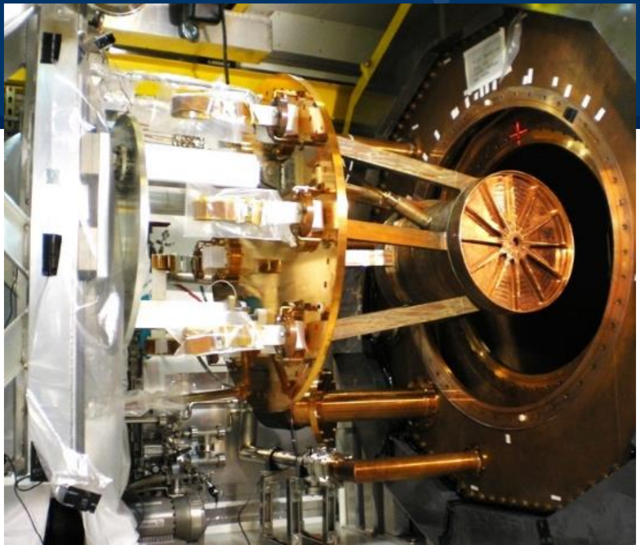
Deep Learning in the EXO-200 experiment

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

Tobias Ziegler
on behalf of the EXO-200 collaboration
DESY, 09/2019



Enriched Xenon Observatory for double beta decay

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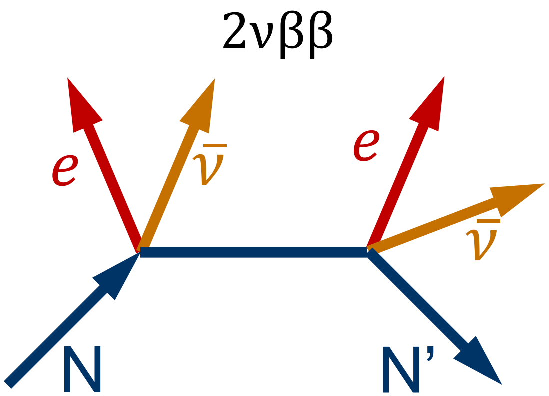
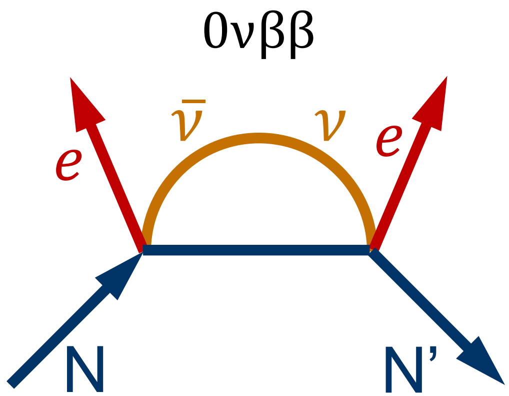
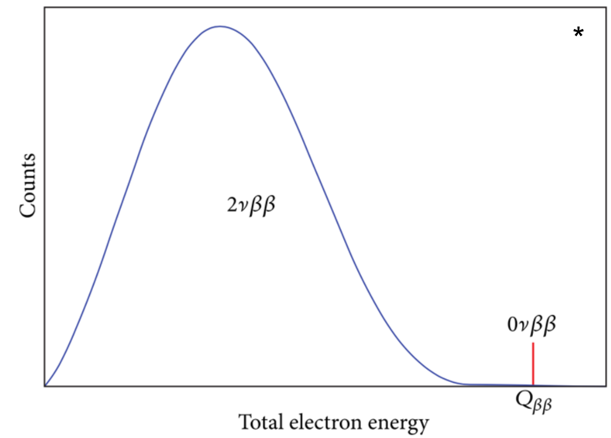
Neutrinoless double beta decay







2νββ decay:

- conventional decay in Standard Model

0νββ decay:

- Rich physics implications
- Majorana neutrino
- Lepton number violation
- Absolute neutrino mass scale

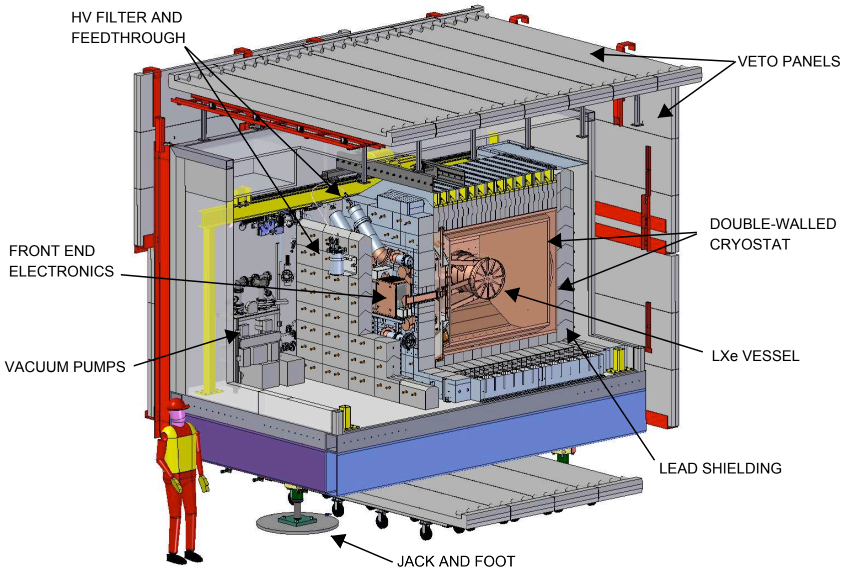
2ν vs 0ν spectrum:

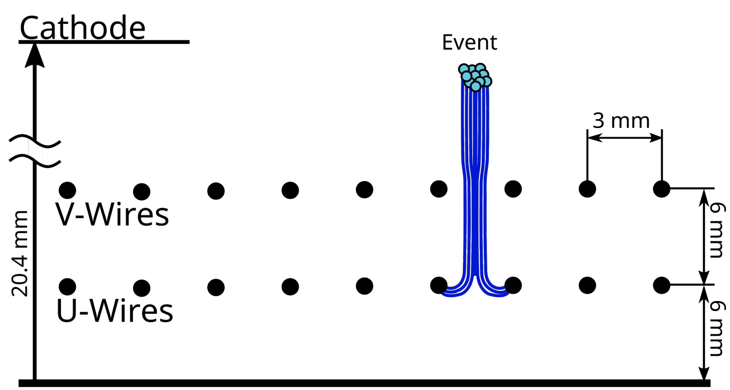
- Continuum vs peak
- Good energy resolution required to separate 0ν from 2ν

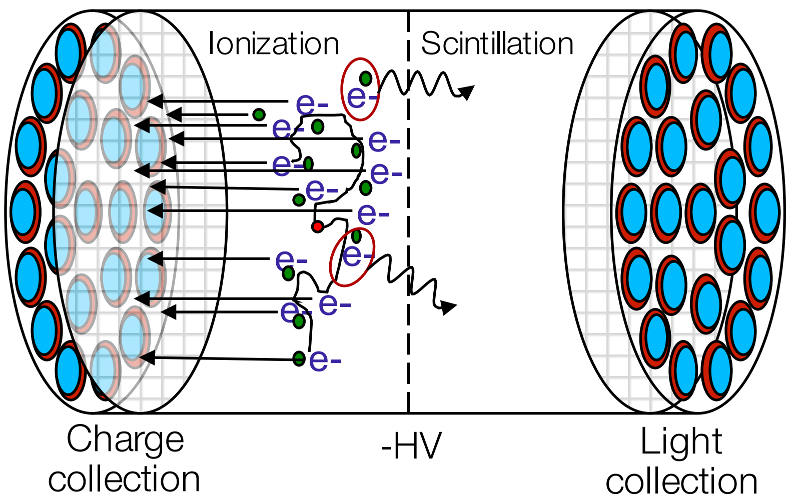
* *Adv. HEP (2016) 2162659*

EXO-200 experiment and event detection

- Located at WIPP in Carlsbad, U.S. (1585 m.w.e. overburden)
- Single phase radiopure time projection chamber (TPC) filled with 200kg LXe enriched to 80.6% in ^{136}Xe (Q = 2.458 MeV)
- Double-sided TPC symmetric around cathode
- Complementary measurements
  - Scintillation light (178 nm) by APDs
  - Ionization charge by 2 crossed wire grids
- Full 3D position reconstruction with charge and light channel

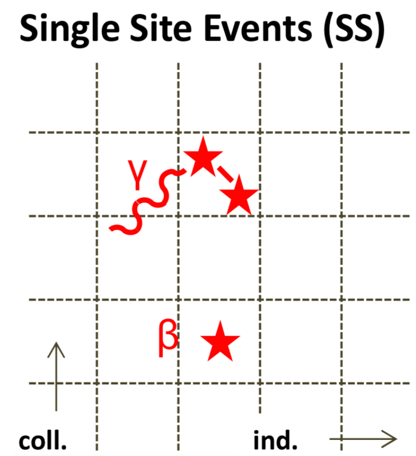




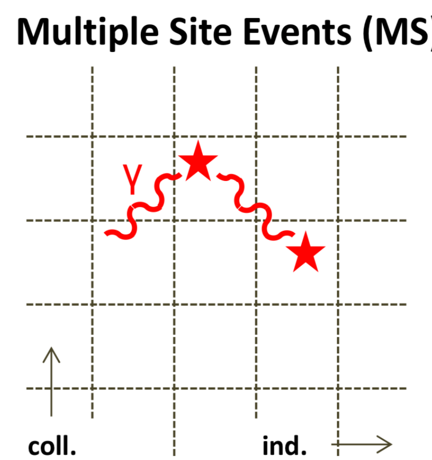


Simple SS/MS classification

- $\beta\beta$ mostly deposits energy at single location (SS)
- Some $\beta\beta$ MS events due to bremsstrahlung
- Example: $0\nu\beta\beta$ 75% SS



- γ backgrounds mostly deposits at multiple locations (MS) due to Compton scattering
- Example: γ ~15% SS (at E_γ=Q)

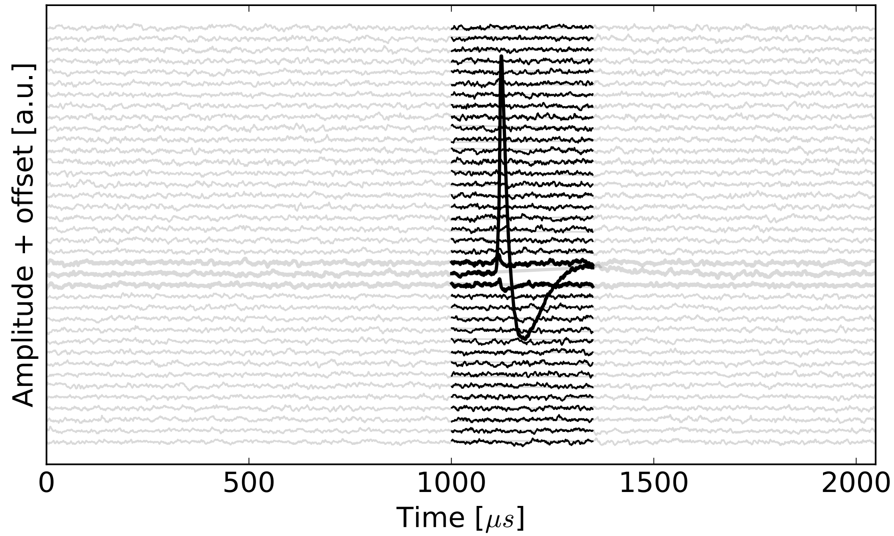


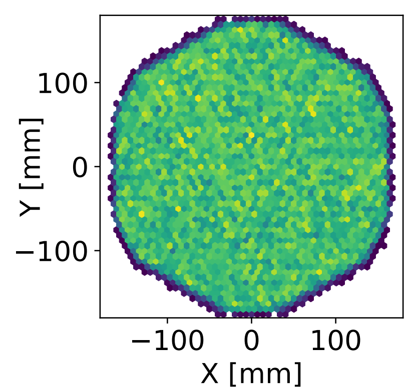
→ SS/MS classification is very powerful for background rejection

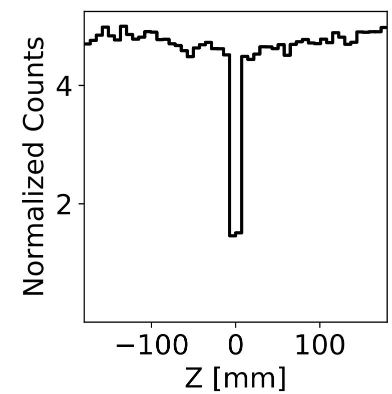
Event energy reconstruction with Deep Neural Networks (DNN)

Charge-only energy reconstruction

- Energy reconstruction from raw data of charge collection (U) wires
- Inputs are greyscale images from arranging the U-wire channels and encoding the amplitudes as pixel values
  - baseline subtraction
  - channel gains correction
  - crop waveforms in time
- Target variable is total energy available in MC that is deposited on any wire
- Uniform training data distribution in energy and in detector volume proved crucial for training
- Implementation in Keras (with TensorFlow backend) on GPU Cluster

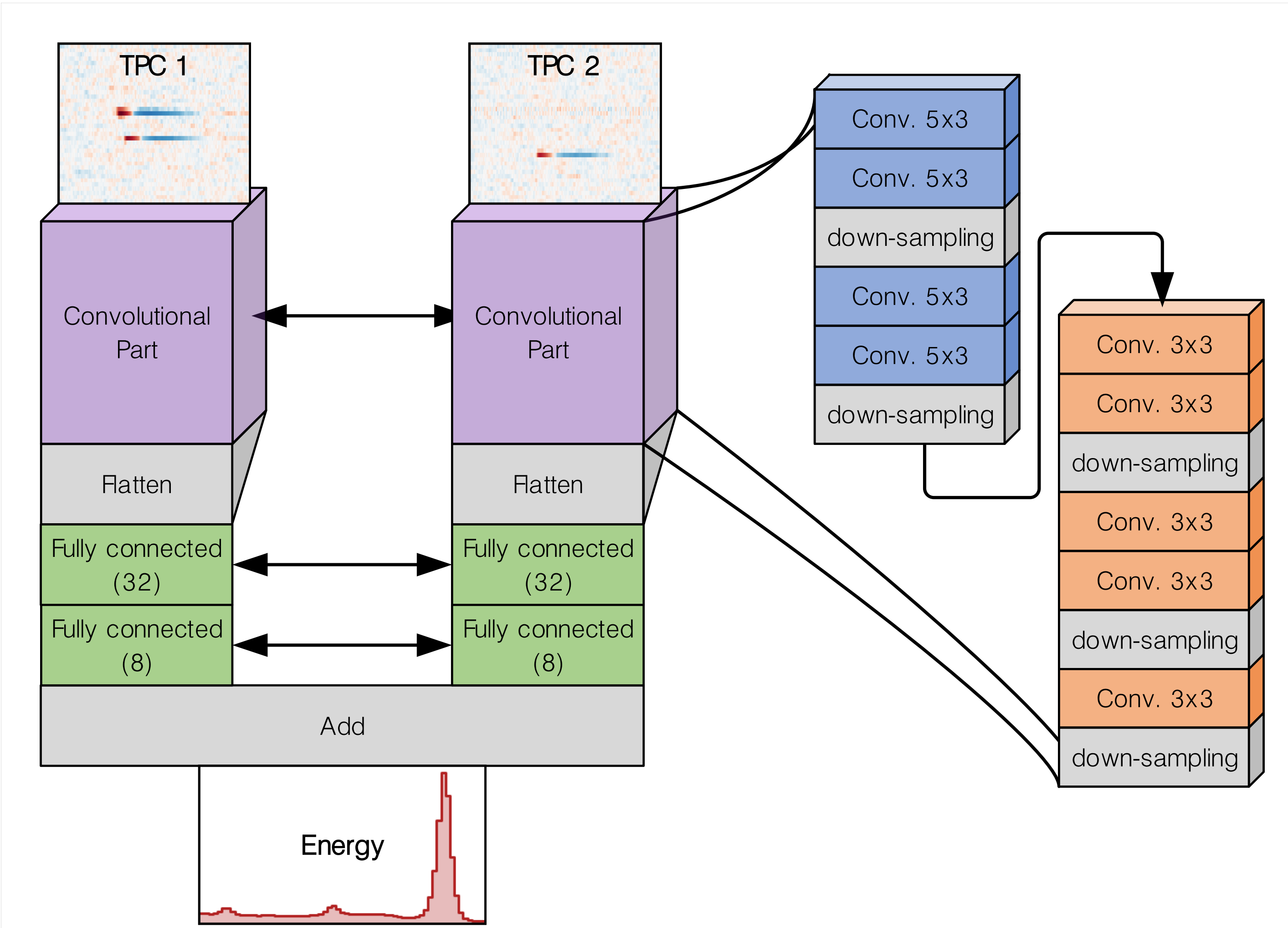






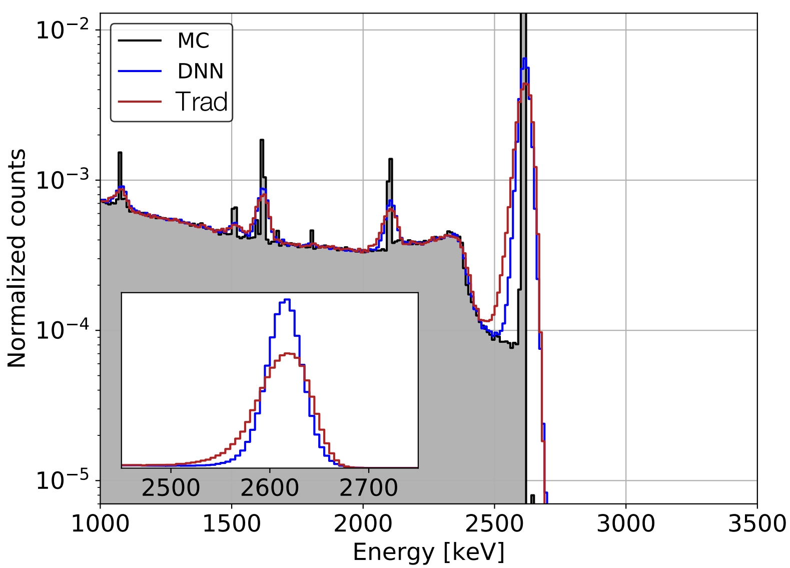
DNN Architecture

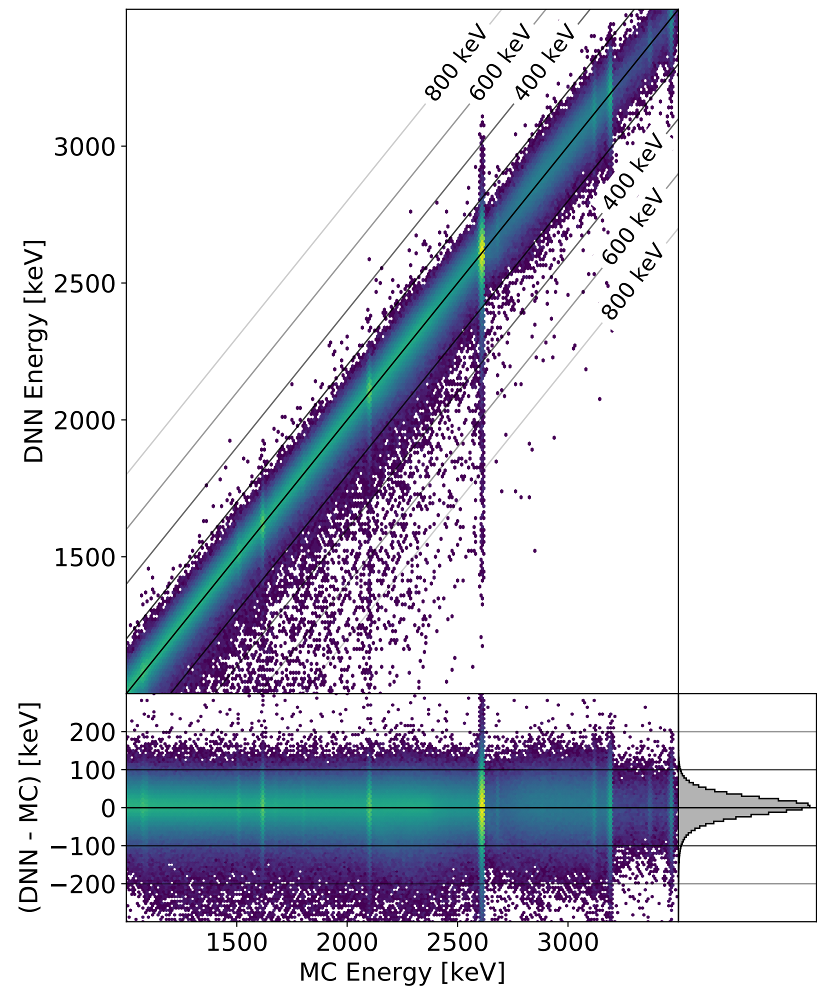
- Network TPC branches share weights



Validation on ^{228}Th MC simulation

- Reconstruction works over the energy range under study
  - Residuals w/o energy dependent features
- Resolution (σ/E) at the ^{208}Tl peak at 2615 keV
  - DNN: 1.21% (SS: 0.73%)
  - Trad.Recon: 1.35% (SS: 0.93%)
- DNN outperforms in disentangling mixed induction and collection signals (see valley right before ^{208}Tl peak)

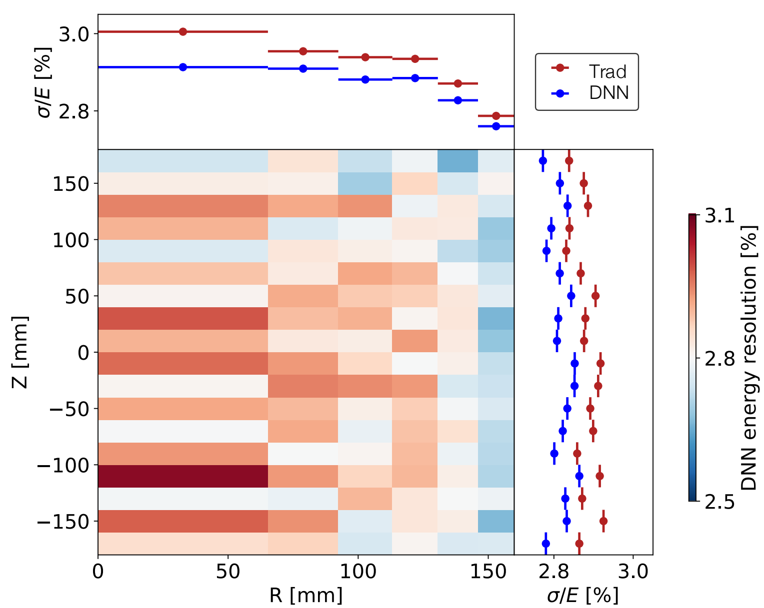


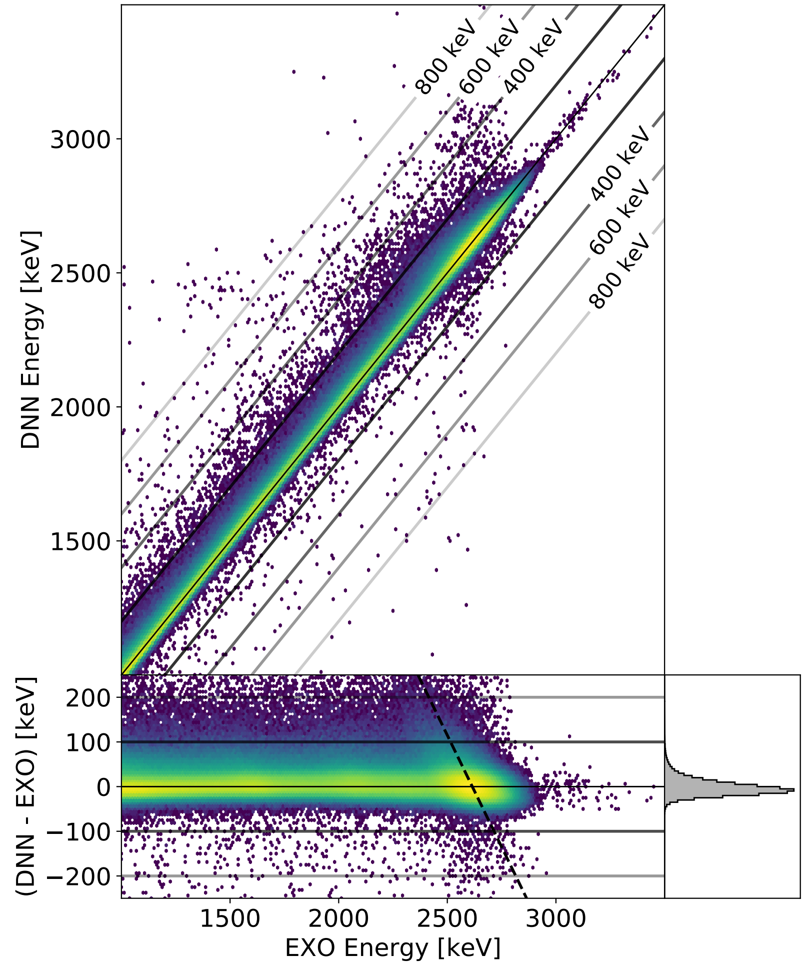


Validation on ^{228}Th calibration data

- Crop window adjusted relative to APD signal to account for different trigger strategies
- Correction applied to account for finite electron lifetime in TPC

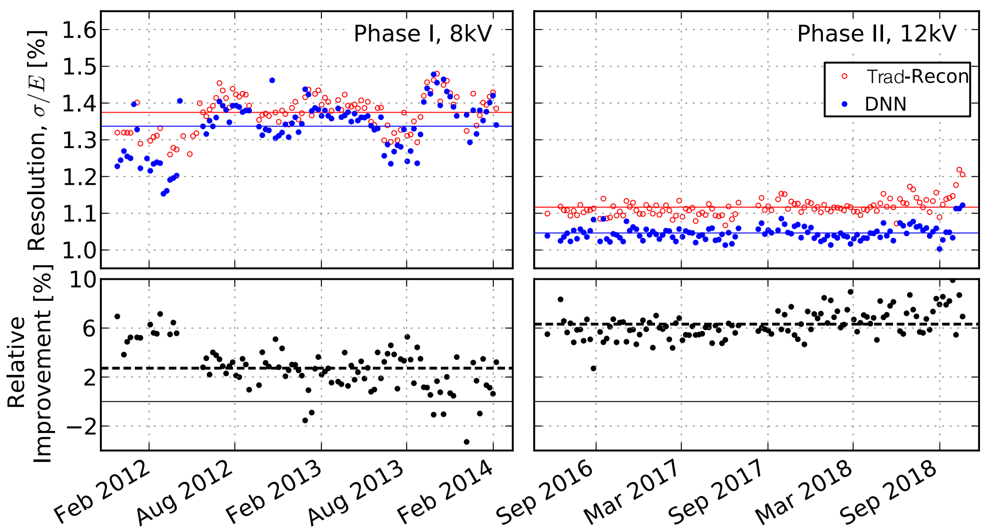
- DNN works on real data
- Residuals w/o energy dependent features
- Resolution variation over detector volume on level observed in traditional reconstruction

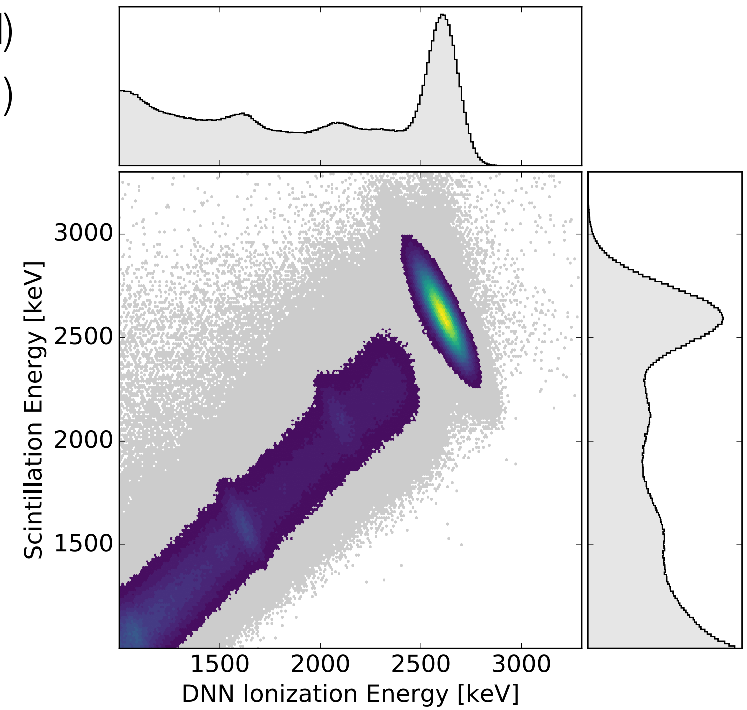




“Rotated“ energy

- Using anti-correlation between ionization (from DNN) and scintillation (from traditional EXO reconstruction)
  - “Rotated” energy provides optimal resolution at the Q value
- MC based fit for weekly calibration
- Reduced APD excess noise in Phase 2
- DNN outperforms traditional reconstruction in almost every week

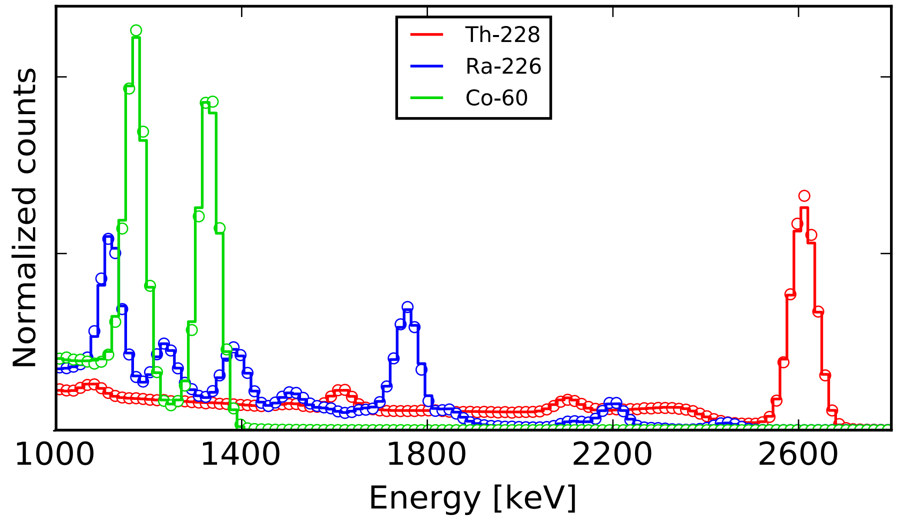


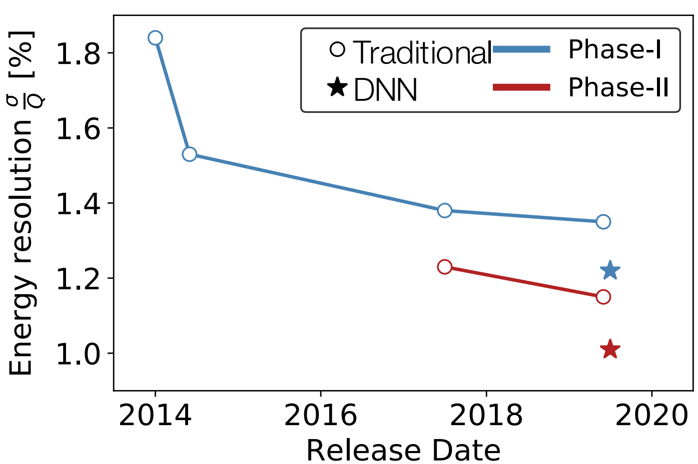


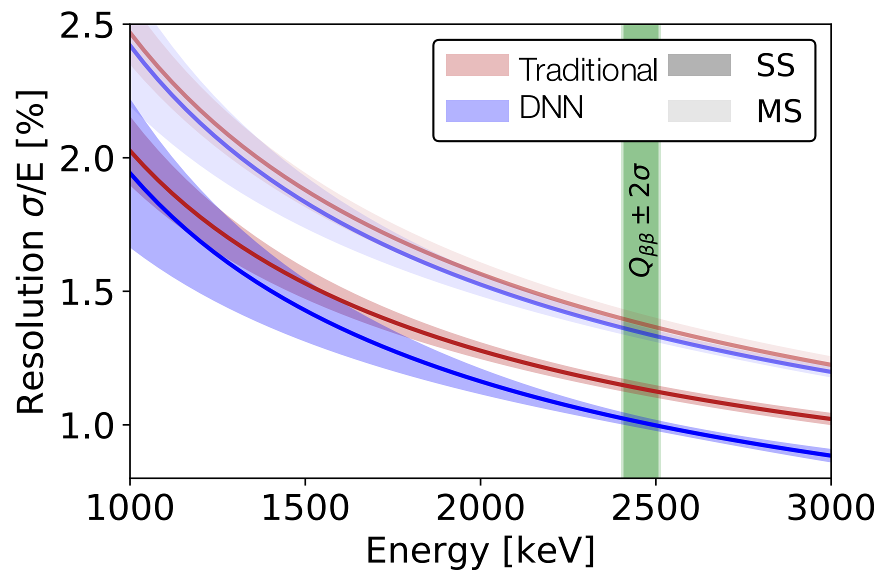
Energy resolution

- Good spectral agreement between source calibration data (points) and MC simulation (lines). On level observed in traditional reconstruction
- Strong improvement in SS energy resolution, esp. at high energies

→ DNN energy measurement shows strong potential toward improving physics goal significantly



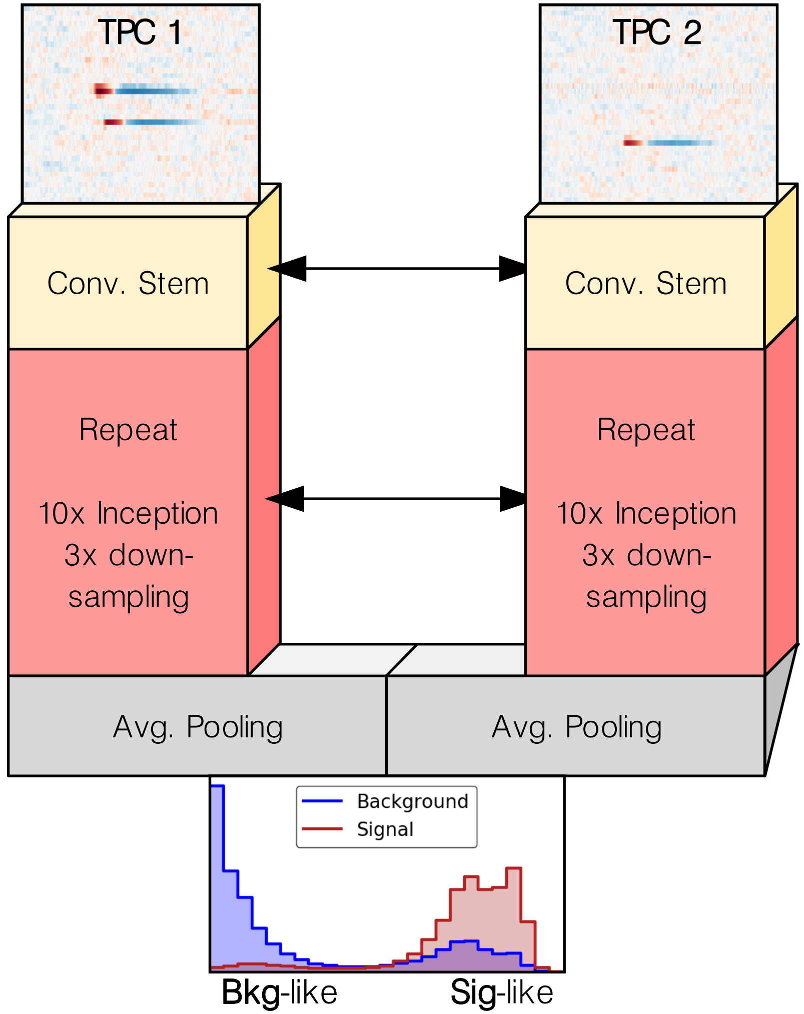




Signal-background discrimination with Deep Neural Networks (DNN)

Design of DNN discriminator

- 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
  - Event 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



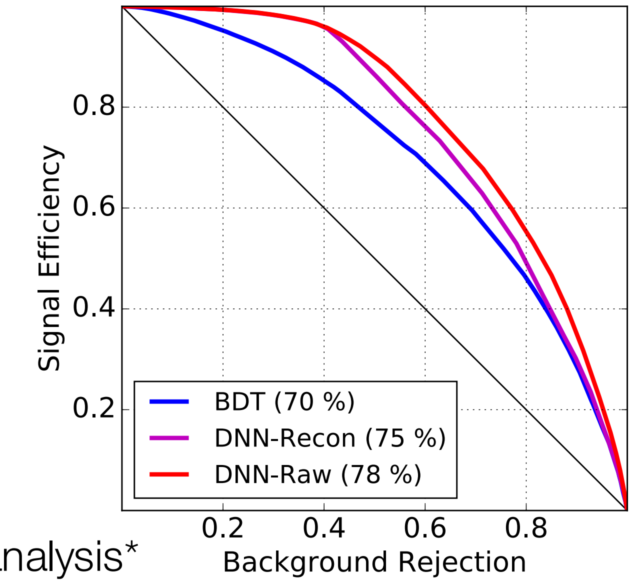
Re-generated images

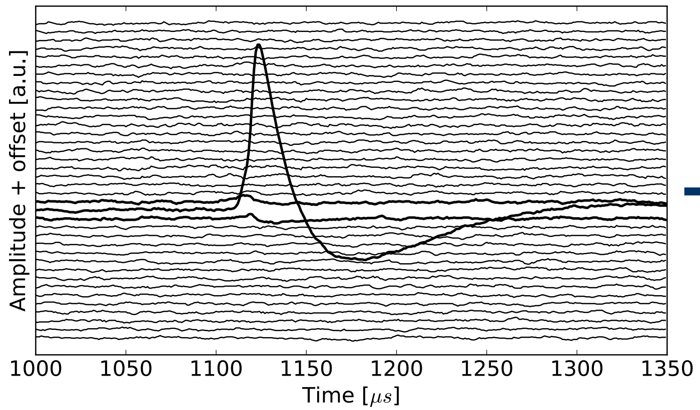
- Replaced raw images with images re-generated from signals found in traditional EXO reconstruction
- DNN then limited to precision of traditional reconstruction
- Natural approach of preserving locality and of handling varying number of signals

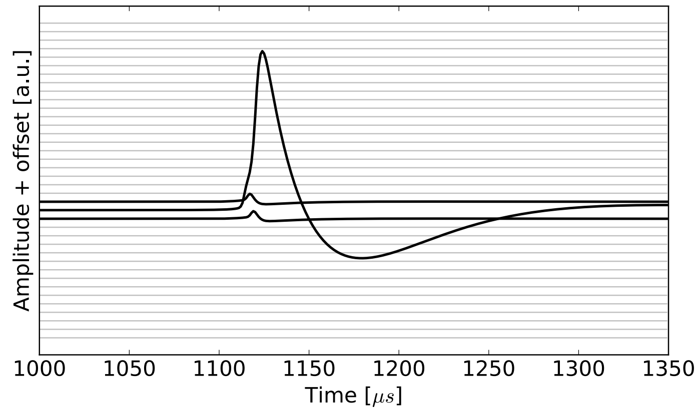
→ DNN prediction is fully based on information available to EXO reconstruction (no strange feature e.g. in noise)

→ Both DNN concepts outperform BDT used in 2018 $0\nu\beta\beta$ analysis*

- Easier to implement at scale because raw data are not needed anymore



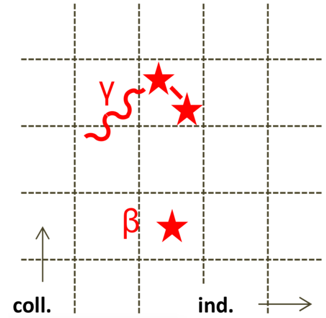




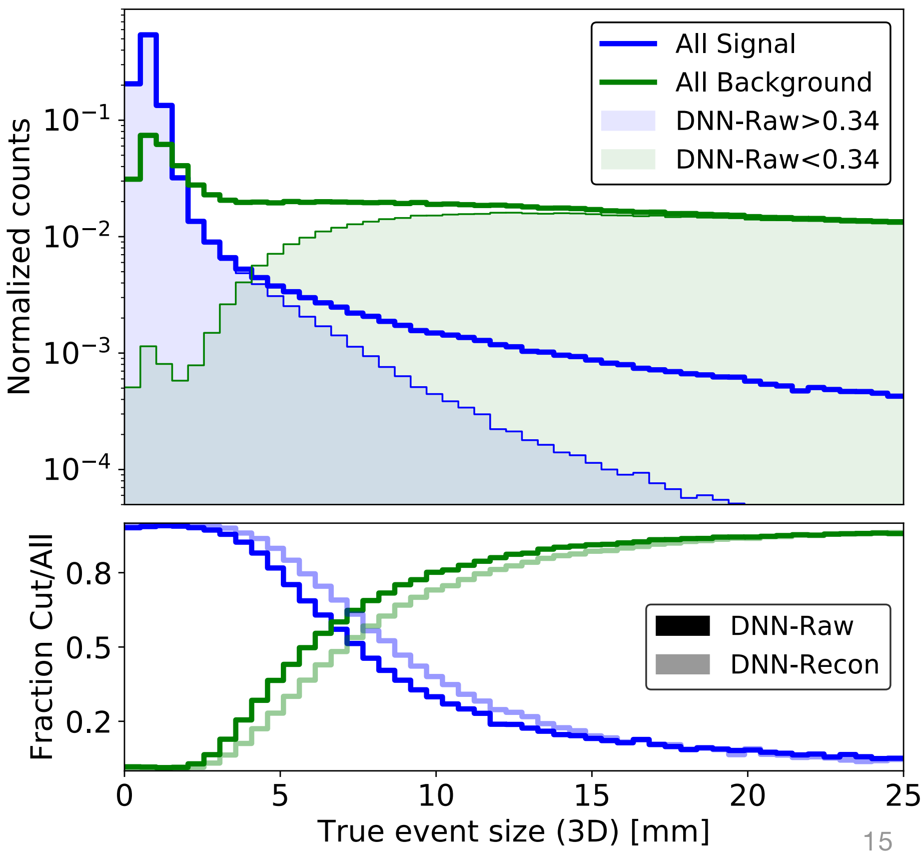
* *Phys. Rev. Lett. 120, 072701 (2018)*

Sanity check – Event size

- Recap:
  - ββ mostly deposits energy at single location
  - γ backgrounds deposits at multiple locations
- ββ event size usually smaller than in γ events

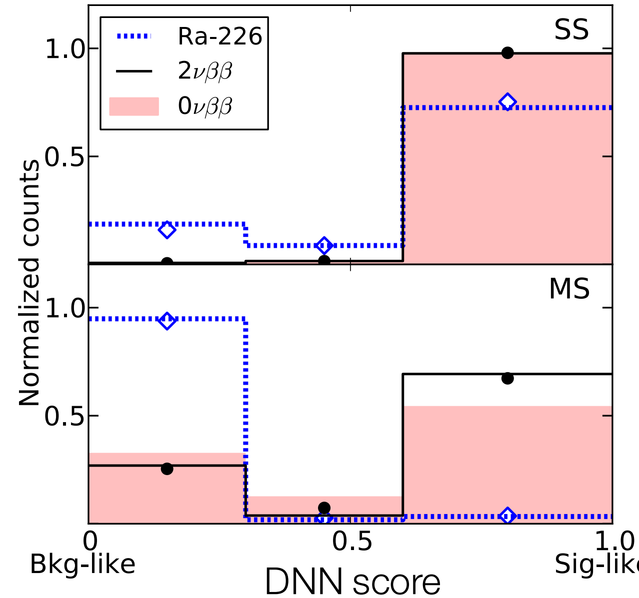


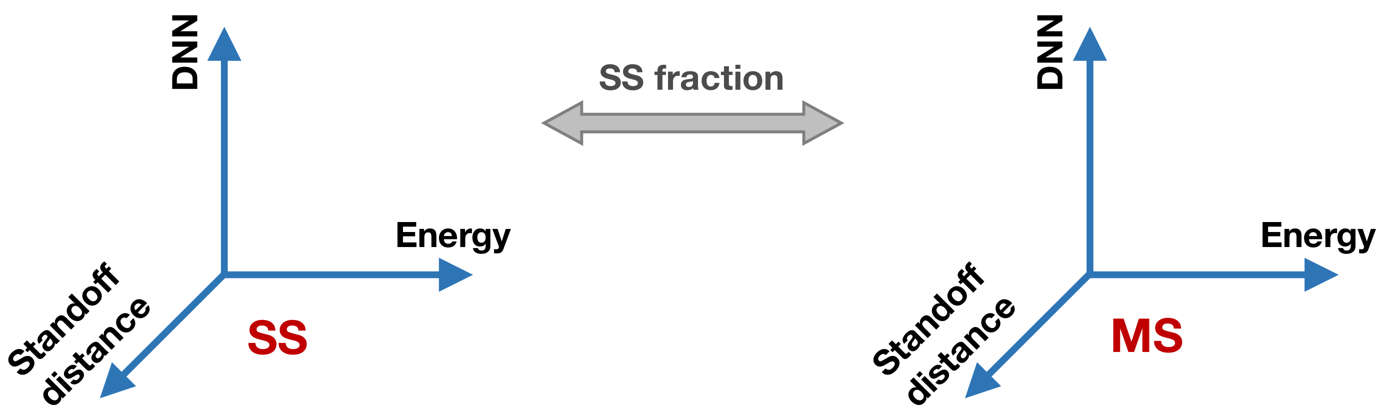
- DNN signal/background identification efficiency correlates with the true event size known in MC simulation
- Indicates the DNNs pick up correct features on the waveform to reconstruct event (find wire signals, cluster signals into energy deposits), thus to discriminate signal/background



2019 $0\nu\beta\beta$ search*

- Reasonable spectral agreement for DNN between data (points) and MC simulation (lines). Validated with γ: ^{226}Ra, ^{228}Th, ^{60}Co $\beta\beta$: $2\nu\beta\beta$
- Blinded $0\nu\beta\beta$ analysis performed
- 3-dimension ML fit in both SS and MS events: Energy + DNN (topology) + Standoff distance (spatial)
  - Make the most use of multi-parameter analysis
  - SS/MS spectra constrained by SS fraction
- Improvement of ~25% in $0\nu\beta\beta$ half-life sensitivity compared to using energy spectra + SS/MS alone



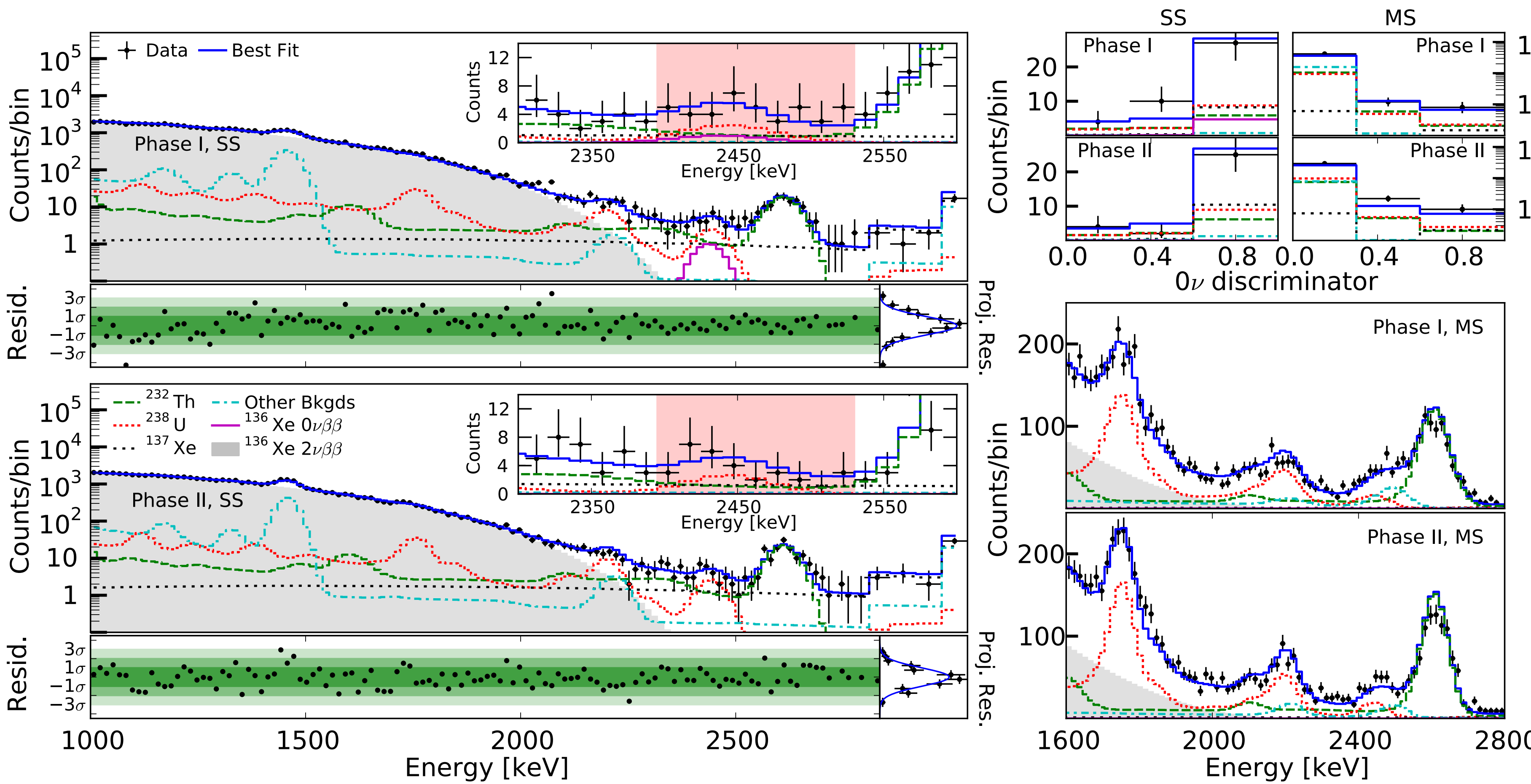


* *arXiv 1906.02723*
submitted to Phys. Rev. Lett.

Best fit

- Energy spectra: SS (left) and MS (bottom right)
- DNN spectra: SS/MS applied to all events. Projection of ROI events (top right)

→ No statistical significant signal observed

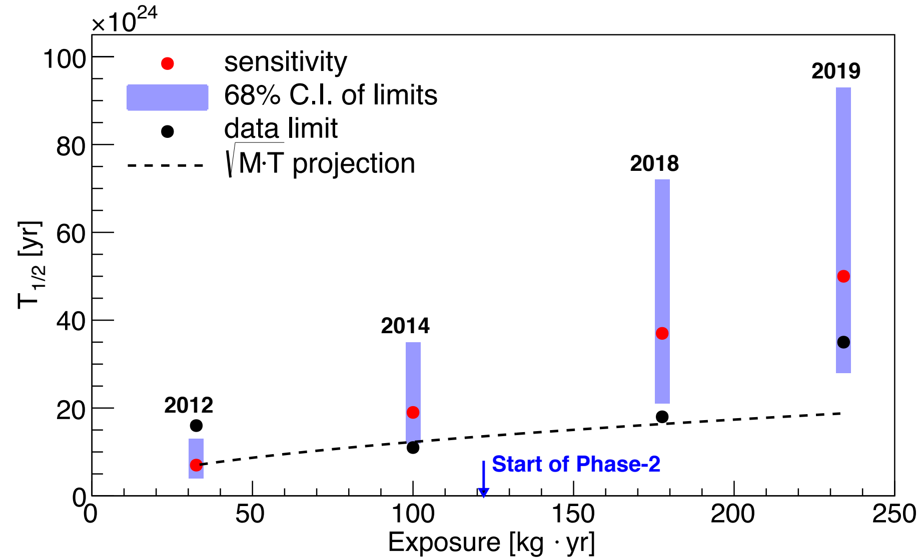


Results

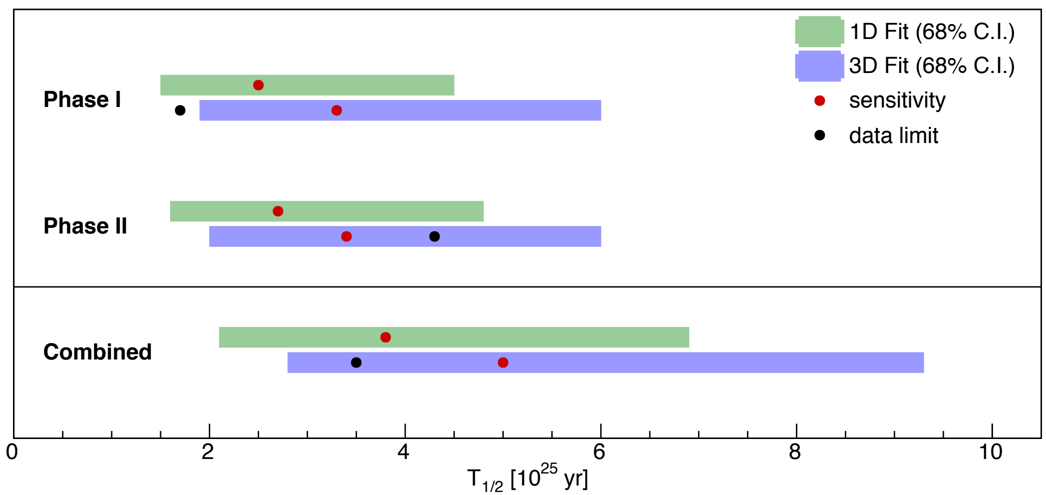
- No statistical significant signal observed

Limit $T^{0\nu\beta\beta}_{1/2} > 3.5 \cdot 10^{25}$yr (90% C.L.)
Sensitivity $5.0 \cdot 10^{25}$yr (90% C.L.)

- Improvement of ~25% in $0\nu\beta\beta$ half-life sensitivity compared to using energy spectra + SS/MS alone



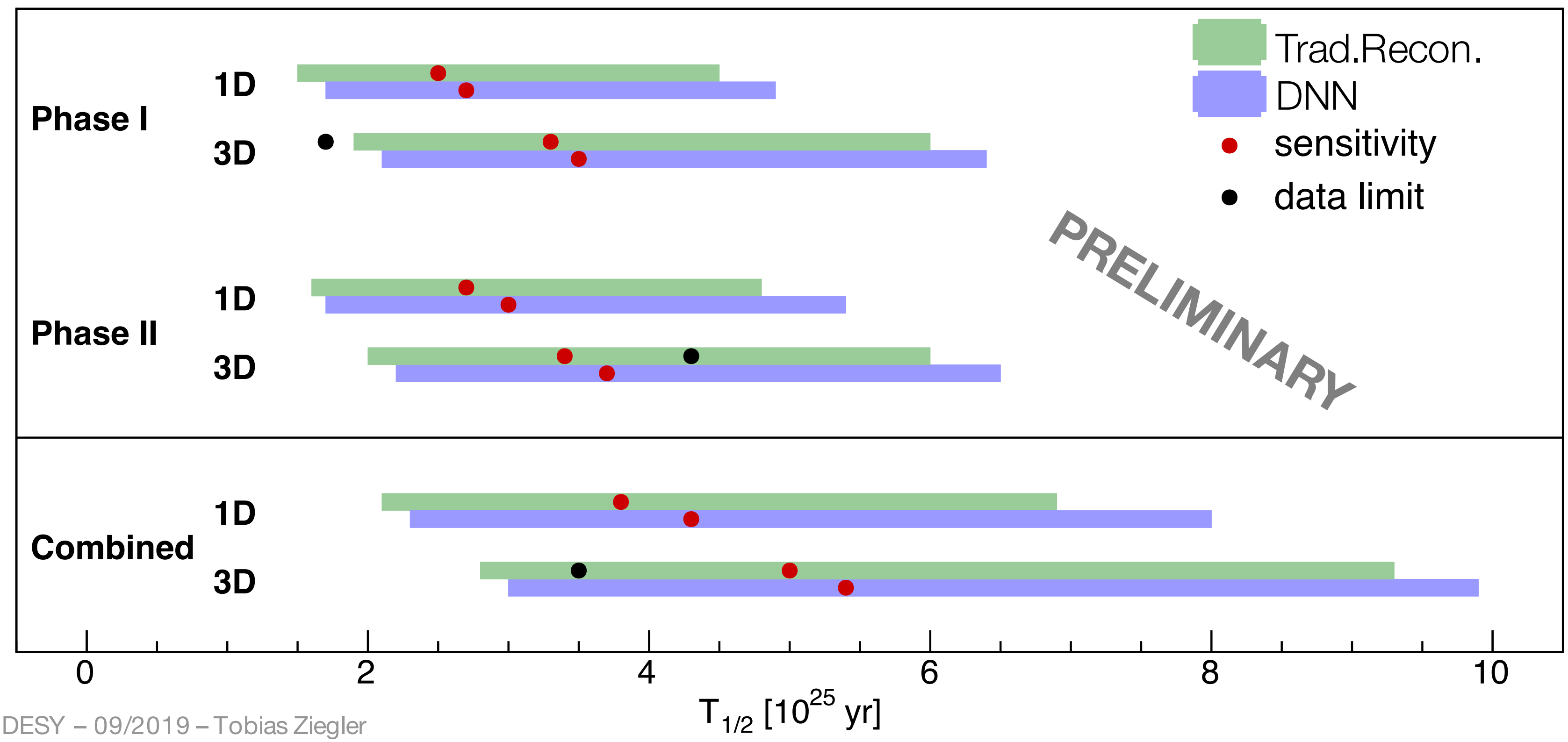
2012: Phys.Rev.Lett. 109 (2012) 032505
2014: Nature 510 (2014) 229-234
2018: Phys. Rev. Lett. 120, 072701 (2018)
2019: arXiv 1906.02723



1D Fit: Energy
3D Fit: Energy + DNN + Standoff

Combining both DNNs

- $0\nu\beta\beta$ half-life sensitivity with DNN energy measurement
  - Re-evaluated all significant contributions to systematic uncertainties
- Improvement over traditional energy spectra + SS/MS alone
  - ~10% in 1D fit configuration (DNN energy)
  - ~40% in 3D fit configuration (DNN energy, DNN discriminator, Standoff)



Summary

- EXO-200 has demonstrated the use of DL for data analysis directly from raw data

- Improved energy resolution with DNN over traditional analysis in both MC and real data*
- Good spectral agreement of data/MC and good detector uniformity on complete dataset

- DNN signal/background discriminators outperform BDT based approach
  - DNN pick up correct features (e.g. size)
  - Reasonable spectral agreement of data/MC on complete dataset
- One of the most sensitive searches for $0\nu\beta\beta$ with the full EXO-200 dataset giving a sensitivity of $5.0 \cdot 10^{25}$yr at 90% C.L. for ^{136}Xe $0\nu\beta\beta$ and first search directly using a DNN discriminator**

- Future experiments (like nEXO) will benefit from DNN methods in simplifying the processing of data and extraction of high level features***

** JINST 13.08 (2018)*
*** arXiv 1906.02723*
**** arXiv 1907.07512*

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Deep Learning in the EXO-200 experiment

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Enriched Xenon Observatory for double beta decay

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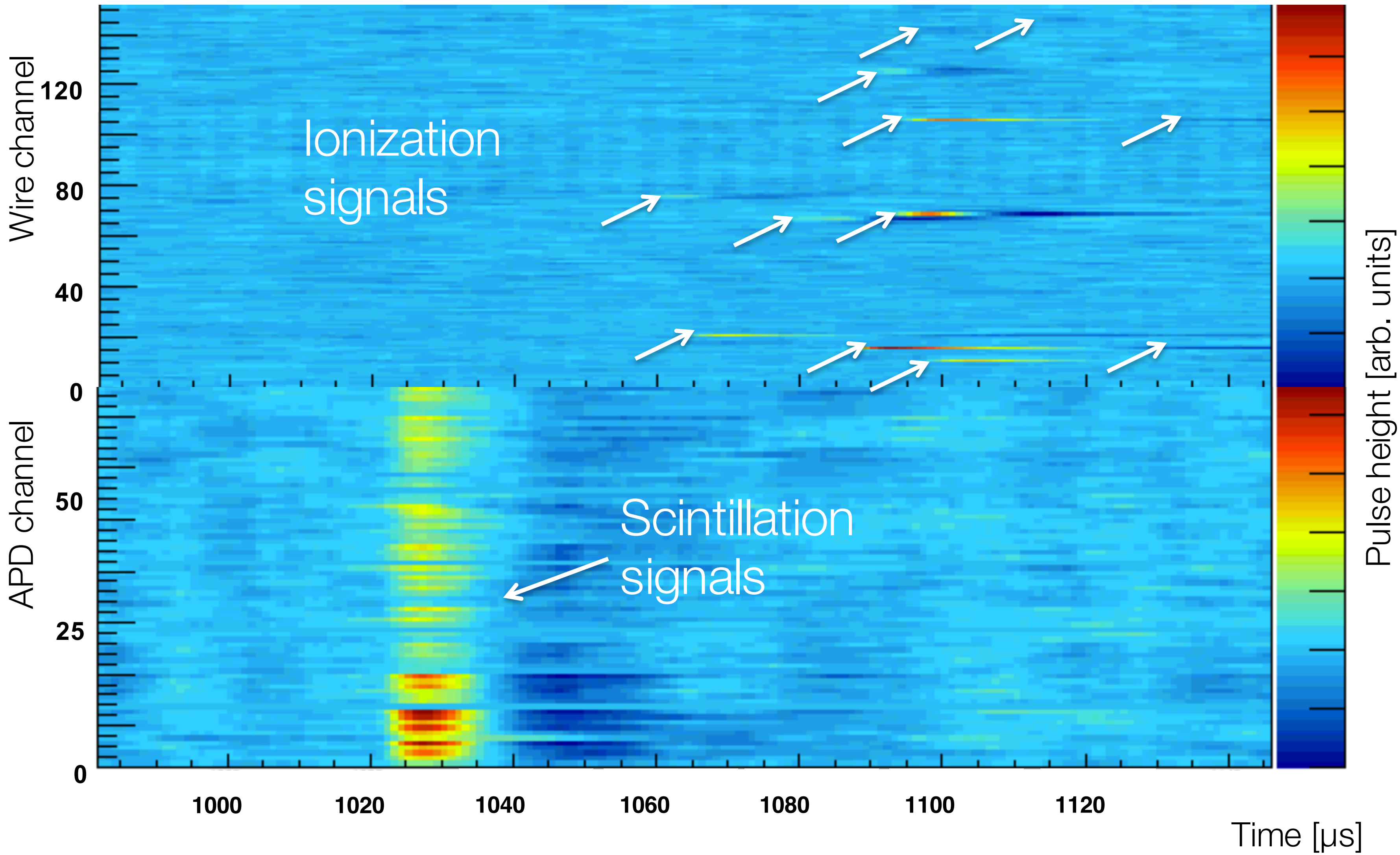
Bonus Slides

Event display

Example multiple-scatter γ event in EXO-200:



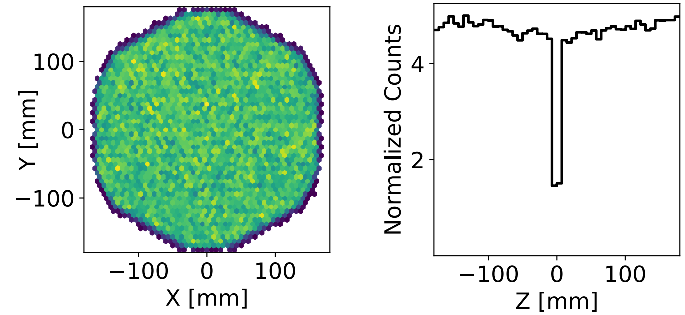
Differences to published DNN

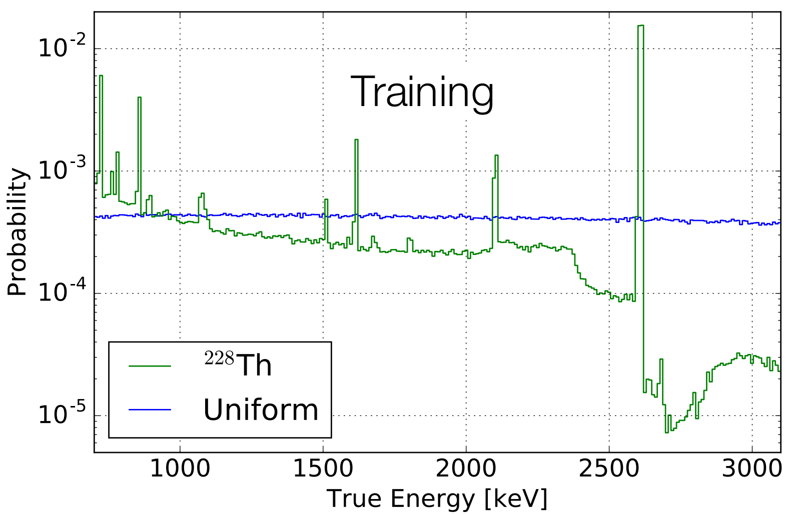
	Published JINST 13.08 (2018)	current
Input size	1024 x 76	2 x (350 x 38)
Particle ID	γ	50% γ, 50% ββ
Particle gun	Center of TPC	Uniform in TPC
Energy [keV]	500—3500	1000—3000
Electron lifetime	3500 μs	infinity

Learning rate	fixed	step-wise reduction
Architecture	6x Conv layers	9x Conv layers

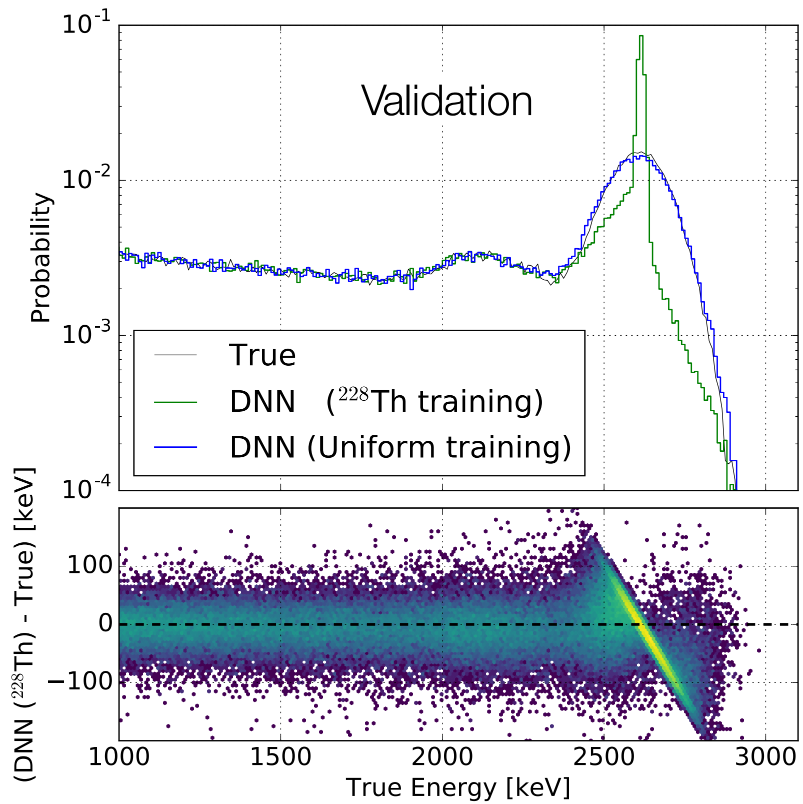
Training distribution pitfall

- Uniform energy spectrum proved crucial for training
- Otherwise overtraining on sharp peaks in training (e.g. with ^{228}Th source, green)
  - DNN shuffles independent validation events towards sharp peaks from training spectrum



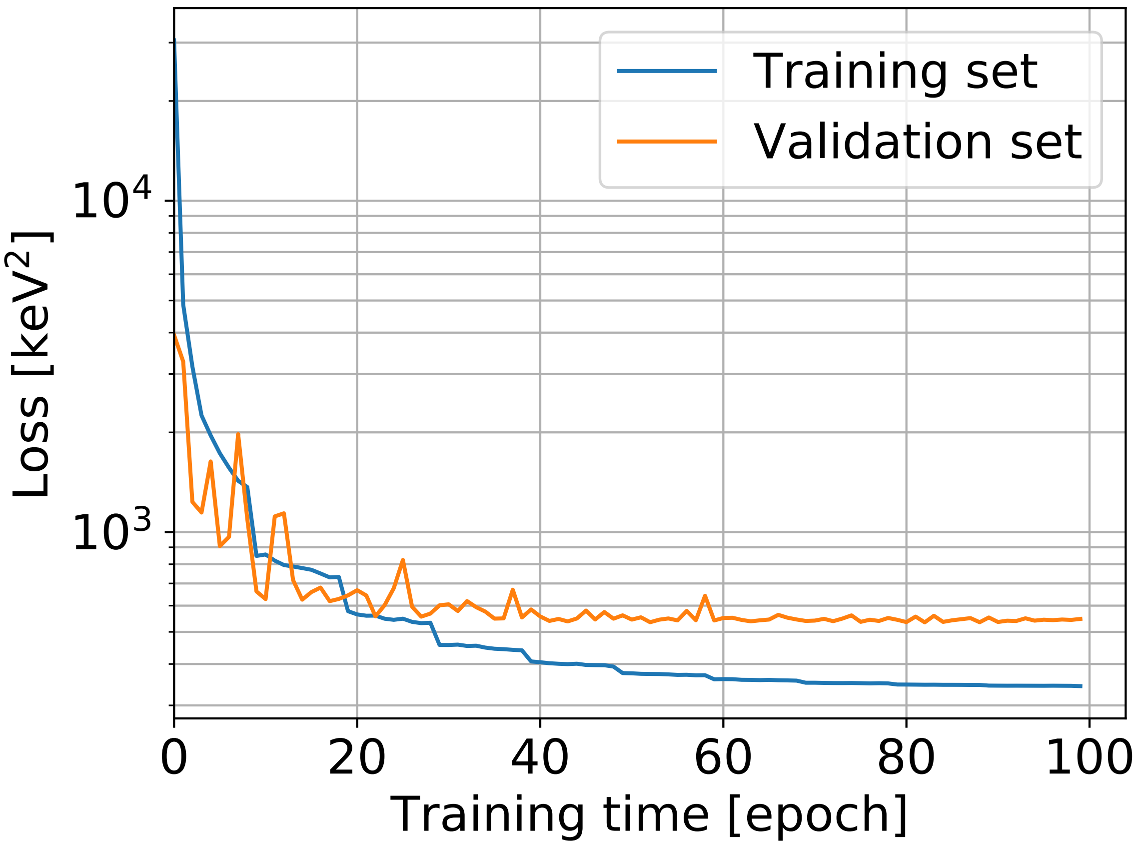


→ use uniform training distribution in energy and in detector volume



Training

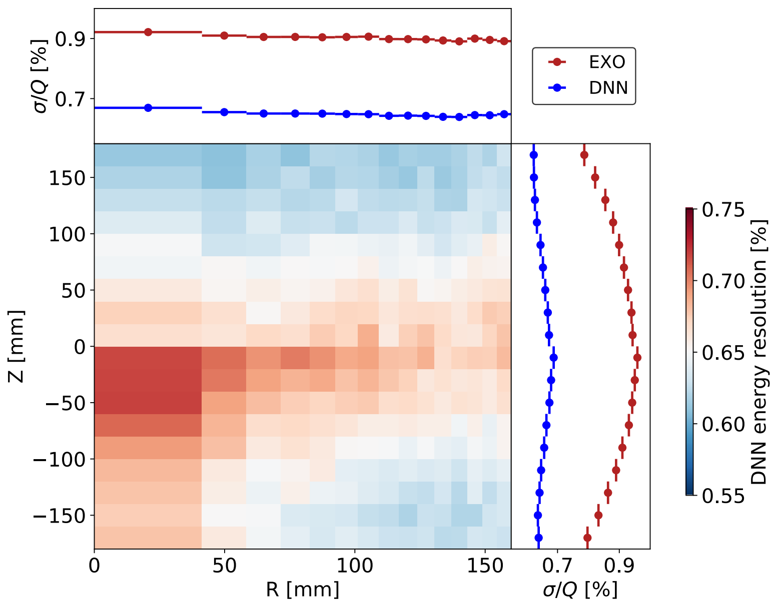
- a

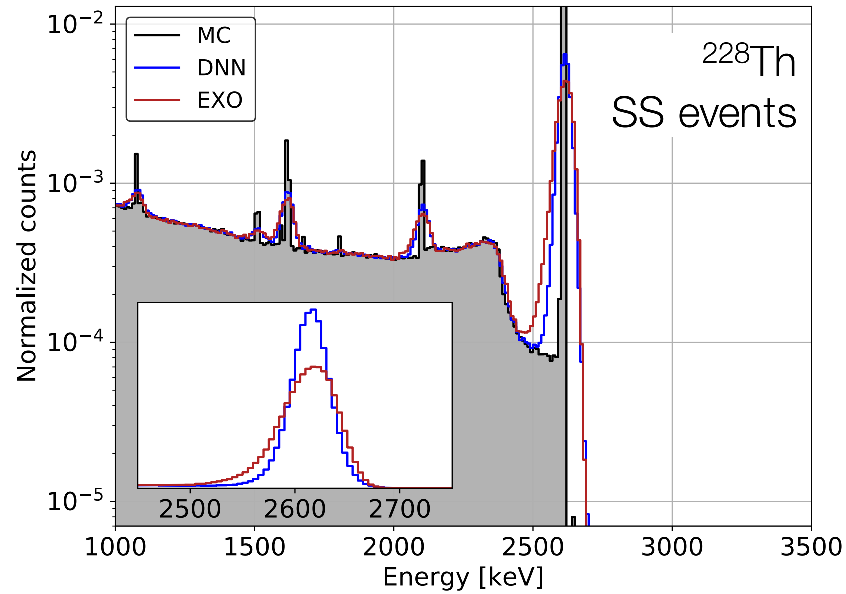


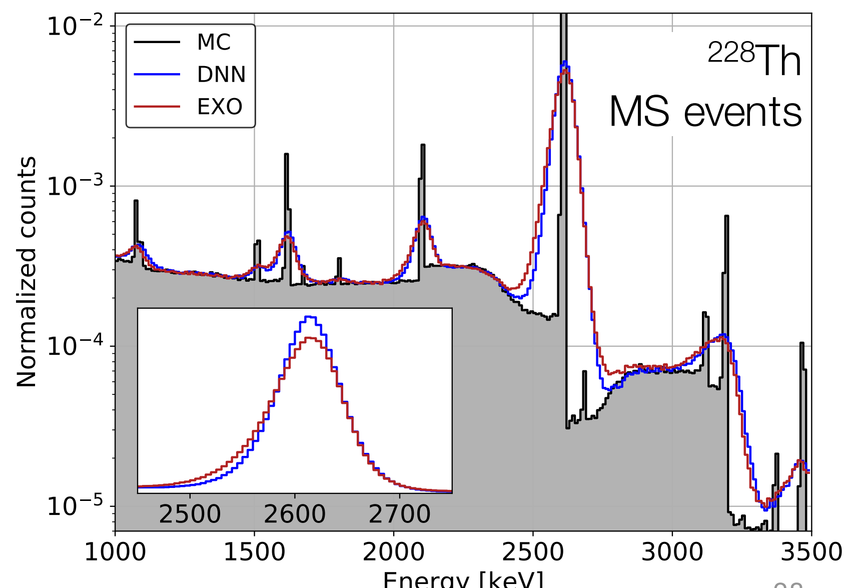
Training set
Validation set
10^4
10^3
Loss [keV^2]
0
20
40
60
80
100
Training time [epoch]

MC simulation

Bb0n MC simulation

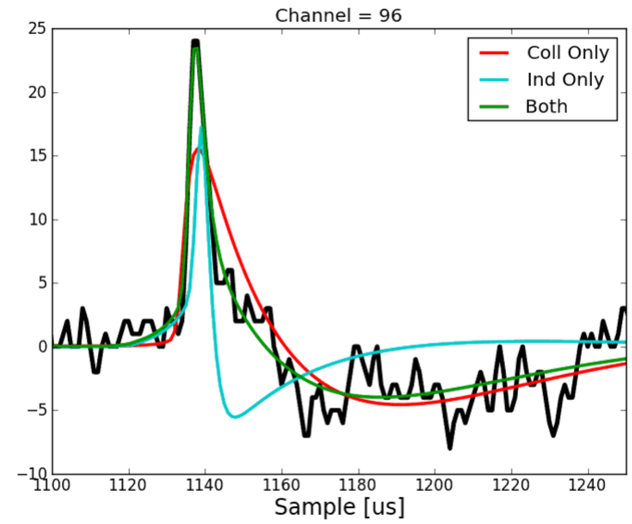






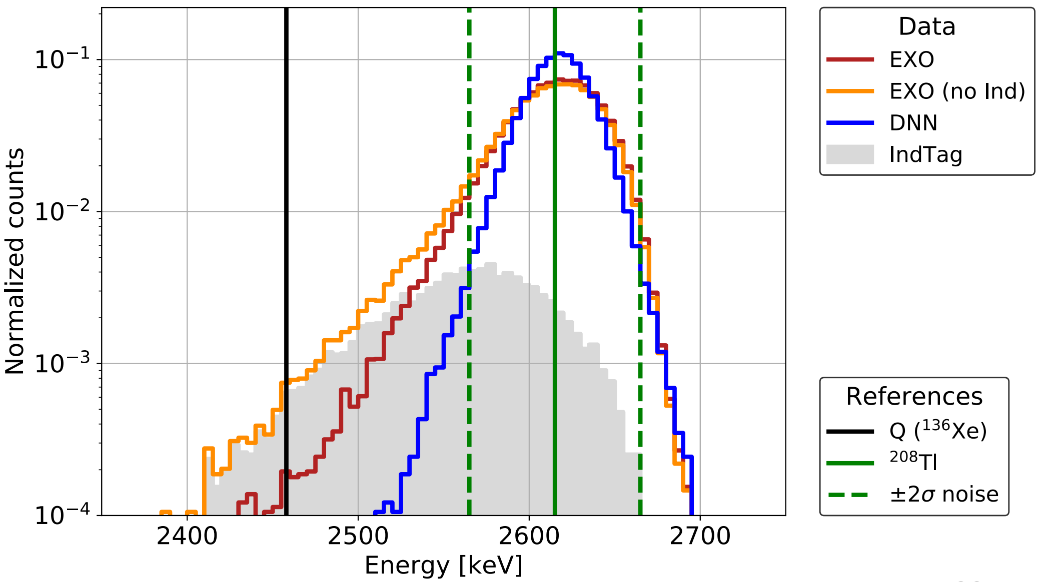
Performance on mixed signals

- Since JINST 13.08 analysis, known issues with mixed induction and collection signals in EXO reconstruction
  - DNN study triggered improvements to traditional EXO reconstruction pipeline (combined fit of both templates) that mitigates this issue
- DNN still outperforms in disentangling mixed induction and collection signals



→ DNN energy measurement more symmetric

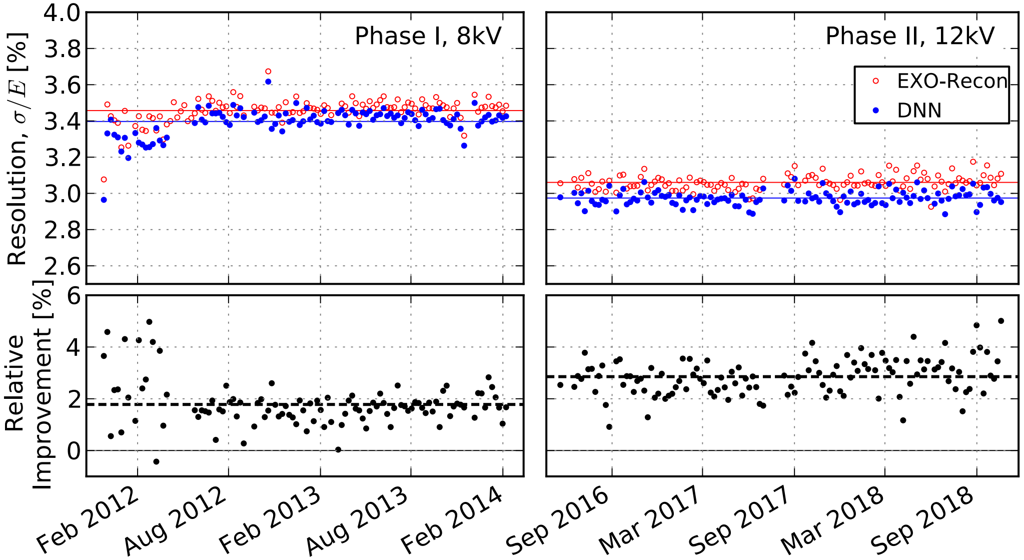
→ Less events leak into ROI of $0\nu\beta\beta$ from ^{232}Th background



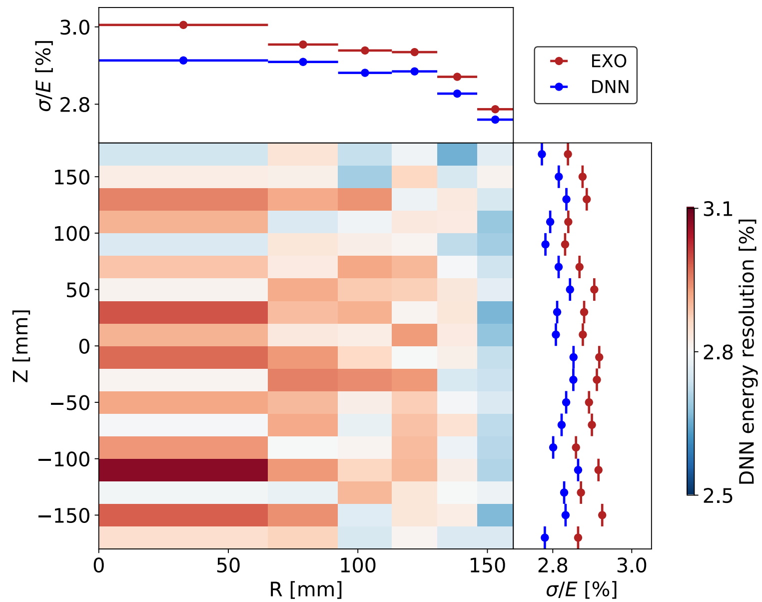
Th-228 calibration data

- a

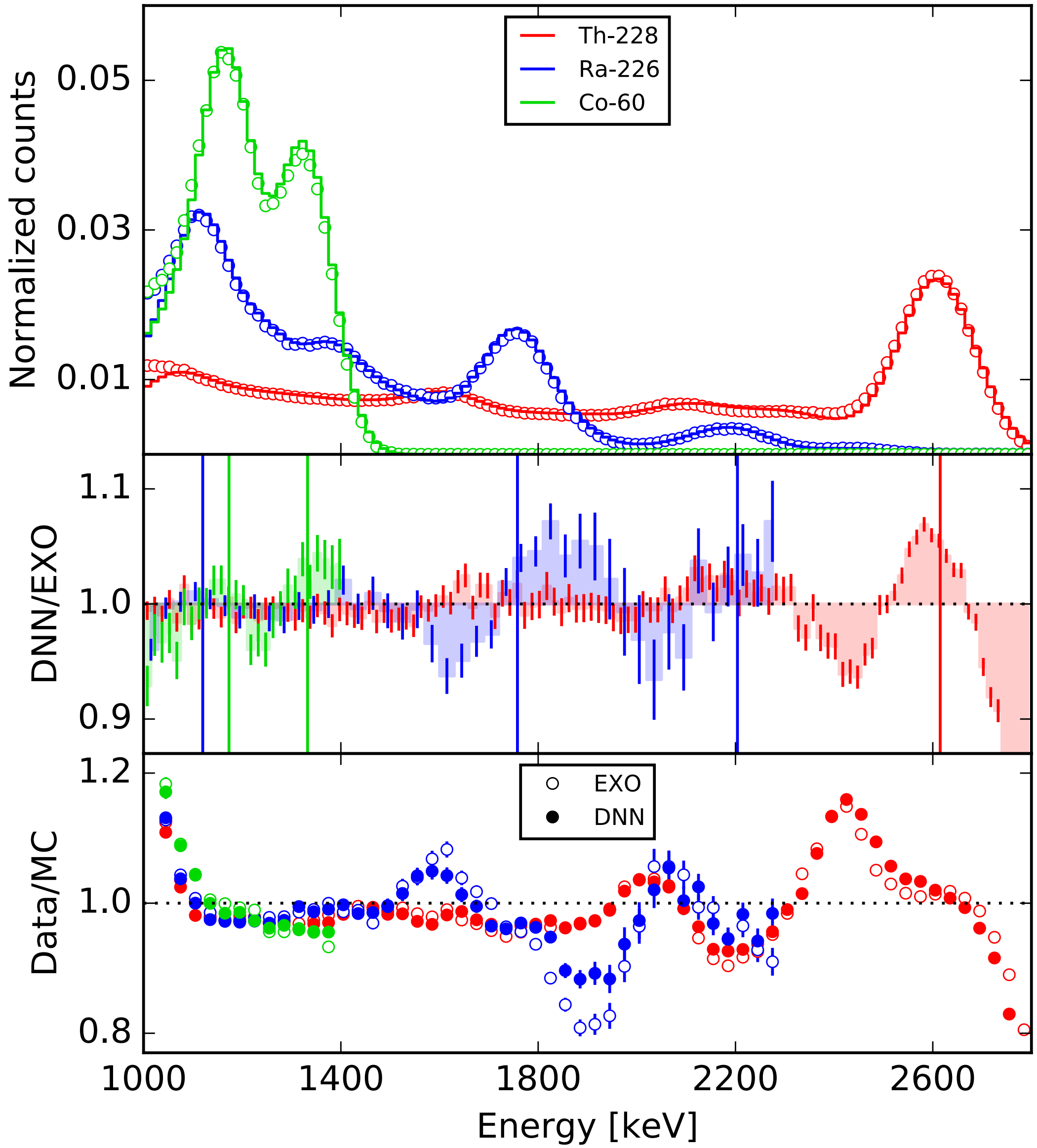
Weekly resolution at ^{208}Tl peak



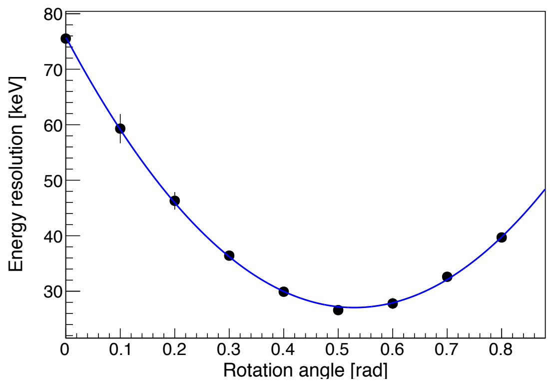
Detector uniformity

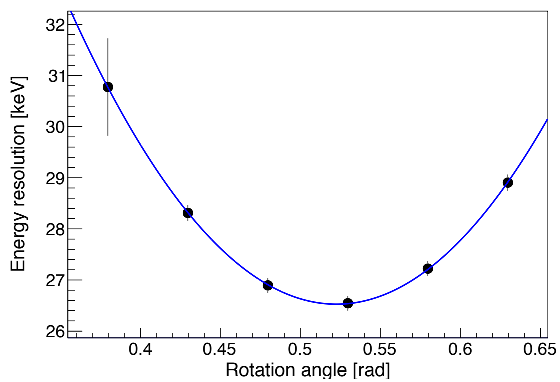


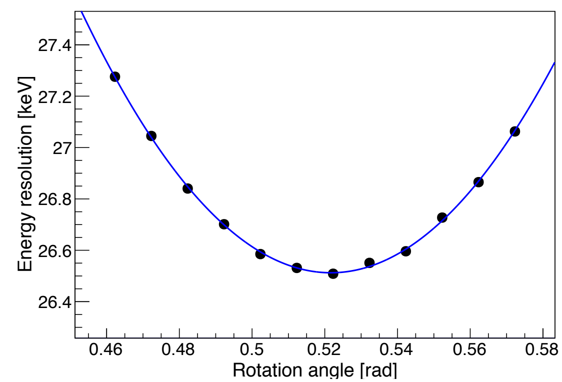
Source calibration data

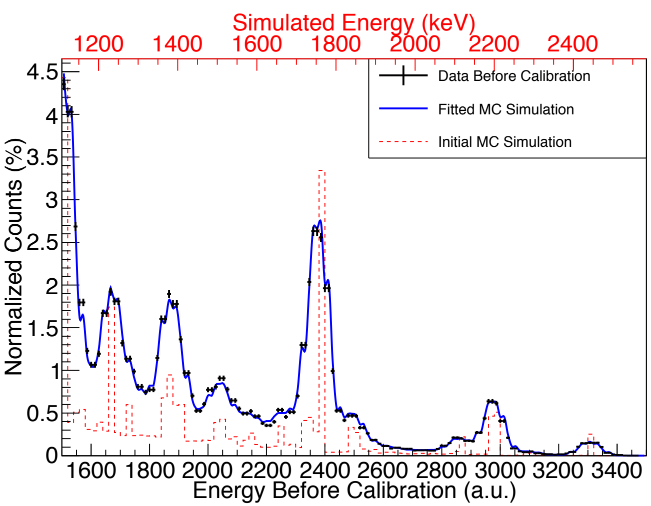


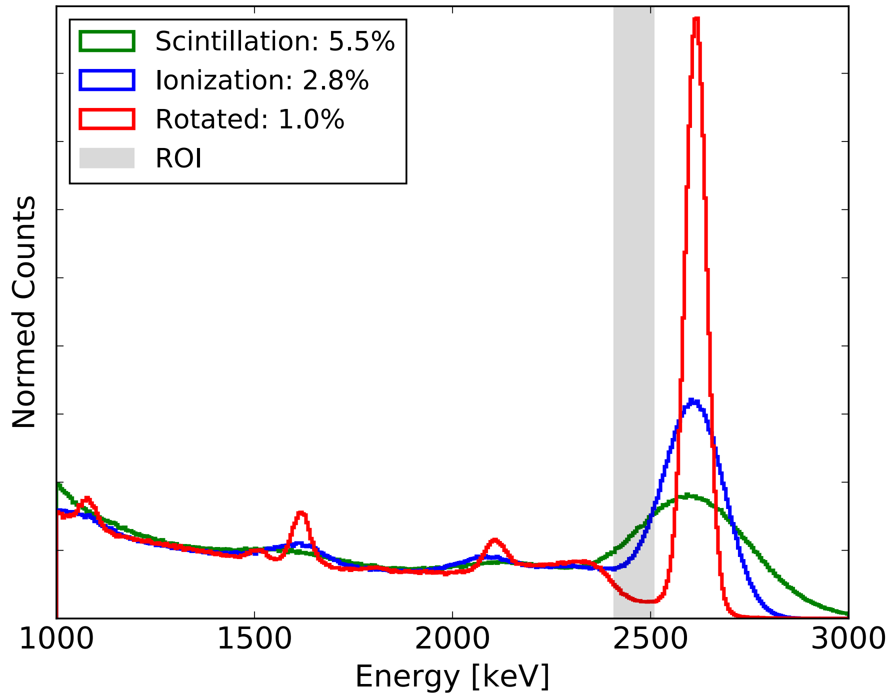
“Rotated“ energy



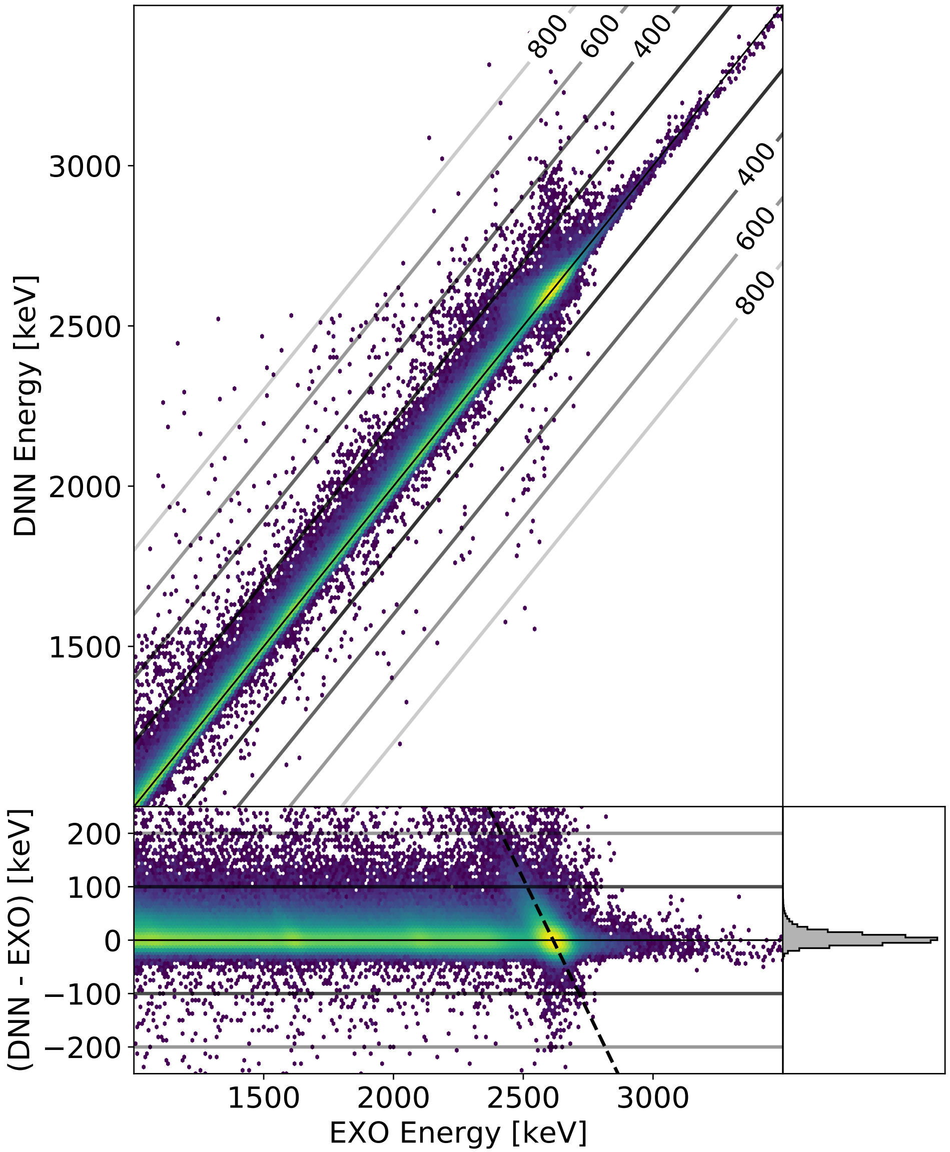




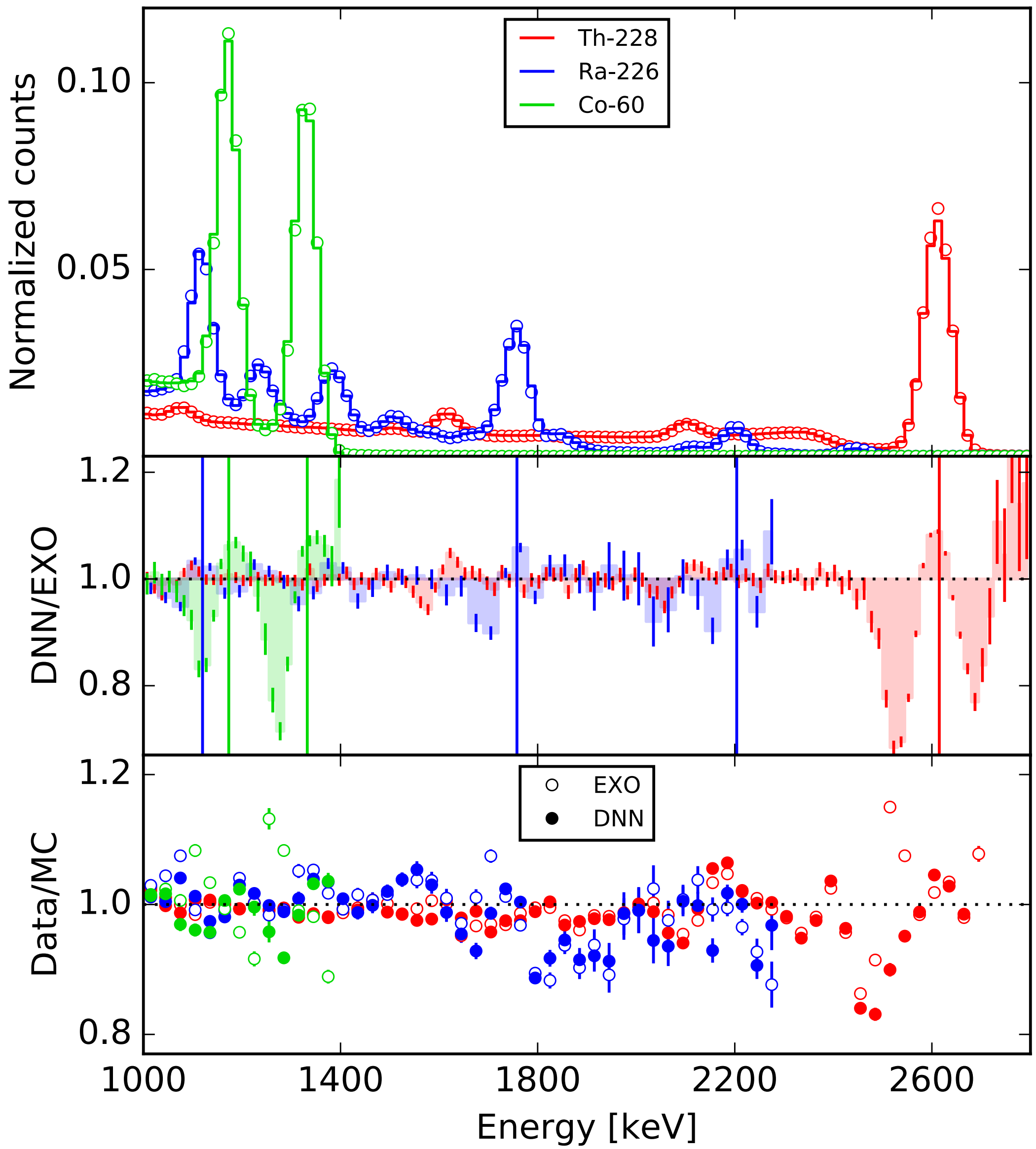




Th-228 calibration data



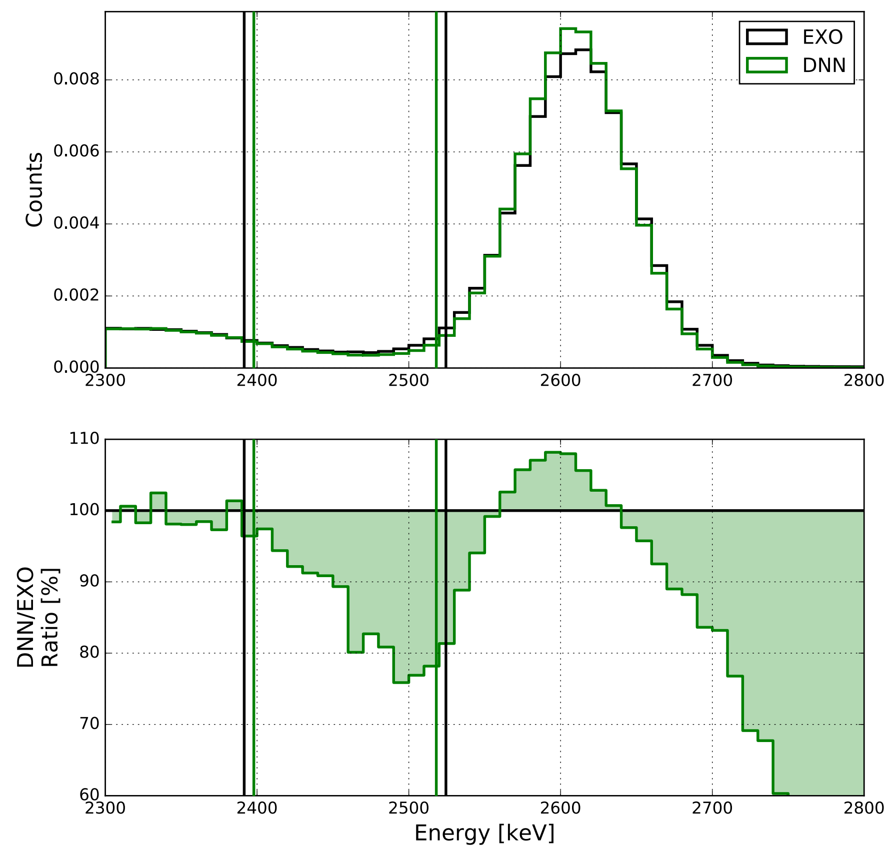
Source calibration data



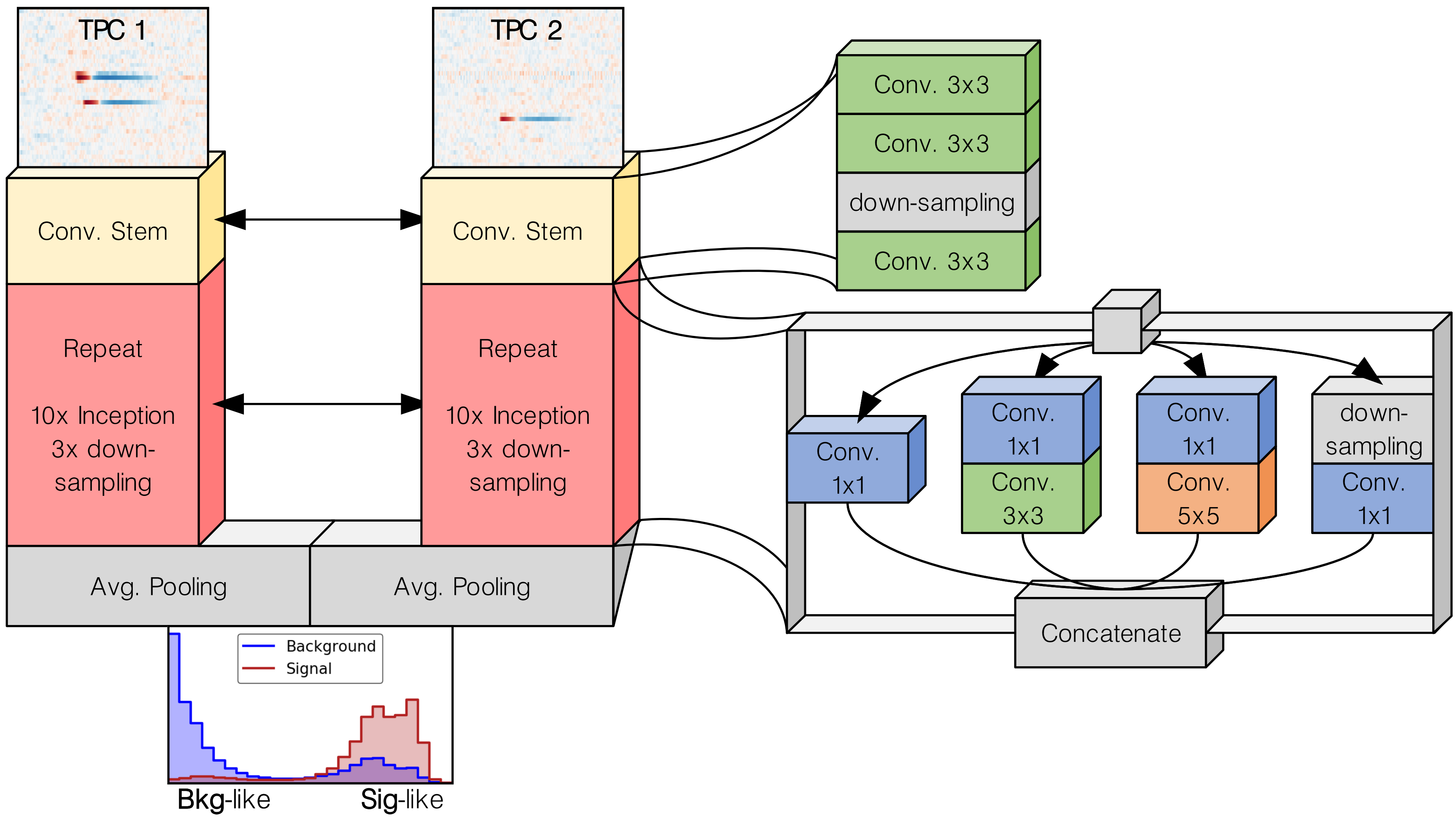
Background reduction in the ROI

- Better induction and collection disentangling and improved energy resolution already make a quantifiable improvement to physics goals (background reduction in ROI)

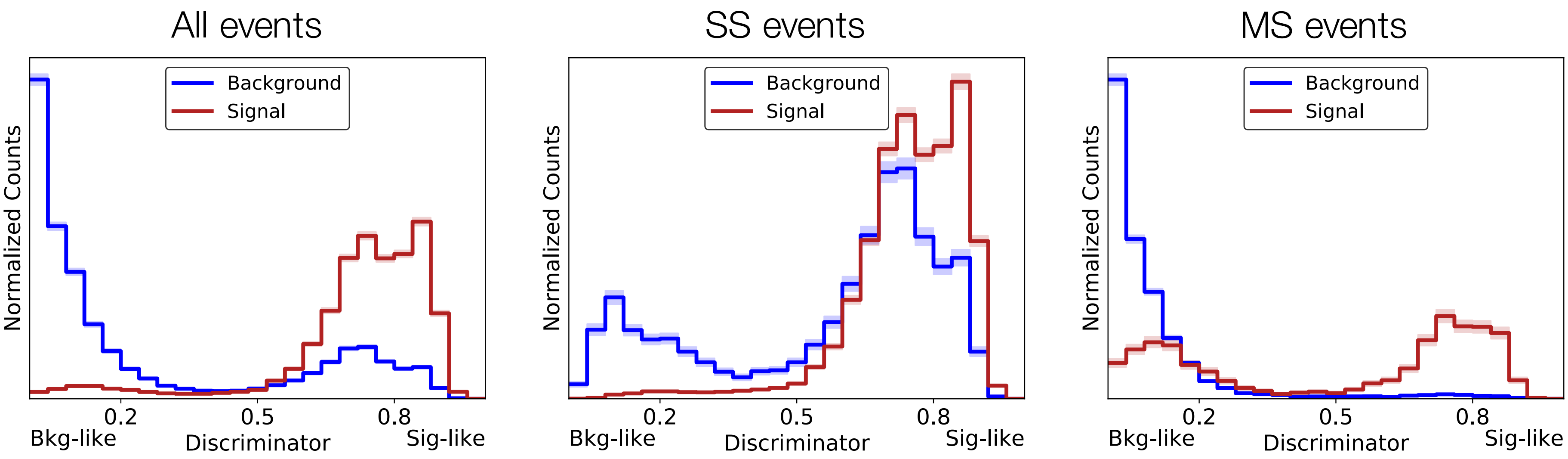
- Projected ~26% (21%) reduction of ^{232}Th background in Phase 1 (Phase 2) compared to EXO reconstruction
  - ~14% (7%) considering induction effect alone, i.e. fixed ROI
  - Using simple $1/\sqrt{B}$ scaling, this suggests at least ~4% (3%) sensitivity improvement for Phase 1 (Phase 2)



Design of DNN discriminator

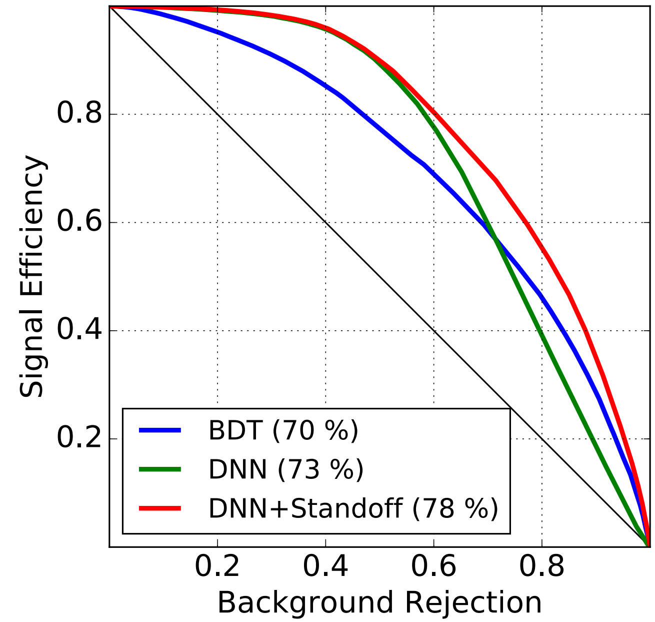


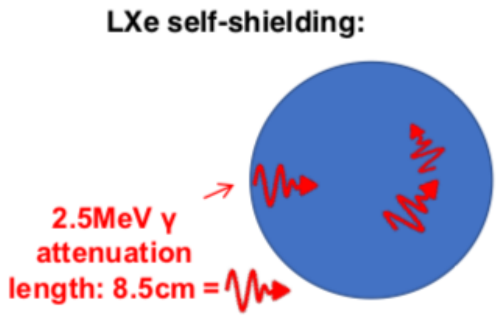
DNN validation

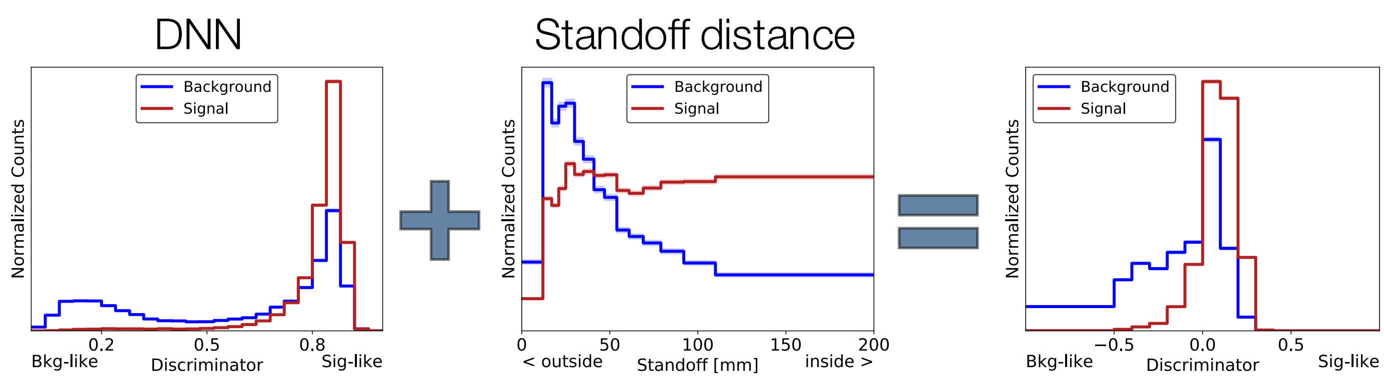


Combining topology and position

- In physics data, γ backgrounds enter detector from materials external to LXe
- Rate is exponentially reduced by LXe self-shielding, providing additional information on γ backgrounds
- Wrapping topology (via DNN) and spatial discriminator (via Standoff distance)
- DNN discrimination outperforms BDT used in 2018 $0\nu\beta\beta$ analysis*

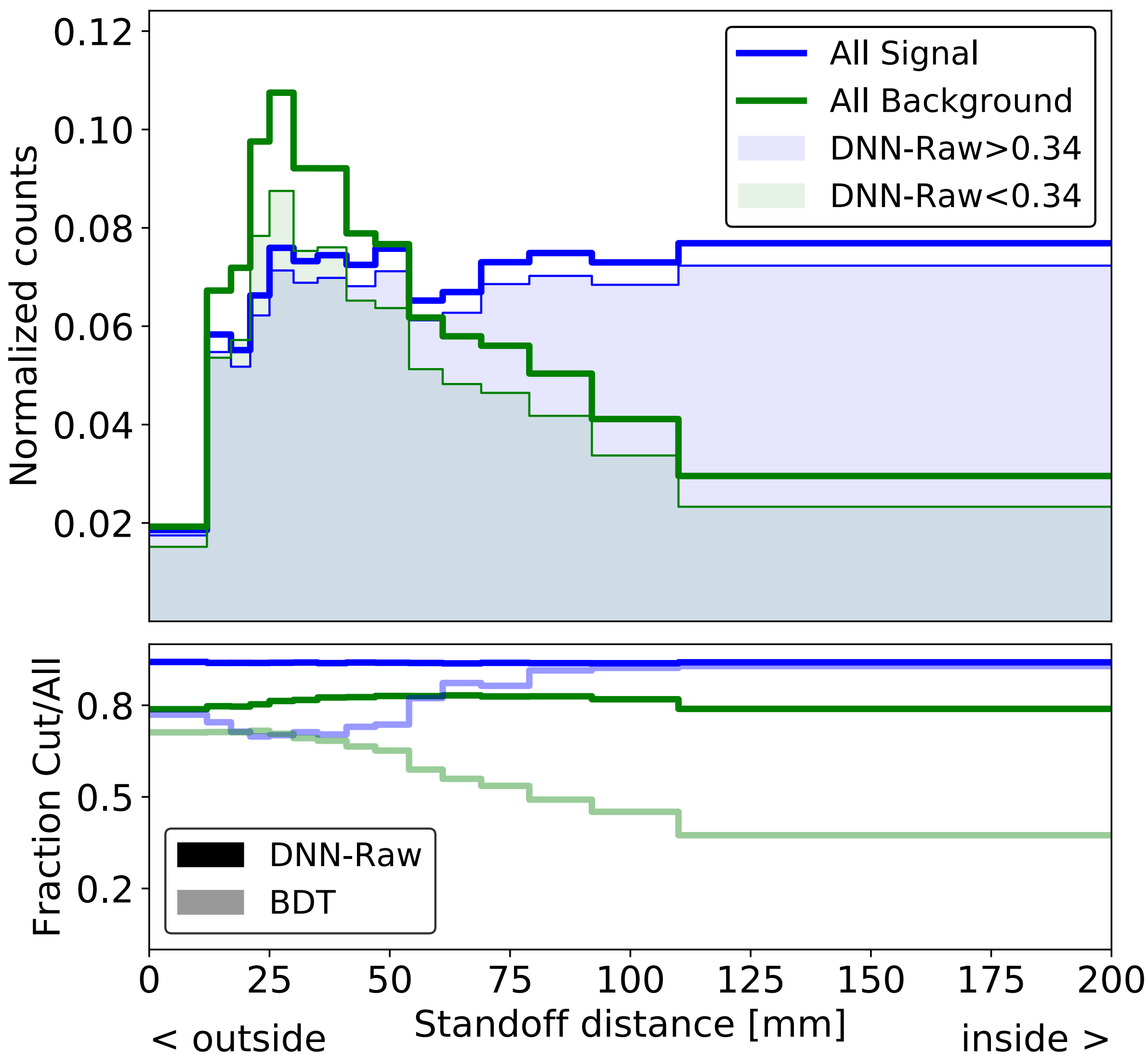






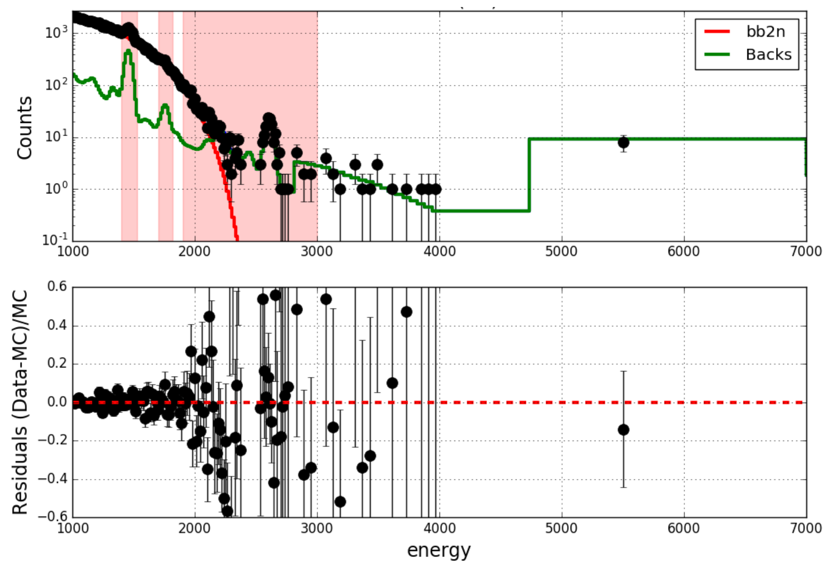
* *Phys. Rev. Lett. 120, 072701 (2018)*

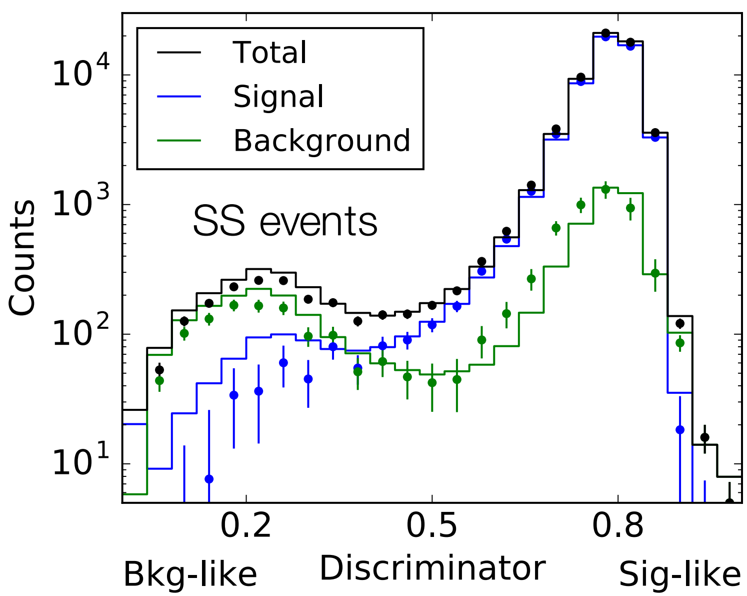
Sanity check – Event position

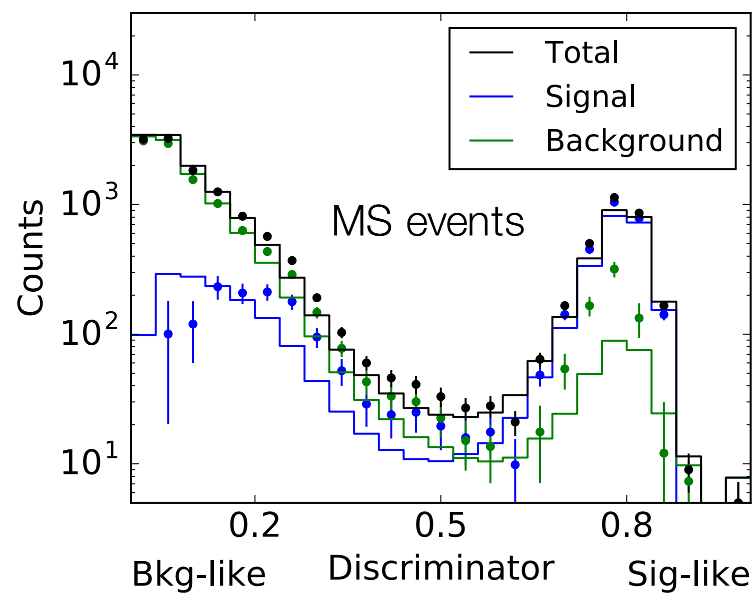


2νββ background-subtracted data

- a

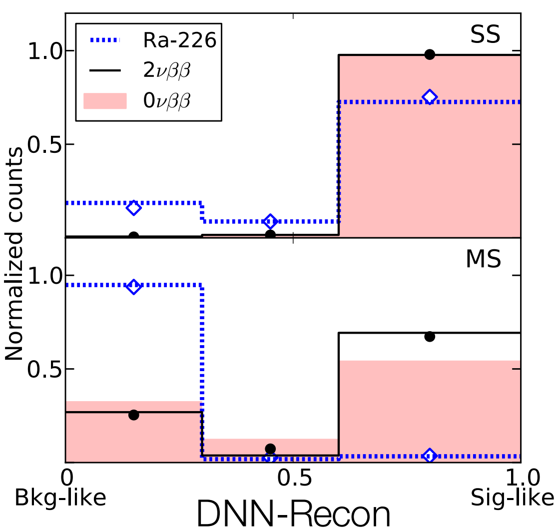


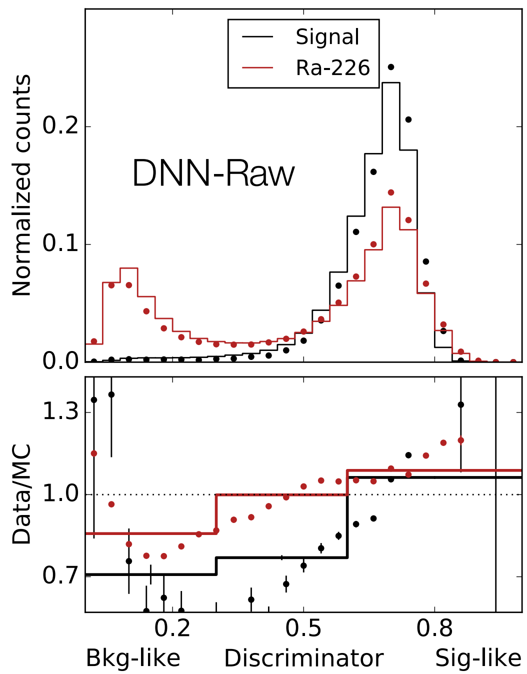


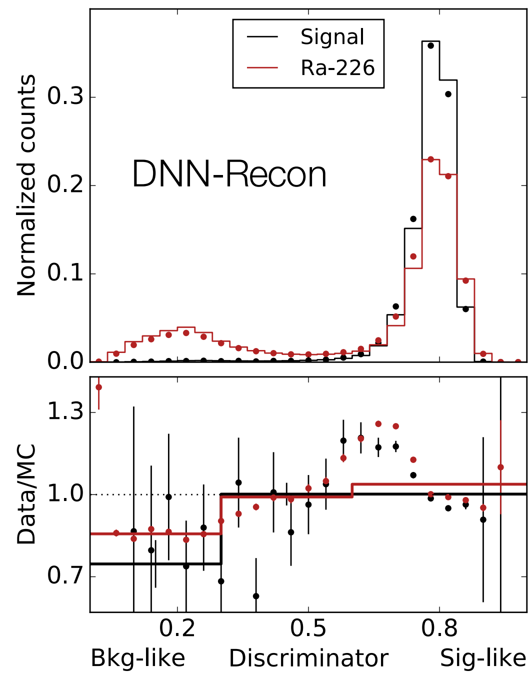


Performance on real data

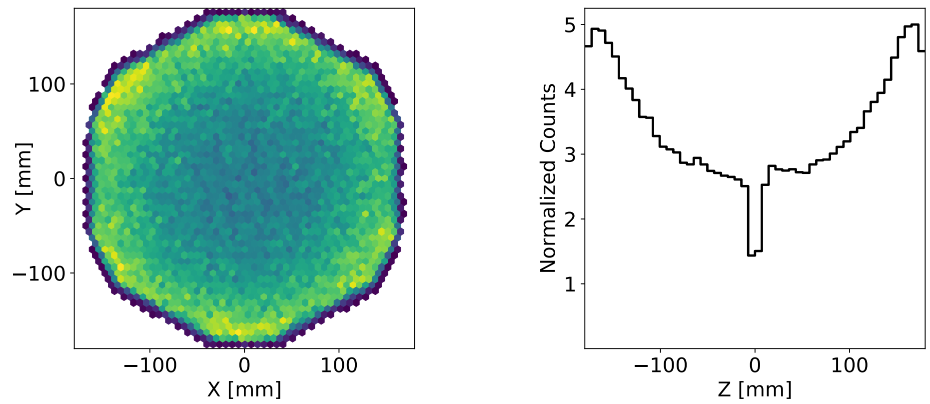
- Data/MC agreement validated with different data (γ: ^{226}Ra, ^{228}Th, ^{60}Co. β: 2νββ data)
- DNN-Raw has systematic trend in residual. Issues especially for ββ signal class
- DNN-Recon shows improved agreement compared to DNN-Raw
  - Shielded from inaccuracies in modelling raw signals and complex detector effects
- Shape error is mitigated by profiling variables at cost of discrimination power
- Remaining shape differences are taken into account as systematic uncertainties

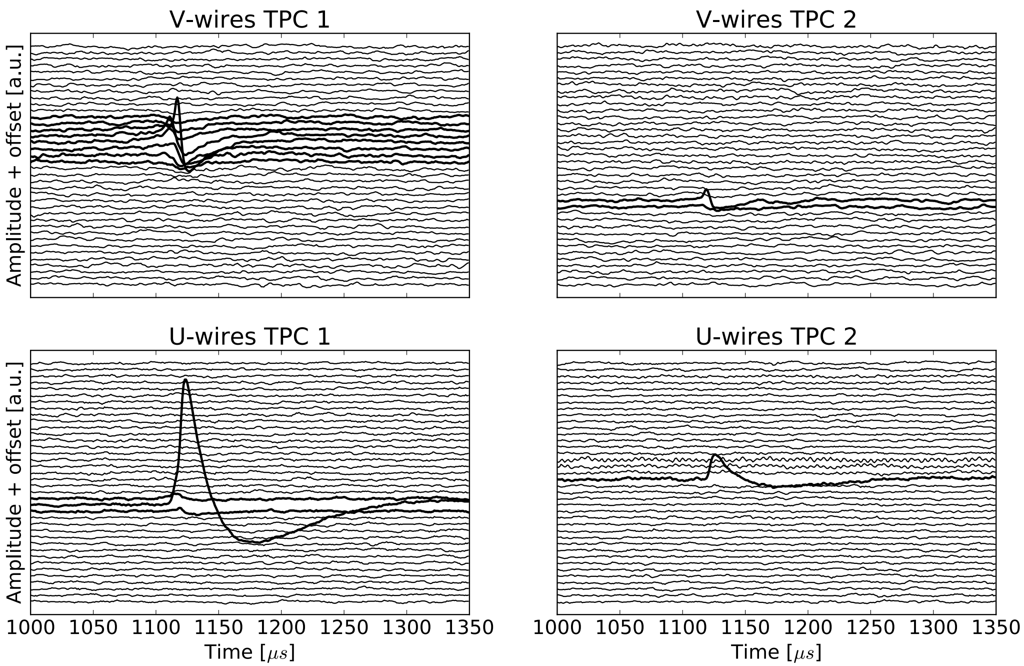






Capturing spatial information in DNN





Capturing spatial information in DNN

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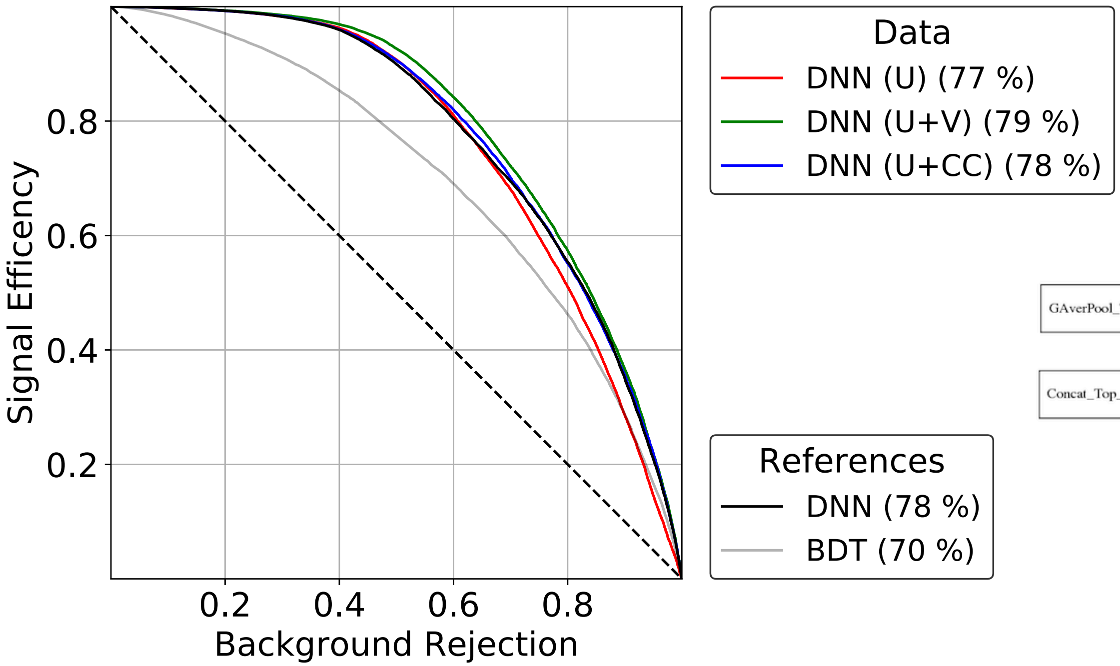

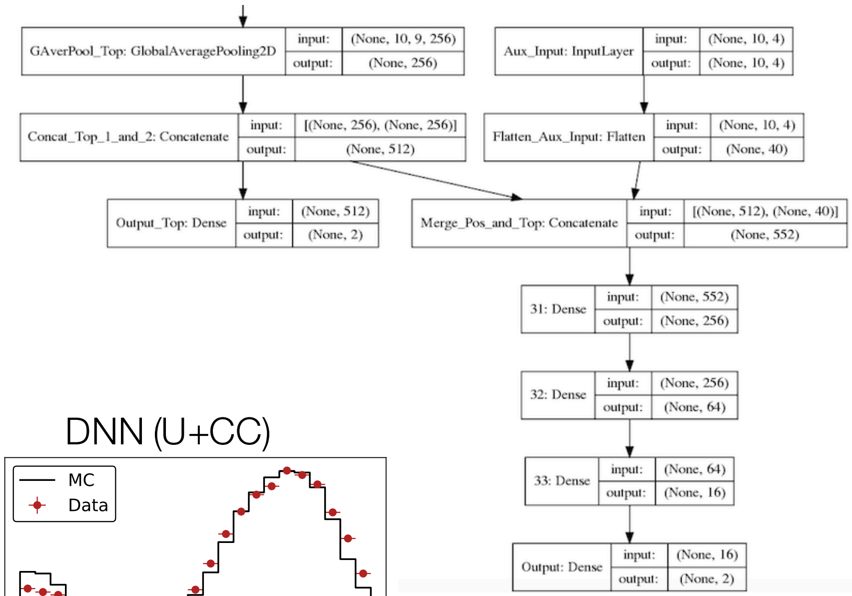

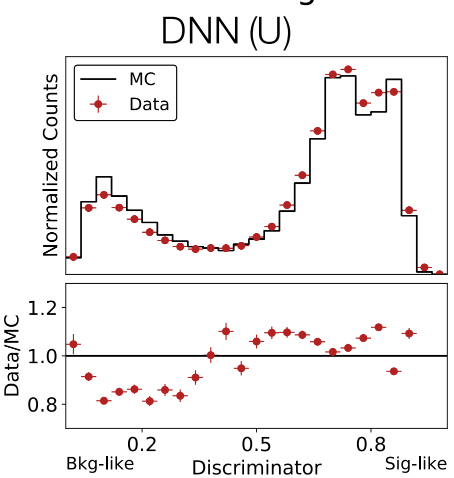

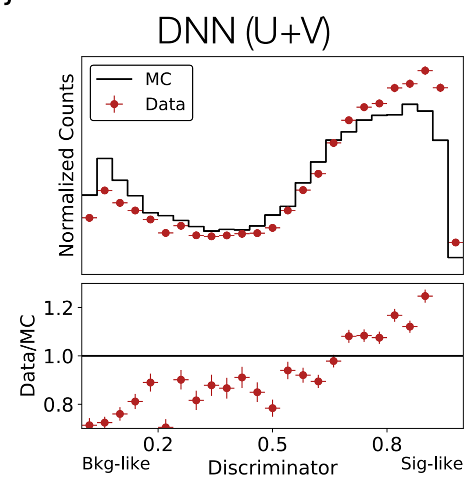

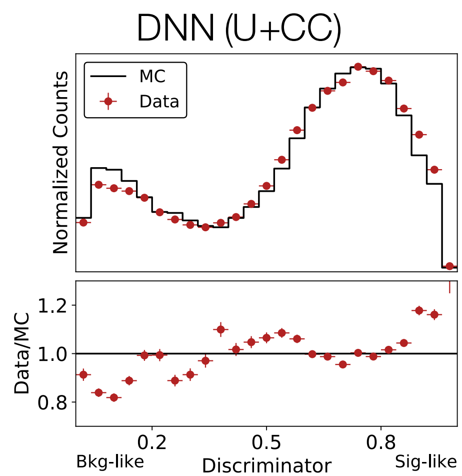

Capturing spatial information in DNN