Sensitivity of CTAO to axion-like particles from blazars

A machine learning approach

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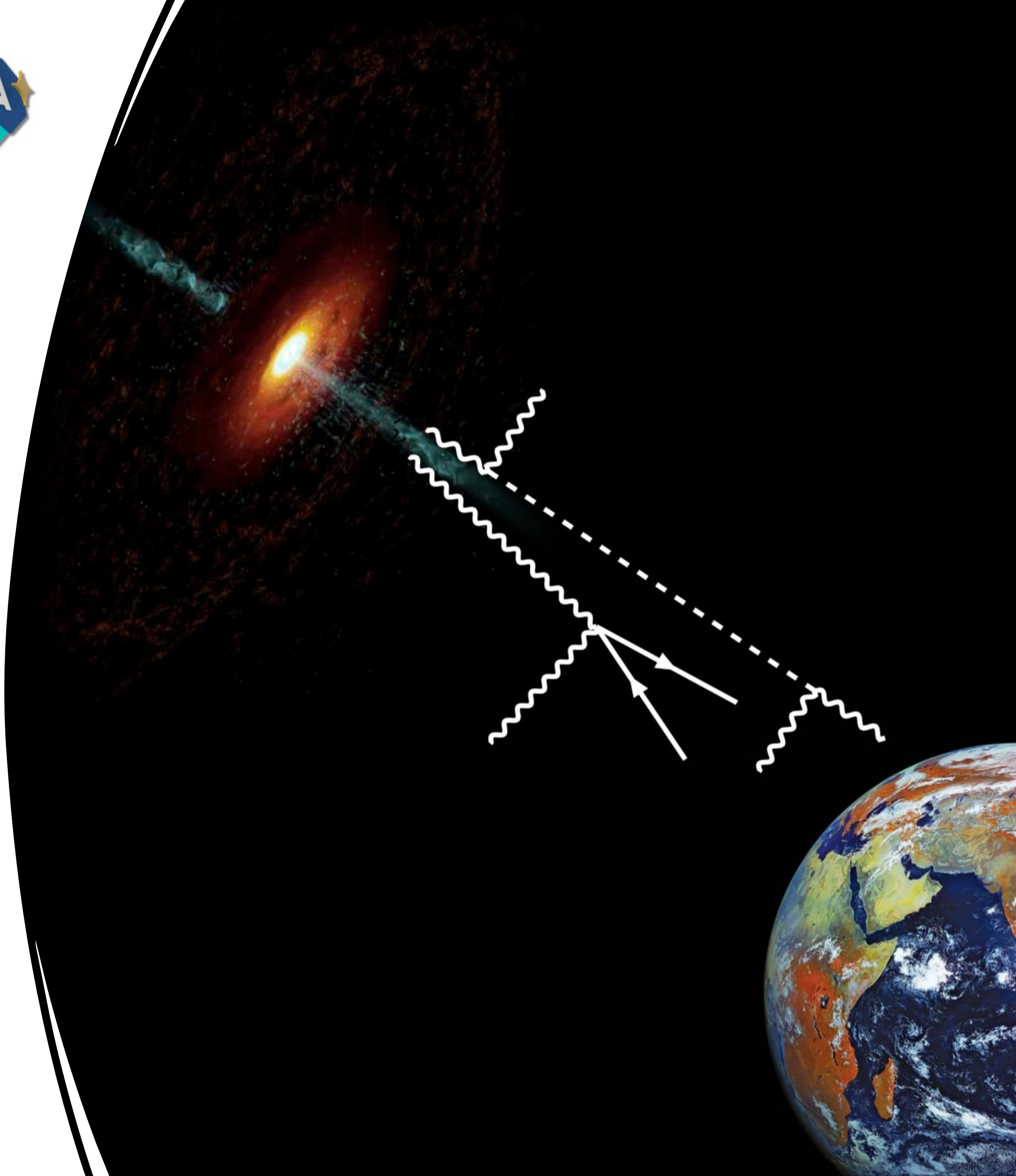
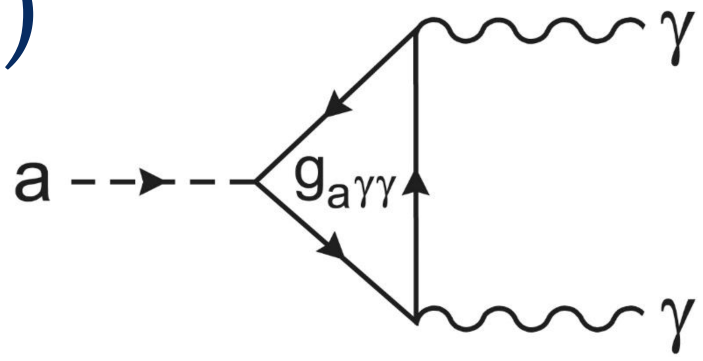
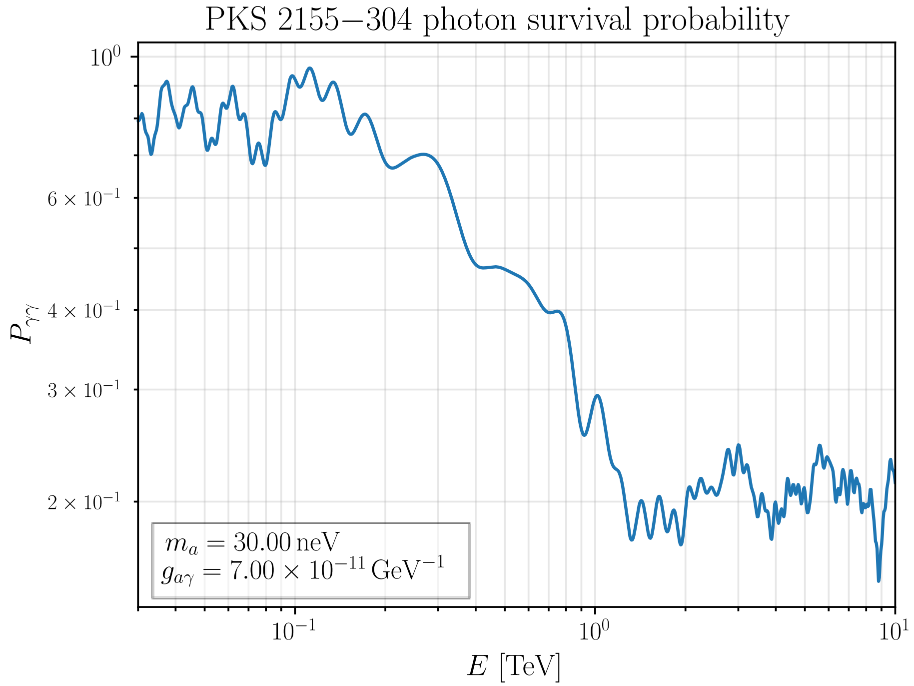


Axion-like particles (ALPs)

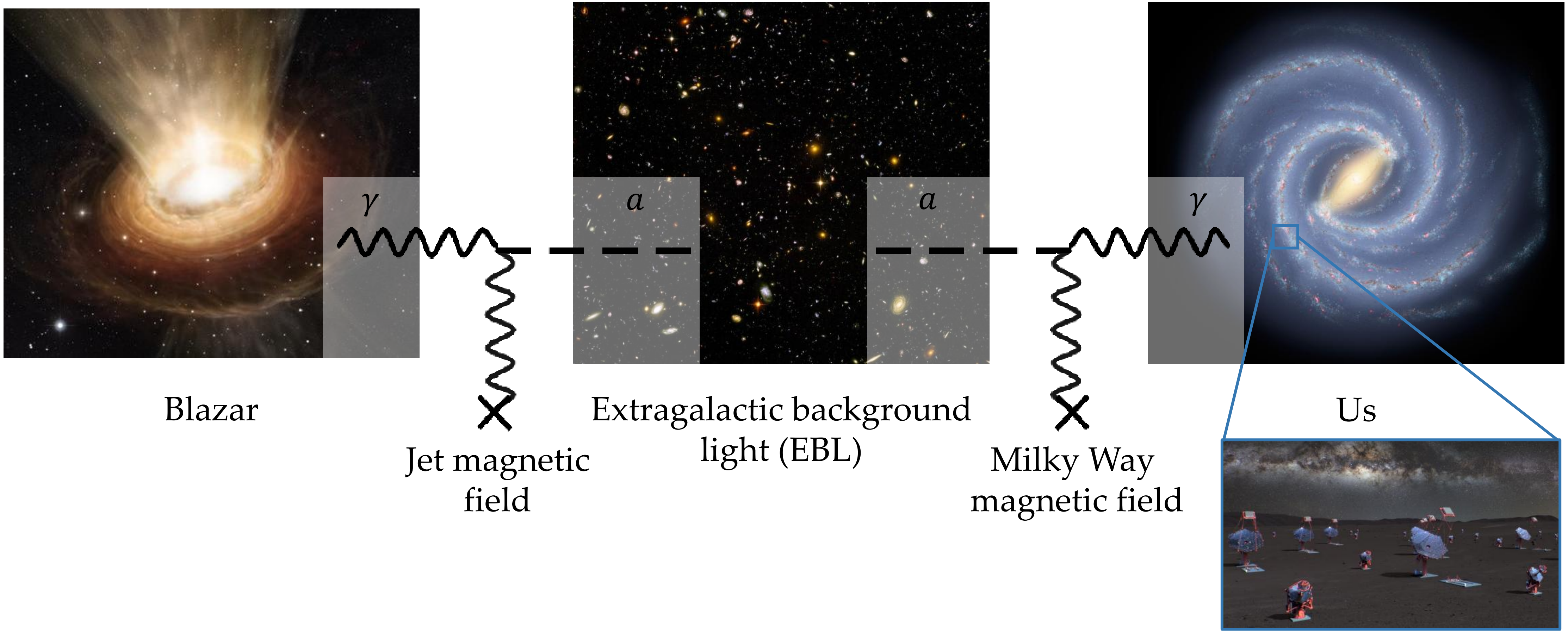


- Hypothetical pseudo-scalar particles with mass m_a and effective coupling to photons $g_{a\gamma}$
- ALP-photon oscillations possible in external magnetic fields
- Potential imprint on the spectra of astrophysical sources:

$$\boxed{\phi_{\text{obs}}(E) = \phi_{\text{int}}(E) P_{\gamma\gamma}(E)}$$



ALP-photon conversions in blazars



Blazar selection

Source	z	RA [deg]	Dec [deg]
Mrk 501	0.034	253.47	39.76
Mrk 421	0.031	166.11	38.21
PKS 2155−304	0.116	329.72	−30.23

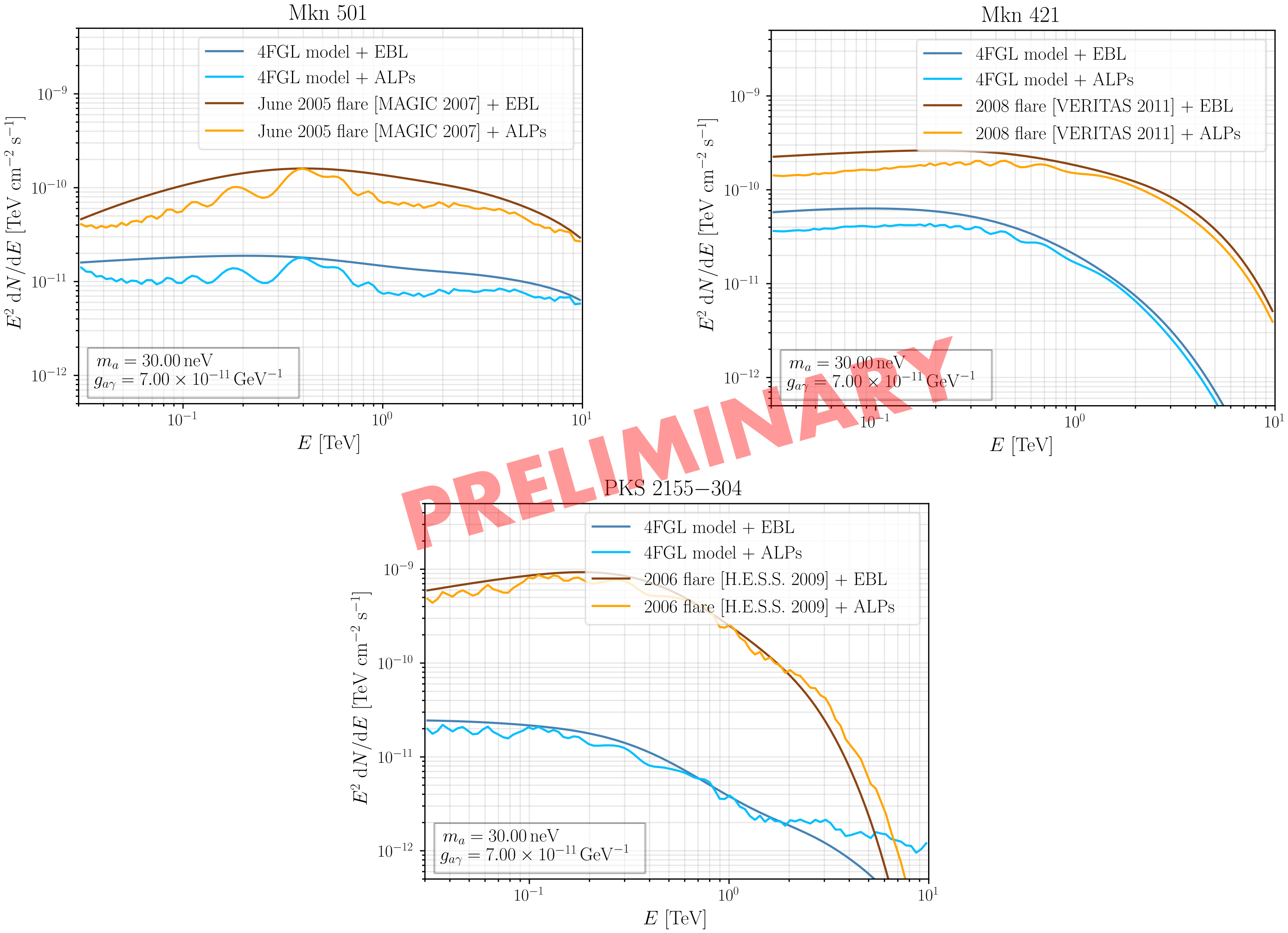
- Some of the most well-known and studied extragalactic gamma-ray sources
- High synchrotron peaked BL Lacs (HBLs) → significant TeV emission
- Available jet magnetic field models
- Included in the CTAO AGN Key Science Project → lots of data to be expected! [arXiv:1709.07997]

Spectral modelling

- Spectral models (assumed valid between 30 GeV and 10 TeV):
  - Baseline states from the Fermi-LAT 4FGL-DR4 catalog
  - Flaring states from past IACT observations
- Photon survival probability $P_{\gamma\gamma}(E)$ computed using GammaALPs, including:
  - Jet magnetic field [Potter & Cotter 2015, arXiv:1508.00567]
  - Milky Way magnetic field [Jansson & Farrar 2012]
  - EBL absorption [Domínguez+ 2011]

https://github.com/me-manu/gammaALPs/
https://gammaalps.readthedocs.io/

ALP effects on gamma-ray spectra



Project outline

- Motivation: CTAO's energy resolution and point-source sensitivity are well-suited to detect the spectral oscillations due to ALPs
- Goal: obtain (better) CTAO sensitivity limits on the ALP parameter space
- Standard method: likelihood-ratio $\mathrm{TS}(m_a, g_{a\gamma})$
  - CTA(O) fundamental physics Consortium Paper [arXiv:2010.01349]
  - MAGIC paper on ALPs from the Perseus Galaxy Cluster [arXiv:2401.07798]
  - Both works focus on the AGN NGC 1275
- Our method: define a grid of machine learning (ML) classifiers, one for each $\left(m_a, g_{a\gamma}\right)$ pair

Dataset simulation

A **Python** package for **gamma-ray** astronomy

- For each source, we consider CTAO prod5 IRFs, 20° zenith distance and
  - 50 h livetime for the baseline states
  - 5 h livetime for the flaring states

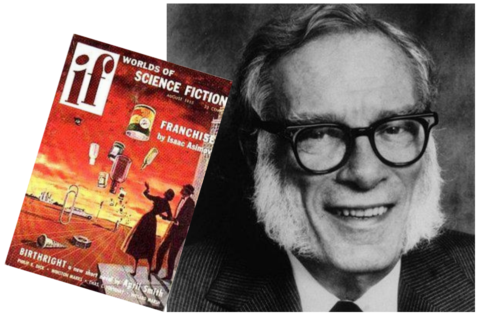
Source	Livetime (h)	IRFs
Mrk 501 (baseline)	50	Prod5-North-20deg-AverageAz-4LSTs09MSTs.180000s
Mrk 421 (baseline)	50	Prod5-North-20deg-AverageAz-4LSTs09MSTs.180000s
PKS 2155−304 (baseline)	50	Prod5-South-20deg-AverageAz-14MSTs37SSTs.180000s
Mrk 501 (flaring)	5	Prod5-North-20deg-AverageAz-4LSTs09MSTs.18000s
Mrk 421 (flaring)	5	Prod5-North-20deg-AverageAz-4LSTs09MSTs.18000s
PKS 2155−304 (flaring)	5	Prod5-South-20deg-AverageAz-14MSTs37SSTs.18000s

PRELIMINARY

Dataset simulation

A **Python** package for **gamma-ray** astronomy

- We simulate ON-OFF observations ($\alpha = 1/3$, 0.7° offset) *without* ALPs, using 40 bins per energy decade as in the Consortium Paper
- Mean sensitivity would require simulating many such datasets (e.g. using `Dataset.fake()` in Gammapy) and averaging the results
- «Asimov» datasets avoid this by eliminating fluctuations (Cowan+ 2010, arXiv:1007.1727)
    - Application to ALPs in Meyer+ 2014 [arXiv:1406.5972, arXiv:1410.1556]



Classifier training

- Define a grid of ML classifiers over the ALP space, based on the XGBoost algorithm
- Train each of those with 2000 simulated spectra with/without ALPs, using excess photon counts in each bin (normalized between 0 and 1) as features
- Present each classifier with the counts in the Asimov dataset
- It will output a probability $p_{\mathrm{ALP},A}(m_a, g_{a\gamma})$ that the dataset contains ALP signatures

https://github.com/dmlc/xgboost
https://xgboost.readthedocs.io/en/release_3.0.0/

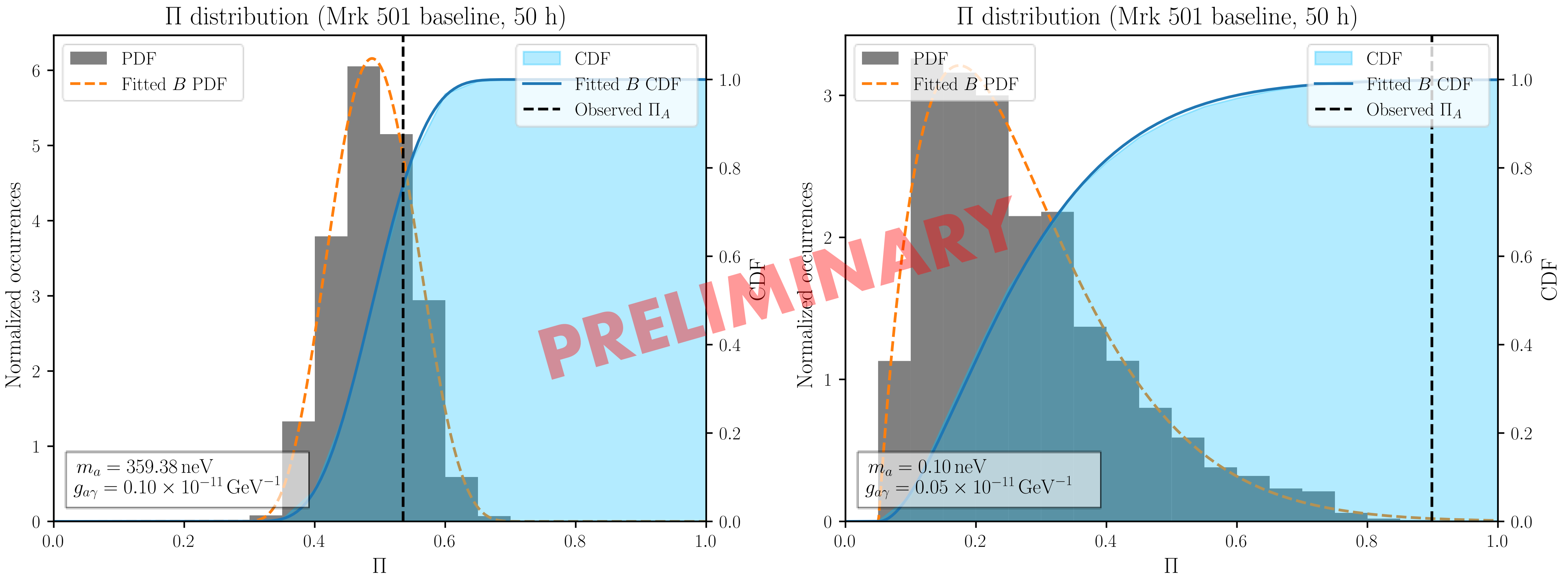
Derivation of limits

- Define $\Pi_A(m_a, g_{a\gamma}) = 1 - p_{\text{ALP},A}(m_a, g_{a\gamma})$
- For each $(m_a, g_{a\gamma})$ point, compute a Π distribution from 2000 simulated ALP datasets
  - small Π: ALP-like dataset
  - large Π: ALP-less dataset
- Fit with a Beta distribution and compute the CDF value at Π_A

$$f(x, \alpha, \beta) = \frac{\Gamma(\alpha+\beta)x^{\alpha-1}(1-x)^{\beta-1}}{\Gamma(\alpha)\Gamma(\beta)}$$

- Estimate exclusion significance in σ as $z = \sqrt{2}\,\mathrm{erf}^{-1}(\text{CDF}_A)$

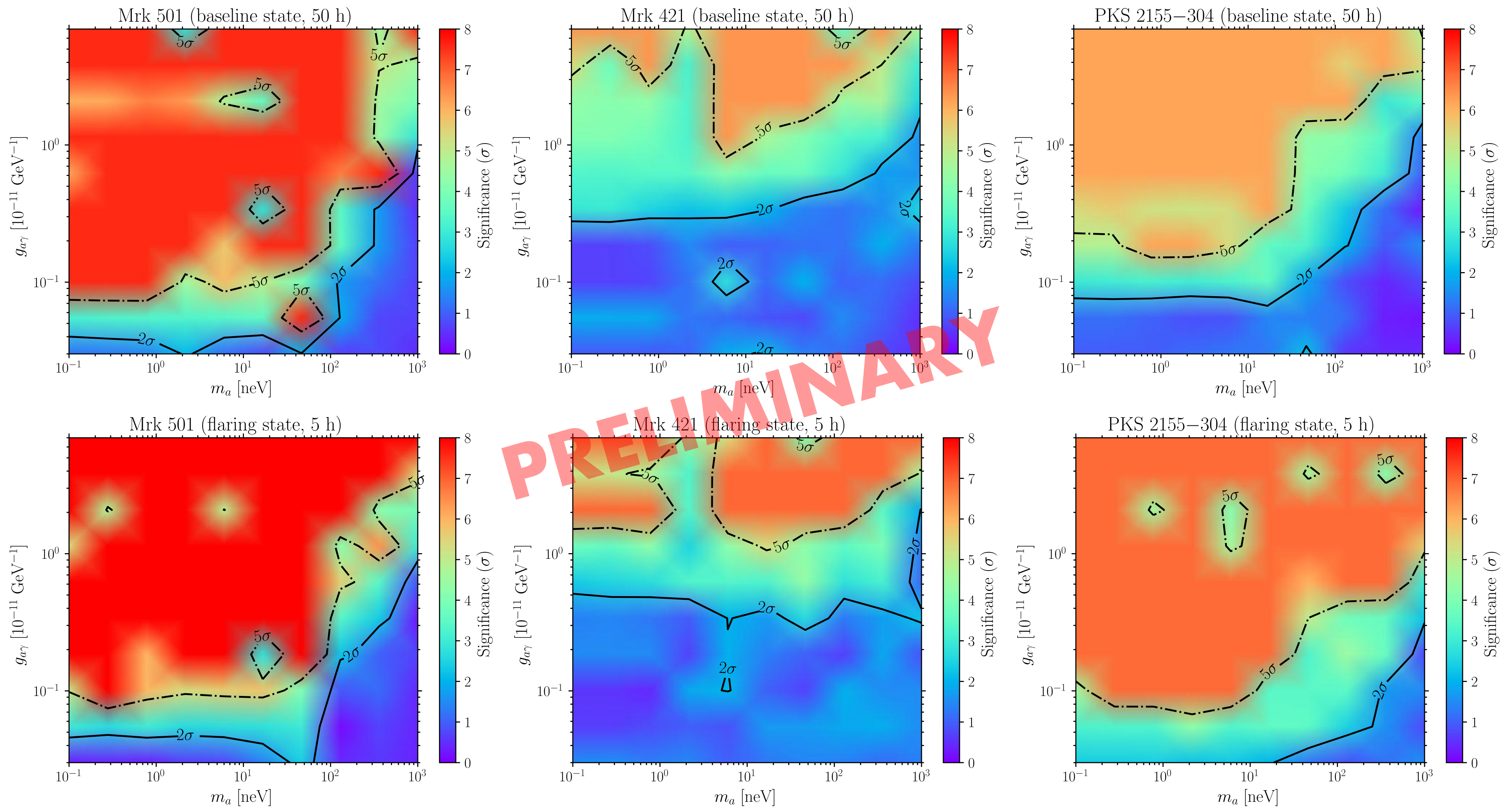
Example Π distributions



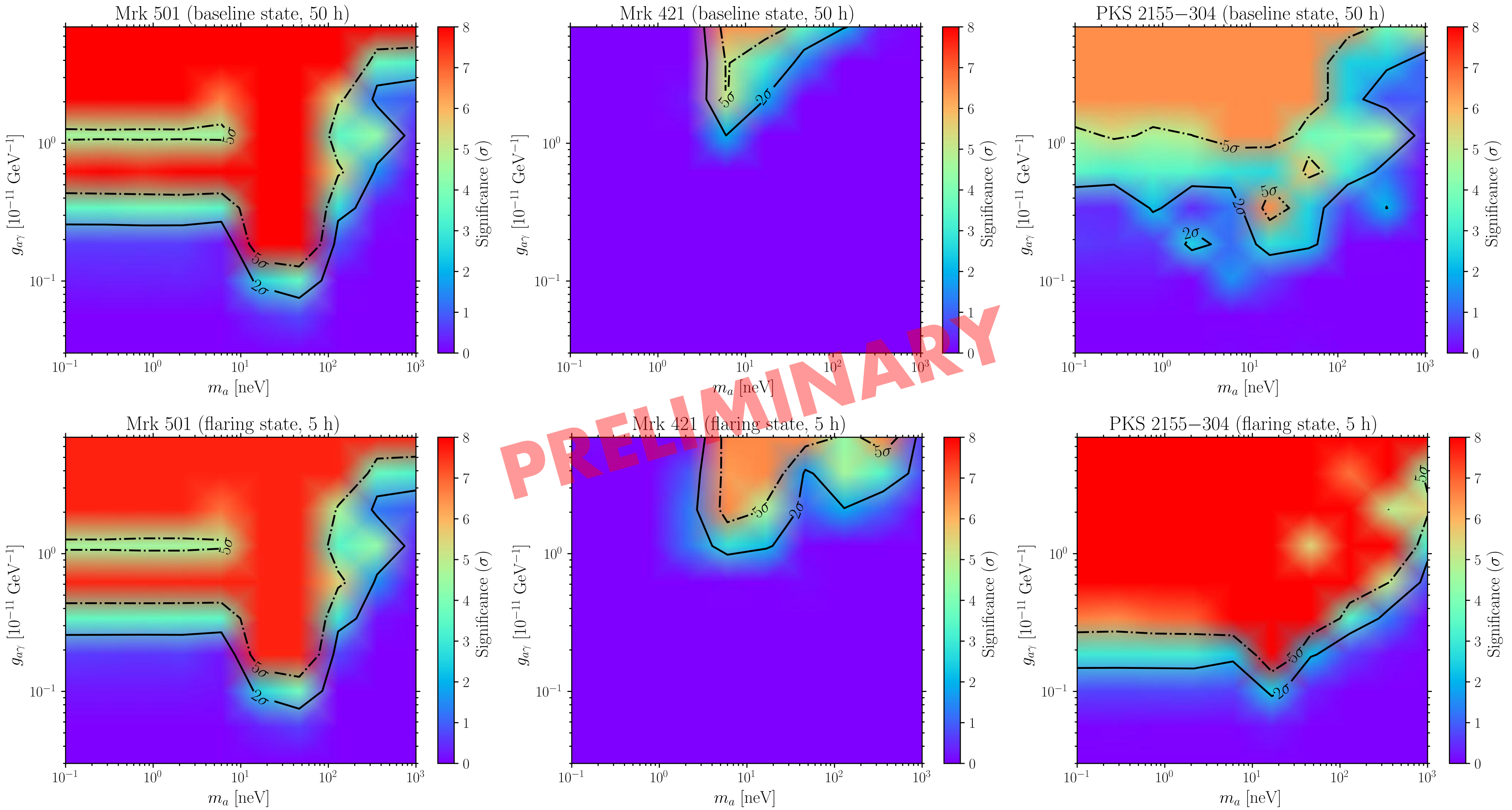
«Bad» distribution – no exclusion

«Good» distribution – exclusion

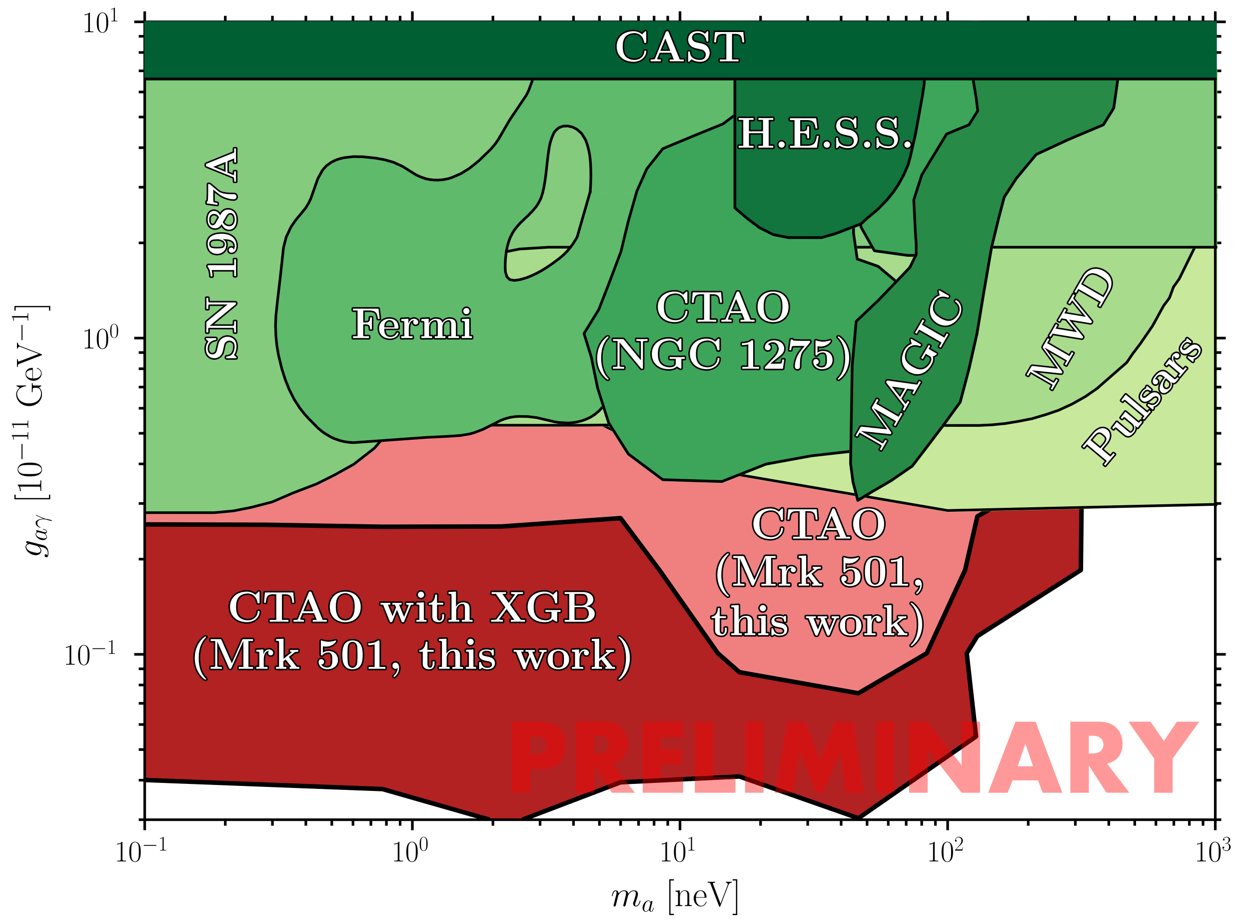
Results (ML approach)



Results (standard likelihood-ratio TS)



Results comparison (Mrk 501 baseline, 50 h)



Reference limits (95% CL) from https://github.com/cajohare/AxionLimits

Conclusions

- Among its many exciting prospects, CTAO will be a great tool to probe new fundamental physics
- Blazars in particular are ideal targets for ALP searches, not fully explored yet
- Previously unconstrained ALP parameter space can be covered with both methods, even with few hours of data
- The ML approach seems to offer some improvement (proof of concept, more systematic tuning needed)
- A paper and a public GitHub repository are currently in preparation – stay tuned!

Thank you for your attention!

All questions and comments welcome :)

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Backup

Source and simulation parameters

Source	z	RA (deg)	Dec (deg)	gammaALPs parameters						
				r_0 (pc)	B0 (G)	gmax	gmin	n0 (cm^{-3})	rjet (pc)	alpha
Mrk 501	0.034	253.47	39.76	0.36	0.81	9	2	4.5×10^4	3.2×10^3	1.68
Mrk 421	0.031	166.11	38.21	7.19	2.91×10^{-2}	12	9	8.5×10^3	9.7×10^4	1.55
PKS 2155-304	0.116	329.72	-30.23	0.33	0.82	15	7	1.65×10^4	3.2×10^3	1.70

Source	Livetime (h)	IRFs	Reference spectrum
Mrk 501 (baseline)	50	Prod5-North-20deg-AverageAz-4LSTs09MSTs.180000s	LP [52]
Mrk 421 (baseline)	50	Prod5-North-20deg-AverageAz-4LSTs09MSTs.180000s	SECPL [52]
PKS 2155–304 (baseline)	50	Prod5-South-20deg-AverageAz-14MSTs37SSTs.180000s	LP [52]
Mrk 501 (flaring)	5	Prod5-North-20deg-AverageAz-4LSTs09MSTs.18000s	LP [53]
Mrk 421 (flaring)	5	Prod5-North-20deg-AverageAz-4LSTs09MSTs.18000s	ECPL [54]
PKS 2155–304 (flaring)	5	Prod5-South-20deg-AverageAz-14MSTs37SSTs.18000s	ECPL [55]

PRELIMINARY

Source	Model	ϕ_0	E_0	α	β	E_{cut}	a	Γ_1	Γ_2	Ref.
	Baseline	[MeV^{-1} cm^{-2} s^{-1}]	[MeV]			[MeV]				
Mrk 501	LP	3.91×10^{-12}	1507.92	1.75	0.018	–	–	–	–	[52]
Mrk 421	SECPL	1.79×10^{-11}	1258.26	–	–	–	0.011	1.74	0.65	[52]
PKS 2155–304	LP	1.34×10^{-12}	1146.89	1.77	0.041	–	–	–	–	[52]
	Flaring	[TeV^{-1} cm^{-2} s^{-1}]	[TeV]			[TeV]				
Mrk 501	LP	1.86×10^{-9}	0.3	1.73	0.13	–	–	–	–	[53]
Mr 421	ECPL	3.58×10^{-10}	1.0	–	–	2.74	–	–	–	[54]
PKS 2155–304	ECPL	2.38×10^{-9}	1.0	–	–	1.0	–	–	–	[55]

Asimov datasets

- Defined so that for each energy bin $N_{\mathrm{on},i} = \mu_i$ (signal + bkg) and $N_{\mathrm{off},i} = b_i/\alpha$ ($\alpha = 1/3$)
- In Gammapy:

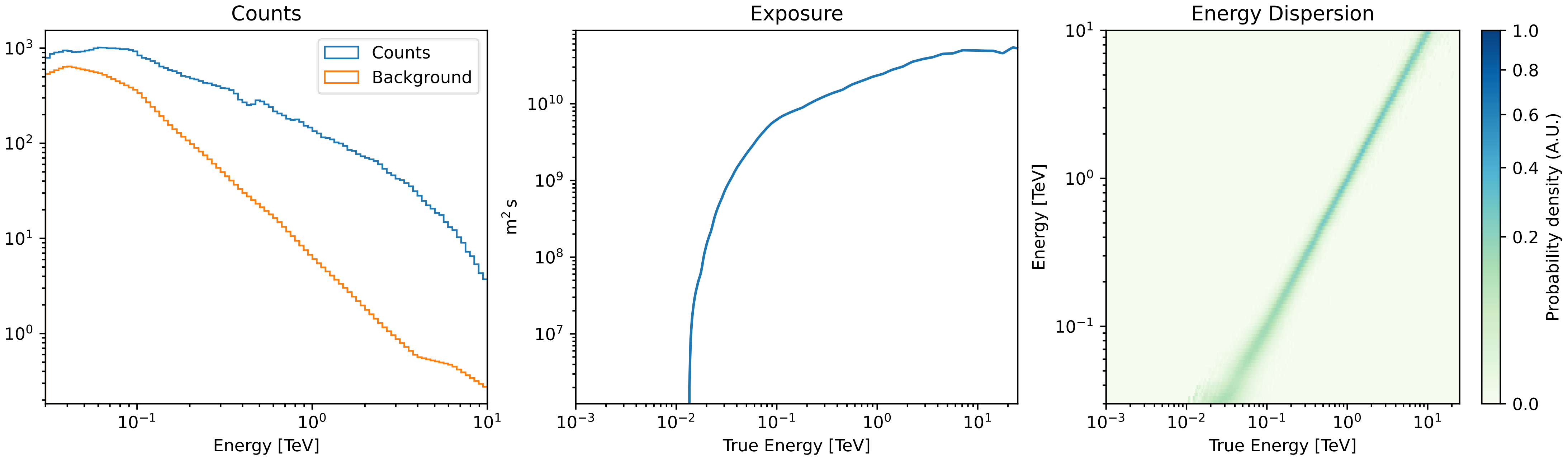
[9]:
```
npred = dataset_on_off_mock.npred()
npred_bkg = dataset_on_off_mock.npred_background()
acceptance = dataset_on_off_mock.acceptance
acceptance_off = dataset_on_off_mock.acceptance_off
exposure = dataset_on_off_mock.exposure
edisp = dataset_on_off_mock.edisp
```

[10]:
```
dataset_asimov = SpectrumDatasetOnOff(counts=npred,
                                      counts_off=npred_bkg/alpha,
                                      acceptance=acceptance,
                                      acceptance_off=acceptance_off,
                                      models=[skymodel],
                                      exposure=exposure,
                                      edisp=edisp,
                                      name=f'{source_name_nospace}_Asimov')
```

```
SpectrumDatasetOnOff
--------------------

  Name                            : Mkn501_Asimov

  Total counts                    : 37960
  Total background counts         : 14647.66
  Total excess counts             : 23313.22

  Predicted counts                : 37960.88
  Predicted background counts     : 14647.66
  Predicted excess counts         : 23313.22

  Exposure min                    : 2.05e+06 m2 s
  Exposure max                    : 5.41e+10 m2 s

  Number of total bins            : 101
  Number of fit bins              : 0

  Fit statistic type              : wstat
  Fit statistic value (-2 log(L)) : 0.00
```

Asimov datasets

- We simulate 40 bins per decade between 30 GeV and 10 TeV
- The choice of binning agrees with the previous Consortium Paper

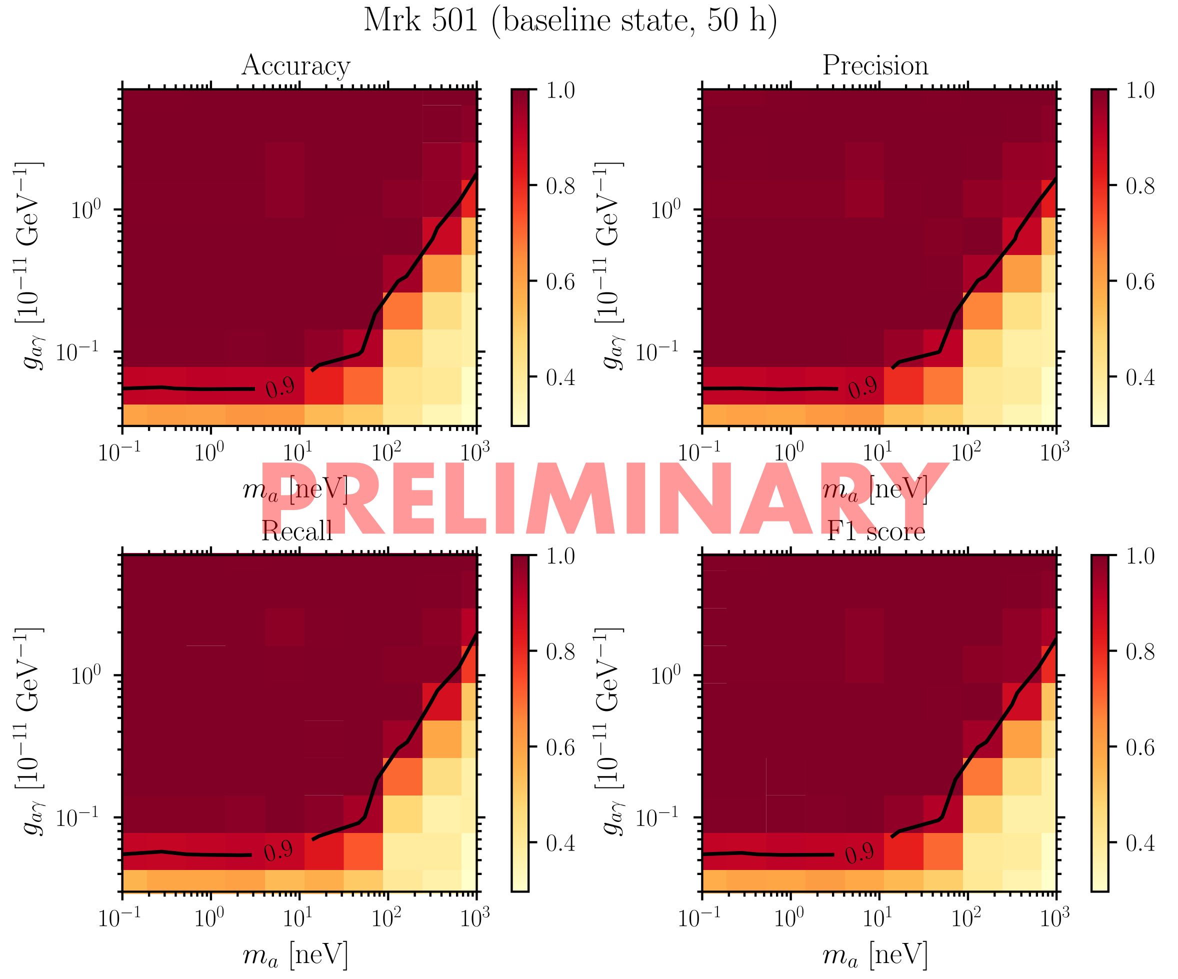


Example Asimov dataset for Mkn 501

Classifier choice

- We chose a classifier based on the XGBoost algorithm
- The choice was motivated by generally good performance on test datasets and ease of use
- As expected, the algorithm accuracy degrades with the telescopes' sensitivity

```
xgb_kwargs = dict(n_estimators=100,
                  max_depth=3,
                  reg_lambda=500.,
                  reg_alpha=10.,
                  eta=.3,
                  random_state=1,
                  n_jobs=-1)
```



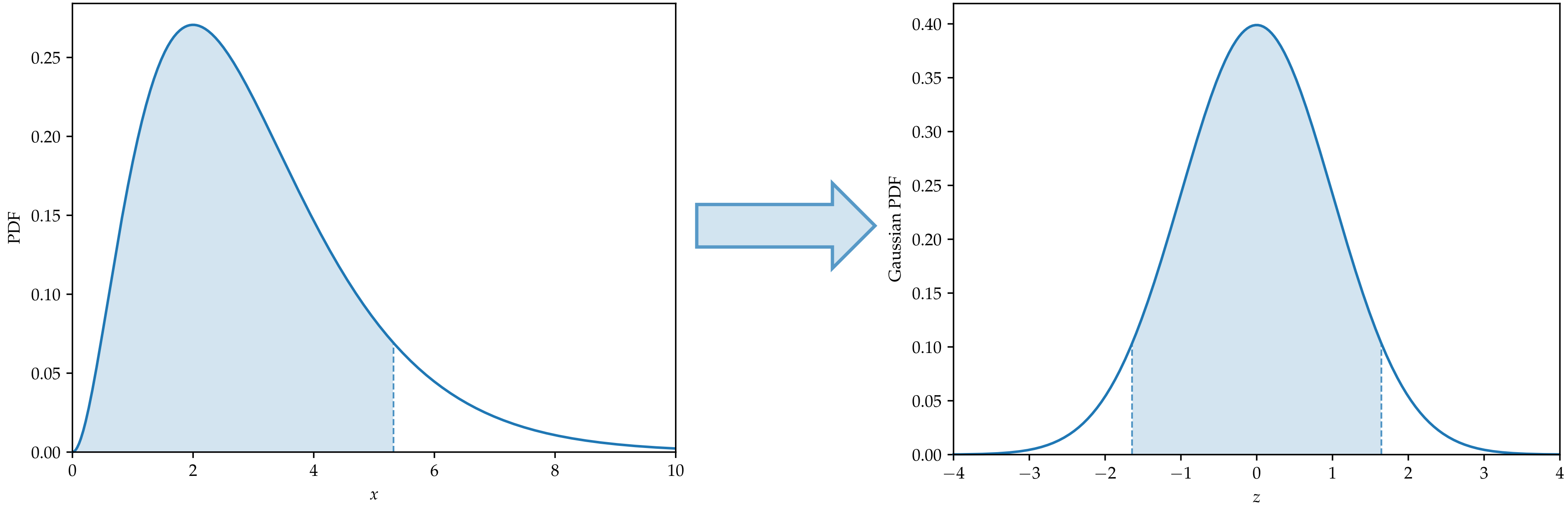
Standard derivation of limits

- Compute the expected spectral model of the source for different ALP parameters
- Compute likelihood-ratio $\mathrm{TS}_A(m_a, g_{a\gamma})$ for the Asimov dataset (cf. MAGIC paper)

$$\mathrm{TS}(m_a, g_{a\gamma}|D) = -2\ln\frac{\mathcal{L}(m_a, g_{a\gamma}|D)}{\hat{\mathcal{L}}(D)}$$

- For each point in the ALP parameter space, simulate 100 observations with ALPs (using Gammapy's `fake()` method) and compute a TS distribution
- Fit with a Gamma distribution and compute the CDF value at TS_A
- Estimate exclusion significance as $z = \sqrt{2}\,\mathrm{erf}^{-1}(\mathrm{CDF}_A)$

Significance estimation



$$\mathrm{CDF}(\mathrm{TS}_A) \equiv 2\frac{1}{\sqrt{2\pi}}\int_0^z e^{-\frac{t^2}{2}}\,\mathrm{d}t = \frac{2}{\sqrt{\pi}}\int_0^{\frac{z}{\sqrt{2}}} e^{-t'^2}\mathrm{d}t' = \mathrm{erf}\left(\frac{z}{\sqrt{2}}\right)$$

Example TS distribution