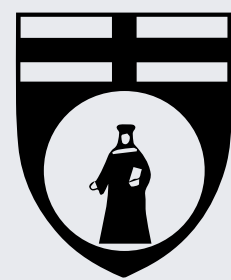


# Machine Learning Assisted Statistical Inference

Marco Raveri



University  
of Genova

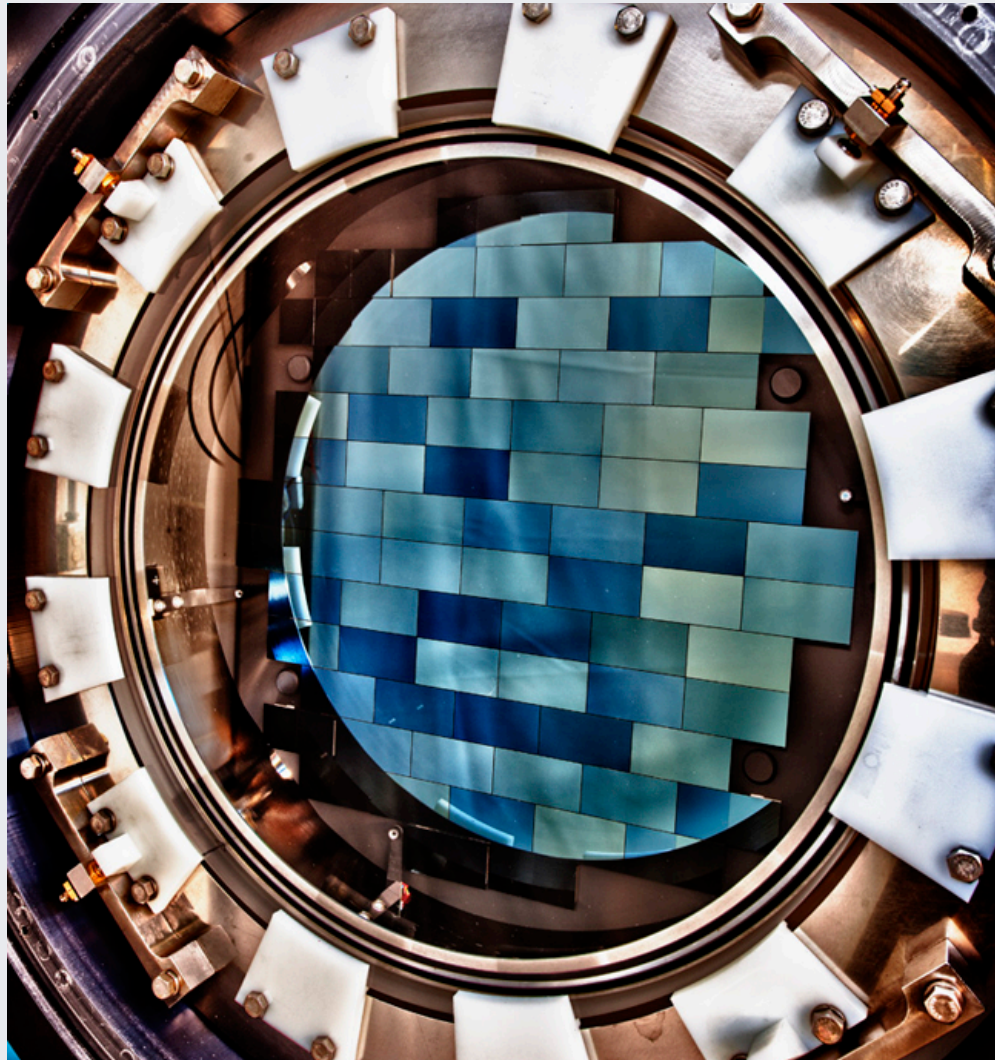
# Plan

Machine learning help with “classic” inference problems

Seemingly easy question: **do experiments agree?**



# The Dark Energy Survey



**570-Megapixel** digital camera, DECam, mounted on the Blanco 4-meter telescope at Cerro Tololo Inter-American Observatory (Chile).

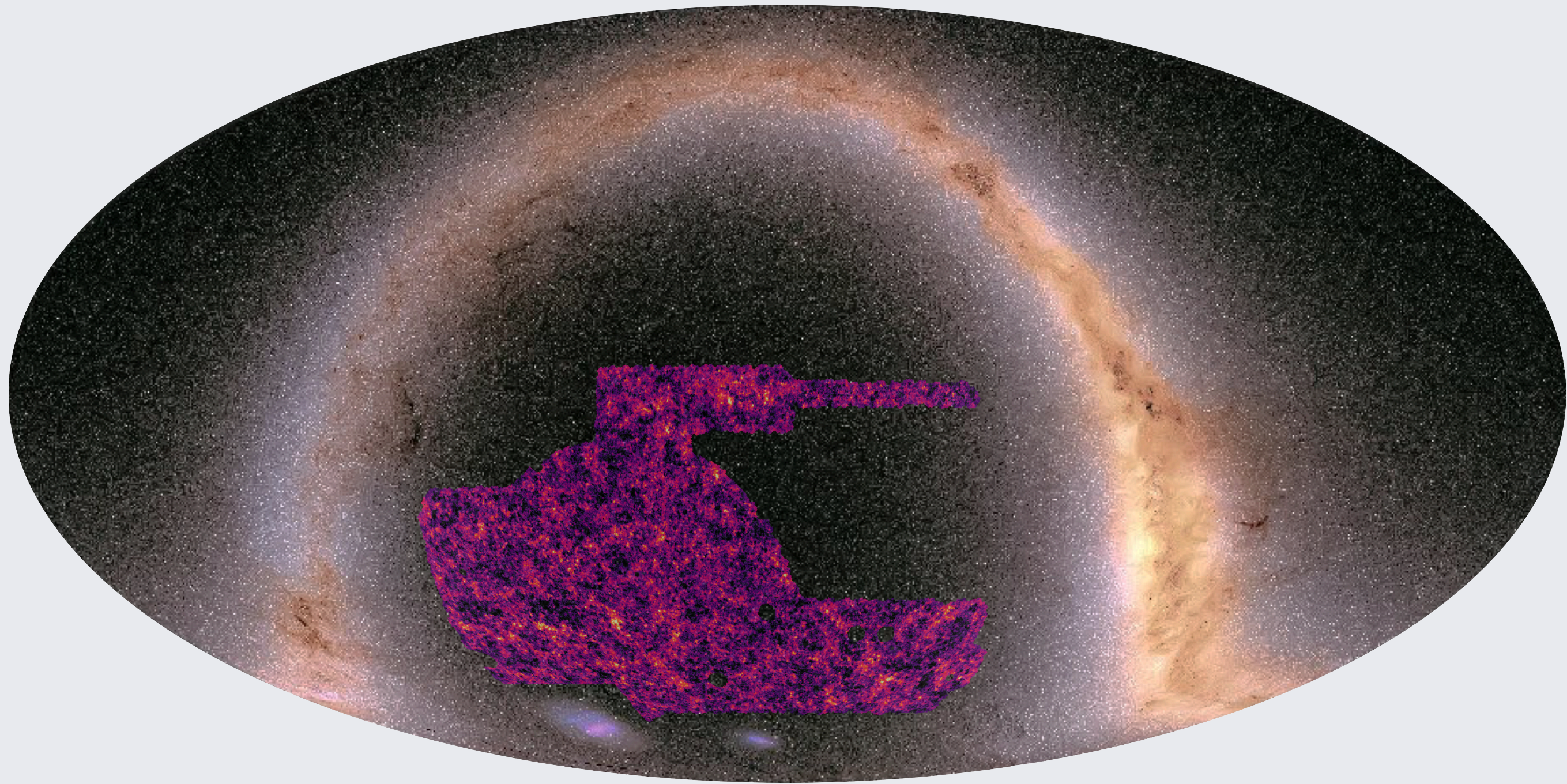
Me and DES:

- \* Led “tensions” working group
- \* Now lead of Dark Energy searches
- \* Several key contributions to main analysis
- \* Builder

( Based on some work in the Dark Energy Survey )



# The Dark Energy Survey



Largest map of the Dark Universe

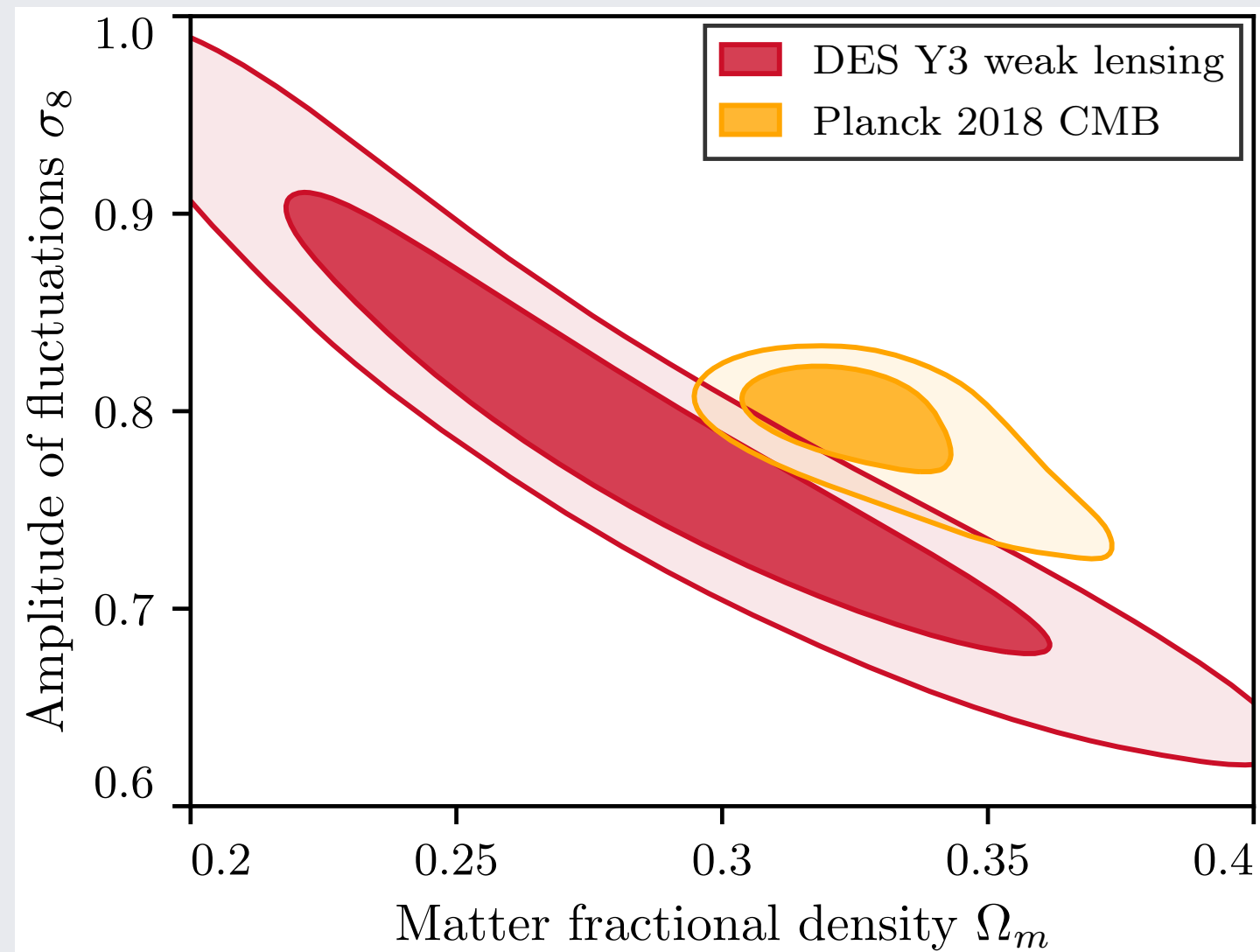
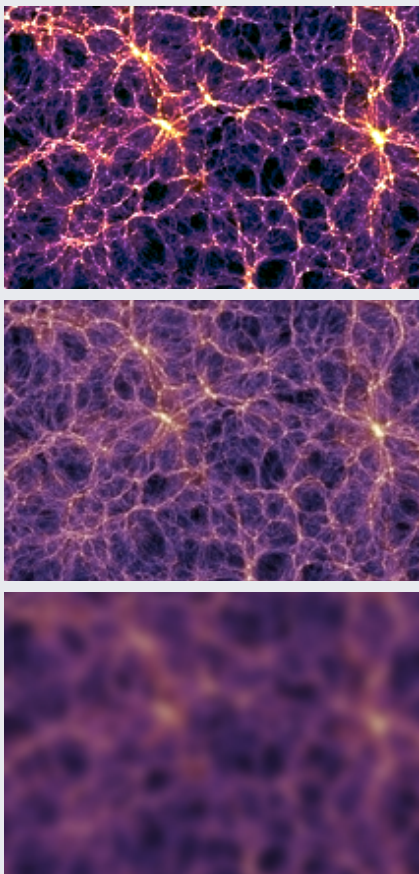
( Based on some work in the Dark Energy Survey )



# Agreement or disagreement?

Seemingly easy question: do experiments agree?

clumpiness of the Universe

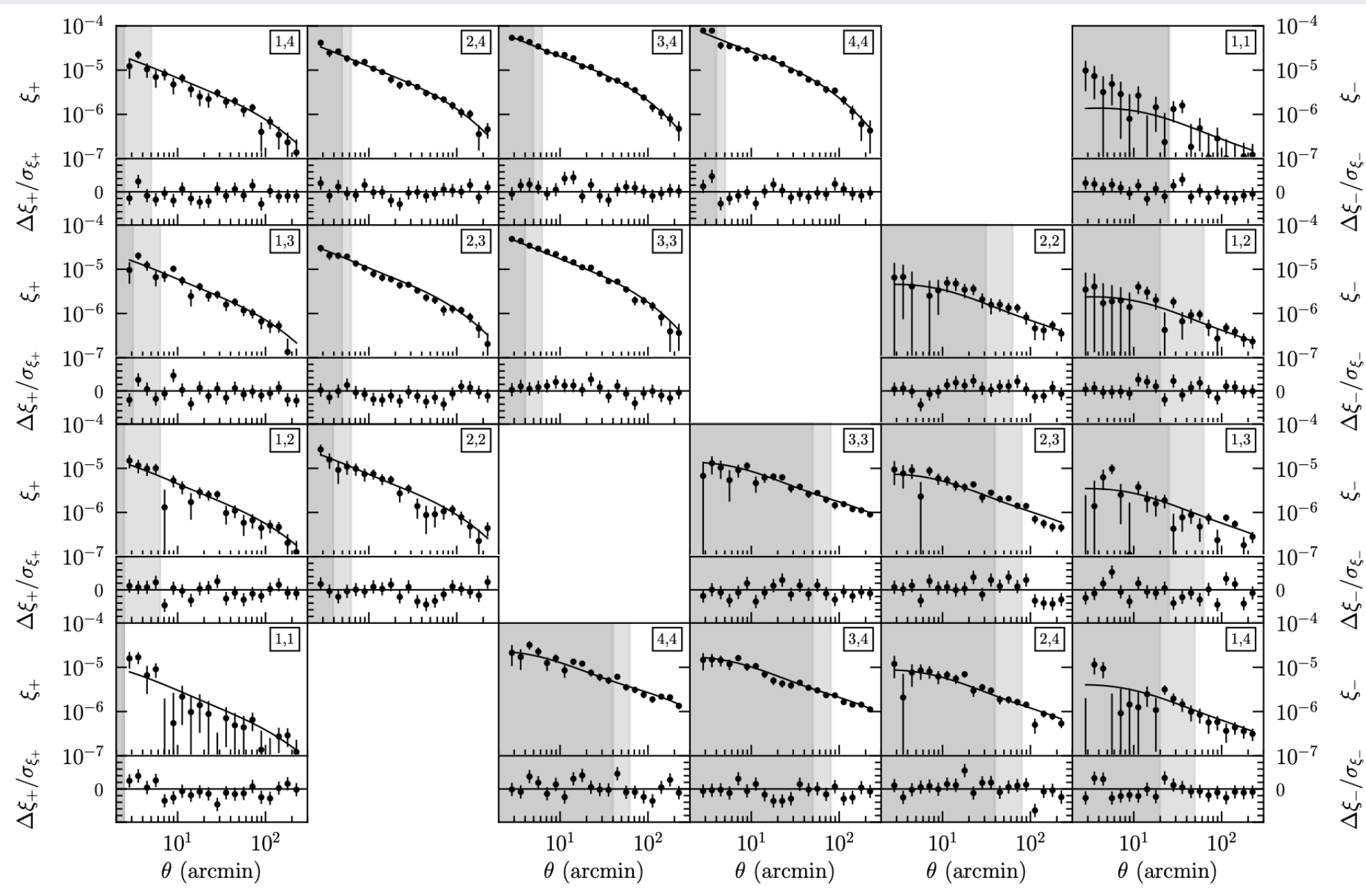


fractional matter abundance  
(everything else is Dark Energy)

( Based on some work in the Dark Energy Survey )

# Testing concordance: the challenges

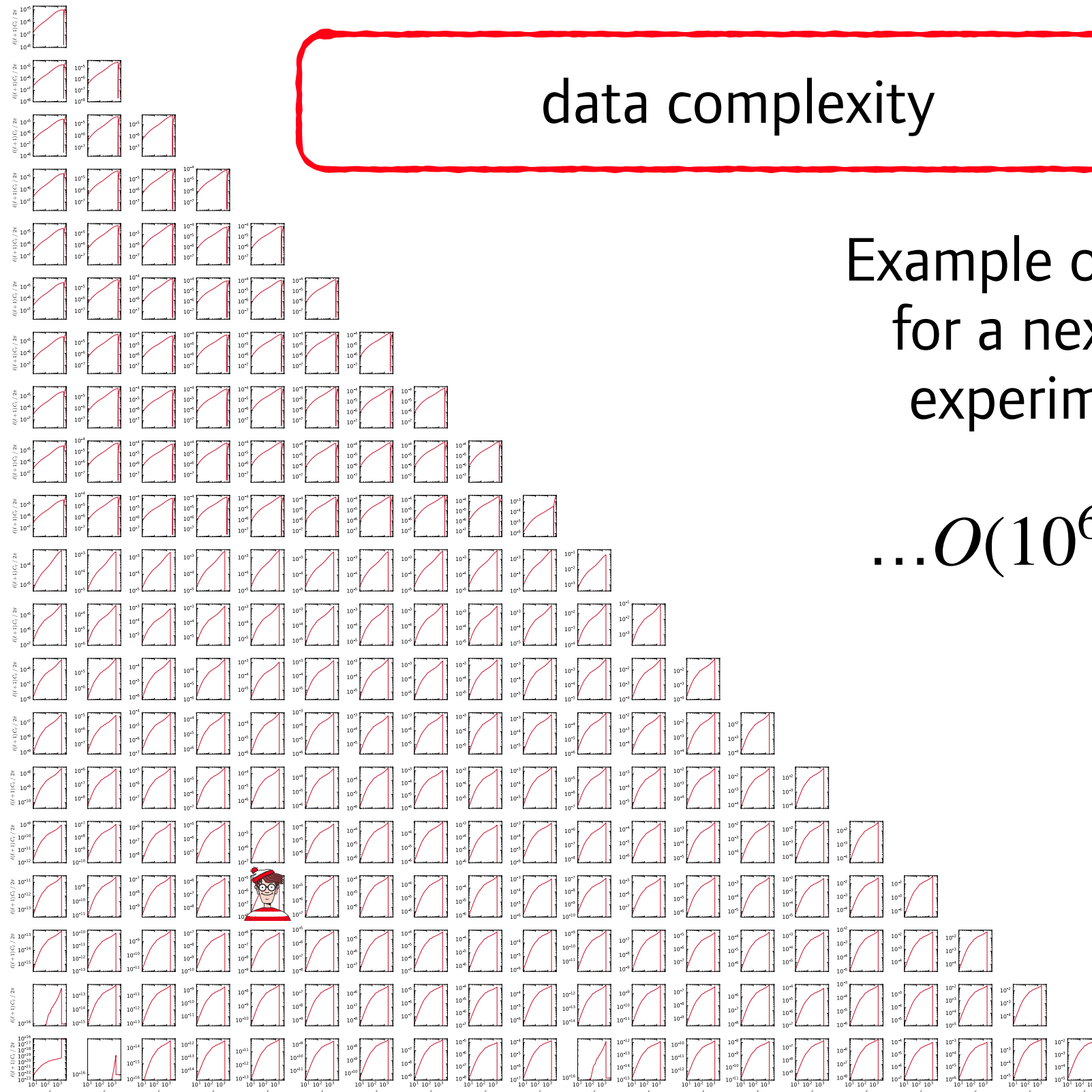
## Data complexity



( Based on some work within the Dark Energy Survey )



# Testing concordance: the challenges



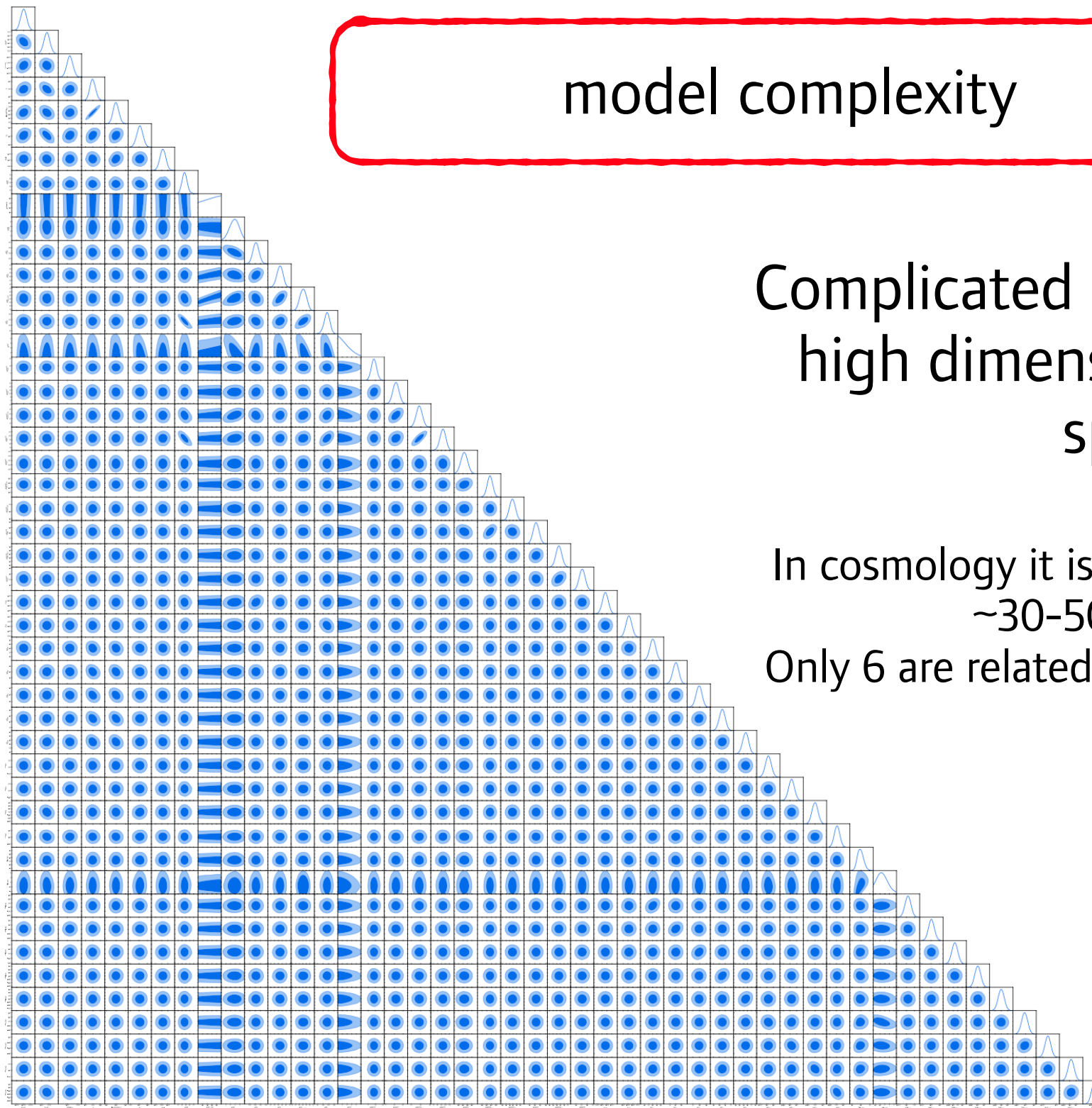
( Based on some work in Euclid )

# Testing concordance: the challenges

model complexity

Complicated models come with high dimensional parameter spaces.

In cosmology it is customary to work with ~30-50 parameters.  
Only 6 are related to fundamental physics.



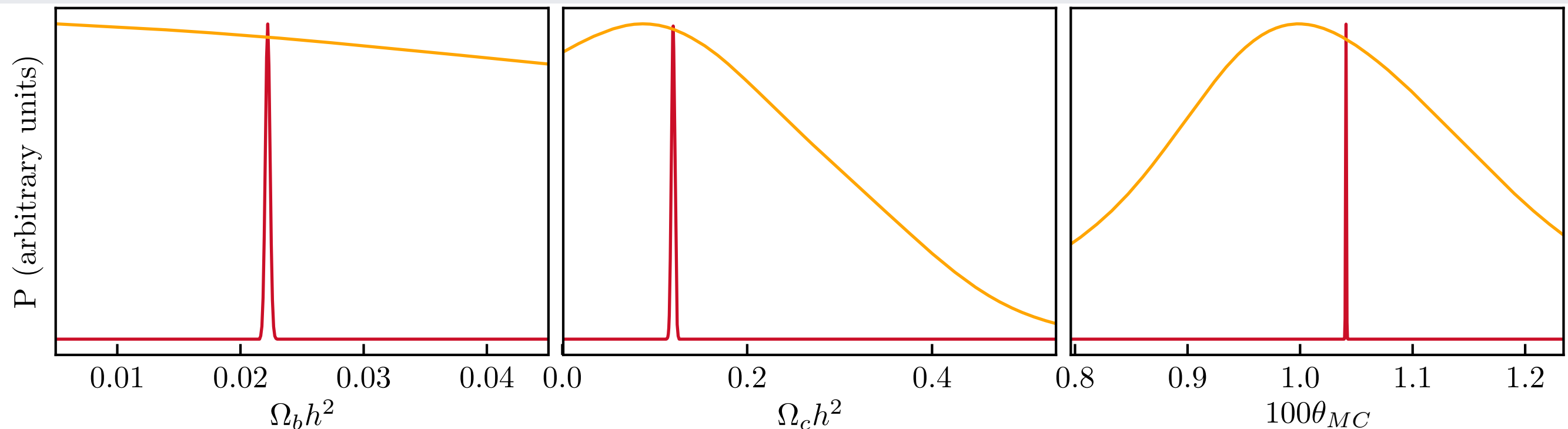
( This is the DES parameter space... )



# Testing concordance: the challenges

Projections of the parameter space might hide discrepancies

Do they agree?

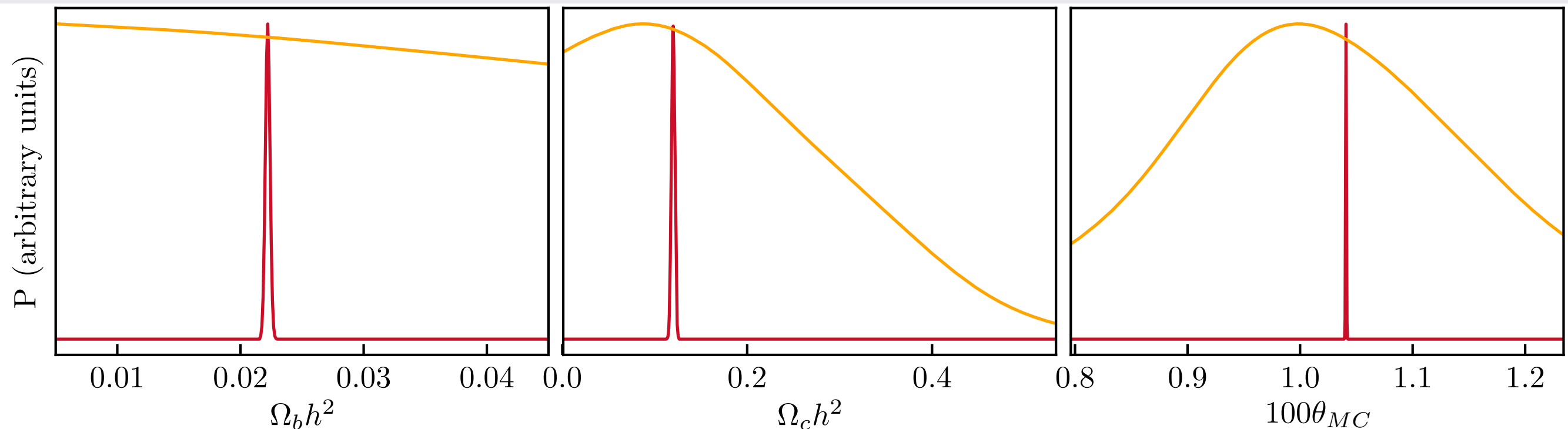


What are these data sets?

# Testing concordance: the challenges

Projections of the parameter space might hide discrepancies

Do they agree? **No, to 5 sigma**

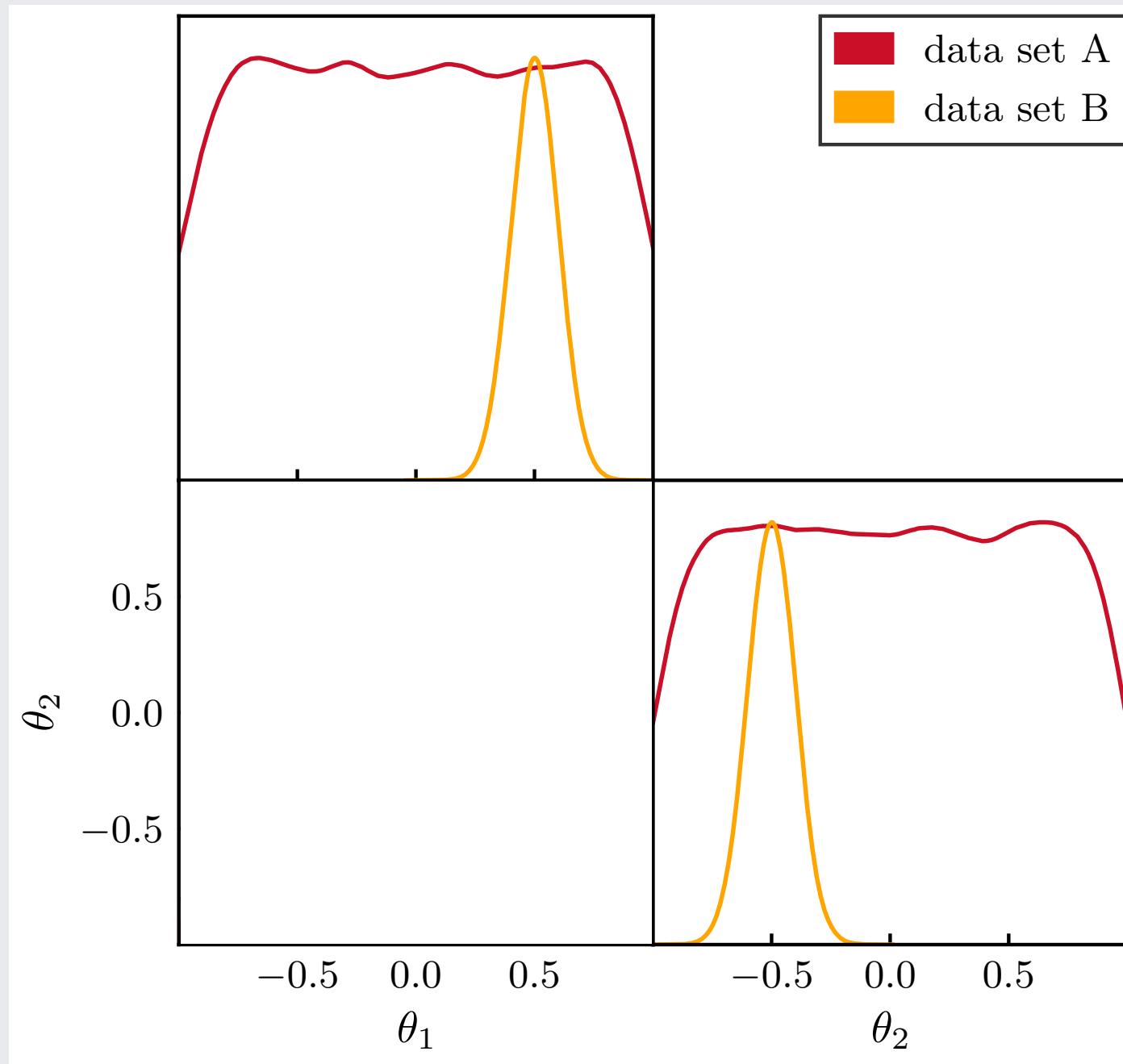


What are these data sets? **Planck CMB and local Hubble constant**



# Testing concordance: the challenges

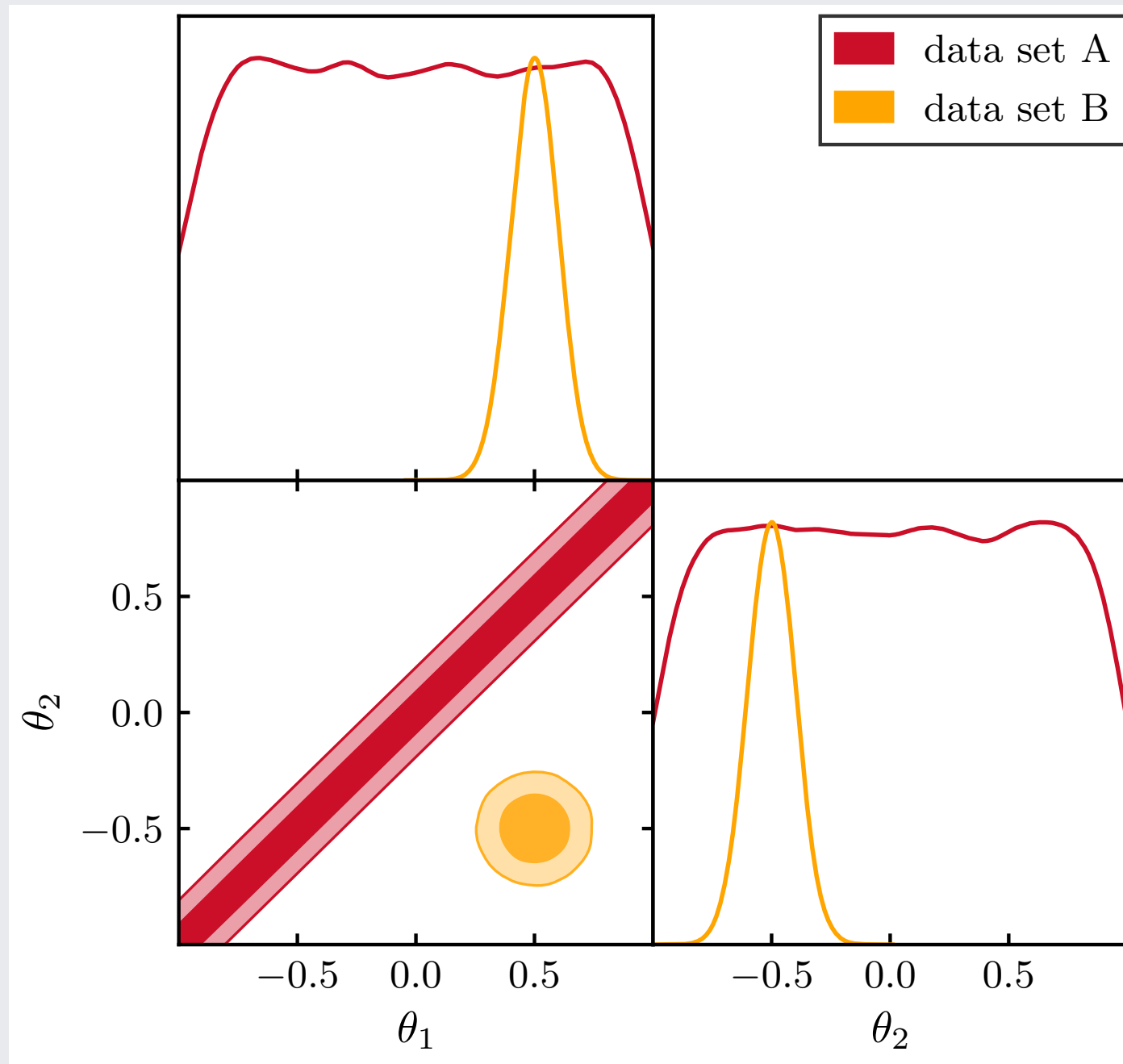
What is going on?



( made up posteriors from Lemos, MR et al arXiv:2012.09554 )

# Testing concordance: the challenges

We are being tricked by low dimensional projections



( made up posteriors from Lemos, MR et al arXiv:2012.09554 )

# Testing concordance when life is hard:

tools of the trade:

Theoretical papers:

- Raveri and Hu, “Concordance and Discordance in Cosmology”  
**arXiv 1806.04649**
- Raveri, Zacharegkas, Hu, “Quantifying concordance of correlated cosmological data sets” **arXiv 1912.04880**
- Raveri and Doux, “Non-Gaussian estimates of tensions in cosmological parameters” **arXiv 2105.03324**

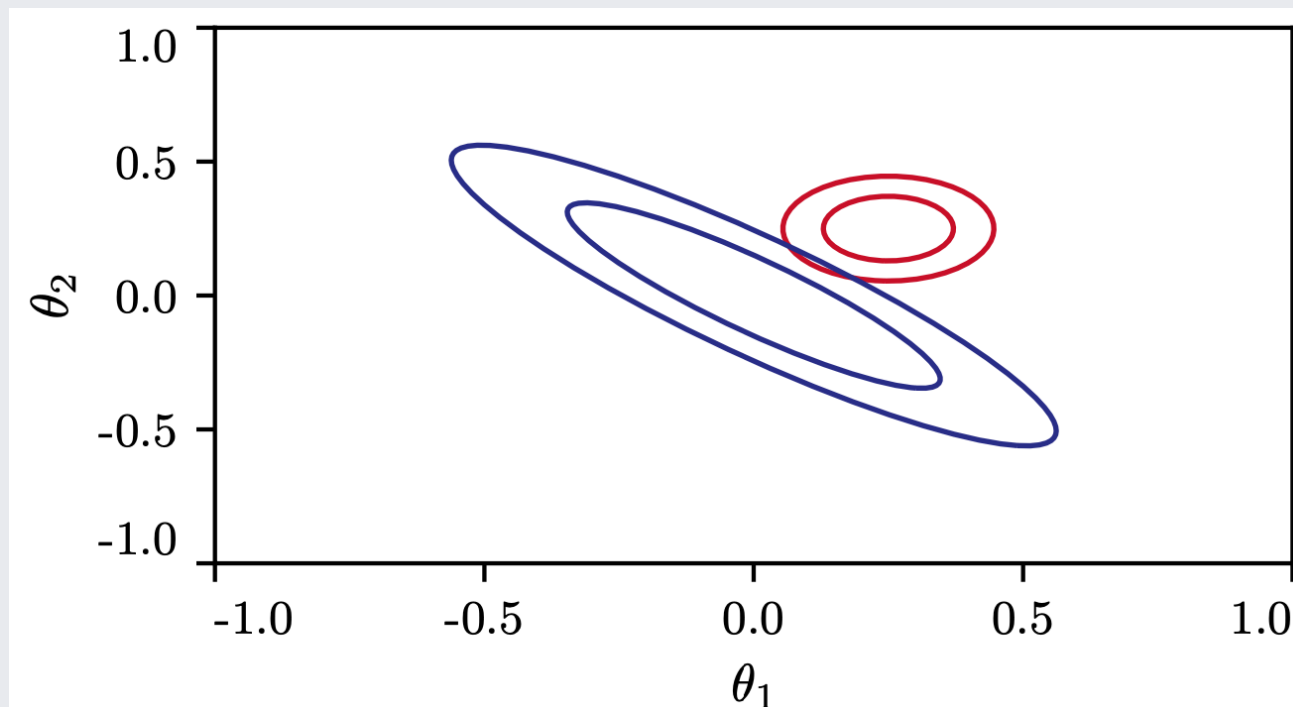
Code implementation (in Python, with several example notebooks)

```
~ pip install tensiometer
```



# Parameter differences

Full dimensional distribution of differences in parameters



Start with:

$$P_1(\theta_1)P_2(\theta_2)$$

change variables:

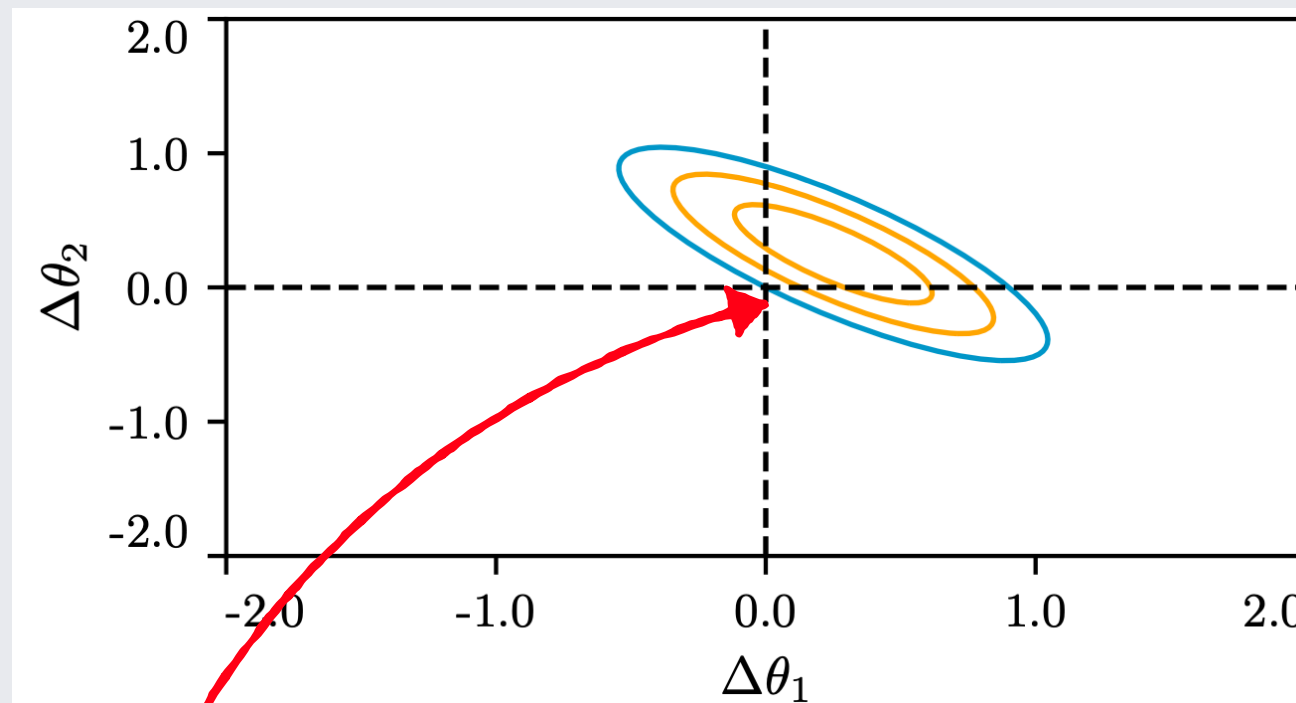
$$P_1(\theta_1)P_2(\theta_1 - \Delta\theta)$$

integrate out

$$P(\Delta\theta) = \int P_1(\theta_1)P_2(\theta_1 - \Delta\theta)d\theta_1$$

# Parameter differences

$$P(\Delta\theta) = \int P_1(\theta_1)P_2(\theta_1 - \Delta\theta)d\theta_1$$



Our goal:

$$\Delta = \int_{P(\Delta\theta) > P(0)} P(\Delta\theta) d\Delta\theta$$

# Parameter differences: the bad news...

$$P(\Delta\theta) = \int P_1(\theta_1)P_2(\theta_1 - \Delta\theta)d\theta_1$$

Usually very high dimensional integral

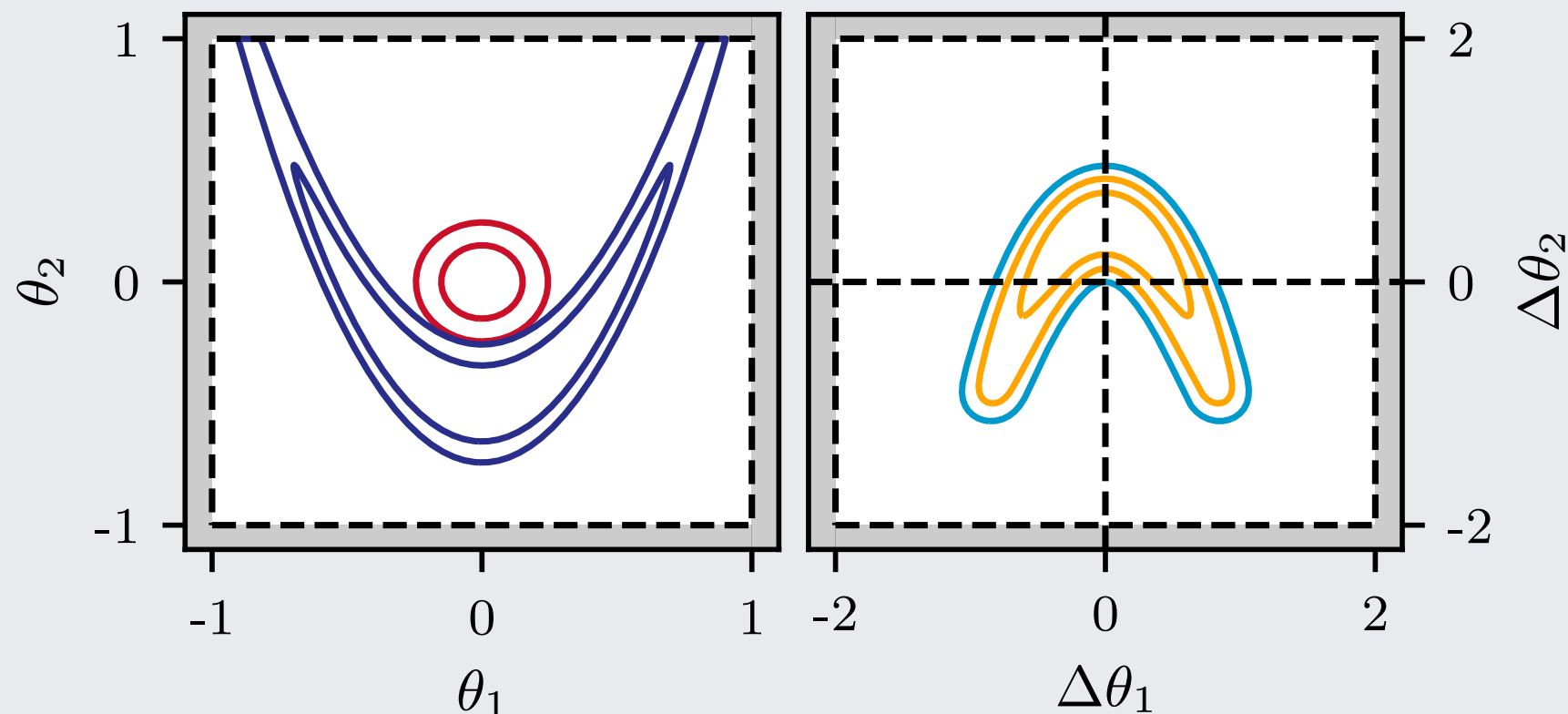
$$\Delta = \int_{P(\Delta\theta) > P(0)} P(\Delta\theta)d\Delta\theta$$

Usually very high dimensional integral

Way out assuming Gaussianity: Raveri & Hu arXiv:1806.04649



# Parameter differences in practice



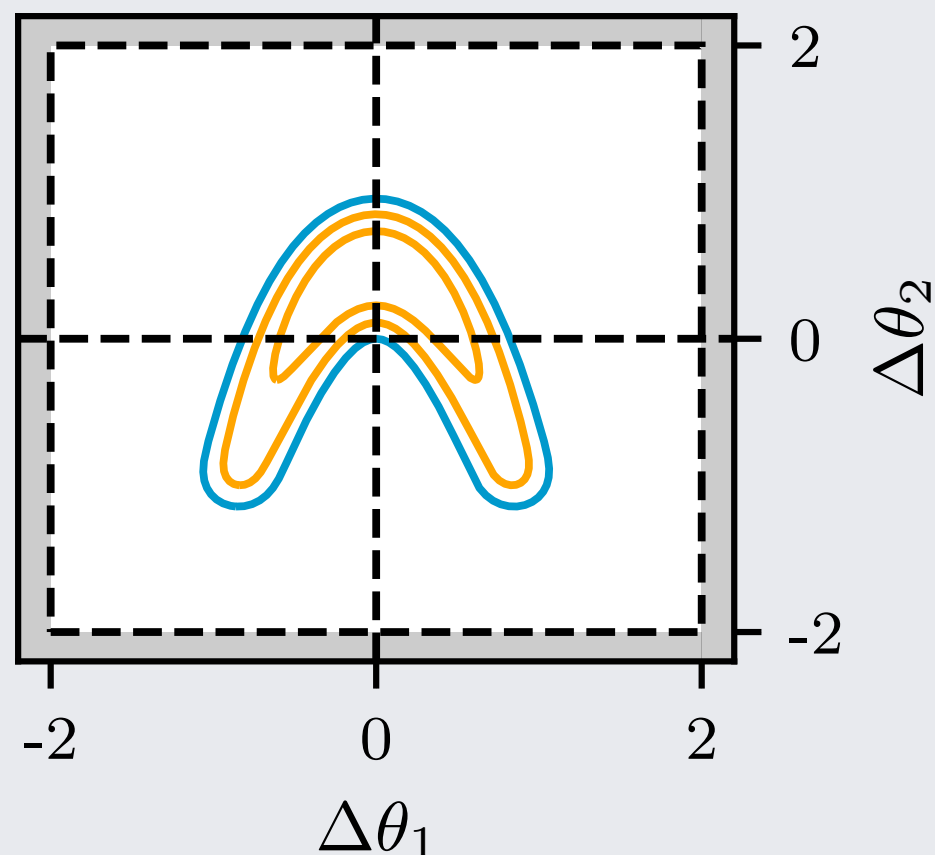
What to do when the distribution is **non-Gaussian**?

No way out of performing the integrals...

$$P(\Delta\theta) = \int P_1(\theta_1)P_2(\theta_1 - \Delta\theta)d\theta_1$$

First integral can be done with Monte Carlo

# Parameter differences in practice



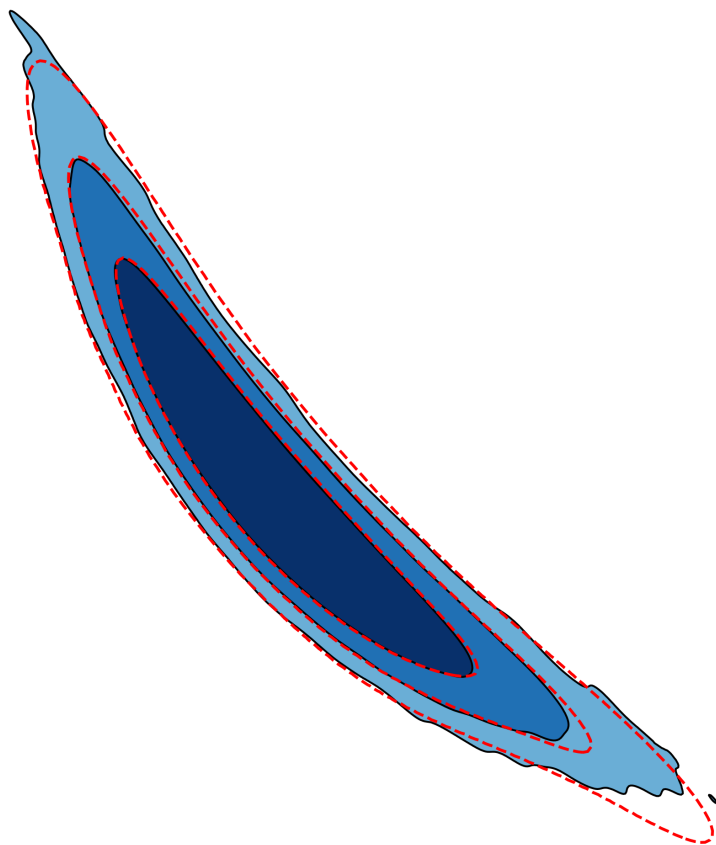
$$\Delta = \int_{P(\Delta\theta) > P(0)} P(\Delta\theta) d\Delta\theta$$

Second integral can be done with KDE but is very expensive

Naive algorithm is  $N^2$  (not doable)  
R&D arXiv:2105.03324 has the  $N \log N$  algorithm which is still very expensive (curse of dimensionality of KDEs)

# Parameter differences and machine learning

$$\Delta = \int_{P(\Delta\theta) > P(0)} P(\Delta\theta) d\Delta\theta$$



## **Solution:**

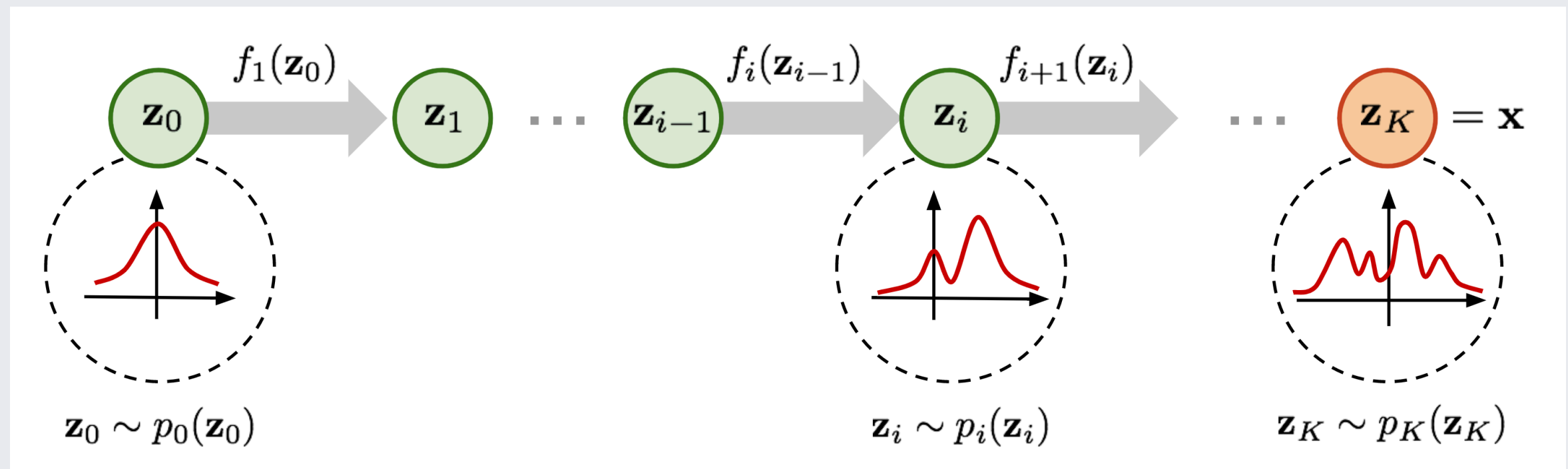
learn the parameter  
difference posterior

$$P(\Delta\theta)$$

...then MC integrate

# Normalizing flows

## MAF normalizing flows



$$y_1 = \mu_1 + \sigma_1 z_1$$

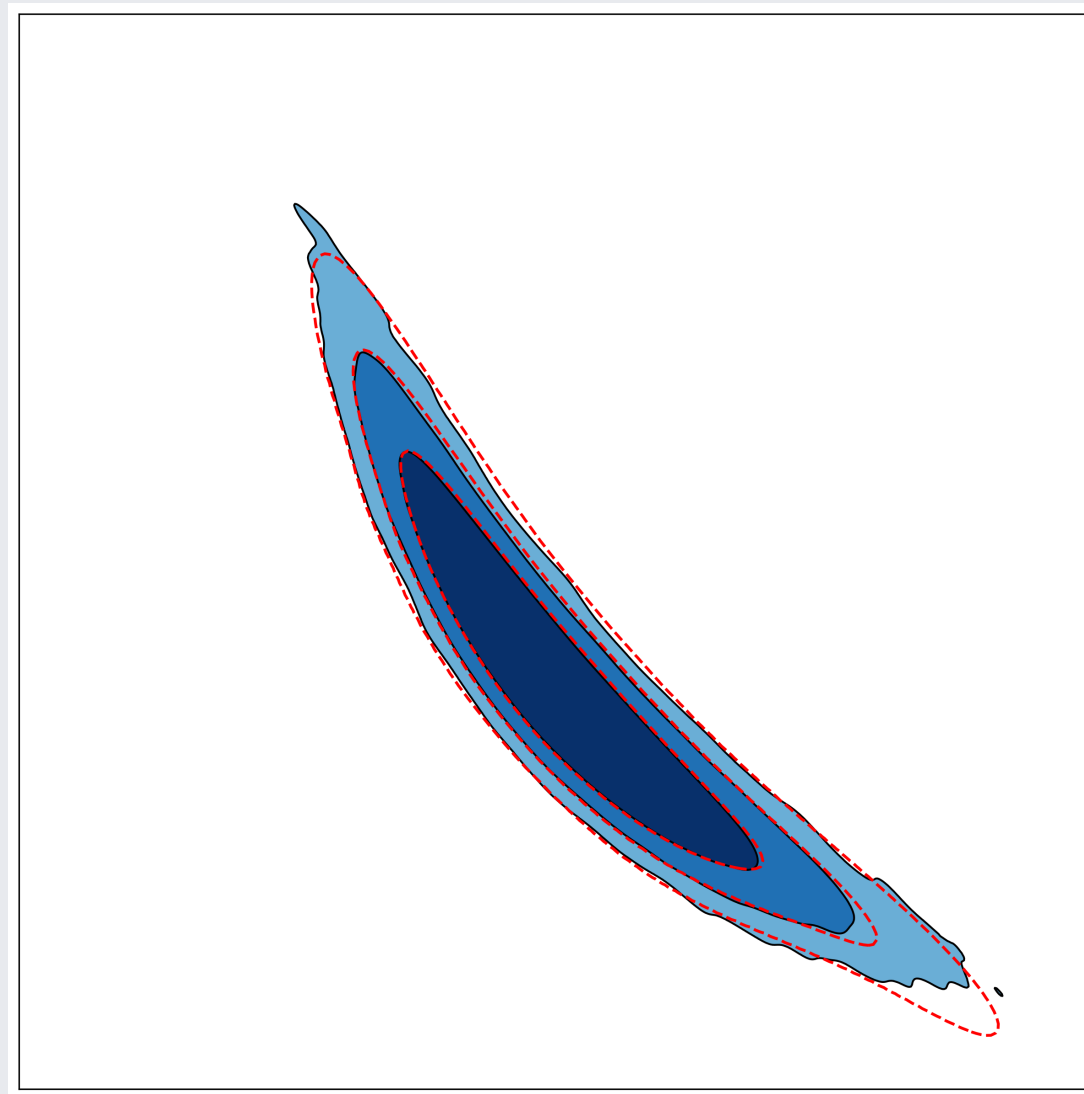
$$y_i = \mu(y_{1\dots i-1}) + \sigma(y_{1\dots i-1}) z_i$$

Stacked with permutations to ensure no coordinate is unlucky



# Normalizing flows performances

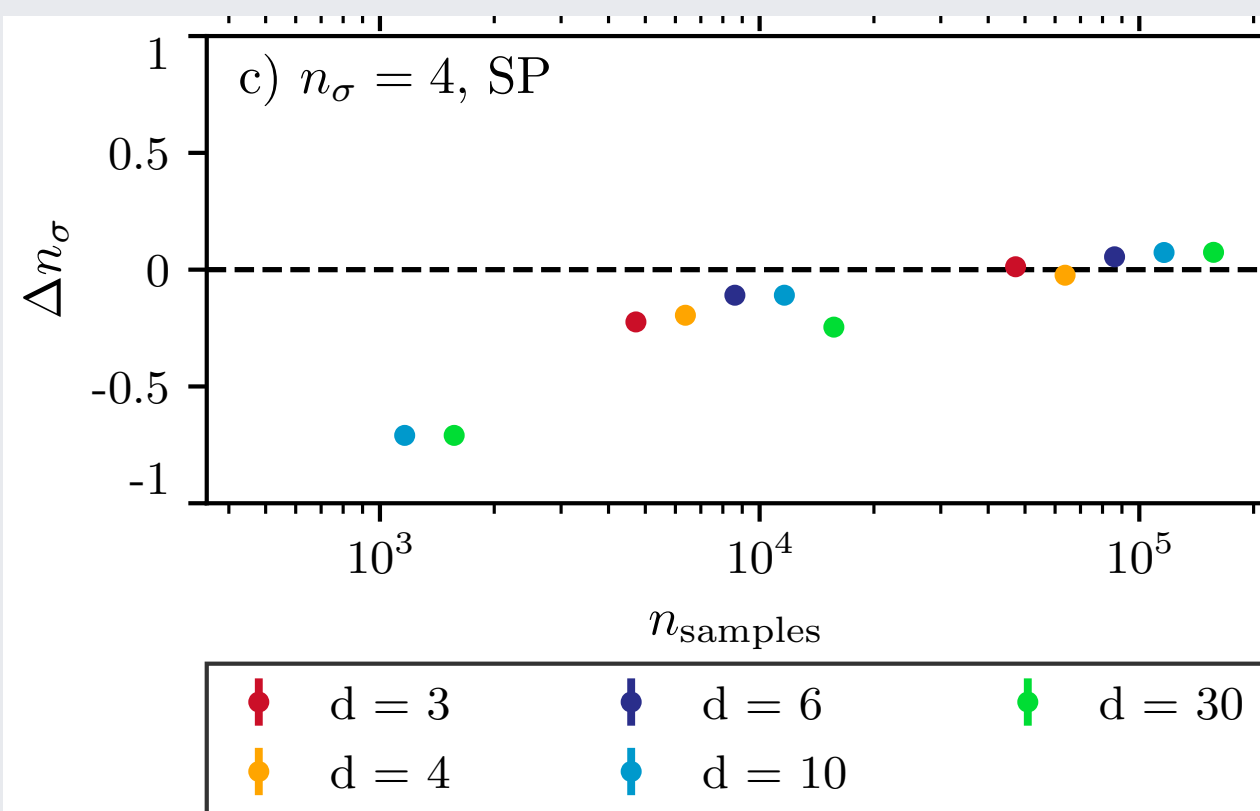
...trained PDFs are indistinguishable from real (KDE) ones...



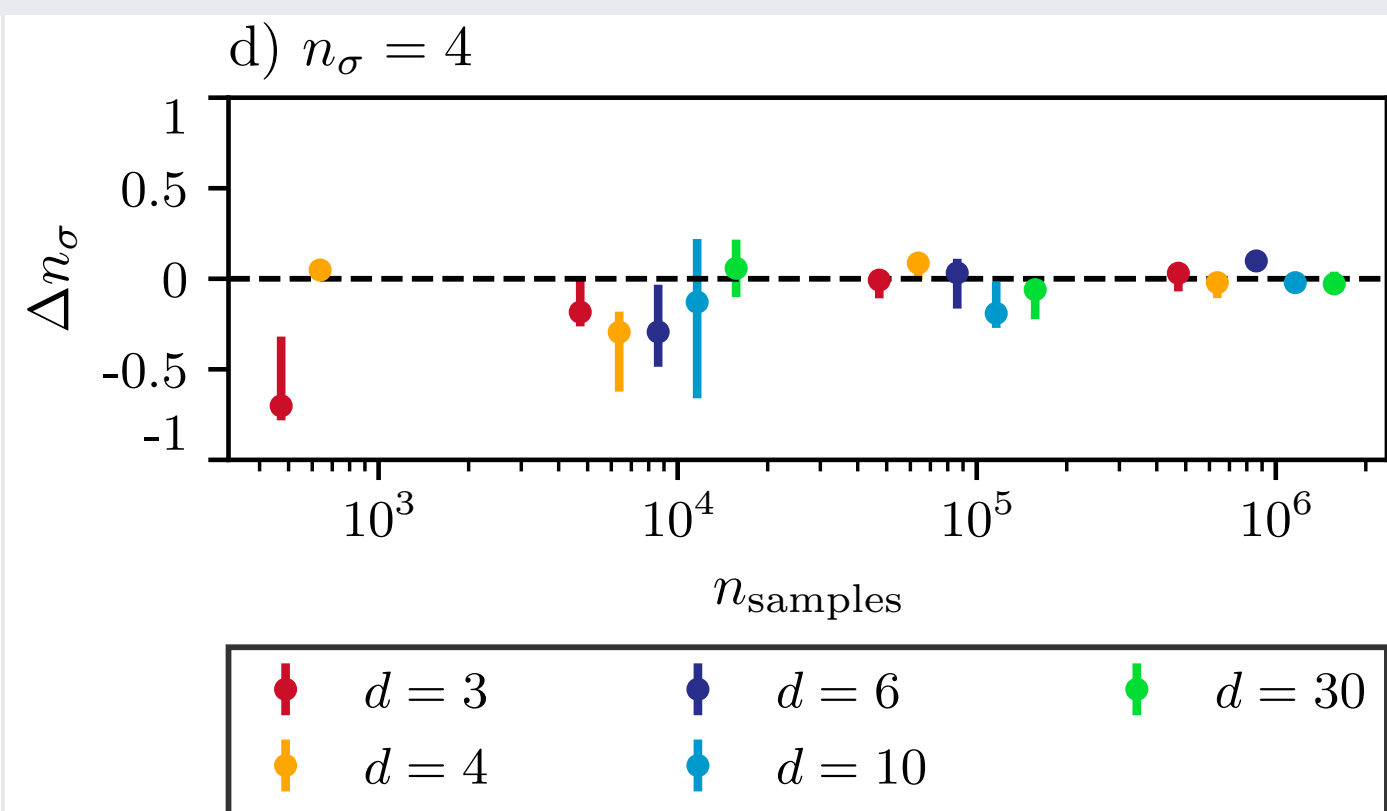
# Normalizing flows performances

Matches or outperforms KDE based methods in all our tests

KDE

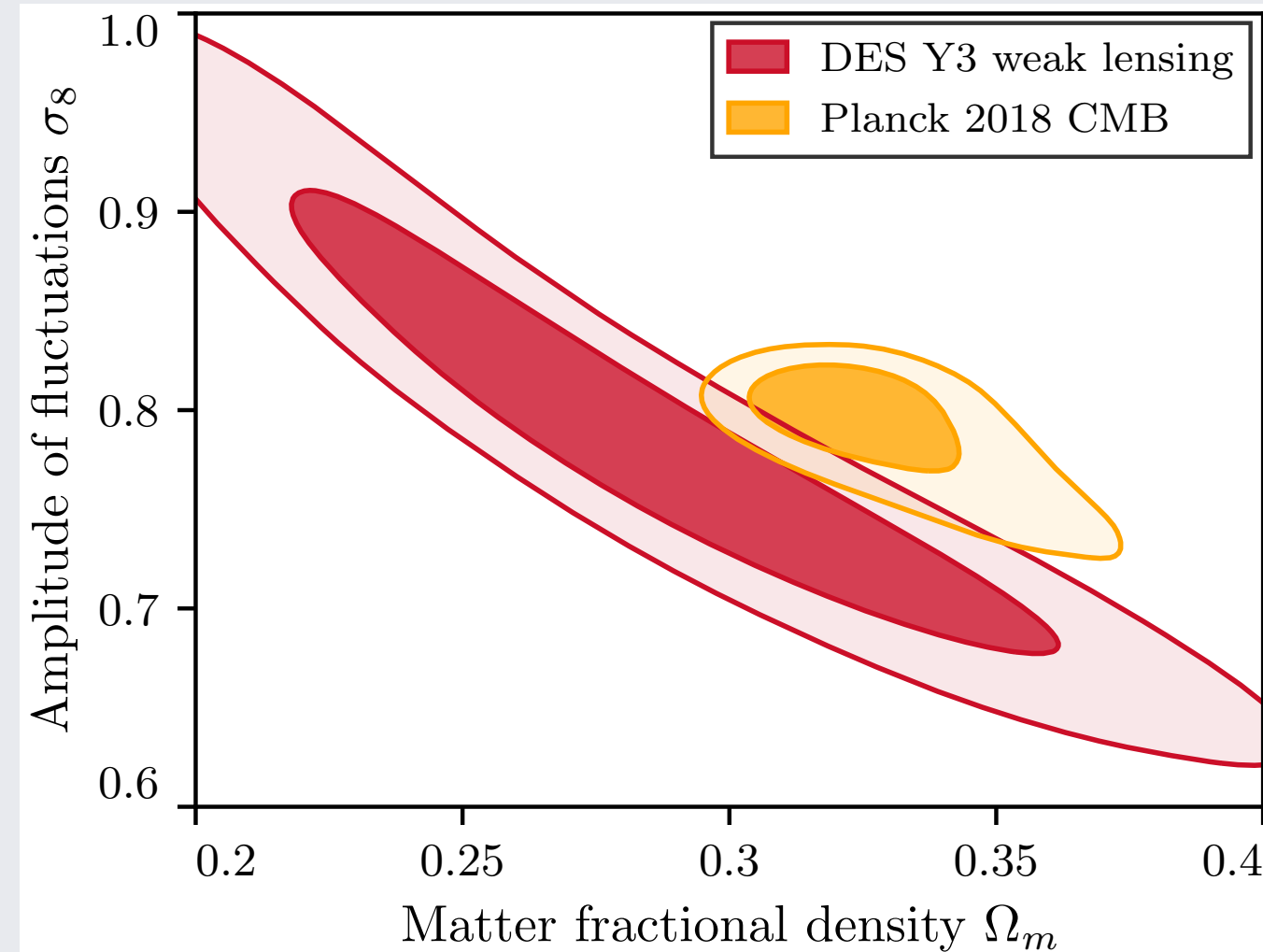


Flow

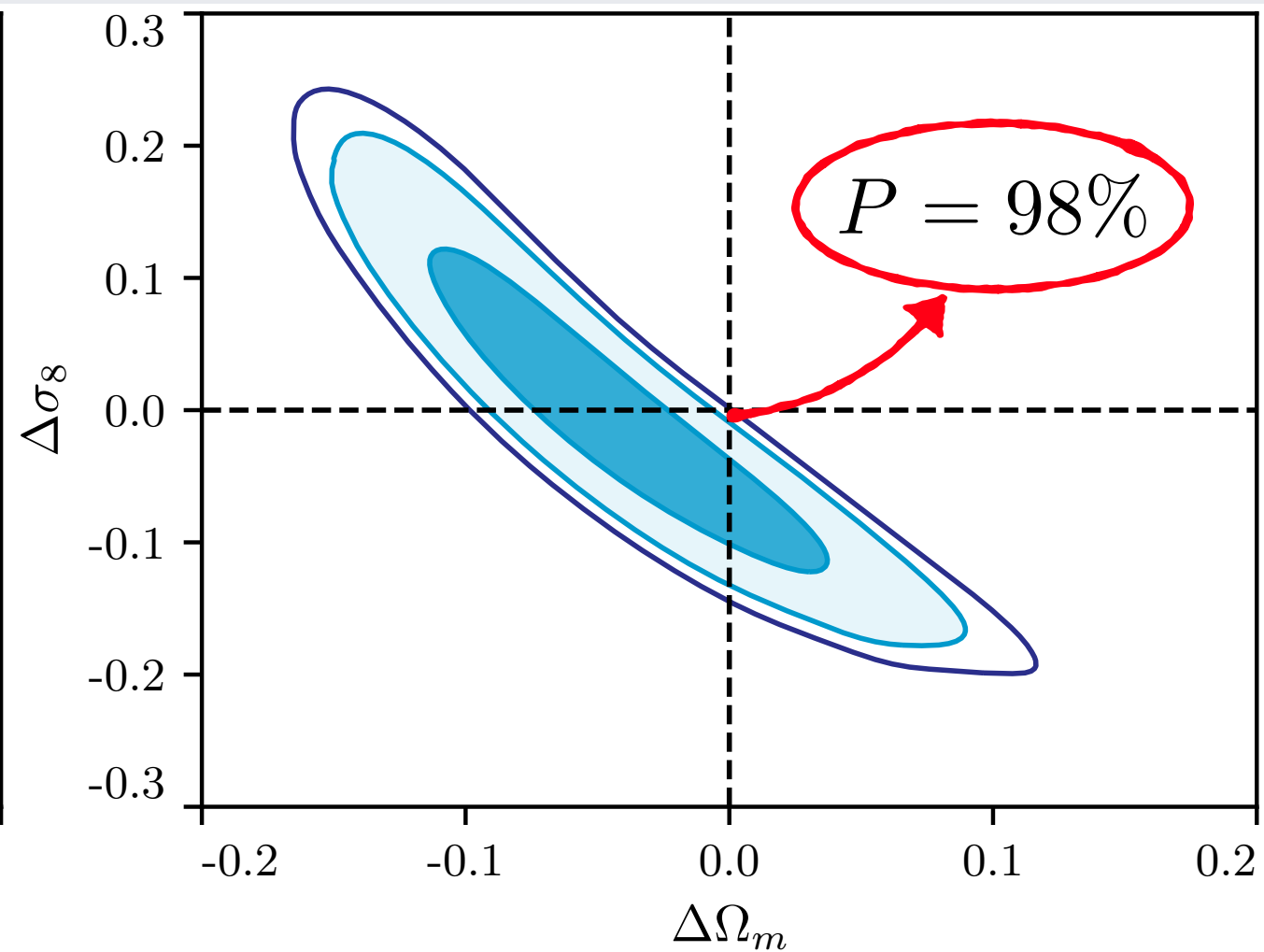


# Application to DES Y3

Original parameter space



Difference parameter space

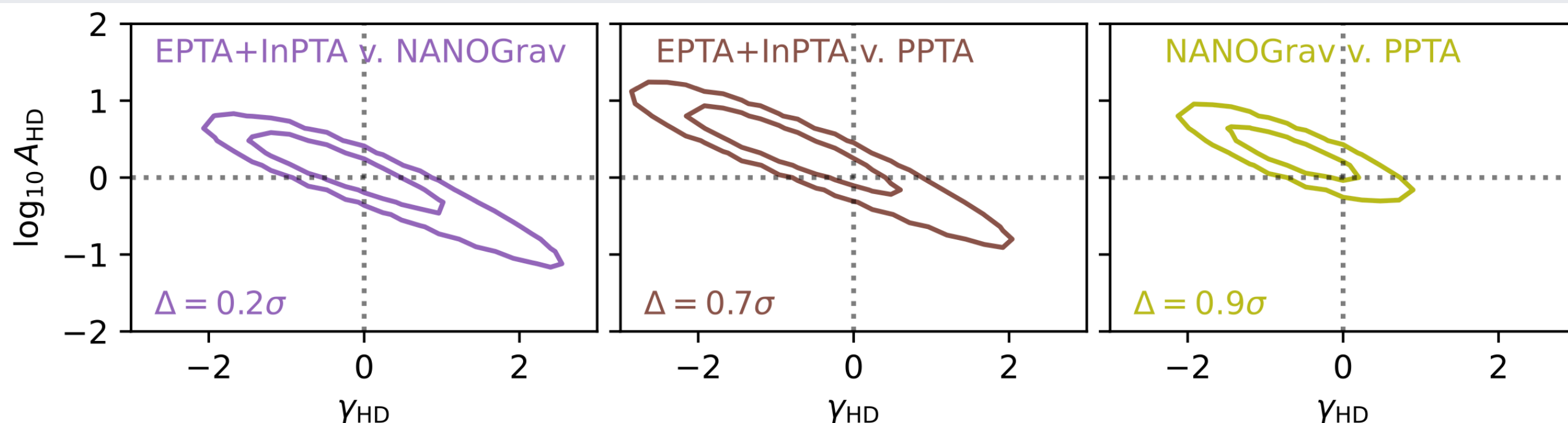


...all other parameters are hidden...

( Based on DES Y3 KP arXiv:2105.13549 )

# Pulsar Timing Arrays

Industry-standard for tension calculations



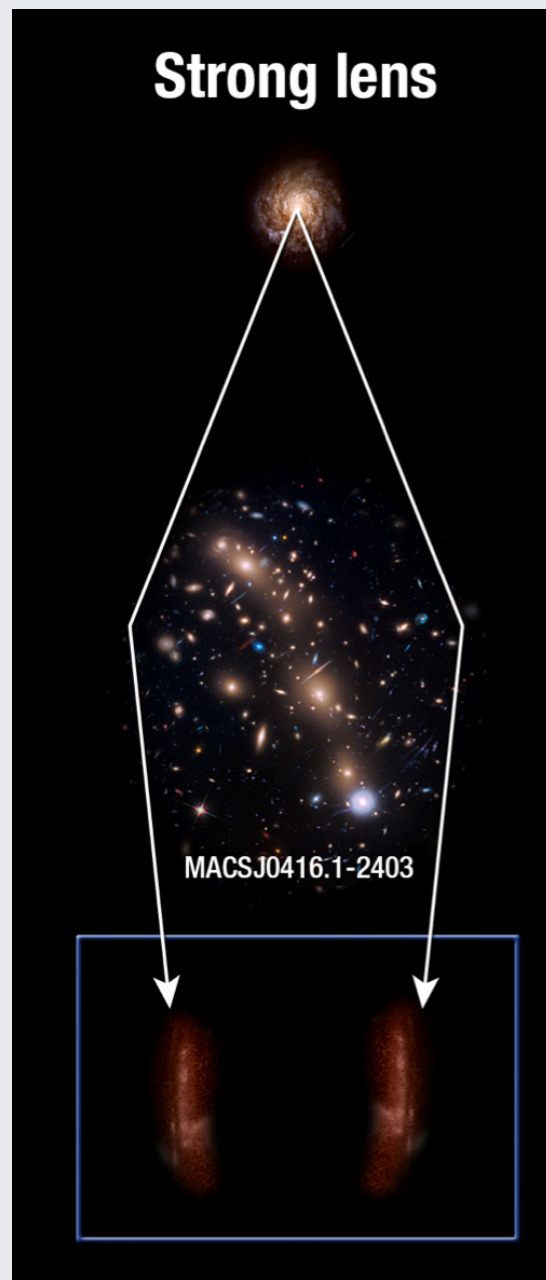
**Figure 2.** Difference distributions for GWB parameters between pairs of PTAs as computed by `tensiometer`. The contours show 68 and 95% of the distribution mass.

Adopted by PTA collaborations - NOT including MR!



# Strong Lensing of Gravitational Waves

Large lumps of matter deflect light and GW



If the geometry is right,  
multiple images form

# Strong Lensing of Gravitational Waves

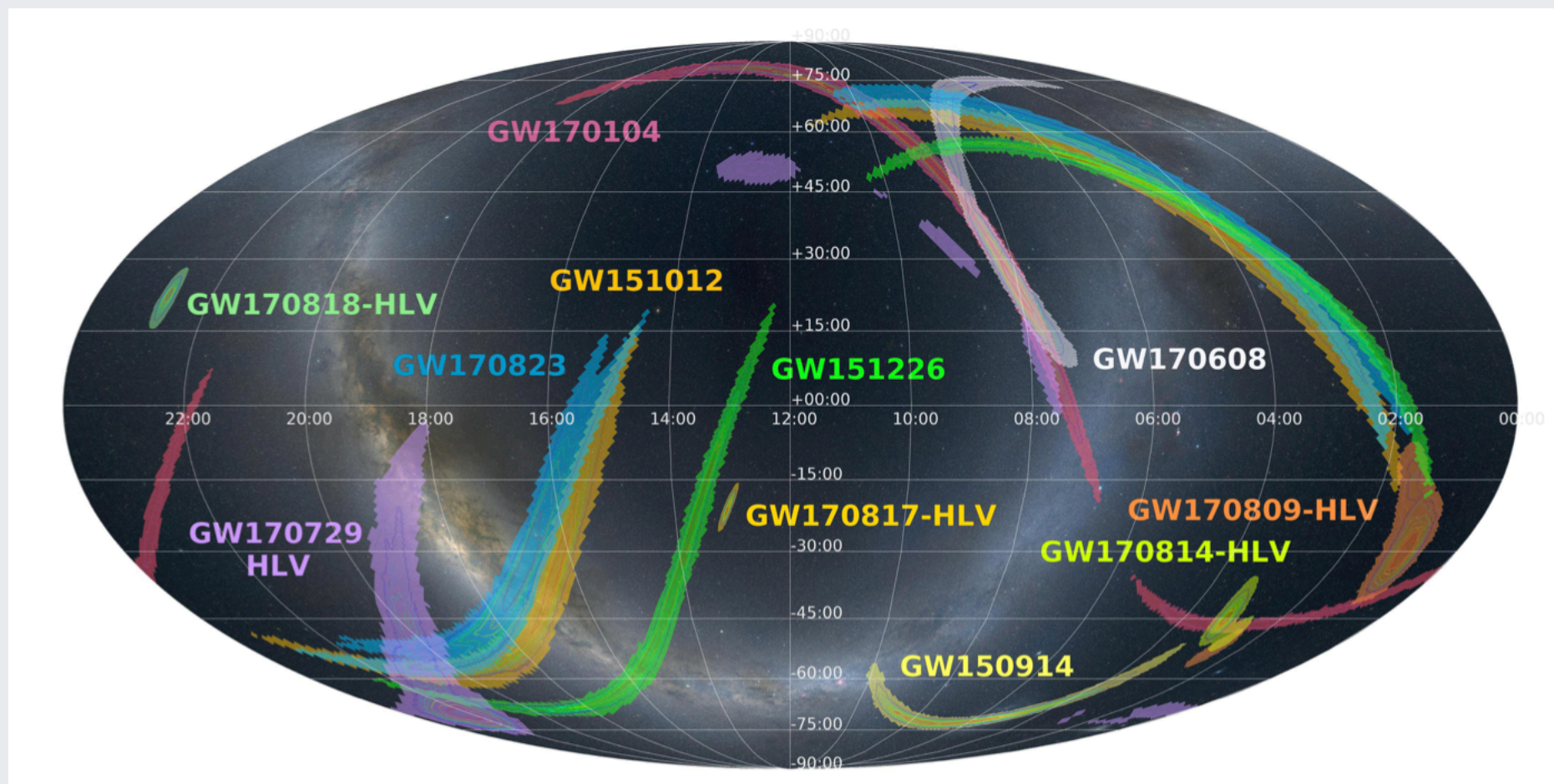
Large lumps of matter deflect light and GW



If the geometry is right,  
multiple images form

# Strong Lensing of Gravitational Waves

GW “images” are not spatially resolved



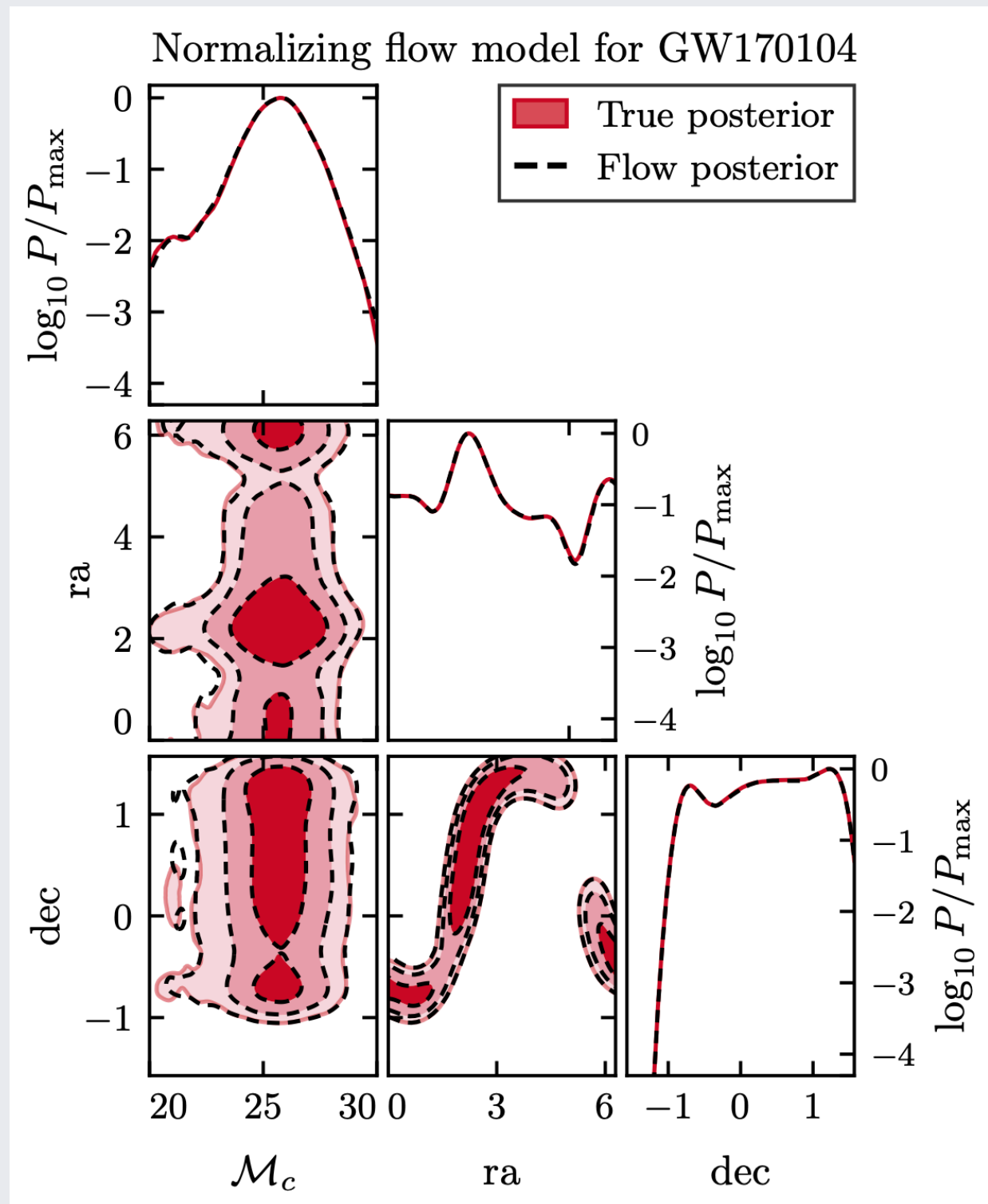
...but they are resolved in time...

# Strong Lensing of Gravitational Waves

Search for all pairs ( $N^2$ ) of GW events and look for ones that have the same physical properties

...inverse exercise with respect to tensions...

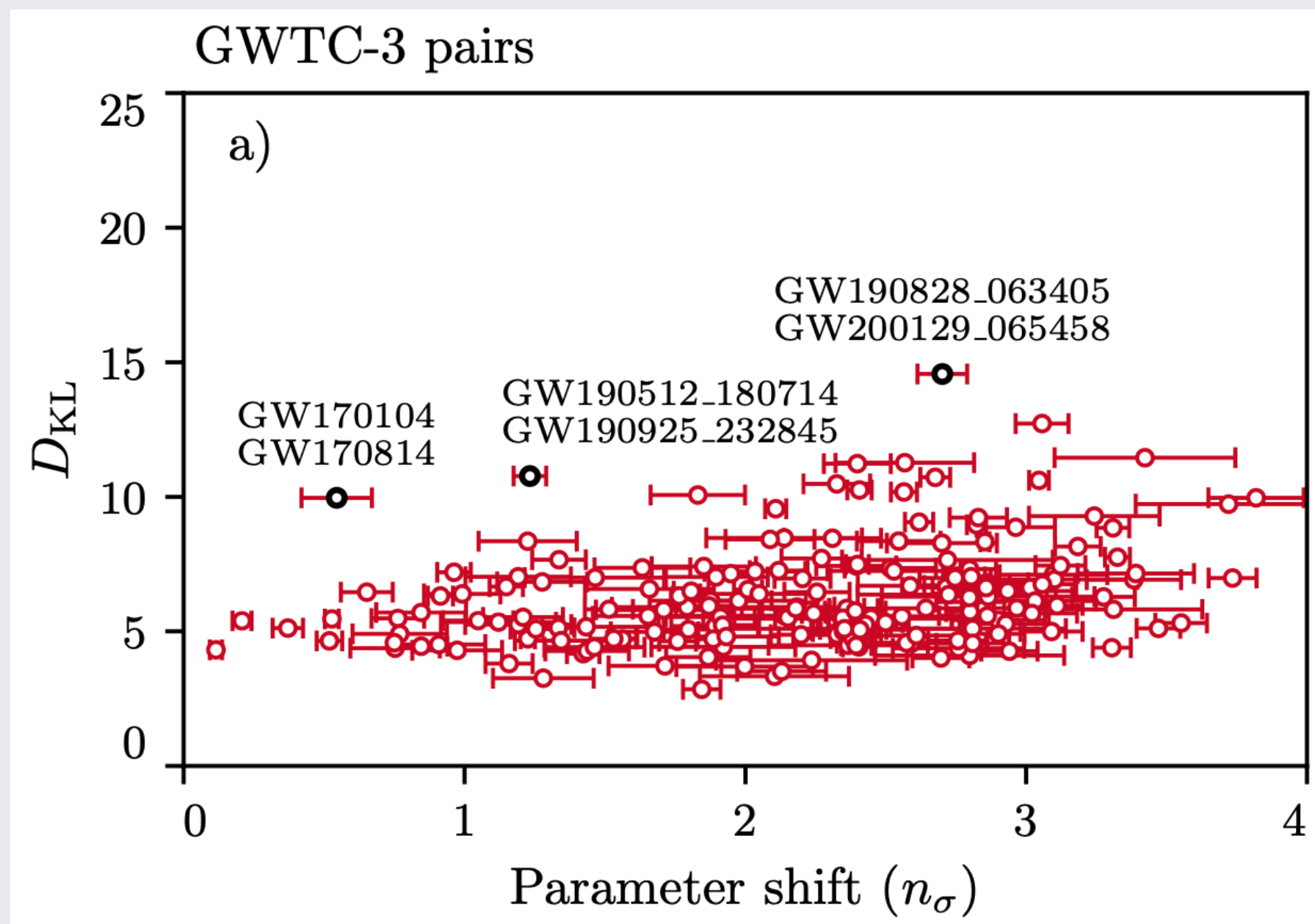
# Gravitational Waves NFs



( Based on arXiv:2509.06901 )



# Strong Lensing search with O3



Few interesting candidates for EM followup!

# Outlook

- \* Machine learning algorithms can help tackling problems in statistical inference that would be unfeasible otherwise
- \* Precisely estimate agreement/disagreement between different experiments
- \* Outperforming any other method...