Summary of Deep Learning activities in EXO-200

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DANCE-ML Workshop

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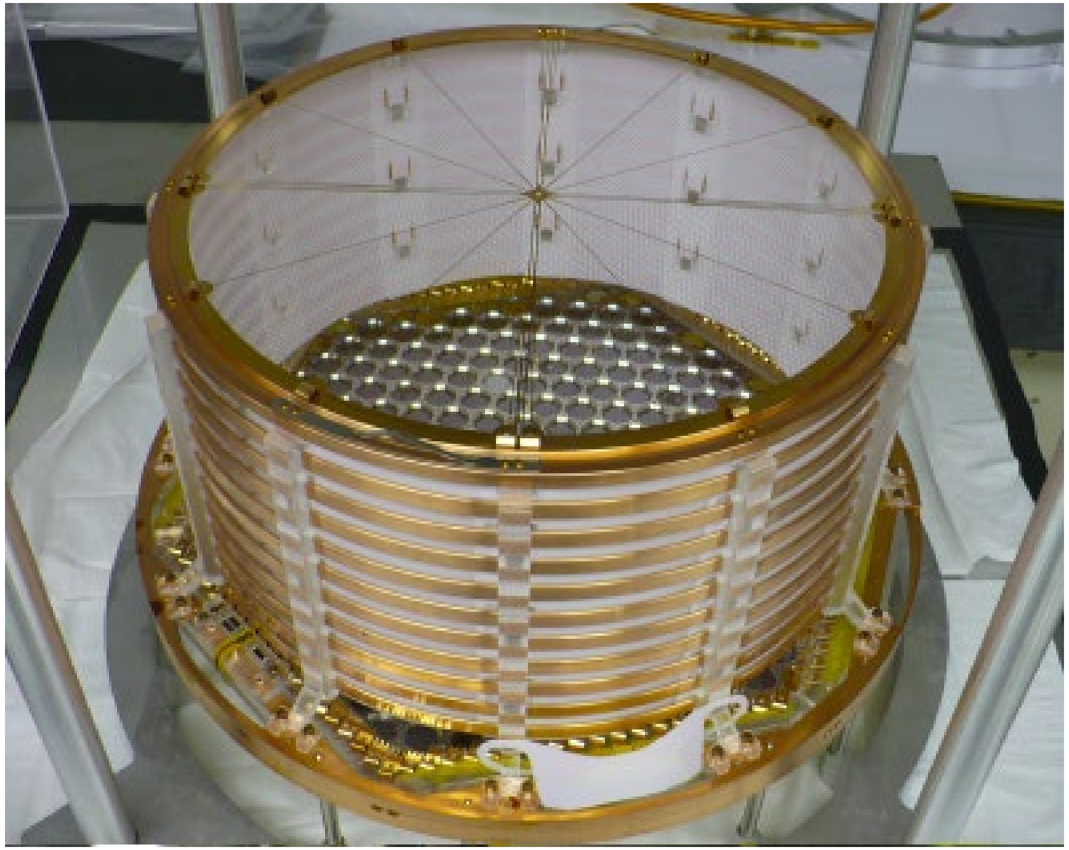
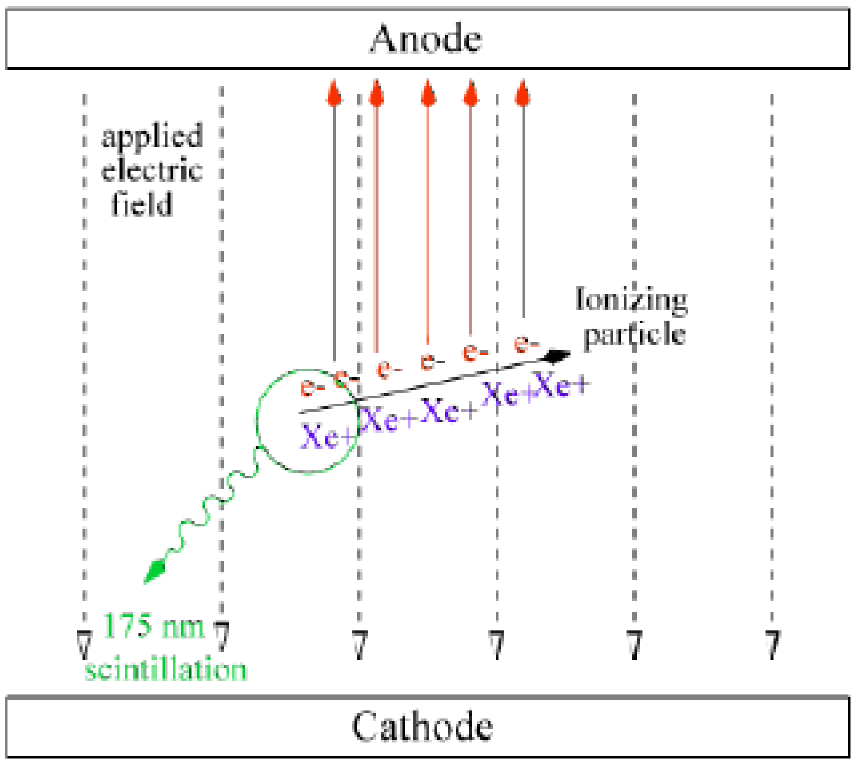
EXO-200 detector

- Double-sided TPC with shared cathode
  - One side shown
  - -8 kV (-12 kV) on cathode in Phase I (II)
- Filled with liquid xenon (single phase)
  - Enriched to 80.6% in ^{136}Xe
  - ~175 kg in liquid phase
  - ~90 kg fiducial mass
- Retired in December 2018

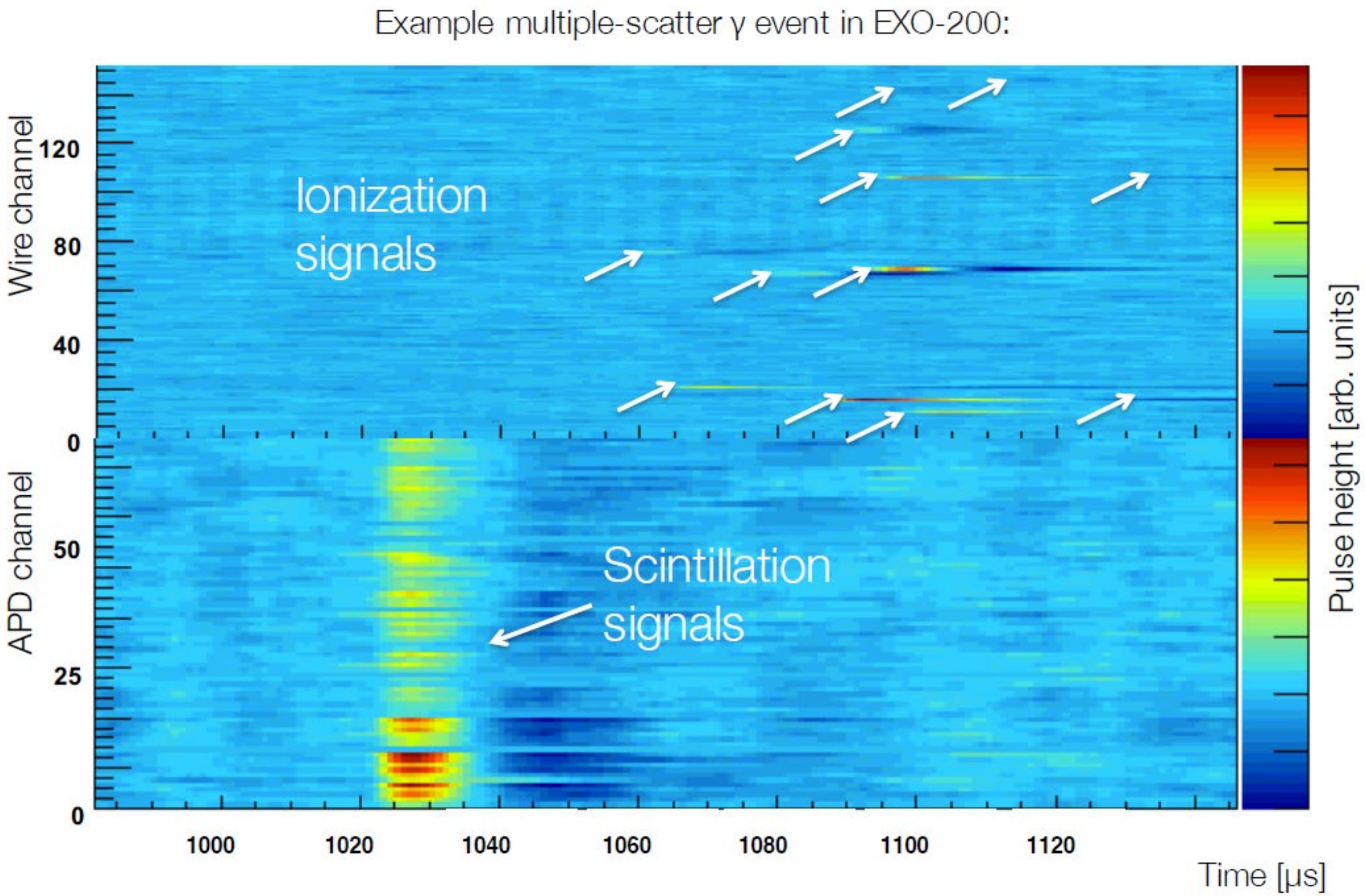


EXO-200 detector

- Each side detects both charge and light
- 38x2 charge collection wires
  - “U-wire” channels
  - 800 e- noise per wire
- 38x2 charge induction wires
  - “V-wire” channels
  - Crossed at 60° with U-wires
- 74x2 light collection channels
  - Each channel is a chain of 7 avalanche photodiodes (APDs)
- Cathode is mostly transparent (mesh)
- Cylindrical Teflon reflector

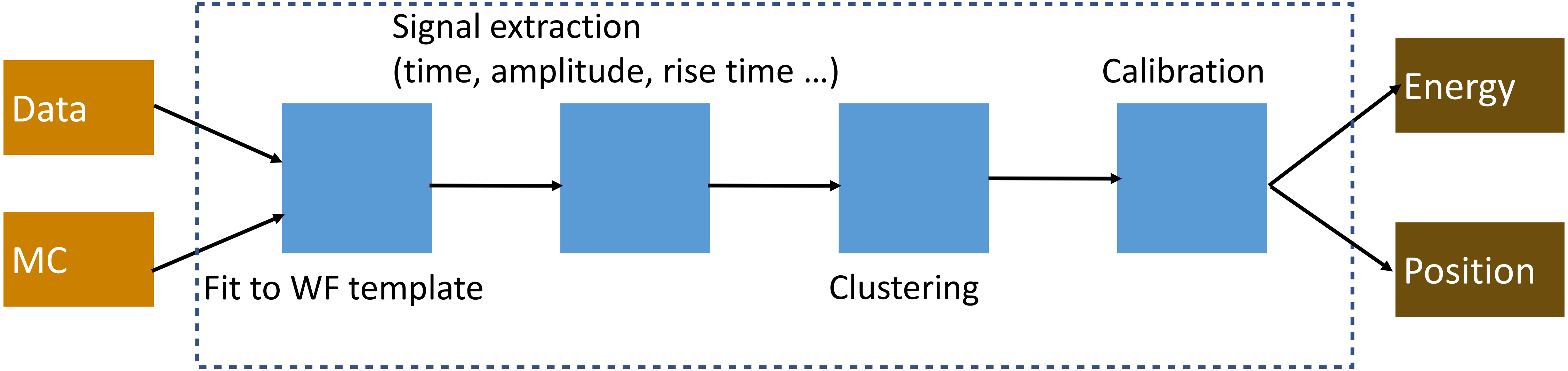


EXO-200 data



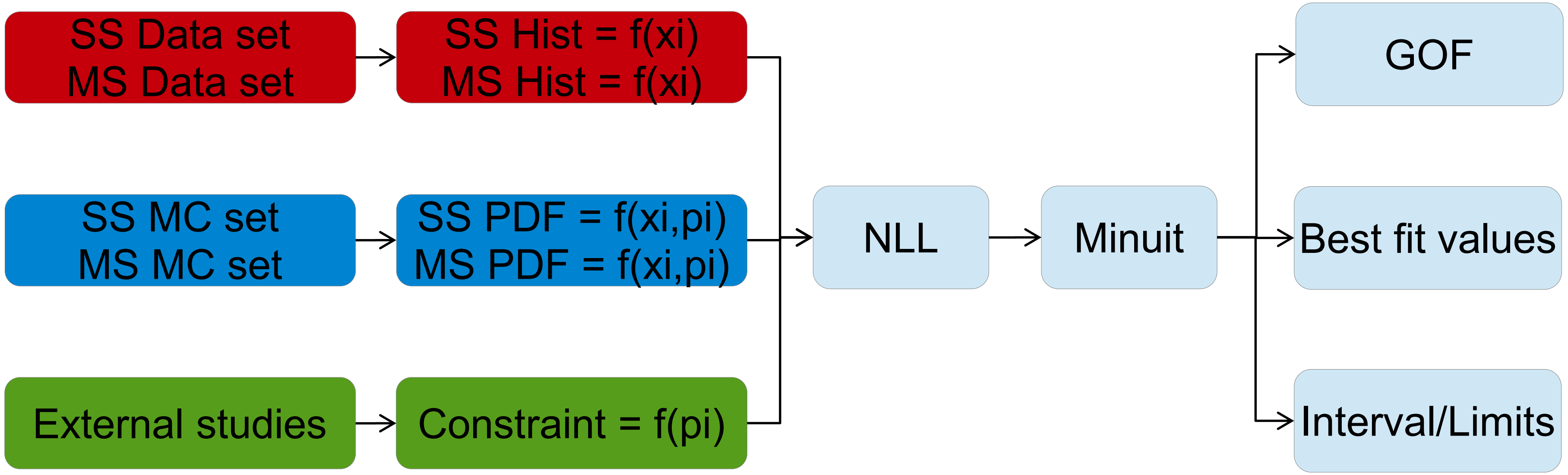
Example multiple-scatter γ event in EXO-200:
Ionization signals
Scintillation signals
Wire channel
APD channel
Pulse height [arb. units]
Time [μs]
120
80
40
0
50
25
0
1000
1020
1040
1060
1080
1100
1120

EXO analysis in broad strokes: traditional recon



- Multiple algorithmic steps
- Done by different people over the course of several years
- Imperfections in each step can add systematics

EXO analysis in broad strokes: point/interval estimation



- MC based PDFs, binned extended NLL with systematics constraints
- Profile likelihood for interval construction
- Systematics due to recon and MC errors. Measured or estimated using calibration data

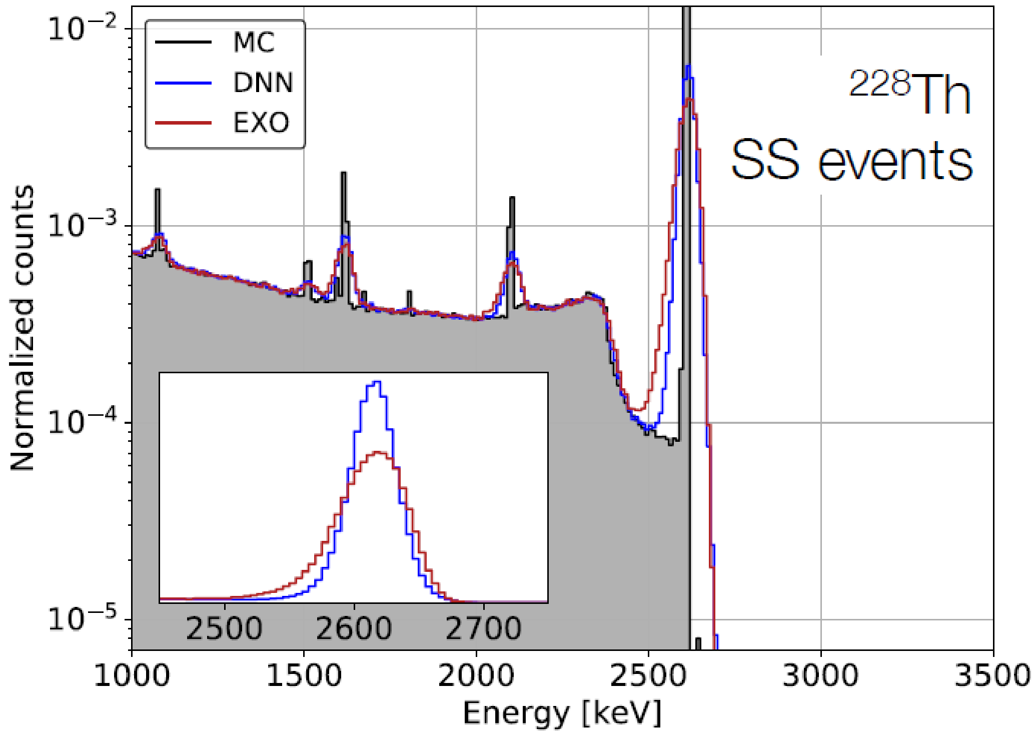
Deep Neural Networks in EXO

- Can circumvent intermediate steps and extract high level information directly from raw waveforms?
  - **YES**
- Can validate results on real detector data, not just MC?
  - **YES**
- Even then, if using MC truth during training, would be limited by how well MC models data. Can reduce reliance on MC?
  - **YES, sometimes**

- JINST **13** P08023 (2018), https://iopscience.iop.org/article/10.1088/1748-0221/13/08/P08023

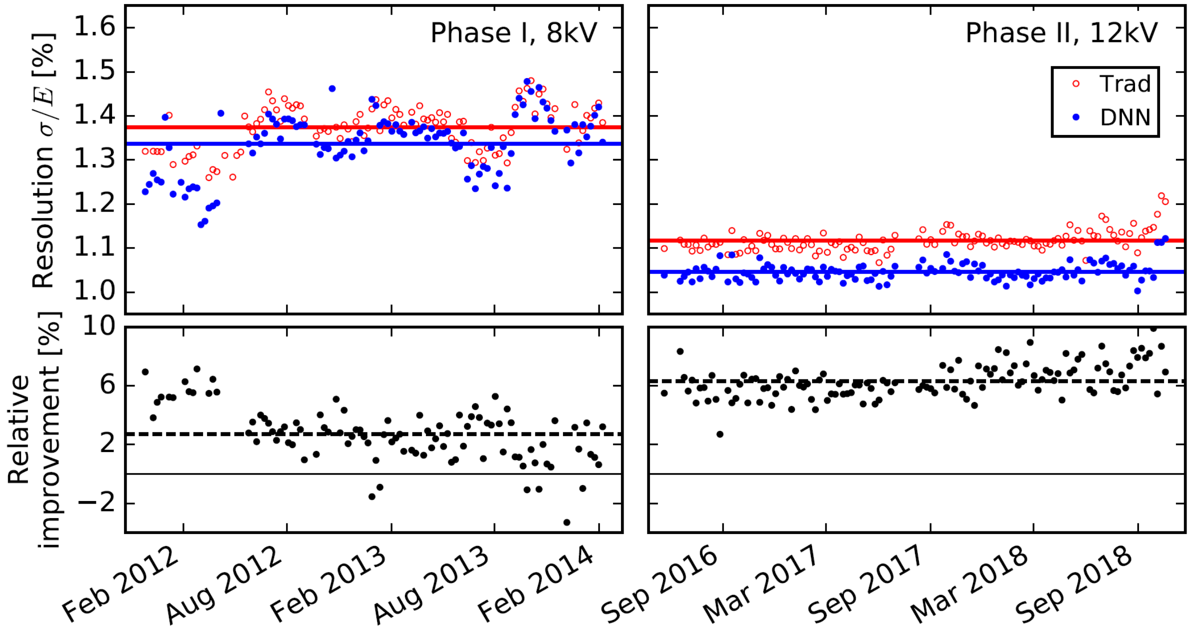
First application: Charge energy reconstruction

- Reconstruction works on MC over the energy range under study
- Resolution (σ) at the ^{208}Tl full absorption peak (2615 keV):
  - **DNN: 1.21% (SS: 0.73%)**
  - **EXO Recon: 1.35% (SS: 0.93%)**
- Network outperforms in disentangling mixed induction and collection signals
  - See valley before ^{208}Tl peak, right in $0\nu\beta\beta$ ROI
- Applied to **data** and anti-corrleated with scintillation (EXO-recon'd), the DNN based "rotated" resolution outperforms EXO-recon by 2-6% depending on the week



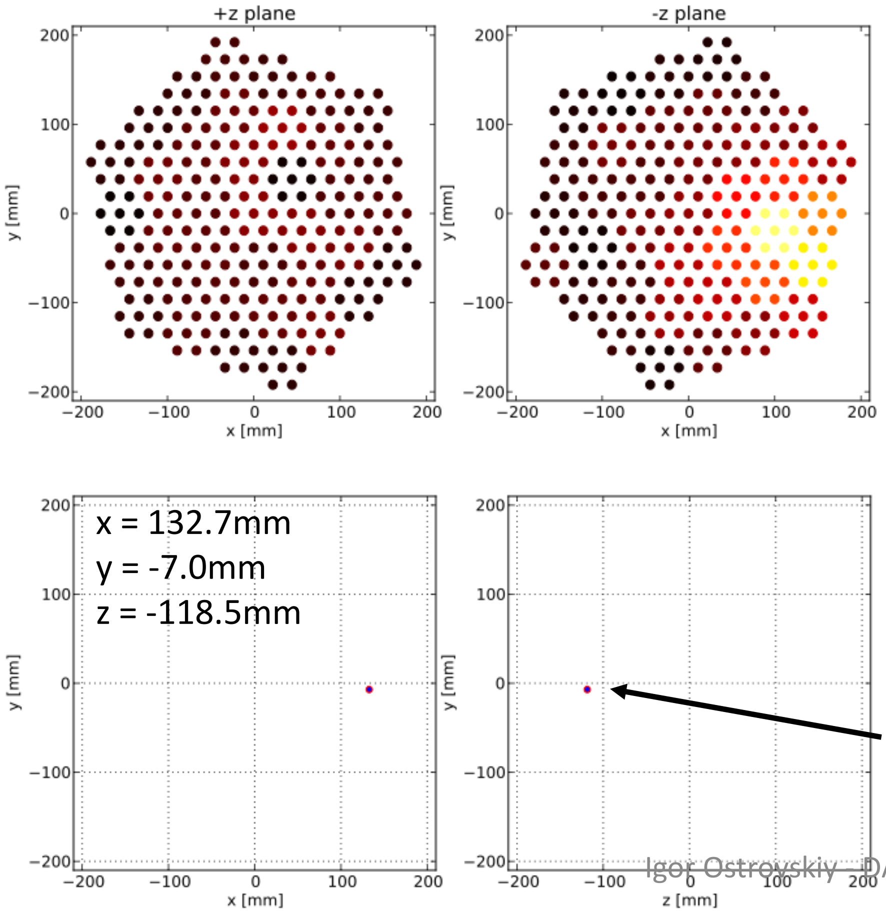
First application: Charge energy reconstruction

- The better performance of the DNN alerted that something was lacking in the traditional approach and triggered improvements in EXO-recon
- While the cause is now largely understood (handling of mixed induction and collection signals), the developed traditional solution in EXO-recon is still outperformed by the DNN



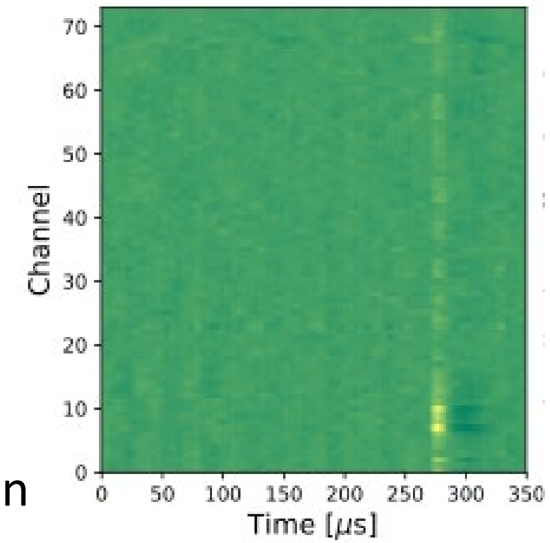
Second application: light position reconstruction

- Event position reconstruction from scintillation light
- Truth label provided by ionization information of real data
- Input are all 74 raw APD **real data** waveforms cropped to 350 μs



Event position is encoded in APD pattern

The time dimension adds information on waveform shape and noise

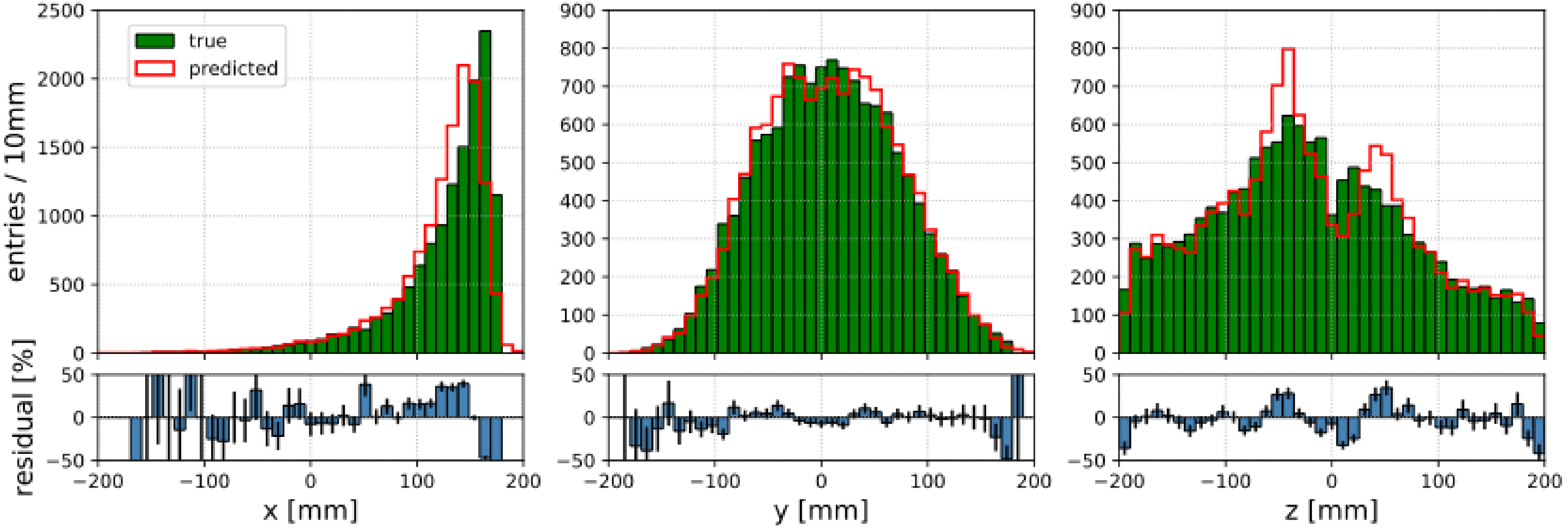


Truth information extracted from ionization signal

Second application: light position reconstruction

- Loss function reaches 200 mm^2 after training the DNN for 200 epochs
- The corresponding resolution in 3D is 25 mm
- The model is tested on different types of source data at different locations
- No light position reconstruction in standard analysis, so no comparison so far

Accuracy: 22.5mm (d_x = 13.6mm, d_y = 11.3mm, d_z = 8.1mm) corresponding to R^2 = 0.99



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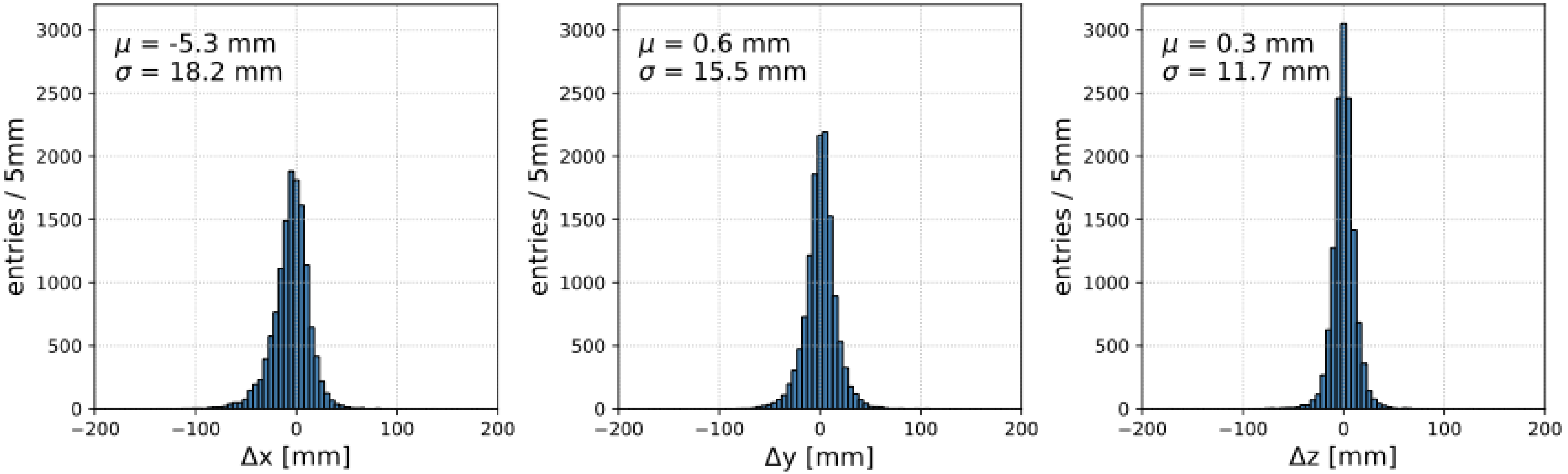
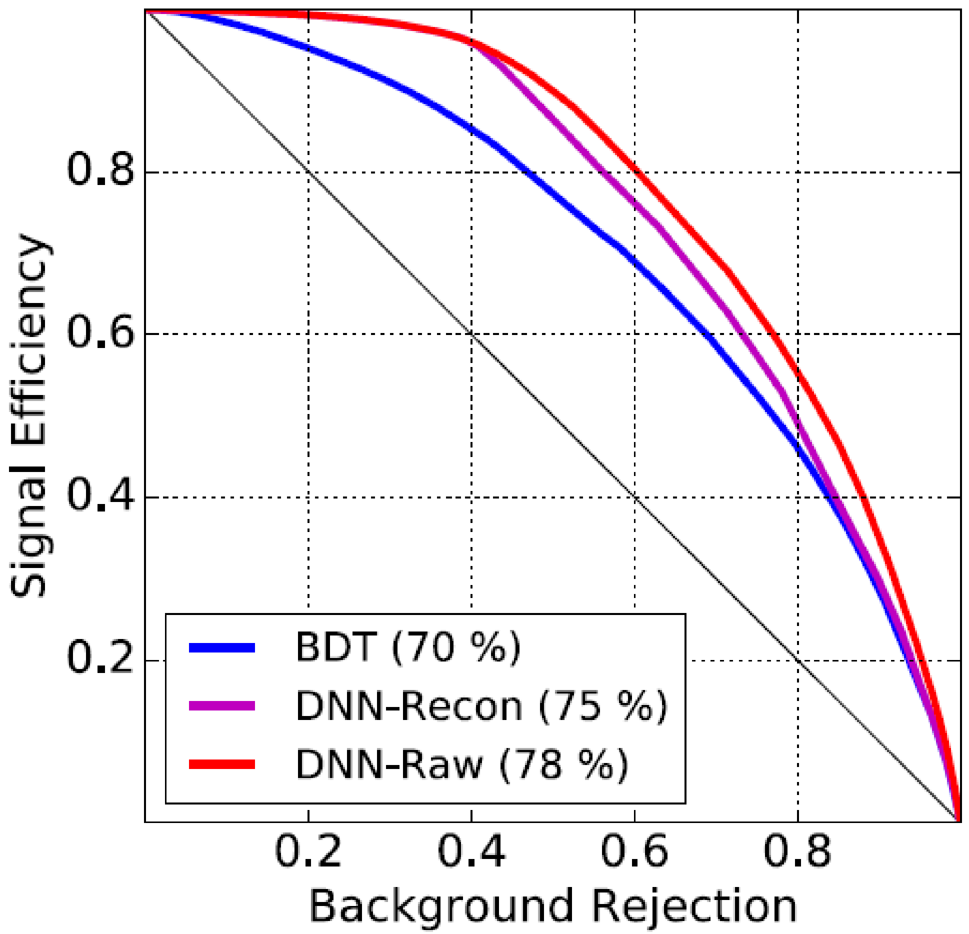


Third application: Signal/Background Discrimination

- A compromise approach
  - Binary ($\beta\beta$ vs γ) DNN based discriminator as an additional variable to the "traditional" ML fit
  - DNN trained on waveforms re-generated from EXO-recon'd signals (not on raw waveforms)
- DNN outperforms previously used BDT discriminator
- Overall 25% sensitivity improvement, compared to non-DNN based analysis
  - *Phys. Rev. Lett.* ***123****, 2019, 161802*
  - Kudos to grad. students who make this happen (Tobias Ziegler&Mike Jewel most of all)

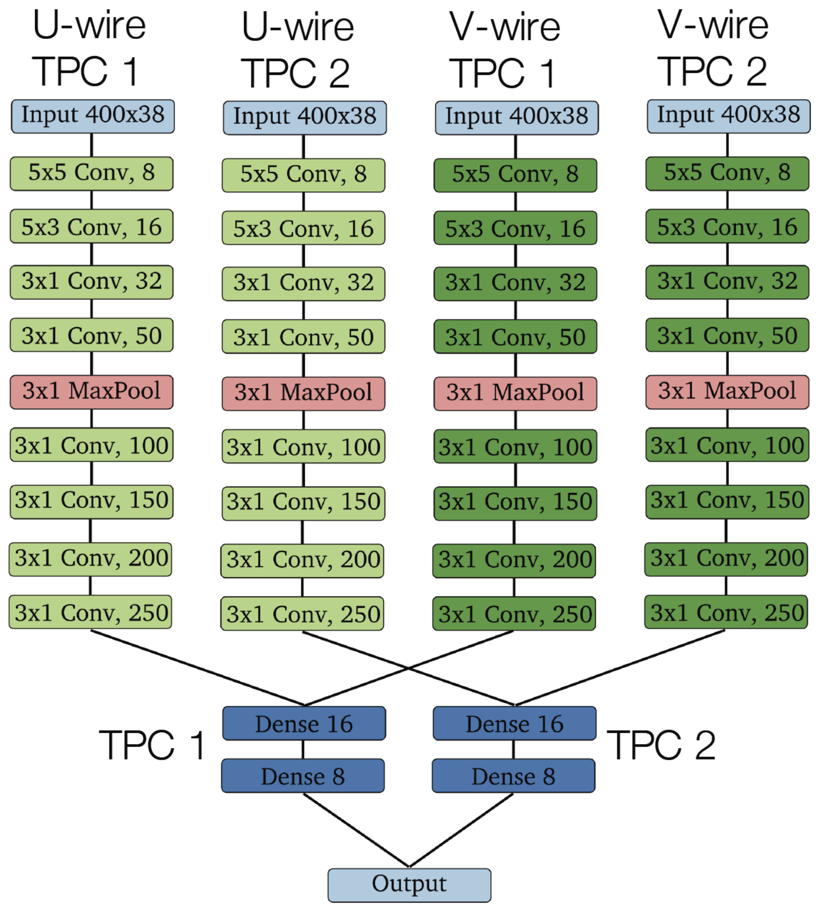


More recent projects

- Reconstruction of both position and energy of charge deposits
- Understanding statistical and systematic uncertainty of a DNN classifier
- Improving traditional simulation of V-wire waveforms using GAN
- Using GAN to simulate APD waveforms
  - Not simulated traditionally in EXO
  - Talk by Shaolei Li later today
- Using DNN to select decays of ^{137}Xe to excited state of ^{137}Cs
  - Talk by Seth Thibado later today

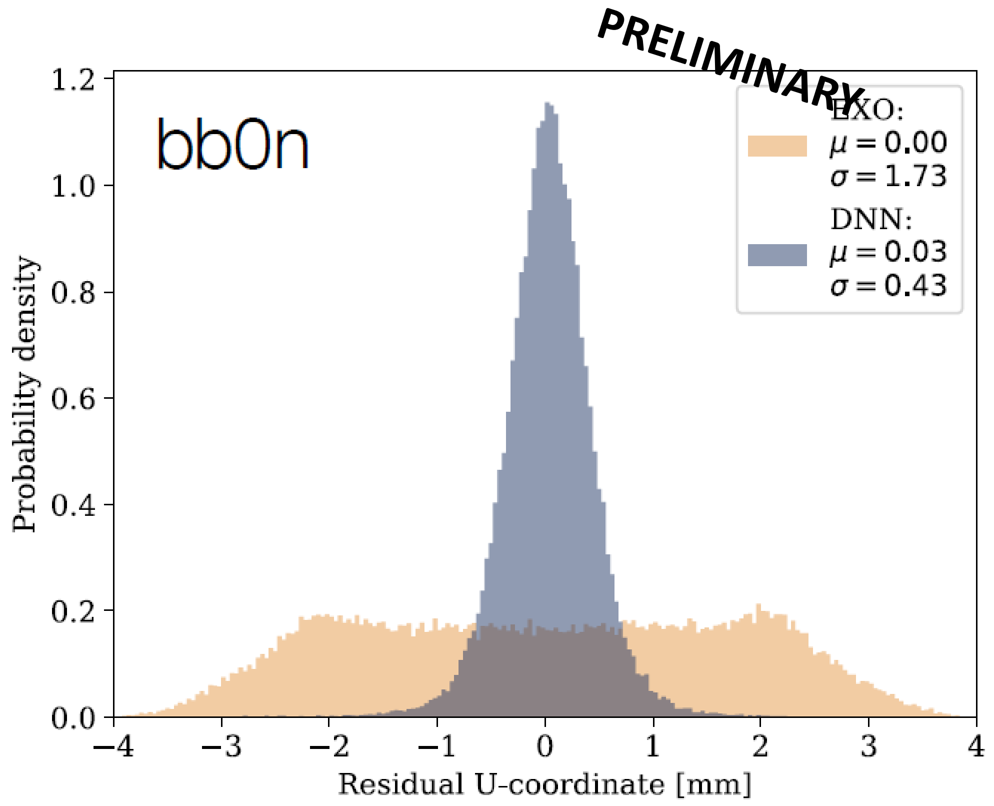
Charge position reconstruction

- Convolutional Neural Network like energy DNN
- Inputs to DNN are U- and V-wires MC waveforms
  - Only single-site events so far
- Same colored network branches share their weights
  - Exploits same signatures in both TPCs with less weights
- Concatenation to TPC 1 and TPC 2
- For each variable (U, V, Z), trained individual network



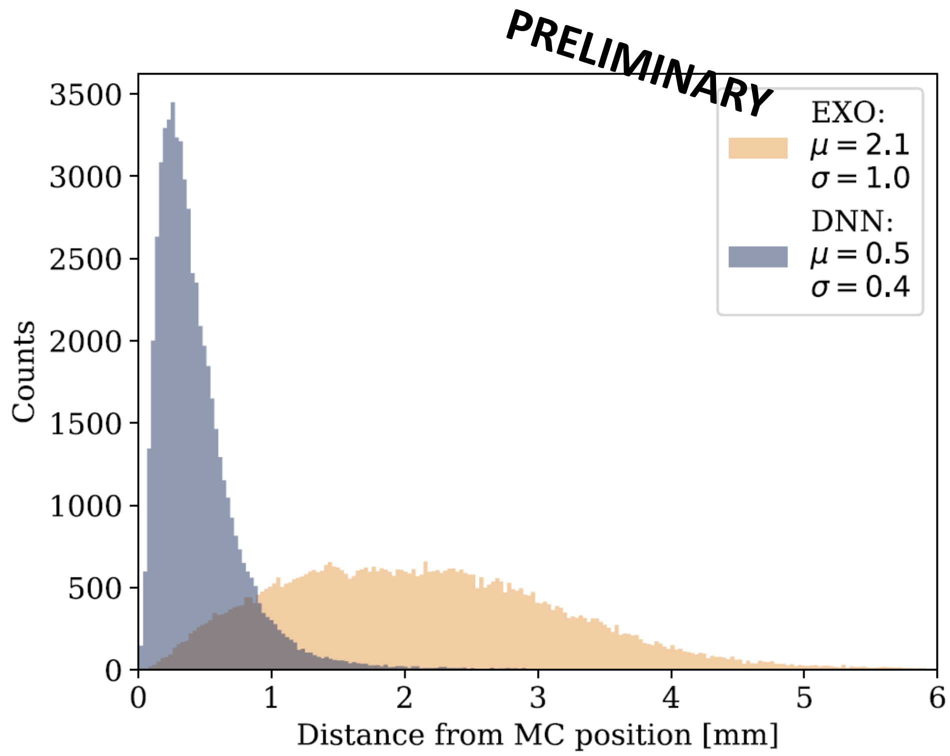
Charge position reconstruction

- A substantial improvement over traditional approach, especially in U coordinate



Charge position reconstruction

- A factor of ~2-3 improvement over conventional approach in all three dimensions
- Scrutinized to ensure the network does not cheat and utilizes information not used before
  - Again, induction on U-wires
- Current issue is extending to multi-site events



Summary

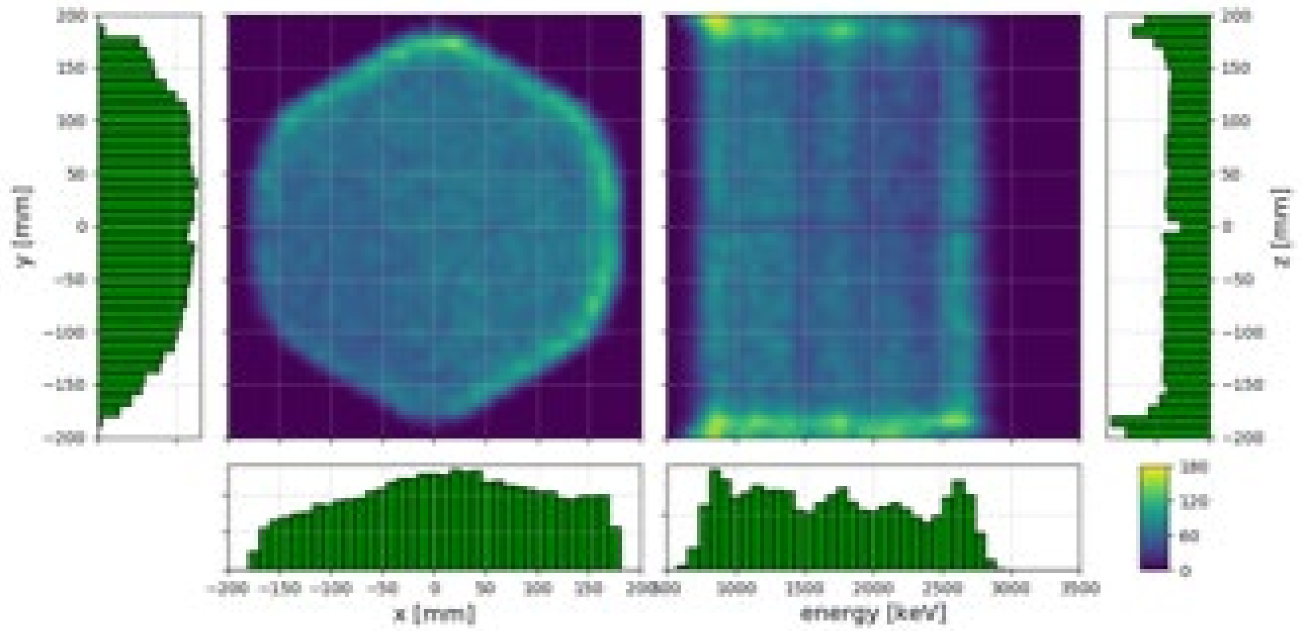
- EXO-200 has demonstrated the potential of DNN for the data analysis of a 0nu experiment directly from raw data
  - Improved energy resolution compared to standard approach
  - Improved sensitivity to neutrinoless double beta decay
  - Reconstructed position using scintillation light without using Monte Carlo
  - Validated on real detector data
- As acceptance of DNN, in particular CNN, increases among DM/ν physicists, we are more readily doing physics with it
  - ^{137}Xe, g.s. → ^{137}Cs, e.s.
- At the same time, continue looking into less established approaches, like GANs, and trying to better understand DNN's statistical properties

Light reconstruction details

- Waveform image is fed to CNN consisting of 4 convolutional and 3 fully connected layers
- Output has three units corresponding to event x-, y-, z-coordinates
- Loss function is Euclidean loss with L2 regularization

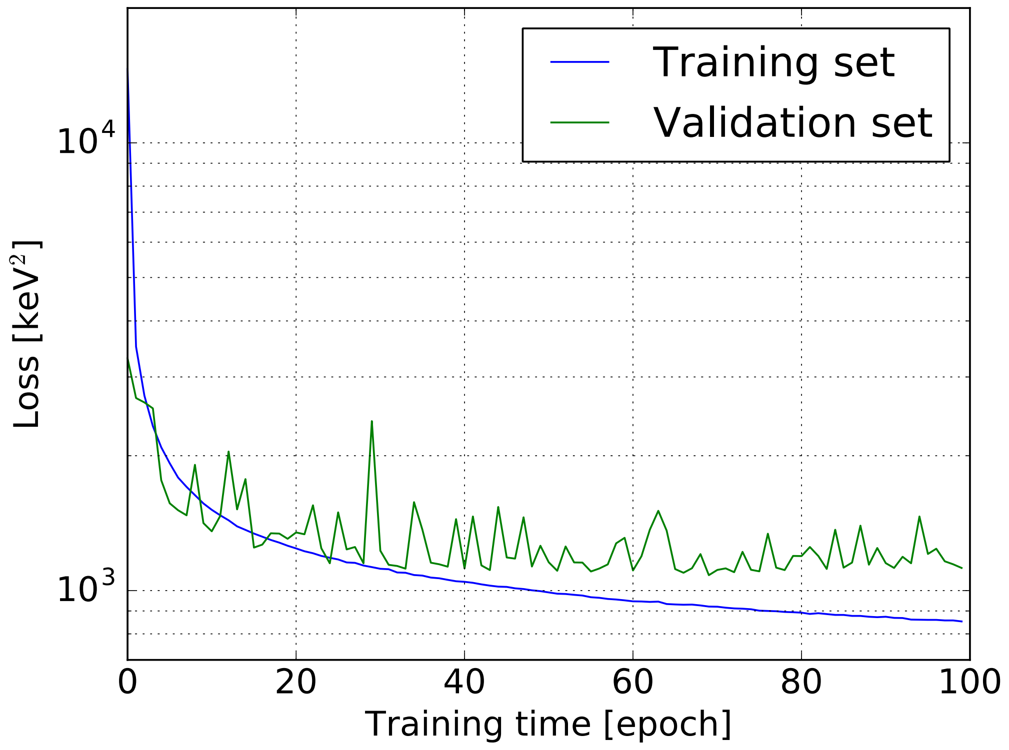
$$L = C + \lambda \cdot R \quad \text{where} \quad C = \frac{1}{3m}\sum_{i=1}^{m}\sum_{k=1}^{3}\left(y_i^k - \hat{y}_i^k\right)^2$$

- Training is done on **real** calibration data with uniform distribution in space and energy



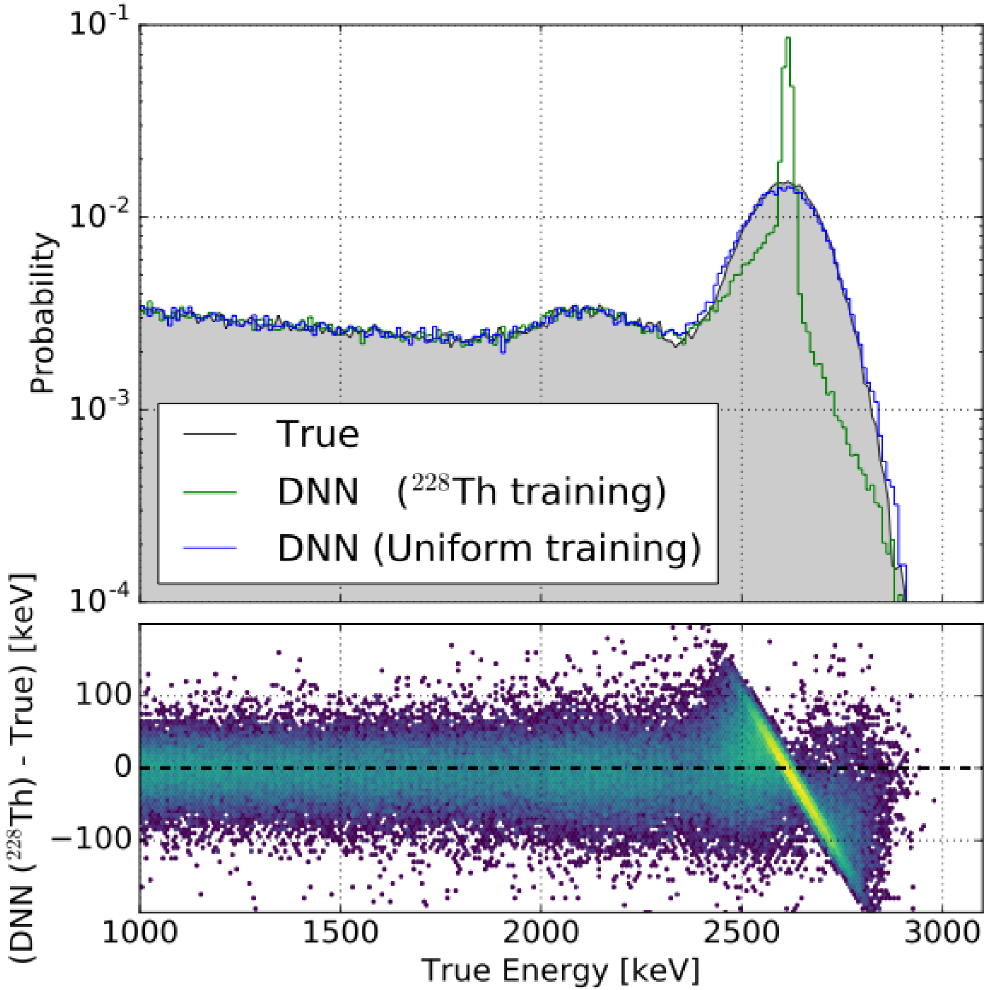
Charge reconstruction training details

- Training data:
  - Simulated events
  - Gamma ray source
  - Detector response uniform in energy
- Training:
  - 720 000 training events
  - 100 epochs
- Technical details:
  - Adam optimizer
  - Minimize mean square error
  - L2 regularization
  - ReLU activation
  - Uniform Glorot initialization



Pitfalls of DNNs

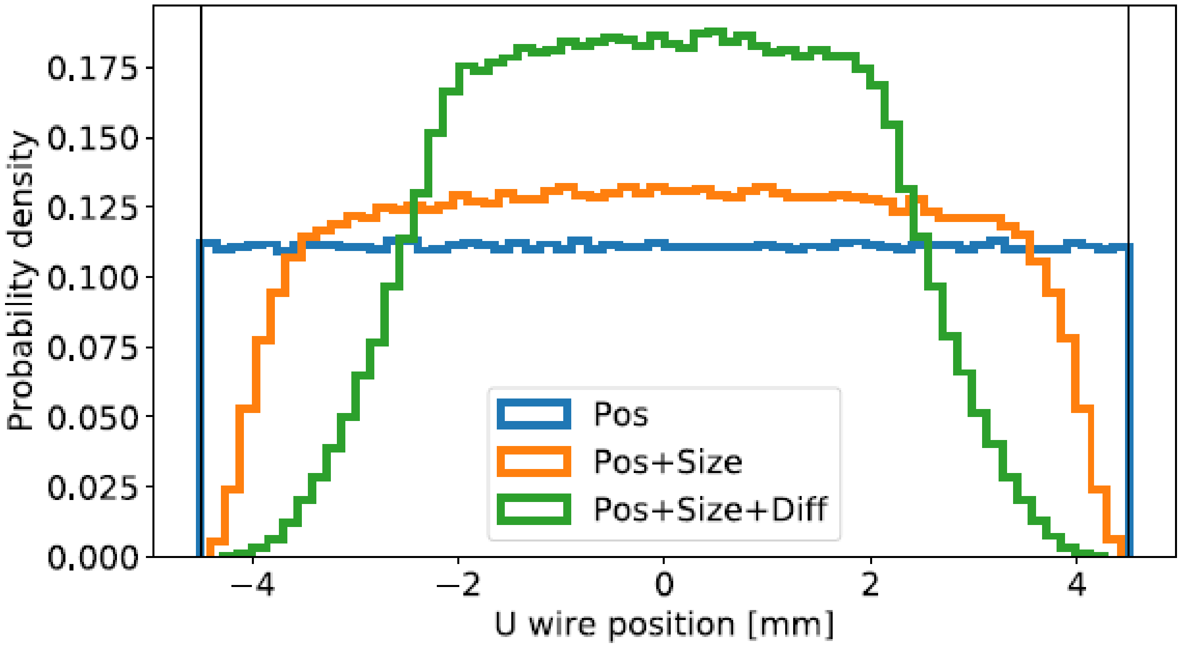
- One of potential dangers of DNN is that they learn to reproduce the training data well, but perform poorly on real data
- We, in fact, experienced this in EXO-200 and learned to mitigate it in our case:
  - Using training events with uniform energy distribution proved crucial
  - Otherwise DNN over-trains on sharp MC training peaks and shuffles independent validation events towards sharp peaks from training



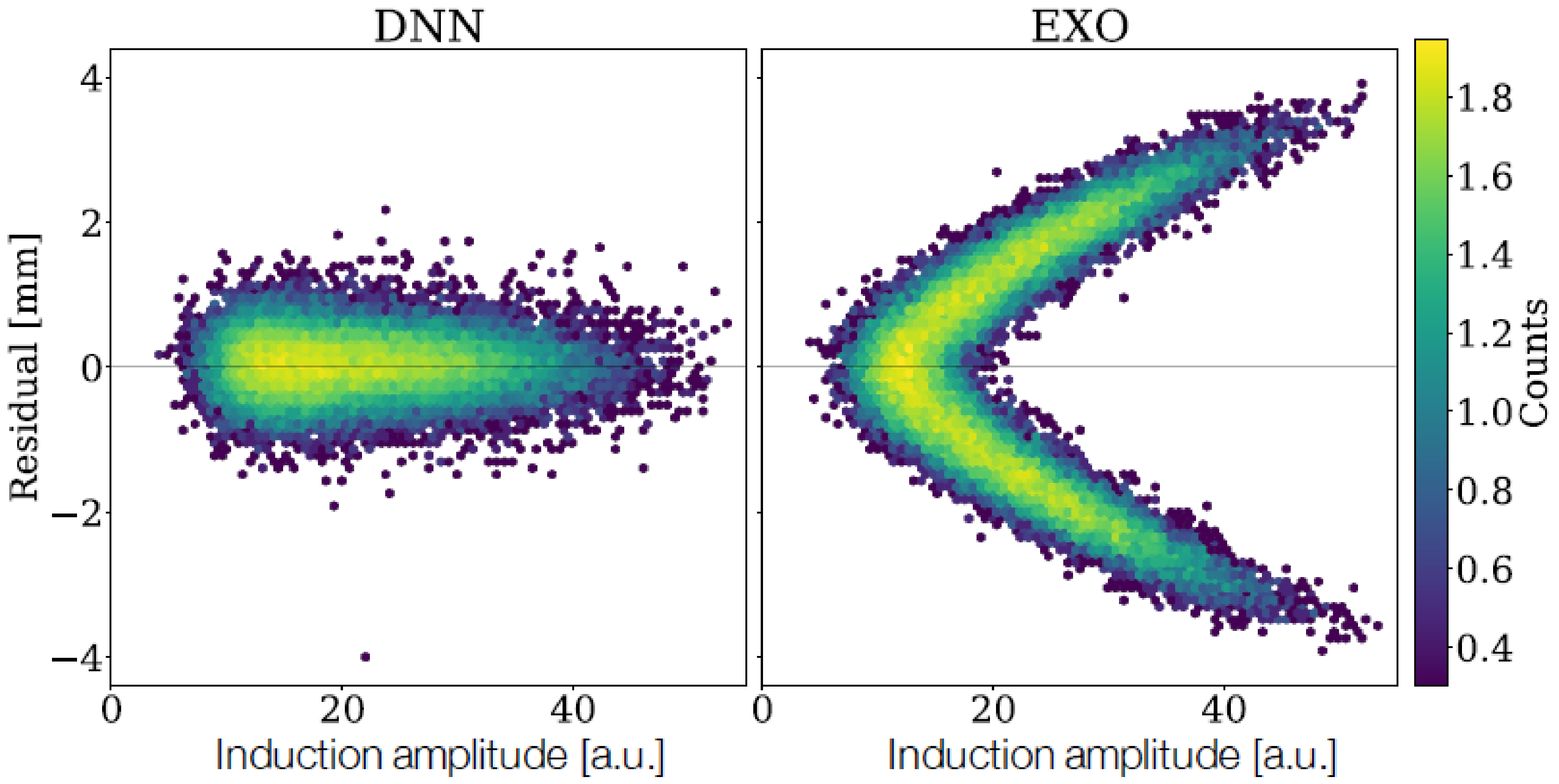
- Naively, the best possible U-coordinate resolution for one-wire SS events is (assuming pointlike charge deposits and no diffusion)

$$\sigma_{\text{best}} = \frac{\text{wirepitch}}{\sqrt{12}} = \frac{9\,\text{mm}}{\sqrt{12}} \approx 2.60\,\text{mm}$$

- Toy MC to estimate the best possible U-coordinate resolution
- Accounting for initial event size distribution $\sigma_{best} = 2.27$ mm
- Also accounting for diffusion during drift $\sigma_{best} = 1.67$ mm
- DNN ($\sigma = 0.43$ mm) still significantly better than σ_{best}



- Standard reconstruction does not use induction signals for position recon
- Maximum amplitude of neighboring channel used to estimate induction signal
- DNN: Residual of position resolution independent of induction signal amplitude
- EXO: absolute value of residual correlated linearly to induction signal



- Evaluate impact of induction signal to position resolution
- Approach: remove potential induction signals (i.e. set neighboring wires to zero)

- DNN resolution significantly worse without induction signal
- DNN uses induction signal to improve U-coordinate resolution
- With induction: $\sigma = 0.43$ mm
- Without induction: $\sigma = 1.56$ mm
- Resolution similar to resolution from simplified toy MC ($\sigma_{best} = 1.67$ mm)