The era of simulation-based inference for gravitational lensing

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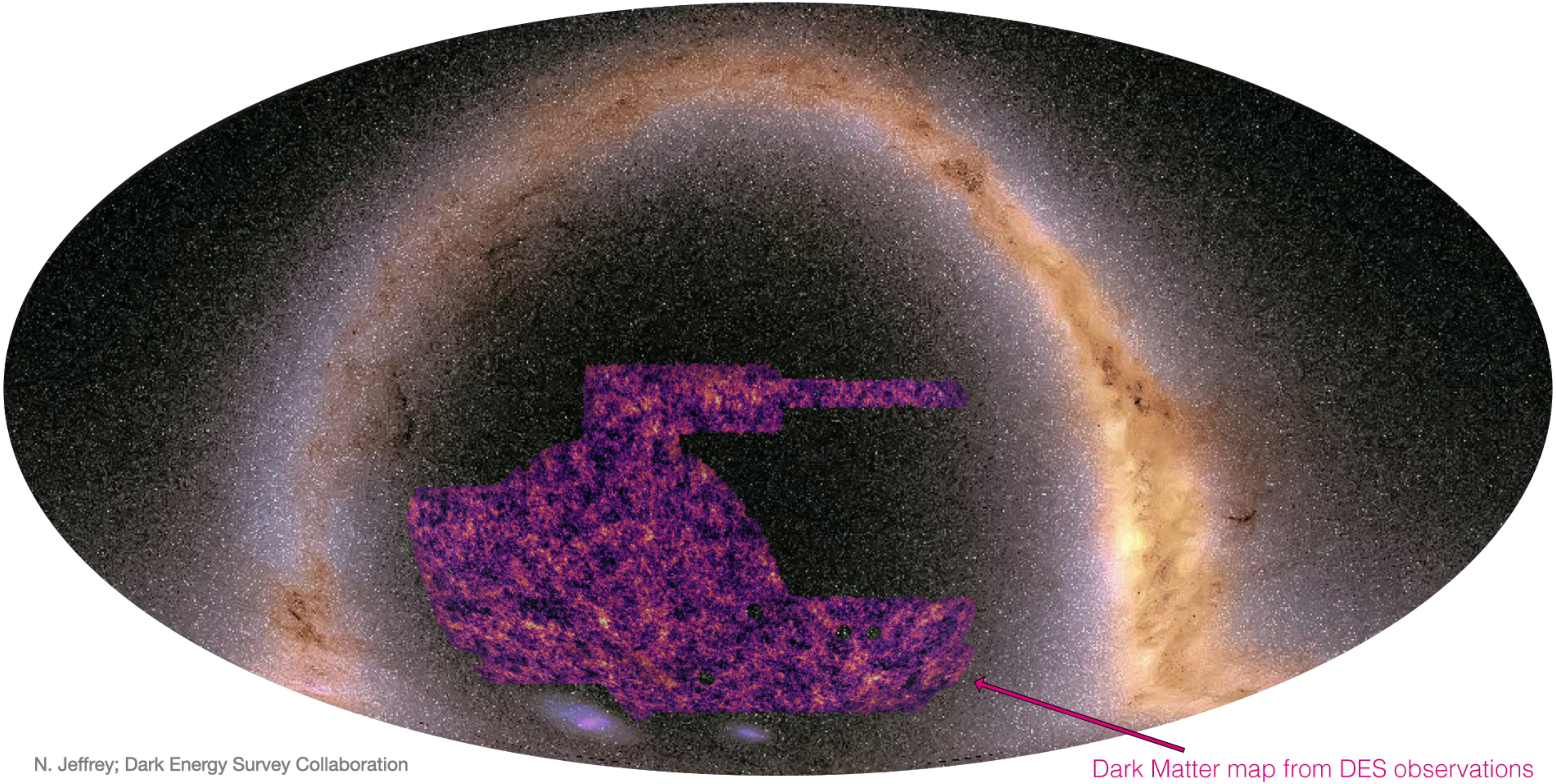


N. Jeffrey; Dark Energy Survey Collaboration

Simulation-based inference:
SBI

Accuracy

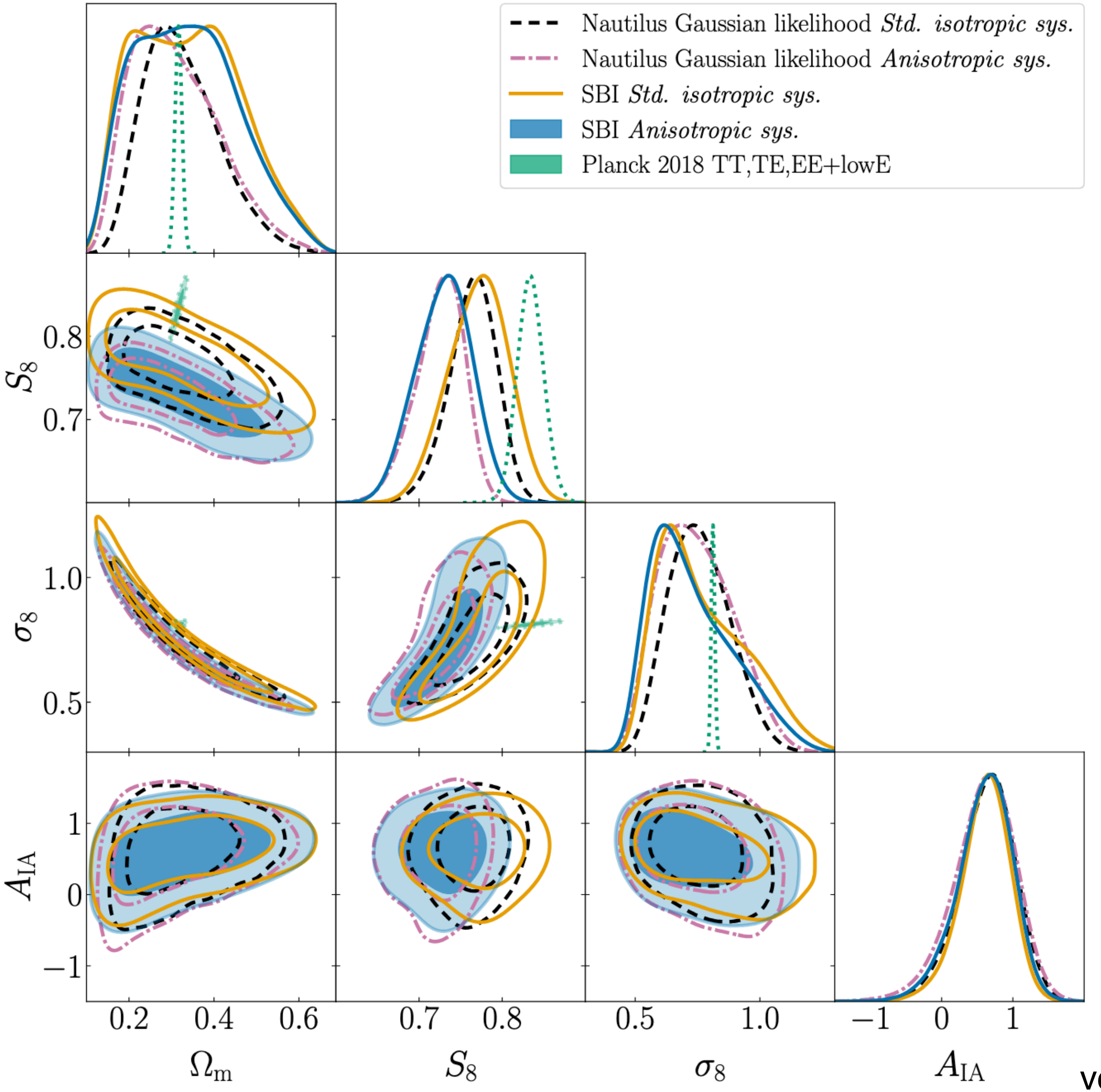
Realistic forward modelling

Precision

Beyond classical statistics
(e.g. power spectra)

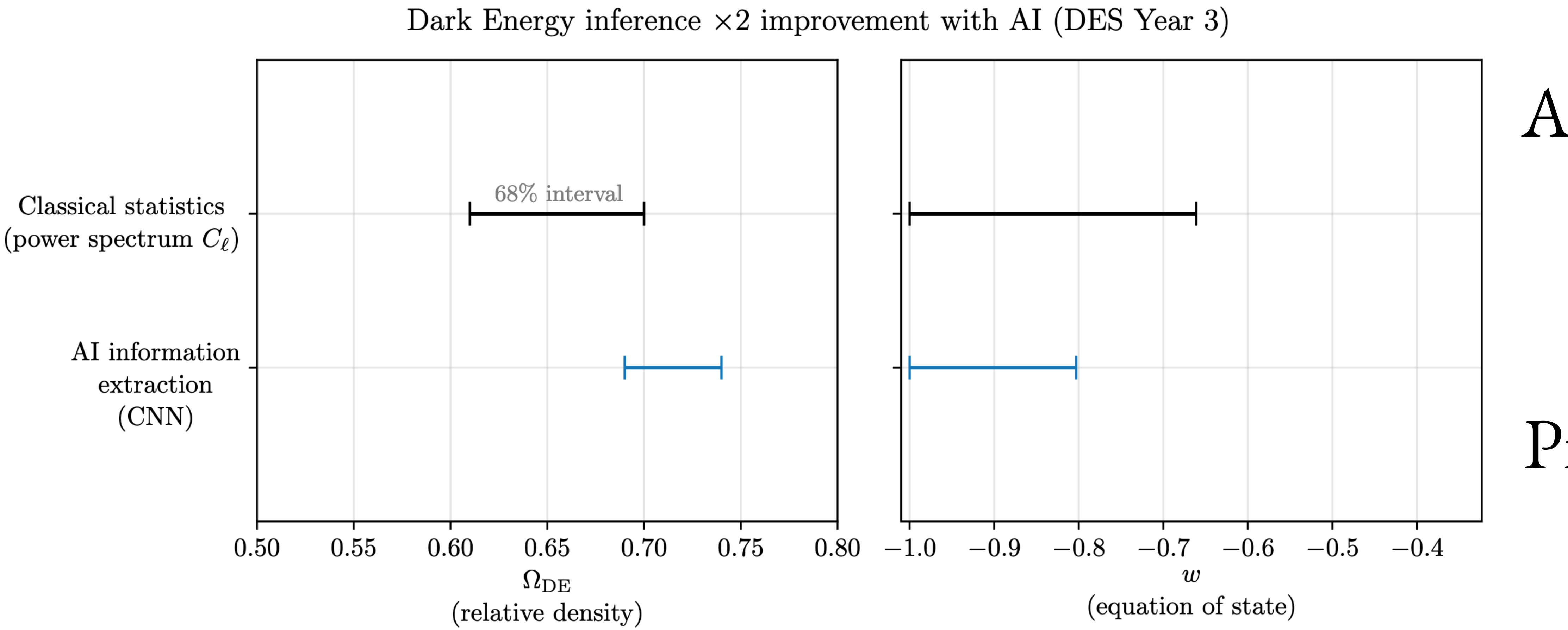
KiDS results

Accuracy



von Wietersheim-Kramsta 2404.15402

Dark Energy Survey (DES) results



Accuracy

+

Precision

New DES results: https://arxiv.org/abs/2403.02314 ; **NJ** et al. DES Collaboration

Outline

1. Simulation-based inference
2. Simulating the data
3. Results — how do I know this is right?

1. Simulation-based inference

Data x, Model M

Model parameters

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

Data x, Model M

Data x, Model M

Model parameters

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

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

Model parameters

$$p(\theta \mid x, M)$$

Data x, Model M $\Rightarrow$

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

if you are interested in model comparison, see https://arxiv.org/abs/2305.11241 **NJ** & Wandelt

Parameter inference:

"Likelihood"

$$p(\theta \,|\, x, M) \propto p(x \,|\, \theta, M)\; p(\theta \,|\, M)$$

Likelihood-free inference

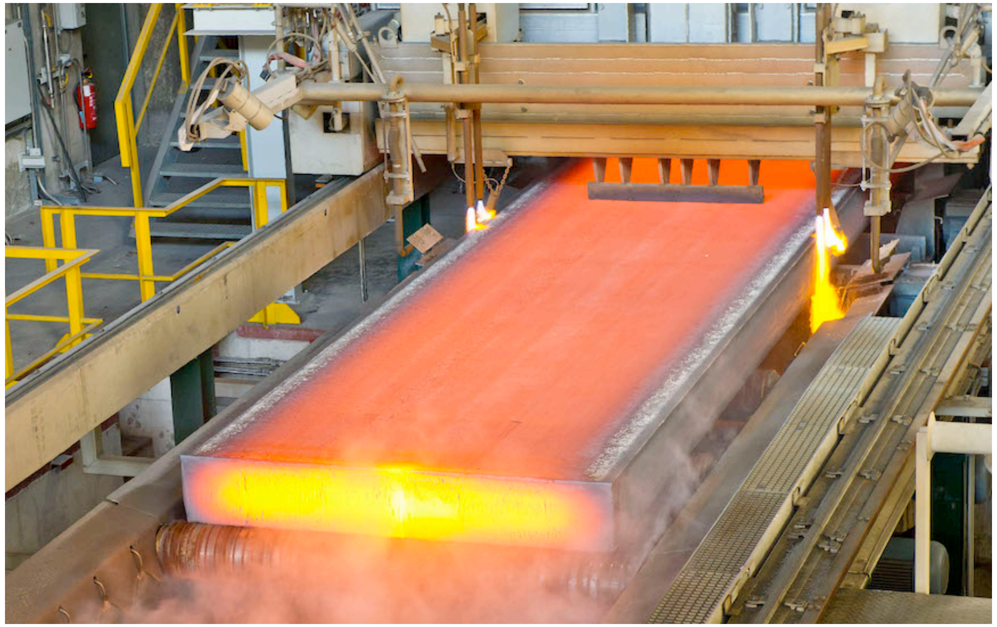
$$p(x \,|\, \theta) \ ?$$

Draw x_i from the distribution $p(x \,|\, \theta_i)$ by running a simulation:

$$\{x_i, \theta_i\}$$

Industry example: inferring Stress

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



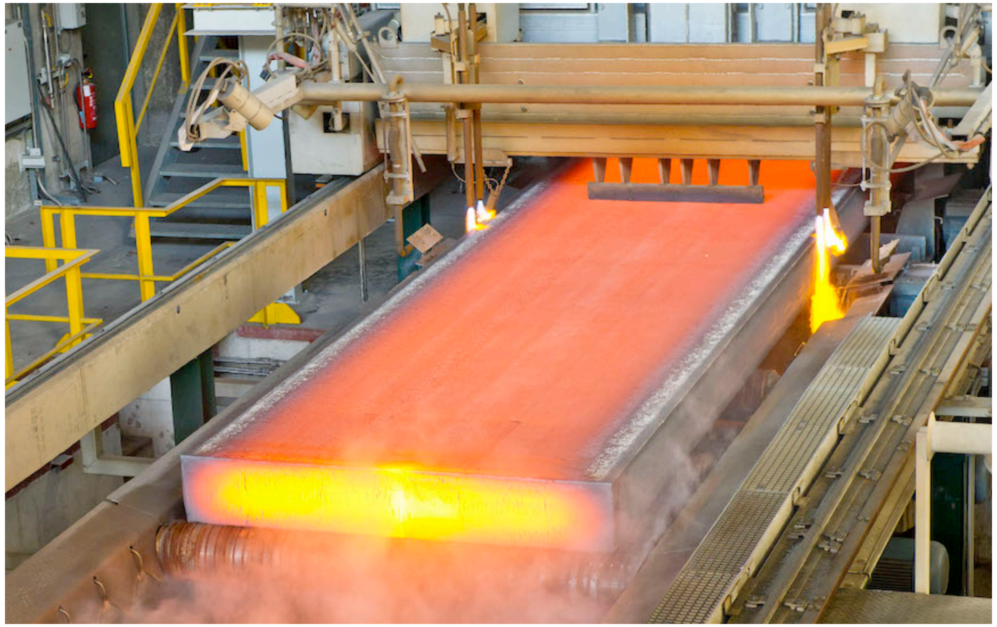
EuroMetal.net

CALDA.AI

Industry example: inferring Stress

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

Data: x
(Temperature / K)



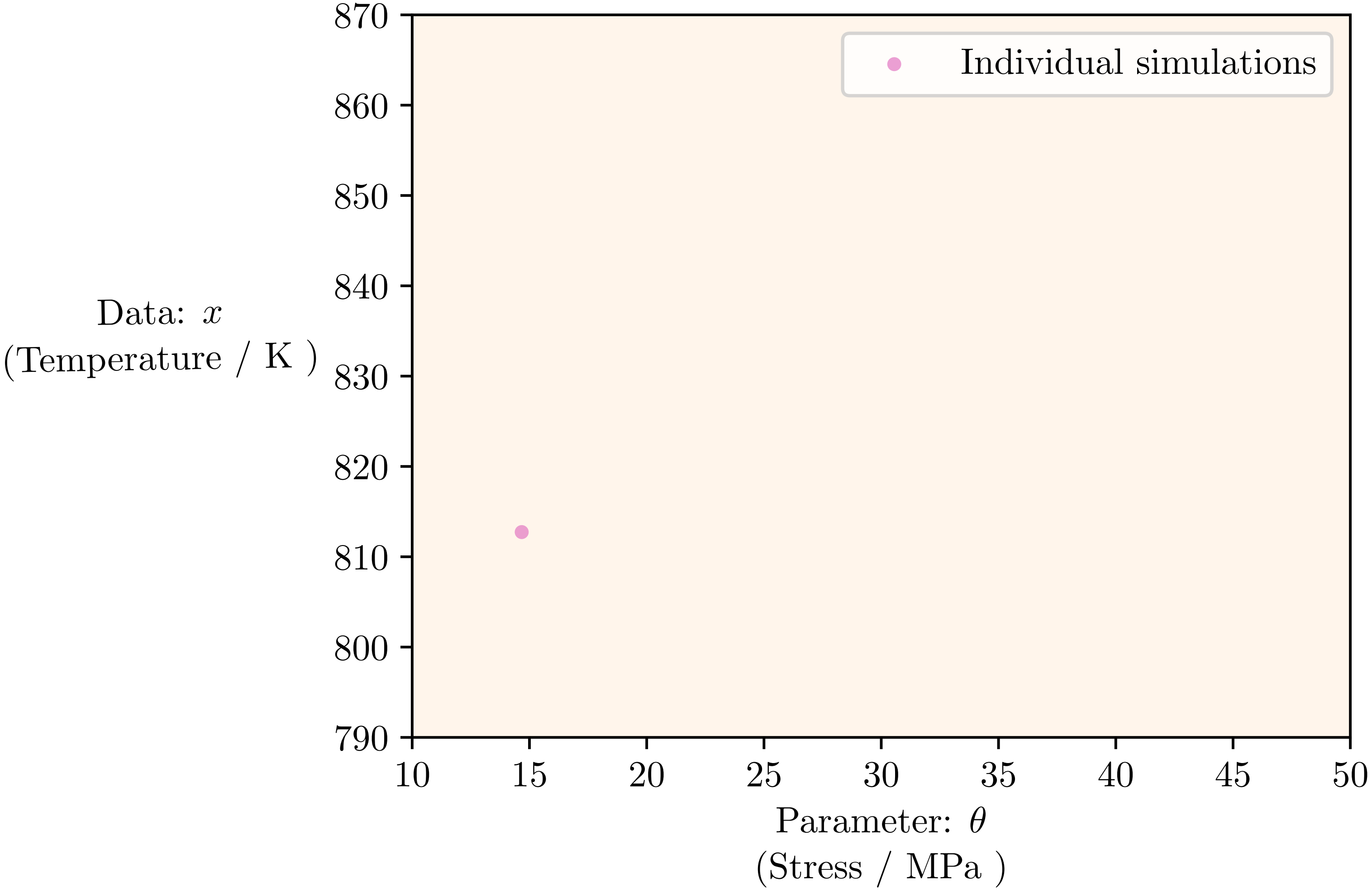
EuroMetal.net

Parameter: θ
(Stress / MPa)

CALDA.AI

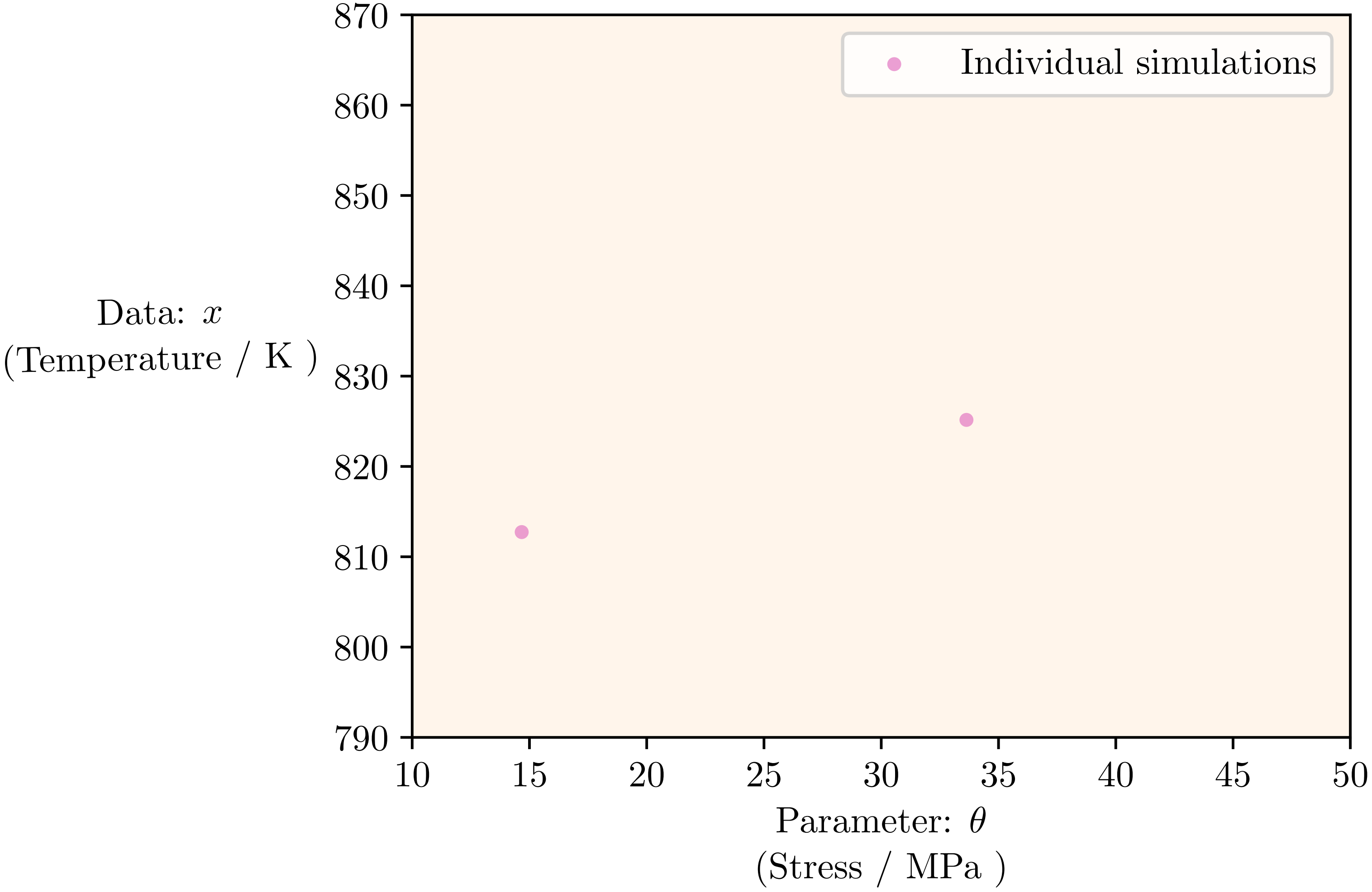
Industry example: inferring Stress

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



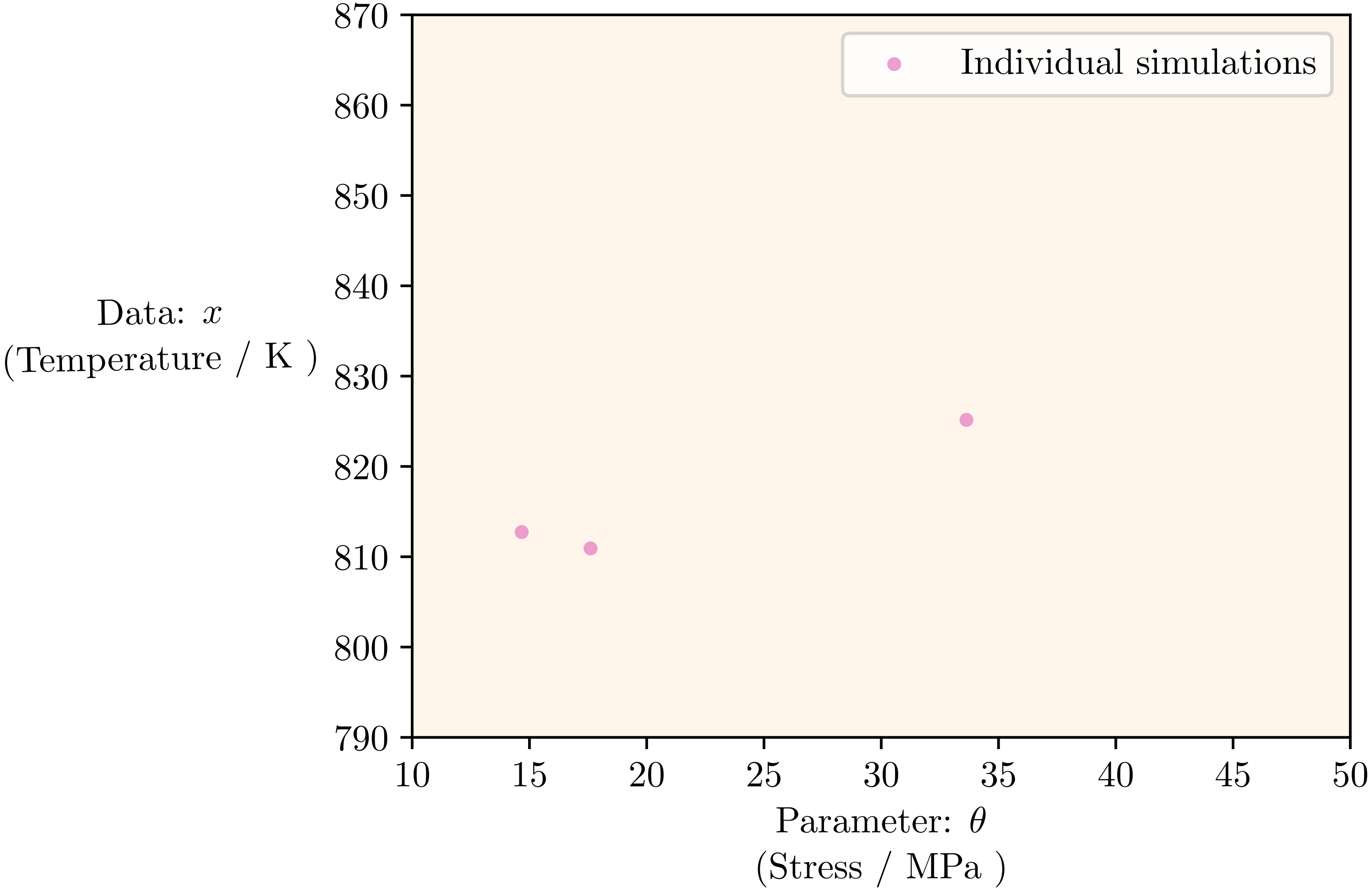
Industry example: inferring Stress

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



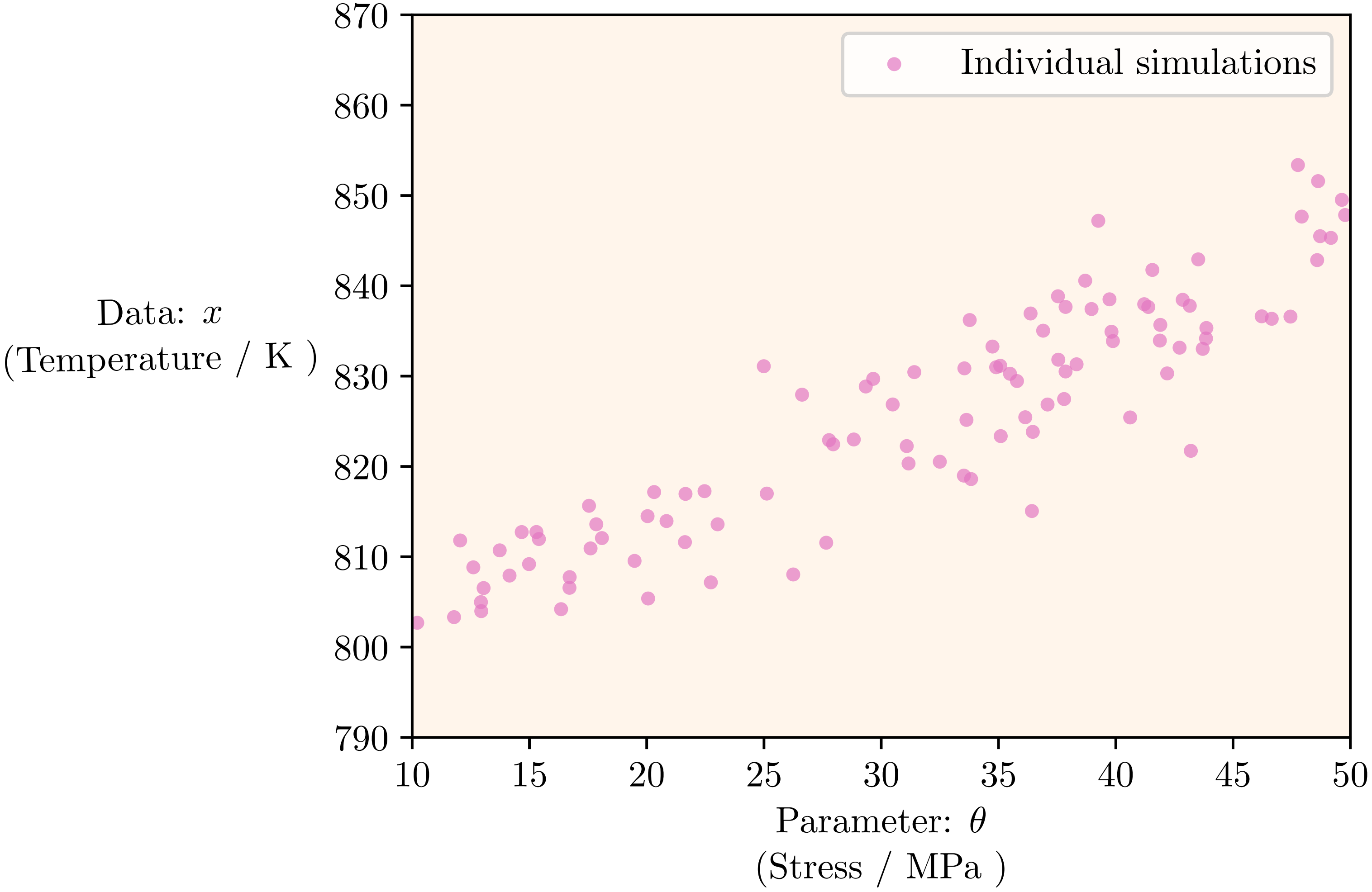
Industry example: inferring Stress

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



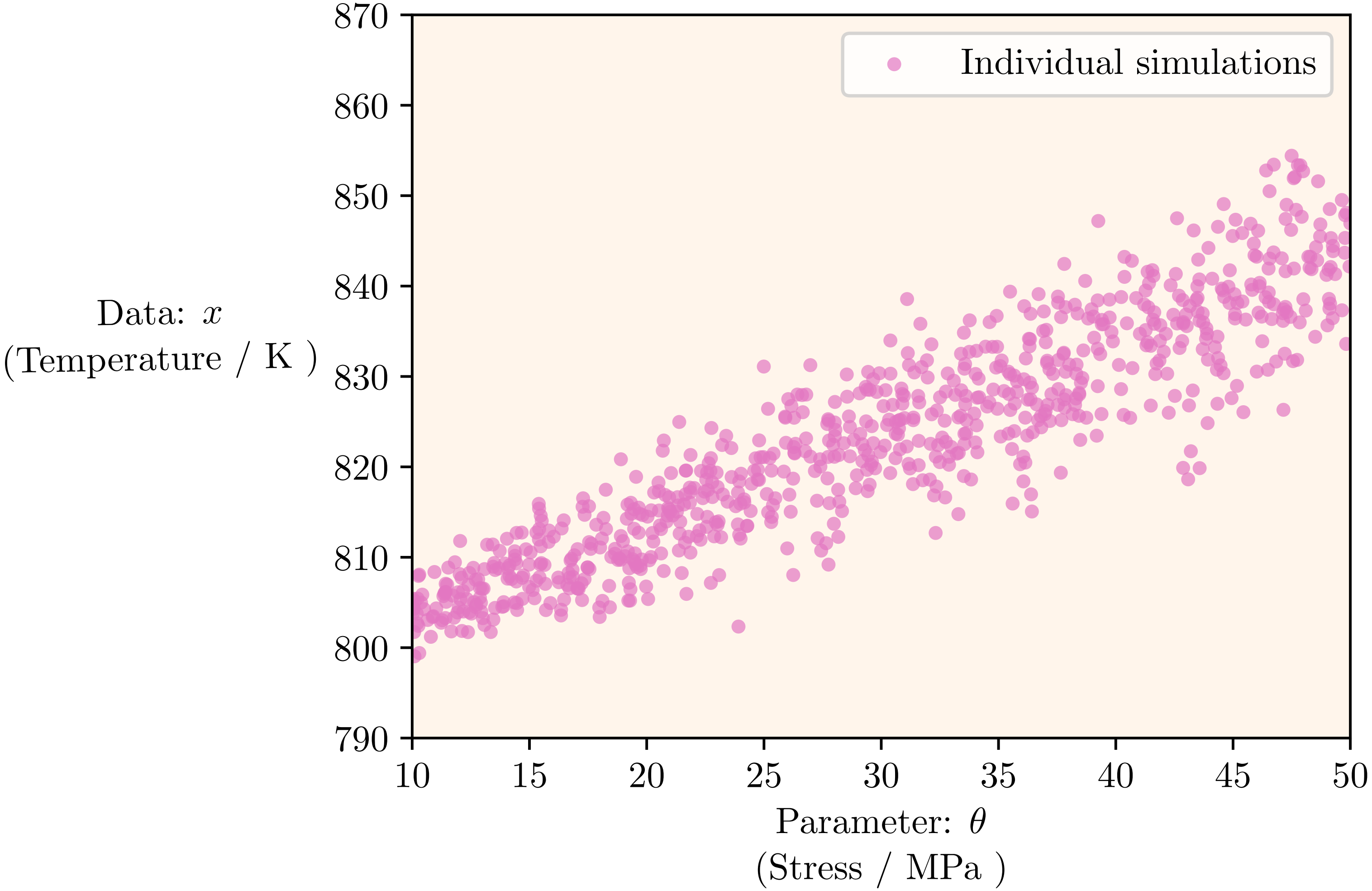
Industry example: inferring Stress

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



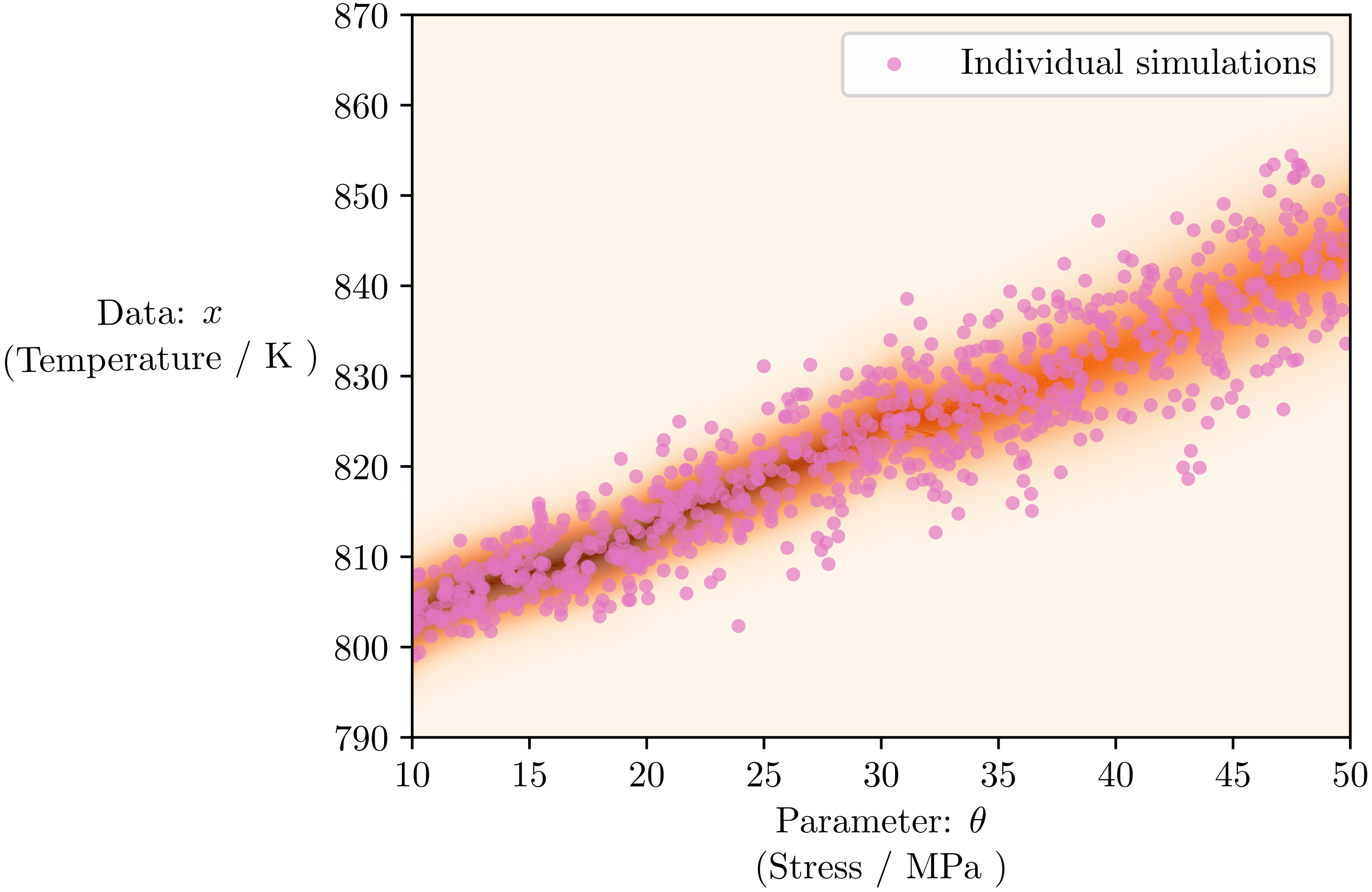
Industry example: inferring Stress

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



Industry example: inferring Stress

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

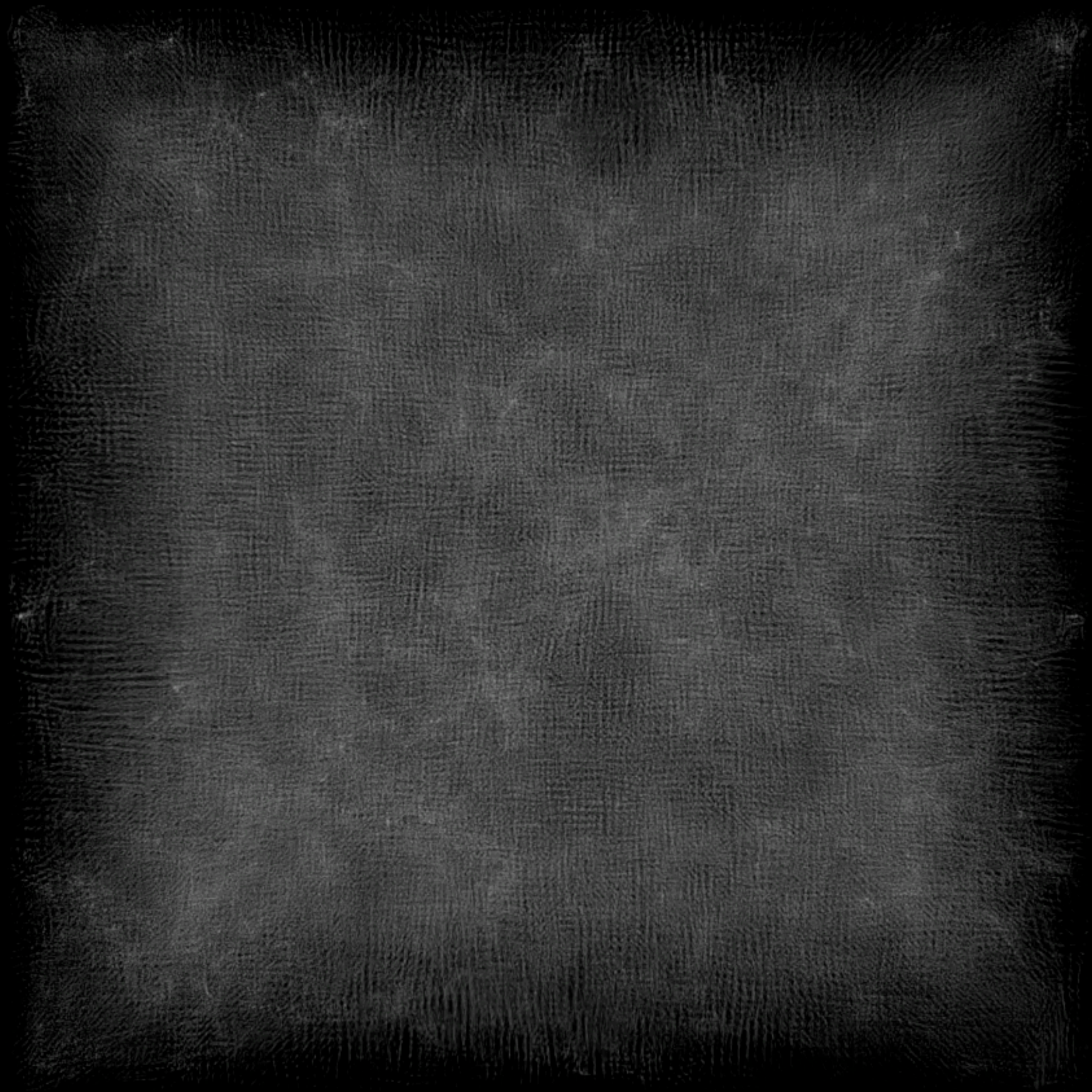


Neural Density Estimation

i.e. learning probability densities with AI

2. Simulating the data

Ω_{DE}
(relative density)

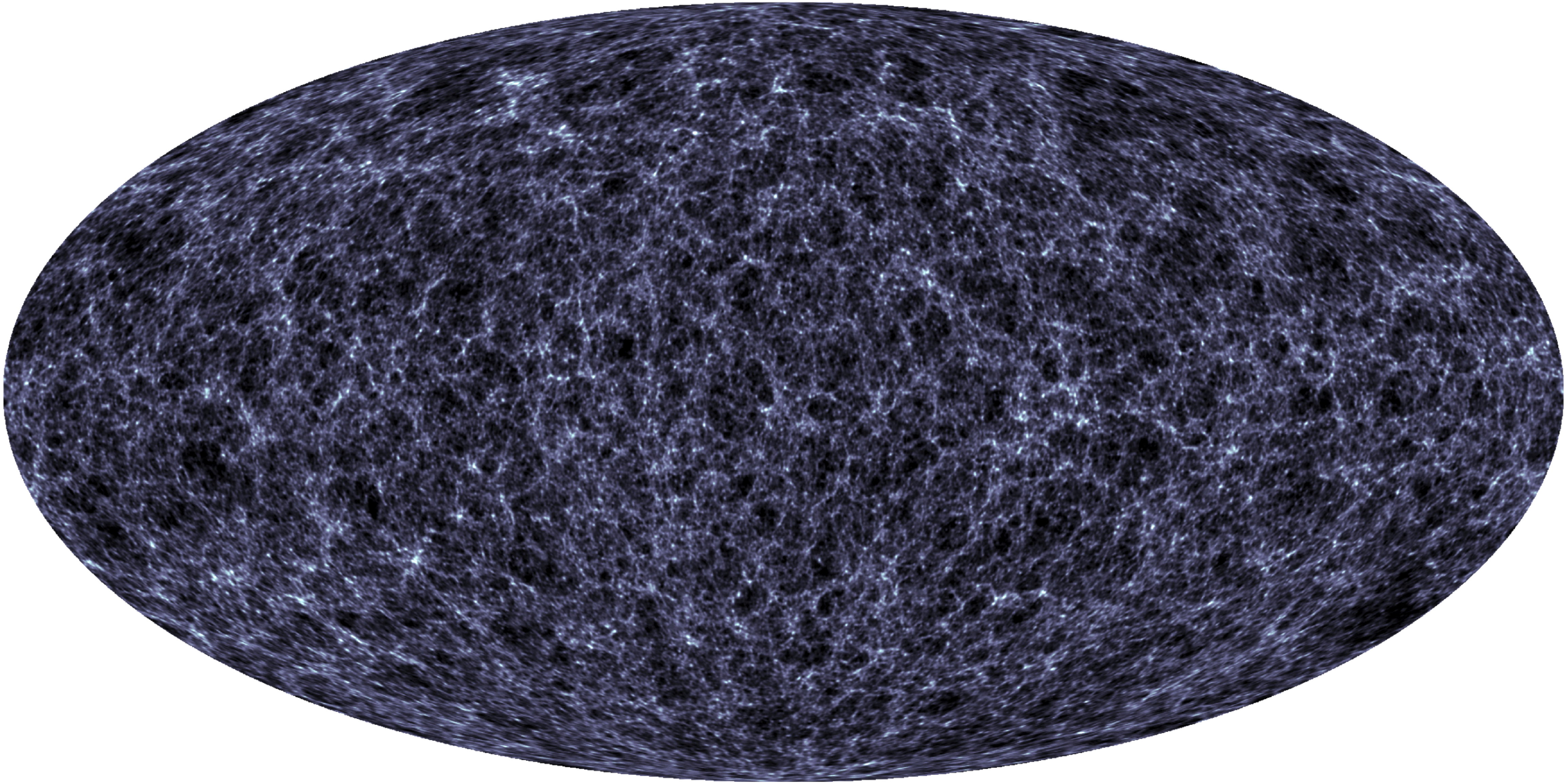


w
(equation of state)

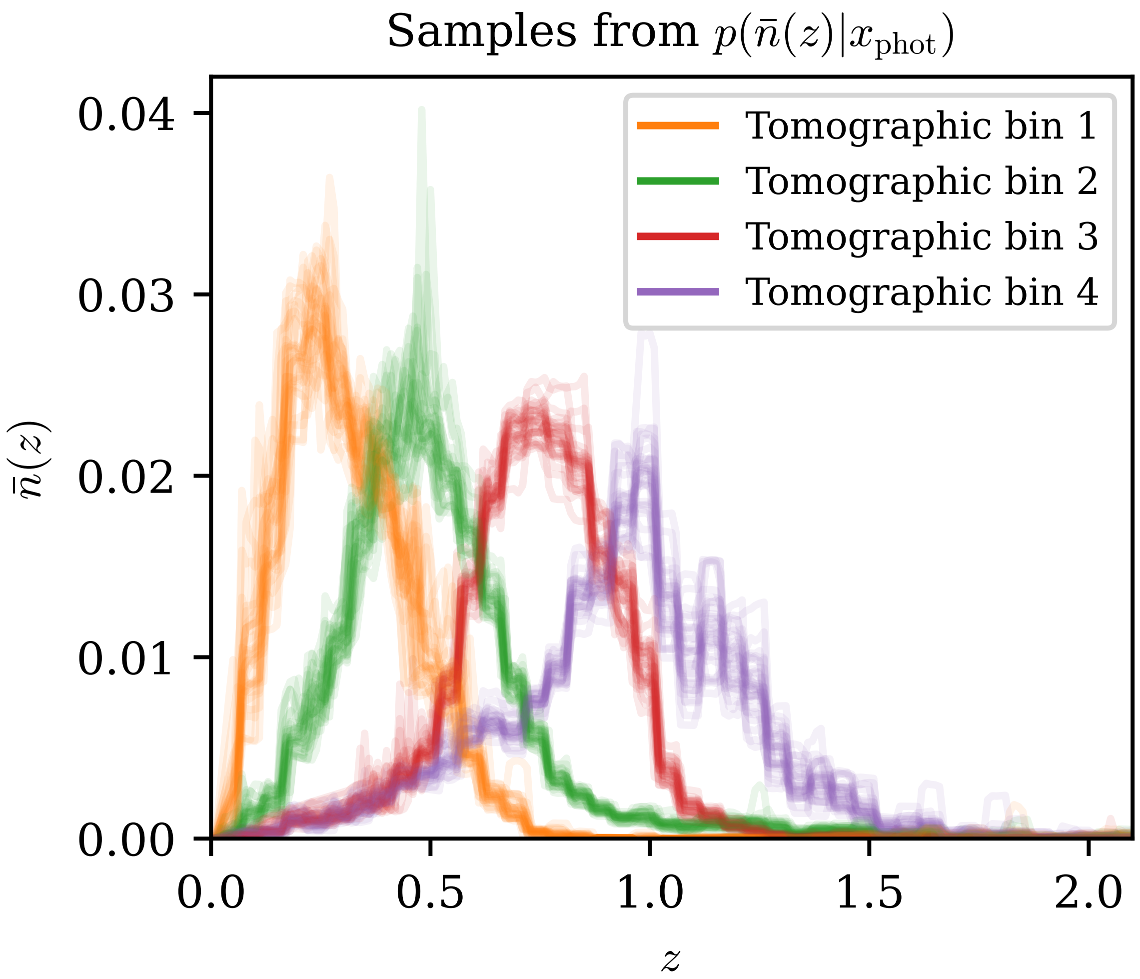
Credit: J. Williamson

Gower St (DiRAC) Simulations: 2403.02314

$\ln(\delta + 1)$

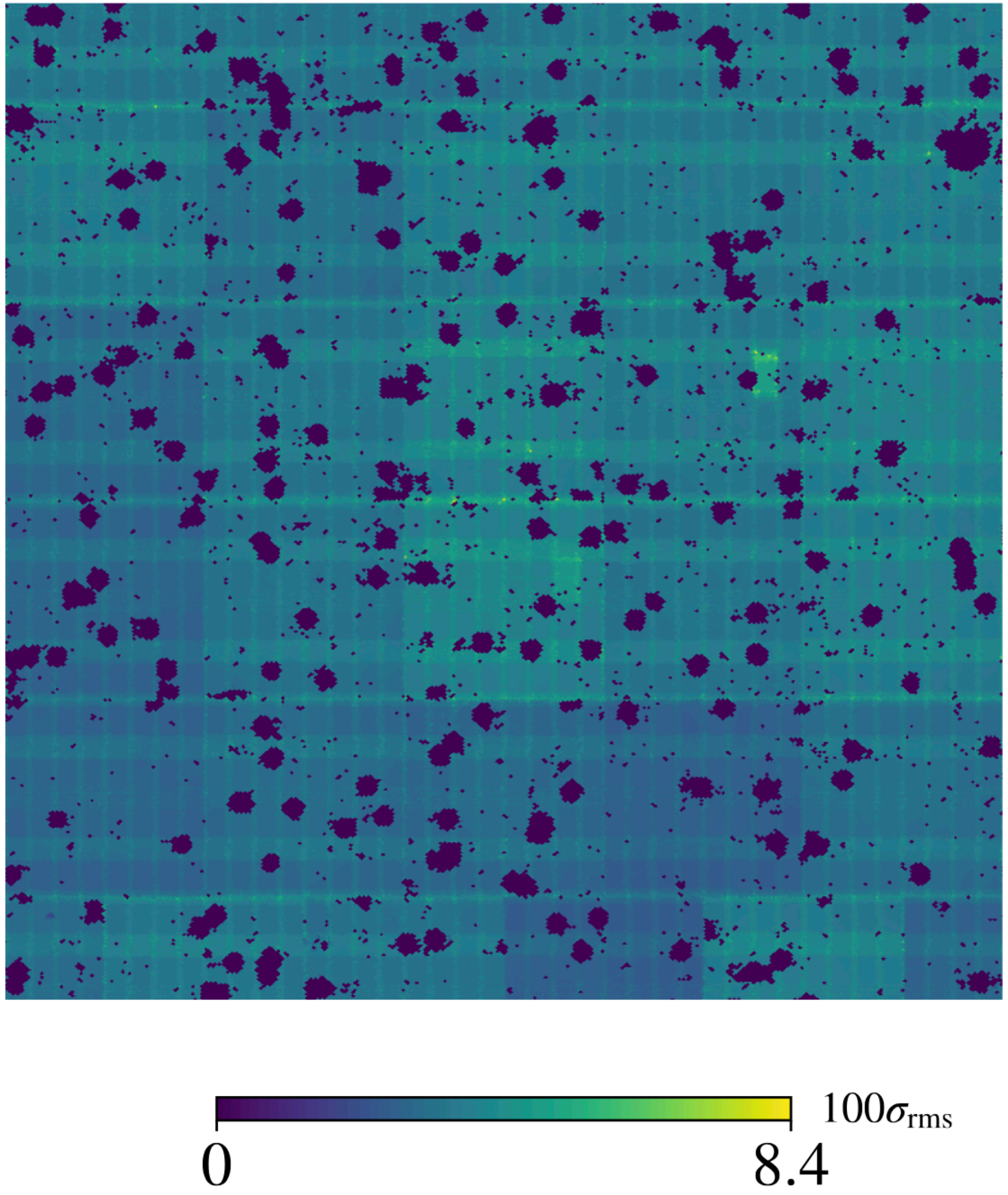


Systematics modelling



Intrinsic alignments

KiDS: spatially varying depth and noise



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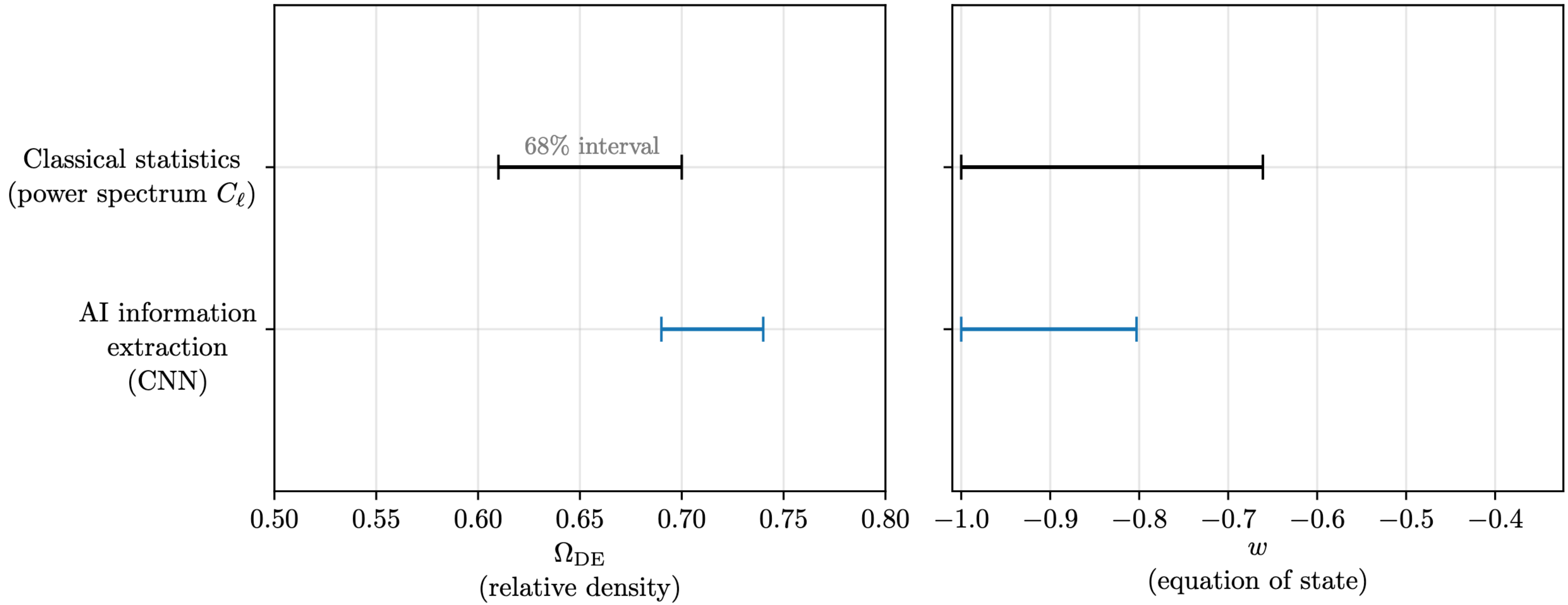
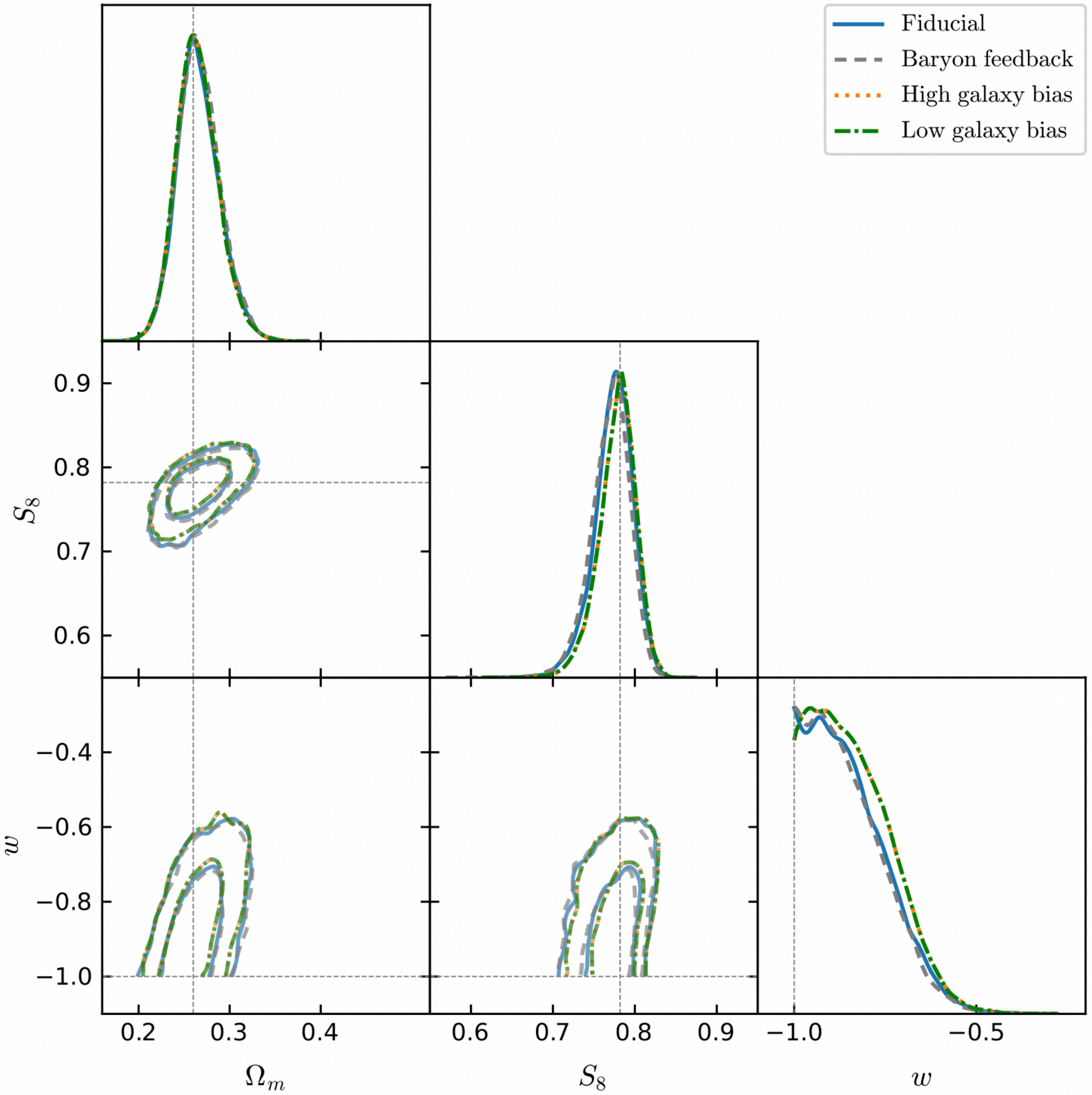
Dark Energy inference ×2 improvement with AI (DES Year 3)



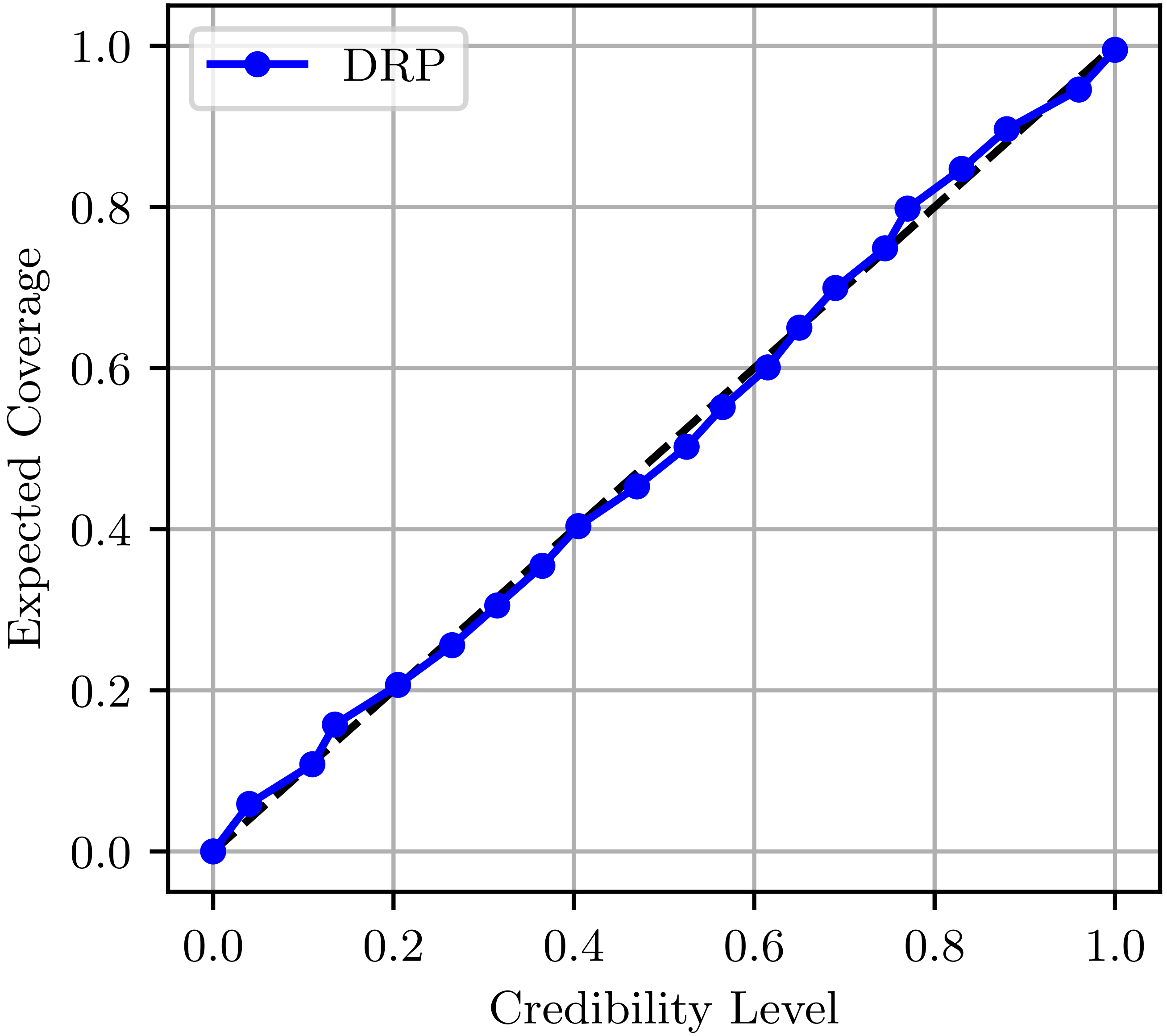
3. Results —

and how do we know this is right?

Injecting systematic error



How do I know this is right?



- Multiple Stage III papers:

  - DES 2-pt + map-level: https://arxiv.org/abs/2403.02314 ; **NJ** et al. DES Collaboration
  - DES wavelet moment results: https://arxiv.org/abs/2405.10881
  - DES persistent homology: https://arxiv.org/abs/2506.13439
  - KiDS 2-pt results: https://arxiv.org/abs/2404.15402
  - KiDS 2-pt methodology: https://arxiv.org/abs/2404.15402

  + if you are interested in model comparison: https://arxiv.org/abs/2305.11241 **NJ** & Wandelt

Summary

- New AI enabled statistical analysis (i.e. SBI) results improve:
    - Accuracy
    - Precision
- Gower St. Simulation Suite now available: http://www.star.ucl.ac.uk/GowerStreetSims/
- Multiple Stage III papers:

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