Reconstruction Improvements in SBND using Machine Learning

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New Perspectives 2.0
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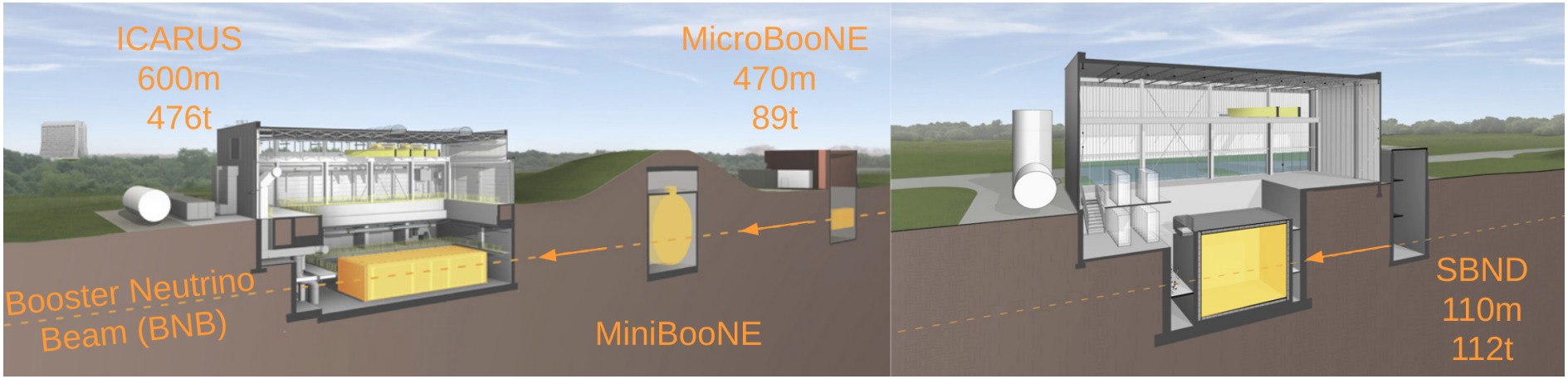
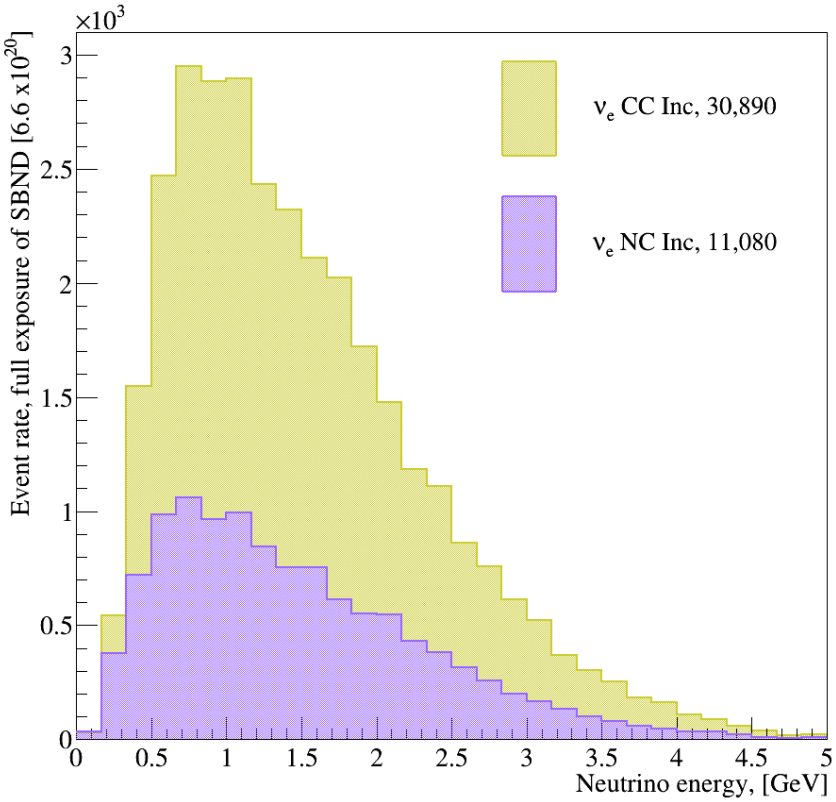
The Short Baseline Near Detector: SBND

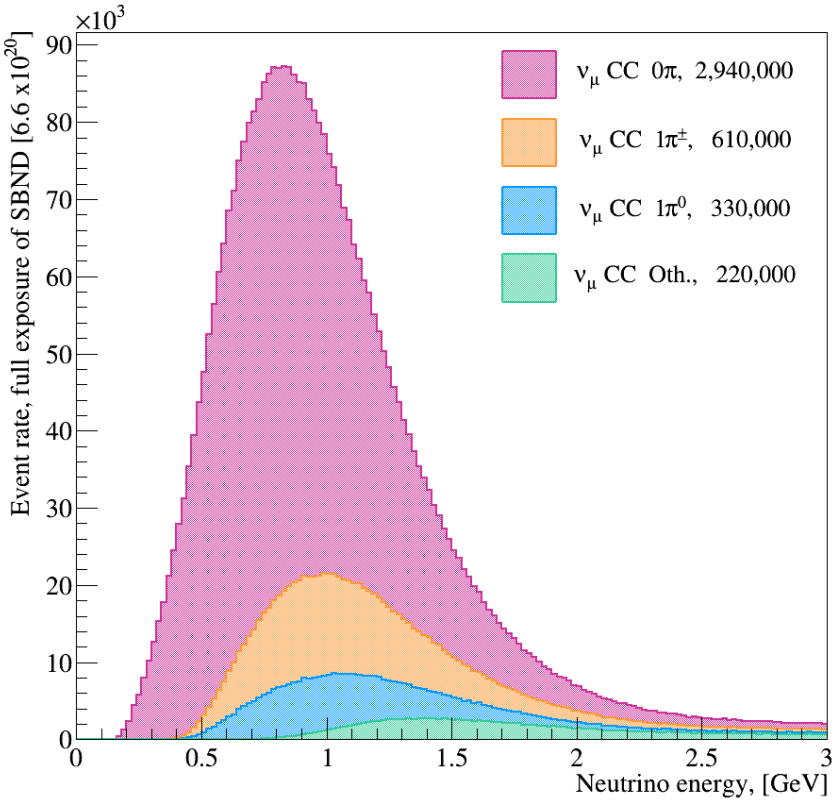
- 112t Liquid Argon TPC (LAr TPC)
- Modern detector with novel R&D detector subsystems
- Closest of three LAr TPCs in the Booster Neutrino Beam at Fermilab
- Critical role in constraining uncertainties for sterile neutrino search
- Rich cross section and BSM physics programmes



SBND Cross Section Measurements

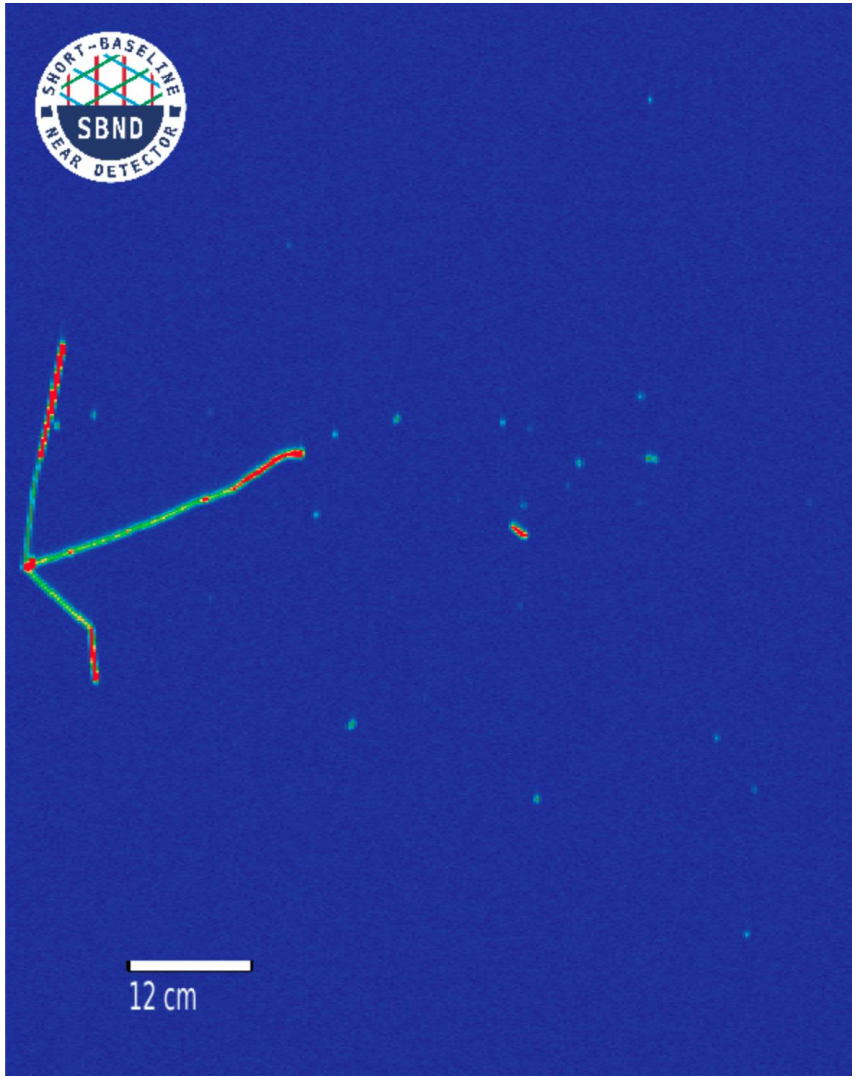
- Powerful subsystems allow for excellent cosmic removal
- SBND has an extremely high event rate
  - Expect over 5.5 million events in 3 years, $\sim$ 5000 per day!
- High granularity detector allows for precision measurements





LAr TPC Reconstruction

- LAr TPCs provide exceptional detector resolution (3mm wire pitch)
- Maximise the information we can extract from the detector
- Run low level reconstruction: Deconvolution and hit-finding
- Pattern recognition is crucial next step



Pandora Reconstruction

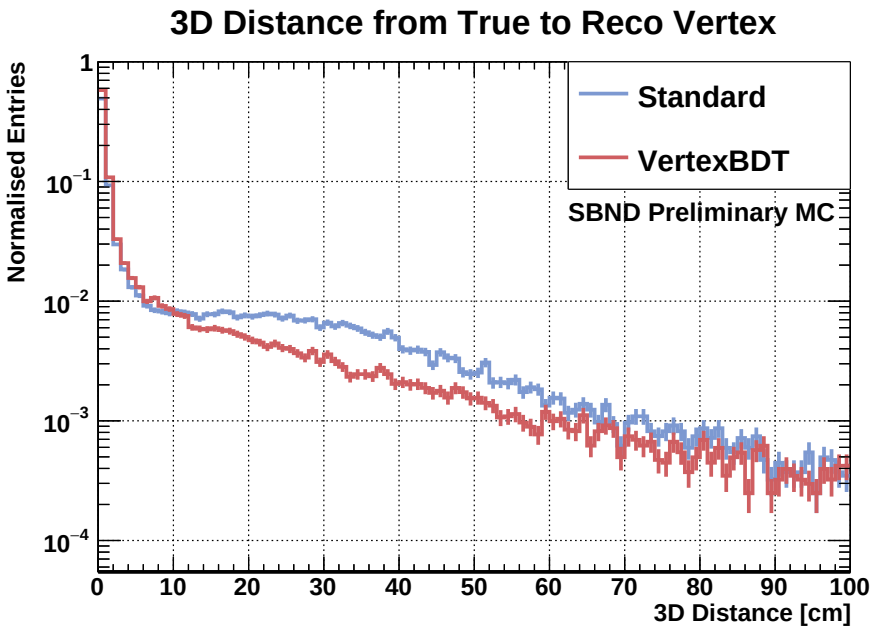
- Pandora multi-algorithm pattern recognition used in many LAr TPCs
- Matches clusters across planes to produce 3D Particle Flow Objects (PFOs)
- Introduce machine learning at critical points to help guide the reconstruction
- Building off work done in MicroBooNE and DUNE
- MicroBooNE Pandora Paper Eur. Phys. J. C 78, 82 (2018).

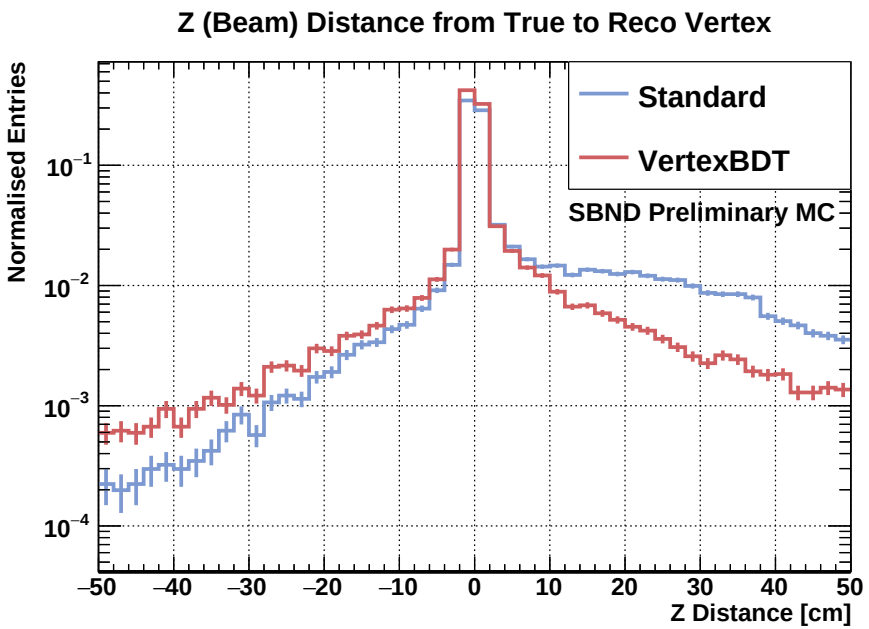
Vertex Reconstruction

- Correctly identifying the neutrino interaction vertex is a critical first step in reconstruction neutrino interactions
- Can "grow" the event from here
- Getting it wrong can cause issues (e.g. broken tracks)
- Pandora creates many 'Vertex Candidates'
- Traditionally choose the vertex based on 'scores':
  - Energy Kick (Closely related to transverse energy)
  - Asymmetry (Ratio of upstream/downstream hits in local region)
  - Beam Deweighting (How upstream vertex candidate is)
- Machine learning can help!
- Use SKLearn AdaBoost BDT:
  - Y. Freund, and R. Schapire, "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting", 1997.
  - Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.

Vertex Reco Performance: BNB Intrinsic ν_e

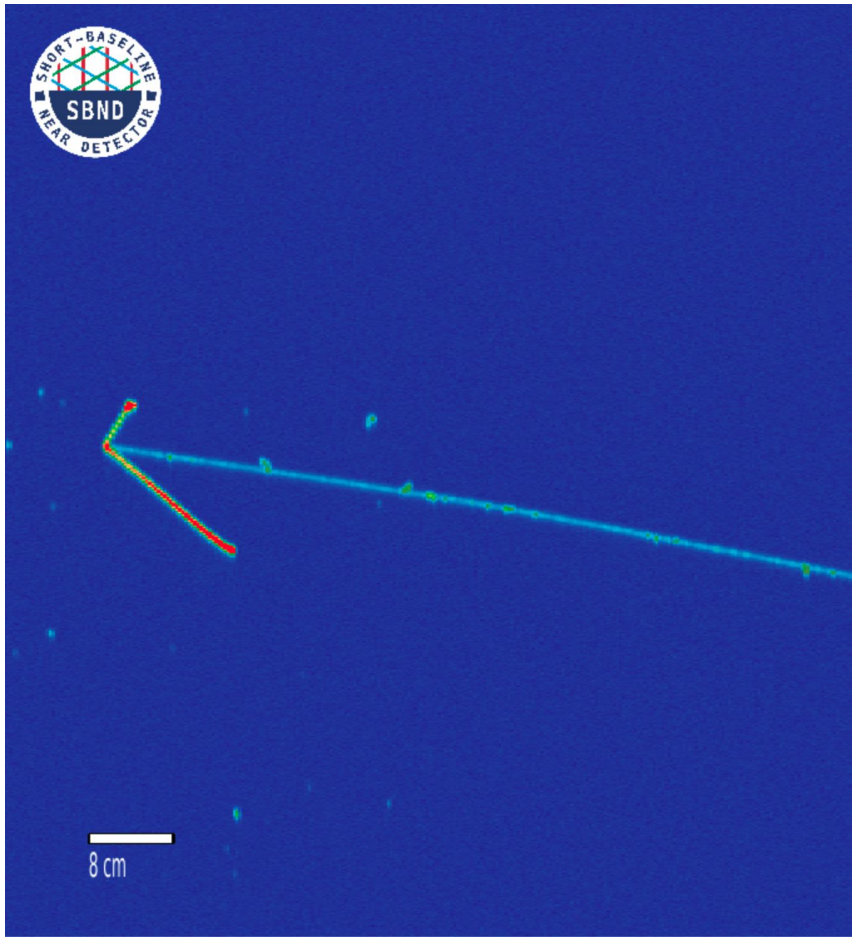
- Overall improvements in vertex resolution
  - Reconstructed within 10cm of true vertex: 69% $\rightarrow$ 81%
- Reduced bias in beam direction
- Modest improvements also seen for ν_μ events ($\sim$ 2%)





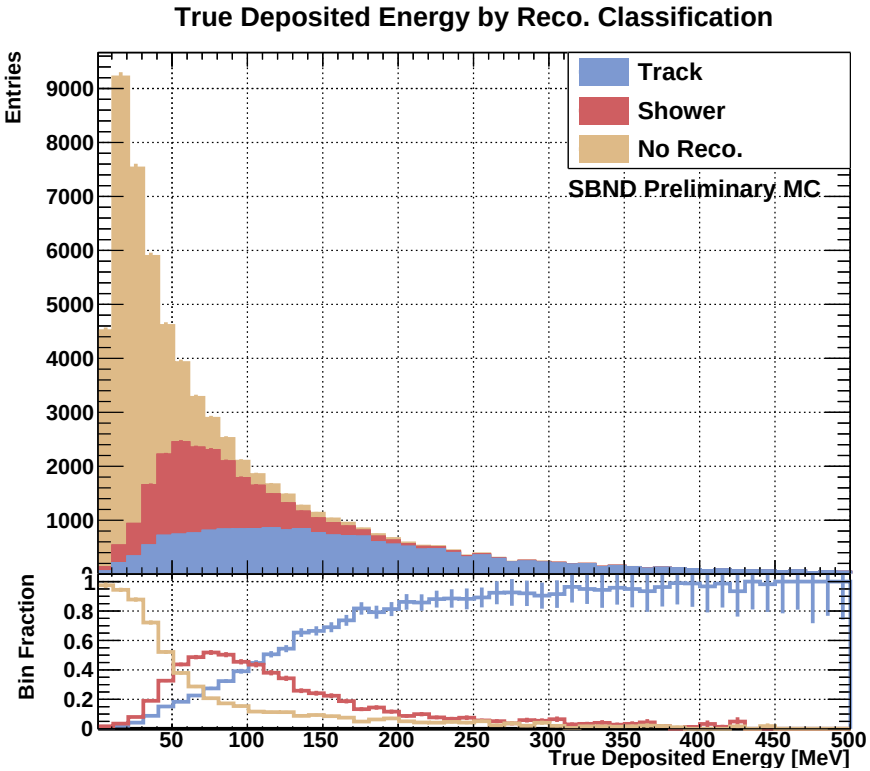
Particle Flow Object Characterisation

- Pandora recreates Particle Flow Objects (PFOs)
- Classify as Track or Shower for downstream reconstruction and PID
- Traditionally use a series of cuts
- Replace cuts with BDT
- Two areas for improvement:
  - Low energy tracks being classified as showers
  - High energy showers being classified as tracks

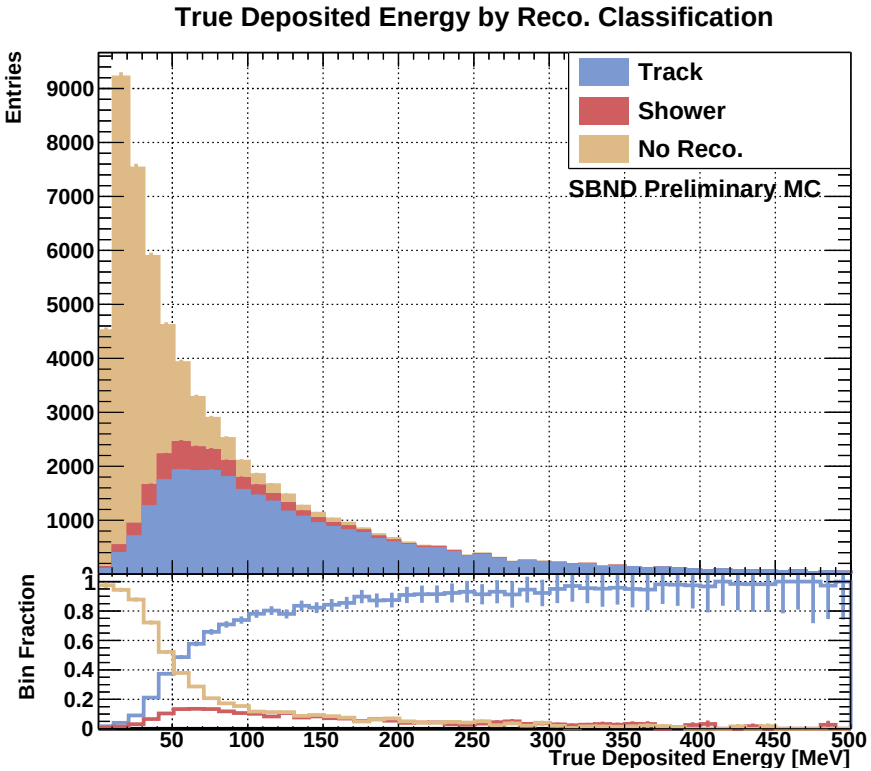


PFO Characterisation Performance: Protons

- Fraction of reconstructed protons identified as tracks: 57% → 88%



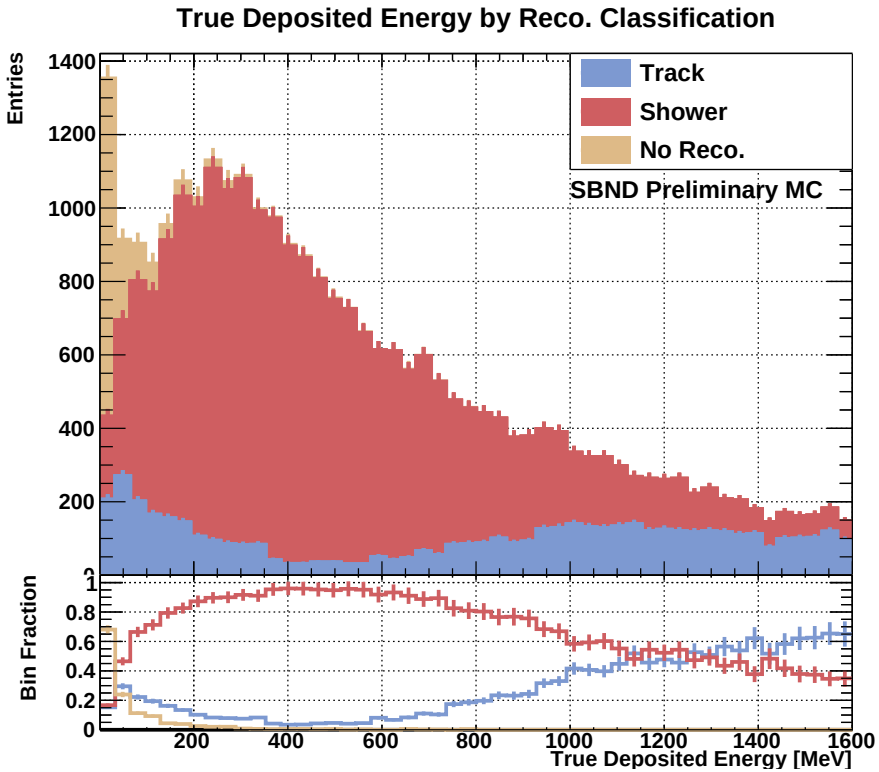
Standard



PFO Characterisation BDT

PFO Characterisation Performance: Electrons

- Fraction of reconstructed electrons identified as showers: 75% → 90%



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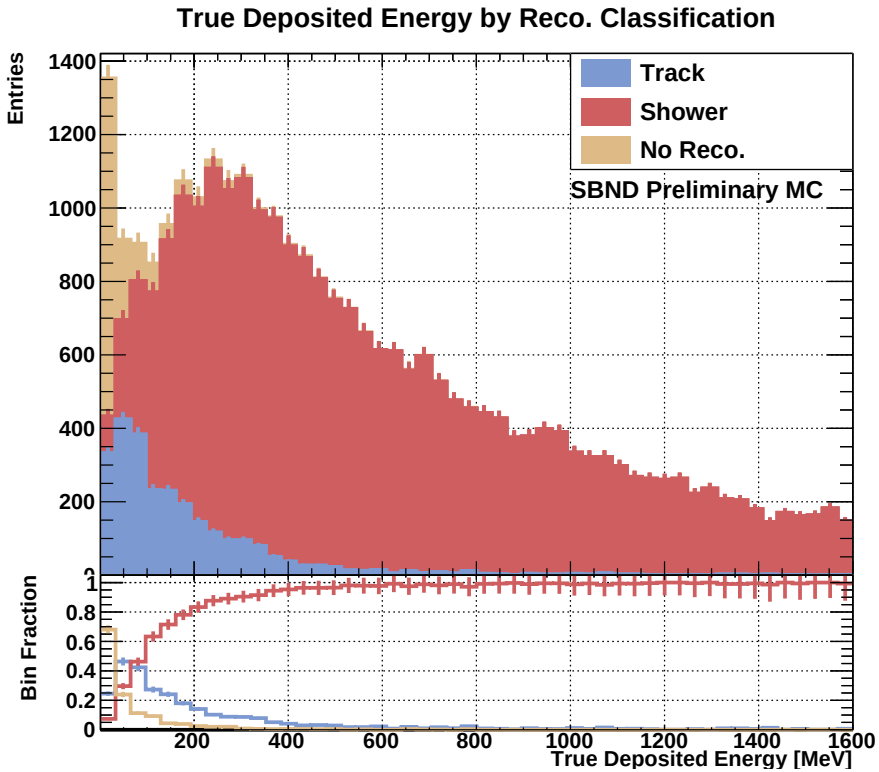
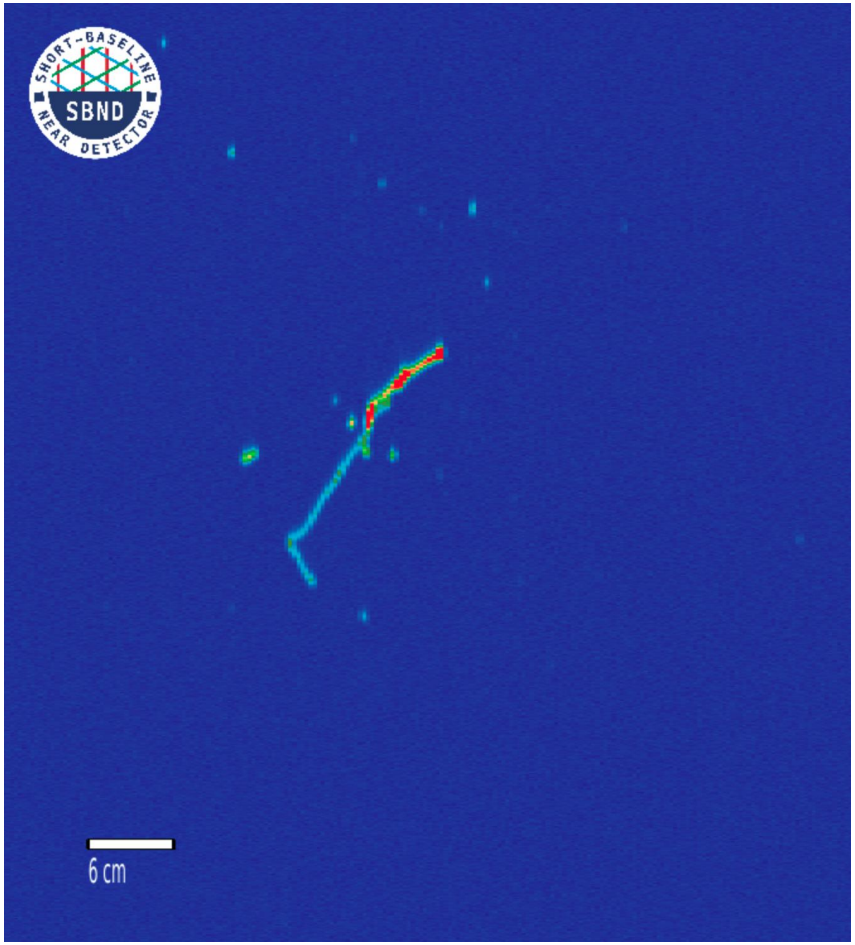
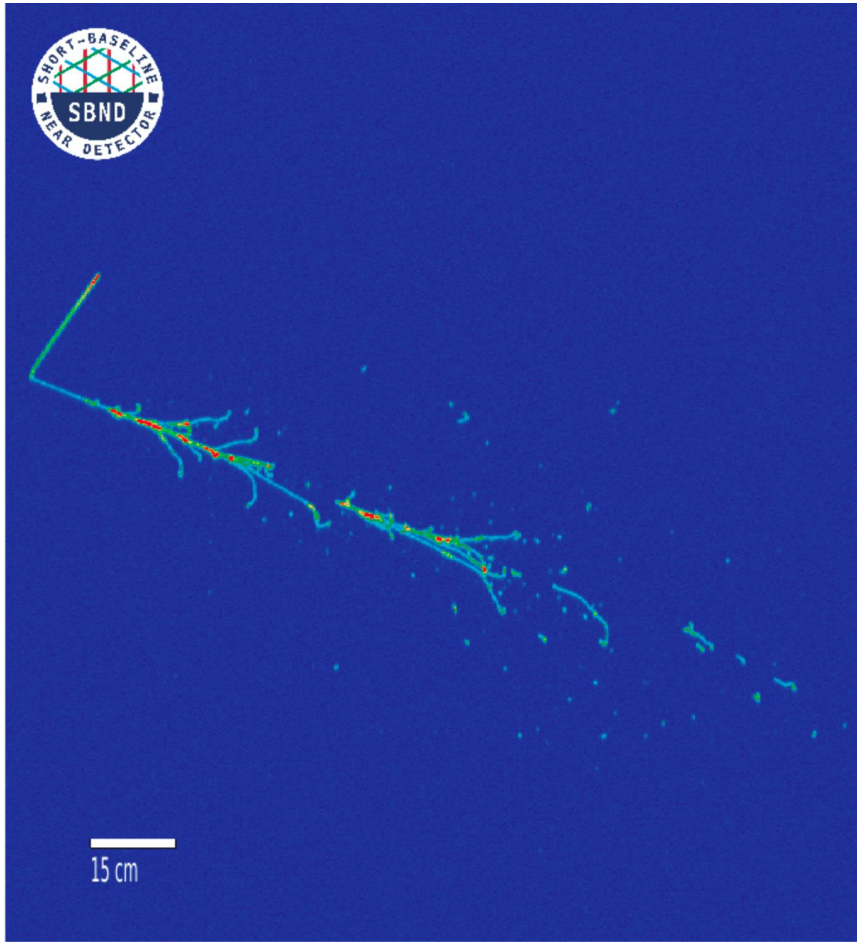


PFO Characterisation BDT

PFO Characterisation Performance: Electrons



Example low energy shower



Example high energy shower

Conclusions

- Machine Learning has been added to help guide in Pandora reconstruction in SBND
- These BDTs replace cuts at crucial points in the reconstruction chain
- Vertex resolution has been improved
  - Reconstructed within 10cm of true vertex: $69\% \rightarrow 81\%$
- Reduced biases in beam direction
- Improved identification of Protons as tracks: $57\% \rightarrow 88\%$
- High energy electrons are now longer identified as showers: $75\% \rightarrow 90\%$
- Work is ongoing to determine the areas to focus future effort
- Future iterations can focus on trying to improve difficult topologies