Reconstructing ALP properties from inaccurate observations with ML

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based on [2308.01353]

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Inverse problem in high-energy physics

Simulation: ✓

BSM parameters $\theta \longrightarrow$ detector measurements x

Inference: ✗

(real) detector measurements $x \longrightarrow$ BSM parameters θ

Why is it complicated? **No direct access to likelihood**

For instance at LHC:

$$p(x|\theta) = \int \mathrm{d}z_d \int \mathrm{d}z_s \int \mathrm{d}z_p \, p(x|z_d)\, p(z_d|z_s)\, p(z_s|z_p)\, p(z_p|\theta)$$

Beam-dump experiments at ECN3

Lower energy, higher intensity:

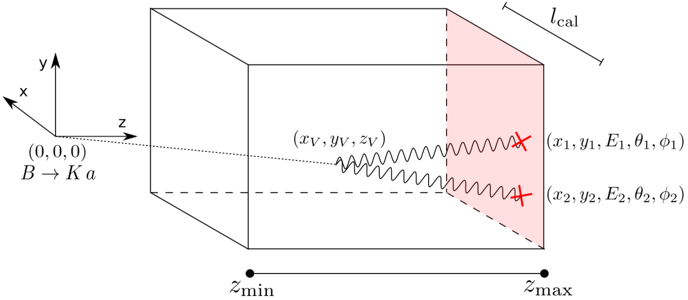
- sensitivity to $m \lesssim 4\,\text{GeV}$
- sensitivity to feebly interacting particles

Physical targets:
Looking for dark scalars, **axions/ALPs**, heavy neutral leptons

Different proposals under consideration [report]:

- HIKE/SHADOWS [letter of intent]
- SHiP [letter of intent]

Detector sketch and input variables



Geometry of the detector: $z_{\text{min}} = 10\text{m}, z_{\text{max}} = 35\text{m}, l_{\text{cal}} = 2.5\text{m}$

Detector readout: hits x_i, y_i, energies E_i, photon direction θ_i, ϕ_i

Problem: inaccurate measurements

We see some signal events and group their features in $\mathbf{x}$,
what can we say about the ALP?

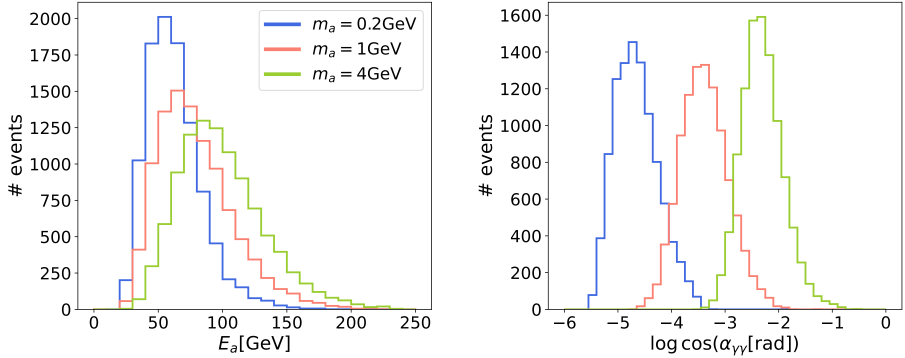
Perfect detector:

- $\mathbf{x} \longrightarrow m_{\gamma\gamma} \longrightarrow m_a$
- $\mathbf{x} \longrightarrow |\mathbf{V}|, \quad |\mathbf{V}| \sim \exp\left(-|\mathbf{V}|\frac{m_a}{|\mathbf{p}_a| c\tau_a}\right)$

Imperfect detector:

- if error is small, should work with $m_{\gamma\gamma}$
- for larger error, signal purity requirements and ad-hoc high-level observables can help
- other?

Variable distributions



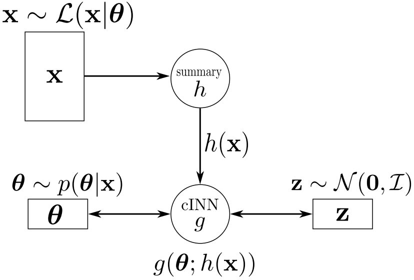
- Mass information also in energy distribution
- Angles useful to infer the mass (but hardest feature to measure)

Simulation-based inference

No direct access to likelihood?
Then use the simulations → simulation-based inference

One possible approach[†]: use ML to approximate likelihood/posterior

In our case: posterior learnt with conditional invertible neural network



†:

- Posterior/Likelihood
- Classifier/NF
- Summary or not

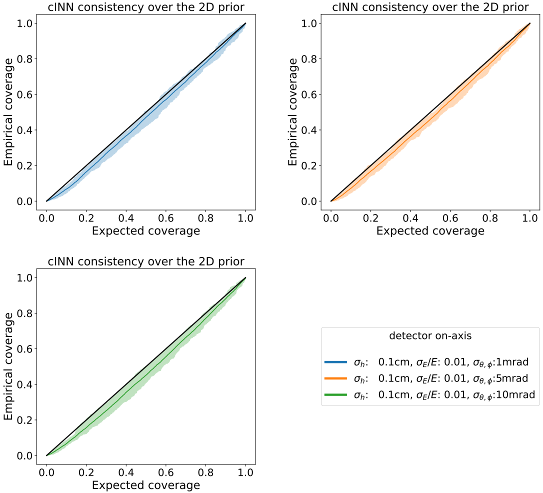
Technical details

Posterior → choose a prior:
$m_a \in [0.1\text{GeV}, 4.5\text{GeV}]$,
$c\tau_a \in [0.1\text{m}, 100\text{m}]$

Input parameters:
$m_a, c\tau_a / m_a$

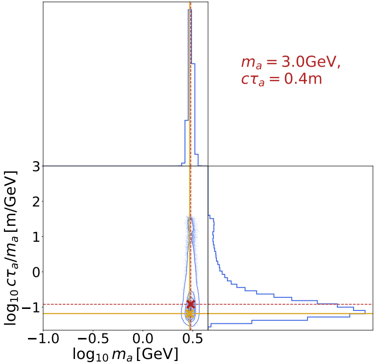
Number of seen events: 3

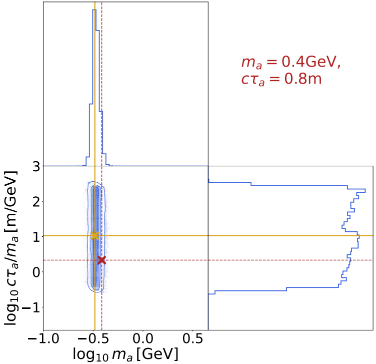
Do we trust the posterior?
Check pp-plot



Posterior: role of mass and lifetime

Can we constrain both the mass and the lifetime?
Depends on detector geometry and lifetime value

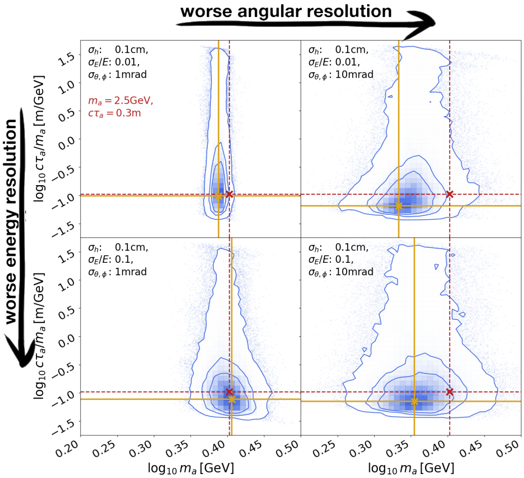




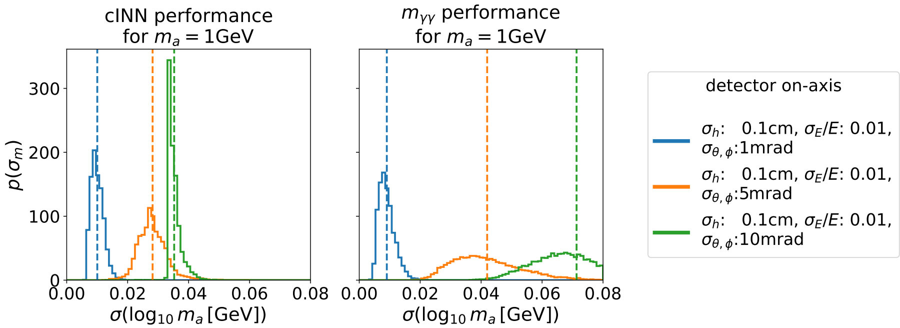
Posterior: role of detector resolution

What if we change the detector?
Then the uncertainties change

Feature resolution	Values scanned
$\sigma(E)/E$	$[0.01, 0.05, 0.1]$
$\sigma(h)$	$[0.1\text{cm}]$
$\sigma(\theta), \sigma(\phi)$	$[1\,\text{mrad}, 5\,\text{mrad}, 10\,\text{mrad}]$

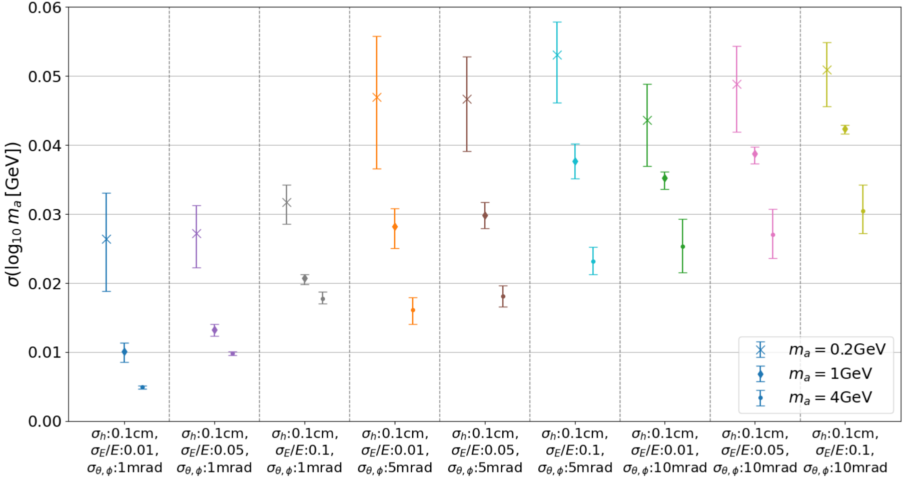


Performance for 1 GeV (role of angle resolution)

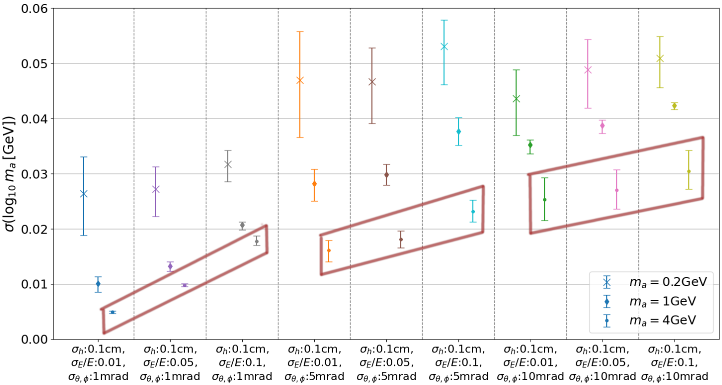


- Agreement with $m_{\gamma\gamma}$ for great resolution
- Considerable outperformance for worse angular resolutions

Performance of different detector setups



Performance of different detector setups (example)



- Major role played by angular resolution
- Interplay between energy and angular resolution

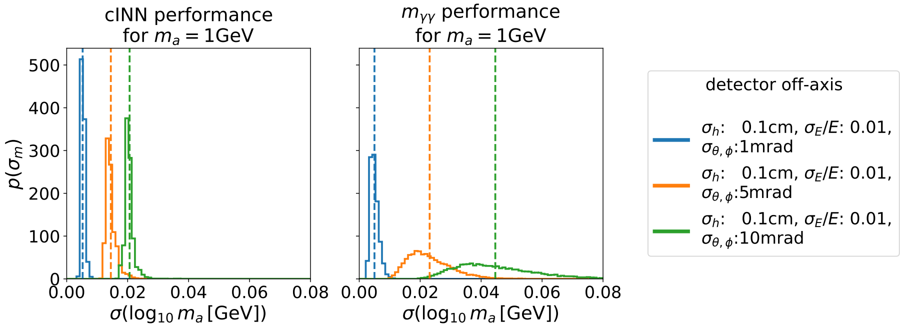
Conclusions

- We can derive fast and reliable parameter estimates **including their uncertainty**
- The considered algorithm **easily adapts** to different setups
- Performance comparisons allow **experimental design**

Thank you!

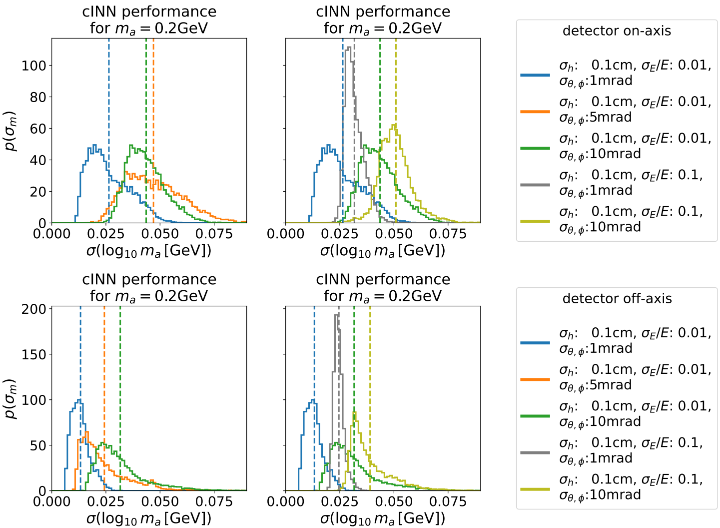
BACKUP

Performance for 1 GeV (displaced case)

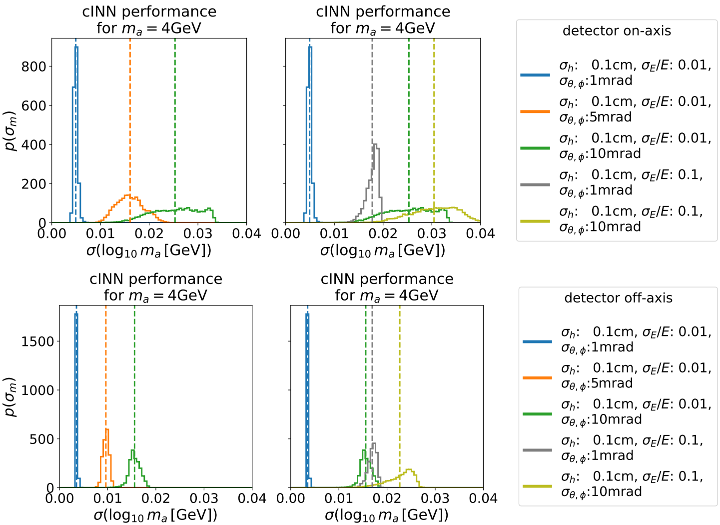


- Same conclusions as in non-displaced case
- Smaller parameter uncertainty (for same number of seen events!)

Performance for 0.2 GeV



Performance for 4 GeV



Performance of different detector setups