Machine Learning Approaches to Segmentation for Reconstruction in the ATLAS Calorimeter

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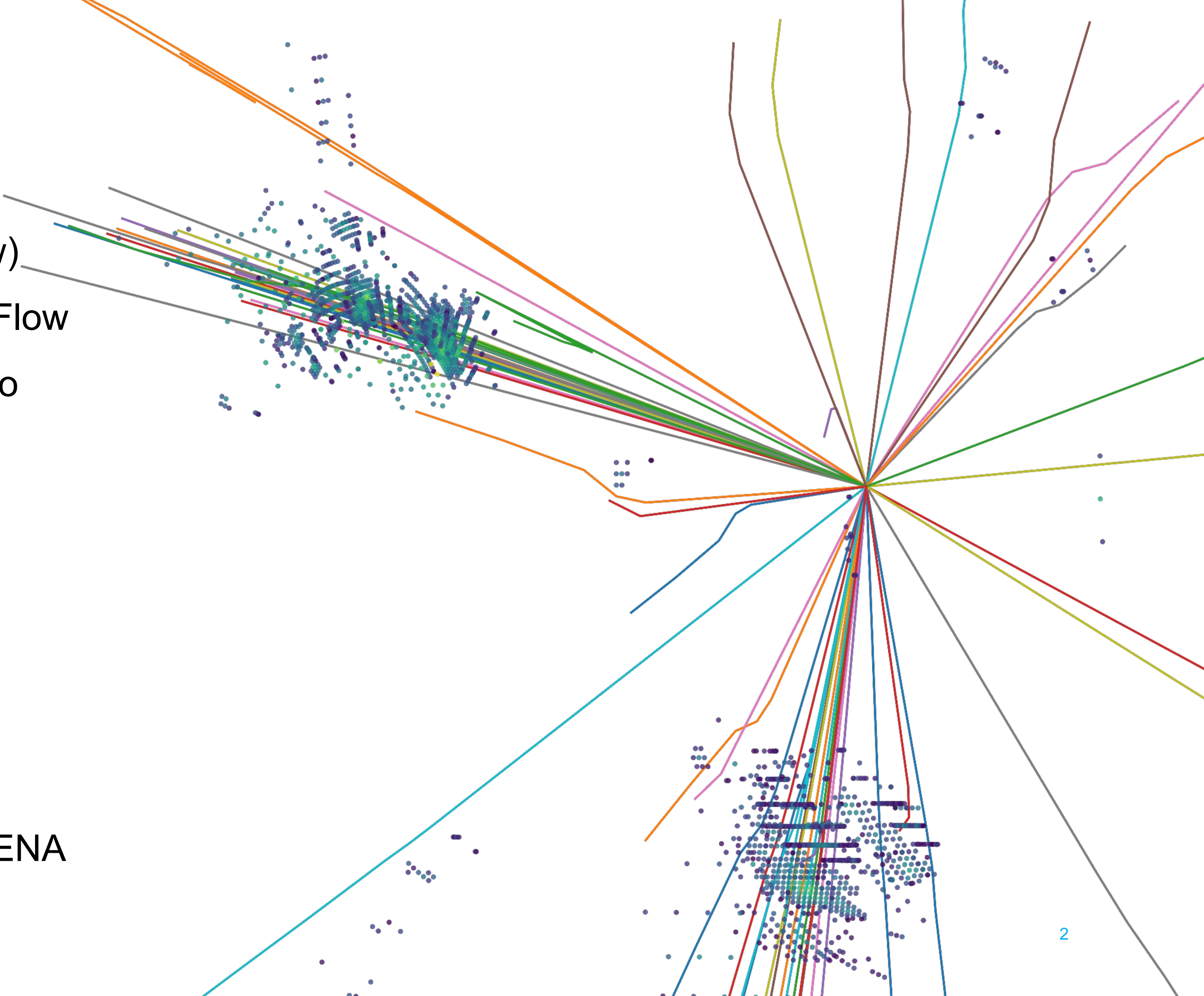
Outline

- Goals of Particle Flow (PFlow)
  - Current approaches to PFlow
- JetPointNet as an approach to PFlow
- Data processing pipeline
  - Data sets
- Loss, metrics
- Preliminary results
- Ongoing work
  - Implementation into ATHENA

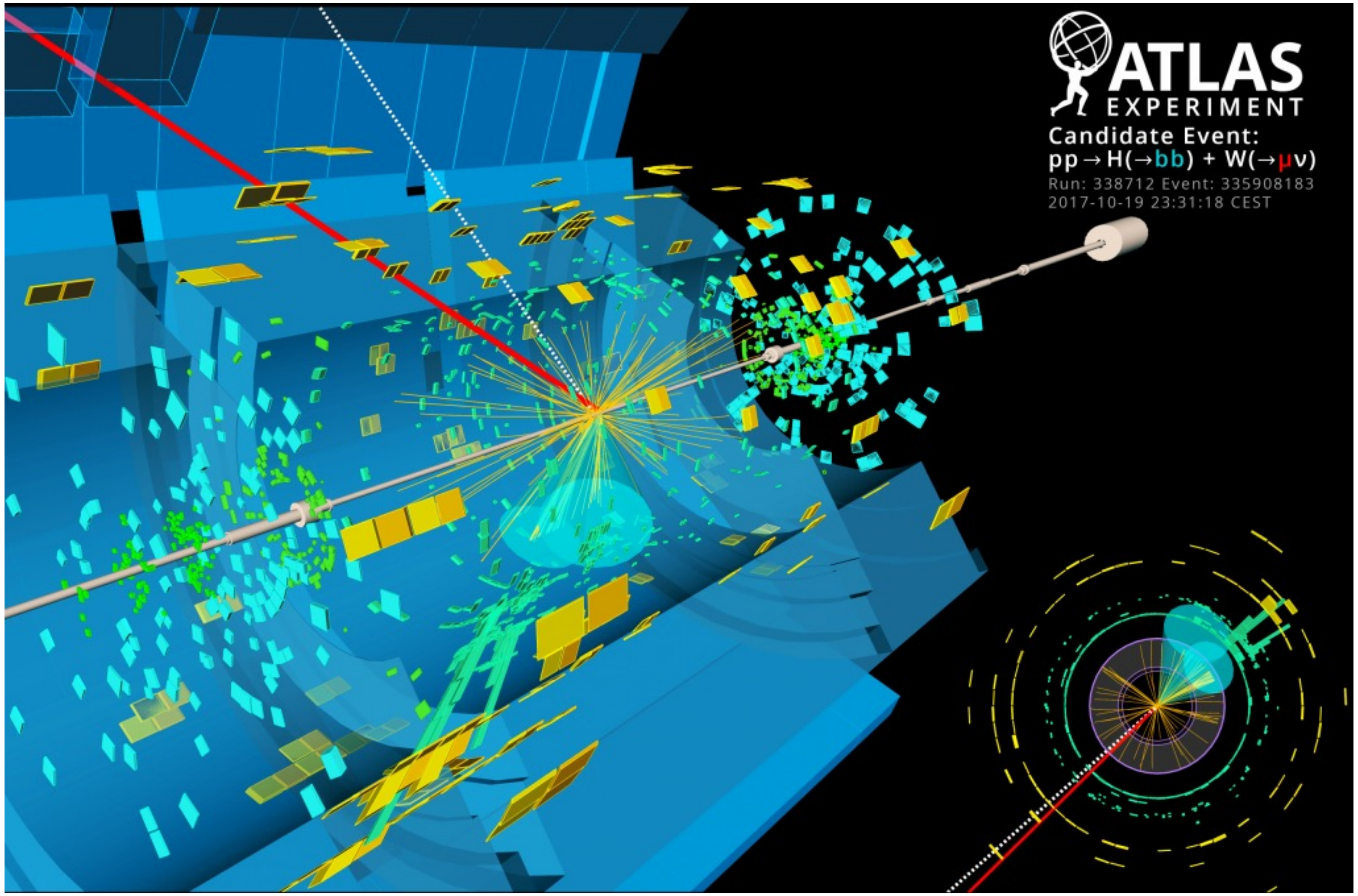


ATLAS is a general-purpose detector at the Large Hadron Collider (LHC)

- ATLAS detects proton-proton collisions (mostly)
- With up to 13.7TeV of energy
- Every 25ns (40MHz)

ATLAS participates in a broad range of research:

- Higgs properties
- Dark matter searches
- Supersymmetry
- Test the standard model



ATLAS uses complementary detector systems to maximize accuracy across the energy domain

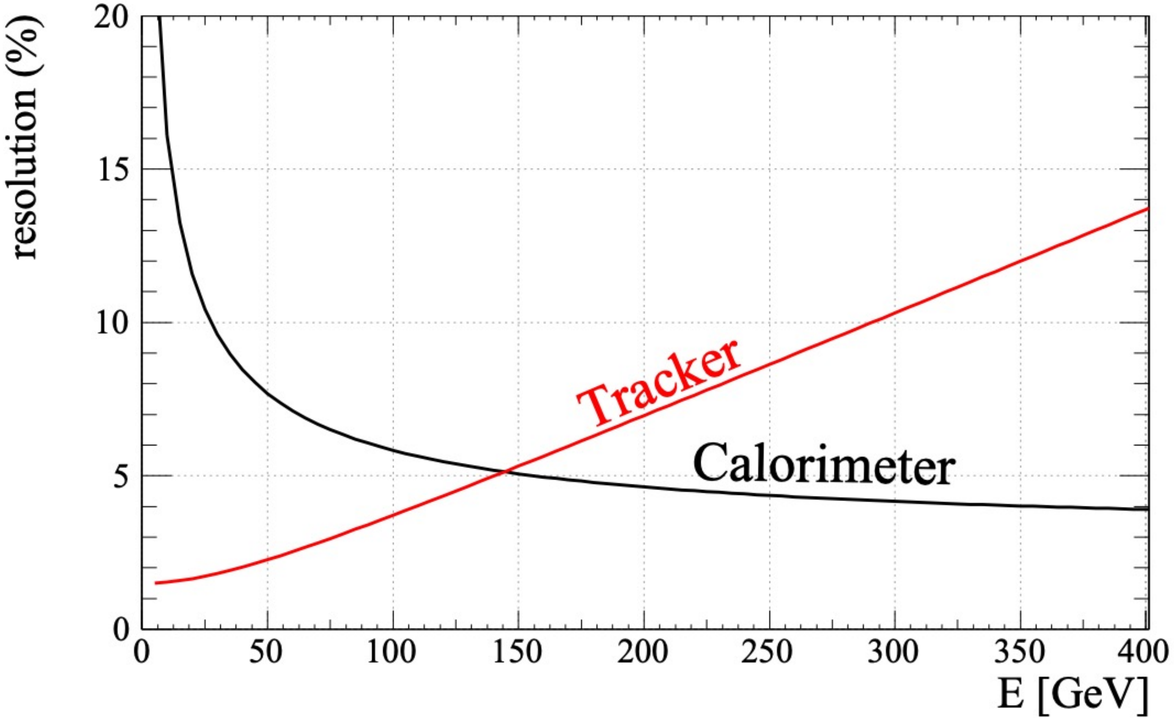
ATLAS employs 2 types of detectors (relevant to this investigation)

Inner Tracker:
- High resolution at low p_T and E
- Detects only charged particles

Calorimeters:
- High resolution at high p_T and E
- Dominated by stochastic terms at low E
- Detects most particles

Particle Flow (PFlow) hopes to combine measurements for excellent overall resolution.

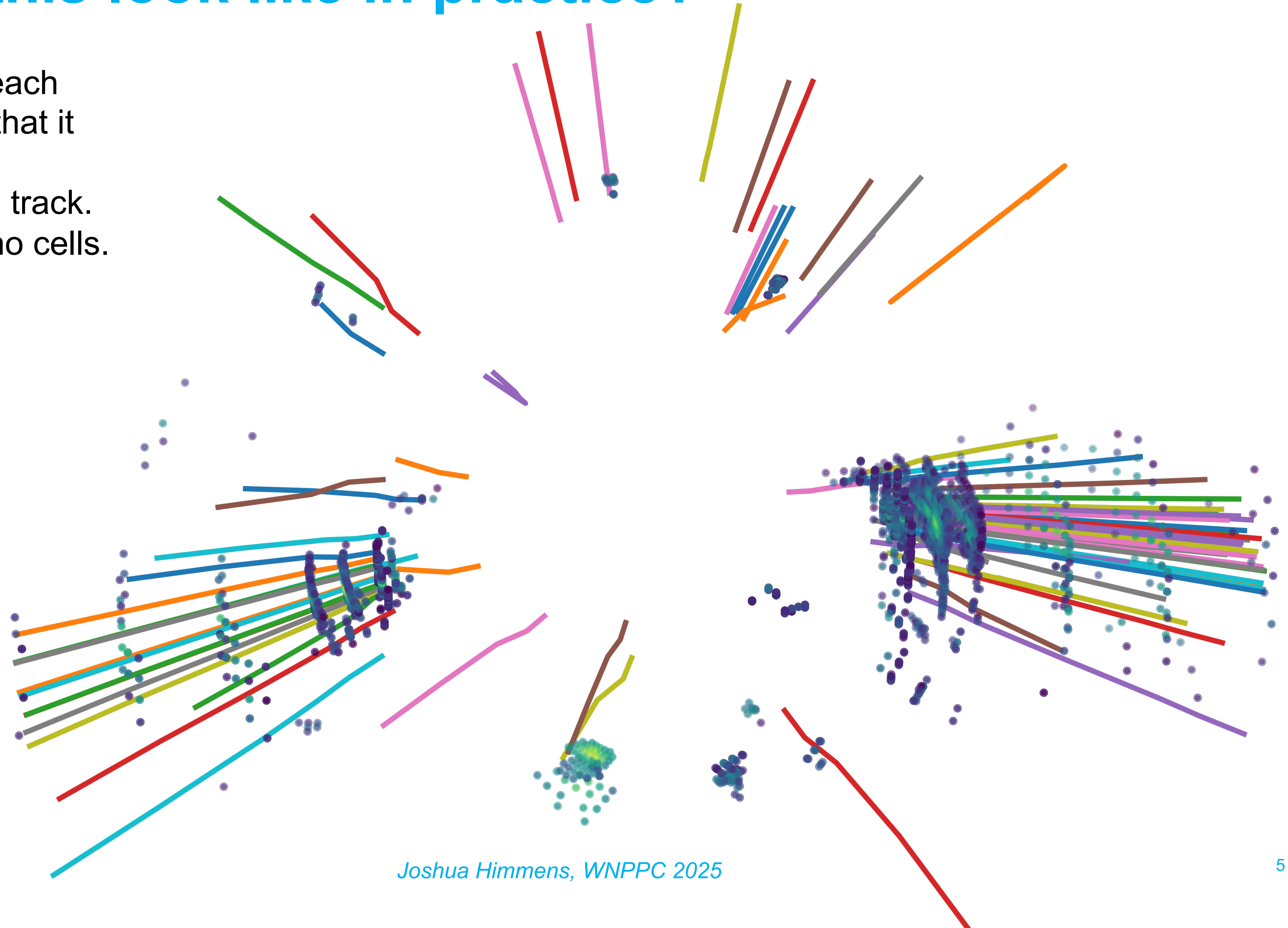
Approximate Single Pion Resolution, $\eta = 0$



[CERN-THESIS-2011-291]

What does this look like in practice?

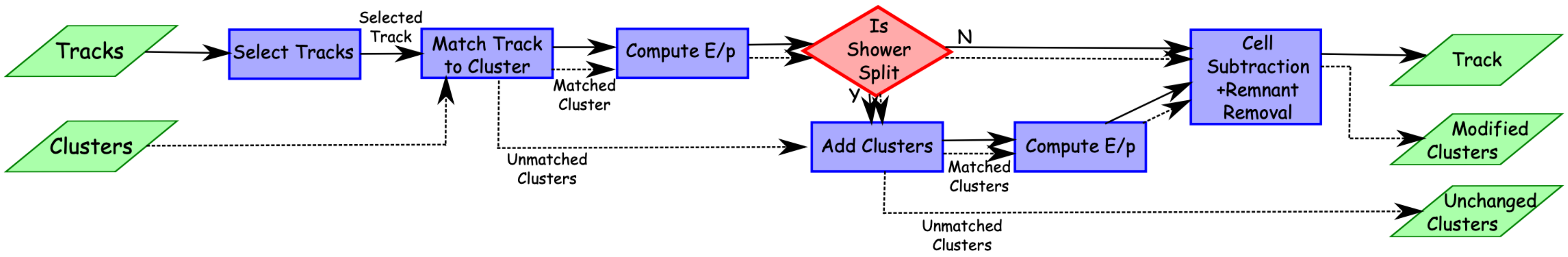
- We want to match each track with the cells that it causes.
- Some cells have no track.
- Some tracks have no cells.



The current segmentation system fails in complex environments

- Clusters are formed by energy deposits
- Segmentation relies on hand tuned distances between tracks and cluster
- The algorithm relies on hand tuned parameters for each step
- In dense environments this system fails to associate tracks to clusters

Ripe for innovation!



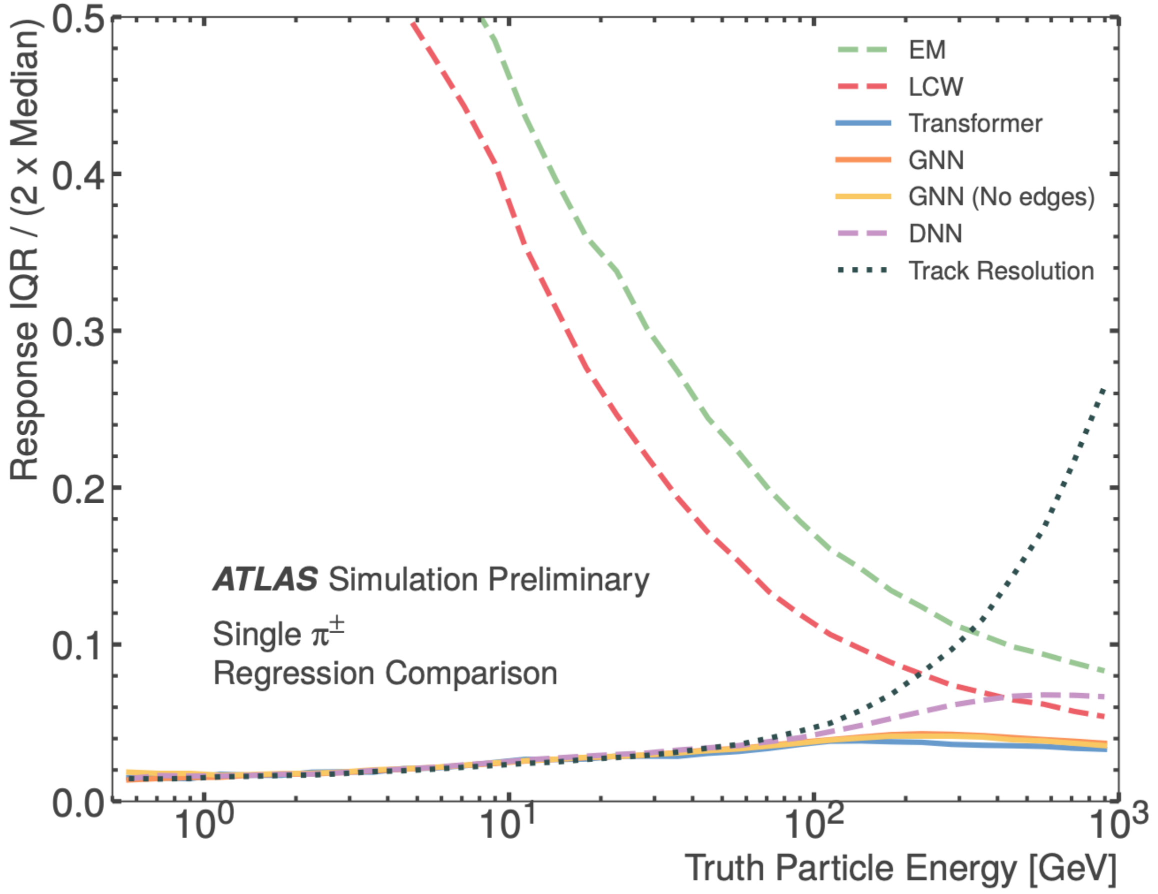
arXiv:1703.10485

Why use machine learning?

Convolution and graph neural nets have shown success already at hadronic calibration.
[ATL-PHYS-PUB-2022-040]

The core advantages:

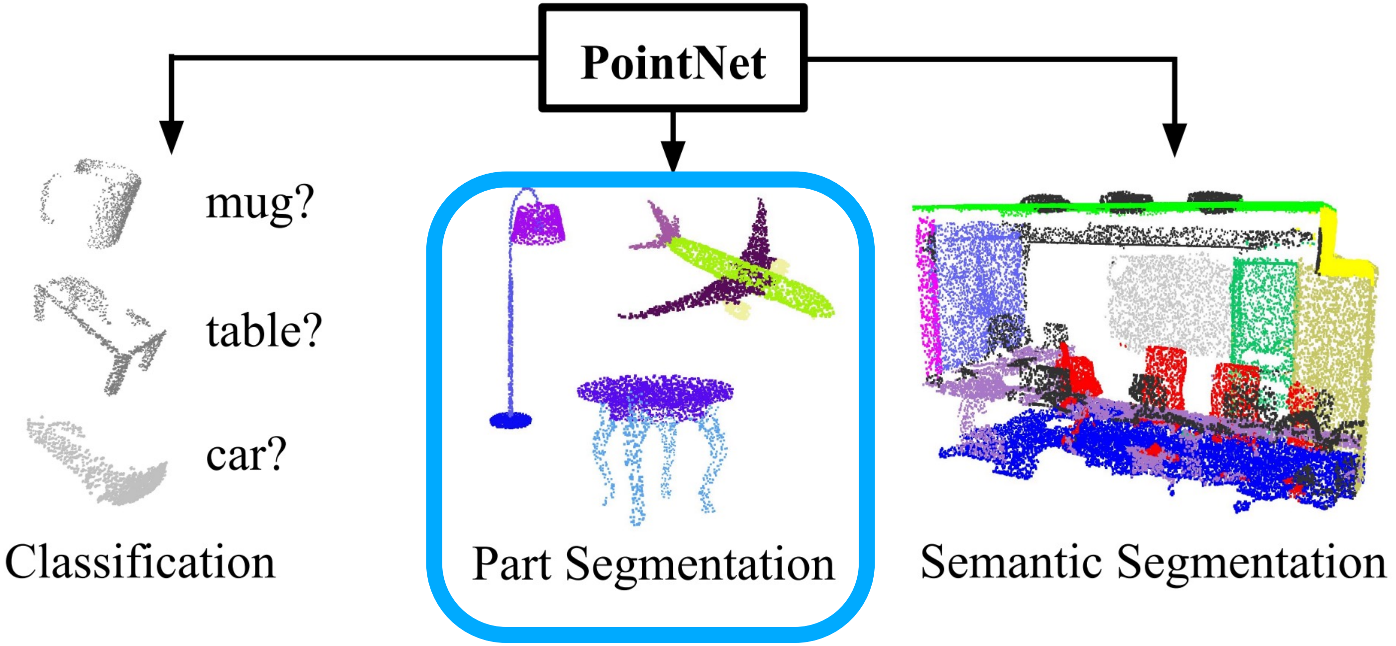
- Dissolve cluster boundaries
  - Permits **cell-wise attribute**
- Higher energy accuracy
  - Enables **partial cell attribution** beyond cluster-cell splitting
- Permits more information during reconstruction, the model can use more **subtle heuristics**
  - **More accurate** than ΔR (distance) in dense environments



[ATL-PHYS-PUB-2022-040]

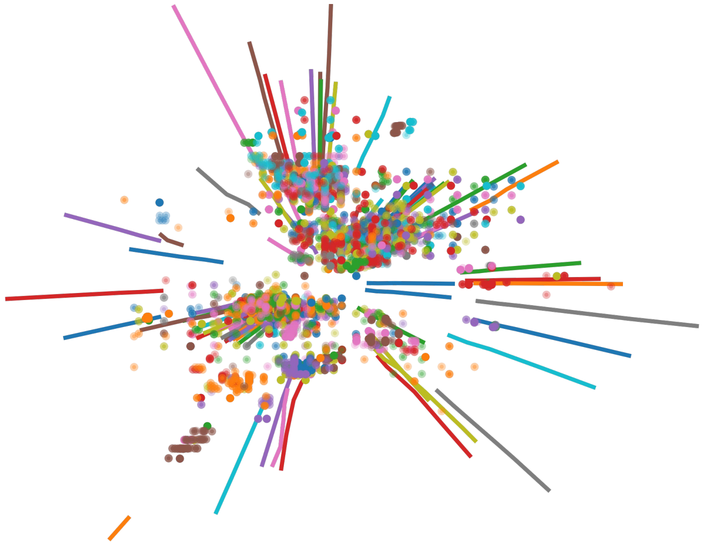
JetPointNet as an approach to PFlow

- Represent hits as 3D points
  - **Sparse** and efficient representation
- Provides spatial invariance

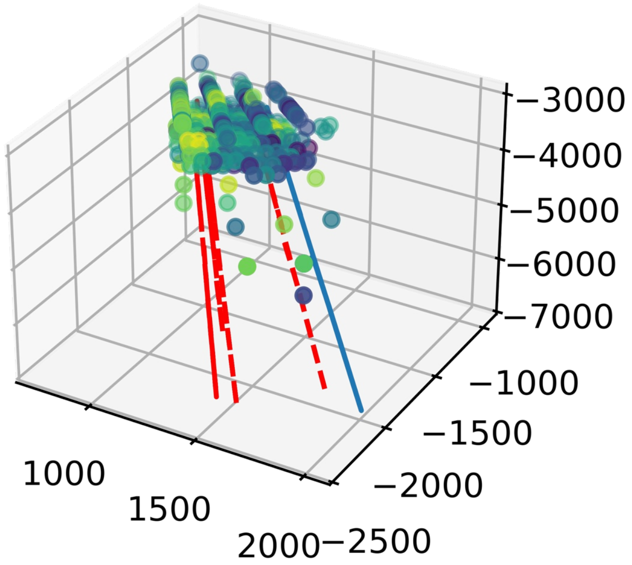


arXiv:1612.00593

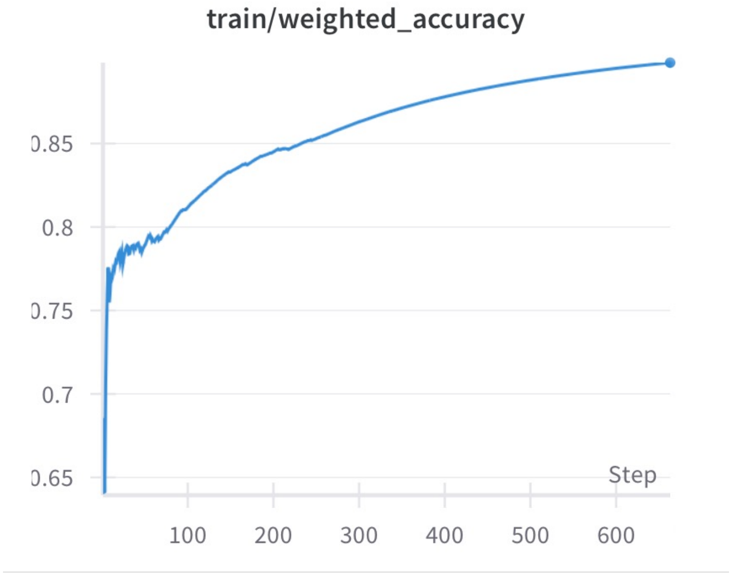
How JetPointNet works



Generate events with Geant4 and Athena or with data augmentation system



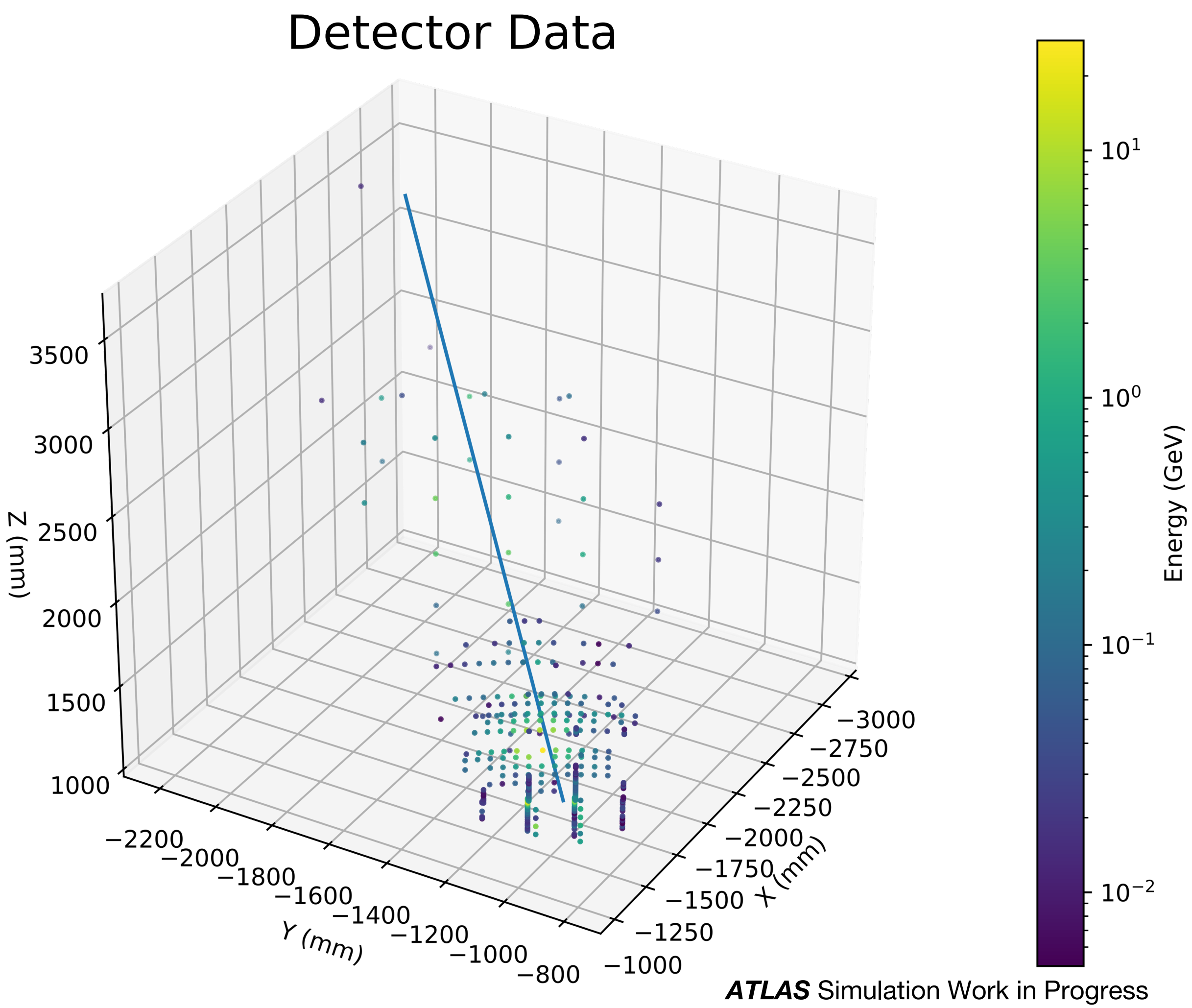
Split into batched training samples using ΔR cut on each track

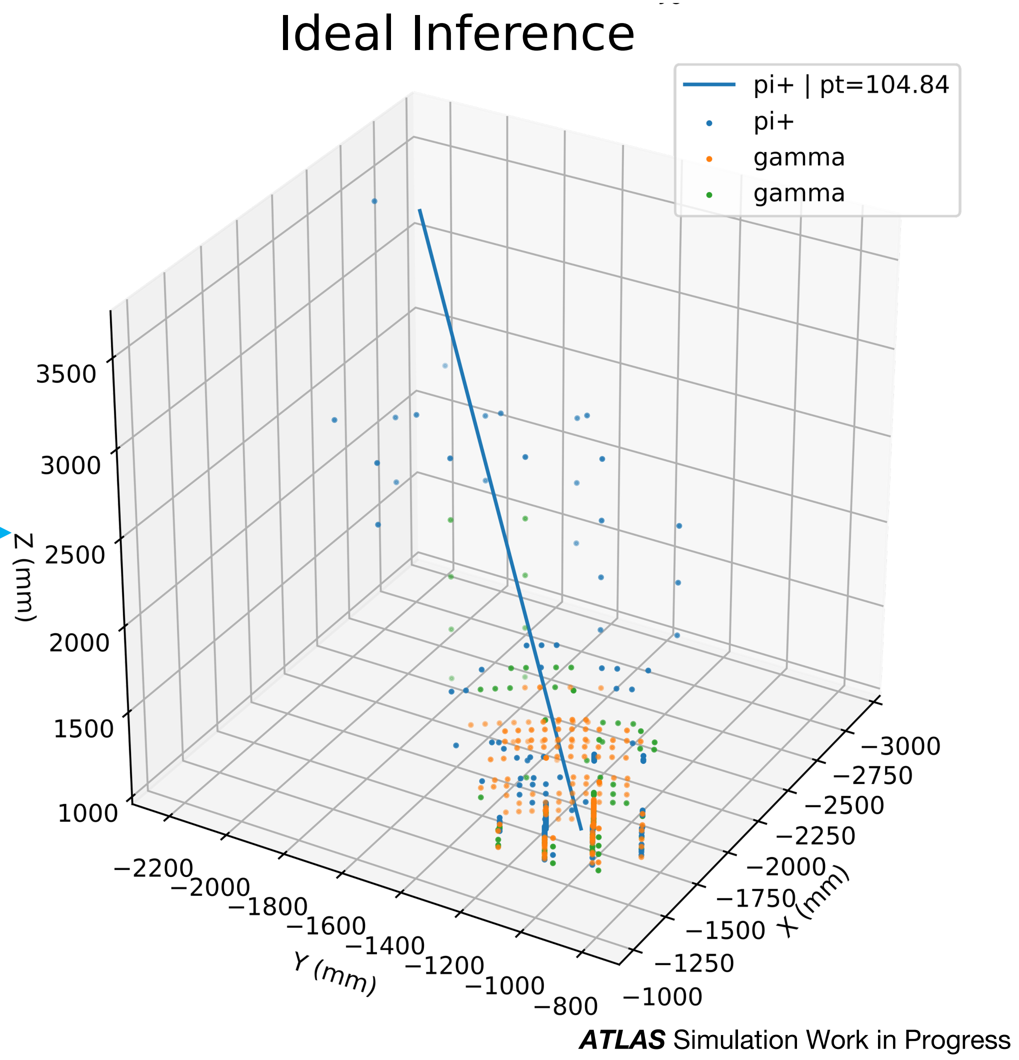


Train on energy deposition by track

** Plots for illustrative purposes only

A visual intuition for the dataset and model aims





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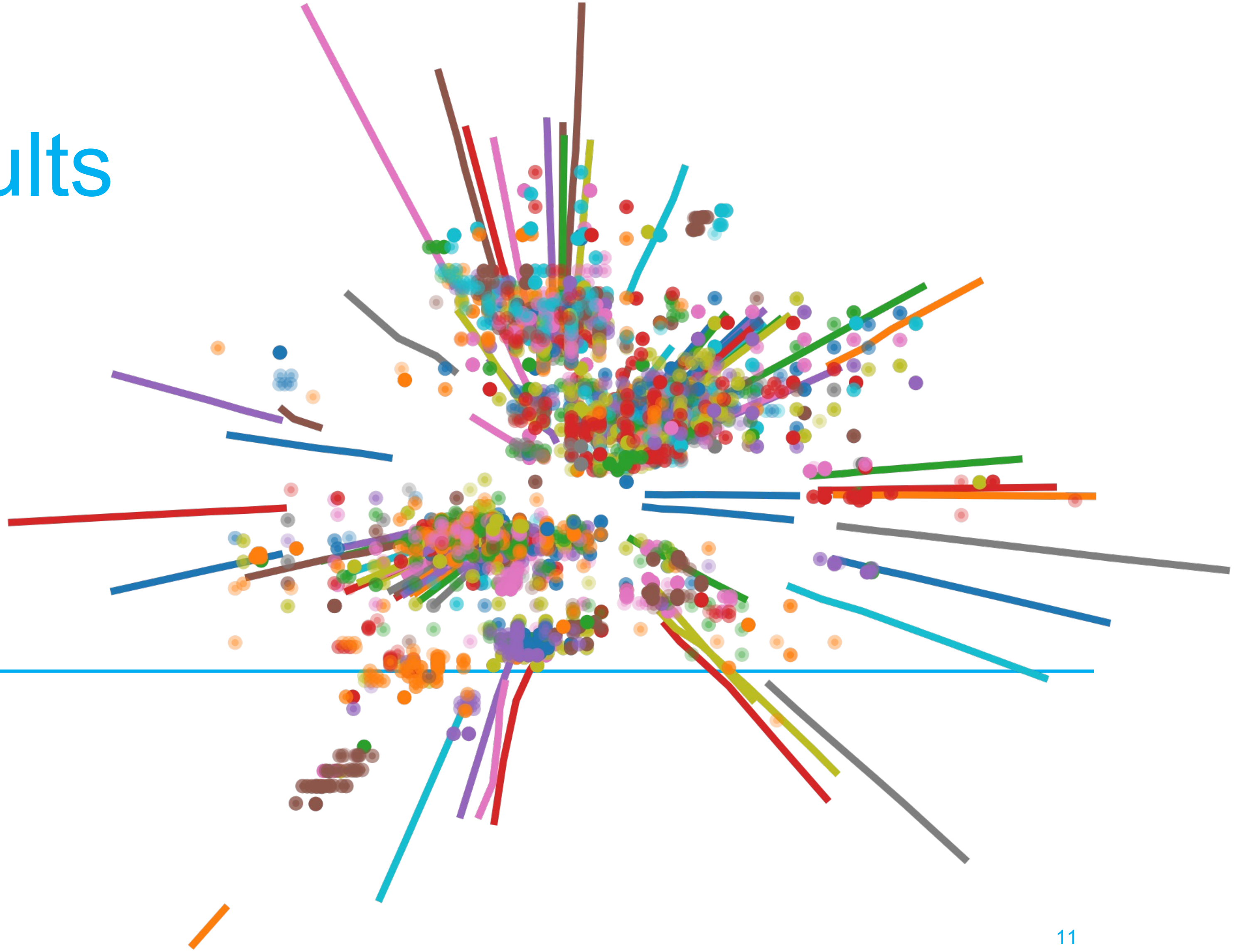
Preliminary Results



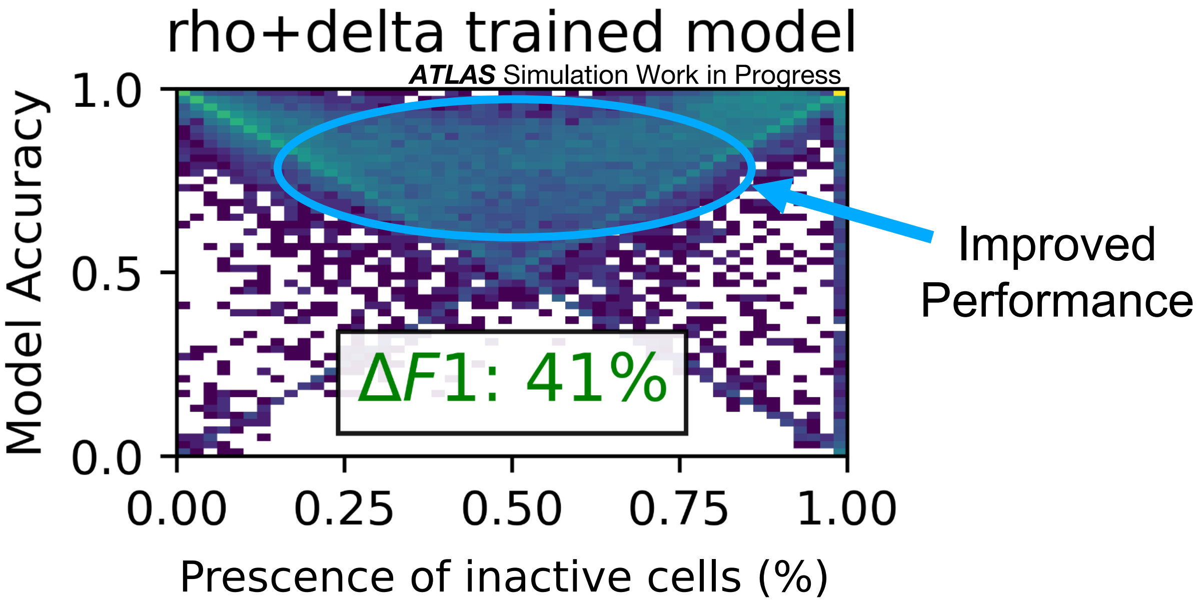
Binary categorization is successful with ρ and Δ meson showers

Goal: Determine which energies come from each decay product (pion and two photons)

The model is successful at attributing simple hadronic showers (events with 1-3 tracks).

Metrics:

- Accuracy: $\frac{cells_{correct}}{cells_{total}}$
- F1 Score: Accuracy trade off factor



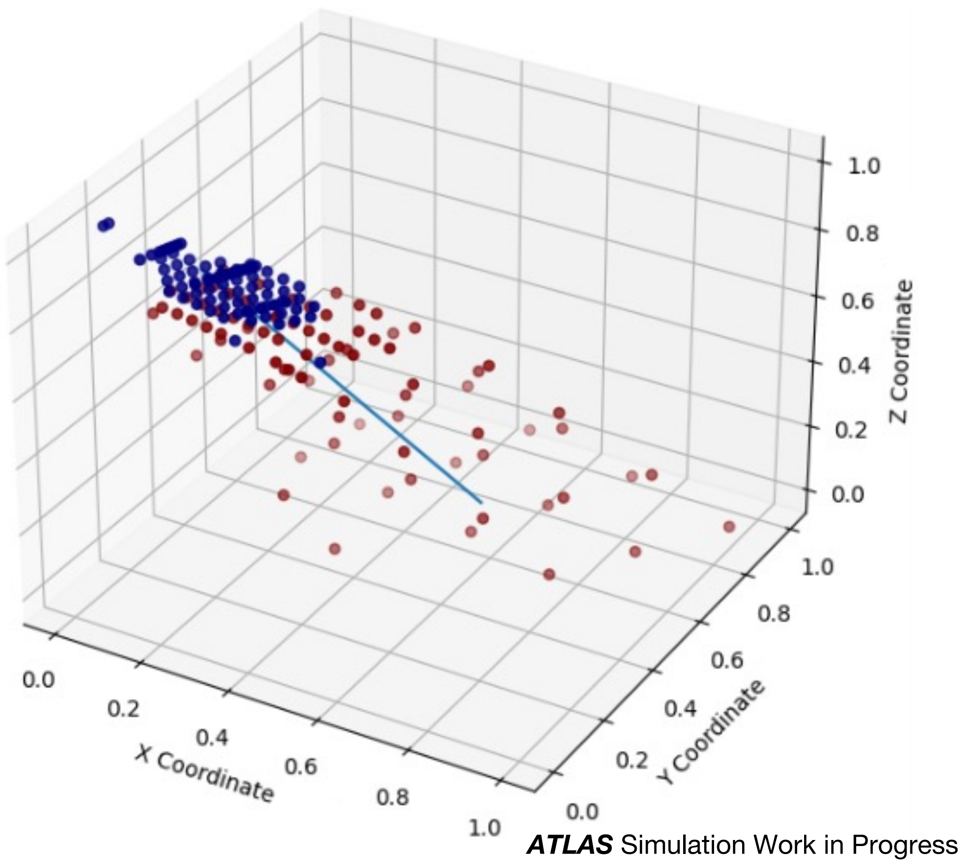
The model shows success on ρ data

Energy Primarily Neutral Particles

Energy Primarily from Track

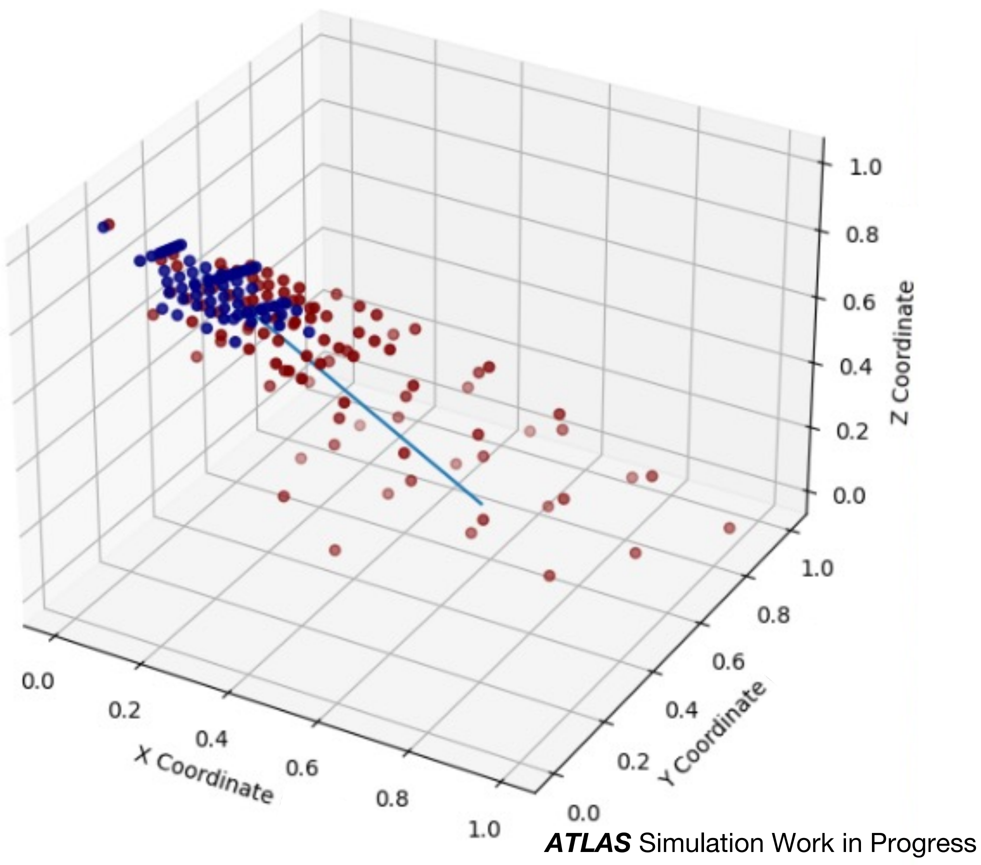
Simplified data: $\rho^{\pm} \rightarrow \pi^{\pm} + \pi^{0}$

Truth Data – 83 Activations



Truth Activation Energy = 1159 GeV

Model Predictions – 98 Activations

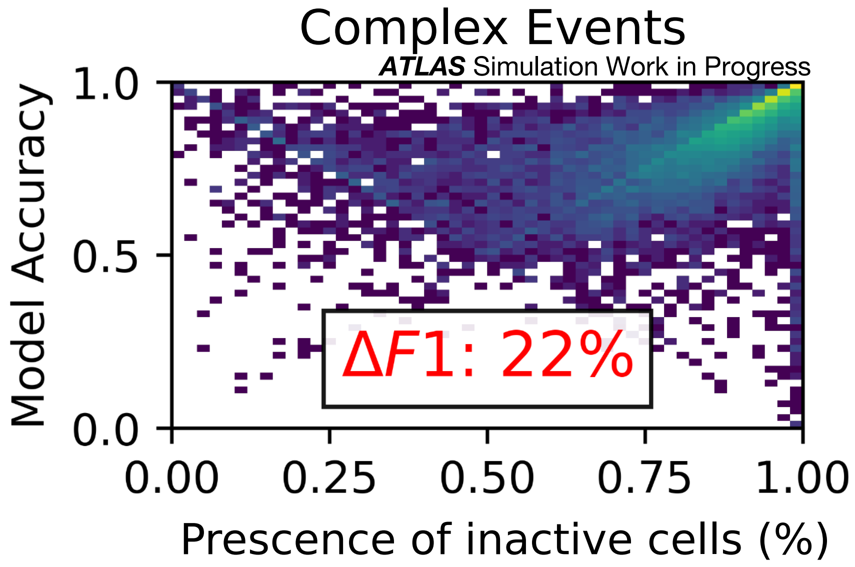


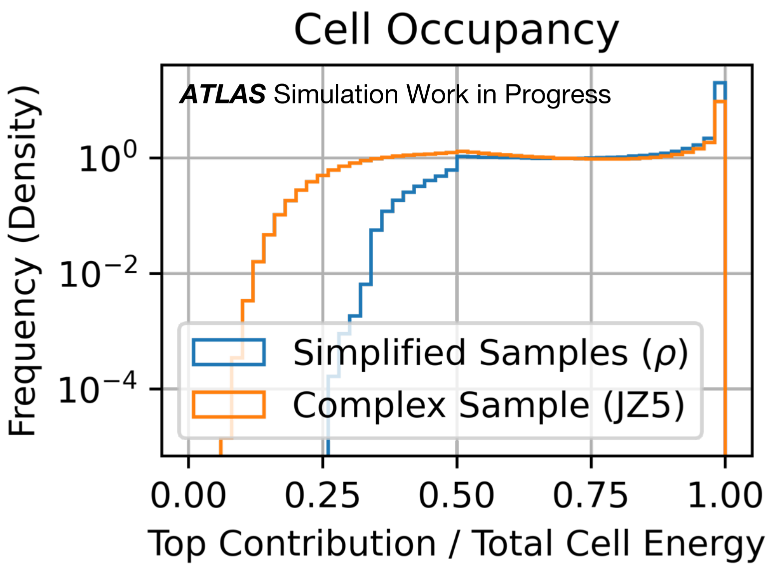
Model Activated Energy = 1179 GeV

** Plots for illustrative purposes only

Limitations of binary classification

- **The model tends to learn lower-order relationships**
  - Modal decay deeply entrenches the loss function
  - Class imbalance where most cells and most energy is not associated with the track
- **Cells do not conform well to a binary**
  - Binary labels are a poor heuristic for particle occupancy of cells in jets
  - In jets, cells can contain significant deposits from many particles





TRIUMF

Ongoing Work

Ongoing work: Implementing inference in ATLAS

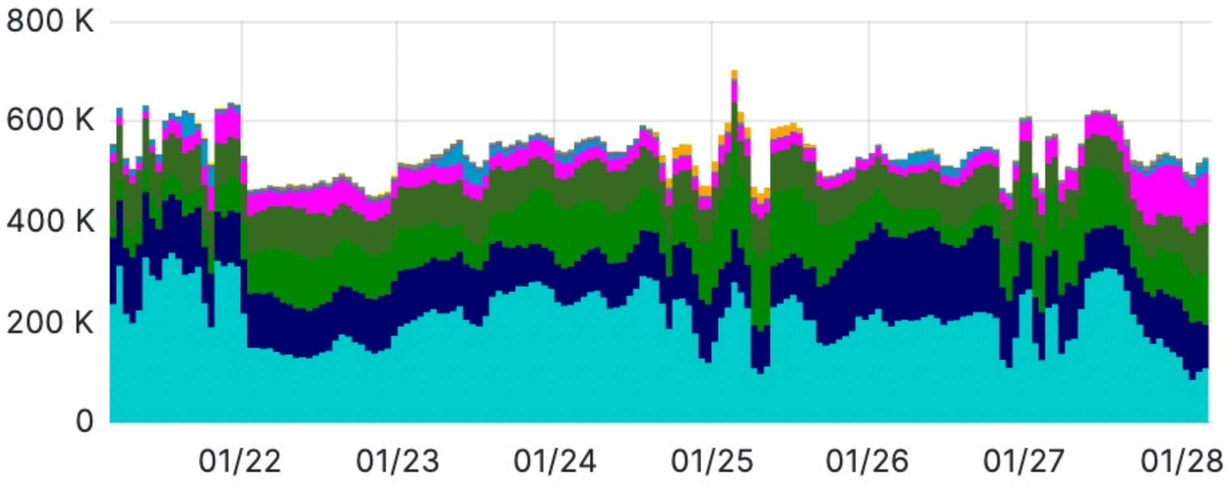
Problem 1: Implementing Machine Learning into ATLAS

- Huge computational effort goes into reconstruction and simulated reconstruction
- Our framework does not natively support machine learning workflows

Problem 2: Developing an algorithm to apply segmentation

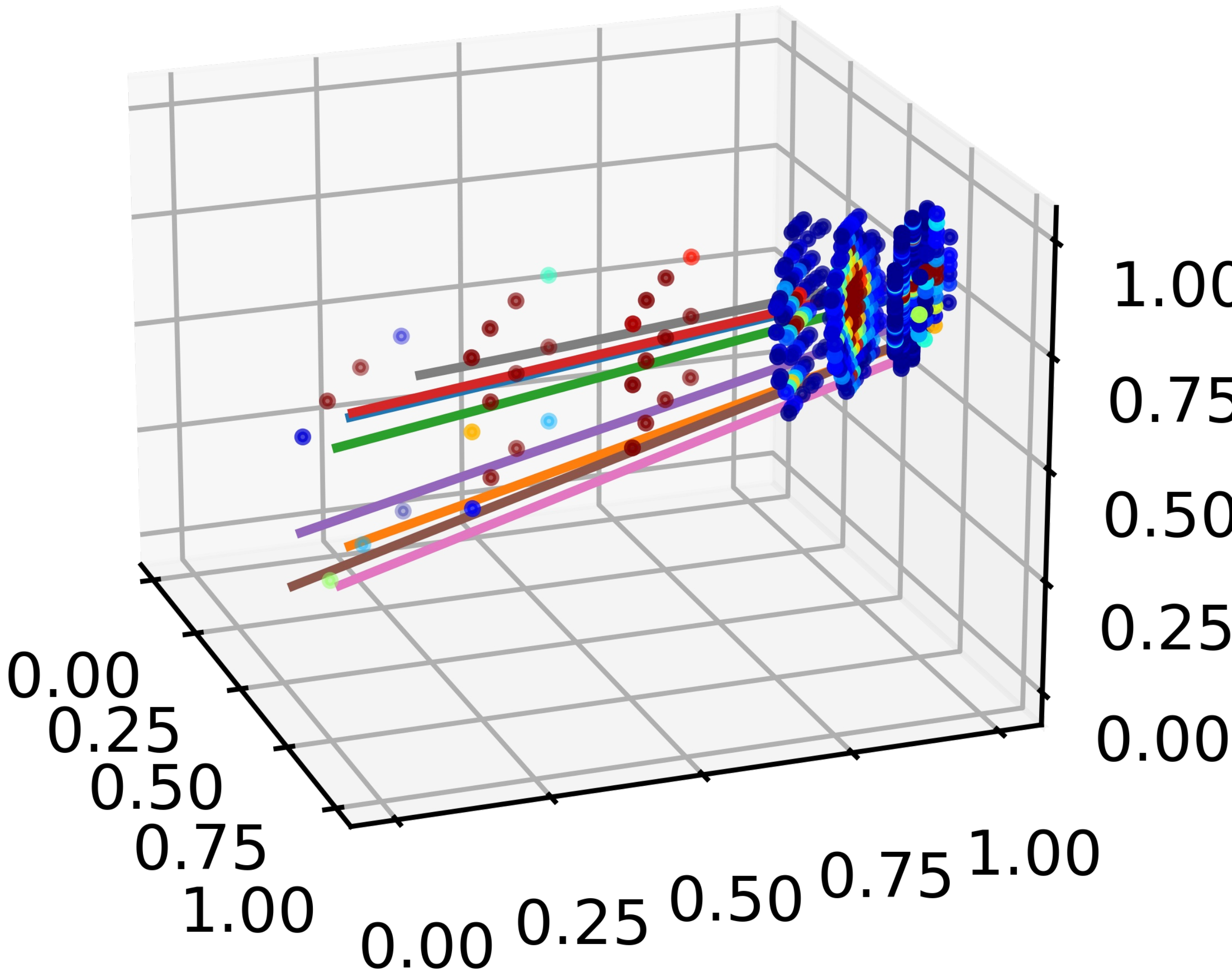
- Inference cannot be complete in isolation.

ATLAS grid processing simultaneous jobs (7 days, 2025)



Summary

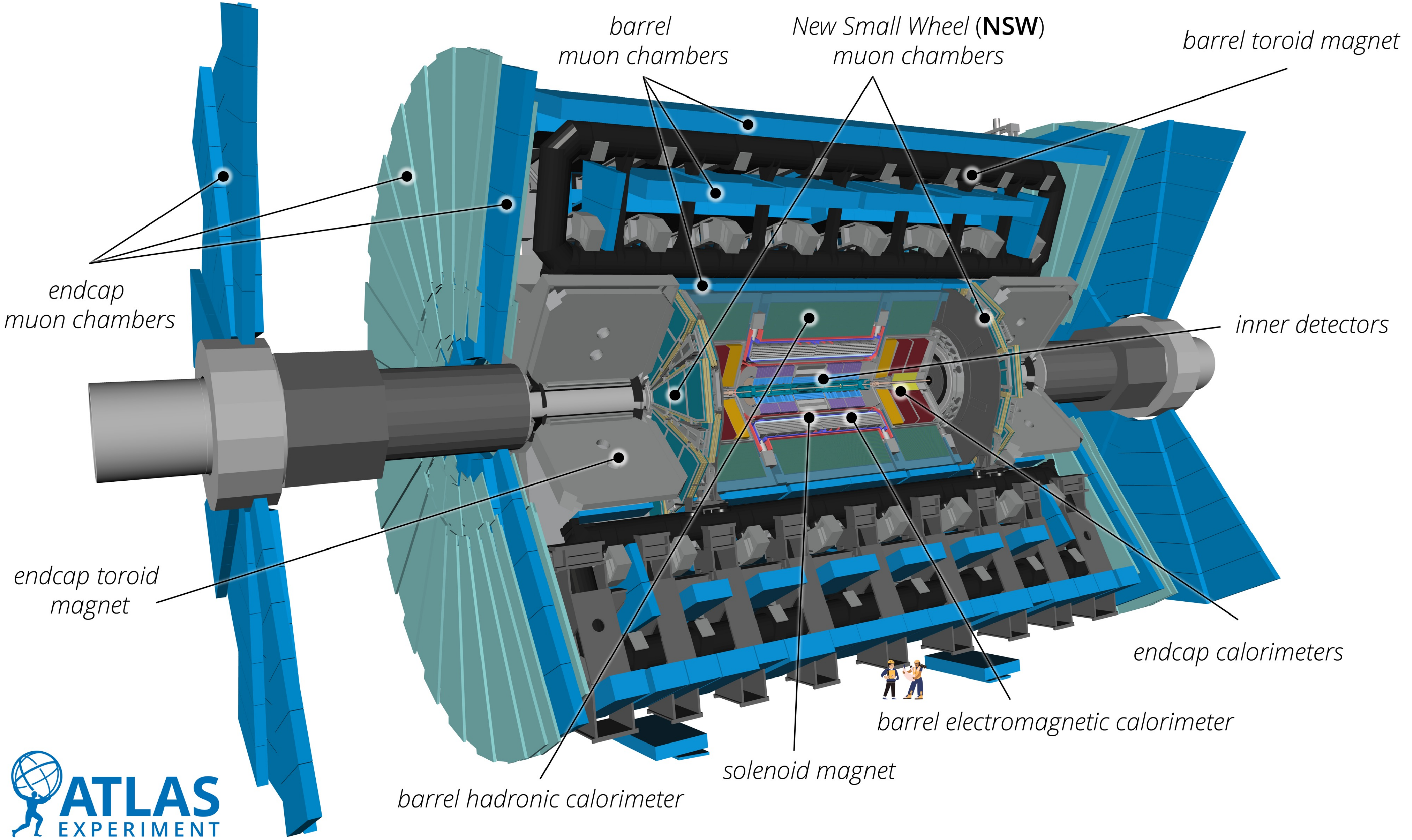
- ATLAS employs complimentary detector system
- PFlow increase precision across the energy domain through coincident signal analysis
- Combining detector signals is a non-trivial problem
- Machine learning approaches to particle flow are promising



TRIUMF

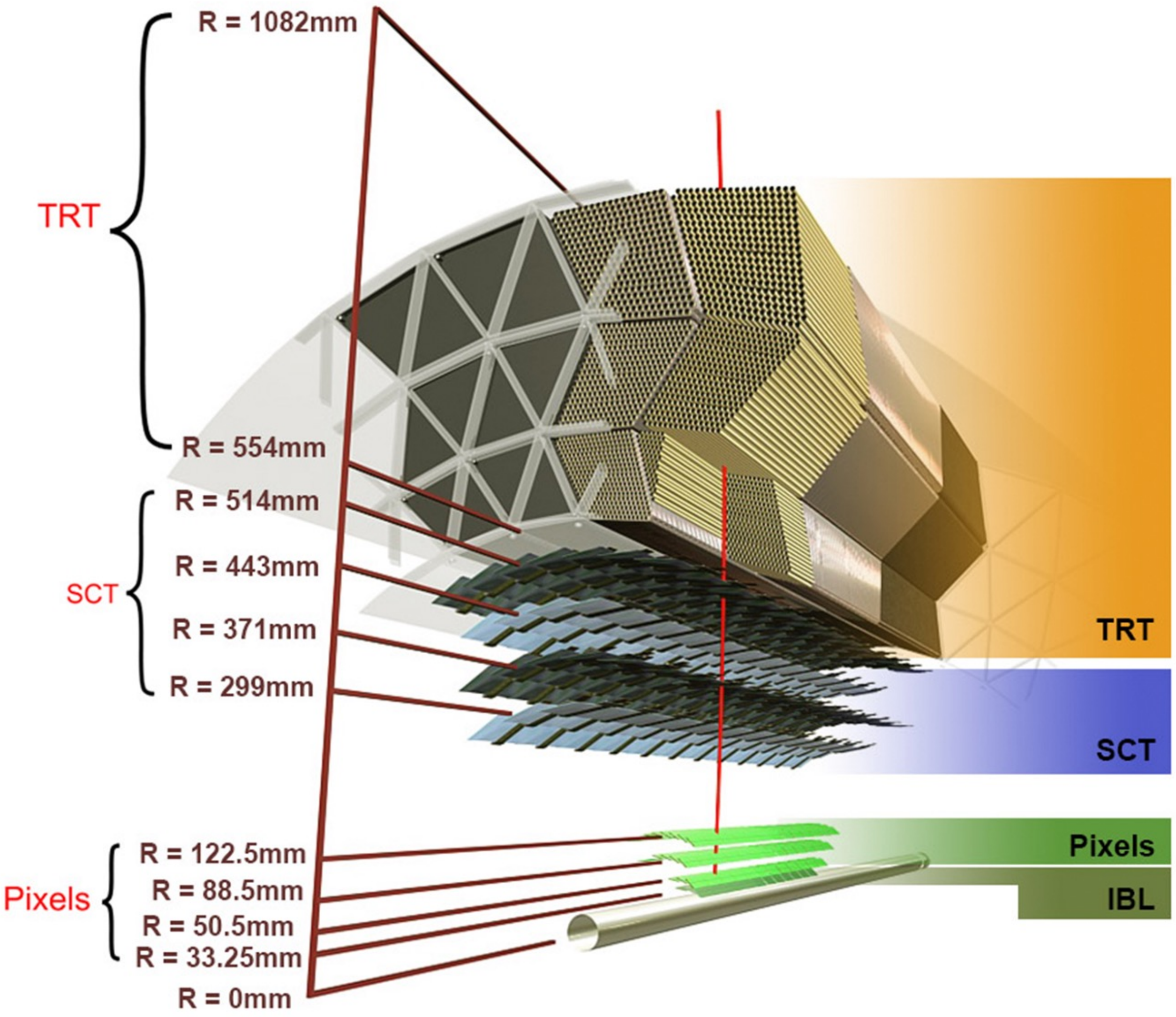
Backup

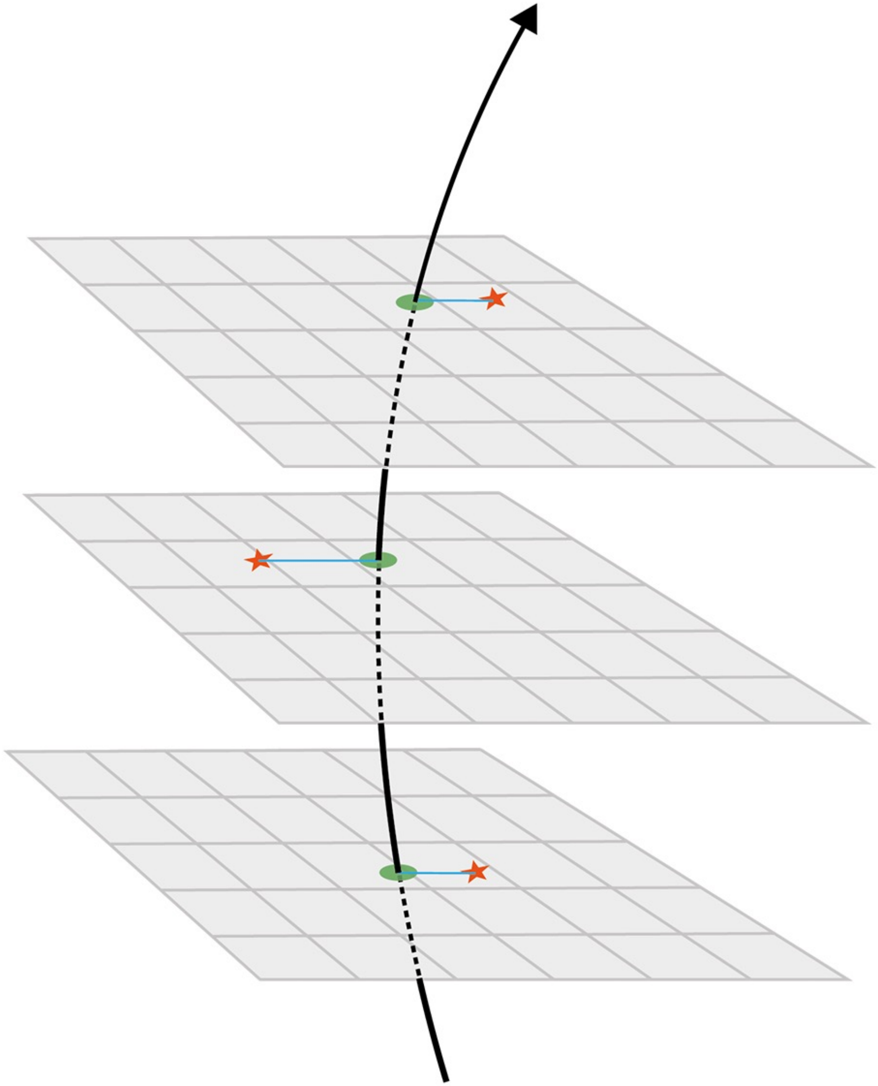
The ATLAS detector



ATLAS EXPERIMENT

The ATLAS Inner Detector





ATLAS p-flow algorithm [ATL-PERF-2015-09]

For track in descending pT:

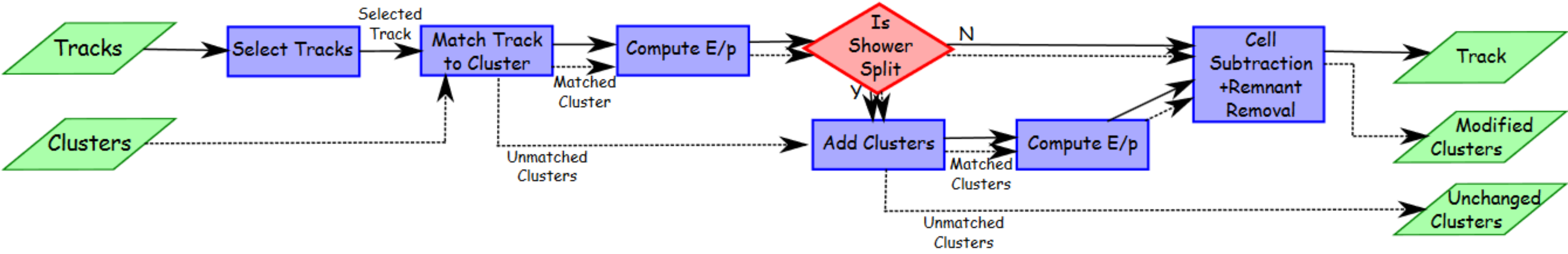
•associate closest topo-cluster based on angular distance ΔR'

•compute expected energy deposit based on the topo-cluster position and track momentum

•if expected and measured energies differ significantly, associate more topo-clusters

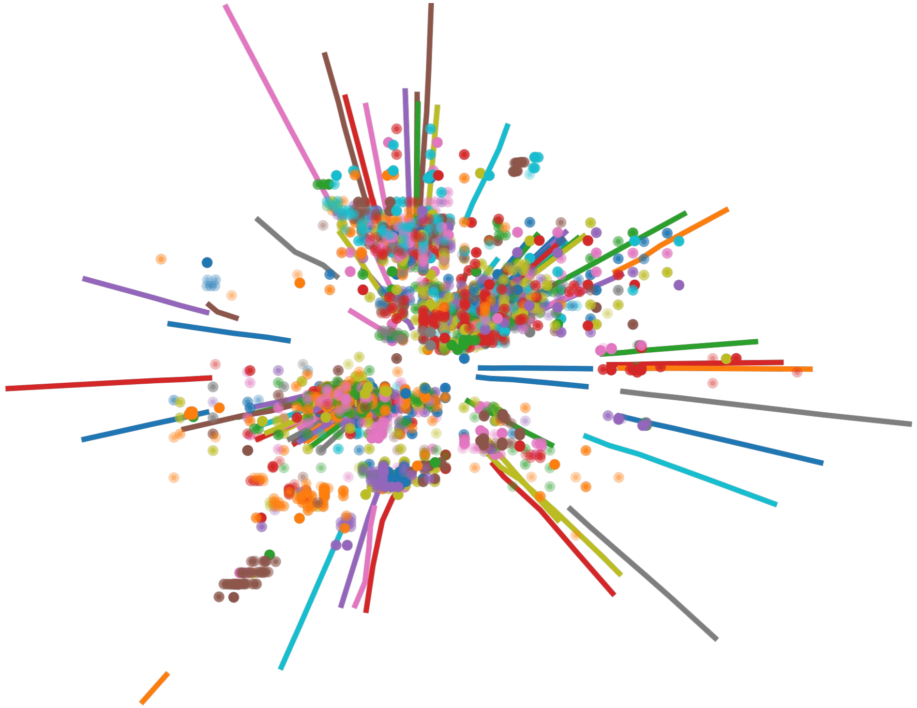
•subtract the expected energy by calo cells

•if remaining energy lies within expected fluctuations, remove the remnants



Data Representation

Data is represented as a single combined point cloud



Data encoded into each point

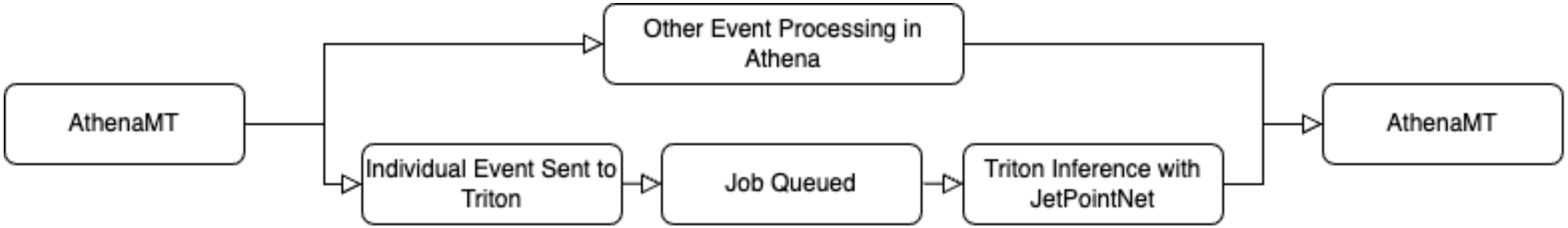
Point type (e.g. cell hit, track, padding)
ΔR
Track Identifier (for tracks)
Normalized coordinates
Track χ^2/dof (for tracks)
Cell E (for cells)
Track pt (for tracks)
Cell Sigma (for cells)

Ongoing work: Implementation into Athena with NVIDIA Triton

With Dr. Sascha Diefenbacher (Lawrence Berkley National Laboratory)

- Create containerized python runtime inside of Athena
  - Permits arbitrary data pre-processing, inference and attribution.
- Use Athena as a gRPC client for event-wise calls to the inference server
- Batching is handled directly by NVIDIA Triton

Thinking about implementation into core framework
Academic solving, solving problems at scale
Speak to how much compute

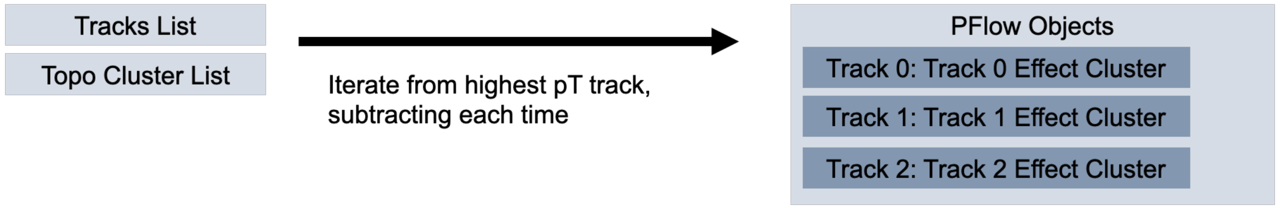


Ongoing work: Building an iterative segmentation system

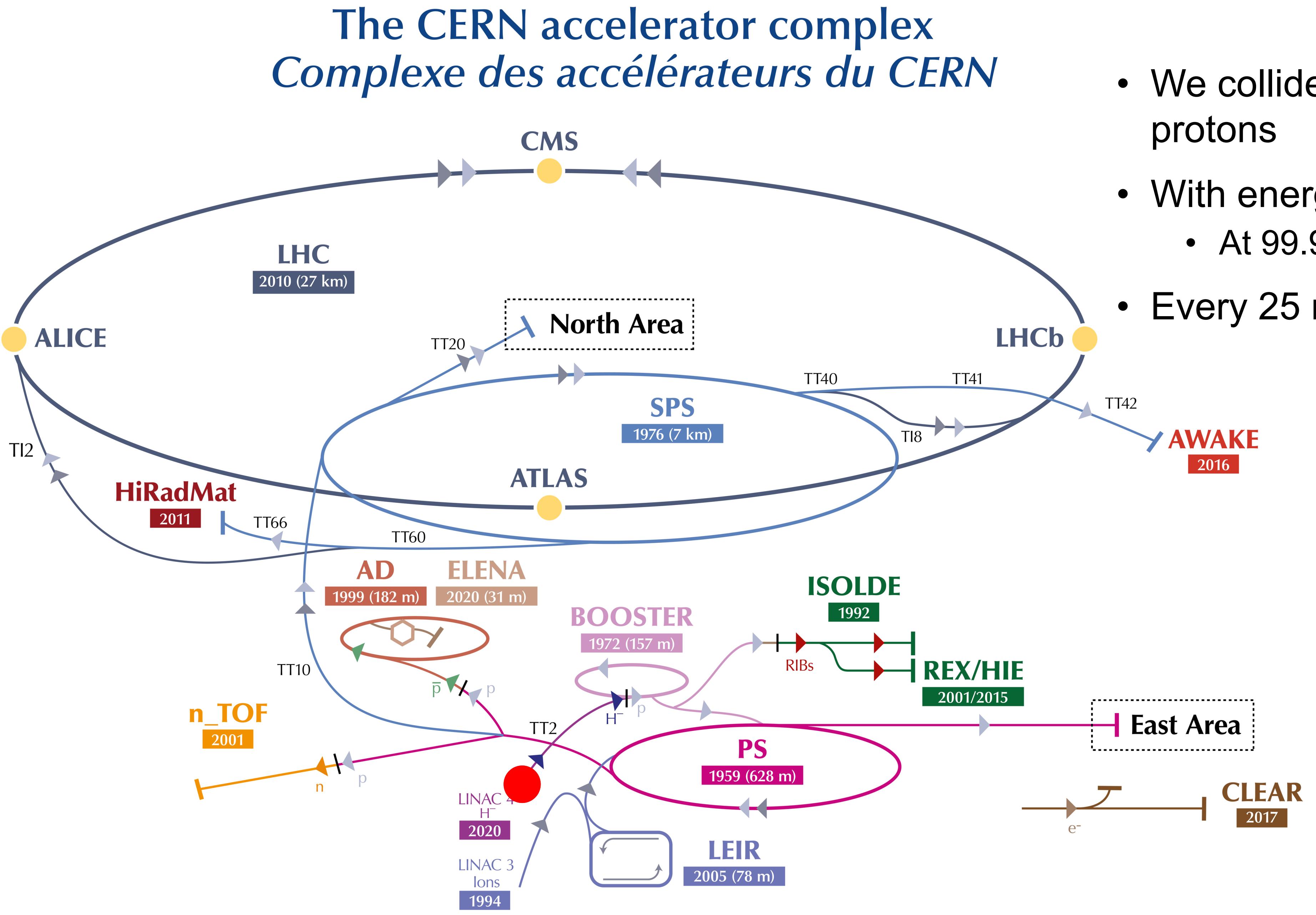
Event level metrics requires inference on all tracks

Iterative inference:
Iterate through all tracks performing segmentation and subtraction at each step.
- May require data augmentation of the training set.
- Requires “garbage collection” to remove remaining partial cell energies.
- Each iteration must resemble an event

Common inference:
Apply inference to each track and assign cell energies based on aggregate predictions.
- Increases overall data complexity as clusters are never removed
- Potentially significantly faster as event data does not need to be modified as an object



How do we collide?



- We collide pairs of bunches of 10^{11} protons
- With energies as high as 13.7 TeV
  - At 99.999999% the speed of light
- Every 25 nanoseconds

What happens when we collide?

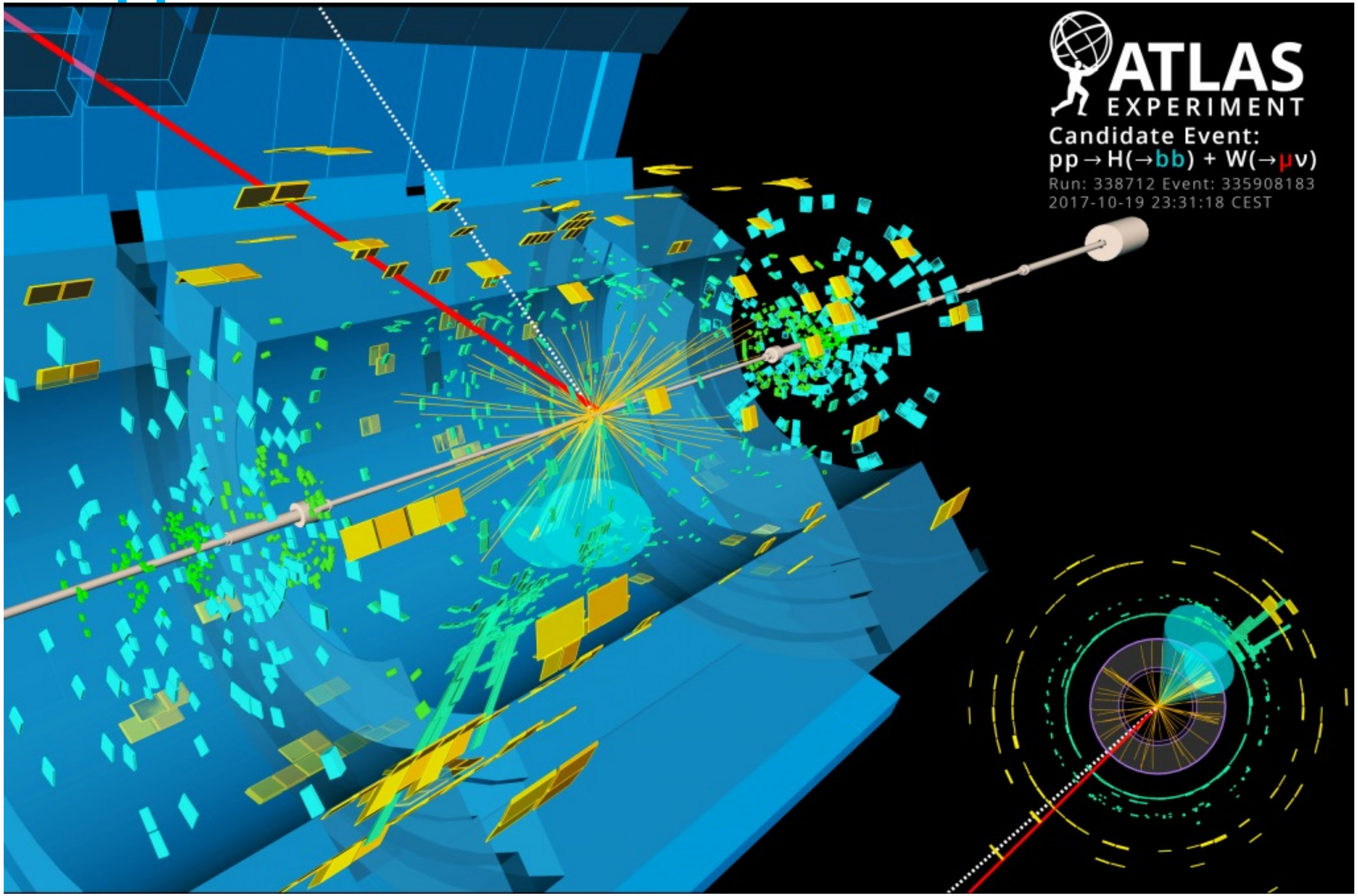
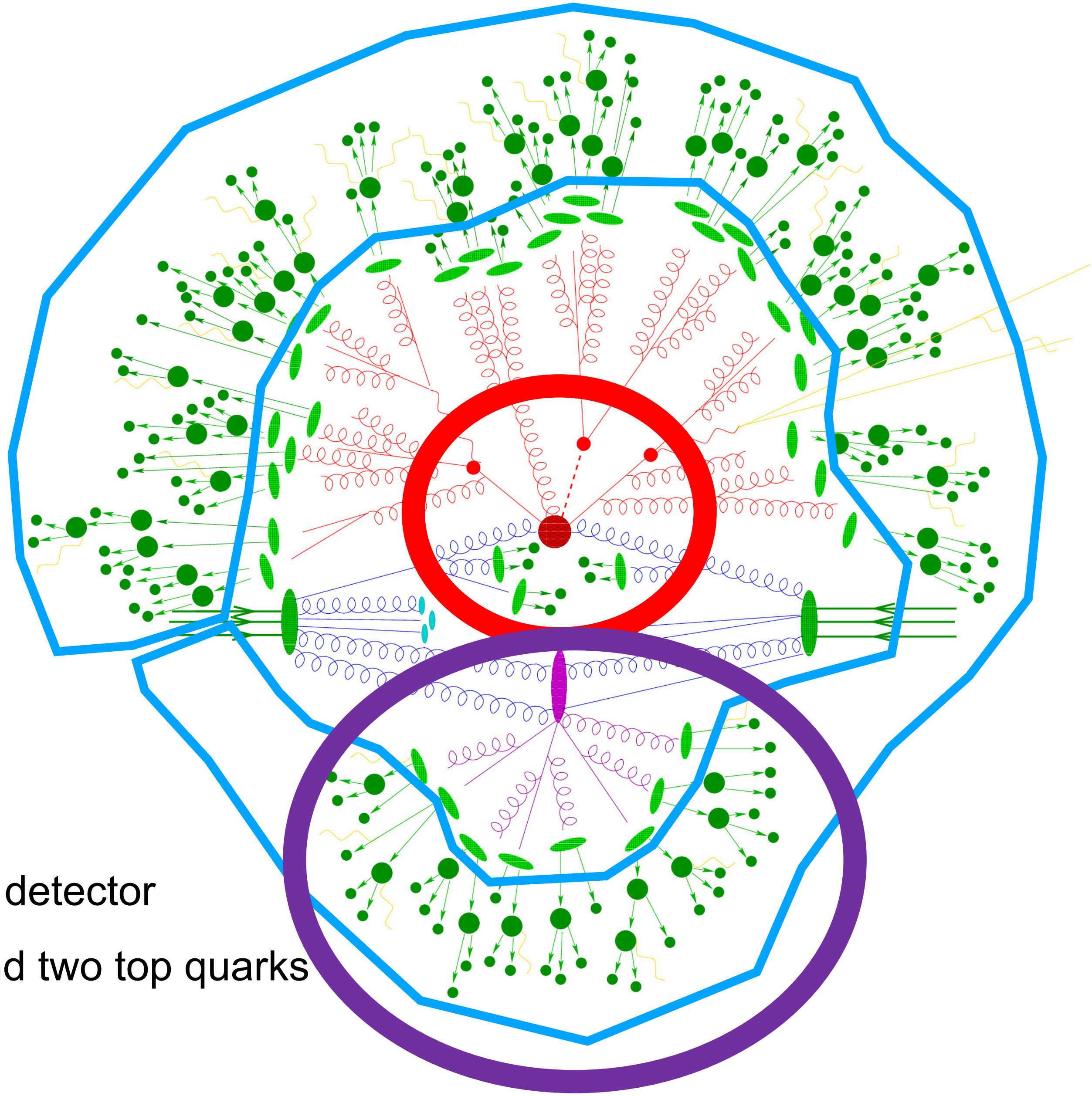


Image: [FNAL Outreach]

Particle Flow

While the results are interesting, **we care about the fundamental physics**, which requires understanding the decay process

PFlow is the practice of **piecing together the signals from multiple detectors** so that we have the information to **reconstruct the event**



Visible to the detector

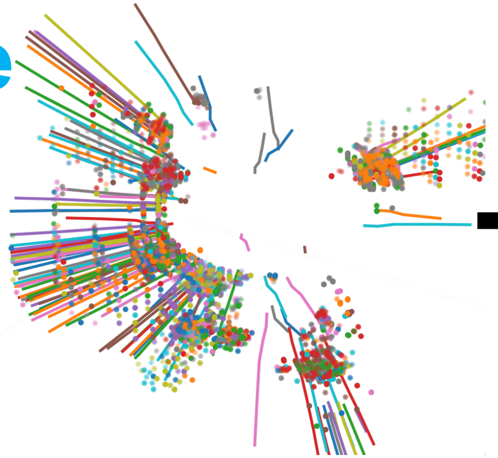
The Higgs and two top quarks

Background

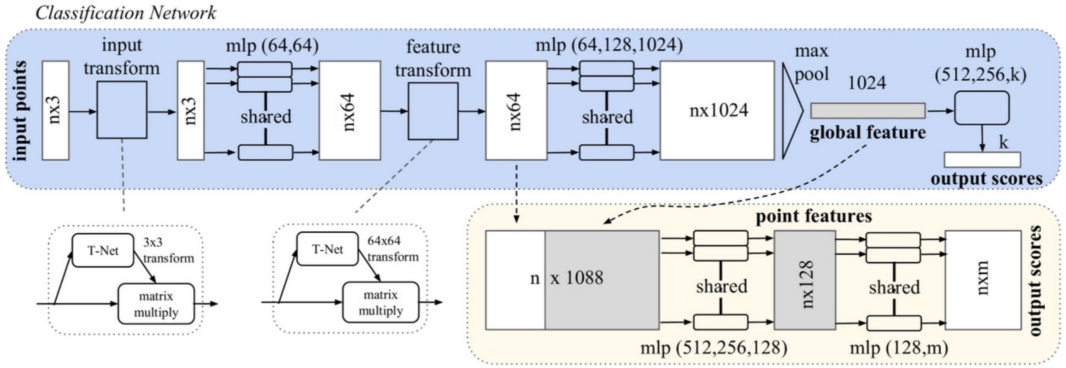
Image: [INFN: ENP]

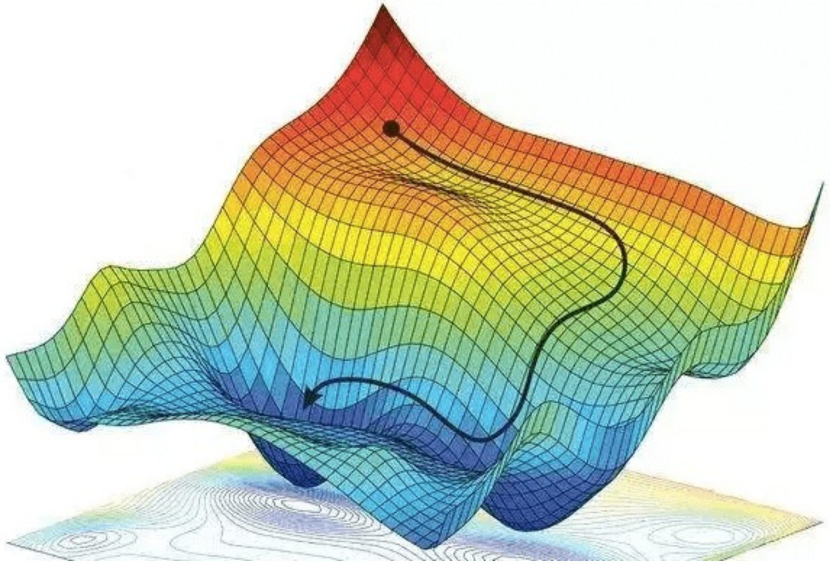
Deep Learning: A Crash Course

- Data needs a standard format (constant size matrix matrix)
- We define a set of matrix operations to the input data
- Each operation contains a set parameters (in our case over 6 million!)
- Gradient Descent: We define a loss function that the model attempts to minimize

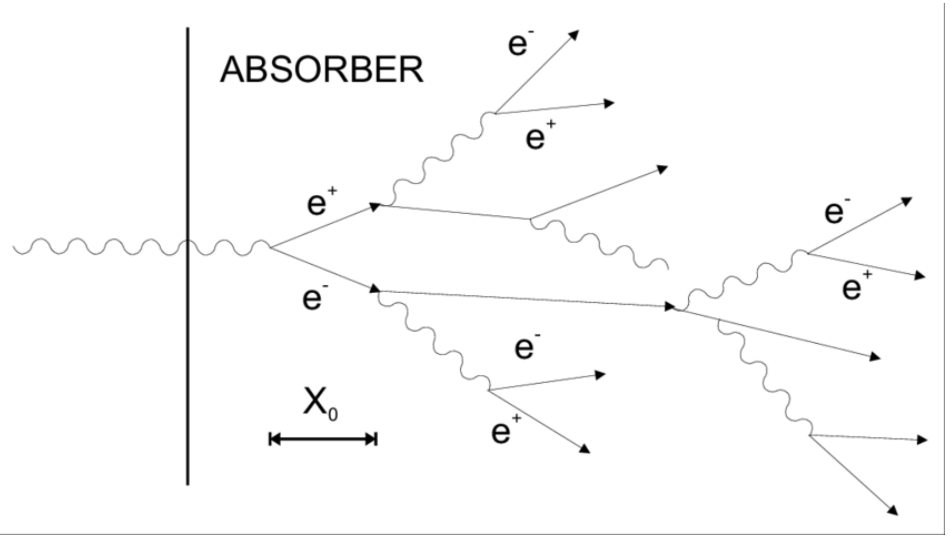


$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1k} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3k} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ a_{j1} & a_{j2} & a_{j3} & \cdots & a_{jk} & \cdots & a_{jn} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mk} & \cdots & a_{mn} \end{bmatrix}$$

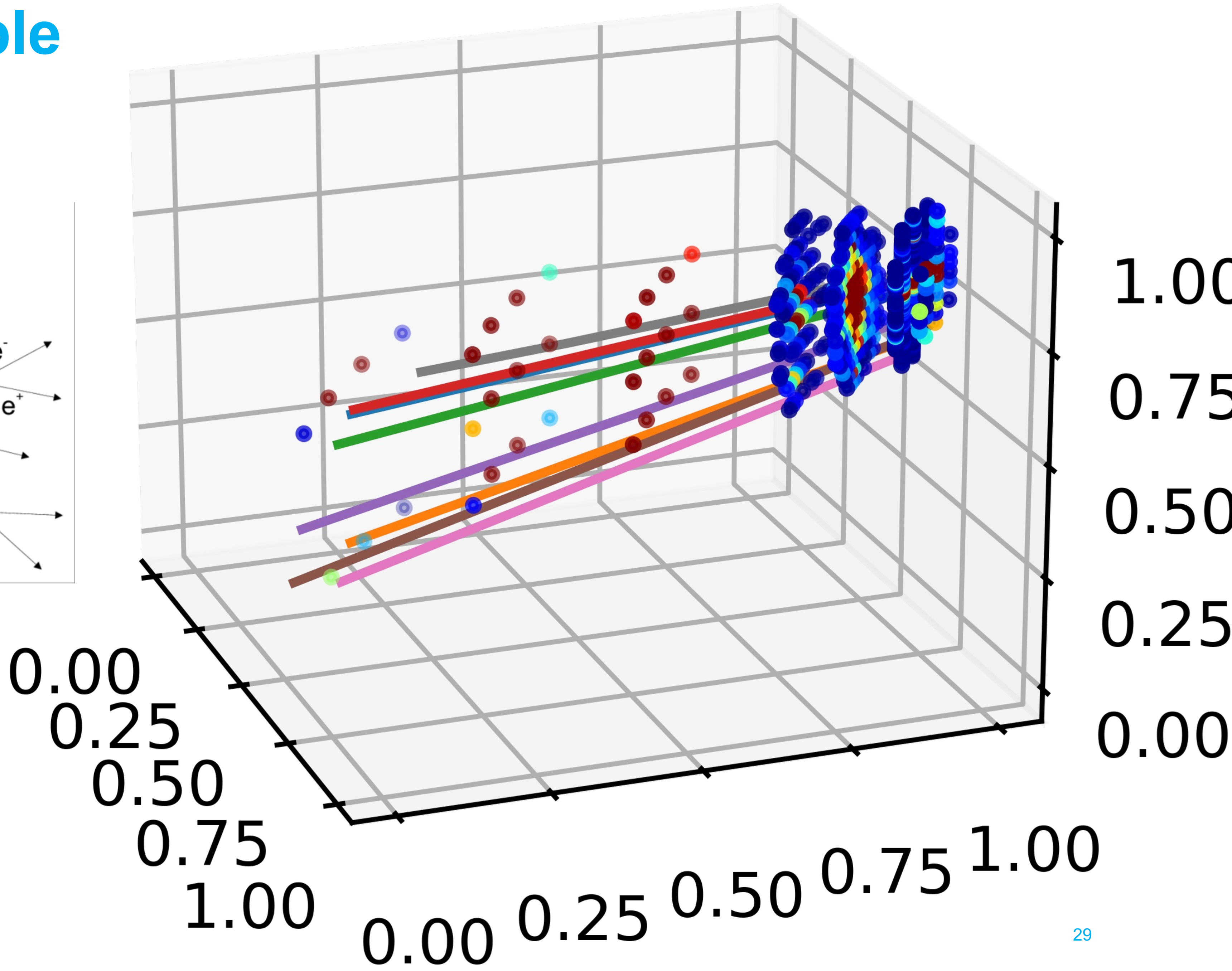




Showers: An example



[CERN: P Lecoq]



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Metrics:

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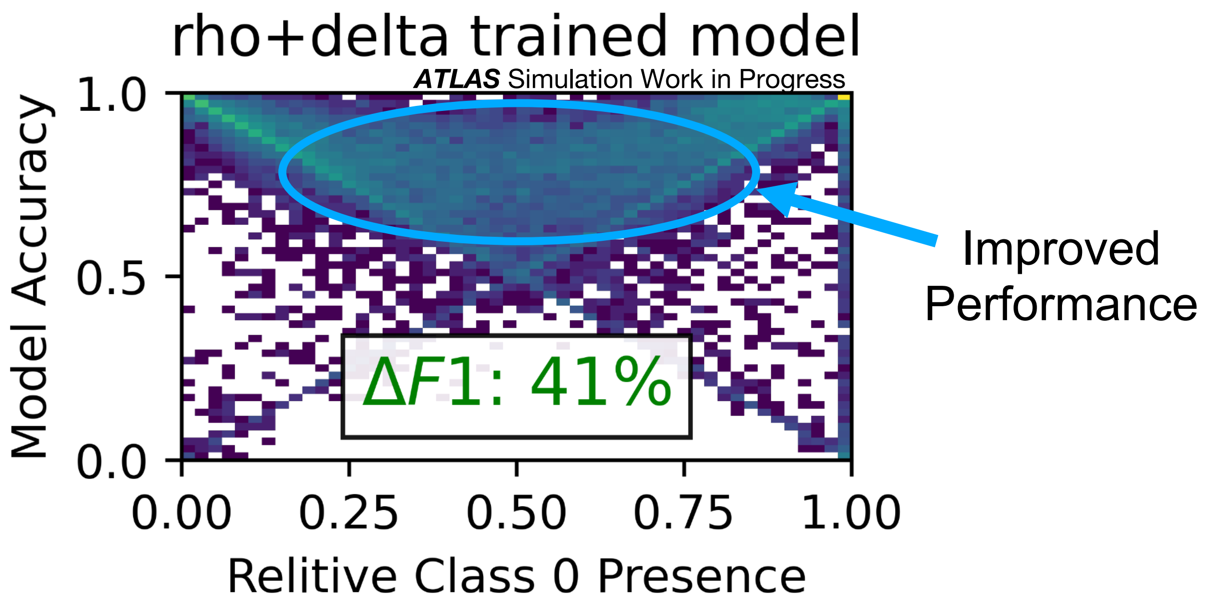
- F1 Score: Accuracy trade off factor
- Baseline: Random model with correct class balance



Dataset	Model	Accuracy	F1-score
rho + delta	*PointNet*	0.83	0.78
	smart_random	0.63	0.37

ATLAS Simulation Work in Progress