Machine Learning for Double Beta Decay with EXO-200

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SLAC ML Workshop
February 19, 2019
On behalf of the EXO-200 Deep Learning Group

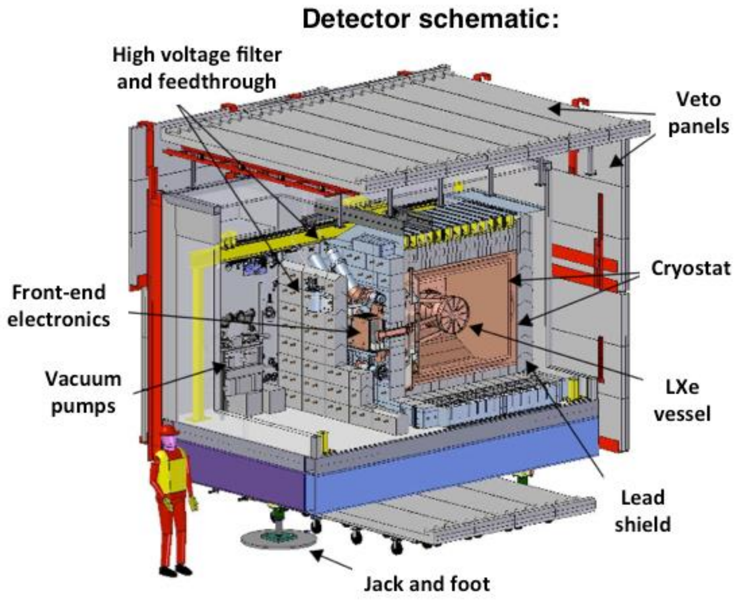
A special thank you to **Mike Jewell, Tobias Ziegler, Johannes Link, Igor Ostrovskiy**

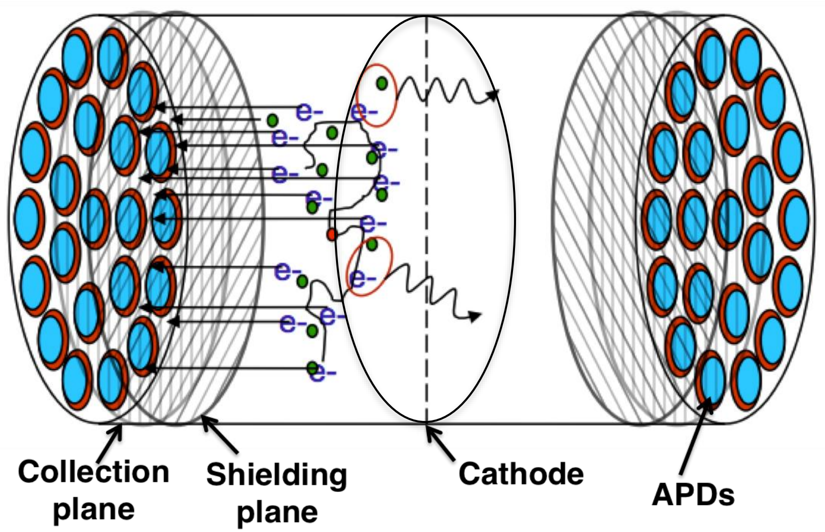
U.S. DEPARTMENT OF ENERGY
Office of Science

SLAC NATIONAL ACCELERATOR LABORATORY

EXO-200 LXe Time Projection Chamber (TPC)

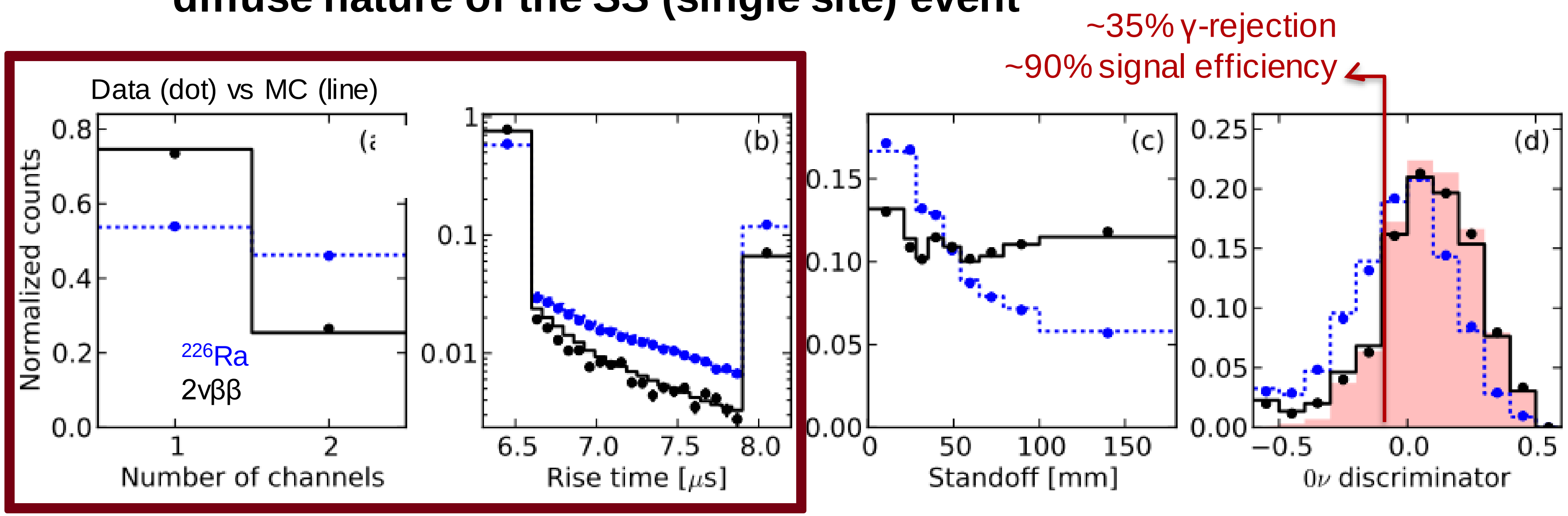
- EXO-200 consists of a radiopure TPC filled with enriched LXe (80.6%)
- Located at Waste Isolation Pilot Plant (WIPP) in Carlsbad, NM, USA
- High-voltage applied between cathode and anodes (opposite ends)
- Two measurements of energy deposited in event
  - Scintillation light (178 nm), by large avalanche photo-diodes (APDs)
  - Ionization charge, by 2 wire grids (induction and collection)





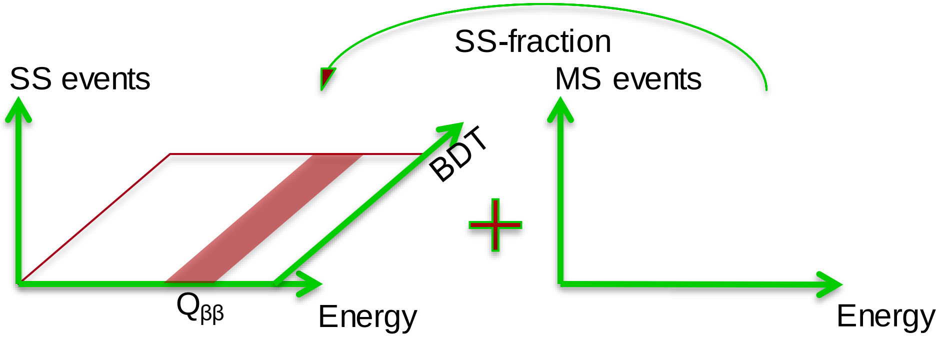
Optimal $0\nu\beta\beta$ Discrimination

Use a boosted decision tree (BDT) variable fed more information about the diffuse nature of the SS (single site) event



Fitting 0νββ discriminators

- **Energy**
- **SS/MS (MS ≡ multi-site)**
- ***BDT → ~15% sensitivity improvement***



J.B. Albert *et al*., Phys. Rev. Lett. 120, 072701 (2018).

Deep Learning Studies

First DL Paper Published in JINST, August 2018.

- DNN reconstructed charge energy a little better than with standard reconstruction
- Validation with real detector data
- Real data events can be used to train networks in some circumstances

Highlights of Current Work

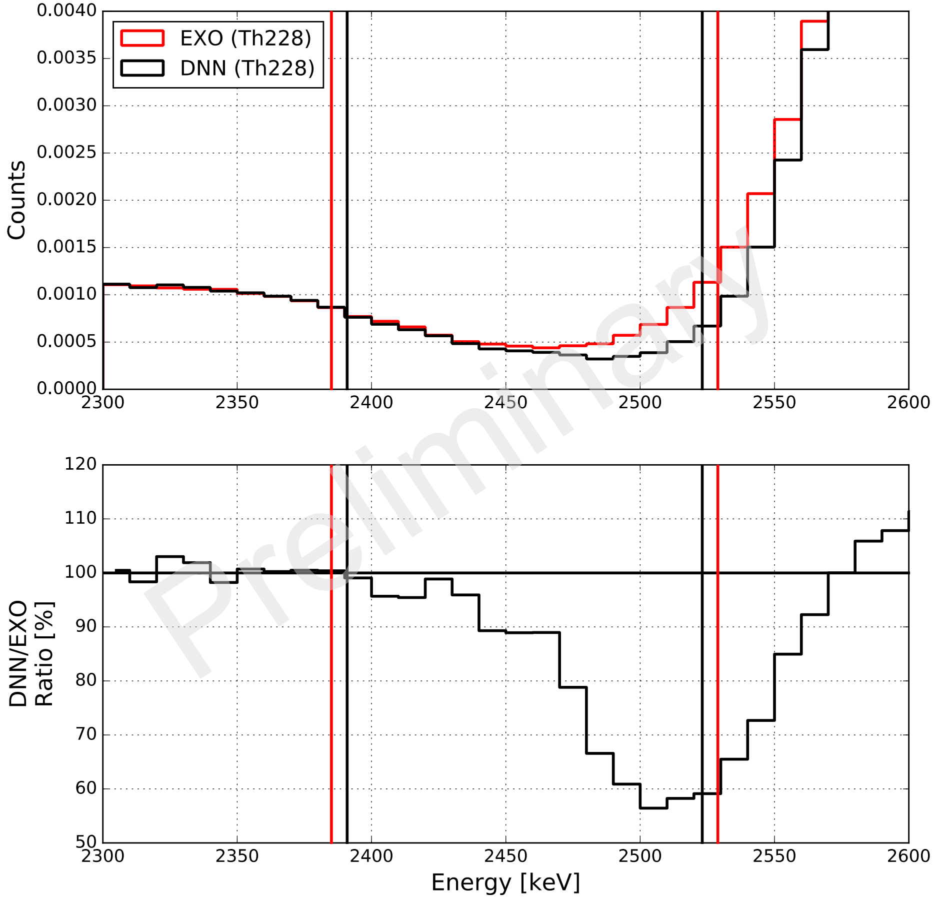
- Build signal-background discriminator with Deep Learning based method based on raw charge signals to be used for both SS and MS events (Tobias Ziegler and Mike Jewell)
- Position and Energy reconstruction using Deep Learning (Johannes Link)
- Improving Monte Carlo simulations using Generative Adversarial Network (GAN) (Federico Bontempo)

Collection and Induction Signal Finding for Energy Determination - DNN

It's not only about reconstruction – better induction disentangling and slightly better rotated resolution already make a quantifiable improvement to physics goals

Projected ~29% reduction of ^{232}Th background in Phase I and ~18% in Phase II compared to standard recon

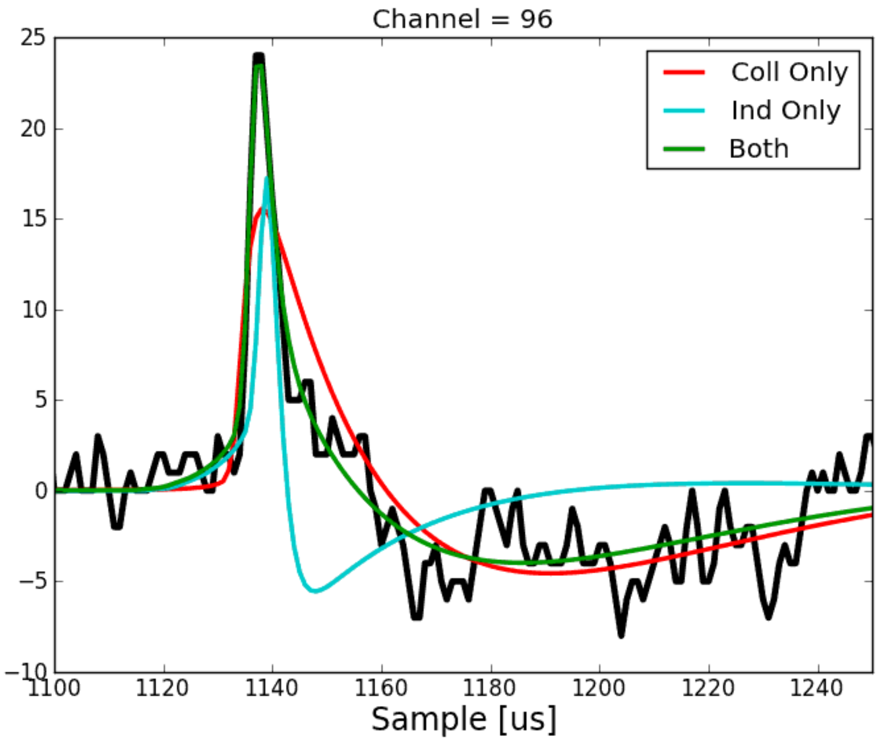
- ~19% and ~11%, respectively, considering induction effect alone
- Using $1/\sqrt{B}$ scaling, this suggests ~9% sensitivity improvement for Phase I and ~5% for Phase II

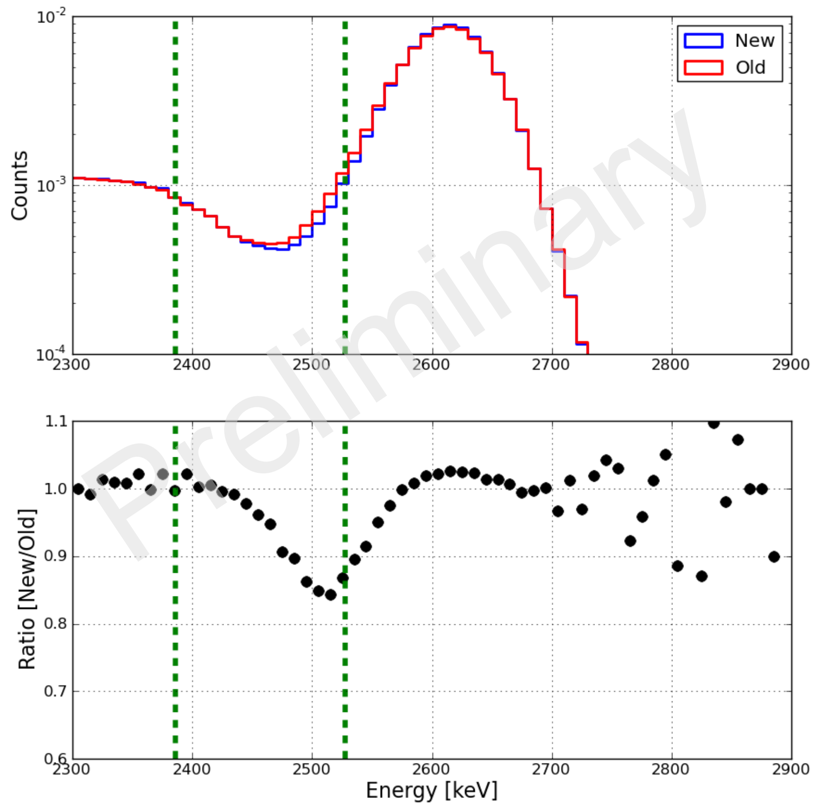


Contribution of ^{232}Th background to ROI when using DNN and (last published) EXO recon

Combined Collection and Induction Fitting – Standard Analysis

- DNN Energy Reconstruction is better at disentangling Induction/Collection Signals
- Standard Reconstruction only allows signals to be fit as pure induction or pure collection
  - Can cause ^{228}Th events to leak into ROI (region of interest) if real collection energy is lost
- Matt Coon developed a fitter which allows a mixture of both
- ~6% fewer events in the ROI after including the improved Fitter (reducing total ^{232}Th background in the ROI by 11.6%
- After including combined induction and collection signal fitting, DNN still outperforms standard EXO-Recon significantly





Contribution of ^{232}Th background to ROI when using new Fitter

Signal-Background Discriminator with DNNs (Tobias Ziegler & Mike Jewell

Goal of study and design choices

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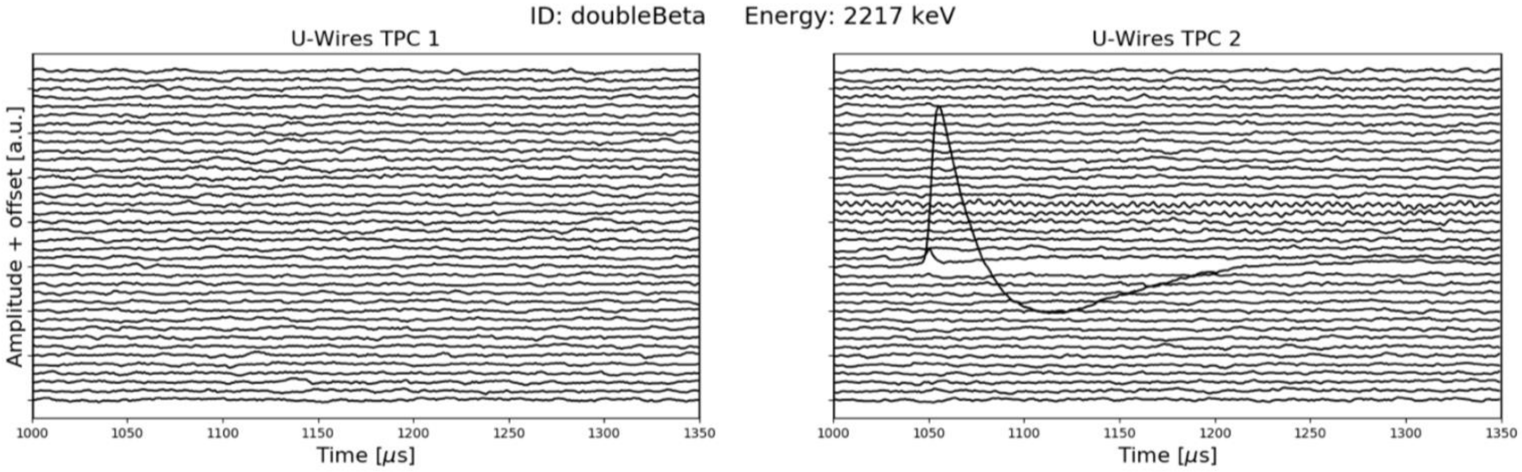
- Binary classifier for background (gamma events) and signal (2beta events)
- Train on full energy range for bkg/sig (1—3 MeV) → No focus on Q value
- Train on uniform spatial distributions for bkg/sig → Focus on topology only
- Use raw U-wire waveforms from Phase II
  - 2 images, one for each TPC, as input to DNN
  - Applied channel gain correction
  - Cropped from 2048 to 350 time samples

** Classifier acts as an additional observable to be used with standard analysis chain



Signal-Background Discriminator with DNNs (Tobias Ziegler & Mike Jewell

DNN architecture

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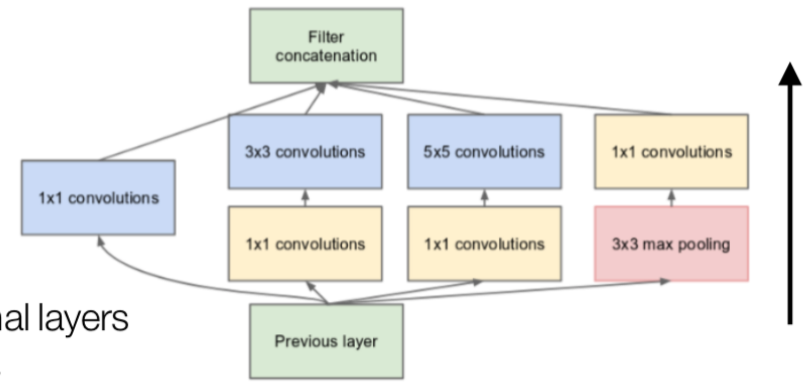
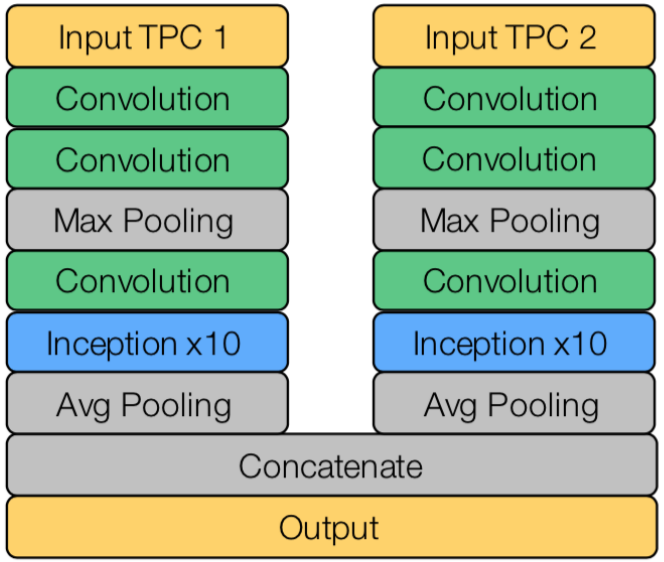
- Similar network architecture compared to DNN energy reconstruction study
- Convolutional layers to extract features from the U-wire ‘images’
  - Use *Inception 3* modules invented by Google instead of plain convolutional layers
  - Capture both small and big features at once and concatenate afterwards
- U-wire images from TPC 1 and TPC 2 pass through the same layers separately
- DNN Output for each event is the probability to belong to the signal class:
  - Background = 0.0
  - Signal = 1.0





- Training performed on GPU Cluster with NVidia GeForce GTX1080 Ti (11GB) at Erlangen.
- Training takes roughly 24-48 hours
- Inference is done on same system or on Cori at NERSC

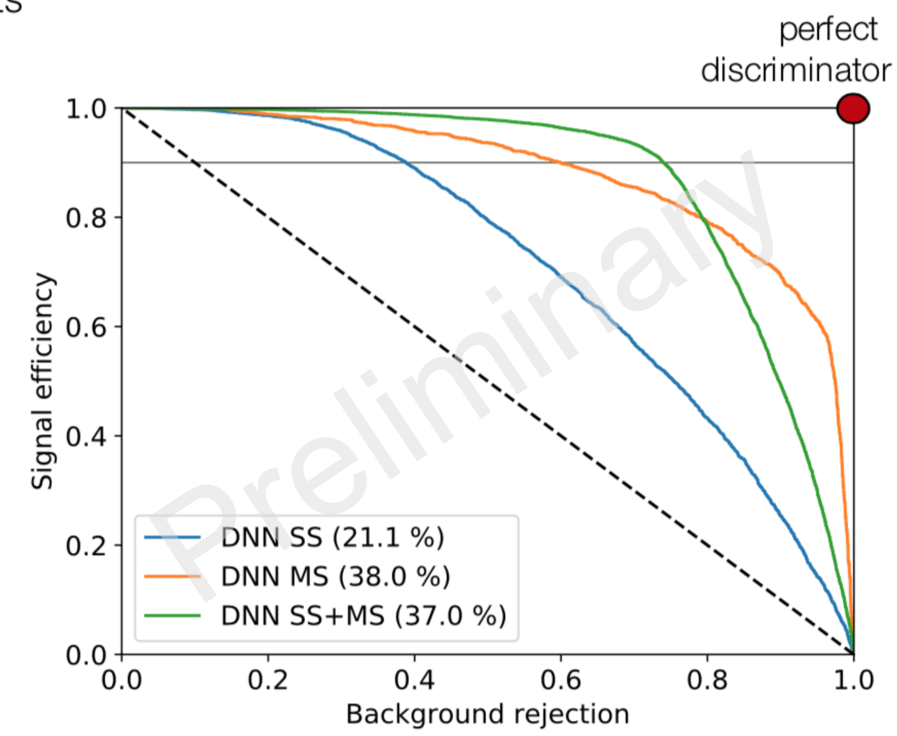
Signal-Background Discriminator with DNNs (Tobias Ziegler & Mike Jewell

ROC curve of validation data

- Signal efficiency and background rejection can be varied by adjusting prediction threshold
- Area under curve to diagonal line ranges from 0.0 (diagonal line, coin toss) to 0.5 (perfect)
- DNN can still recover many signals from MS channel while rejecting most of the background events

- Bkg rejec @ 90% sig eff:
  - SS ~ 40%
  - MS ~ 60%

- Sig eff @ 90% bkg rejec:
  - SS ~ 20%
  - MS ~ 65%



Position and Energy Resconstruction using DL (Johannes Link)

Aim of the study

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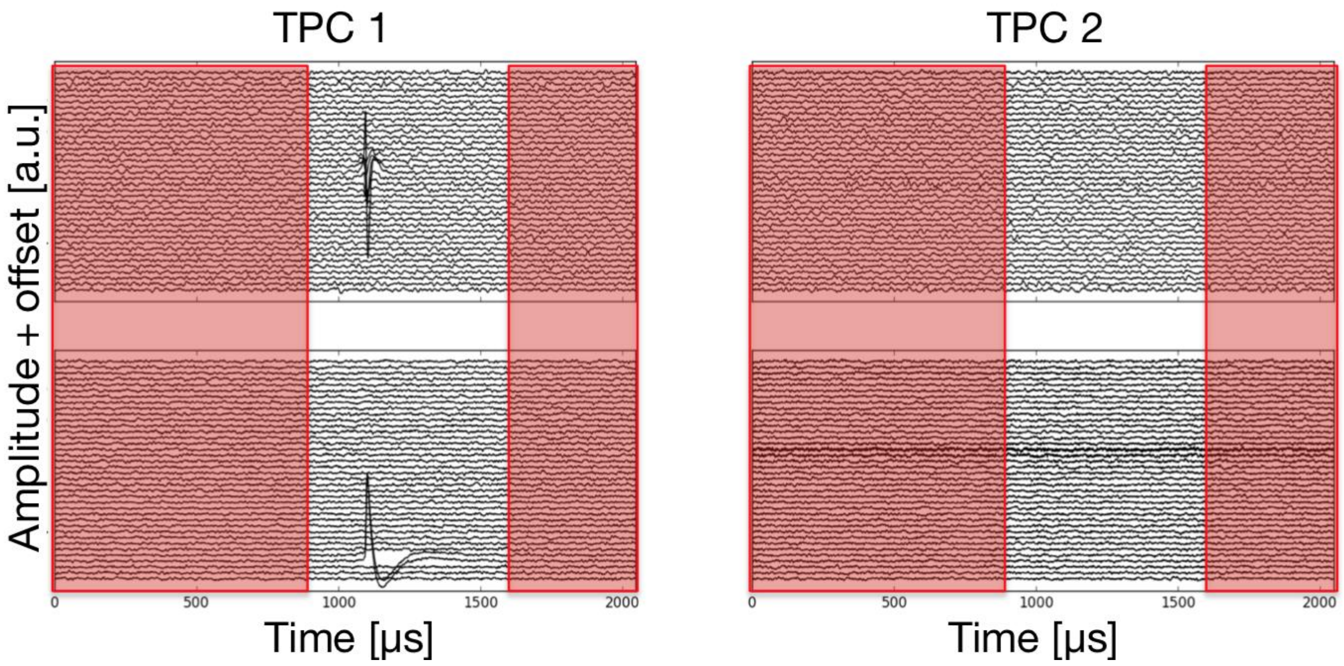
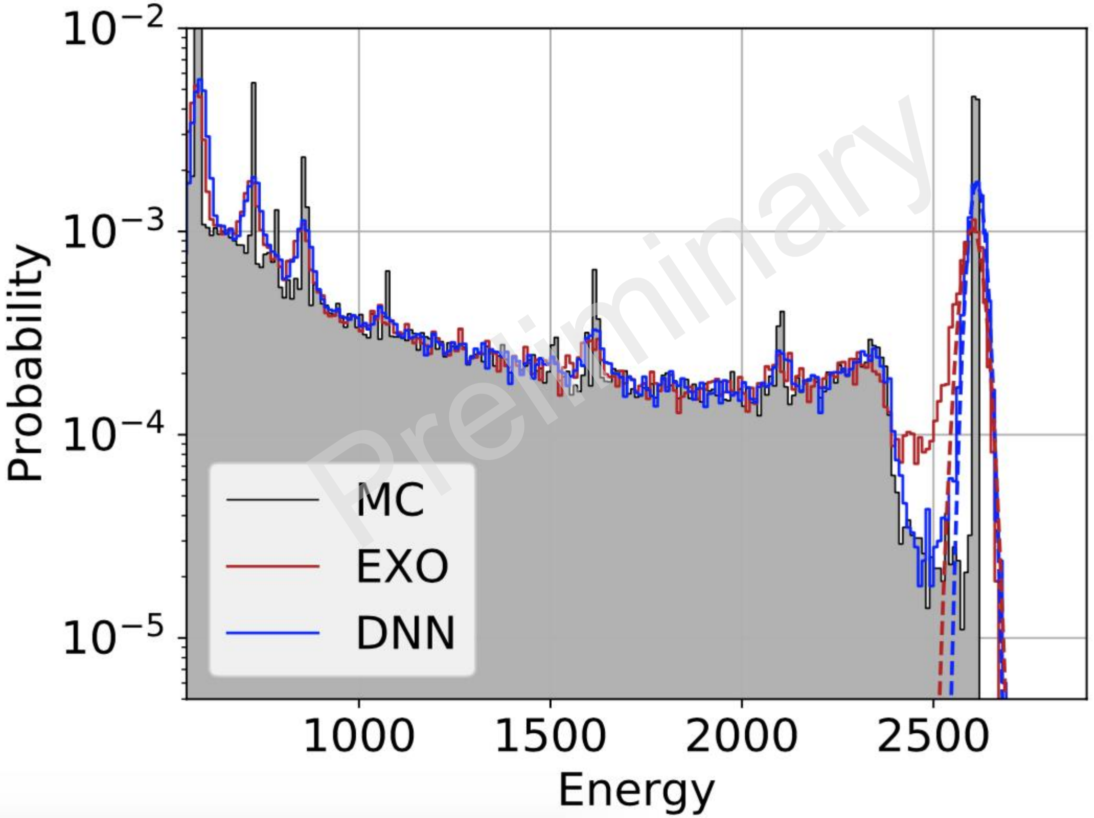
- Reconstruct position and energy for SS event in TPC
- Input: Raw cropped waveforms of U- and V-wires (4 x 700 x 38)
- Output: energy and position (U, V, Z) of deposit
- Training: MC data uniformly distributed (in positon and energy)



Position and Energy Resconstruction using DL (Johannes Link)

DNN on SS events

- Validation on Th228 Monte Carlo at S5
- Energy resolution at peak:
  - EXO: 1.01 %
  - DNN: 0.75 %



When extending to MS events, difficulty is that they have no MC true position

Improved MC Simulations using GANs (Federico Bontempo)

Accuracy & Prediction V-wires

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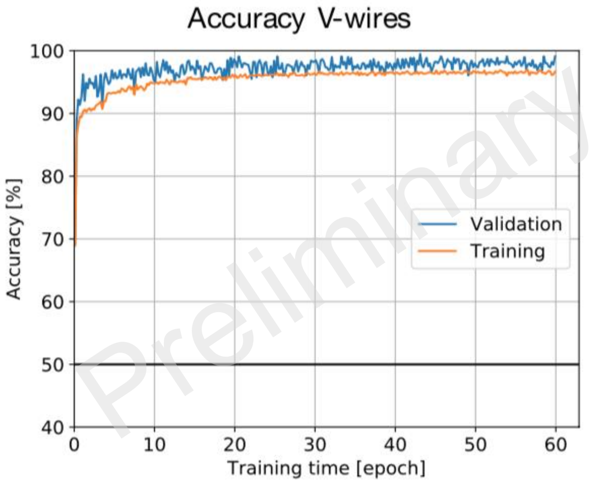
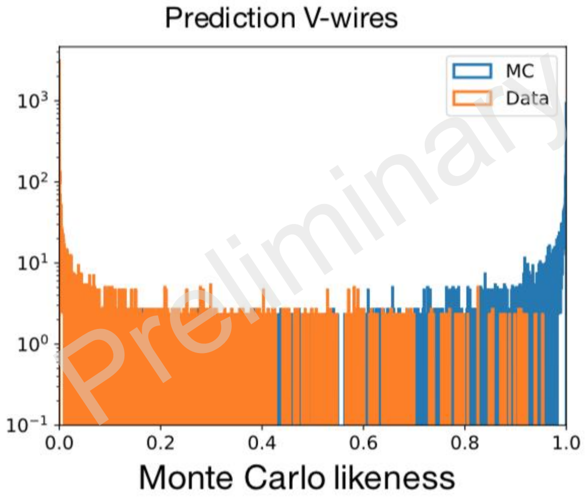
- Trained Convolutional Neural Network to distinguish Monte Carlo and real events
- The Accuracy for V-wires was very high:
  - V-wires: 0.96+



- The Prediction is the probability given by the CNN to every event to belong to Monte Carlo class
  (1=MC, 0=real data).

→ The network is able to distinguish between real and Monte Carlo events

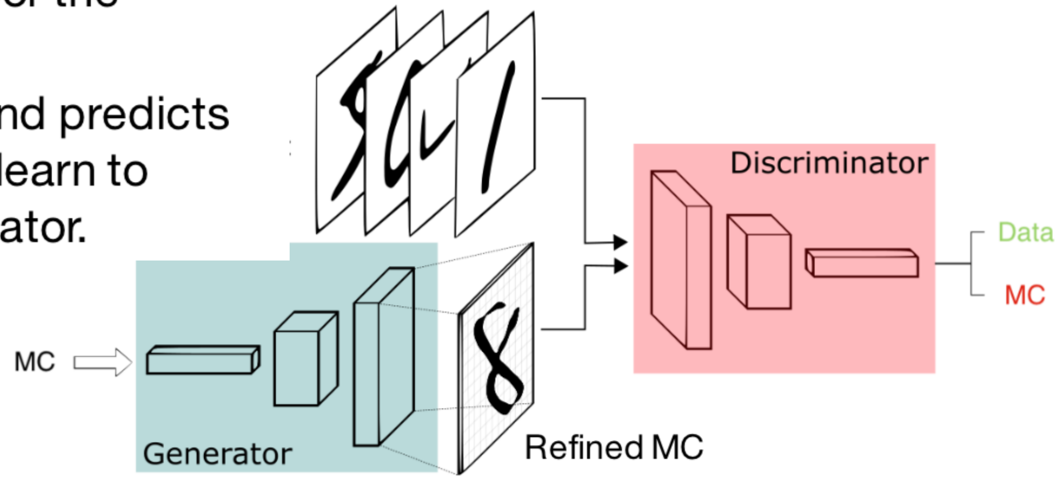
→ To fully use raw V-wire signals (in other DL studies) we need to refine MC events



Improved MC Simulations using GANs (Federico Bontempo)

- Aim: Improve Monte Carlo raw signals using Generative Adversarial Network (GAN)
- Refine Monte Carlo raw signals to be indistinguishable to real signals
- In progress

- The game approach:
  - Generator (G): receives MC events as input and modifies them so that they look as similar as possible to real data. His goal is to fool the Discriminator.
  - Discriminator (D): receives as input a data or a MC image, and predicts (giving a probability) whether it is real or fake. His goal is to learn to distinguish Data and MC and not being fooled by the Generator.



Source: https://skymind.ai/wiki/generative-adversarial-network-gan

Conclusion

Additional Studies:

- Scintillation energy determination/denoising – Shilo Xia
- Converting an event-by-event discriminator output to a statistically interpretable limit, including systematic errors - Mohamed Elbeltagi
- Signal/Background discriminator using CNN approach - Hank Richards

Summary

- We're generally interested in using DL techniques to improve current reconstruction methods and perform DL-only analysis
- Ultimately would like to build signal/background discriminator that works using only raw signals

Thank you

Signal-Background Discriminator with DNNs (Tobias Ziegler & Mike Jewell

Training data

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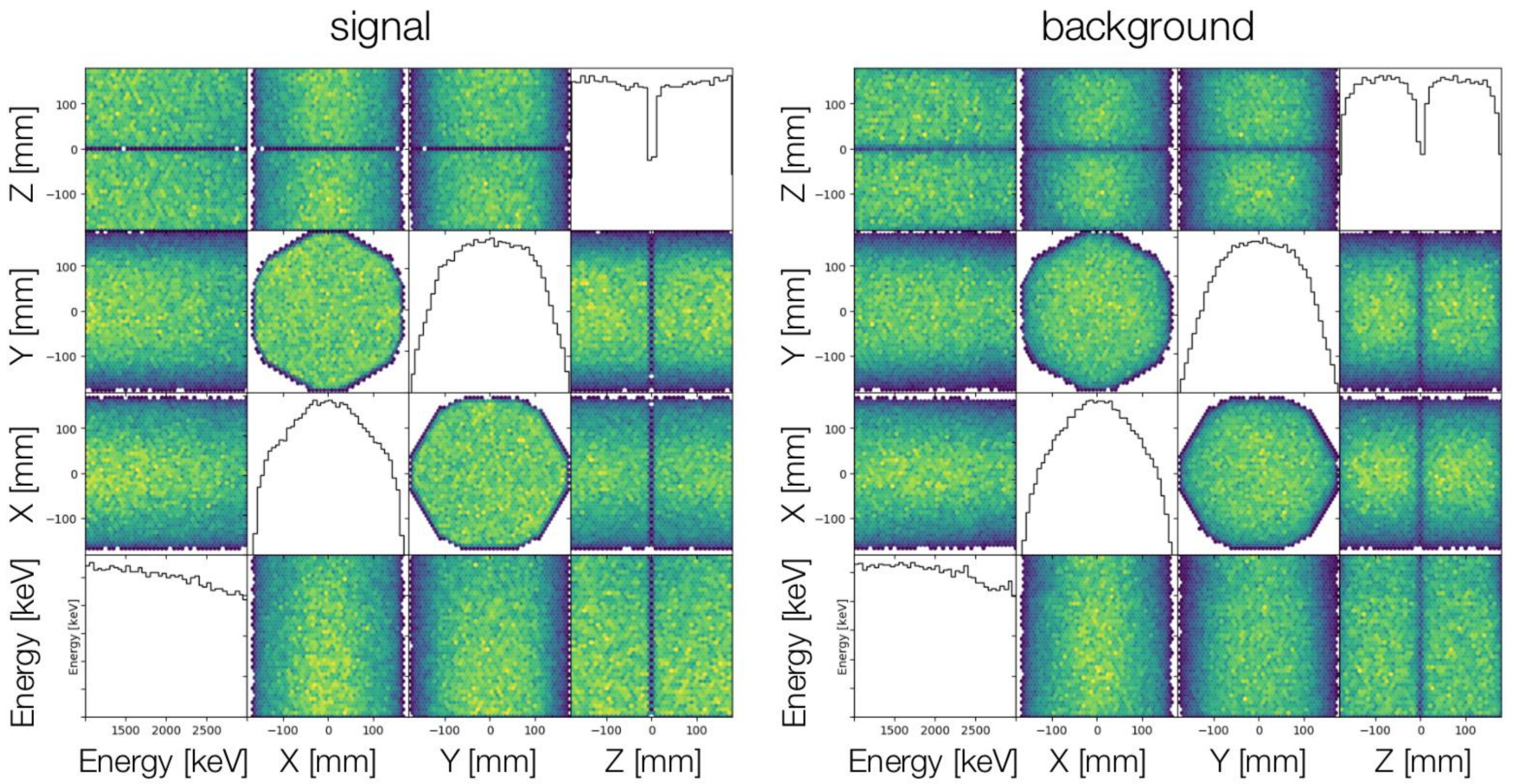
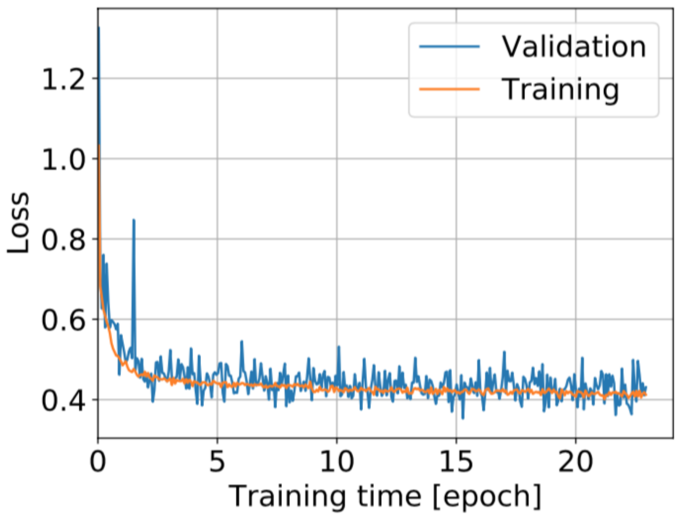
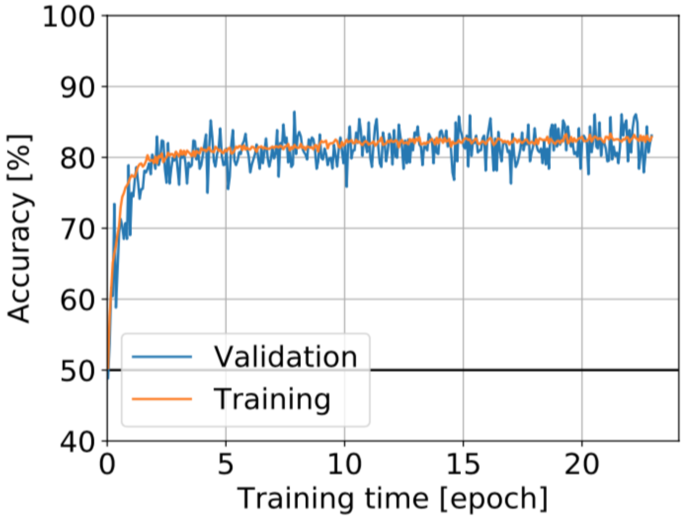
- Background: uniform (both spatial/energy) gamma events
- Signal: uniform (both spatial/energy) bb0n events
  - Use bb0n generator but take random Q-value for each bb0n event



Training

- Training is done by minimizing categorical cross-entropy
  - Common loss function for classification tasks
- Epoch means using every event for training once (220k, 50% signal, 50% bkg)
  - Validation data is not used for training!
- Training for ~25 epochs without over-fitting (~20 hours on GPU)
- Converges to ~82% accuracy (fraction of correct predictions)





Signal-Background Discriminator with DNNs (Tobias Ziegler & Mike Jewell

Validation (on independent data)

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- For default prediction threshold of 0.5:
  - Accuracy: 82 %
    - are predicted correctly
  - Sensitivity: 91 %
    - Of signals are predicted correctly
  - Precision: 77%
    - Of signal predictions are in fact signals

		Predicted		
		bkg	signal	
True	bkg	73%	27%	100%
True	signal	8%	91%	100%
		81%	118%	

- Distributions of predictions (SS/MS) for background (blue) and signal (orange) show how well the network can discriminate signal and background