A Bayesian analysis with Machine Learning in DM Direct Detection

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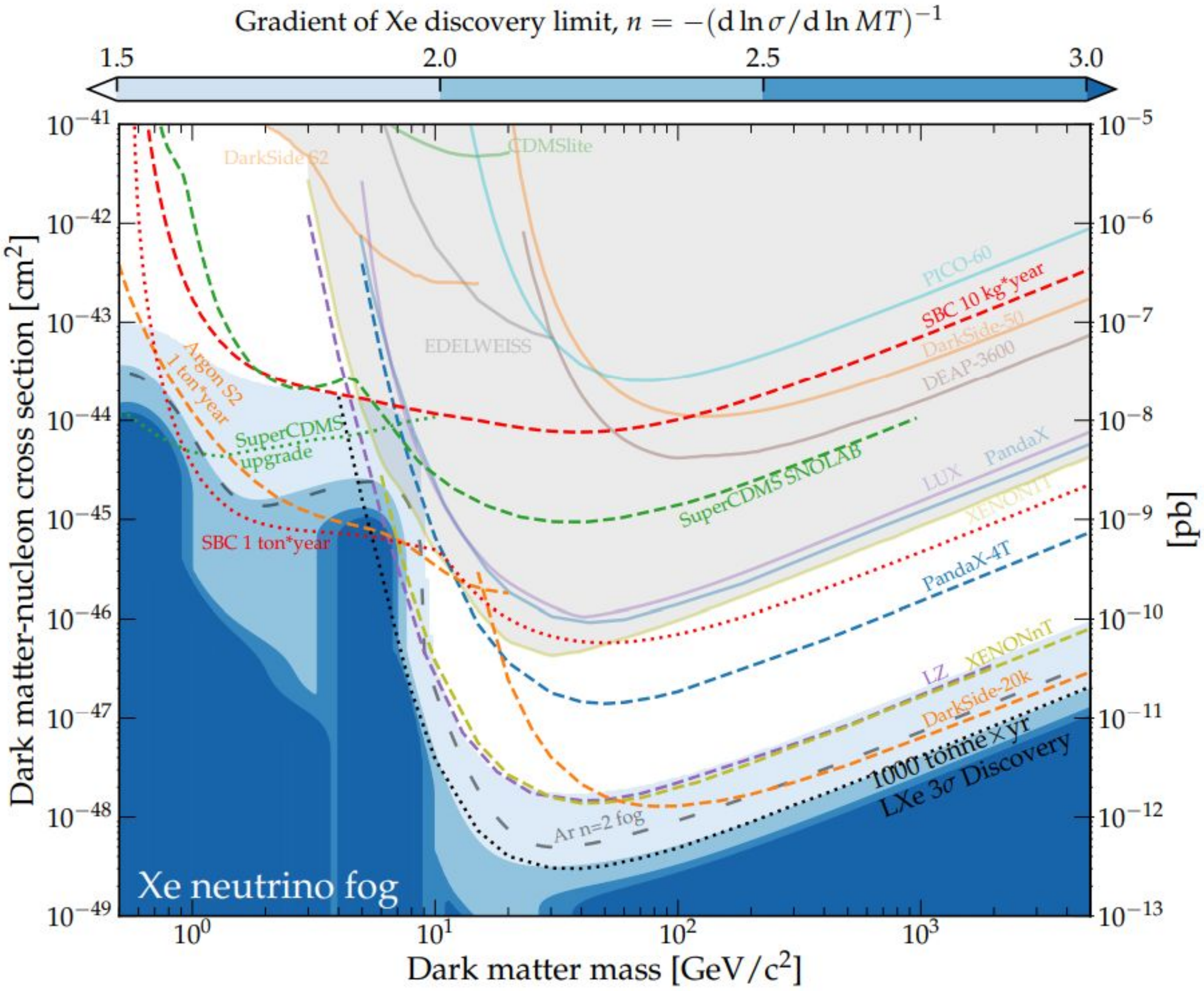
CSIC

EXCELENCIA SEVERO OCHOA



Gradient of Xe discovery limit, $n = -(\mathrm{d}\ln\sigma/\mathrm{d}\ln MT)^{-1}$
1.5
2.0
2.5
3.0
Dark matter-nucleon cross section [cm^2]
[pb]
Dark matter mass [GeV/c^2]
DarkSide G2
CDMSlite
EDELWEISS
PICO-60
SBC 10 kg*year
DarkSide-50
DEAP-3600
Argon S2 1 ton*year
SuperCDMS upgrade
SuperCDMS SNOLAB
LUX
PandaX
XENON1T
SBC 1 ton*year
PandaX-4T
LZ
XENONnT
DarkSide-20k
1000 tonne×yr
LXe 3σ Discovery
Ar n=2 fog
Xe neutrino fog

Outline

ML analysis to obtain posteriors

DM-nucleon interaction with NR-EFT

DM differential rate for a DD experiment

Simulate the expected signal

Parameter space that can be reconstructed

Machine Learning
Bayesian Analysis

Bayesian Analysis

$$P(\theta|x) = P(x|\theta) \quad P(\theta) \;/\; P(x)$$

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Posterior probability of the parameters θ of interest given the data x.

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Prior probability of the parameters θ.

Bayesian Analysis

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Posterior probability of the parameters θ of interest given the data x.

Probability of the data x given the parameters θ.

Prior probability of the parameters θ.

Probability of the data x also call evidence.

Bayesian Analysis with Swyft

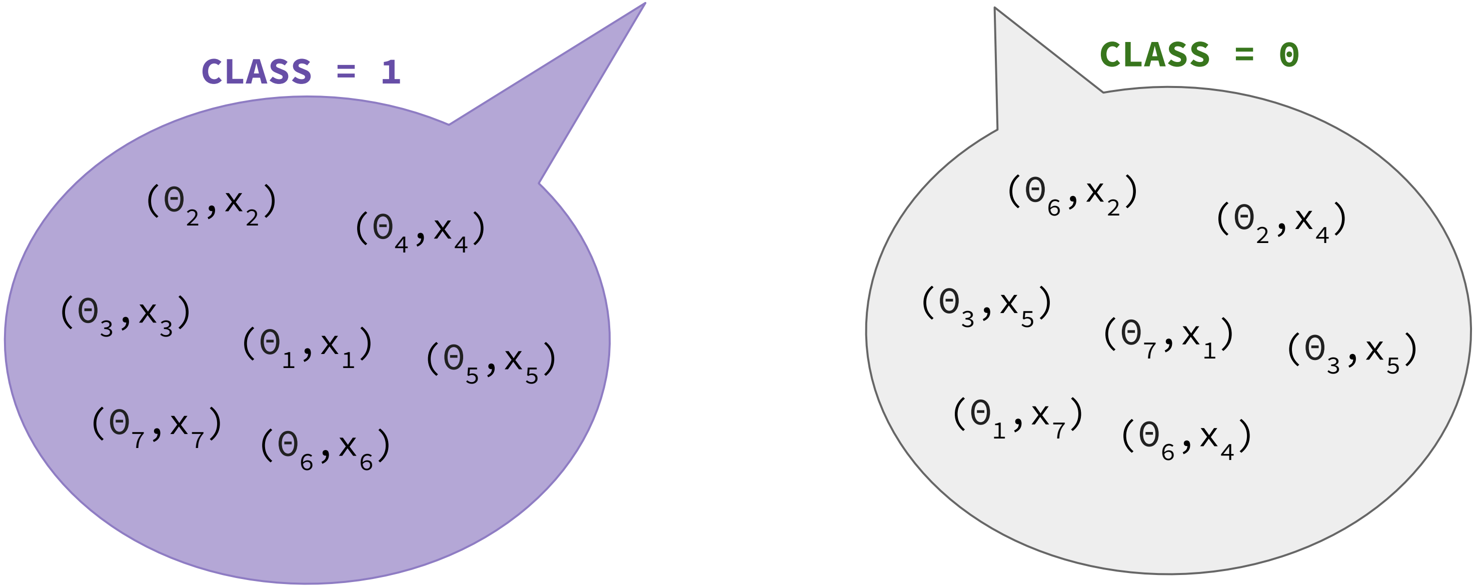
Marginal Neural Ratio Estimation

https://swyft.readthedocs.io/
https://arxiv.org/abs/2107.01214

$$r(\theta, x) \coloneqq P(\theta|x)/P(\theta) = P(x|\theta)/P(x) = P(x,\theta)/P(\theta)P(x)$$

Bayesian Analysis with SWYFT

$$r(\theta,x)=P(\theta,x)/P(\theta)P(x)$$



Bayesian Analysis with SWYFT

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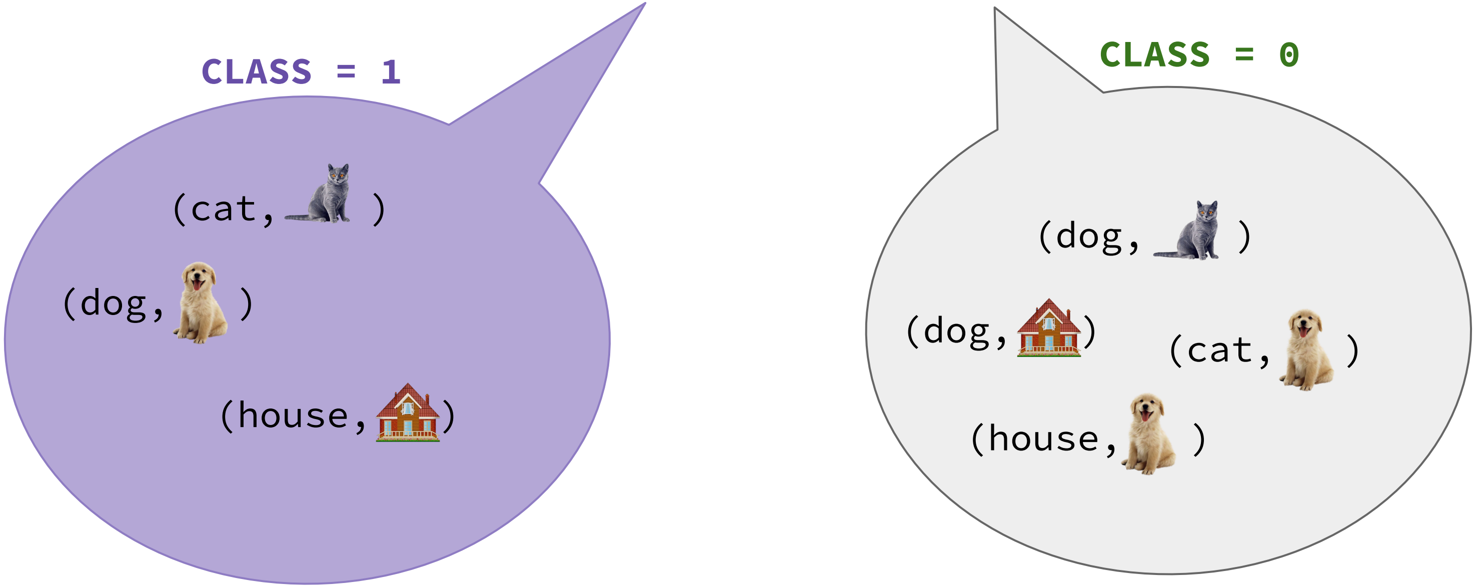
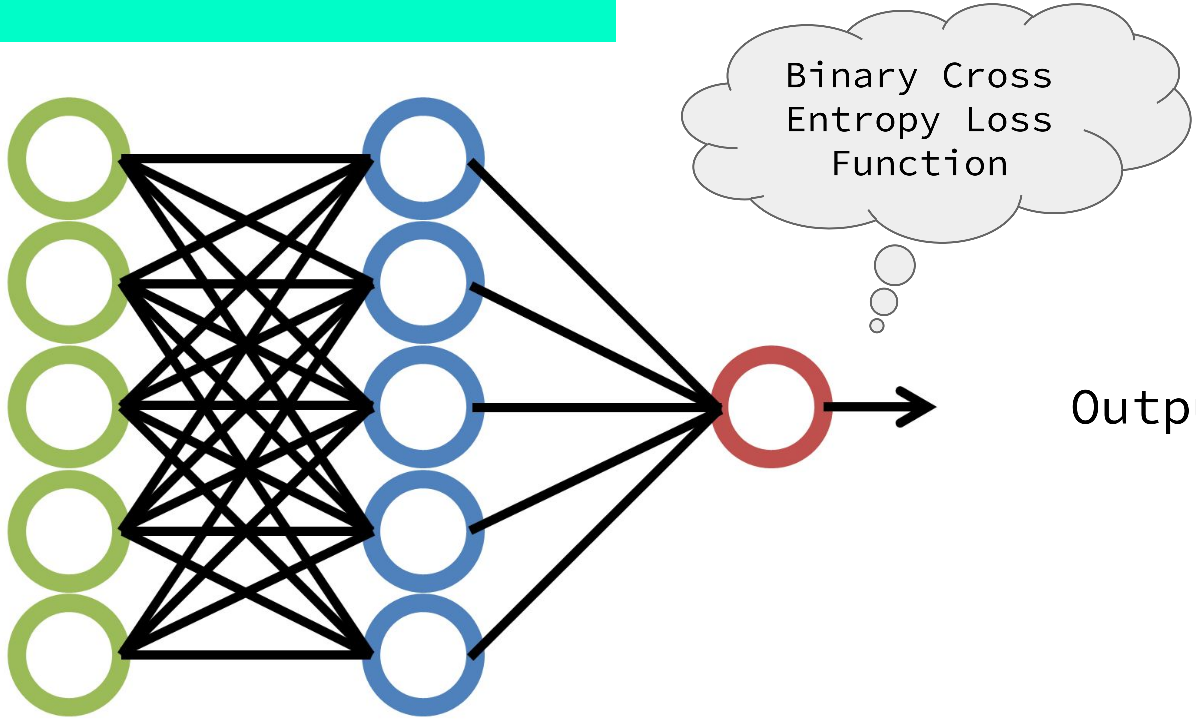
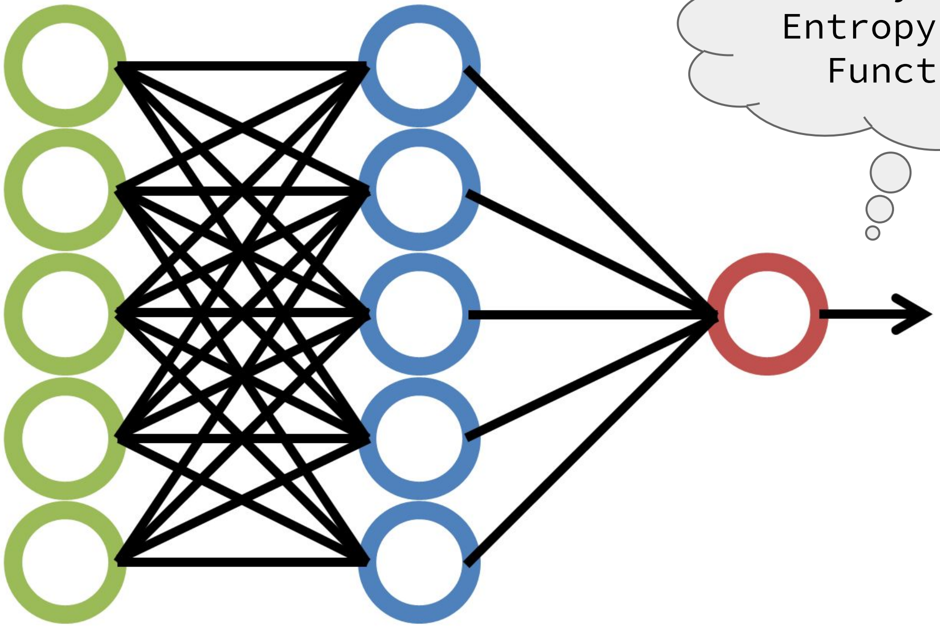


Binary Classification



Output = P(K=1|(Θ,X))

Binary Classification



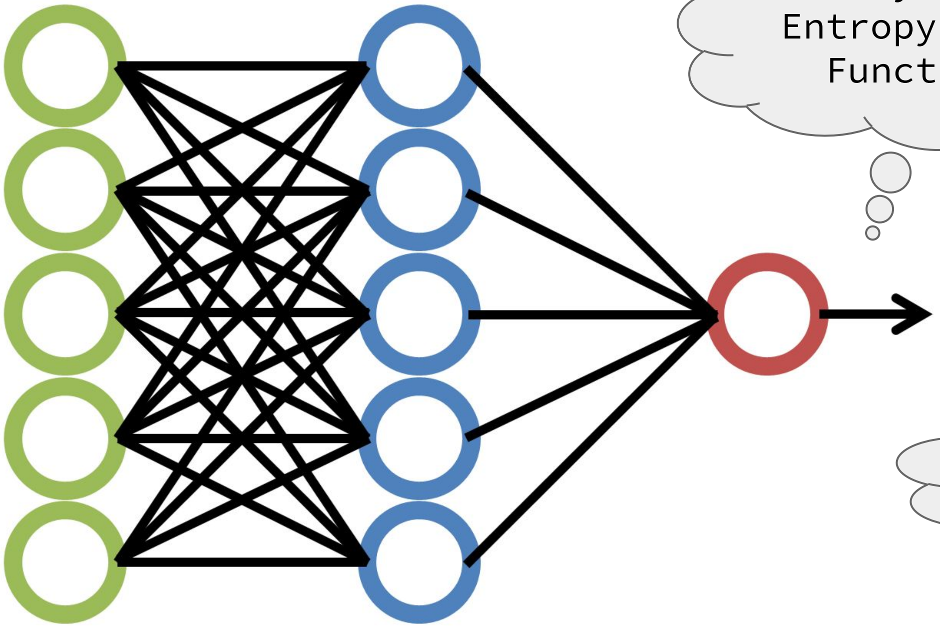
Binary Cross Entropy Loss Function

$P(k=0|(\Theta,x)) = 1-P(K=1|(\Theta,x))$

Class 0 => $P(x)P(\Theta)$

Output = $P(K=1|(\Theta,X))$

Binary Classification



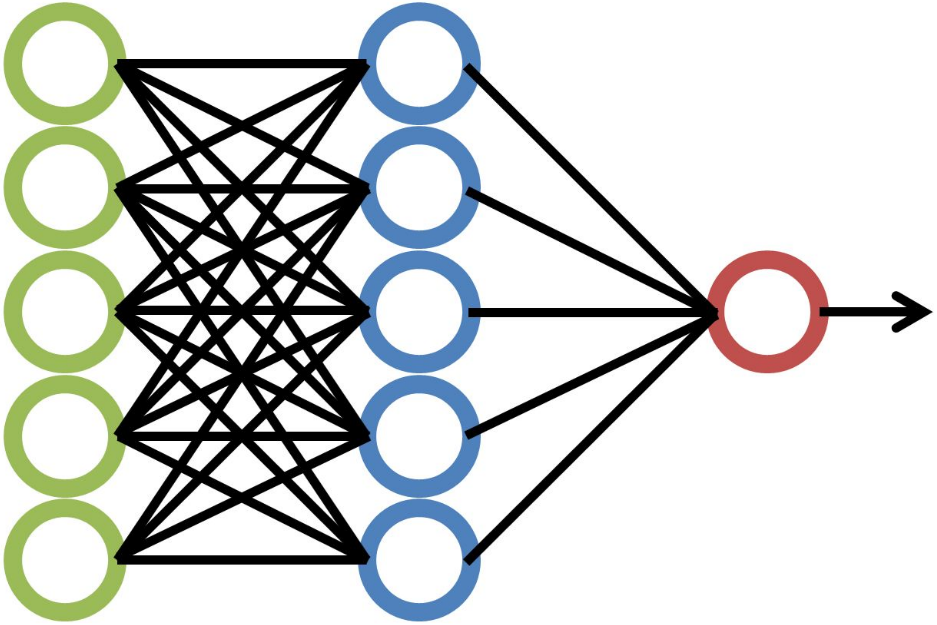
Binary Cross Entropy Loss Function

P(k=0|(θ,x)) = 1-P(K=1|(θ,x))
Class 0 => P(x)P(θ)

Output = P(K=1|(Θ,X))

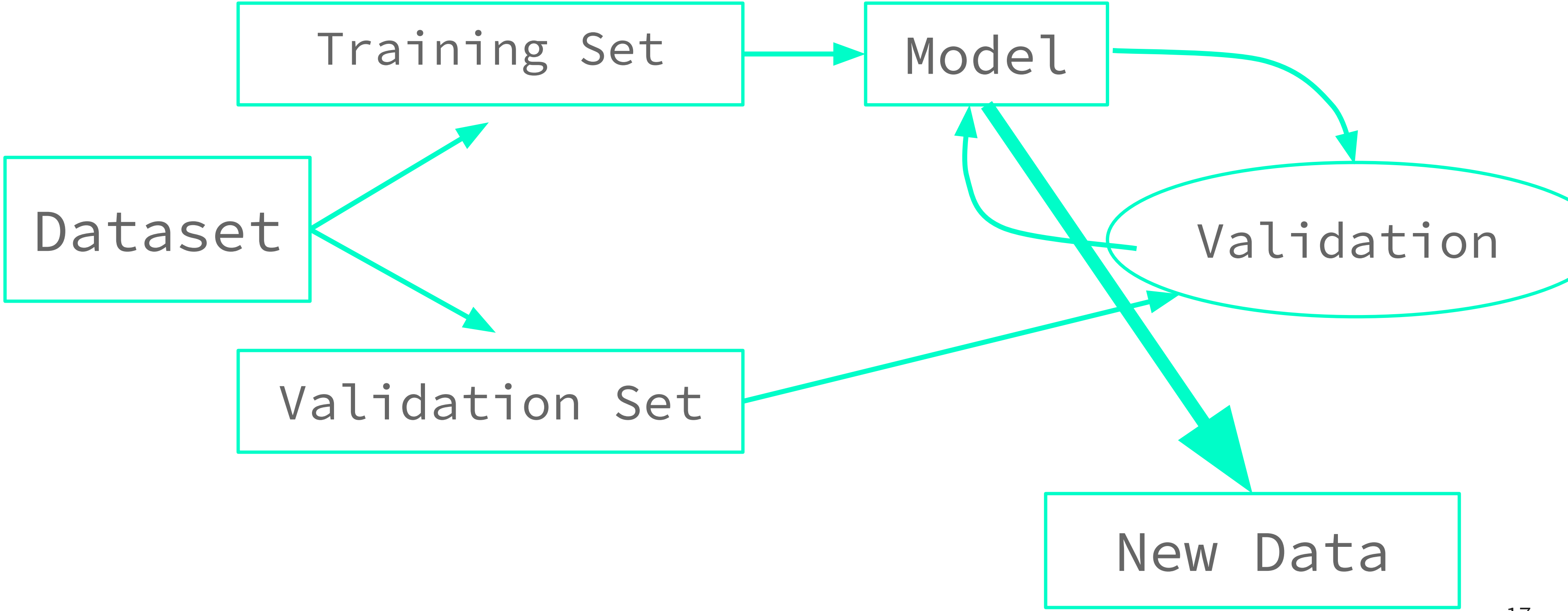
Class 1 => P(x,θ)

Binary Classification



P(K=1|(Θ,X)) = r(Θ,x)/[1+r(Θ,x)]

Supervised Learning



So...

1) We measure some data x

2) We sample model parameters θ from prior $P(\theta)$

3) We feed the neural network with pairs (x,θ), and the network gives back de $r(\theta,x)$

4) We multiply $r(\theta,x)$ by $P(\theta)$ and obtain $P(\theta|x)$

- In our case the parameters of interest will

  be the EFT parameters and the DM mass.

- In our case, the data x will be the signal measured by XENONnT, this can be:
    - The total number of events.
    - The differential rate.
    - The full s1-s2 plane.
    - We also add all the relevant

      backgrounds, including Ceνns

Data sample generation

DM-nucleon non-relativistic effective field theory (NR-EFT)

For DM particles with spin up to ½ , the effective DM-nucleon scattering interaction Lagrangian

$$\mathcal{L}_{\rm EFT} = \sum_{\tau} \sum_{i} c_i^{\tau} \mathcal{O}_i \overline{\chi} \chi \overline{\tau} \tau$$

nucleon basis:

c^p: proton

c^n: neutron

$$c_i^0 = \frac{1}{2}\left(c_i^p + c_i^n\right)$$

$$c_i^1 = \frac{1}{2}\left(c_i^p - c_i^n\right)$$

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i=14
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O1:
spin-independent
O4:
spin-dependent

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Change to polar coordinates:

$$c_i^0 = \frac{1}{2}\left(c_i^p + c_i^n\right) = A_i \sin(\theta_i)$$

$$c_i^1 = \frac{1}{2}\left(c_i^p - c_i^n\right) = A_i \cos(\theta_i)$$

Natural choice for the EFT parameter space because the interaction cross section:

$$\sigma_i \propto A_i^2$$

For SI (O1) $$\sigma_{\chi N}^{SI} = \frac{A_1^2\ \mu_{\chi N}^2}{\pi}$$

DM-nucleon reduced mass

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For each operator 2 parameters:

- amplitude (cross-section)
- phase

+ DM mass

(σ_i, θ_i, m_{DM})

DM Differential rate

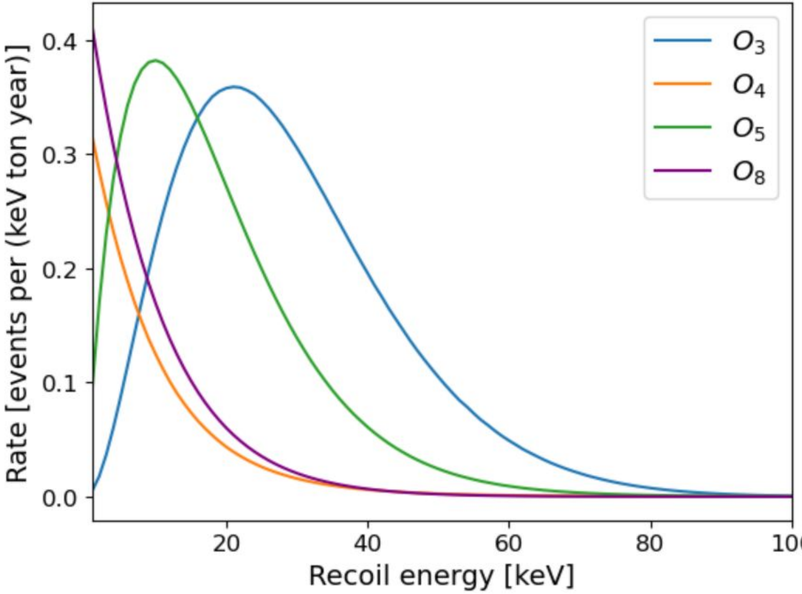
https://wimpydd.hepforge.org/
https://arxiv.org/abs/2106.06207

From NR-EFT operators to differential rate with WimPyDD

Inputs:

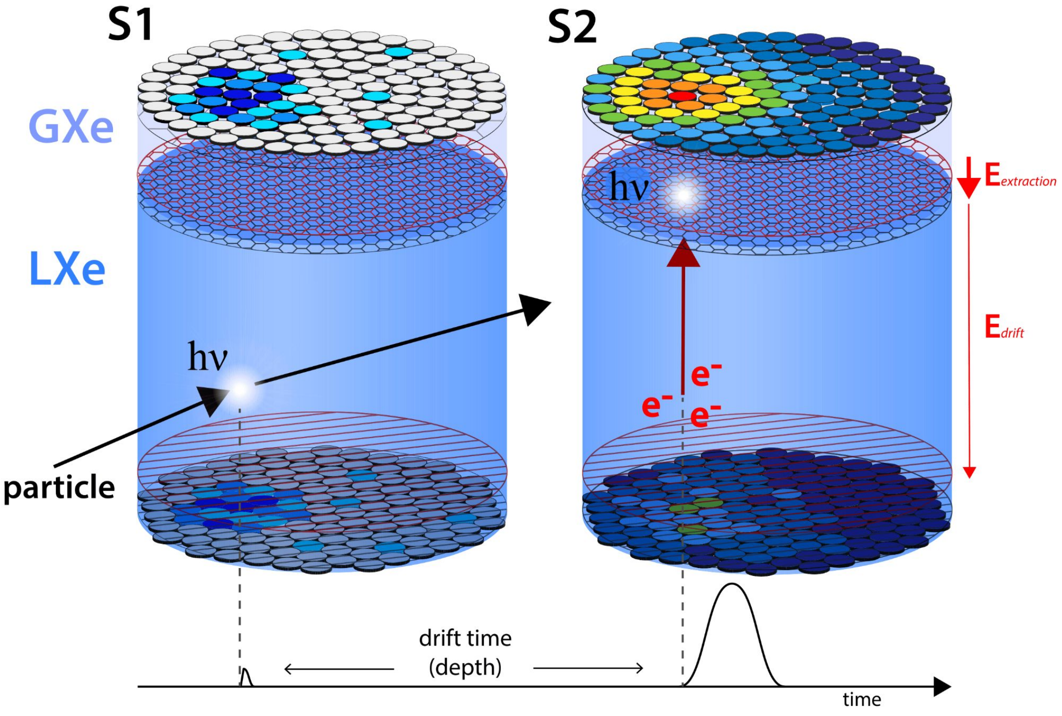
- Operator
- Parameters:
  - amplitude (cross-section)
  - phase
  - DM mass
- DM halo model
- DD experiment (XENONnT)

Output:

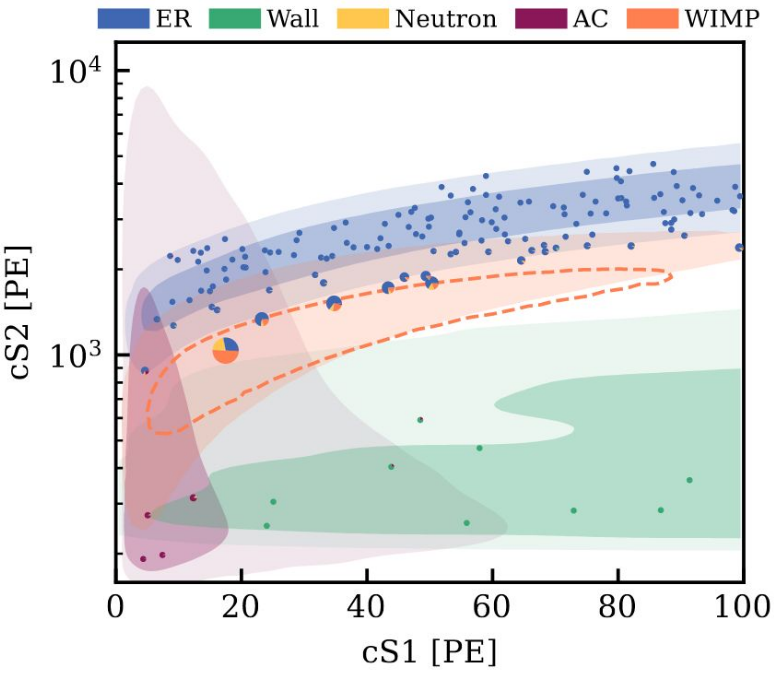


DM signal

XENONnT



Universe **2021**, *7*(8), 313

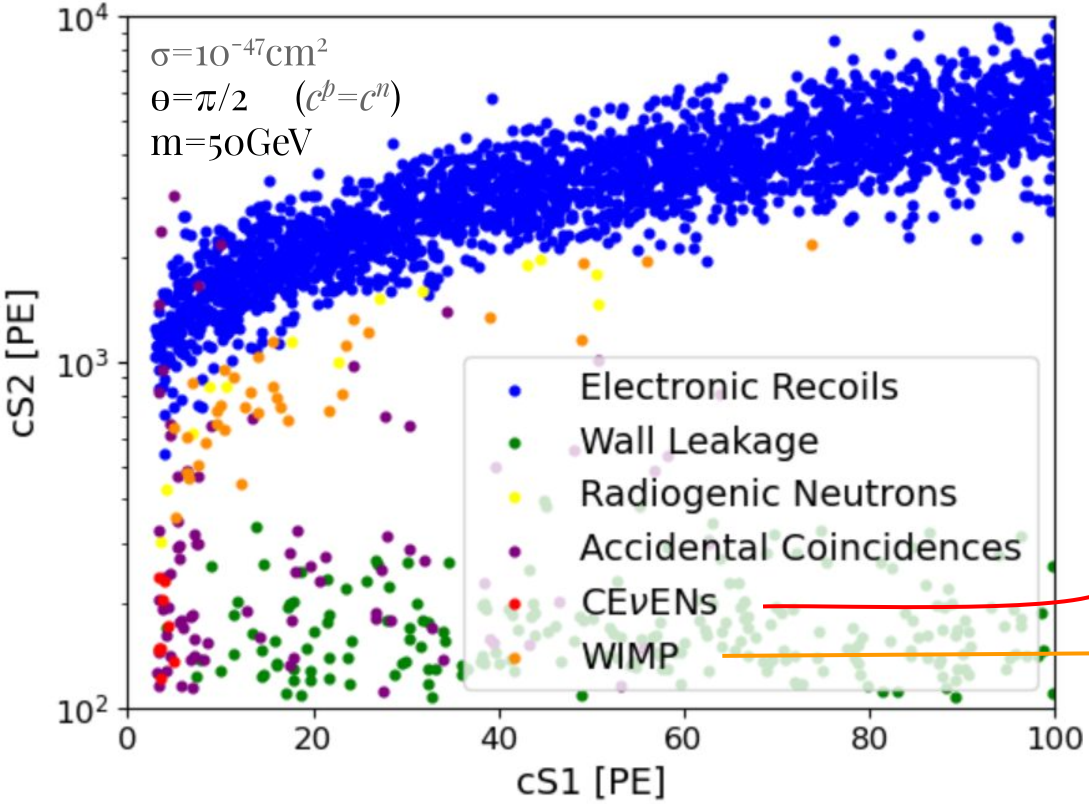


Phys. Rev. Lett. 131, 041003 (2023)

DM signal

XENONnT 20ty

NR-EFT: O1



XENONnT simulator

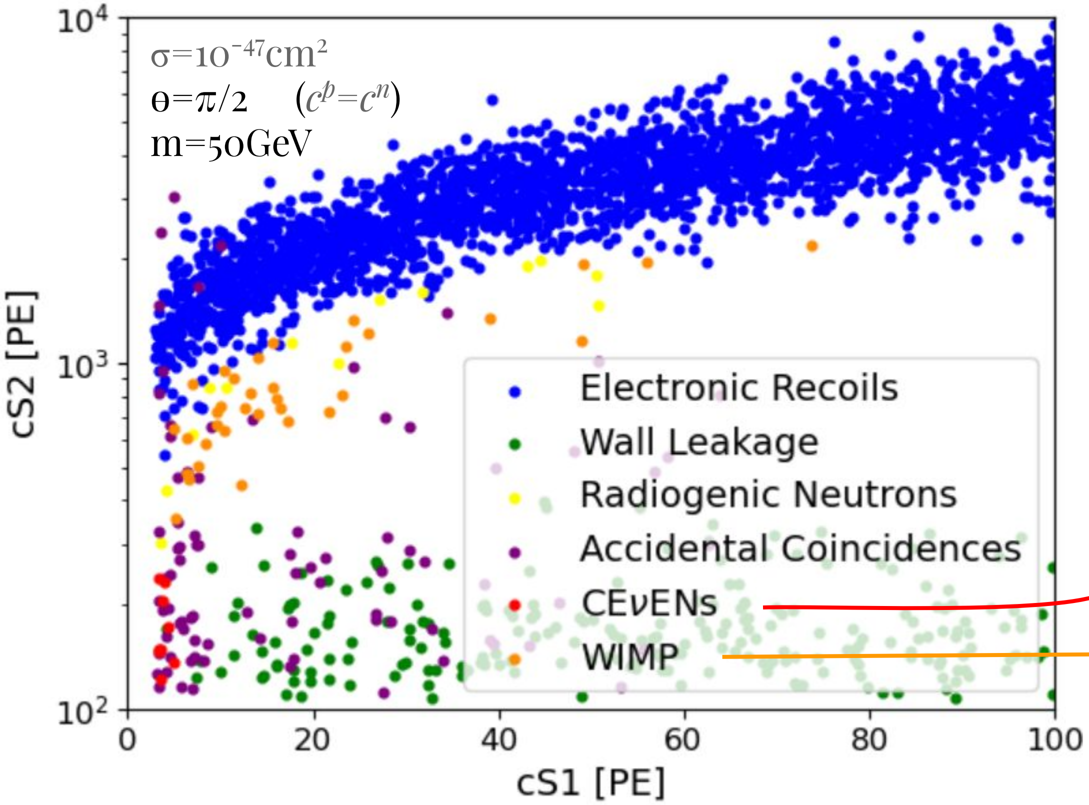
We specify background and signal characteristics

differential rate compute with SnuDD

differential rate compute with WimPyDD for a particular operator, amplitud, phase and DM mass.

DM SIGNAL

NR-EFT: O1



XENONnT simulator

We specify background and signal cha…

https://github.com/SNuDD/SNuDD
https://arxiv.org/abs/2302.12846

differential rate compute with SnuDD

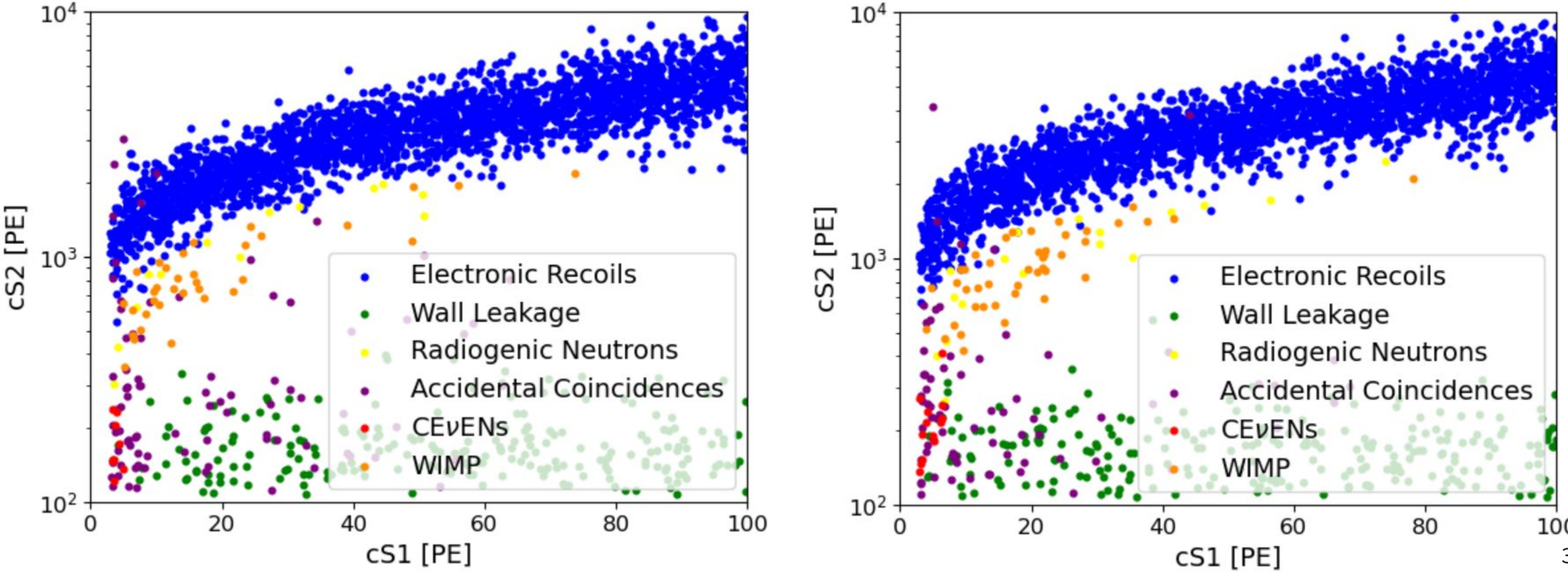
differential rate compute with WimPyDD for a particular operator, amplitud, phase and DM mass.

Data Representation: S1 vs S2 plane

XENONnT 20ty

We generate a 10k pseudo experiments per operator varying σ, θ, and m_{DM}

NR-EFT: O1
$\sigma = 10^{-47} cm^2$
$\theta = \pi/2 \quad (c^p = c^n)$
m=50GeV



Data Representation: number of events

NR-EFT: O1

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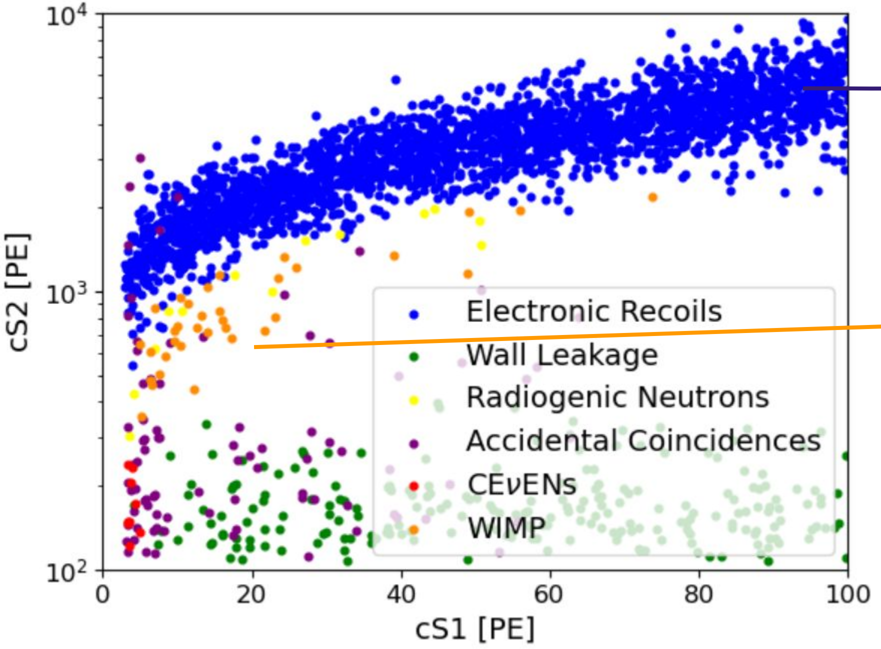
$\theta = \pi/2 \quad (c^p = c^n)$

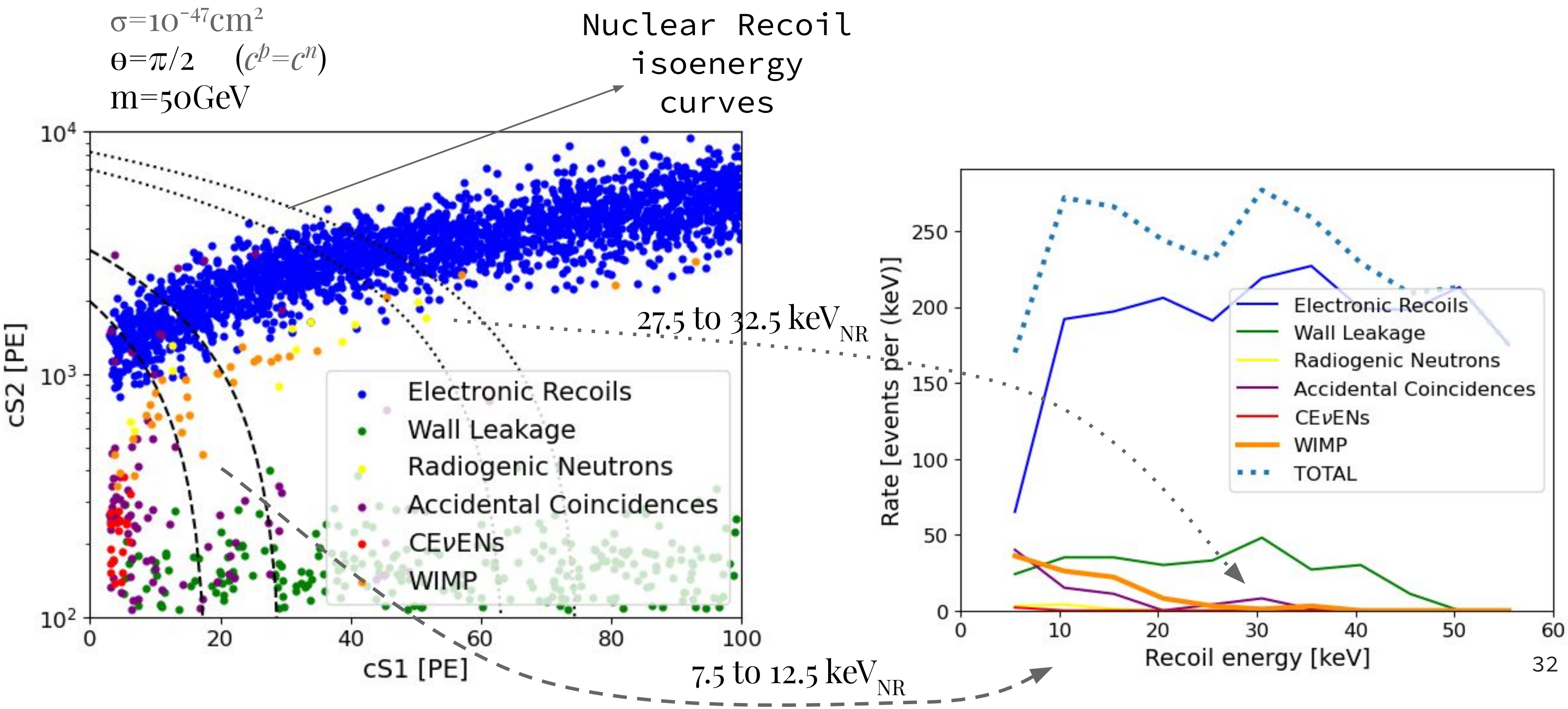
m=50GeV



	name	pseudo_exp_events
0	er	2459
1	radiogenics	17
2	ac	71
3	wall	246
4	WIMP	43
5	CEVNS-SM	13

Data Representation: differential rate

NR-EFT: O1
$\sigma=10^{-47}\text{cm}^2$
$\theta=\pi/2 \quad (c^p=c^n)$
m=50GeV



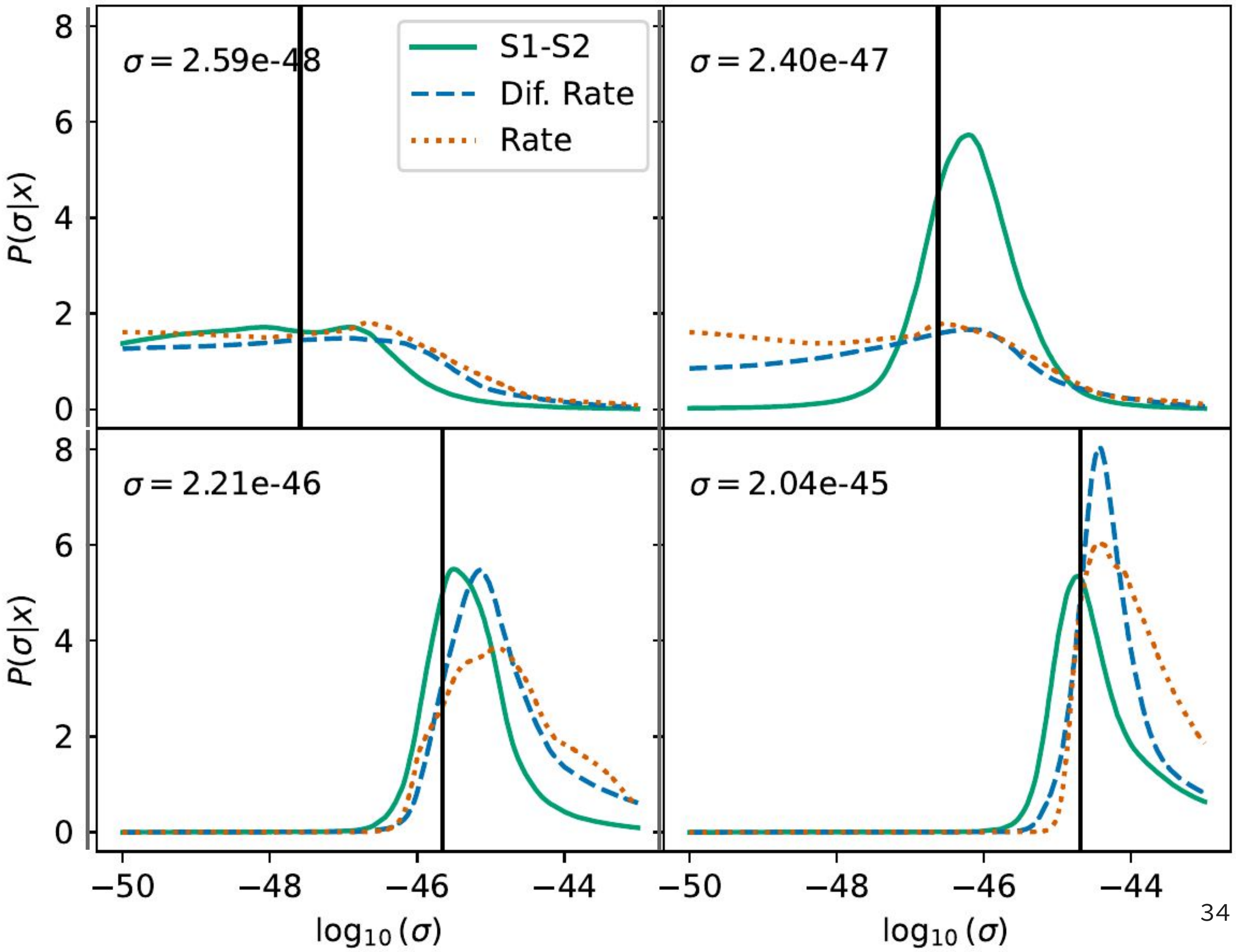
Results

Results

Data:

S1 vs S2 plane
differential rate
total number of events

examples with
O1 (SI)
$m_{DM} \simeq 100$ GeV $\longrightarrow$ fixed
$\theta = \pi/2$ $\longrightarrow$ fixed



Results

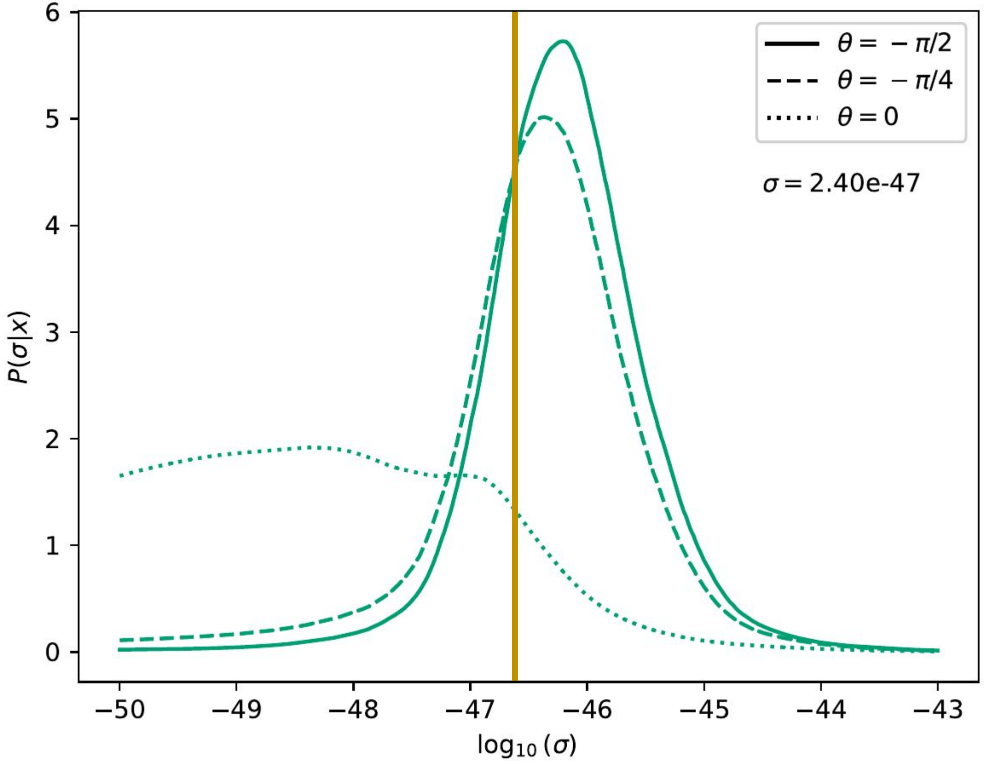
Data:

S1 vs S2 plane

These are all the posteriors for

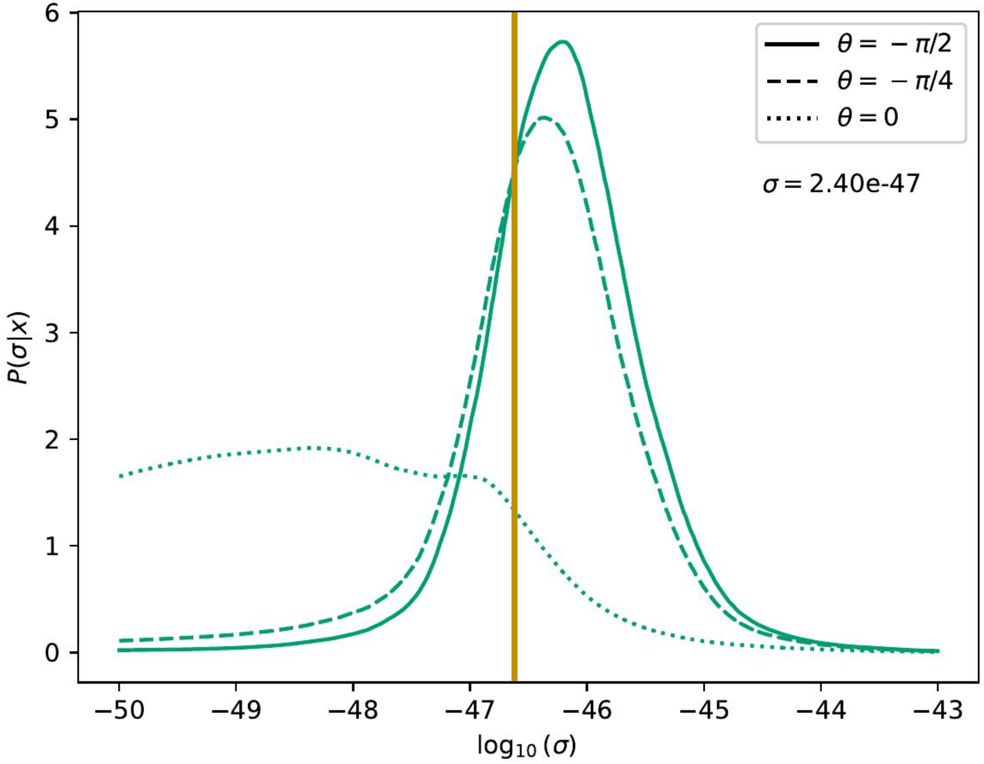
O1 (SI)
$m_{DM} \simeq 100$GeV $\longrightarrow$ fixed
$\sigma = 2.4\ 10^{-47} cm^2$ $\longrightarrow$ fixed

S1 vs S2



Results

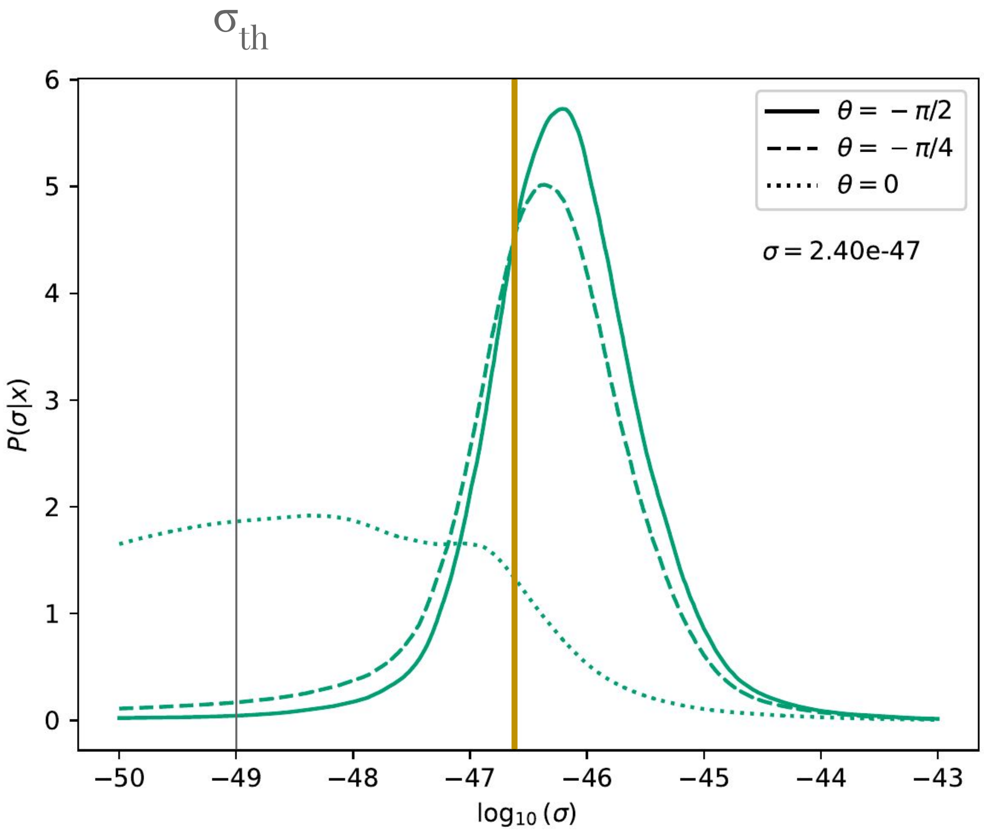
S1 vs S2



Results

S1 vs S2

threshold:
$\sigma_{th}=10^{-49}cm^2$



Results

S1 vs S2

threshold:
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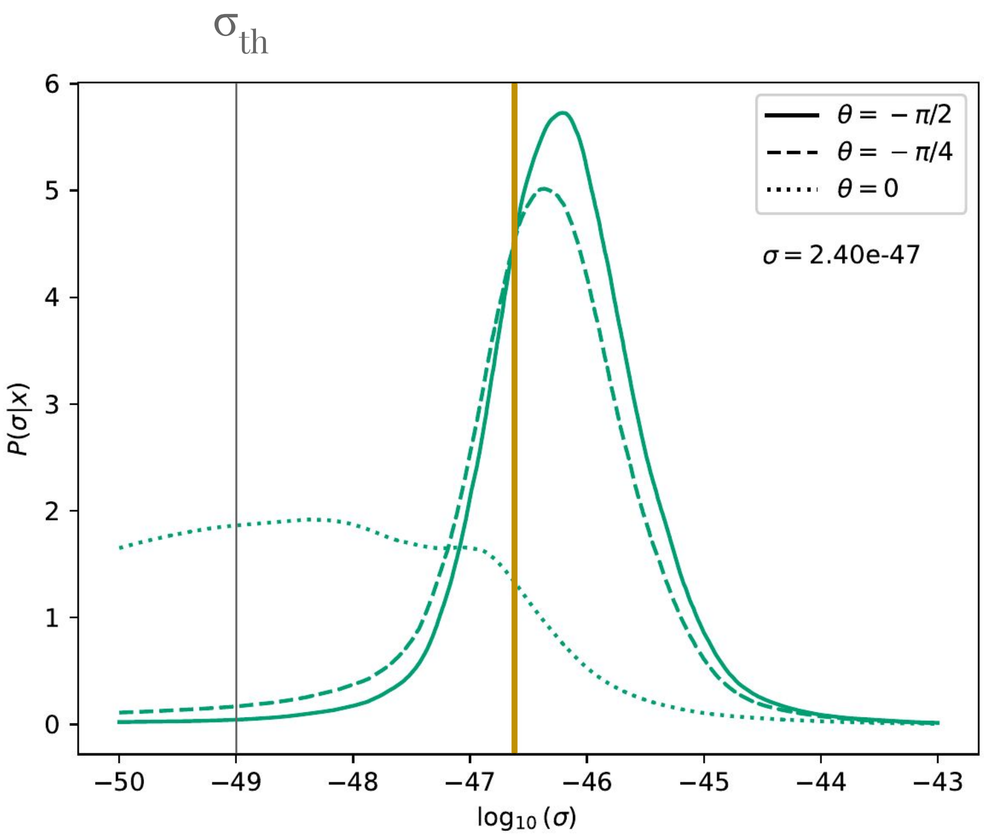
$$\int_{\sigma_{th}}^{inf} P(\sigma|x)$$



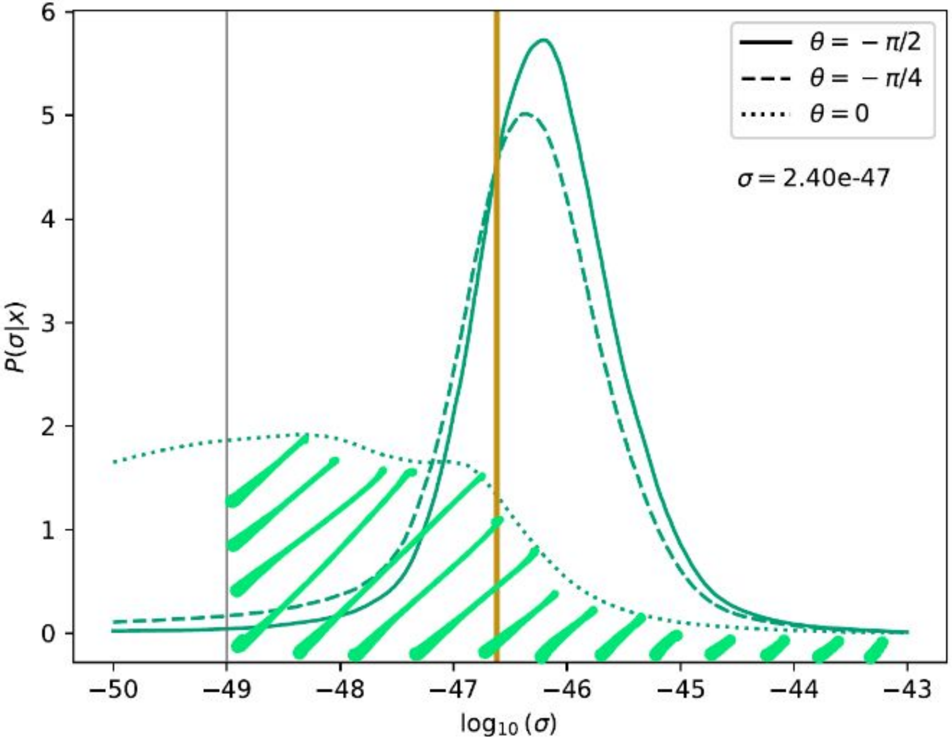
Results

S1 vs S2

σ_{th}

threshold:
$\sigma_{th}=10^{-49}cm^2$

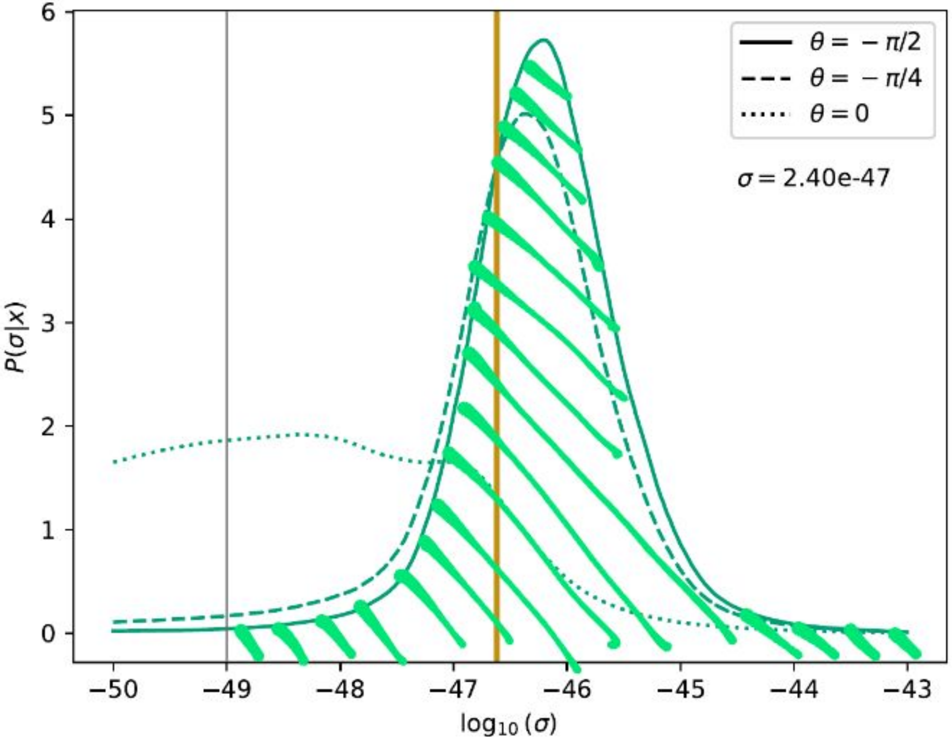
$$\int_{\sigma_{th}}^{inf} P(\sigma|x) < 0.90$$



Results

S1 vs S2

σ_{th}



threshold:
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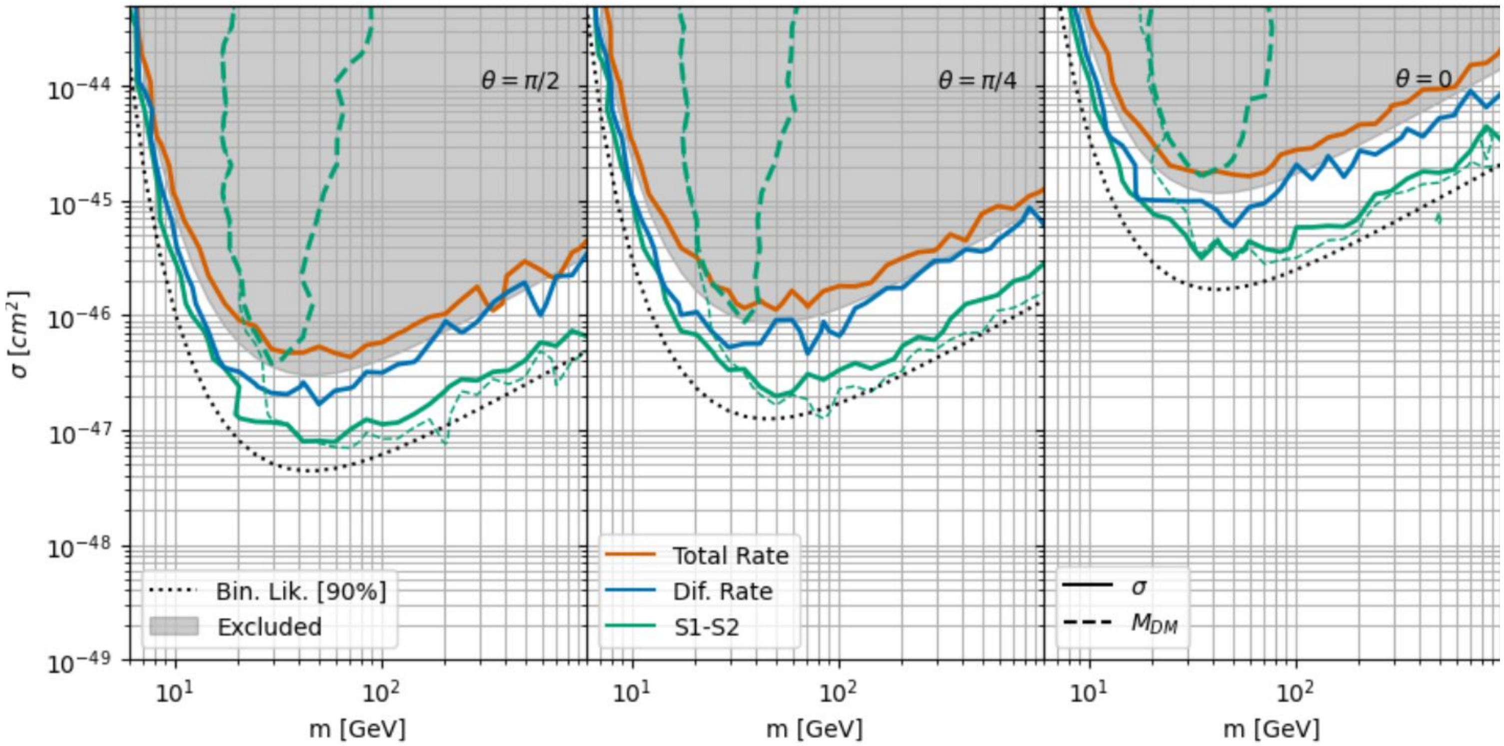
$$\int_{\sigma_{th}}^{inf} P(\sigma|x) > 0.90$$

Results: σ Detection plot

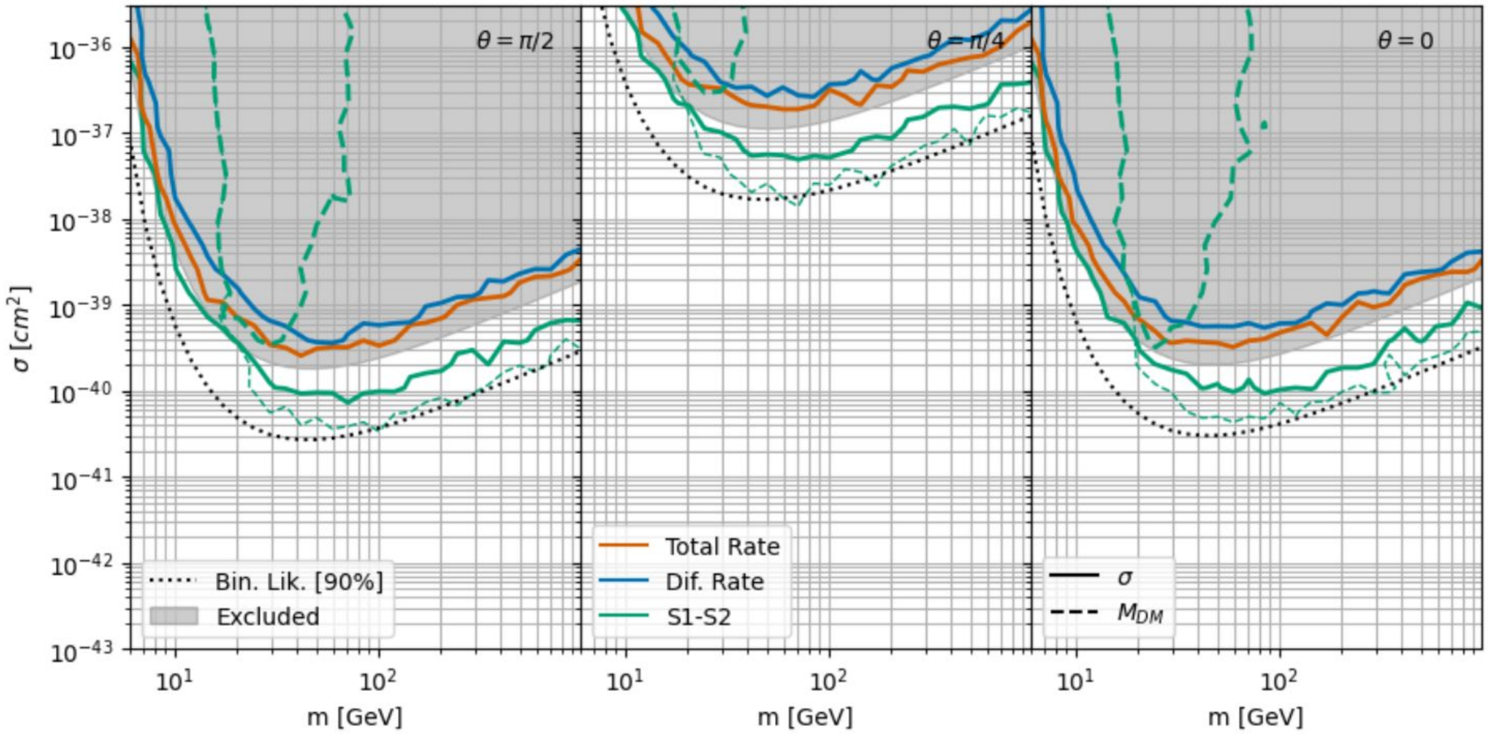
XENONnT 20ty
O1 operator



Data: total number of events
differential rate
S1 vs S2 plane

RESULTS: σ DETECTION PLOT

XENONnT 20ty
O4 operator



Data: total number of events
differential rate
S1 vs S2 plane

Conclusions

Conclusions

- We developed a bayesian analysis to explore the reach of direct detection experiments.
- The ML implementation (SWYFT) is fundamental for estimating the posteriors in a fast way.
- We presented here O1 (SI) & O4 (SD) as first examples.

- We computed the parameter space where σ and m can be reconstructed.

- We compared: total number of events vs the differential rate vs the full S1-S2 space.

NEXT...

- Apply to other NR-EFT operators $\longrightarrow$ combine operators
- Different DD experiments $\longrightarrow$ combine experiments
- Compare with MCMC analysis.

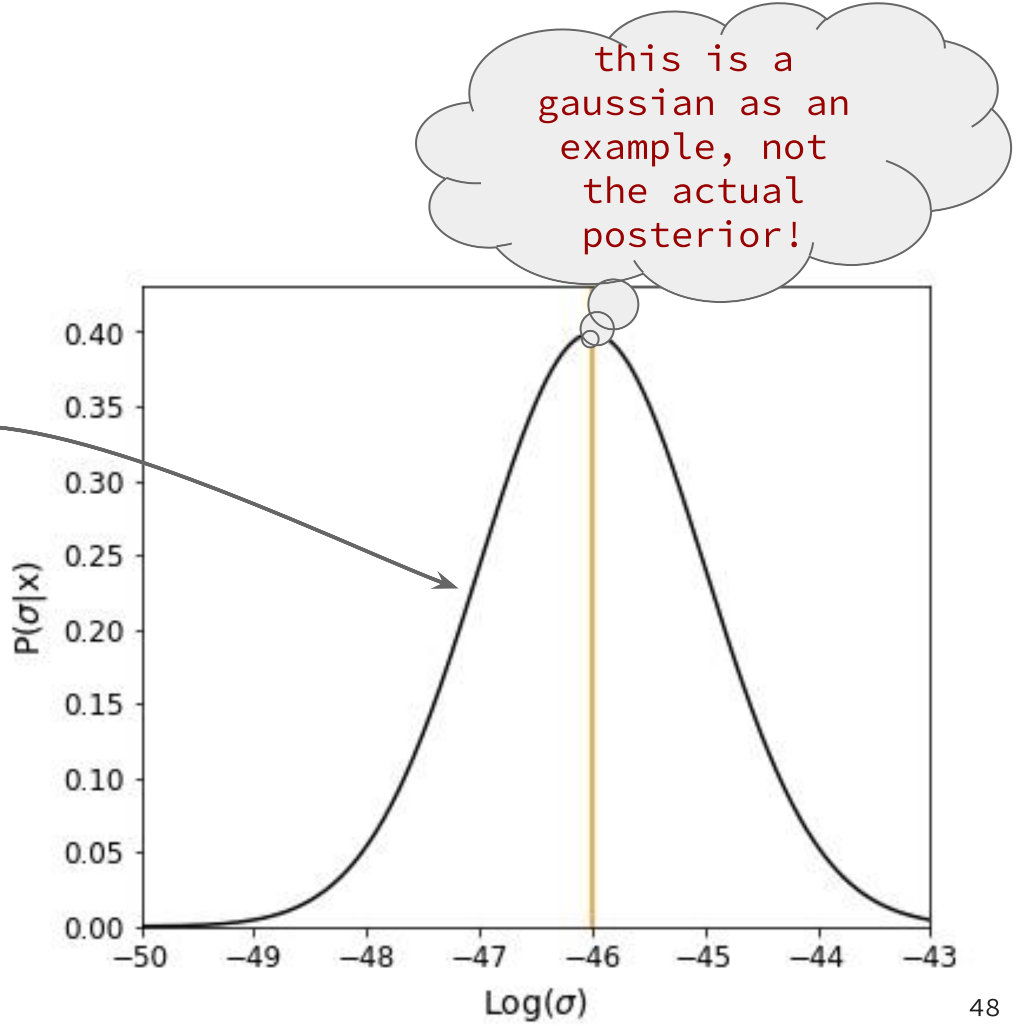

THANK YOU

Back-up

Reconstruction of parameters

Once we trained SWYFT we can compute the posterior for any new pseudo experiment

For example $P(\sigma|x)$



RECONSTRUCTION OF PARAMETERS

this is a gaussian as an example, not the actual posterior!

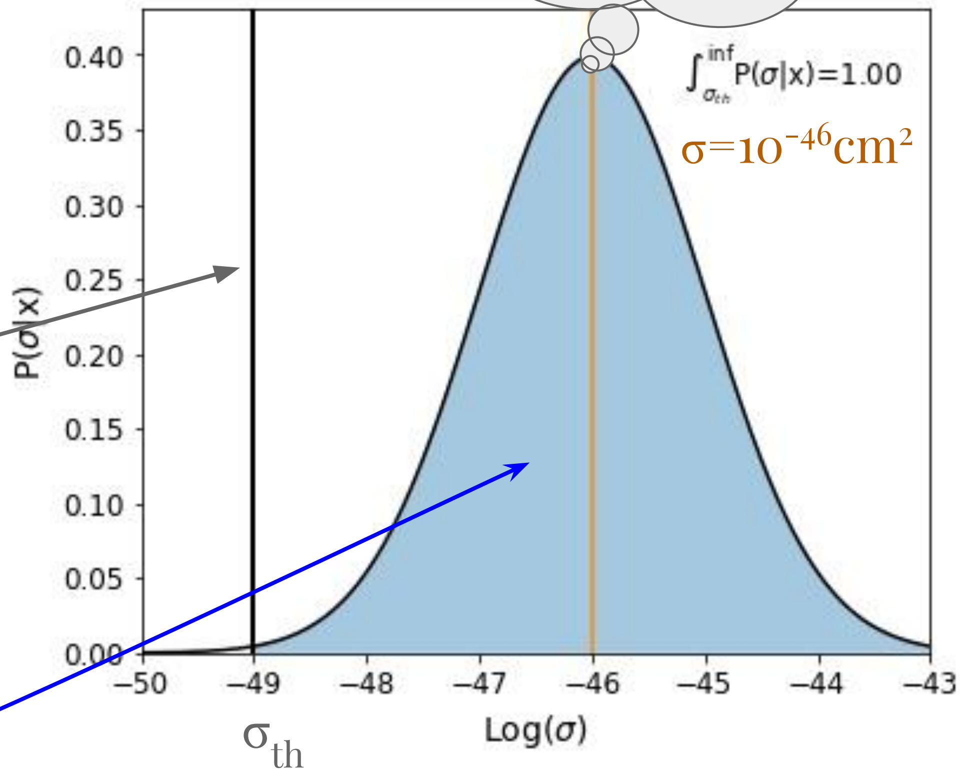
Once we trained SWYFT we can compute the posterior for any new pseudo experiment

We define a σ_{th} threshold:

$\sigma_{th}=10^{-49}cm^2 \longrightarrow$ NO SIGNAL!

Then, we can *reconstruct* σ if:

$$\int_{\sigma_{th}}^{inf} P(\sigma|x)>0.90$$



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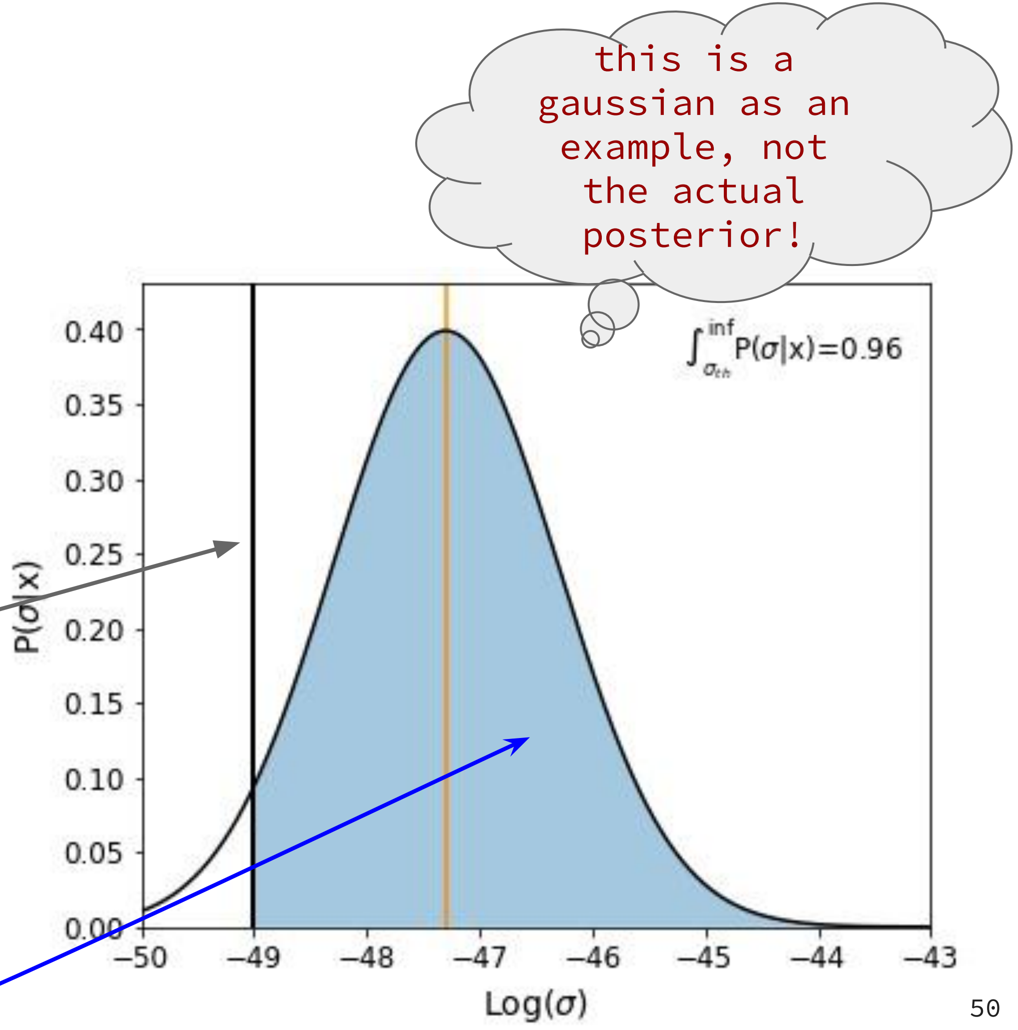

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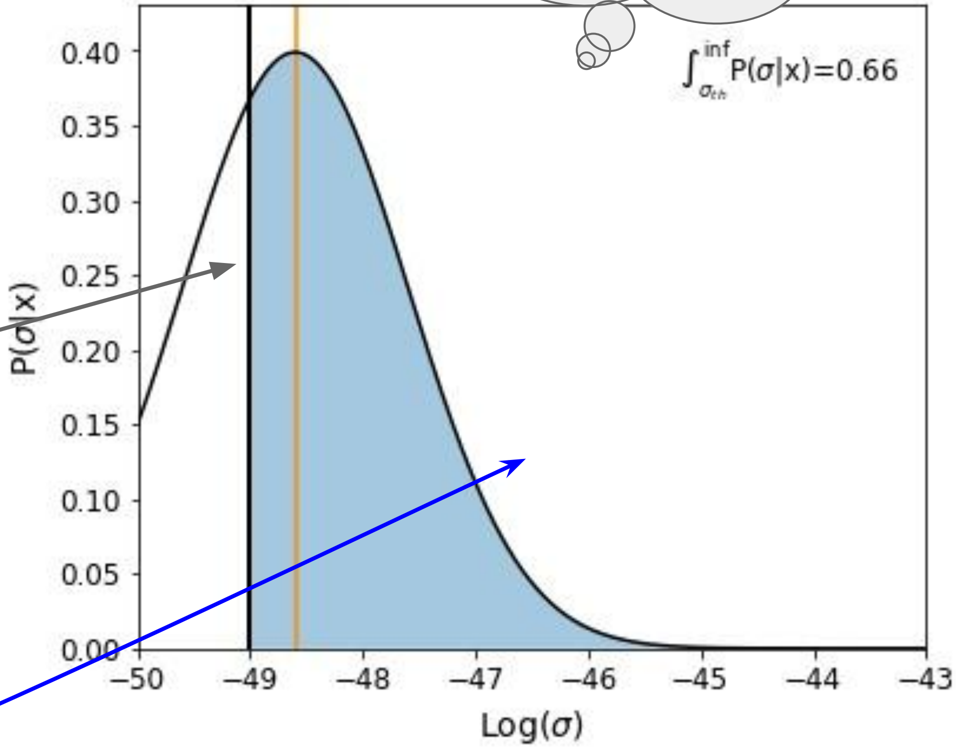
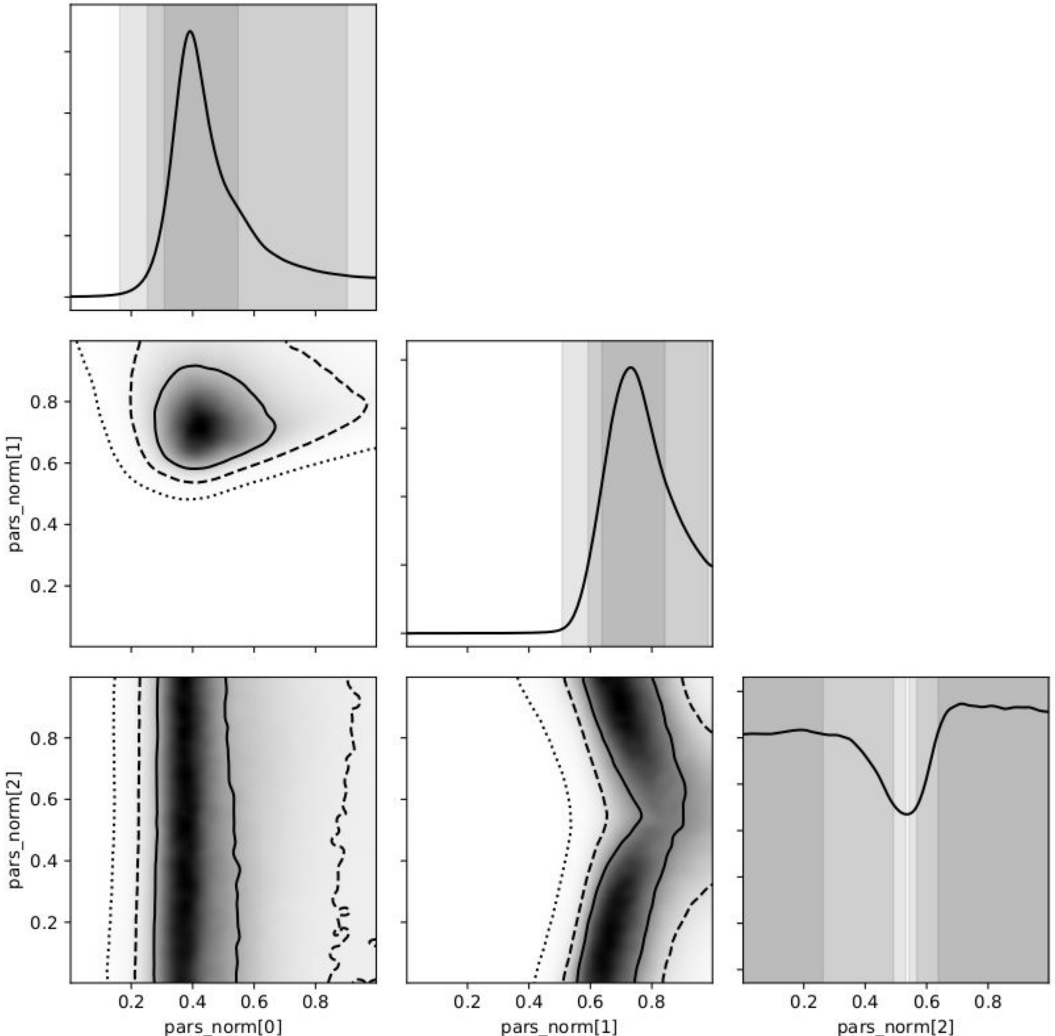
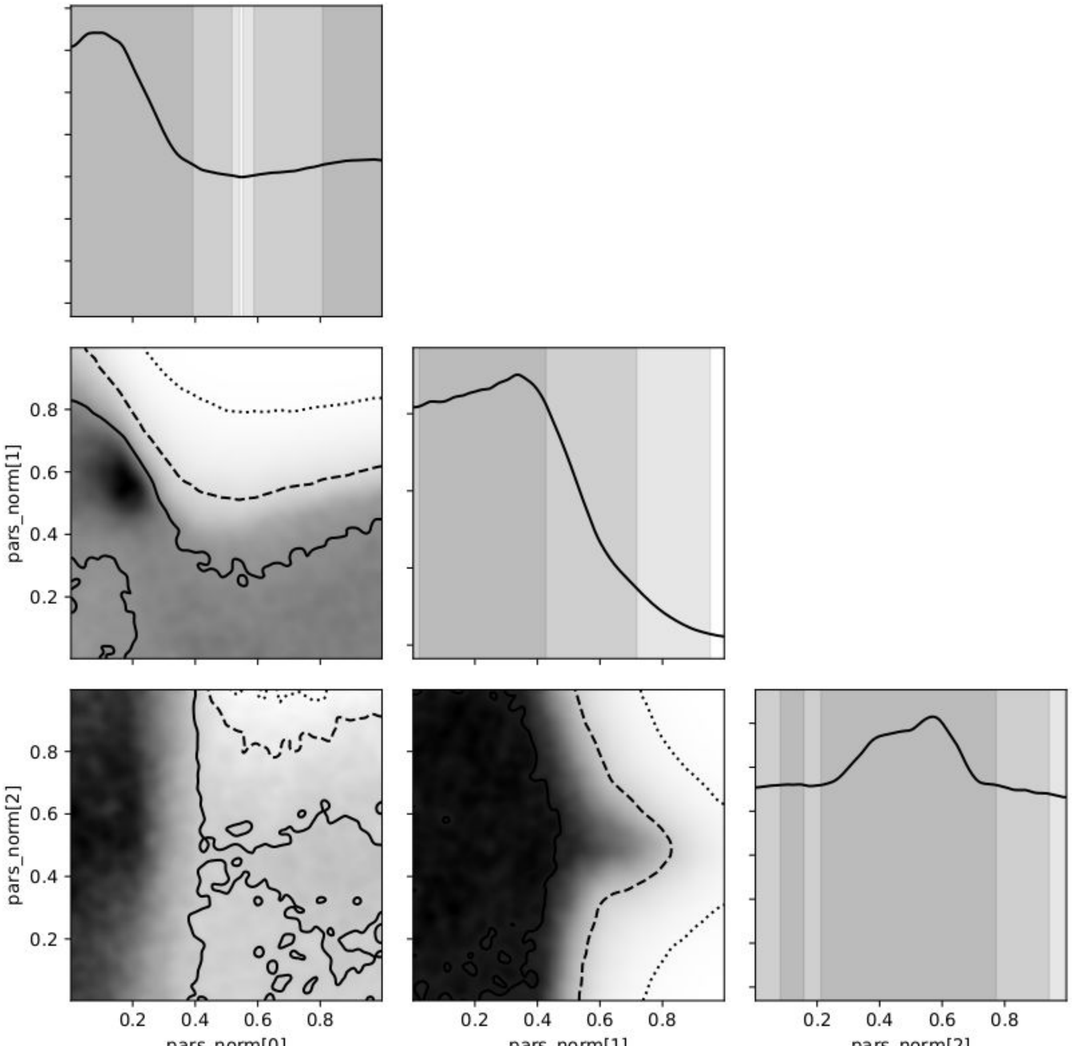


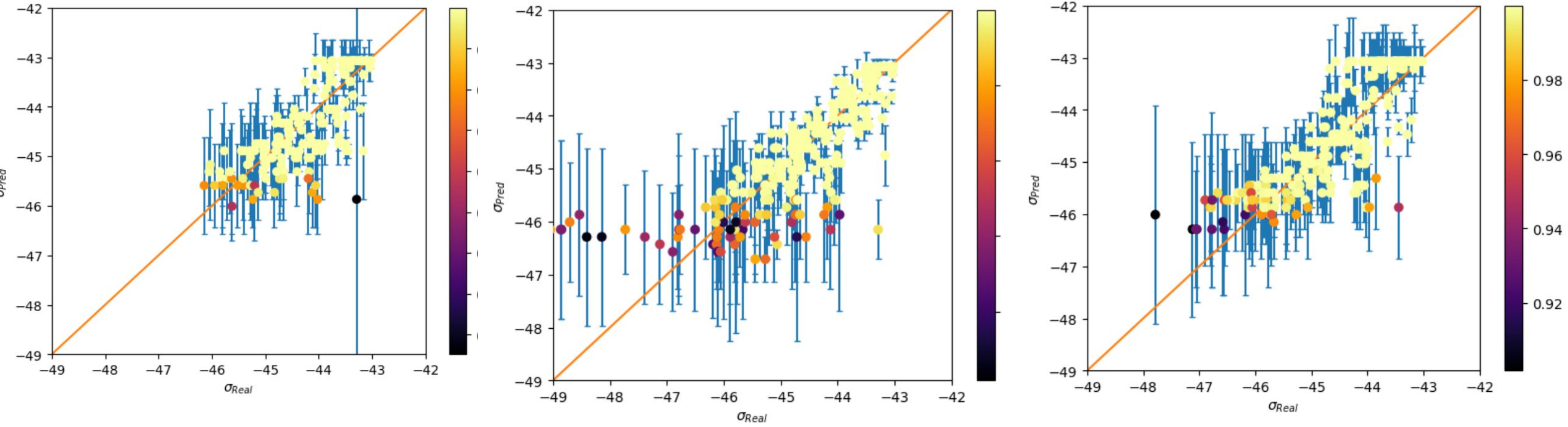
2D Posterior. Discovery s1-s2 (01)



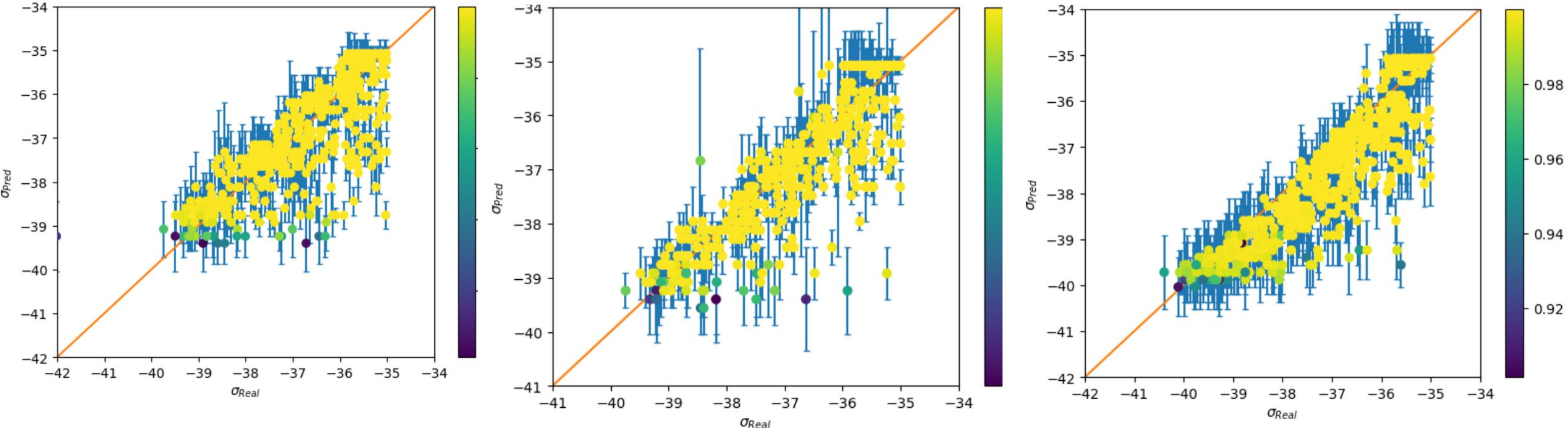
2D Posterior. Exclusion s1-s2 (01)



01 uncertainties

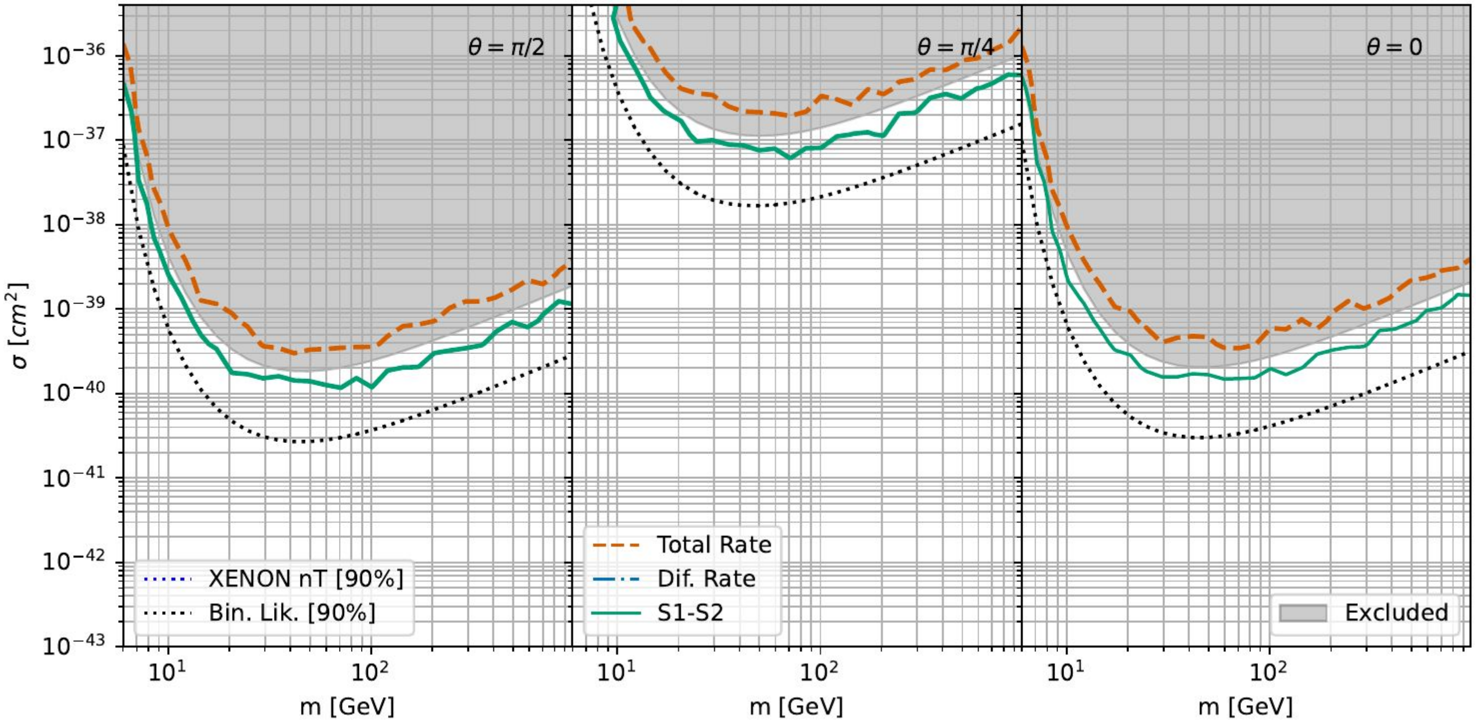


04 uncertainties



Results: σ reconstruction plot

XENONnT 20ty
O11 operator



Data: total number of events
differential rate
S1 vs S2 plane