Pixel vs. Wire Detectors

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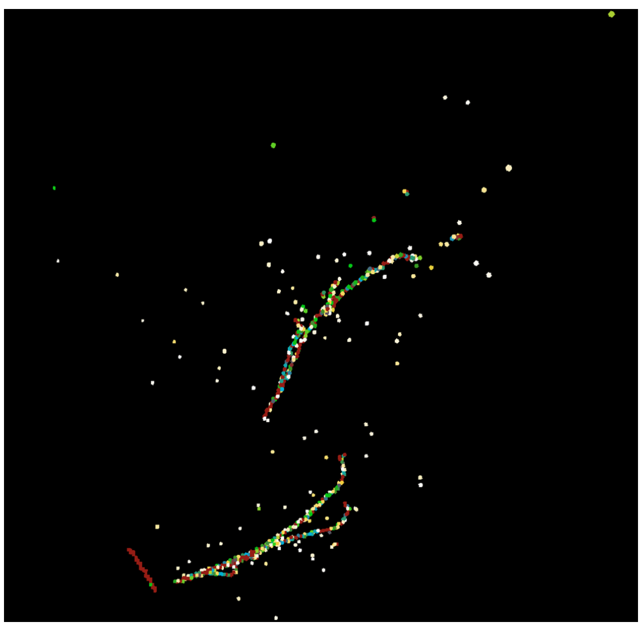
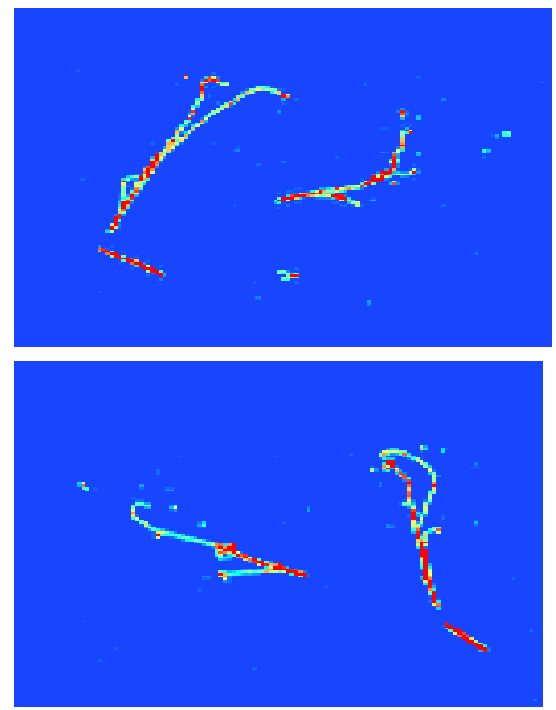
What’s the problem?

Q: Are pixel detectors better than wire detectors?
A: Yes.

Or, we all believe this intrinsically...





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Pixel detectors promise 3D data without the compression of spatial information that 2D wire detectors force (not to mention wrapped wire ambiguities).

They also come with their own set of challenges: bigger data sizes, need for new reconstruction techniques, novel hardware design, etc.

How do you prove 3D is better than 2D?

Comparison Technique

Need to disentangle "quality of reconstruction and analysis" from "quality of detector"

- ➔ Need a comparable reconstruction and analysis technique

Need to consider the ability to perform analyses "at scale"

- ➔ If you have 1mm voxels and beautiful 3D reconstruction but need the worlds largest super computer to run reconstruction, you lose the benefits.

Deep Learning

A lot of exciting progress recently on deploying deep learning in neutrino physics – this is our technique for this study:

- "Easy" to compare across 2D and 3D.
- Doesn't rely on handcrafted algorithms – no bias based on developer skill.
- Can build on advances in simulation and deep learning tools with quick retraining and reevaluation.
  - Clearly, this is a bigger effort than what is presented here.

Baseline Studies

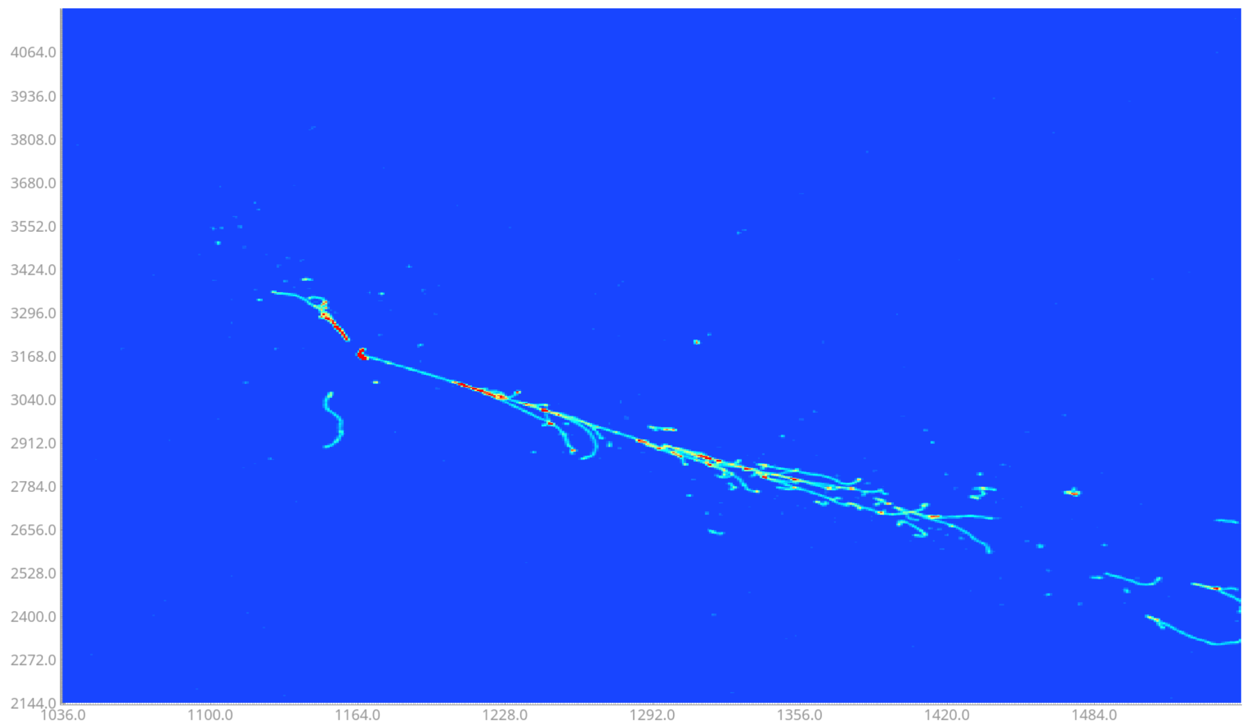
The core of any physics analysis is to select signal events and reject backgrounds – we started our comparison by using Deep Learning to classify events into broad categories for physics selections:

- Neutrino Classification (nue, numu, NC)
- Proton Multiplicity (0, 1, 2+)
- Charged Pion Presence (0, 1+)
- Neutral Pion Presence (0, 1+)

Each event is given a probability for each of these categories by the network in 2D and 3D

Simulated Neutrino Events

We picked the simulation we knew best:
BNB and SBN

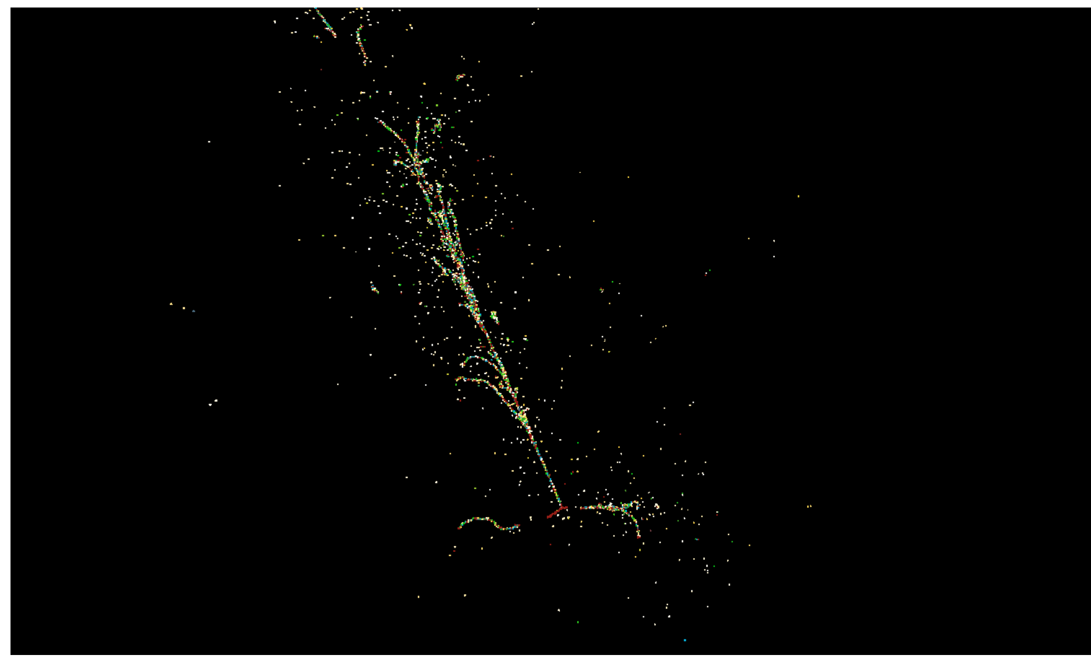


Events generated with BNB flux (~1GeV) and with GENIE and GEANT models

2D Simulation

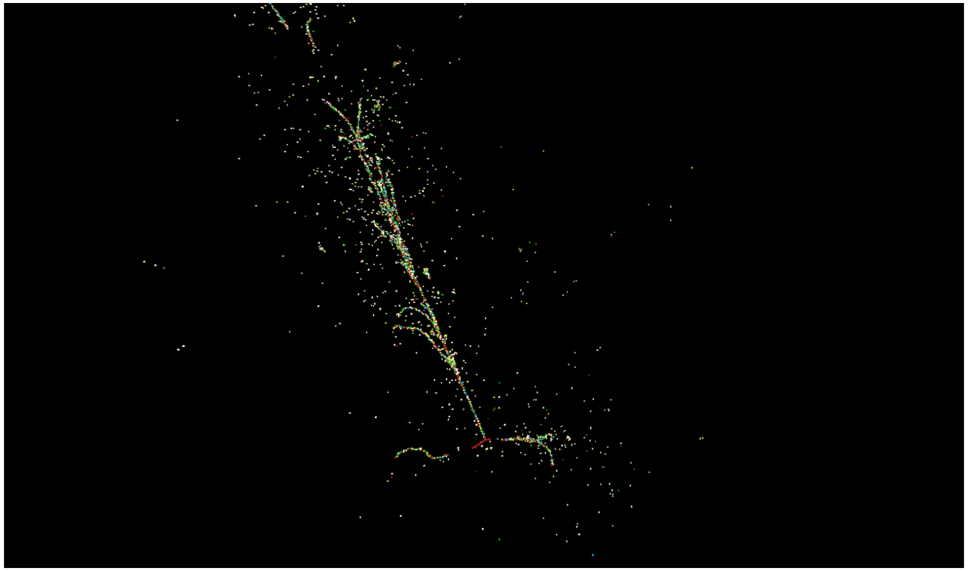
Using SBN (very basic) noise models, signal response and deconvolution, simulated neutrino interactions and cropped 512x512 regions for 3 planes.

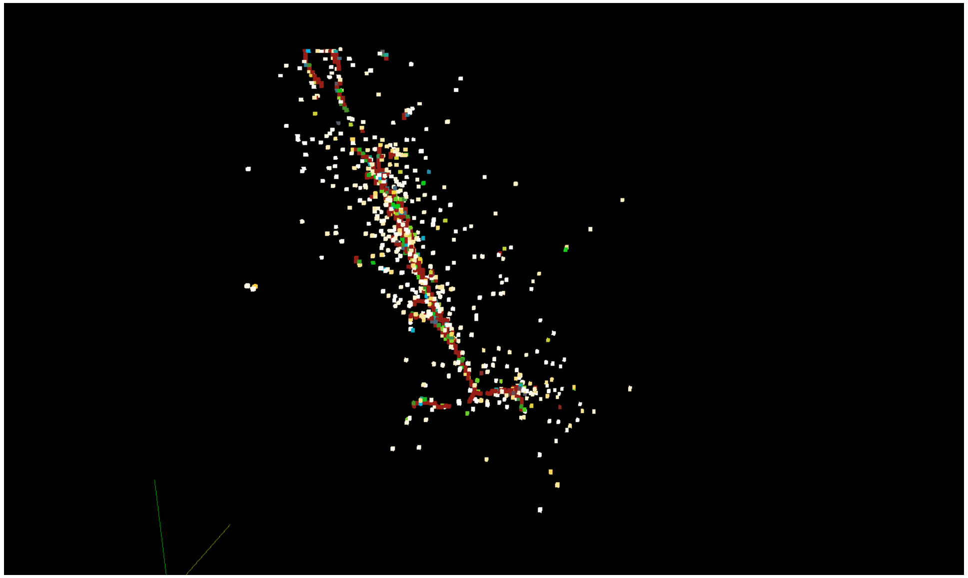
Taking discrete geant depositions and binning into 3mm voxels, the same events are built into 512**3 3D images.



Technical Limitations

512x512x512 is a lot of voxels. This doesn't fit easily onto any modern GPU hardware, so we downsample by x4:

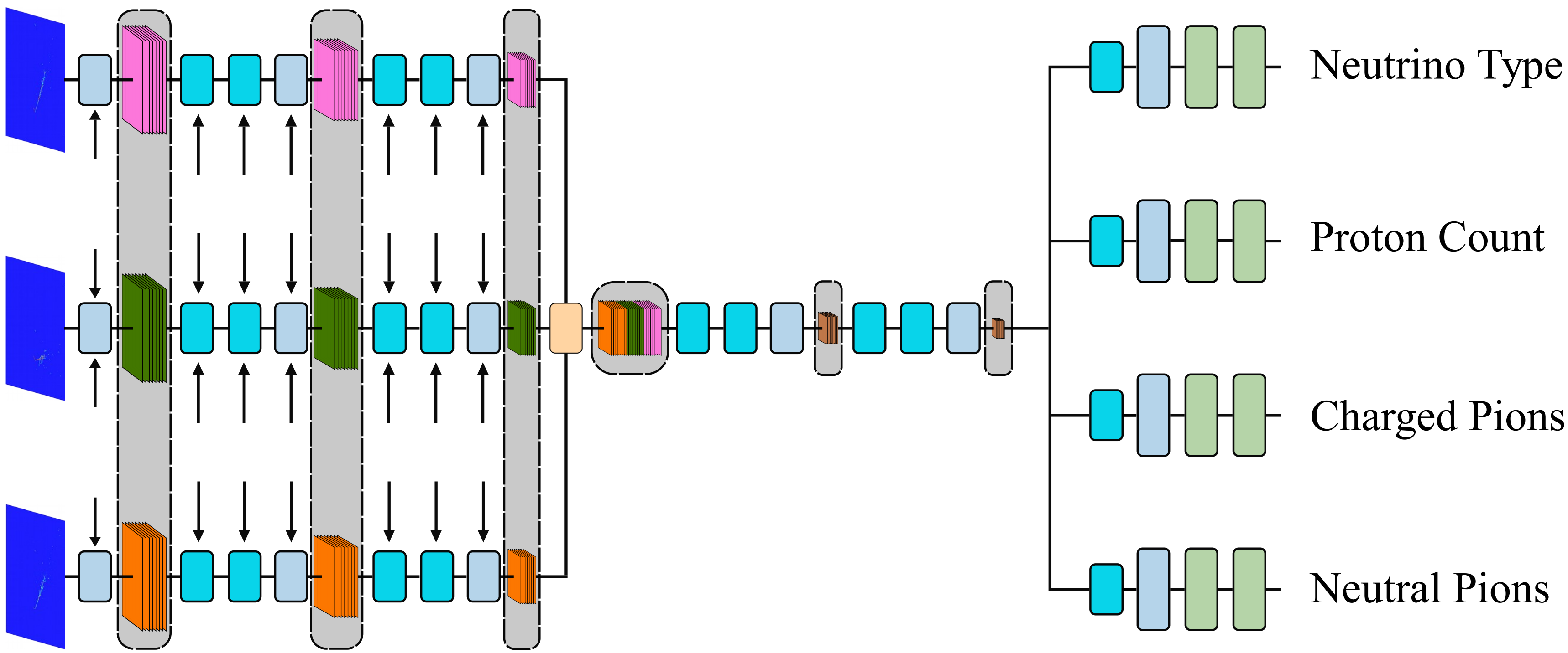




This is not a unique problem to this study – to do machine learning on pixel detectors, we have to be smarter about sparse data.

Comparison Technique

2D Network and 3D network make simultaneous predictions for physics quantities in the images.



Same events, similar networks, can do a direct comparison of 2D vs 3D.

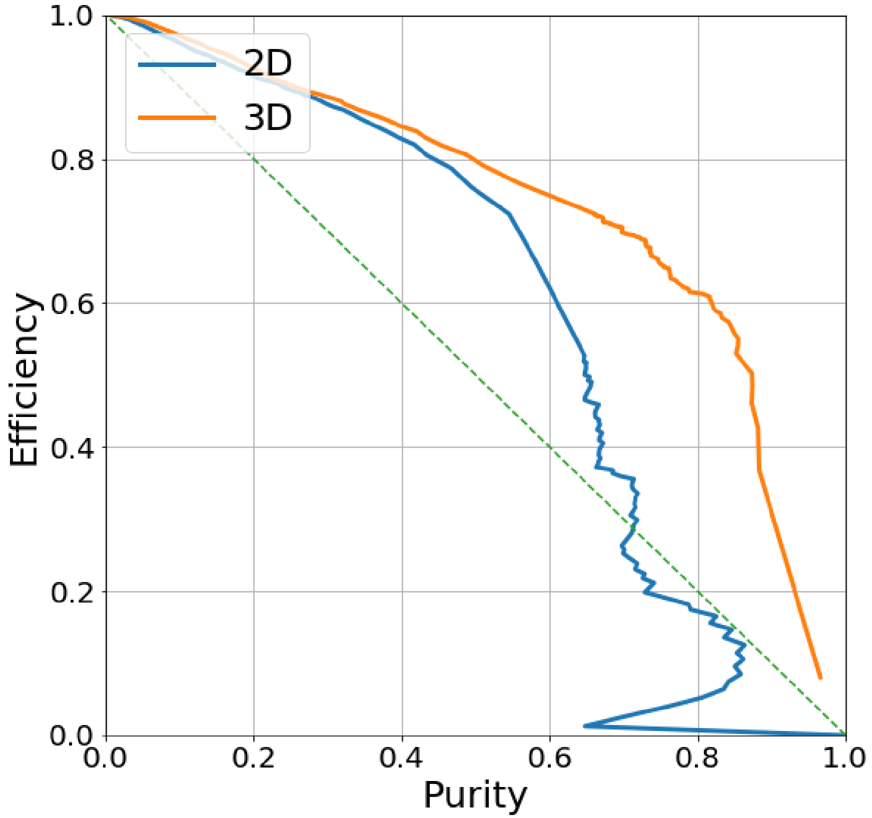
Accuracy Comparison

2D	*nueCC:*	0.9492		*0 pi0:*	0.9885		*0 proton:*	0.9329		*0 ch pi:*	0.9558
	numuCC:	0.9320		*1+pi0:*	0.8160		*1 proton:*	0.9044		*1+ ch pi:*	0.7525
	NC:	0.8586					*2+ proton:*	0.8839			
3D	*nueCC:*	0.9504		*0 pi0:*	0.98082		*0 proton:*	0.9151		*0 ch pi:*	0.9584
	numuCC:	0.9119		*1+pi0:*	0.8841		*1 proton:*	0.8826		*1+ ch pi:*	0.7779
	NC:	0.9149					*2+ proton:*	0.8751			

Electron Neutrino Selection

Select CC inclusive events by just asking the network, “is this event nueCC?”

By varying the cut threshold and assuming BNB beam statistics for the backgrounds, 3D dramatically outperforms 2D.

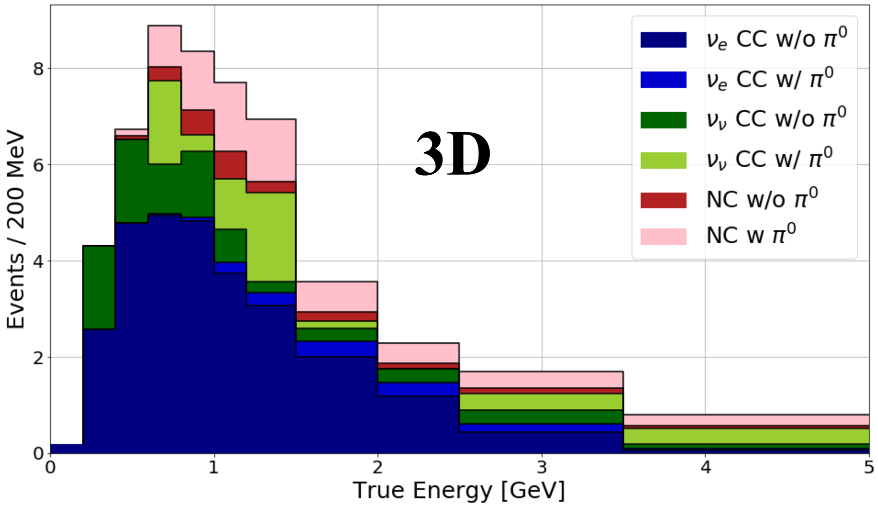


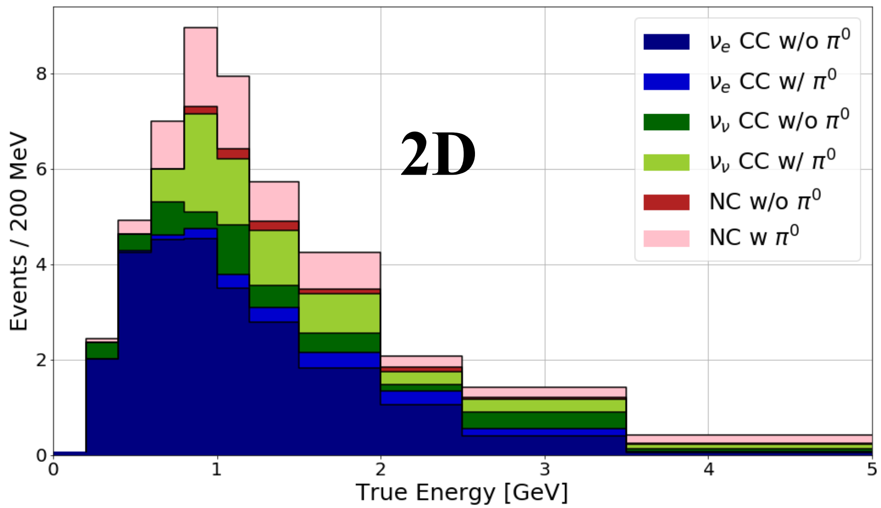
Can set a cut to achieve (artificial) goals: 50% purity?

Electron Neutrino Selection

Can set a cut to achieve (artificial) goals:
50% purity?

Relatively balanced performance
between 2D and 3D.



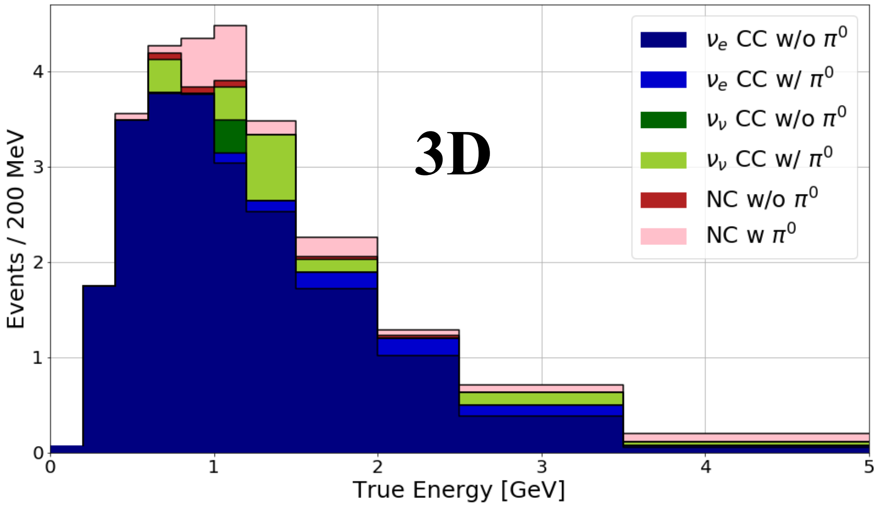


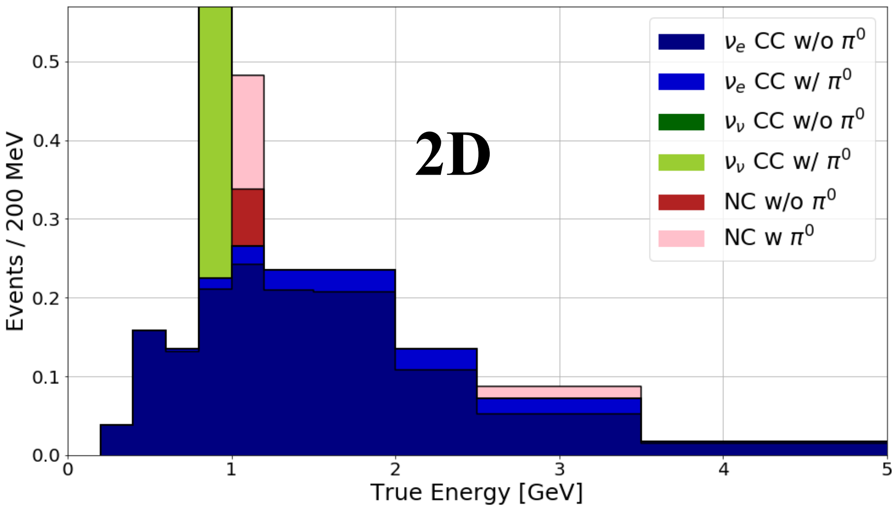
Electron Neutrino Selection

Can set a cut to achieve (artificial) goals: high purity?

High purity in 2D loses a large portion of efficiency that the 3D network maintains.

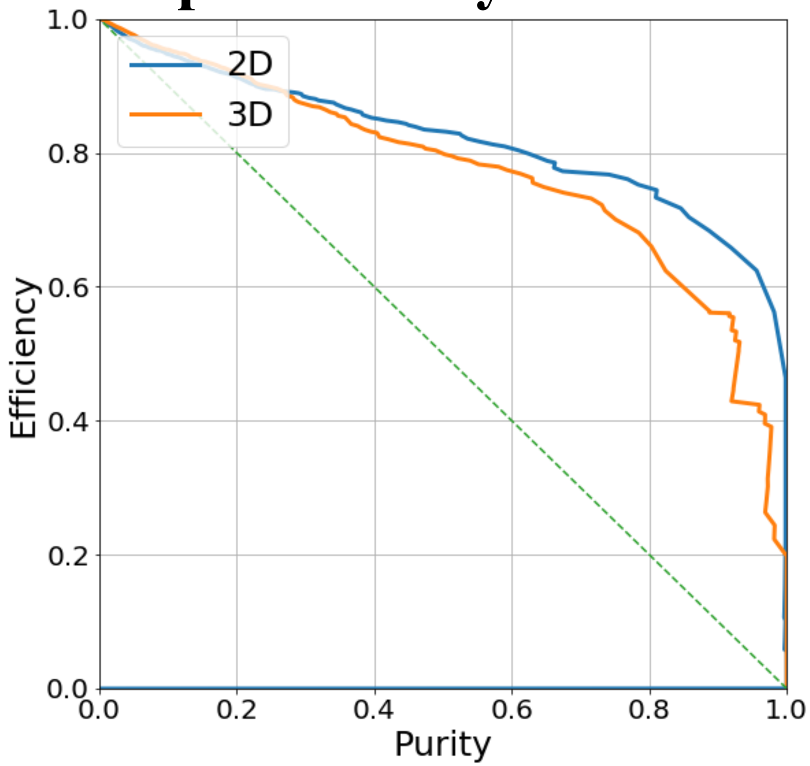
Takeaway: across all backgrounds and event types, the information available for discrimination is more robust in 3D than 2D.



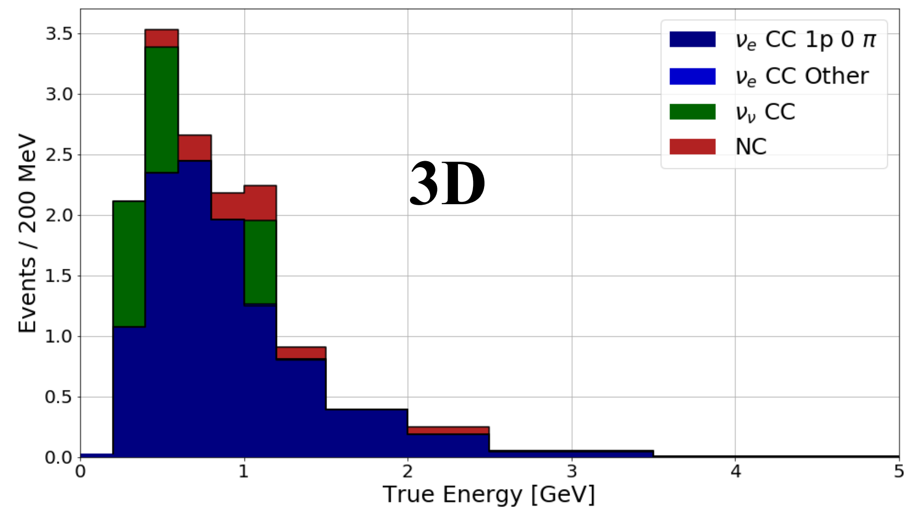


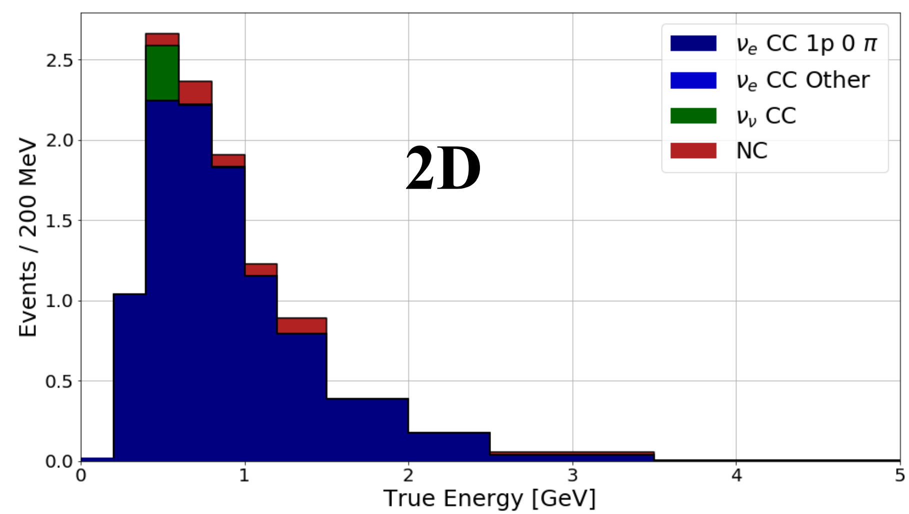
CCQE Like Selection

Require: nueCC, 1 proton, no pions of any kind.



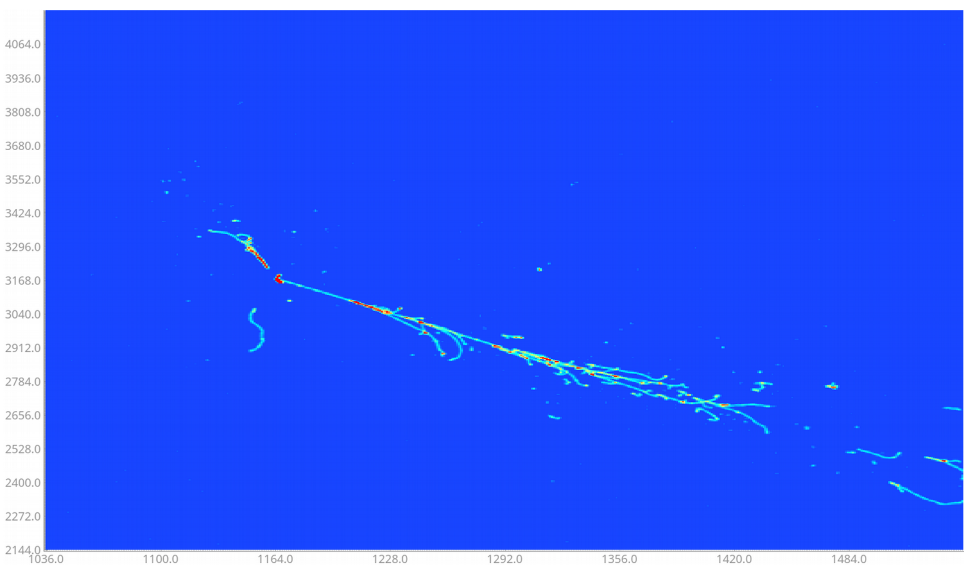
Takeaway: high granularity in is important for particle ID (such as protons)

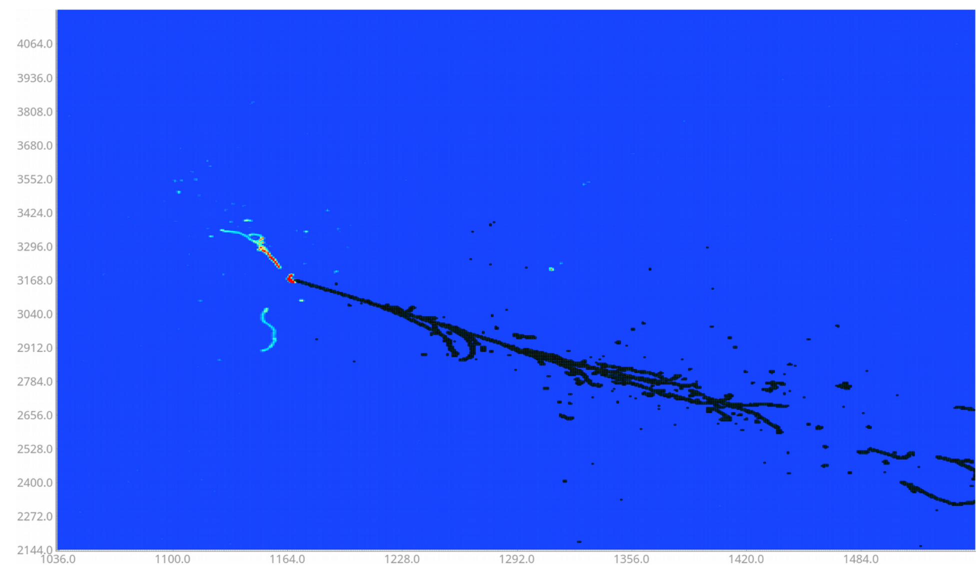




Towards Neutrino Energy

We can use a pixel labeling network to discriminate between the charge depositions from the primary lepton and everything else.



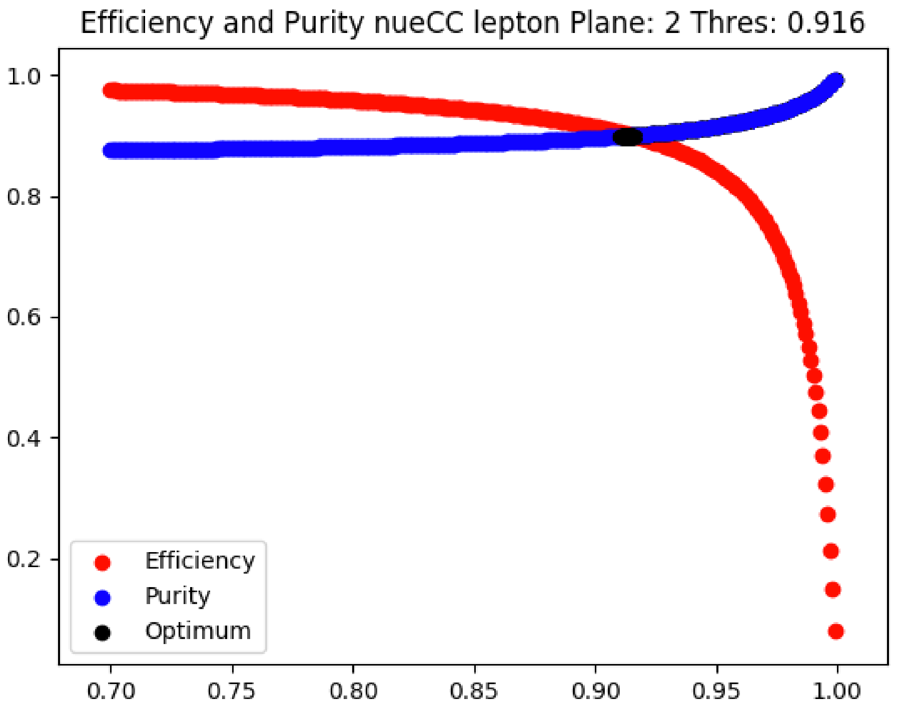


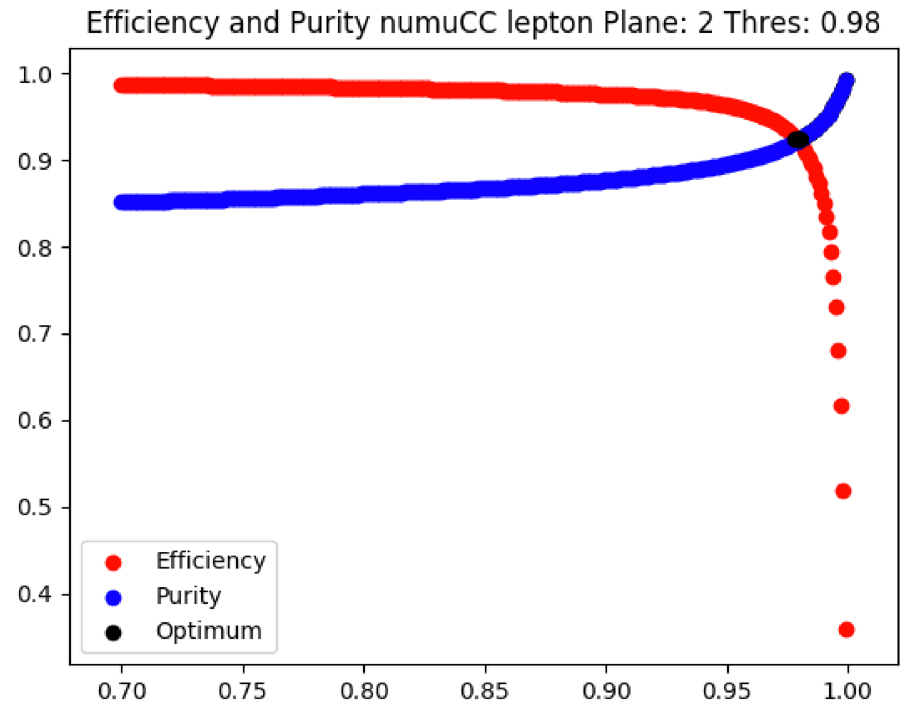
This is just a short hop from neutrino energy and a demonstration of the ability of deep learning to quickly get to physics results.

If you have the lepton pixels correct, you could use (for example) CCQE energy reconstruction

Towards Neutrino Energy (2D)

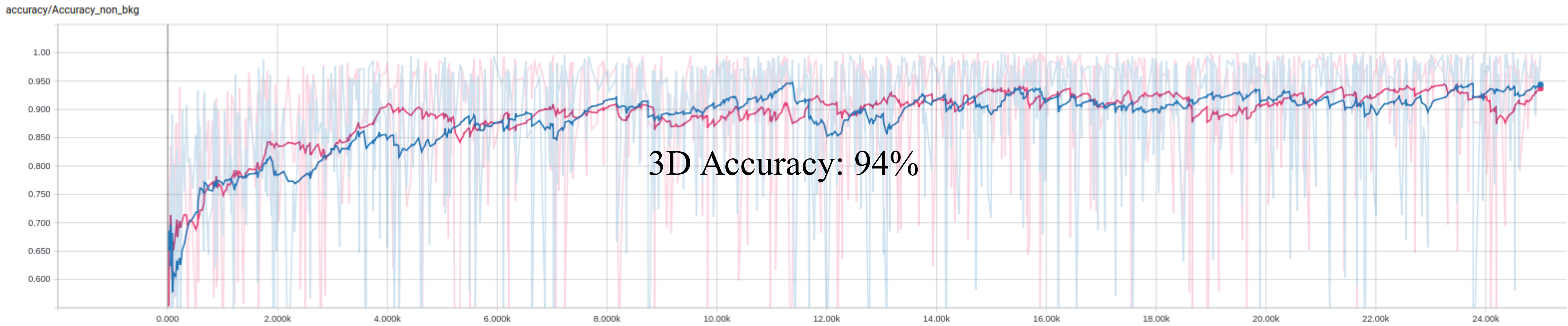
Efficiency: number of lepton pixels classified as lepton
Purity: percent of pixels predicted to be lepton that are actually lepton

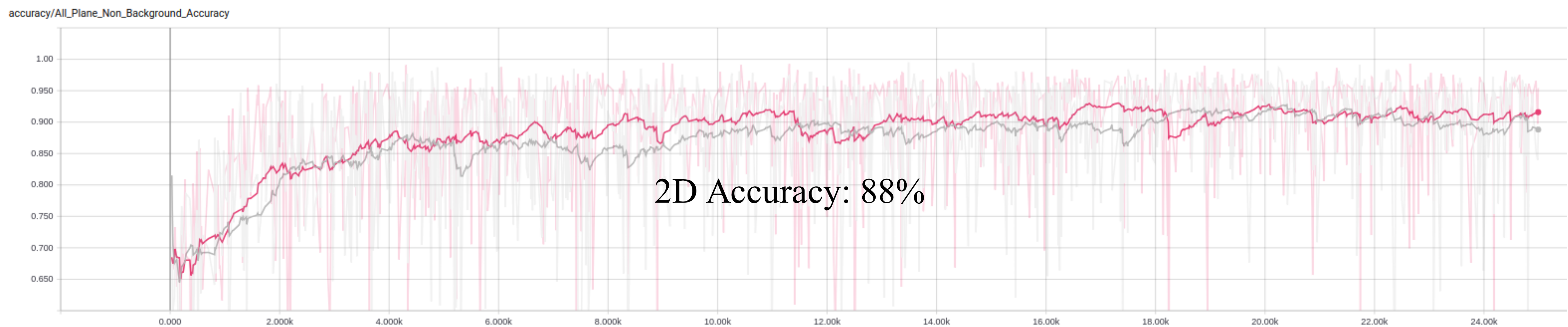




Takeaway: network can tag 90% of the lepton pixels (electron on muon) with 90% purity.

Neutrino Energy (2D vs 3D)

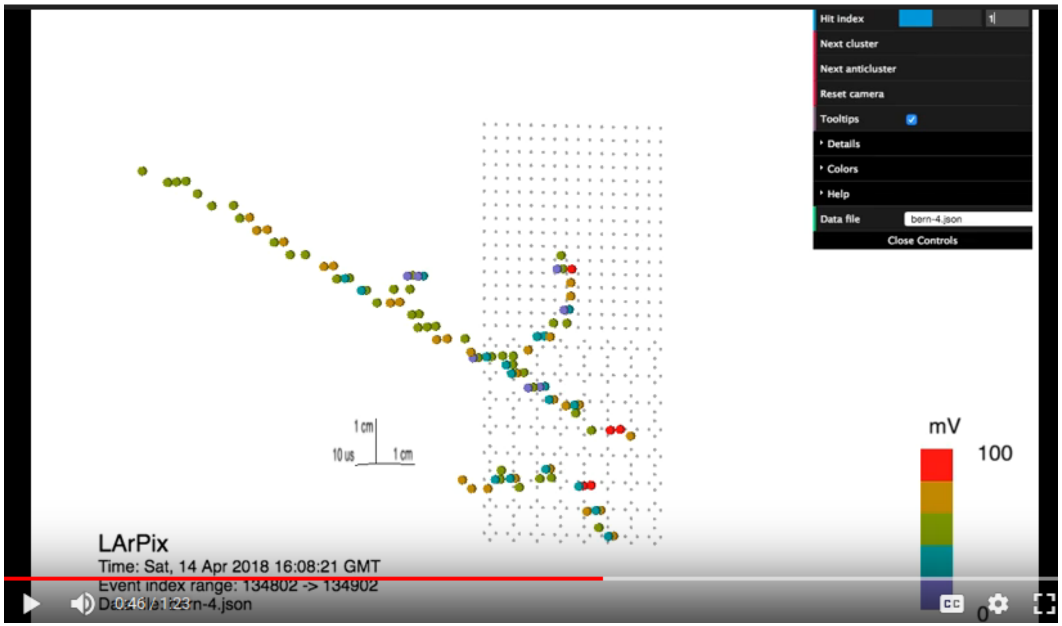




Takeaway: 3D network is performing better at lepton classification task even at 1.2cm voxels – better spatial information

Looking Forward

We've learned a lot about what's important in comparing 2D and 3D.



It's time to update the 3D model with as close-to-expected performance as we can.

We have to address some technical issues to get to full 3D resolution for a full result.

Deep learning has been a good tool for getting quickly to physics results, and will allow to update and produce robust physics conclusions.

With updated flux and simulations, and solved technical issues, we have a credible path forward to quantify 2D vs 3D with physics information.

Also ...

We've learned a lot about what's important in comparing 2D and 3D.

No more Saturday meetings.

With updated flux and simulations, and solved technical issues, we have a credible path forward to quantify 2D vs 3D with physics information.