

# Simulation based inference for axions at colliders

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work in progress with Felix Kahlhoefer and ETP



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# Inverse problem at LHC

**LHC chain simulation:** MadGraph + Pythia + Delphes

Input: BSM parameters  $\theta$   $\rightarrow$  Output: detector measurements

**Inference:**

Input: (real) detector measurements  $x$   $\rightarrow$  Output: BSM parameters  $\theta$

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

$$p(x|\theta) = \int dz_d \int dz_s \int dz_p p(x|z_d) p(z_d|z_s) p(z_s|z_p) p(z_p|\theta)$$

# Beamdump experiments

Simpler (?) setup: **beamdump experiment**

**Theoretical motivation:**

looking for sub-GeV new particles

**Experimental motivation:**

lower energy, higher intensity, lower cost

Sensitivity in range 100MeV – 4GeV

Sensitivity to dark scalars, **axions/ALPs**, heavy neutral leptons

# SHADOWS and LUXE-NPOD

Two specific examples (ETP at KIT work on these)

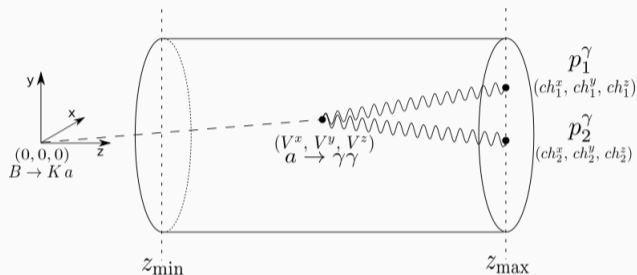
**SHADOWS:** [\[2110.08025\]](#)

- located at LHC, close to NA62
- proton energy of 400GeV
- $B \rightarrow K + a$

**LUXE-NPOD:** [\[2107.13554\]](#)

- located at DESY
- electron-laser collision,  $E(e^-) \sim 16\text{GeV}$
- $\gamma + N \rightarrow N + a$

# Simulation



## Dataset:

- 100k unweighted events ( $\mathcal{O}(10s)$ , but depends on  $m_a, \tau_a$ )
- $z_{\min} = 10m, z_{\max} = 100m$
- $m_a \in [0.1 \text{ GeV}, 4 \text{ GeV}]$ ,  $\tau_a \in [0.01m, 10m]$  (with log-priors)

# Observables (perfect scenario)

## What can we measure?

- calorimeter hits of the photons
- four-momenta of the photons
- decay vertex position (maybe reconstructed through ML)

If that was the real case, no need for complicated stuff for inference

$$m_{\gamma\gamma} \rightarrow m_a$$

$$c\tau \sim \frac{m_a}{|\vec{p}_a|} |\vec{V}| w(z_{\min}, z_{\max})$$

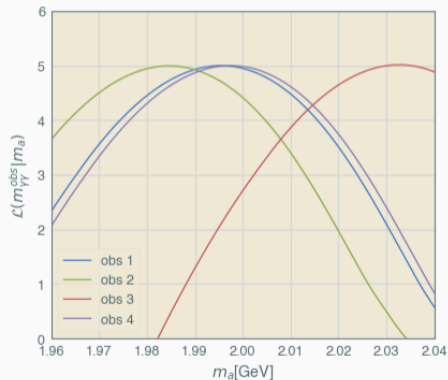
# Issue 1: imperfect reconstruction

In a very ideal scenario:  
we might measure **all the observables**,  
but with some error

Still use high level observable,  
**but** it is necessary to learn the distribution

Likelihoods can be easily combined

Safety check: verify coverage

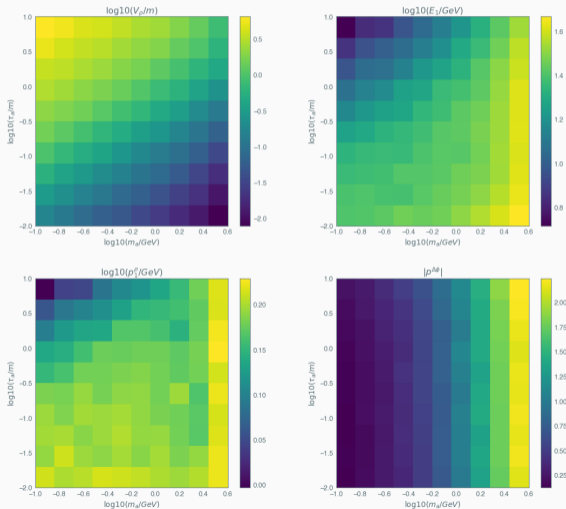


# Issue 2: missing information

In a realistic scenario:  
we cannot measure some quantity  
(e.g. no vertex tracking)

Use available information,  
find **informative variables**

Combine information cleverly





# Simulation based inference to counteract issues

Same approach for imperfect reconstruction and missing information

We do not have  $\mathcal{L}(x|m_a, \tau_a)$ , but we can try to **approximate it**

Different ML algorithm return different PDFs,

but they are all based on the same event generation scheme:

- $(m_a, \tau_a) \sim p(m_a)p(\tau_a)$  (sample parameters according to prior)
- $x \sim \mathcal{L}(x|m_a, \tau_a)$  (use simulator to derive  $x$ )
- Feed  $(m_a, \tau_a, x)$  to ML which returns  $\tilde{\mathcal{L}}(x|m_a, \tau_a)$  or other PDF
- Use approximated likelihood/posterior to perform inference

# ML algorithms for NLE or NPE

- Normalizing flows (NF):

Input  $(x, m, \tau) \rightarrow p(x, m, \tau) = \mathcal{L}(x|m, \tau)p(m)p(\tau)$

- Conditional invertible neural network (cINN):

Input  $(x)$ , condition  $(m, \tau) \rightarrow \mathcal{L}(x|m, \tau)$

Input  $(m, \tau)$ , condition  $(x) \rightarrow p(m, \tau|x) = \mathcal{L}(x|m, \tau)p(m)p(\tau)/p(x)$

- Classifier:

Input  $x_1 \sim \mathcal{L}(x|m, \tau)$ ,  $x_0 \sim \mathcal{L}(x|m_0, \tau_0) \rightarrow \mathcal{L}(x|m, \tau)/\mathcal{L}(x|m_0, \tau_0)$

- All algorithms implemented and checked in simple scenarios

## Issue (opportunity?) 3: detector design

Previous tasks are not easy, but doable with established ML methods

SHADOWS and LUXE are not finalized:  
we **do not know** the experimental properties

This raises the question:

**what should we measure and how well?**

How much do we need vertex reconstruction?

How precise should be the angular resolution?

How long does the detector need to be?

# Outlook: when things get complicated

At this stage we have:

- a couple model parameters
- $\mathcal{O}(10)$  observables

We might require efficient and reliable inference software when considering different detector scenarios

**New parameters to be introduced:**

- detector resolution for each observable
- experimental geometric size
- which observables are measured

# BACKUP

# LUXE design

