Energy Reconstruction with CALIFA

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Tobias Jenegger

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TUM Members:
Roman Gernhäuser, Mrunmoy Jena, Tobias Jenegger

CALIFA Detector @ R^{3}B

CALorimeter for the **I**n **F**light detection of γ-rays and light charged p**A**rticles

Endcap:

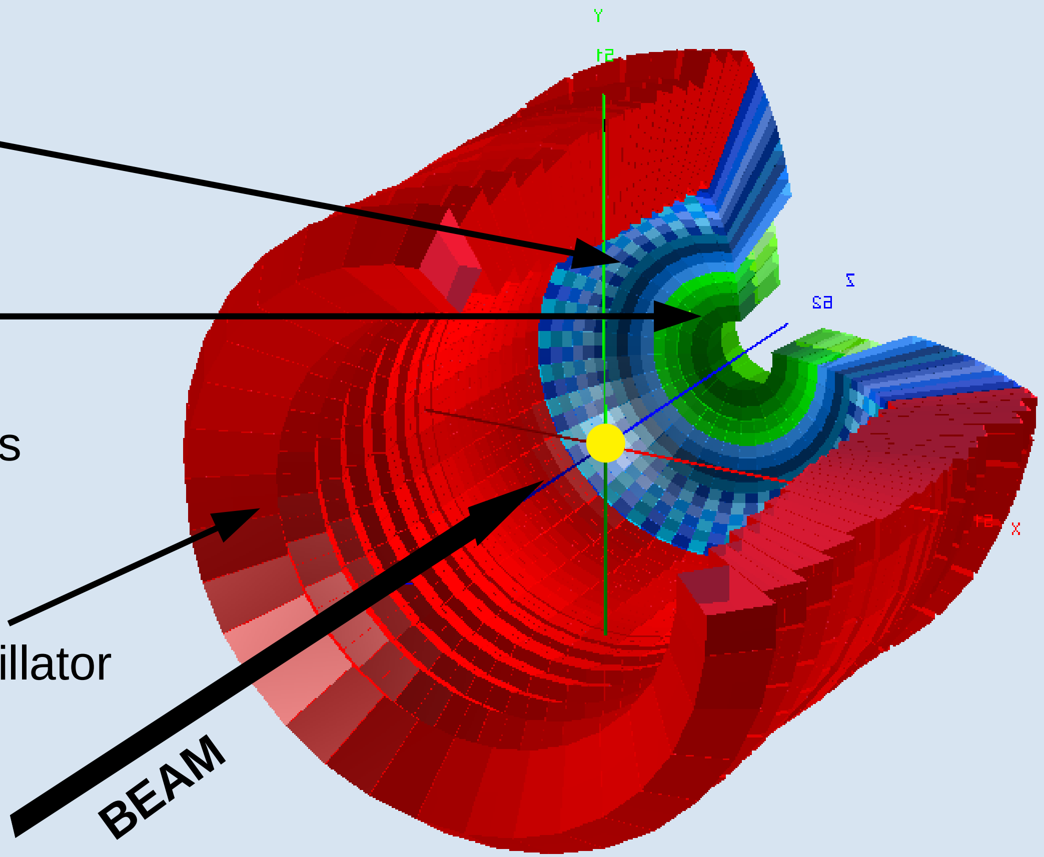
iPhos:

512 CsI(Tl) crystals

CEPA:

96 LaBr3 &

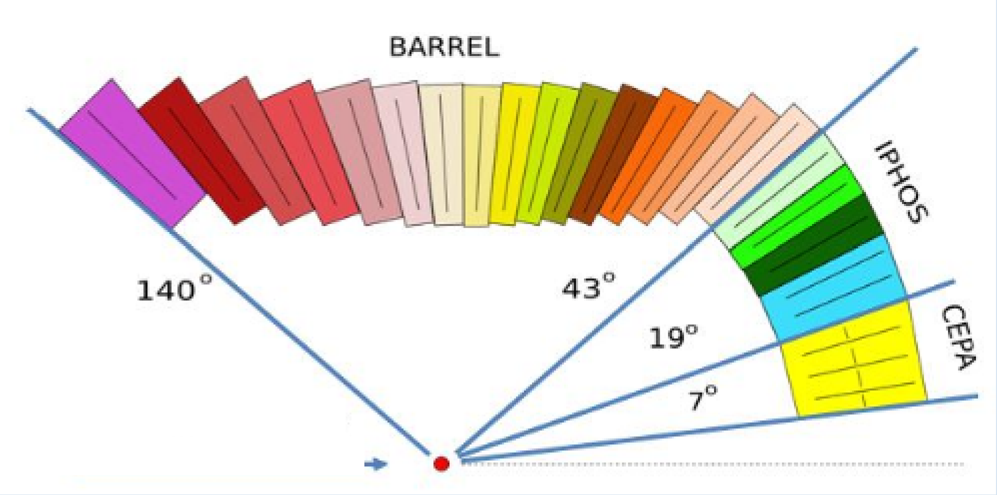
LaCl3 crystals



Barrel:
1952 CsI(Tl) scintillator crystals

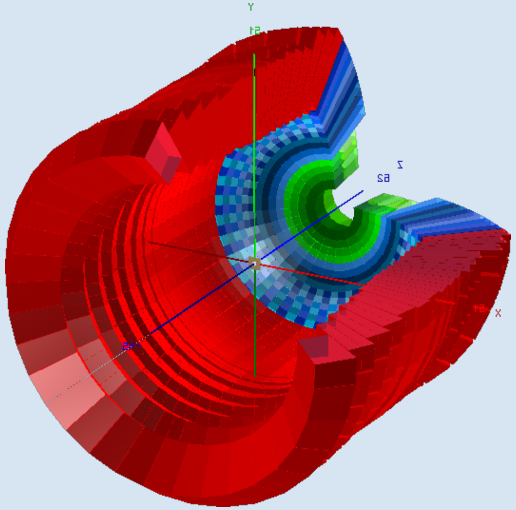
Over 2500 crystal channels!

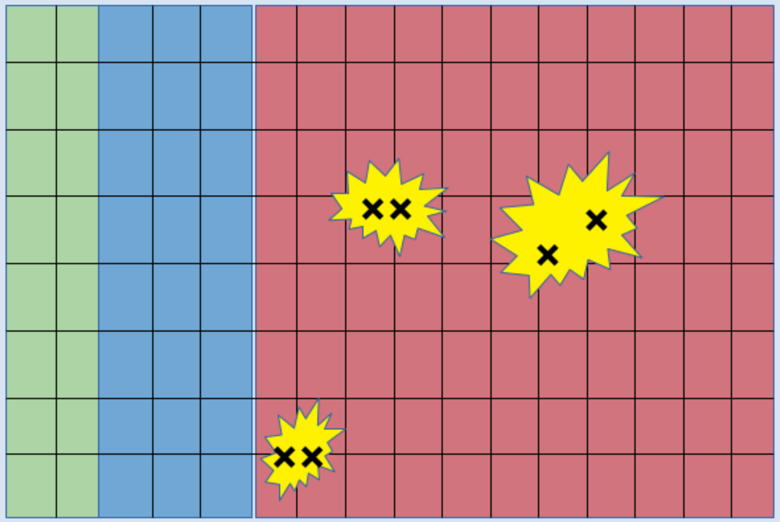
Requirements:
- high dynamic range:
  100 keV γ-rays – 700 AMeV charged particles
- high efficiency
- high granularity → Doppler correction
- particle identification



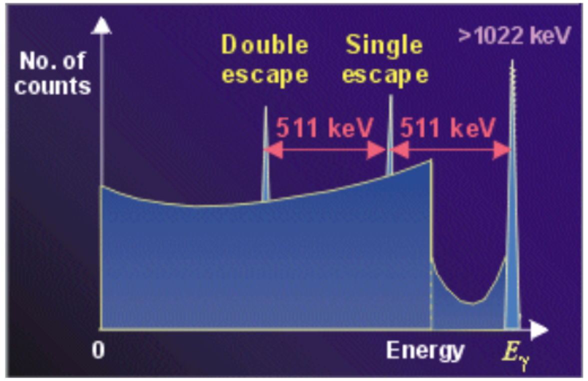
Observables

- **Energy**
- **Polar Angle θ**
- **Azimuthal Angle φ**
- **Time (not used in Standard Algorithm)**



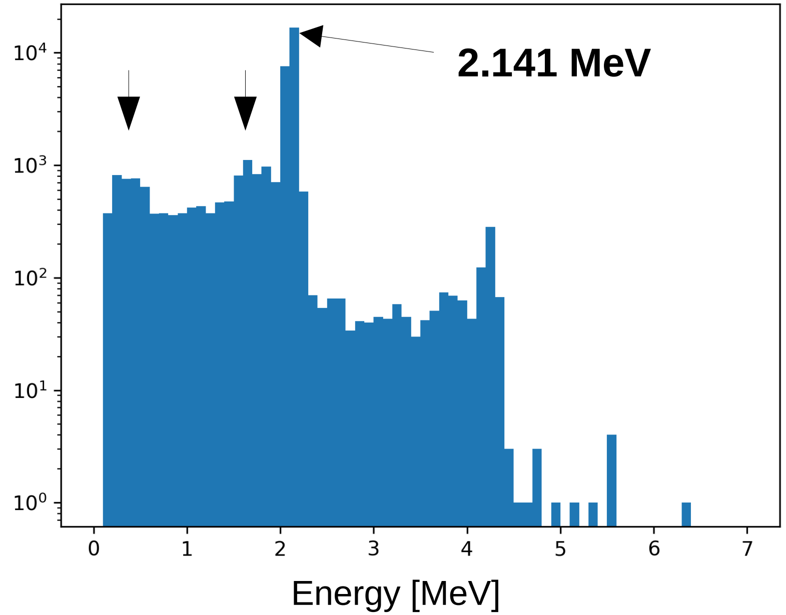


In a real detector, if the incident gamma energy is above 1022 keV, pair production events result in the production of two 511 keV annihilation gamma-rays.



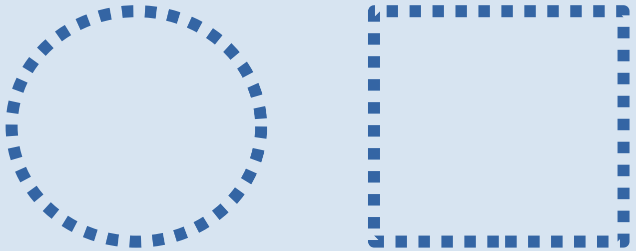
If only one of these gamma-rays escapes while the other is completely absorbed in the detector, 511 keV will be lost from the detector. This results in a separate peak in the spectrum representing Eg-511 keV, called the **single** escape peak.

If both annihilation gamma-rays escape this gives rise to the **double** escape peak at Eg-1022 keV.



Standard Cluster Algorithm

User defines shape and size of cluster:



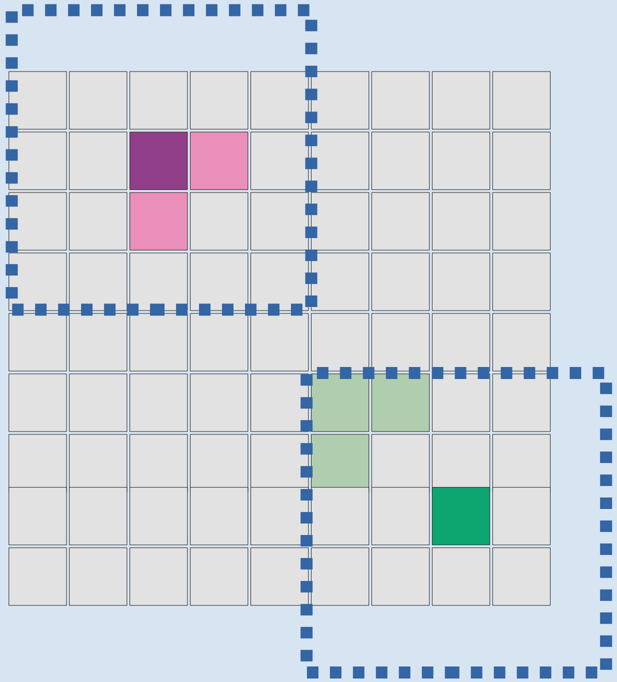
(and set energy threshold for single crystals)

Sort the hit list according to their energy

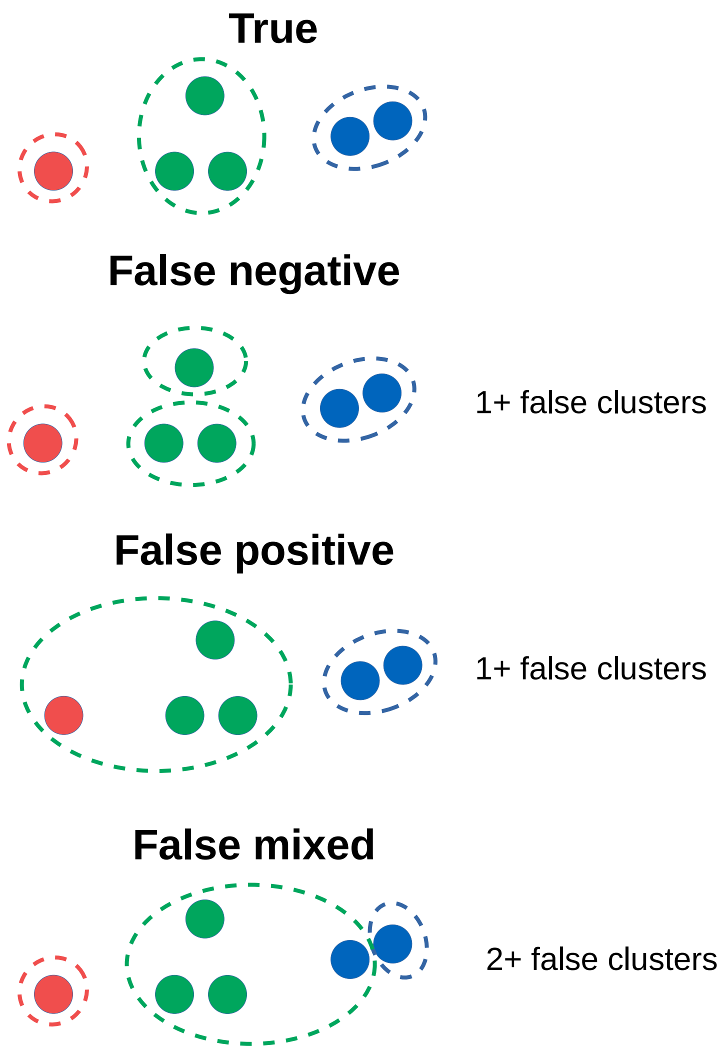
30. MeV
22. MeV
10. MeV
5. MeV
3. MeV
2.5 MeV
0.7 MeV

1. create cluster centered around first hit
2. loop over all hits in list
   → if hit inside cluster add it and remove it from the list

3. Do this procedure until list is empty



Metrics Definition & Datasets



Well reco: $\dfrac{\#corr\_reco\_clusters}{\#total\_clusters}$

Data Used:

- Simulation with true labels
- Each event has **three true clusters**
- Time simulation: event:+-4us block
- Cluster time uniformly distributed, σ_t of hit in cluster = 200 ns

Datasets:

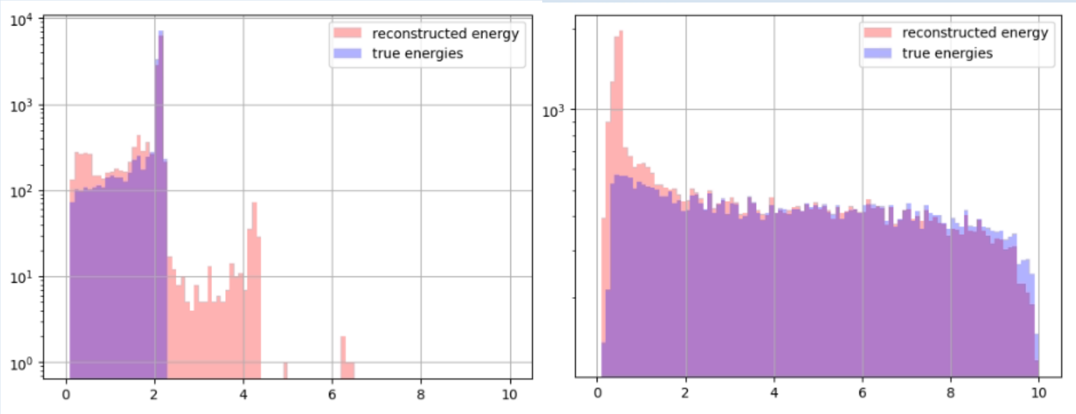
2.MeV Data
Training: 10 kEvents
Test: 4.5 kEvents
false_neg_agglo: 1.8 kEvents
false_neg_classic: 1.5 kEvents

Uniform (0.3-10MeV) Data
Training: 13 kEvents
Test: 7.1 kEvents
false_neg_agglo: 4 kEvents
false_neg_classic: 3.2 kEvents

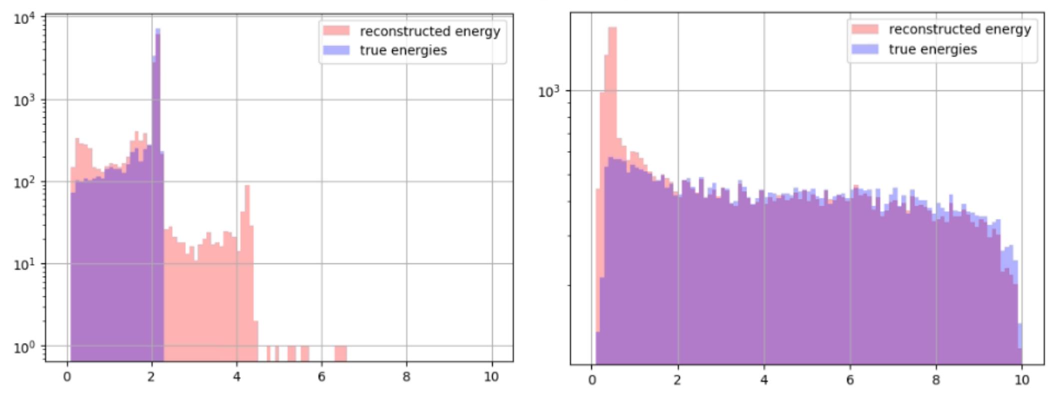
Agglomerative Model (with time info) vs Classical Clustering

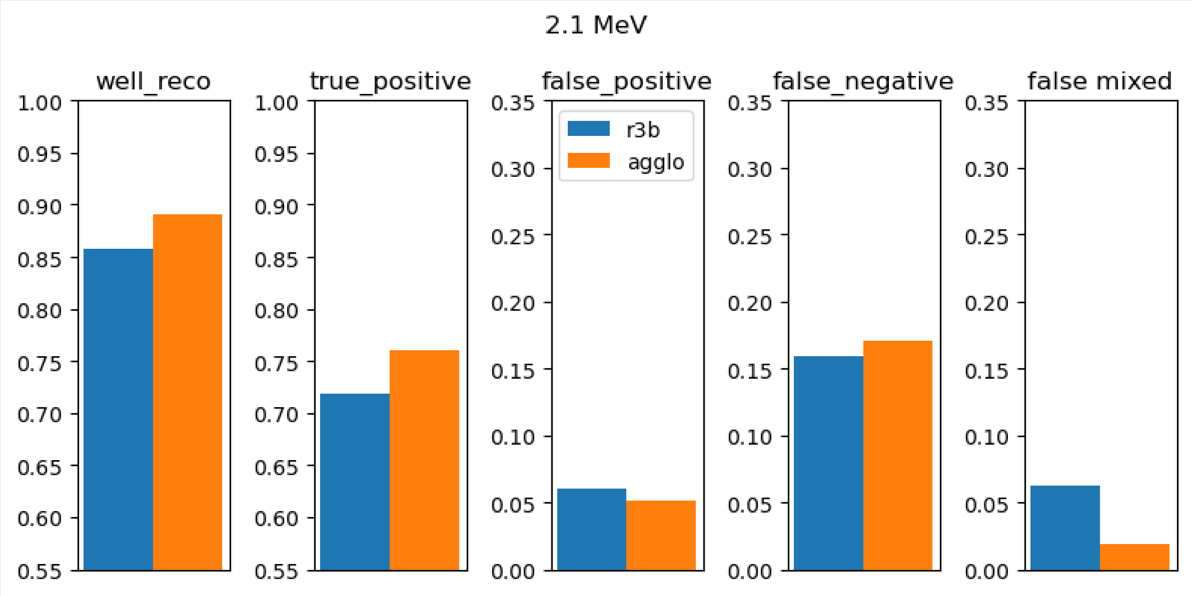
Agglomerative Model

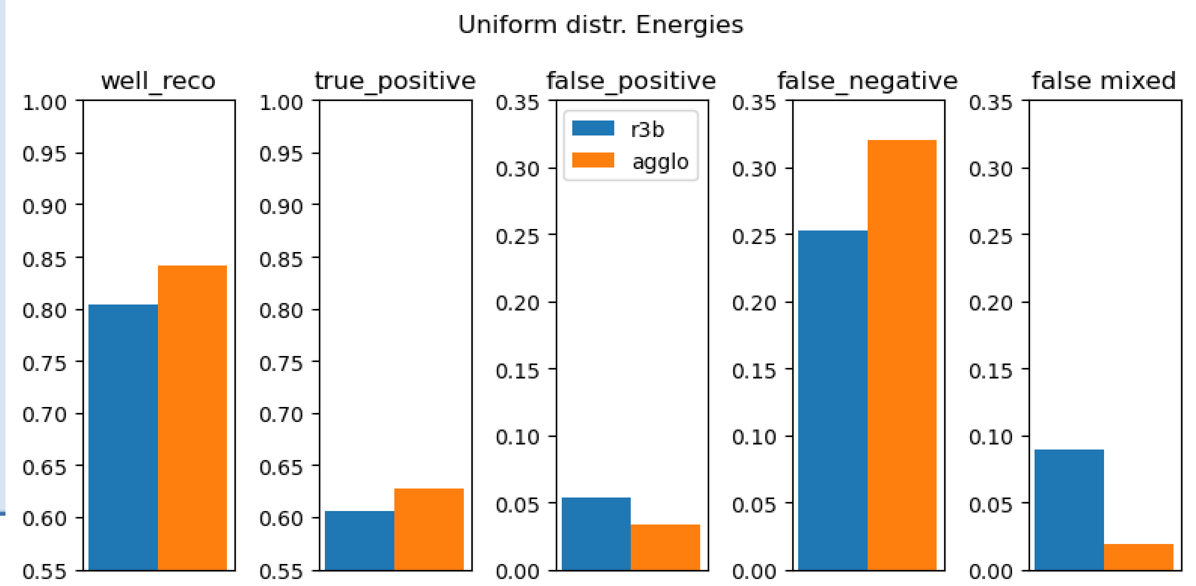
- from scikit library
- use time (+ offset) as radius → 3D clustering



Classical Clustering







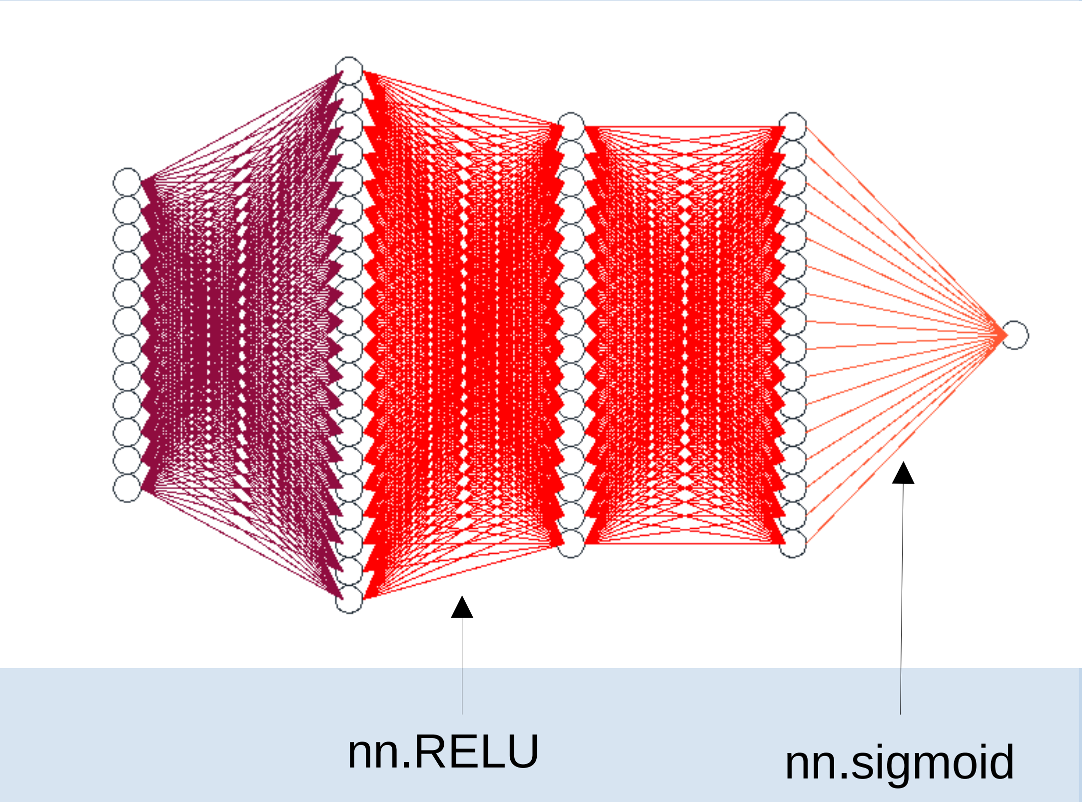
Edge Model

Pairwise comparison of all hits in event

Input Features: $E_1,\theta_1,\varphi_1,t_1,E_2,\theta_2,\varphi_2,t_2,$ **$\Delta E,\Delta\theta,\Delta\varphi,\Delta t$ → 12 features**

Two hidden layers:
1st layer: 1000 nodes
2nd layer: 100 nodes
3rd layer: 100 nodes

Learning rate: 5e-3
n_epochs: 50k



Output: [0,1]

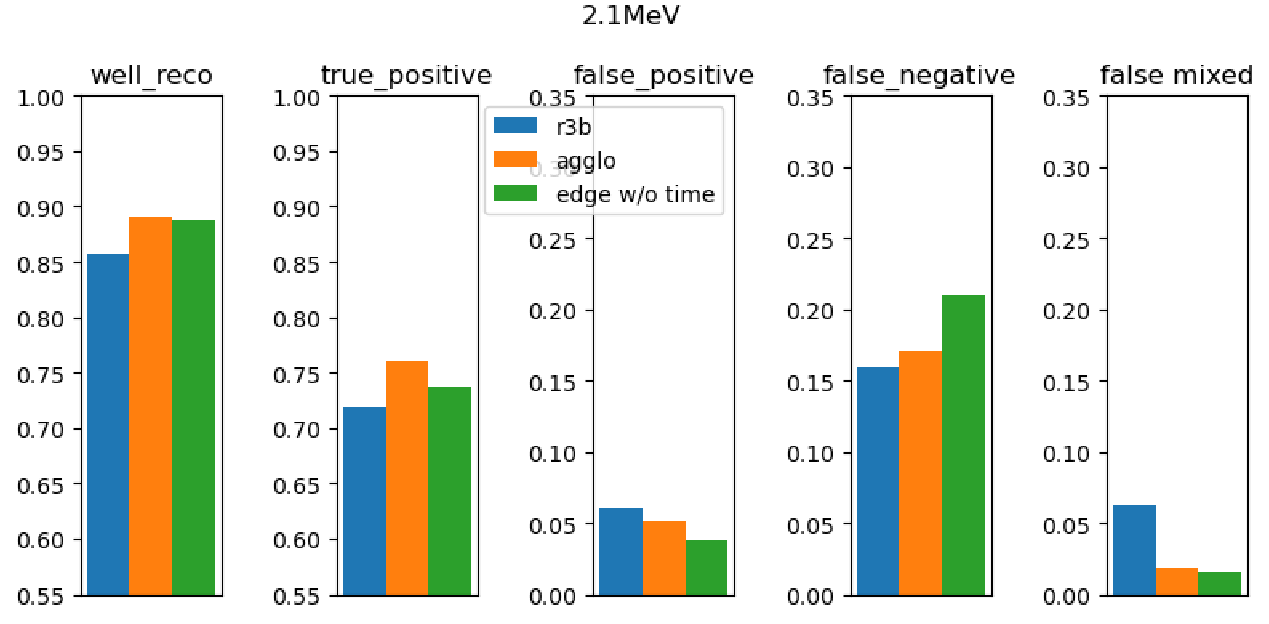
Indep. hits

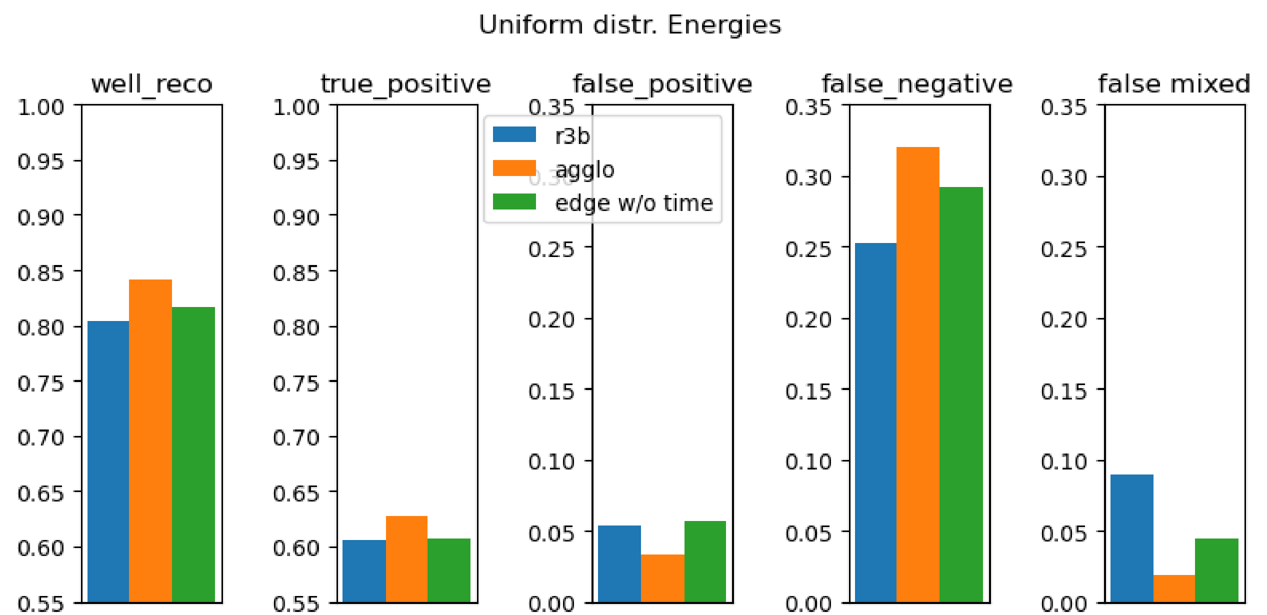
Hits belonging together

Lossfcn: nn.BCELoss
Optimizer: stochastic gradiend descent (SGD)

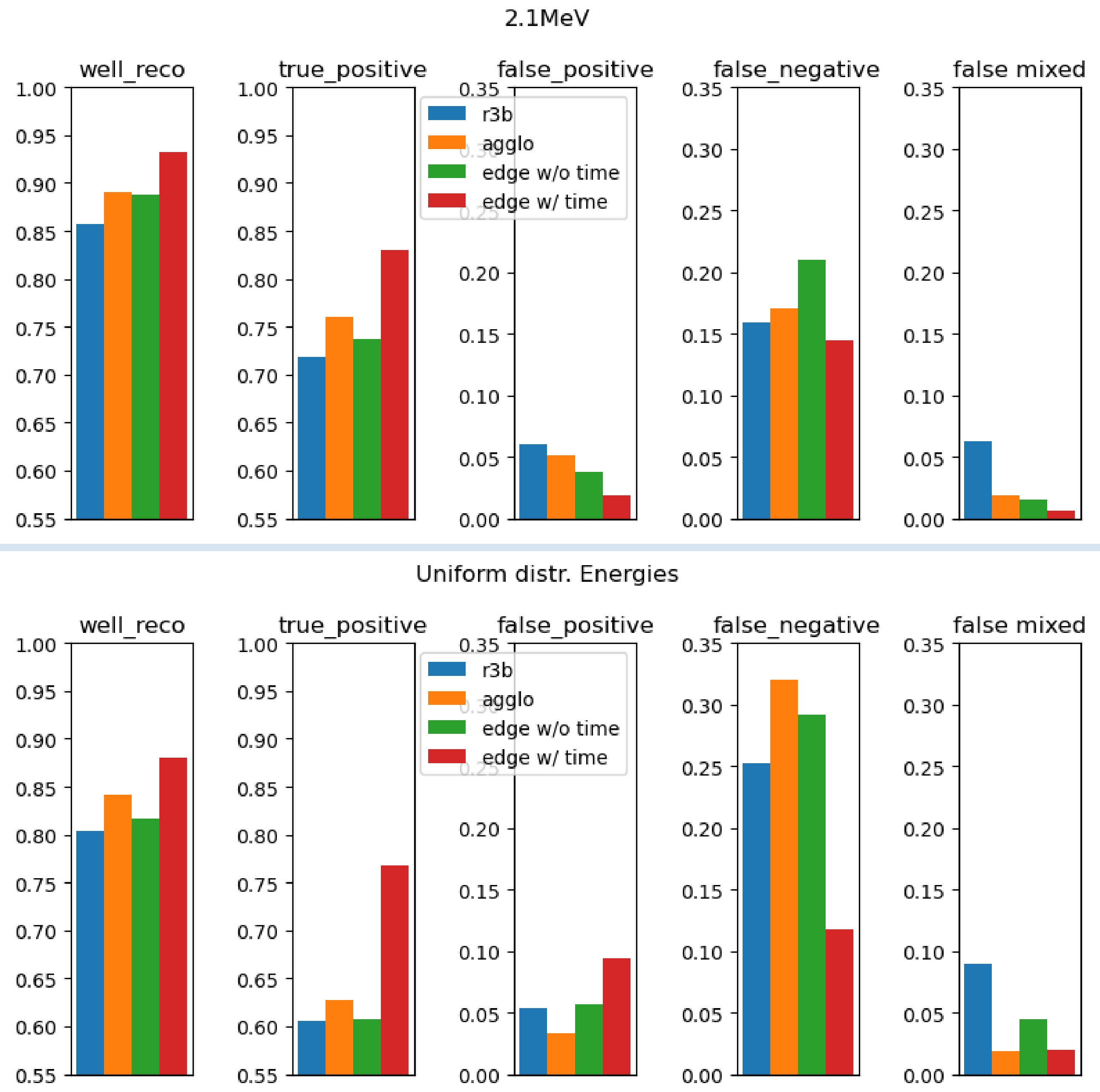
Prediction value cut: 0.75

Results from Edge Model - no time info





Results from Edge Model - with time info



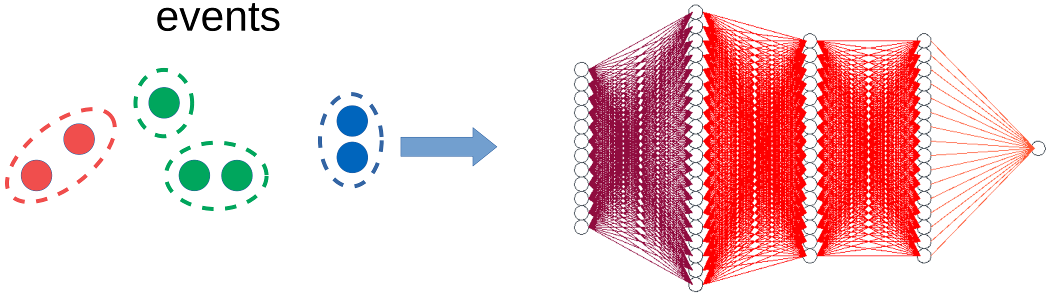
Edge Model works well…
However relative large false_neg level

→ try to train on false_neg events!

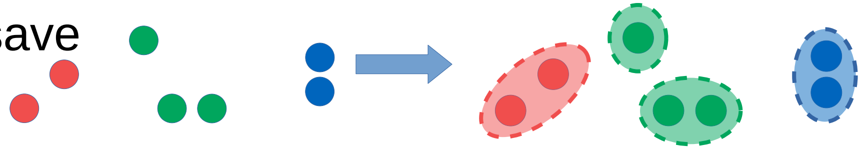
Agglomerative + Edge Model

Step 1:
Train edge model on false-negative events (when using agglo model)

False negative events

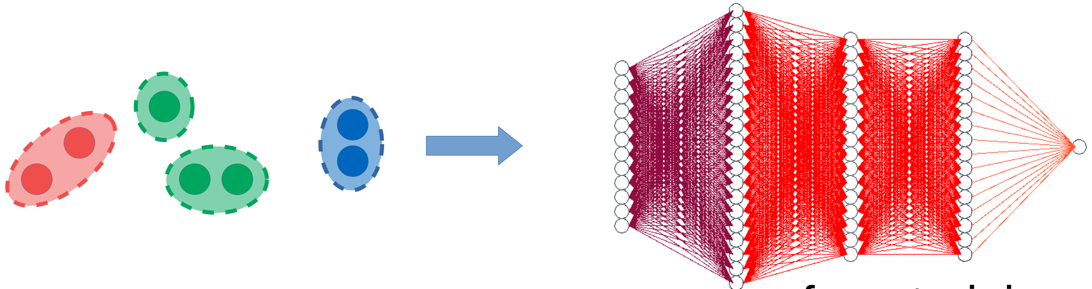


Step 2:
Run agglo model on test dataset and save "preclustered dataset"



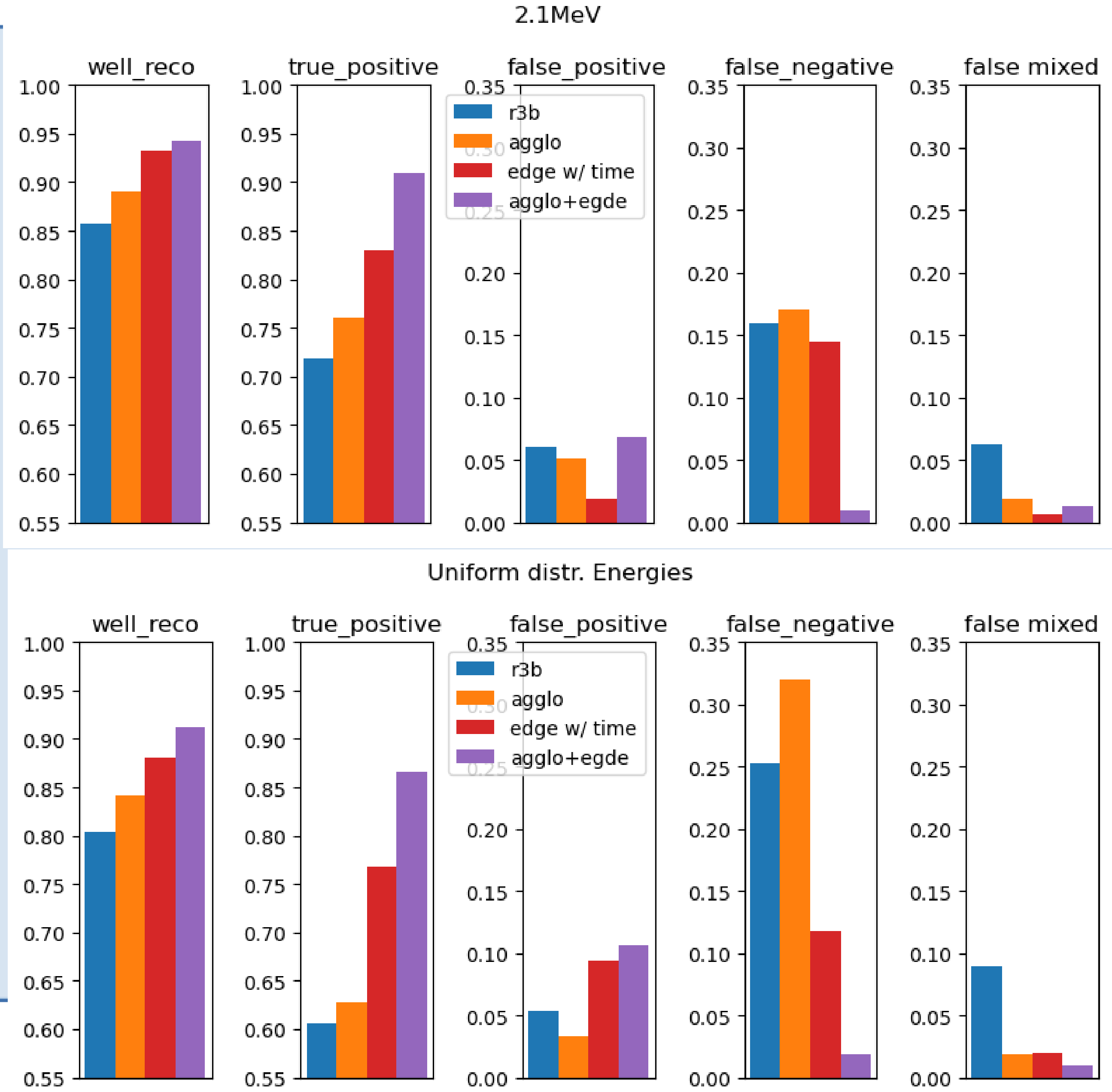
Create cm of clusters and save as "preclustered dataset

Step 3:
Run edge model on "preculstered dataset" with parameters from training (Step1)

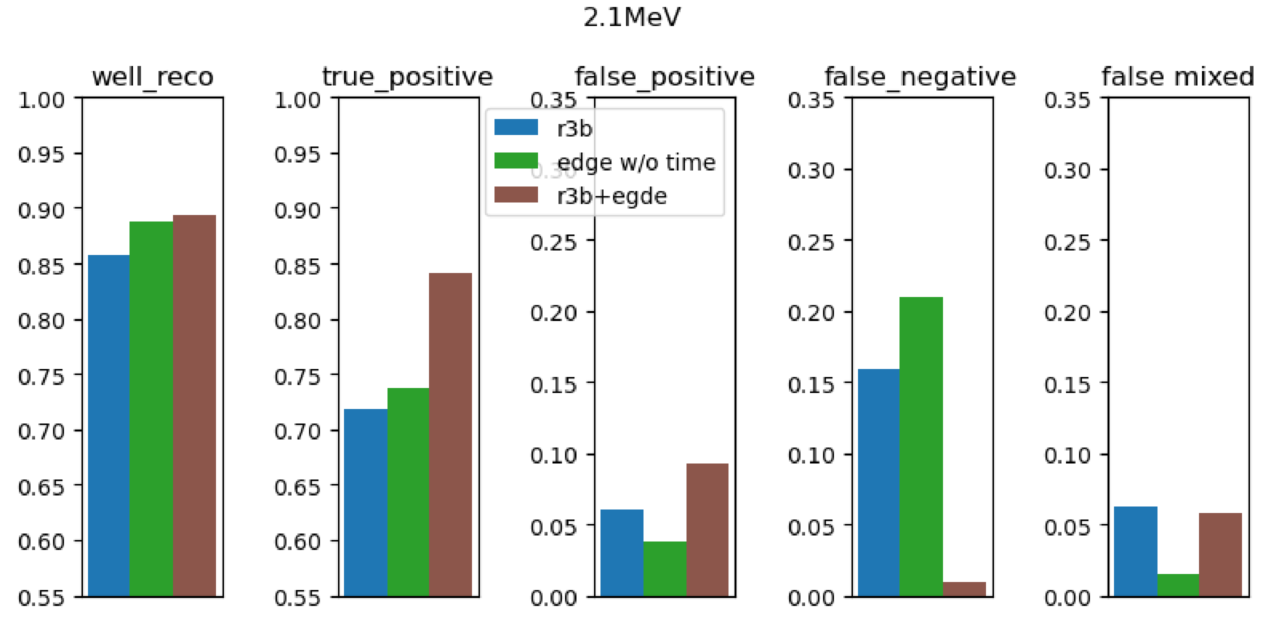


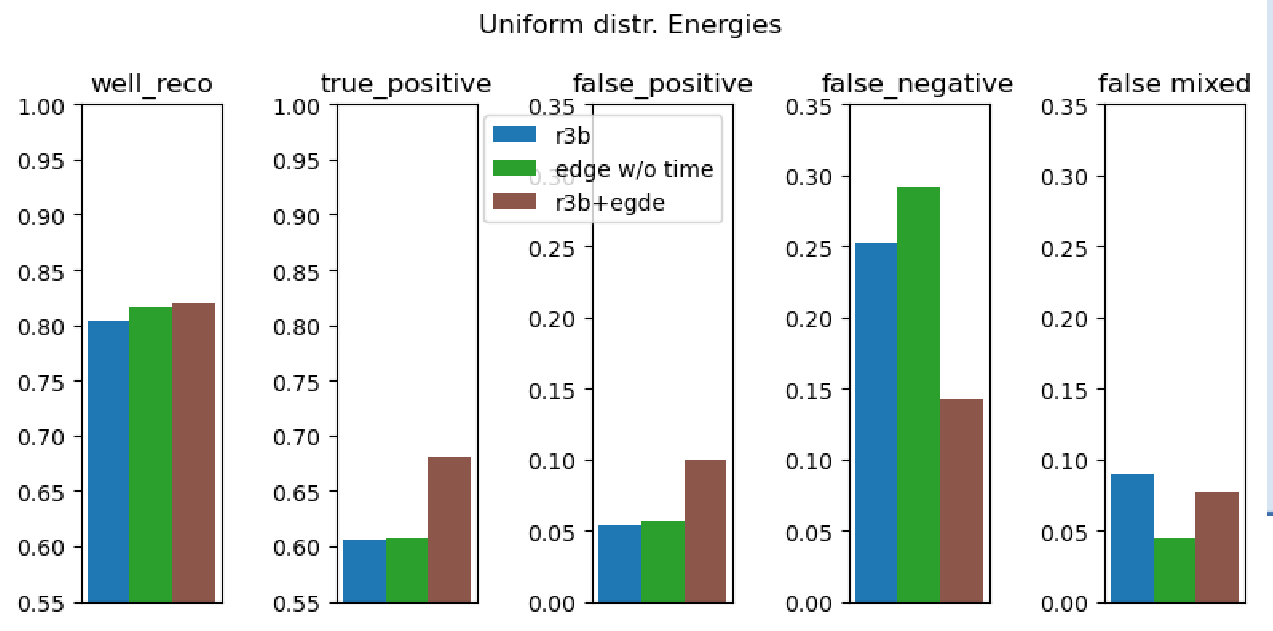
params from training

Results from Agglo + Edge Model



Classical Clustering + Edge (no time info)





For Classic Clustering + Edge I pushed a little bit more:
Lr: 5e-3 → 9e-2
n_epochs: 50k → 80 k

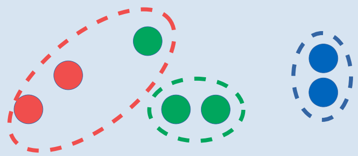
This could be applied directly to our real data, out of the box!

Well reco: ~ 2.5% better!

true_positive: ~ 12% better!

Input to the Model:

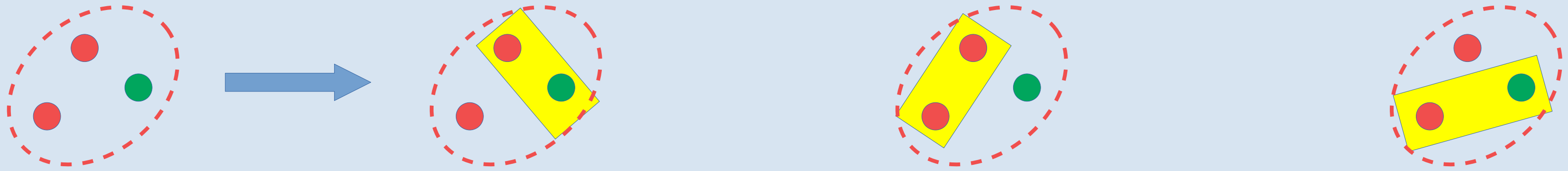
False positive events



This model keeps track of the information of all hits inside each cluster

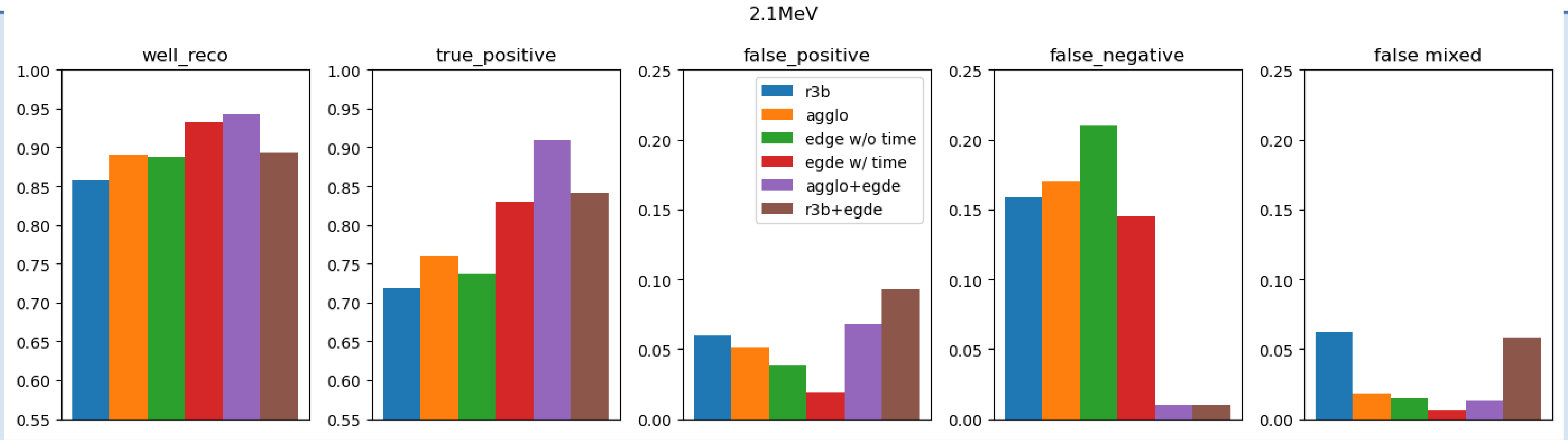
https://arxiv.org/pdf/1810.05165

Pairwise checking all combinations in clusters, eg:

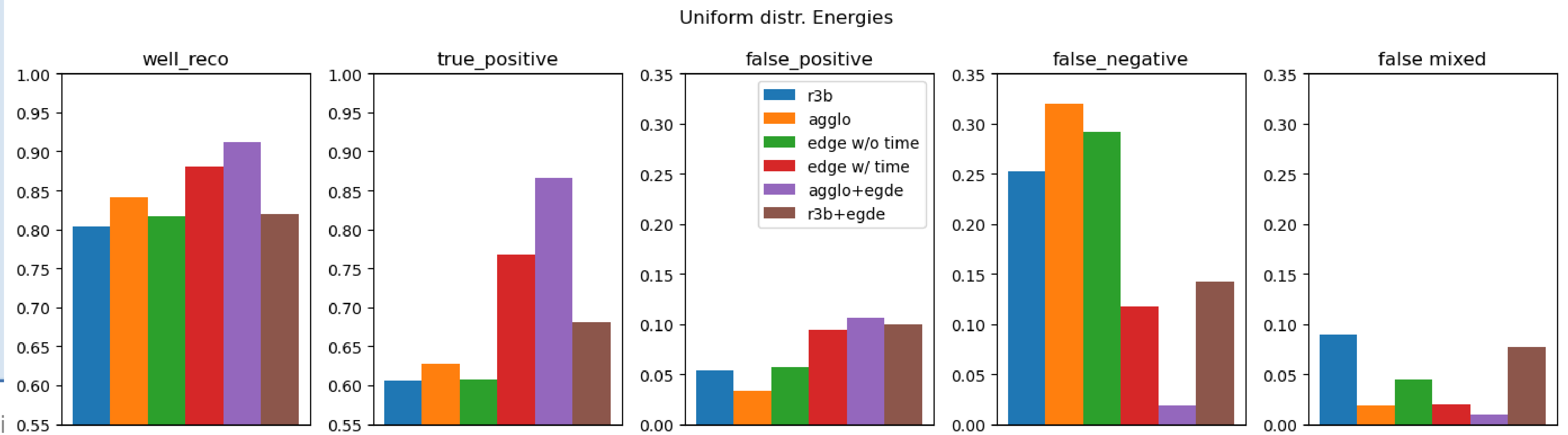


We could create: Agglo + Edge + Deep Sets…..

Results



2.1MeV
well_reco
true_positive
false_positive
false_negative
false mixed
r3b
agglo
edge w/o time
egde w/ time
agglo+egde
r3b+egde



Uniform distr. Energies
well_reco
true_positive
false_positive
false_negative
false mixed
r3b
agglo
edge w/o time
edge w/ time
agglo+egde
r3b+egde

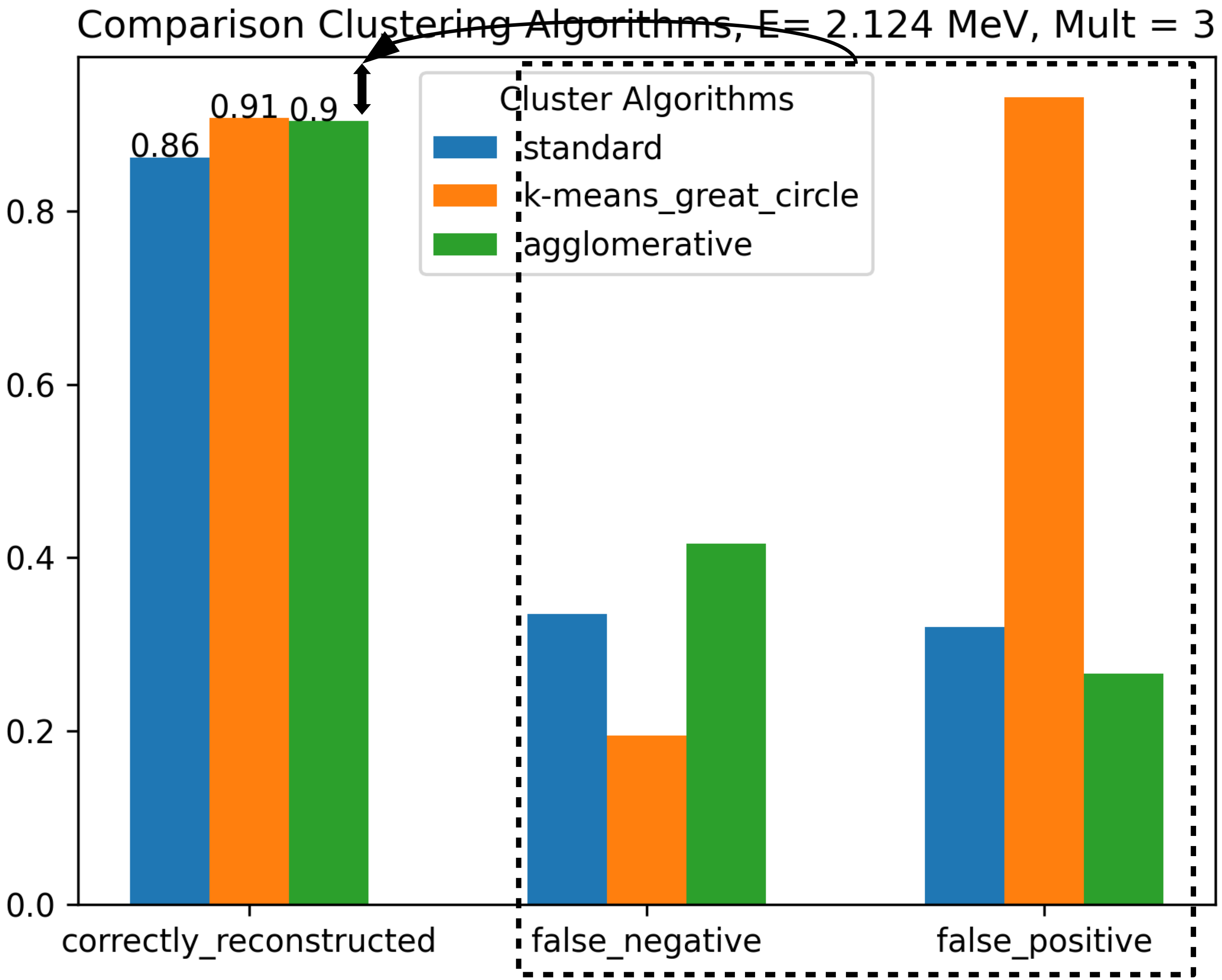
Thank you!

CALIFA @ Technical University of Munich (TUM)

Roman Gernhäuser, Lukas Ponnath, Philipp Klenze, Tobias Jenegger

Backup

Summary Clustering Methods



false_negative:

true cluster $\begin{pmatrix} 1.2 \\ 0.8 \\ \color{red}{\mathbf{0.124}} \end{pmatrix}$ reconstructed cluster $\begin{pmatrix} 1.2 \\ 0.8 \\ 0.511 \end{pmatrix}$ $\rightarrow$ false negative $= \frac{0.124}{2.124}$

false_positive:

true cluster $\begin{pmatrix} 1.2 \\ 0.8 \\ 0.124 \end{pmatrix}$ reconstructed cluster $\begin{pmatrix} 1.2 \\ 0.8 \\ \color{red}{\mathbf{0.511}} \end{pmatrix}$ $\rightarrow$ false positive $= \frac{0.511}{2.124}$