From Pixels to Neutrinos
Convolution Neural Networks Applied to the MicroBooNE experiment

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Outline

Discuss efforts on the MicroBooNE experiment to use convolutional neural networks to improve physics analysis

- What are we trying to solve with CNNs? -- and why?
- From physics problem to ML problem
- Current Analysis Effort
- Developments

“Eyes” of the MicroBooNE detector -- a time-projection chamber,-- before installation
The MicroBooNE Experiment in a nutshell

“An accelerator neutrino oscillation experiment”
Neutrinos

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Neutrinos

Neutrinos are a type of the fundamental particle

Key stats:

- No electric charge
- Interacts only via weak force and gravity
- Very, very small mass: ~8 orders smaller than next heaviest particle!
- Come in three “flavors” -- based on what other particle they make during certain interactions
Life as Neutrino Physicist

No electric charge
=> observe indirectly

Only Weak Force
=> rare process

Flavor related to particle produced during certain interaction
=> key to identifying type
Neutrino Source

“An *accelerator* neutrino oscillation
*experiment*”

MicroBooNE uses a high-intensity beam of neutrinos made at
Fermi National Accelerator Lab
Neutrino Oscillations

“An accelerator neutrino oscillation experiment”

Goal is to look for evidence of Neutrino Oscillations

Flavor detected oscillations over distance traveled

Neutrino created in certain flavor ...
can later be detected in other flavor ...
or later in original ...
Neutrino Oscillations

Anomalies in other past experiments can be interpreted as oscillations occurring because of new flavor or neutrino

Exciting if true!
MicroBooNE setup

Beam created as almost entirely muon neutrinos

Given distance traveled and energy of neutrinos, **Should** be the case @ detector
MicroBooNE setup

But if consistent with past Anomaly (measured in same beam line)

We will see excess of electron neutrinos (at low energies)
Our target measurement, then, is the energy of neutrinos and the counts of the different flavors.

The detector, a liquid argon time projection chamber, provides high resolution images with which we can extract these measurements.
Capturing Images of Neutrino Interactions

1. Charged particles interact in Ar
   - Ionize electrons
   - Produce scintillation light
2. Ionized e- drift toward anode
3. Wire planes detect drift e-
Capturing Images of Neutrino Interactions

A neutrino (dashed grey) passes into the detector and interacts producing charged particles (solid yellow)

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Charged particles produce ionization electrons along path
(neutrino neutral and leaves no directy signature)
Capturing Images of Neutrino Interactions

Light also produced by charged particles.

Travels to sensors on short (ns) timescales.

Light provides timing for event -- and course position info.

GPU-accelerated photon simulation, showing final location of photons

Red: hit photo-sensor (PMT)
Blue: absorbed on surface
Green: absorbed in bulk
White-lines: particle trajectories
Capturing Images of Neutrino Interactions

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Ionization electrons drift towards wireplanes
Capturing Images of Neutrino Interactions

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Ionization induce detectable signals on nearby wires
Capturing Images of Neutrino Interactions

Three Wire Planes

U plane (induction) ⊕ V plane (induction) ⊕ Y plane (collection) =

8256 wires w/ pitch = 3mm
(Y, Z) = coincidence on wire
Capturing Images of Neutrino Interactions

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Combine timing and wire info. to get 3D reconstruction.

In principle: enough information for 3D reconstruction

(Y,Z) position of ionization recorded through coincident signals on different wire planes

X position given by time delay from light signal

"Cold" (in LAr) readout electronics greatly reduces the noise level
Capturing Images of Neutrino Interactions

Recording wire signals over time, detector produces image-like data.
Example of data event in MicroBooNE. View of same event for each projection.

Color scale indicates amount of ionization electrons seen on wire at given time.
Measurables in the image

Flavor determined from finding partner lepton (muon, electron) produced in interaction

Neutrino energy inferred from momenta of resulting particles

\[ \nu_\mu + n \rightarrow \mu + p \]

\[ \nu_e + n \rightarrow e + p \]
Measurables in the image

From ML perspective: **the problem is predicting class and energy from images**

We have simulations that can produce training examples with various labels

\[ \nu_\mu + n \rightarrow \mu + p \]

\[ \nu_e + n \rightarrow e + p \]
One approach: directly predict values

Example: CNNs have been used (another experiment) to predict the neutrino flavor

\( \nu_e \) interaction

\( \nu_\mu \) interaction

Aurisano, A. et al. JINST 11 (2016) no.09
One approach: directly predict values

Issue with training network to target final observable: modeling uncertainties

- Neutrinos hit constituents of the nucleus -- an extremely complicated system to model
- Neutrino energy inference influenced by knowing “type” of interaction
- Can produce particles that cause patterns which fake the signal (primary e.g. photons from interaction can look like electrons)

Risk of model errors being trained into the networks
MicroBooNE specific issue: backgrounds

For MicroBooNE, lots of backgrounds from cosmic rays since detector is on the surface.

Requires parsing of image to find neutrinos.

Images with target events only 1 in 1000-10,000.
DL Reconstruction

Our goal is to produce constituent particles. Many techniques available

- Need object detection
- Classification

Evaluation with respect to analysis performance important
Current Analysis

Have built a full reconstruction/analysis chain to search for the oscillation signal

A mixture of CNNs and traditional algorithms

Working analysis benchmarks improvements from CNN techniques

Pre-selection using light
Choosing interesting regions and removing obvious backgrounds
CNN for shower (electron) versus track (muon) patterns
Reconstruct neutrino interaction
Particle classification
First applications chosen as they are techniques where we could use non-signal data to evaluate network behavior on real data.
Preparing the data

- **Images preparation:**
  - Noise filtering
  - Pulse finding + zero suppression
  - Deconvolve wire response
    - Accounting for electronics response + expected induced signal
  - Downsample in time (summed) by factor of 6

- **3D consistent cropping**
  - Full size: 3456 (wire) x 6448 (ticks)
  - Downsampling size: 3456 x 1008 -- both dimensions about 3 mm
  - Cropped into 832 wire x 512 ticks (24 images per plane)
Pixel labeling

In reconstructing events, useful to be able to separate two types of patterns: tracks and showers

The Goal

yellow: track
cyan: shower
Pixel labeling

We use a U-Net for this problem
Pixel labeling: behavior on real versus sim. images

- Sample: stopping muons
- Score distributions similar
- Robust to moderate difference in images as shown by peak pixel distributions

These are cosmic particles that come to rest in the detector

Mostly muons, many of which decay into electrons

Use to check track and shower labeling
Analysis components complete

Evaluating:
- Data versus sim. differences through distributions of particle kinematics
- Sensitivity of analysis to see anomalous signal (or excluding it)

Not yet ready
- Hitting various performance milestone with simulation dataset
- Aim is to release result within year
Further CNN techniques in the works

- Also tackling more parts of the reconstruction chain
- Finding and removing non-neutrino tracks
- Providing 3D spacepoints to perform 3D reconstruction at earlier stage
- “Reparing” images to assist track reconstruction
Applying Instance Aware Segmentation

Currently adapting Detectron

Mask-RCNN network
Mask R-CNN for cosmic detection and rejection

Example application on MicroBooNE cosmic data
Mask R-CNN: evaluating performance

\[
Purity = \frac{\text{Sum}[(\text{Prediction}) \times (\text{Ground Truth}) \times (\text{ADC Binary})]}{\text{Sum}[(\text{Prediction}) \times (\text{ADC Binary})]}
\]

\[
Efficiency = \frac{\text{Sum}[(\text{Prediction Union}) \times (\text{Ground Truth}) \times (\text{ADC Binary})]}{\text{Sum}[(\text{Ground Truth}) \times (\text{ADC Binary})]}
\]
Mask R-CNN: evaluating performance

- MCC 8 Simulation
- y – Plane
- Log Z Axis

- Specialized Epochs correspond to training on a dataset with more overlapping clusters
Image Repair and Tracking

- In industry: filling in blanked-out regions in images
- Using a similar idea to fill in missing parts of track in MicroBooNE
- Useful for 3D track reco (trajectory only, not calorimetry)

Image Repair and Tracking

- Tracking: clustering of continuous clusters of 3D points
  - difficult in regions with dead readout channels: track gaps

Gaps impair ability to track reconstruction to accurate get momentum

Currently try to detect when track ends in gap and remove events

Overcoming this can also help with efficiency
Fills in tracks -- but can produce regions that are “odd” looking

Research ways to penalize net for producing odd shapes -- similar to way GANs are trained
3D Space Points

- To reconstruct 3D position of a charge deposit: need to match charges in same time window on at least 2 wire planes
- 3D position from wire intersection
3D Space Points

- Goal of dense pixel correspondence: match regions of one image to another, connecting semantically similar items

Choy et al. “Universal Correspondence Network” NIPS 2016


LArFlow

matchability = 0 when true target pixel in dead wires, below thresh, etc.

enforce same-time tick, so only wire-direction flow predicted
Network predicts correspondence between pixels (charges) in Y, U, V ADC images

For pixel $i$ in Y plane: the CNN is asked to predict a shift needed to move to pixel 1175

Which is where the corresponding pixel is in U plane

Correspondence prediction gives 3D space-point for that charge
LArFlow: Network

2D ADC image

U → conv

Y → CNN

V → CNN

Encoder:

(concat)

Decoder:

(deconv)

Loss function:

\[ \mathcal{L} = \lambda M + F \]

For future: enforce 3D consistency loss between Y→U and Y→V prediction
LArFlow: Loss

reconstructed
truth (core)
truth (edge)
LArFlow: Initial Performance

Have plans to use cosmic muon data to evaluate similar metrics

Good enough for cosmic rejection

Improvements in precision needed for neutrino reconstruction

Within 10cm for 92% of hits
Within 50cm for 95% of hits
If flow prediction (U or V wire) is wrong, we shift to incorrect y
LArFlow: Initial Performance

Top: combining 3D points with track/shower labeling

Bottom: using Mask-RCNN network to cluster cosmic muon candidates
Towards 3D space-point reconstruction

Our work is in collaboration with DL-based reconstruction of space-points done here at SLAC.
CNNs well-suited to analysis of LArTPC images

Applications developed in conjunction with physics analyses -- important for knowing effect on ultimate goal

Moving towards an end-to-end reconstruction chain using networks

Stay tuned for analysis result!

Results from work by:

Katie Mason (grad)
Joshua Mills (grad)
Ralitsa Sharanova (post-doc)