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Exploring the Dark Sector in MicroBooNE Through e^+e^- Final States

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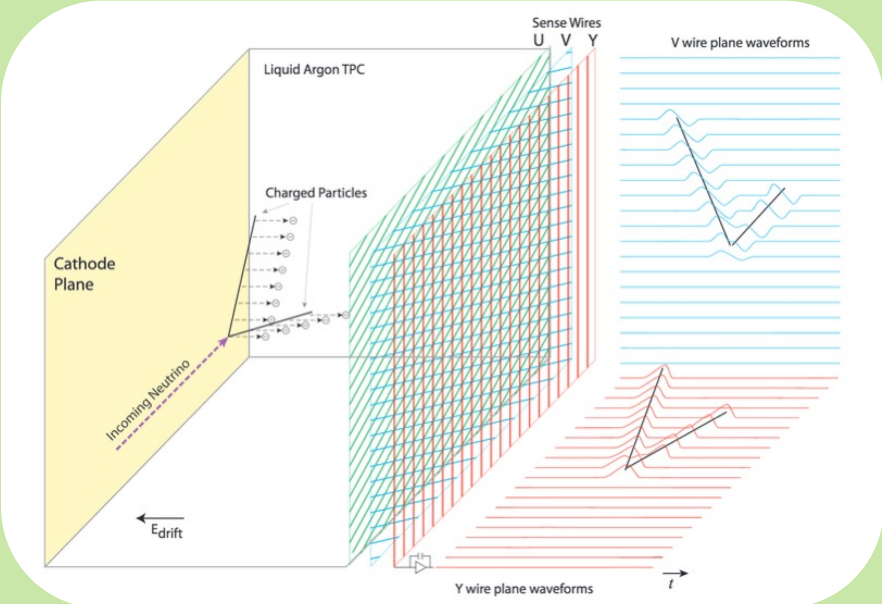
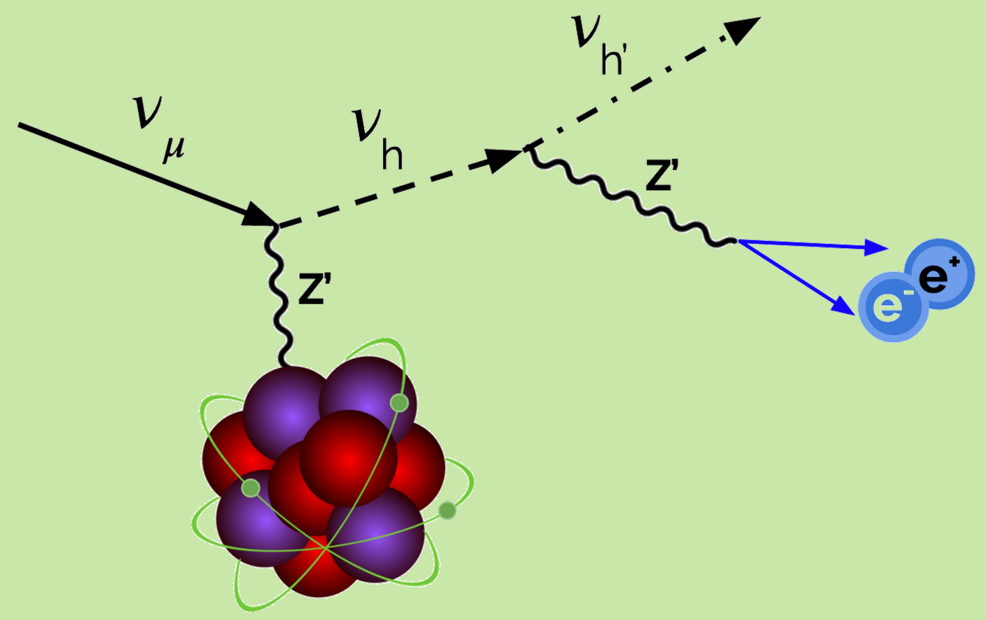
(1) Introduction

MicroBooNE is a liquid Argon time projection chamber that tracks the path of charged particles produced by neutrino interactions.



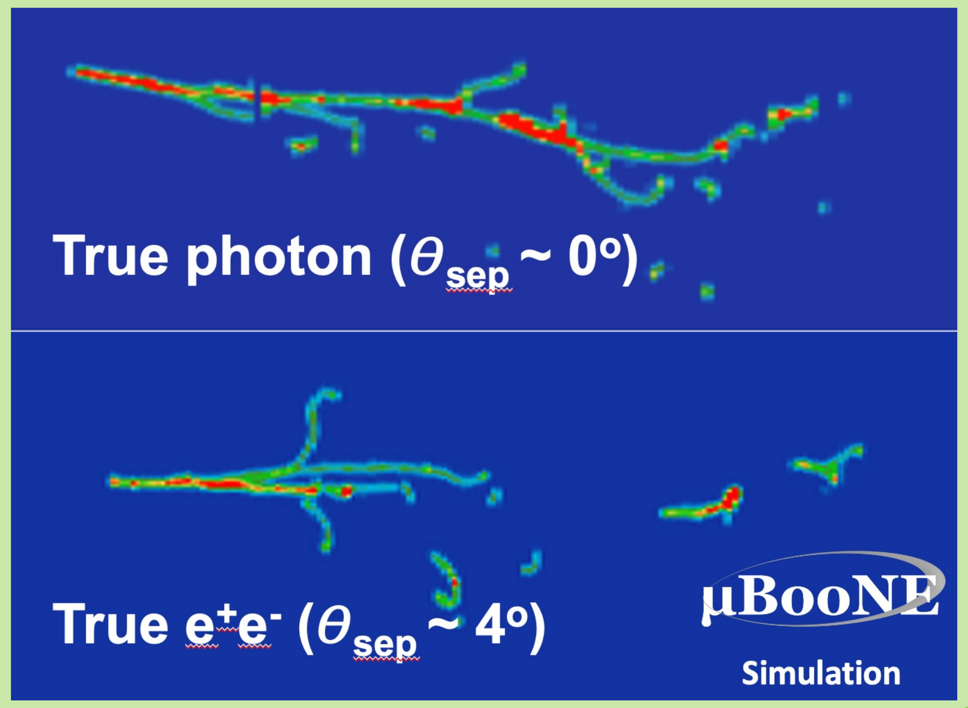
Some dark sector models predict the existence of heavy neutrinos that decay to e^+e^- pairs. [1][2]



e^+e^- from heavy neutrinos are predicted to have small average opening angles, making them difficult to distinguish from photons.

→Would be indistinguishable to predecessor MiniBooNE, making them a potential source of the MiniBooNE low energy excess.

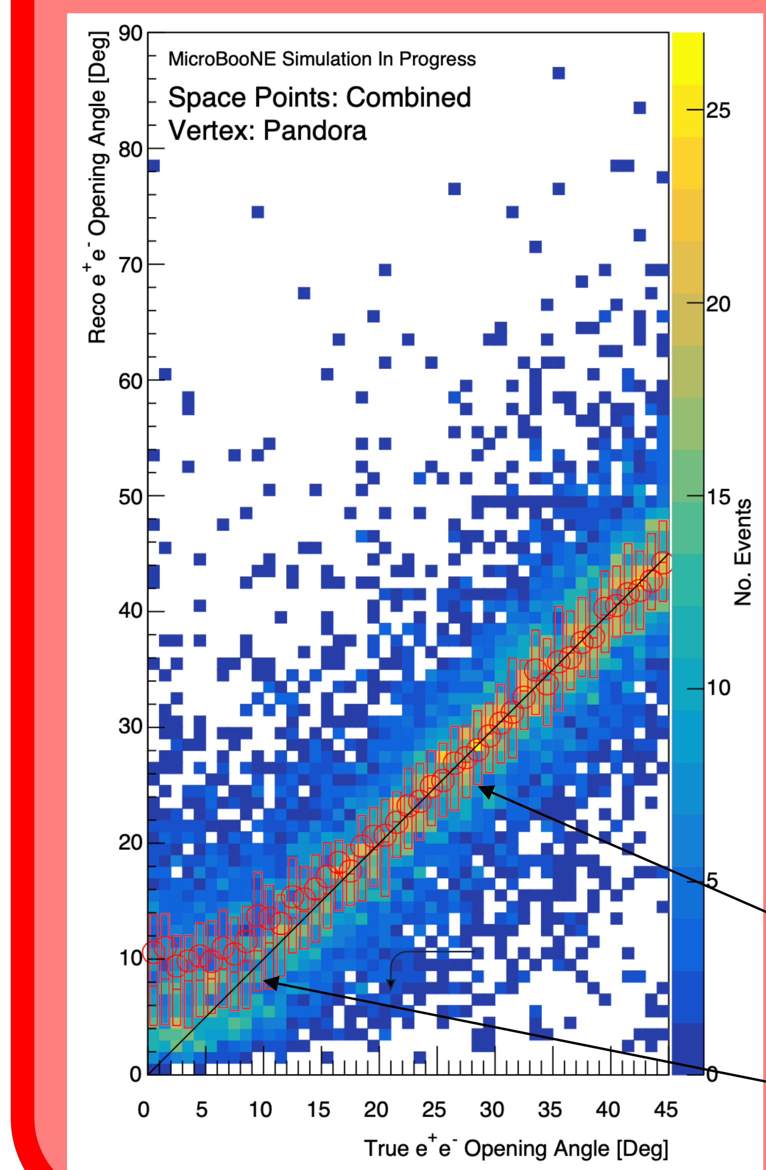
We've developed two algorithms for calculating e^+e^- opening angles in MicroBooNE, both to help differentiate e^+e^- from photons and to compare the opening angle distribution with those predicted by various models.



(2a) Line-fitting

Steps:

1. Retrieve reconstructed 3D space points and vertex.
2. Weight space points by distance from vertex.
3. Split space points through the middle to obtain two showers.
4. Fit line through each shower and calculate the angle between the lines.



When fitting, points closer to vertex given more weight using a logistic function with a 10 cm midpoint.

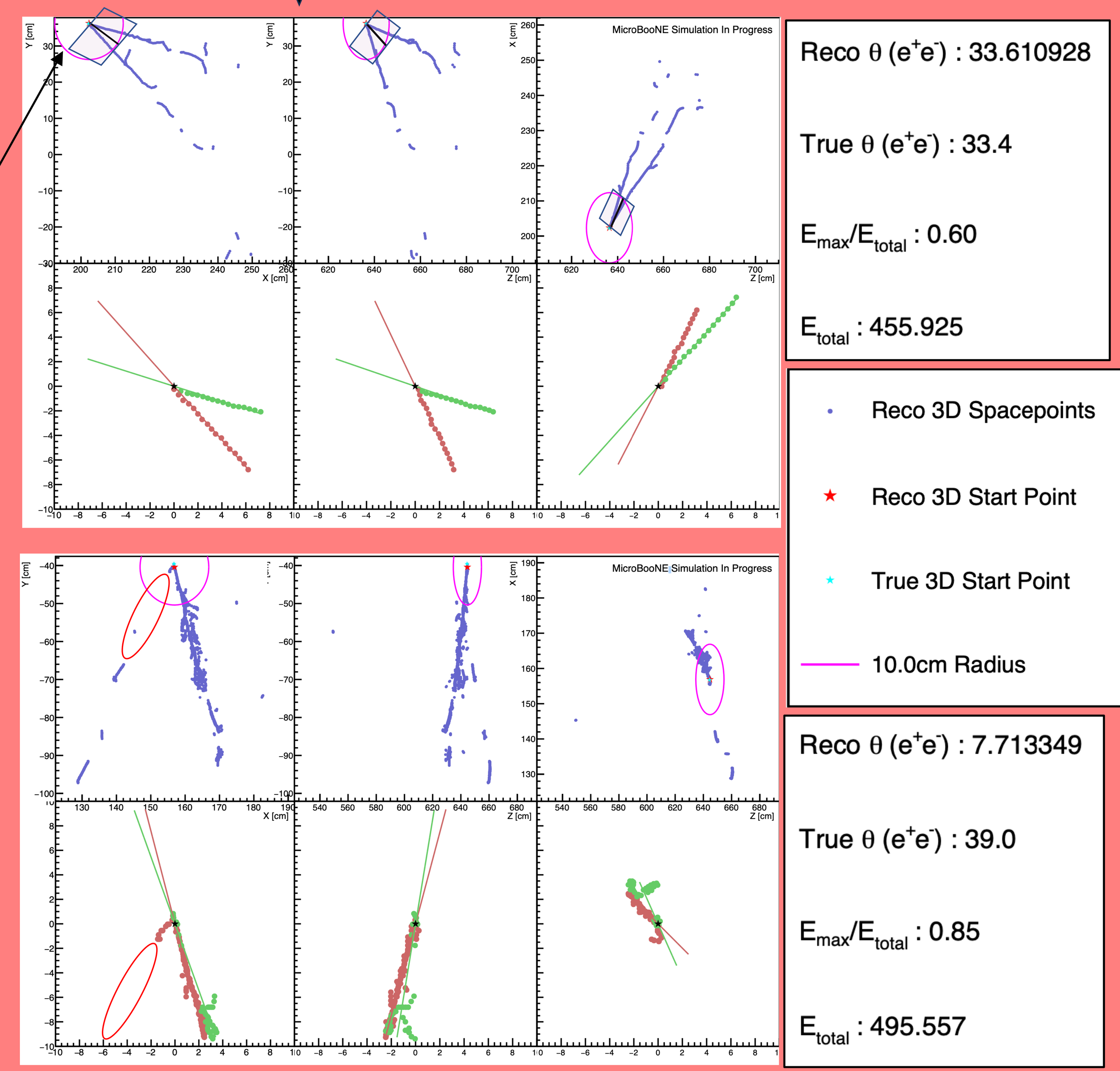
Pandora space points are also given a reduced weight due to their greater quantity.

Optimal results are achieved by combining space points from two MicroBooNE reconstruction frameworks (Pandora [3] and Wire-Cell [4]). We obtained a standard deviation in the reconstructed angle error of 8.34°.

Symmetric errors above ~15°

Poorly reconstructs low opening angles

Some events are easily fit.



Others, less so.

Event Parameters	True θ_{sep}: 0° – 45° E_{tot}: 100 – 800 MeV $E_{assymetry}$: 0.50 – 0.90	Events where the reconstructed vertex was more than 1 cm from the true vertex were excluded from analysis.

(2b) PointNet++

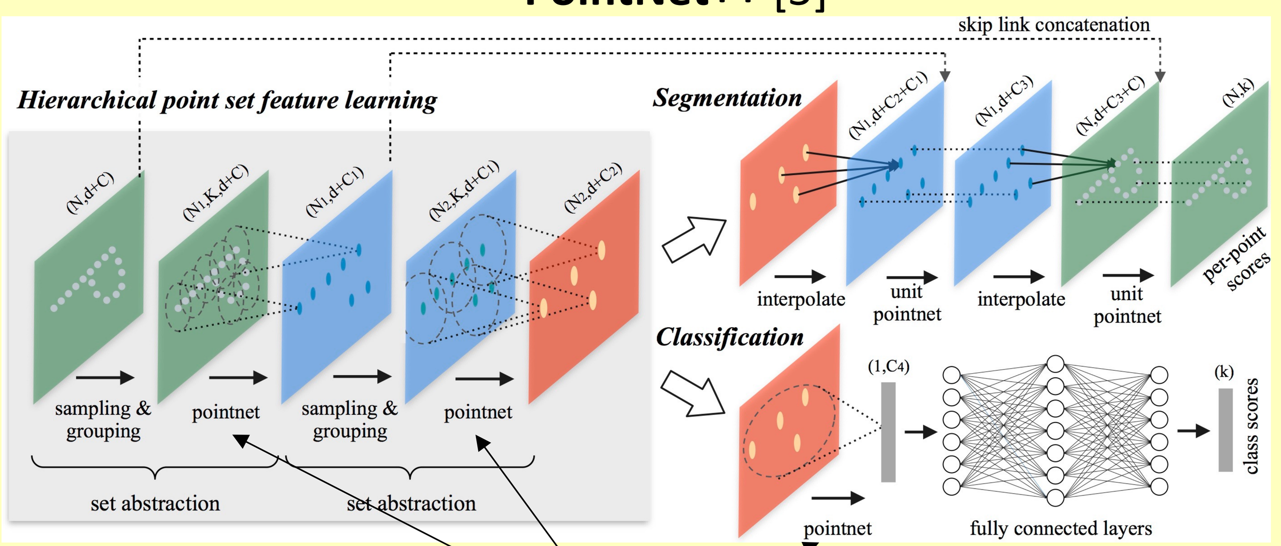
The successes and shortcomings of line fitting led us to explore machine learning.

PointNet++ is a graph neural network that operates directly on 3D point clouds such as our data.

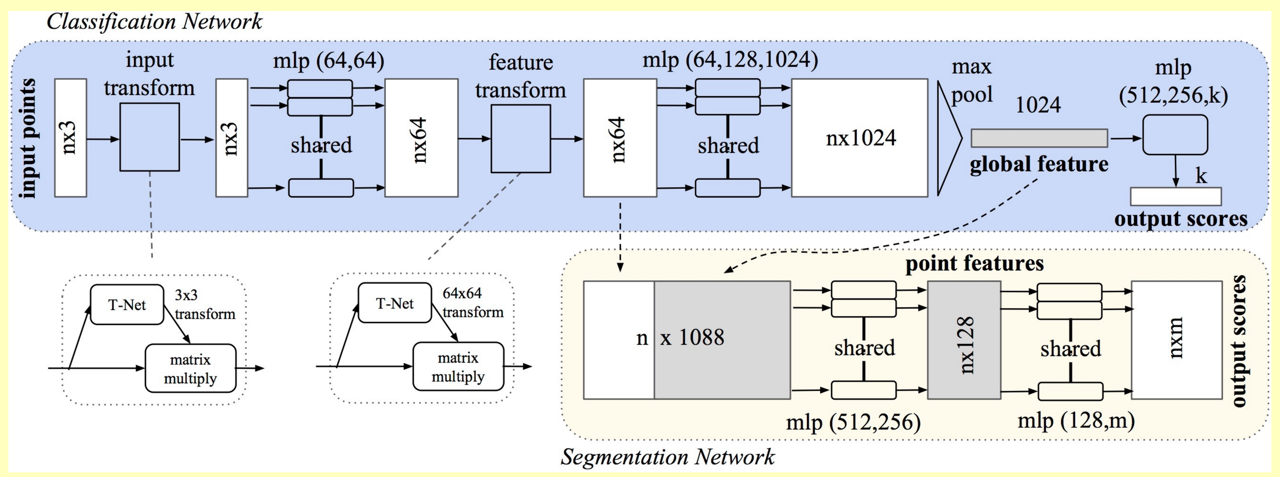
- Samples and groups points to form neighborhoods
- Uses PointNet, an order and transformation invariant network, to extract features from each neighborhood.
- Repeats the process at different scales to learn from a hierarchy of features.
- Uses the final layer of features to make predictions on graph or point features of interest.

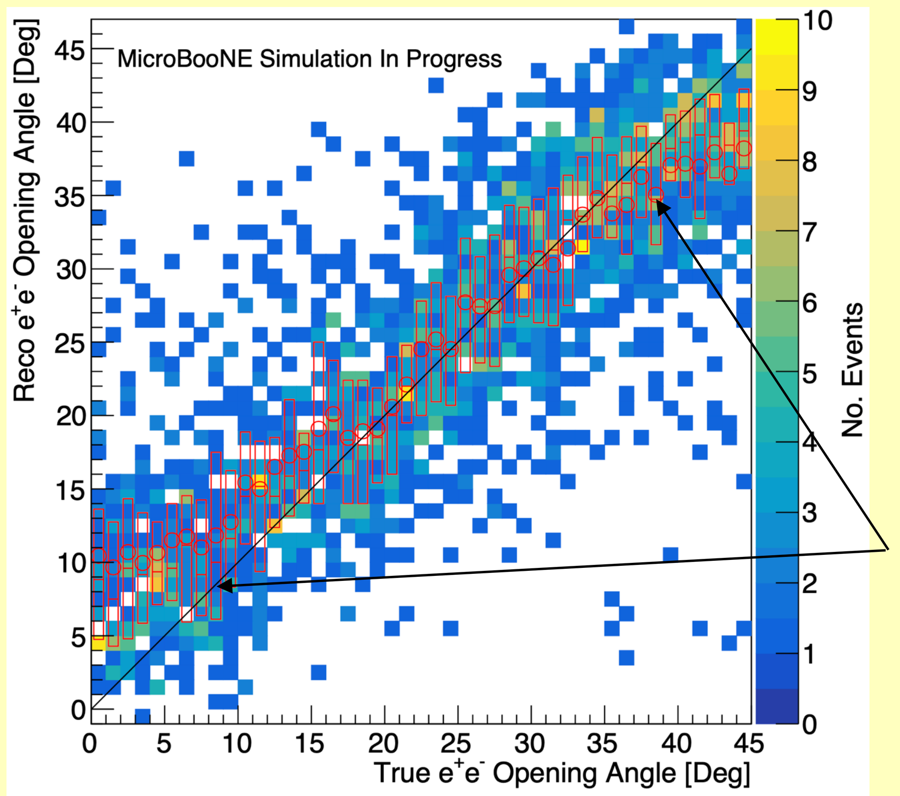
PointNet++ was developed for classification and point segmentation, but we've adapted it for regression to output opening angles.

PointNet++ [5]



PointNet [6]





Poorly reconstructs low and high opening angles

Out of ~7,900 events, 75% were used for training and 25% for validation. We used combined, labeled Pandora and Wire-Cell space points as input and got best results by limiting to points within 10 cm of Wire-Cell's reconstructed vertex. First generation results show promise, producing a standard deviation in the reconstructed angle error of 7.30°.

(3) Conclusion

- Developed tools to reconstruct exotic e+e- opening angles from 3D space points.
- Line fitting algorithm determined an optimal fitting radius and set a baseline result using a straightforward approach.
- Early results from PointNet++ demonstrate suitability of graph neural networks for space point data and regression task.
- Goal of reconstructing small opening angles that characterize dark sector e^+e^- pairs not yet achieved.

Future Work:

- Generate and train on more events
- Improve neural network architecture and try others.
- Add more point features.
- Test on true photons.
- Use to search for dark sector candidates in real events.

[1] E. Bertuzzo, S. Jana, P. A. Machado, and R. Z. Funchal, Physical Review Letters 121 (2018), 10.1103/physrevlett.121.241801.
[2] P. Ballett, S. Pascoli, and M. Ross-Lonergan, Phys. Rev. D 99, 071701 (2019), arXiv:1808.02915 [hep-ph].
[3] MicroBooNE collaboration et al., (2017), arXiv:1708.03135 [hep-ex].
[4] P. Abratenko et al., Journal of Instrumentation 17, P01037 (2022).
[5] C. R. Qi, L. Yi, H. Su, and L. J. Guibas, (2017), arXiv:1706.02413 [cs.CV].
[6] C. R. Qi, H. Su, K. Mo, and L. J. Guibas, (2017), arXiv:1612.00593 [cs.CV].

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