Parametric component separation on filtered maps in Simons Observatory.

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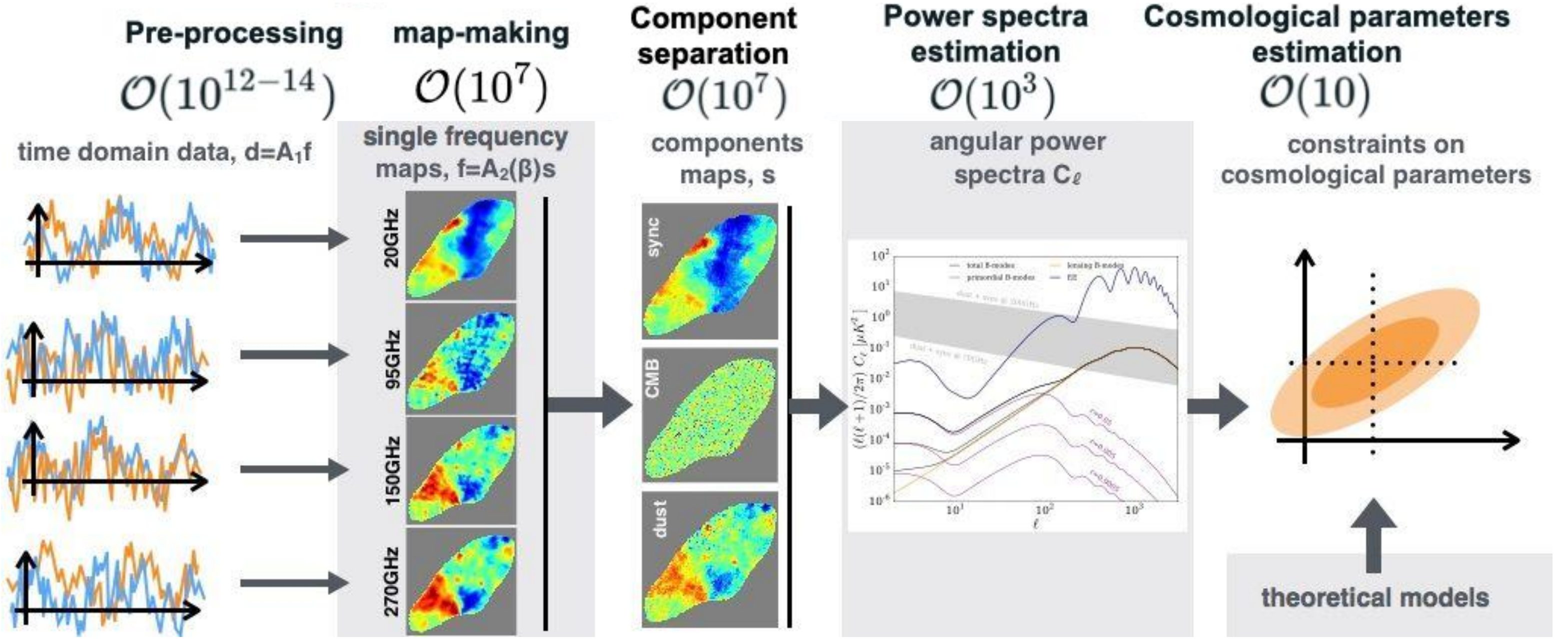
Outline:

I. Filtering

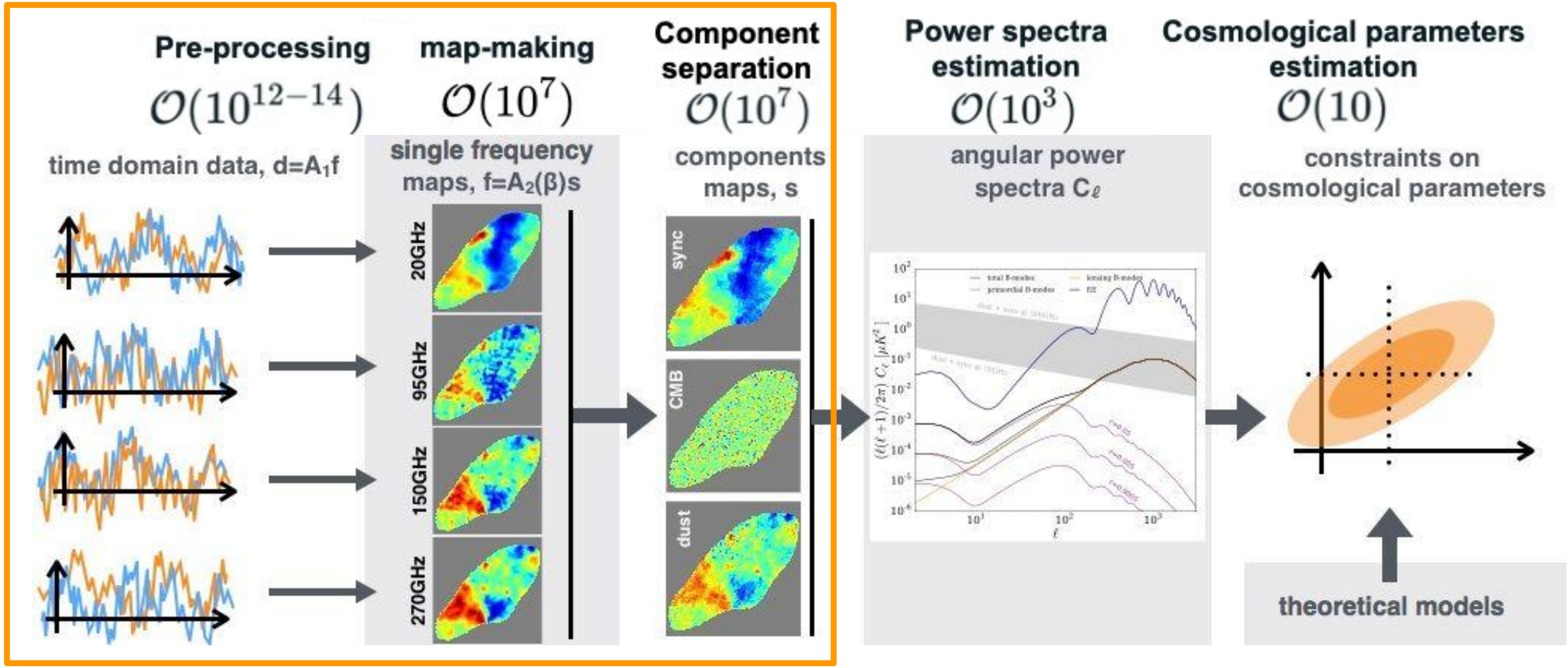
II. Map-Based Parametric Component Separation

Analysis Pipeline



Source: J. Errard

Analysis Pipeline



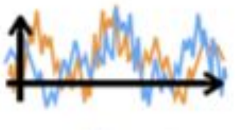
Source: J. Errard

Map making

Data model:

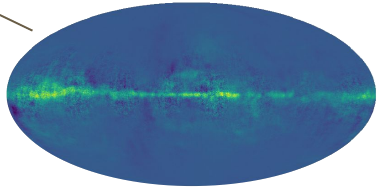
$$\mathbf{d}_t = \mathbf{P}_{tp}\mathbf{m}_p + \mathbf{n}_t$$

Noise



Time Ordered Data (TOD)

Pointing matrix



True underlying map

The pointing matrix relates time samples to coordinates on the sky. It is a sparse matrix (Tegmark 1997)

Map making

Broadly speaking, map-making consists in solving: $\mathbf{m}_p = \mathbf{L}_{pt}\mathbf{d}_t$

The least square solution is an unbiased estimator that minimises the variance:

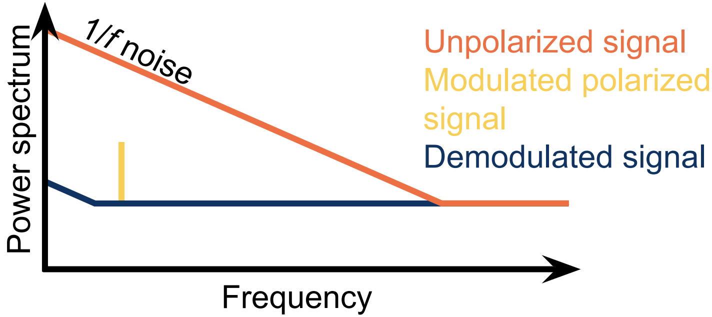
$$(\mathbf{P}_{tp}^T \mathbf{N}_{tt'}^{-1} \mathbf{P}_{t'p'})\mathbf{m}_{p'} = \mathbf{P}_{tp}^T \mathbf{N}_{tt'}^{-1} \mathbf{d}_{t'}$$

This maximum likelihood technique is however costly. Especially since the noise can be highly correlated.

Signal Filtering and Modulation

To simplify the problem, we filter the data to remove possible correlations:

- ground pick-up
- scan-synchronous signal
- half-wave plate synchronous signal



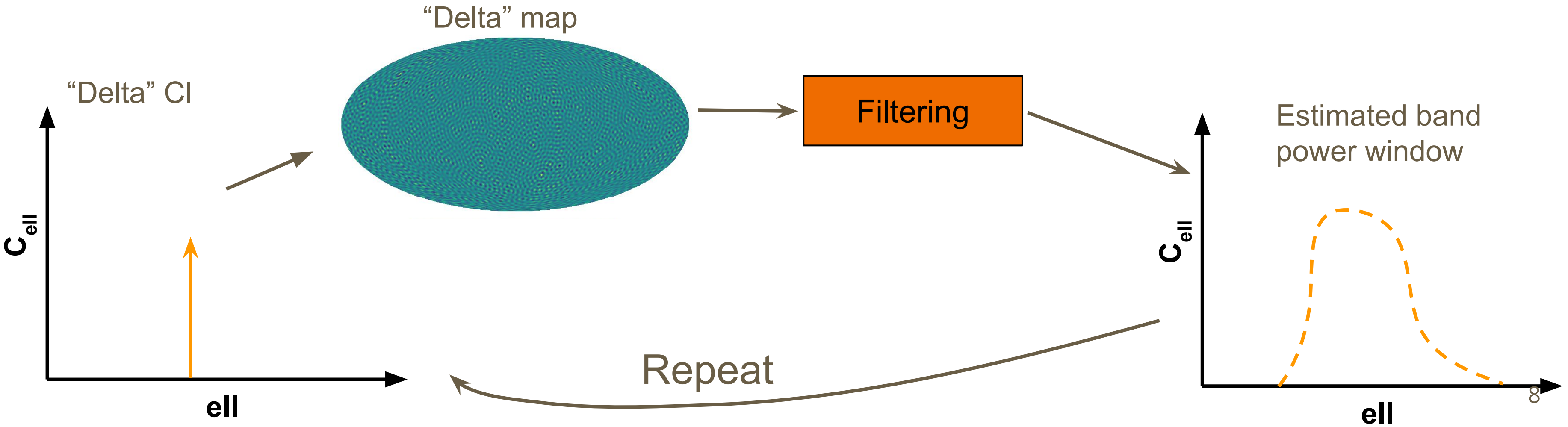
HWP modulates polarized signal ⇒ helps "whitening the noise" and extract the signal

Filtered-binned map-making: faster, helps with correlated noise, but is a **biased estimator** ⇒ Transfer function required to correct the bias.

Correcting for the Bias (Power Spectra)

Pass simulations through same pipeline as data and compare with output (e.g. J. T. Sayre et al. 2020, J.S.-Y. LEUNG et al 2022)

- Requires many simulations
- Assumes anisotropy to some extent as it works in Cl
- Relatively straight forward. Most relevant for spectra based analysis.



Correcting for the Bias (Pixel)

Filtering operations expressed as a linear operator to create an **observation matrix** (Keck Array, BICEP2 Collaborations 2016):

$$\mathbf{m}_p^{\text{out}} = \mathbf{O}_{pp'} \mathbf{m}_{p'}^{\text{in}}$$

$$\mathbf{O}_{pp'} = (\mathbf{P}^T \mathbf{N}^{-1} \mathbf{P})^{-1} \mathbf{P}^T \mathbf{N}^{-1} \mathbf{Z} \mathbf{P}$$

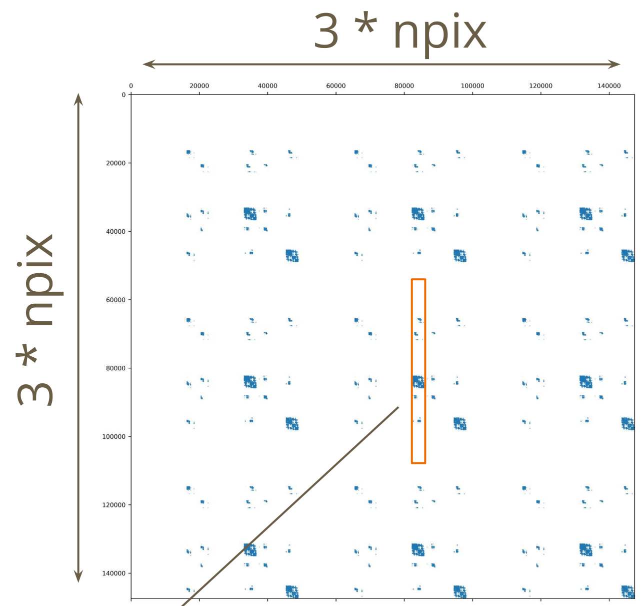
Z encodes the time domain filtering

- Allows to encode spatial variability and correlation from the filtering
- No need for simulation.
- Better suited for pixel based analysis.
- **Generating** and **applying** observation matrices is quite costly…

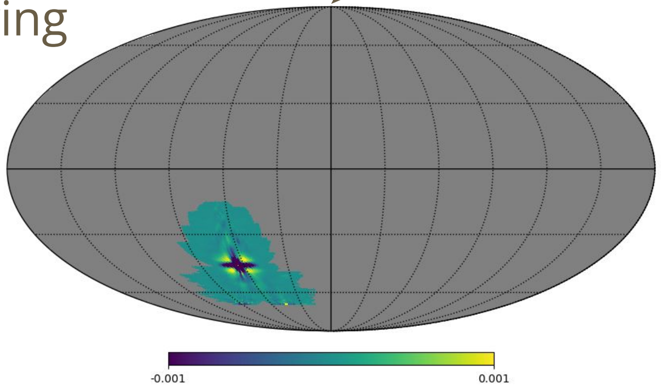
Observation matrix

They are large matrices, e.g. for SO survey at nside 128

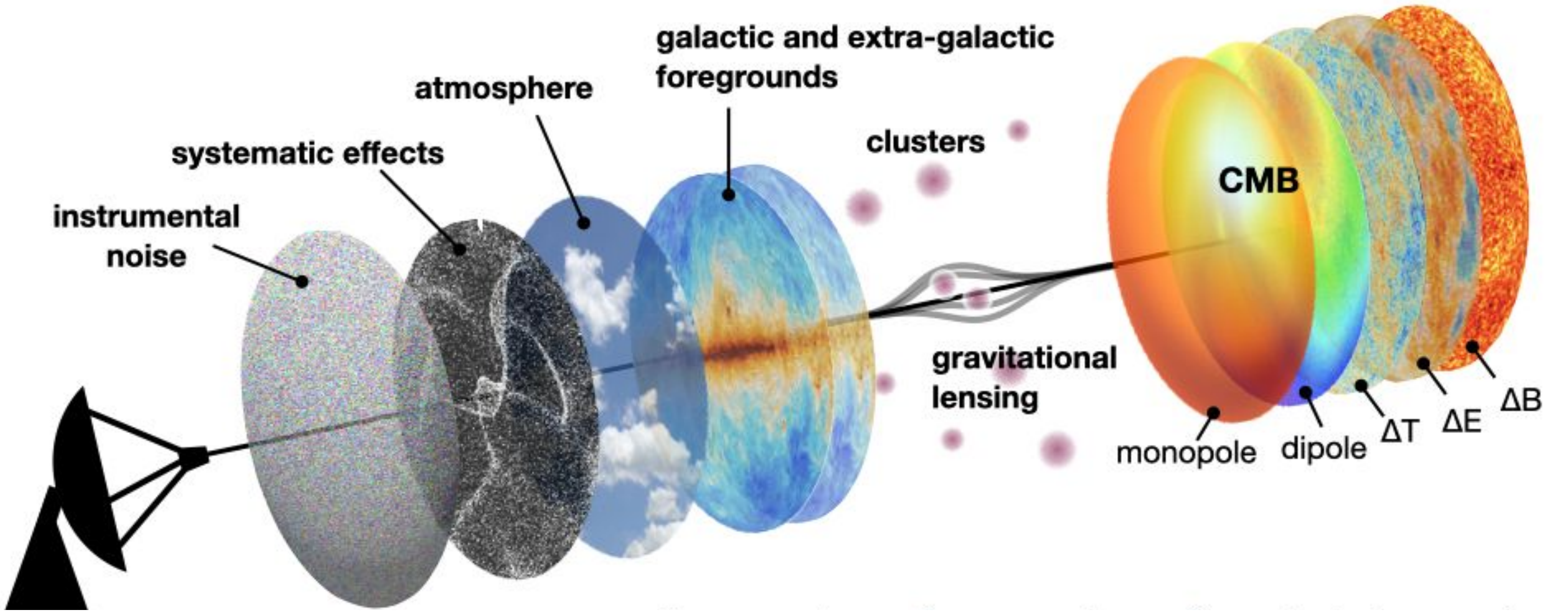
- 600 000 x 600 000 elements
- >11 GB per map / frequency channel
- Very sparse ~0.4% non-zero elements



Higher resolution/larger surveys ⇒ simplifying the observation matrix is necessary.



Parametric Map-Based Component Separation

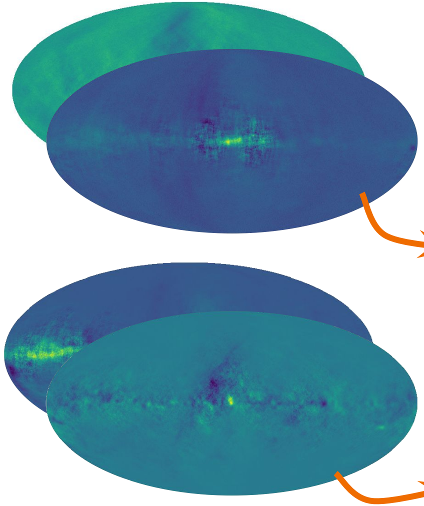


Source: J. Errard

The Standard Data Model

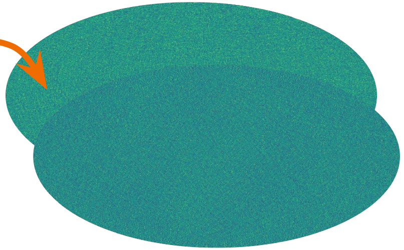
$$\mathbf{d}_p = \mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p$$

noise



$$\begin{pmatrix} Q_1 \\ U_1 \\ \vdots \\ Q_n \\ U_n \end{pmatrix}$$

$$\begin{pmatrix} Q^{CMB} \\ U^{CMB} \\ Q^d \\ U^d \\ Q^s \\ U^s \end{pmatrix}$$



Input frequency maps

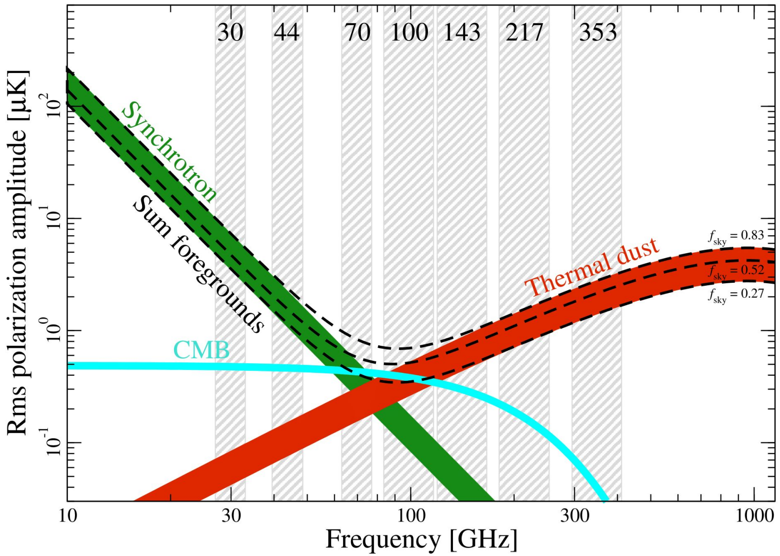
Component maps

The Mixing Matrix

$$\mathbf{d}_p = \mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p$$

$$\mathbf{A}(\{\beta_{\rm fg}\}) = \begin{pmatrix} 1 & A_1^d & A_1^s \\ \vdots & \vdots & \vdots \\ 1 & A_n^d & A_n^s \end{pmatrix}$$

CMB | **Dust** T_d, β_d | **Synchrotron** β_s



Source: Planck Collaboration 2018

Matrix encodes modelled foreground emission laws:

- **modified black-body** for dust
- **power law** for synchrotron

Variation across the sky is possible (Errard et al. 2019)

The Spectral Likelihood

We use the ***spectral likelihood*** (Stompor et al 2008) to estimate those parameters and remove foregrounds contamination:

fgbuster

$$\mathbf{d}_p = \mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p$$

$$-2\ln\mathcal{L}_{\rm spec}(\beta) = {\rm cst} - \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{d}\right)^t \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{A}\right)^{-1} \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{d}\right)$$

$$\hat{\mathbf{s}} = \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{A}\right)^{-1}\mathbf{A}^t\mathbf{N}^{-1}\mathbf{d}$$

Can deal with spatial variation, both in noise properties and foreground parameters

Parametric Component Separation Extensions

This class of parametric method is versatile and can be updated to accommodate different systematic effects by adding more parameters:

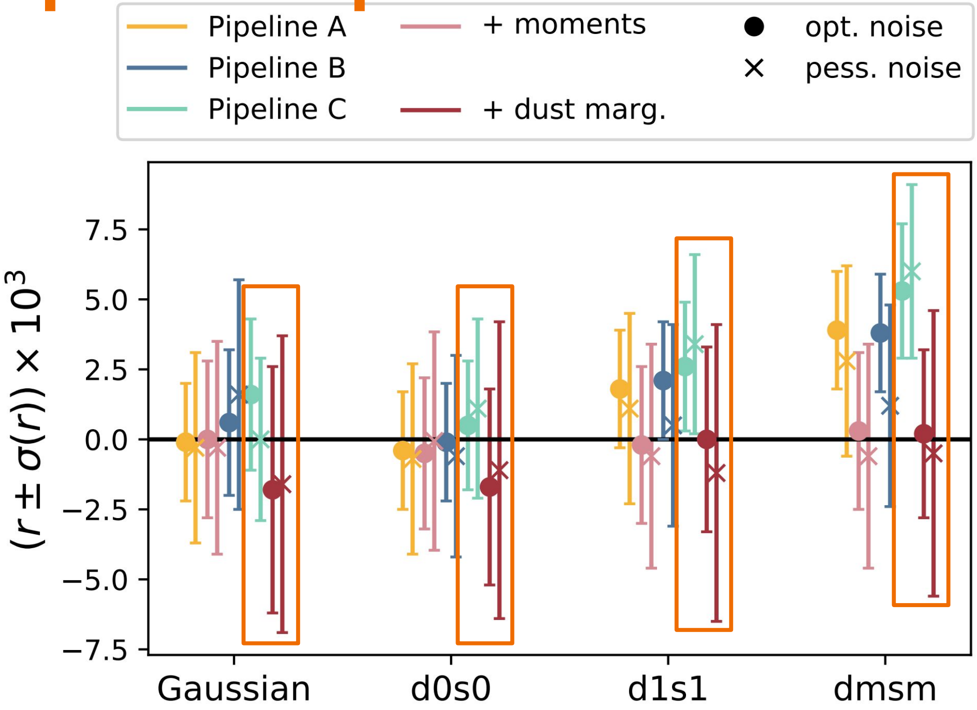
- Half-wave plate and bandpass systematics (Vergès et al 2021)
- Polarization angle miscalibration (Jost et al. 2023)
- Inclusion of main beam (Rizzieri et al. 2024)

Outputs both CMB and foreground maps ⇒ In cosmological likelihood we can marginalise over residual foreground spectra estimated from output maps (Errard et al. 2019)

Map-Based Parametric Component Separation

Map-based method has been tested on Simons Observatory simulations (Wolz et al. 2024):

- comparable to other methods: ILC, Cross-spectra parametric method
- Robust to complex foregrounds thanks to dust marginalization



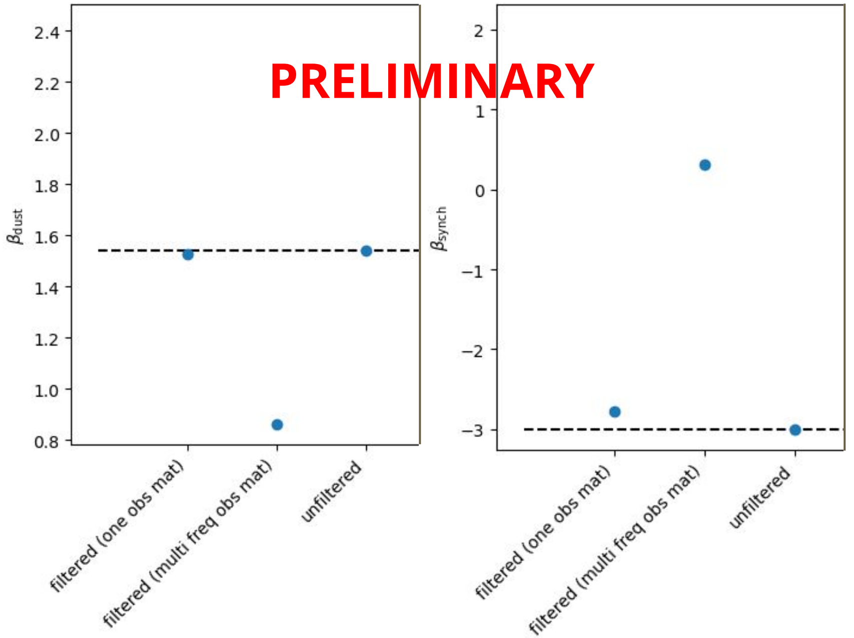
Source: Wolz et al 2024

Map-Based Parametric Component Separation On Filtered Data

We run the map-based pipeline on simulations with CMB + d0s0 for SO SAT survey (**See Adrien La Posta's talk**) in 3 different cases:

- no filtering
- Filtered using realistic observation matrix for SO (credit: SO simulations team), the same matrix is used for all frequency bands
- Filtered using frequency dependent observation matrix

Integration of observation matrix is the likelihood is necessary: MEGATOP



Accounting for Filtering in Component Separation

Include the observation matrix in the data model:

$$\mathbf{d}_p = \mathbf{O}_{pp'} \mathbf{A}(\beta) \mathbf{s}_{p'} + \mathbf{n}_p$$

Rearranging the problem for better handling of sparse matrix:

spectral likelihood

$$(\mathbf{A}^T \mathbf{O}^T \mathbf{N}^{-1} \mathbf{O} \mathbf{A}) \mathbf{s} = \mathbf{A}^T \mathbf{O}^T \mathbf{N}^{-1} \mathbf{d}$$

$$-2 \log(\mathcal{L})(\beta) = -\mathbf{d}^T \mathbf{N}^{-1} \mathbf{O} \mathbf{A} \mathbf{s}$$

Best fit A

$$(\tilde{\mathbf{A}}^T \mathbf{O}^T \mathbf{N}^{-1} \mathbf{O} \tilde{\mathbf{A}}) \tilde{\mathbf{s}} = \tilde{\mathbf{A}}^T \mathbf{O}^T \mathbf{N}^{-1} \mathbf{d}$$

Accounting for Filtering in Component Separation

The repeated use of the observation matrix significantly slows down the component separation and makes it more resource intensive

We explore different simplifications of the matrices:

- Lower resolution
- Remove smallest elements of the matrix
- Lower matrix rank via svd decomposition

CPU/GPU implementation of the spectral likelihood within the FURAX framework (**see Simon Biquard's talk!**) for potential speed up.

Back of the envelope estimation suggest ~40min to converge, although the full likelihood is not completely implemented yet.

Conclusion

Map-based component separation is a versatile tool and provides cross-check for current and future CMB experiments.

Including observation matrix necessary to handle filtered data

We are applying this technique for the Simons Observatory map-based pipeline: MEGATOP

A more general GPU framework for component separation is also being developed: FURAX

Non-parametric hybrid methods are also explored: MICMAC (Leloup et al 2023, Morshed et al 2024) → **See Magdy Morshed's talk!**

THANK YOU!