

ML for reconstruction at FCC-ee

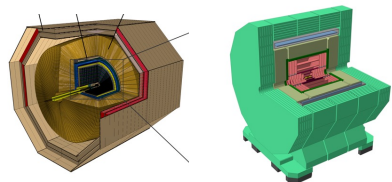
Dolores Garcia

Motivation

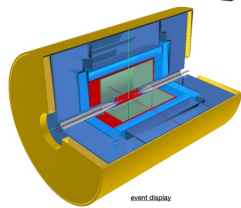
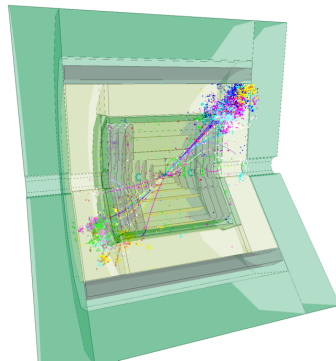
- ❑ FCC-ee has been recommended by the European Strategy as CERN's next flagship collider [\[1\]](#)
- ❑ FCC-ee will collide $e+e-$ at Z, WW, ZH and $t\bar{t}$ thresholds with large luminosity
- ❑ Experiments aim to measure Higgs couplings, electroweak parameters, flavour observables with extremely high precision
- ❑ Achievable sensitivity on SM parameters is driven by the resolution with which visible final state particles and their invariant masses can be reconstructed

Precisions depends on:

High performance detectors

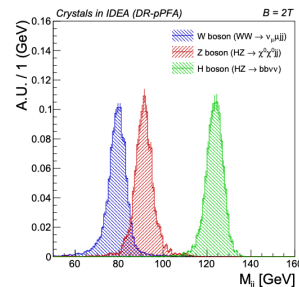


High quality reconstruction

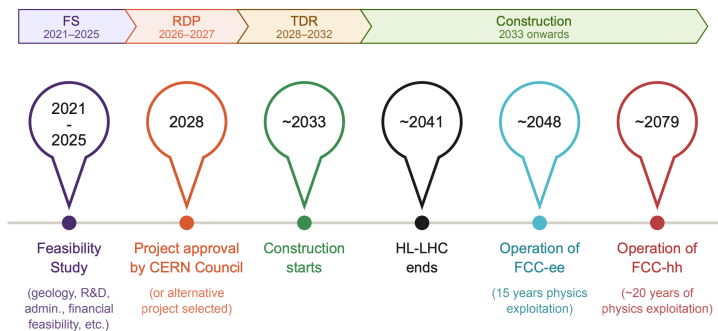


Best resolution translates into best physics sensitivity

- ❑ 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



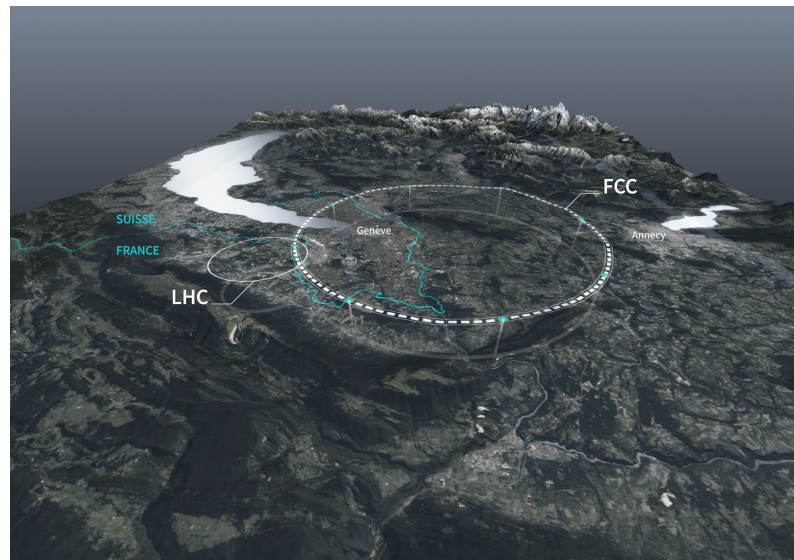
Entering the Reference Design Phase era



- Excellent test ground for development of reconstruction algorithms that could be translated to HL-LHC, complex detectors with many channels and low pile-up

- Goal: enable FCC-ee detector design optimization
- Solidify the physics-reach and physics case with robust full-simulation implementations
- Need general reconstruction algorithms to apply to multiple detector geometries and technologies

Adapted from F.Beirer@FCC Week 2026



Summary of the talk

ML for reconstruction

Particle Flow

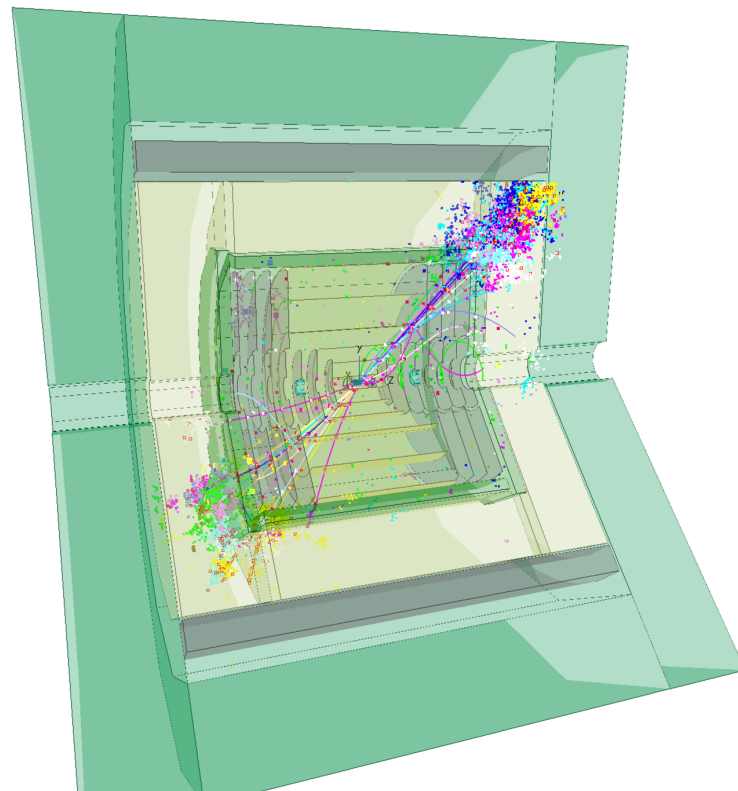
Tracking

Other works at FCC (will not be covered in this talk):

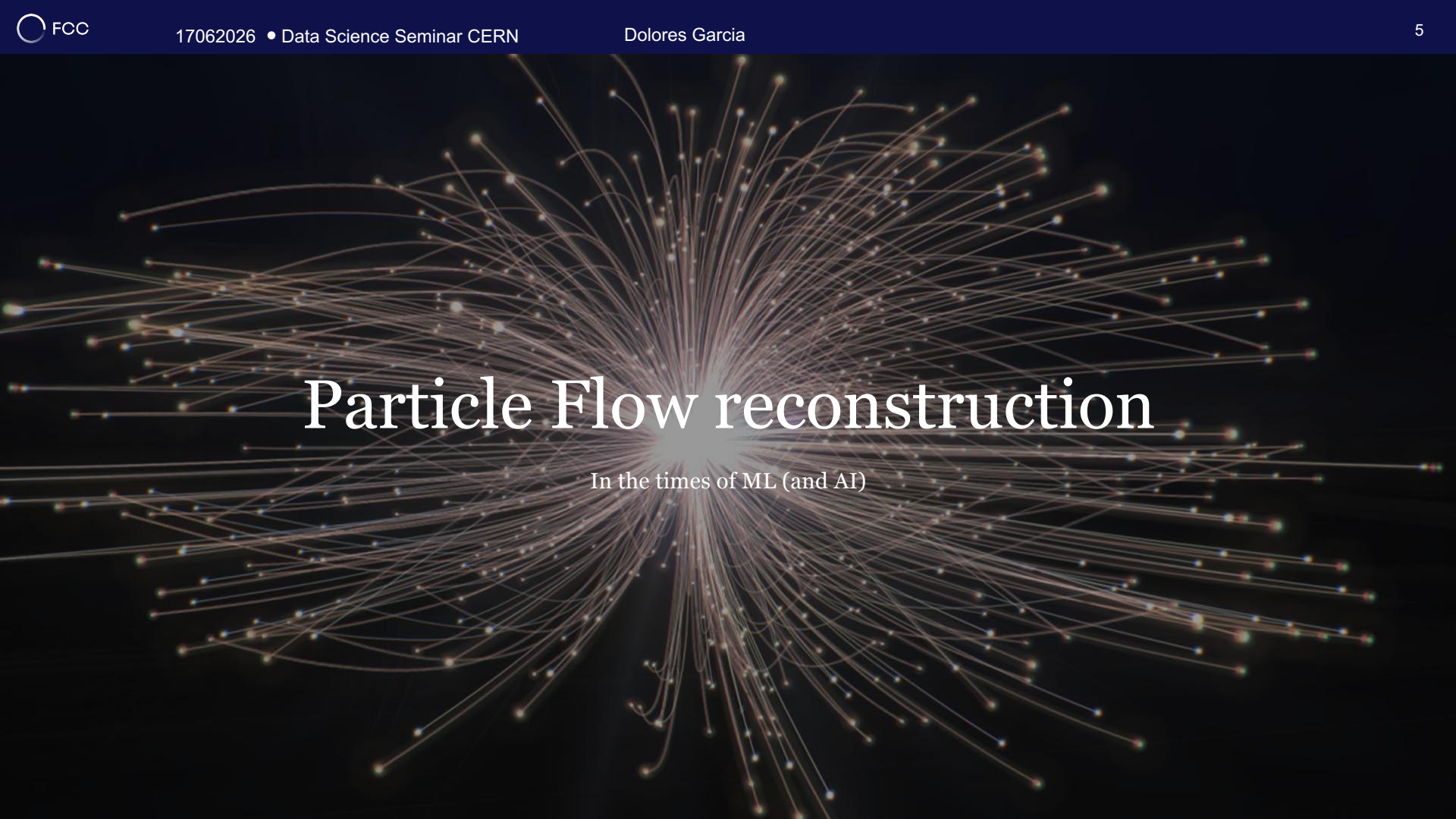
Tau reconstruction

Tagging

...



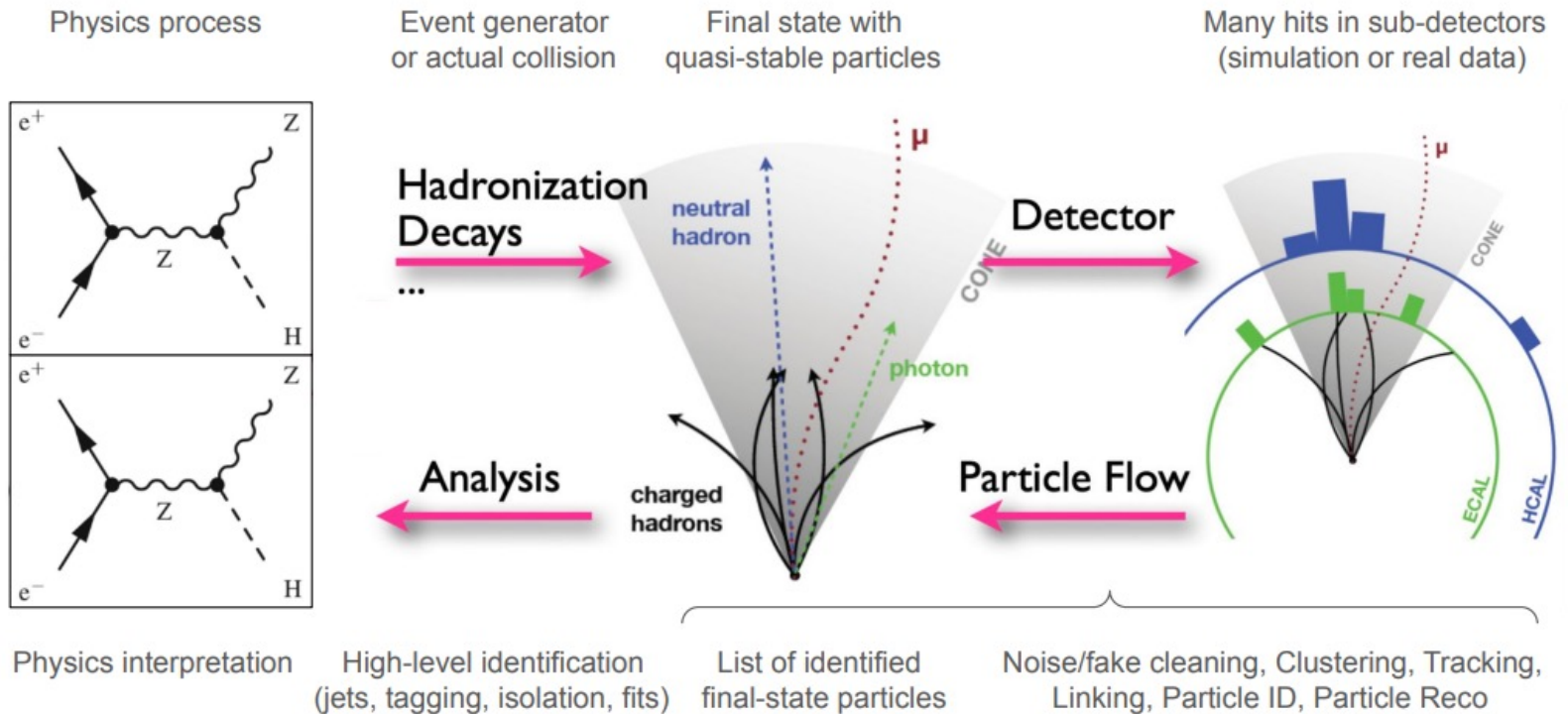
Event display in the CLD detector for a $Z/\gamma^* \rightarrow qq$ event 365 GeV. From Bacchetta et al 2019.

A complex visualization of particle flow reconstruction. It features a dense, radial pattern of numerous thin, light-colored lines (representing particle tracks) originating from a central bright point and extending outwards in all directions. The lines are slightly curved and have small, glowing dots at their endpoints, creating a starburst or explosion-like effect against a dark background.

Particle Flow reconstruction

In the times of ML (and AI)

What is Particle Flow?



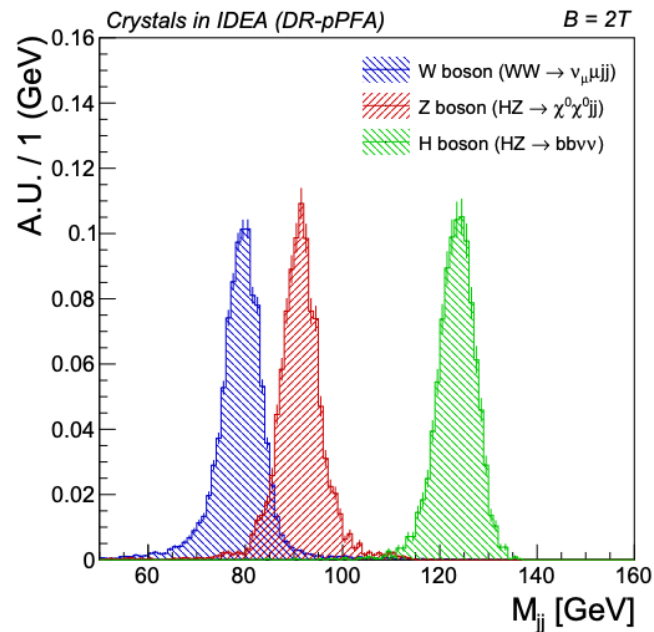
What is Particle Flow?

- ❑ **The goal:** Optimally combine measurements from all sub-detectors
 - Vertex, tracker, ECAL/HCAL, muon detector
 - From **hits** to **identified final state particles**
- ❑ For each ~**stable particle**, this combination aims at returning a **reco particle**
 - With the best **direction** and **energy** estimate
 - With the most likely **type** (photon, electron, muon, charged hadron, neutral hadron)
 - With its origin vertex (primary, secondary, etc.)
- ❑ The list of individual particles can then be used
 - To determine the **total/missing energy** and momentum; build jets; tag **jet flavour**; identify and reconstruct **taus** from their decay products; select leptons or photons; etc.
 - With the best possible energy/angular **resolution**, efficiency, purity, ...
 - With **no** overlap or **double counting** - as with a generator-level analysis

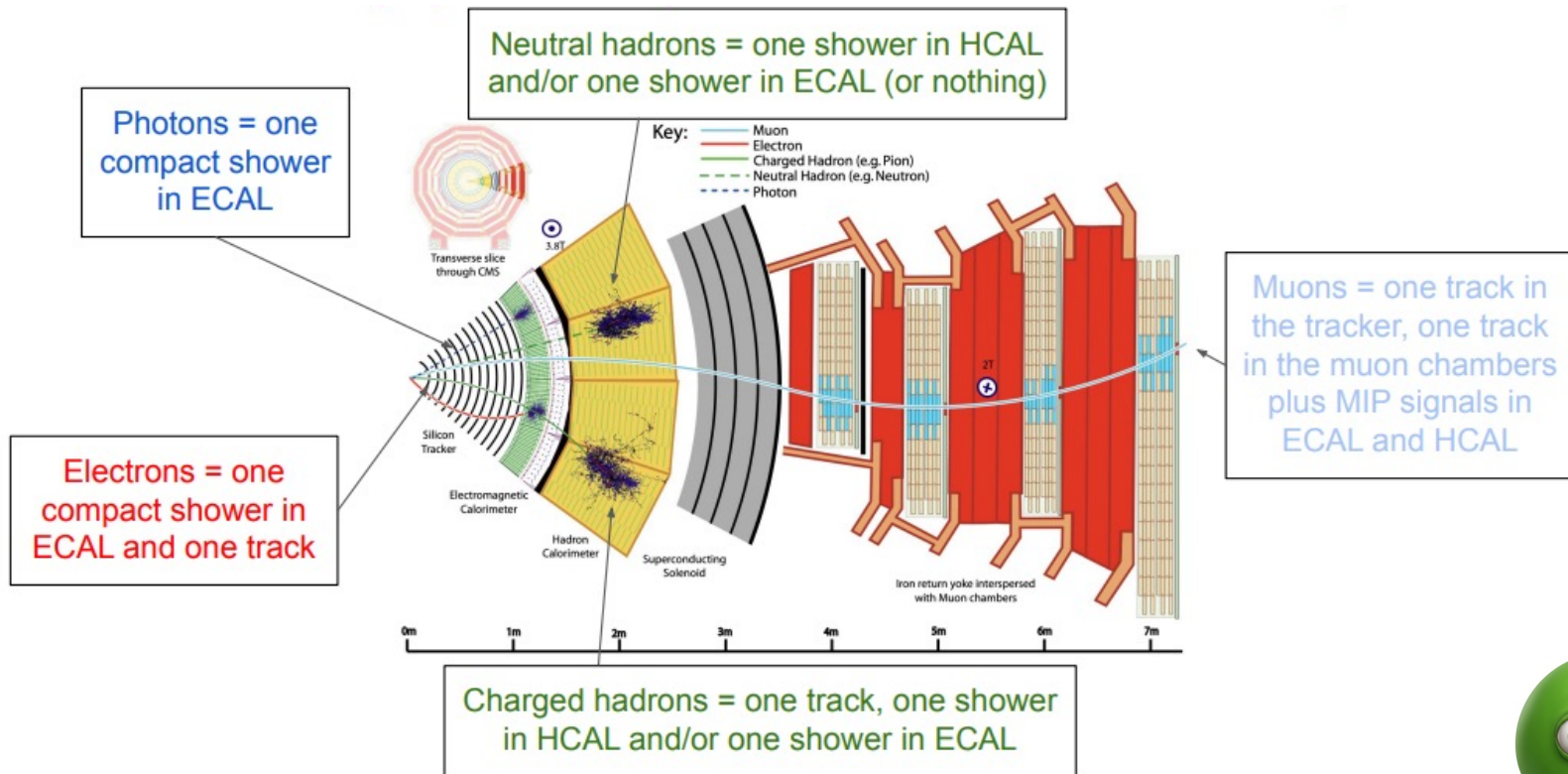
Why Particle Flow reconstruction?

From raw data to physics observables

- ❑ Reconstructing individual particles from raw signals connects experimental measurements with physics observables
- ❑ Achievable sensitivity on key SM measurements is driven by the resolution with which the visible final state particles and their invariant masses can be reconstructed
- ❑ Rare higgs decays ($H \rightarrow cc$, $H \rightarrow ss$, relative uncertainty scale is sensitive to visible mass resolution)
- ❑ Hadronic final states large particle multiplicity and geometrical overlap

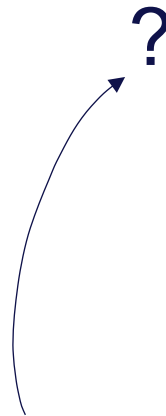


The 'game'



Why is it hard?

- ❑ Classically, multiple algorithms, many moving pieces:
 - Tracking (one per sub-detector), clustering (ECAL/HCAL), and linking tracks and clusters
- ❑ We want every particle in the event, but not fakes, hard to tune
- ❑ **Fake tracks**
- ❑ **Lonely tracks** (tracks that are real but left no clusters)
- ❑ **Displaced tracks** (less hits, tracking classically not tuned for that)
- ❑ Physics:
 - Photons conversion in the tracker (detached vertex + e+e-, maybe two tracks maybe none)
 - Electrons radiation ('double counting')
 - Hadrons interaction (detached vertex + more particles)
 - Neutral hadrons decay (e.g., K_S^0 or Λ)
 - Many edge cases that are rare (hard to take all into account)



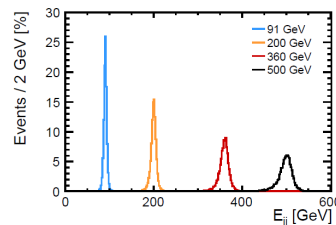
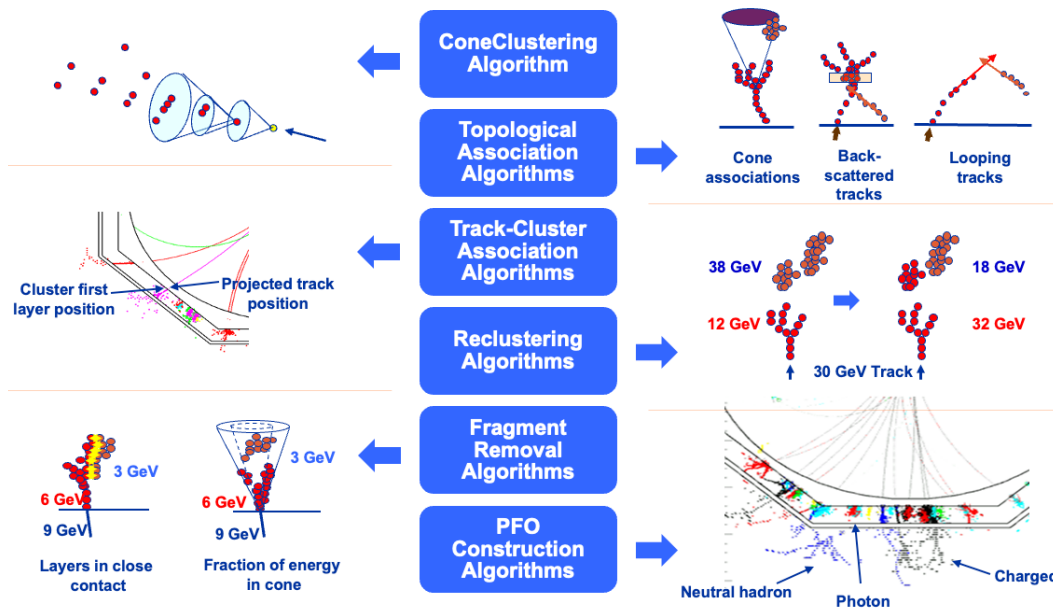
How is it tackled?

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)

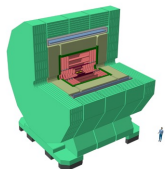
- Series of distributed algorithms
- Iterative clustering
- Track cluster association and reclustering
- Neutral identification
- Relies on tuning, limiting flexibility during detector design phase (allows for geometry studies e.g transverse calo segmentation)



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

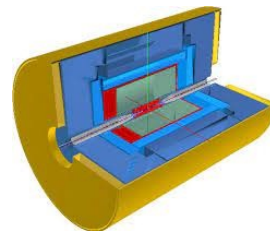
□ Adaptable reconstruction is crucial for a systematic **design optimization**:

- 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

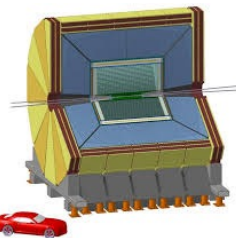


ALLEGRO

- 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

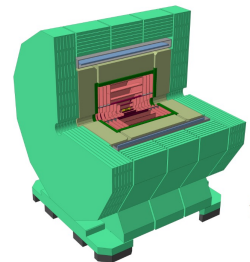
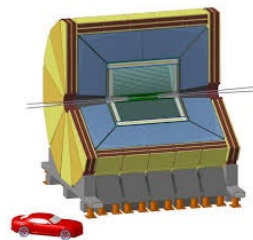
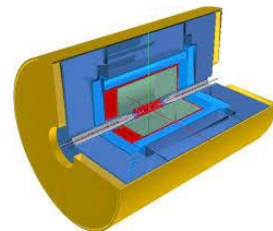


And others... ALFA, ILD

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



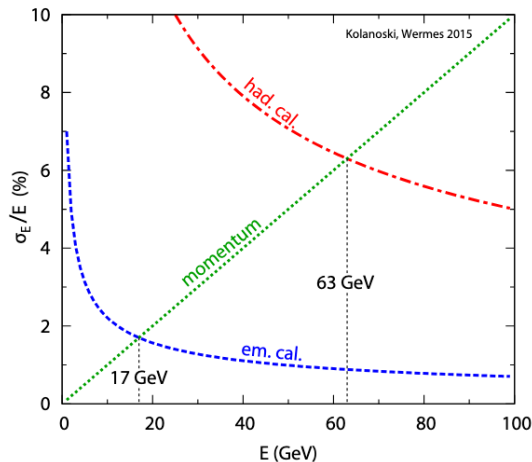
The need for an end-to-end approach

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

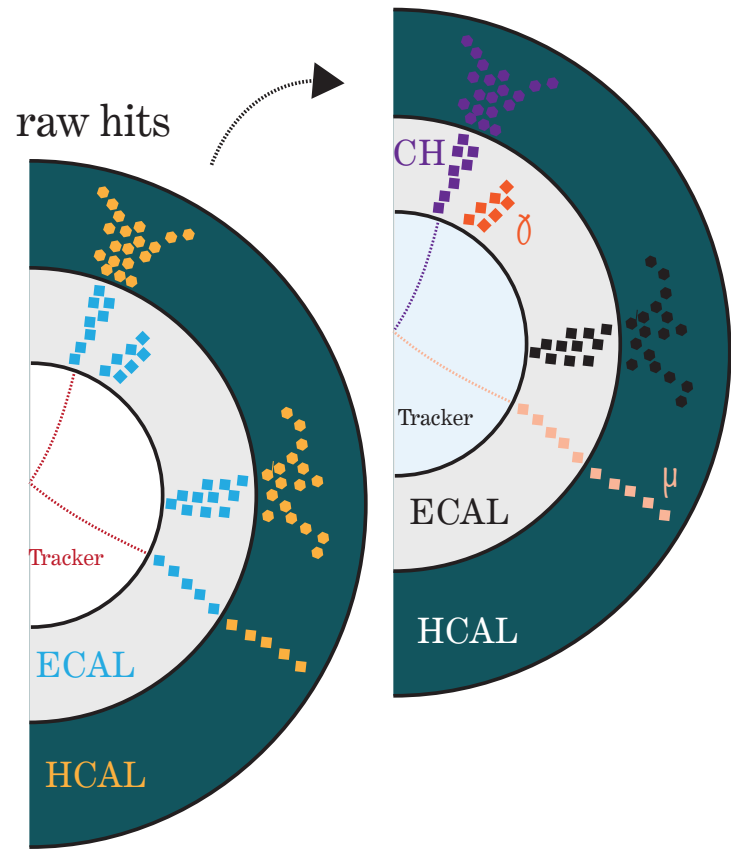
- 60% charged particles
- 30% photons
- 10% neutral particles

Superior System

- tracker
- ECAL
- HCAL

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

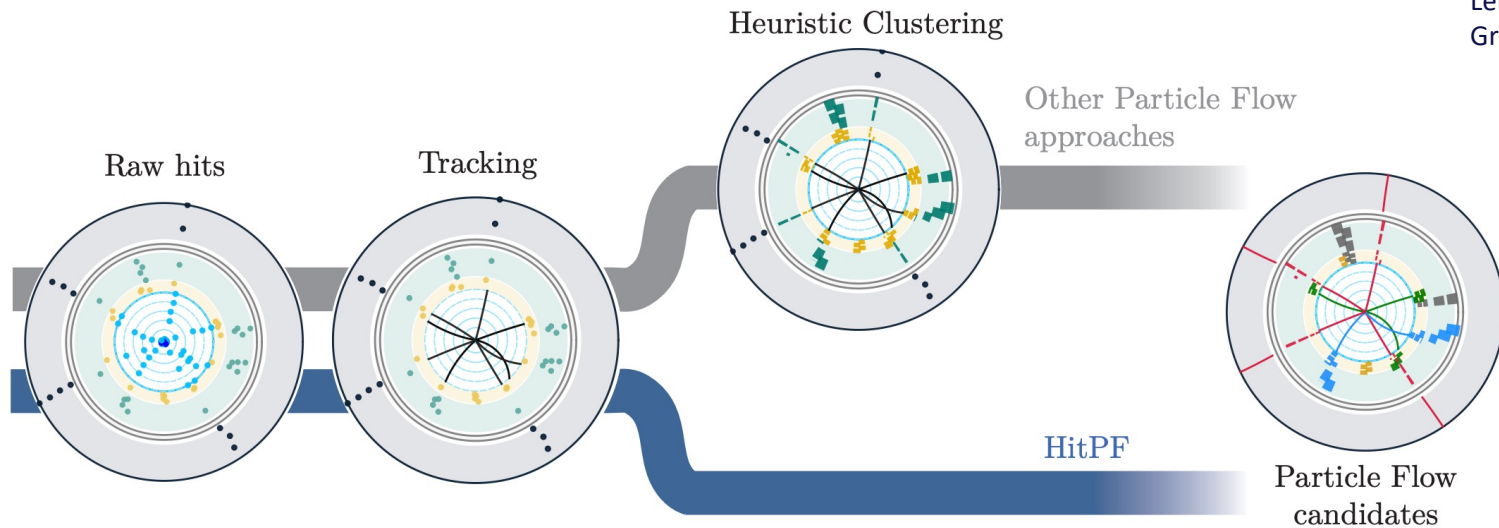
How to set it as an ML problem



Hit-based approach to Particle Flow



Michele Selvaggi
Lena Herrmann
Gregor Krzmar



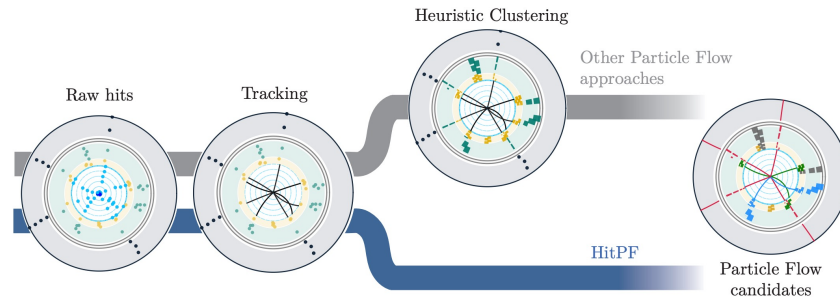
Comparison with other methods

Other PF approaches

- ❑ Require heuristic clustering step + cluster track matching
- ❑ Complex parameter tuning for new detector
- ❑ Requires geometry navigation

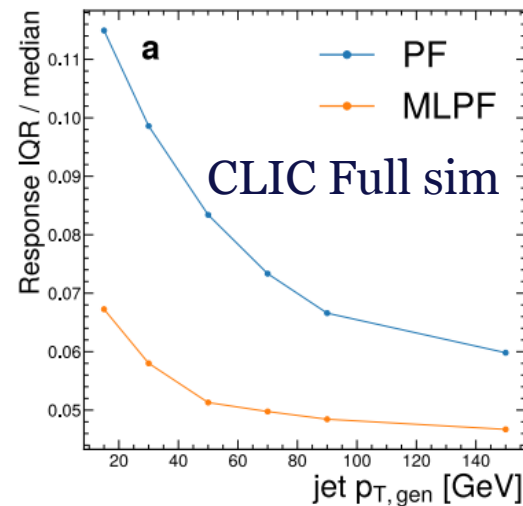
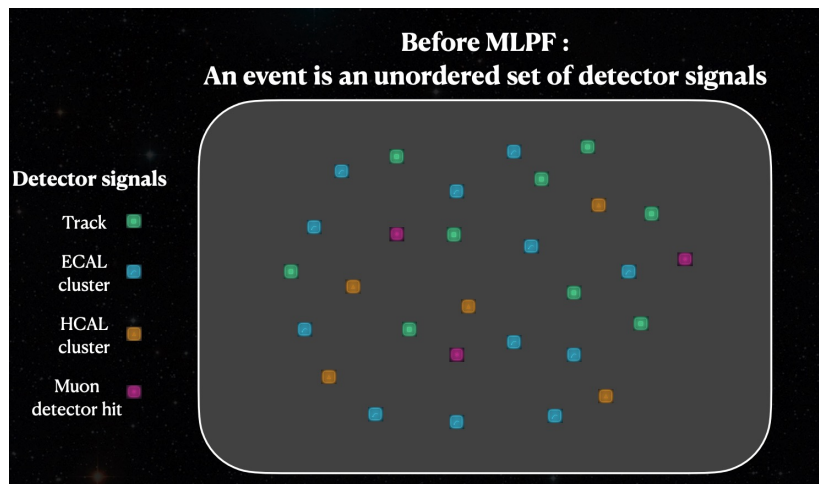
HitPF

- ❑ 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



J.Pata et al 2024

Know problem in ML

Classification



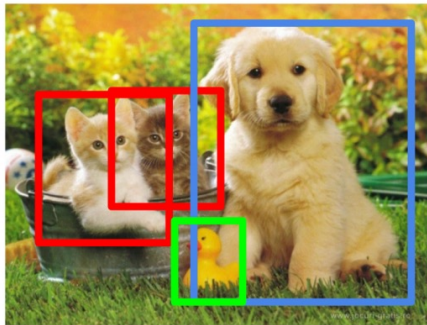
CAT

Classification + Localization



CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation

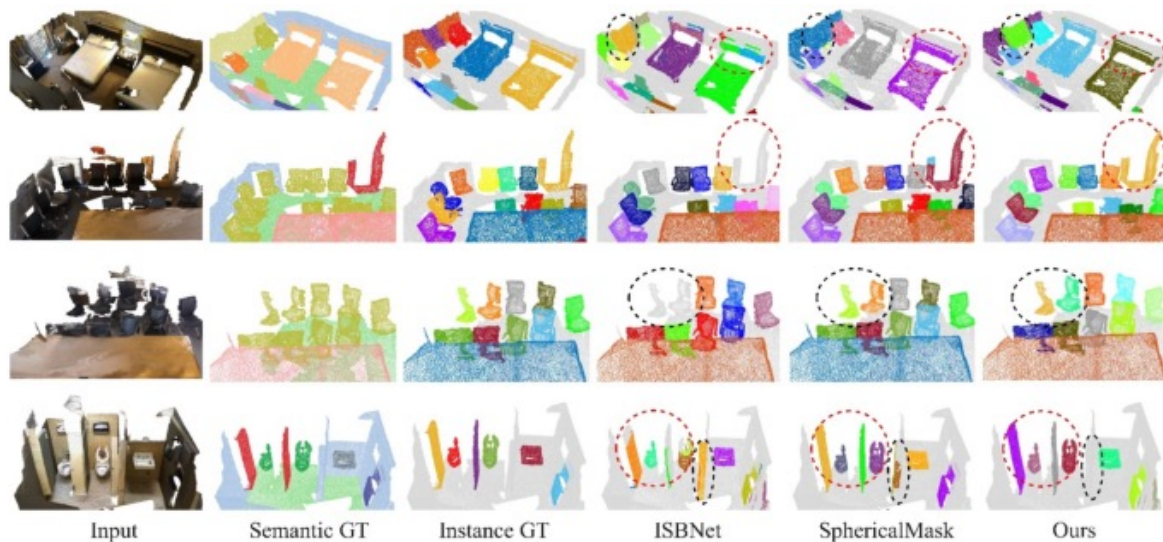


CAT, DOG, DUCK

Single object

Multiple objects

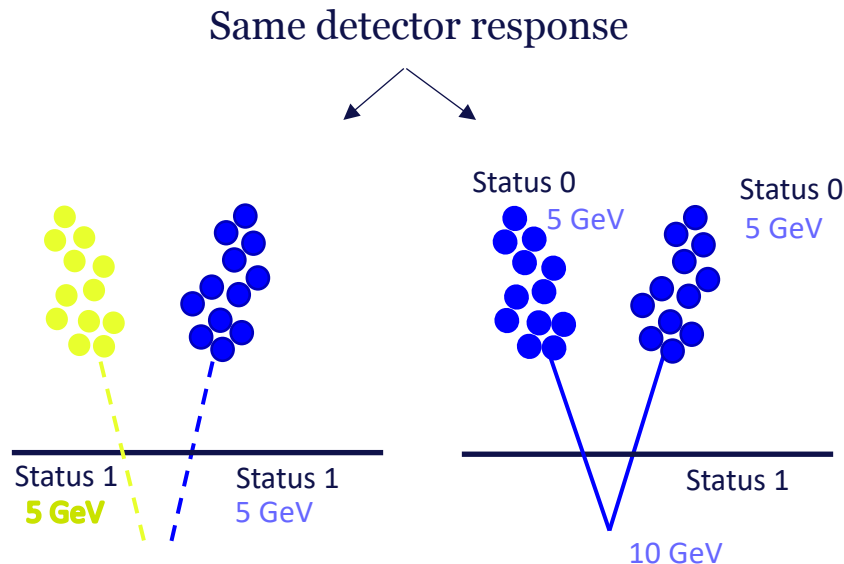
Know problem in ML



Supervision: Target definition

What is the best reconstruction target?

- ❑ Ideally, we would recover the stable particles that entered the detector (status 1) (previous studies)
- ❑ BUT this gives the algorithm conflicting training examples (why this is hard slide)
 - Conversions
 - Backscattering (clusters appear far in the detector)
- ❑ The **target** is defined as:
 - Resolvable detector objects
 - Ongoing work to add detector resolution
 - Defined in practice by the calorimeter boundary
 - This is what it is supervisable
 - And means that we are solving the L1 problem



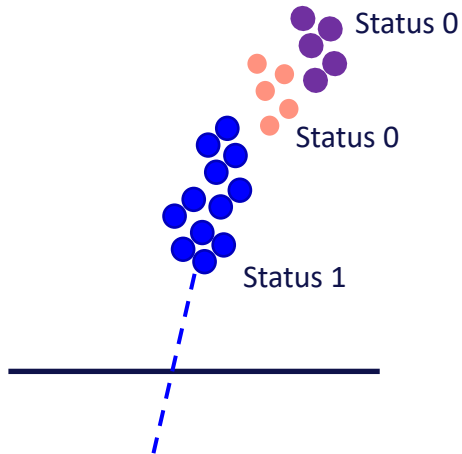
Different label?

Target definition

What is the best reconstruction target?

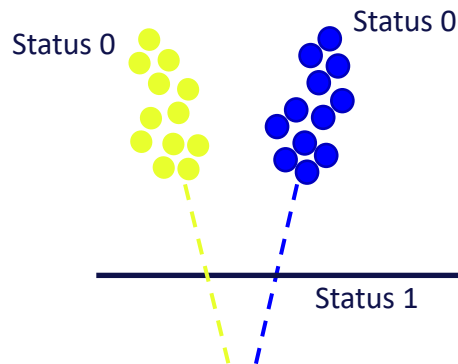
L0

- all Status 0 and status 1 particles eg. Hadronic showers resulting from nuclear interactions



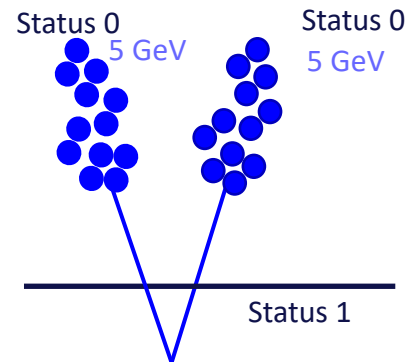
L1

- Calorimeter boundary abstraction
- Reconstruct two clusters for conversions, etc



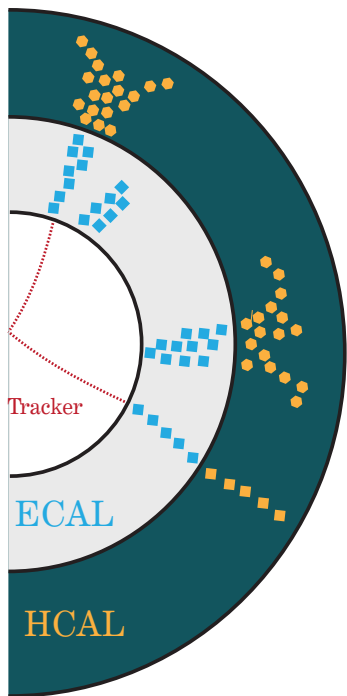
L2

- Status 1
- Complex topologies
- Brems, kinks, K_S^0



The workflow: Inputs

raw hits



● Track 'hits:
Reference point in calorimeter (position)
 $\mathbf{p}$ 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

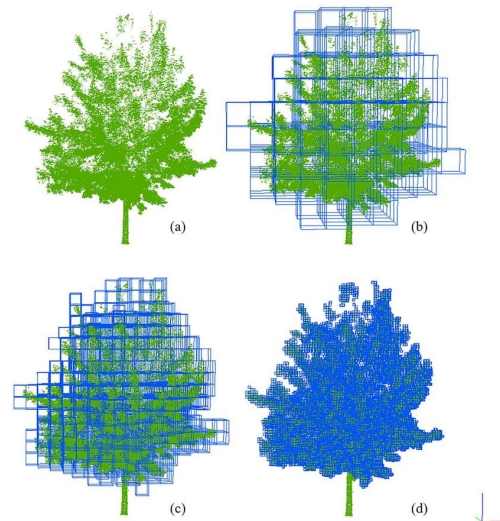
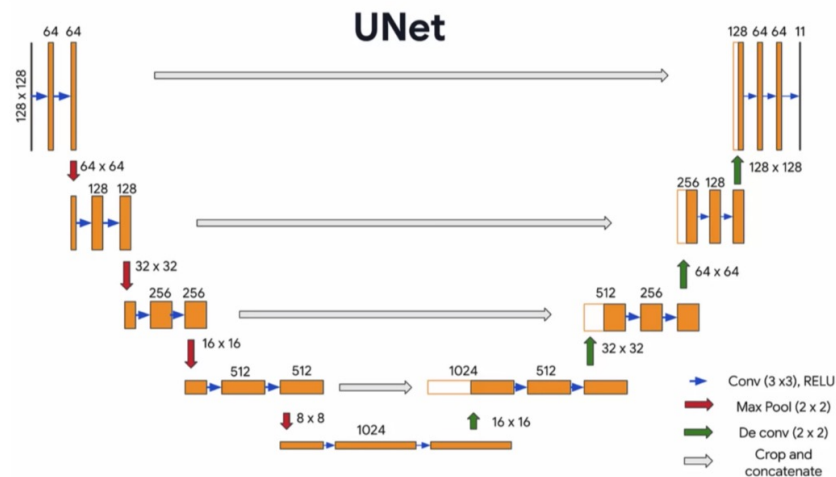
● Muon hit
Position (x,y,z)
E energy
Sub-detector ID

● Other sub-detectors?
eg. ARC

pointcloud

The 3D ML architectures

UNet backbone + with voxelization



Inductive bias

Assumptions about the **relationship between the input and output** of a learning problem that are built into the model

Can improve generalization

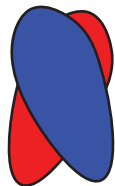
Can reduce required dataset size

Adapting ML methods to PF

Inductive bias

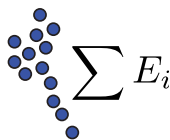
Self- intersections

No equivalent in 3D ML dataset



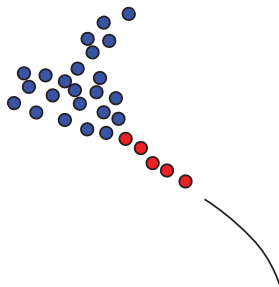
Multiple measurements in different subdetectors that 'add up' --> Optimal transport

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



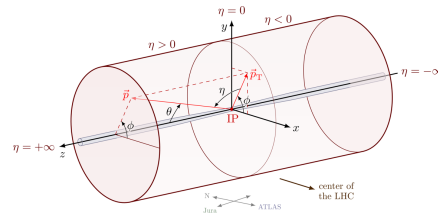
Need to preserve 'fine' structures in ECAL/tracker

Prevents voxelization and standard pulling operations



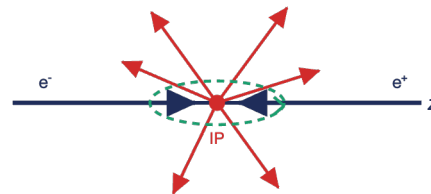
SO(2) + z mirror (endcaps)

~E(3) rotations, translations, and reflections



Beam direction

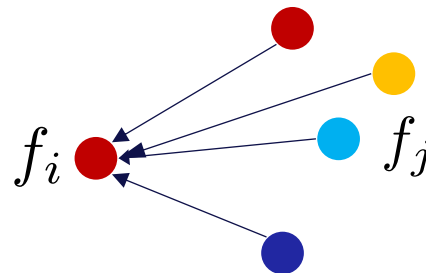
Preferred direction set by gravity



ML 3D data

Detector data

Model GNNs, transformers



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

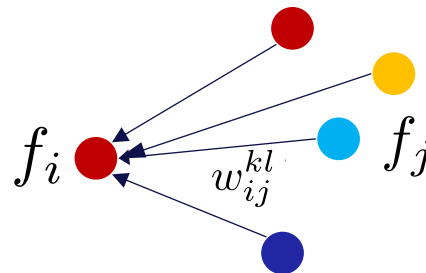
Building block 1

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

h_{Θ} 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

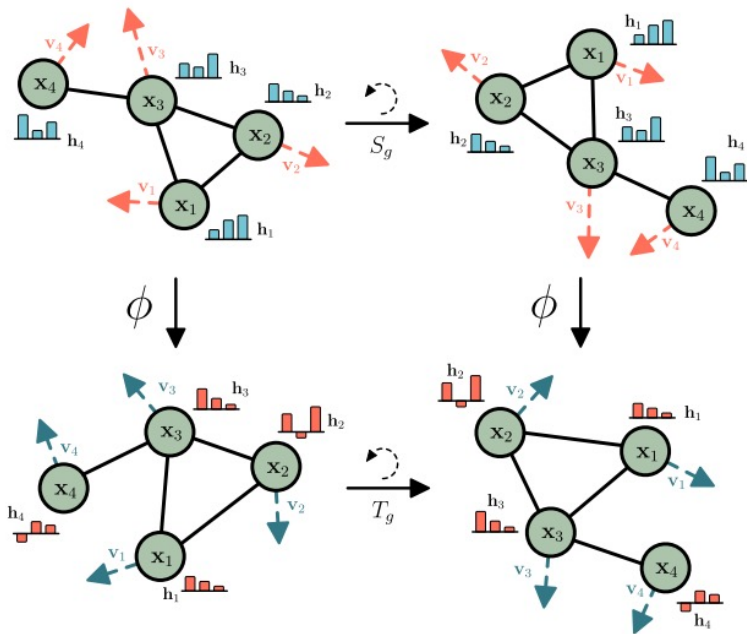
$$\square_{j:(i,j) \in \mathcal{E}} \longrightarrow f'_i = \sum_{j:(i,j) \in \mathcal{E}}$$

Non-linear function with learnable parameters

$$h_{\Theta} \longrightarrow h_{\Theta}(\mathbf{f}_i^l, \mathbf{f}_j^l) = w_{ij}^{kl} \mathbf{V}^{kl} \mathbf{f}_j^l,$$

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

Equivariant networks



Building block 2

A symmetry group $\mathfrak{G}$
 With a group representation

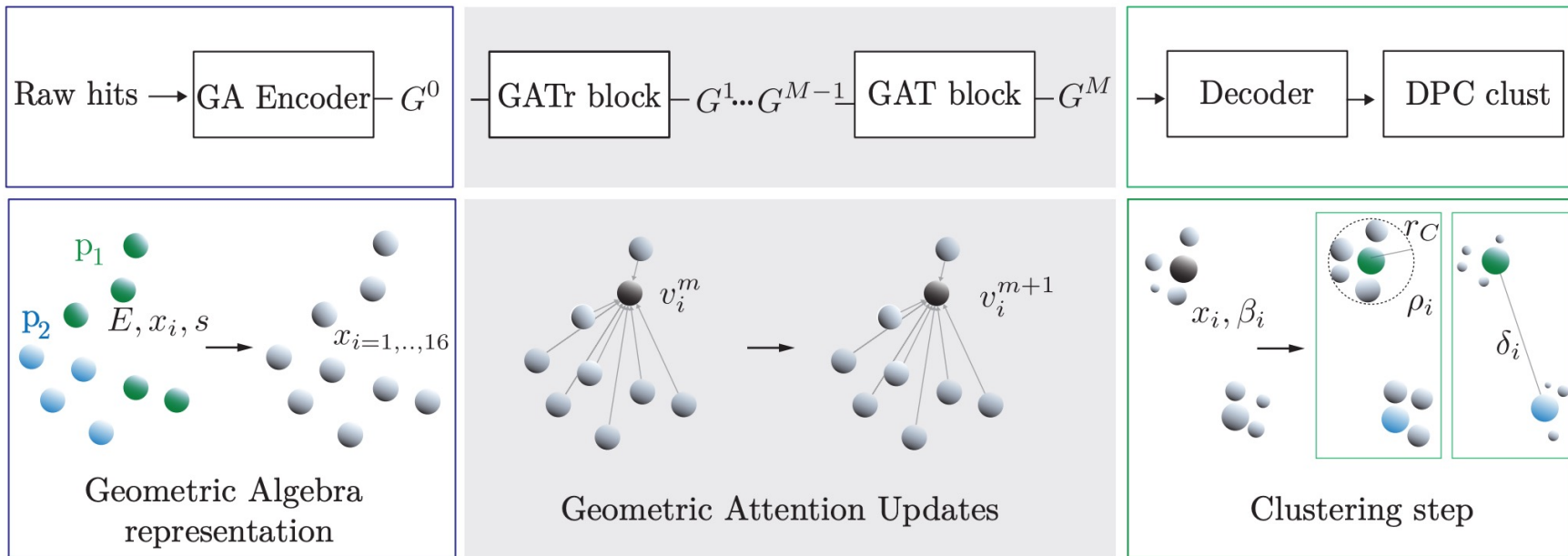
$$\rho : \mathfrak{G} \rightarrow GL(\mathcal{X}(\Omega))$$

Equivariant if

$$f(\rho(g)x) = \rho(g)f(x)$$

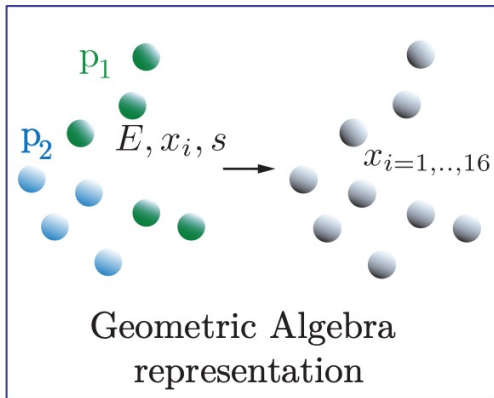
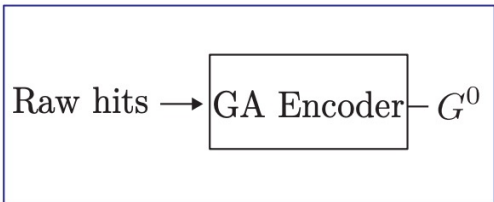
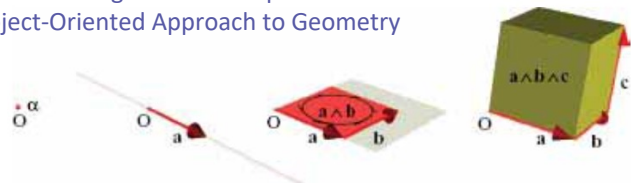
Figure from E(n) equivariant GNN

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
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

Equi
linear

K-blade projections, no grade mixing

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

Geo
bilinear

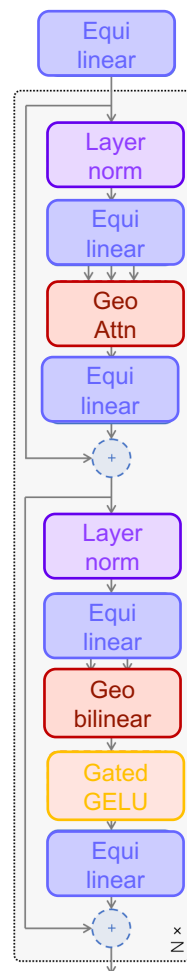
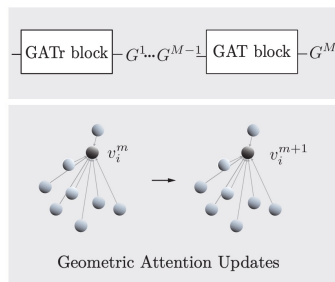
Geometric product $x, y \rightarrow xy = \langle x, y \rangle + x \wedge y \rightarrow$ grade mixing
Join product $x, y \rightarrow (x^* \wedge y^*)^*$

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

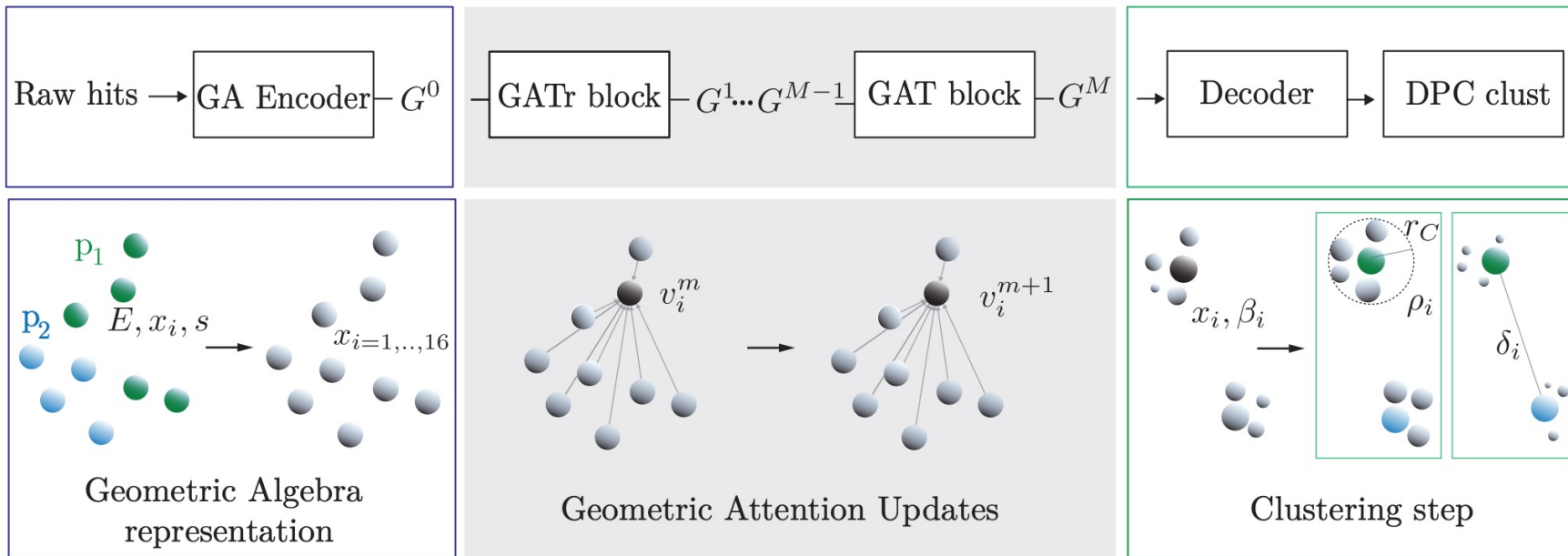
Geo
Attn

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

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

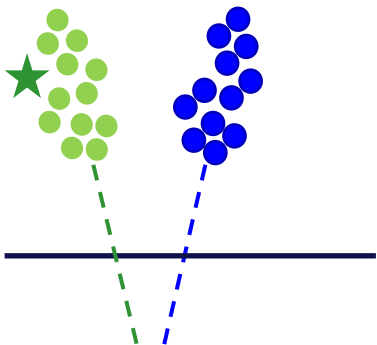


Geometric Algebra Transformer



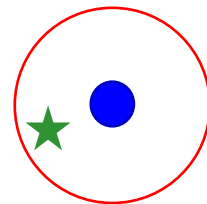
Loss: object condensation

Inputs (K=2)



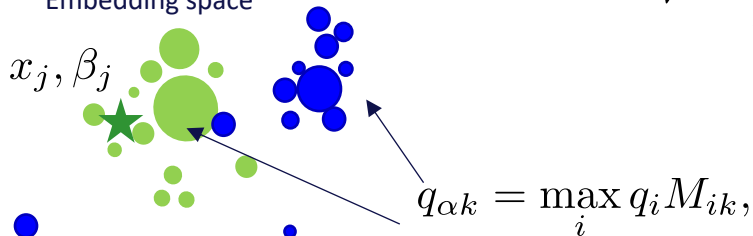
$$\star \bullet \quad \check{V}_k(x) = \|x - x_\alpha\|^2 q_{\alpha k},$$

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



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

Embedding space

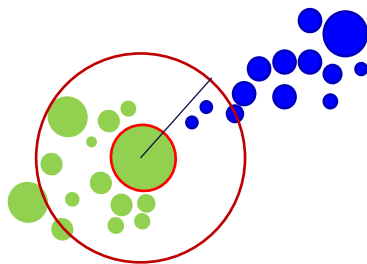


Clustering in embedding space

Two methods

Beta based clustering [1]

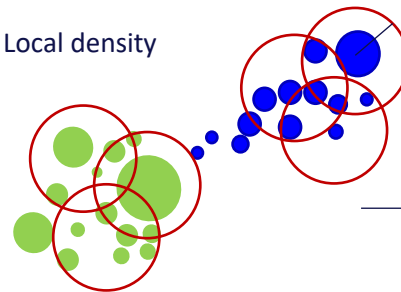
x_j, β_j



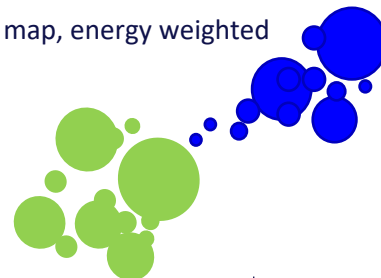
- Two parameters, $\beta_{\min}$, distance threshold
- Depends on good training of β distribution

Density Peak clustering [2]

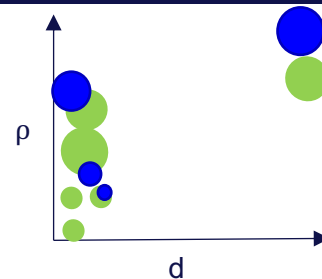
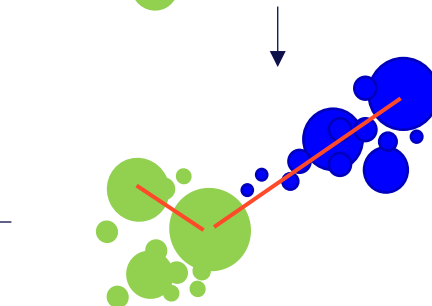
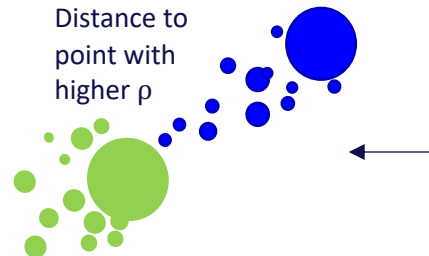
Local density



ρ map, energy weighted



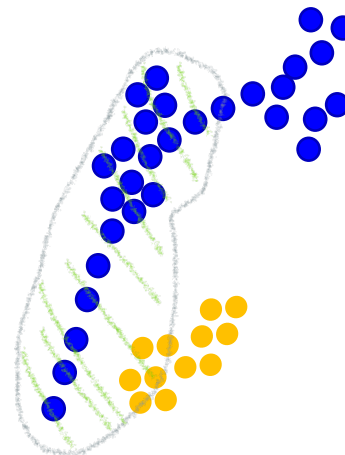
Distance to point with higher ρ



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

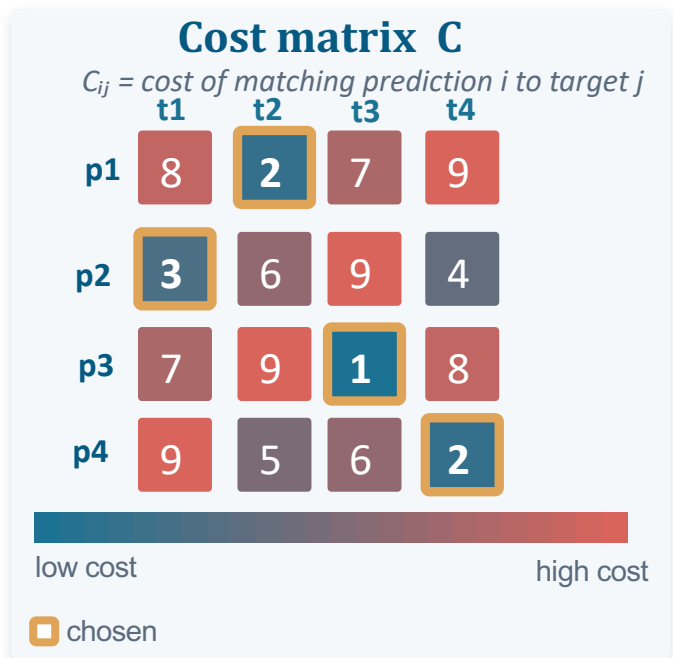
$$\text{IoU} = \frac{\text{Intersection}}{\text{Union}}$$

Matching

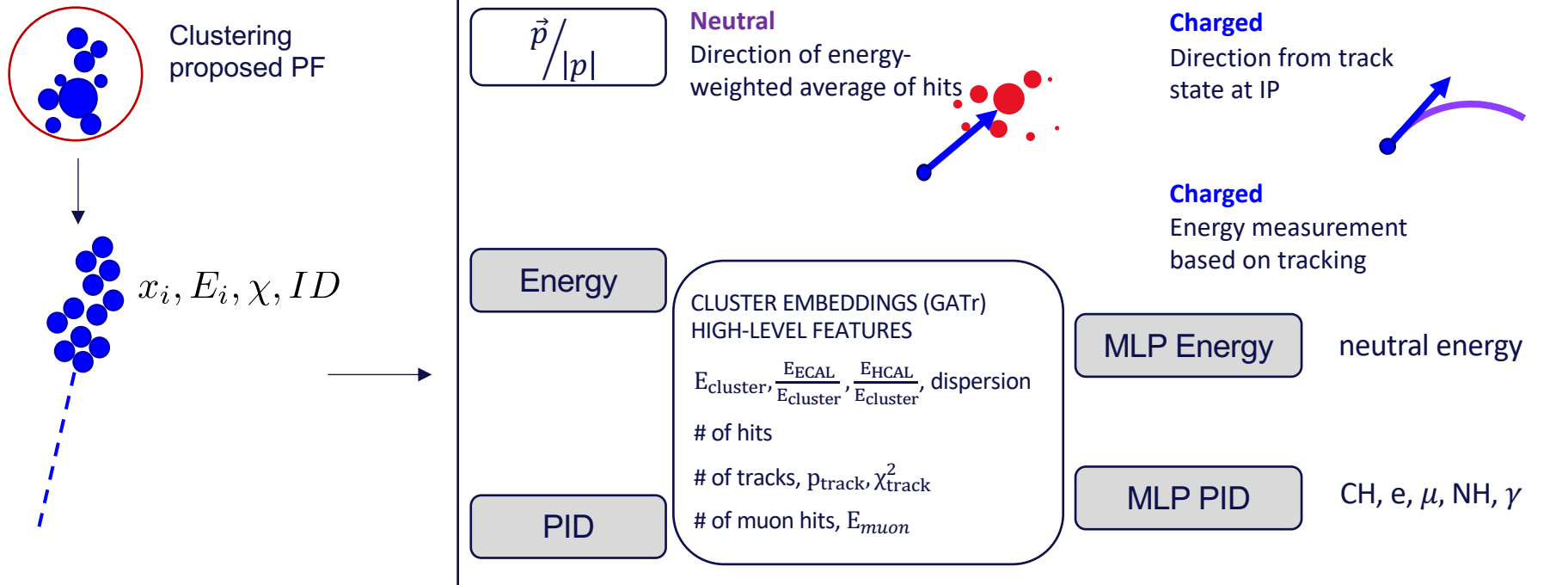
- We use a **Hungarian matching** to match a reco particle to a target particle with the intersection over union cost
- Builds a cost matrix
- One-to-one constraint
- Cost minimization

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



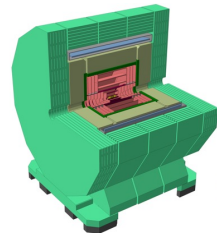
Regression & Classification

Per PF candidate property determination



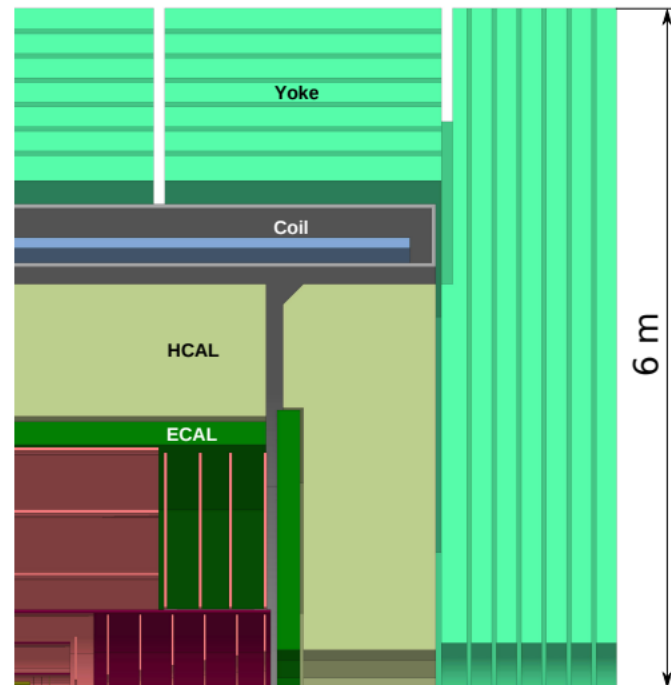
CLD a classic detector

Key4hep

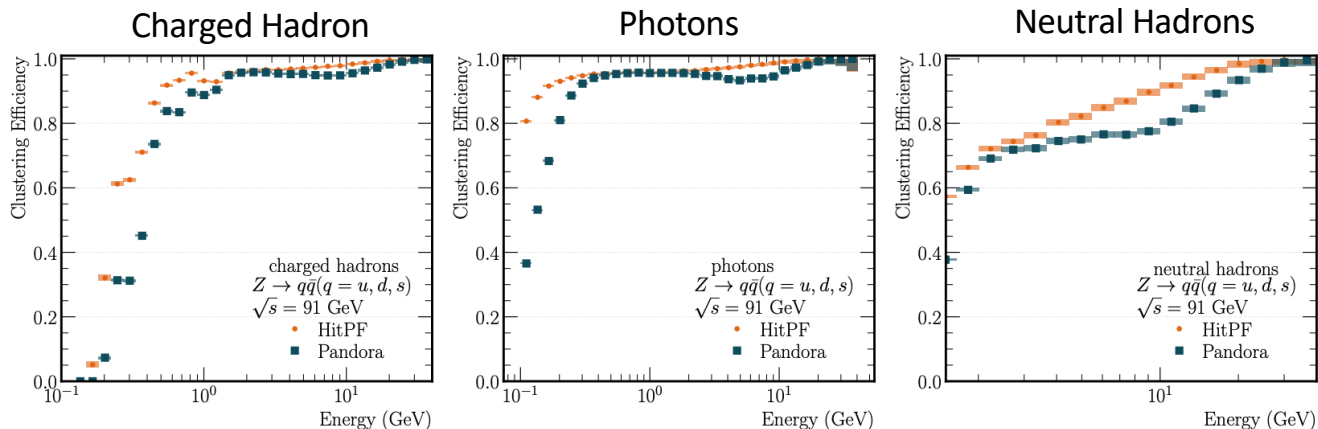


Full simulation

- ☐ Implemented in DD4hep
- ☐ Full simulation in Key4hep
- ☐ Comparison againsts 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



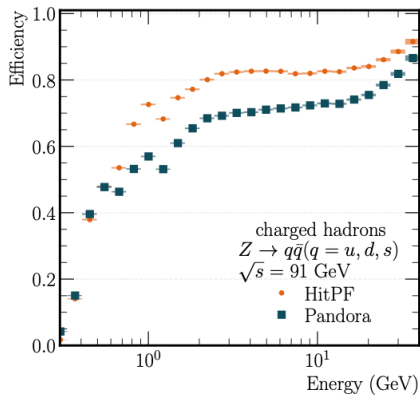
Clustering performance



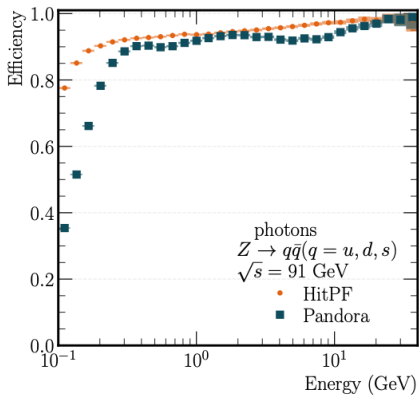
- It is efficient if for a given target particle it finds a reco particle (no PID), purely a measure of clustering performance
- vs the energy of the deposited hits (reco)
- Higher efficiency for all momentum range, substantial at energies below 1 GeV

PID: Efficiency and fake rate

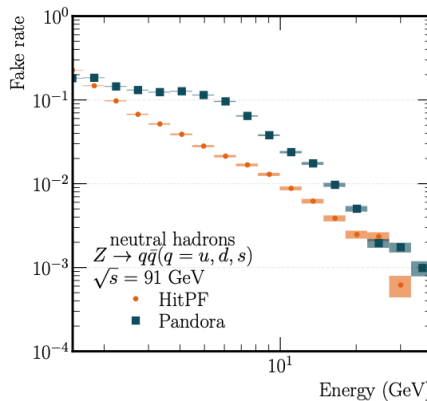
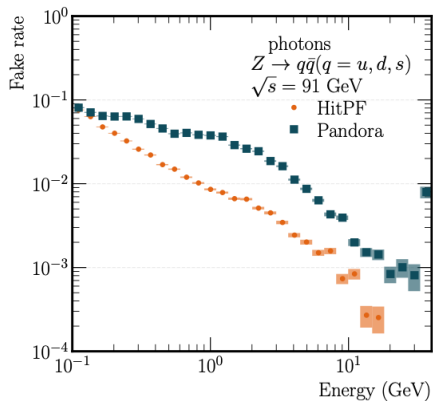
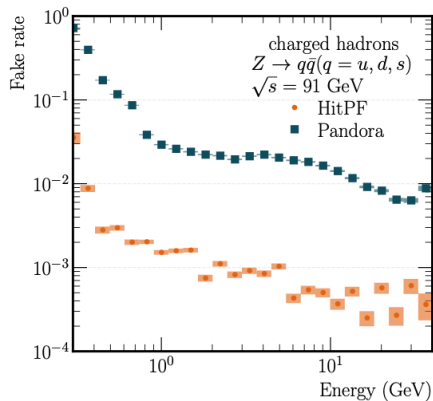
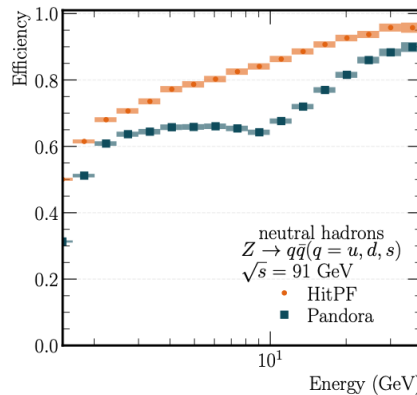
Charged Hadron



Photons



Neutral Hadrons



CH:

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

Photons:

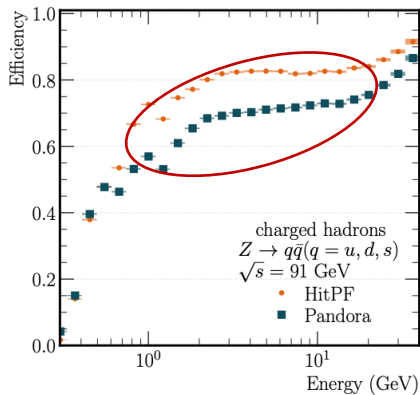
- ~5% higher eff. at high E
- Improvement by up to factor 2 for low E
- Fake rate up to $\sim \mathcal{O}(1)$

NH:

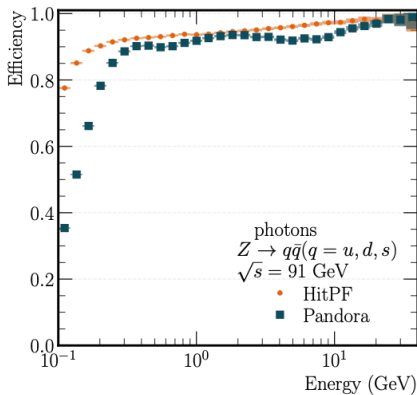
- Up to 20% higher eff. with Fake rate reduced by almost factor 5 in this region
- Better clustering (no fake clusters from splitting)

PID: Efficiency and fake rate

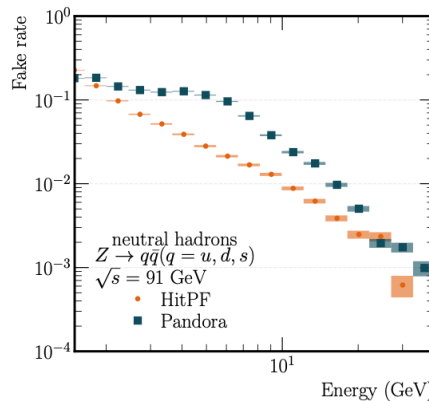
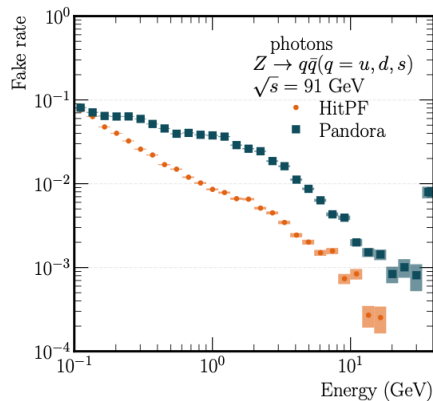
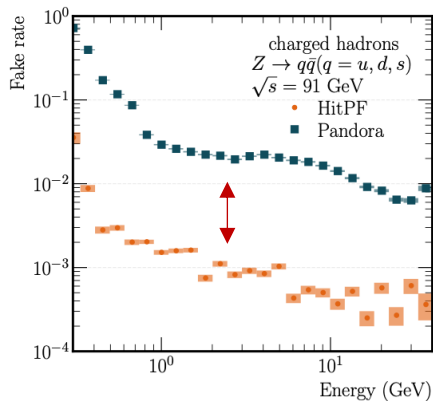
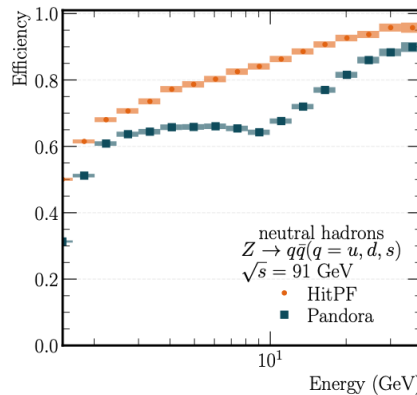
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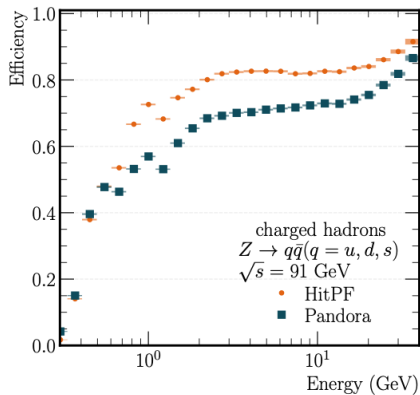
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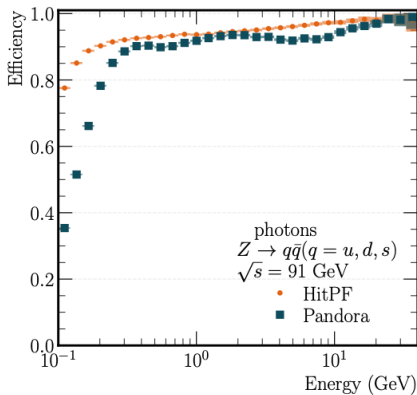
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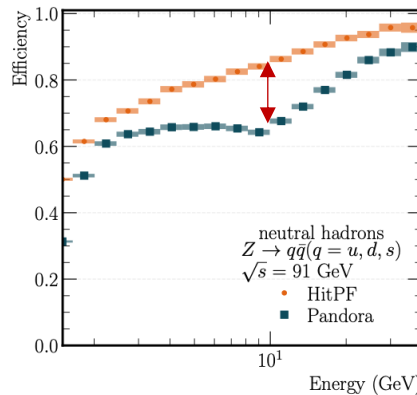
Charged Hadron



Photons



Neutral Hadrons



CH:

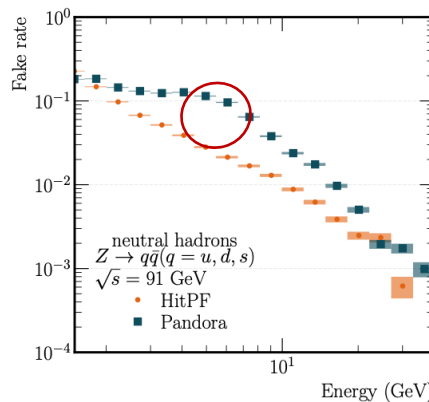
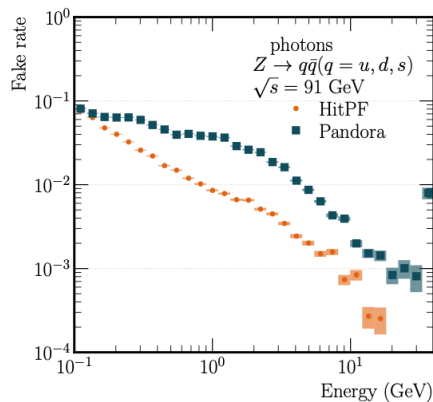
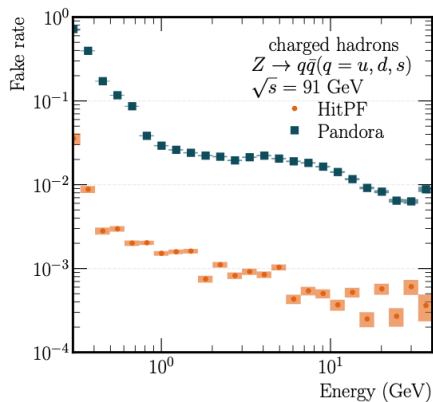
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Photons:

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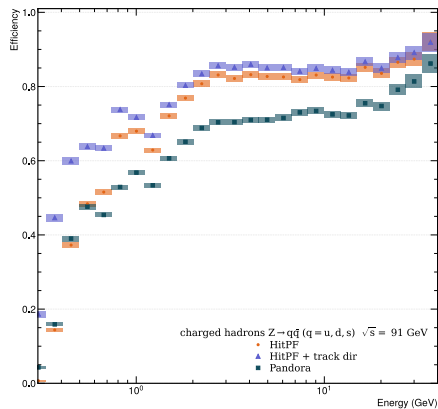
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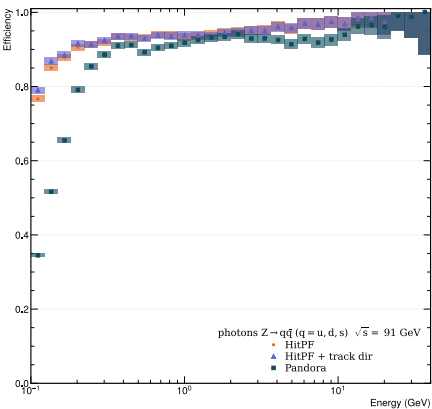


PID: Efficiency and fake rate

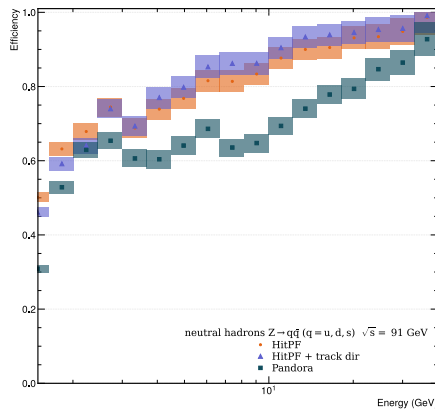
Charged Hadron



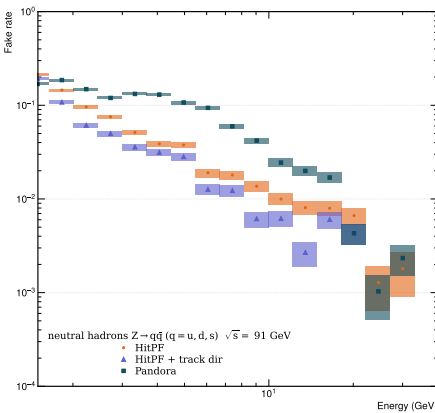
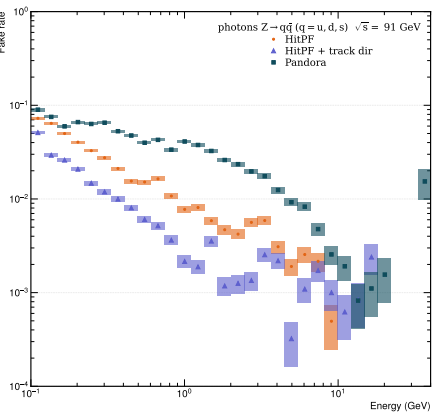
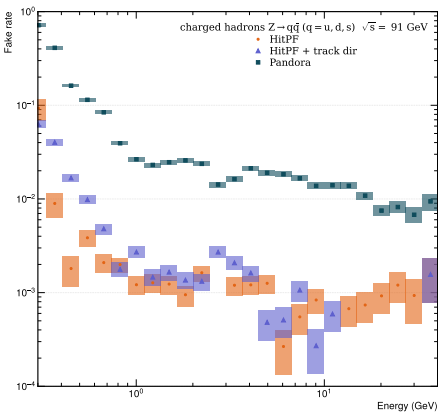
Photons



Neutral Hadrons

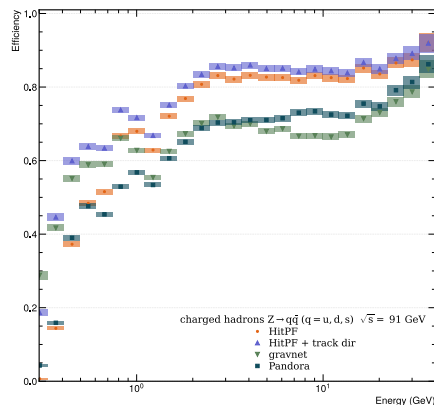


- Track direction at calo included as a vector in the GA.
- Improved efficiency and lower fake rate

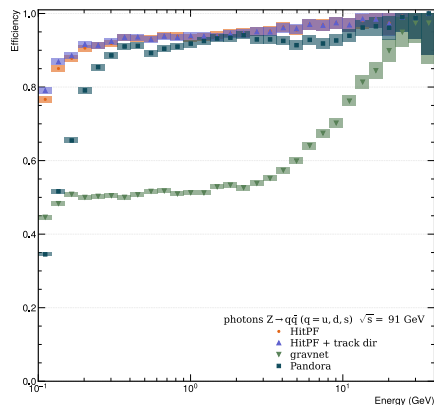


PID: Efficiency and fake rate

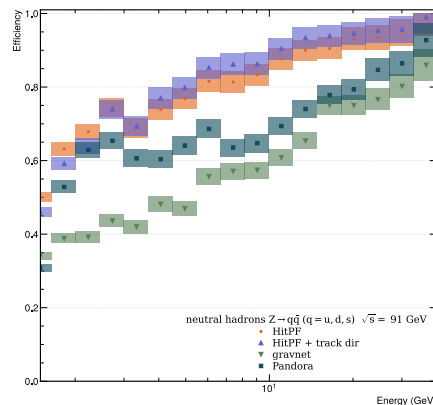
Charged Hadron



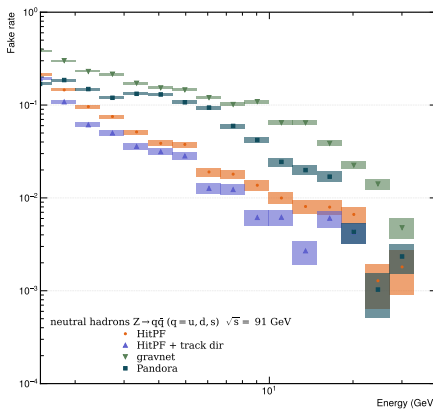
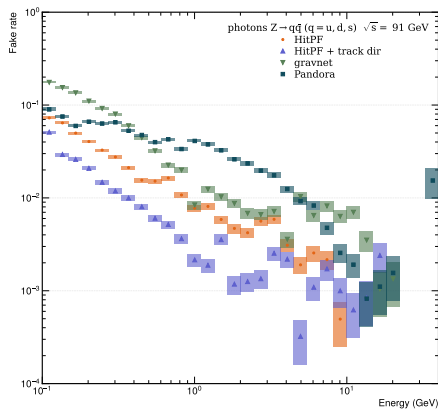
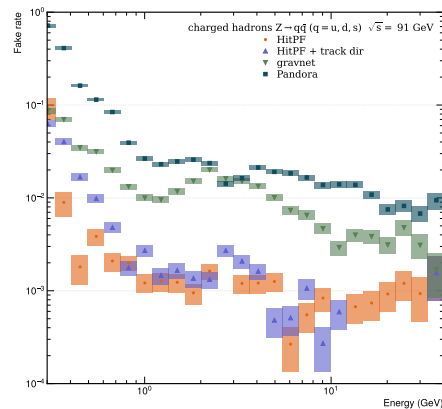
Photons



Neutral Hadrons

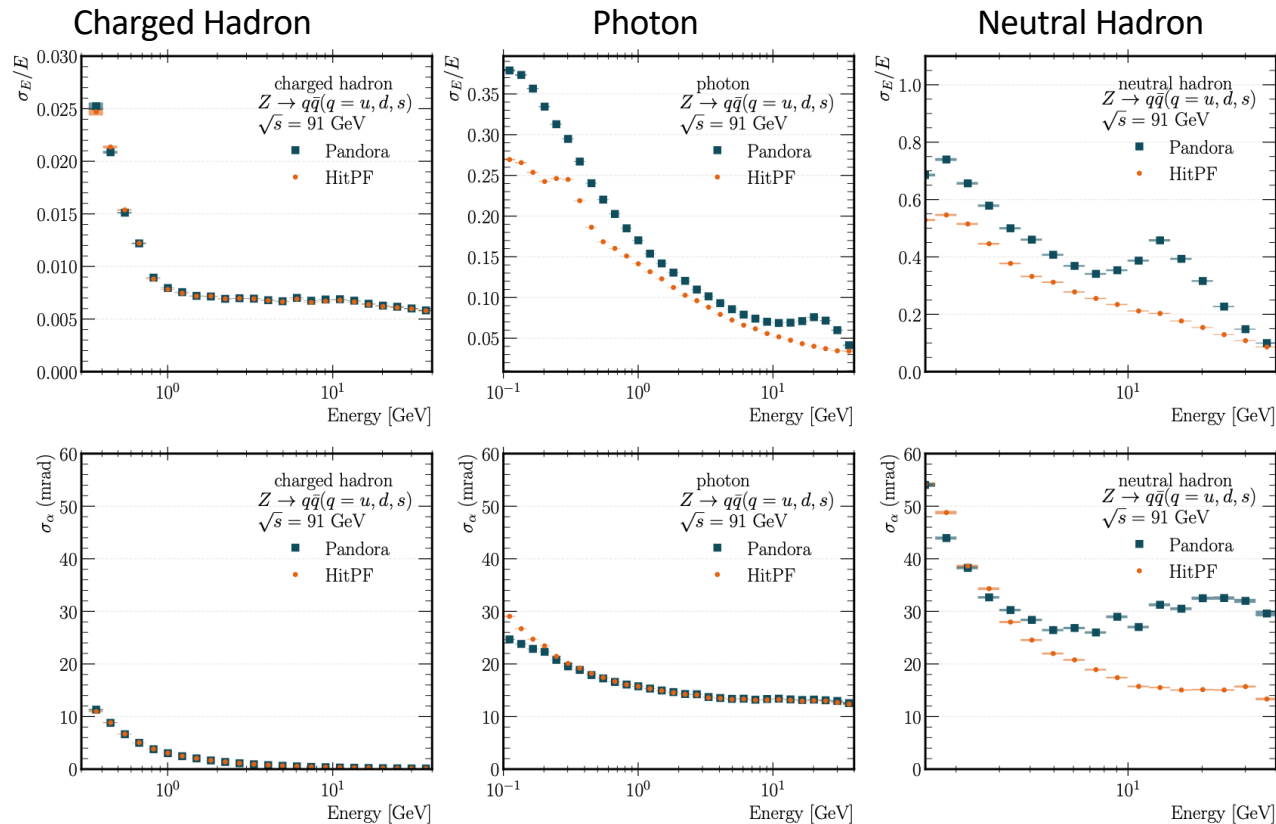


- ❑ Track direction at calo included as a vector in the GA.
- ❑ Improved efficiency and lower fake rate
- ❑ More 'classic' GNN architecture (Gravnet) does not achieve the same performance



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

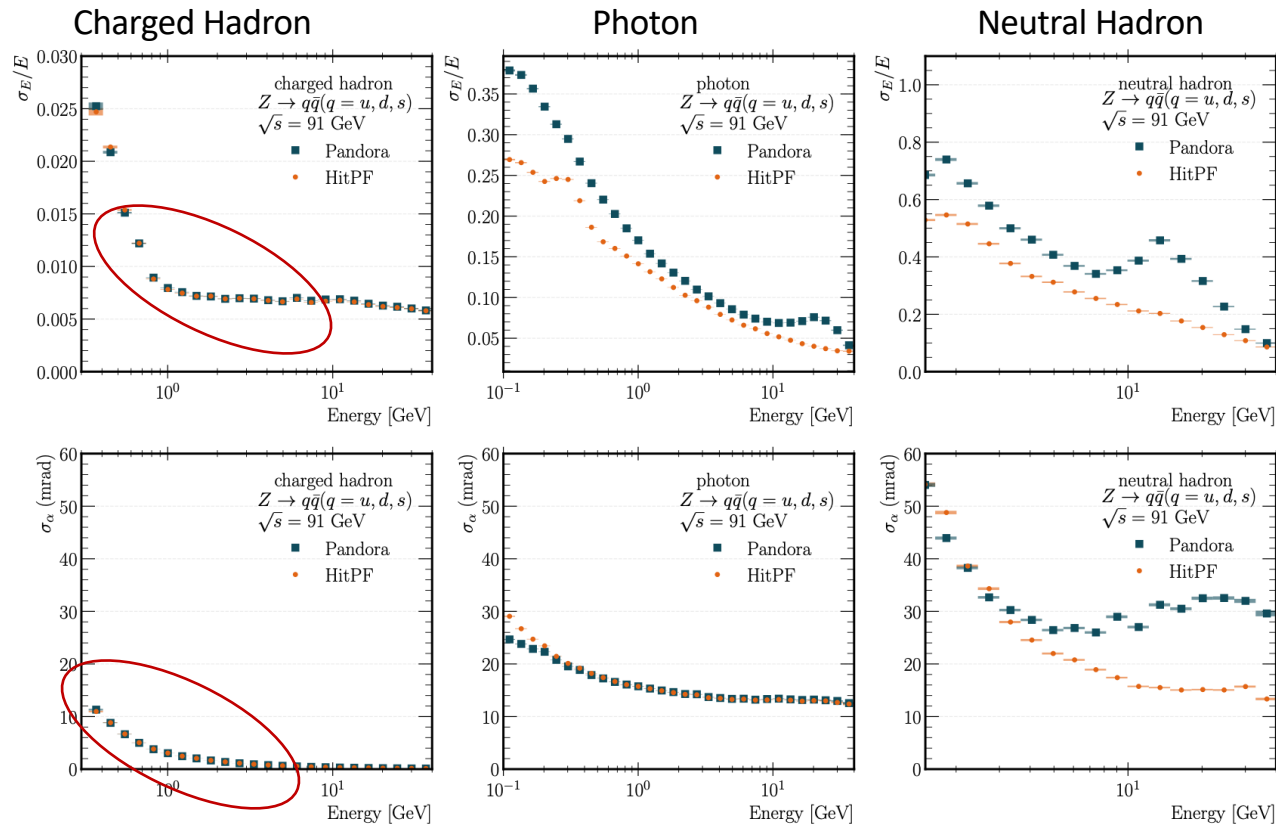
NH:

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

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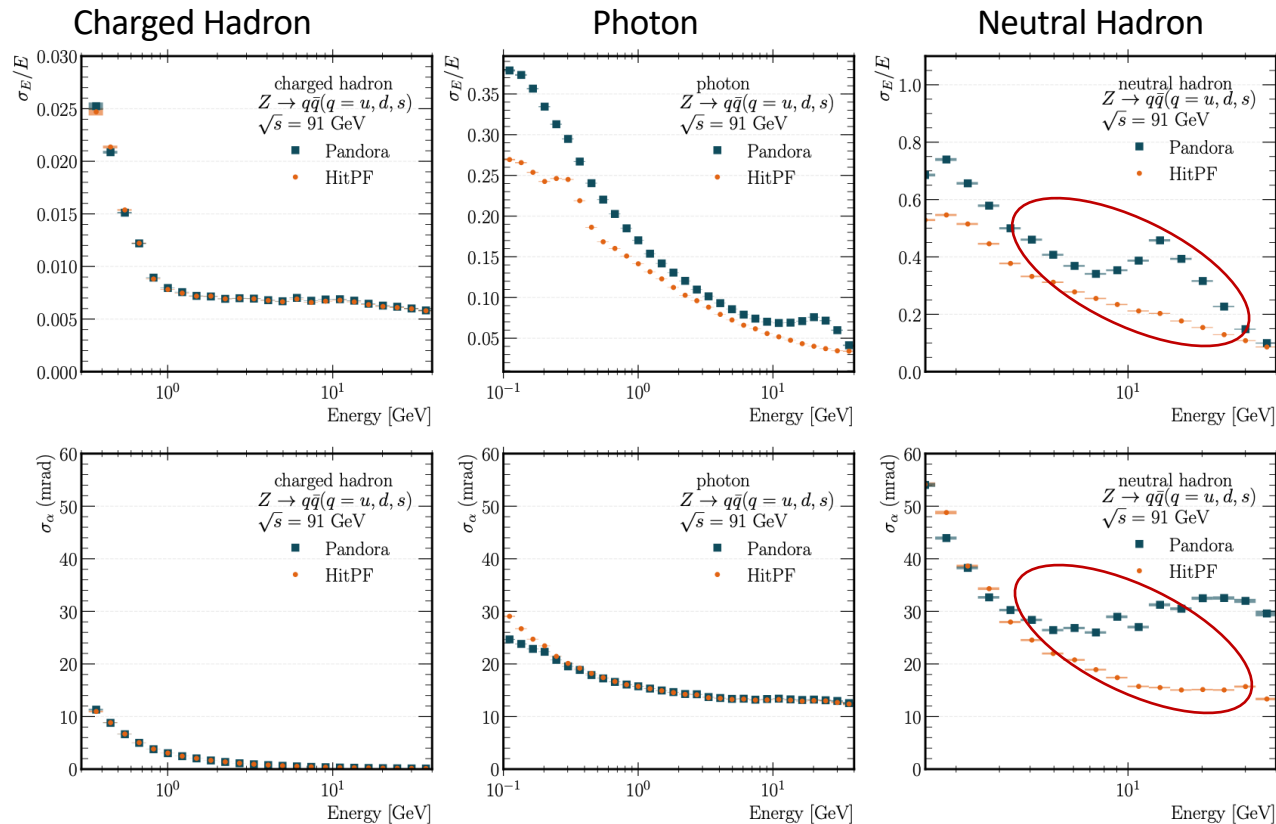
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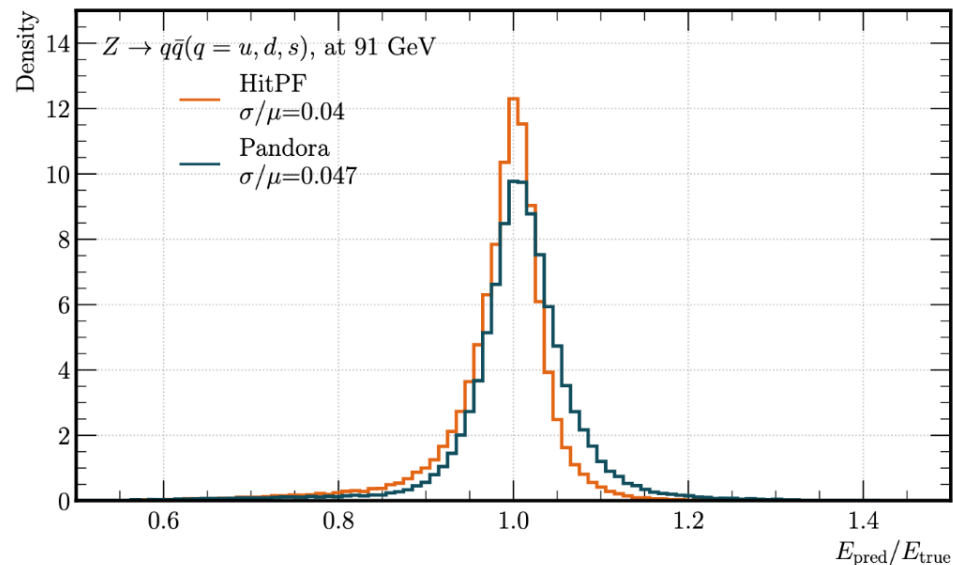
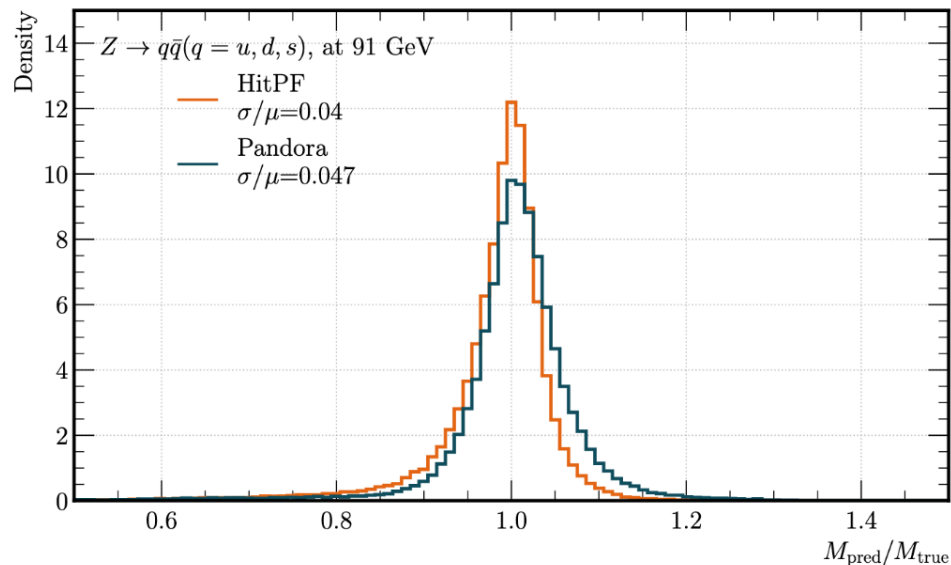
NH:

- **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

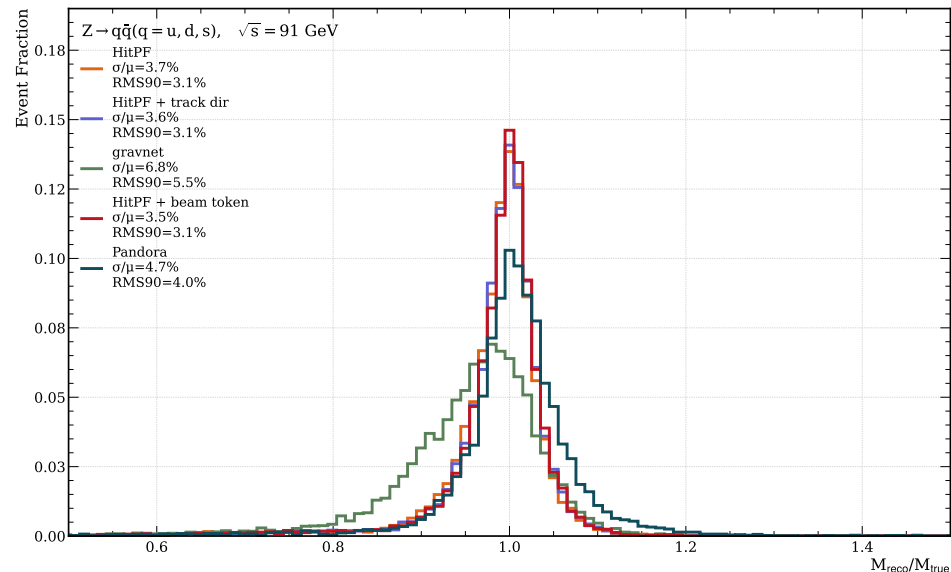
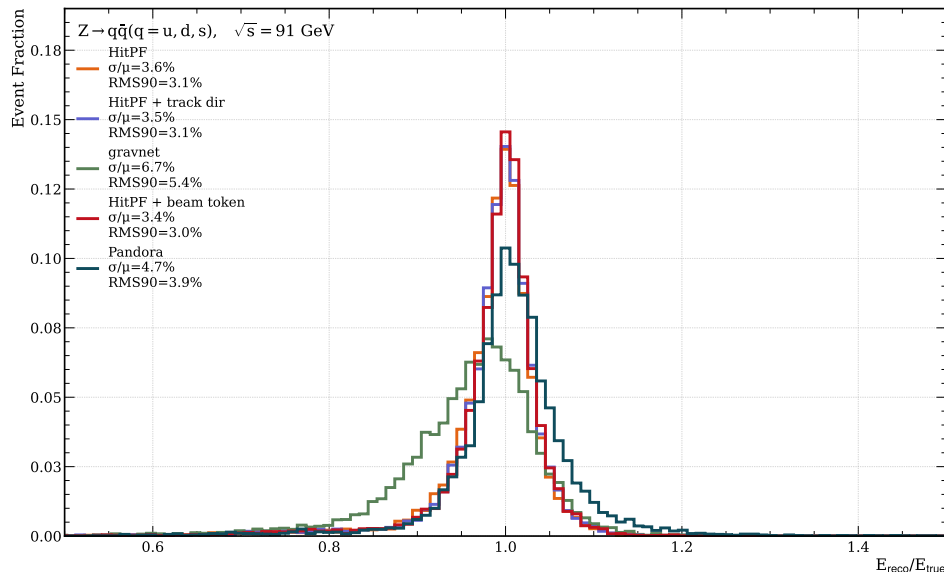
22% relative improvement
of HitPF compared to
Pandora



Visible mass and energy

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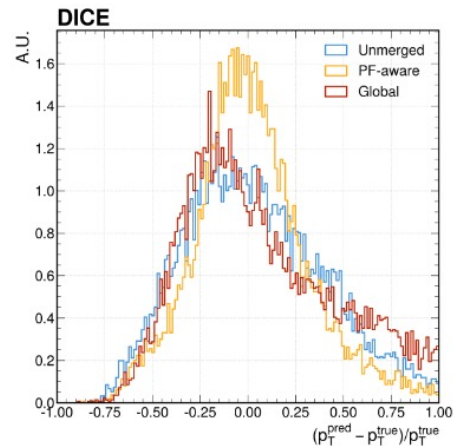
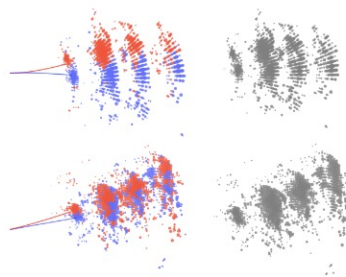
**26% relative improvement
of HitPF compared to
Pandora**



The impact of the truth definition

Detector aware-target

- ❑ Define a shower merging algorithm based on a resolvability score and a connection score
 - Resolvability: what fraction of shower is not shared
 - Connection: show strongly shower B overlaps with A
- ❑ Graph with sim showers as nodes and possible absorptions as directed edges
- ❑ Algorithm to determine merging steps



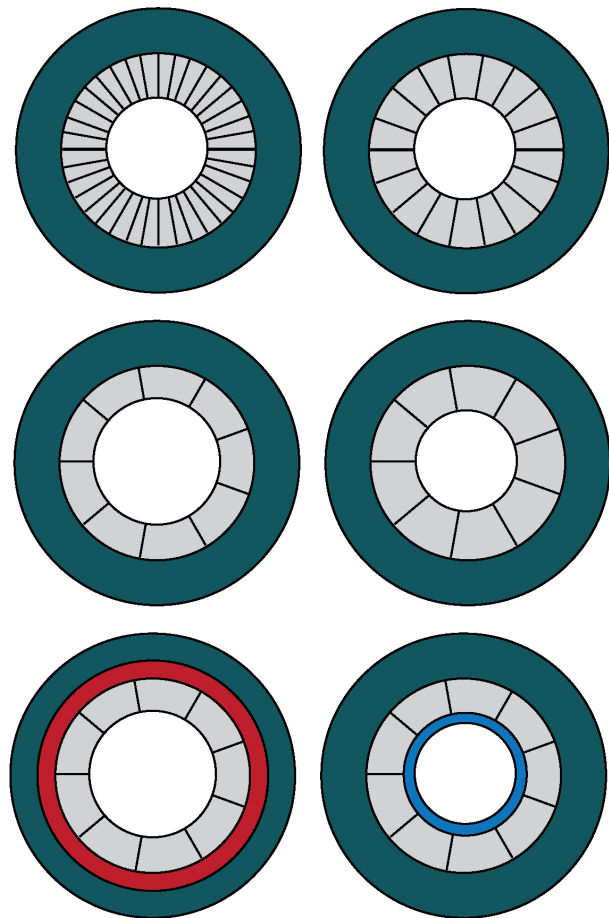
Transverse momentum response
in tau jet sample for models
trained with different target
definition



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

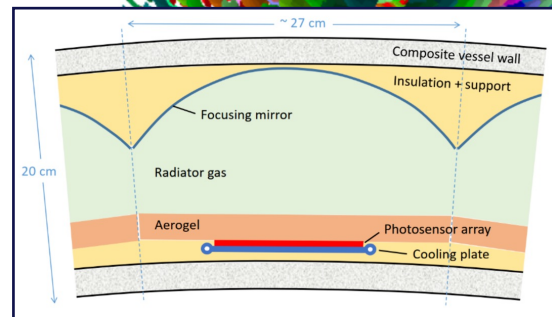
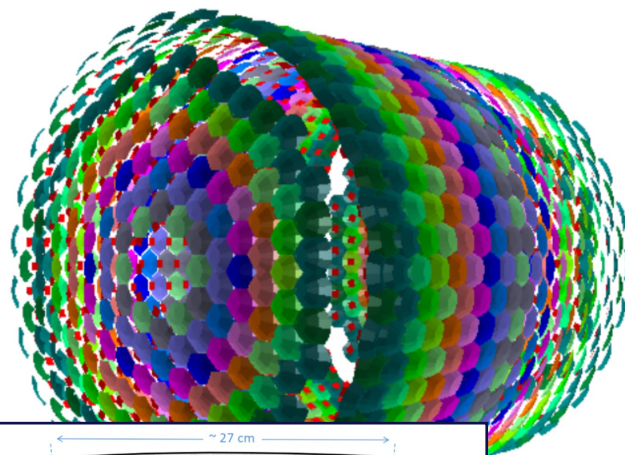


Impact of the ARC's material



Vincent Richers

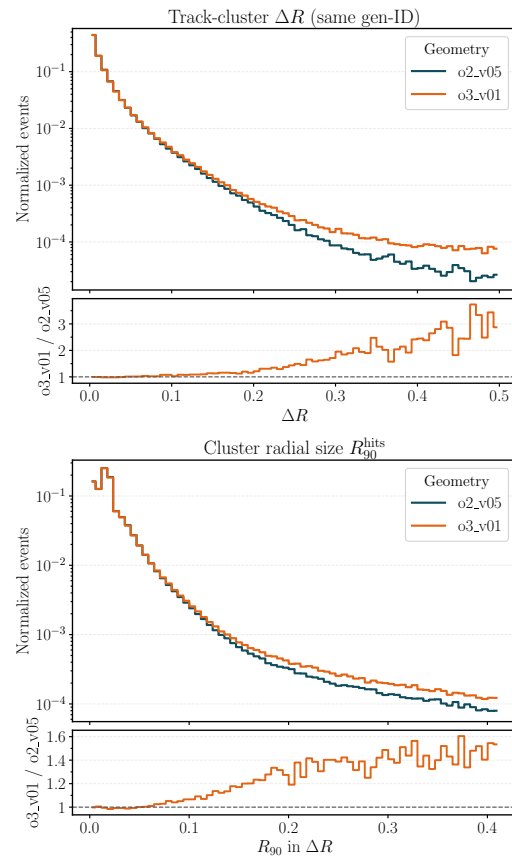
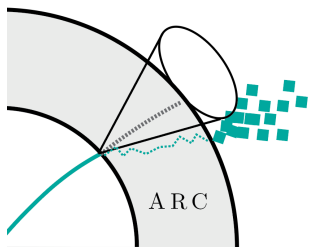
- ❑ ARC adds charged-hadron PID capability to CLD, but its integration places material upstream of the ECAL and compresses the tracker
- ❑ Compact RICH-based PID concept for charged-hadron separation ($\pi/K/p$) via Cherenkov radiation.
- ❑ Uses gas and aerogel radiators with spherical focusing mirrors and SiPM-based photon detection.
- ❑ Tracker is compressed to accommodate ARC: outer radius reduced from 2145 to 1900 mm. Studies have assessed impact on track resolution but not effect on PF



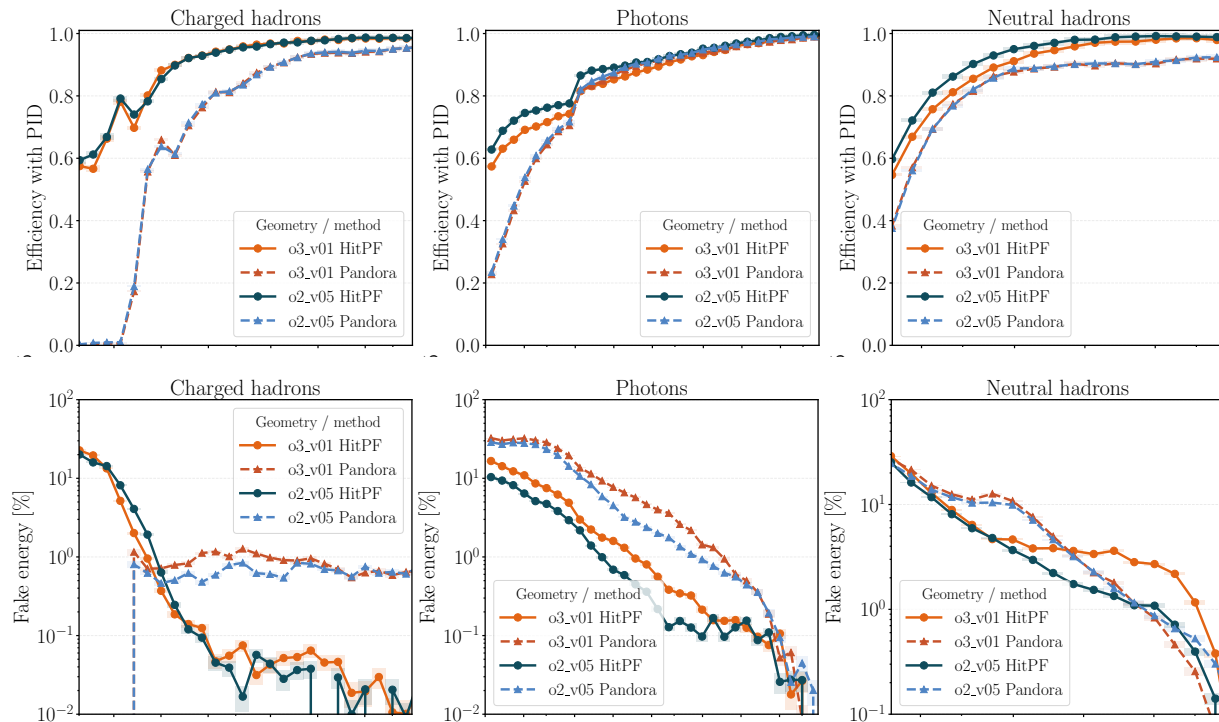
The ARC

Impact of the ARC's material

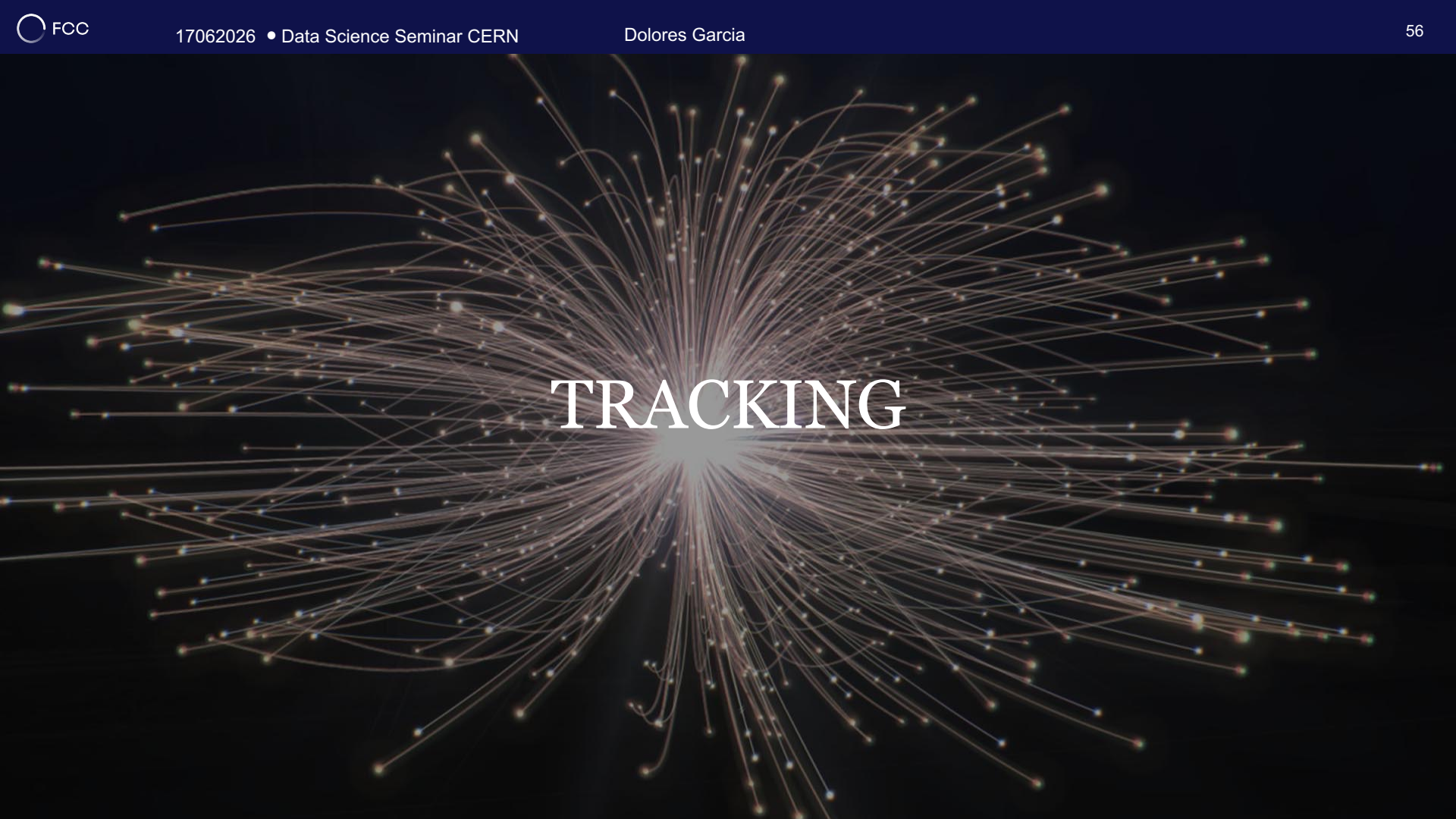
- ❑ Tracker is shrunk resulting in impact on momentum resolution [1] (track lever arm) (~15%) not necessarily a big impact on PF in itself
- ❑ But tracking-cluster linking might be impacted (multiple scattering)
- ❑ Tracking efficiency is also impacted
- ❑ R90 is impacted by earlier showering



Impact of the ARC's material



- ❑ Charged-particle reconstruction remains stable once tracking effects are controlled.
- ❑ The visible ARC impact is concentrated in photons and neutral hadrons.
- ❑ Photons and neutral hadrons show reduced PID efficiency, increased fakes, and broader response



TRACKING

Gaseous trackers

L.Centeno Gas trackers

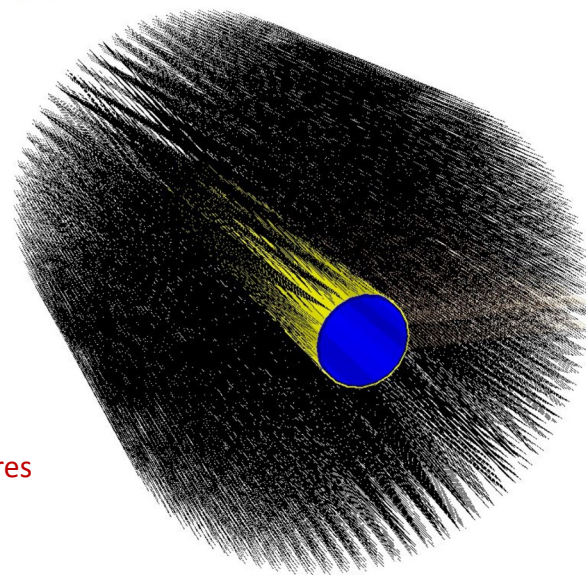
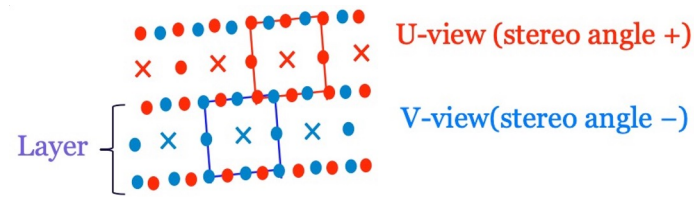
Why Gaseous Trackers?

Low material in tracking system

- ❑ Minimise contribution of multiple scattering (MS) to momentum resolution
- ❑ Favourable for Particle Flow

Continuous tracking volume

- ❑ Large number of hits beneficial for tracking combinatorics
- ❑ Enhanced sensitivity to displaced vertices
- ❑ PID capabilities via dN/dx (cluster counting)

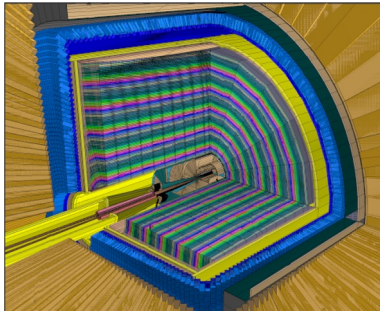
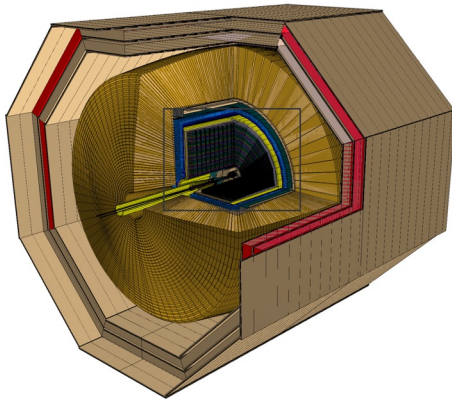


O(300k wires)
56 448 sense wires

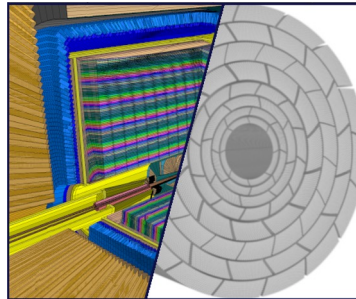
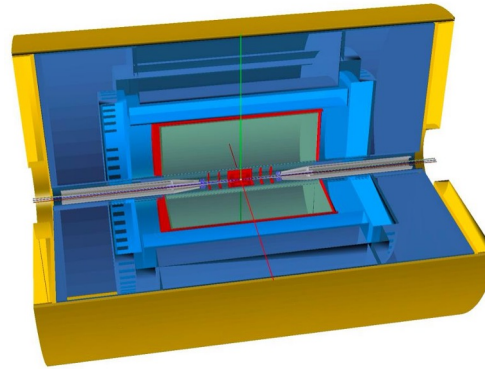
Gaseous Trackers in FCCee

L.Centeno Gas trackers

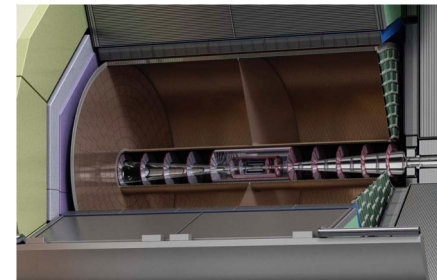
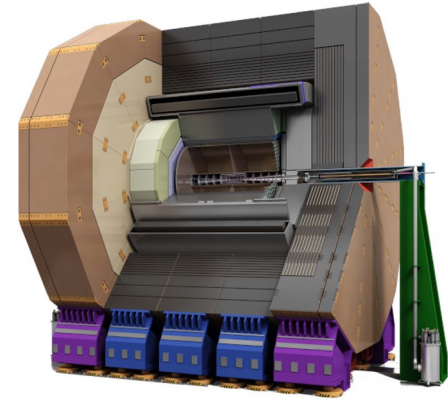
IDEA



ALLEGRO



ILD



Drift Chamber

❑ Drift chambers measure a charged particle's path by timing how long ionization electrons take to drift through a gas to sense wires:

- The particle ionizes the gas along its track, the liberated electrons drift in an applied electric field toward thin anode wires, and the measured drift time ($\times$ known drift velocity) gives **the distance of closest approach to each wire**
- The **z coordinate** obtained from stereo angle and the difference in signal arrival times at the two ends of the wire
- Hits are 'isochrones'

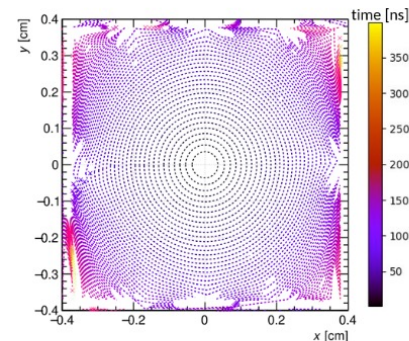
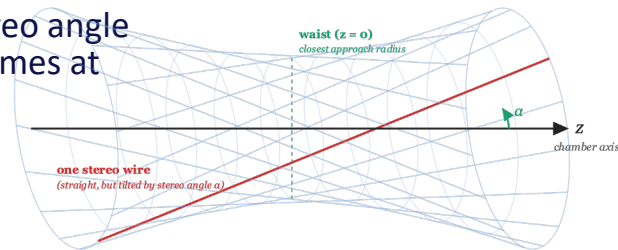
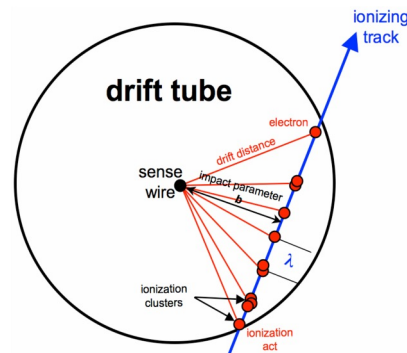
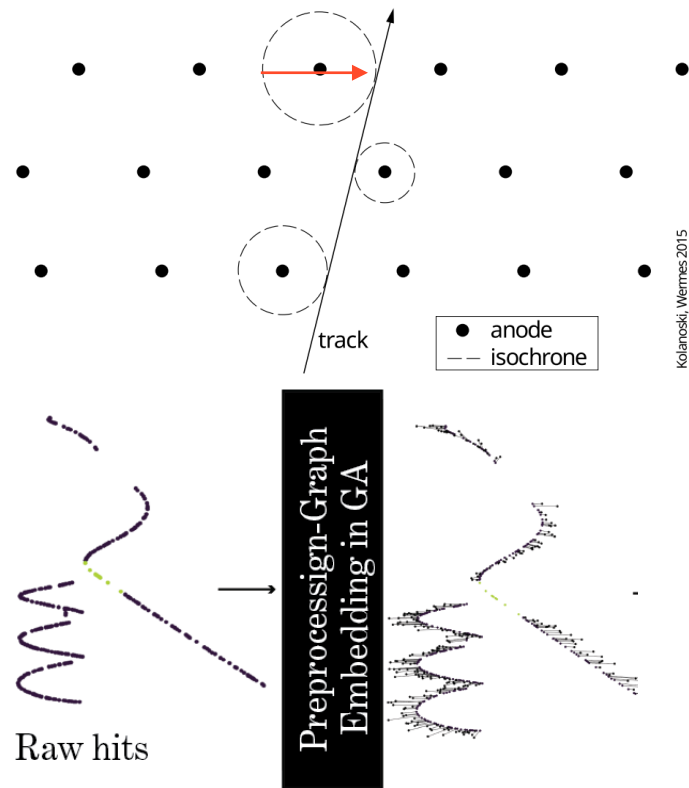
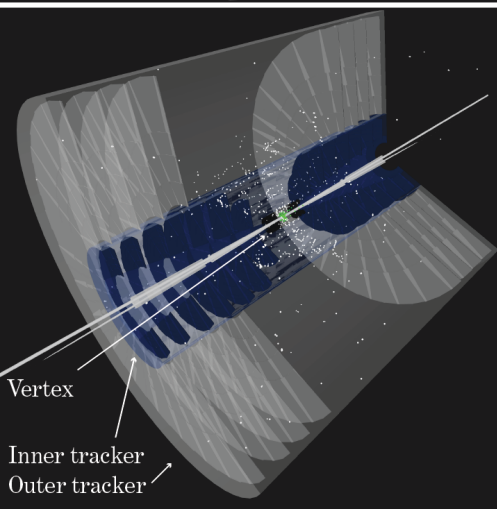
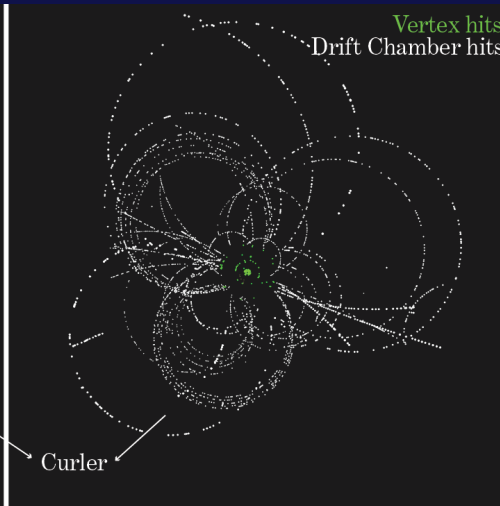
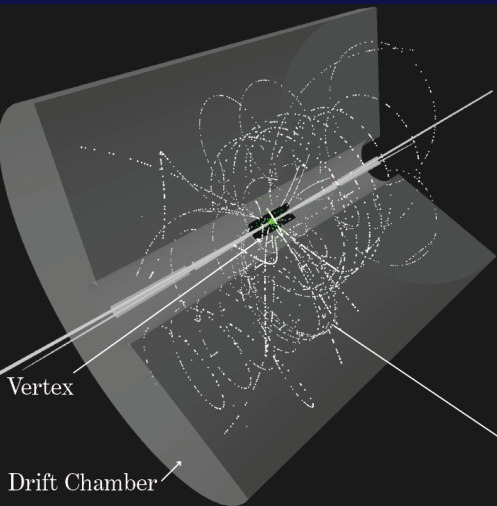


Figure 15 An example of the lines connecting points with the same drift time towards the sense wire ("isochrones").

The workflow: Input representation

- ❑ The geometric algebra representation allows for the left right hit ambiguity in pattern recognition
- ❑ Encoded as a vector (choose direction L to R)
- ❑ A new conformal algebra representation allows to input the circle (the 'natural' representation)
- ❑ Ongoing work Marko Cechovic et al. FCC week 2026 Poster.

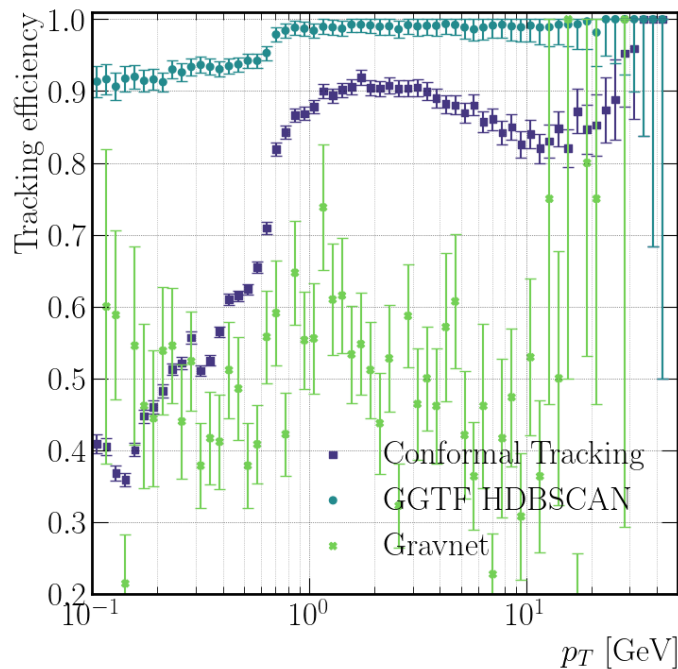
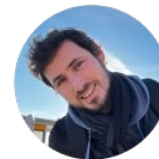




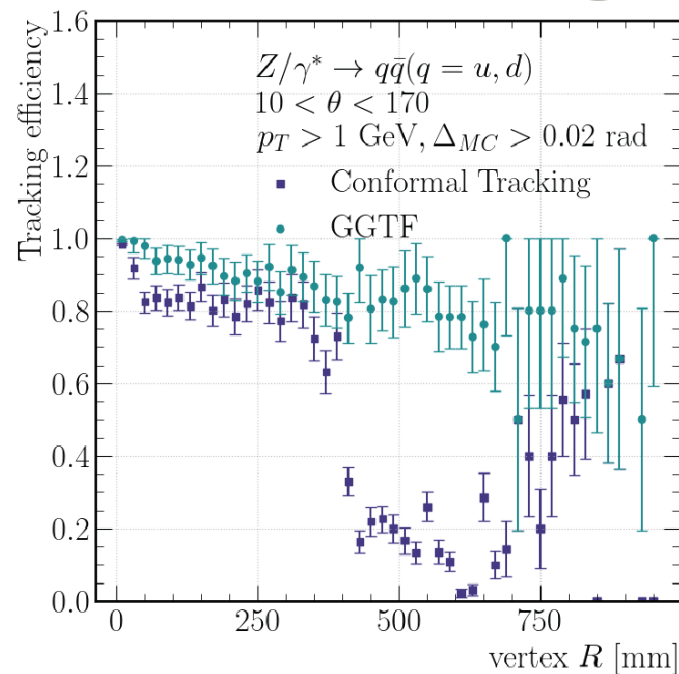
The workflow: Inputs

-  Vertex detector hits
 - Position
 - Type
-  Drift chamber hits
 - Position (left right)
 - Type

Comparison to other methods



Comparison to GNN without geometric bias

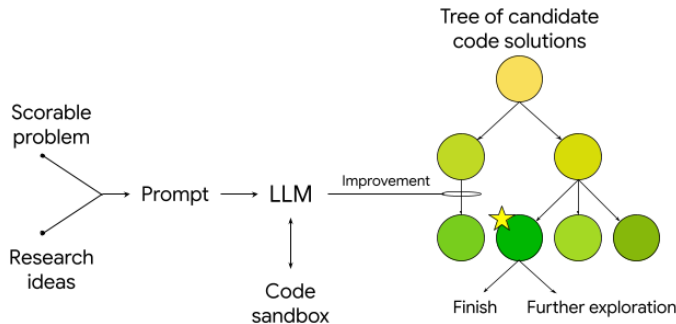


Improved efficiency for displaced tracks

AI is being used to further improve scientific codebases

- Agents modify architecture, optimizer, hyperparameters to improve a loss function
- Fast, fixed-budget trial-and-error loop experiments result in improved loss

- Automatically write and iteratively improve scientific code that maximizes a quality metric
- Applied to multiple fields (Covid prediction to geospatial segmentation) obtains improved results over baselines
- A large share of the top-performing results came from recombination



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 26%)
- ❑ New geometric models could further improve performance, but development is needed as the properties of HEP are not the same as classic 3D datasets
- ❑ Similar methods apply to tracking and have been shown to improve over baseline approaches
- ❑ Can AI help? Ongoing work, stay tuned.

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Thank you
for your attention.

