Deep neural networks for energy and position reconstruction in EXO-200

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

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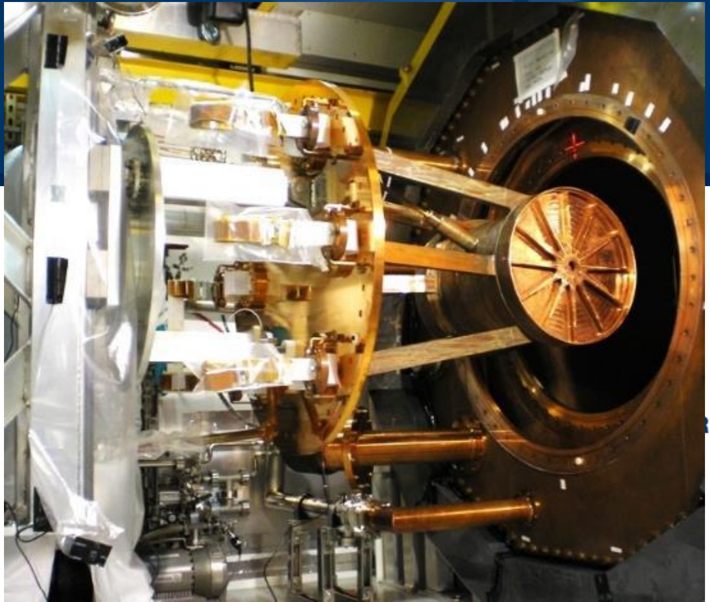
HAP Workshop
Aachen 2019



Enriched Xenon Observatory
EXO
for double beta decay

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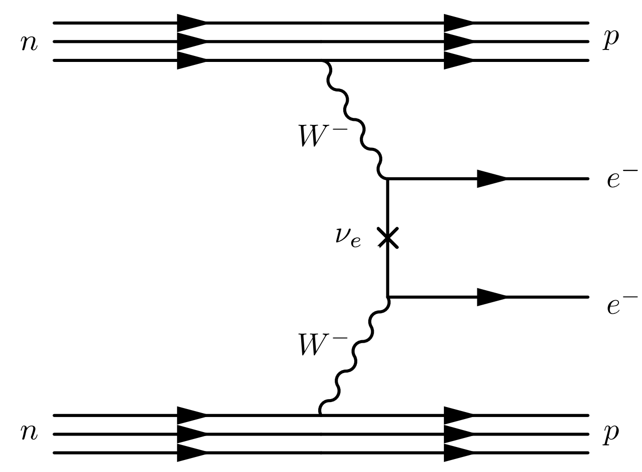
PHYSICS

Neutrinoless double beta decay

- Two neutrino mode:
  - Rare but allowed process
  - Half-lives of $10^{18} – 10^{21}$ yrs
- Only few nuclei (Xe136, Ge76, Cd116)
- 2^{nd} order weak process



Requirements:

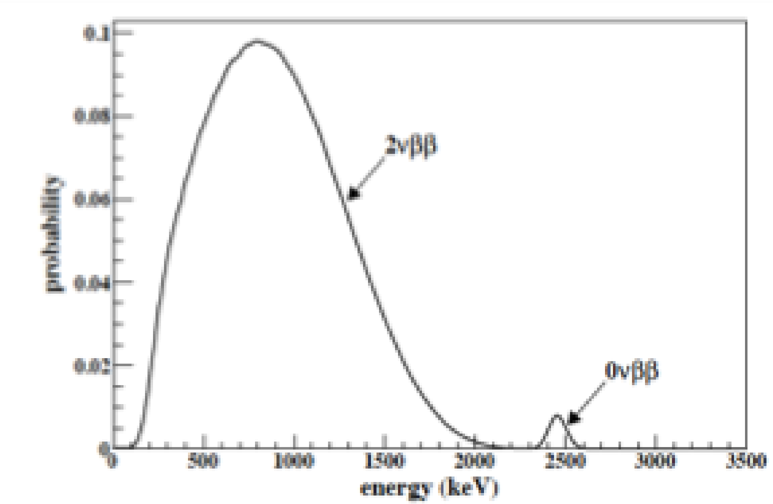
- Neutrino has mass
- Neutrino is its own anti-particle

→ Physics beyond the Standard Model

→ Enormous half-life
  e.g. $T_{1/2}$(Xe136) > 1.1 x 10^{26} yrs

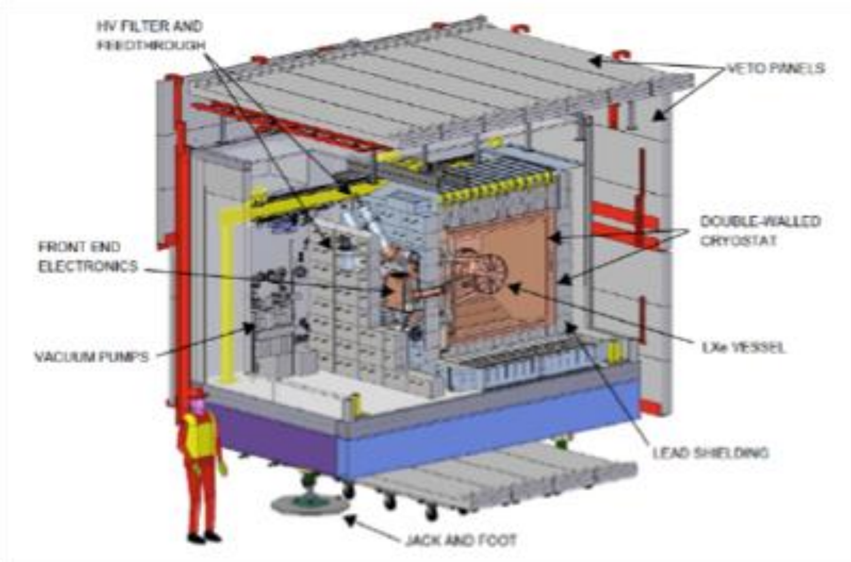
→ Hypothetical

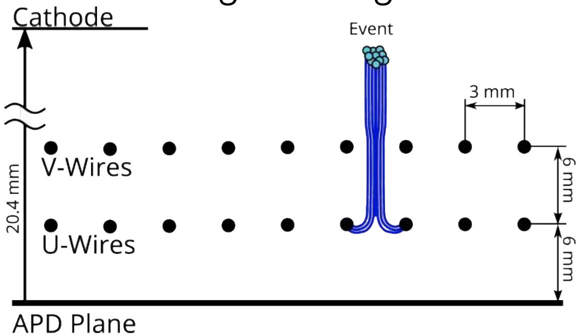
→ Good energy resolution crucial

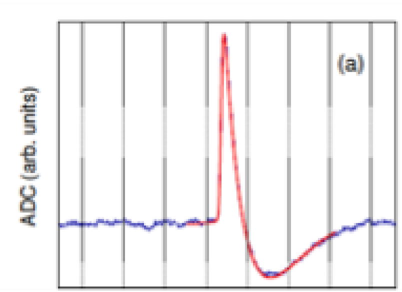


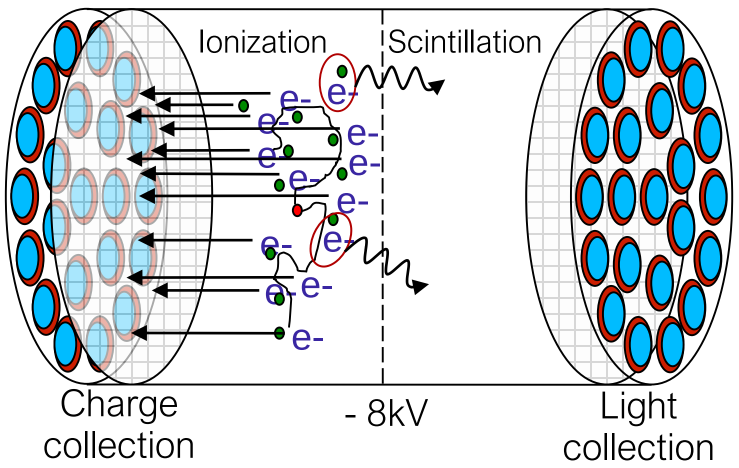
EXO-200 experiment and event detection

- Located at WIPP in Carlsbad, U.S. (1585 m.w.e. overburden)
- Double-sided single phase radiopure time projection chamber (TPC) filled with 200kg LXe enriched to 80.6% in Xe136 (Q = 2.458 MeV)
- Two complementary measurements
  - Scintillation light (178 nm), by APDs
  - Ionization charge, by 2 wire grids
  - → Collection signals carry energy
  - → Induction signals do not carry energy
- Full 3D position reconstruction with charge and light channel



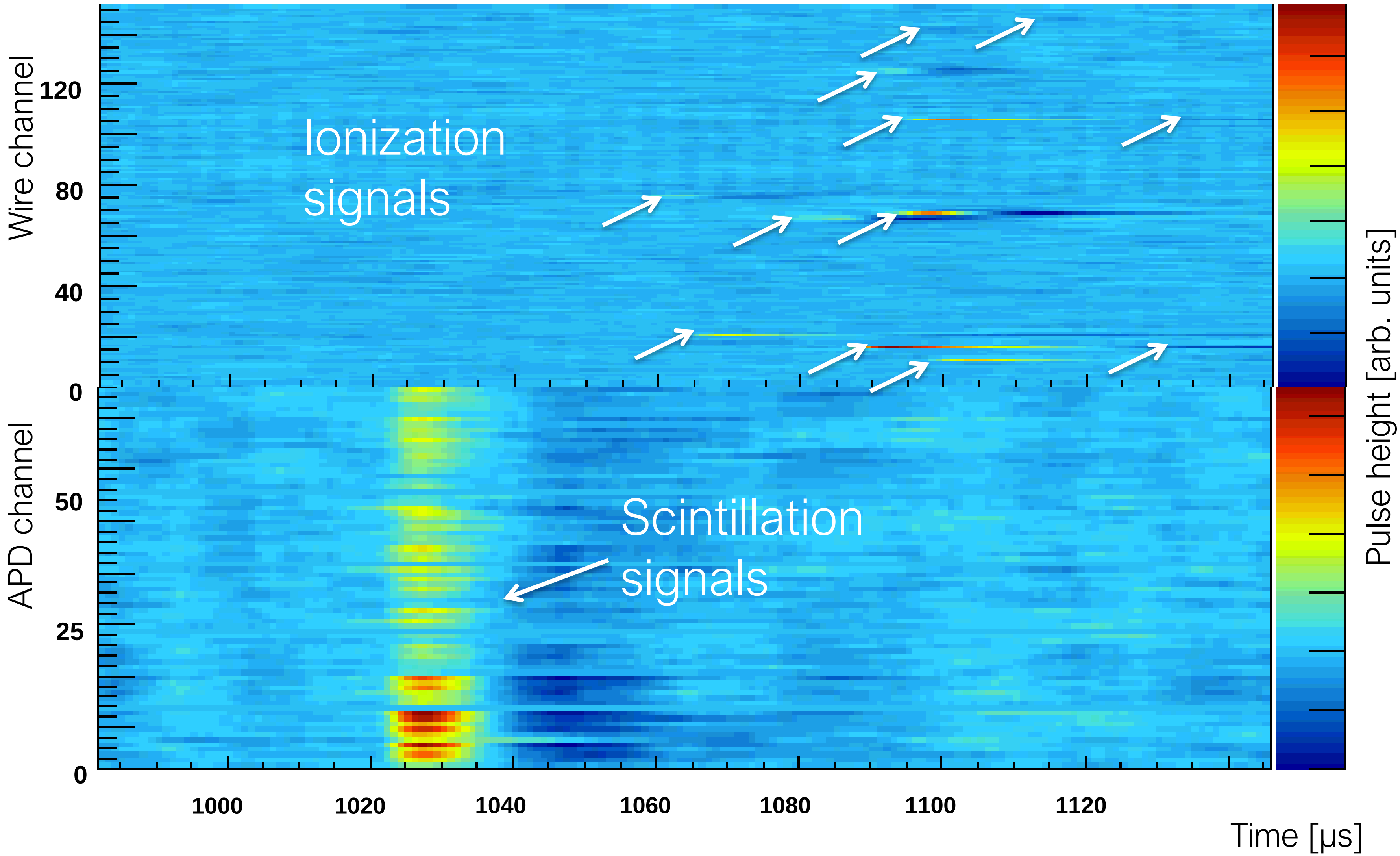






Event display

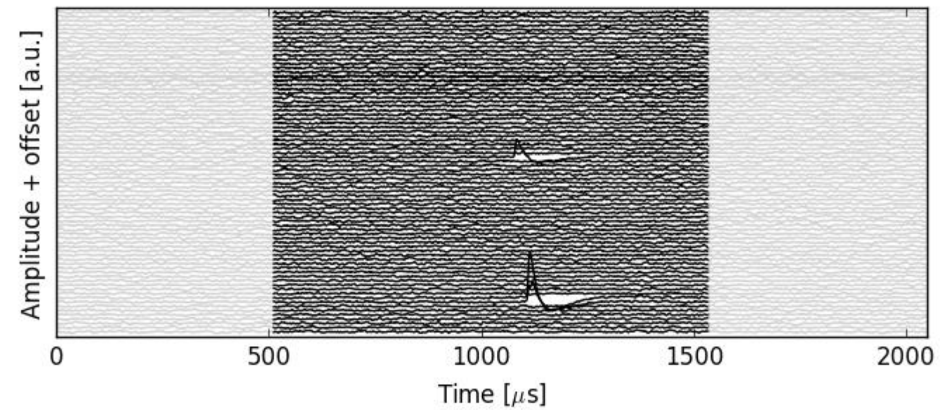
Example multiple-scatter γ event in EXO-200:



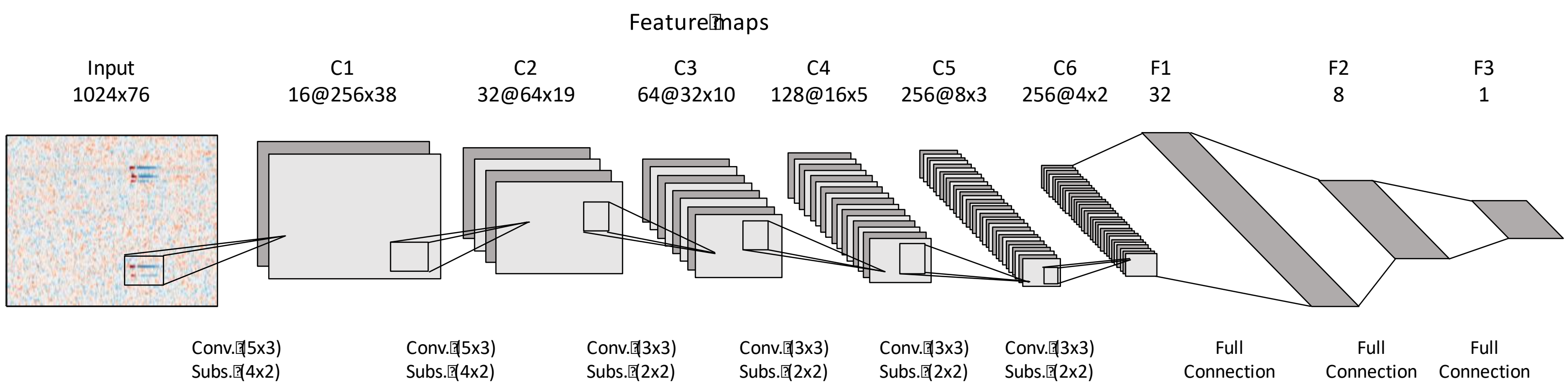
Energy reconstruction using charge signals

Charge-only energy reconstruction

- Energy reconstruction from raw signals of charge collection (U) wires
- Single (SS) and multiple (MS) charge deposits in LXe from 500-3500 keV
- Preprocessing: baseline subtraction, channel gains correction, crop waveforms to 1024 time samples

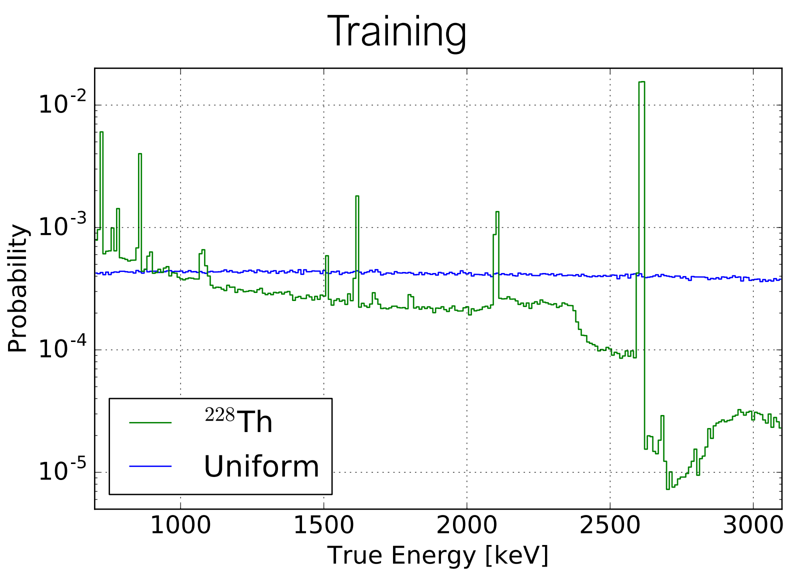


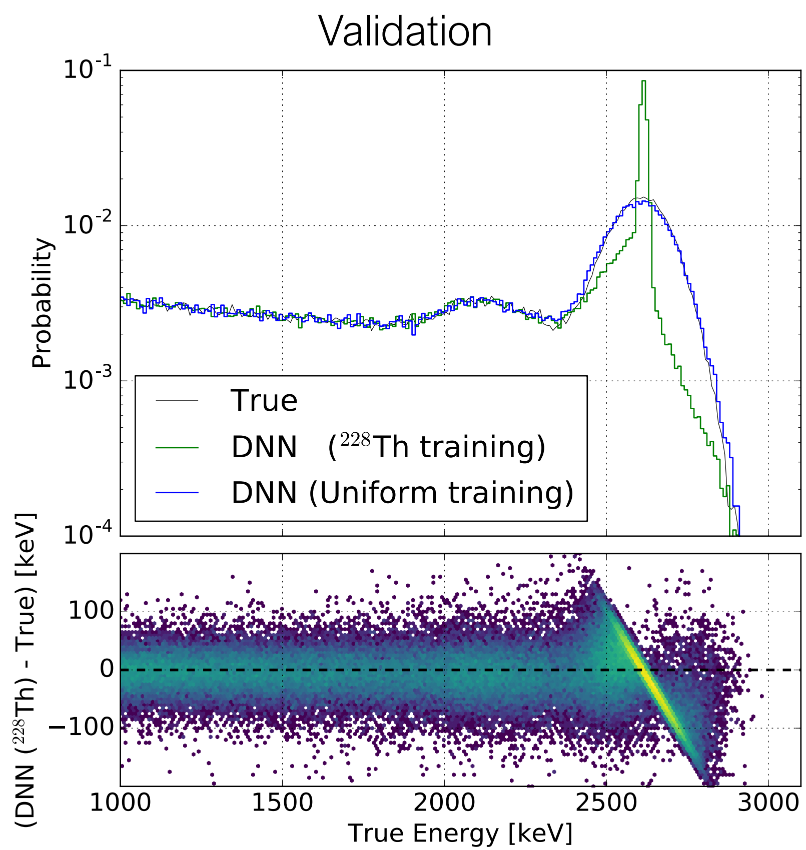
- Training on 750k Monte Carlo events with real noise. Minimizing MSE
- Input waveform image → Convolutional part → Fully connected part → Energy
- Implementation in Keras (with TensorFlow backend) on GPU Cluster (GTX1080)



Importance of uniform training spectrum

- Uniform energy spectrum (blue) proved crucial for training
- Otherwise (e.g. Th228 source, green) overtraining on sharp peaks in training
  - Neural network shuffles independent validation events towards sharp peaks from training spectrum



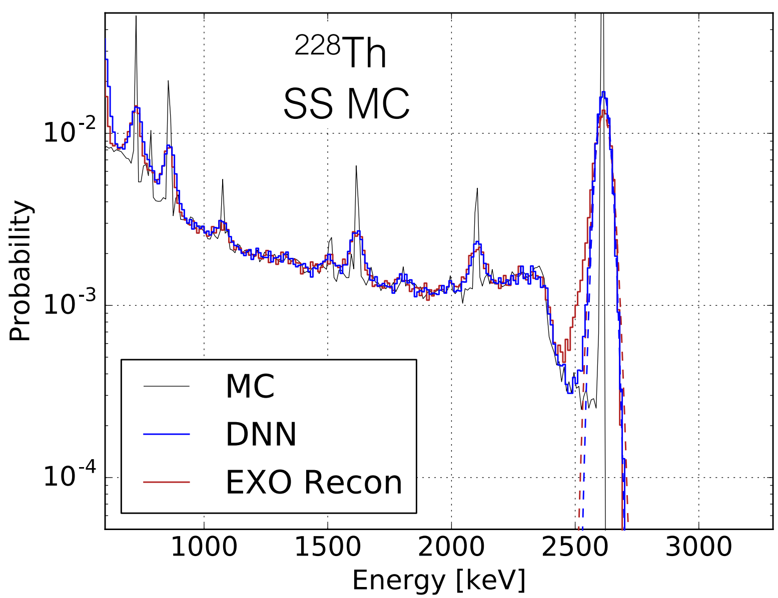


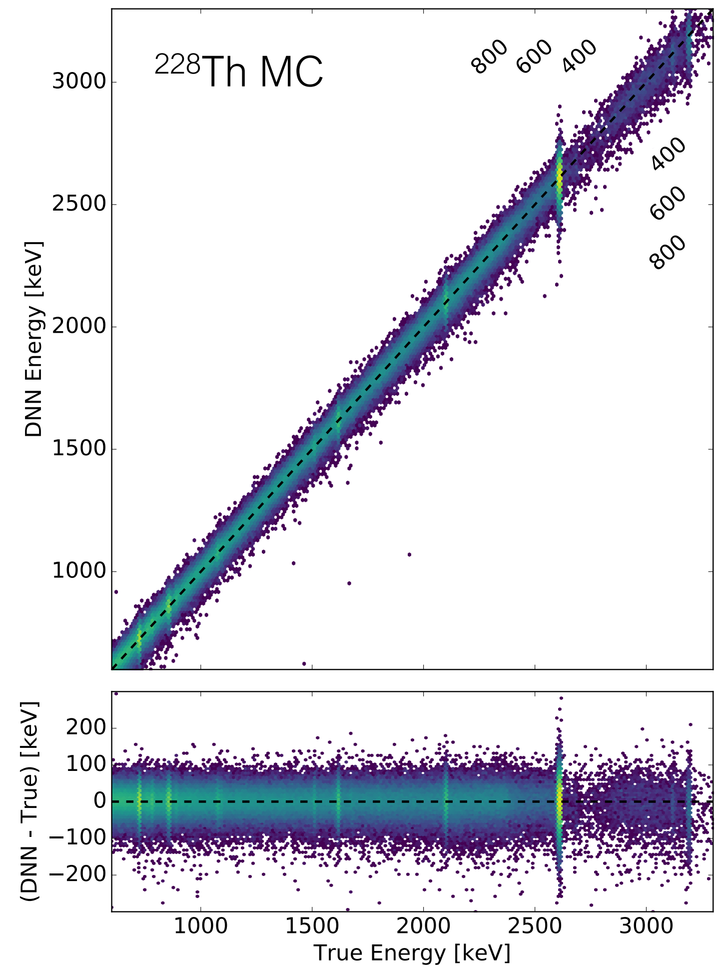
Validation on ^{228}Th Monte Carlo data

- Reconstruction works over the energy range under study
  - Residuals w/o energy dependent features
- Resolution (σ) at the ^{208}Tl peak full absorption peak (2.6 MeV):

  DNN: 1.22% (SS: 0.94%)

  (EXO-200 Recon: 1.29% (SS: 1.15%))
- Neural Network outperforms in disentangling mixed induction and collection signals (see valley right before ^{208}Tl peak)



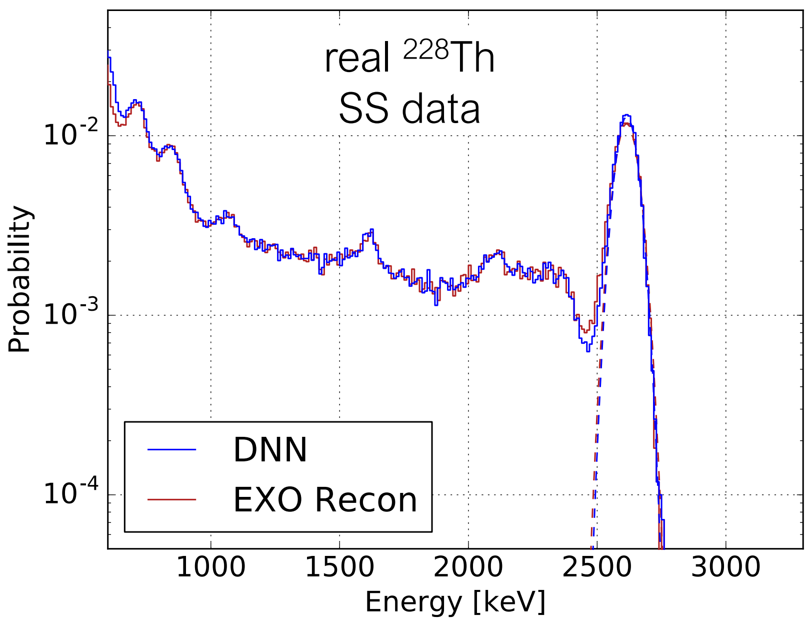


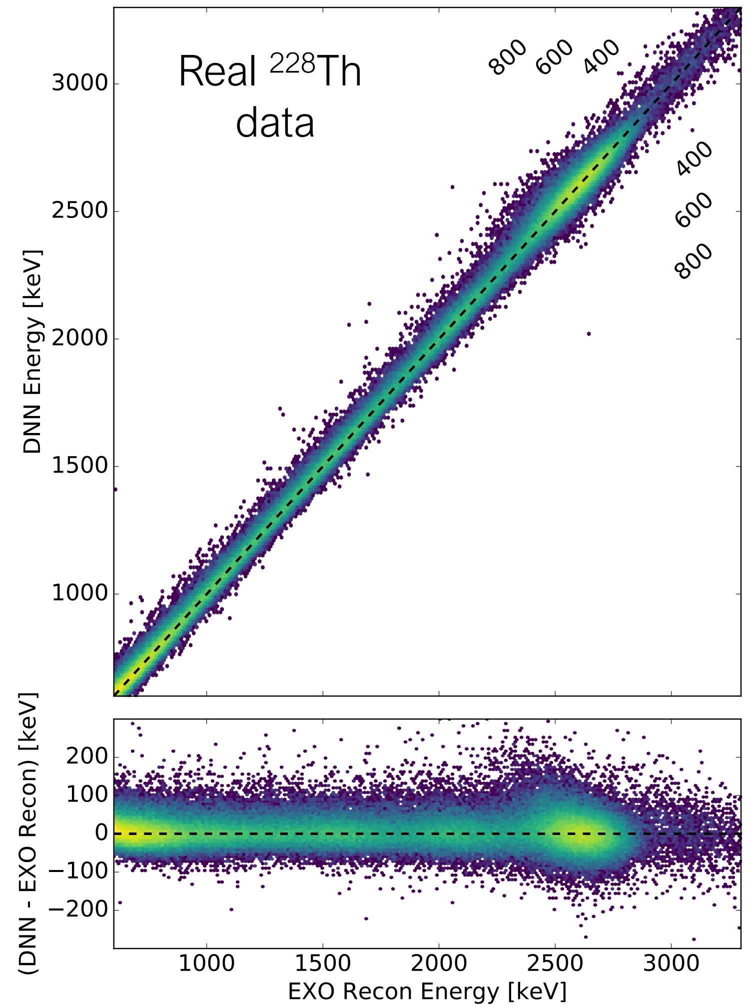
Validation on ^{228}Th real calibration data

- 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 scintillation channel from EXO-200 reconstruction:

  DNN: 1.65% (SS: 1.50%)

  (EXO-200 Recon: 1.70% (SS: 1.61%))

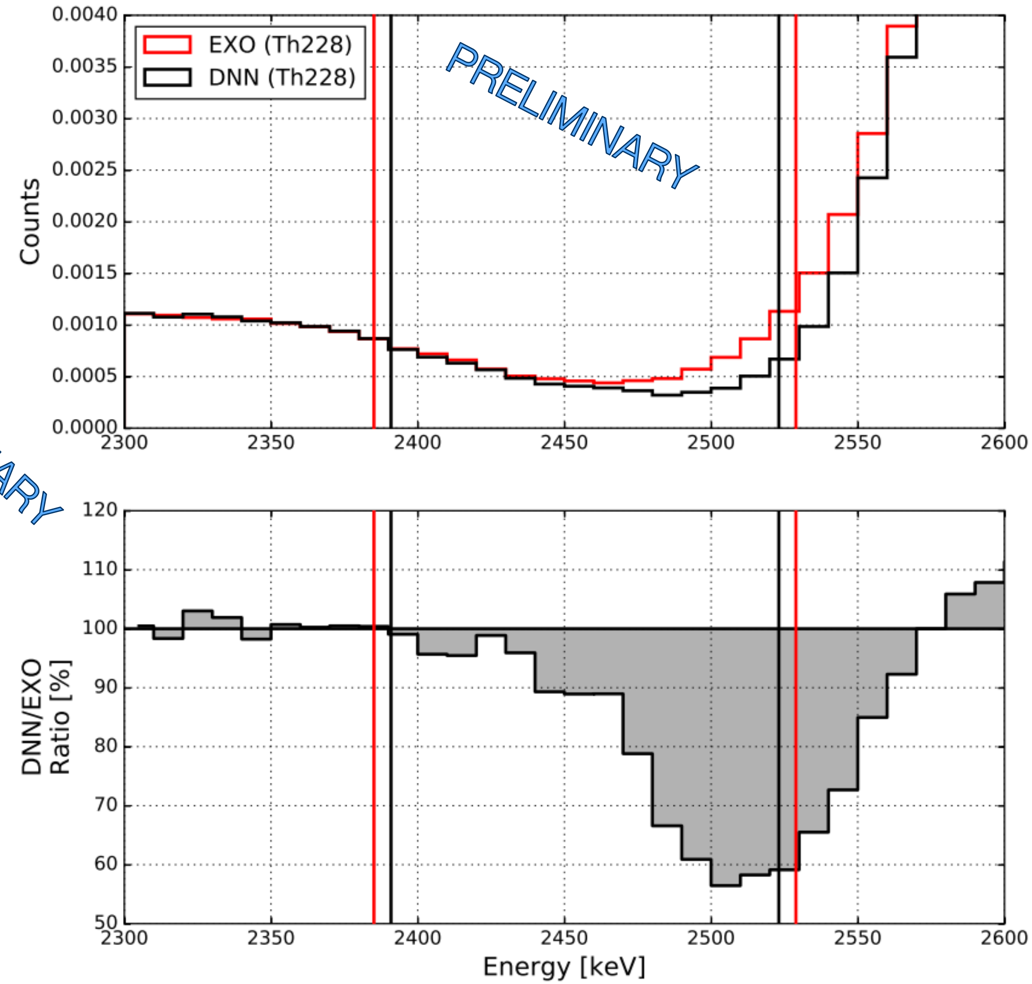




Estimating background in the ROI

- Better induction and collection disentangling and slightly better rotated resolution already make a quantifiable improvement to physics goals
- Projected ~29% reduction of ^{232}Th background in Phase I compared to standard recon
  - ~19% considering induction effect alone, i.e. fixed ROI
  - Using $1/\sqrt{B}$ scaling, this suggests ~8% sensitivity improvement for Phase I and probably smaller for Phase II due to better energy resolution (work in progress)

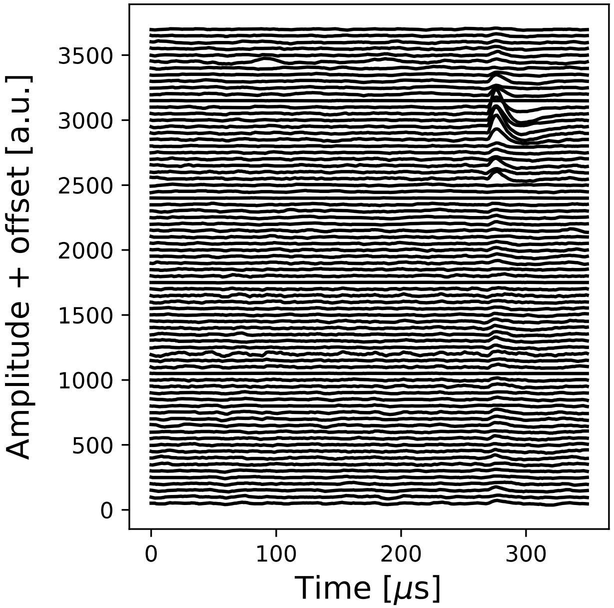
PRELIMINARY

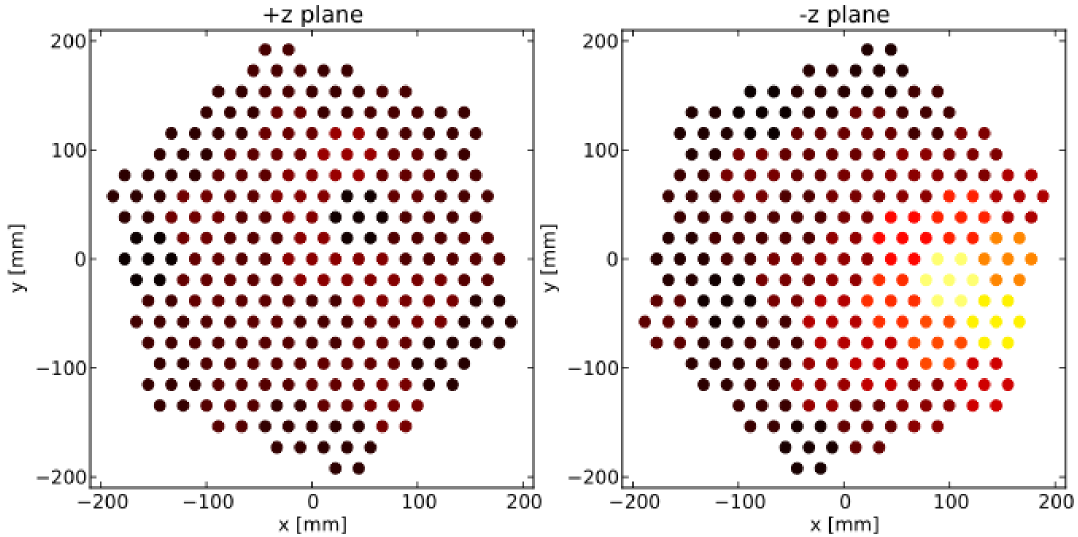


Data driven position reconstruction using scintillation light

Data driven position reconstruction

- Event position reconstruction from raw light signals
- Completely data driven training against truth labels provided by reconstructed charge signals
- 3D Event position is encoded in hit pattern



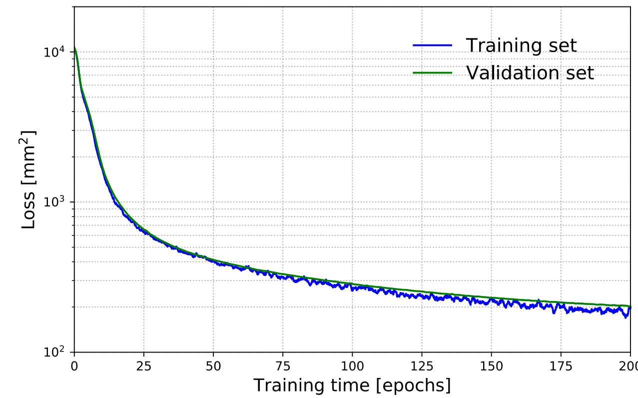


x = 132.7 mm
y = -7.0 mm

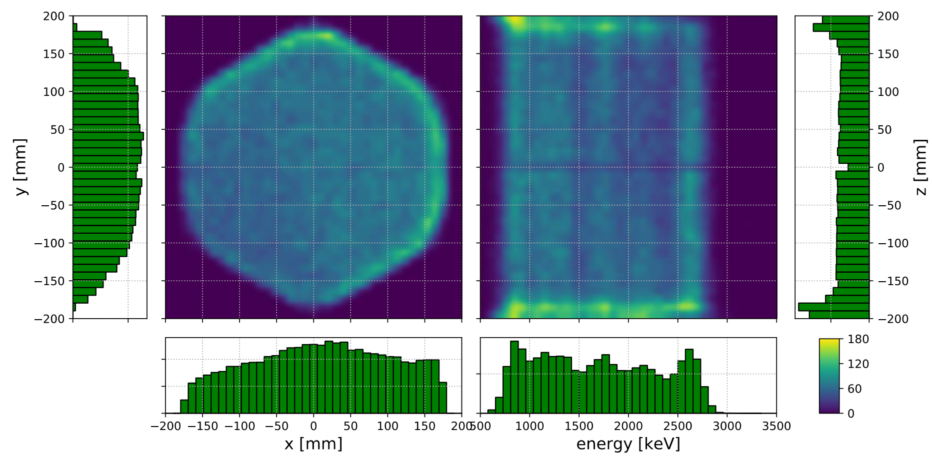
Data driven position reconstruction

- Waveform image is fed to convolution neural network (CNN)
- Output has three units corresponding to event position in x-, y-, z-coordinate
- Loss function is Euclidean loss with L2 regularization

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

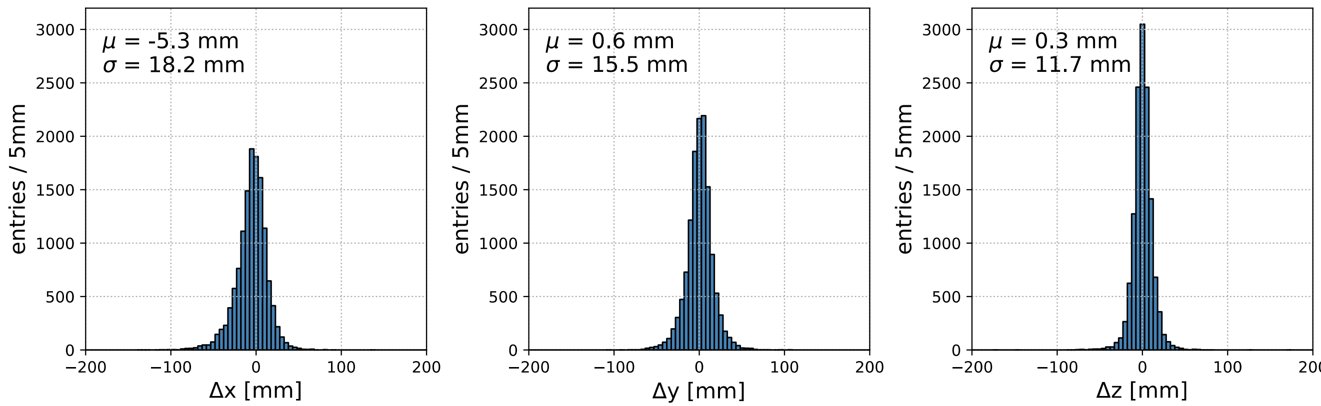


- Training is done on real calibration data flattened in both space and energy

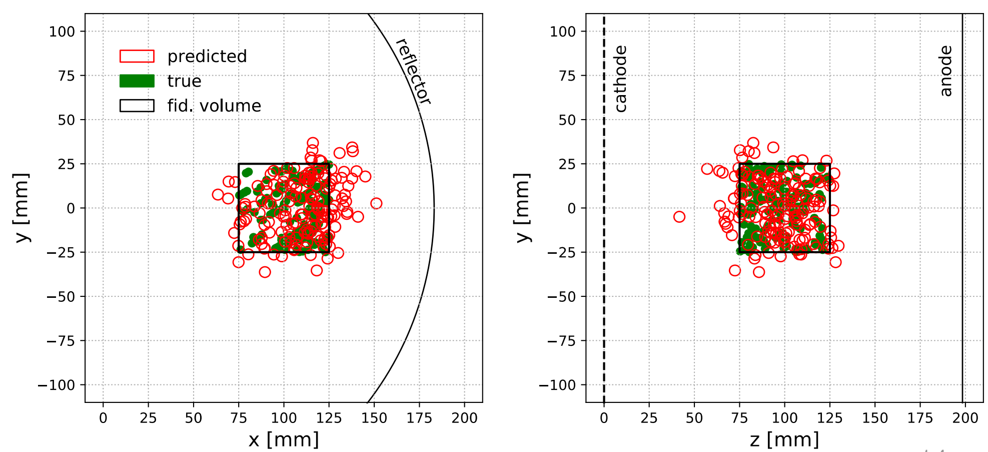


Data driven position reconstruction

- Loss function reaches 200mm^2 after training for 200 epochs
- Corresponding to a position resolution of σ_{3D} = 25 mm
- Theoretical limit is given by resolution of truth labels that is σ_{3D} = 3 mm



- The model is also applied to a test set manually constructed by applying fiducial cut to truth labels
- The accuracy reached is σ_{3D} = 13mm



Summary

- EXO-200 has demonstrated the use of Deep Learning methods for the data analysis directly from raw data
- Improved energy resolution compared to classical approach both for MC and for real data
- We have shown the importance of carefully selecting training data in order to avoid bias
- The trained DNN were evaluated on real detector data
- We demonstrated that training on real detector data is possible in certain cases and avoids reliance on MC
- Future experiments (like nEXO) may benefit from such approaches in simplifying the processing of data and extraction of high level features

Currently working on:

- Full event reconstruction including both wire planes
- Signal-background classification
- Reducing Monte Carlo simulation inaccuracies via GAN

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University of California, Irvine, Irvine CA, USA — M Moe
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Deep neural networks for energy and position reconstruction in EXO-200

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Enriched Xenon Observatory for double beta decay

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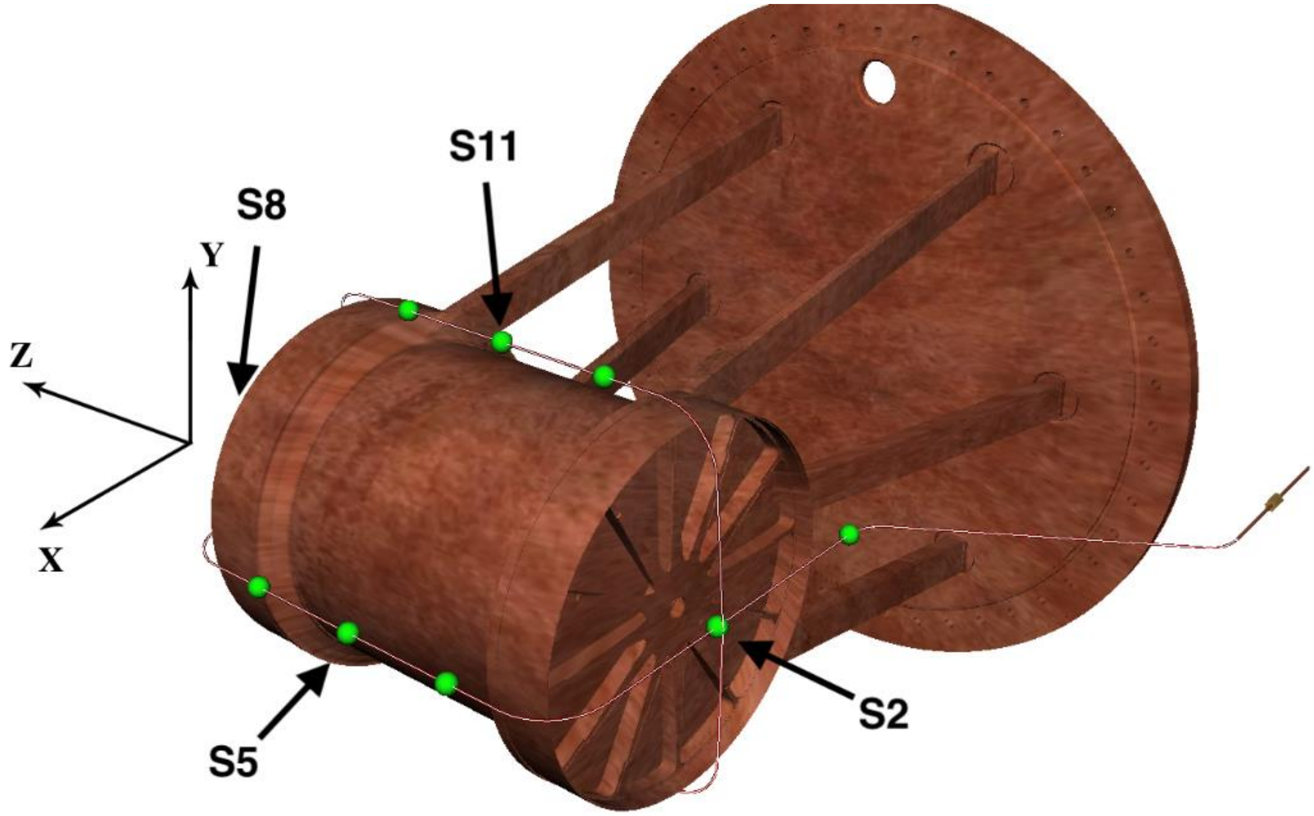
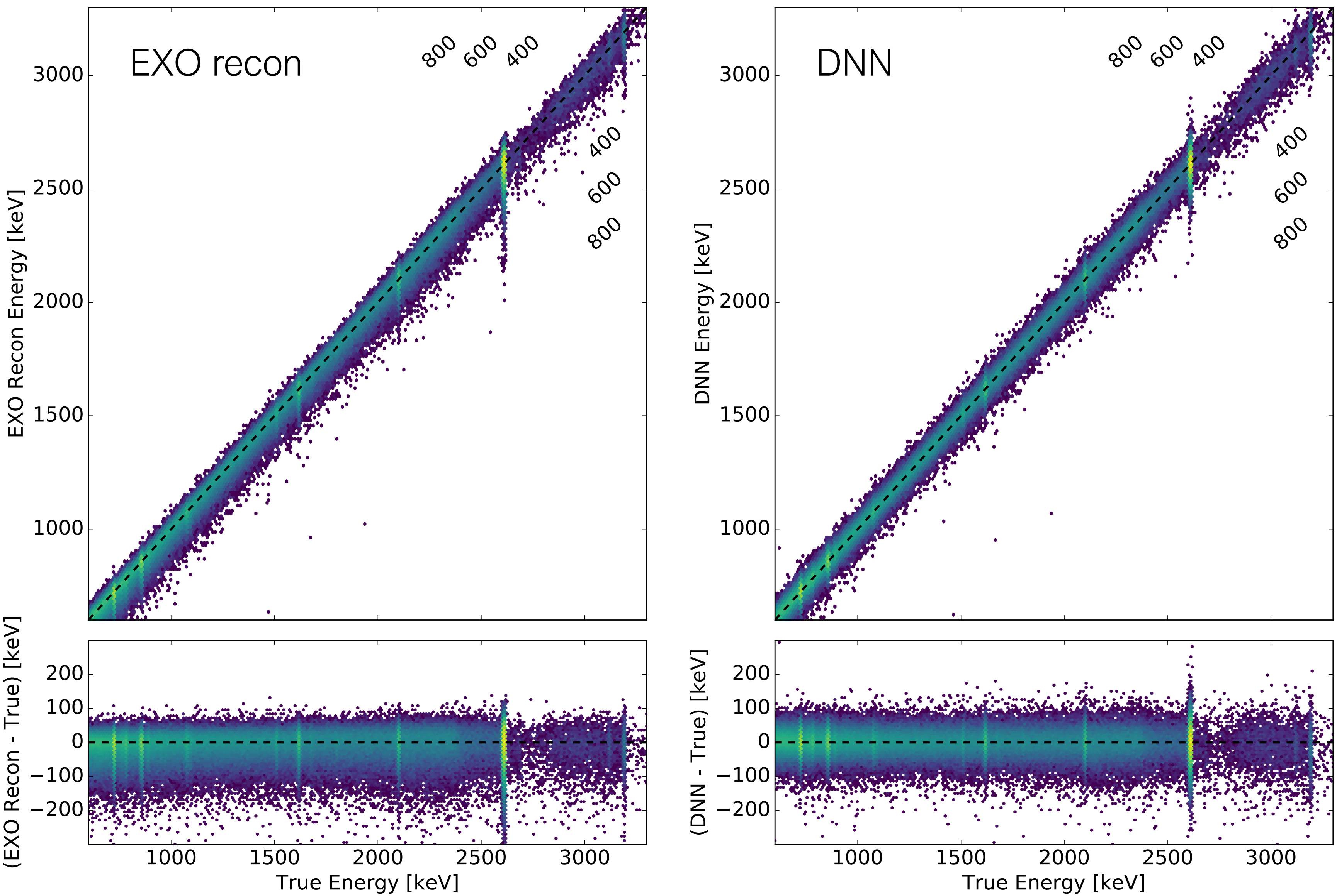
Bonus Slides

Source calibration positions

- Th228
- Ra226
- Co60

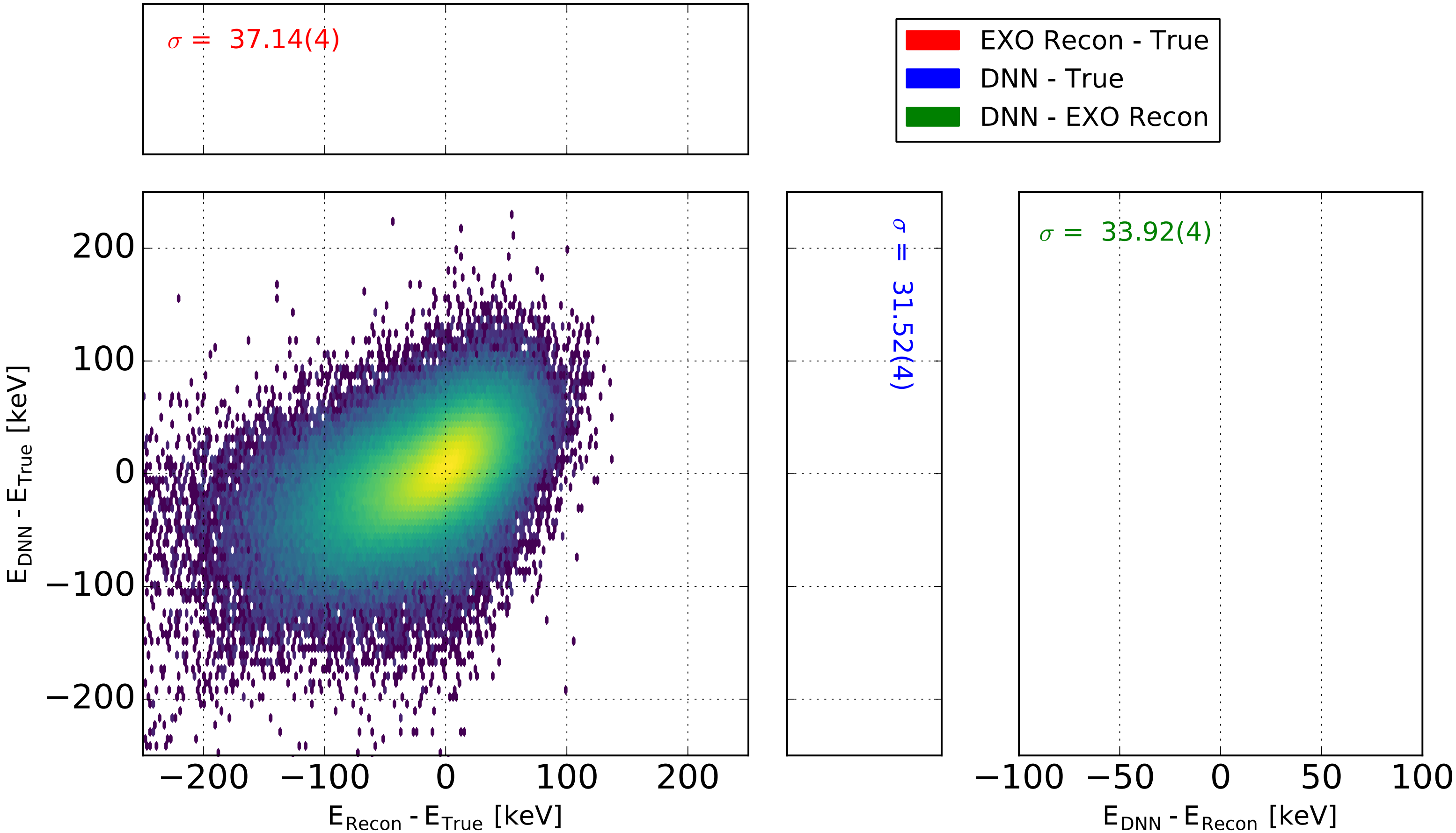


Validation – MC – DNN vs EXO Recon



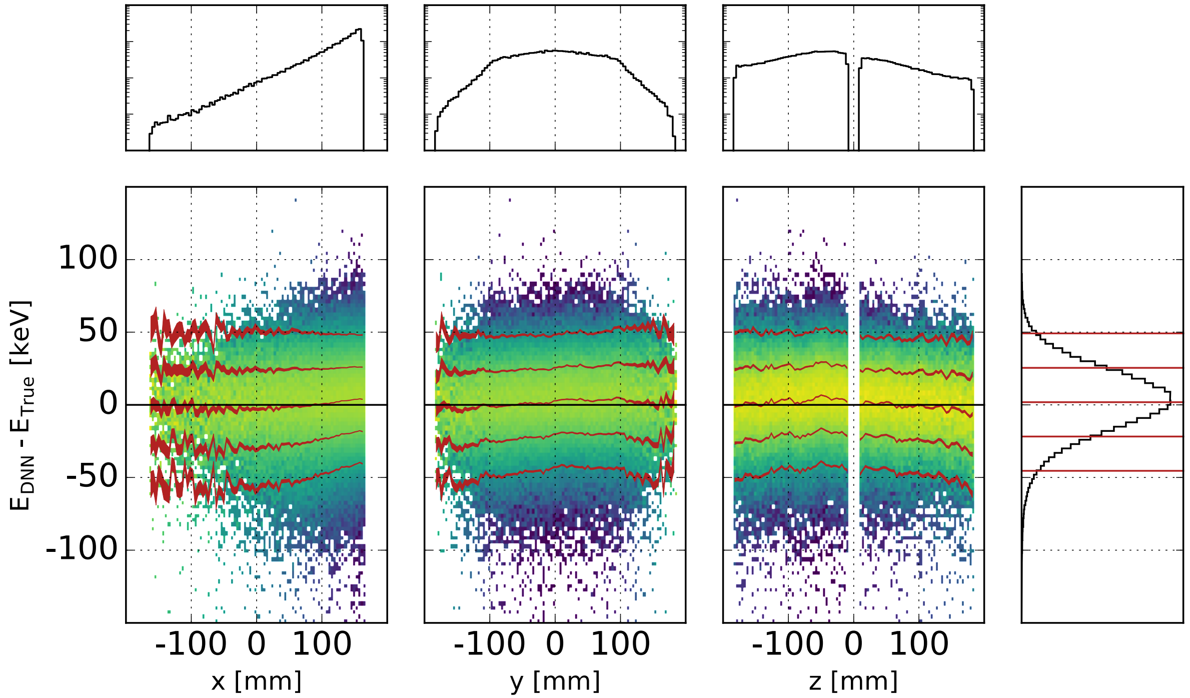
Validation – comparing to EXO recon

- Residuals of both methods indicate positive correlation



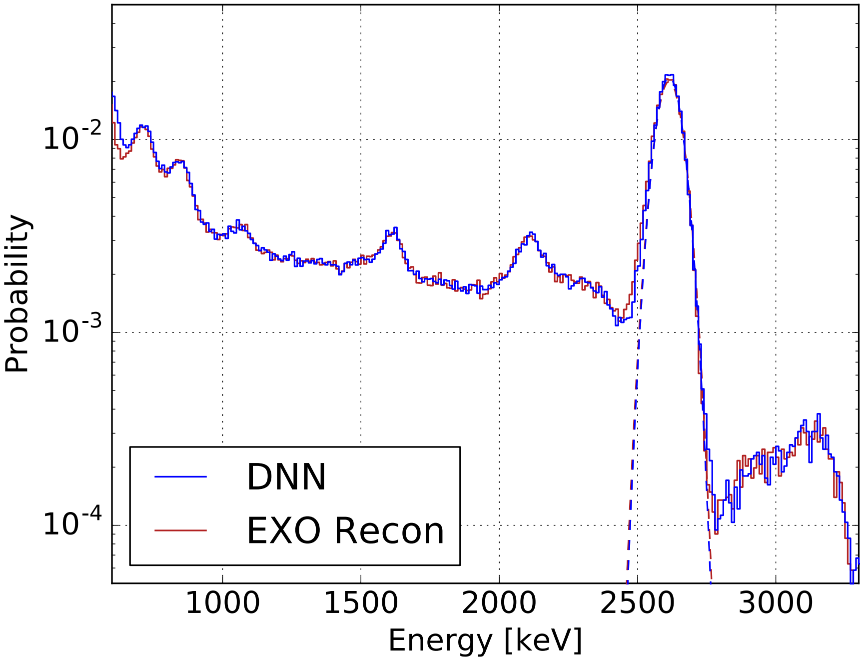
Validation – Position dependency

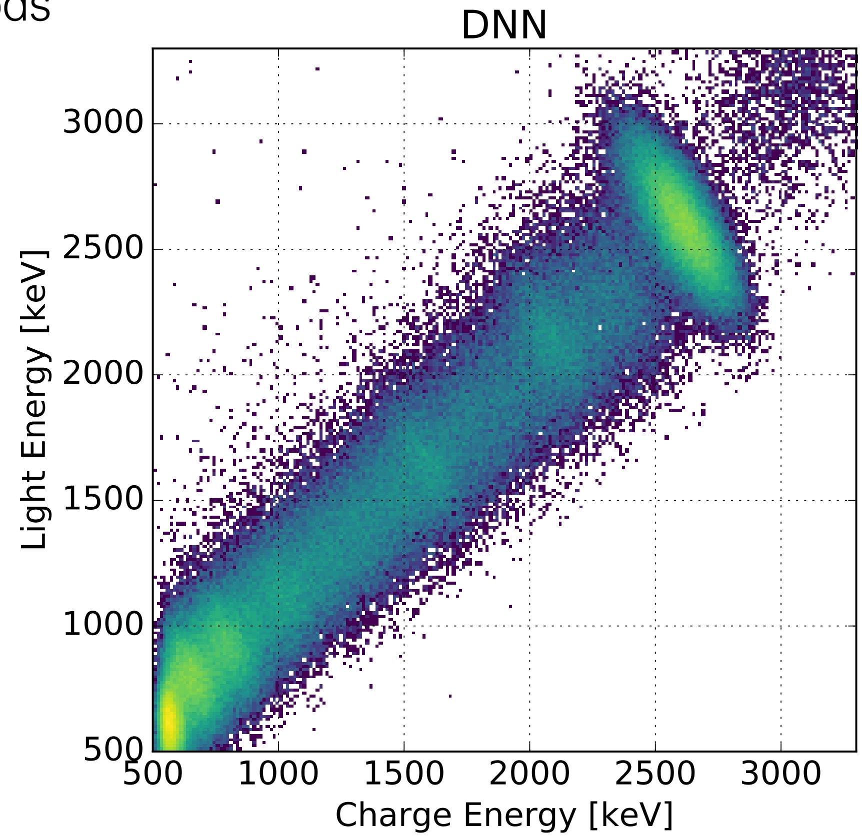
- Check network performance as function of event position (SS-only events)
  - Upper plots: position distribution of events. Source @ S5 (x=200,y=0,z=0)
  - Right plot: distribution of residuals ($E_{DNN} – E_{True}$)
  - Center heatmap: position-normalized distribution of residuals
  - Center red: mean and (+- 1, 2) stddev of residuals with uncertainty



Combination with light channel

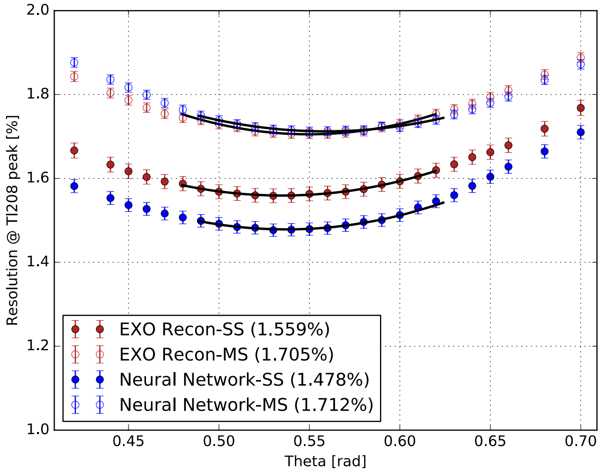
- Intrinsic fluctuation in LXe into scintillation and ionization channels
- Apply optimal linear combination of both channels to achieve optimal energy estimation (standard EXO analysis procedure)
- Good shape agreement between DNN and EXO recon
- Similar energy resolution of both methods



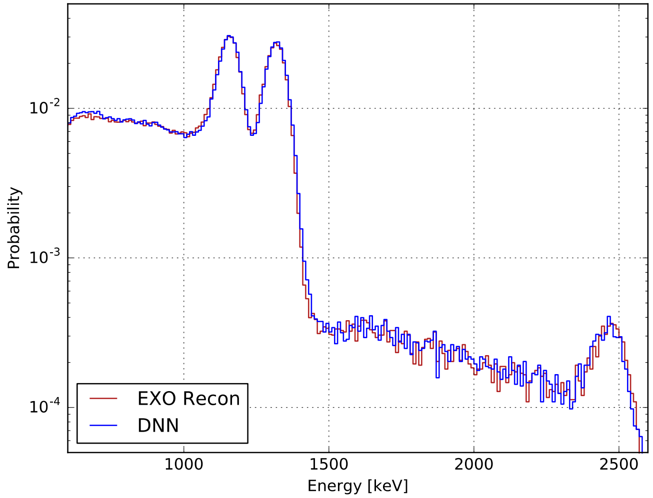


Combination with light channel

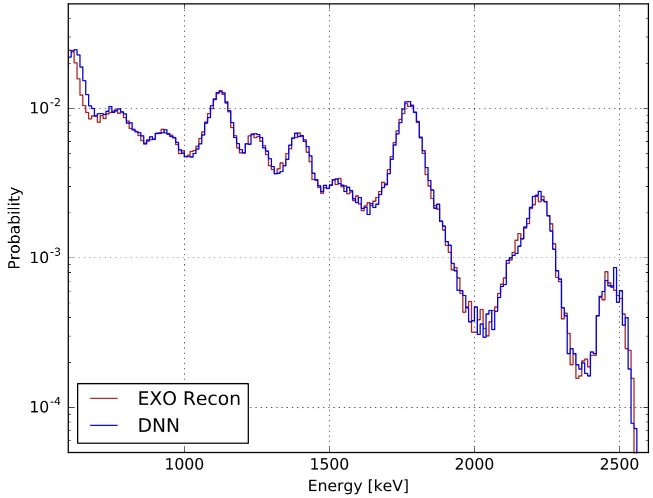
- Optimize rotation angle of scintillation and charge channel by minimizing energy resolution @ Tl208 full absorption peak
- Good shape agreement on other calibration source @S5 as well



Co60

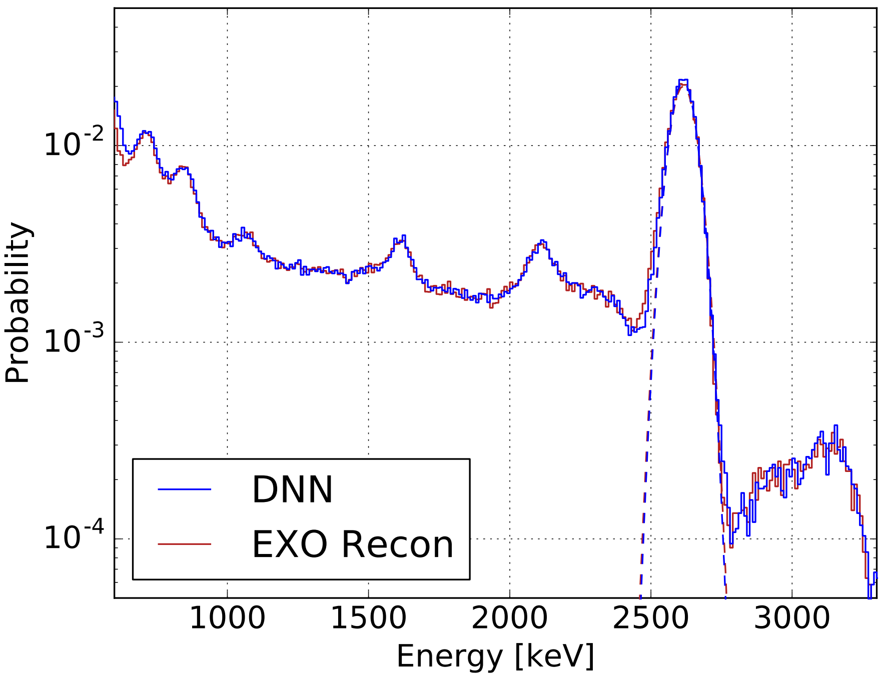


Ra226

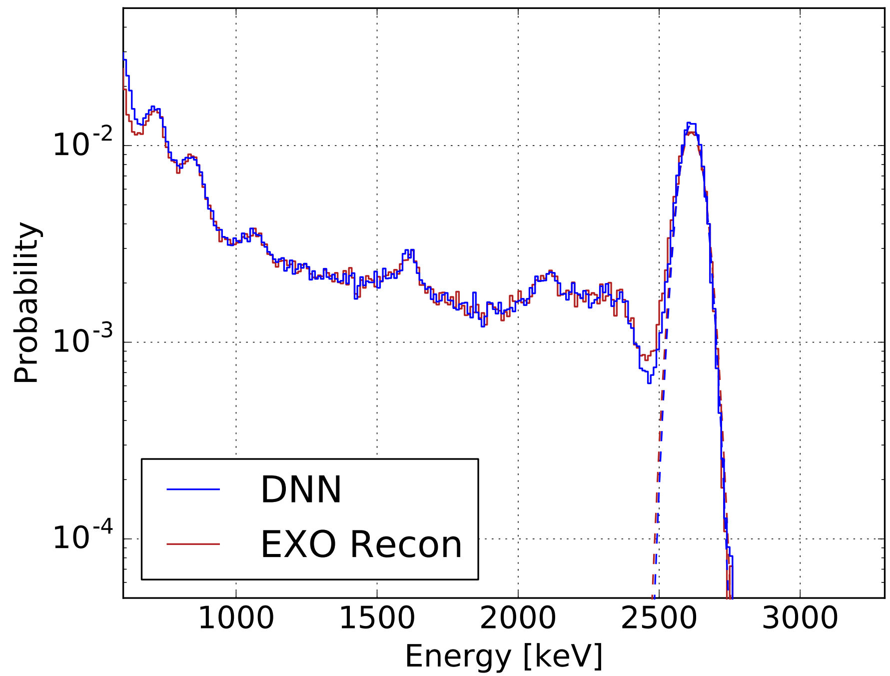


Combination with light channel

SS+MS

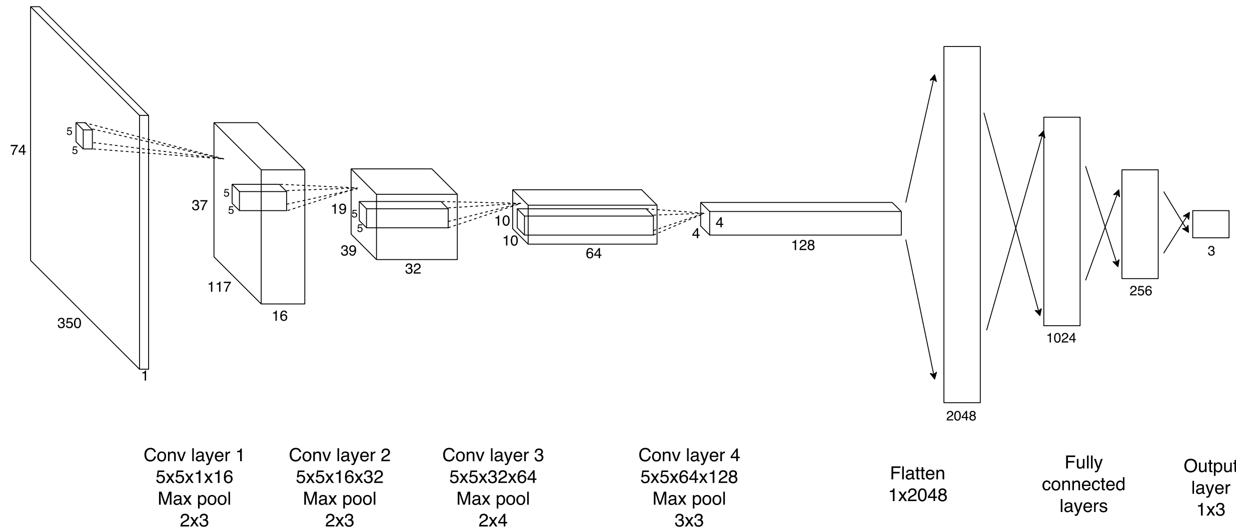


SS-only



Data driven position reconstruction

- Input are all 74 raw APD waveforms cropped to 350µs
- Waveform image is fed to convolution neural network (CNN) consisting of 4 convolutional layers and 3 fully connected layers



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