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Machine Learning Pattern Recognition for Online Monitoring and Visualization in the SpinQuest Experiment

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SpinQuest will measure the sea quarks' Sivers Asymmetry, a left-right asymmetry, with a target transversely polarized to the incoming 120 GeV proton beam. An online monitoring system has been developed to scan the polarized target system and polarization data while integrating information from detectors and event reconstruction for near-continuous quality checking of the incoming data. Online monitoring of the target system and detector package will play a vital role in ensuring optimal performance of the target while achieving the highest figure of merit possible given the experimental circumstances. This novel monitoring system enhances the debugging process during commissioning and data acquisition through the use of machine learning pattern recognition techniques and anomaly detection. The scheme outlined promises to aid target operations by ensuring data quality and getting issues addressed soon via a system of alarms during the two-year-long production runs to begin 2024 at Fermilab.

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1. Introduction

Since the discovery of quarks at the Stanford Linear Accelerator Center (SLAC), significant efforts have been made to describe the partonic structure of the nucleon. The origin of nucleon spin, an intrinsic angular momentum, has been particularly puzzling since the "proton spin crisis" emerged in the late 1980s. Before this period, hadrons were understood to be composed of three quarks, with the quarks theoretically contributing most of the nucleon's spin, each with a spin magnitude of $\frac{1}{2}\hbar$. In the late 1980s, the European Muon Collaboration (EMC) experimented to investigate the spin contributions of individual quarks within the nucleon, expecting results consistent with the parton model. Contrary to these expectations, their findings revealed that the quarks within the proton accounted for only $(14 \pm 9 \pm 21)\%$ of the total spin, much lower than predicted [14]. This discrepancy, known as the "proton spin crisis," prompted the development of spin physics, a field dedicated to exploring the internal dynamics within protons that generate their spin.

To address this enigma, nuclear physicists embarked on a collaborative quest to uncover the missing spin. The STAR experiment at the Relativistic Heavy Ion Collider (RHIC) determined that valence quarks contribute around 30% of the proton's spin [4]. More accurate descriptions of hadron spin have since been developed, using sum rules that account for quark and gluon spin and orbital angular momentum (OAM). The Jaffe-Manohar and Ji sum rules are pivotal in this context. Jaffe-Manhar connected the spin contribution summed over the quarks $\Delta\Sigma$ and gluon ΔG and their OAM components [11].

$$\Delta S = \frac{1}{2}\Delta\Sigma + \Delta G + L_q + L_g \tag{1}$$

Ji's decomposition is a gauge-invariant decomposition of the nucleon spin into the quark helicity $\Delta\Sigma$, the quark OAM L_q^Z, and the gluon contribution J_g^Z [16].

$$\Delta S = \frac{1}{2}\Delta\Sigma + L_q^Z + J_g^Z \tag{2}$$

Spin follows the same algebra as angular momentum, therefore adding two particles' spins together will result in a total spin.

Numerous experiments are now poised to shed further light on the spin puzzle. Among these is SpinQuest, a Drell-Yan Transversely Polarized fixed target experiment at Fermilab. SpinQuest aims to probe the quark sea, which consists of quark-antiquark pairs from gluon splitting that rapidly recombine. Despite being virtually elusive, predictions from lattice QCD suggest the quark sea significantly contributes to overall spin [8].

SpinQuest investigates the sea quarks through the Sivers function. Notable transverse single-spin asymmetries have been observed in hadron-hadron collisions. D. Sivers proposed that these asymmetries arise from the azimuthal asymmetry of transverse momentum when the hadron is polarized [3]. The Sivers function correlates the transverse momentum of an unpolarized parton with the spin of a transversely polarized nucleon [2]. The function is calculated as the ratio of the difference and sum of cross-sections from two divisions of the collision. For instance, an example of an asymmetry is shown below, the UP arrow shows the spin polarization.

$$A = \frac{d\sigma \uparrow_L - d\sigma \uparrow_R}{d\sigma \uparrow_L + d\sigma \uparrow_R} \tag{3}$$

In the SpinQuest experiment, asymmetries will be experimentally determined by detecting dimuons from quark-antiquark interactions in the Drell-Yan process [2]. Due to the time-like nature of the Drell-Yan process, the kinematics of these interactions can be directly correlated with the detected dimuons' kinematics. By analyzing the detected muons, the experiment can be divided into different regions to study various asymmetries based on polarization direction. The left-right asymmetry, using reconstructed tracks' transverse azimuthal angles, can be visualized as the interaction's impact on the quark-antiquark pair's dynamics. This can be described as the Left-Right asymmetry through the number of reconstructed tracks, N, divided in ϕ_{q_t} left and right 4.

$$A_n(\Phi_{q_t}) = \frac{N_L(\Phi_{q_t}) - N_R(\Phi_{q_t})}{N_L(\Phi_{q_t}) + N_R(\Phi_{q_t})} \tag{4}$$

Previous experiments like COMPASS, Jefferson Lab, and HERMES have studied spin structure using semi-inclusive deep inelastic scattering (SIDIS), but Drell-Yan statistics are less robust in comparison [17][9][13]. SpinQuest aims to fill these statistical gaps using Drell-Yan and test a fundamental QCD prediction: the Sivers function should change sign when switching from SIDIS to Drell-Yan [2].

$$f^{\perp q DY}(x, p_T^2) = -f^{\perp q SIDIS}(x, p_T^2) \tag{5}$$

Maintaining the experimental integrity of SpinQuest requires a deep understanding of spin asymmetries and the identification of false asymmetries. False asymmetries, or non-physical asymmetries, can result from diurnal effects, beam variations, detector drifts, and other instrumental changes. To counteract these, real-time data analysis and robust online monitoring are essential. Monitoring several asymmetries and detecting trends can help isolate the cause of false asymmetries. For instance, if a slope change occurs in the left-right asymmetry, it might indicate a detector issue. Quick and reliable reconstruction is necessary for real-time analysis, and this is achieved using GPU acceleration.

SpinQuest employs two reconstruction techniques: K-Tracker, which uses the Kalman filter for geometric reconstruction of dimuon four-momenta, and Q-Tracker, a faster method leveraging a hit matrix and neural networks. Q-Tracker's speed makes it suitable for online monitoring purposes [5] [1].

We aim to develop an online monitoring system to quickly display real-time physics data during each spill. This system includes displays and alarm mechanisms to alert for issues during experimental runs. The ultimate goal is to identify false asymmetry sources, which are the leading cause of systematic error in our experiment. False asymmetry detection involves calculating several asymmetries and displaying/analyzing data quickly. By monitoring the number of hits in different sections (Left-Right) or the Left-Right spin asymmetry from ϕ_{q_t}, we can track data trends over multiple runs, locate false asymmetry sources, and train models to recognize patterns. Real-time displays paired with a robust alarm system using these models will enhance the level of merit of the experiment.

In this talk, we presented the early development of our online monitoring system. We simulated realistic spills using Monte Carlo methods and occupancy studies from SeaQuest to understand spectrometer and reconstruction patterns. Analyzing reconstruction is crucial for online monitoring and training models for anomaly detection. We discussed methods to display vital information for detecting anomalies and previewed our approach to identifying false asymmetries.

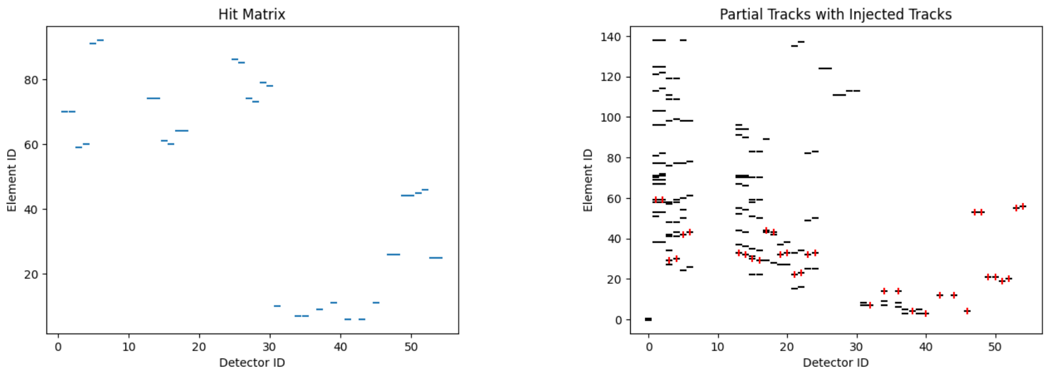
2. Integrating Information Between the Hit and the Reconstruction.

All the software developed is on the GitHub repository, which can be found here: [6]. A collection of the simulated data used to create the background can be found on the University of Virginia computer cluster, Rivanna, Path:/project/ptgroup/Jay. This procedure will replicate some of the logical steps taken during the preliminary stages of the online monitoring and visualization process done for SpinQuest.

2.1 Creating a Realistic Spill

As SpinQuest prepares to launch, we use Monte Carlo to create theoretical predictions on what an actual Spill from SpinQuest would look like. This Monte Carlo was done using Geant4 and PYTHIA6 tuned for SpinQuest's setup [12] [15]. We used spills and occupancy studies from the SeaQuest experiment done for run 6 by Kenichi Nakano, to tune our simulated spill.

As shown below in Fig. 1a, we generated a set of events for a single muon track. We randomly selected complete tracks and randomly sampled pieces of these events at different sections of the detector, placing them into a simulated hit matrix. This creates a hit matrix with partial tracks. We then add random hits to simulate random cosmic noise to complete the background for the event. This background simulates hits coming from the dump that need to be filtered for proper reconstruction. With the simulated background completed, we inject a complete track to test software, as shown in Fig. 1b.



(a) A complete event without any background tracks.

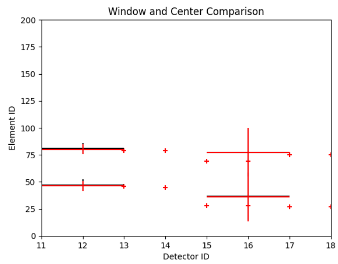
(b) The same event with background tracks added.

Figure 1: A complete event going from the start of the detector to the end of the detector. The Drift chambers consist of detector IDs 1-30, 30-45 are the horoscopes, and 45-55 are the proportion tubes. Each Station in the drift chamber consists of 6 hits. Consisting of hit pairs in 6 planes. The hit matrix is an array of element IDs (y-axis) and detector IDs (x-axis). The Background is made up of the hits randomly taken from several complete tracks allowed to go to randomly selected depths of the detector.

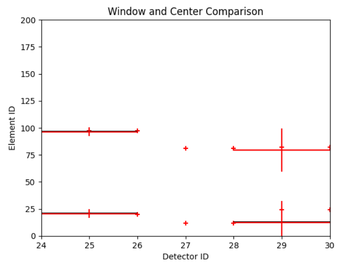
2.2 Visualising Reconstruction

The geometric approach has been widely adopted in the nuclear physics community and is considered the standard for reconstruction. To be effective for online monitoring and visualization, the process must first be thoroughly understood and dissected to extract useful information beyond the four-momenta. From our study of the geometric approach, we decided to focus on how hits form into tracks and visualize this process to understand what data is retained and what is discarded. We conducted studies on the hit-pairing technique, which matches hits in paired planes—VV', XX', and UU'—to identify their partners. This process is detailed in Kei Nagai's thesis [7].

After the hit pairs are determined, the geometric approach uses the detector's geometry to define windows where hits can occur. This straightforward method transforms into a combinatorics problem when processing multiple hits. Below in Fig. 2a and Fig. 2b are examples of the windows created and visualized to check for errors. How well does the theoretical detection agree with the experimental detection could show if an error is within a certain region of the drift chamber. The display of these windows also allows us to see where hits are kept and where they are rejected.



(a) Station 2 window comparison.



(b) Station 2 window comparison.

Figure 2: The U plane and V plane windows, vertical bar, and the U and V center, horizontal bar, for the station. The red marker is what K-Tracker produced and the black marker is what the software produced. The hit matrix is an array of element IDs (y-axis) and detector IDs (x-axis)

In the geometric approach, these windows are used to select hits from the event for hit selection and tracklet creation. Hits are chosen based on the V and U hits that define the windows. To enhance the likelihood that the selected hits originate from the target, they are matched with corresponding hodoscope hits, providing an additional filter. An example of these selected tracks can be seen here in Fig. 3. Being able to see how the hits are correlated, if tracks are being found, and their location in the detector is key to finding the source of an anomaly.

Our drift station display can be expanded to the entire detector and ordered geometrically. If a detector goes offline we will be able to see gaps within the hit display. By feeding hit information into a machine learning model, the model can learn what a normal track or hit pattern looks like and sound an alarm when an anomaly is found.

2.3 Machine Learning and Hit Patterns

Machine learning is aiding in the advancement of nuclear physics at a rapid rate. This project's goal is to use machine learning models to make predictions on the parameters concerning the experiment. Examples of these parameters are particle ID, momentum, and hit location. We aim to use unsupervised and supervised machine learning to find patterns that correlate the hit matrix to the four-momenta reconstructed.

Our preliminary approach to experiment with this method was to use supervised machine learning trained on the slopes and xy intercepts of dimuons simulated from Monte Carlo. To determine the slope and intercepts of the tracks, we used 10,000 simulated single muon events that made it through the geometric reconstruction. We used the hit matrices from these events as examples and the slopes and intercepts as labels [5]. We used validation loss to measure the model's efficiency, and the approximate error can be seen in Fig. 4.

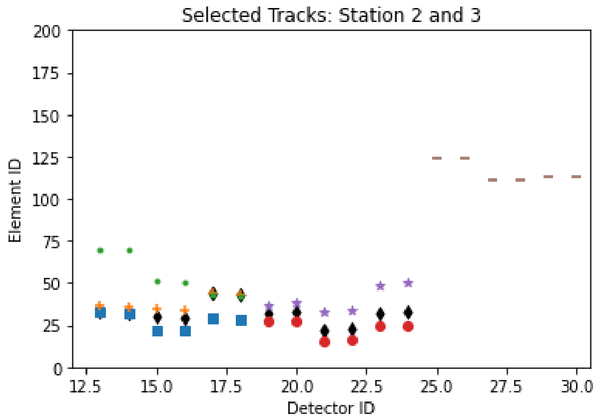


Figure 3: A figure of the Selected Tracks after the hodoscope masking. The hit matrix is an array of element IDs (y-axis) and detector IDs (x-axis). Here there are six, three in both stations. The black diamond is a reference to know where the actual track is.

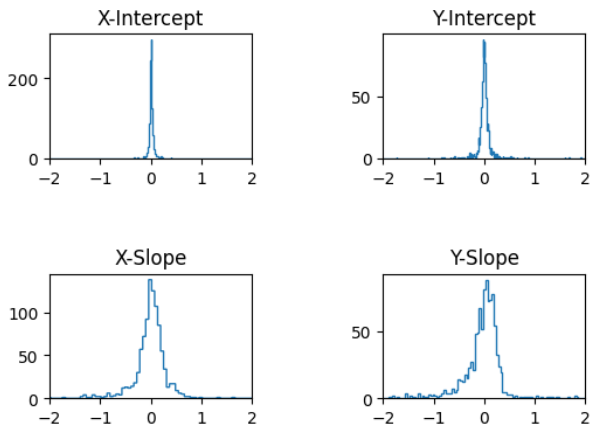
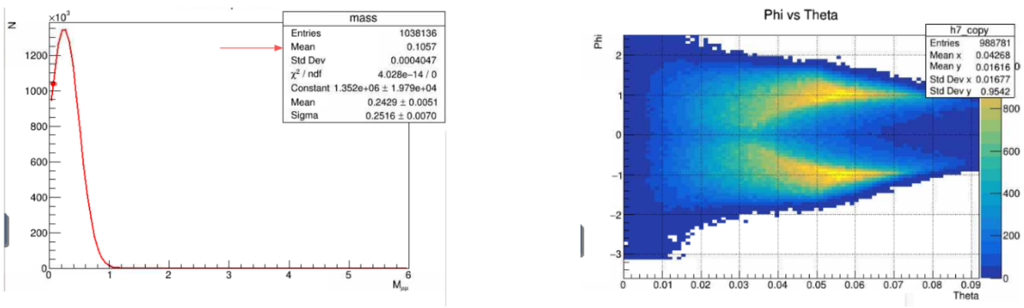


Figure 4: This figure shows the 1D histograms of approximate error of the X-Intercept, Y-Intercept, X-Slope, and Y-Slope. This is done by dividing the difference between the prediction and truth with the truth values.

To study the particle ID, we created one million events, recording their four-momenta, particle ID, phi, and theta, as seen in Fig. 5a. During the generation, we fixed all variables except theta to determine how changing theta affects the hit pattern and particle ID. These variables were fixed by applying tight cuts around the mean of the fixed value. This can be observed for phi in Fig. 5b around 1 to obtain the most statistics in changing theta.

The primary learning model suite will encompass the reconstruction package intended for use with the graphical user interface (GUI). Ongoing efforts at the University of Virginia (UVA) aim to develop this reconstruction package, Q-Tracker, utilizing a series of deep neural networks and convolutional networks to filter events and extract dimuon tracks from the target. This approach provides kinematic and reconstructed information more quickly compared to the geometric method. The online monitoring effort is collaborating closely with the reconstruction team to integrate this rapid reconstruction into the online monitoring scheme. More information on QTracker can be found from Arthur Conovers talk from Spin 2023 [1].

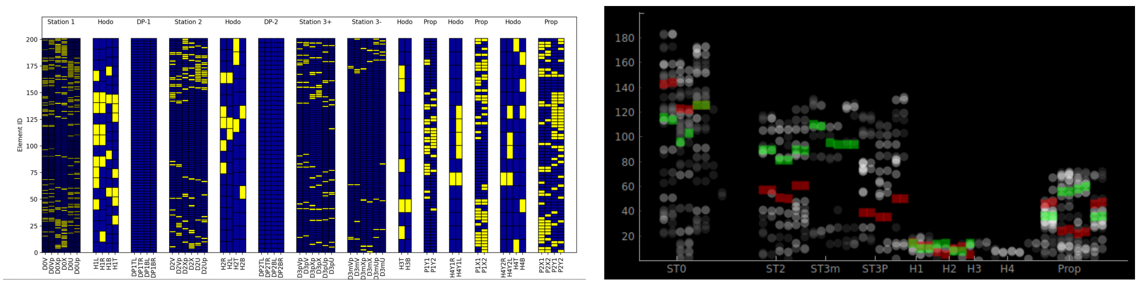


(a) Mass plot of a single muon positive events.

(b) Plot of Phi vs Theta to determine where to fix Phi.

Figure 5: The above shows the process in which the range of the four momenta and phi was constrained. The cuts were made around the peaks of each plot.

This integrated scheme will allow for the inclusion of other models to create displays for the online monitoring GUI. An example GUI was built using PYQT5 to actively display hit information. The preliminary designs, depicted in the images below, displays hit information using the raw detector data and Q-Tracker's quick reconstruction. The First display represents the hit matrix in a geometric sense with the element size correctly scaled with the detector. The Yellow patches are raw hits detected and tracks can be identified with the eye in the drift stations Fig. 6a. The second hit display is similar to the first, a hit matrix, but is integrating information from QTracker to display tracks clearly 6b. These displays are inserted into the main GUI, the initial GUI features a robust backend that monitors new spills from the detector, updates the GUI upon detecting a new spill, and displays several events with a high probability of containing a complete dimuon track from the target. The modular nature of the GUI allows for easy addition of displays such as readouts, vertex information, and mass information.



(a) A geometric approach to the hit matrix which element ID scaled per detector.

(b) A hit pattern as a hit matrix intergrating QTrackers Track finding.

Figure 6: The above shows two displays that can be integrated into the main GUI Scheme for Online Monitoring. 6a with the Y representing the element ID and the X axis representing the detector ID. Each detector has a different set of elements that are scaled correctly to align tracks geometrically. The Yellow patches are raw hits from the detector. 6b a hitmatrix intergrating QTracker fast track finding. There are three types of hits: the raw hit information from the detector in grey, the hits after declustering in white, and the dimuon track in red(muon +) and green(muon -).

As data streams from the detector and accelerator to the machine models, our primary goal is to display spin asymmetries and detect false asymmetries. Key displays include vertex information to ensure target health, a full hit display to monitor detector health, and the beam profile to maintain beam health. The display of spin asymmetry is the final point of interest.

3. False Asymmetries

The objective of SpinQuest is to calculate spin asymmetries, and to ensure the merit of the experiment, it is essential to quickly identify false asymmetries. False asymmetries are those not correlated to the physics of the interaction, caused by external factors such as changes in weather, time, target, or detector conditions. These factors can affect the polarization or the detection of muons from the spectrometer. Predicted sources of false asymmetries include changes in pressure, temperature, malfunctions, weather effects, and diurnal variations [2]. The method for detecting false asymmetries is similar to that for physics asymmetries, but false asymmetries follow trends that may persist over the course of the experiment. These trends can be observed in the changing occupancy of the hit display over time, shifts in the slope of the Sivers asymmetry with the time of day, or changes in the event vertex. Therefore, to detect false asymmetries, we must accurately display various asymmetries throughout the experiment, including those related to hits and reconstructed tracks.

Our strategy for addressing false asymmetries comprises three stages: detection, training, and implementation of alarm systems. The initial stage, detection, involves continuous monitoring using displays that showcase relevant experimental parameters and asymmetries, such as left-right asymmetries based on magnet polarization and spin asymmetries. Subsequently, data is analyzed offline to extract patterns, which could be sets of ideal events with the desired physics or sets of events with false asymmetries. Finally, this data is used to train a machine learning model tailored to recognize these patterns, and these models are integrated into an alarm system to promptly notify workers. Below, I explain the theory behind how we plan to extract the spin asymmetry for the experiment.

From the Drell-Yan cross-section in terms of Sivers asymmetry 6, we can obtain the experimental asymmetry A_N 7.

$$\sigma_{DY}^{\uparrow\downarrow} \propto 1 \pm |S_T| \sin(\phi_S) A_T^{sin(\phi_S)} \tag{6}$$

$$A_n(\phi_S) = \frac{1}{|S_T|} \frac{\sigma_{DY}^{\uparrow} - \sigma_{DY}^{\downarrow}}{\sigma_{DY}^{\uparrow} + \sigma_{DY}^{\downarrow}} = \sin(\phi_S) A_T^{sin(\phi_S)} \tag{7}$$

Fig.7 shows the rest frame of the detector where q_T is the dimuon's transverse momentum. The target spin vector S_T is aligned with the Y-axis. Experimentally we measure ϕ_{qT}, the azimuthal angle of the q_T vector. By diving up the cross section in region of spin up or down, we can make a comparison and determine if there is any asymmetry.

We can obtain azimuthal angle ϕ_S from equation 8.

$$\phi_S = \pm\frac{\pi}{2} - \phi_{qT} \tag{8}$$

It was discovered that the false asymmetries from diurnal effects can be minimized by flipping the spins periodically. At 8-hour intervals, the systematic error is minimized to less than .10% [2].

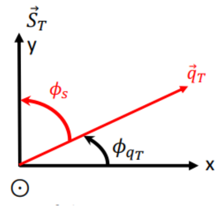


Figure 7: The rest frame of the detector with the muon momentum vector shown. The target spin vector is aligned with the Y-axis. The azimuthal angles are displayed with ϕ_{qT} being the transverse spin azimuthal angle.

Other patterns could be detected using an unsupervised machine-learning model. Machine-learning models are ideal for pattern recognition and could take spin asymmetry data to pull out patterns. Other studies are underway for SpinQuest, focusing on false Sivers asymmetries from different aspects of the experiment. One aspect of interest is the effects on Silver's asymmetries from the alignment of the target insert. During target reloading, the arm is manually inserted into the magnet, and the alignment could change per run. A misalignment in the target insert is predicted to cause a false asymmetry due to the amount of the target exposed to the beam changing. This can be studied by shifting/rotating the geometry of the target insert by a set amount on the X or Y axis inside of Geant4, with rotations around the X and Y axes. By producing Monte Carlo using this edited geometry we can create Sivers asymmetries using the equation 4.

4. conclusion

A robust online monitoring scheme is currently in development for the SpinQuest experiment. Throughout the run, as the target decays, it is crucial for the shift worker to receive real-time feedback on target interactions. The monitoring software will play a vital role in displaying the number of events from both the target ladder and the target cell to ensure precise positioning. Additionally, it will verify detector counts, aiming for around 30 counts per spill for J/psi detection, while also ensuring consistency in hit patterns.

Integrating beam, trigger, and DAQ information swiftly is imperative. This includes parameters such as beam intensity and structure from the Beam Intensity Monitor (BIM) and Cherenkov detector, DAQ and trigger error rates, and TDC-timing information. We are focusing on studying reconstruction patterns and detected hits by the spectrometer to preemptively identify potential false asymmetries. Detecting such anomalies is crucial as they may stem from detector malfunctions.

To meet SpinQuest's monitoring requirements, we are implementing a rapid reconstruction process tightly linked to the online monitoring suite. This necessitates the use of GPU-accelerated software for swift analysis, enabling visualization through a user-friendly interface. This GUI will not only visualize data but also trigger alarms to notify shift workers promptly of any anomalies.

During our presentations, we showcased several preliminary methods for integrating experimental data into an online display, which can then be paired with various machine-learning models. These displays highlight key steps in the geometric approach for reconstruction and demonstrate how such information can be utilized to train learning models. With this framework established, we are poised to refine our system, ultimately creating a robust platform capable of swiftly displaying vital information and leveraging pattern recognition to meet the high standards set by SpinQuest.

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