# Progress in statistical data analysis methods for 21cm surveys

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# Overview

Statistical challenges in 21cm analysis

Foreground removal and signal loss

Flagging and ringing

Bayesian anomaly detection

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European Research Council
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# Statistical challenges in 21cm analysis

- Gigantic dynamic range between foregrounds and signal
  - Need to weight data carefully to improve SNR
  - Need to subtract foregrounds very carefully to avoid destroying signal
- Complexity of spectral/temporal response of instruments
  - Difficult to come up with accurate simulations (c.f. galaxy surveys, who can simulate their covariance matrices!)
  - Unknown systematics, calibration errors

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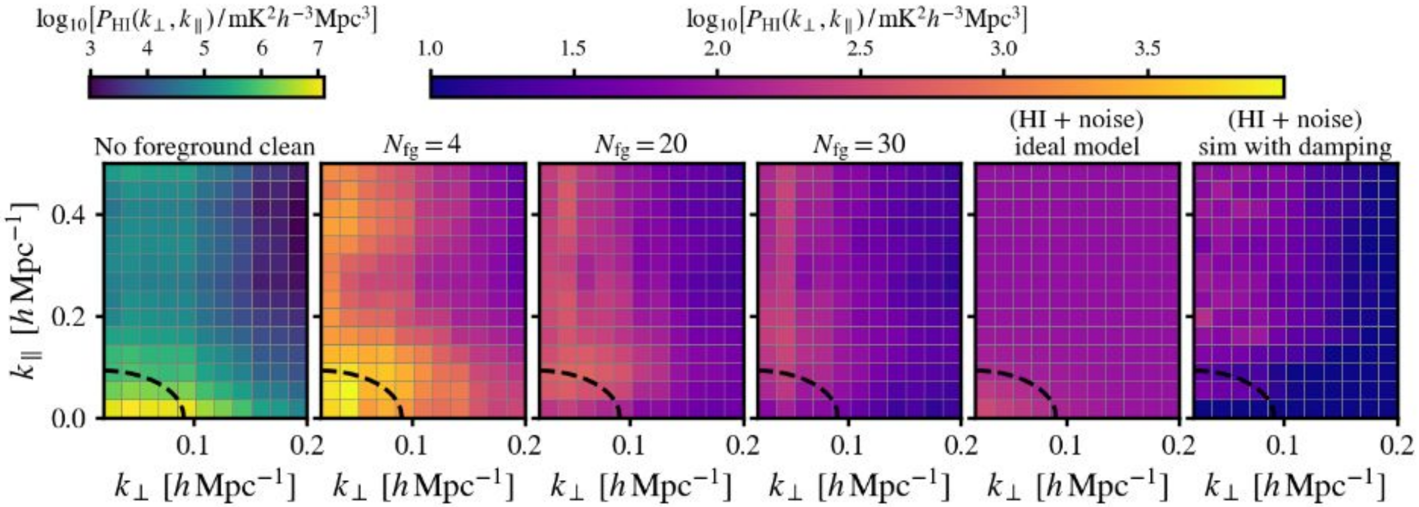
**Challenge:** How do we extract the extremely delicate 21cm signal:

(a) without wrecking everything; or

(b) at least knowing if/when we've wrecked everything!

# Foreground removal and signal loss

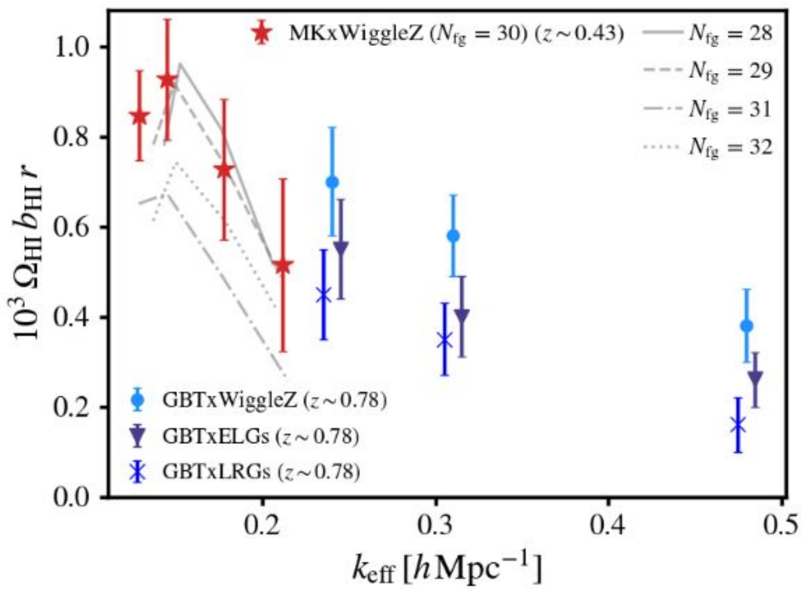
- Foregrounds: much brighter than 21cm signal + corrupted by instrument response
- "Blind" methods construct **filters** from data and subtract limited number of modes
- Modes are not orthogonal to 21cm signal, so some **signal loss** unavoidable




Cunnington, Li et al. [2206.01579]

# Foreground removal and signal loss

- Signal loss is a major problem for science interpretation
- **Do we trust methods that "undo" the loss?** (i.e. transfer function method)
    - *TF method: Inject mock data into real data, apply filter, cross-correlate with unfiltered mock to infer scale-dep.. signal loss transfer function T(k)*

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# Foreground removal and signal loss

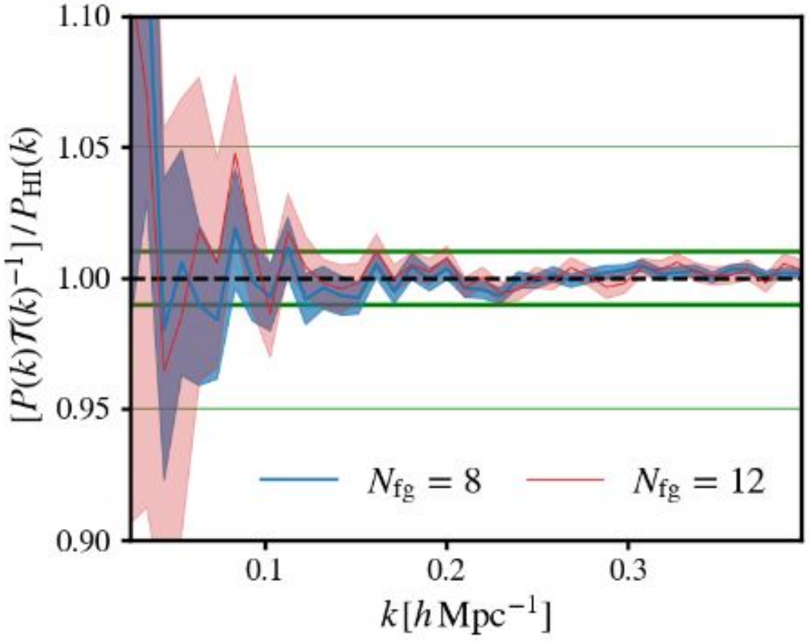
**Cunnington et al. [2302.07034]**

- TF method is robust if implemented properly!
- Need to account for variance of TF
- Beware over-application of TF!

```
P(auto) = P(clean) / T(k)
```

*not*

```
P(auto) = P(clean) / T²(k)
```



# Foreground removal and signal loss

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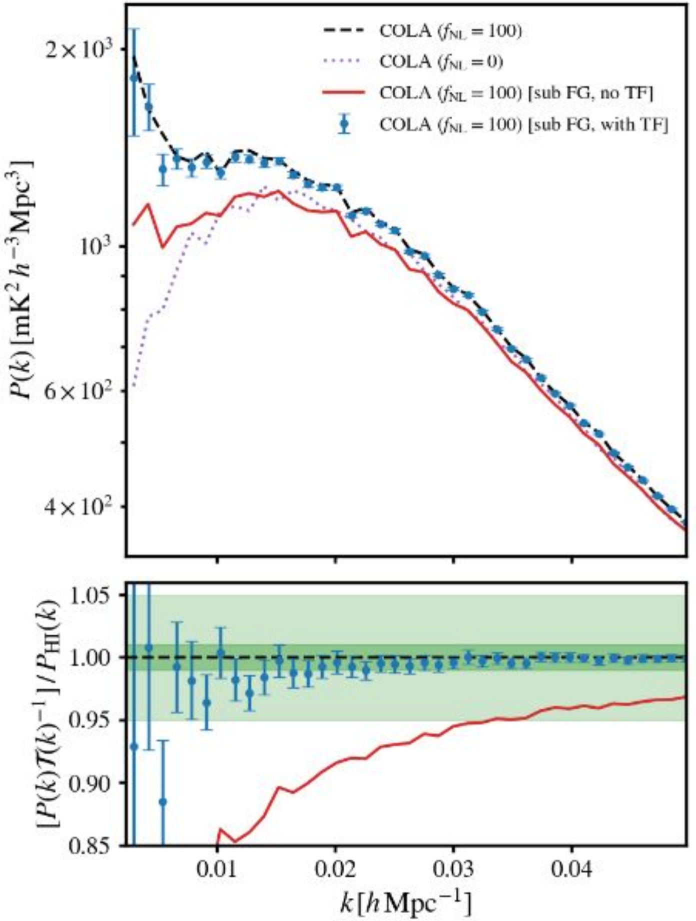
$$P(auto) = P(clean) / T^2(k)$$

- **Results are robust to simulated model**



# Kernel PCA

- Many blind filtering methods are related to Principal Component Analysis (PCA)
    - Construct freq.-freq. covariance from observed data
    - Do eigendecomposition
    - Use highest-SNR modes as FG templates
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  - Construct freq.-freq. covariance from observed data
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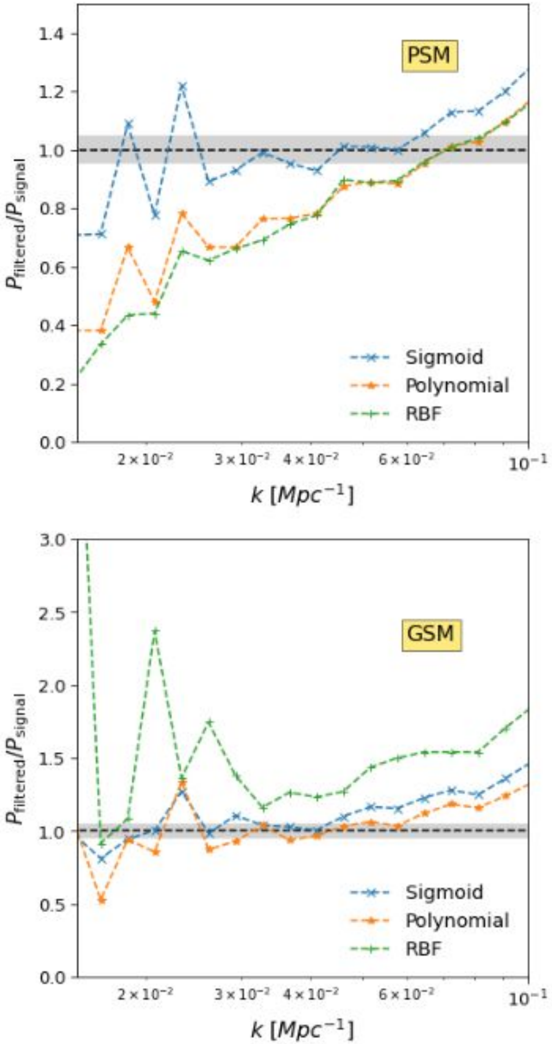
  - Use highest-SNR modes as FG templates
- PCA is lossy, and can quickly eat the 21cm signal
- **Kernel PCA** is a related method that permits non-linear combinations of the data to be used in constructing FG modes
- If tuned carefully, acts like “fractional” PCA




Irfan & Bull [2107.02267]

# Flagging and ringing

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  - Missing data causes ringing (very bad for 21cm due to dynamic range)

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  - **Infer the masked data** → *Gaussian constrained realisations*

All involve implicit models of missing data

# GCR and Gibbs sampling

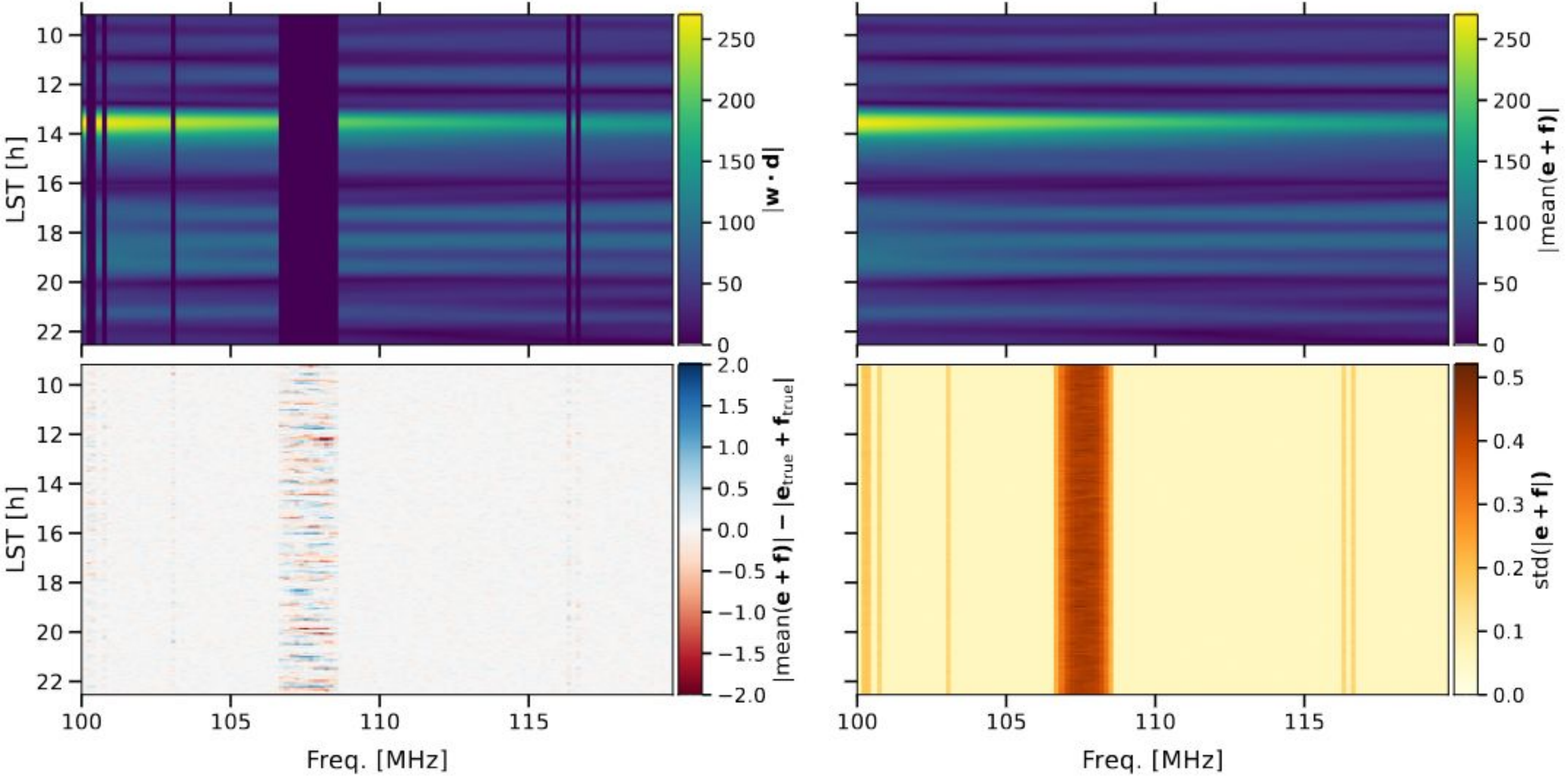
Kennedy et al. [2211.05088]

- **GCR:** Draw samples of the 21cm signal + foregrounds given **observed data**, **foreground basis functions**, **noise** and **21cm signal covariance** estimates

$$p(\mathbf{e}, \mathbf{a}_{\rm fg} | \mathbf{E}, \mathbf{g}_j, \mathbf{N}, \mathbf{d}) \propto p(\mathbf{d} | \mathbf{e}, \mathbf{a}_{\rm fg}, \mathbf{g}_j, \mathbf{N}) p(\mathbf{e} | \mathbf{E})$$

- Each sample has **no gaps**, so Fourier analysis can be applied exactly (no ringing). Repeat many times to build up statistical distribution.
- What if the 21cm signal covariance is poorly known? → **Gibbs sampling method**
  - Iteratively sample 21cm signal (+ foregrounds), then 21cm covariance

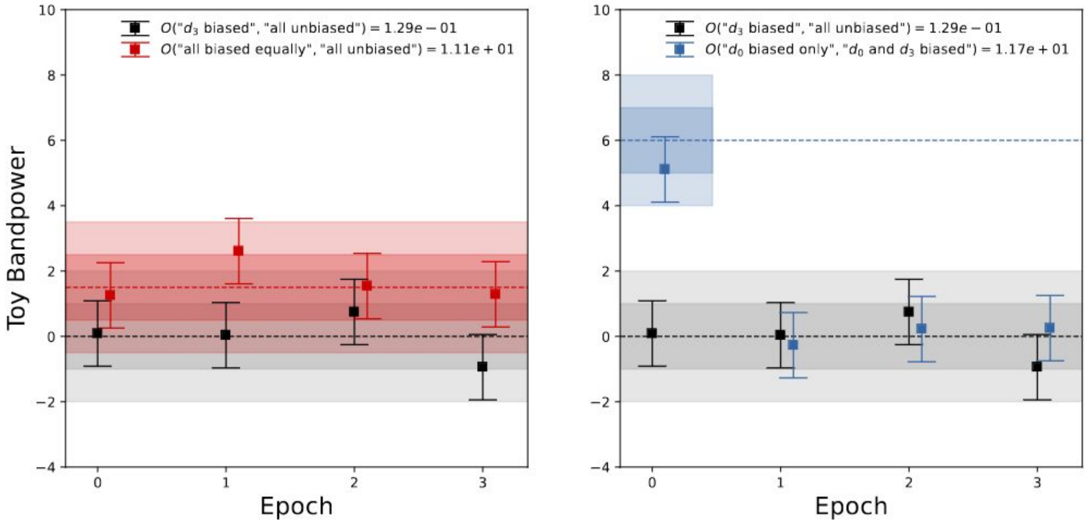
$$\mathbf{s}_{i+1} \leftarrow p(\mathbf{s}_i | \mathbf{S}_i, \mathbf{N}, \mathbf{d})$$
$$\mathbf{S}_{i+1} \leftarrow p(\mathbf{S}_i | \mathbf{s}_{i+1}).$$




Kennedy et al. [2211.05088]

# Bayesian anomaly detection

- So many ways of splitting the HERA data, not enough humans to inspect it all
- **Chiborg:** an automated, statistically-principled way of doing **null/jackknife** tests
  - Can handle a few subsets with different weights (i.e. not just equal halves)
  - Big hierarchy of hypotheses + simple parametrisation for “biased” data




Wilensky+ [2210.17351]

GitHub: [mwilensky768/chiborg](https://github.com/mwilensky768/chiborg)

# Bayesian anomaly detection

- Basic idea: enumerate every possible combination of systematic-affected vs not-affected subsets of the data, then calculate odds ratios
- Systematic level does not have to be known/assumed (i.e. can be drawn from a distribution, and hyperparameters of distribution can be marginalised)

$$P(\mathbf{d}|\mathbf{C}_0, \mathcal{H}_0) = \int_{\mathbb{R}} d\mu_0 P(\mu_0) P(\mathbf{d}|\mathbf{C}_0, \mu_0, \mathcal{H}_0)$$

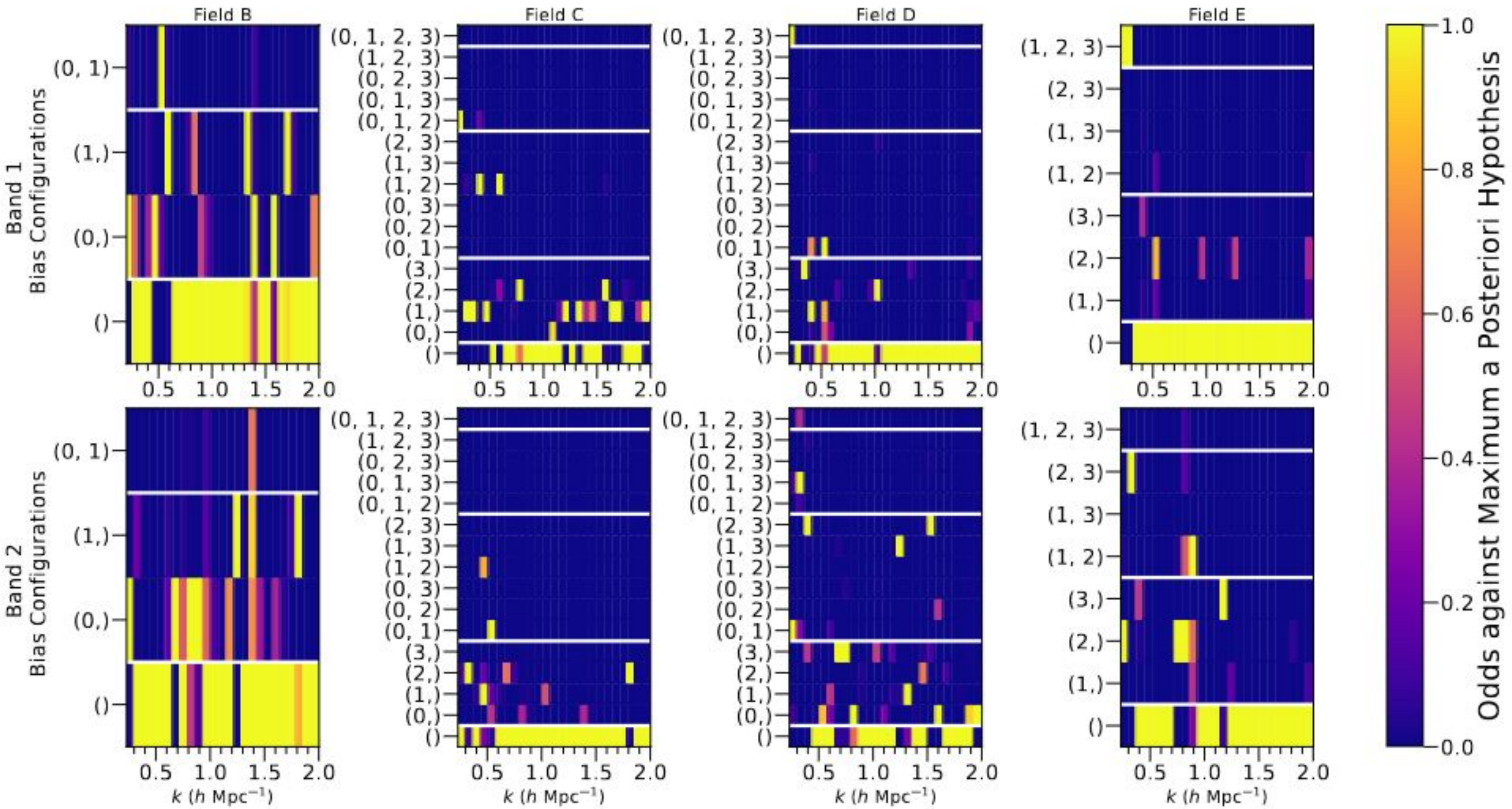
Null hypothesis
(no systematic)

$$P(\mathbf{d}|\mathbf{C}_0, \mathcal{H}_i) = \int_{\mathbb{R}} d\mu_0 P(\mu_0) \int_{\mathbb{R}^N} d\boldsymbol{\varepsilon} P(\boldsymbol{\varepsilon}|\mathcal{H}_i) P(\mathbf{d}|\mathbf{C}_0, \mu_0, \boldsymbol{\varepsilon}, \mathcal{H}_i)$$

Systematic-affected
hypothesis

Wilensky et al. [2210.17351]

# Which epochs of the HERA data have anomalous power? *(by field/band, vs scale cut)*




Wilensky et al. [2210.17351]

# Summary

- Building a statistical model of the data allows us to treat sensitive filtering and power spectrum estimation steps in a principled manner
- Principled approach improves robustness!
- Also allows sense-checking of data in automated fashion (null tests etc.)
- **Please use our software!**

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# EXTRA SLIDES