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Overcoming Limitations to ALP Parameter Inference Using Neural Ratio Estimation

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In the hunt for new physics phenomena, such as Axion-like particles (ALPs), it is crucial to compare experimental data to theoretical models. This involves inferring the most likely values of a model's parameters — such as particle masses and cross sections. However, traditional likelihood-based inference techniques are oftentimes not practically feasible without making significant simplifying assumptions, which decrease the reliability of the inference. This is especially the case for ALP-searches with gamma-ray telescopes such as the upcoming Cherenkov Telescope Array. Recently however, new likelihood-free inference (LFI) techniques based on machine learning have emerged to help overcome these limitations. In particular, "Neural Ratio Estimation" (NRE) stands out with its reported accuracy and efficiency. In this contribution, we have applied NRE to simulated CTA-data of the active galactic nucleus NGC1275 in the Perseus Cluster, in order to probe the viability of this technique for ALP-searches with cosmic gamma-rays. Our example-inferences provide encouraging evidence that NRE will be applicable to deriving sensitive and accurate limits. We also identify some challenges in the practical execution of such an analysis, as well as concrete next steps towards deriving formal and reliable limits on the ALP mass and coupling to photons.

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1. Introduction

Axion-like particles (ALPs) arise in many theories beyond the standard model, and are popular dark matter candidates [1]. Unlike the QCD-axion, their mass m_a and coupling to photons $g_{a\gamma}$ (hereafter their "coupling") are not dependent on each other. However, ALPs retain the property that when travelling in magnetic fields, they may oscillate into photons (and vice versa) with a probability that depends on m_a and $g_{a\gamma}$, the energy of the ALP (or photon), and the magnetic field [1]. Therefore, photons from the bright active galactic nucleus (AGN) NGC1275 in the Perseus Cluster, which has particularly strong magnetic fields, may arrive at earth as ALPs instead [2]. This would result in energy-dependent attenuations of the AGN's γ-ray flux[1], which may be resolvable by the upcoming Cherenkov Telescope Array (CTA) [2], making inference of m_a and $g_{a\gamma}$ possible. However, modelling the ALP-photon mixing is dependent on many nuisance parameters, making likelihood-based inference techniques prohibitively expensive, unless the (large) uncertainties on several parameters are neglected. Here, we probe the viability of using the likelihood-free inference technique *Neural Ratio Estimation (NRE)*, to avoid deriving overconfident limits on m_a and $g_{a\gamma}$.

2. Modelling expected γ-ray spectra of NGC1275

We assume that the intrinsic spectrum of NGC1275 follows an exponentially cut-off power law [3] with reference energy 153.86 GeV, and treat its amplitude Φ, powerlaw index Γ and cutoff-energy E_{cut} as nuisance parameters. We convolve the intrinsic spectrum with the CTA instrument response function[2] using `gammapy` version 0.19. [4, 5]. ALP-photon mixing and attenuation by the extragalactic background light is implemented using `gammaALPs` [6], and we model the magnetic field configuration of NGC1275 as a Gaussian turbulence field as described in Ref. [6]. For inference, we assume log-uniform priors with bounds 1–10^3 neV and 10^{-11}–10^{-8} GeV^{-1} for m_a and $g_{a\gamma}$ respectively, and we assume the nuisance parameter values and priors indicated in Table 1.

3. Inferring parameters of interest from (simulated) data using NRE

In NRE, the Bayesian posterior is estimated by means of a neural network (we refer to Ref. [7] for a comprehensive explanation). The network is trained on simulated observations, in this case of the γ-ray spectrum of NGC1275, generated from values of the model parameters (m_a, $g_{a\gamma}$ and nuisance parameters) that were drawn from their Bayesian prior distributions. We generate the training set according to the specifications in Section 2. We perform NRE using `SWYFT` version 0.3.2 [8], and use the default network architecture provided by the class `swyft.get_marginal_classifier`.

As shown in Table 1, we neglect several parameter uncertainties to avoid overcomplicating this initial study. However, we highlight that the uncertainty in the magnetic field configuration of the Perseus Cluster, which is particularly difficult to account for in likelihood-based inference, is naturally accounted for in this study. This is because every simulation of the neural network's training set will correspond to a different random field configuration. Its uncertainty is therefore reflected in the variability of the training set.

[1]*Enhancements* of the flux are also possible, as photons may avoid absorption by the extragalactic background light, if temporarily travelling as ALPs.

[2]We use the publically available prod3 IRF for CTA south at zenith 20° and for 50h of observation time

	Φ	Γ	E_{cut}	B_0	n_0/n_2	r_{abell}	$r_{\mathrm{core}}/r_{\mathrm{core2}}$	β/β_2	η	$k_{\mathrm{L}}/k_{\mathrm{H}}$	q
Value	4.47–7.08	2.37–2.66	10^{-2}–10	10	39/4.05	500	80/200	1.2/0.58	0.5	0.18/9	−2.80
Units	10^{-9} cm^{-2} s^{-1} TeV^{-1}		TeV	μG	10^{-3} cm^{-3}	kpc	kpc	kpc		kpc^{-1}	

Table 1: Nuisance parameter values and units used in the APL mixing and propagation model. Columns 4-11 refer to parameters used in the gaussian turbulence B-field model that is implemented in `gammaALPs` [6]. Where a range is indicated, we assume a log-uniform prior over that range for that parameter.

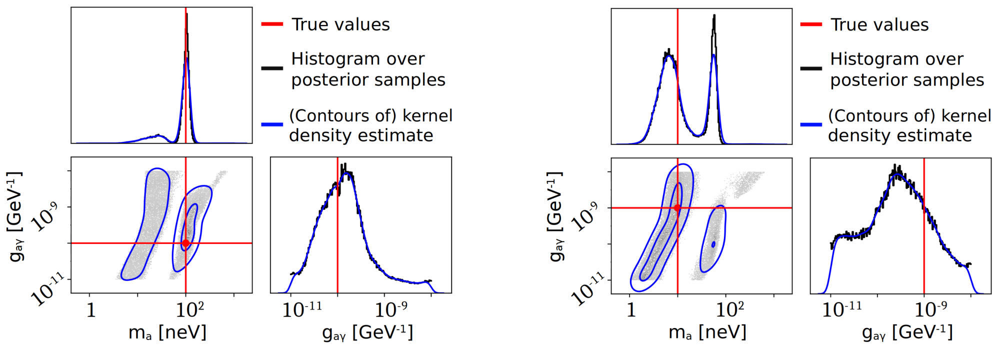

Figure 1: Posteriors from two different simulated observations. The contour lines divide the multivariate distribution into sections of equal probability mass. The neural network used for inference was trained on $\sim 10^6$ simulations, and validation loss did not plateau. Plots made using `SWYFT` version 0.3.2 [8]

We validate our posterior using a *distance to random point (DRP) coverage test*, proposed by Lemos et. al. [9]. This test establishes the (non-)equivalence between a posterior estimator and the Bayesian posterior function on the condition that the estimator's *expected coverage probability (ECP)* (i.e. the expectation that any chosen credible region will encompass the true parameter values) is (not) always equal to the chosen credibility level. We refer to ref. [9] for details.

4. Results and discussion

We simulate the γ-ray spectrum of NGC1275 as described in Section 2 (in histograms of 200 bins, assuming 50 h of observation time), and infer the corresponding posteriors, for specific points in $(m_a, g_{a\gamma})$-parameter space where other γ-ray experiments have excluded ALPs[3]. This way, we avoid that the quality of the inference is obscured by low experimental sensitivity, assuming that CTA will be similarly or more sensitive than existing γ-ray experiments at very high energies [2].

Figure 1 shows example-posteriors for two such points in excluded parameter space. We make the heuristic argument that these posteriors exclude the null hypothesis (no ALPs), as the posterior volume is insignificant at low values of the ALP-mass m_a. The convergence around the true value of the coupling $g_{a\gamma}$ is clearly less decisive. It remains to be seen how much future, more advanced applications of NRE (see below) will be able to improve on this.

[3]see https://cajohare.github.io/AxionLimits/docs/ap.html for an overview.

The coverage plot in Figure 2 shows that the ECP deviates visibly from the credibility, indicating that our posterior estimator may be improved, although it is not clear how much. However, the lack of any *systematic* deviations provides evidence that our posteriors are not significantly overconfident, underconfident, or biased [9].

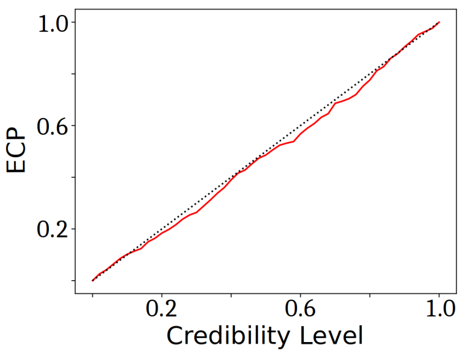

Figure 2: Coverage plot for our posterior estimator, based on a DRP coverage test [9].

A major limitation in our analysis is that we have not employed a GPU, in practice preventing us from training our neural network to the point where validation loss has plateaued. This is a further, strong indication that our posteriors may be improved by longer training. This will be clarified in future work. Beyond this, deeper neural network architectures, larger training sets, and even different loss functions may be explored for improved inference.

Future analyses will aim at deriving formal limits on ALPs by exploring a larger section of the ALP parameter space, while neglecting uncertainties of fewer nuisance parameters. Based on the results presented here, and given the large potential for improvements, Neural Ratio Estimation appears promising in terms of performing more reliable searches for ALPs using cosmic γ-ray data.

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