Applying Deep Neural Network Techniques for LArTPC Data Reconstruction

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Plan

1. LArTPC & Deep Learning
2. Examples of applications: UResNet & PPN networks
3. Sparse convolutions
LArTPC & Deep Learning
Liquid Argon Time Projection Chamber (LArTPC)

Neutrino detectors

Ex: MicroBooNE @ Fermilab, 150 tons

2D or 3D data

Bigger and bigger! (DUNE)
Deep Neural Networks (DNN) & Computer Vision

![Graph showing ImageNet error rate from 2010 to 2015 with decreasing error rates. The graph includes a label for Deep learning techniques and a comparison to Human Performance.](Image from Martin Görner)
Deep Neural Networks (DNN) & Computer Vision

Object detection & classification

Semantic segmentation

...LET'S GO EXPLORING!
Towards a full reconstruction chain with DNN

- Currently: Lots of heuristic algorithms
- Goal: Replace them with a set of DNN algorithms which ideally will
  - Run faster
  - Have a better performance
Towards a full reconstruction chain with DNN

Steps:

1. Point detection (track edge)
Towards a full reconstruction chain with DNN

Steps:

1. Point detection (track edge)
   PPN
Towards a full reconstruction chain with DNN

Steps:

1. Point detection (track edge)

   PPN

2. Pixel-wise labeling (particle track vs electromagnetic shower)
Towards a full reconstruction chain with DNN

Steps:

1. **Point detection (track-edge)**
   - PPN
2. **Pixel-wise labeling (particle track vs electromagnetic shower)**
   - UResNet
Towards a full reconstruction chain with DNN

Steps:

1. Point detection (track edge)
   PPN
2. Pixel-wise labeling (particle track vs electromagnetic shower)
   UResNet
3. Clustering of energy deposits and instance segmentation
Towards a full reconstruction chain with DNN

Steps:

1. Point detection (track-edge)
   PPN
2. Pixel-wise labeling (particle track vs electromagnetic shower)
   UResNet
3. Clustering of energy deposits and instance segmentation
   Work in progress!
Towards a full reconstruction chain with DNN

Steps:

1. Point detection (track edge)  
   PPN
2. Pixel-wise labeling (particle track vs electromagnetic shower)  
   UResNet
3. Clustering of energy deposits and instance segmentation  
   Work in progress!
4. Particle identification and energy estimate
5. Hierarchical reconstruction

Non-contractual picture - Actual product may differ
Examples of applications: UResNet and PPN networks
Semantic Segmentation: UResNet
Semantic Segmentation: UResNet

Encoder

Decoder

Residual connections

- conv 3x3, ReLU
- copy and crop
- max pool 2x2
- up-conv 2x2
- conv 1x1

Input image tile

Output segmentation map
Semantic Segmentation: UResNet

A Deep Neural Network for Pixel-Level Electromagnetic Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber.
Point-finding: PPN

Inspired by Faster-RCNN architecture

- Region Proposal Network detects regions of interest
- Replace regions with points = Pixel Proposal Network (PPN)

Why not Mask-RCNN?

- Computations expensive
- Our features topology is different (track, shower)
PPN proposals
PPN needs post-processing
PPN needs post-processing

Option 1: DBSCAN
- Density estimation algorithm
- No prior on the number of clusters.

Option 2: NMS (Non-Maximal Suppression)
- Popular post-processing method for object detection
- Order by score and prune boxes with too much overlap
NB: independently of DBSCAN vs NMS, these plots also benefit from debugged ground truth pixels position.
Training UResNet + PPN / Architecture

- Encoder
- Decoder
- UResNet output
- PPN output

Legend:
- Dark grey: Convolutions (with residual connections) Common between both networks
- Red: Transposed Convolutions (with residual connections) - UResNet upper layers
- Yellow: Convolution + fully connected layer
- Yellow: PPN prediction layers
- Dashed: Skip connections
- Dashed: Crop layer
UResNet + PPN

3D Analysis

6mm/voxel
UResNet + PPN
Sparse UResNet
How do we handle sparse data?
Naive approach

Input: dense 3D matrix of energy deposits.

- Crop your data
- Run the network on small cropped images
- Stitch together results

Many cropping algorithms possible

Compromises to make:

- Maximize the number of overlapping boxes (accuracy)
- Minimize the number of boxes (computation time)
Sparse Convolutions

Many possible definitions and implementations of ‘sparse convolutions’...

Submanifold Sparse Convolutions: [https://github.com/facebookresearch/SparseConvNet](https://github.com/facebookresearch/SparseConvNet)

Submanifold?

“input data with lower effective dimension than the space in which it lives”

Ex: 1D curve in 2+D space, 2D surface in 3+D space

Our case: the worst! 1D curve in 3D space...
Sparse Convolutions

Submanifold Sparse Convolutions: https://github.com/facebookresearch/SparseConvNet
Sparse UResNet

Input: list of points coordinates and their features (e.g. energy deposition)

With UResNet architecture:

- >99.9% accuracy in 3D
- Faster training (less computations!): only a few hours
- Much lower memory usage

Example in larcv-viewer
Summary

- Extract interesting / useful features with deep neural networks:
  - Points of interest with PPN
  - Pixel-wise classification track vs shower with UResNet
- Currently working on clustering and instance segmentation (particle type, particle instances)
- Sparse techniques are very exciting!

Join DeepLearnPhysics group!

- Technical discussion on ML applied to experimental physics data
- Data + code sharing for reproducibility
Thank you!
Backup slides
PPN Loss: details