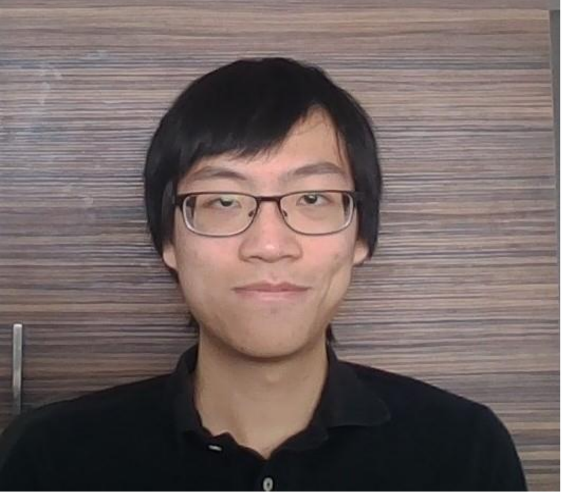

Understanding the impact of Bayesian inference on ultra-light axion limits

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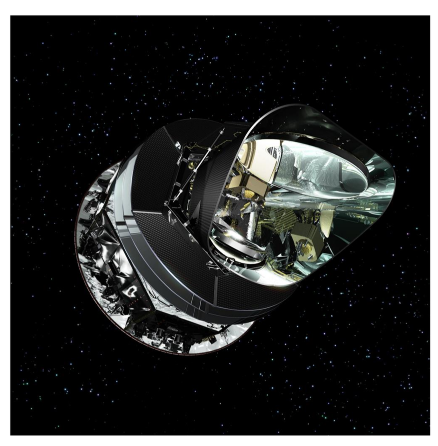
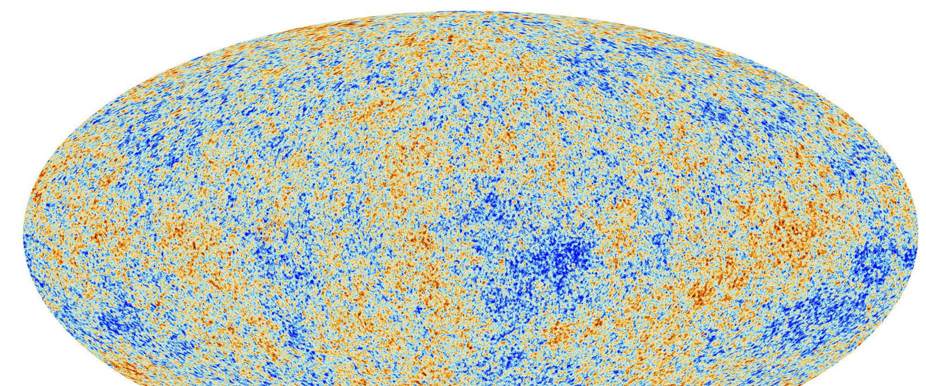
What are ultra-light axions?

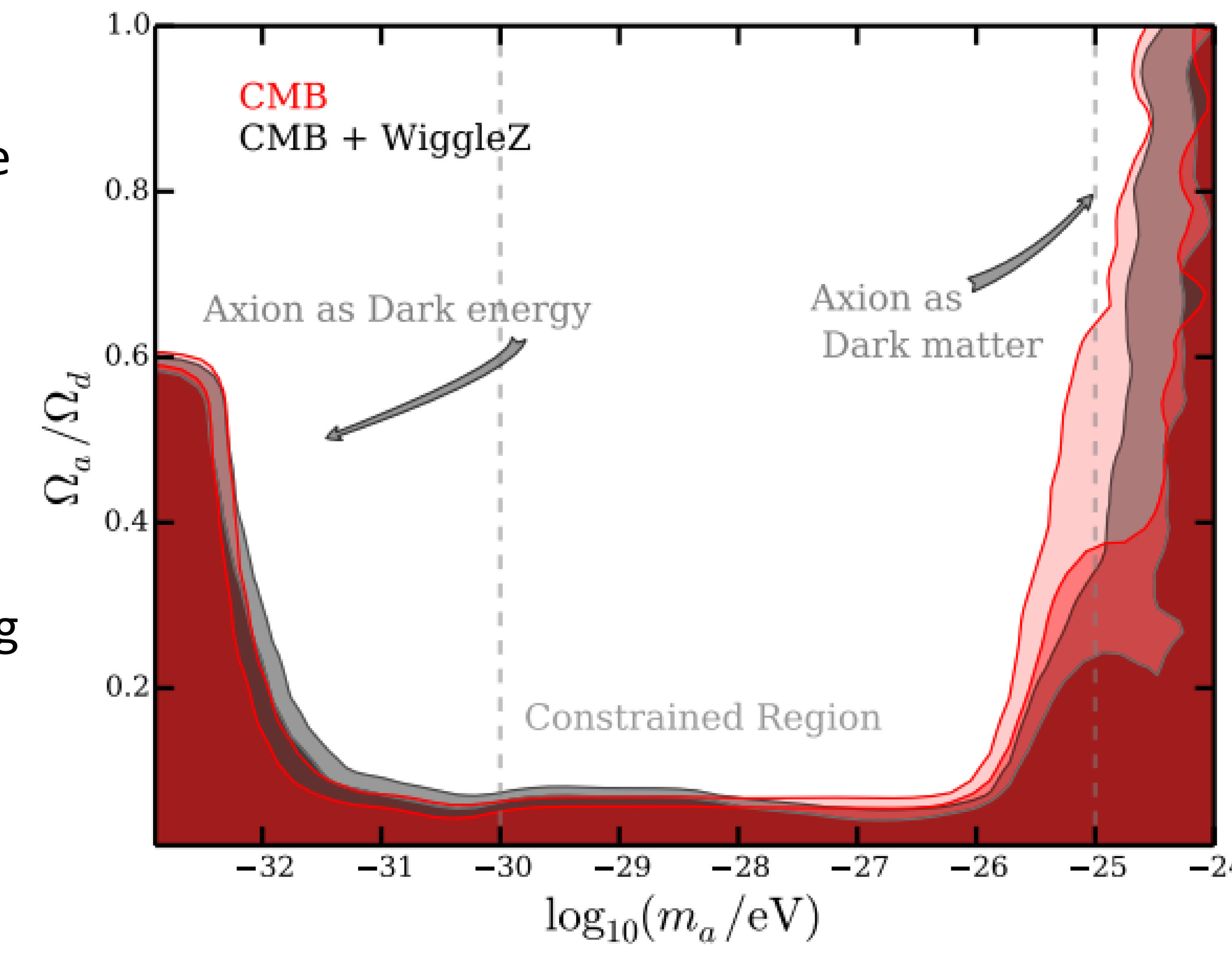
- **Axions** are theoretical elementary particles that are a well-motivated dark matter candidate
- **Ultra-light axions** (ULAs) have masses ranging from 10^{-33} to 10^{-20} eV
  - Behave either like **cold dark matter** or **dark energy** depending on their mass
  - Distribution of ULAs in parameter space is a 4-D distribution depending on axion, dark matter and dark energy densities $\boldsymbol{\Omega_a}, \boldsymbol{\Omega_{DE}}$ and $\boldsymbol{\Omega_c}$ respectively, and axion mass $\boldsymbol{m_a}$
- **Objective:** to develop a robust method of sampling the full 4-D ULA distribution
  - We use CMB data from the ***Planck*** telescope (below) to constrain axion distribution
  - Prior studies only sampled "slices" of the distribution (right) due to high cost of computing CMB power spectra
  - However, new ML methods using **axionEmu** software make emulating CMB power spectra *much* faster!



Planck satellite



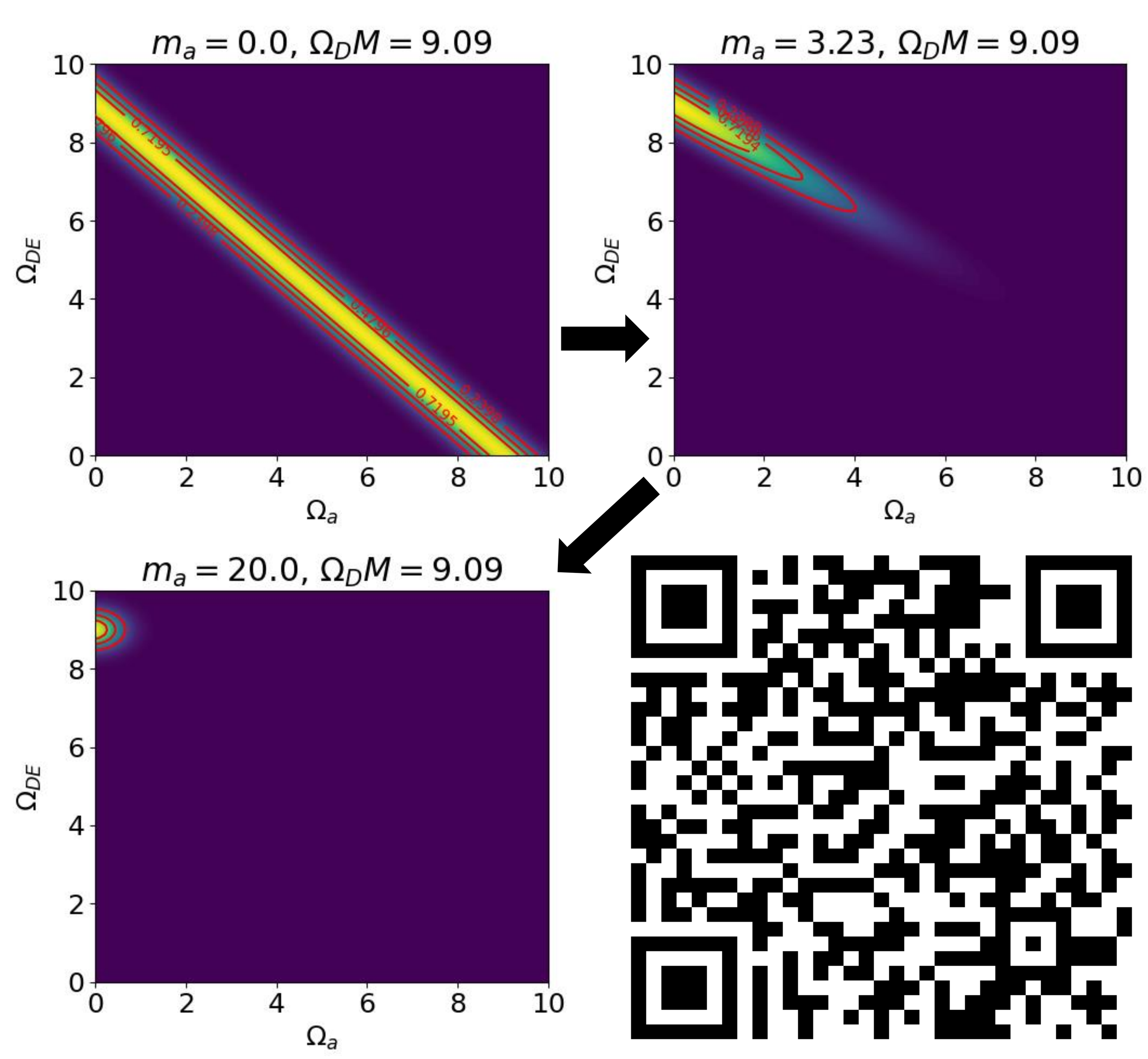
Planck CMB map



Hložek et al (2015). Previously estimated contours of the marginal distribution of ultra-light axions (ULAs) in the m_a - Ω_a plane.

What does the ULA distribution look like?

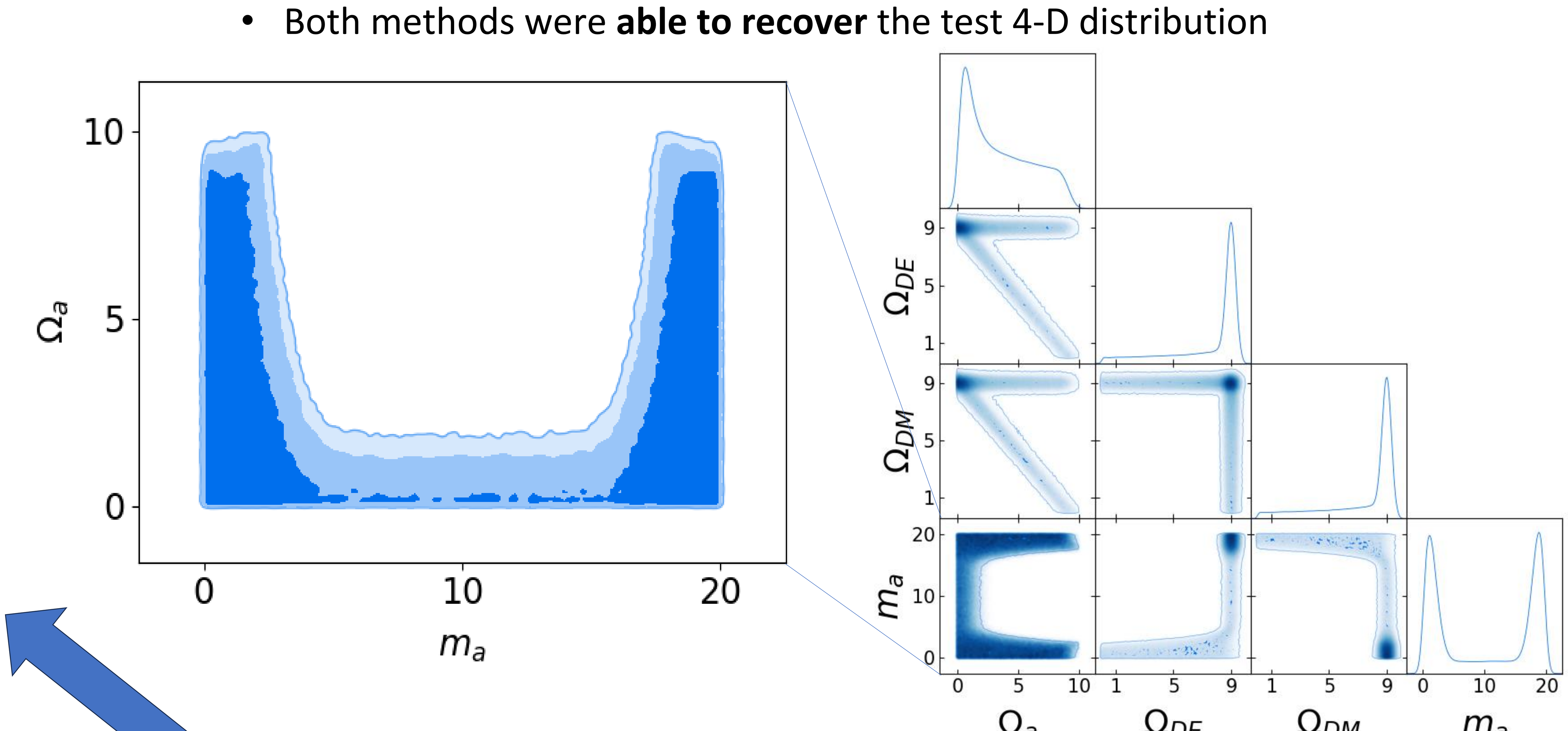
First design a **4-D test distribution** with qualitatively similar shape to the previously estimated axion distribution



Demonstrating how the 2-D marginal distribution of ULAs in the $\mathbf{\Omega_a - \Omega_{DE}}$ plane changes as axion mass increases

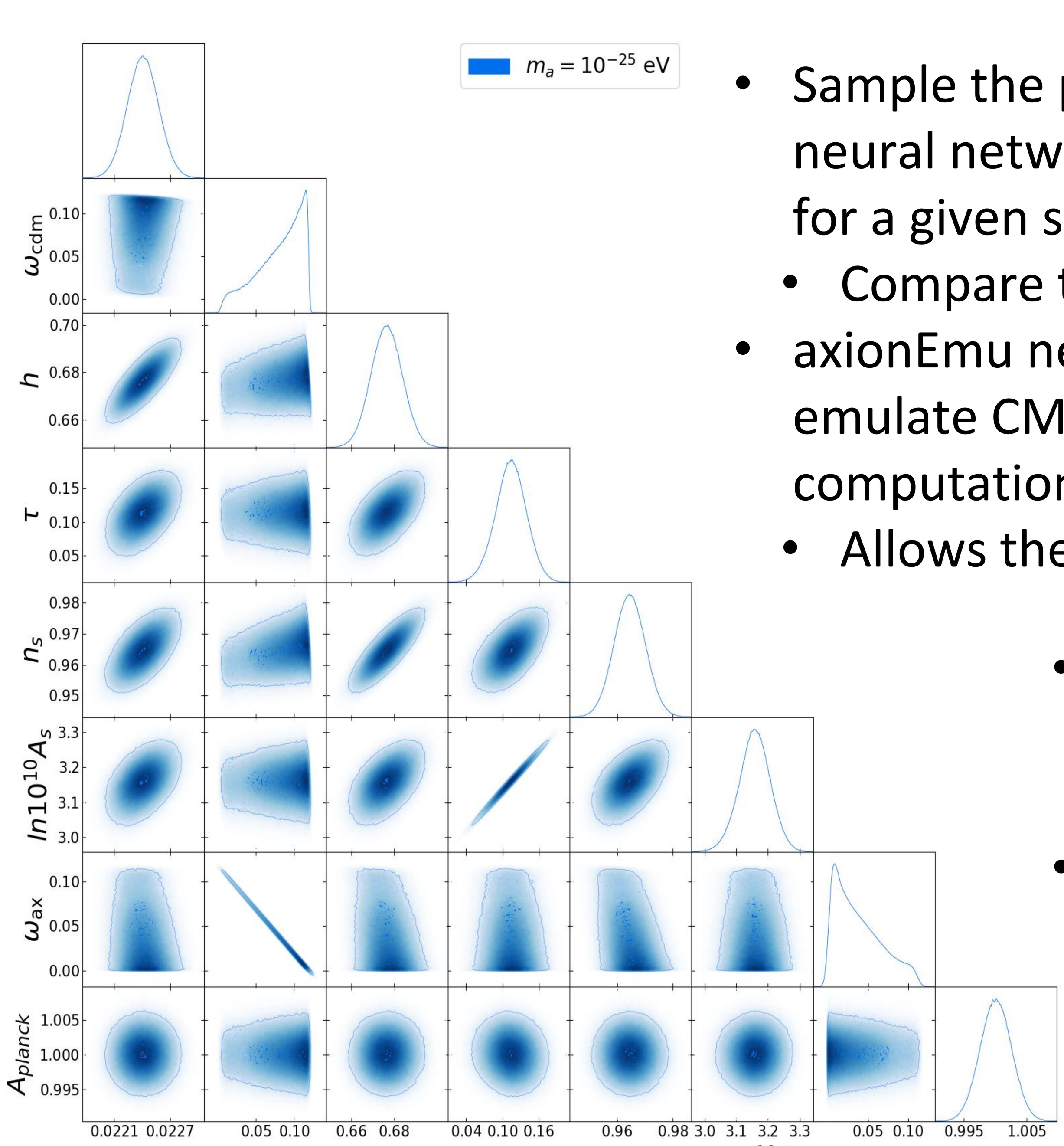
Scan or CLICK HERE for animation

- Evaluate the performance of two different sampling algorithms, **Markov chain Monte Carlo (MCMC)** and **Nested Sampling**, on a test distribution
- Both methods were **able to recover** the test 4-D distribution

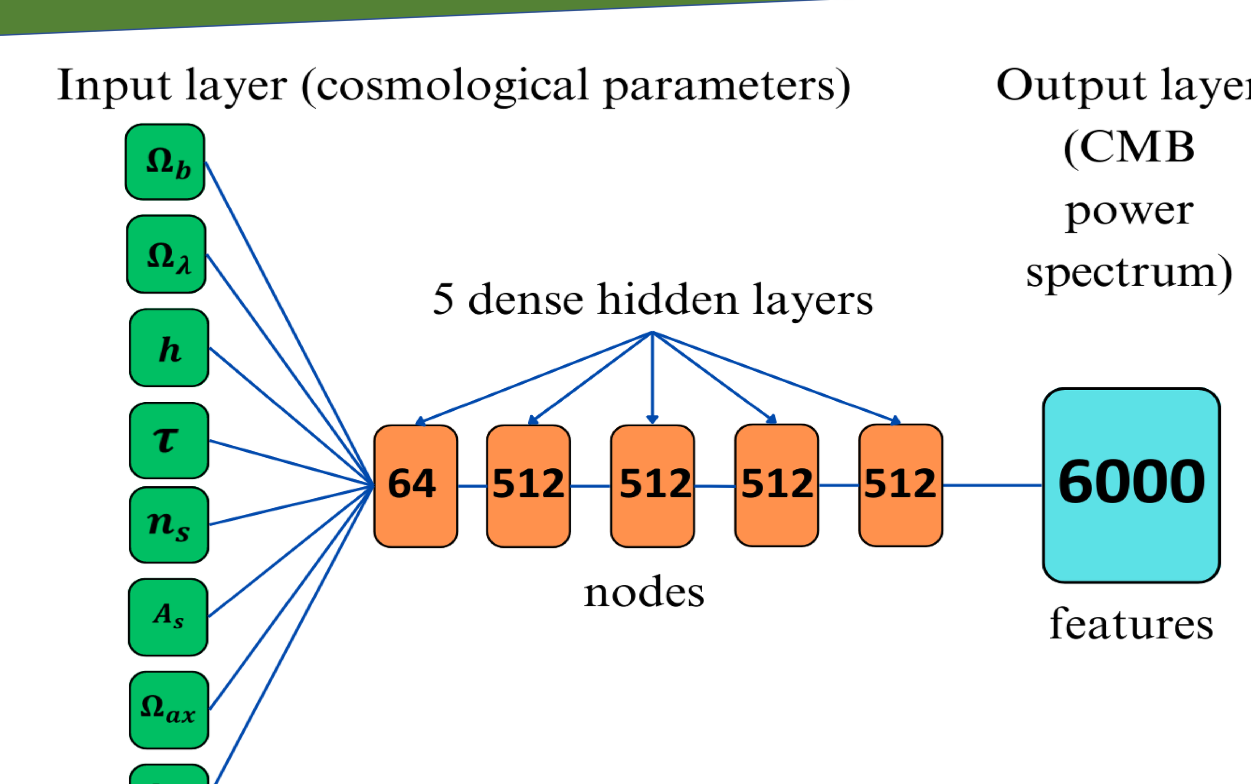


1, 2, and 3σ contours for the 2-D marginal posterior of the test function in the m_a - Ω_a plane (left) and for all 4 parameters (right), generated using MCMC sampling. Note that units for the test function are arbitrary.

How do we sample the true ULA distribution?



- Sample the parameter space with MCMC, using the **axionEmu** neural networks (right) to emulate the CMB power spectrum for a given set of axion parameters
  - Compare the axionEmu power spectrum to **Planck** data
- axionEmu neural networks (**10 seconds** per MCMC chain) can emulate CMB power spectra ***much* faster** than previous computational methods (**30 hours**)!
  - Allows the **full distribution** to be sampled for the first time



The axionEmu neural network architecture

- Preliminary results (left) showing contours for the 2-D marginal posteriors of the ULA distribution, at fixed axion mass of 10^{-25} eV
- **Next steps:** Sample over the full ULA distribution, letting axion mass vary as well

Conclusions

- Using MCMC and nested sampling, we recover a test ULA distribution in 4-D parameter space
- Apply sampling methods to derive constraints on true ULA distribution from Planck CMB data in conjunction with new axionEmu neural network