ABSTRACT

Weakly Interacting Massive Particles (WIMPs) are a hypothesized model of dark matter. Many experiments intended to directly observe WIMPs are being developed; if successful, they would contribute greatly to our understanding of the fundamental composition of the universe.

In all such experiments, it is essential, yet often challenging, to develop a classifier that can distinguish potential WIMP events from background radiation. Most often, classifiers are developed manually, via physical modeling and empirical optimization; however, these approaches take extensive time and effort, and the resulting classifiers often perform suboptimally. Machine learning (ML) is a promising but non-trivial solution. In this research, two major challenges facing particle classifiers, (both ML and conventional) have been identified and successfully addressed: impure calibration data, and chaotic physical dynamics within the detector. This has permitted a substantial improvement in accuracy compared to existing comparable classifiers.

Approaching the former challenge, I developed two new algorithms based on semi-supervised learning, iterative cluster nucleation and gravitational differentiation. Semi-supervised learning is a set of techniques used primarily for incompletely labeled data; I hypothesized that these two new techniques would apply to data that is completely but impurely labeled. Data from the PICO-60 bubble chamber was used for training and evaluation. I observed 98.3% classification accuracy, while the previous best ML method reached 80.2%.

To solve the latter challenge using simulated data from the DEAP-3600 scintillation detector, standard multi-layer perceptrons were unsuccessfully implemented and tested. I hypothesized that the issue was related to the lack of spatial information inherent to perceptrons, and that the spatial data in spherical images must be taken advantage of. I developed two 3D adaptations of convolutional neural networks: an approximate cylindrical projection modeled after cartographic projections, and a new type of CNN called a topological CNN, which operates on arbitrarily curved images. Compared to the best conventional classifier, the rate of successful identification of WIMP events was increased by 170%. Real-world data was used for verification.

Both of these experiments and corresponding results have the potential to enable considerably more efficient collection of conclusive observations in future WIMP detection experiments.