



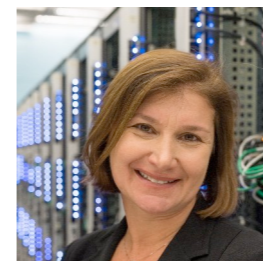
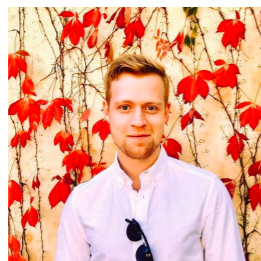
Estonian
Research Council

Scalable neural network models and terascale datasets for particle-flow reconstruction

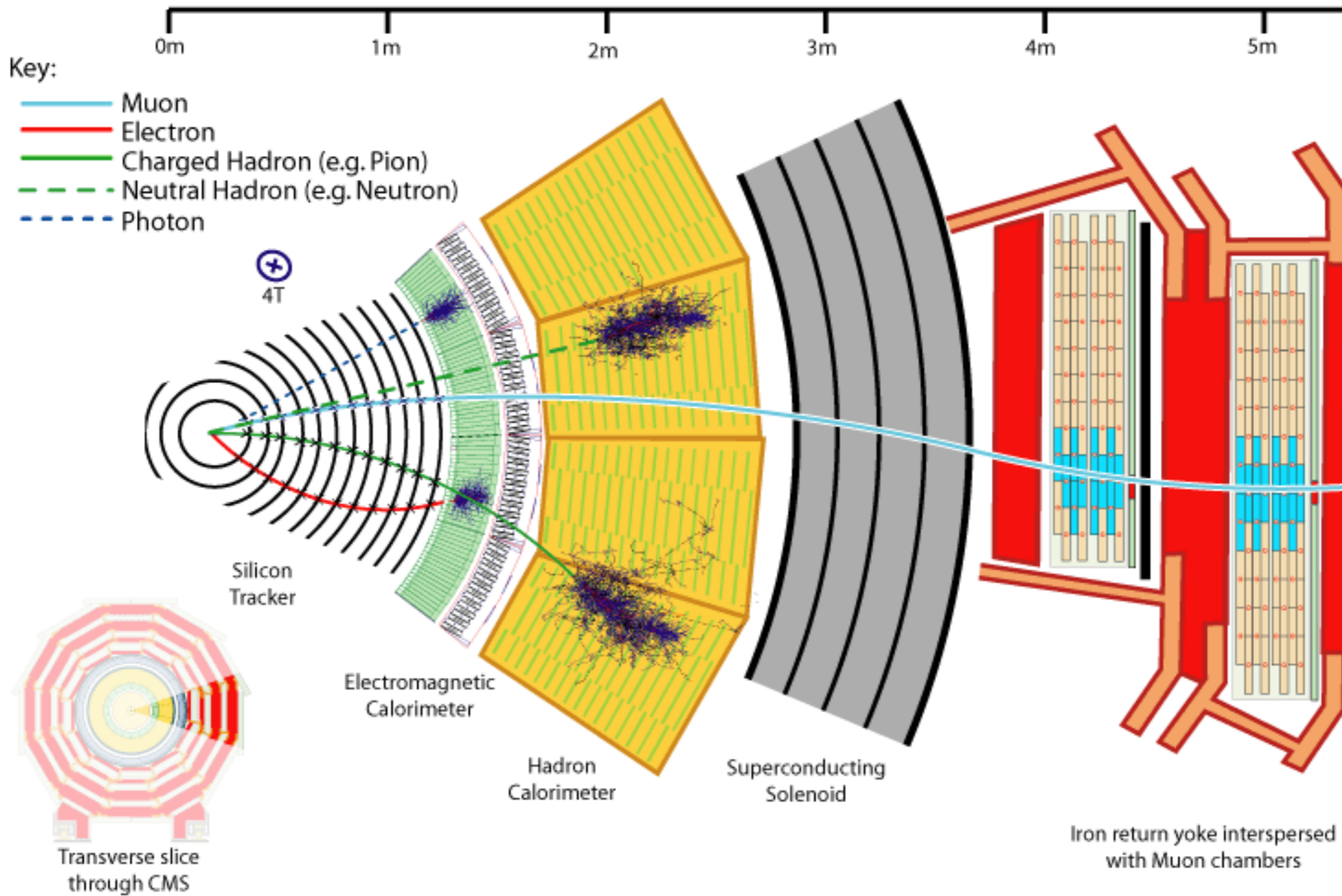
Eric Wulff (CERN), Farouk Mokhtar (UCSD), David Southwick (CERN), Mengke Zhang (UCSD), Maria Girone (CERN), Javier Duarte (UCSD), Joosep Pata (KBFI)

ML4Jets @ Hamburg

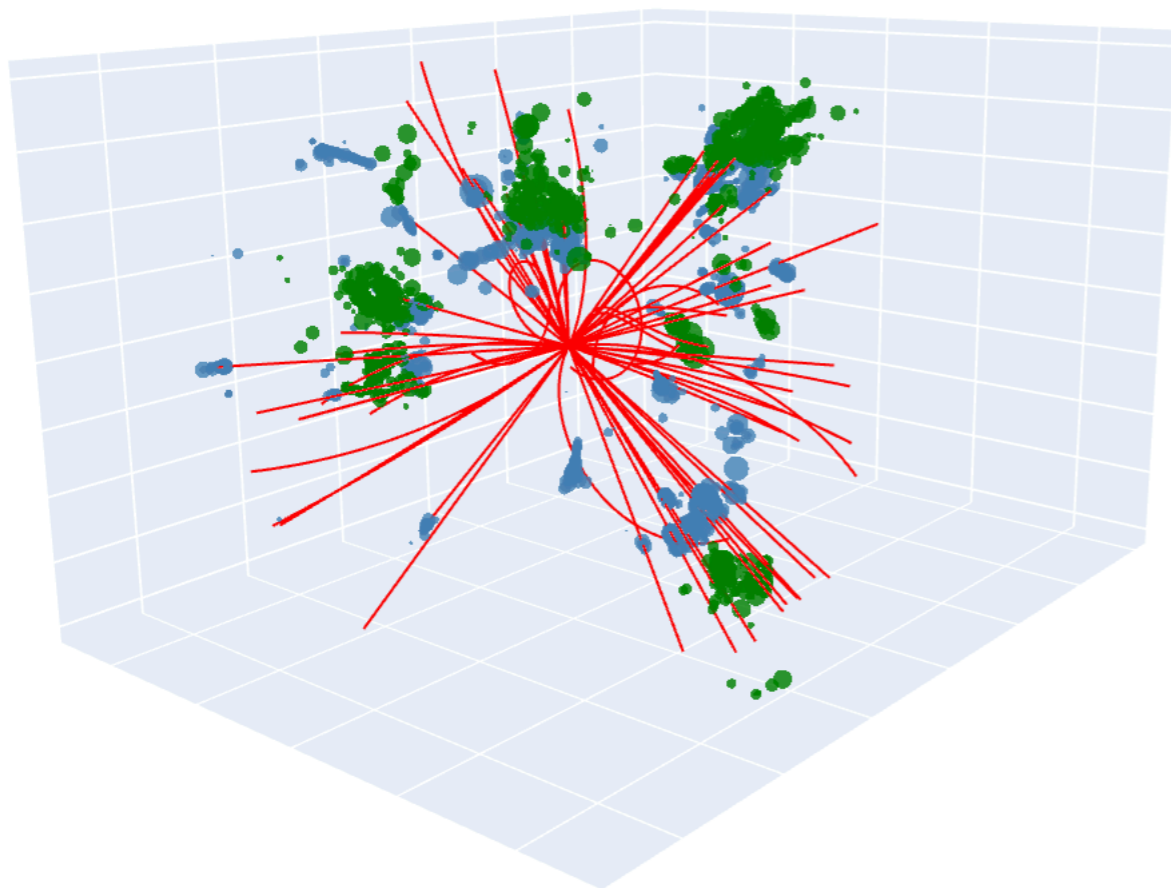
November 6, 2023



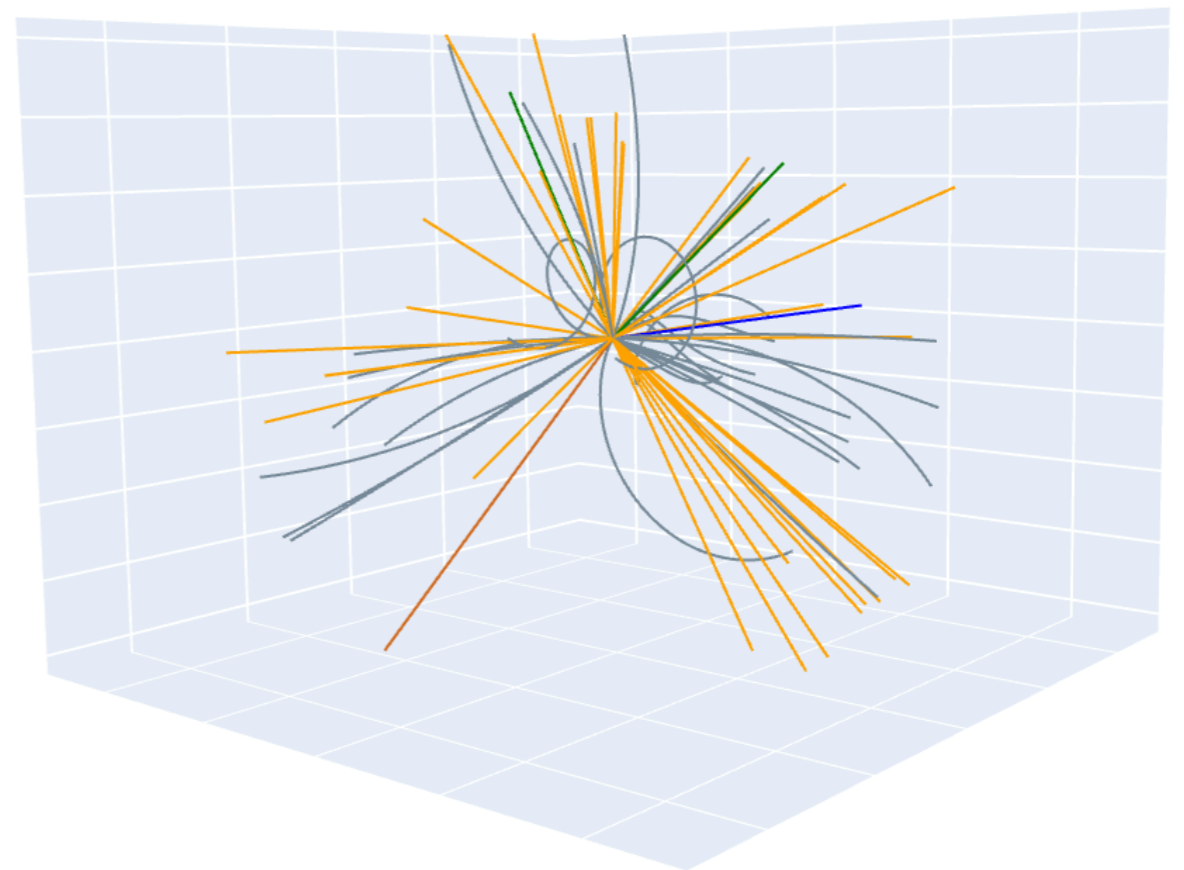
Multilayered detectors



need complex data reconstruction.

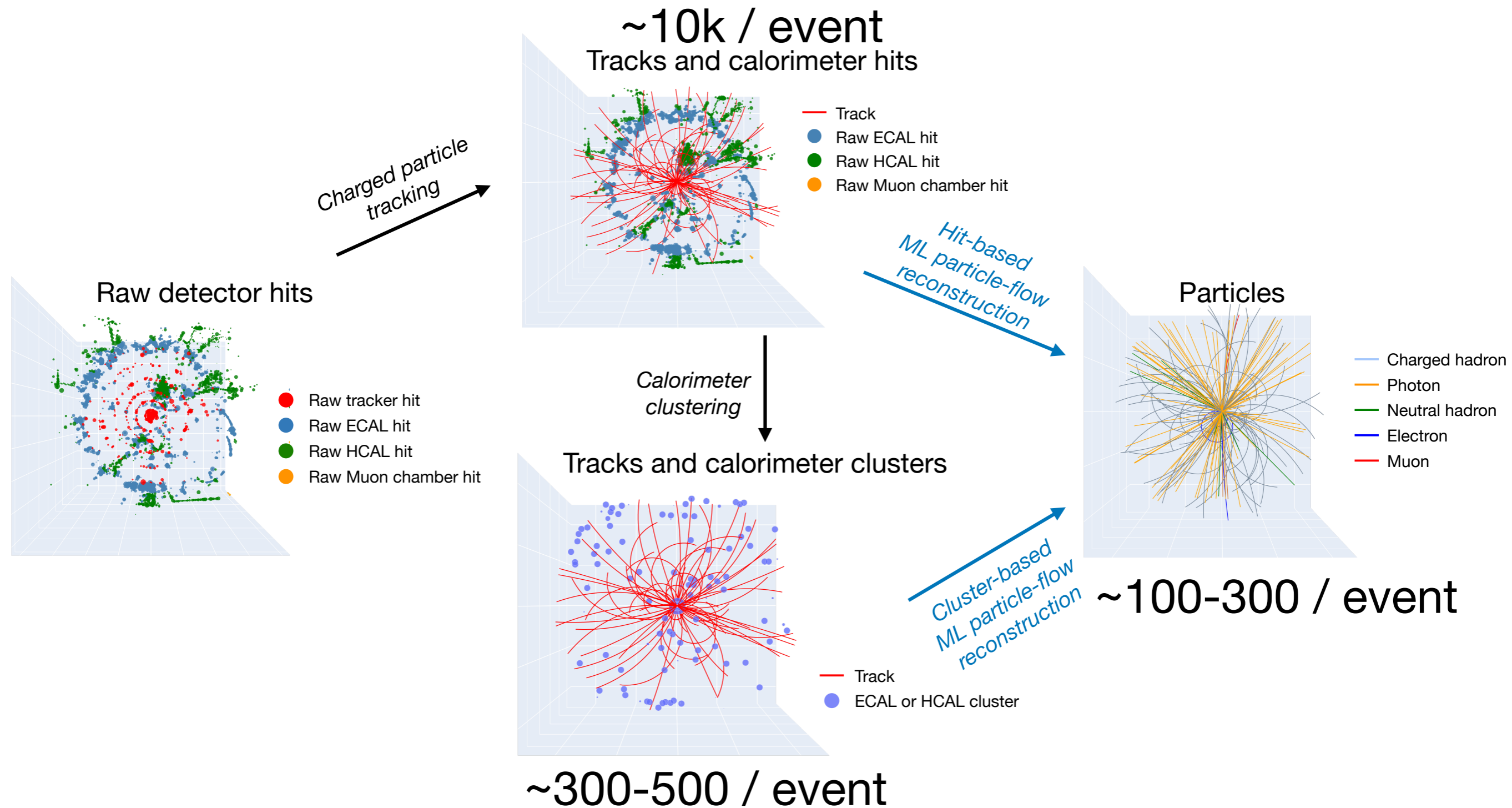


tracks and hits



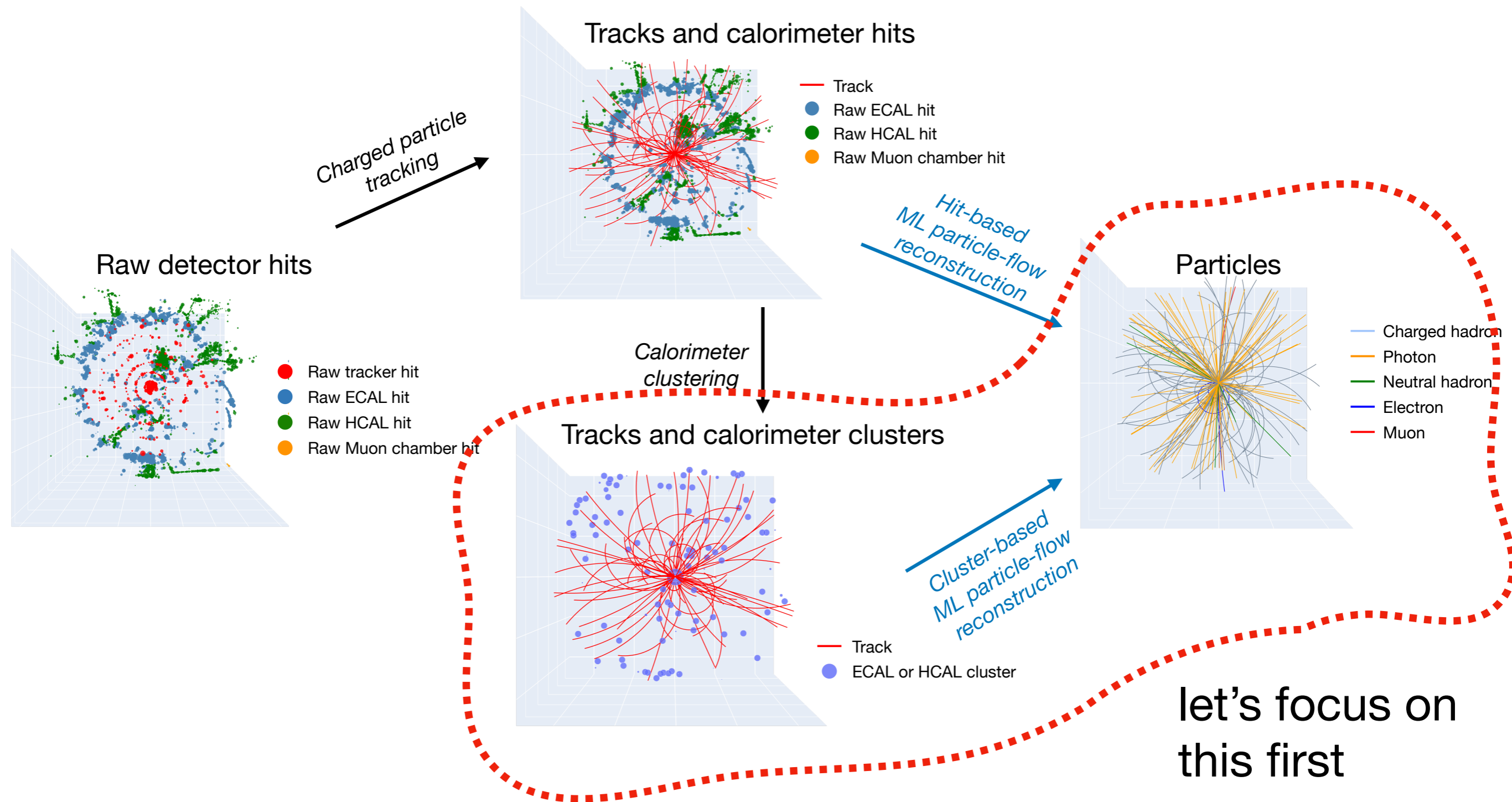
particles

We have created a new **open dataset** with Key4HEP and Geant4

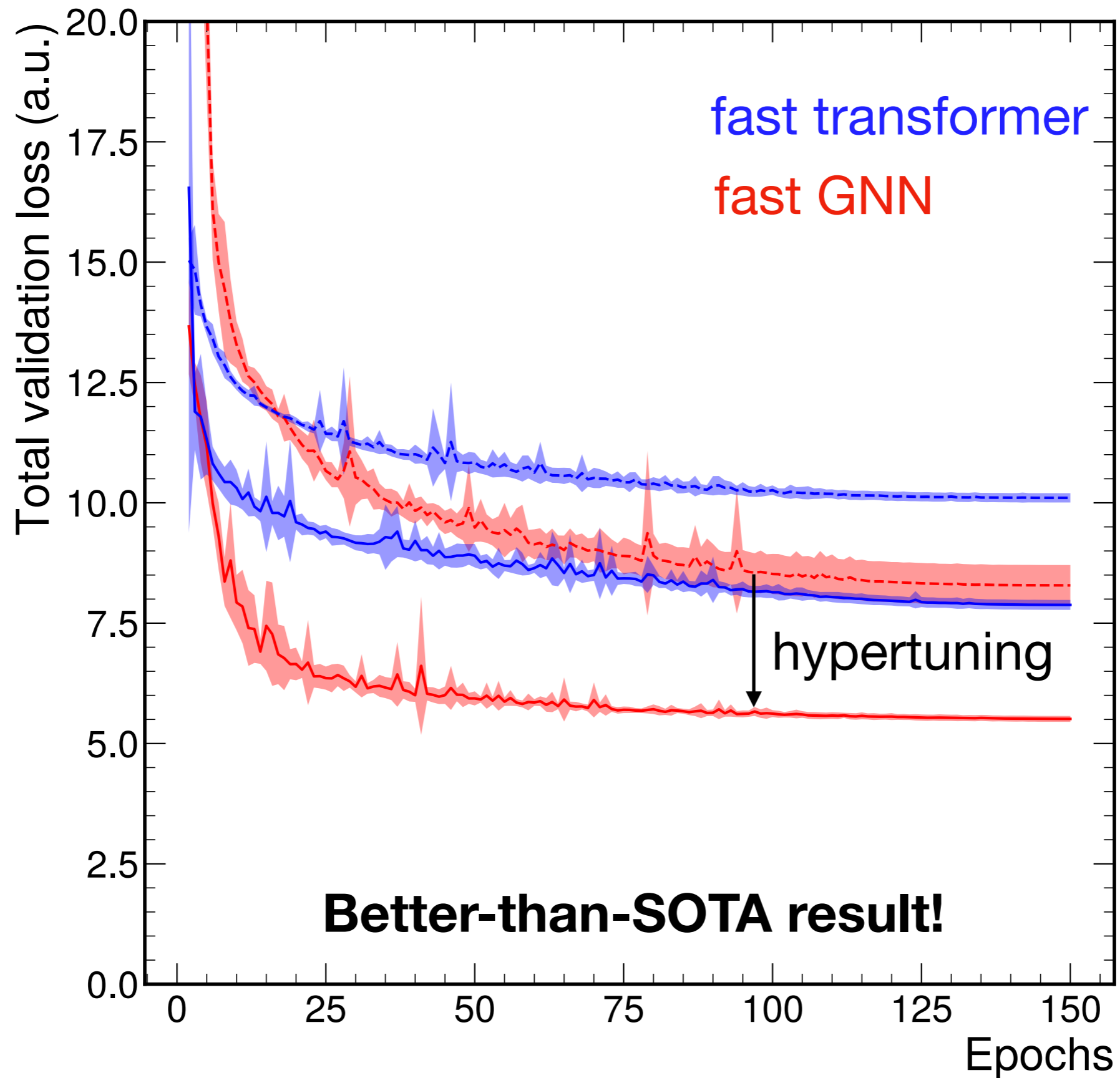


calo/tracker hits, tracks and calo clusters, baseline & target particles

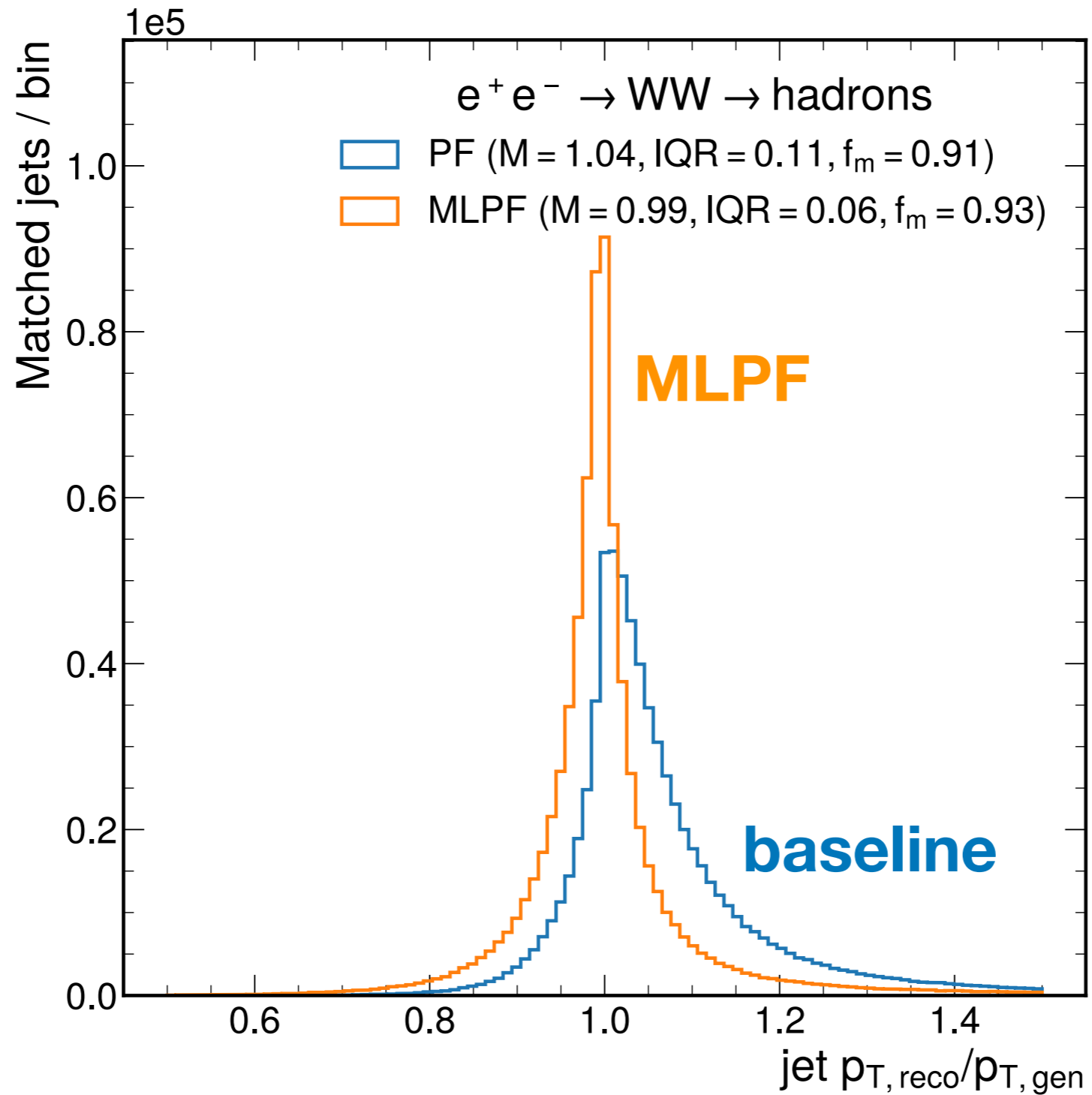
MLPF(tracks and clusters) → particles



Extensive hyperparameter tuning and model comparison...

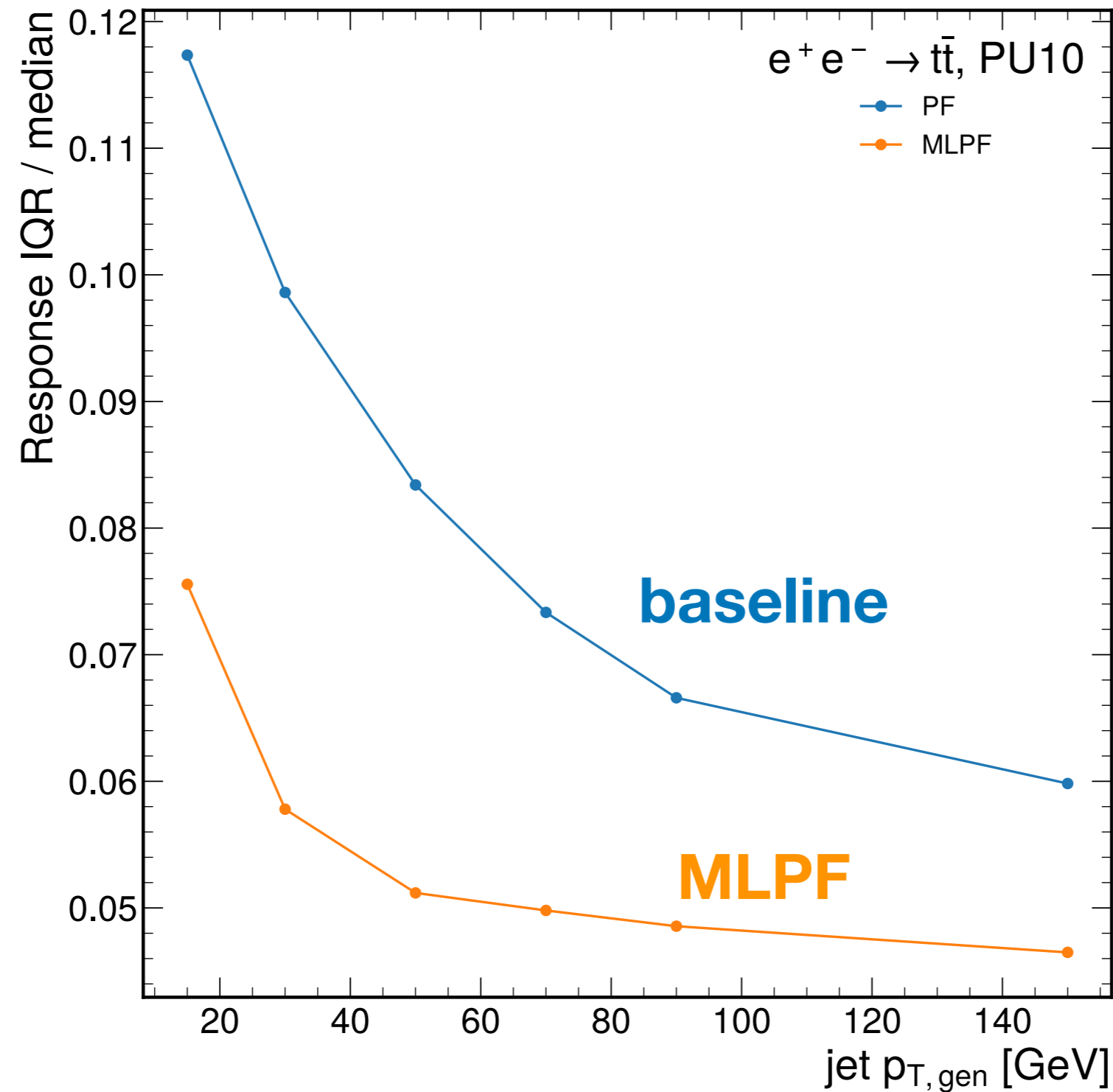


In samples never used in training...



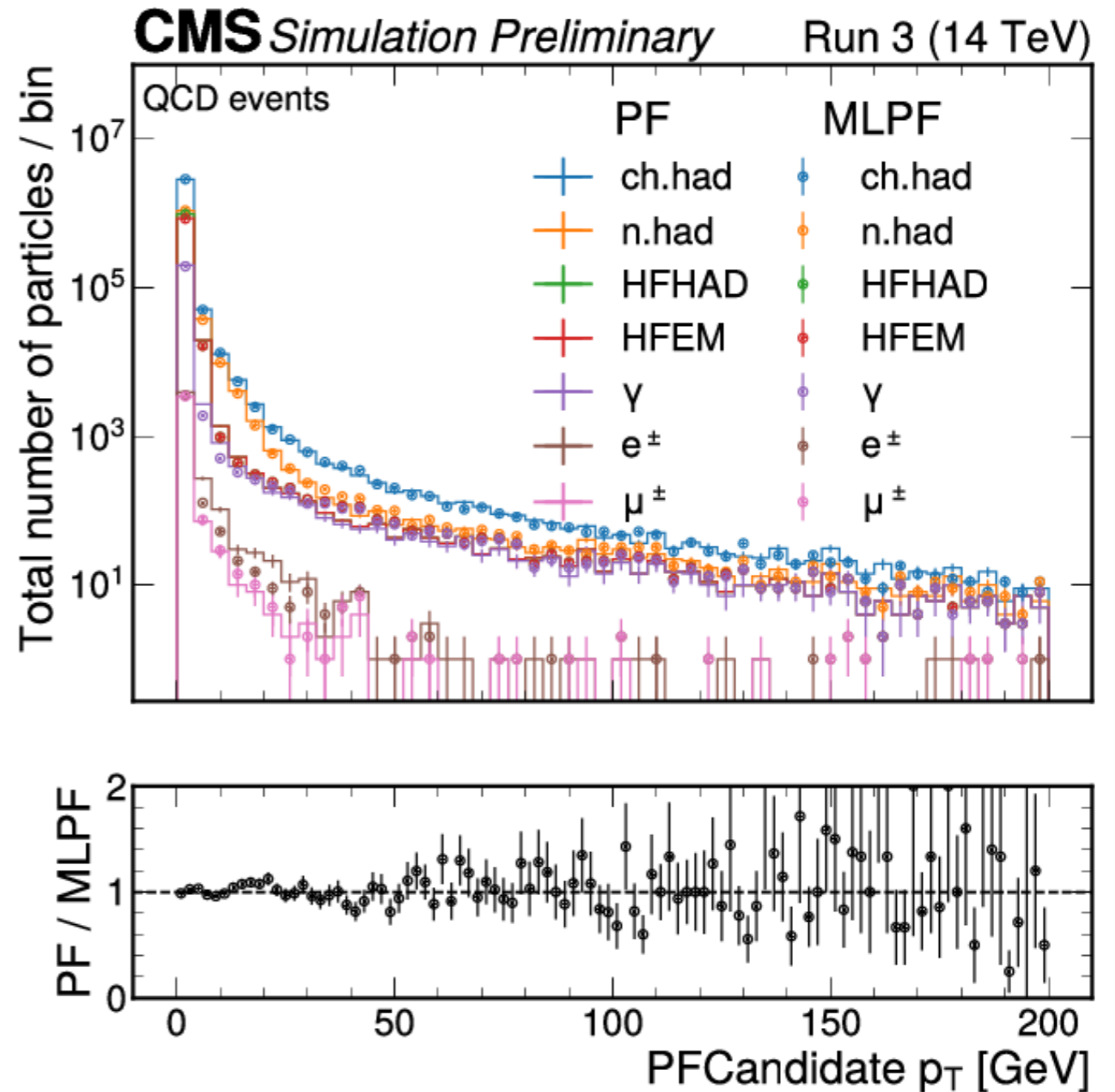
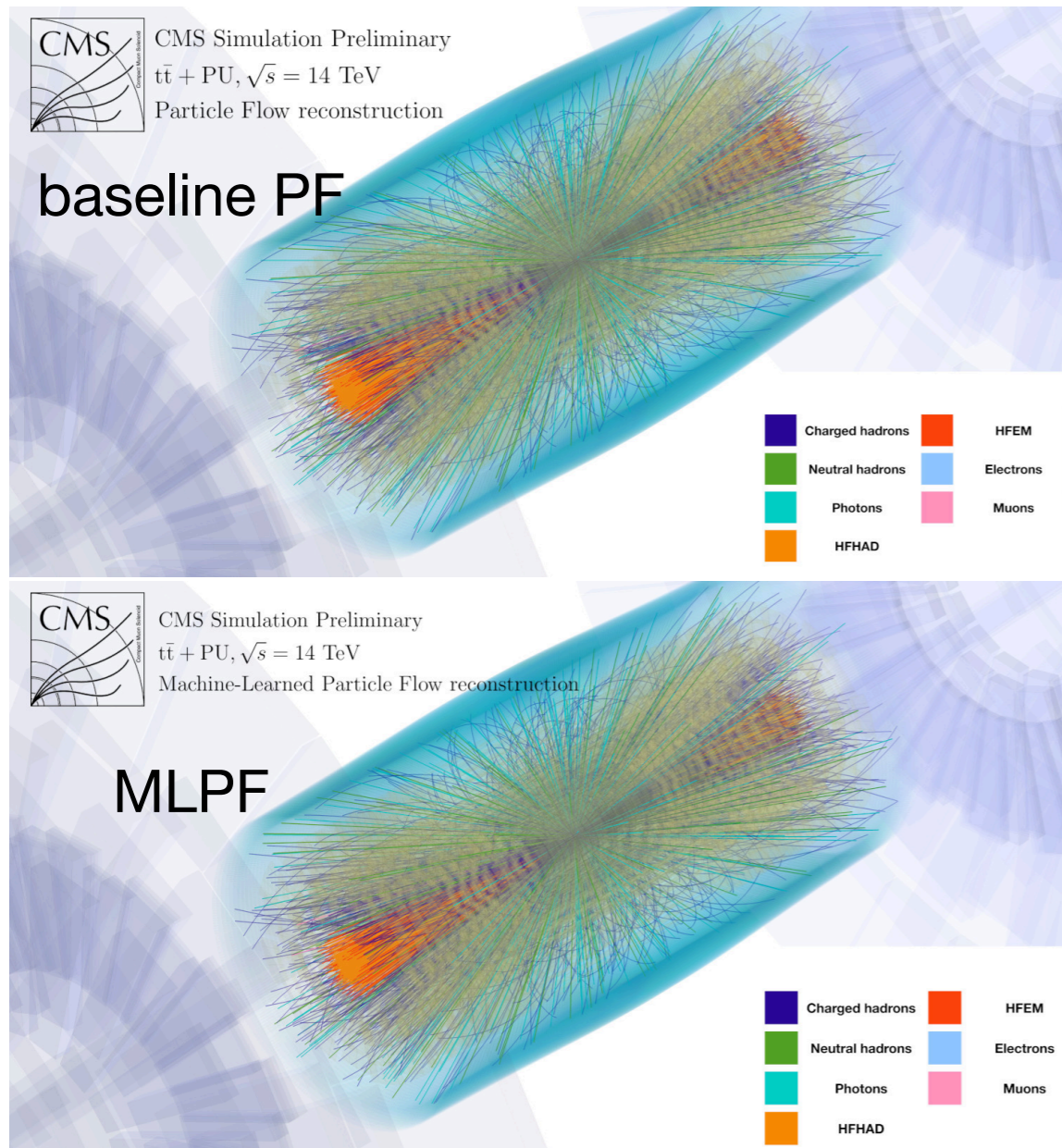
almost 50% improvement in jet response width over the baseline

In samples never used in training...



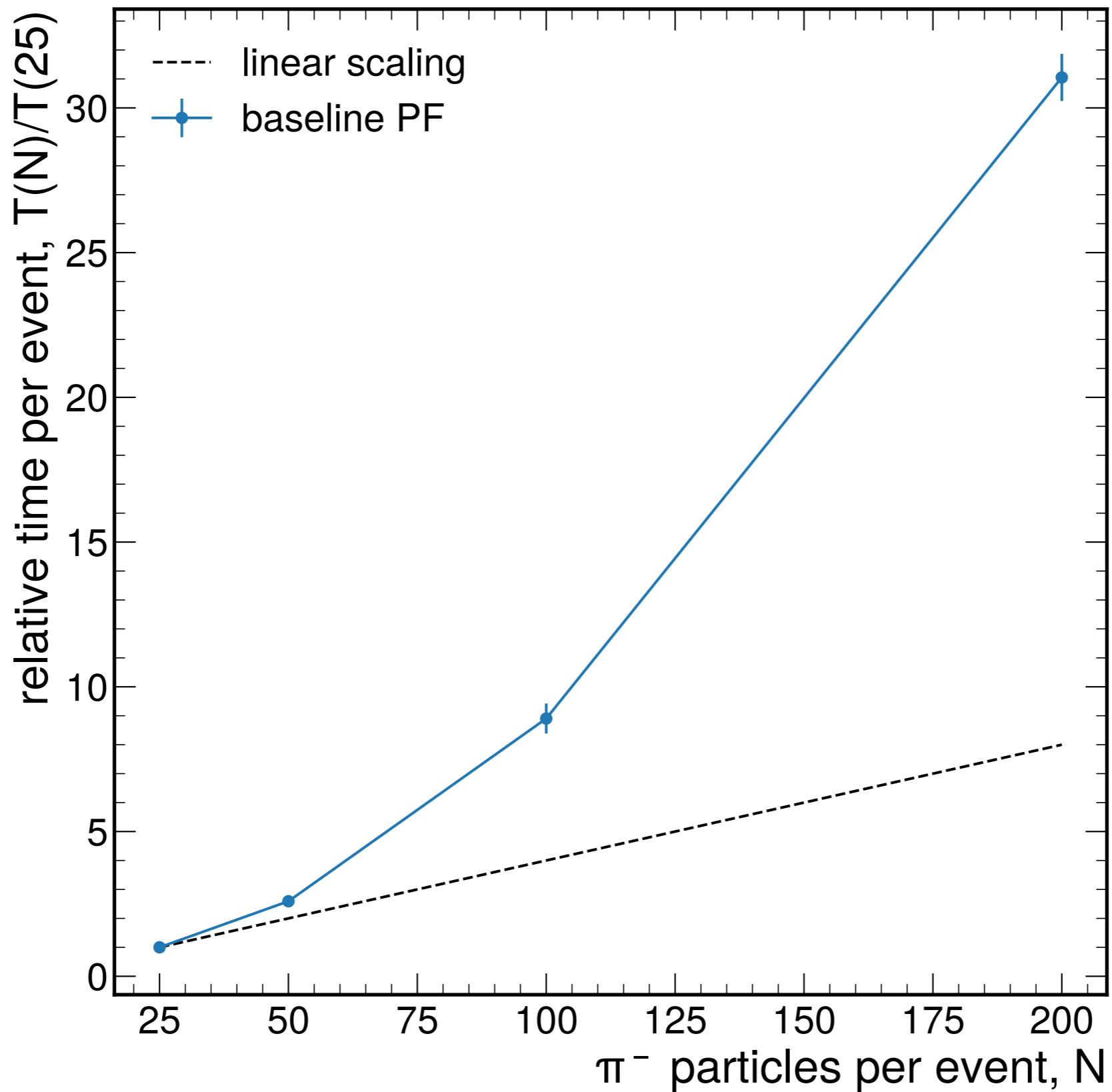
a consistent improvement over the full p_T spectrum

Also tested in a real detector (2022), now in the process of updating

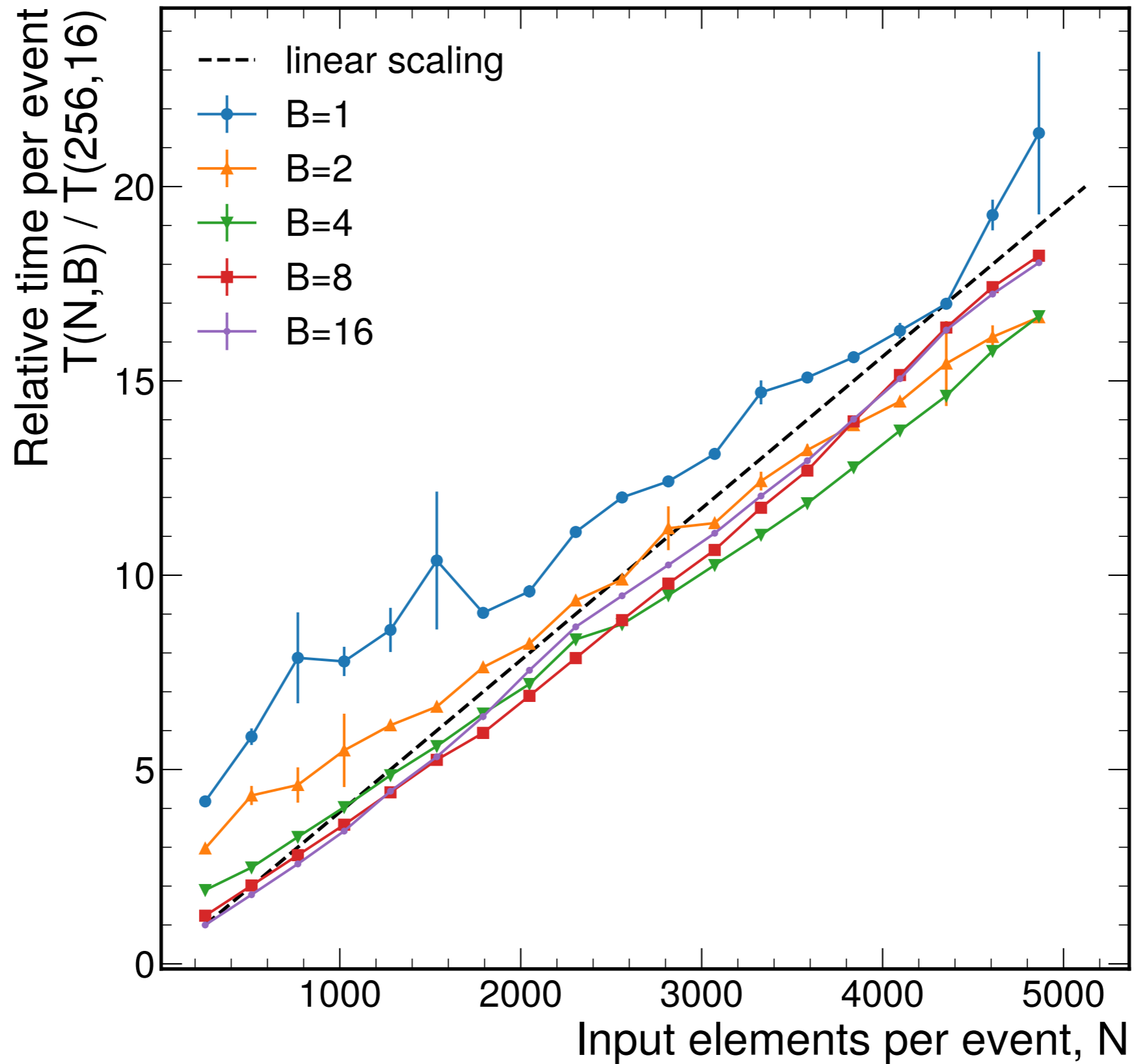


JP, Javier Duarte, Farouk Mokhtar, Eric Wulff, Jieun Yoo, Jean-Roch Vlimant, Maurizio Pierini, Maria Girone. Machine Learning for Particle Flow Reconstruction at CMS. ACAT 2021. <https://doi.org/10.48550/arXiv.2203.00330>, <http://cds.cern.ch/record/2792320>

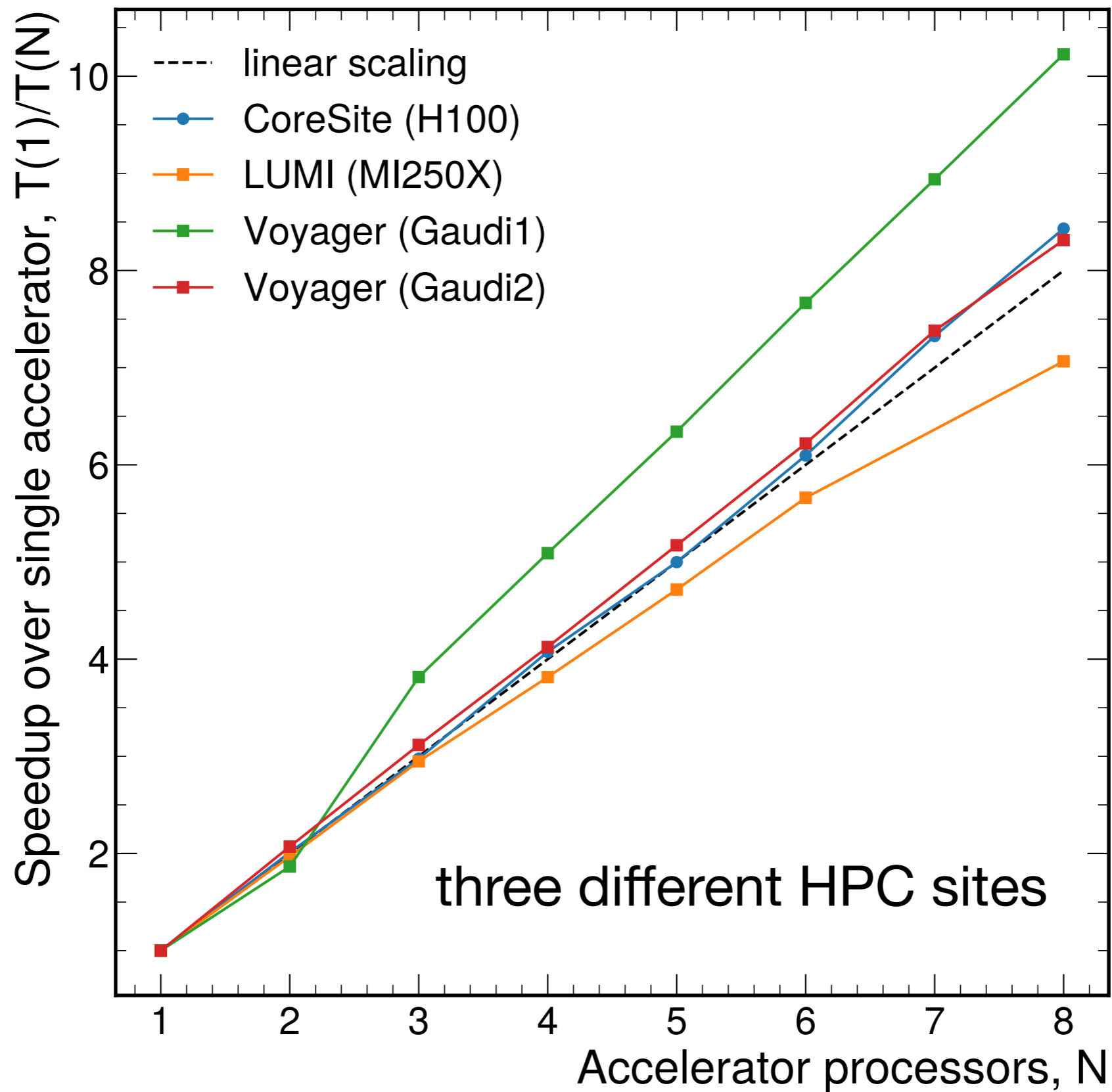
Baseline (untuned) algo runs only on CPU, scales
~quadratically, runtime per event is in seconds.

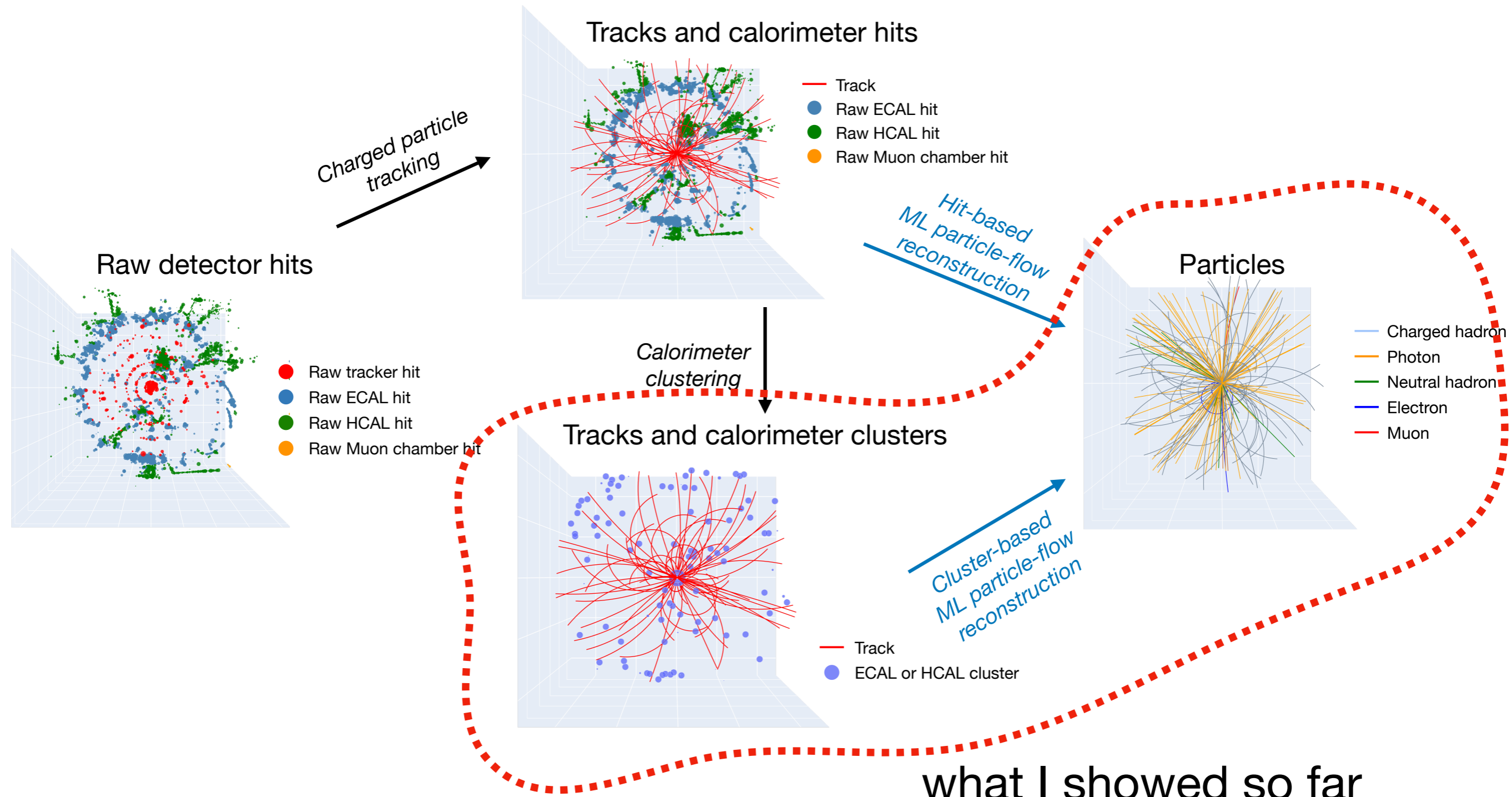


ML model scales linearly, runs in milliseconds

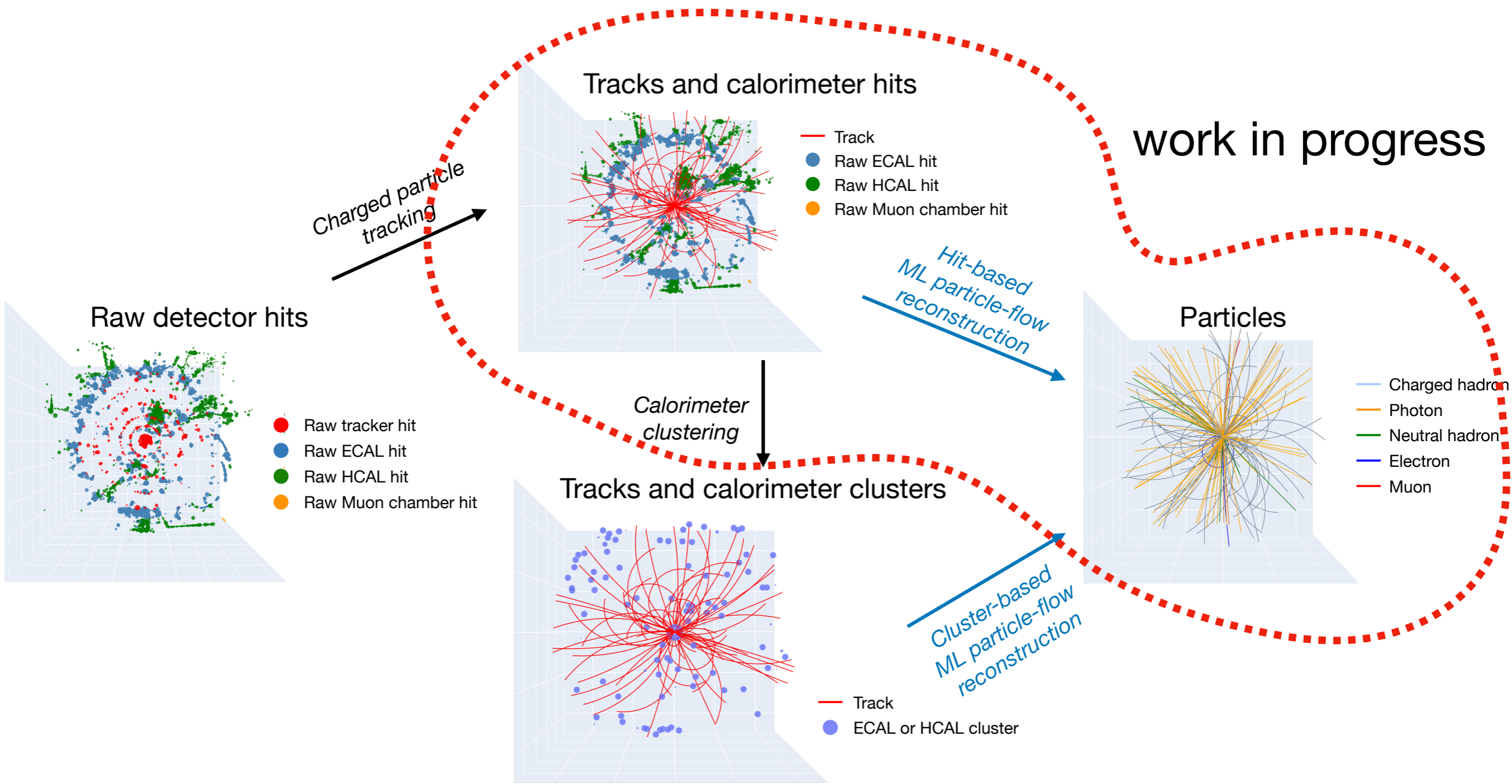


Portable on CPU, nVidia & AMD GPU, Intel Habana Gaudi chips

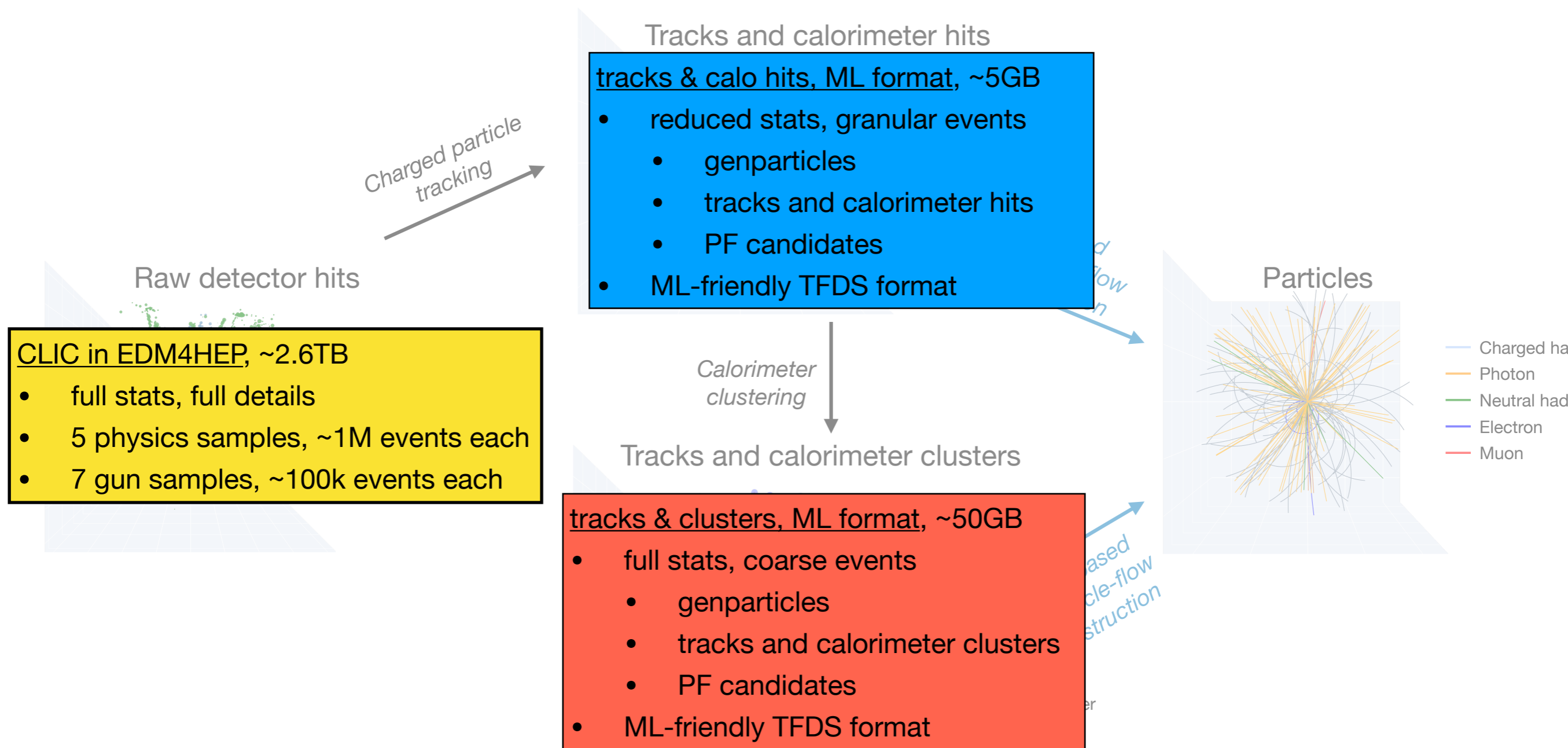




work in progress



Open datasets!



- <https://doi.org/10.5281/zenodo.8260741>
- <https://doi.org/10.5281/zenodo.8414225>
- <https://doi.org/10.5281/zenodo.8409592>

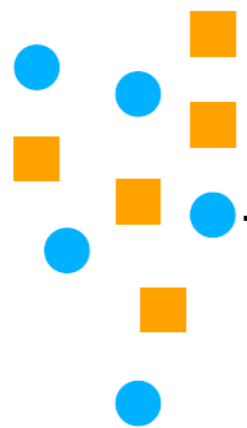
Summary

- Particle flow reconstruction is a complex and interesting problem to address with end-to-end ML
- ML can improve jet/MET response significantly over a naive baseline
- Scalable ML models allow processing of full events with high throughput and portability
- Open datasets & code can accelerate research
- More granular events, updates & integration tests with a real detector on the way

Backup

Event as input set

$$X = \{x_i\}$$

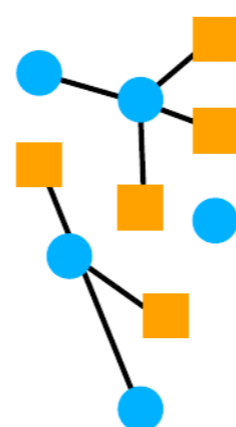


Graph building

$$\mathcal{F}(X | w) = A$$

Event as graph

$$X = \{x_i\}, A = A_{ij}$$



Message passing

$$\mathcal{G}(X, A | w) = H$$

Transformed inputs

$$H = \{h_i\}$$



Target set $Y = \{y_j\}$



Elementwise loss $L(y_j, y'_j)$
classification & regression

Output set $Y' = \{y'_j\}$



Elementwise decoding

$$\mathcal{D}(x_j, h_j | w) = y'_j$$

$$x_i = [\text{elem. type}, p_T, E_{\text{ECAL}}, E_{\text{HCAL}}, \eta, \phi, \eta_{\text{outer}}, \phi_{\text{outer}}, q, \dots]$$

$$y_j = [\text{PID}, p_T, E, \eta, \phi, q], \text{PID} \in \{\text{none, charged hadron, neutral hadron, } \gamma, e^\pm, \mu^\pm, \dots\}$$

$$h_i \in \mathbb{R}^{N_{\text{hidden}}}$$

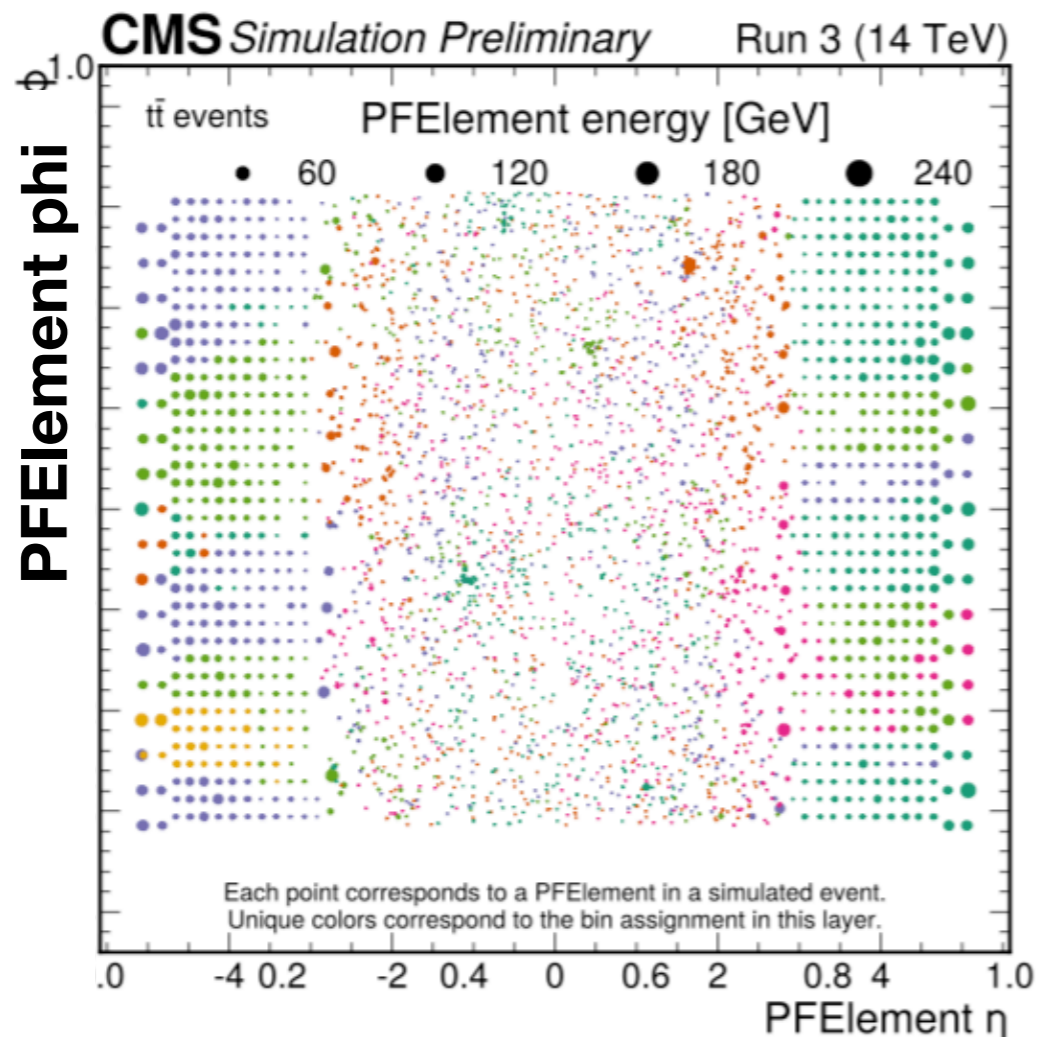
Trainable neural networks: $\mathcal{F}, \mathcal{G}, \mathcal{D}$

● - track, ■ - calorimeter cluster, ■ - encoded element

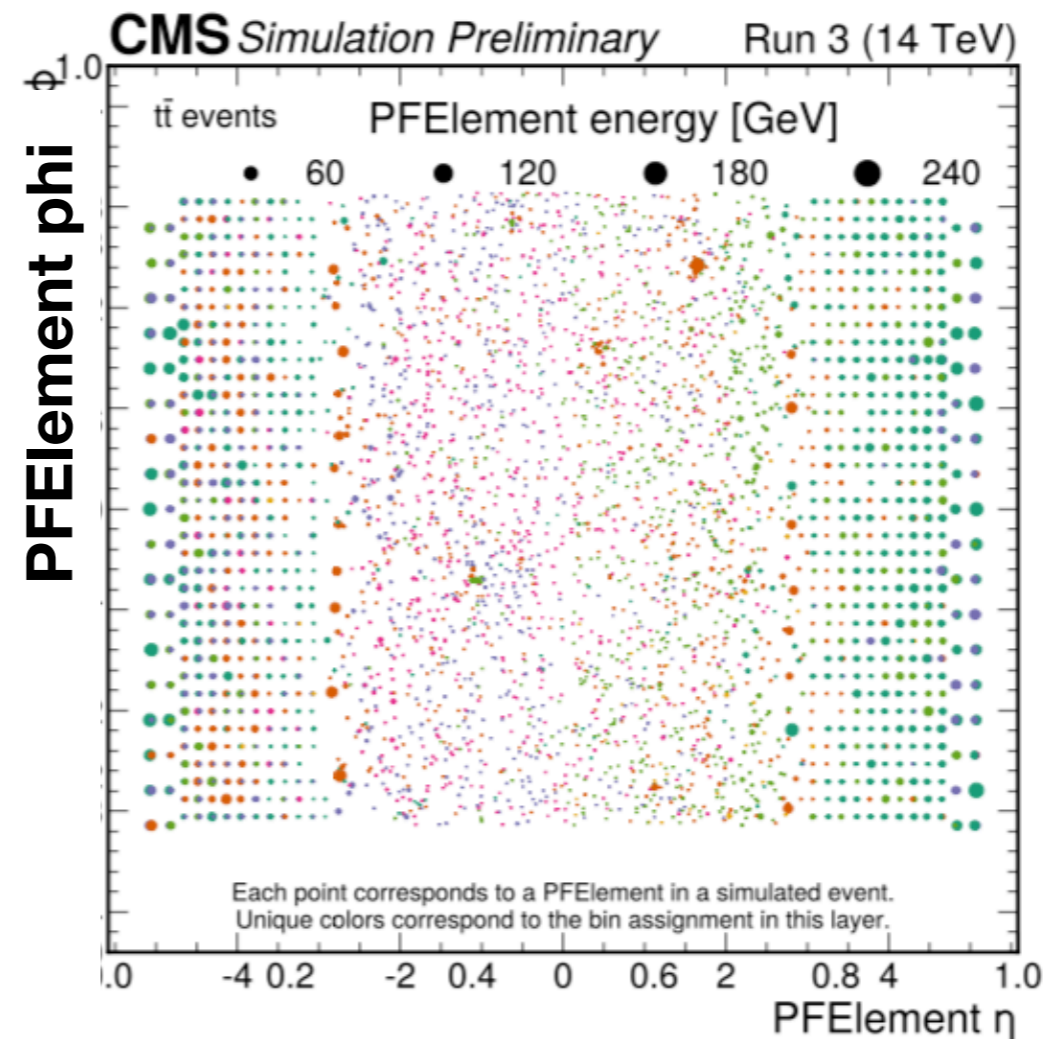
■ - target (predicted) particle, ■ - no target (predicted) particle

Clustering to reconstruction

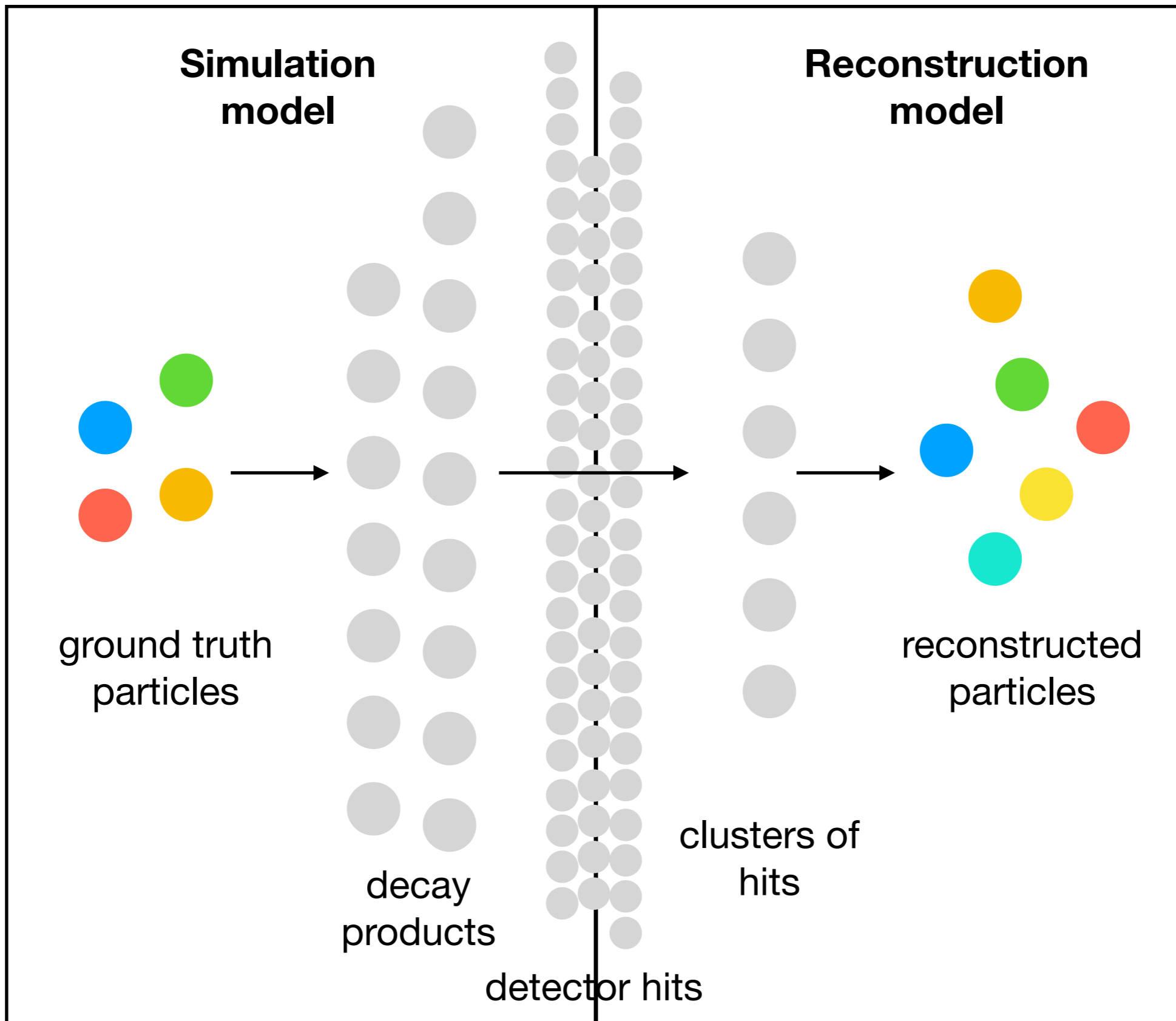
Clustering (graph building) is an internal detail, not a model target. **Particle reconstruction is the real goal!**



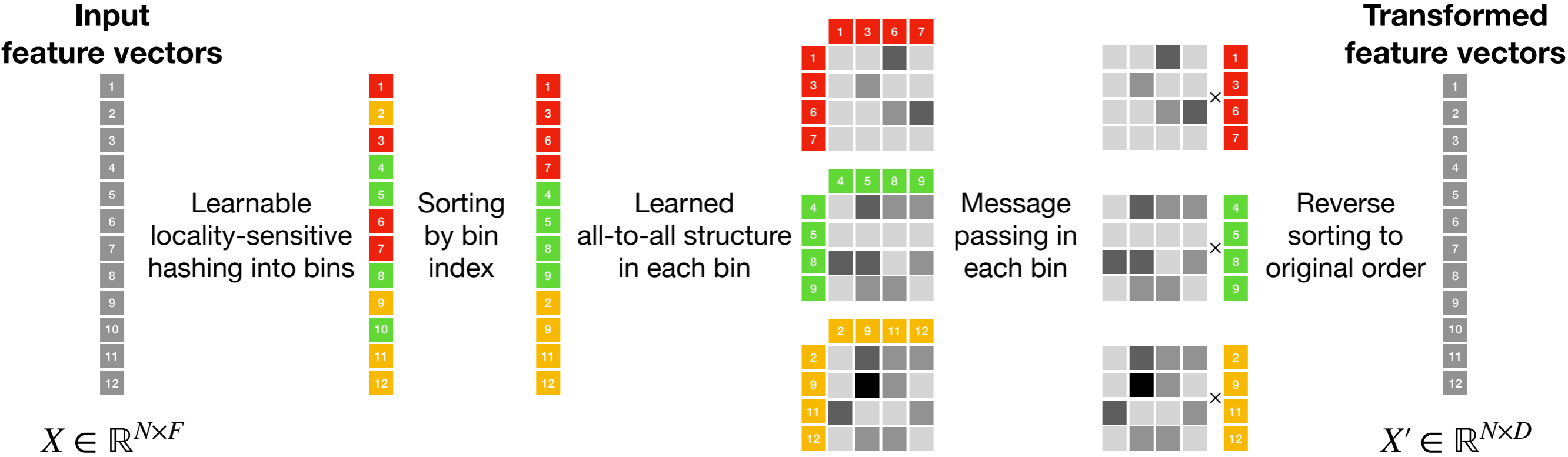
PFElement eta



PFElement eta



One layer of learnable graph building with locality sensitive hashing and message passing



One layer of kernel-based self attention with the FAVOR mechanism.

