with game theory to analyze client activities in the RHIC control systems [4]. Prognostics and errant beam prevention are becoming increasingly important in an age where we have many superconducting accelerators (superconducting magnets and superconducting radio frequency), with high repetition rates and high power, and complex sensitive components. There is a much greater need for improved prognostics to avoid faults and to improve on recovery from faults. Many groups have efforts focusing on these areas, including improving mining large repositories of accelerator engineering data and introducing methods for real-time anomaly detection in operating systems.

An ongoing project at Jefferson Lab leverages ML to automate cavity trip classification. Traditional methods have been effective at identifying superconducting radiofrequency (SRF) trip causes, but are labor intensive and generate results in an asynchronous fashion. Identifying and correcting faults in real-time will have numerous benefits including improving the stability of the SRF system, providing a more reliable and available accelerator, and extending the energy reach. It will also provide important statistics and insights on cryomodule operations to engineering and SRF R&D staff while freeing them to focus on the future design and fabrication of SRF cryomodules. The project established a prototype system that reads data from the control system as faults occur, classifies it with a trained ML model, and outputs the result to subject matter experts. The system provides a cavity trip type, identifies the cavity causing the instability, and, potentially, can predict a trip before it occurs. It is a first step towards a diagnostic tool for daily use by operators to accurately identify a cause of a trip and apply precise response measures, avoiding unnecessary gradient reduction [10,11].

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).

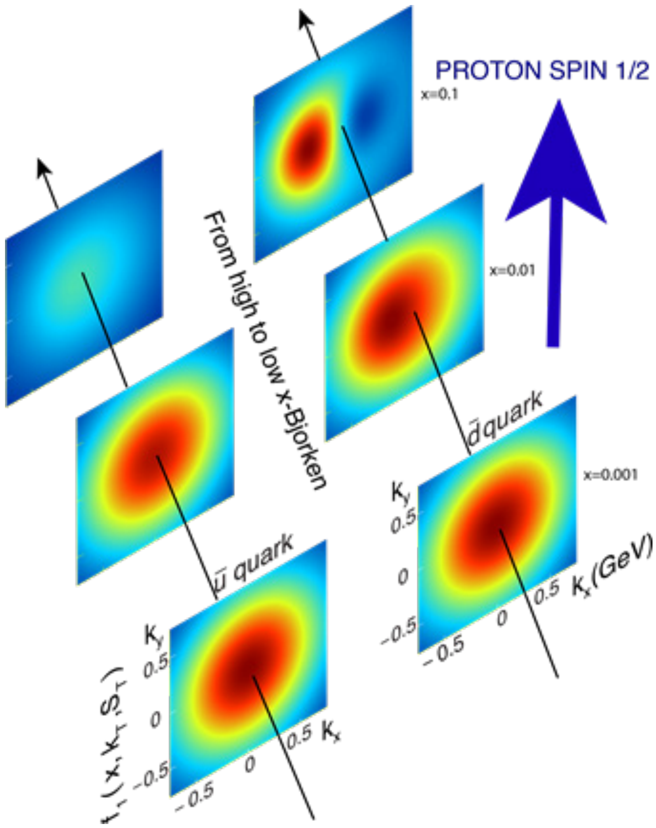

Figure 5.3 *A momentum space tomography of a hadron at difference slices in Bjorken x, for u and d anti-quarks. The images show how the variable x provides a filter to select different aspects of nucleon or nuclear partonic structure.*

In the Electron-Ion Collider (EIC) era, such methods need to be dramatically improved upon so that the full impact of the science can be assessed in real-time. This provides an important opportunity to utilize AI/ML techniques to obtain approximate solutions to the associated inverse problems. That is, to find an efficient mapping between the exabytes of experimental cross-section data and the theoretical objects of interest, namely the quantum probability distributions. Such a project will produce the next generation of QCD analysis tools that will provide rapid feedback between experimental data and a deeper understanding of strong interaction dynamics. Therefore, AI/ML methods will help guarantee maximum science output from the EIC.

Increase the understanding of matter/anti-matter in the universe. A better understanding of electroweak interactions are fundamental to understanding matter/antimatter asymmetry in the universe and neutrinoless double beta decay offers a window into these phenomena. CNNs offer the ability to reach beyond current technologies for neutrinoless double beta decay, thanks to the ability to quickly learn pattern recognition and discriminate important topological features. A significant challenge, however, will be validating a ML technique sufficiently well to ensure it performs on data in the energy region of interest.

With the availability of radioactive sources for calibration, such as Thallium in high pressure Xenon TPCs, researchers have access to a dataset with signal-like and background-like events that have a very similar topological signature to a neutrinoless double beta decay signal and background events, but at a different energy and with high statistics. The combination of available simulation, validation datasets, and very fast training times will allow experiments to perform an optimization campaign to build a robust neural architecture for fast analysis of neutrinoless double beta data with high confidence of similar performance on data and simulation. Additionally, the introduction of Generative Adversarial Networks (GANs) to model data/simulation discrepancies, with the ability to validate over large energy regimes, increases the confidence in a network trained on simulation + GAN datasets. The grand challenge in this space is to create an AI-centric workflow to distinguish neutrinoless double beta decay candidates from background, while using AI to validate simulations and ensure high-quality inference results on data.

Advance the understanding of nucleo-synthesis. Our understanding of nucleosynthesis is growing through studies of astronomical measurements, theoretical calculations, and experimental measurements of exotic nuclei generated at advanced experimental facilities.

Researchers are now working to extend deep learning to a wide range of important properties that govern the production of nuclei in the Cosmos. Further developments include applications to measure electromagnetic and weak transition rates in both stable and unstable nuclei. In addition, applications to improve scattering and reaction cross-sections based on fundamental theory appear feasible in light of the initial successes with binding energies. For example, incompletely converged supercomputer calculations of nucleon-nucleus cross-sections based on microscopic theory have appeared recently and, as with the binding energy example, a DL approach could extend those results to produce cross-sections at convergence with quantified uncertainties.

Nuclear astrophysics simulations—including core-collapse supernovae, X-ray bursts, and neutron star mergers—continue an inexorable march towards higher computational intensity, as increased physical fidelity is realized using higher spatial resolutions, longer physical times, and more complete microphysical descriptions. Anomaly detection for these very expensive (i.e., of order tens of millions of LCF node-hours) calculations becomes essential to ensure that scarce computational resources are not consumed in error. In addition, many of the requisite microphysics in these simulations (e.g., neutrino-matter interaction rates, thermonuclear reaction rates, and high-density equations of state) are recovered via the use of high-dimensional interpolation tables. ML techniques such as Gaussian process models and deep neural networks can replace traditional interpolation techniques while providing superior robustness.

When completed in 2022, the Facility for Rare Isotope Beams (FRIB) will be the world's most powerful rare isotope research laboratory. By producing intense beams of nearly 80 percent of the predicted isotopes for elements up to uranium, FRIB will enable researchers to make major advances in the structure, stability, and limits of nuclear matter, as well as in their interactions and decays (Figure 5.4). We anticipate that a variety of AI/ML approaches will be developed to address specific needs at FRIB, including beam generation, event characterization, detector response, experiment optimization, and data analysis.

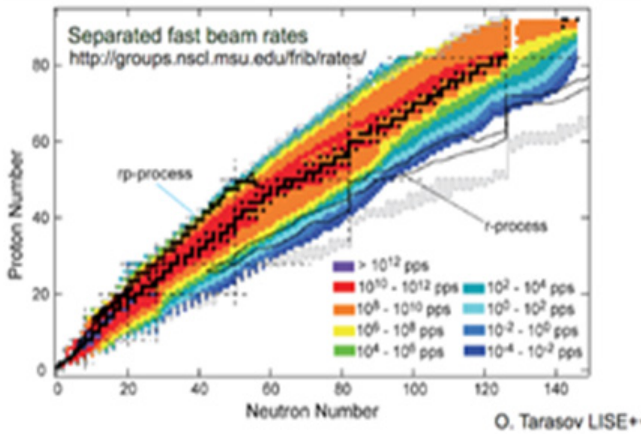

Figure 5.4 *The Facility for Rare Isotope Beams (FRIB) will provide unparalleled beam intensities of the most exotic nuclei.*

Transform the operation of accelerators and detector systems. In data analysis, experimental design and optimization, and even facility operation, AI/ML may provide approaches that are complementary to and offer improvement over traditional techniques. AI/ML studies can offer transformative progress in optimal operations of accelerators. In addition to the ongoing work at BNL and Jefferson Lab, FRIB operations will surely benefit. Production of high-purity, high-intensity beams of unstable nuclei and delivery with high efficiency to the FRIB experimental end stations present a daunting challenge. As data-taking runs for each measurement can be short, tuning time is important.

Time-consuming, multi-step beam generation efforts potentially limit the overall scientific productivity of the facility, as will the need to (on occasion) use sub-optimal beams with lower intensity. By utilizing supervised ML methods or reinforcement learning, it is anticipated that beam generation times can be significantly reduced compared to manual efforts, while simultaneously improving the quality of beams delivered to the end stations.

Detector systems used in nuclear physics experiments and nuclear physics applications will continue to generate higher fidelity data, which will drive needs for better data analysis methods, and, in some cases, for faster and high-fidelity edge-driven analysis.

AI techniques are being developed for event characterization, particle and photon tracking, particle identification, and energy reconstruction. Reconstruction of tracks in time projection chambers could be greatly improved with such approaches. At FRIB, logistic regression, fully connected neural networks, convolutional neural networks, and other approaches are being explored to identify event tracks in the Active Target Time Projection Chamber (AT-TPC). This step could be decoupled from fitting the tracks to determine reaction kinematics.

The enormous particle multiplicities in TPC's at heavy ion colliders cause track reconstruction to be slow and require complex correction for distortions due to the large charge load in the TPC. Application of ML to this problem would greatly simplify calibration and track reconstruction.

Methods to improving particle tracking through sophisticated magnetic spectrometers are also being developed through AI/ML. While the exact technique differs for different magnet configurations, room for improvement exists at all DOE Nuclear Physics (NP) accelerator facilities. At FRIB, correlating signals in the focal plane detectors of the magnetic spectrometers using a series of masks at the target location could be used to train corrections for offsets in initial particle angle and position. This could markedly improve the energy/momentum resolution of the focal plane spectra.

DNNs are being applied to complement existing Monte Carlo approaches for particle identification. Event shapes in multi-dimensional (detector signal) space can be used to train ML algorithms to recognize the location of foreground events in the presence of significant backgrounds. In calorimeters, DDN's allow sophisticated analysis of shower shapes to separate single photons, hadrons, and their decays.

Many modern detectors digitize the signals (waveforms) from each event. For example, new large-volume germanium detectors for gamma-ray spectroscopy will enable position sensitivity, i.e., determining not only the total energy deposited via gamma rays, but also the energy and position of the individual interactions within the detector. Spatial resolutions of a few millimeters will be possible, enabling so-called gamma-ray tracking, another area where ML is applicable. Gamma-ray tracking is the core operating principle of the Gamma-Ray Energy Tracking Array (GRETA) spectrometer, and AI/ML methods may transform current approaches using deterministic and probabilistic methods to reconstruct the path of multiple gamma rays from measured interaction positions and corresponding deposited energies. ML algorithms could be trained on the pattern of interaction points and energies with no assumptions of the underlying scattering processes. By focusing on differentiating events that are completely absorbed versus those that are partially absorbed, significant improvements are anticipated in determination of the peak-to-total, Doppler correction, angular distributions, and linear polarizations of events in GRETA. Improving the determination of gamma-ray transport parameters and transfer functions will improve the position resolution of the detector, especially for lower energy interaction points. Among other more established approaches, the use of GANs [3] for the discovery of these transfer functions is an attractive avenue of investigation. These techniques will be applicable to other detector systems, as well.

3. Advances in the Next Decade

The growth of AI techniques and the familiarization of nuclear physicists with those techniques is anticipated to result in substantial advances in the next decade, which is particularly important given the planned increase in date volume and fidelity resulting from new experiments and facilities. In particular, the following advances are anticipated.

Extracting physics from simulations and other large-scale inverse problems. The coupling of higher-fidelity simulations that leverage HPC environments with the ability to conduct an ever-increasing number of simulations provides great opportunity to leverage AI to infer physics, manage and plan simulations, and tackle many other large-scale inverse problems, including 3D tomography, which relates to precision medicine (see Chapter 10, AI Foundations and Open Problems).

Data analysis. Data analysis methods will continue to advance the AI methods that are being leveraged for data analysis in both online and offline scenarios, where the online AI activities may be pushed closer to the sensor edge. Advances in particle tracking, particle identification, data fusion, and background reduction, as well as methods such as using shallow neural networks for curve fitting and other data analysis methods, will continue (see Chapter 10, AI Foundations and Open Problems).

Data management. Similar to data analysis methods, methods used to provide metadata, facilitate data discovery and data retrieval, and enable cross-experiment analyses will evolve thanks to AI methods that can reduce the now human-intensive task of curating data (see Chapter 12, Data Life Cycle and Infrastructure).

Facility operation. Experimental facilities are major investments in capital. Operating these facilities with minimal down-time and maximal user value provides the best return on investment and scientific outcomes. Improvements in beam diagnostics and control and beam-line planning will save human effort and produce better stewardship of the major investments (see Chapter 14 AI for Imaging).

Experimental design. More capable, AI-driven computing at the sensor edge will enable higher precision instruments to be developed and fielded at NP experiments. These advances may result in near-real-time tuning of detector parameters and better data acquisition decisions (see Chapter 15, AI at the Edge).

4. Accelerating Development

As outlined above, the sheer volume and complexity of nuclear physics data is increasing at a rapid pace. These increases are occurring across the enterprise of nuclear physics, from nuclear theory to experiment, and to the operation of facilities and the collection of data in support of nuclear science applications. Inference from these increasingly complex sources, and therefore physical understanding, is constrained even now by physicists' ability to examine, analyze, and interrogate data. The effective continued adoption of AI techniques into the nuclear physics workflow depends most critically on several factors:

- The development of AI/ML/DL techniques that are scalable from modest or scarce data volumes, to data volumes that can be exponentially larger (see Chapter 10, AI Foundations and Open Problems).
- AI approaches for anomaly detection and decision support that can be used in operating environments where expensive resources (e.g., accelerator beamlines and leadership-class supercomputers) are being used (see Chapter 15, AI at the Edge).
- Creation of new data analysis techniques for analyzing and interpreting the large multidimensional data sets produced by heterogeneous sensor networks, and methods of performing online sensor and sensor network reconfiguration to optimize performance. Two techniques of particular interest are the use of unsupervised learning

methods for the discovery of multi-dimensional patterns and the development of underlying models, as well as online learning techniques that are able to use streaming data to adapt to changing conditions across a network in real time (see Chapter 10, AI Foundations and Open Problems and Chapter 15, AI at the Edge).

- AI techniques that can optimize the design of complex, larger scale experiments could completely revolutionize the way experimental nuclear physics is done (see Chapter 10, AI Foundations and Open Problems).
- AI techniques can facilitate the collection and analysis of metadata, facilitating data reduction tasks to better document experimental conditions and better facilitate nuclear data evaluation and the 'interoperability' of data resulting from complex experiments (see Chapter 12, Data Life Cycle and Infrastructure).

5. Expected Outcomes

- One of the fundamental goals of nuclear physics is to understand how interactions between quarks and gluons ultimately manifest in the structure and binding of nucleons and nuclei. Approximate symmetries found in nuclear physics are thought to have origins not only in the underlying interaction, but also in the complicated many-body physics of the problems. AI has the potential to aid human understanding of these complex systems through improved methods that discern the origins of these symmetries and the emergent behavior that is often observed.
- Applications of AI in nuclear physics will produce a paradigm shift in the way information is gathered, stored, analyzed, and interpreted from the large amount of data obtained from scattering and decay experiments. With the aid of AI, experiments that require years of analysis will see decisions on optimization and results in near real-time. The accessibility of the data to the wider nuclear physics community would create a connectivity across experiments not seen before. This connectivity will become the standard rather than the exception in understanding nuclear phenomena from the laboratory to the universe.
- In a practical sense, radioactive and stable isotopes are critical to several societal needs. They are essential for energy exploration and innovation, medical applications, national security, and basic research. The utilization of AI to optimize the choice of reactor parameters, exposure time, and sample composition poses the potential to significantly increase the reliable and cost-effective production of isotopes, thereby impacting national needs in these areas.

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