





Office of Science



# Reconstructing v<sub>µ</sub> with Deep Learning in MicroBooNE

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# Low Energy v<sub>e</sub> appearance Excess MicroBooNE experiment MicroBooNE LEE searches The Deep Learning LEE search





# Low Energy Excess

- LSND and MiniBoonE observed an excess of v<sub>e</sub> appearance at low energies
- Best fit in tension with global 3+1 neutrino models

MiniBooNE Detector







# Low Energy Excess



(here we call signal a  $2\sigma$  effect)

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Disappearance

Appearance

# Fermilab Neutrino Beamlines

Booster v beam MiniBooNE, MicroBooNE, SBN program

**Booster** proton energy : 8 Ge\

**DUNE v beam** 





### The Booster Neutrino Beamline



- 8 GeV protons from the Booster, beam spill at 5Hz
- Hosts the Short Baseline Neutrino Program :
  - SBN Near Detector
  - MicroBooNE
  - ICARUS
- Definitive test of LSND oscillation using three baselines

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• 3 detectors, same target nucleus, same operational technology Simultaneous vµ disappearance and v<sub>e</sub> appearance searches



# The MicroBooNE Experiment

- MicroBooNE is a neutrino experiment using a Liquid Argon Time Projection Chamber (LArTPC)
- Physics Goals of MicroBooNE :
  - To investigate the MiniBooNE and LSND ve appearance excess at low energy – to confirm or deny potential evidence for sterile neutrinos
  - To measure neutrino-argon cross section around 1 GeV
  - To pursue R&D studies for LArTPC operations and exploitation for larger programs (SBN, protoDUNE, DUNE)









### The MicroBooNE Detector









- Micro Booster Neutrino Experiment
- 85 ton active mass Liquid Argon TPC
- $v_{\mu} \rightarrow v_{e}$  appearance experiment
- Booster Neutrino Beam-line
- Taking data since October 2015
- Cosmic ray tagger added in 2016
- > 97% detector up time
- 1.1x10<sup>21</sup> POT delivered



### The MicroBooNE Detector



- Time Projection Chamber
- 85 active tons of Liquid Argon
- 32 cryogenic PMTs
- 2400 U-wires (+60°)
- 2400 V-wires (-60°)
- 3456 Y-wires (vertical)
- 3mm wire pitch









### Raw Event Example







### The MicroBooNE Detector



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- A charge deposition in the detector drifts into a "unique" combination of U,V and Y wires
- There is actually a time degeneracy
- In the drift dimension, we need a T0, and the • known drift speed to get the position
- T0 is given by
  - trigger time (we know when neutrinos interact)
  - PMT signal



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### LArTPC : why are they so cool?



- LArTPCs produce bubble chamber-like images!
- Able to "see" the interaction
  - more "intuitive"
  - rely less on the light production model
  - can use event topology to reject background
- LArTPCs are ~1000x faster than bubble chambers
- LArTPCs produce digitized images, processed by computer











# LArTPC : why are they so hard?





- Huge amount of data to process
- Pattern, topology (i.e. kinematics) is an important parameter, need algorithms smart enough to recognize them without bias and recognize backgrounds
- Some events are hard to identify, even for a trained human!







# The Road to Low Energy Excess

### Commissioning

### **Detector Physics**

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### Low Energy Excess Investigations

### **Cross section measurements**

### Reconstructions



# **Recent Physics Results**

### **CC Inclusive Cross Section**











# Signal Definition







- Excess region at low energy, dominated by CCQE process Most events with simple topology





### Signal Definition



- We will be focusing on a 1 lepton and 1 proton topology:
  - 1 e or  $\mu$  with KE > 35 MeV
  - 1 p with KE > 60 MeV
  - any number of tracks below threshold
- We will work under the assumption of a CCQE interaction





### Machine Learning



### Categorization

- LArTPCs provide high resolution pictures of neutrino interactions
- Convolutional Neural Networks (CNN) are design to identify content of images (i.e. self driving cars, bio imagery, etc.)
- CNN look for patterns, most basic => more complex

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#### Detection



#### **Semantic Segmentation**







# Machine Learning for LArTPC

#### flower

Green = nature



Bird (Golden-crowned kinglet)



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- CNNs look for patterns, pattern associations on rich images
- LArTPCs images are mostly empty (99% of pixels are empty)
- Neutrinos interactions are a small fraction of the total image
- Particles are mostly **tracks or shower**, without much pattern

"Convolutional Neural Networks Applied to Neutrino Events in a Liquid Argon Time Projection Chamber" JINST 12, P03011 (2017)







# Analysis Chain

### MicroBooNE images

### Cosmic tagger

Track/shower separation

### v<sub>e</sub> selection

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### 3D reconstruction

### Multi part. PID

### $v_{\mu}$ selection

and the second



### **Cosmic Tagger**





- Follow the charge distribution from one end to the other
- Tracks with only one exit point are labelled as "stopping muons"
- Only "contained" charge remains (no entry/exit point)





# **Semantic Segmentation Networks**

- SSNets identify the content of an image, and work the convolution chain back to the location of the identified objects
- Pixel-level identification
- Trained to recognize tracks to shower
- Track/shower boundaries can be potential vertex!
- How to validate such network?











### **Network on Data**

- Run on a data sample (selection of  $v_{\mu}$  CC $\pi^{0}$  events)
- "Truth" labelled by a trained human physicist

### Input Image

### Human Labeling



"A Deep Neural Network for Pixel-Level Electromagnetic Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber "arXiv:1808.07269, submitted to PRD

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Network trained on a simulation sample to identify tracks and showers

### **Network Labeling**



### Vertex Finding



- Identify potential neutrino vertices
- Use SSNet's output track-only and shower-only images
- OpenCV libraries for image processing
- First, identify seeds in each image separately
  - Track/shower boundary
  - Kinks on tracks













- Break down the track-only pixel cluster in sub-clusters :
  High-Charge / Low-Charge
  Linear clusters
- Fit each linear clusters by a line (Principal Component Analysis)
- Vertex Seeds are the cluster break-down points and PCA crossing points



### **Best Seed Position**









- Scan the track-only pixels around found vertex seeds
- For each location, draw a circle centered on the considered point
- Look for crossing points
- define angles  $\theta$  and  $\Phi$
- Optimal seed position is achieved when  $\theta \sim \Phi$



### **Best Vertex Location**



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Seeds are then compared across images

- temporal coincidence
- 3D consistency
- only 2 prongs coming out of the vertex
- Cluster pixels coming out os the reconstructed vertex point

### Spatial resolution of the vertex finding:

68% of the neutrino candidates have a reconstructed vertex within **0.75 cm** of the true vertex





### **Track Reconstruction**



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Random points in 3D in:

### Sphere around the last found point

 "physics independent" : no assumption on expected curvature radius, kinks, ...

### • Forward cone

- $r_{cone} = 2.r_{sphere}$
- $\theta_{open} = 30^{\circ}$
- average direction of last 10 cm of the track
- Assumes a globally straight track
- Helps jumping over dead regions and faint tracks

**MICROBOONE-NOTE-1042-PUB** 



### **Reconstruction Example**



- Kinetic energy from the reconstructed range
- Proton/muon candidate based on average pixel intensity
- Neutrino energy :  $E_{\nu}^{\text{range}} = \text{KE}_{p}^{\text{range}} + \text{KE}_{\mu}^{\text{range}} + m_{\mu} + m_{p} m_{n} + B$
- B is an effective nuclear binding energy for the CCQE interaction (~40 MeV)

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true		
Εv	= 974.8 MeV	
KE μ	= 602.9 MeV	
KEp	= 225.9 MeV	

#### reconstructed = 993 MeV KE $\mu$ = 626.8 MeV $KE_{p} = 220.6 \text{ MeV}$



### Tracking diagnostic

- At the end of each track throw 3D points in a forward spherical cap of radius 3 cm and opening angle 37°
- 3 possible cases:
  - points in dead region
  - points in empty region
  - points on a non-empty region
- All in empty pixel = reached end of track
- 2 planes in dead regions and 1 plane empty = tracker stopped in dead region
- Other cases are failing in the middle of tracks Attribute a "good reconstruction" label to each track found in the vertex

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NE-NOTE-1042-PUE MICROBOC

### **Reconstruction Example**



• Reach dead wires in two planes :

- Estimate direction before dead wires
- Push through dead region
- hopefully reconnect to rest of the track
- Mange to recover ~20% additional events

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Eν	=	496.5	MeV
$KE_{\mu}$	=	195.5	MeV
$KE_p$	=	157.1	MeV

 $E_v = 498$  MeV KE  $_{\mu}$  = 201.2 MeV





### **Angular Resolution**



- - with respect to the X axis
- Define the opening angle as the angle between two tracks



### **Track Reconstruction performances**



- Kinetic energy estimated on the range of the reconstructed tracks
- Residual error show no systematic bias with respect to true kinetic energy
- About 4% energy resolution on each individual particle





### **3 energy definitions**

$$E_{\nu}^{\text{range}} = \text{KE}_{p} + \text{KE}_{\mu} + M_{\mu} + M_{p} - (M_{n} - B)$$

$$E_{\nu}^{QE}[p] = 0.5 \cdot \frac{2 \cdot (M_{n} - B) \cdot E_{p} - ((Mn - B)^{2} + M_{p}^{2} - M_{\mu}^{2})}{(M_{n} - B) - E_{p} + \sqrt{(E_{p}^{2} - M_{p}^{2})} \cdot \cos \theta_{p}}$$

$$E_{\nu}^{QE}[\mu] = 0.5 \cdot \frac{2 \cdot (M_{n} - B) \cdot E_{\mu} - ((Mn - B)^{2} + M_{\mu}^{2} - M_{p}^{2})}{(M_{n} - B) - E_{\mu} + \sqrt{(E_{\mu}^{2} - M_{\mu}^{2})} \cdot \cos \theta_{\mu}}$$

- Access to the full kinematics of the muon and the protons

- All three energies should (roughly) agree for 111p CCQE events, but not for more complex topologies, or cosmic background
- The same can be done with an electron hypothesis in the  $v_e$  case

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• Assuming 1µ1p CCQE interaction, we can access the neutrino energy MiniBooNE used only the muon kinematics to estimate the neutrino energy



### **Track Reconstruction Performance**



- Estimate the resolution for:
  - contained  $1\mu 1p v\mu$  interactions,
  - true muon kinetic energy > 35 MeV,
  - true proton kinetic energy > 60 MeV
- Overall energy range : (2.2±0.1)%
- Evolution in 1/JE typically dominated by stochasticity

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•  $81\%/\sqrt{E(MeV)} = 2.5\%/\sqrt{E(GeV)} = meets DUNE resolution target$ 

![](_page_35_Picture_15.jpeg)

# **MICROBOONE-NOTE-1042-PUB**

![](_page_35_Picture_17.jpeg)

### Particle ID

- around the reconstructed tracks

![](_page_36_Figure_3.jpeg)

"Convolutional Neural Networks Applied to Neutrino Events in a Liquid Argon Time Projection Chamber" JINST 12, P03011 (2017)

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Use a categorization CNN to identify contents of the image centered

• Classify the probability of presence of 5 types of particles :  $p,\mu,\pi,e$  and  $\gamma$ 

![](_page_36_Figure_8.jpeg)

![](_page_36_Picture_9.jpeg)

![](_page_36_Picture_10.jpeg)

# **Data/Simulation Comparison**

- We developed a chain of reconstruction and selection of neutrinos based on MC studies
- Need to ensure their performance on data
  - Respect blindness : small data sample of ~4x10<sup>19</sup> POT
  - Off-beam sample for cosmic rays studies
  - MC sample of beam neutrino interactions
- Simulated beam neutrino interactions and cosmic sample are normalized to 4x10<sup>19</sup> POT and for a predicted spectrum to be compared to data
- Look for significant shape-only differences

![](_page_37_Picture_11.jpeg)

# **Data/Simulation Comparison**

![](_page_38_Figure_1.jpeg)

- No significant distortion in data compared to predictions (within our statistically limited sample) Reconstruction, identification and selection seem to behave similarly on data and Monte Carlo

![](_page_38_Figure_5.jpeg)

![](_page_38_Picture_6.jpeg)

![](_page_39_Picture_1.jpeg)

- **Currently available :**  $\bullet$ 
  - Beam flux uncertainties  $\bullet$
  - v-Ar uncertainties
  - Oscillation fit and sensitivity study machinery  $\bullet$ taking into account full systematics

- In progress : detector-based systematics:  $\bullet$ 
  - One simulated beam neutrino sample
  - Vary detector parameters in multiple possible "universes"
  - Build correlations and covariance matrices from the universes

![](_page_39_Picture_11.jpeg)

# Coming soon

![](_page_40_Figure_1.jpeg)

![](_page_40_Picture_2.jpeg)

![](_page_40_Picture_3.jpeg)

- 2D deconvolution : tracks clearer, easy to follow
- Wire-to-wire cross-talk better accounted for

- between the planes

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![](_page_40_Picture_9.jpeg)

 Work on a new SSNet that learns spatial coherence Knows about rotations

- Work on a new CNN to fill in gaps in images
- No more dead wires!

![](_page_40_Picture_13.jpeg)

### Conclusions

- MicroBooNE employs a novel technology to investigate MiniBooNE's low energy excess
- Several analyses in parallel, developing independent tools that can be valuable for later LArTPC programs
- shows good maturity of the chain
- reliability of the predictions and robustness of the Monte Carlo events

Data/prediction only show minor disagreement (not statistically significant),

Upcoming improved signal processing and neutrino generators will improve

![](_page_41_Picture_9.jpeg)

![](_page_42_Picture_0.jpeg)

![](_page_42_Picture_2.jpeg)