Understanding Misclassification in a Five Particle CNN

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Outline

• Introduction to MicroBooNE
• Introduction to CNNs
• My research!
MicroBooNE

• Liquid argon time projection chamber (LArTPC)
• Located at Fermilab
• On the booster neutrino beamline (BNB)
• Purposes
  • Follow up to MiniBooNE: investigate low energy excess
    • Sterile neutrinos?
  • Measure neutrino cross sections in argon
  • R&D for future LArTPCs
The detector

- XYZ dimensions 2.5m x 2.3m x 10.4m
- Neutrino beam in Z direction
- Encased in cryogenics
- Filled with liquid argon
- Applied electric (273V/cm) field in x direction
- Wire planes at anode
- Two subsystems- TPC and PMT

  - PMT
    - Behind the wire planes
    - Collect light emitted by charged particles in the detector
    - Nanosecond scale
TPC

• 3 wire planes at anode
• All in the YZ plane
• Third plane has wires vertical and acts as a collection plane
• First two planes have wires oriented $\pm 60^\circ$ from the Y axis
• Charged particles produce ionization trails in liquid argon
• Applied electric field makes ionized particles drift towards wire planes
• Each plane records drift time and wire number when particle interacts with wire
• Result: image with 2D projection of particle trajectory
• Intensity in image corresponds to ionization charge deposited
Example Event Display

Colors correspond to pixel intensity

Bragg Peak

Wire Number

Time tick
Neural Networks

• Goal: classify image as one of $C$ classes
• Score function: acts on image and outputs $C$ dimensional score vector
  - $F_{\overrightarrow{w}}(image) = score$, where $\overrightarrow{w}$ is a set of weights
• Train network on images where the true class is known
• Loss function $L(score, \overrightarrow{w})$ measures how far the score is from the truth
• Update weights in direction of $-\nabla_{\overrightarrow{w}}L$
• Keep training until network “learns” features of classes
Convolutional Neural Networks (CNNs)

• Special type of neural network
• Particular form of score function
  • Score function composed of several layers
  • Layers broken up into filters
    • Filter: small matrix of weights
  • Run each filter over the input and take inner product of filter with parts of input, making a layer of output
  • Each filter creates a different layer of output
• Allows the network to learn local features
  • Each filter trained to look for a particular local feature
• Can find many different features
  • Filters are independent of each other
• Don’t have to tell network which features to look for
  • Don’t know which features the network picks up on
Single Particle Classification Network

• Deep learning group used CNNs on images with one of five particles
  • Electron, gamma, muon, pion, proton
• Tech note: docdb #5905
• Not always accurate
• My project: explain why the network misclassifies particles
  • Particularly interested in muon/pion separation
Data Sample

• Single particle MC sample
  • Electron, gamma, muon, pion, proton

• Flat energy distribution
  • Ranging from 100 MeV to 1 GeV
  • Except protons, which have kinetic energy ranging from 100 to 788 MeV

• Initial position uniformly distributed throughout TPC

• Initial momentum direction distributed isotropically

• Using AlexNet run on collection plane images
  • Images cropped to 576 X 576 pixels
Accuracy

- True particle: $e^-$
- True particle: $\gamma$
- True particle: $\mu^-$
- True particle: $\pi^-$
- True particle: $p^+$

Particle types: electron, gamma, mu_minus, pi_minus, proton
Muon classification vs. energy
Muons with high scores (> 0.9)  
(selected randomly)
Muons with low scores (< 0.1)
(selected randomly)
Pions with high scores (> 0.9)
(selected randomly)
Muon-michels

• Most muons leave the detector before emitting Michel electrons
• Less than 10% of our simulated muons emit michels in the TPC
• Low energy muons more likely to give off Michel in the TPC
Muon-Michels: decreased accuracy

Accuracy: 0.89

Accuracy: 0.69
Muons with Michel electrons
(selected randomly)
Is Michel the whole story?

No!
So what else?

- Muon-Michels give us insight into why other muons may be misclassified as pions
  - Kinks for other reasons (e.g. multiple coulomb scattering)
- Images with high muon scores seem to have long, straight tracks
- Image with low muon scores have kinks
- Hypothesis: muon score distribution related to how much the image is a straight track
How do we show that?

• Quantify how much an image is a long, straight track and show correlation with muon score
  • Independent from CNN

• Use OpenCV feature detection
  • Houghline algorithm to find straight line
  • Plus custom algorithm to stitch lines together
    • Validate
  • Goal: find single straight line that classifies image
Unstitched Houghlines

Muon score: 0.940

Muon score: 0.154

original image points

overlaid unstitched houghlines

overlaid unstitched houghlines

original image points
Stitched Houghlines

Muon score: 0.940

original image points

Muon score: 0.154

original image points
Line length vs. muon score

- Increasing score with increasing line length
- Cropped image is 576x576: line length ~400 means that line goes across most of image region
Line length vs. muon score

normalized histograms of muon scores for different houghline lengths

- Blue: $0 < \text{length} < 100$
- Green: $100 < \text{length} < 200$
- Orange: $200 < \text{length} < 300$
- Pink: $300 < \text{length} < 400$

Counts (normalized) vs. Muon score
Summary

• Investigated CNN misclassification for 5 particle network
  • Track vs. shower separation is reasonable
  • Studied misclassification of muons as pions

• Low energy muons more likely misclassified as pions
  • Muons giving off michels (kink-like feature)
  • Shorter tracks

• Found correlation between stitched line length and muon score
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Back up slides
Muons with high scores (> 0.9) (selected randomly)
Muons with low scores (< 0.1)  
(selected randomly)
Pions with high scores (> 0.9) (selected randomly)
Muons with Michel electrons
(selected randomly)
Debug algorithm (unit test)

• Results for distance to line didn’t seem right

• Test algorithm: do the opposite
  • Randomly choose:
    • endpoints of line
    • Region of box
    • distance
    • angle for regions 1 and 2
    • Point on line for regions 3 and 4
  • Find point
  • Use original algorithm to find distance from point to line
  • Compare resulting distance to distance chosen for backwards algorithm
Classification vs. Energy

- **true particle: $e^-$**
- **true particle: $\gamma$**
- **true particle: $\mu^-$**
- **true particle: $\pi^-$**
- **true particle: $p^+$**
Classification vs. Pz/P

- True particle: $e^-$
- True particle: $\gamma$
- True particle: $\mu^-$
- True particle: $\pi^-$
- True particle: $p^+$

Graphs showing the fraction of particles classified at each $Pz/P$ value for different particle types.
Average distance to stitched line and score correlation

all muons with average distances < 20
Energy and stitched line length correlation

Muon energy and houghline length correlation

Initial energy vs. houghline length