Scientific motivations behind a 3D readout for DUNE

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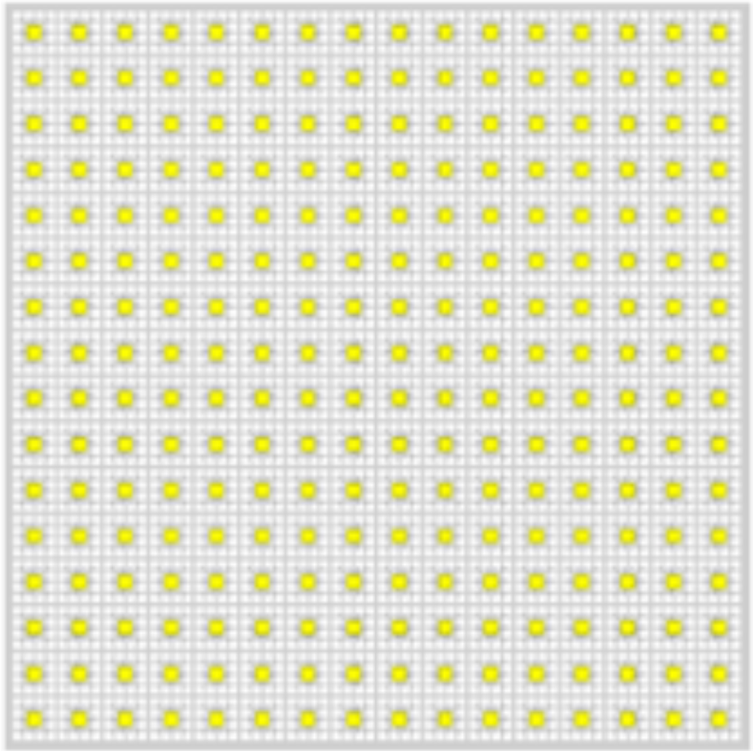
Elena Gramellini



Module of Opportunity for Dune Workshop
12-13 November 2019, BNL

DUNE Far Detector

- DUNE will be a unique detector, taking data for over a decade, and will provide great physics opportunities.

- Enhancing the physics capabilities of the Far Detector could have large scientific impact and should be seriously considered.

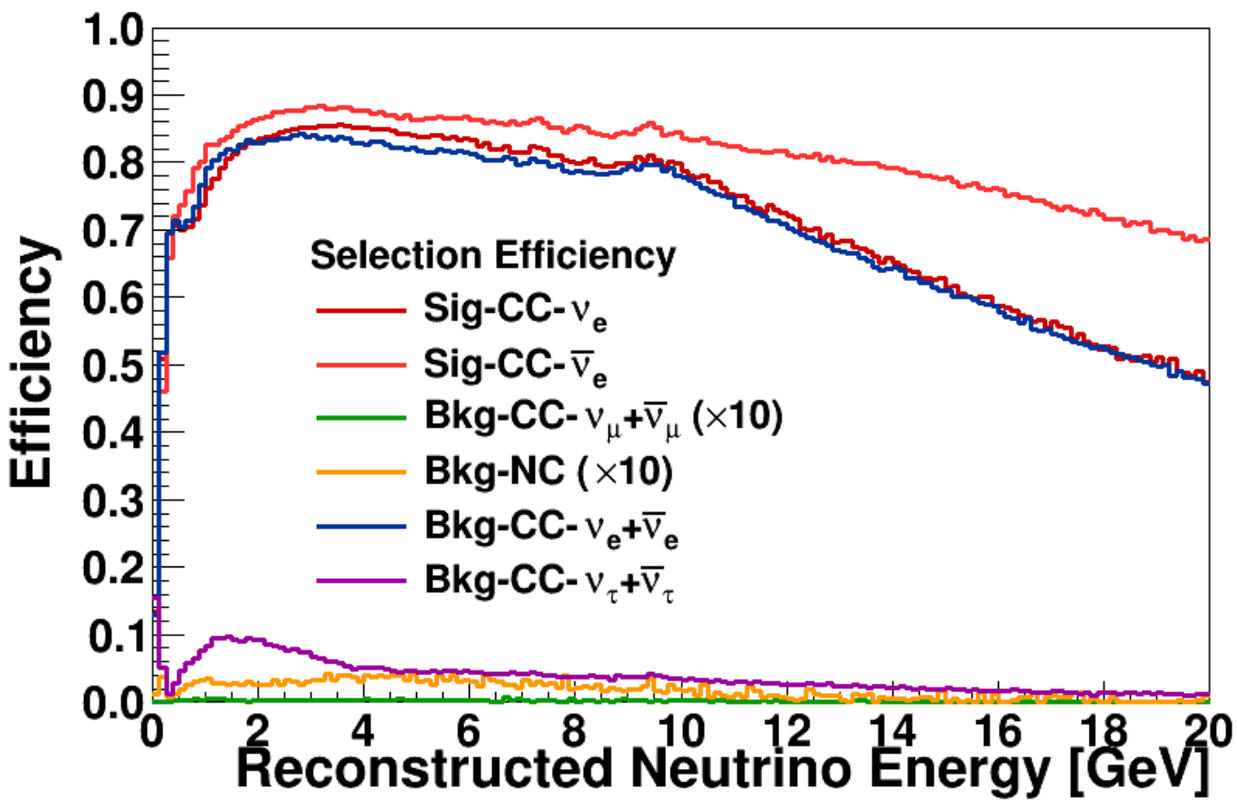
- The current DUNE design has been optimized for the oscillation physics goals (with special attention to proton decay and supernova neutrinos studies).

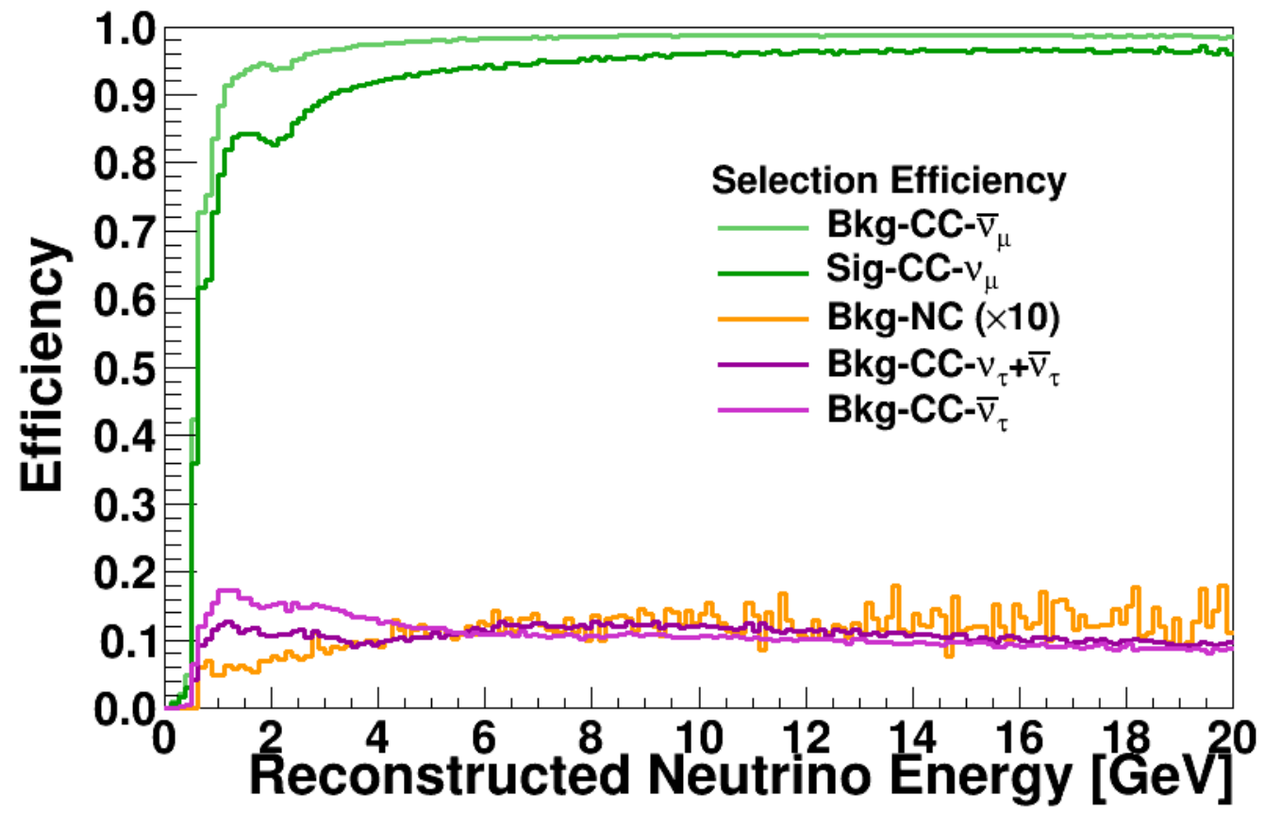
- There are several physics opportunities that could benefit from an enhanced-capability detector (solar neutrinos, BSM physics searches, …)

DUNE main physics

- Our TDR physics studies assume the following for oscillation:
  - ✓ Electron neutrino selection efficiency: 80-85% (1-5GeV)
  - ✓ Muon neutrino section efficiency: 80-90% (1-5GeV)
  - ✓ NC contamination: ~4% (for nue) and ~6% (for numu)

Sharp fall off at low energies, where 2nd maximum is…





DUNE CDR

DUNE main physics

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  - ✓ NC contamination: ~4% (for nue) and ~6% (for numu)

Sharp fall off at low energies, where 2nd maximum is…

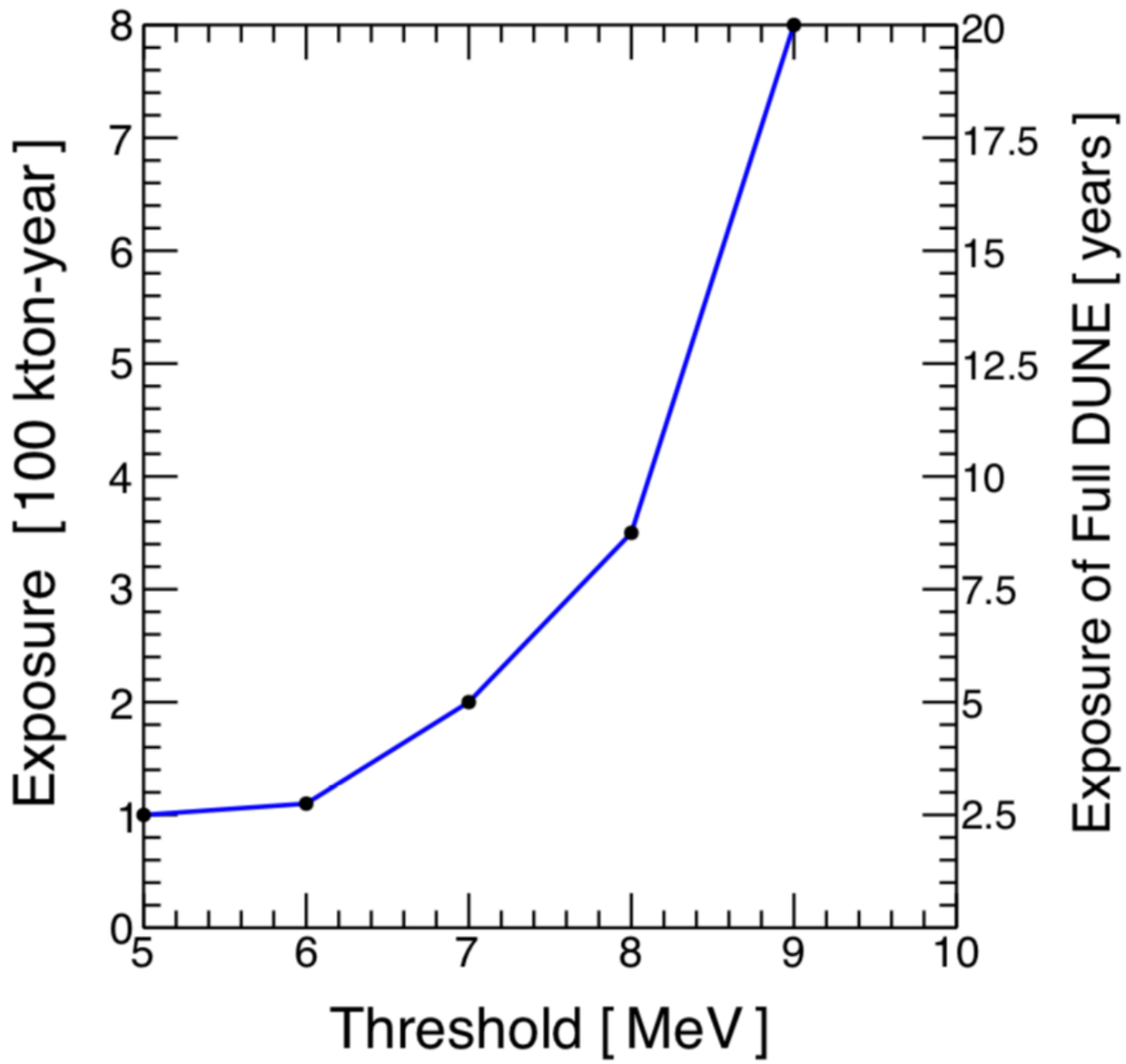
- Perspective: # of nue events per year per module: ~60 $\nu_e/\bar{\nu}_e$

- Supernova: ~100% above 10MeV (sharp fall off around threshold at 5MeV)

- Proton Decay: Selection efficient for ($p \rightarrow K^+\nu$): originally 97% (now estimated at ~30%)

Other physics

- Solar neutrinos have attracted a lot of interest in the theory community recently (*e.g. Capozzi et al., arxiv:1808.08232*), and having capabilities to study them with DUNE would be great! (E > 5MeV)



Capozzi et al., arxiv:1808.08232

Other physics

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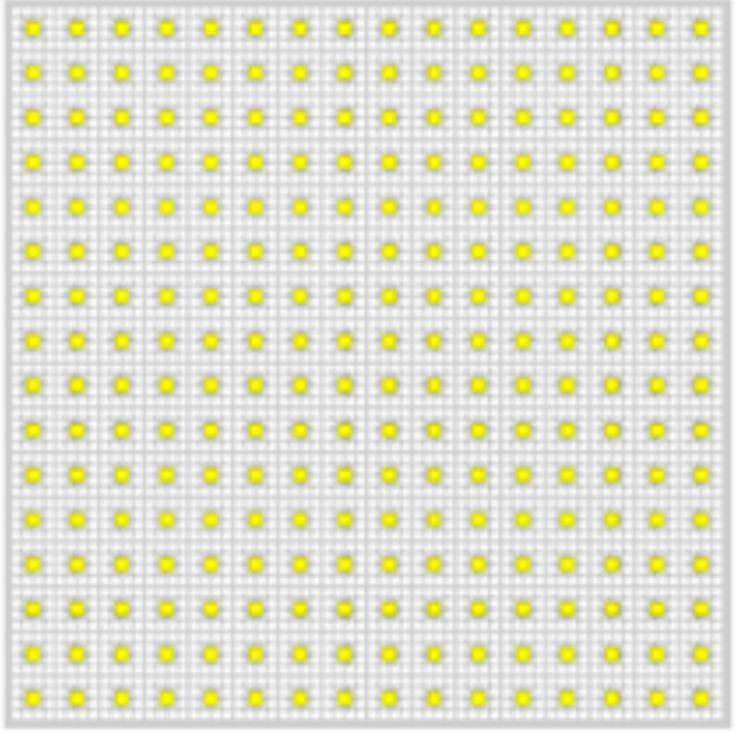
- Our supernovae physics could highly benefit from lower energy thresholds.

- Models for BSM will also benefit from enhanced physics capabilities.

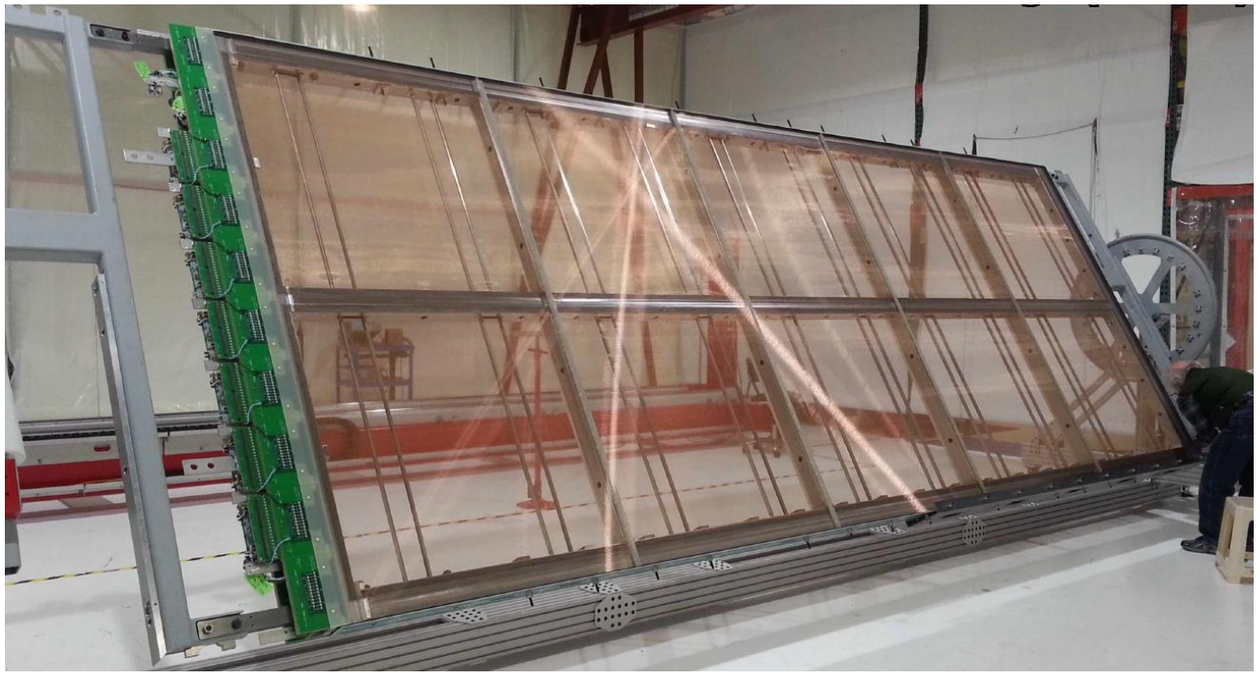
Potential benefits of a 3D readout

- No reconstruction ambiguities
- Impact of dead channels is less important than for wires
- Potential to offer “self-triggering” capabilities, which makes non-beam events readout much simpler
- Potentially lower energy threshold

3D Pixel readout



2D Wire (projective) readout



How can we demonstrate that 3D improves over 2D?

- In theory, the ambiguities from the 2D projective readout are a challenge compared to a 3D readout.
- In a perfect detector, the effect may be less significant, but any gain in reconstruction efficiency and background rejection is worth it!
- In a case where we have dead channels or high noise, the impact on 2D reconstruction should start to be more severe (loose more information) than in 3D.
- **But this needs to be demonstrated!**

Comparing 3D and 2D readouts

- Focus on even reconstruction

- Ideally, one would proceed similarly with 3D physics studies than what has been done for 2D (e.g. TDR results), but this is unrealistic! The amount of work needed for this is several FTEs/years for few years (even then, it would not be a fair comparison based on the effort to develop 2D reconstruction algorithms)

- When comparing physics studies, one have to make sure not to be comparing the efficiency of the reconstruction algorithms (2D/3D) alone.

- **Our strategy**: Compare 3D and 2D performances based on Machine Learning reconstruction. These algorithms are state-of-the-art in multi-disciplinary fields, given a better opportunity to focus on physics performances (instead of algorithm performances). (**It still has some caveats, but it's the best we can do now**)

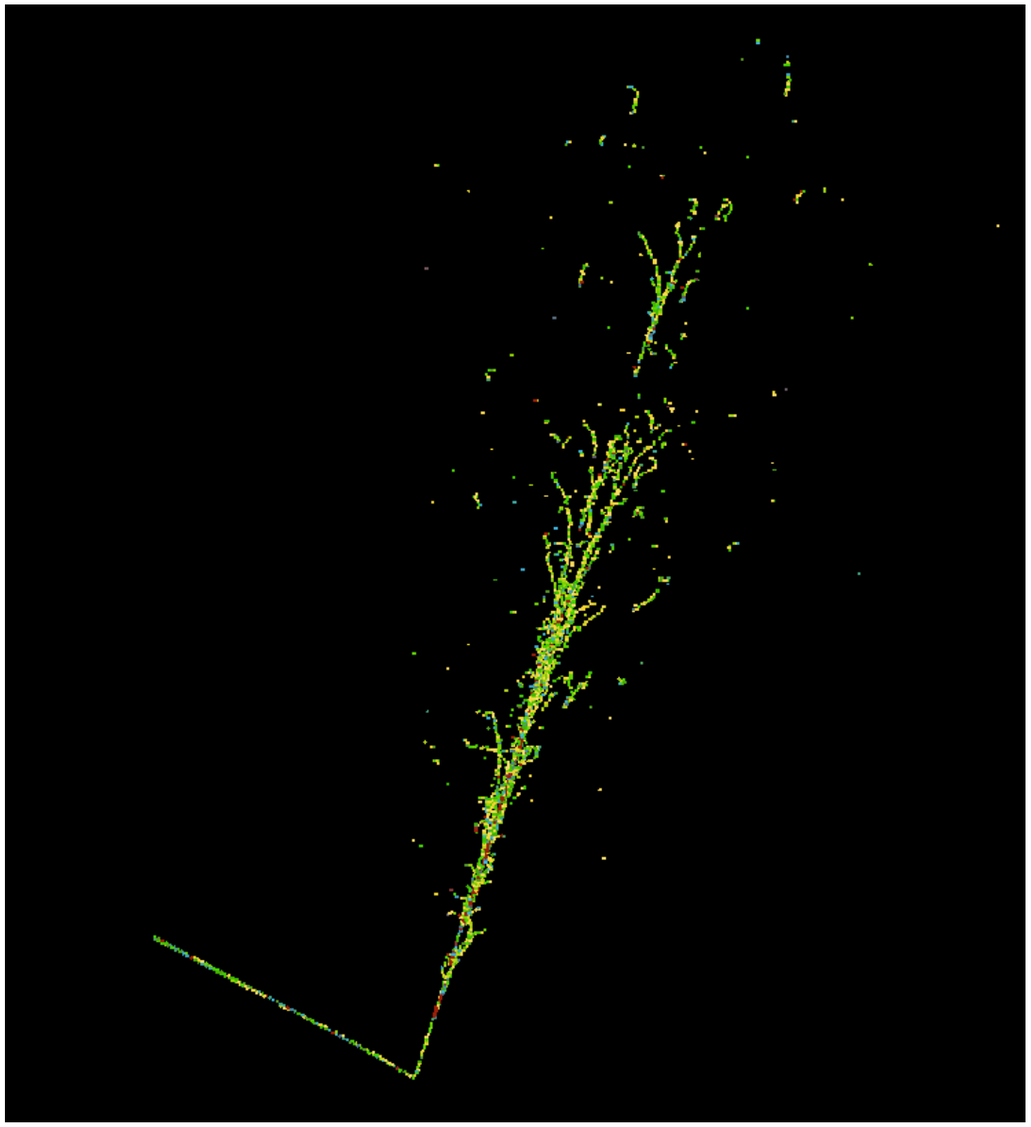
2D vs 3D studies

- Use DUNE fluxes to generate events in DUNE-like LAr volume (using LArGeant)
- Start with perfect detectors (no loss of signal, no noise, perfect readout) for both 2D (with **no wrapped wires**) and 3D
- Simulate 4mmx4mm voxels for both readout
- Use Machine Learning tools to train on multi(3)-plane 2D image events, and single 3D volume images in 3D events
- Extract physics performances (selection efficiencies and background contamination)

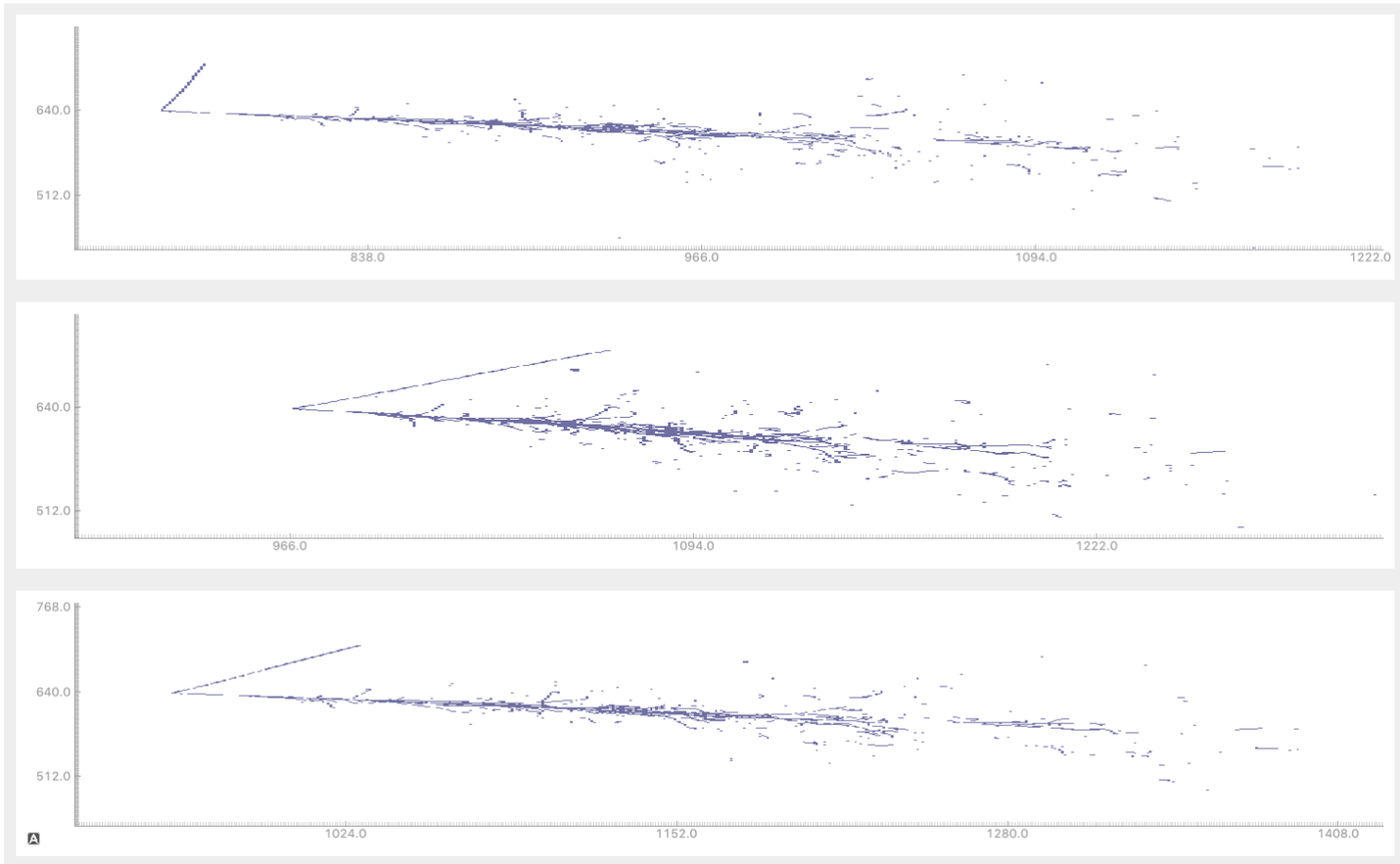
All ML results are from Marco Del Tutto (Harvard) and Corey Adams (ANL)

Simulated events

Same ν_e event in 3D and projected onto 3 2D views.



4x4 mm voxels

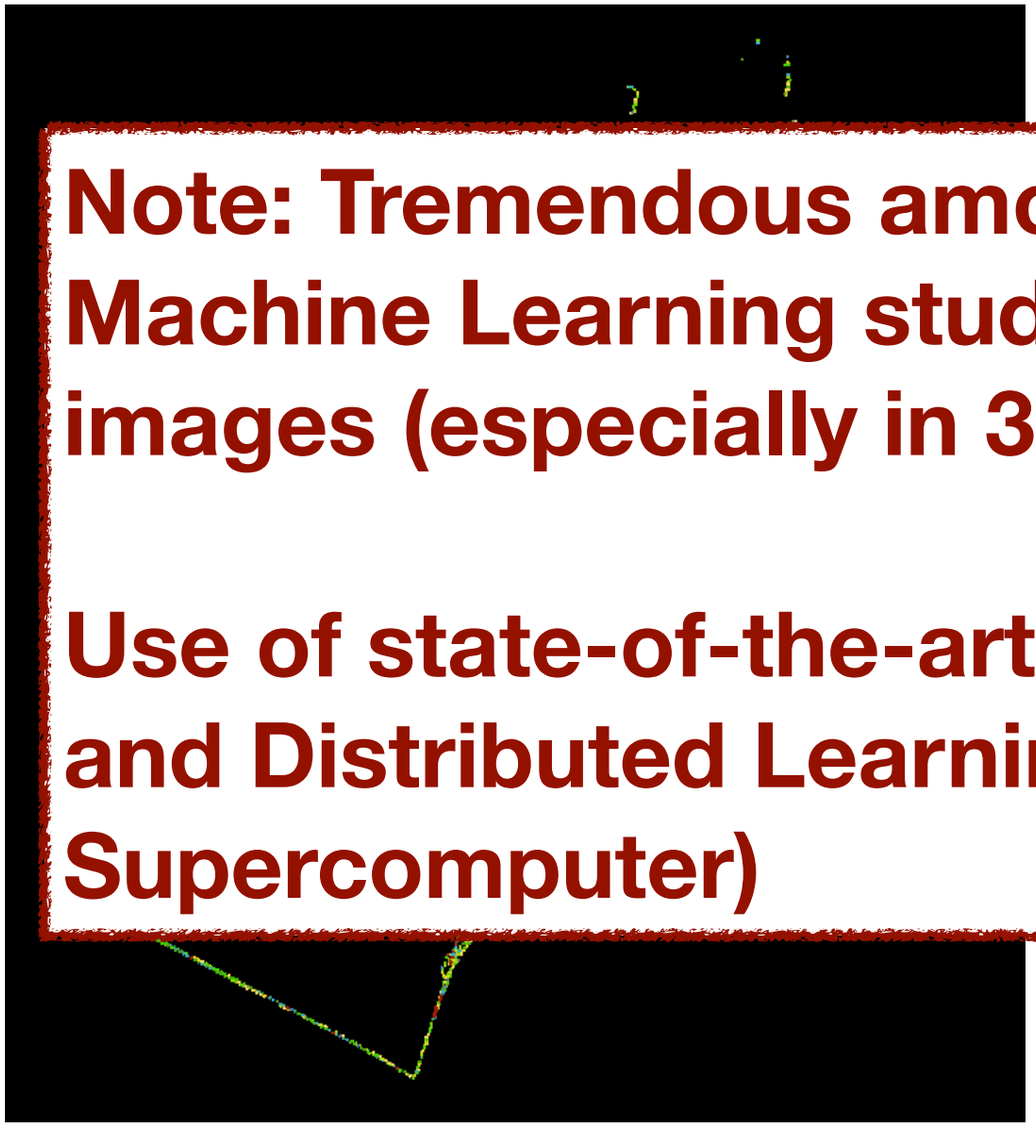


4 mm wire spacing

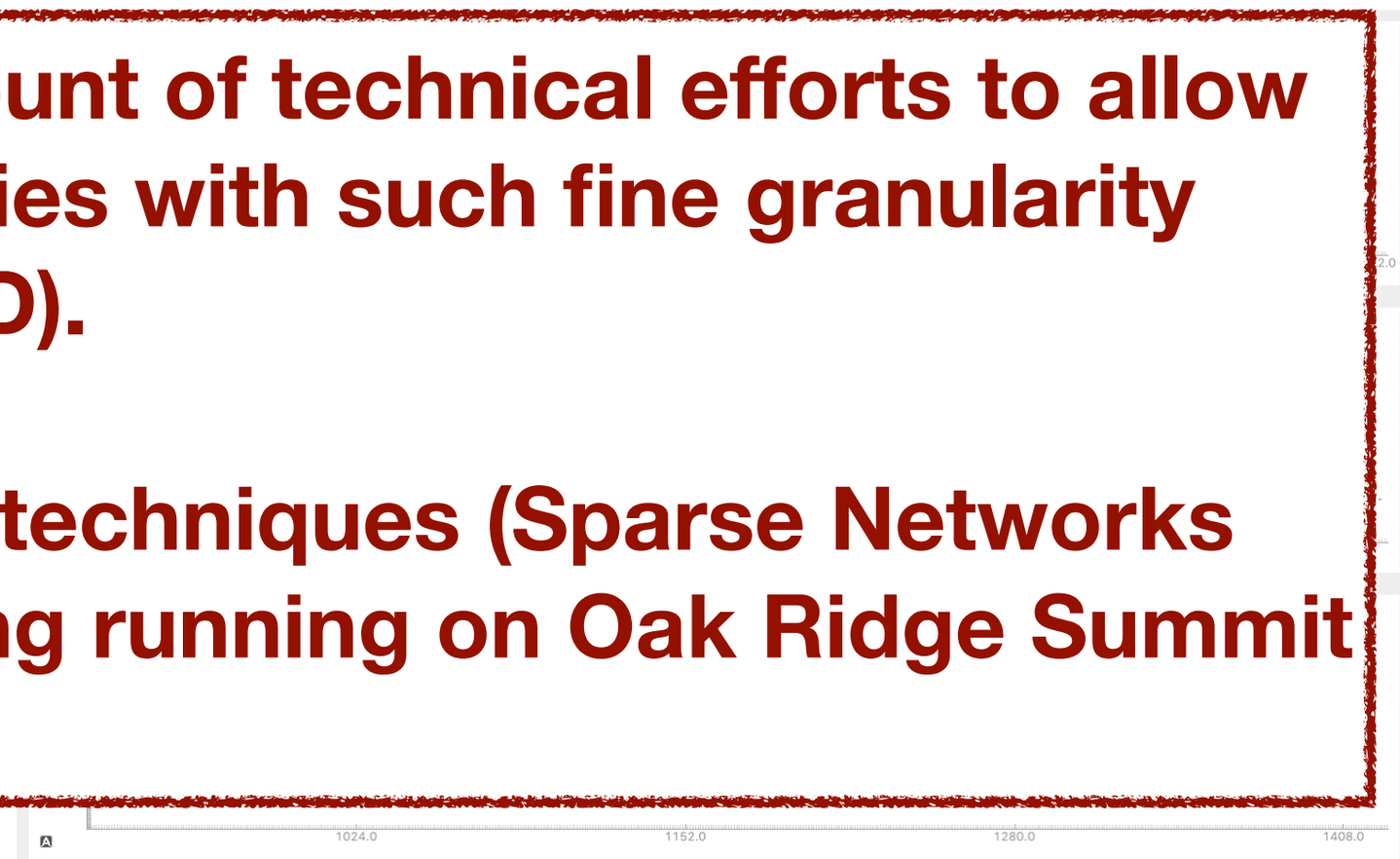
Events are simulated using DUNE neutrino flux.

Simulated events

Same ν_e event in 3D and projected onto 3 2D views.



4x4 mm voxels



4 mm wire spacing

Note: Tremendous amount of technical efforts to allow Machine Learning studies with such fine granularity images (especially in 3D).

Use of state-of-the-art techniques (Sparse Networks and Distributed Learning running on Oak Ridge Summit Supercomputer)

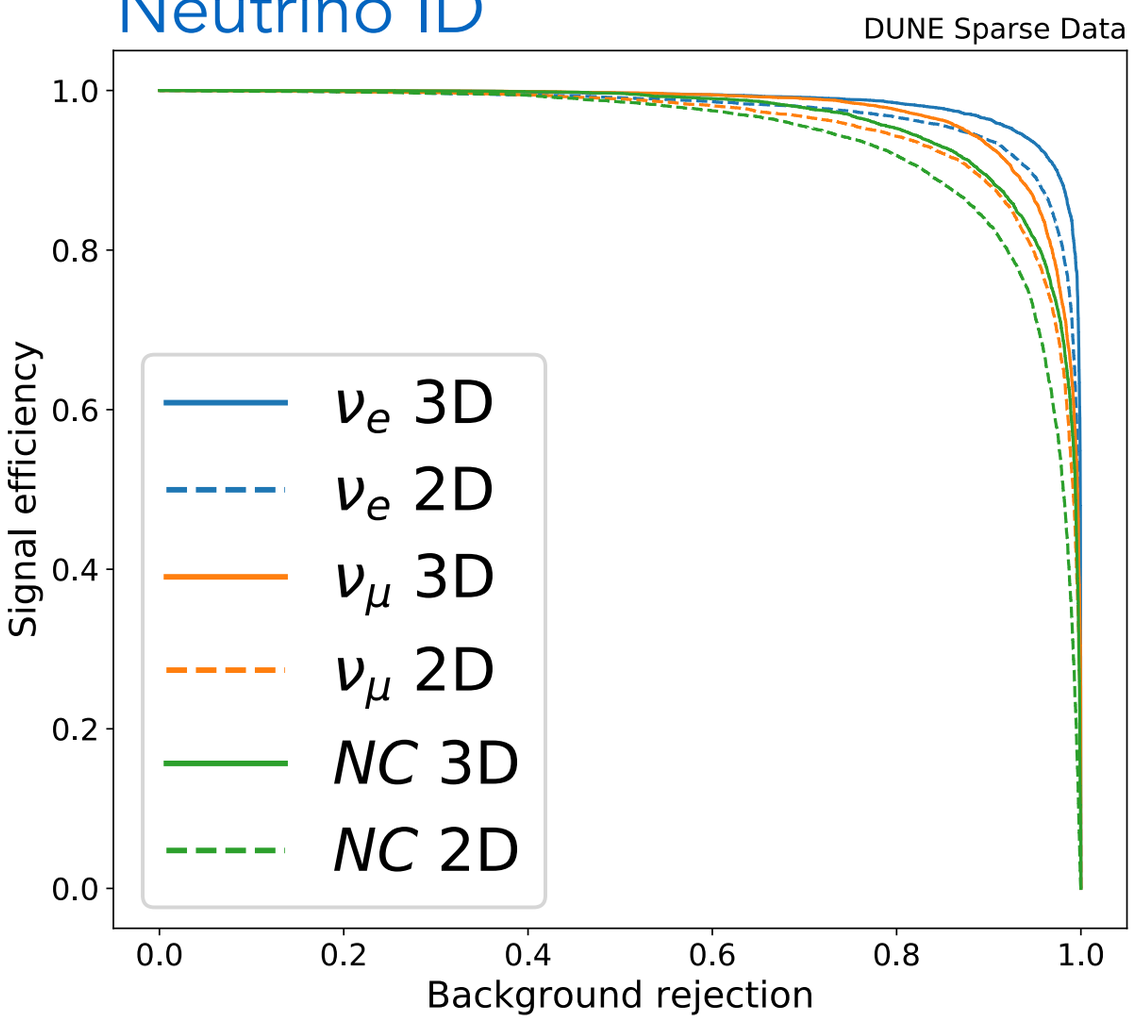
Events are simulated using DUNE neutrino flux.

Event classification

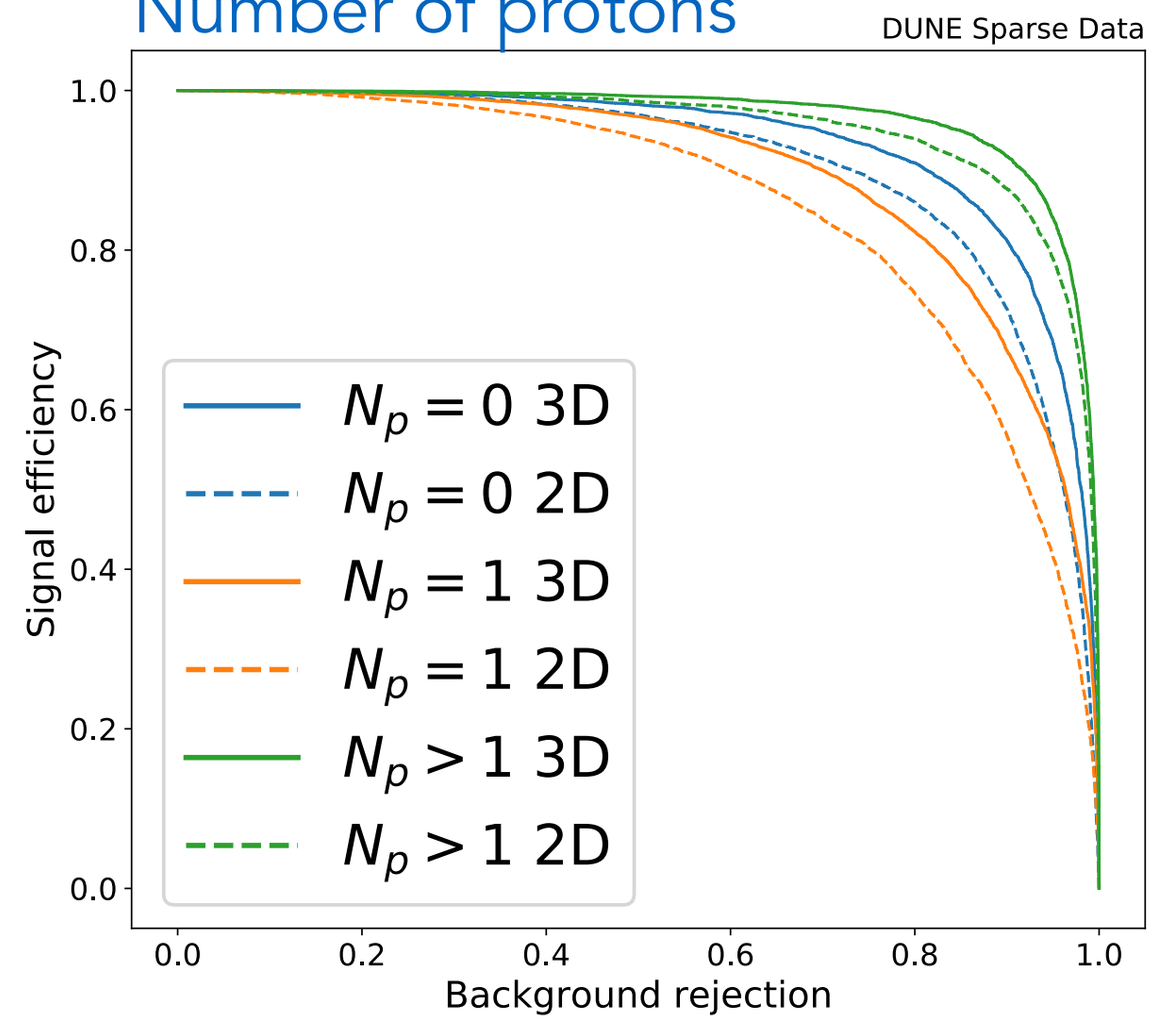
4 types of classification:

- **Neutrino** ID: CC ν_μ, CC ν_e, NC
- Number of **protons**: 0, 1, 2+
- Number of **$\pi^\pm$**: 0, 1+
- Number of **π^0**: 0, 1+

Neutrino ID



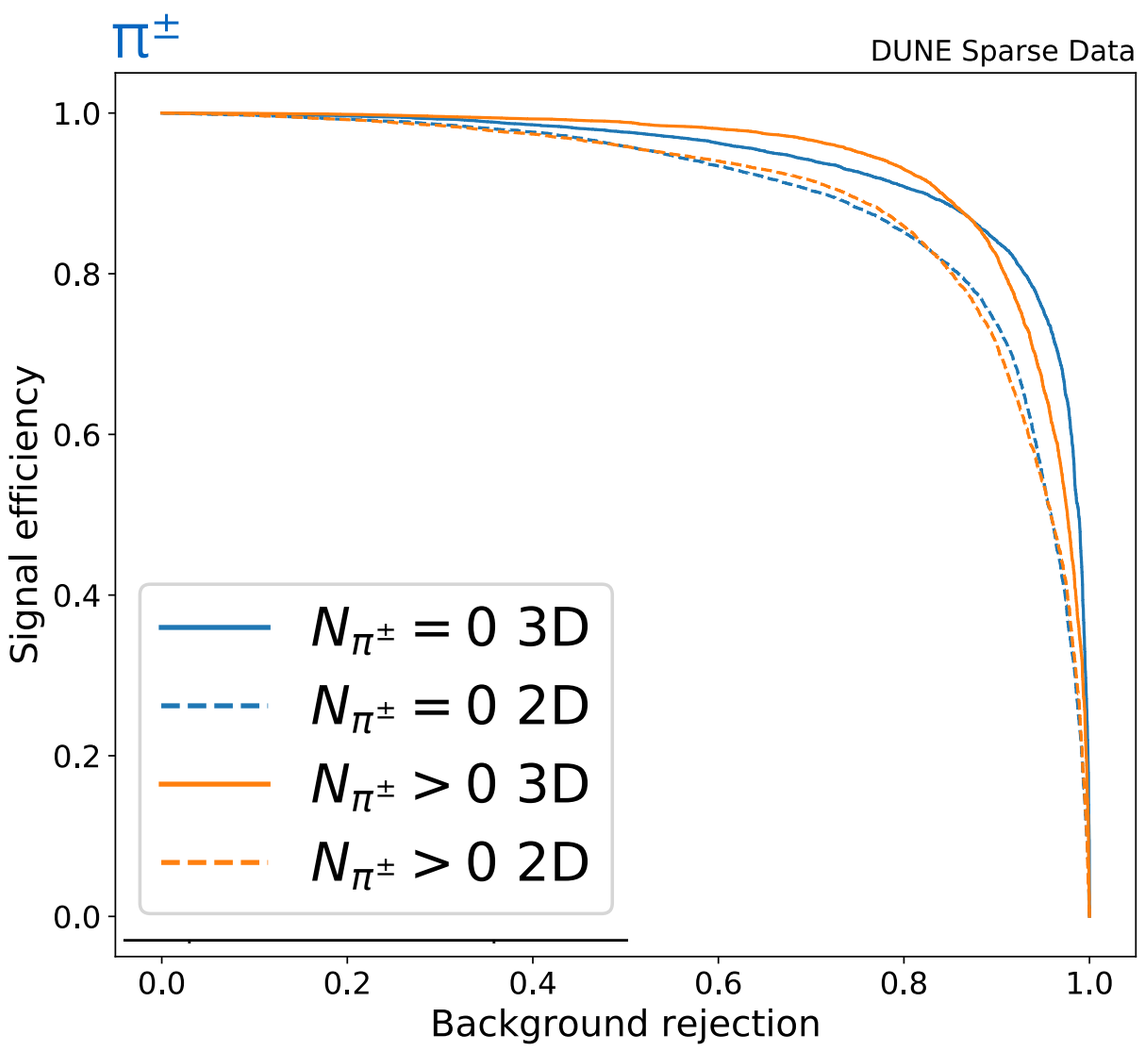
Number of protons

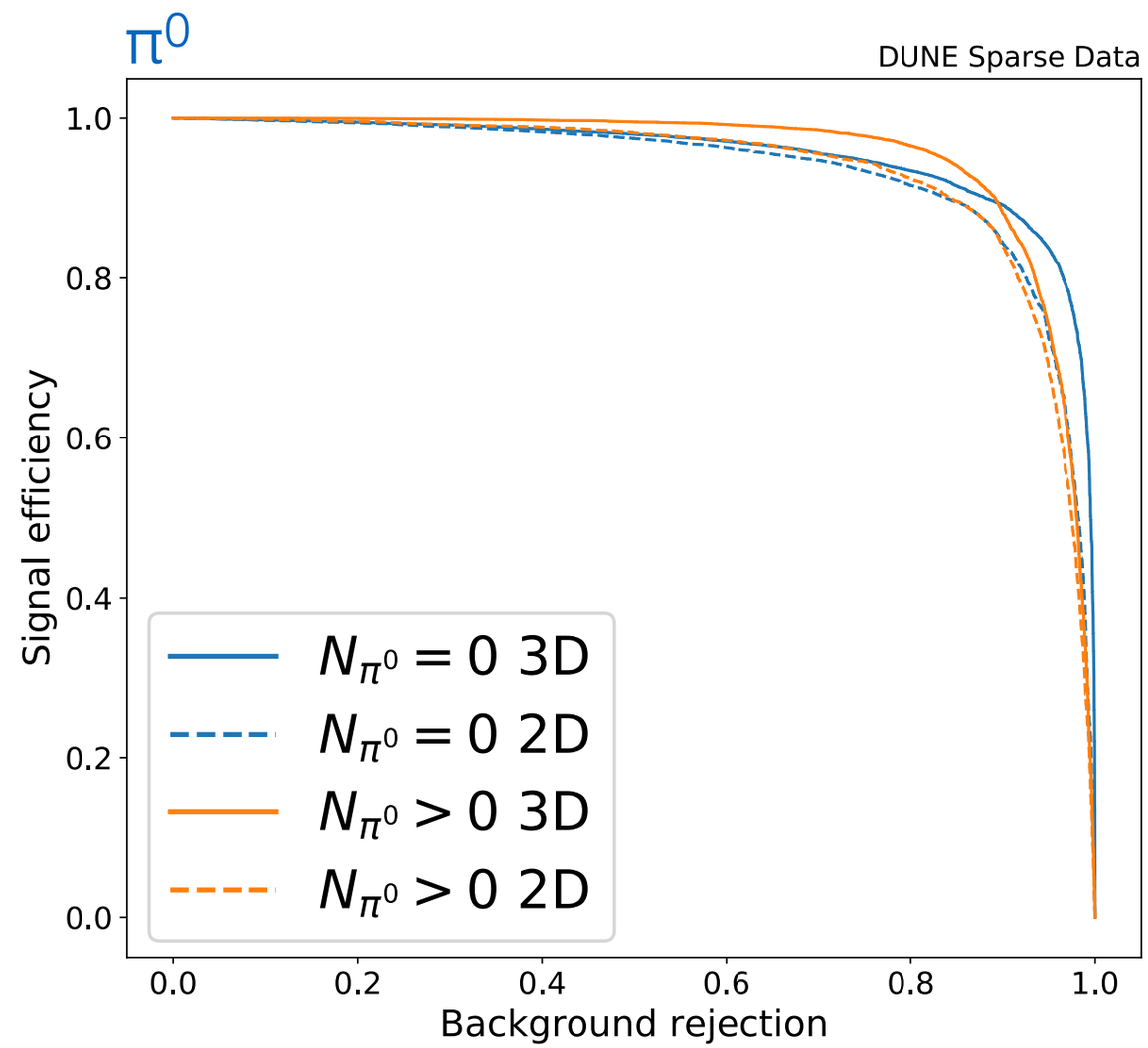


Solid line: 3D **Dashed line: 2D**

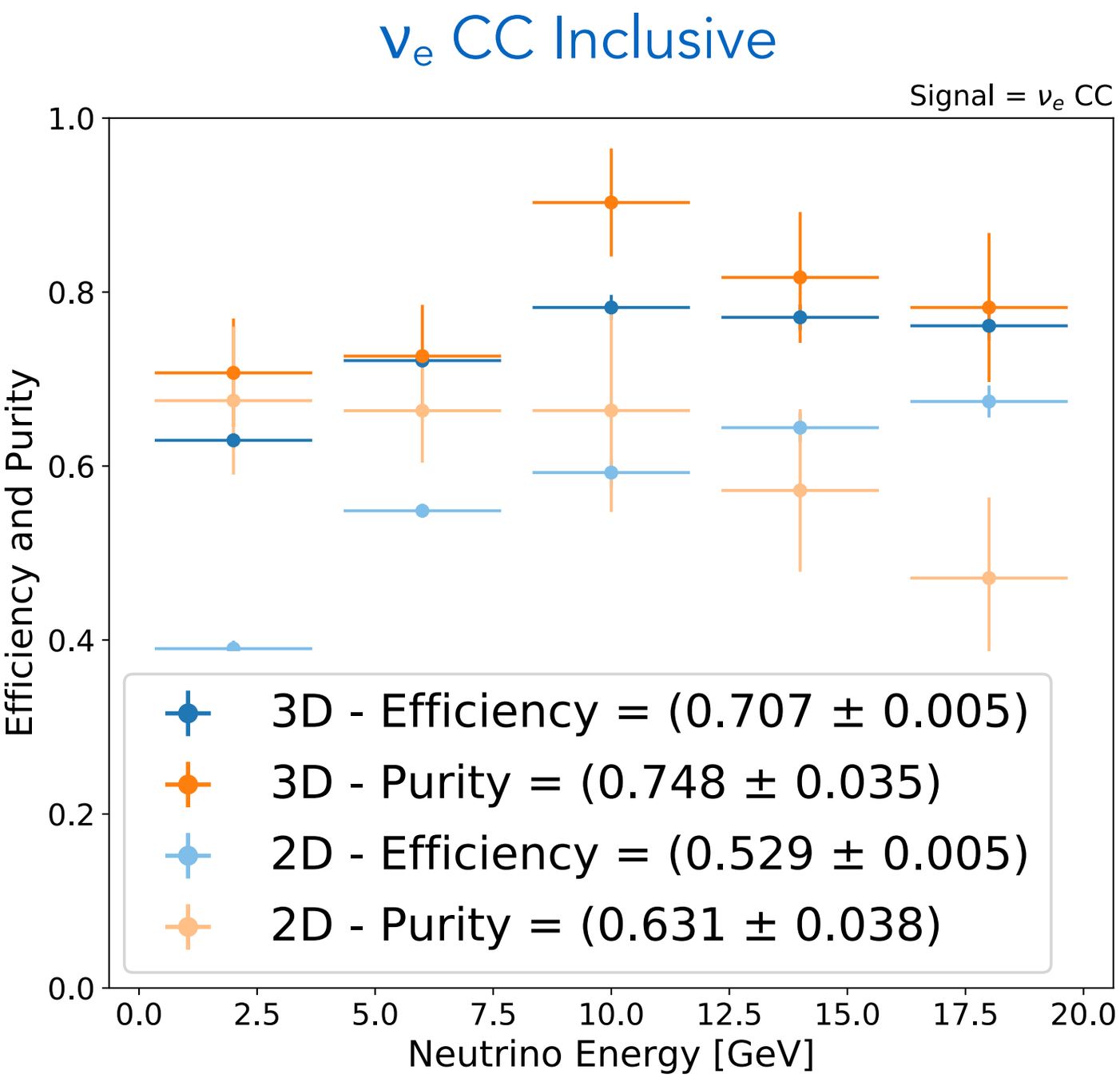
Event classification

Solid line: 3D **Dashed line: 2D**





Focusing on ν_e. Efficiency and Purity



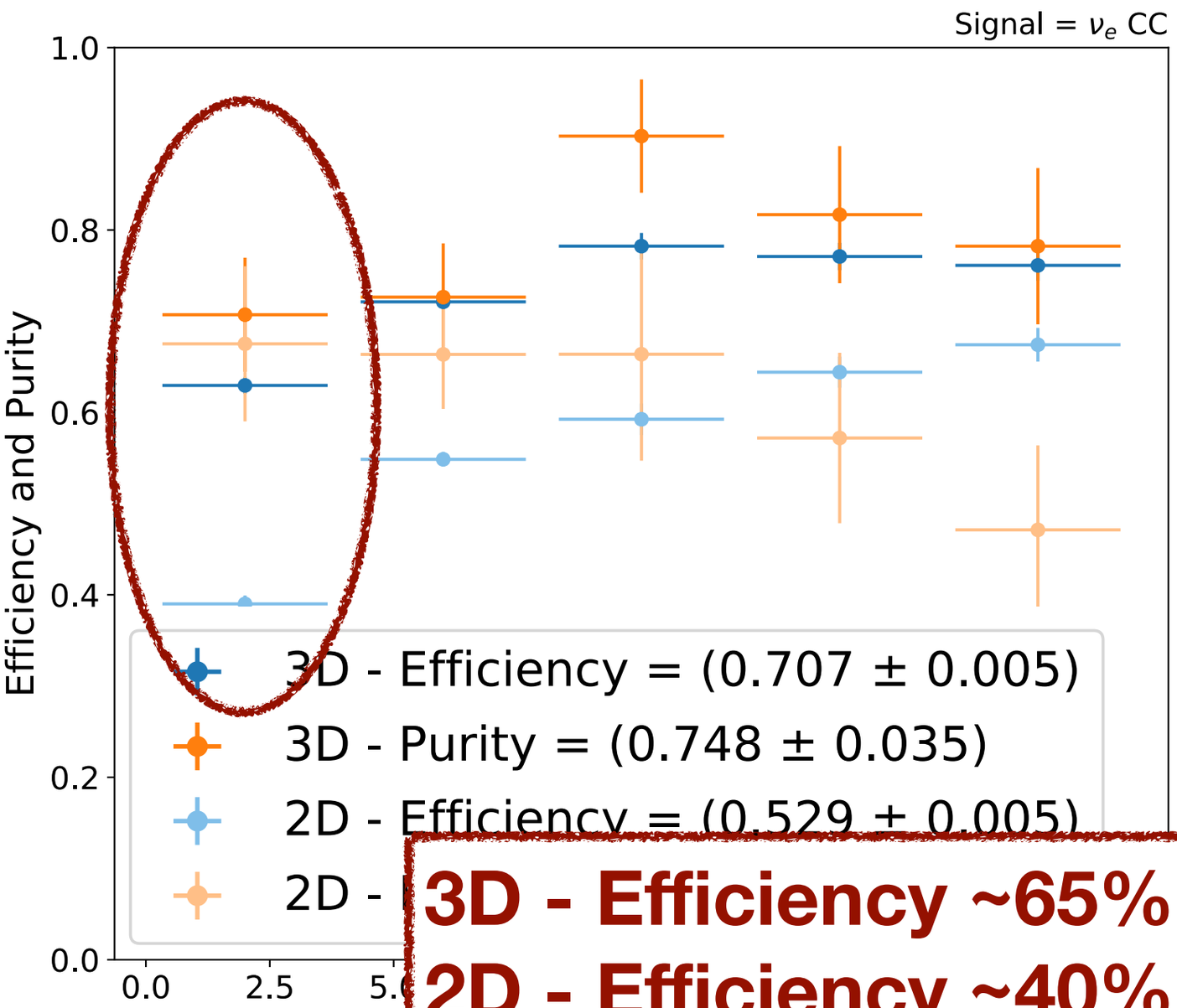
Overall:

3D offers a gain of 17% in **efficiency**

3D offers a gain of 12% in **purity**

Focusing on ν_e. Efficiency and Purity

ν_e CC Inclusive



3D - Efficiency ~65%
2D - Efficiency ~40%
Gain or 25%!
(for similar purity)

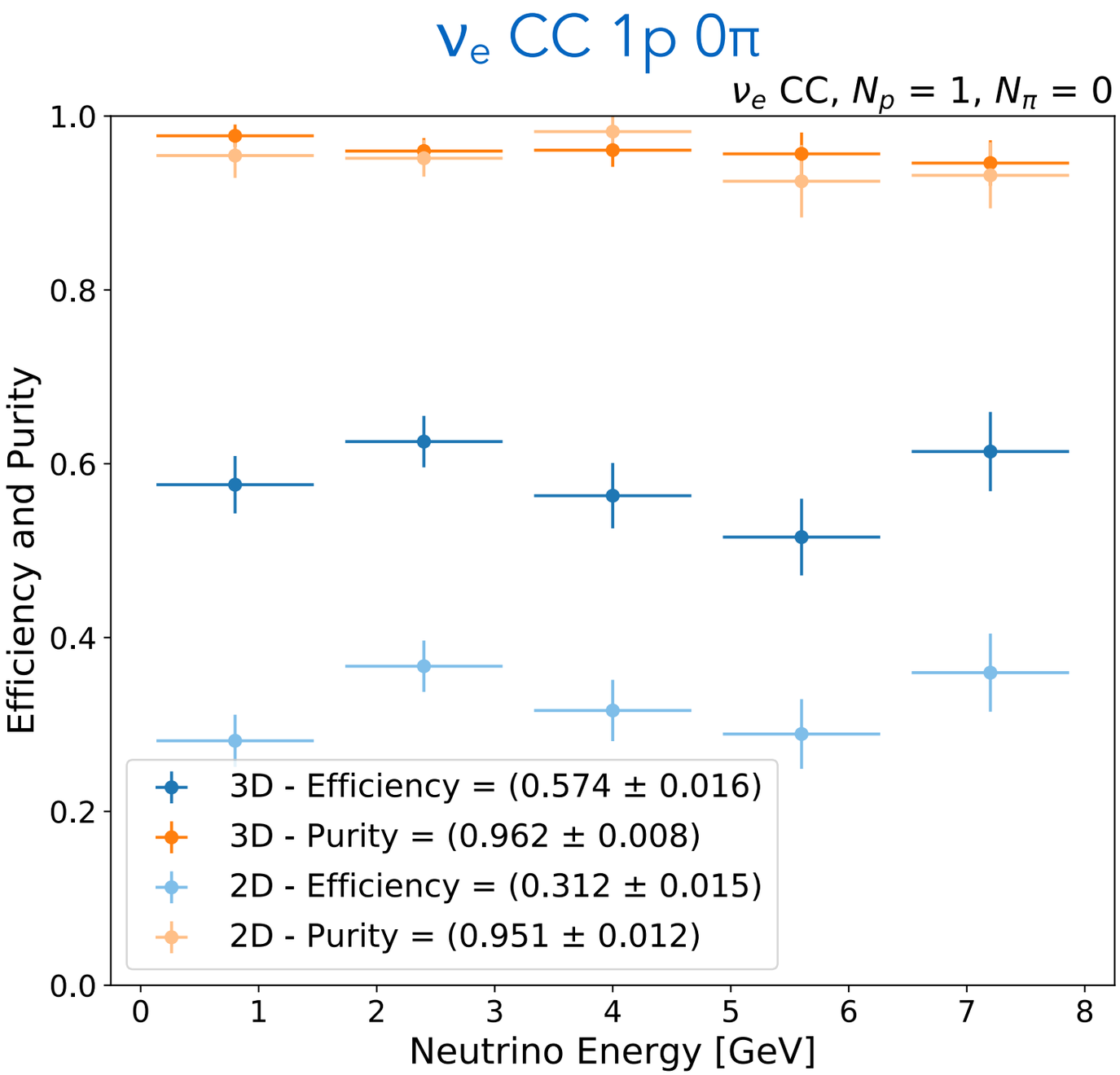
Overall:

3D offers a gain of 17% in **efficiency**

3D offers a gain of 12% in **purity**

At **low neutrino energy**, the **efficiency** is considerably higher in 3D than in 2D

Focusing on ν_e topologies

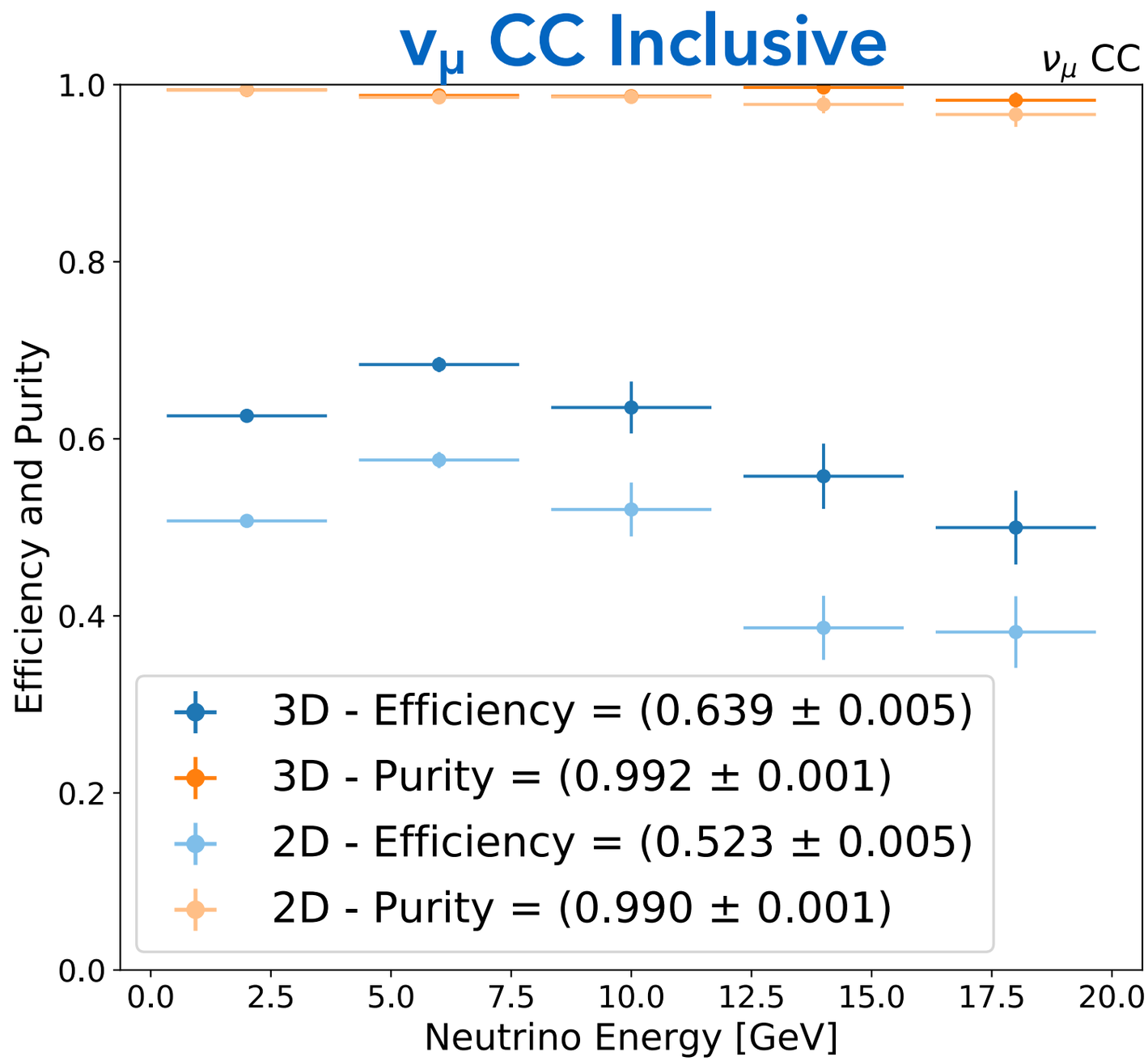


Overall:

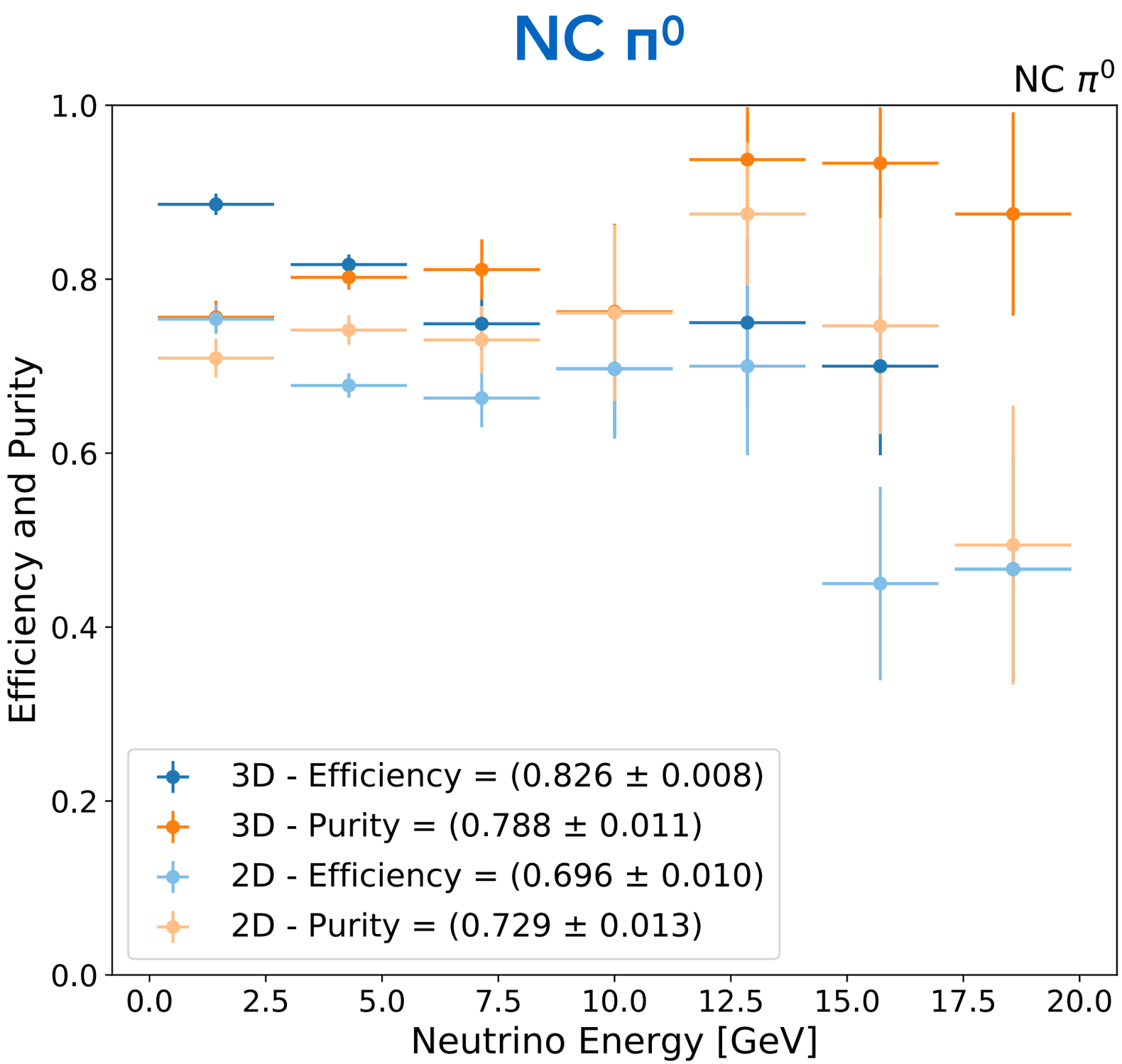
3D offers a gain of 26% in **efficiency** overall **all energies**

Muon neutrinos

- Impact on efficiency depends on purity requirements. But as an example, requiring high purity for both 2D and 3D leads to significantly higher efficiencies for 3D (**12% gain**)



NC contamination



Overall:

3D offers a gain of 13% in **efficiency**

3D offers a gain of 6% in **purity**

Summary of our studies

- Using ML reconstruction tools, **3D readout offers higher event selection efficiencies on all studied topologies**. Also some gain in purity.
- Remember that these studies have optimistic readouts (especially true for 2D readout)
- Caveats:
  - ✓ Despite our best efforts, performance comparisons do include some algorithm comparisons (impossible to address now).
  - ✓ We have mitigated algorithm comparisons by training many configurations of network in 2D and in 3D and comparing the best-of-2D to best-of-3D
  - ✓ We are using perfect detectors (and optimistic 2D simulations (no wrapped wires and smaller wire separation)), however, we expect results to diverge more with more realistic detector effects (to be demonstrated)

What's next

- Repeat these studies with different noise levels and dead channels (individual or grouped)

- Study the performances for lower energy events (supernova neutrinos) and for proton decay events

Discussion points

- Does anyone have suggestions on how to perform the physics studies other than with ML?

- Can we use for example WireCell to reconstruct events (they already work in 2D, could work in 3D too?).

- How much efforts should we invest in simulation studies?

Summary

- Enhancing the physics potential of DUNE is of high importance
- 3D readout could offer advantages over projective 2D readouts
- Machine learning studies show promising improvement in reconstruction of 3D over 2D for beam physics
- Further studies dedicated to more *realistic* detectors and to lower energy physics are underway
- It would be good to get feedback from the community on what people expect regarding physics studies of new technologies
- Having two parallel R&D approaches is very good idea

Current DUNE design challenges

- TDR assumptions for physics sensitivities are not trivial to achieve.

- Wrapped wire design leads to unavoidable ambiguities (impacting shower reconstruction mostly (leading signal and background).

-

Do we really need two 3D readout designs?

- LArPix and QPix share some similarities, but could also have significant differences. We can choose and optimize the design.

- The physics at the Near Detector (currently LArPix) is very different than the physics at the Far Detector (potentially QPix)

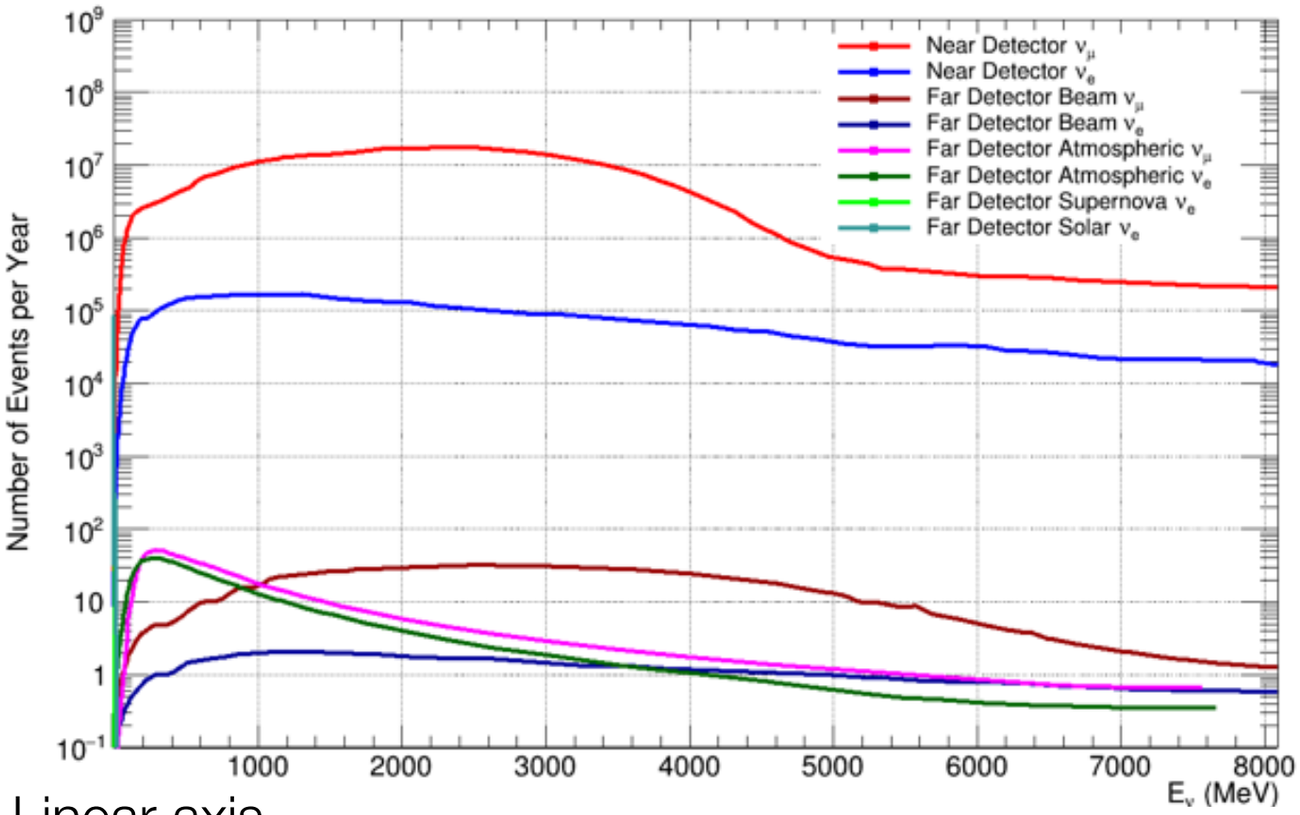
Near Detector

- 50 tons
- Driven by beam physics (**0.5 - 10 GeV**)
- Very **high** Event rates (pile-up issues)

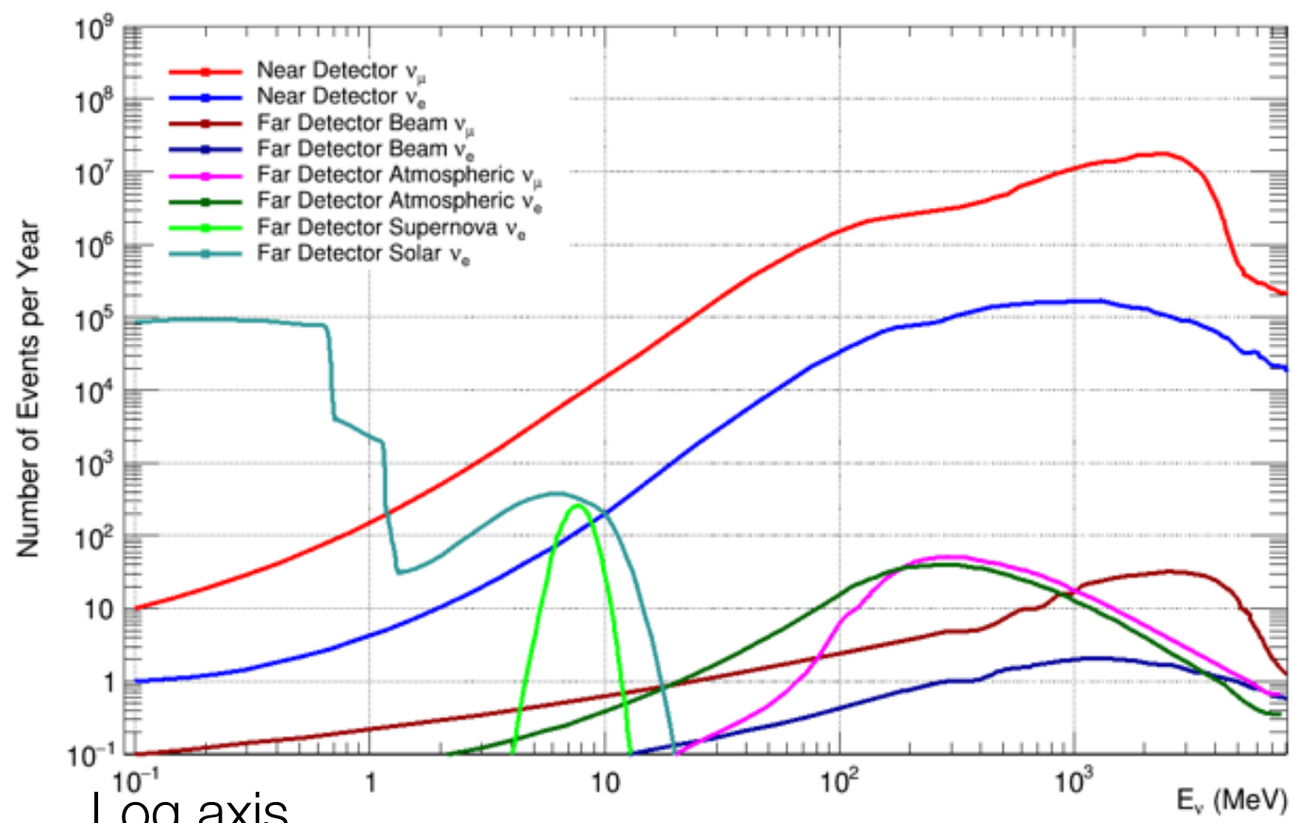
Far Detector

- 10 kilo-tons
- Wide range of physics goals (beam, supernova, proton decay…) (from **~10 MeV to 10 GeV**)
- Very **low** data rates

Near/Far differences



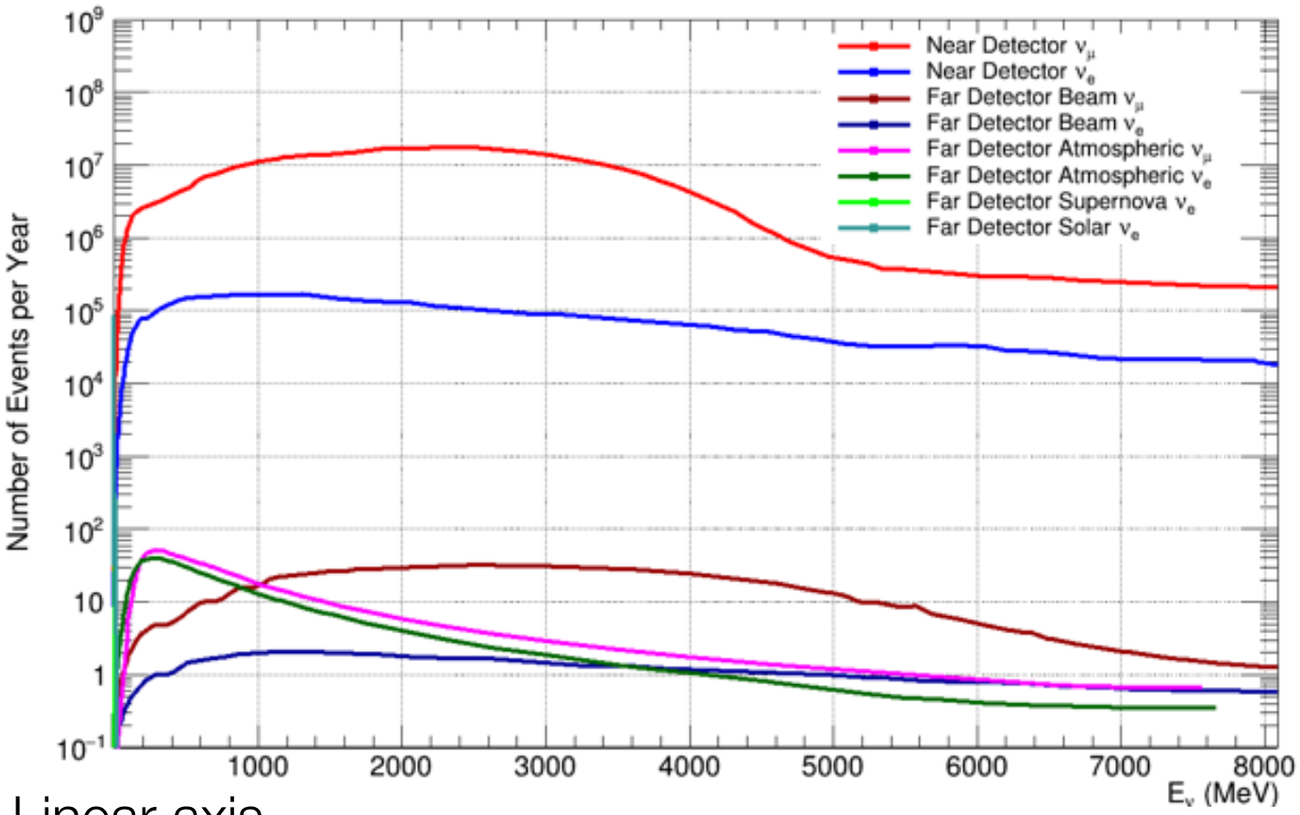
Linear axis



Log axis

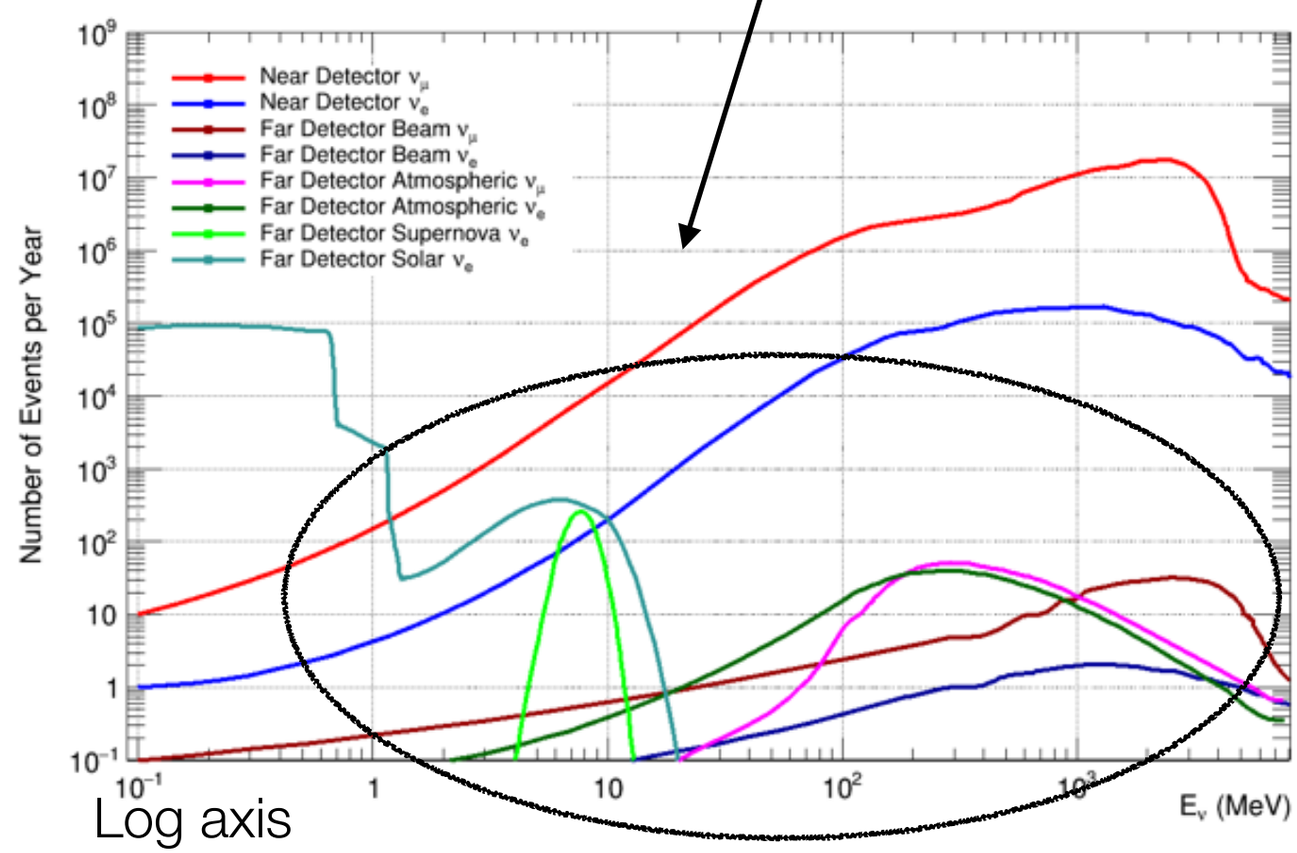
Courtesy of Jonathan Asaadi

Near/Far differences



Linear axis

Rich physics at lower energies



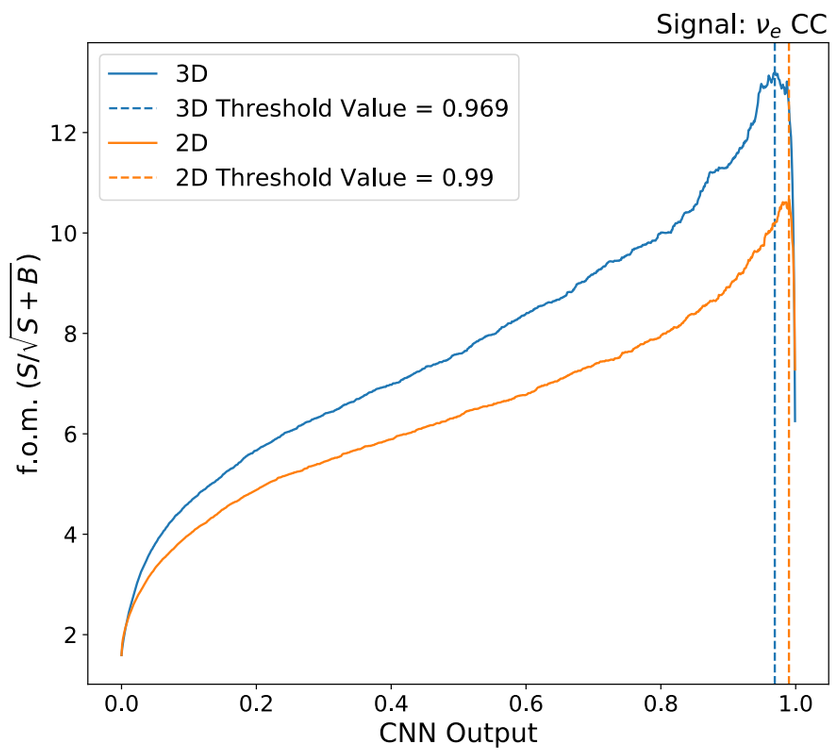
Log axis

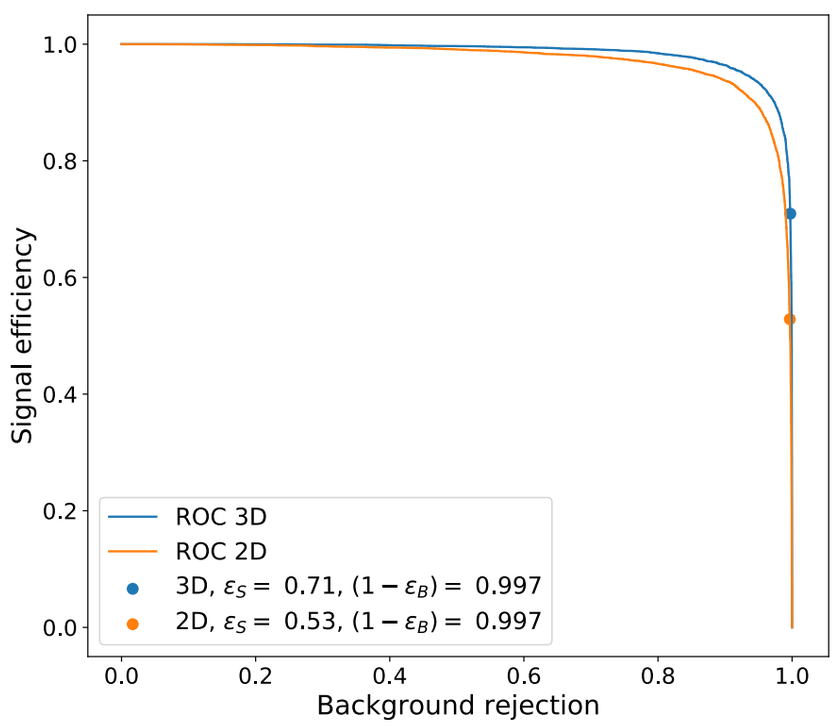
Clear that the readouts will have very different challenges, and both deserve their own R&D (while working in synergy of course!)

Courtesy of Jonathan Asaadi

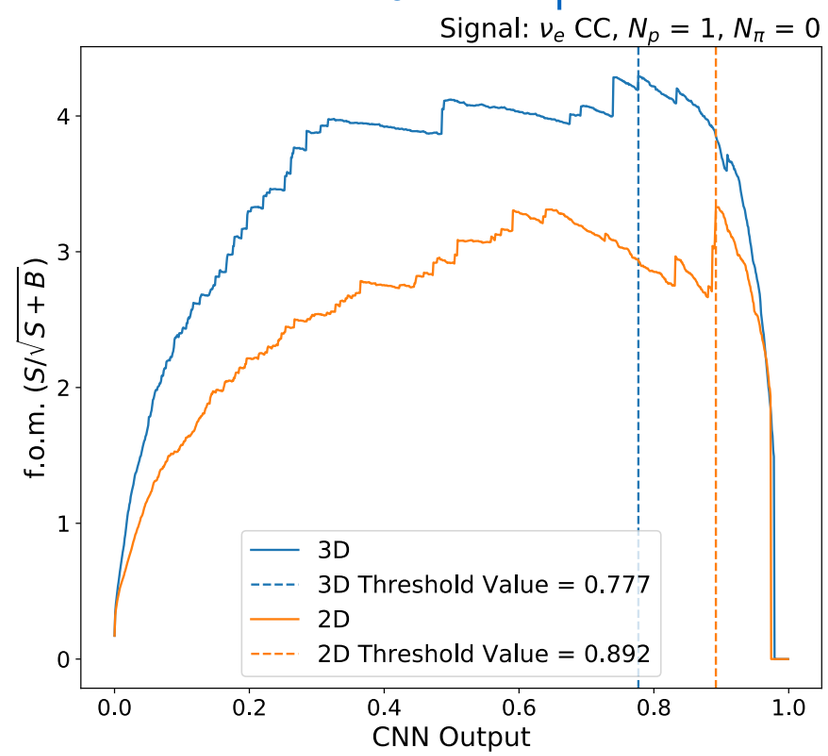
Focusing on ν_e. Figure of merit

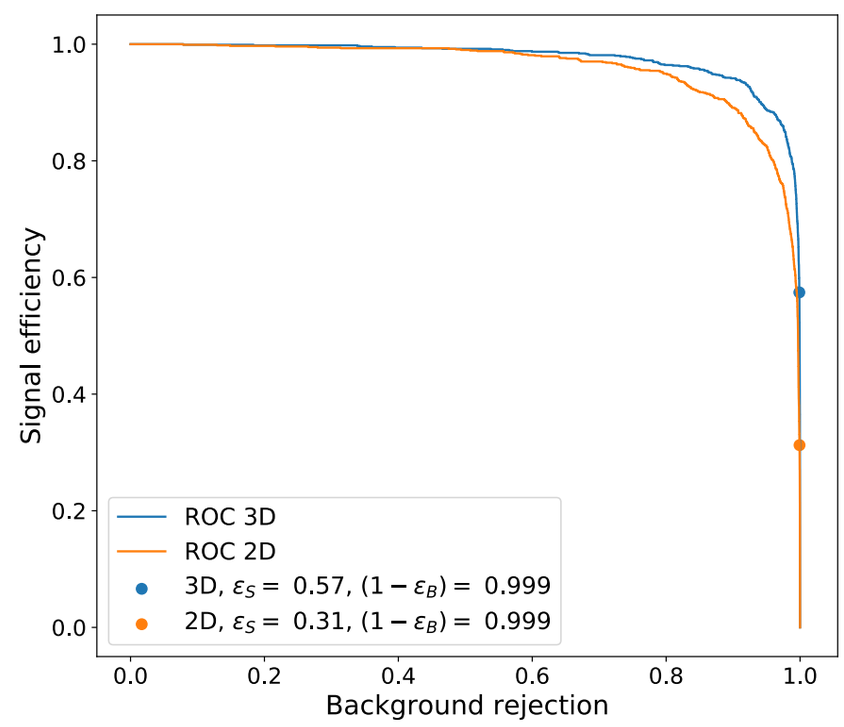
ν_e CC Inclusive



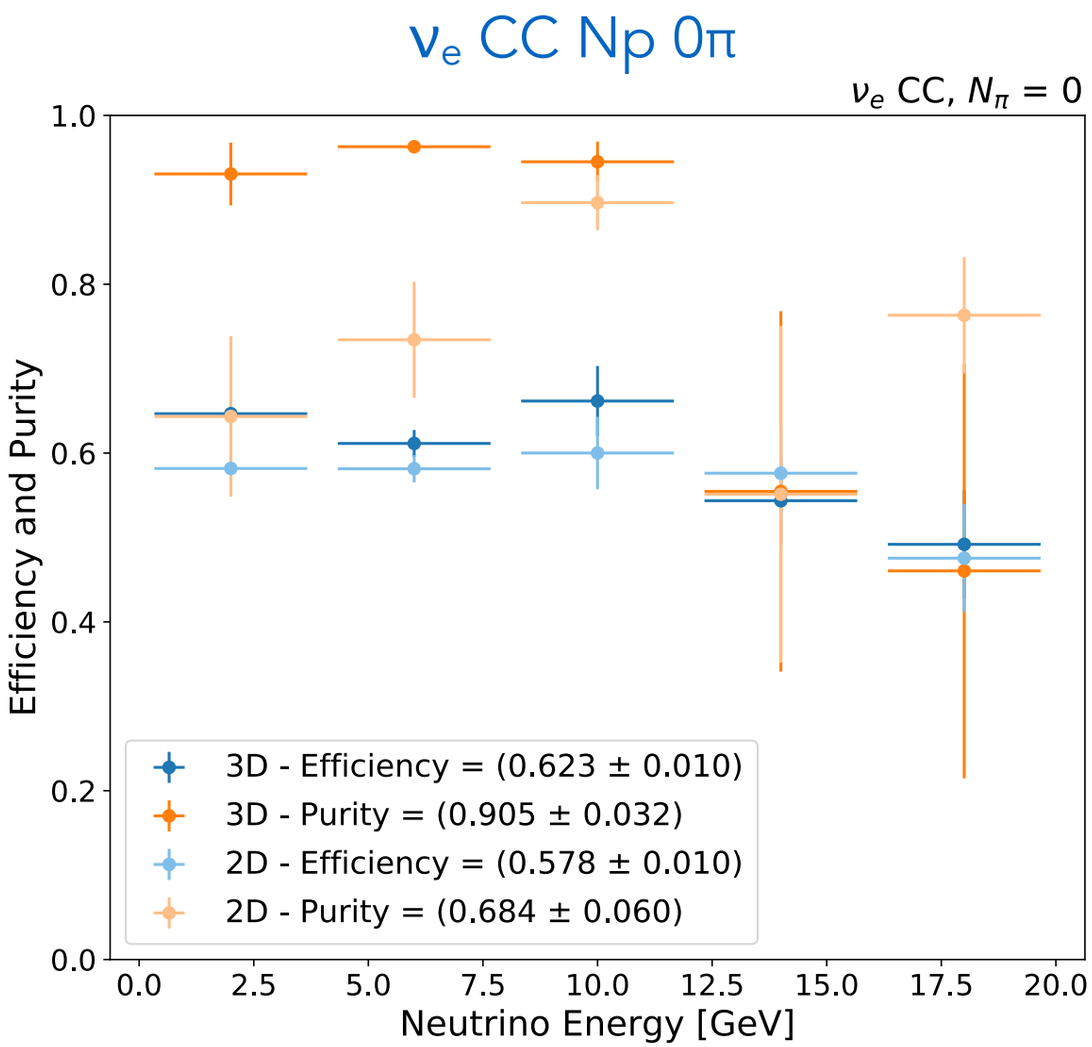


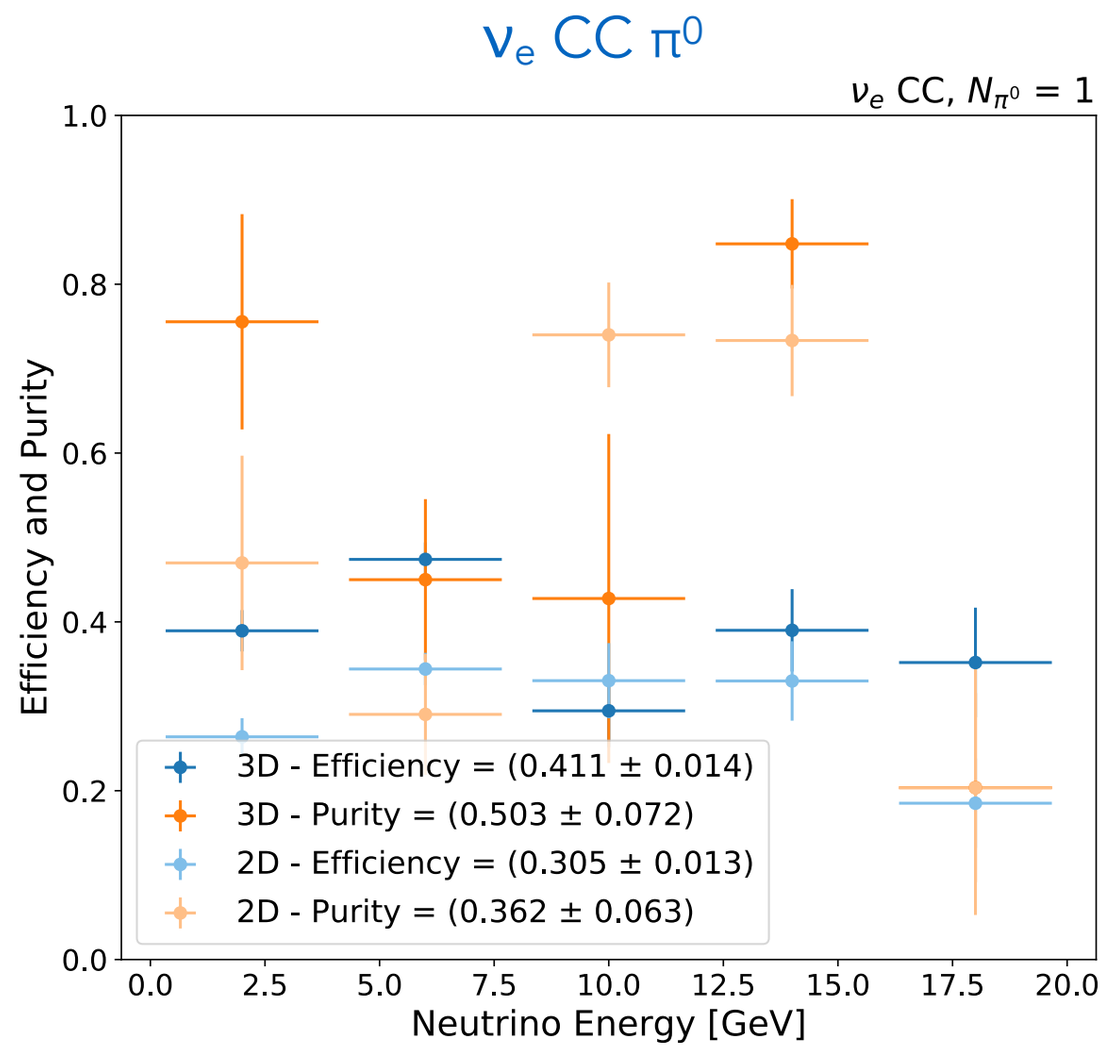
ν_e CC 1p 0π





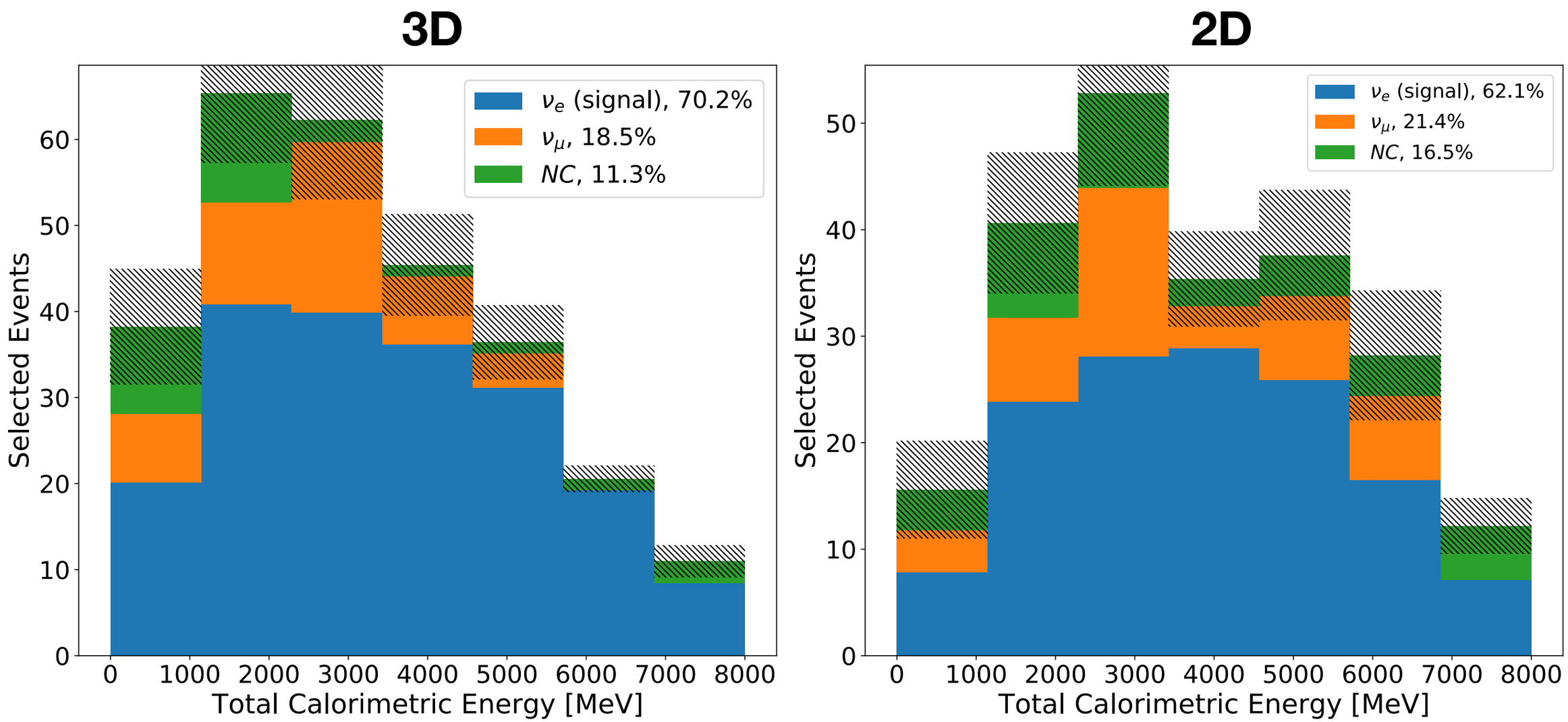
Electron Neutrino Selection: Efficiency and Purity





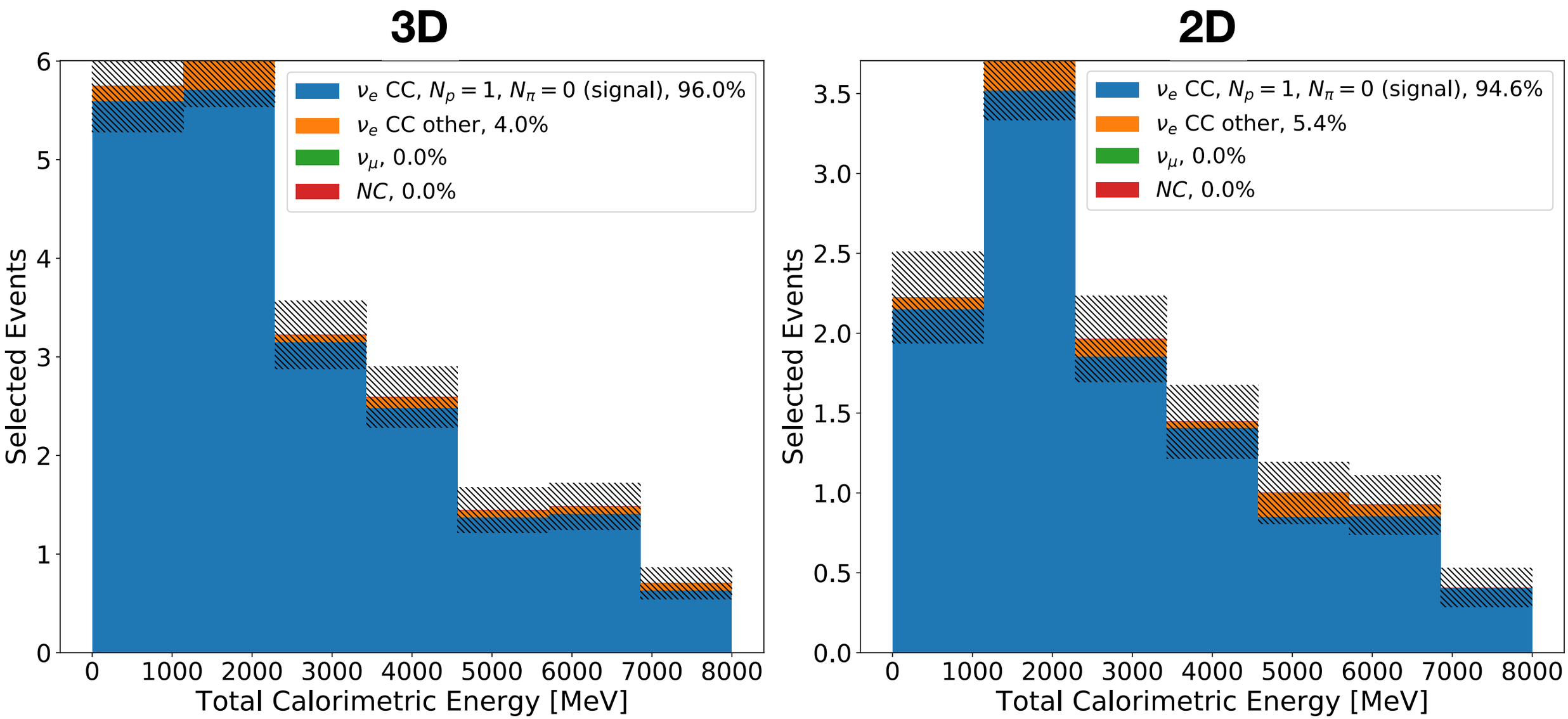
Focusing on ν_e. Energy spectra

ν_e CC Inclusive



Focusing on ν_e. Energy spectra

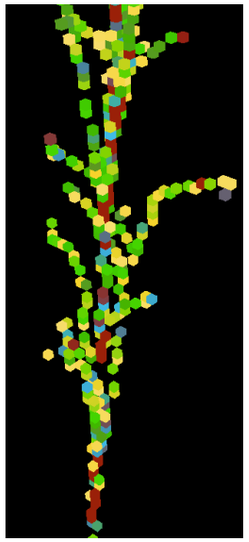
ν_e CC 1p 0π



Software and Computing: Key Points

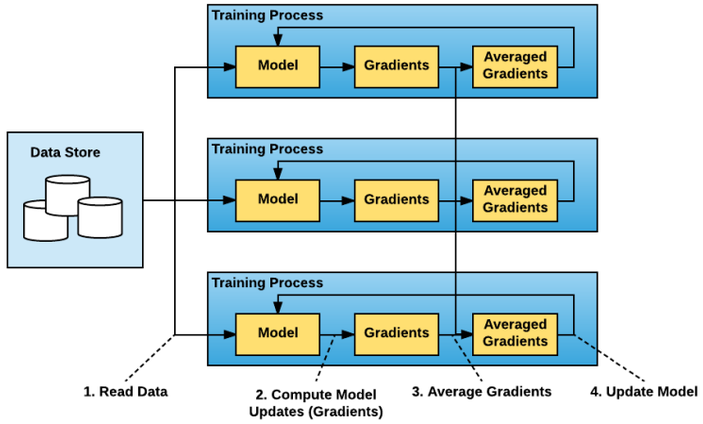
Sparse Network

- While CNNs are usually applied to dense images, in TPC data most of the voxels are empty
- Contrary to a dense network, a sparse one trains only on voxels with non-zero energy deposition.
- This allows us to train on full 3D images, and can be scaled to larger detectors.



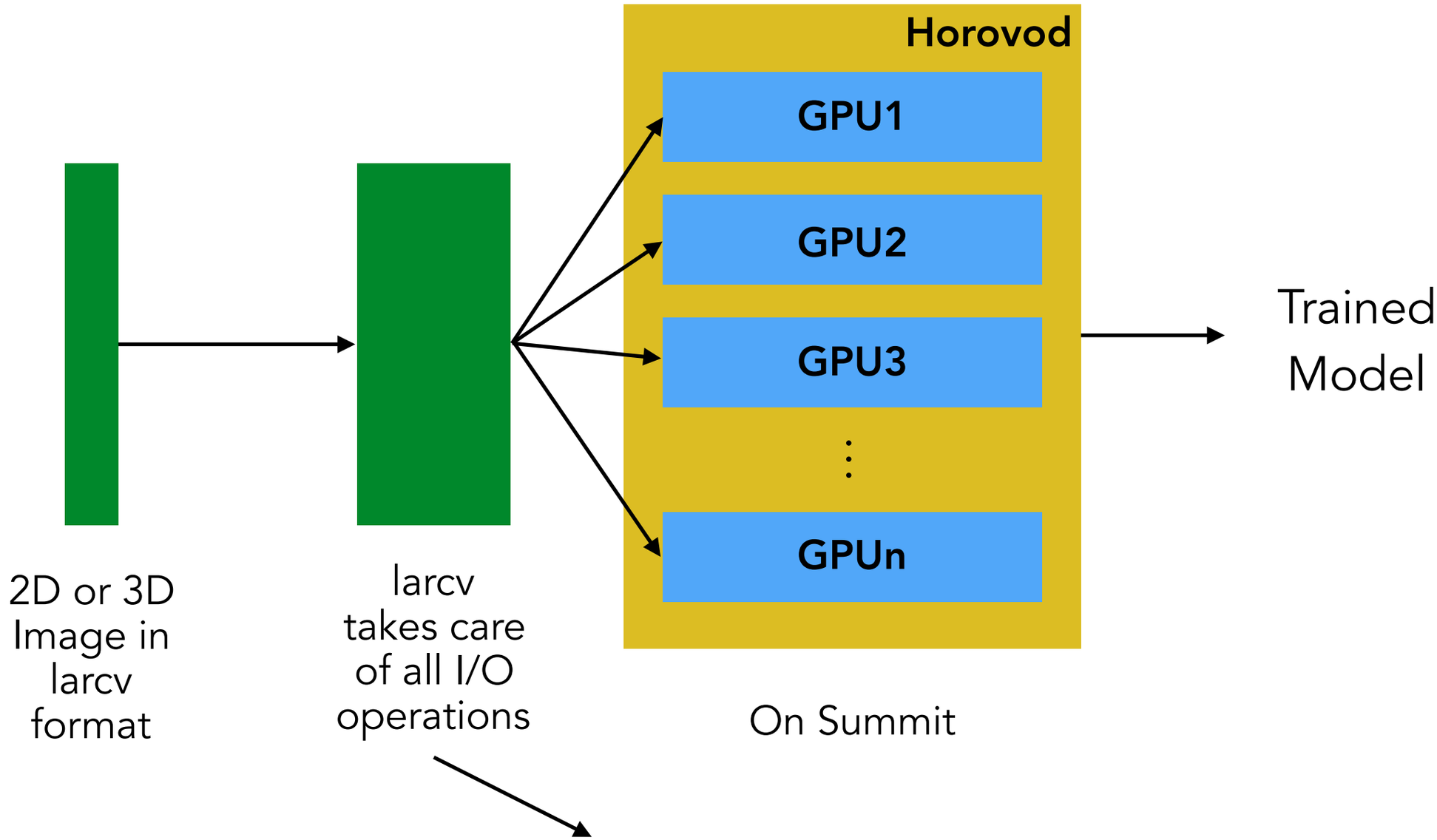
Distributed Learning

- We are using distributed learning to train on multiple devices simultaneously.
- Training on multiple GPUs allows us to have results in a significantly shorter timescale (the time to fully train the networks in this presentation is ~1h)



Running on Summit Supercomputer at Oak Ridge

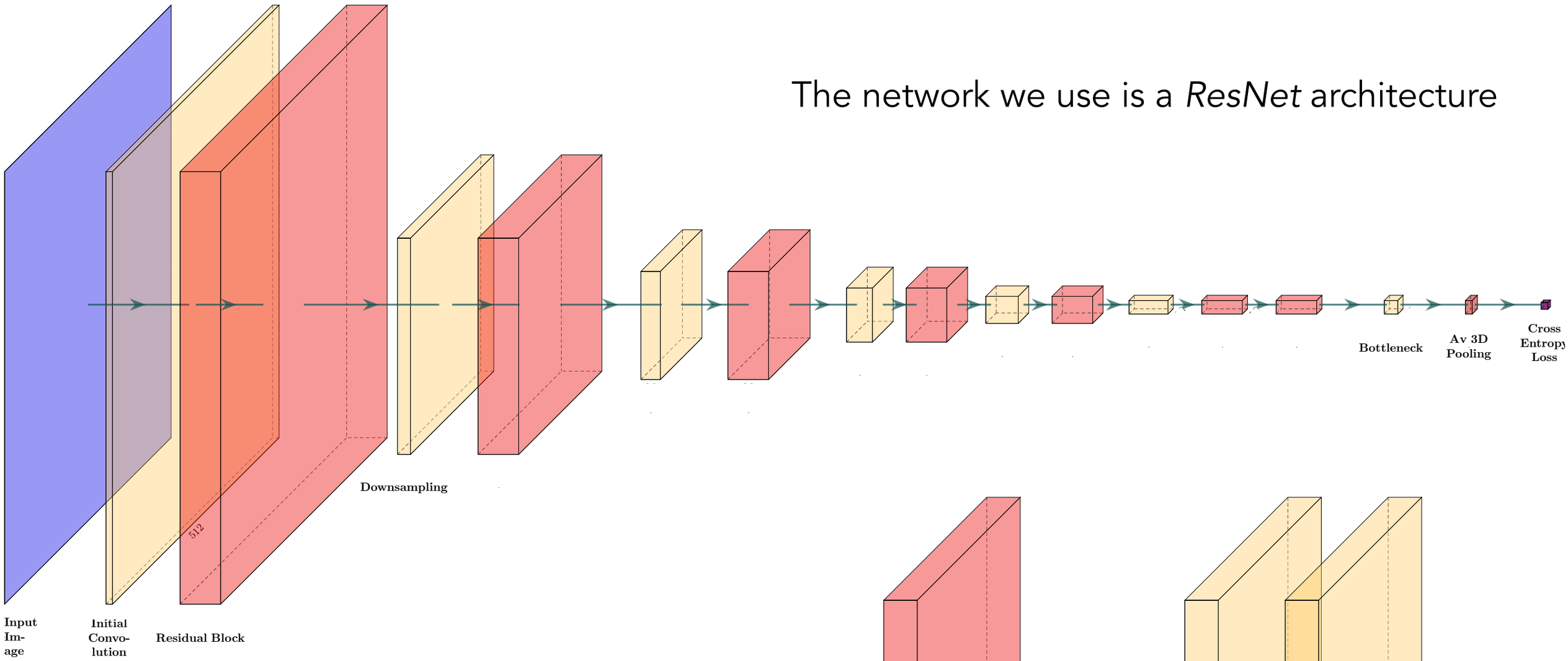
- We are making use of the resources at Summit which offers 4608 nodes with 6 NVIDIA V100 GPUs each

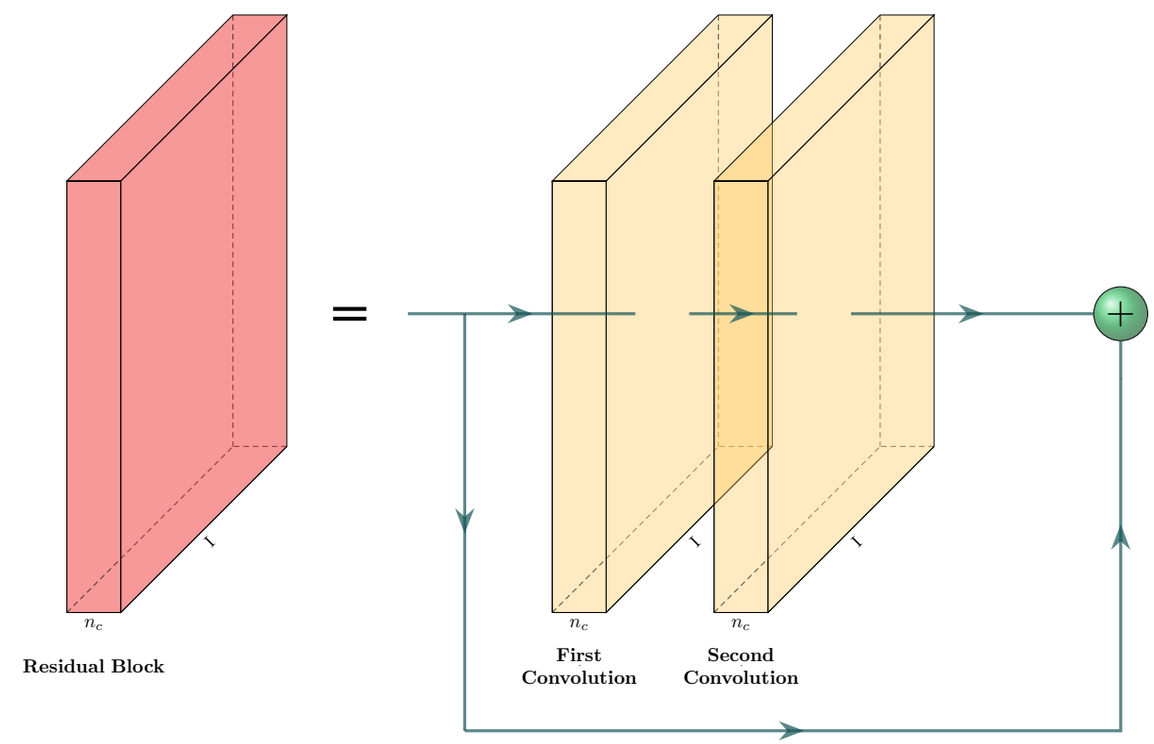


https://github.com/DeepLearnPhysics/larcv3

Network Architecture

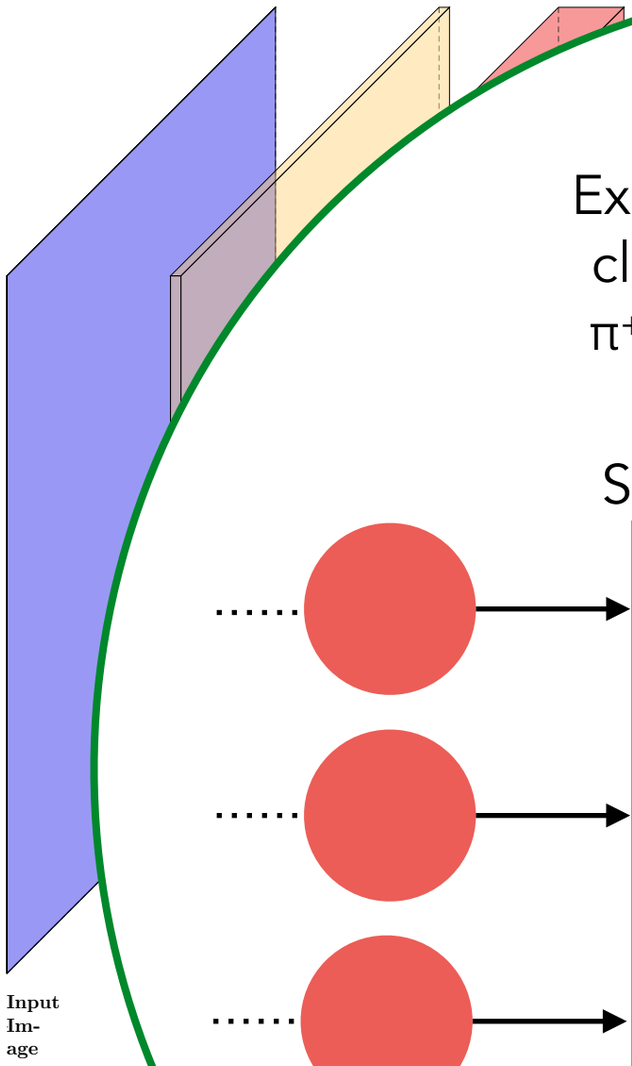
The network we use is a *ResNet* architecture





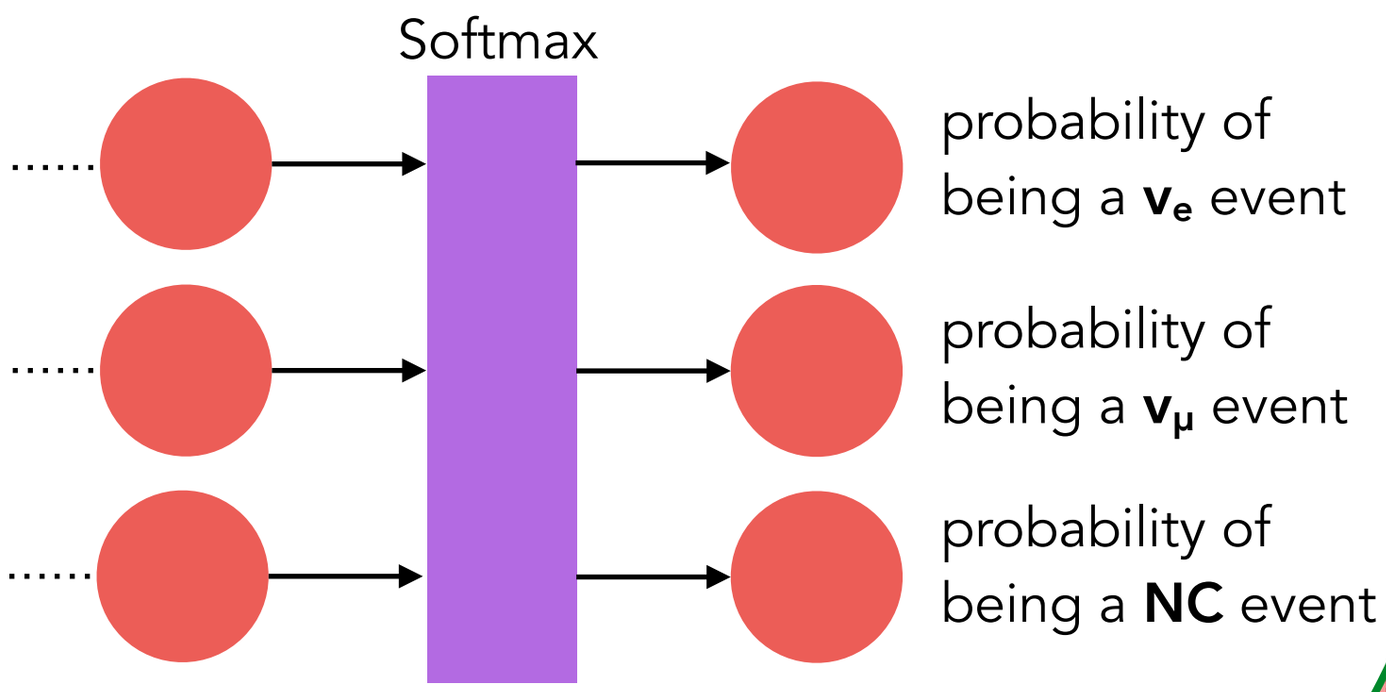
The input images are 3D sparse images or 3 2D sparse images.

Network Architecture



Network output

Example with neutrino ID classification, similar for $\pi^{+/-}$, π^0, N_p classification

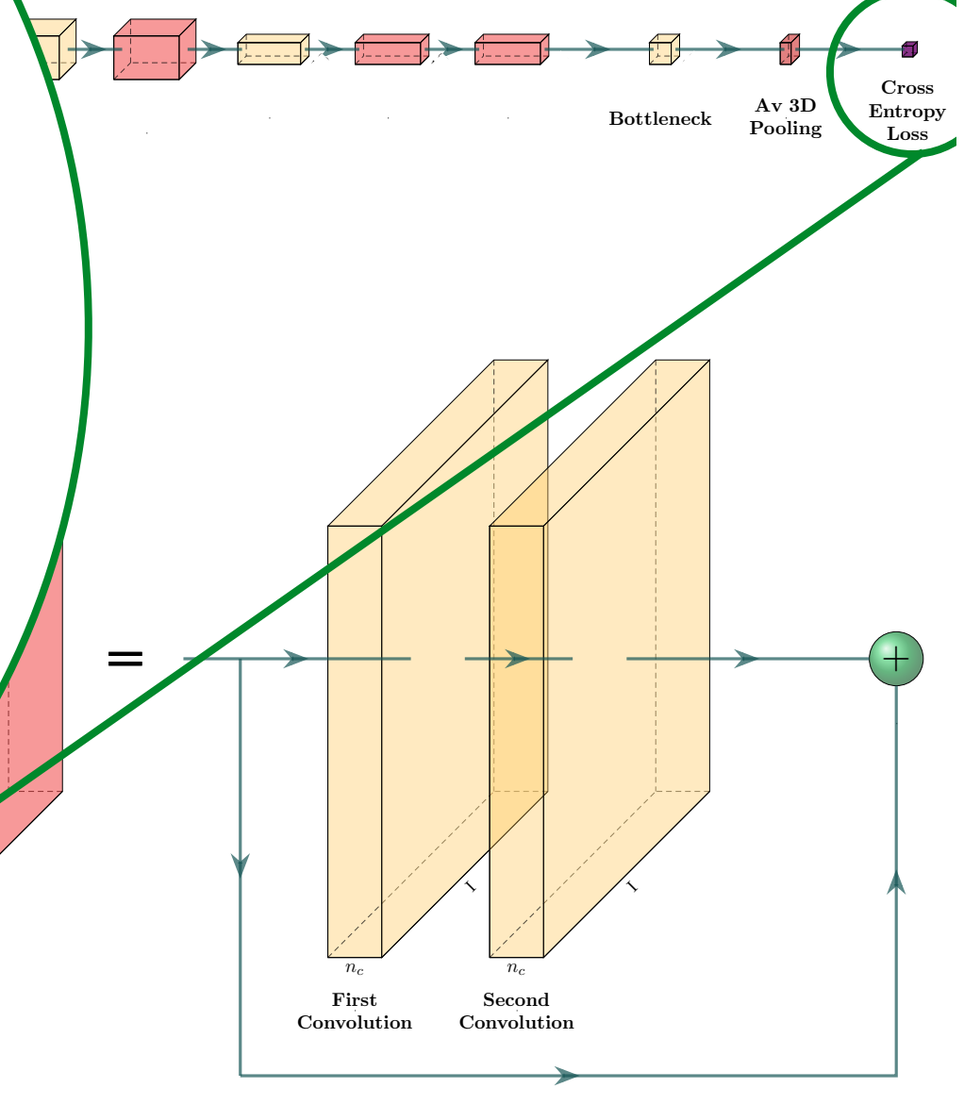


The inpu

or 3 2D spars

The network we use is a *ResNet* architecture

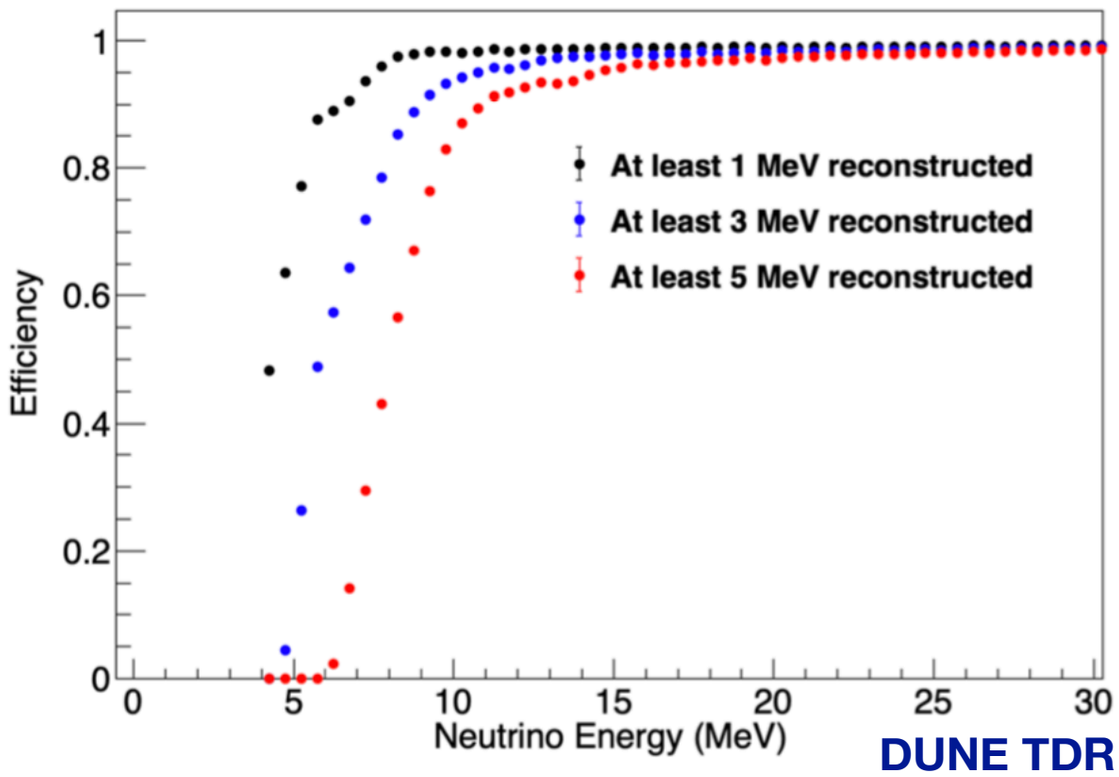
baseline, can be improved)



This is the best training that we were able to obtain for both 2D and 3D.

2D - best training obtained with batch size of 384 (distributing over 6 GPUs)

3D - best training obtained with batch size of 3840 (distributing over 60 GPUs)


Efficiency
Neutrino Energy (MeV)
At least 1 MeV reconstructed
At least 3 MeV reconstructed
At least 5 MeV reconstructed
0
0.2
0.4
0.6
0.8
1
0
5
10
15
20
25
30
DUNE TDR