Overcoming limitations to ALP parameter inference using *Neural Ratio Estimation*

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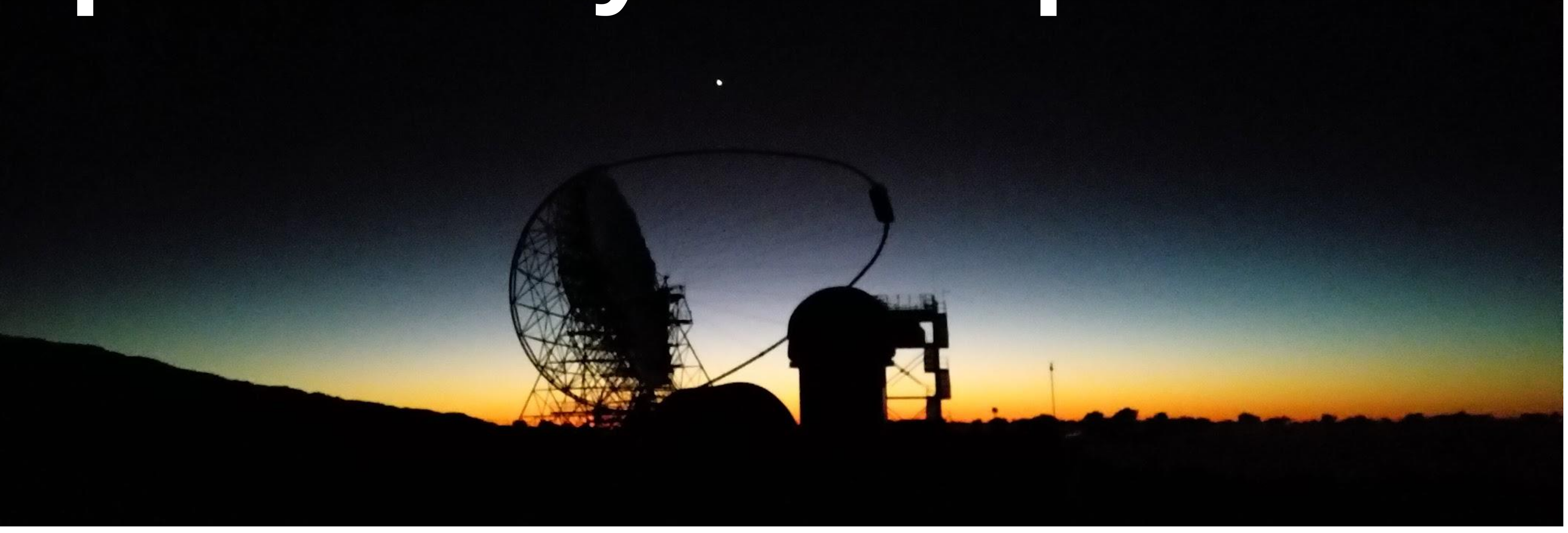
Likelihood-free inference may allow us to compute astrophysics limits that were previously incomputable



Our challenge:

Finding **Axion-like Particles (ALPs)** using **cosmic γ-ray data**

- ALPs are hypothetical particles which are also popular **dark matter candidates** (review: [1]).
- They interact with photons in the presence of strong magnetic fields
- Their influence may be visible in γ-ray spectra of astrophysical sources that feature strong magnetic fields.
- Accurately modelling that influence requires knowledge about astrophysical nuisance parameters, such as the local magnetic field strength and configuration of the source.
- The large number of nuisance parameters makes it **computationally impossible** to perform the integrations involved in a standard Bayesian parameter inference, **without neglecting our uncertainty** in many of those parameters.

A variation of *Likelihood-free inference*, or *Simulation-based inference*

A crash course in using *Neural Ratio Estimation*:

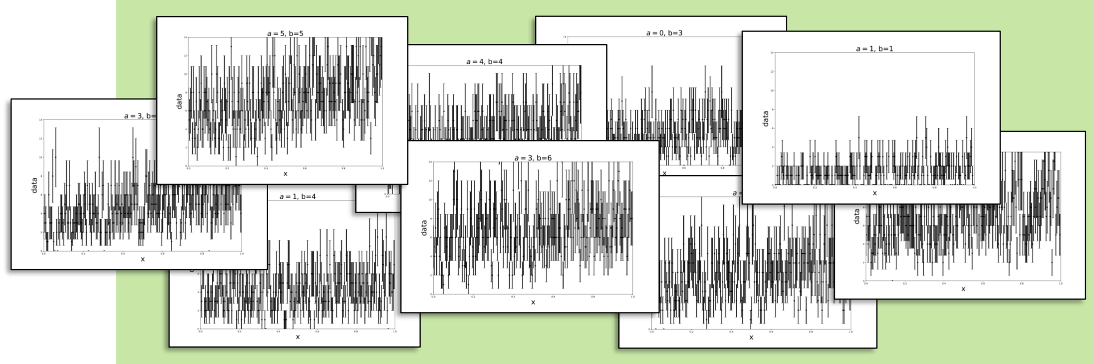
Beginner:

Fit a line to data using a neural network

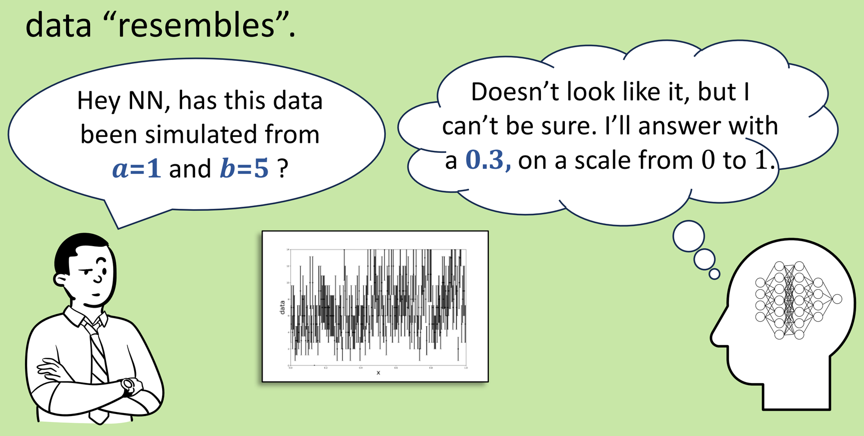
1. Simulate data of the form

$$\mathbf{data}(x) = ax + b + \mathbf{Noise},$$

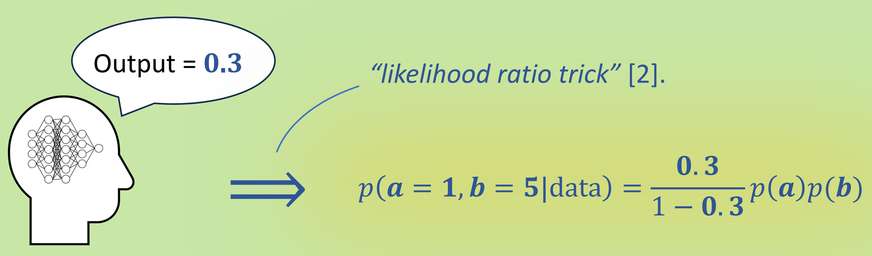
and do this for many different values of a and b, which are distributed according to some prior $p(a)p(b)$.



2. Use the simulations to train a neural network to classify the simulated data according to which true values that data "resembles".



3. The neural network's output can now be directly related to the **Bayesian posterior**, that is, $p(a, b|\text{data})$:



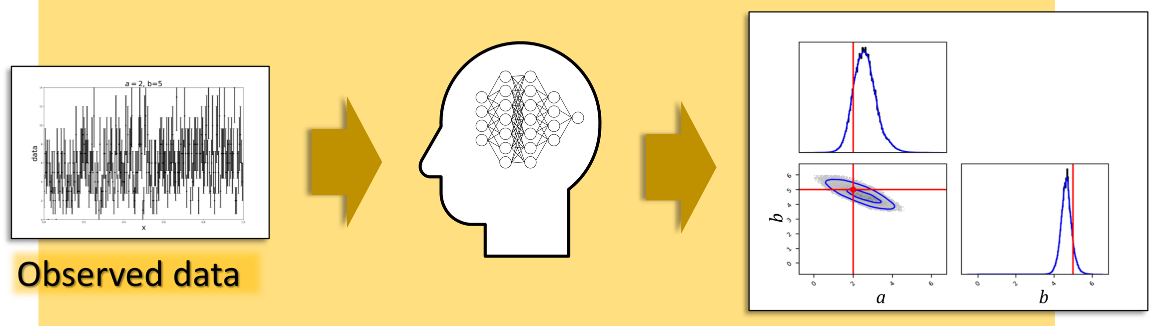
$$\Longrightarrow \quad p(a=1, b=5|\text{data}) = \frac{0.3}{1-0.3} p(a)p(b)$$

We do this inference process using the python package SWYFT [3].

Intermediate:

Prove that your inference is correct!

Neural networks can be very efficient at inferring model parameters according to the method to the left.



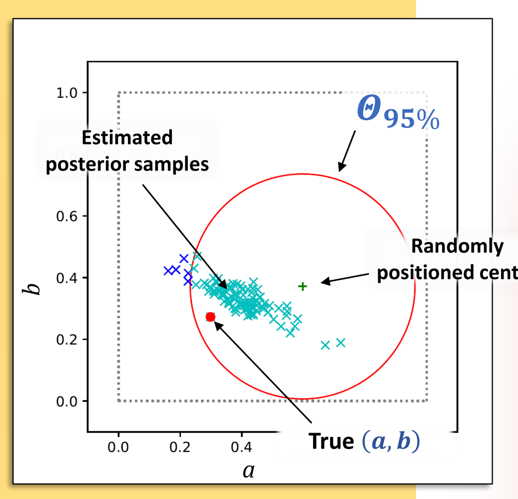
But studies show that the estimated posteriors cannot be trusted blindly to be accurate [4]!

<u>How to establish the (in)accuracy of the estimated posteriors:</u>

1. Draw **samples from a posterior estimate** for which you know the true value of (a, b).
2. Define a **randomly positioned** region Θ_α that contains a predetermined proportion α of the samples. Check if Θ_α contains (a, b).
1. Repeat 1. and 2. for **many samples of the true value** (a, b), drawing from the prior $p(a)p(b)$.

The posterior estimate is accurate if:

The **proportion of cases** where $(a, b) \in \Theta_\alpha$ is α, for **any chosen value of** α.



This was recently proven (and explained in more detail) by Lemos et. al [5].

Pro:

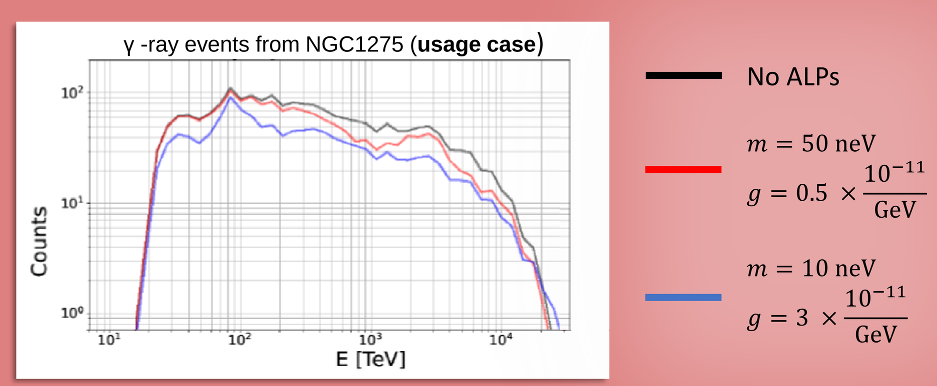
Do it all for ALP-induced signals in γ-ray data (instead of line-fits)

Instead of fitting a line, we want to estimate the mass m and coupling to photons g of Axion-like particles.

Our data is the (simulated) **γ-ray spectrum of the Perseus galaxy cluster,** measured by the upcoming telescope **CTA** [6].

<u>What are the challenges?</u>

- The γ-ray signal from ALPs is complex, and often dominated by statistical noise.



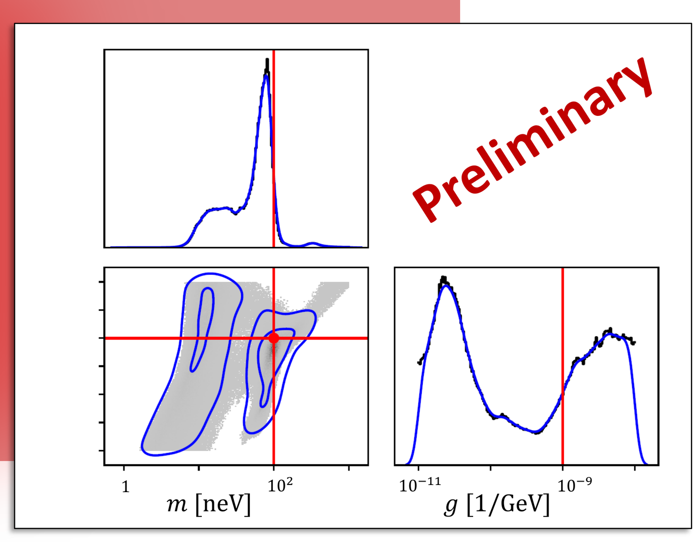
The spectra are convolved with the preliminary CTA IRF prod3, as a usage case. Simulations are made using gammaALPs [7] *and* gammapy *v0.19* [8].

- Modelling the γ-ray signal involves $\sim$**15 nuisance parameters**, introducing extra variation in the signal.

This makes accurate posteriors more hard-earned than for a line-fit.

<u>What is (probably) required?</u>

- Higher simulation budgets to train NNs on
- More sophisticated NN-architectures



Example posterior for data simulation with $m = 10^2$ neV and $g = 10^{-9}$ GeV^{-1}

- *NN trained on 10^6 simulations*
- *Using default general-purpose NN of SWYFT-package [2].*

References

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