Deep Learning applied to hit classification for BESIII drift chamber

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Introduction

Machine learning , which is seen as an important method of artificial intelligence implementation, has become a hot area recent years, and performs well in many domains. Combining machine learning technology with high energy physics experiment is one of trends in high energy physics.

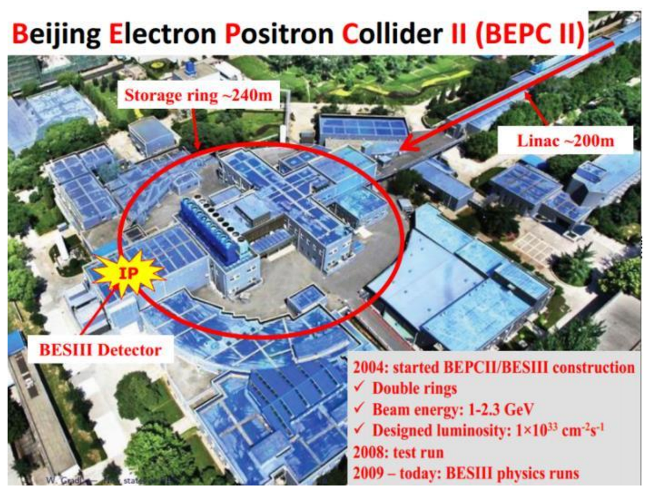
Identifying signal and background is important in processing data from experiment, which affects the subsequent reconstruction in drift chamber and physics analysis. However, the efficiency of traditional method to solve this problem may be low and machine learning technology is expected to perform better.

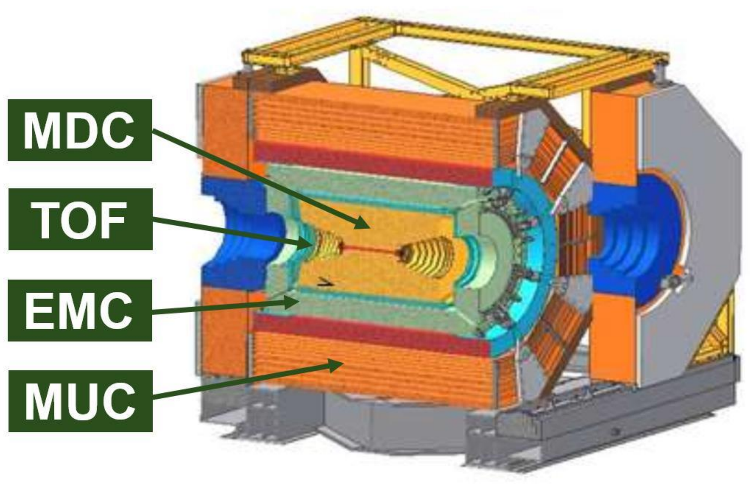
As the beginning of machine learning research, Bhabha events are used to identified signal and background since it is simple and clear. After testing large scale of samples for training and cross-validation, the identification efficiency of signal-background separation is improved

BESIII

Operating on BEPCII, BES III detector is designed to study hadronic structure and particle properties in the τ-charm energy region. The detector covers 93% of the full solid angle and provides an excellent momentum resolution of charged tracks and good energy resolution of neutral particles. It consists of four subdetectors:

- Main Drift Chamber
- Time-Of-Flight system
- Electromagnetic Calorimeter
- Muon Counter system





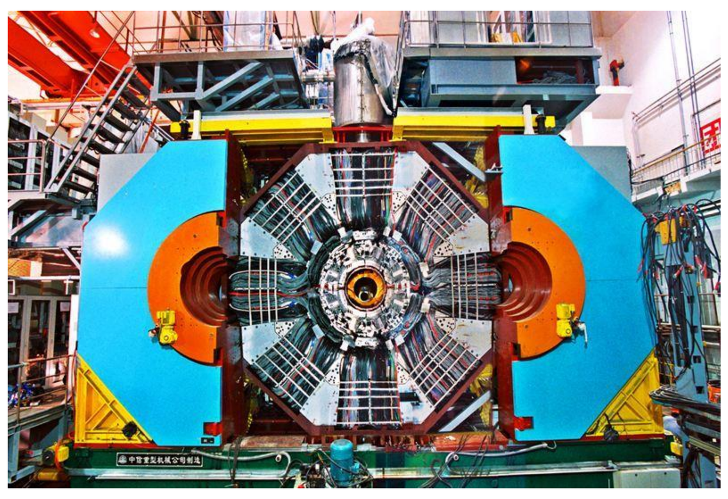


Fig. 1 BESIII

Method

In traditional, we can remove the background by T-cut. But this method is too simple and the performance is poor.

In our work, we use neural network model, which includes an input layer, an output layer and 2 full connected hidden layers, and there are 256 neuron nodes in each hidden layer.

We can get rawtime, ADC and location of each hit from event. In order to obtain the information of hits structure of event, we consider the neighbor 20 wires around each hit, as Fig 2 shows, and we construct an array to describe which neighbor wires are fired. We use the above 24 features (rawtime, ADC, r, φ and 20 neighbors) to do machine learning.

In order to get training and cross-validation data set, we label hits in the tracks which are reconstructed from GBBhabha events as signal, and label hits from random trigger as background, and then, mix them event-to-event as the data set. There are ~ 60,000 events, ~7.6 million hits in our data set. Avoid loss of track, possibility of signal hits being misclassified as background must at ~1% level. So we should modify the cross entropy loss function and increase the loss of signal hits being misclassified as background.

We combine neural network above with T-cut classifier to identify signal and background, using "AND" logic, as Fig 3 shows.

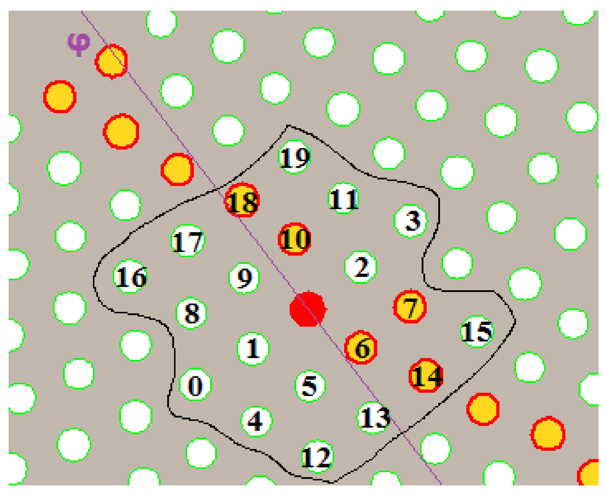


Fig. 2 Neighbors
The Neighbor Array of the red hit is
[0,0,0,0,0,0,1,1,0,0,1,0,0,0,1,0,0,0,1,0]

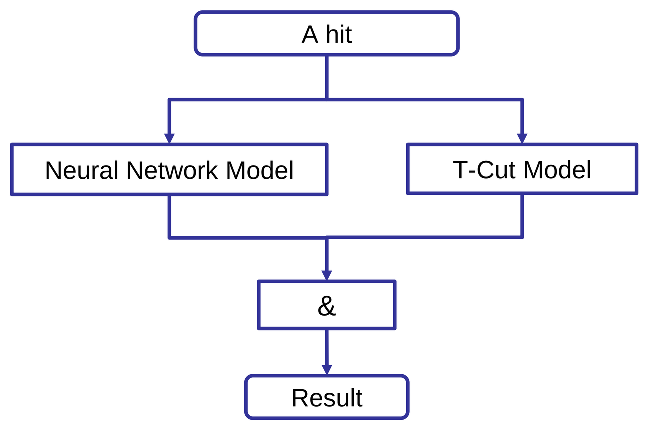


Fig. 3 Combining neural network model with T-cut model

Result

We have done 6-fold cross validation in our data set and the result of each event in our data set is shown in Fig 4. We obtain that the background removal rate is 84.75% provided that the signal reserve rate is 98.99%. For comparison, only using T-cut in our data set, the result is BR rate is 63.88% provided that the SR rate is 99.13%. And Fig 5 shows an background removal result for an event.

In order to maintain and extend the algorithm more easier, the model has already been deployed on TensorFlow serving system, which is a flexible, high-performance system for machine learning models.

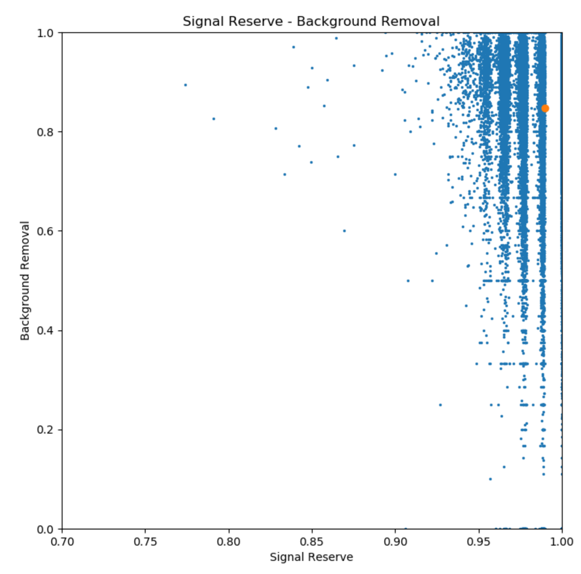


Fig. 4 The cross validation result of our data set. Each blue point represent an event in our data set, and the orange point represent the average.

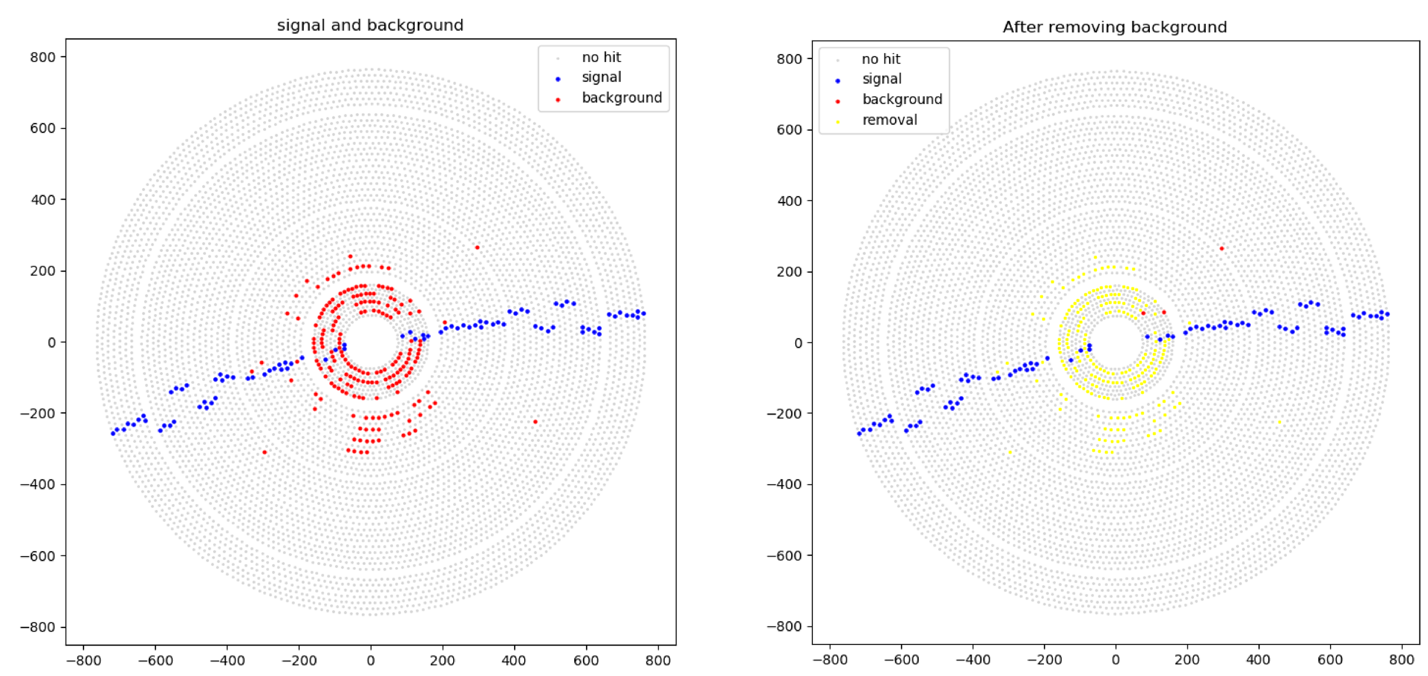


Fig. 5
Left: A labeled original event
Right: After background removal

Conclusions

In our research, we find that machine learning has a great power in signal and background identifying. Research on a simple question and a type of events shows promising future. We can do some further research in the future, such as considering other types of events, and considering other question, e.g. tracking or particle identification.