LOW-Q^2 TAGGER ACTIVITIES

EIC UK meeting, York

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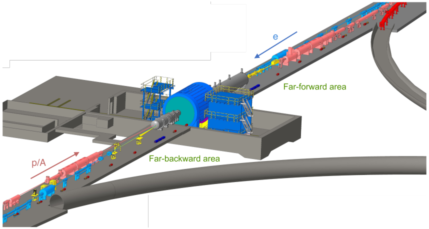
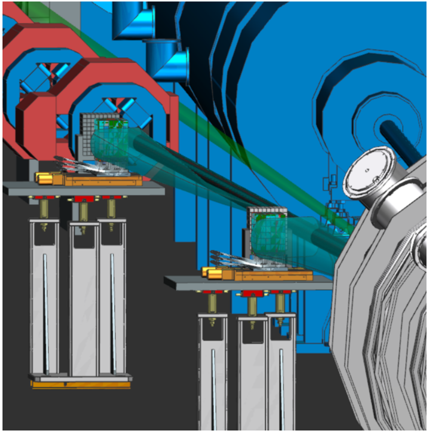




INTRODUCTION

ePIC Low-Q^2 Tagger

- For precise measurements of photoproduction and vector mesons.
- The ePIC Low-Q^2 Tagger extends the reach of the central detector down to effectively Q^2=0.
- Located after the first group of beamline steering and focusing magnets.
- Scattered electrons follow a unique path through the magnetic optics, resulting in a unique measured electron vector.
- Electrons with reduced energy are steered away from the main beam.
- Transforming the vector back through the magnetic optics accesses the original scattered vector.
- 4-momentum of the virtual photon interaction can be inferred.

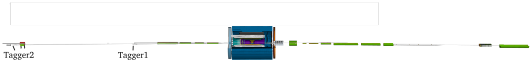


Figure 1: ePIC Low-Q^2 Tagger in Far Backward region.

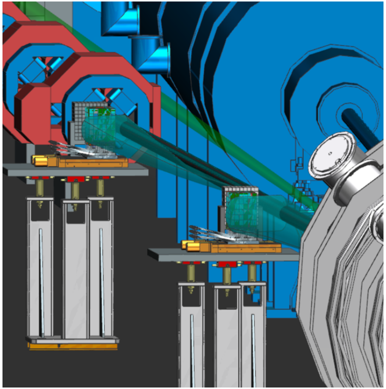
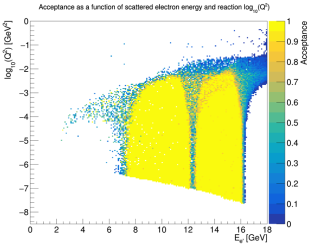
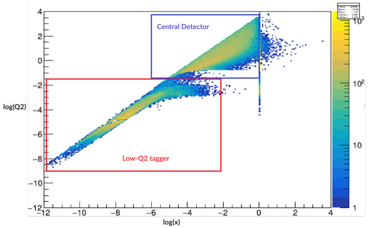


Figure 2: 2 Low-Q^2 Tagger stations placed beside the outgoing electron beamline.

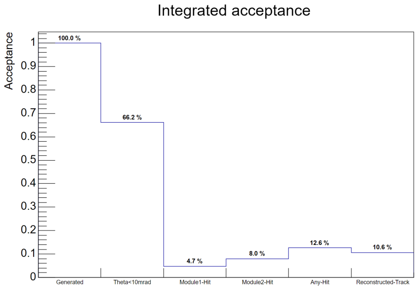
EPIC LOW-Q^2 TAGGER - ACCEPTANCE



Acceptance of reconstructed low-Q2 tagger electrons as a function of energy and Q^2



x-Q^2 acceptance showing central and low-Q^2 tagger.



Limitations

- Integrated acceptance or Quasi-real photoproduction events.
- Most events are produced at the highest energy, too close to the electron beam.
- Low energy lost in beamline magnets.
- Q^2 gap between central detector due to beamline magnet configuration.

EPIC LOW-Q^2 TAGGER - RESOLUTION

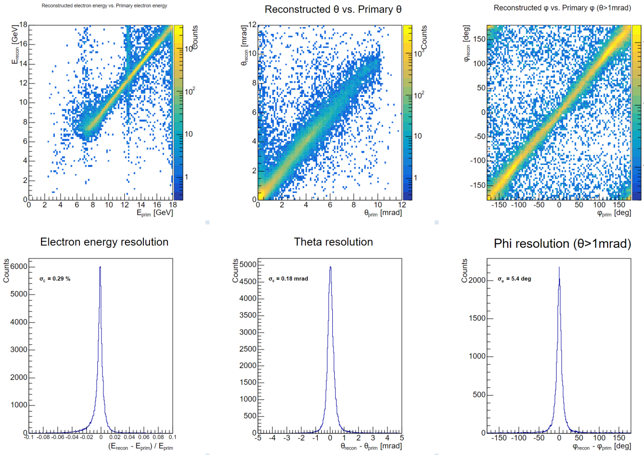


Figure 3: Reconstructed kinematics and resolution of Quasi-Real photoproduction electrons. ϕ has been limited to where θ>1 mrad

Limitations

- Fundamentally limited by the beam divergence.
- ϕ can never be extracted below the beam divergence limit.
- Limited acceptance where polarization observables will be possible.

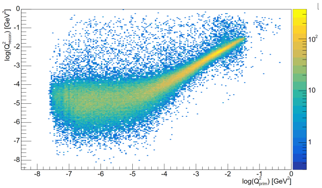


Figure 4: Reconstruction of Q^2

DESIGN

Tagger Design

- Two tagger stations covering different energy ranges.
- Tracker consisting of 4 layers of Timepix4 detectors.
- Detector layer consisting of tiled Timepix4 ASICs using TSV.
- SPIDR4 readout
- Calorimeter based on the luminosity systems design for high rates.

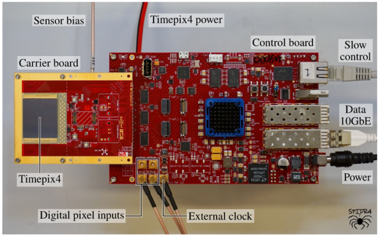


Figure 5: SPIDR4 readout - K. Heijhoff et al 2022 JINST 17 P07006

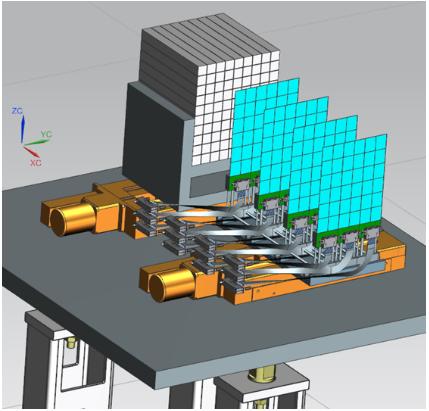


Figure 6: CAD model of a tagger station

EIC COMPLICATIONS

EIC complications

- 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 at full ep luminosity (10 ns).
- Additional, significant but currently unquantified backgrounds, from electron beam gas interactions and synchrotron radiation.
- **Need to be able to read out all hits and pick out the tracks from the interaction of interest.**

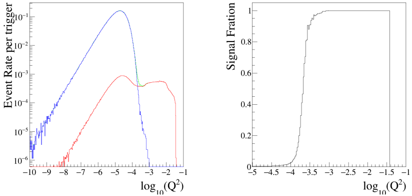


Figure 7: Left - Distribution of Bremsstrahlung (blue) and signal Quasi-real (red) events across Q^2. Right - Fraction of signal

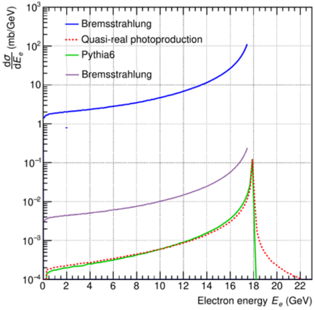


Figure 8: Cross section of Bremsstrahlung (Blue) and Quasi-Real photoproduction events from two models (Red and Green). Purple shows coincidence scaled Bremsstrahlung rate.

CHALLANGES

Challanges

- EIC integration
  - Interface between the accelerator and detectors needs to have minimal effect on either.
  - Impedance on electron bunches at 10 ns a big concern.
  - Ideal measurement would have detector in the vacuum.
  - Ideal accelerator would have perfect cylindrical pipe.
  - Compromise with exit window and thin foil.
  - Changes coming to beamline magnets might throw everything up in the air.
  - Studies to be carried out by Lancaster University.
- Data Rate
- Background Rejection
- Momentum Reconstruction

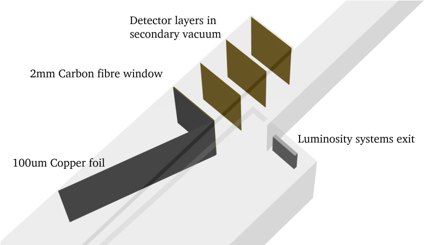
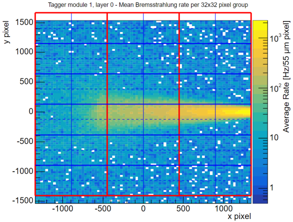
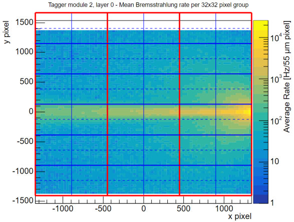


Figure 9: Design of tagger station. Carbon fibre vacuum exit window perpendicular to the beam to minimize material. Sloped copper foil to minimize beam impedance.

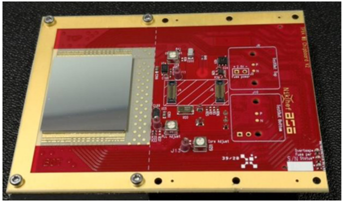
Challanges

- EIC integration
- Data Rate
  - Timepix4 technology choice due to high segmentation and timing resolution.
  - Data rate mostly from backgrounds.
  - Reduce in main detector coincidence.
  - Hard to identify tracks in real time.
  - Investigating Graph neural networks - See Backup
- Background Rejection
- Momentum Reconstruction





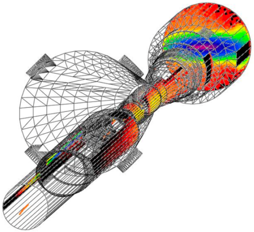
			Timepix3 (2013)	Timepix4 (2019)
Technology			130nm – 8 metal	65nm – 10 metal
Pixel Size			55 x 55 μm	55 x 55 μm
Pixel arrangement			3-side buttable 256 x 256	4-side buttable 512 x 448 **3.5x**
Sensitive area			1.98 cm^2	6.94 cm^2
Readout Modes	Data driven (Tracking)	Mode	TOT and TOA	
		Event Packet	48-bit	64-bit **33%**
		Max rate	0.43×10^6 hits/mm^2/s	**3.58×10^6 hits/mm^2/s**
		Max Pix rate	1.3 KHz/pixel	**10.8 KHz/pixel** **8x**
	Frame based (Imaging)	Mode	PC (10-bit) and iTOT (14-bit)	CRW: PC (8 or 16-bit) **10x**
		Frame	Zero-suppressed (with pixel addr)	Full Frame (without pixel addr) **5x**
		Max count rate	~0.82×10^9 hits/mm^2/s	~5×10^9 hits/mm^2/s **8x**
TOT energy resolution			< 2KeV	< **1Kev**
Time resolution			1.56ns	**~200ps**
Readout bandwidth			≤5.12Gb (8x SLVS@640 Mbps)	**≤163.84 Gbps (16x @10.24 Gbps)**



[a] Timepix4, a large area pixel detector readout chip which can be tiled on 4 sides providing sub-200 ps timestamp binning

Challanges

- EIC integration
- Data Rate
- Background Rejection
  - Synchrotron background can be eliminated through hits not belonging to a track or producing clusters. *Not studied...*
  - Electron beam-gas gives a different distribution of vectors than electrons from interaction point.
  - Limited separation of interaction point Bremsstrahlung - Statistical methods will be required.
- Momentum Reconstruction



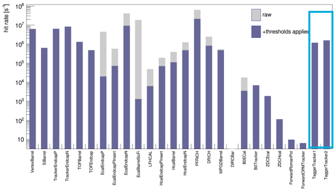


Figure 9: Electron beamgas rates originating from upstream of the IP

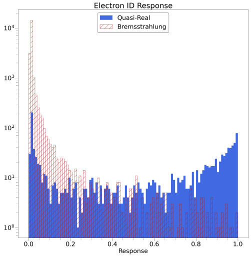


Figure 10: NN Bremsstrahlung vs QR response.

EPIC LOW-Q^2 TAGGER - FOUR KEY CHALLENGES

Challanges

- EIC integration
- Data Rate
- Background Rejection
- Momentum Reconstruction
  - Not trivial reconstruction through accelerator magnetic optics.
  - Machine learning trained on measured electron vector vs generated vector.
  - Not yet considered are instabilities/uncertainties in magnetic and online calibration/training,

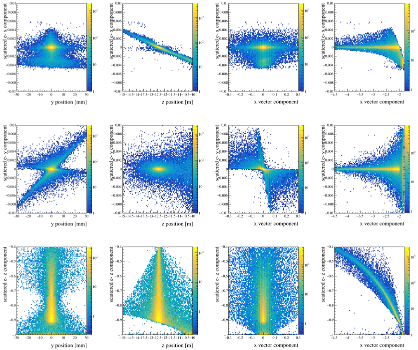


Figure 9: Correlations between the measured and truth variables.

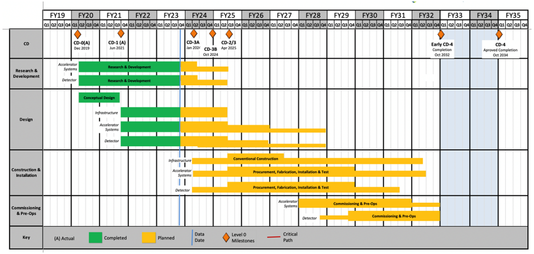
STATUS AND PLANS

Tracker

Date	
Jan 2024	2 x SPIDR4 kits in Glasgow
May 2024	Engineering test model
Summer 2024	Engineering tests in Europe
September 2024	Engineering + DAQ tests in JLab
May 2025	Final Design complete
Oct 2026	Start of construction
Oct 2030	Ready for installation

Calorimeter

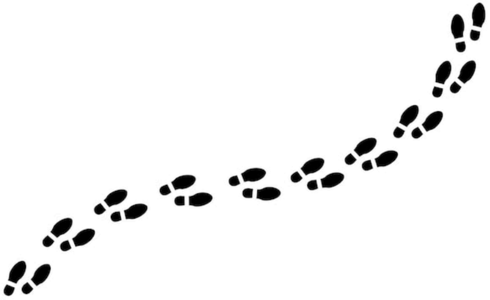
Date	
May 2025	Final design complete, review, start of construction
Oct 2030	Ready for installation



CONCLUSIONS

Conclusions

- Design advanced, underwent preliminary design review Feb 2024.
- Simulation, analysis and benchmarks included in ePIC software framework.
- Some items still not in production branch so need custom analysis.
- Investigating more advanced machine learning methods for FPGA data reduction.
- Waiting for beamline to settle before progressing with integration studies.
- Hardware received and starting tests.
- Questions?



BACKUP

Challenge

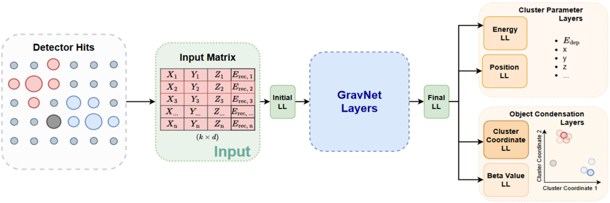
- From a varying number of N_{hits} reconstruct an unknown number of $M_{particles}$.
- Conventional approaches require looping over valid combinations of hits.
- High order of combinations to check computationally expensive.
- Latency per sample can fluctuate wildly.

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

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

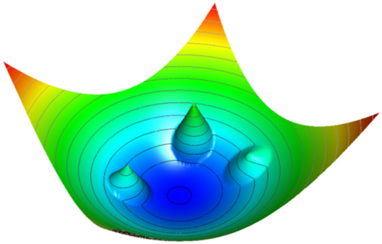


Fig. 1 Illustration of the effective potential that is affecting a vertex belonging to the condensation point of the object in the centre, in the presence of three other condensation points around it

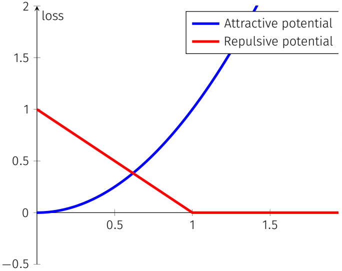
Is this a sledgehammer to crack a nut for the Low-Q^2 tagger? -Maybe... But the unknown backgrounds are expected to be high.

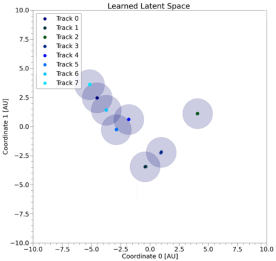
$$
\left\{ \begin{bmatrix} x_0 \\ y_0 \\ mod_0 \\ lay_0 \\ t_0 \\ E_0 \end{bmatrix} \begin{matrix} \vdots \\ \vdots \end{matrix} \right\}_{N_{hits}} \rightarrow ? \rightarrow \left\{ \begin{bmatrix} Px_0 \\ Py_0 \\ Pz_0 \\ \beta_0 \\ LatentX_0 \\ LatentY_0 \\ Primary_0 \\ Brems_0 \end{bmatrix} \begin{matrix}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

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 $\beta \to 0$ 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.

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.

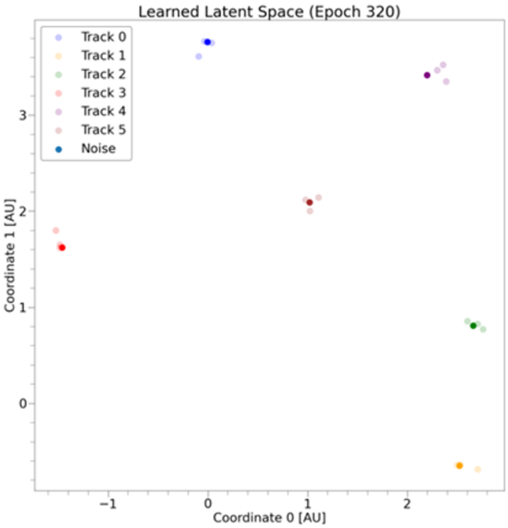
[4] GETaLM: A generator for electron tagger and luminosity monitor for electron - proton and ion collisions

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.
  - $\frac{TP}{TP+FP}$



TRAINED METRICS

Original data sample with maximum 15 true tracks per event.

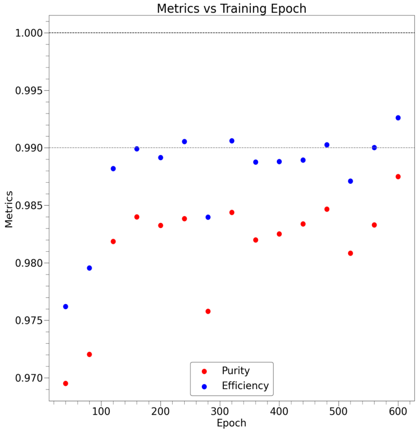


Figure 10: Tracking metrics as a function of training epoch.

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

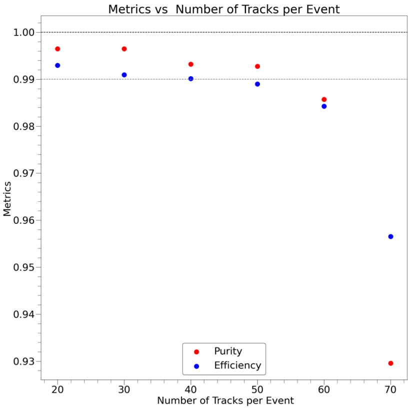


Figure 11: Tracking metrics against the number of true tracks in an event.

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

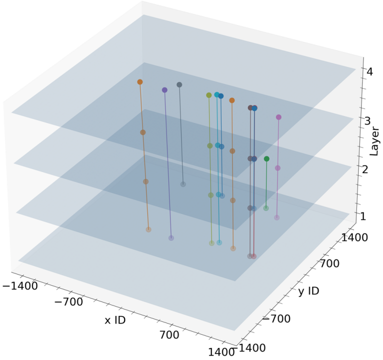


Figure 12: Hits from tracks in 4 layers with inefficiencies added.

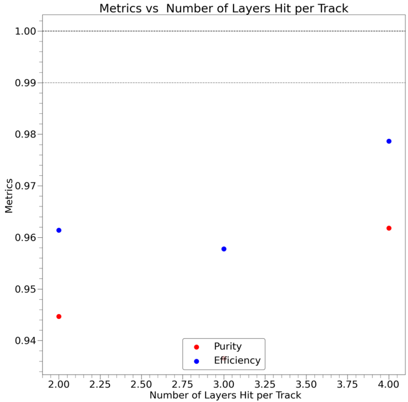


Figure 13: Tracking metrics against the number of hits per track.

Real detector efficiency expected to be >99%

ADDING ARTIFICIAL NOISE

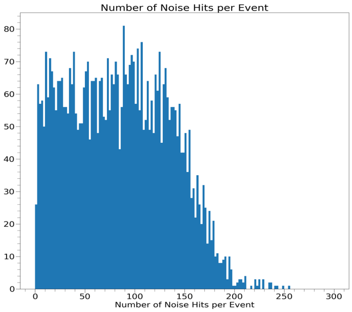


Figure 14: Distribution of artificial noise hits added to event.

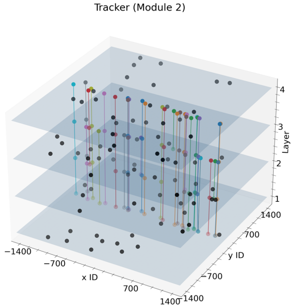


Figure 15: Sample event showing tracks identified in module 2 with inefficiencies and noise added

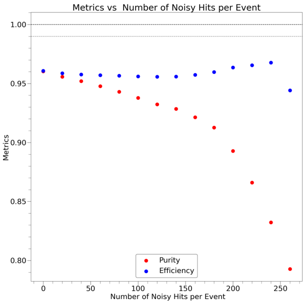


Figure 16: Efficiency and purity as a function of included noise

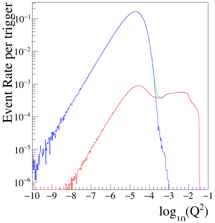


Figure 17: Rates per trigger as a function of Q^2 for Bremsstrahlung (blue) and Quasi-Real (red)

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.

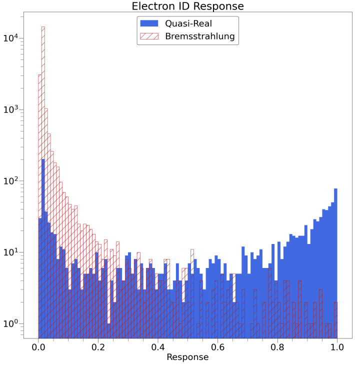


Figure 18: Learned response showing separation of QR and Bremsstrahlung events.

- 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)

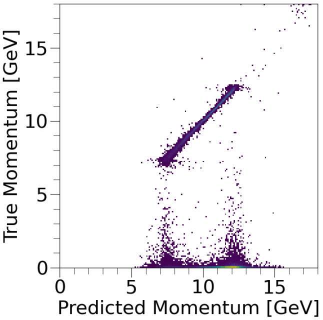


Figure 19: Predicted momentum for all condensation points.

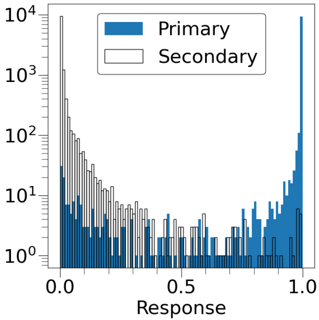


Figure 20: Learned response separating condensation points from primary and secondary tracks.

[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.

- 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.
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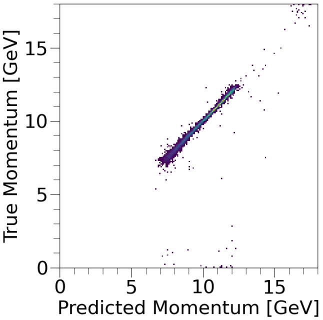


Figure 19: Predicted momentum cut on primary classification response >0.8.

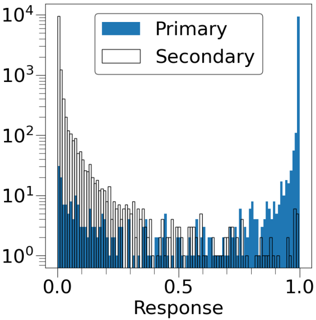


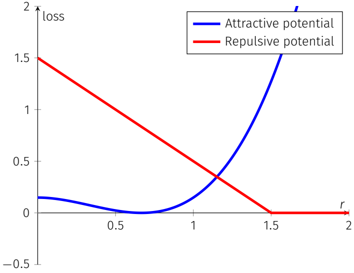
Figure 20: Learned response separating condensation points from primary and secondary tracks.

[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.

FUTURE PLANS

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?