OBJECT CONDENSATION RECONSTRUCTION FROM LOW-Q^2 TAGGER HITS

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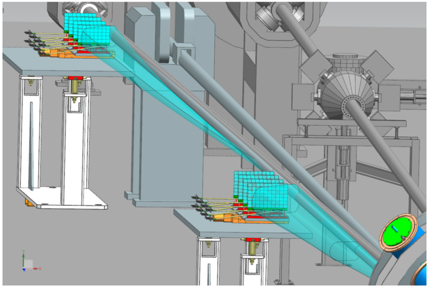
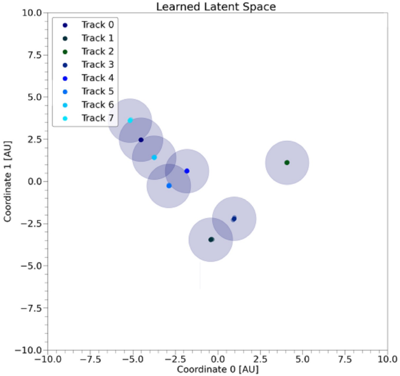




Learned Latent Space
Track 0
Track 1
Track 2
Track 3
Track 4
Track 5
Track 6
Track 7
Coordinate 1 [AU]
Coordinate 0 [AU]
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0

INTRODUCTION

MOTIVATION

ePIC Low-Q^2 Tagger

- The ePIC Low-Q^2 Tagger extends the reach of the central detector down to effectively Q^2=0.
- Electrons with reduced energy are steered away from the main beam.
- Scattered electrons from DIS events will be swamped by a background of Bremsstrahlung.
- A total of O(10) electron tracks from the IP are anticipated per bunch crossing.
- Additional, significant but currently unquantified backgrounds, from electron beam gas interactions and synchrotron radiation.

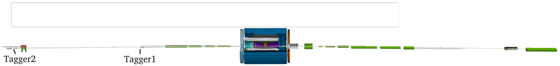


Figure 1: ePIC Low-Q^2 Tagger in Far Backward region.

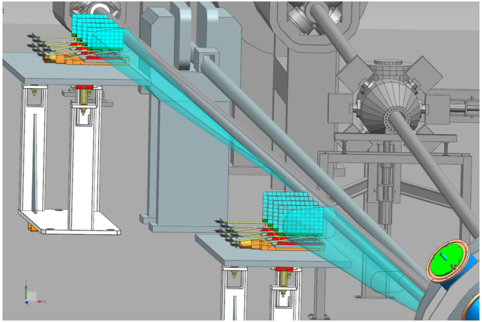


Figure 2: Low-Q^2 Tagger stations placed beside the outgoing electron beamline. Each station consisting of 4 tracker layers.

- For precise measurements of photo production and vector mesons.

THE TRACKING CHALLENGE

Challenge

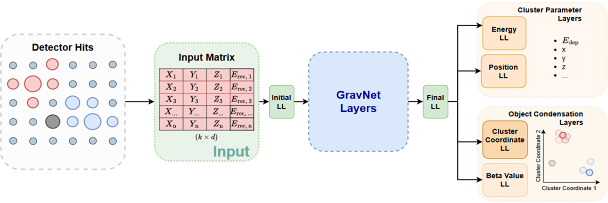
- From a varying number of N_{hits} reconstruct an unknown number of $M_{particles}$.
- Conventional approaches require looping over valid combinations of hits.
- High order of combinations to check computationally expensive.
- Latency per sample can fluctuate wildly.

$$\left\{ \begin{bmatrix} x_0 \\ y_0 \\ mod_0 \\ lay_0 \\ t_0 \\ E_0 \end{bmatrix} \\ \vdots \\ \vdots \right\}_{N_{hits}} \rightarrow ? \rightarrow \left\{ \begin{bmatrix} Px_0 \\ Py_0 \\ Pz_0 \end{bmatrix} \\ \vdots \\ \vdots \right\}_{M_{particles}} \tag{1}$$

Current Approach

- Separate hits by module.
- Cluster hits in layer.
- Linear least squares fit and χ^2 filter all combinations of hits in 4 layers.
- Project track onto common plane.
- Use position and direction vector as input into DNN, reconstructing electron momentum at interaction vertex.
- Good for single particle simulations but doesn't extend well for backgrounds and streaming.

OBJECT CONDENSATION



- Object Condensation method presented by Jan Kieseler 2020[1].
- Graph network architecture taking each hit as a node.
- GravNet layers pass messages between closest neighbours in learned space[2].
- After passing through the graph layers, every node now has the information encoded for a track.
- A single hit per track is identified as a ”condensation point”, should provide the best estimate of track properties.
- Hits from the same track are clustered around the the condensation point.
- Classification and regression can additionally be carried out on the encoded information.
- Recent study on simulations for Charged Particle Tracking at the High Luminosity LHC[3].

[1] Object condensation: one-stage grid-free multi-object reconstruction in physics detectors, graph, and image data
[2] Learning representations of irregular particle-detector geometry with distance-weighted graph networks
[3] An Object Condensation Pipeline for Charged Particle Tracking at the High Luminosity LHC

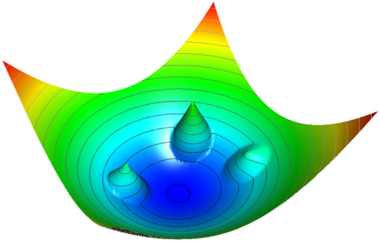


Fig. 1 Illustration of the effective potential that is affecting a vertex belonging to the condensation point of the object in the centre, in the presence of three other condensation points around it

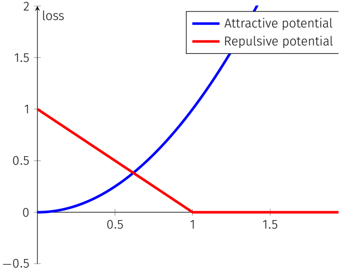
Is this a sledgehammer to crack a nut for the Low-Q^2 tagger? -Maybe... But the unknown backgrounds are expected to be high.

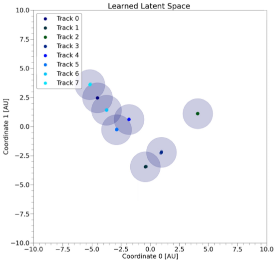
$$\left\{ \begin{bmatrix} x_0 \\ y_0 \\ mod_0 \\ lay_0 \\ t_0 \\ E_0 \end{bmatrix} \begin{matrix} \vdots \\ \vdots \end{matrix} \right\}_{N_{hits}} \rightarrow ? \rightarrow \left\{ \begin{bmatrix} Px_0 \\ Py_0 \\ Pz_0 \\ \beta_0 \\ LatentX_0 \\ LatentY_0 \\ Primary_0 \\ Brems_0 \end{bmatrix} \begin{matrix} \vdots \\ \vdots \end{matrix} \right\}_{N_{hits}} \xrightarrow{\beta - Filter} \left\{ \begin{bmatrix} Px_0 \\ Py_0 \\ Pz_0 \end{bmatrix} \begin{matrix} \vdots \\ \vdots \end{matrix} \right\}_{M_{particles}} \tag{2}$$

OBJECT CONDENSATION LOSS

Latent Space Potential Loss

- Loss from the potential calculated from hits from each particle with maximum .
- The potential is scaled by the product of the charges $q_i = arctanh^2 \beta_i + q_{min}$
- A well trained network should see only hits belonging to the same particle within r<1.





Beta Loss

- The product of β in the potential loss pushes $\beta \rightarrow 0$ for every hit.
- Need one high β for each track for condensation point to form. Force sum over β hits from track = 1
- $loss_\beta$ = 1-β

Noise Loss

- β values for noise are not pushed to 0
- Additional loss term is needed, summing/averaging over noise hit β values.

Additional Losses

- Regression/Classification tasks can be performed per node or subset of nodes as required.
- Requires loss balancing via hyperparameters.

SIMULATION SETUP

SIMULATION STUDIES

Event sample

- Mixed Bremsstrahlung-QR photoproduction events generated using GeTaLM[4]- Custom generator for EIC.
- Single QR photoproduction electron from 18x275 GeV collision.
- Bremsstrahlung sample from maximum luminosity 18x275 GeV bunch crossing. Average O(10) per event.
- No additional backgrounds input, only originating from secondaries produced by Geant4.

Simulation

- Initial studies were carried out using the default ePIC geometry. A custom ePIC geometry configuration is required for full truth matching.
- Default geometry currently doesn't save secondary particles outside of central tracking region.
- Around 30% of events contain particles which create a shower of secondary hits which all get handed the truth id of the primary.
- Initial studies cleaned this data by cutting on a max 4 hits per track.
- Custom geometry extends the tracking region.

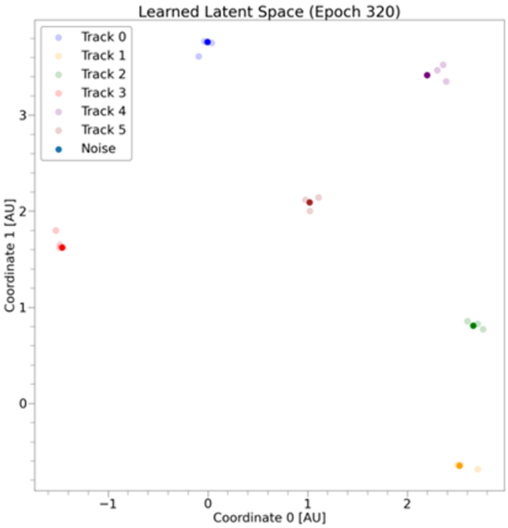
[4] GETaLM: A generator for electron tagger and luminosity monitor for electron - proton and ion collisions

Track Building

- Cut on β to select condensation points.
- Calculate distance between condensation points and other points.
- For each layer, select hit closest to condensation point.

Tracking Metrics

- True positive (TP) defined as a true track predicted by network - All hits belong to the same track.
- False Positive (FP) defined as any other track predicted by network.
- Efficiency: Proportion of true tracks that were recovered by the network. Expected number of true tracks (N)
  - $\frac{TP}{N}$
- Purity: Proportion of true tracks in all tracks predicted by the network.
  - $\frac{TP}{TP+FP}$



SELECT STUDIES

TRAINED METRICS

Original data sample with maximum 15 true tracks per event.

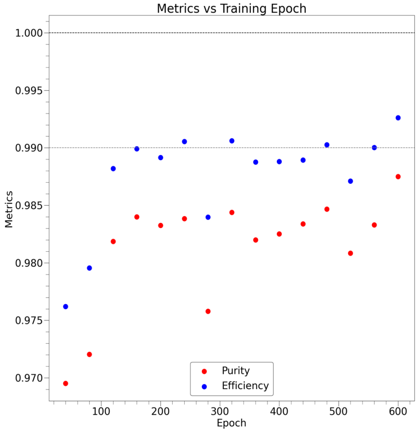


Figure 3: Tracking metrics as a function of training epoch.

High occupancy data sample combining 10 events into one with maximum 82

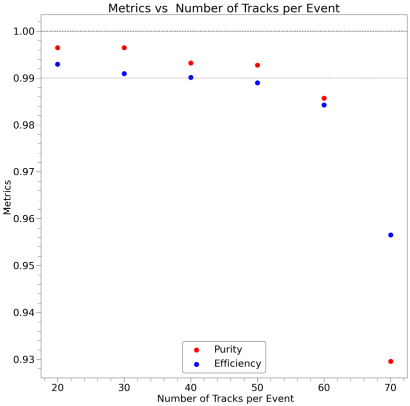


Figure 4: Tracking metrics against the number of true tracks in an event.

ADDING INEFFICIENCIES

80% detector hit efficiency added - 20% of hits removed from sample.

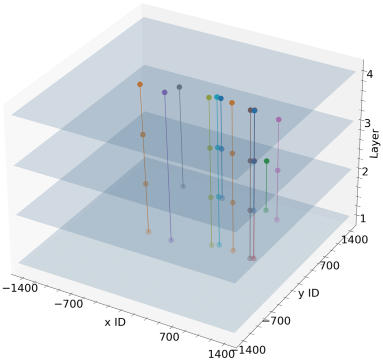


Figure 5: Hits from tracks in 4 layers with inefficiencies added.

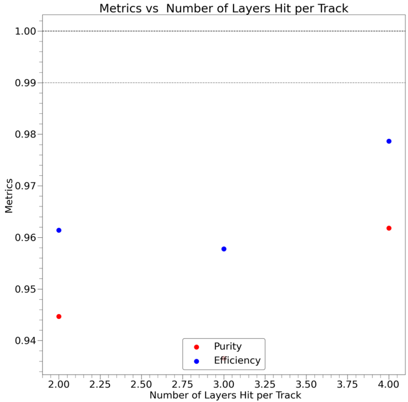


Figure 6: Tracking metrics against the number of hits per track.

Real detector efficiency expected to be >99%

ADDING ARTIFICIAL NOISE

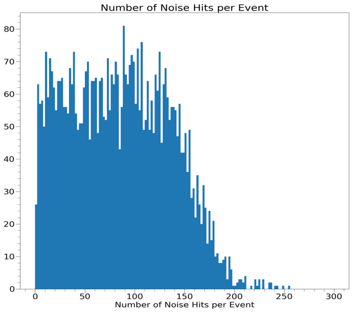


Figure 7: Distribution of artificial noise hits added to event.

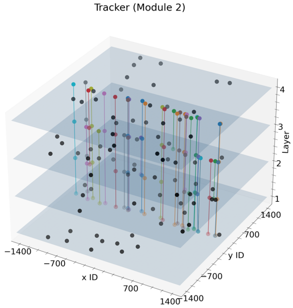


Figure 8: Sample event showing tracks identified in module 2 with inefficiencies and noise added

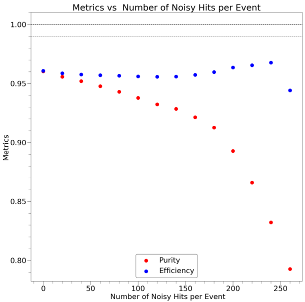


Figure 9: Efficiency and purity as a function of included noise

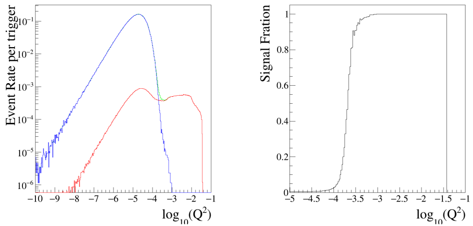


Figure 10: Rates per trigger as a function of Q^2 for Bremsstrahlung (blue) and Quasi-Real (red)

Quasi-Real Identification

- Appears to do better than a simple Q^2 cut by using the full electron momentum.
- Only has access to the relative momentum distributions of the samples, cannot beat the beam divergence.
- Exclusivity restrictions imposed by other detectors should improve this.

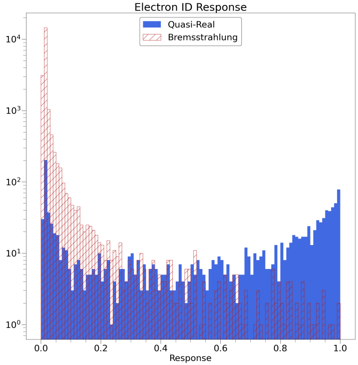


Figure 11: Learned response showing separation of QR and Bremsstrahlung events.

RECONSTRUCTING MOMENTUM

- Using custom ePIC geometry.
- Only hits from single event.
- Refurbished code to allow direct use of Ragged Tensors[5].
- Momentum loss only measured for primary tracks.
- Condensation point allowed for any track >3 hits
- Classification of whether an track is from primary vertex or a secondary interaction.
- Separated data by tagger module. (Tagger 1 shown)

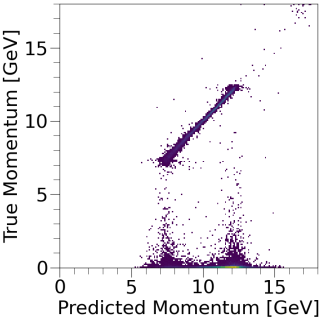


Figure 12: Predicted momentum for all condensation points.

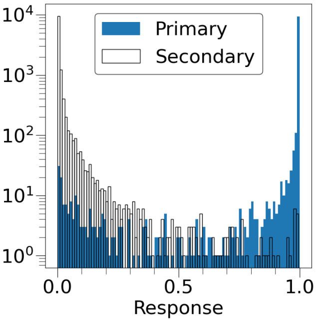


Figure 13: Learned response separating condensation points from primary and secondary tracks.

[5] We used and adapted the original code written in Tensorflow due to familiarity, rather than updating to the recommended PyTorch implementation which is still under development.

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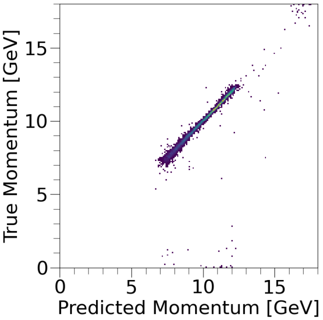
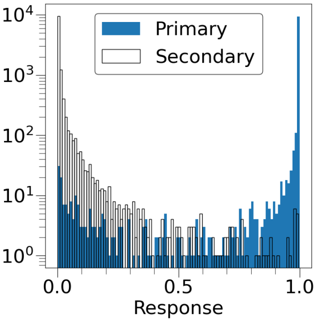


Figure 12: Predicted momentum cut on primary classification response >0.8.



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FUTURE PLANS

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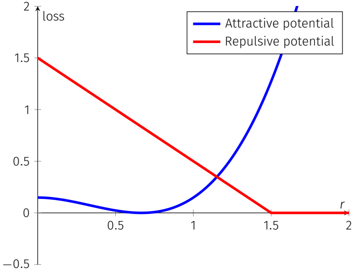
Shared hits

- Hits with contributions from more than one track will have conflicting potentials.
- In order to allow these to minimize to 0 loss, a potential with a repulsive core may be considered



Balancing losses

- Current results produced in a variety of networks, need to bring together.
- Simultaneous training on the condensation, classification and regression requires weighted losses.
- Hyper-parameters need optimisation to get the best results, ideally automatically tuned.

Improvements and Integration

- The ePIC simulation is rapidly evolving.
- Needs particles to potentially producing hits in multiple pixels to be clustered.
- Addition of beamgas and synchrotron backgrounds will increase the number of hits.
- Multi-class classification of hit source can be investigated,
- Integrate the training and inference into the ePIC software stack.
- How does this best translate to streaming readout data?

CONCLUSIONS

Conclusions

- Very promising one step particle reconstruction method.
- Good results across a range of studies.
- Lots more work to tune and extend model.
- Questions?