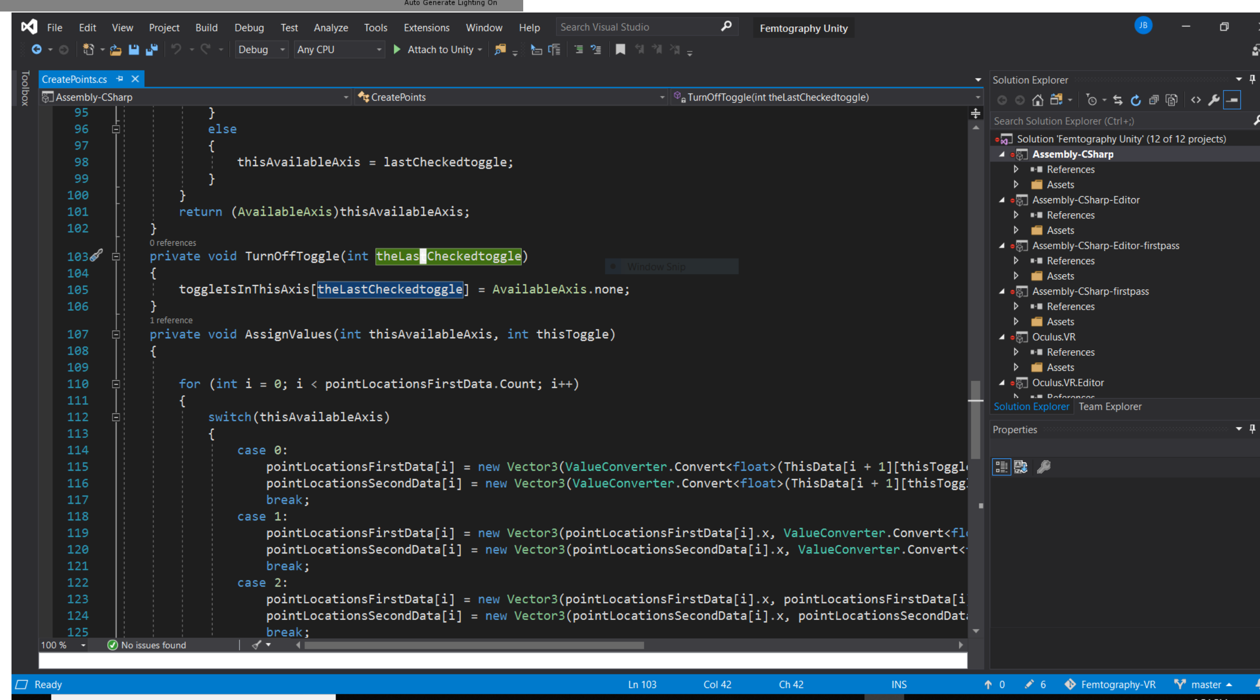






Stab at visualizing UMAP





Communication

Data Management Plan

Dissemination

Webpage/github

Code sharing
Open-sourcing

See Pete Alonzi's talk on Monday

Deliverables

Summary

- We developed a strategy and specifically ML tools for analyzing deeply virtual exclusive experiments within a truly interdisciplinary effort
- Visualization tool for outreach
- Impact on Education: many undergradauate students from various departments involved in research, CEU presentations
- Several manuscripts in progress
- Website and model for both fostering and regulating community interactions

Future Work

Issues with data: situations where data are scarce, how to add in dynamically new sets of data,

Including lattice QCD results/constraints → Fourier transforms

More work to come on Wigner Distributions and Quantum Information

Developing Unsupervised Learning tool

Visualization tools for research and more animations/movies for outreach tool


SIWF