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**This will be a board talk, so the slides are not comprehensive**

(Caveat emptor)



UCL

# **Intro to Machine Learning in Astrophysics & Cosmology**

**(with inescapable personal bias)**

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**Making the impossible, possible**

# ***Astrophysics and Cosmology: questions***

# Astrophysics and Cosmology: questions

AGN feedback

$\Lambda$ ?

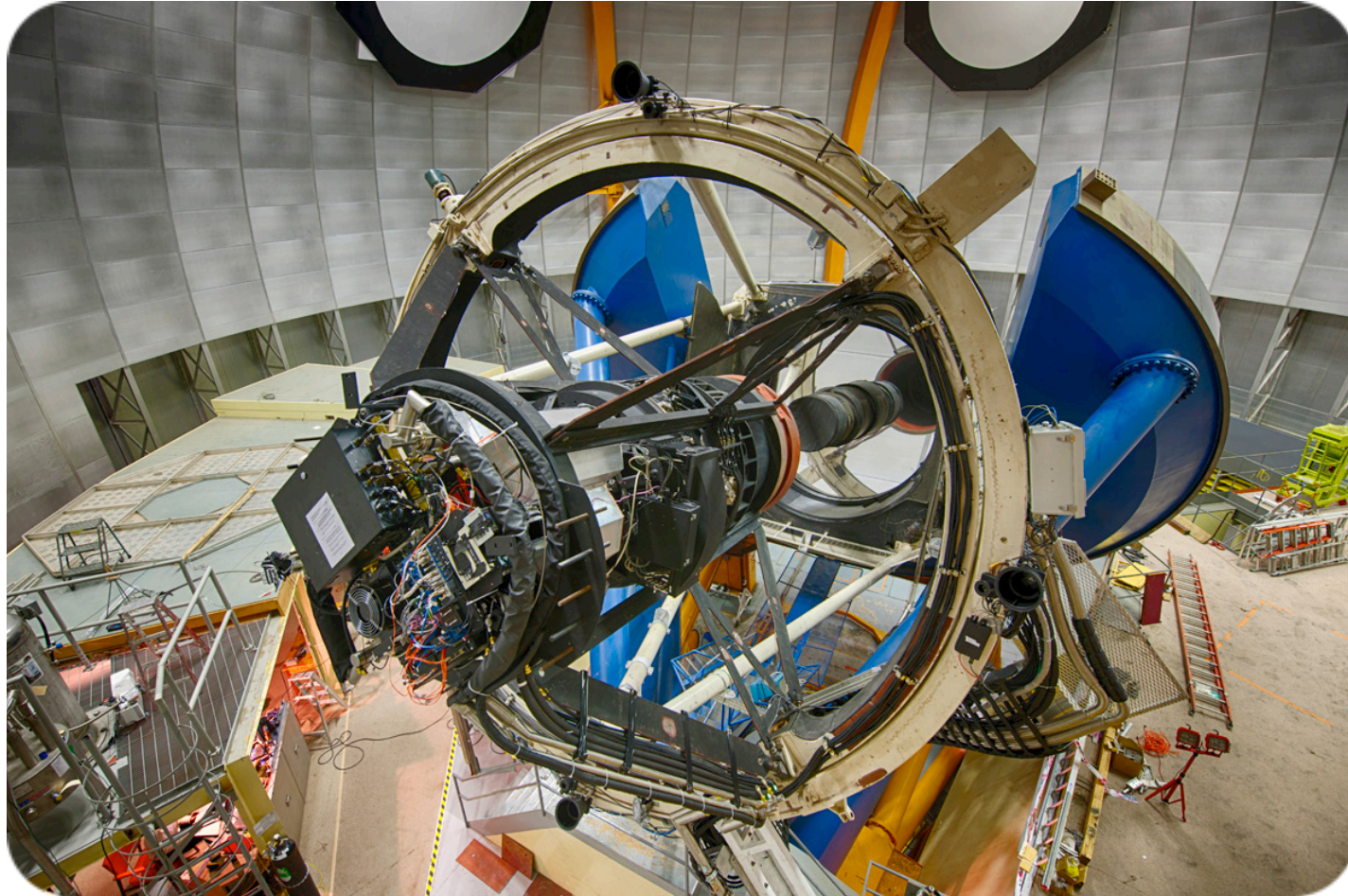
$H_0$ ?

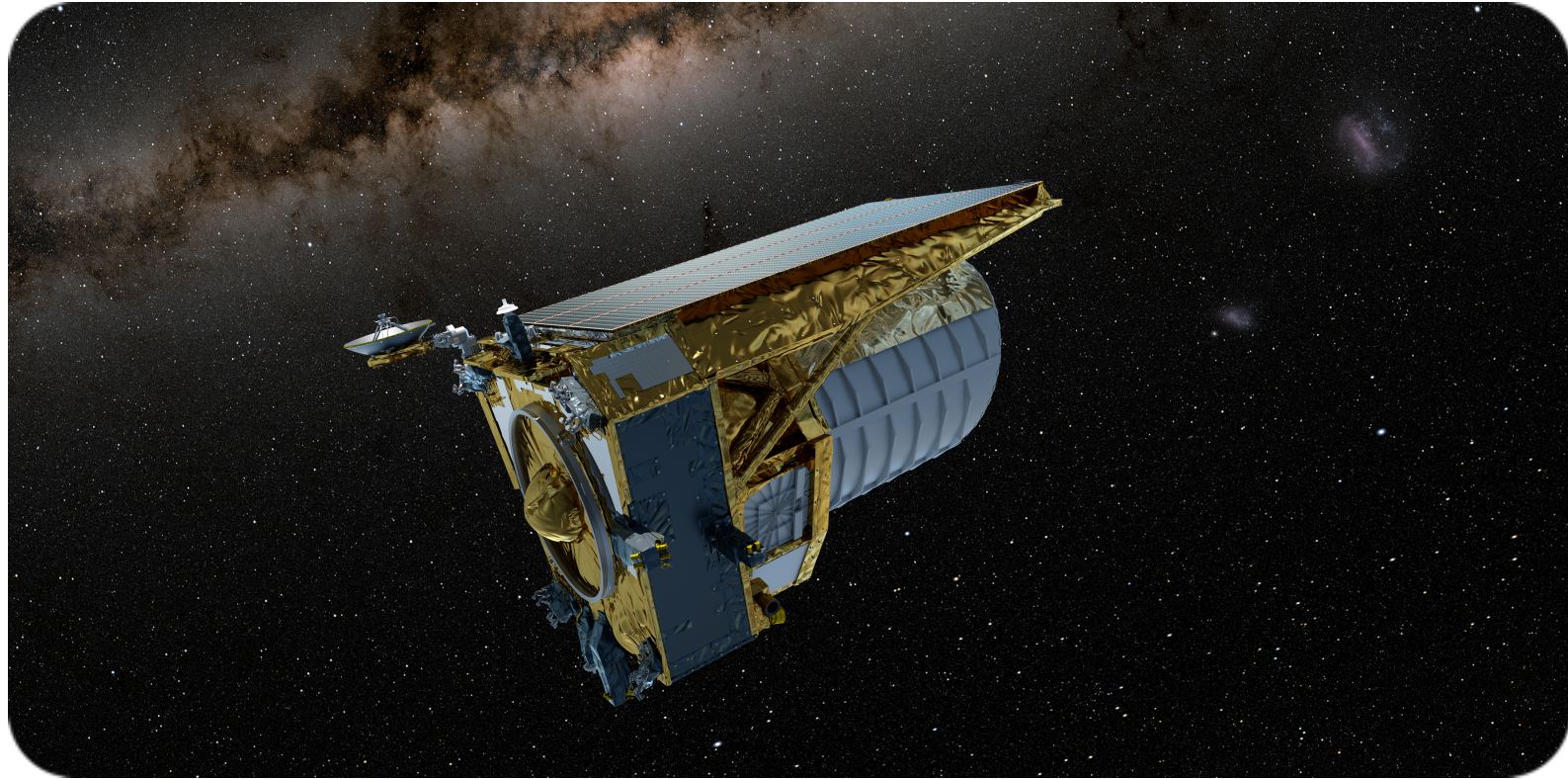
Dust modelling

Galaxy-halo connection

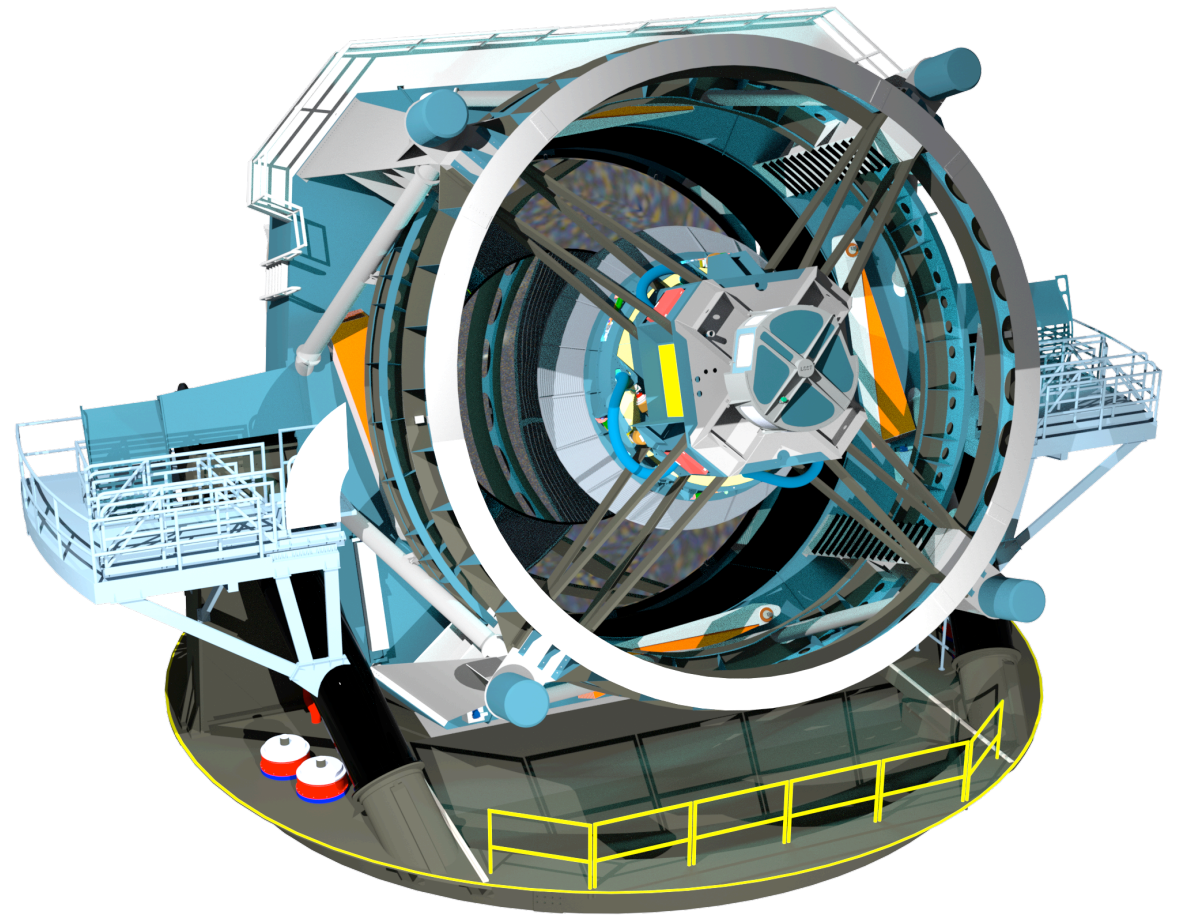
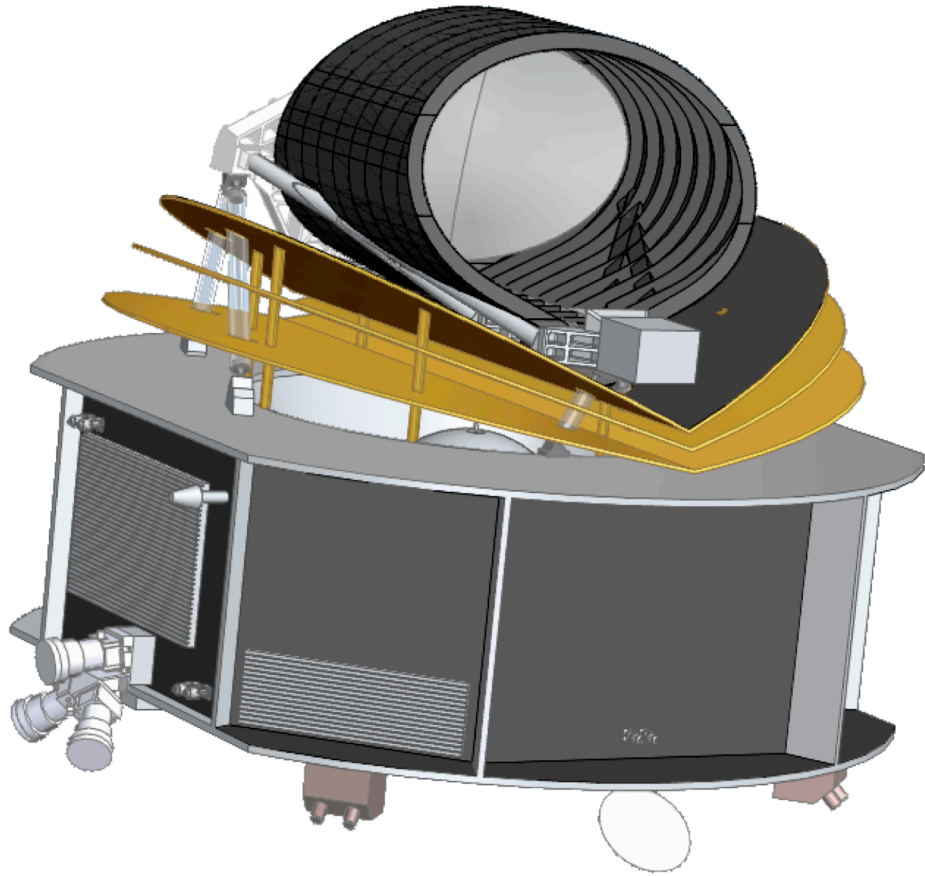
# ***Astrophysics: data***

# DECam











Data  $x$ , Model  $M$  

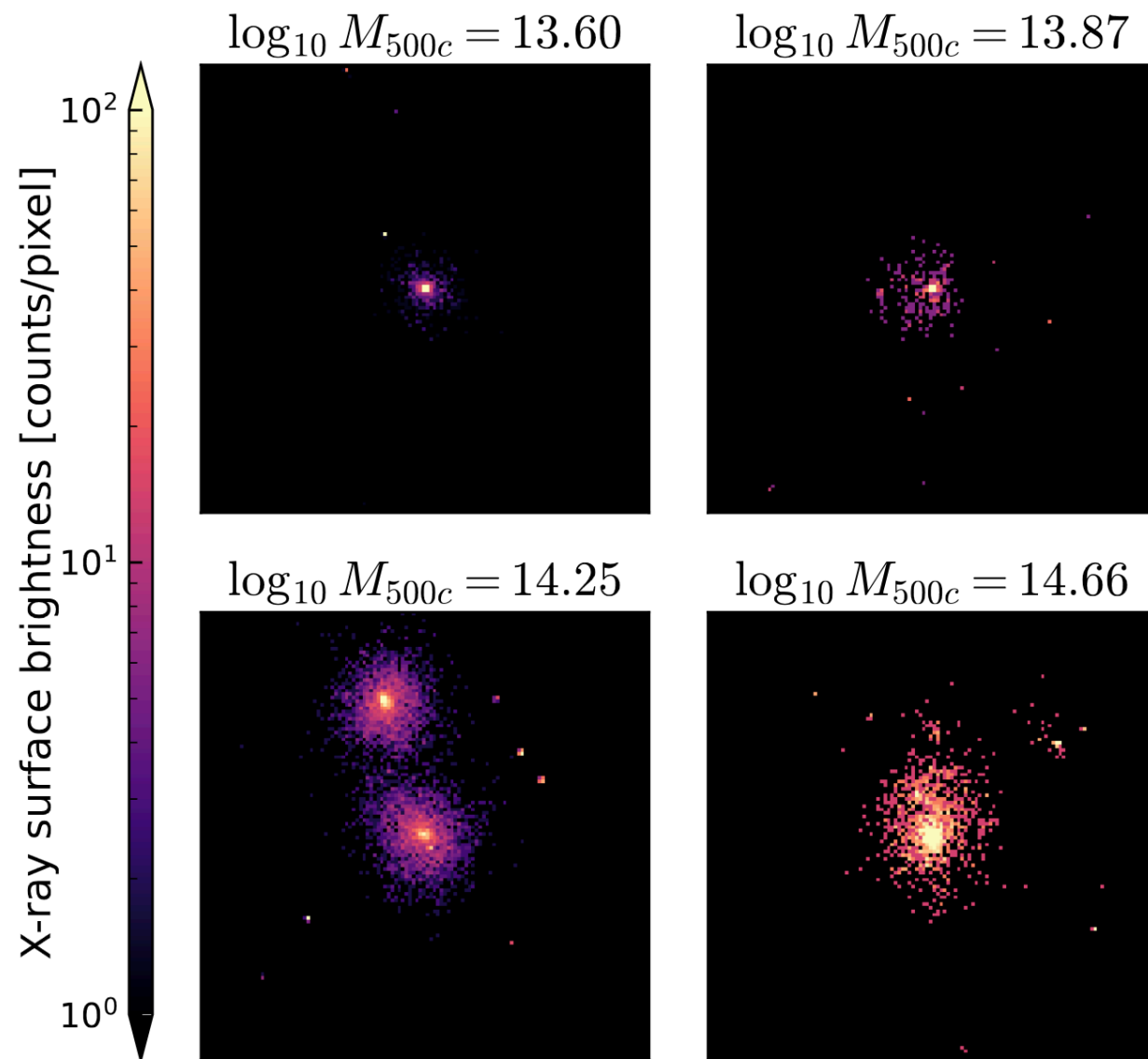
Data  $x$ , Model  $M$  

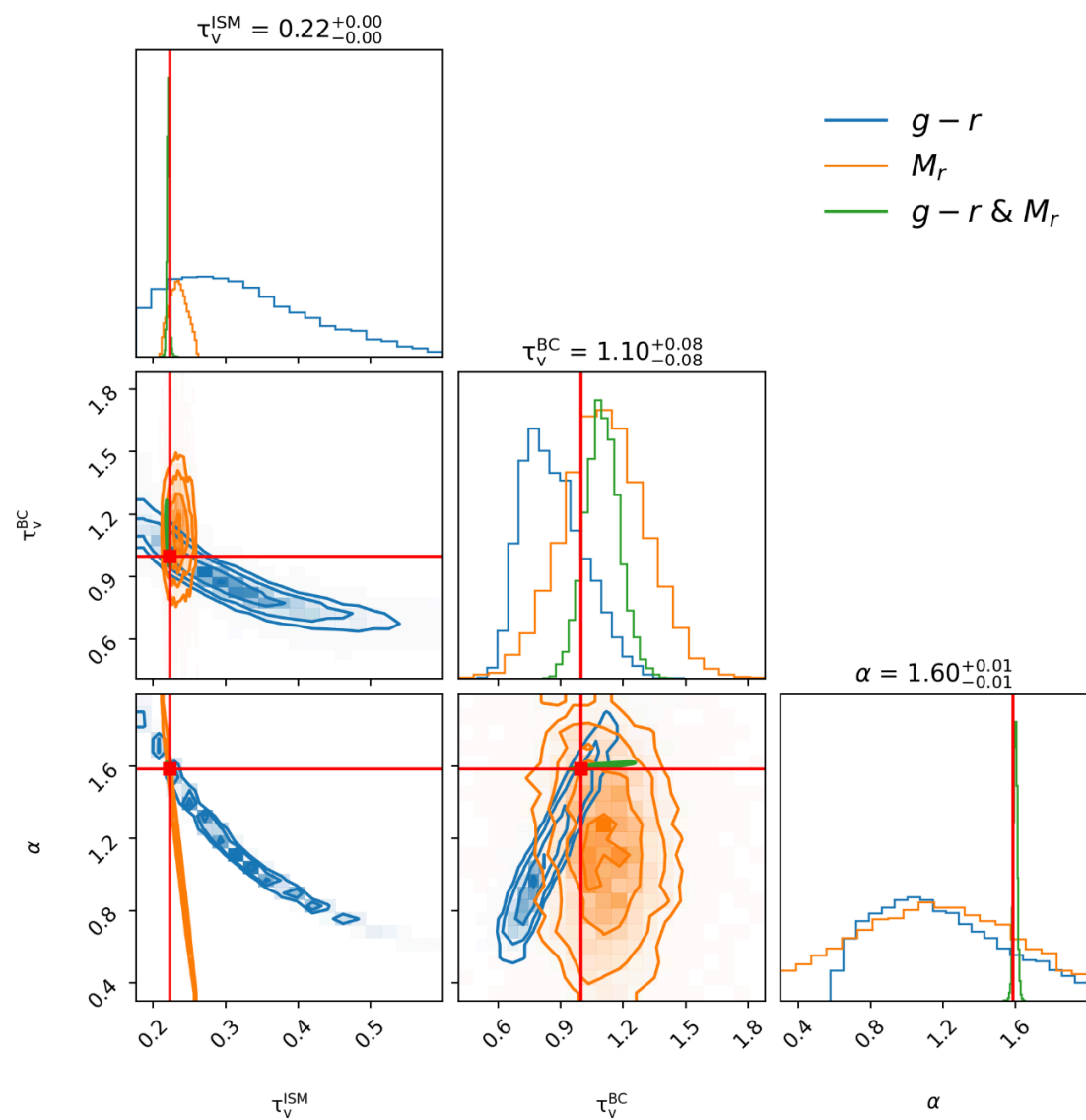
Model parameters  
  
 $p(\theta | x, M)$

Data  $x$ , Model  $M$  

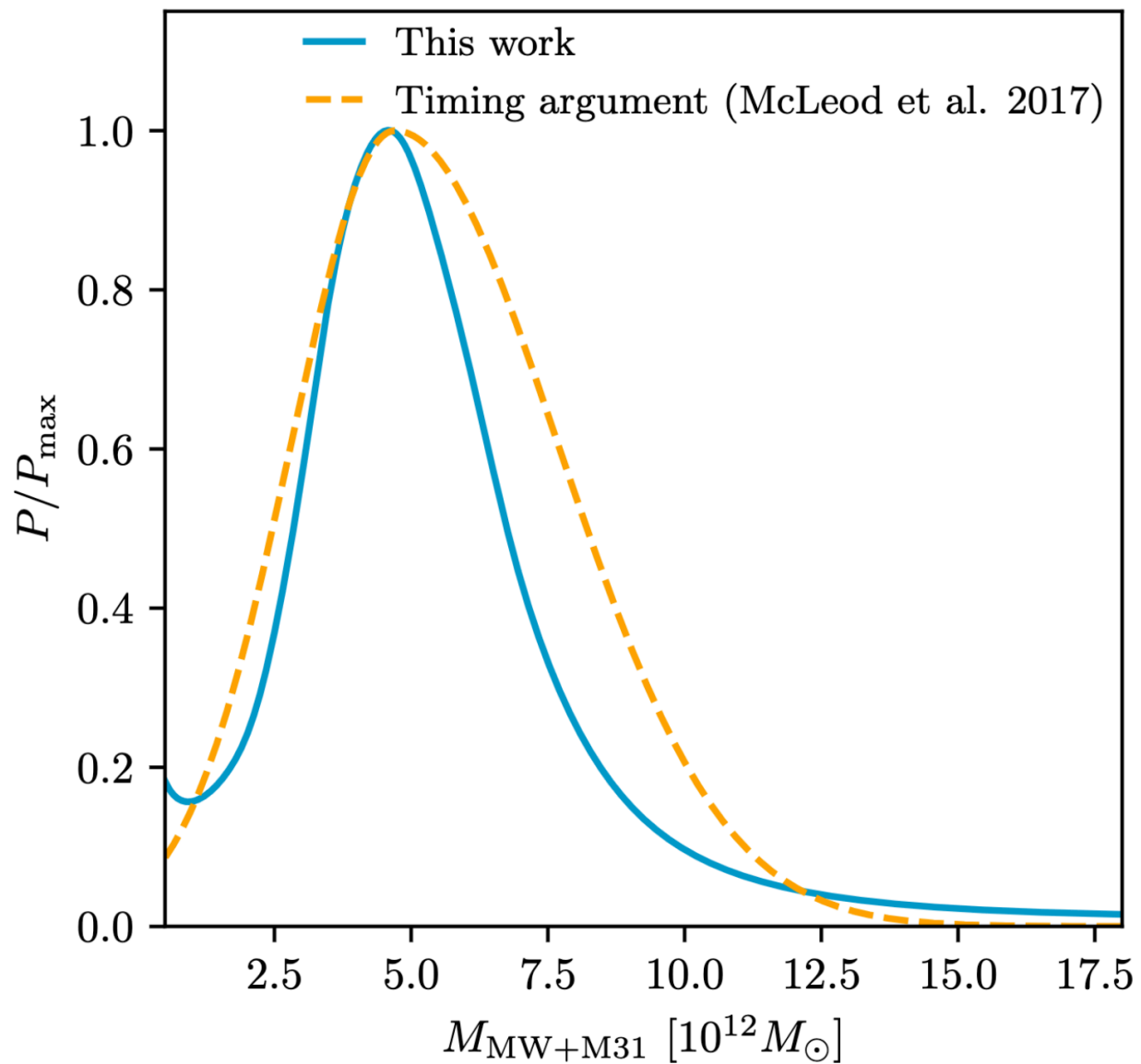
Model parameters  
  
 $p(\theta | x, M)$   
 $p(M_1 | x)$  vs  $p(M_0 | x)$

**Some examples...**



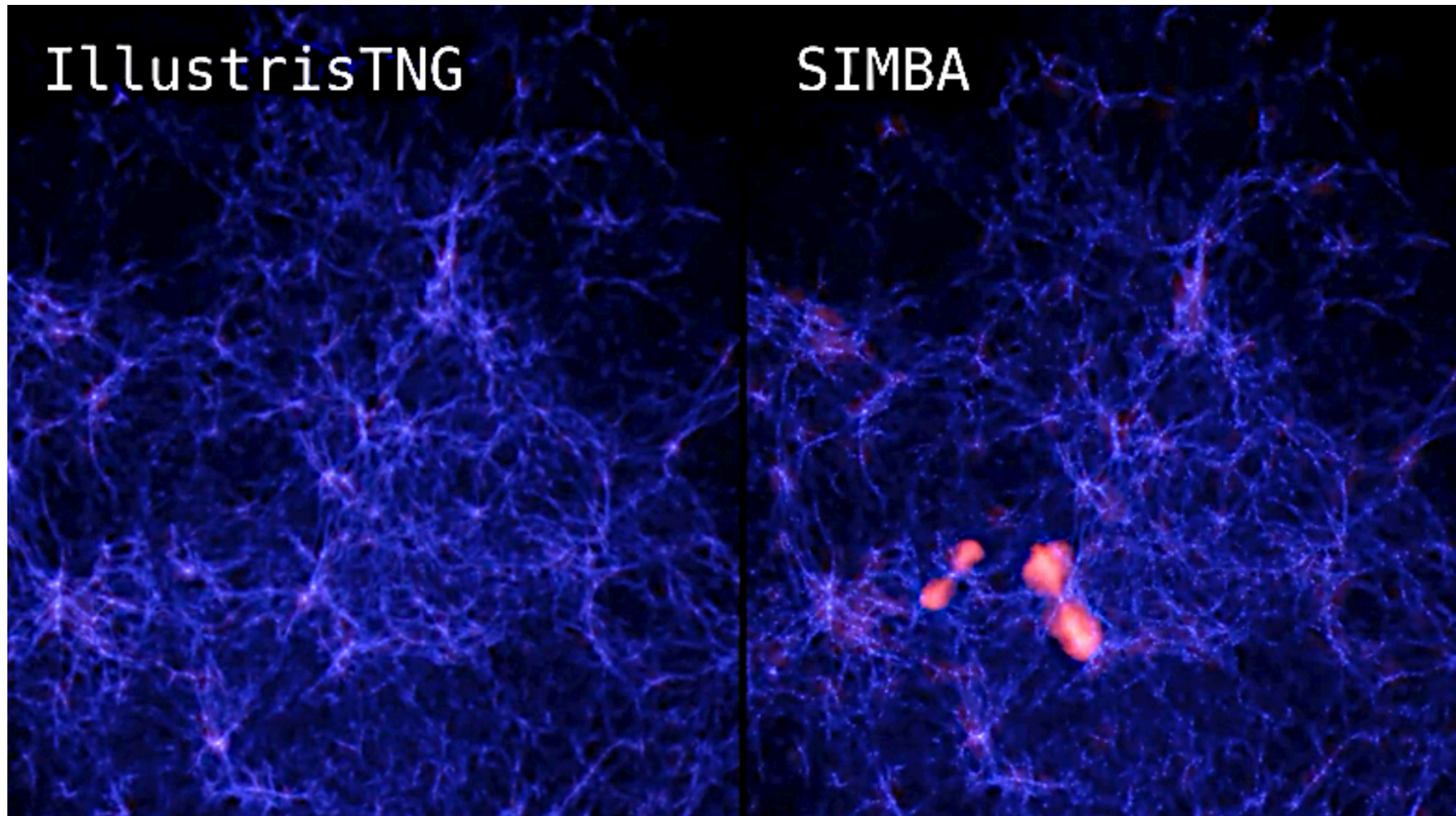


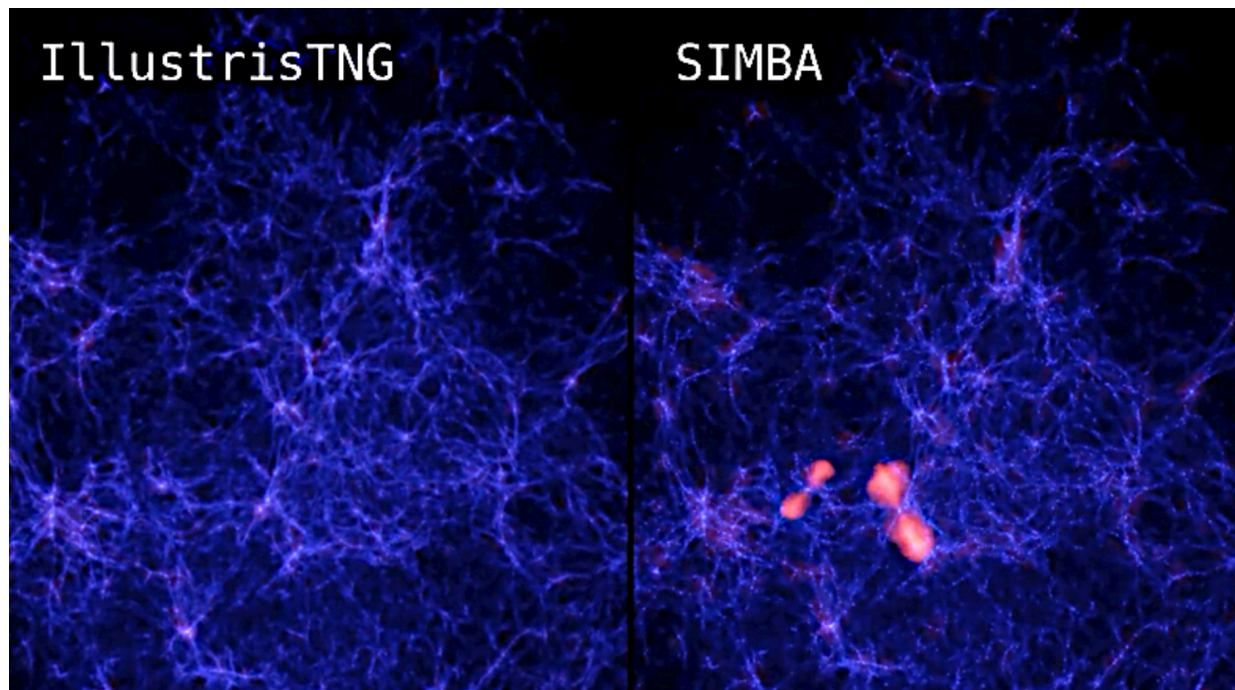
Dust model inference using simulations (Lovell et al. in prep.)



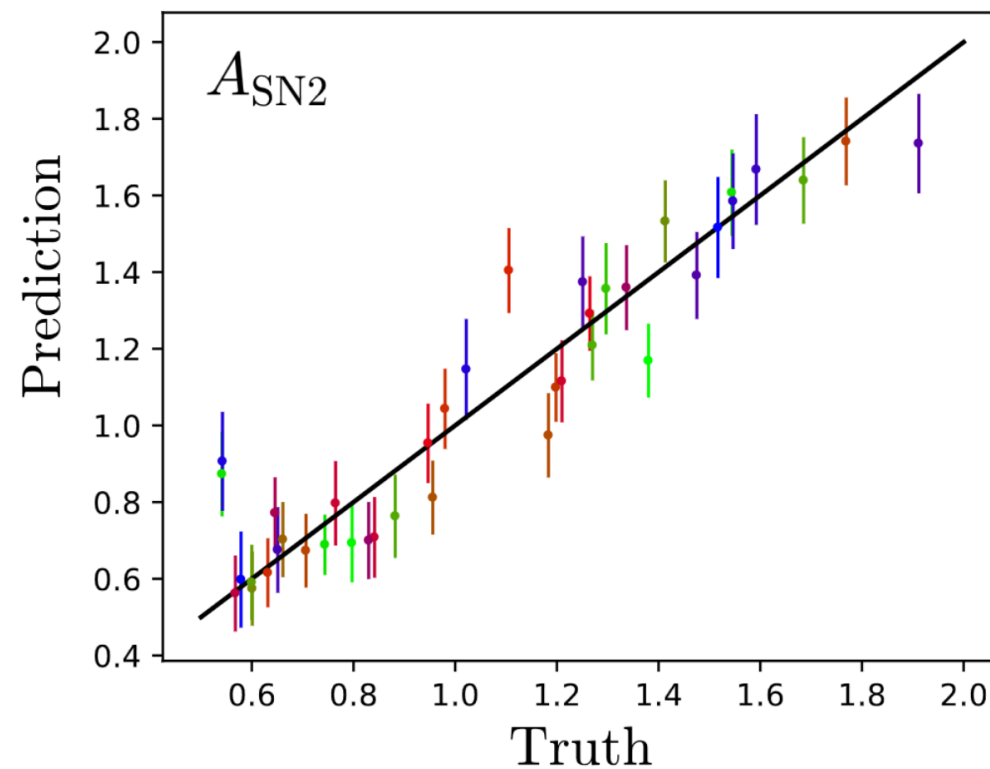
Mass of the local group (Lemos, NJ, et al. 2010.08537)



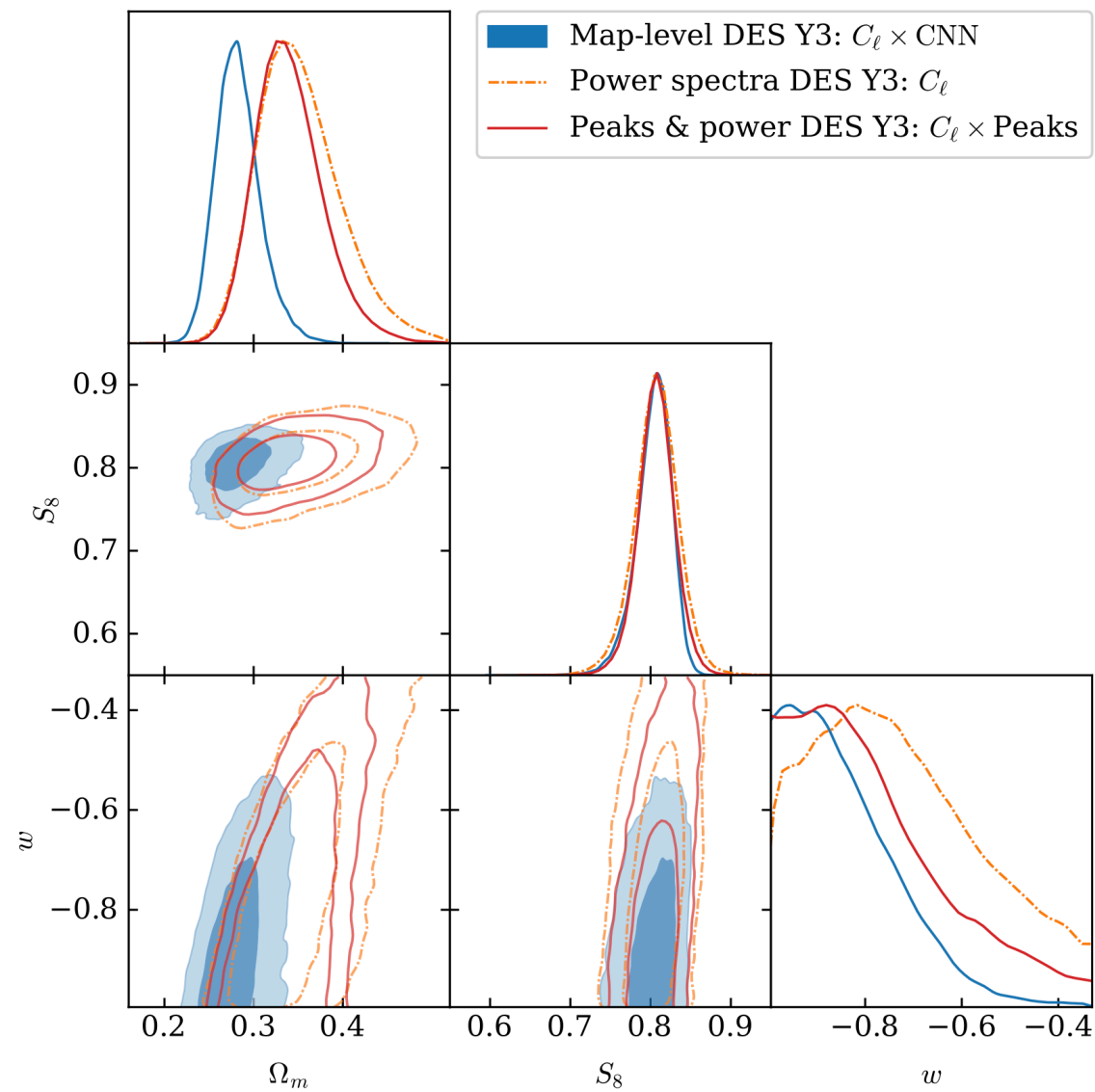




CAMELS: *Villaescusa-Navarro et al. 2109.10915*



Using Moment Networks (NJ & Wandelt 2011.05991)



Model 1: galaxies are intrinsically aligned



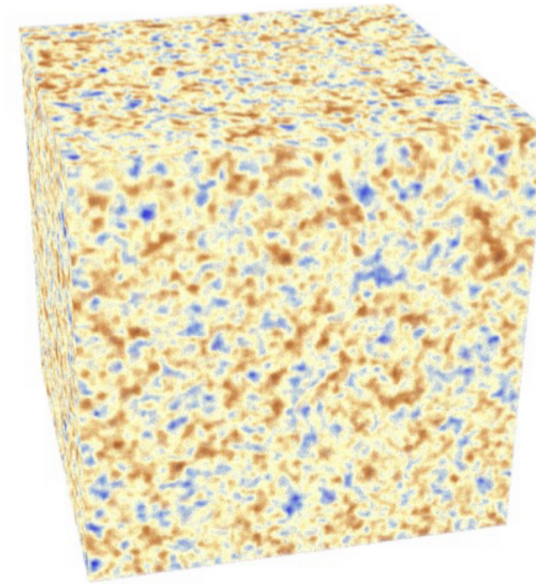
Simple “Evidence Network” result:

$$\log_{10} K = -0.8 (\pm 0.3)$$

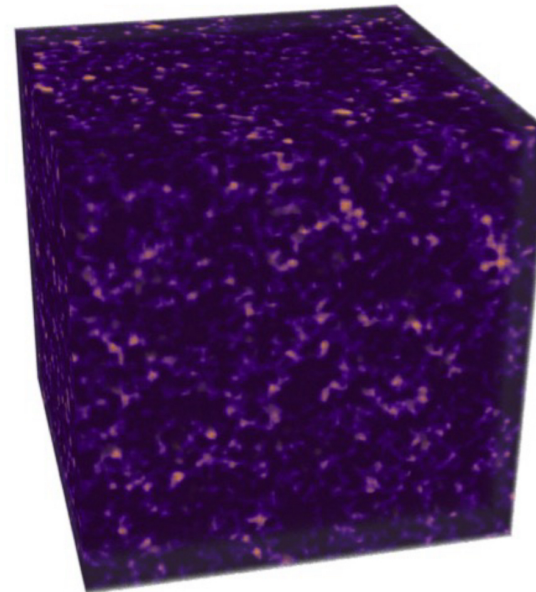


GPT4 - “Can you draw me a scientist looking at a galaxy from London?”

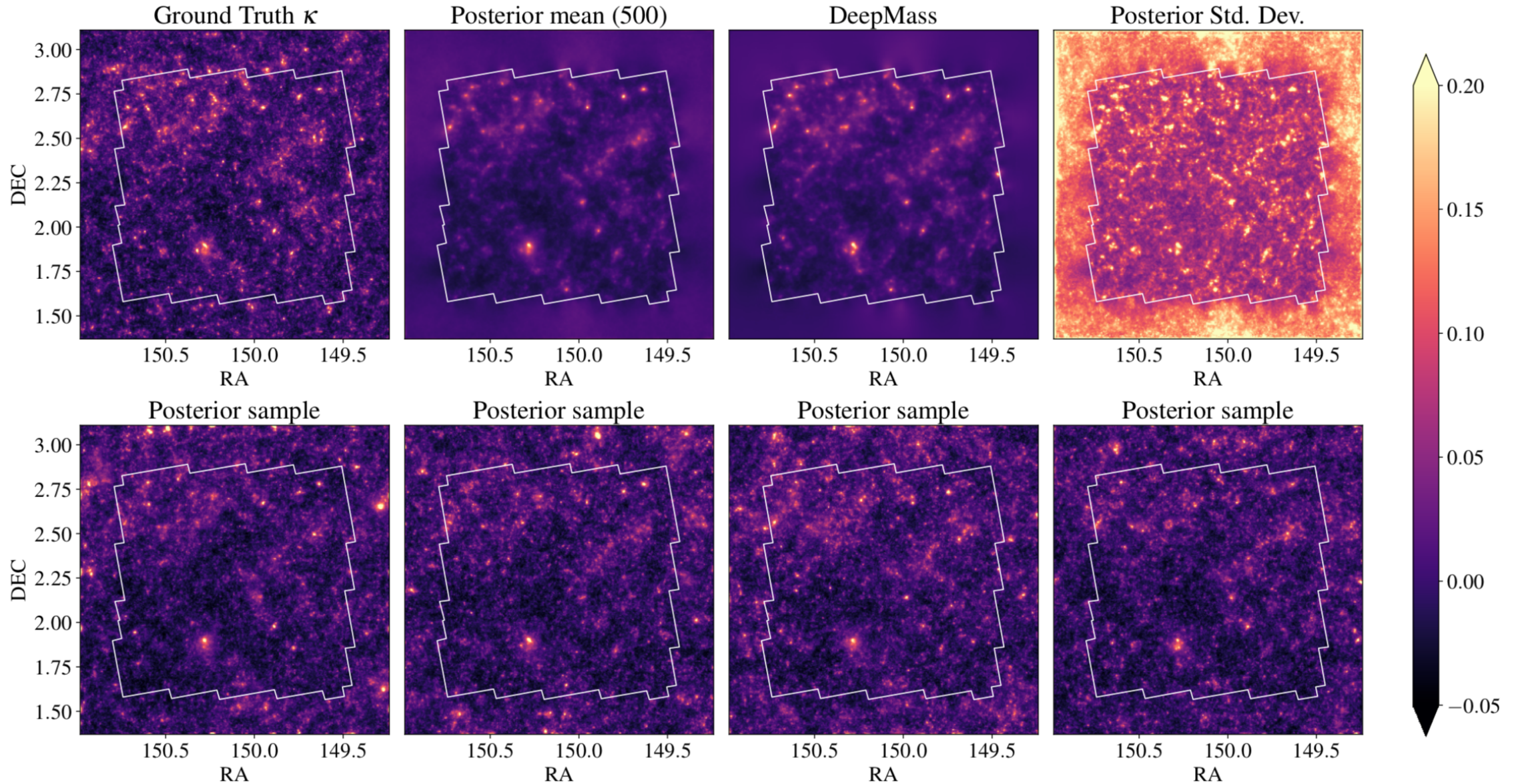
Initial conditions (density field):

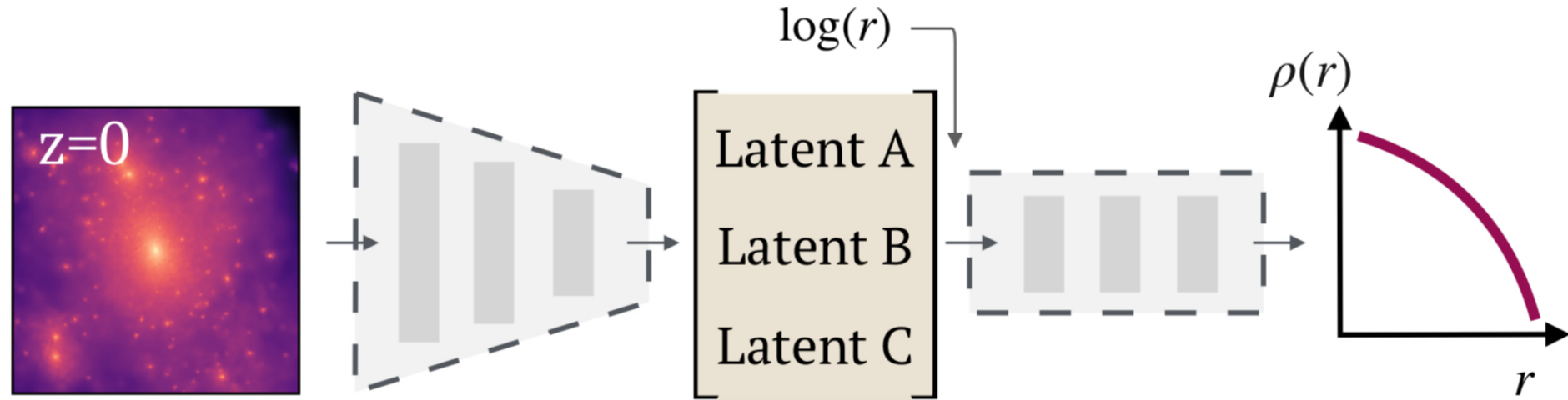


Late Universe, i.e. now (density field):

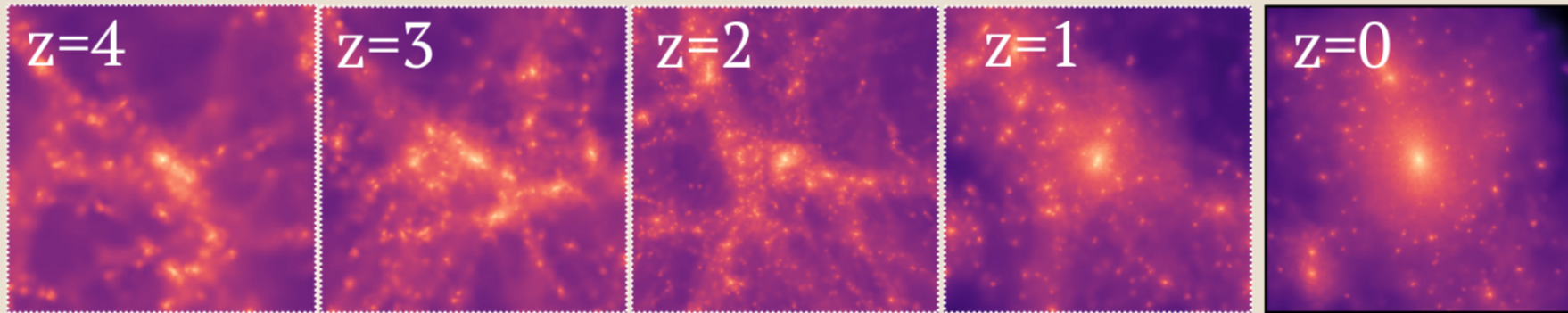


# Generative AI: Diffusion models for inverse problems



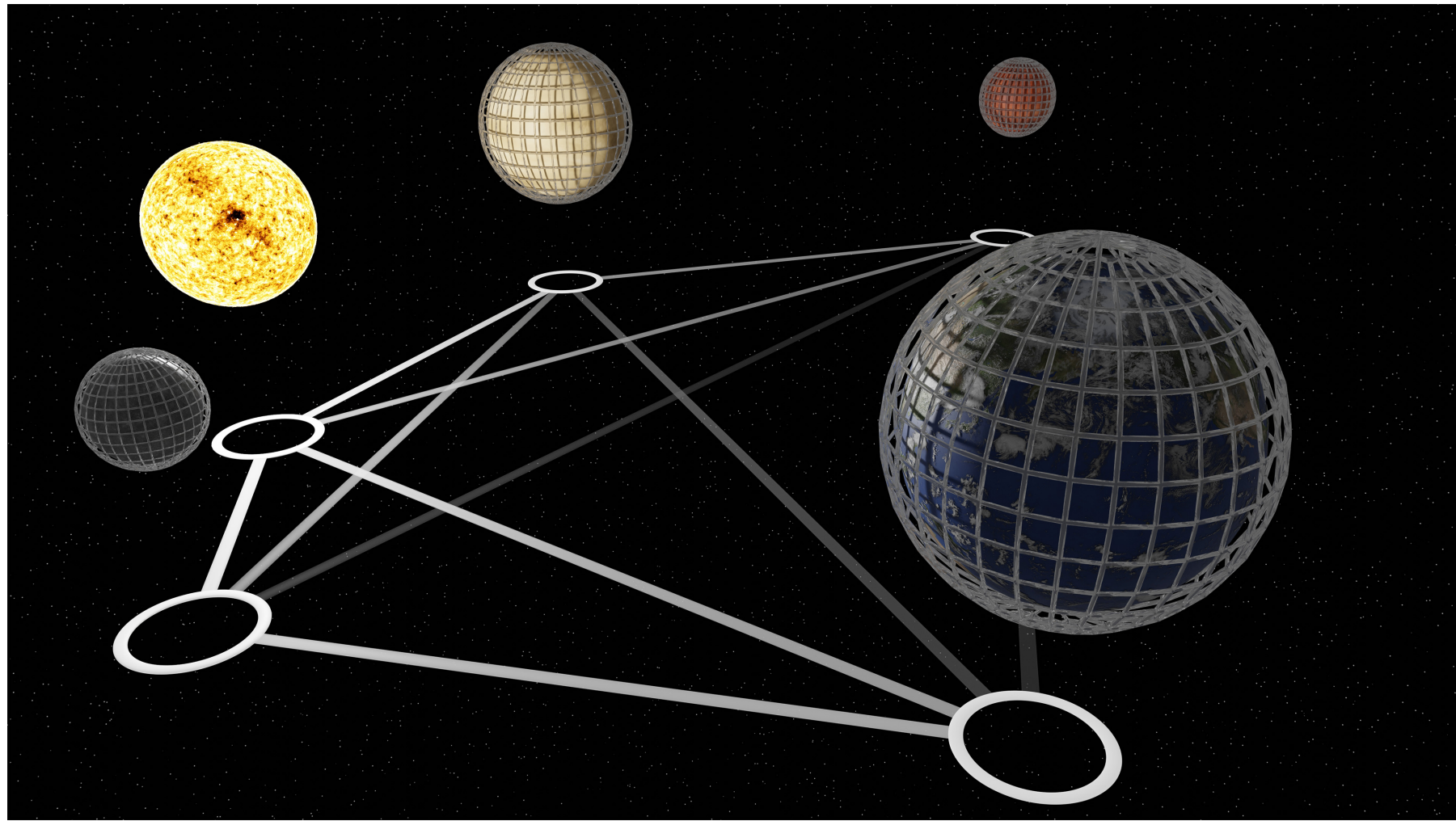


*Mutual information between latents and halo assembly history*



Cosmological simulation



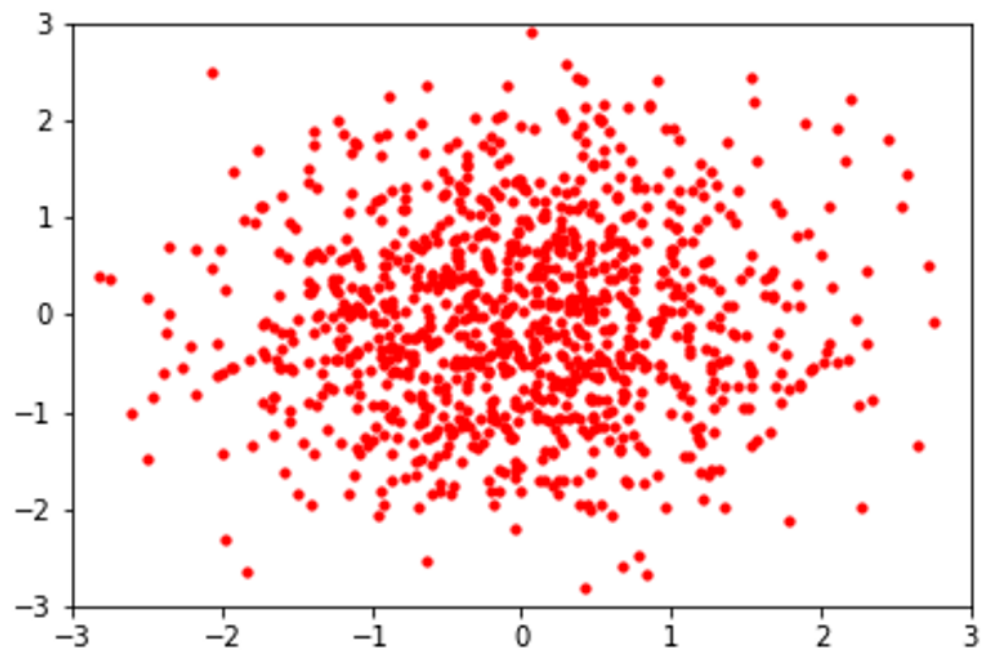


“Rediscovering” Newton’s gravity equation from data with graph networks:  
Lemos, NJ, Cranmer, Ho, Battaglia 2202.02306

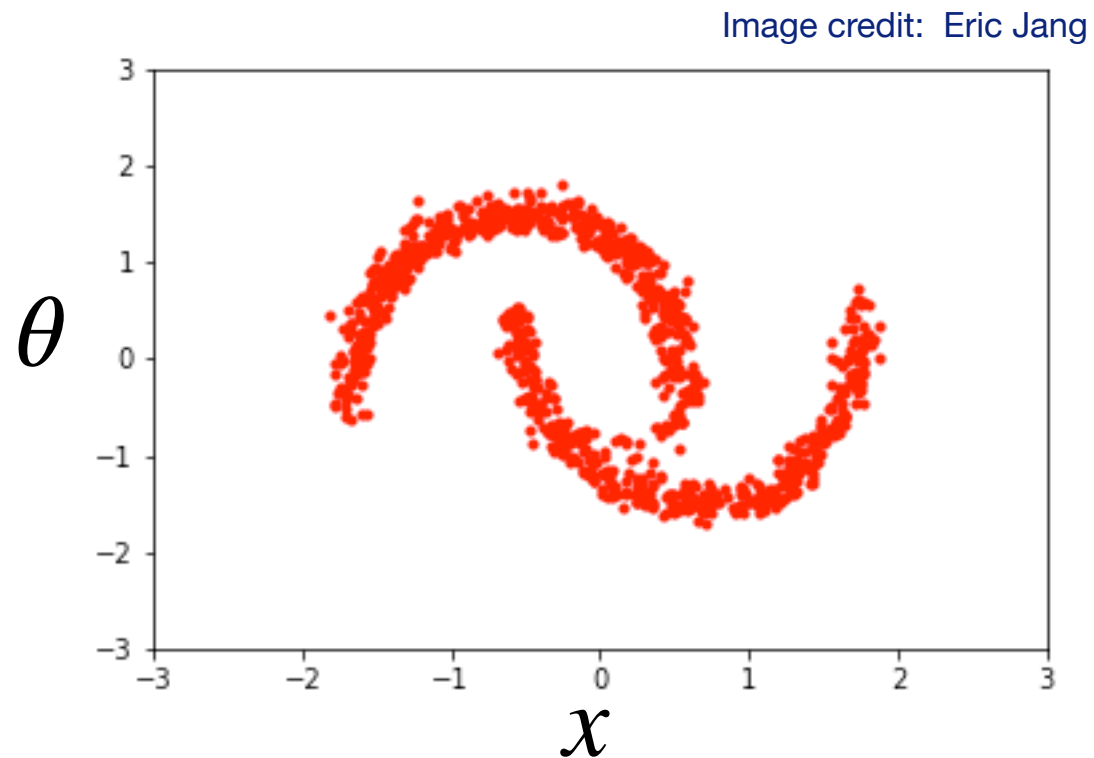


**Back-up slides...**

$$p(x | \theta) ?$$



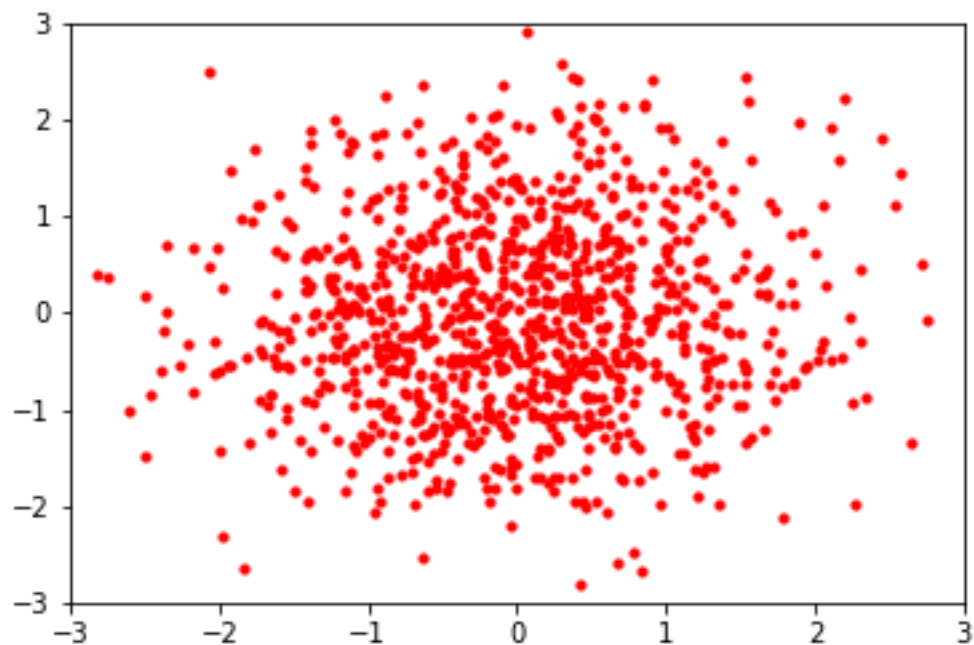
*Normalising Flow*



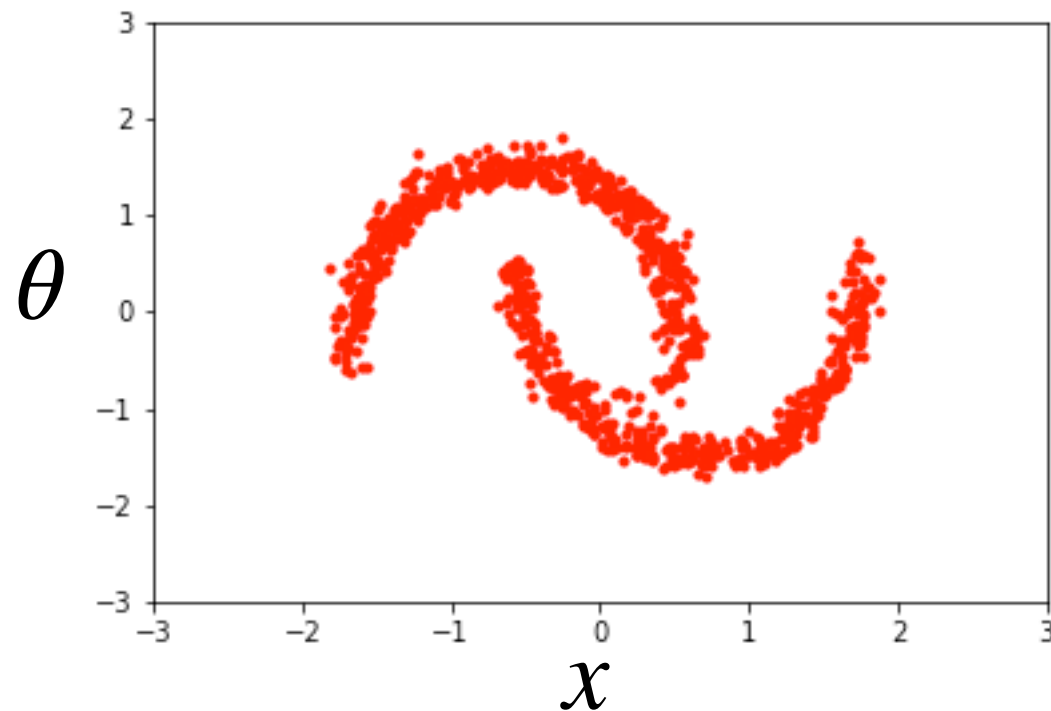
*Simulated data*

$$p(x | \theta) ?$$

Image credit: Eric Jang

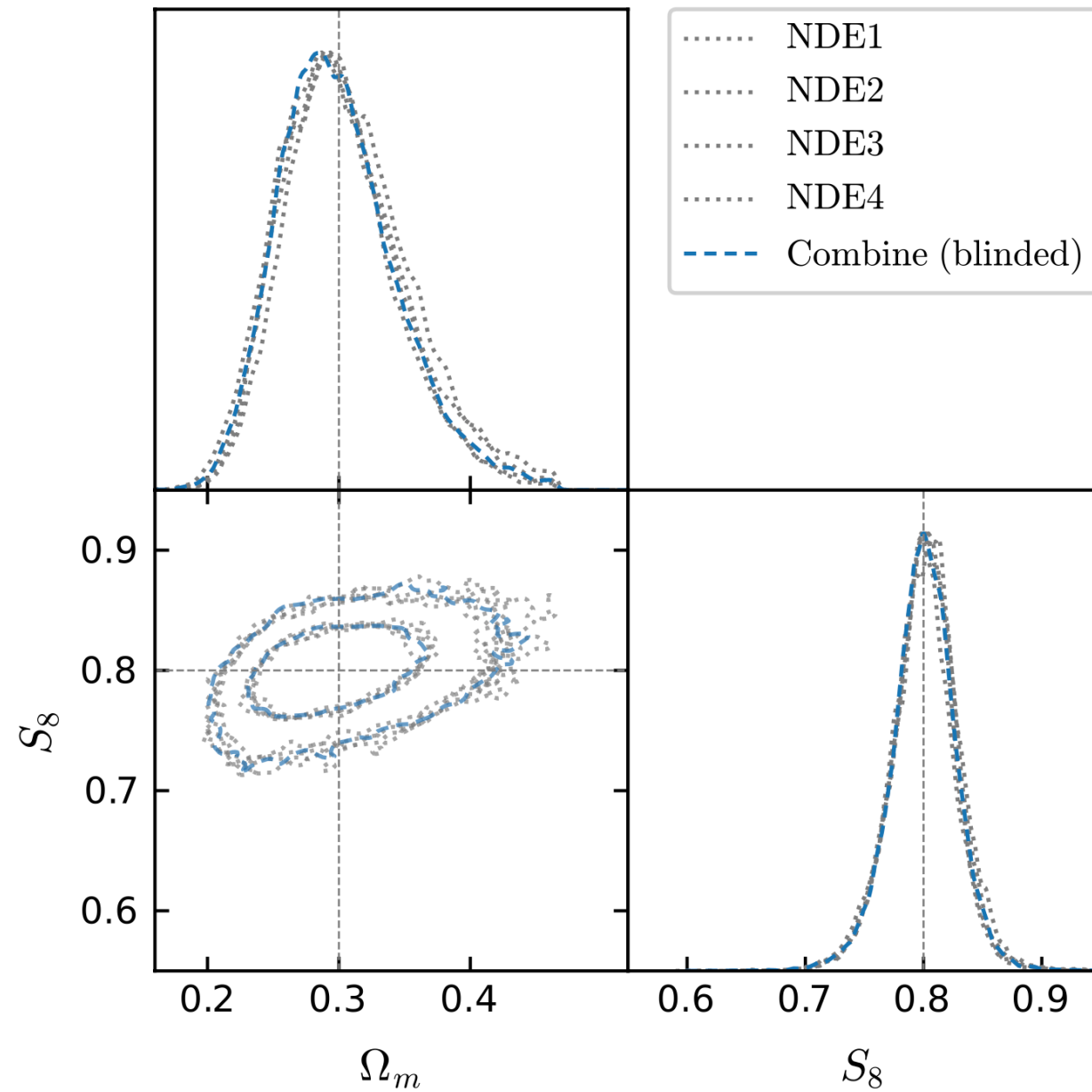


*Normalising Flow*

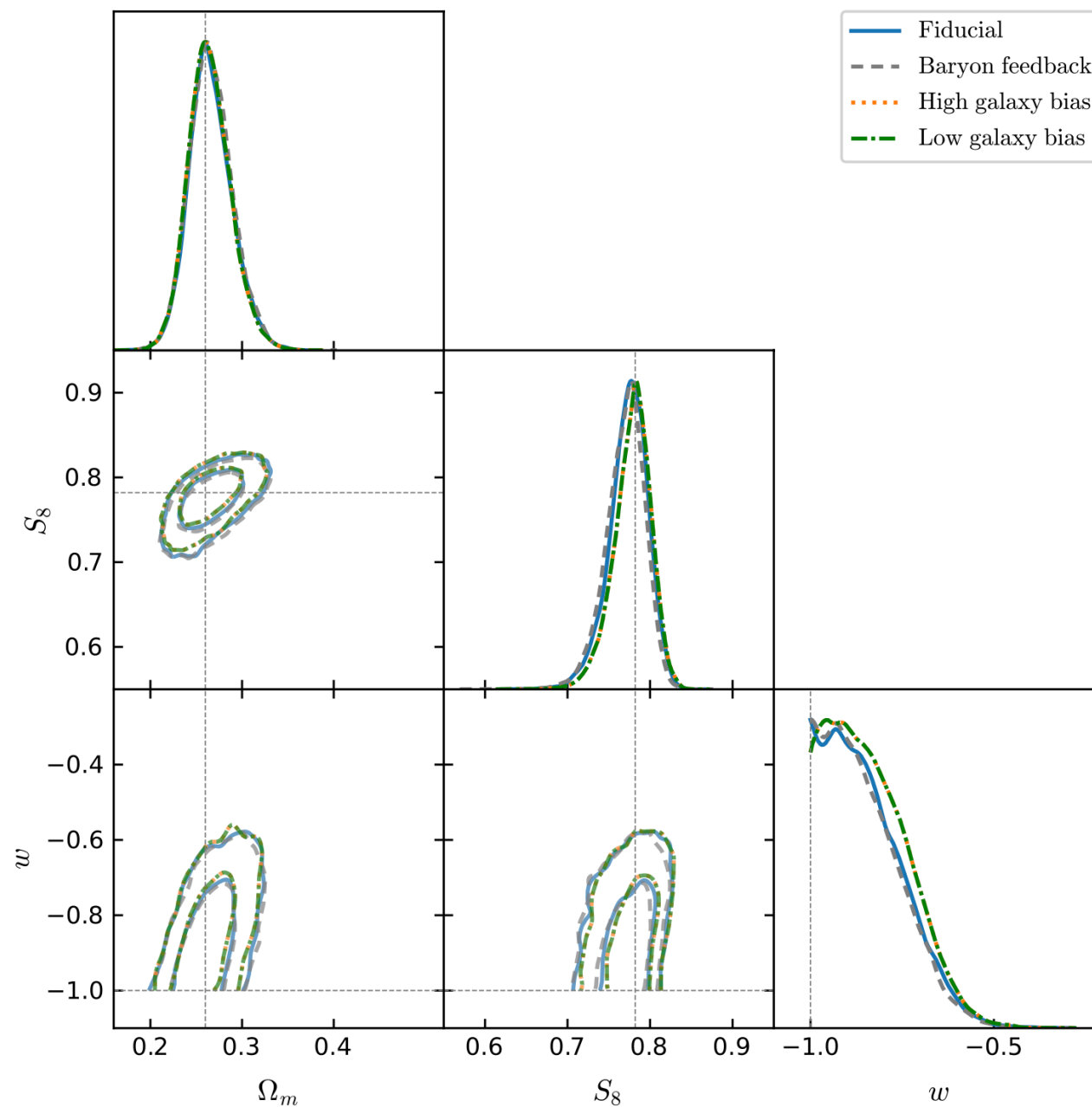


*Simulated data*

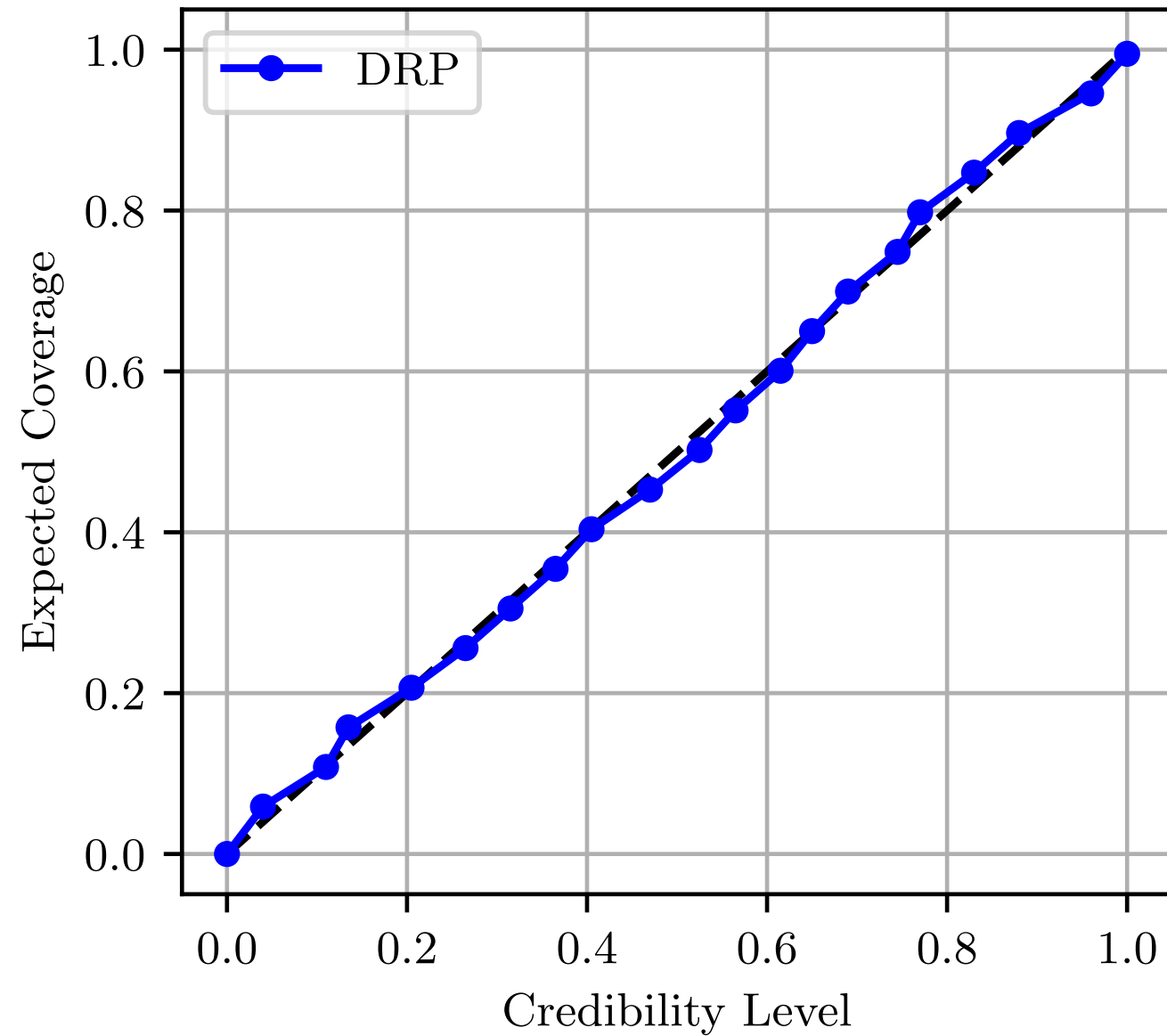
# How do I know this is right?



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# How do I know this is right?





# The challenge of model comparison

$$p(M_1 | x) \text{ vs } p(M_0 | x)$$

Bayes factor:  $K = \frac{p(x_O | M_1)}{p(x_O | M_0)}$

Marginal likelihood:

$$p(x_O | M_1) = \int p(x_O | \theta, M_1) p(\theta | M_1) d\theta$$

# Evidence Networks

1. Generate/collect data for each model:  $x_i \sim p(x | M_1)$
2. Bespoke loss function:  $\mathcal{V}(f(x), m)$
3. Train networks to estimate Bayes factor:  $f^*(x_O) = \log K$

What does training a neural network do?

What does training a neural network do?

$$I[f] = \sum_{m \in \{0,1\}} \int \mathcal{V}(f(x), m) p(x, m) dx$$

↑  
neural network

What does training a neural network do?

$$I[f] = \sum_{m \in \{0,1\}} \int \mathcal{V}(f(x), m) p(x, m) dx$$

↑  
model label

↑  
loss

↑  
training data  
distribution

$$I[f] = \sum_{m \in \{0,1\}} \int \mathcal{V}(f(x), m) p(x, m) dx$$

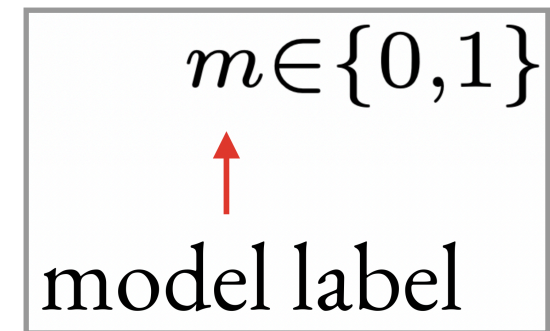


$$\mathcal{V}(f(x), m) = e^{(\frac{1}{2} - m)f(x)}$$

Exponential loss



$$\mathcal{V}(f(x), m) = e^{(\frac{1}{2} - m)} f(x)$$



$$\mathcal{V}(f(x), m) = e^{(\frac{1}{2} - m)f(x)}$$

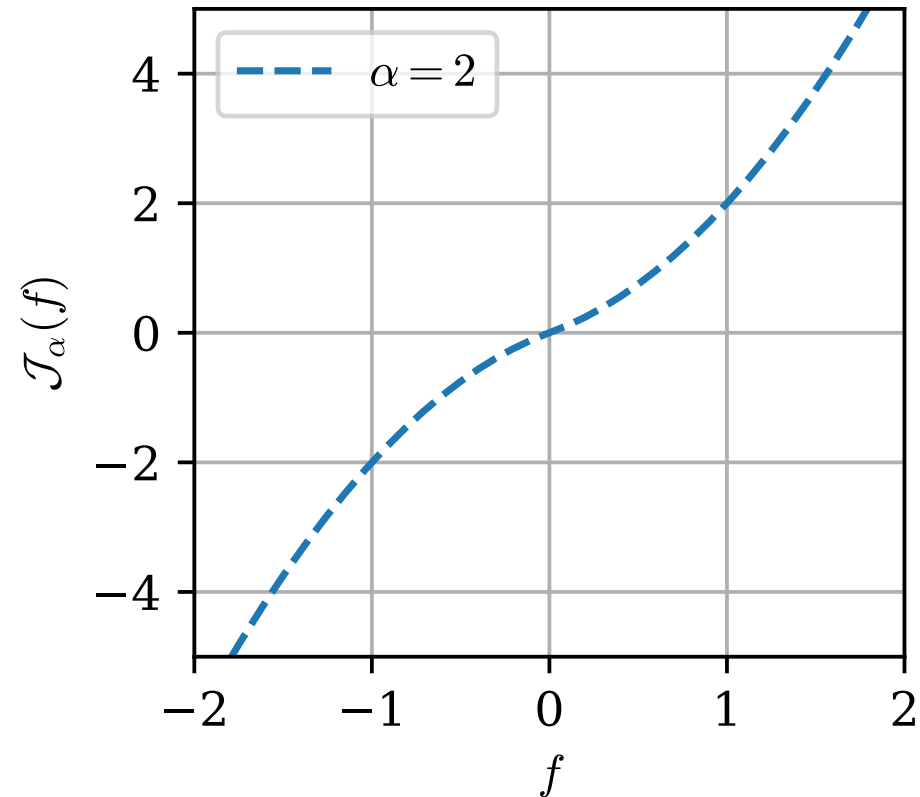


$$f^*(x_0) = \log K$$

$$\mathcal{V}(f(x), m) = e^{\left(\frac{1}{2} - m\right)} \mathcal{J}_\alpha(f(x))$$

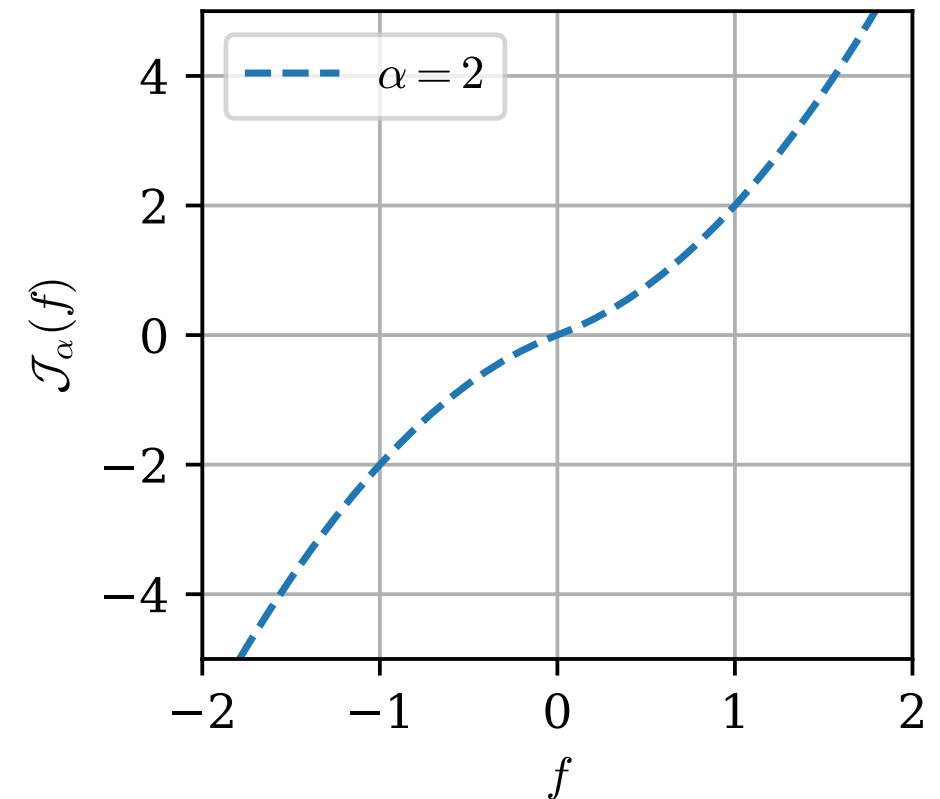


leaky parity odd power  
(l-POP) transform



$$\mathcal{V}(f(x), m) = e^{\left(\frac{1}{2} - m\right)} \mathcal{J}_\alpha(f(x))$$

leaky parity odd power  
(l-POP) transform



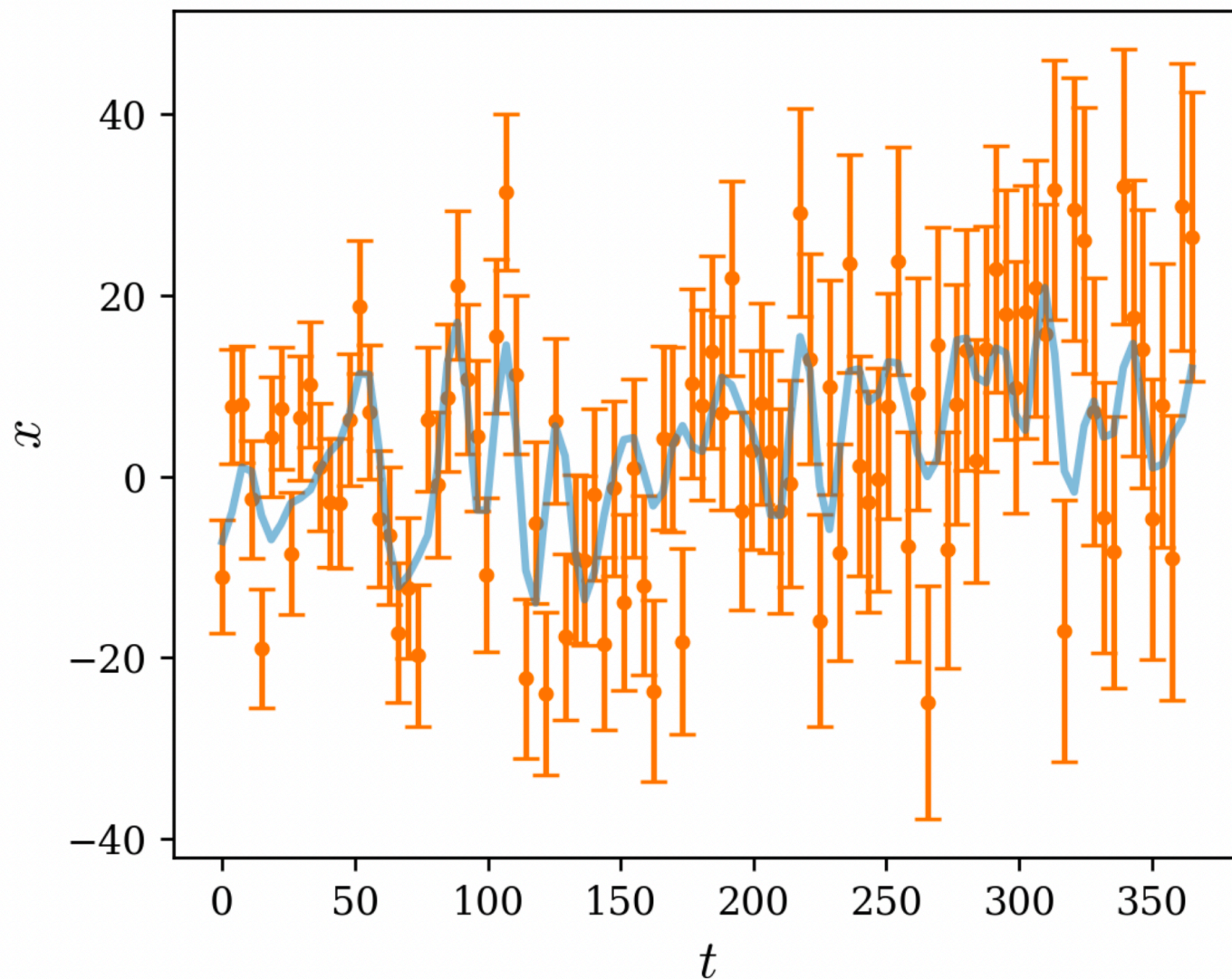
$$\tilde{\mathcal{J}}_\alpha(x) = \text{sgn}(x) |x|^\alpha$$

$$\tilde{\mathcal{J}}_\alpha(x) := x |x|^{\alpha-1} \quad \forall x \in \mathbb{R} \text{ where } \alpha \in \mathbb{R} \text{ and } \alpha \geq 1$$

Demonstration: does this work with data?

Example data sample  $x$  from  $p(x, m)$

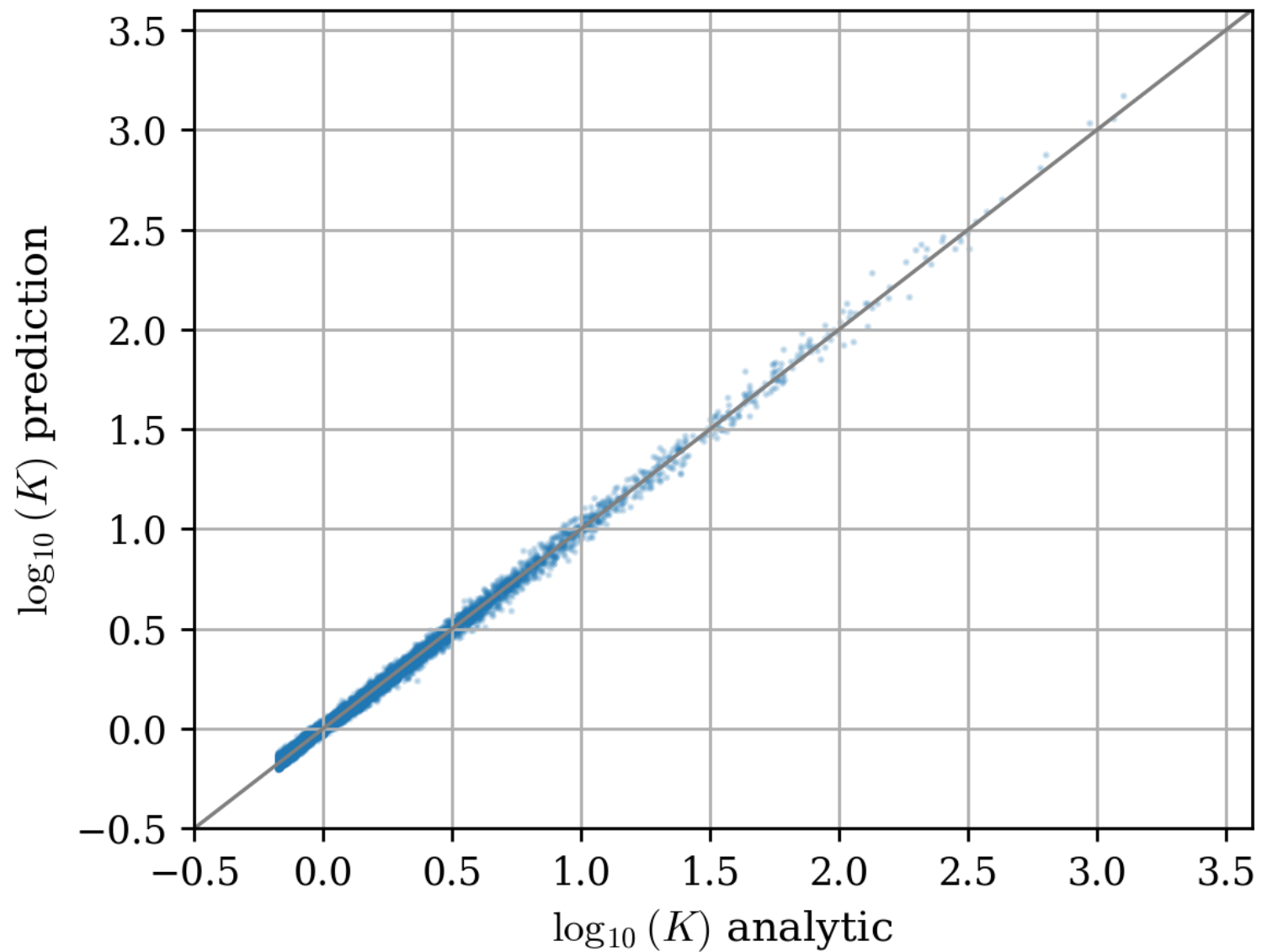
$\log_{10} K = 0.82$



Model 1: Linear growth term

Model 2: No linear growth term

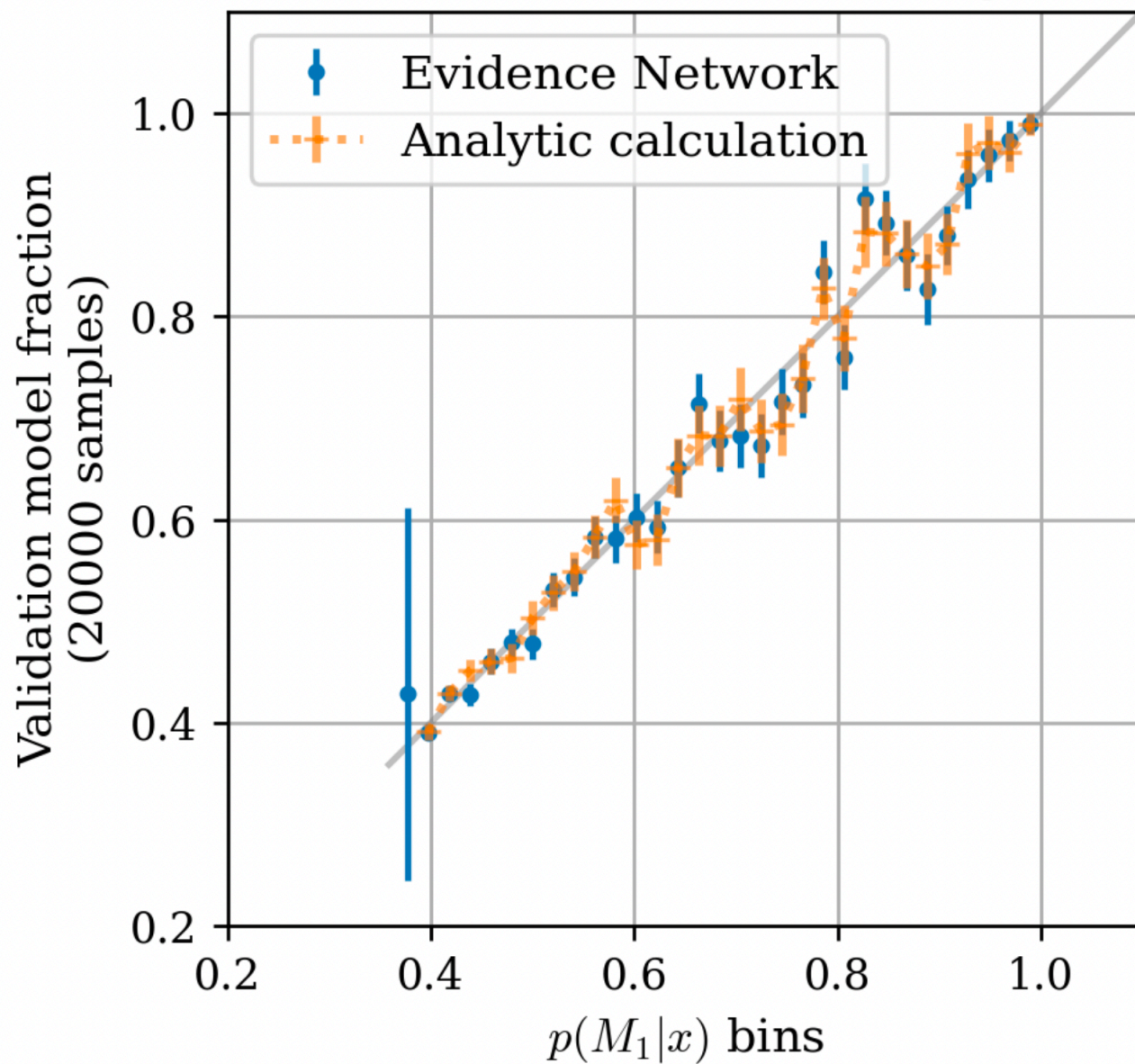
100 parameters, RMSE=0.017



How do we know it worked?



## Model posterior blind coverage test



“Likelihood-free”?

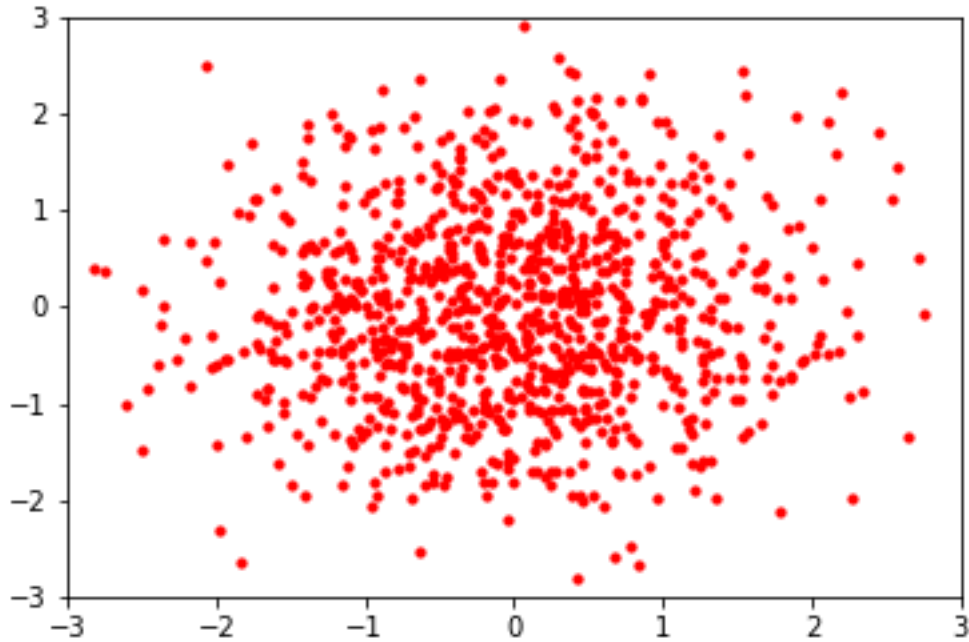
$$p(x_O | M_1) = \int p(x_O | \theta, M_1) p(\theta | M_1) d\theta$$

“Likelihood-free”?

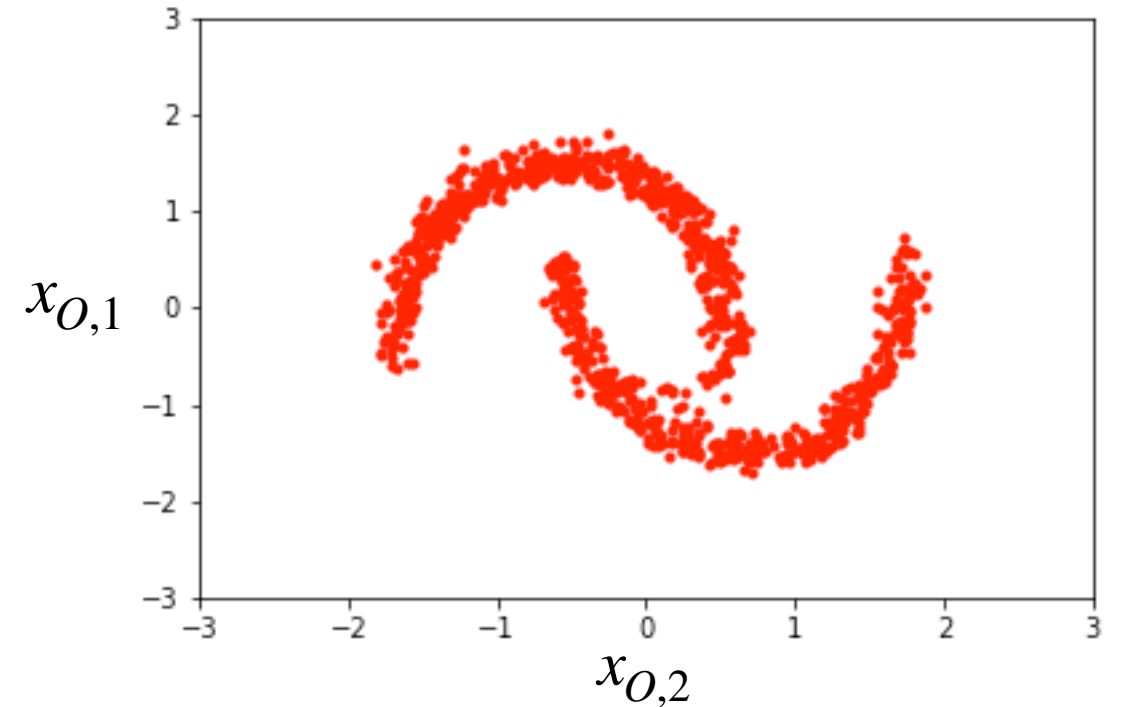
$$p(x_O | M_1)$$

“Likelihood-free”?

$$p(x_O | M_1)$$

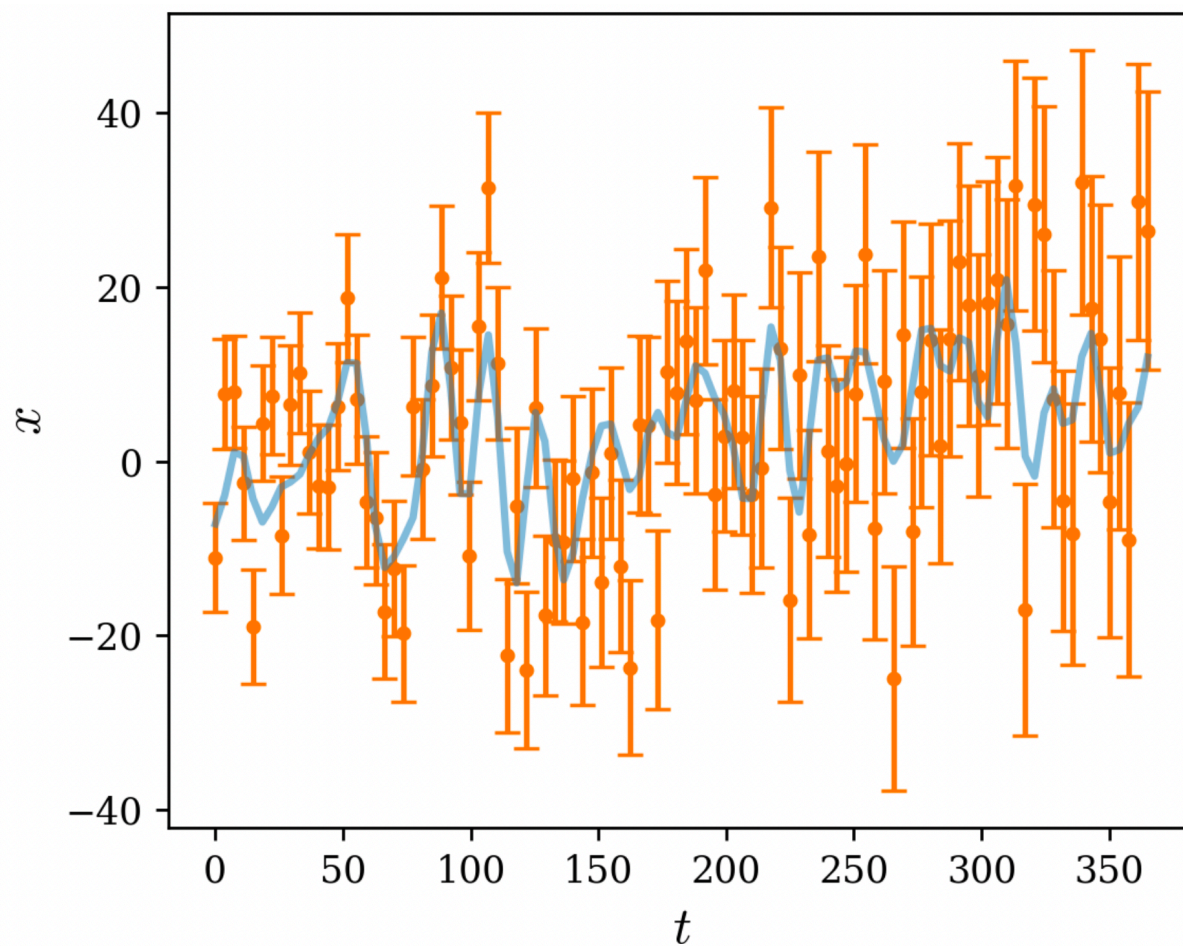


*Normalising Flow*



*Simulated data*

# Neural density estimation: $p(M_1 | x)$ & $p(M_0 | x)$



# PolyChord (assumed likelihood)

