Future of Data Analysis: a Glimpse from EXO-200

Igor Ostrovskiy – University of Alabama

DANCE Workshop

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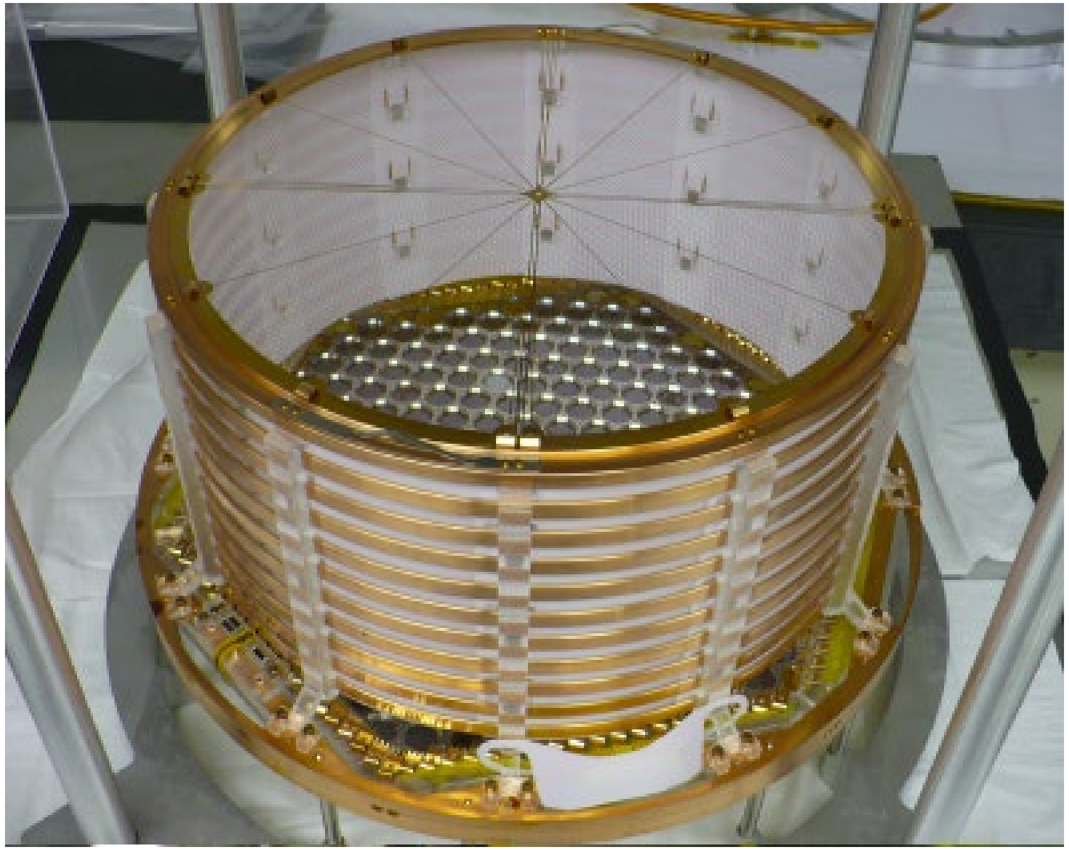
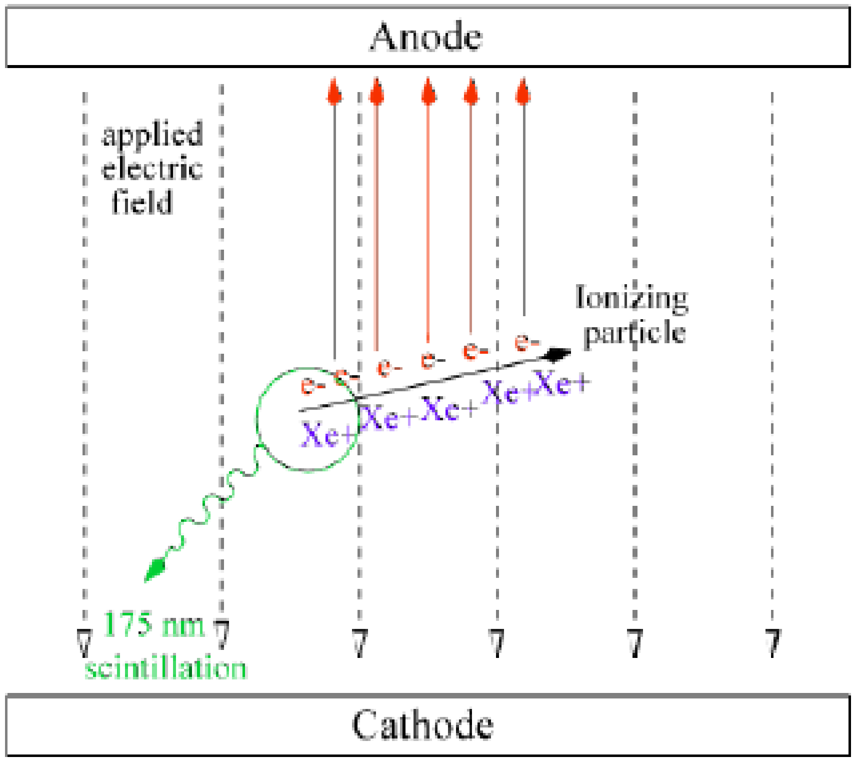
EXO-200

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



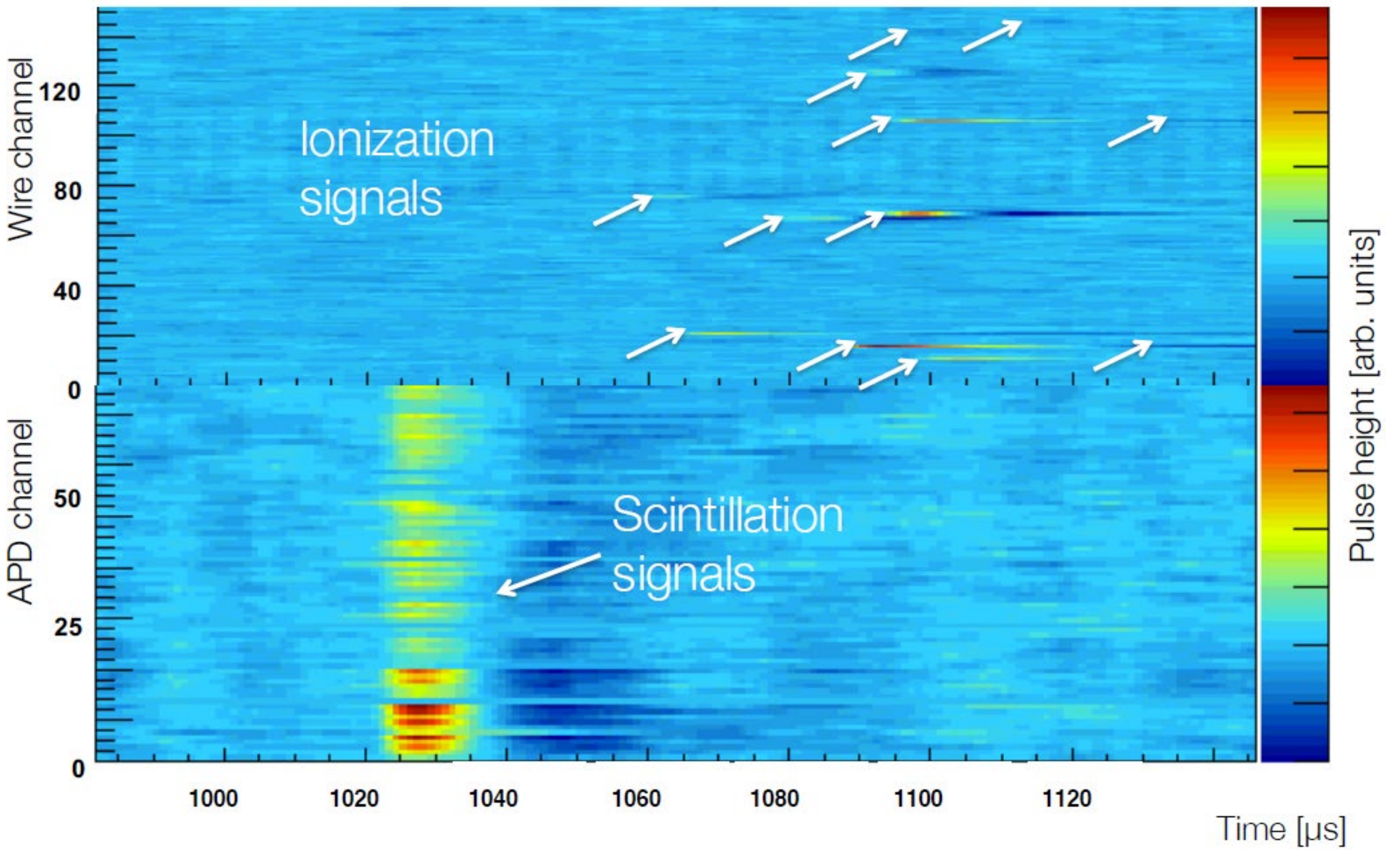
EXO-200

- Each side detects both charge and light
- 38x2 U-wire channels for charge collection
  - 800 e- noise per wire
- 38x2 V-wire channels for charge induction
  - Crossed at 60^o with U-wires
- 74x2 APD channels for light
  - Each channel is a chain of 7 LAAPDs
  - Cathode is mostly transparent (mesh)
  - Cylindrical Teflon reflector

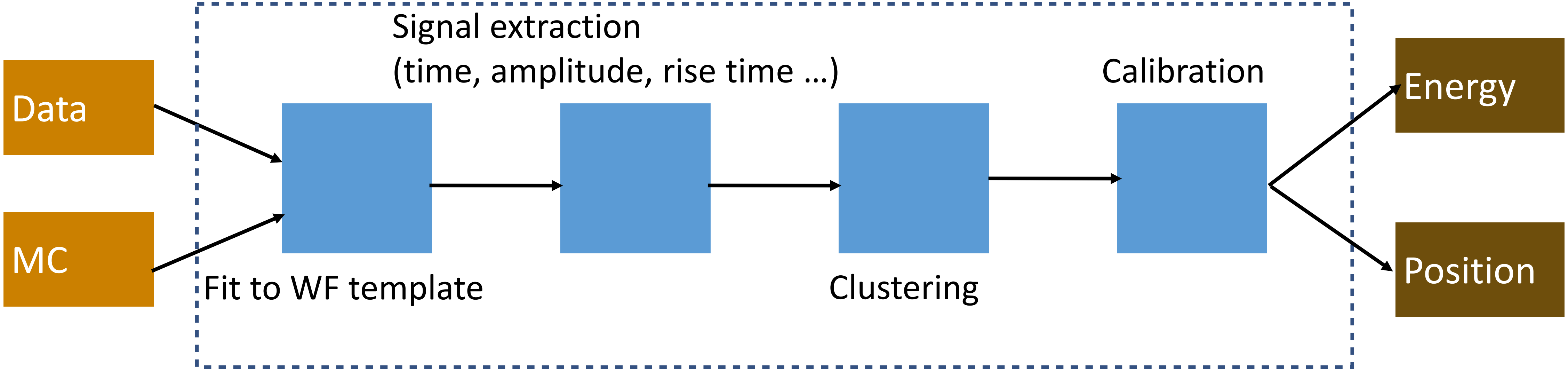


EXO-200 data

Example multiple-scatter γ event in EXO-200:

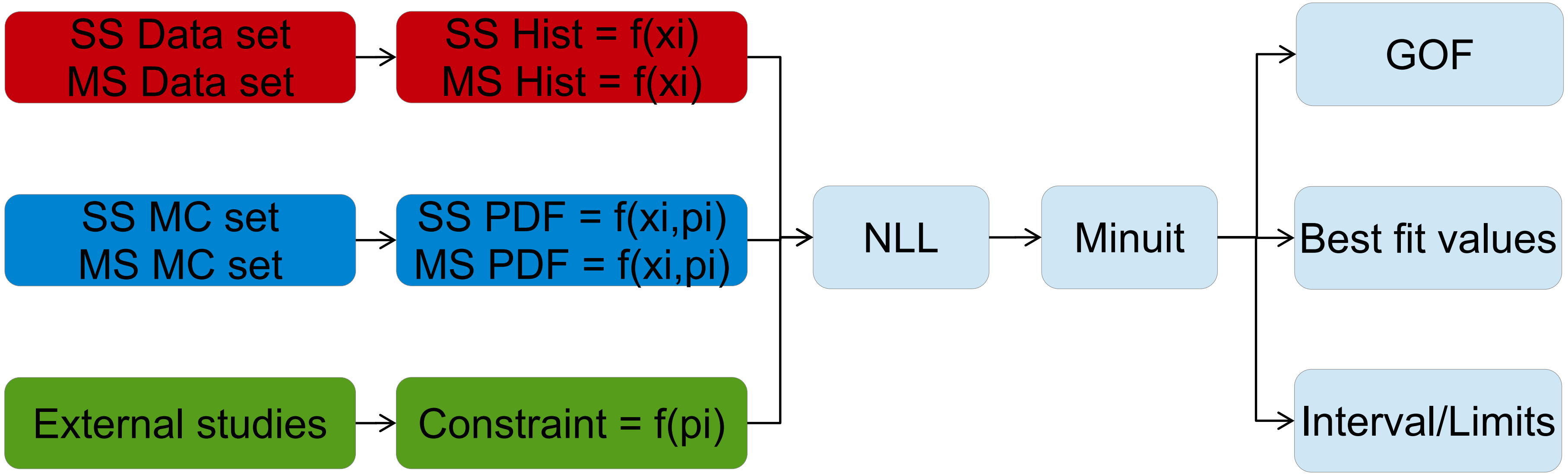


EXO analysis in broad strokes: reconstruction



- 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 (DNN) in broad strokes

- DNN contains many tunable (trainable) parameters
- Training is done by minimizing discrepancy between truth and network's output
  - E.g., RMS deviation between known and predicted energy
- Minimization is done, essentially, by gradient descent (like MIGRAD), but with some new tricks to efficiently handle multitude of parameters

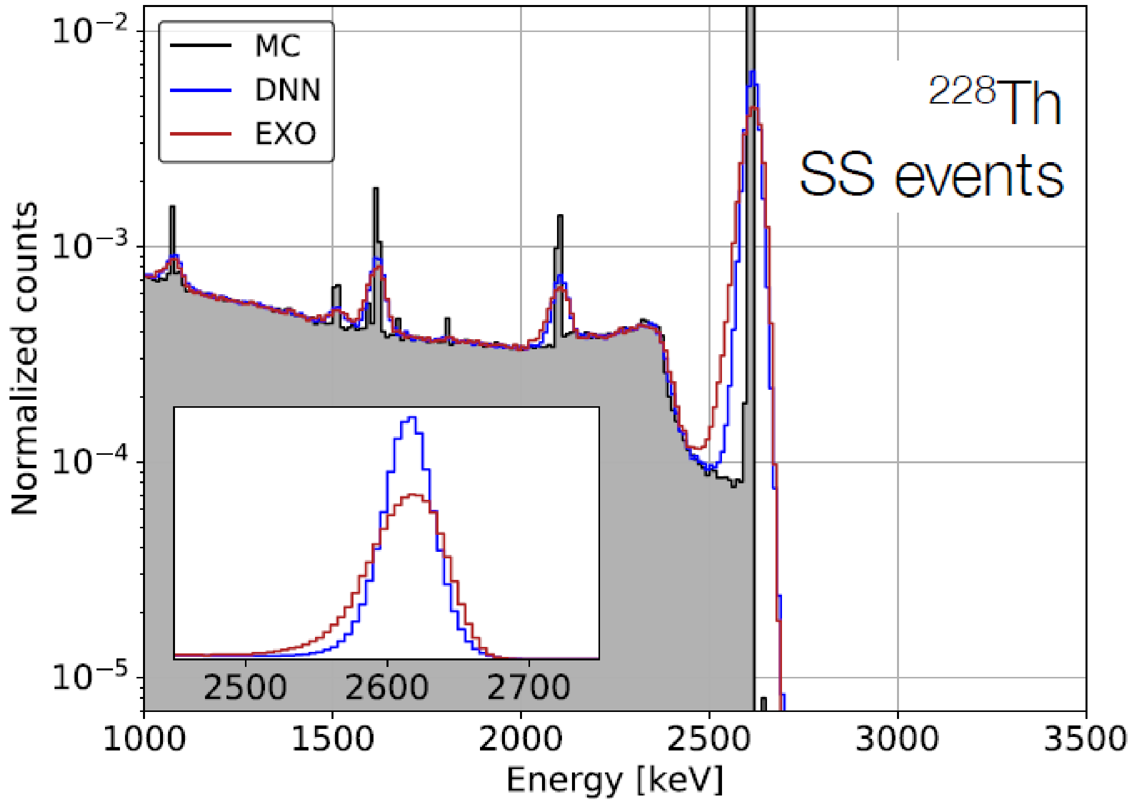
Deep Neural Networks in EXO

- 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 (as some standard analysis steps are). Can reduce reliance on MC?
  - **YES (Sometimes)**

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

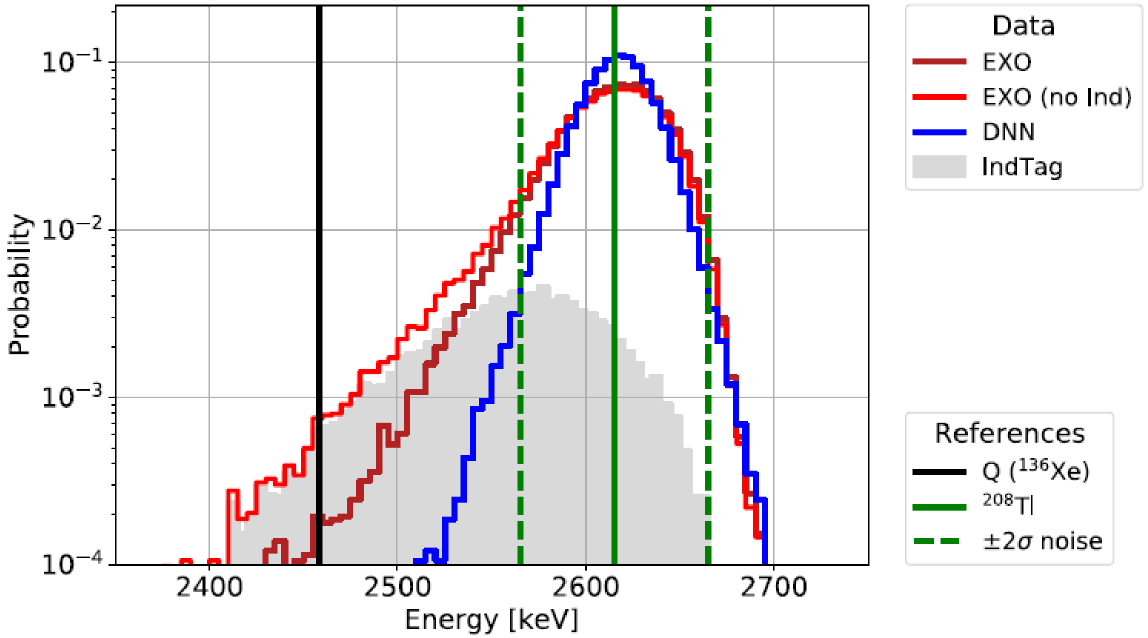
First application: Charge energy reconstruction

- 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 by 2-6% (depending on the week)



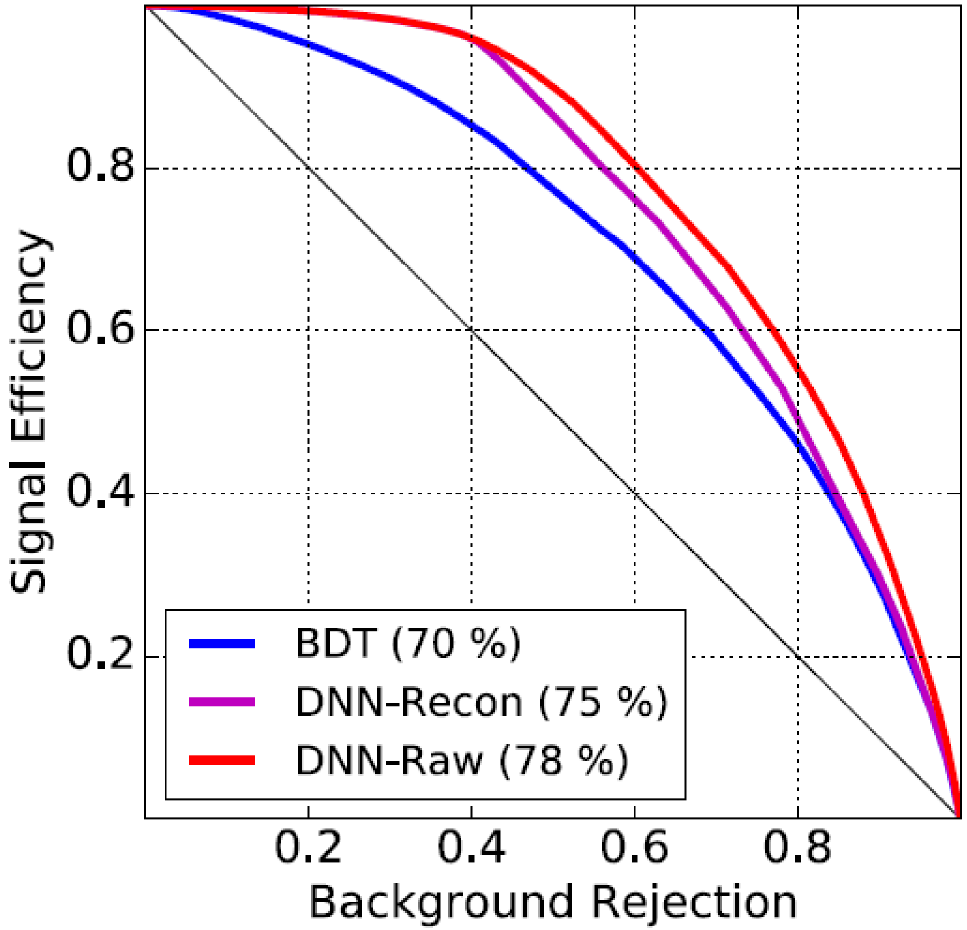
First application: A note on the “Black box”

- 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 is still outperformed by the DNN



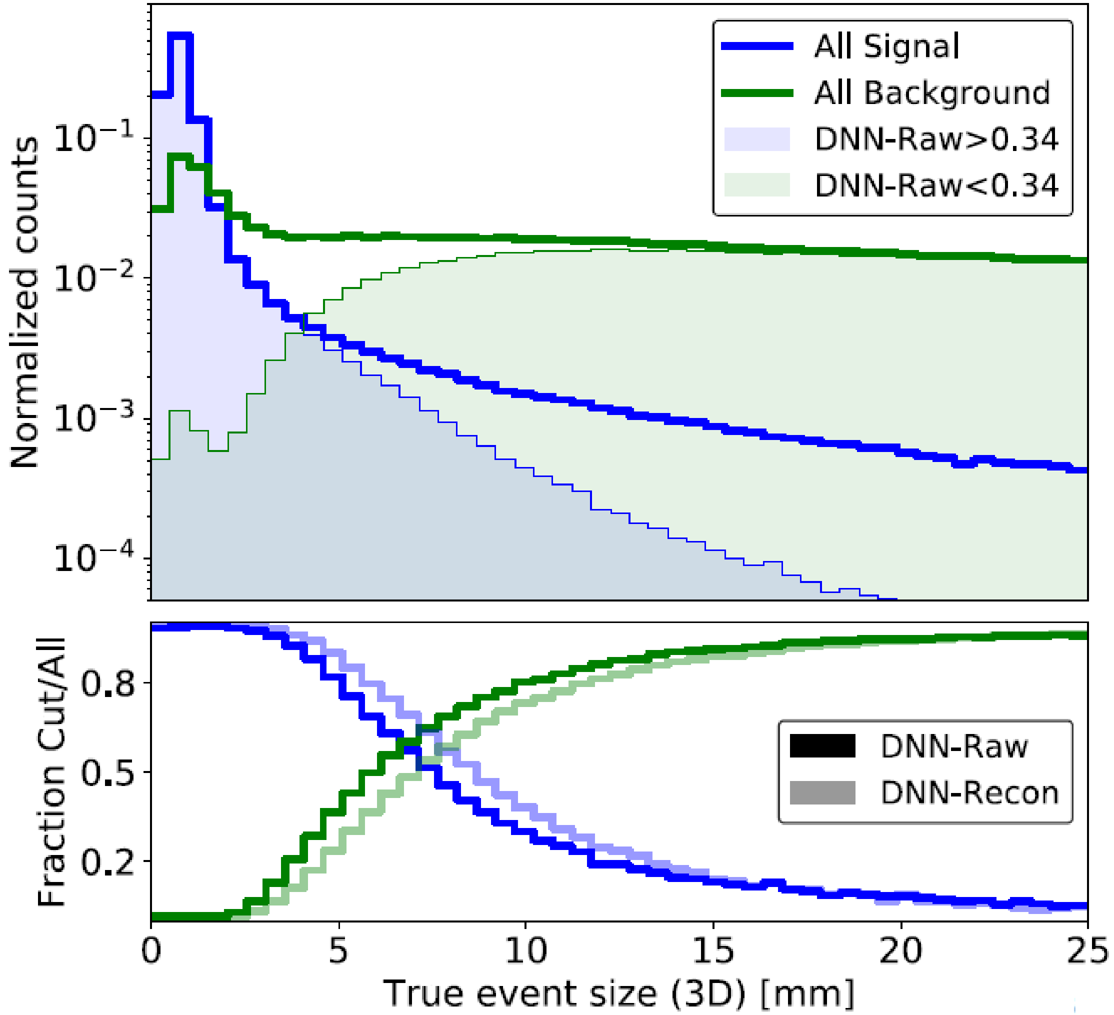
Second application: Signal/Background Discrimination

- A compromise approach (to make it by externally constrained timeline of the final EXO-200 paper)
  - 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-ML based analysis
  - *Phys. Rev. Lett.* ***123****, 2019, 161802*
  - Kudos to grad. students who make this happen (Tobias Ziegler&Mike Jewel most of all)



Second application: Signal/Background Discrimination

- ββ events are more localized than γ
- DNN efficiency demonstrates correlation with the true event size in the MC
- Indicates that the DNN picks up correct features of the waveform when reconstructing events
- Data/MC agreement of the “DNN variable” validated with real calibration data
  - Agreement not perfect, but comparable to other “shape” errors.



Where all this might be going + Current Challenges

- Can we throw away most of the traditional analysis infrastructure and go from ~waveforms directly to physics result?
  - Requires only MC and existing widely used DL software frameworks
- We know that we can go from waveforms directly to high level features (Energy, Position, etc.)
- The open question is what to do with event classification? **How to get from waveforms to the Final Physics Result?**
  - Currently used EXO-200 solution is a half-measure
  - **Need a rigorous treatment of statistical and systematic errors of a DNN**
  - More on this in Mo's talk

+ Current Challenges

- The "black box" critique remains a hard challenge
  - Doing what we can – validating on data whenever possible, trying to correlate chosen events with salient properties

- Since we need waveforms, scaling to next generation may become an issue
  - In EXO-200, 0.5M training events take up 0.25 TB full (ROOT), but this gets cropped down to 25 GB when cropped and pre-selected (hdf5)

Summary

- EXO-200 has demonstrated the potential of deep neural networks 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

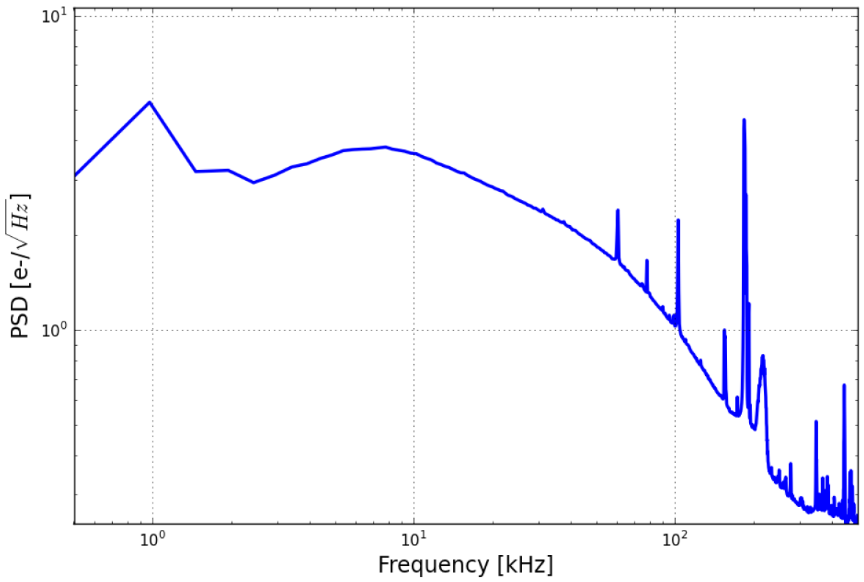
- DNNs can potentially revolutionize the way we do analysis, completely or significantly reducing the need for dedicated experiment- or even field-specific software frameworks
    - The advantage is less overhead for doing physics

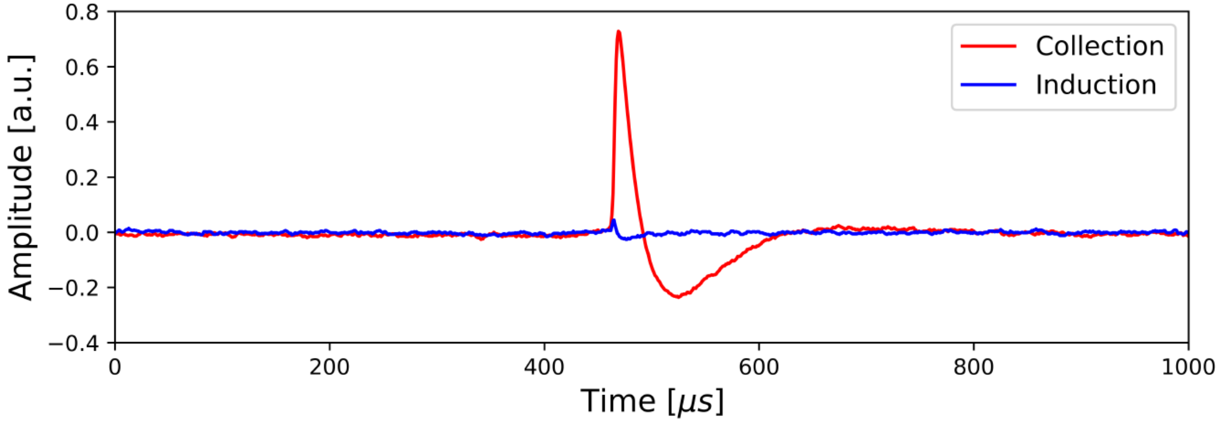
- Before this can happen, need to better understand statistical and systematic properties of DNN based discriminators

Backup slides

First application: charge energy reconstruction

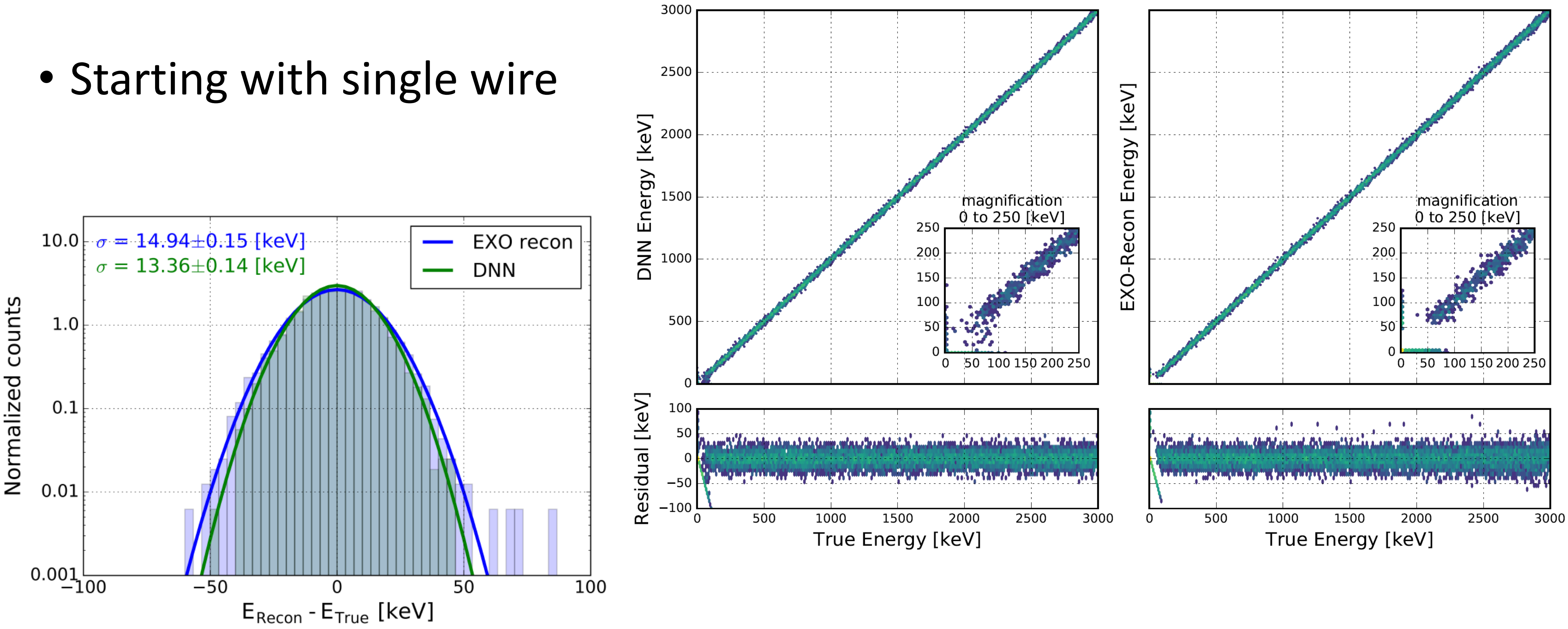
- The main challenges of charge reconstruction are noise and disentangling U-wire signal into induction and collection





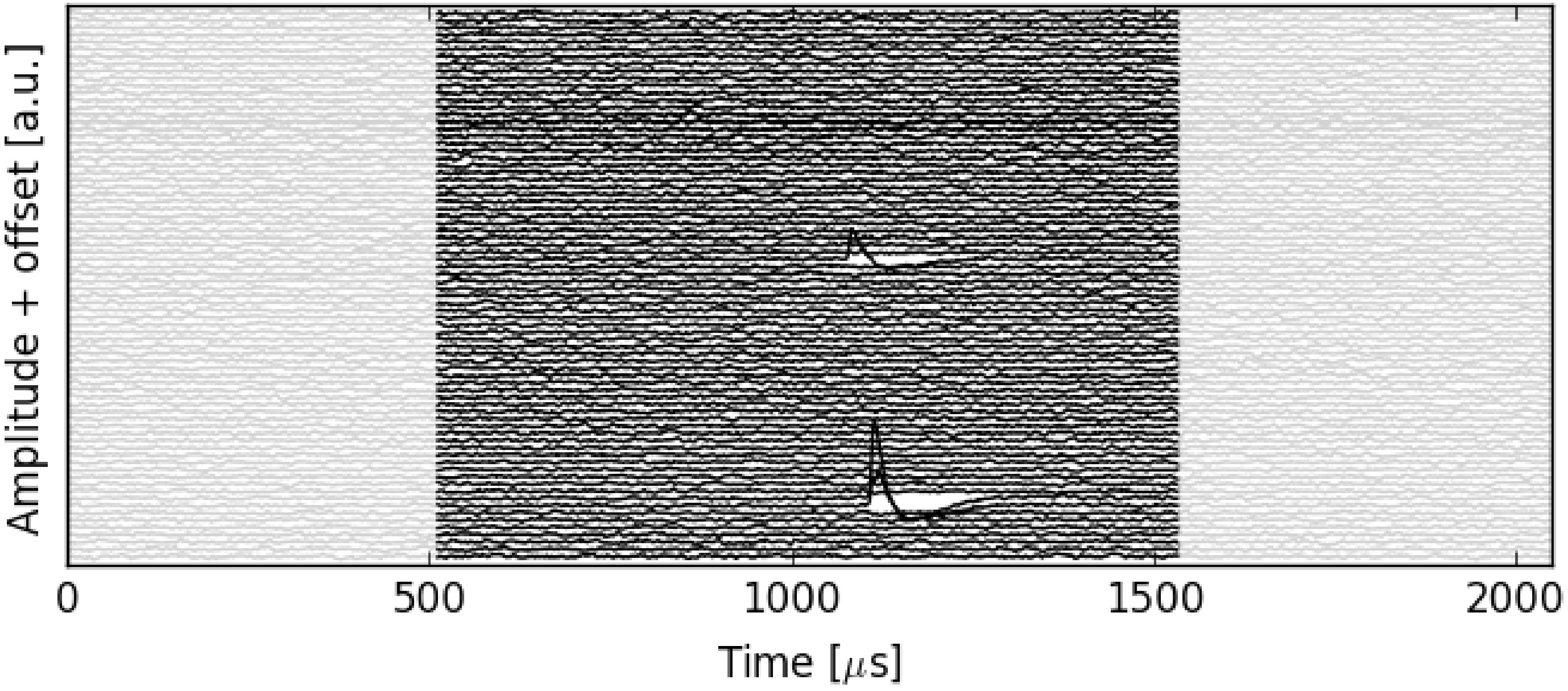
First application: charge energy reconstruction

- Starting with single wire



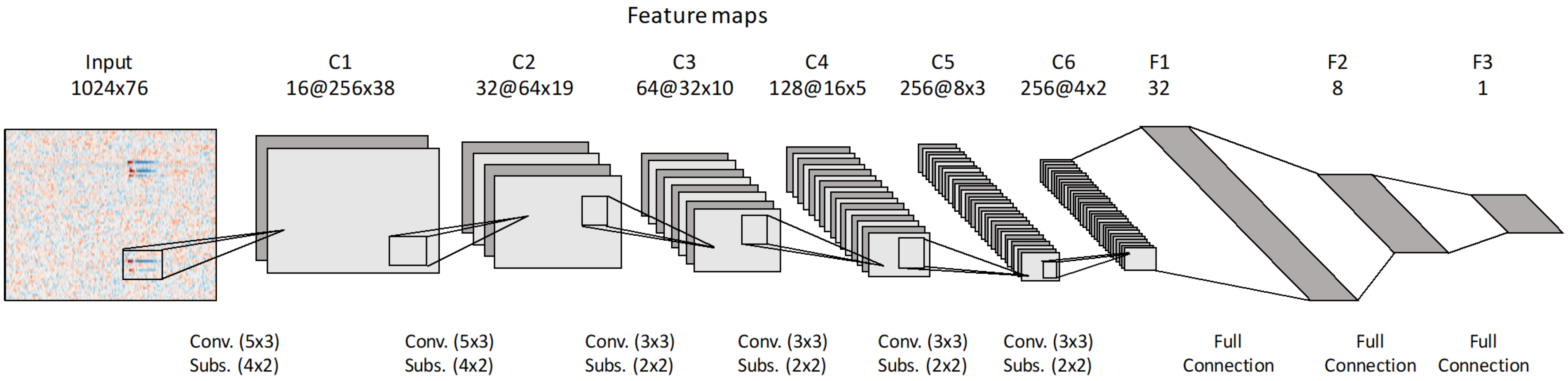
First application: charge energy reconstruction

- Now full events – all 76 U-wire waveforms (1024 time samples)
- Minimal Preprocessing: correct channel gains + crop waveforms



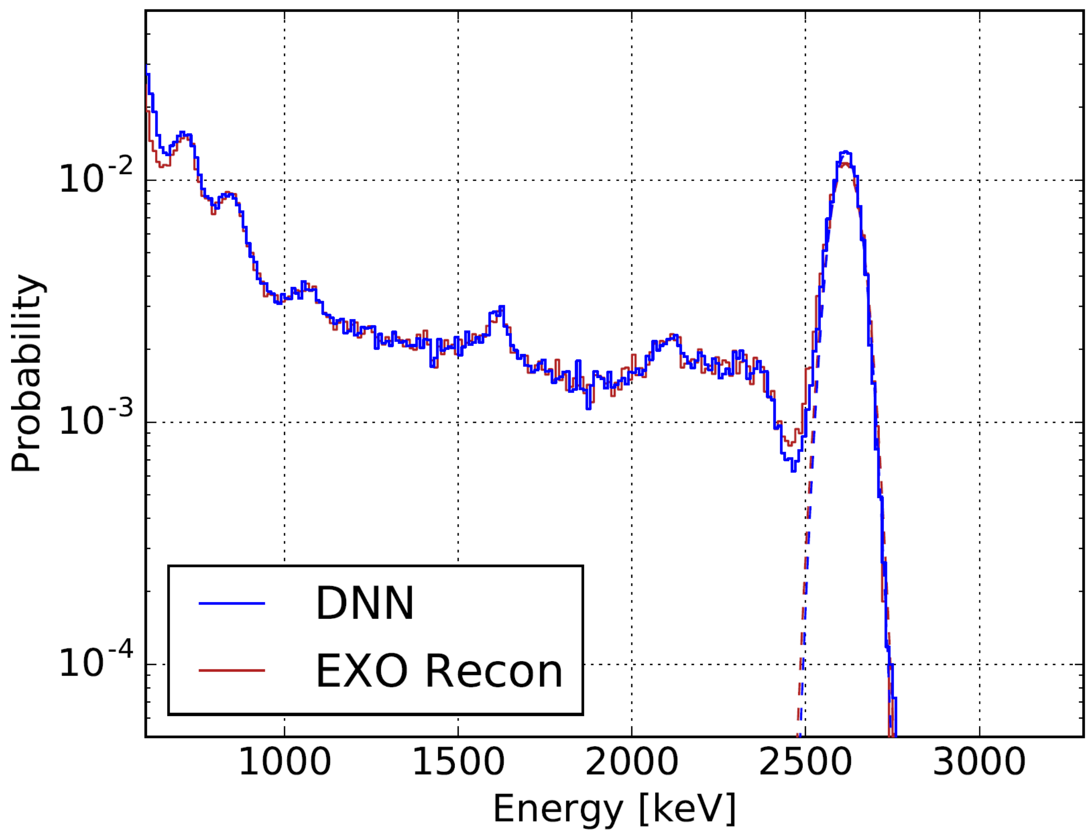
First application: charge energy reconstruction

- Input waveform image
- Convolutional part extracts features from image
- Dense part extracts target variable(s) from features



First application: charge energy reconstruction

- Works on real calibration events over the energy range under study
  - Residuals w/o energy dependent features
- Resolution (σ) at the ^{208}Tl full absorption peak when combining with light channel from EXO Recon:
  - DNN: 1.65% (SS: 1.50%)
  - EXO Recon: 1.70% (SS: 1.61%)
- Fewer events in the dip means less Th background in ROI

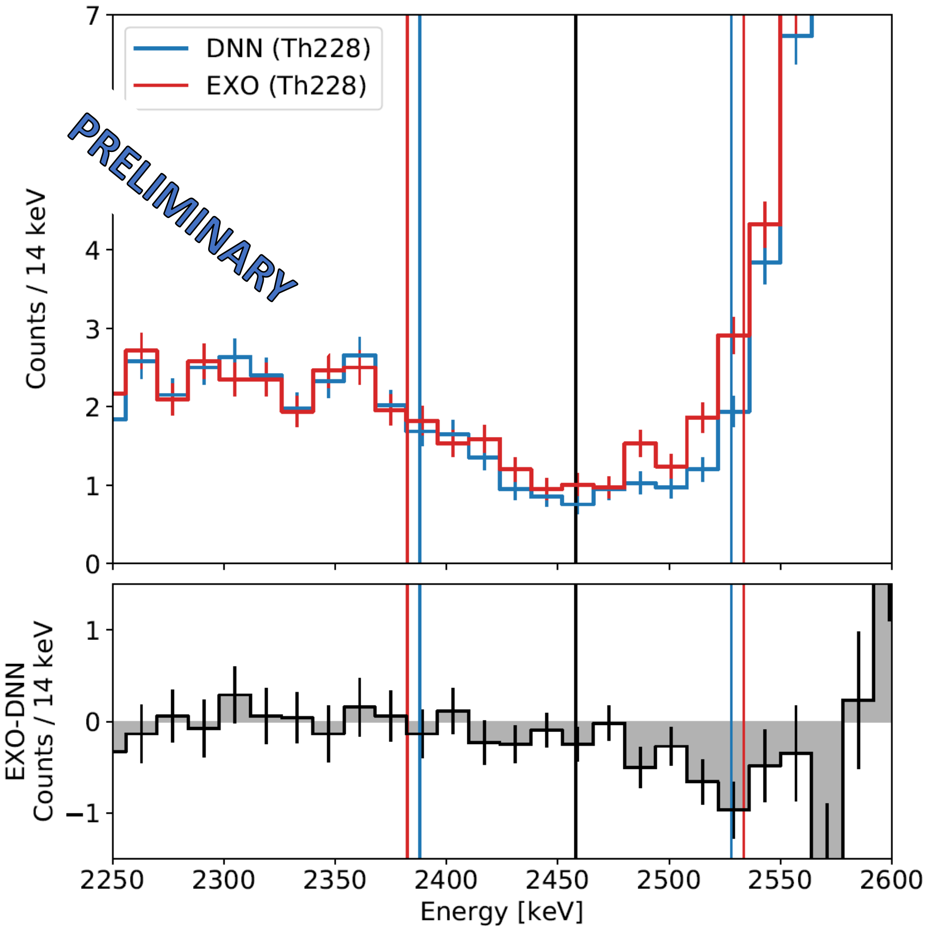


^{228}Th spectra, SS-only events

First application: charge energy reconstruction

- It's not only about reconstruction – better induction disentangling and slightly better rotated resolution already make a quantifiable improvement to physics goals
- Projected ~26% reduction of ^{232}Th background in Phase I and ~18% in Phase II compared to standard recon
  - ~15% 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

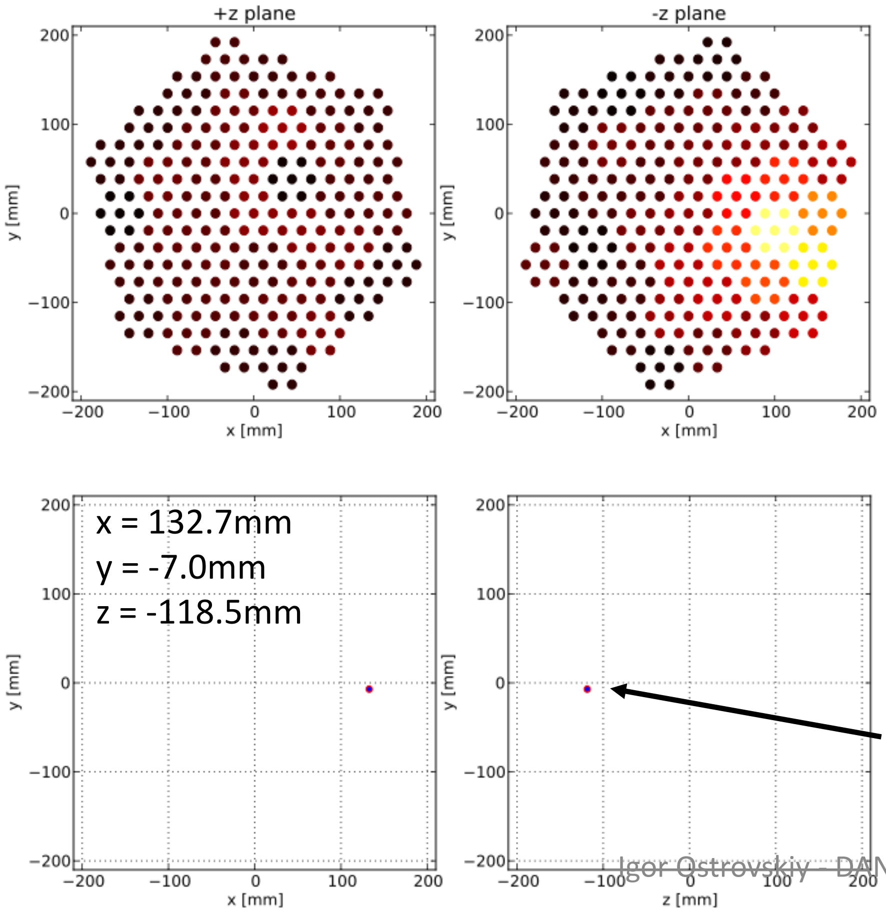
PRELIMINARY



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

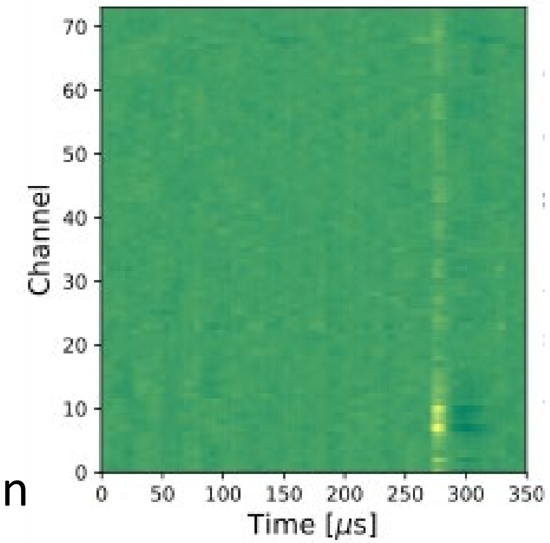
Second application: light position reconstruction

- 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

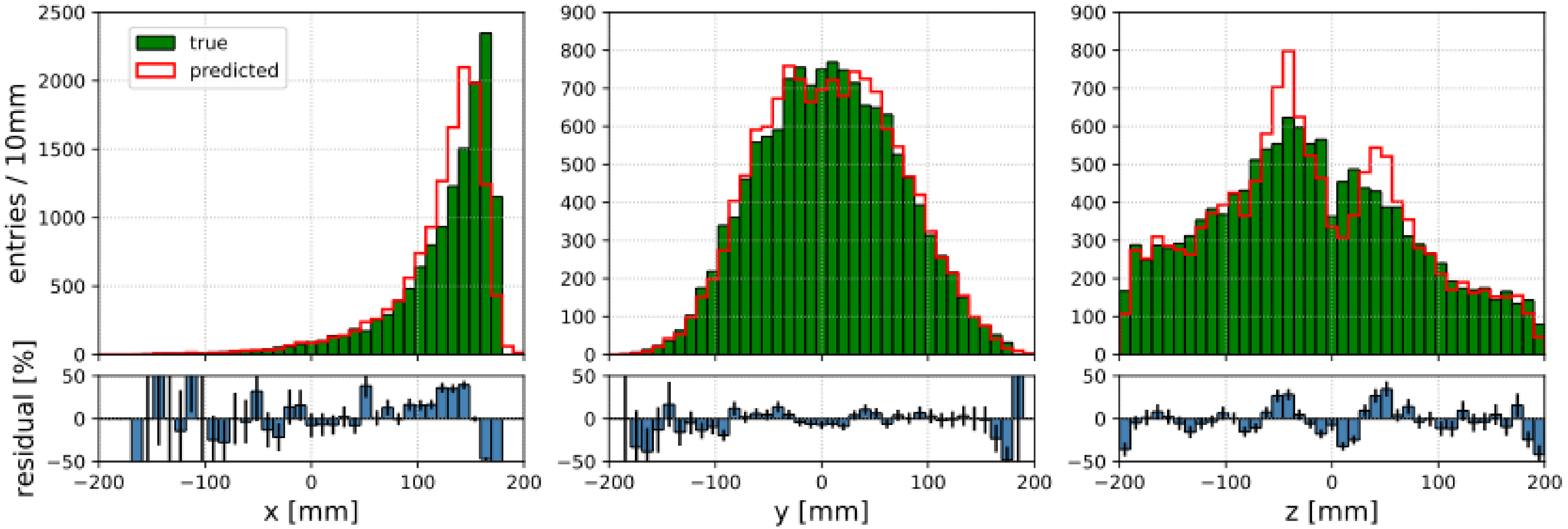


Truth information extracted from ionization signal

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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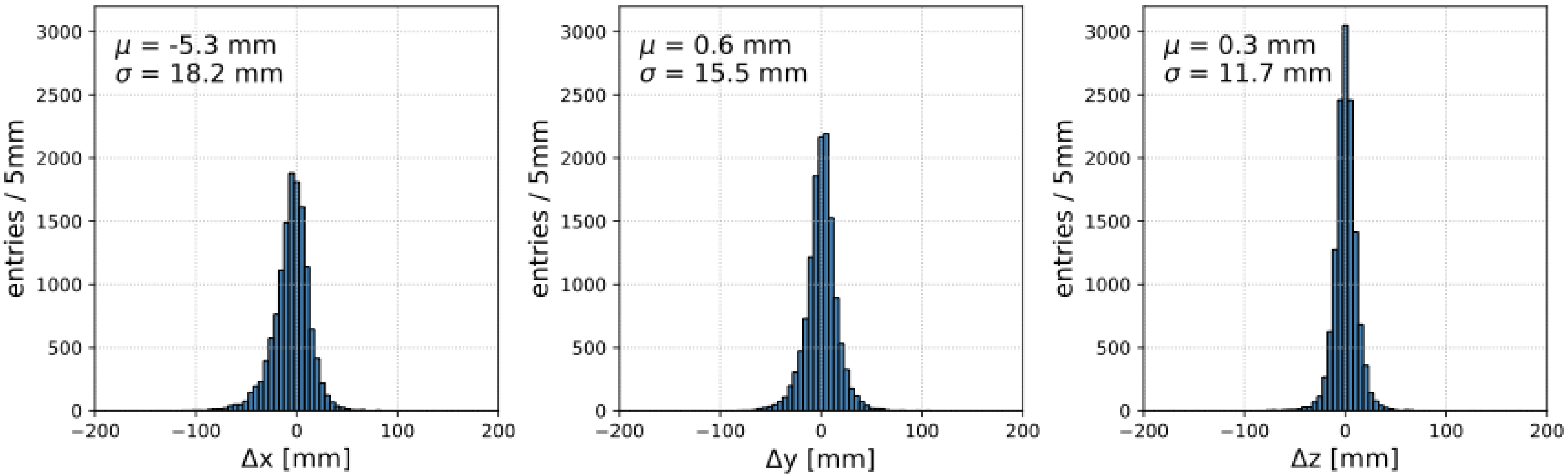
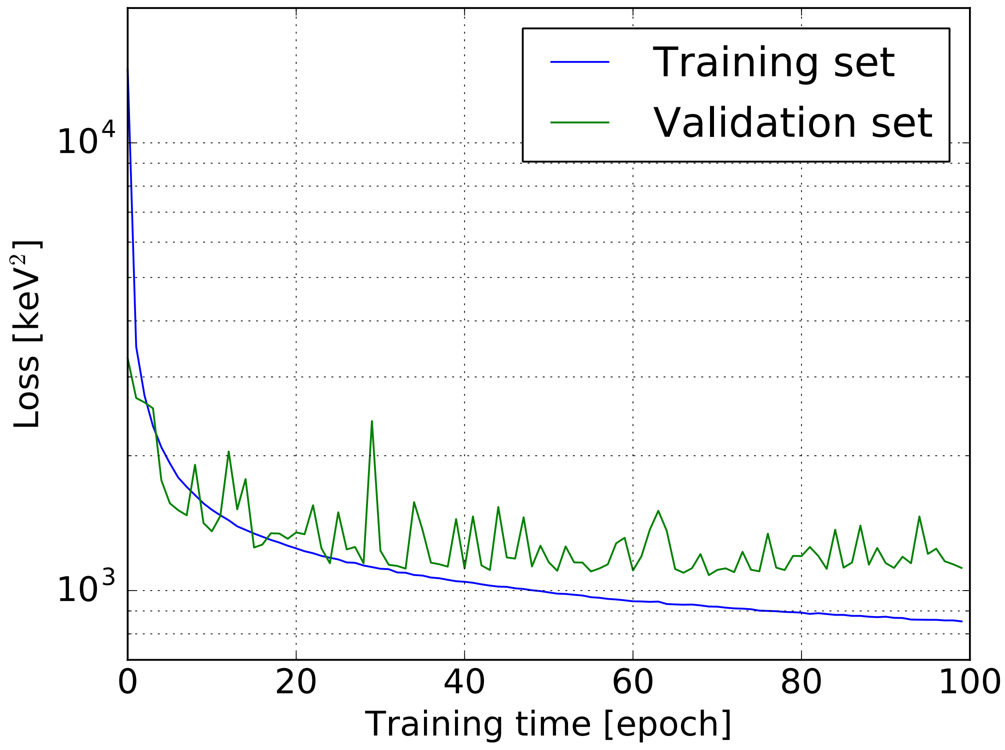


Charge reconstruction training details

- 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

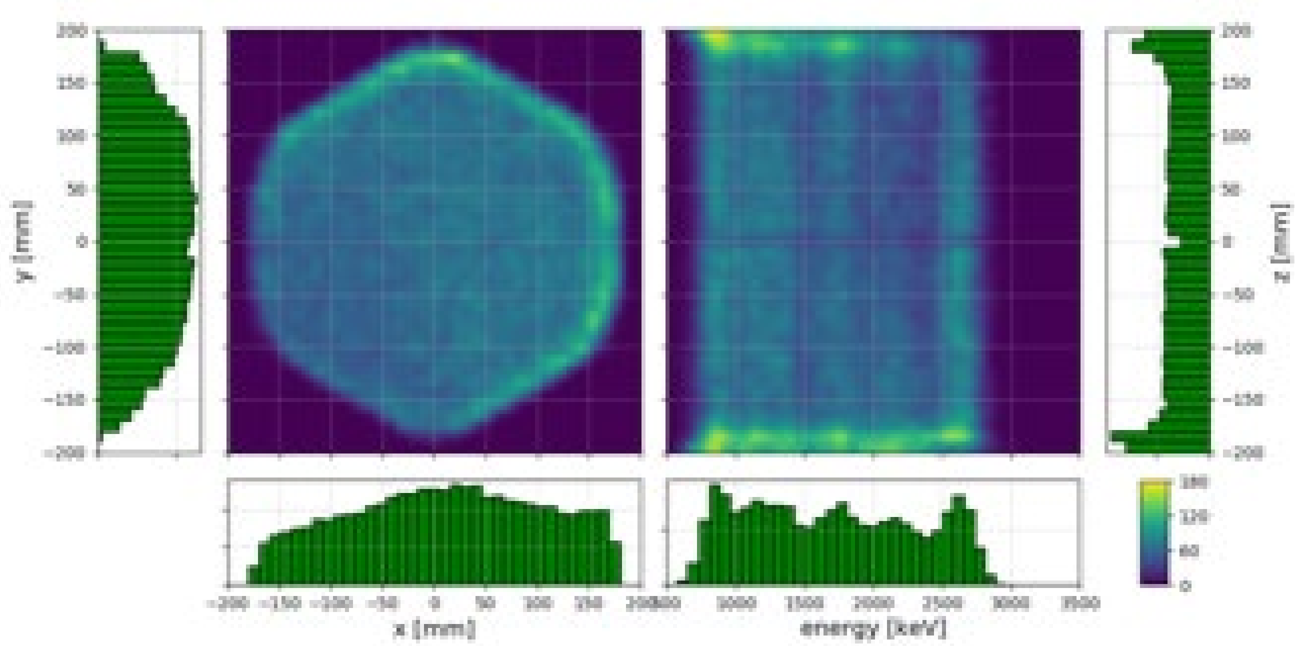


Light reconstruction details

- 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

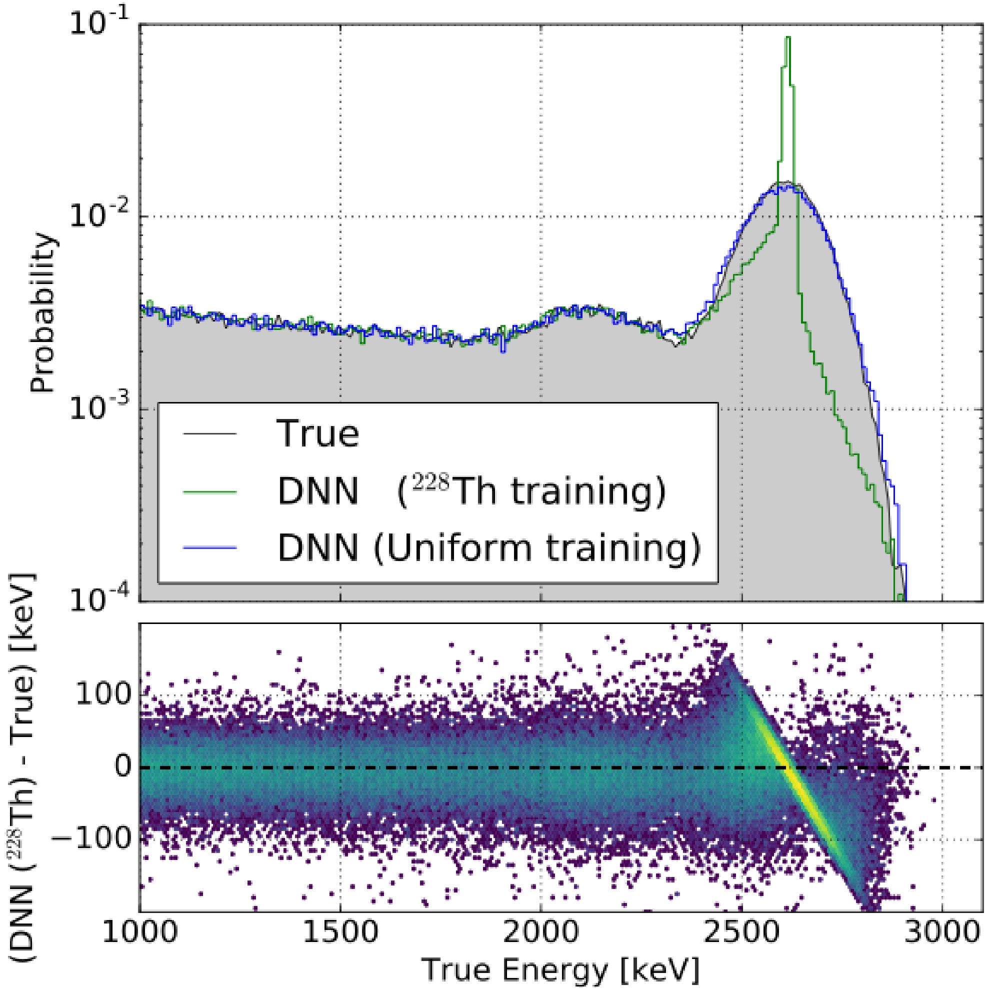
$$L = C + \lambda \cdot R \quad \text{where} \quad C = \frac{1}{3m}\sum_{i=1}^{m}\sum_{k=1}^{3}\left(y_i^k - \hat{y}_i^k\right)^2$$

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

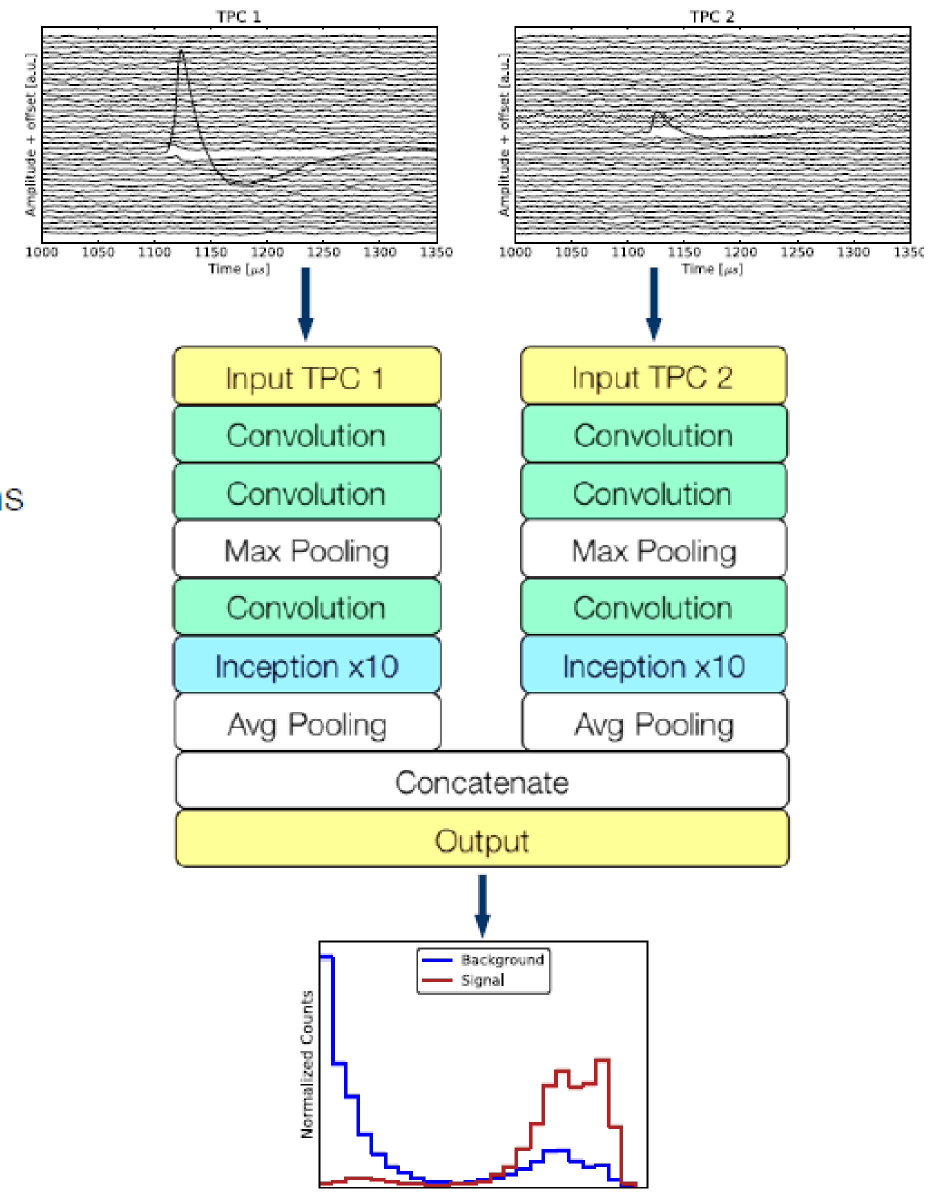


Pitfalls of DNNs

- 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



- Binary discriminator for ββ vs γ events
- Training data is identical to energy DNN
    - 50% ββ signal, 50% γ background
- MC event distributions uniform in detector volume
    - Topological discrimination only
    - No assumption on spatial distributions
- MC event distribution uniform in energy
    - validation on $2\nu\beta\beta$ data possible
- DNN architecture inspired by the Inception architecture
- Shared weights in TPC braches



- Blinded analysis performed
- SS/MS classification
- 3-dimension fit in both SS and MS events:
  Energy + DNN (topology) + Standoff distance (spatial)
  - Make the most use of multi-parameters for background rejection
  - SS, MS relative contributions constrained by SS fraction
  - Fit Phase-1 and Phase-2 separately
- Improvement of ~25% in $0\nu\beta\beta$ half-life sensitivity
  compared to using energy spectra + SS/MS alone

- Energy spectra: SS (left) and MS (bottom right)
- DNN spectra: SS/MS (top right) of projected for ROI events