Beating Nature at its own game: developing a machine-learning-based trigger decision system for DUNE

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The current and future programs for accelerator-based neutrino detectors feature the use of Liquid Argon Time Projection Chambers (LArTPCs) as the fundamental detection technology. These detectors combine high-resolution imaging and calorimetry to allow for the identification of charged particles and the reconstruction of neutrino interactions to neutrino energies at 10 MeV or below. However, the volume of data from LArTPCs is large and event reconstruction techniques are complex, requiring significant computational resources. These aspects make using TPC data in online event-triggering and event-filtering algorithms that can effectively distinguish neutrino interactions from background activity (like cosmic-ray interactions or radiological backgrounds) very difficult, which limit detection efficiency to low-energy neutrino interactions. I propose developing a machine-learning based trigger decision system for the Deep Underground Neutrino Experiment (DUNE) to extend the sensitivity of the detector, particularly for low-energy neutrinos that do not come from an accelerator beam. Building off of recent research in using machine learning to improve artificial intelligence in games, this new trigger decision system will employ software to optimize the data collection, pre-processing, and algorithms used to make a final trigger decision. Development and testing of the trigger decision system will highly leverage data from the ProtoDUNE and Short Baseline Neutrino (SBN) LArTPC detectors, and will also provide benefits to the physics programs of those experiments.

Due to their ability to detect interactions with excellent spatial and energy resolution in a large, fully active volume, LArTPCs are an excellent choice for use as neutrino detectors. The Short Baseline Neutrino (SBN) program at Fermilab [1] will include three LArTPCs – MicroBooNE (currently operating), the Short Baseline Near Detector (SBND), and ICARUS – on the Booster Neutrino Beamline (BNB) at Fermilab, searching for non-standard $\nu_\mu \rightarrow \nu_e$ oscillations. The Deep Underground Neutrino Experiment (DUNE) [2] will see an intense beam of neutrinos from Fermilab at a long baseline, measuring $\nu_\mu \rightarrow \nu_e$ and $\overline{\nu_\mu} \rightarrow \overline{\nu_e}$ oscillation parameters to search for leptonic CP violation and determine the neutrino mass hierarchy. Importantly, DUNE will pursue physics beyond that resulting from an accelerator-based neutrino beam, including searches for atmospheric and solar neutrino interactions, beyond-Standard-Model proton decays, and signatures of ν_e bursts from nearby core-collapse supernovae. Each experiment relies on reconstruction of the fine details of interactions in LArTPCs to fully characterize them – to distinguish signal from background and to extract kinematics of the initial interactions.

However, while LArTPCs are powerful detectors, many of the traits that make them powerful pose significant challenges to the collection of data and reconstruction of interactions. Ionization electrons can be drifted over large distances, allowing LArTPCs to have the large, fully active volumes needed for rare-interaction physics. But, with electron drift times on the order of milliseconds, LArTPCs require very long readout windows. This long exposure time leads to a large volume of data per event, and the potential for significant contamination from “out-of-time” particle interactions, such as cosmic rays in surface detectors and radiological backgrounds in detectors deep underground. Similarly, while the high spatial and energy resolution in LArTPCs allows for precise interaction reconstruction, it again comes at the cost of increasing the volume of data and complexity of event reconstruction. Traditional [3], tomographic [4], and image-based (e.g. deep-learning-based) [5] reconstruction techniques all require simultaneous consideration of data from large portions of the TPC, even if only to identify a localized region of interest.

These unique features of LArTPCs lead to significant challenges for data acquisition, data storage and access, and processing times for full reconstruction that can significantly influence the physics reach of the SBN and DUNE experiments. Trigger and early filtering algorithms for LArTPCs typically exclude information from the TPC because of the volume of data and time needed to make use of it, instead relying on detection of scintillation light and external muon tagger systems to trigger and reduce out-of-time backgrounds. For the surface SBN experiments, this reduces the rate of beam-coincident interactions to (barely) manageable levels, but the collected data are still dominated by cosmic rays and can only be further reduced by analysis of TPC activity. For DUNE, efficiently detecting low-energy interactions that are not in-time with a neutrino beam spill will require consideration of TPC information to trigger the readout – particularly daunting due to the detector's massive size.

While TPC reconstruction algorithms continue to become more sophisticated and robust, it is not yet understood how those (and future) algorithms can be brought together and performed within an online data acquisition system, where limitations on the available processing power, data bandwidth, and time to make a decision are key. A complicated decision-making and optimization problem must be performed: we must decide what subsets of data to look at and what algorithms to perform on that data to learn decision-critical information, and do so while accounting for the cost of retrieving and processing that data. This decision process is also naturally iterative, which can allow for better potential performance but only adds to the potential complexity.

I propose using principles of machine learning to develop a trigger decision system to solve this complicated triggering problem in LArTPCs. Machine learning has been used to solve many problems in analysis of large and complicated data, including analysis of data in high-energy and neutrino physics [6]. An application that seems particularly promising to help solve the triggering problem for LArTPCs is in the use of machine learning to improve artificial intelligence (AI) for games. Deep neural networks can be encoded with only the rules of the game and trained purely via 'self-play' to optimize movement through a decision tree and learn a 'feel' for winning strategies in the game, rather than focusing on brute force processing of possible outcomes. These networks and training strategies have been used to develop super-human AI engines for games with perfect information (e.g. chess [7]) and imperfect information (e.g. poker [8]). Triggering in LArTPCs (and other kinds of detectors) is essentially a game too, where the goal is to pick the greatest number of interesting events in a period of time, and where rules and limitations on data transfer and processing can be encoded in the training network.

To develop and apply this machine-learning-based trigger decision system to the SBN and DUNE detectors, I propose a staged approach that makes use of large datasets from the existing MicroBooNE and ProtoDUNE LArTPCs. A first demonstration of the technique will be to train a network to analyze optical data from MicroBooNE and demonstrate that it can reproduce (or even improve upon) MicroBooNE's light-based trigger algorithm.

An early physics milestone will be to train a decision network to make use of TPC information alongside optical information to reject events that pass MicroBooNE's current neutrino trigger but originate from through-going or stopping cosmic muons entering into the detector. This application would immediately aid in filtering MicroBooNE's large collected dataset, and would then be applied to the other SBN detectors where early rejection of cosmic events will improve the data acquisition and event processing chain. Modifying the conditions of the training to optimize for different available latencies and dataflow architectures will allow for performance measurements under different conditions. This application can then also be applied to ProtoDUNE data to inform developments necessary for application and scaling to DUNE.

A second physics milestone will be to add to the trigger decision network the ability to positively identify neutrino and neutrino-like interactions, particularly focused on electromagnetic showers. From a technical perspective this will probe the ability to handle multiple types of algorithms and triggers to pick out signal interactions in the presence of backgrounds. However, it will also have a significant impact on the physics of the SBN program. Because of their location near the surface of the earth, the SBN experiments face a significant background of cosmic-ray induced electromagnetic showers in reconstructed ν_e energies below 500 MeV, a region of high interest due to the "low-energy" excess reported by MiniBooNE. While these cosmic ray-induced backgrounds can be perfectly modeled by taking a sample of "off-beam data", currently it is highly inefficient to do so, as the final event selection imposes specific event topologies that are relatively rare in cosmic-ray-only events and are dependent on a reconstruction of TPC data. Online identification of signal-like events in this off-beam data sample will allow a higher statistics sample of relevant data to be collected, and significantly reduce the errors on data-driven background models, improving SBN oscillation searches, especially in the lowest ν_e energy ranges.

Finally, a third major milestone will be demonstrating a trigger decision network can work for low-energy ν_e interactions, like from solar and supernova-induced neutrinos, at the scale of DUNE. Supernova burst neutrinos will lead to signatures in DUNE that will be spread across the volume of the large detector, will be produced over long periods of times (several tens of seconds), and must be identified amongst a sea of low-energy radiological backgrounds. Solar neutrino signatures will be of similarly low energies, and not have the benefit of occurring in time-coincident bursts, and so may be even more challenging to detect above low-energy backgrounds. Along with simulations of signal and background signatures, detailed and realistic models of data transfer and processing will be developed to inform optimal triggering strategy over the entire detector, and can provide feedback on final DUNE DAQ design and dataflow strategy. Tests on simulated dataflow models along with algorithms using information from both TPC and light collection systems in real time will be further validated on the readout hardware and data of ProtoDUNE.

To perform this proposed plan of research, I am requesting support for myself (the PI) and two post-doctoral research associates. Funds will be used to purchase computing and networking hardware for machine-learning training and inference testing, as well as to test and develop large-scale data transfer models. Funds would also support the work of a computing professional at Fermilab to assist in the development of those models.

The use of LArTPCs in large-scale neutrino physics is moving towards a mature state, but the large volume of data and complicated event identification and reconstruction pose major challenges to future detectors, pointing to a need for smarter triggering algorithms that can make use of TPC information in an efficient way and allow us to get to physics results faster. Following from successful applications of machine learning to solve similar problems in AI for games, I propose to develop a machine-learning based approach to determine optimal triggering strategy for future LArTPCs, leading ultimately to an efficient and performant trigger system for DUNE.

References:

1. Antonello, M. *et al.* arxiv:1503.01520 [physics.ins-det] (2015).
2. Abi, B. *et al.* arxiv:1807.10334 [physics.ins-det] (2018).
3. Acciarri, R. *et al.* Eur. Phys. J. C78, 1, 82 (2018).
4. MicroBooNE Collaboration, MICROBOONE-NOTE-1040-PUB (2018).
5. Adams, C. *et al.* arxiv:1808.07269 [physics.ins-det], submitted to Phys. Rev. D (2018).
6. Radovic, A. *et al.* Nature 560, 41-48 (2018).
7. Silver, D. *et al.* Science 362, 6419, 1140-1144 (2018).
8. Moravčík, M. *et al.* Science 356, 6337, 508-513 (2017).

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