Application of Machine Learning with the Minimum Bias Detector (MBD) in sPHENIX

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Abstract

The PHENIX detector was one of two main detectors used to track high-energy collisions at the Relativistic Heavy Ion Collider (RHIC) at Brookhaven National Laboratory. Designed to collect nuclear data for analysis, these detectors have expanded our collective knowledge of the quark-gluon plasma (QGP). An upgrade to PHENIX, called sPHENIX, will enable far better measurements of upsilon production and heavy flavored jets. The minimum bias detector (MBD) is a subsystem of sPHENIX that acts as the primary trigger for collisions and uses the original beam-beam counter (BBC) from PHENIX. Instead of using standard digital signal processing techniques to extract the time of arrival and charge in the MBD, I used machine learning techniques such as Adaboost, random forest trees, and convolutional neural networks to obtain these values. I have built various models utilizing these techniques to compare the accuracies and mean-squared errors (MSE), as well as the speed of execution. At the beginning of sPHENIX data-taking this program could be used in the reconstruction of the MBD data.

Methods

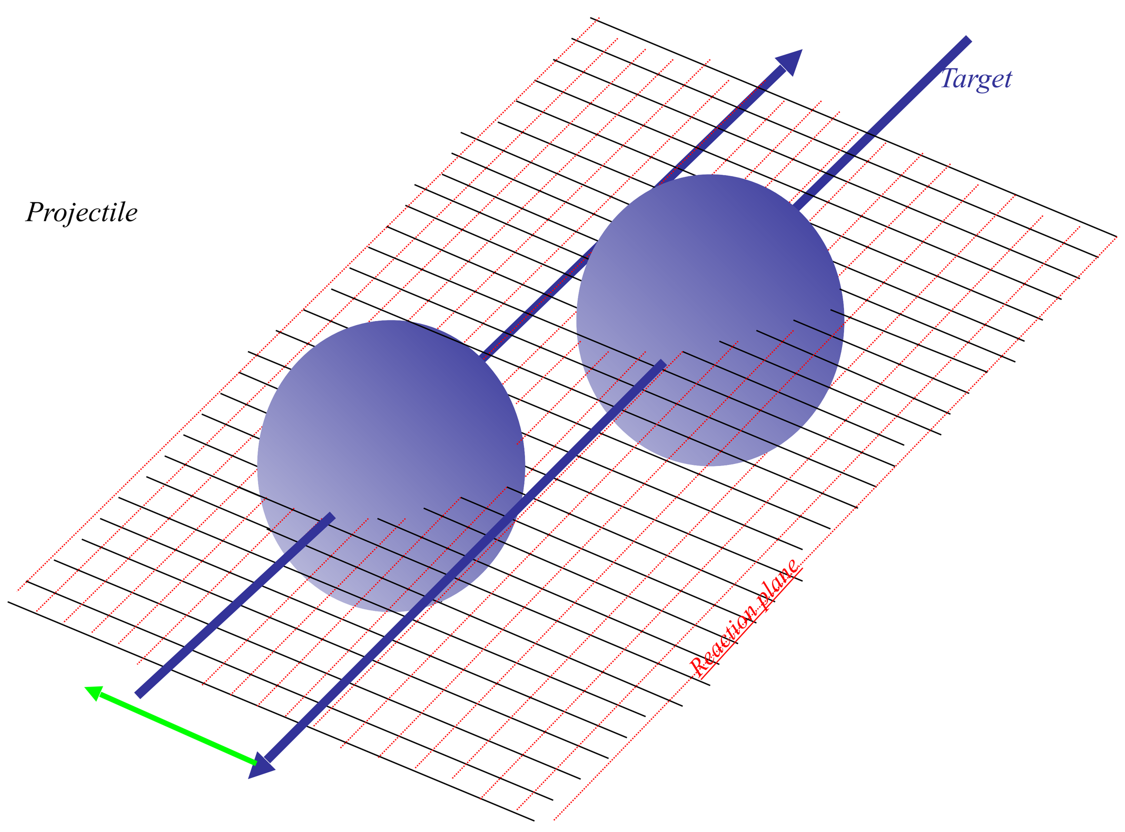
Adaboost - Adaboost is an adaptive boosted-decision tree regression model that takes in input variables (X) and produces a discrete output (y). It makes initial weak predictions. Then it uses individual binary classifiers, called "stumps", to generate another branch of stronger predictions. These predictions are then run through a linear loss function to judge their accuracies. This process iterates over a given number of branches, and only terminates when it makes a prediction that is consistent with the test data.

Random Forest Regression- This model uses the boosted decision trees, and ensembling, to produce an averaged output (y). By running different subsets of data through a set number of trees, the preditions made become less biased, and thus the chance of over fitting is mitigated.

Convolutional Neural Networks- CNNs are deep-learning models that take in input features (X) into a set of nodes and produces a floating point output (y). This model uses regression and classification to find patterns in the data, and assign weights and biases to best fit the data. It is structured with an initial "unhidden" layer, a set number of hidden layers, and an output layer. The dataset is broken into mini-batch tensors and spread among every node in each layer. The hidden layers use nonlinear activation functions to visualize the mini-sets of data. Using back propagation, gradient descent, and an optimizer, the data is fitted to the given activation function with weights and biases. These parameters are stored as the data goes through each layer.

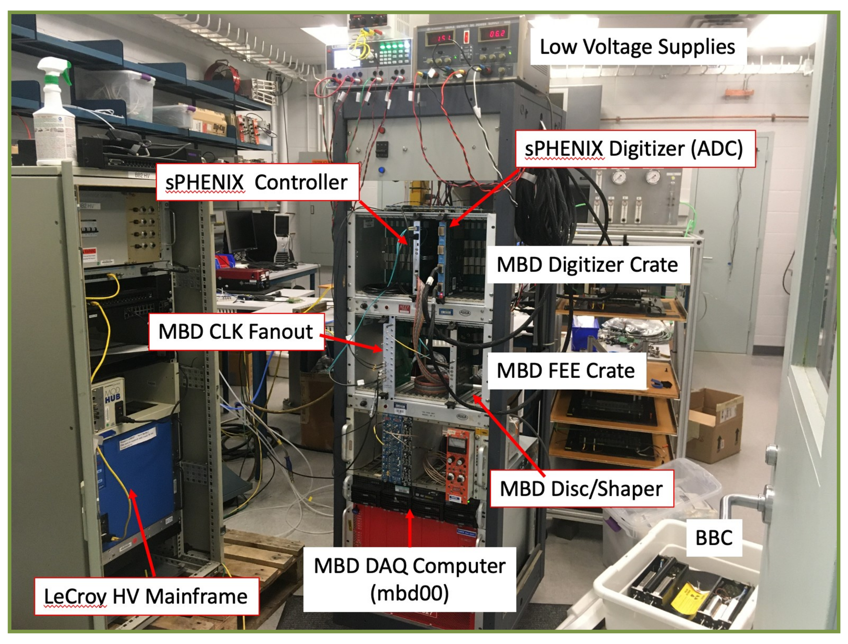
Background

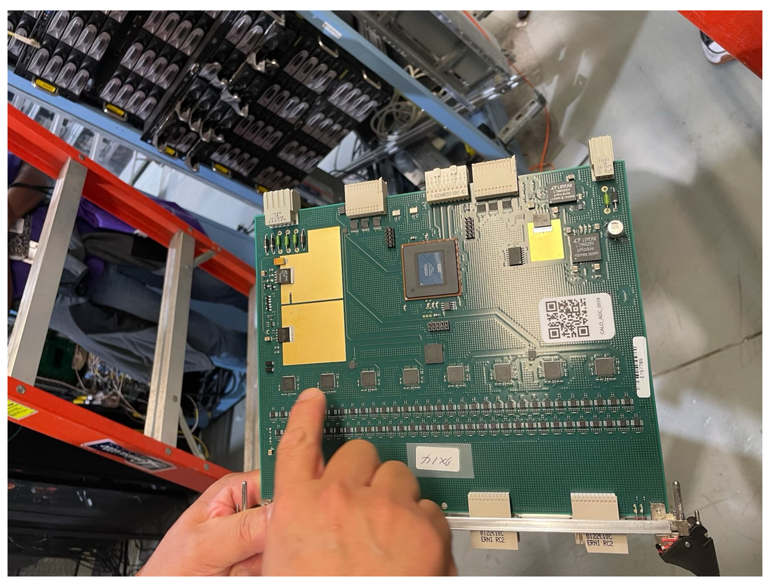
- *Quark-gluon plasma is an exotic state of matter that we have only ever known to be naturally occurring in the earliest moments of the universe, one millionth of a second after the Big Bang. It is incredibly hot and will melt nuclei into their constituent quarks and gluons.*
- *Hadronic jets are another rare occurrence that can be observed in high-energy collisions. They are created in the QGP and are heavily modified as they traverse the QGP. These modifications give scientists information on the properties of the QGP.*
- *In order to fully understand the implications of each collision, we must know the orientation and location of these heavy-ion interactions. Since particles are incredibly tiny and not uniformly circular, their collisions in the beam line are rarely head-on. Usually, the overlapping colliding area forms an ellipse. In each collision, the reaction plane is the plane between the centers of the two nuclei. Knowing the reaction plane angle allows scientists to recreate the geometry of these events so they can study what happens to that QGP as a function of the reaction plane. The MBD is one of the primary detectors that helps sPHENIX measure the reaction plane.*



Motivations

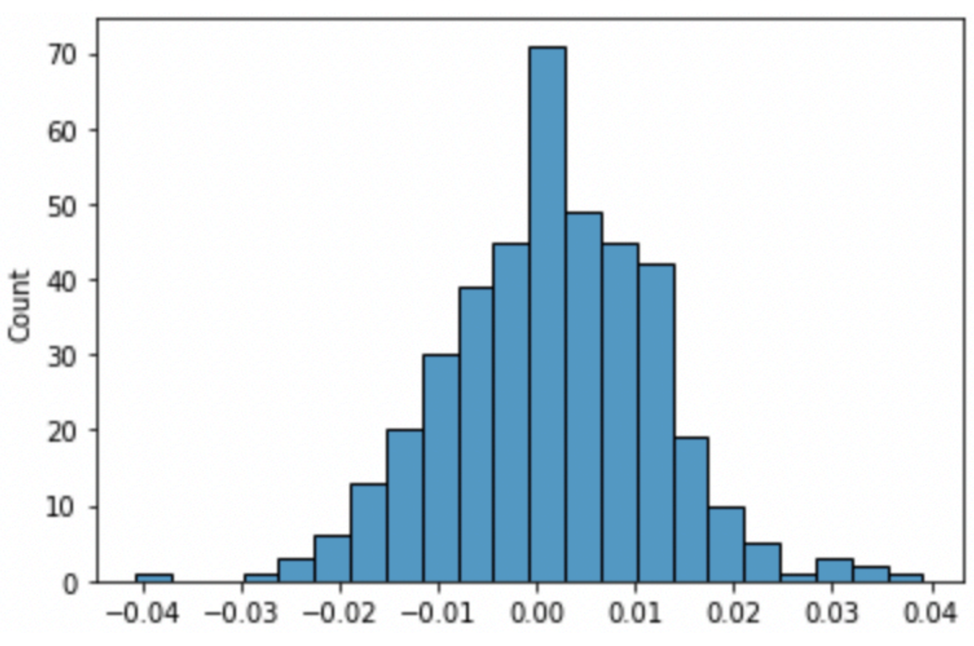
The BBC detector from the PHENIX experiment uses photomultiplier tubes (PMTs) to detect charge particles created by colliding ions. This technology is now the basis for the MBD, the primary interaction trigger detector for sPHENIX. The MBD works by taking the PMT signals from the BBC into a crate of discriminator/shaper (D/S) boards which split and process the signals to measure time and charge respectively. Following right after this, the analog signals are converted into digital signals using a set of digitizers. There will be a total of 16 D/S boards in the MBD crate, but currently we are only working with the prototype boards. Traditionally standard digital signal processing techniques were used to extrapolate timing and charge from each event. This was done by plotting the ADC (analog-digital converted) values over the total sample size from each event, then measuring the amplitude of the resulting curve. Machine learning offers the ability for software to identify patterns in data, make accurate predictions from those observations, and is an alternative way to extract charge and time.





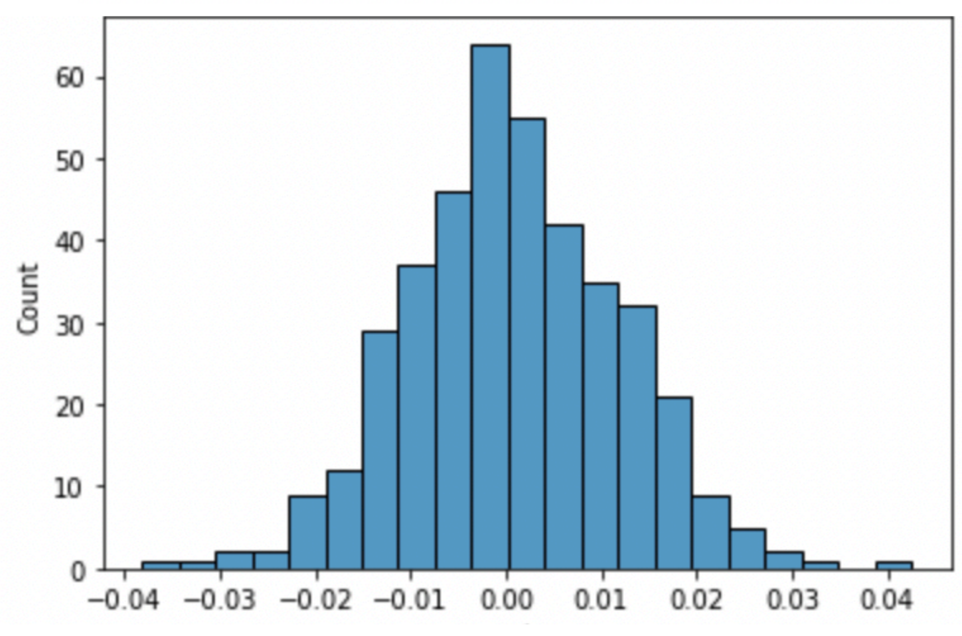
Random Forest Results

```
print(mean_absolute_error(val_y, cpred)
0.008352111329211575
```



Predicted q- Measured q

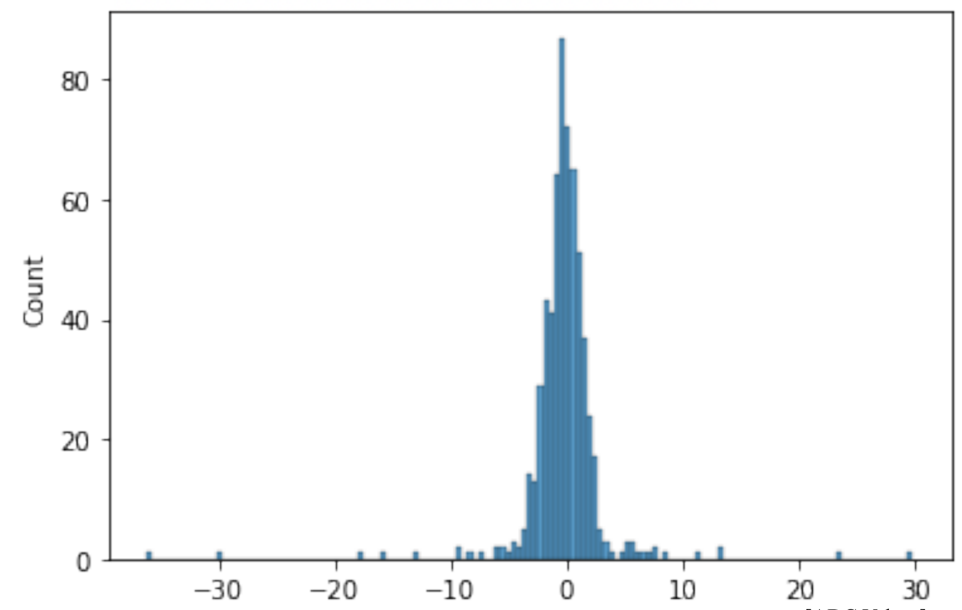
```
print(mean_absolute_error(val_y, cpred))
0.008177229091698733
```



Predicted t- Measured t

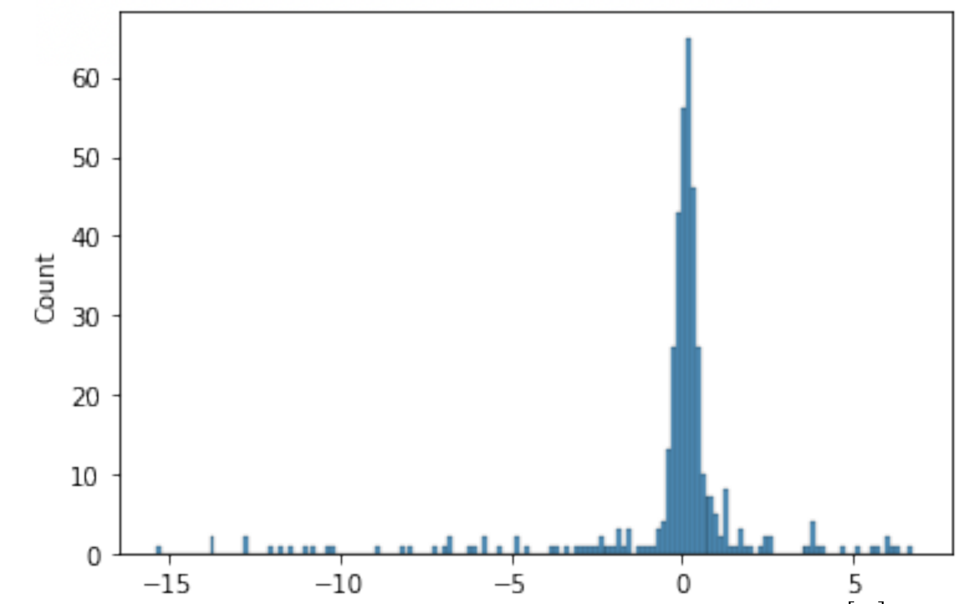
Convolutional Neural Network Results

```
mean = -0.2432822306582805
rms = 3.405248414545357
```



Charge (Predicted - Actual)

```
mean = -0.14697049360212106
rms = 0.36510616746186064
```



Time (Predicted - Actual)

Conclusions

-The overall goal is to be able to use ML techniques to accurately extract the timing and charge from each event recorded by the MBD. This will provide greater insight to the nature of these collisions and will allow us to perform more advanced analyses for sPHENIX, such as the extraction of the reaction plane.

-In the near future, I plan to use these ML techniques for different aspects of data analysis in sPHENIX. I am currently working with a HBCU collider group, which includes Howard University, that works with ultra peripheral collisions (UPC). I will apply these techniques to the detection of these events as well.

Acknowledgements

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