Enhancing signal/background discrimination using novel likelihood evaluation in noble element detectors

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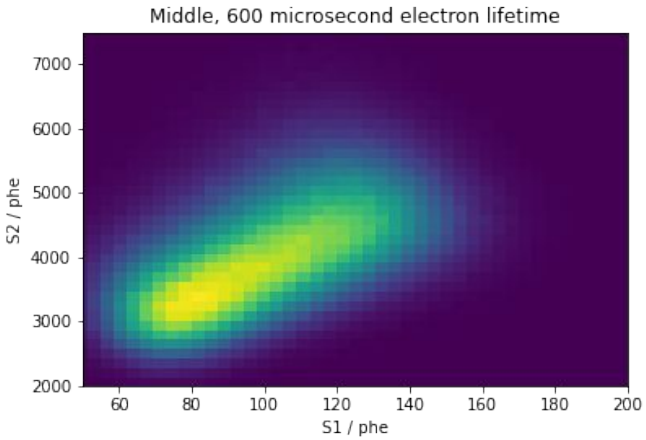
Templates: a problem



- To do statistical inference with noble element detectors, we want to evaluate the **likelihood**

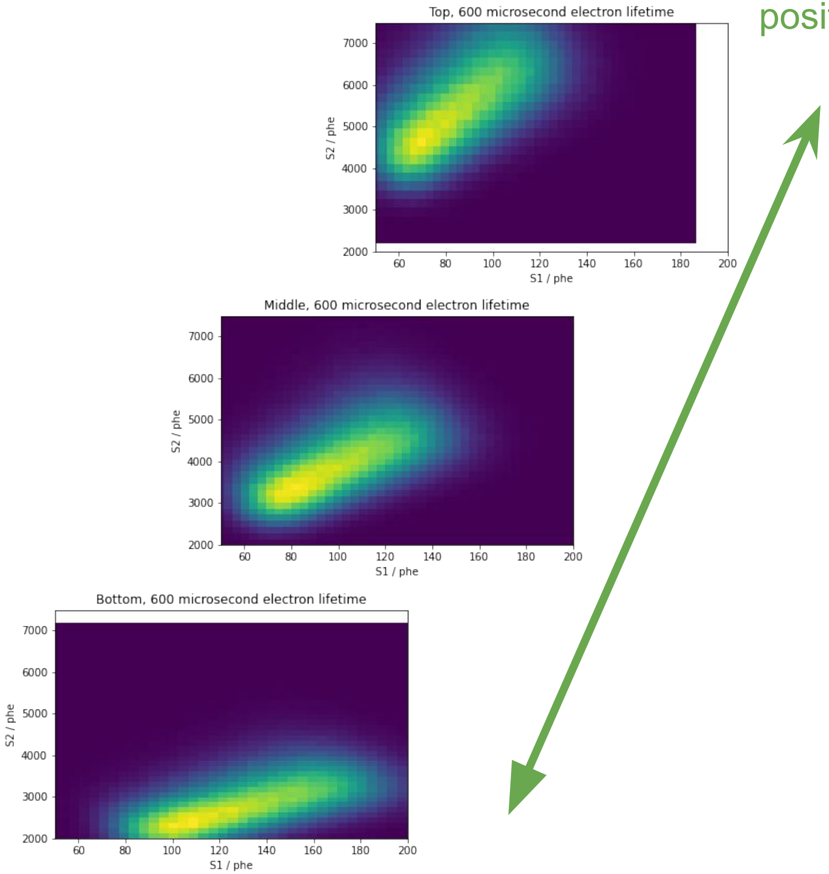
- Build detector response model to signal/background sources to do this

- Traditionally, likelihood evaluation done by approximating event probabilities with Monte Carlo **templates** in observable space

- This is okay if done per source in the space of **2 observables** and with **all nuisance parameters fixed**

Templates: a problem

template for each vertical TPC position

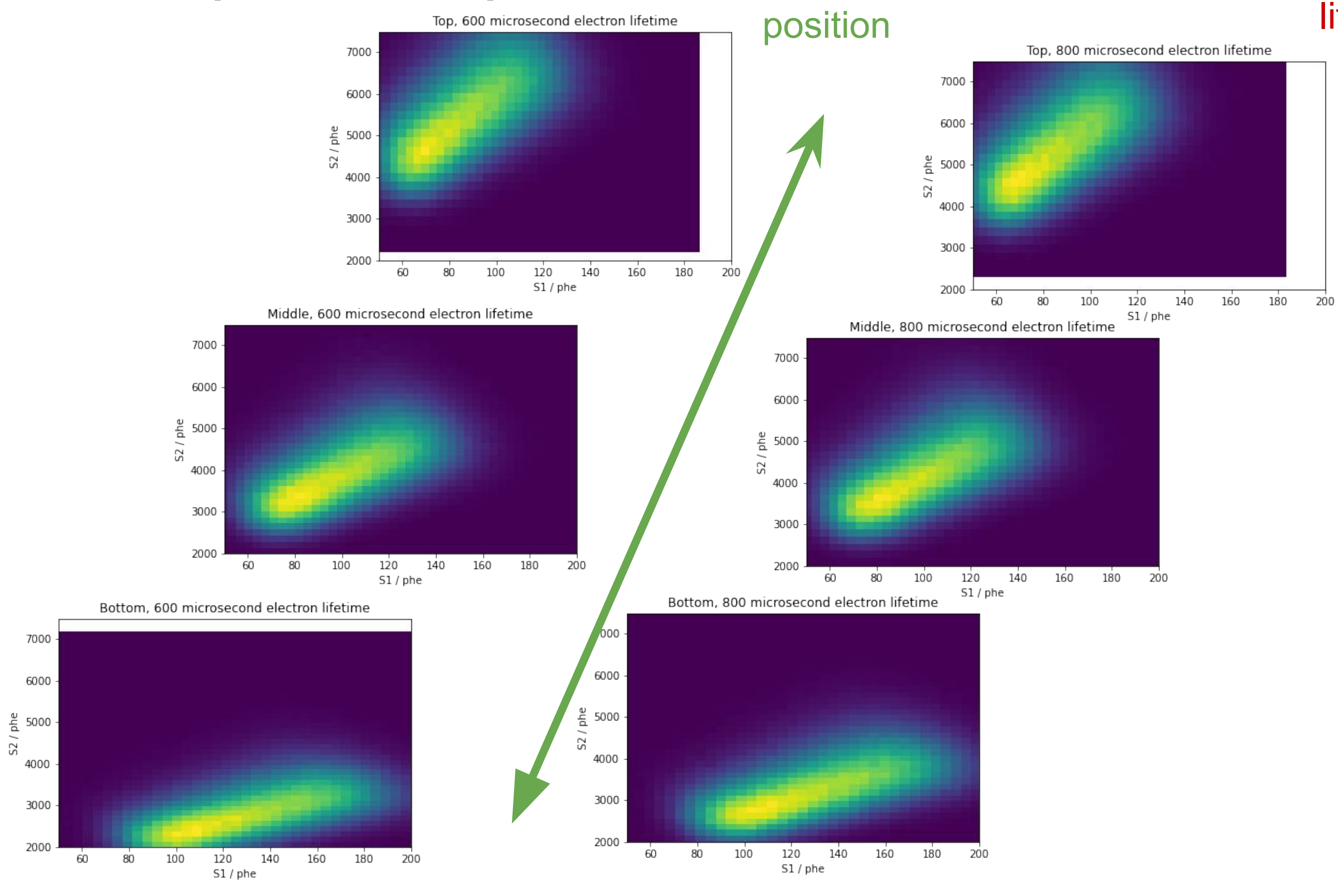


- Signal/background discrimination better at the top of the detector
- So rather than normalising signals to some fixed vertical position, better to include vertical position as an **additional observable**
- This means generating templates finely binned in this new coordinate

Templates: a problem

template for each vertical TPC position

template stack for each electron lifetime



- What if we have some uncertainty in the electron lifetime
- We should include it as a **nuisance parameter**
- Now we are generating a stack of templates for a large number of electron lifetimes

Template construction scales exponentially

z-dependence of (S1,S2)

z-dependence of electric field

...

r-dependence of energy deposition

r-dependence of electric field

...

Template space dimensionality

$(S1,S2) + z + r + t + n_1 + n_2 + \ldots$

t-dependence of energy deposition

t-dependence of electron lifetime

...

uncertainty in electron lifetime: nuisance parameter n_1

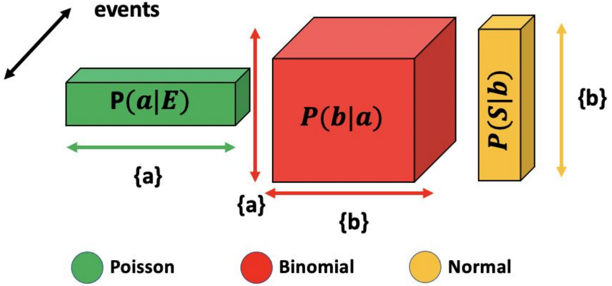
uncertainty in g1: nuisance parameter n_2

...

...

Evaluating likelihoods directly

$$P(a|E) \sim Poisson(\mu(E, n_1, \ldots))$$
$$P(b|a) \sim Binomial(n(a, n_2, \ldots), p(a, n_3, \ldots))$$
$$P(S|b) \sim Normal(\mu(b, n_4, \ldots), \sigma(b, n_5, \ldots))$$

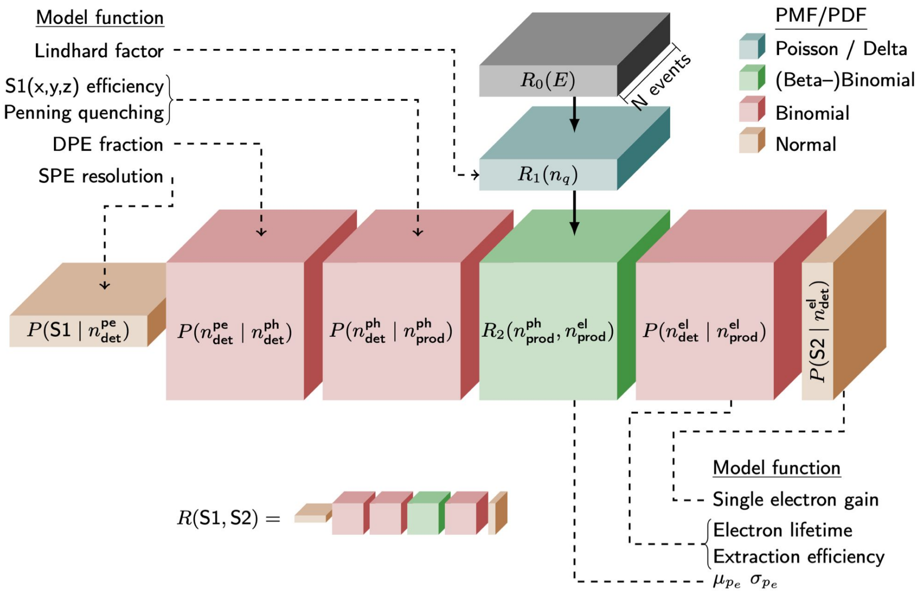


$$P(S|E) = \sum_{a,b} P(a|E)P(b|a)P(S|b)$$

- Consider a **simple model** where some **energy deposition E** leads to some **detected signal S** via these processes - **hidden variables a,b**, **nuisance parameters n_1,n_2,...**
- To evaluate P(S|E) via **template filling**, we would have to do **MC simulation** via these distributions, **repeated over all n_i**
- More direct way: perform the **convolution of probability elements** directly. Can represent this as a **matrix multiplication**
- This means you do a **single calculation** to evaluate the likelihood for some observed S, and given set of n_i

J Aalbers et al., Phys. Rev. D 102, 072010 (2020)

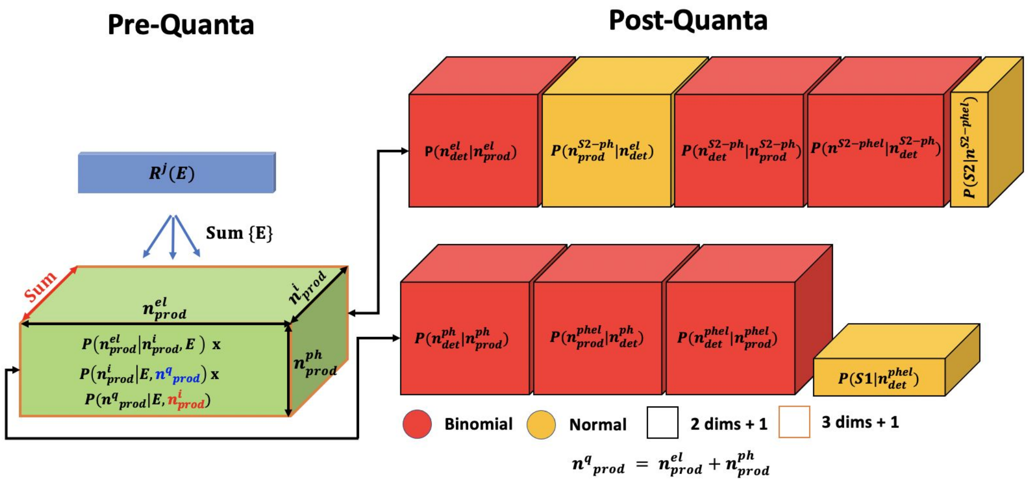
FLAMEDISX



Computing the range of hidden variables for each tensor (bounds computation) was semi-analytic and model-dependent

- FLAMEDISX (2020) aimed to implement a full detector response model for liquid xenon TPCs in this way
- Computation done in TensorFlow: GPU-accelerated, easy Hessian computation via automatic differentiation
- **Problems:** models tailored to XENON1T response, not easily extensible (bounds computation!), tensors too big for high energy events

Our work: FlameNEST



- NEST is the state-of-the-art for Monte Carlo noble element yield physics, contains very good models for detector response
- Applicable across a wide range of energies and electric fields
- Extensible beyond liquid xenon (gaseous xenon, solid xenon, liquid argon models currently implemented)
- We created a new FLAMEDISX framework which entirely captures the NEST models: FlameNEST

photon yield - > S1 detector response

energy -> electron/photon yields

electron yield - > S2 detector response

$$\sum_{E,e,\gamma,i,j,k,l,m,n,\dots} \underbrace{P(S1|i)P(i|j)P(j|\dots)\dots P(k|\gamma)}_{\text{photon yield -> S1 detector response}}\underbrace{P(e,\gamma|E)R^j(E)}_{\text{energy -> electron/photon yields}}\underbrace{P(l|e)\dots P(m|\dots)P(n|m)P(S2|n)}_{\text{electron yield -> S2 detector response}},$$

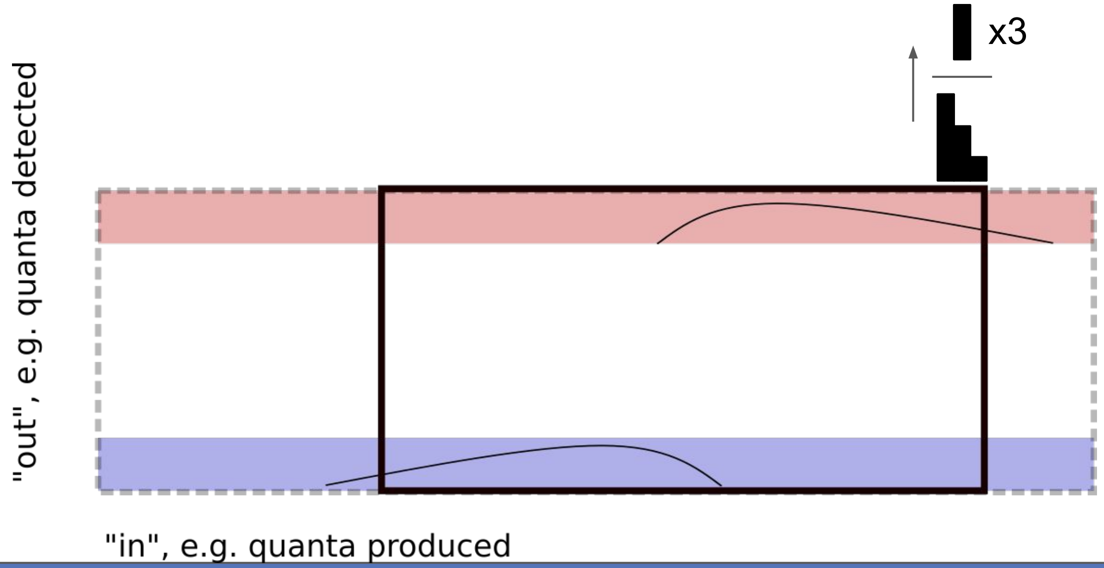
Necessary modifications to core framework

Bayes bounds (slides)

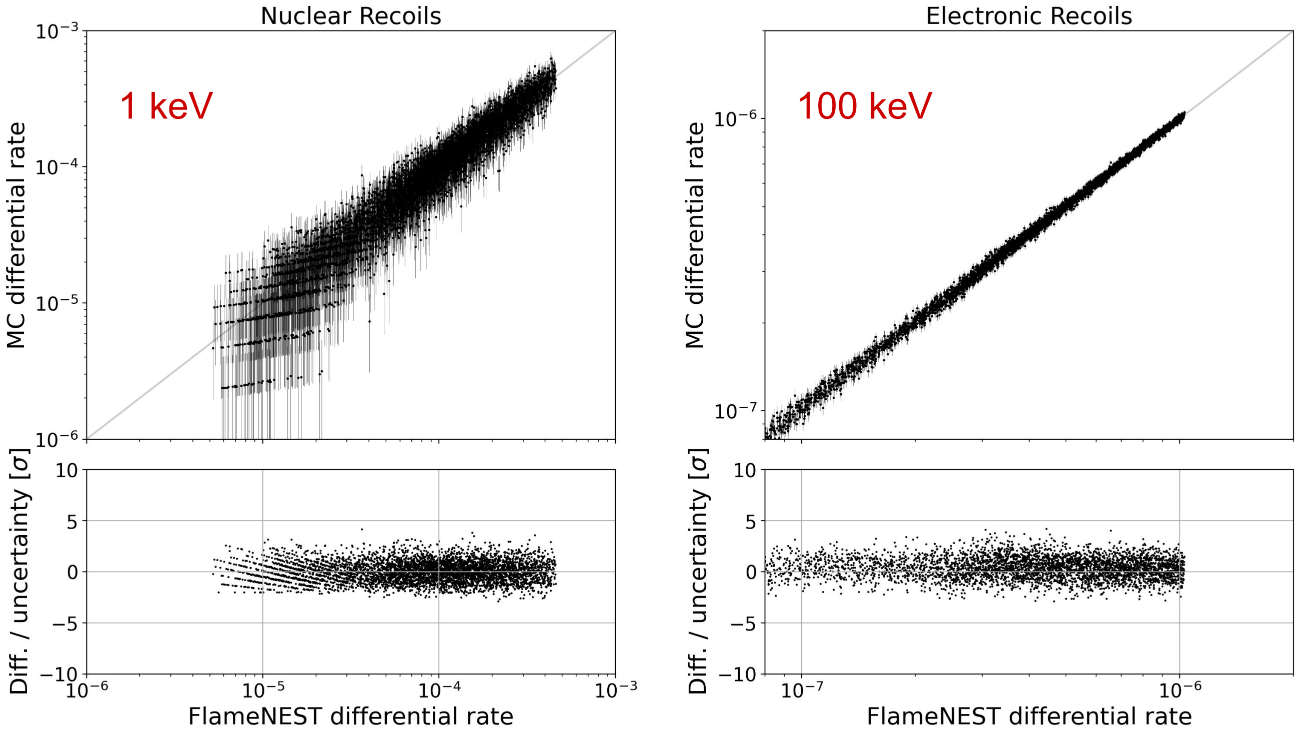
Obtain tensor bounds for a block's "in" dimension by constructing posterior PDF using bounds for "out" dimension, evaluated over a range of "in" values.

Variable stepping (slides)

Enable extension to higher energy sources by scaling probability elements evaluated at stepped hidden variable values, enabling smaller tensor construction.



Validations



Methodology

- Fill S1/S2 histograms for sources at fixed (x,y,z,t) using NEST
- Count events in each bin - 'MC differential rate'
- Compute expected events at the bin's central (S1,S2) and the fixed (x,y,z,t) via FlameNEST - 'FlameNEST differential rate'
- Check they agree within statistical + binning errors from the MC

Outlook

- Publication in progress on the structure of the FlameNEST tensor structure and new computational features enabling it
- A little more work remaining to address certain nuances with doing the computation for general energy spectra
- Code will all be publicly available on the FLAMEDISX GitHub repository: link
- Looking forward to working with the noble element community to allow FlameNEST to be used for experiments extending beyond liquid xenon TPCs