



The uncertain uncertainties in the Galactic Faraday sky

Niels Oppermann

with

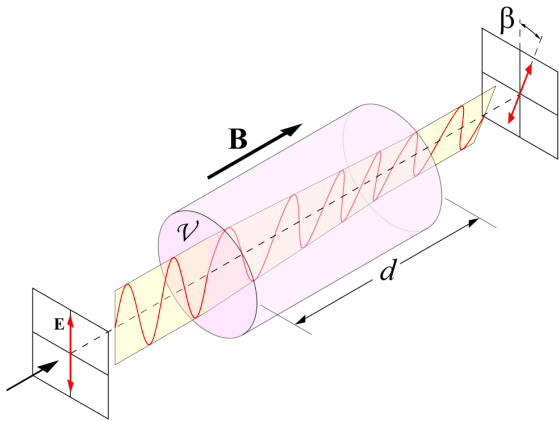
G. Robbers, T.A. Enßlin, H. Junklewitz, M.R. Bell, A. Bonafede, R. Braun, J.-A.C. Brown, T.E. Clarke, I.J. Feain, B.M. Gaensler, A. Hammond, L. Harvey-Smith, G. Heald, M. Johnston-Hollitt, U. Klein, P.P. Kronberg, S.A. Mao, N.M. McClure-Griffiths, S.P. O'Sullivan, L. Pratley, T. Robishaw, S. Roy, D.H.F.M. Schnitzeler, C. Sotomayor-Beltran, J. Stevens, J.M. Stil, C. Sunstrum, A. Tanna, A.R. Taylor, and C.L. Van Eck

Bayes Forum, MPE, 2012-05-25

Outline

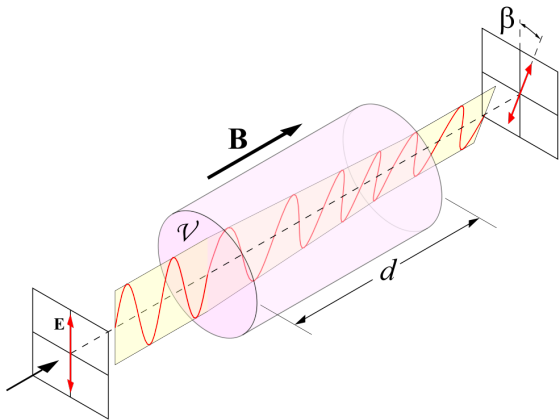
1. **The physics**
Faraday depth – measuring magnetic fields (sort of)
2. **The statistics**
priors, marginalizations, and the Gibbs free energy
3. **The application**
...of the *extended critical filter* to the Faraday sky
4. **Why we bother**
if there's time left...

The Physics



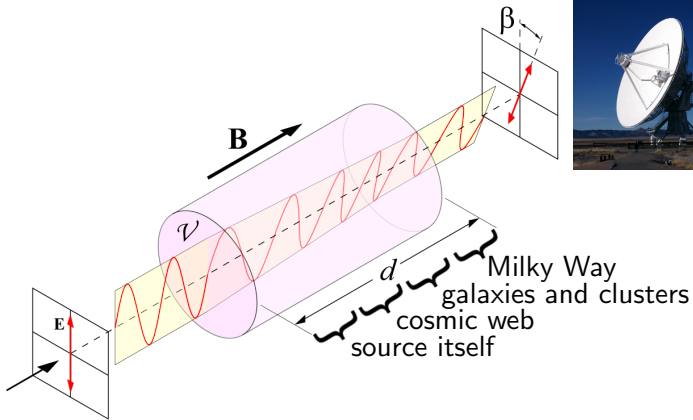
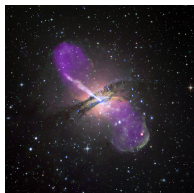
$$d\beta \propto \lambda^2 n_e(\vec{x}) B_r(\vec{x}) dr$$

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



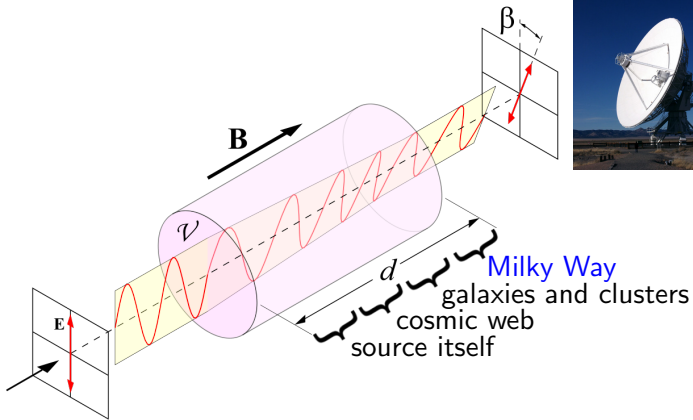
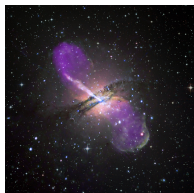
$$\text{Faraday depth: } \phi \propto \int_{r_{\text{source}}}^0 n_e(\vec{x}) B_r(\vec{x}) dr$$

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



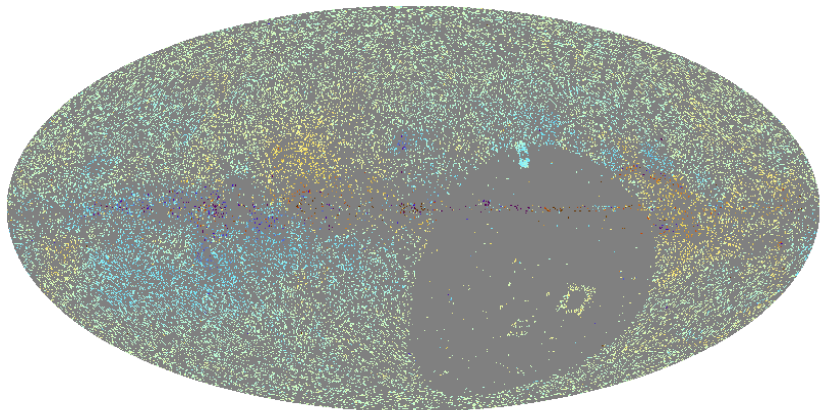
$$\text{Faraday depth: } \phi \propto \int_{r_{\text{source}}}^0 n_e(\vec{x}) B_r(\vec{x}) dr$$

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

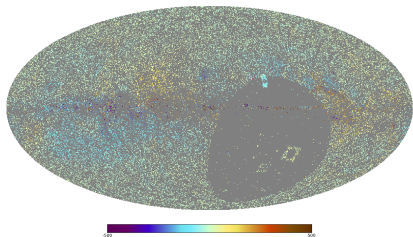


Galactic Faraday depth:

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



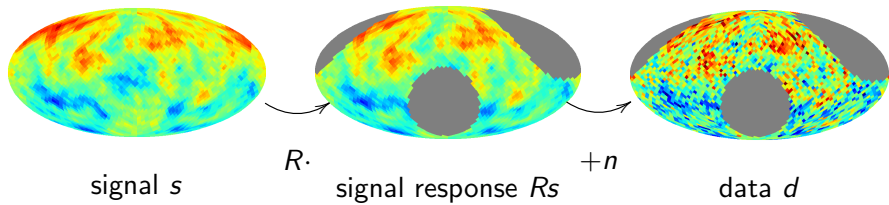
41 330 data points



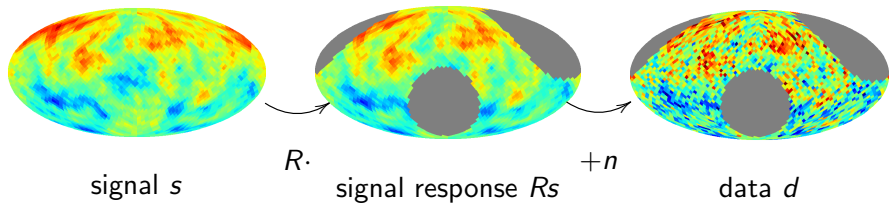
Challenges

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

The Statistics



$$d = Rs + n$$

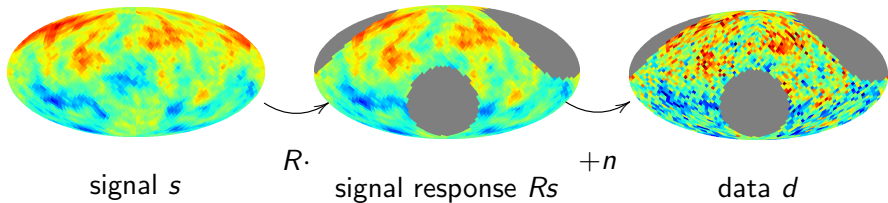


$$d = R_s + n$$

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

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

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



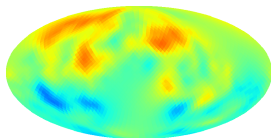
Wiener Filter

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

$$d = Rs + n$$

$$m = Dj, \text{ where } \begin{aligned} j &= R^\dagger N^{-1} d \\ D &= (S^{-1} + R^\dagger N^{-1} R)^{-1} \end{aligned}$$

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



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

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

$$\begin{aligned} S(\hat{n}, \hat{n}') &= \int \mathcal{D}s \, s(\hat{n})s(\hat{n}')\mathcal{P}(s) \\ &= S(\hat{n} \cdot \hat{n}') \end{aligned}$$

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

↪ angular power spectrum

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

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

(uncorrelated noise)

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

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



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

Enter the prior



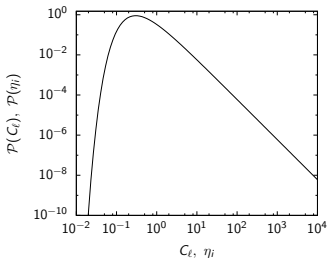
$$S_{(\ell m),(\ell' m')} = \delta_{\ell \ell'} \delta_{m m'} C_{\ell} \quad N_{ij} = \delta_{ij} \eta_i \sigma_i^2$$

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



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

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

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

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

EnBlin & 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

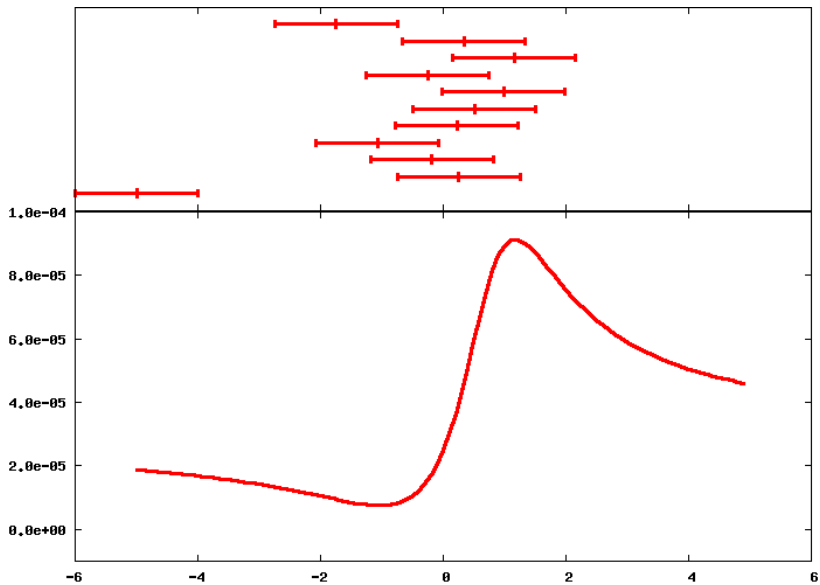
$$m = Dj, \quad D = \left[\sum_{\ell} C_{\ell}^{-1} S_{\ell}^{-1} + \sum_i \eta_i^{-1} R^{\dagger} N_i^{-1} R \right]^{-1},$$

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

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

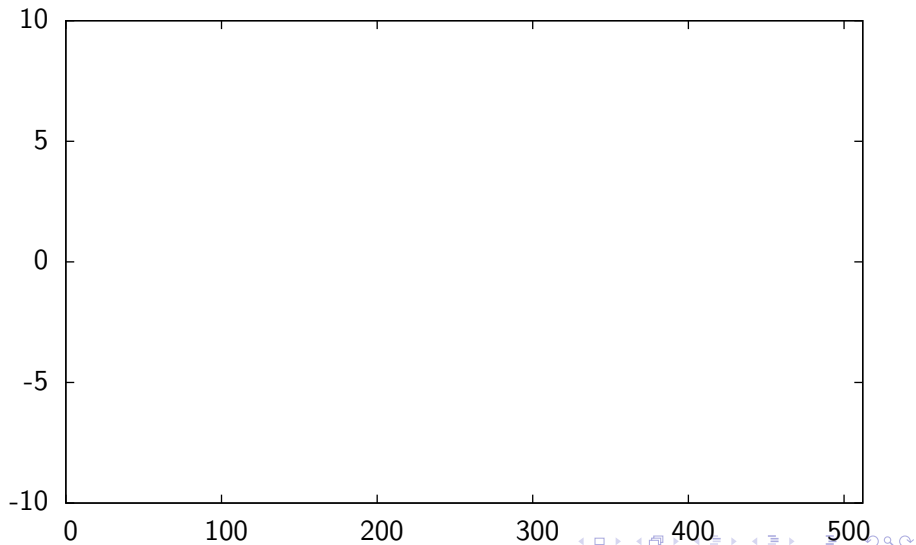
$$\eta_i = \frac{1}{\alpha_i} \left[q_i + \frac{1}{2} \text{tr} \left(((d - Rm)(d - Rm)^{\dagger} + D) N_i^{-1} \right) \right]$$

0D test case



1D test case

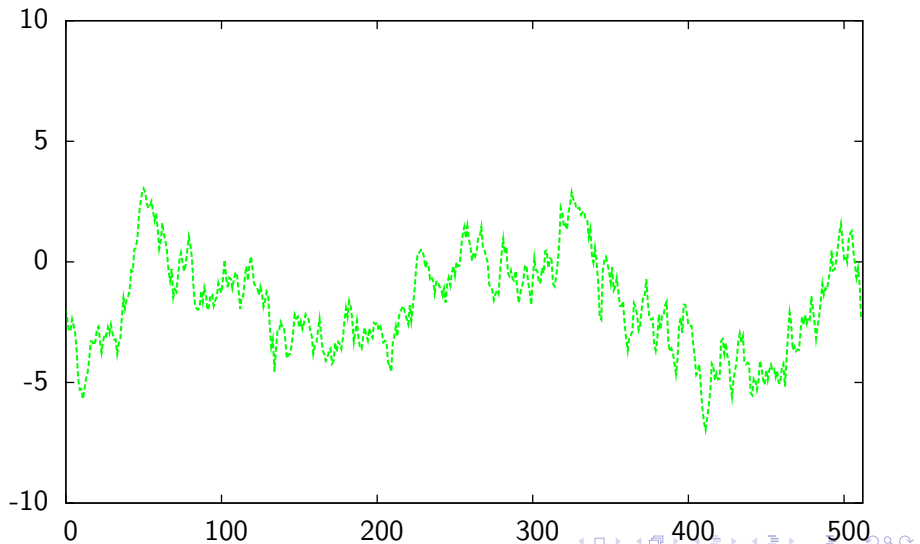
Assumptions:



1D test case

Assumptions:

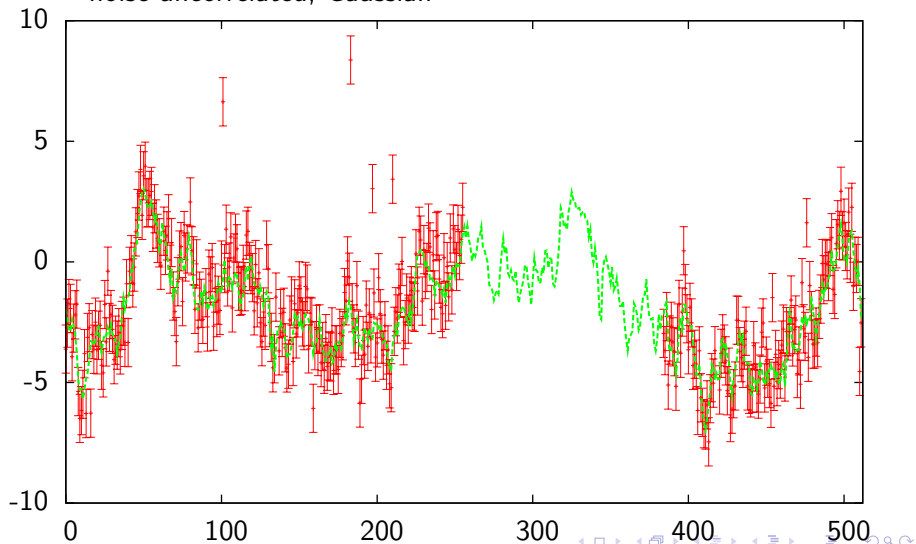
- ▶ signal field statistically homogeneous Gaussian random field



1D test case

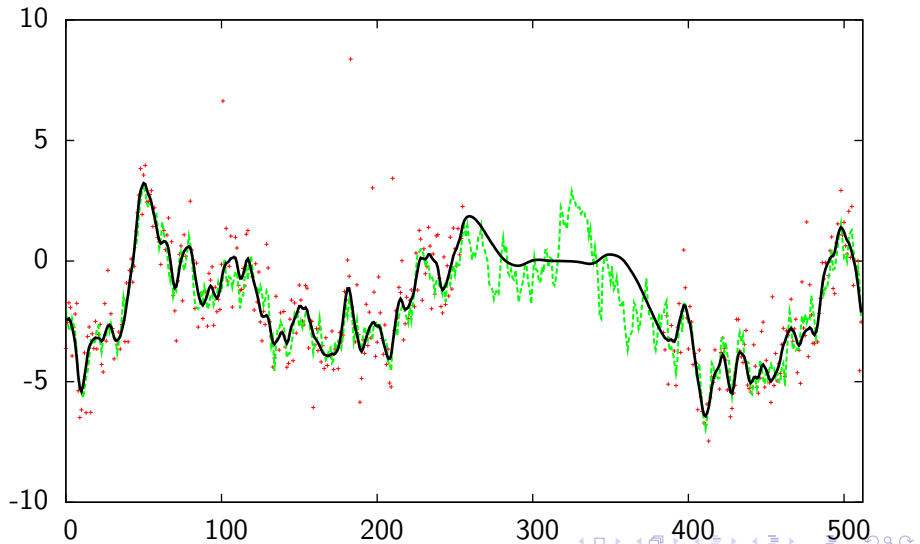
Assumptions:

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



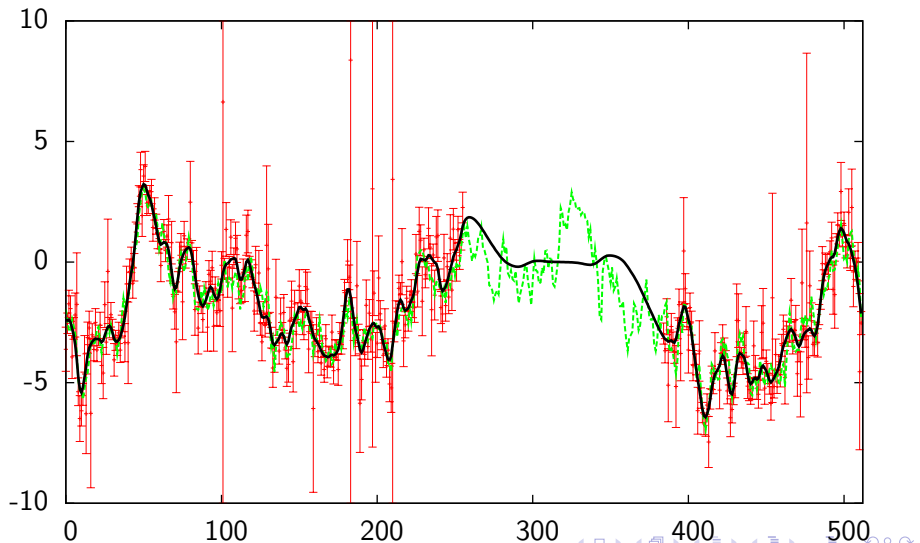
1D test case

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

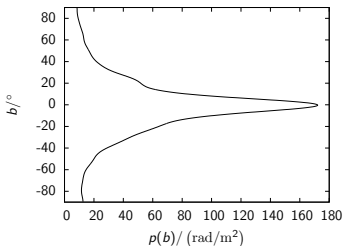
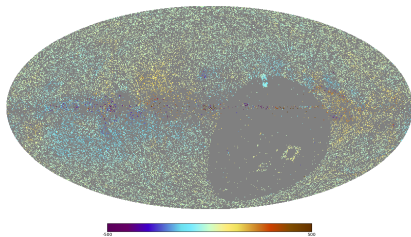


1D test case

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

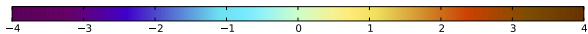
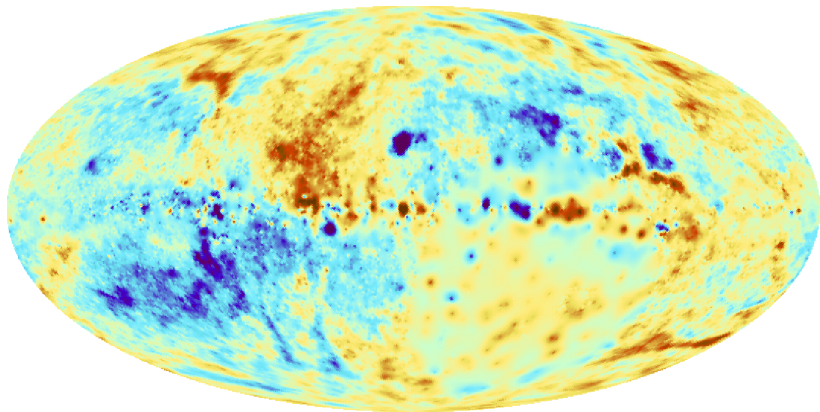


The Application



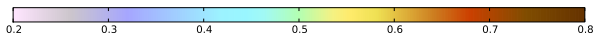
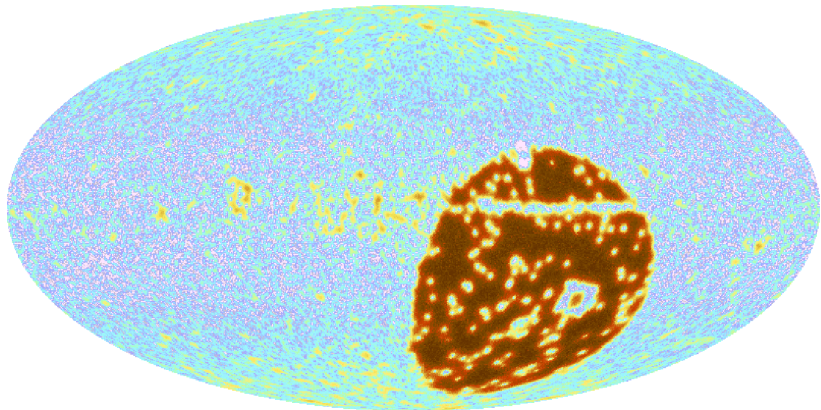
- ▶ Approximate $s(b, l) := \frac{\phi(b, l)}{\rho(b)}$ as a statistically isotropic Gaussian field
- ▶ R : multiplication with $\rho(b)$ and projection on directions of sources
- ▶ $N_{ij} = \delta_{ij} \eta_i \sigma_i^2$

posterior mean of the signal



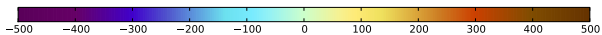
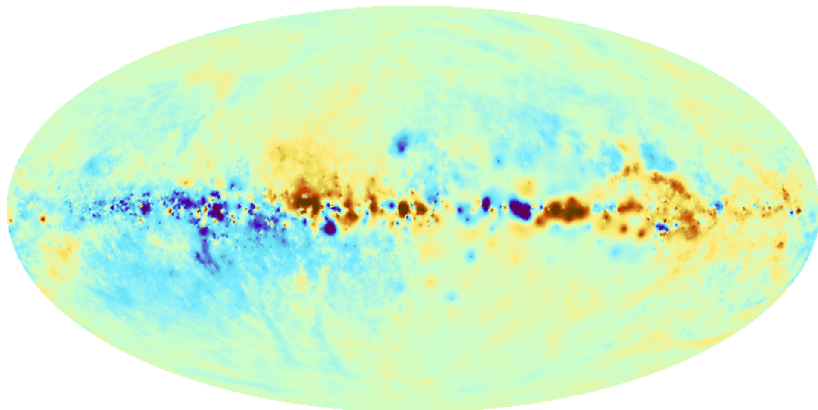
m

uncertainty of the signal map



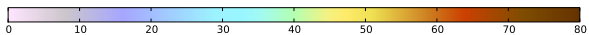
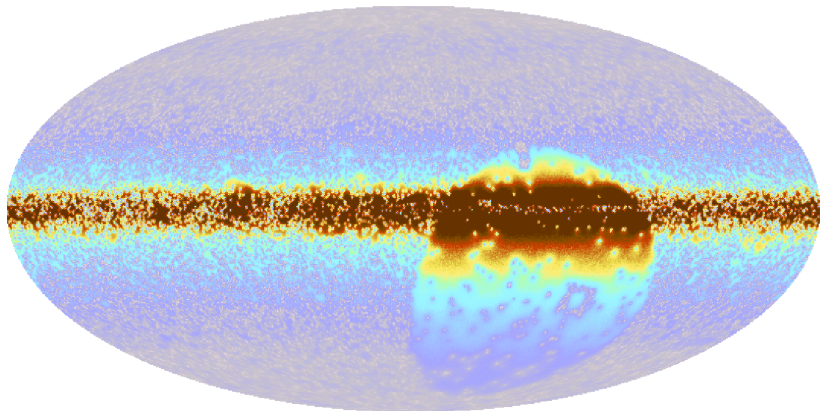
$$\sqrt{\text{diag}(D)}$$

posterior mean of the Faraday depth



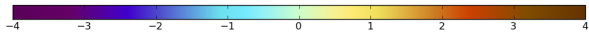
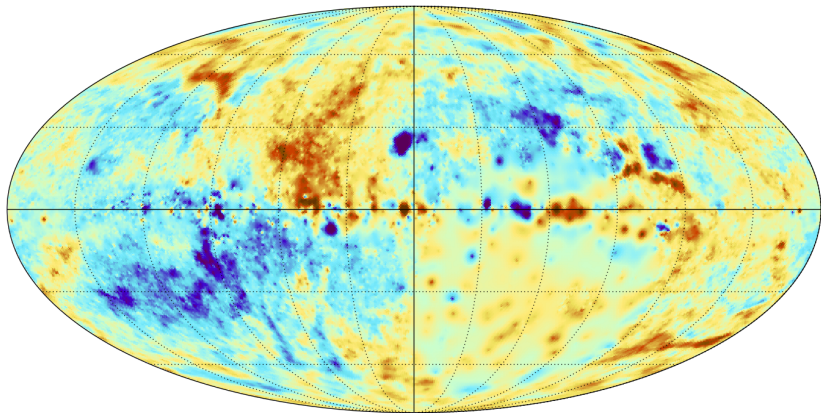
pm

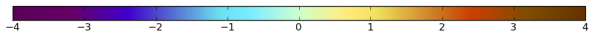
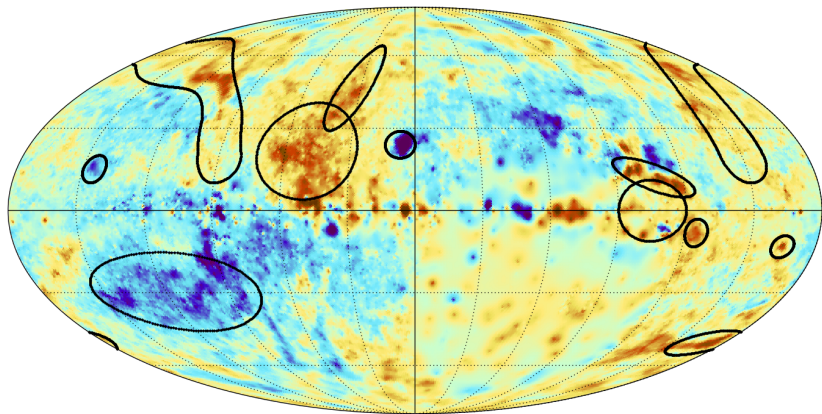
uncertainty of the Faraday depth

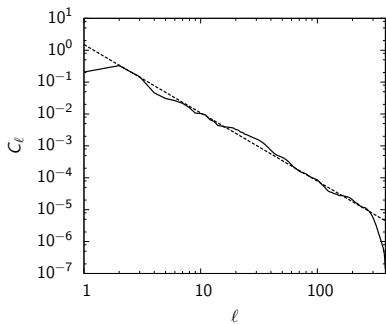


$$\rho \sqrt{\text{diag}(D)}$$

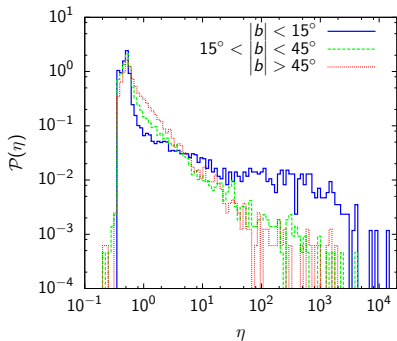
Why we bother



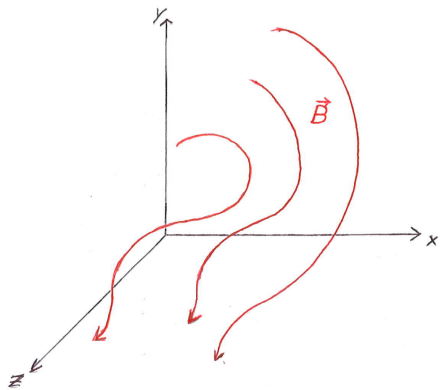


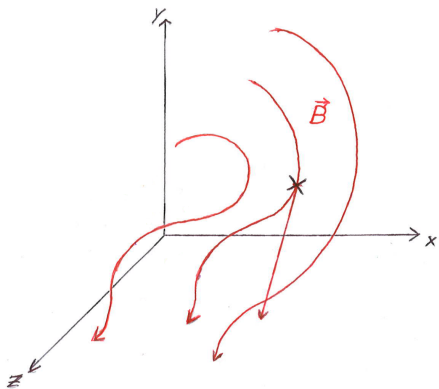


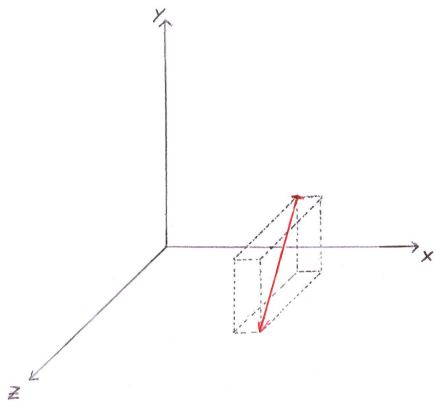
$$C_l \propto l^{-2.14}$$

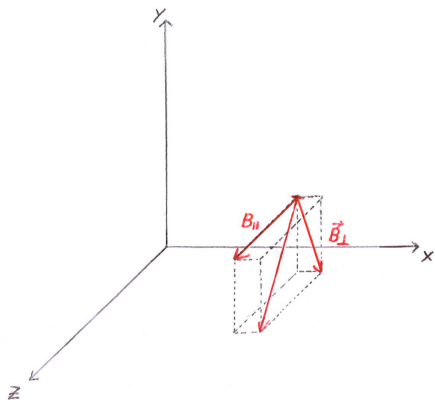


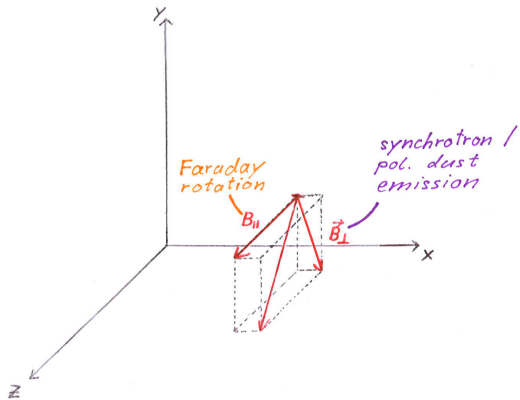
$$N_{ij} = \langle n_i n_j \rangle = \delta_{ij} \eta_i \sigma_i^2$$

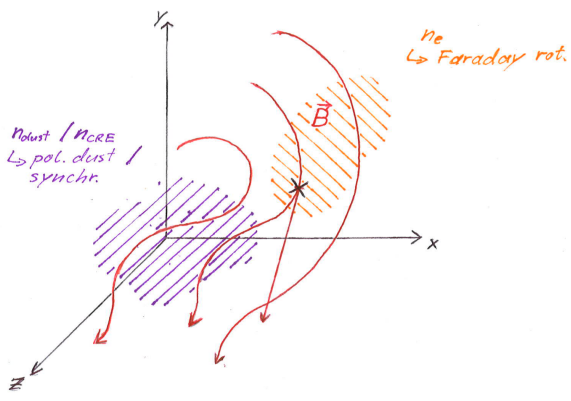










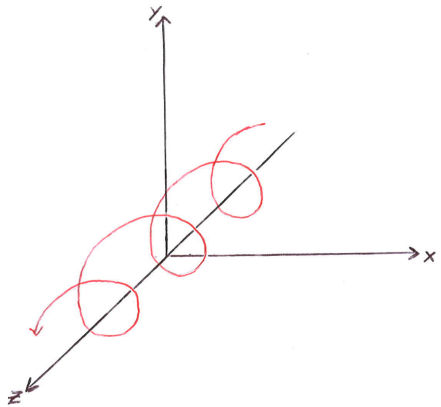


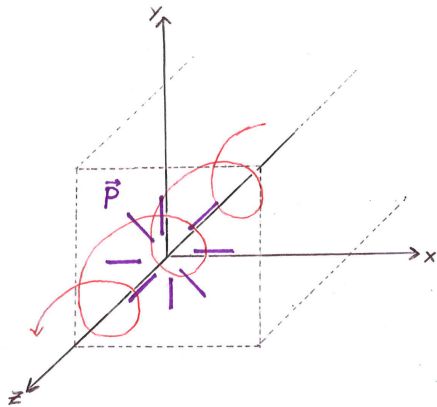
Summary

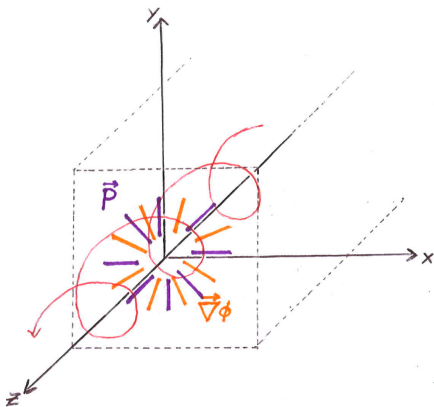
1. The *extended critical filter* reconstructs
 - ▶ “smooth” signals
 - ▶ from data that are
 - ▶ noisy
 - ▶ and incomplete.
2. It makes use of the
 - ▶ signal covariance
 - ▶ and noise covarianceeven though they are unknown.
3. Only the eigenvectors of these matrices have to be known.

<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