

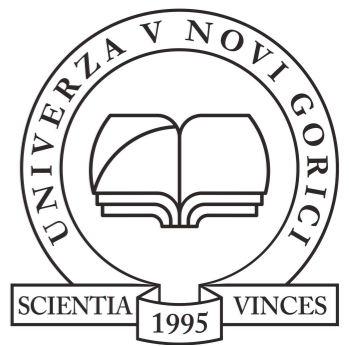


# SMASH

machine learning for science and humanities postdoctoral program



Co-funded by  
The European Union



# Characterizing the *Fermi*-LAT high-latitude sky with simulation-based inference

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University of Nova Gorica,

Center for Astrophysics and Cosmology, Slovenia

30th of April 2024

$$p(Z|X) = \frac{p(X|Z)p(Z)}{p(X)}$$

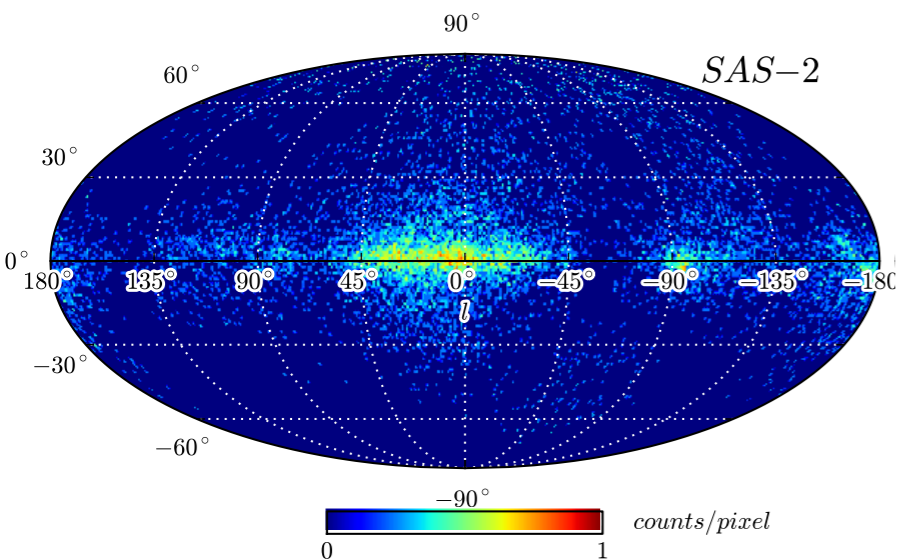
European AI for Fundamental Physics Conference (EuCAIFCon)

Amsterdam, Netherlands

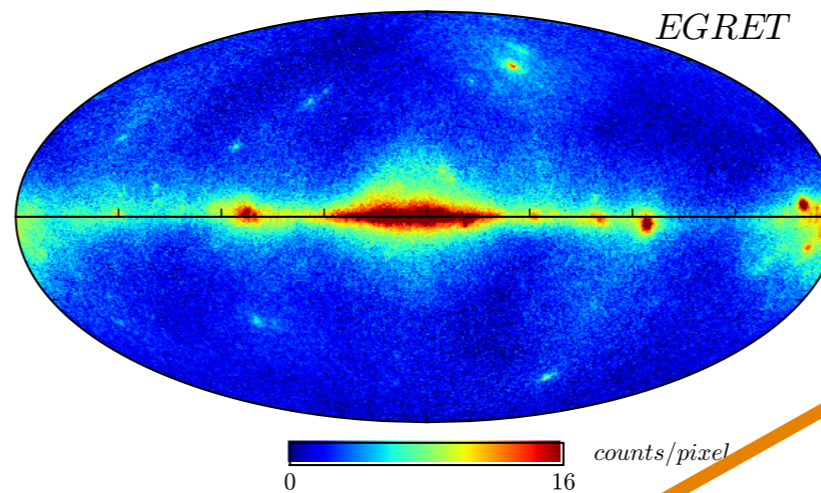
# Fundamental physics with gamma rays is hard

The high-energy gamma-ray sky seen over the decades (space-borne telescopes).

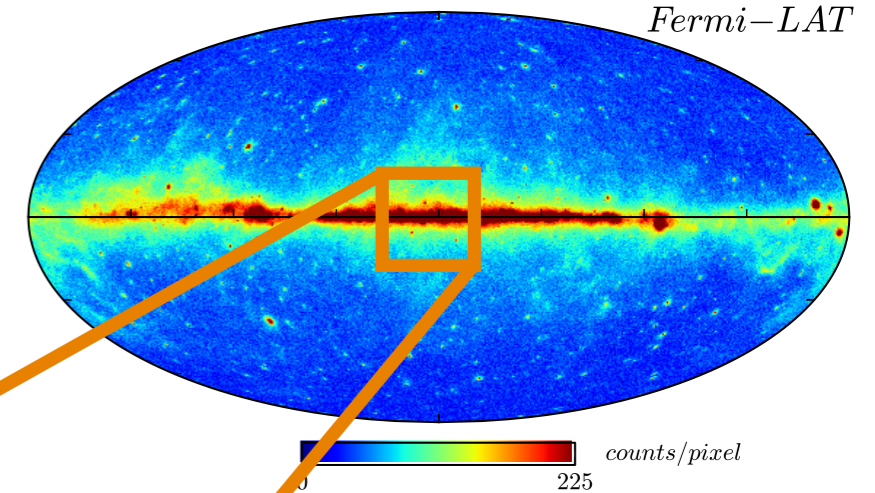
1972-73



1991-2000



2008-now



[Fermi-LAT collaboration, ApJS 223 (2016) 2]



[Bertone, Tait, Nature 562 (2018) 7725]

Signatures of fundamental physics are potentially hiding there!  
→ How to deal with the **complexity** of all the astrophysics?  
**There is a lot to model ...**

# Simulation-based inference brings back physics

Ratio estimation as a form of simulation-based inference (SBI):

Bayes' Theorem

posterior

Likelihood-to-evidence ratio



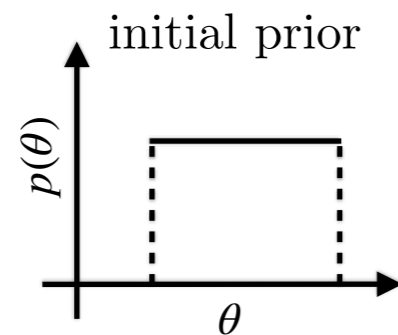
Truncated  
Marginal  
Neural  
Ratio  
Estimation

parameters  $Z$ , data  $X$

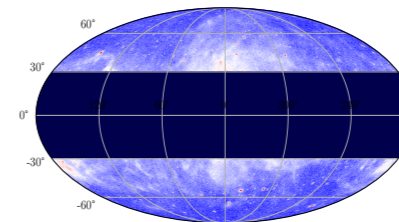
prior

$$p(Z|X) = \frac{p(X|Z)}{p(X)} = \frac{p(X, Z)}{p(X)p(Z)}$$

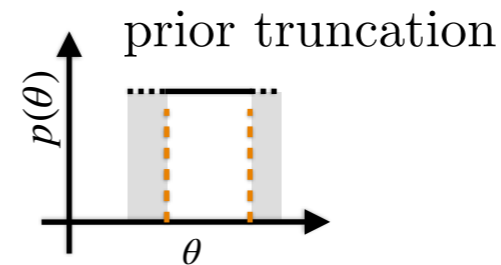
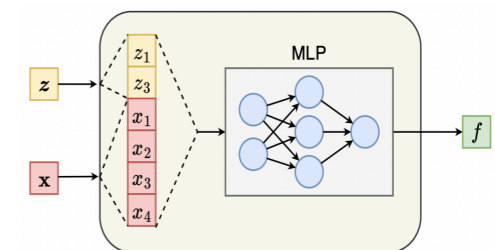
[B. Miller et al., J. Open Source Softw. 7 (2022) 75]



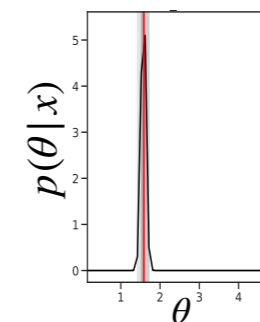
forward simulation



MNRE



parameter inference



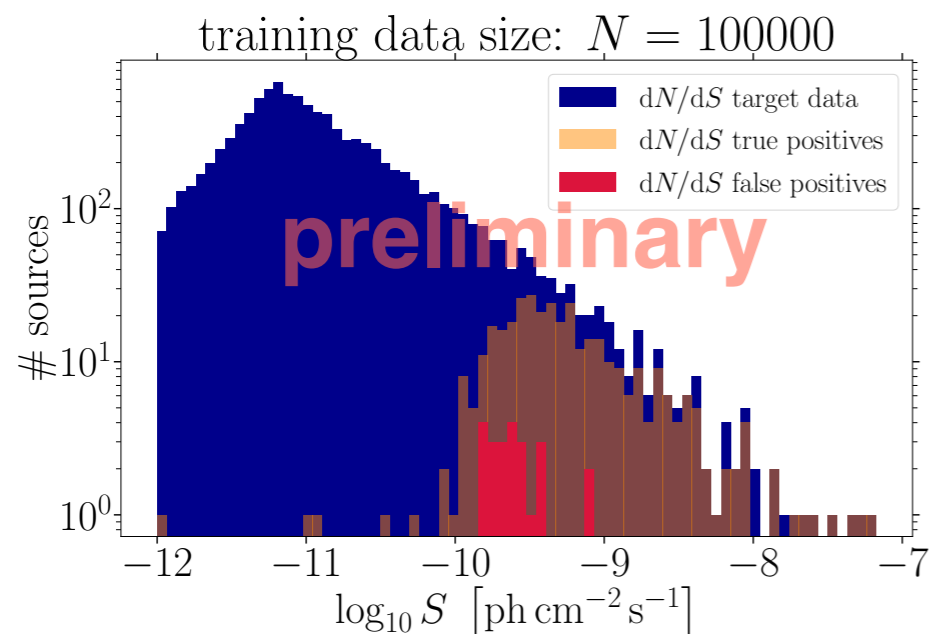
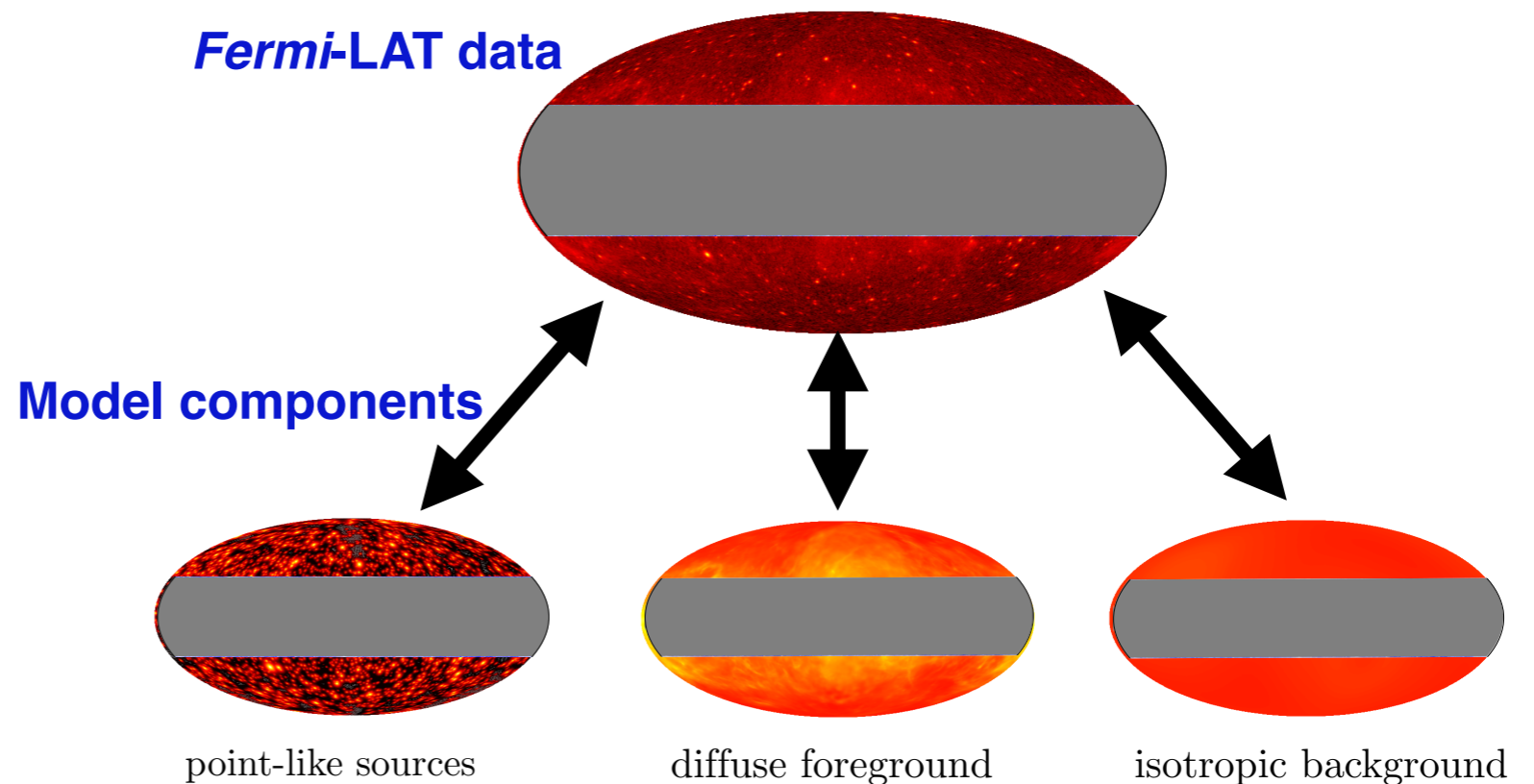
The great scheme of TMNRE:  
 → Inference on high-dimensional models using a binary classification network and an overall reduction of computation costs.

# First Application to Gamma Rays: High-Latitude Sky

We tune our SBI approach to gamma-ray data with observations of the high latitudes  
→ Less backgrounds and more opportunities to cross-check with literature results!

## Scientific Objectives:

- (1) What is the distribution of point-like gamma-ray sources as a function of their flux?
- (2) Which of them can we robustly detect?



You may wonder:

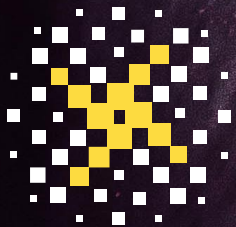
1. How does it work?
2. What does the astro model look like?
3. What are your plans?

**Let's have a chat, Wednesday 12 - 3 pm  
in poster session A!**

# Neural Simulation-Based Supernova Ia Cosmology

Kosio Karchev

Roberto Trotta, Christoph Weniger



SISSA

**DATASCIENCE**

Machine Learning for the Natural Sciences



EUROPEAN AI FOR  
FUNDAMENTAL PHYSICS  
CONFERENCE  
**EuCAIFCon 2024**

# Supernova Ia cosmology

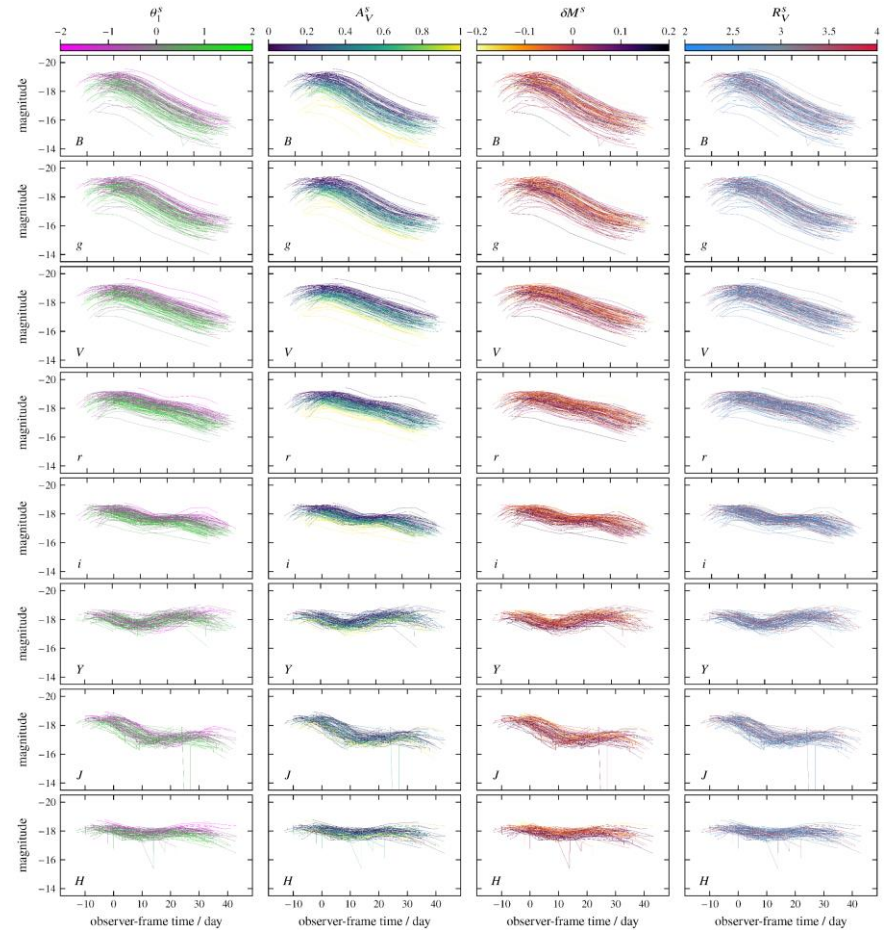
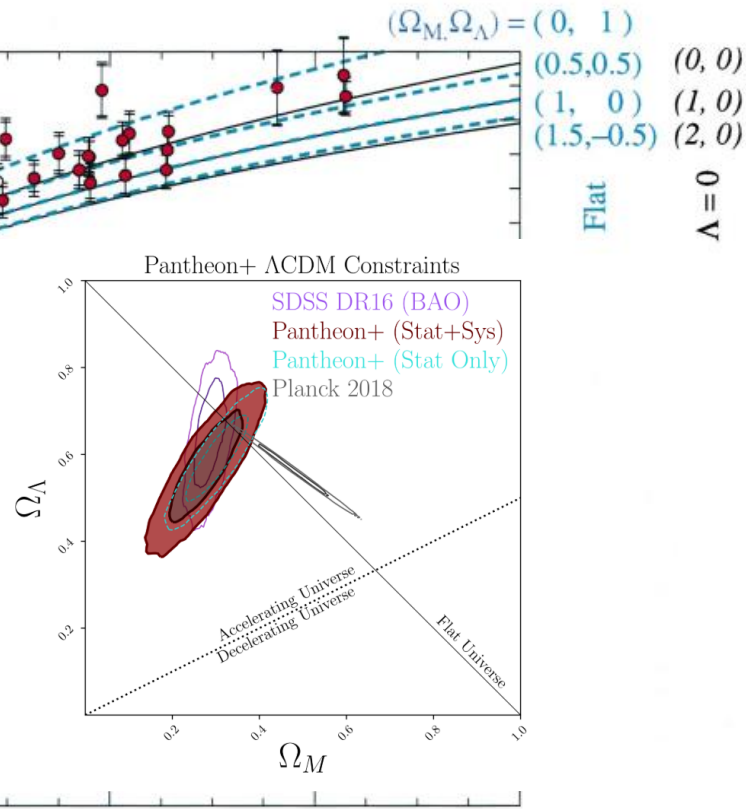


effective  $m_B$

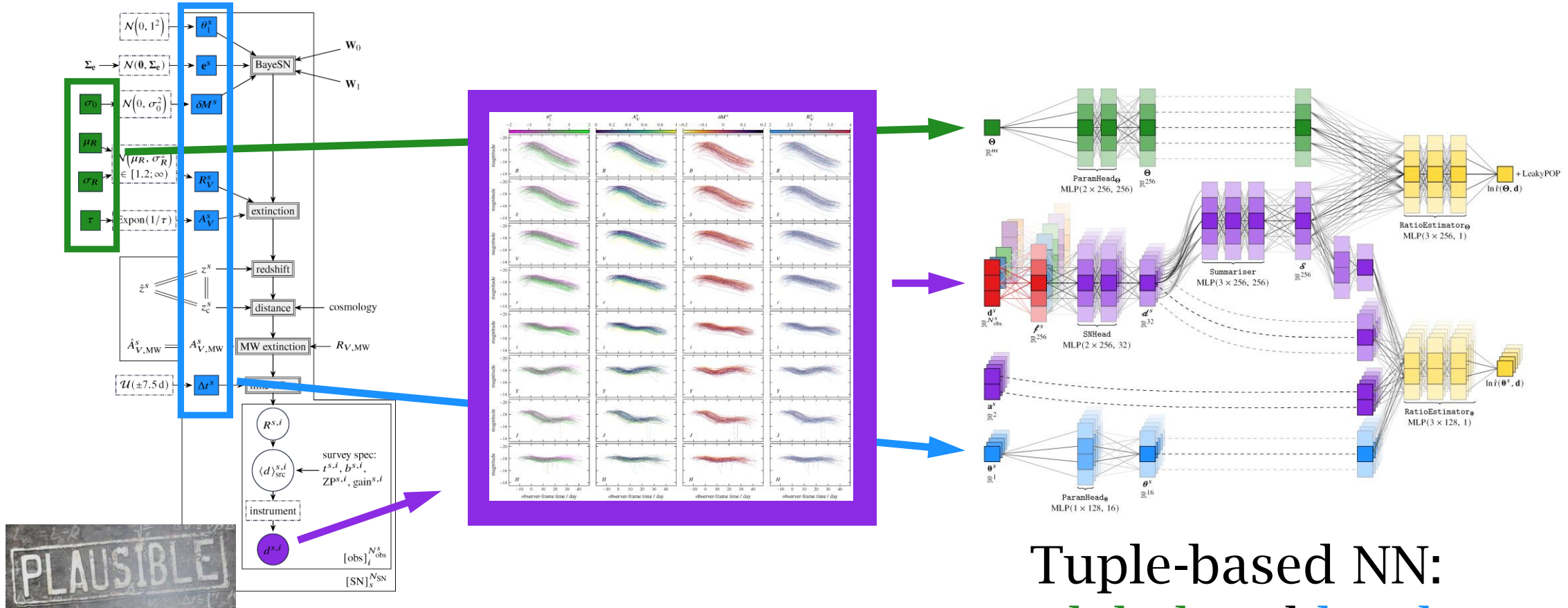
20  
18  
16  
14

MYTH

redshift  $z$



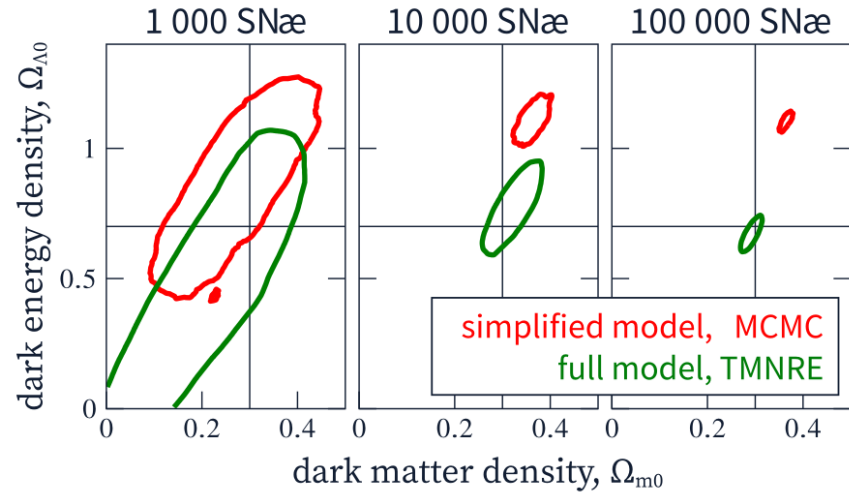
# TMNRE for supernova light curves



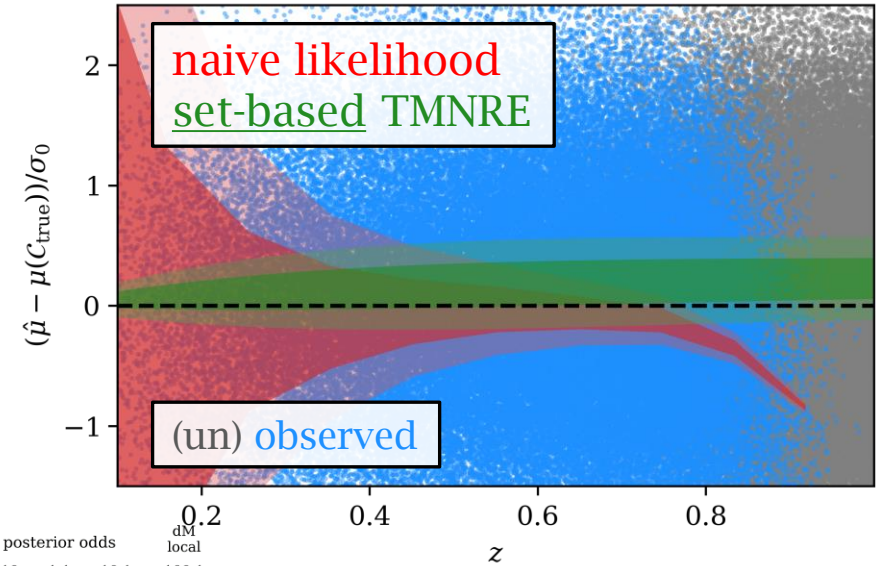
SLiCsim

Tuple-based NN:  
 global and local  
 NRE

# The importance of being principled

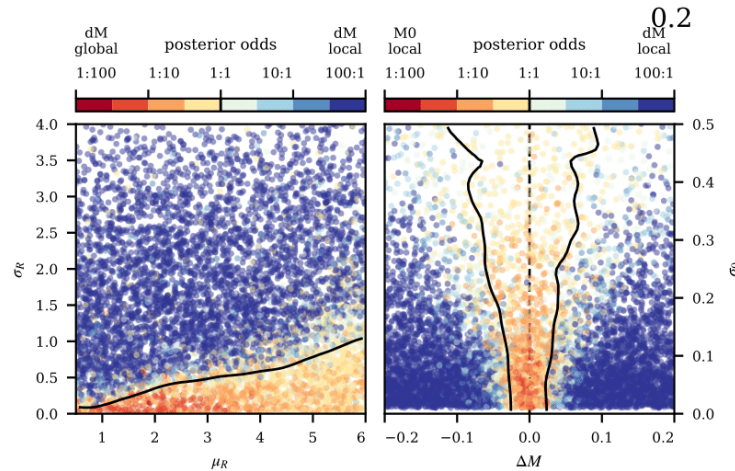
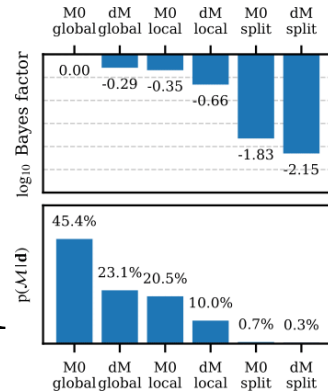


$10^5$   
SNæ



systematics

Bayesian  
model selection



selection  
effects



# Fast likelihood-free inference in the LSS Stage-IV era

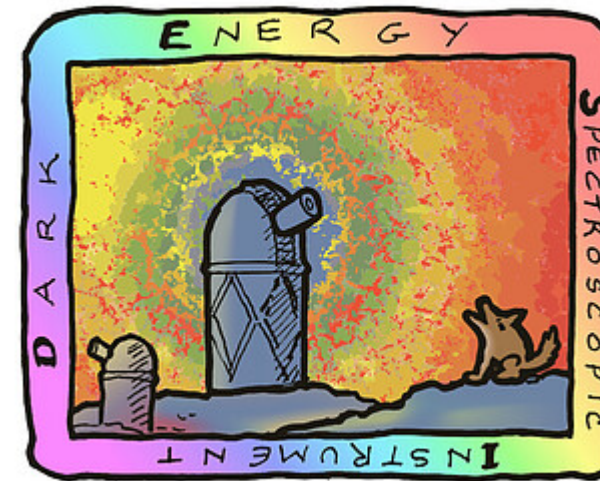
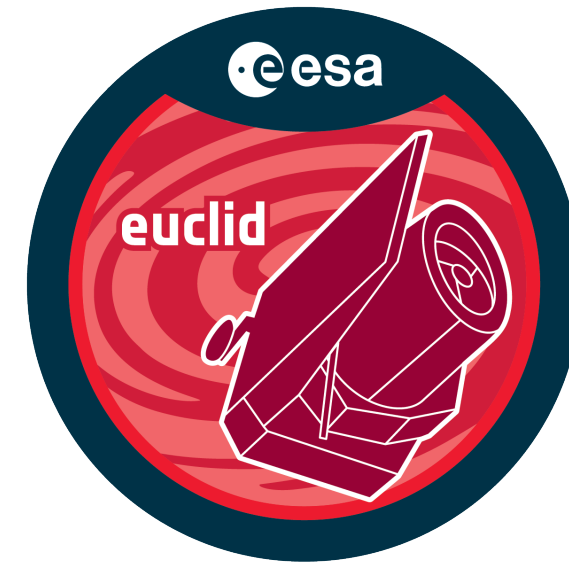
Guillermo Franco Abellán



Based on [arXiv:2403.14750](https://arxiv.org/abs/2403.14750)  
with Guadalupe Cañas-Herrera,  
Matteo Martinelli,  
Oleg Savchenko,  
Davide Sciotti,  
& Christoph Weniger

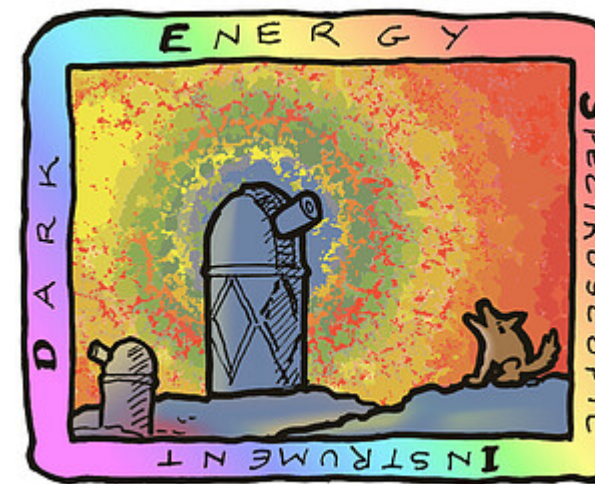
EuCAIFCon - 30th April 2024

Forthcoming **cosmological surveys** will provide us with unprecedented data to probe the **dark sector**...



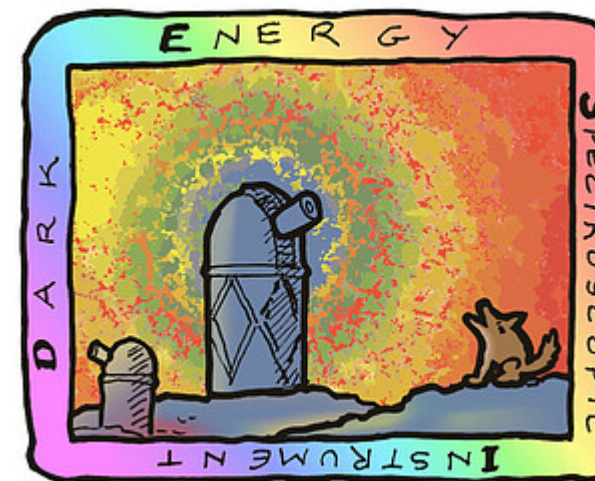
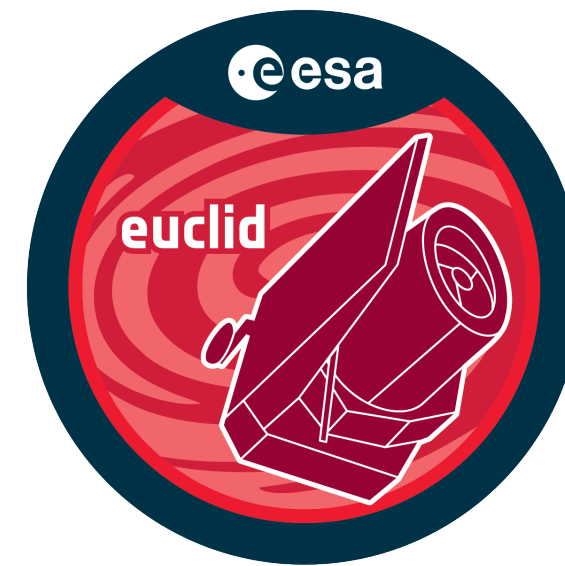
Forthcoming **cosmological surveys** will provide us with unprecedented data to probe the **dark sector**...

...but analysing these data will be **challenging** with classical methods



Forthcoming **cosmological surveys** will provide us with unprecedented data to probe the **dark sector**...

...but analysing these data will be **challenging** with classical methods

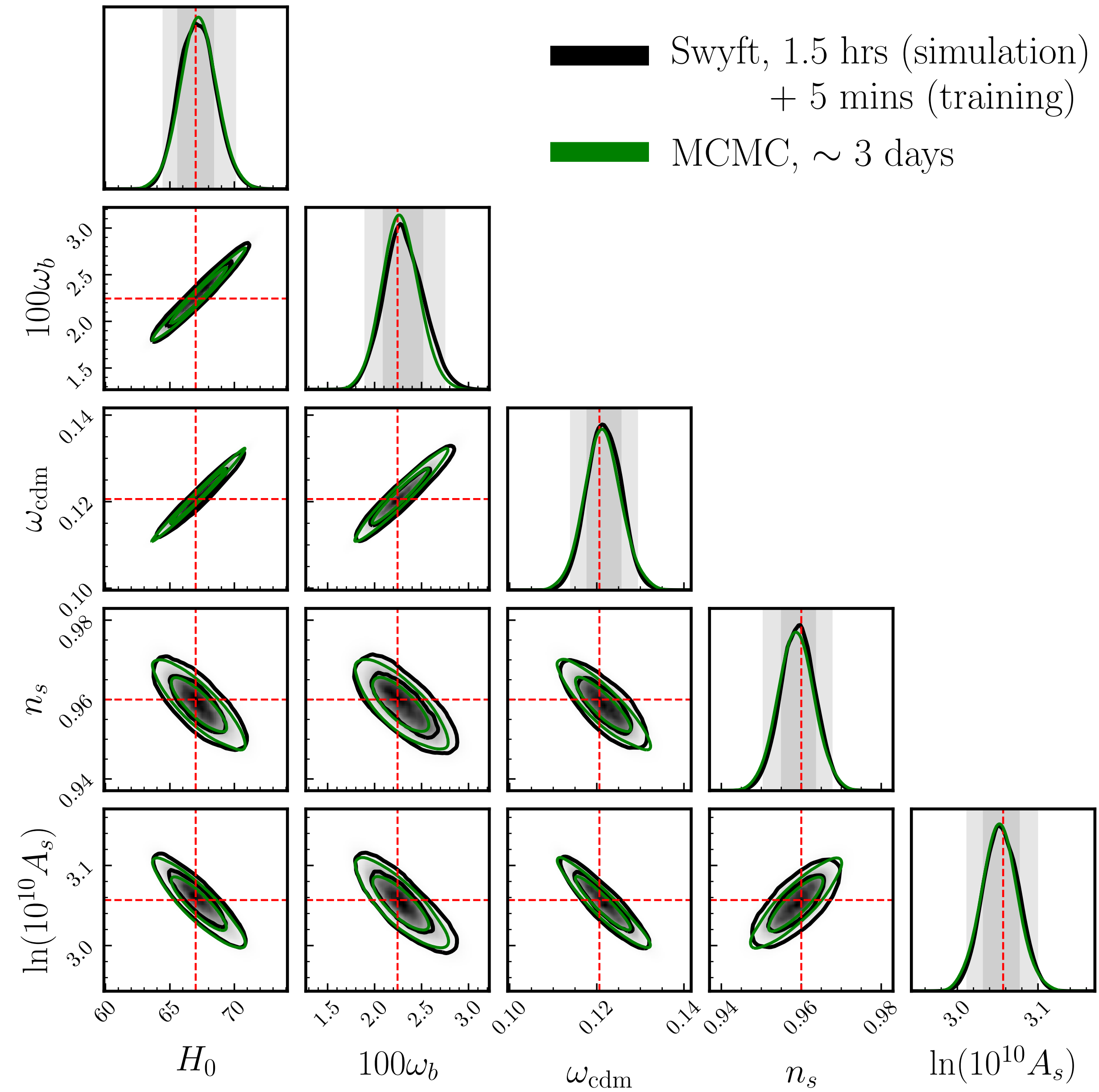


## Our **GOAL**

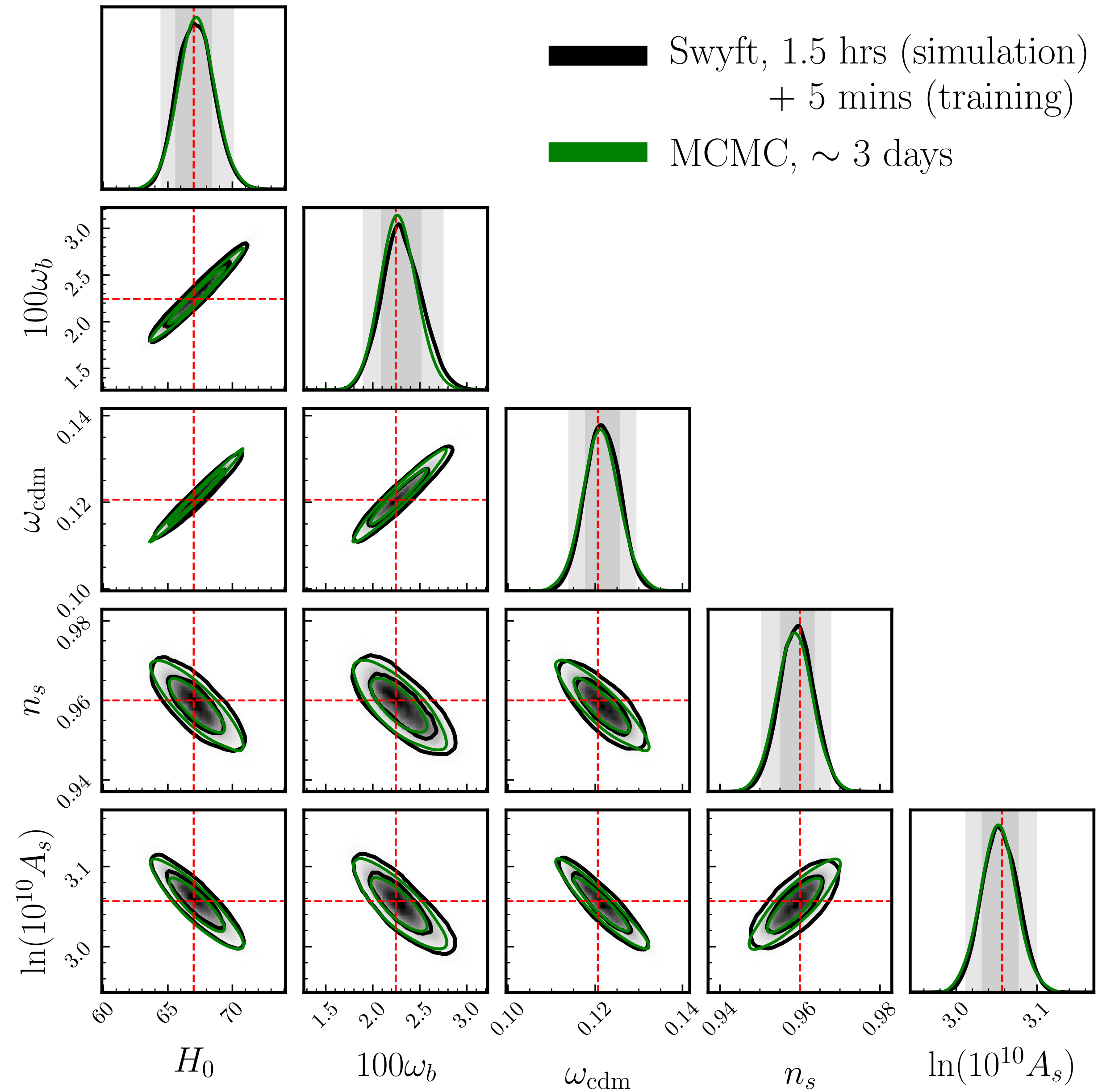
Accelerate parameter inference from Stage-IV photometric surveys (i.e. **Euclid**) using **Marginal Neural Ratio Estimation\*** (MNRE, a new approach in **SBI**)

\*Implemented in **Swyft** [Miller+ 20]

# Forecast $\Lambda$ CDM posteriors

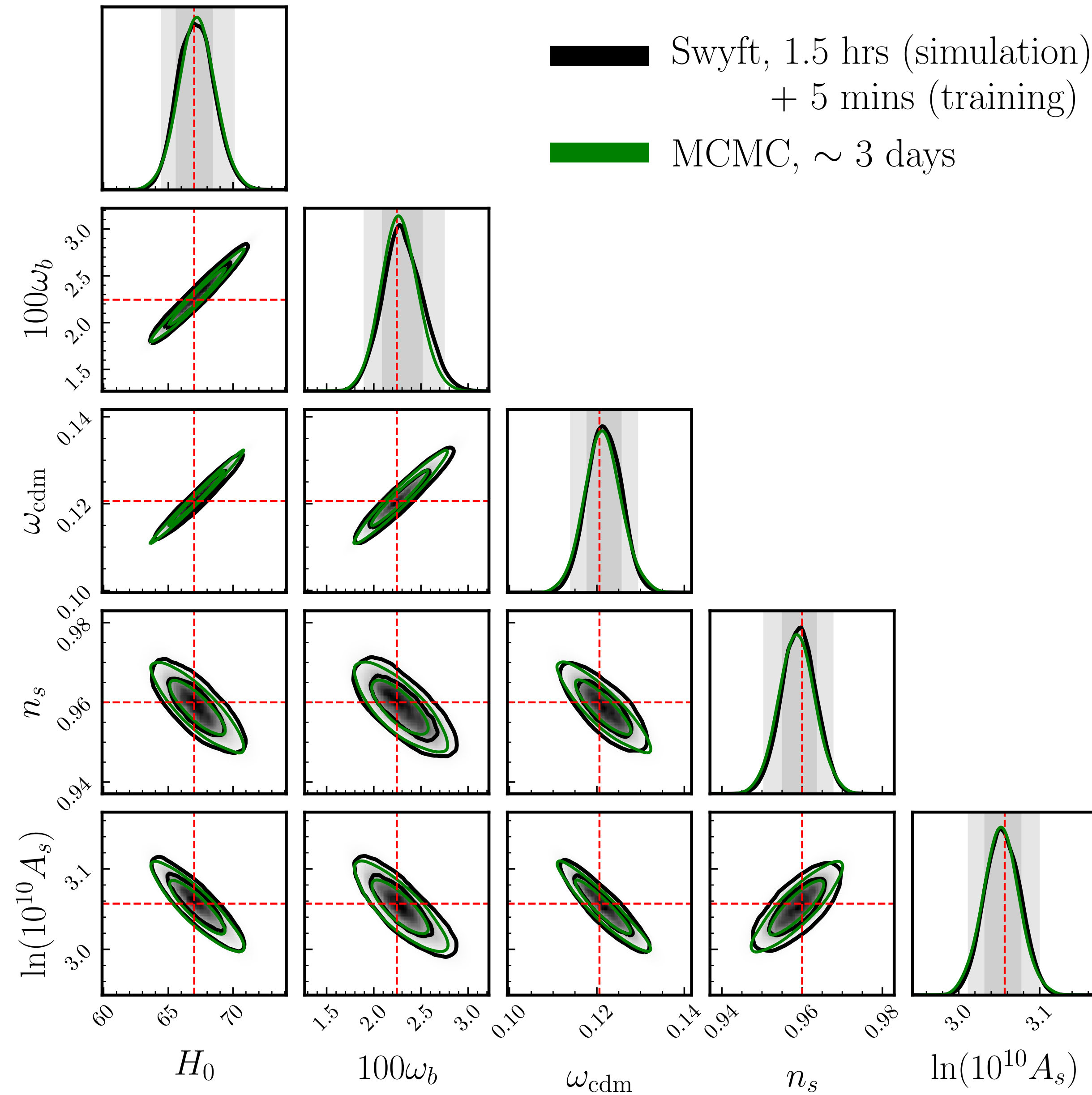


# Forecast $\Lambda$ CDM posteriors



MNRE & MCMC are in excellent agreement!

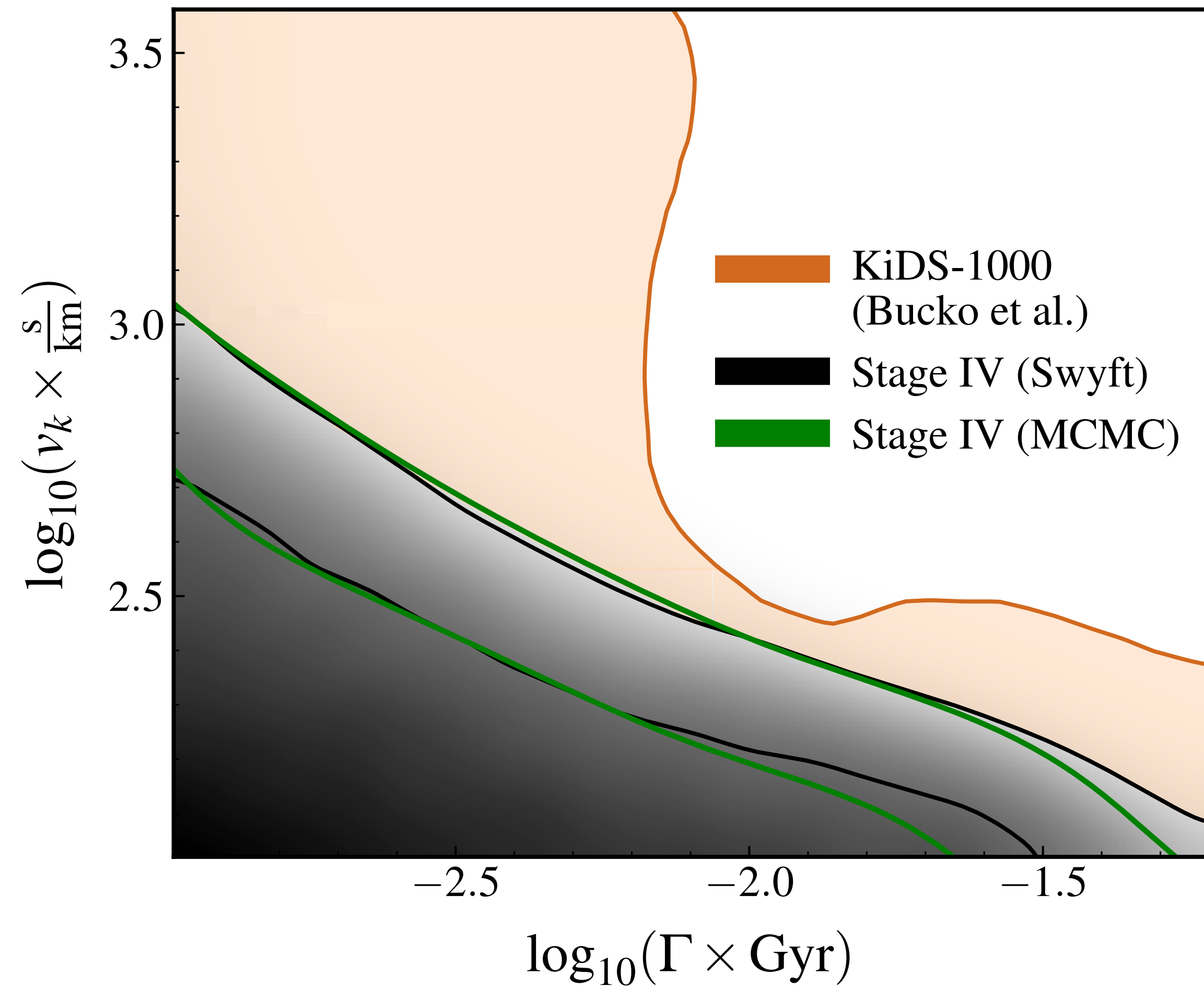
# Forecast $\Lambda$ CDM posteriors



MNRE & MCMC are in excellent agreement!

Dramatic reduction in CPU time!

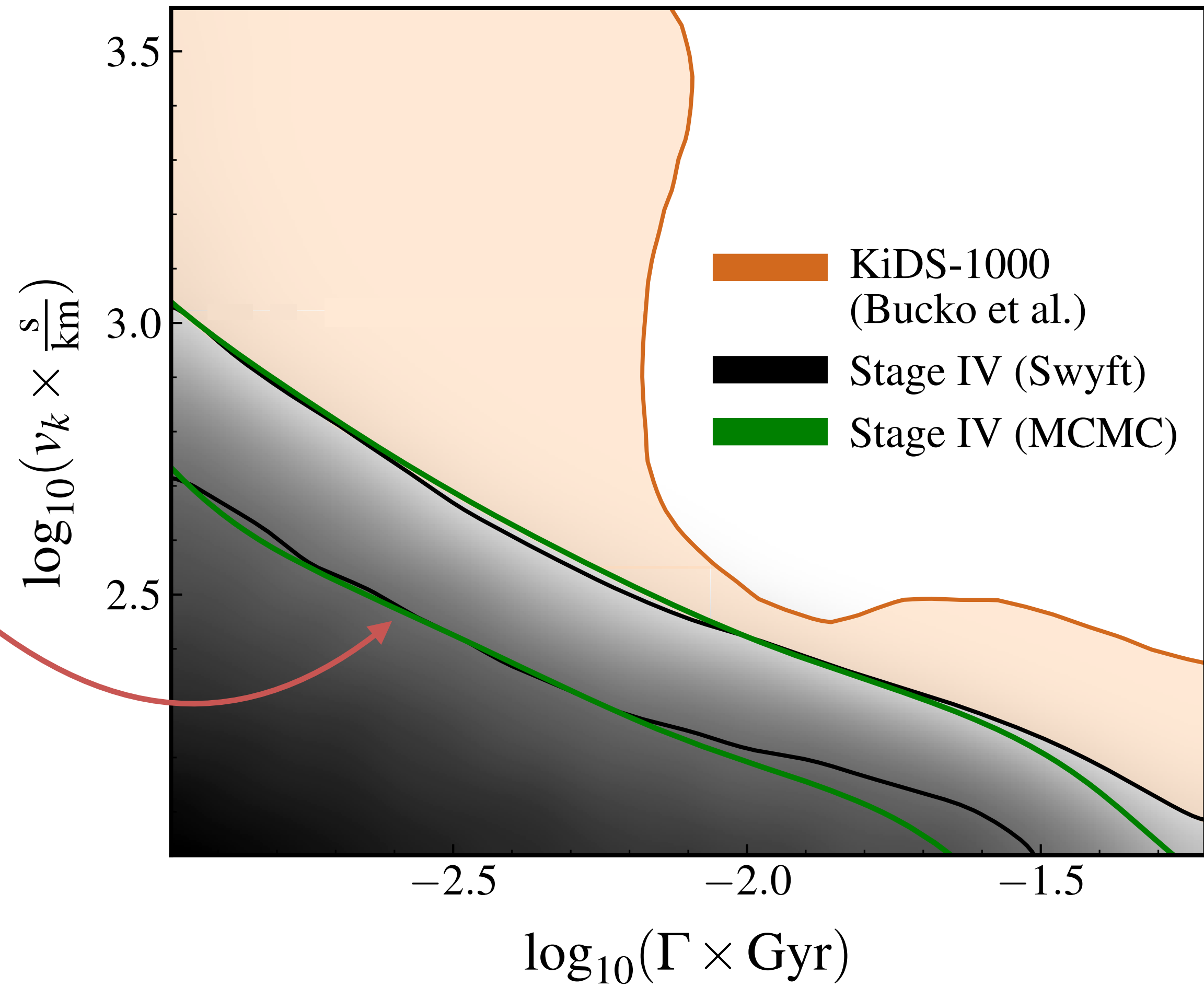
# Forecast constraints on decaying DM



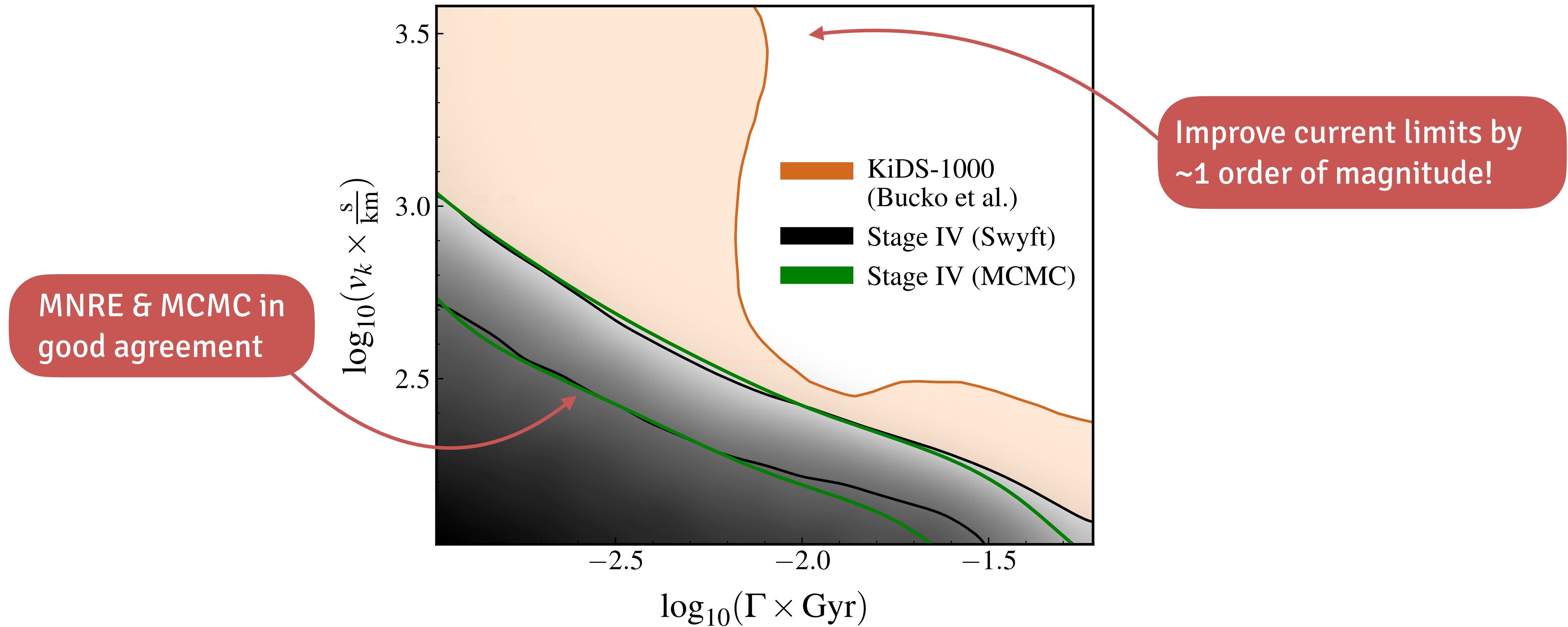


# Forecast constraints on decaying DM

MNRE & MCMC in good agreement



# Forecast constraints on decaying DM



**JAMES ALVEY**  
Postdoc  
University of Amsterdam  
j.b.g.alvey@uva.nl



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# SIMULATION BASED INFERENCE

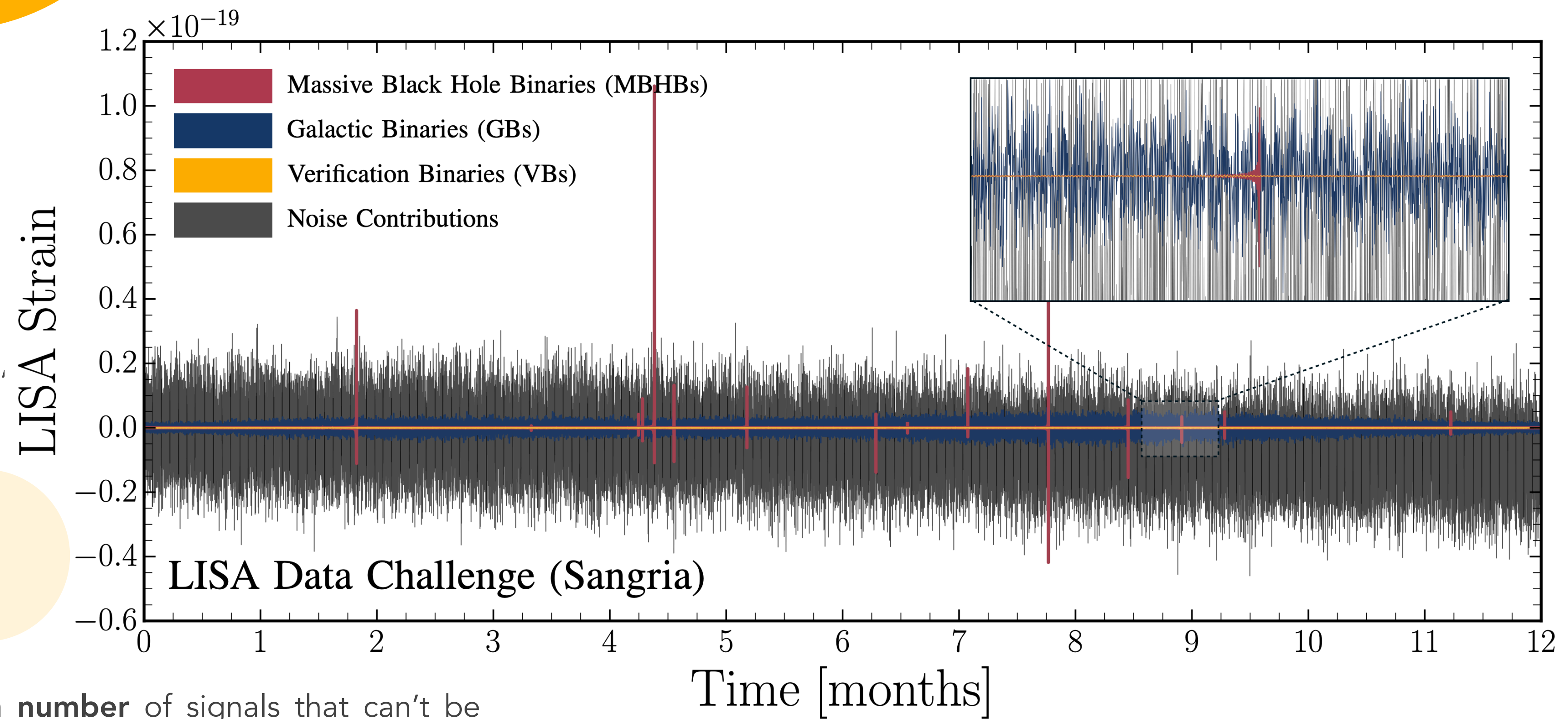
• FOR THE STOCHASTIC GW BACKGROUND •

Loads of **different signal classes**, all in the same data stream

**THE EVERYTHING ALWAYS ALL-AT-ONCE PROBLEM**

Unknown number of signals that can't be separated (highly **overlapping**, unlike LIGO)

So, (someone) has to carry out a joint analysis, naively **10000s of parameters**



**POSTER: LOC 15, WEDNESDAY**

**STATEMENT #1 LISA DATA ANALYSIS IS A BIG CHALLENGE**

**JAMES ALVEY**  
Postdoc  
University of Amsterdam  
j.b.g.alvey@uva.nl



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# SIMULATION BASED INFERENCE

• FOR THE STOCHASTIC GW BACKGROUND •

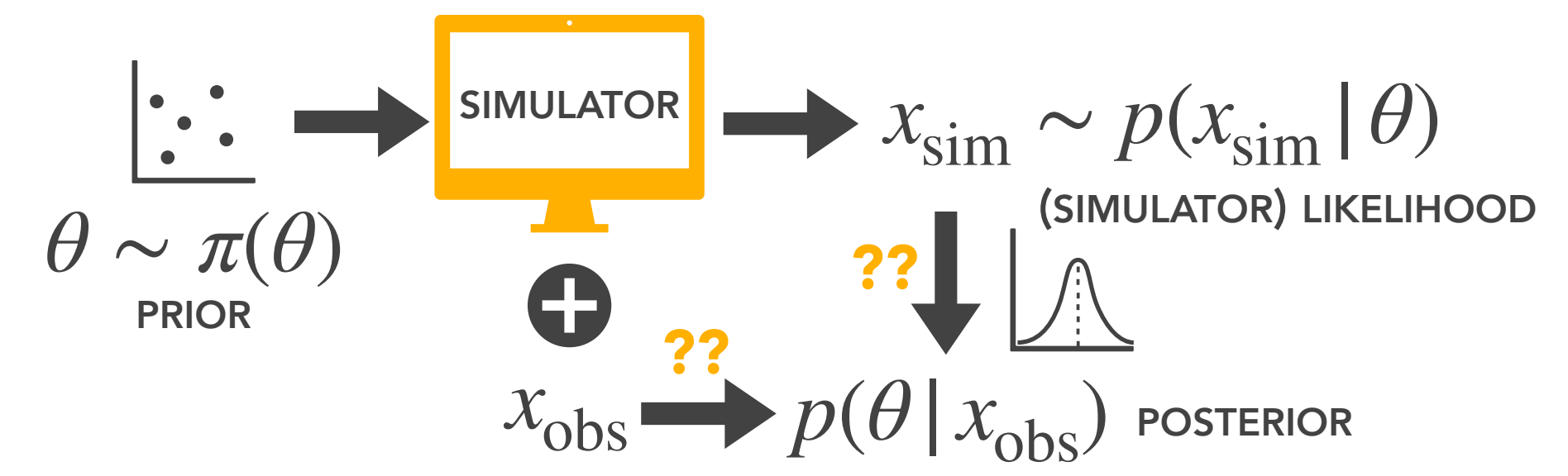
- **MARGINALISE** | SBI is naturally able to marginalise  
"Turn the 10000-dim problem you don't want to solve into the 10-dim one you do"
- **AMORTISE** | SBI can (sometimes) be fully amortised  
"Do the hard work once, and do it right"
- **TRANSFORM** | SBI can (in principle) look at the data in whatever (compressed) form you want  
"Don't be constrained by data likelihoods"

Loads of **different signal classes**,  
all in the same data stream

**THE  
EVERYTHING  
ALWAYS  
ALL-AT-ONCE  
PROBLEM**

Unknown number of signals that can't be separated (highly **overlapping**, unlike LIGO)

So, (someone) has to carry out a joint analysis, naively **10000s of parameters**



**POSTER: LOC 15, WEDNESDAY**

STATEMENT #2 **SBI CAN HELP**