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DeepMass
Deep learning dark matter map reconstructions from weak lensing data

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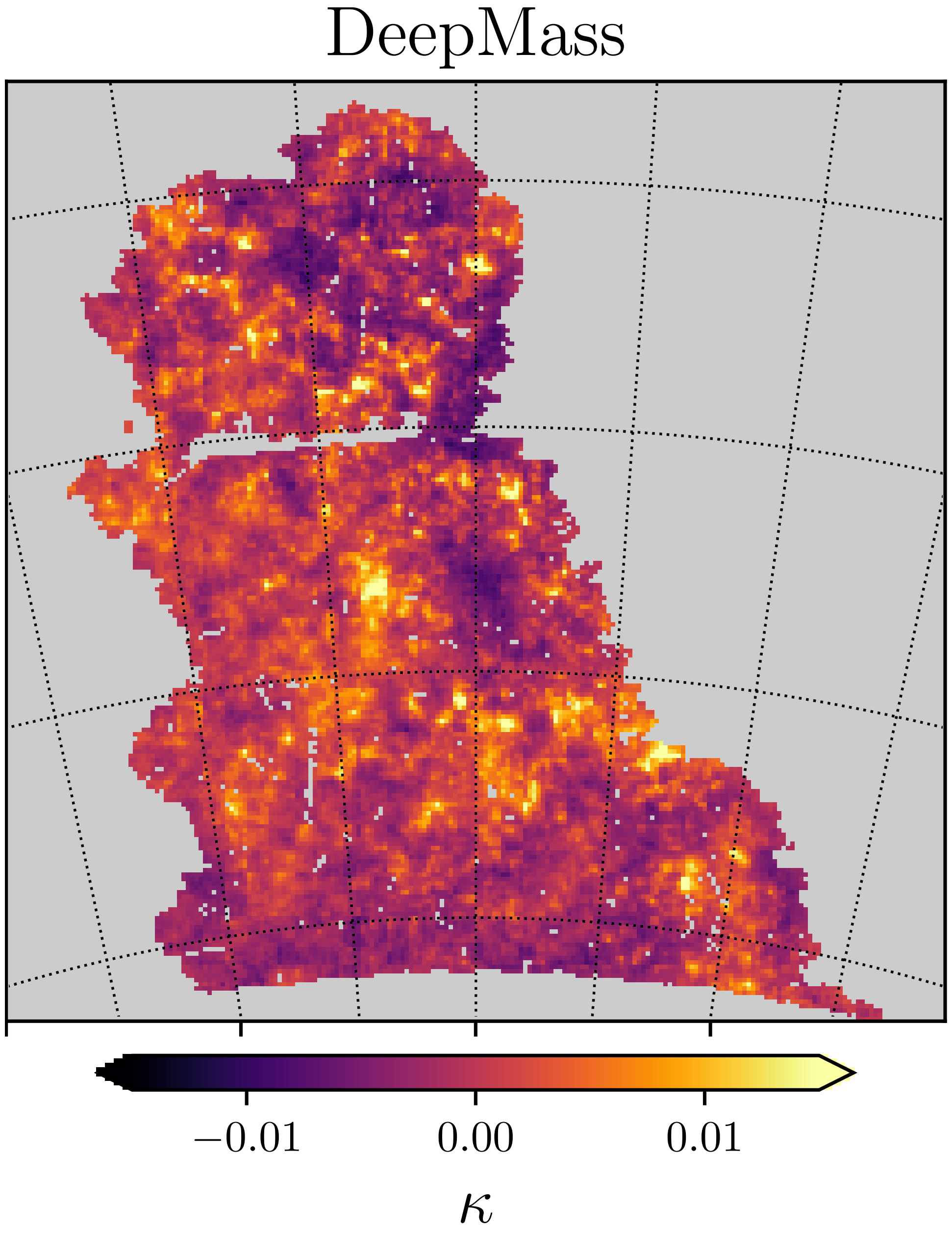

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arXiv:1908:00543

Outline

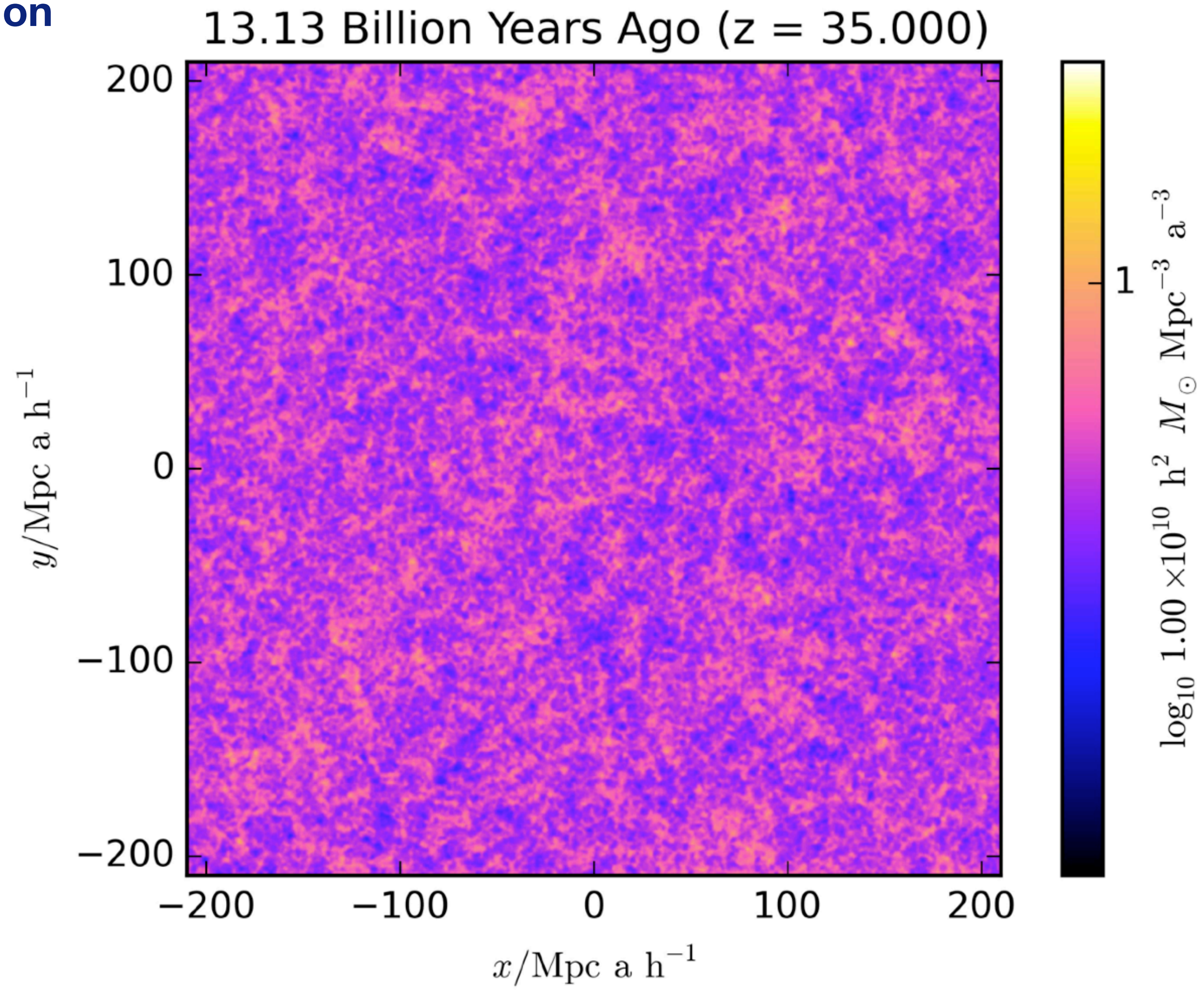
1. Weak lensing map reconstruction
2. Deep learning a Bayesian estimate
3. Dark Energy Survey SV results
4. Likelihood-free parameter inference

01

Weak lensing mass maps

Growth of structure

L-PICOLA simulation



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Mass mapping

Linear data model

$$\gamma = \mathbf{A}\kappa + \mathbf{n}$$

DATA

LINEAR TRANSFORM

SIGNAL
(MASS MAP)

SHAPE NOISE

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Mass mapping

Linear data model

$$\gamma = \mathbf{A}\kappa + \mathbf{n}$$

DATA

LINEAR TRANSFORM

SIGNAL

(MASS MAP)

SHAPE NOISE

Kaiser-Squires 1993 Estimator

$$\hat{\gamma}(\vec{l}) = \pi^{-1}\hat{\mathcal{D}}(\vec{l})\hat{\kappa}(\vec{l})$$

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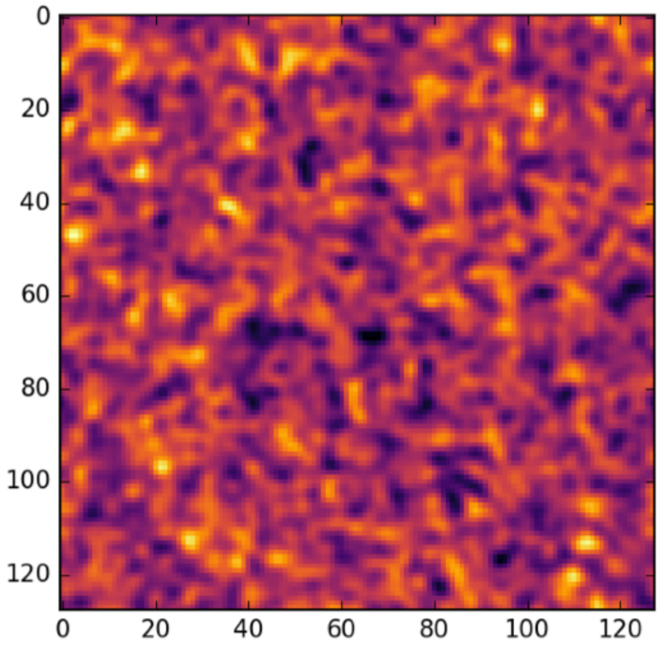
Mass mapping inference

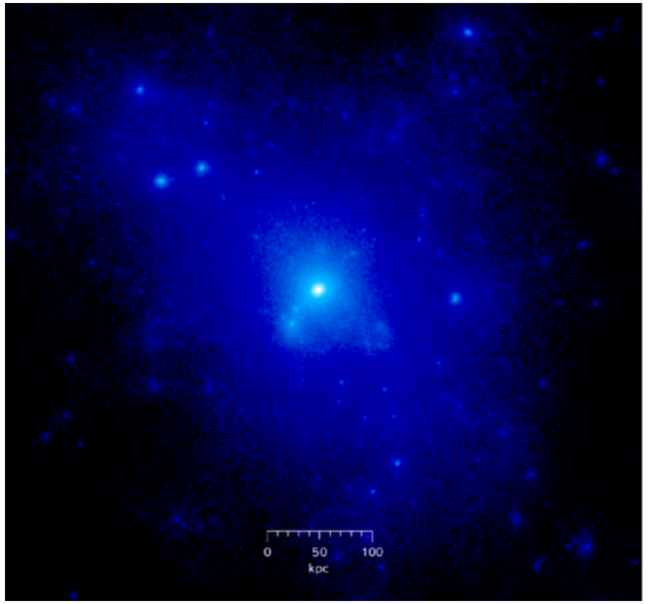
Bayesian "*maximum a posteriori*"

$$\hat{\kappa} = \arg\max_{\kappa} \; \log P(\gamma|\kappa, \mathcal{M}) + \log P(\kappa|\mathcal{M})$$

Gaussian Random Field?



Dark Matter Halos?



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arXiv:1801.08945

The perfect prior?

No closed-form probability distribution of the matter field for the late Universe…

$$P(\kappa|\theta, \mathcal{M})$$

Parameters

Cosmological model

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The perfect prior?

But, we can sample from the prior distribution…

$$\longleftarrow P(\kappa|\theta, \mathcal{M})$$

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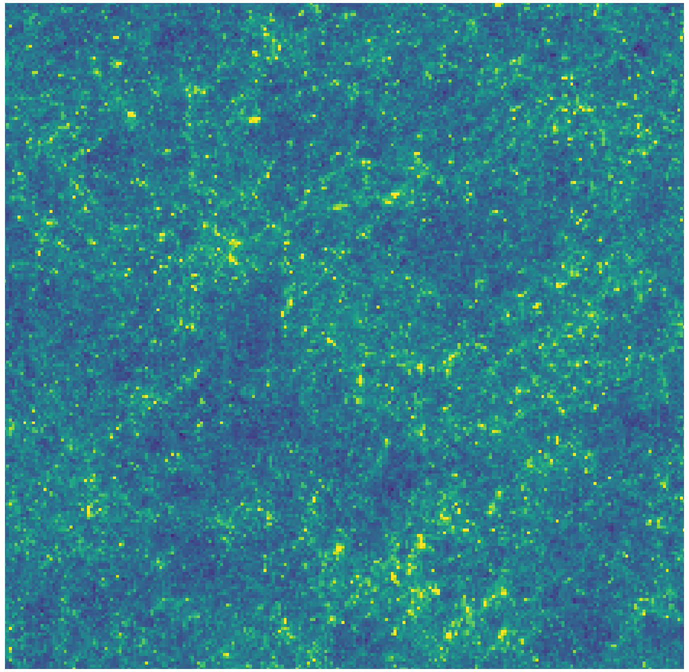
The perfect prior?

But, we can sample from the prior distribution…



simulated convergence map

$$P(\kappa|\theta, \mathcal{M})$$

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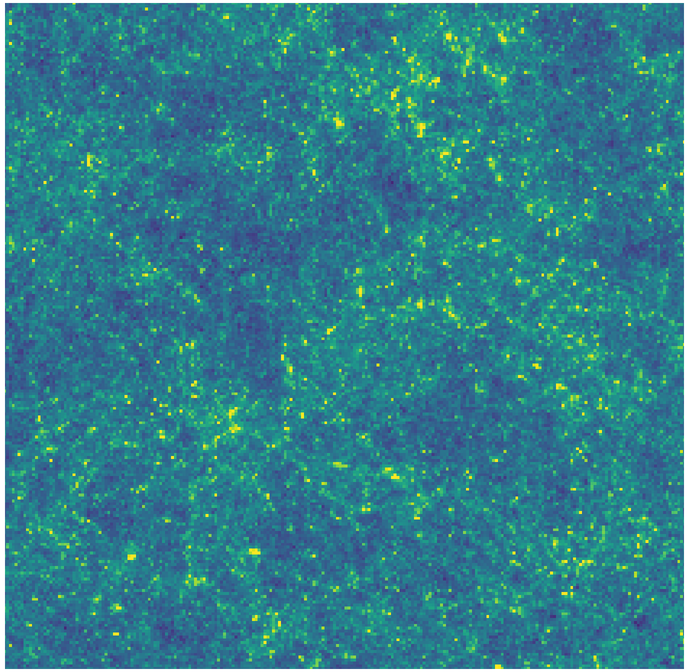

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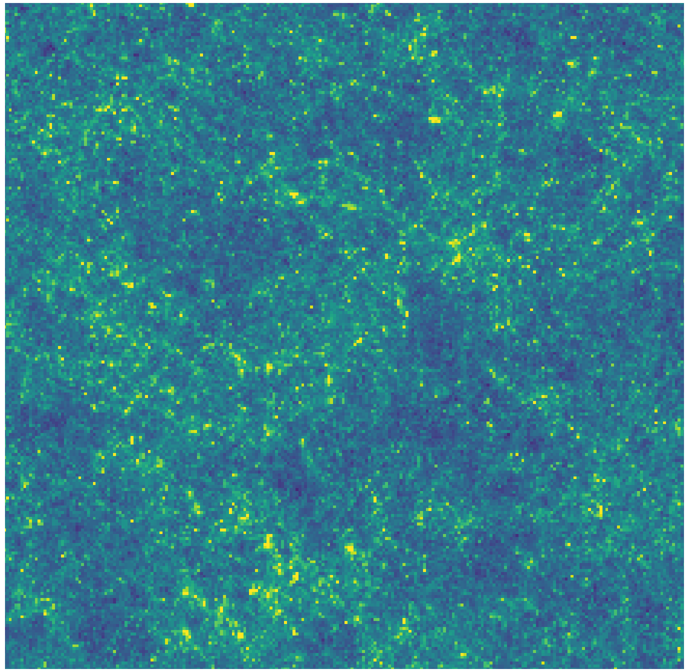

simulated convergence map

$$P(\kappa|\theta, \mathcal{M})$$

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02

Deep learning a Bayesian estimate

Mean posterior estimate

Deep learning framework

I. We seek to approximate the mean posterior:

$$\hat{\kappa} = \mathscr{F}_{\Theta}(\gamma) = \int \kappa \, P(\kappa | \gamma) \, \mathrm{d}\kappa$$

II. This is achieved by minimising:

$$J(\Theta) = ||\mathscr{F}_{\Theta}(\gamma) - \kappa_{\mathrm{true}}||_2^2$$

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A brief aside

Mean posterior estimation

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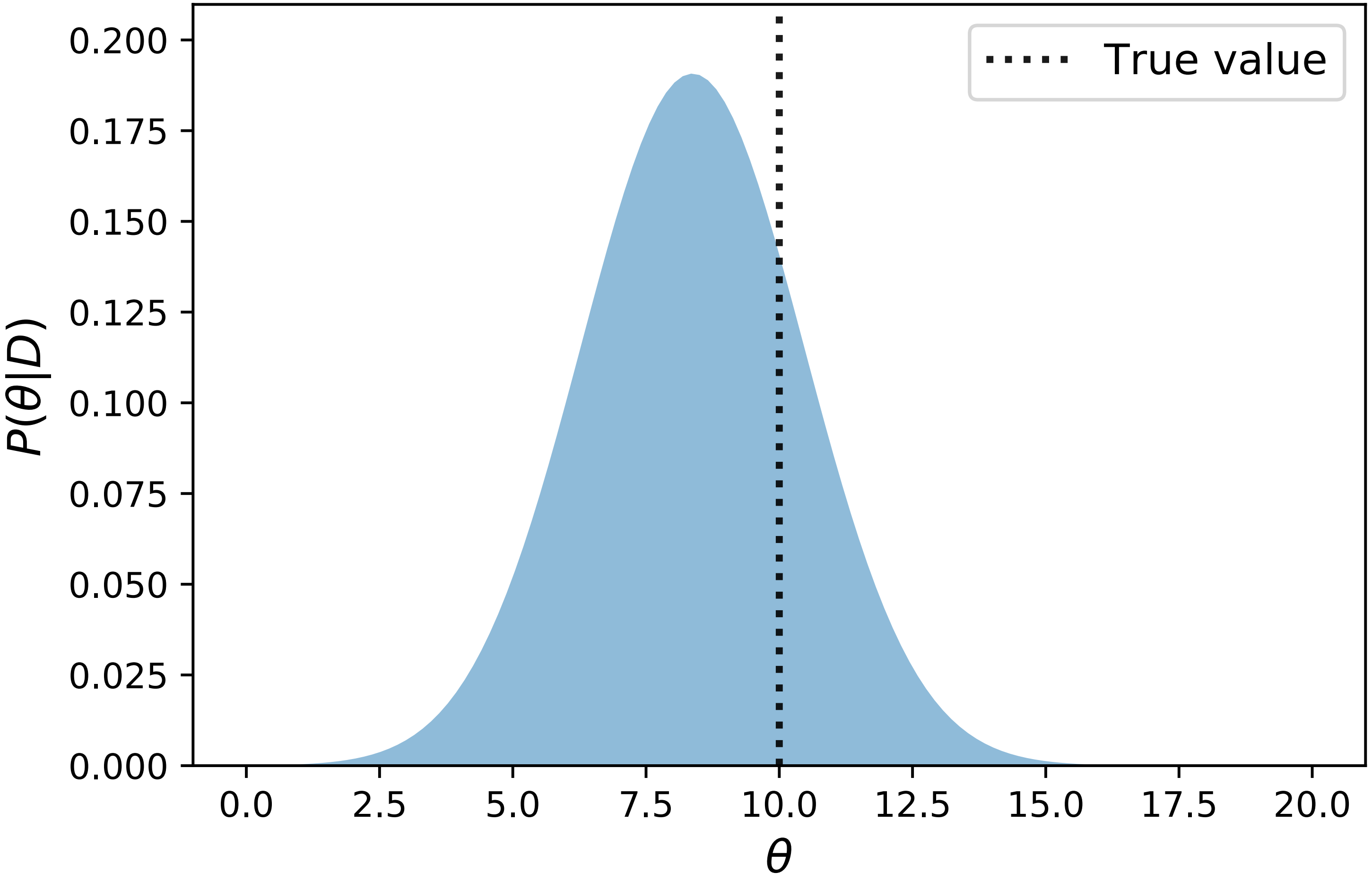
Mean posterior estimation



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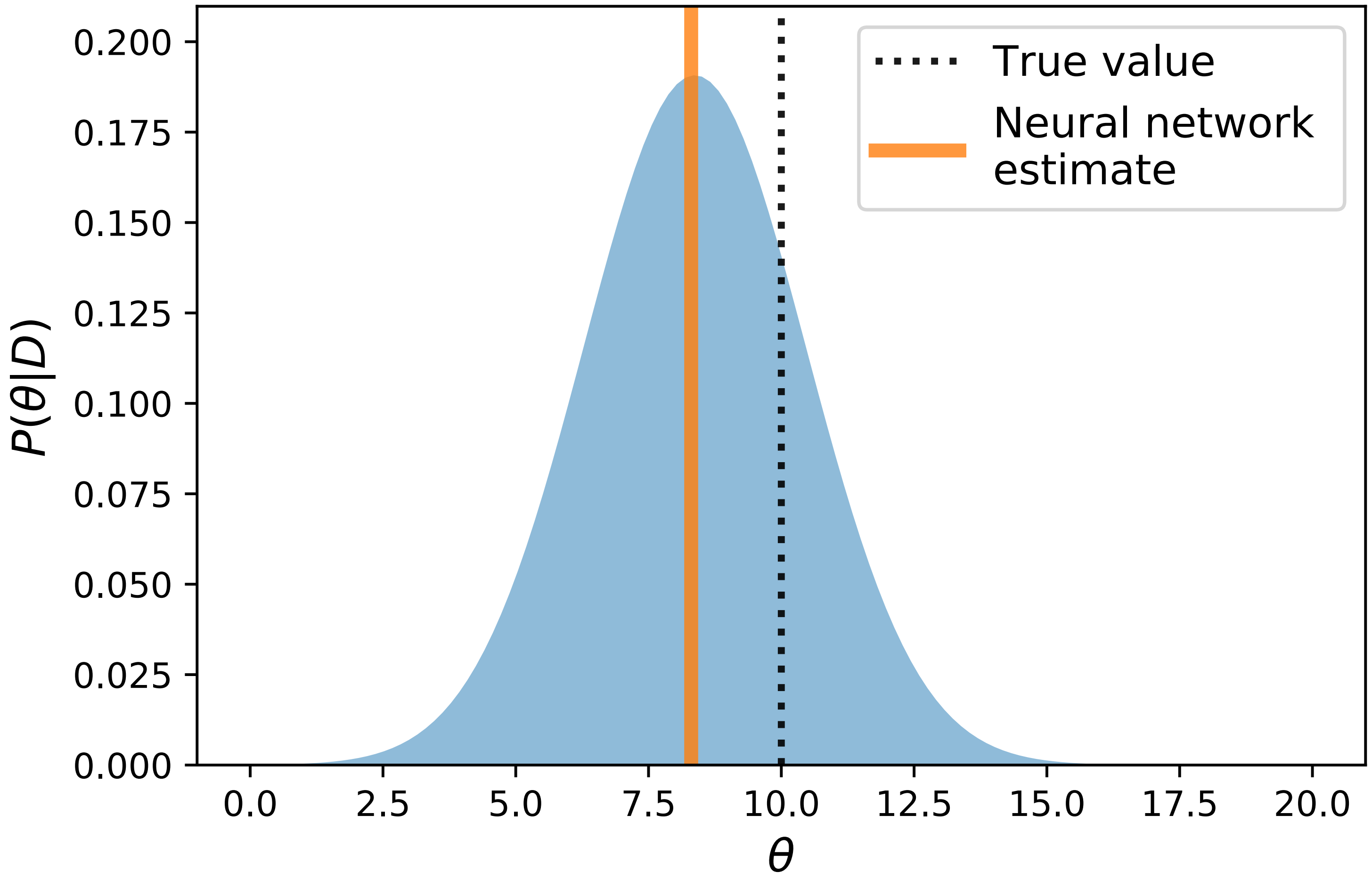
A brief aside

Mean posterior estimation



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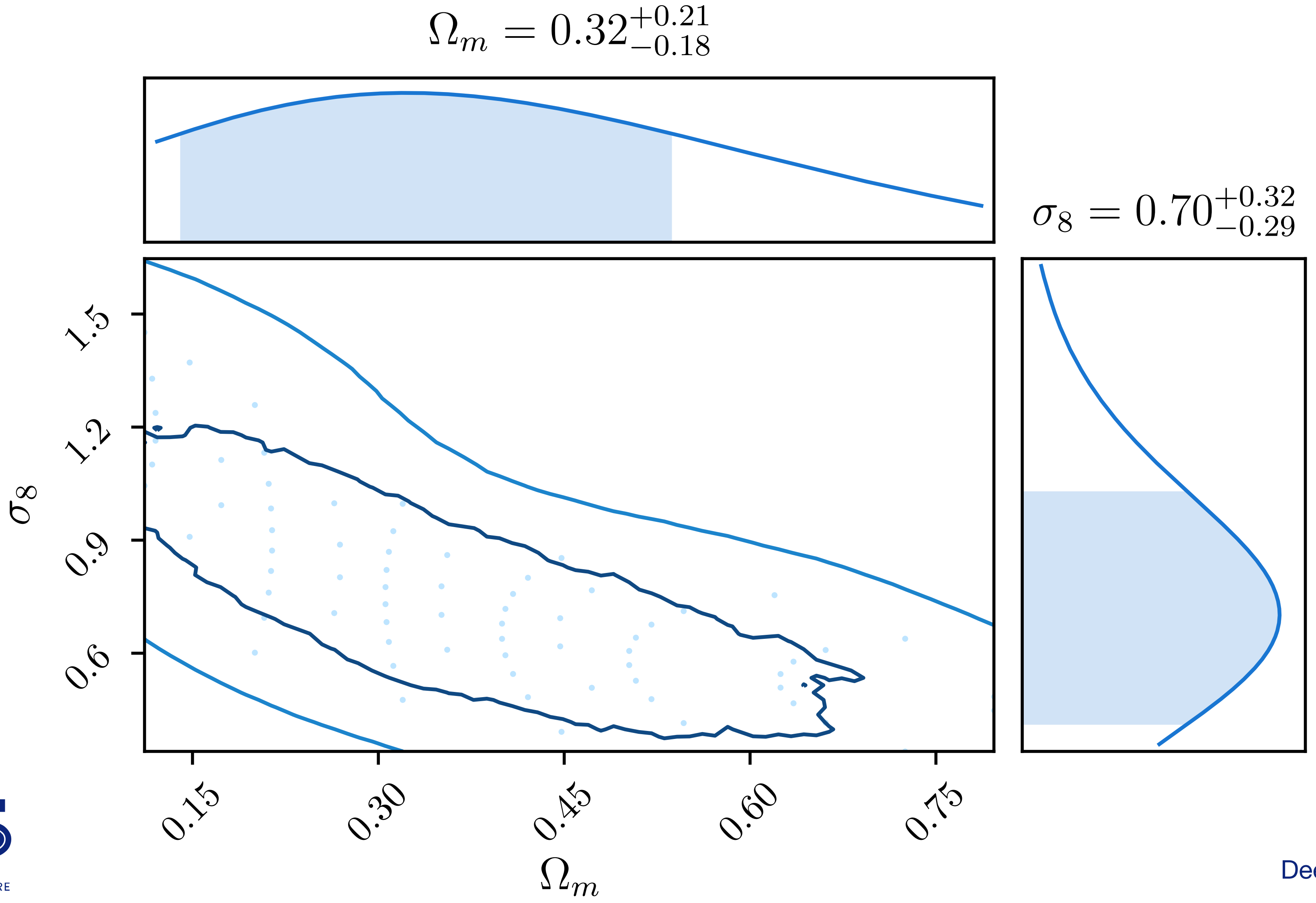
Step 1

Simulations parameters distributed from prior $P(\theta)$



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Step 2
Learn the unknown function

$$\hat{\kappa} = \mathscr{F}_{\Theta}(\gamma)$$

I. Approximate function as a Convolutional Neural Network (CNN)

II. Unknown parameters Θ are mainly convolution filters

III. Minimise $J(\Theta)$ using 3×10^5 {clean map, noisy data} realisations

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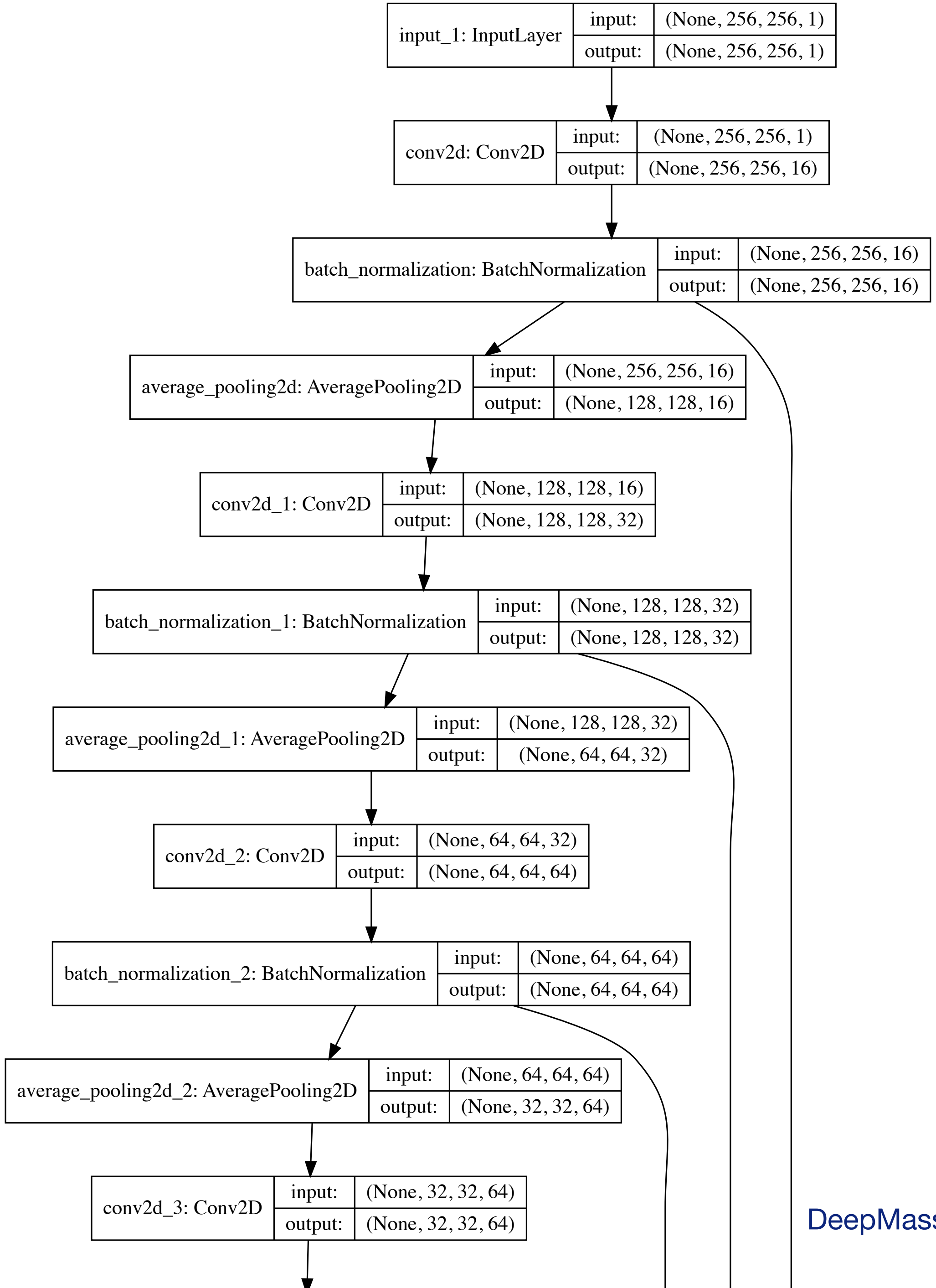
DeepMass architecture: U-Net

Expanding and contracting paths

I. Hierarchy of downsampling i.e. “pooling”

II. Increasing filter “receptive area”

III. Multiscale filters



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03 Results with Dark Energy Survey data

Dark Energy Survey

SV weak lensing data

I. Science Verification (SV) data are <5% of final area, but has final SNR

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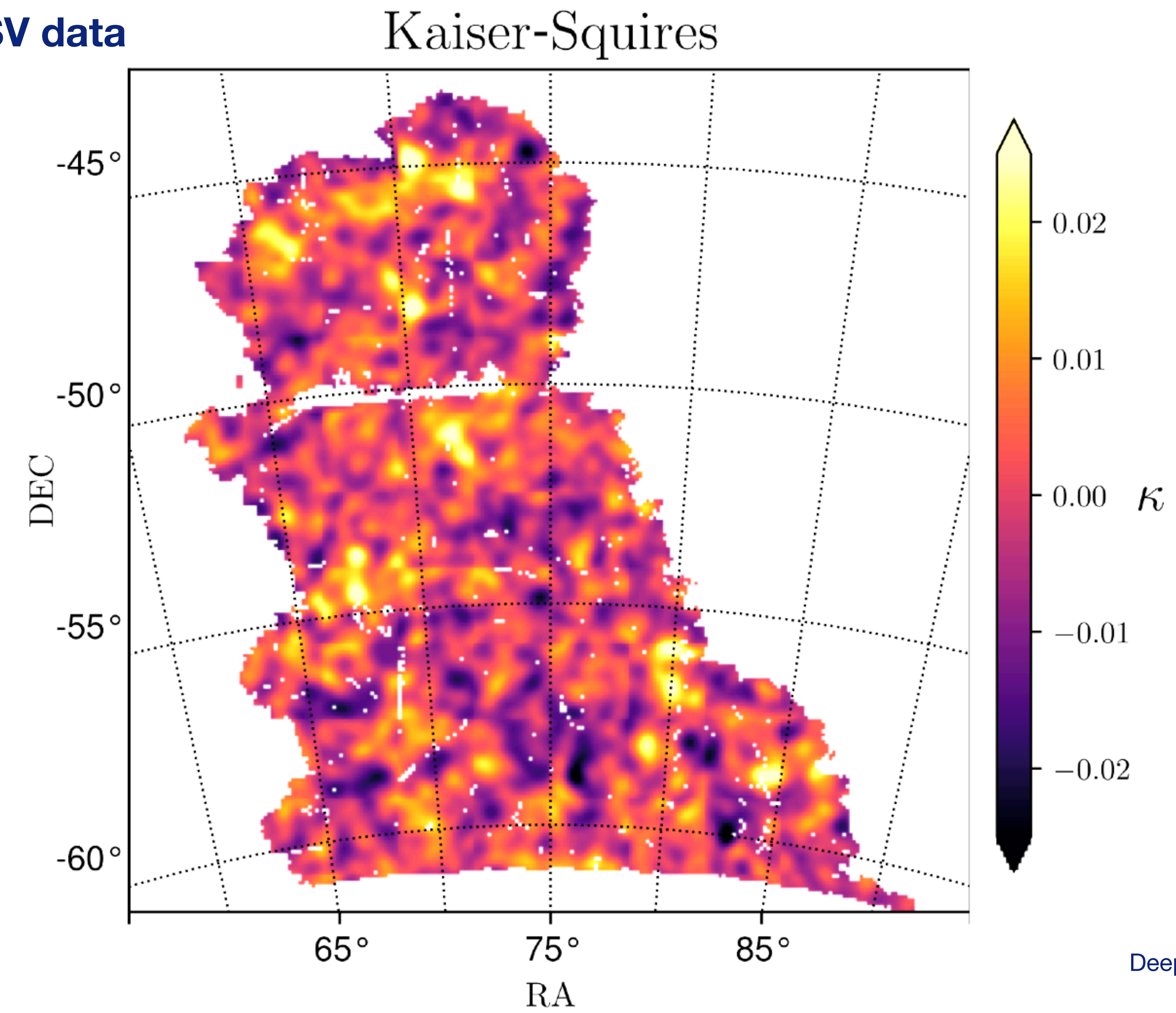
Results

Dark Energy Survey SV data



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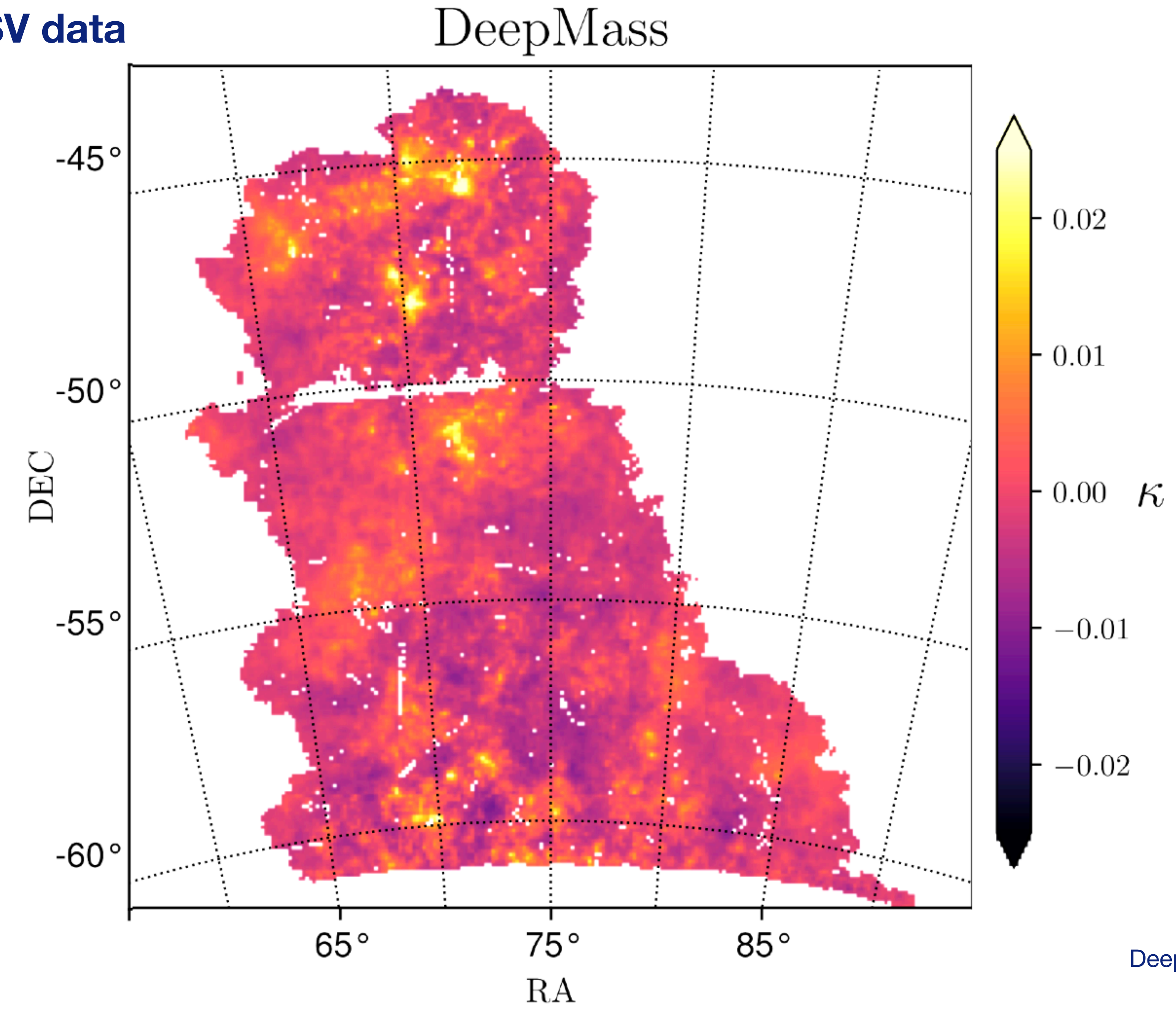
Results

Dark Energy Survey SV data



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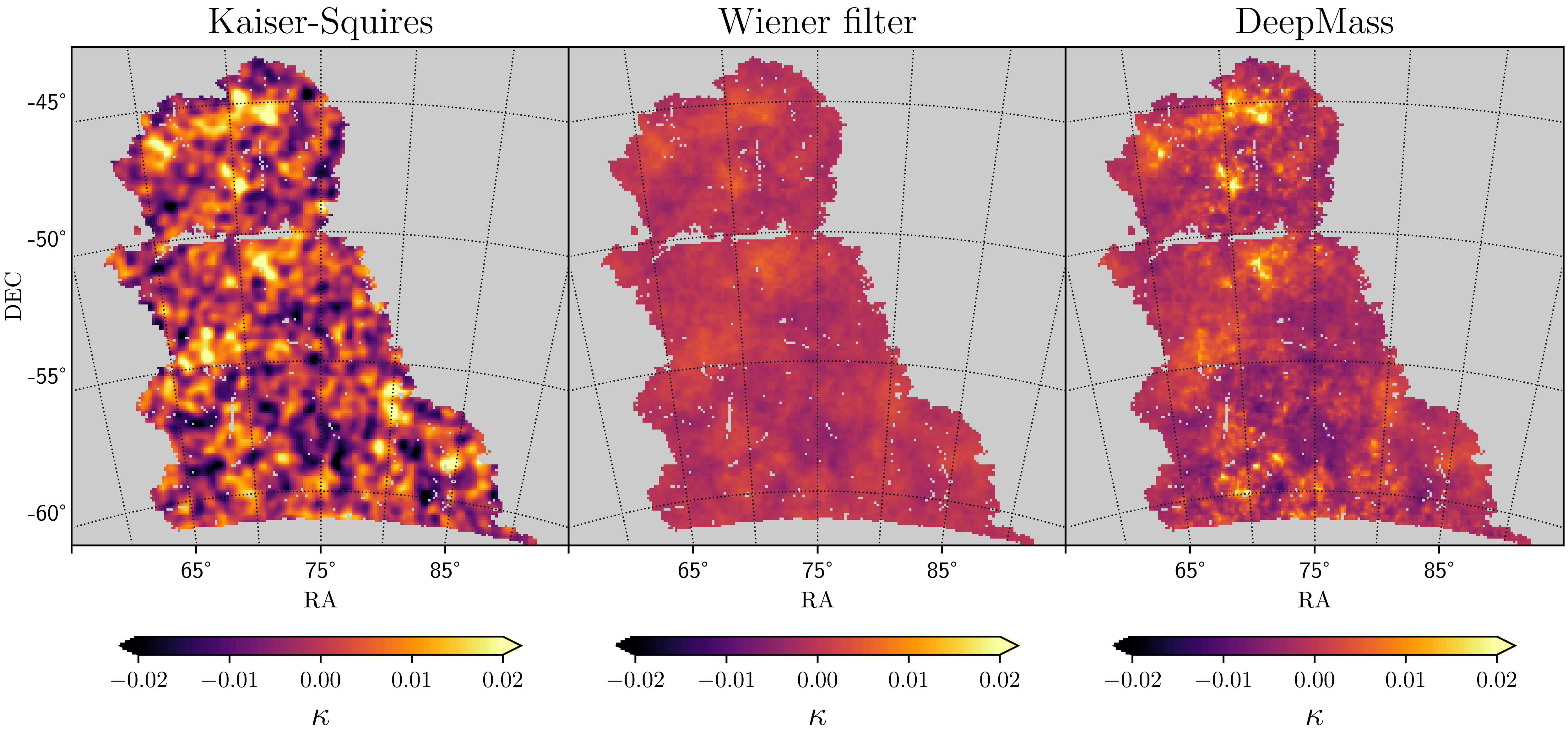

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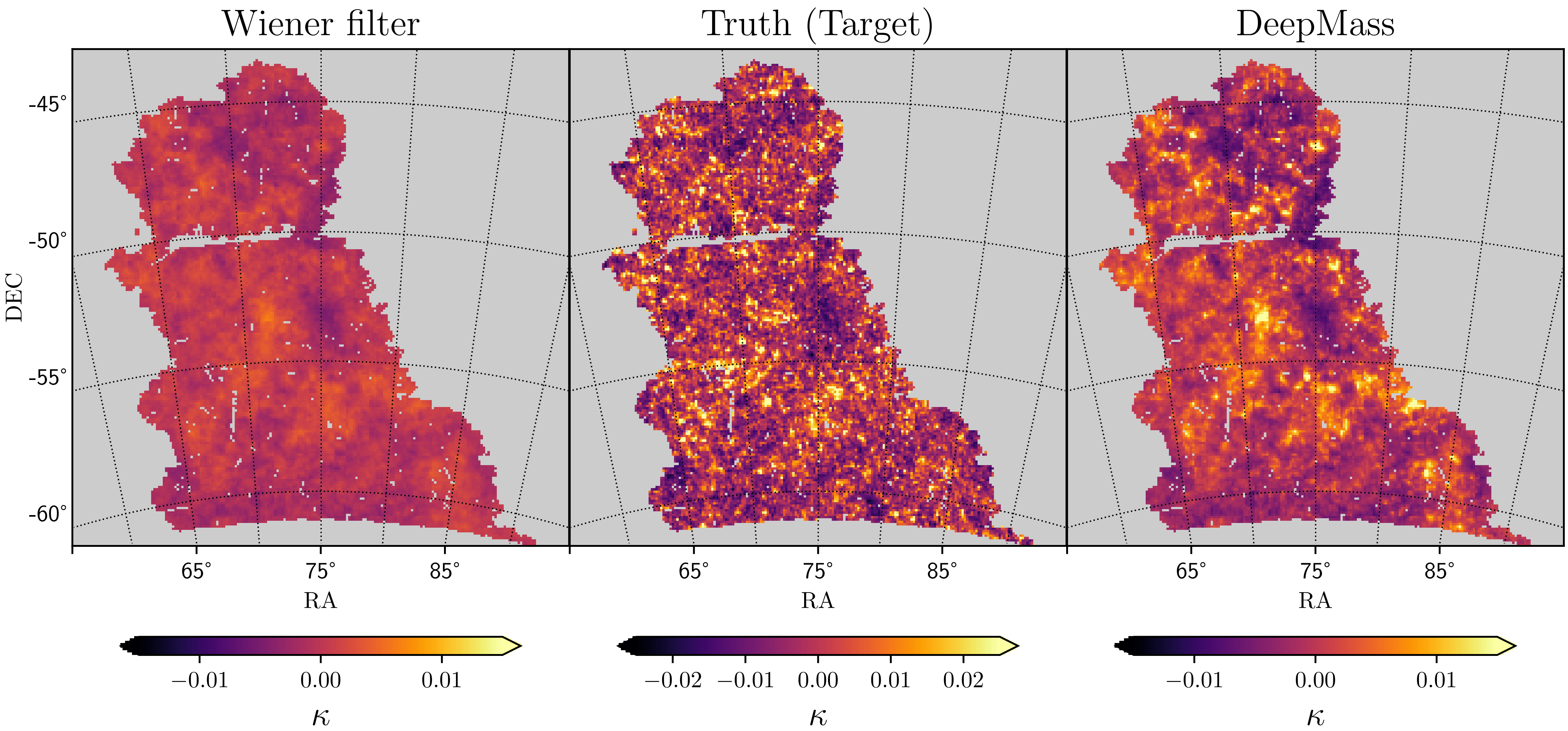

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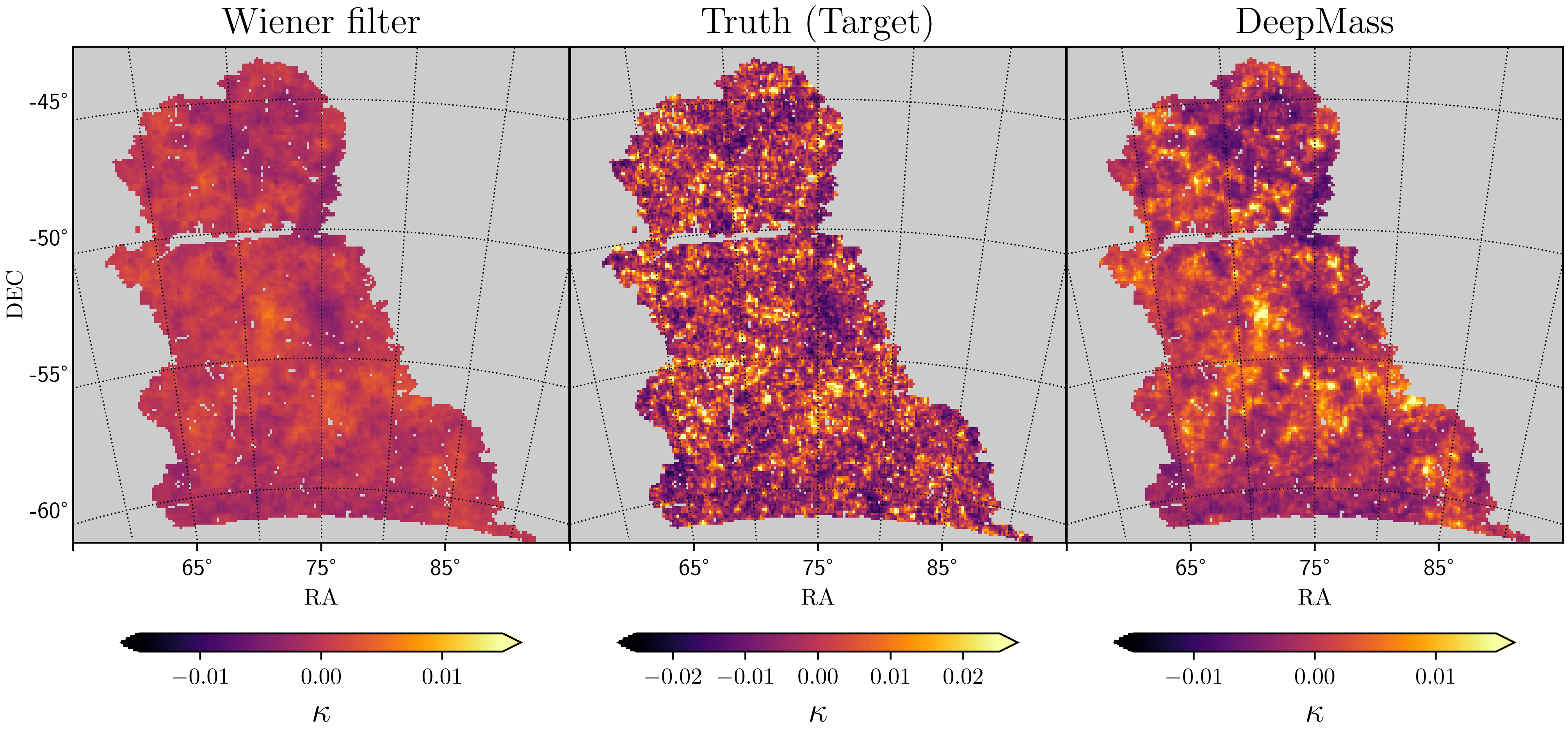

I. Wiener filter is optimal linear MSE filter

II. 8000 sample maps not used for training

III. **DeepMass improves MSE by 11% compared to Wiener**

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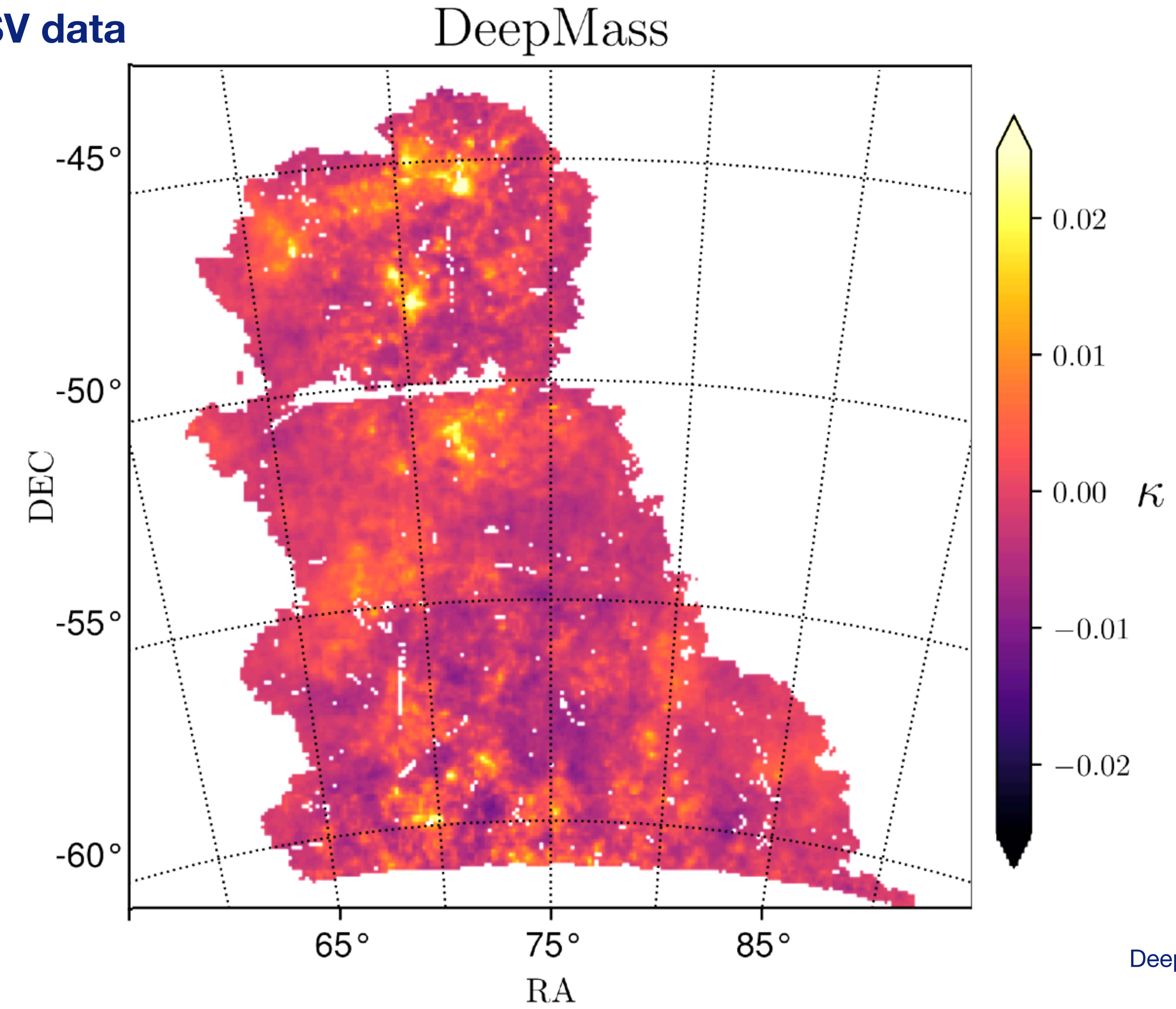
04

Likelihood-free inference

Results

Dark Energy Survey SV data



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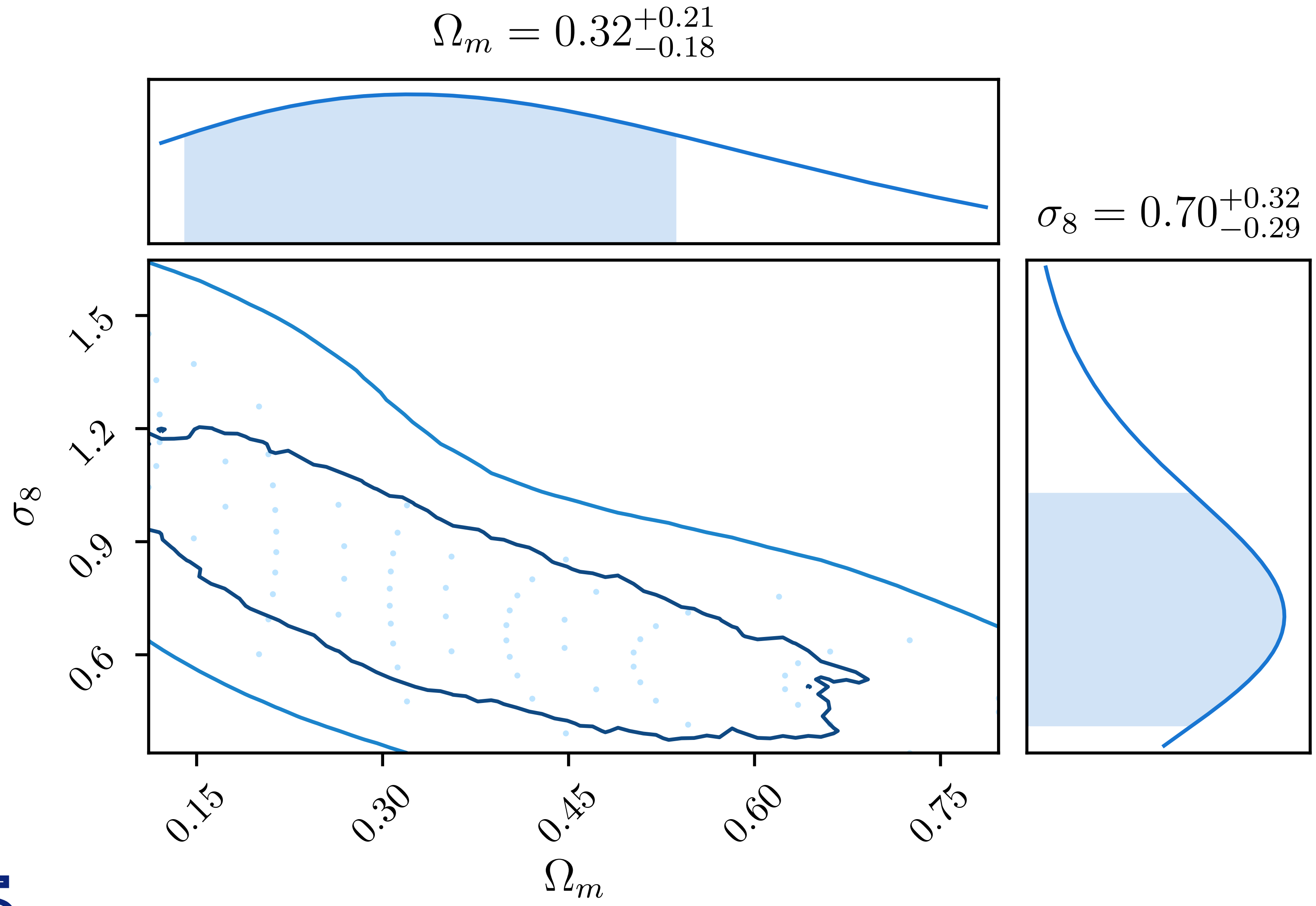
Forward modelled data

Few data-model assumptions



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Forward modelled data

Few data-model assumptions

$$P(\boldsymbol{\theta} \,|\, \boldsymbol{D}, \mathscr{M})$$

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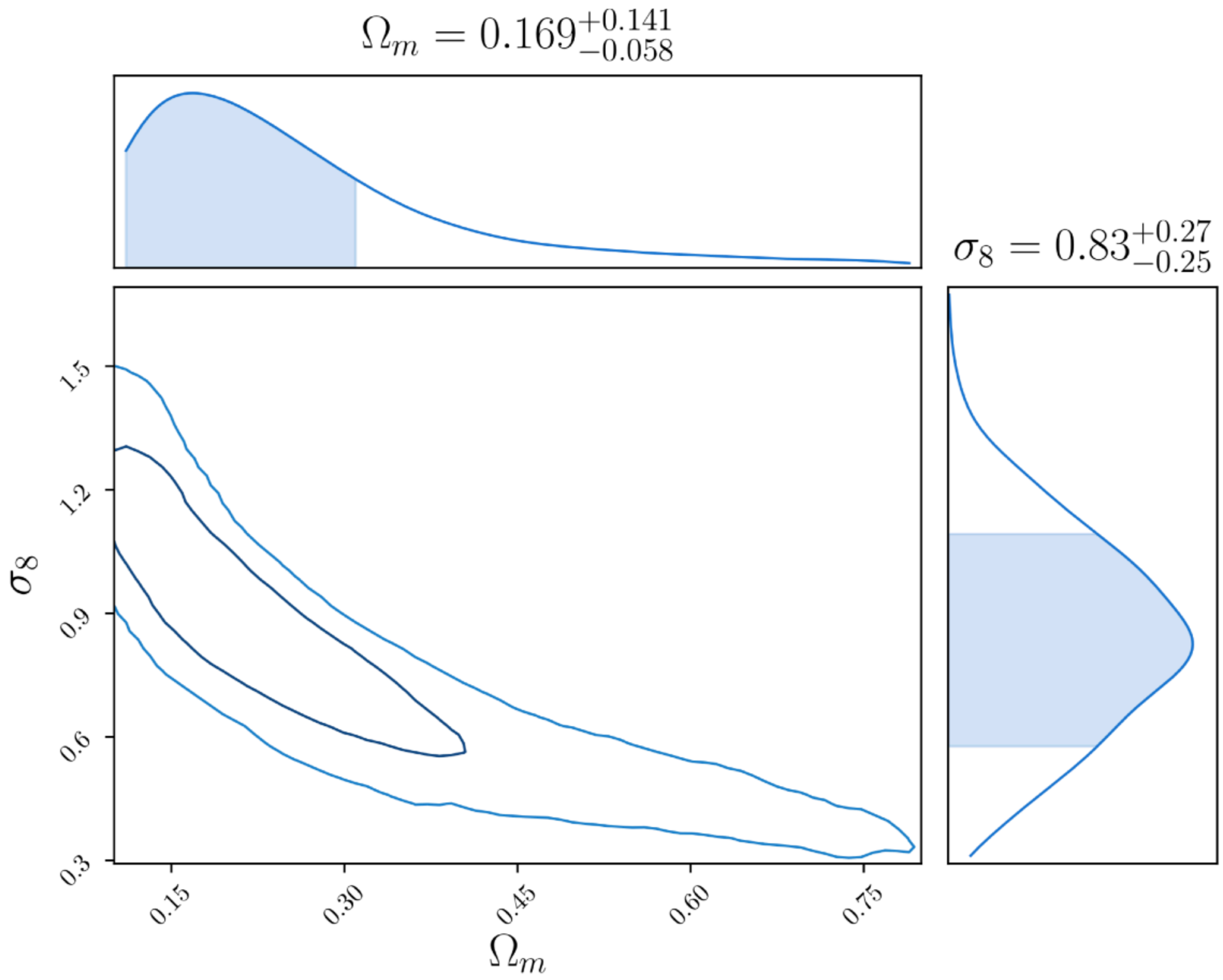
Forward modelled data

Few data-model assumptions

$$P(\boldsymbol{\theta} \,|\, \boldsymbol{t} = F(\boldsymbol{D}), \mathscr{M})$$

DELFI (Alsing 1903.00007) estimated posterior

Compressed [peak counts x power spectrum]



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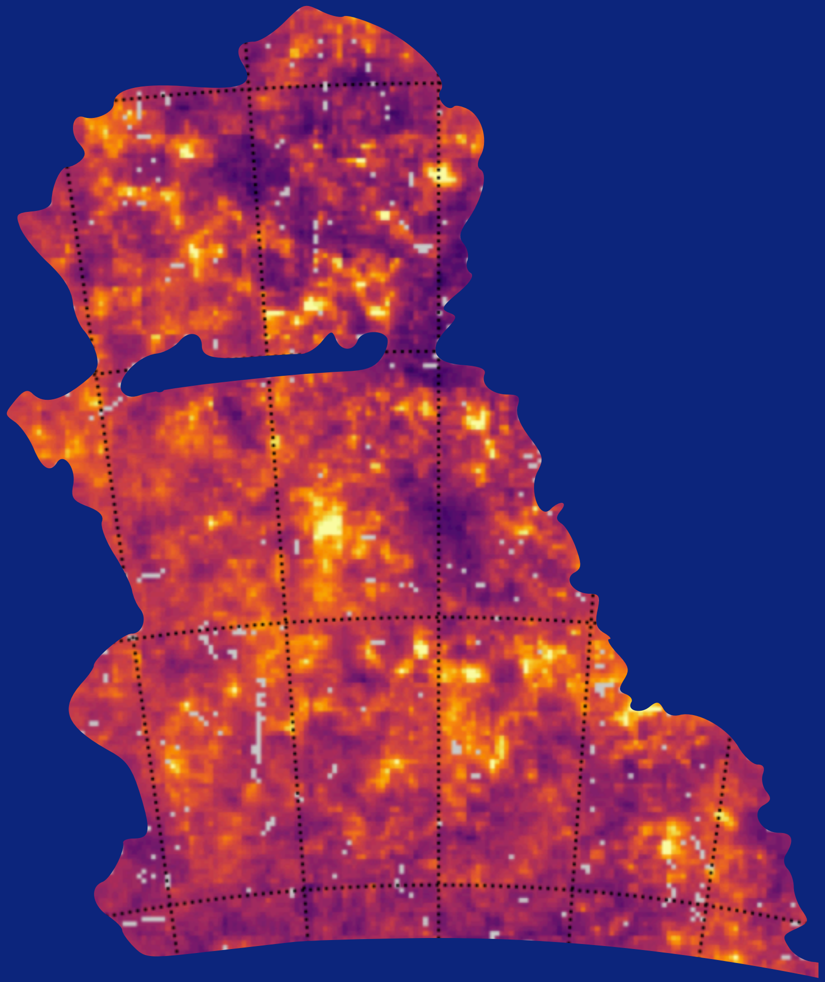

Merci !

arXiv:1908:00543

github.com/NiallJeffrey/DeepMass

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