



SCUOLA
NORMALE
SUPERIORE

Simulation-Based Inference of the cosmic 21-cm signal

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PhD @ SNS Pisa

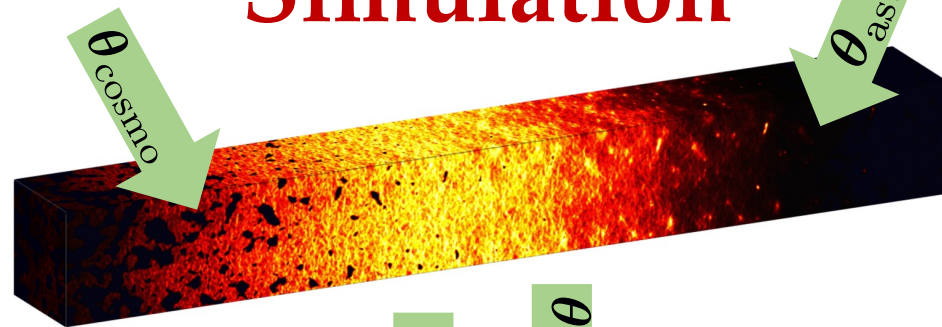
Supervisor: prof. Andrei Mesinger



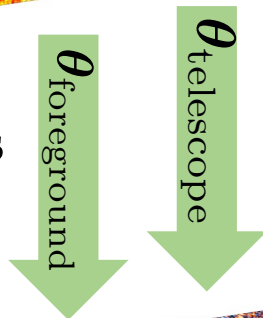
Cosmology

Astrophysics

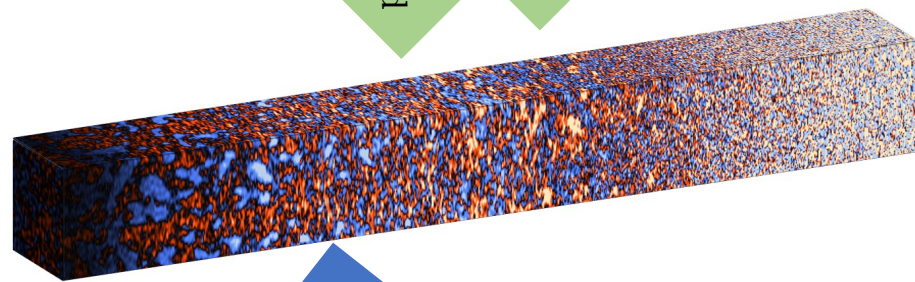
Simulation



Foregrounds simulator



Telescope simulator

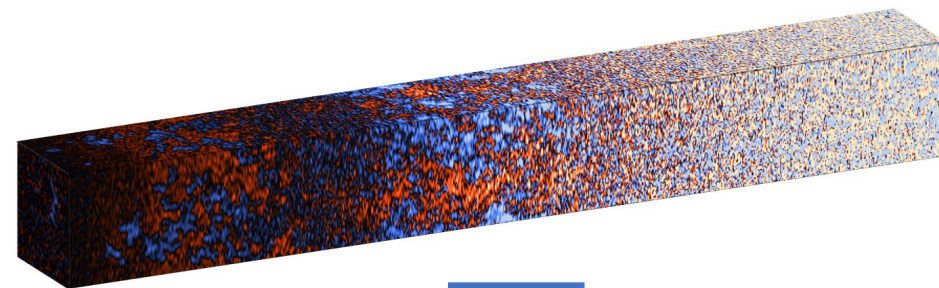


\mathcal{S}_{model}



\mathcal{S}_{data}

Observation



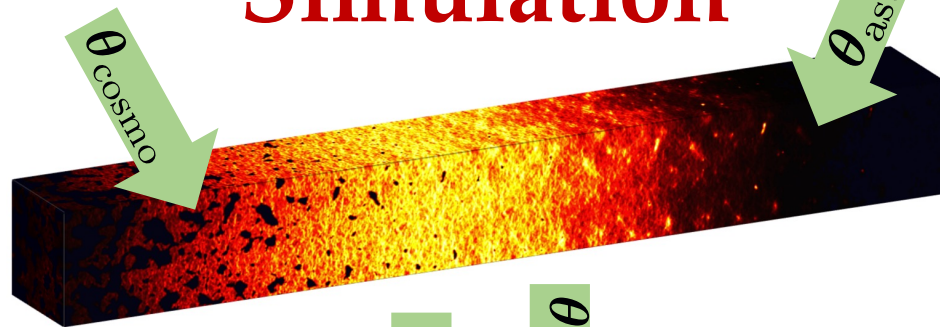
$P(\boldsymbol{\theta} | \mathcal{S}_{data})$



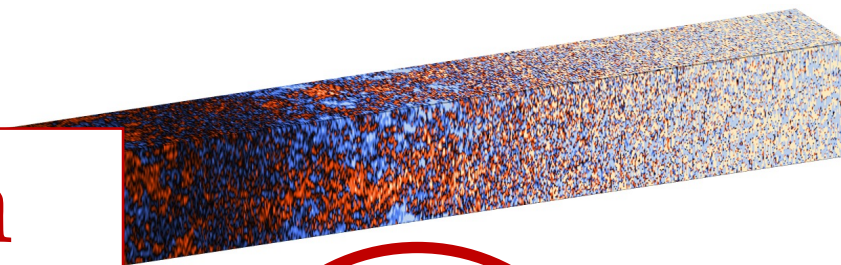
Cosmology

Astrophysics

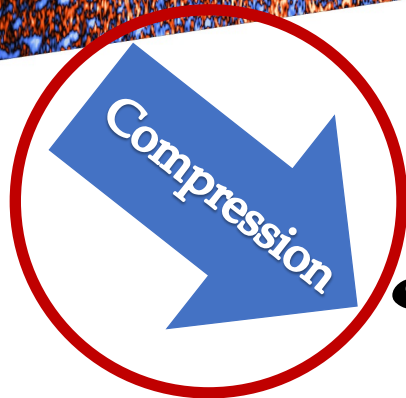
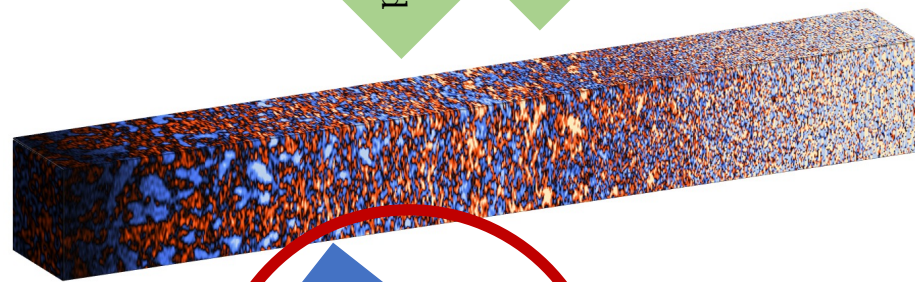
Simulation



Observation



1 – optimal compression



\mathcal{S}_{model}

Likelihood (analytic / SBI)

\mathcal{S}_{data}



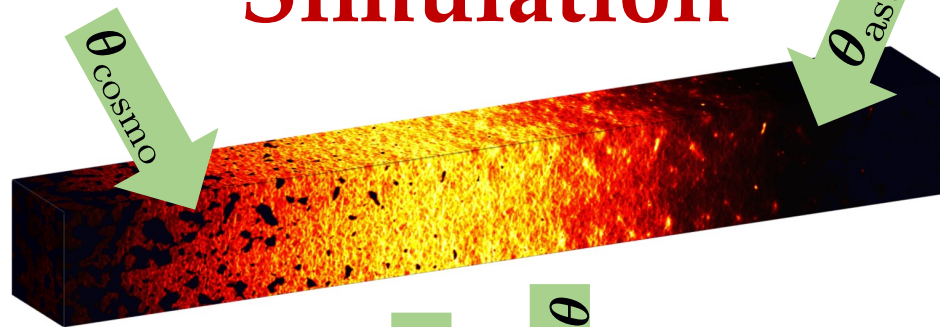
$$P(\theta | \mathcal{S}_{data})$$



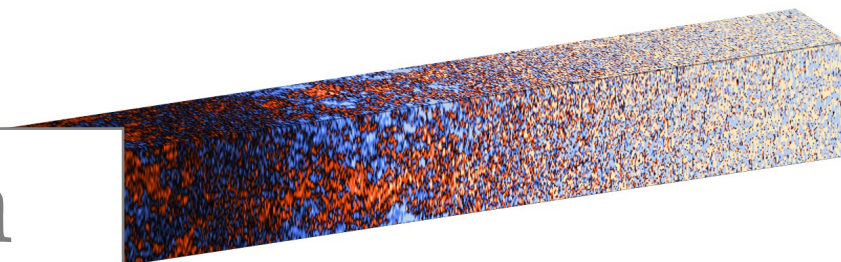
Cosmology

Astrophysics

Simulation



Observation



1 – optimal compression

2 – “optimal” likelihood



\mathcal{S}_{model}



\mathcal{S}_{data}

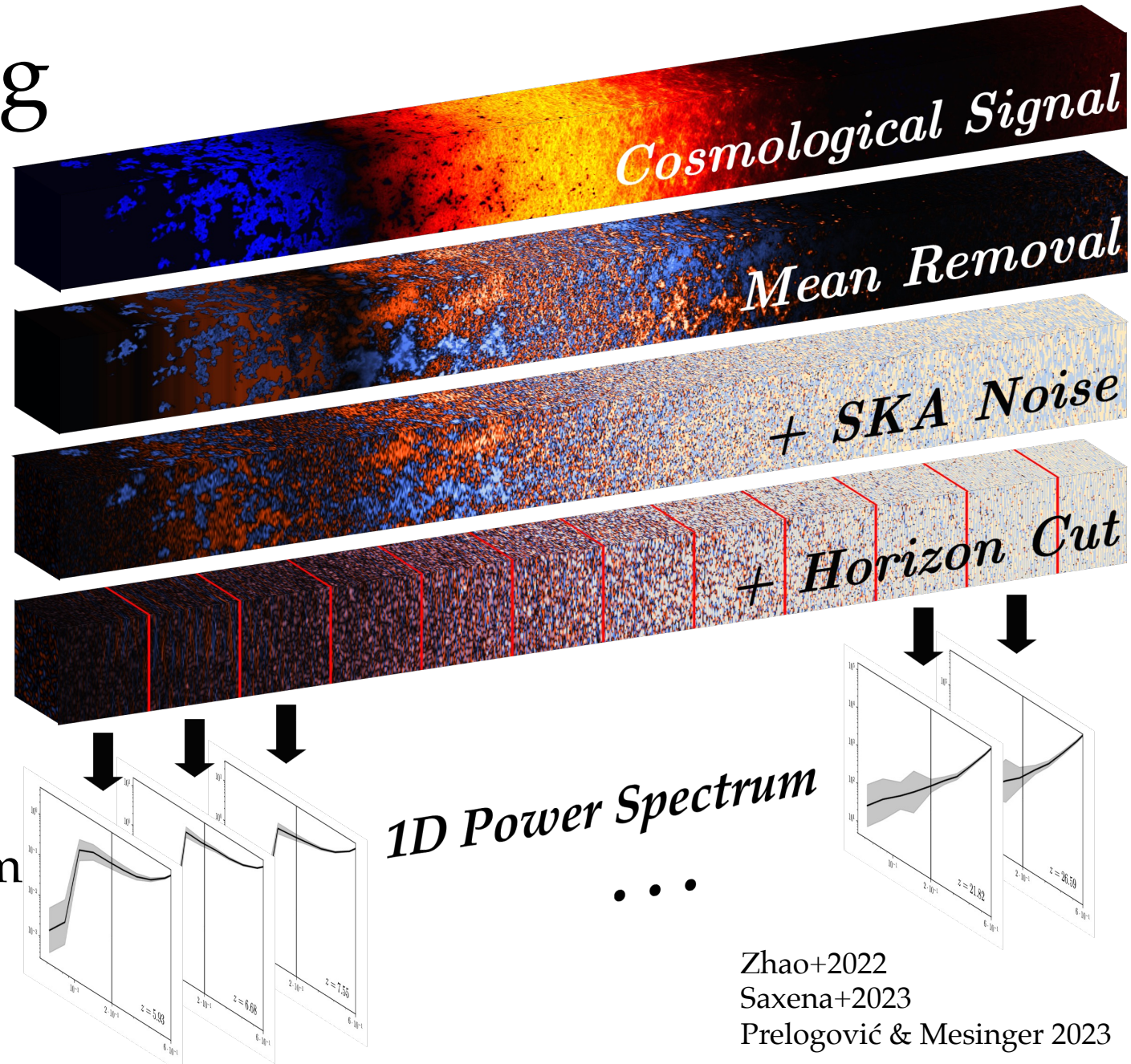


$$P(\theta | \mathcal{S}_{data})$$



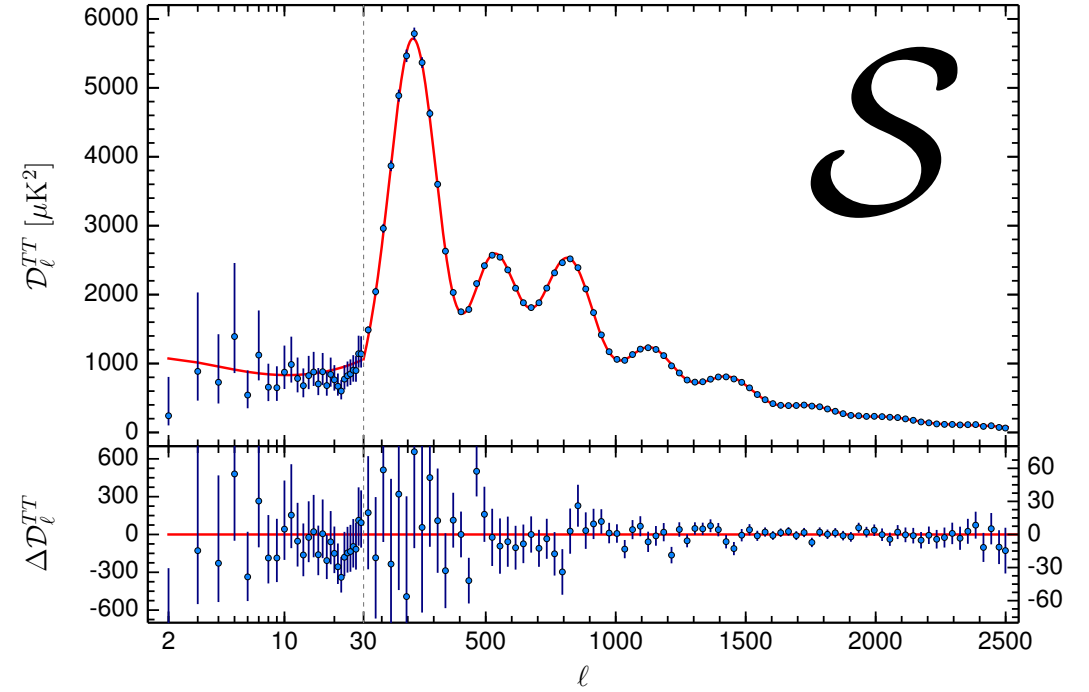
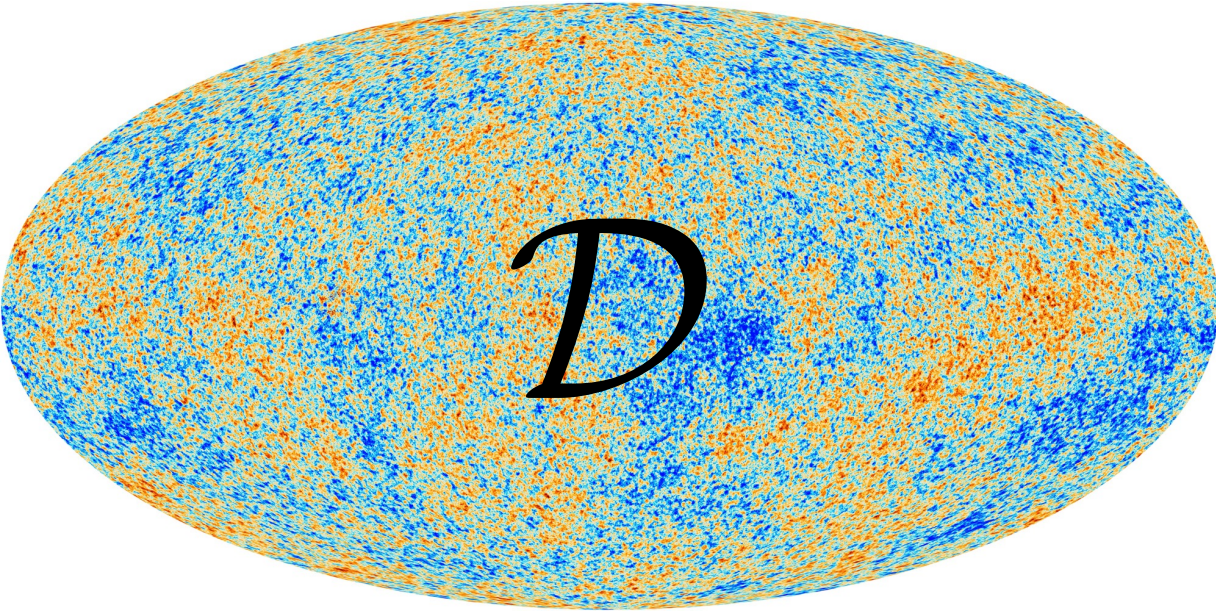
Forward-modelling

- Signal simulation: 21cmFAST
- SKA not sensitive to the mean
- UV coverage of the SKA and its noise
- Removing modes contaminated with foregrounds
- Compressing it to the power spectrum





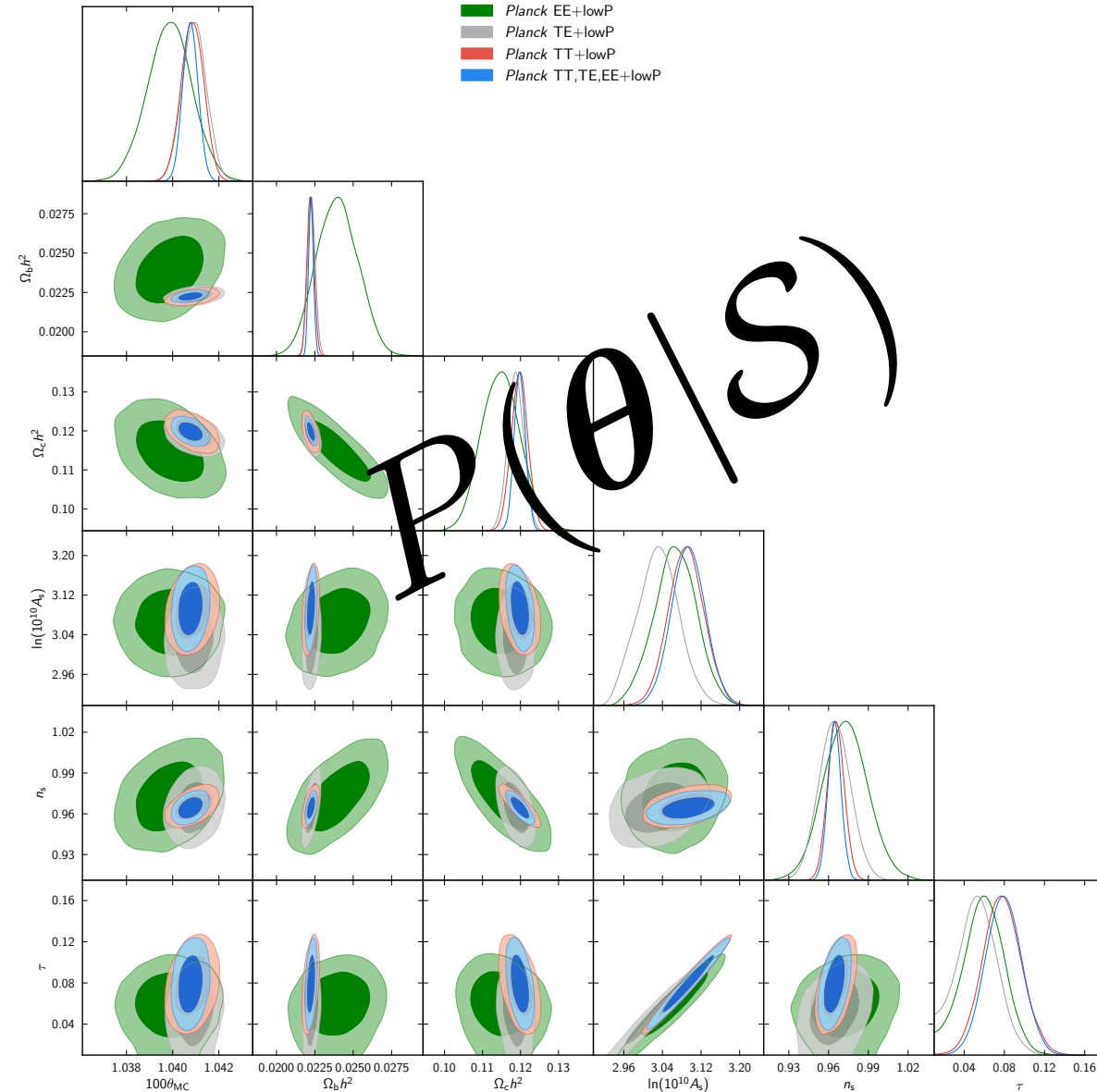
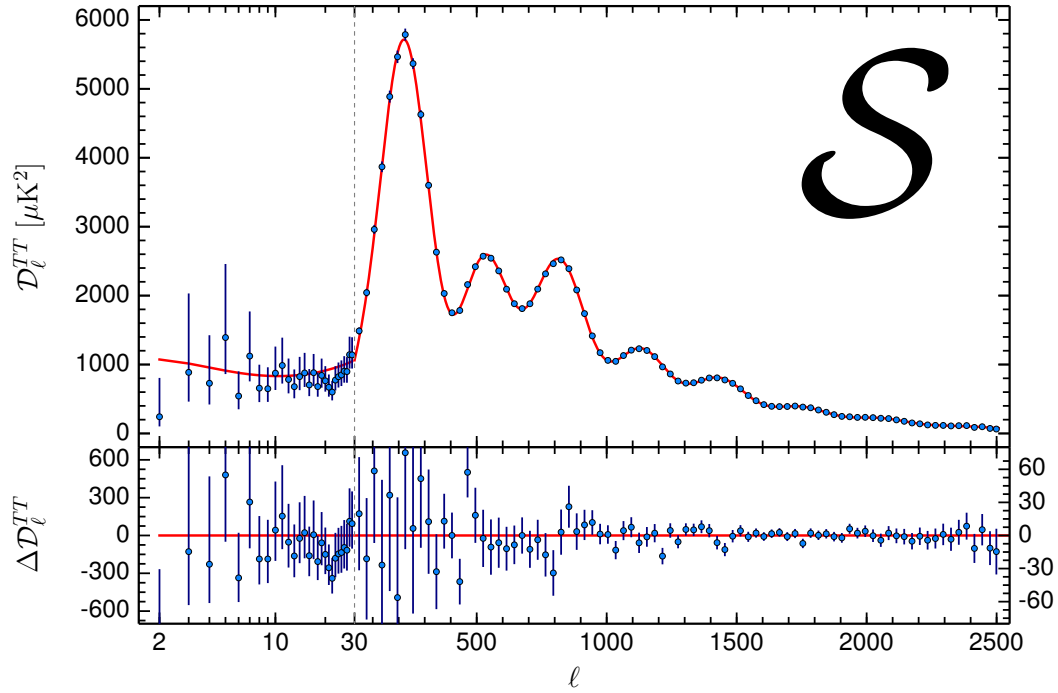
Example: CMB



- Full sky map compressed to PS



Example: CMB



- Full sky map compressed to PS
- From it we infer the cosmology
 - Known compression, known likelihood



Likelihood of the 21-cm

- Analytically not available
- Numerically non-tractable



Likelihood of the 21-cm

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- Numerically non-tractable
- Eg. – power spectrum

$$\mathcal{L}(\boldsymbol{\sigma}, \boldsymbol{\mu}; \mathbf{x}) = \frac{1}{(2\pi)^{n/2} \sqrt{\prod_i \sigma_i^2}} e^{-\frac{1}{2} \sum_i (x_i - \mu_i)^2 / \sigma_i^2}$$

$$\mathcal{L}(\boldsymbol{\Sigma}, \boldsymbol{\mu}; \mathbf{x}) = \frac{1}{(2\pi)^{n/2} \sqrt{|\boldsymbol{\Sigma}|}} e^{-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu})}$$



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Classical inference simplifications

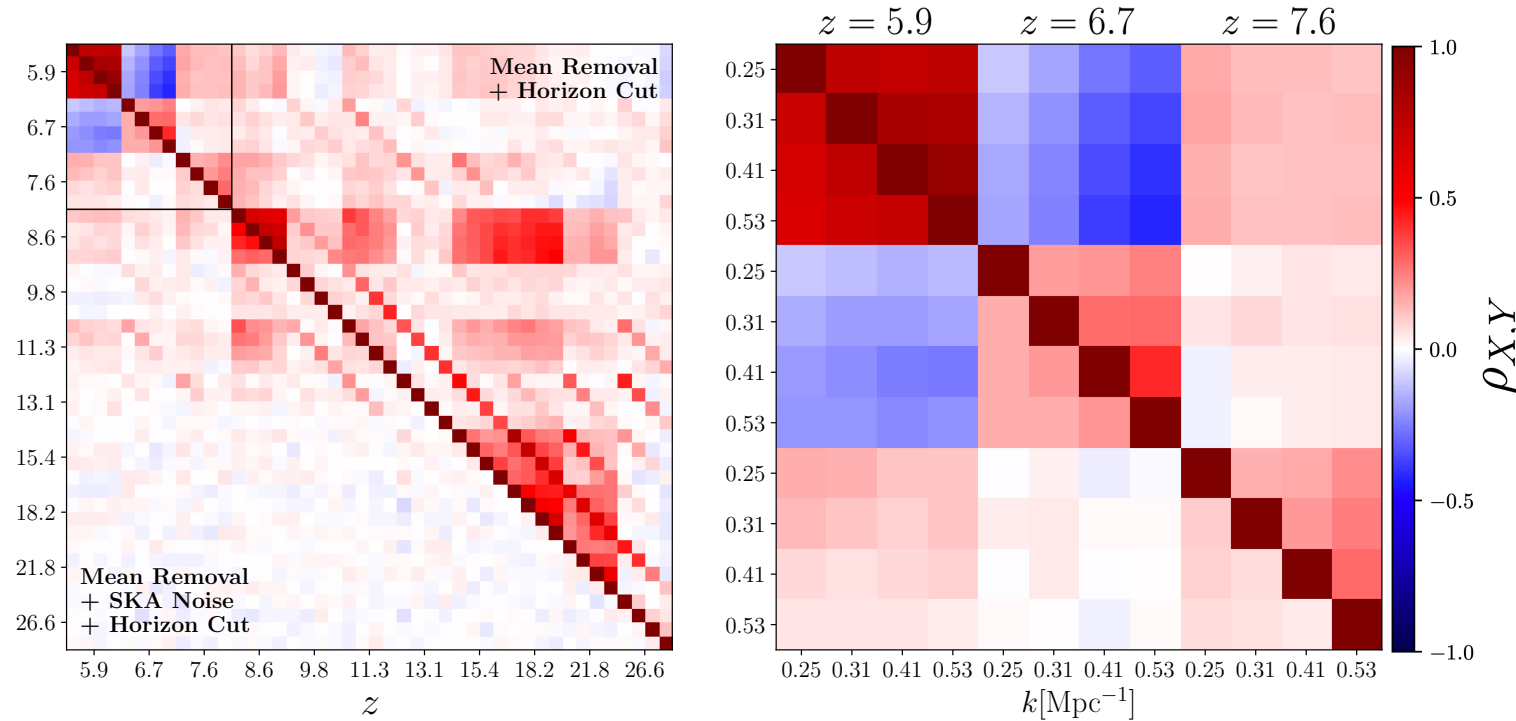
- 1) $\boldsymbol{\mu}$ estimated from one sim.
- 2) $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_{\text{fid}}$
- 3) No higher order terms

→ Simulation-Based Inference



Likelihood of the 21-cm PS

- Is inclusion of the covariance worthwhile?



- Large correlations across z and k
- Only diagonal taken into account in usual analyses



Simulation-Based Inference (SBI)

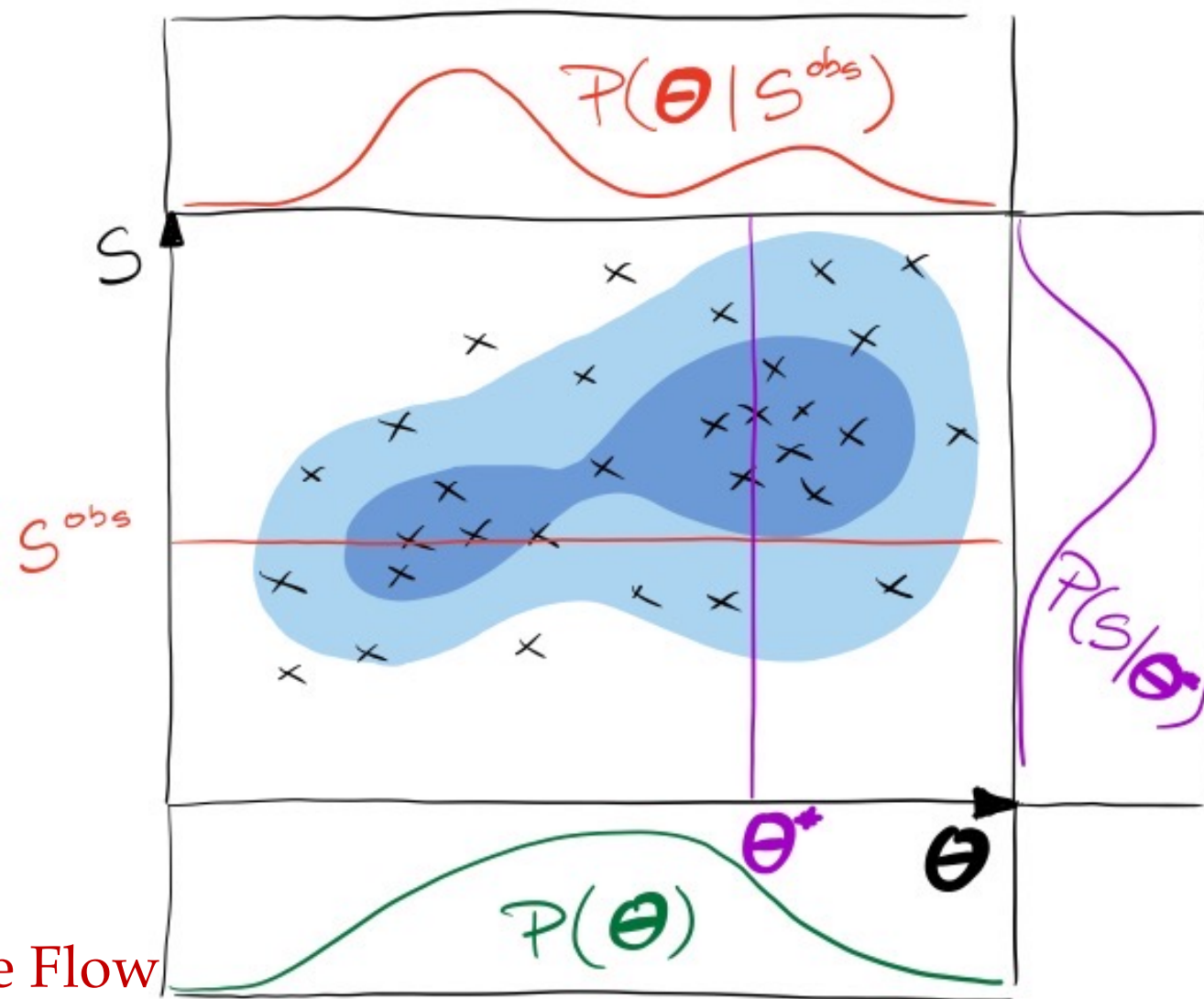
- Pull from the prior $\theta^* \sim P(\theta)$
- Pull from the likelihood

$$S^* \sim P(S|\theta^*)$$

i.e. simulate and compress

$$S^* = \text{compress}(\text{simulate}(\theta^*))$$

- Repeat many times
- Fit the distribution with **NDEs**
 - Gaussian
 - Gaussian mixture
 - Conditional Masked Autoregressive Flow





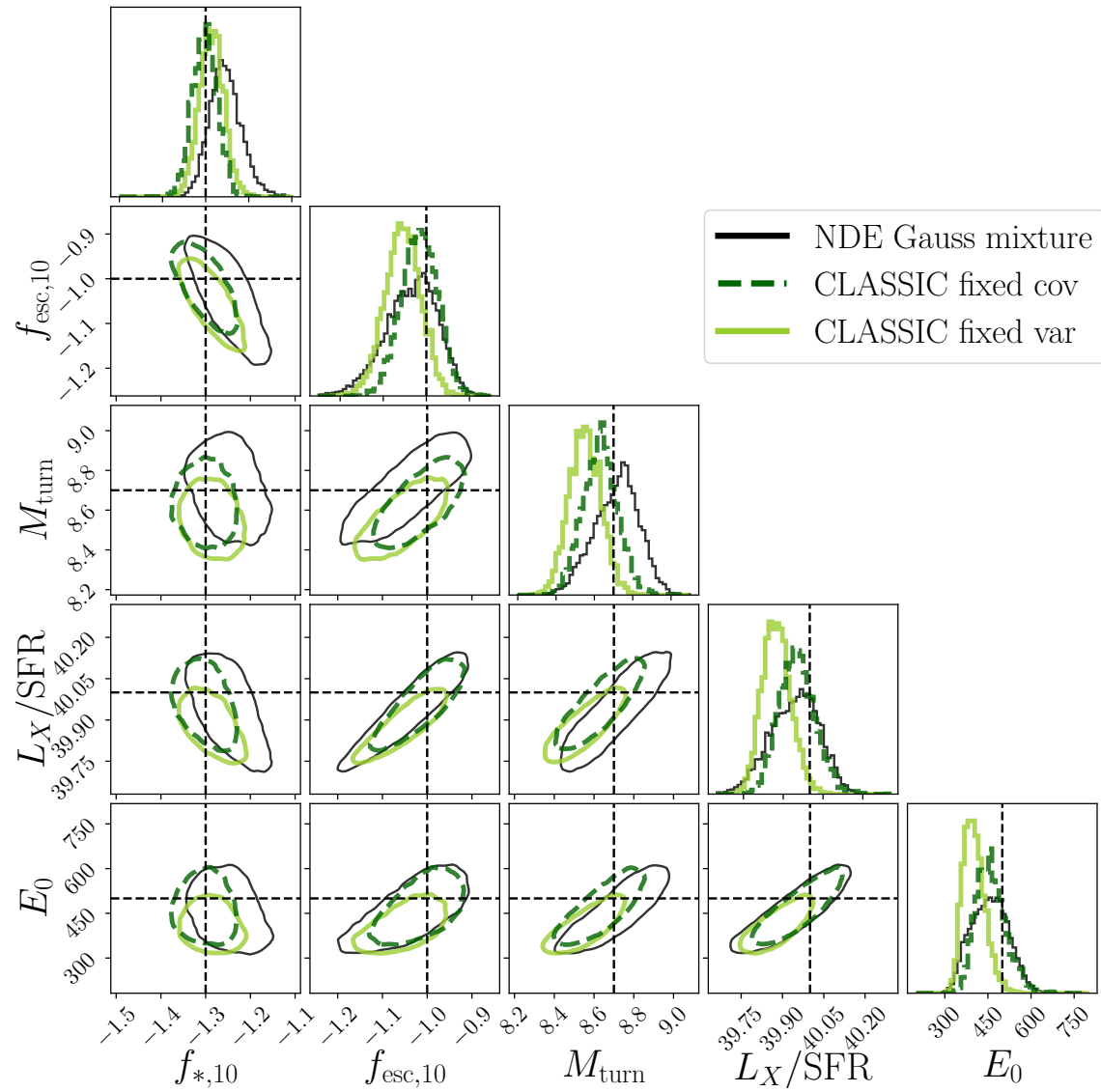
Inference for the 21-cm PS

- Two classic likelihoods
 - CLASSIC fixed var
 - CLASSIC fixed cov
 - Neural density estimators
 - NDE fixed var
 - NDE fixed cov
 - NDE varying var
 - NDE varying cov
 - NDE CMAF
 - NDE Gauss mixture
 - Fixed covariance (variance)
 - Mean estimated from one simulation
- 1) Fitting the mean
 - 2) Fitting the mean and covariance
 - 3) Adding all higher-order moments and multimodalities



Inference for the 21-cm PS

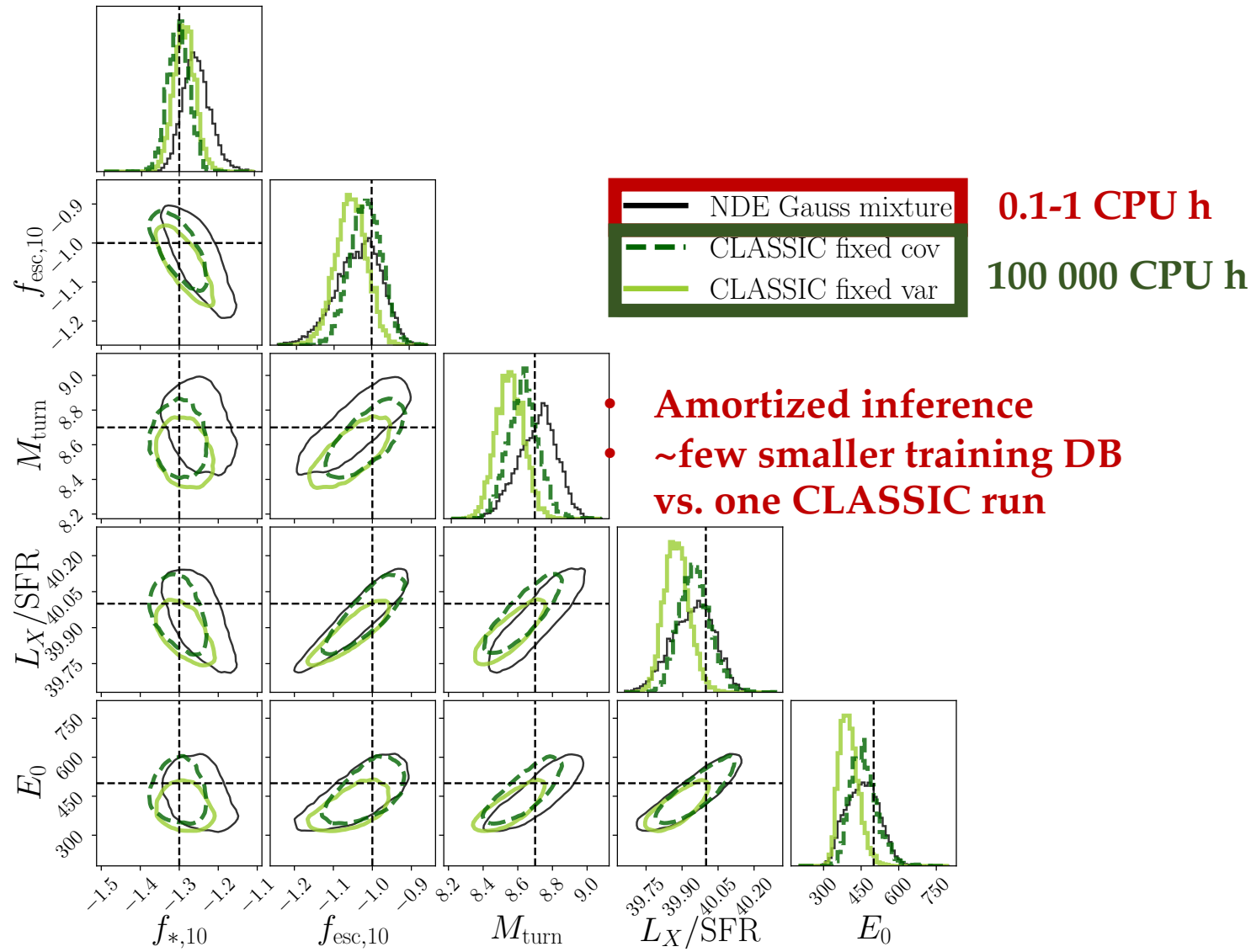
Including more realistic likelihood
≠
more constraining posterior





Inference for the 21-cm PS

Including more realistic likelihood
≠
more constraining posterior



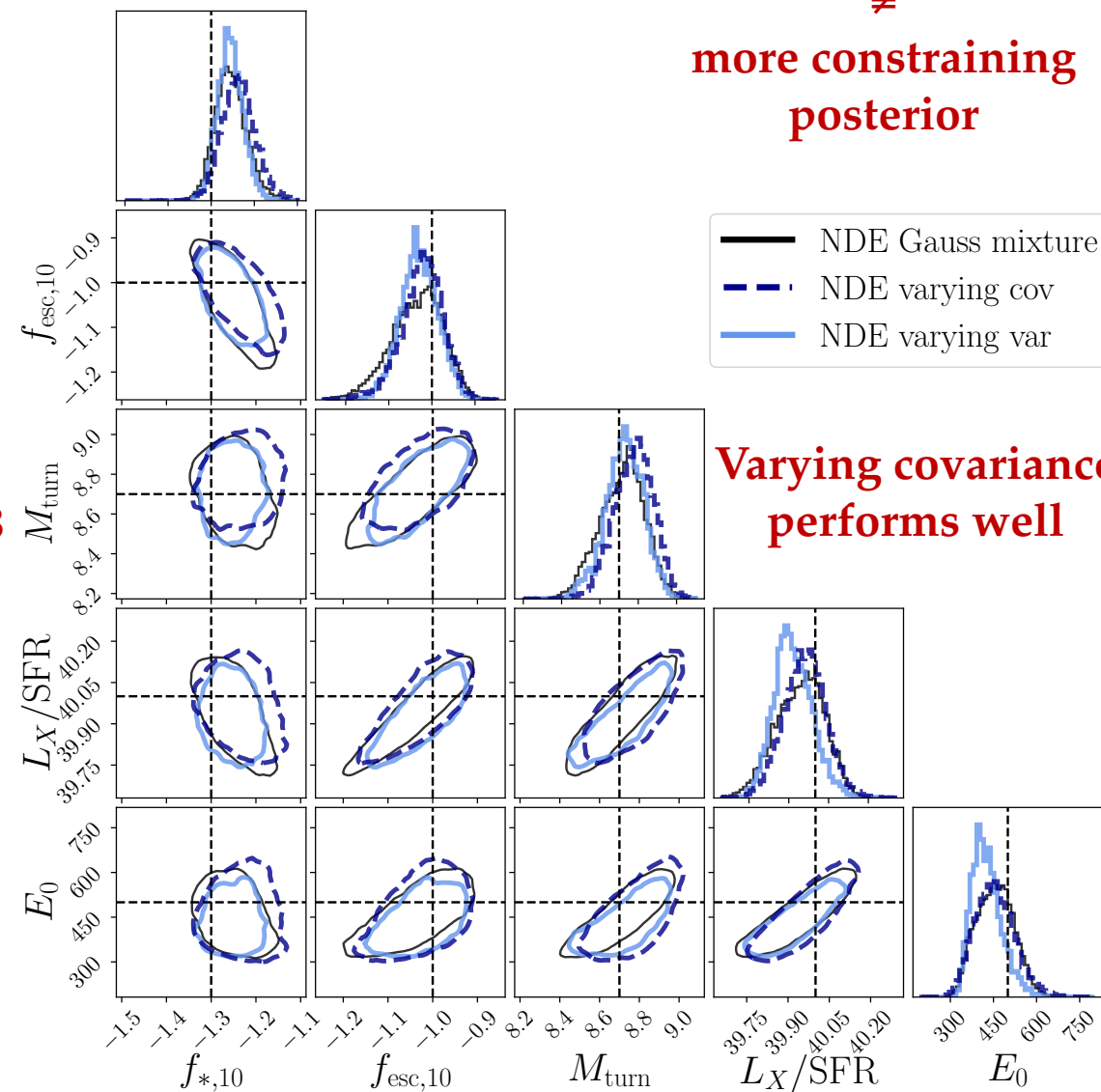
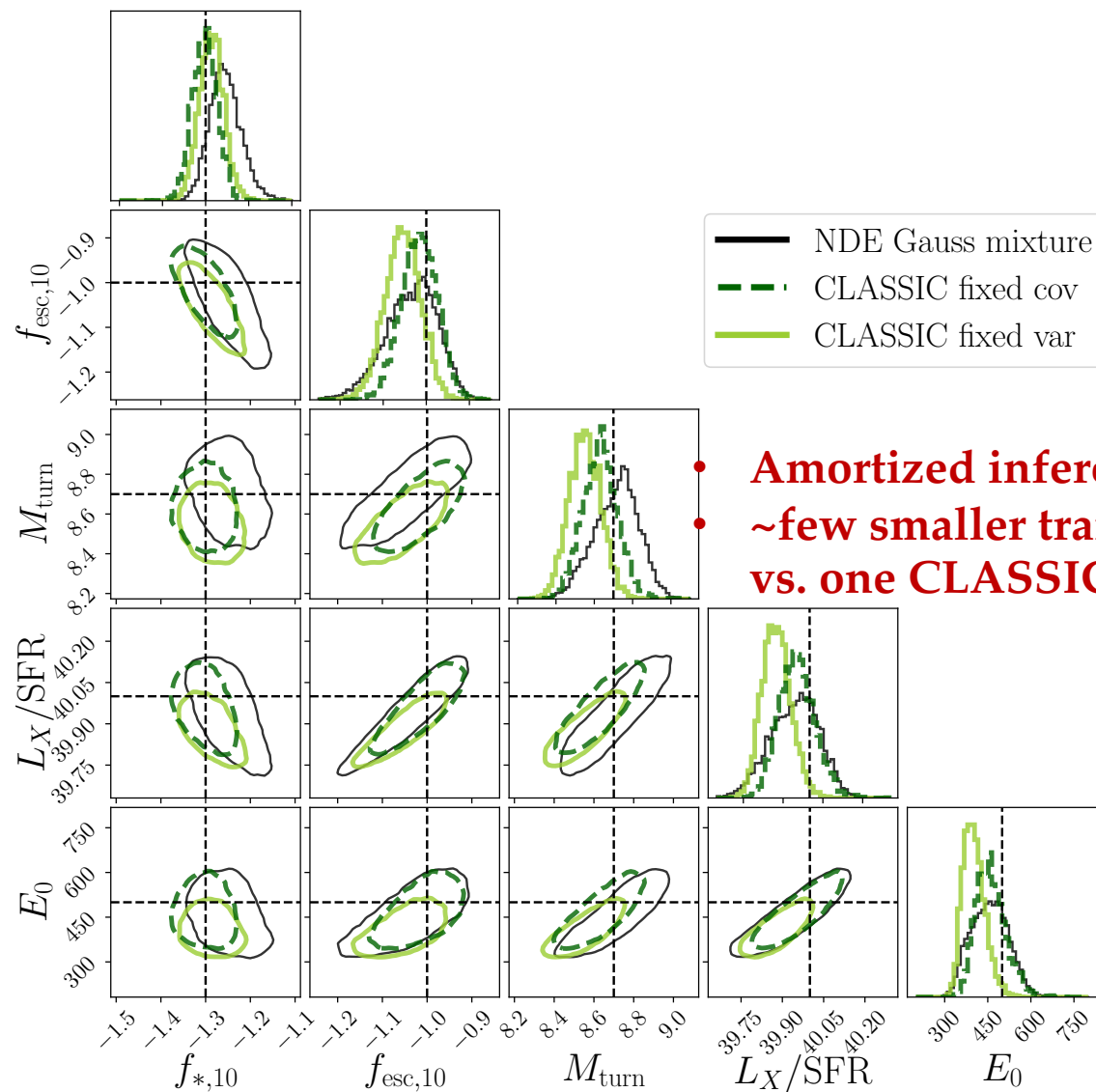


Inference for the 21-cm PS

Including more realistic likelihood

≠

more constraining posterior





Inference for the 21-cm PS

BUT:

This is only qualitative description, and only for the **mock observation**

- How does it perform for other points in the parameter space?
- Did the training converge?
- Can we quantify the best model?

→ Simulation-Based Calibration



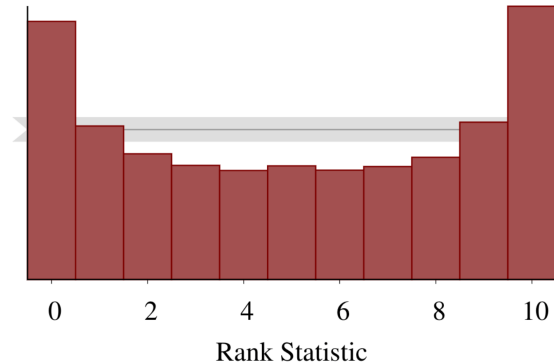
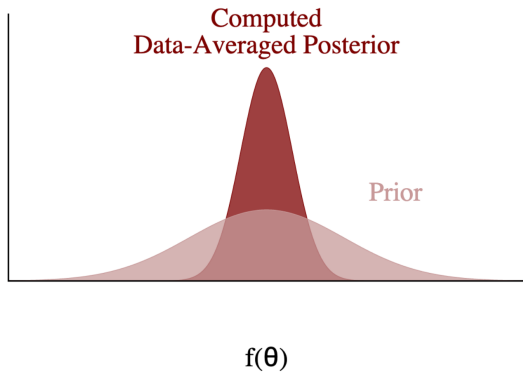
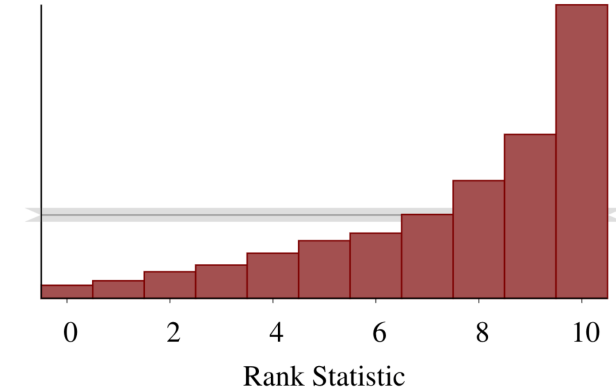
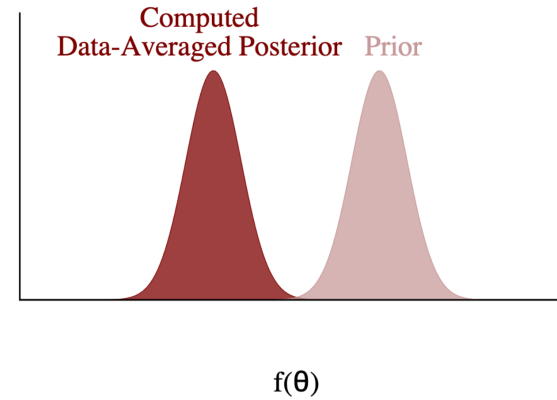
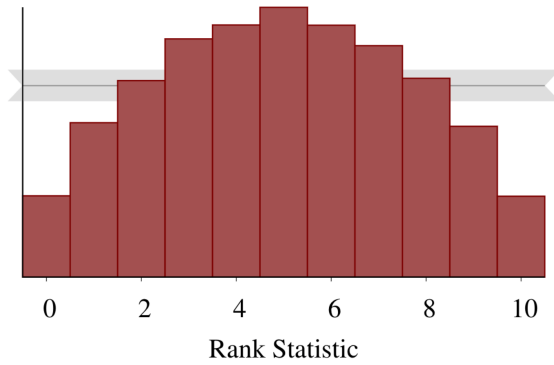
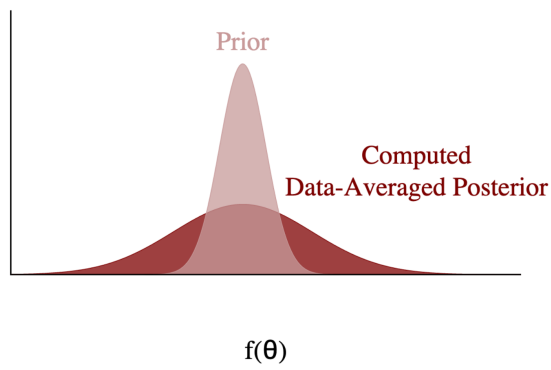
Simulation Based Calibration (SBC)

- “prior” = “data averaged posterior” $P(\boldsymbol{\theta}) = \int P(\boldsymbol{\theta}|\tilde{\mathbf{y}}) P(\tilde{\mathbf{y}}|\tilde{\boldsymbol{\theta}}) P(\tilde{\boldsymbol{\theta}}) d\tilde{\mathbf{y}} d\tilde{\boldsymbol{\theta}}$



Simulation Based Calibration (SBC)

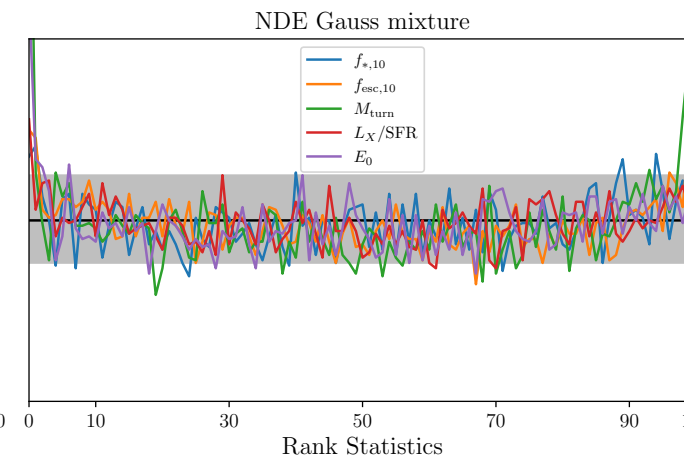
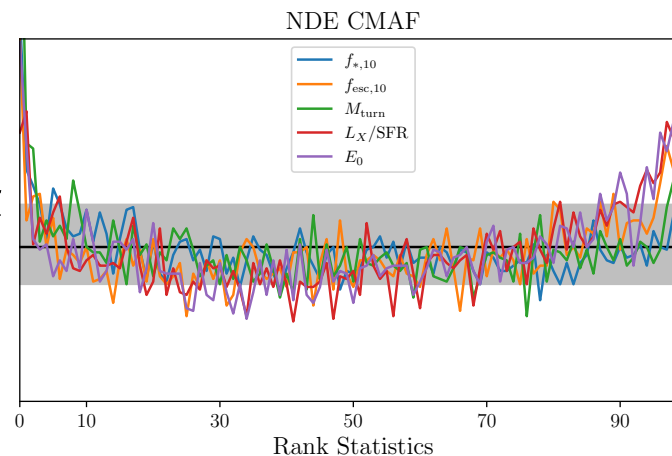
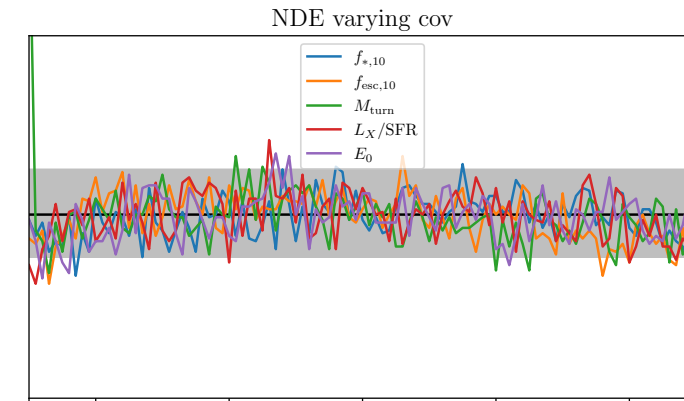
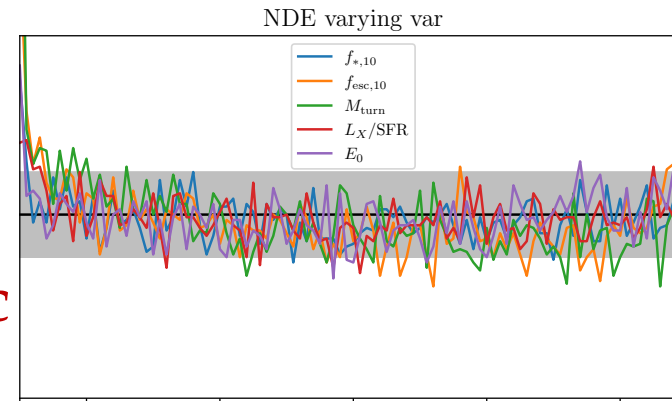
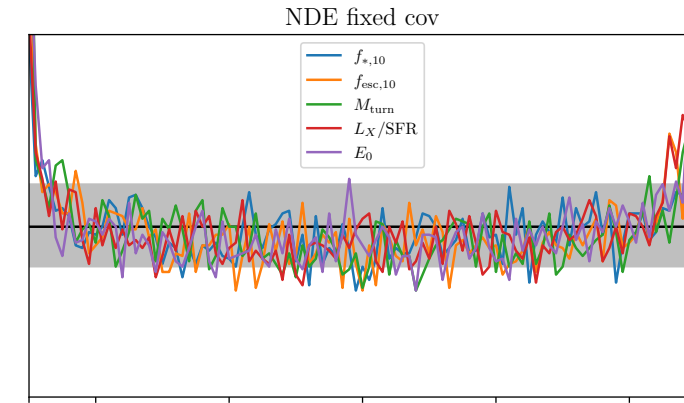
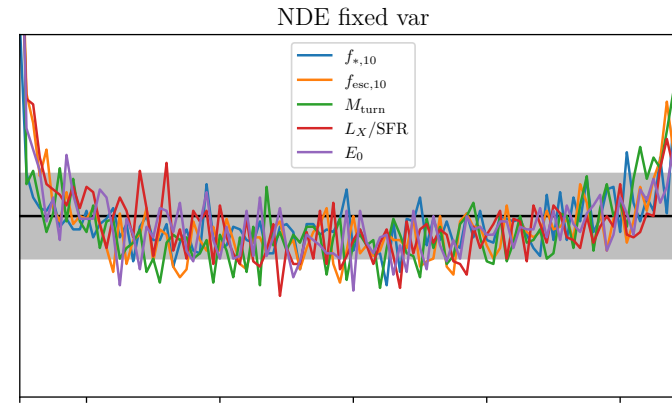
- “prior” = “data averaged posterior” $P(\theta) = \int P(\theta|\tilde{y}) P(\tilde{y}|\tilde{\theta}) P(\tilde{\theta}) d\tilde{y} d\tilde{\theta}$
- SBC – casting integral into 1D rank statistics distribution





SBC for 21-cm PS

- *Expensive to compute!*
 - 10 000 posteriors
- However, once likelihood is trained, no new simulations are needed
 - “amortized inference”
- Procedure **would be useful for classic inference too**, but is impossible to compute
- NDE fixed var & cov – overconfident
- NDE varying var & cov – good
- NDE CMAF – overconfident
- NDE Gauss mixture – the best





Conclusions

- 21cm – likelihood unavailable
- Simulation-Based Inference
 - Offers a way out
 - With crucial caveats to be taken care of
 - Consistency checks (SBC)
- Future (current) prospects
 - PS for non-Gaussian data is lossy
 - Other summaries paired with SBI might perform better

arXiv: [2305.03074](https://arxiv.org/abs/2305.03074)

github: [dprelogo/21cmLikelihoods](https://github.com/dprelogo/21cmLikelihoods)