



Implications of GNN at END

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- Goal: give an overview of the work done in both papers and also an outlook to what could be done
- Outline
 - GNNs vs fitQun
 - Near Detector design variations
 - Outlook



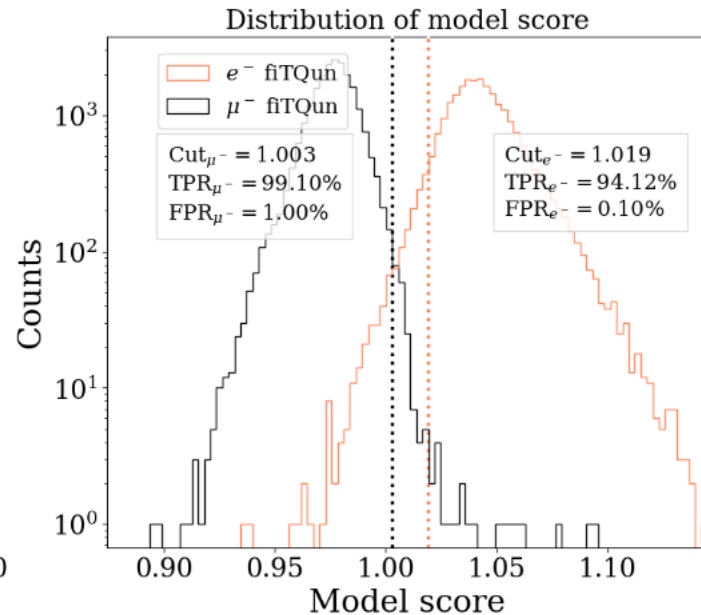
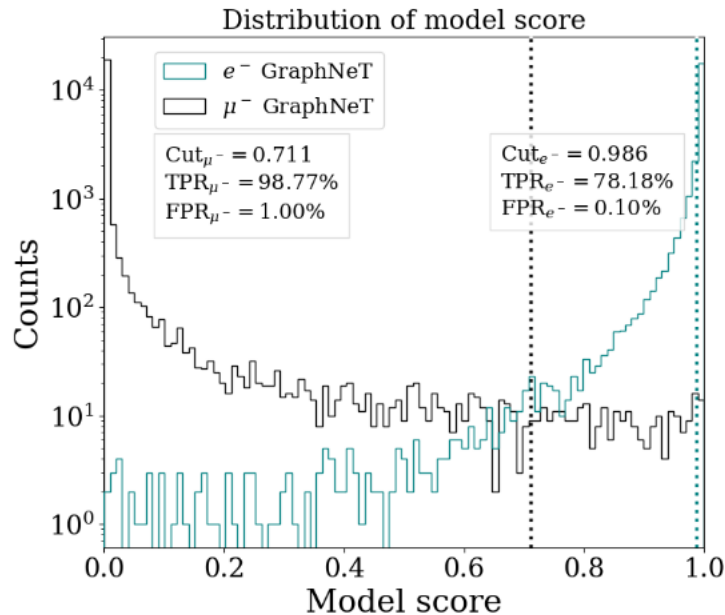
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Why ML?

- A lot of work to produce the CDR data
 - WCSim + fitQun
- fitQun is largely a “black” box
 - With two “black” boxes one can at least compare their output and learn in this way when they do well and not so well
- Opportunity
 - GNNs were heavily developed by Copenhagen team for IceCube
 - GraphNeT: <https://arxiv.org/abs/2210.12194>
 - GNNs are very flexible since they can be applied to a complex geometry

Important first result: for leptons fitQun is better!

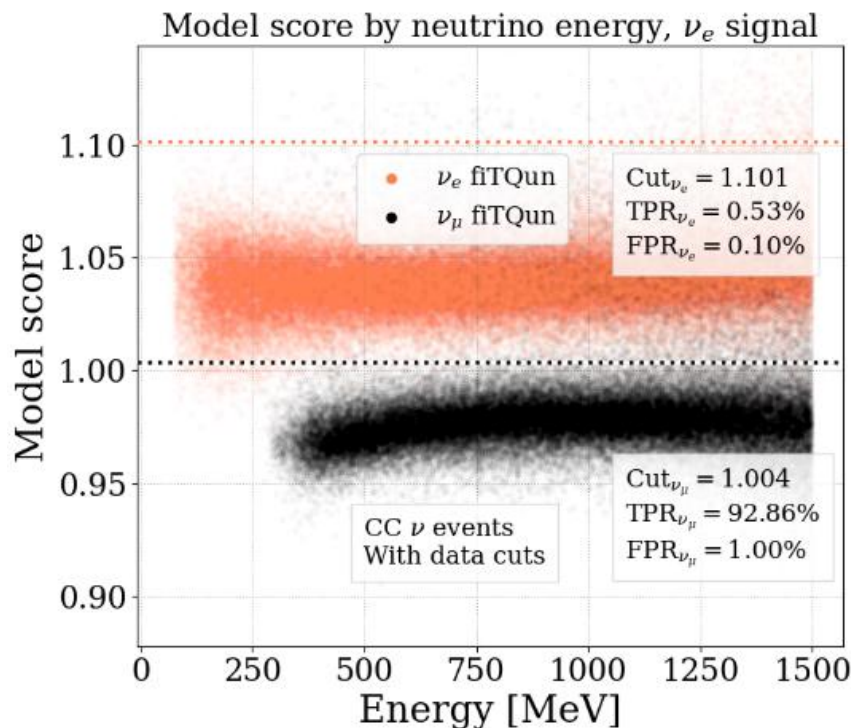


- I think this makes a lot of sense
 - This is clean events and fitQun is optimized for that
- Important lesson:
 - ML is faster and smart because it can learn by itself
 - Traditional algorithms can likely outperform, but needs a lot of human optimization (expensive)

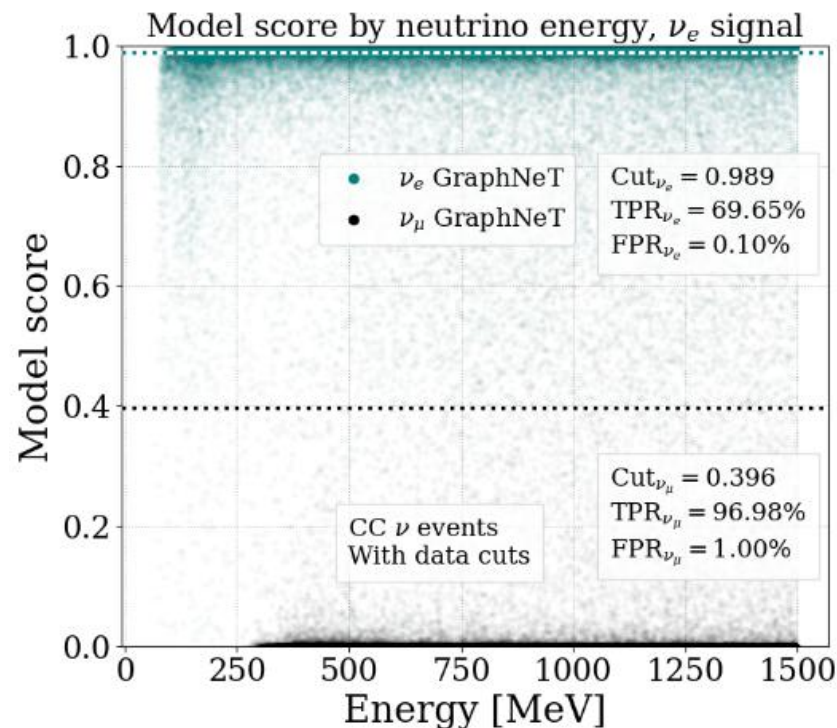


Neutrinos with GNNs

CDR performance

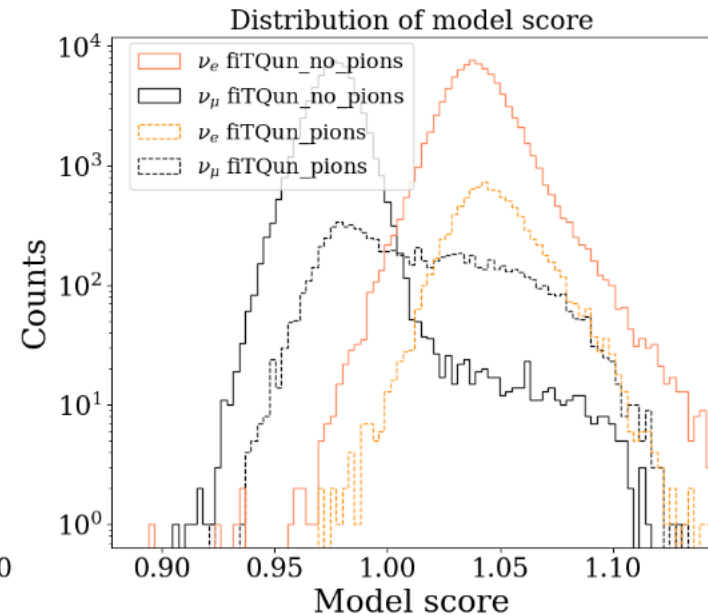
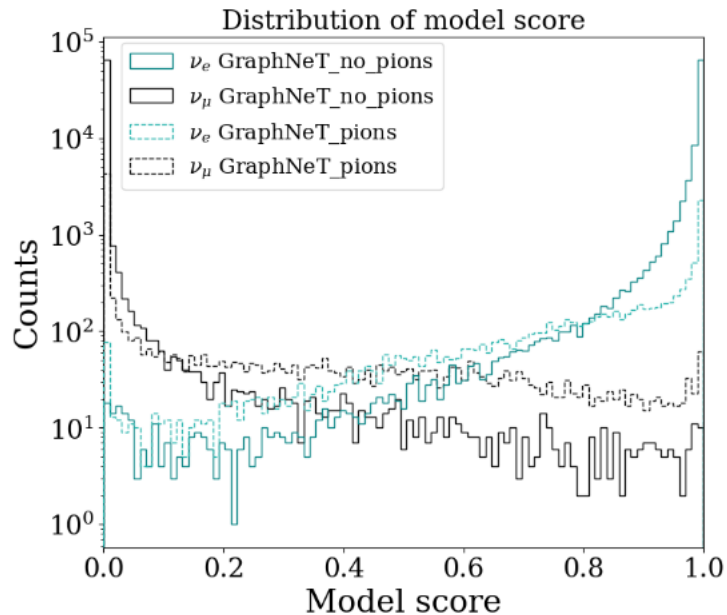


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- We do slightly better for neutrinos with ML
 - In particular for more complicated event topologies, e.g., interactions involving pions

Pions are big difference makers (1/2)

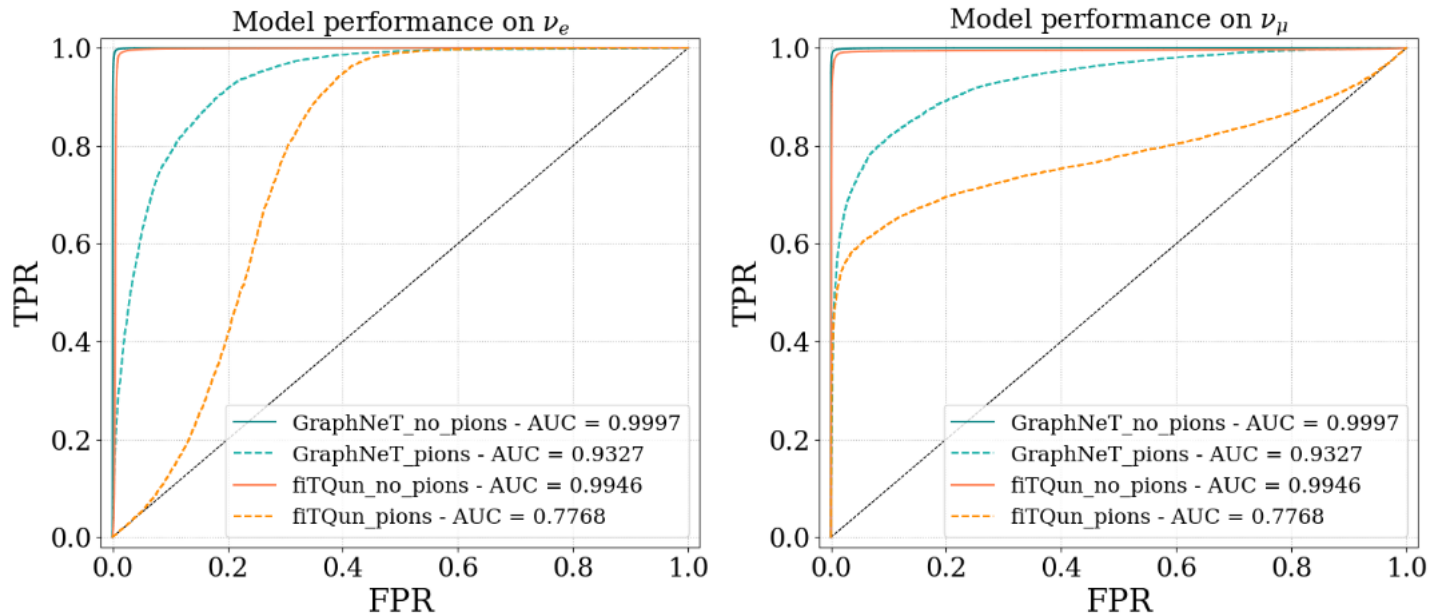


- ML is better than the traditional algorithms



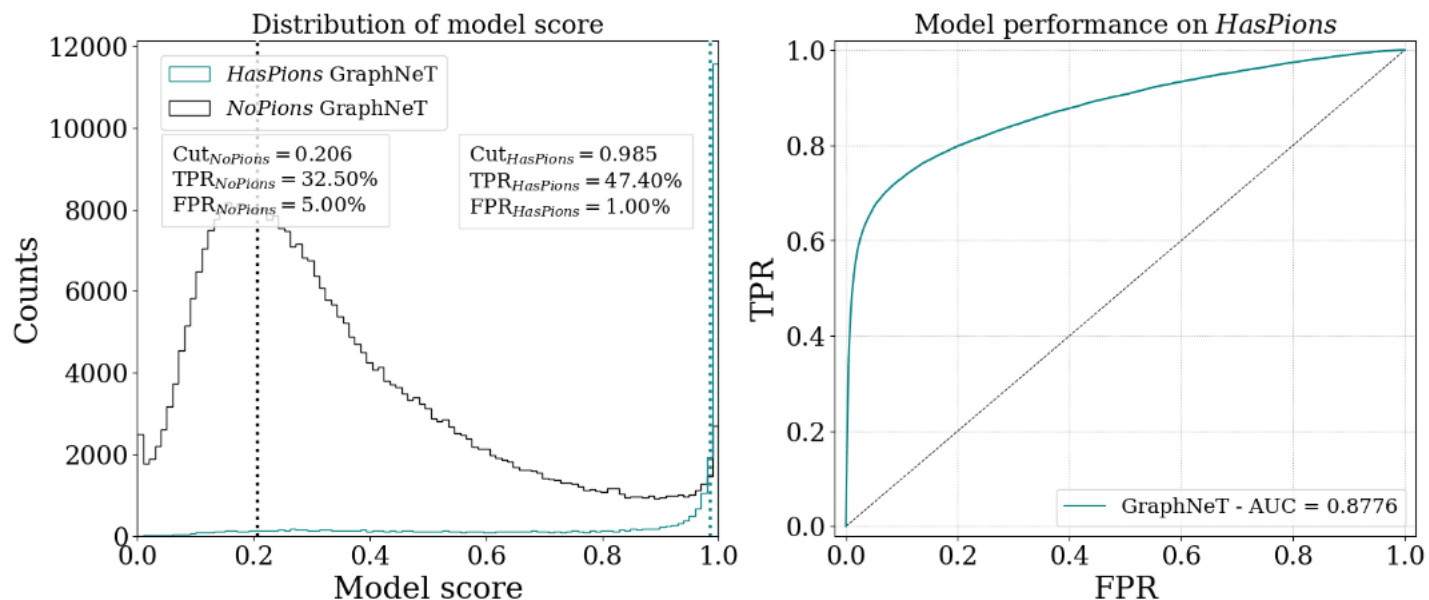


Pions are big difference makers (2/2)



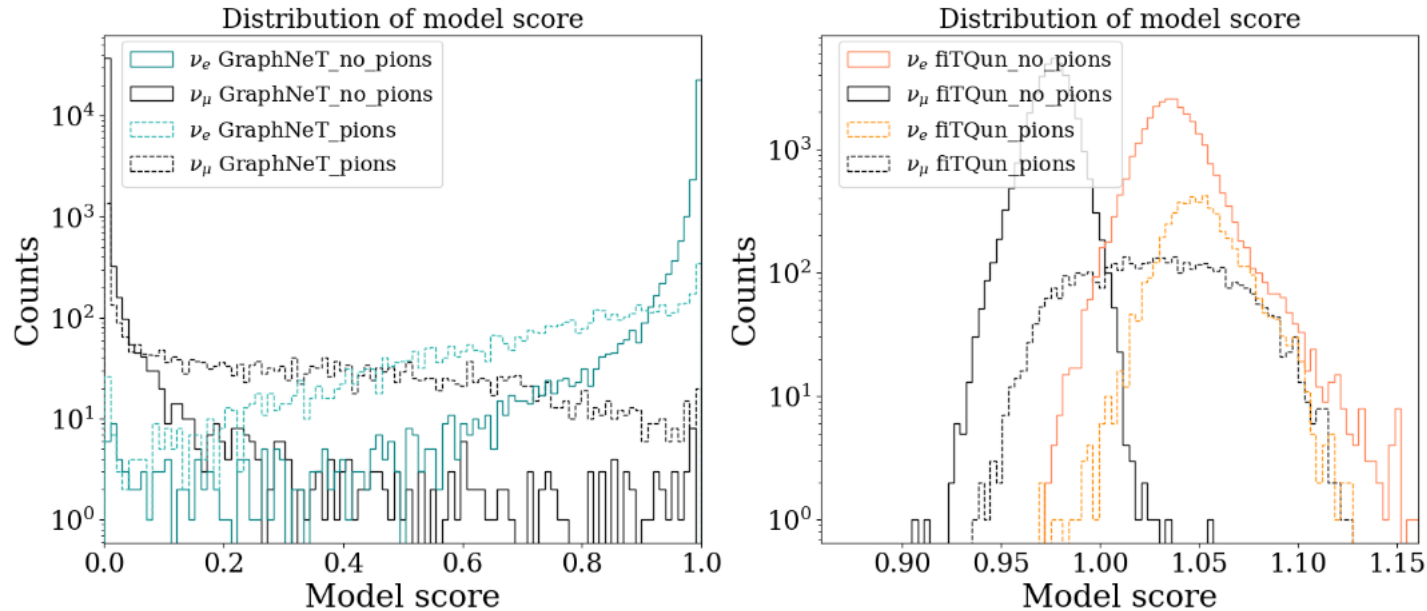
- Another way to illustrate this
 - True Positive Rate = Correctly identify signal as signal (efficiency)
 - False Positive Rate, e.g., Wrongly identify background as signal

Make a pion classifier



- We can select relatively clean events (no pions) with 32.5% efficiency
 - And also pion enhanced samples!

Performance with pion suppression and enhancement



- We can recover a very good performance of both algorithms by rejecting pions





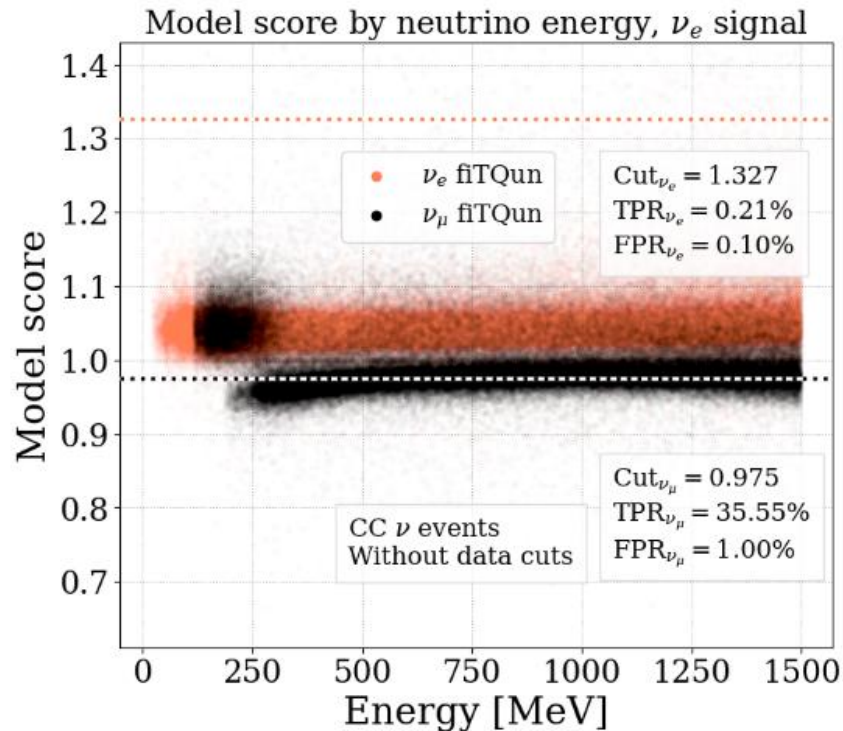
Also points to another way to utilize ML

- We can use ML to find weaknesses in our human optimized algorithms
- We clearly learn here that for pions fitQun needs further optimization
 - Note that this can be due to the simulations we make
 - fitQun could be optimized for more realistic simulations

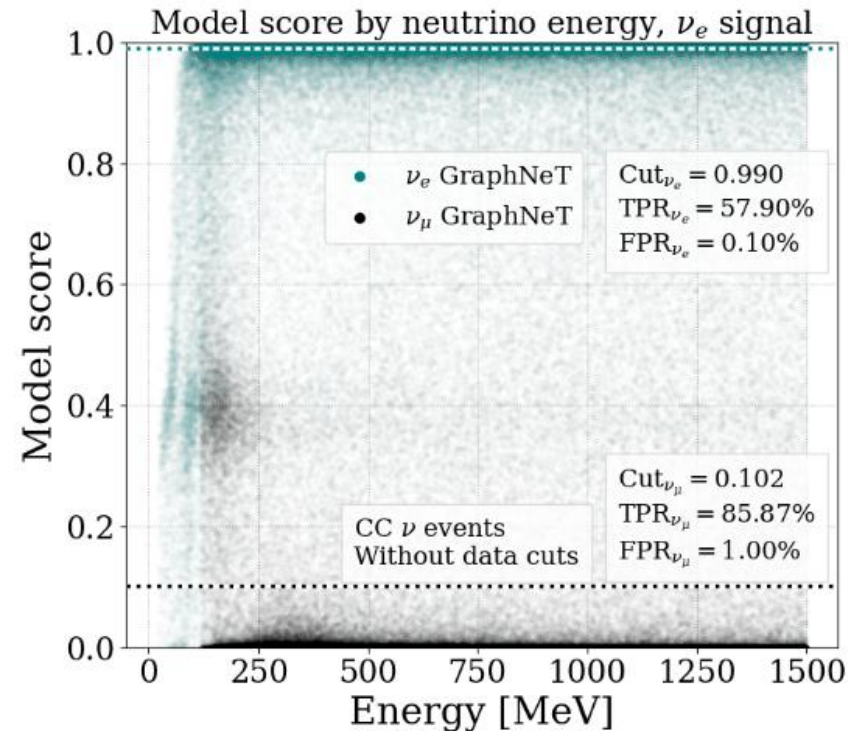


The real kicker with the GNNs is that they are agile

CDR performance



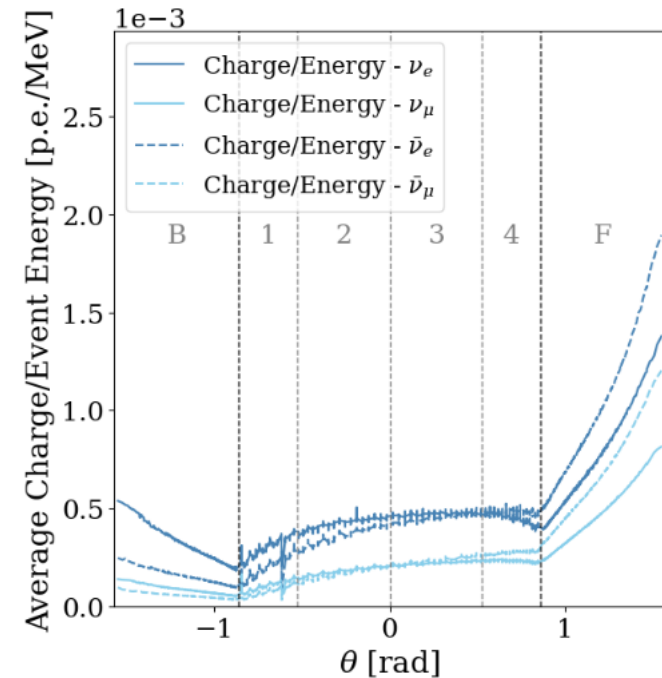
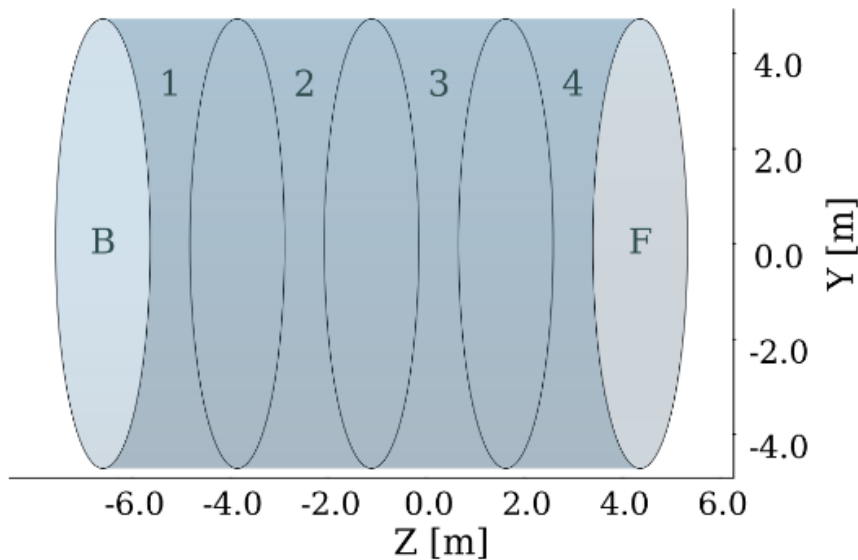
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- With traditional methods we had to do a lot of cleaning up to get the good performance
 - Machine learning also learns to clean up! (scores of ~ 0.4)



Understand the effect of reducing PMT coverage

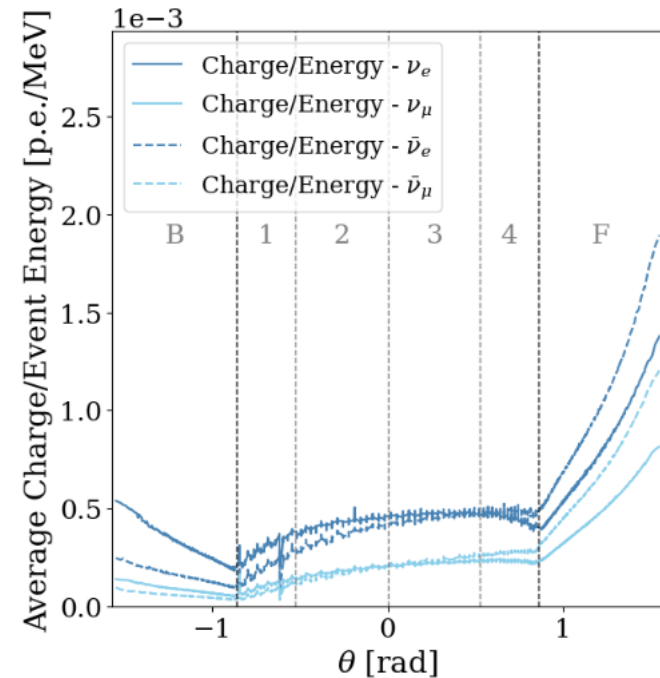
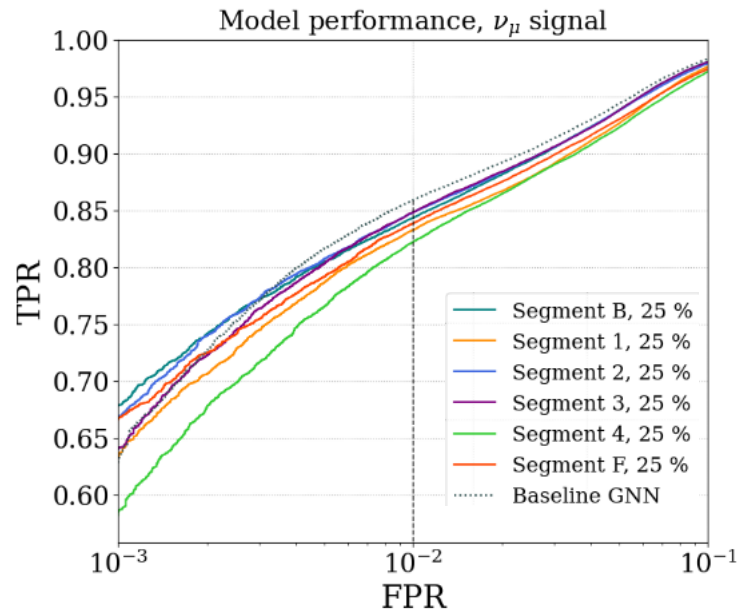


- Default is 30% coverage



Muon neutrinos

<https://arxiv.org/abs/2608.23773>, submitted to JINST

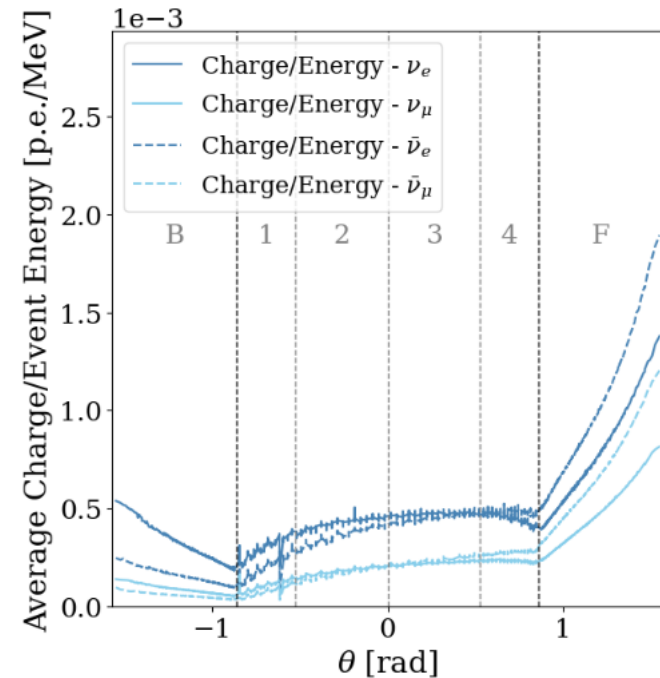
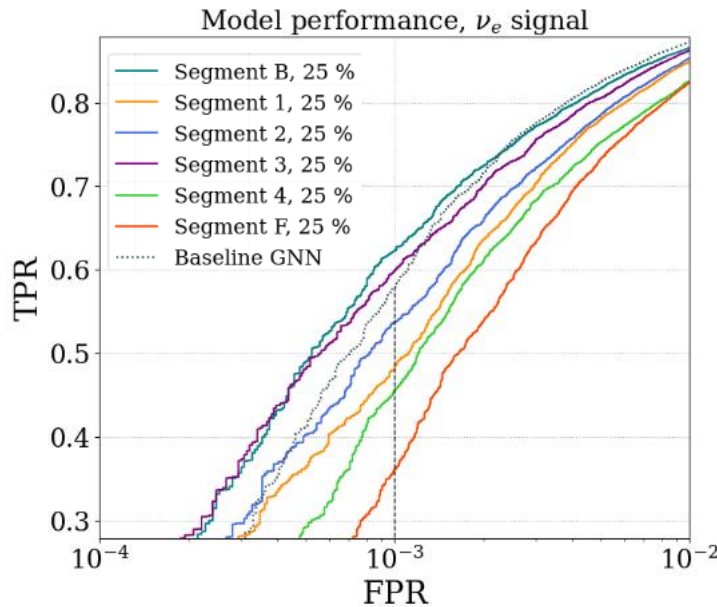


- For most regions you get the same separation performance with 25% of PMTs



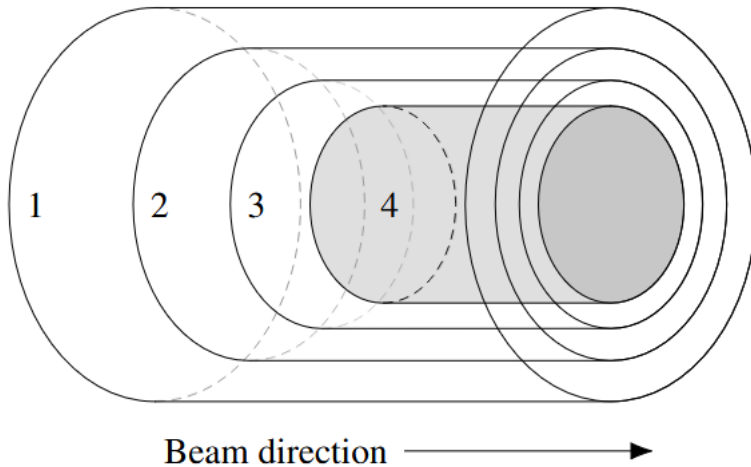
Electron neutrinos

<https://arxiv.org/abs/2608.23773>, submitted to JINST



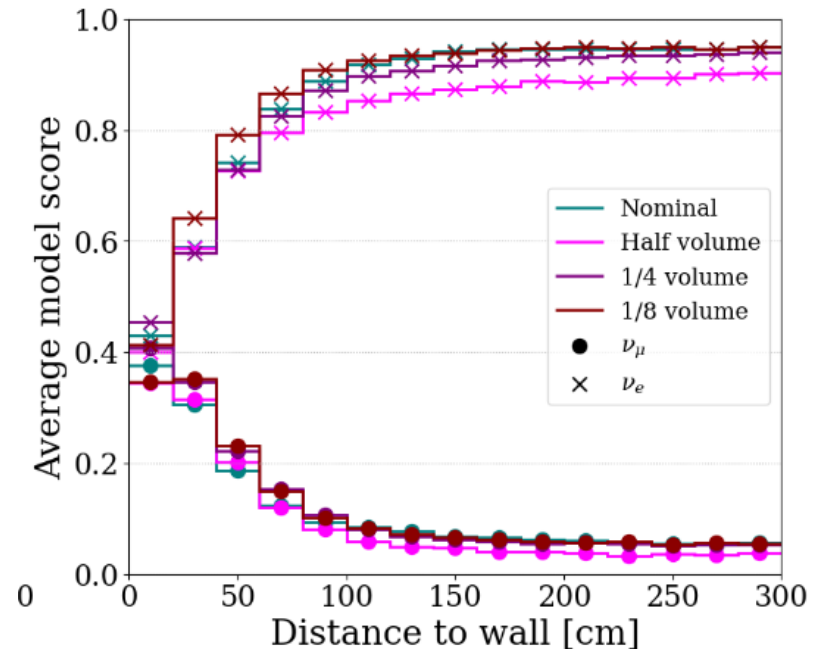
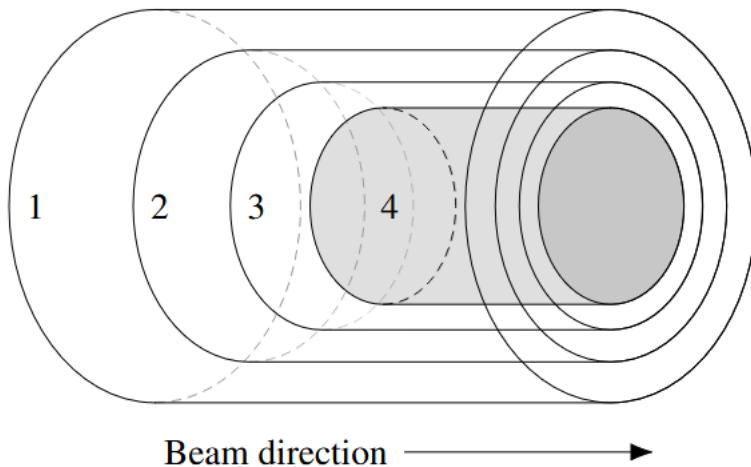
- For most regions you get the same separation performance with 25% of PMTs
 - Forward region needs more PMTs than backward region

We can also vary the detector volume



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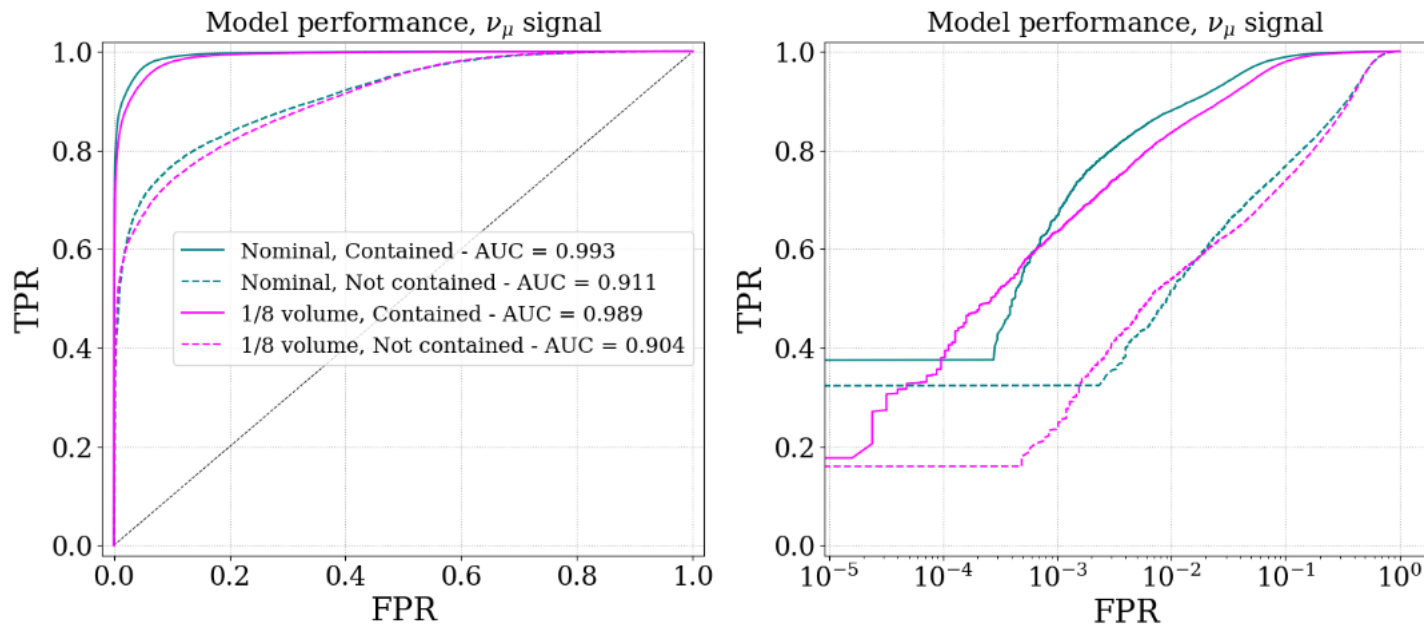
- We can have a much smaller detector!
- ML reconstruction veto neutrinos (score ~ 0.4) that produces leptons with short flight path to the wall!





Muon neutrinos

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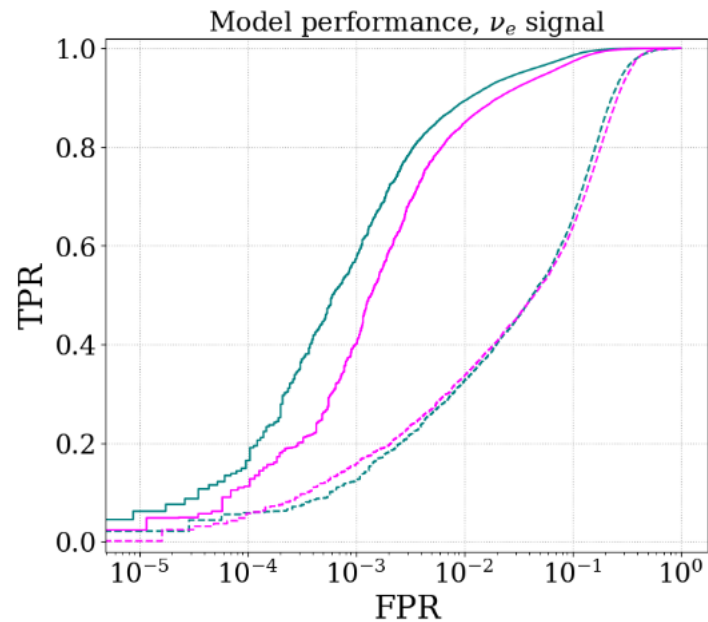
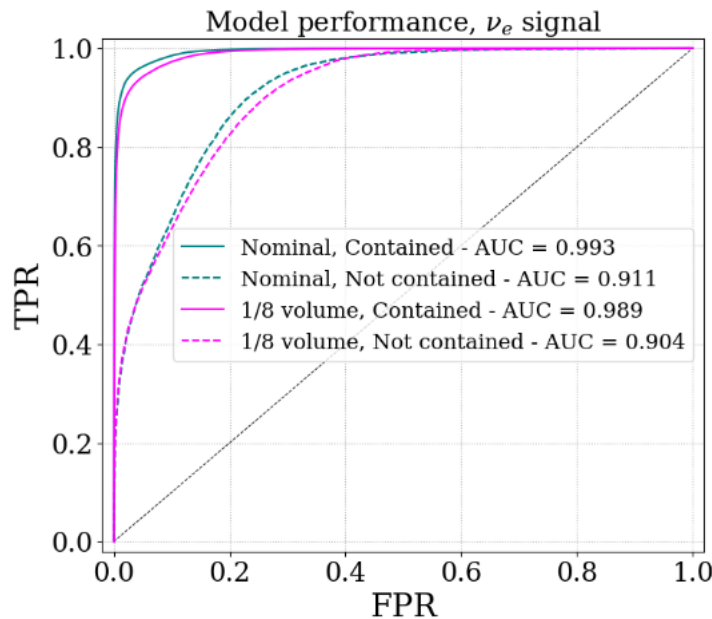


- Achieve similar performance for events that are contained and not contained
 - But relative fraction changes!



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 - But relative fraction changes!



Outlook (1/3)

- To me the most interesting outlook is the ability to play with the detector design
- We started this now but I think that one could really gain there
- Maybe also for Far Detector



Outlook (2/3)

- Some things we do not understand
 - Why does the events it cannot identify end up around 0.4 and not 0.5? Is this because many muon events also contain an electron?
 - There are performance fluctuations when we reduce PMTs and Volume that are not easy to understand, e.g., better performance with less PMTs. How can we understand those better?



Outlook (3/3)

- So far, the focus was on event classifying and not on, for example, energy reconstruction
 - Similar for interaction point and direction
 - Some indication that the energy could be better reconstructed
- Would be important to validate that also for smaller geometries
- Similarly, it would be important to validate the performance on real data, e.g., using the CERN test beam WC data



Conclusions

- The combination of GNNs and fitQun has provided a powerful understanding of the simulated data
- GNNs can both on their own do well but one should also think of them as a way to improve fitQun or similar conventional algorithms
- The flexibility of GNNs makes them ideal for optimizing the detector geometry
- Some work left for future studies to understand outlier results and to obtain final performance