BAYESIAN INFERENCE WITH PHYSICS INFORMED PRIORS

FROM SIMULATIONS

New Strategies for Extracting Cosmology from Future Galaxy Surveys II, 03.07.2024

Simon Ding in collaboration with **Ludvig Doeser**

supervised by **Guilhem Lavaux** (IAP) & **Jens Jasche** (Stockholm University)



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Goal: Cosmological inference with large scale structures

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Data: Galaxy clustering surveys e.g. Euclid, DESI, LSST, ...

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e.g. higher-order terms in EFT, neural networks, ...

We only have one Universe!
→ Data unable to constrain both physics and nuisance parameters

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Possible solutions:

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1. Reduce parameter space

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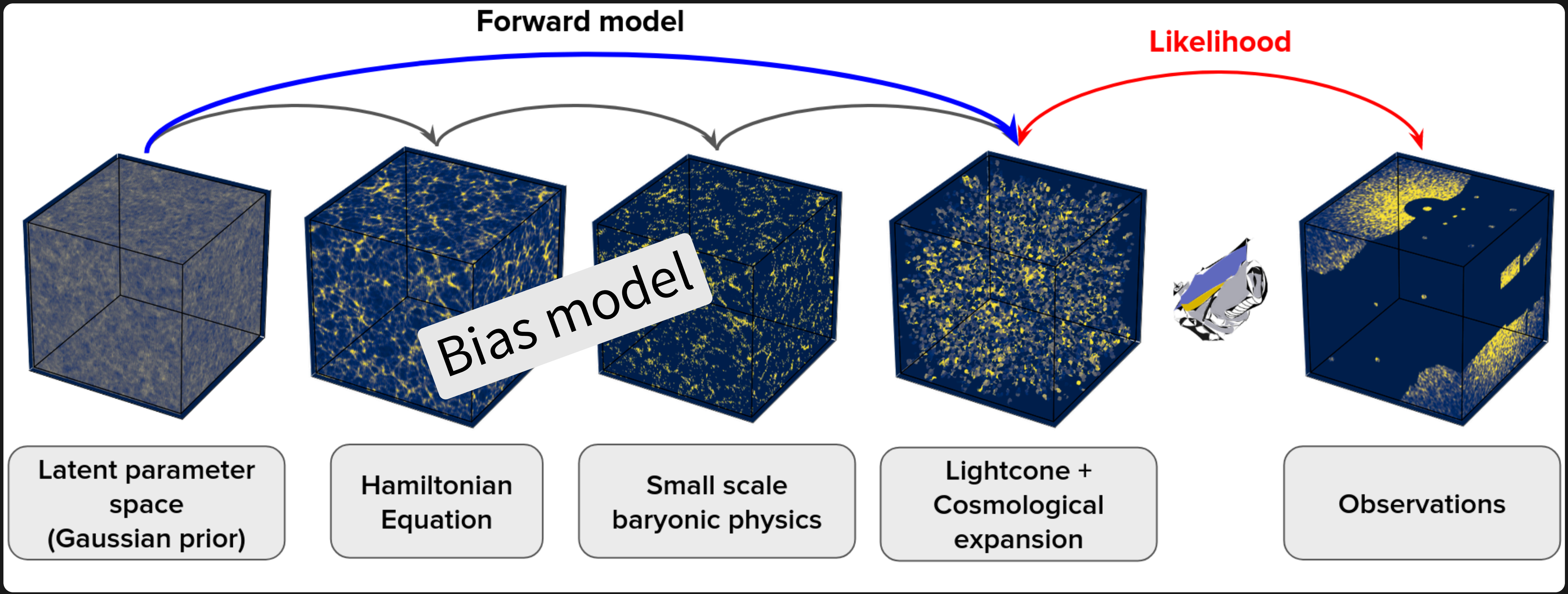
1. Reduce parameter space
2. Use better (behaved) priors $P(\theta)$

BAYESIAN INFERENCE
WITH
PHYSICS INFORMED PRIORS FROM SIMULATIONS

PHYSICS INFORMED PRIORS FROM SIMULATIONS

— AN INFERENCE EXAMPLE —

FIELD-LEVEL INFERENCE FROM GALAXY SURVEYS WITH BORG



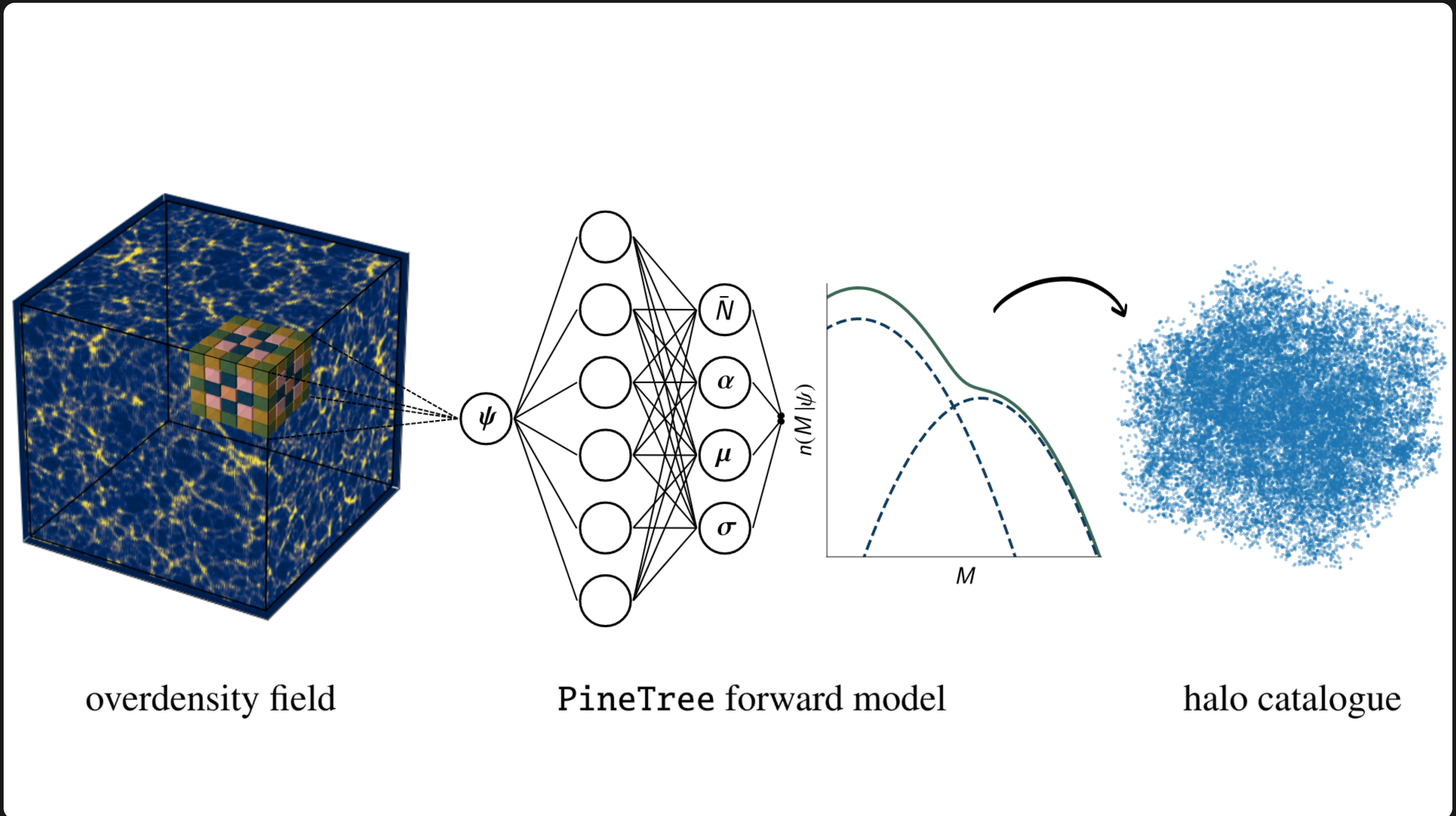
$\approx 2.1 \times 10^6$ parameters

Jasche & Wandelt (2013), Jasche, Leclercq & Wandelt (2015),
Lavaux & Jasche (2016), Jasche & Lavaux (2019)

Image credit: D.K Ramanah

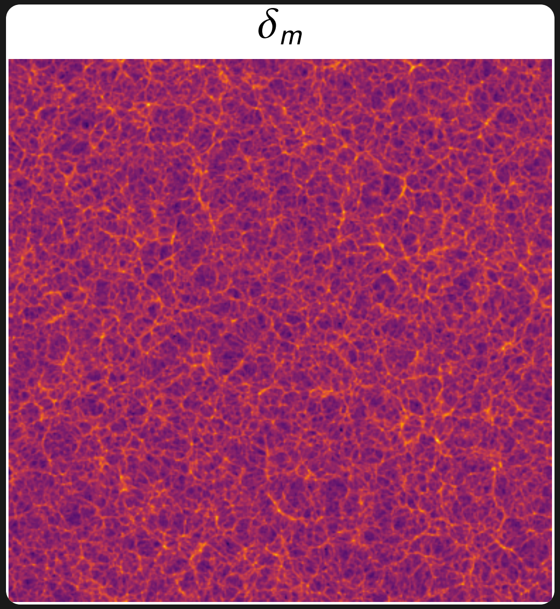
Galaxy bias model: $\delta_m(x) \rightarrow \delta_g(x)$

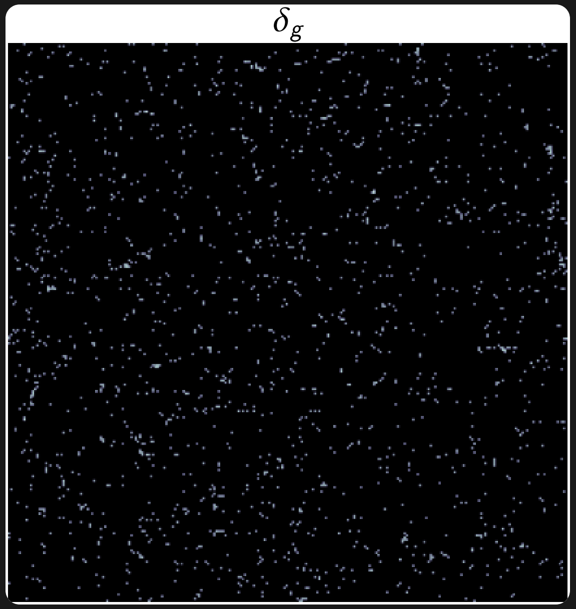
Galaxy bias model: $\delta_g(x) = b_1 \delta_m(x)$



Ding, Lavaux, Jasche 2024; ArXiv: 2407.01391

PHYSICS INFORMED PRIORS FROM SIMULATIONS





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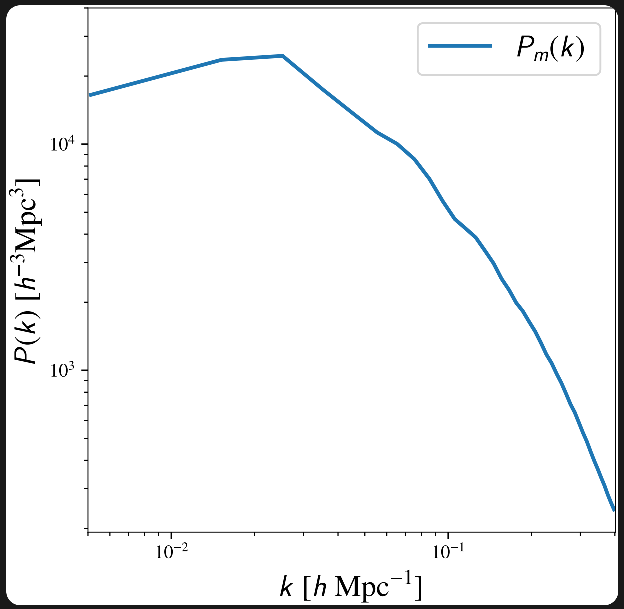

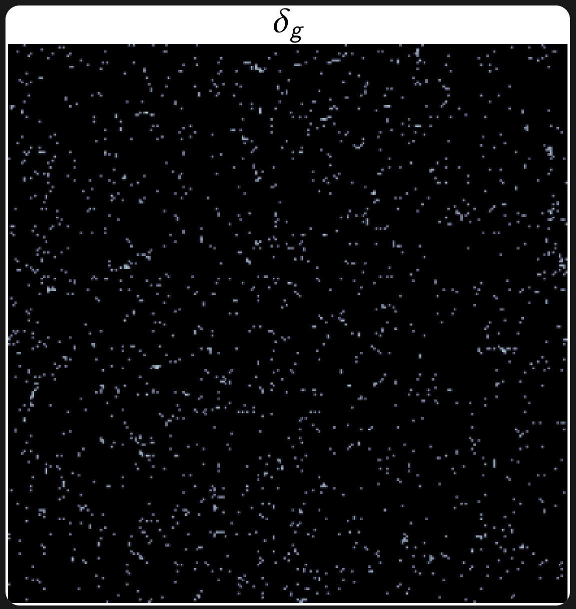

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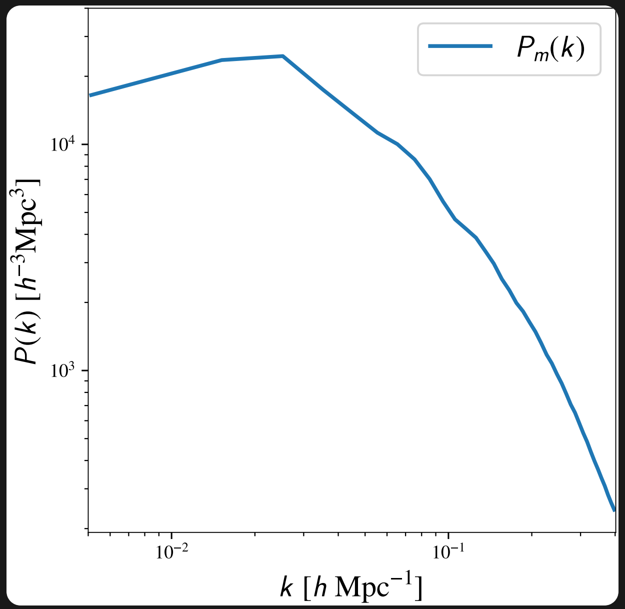

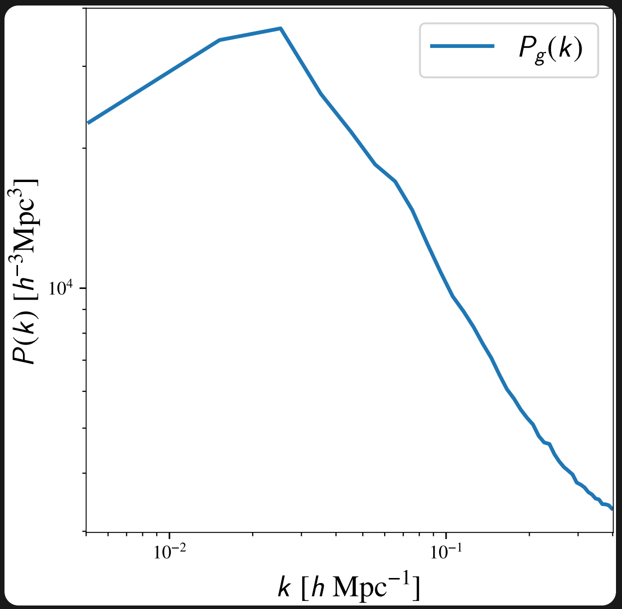

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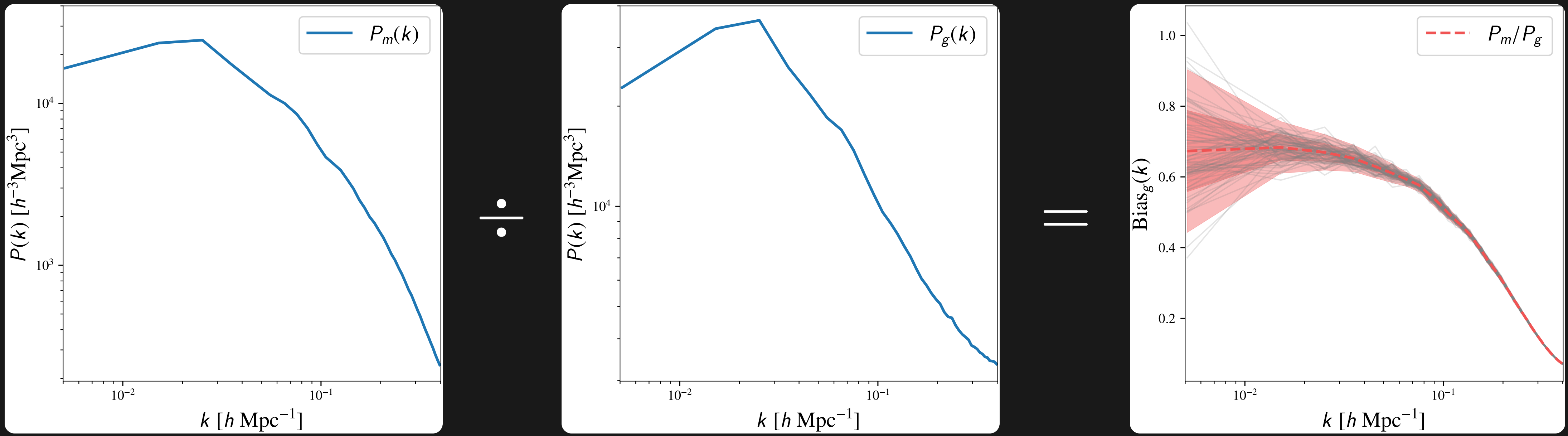

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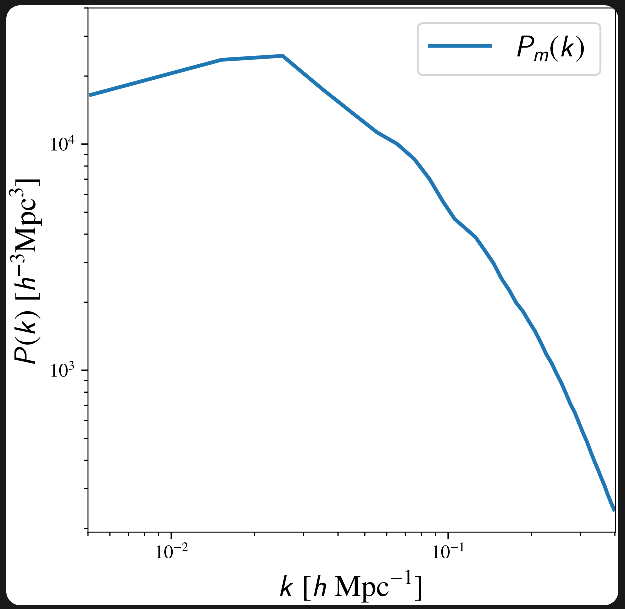

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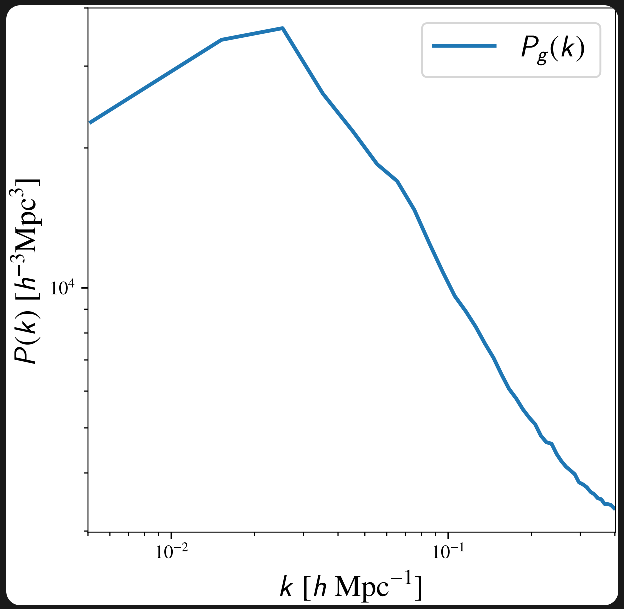

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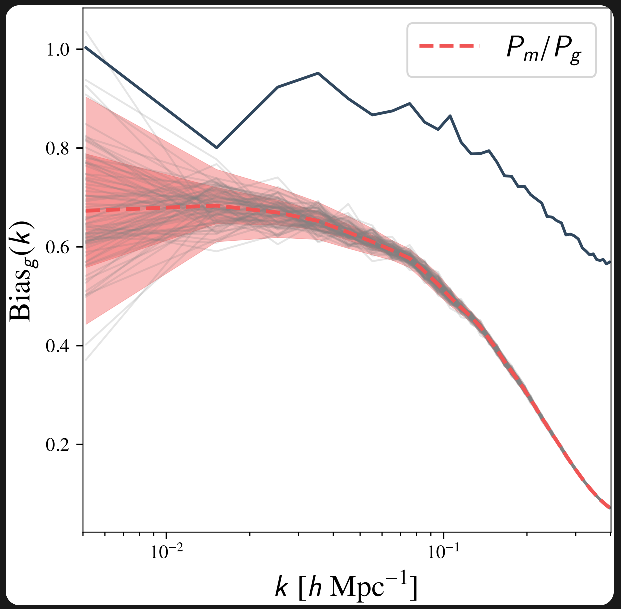

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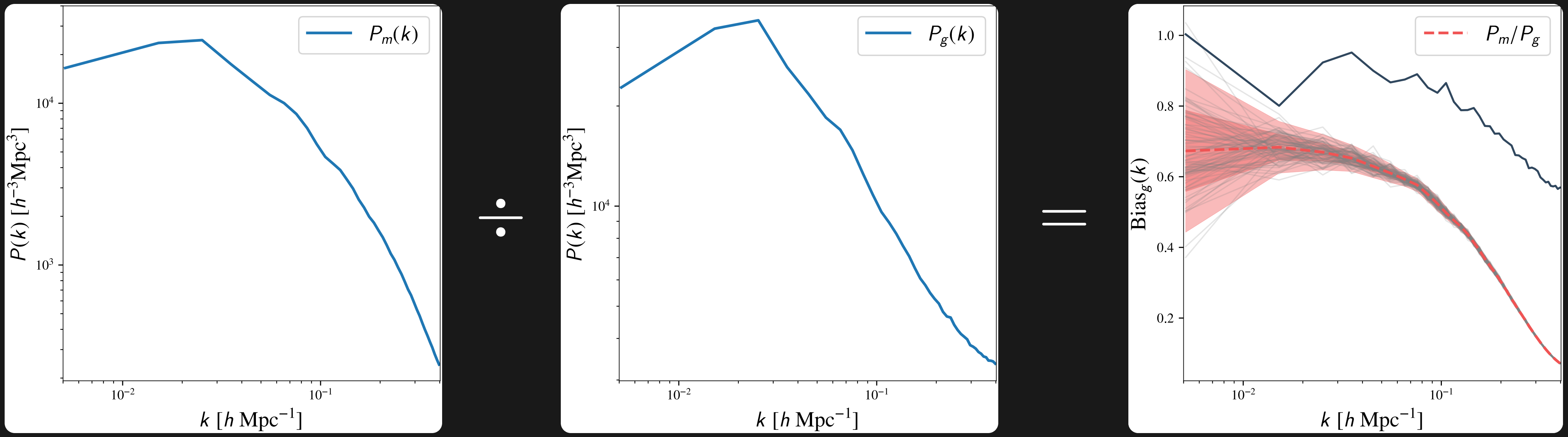

$\Rightarrow$ New constraint from simulations $r = \dfrac{P_m(k)}{P_g(k)}$

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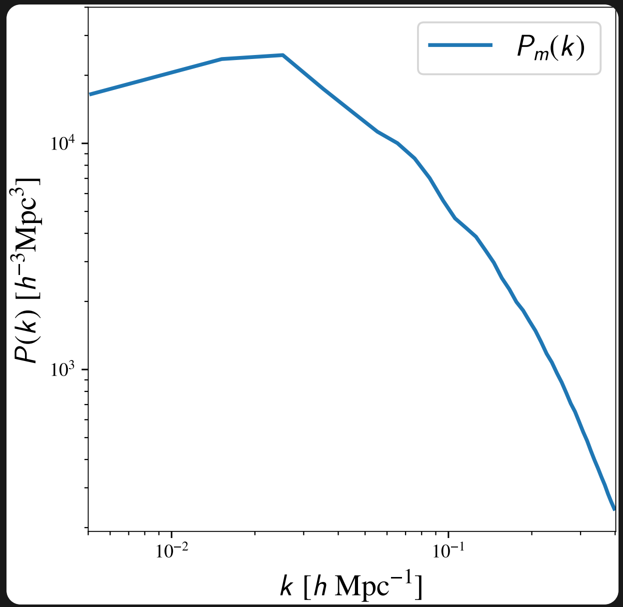

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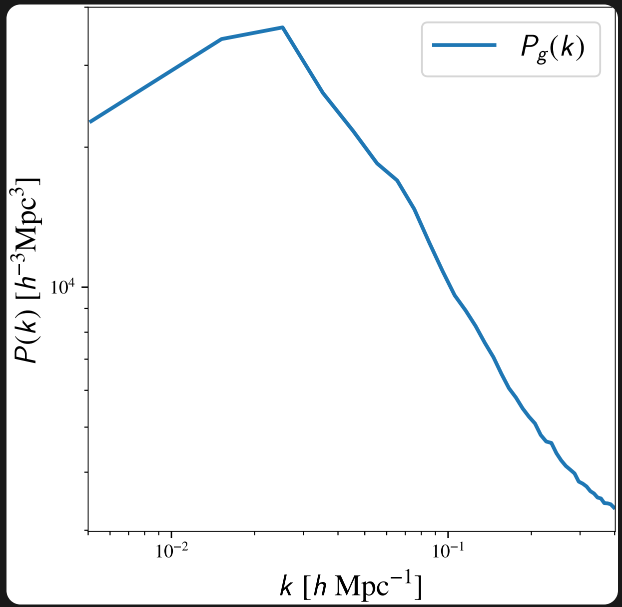

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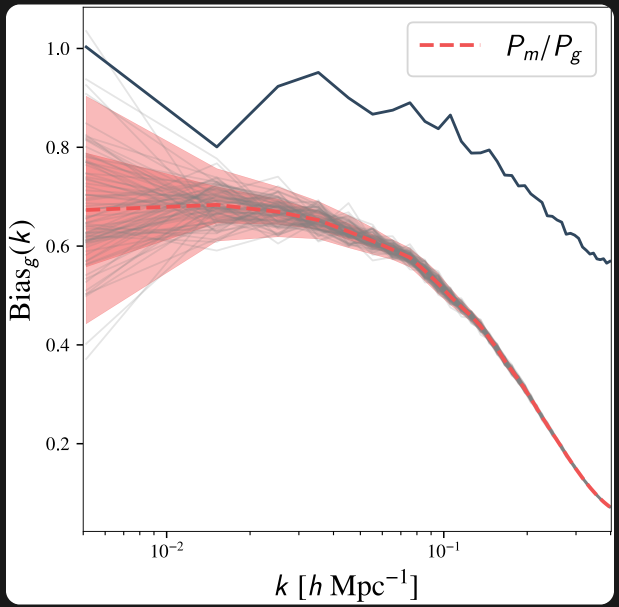

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Note: Any summary statistic other than power spectrum may be used

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Conditional independent constraint r :

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Conditional independent constraint $r:\ \ P(\mathrm{data}|r) = P(\mathrm{data})$

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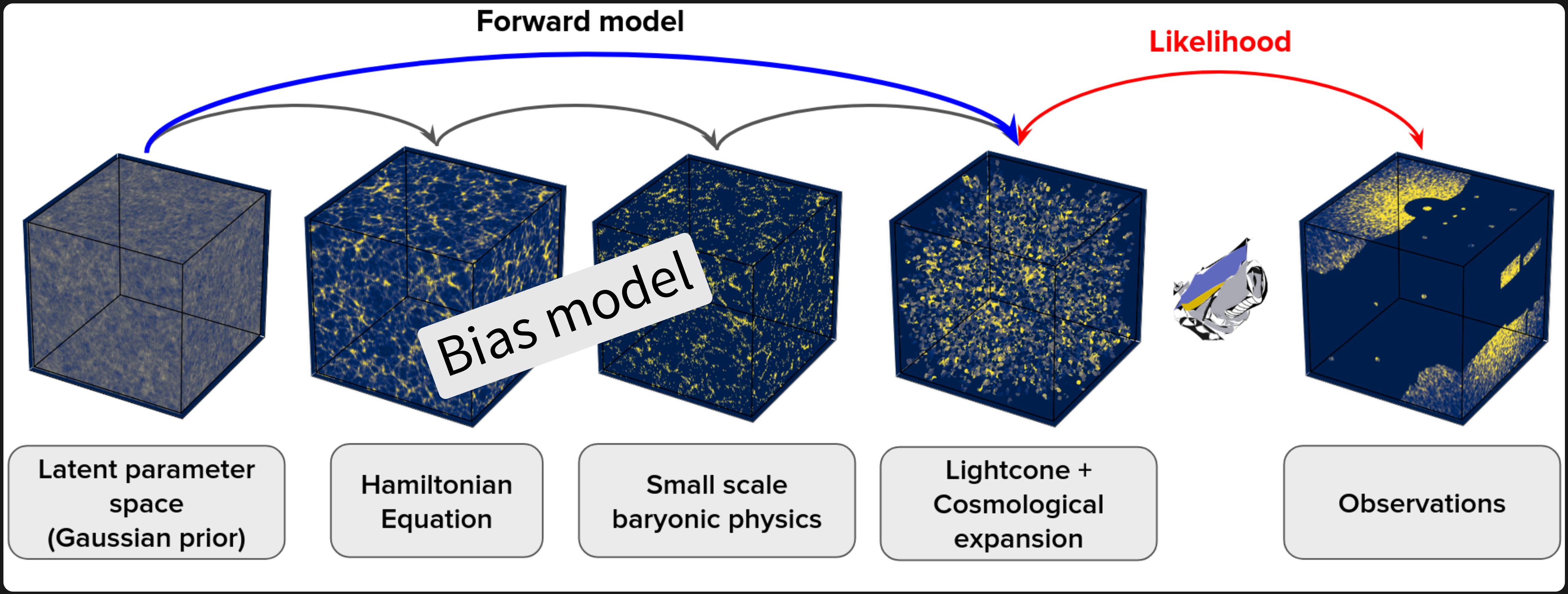
$$\propto P(\mathrm{data}|\theta)P(r|\theta)P(\theta)$$

RObust **B**ayesian **IN**ference with **P**hysics-**i**nformed **P**rior

ROBIN-PiP

FIELD-LEVEL INFERENCE FROM GALAXY SURVEYS WITH BORG



$\approx 2.1 \times 10^6$ parameters

Jasche & Wandelt (2013), Jasche, Leclercq & Wandelt (2015),
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Image credit: D.K Ramanah

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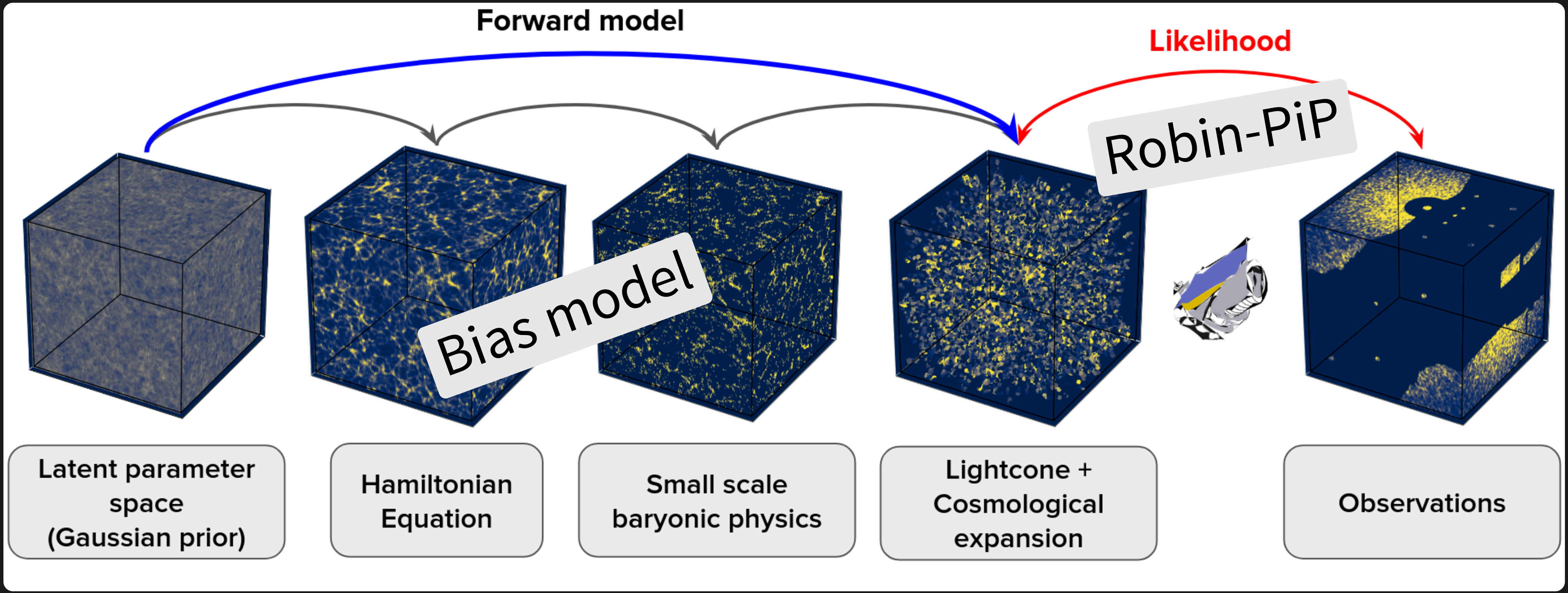

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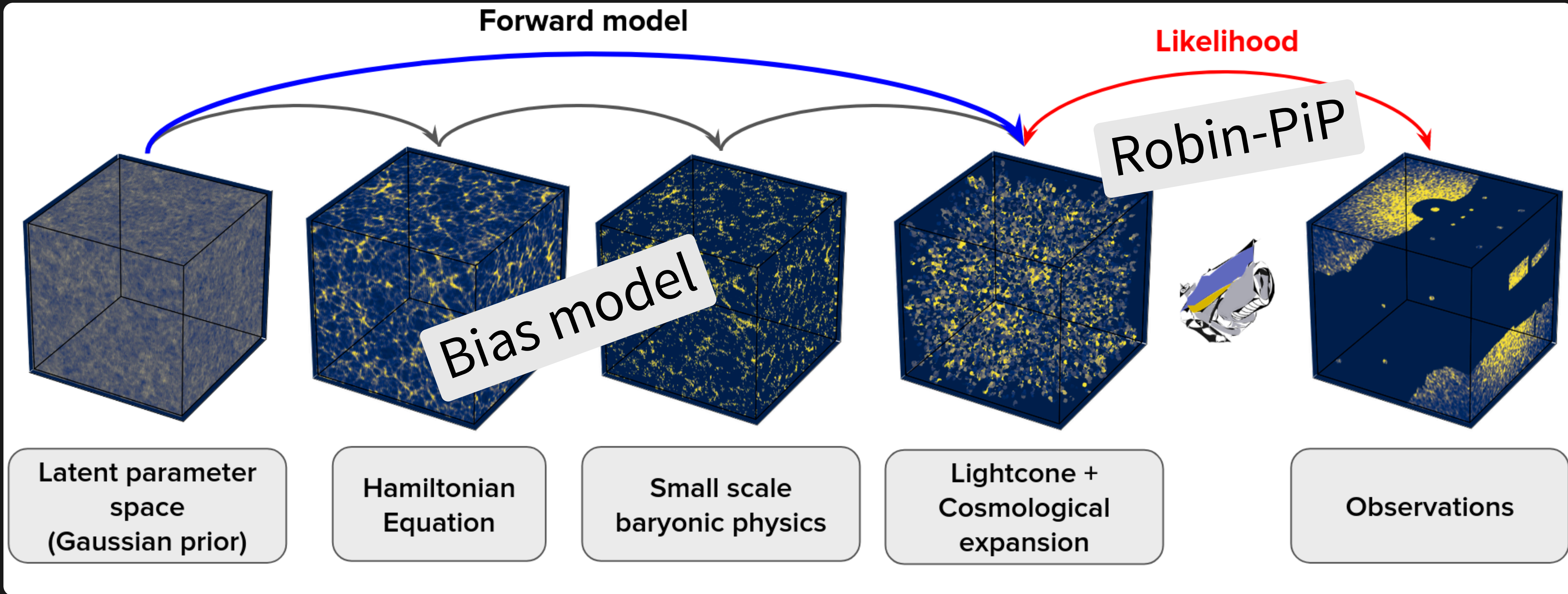

$\approx 2.1 \times 10^6$ parameters

Use self-consistent simulations & mock observables

Jasche & Wandelt (2013), Jasche, Leclercq & Wandelt (2015),
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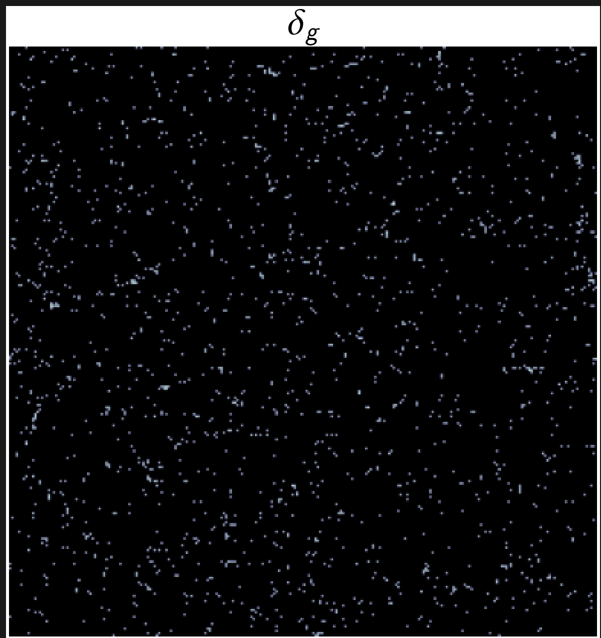
ROBIN-PiP × BORG

ROBIN-PiP $\times$ BORG



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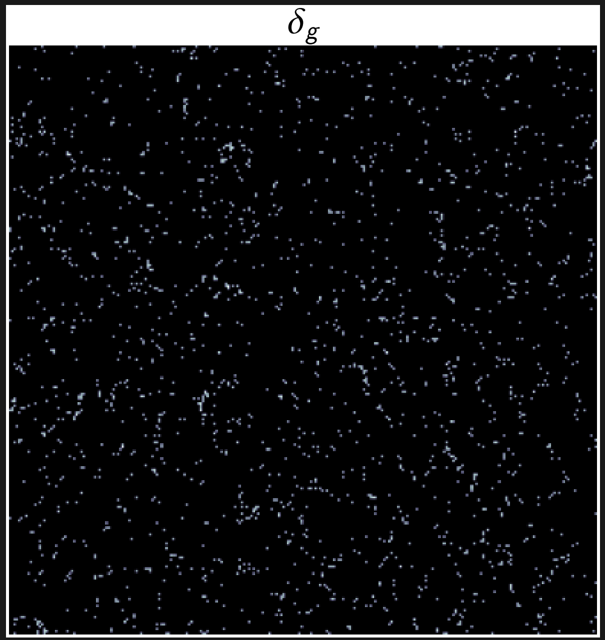

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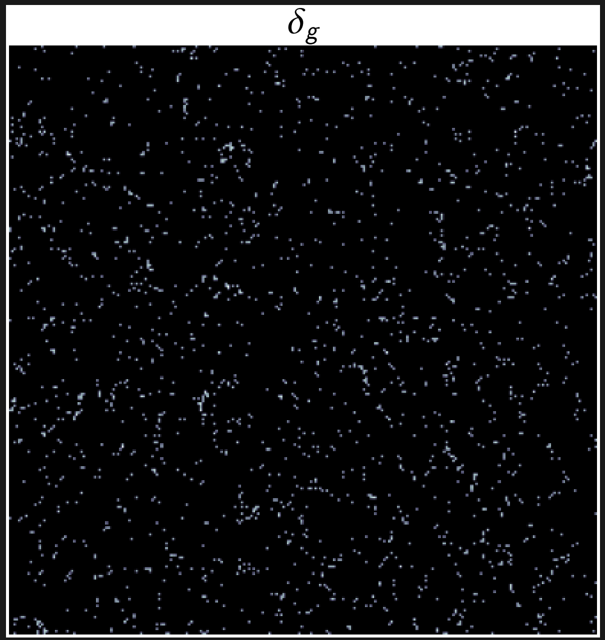
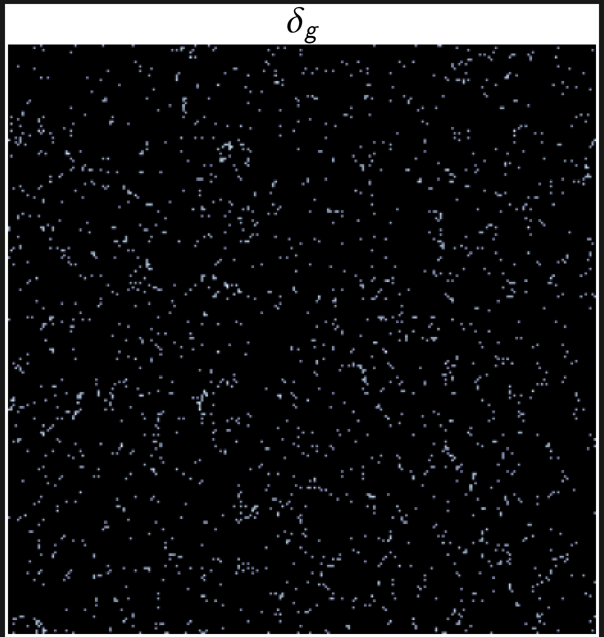
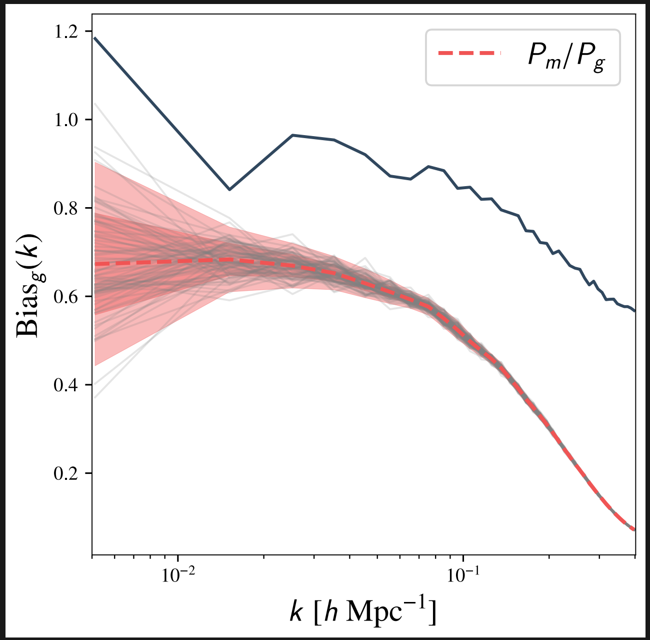


Galaxy clustering log-likelihood

ROBIN-PiP × BORG





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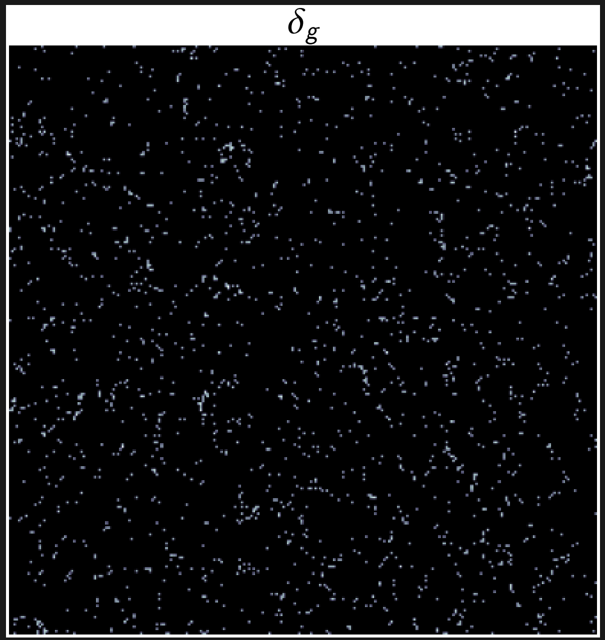
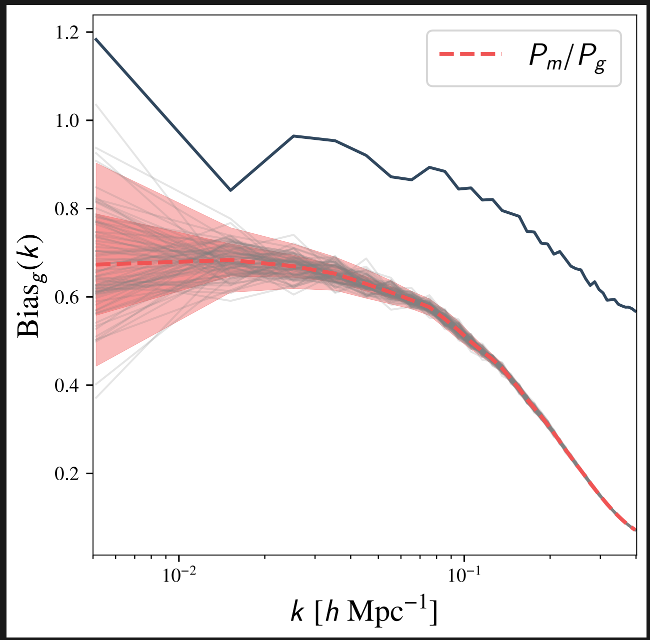
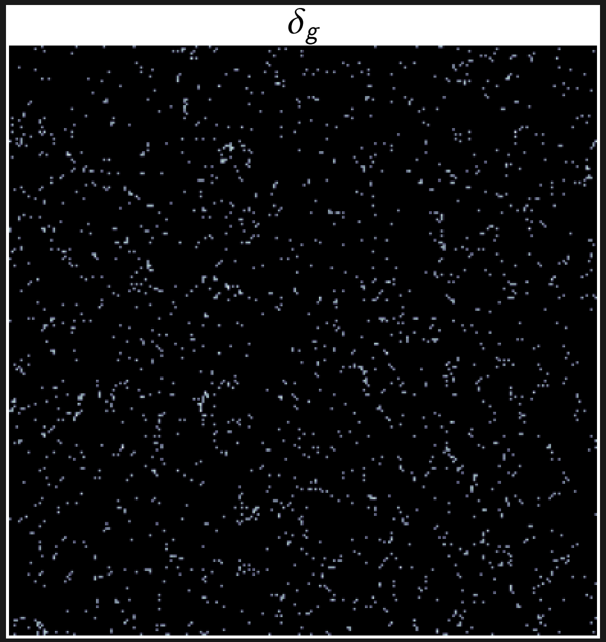
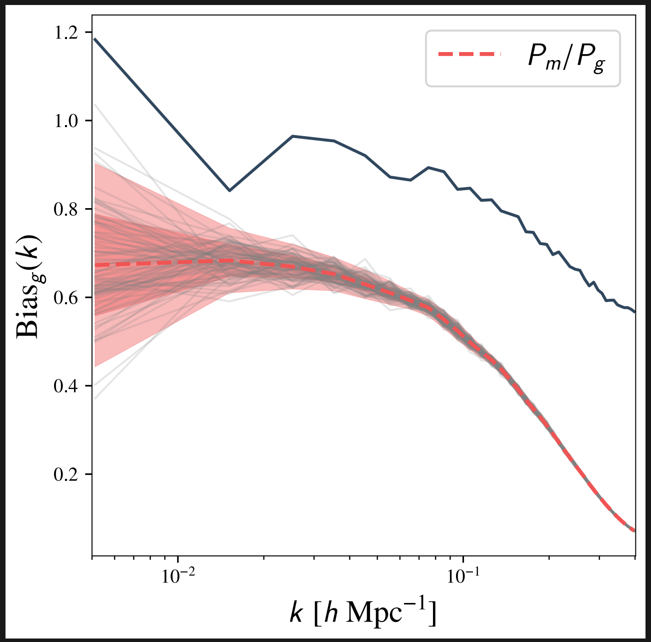




Galaxy clustering log-likelihood + Robin-PiP

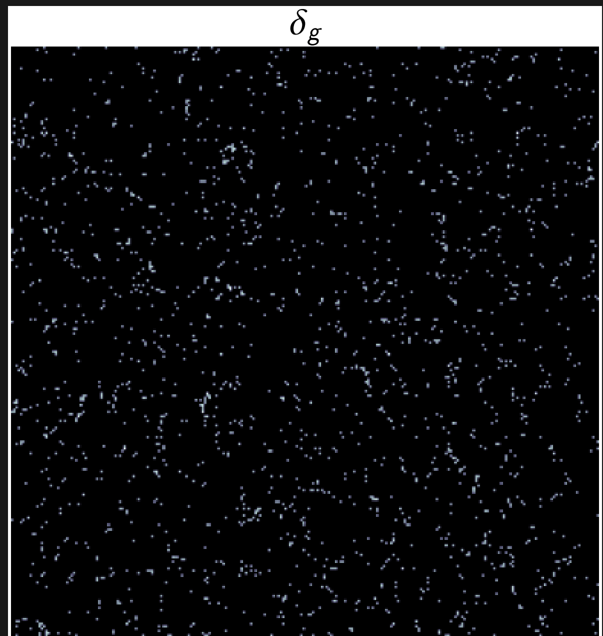
ROBIN-PiP $\times$ BORG

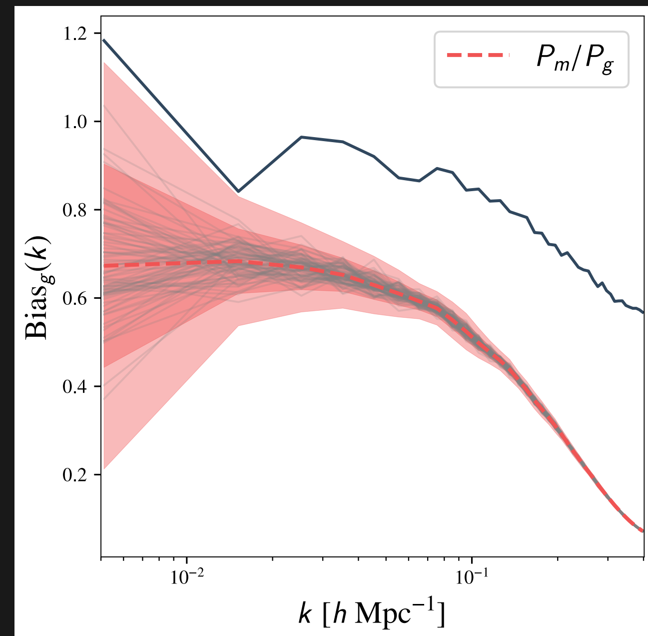




Galaxy clustering log-likelihood $+$ w Robin-PiP

ROBIN-PiP $\times$ BORG





Galaxy clustering log-likelihood $+$ w Robin-PiP

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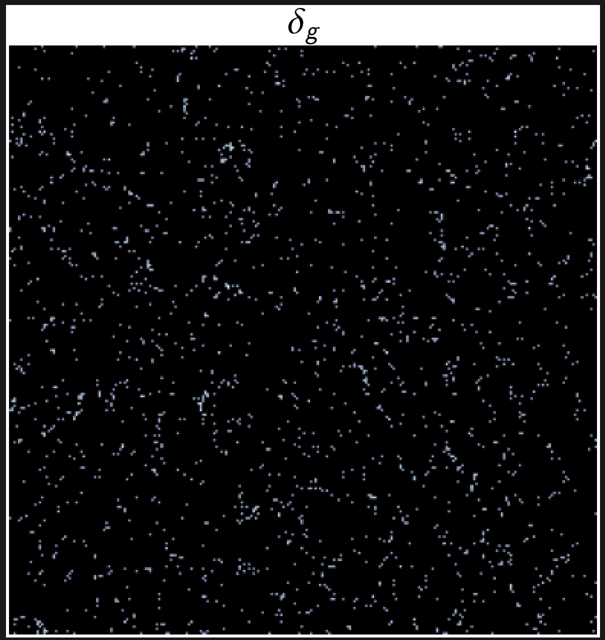
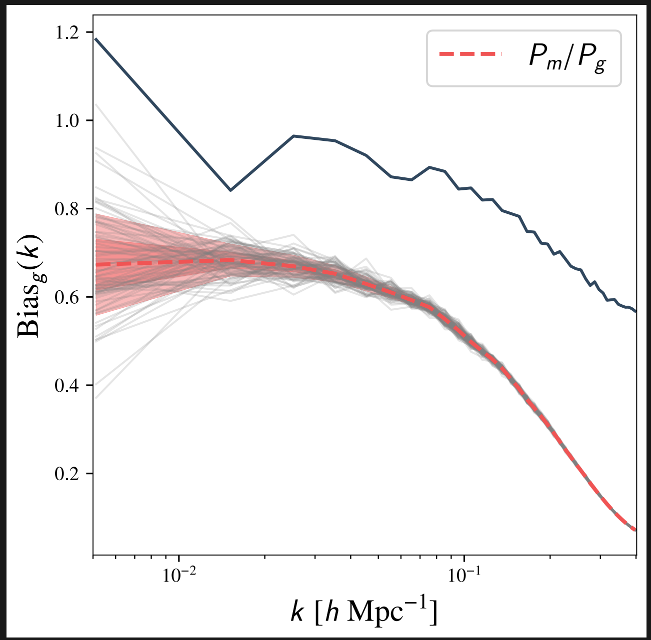
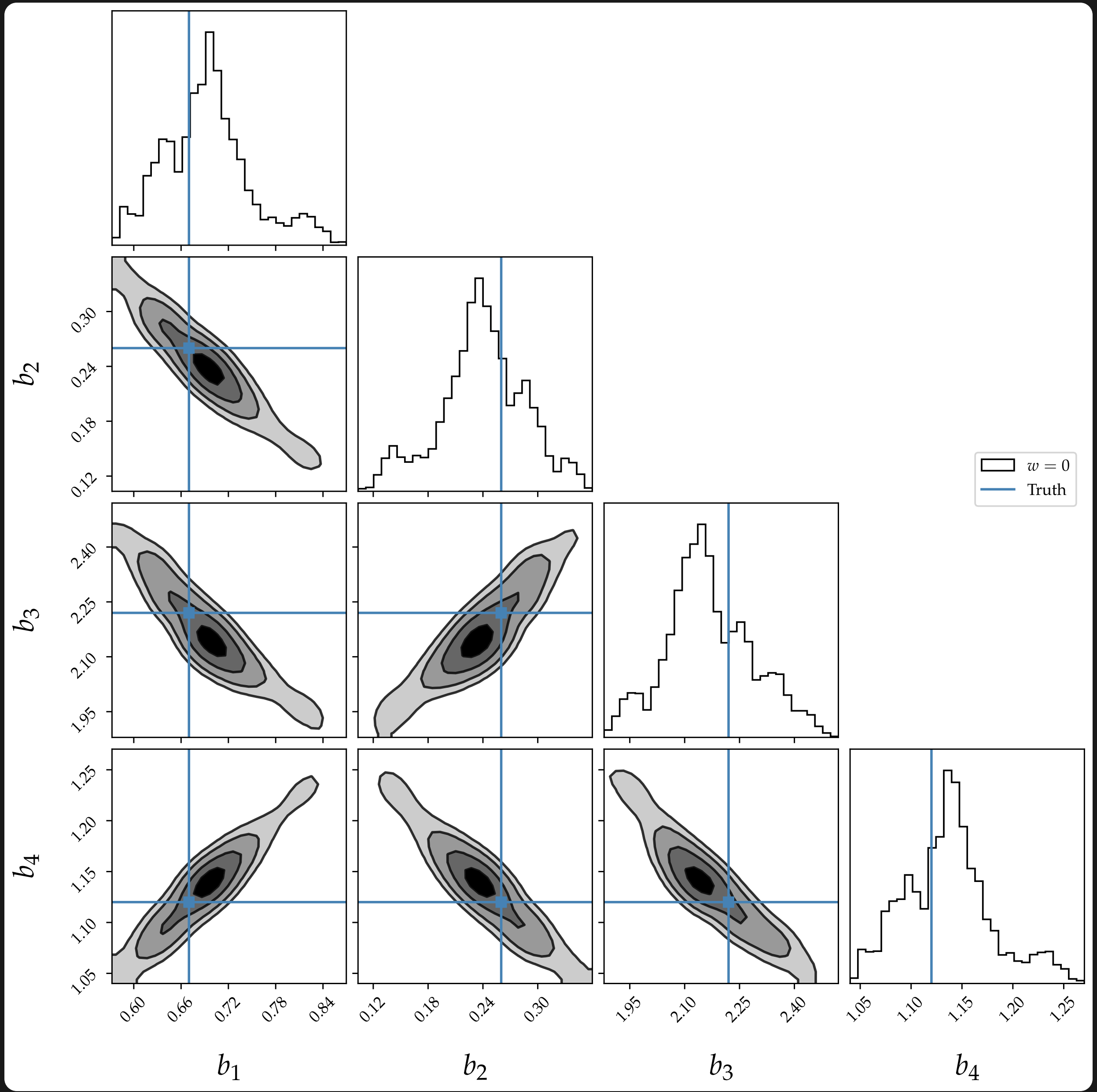
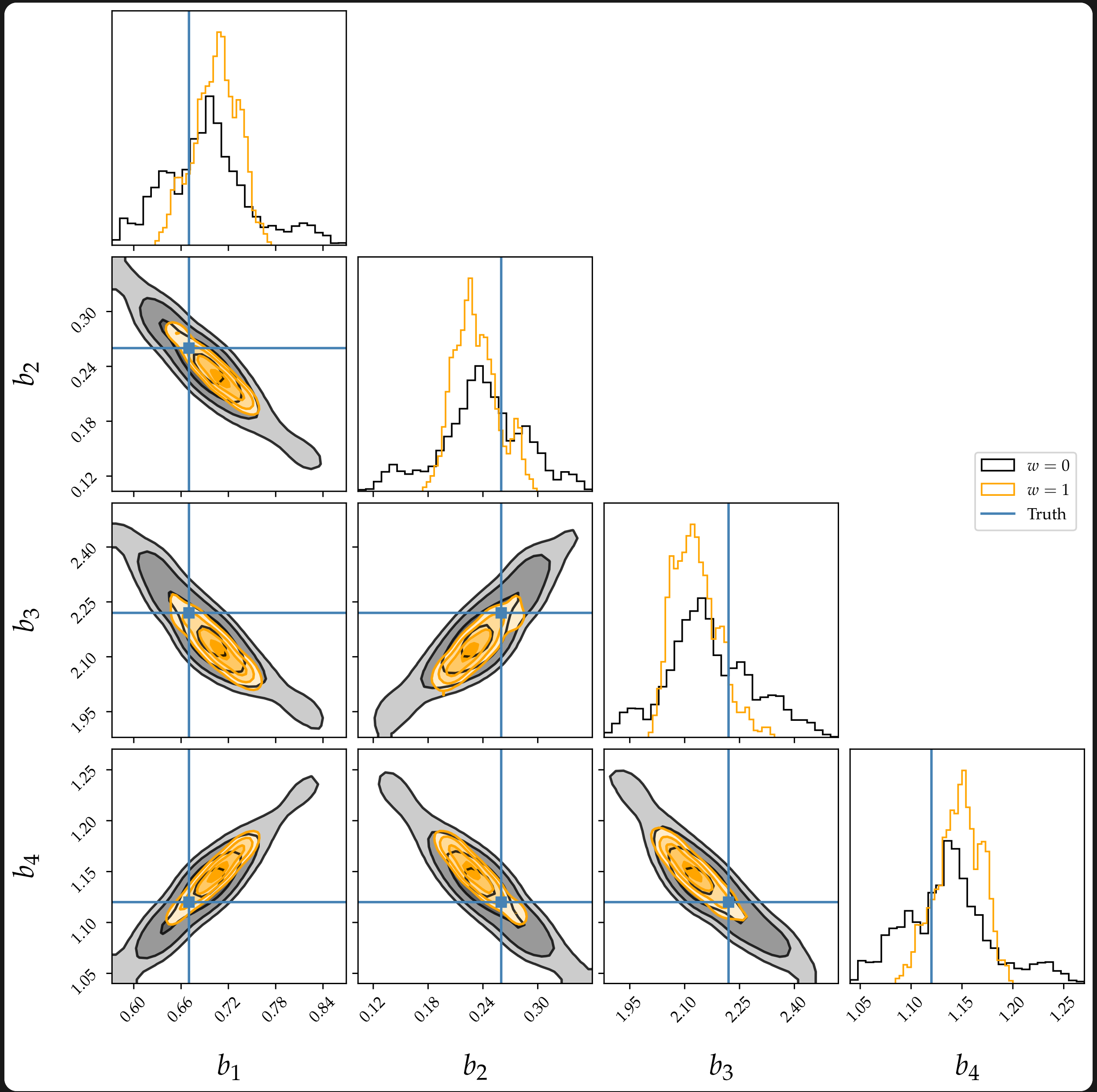


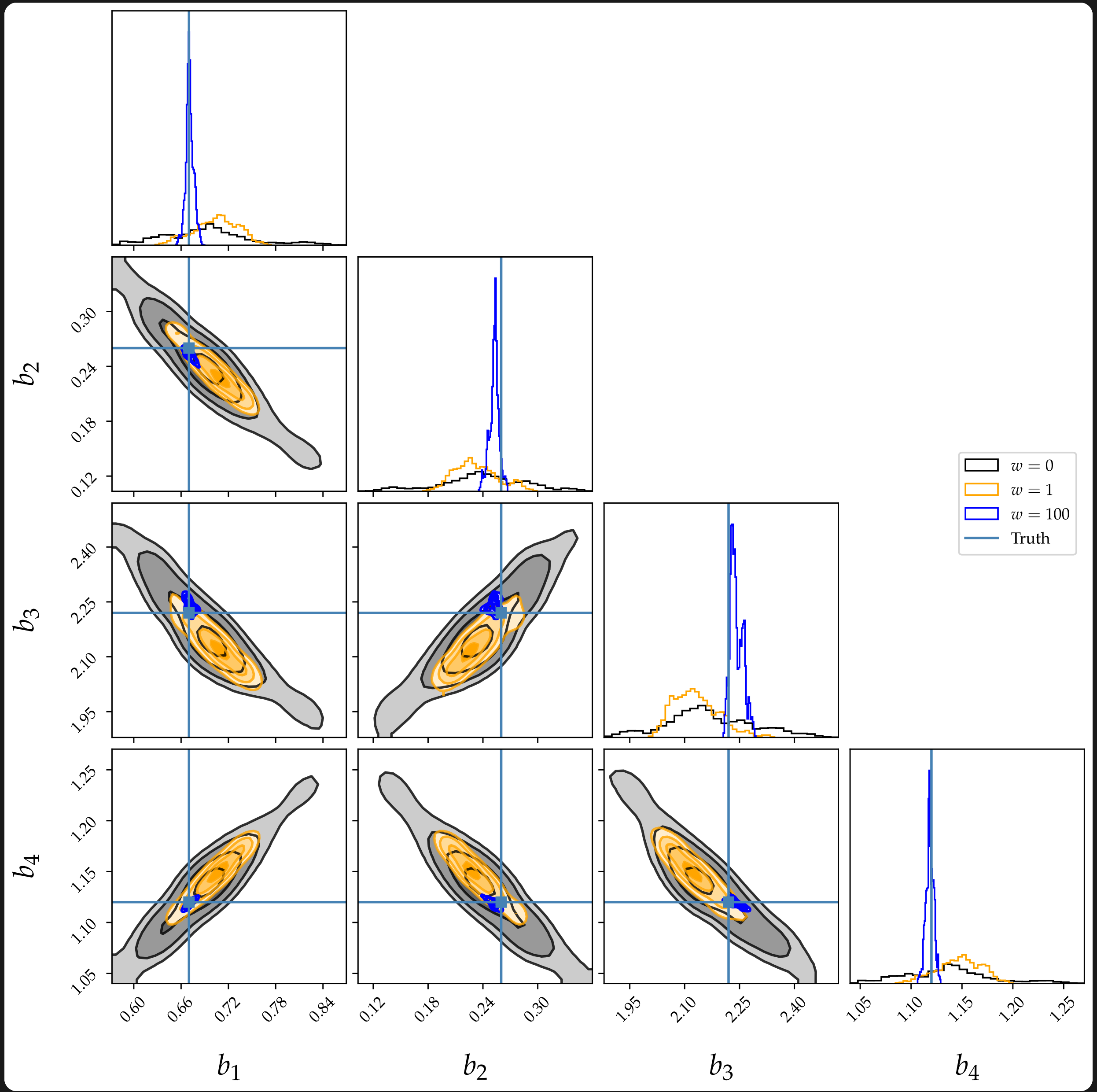


Galaxy clustering log-likelihood $+$ w Robin-PiP


$w = 0$
Truth
b_1
b_2
b_3
b_4

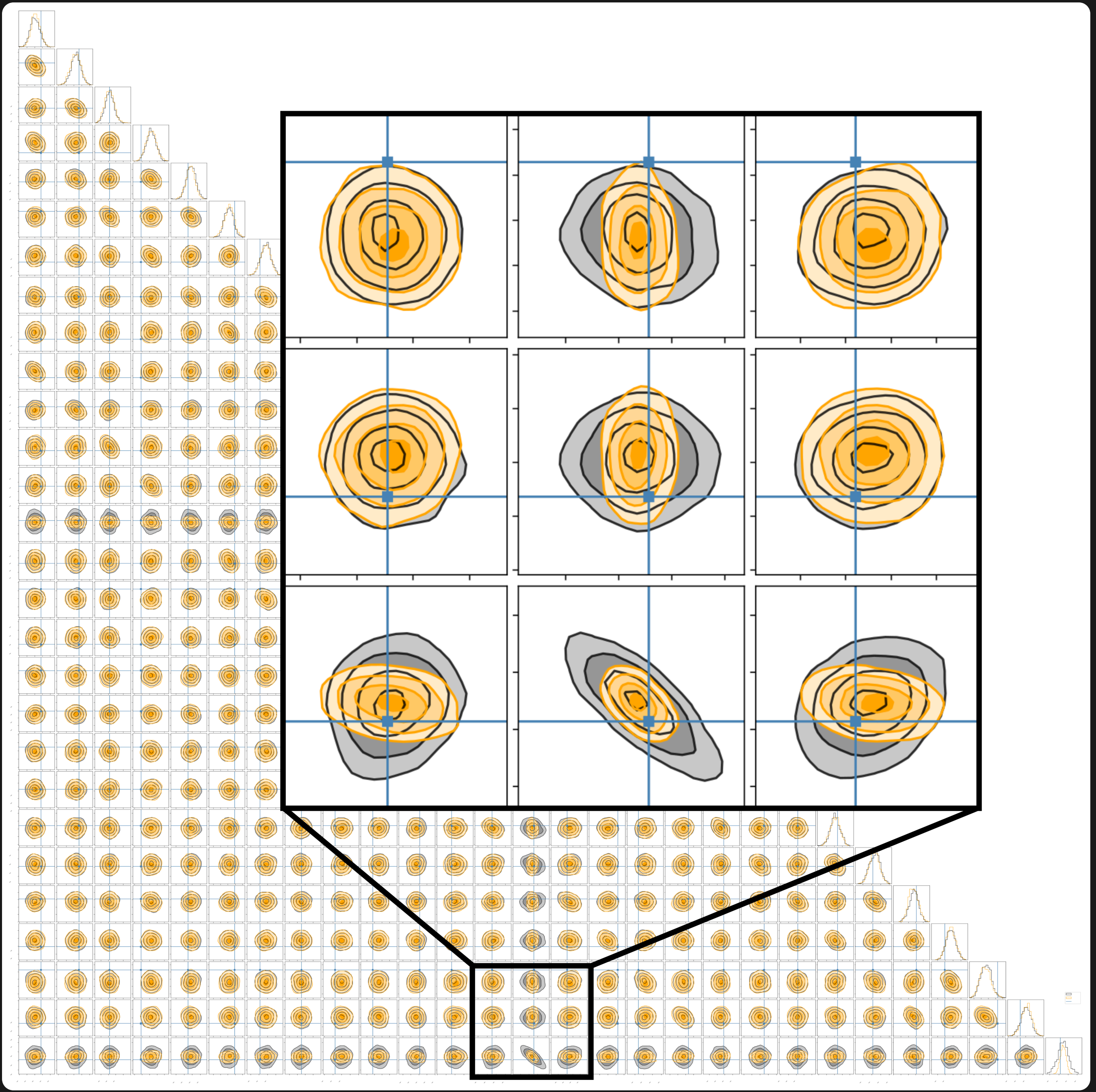


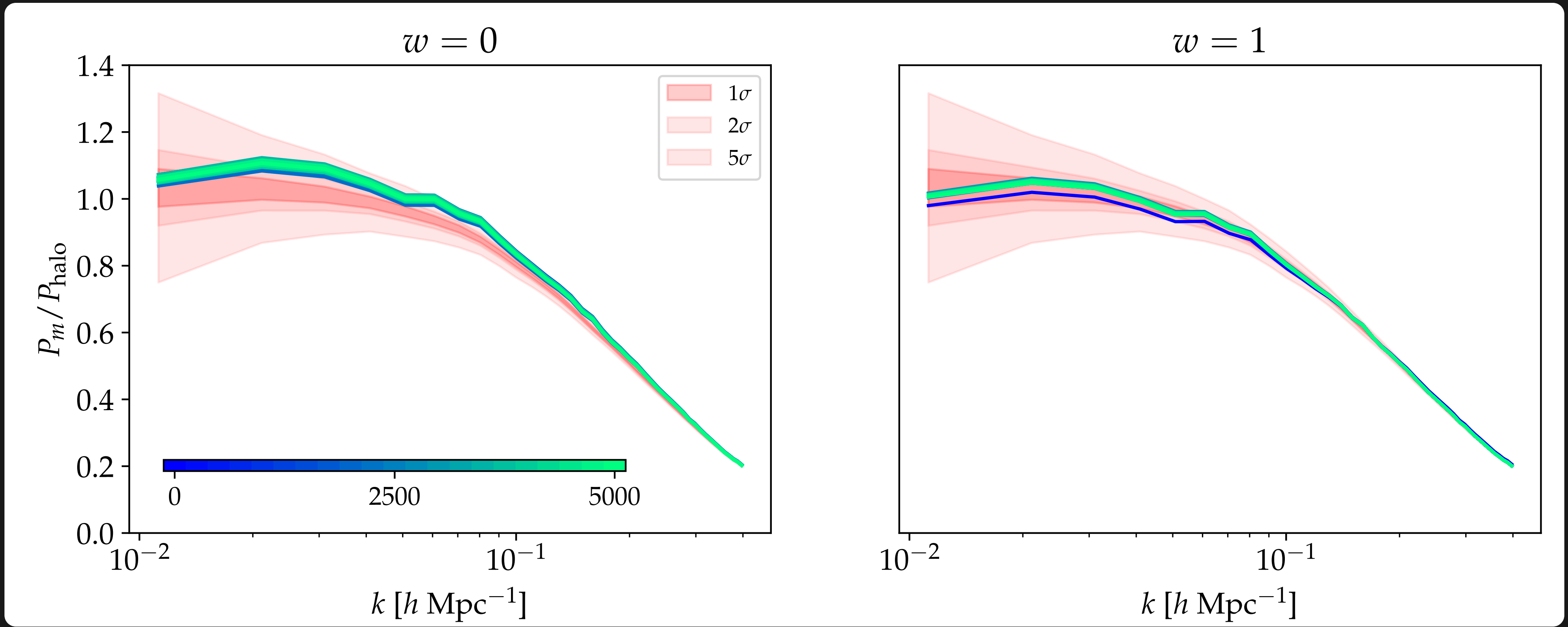
$w = 0$
$w = 1$
Truth
b_1
b_2
b_3
b_4
0.60
0.66
0.72
0.78
0.84
0.12
0.18
0.24
0.30
1.95
2.10
2.25
2.40
1.05
1.10
1.15
1.20
1.25



w = 0
w = 1
w = 100
Truth
b1
b2
b3
b4
0.60
0.66
0.72
0.78
0.84
0.12
0.18
0.24
0.30
1.95
2.10
2.25
2.40
1.05
1.10
1.15
1.20
1.25

14.2




$w = 0$
$w = 1$
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
P_m / P_{halo}
1σ
2σ
5σ
0
2500
5000
10^{-2}
10^{-1}
k [h Mpc^{-1}]

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using ROBIN-PiP

BAYESIAN INFERENCE WITH PHYSICS INFORMED PRIORS

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- Principled way of incorporating simulations into inference

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using ROBIN-PiP

- Principled way of incorporating simulations into inference
- Model agnostic

BAYESIAN INFERENCE WITH PHYSICS INFORMED PRIORS

using ROBIN-PiP

- Principled way of incorporating simulations into inference
- Model agnostic
- Can enable direct inference of more sophisticated model e.g. neural networks