

A(I)LERT Track Finding

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CLAS Collaboration (November 12th, 2024)



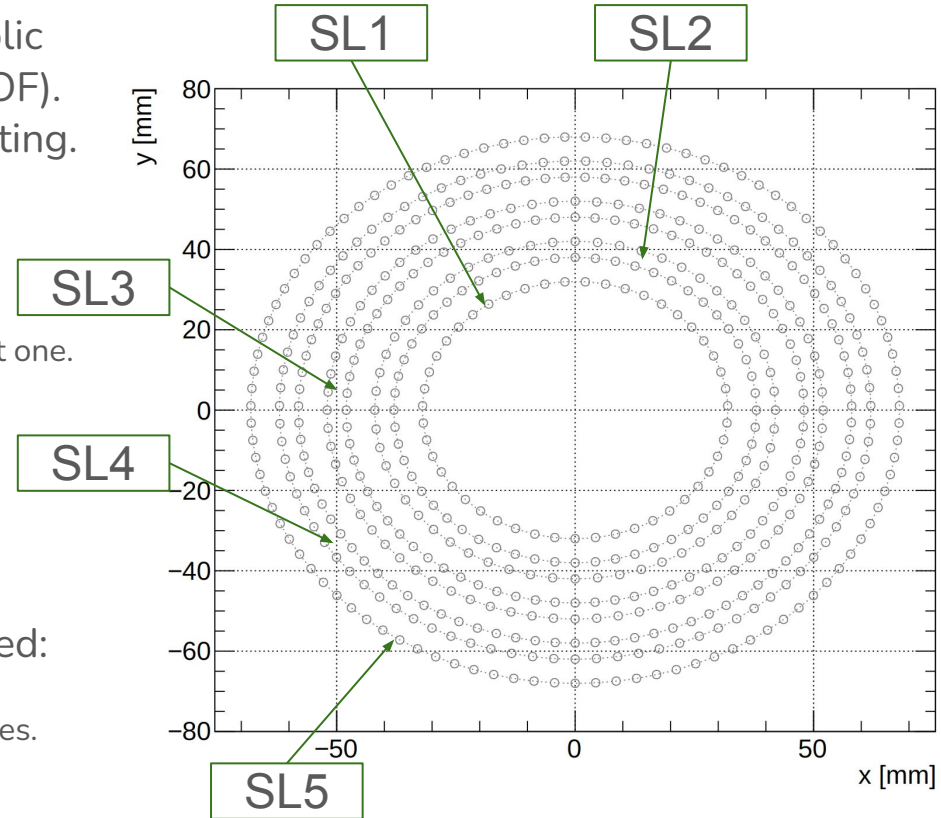
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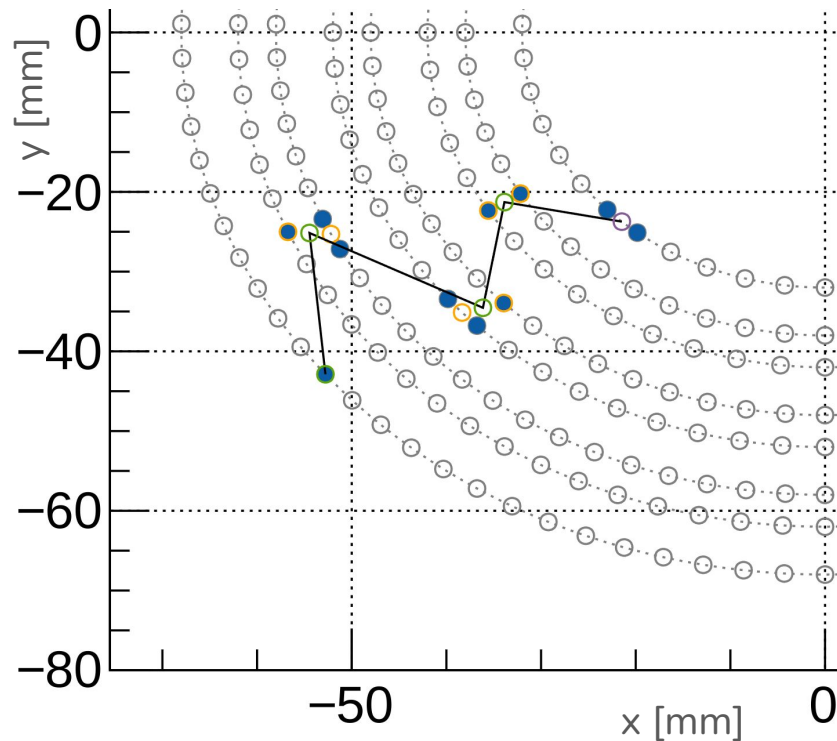
Jefferson Lab

The ALERT Detector

- ALERT comprises two sub-detectors: A Hyperbolic Drift Chamber (AHDC) and A Time of Flight (ATOF).
- Focus on the AHDC used for track finding and fitting.
- The AHDC is composed of:
 - 5 superlayers with 2 layers each except for the first and last one.
 - Each layer has a given number of cells.
 - A cell is 6 field wires and 1 signal wire.
- A stereo angle of 20° between each superlayer.
- AHDC is composed of 576 signal wires distributed:
 - 47, 56, 57, 72, 87, 99 for each superlayer.
 - Layer in each superlayer has the same amount of signal wires.

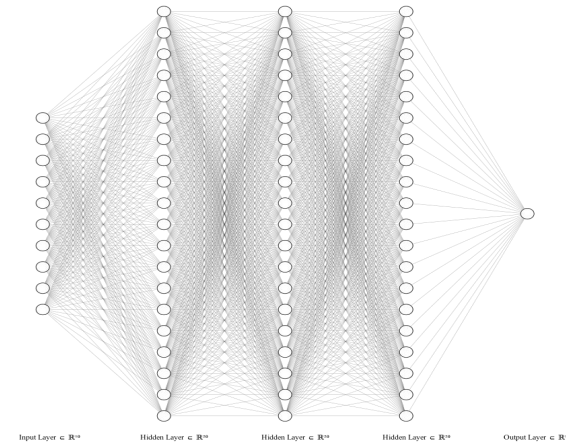
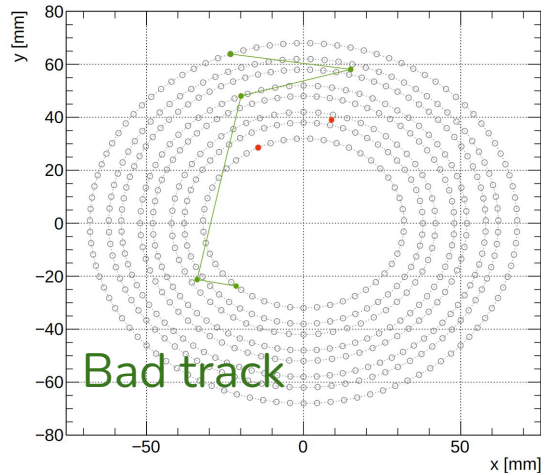
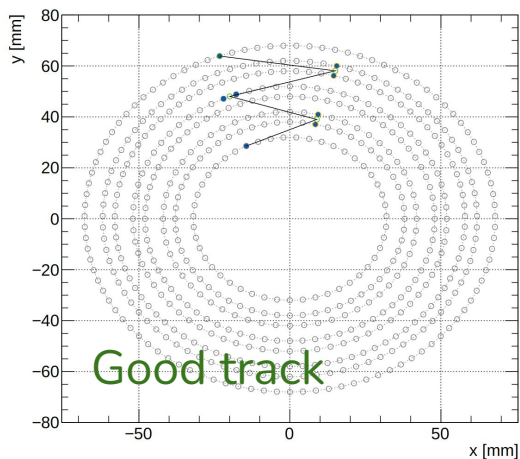


- The first step before the model is clustering. Goal: reduce the combinatorics to find track.
- Test different clustering:
 - Raw hits in blue.
 - Merge hits that are on the same layer and 1 wire away together into **precluster** (orange circle).
 - Merge precluster that are on the same superlayer and 8mm away into **super-precluster** (green circle).
 - End up with 5 super-preclusters.
- Look for a track with 5 super-clusters.
- Test the AI model with preclusters and super-preclusters.



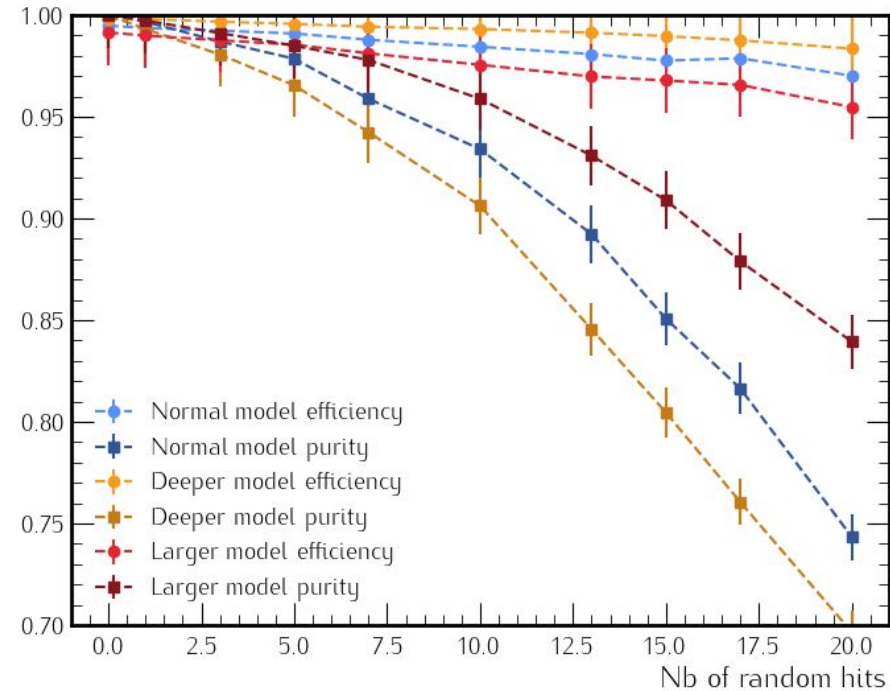
Model: MLP

- The input for the model is 5 combinations for x and y which represent the super-preclusters.
- Good tracks are generated by GEMC:
 - proton with $p \in [60, 250]$ MeV/c, $\varphi \in [0, 360]^\circ$, $\theta \in [60, 120]^\circ$ and $v_z \in [-15, 15]$ cm.
- False tracks: interchanging randomly up to two super-precluster, with a adjacent event.
- Model: MLP 10 inputs, 3/5 hidden layer (20/100), 1 output.
- Output of the model: Probability 1-good track or 0-bad track



Efficiency and purity as function of occupancy

- Efficiency: Number of good tracks classified as good / number of event.
 - Purity: Number of good tracks classified as good / number of tracks (good or bad) classified as good.
 - To compute the efficiency/purity: Add some random hits in the drift chamber and generate all possible tracks per event.
 - Expect around 15 random hits per events (5% occupancy).
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- Blue line/dot: model with 20 neurons in the 3 hidden layers
 - Red line/dot: model with 100 neurons in the 3 hidden layers
 - Orange line/dot: model with 20 neurons in the 5 hidden layers

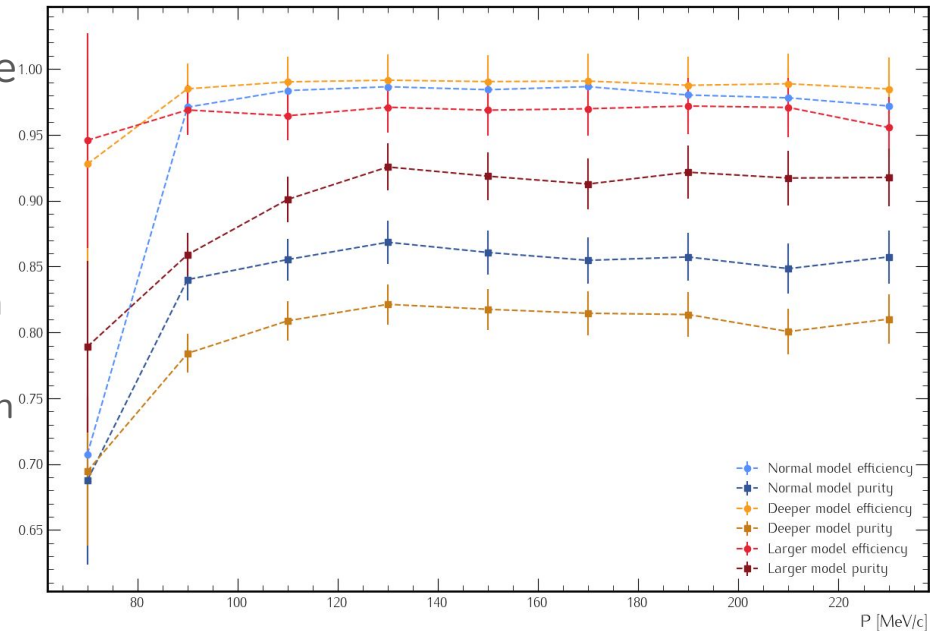


Efficiency and purity as function of momentum

- Can also compute the efficiency as function of the momentum of the proton:
 - Using event with 1 track + 15 random hits
 - proton with $p \in [60, 250]$ MeV/c, $\varphi \in [0, 360]^\circ$, $\theta \in [60, 120]^\circ$ and $v_z \in [-15, 15]$ cm

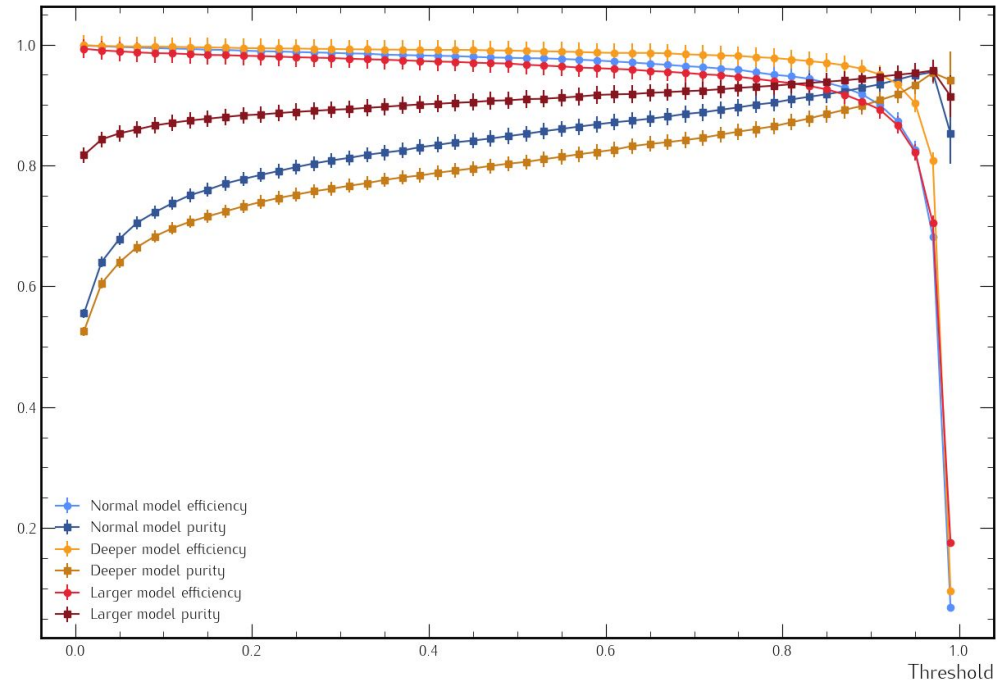
- Efficiency and purity almost constant for the range of momentum.

- Blue line/dot: model with 20 neurons in the 3 hidden layers
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- Orange line/dot: model with 20 neurons in the 5 hidden layers



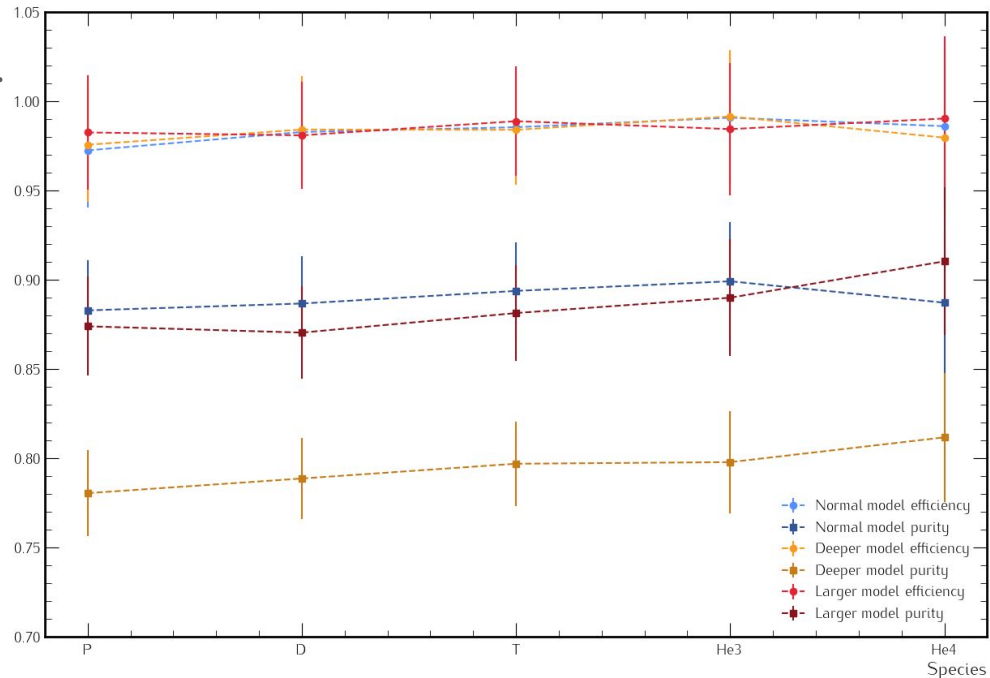
Efficiency and purity as function of threshold

- Can look at the efficiency as function of the threshold.
- Threshold: value above what we consider the output of the model 1 and below 0.
- Want high efficiency and purity, but not possible.
- Prefer high efficiency to high purity.
- Blue line/dot: model with 20 neurons in the 3 hidden layers
- Red line/dot: model with 100 neurons in the 3 hidden layers
- Orange line/dot: model with 20 neurons in the 5 hidden layers



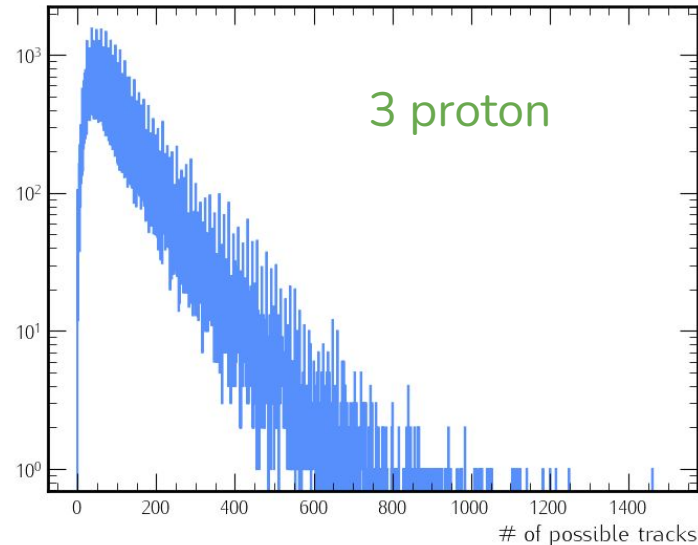
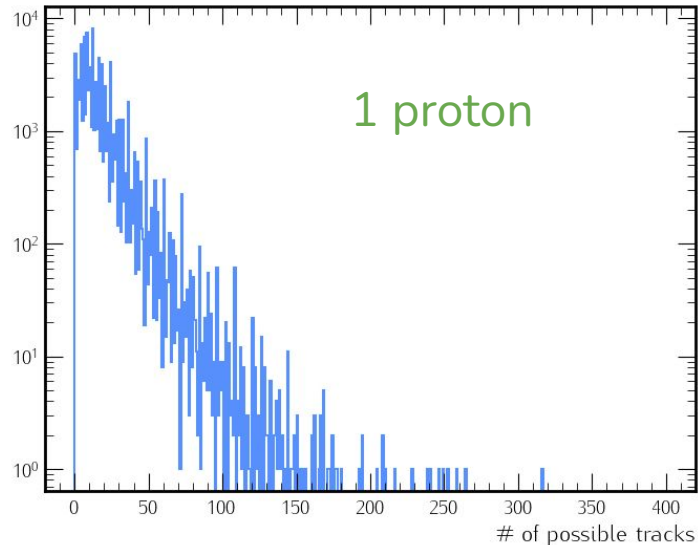
Efficiency and purity as function of species

- Can look at the efficiency as function of the particle.
- Train the model with tracks from proton, deuterium, tritium, helium 3 and helium 4.
- Constant for all species. Purity of the deeper model is lower.
- Blue line/dot: model with 20 neurons in the 3 hidden layers
- Red line/dot: model with 100 neurons in the 3 hidden layers
- Orange line/dot: model with 20 neurons in the 5 hidden layers



Inference time and number of possible tracks

- For the normal model, the inference time is around $15\mu\text{s} \mapsto 60\text{KHz}$.
- For a typical event, with 1 proton track and 15 random hits:
 - Mean of 16 possible tracks but can have up to 300 possible tracks for some events
- For a busy event with 3 proton tracks and 15 random hits:
 - Mean of 100 possible tracks but can have up to 1500 possible tracks for some events (need a threshold)



Summary and Outlook

- Develop an MLP for track finding for ALERT
 - New clustering to reduce the number of possible tracks
 - Evaluated the model's efficiency and purity as a function of a number of random hits added.
 - Evaluated the model's efficiency and purity as a function of momentum / threshold
 - Evaluated the model's efficiency and purity for different particles
- Remaining tasks:
 - Compare AI to conventional track finding
 - Use luminosity simulation to have a more realistic occupancy.
 - Implementation in COATJAVA using Deep Java Library
 - Already started, can load the pytorch model in Java and predict output
 - Same prediction between pytorch and DJL
 - Develop an AI for PID using MLP and a classifier with 5 classes.

Work done by Uditha Weerasinghe and me.