AIOP
AI OPTIMIZED POLARIZATION

AI for Optimized Polarization

David Lawrence, Jefferson Lab
(and a bunch of other people)

Jefferson Lab
Thomas Jefferson National Accelerator Facility

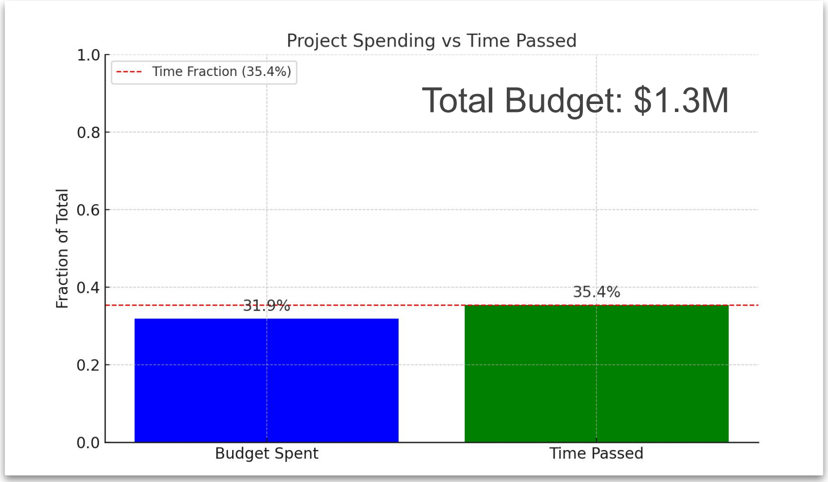
Carnegie Mellon University

William & Mary
CHARTERED 1693

Budget and Staffing

Project funds became available in March 2024.

Spending roughly on schedule for 2 year project.

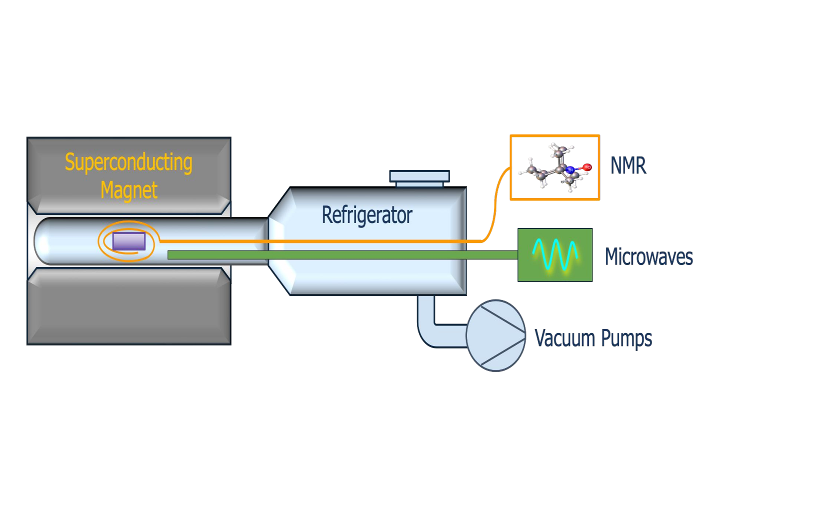


Staffing profile (estimated at start of project)

	FY2024									FY2025												FY2026						
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Total
Thomas			5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%		5.0%
Torri			75%	75%	50%	50%	25%	25%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%		50.0%
Malachi			5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%		5.0%
DS SCSII - Target							25%	50%	50%	25%	25%	25%	25%	25%	50%	50%	50%	50%	50%						50%	50%		25.0%
DS SCSII - Beam					25%	50%	50%	25%	25%	25%	25%	25%	25%	25%						50%	50%	50%	50%	50%	25%	25%		25.0%
Cristiano																			42%	42%								3.5%
W&M Postdoc			100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%		100.0%
CMU Grad Student			100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%		100.0%

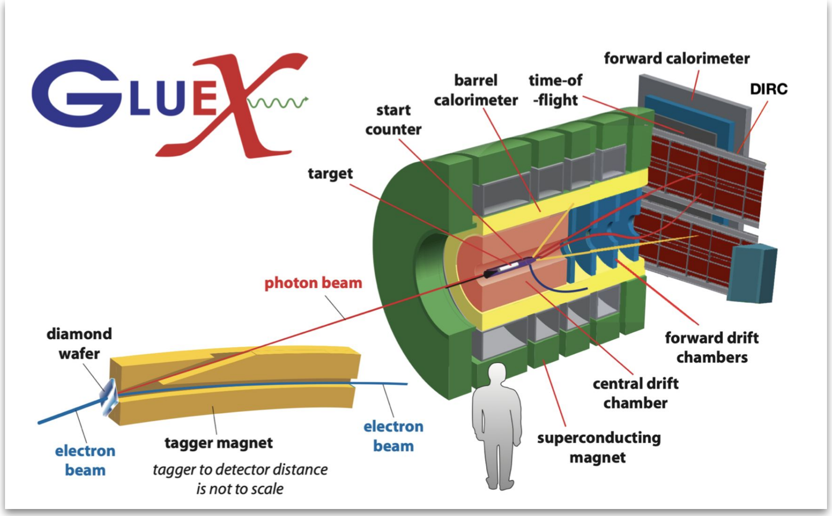
Polarization at Jefferson Lab

Polarized cryotargets are used throughout Jefferson Lab to study nuclear spin structure



Polarized targets

Hall-D uses a polarized photon beam to search for and measure exotic hybrid mesons



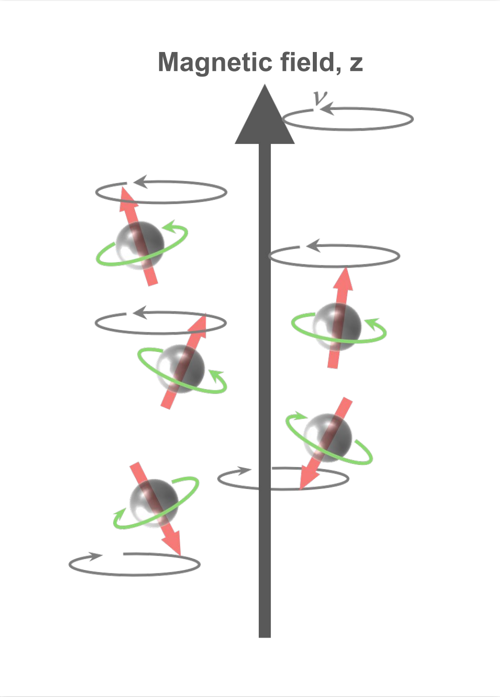
Polarized photon beam

Polarized Target

Dynamic Nuclear Polarization

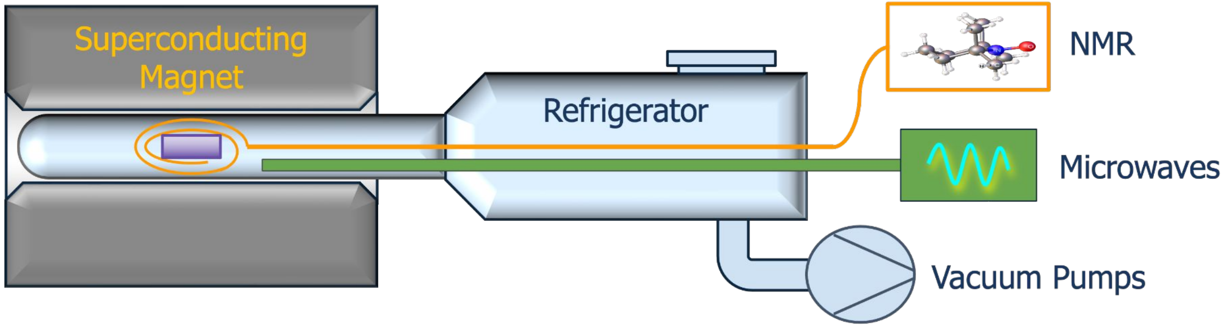
Polarization is a measure of how many target spins are pointing in a specified direction (usually a magnetic field)

Dynamic nuclear polarization involves polarizing electrons at moderate field and temperature and transferring the electron polarization to the nuclei



Polarized Target

Equipment



For best results, the field-to-temperature ratio should be at least 5:1. Historically, this corresponds to 2.5T: 0.5K and 5T:1K

Major components to a typical solid polarized target system:

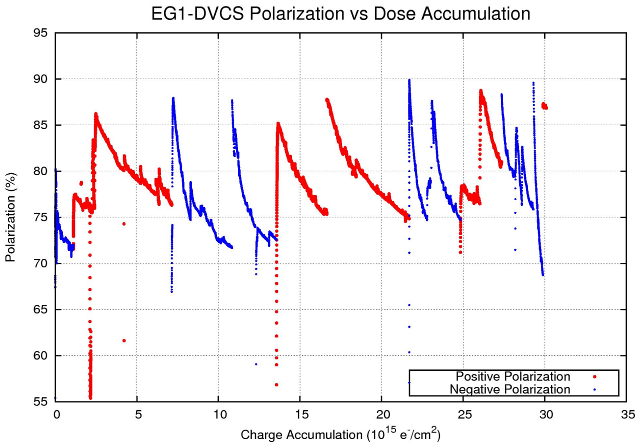
1. Target sample (material)
    a. Maximum polarization
    b. Radiation resistance
    c. Dilution factor
2. Magnet
    a. Require 2.5-5T field generated by superconducting magnets
3. Refrigerator
    a. Maximum polarization requires cooling the target sample to < 1K
4. Microwaves
    a. Microwave frequency determined by the magnet
5. NMR
    a. Continuous wave NMR to measure the nuclear polarization

Polarized Target

Dynamic Nuclear Polarization

The optimal polarization decreases due to the electron beam creating additional radicals, requiring further adjustments from the shift crew.

Target samples are warmed up (annealed) to ~100k to remove unwanted impurities, with eventual replacement after 5-10 anneals



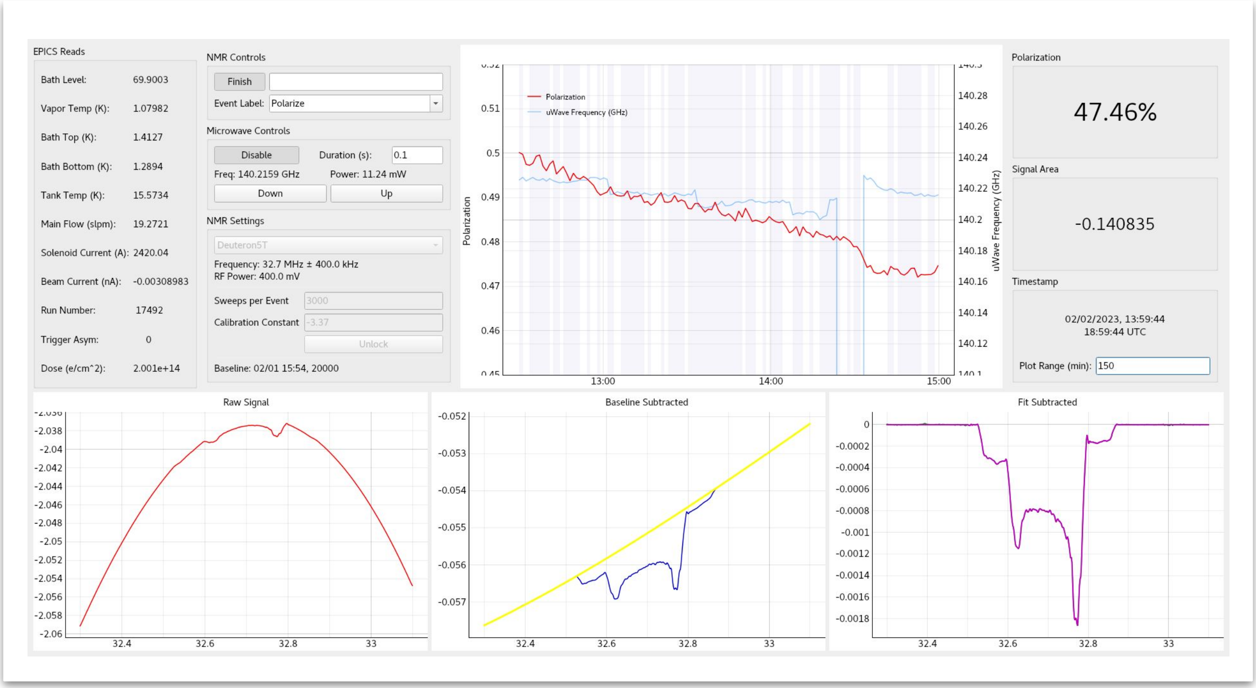
Beam spot on target

Polarized Target

Standard Operation

Shift workers adjust the microwave frequency as needed to maintain the target polarization.

The experience of the shift workers significantly influences the average target polarization maintained throughout an experiment.



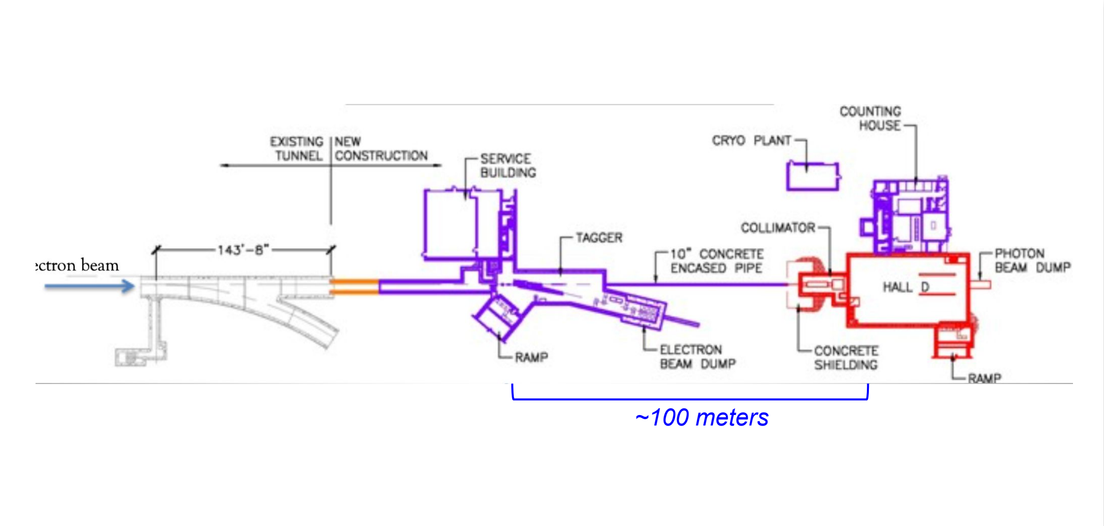
Polarized Photon Beam

Coherent Bremsstrahlung

Polarization indicates fraction of high energy photons with electric field pointing in the same direction

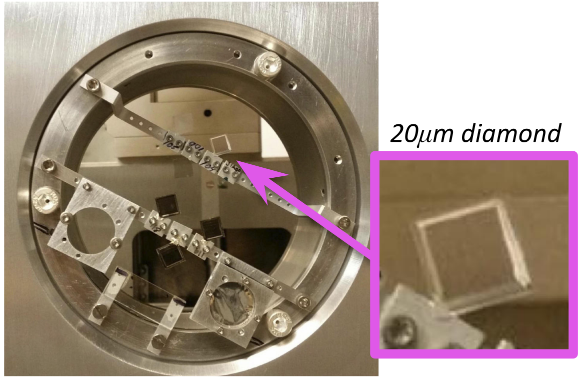
Linearly Polarized Photons are generated by passing the electron beam through a diamond which has regular crystal structure

Enhancements in the bremsstrahlung energy spectrum are correlated with the angle of the produced photon



Polarized Photon Beam

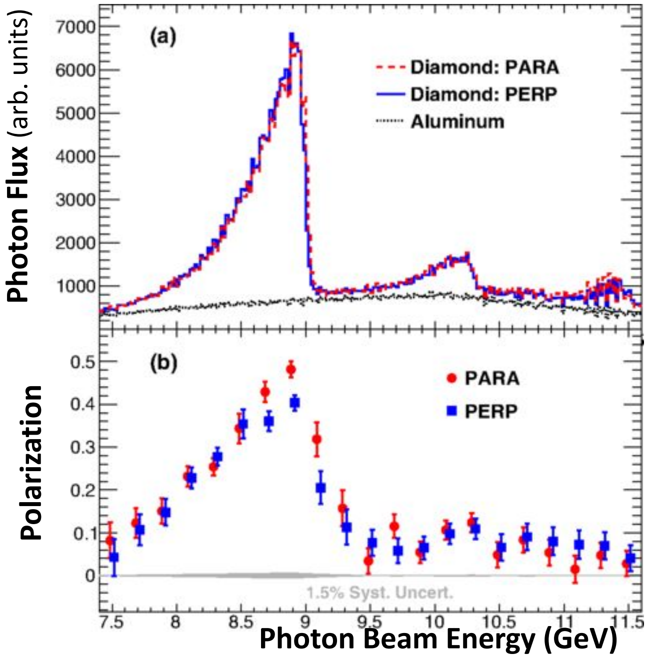
Diamond Radiator



Radiators on goniometer

	e^- beam	Coherent peak
GlueX	11.7 GeV	9 GeV
CPP	11.7 GeV	6 GeV

PHYSICAL REVIEW C **95**, 042201(R) (2017)



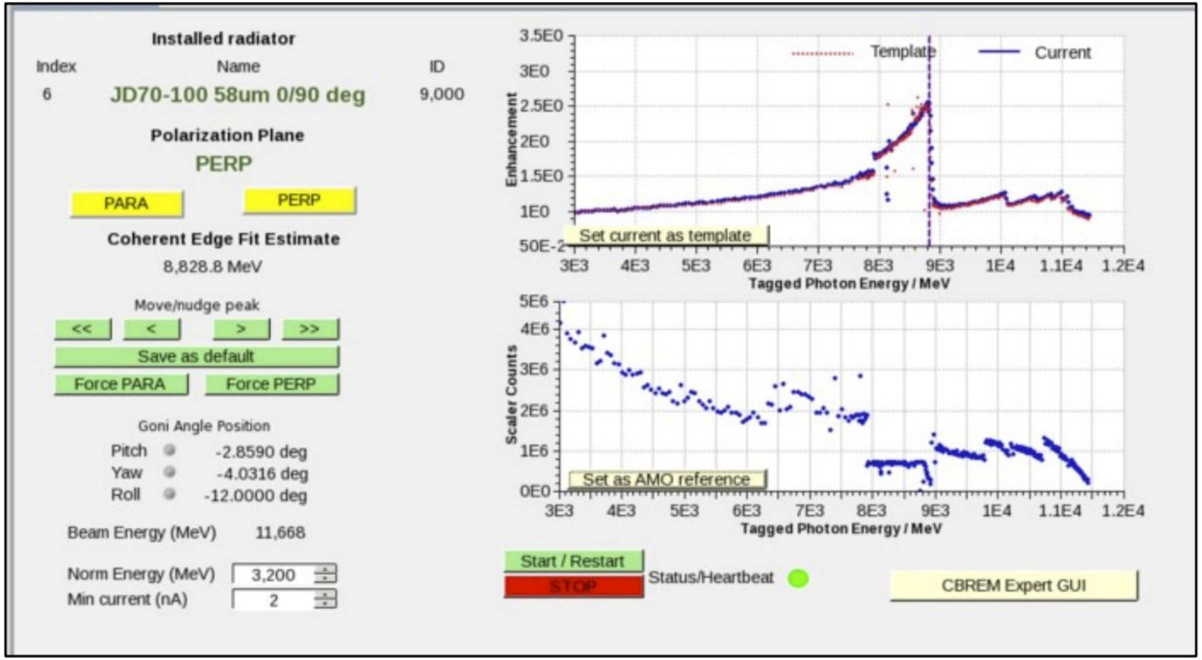
(a) Photon beam intensity versus energy as measured by the pair spectrometer (not corrected for instrumental acceptance)
(b) Photon beam polarization as a function of beam energy, as measured by the triplet polarimeter, with data points offset horizontally by ±0.015 GeV for clarity.

Polarized Photon Beam

Standard operation

Experts determine the ideal coherent edge position for each run period.

The shift crew is responsible for maintaining this position throughout data taking by “nudging” the orientation of the diamond via pitch and yaw angles.



Manual tuning could be replaced by AI/ML control systems

Polarized Targets

Learn the optimal microwave frequency control policy to maximize the target polarization continuously throughout an experiment

Polarized photon beam

Learn and apply autonomous, real-time angular shifts to the goniometer that nudge the coherent peak to its nominal position

Benefits

Reduced systematics

Improved control of the goniometer angles would reduce the systematic uncertainty of the measured photon polarization

Increased beam time

Increase the available beam time for both applications by reducing the number of anneals and keeping the coherent edge position stable

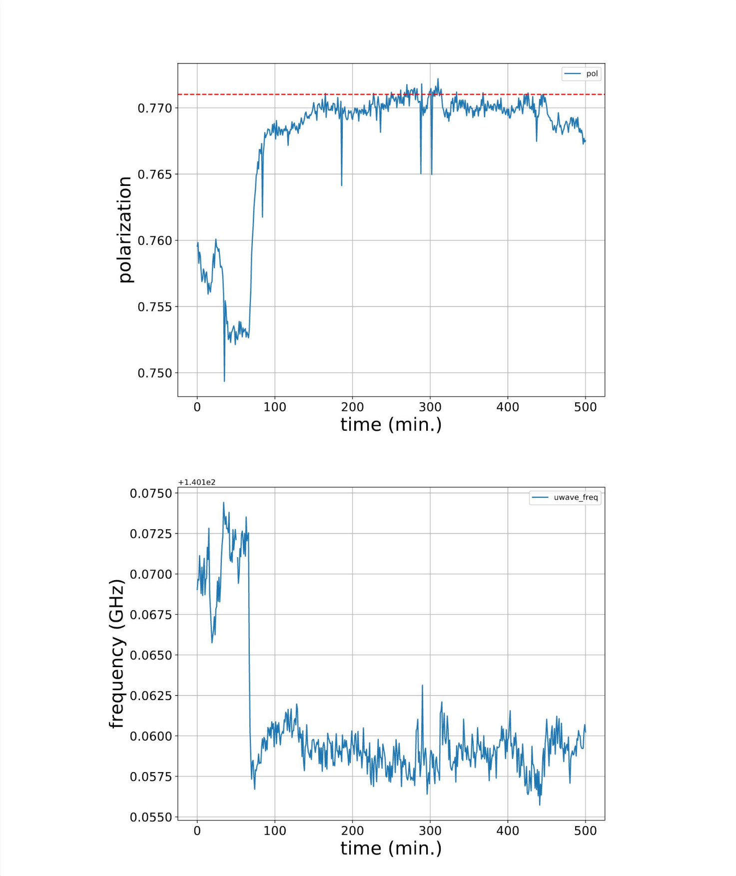
Minimize inconsistency

Shift crews perform shift responsibilities differently, even with established policies

Polarized Target

Benefit

Automatic adjustments to the microwave frequency can prevent large drifts, maximizing polarization during the run.

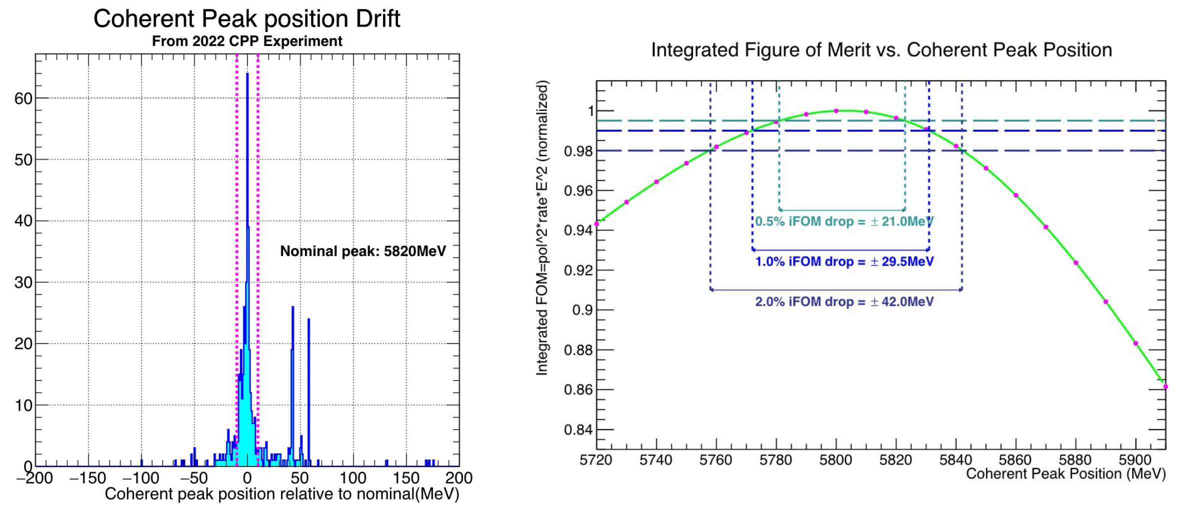


These plots show the polarization (top) and corresponding microwave frequency (bottom) for 500 min. of the CLAS12 Run Group C data from 2022

Polarized Photon Beam

Benefit

Experiments select events with photons in a narrow energy window. Drifts in the coherent spectrum cause the polarization peak to move in/out of the window resulting in a reduced Figure of Merit for the beam time.



Surrogate Models for Reinforcement Learning

Limited real world data

RL is required to sample the environment to gain experience and learn what to do and what not to do

Gaussian processes (GP) naturally provide uncertainty quantification

This ensures we are training on in-distribution experiences

Use surrogate model to pretrain RL model

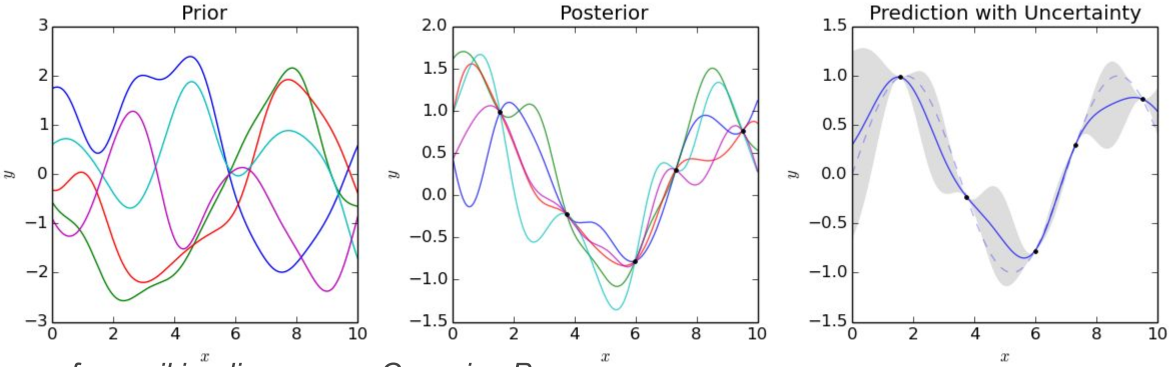
Minimal retraining to fit the deviations from simulation to the real system

Surrogate Models

Gaussian processes

Provide uncertainty quantification

Fast training and inference



from wikipedia page on Gaussian Processes

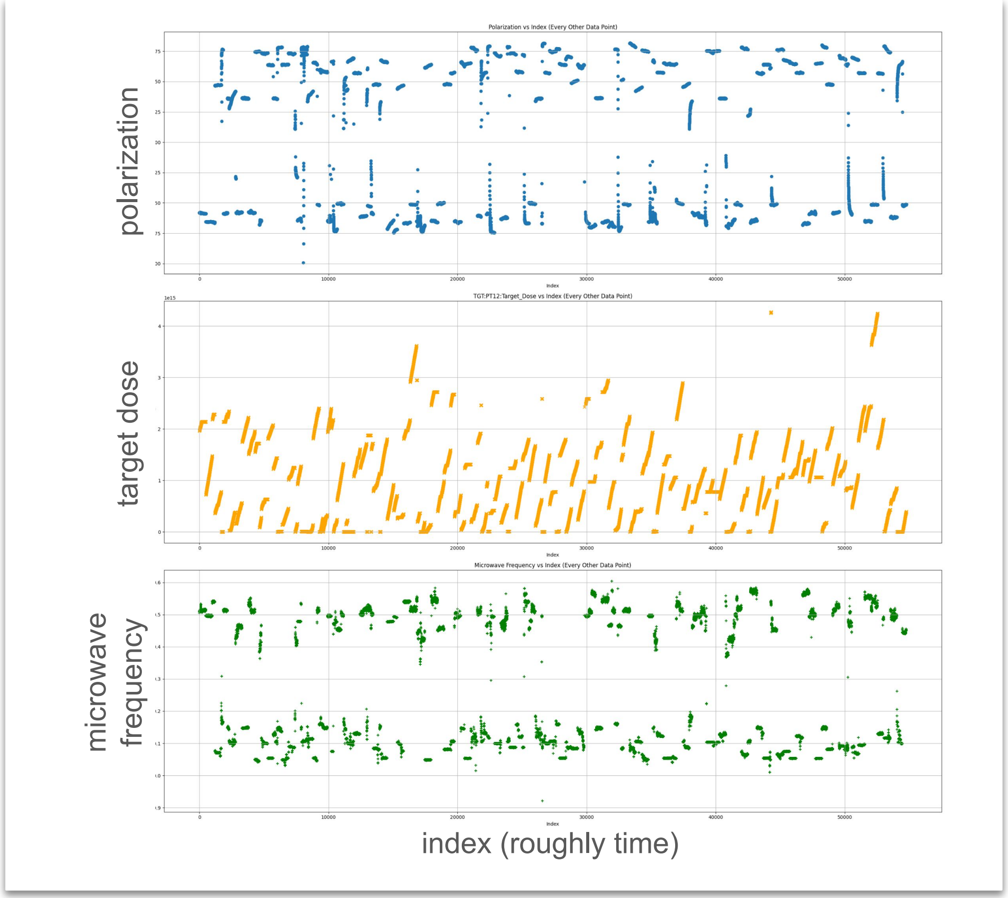
Polarized Target

Input features

Initial set of input features include:

Experimental
Solenoid current
Electron beam current
Target temperature
Target dose
Microwave frequency

Data-driven
Calibration constants
Signal mean and standard deviation
Background mean standard deviation



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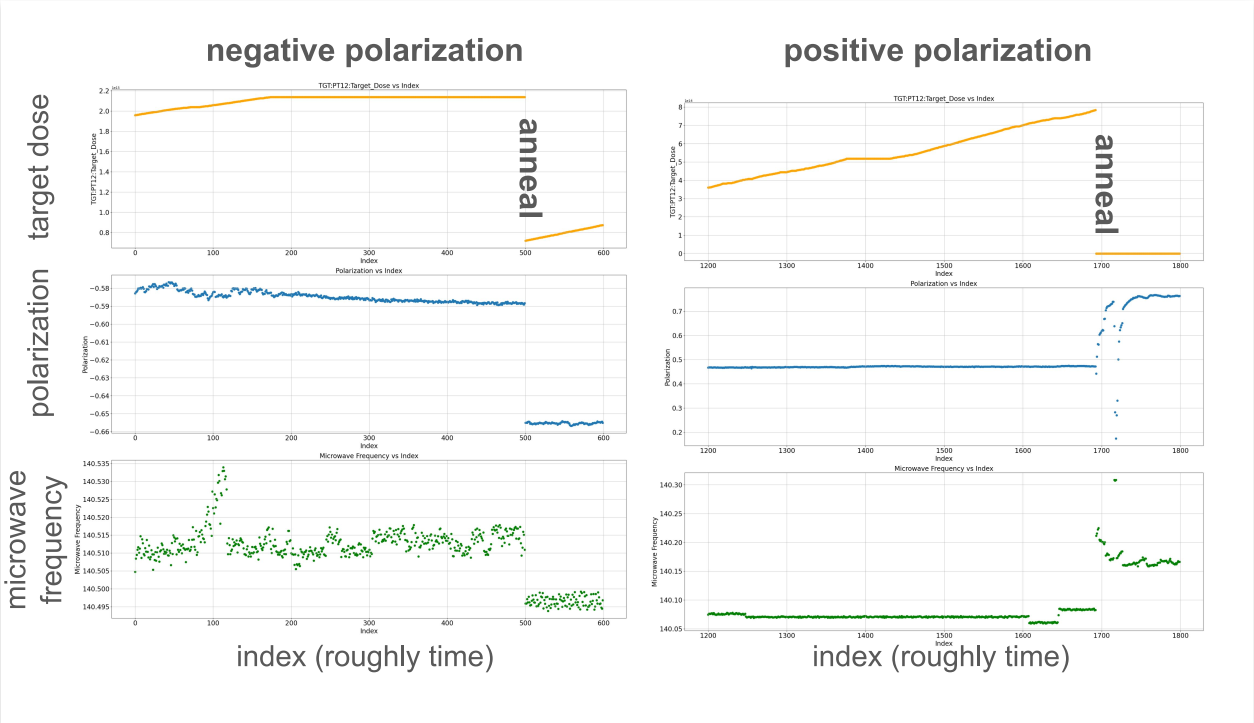

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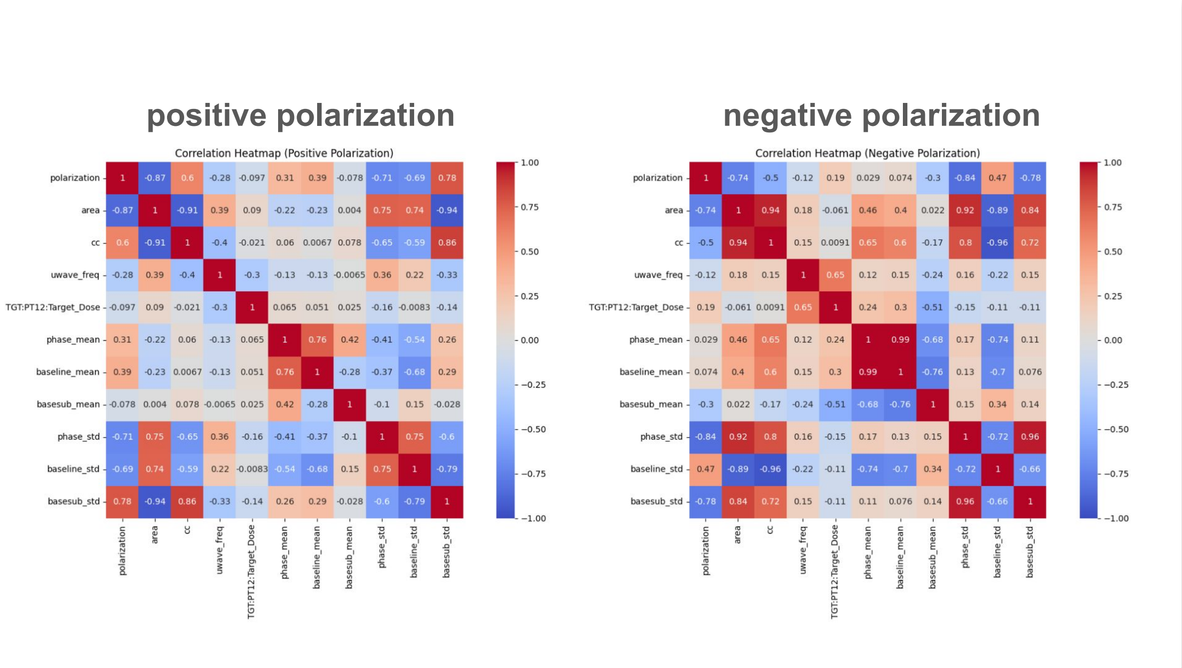


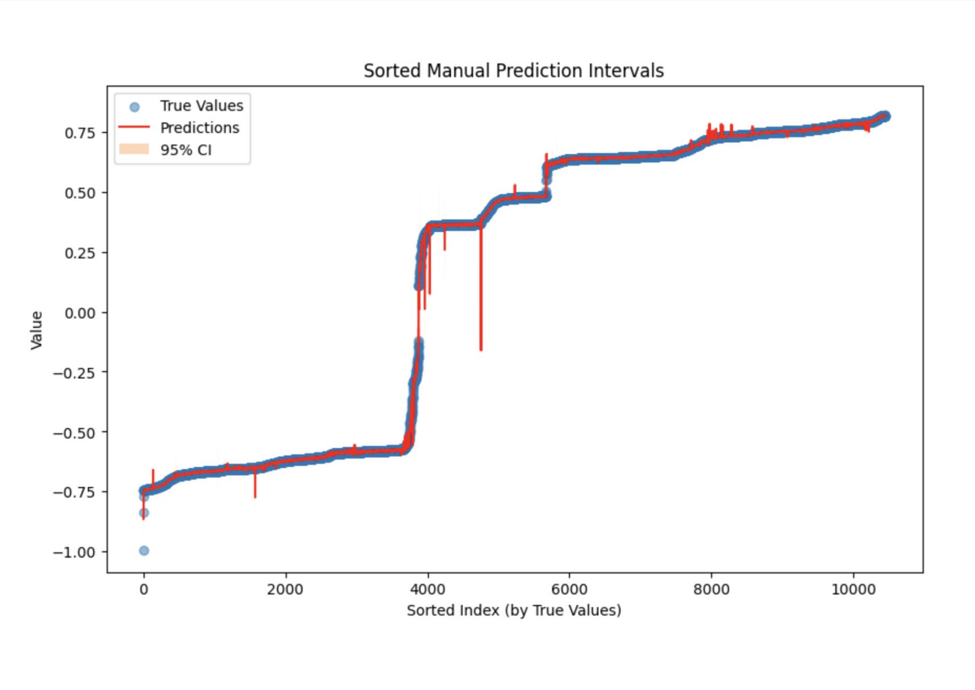
Polarized Target

GP performance

Model training results for predicting proton polarization (vertical axis) trained with both positive and negative polarization values.

Model reproduces measured polarization well with good confidence.

Large outliers are still under investigation.



Polarized Target

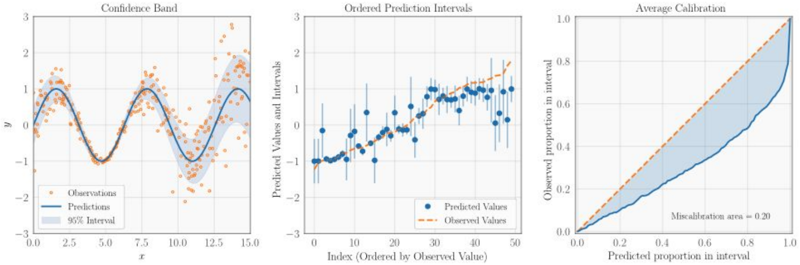
Uncertainty calibration

GPs return a prediction along with an uncertainty

We want to determine if our uncertainties are accurate and well calibrated.

A well calibrated GP would have its predicted values lying on the line y=x.

overconfident (too little uncertainty)



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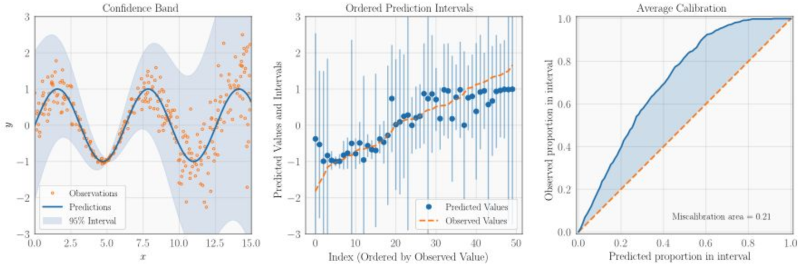
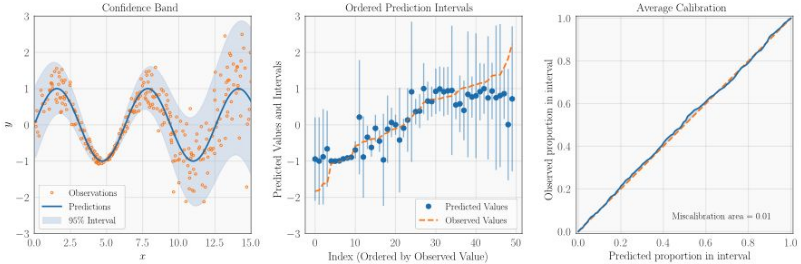


Well calibrated



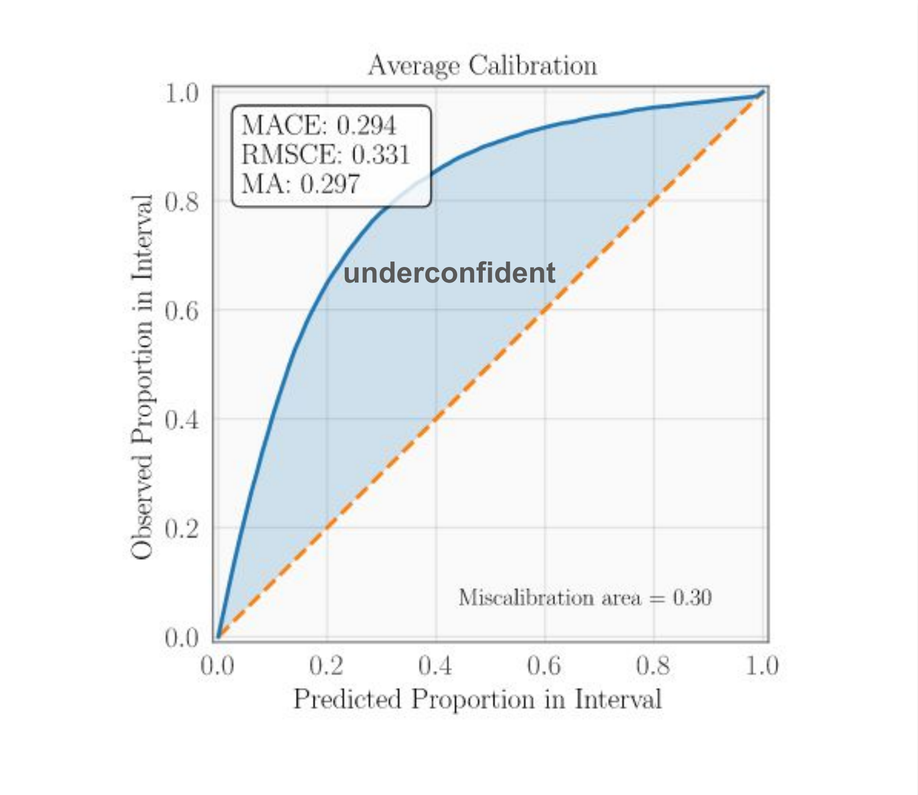
Polarized Target

Uncertainty calibration

We can form an alpha-prediction interval that aims to capture observed values alpha % of the time

Calibration plots show the predicted proportion of the test data we expect to lie inside the interval on the x-axis and the observed proportion of the test data inside the interval on the y-axis.

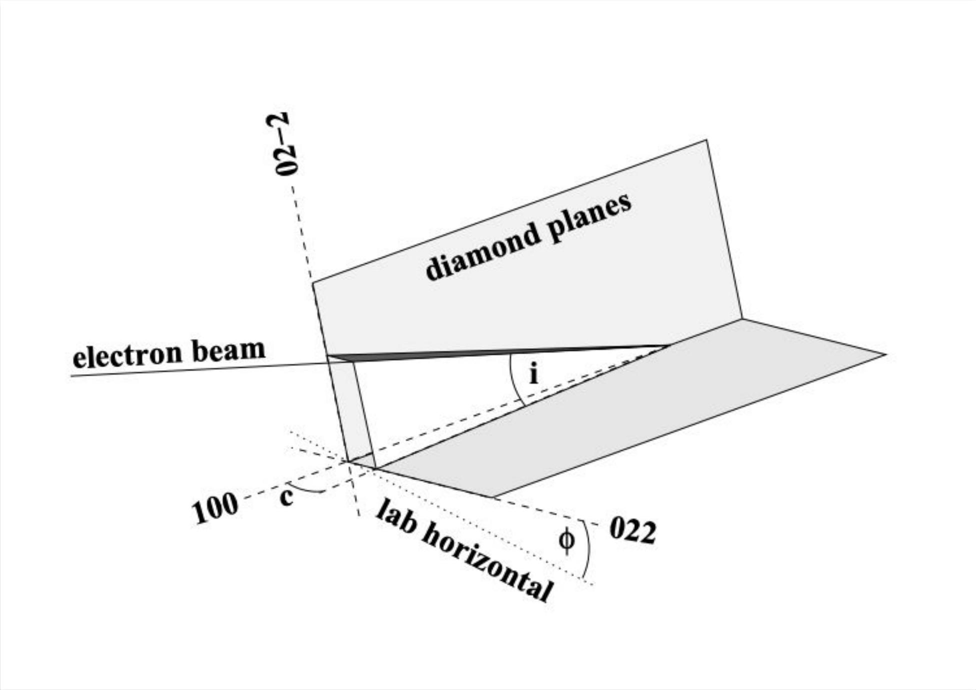
We can accurately predict the polarization, but we should recalibrate the model uncertainties.



Polarized Photon Beam
Surrogate Model

Livingston[1] defines an analytic approximation that describes the angle, c, between the beam and the [022] planes which fixes the position of the coherent edge.

This model does not take into account fluctuations in the electron beam position provided from CEBAF.



[1] NIM Volume 603, Issue 3, 21 May 2009, Pages 205-213

Conclusions

Strong collaboration between physicists and data scientists

Polarized targets and polarized photon beams are complicated systems that require continuous attention and frequent tuning

Surrogate models are under development to aid in training RL models for control

This work was supported by the US DOE as **DE-FOA-0002875**.

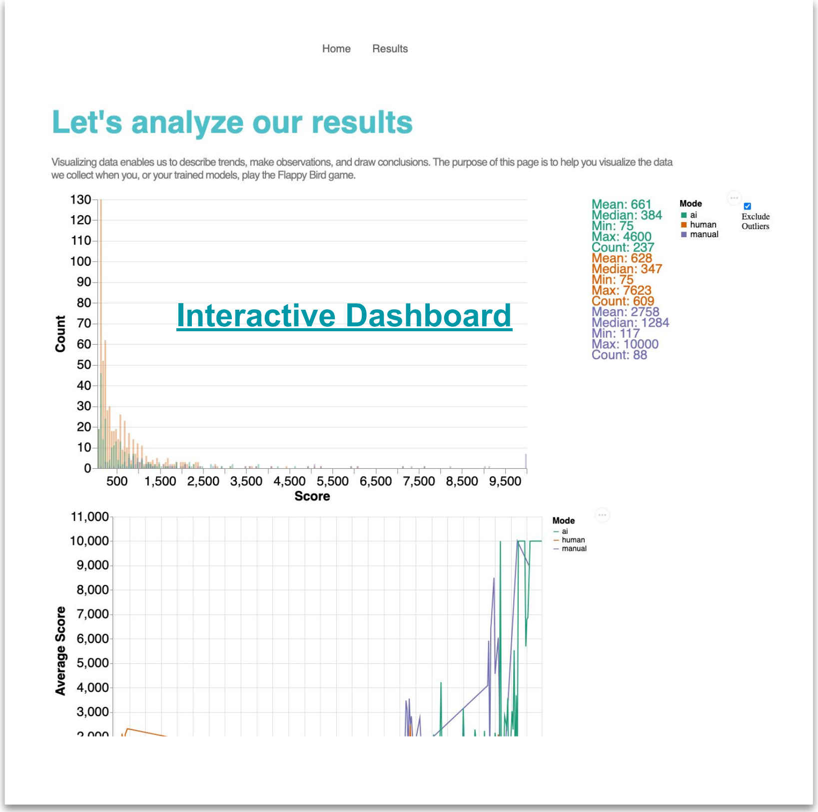
Jefferson Lab supported by the U.S. Department of Energy, Office of Science, Office of Nuclear Physics under contract DE-AC05-06OR23177

Middle School Data Science Workshop

Hosted 30 students from Newport News Public Schools at Jefferson Lab

Students trained a RL model to play Flappy Bird

Interactive dashboard was developed to show the students scores compared to their RL models.



HUGS Lectures

HUGS included topical seminars on Machine Learning for Nuclear Physics

Thomas Britton led the ML in NP hands on activities

Torri Jeske presented applications of ML in NP

Milestones: Polarized Target

3/1/2024	Identify and curate appropriate historical data sets of measured polarization.
6/30/2024	Develop simulation of target polarization behavior based on historical archives that can be used for AI/ML model development
7/31/2024	Collect historical waveform data for NMR signal from polarized target and prep for use in model training
11/30/2024	Implement signal extraction technique for accurate extraction of NMR signal from background
2/28/2025	Identify and train appropriate model for controlling microwave frequency
6/30/2025	Test model against simulation data and adjust to optimize performance
11/30/2025	Utilize the polarized target group’s test facility to test the model
2/28/2026	Integrate models and appropriate codes into the AI/ML controls ecosystem

Milestones: Polarized Source

3/31/2024	Identify all potentially relevant parameters, gather historical data, curate into form suitable for AI
5/31/2024	Identify nudge events and responses to build data set
6/30/2024	Perform shapley analysis based on polarization FOM (=pol^2 x photon energy) to determine most relevant parameter set
11/30/2024	Develop and train model to predict polarization FOM based on available inputs
3/31/2025	Connect AI/ML model from the larger lab DS ecosystem to the control system for the goniometer.
6/30/2025	Develop and implement safety policies for operation of the system, including interfacing with the EPICS alarm system
8/31/2025	Create outward facing monitoring pages for the system using Grafana or similar
11/30/2025	Create simulation of realistic operating conditions that includes regular beam trips, DAQ transitions and configuration changes.
2/28/2026	Refine model and deployment to operate in continuous mode

Team Members

PI

David Lawrence, PhD (physics)

Expertise: Physics, C++, software framework, online systems

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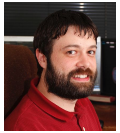

Co-PI

Thomas Britton, PhD (physics)

Expertise: Physics, software, OSG, AI DQM

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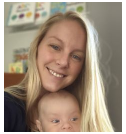

Torri Jeske, PhD (physics)

Expertise: Experimental Nuclear Physics, Data Analysis, Detector Calibration

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Armen Kasparian, MS (CpE)

Expertise: Data Science, Reinforcement Learning

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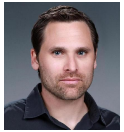

Malachi Schram, PhD (physics)

Expertise: Data Science Dept. Head

Jefferson Lab

**consulting*

Hovanes Egiyan, PhD (physics)

Expertise: Physics, Polarized Photon Source

Jefferson Lab

Co-PI
**consulting*

Naomi Jarvis, PhD (physics)

Expertise: Physics, Detectors, Calibration

Carnegie Mellon University

Jiawei Guo, Grad. Student CMU

Carnegie Mellon University

Co-PI

Cristiano Fanelli, PhD (physics)

Expertise: Faculty - Physics, Data Science

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Patrick Moran, PhD (physics)

Expertise: Postdoc - Physics, Data Science

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**consulting*

James Maxwell, PhD (physics)

Expertise: Polarized Cryotargets

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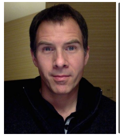

**consulting*

Chris Keith, PhD (physics)

Expertise: Target Group Lead

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Backups

Budget

	FY24 ($k)	FY25 ($k)	FY26 ($k)	Totals ($k)
a.) Funds allocated	1,300	0	0	1,300
b.) Actual Costs to date	318	97	0	415