



The uncertain uncertainties in the Galactic Faraday sky

Niels Oppermann

with

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Bayes Forum, MPE, 2012-05-25

Outline

1. The physics

Faraday depth – measuring magnetic fields (sort of)

2. The statistics

priors, marginalizations, and the Gibbs free energy

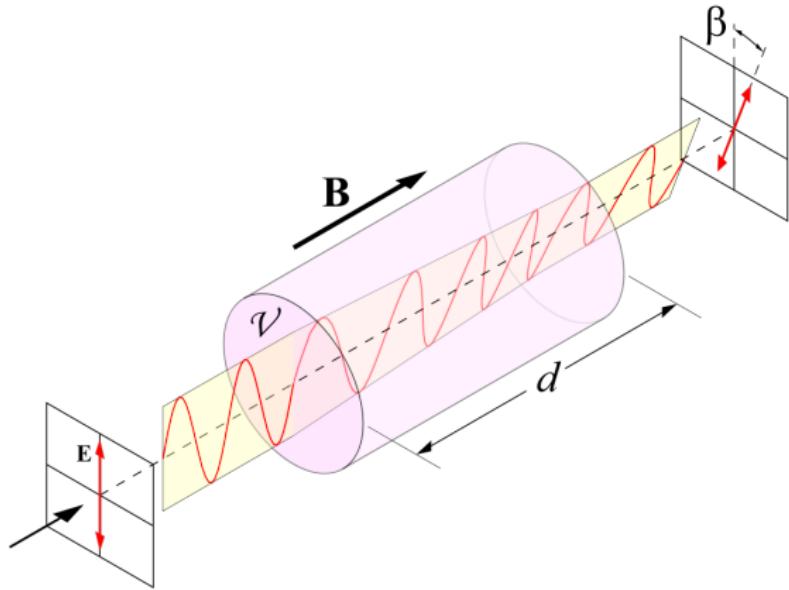
3. The application

...of the *extended critical filter* to the Faraday sky

4. Why we bother

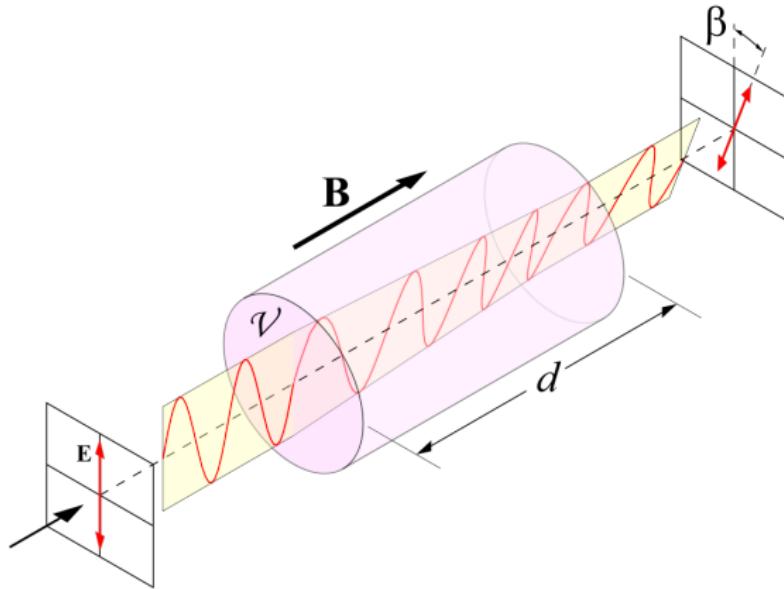
if there's time left...

The Physics



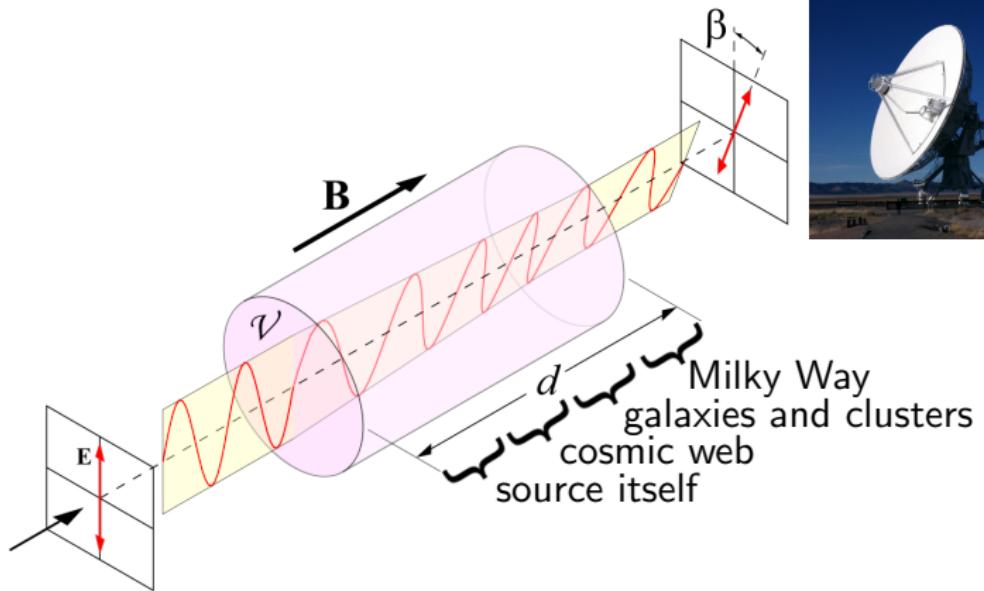
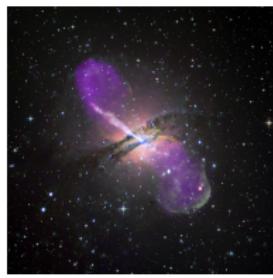
$$d\beta \propto \lambda^2 n_e(\vec{x}) B_r(\vec{x}) dr$$

$$\Rightarrow \beta \propto \lambda^2 \int_{r_{\text{source}}}^0 n_e(\vec{x}) B_r(\vec{x}) dr$$

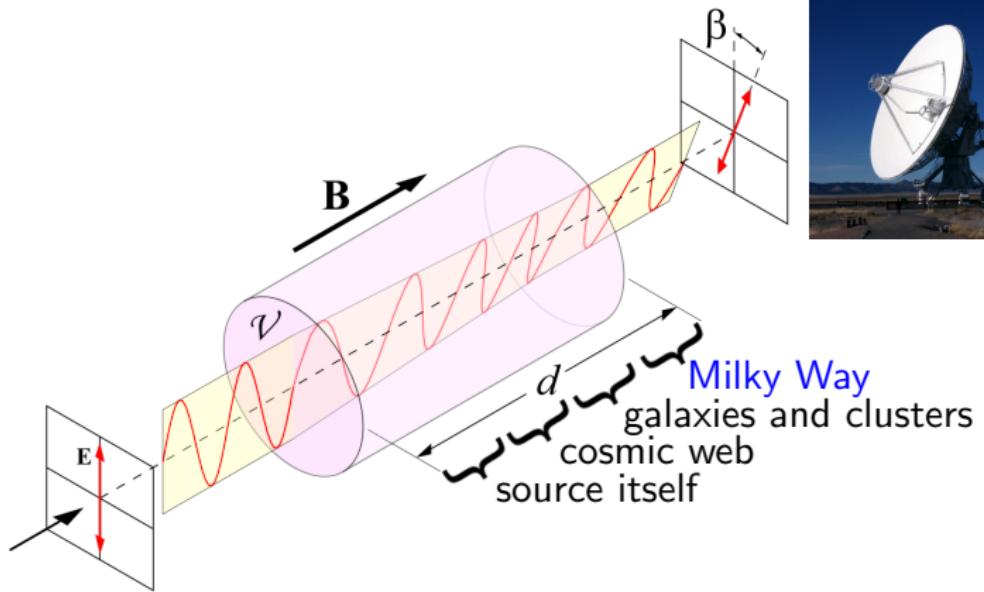
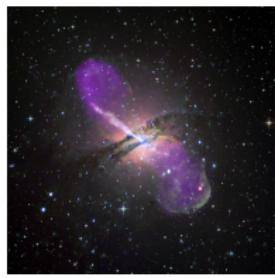


Faraday depth: $\phi \propto \int_{r_{\text{source}}}^0 n_e(\vec{x}) B_r(\vec{x}) dr$

$$\beta = \phi \lambda^2$$

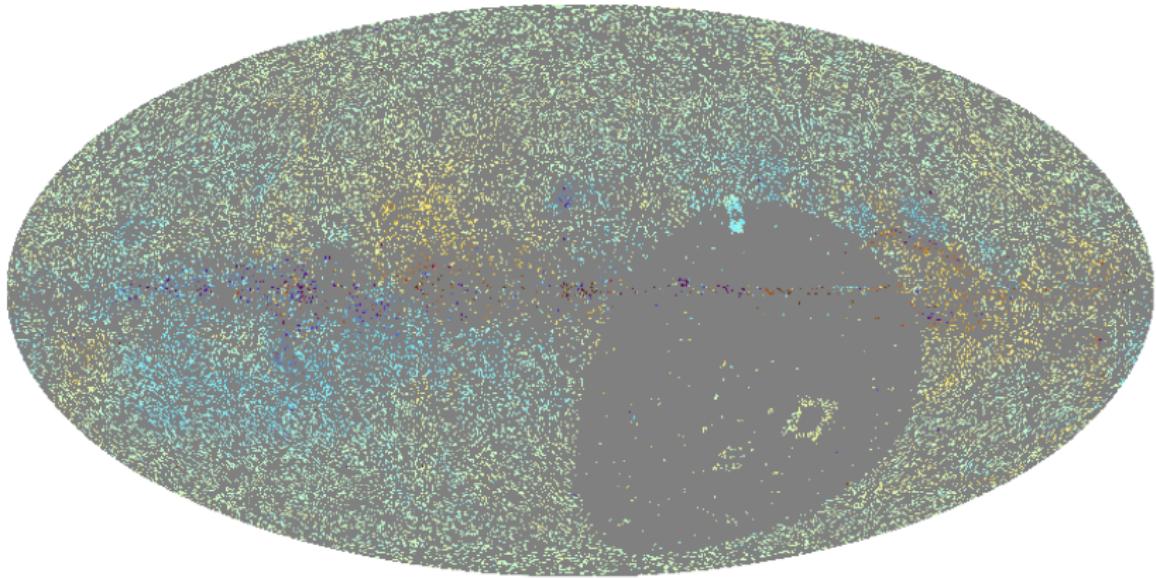


$$\text{Faraday depth: } \phi \propto \int_{r_{\text{source}}}^0 n_e(\vec{x}) B_r(\vec{x}) dr$$
$$\beta = \phi \lambda^2$$

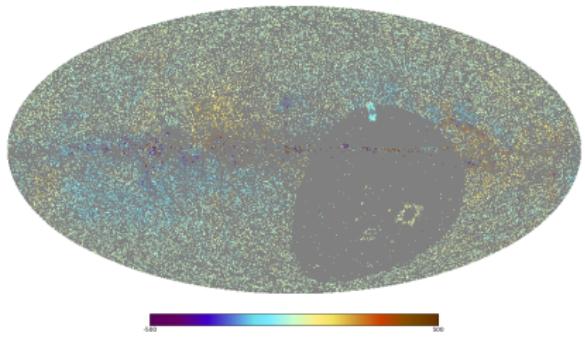


Galactic Faraday depth:

$$\phi \propto \int_{r_{\text{MilkyWay}}}^0 n_e(\vec{x}) B_r(\vec{x}) dr$$



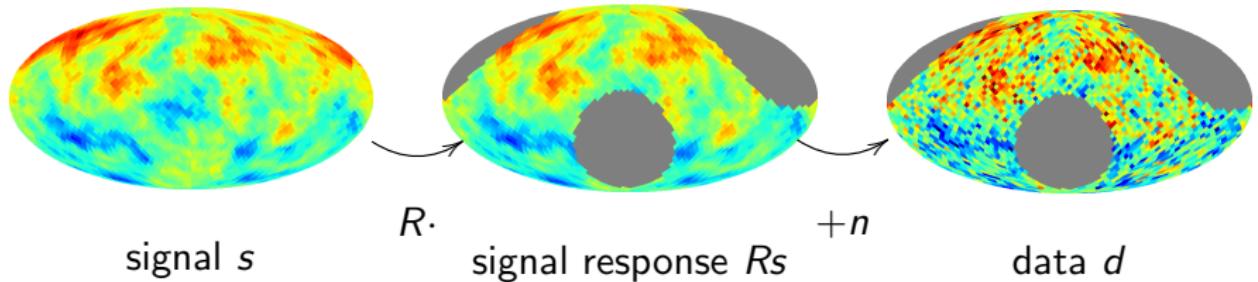
41 330 data points



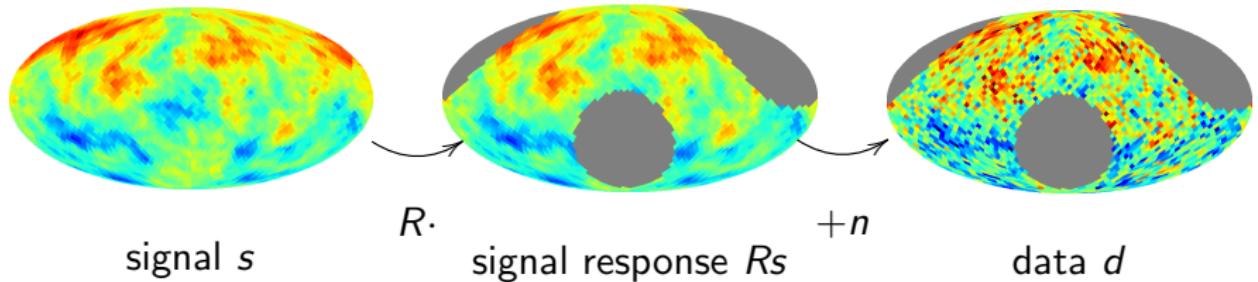
Challenges

- ▶ Regions without data
- ▶ Uncertain error bars:
 - ▶ complicated observations
 - ▶ $n\pi$ -ambiguity
 - ▶ extragalactic contributions unknown

The Statistics



$$d = Rs + n$$

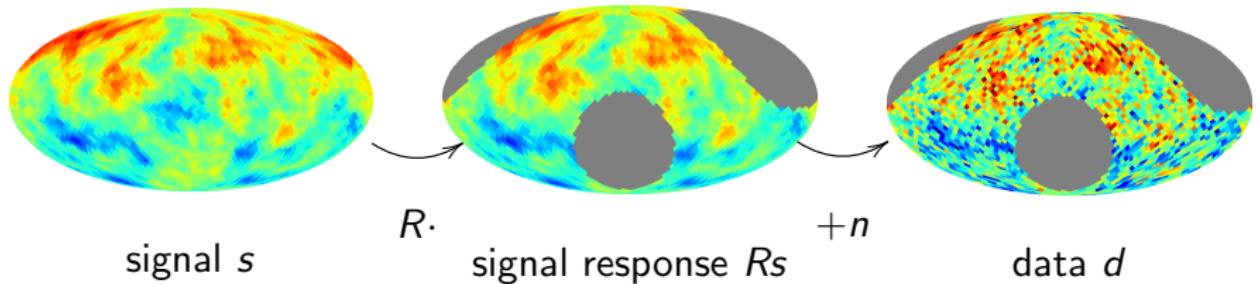


$$\mathcal{P}(s) = \mathcal{G}(s, S)$$

$$\mathcal{P}(n) = \mathcal{G}(n, N)$$

$$d = Rs + n$$

$$\mathcal{G}(s, S) = \frac{1}{|2\pi S|^{1/2}} \exp \left[\frac{1}{2} s^\dagger S^{-1} s \right]$$



Wiener Filter

$$m = \int \mathcal{D}s \ s \ \mathcal{P}(s|d)$$

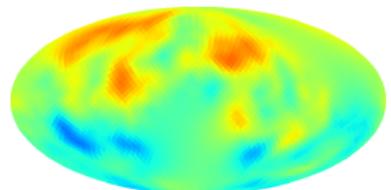
$$d = Rs + n$$

$$m = Dj, \text{ where}$$

$$j = R^\dagger N^{-1}d$$

$$D = (S^{-1} + R^\dagger N^{-1} R)^{-1}$$

$$\downarrow DR^\dagger N^{-1}.$$



$$S(\hat{n}, \hat{n}') = \int \mathcal{D}s \ s(\hat{n})s(\hat{n}')\mathcal{P}(s)$$

$$\Rightarrow S_{(\ell m), (\ell' m')} = \int \mathcal{D}s \ s_{\ell m} s_{\ell' m'}^* \mathcal{P}(s)$$

$$\begin{aligned}
S(\hat{n}, \hat{n}') &= \int \mathcal{D}s \ s(\hat{n})s(\hat{n}')\mathcal{P}(s) \\
&= S(\hat{n} \cdot \hat{n}') \\
\Rightarrow S_{(\ell m), (\ell' m')} &= \int \mathcal{D}s \ s_{\ell m} s_{\ell' m'}^* \mathcal{P}(s) \\
&= \delta_{\ell \ell'} \delta_{m m'} C_\ell
\end{aligned}$$

↪ angular power spectrum

$$\begin{aligned} S(\hat{n}, \hat{n}') &= \int \mathcal{D}s \ s(\hat{n})s(\hat{n}')\mathcal{P}(s) \\ &= S(\hat{n} \cdot \hat{n}') \\ \Rightarrow S_{(\ell m), (\ell' m')} &= \int \mathcal{D}s \ s_{\ell m} s_{\ell' m'}^* \mathcal{P}(s) \\ &= \delta_{\ell \ell'} \delta_{m m'} \textcolor{blue}{C_\ell} \\ &\hookrightarrow \text{angular power spectrum} \end{aligned}$$

$$N_{ij} = \delta_{ij} \sigma_i^2$$

(uncorrelated noise)

$$S_{(\ell m), (\ell' m')} = \delta_{\ell \ell'} \delta_{mm'} \textcolor{red}{C}_{\ell} \quad N_{ij} = \delta_{ij} \eta_i \sigma_i^2$$

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Enter the prior

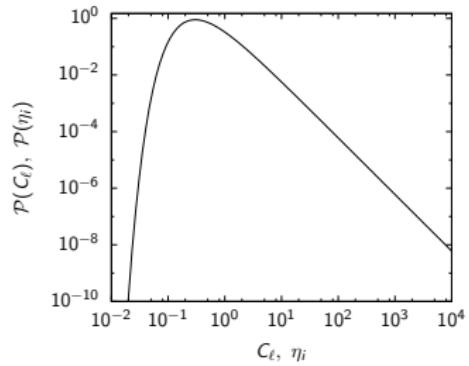


$$S_{(\ell m), (\ell' m')} = \delta_{\ell\ell'} \delta_{mm'} \textcolor{red}{C_\ell} \quad N_{ij} = \delta_{ij} \eta_i \sigma_i^2$$

assume priors for parameters

$$\mathcal{P}((C_\ell)_\ell) = \prod_\ell \frac{1}{q_\ell \Gamma(\alpha_\ell - 1)} \left(\frac{C_\ell}{q_\ell} \right)^{-\alpha_\ell} \exp \left(-\frac{q_\ell}{C_\ell} \right)$$

$$\mathcal{P}((\eta_i)_i) = \prod_i \frac{1}{q_i \Gamma(\alpha_i - 1)} \left(\frac{\eta_i}{q_i} \right)^{-\alpha_i} \exp \left(-\frac{q_i}{\eta_i} \right)$$



⇒ marginalize over all possible parameters

$$S_{(\ell m), (\ell' m')} = \delta_{\ell\ell'} \delta_{mm'} \textcolor{red}{C}_{\ell} \quad N_{ij} = \delta_{ij} \eta_i \sigma_i^2$$

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⇒ marginalize over all possible parameters

Problem: $\mathcal{P}(s|d)$ is non-Gaussian.

Solution: Find Gaussian $\mathcal{G}(s - m, D)$, that best approximates $\mathcal{P}(s|d)$.

- ▶ Minimize Kullback-Leibler divergence

$$d_{\text{KL}} = \int \mathcal{D}s \mathcal{G}(s - m, D) \log \left(\frac{\mathcal{G}(s - m, D)}{\mathcal{P}(s|d)} \right)$$

or

- ▶ Minimize approximate Gibbs free energy

$$G = \langle H_{\mathcal{P}(s|d)} + \log(\mathcal{G}(s - m, D)) \rangle_{\mathcal{G}(s - m, D)}$$

Enßlin & Weig (2010)

Problem: $\mathcal{P}(s|d)$ is non-Gaussian.

Solution: Find Gaussian $\mathcal{G}(s - m, D)$, that best approximates $\mathcal{P}(s|d)$.

Extended Critical Filter

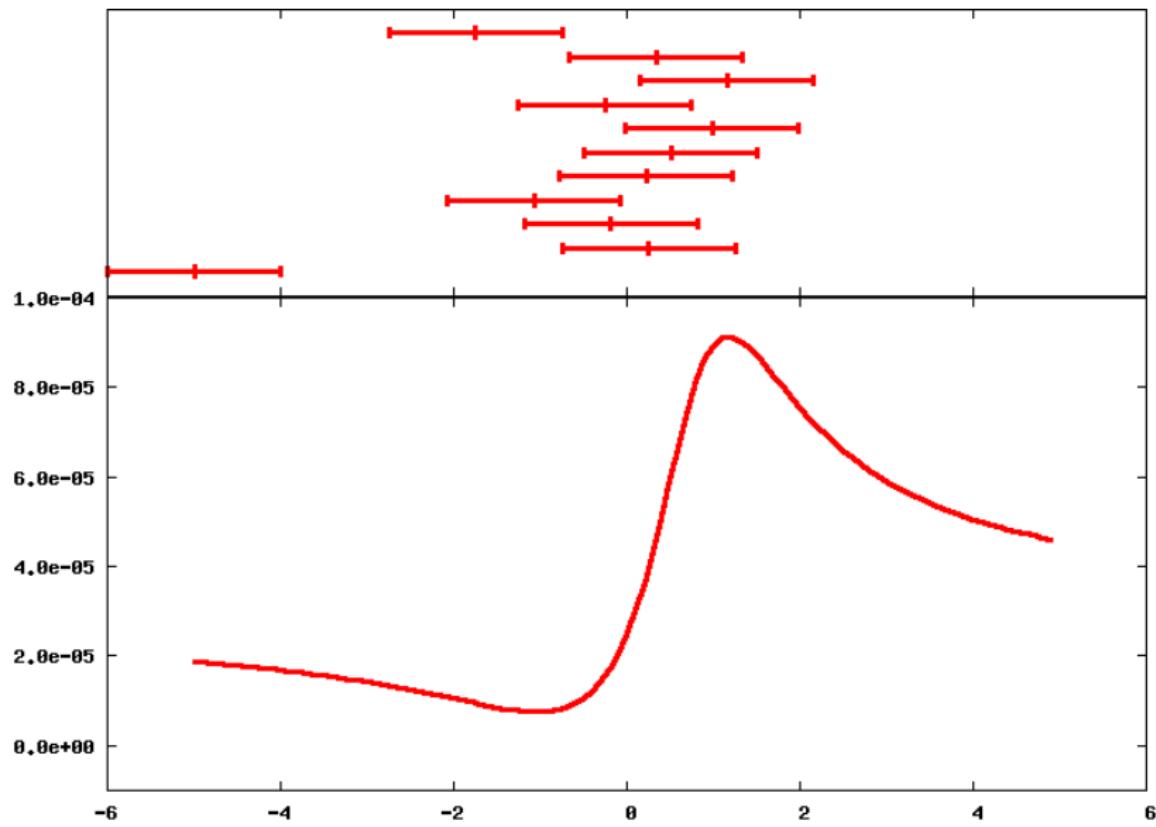
$$m = Dj, \quad D = \left[\sum_{\ell} C_{\ell}^{-1} S_{\ell}^{-1} + \sum_i \eta_i^{-1} R^{\dagger} N_i^{-1} R \right]^{-1},$$

$$j = \sum_i \eta_i^{-1} R^{\dagger} N_i^{-1} d$$

$$C_{\ell} = \frac{1}{\alpha_{\ell} + \ell - 1/2} \left[q_{\ell} + \frac{1}{2} \text{tr} \left(\left(mm^{\dagger} + D \right) S_{\ell}^{-1} \right) \right]$$

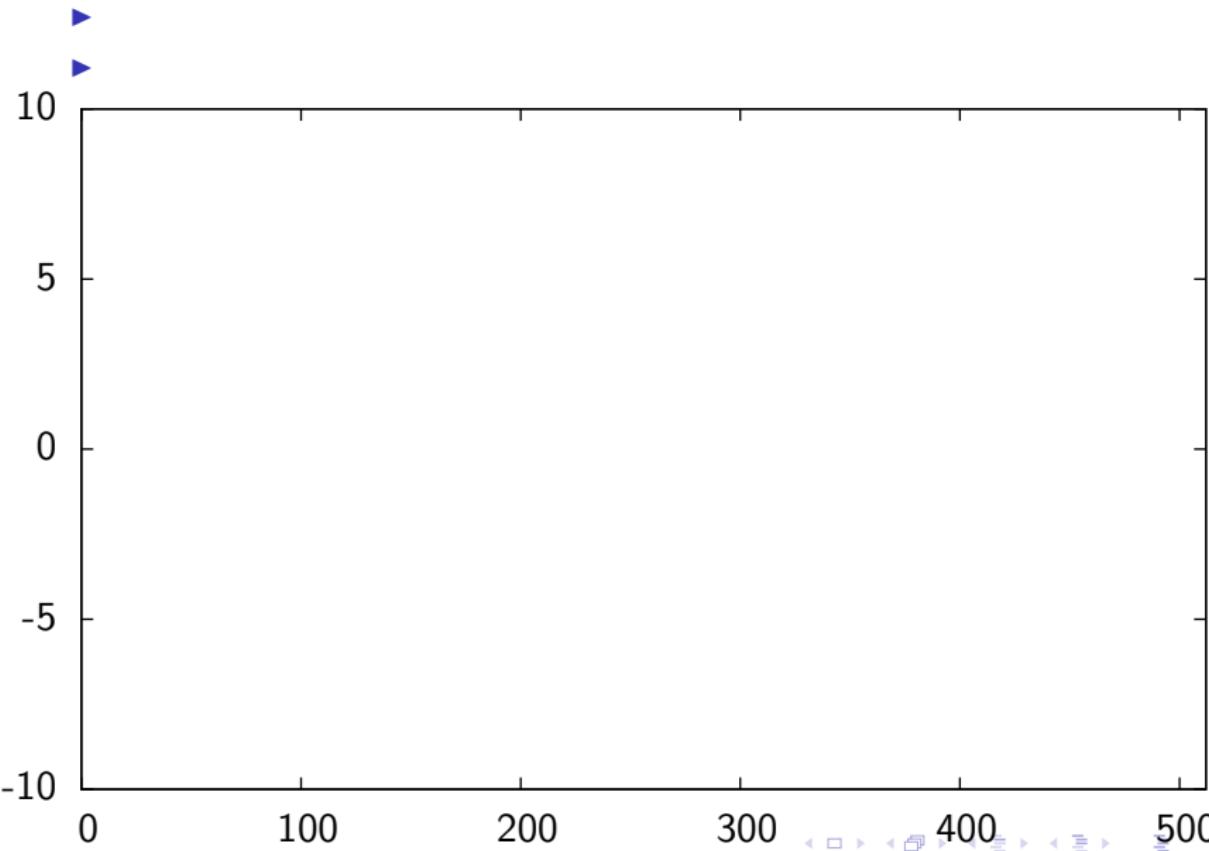
$$\eta_i = \frac{1}{\alpha_i} \left[q_i + \frac{1}{2} \text{tr} \left(\left((d - Rm) (d - Rm)^{\dagger} + D \right) N_i^{-1} \right) \right]$$

0D test case



1D test case

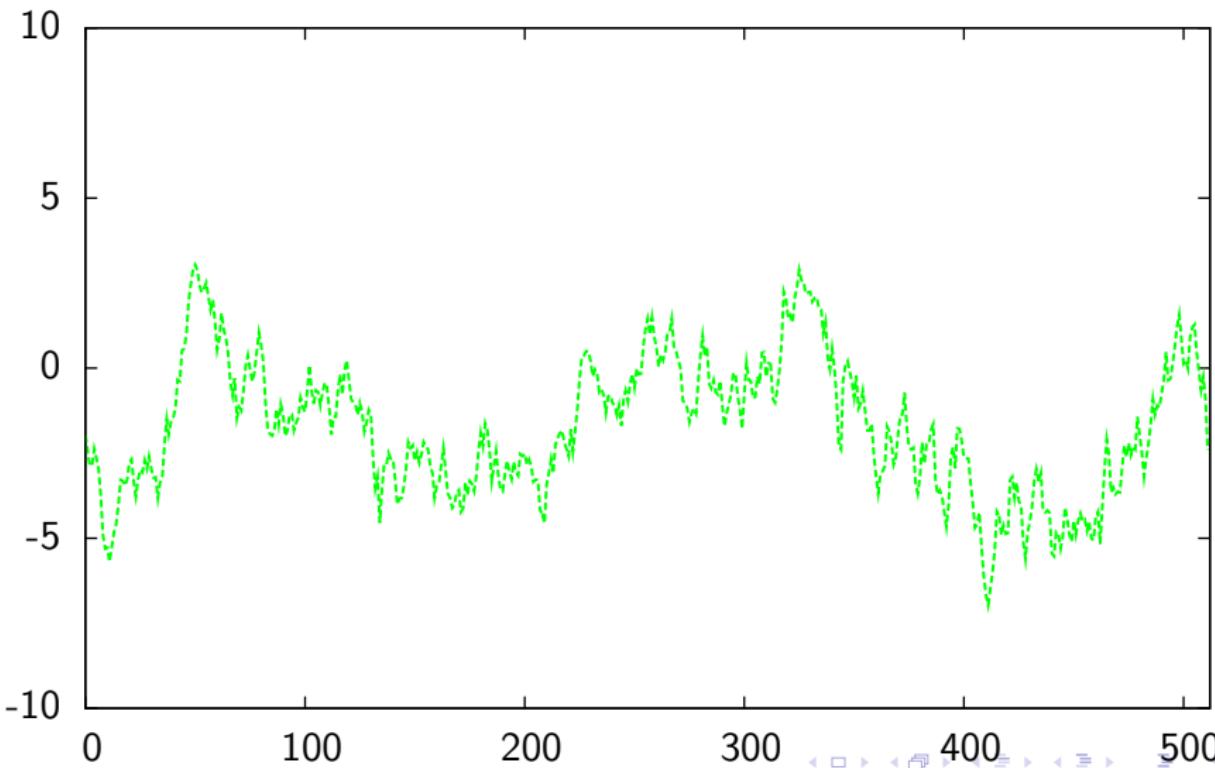
Assumptions:



1D test case

Assumptions:

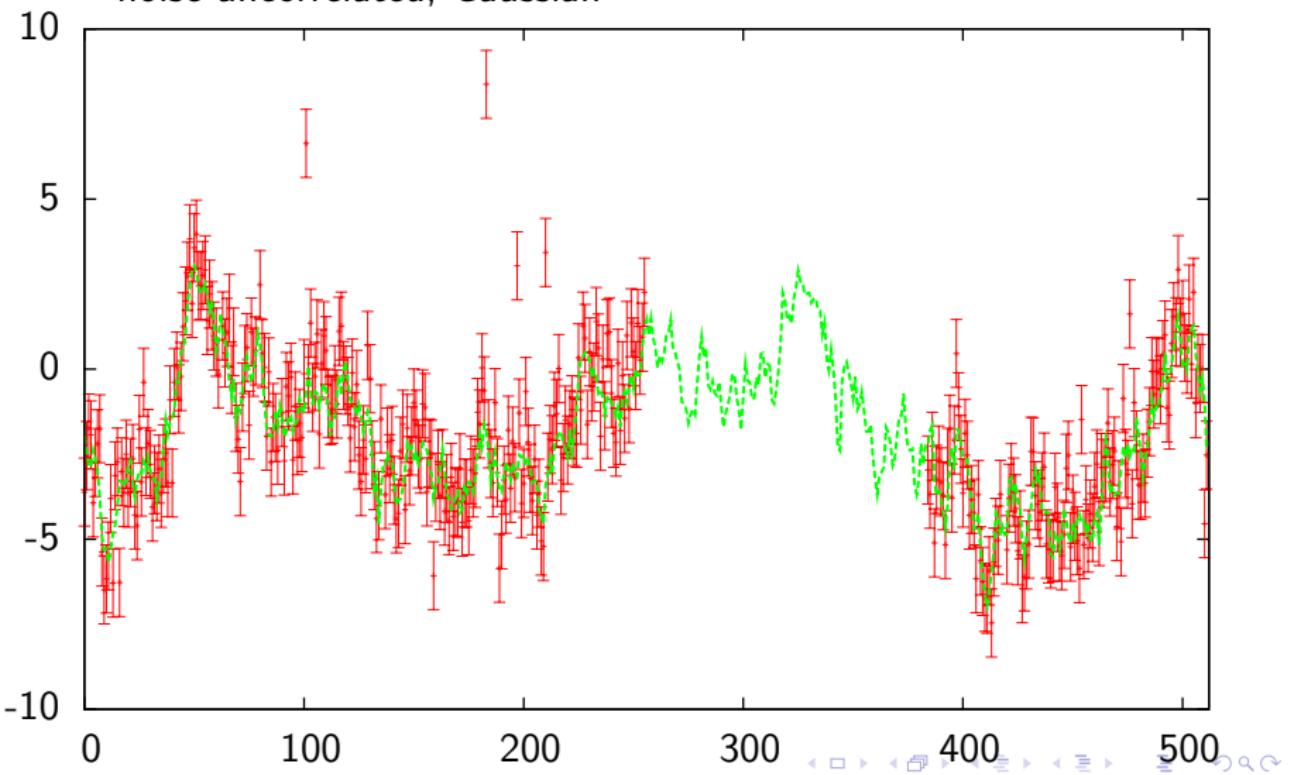
- ▶ signal field statistically homogeneous Gaussian random field
- ▶



1D test case

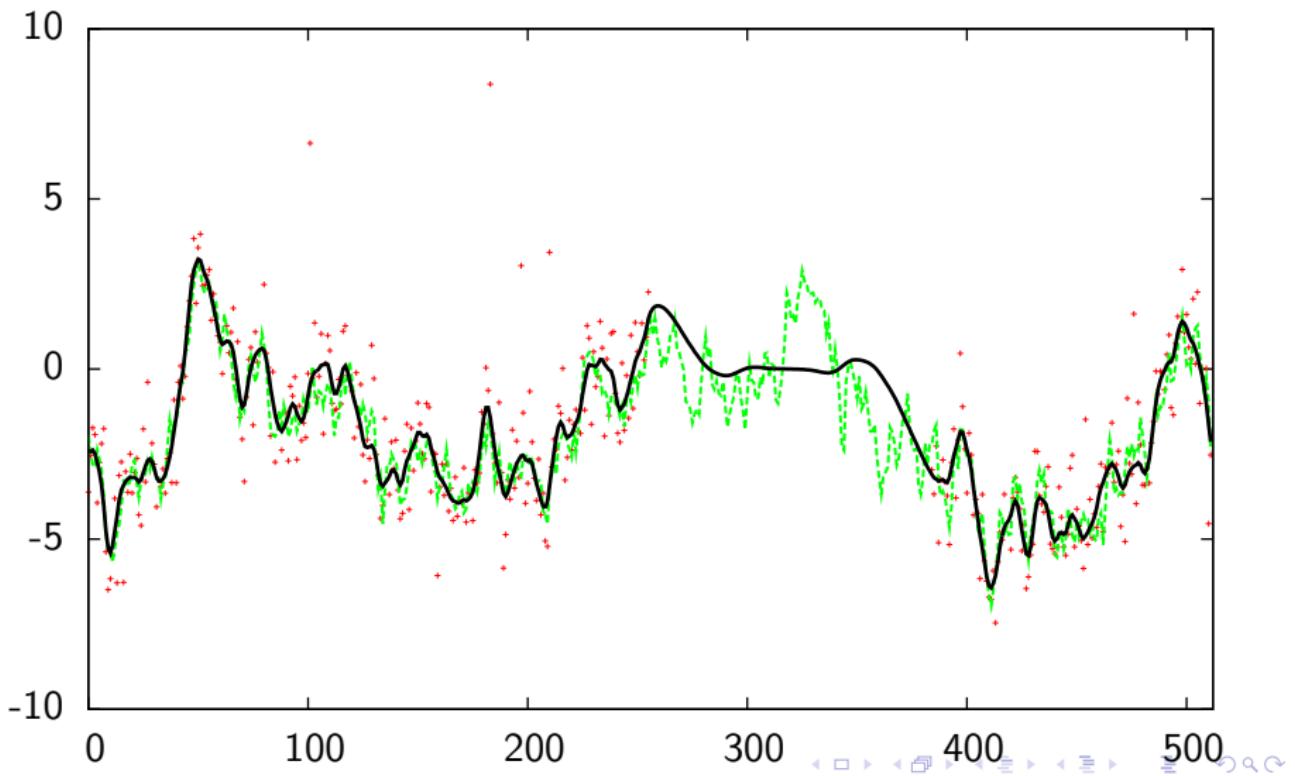
Assumptions:

- ▶ signal field statistically homogeneous Gaussian random field
- ▶ noise uncorrelated, Gaussian



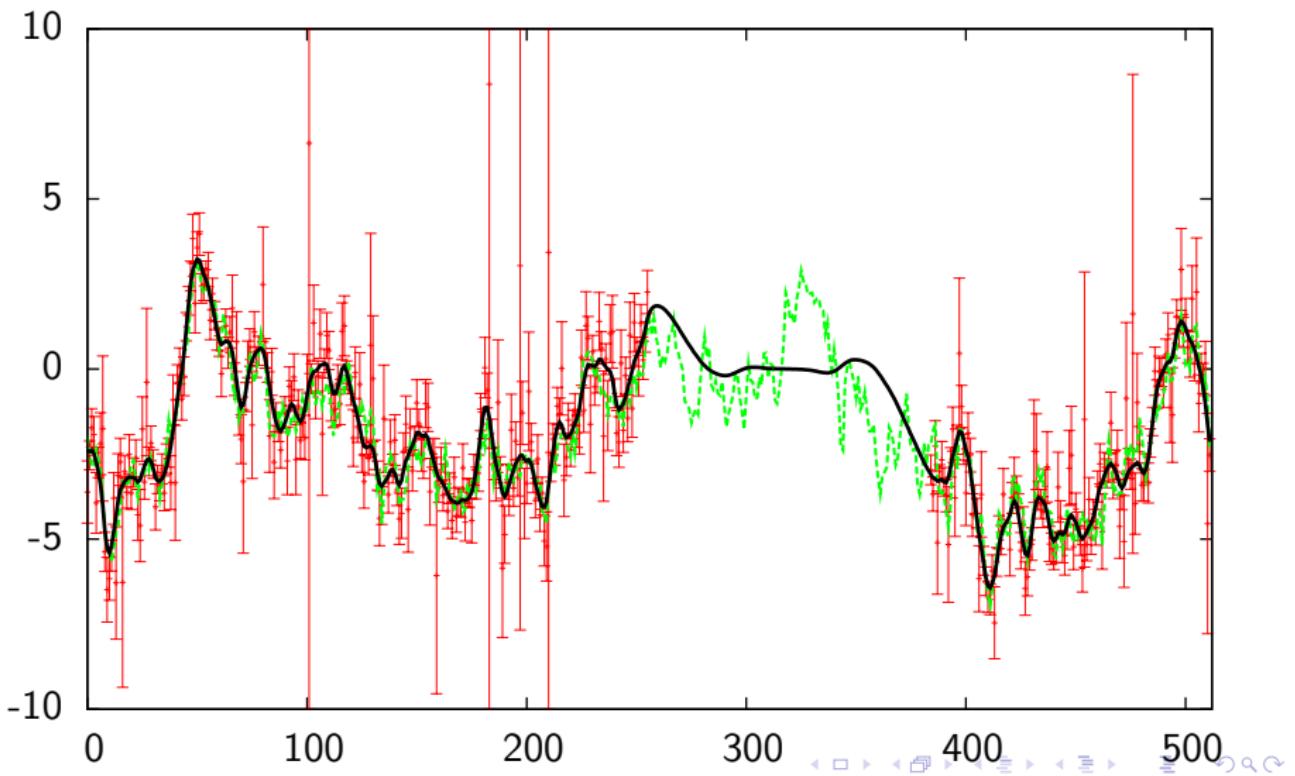
1D test case

- ▶ Reconstruct (iteratively):
signal, power spectrum, noise variance

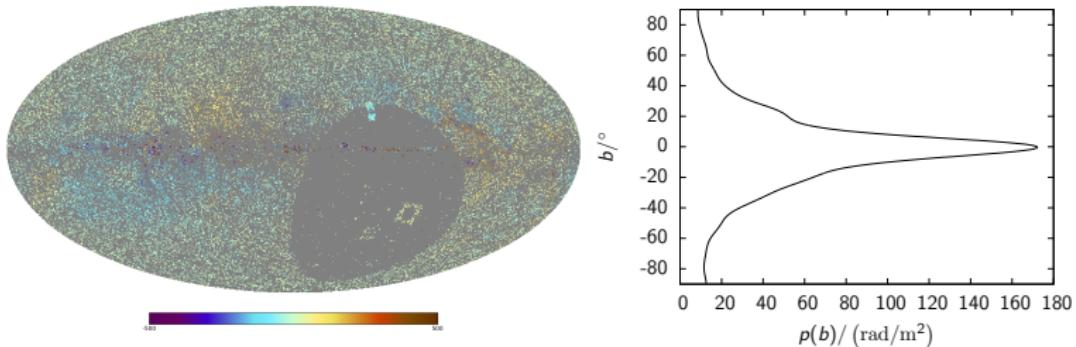


1D test case

- ▶ Reconstruct (iteratively):
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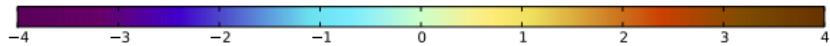
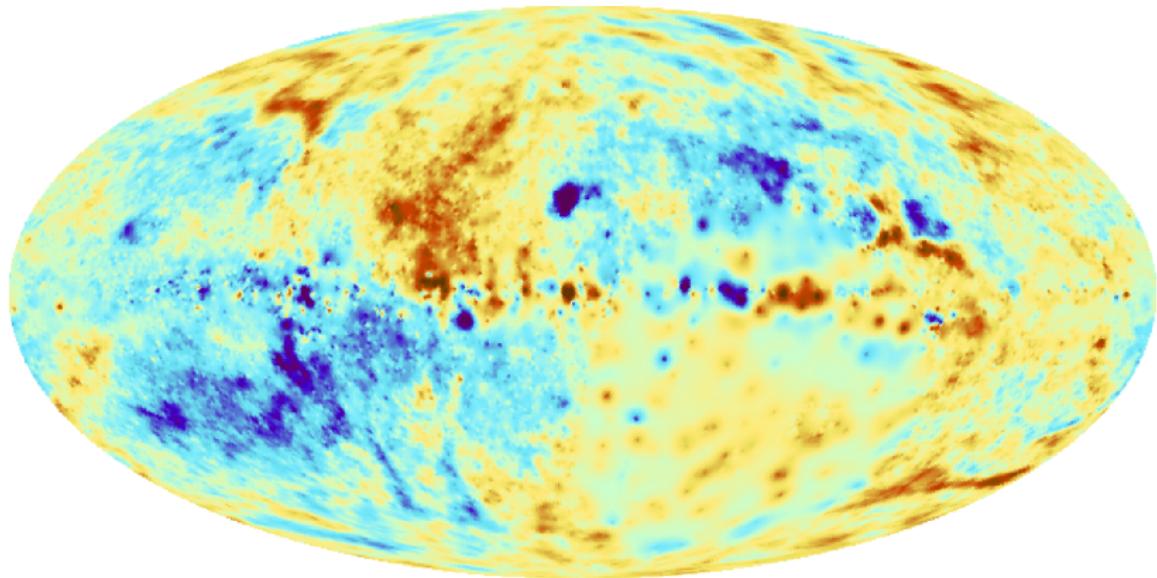


The Application



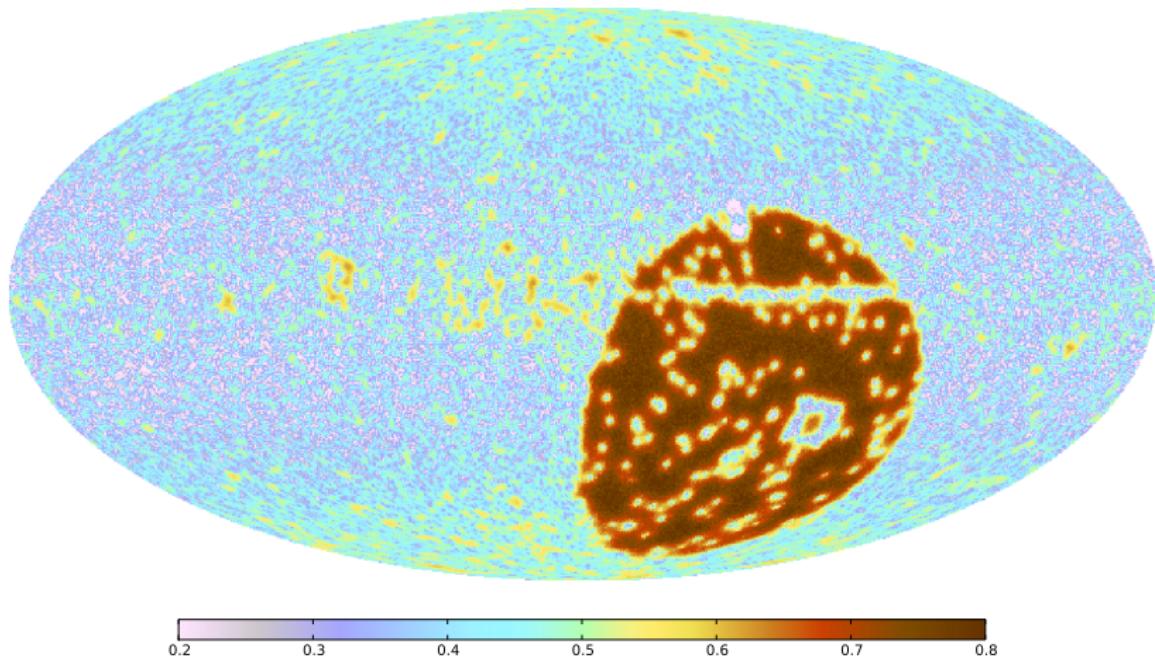
- ▶ Approximate $s(b, l) := \frac{\phi(b, l)}{p(b)}$ as a statistically isotropic Gaussian field
- ▶ R : multiplication with $p(b)$ and projection on directions of sources
- ▶ $N_{ij} = \delta_{ij}\eta_i\sigma_i^2$

posterior mean of the signal



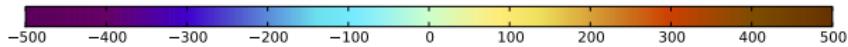
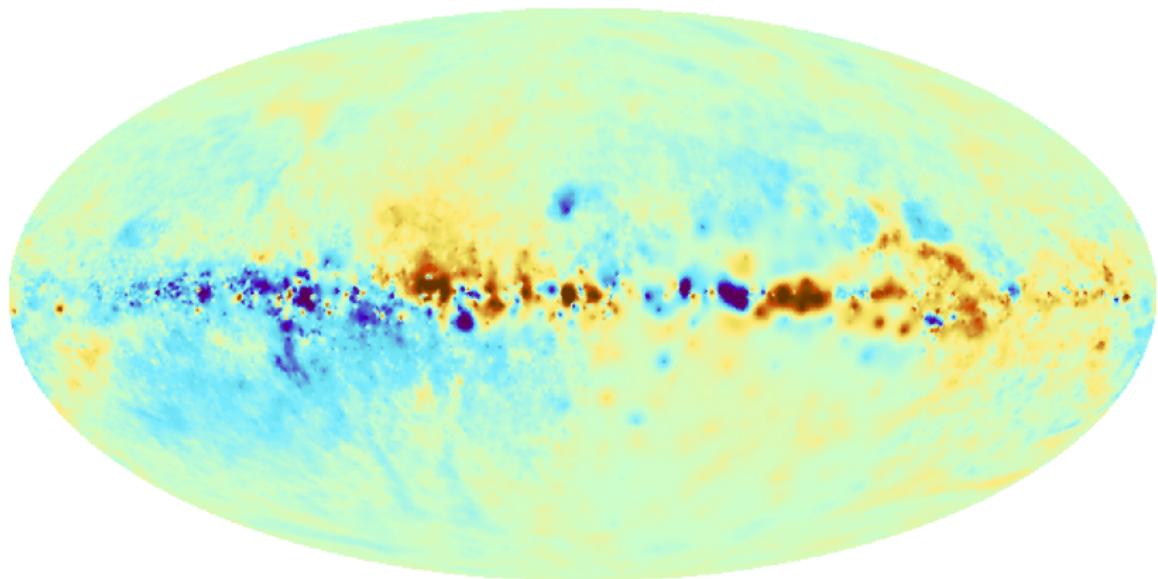
m

uncertainty of the signal map



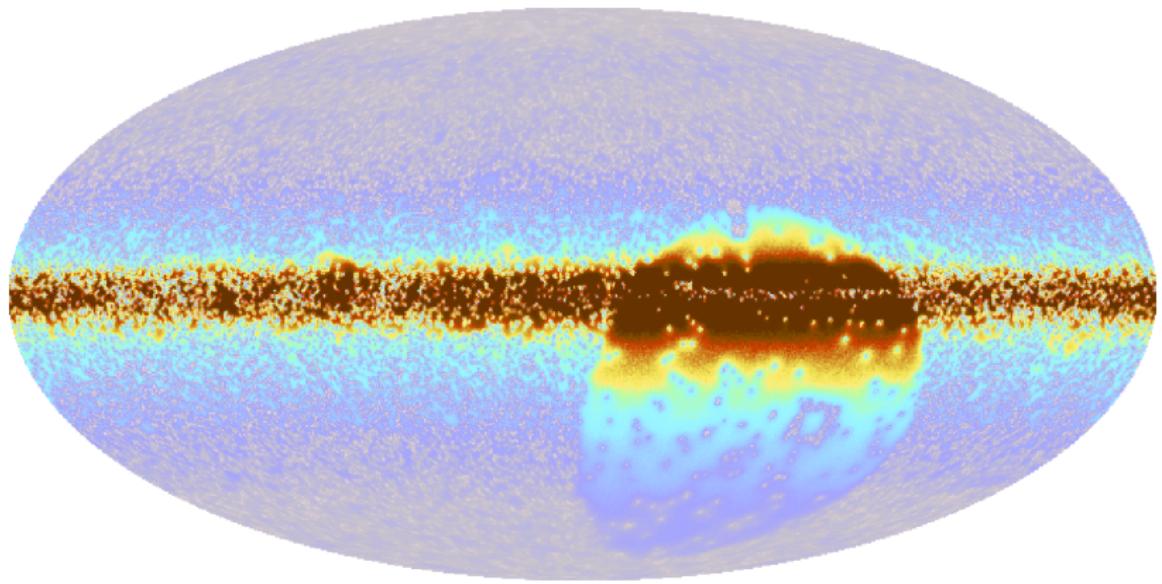
$$\sqrt{\text{diag}(D)}$$

posterior mean of the Faraday depth



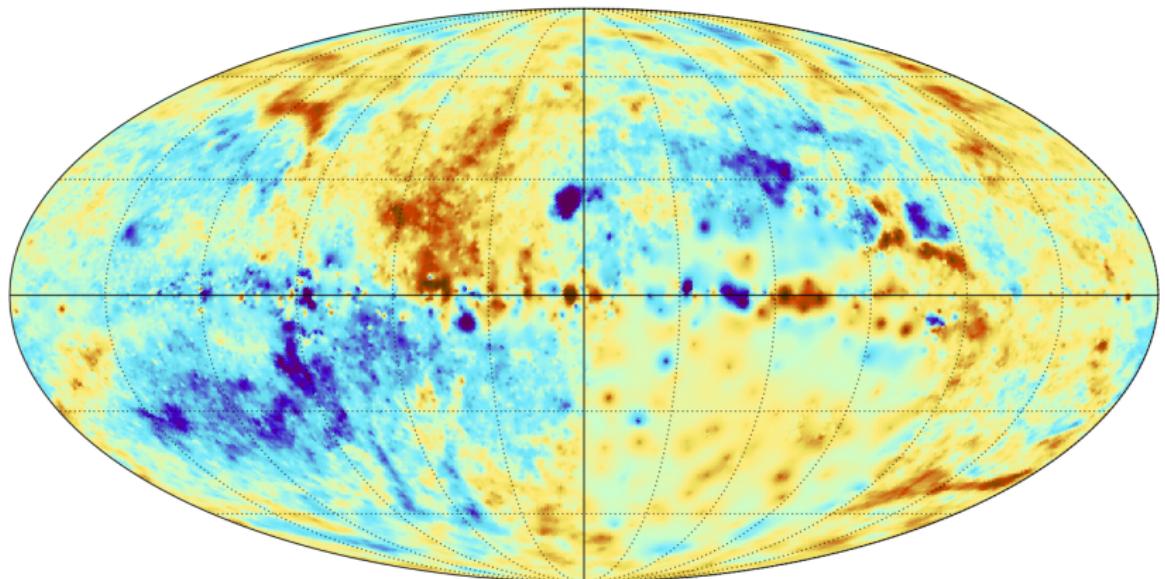
pm

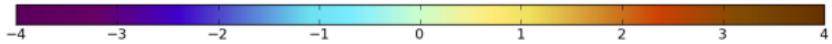
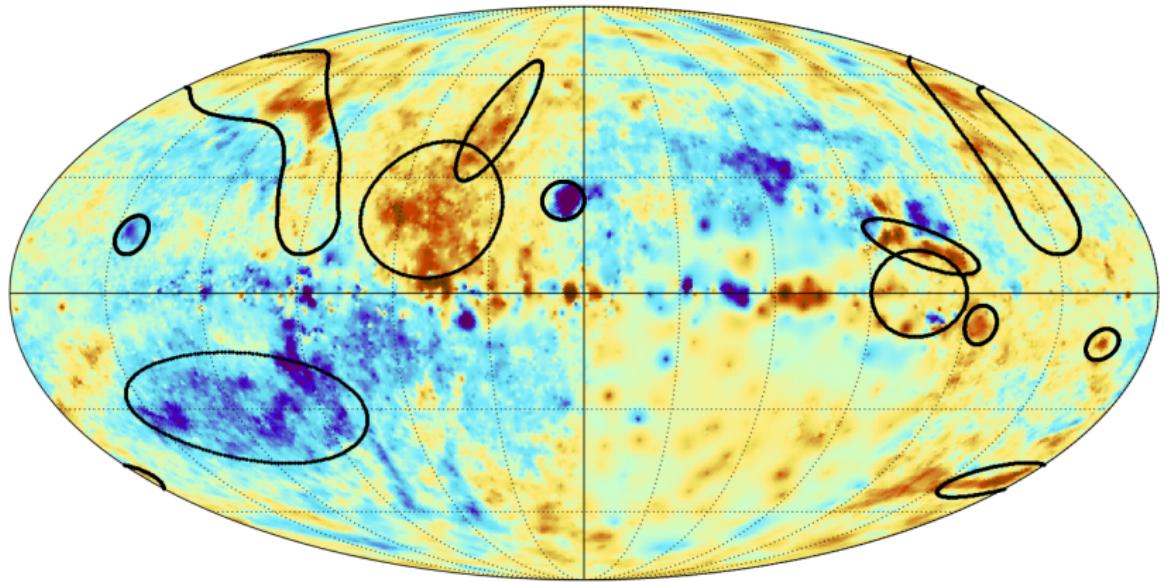
uncertainty of the Faraday depth

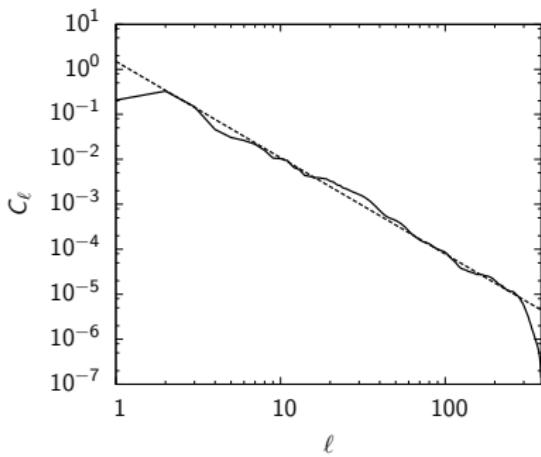


$$p\sqrt{\text{diag}(D)}$$

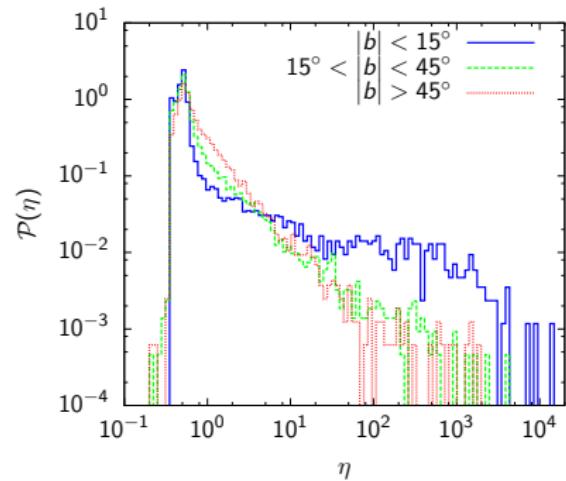
Why we bother



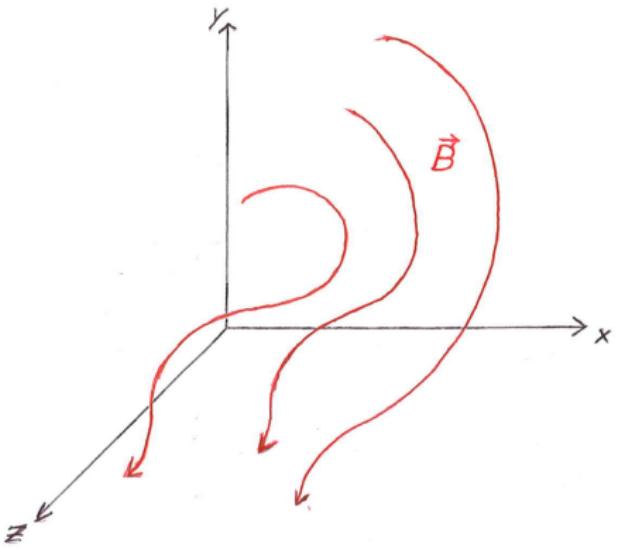


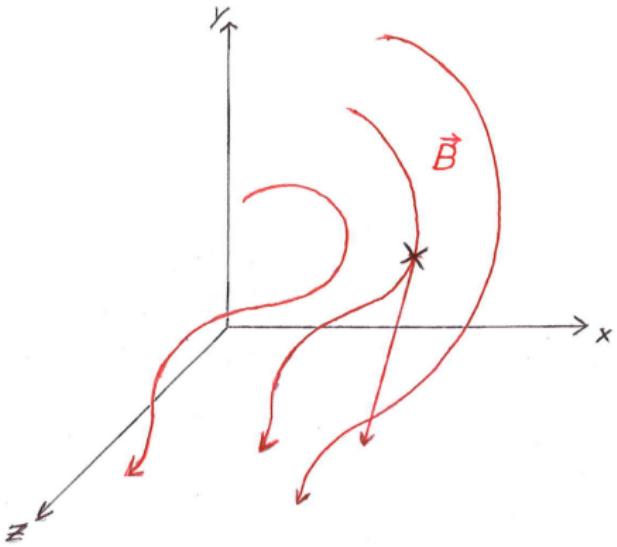


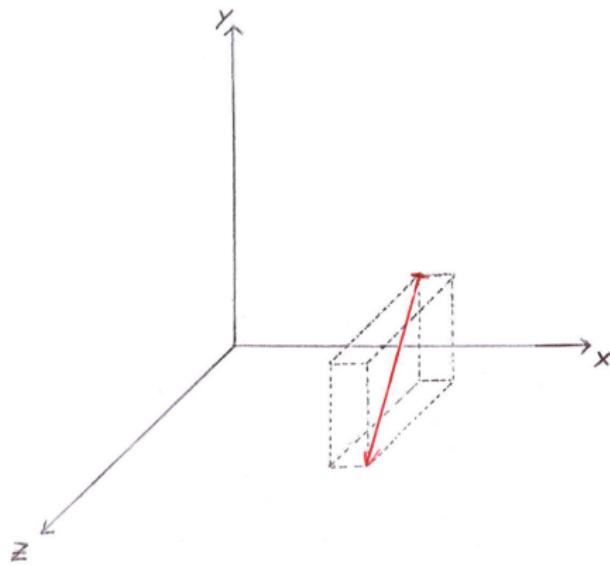
$$C_\ell \propto \ell^{-2.14}$$

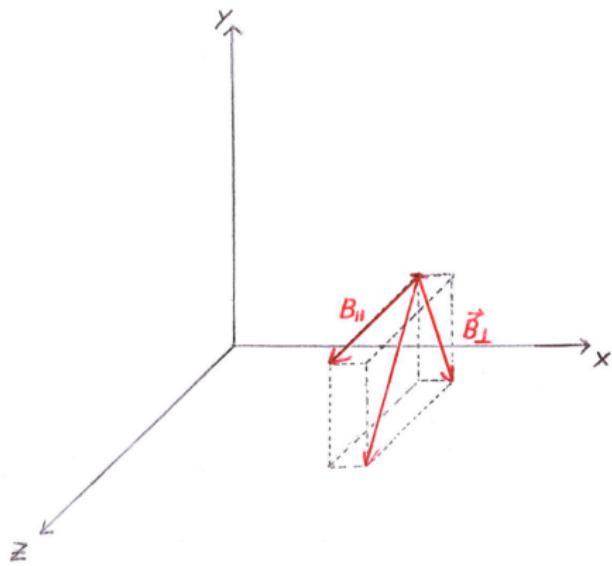


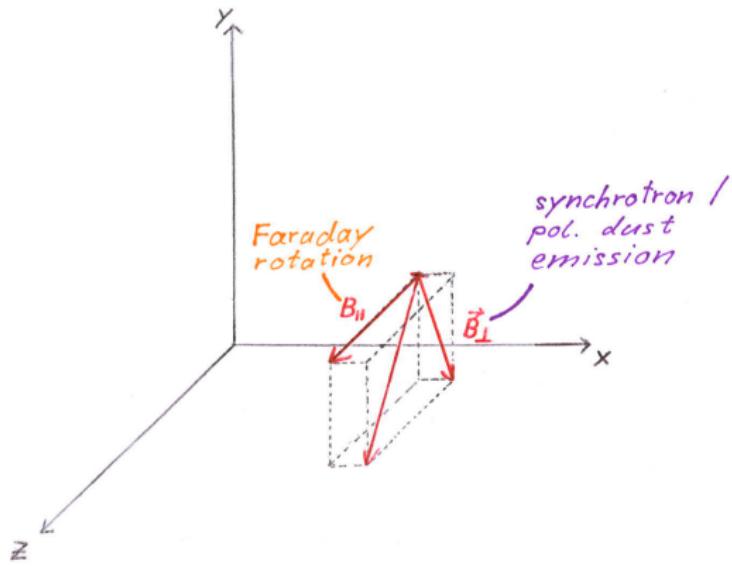
$$N_{ij} = \langle n_i n_j \rangle = \delta_{ij} \eta_i \sigma_i^2$$

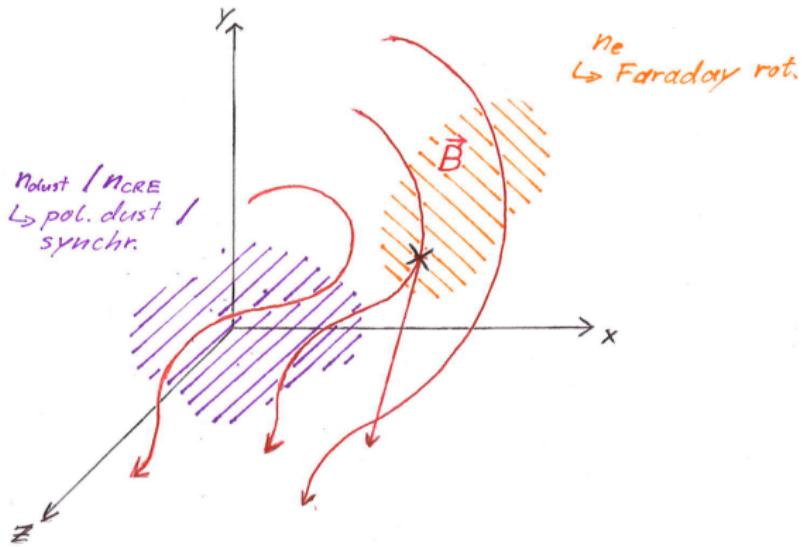










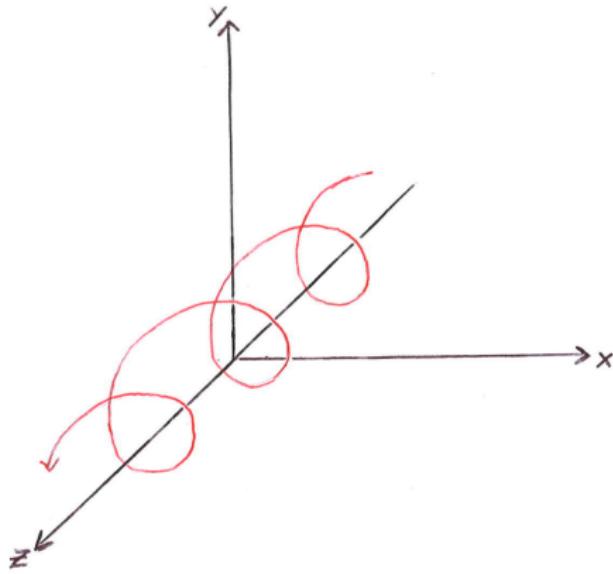


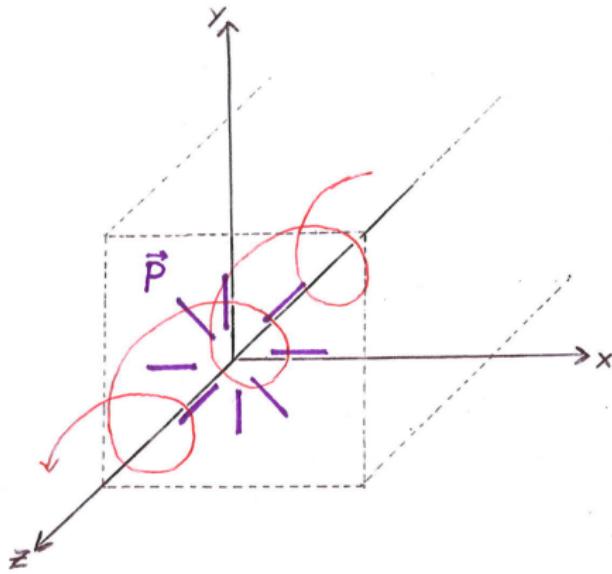
Summary

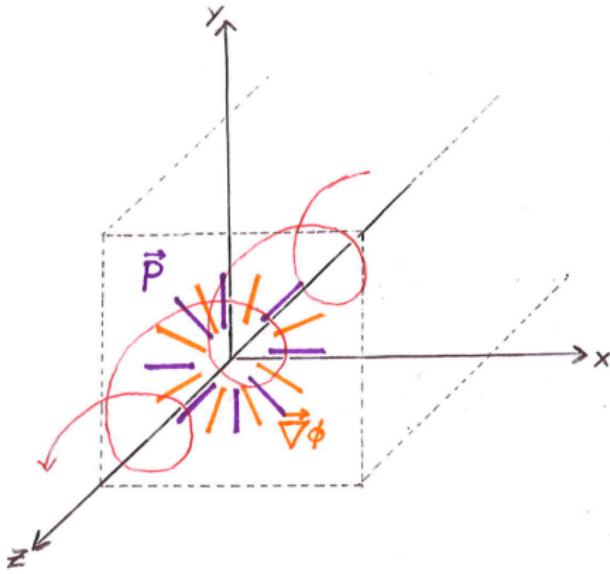
1. The *extended critical filter* reconstructs
 - ▶ “smooth” signals
 - ▶ from data that are
 - ▶ noisy
 - ▶ and incomplete.
2. It makes use of the
 - ▶ signal covariance
 - ▶ and noise covarianceeven though they are unknown.
3. Only the eigenvectors of these matrices have to be known.

<http://www.mpa-garching.mpg.de/ift/faraday/>

Backup







known as **LITMUS** procedure

Junklewitz et al. 2011A&A...530A..88J
Oppermann et al. 2011A&A...530A..89O