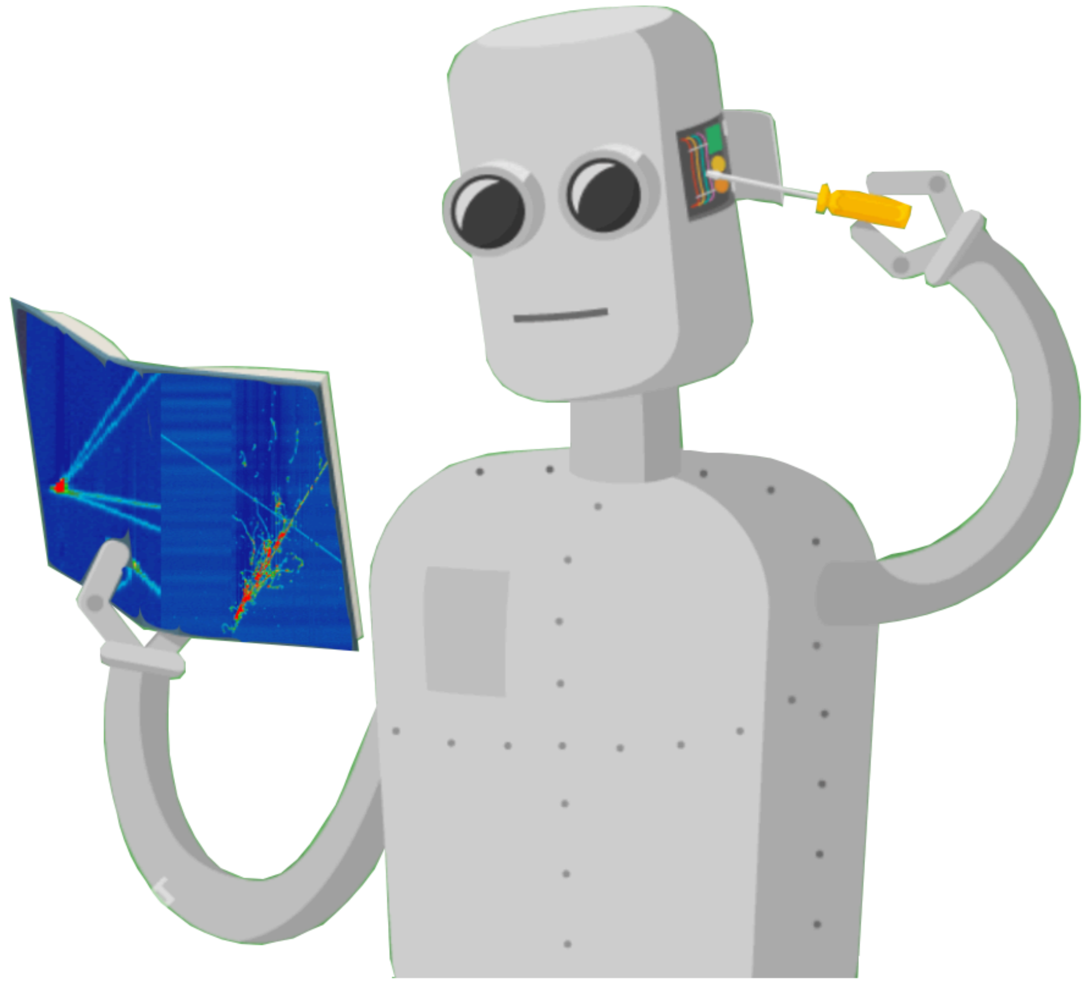
A Multiple Particle IDentification Convolutional Neural Network for LArTPC



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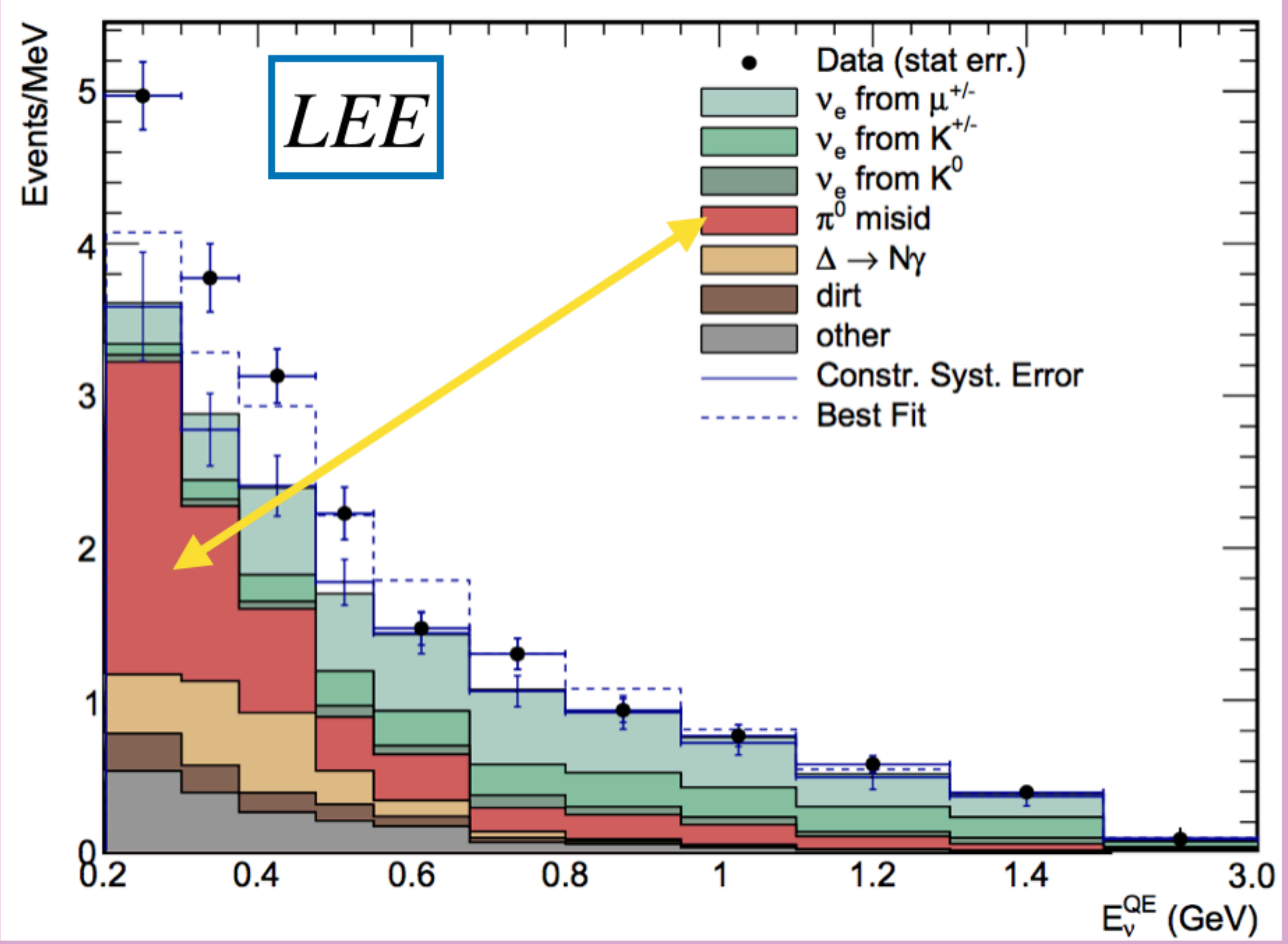
On Behalf of MicroBooNE Collaboration

Why MPID ?



MiniBooNE ν_e measurement shows a significant excess of ν_e-like interactions below 500MeV (Low Energy Excess) with:

- Large misidentification (mis-ID) rate from π^0.
- γ is then a potential unaccounted background for ν_e detection

Liquid argon time projection chambers (LArTPC) has shown great ability in the e^-/γ separation. We present a MPID CNN network developed MicroBooNE's LArTPC addressing the PID challenge.

What is MPID ?

Multiple particle identification (MPID) network,

- A convolutional neural network application.
- Takes as input,
  - reconstructed interaction,
  - full pixels around vertex as input.
- Calculates the probabilities of having particles among e^-, γ, μ^-, $\pi^\pm$ and $proton$.

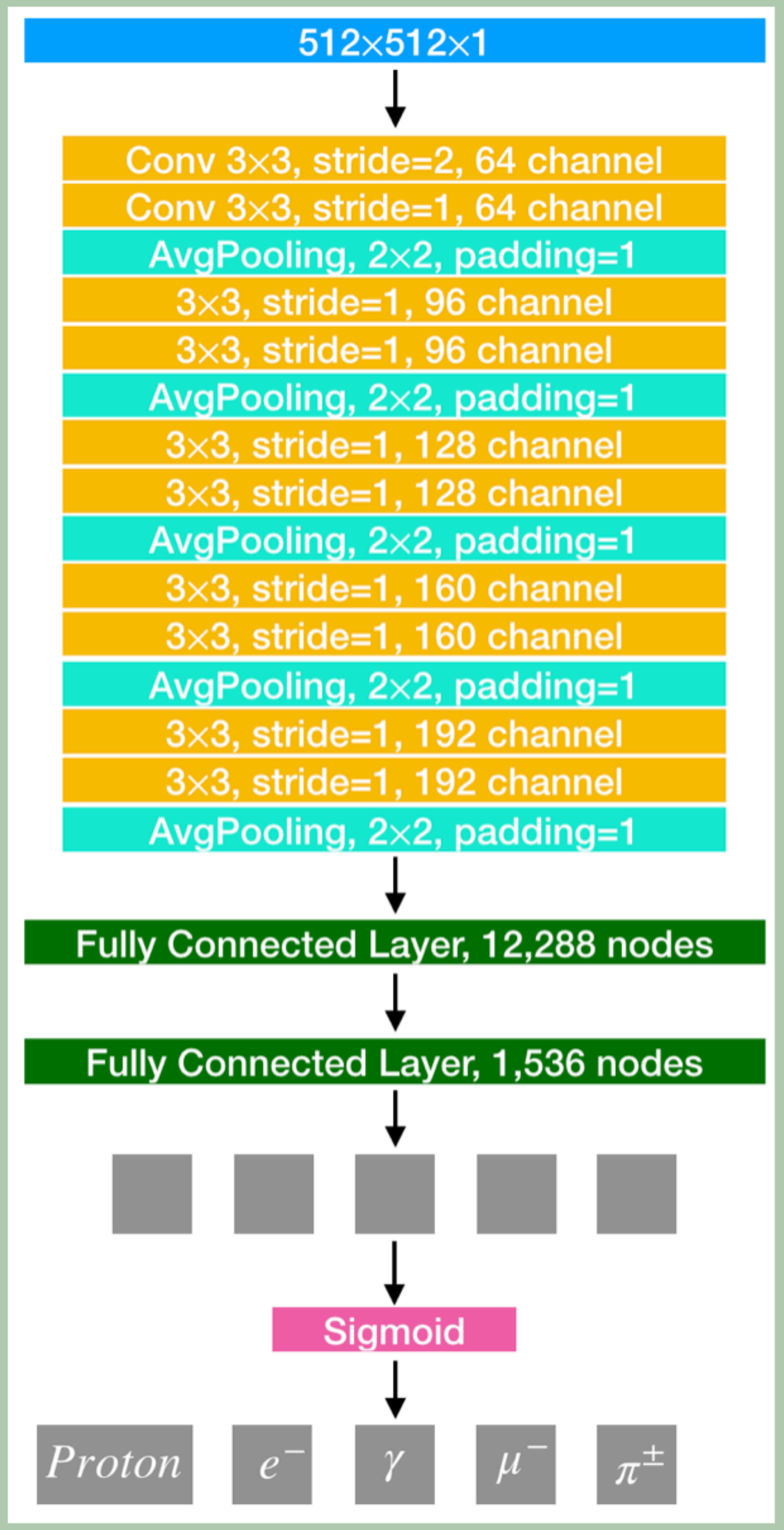
An important PID tool in MicroBooNE's deep learning based LEE analysis.

- Retains PID handle even vertex reconstruction has an offset or particles are not fully reconstructed.

Three questions we ask when applying a Deep Learning tool to physics:

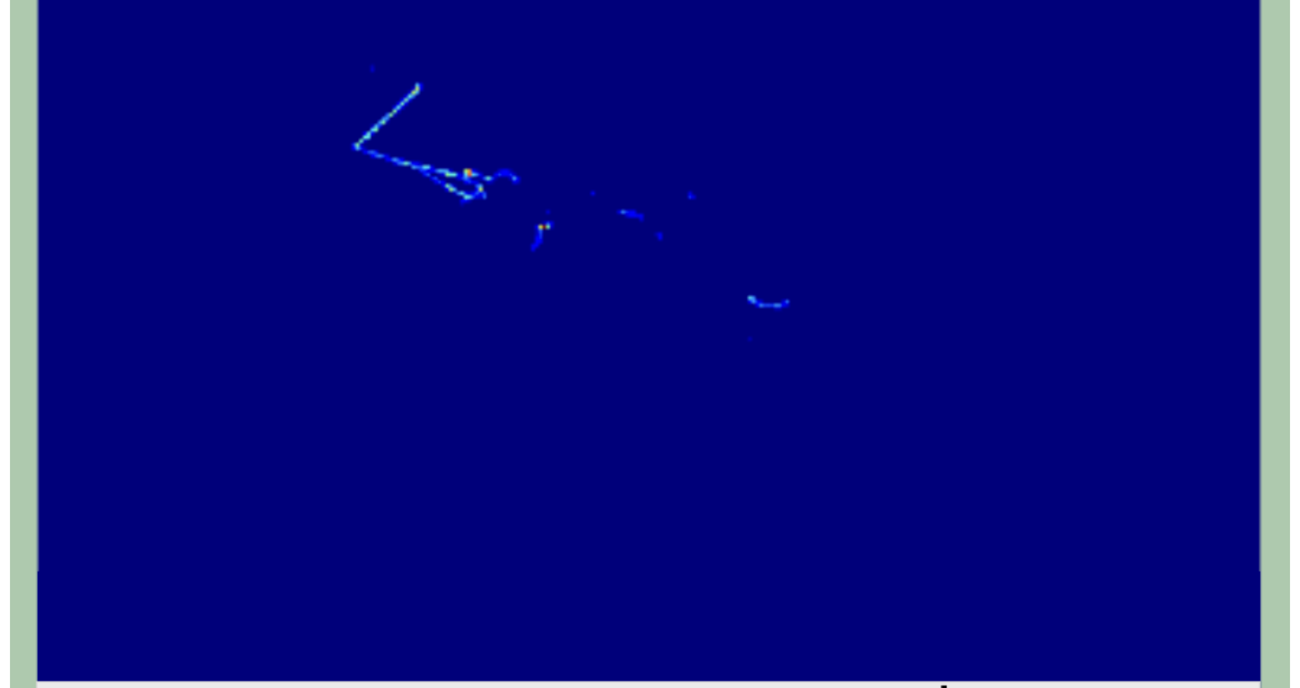
Q(1): How to make sure the network is not biased by neutrino models?

- Generate training and test samples using particle guns.
- Single particles are then concatenated at a random vertex.



MPID on Simulation Example I: $1e-1p$

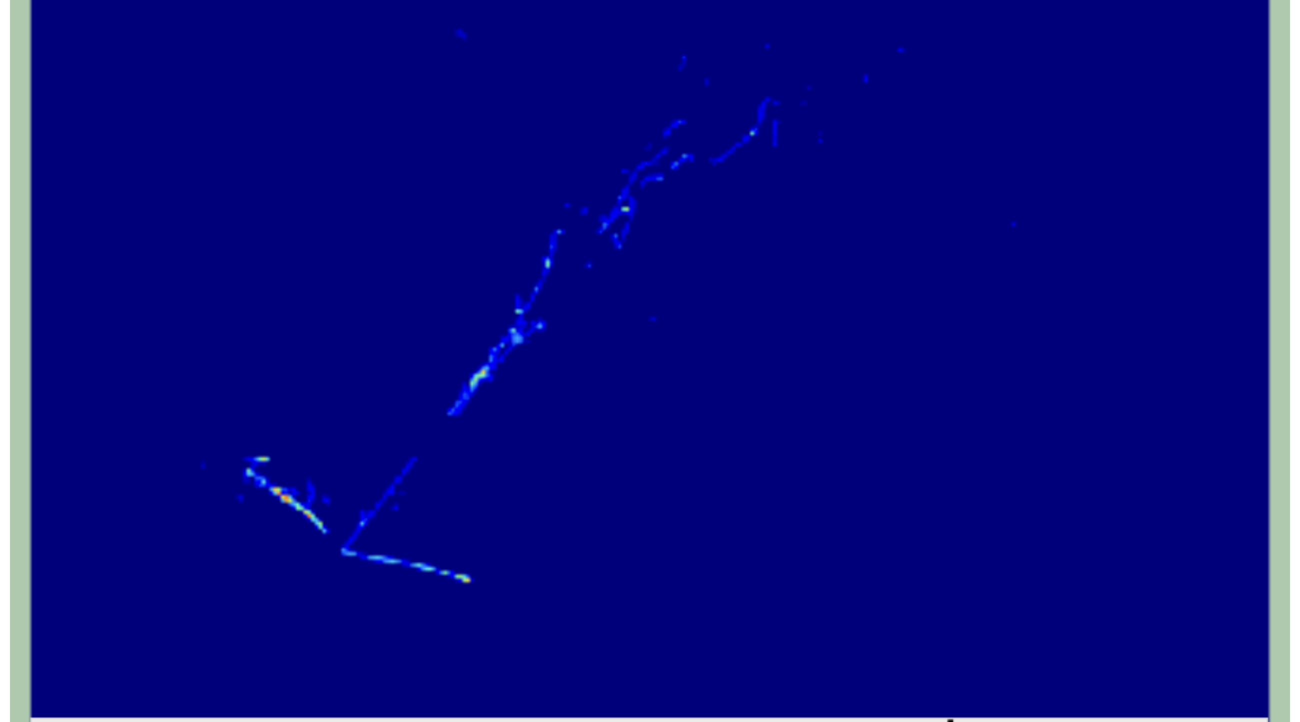
µBooNE Preliminary



e^-	γ	μ^-	$\pi^\pm$	$proton$
0.98	0.1	0.02	0.03	0.97

MPID on Simulation Example II: $1e-1\gamma-1p$

µBooNE Preliminary

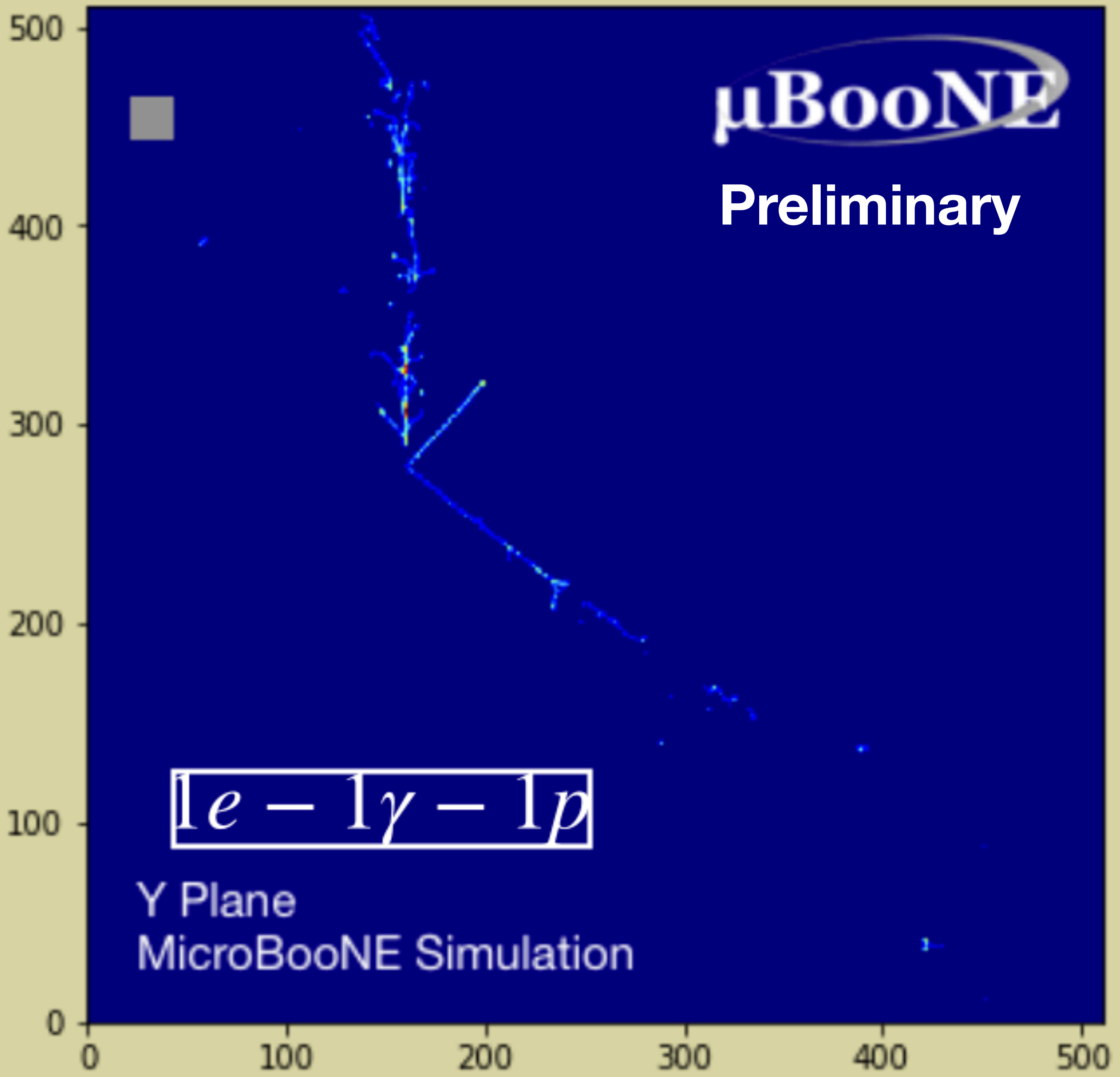


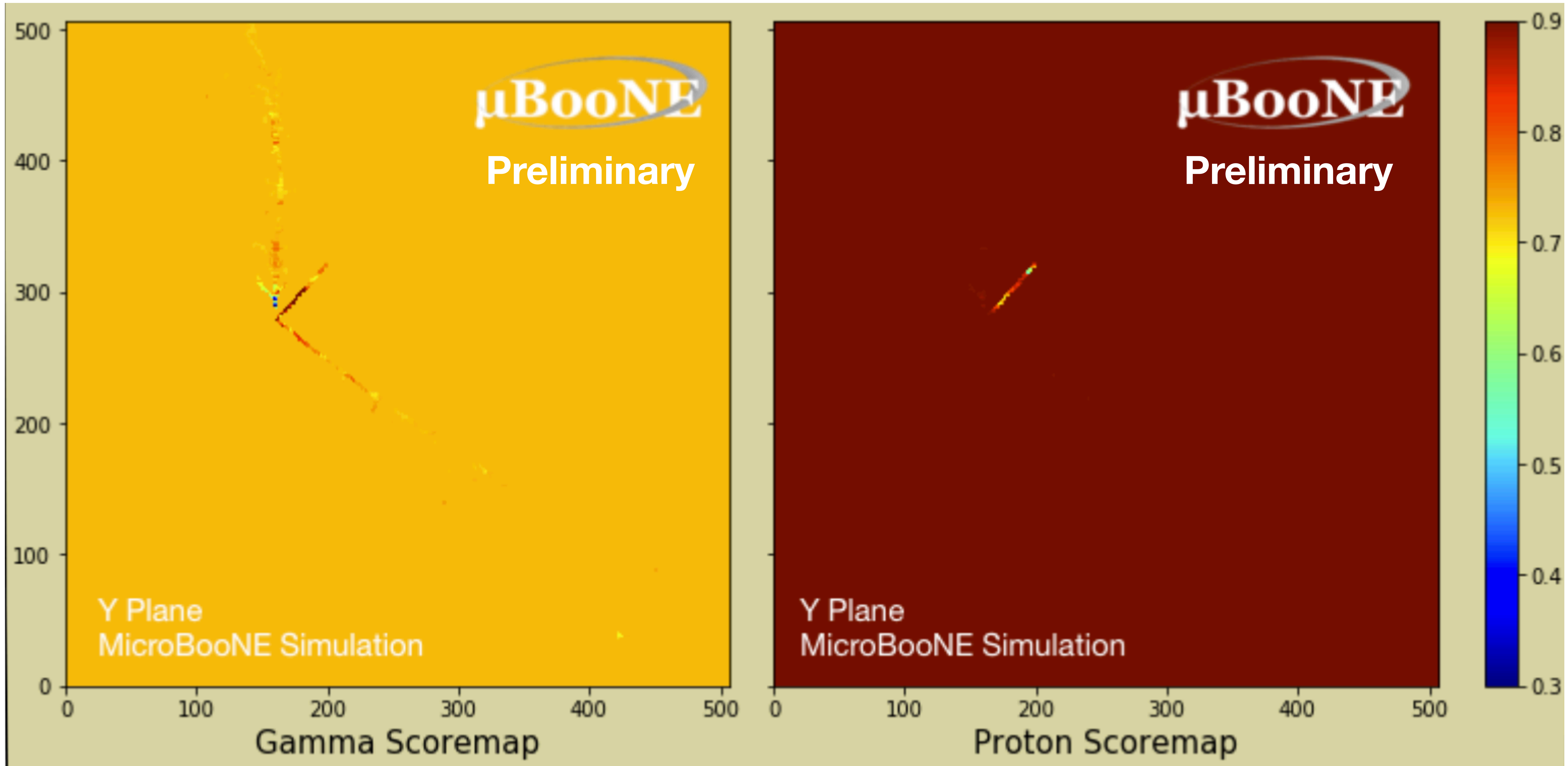
e^-	γ	μ^-	$\pi^\pm$	$proton$
0.63	0.98	0.02	0.08	0.97

What has MPID learned?

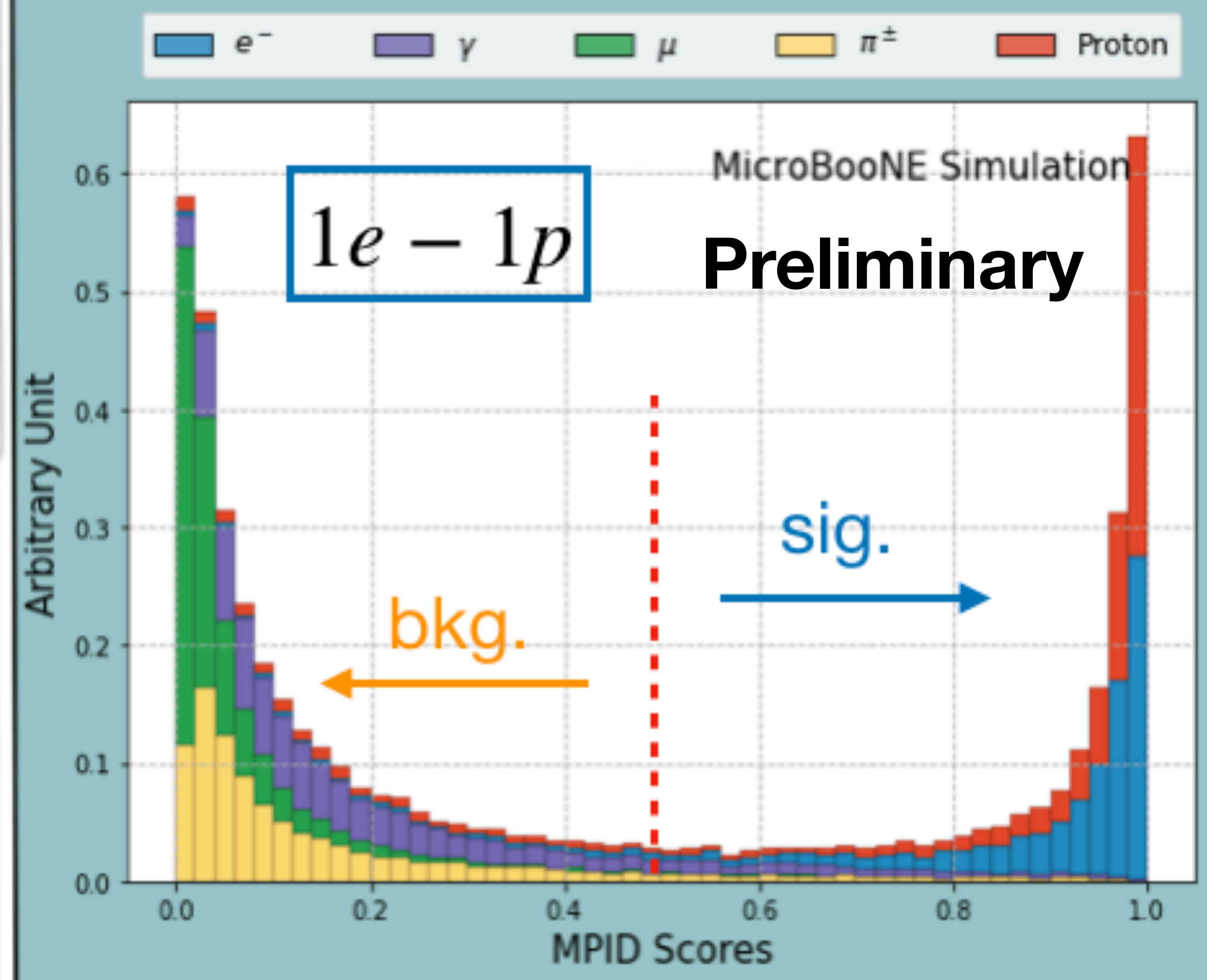
<u>**Q(2):** How to make sure network has learned physics to make the prediction?</u>

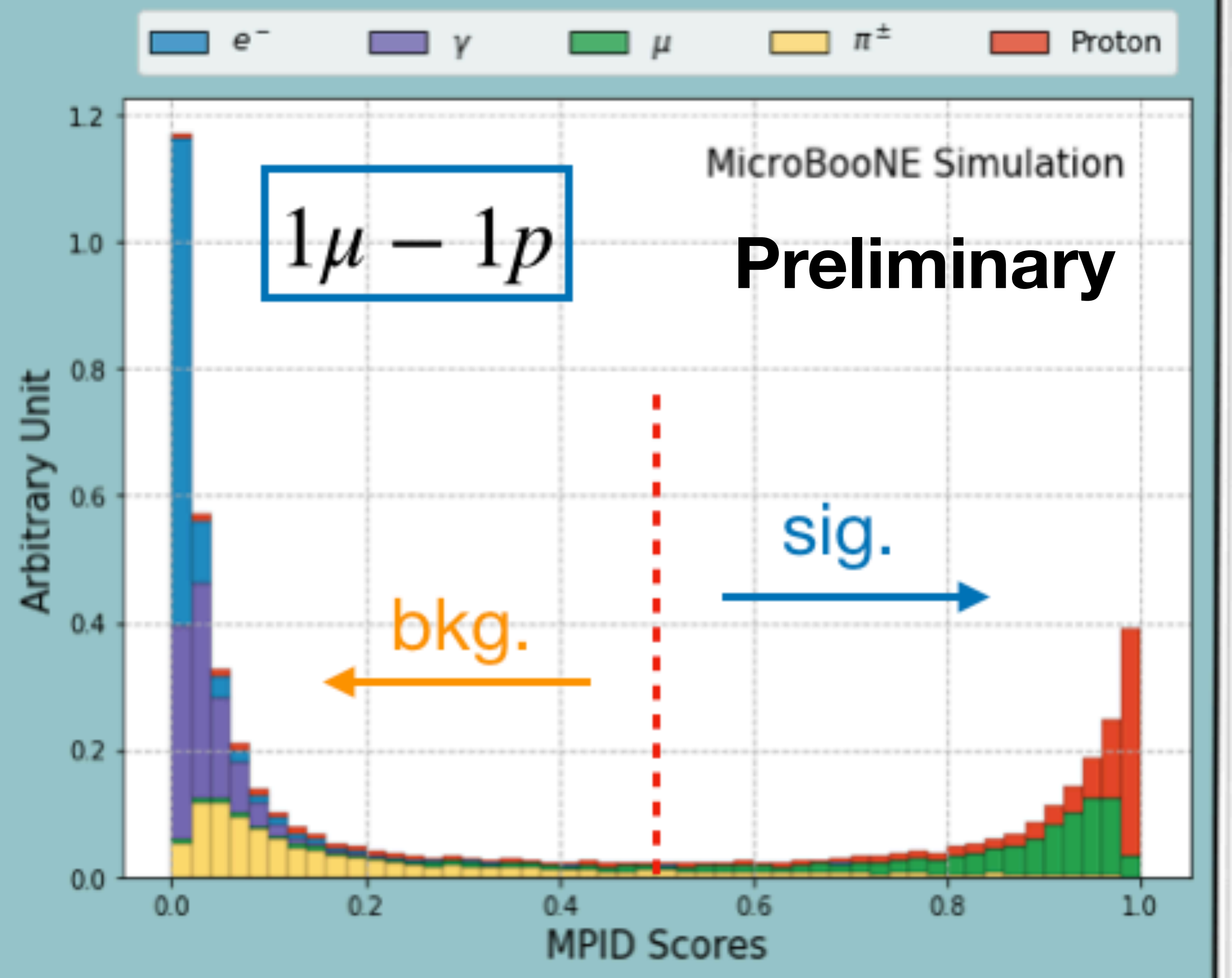
- Peak with an **<u>occlusion analysis</u>**.
- Validate network responses when 9x9 pixels are masked with zeros.
- γ score drops when the γ trunk regions are masked,
- p score drops when the p Bragg peak regions are masked.





Does MPID work on Simulation?





Sample I: $1e-1p$,

- Signal interaction for LEE, contains one e^- and one $proton$.

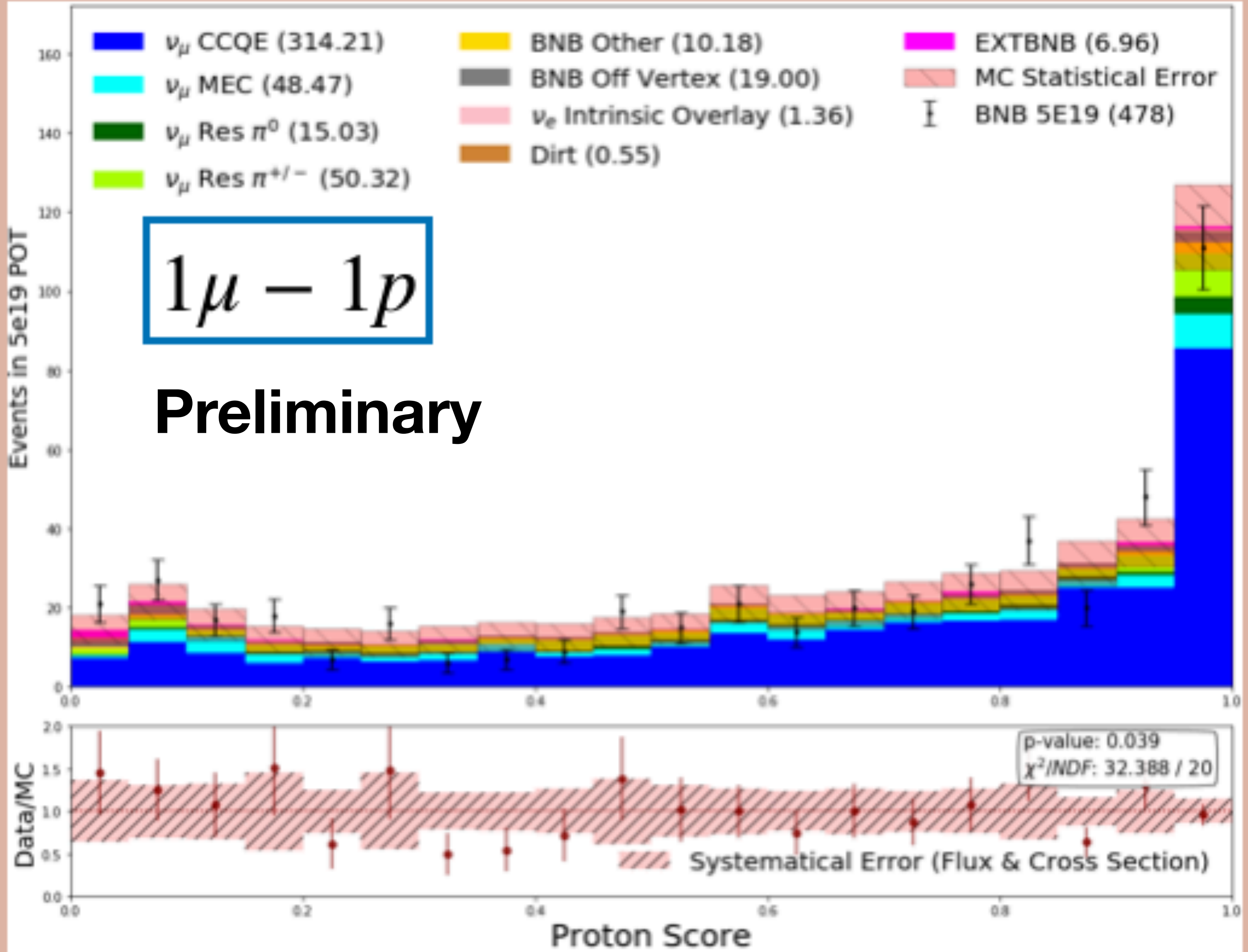
Sample II:$1\mu-1p$,

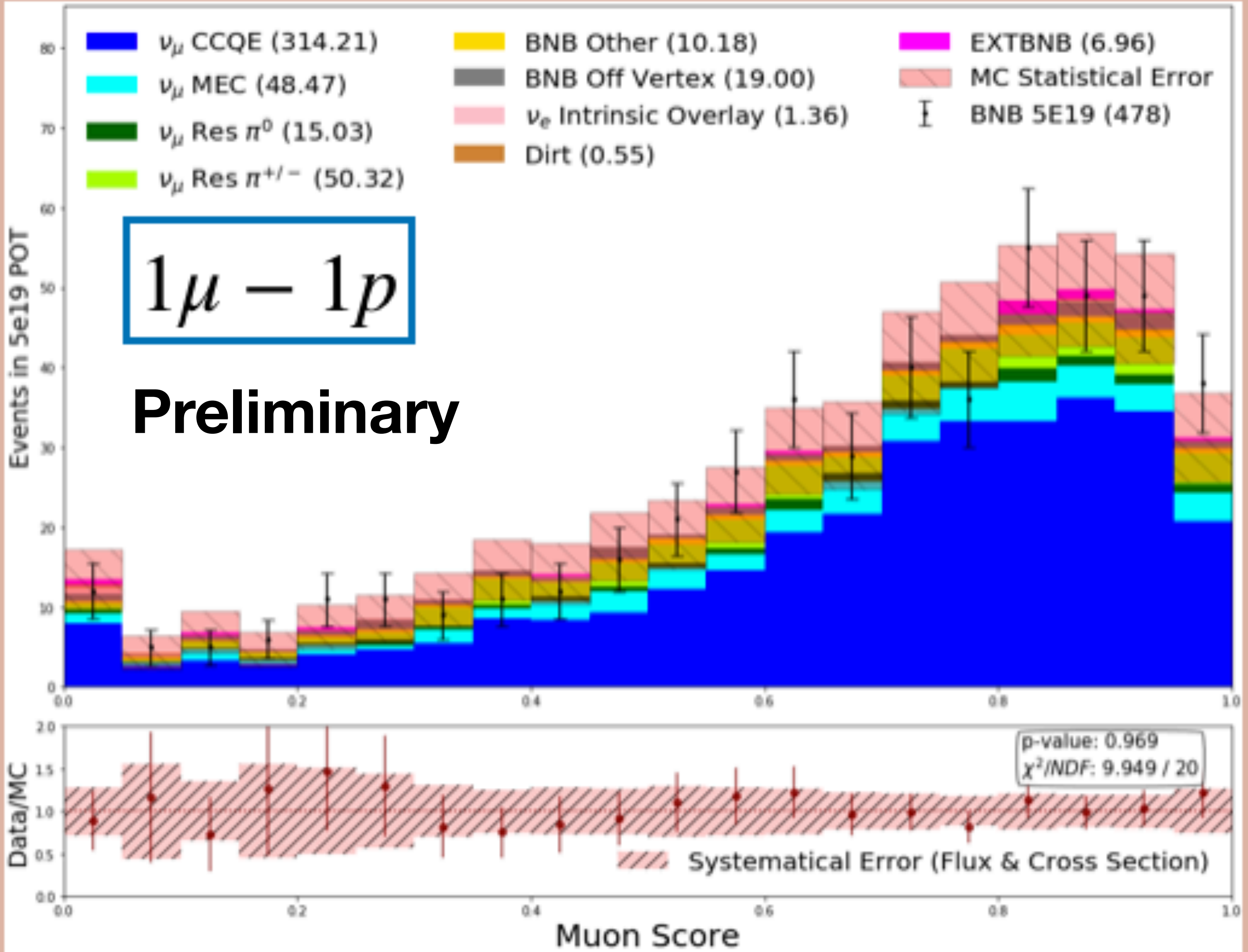
- largest beam flux used for constraining, has one $\mu^-$and one $proton$.

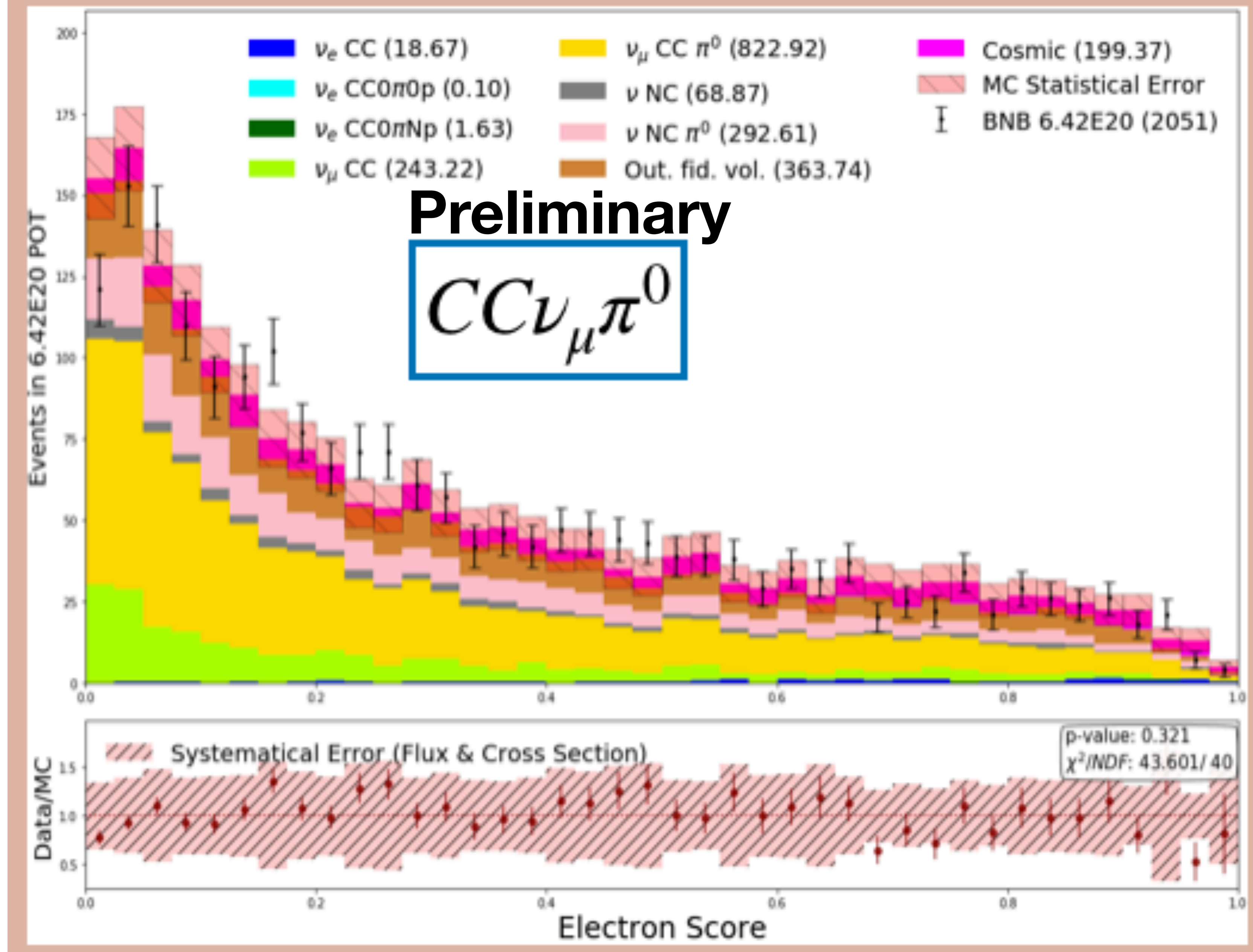
Excellent MPID prediction over the two golden simulation samples.

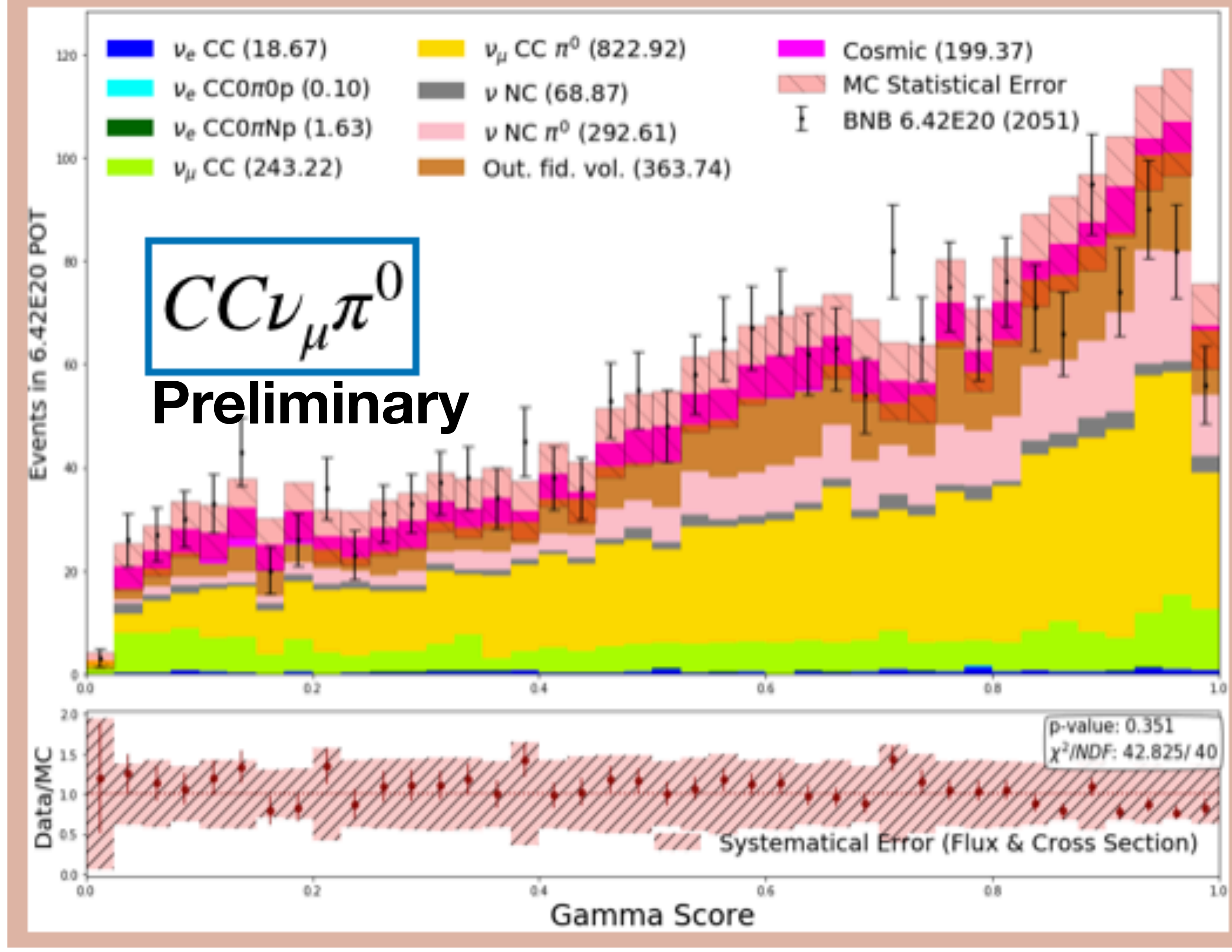
- $1e-1p$, 82% and 91% efficiency tagging $proton$ and e^-. 15% mis-ID from γ and 1% mis-ID for μ^-, $\pi^\pm$.
- $1\mu-1p$, 82% and 85% efficiency tagging $proton$ and μ^-. 13% mis-ID from $\pi^\pm$ and less than 1% mis-ID for e^-, γ.

Does MPID work on Real Data?









Q3: Does the network work as good on real data?

- Check MPID's performance from datasets selected without MPID.

Data sample I: $1\mu - 1p$ (67% purity)

- High scores of μ^- and $proton$ existences, low scores for other particles.
- Good data-MC agreements with χ^2/NDF at 32.4/20 and 9.9 /20.

Data sample II: $CC\nu_\mu\pi^0$ (58% purity, input images have cosmic rays), **selection**

- High score for γ and low score for e^- existences.
- Good agreements with χ^2/NDF at 43.6/20 and 42.8 /20.
- Robustness of MPID (trained on images with no cosmic rays.)

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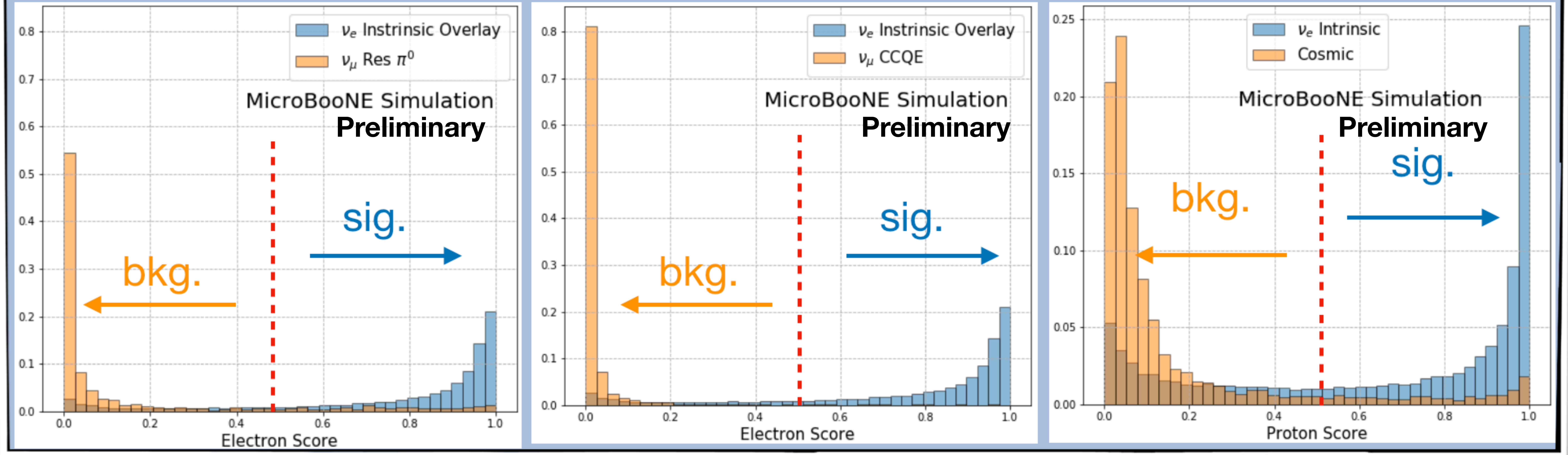
How does MPID help LEE in $1e-1p$?

- Using electron score only,
  - ν_e vs. $\nu_\mu\pi^0$, 91% selection efficiency, 76% rejection rate.
  - ν_e vs. CCν_μ, 91% selection efficiency, 95% rejection rate.
- Using proton score only, ν_e vs. cosmic rays, 81% selection rate, 79% rejection rate.



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