4-2022

Physics-Informed Neural Networks (PINNs) For DVCS Cross Sections

Manal Almaeen
Old Dominion University

Jake Grigsby
University of Virginia

Joshua Hoskins
University of Virginia

Brandon Kriesten
Center for Nuclear Femtography

Yaohang Li
Old Dominion University

See next page for additional authors

Presenter and Co-Authors

Manal Almaeen, Jake Grigsby, Joshua Hoskins, Brandon Kriesten, Yaohang Li, Huey-Wen Lin, Simonetta Liuti, and Sorawich Maichum

Physics Informed Deep Learning for Deeply Virtual Compton Scattering

Manal Almaeen[1*], Jake Grigsby[2], Joshua Hoskins[2], Brandon Kriesten[3], Yaohang Li[1], Huey-Wen Lin[4], Simonetta Liuti[2], Sorawich Maichum[2]
[1] Old Dominion University, Norfolk, Virginia 23529, [2] University of Virginia, Charlottesville, VA 22904,
Center for Nuclear Femtography, Washington DC 20005, [4] Michigan State University, East Lansing, MI 48824.
malma004@odu.edu *

1. Introduction

- Training deep learning models often requires a large amount of data that might be not always available or possible to obtain in physics applications.
- Purely data-driven models may perfectly fit observations, but predictions might be inconsistent, as a result of extrapolation or observational biases that may lead to poor generalization performance.
- For better accuracy and generalization, deep learning models can be trained using additional knowledge gained by enforcing some physics laws.
- **Deeply Virtual Compton Scattering (DVCS)** data is obtained from Jefferson lab [1], consisting of [x_{bj}, t, Q^2, E_b, ϕ,L, σ,$\Delta\sigma$, $\delta\sigma$] where L is a label for polarization of beam and target - 1 is unpolarized beam/unpolarized target, 2 is polarized beam/unpolarized target, σ is the cross section value, $\Delta\sigma$ is the statistical error, and $\delta\sigma$ is the systematic error.
- The previous work by [2] demonstrates that using deep learning is essential to extract information from DVCS data.

2. Mission

Developing **Physics-Informed Neural Networks (PINNs)** by incorporating some physics constraints to accurately predict the DVCS cross sections and for better generalization on unseen kinematics.

3. Methodology

- We implement PINNs shown in Figure 1, consisting of an input layer whose nodes denote the array of the kinematic [x_{bj}, t, Q^2, E_b, Φ].
- The input layer is followed by three fully-connected layers with 512 neurons activated by a Leaky ReLU function. The final output represents our target cross section.
- Our model is optimized using a joinit of two loss functions:
  1. Mean absolute error (MAE) to minimize the error between the predicted and observed cross sections.
  2. Physics constraints loss to ensure that our predicted cross sections are symmetric as well as the start and end data points.
- We also use data augmentation to increase the size of our DVCS data by sampling the statistical error of the existing σ.

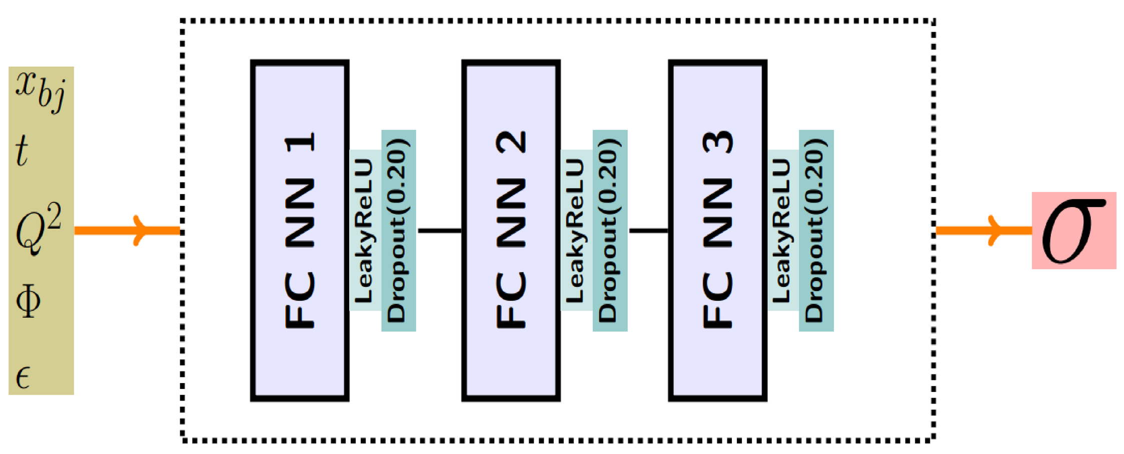

Figure 1 :PINNs architecture.

4. Results

- We test our PINNs ability to generalize in a range of ϕ on unseen kinematic bins [x_{bj}, t, Q^2, E_b] and compare the results using the basic network that is trained with no physics law incorporated. PINNs in figure 2, demonstrate a significant improvement over the basic Neural Networks (NNs) in the generalization tasks.

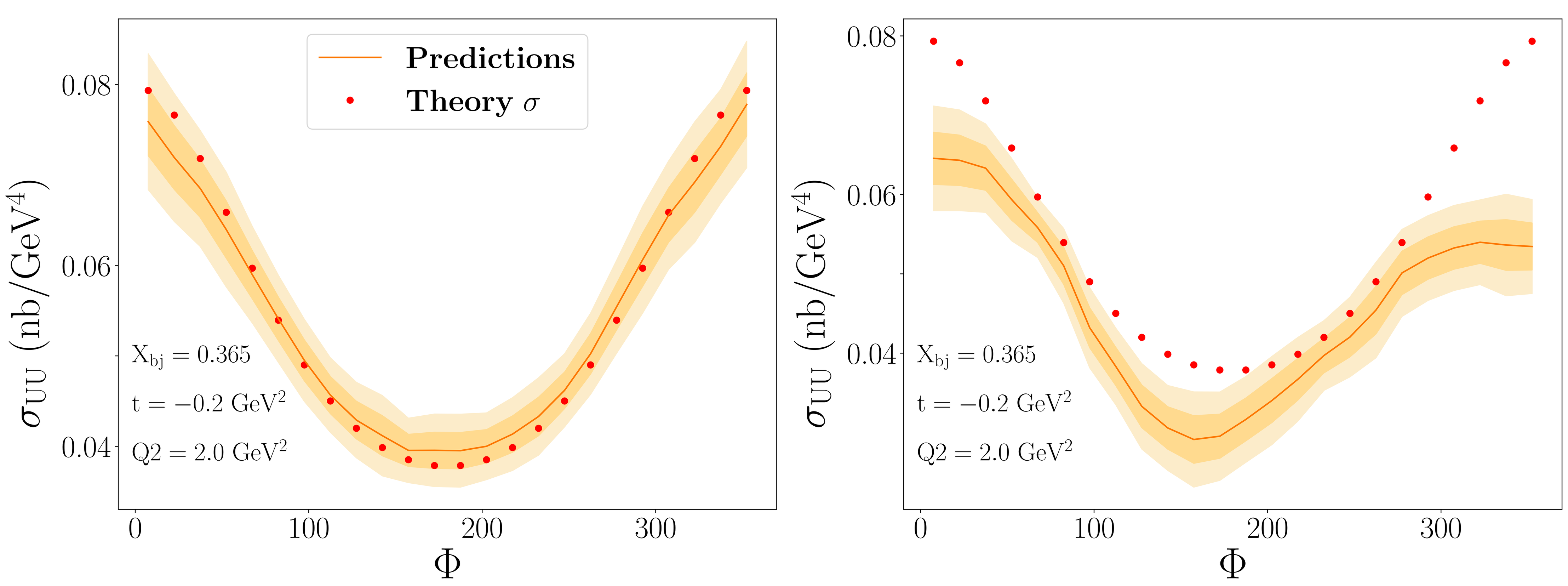

Figure 2 : DVCS generalization on kinematics outside of the range covered by the training samples. Left is the results using PINNs, right shows the results using basic NNs without physics knowledge incorporated.

- To further validate PINNs ability to generalize, we use pseudo data for the Bethe-Heitler (BH) process where the sigmas σ are calculable. In figure 3, we test on a larger grid of unseen kinematics bins where the median absolute percentage error (MAPE) metric is calculated, demonstrating that smaller errors produced by PINN comparing to NN.

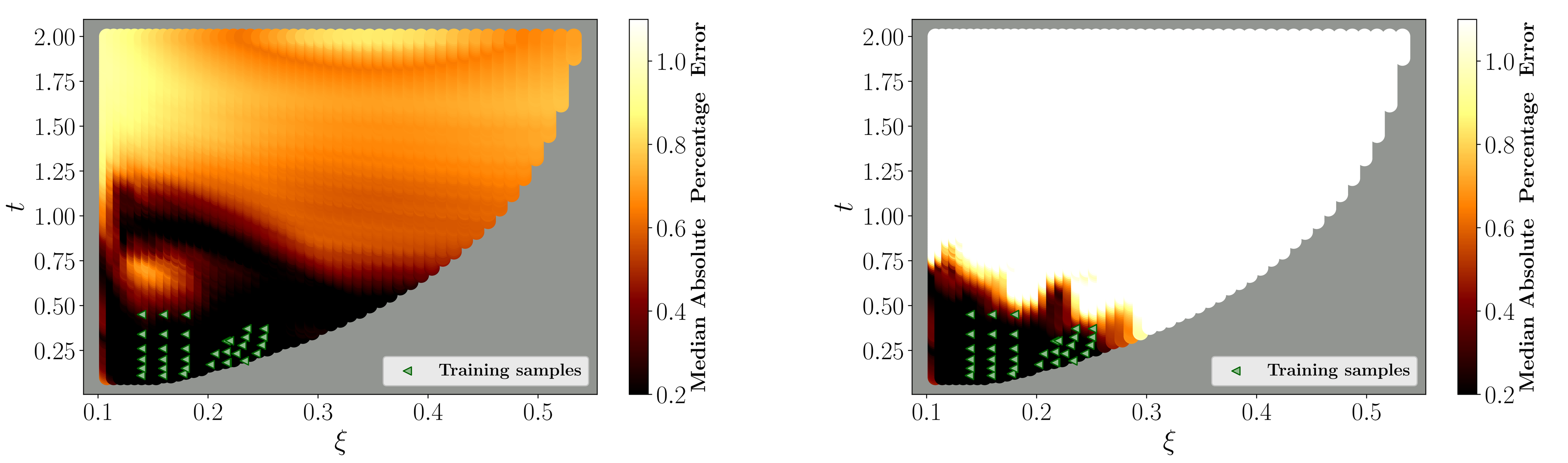

Figure 3 : BH generalization on unseen kinematics. Left represents MAPE produced by PINNs. right represents MAPE produced by basic NNs.

5. Conclusions

- We have developed our first version of PINNs to DVCS cross sections by incorporating some physics information such as angular symmetry.
- Testing on DVCS and BH data, our PINNs demonstrate promising results on the unseen kinematics.
- Future work: Uncertainty quantification analysis, Compton form factor extraction using [3].

6. Acknowledgement

This work has received a CY2021 Center for Nuclear Femtography (CNF) Graduate Fellowship to M. Almaeen and partially was supported by a grant from CNF, administrated by the Southeastern Universities Research Association (SURA) under an appropriation from the Commonwealth of Virginia.

7. References

[1] Julie Roche. The DVCS program in Hall A at JLab. *PoS*, QNP2012:036, 2012.

[2] Grigsby and et al. *Phys. Rev. D*, 104(1):016001, 2021.

[3] Almaeen and et al. Variational autoencoder inverse mapper: An end-to-end deep learning framework for inverse problems. In *2021 International Joint Conference on Neural Networks (IJCNN)*, 2021.