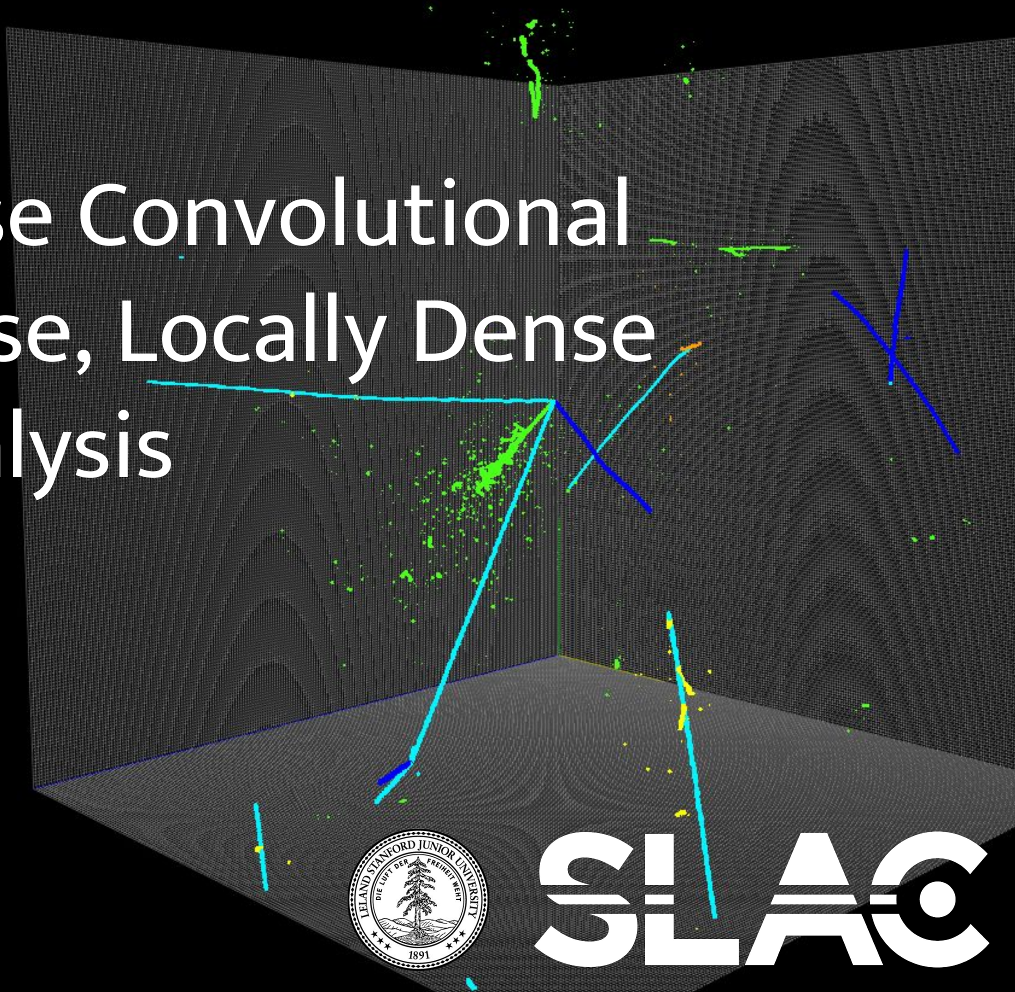
Submanifold Sparse Convolutional Networks for Sparse, Locally Dense Particle Image Analysis



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2018 CPAD Instrumentation Frontier Workshop

Outline

1. Particle image analysis & Convolutional networks
2. Submanifold Sparse Convolutions
3. Comparison study between a dense and sparse network

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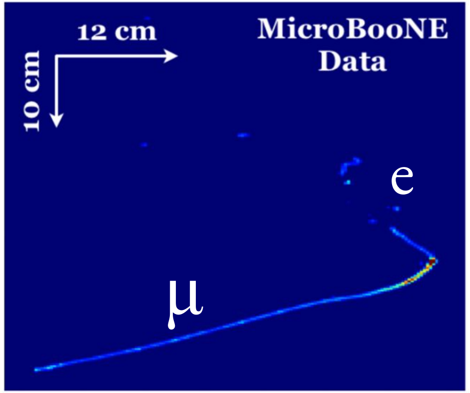
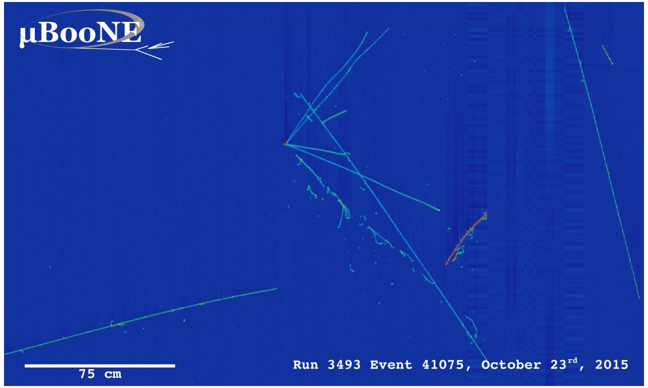


Particle Image Analysis with LArTPCs

Liquid Argon Time Projection Chamber (LArTPC) = particle imaging detector

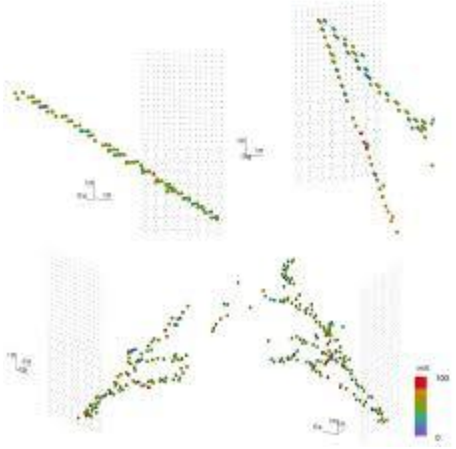
~3mm resolution

Wire LArTPC (2D projections)



Neutrino interaction candidate from MicroBooNE experiment @ Fermilab

Pixel LArTPC (native 3D)

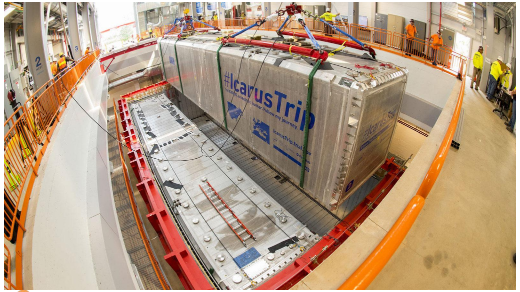


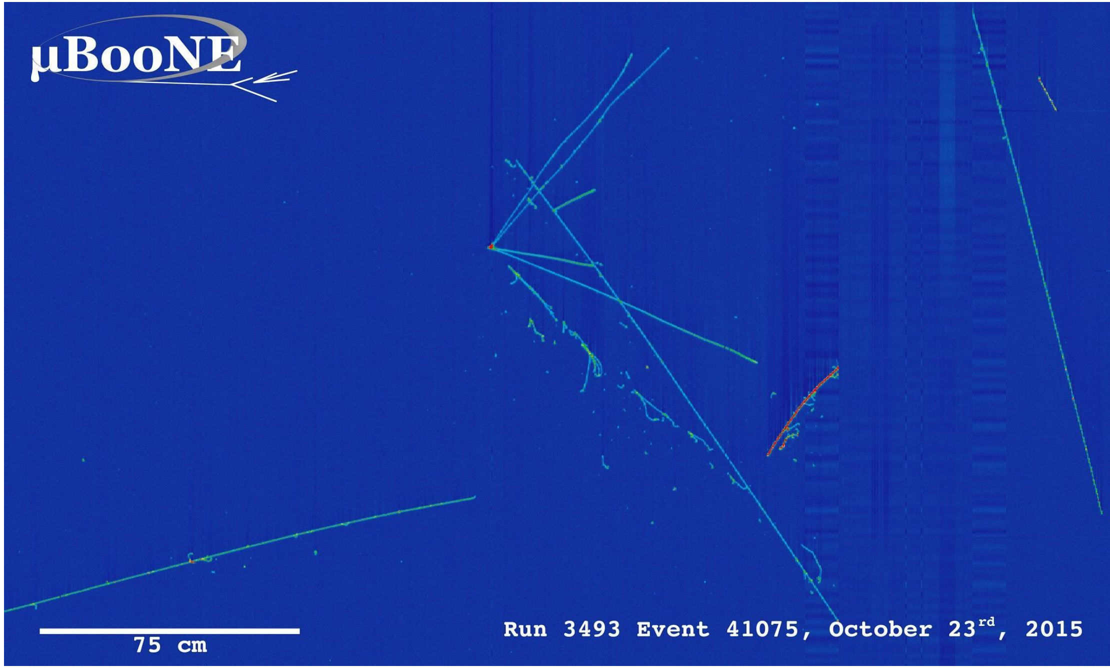
Cosmic rays in a 3D LArTPC charge readout (arxiv:1808.02969) @ LBNL

Particle Image Analysis with LArTPCs for neutrinos

Neutrino detectors & LArTPCs

Goal: Extract ν flavor + energy





SBND
SHORT-BASELINE NEAR DETECTOR

DUNE
DEEP UNDERGROUND NEUTRINO EXPERIMENT

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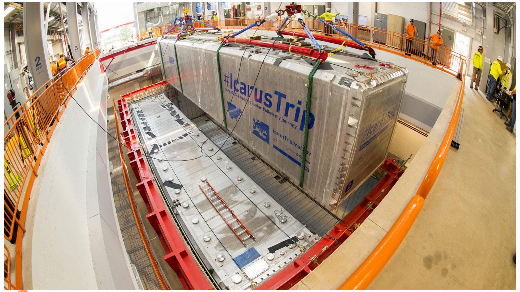

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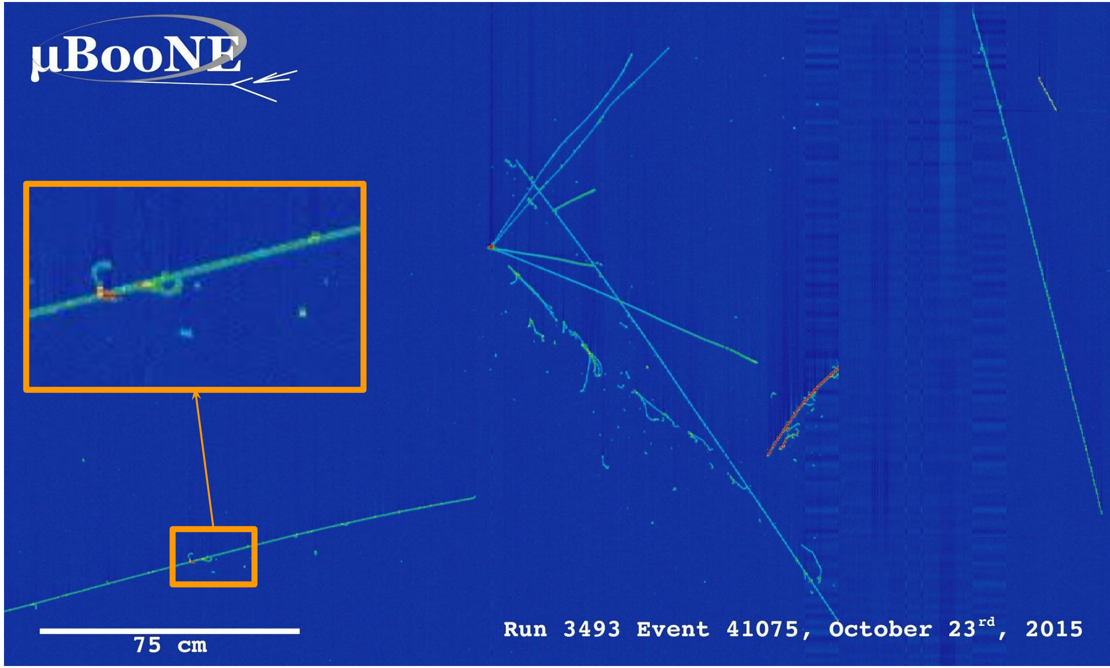
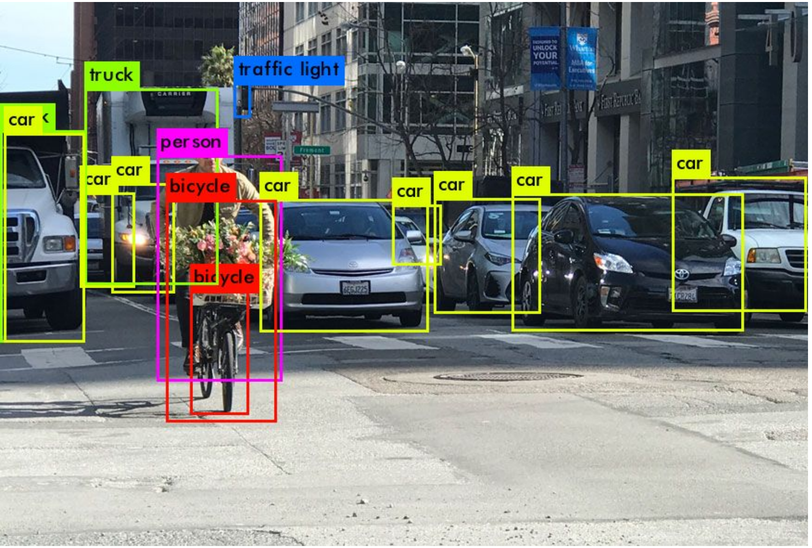


Convolutional Neural Networks

Now state-of-the art technique in computer vision for complex image analysis tasks:

Object detection & classification



Semantic segmentation

Sparse, locally dense data

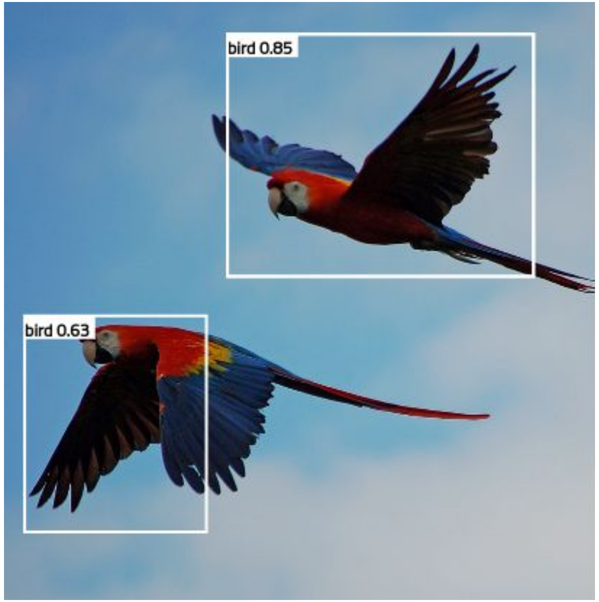
Less than 1% of voxels are nonzero in LArTPC images

% of nonzero voxels:

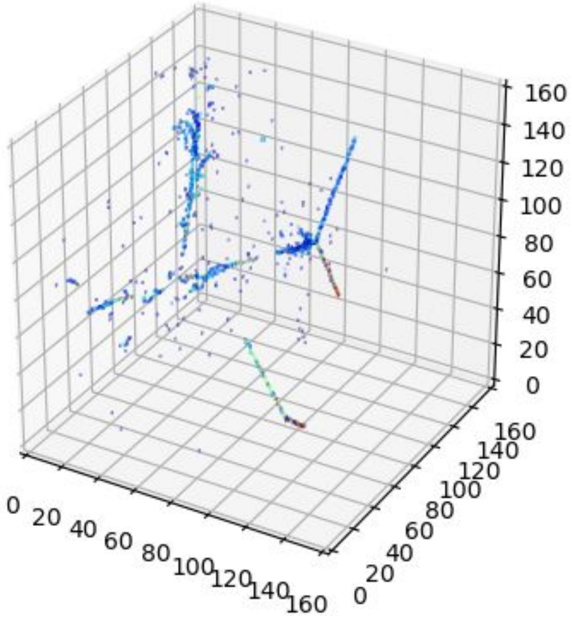
- ~0.05% for 192px^3
- ~0.01% for 512px^3

But CNNs rely on dense matrix multiplications!

Dense



Sparse (but locally dense)



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Submanifold Sparse Convolutions

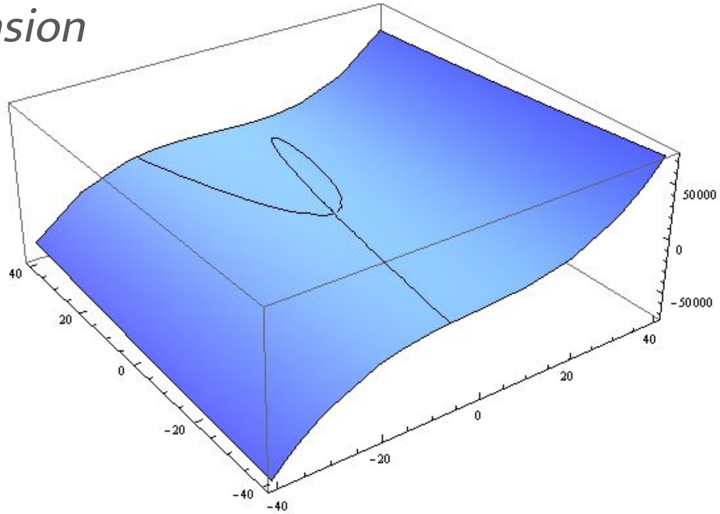
Many possible definitions and implementations of *‘sparse convolutions’*…

Submanifold Sparse Convolutions (arxiv:1711.10275, CVPR2018):
https://github.com/facebookresearch/SparseConvNet

State-of-the-art on ShapeNet challenge (3D part segmentation)

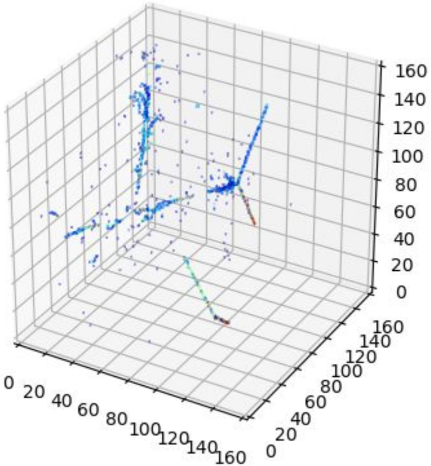
Submanifold Sparse Convolutions

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…**



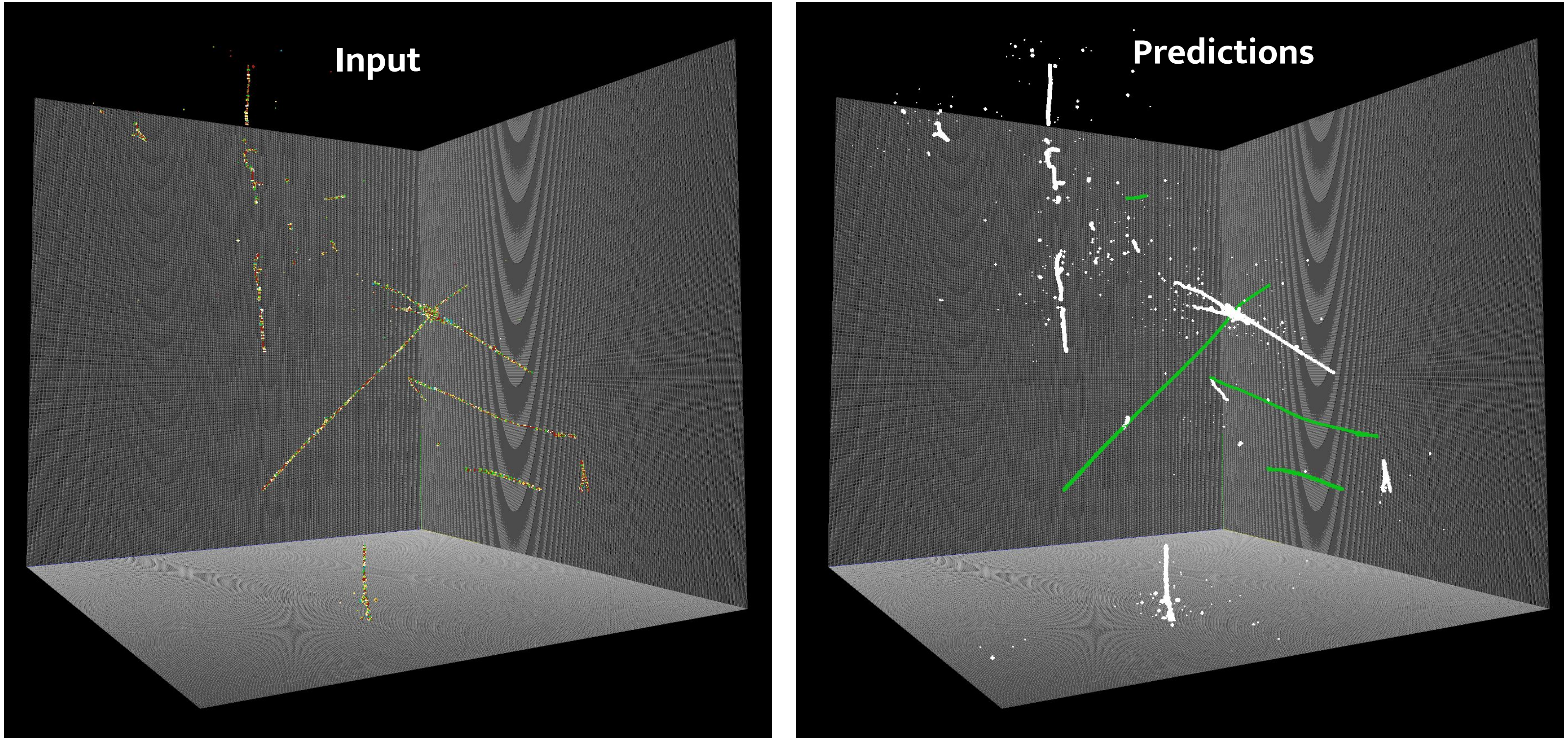
Submanifold Sparse Convolutions

Dilation problem

- 1 nonzero site leads to 3^d nonzero sites after 1 convolution
- How to keep the same level of sparsity throughout the network?

[3D Semantic Segmentation with Submanifold Sparse Convolutional Networks](#) (arxiv: 1711.10275)

Submanifold Sparse Convolutions



*2-classes (particle track vs electromagnetic shower) pixel-level **segmentation** on 512px 3D images.*

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    a. Dataset
    b. Task
    c. Metrics
    d. Network architecture

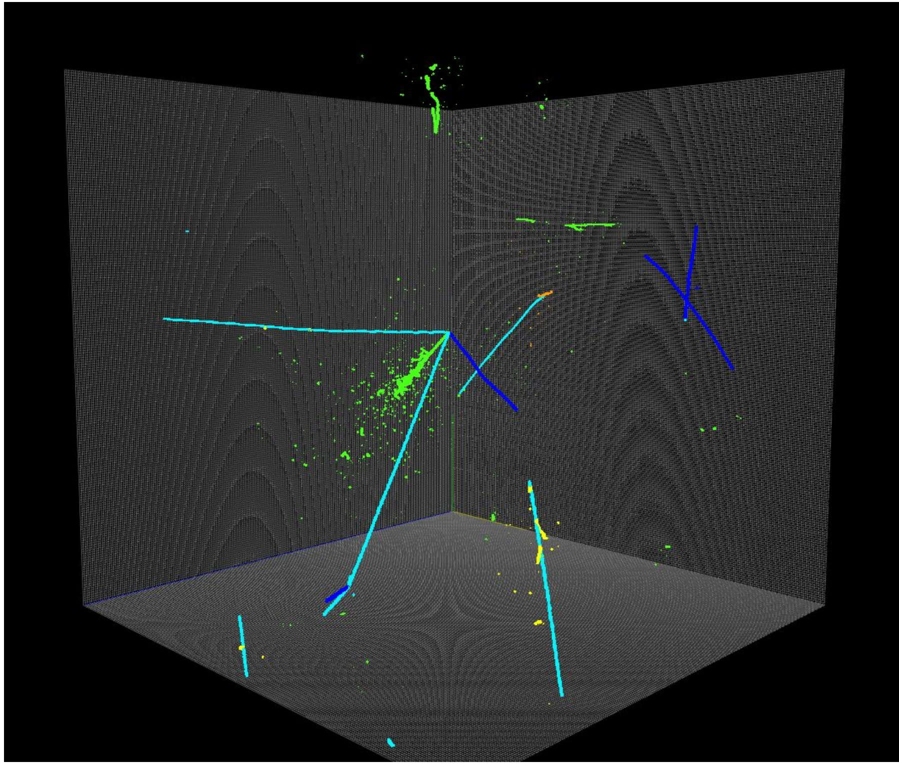
1. Dataset & 2. Task

Total: 100,000 simulated 3D events

Spatial size: 192px / 512px / 768px (~3mm/pix)

Semantic segmentation with 5 classes

- Protons
- Minimum ionizing particles (muons and pions)
- Electromagnetic shower
- Delta rays
- Michel electrons



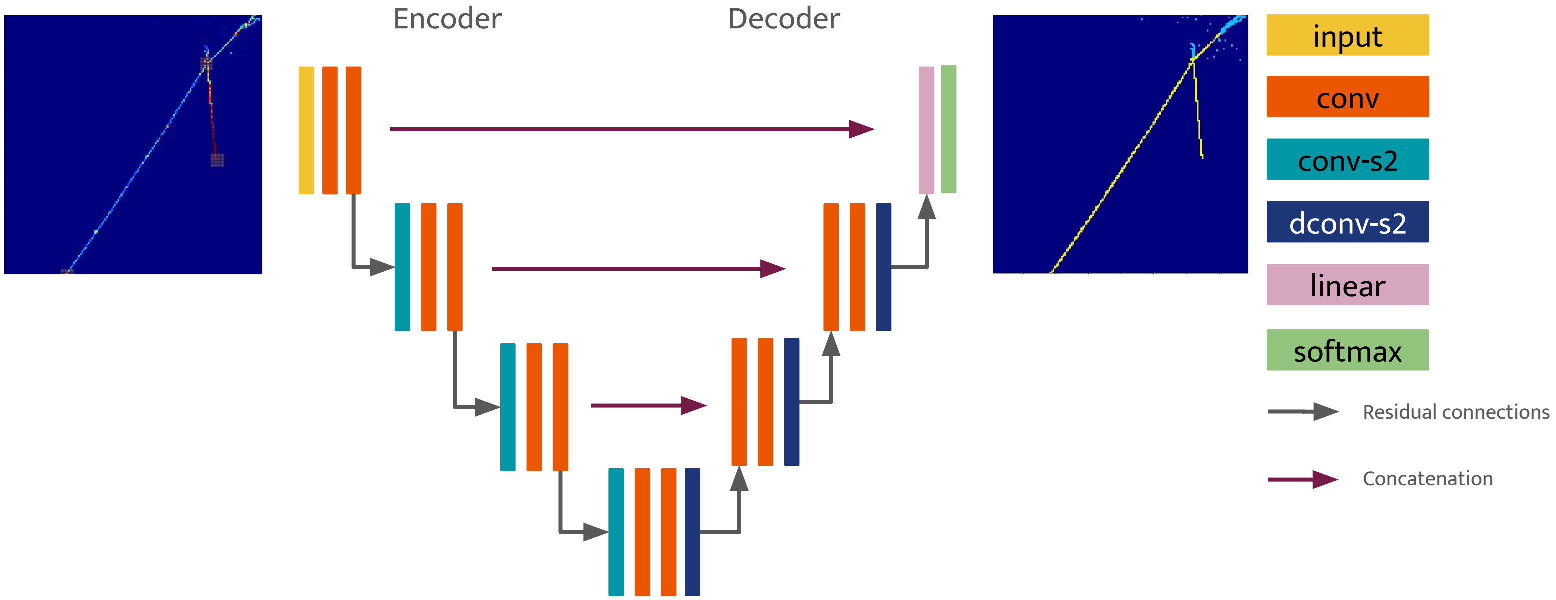
Publicly available: https://osf.io/vruzp/

3. Metrics

- Nonzero accuracy: fraction of correctly labeled pixels, i.e.
  # nonzero voxels whose predicted label is correct / # nonzero voxels
- GPU memory (hardware limitation)
- Computation time

4. Network architecture: UResNet

UResNet = U-Net + ResNet (residual connections)



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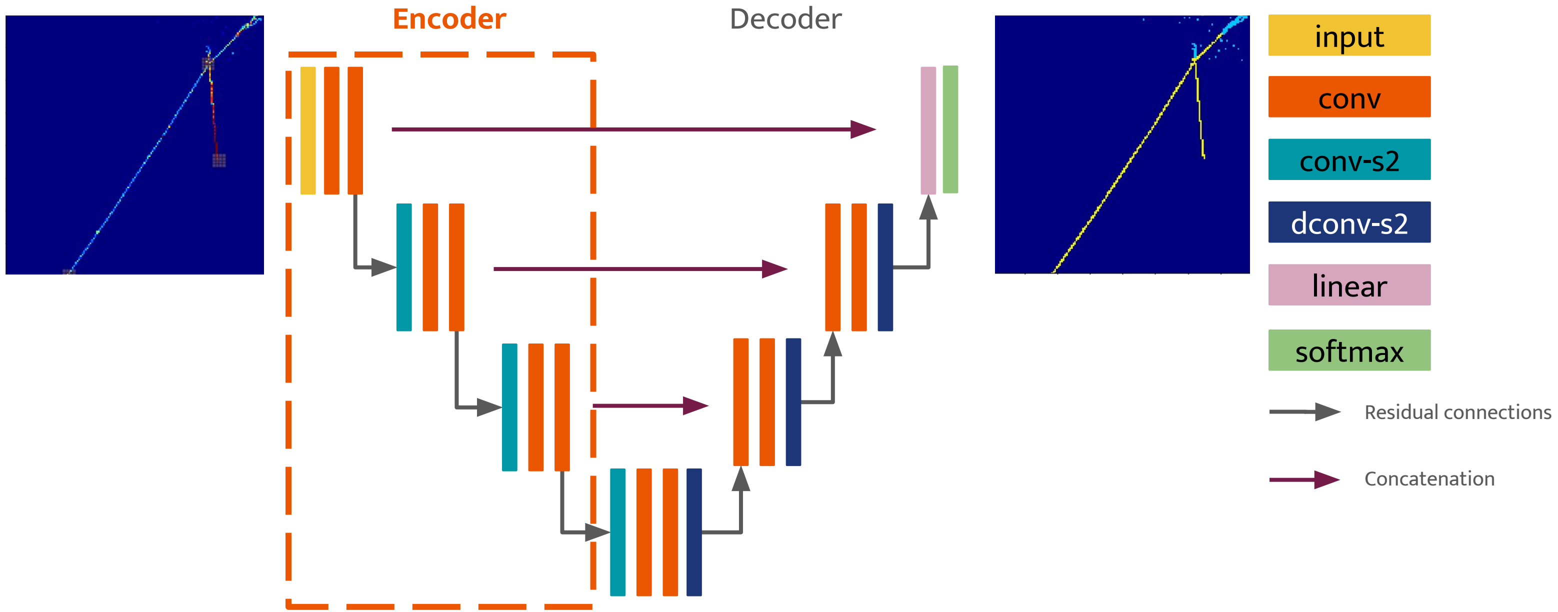

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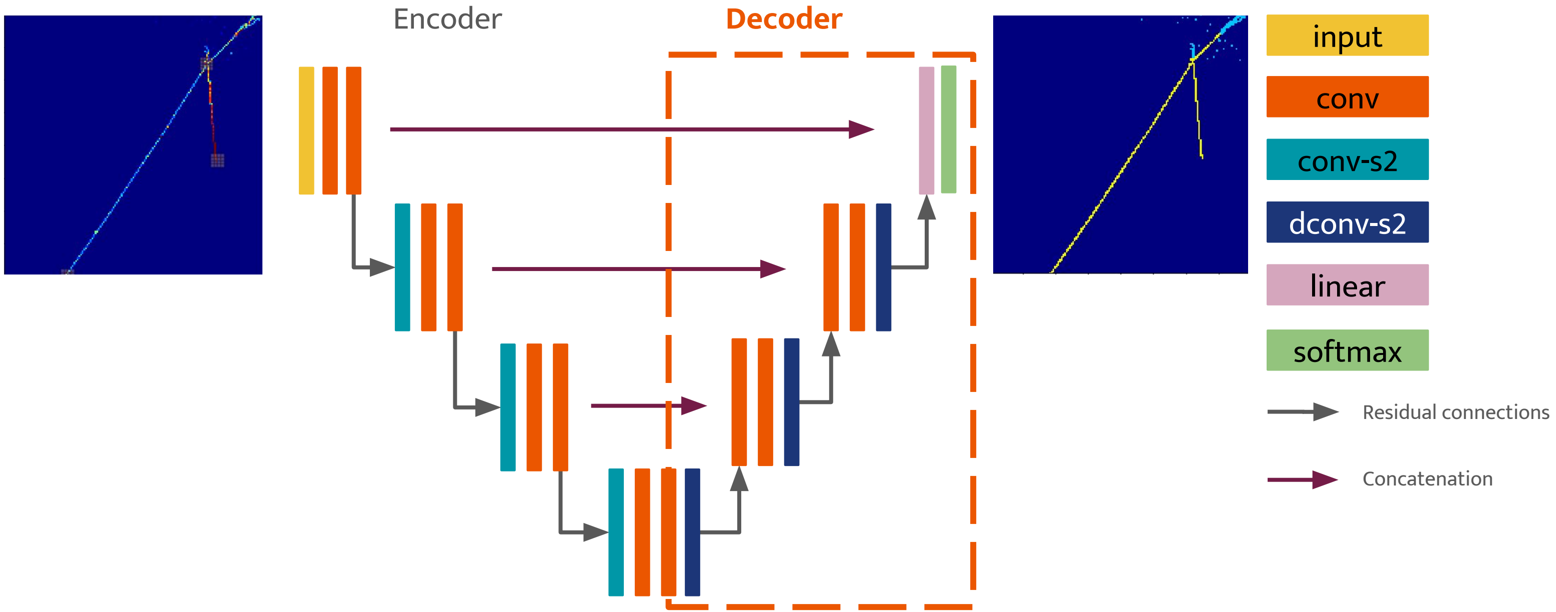

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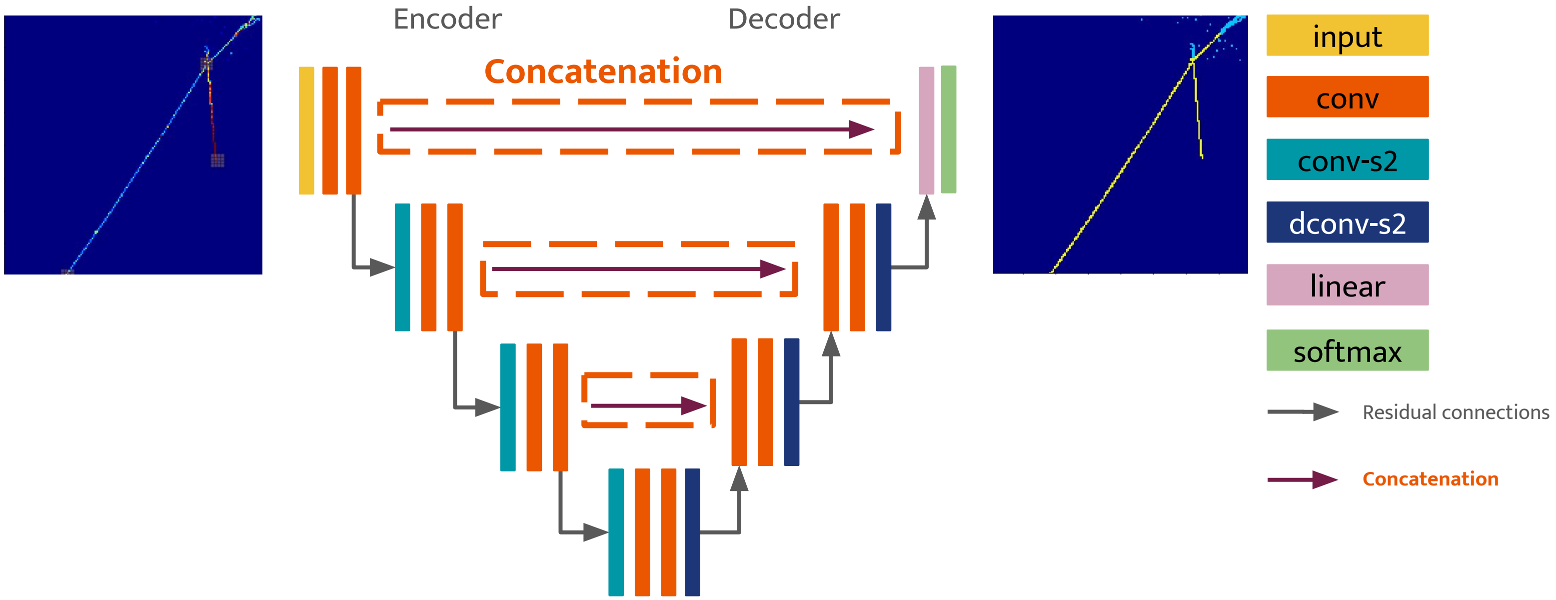

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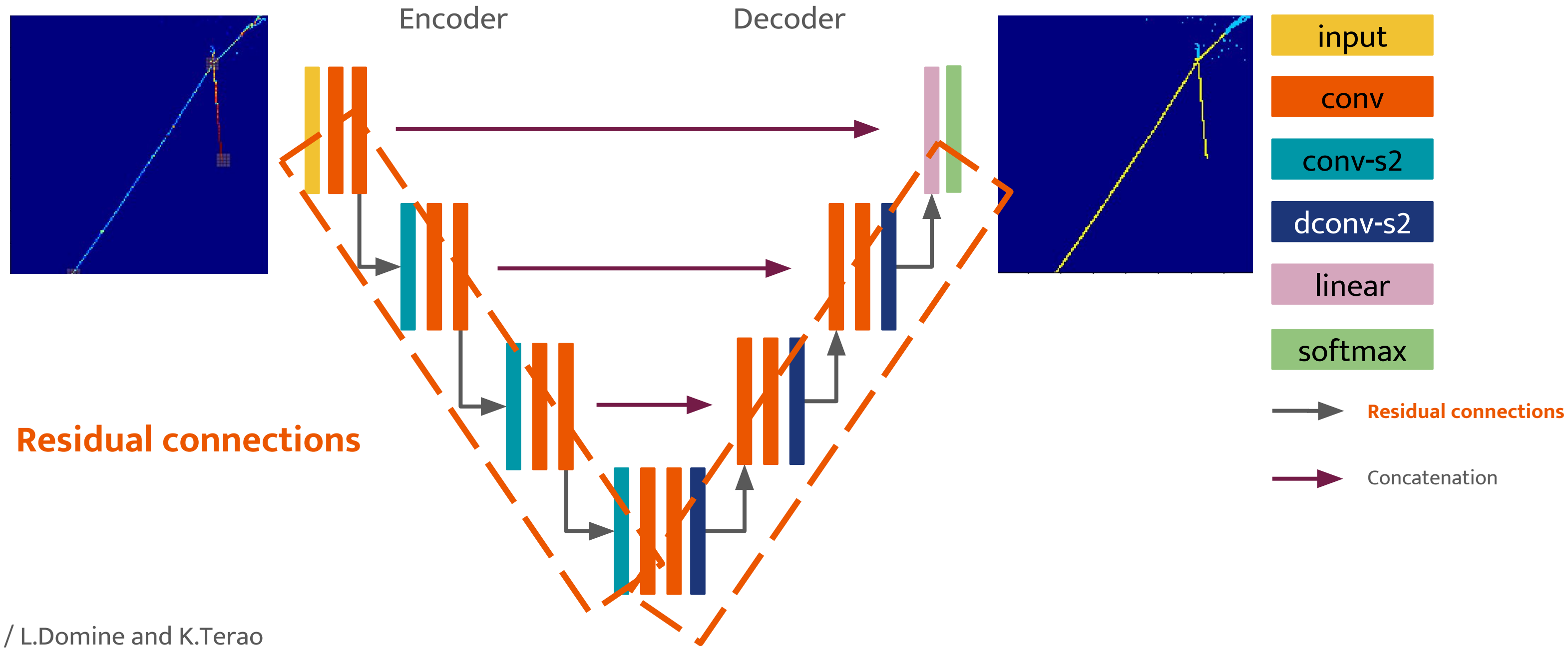
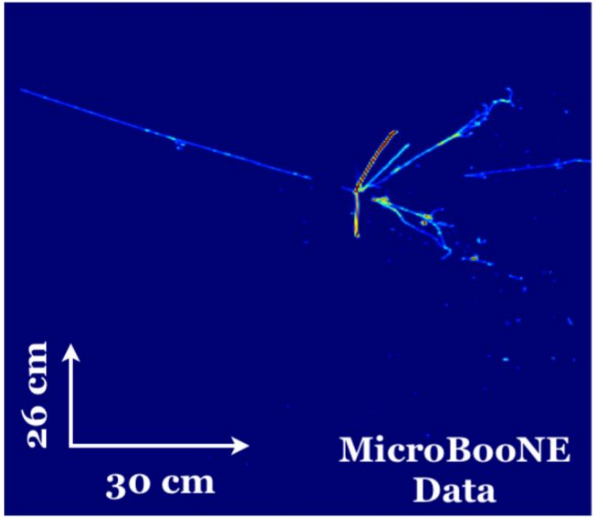
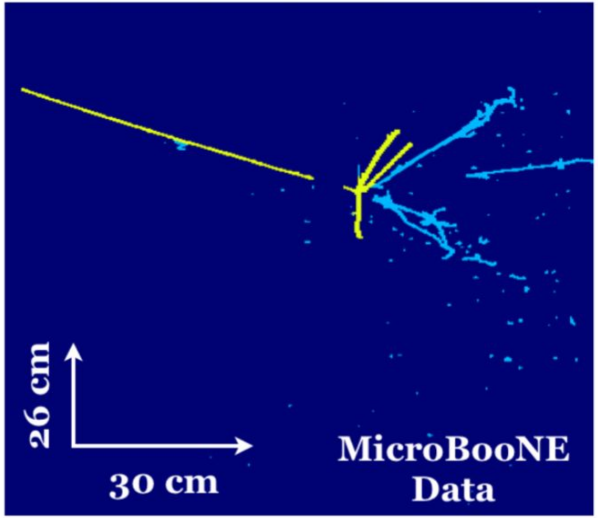


Semantic Segmentation with UResNet: it works.

Data



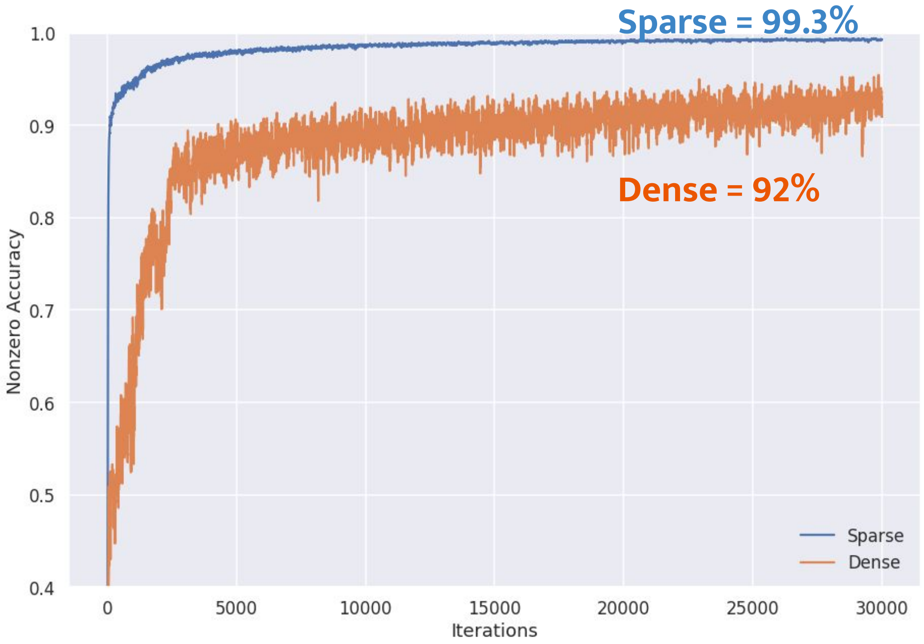
Network's output



A Deep Neural Network for Pixel-Level Electromagnetic Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber. (arxiv:1808.07269)

Dense vs Sparse UResNet

Dense & Sparse both trained with 80k events



Nonzero Accuracy (training) vs Iterations

Dense vs Sparse UResNet

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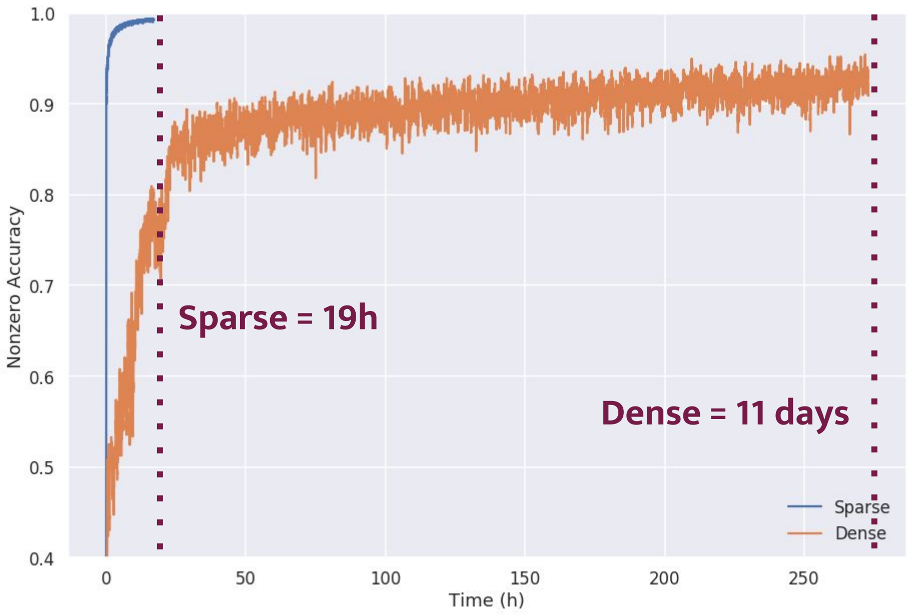


Nonzero Accuracy (training) vs Wall Time

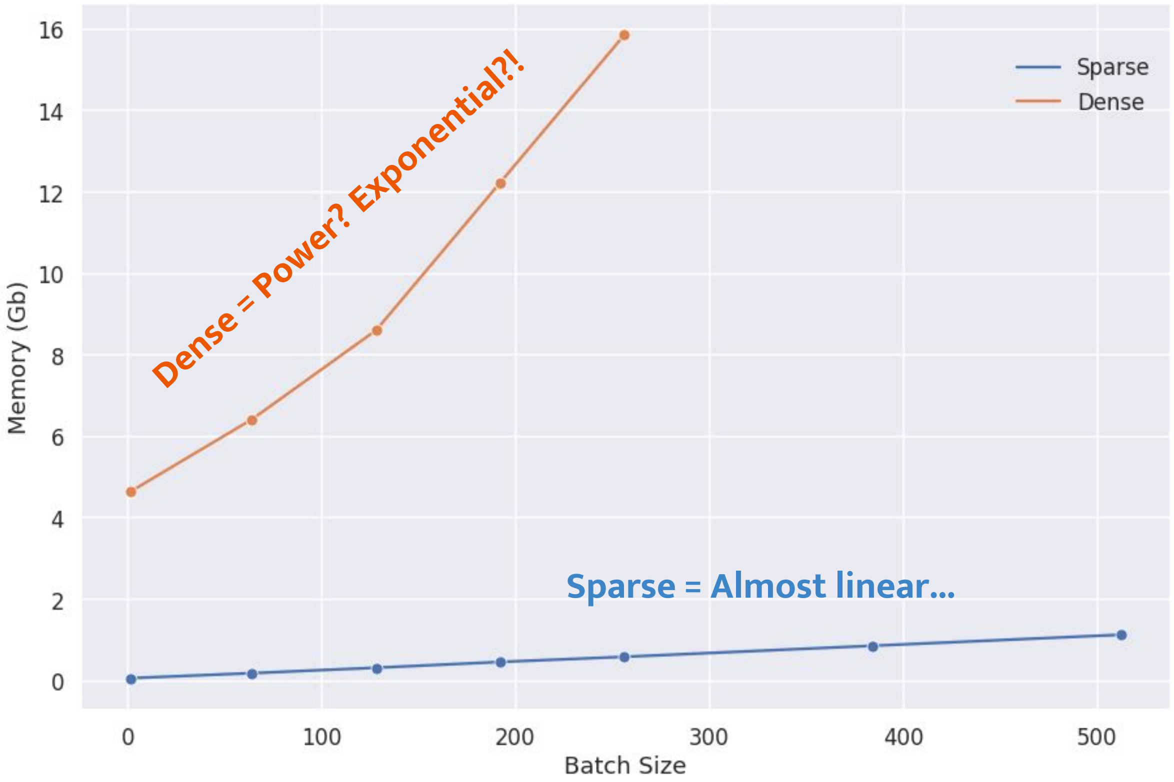
Dense vs Sparse UResNet

Performance for different input spatial size

	Sparse			**Dense**
Input Spatial Size	**192px**	**512px**	**768px**	**192px**
Final nonzero accuracy	98%	98.8%	98.9%	92%*
GPU memory usage (Gb)	0.066	0.57	1.0	4.6
Forward computation time (s)	0.058	2.6	3.6	0.68

**Training time accuracy.*

Dense vs Sparse UResNet



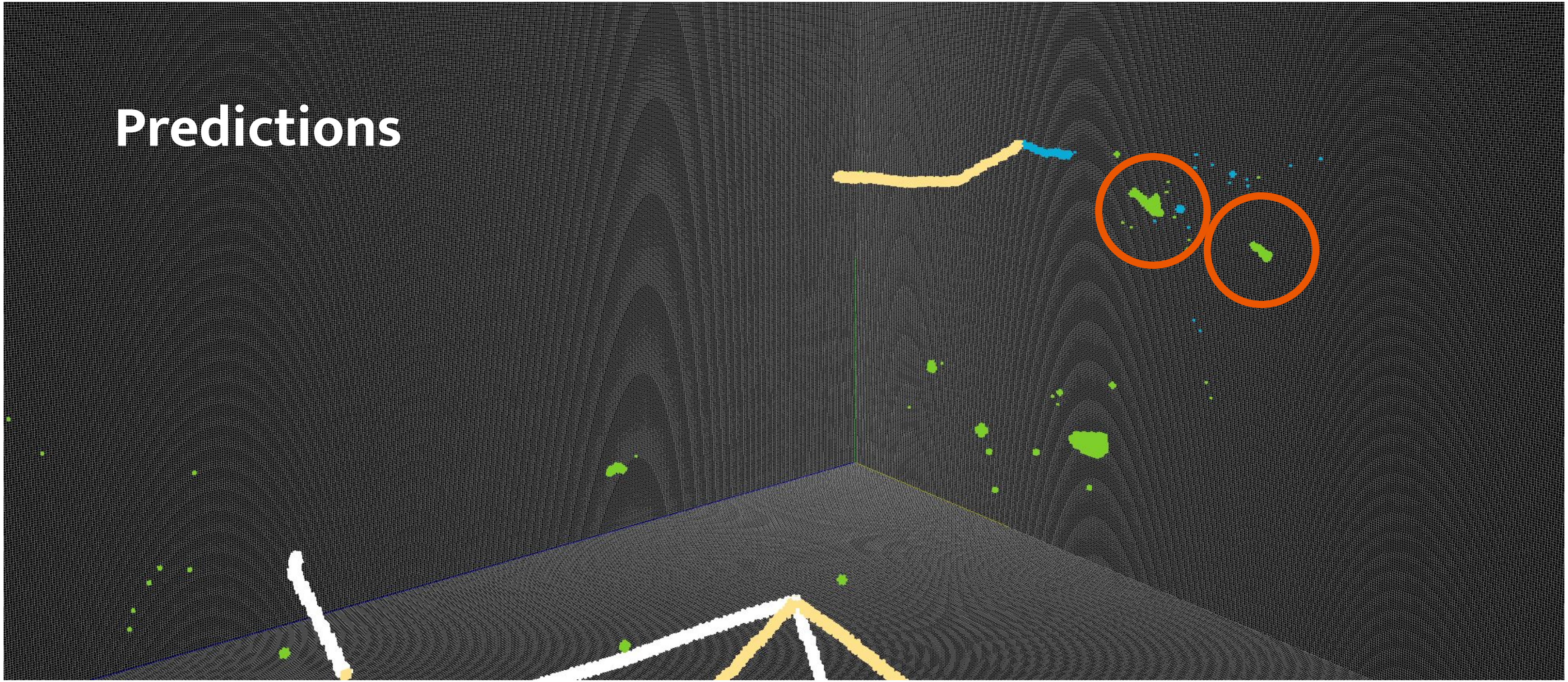
Learning from mistakes: the case of Michel electrons

	Mean % of nonzero voxels in an event	Nonzero accuracy per class
HIP	12%	98.4%
MIP	43%	99.5%
EM shower	42%	99.1%
Delta rays	2%	87.5%
Michel electrons	1%	62.8%

Nonzero accuracy per class

= # correctly predicted voxels in this class / # voxels in this class

Learning from mistakes: the case of Michel electrons



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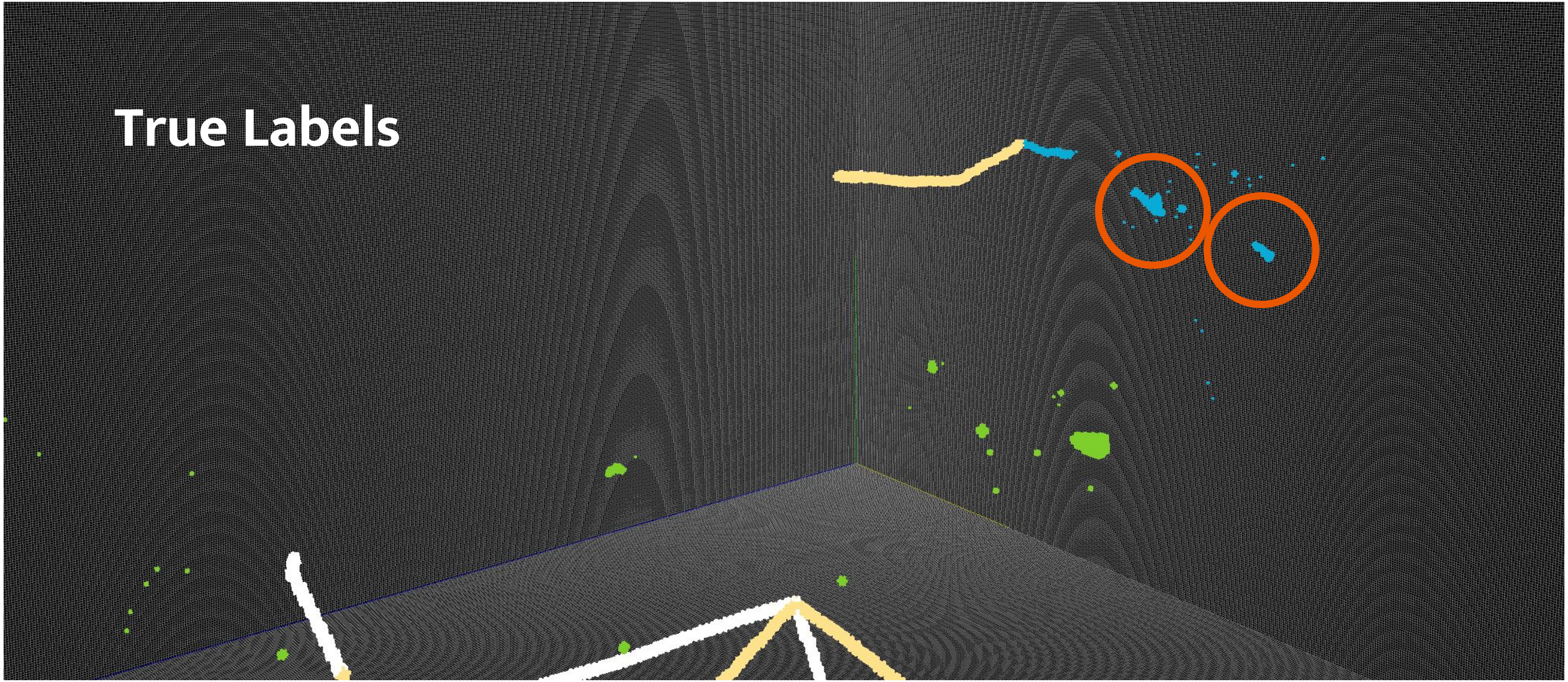

Summary

Submanifold sparse convolutions...

- Run faster
- Use less GPU memory
- ... and outperform standard convolutions.

Better performance and better scalability!

Reproduce our results / start using SSCN:

- Open dataset
- Software containers available