



HitPF

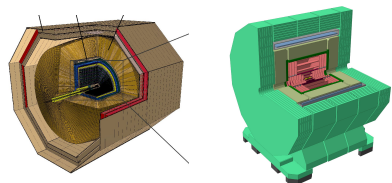
Dolores García, Bohdan Durdar, Lena Herrmann, Gregor Krzmanc, Michele Selvaggi

Motivation

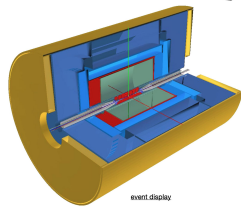
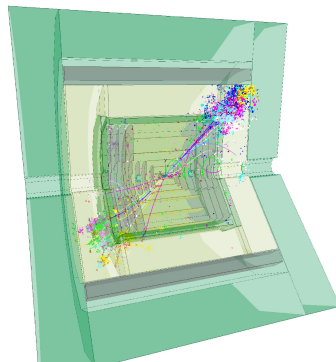
- ❑ FCC-ee has been recommended by the European Strategy as CERN's next flagship collider [\[1\]](#)
- ❑ FCC-ee will collide $e+e-$ at Z, WW, ZH and $t\bar{t}$ thresholds with large luminosity
- ❑ Experiments aim to measure Higgs couplings, electroweak parameters, flavour observables with extremely high precision

Precisions depends on:

High performance detectors

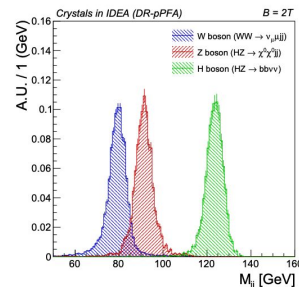


High quality reconstruction



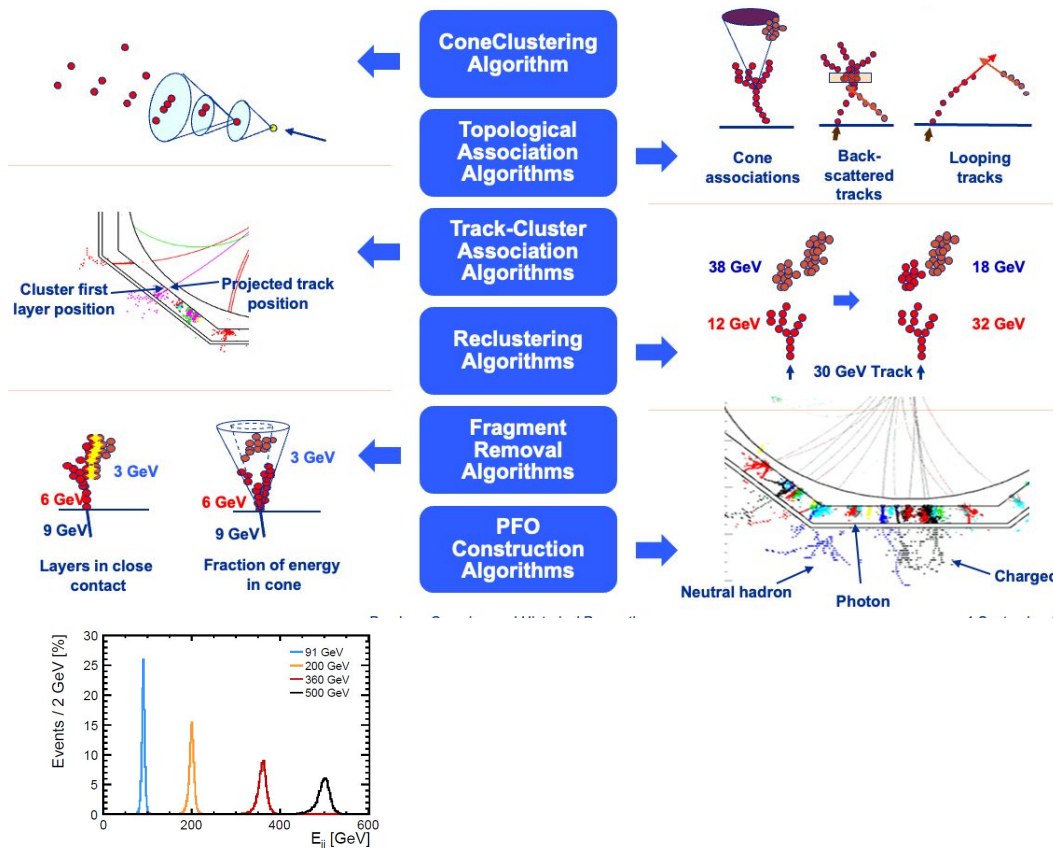
Best resolution translates into best physics sensitivity

- ❑ Modern jet flavour tagging makes use of full jet per particle level data
- ❑ W/Z hadronic mass separation for $H \rightarrow WW, ZZ$
- ❑ Rare $H \rightarrow s\bar{s}, H \rightarrow c\bar{c}$ relative uncertainty scales with mass resolution



How is it tackled?

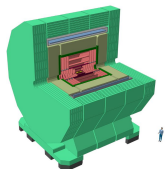
- ❑ Classically, multiple algorithms:
 - Tracking (one per sub-detector), clustering (ECAL/HCAL), and linking tracks and clusters
 - ALEPH, DELPHI, CMS, ATLAS, CLIC,...
- ❑ Pandora SDK (baseline FCC)
 - Series of distributed algorithms
 - Iterative clustering
 - Track cluster association and reclustering
 - Neutral identification
 - Relies on tuning, limiting flexibility during detector design phase (allows for geometry studies e.g transverse calo segmentation)



The need for an end-to-end approach: Multiple detectors

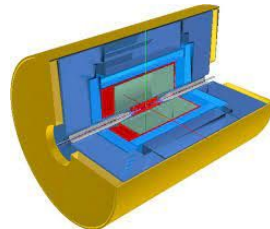
□ Adaptable reconstruction is crucial for a systematic **design optimization**:

- Parameter tuning is not straight forward; the detector will still change + different detectors
- Costly conventional implementation



CLD

- Silicon pixel + silicon tracker
- ECAL Granular Silicon-Tungsten 5x5 mm² cells (15-17 %)
- Scintillator-steel, 44 layers, 30x30 mm²
- Solenoid outside calo

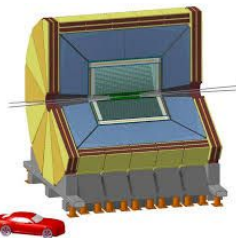


ALLEGRO

- Silicon pixel + drift chamber + silicon wrapper
- ECAL granular noble-liquid sampling LAr (8-10 %)
- Scintillating-tile HCAL
- Solenoid behind ECAL

IDEA

- Silicon pixel + drift chamber + silicon wrapper
- Dual-readout crystal
- Dual-readout fiber scintillating and cherenkov
- Solenoid between ECAL/HCAL



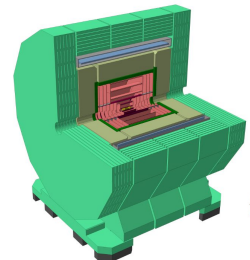
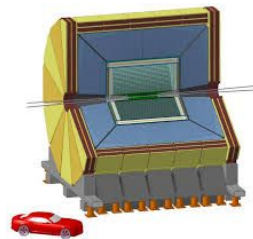
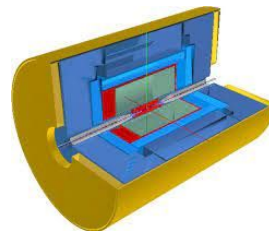
And others... ALFA, ILD

The need for an end-to-end approach:

Multiple detectors

- ☐ The detector determines how the showers 'look':
 - ☐ What is the shape of an electron
 - How wide (Molière radius)
 - How long (longitudinal shower profiles)
 - ☐ How do hadrons shower in the HCAL, what is the shower geometry like, what are acceptable patterns?
 - ☐ What is the 'correct' threshold for a track-cluster separation to link them?

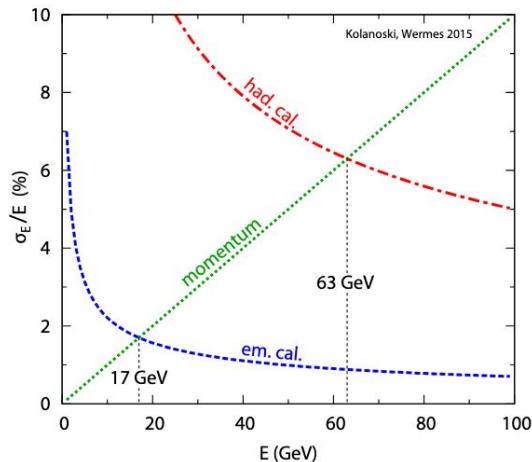
All these questions can be answered from data



The need for an end-to-end approach

Increased performance?

- ❑ Asymptotic resolution is 1-2% @100 GeV. Current performance 3-4% @100 GeV [arXiv:0907.3577v1](https://arxiv.org/abs/0907.3577v1)
- ❑ Key drivers of performance:
 - Tracking & calo cluster efficiency/purity
 - → Cluster merging: if two clusters are merged, with a track we lose resolution because we use the total calorimeter energy
 - → Shower splitting: double counting energy
 - Track cluster matching
 - Arbitration of track vs cluster energy



Average Jet Composition

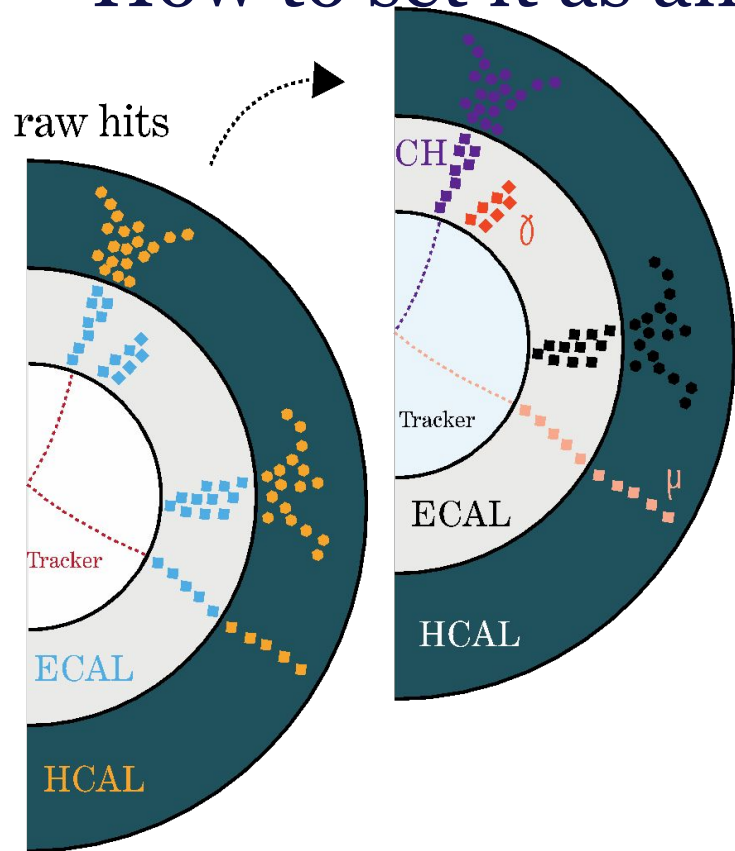
- 60% charged particles
- 30% photons
- 10% neutral particles

Superior System

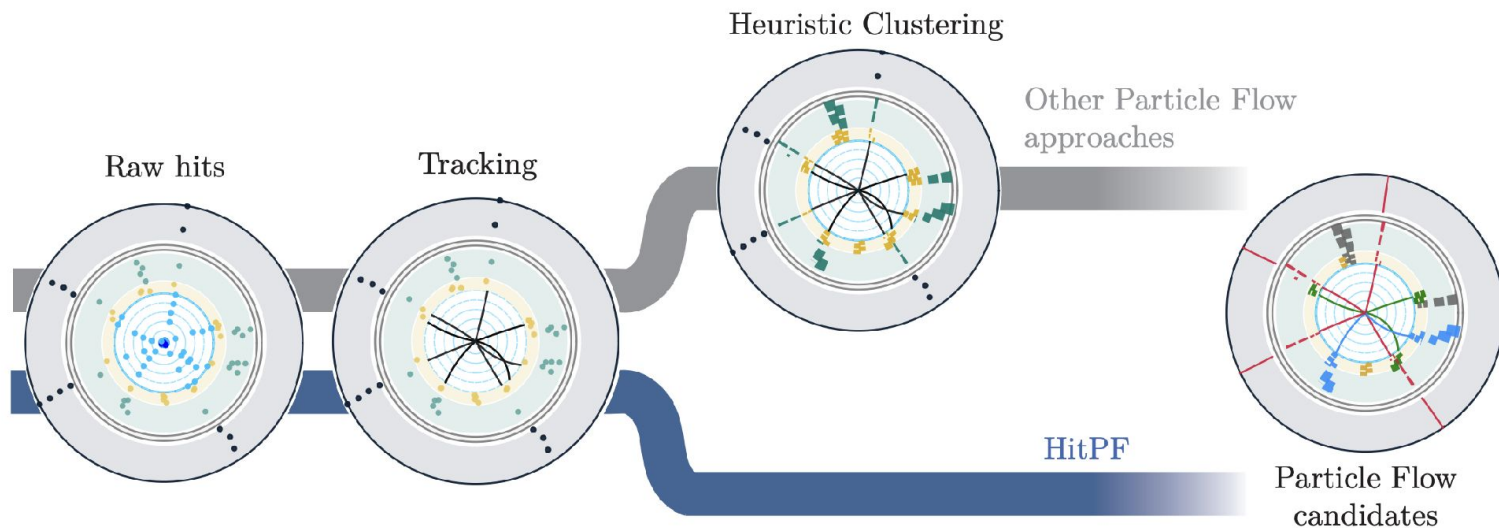
- tracker
- ECAL
- HCAL

$$\sigma_{jet}^2(E_{vis}) = \sum_{i \in tr} \sigma_{tr}^2(E_{tr}^{(i)}) + \sum_{i \in \gamma} \sigma_{ECAL}^2(E_{ECAL}^{(i)}) + \sum_{i \in h^0} \sigma_{HCAL}^2(E_{h^0}^{(i)})$$

How to set it as an ML problem



Hit-based approach to Particle Flow

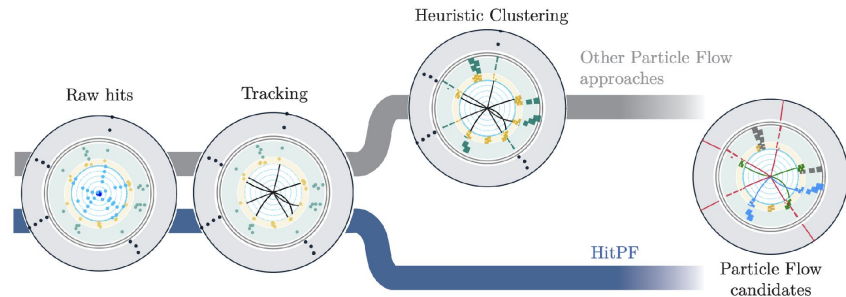


Comparison with other methods

Other PF approaches

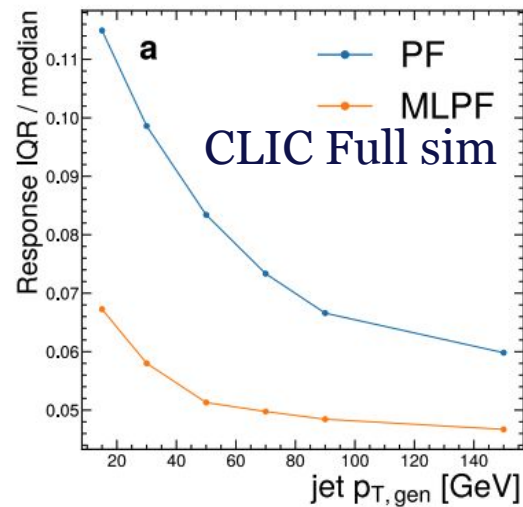
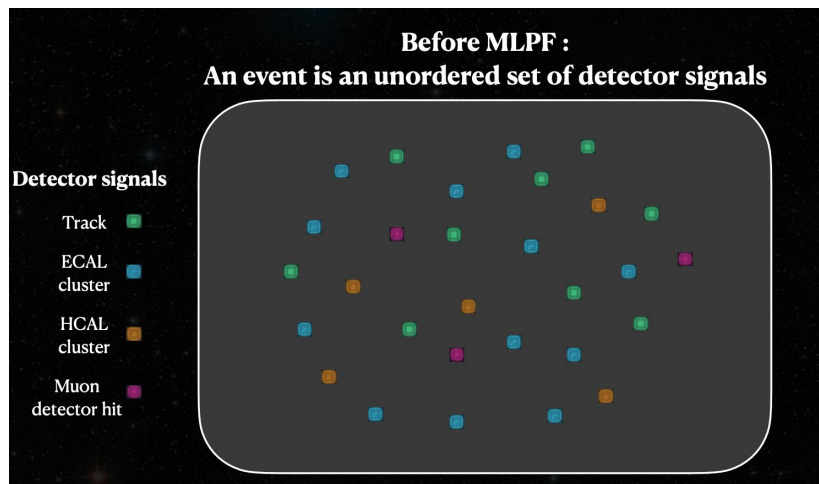
HitPF

- ☐ Require heuristic clustering step + cluster track matching
- ☐ Complex parameter tuning for new detector
- ☐ Requires geometry navigation
- ☐ ML-based Clustering + track matching
- ☐ Out of the box with multiple detector and hit geometries
- ☐ Does not require the explicit detector geometry (navigation)



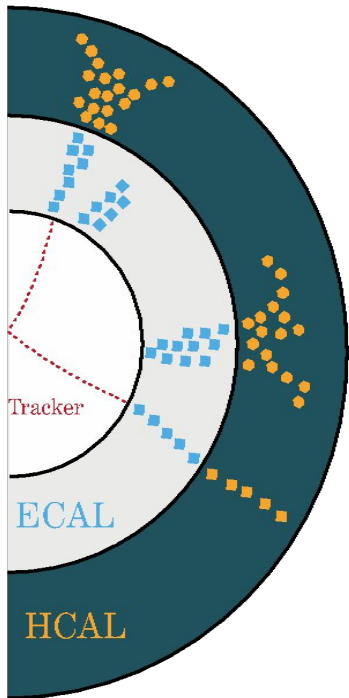
MLPF

- Cluster based approach:
 - Starts from pandora clusters and reconstructed tracks
 - In practice, very different problem
 - Improves the track-cluster linking and properties regression
 - 1 node in MLPF ~ 600 nodes in HitPF
 - Does not solve the geometry adaptation problem
 - New results for CMS



The workflow: Inputs

raw hits



● Track 'hits':
Reference point in calorimeter (position)
 p at vertex and calo
 χ from track fit
Sub-detector ID

● ECAL hit
Position (x,y,z)
E energy
Sub-detector ID

● HCAL hit
Position (x,y,z)
E energy
Sub-detector ID

● Muon hit
Position (x,y,z)
E energy
Sub-detector ID

● Other sub-detectors?
eg. ARC

pointcloud

Adapting ML methods to PF

Inductive bias

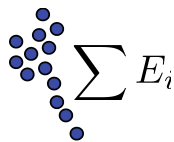
Self- intersections

No equivalent in 3D ML dataset



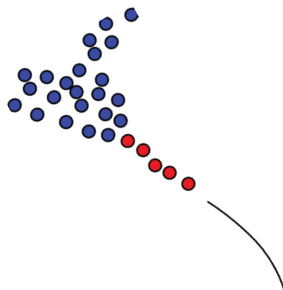
Multiple measurements in different subdetectors that 'add up' --> Optimal transport

No equivalent in 3D ML datasets (LiDAR scans of chairs do not add up to their mass)



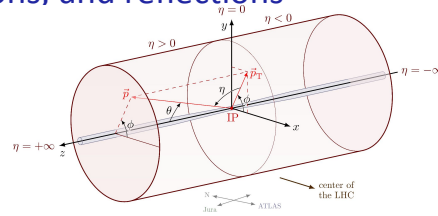
Need to preserve 'fine' structures in ECAL/tracker

Prevents voxelization and standard pulling



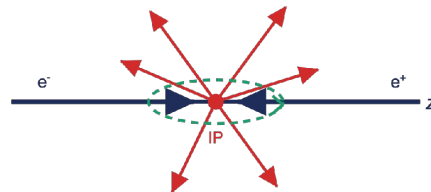
SO(2) + z mirror (endcaps)

~E(3) rotations, translations, and reflections



Beam direction

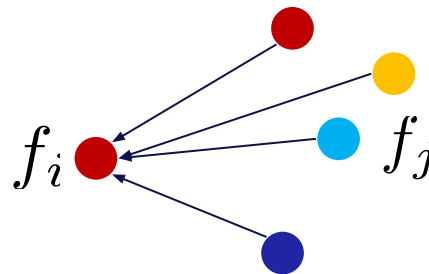
Preferred direction set by gravity



ML 3D data

Detector data

Model GNNs, transformers



$$f'_i = \square_{j:(i,j) \in \mathcal{E}} h_{\Theta}(\mathbf{f}_i, \mathbf{f}_j).$$

Building block 1

$$\square_{j:(i,j) \in \mathcal{E}}$$

Aggregation operator

$$h_{\Theta}$$

Non-linear function with learnable parameters

Model GNNs, transformers

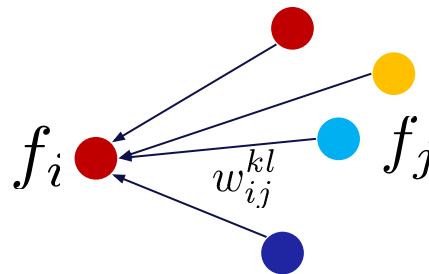
$$f'_i = \square_{j:(i,j) \in \mathcal{E}} h_{\Theta}(\mathbf{f}_i, \mathbf{f}_j).$$

Aggregation operator

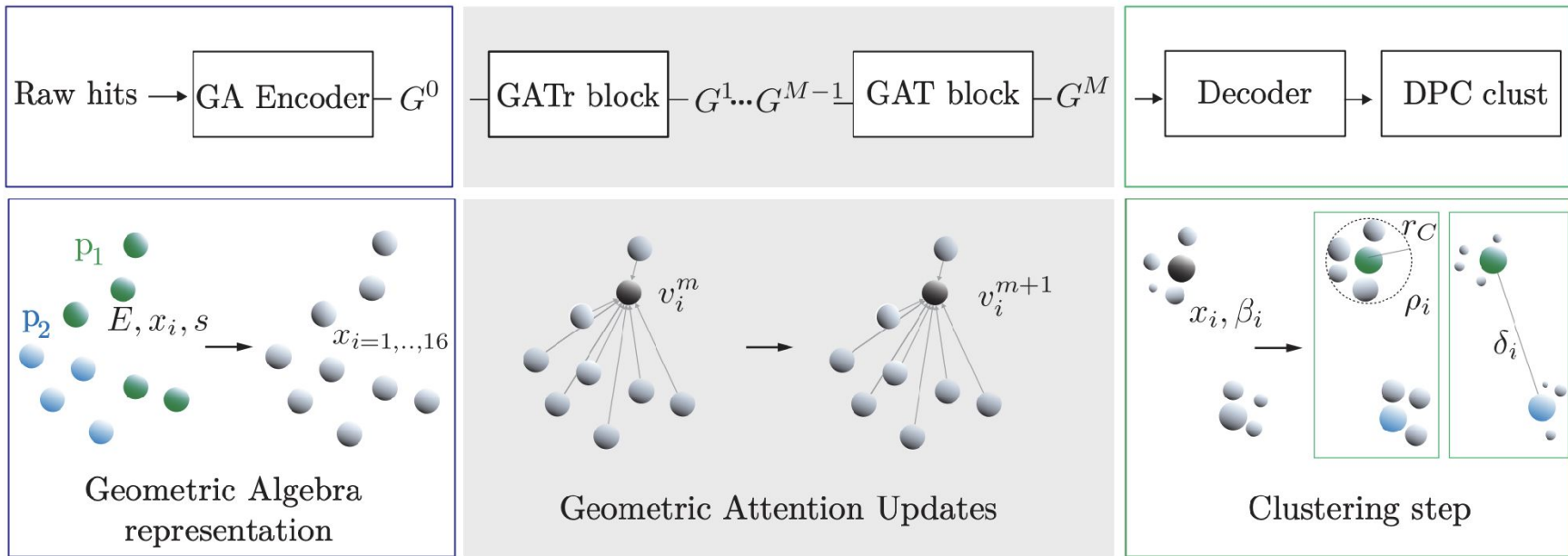
$$\square_{j:(i,j) \in \mathcal{E}} \longrightarrow f'_i = \sum_{j:(i,j) \in \mathcal{E}}$$

Non-linear function with learnable parameters

$$h_{\Theta} \longrightarrow h_{\Theta}(\mathbf{f}_i^l, \mathbf{f}_j^l) = w_{ij}^{kl} \mathbf{V}^{kl} \mathbf{f}_j^l,$$
$$w_{ij}^{kl} = \text{softmax}_j \left(\frac{(\mathbf{Q}_q^{kl} \mathbf{f}_i^l)^{\top} (\mathbf{K}_k \mathbf{f}_j^l)}{\sqrt{d}} \right)$$

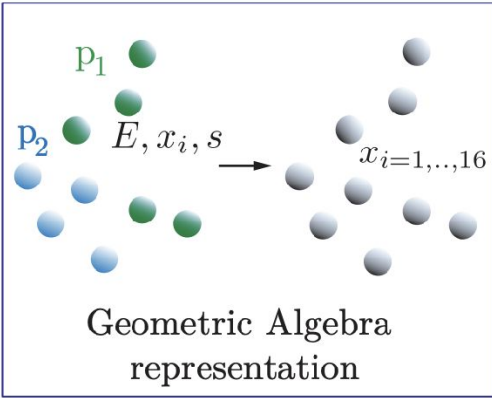
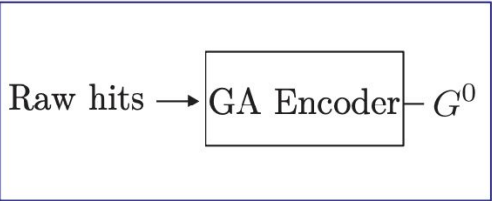
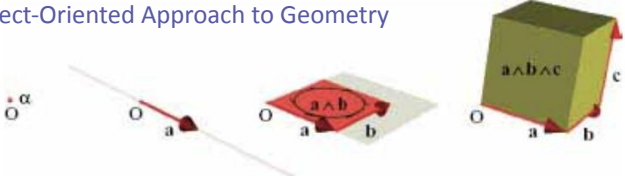


Geometric Algebra Transformer



Multivectors

Geometric Algebra for Computer Science : An Object-Oriented Approach to Geometry



- Representation of multiple geometric objects of different grades
- Outer product $a \wedge b$ (oriented span of a and b)
- Projective algebra (adds displacement from the origin)
- 3D object representation:
 - Planes are represented as vectors (normal + displacement)
 - Lines are intersection of two planes (bivectors)
 - Points are intersections of three planes (trivectors)
- Multivectors:
 - $x = x_s + x_1 e_1 + x_2 e_2 + x_3 e_3 + x_{12} e_1 e_2 + x_{13} e_1 e_3 + x_{23} e_2 e_3 + x_{123} e_1 e_2 e_3$, x_i real coefficients
 - Built with the geometric product (metric)

Object / operator	Scalar 1	Vector $e_0 \ e_i$		Bivector $e_{0i} \ e_{ij}$		Trivector $e_{0ij} \ e_{123}$		PS e_{0123}
Scalar $\lambda \in \mathbb{R}$	λ	0	0	0	0	0	0	0
Plane w/ normal $n \in \mathbb{R}^3$, origin shift $d \in \mathbb{R}$	0	d	n	0	0	0	0	0
Line w/ direction $n \in \mathbb{R}^3$, orthogonal shift $s \in \mathbb{R}^3$	0	0	0	s	n	0	0	0
Point $p \in \mathbb{R}^3$	0	0	0	0	0	p	1	0
Pseudoscalar $\mu \in \mathbb{R}$	0	0	0	0	0	0	0	μ
Reflection through plane w/ normal $n \in \mathbb{R}^3$, origin shift $d \in \mathbb{R}$	0	d	n	0	0	0	0	0
Translation $t \in \mathbb{R}^3$	1	0	0	$\frac{1}{2}t$	0	0	0	0
Rotation expressed as quaternion $q \in \mathbb{R}^4$	q_0	0	0	0	q_i	0	0	0
Point reflection through $p \in \mathbb{R}^3$	0	0	0	0	0	p	1	0

Geometric Algebra Transformer

K-blade projections, no grade mixing

Equi
linear

$$\phi(x) = \sum_{k=0}^{d+1} w_k \langle x \rangle_k + \sum_{k=0}^d v_k e_0 \langle x \rangle_k$$

Geo
bilinear

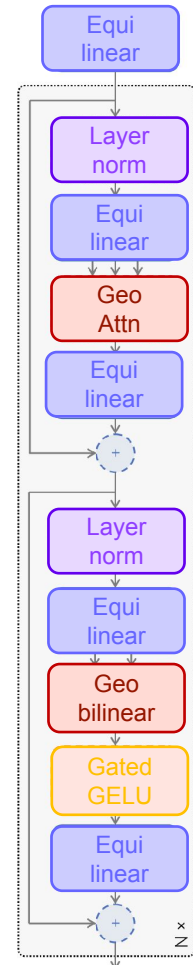
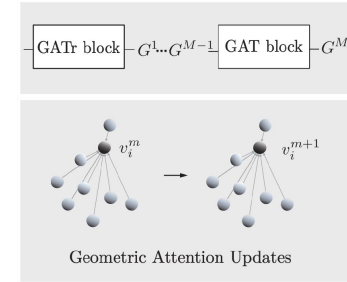
Geometric product $x, y \rightarrow xy = \langle x, y \rangle + x \wedge y \rightarrow$ grade mixing
Join product $x, y \rightarrow (x^* \wedge y^*)^*$

$$\text{Geometric}(x, y; z) = \text{Concatenate}_{\text{channels}}(xy, \text{EquiJoin}(x, y; z))$$

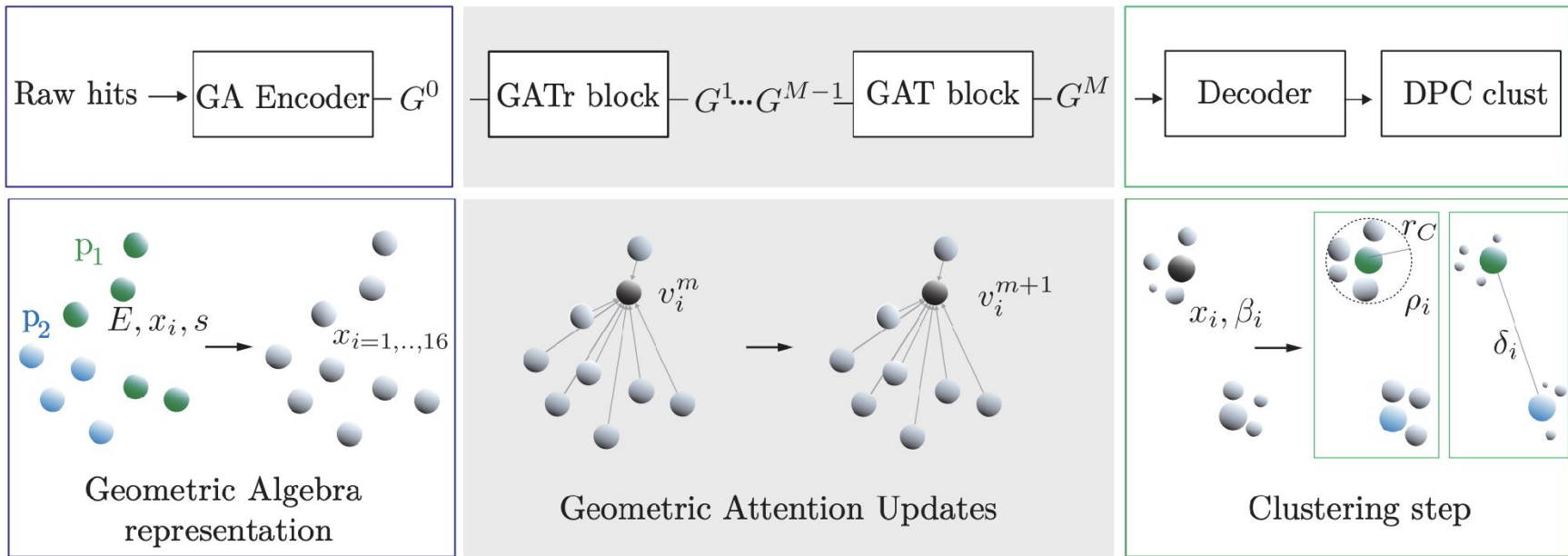
Geo
Attn

Attention mechanism as described previously but with inner product of the algebra

$$\text{Attention}(q, k, v)_{i'c'} = \sum_i \text{Softmax}_i \left(\frac{\sum_c \langle q_{i'c}, k_{ic} \rangle}{\sqrt{8n_c}} \right) v_{ic'}$$

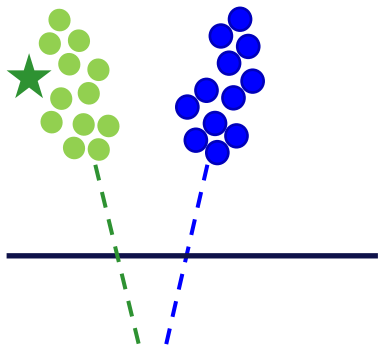


Geometric Algebra Transformer



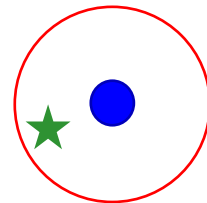
Loss: object condensation

Inputs (K=2)



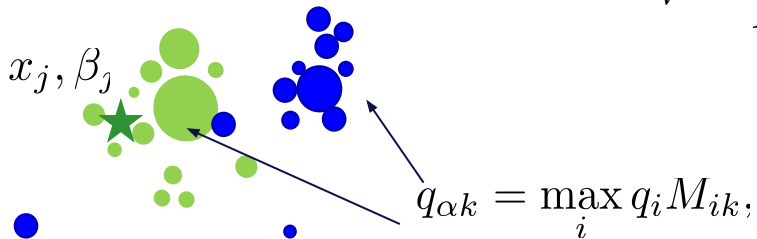
$$\star \bullet \quad \check{V}_k(x) = \|x - x_\alpha\|^2 q_{\alpha k};$$

$$\star \bullet \quad \hat{V}_k(x) = \max(0, \underline{1 - \|x - x_\alpha\|}) q_{\alpha k}$$



Embedding space

$$L_V = \frac{1}{N} \sum_{j=1}^N q_j \sum_{k=1}^K \left(M_{jk} \check{V}_k(x_j) + (1 - M_{jk}) \hat{V}_k(x_j) \right)$$



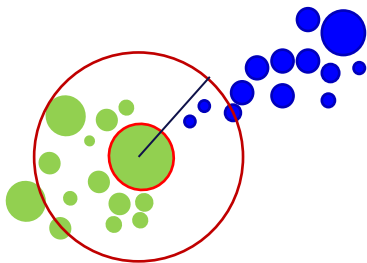
Object condensation @Jan K.

Clustering in embedding space

Two methods

Beta based clustering [1]

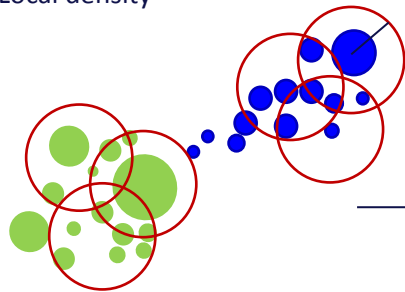
x_j, β_j



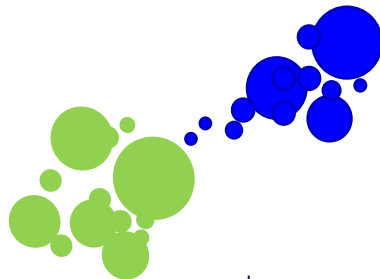
- Two parameters, $\beta_{\min}$, distance threshold
- Depends on good training of β distribution

Density Peak clustering [2]

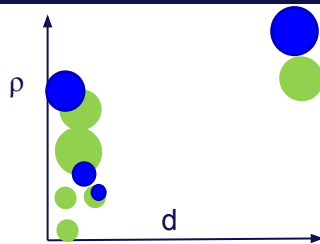
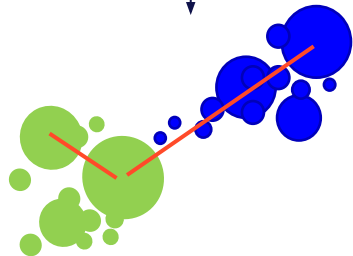
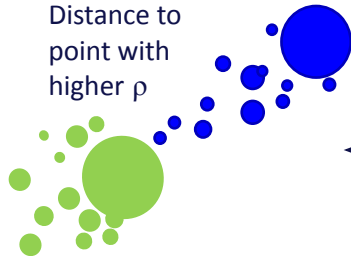
Local density



ρ map, energy weighted

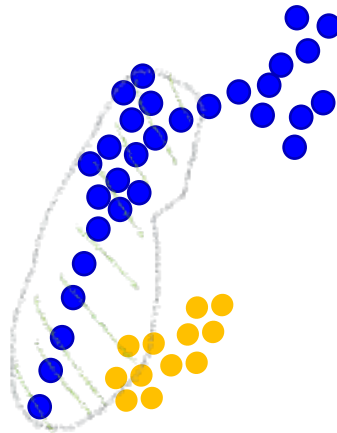
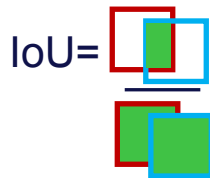


Distance to point with higher ρ



Matching

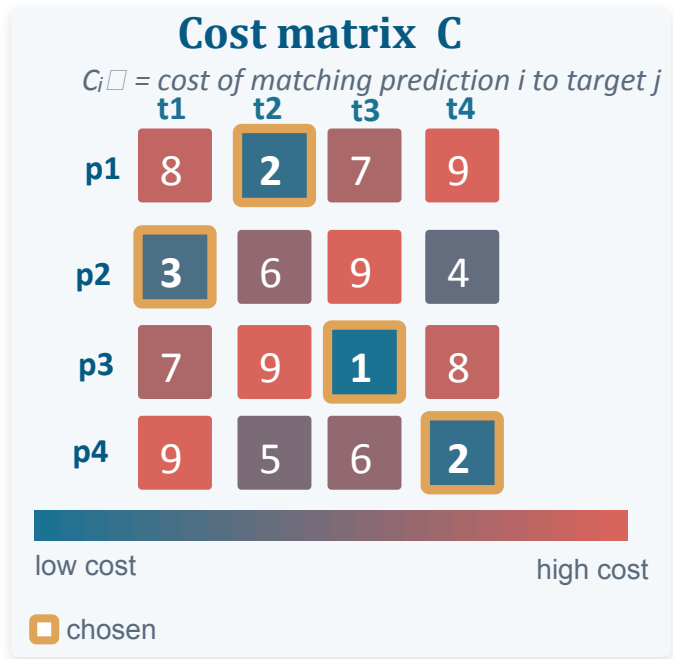
- We use a **Hungarian matching** to match a reco particle to a target particle with the intersection over union cost
- Builds a cost matrix
- One-to-one constraint
- Cost minimization



Matching

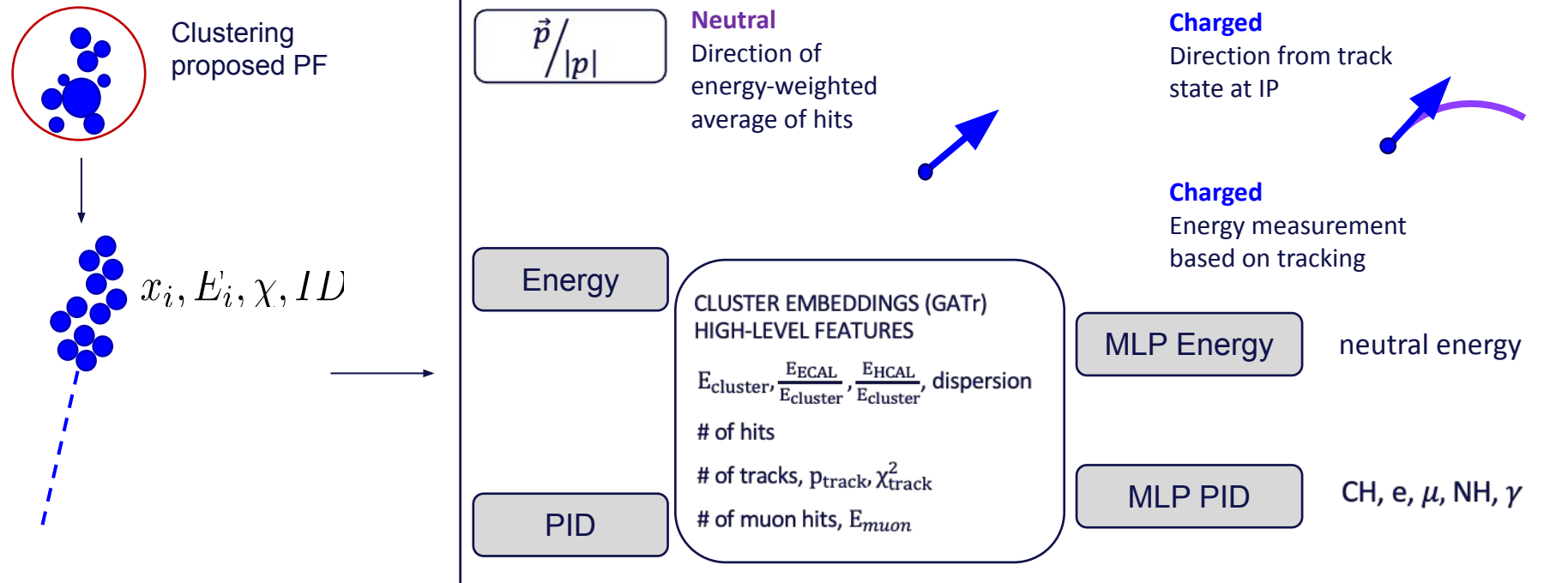
- We use a **Hungarian matching** to match a reco particle to a target particle with the intersection over union cost
- Builds a cost matrix
- One-to-one constraint
- Cost minimization

$$\min_{X \in \{0,1\}^{N \times N}} \sum_{i=1}^N \sum_{j=1}^N C_{ij} X_{ij} \quad \text{s.t.}$$
$$\sum_j X_{ij} = 1 \quad \forall i, \quad \sum_i X_{ij} = 1 \quad \forall j.$$



Regression & Classification

Per PF candidate property determination

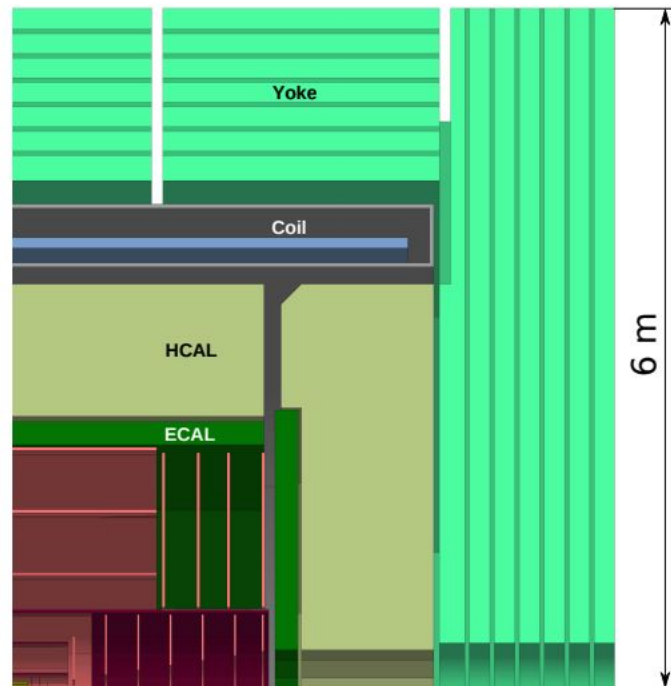
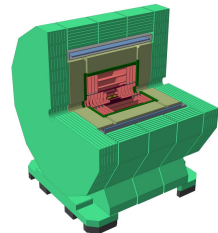


CLD

Full simulation

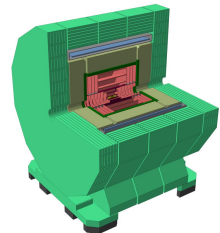
- ☐ Implemented in DD4hep
- ☐ Full simulation in Key4hep
- ☐ Comparison against Pandora tuned for CLD (CLD_o2_v05)
- ☐ $Z \rightarrow q\bar{q}, q = (u, d, s)$ 91 GeV
- ☐ Jet like events:
 - ☐ Close particles
 - ☐ High particle multiplicity

Key4hep



ILD

Key4hep



Full simulation

- ☐ Implemented in DD4hep
- ☐ Full simulation in Key4hep
- ☐ Comparison againsts Pandora tuned for ILD_I5_o1_v02

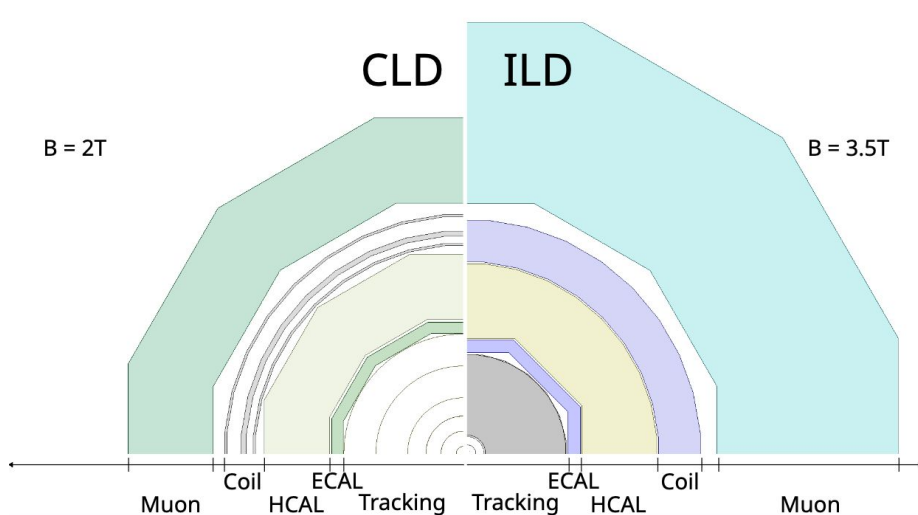
☐ $Z \rightarrow q\bar{q}, q = (u, d, s)$ 91 GeV

☐ Jet like events:

- ☐ Close particles
- ☐ High particle multiplicity

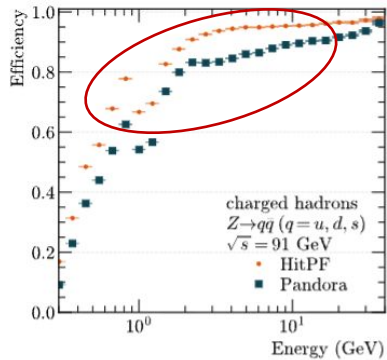
Trained on 1M events

Evaluated on 100k events

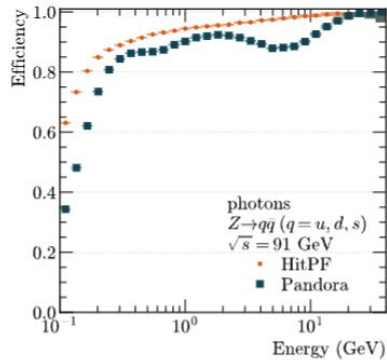


PID: Efficiency and fake rate

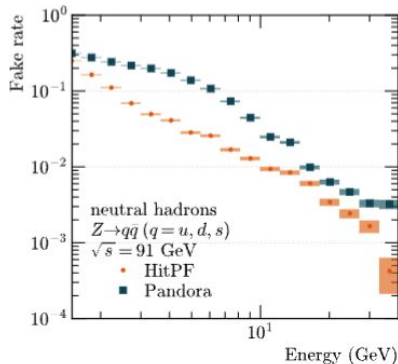
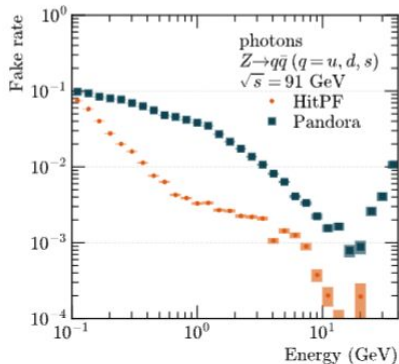
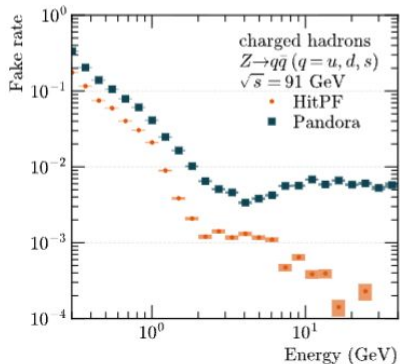
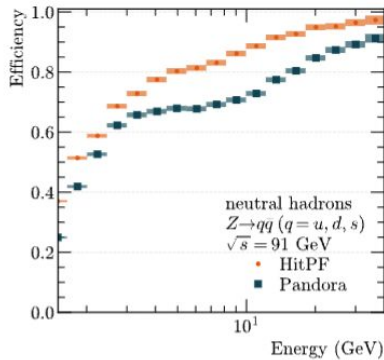
Charged Hadron



Photons



Neutral Hadrons



CH:

- Up to 15% higher eff.
- Fake rate $\mathcal{O}(2)$ smaller
- Eff. limited by track reco.

Photons:

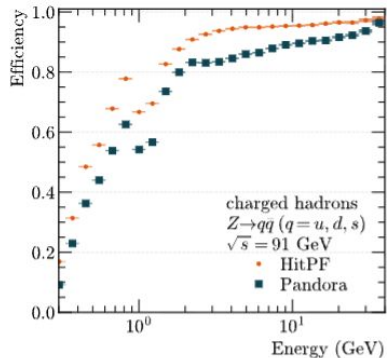
- ~5% higher eff. at high E
- Improvement by up to factor 2 for low E
- Fake rate up to $\sim \mathcal{O}(1)$

NH:

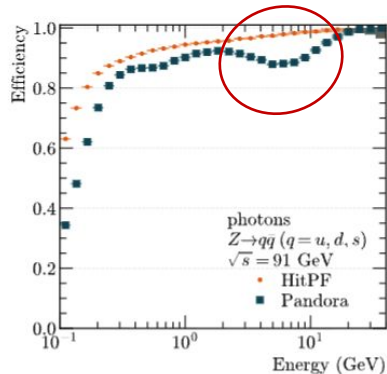
- Up to 15% higher eff. with Fake rate reduced by almost factor 5 in this region
- Better clustering (no fake clusters from splitting)

PID: Efficiency and fake rate

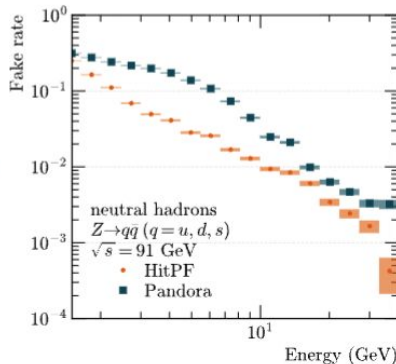
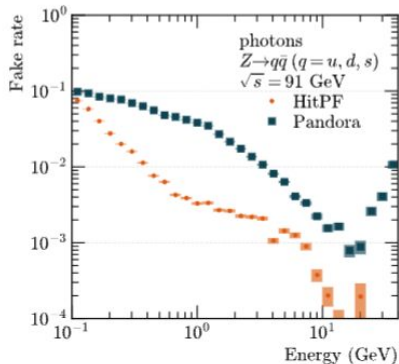
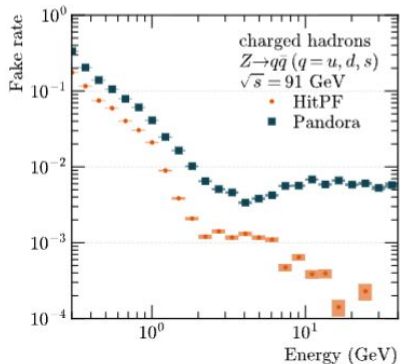
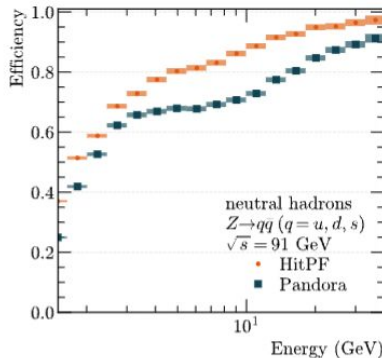
Charged Hadron



Photons



Neutral Hadrons



CH:

- Up to 15% higher eff.
- Fake rate $\mathcal{O}(2)$ smaller
- Eff. limited by track reco.

Photons:

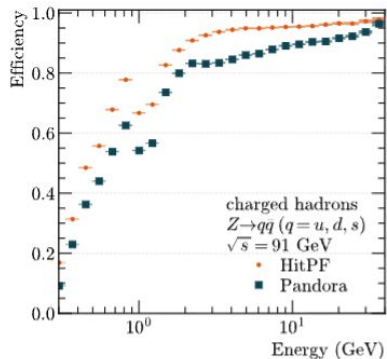
- ~5% higher eff. at high E
- Improvement by up to factor 2 for low E
- Fake rate up to $\sim \mathcal{O}(1)$

NH:

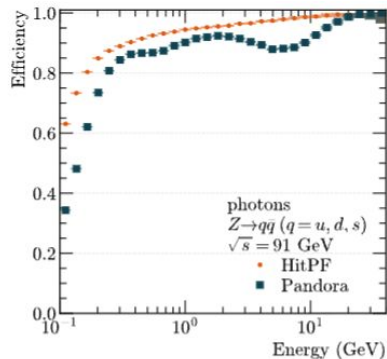
- Up to 15% higher eff. with Fake rate reduced by almost factor 5 in this region
- Better clustering (no fake clusters from splitting)

PID: Efficiency and fake rate

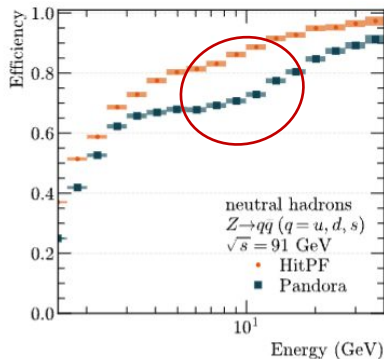
Charged Hadron



Photons



Neutral Hadrons



CH:

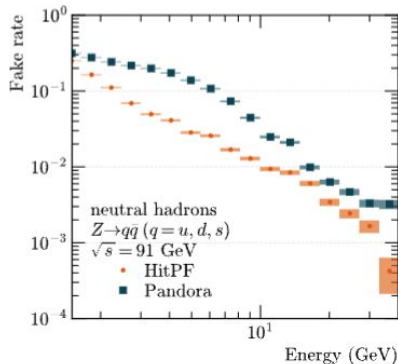
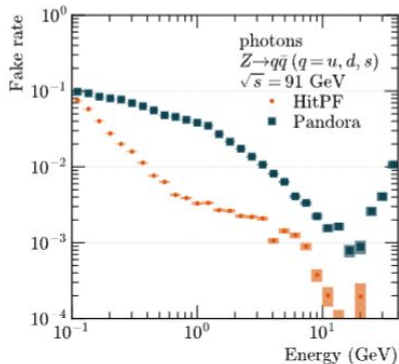
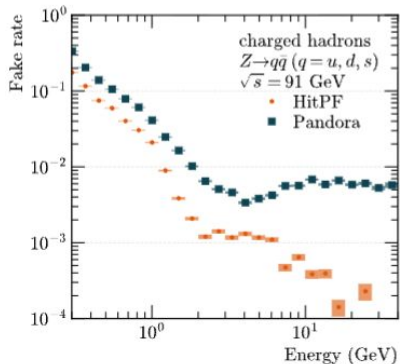
- Up to 15% higher eff.
- Fake rate $\mathcal{O}(2)$ smaller
- Eff. limited by track reco.

Photons:

- ~5% higher eff. at high E
- Improvement by up to factor 2 for low E
- Fake rate up to $\sim \mathcal{O}(1)$

NH:

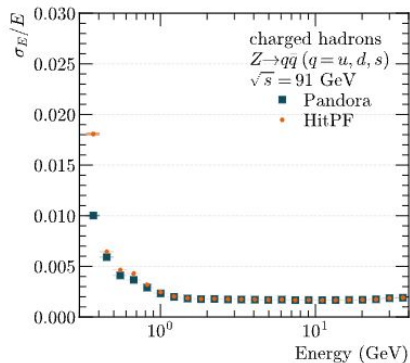
- Up to 15% higher eff. with Fake rate reduced by almost factor 5 in this region
- Better clustering (no fake clusters from splitting)



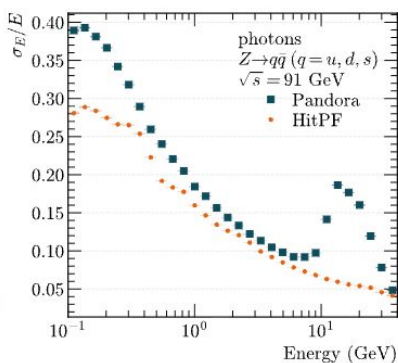
Energy and angular resolution

Energy Resolution: half-width of 16th-84th percentile normalized to median
Angular resolution: 68th percentile of the opening angle between rec and true

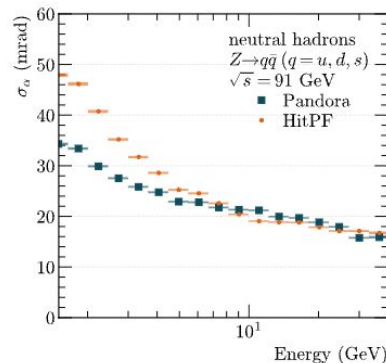
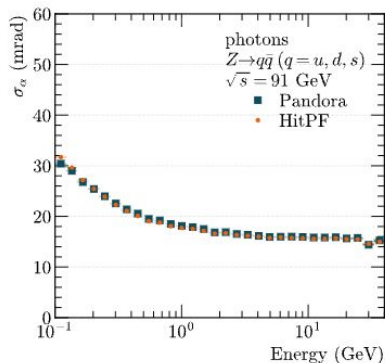
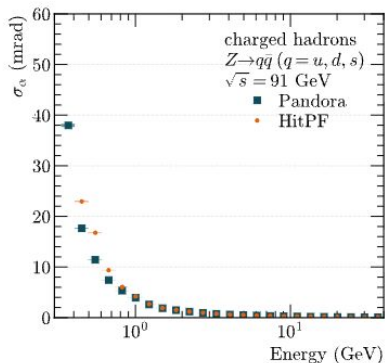
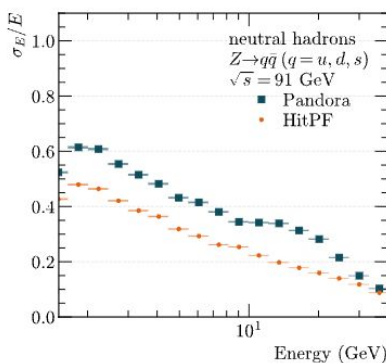
Charged Hadron



Photon



Neutral Hadron



CH:

- Comparable by construction
- solely tracker information used

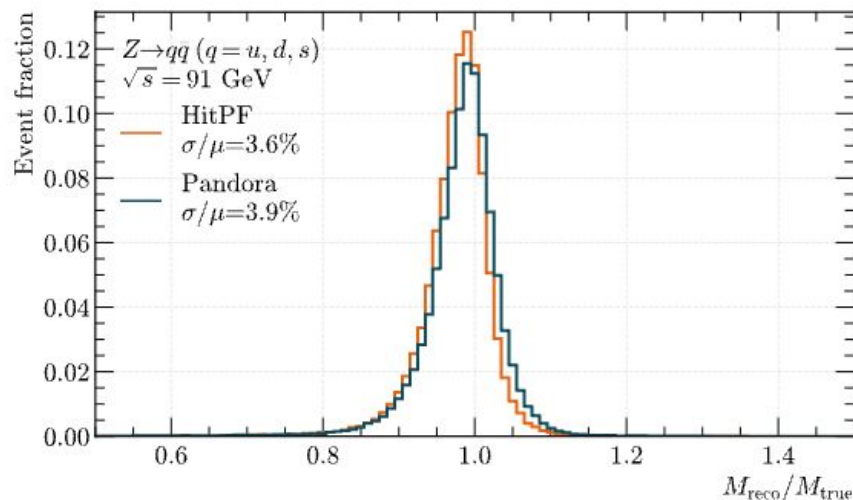
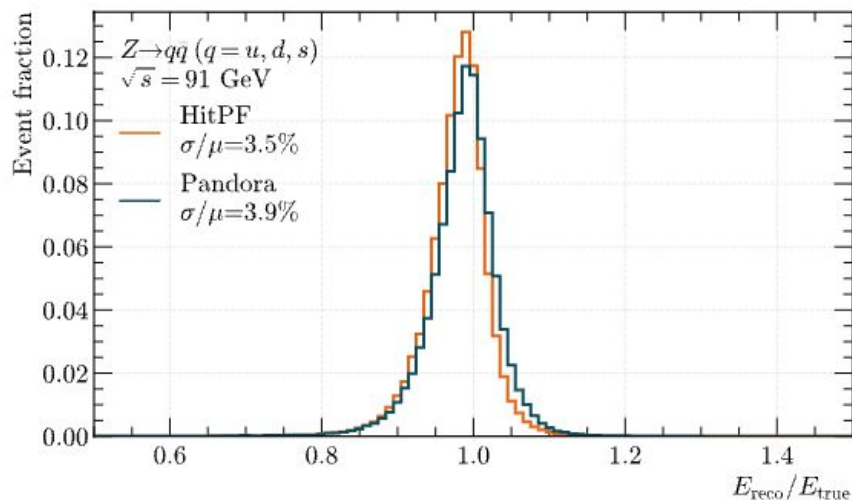
NH:

- Largest gain in energy/ angular resolution
- Less shower merging, better hit capture

Visible mass and energy

- Good complementary metric to per-particle metrics
- Improved mass resolution due to:
 - Higher efficiency in low energy neutrals
 - Improved energy resolution
 - Better track cluster-linking

7.7% relative improvement
of HitPF compared to
Pandora



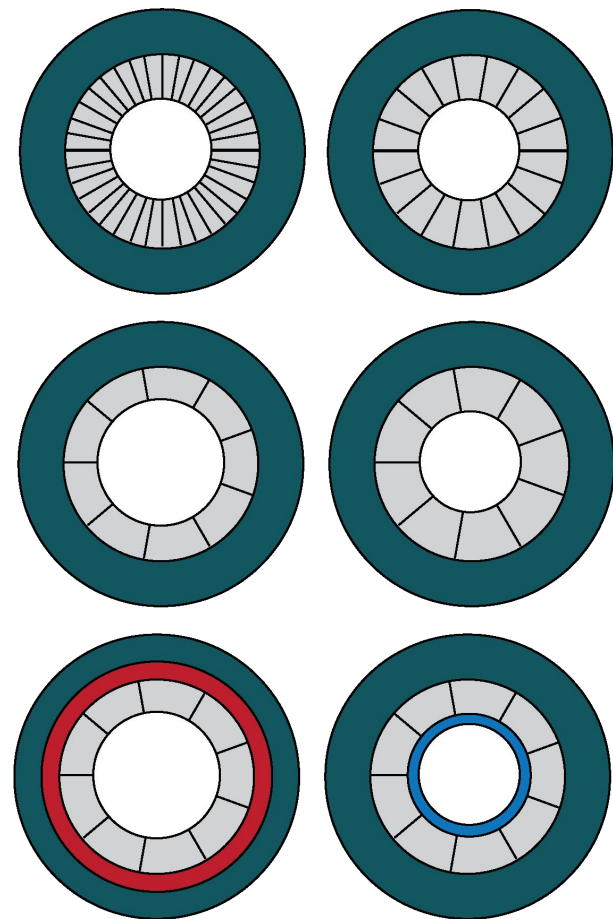
Isolated particles

		Efficiency		Fake rate		σ_E/E [%]		σ_α [mrad]	
process		HitPF	Pandora	HitPF	Pandora	HitPF	Pandora	HitPF	Pandora
e^+e^-	(t -ch.)	0.95	0.93	1.5×10^{-4}	3.3×10^{-3}	8.0	8.1	0.1	0.1
$\gamma\gamma$	(t -ch.)	1.00	1.00	1.7×10^{-4}	8.3×10^{-5}	3.6	3.0	11.7	11.7
$\mu^+\mu^-$	(s -ch.)	0.99	0.96	5.4×10^{-5}	3.6×10^{-3}	0.2	0.2	0.1	0.1
e^+e^-	(s -ch.)	0.97	0.95	5.6×10^{-5}	1.4×10^{-3}	6.5	6.3	0.1	0.1

What does this give access to?

Full simulation physics studies

- ☐ Impact of beam background
- ☐ Effect of timing information in clustering
- ☐ Impact of low momentum tracks reco on PF
- ☐ Impact of acceptance
- ☐ Tau reconstruction
- ☐ Physics validation
 - Retrain jet taggers with HitPF input
 - Deploy for physics analysis in CLD



Summary

- ❑ Developments in ML allow for improved data representation for hit-based particle flow
- ❑ Improved performance in PF compared to classical approaches across all metrics: efficiency in complex hadronic topologies, neutral hadron efficiency, fakes and visible mass resolution (improvements by 24% CLD- 7.7% ILD)
- ❑ New geometric models could further improve performance, but development is needed as the properties of HEP are not the same as classic 3D datasets

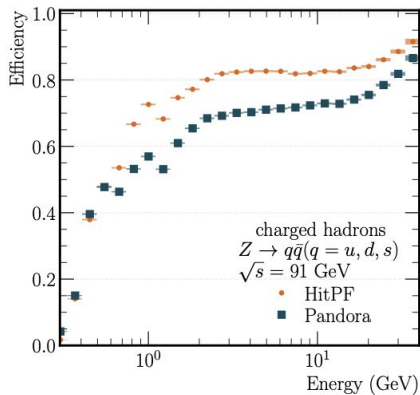


Thank you
for your attention.

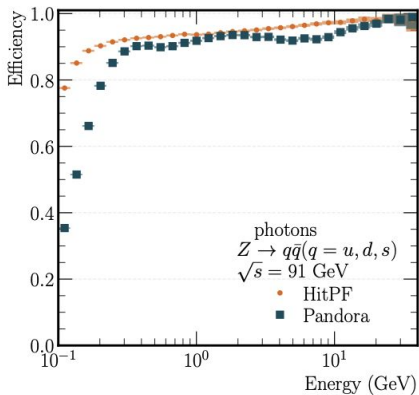


PID: Efficiency and fake rate

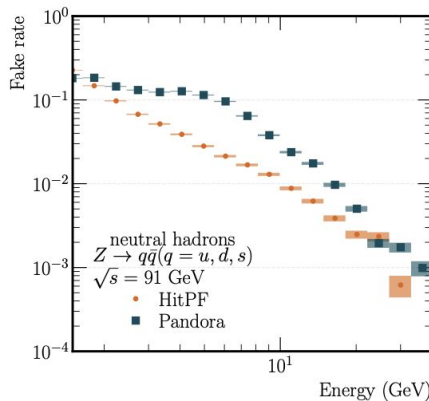
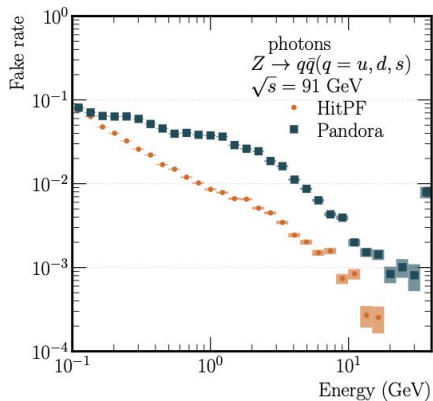
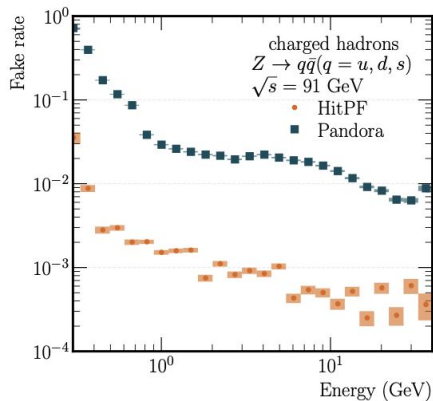
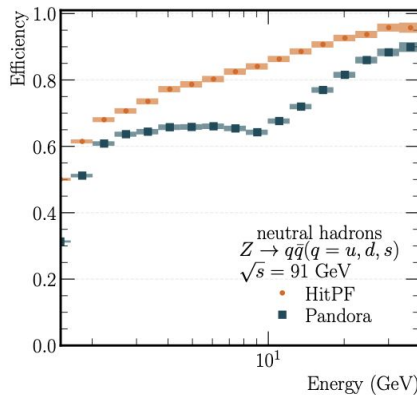
Charged Hadron



Photons



Neutral Hadrons



CH:

- Up to 20% higher eff.
- Fake rate $\mathcal{O}(2)$ smaller
- Eff. limited by track reco.

Photons:

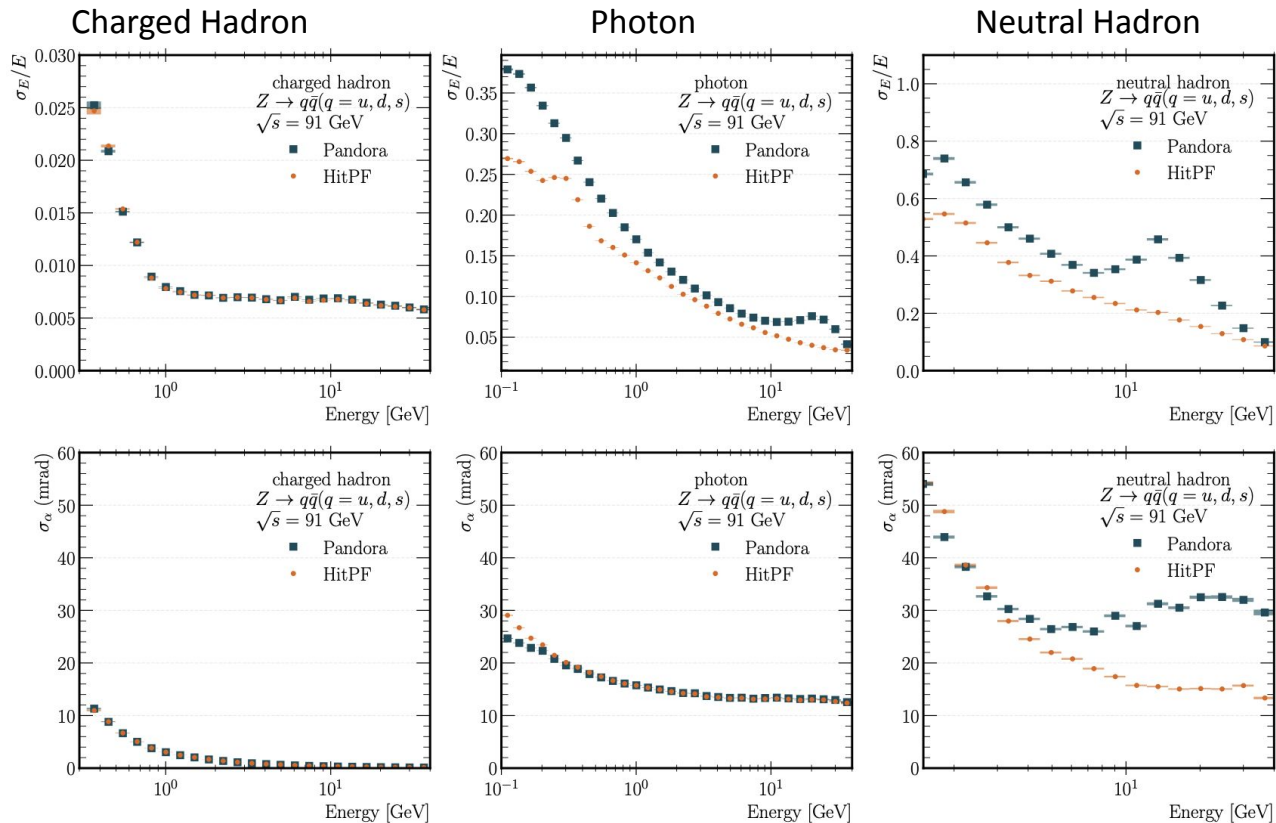
- ~5% higher eff. at high E
- Improvement by up to factor 2 for low E
- Fake rate up to $\sim \mathcal{O}(1)$

NH:

- Up to 20% higher eff. with Fake rate reduced by almost factor 5 in this region
- Better clustering (no fake clusters from splitting)

Energy and angular resolution

Energy Resolution: half-width of 16th-84th percentile normalized to median
Angular resolution: 68th percentile of the opening angle between rec and true



CH:

- Comparable by construction
- solely tracker information used

NH:

- Largest gain in energy/ angular resolution
- Less shower merging, better hit capture