

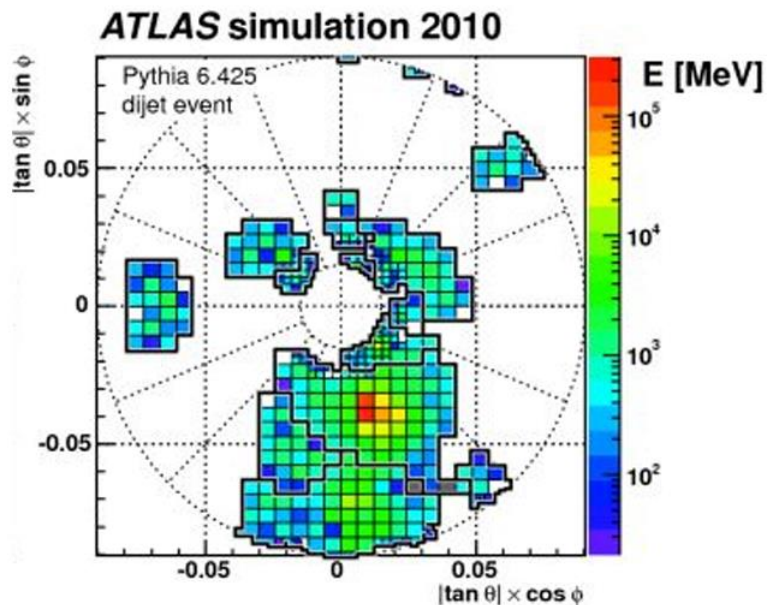


Energy Regression w/ ML

ELPH-ZDC Test Beam Meeting@20240604

Jen-Chieh Peng, Wen-Chen Chang, Chih-hsun Lin,
Chia Ming Kuo, Rong-Shyang Lu, Po-Ju Lin,
Kai-Yu Cheng, Chia-Yu Hsieh (presenter), **Yu-Siang Xiao, Shao-Yang Lu,**
Yuji Goto, Tatsuya Chujo, Motoi Inaba, Subaru Ito, Kentaro Kawade, YongsunKim,

Energy Regression Calibration with Machine Learning Method

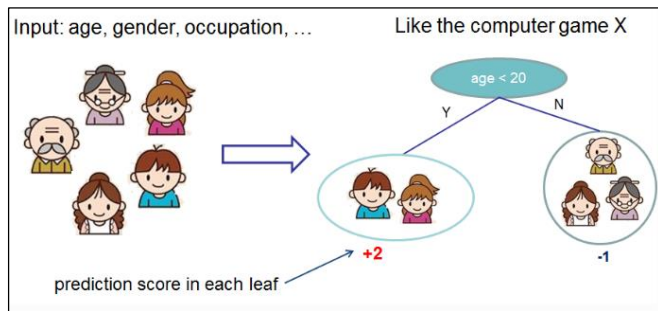


- **Purpose of energy regression** : Energy deposited in the calorimeter may not always be directly proportional to the energy of the incident particle due to **leakage, noise**, etc. By accurately estimating the particle energy, energy regression **improves the energy resolution**.
- **Machine learning techniques** can be used as a method to perform the energy regression.
 - (1) Collect large MC sample and **select training parameters (E_{max} , $E_{3 \times 3}$, $E_{5 \times 5}$) and target parameters (ratio of $E_{\text{beam}}/E_{5 \times 5}$)**.
 - (2) Model training with large MC sample.
 - (3) Validate trained model with separated MC sample.
 - (4) Apply the trained MC to data.
- Attention : One have to make sure **MC and data are agreed at certain level. (We are still working on it!)**

XGBoost (Extreme Gradient Boosting)

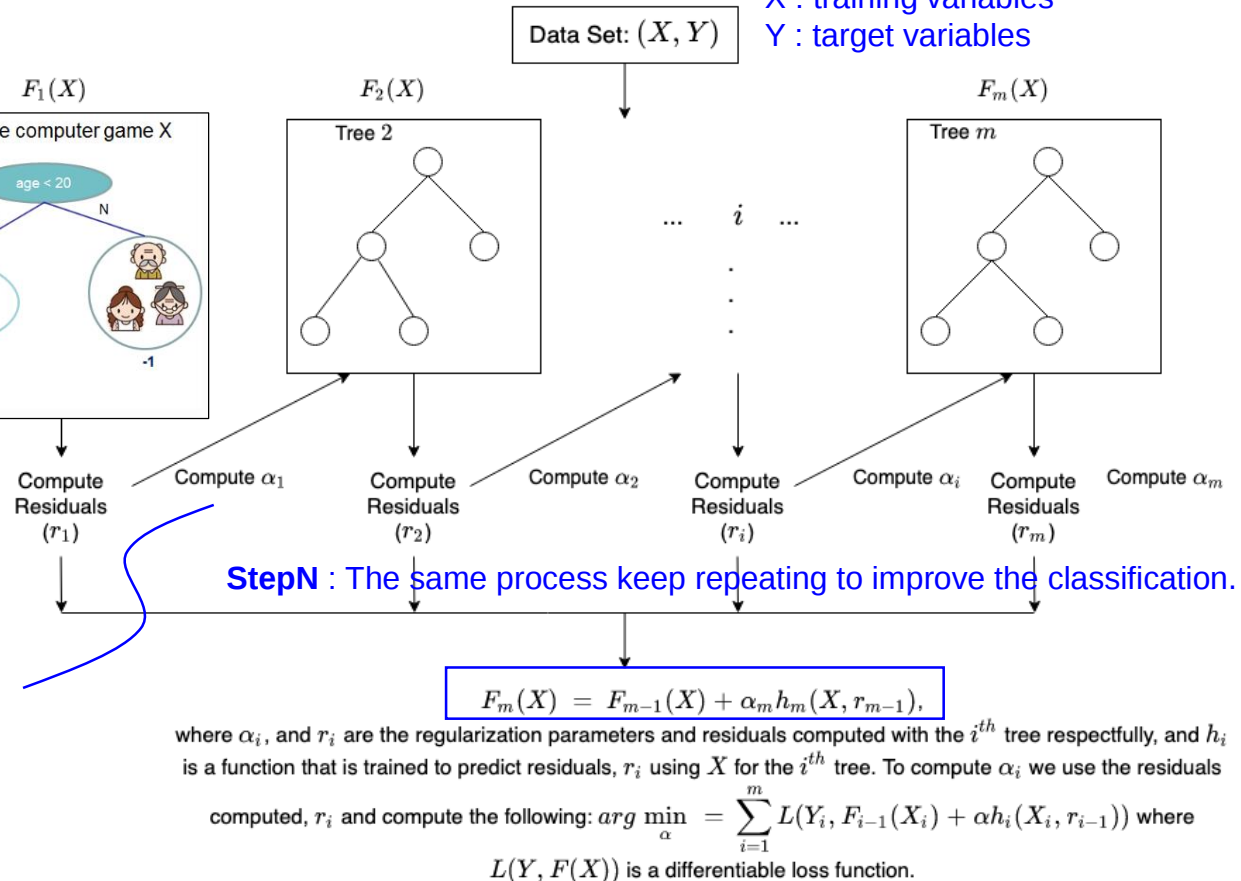
Step0 : Data set
X : training variables
Y : target variables

Step1 : Classify events $F_1(X)$



Step2 : Compute the residue and loss function(avoid over fitting) of 1st tree/classification

Step3 : The 1st tree is usually not the best classification. The 2nd tree/classification add a parameter obtained from the 1st tree, α_1 , to improve the classification.



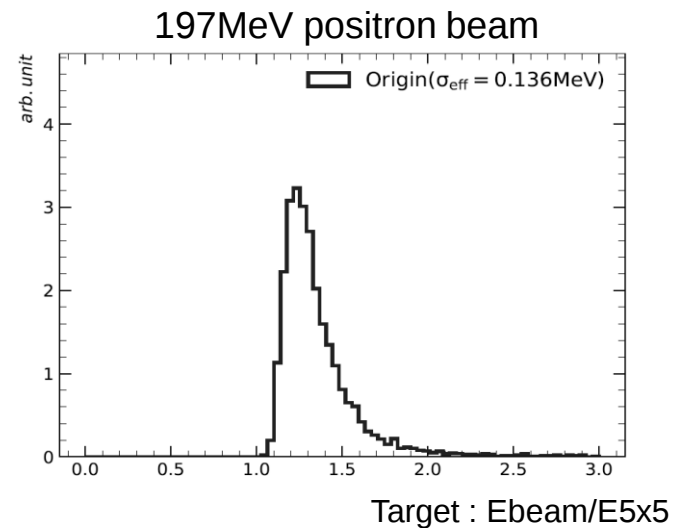
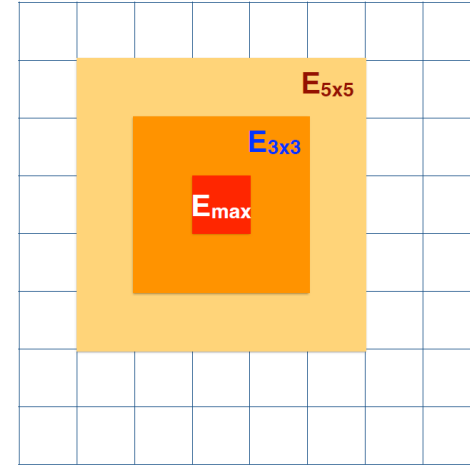
➔ **Final output :**

The predictions of all trees/classifications are combined to produce the final output.

Reference : <https://xgboost.readthedocs.io/en/stable/tutorials/model.html>
https://docs.aws.amazon.com/zh_tw/sagemaker/latest/dg/xgboost-HowItWorks.html

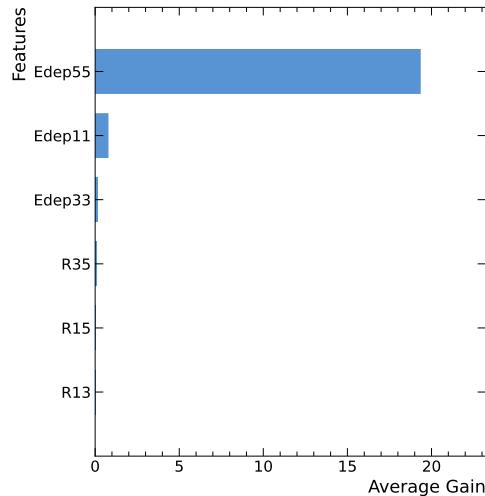
Training Conditions

- XGBoost in Python
- Training MC sample
 - ① 197MeV
 - ② 30k events
(20% test, 80% training)
- Training variables (X):
 - ① E1x1
 - ② E3x3
 - ③ E5x5
 - ④ E1x1/E5x5
 - ⑤ E1x1/E3x3
 - ⑥ E3x3/E5x5
- Target variable (Y) :
 - ① Ebeam/E5x5

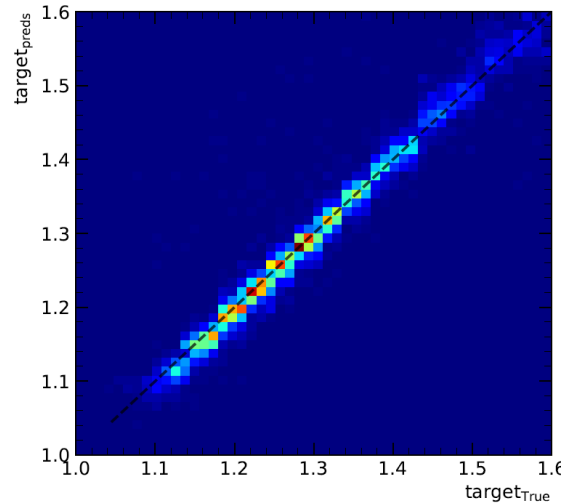


Validate ML Model

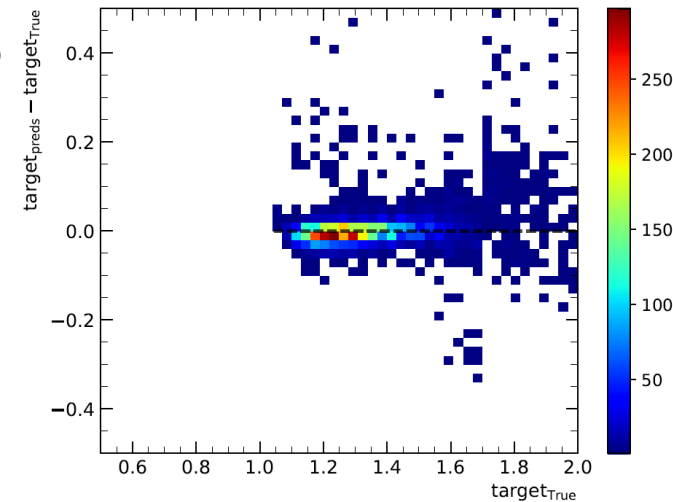
Importance of train variables, X



Target = Ebeam/E5x5
True VS predicted

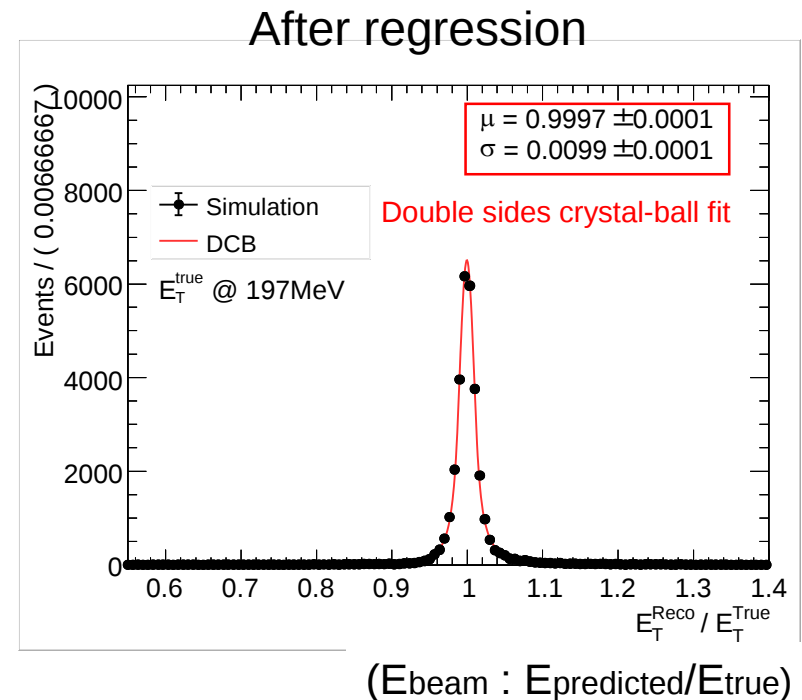
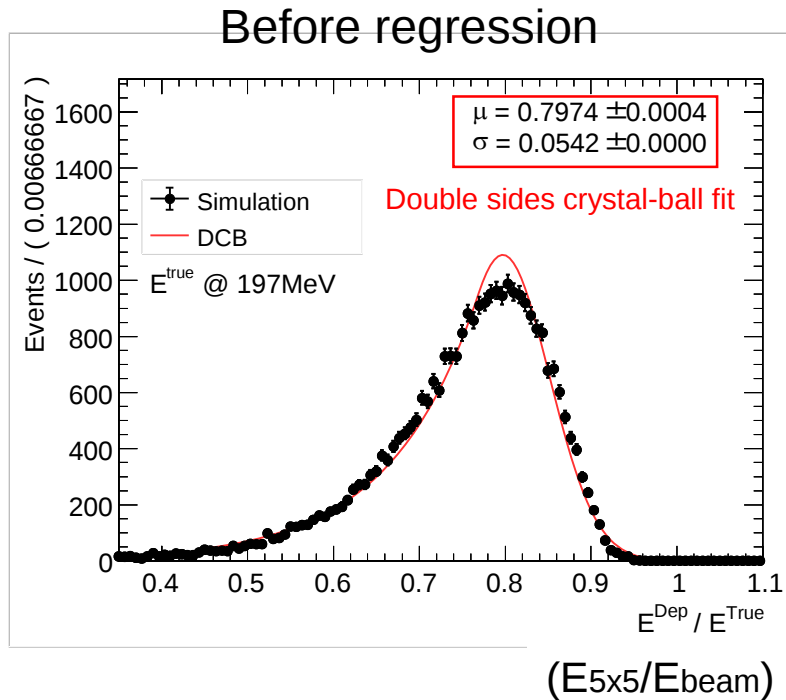


Target = Ebeam/E5x5
uncertainty



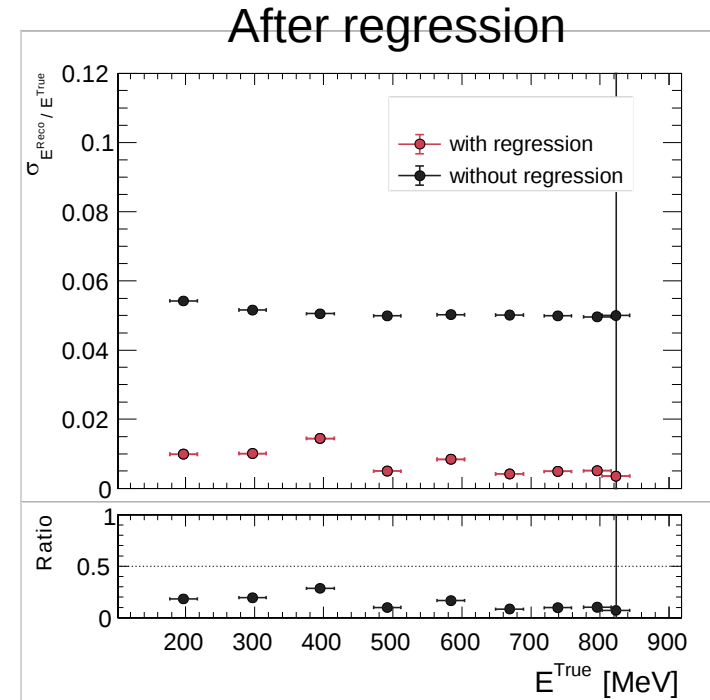
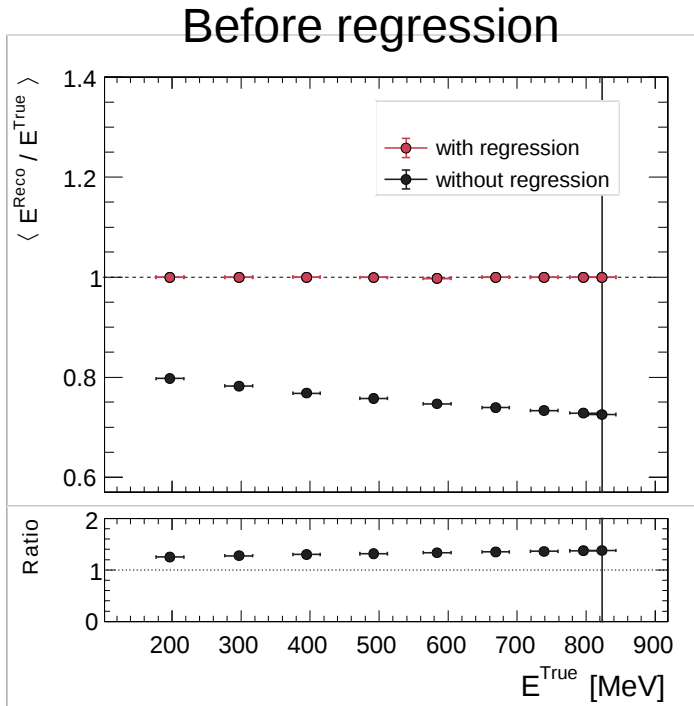
- Among all the training variables, E5x5 is the most important one.
- The training output shows reasonable prediction of target variable, Ebeam/E5x5, with less than 5% uncertainty.

Impact of Energy Regression



- A **new** MC sample generated w/ 197MeV positron beam w/ 30k events.
- After applying energy regression, the beam energy is will reconstructed by ML model and energy resolution improved from 5% to 1%.

Impact of Energy Regression



- New MC samples with energy beam = 197MeV to 823 MeV are tested.
- Ebeam is well predicted and energy resolution is also improved after regression regardless the beam energy.

Summary and To Do

- A method of energy regression w/ machine learning technique is developed. We use XGBoost package provided by Python.
- MC sample is used as both training and test sample for now. The ML regression model shows a great performance to improve the prediction of beam energy (20%) and reduce the energy resolution (5%→1%).
- We will apply this technique once we have relatively more realistic MC simulation ready.