Particle Instance Identification Using a Sparse 3D Mask-RCNN

Felix Yu

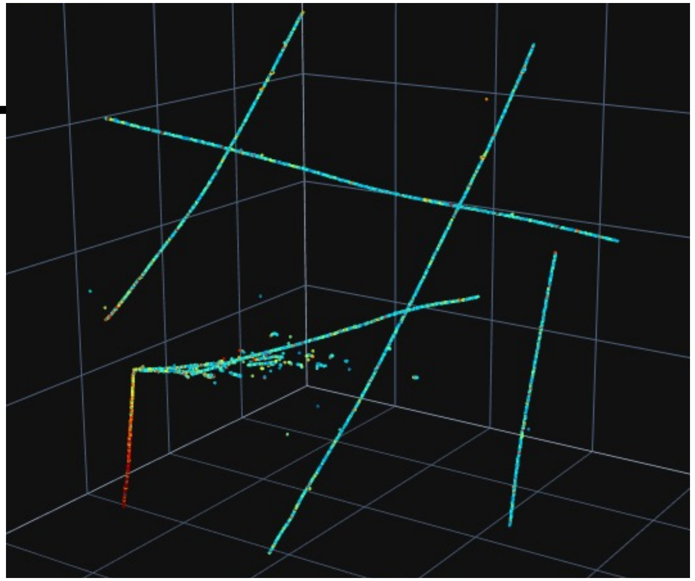
Purpose

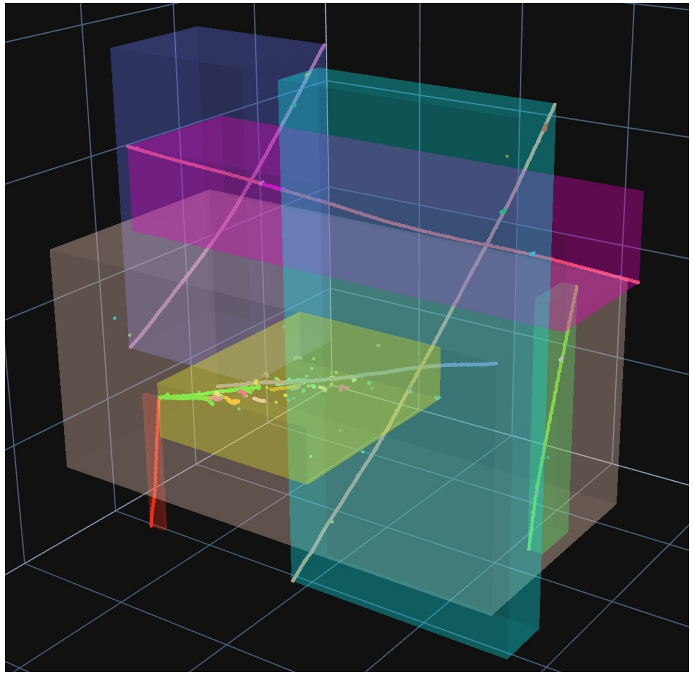
3D Mask-RCNN is a deep learning approach to particle clustering, which will hopefully:

- Detect all particle instances given 3D input data from detector. Detection is done with a bounding box drawn around the particle.

- Classify each bounding box with the correct particle label.

- Cluster each particle by identifying each pixel belonging to every particle instance in the input data. Clustering is done with a “mask” drawn on each pixel of each particle.

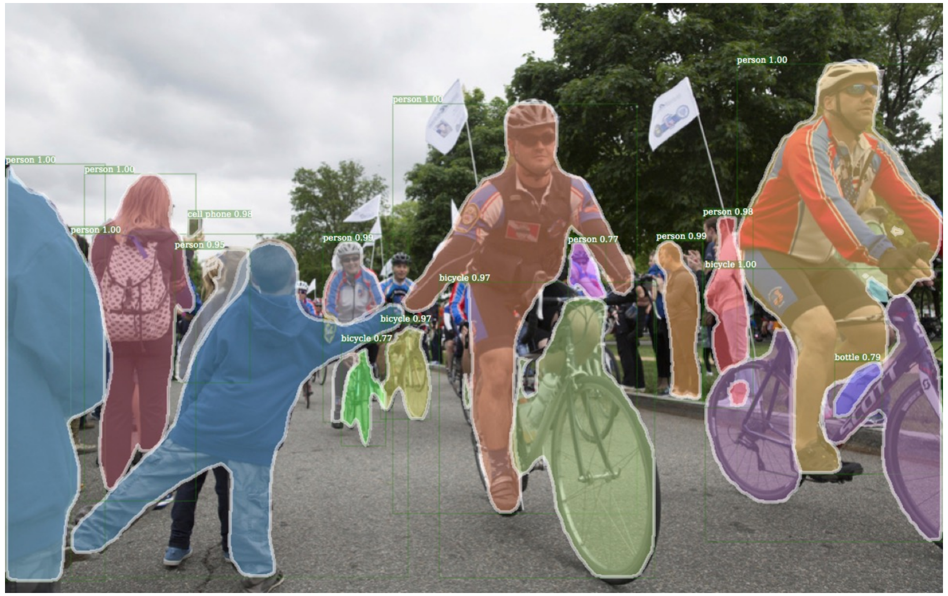




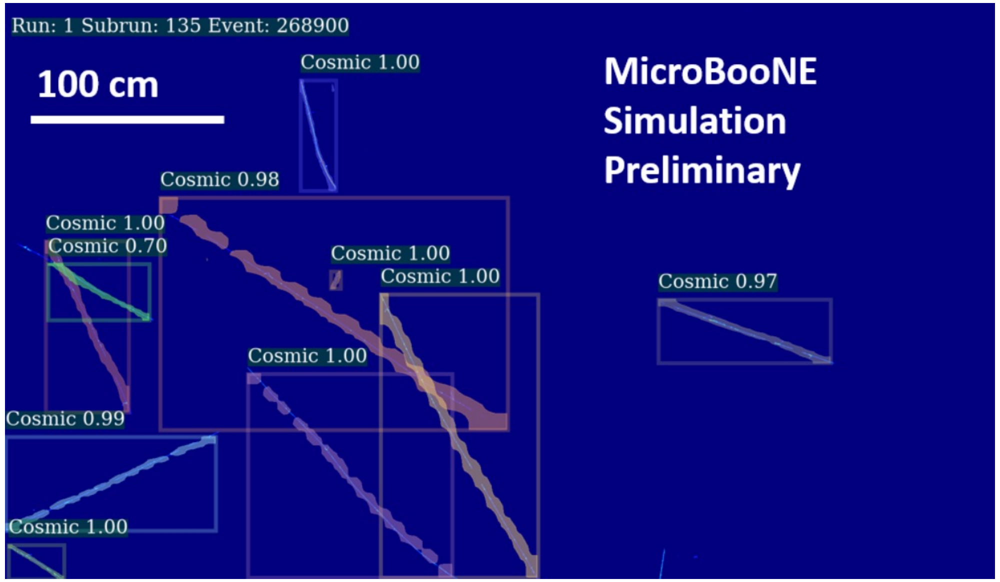
2D Mask-RCNN and Background

Mask-RCNN is a convolutional neural network for object detection and segmentation. Traditionally, it is used to detect objects in everyday 2D images.

Recently, a 2D Mask-RCNN has been developed for particle data from the output planes of the MicroBooNE experiment.

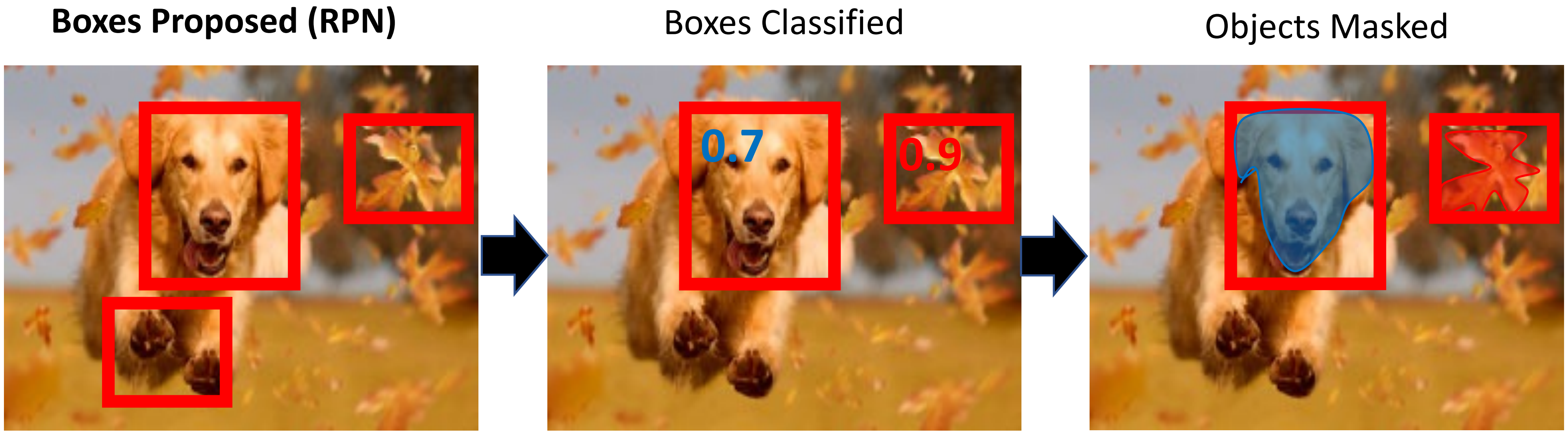


Source: K. He et al., Mask R-CNN



Source: [MicroBooNE Public Note 1081]

RPN (Region Proposal Network)

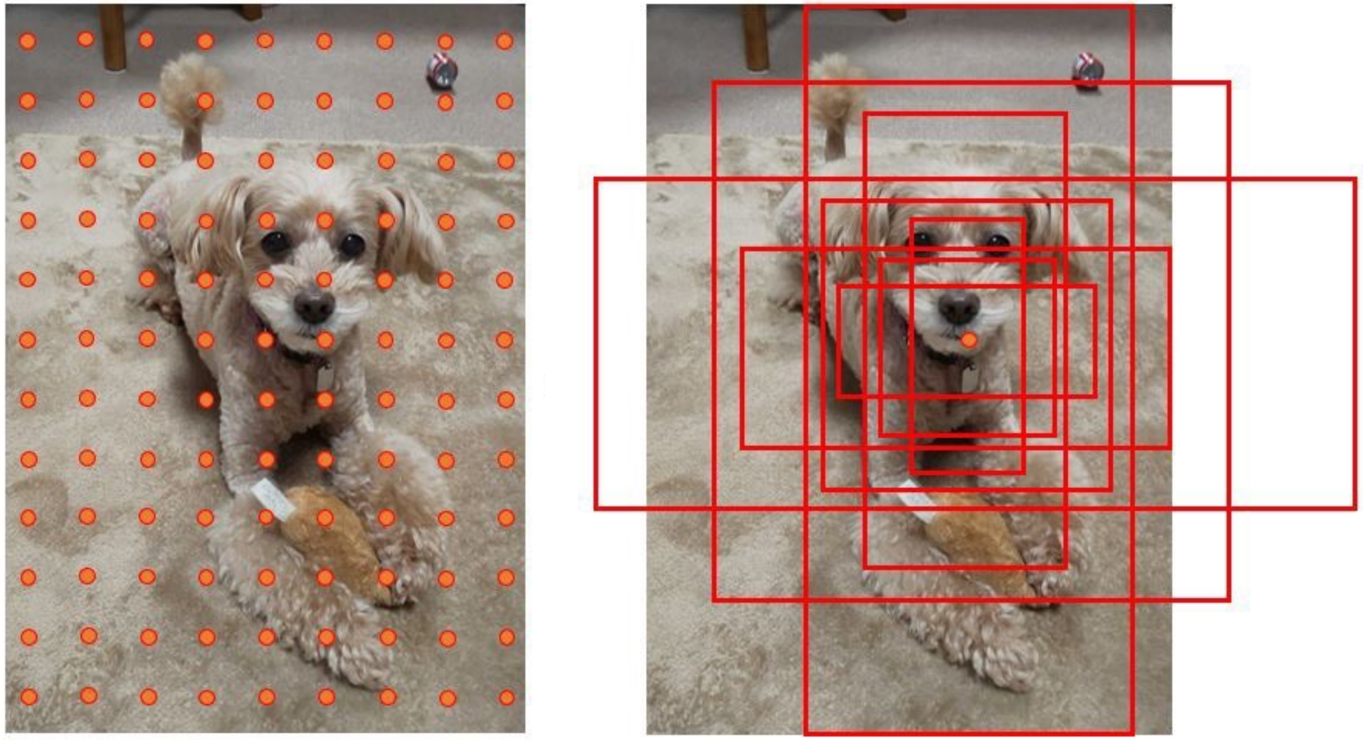


RPN, or Region Proposal Network, serves as the bounding box generator. It proposes boxes for where objects might be, based on extracted features.

RPN – Anchor Box Generation

The RPN begins with anchor box generation.

- Runs once at the beginning of training
- Generates "anchor boxes", a starting point for bounding box generation
- Original implementation: a set of anchor boxes is generated in a grid-like pattern across the whole feature map
- Configurable aspect ratios and scales
- An "offset" is then predicted by the network to make a proposal



Source

RPN – Sparse Bounding Box Proposals

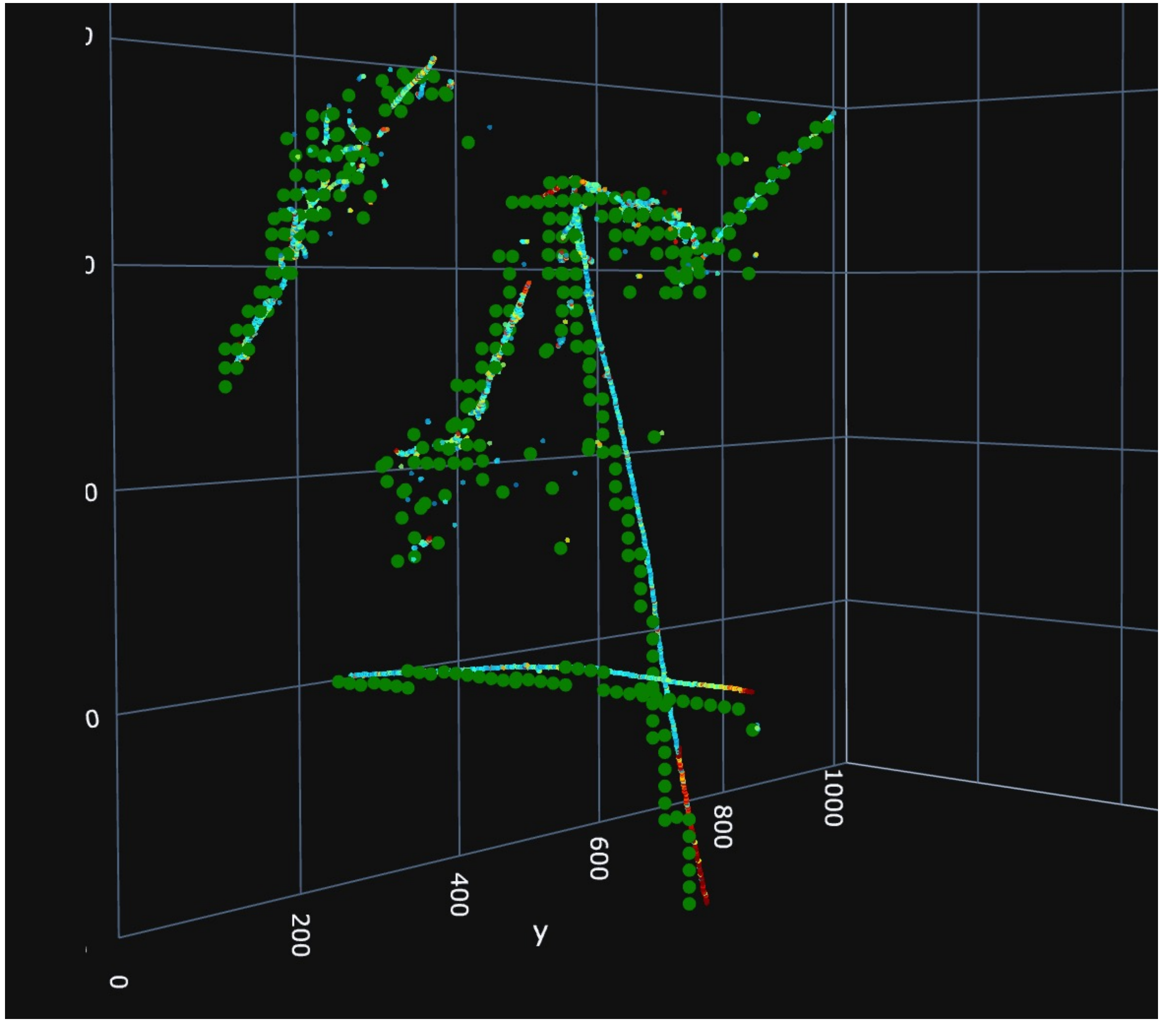
- This ”anchor-based” method of box proposal has been very successful, but it presents issues when used on our sparse 3D data

- Procedural grid-like generation of anchors is very inefficient on sparse data. Many are centered over nothing

- Number of anchors gets very large, especially on 3D images

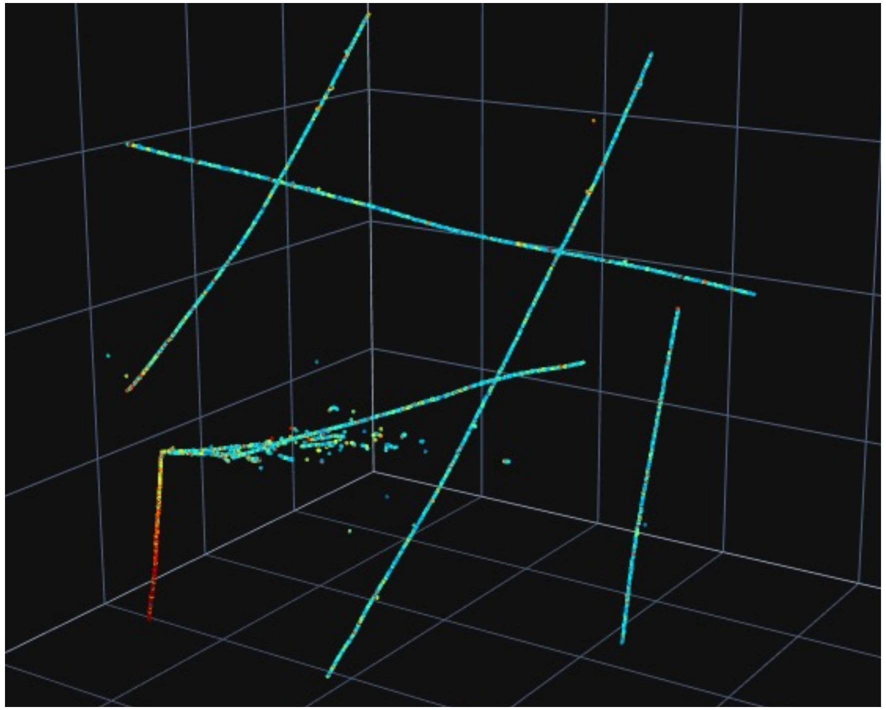
RPN – Sparse Bounding Box Proposals

- To this end, we introduce a few adjustments to improve efficiency of the proposal method:
- Anchors are no longer generated in a grid over the entire feature map. Instead, the center points align with the non-zero voxels of the input image.
- Convolutional layers are replaced with sparse submanifold convolutions, like ResNet



Training

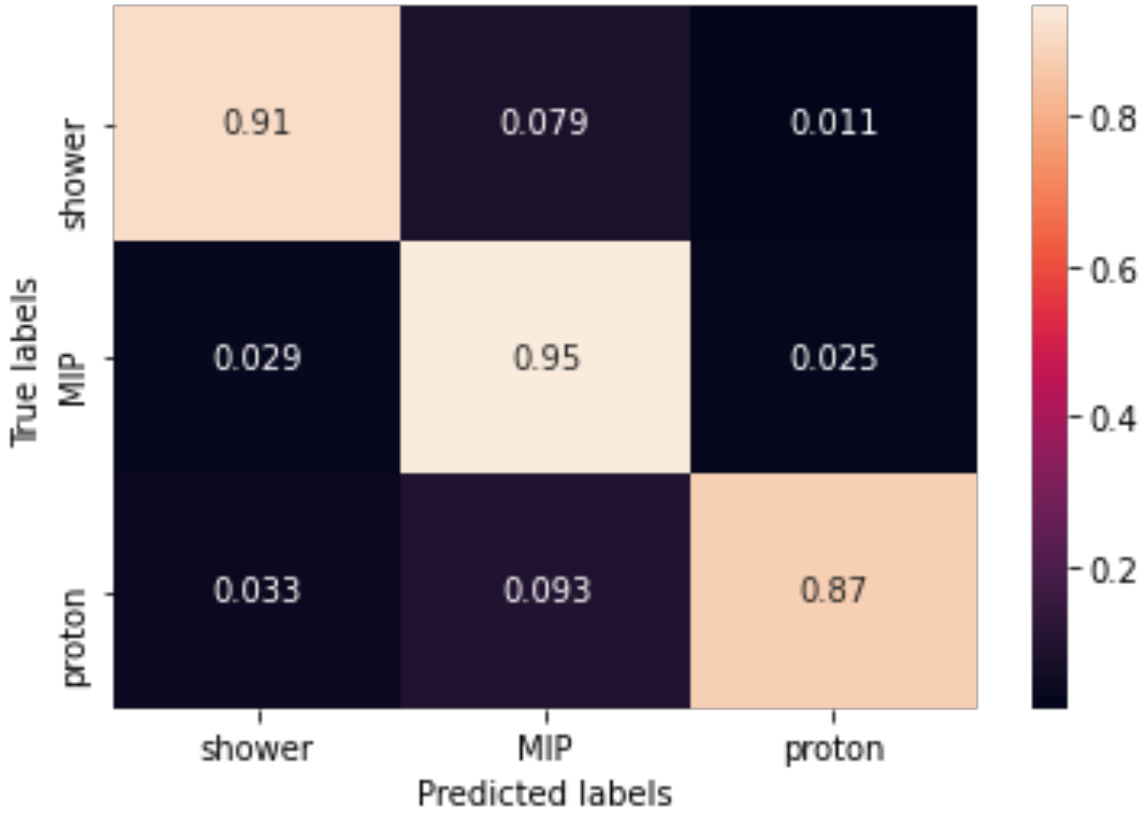
- Trained on simulation dataset for 350k iterations (~5.7 epochs)
- Results shown were inferred on a test dataset of 1000 events
- Dataset info: 1024x1024x1024 images, showers (photon, electron) and tracks (muon, pion, proton)



Classification Results

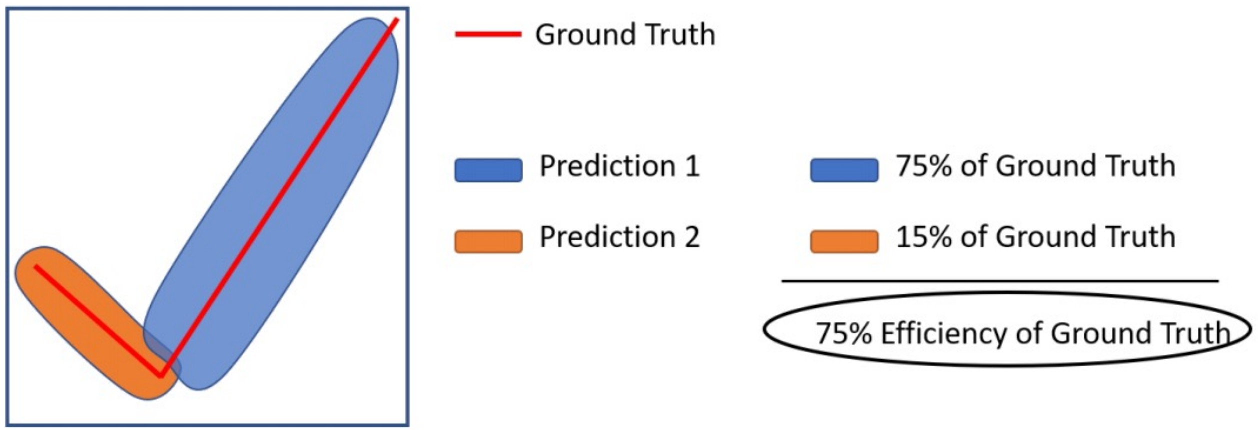
3 Class Particle Classification per GT Particle

- For each ground truth box, we use the class label of the most overlapping prediction box for the predicted label
- Shower class is separated well from the track classes
- Some confusion within the track/shower classes



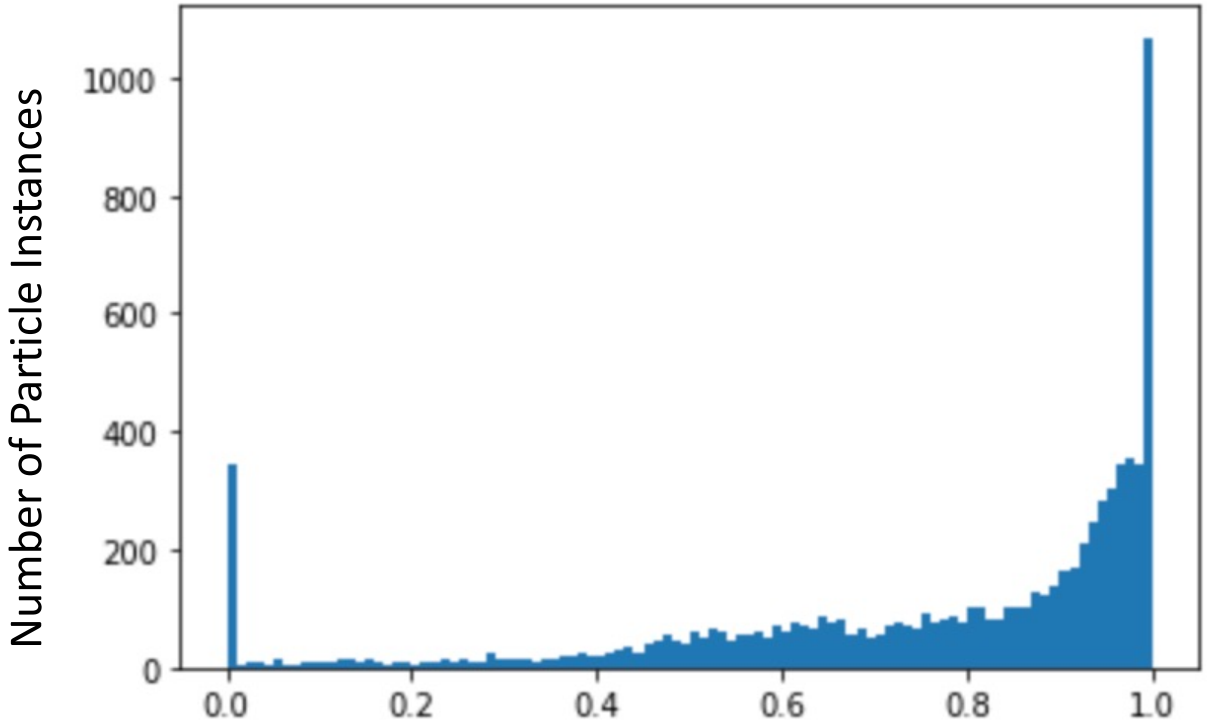
Bounding Box and Clustering Results

- Although the masking network for particle clustering has not yet been included in our training, the bounding box prediction results can give an indication for what to expect from the masking network when it is added
- Efficiency is a metric we use to measure clustering performance. It is defined as the fraction of the ground truth voxels covered by the predicted mask



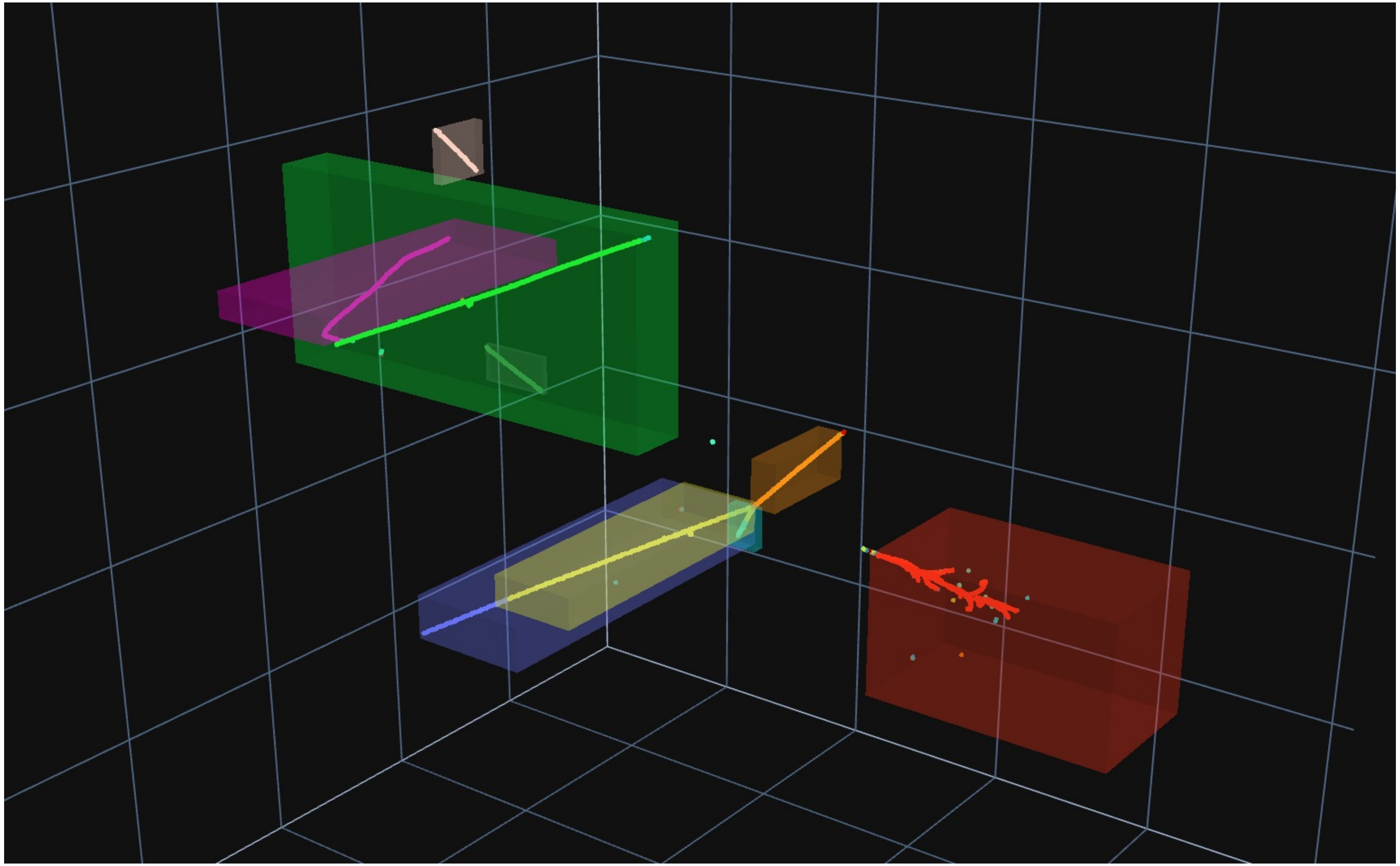
Bounding Box and Clustering Results

- A similar metric we can use with bounding boxes is to calculate the fraction of ground truth voxels which are enclosed within the predicted bounding box per ground truth particle

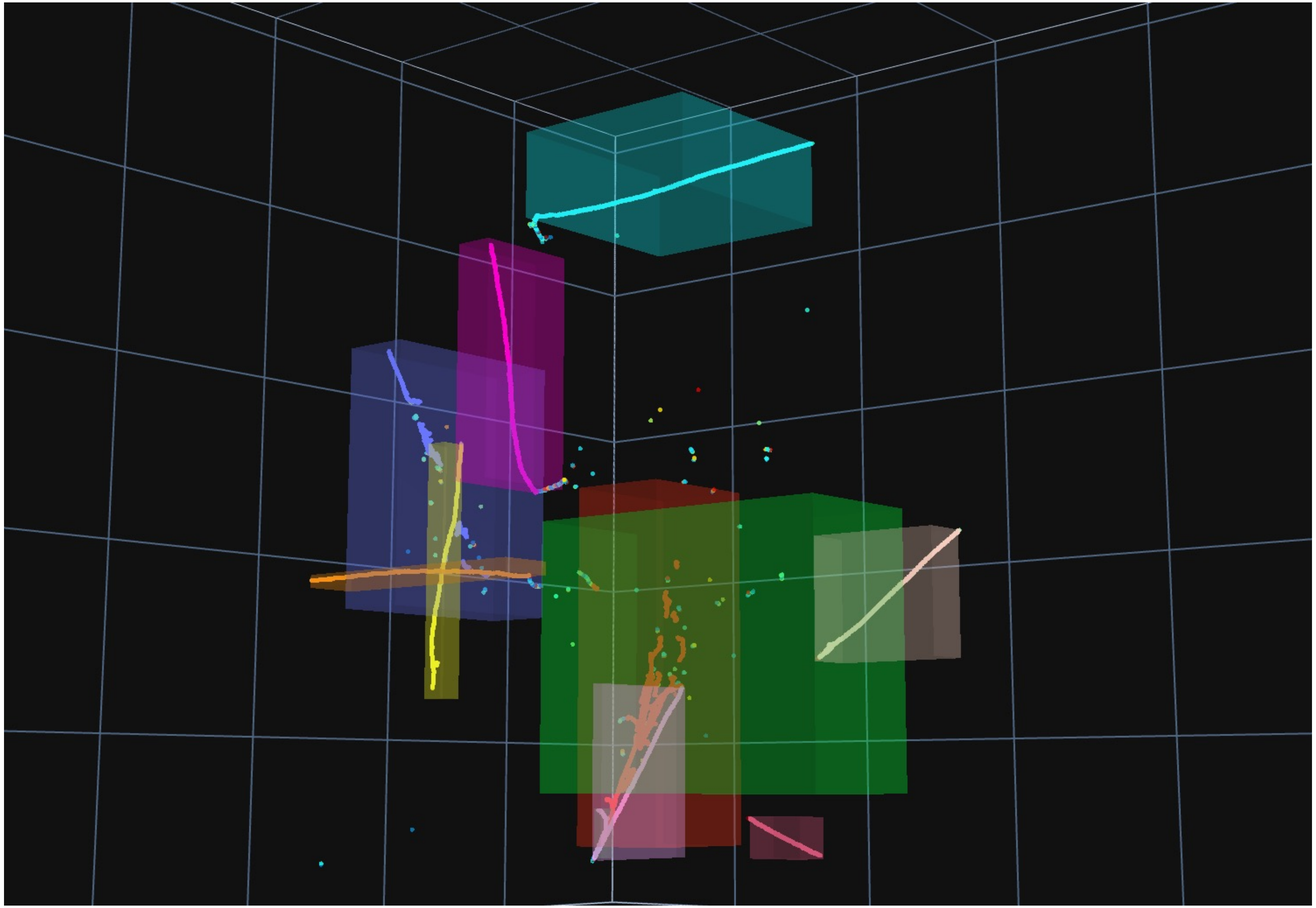


Fraction of GT Voxels Enclosed in Predicted Box per GT Particle

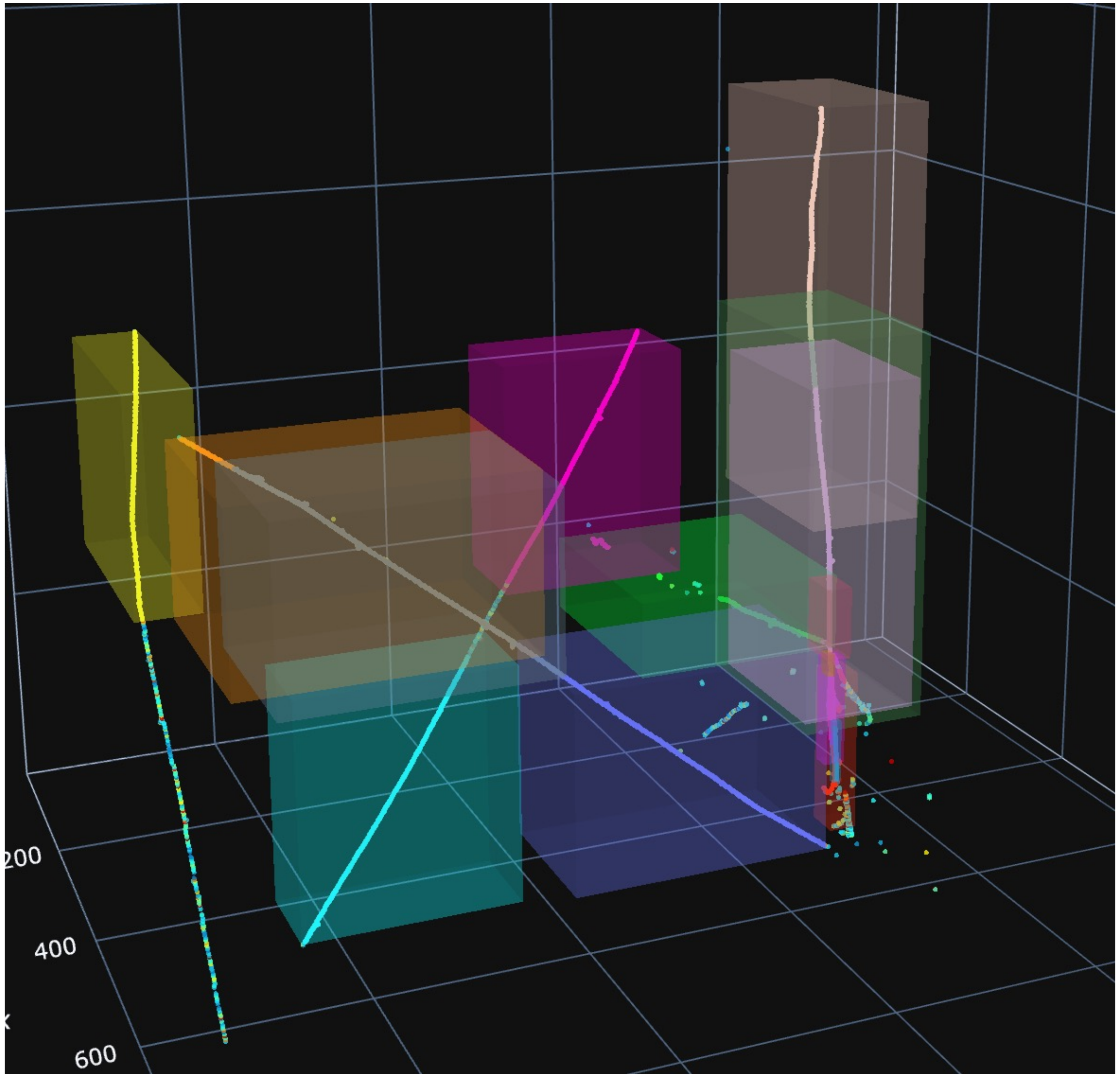
Event Displays



Event Displays



Event Displays



Future Plans

- Masking network (FCN) for clustering is also highly inefficient in 3D, so this portion of the network should also be converted to sparse
- Post-processing grouping algorithm to address the issue of multiple boxes trying to detect the same long track. This can also be used for the 2D network
- Parameter optimization, especially with the RPN

Acknowledgements

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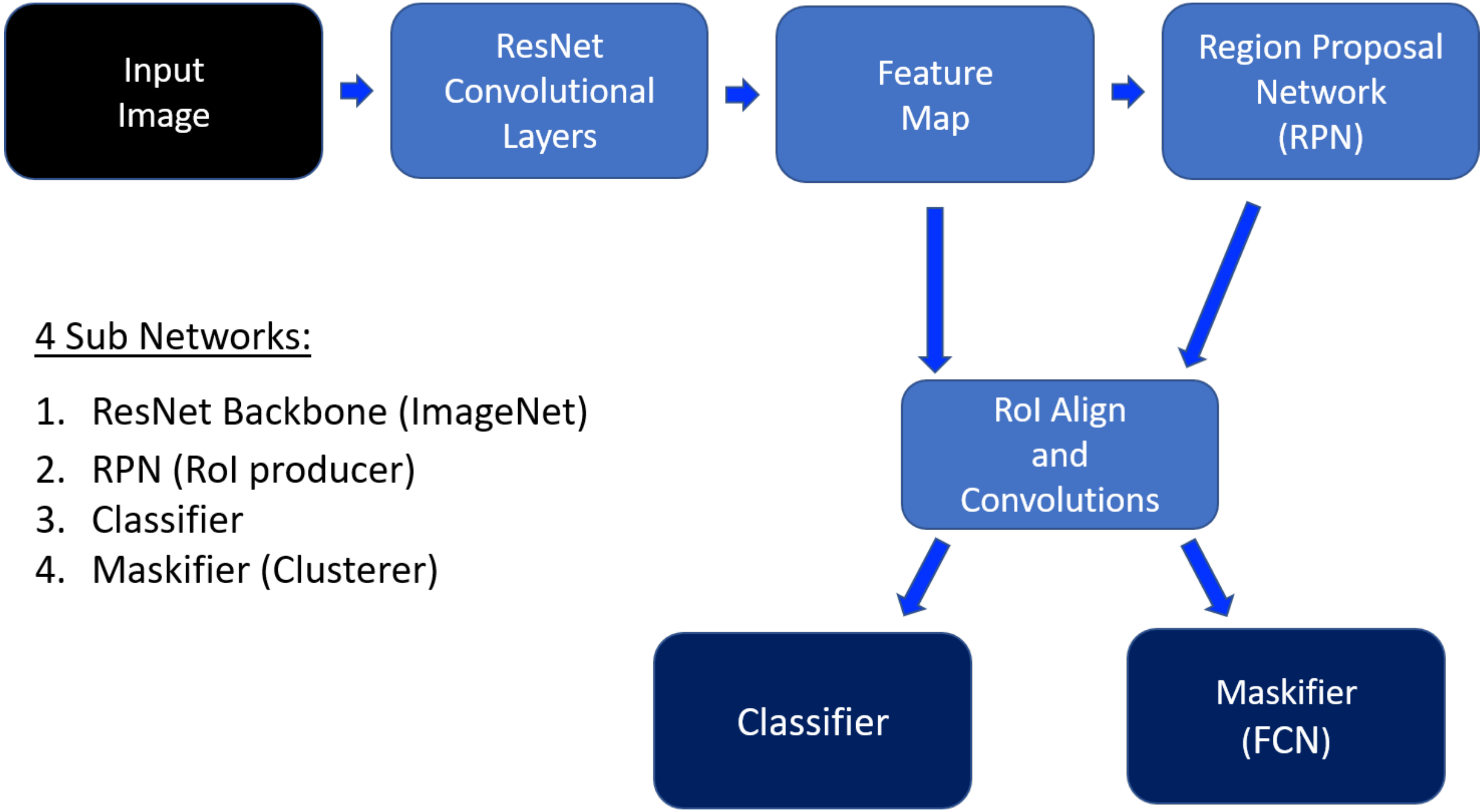
Backup

Network Architecture



4 Sub Networks:

1. ResNet Backbone (ImageNet)
2. RPN (RoI producer)
3. Classifier
4. Maskifier (Clusterer)

2D Mask-RCNN for MicroBooNE has already been developed and trained and works well. My approach is to convert this project to 3 dimensions.