Karlsruhe Institute of Technology

Probabilistic Position Reconstruction in the XENONnT Experiment

Sebastian Vetter

on behalf of the XENON Collaboration

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xenonexperiment.org XENONexperiment @xenonexperiment @xenon_experiment

The XENON Collaboration

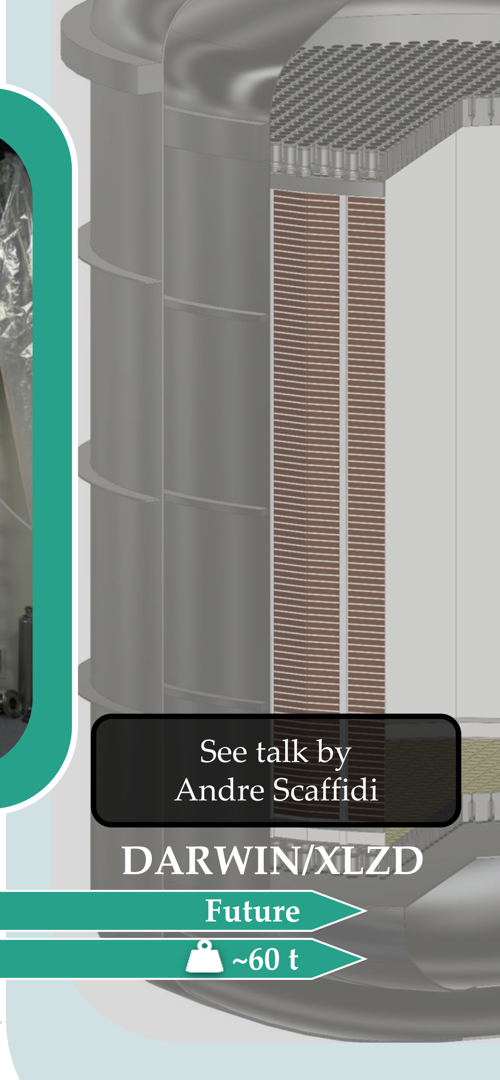
XENON Collaboration Meeting March 2024 at Laboratori Nazionali del Gran Sasso (LNGS)

29 institutions

200+ scientists

XENON Experiments

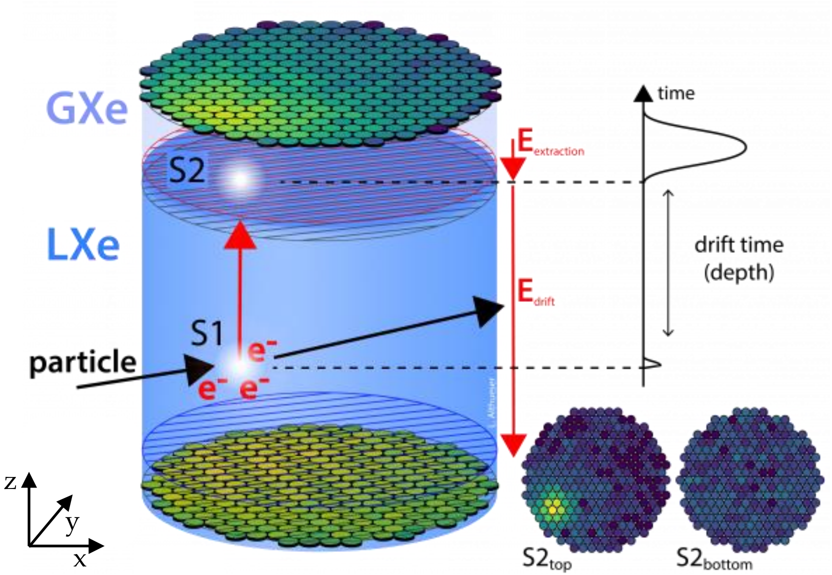
XENON dark matter (& neutrino) observatory
at Laboratori Nazionali del Gran Sasso (LNGS)



See talk by
Andre Scaffidi

XENON10	XENON100	XENON1T	XENONnT	DARWIN/XLZD
2005 - 2007	2008 - 2016	2016 - 2019	2020 - Now	Future
15 kg	161 kg	3.2 t	8.5 t	~60 t

Dual-phase Time Projection Chamber (TPC)



- Initial scintillation light: S1
- Proportional scintillation signal: S2
- Energy: S1 area, S2 area
- Z-position: drift time

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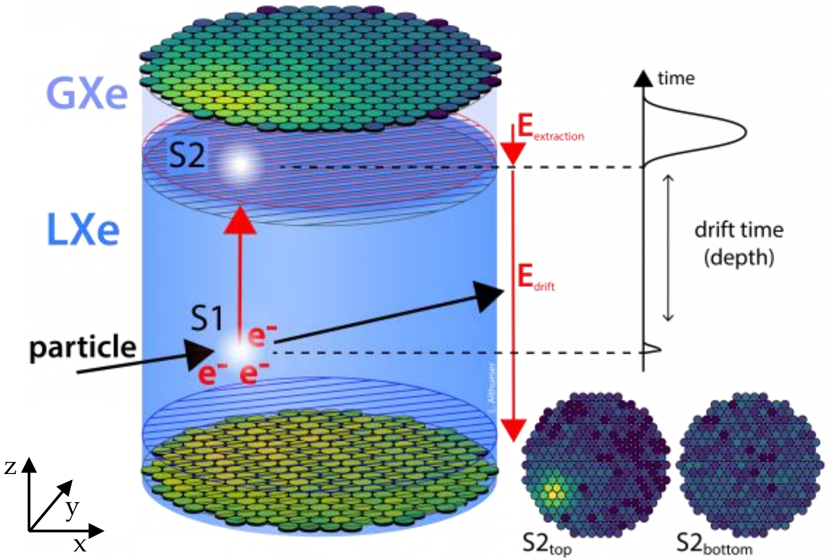

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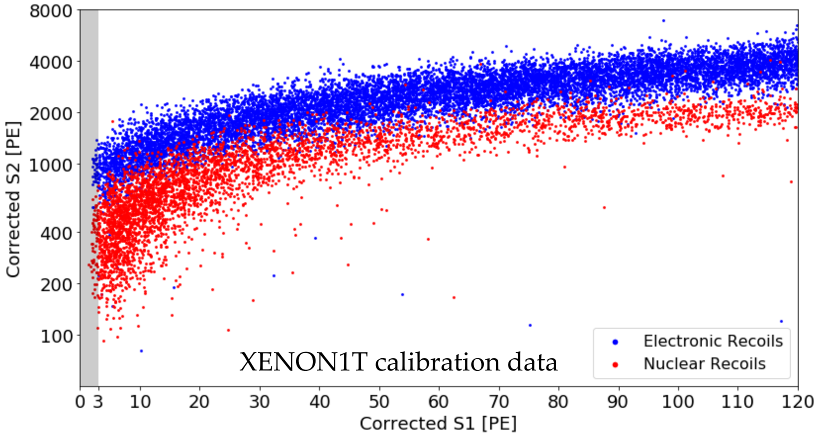
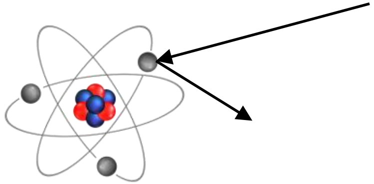
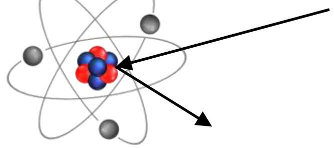
- Interaction type: S2/S1 ratio (**ER**/**NR**)



Electronic Recoils:
E.g. β, γ



Nuclear Recoils:
E.g. n, WIMPs,
ν (Coherent Elastic ν Nucleus Scattering)



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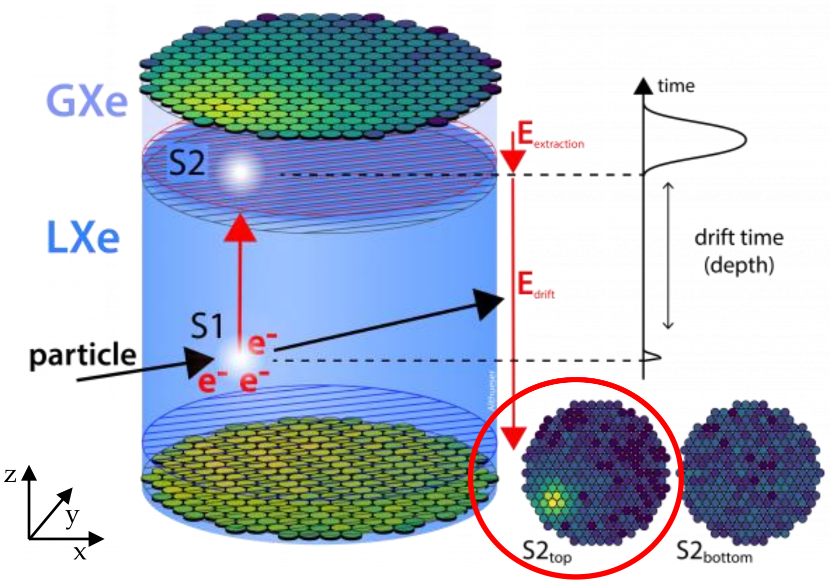

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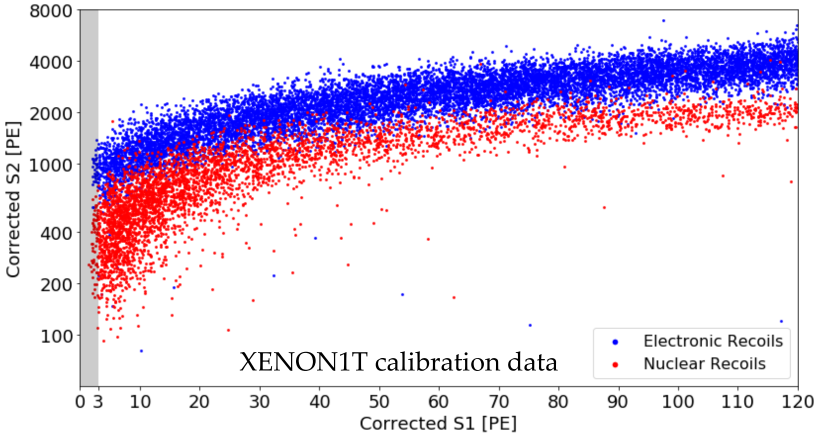
- Energy: S1 area, S2 area
- Z-position: drift time
- Interaction type: S2/S1 ratio (**ER**/**NR**)
- **X-Y-position: S2 hitpattern**



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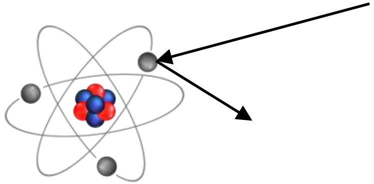
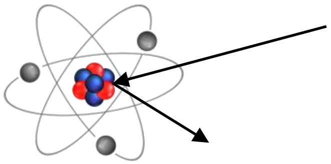


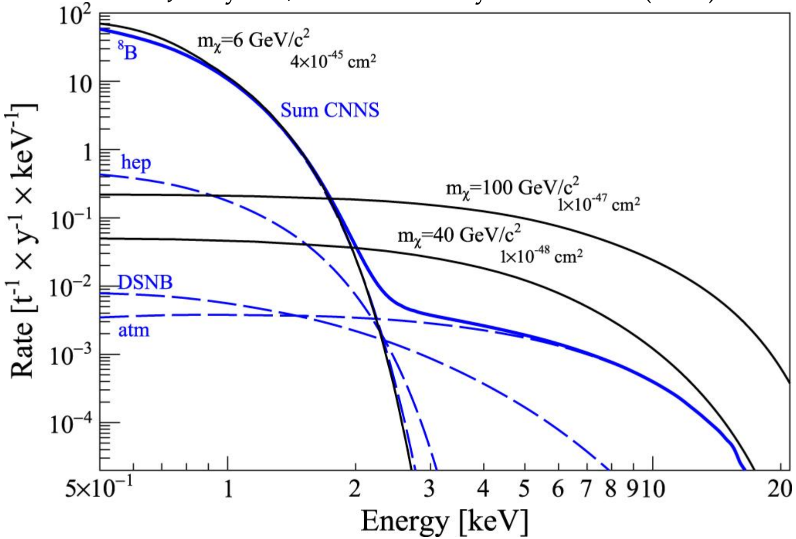


Signal and Background Rates (Example: CEνNS)

Signal rate (CEνNS):

- $R = \phi_\nu \cdot \sigma_\nu \cdot N_{\mathrm{Xe}}$
  ~600 recoils / (tonne x year)
- Energy dependent detection efficiency
- O(10) detected events

J. Phys. G; Nucl. Part. Phys. 46 103003 (2019)



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Background rate:
- $>10^7$ recoils / (tonne x year)
  from detector materials alone

→ **Tiny needle in a massive haystack**

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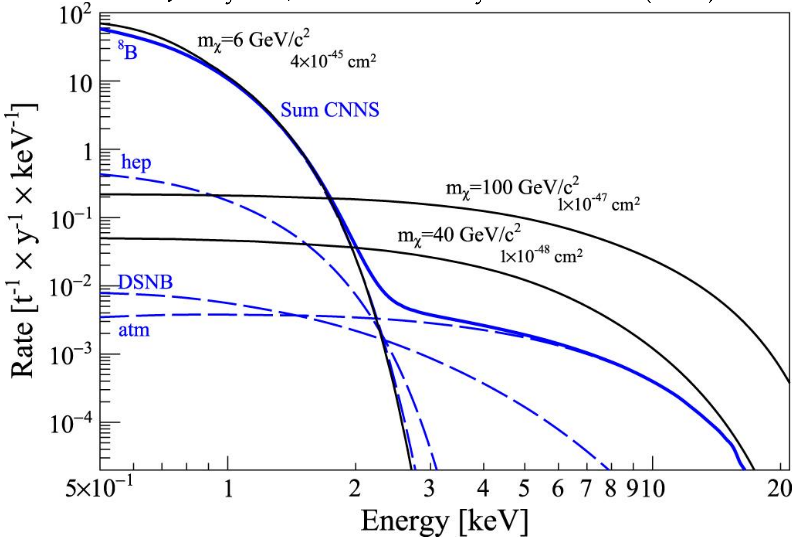

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Great efforts on background reduction: O(10) detected events

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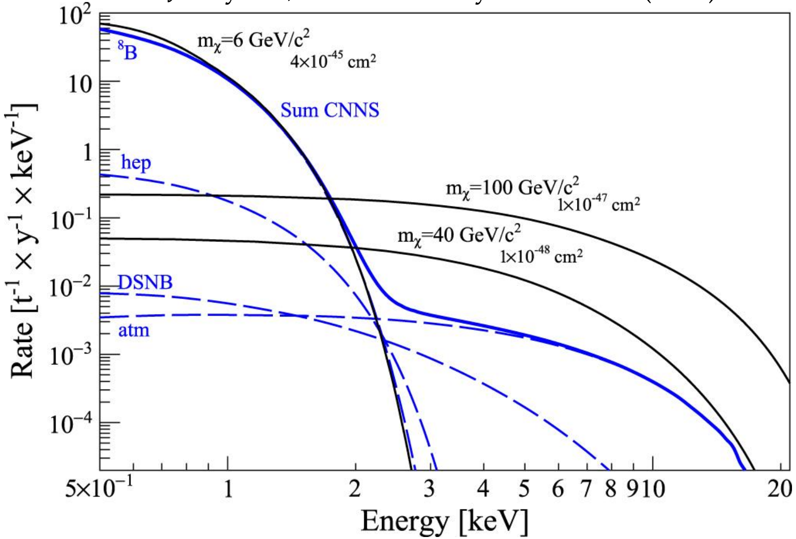


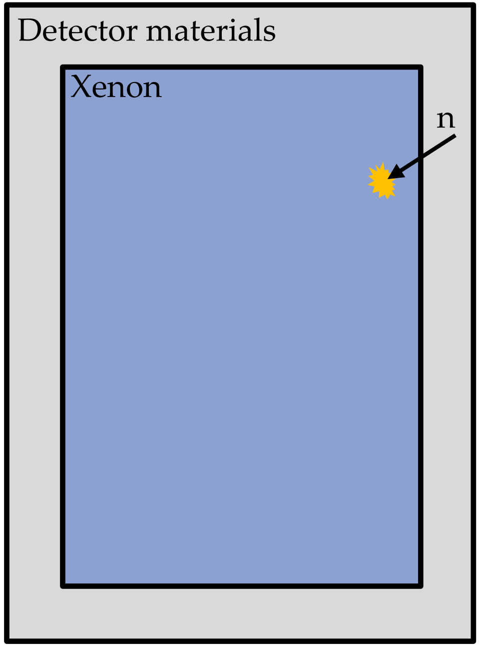
Source	CEνNS	Background	Total	Observed
Count	2.1	5.4	7.5	6

XENON1T CEνNS Search: PRL 126, 091301 (2021)

Background reduction via Fiducialization

Background radiation from detector materials

Self-shielding properties of Xe:
Background short range



Background reduction via Fiducialization

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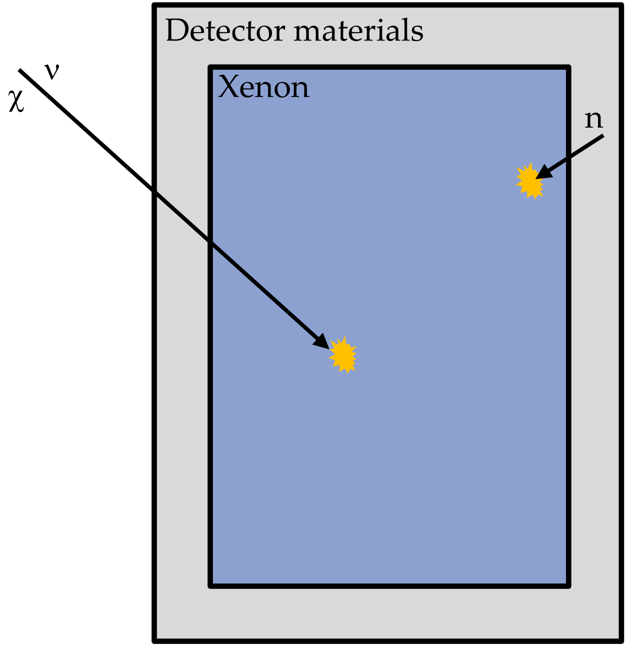
Self-shielding properties of Xe:
Background short range, WIMPs/neutrinos long range

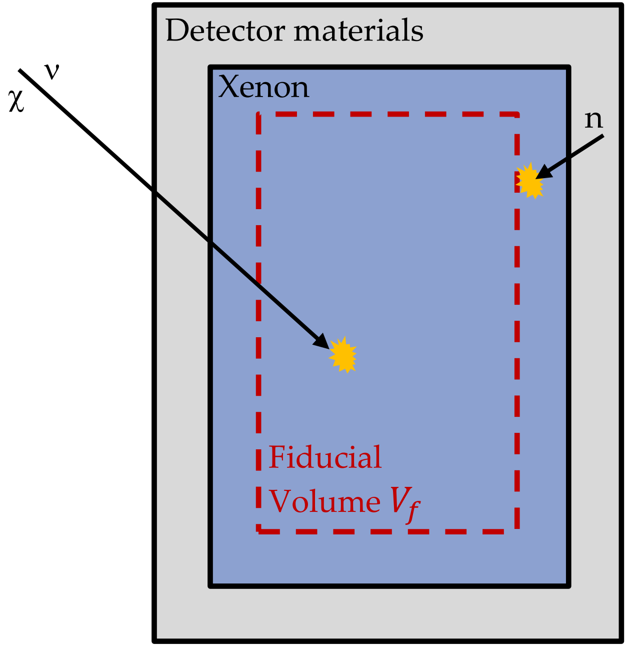


Background reduction via Fiducialization

Background radiation from detector materials

Self-shielding properties of Xe:
Background short range, WIMPs/neutrinos long range

Define fiducial volume V_f with
$P(\mathrm{BGD} \in V_f) \ll 1$
and $P(\nu \in V_f) \approx P(\nu \in \mathrm{Xe})$



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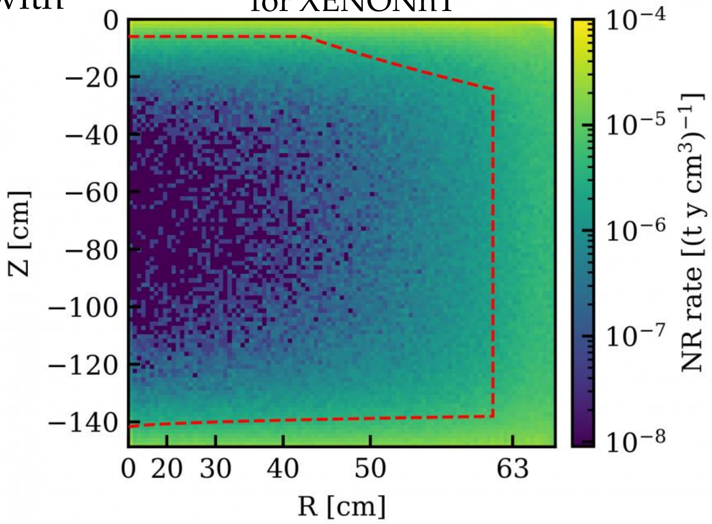
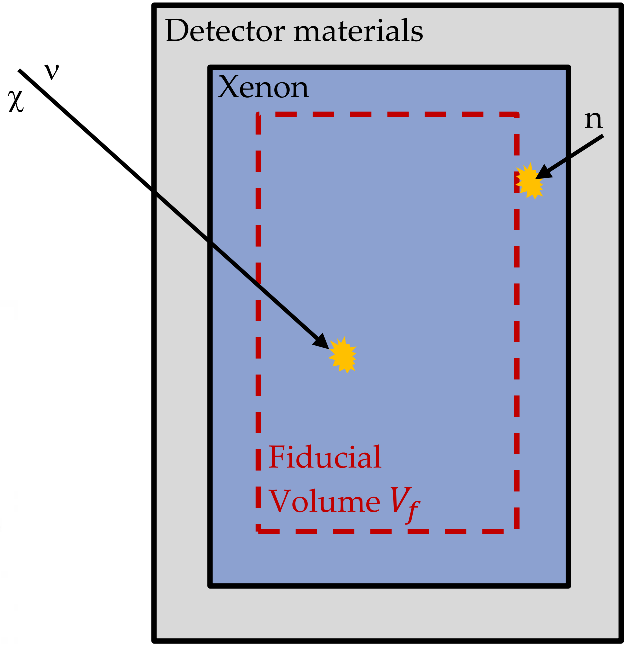
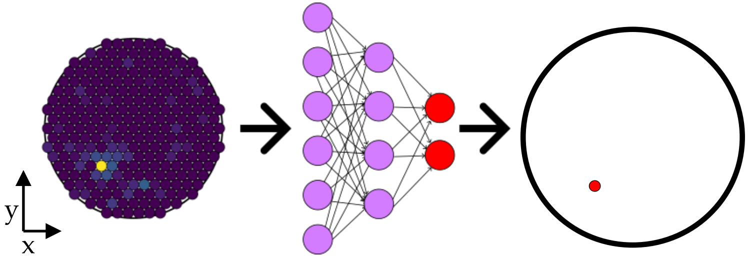
Simulated data
for XENONnT





Probabilistic Position Reconstruction

Default:
Photosensor output → NN → point in x-y plane



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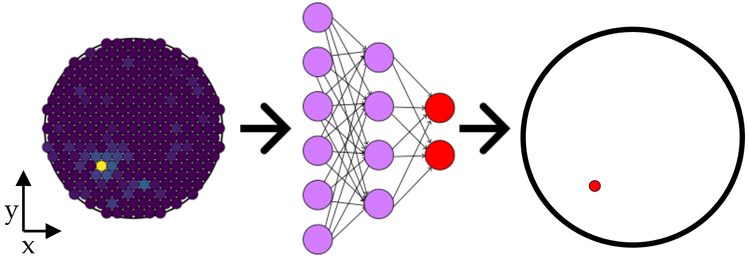
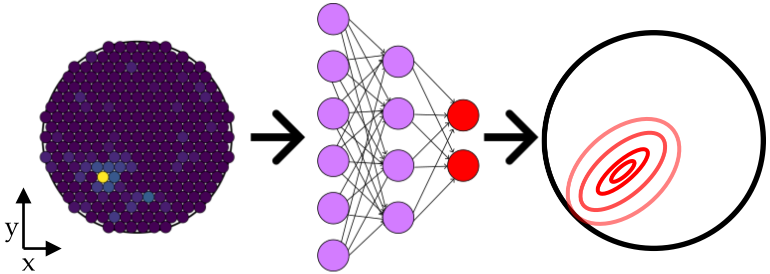


Goal:
Photosensor output → NN → PDF in x-y plane



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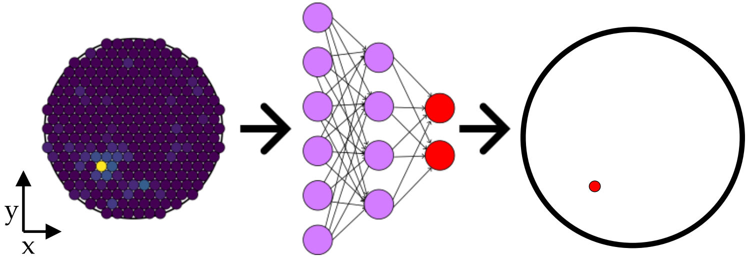

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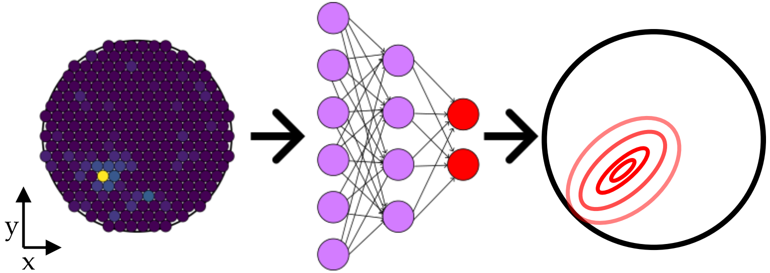
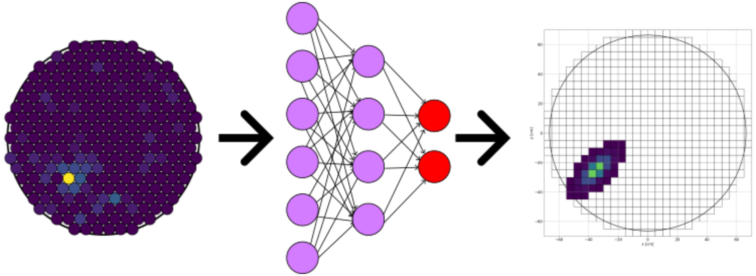


Motivation:
- ❖ Insight into the reasoning of the NN: What kind of event leads to large uncertainties?
- ❖ Identification of poorly reconstructed events
- ❖ Refinement of fiducial volume
- ❖ Propagation of position uncertainty into full event reconstruction chain

Models

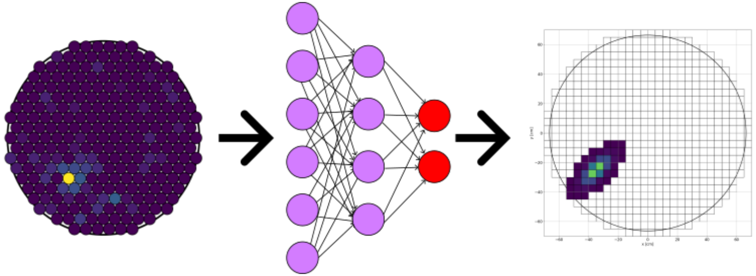
One-Hot Model



- Binned output space
- Trained as classifier
- Predicted value of bin
  = Probability of truth being in this bin

Models

One-Hot Model



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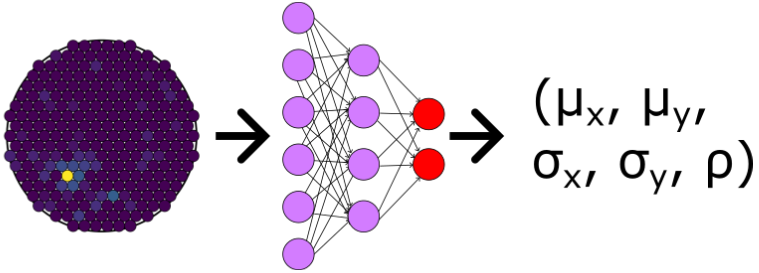
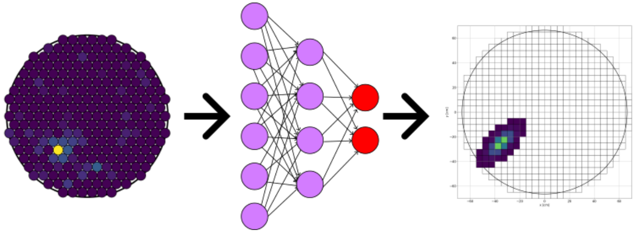
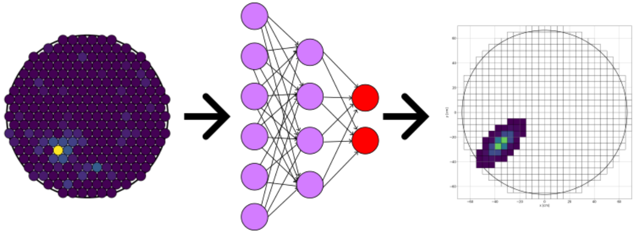
Parameterized Model

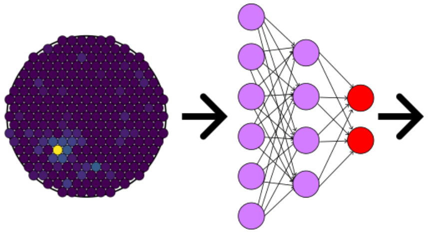


- Output: Parameters of pre-defined PDF
- Amortized Variational Inference
- Trained on Likelihood of this PDF



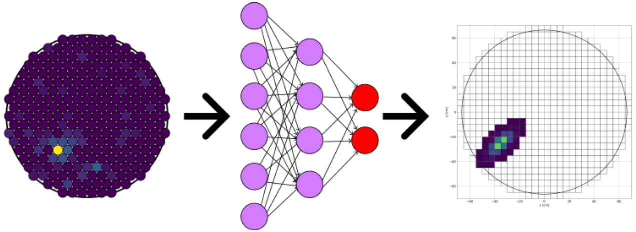
One-Hot Model
Arbitrary PDF
Easy way to increase resolution: Reduction of bin width
Large number of parameters = Increased inference time & Increased training time & Increased risk of overfitting
Output not mathematically well-defined

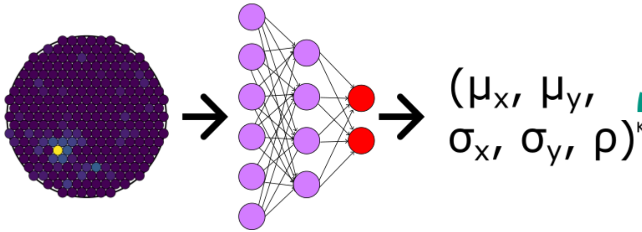




$(\mu_x, \mu_y, \sigma_x, \sigma_y, \rho)$

One-Hot Model	Parameterized Model
Arbitrary PDF	Only pre-defined PDF
Easy way to increase resolution: Reduction of bin width	Static output for given PDF Increase in performance has to come from model architecture and training data
Large number of parameters = Increased inference time & Increased training time & Increased risk of overfitting	Only slightly more parameters than point-like prediction model
Output not mathematically well-defined	Output mathematically well-defined





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Output not mathematically well-defined	Output mathematically well-defined

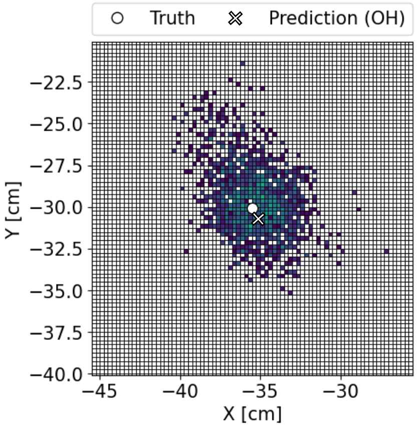
Best suited if:
- Training and inference time of no concern
- Great amount of data available

Best suited if:
- Underlying PDF known
- Small model preferable
- Interest in mathematical interpretation of output

Combination of both Models

- Train One-Hot model with extra fine binning

- Fit different pre-defined PDFs to One-Hot output



Combination of both Models

- Train One-Hot model with extra fine binning
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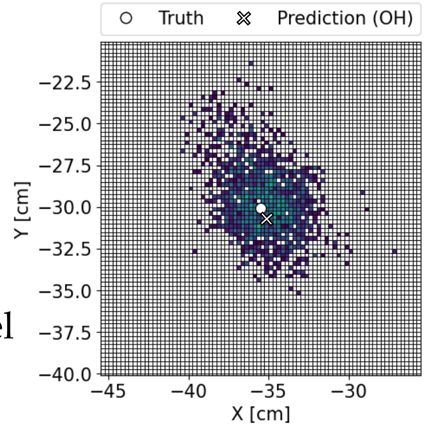
- Skew-Gaussian (SG) model fits distribution best



2D Normal PDF

2D Normal CDF

$$P(x, y; \mu, \Sigma, D) = 2P_N(x, y; \mu, \Sigma) \cdot \Phi(\delta_x(x - \mu_x) + \delta_y(y - \mu_y))$$

Mean

Variance matrix

Skewness

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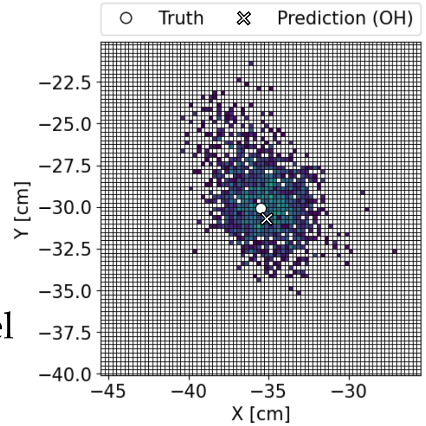

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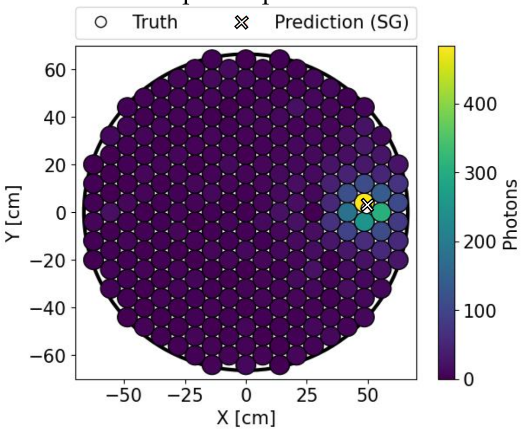
Mean

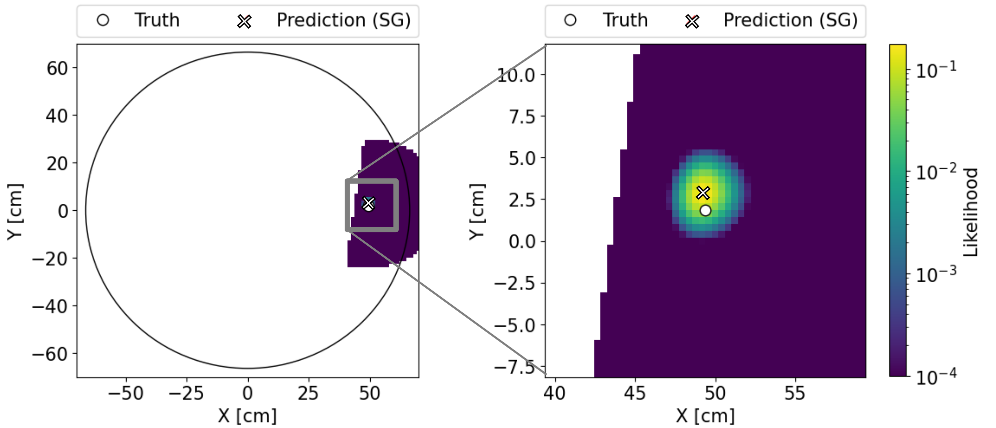
Variance matrix

Skewness

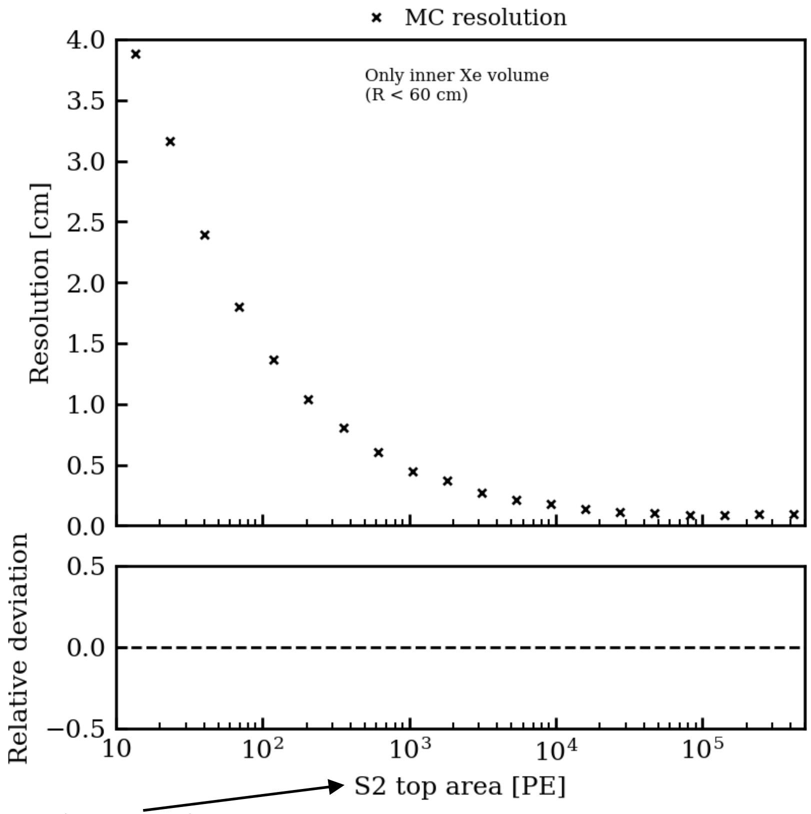
Input hitpattern



Predicted PDF



Resolution: Monte-Carlo vs Probabilistic Model

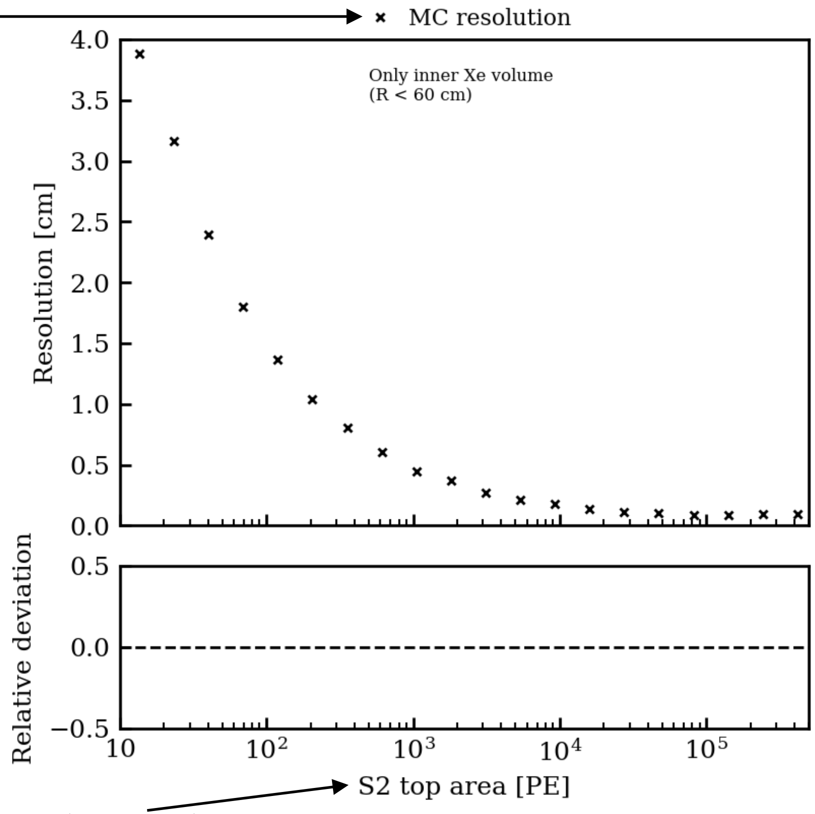


~number of photon hits in the top PMT array

Resolution:
2D standard deviation of the difference between true and reconstructed position

Resolution: Monte-Carlo vs Probabilistic Model

Derived empirically from simulations, only available for big sets of samples, uses MC truth



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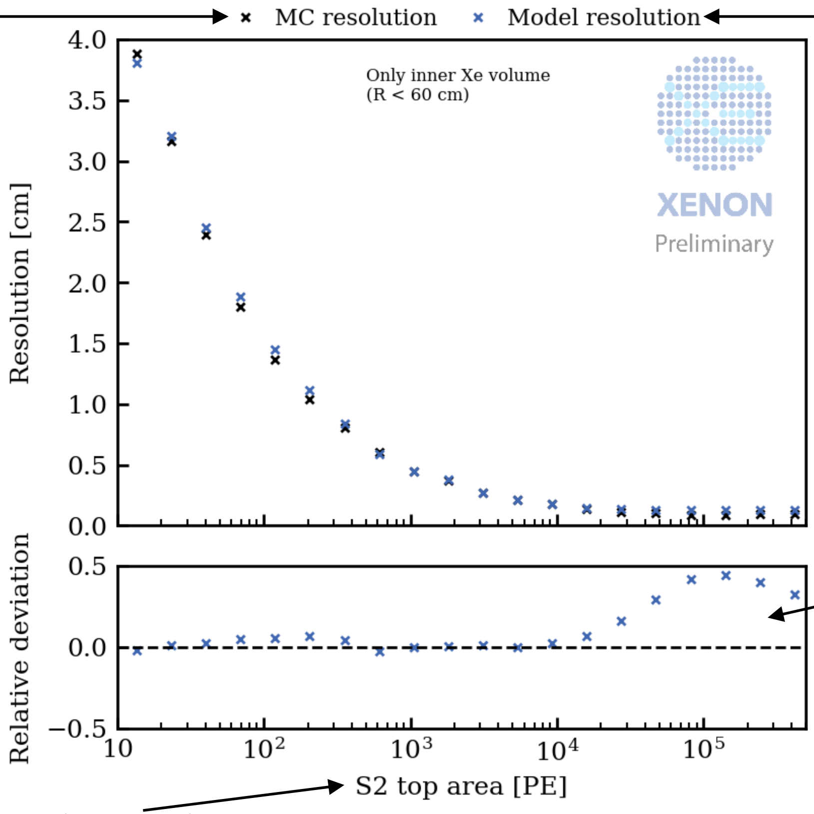
(Model – MC) / Model



~number of photon hits in the top PMT array

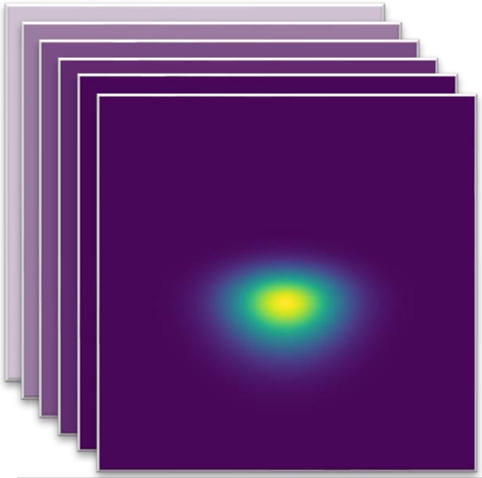
Direct output of the model, available on event-to-event basis, independent of MC truth

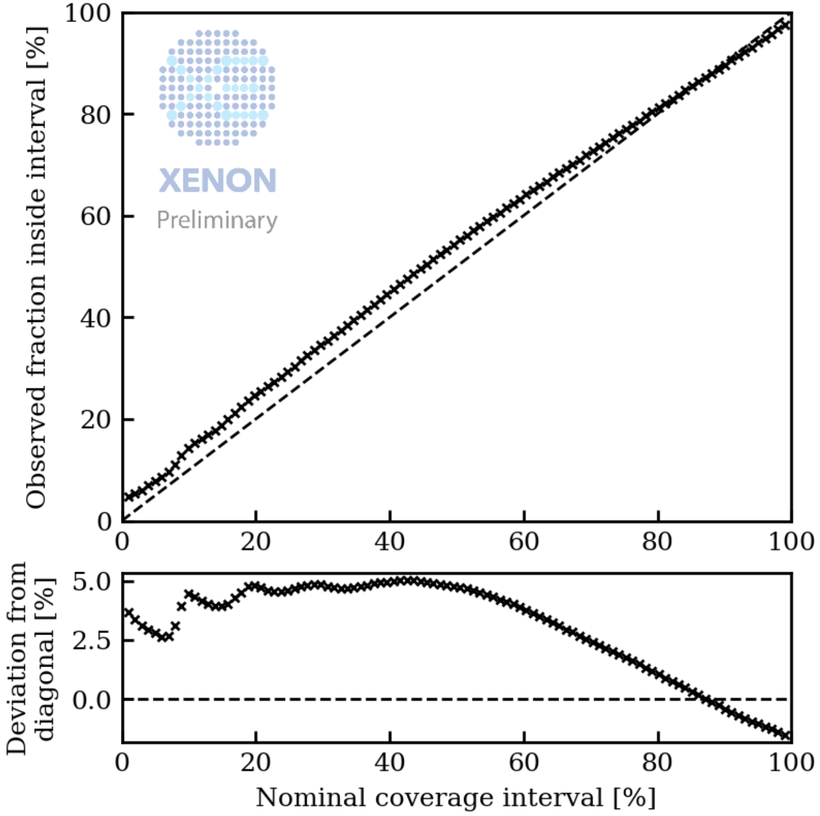
Model overestimates resolution for large signals, absolute deviation <0.5 mm

Overestimation of resolution
=
Model is too conservative

Empirical coverage

❖ Predict position-PDFs of simulated events





Empirical coverage

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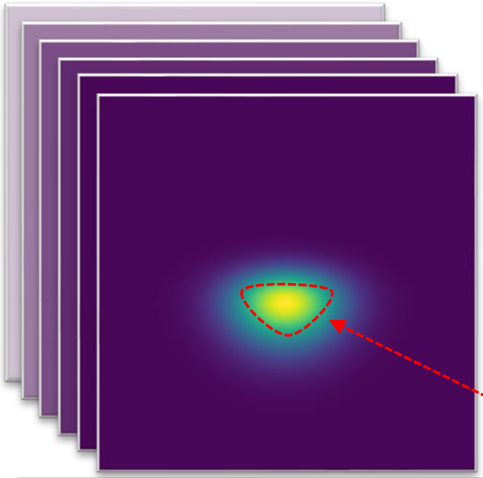
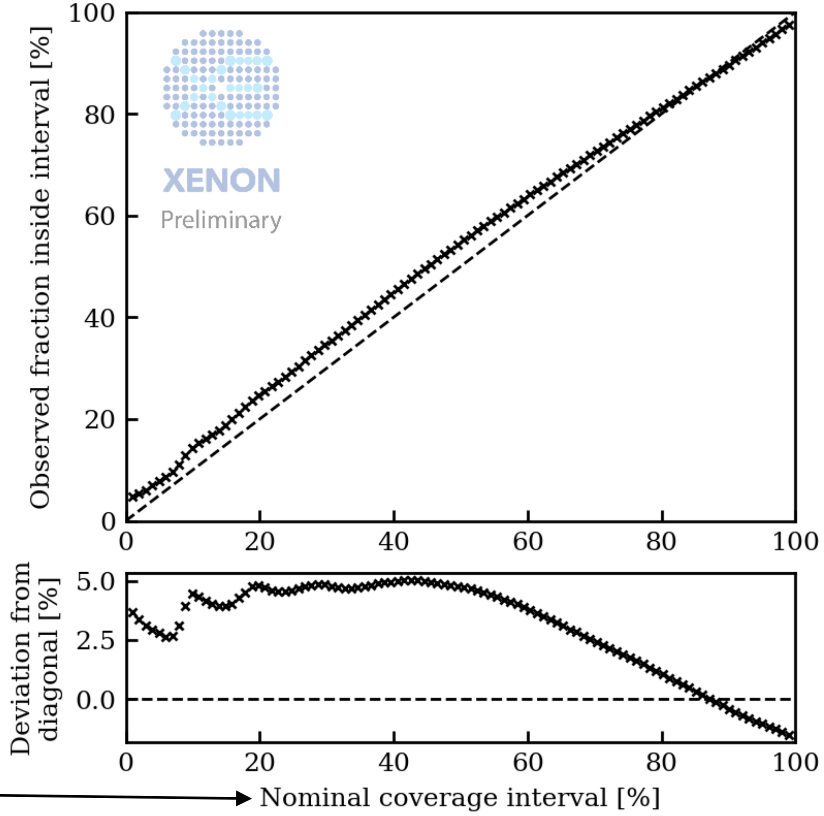
- Predict position-PDFs of simulated events
- Draw areas containing n% of each PDF

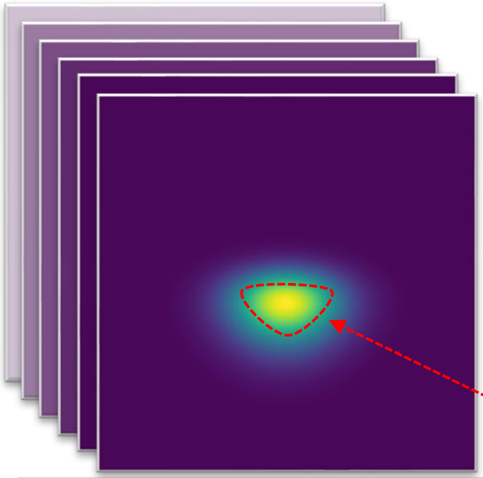


Area containing n% of PDF



Empirical coverage

- Predict position-PDFs of simulated events
- Draw areas containing n% of each PDF
- Check whether MC truth lies inside area
- If fraction of events with truth inside area = n, model estimates uncertainty correctly



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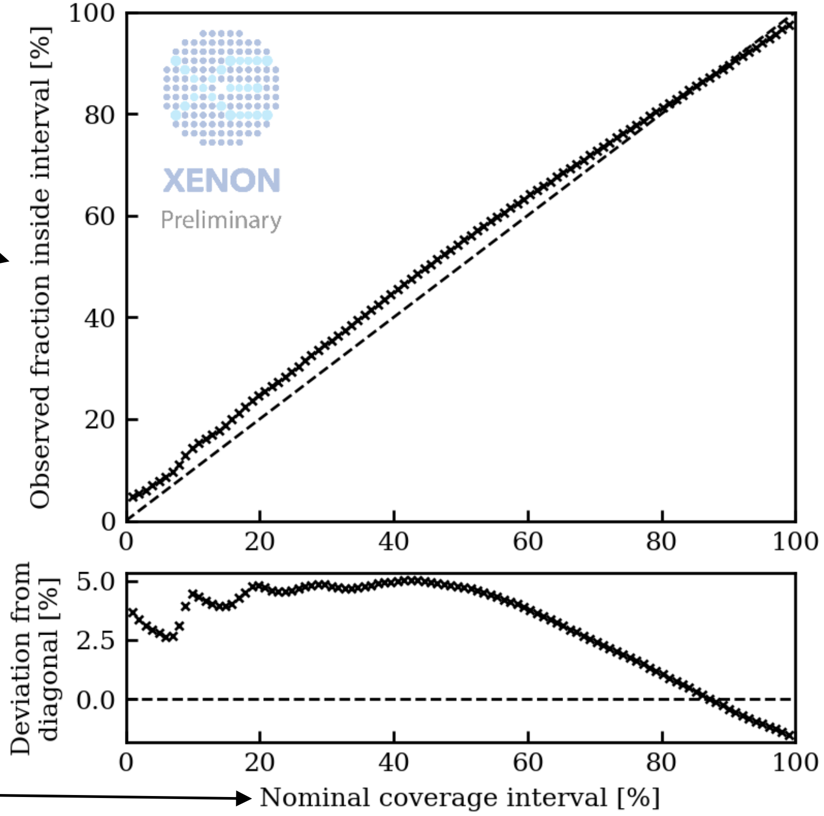

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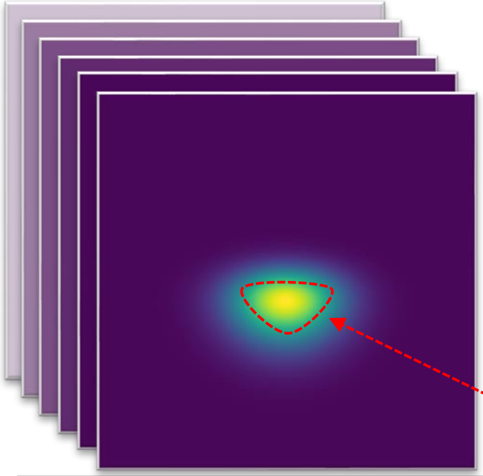
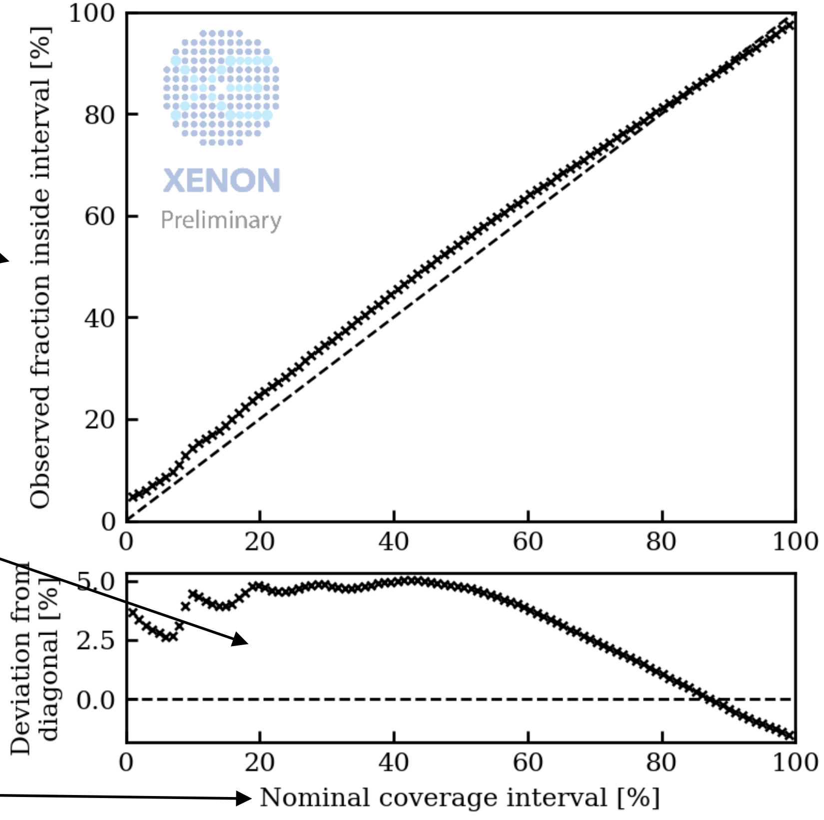


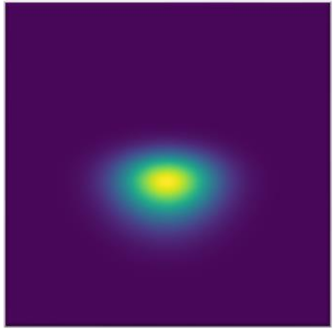


Slight overestimation of position uncertainty (model is too conservative)

Area containing n% of PDF

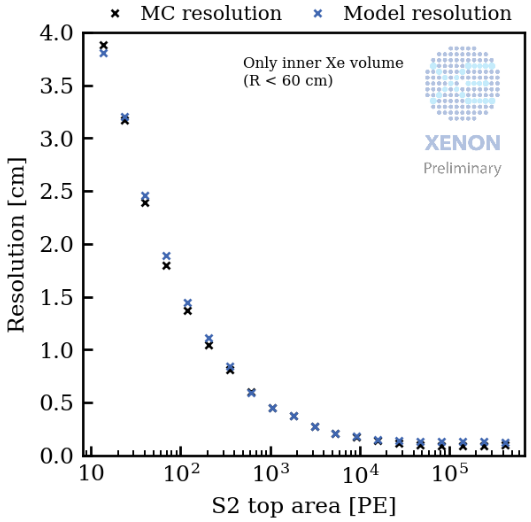
Summary

- XENONnT experiment searches for rare events (Dark Matter, CEνNS, …)
  → Requires accurate event reconstruction



- Probabilistic extensions of NNs allow for prediction of PDFs instead of points

- Probabilistic NN correctly estimates resolution of position reconstruction



Backup

Various model outputs: Average shape of ellipse

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