Machine learning applications on event reconstruction and identification for ISS-CREAM

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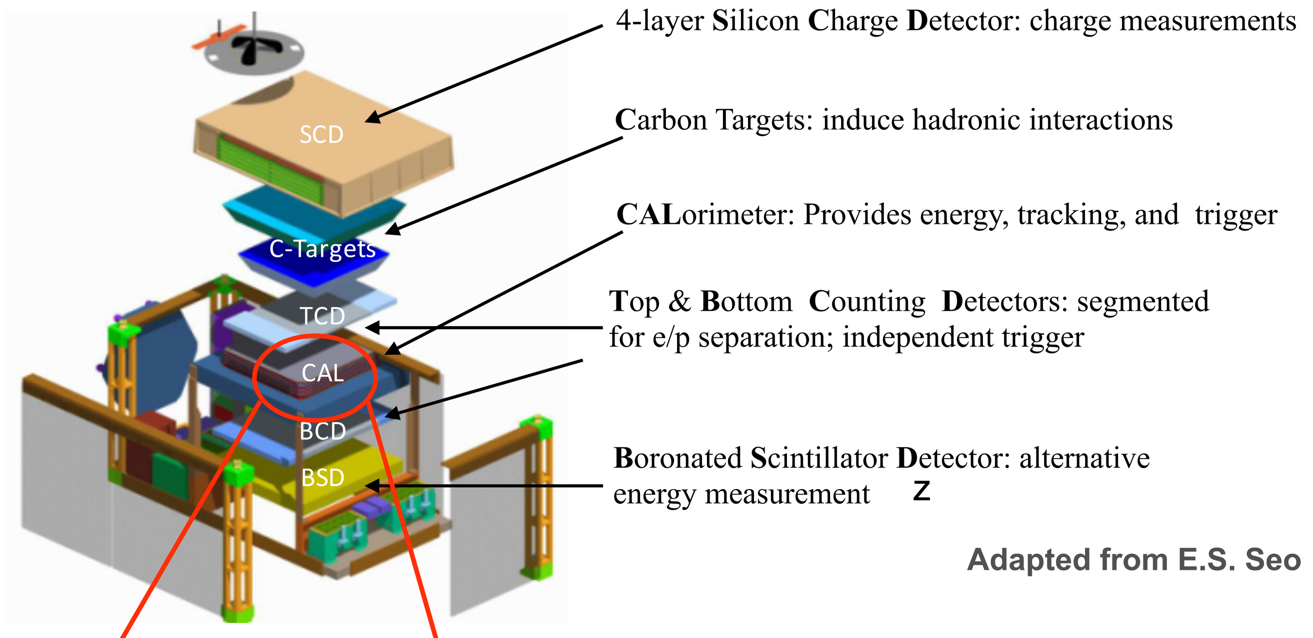
Motivation

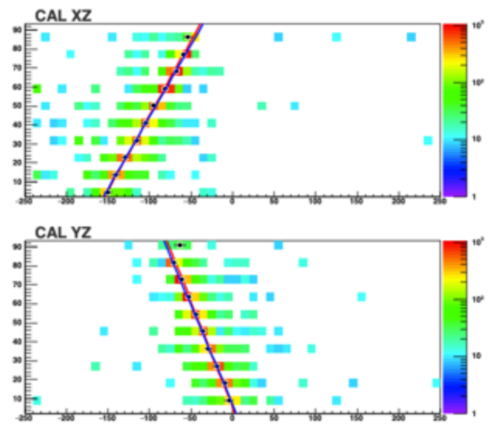
The machine learning techniques, especially the convolutional neural network (CNN), have been successfully applied to image-related scenarios. In the field of high energy physics (HEP), the detectors can be used as imaging devices, for example, the Calorimeter (CAL) of ISS-CREAM. We would like to explore alternative methods based on machine learning for ISS-CREAM data analysis.

Objective

1. Reconstruct the total CR primary energy.
2. Check and calibrate the sampled energy of the calorimeter.
3. Identify CR events from among noise events.



Adapted from E.S. Seo



The ISS-CREAM Calorimeter (CAL)

The CAL has two carbon targets and a sampling electromagnetic calorimeter with 20 layers of high purity tungsten and scintillating-fiber ribbons. It measures the energy of incident CR particles in the range of 10^{12} ~ 10^{15} eV. The output from the CAL for analysis can be represented by two images which provide a three-dimensional track reconstruction: energy deposition in the X-Z plane and in the Y-Z plane, with Z the vertical direction. Layers in the X-Z view are perpendicular to those in the Y-Z view.

This is a typical CR-induced shower developing in the CAL, adapted from the ISS-CREAM Event Display. For the full version of the Event Display, see See poster 1051 by Kenichi Sakai. For more information about ISS-CREAM, see poster 696 by Scott Nutter.

Other posters in this conference about this analysis:

1. ISS-CREAM instrument: Poster 696 by Scott Nutter: Analysis Results from the Cosmic Ray Energetics And Mass Instrument for the International Space Station (ISS-CREAM)
2. Tracking overview: Poster 1051 by Kenichi Sakai: ISS-CREAM detector performance and tracking algorithms.
3. CAL & BSD energy calibration: Poster 866 by Yu Chen: On-Orbit Energy Calibration of the Calorimeter on the ISS-CREAM Instrument Using the Boronated Scintillator Detector

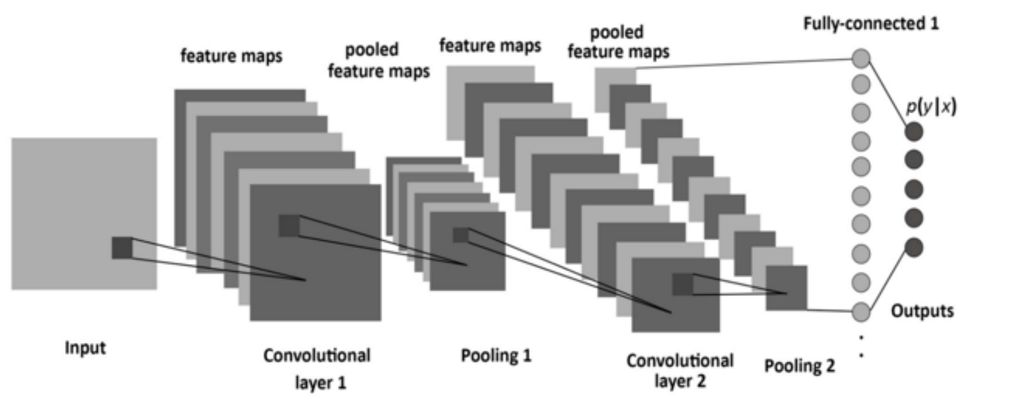
Tools & Materials

- Packages: Tensorflow 2.0, Python 3.7, Sklearn, Scipy, Keras and other supporting packages
- Computer: Intel Core i7-6400 @3.4GhZ × 8 with a Ubuntu 16.04 operating system.
- The networks are trained separately for

Objective 1: A regression model that uses a mixed component of H, He, C, O, Fe with equal fraction. The model is trained on 40,179 showers. All events in this task are generated by Monte Carlo. Tracking angle is also used as an input.

Objective 2: A regression model that uses a mixed component from B to Fe with balanced fractions matched to existing CR composition data. The model is trained on 22,037 events. All events in this task are generated by Monte Carlo. Tracking angle is not used.

Objective 3: A classification model that uses 1246 CR events and 2524 noise events. The events used in this task are selected from on-orbit data.

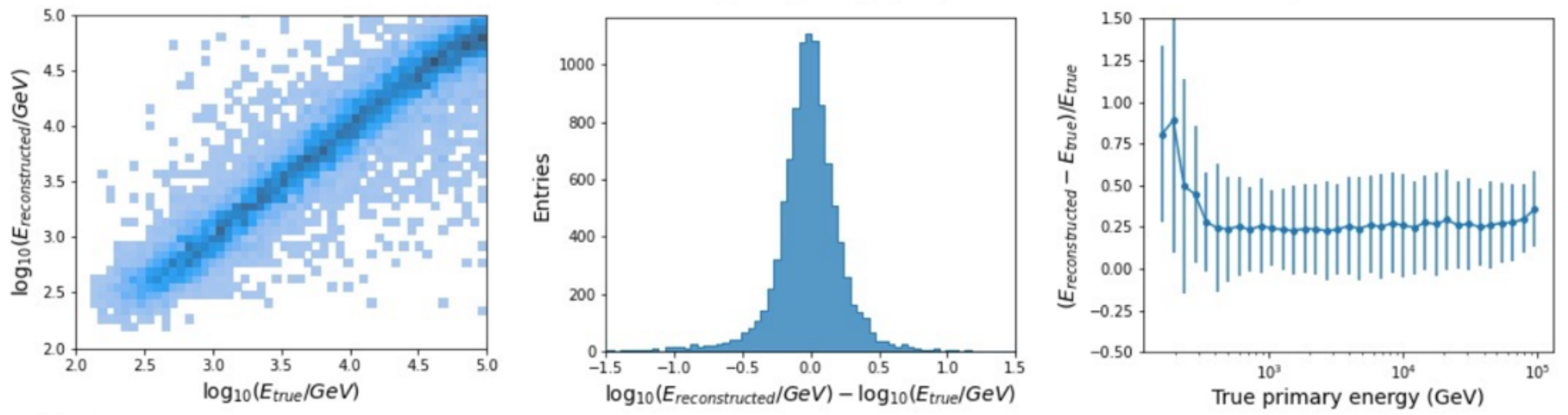


A Convolution Neural Network: courtesy MDPI.com

Result 1

By analyzing10,000 additional testing samples not participated in the training process, the energy reconstruction based on a machine learning method

- Can in principle achieve a resolution of as good as 25%. Better than 50% using traditional method for an on-orbit program.
- The 2D distribution shows a smooth reconstructed energy path.
- In the 100 TeV region, there is a small bias, as illustrated in the 2D distribution plot. This is because our training set has fewer high-energy samples.

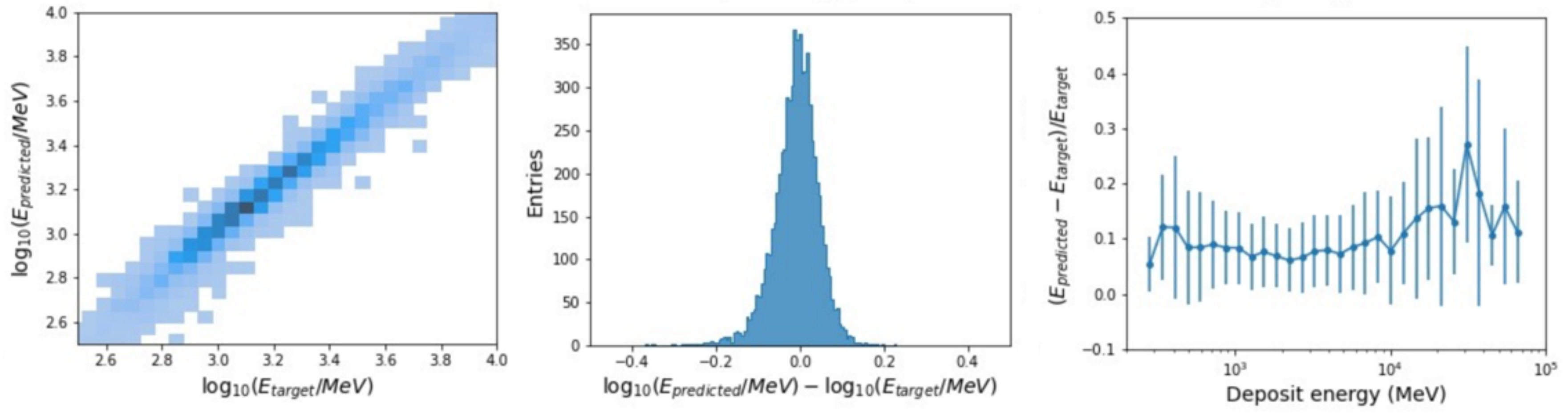


From left to right: Distribution of reconstructed energy as a function of true energy; Residual distribution of the logarithm of the reconstructed energy; Relative energy resolution as a function of true energy.

Result 2

By analyzing 6630 additional testing samples, we achieved

- An energy resolution as good as 8%.
- The 2D distribution shows a smooth path which is better than the one in result 1, since predicting the sampled energy in CAL is more direct. It avoids the additional degree of freedom, i. e., the tracking angle.



From left to right: Distribution of predicted energy as a function of target energy; Residual distribution of the logarithm of the predicted energy; Relative energy resolution as a function of true deposited energy.

Result 3

By analyzing 353 CR events and 20,000 noise events as testing samples, we achieved a model that has

- A true positive rate of 93.2% and a true negative rate of 99.4%.
- This could help us preserve most of the "CR like" events and reject a significant fraction of the noise events that triggered the instrument acquisition electronics.
- It gives an unbiased result that does not relate to any detector calibration.

	Actual True (CR)	Actual False (Noise)
Predicted Positive (CR)	True Positive = 93.2%	False Positive = 0.6%
Predicted Negative (Noise)	False Negative =6.8%	True Negative = 99.4%

The confusion matrix of this classification model. Since we train the X-Z view and Y-Z view separately, we define that a CR event is one where both views have likelihoods of 50% or higher of being "CR like," otherwise the event is classified as noise.

Conclusions

- The results show that these approaches have the same or even better performance compared to traditional methods.
- Less computing power is needed compared to the traditional method that requires detailed Monte Carlo simulations.
- Machine-learning based methods make the analysis of complex showers straightforward.
- Independent of any detector calibration.
- It leads to ever increasing applications in high energy physics and particle astrophysics.

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