Using Deep Neural Networks to Analyze Collisions in High Energy Physics

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ABSTRACT

At the forefront of experimental particle physics is the Large Hadron Collider in Geneva, Switzerland. There, protons collide at nearly the speed of light with a rate of over 40 million collisions per second. Due to computing and resource limitations, the raw data that these collisions produce cannot be recorded at such a rate. Furthermore, within this data is an incredibly small subset of collisions that are particularly useful for helping us prove or discover theories in physics. To use an analogy, you can imagine that each particle of sand on a beach is one collision and the goal is to find the rare set of particles that have a specific orange-red tint. The detector uses analysis methods to first remove all of the sand that is obviously not red or orange. Then, the remaining sand is analyzed by more complex analysis tools on a larger computing grid to isolate the sand that includes both red and orange characteristics. Finally, an analysis method needs to be used to discern one reddish-orange sand particle from another. Due to recent advances in machine learning, there is reason to believe that using deep learning techniques, such as neural networks, could improve the accuracy of isolating such events. One such exotic collision, the production of a Higgs boson paired with a top quark, is of particular interest to us. This research into a better algorithm should enable us to analyze these collisions more efficiently and accurately than current methods.

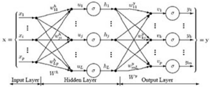
NEURAL NETWORKS

- Machine learning is a field of study that uses algorithms to train computers to be able to recognize and discern relationships of interest in data.
- Neural networks are models that are designed after the way the human brain works - sending information from one neuron to the next, where each neuron has its own function with a certain purpose.

A Basic Network

A small neural network is outlined below.

- In this diagram every black circle can be thought of as a neuron.
- Every arrow is a passing of information from one neuron to the next.
- Every large circle is a function a specific neuron applies to its information.



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Relevance to physics?

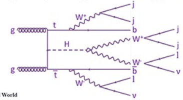
The recent surge in use of neural networks is a result of their ability to learn very difficult and blurred concepts, such as those in facial recognition, self-driving cars, and Google's search engine. This is the same reason why we decided to use neural networks for analyzing physics collisions.

DATA OF INTEREST

The Higgs boson is a particle so rare that it only appears roughly once every three billion collisions. Additionally, not only is it rare, but it can be incredibly difficult to discern an event with a Higgs boson from other events with identical decay patterns.

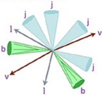
Ideal World

- Our research is specifically interested in identifying collisions that produce two top quarks and a Higgs boson (a ttHiggs event). Below is a Feynman diagram of the decay process that produces a ttHiggs event from the mind of a physicist.



Real World

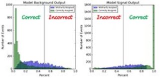
- Our data is not this clear and more closely resembles the diagram below, where any one of the blue jets could be matched to any of the "j"s in the above diagram. Even after making as many assumptions as reasonably possible, there are still 840 ways for these particles to properly align with the first diagram.



IDEALIST VS REALIST

- When simulating data we can observe the decay process and replicate the properly assigned diagram, but real data is arbitrarily assigned.
- We decided to explore the difference between these two data formats with models trained on each.
- We obtained the following results, where accuracy represents the fraction of the time that the model correctly identifies an event as signal or background.

	Accuracy
Correctly Assigned (CA)	87.3%
Arbitrarily Assigned (AA)	68.9%



DIGGING DEEPER

Simulating the Simulator

What we can see from these results is that a collision is much easier to classify when you can properly identify where each particle belongs in the Feynman diagram. This has led us to focus on implementing techniques to try and attain accuracies comparable to the correctly assigned data using the randomly assigned data.

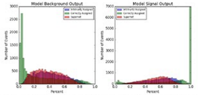
Currently, our most promising model is one we have designated "Supernet". Supernet is a model with the following design:

The structure is:

- **I** – the input layer that takes an event and feeds it into the model
- **P** – the permutation layer, which takes that event and generates all 840 combinations of that event
- **CAN** – the "Correctly Assigned Network", which is the model trained on correctly assigned data mentioned in the data table earlier
- **DNN** – a new deep neural network of arbitrary size that learns how to interpret the previous layers
- **C** – a classification function that decides what type of event was put into the model

On its Way to Being Super

- Supernet has achieved small improvements on the AA network so far.
- We hope to be able to fine-tune this network to reach levels comparable to the correctly assigned data models, but we are not there yet.
- Below, there is a graph displaying Supernet's output compared to the outputs of the CA and AA networks from the table.



This is promising behavior that could mean we're on the right path to reach accuracies comparable to models trained on the correctly assigned data. Regardless, we expect these models to be an improvement upon current analysis techniques.

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