Probing the Parameter Space of Axion-Like Particles Using Simulation-Based Inference

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On behalf of CTAO Collaboration

TeV Particle Astrophysics TeVPA Valencia 2025

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I FEEL SLOVENIA
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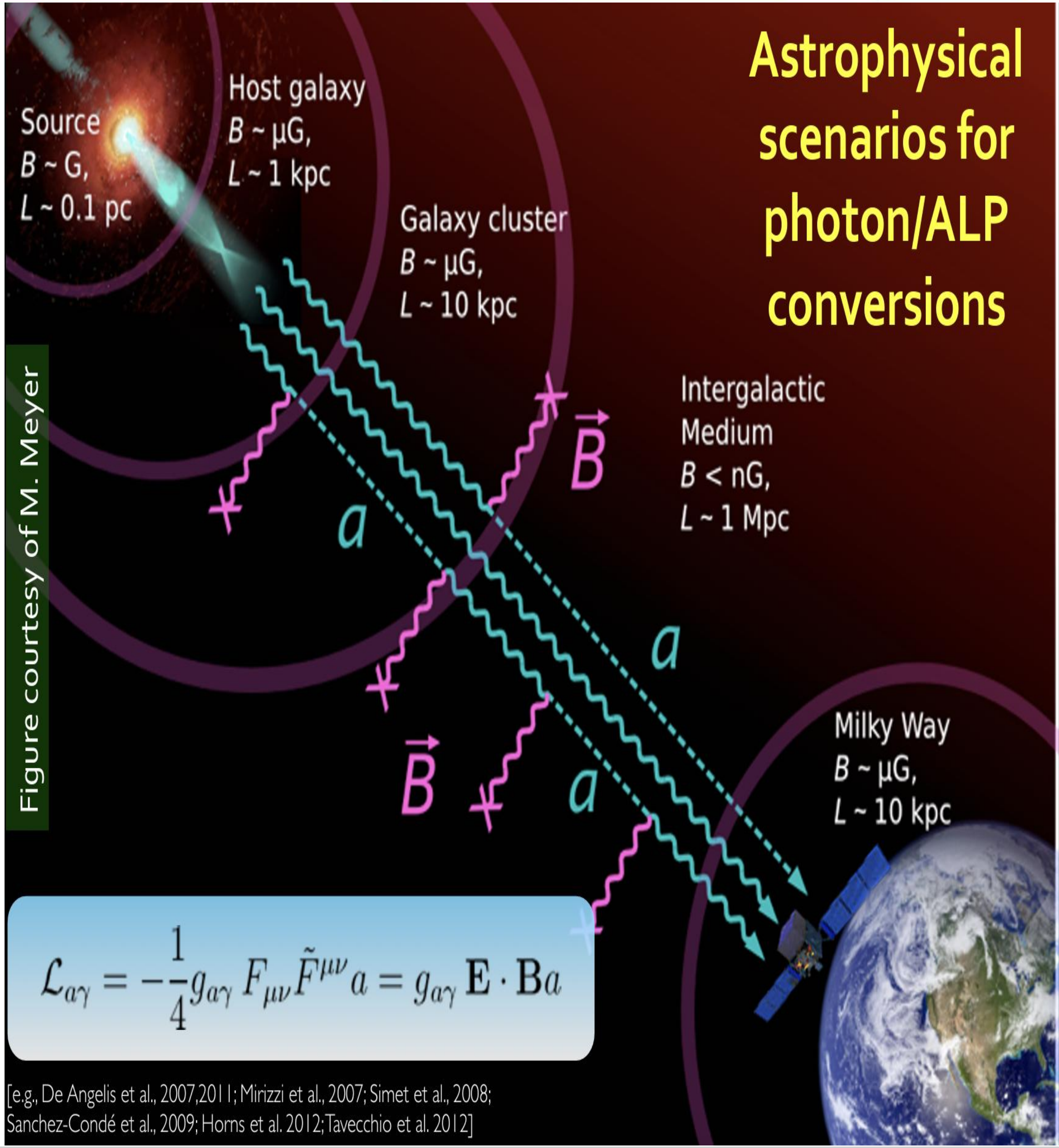
Outlook

- **What are Axion-like particles (ALPs)**
- **How to detect ALPs**
- **Cherenkov Telescope Array Observatory (CTAO) and ALPs detection**
- **Advantage of Simulation-Based Inference (SBI)**
- **Current status and Future Prospects**



What are Axion-like Particles (ALPs)

- Axions were proposed by R. D. Peccei & H. Quinn, and later developed by S. Weinberg & F. Wilczek, **as new particles to address a long-standing puzzle in the strong force known as the Strong CP problem**.

- **Axion-like particles (ALPs) are extremely light, spin-zero, neutral particles.**

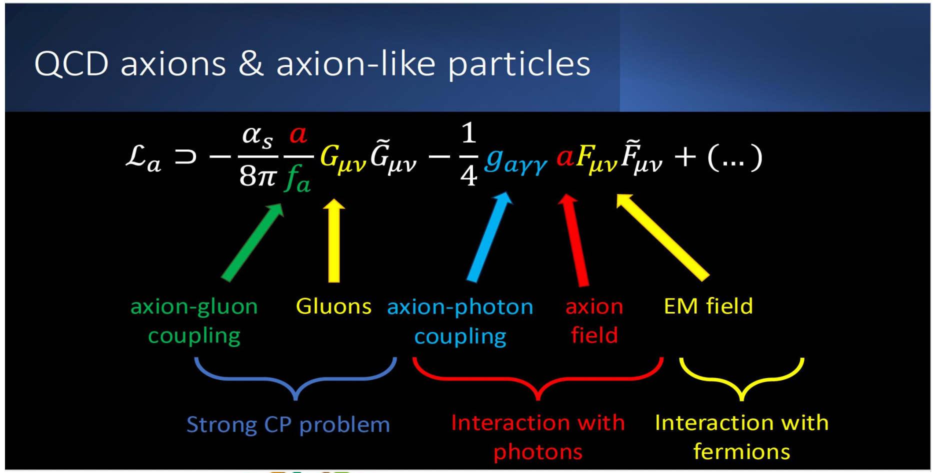
- Unlike axion, **ALPs have independent masses and couplings**, spanning significantly wider parameter space and making them compelling **candidates for dark matter**.

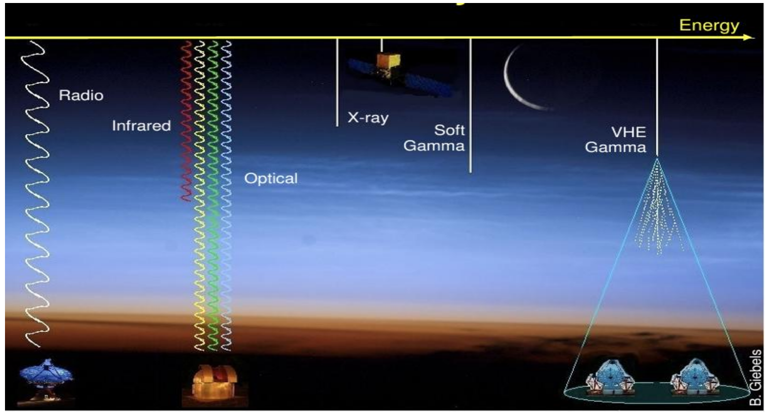
- In the presence of magnetic field, **ALPs oscillate into gamma rays** and could lead to irregularities in the spectra of astrophysical objects.

  → **Mixing/ "wiggles" happens near the critical energy, E_{crit},** and is directly testable with current/future telescopes.

Plenery Talk by Javier Redondo
Parallel Talk by Francesco Schiavone (CPP), Ivana Batković (DMI), ...

Credit: Elena Pinetti, CosmicWISPers





How to detect ALPs in very high energy (VHE) gamma rays

→ Understand how ALP-photon mixing occurs in external magnetic field

→ Detectors' Sensitivity

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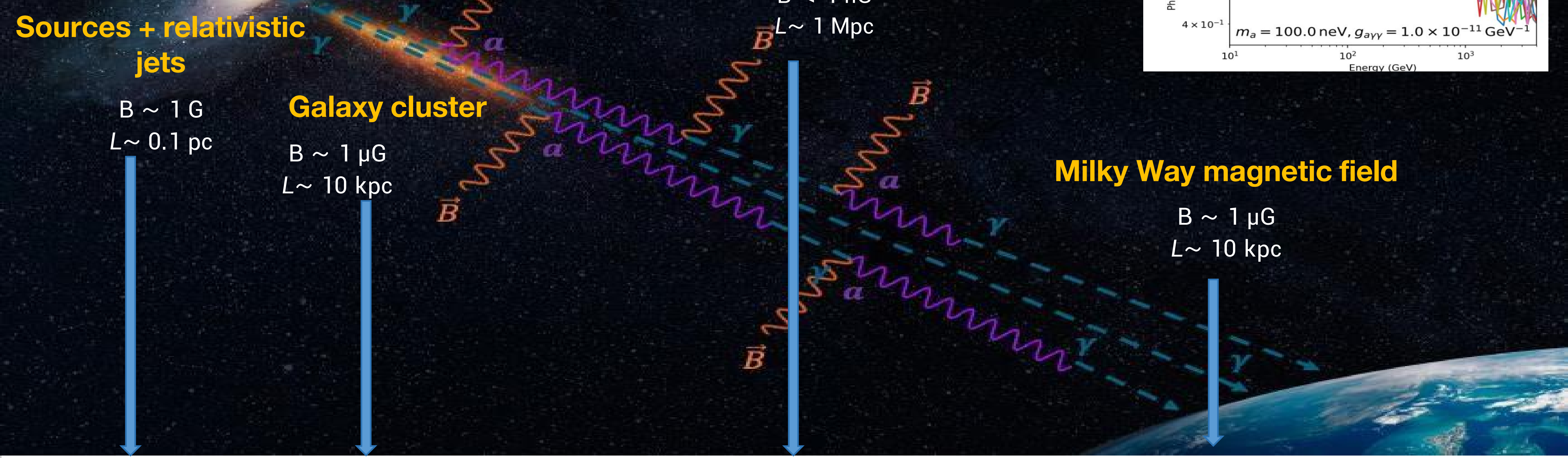
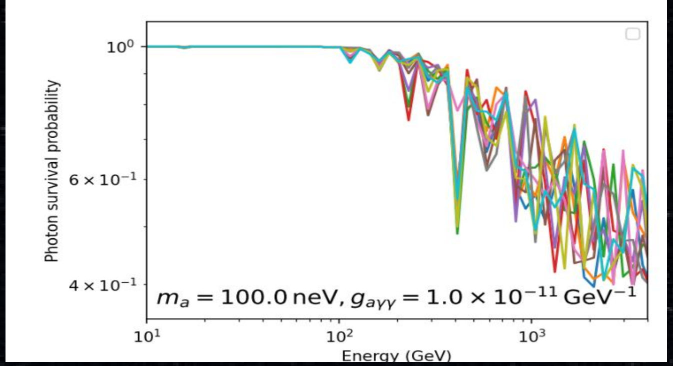
ALP-photon conversion in magnetic fields





Sources + relativistic jets

B ~ 1 G

$L\sim$ 0.1 pc

Mixing is crucial for blazars, where jets are closely aligned with our line of sight.

Davies et al., PRD 103, 023008 (2021)

Galaxy cluster

B ~ 1 μG

$L\sim$ 10 kpc

Gaussian turbulent random field (homogeneous, isotropic)

Meyer et al., JCAP 09 (2014) 003.

Intergalactic magnetic field

B < 1 nG

$L\sim$ 1 Mpc

Weak field but its irregularity depends on target and distance. Extragalactic Background Light (EBL) also plays a role here

(A. Dominguez et. al, 2011)

Milky Way magnetic field

B ~ 1 μG

$L\sim$ 10 kpc

Mixing occurs in the turbulent and regular component of stable Galactic magnetic field.

(Jansson & Farrar, 2012)

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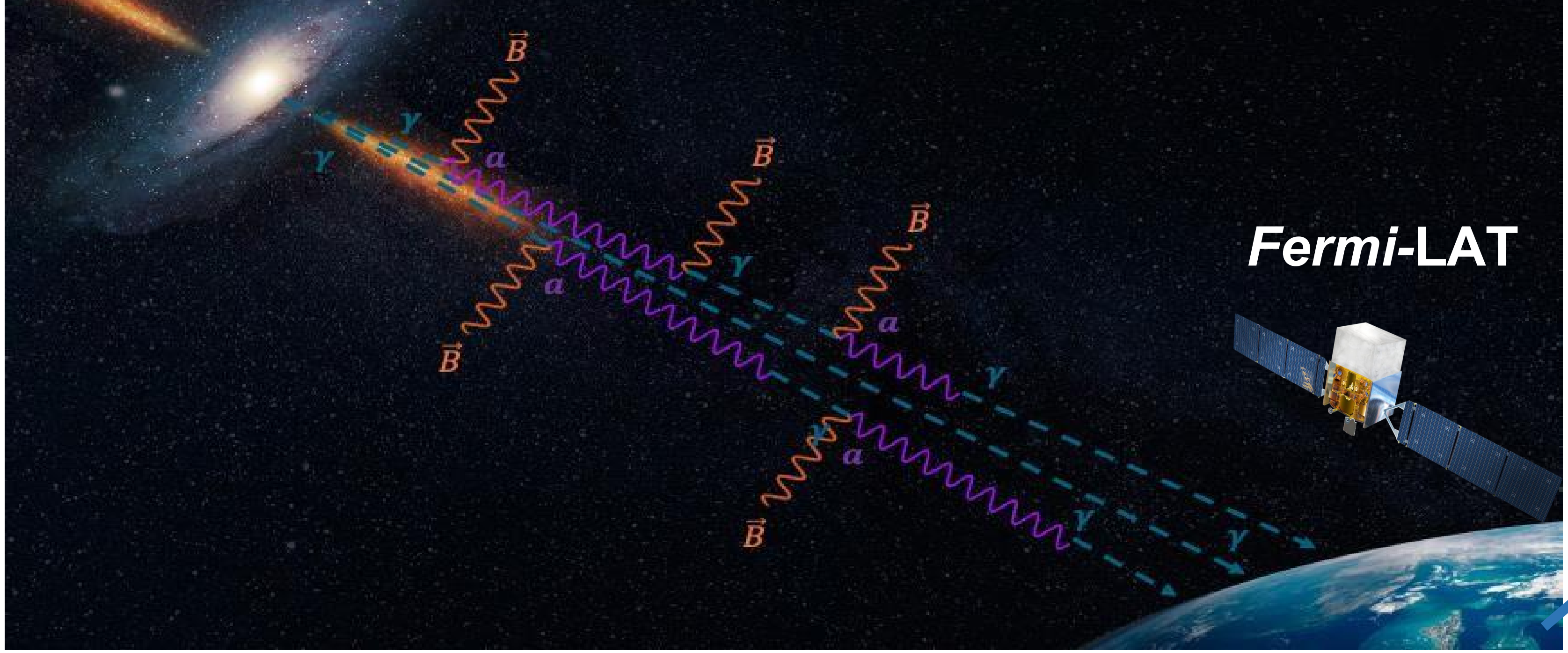
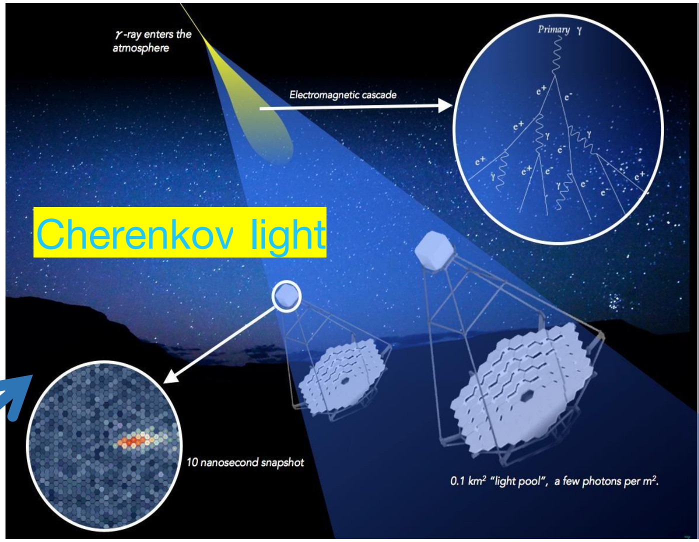
ALPs Detection in VHE



Imaging Atmospheric Cherenkov Telescopes (IACTs)



Daniel López / Instituto de Astrofísica de Canarias

H.E.S.S. collaboration, Clementina Medina

Operating IACTs in GeV-TeV range

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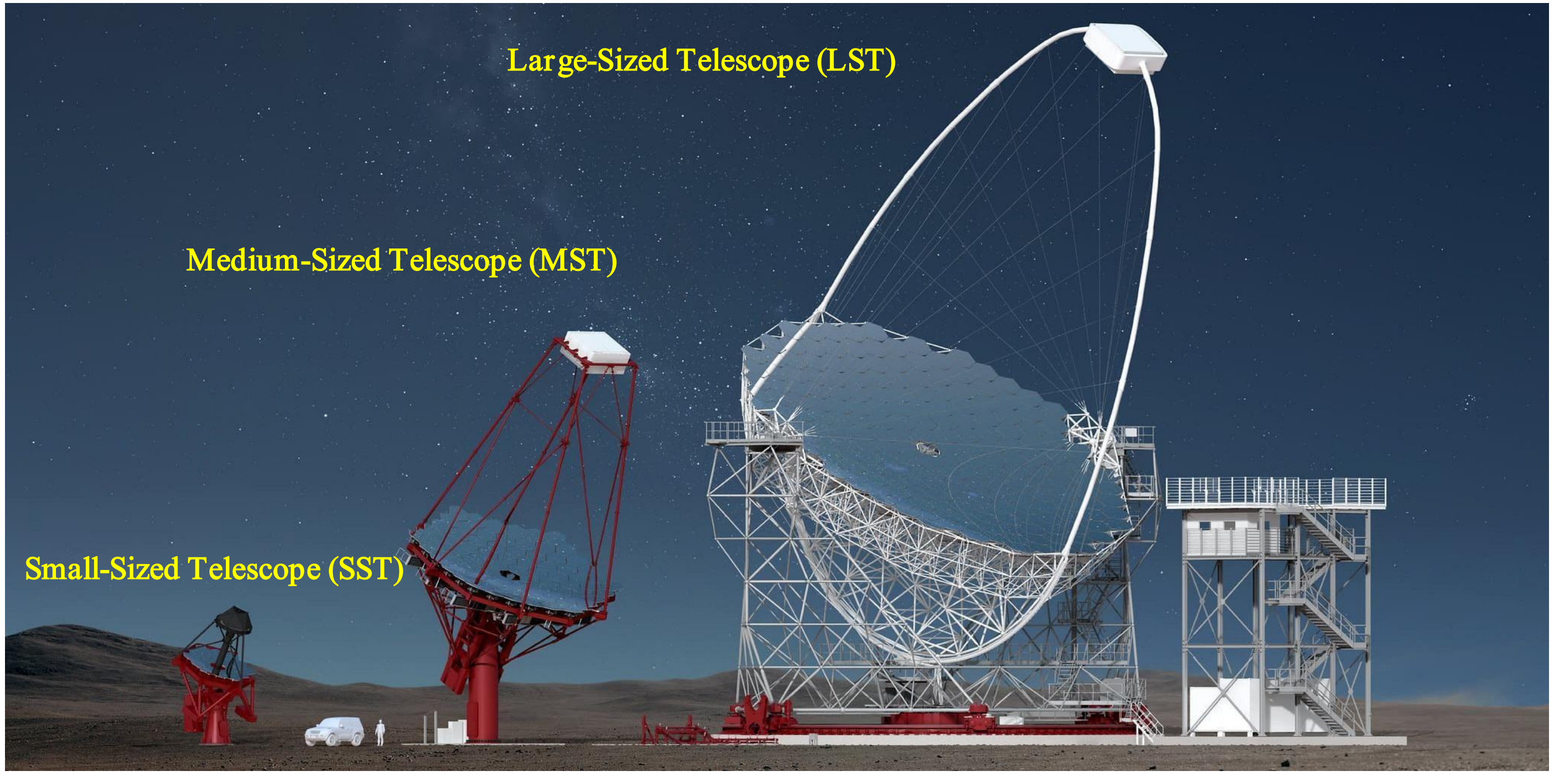
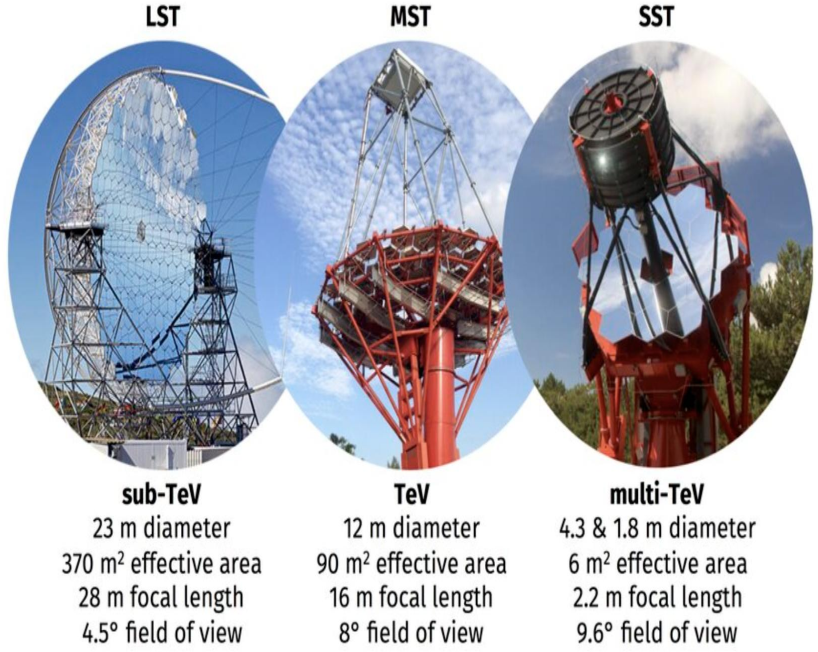
Cherenkov Telescope Array Observatory (CTAO)

- Next-generation gamma-ray observatory with two sites (La Palma & Paranal) covering 20 GeV–300 TeV.
- Consists of Large, Medium, and Small Telescopes to achieve broad energy coverage for full sky.
- 5–10 × higher sensitivity than current IACTs.
- Better energy and spatial resolution, faster time response to transients.





https://www.ctao.org/for-scientists/technical-specifications/

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Current status of our Neural Ration Estimation treatment for ALPs with CTAO

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The Perseus Cluster and NGC 1275

■ The Perseus galaxy cluster is the brightest X-ray galaxy cluster in the sky, and is located at a redshift of 0.0176. It displays a dense population of electrons and a strong magnetic field at its core.

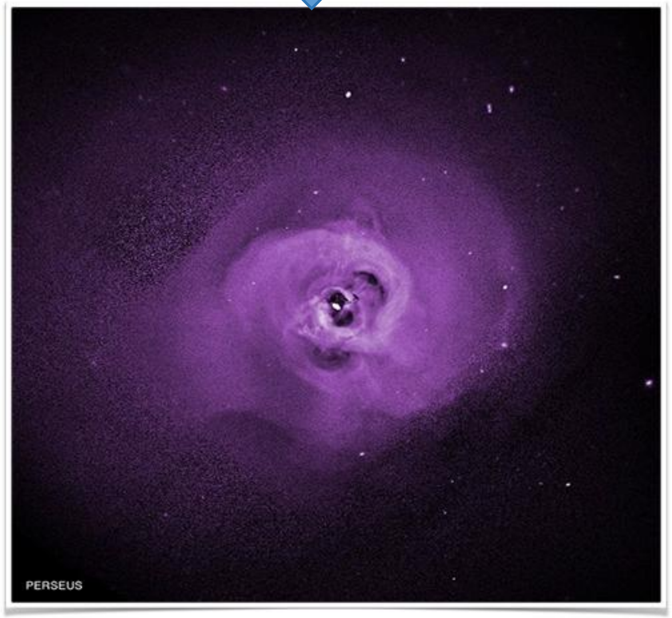
■ In its center, **Perseus hosts a very bright TeV-emitting radio galaxy: NGC 1275** which hosts a very bright Active Galactic Nucleus (AGN).

■ **Perseus cluster contains a strong magnetic field, as large as 25 μG that makes it an excellent target to search for ultralight ALPs.**

■ Observable flux: $\phi\_obs(E) = P\gamma\gamma(E) \times \phi\_int(E)$.

■ **Literature data available to test our trained network on ALP limits** from NGC 1275 - *[MAGIC collab., Phys.Dark Univ. 44 (2024)], [Fermi-LAT collab., PRL 116 (2016) 16], [The CTA Consortium; JCAP 02 (2021) 048]*

Our Target



Perseus cluster in X-ray. Credit: NASA, Chandra

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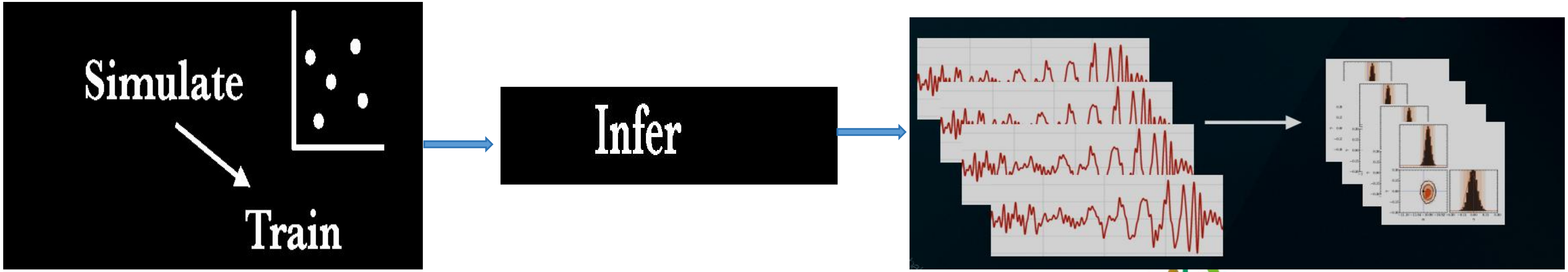
Why Machine Learning (ML) Application for ALPs?

- **ALP-photon conversion** is strongly dependent on the **propagation environment and the treatment of the uncertainties of magnetic fields.**
- **Traditional Likelihood test often struggles** when we deal with a large number of parameters with uncertainties and biases our results. For a complex system like ALPs, it is not practically feasible without making significant simplifying assumptions, **which decrease the reliability of the inference.**
- To address this, we adopt **Simulation-Based Inference (SBI) using Truncated Marginal Neural Ratio Estimation (TMNRE)**, a likelihood-free approach suited to complex, nonlinear forward models.
- This treatment will provide **a more robust avenue for ALP parameter space** and demonstrate its potential to extract meaningful limits from future real gamma-ray data with CTAO.



Credit: James Alvey, EuCaifCon 2025

Simulation-Based Inference (Neural Ratio Estimation)

The Likelihood Ratio Trick

Given two distributions $p_1(\boldsymbol{x})$ and $p_2(\boldsymbol{x})$, where xi is observed counts:

$\boldsymbol{x}_0, \boldsymbol{x}_2, \boldsymbol{x}_4, \boldsymbol{x}_6, \ldots \sim p_1(\boldsymbol{x})$

$\boldsymbol{x}_1, \boldsymbol{x}_3, \boldsymbol{x}_5, \boldsymbol{x}_7, \ldots \sim p_2(\boldsymbol{x})$

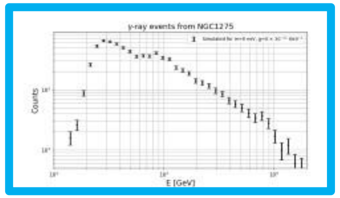
1. Draw many samples $(\boldsymbol{x}_i, m_i, g_i)$
2. Train network to distinguish the samples

from $p(\boldsymbol{x}|m,g)p(m,g)$

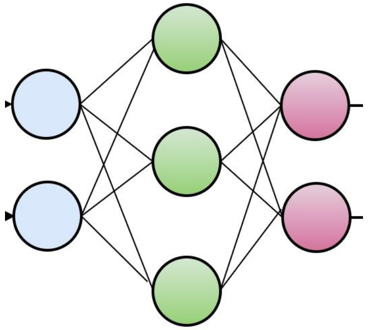
i.e. Sample (m_i, g_i) from the prior $p(m,g)$, then simulate $\boldsymbol{x}_i$ from (m_i, g_i).

and from $p(\boldsymbol{x})p(m,g)$

i.e. Sample (m_j, g_j) from the prior $p(m,g)$, then simulate $\boldsymbol{x}_i$ from (m_j, g_j).
Then draw (m_i, g_i) from the prior.

$\boldsymbol{x}_i =$  $m_i = 2$ neV, $g_i = 3 \times 10^{-11}$ GeV^{-1}

Input



Trained Neural network

Modified Output

$$\frac{p(\boldsymbol{x}_i \mid m_i, g_i)\ \cancel{p(m_i, g_i)}}{p(\boldsymbol{x}_i)\ \cancel{p(m_i, g_i)}} = \frac{p(m_i, g_i|\boldsymbol{x}_i)}{p(m_i, g_i)}$$

By Bayes' theorem

Posterior!

Prior

Vary m_i and g_i to scan parameter space

$$\boxed{\text{Posterior} = \text{Modified Output x Prior}}$$

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Slide Credit: Gert Kluge, TeVPA, 2023

Analysis Workflow

Define a function that outputs a simulated observation
(as a function of parameters of interest and nuisance parameters)

⇩

Simulate enough observations to train a neural network
(according to a defined prior)

⇩

Train a neural network

⇩

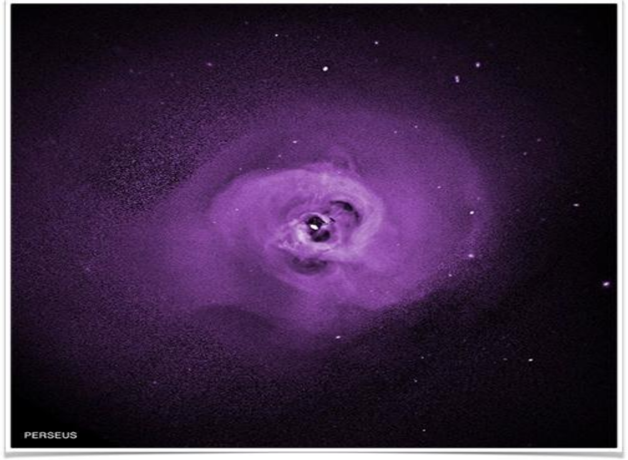
Scan the parameter space using the neural network

Credit: Gert Kluge,
TeVPA, 2023

gammapy version:1.3
https://gammapy.org/
gammaALPs by Manuel Meyer
https://gammaalps.readthedocs.io/

SBI with **SWYFT** v0.4.0
https://swyft.readthedocs.io/en/stable/

10 h of flaring states



Perseus cluster in X-ray. Credit: NASA, Chandra

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Define a function that outputs a simulated observation (as a function of parameters of interest and nuisance parameters)

Parameters from ALP-model

- ALP mass, m
- ALP coupling to photons, g

- NGC1275 intrinsic spectrum amplitude
- NGC1275 intrinsic spectral index
- NGC1275 intrinsic cut-off energy

- Magnetic field strength of NGC1275
- Magnetic field configuration
- Extension of Perseus cluster
- 7 electron density-related parameters
- 3 turbulence-related parameters

Parameters of interest

Nuisance parameters

Simulated data

Search for imprints of ALPs in the simulated spectrum of NGC 1275

γ-rays spectra (**10 h of flaring states**)

×

Instrument response (**Prod5-North-20deg-AverageAz-4LSTs09MSTs.180000s-v0.1.fits.gz**)

×

Absorption from **EBL**

x

"Wiggles" from photon-ALP-oscillations

Parameter of interest (Intrinsic + ALP)

ALP mass, ***ma* (vary)**

ALP coupling to photons, ***gaγ* (vary)**

NGC1275 intrinsic spectrum amplitude**(fixed)**

NGC1275 intrinsic spectral index**(fixed)**

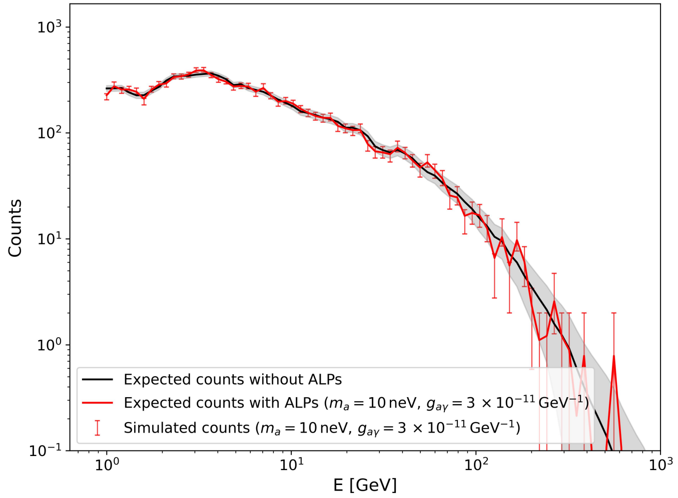
NGC1275 intrinsic cut-off energy**(fixed)**

Other Nuisance **(fixed)**

Spectral_model = Exp cutoff power law x wiggles

EXPCustomSpectralModel(
amplitude="1.54e-11 cm-2 s-1 TeV-1",
reference="0.3 TeV",
index="2.11",
ecut="0.56 TeV",
m_a="m_a neV",
$g_{a\gamma}$="$g_{a\gamma}$ GeV-1")

Expected counts, will be used as input while training.



Parameters taken from CTAO consortium paper: JCAP 02 (2021) 048

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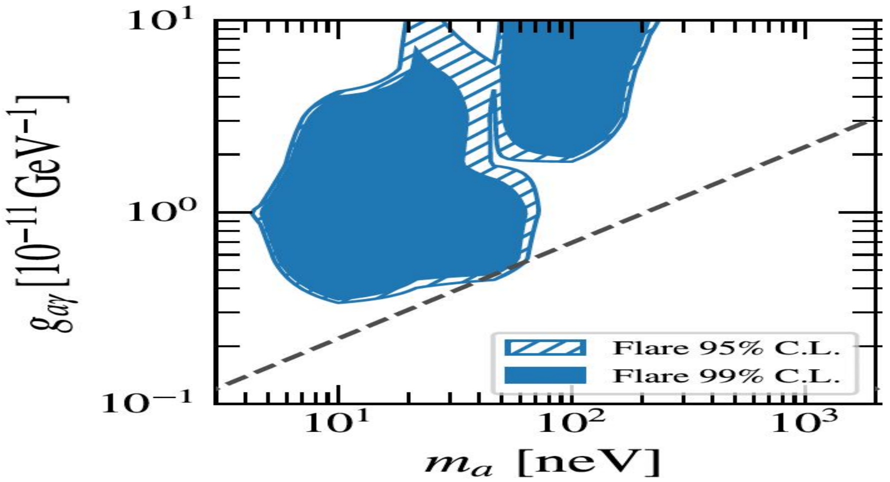
Training through SBI

Parameters (m_a, $g_{a\gamma}$) taken from CTAO consortium paper: JCAP 02 (2021) 048



Setup:

~ 1000000 simulations used in training

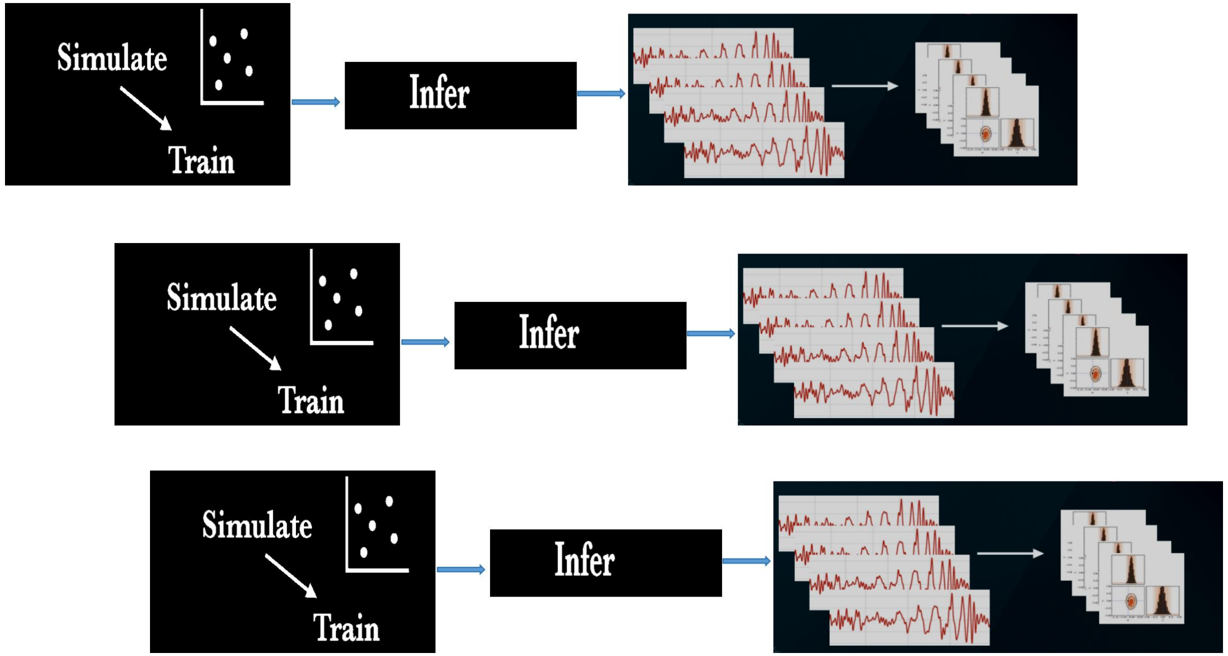
Prior: uniform on log scale

Assumed observation time = 10 hr

200 energy bins in range between 10 GeV and 100 TeV

Neural network trained on simulated spectra

ma: [1: 10^3] neV
$ga\gamma$: [0.01: 10] 10^{-11} GeV^{-1}



Credit: James Alvey, EuCaifCon 2025

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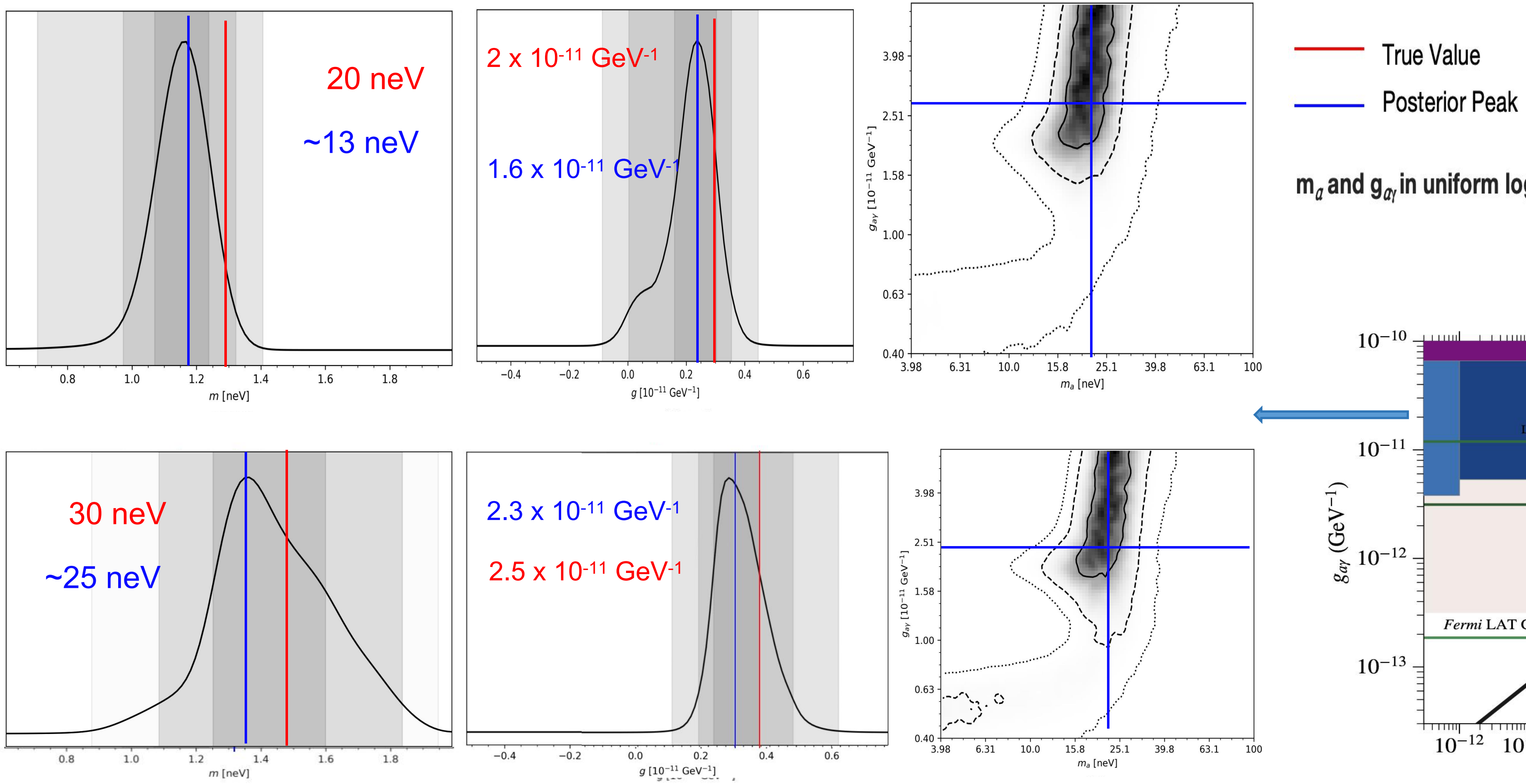
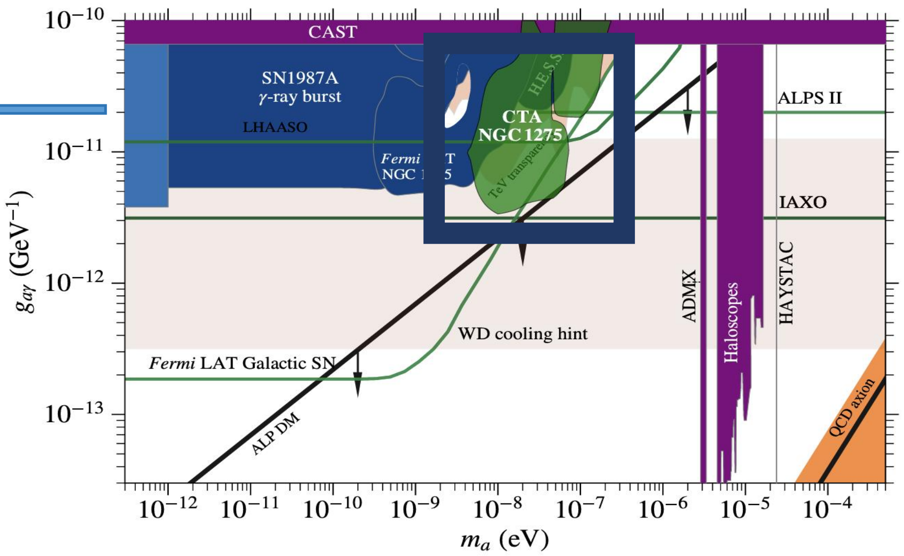
Posterior Plots

10^6 simulations used in training

PRELIMINARY



m_a and $g_{a\gamma}$ in uniform log-scale



JCAP 02 (2021) 048

- **Posterior peaks near true values, seems to be sensitive in our chosen parameter space.**
- **“Broad contours” persist due to limited training density and parameter degeneracies.**

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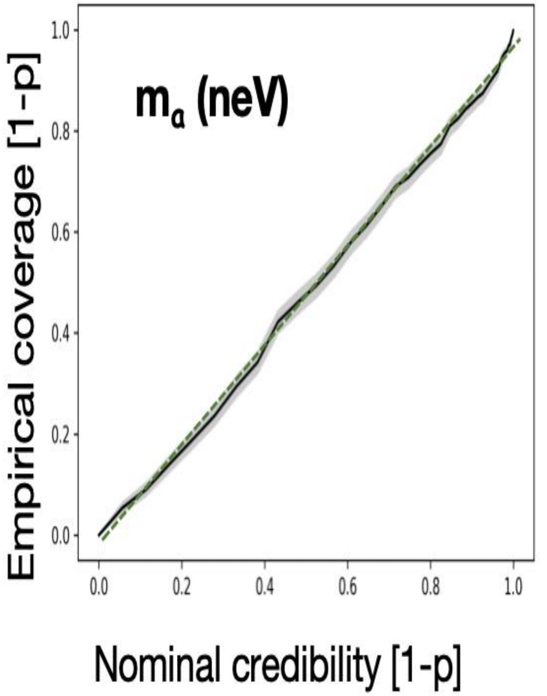
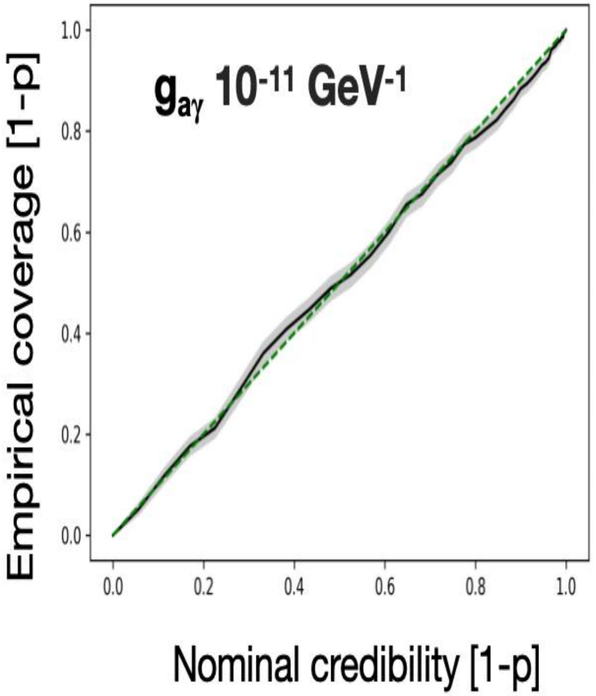
Coverage Test

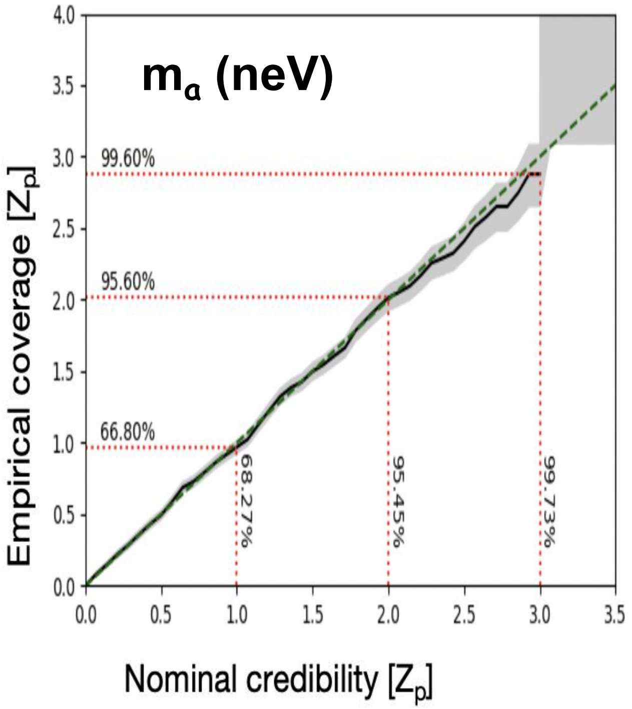
10^6 simulations used in training

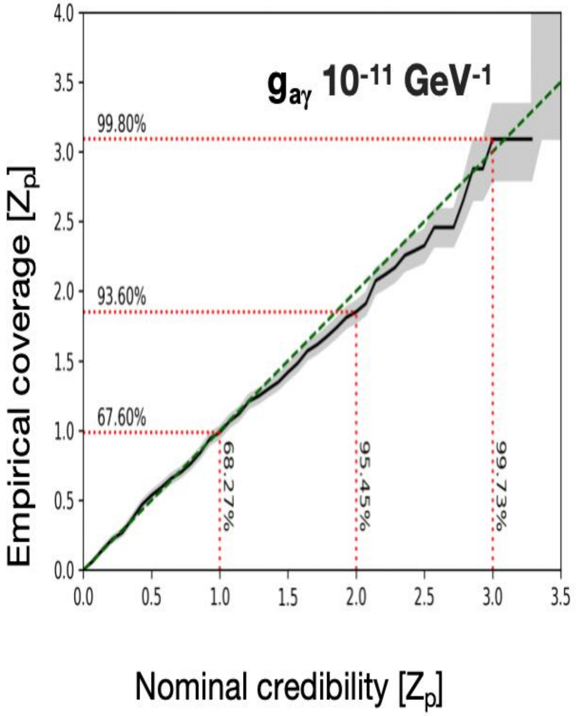
Expected Coverage Probability (ECP) test compares the empirical coverage of credibility regions to their nominal credibility.

PRELIMINARY





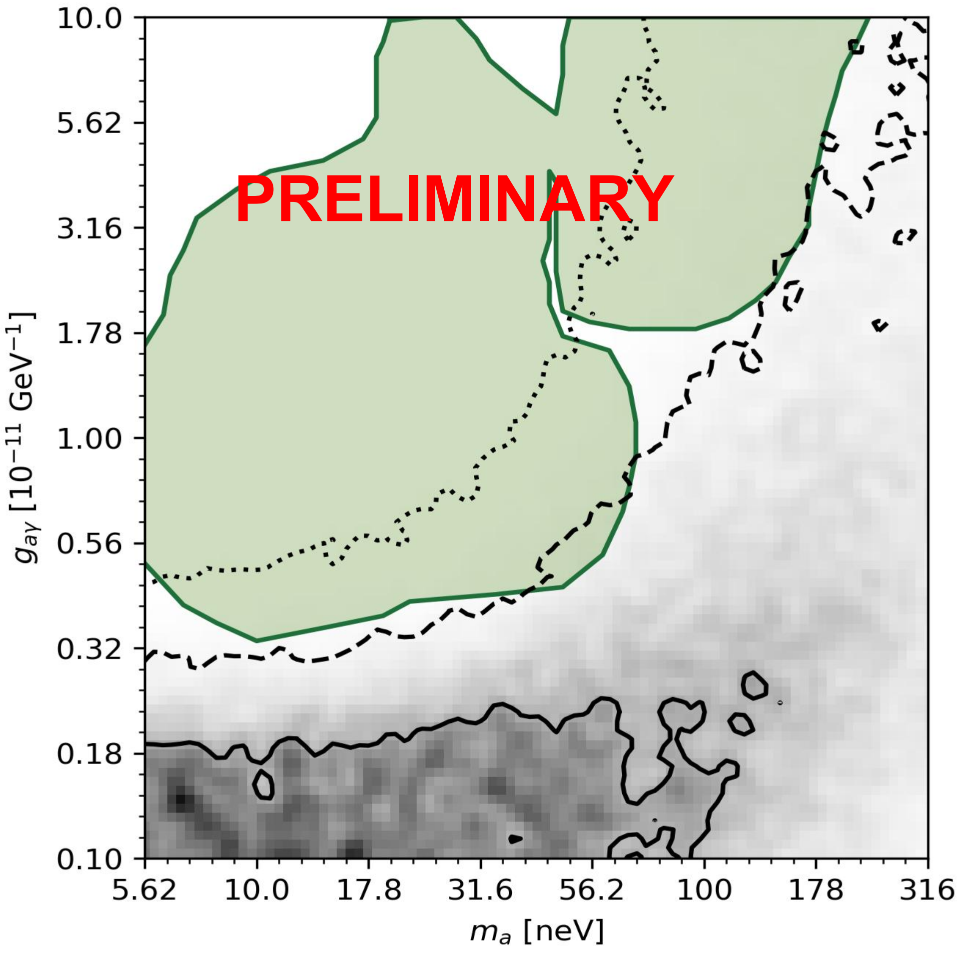


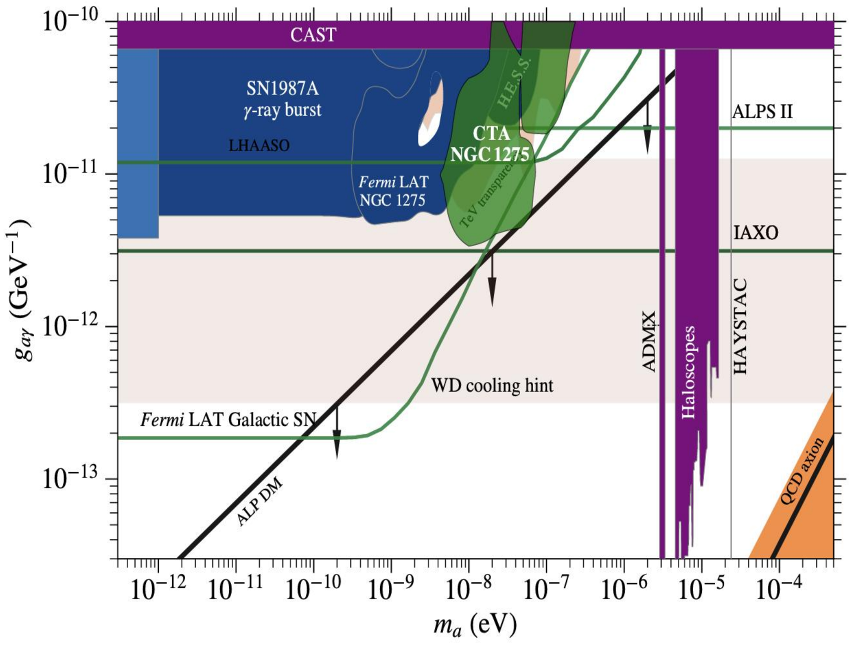


PP plot tracks the diagonal line well.

ZZ plot tracks the diagonal line well upto 1-2 sigma region. Suggesting mild overconfidence or reduced calibration

Comparison with existing CTAO limits





SBI exclusion limits (1σ–2σ) overlap with CTAO limits, showing agreement between simulated constraints and CTA sensitivity.

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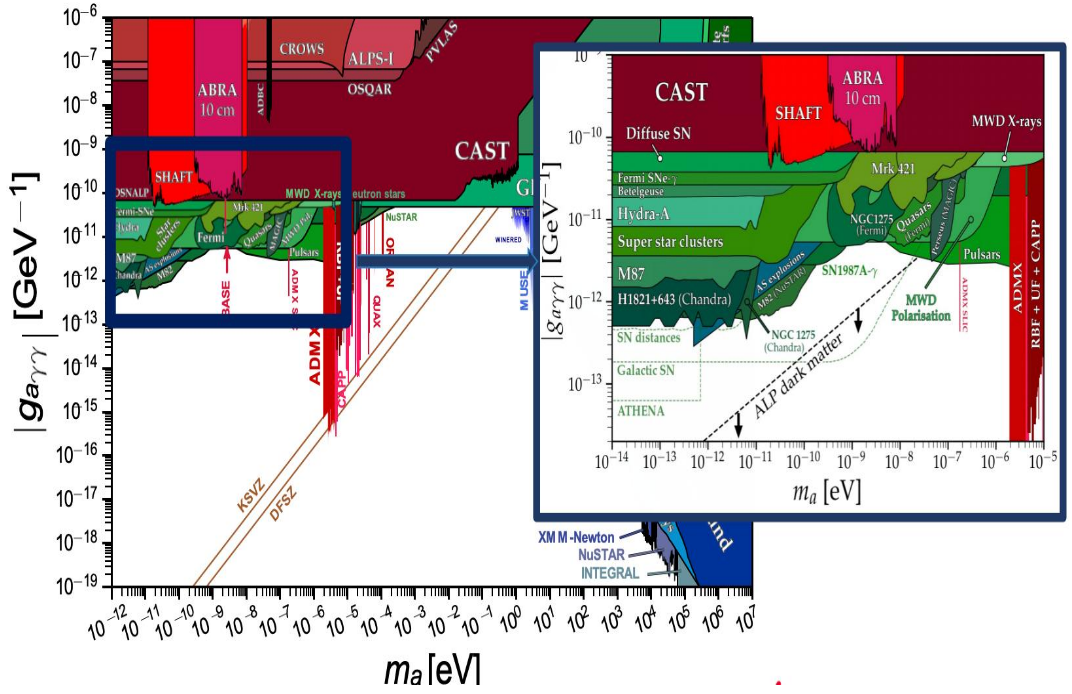
ALP searches - Future prospects

- ALP models are complex, with numerous 'nuisance parameters'.
- With ML approach, we seek to yield robust constraints on ALP-photon interactions.
- Our preliminary results indicate that SBI is a viable method for distinguishing ALP Parameter Inference. Shows agreement between classical likelihood ratio test and SBI method.
- SBI approach allows us to combining data from multiple targets to enhance sensitivity- something not easily achievable with a likelihood approach. Possible to generalize to more parameters and sources and can be readily applied to real data.
- Steps to improve the reliability of our trained model:
  - Train our models with larger, denser datasets- Use of HPC Vega Cluster.
  - Include astrophysical systematics (magnetic fields, plasma effects).
  - Upgrade neural networks (deeper models, new loss functions, calibration tools).



limits on ALPs parameter space,

Source: C. O'Hare, github.com/cajohare/AxionLimits

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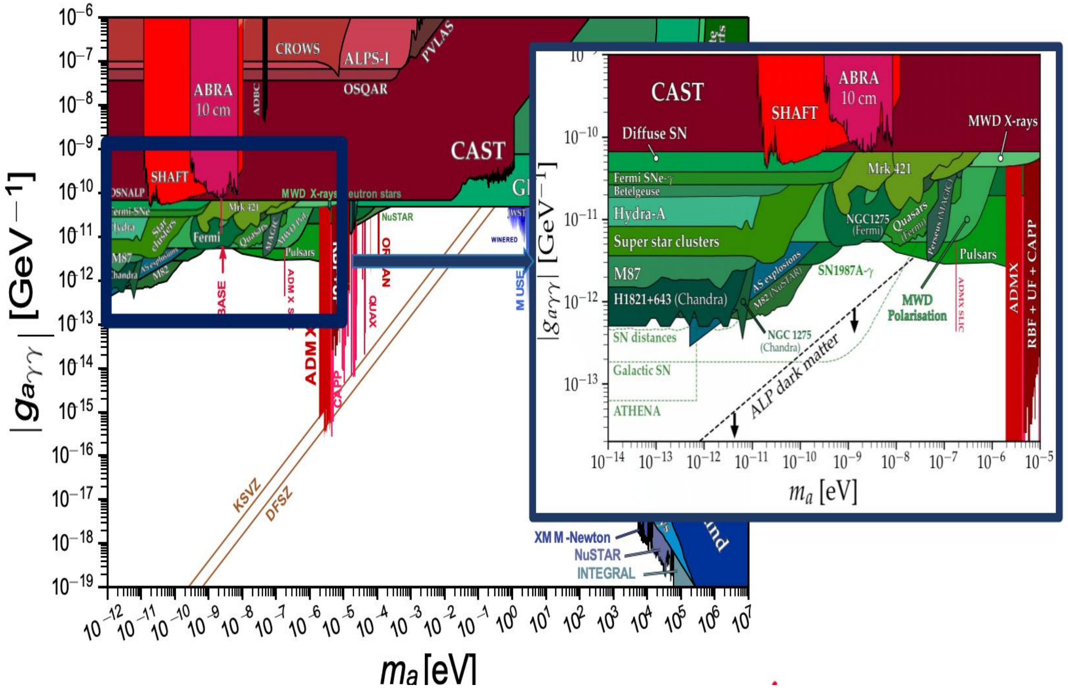


limits on ALPs parameter space,

Source: C. O'Hare, github.com/cajohare/AxionLimits

Contact: pooja.bhattacharjee@ung.si

Thank you for your attention!!!

Backup slides

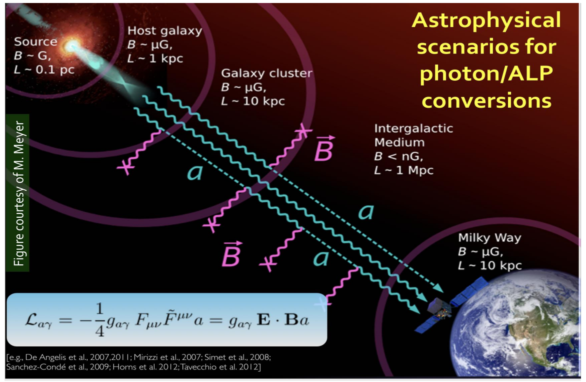
Why ALPs

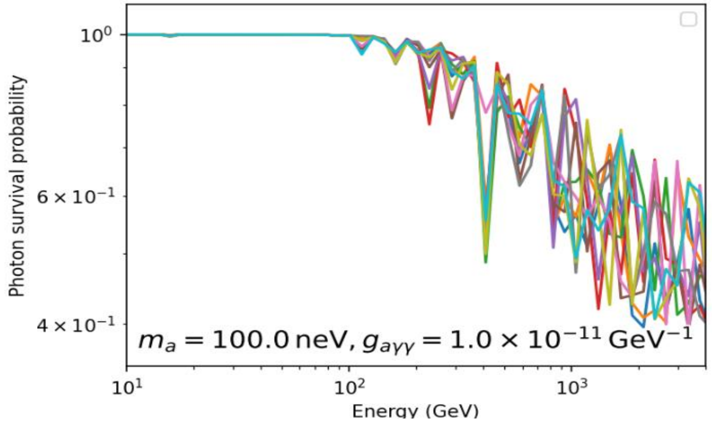
- ALPs are **excellent dark matter candidates** - cold, light, and weakly interacting.
  → Probe physics beyond the Standard Model

- Can be produced in **extreme astrophysical environments**,
  → AGN jets, galaxy clusters, supernovae

- In the presence of magnetic field, **ALPs oscillate into gamma rays** and could lead to irregularities in the spectra of astrophysical objects.
  → **Mixing/ "wiggles" happens near the critical energy, E_{crit},** and is directly testable with current/future telescopes.

- With **supervised machine learning and + large datasets**, it is possible to obtain tighter, robust constraints.
  → carve out parameter space beyond current lab bounds.





Obtained using the gammaAlps,

https://github.com/me-manu/gammaALPs

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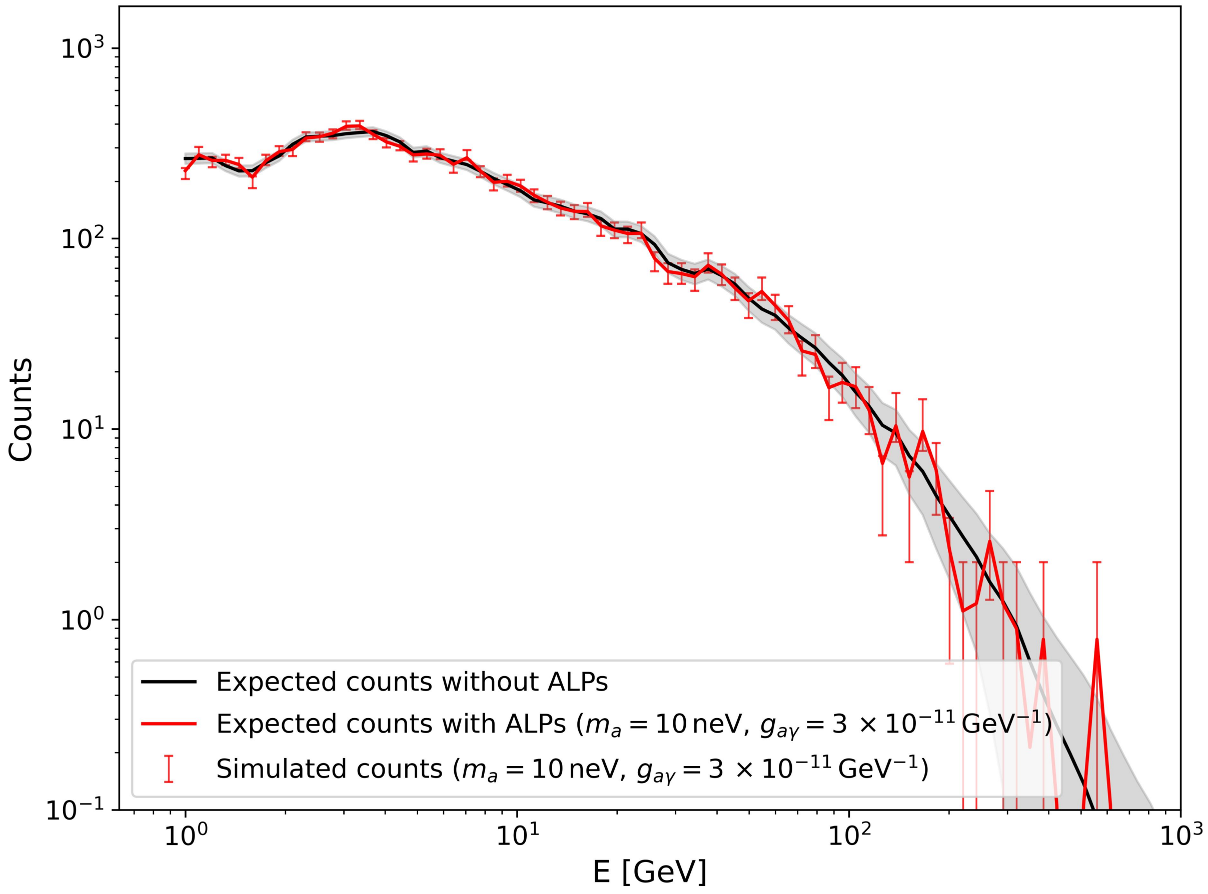
Events with Simulated Noise



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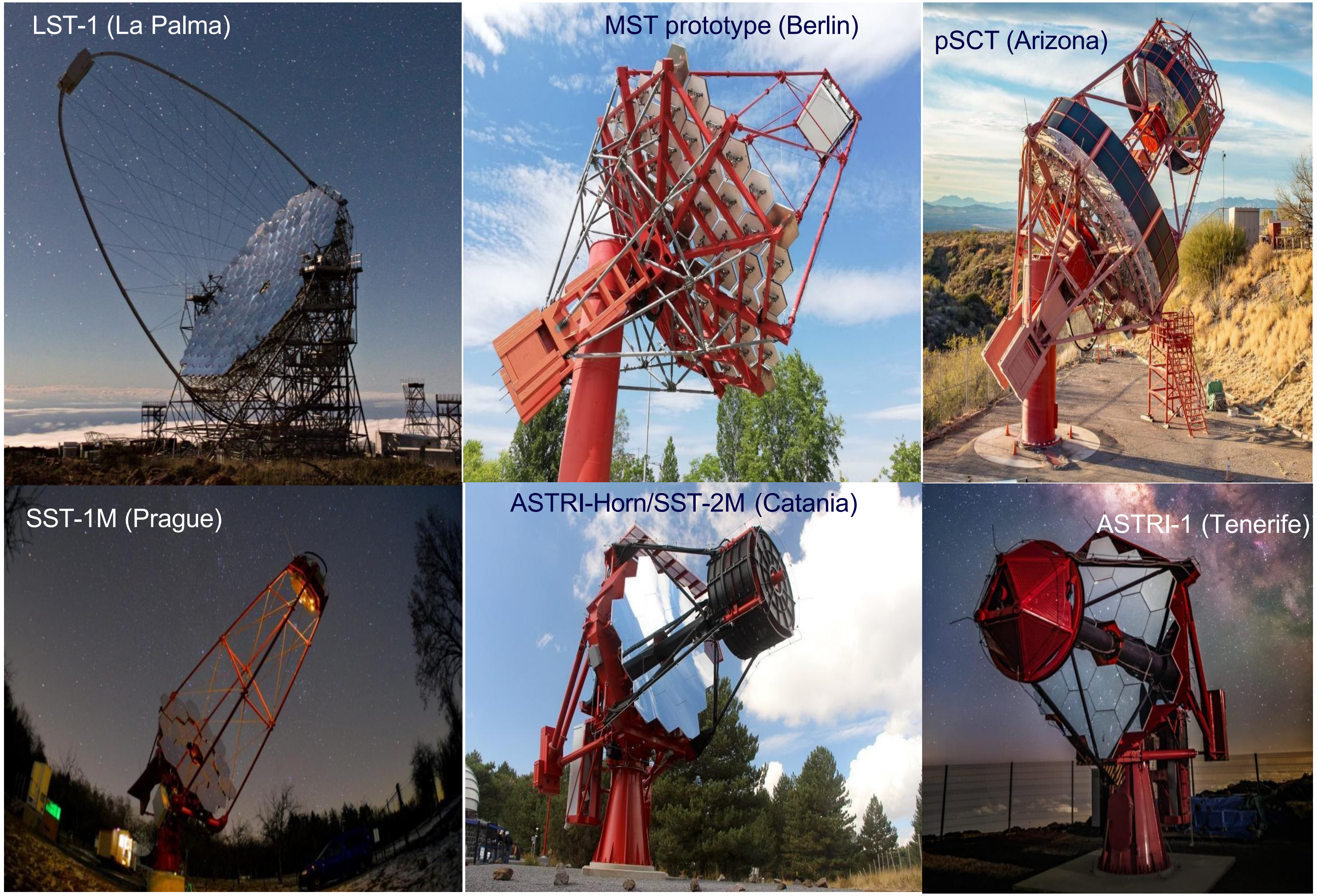
CTAO prototypes at different location



Sites Locations

- LST-1 in La Palma
- MST prototype in Berlin
- ASTRI-Horn/SST-2M in Catania
- ASTRI-1 in Tenerife
- SST-1M in Prague
- Schwarzschild-Couder Telescope prototype (pSCT) in Arizona, US

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Simulation-Based Inference (Neural Ratio Estimation)

Given two distributions $p_1(\boldsymbol{x})$ and $p_2(\boldsymbol{x})$, where xi is observed counts:

$\boldsymbol{x}_0,\ \boldsymbol{x}_2,\ \boldsymbol{x}_4,\ \boldsymbol{x}_6,\ \ldots \sim p_1(\boldsymbol{x})$

$\boldsymbol{x}_1,\ \boldsymbol{x}_3,\ \boldsymbol{x}_5,\ \boldsymbol{x}_7,\ \ldots \sim p_2(\boldsymbol{x})$

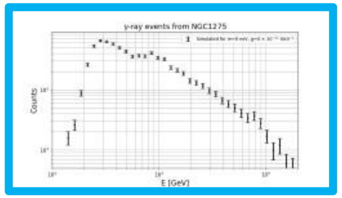
1. Draw many samples $(\boldsymbol{x}_i, m_i, g_i)$
2. Train network to distinguish the samples

from $p(\boldsymbol{x}|m, g)p(m, g)$

i.e. Sample (m_i, g_i) from the prior $p(m, g)$, then simulate $\boldsymbol{x}_i$ from (m_i, g_i).

and from $p(\boldsymbol{x})p(m, g)$

i.e. Sample (m_j, g_j) from the prior $p(m, g)$, then simulate $\boldsymbol{x}_i$ from (m_j, g_j). Then draw (m_i, g_i) from the prior.

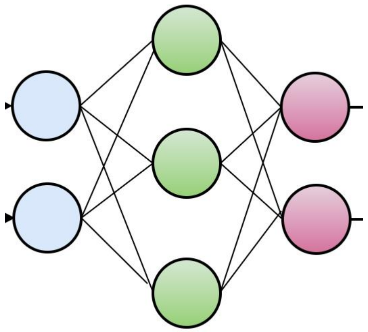
$\boldsymbol{x}_i =$ 

$m_i = 2$ neV

$g_i = 3 \times 10^{-11}$ GeV^{-1}

Vary m_i and g_i to scan parameter space

Input



Neural network

Modified Output

$$\frac{p(\boldsymbol{x}_i \mid m_i, g_i)}{p(\boldsymbol{x}_i)} \text{ x Prior } = \textbf{Posterior!}$$

$$\boxed{\text{Posterior} = \text{Modified Output x Prior}}$$

Slide Credit: Gert Kluge, TeVPA, 2023

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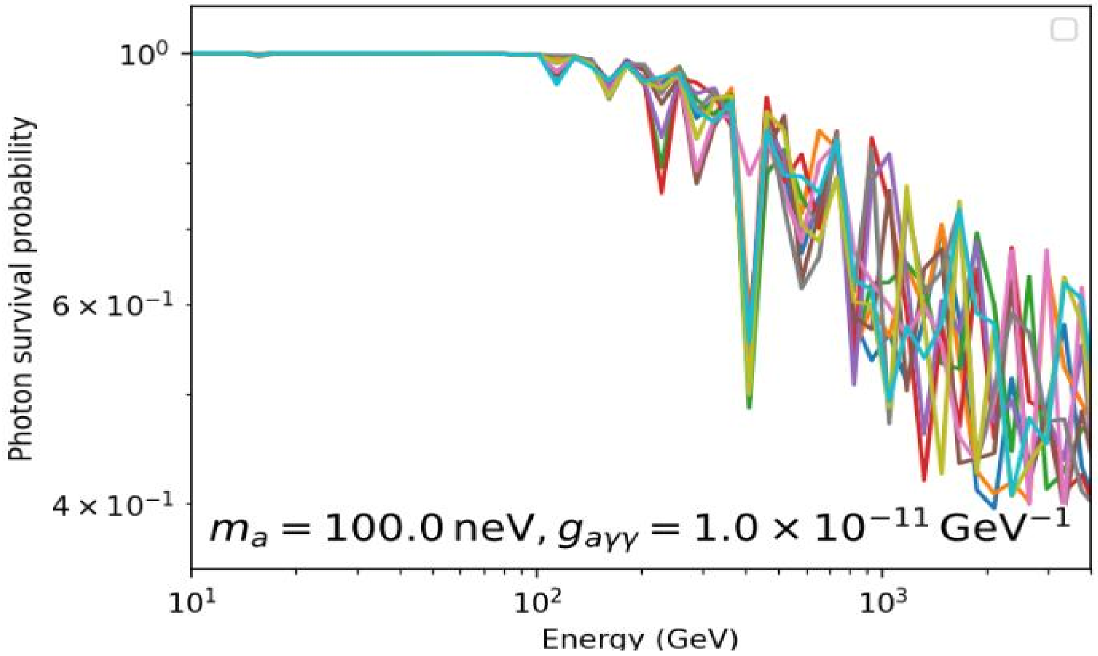
Photon Survival Probability

Photons can convert to ALPs by mixing induced in the external magnetic field –

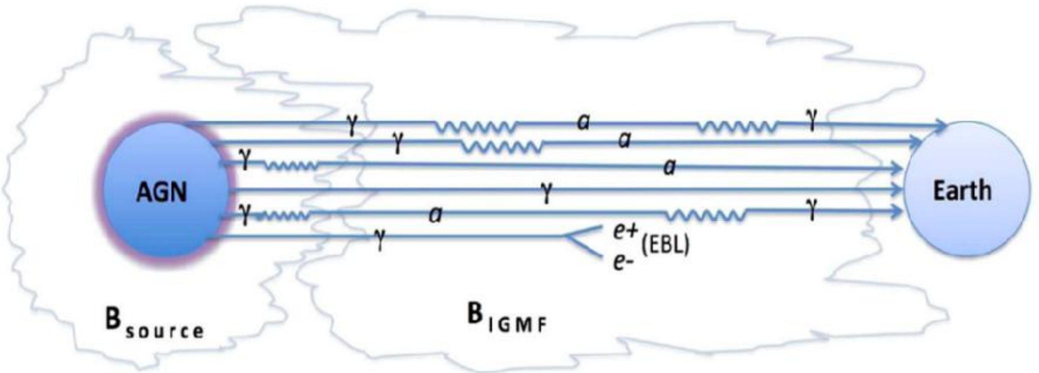
causing the so called "wiggles", irregularities in the spectra of astrophysical objects



Obtained using the GAMMAALPs code: https://github.com/me-manu/gammaALPs

Conversion/oscillation in the presence of magnetic field

M. Sánchez-Conde, D. Paneque et al., 0905.3270



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