GNN-based E2E reconstruction in different highly granular calorimeters

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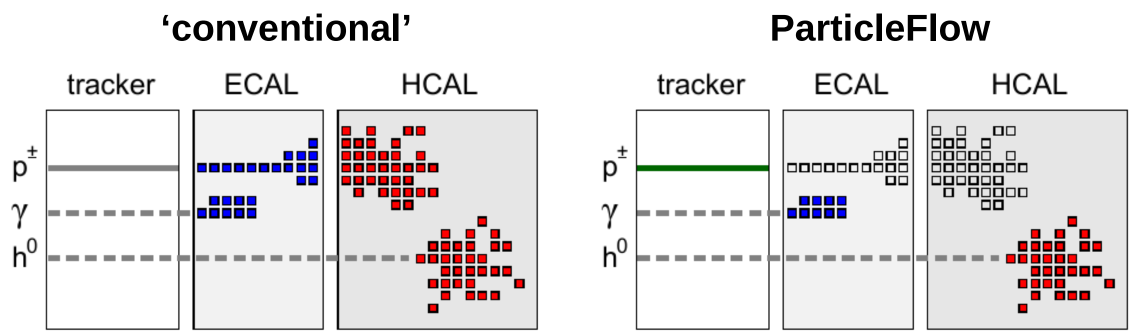
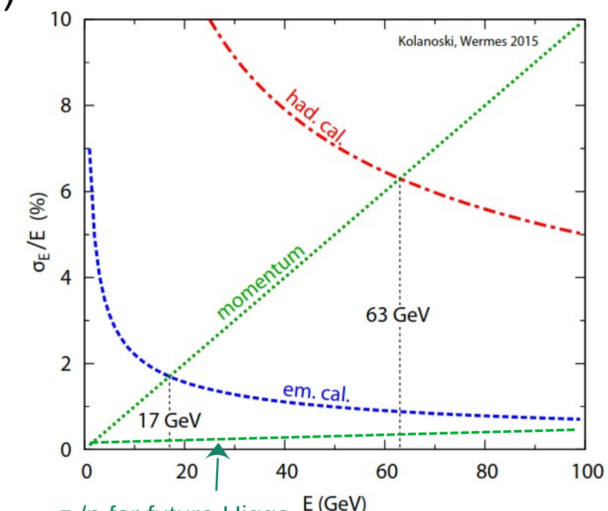
Calorimetry overview

- ParticleFlow: utilise the best subdetector for each particle / jet constituent
  - work horse: highly granular calorimeter
  - future collider detectors (e.g. ILD) developed with PFlow in mind, also applied to existing detectors (e.g. CMS HGCAL for HL-LHC)



$$\sigma_{jet} = f_{charged} \cdot \sigma_{Tracker} \oplus f_{\gamma} \cdot \sigma_{ECal} \oplus f_{neutral} \cdot \sigma_{HCal} \oplus \sigma_{confusion} \oplus \sigma_{leakage}$$

example for one particuar setup
by Kolanoski & Wermes

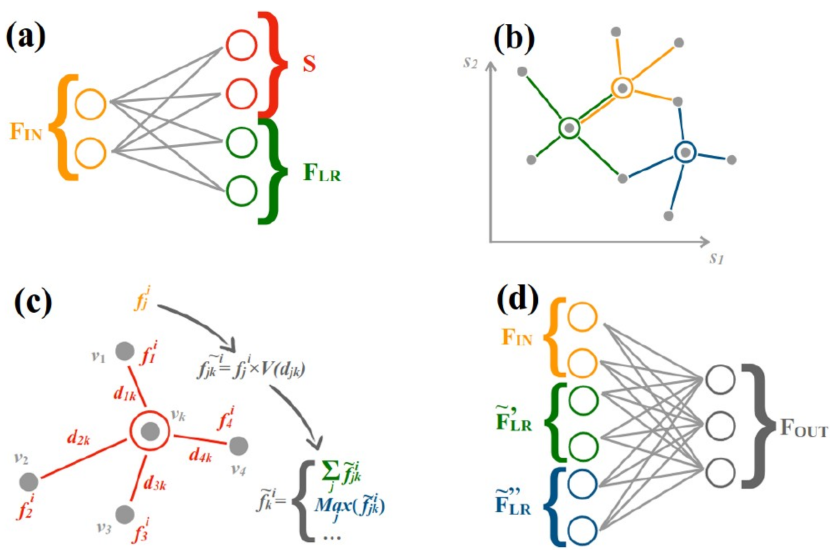


σ_p/p for future Higgs factory detectors

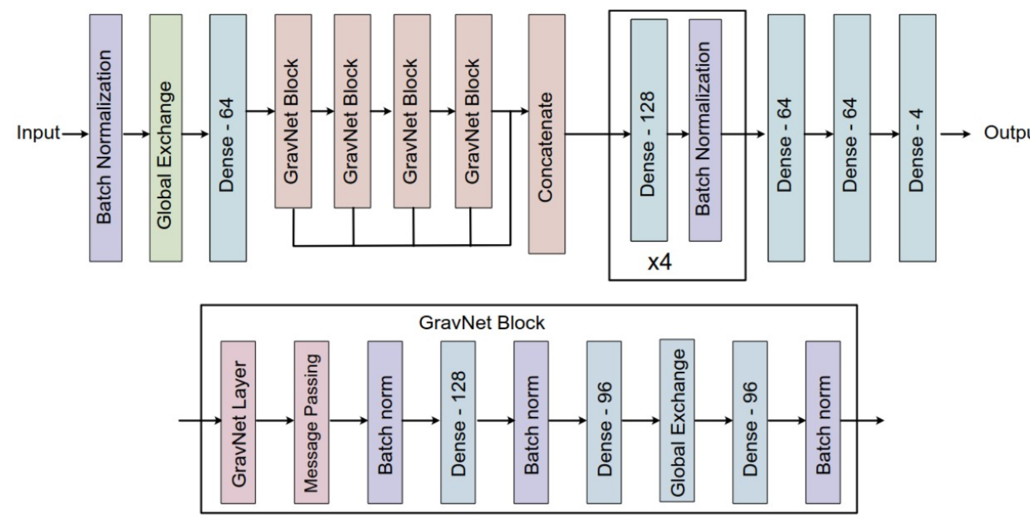
- Use Neural networks to reduce confusion term
- Issue with number of channels for fixed-geometry NN (e.g. CNN) → use GNN

Overview GravNet + Object Condensation

- ‘Holistic’ approach with end-2-end reconstruction - clustering and features reconstruction (position, energy, PID) in one integrated GravNet network
- Calorimeter hits are clustered in latent space S
- Feature properties F_{LR} of nearest neighbours in S are combined with different aggregator function to predict object features



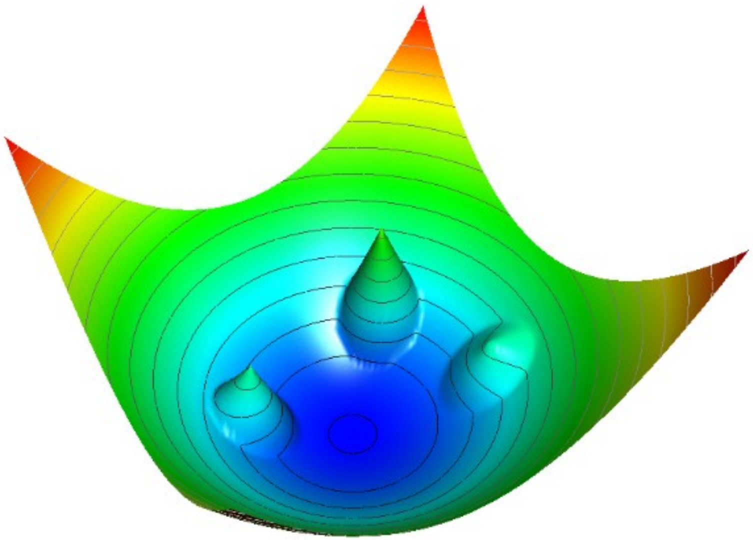
visualisation of the GravNet steps
[arxiv:1902.07987](https://arxiv.org/abs/1902.07987)



GravNet model setup we used

Object Condensation

- For clustering introduce attractive potential for all hits belonging to an objects towards each other, and a repulsive potential towards all other hits
- To reduce computational effort, introduce β quantifying similarity to object properties, only use hit with highest β per object to generate combined potential
- Additional loss per object of 1-β of the condensation point encourages one hit per object to become representative of object and ‘gather’ related hits into a cluster

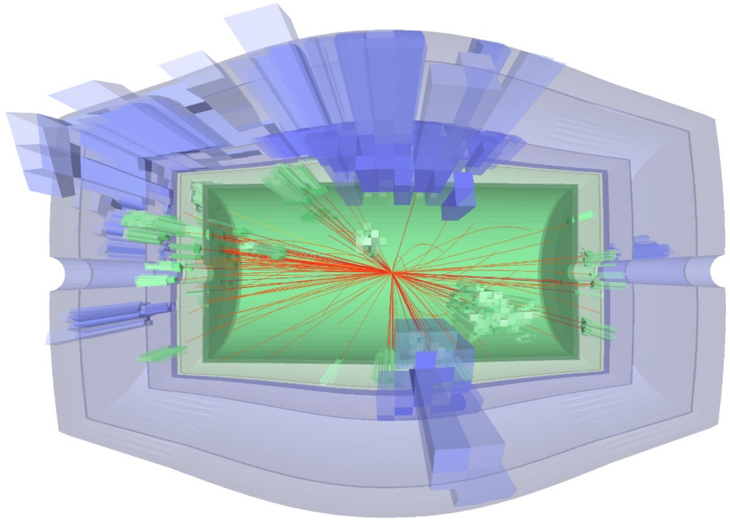


Object condensation attractive + repulsive potential visualisation
arxiv:2002.03605

Setup for COCOA simulation

- "COnfigurable Calorimeter simulatiOn for Ai"
  - highly configurable generic detector with focus on calorimeter
  - using geant4 for detailed simulation of showers
- Our setup: 'default' COCOA detector
  - 5 tracker layers for material budget, 3.8 T
  - barrel: $\eta < 1.5$, endcap: $1.5 < \eta < 3$
  - ECal: 256x256 cells in $\varphi \times \eta$ in 3 layers
    - 3.6x3.6 cm^2 at $\eta=0$, 8x8 mm^2 at $\eta=3$
  - HCal: 64x64 cells in $\varphi \times \eta$ in 3 layers
    - 19x19 cm^2 at $\eta=0$, 3.6x3.6 cm^2 at $\eta=3$

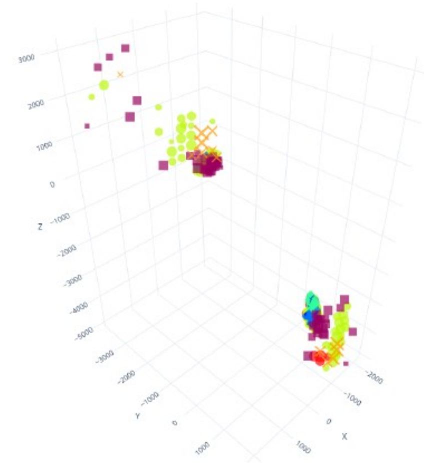
highly granular in endcaps, similar to HGCAL



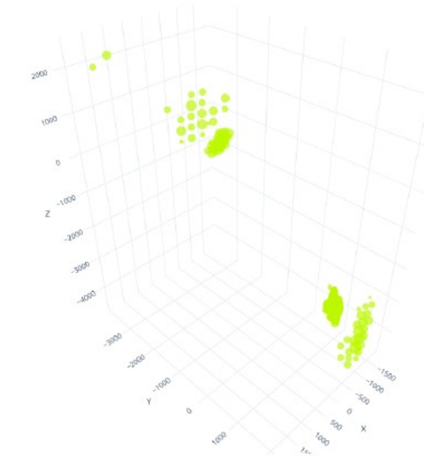
COCOA default detector setup visualisation
arxiv:2303.02101

Setup issues

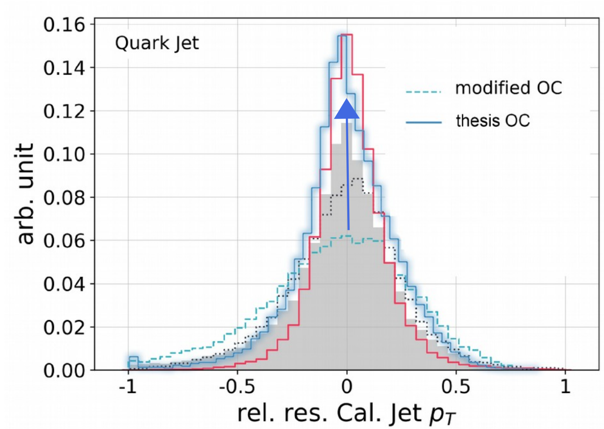
- Unfortunately, two issues limited the achieved conclusions:
- A large fraction of events had erroneous truth association, where hits on opposite detector side would be added to an object
  → cut: only accept objects with 90% energy within $\Delta\varphi < 0.5$ and $\Delta\eta < 0.5$
  → applied only to training, not test data
  → previous study showed significant improvement through this
- Recently, it was found that geant4 volumes partially overlap, which then leads to an undefined behaviour of the simulation



hits of all objects, with association



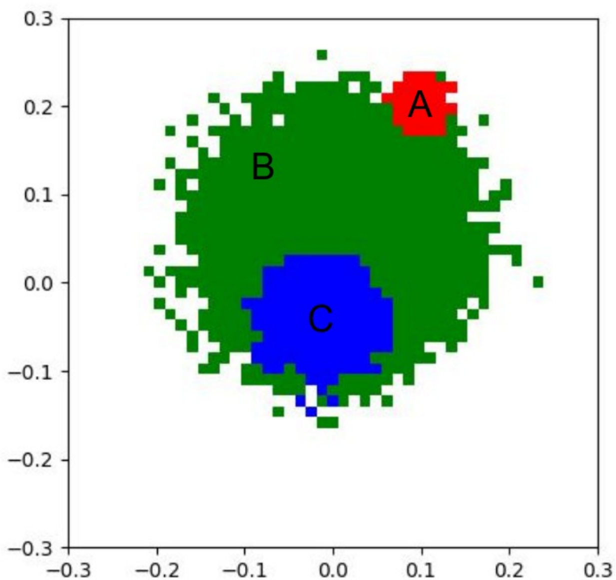
hits of one object



plot adapted from [arxiv:2212.01328]

Truth definition

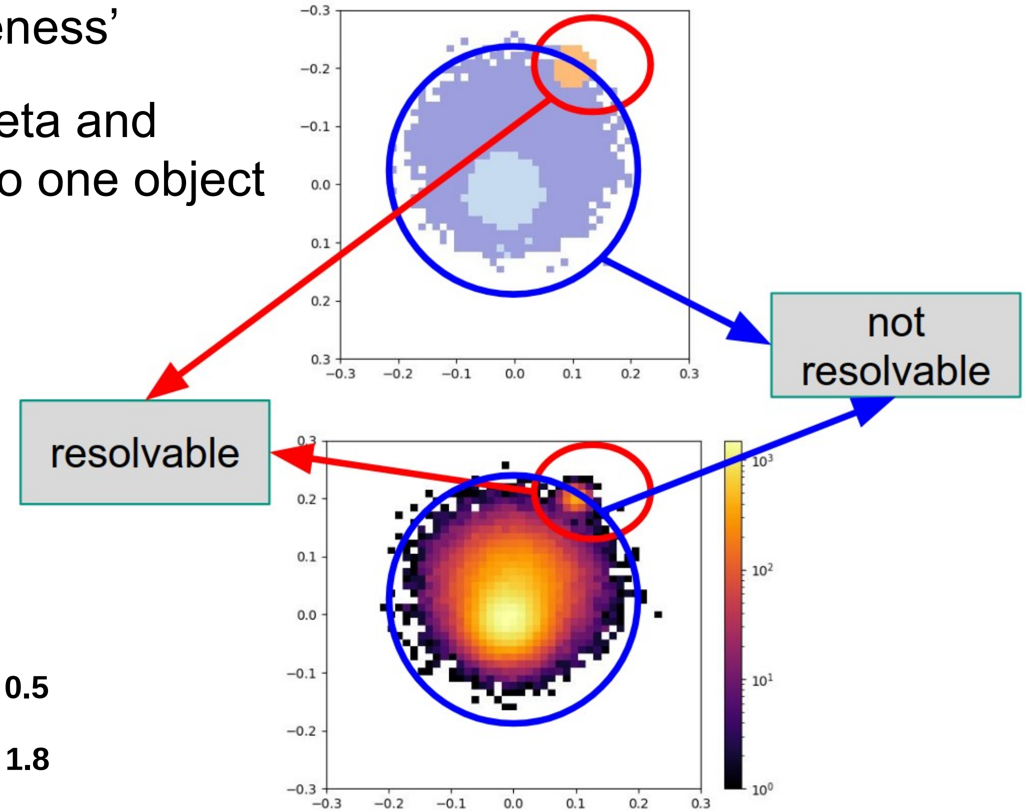
- True objects needs to be defined on the shower-level to adjust for resolution and thus ‘resolvableness’
- Calculate overlap between showers in phi-eta and merge showers above certain threshold into one object
- For details check [poster]() by Katharina!



A vs. B score: 0.5

C vs. B score: 1.8

result: merge C into B



Data set

- Start with 10 τ of 10-100 GeV per event, which decay into multiple prongs
- All objects reaching the calorimeter with $E < 100$ MeV are truth-classified as noise
- O(1000) hits per event
- 21k events (80/20 train/val), 200 epochs

Properties used

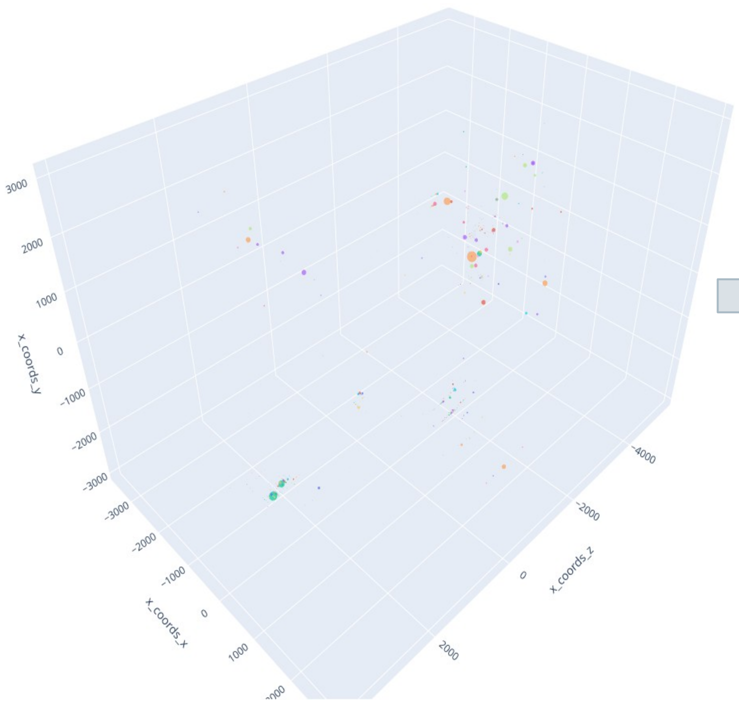
- Input: 9 properties of calorimeter hits
  - x, y, z, $r_{x,y}$, θ, η, E (p for a track), time, ID (isTrack)
- Output: 12
  - target: beta, cluster coordinates (x,y,z), energy, position (θ, η), PID (4 channels)
- Loss:
  - object condensation → beta, cluster coordinates (in cluster space)
  - hit loss → energy, position, class (not used atm)
- $L_{pos} = Huber\left(\sqrt{\Delta\sin\theta^2 + \Delta\cos\theta^2 + \Delta\eta^2 + 10^{-3}}, 0.1\right)$

  $L_E = \ln\left(\left(E_{true} - E_{pred}\right)^2 + 1[MeV]\right)$

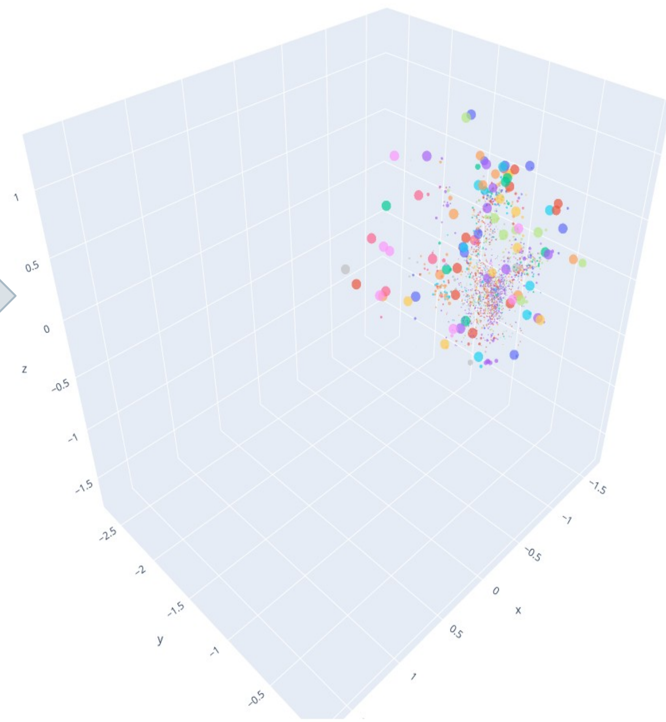
Data set: taus

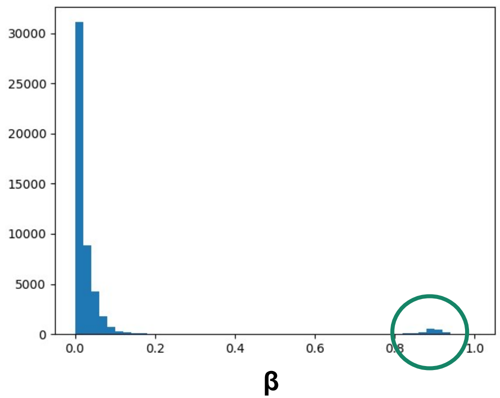
- Predicted objects (large dots) are few with high β value

real space



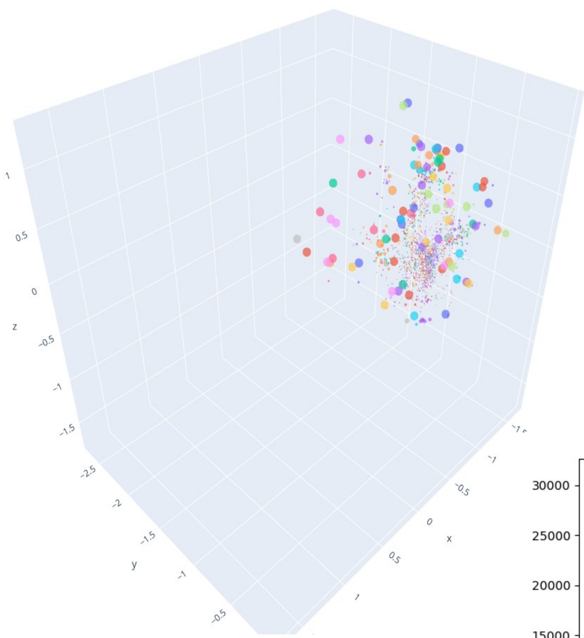
cluster space



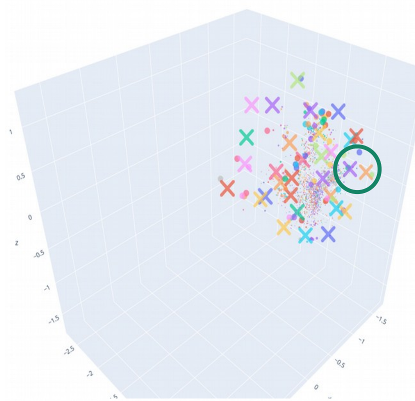


Clustering results

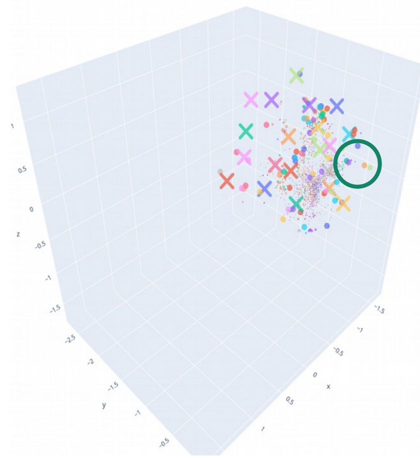
- Selecting predicted objects depends on β cut and cut on cluster radius d
- Here: Try to catch all coloured points, avoid grey points (from noise)

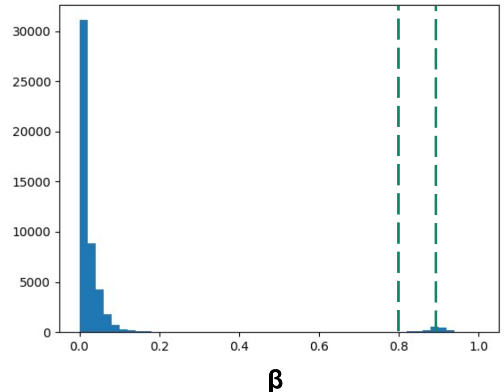


β > 0.8
d > 0.3

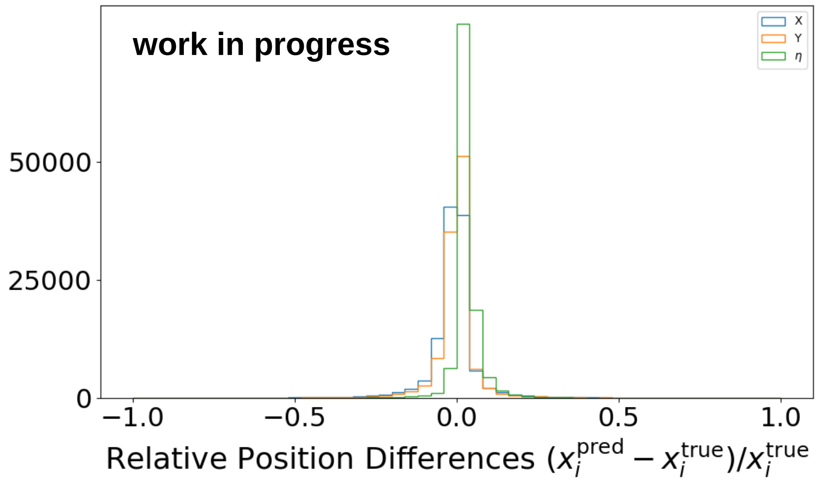


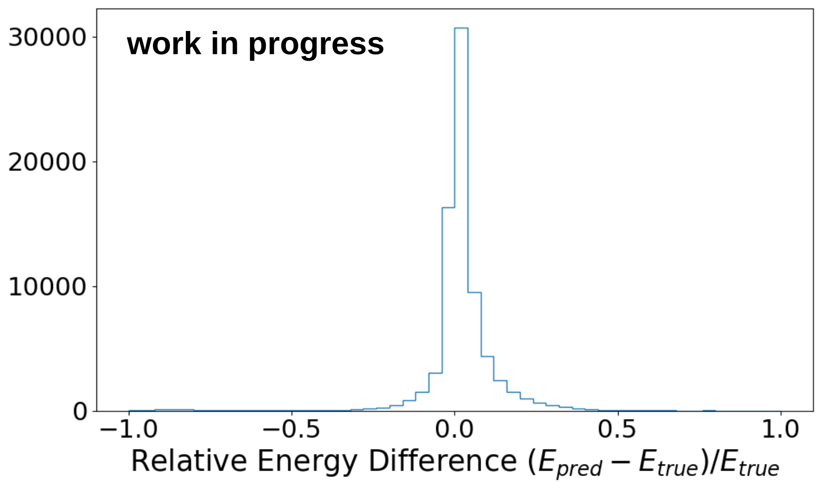
β > 0.9
d > 0.3





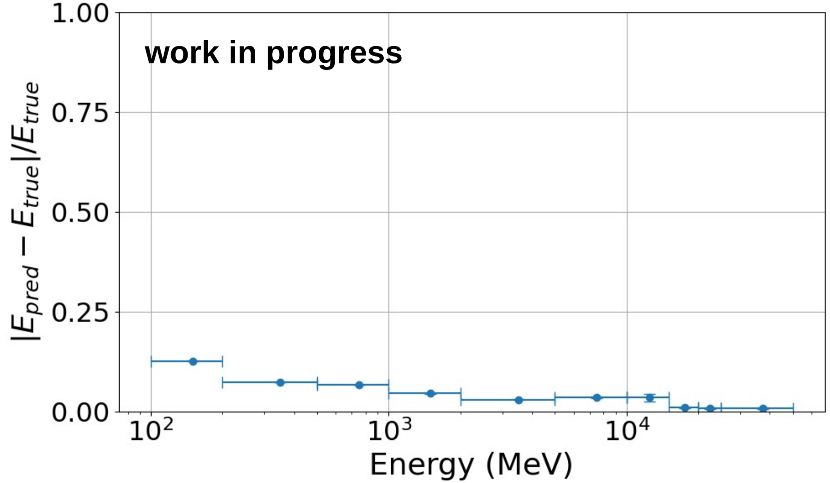
Performance: position and energy





- Position and energy resolution < 10%, following roughly 1/sqrt(E)

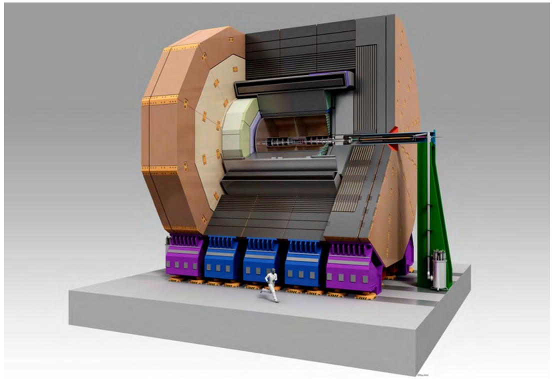
β > 0.8
d > 0.3



ILD detector setup

- “International Large Detector”, developed for ILC, now also proposed for FCC-ee
- Detailed detector description (~ PCB) with full-sim, i.e. geant4, with interaction and ionisation used for reconstruction of hits
- Simulation and reconstruction chain ‘battle-proven’ in large MC productions
- Setup:
  - Si vertex + gaseous tracker, calorimeter inside 3.5 T magnet
  - ECal: 5x5 mm² in 30 layers
  - HCal: 3x3 cm² in 48 layers

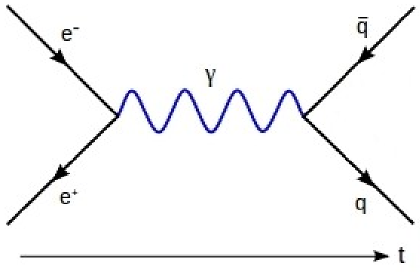
highly granular in barrel and endcap, also longitudinally



arxiv:2003.01116

Data set

- Use data set of $e^+e^- \rightarrow (\gamma)q\bar{q}$ at 250 GeV, 45k events, 32 epochs
- O(a few 1000) hits per event
- Truth: properties of MCParticle that entered calo and caused energy depositions
  - full MCParticle chain before calo from geant4 is available; in case of multiple contributions to the same hit, largest energy fraction is chosen
  - index, end point in calo (x,y,z), energy, PID
  - issue: particles that backscatter from the calorimeter sometimes are not registered, and hits are associated with the original particle that entered the calorimeter
- Simplification cut: all hits with $r_{\varphi,\theta}$ > .5 m from true object are ommitted



- Implementation and first successful application very recent – hot of the press!

Properties used

- Input: 9 properties of calorimeter hits
  - x, y, z, $r_{x,y}$, θ, η, E (p for a track), time, ID (isTrack)
- Output: 12
  - target: beta, cluster coordinates (x,y,z), energy, position (x,y,z), PID (4 channels)
- Loss:
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- $L_{pos} = Huber\left(\sqrt{\Delta x^2 + \Delta y^2 + \Delta z^2 + 10^{-6}}, 0.1\right)$

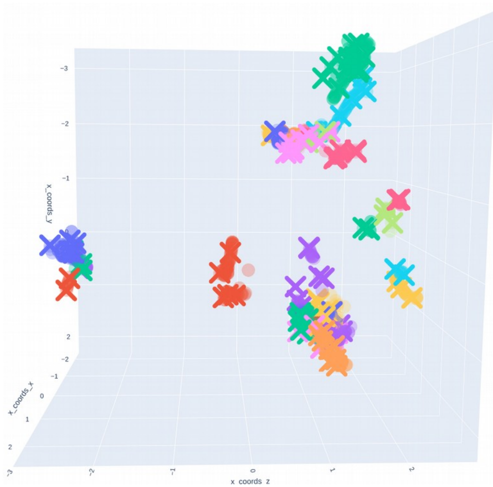
  $L_E = Huber\left(\left(E_{true} - E_{pred}\right) / \sqrt{E_{true} + 0.1}, 2 \cdot \sqrt{E_{true}}\right)$

same as with COCOA,
but cartesian coordinates
and with energy resolution
taken into account

Clustering example

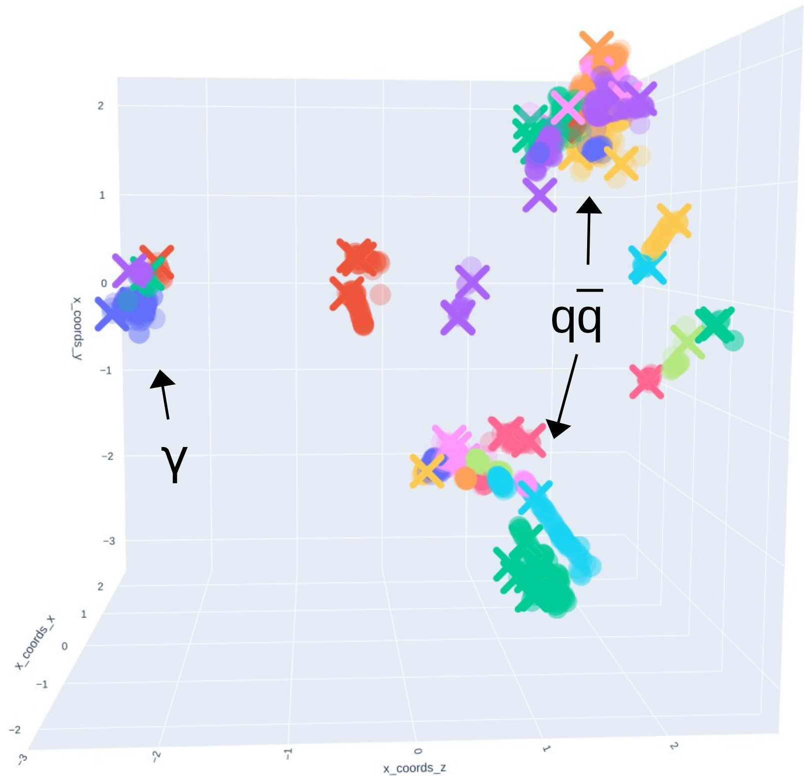
- Very good clustering and overlap of predicted positions with PFO positions
- Inference-level parameter optimisation to get best prediction performance

β > 0.1   d > 0.1

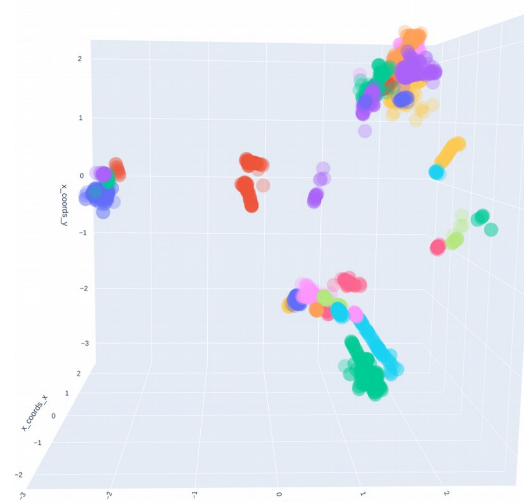


too many predicted objects

β > 0.1   d > 0.3



β > 0.2   d > 0.3



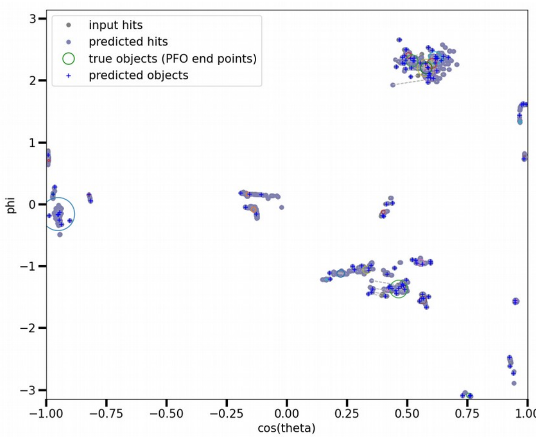
too few predicted objects (0)

Clustering example

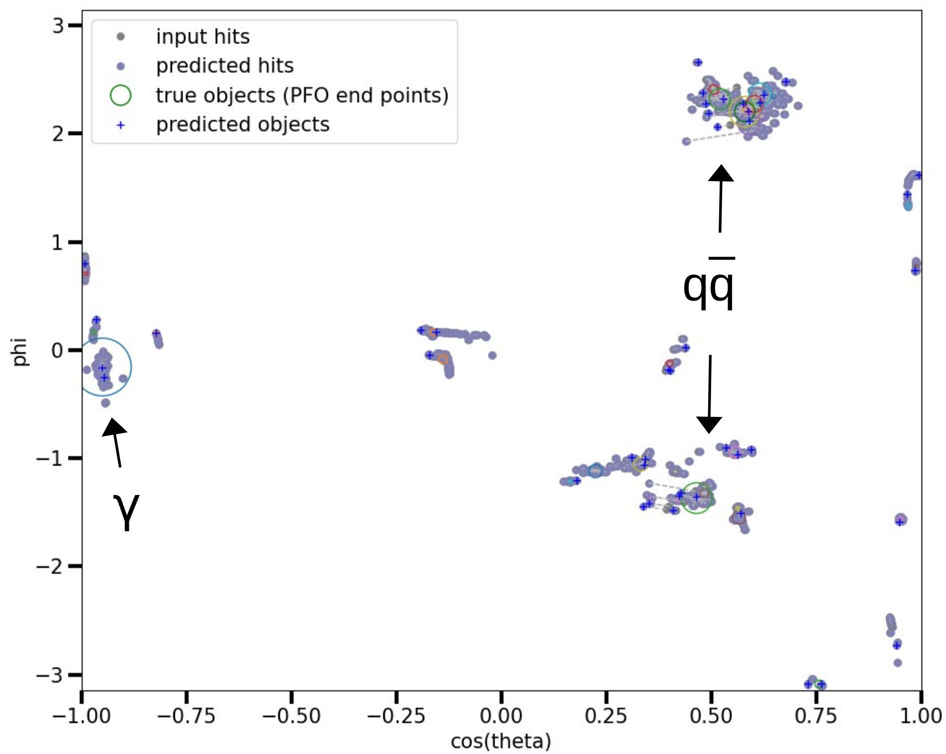
- Same event in angular projection of cos(θ) and φ
- Missing β values close to 1 indicate expected improvement simply from more training

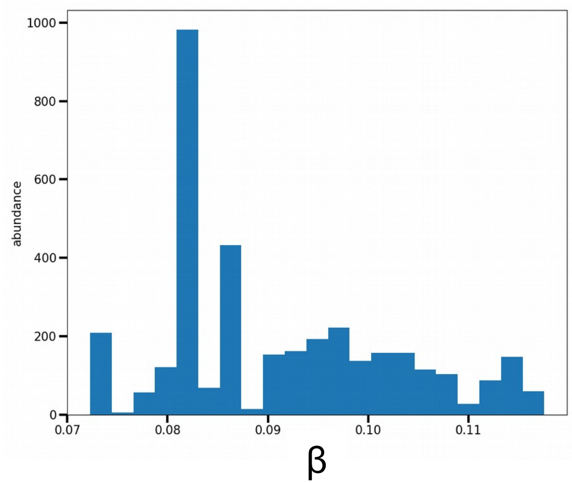
β > 0.1   d > 0.3

β > 0.1   d > 0.1



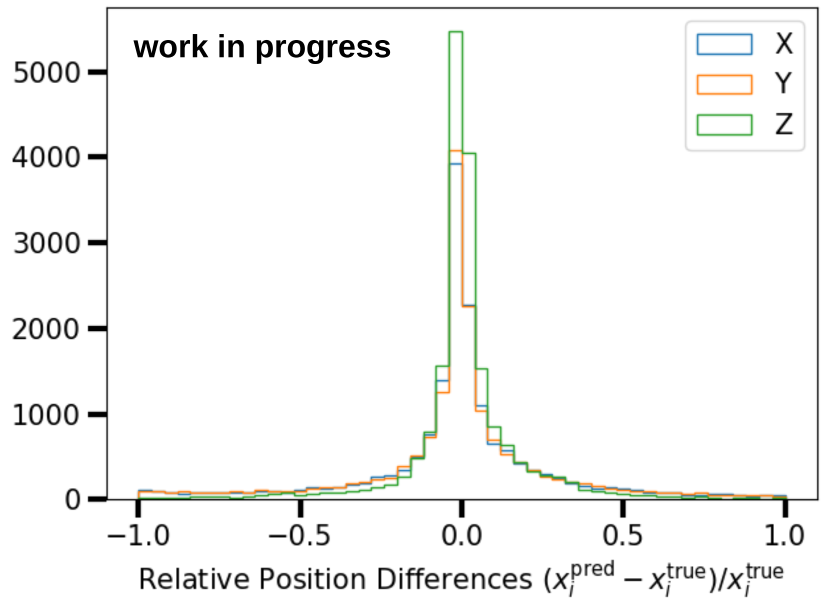
too many predicted objects





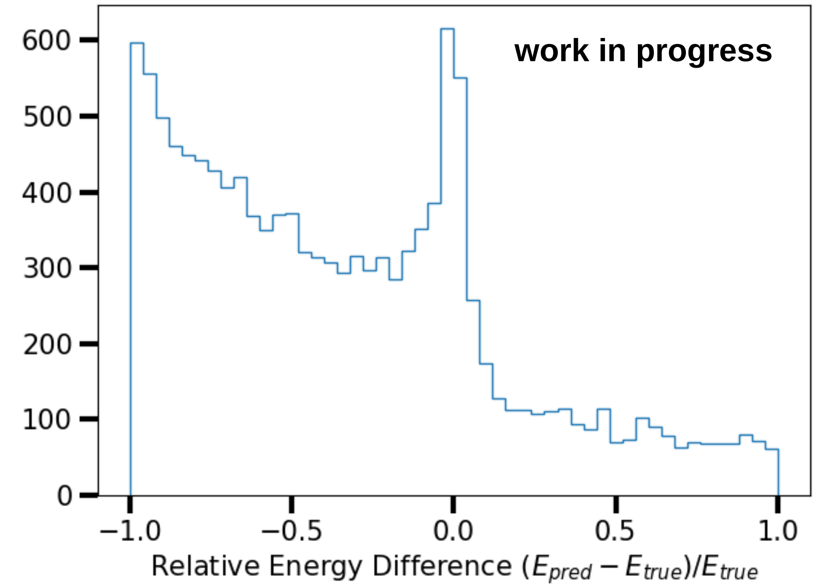
Reconstruction performance

- Quite good position reconstruction of < 10% throughout, similar to COCOA results



Reconstruction performance

- Energy reconstruction still very much work-in-progress…
- Illustrates the effect of higher granularity:
  - object energy (= NN target) is distributed over O(100) hits (= NN input)
  - more difficult to sum larger number of contributions
  - works for some fraction of objects, work-in-progress to make it work for ~all



Conclusion & Outlook

- **Promising results** with GravNet + Object Condensation for highly granular calorimeters: clustering works well, but feature prediction still a work in progress
- **Truth reference** remains an open question: careful consideration also of rare events needed for reliable predictions
- Application of tools made for current colliders to future colliders is a welcome exchange and hightlights the challenges **advanced detector geometries** bring
- One major focus in the future is **ps-timing**: How does exploiting time information in the calorimeter impact the confusion, and thus the jet energy resolution and potentially the jet clustering? → Optimisation problem for detector design!