## Particle ID in the AHCAL + Single Shower Substructure (bonus)

**CALICE Collaboration Meeting** 

Vladimir Bocharnikov, DESY Sep 30, 2020







P.N.Lebedev Physical Institute of the Russian Academy of Science





### **Outline**

AHCAL Particle ID using BDTs

#### Particle identification

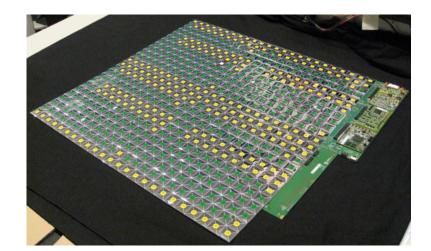
- Motivation and method overview
- Data preparation
- Boosted Decision Tree method description
- Parameters and input
- Resulting metrics
- Application to test beam data
- Summary and outlook (1st part)
- Bonus: Detailed single hadron shower structure
- Motivation
- Method and data preparation
- Challenges
- Summary and outlook



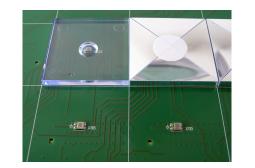
Test beam prototype.

38 active layers of 24x24 scintillator tiles ( $3x3 \text{ cm}^2$ ) alternating with 1.7 cm steel absorber + 1 "Tokyo" layer with  $6x6 \text{ cm}^2$  tiles

In total: ~22000 channels, ~4  $\lambda$ 

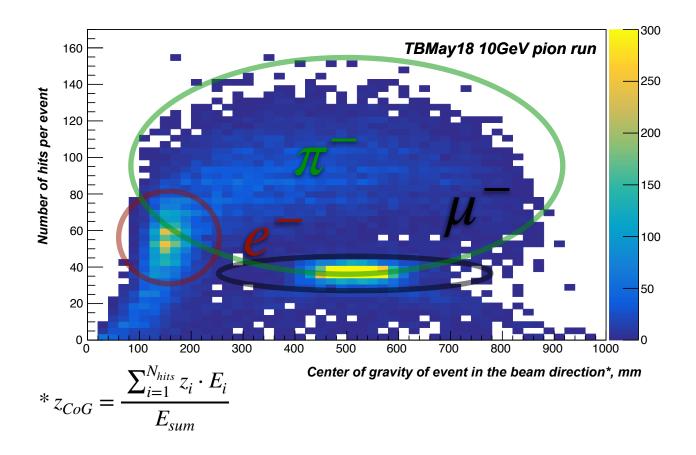






### **Motivation for particle ID**

In test beam data



We always deal with admixture of other particles.

 $\Rightarrow$ To investigate detector response to

particles of given type we need to perform particle identification

### **Particle ID workflow**

**Classification procedure** 



### Pre-analysis

- Calculation of common observables
- Clustering and track finding\*

#### **Event filtering**

- By number of hits:
  nHits > nHits\_min
- multi-particle and upstream

#### **BDT** multiclass model

trained on simulations (10-200GeV).

### 3 classifiers:

#### **Hadron classifier**

Trained on showering pions

#### **Electron classifier**

Trained on electrons

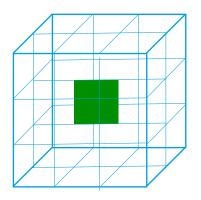
#### Muon (muon-like) classifier

Trained on muons

\* Described during CALICE Collaboration Meeting at CERN: https://agenda.linearcollider.org/event/8213/contributions/44343/attachments/34812/53758/VBocharnikov\_CALICE\_meeting\_CERN.pdf

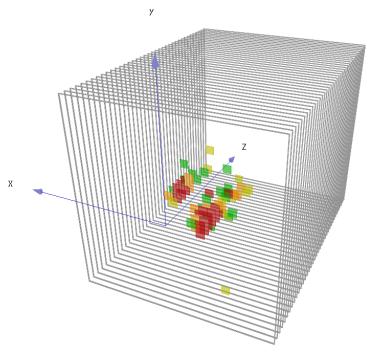
### **Event filtering**

#### Simplified algorithms.



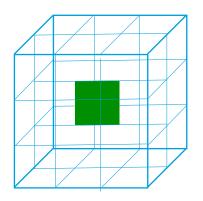
**Clustering:** Hits are grouped in clusters if if they are neighbours in volume. First 5 layers are taken into account

If *N<sub>Clusters</sub>* > 1 => multi-particle event (or upstream shower)



### **Event filtering**

#### Simplified algorithms.

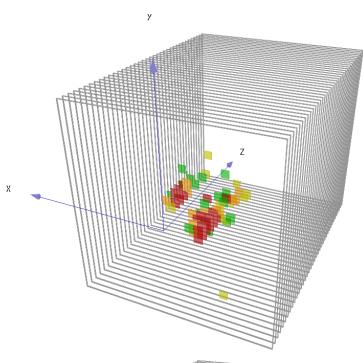


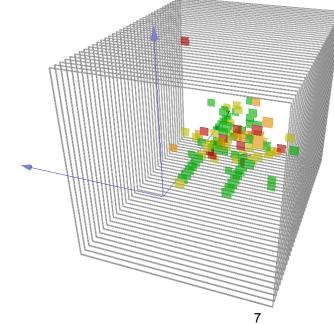
**Clustering:** Hits are grouped in clusters if if they are neighbours in volume. First 5 layers are taken into account

If *N<sub>Clusters</sub>* > 1 => multi-particle event (or upstream shower)

**MIP tracking:** Construct towers with same x and y coordinates. First 5 layers are taken into account.

If *N<sub>MIPTracks</sub>* > 1 => multi-particle event





Model and input. TBJune18.

#### Software and model:

- LightGBM package
- Multi-class Gradient Boosted

**Decision Tree** 

Multi log loss function

Model and input. TBJune18.

#### Software and model:

- LightGBM package
- Multi-class Gradient Boosted

**Decision Tree** 

Multi log loss function

#### **Gradient Boosting:**

Method combines many sequential decision trees with weights. Weights are optimised during training by calculating the gradience of loss function

Model and input. TBJune18.

#### Software and model:

- LightGBM package
- Multi-class Gradient Boosted

#### **Decision Tree**

Multi log loss function

#### Multi log loss:

$$L = -\frac{1}{N} \sum_{i}^{N} \sum_{j}^{3} Y_{ij} ln(p_{ij})$$

Where *N* - number of events in the test sample, 3 - number of classes,  $Y_{ij}$  is binary variable with the expected labels and  $p_{ij}$  is he classification probability output by the classifier for the *i*-instance and the *j*-label.

### **Gradient Boosting:**

Method combines many sequential decision trees with weights. Weights are optimised during training by calculating the gradience of loss function

DESY. | Particle ID + Single Shower Substructure | CALICE Collaboration Meeting | Vladimir Bocharnikov

Model and input. TBJune18.

### Software and model:

- LightGBM package
- Multi-class Gradient Boosted
  - **Decision Tree**
- Multi log loss function

### Training and test set:

- MC particles 10-200GeV QGSP\_BERT\_HP physics list simulated and reconstructed using June 2018 setup:
  - pions (st  $\leq$  40)
- electrons
- muons
- Simulated data is split 50/50 test/train

#### **Observables:**

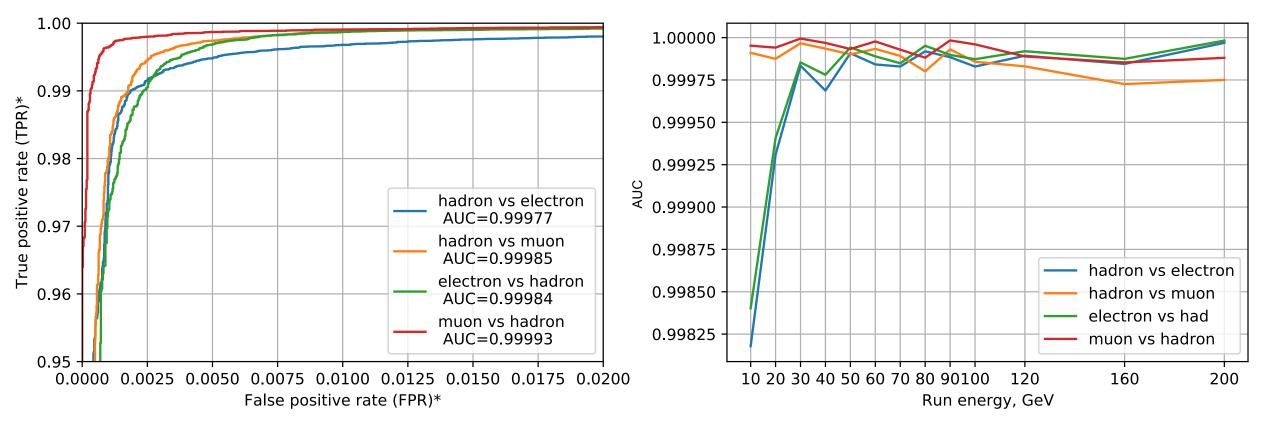
- Number of hits
- Shower start
- Event radius
- Center of gravity in z
- Energy fraction in first 22 layers
- Energy fraction in shower center
- Energy fraction in shower core
- Fraction of track hits
- Number of track hits
- Number of layers with hits from last 5
- Mean hit energy after shower start

### **Resulting metrics**

#### After training

ROC curves for the test data

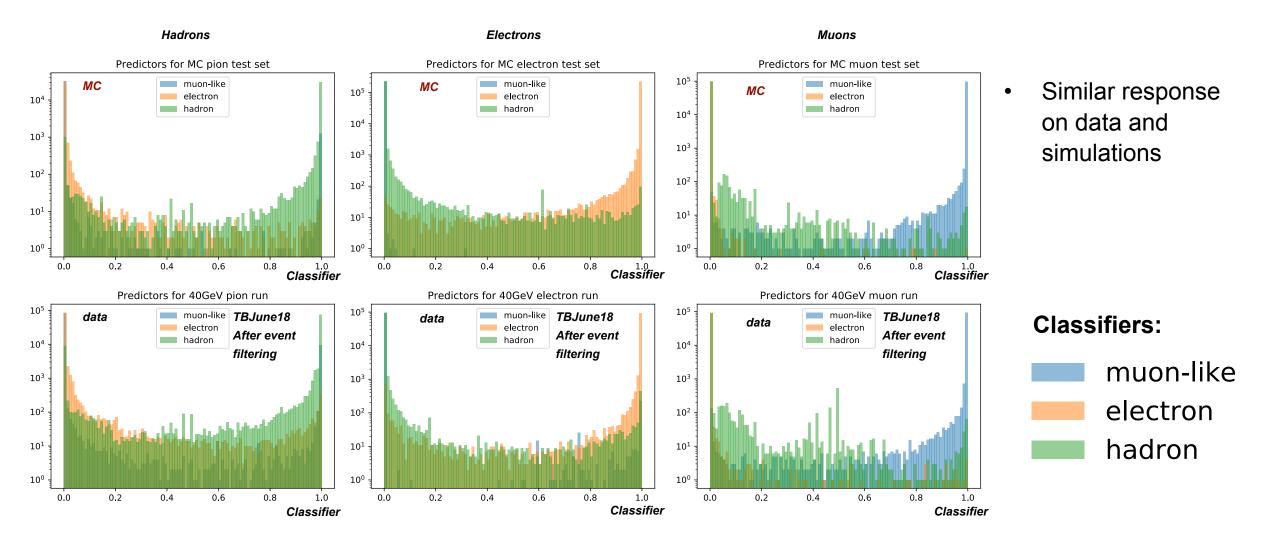




 $*TPR = \frac{TP}{TP + FN}, FPR = \frac{FP}{FP + TN}$ 

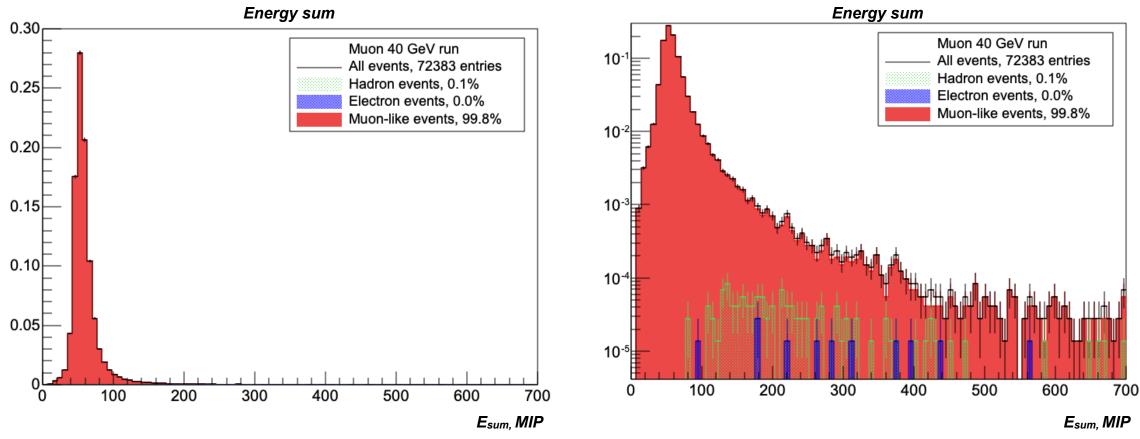
DESY. | Particle ID + Single Shower Substructure | CALICE Collaboration Meeting | Vladimir Bocharnikov

### Output. Comparison with data.



### **Results on test beam data taken in June 2018**

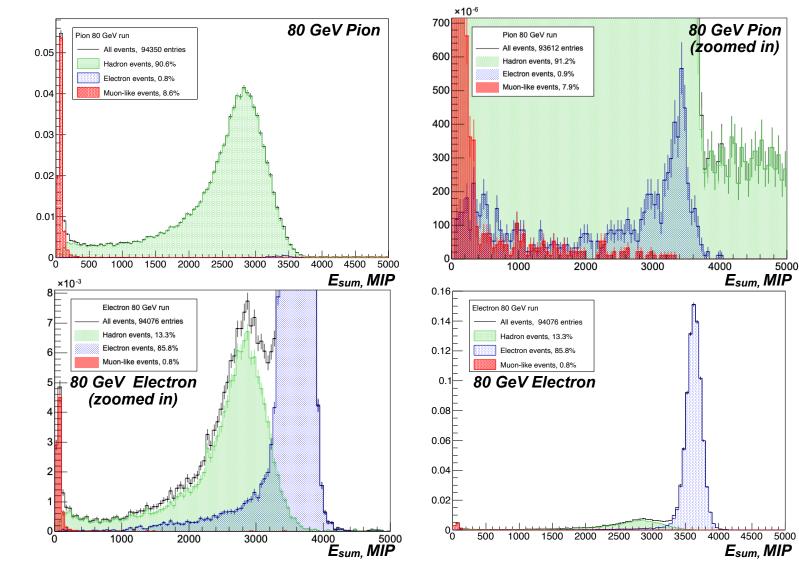
**Energy sum distribution for 40GeV muon run** 



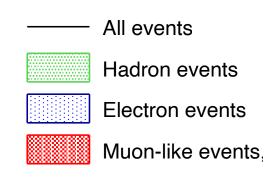
- Very low admixture of other particles
- Little fraction of delta electrons can be classified as hadron event

### **Results on test beam data taken in June 2018**

#### **Energy sum distributions for 80GeV runs**

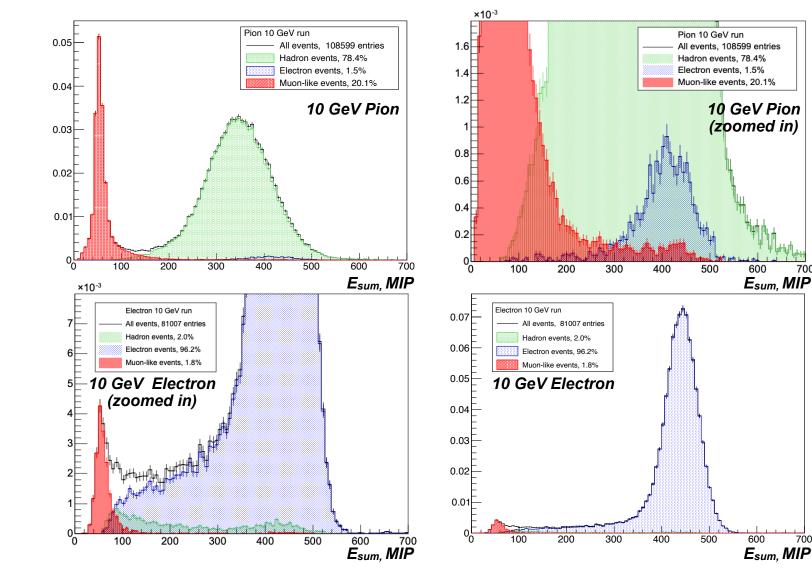


- Energy expectation for electron events in pion run is close to real electron run
- Energy distribution of hadron events in 80GeV electron run looks very similar to actual 80GeV pion



### Results on test beam data taken in June 2018

#### **Energy sum distributions for 10GeV runs**

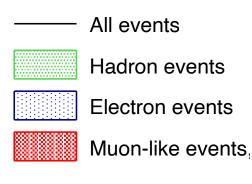


- Energy expectation for electron events in pion run is close to real electron run
- Long high energy tail of muon-like events
- Low energy tail for electrons •

700

700

Most of hadron events in electron run are at low energy



### Summary and outlook (1st part)

**AHCAL Particle ID using BDTs** 

**Model** BDT particle ID method in the AHCAL was discussed

Method shows good performance

☑ Similar response on data and MC

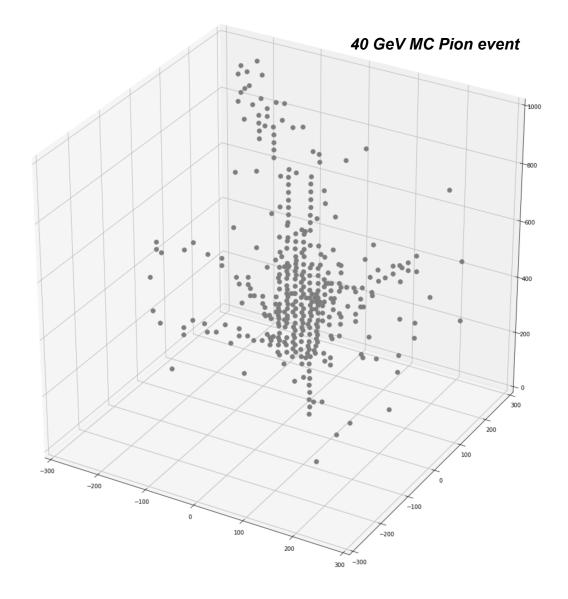
□ Sort input observables by importance to drop less useful ones

Final documentation



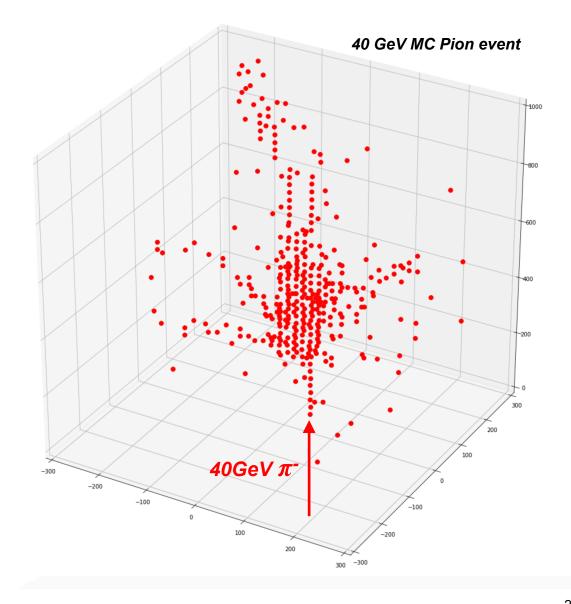
#### **Motivation**

• Standard pattern recognition techniques for highly granular calorimeters provide connection between hits and particle entering a calorimeter



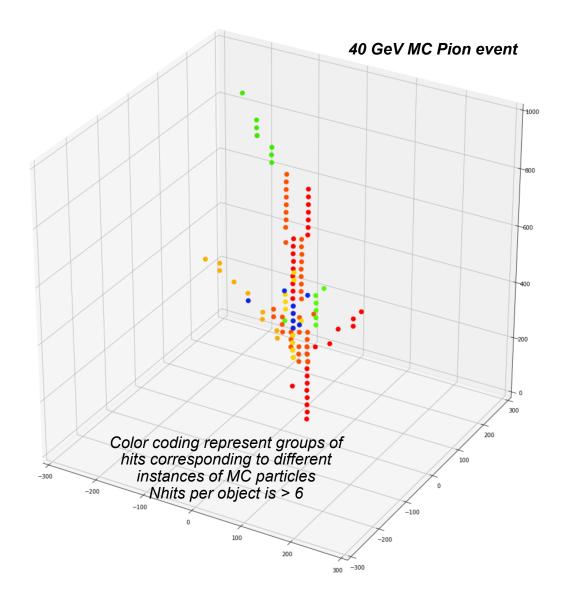
#### **Motivation**

• Standard pattern recognition techniques for highly granular calorimeters provide connection between hits and particle entering a calorimeter



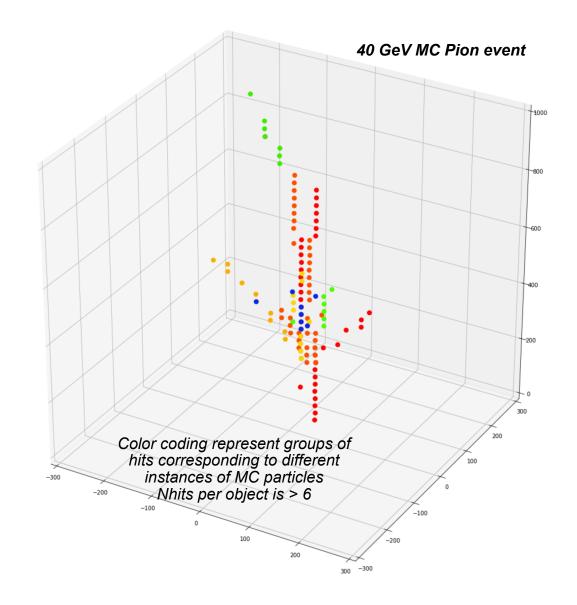
#### **Motivation**

- Standard pattern recognition techniques for highly granular calorimeters provide connection between hits and particle entering a calorimeter
- High granularity combined with the latest advances in Computer Vision (CV) algorithms can allow us to detect single particles within a shower and fully exploit imaging capability of highly granular calorimeters



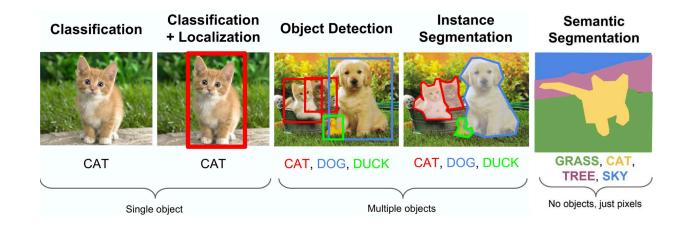
#### **Motivation**

- Standard pattern recognition techniques for highly granular calorimeters provide connection between hits and particle entering a calorimeter
- High granularity combined with the latest advances in Computer Vision (CV) algorithms can allow us to detect single particles within a shower and fully exploit imaging capability of highly granular calorimeters
  - Can help to:
    - Benchmark simulations and other object detection studies (track finding)
    - Study shower shapes from different perspective
    - Improve software compensation
    - Separate showers



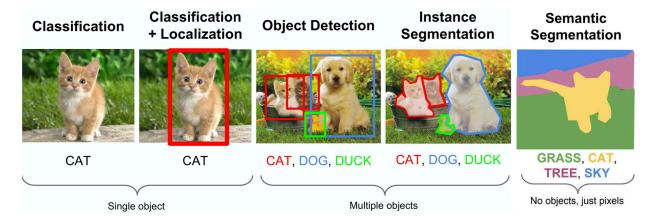
#### Method and data preparation

• In CV this problem is classified **instance segmentation** 

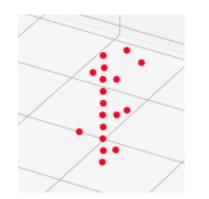


#### Method and data preparation

- In CV this problem is classified instance segmentation
- Data set with links between simulated hits and MC objects has been prepared
  - **MC object** is MC particle + daughters w/o parent's endpoint (hard ionization, Bremsstrahlung, elastic interactions, etc.)



MC object



#### Method and data preparation

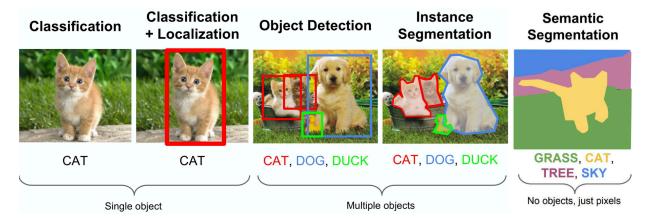
- In CV this problem is classified **instance segmentation**
- Data set with links between simulated hits and MC objects has been prepared
  - **MC object** is MC particle + daughters w/o parent's endpoint (hard ionization, Bremsstrahlung, elastic interactions, etc.)
- Roadmap:
  - Point Cloud input data (X,Y,Z,E,(T))

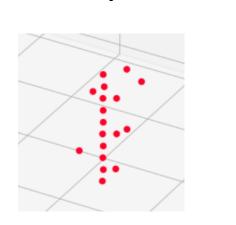
Recent implementation in HEP:

Jet tagging: <u>https://arxiv.org/abs/1902.08570</u>

Calorimetry: <u>https://arxiv.org/abs/1902.07987</u>

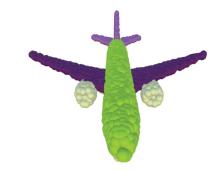
• Machine learning model is being developed, existing implementations of similar problem can be adapted to the task (work in progress)





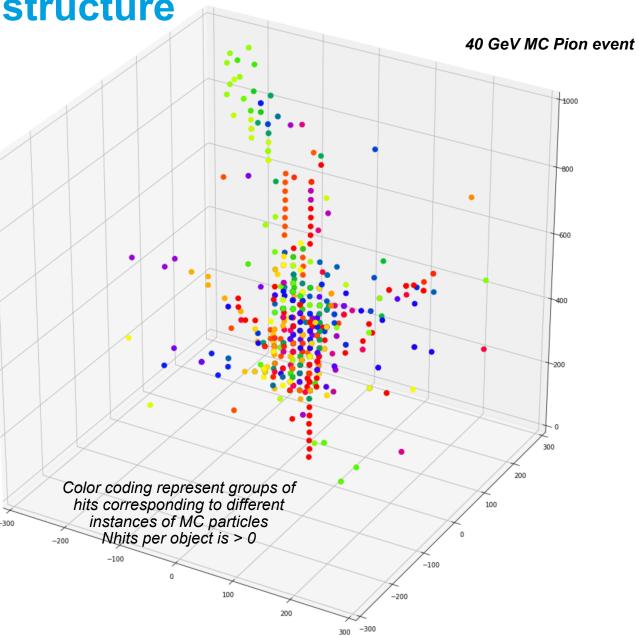
MC object

Point cloud segmentation



### **Challenges of proposed method**

- Large disk space usage
  - O(1000) MC instances per 40 GeV pion event including single hit objects
- Interpretability of segmentation output & training data
  - Many complicated objects to plot distributions
  - Hierarchical structure
- One hit can be connected to several MC objects
  - Main difference from the standard CV problems



### **Summary and outlook**

**AHCAL Particle ID using BDTs and Single Shower Substructure** 

**Mathebra Sector** BDT particle ID method in the AHCAL was discussed

- Method shows good performance
- Similar response on data and MC
- □ Sort input observables by importance to drop less useful ones
- Final documentation
- Single shower substructure analysis is ongoing
  - Training data preparation is done
  - □ Machine learning model is being developed
  - □ Model performance and limitations study will help to review true segmentation on MC level
  - □ Physical interpretation of results

# Thank you

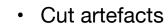
# **Backup slides**

## **Disadvantages of cut-based method**

#### **Towards BDT ID**

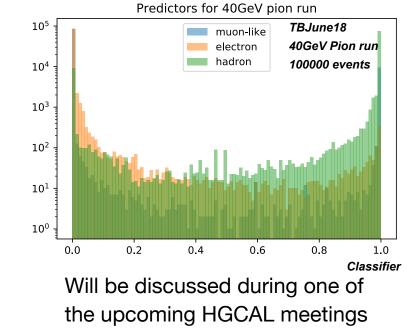
#### Cut-based method:

- > 10 steering parameters for each energy
- Asymmetric distributions/ long tails can be problematic

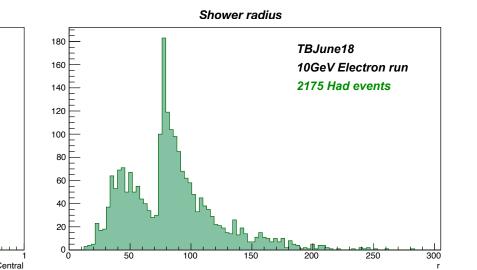


#### **Multivariate methods:**

- Can provide probabilistic classifier trained on given distributions of observables
- One model can be used for whole dataset

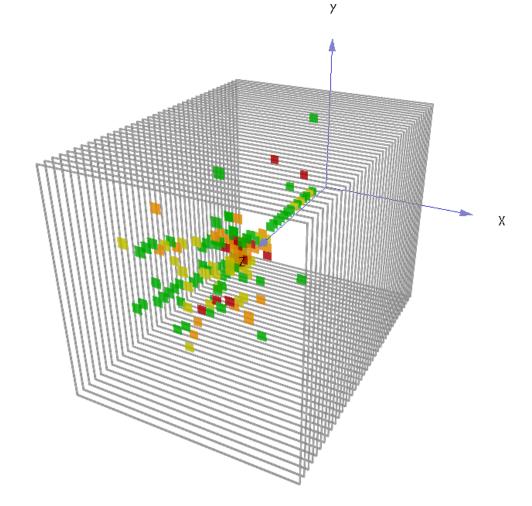


#### Central energy fraction 10<sup>5</sup> TBJune18 MC 40GeV ele 1000000 evts 1000000 evts 10<sup>4</sup> mu 1000000 evts No selection 10<sup>3</sup> 10<sup>2</sup> 10 0.2 0.3 0.4 05 0.6 0.7 0.8 0.9 0.1 fracCentral



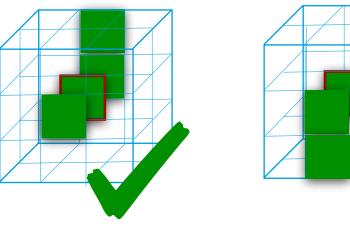
### **Track finding**

Important tool for shower characterisation, Can be used for particle ID



#### Track candidates:

2/3 neighbours in surrounding volume. 2 of them on different sides

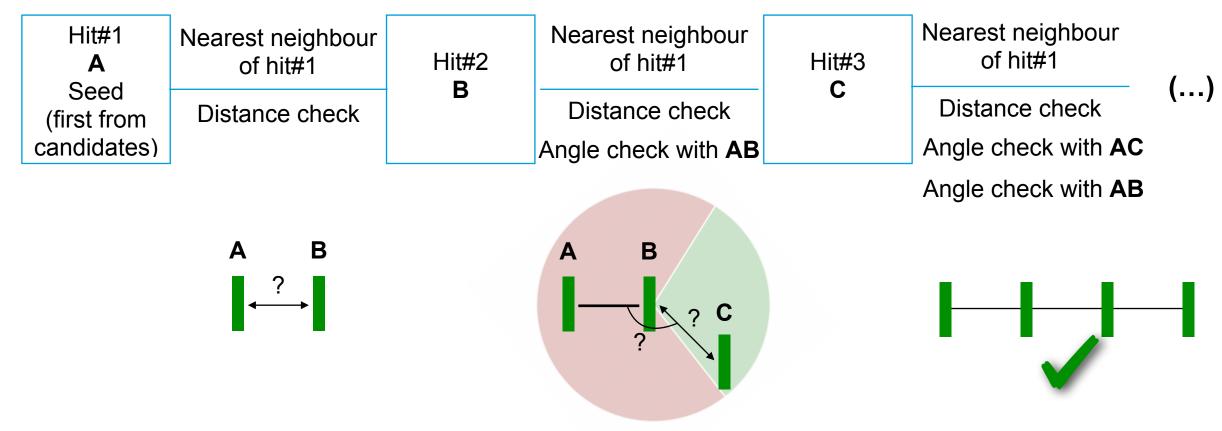


Candidates ordered:

- z-coordinate
- Distance to (0,0,z) in same layer

### **Track finding**

#### **Grouping candidates into tracks**

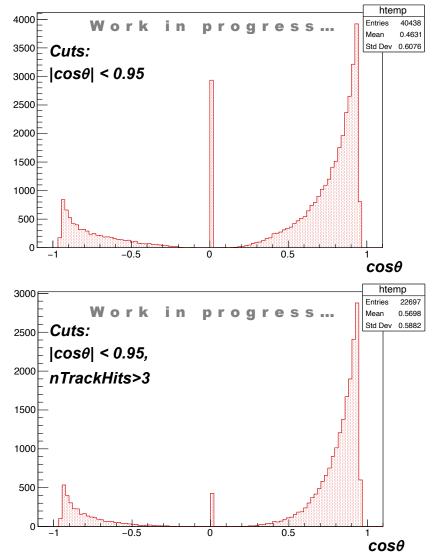


After grouping, track angle is obtained using MSE linear regression

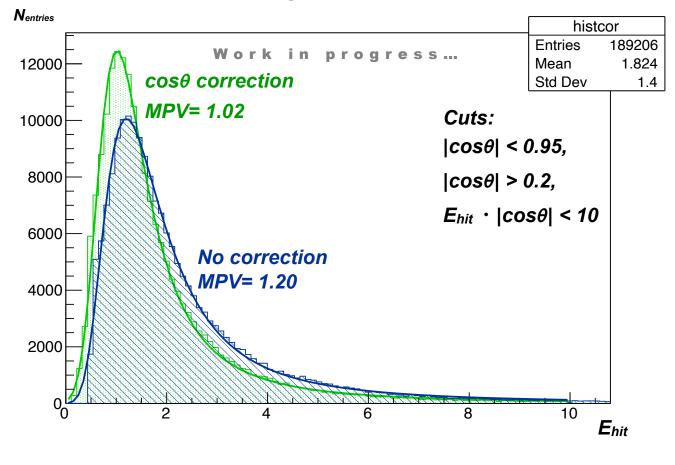
\*\* Procedure repeated iteratively \*\*

### **Tracking quality check**

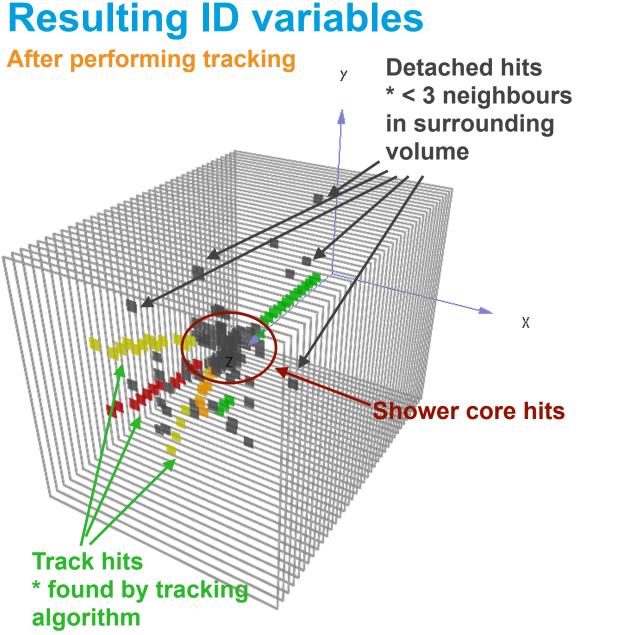
TBMay18 10GeV pion run. 50039 events.



#### Scintillator path length correction for track hits

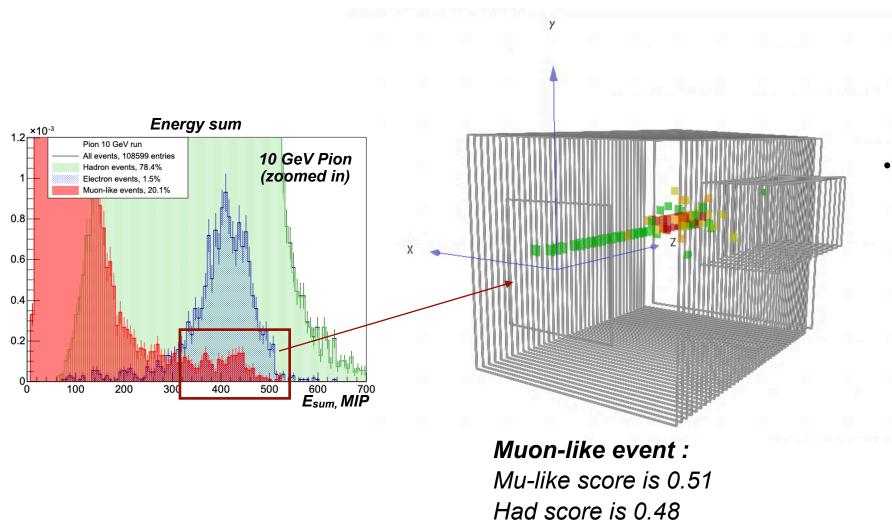


DESY. | CALICE Collaboration Meeting, 2 Oct 2019 | Vladimir Bocharnikov



### **Sources of confusion**

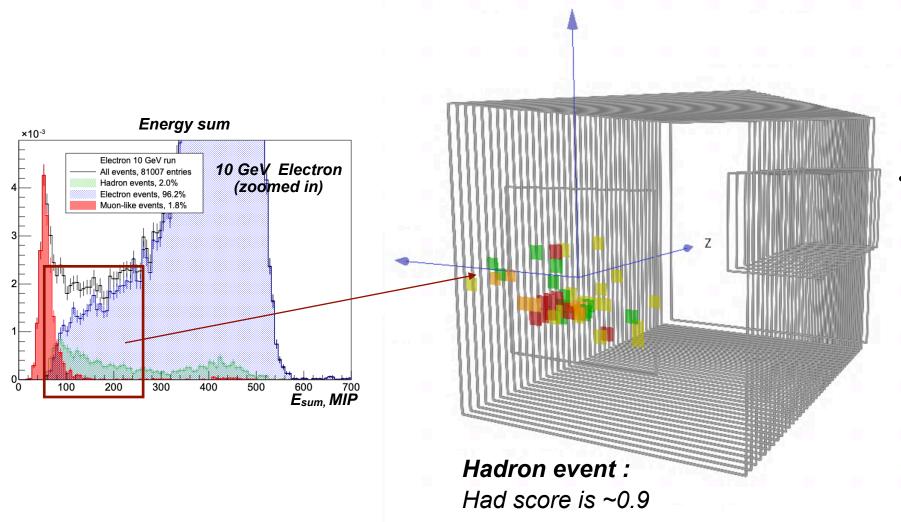
#### From 10GeV pion run



- Compact pion showers with late shower start can be classified as muons
  - Additional variables can
    improve identification
  - Fraction << 1%

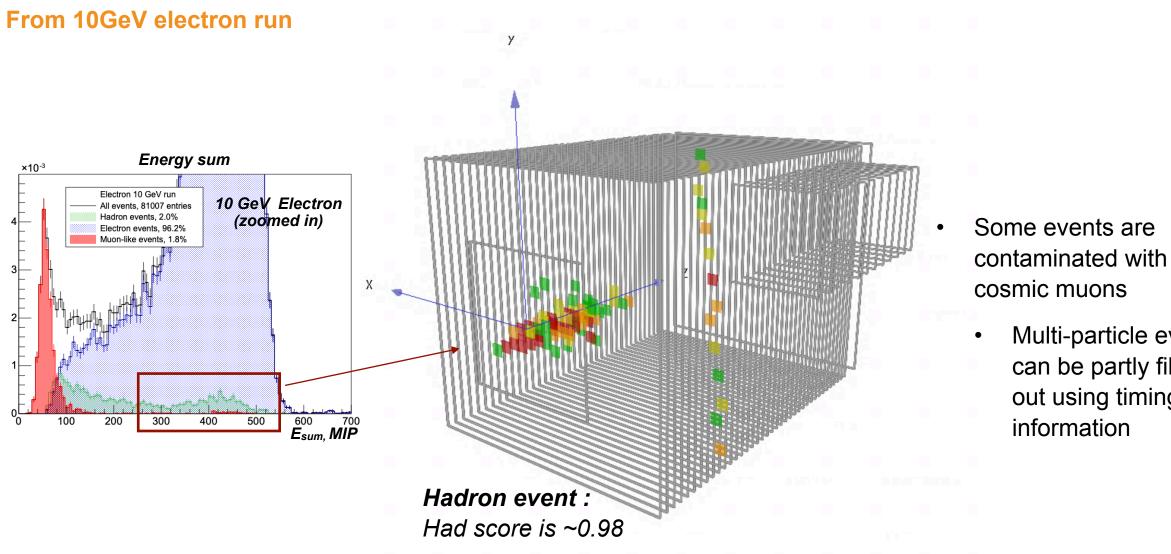
### **Sources of confusion**





- Multi-particle/upstream shower events with small fragments can be classified as hadron events
  - Multi-particle events can be partly filtered out using timing information

### **Sources of confusion**



DESY. | Particle ID + Single Shower Substructure | CALICE Collaboration Meeting | Vladimir Bocharnikov

Multi-particle events

can be partly filtered

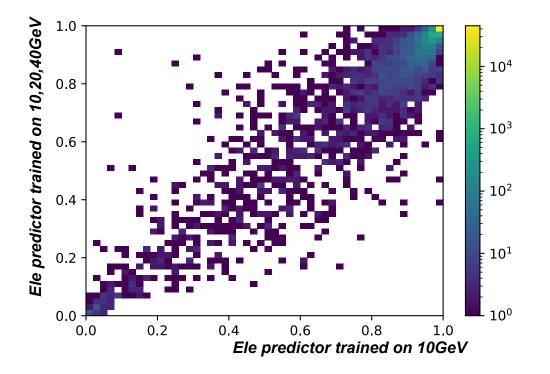
out using timing

information

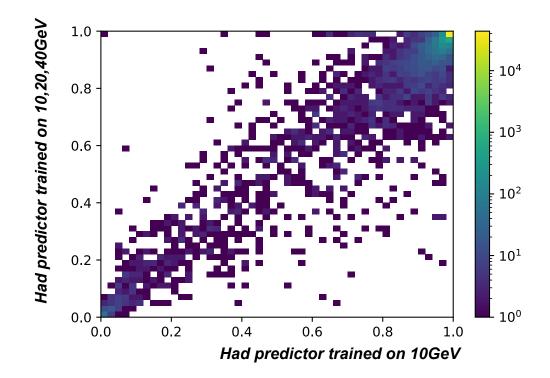
### **BDT output**

Comparison with separate model trained only on 10GeV particles.

**10GeV MC electron** test sample 50000 events

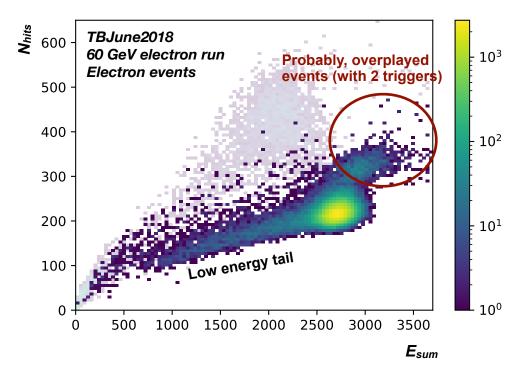


## **10GeV MC pion** test sample 50000 events



### **Application on electron data**

**Of trained BDT model** 



Electron events: classifier<sub>ele</sub>>0.5

