A machine-learning based raw waveform ROI Finder in LArSoft

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LArSoft Coordination Meeting

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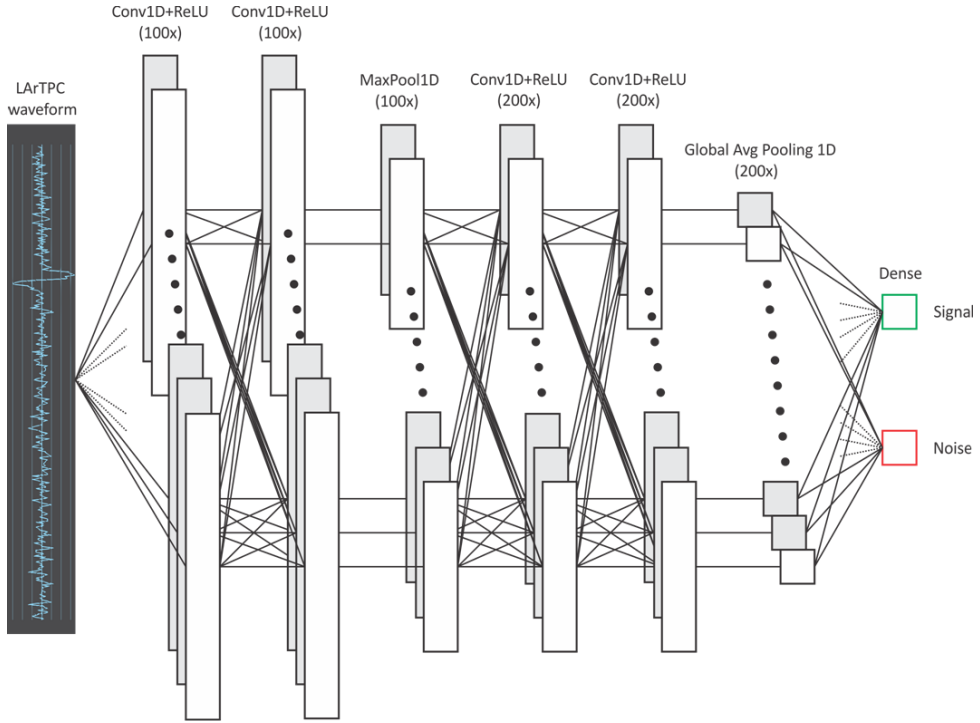
Introduction

- Motivation:
  - 10k's of wires in a typical LArTPC-based neutrino experiment
  - potential problem considering amount of data from all these channels that need to go through the computationally intensive signal processing algorithms (fft deconvolution, etc.) typically used by neutrino experiments to find signals
  - serious challenge for experiments that have to deal with huge backgrounds
  - or those that are interested in extracting small signals from low-energy phenomena
- Approach:
  - use modern deep learning (DL) methods
  - DL nothing new and now commonly used in neutrino experiments, but these algorithms tend to deal with higher-level reconstructed objects
  - in fact, some now investigating use of DL on raw LArTPC data, but these still tend to look at data across planes or multiple wires to form 2D images
  - common notion that Deep Neural Nets (DNNs only effective if data presented as pictures, images or in 2D form
  - no such constraint for DNNs, and in this talk, we describe our novel approach of using simple 1D-CNNs to look directly at raw temporal waveforms from single LArTPC wires

Initial Attempt

- Began this effort about a year ago with David Ruth (Fermilab TRAC-program teacher/intern) where we adapted 1DCNNs used to analyze cell phone accelerometer data to the analysis LArTPC waveforms:

Applied this to simulated DUNE data samples with promising results in signal/noise discrimination



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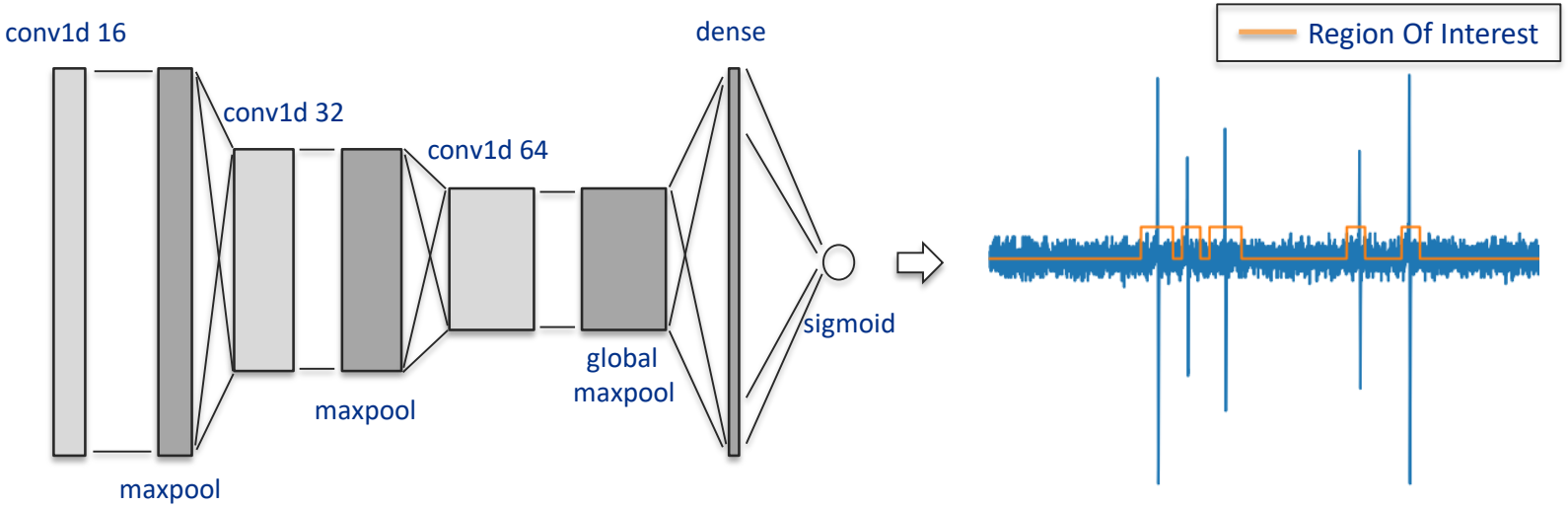
Further Development & Current Model

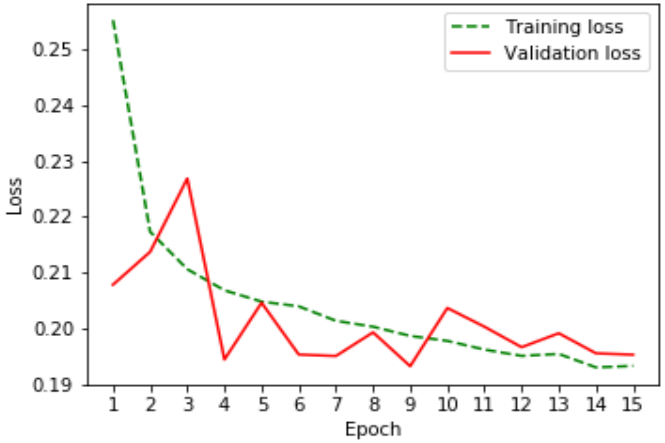
- Based on the promising results, we continued developing the idea and model with Lorenzo Uboldi (Fermilab Italian Students Summer program)
- Two major developments:
  - Significantly simplified the 1DCNN model we had used initially
  - Extended the technique to the identification of the Region Of Interest (ROI) in the waveform

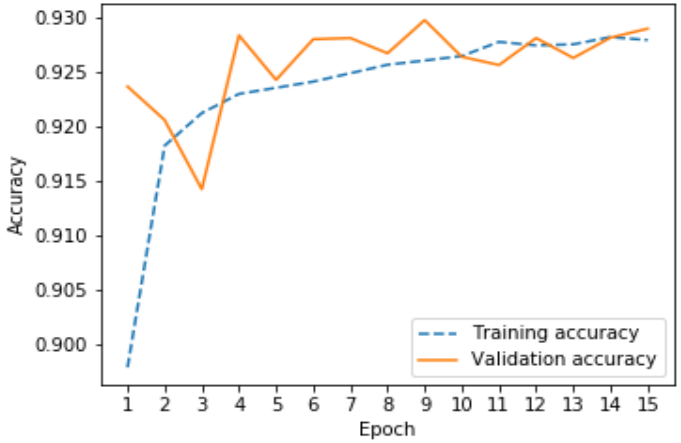


Training and Validation on simulated ProtoDUNE samples

From Lorenzo

- Trained on 112k samples, validation set 28k samples
- Half signal and half noise waveforms
- Binary cross entropy loss with adam optimizer
- 15 epochs, batch size 64 optimized for learning convergence
- Very fast: 6 minutes on a Nvidia GTX1060





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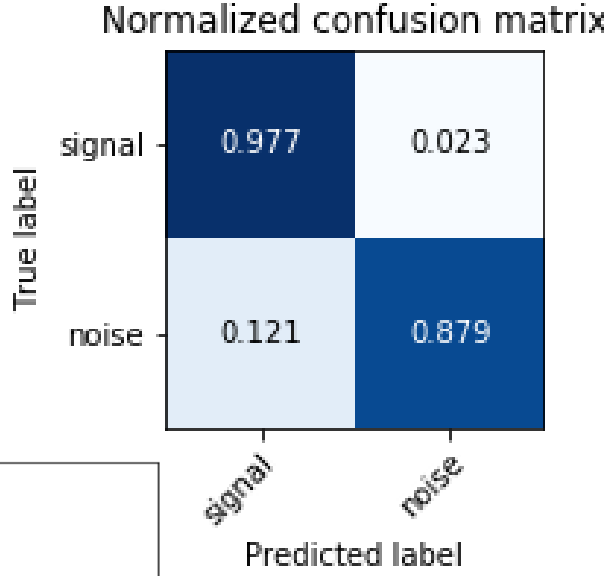
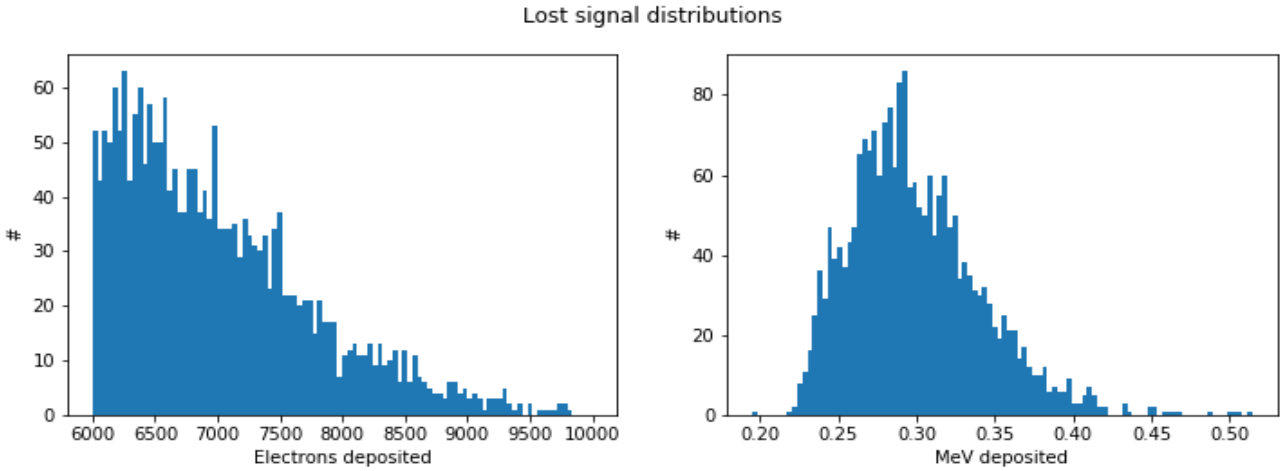
Testing Results on ProtoDUNE samples

From Lorenzo

- Test set with 35k examples
- 1.8 seconds on Nvidia GTX1060
- Test accuracy 0.93





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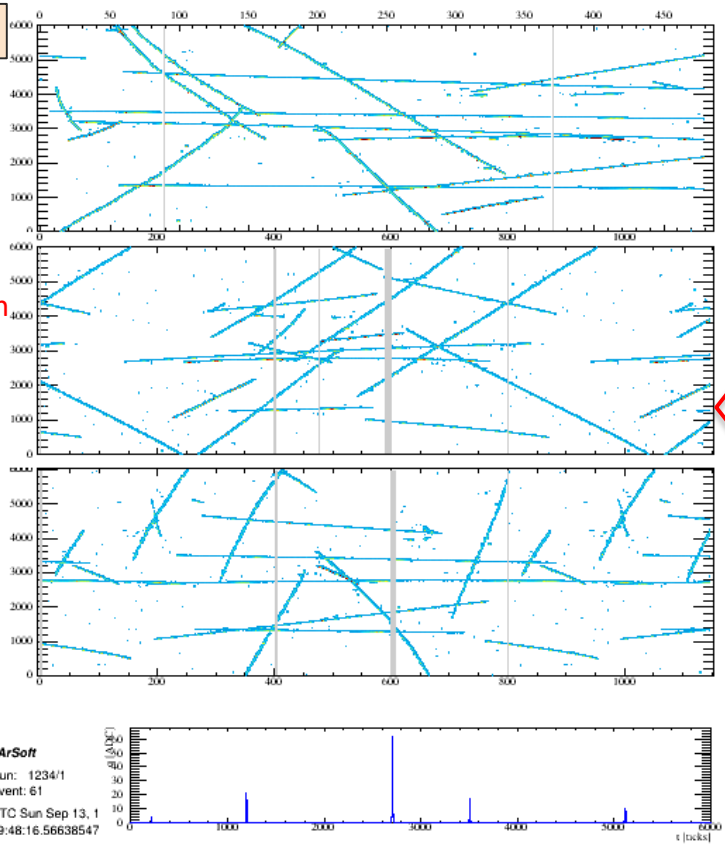
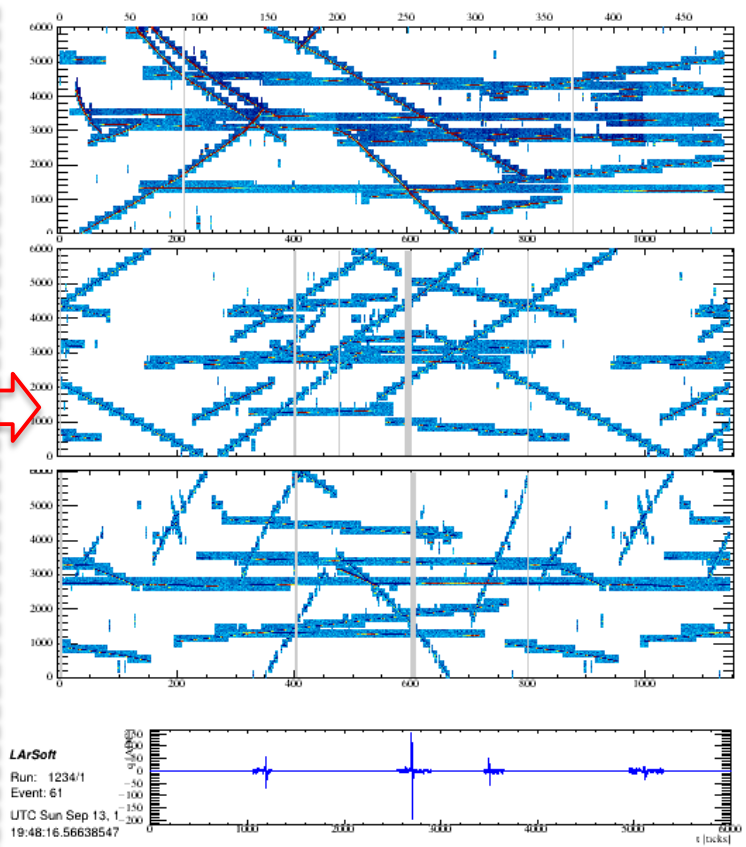
Trained model applied to simulated ProtoDUNE samples

From Tingjun

Deconvolution based ROIs





1D CNN based ROIs

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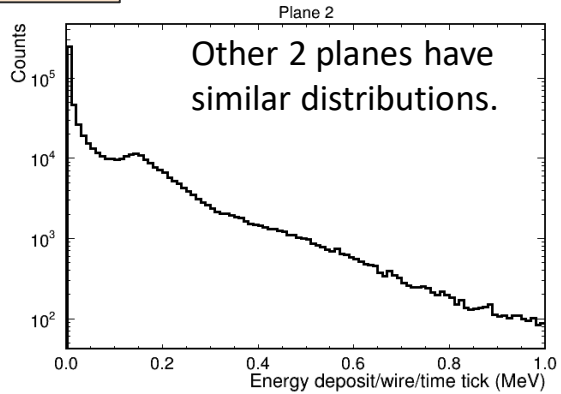
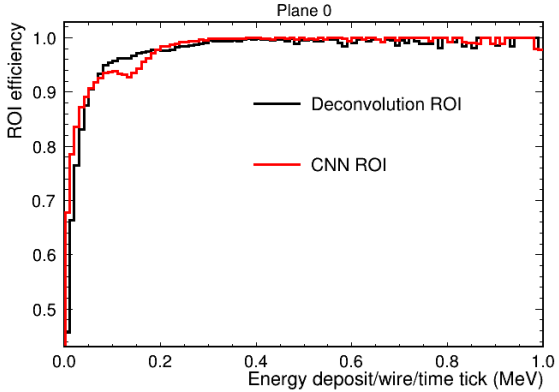
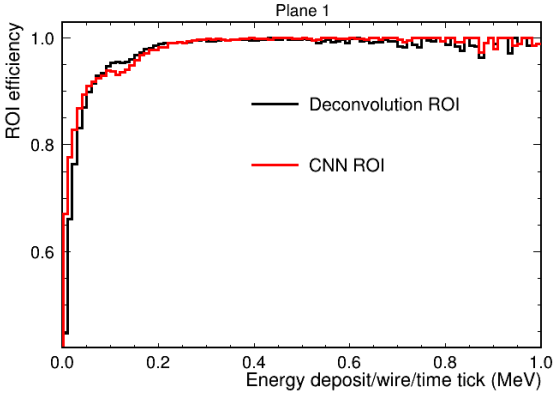
Efficiencies determined from simulated ProtoDUNE samples

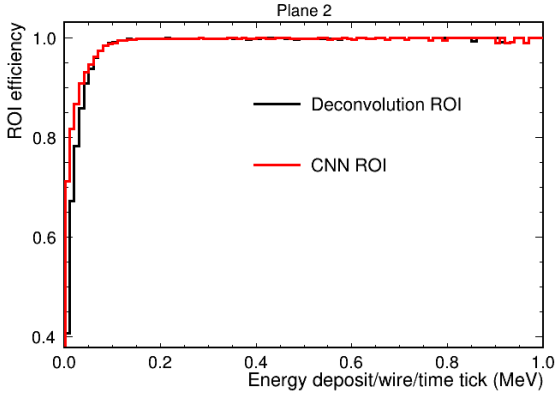
From Tingjun

Efficiency of ROI finding algorithms









Two components in the energy distribution: radiological backgrounds (^{39}Ar etc.) at low energy and muons at high energy.

CNN based ROI finder gives comparable results versus the deconvolution based ROI finder.

CNN based ROI has a fixed size, so it is not a direct comparison.

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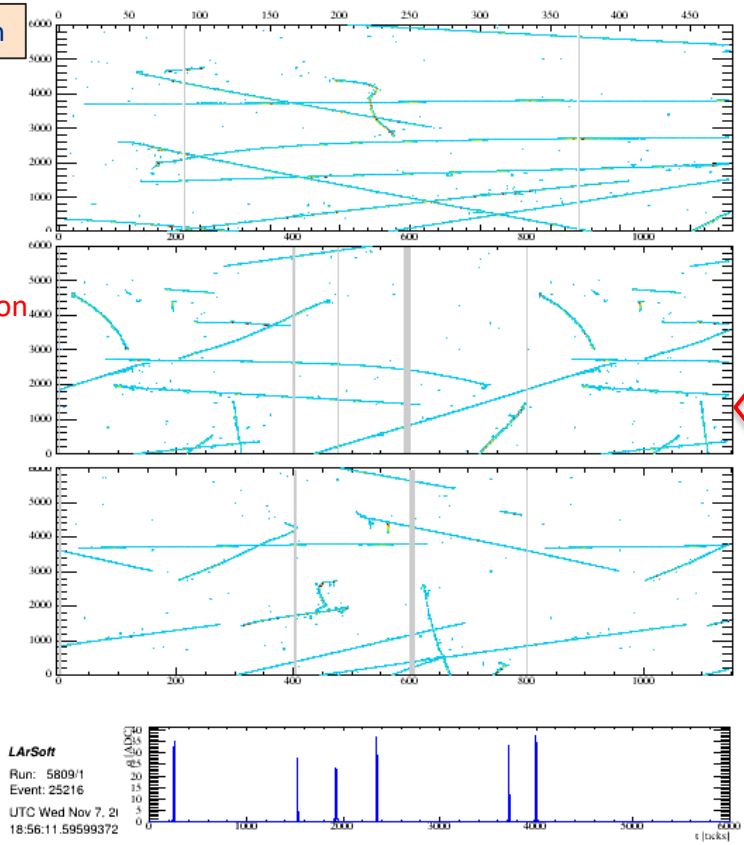
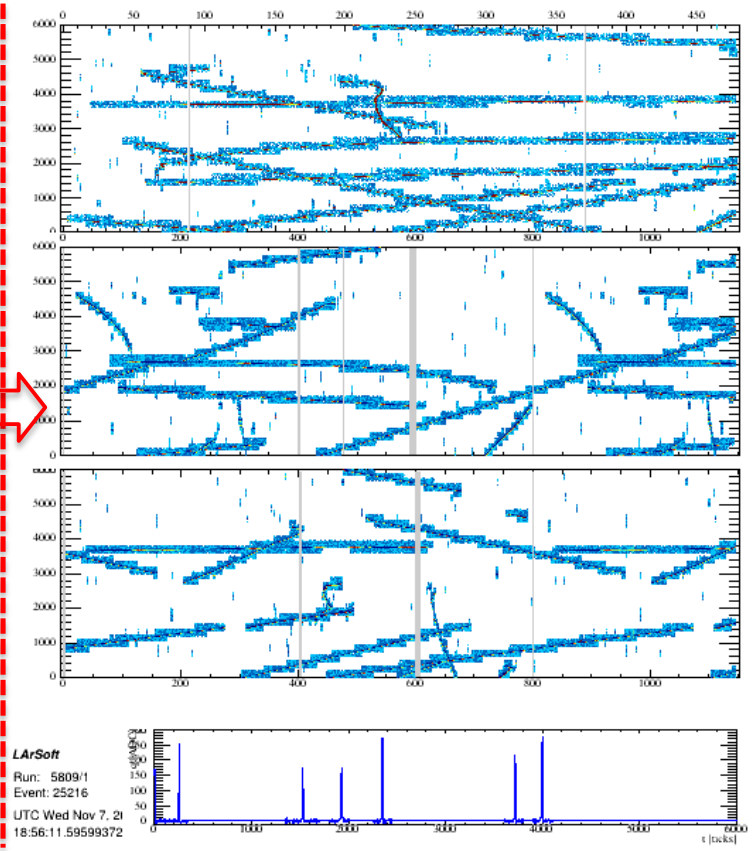
Trained model applied to real ProtoDUNE data

From Tingjun

Deconvolution based ROIs





1D CNN based ROIs

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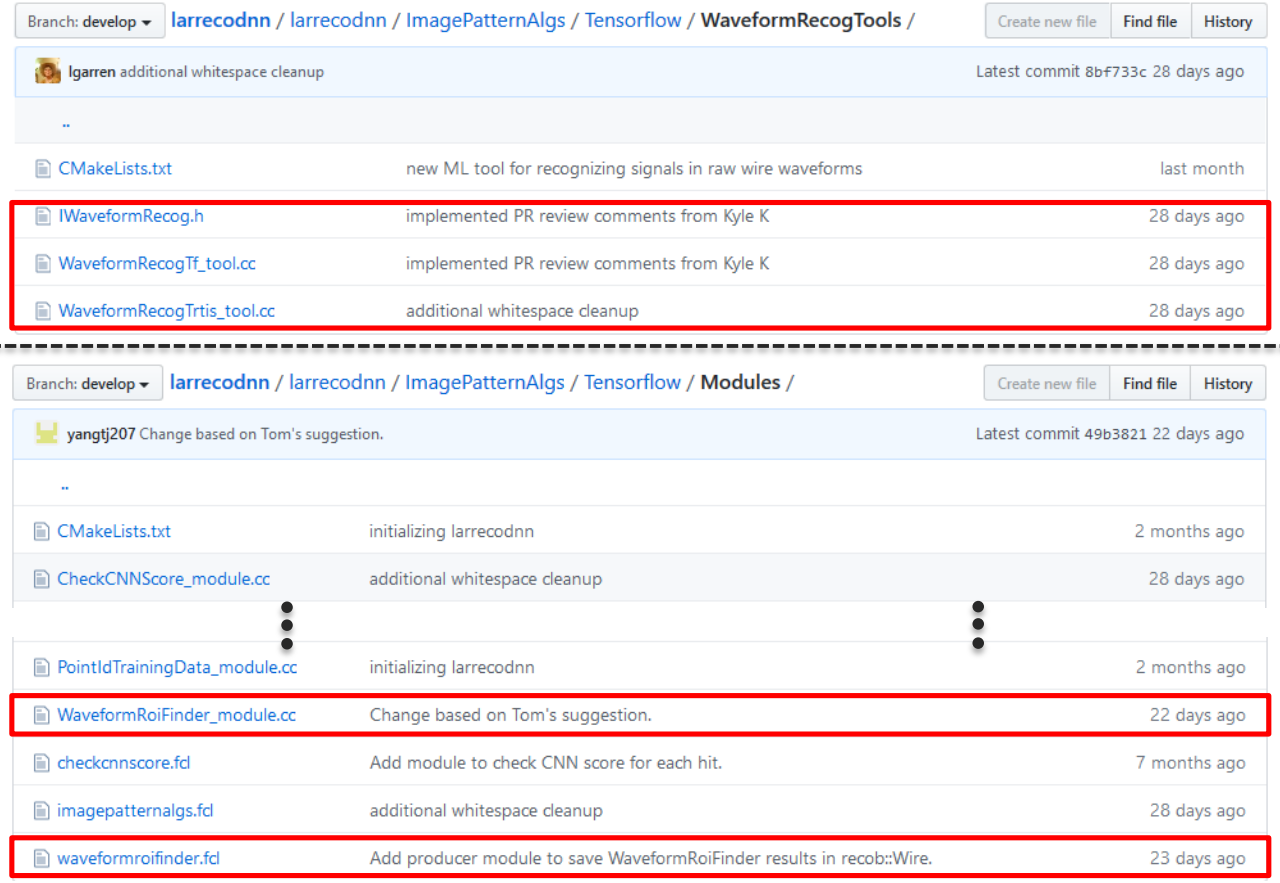
Significance of ProtoDUNE studies

- Main takeaways from previous two slides
  - Certainly, traditional deconvolution based ROI finder does a better job in localizing the signal
  - Main point, however, is that the CNN-based tool approximates the results very well by dealing directly with unprocessed raw waveforms, without relying on the computationally demanding algorithms in the typical LArTPC signal processing pipeline
  - Implications:
    - Offline use: can be implemented in early stages of offline reconstruction as a very effective filter or sophisticated zero-suppression algorithm, so later stages can implement more sophisticated signal processing on much less data
    - Online use: simple CNN architecture can be implemented in hardware and deployed in front-end boards for intelligent filtering or as a trigger
  - Also important to note preliminary nature of results, algorithm is likely not optimal yet and can be further improved

LArSoft Tool and Module



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Conclusion

- Shown that DL techniques can be applied to single LArTPC wires not only to discriminate signal from noise waveforms but also to localize the signals within the waveform
- Deployed a new tool and module in LArSoft that performs this functionality
- Tested the tool/module on real ProtoDUNE data with very encouraging results
- Implications for intelligent offline and online filtering applications
- Next steps:
  - More studies to characterize performance of algorithm
  - Optimize the algorithm further for performance and computational speed
  - Started looking at Argoneut data, looking into to developing better noise model so the model can be trained effectively
  - Look into possible hardware implementation for online applications

End