Machine Learning Methods for Event Classification in The Active-Target Time Projection Chamber

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1 Objectives

Over the summer I am hoping to work with the ALPhA team on a machine learning algorithm for event classification with the Active-Target Time Projection Chamber (AT-TPC) located at the Facility for Rare Isotope Beams (FRIB) in East Lansing, Michigan.

2 Deliverables

After the fellowship ends we will have made a pretrained model that can be used by other collaborations, in addition to a program that will allow other groups to fine-tune the model to their needs.

3 Background

The AT-TPC is a detector for rare isotopes where a gas volume is a target and detector medium using inverse kinematics. Inverse kinematics is when the target is smaller than the projectile. This is used because rare isotopes can only be made into beams through projectile fragmentation making the alternative impossible. The problem is that the detector will record many events while we probably only need information for one or two. As a result, there is a need for a machine learning algorithm that can filter for events of interest.

Our goal is to make a self-supervised deep learning model that requires little to no manual dataset curation. Deep learning is a facet of machine learning where it is inspired by biological neural networks. Self-supervised learning would allow the algorithm to learn from an unlabeled input. The advantage of using these methods is the model's ability to self-search for correlating features unlike simpler algorithms which requires it to be done manually. The data will be in the form of a 3D point cloud which represents the trajectory of the projectile particle. Using PointNet, the model will be trained to look at the event and determine what kind of reaction.

PointNet is primarily used to classify 3D point clouds using deep learning. A point cloud is simply a set of data points in a space. PointNet exploits the properties of point sets in its architecture. These properties include:

- Order Invariance: Unlike an array, point clouds are a set of points without any specific order
- Transformation Invariance: If an object moves (rotation, translation) it maintains its classification
- Point Interactions: PointNet takes into account that points are not isolated objects and their distance between one another should be taken into account

The events being studied include $^{22}Mg+\alpha$, $^{10}Be+\alpha$, and $^{46}Ag+p$ scattering reactions. In this context, collisions off of a potential $V(r)$ can be represented by the solution of the time independent Schrödinger equation:

$$\nabla^2\Phi + \frac{2m}{\hbar^2}[E - V(r)]\Phi = 0 \tag{1}$$

The two types of scattering are elastic and inelastic. In perfect elastic scattering, kinetic energy is conserved meaning the incoming particle will not lose or gain energy after impact. However, in inelastic scattering the energy of the incident particle changes making kinetic energy not conserved. This can lead to many different types of events like emission, decay, fusion, fission, etc.

The thing all the reactions we will be studying have in common is the nuclei are all rare isotopes. This means that the isotope is rich in protons or neutrons and has a very short lifetime. There is still a lot we do not know about rare isotopes and it is a popular topic in nuclear physics currently. Most of this research is done to figure out more about the nuclear landscape (i.e. the table of nuclides) displayed in Figure 1. This makes it especially useful to use these reaction's data for our research.

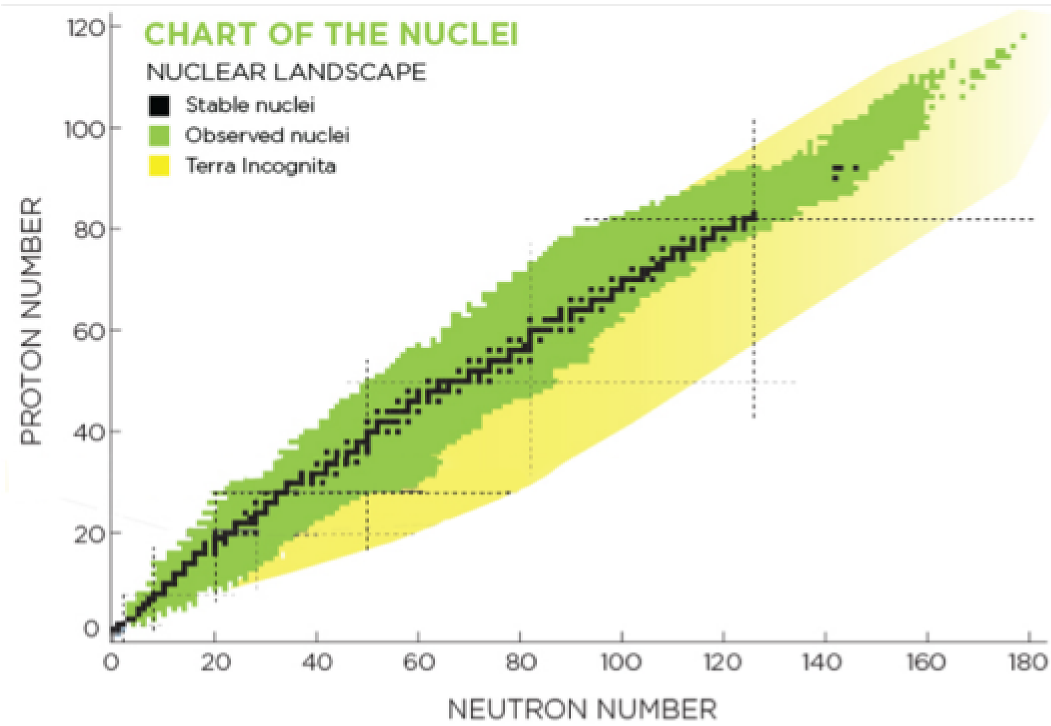

Figure 1: Fig. 1 shows the table of nuclides. Z (proton number) increases on the y-axis while N (neutron number) increases on the x-axis. Terra Incognita represents where potential undiscovered nuclei could reside.

4 Project Timeline

May 23 - June 5	June 6 - July 3	July 4 - July 25
Onboarding, getting to know data, and getting up to speed with the rest of the collaboration	Creating the model	training running, and testing the algorithm

References

[1] Jonathan Sauder, Bjarne Sievers (2019) Self-Supervised Deep Learning on Point Clouds by Reconstructing Space, 33rd Conference on Neural Information Processing Systems

[2] Charles R. Qi, Hao Su, Kaichun Mo, Leonidas J. Guibas (2017) PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation, arXiv:1612.00593

[3] Jack Ziegler Taylor (2018) , Evaluating Machine Learning Methods for Event Classification in the Active-Target Time Projection Chamber