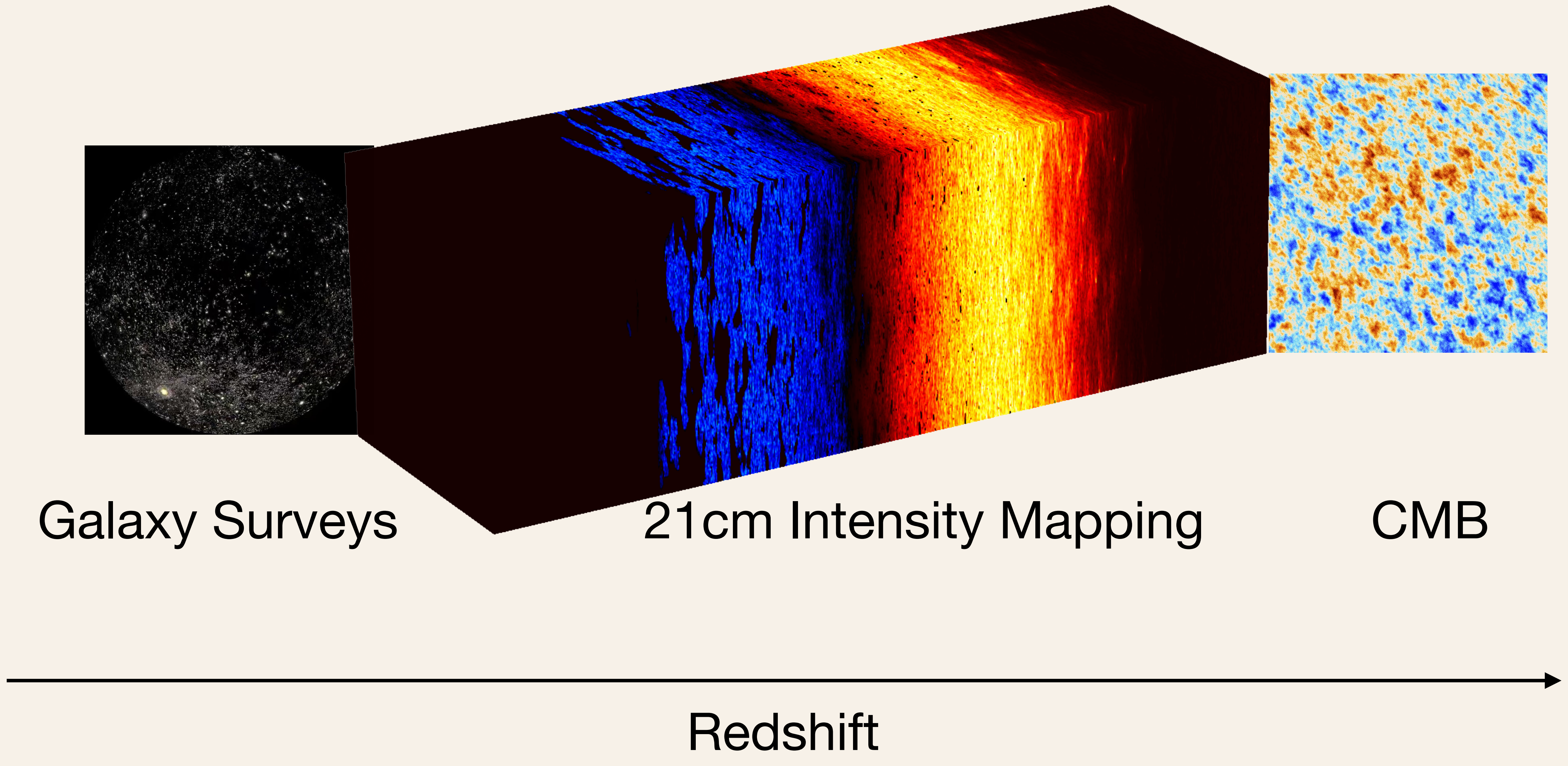
Optimal, fast, and robust inference of reionization-era cosmology with the 21cmPIE-INN



Benedikt Schosser — May 1, 2024 — EuCAIFCon 2024 — Poster Location: 108

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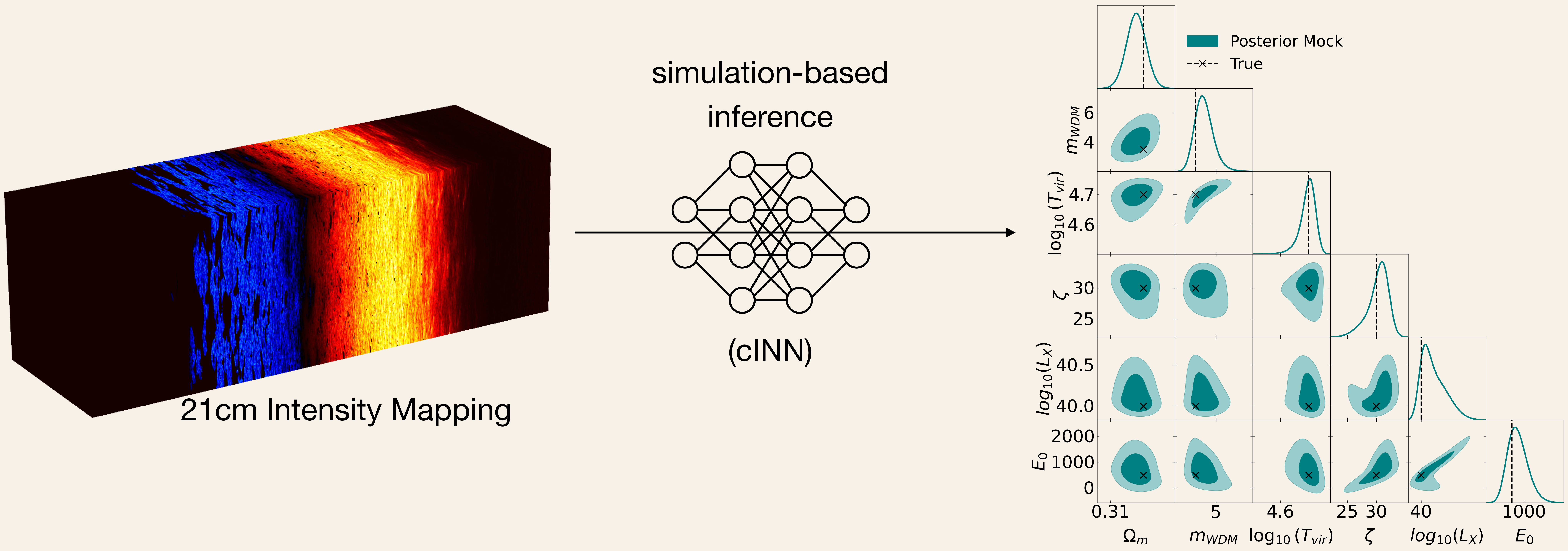

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Simulation-Based Inference from the CD-EoR 21-cm signal

Anchal Saxena, Alex Cole, Simon Gazagnes, Daan Meerburg, Christoph Weniger, Samuel Witte

Goals

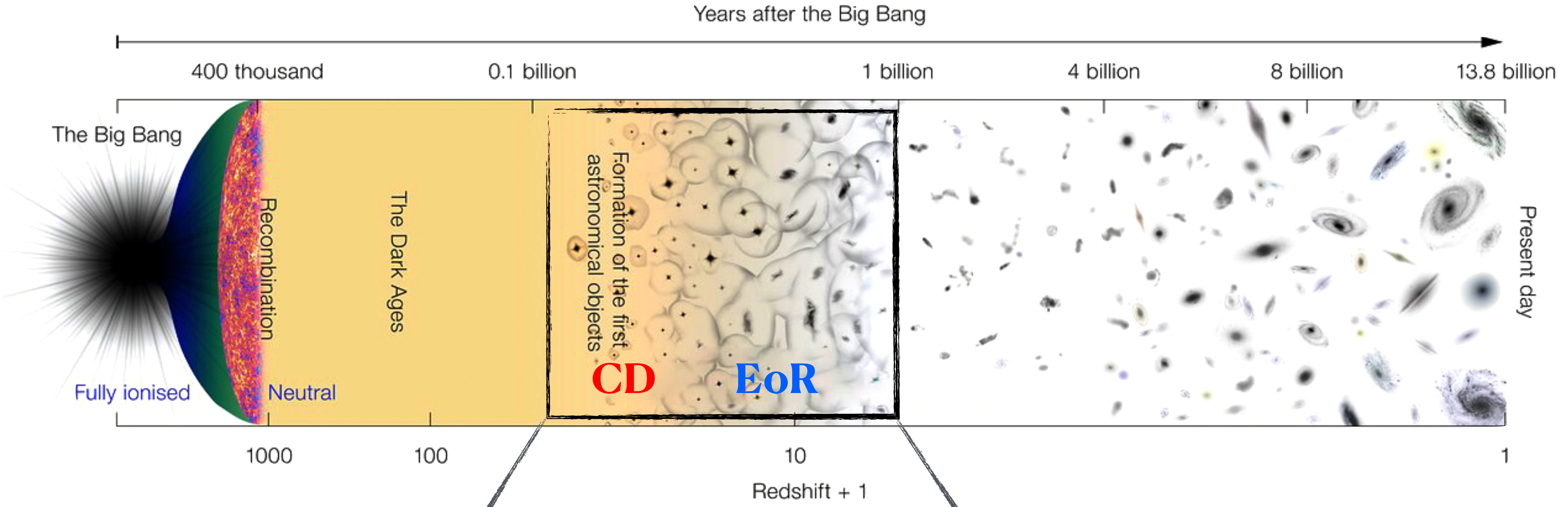
- Constrain the astrophysics of the early Universe with 21-cm line
- Solving the inverse problem!

Challenges

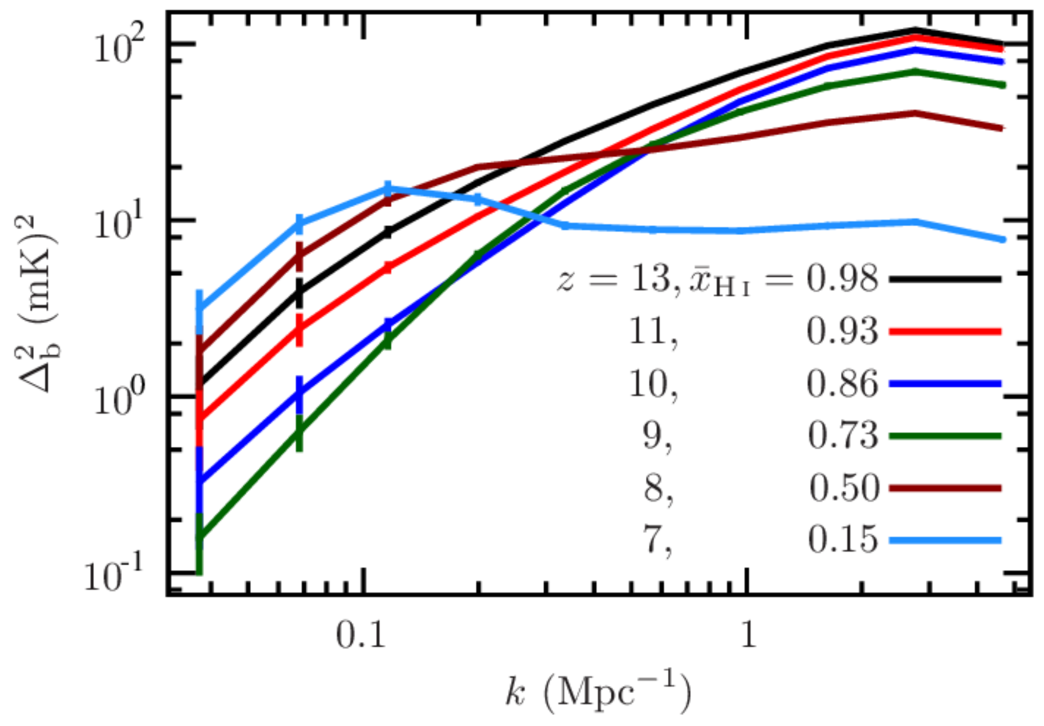
- Scalability of the conventional methods to high dimensional parameter spaces
- Expensive forward models
- Likelihood of the 21-cm power spectrum?

Solution

- Simulation-Based Inference through Marginal Neural Ratio Estimation



Square Kilometer Array



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EUCAIFCON 2024 | University of Amsterdam | MAY 2024

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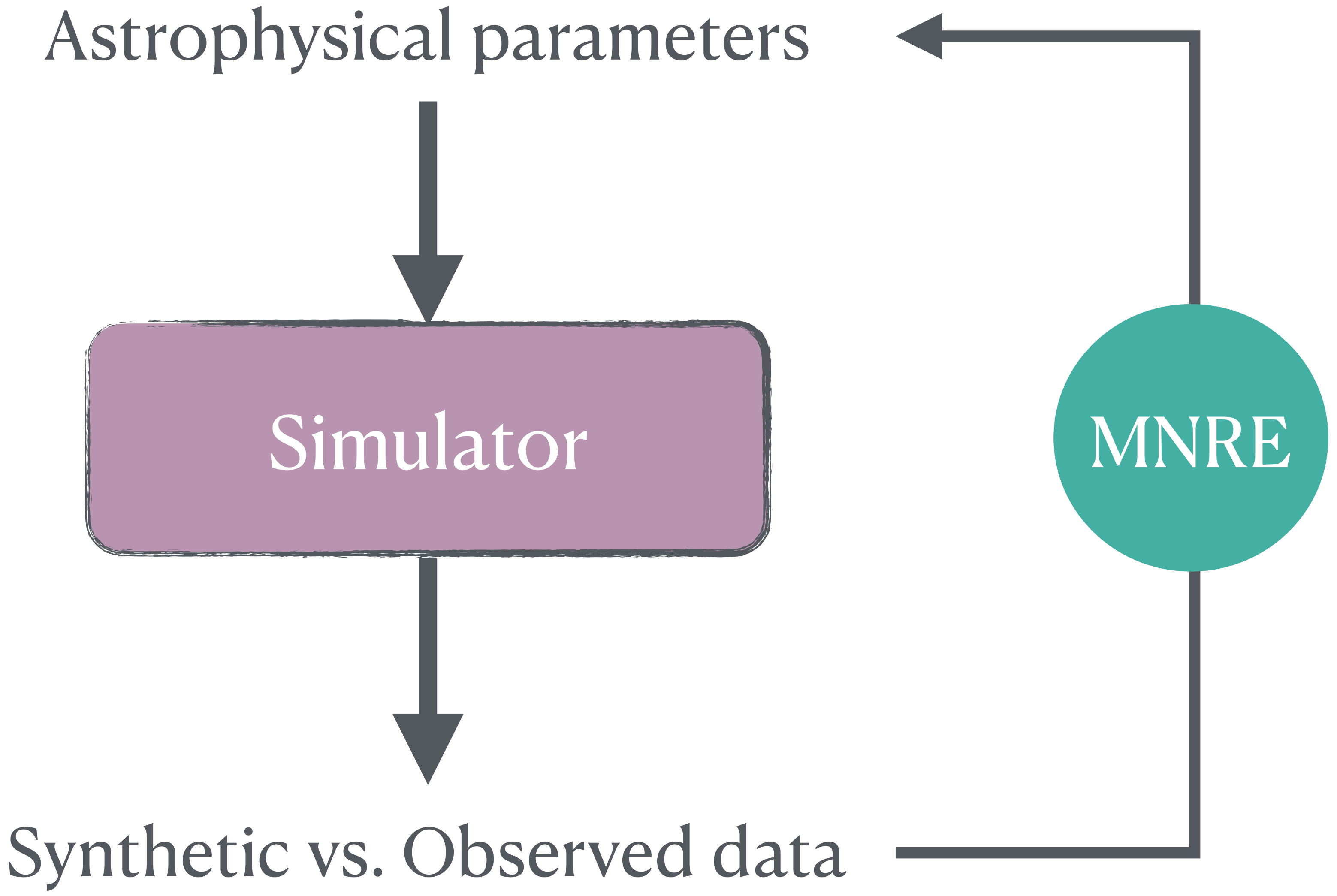
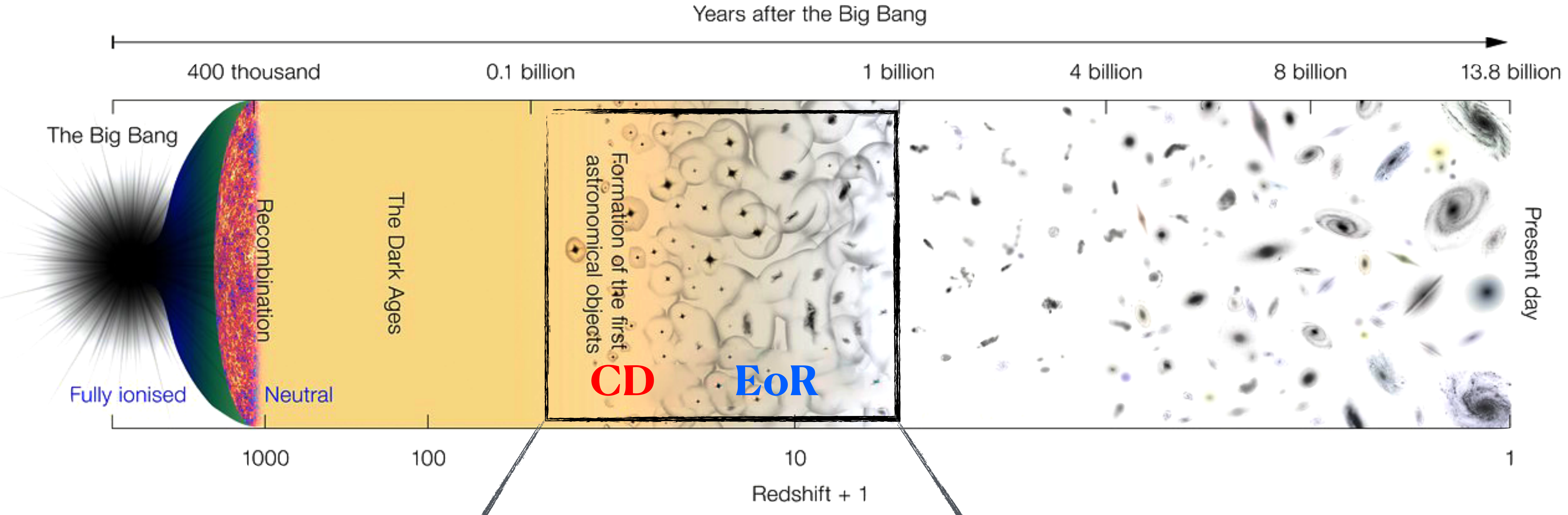
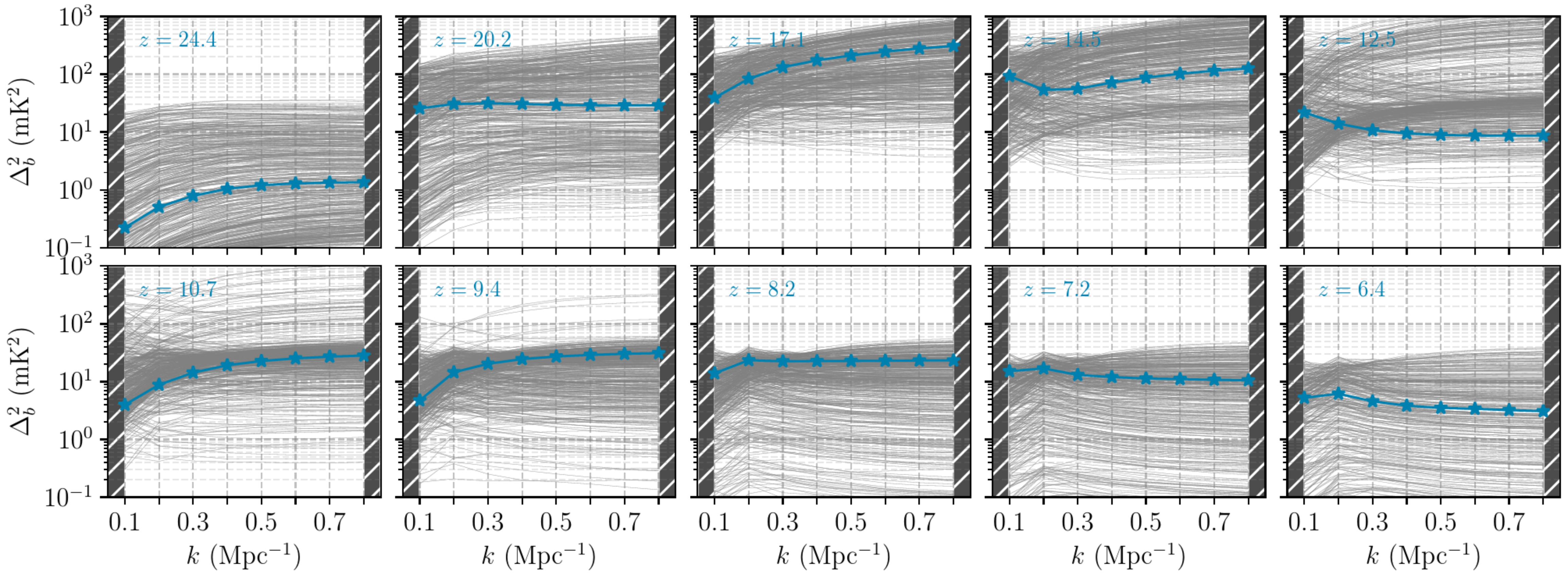
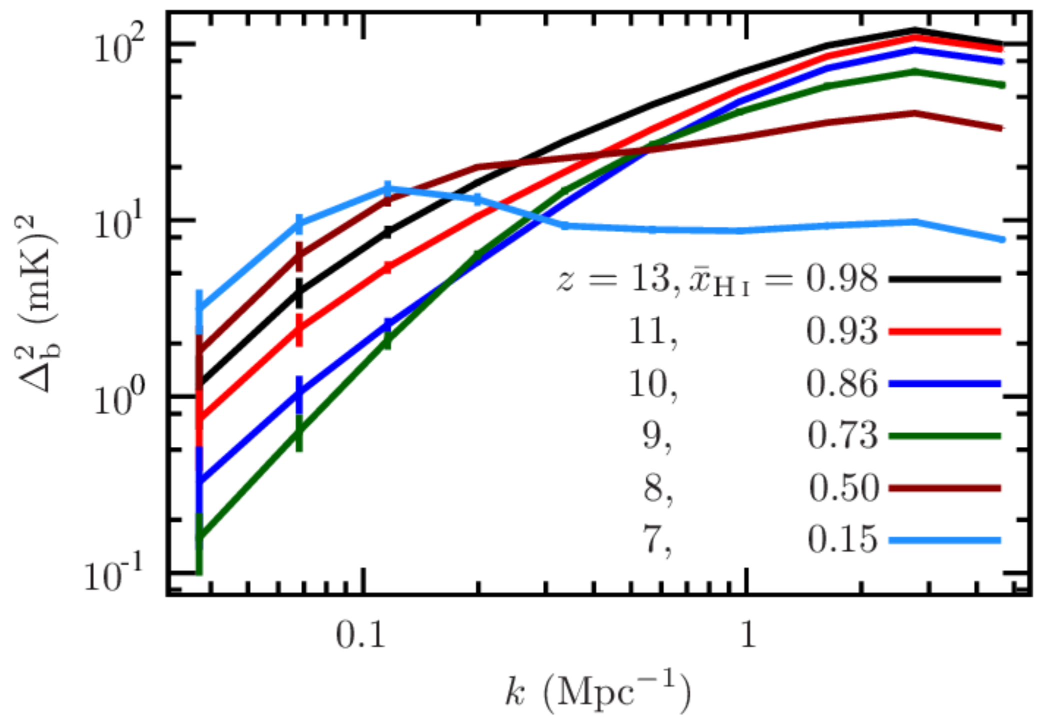






Square Kilometer Array



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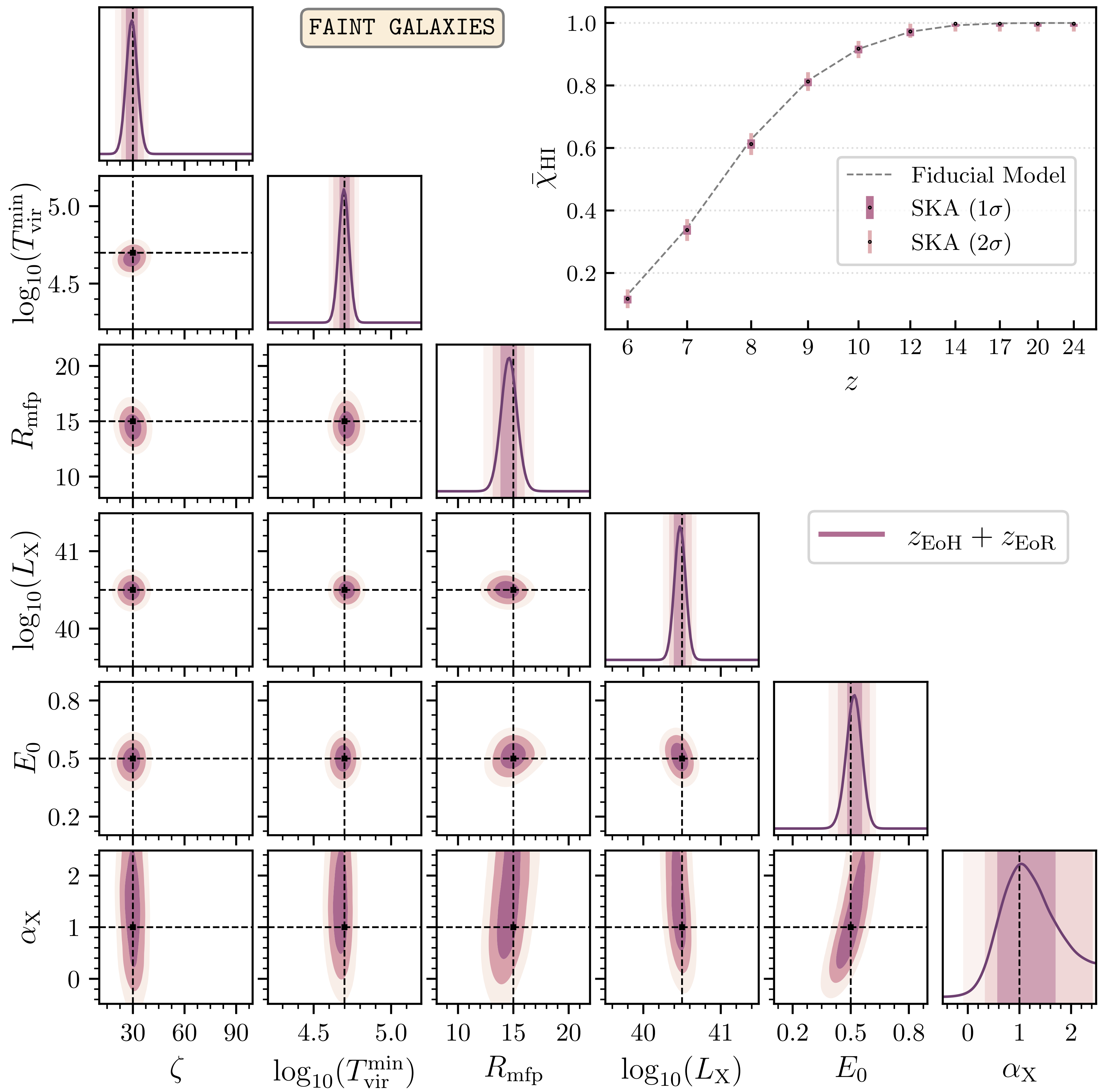
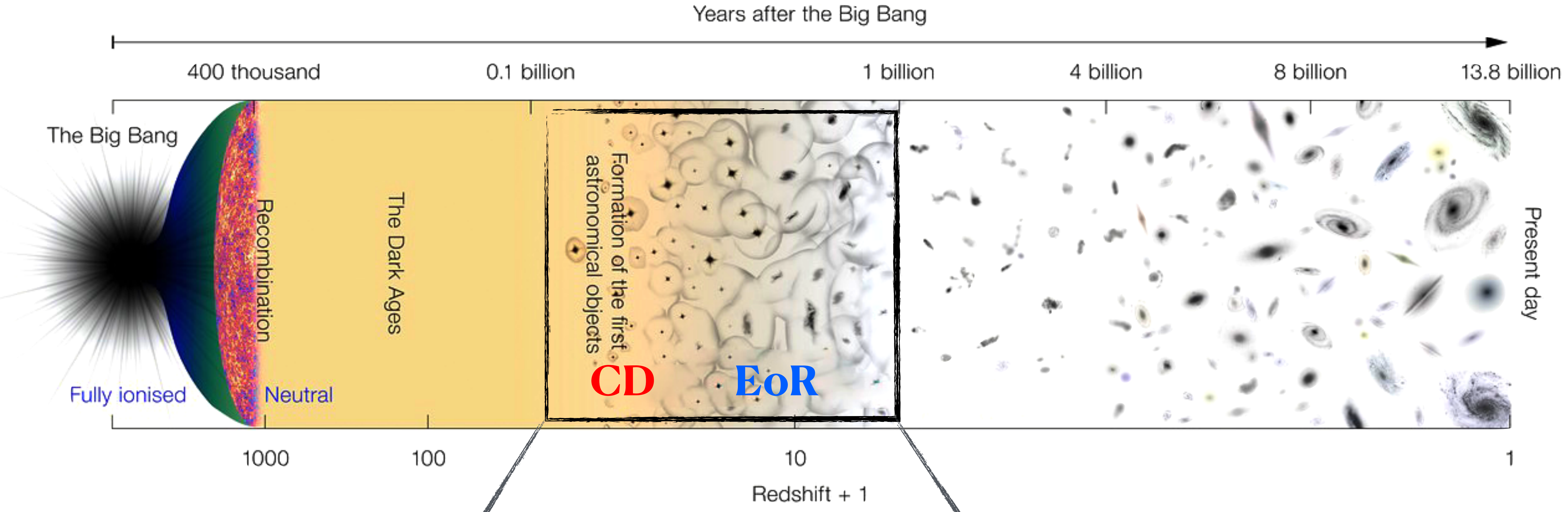
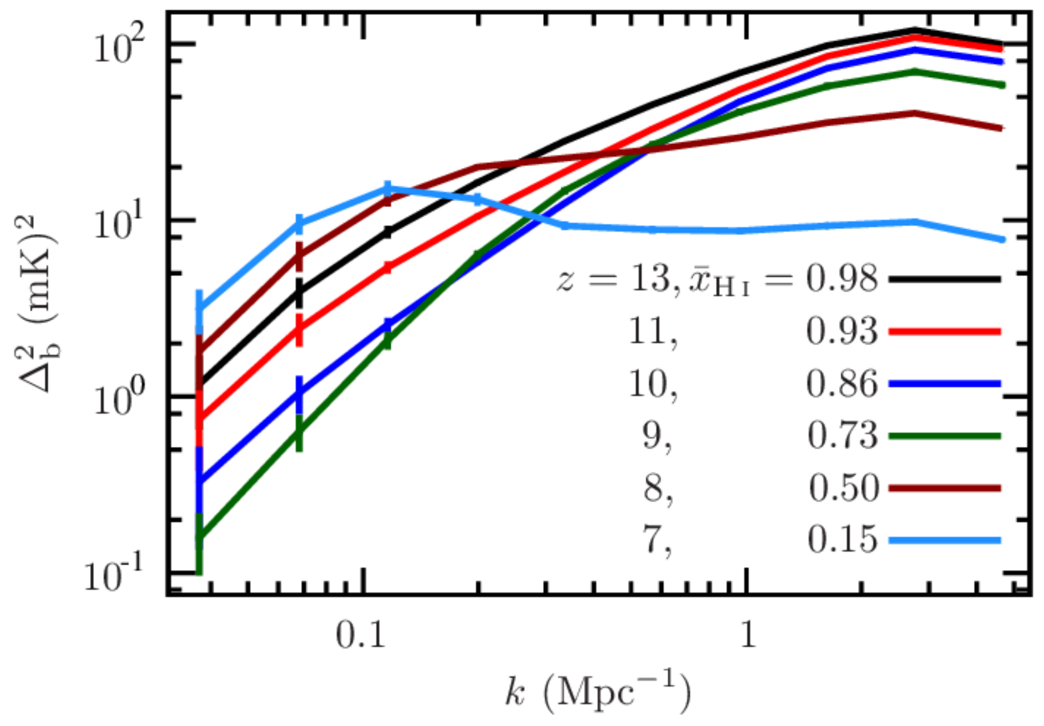


Posterior on the astrophysical parameters with an order of magnitude fewer samples than MCMC



Square Kilometer Array



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Flexible conditional normalizing-flow distributions over manifolds: the jammy-flows toolkit

Thorsten Glüsenkamp, May 1st 2024, EuCAIFCon flash talk

UPPSALA UNIVERSITET

CARL TRYGGERS STIFTELSE
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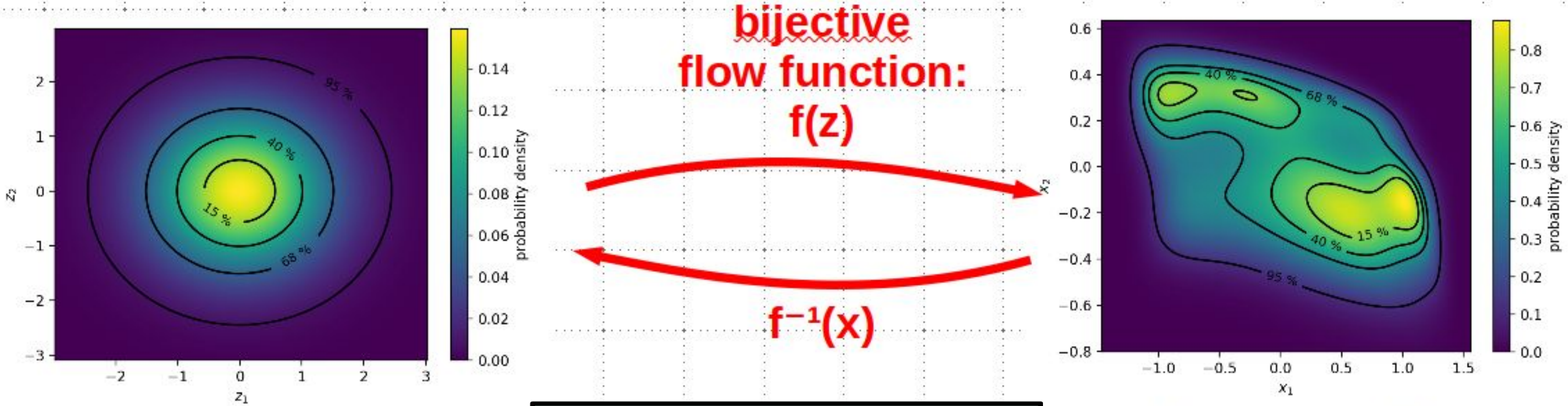
Normalizing flows are great, but….



Auxiliary base space "z":

$p_0(z) = \mathcal{N}(z; \mathbf{0}, \mathbb{1})$

Target space "x":

$p_\theta(x|y) = p_0(f^{-1}_{g_\theta(y)}(x)) \cdot |\mathrm{det} J^{-1}_{g_\theta(y)}(x)|$

… implementations are
- often scattered around in their own repositories
- often not really suited for physics ("image-focused flows")
- often complicated to set up, especially the conditioning

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Jammy Flows
([1] https://github.com/thoglu/jammy_flows)

Joint **A**utoregressive **M(MY)**anifold normalizing **flows**
setup complex normalizing flows in 1 line of code [1]

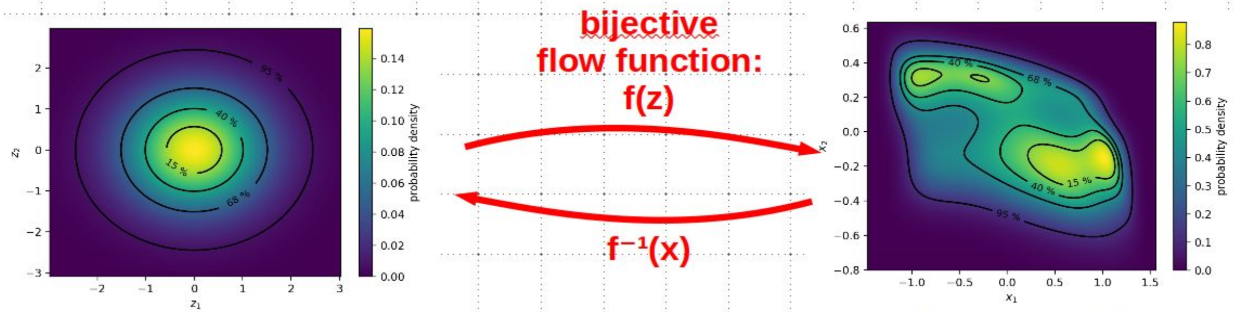
Euclidean ($\mathbb{R}^4$)

$$f(\vec{z}) = \Phi_t(\Phi_g(\Phi_g(\vec{z})))$$

Arg 1: Manifold

Arg 2: Flow function f(z)

```
pdf=jammy_flows.pdf("e4", "ggt")
```



Auxiliary base space "z":

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Target space "x":

$p_\theta(x|y) = p_0(f^{-1}_{g_\theta(y)}(x)) \cdot |\det J^{-1}_{g_\theta(y)}(x)|$

Poster No: 110

Supports various manifolds + autoregressive linking

Joint Autoregressive M(MY)anifold normalizing flows
setup complex normalizing flows in 1 line of code [1]

Euclidean ($\mathbb{R}^4$)

Arg 1: Manifold

$$f(\vec{z}) = \Phi_t(\Phi_g(\Phi_g(\vec{z})))$$

Arg 2: Flow function f(z)

```
pdf=jammy_flows.pdf("e4", "ggt")
```

Interval (-3 to 3)

$$f(\vec{z}) = \Phi_r(\Phi_r(\Phi_r(\Phi_r(\Phi_r(\vec{z})))))$$

```
pdf=jammy_flows.pdf("i1_-3_3", "rrrrr")
```

Autoregressive ($S^2 \times \Delta^2 \times \mathbb{R}^3$)

$$f(\vec{z}) = \begin{bmatrix} \Phi_n(\Phi_n(\vec{z_1})) \\ \Phi_{w,x1}(\vec{z_2}) \\ \Phi_{g,x1,x2}(\Phi_{g,x1,x2}(\Phi_{g,x1,x2}(\Phi_{g,x1,x2}(\vec{z_3})))) \end{bmatrix}$$

```
pdf=jammy_flows.pdf("s2+c2+e4", "nn+w+gggg")
```

Syntax reflects normalizing flow-defining function f(z)

2-sphere (S^2)

$$f(\vec{z}) = \Phi_v(\Phi_v(\Phi_v(\vec{z})))$$

```
pdf=jammy_flows.pdf("s2", "vvv")
```

Probability simplex (Δ^3)

$$f(\vec{z}) = \Phi_w(\Phi_w(\vec{z}))$$

```
pdf=jammy_flows.pdf("c3", "ww")
```

Flow abbreviations:

- "t" – affine flow
- "g" – Gaussianzation flows [2]
- "v" – Exponential map flows [3]
- "n" – Recursive flows on the 2-sphere [5]
- "w" – Simplex flow [6]
- "r" – neural spline flows [4]

+ a few more in the package

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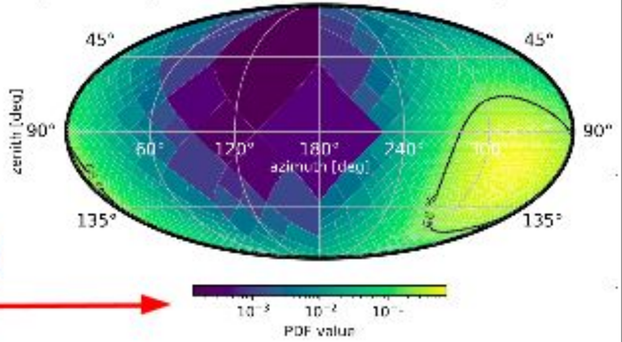
Features

Many state-of-the-art normalizing flows that can be autoregressively linked, customized, and made conditional. Autoregressive routing generalizes structure from inverse autoregressive flows [7].

Convenience functions for ...

- 1st + 2nd moments
- asymmetry measure (higher order moments) (see [9])
- entropy
- coverage (Gaussian base used for all manifolds – see [8])
- plotting (adaptive healpix for spherical PDFs)
- easy to add new layers



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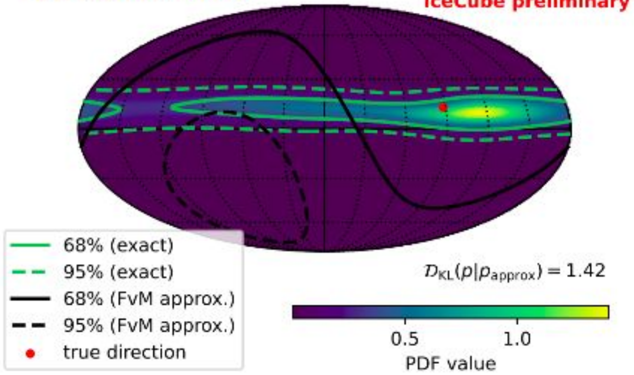
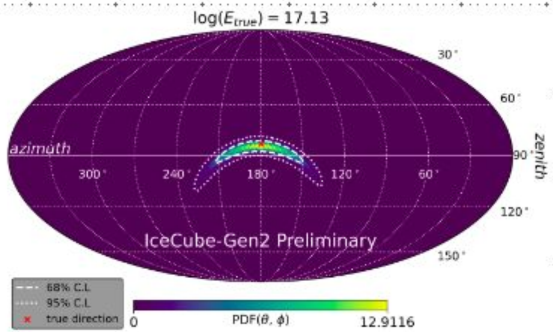
Applied in IceCube and IceCube-Gen2 for per-event posterior inference

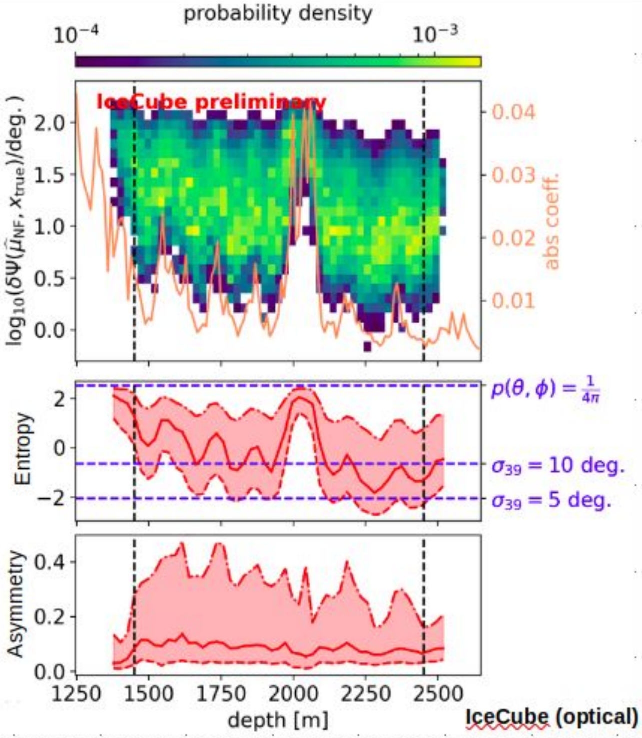
IceCube (optical) [9]





IceCube-Gen2 (radio) [10]

Directional posterior resolution vs depth (~50k electron neutrinos)



IceCube (optical) [9]

Posterior properties reflect detector properties
(South Pole ice properties vary with depth)

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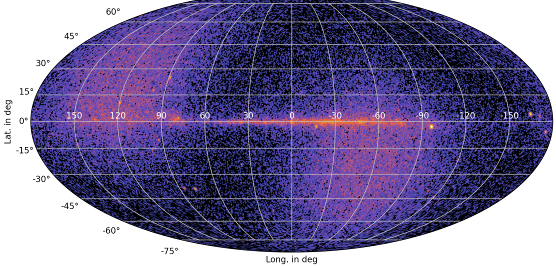
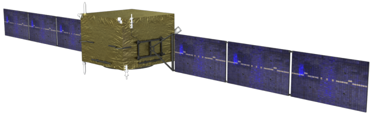




A deep learning method for the trajectory reconstruction of gamma rays with the DAMPE space mission

Parzival Nussbaum, Chiara Perrina, Jennifer Frieden

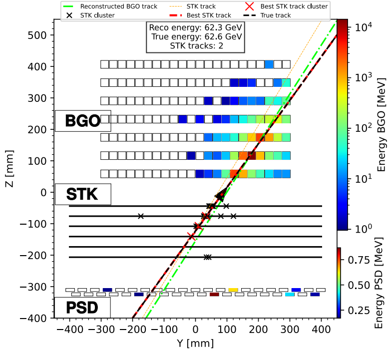
01.05.2024 EuCAIFCon

EPFL

DAMPE
DARK MATTER PARTICLE EXPLORER

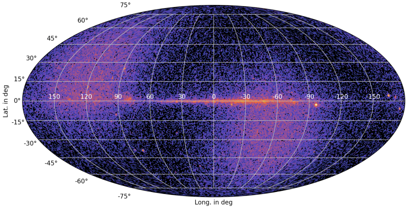
Standard approach to trajectory reconstruction

1. Shower profile $\Longrightarrow$ BGO reco track
2. Clustering the STK hits
3. Track-finding algorithm on clusters in the STK:
   - Seeding (calorimeter-seed or blind-seed).
   - Propagating using a **Kalman Filter**.
   - Filtering based on χ^2 and cluster count.
4. Multiple track candidates
   $\Longrightarrow$ metric (TQ) to choose the best track



Next generation experiments

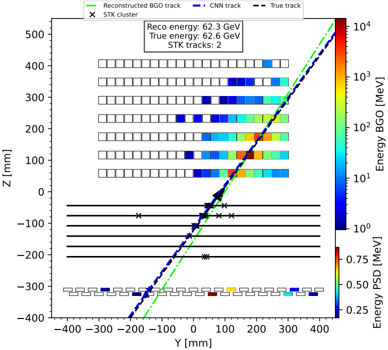
Standard reco is more challenging at higher energies since systematic uncertainties increase



CNN approach to trajectory reconstruction

1. Shower profile $\Longrightarrow$ BGO reco track
2. Clustering the STK hits
3. Hough transform of STK hits
4. CNN model prediction
   - Seeding (calorimeter-seed or blind-seed).
   - ~~Propagating using a **Kalman Filter**.~~
   - ~~Filtering based on χ^2 and cluster count.~~
5. ~~Multiple track candidates~~

   ~~$\Longrightarrow$ metric (TQ) to choose the best track~~



Results

- 300 times faster than standard reco
- One third of standard method precision
- Successful proof of concept on flight data