END-TO-END RECONSTRUCTION ALGORITHM FOR HIGHLY GRANULAR CALORIMETERS

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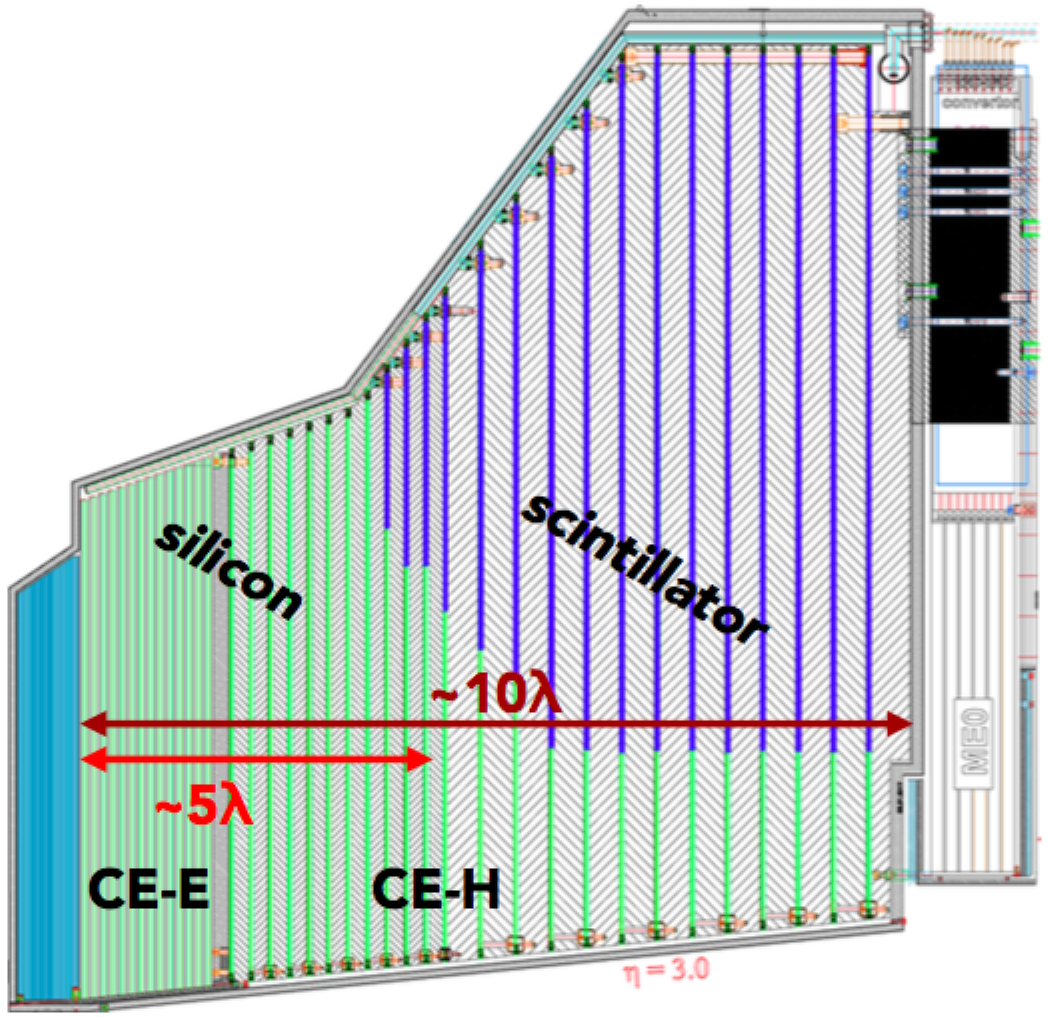
MOTIVATION

HIGH-LUMINOSITY-LHC

- CMS will observe 200 pile-up (PU) events
- Upgrade for end-cap calorimeter
  High **G**ranularity **CAL**orimeter (HGCAL)
- HGCAL: 2x ~3M readout channels
  52 sampling layers each side
- Silicon sensors and scintillators

RECONSTRUCTION GOALS

- Combine calorimeter hits with tracks
- **Cluster** hits to build showers
- **Regress** energy of showers
- **Classify** particle ID
- All of this using one **differentiable** network



https://cds.cern.ch/record/2293646/

CMS - HGCAL

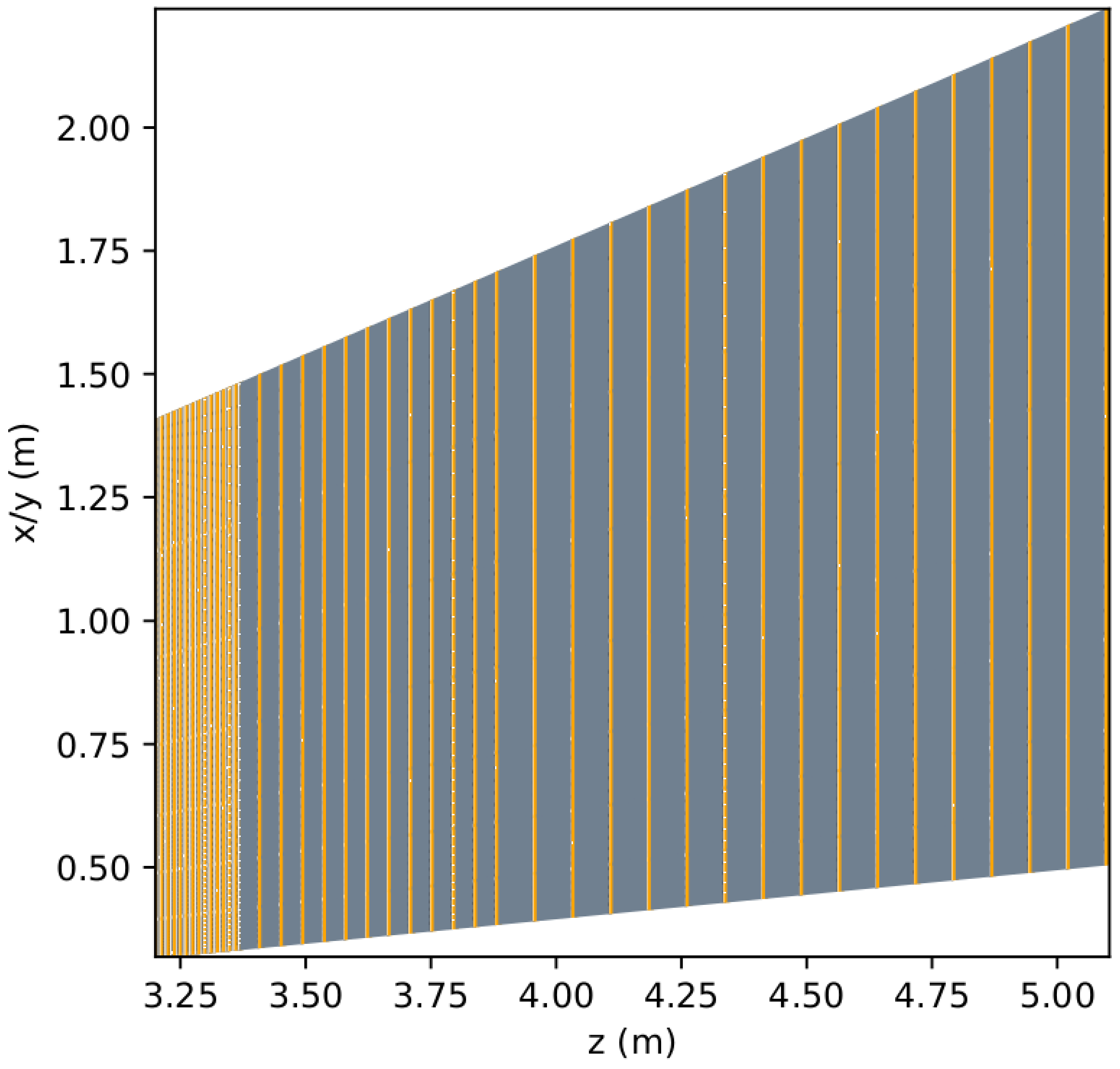
METHODS

- Graph-based neural network
  implemented in TensorFlow
- Object Condensation Loss
  allowing points to represent objects
- GravNet Architecture
  A dynamic GNN that operates on point clouds

REFERENCES

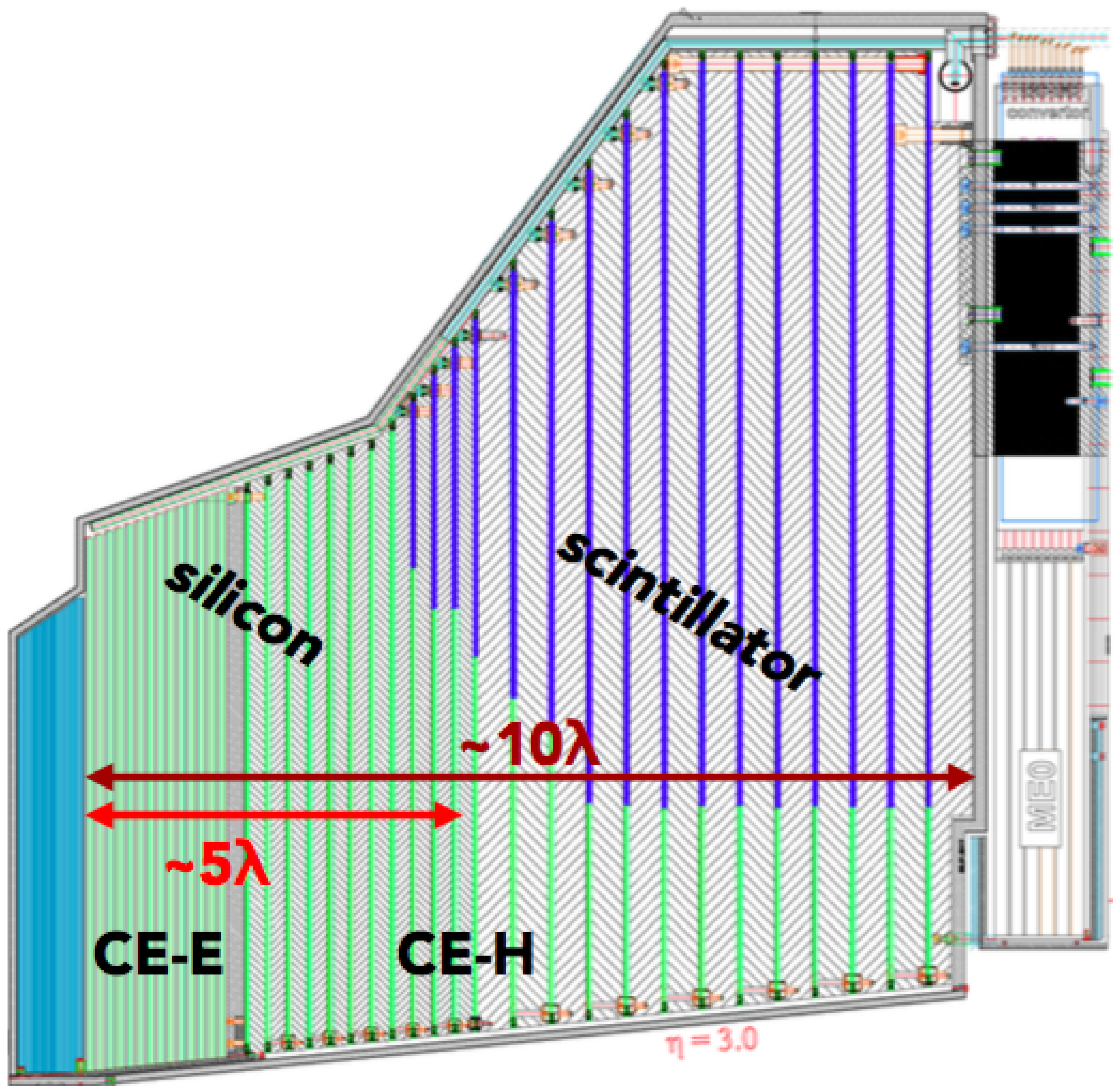
- Object Condensation
- GravNet
- End-to-End Reconstruction
- ACAT 2021
- ACAT 2022

TOY DETECTOR



- 56 Sampling layers with 200 μm silicon sensors as active material
- Sensors square in η and φ
- ~3 Million readout channels per end-cap
- Standalone simulation using Geant

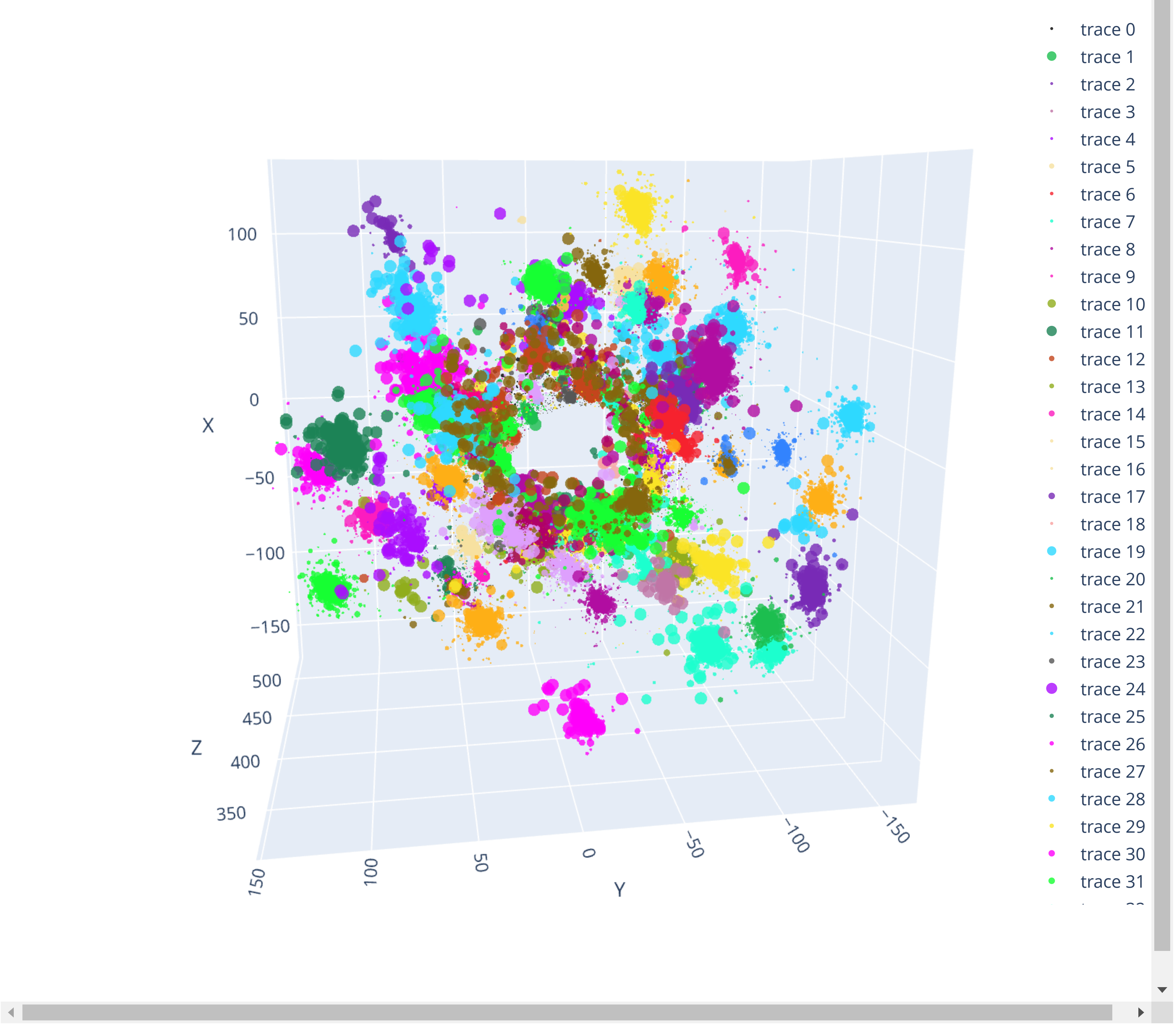
HGCAL



- 52 Sampling layers with 120 μm, 200 μm, 300 μm silicon and scintillators
- Heaxgonal silicon sensors
- ~3 Million readout channels per end-cap
- Simulation within CMS Software (CMSSW)

TRAINING EVENTS

Training Event with ~90 Showers

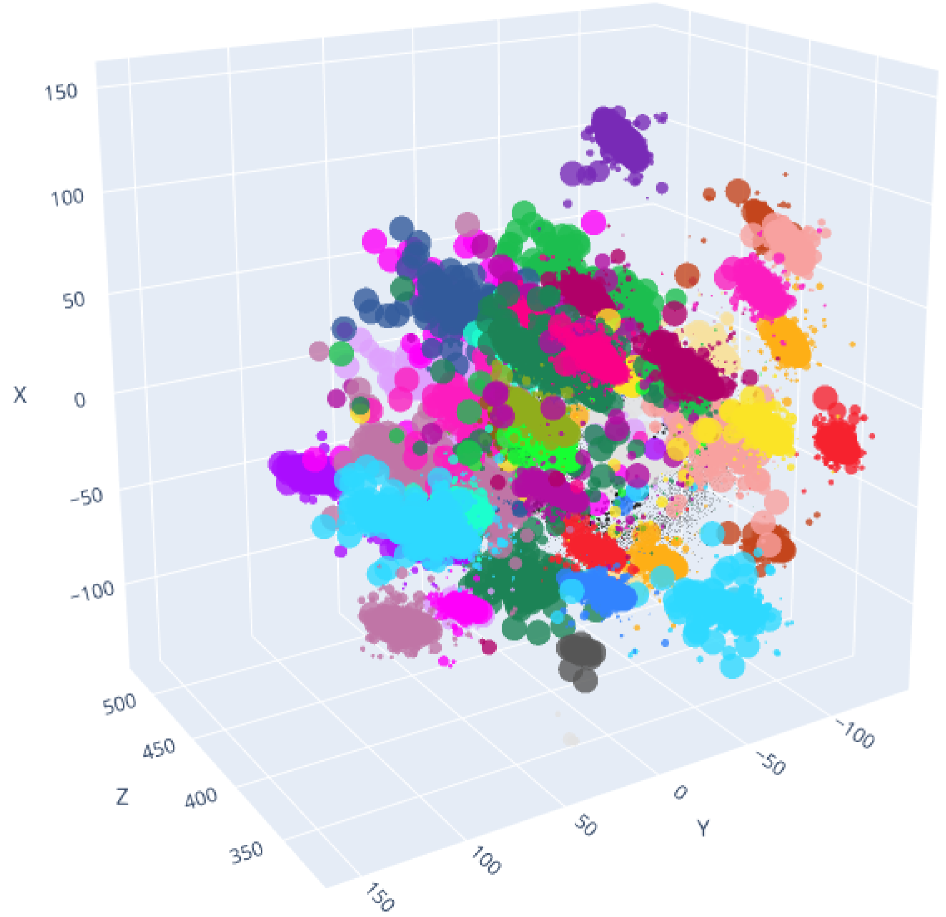


DATA SETS

- **Particle Showers**
  - Electrons, photons, charged pions, or kaons (K-long)
  - 0.1 GeV < E < 200 GeV
  - 1.5 < η < 3.0
- **Minimum bias**
  - Proton-proton collisions at 13 TeV
  - Simulated with PYTHIA8
  - Used for pile-up
- **Tracks**
  - Tracks are added for all charged particles
  - Tracks are flagged as such and have the particles original smeared out energy
- **Train Data**
  - Multiple showers + Gaussian noise
  - Multiple showers + Gaussian noise + 200 PU in random 30° φ region
- **Test Data**
  - Multiple showers + Gaussian noise
  - Single shower + Gaussian noise + 200 PU in full detector

OVERVIEW

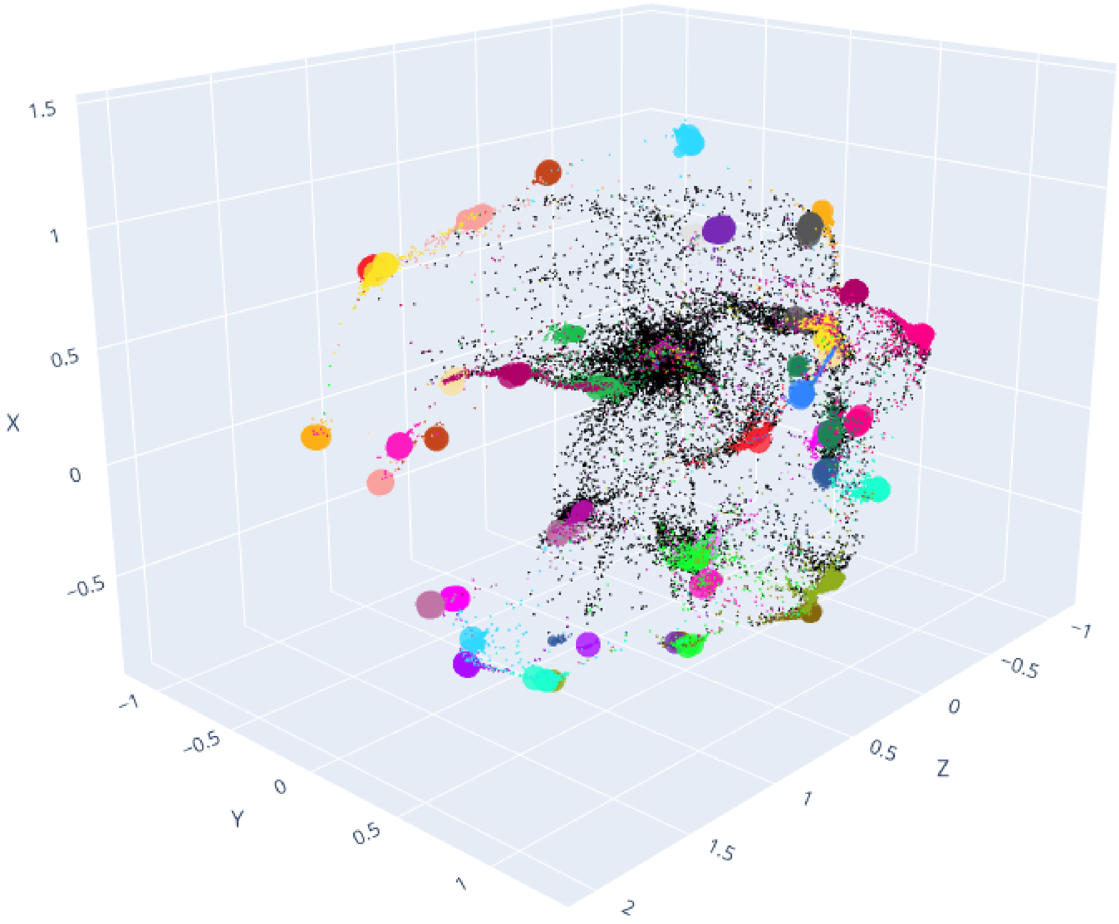
DETECTOR SPACE



CONCEPT

- Colour represents different showers
- Overlapping showers make clustering in detector space difficult
- Learn mapping into clustering space
- Learn confidence β
- β close to 1 → hit can represent shower
- In clustering space hits from the same shower should be close
- Every shower should have at least one hit with high β (condensation point)

CLUSTER SPACE



OBJECT CONDENSATION

Highest confidence β for every shower gets assigned as condensation point, indicated by

Charge $$q_\alpha = \tanh^2(\beta_\alpha)$$

Attractive Potential $$V_{\text{att}} \propto q_\alpha \cdot |x - x_\alpha|^2$$

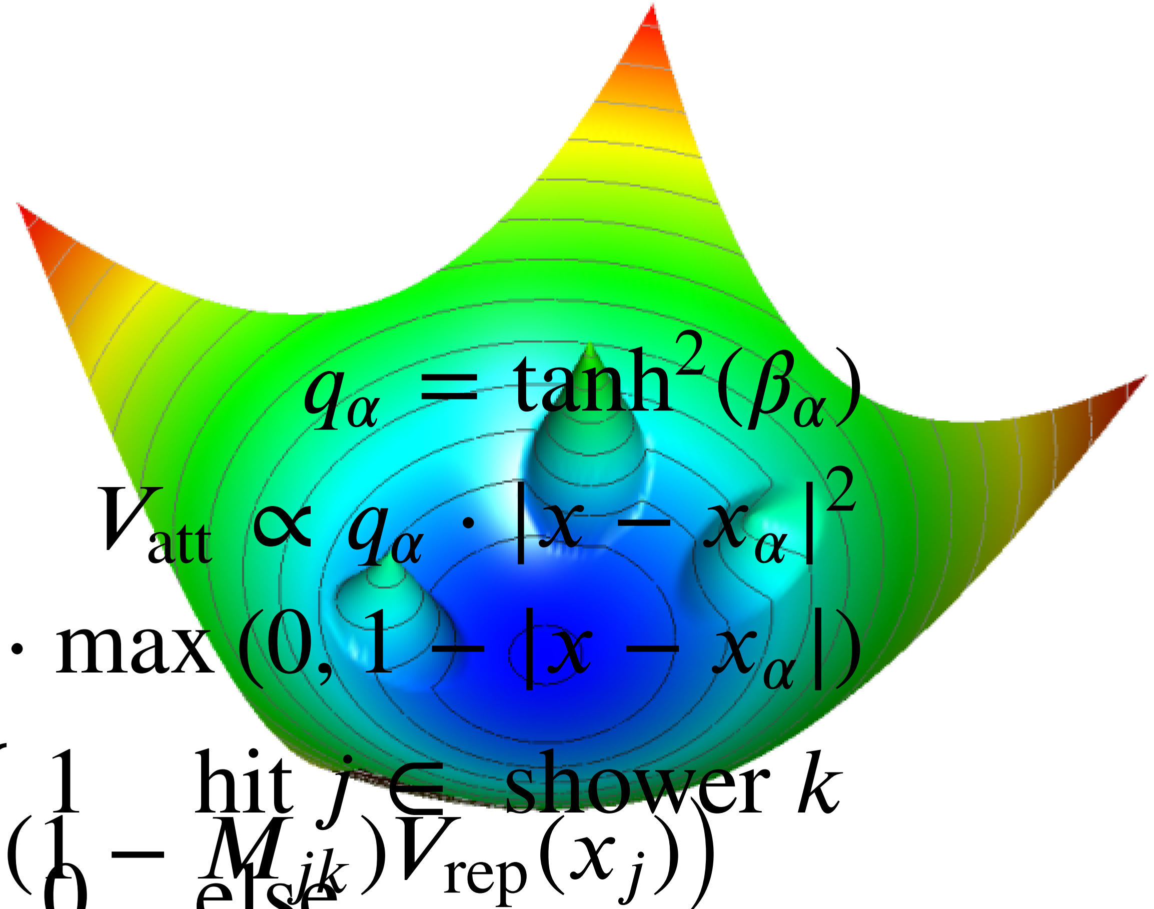
Repulsive Potential $$V_{\text{rep}} \propto q_\alpha \cdot \max\left(0, 1 - |x - x_\alpha|\right)$$

Shower Matrix $$M_{jk} = \begin{cases} 1 & \text{hit } j \in \text{ shower } k \\ 0 & \text{else} \end{cases}$$

Loss terms

$$L_V = \frac{1}{N} \sum_{j=1}^{N} q_j \sum_{k=1}^{K} \left(M_{jk} V_{\text{att}}(x_j) + (1 - M_{jk}) V_{\text{rep}}(x_j) \right)$$

$$L_\beta = \frac{1}{K} \sum_{k=1}^{K} \left(1 - \beta_\alpha^k\right) + \frac{1}{N_{\text{noise}}} \sum_{j \in N_{\text{noise}}} \beta_j$$

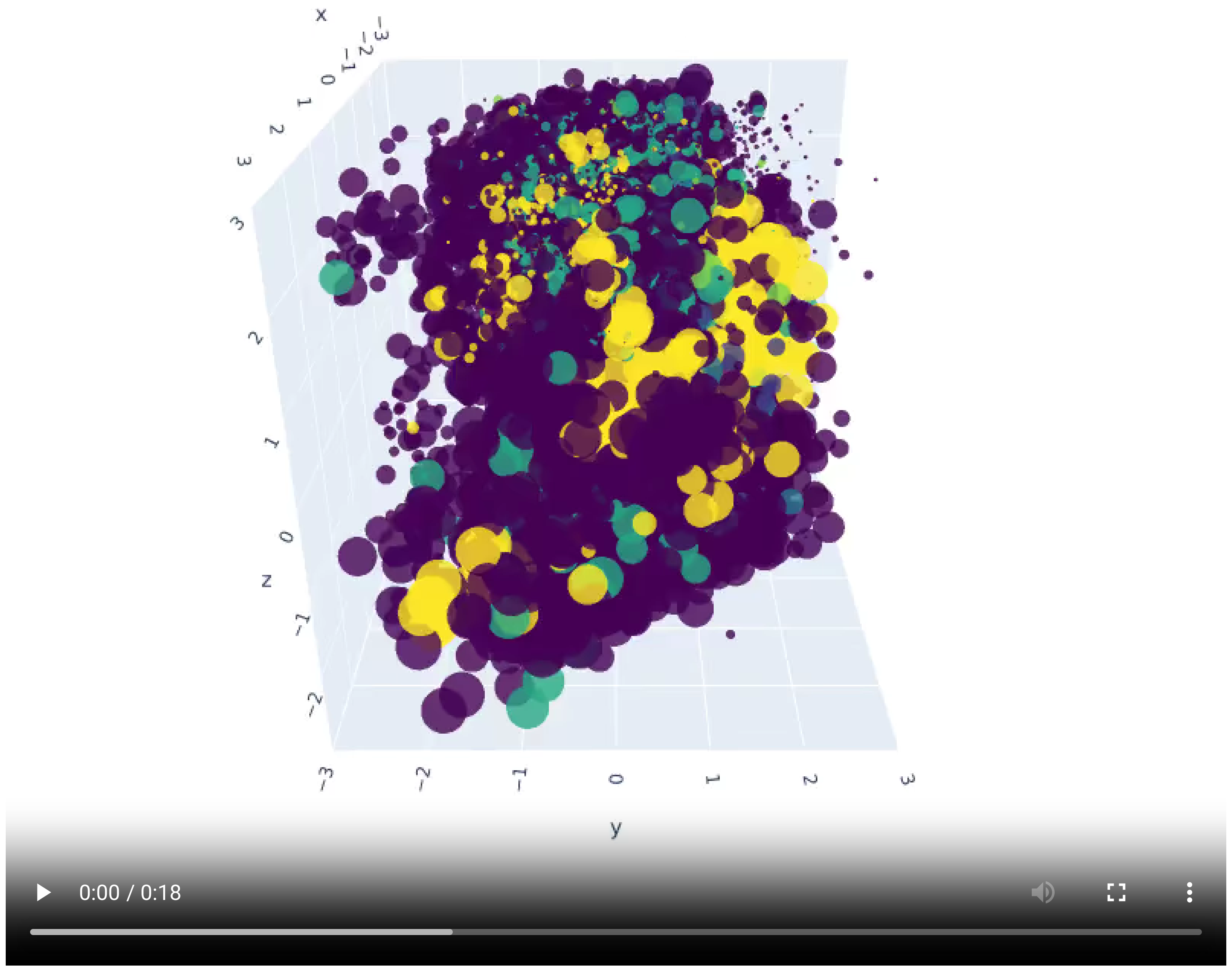


Object Condensation

Potential in cluster space seen by a single hit

- Minimum: Matching condensation point
- Local peaks: Condensation points from 3 other showers

OBJECT CONDENSATION IN TRAINING



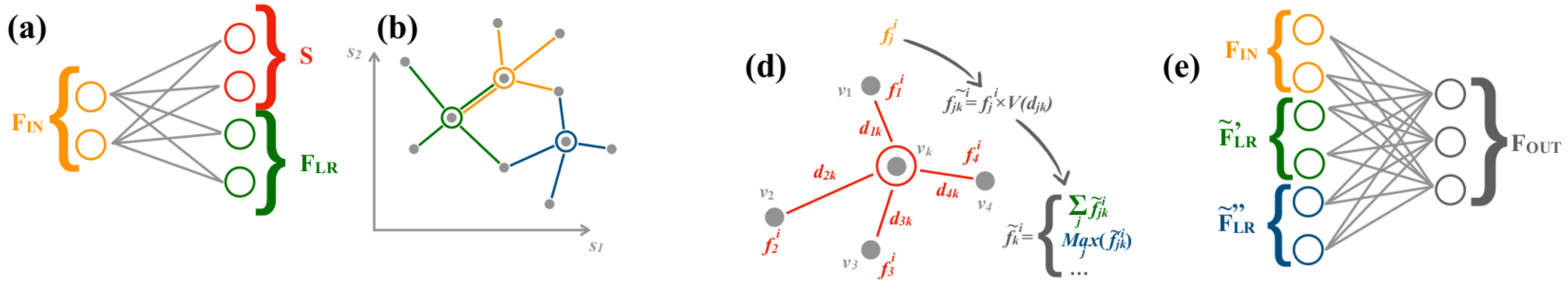
GRAVNET

NETWORK ARCHITECTURE

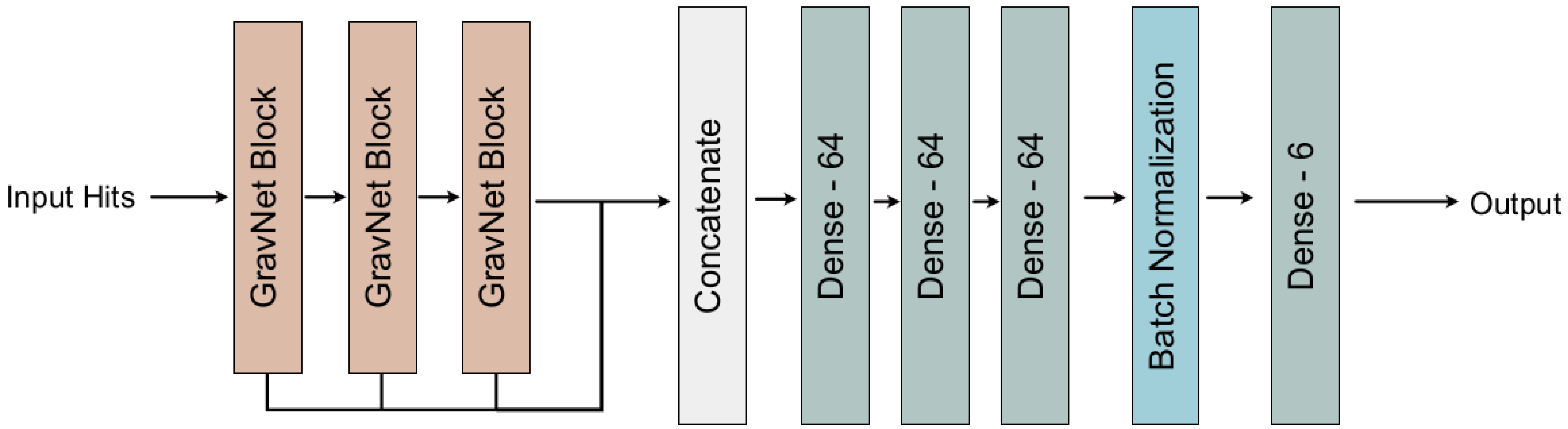
GRAVNET LAYER

1. Transform input features via dense layer into F_{in}
   - transformed features F_{LR}
   - low-dimensional GravNet coordinates S
2. Use GravNet coordinates to build graph
   connect nearest neighbours (KNN) K
3. Aggregate weighted $\rightarrow$ over neighbours F_{LR}
   - Weights depend on distance between nodes
   - Aggregation is mean and max value of all neighbours
4. Concatenate to produce output F_{out}

1. Transform and normalize inputs
2. Use several GravNet layers to exchange information among neighbours
3. Create ouputs using information from all Gravnet layers
   - Cluster coordinates
   - Confidence β
   - Energy correction factor
   - Particle ID



https://arxiv.org/abs/1902.07987



https://arxiv.org/abs/2204.01681v2

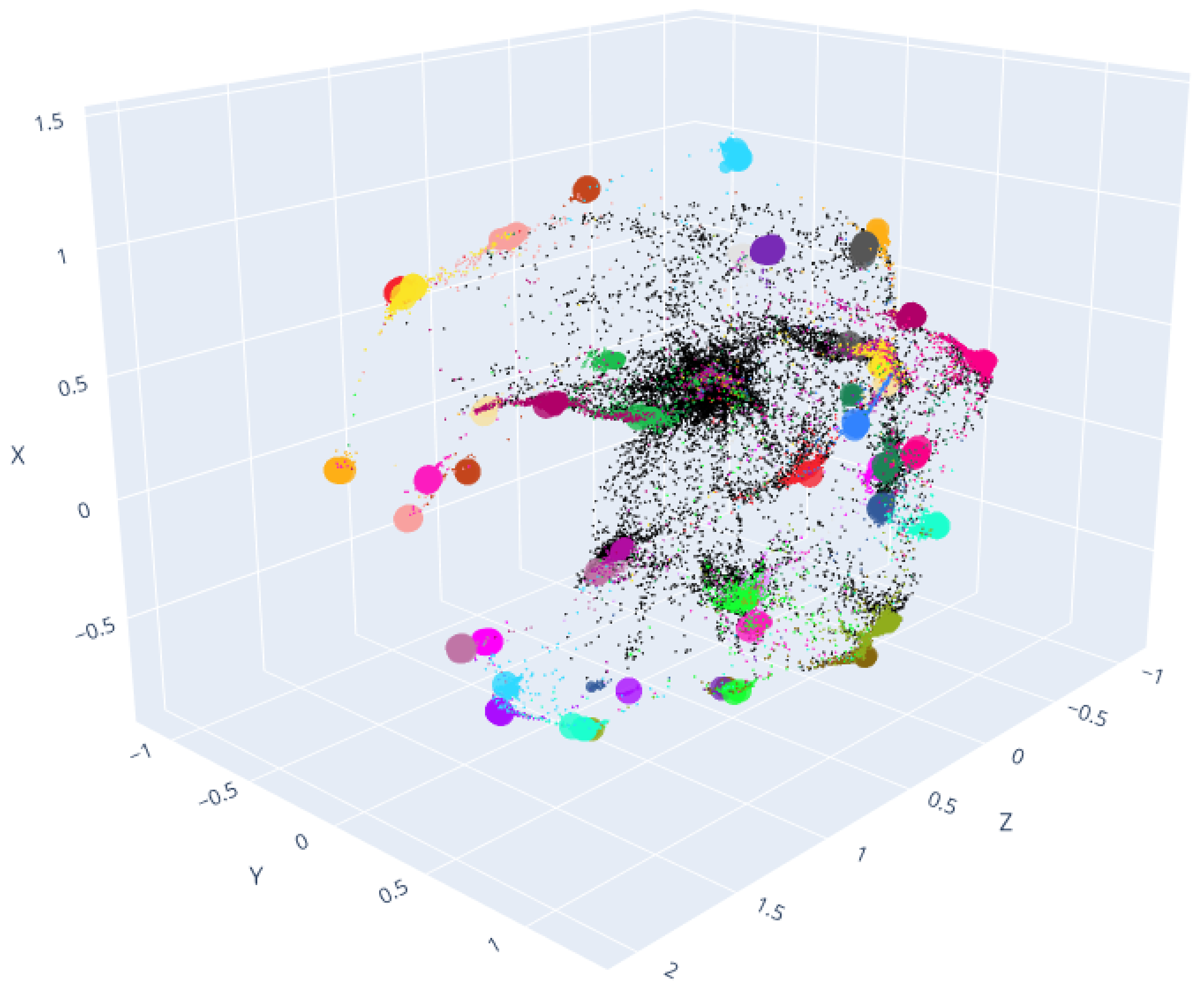
CREATING SHOWERS

FAST CLUSTERING ALGORITHM

1. Sort hits by confidence
2. Highest β is first condensation point
3. Hits within distance threshold t_d = 0.25 around β are assigned to first shower
4. Remove already assigned hits from list
5. Repeat steps 2 - 4 as long as highest β value is larger then threshold t_β =0.3
6. Remaining hits are classified as noise

More sophisticated clustering algorithms such as HDBSCAN can improve our performance at the cost of speed

CLUSTER SPACE



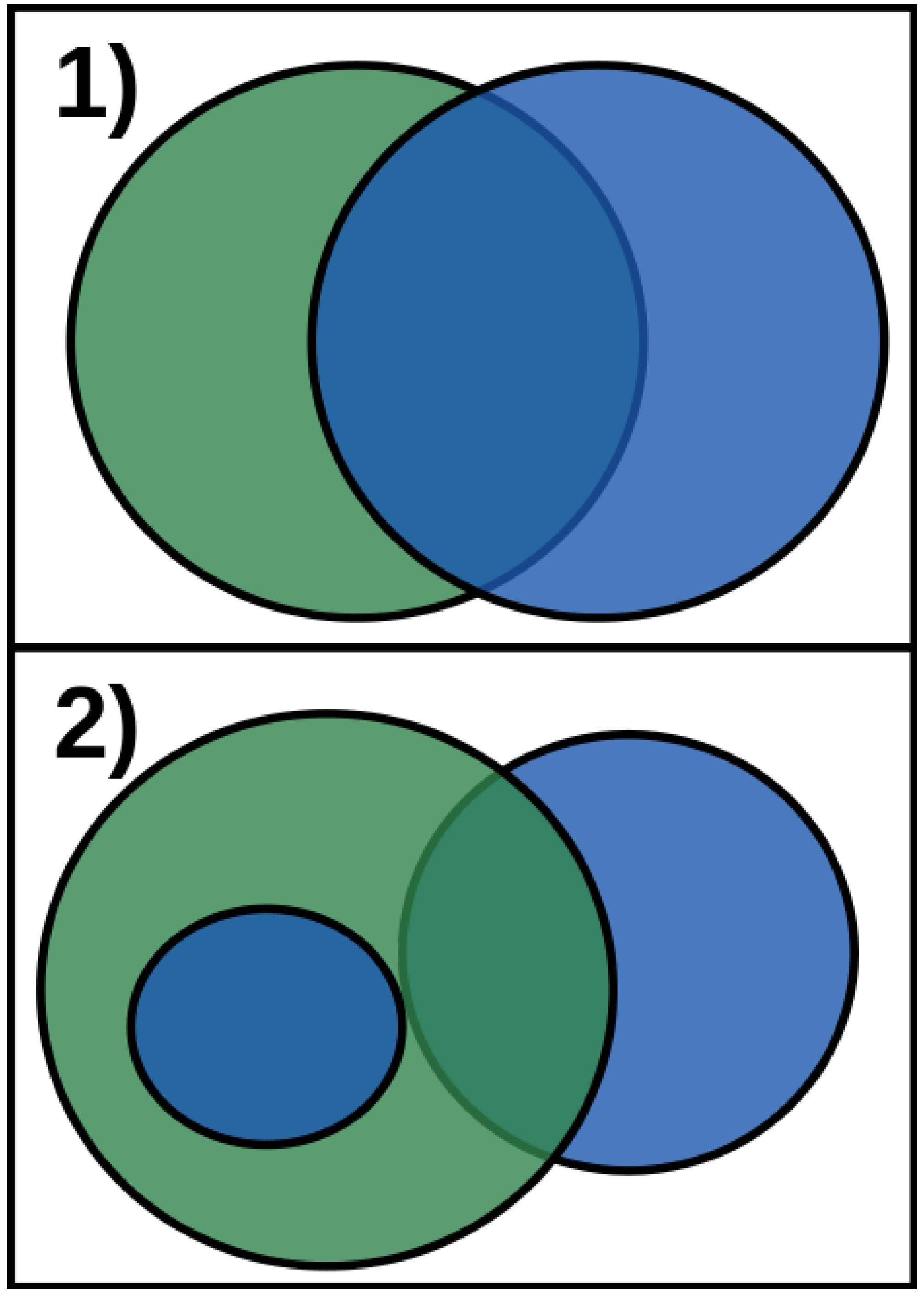
MATCHING SHOWERS

MATCHING CONDITIONS

To evaluate the performance of the algorithm, reconstructed showers are matched with truth showers.

- Reconstructed showers are matched with true showers based on their energy weighted overlap.
- More precisely: The intersection over union between two showers has to be larger than 33%
- If truth shower and reconstructed shower have equal energy, this translates that at least 50% of each shower overlaps

Important:
The matching conditions influence the performance metrics, but do not change the performance of the algorithm.
A low threshold allows to find a match for nearly every shower but comes at the cost of degraded energy resolution and vice versa.



1) True shower and predicted shower overlap
2) More complicated matching scenario

DATASETS

to evaluate

CLUSTERING & ENERGY

- Single shower
  - Electrons, photons, charged pions, or kaons (K-long)
  - E = 20 GeV, 50 GeV, 100 GeV, 200 GeV
  - $\eta = 2.0$
- Random Gaussian noise
- 200 (40) minimum bias proton-proton collisions

to evaluate

PARTICLE IDENTIFICATION

- 60-90 showers
  - Electrons, photons, charged pions, kaons (K-long)
  - $0.1\ \text{GeV} \leq E \leq 200\ \text{GeV}$
  - $1.5 \leq \eta \leq 3.0$
- Random Gaussian noise
- No pile-up

SHOWER QUALITY

EFFICIENCY

Percentage of truth showers that are matched to a reconstructed shower

PURITY

Energy of a reconstructed shower that belongs to matched truth shower

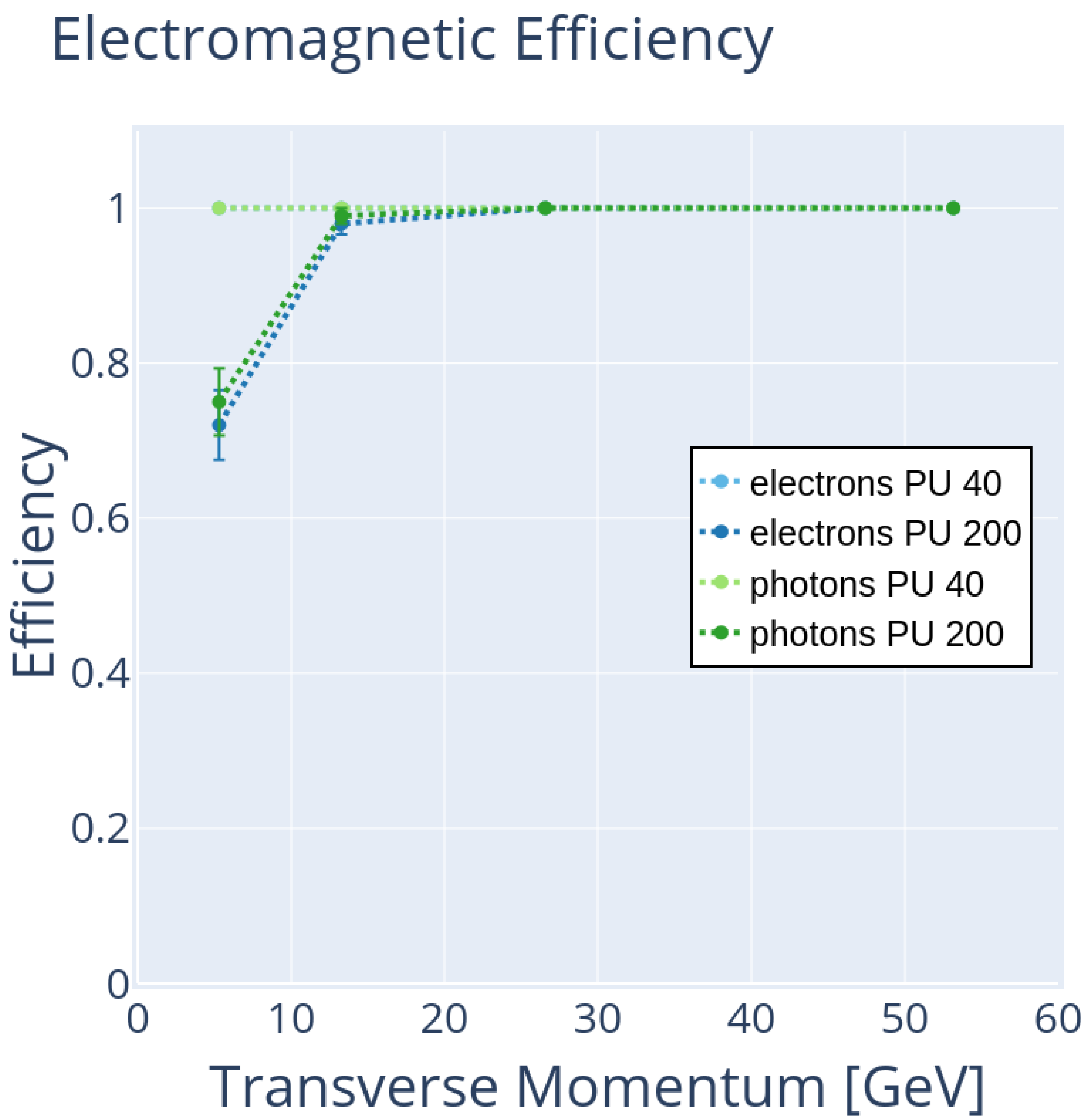
CONTAINMENT

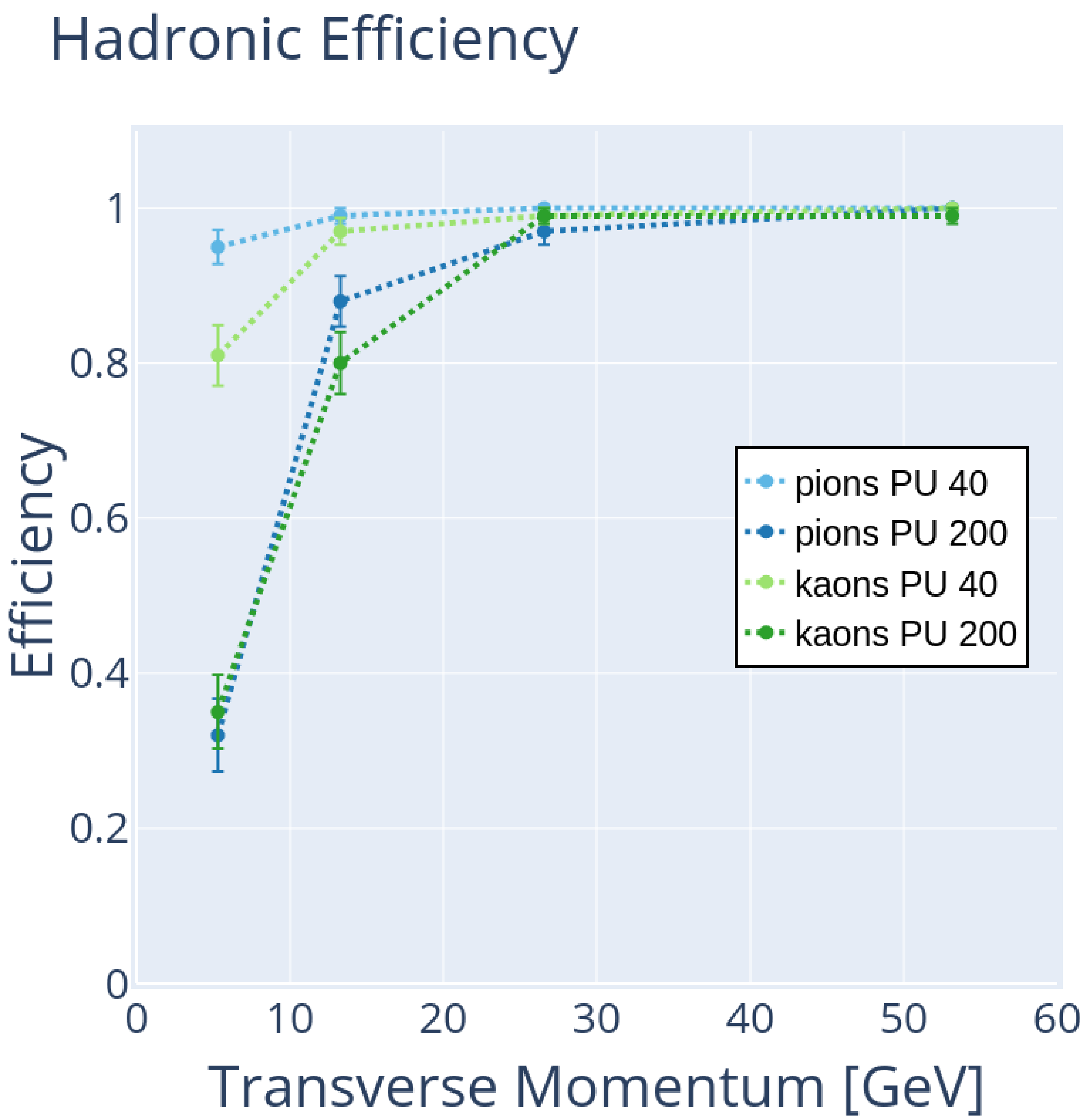
Energy of truth shower that is contained in the matched reconstructed shower

Trade-off between Purity and Containment

- Algorithms that tend to **merge showers** will have **high containment**, but low purity
- Algorithms that tend to **split showers** will have low containment, but can have **high purity**

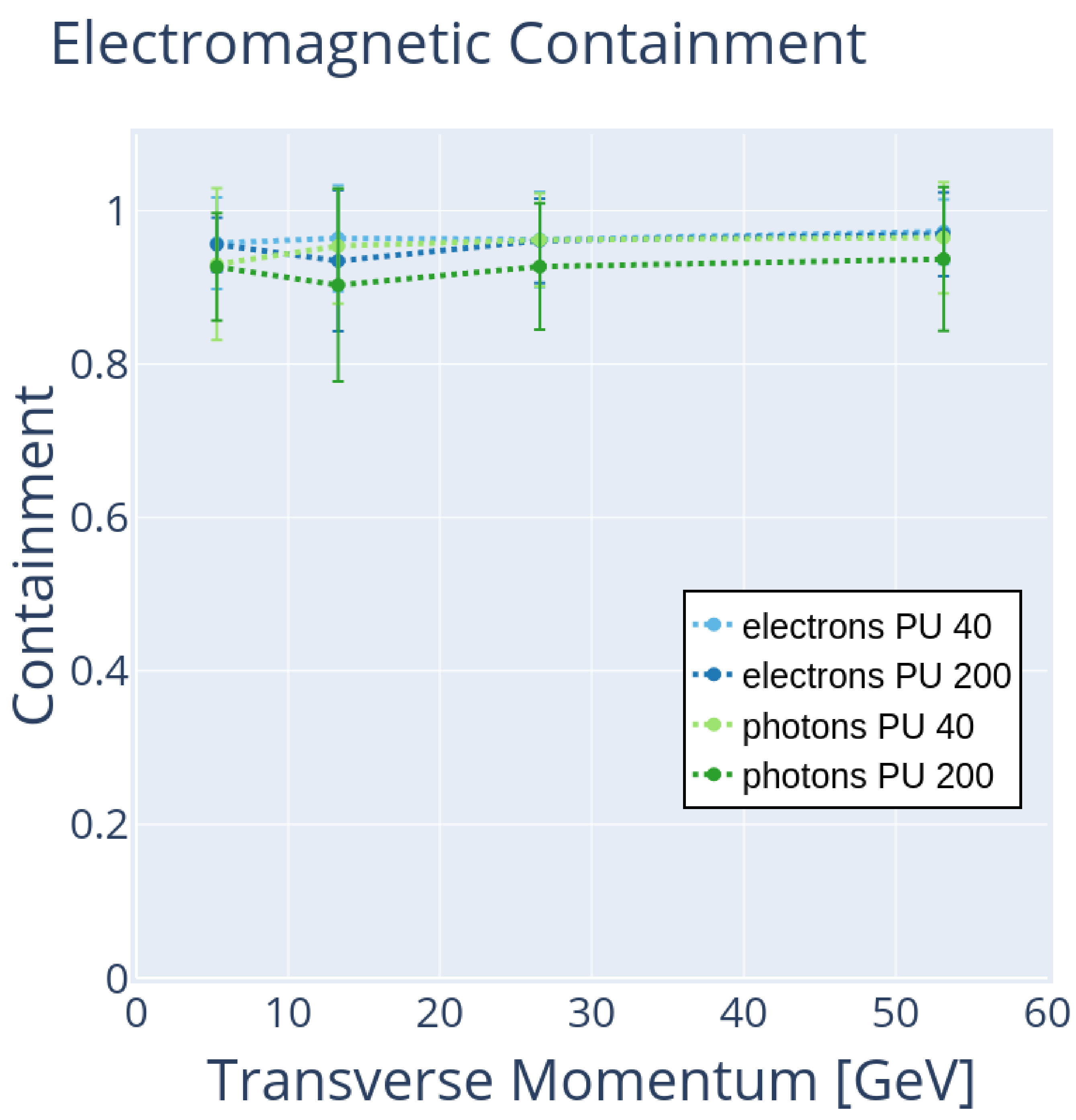
EFFICIENCY

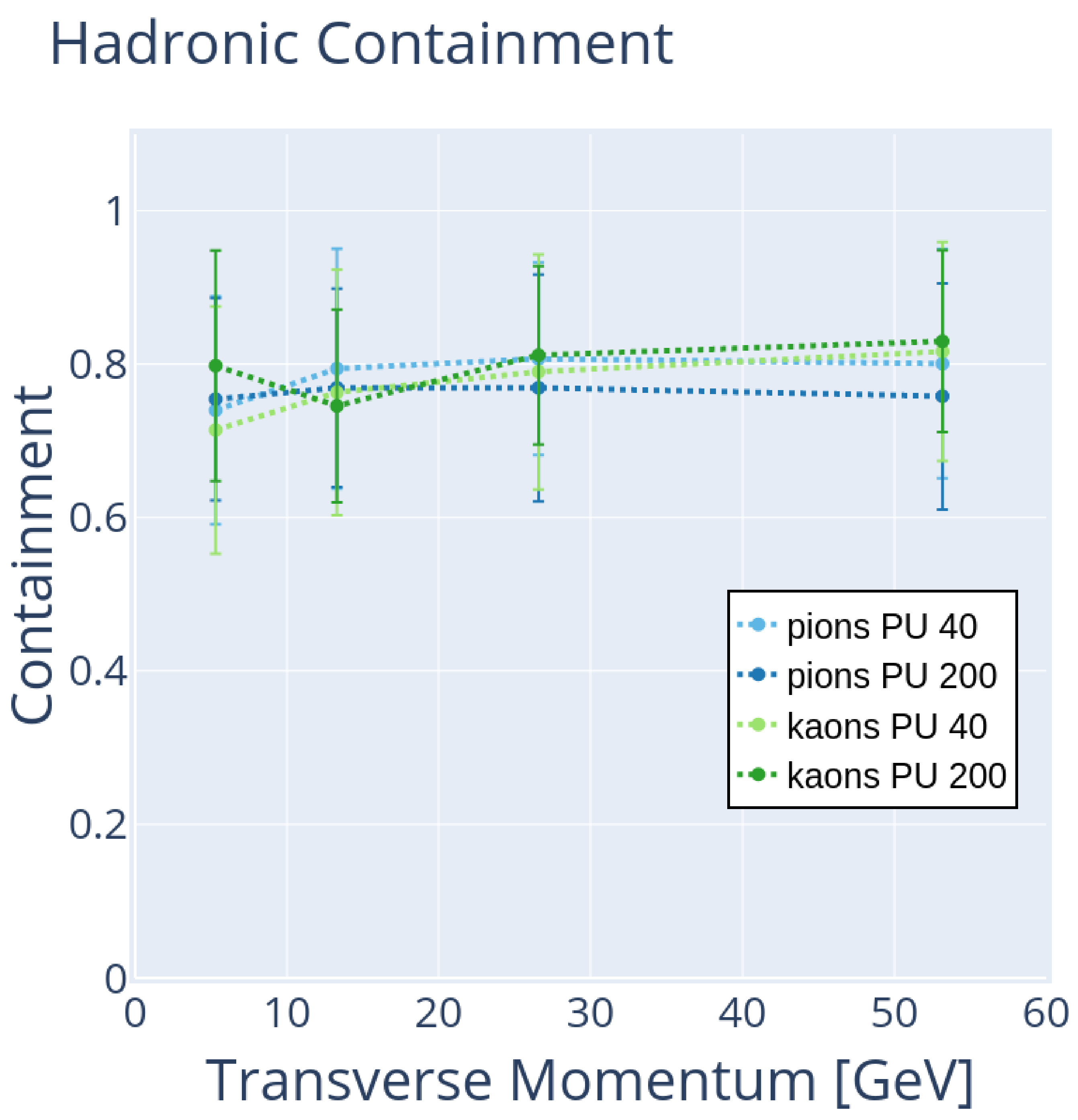




Above 13 GeV p_T almost perfect efficiency except for hadrons in 200 pile-up

CONTAINMENT





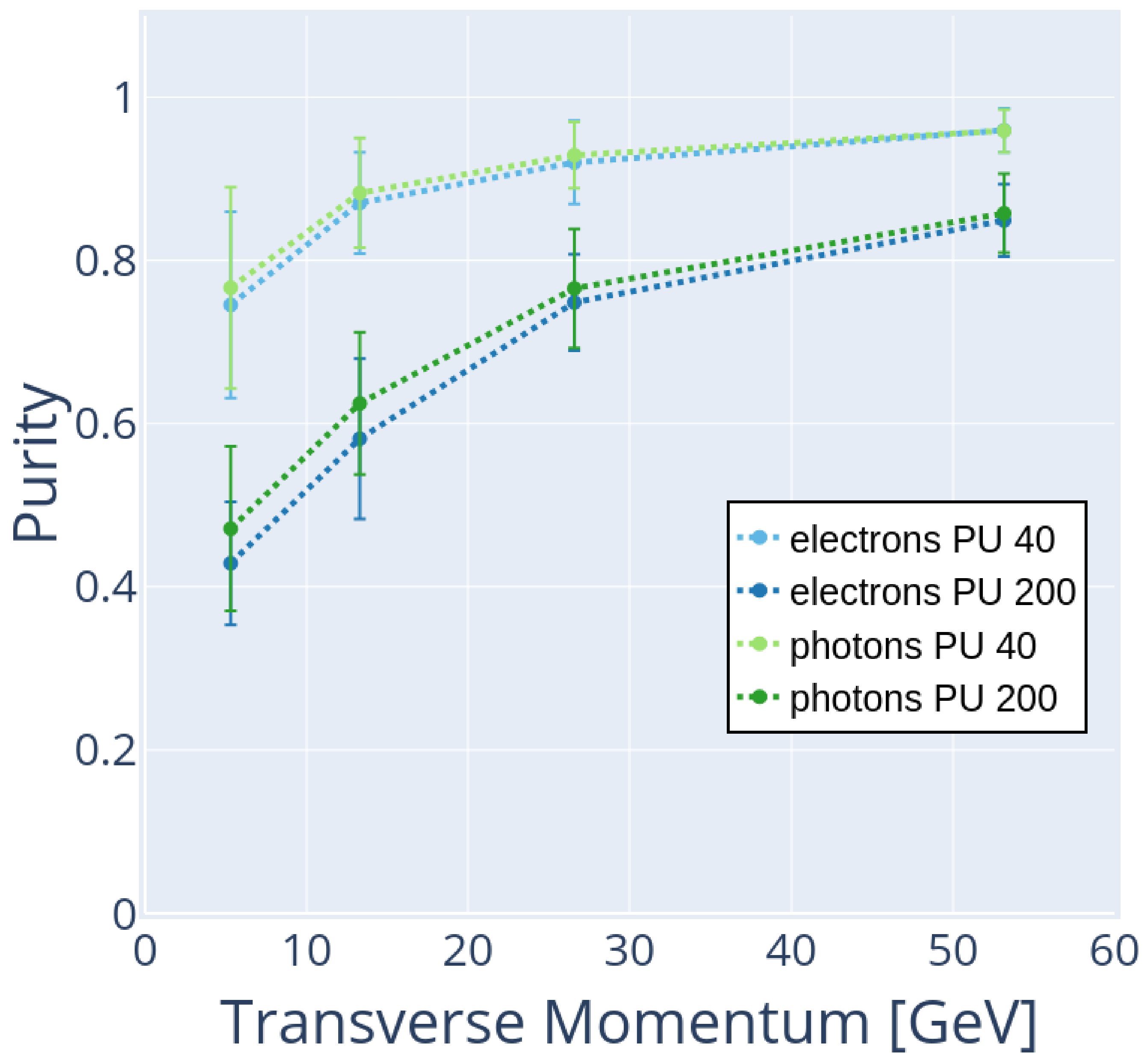
Reconstructed showers almost fully contain true showers

Reconstructed showers contain most of true showers

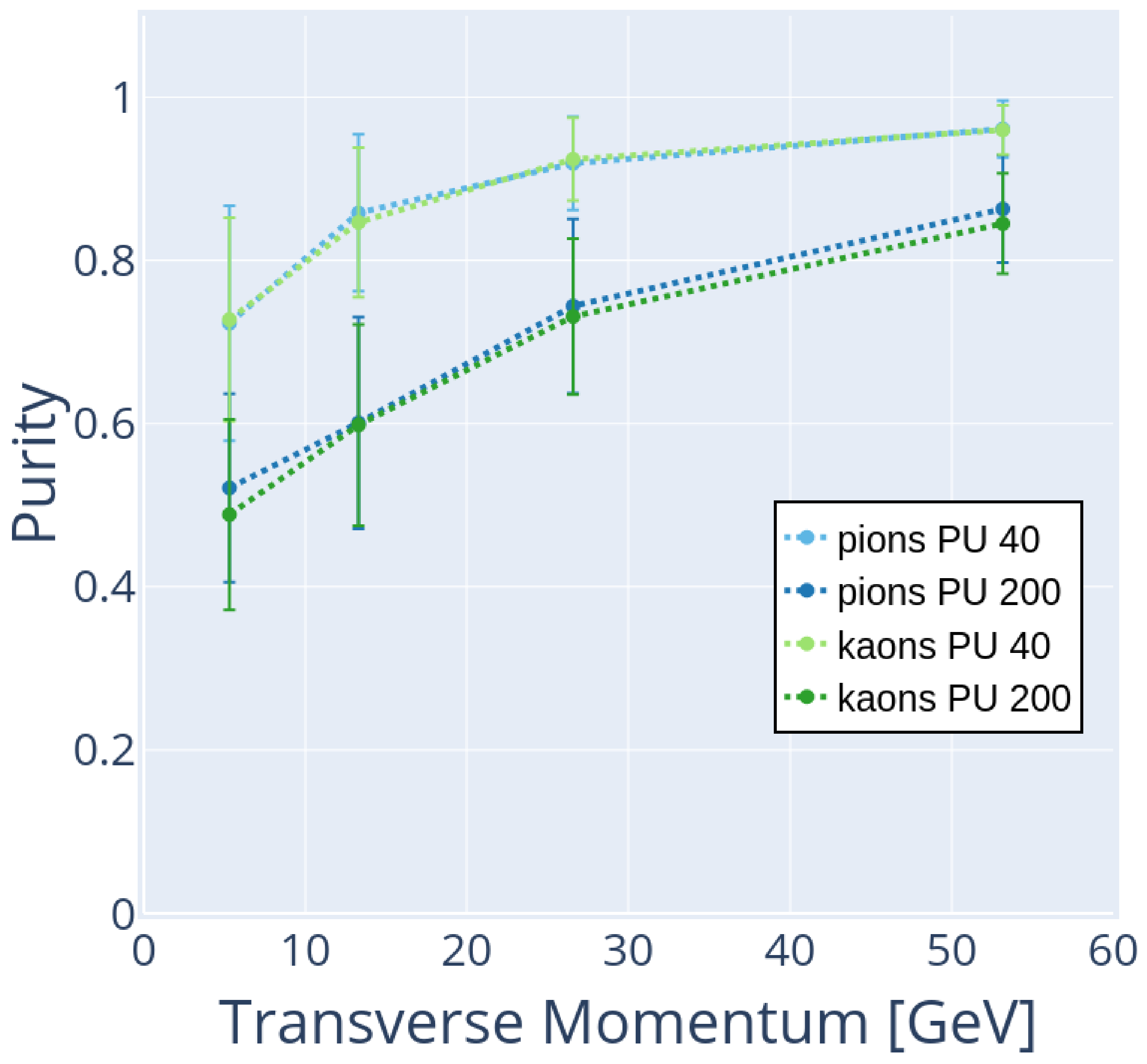
Containment is independent of pile-up or momentum but differs between EM and HAD showers

PURITY

Electromagnetic Purity



Hadronic Purity



- Reconstructed showers also contain PU-hits
- This effect is strongest for low energies and high pile-up
- Can be improved at the cost of containment

RESPONSE AND RESOLUTION

Metrics for matched showers

RESPONSE

Mean of predicted energy over true energy

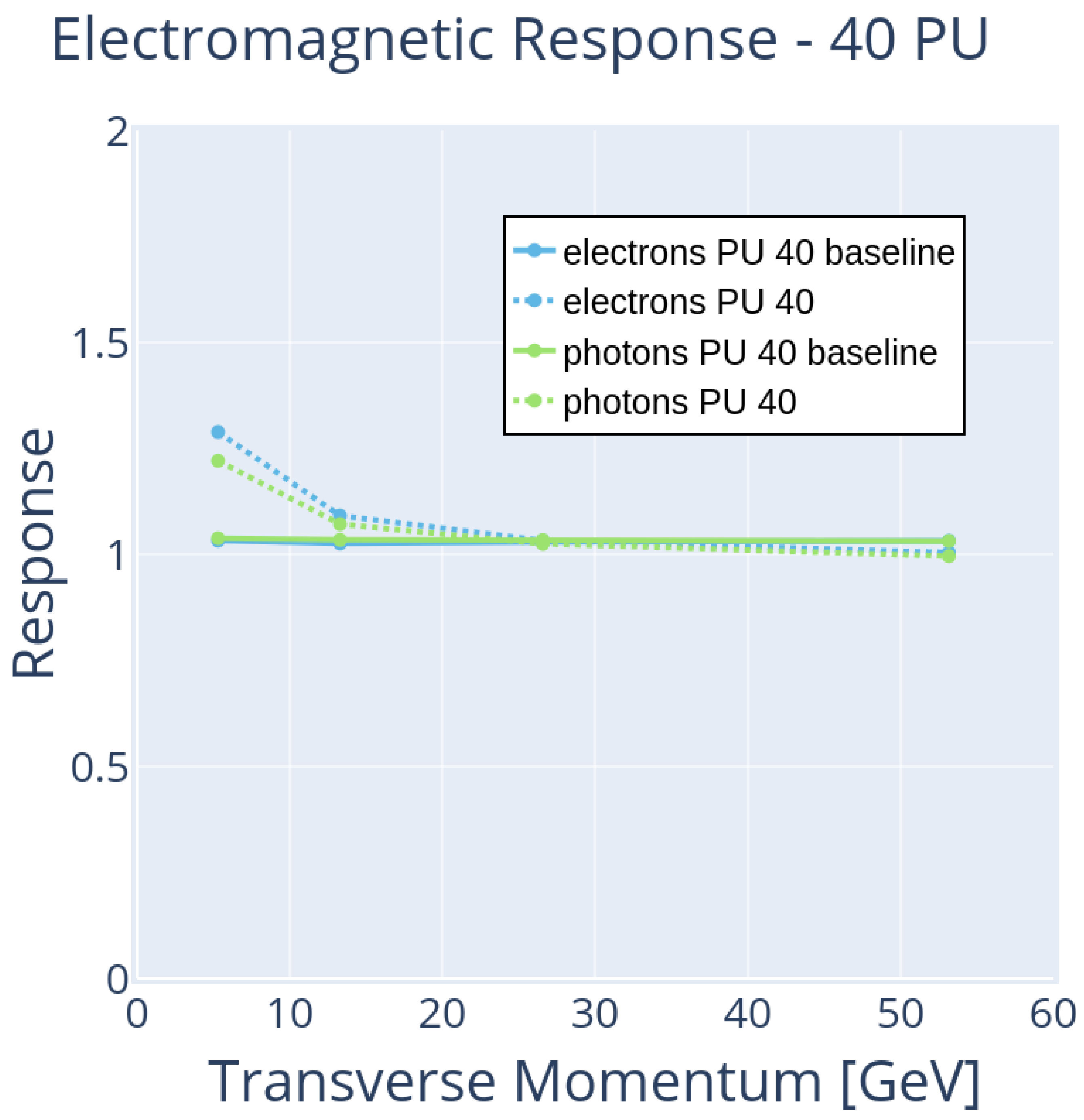
RESOLUTION

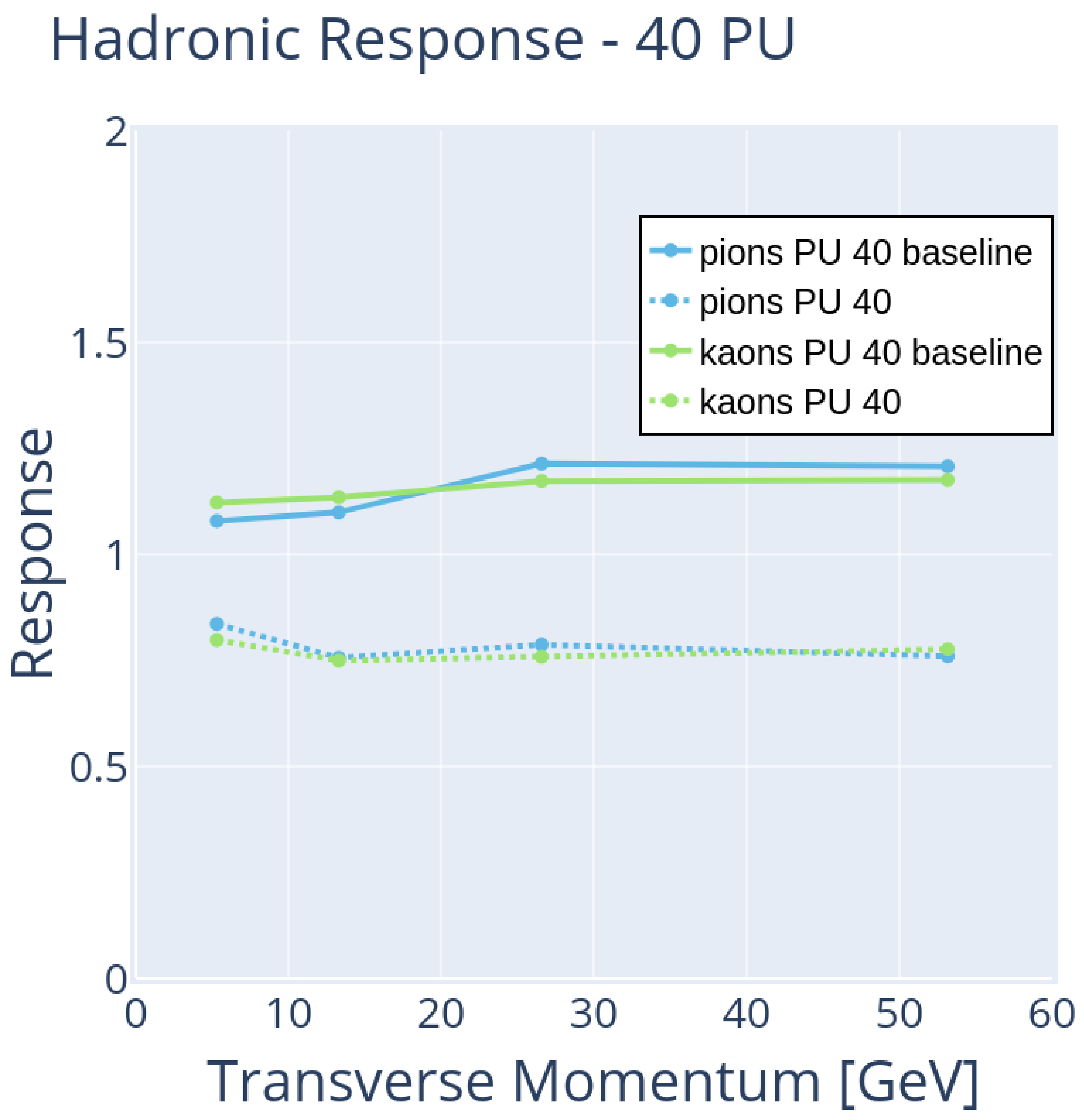
Standard deviation of predicted energy over true energy divided by response

Baseline: Ideal Clustering

- Use truth information for clustering
- Energy is sum of all hit energies belonging to shower
- Pile-up may contaminate truth information for overlapping hits

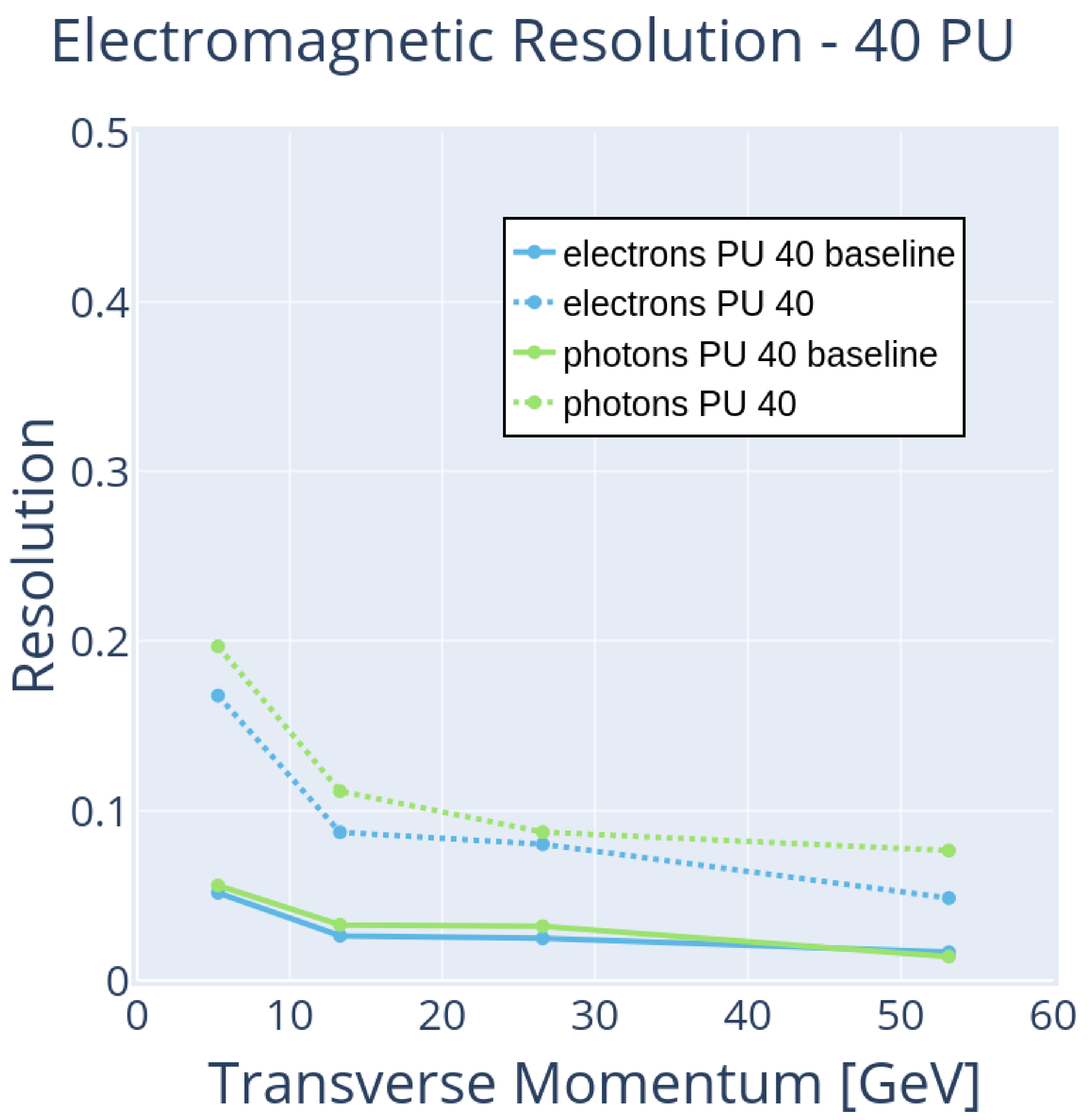
RESPONSE - 40PU

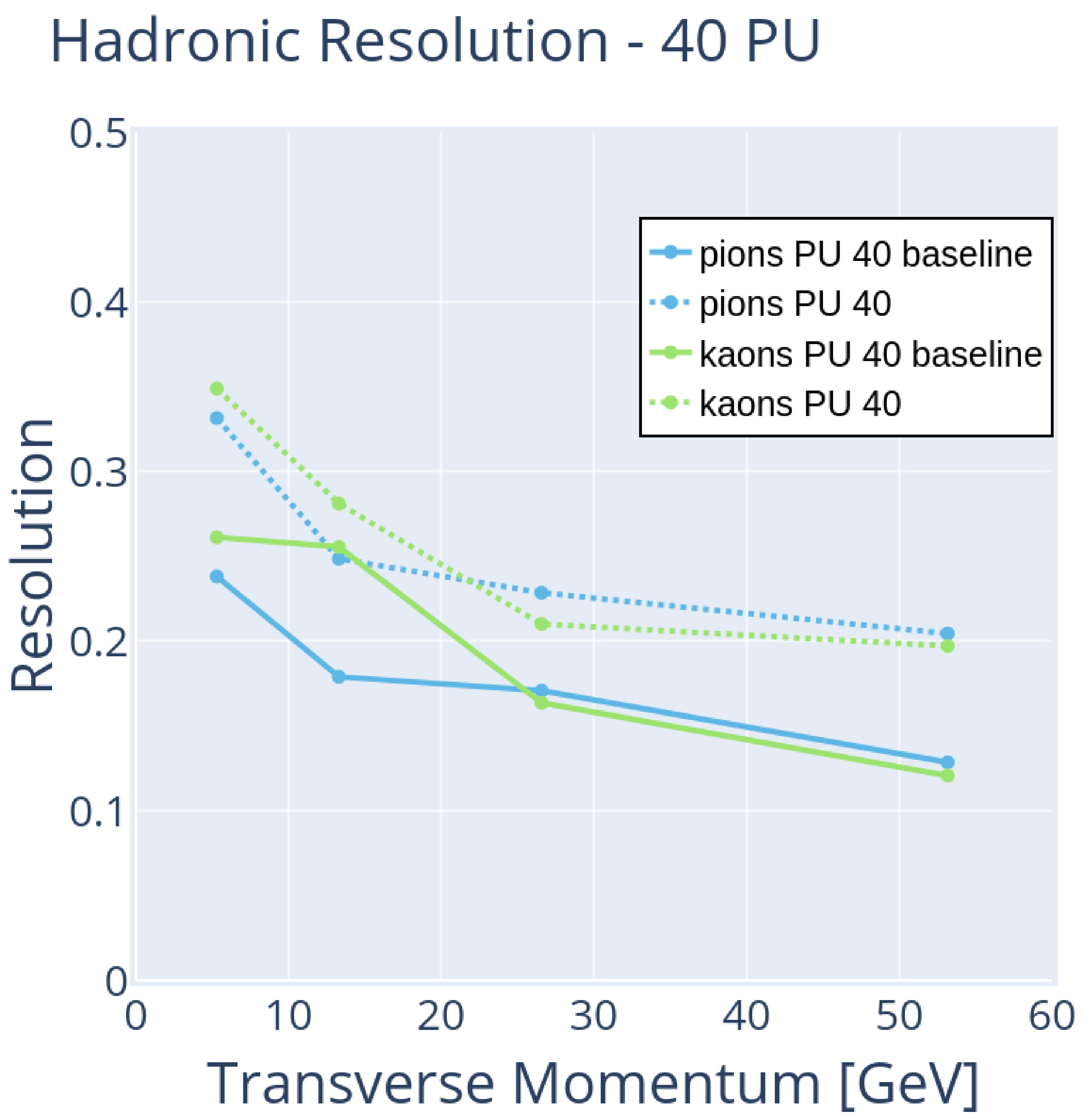




Response mostly flat for both EM and HAD showers

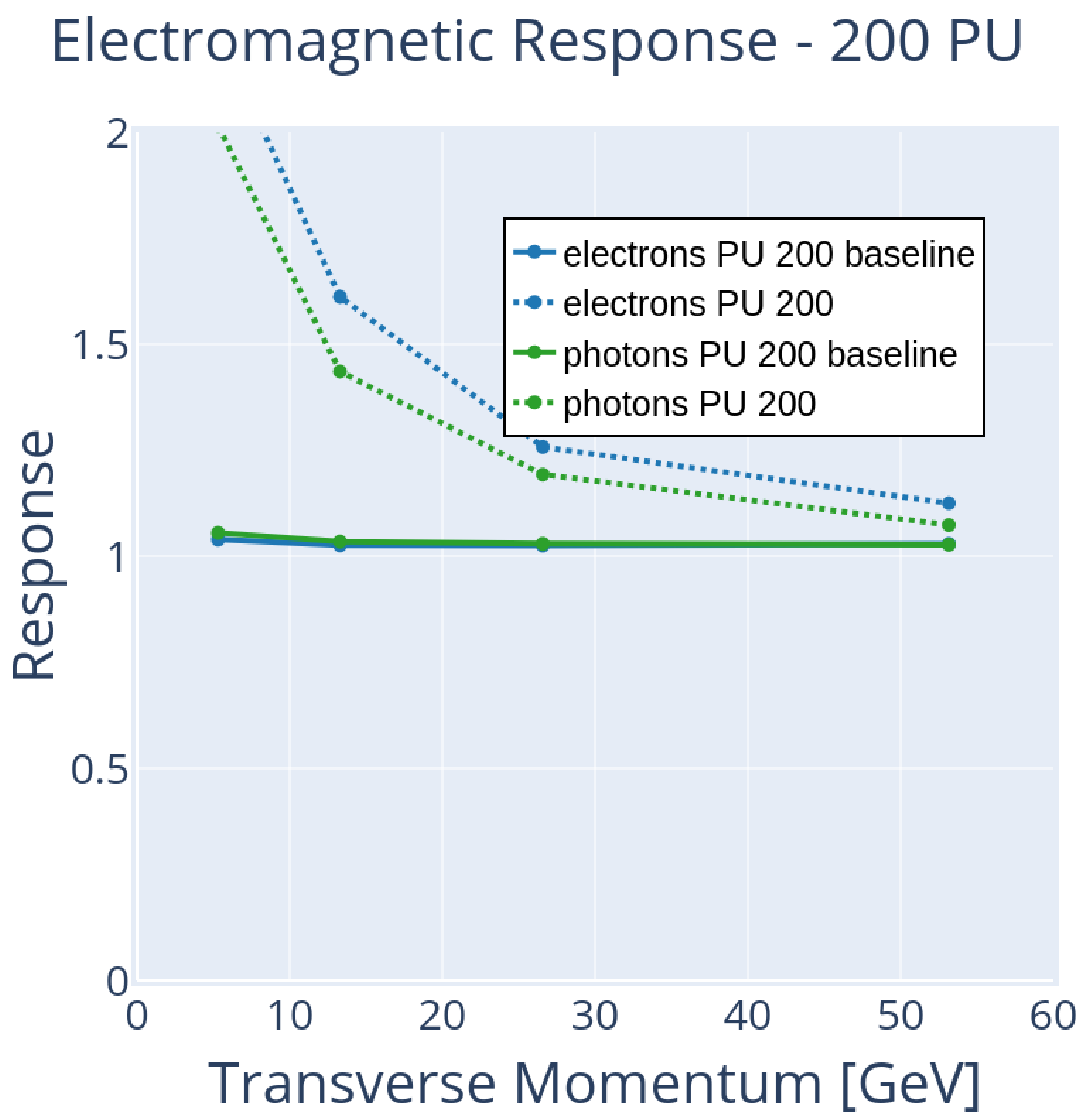
RESOLUTION - 40PU

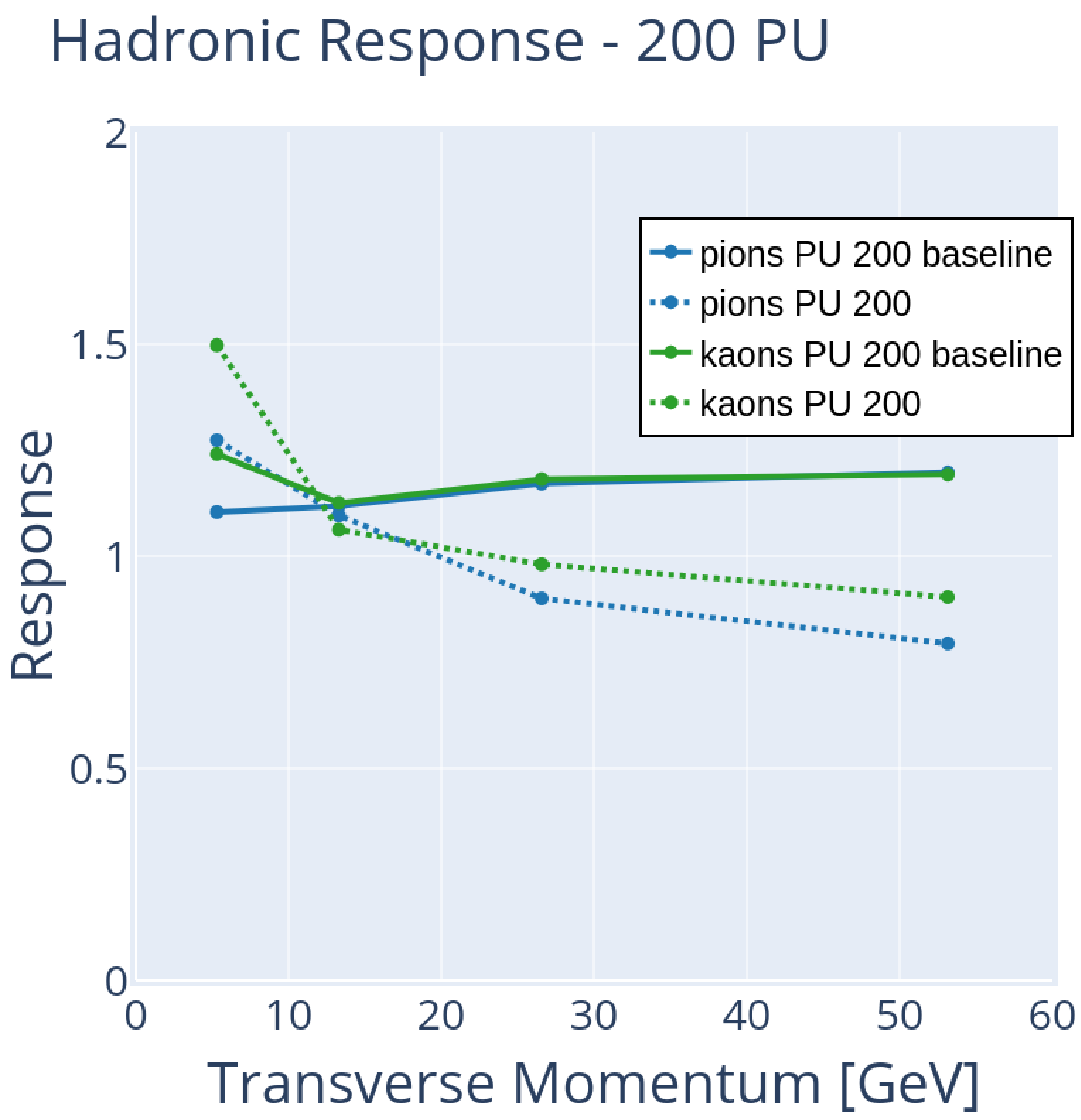




- Calorimetric energy resolution improves with higher energies
- Track information improves electron reconstruction
- Offset between optimal clustering and reconstruction between 3% and 8%

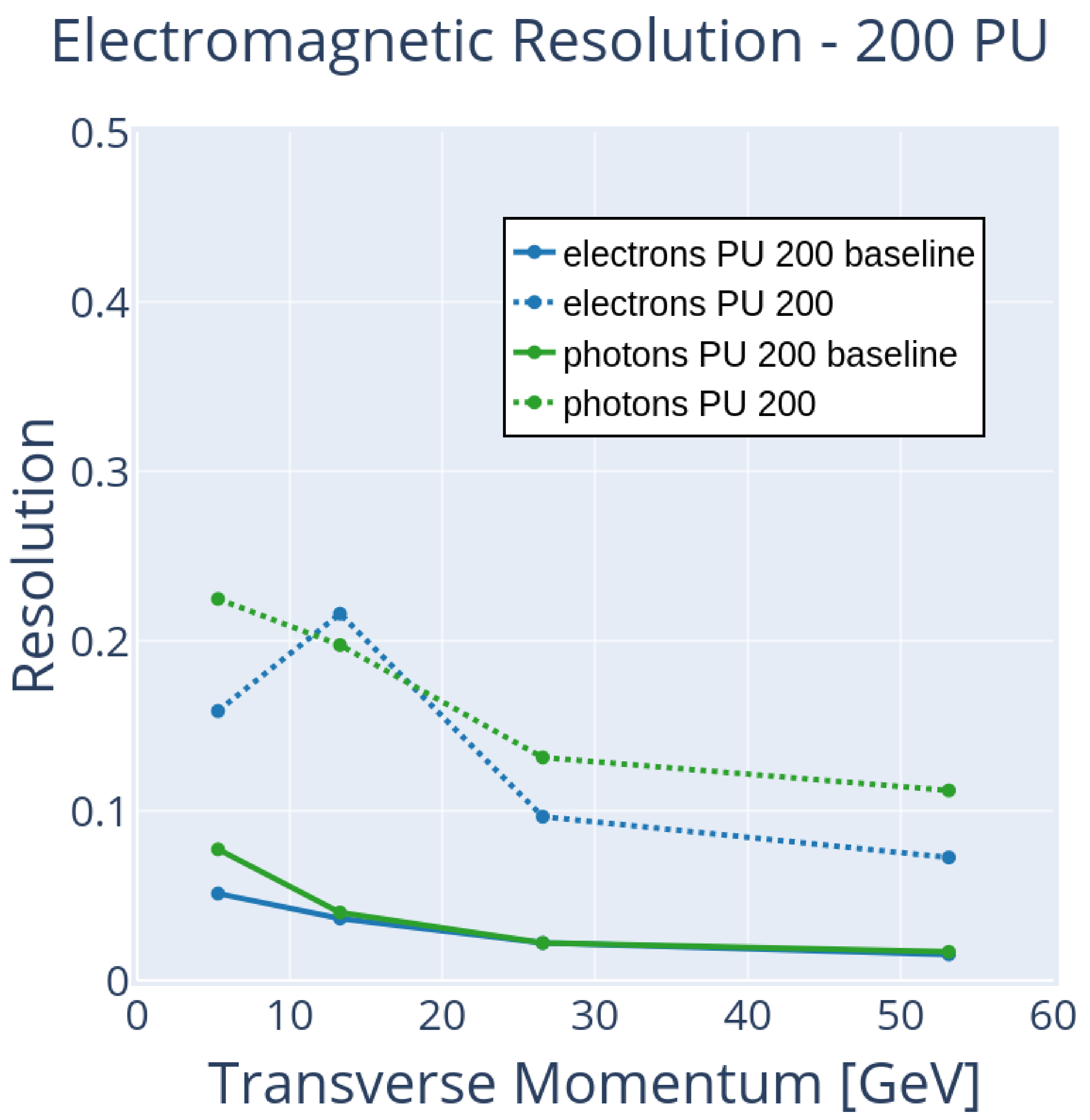
RESPONSE - 200PU

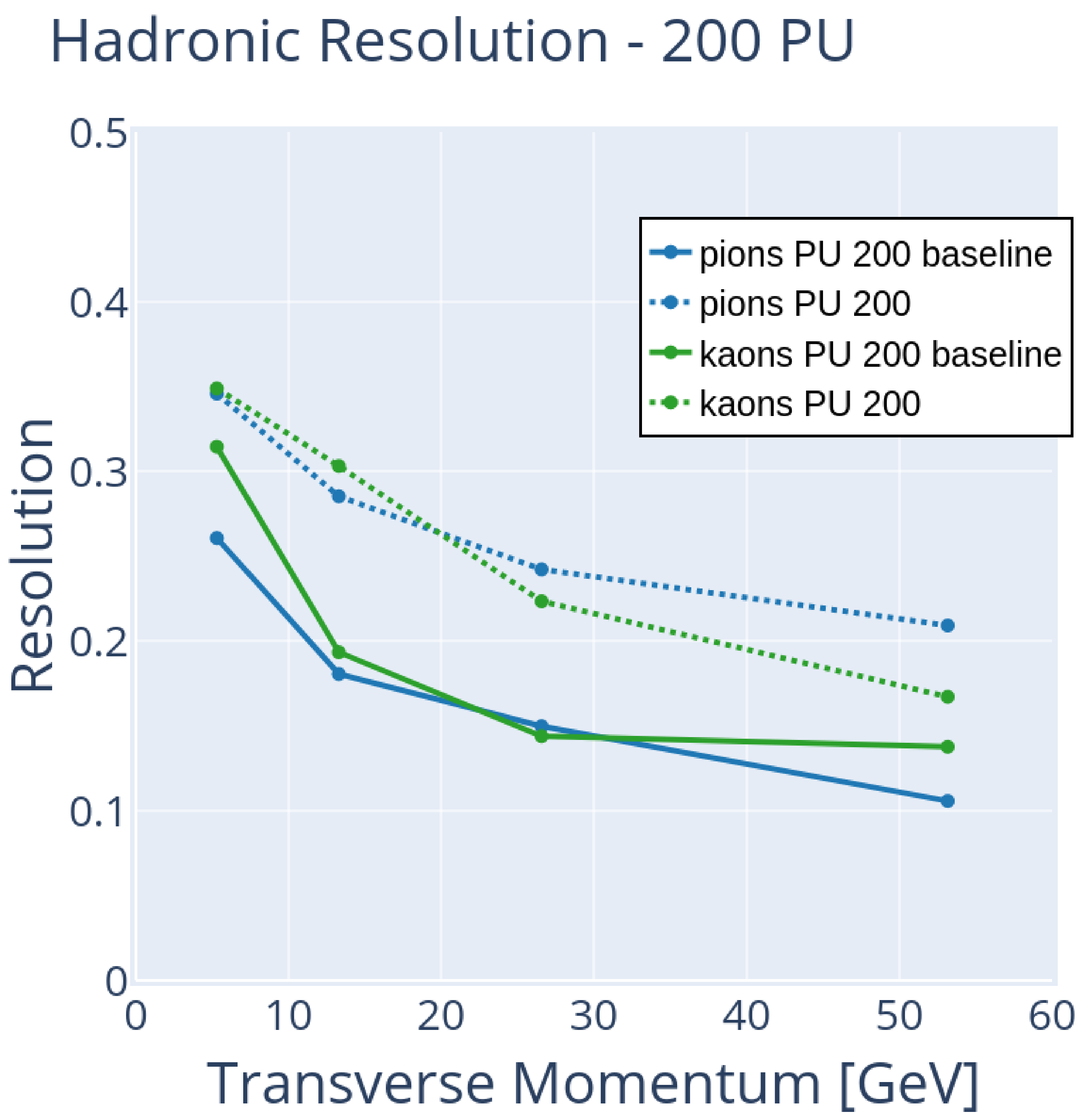




- Increased impurities from higher pile-up deteriorate response
- Expected from the purity metrics
- Plan to investigate more sophisticated clustering algorithms (e.g. HDBSCAN)

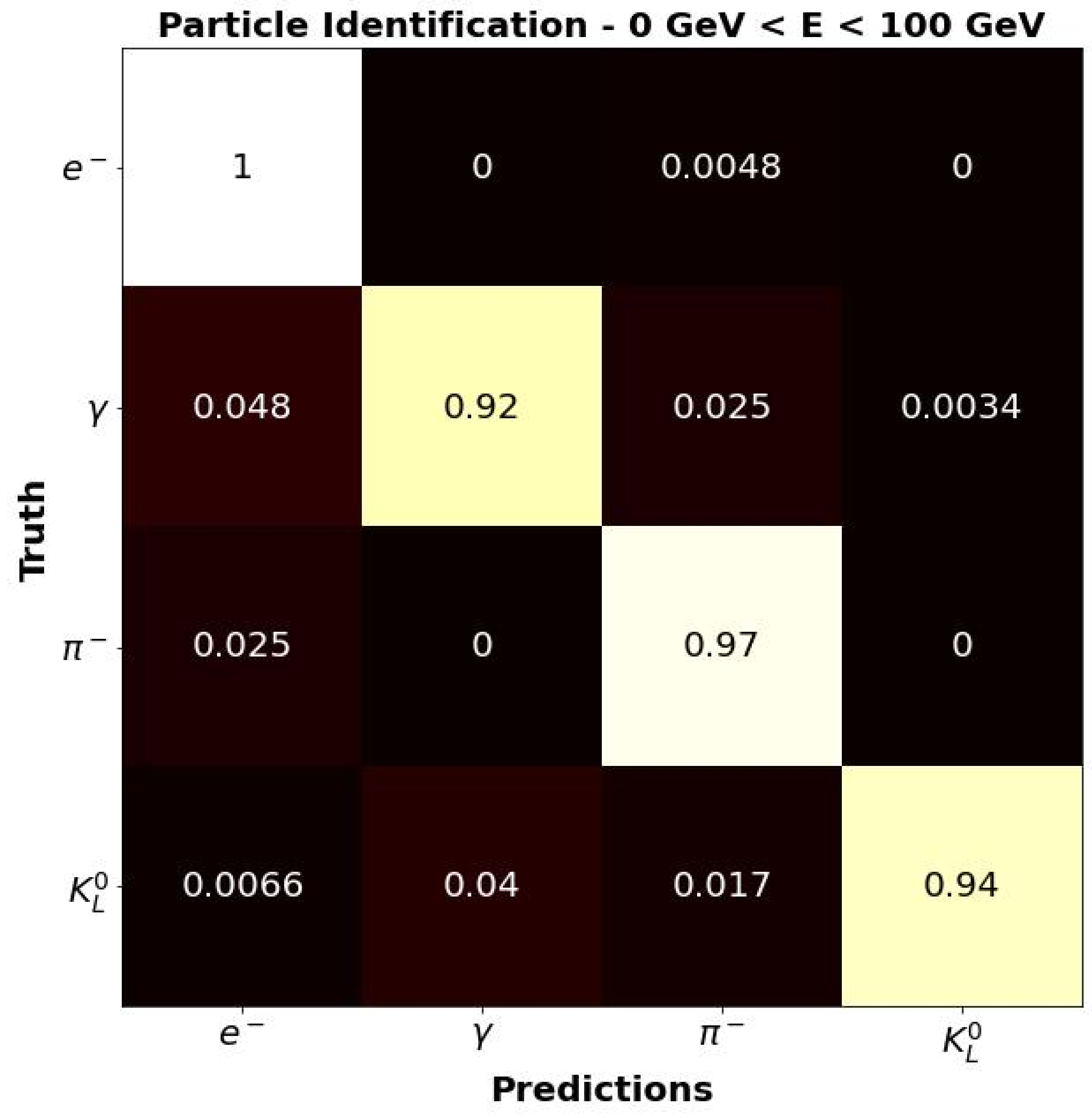
RESOLUTION - 200PU

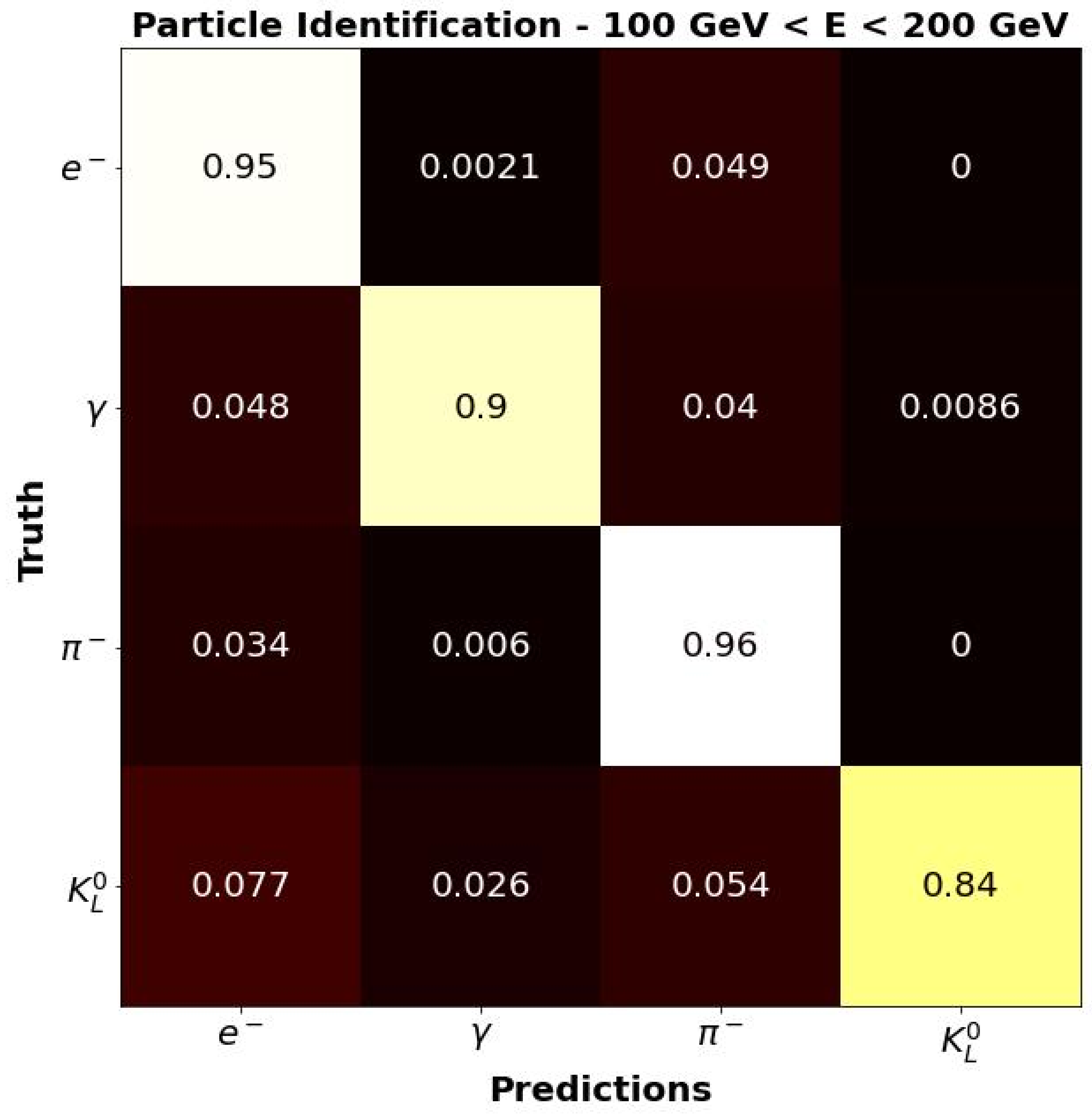




- Calorimetric energy resolution improves with higher energies
- Track information improves electron reconstruction
- Offset between optimal clustering and reconstruction larger of electromagnetic showers

PARTICLE IDENTFICATION



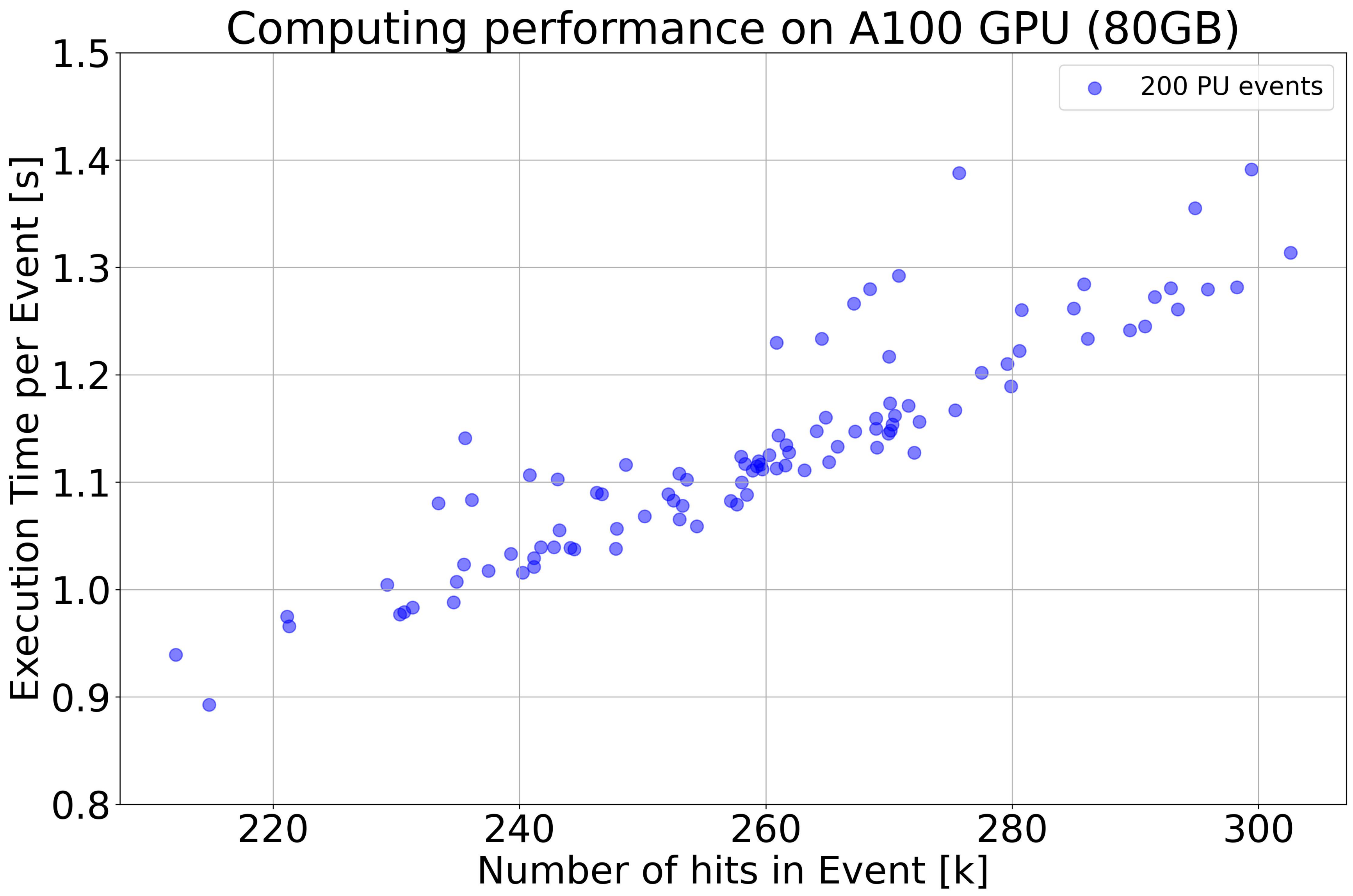


Particle identification better for lower energies

COMPUTATIONAL REQUIREMENTS

Inference time for 200 PU events only including the network prediction and no clustering (as this can be done in multiple ways).

- Inference time scales linear with number of input hits
- In 200 PU events inference needs around one second per event
- We have yet to explore potential optimizations



SUMMARY

- Able to **efficiently** reconstruct showers within **200 Pilup**
- Learn **energy correction** factor to improve energy resolution
- **Particle ID** in multi-shower events
- Step towards an end-to-end differntiable particle-flow algorithm by adding track information

OUTLOOK

- Continuing to improve the network architecture
- Exploring other clustering methods
- Particle identification in pile-up events
- Train on HGCAL simulations

THANK YOU FOR YOUR ATTENTION!

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