Extensions and first applications of the minimally informed component separation approach, MICMAC and MICS

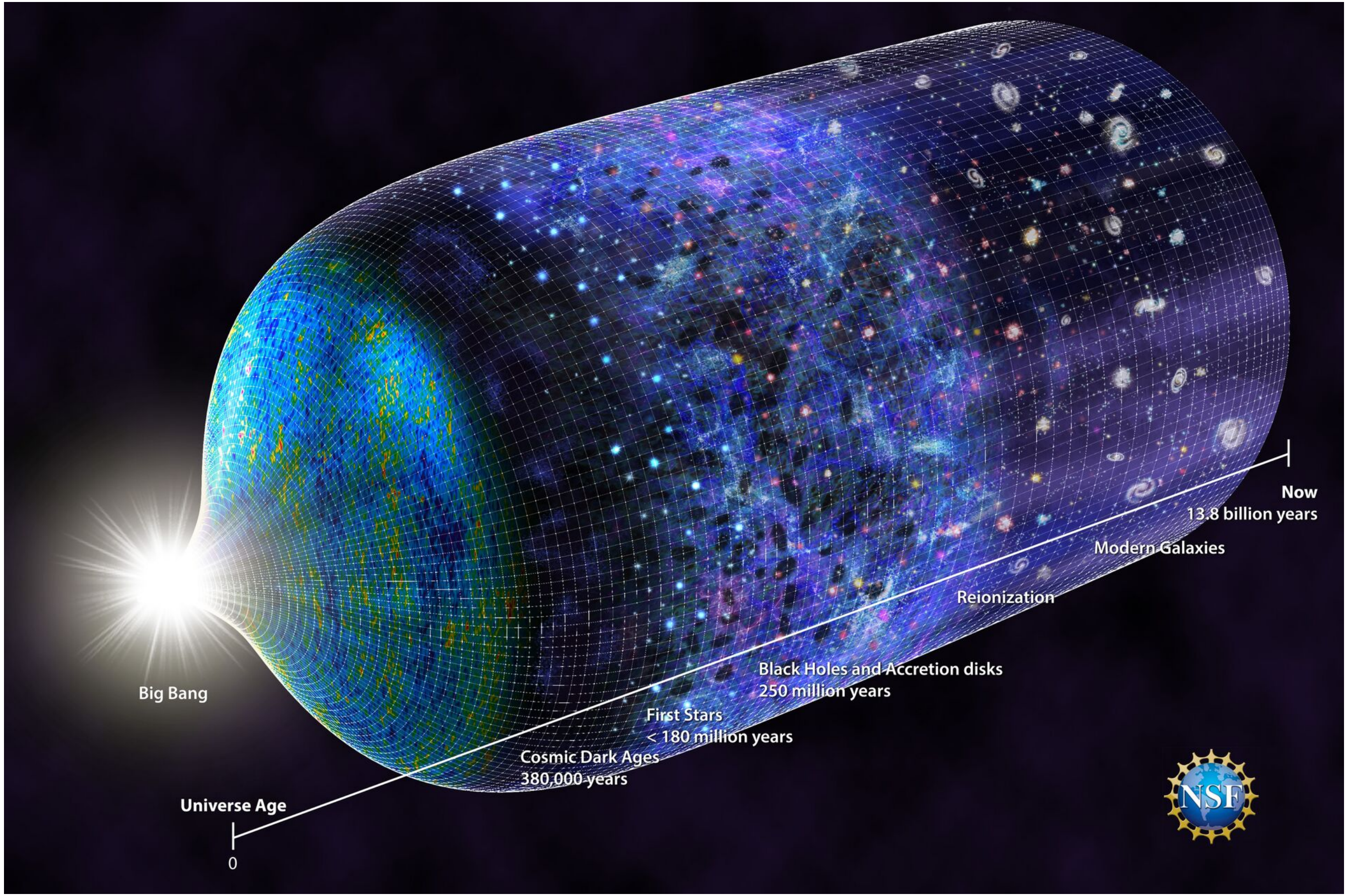
CMB-France #6

Institut Henri Poincarré

2024, December 18-19th

Magdy MORSHED
postdoc at INFN Ferrara (Italy)

Tracking Inflationary signature



Credit: N.R.Fuller, National Science Foundation

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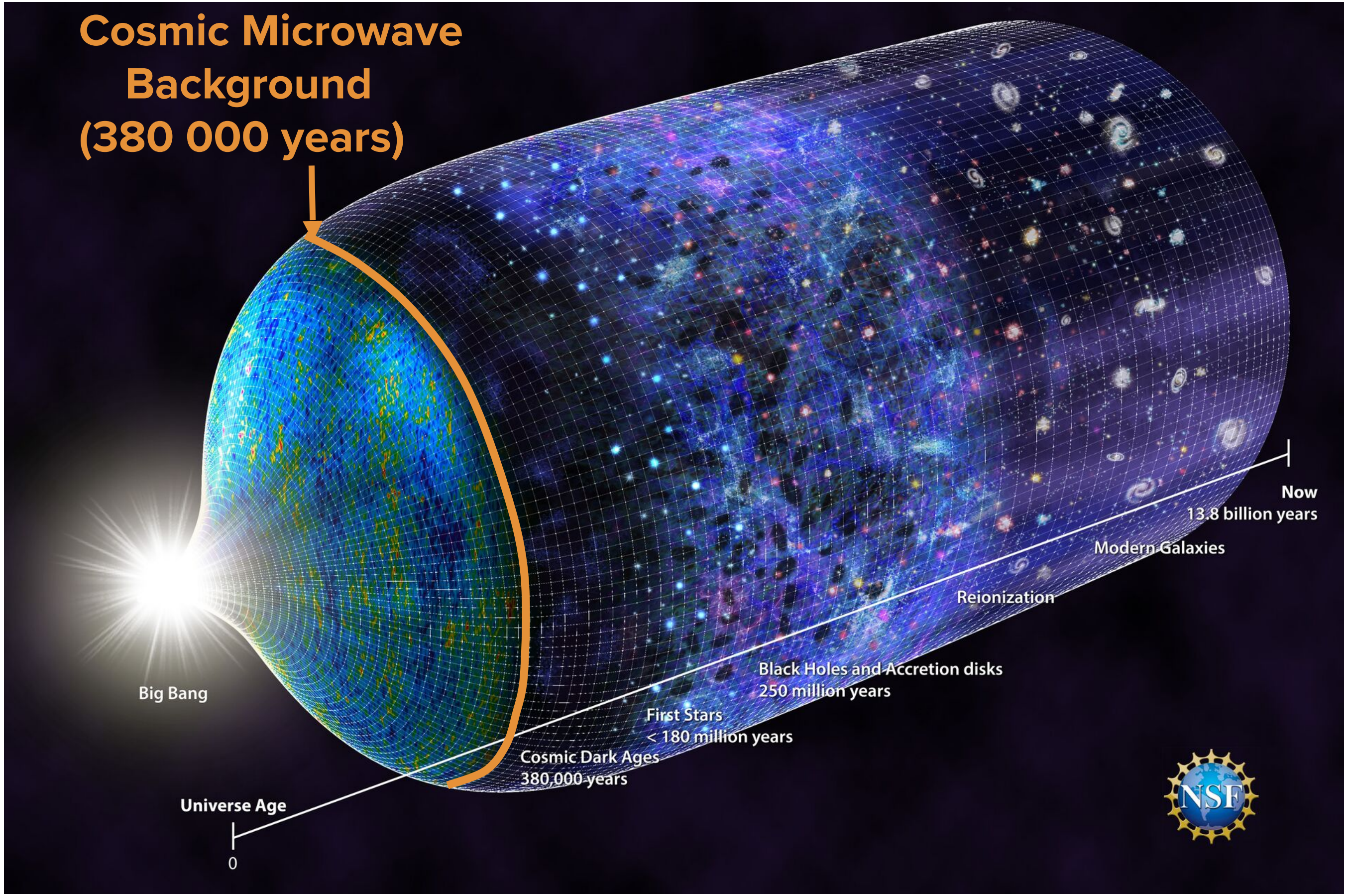

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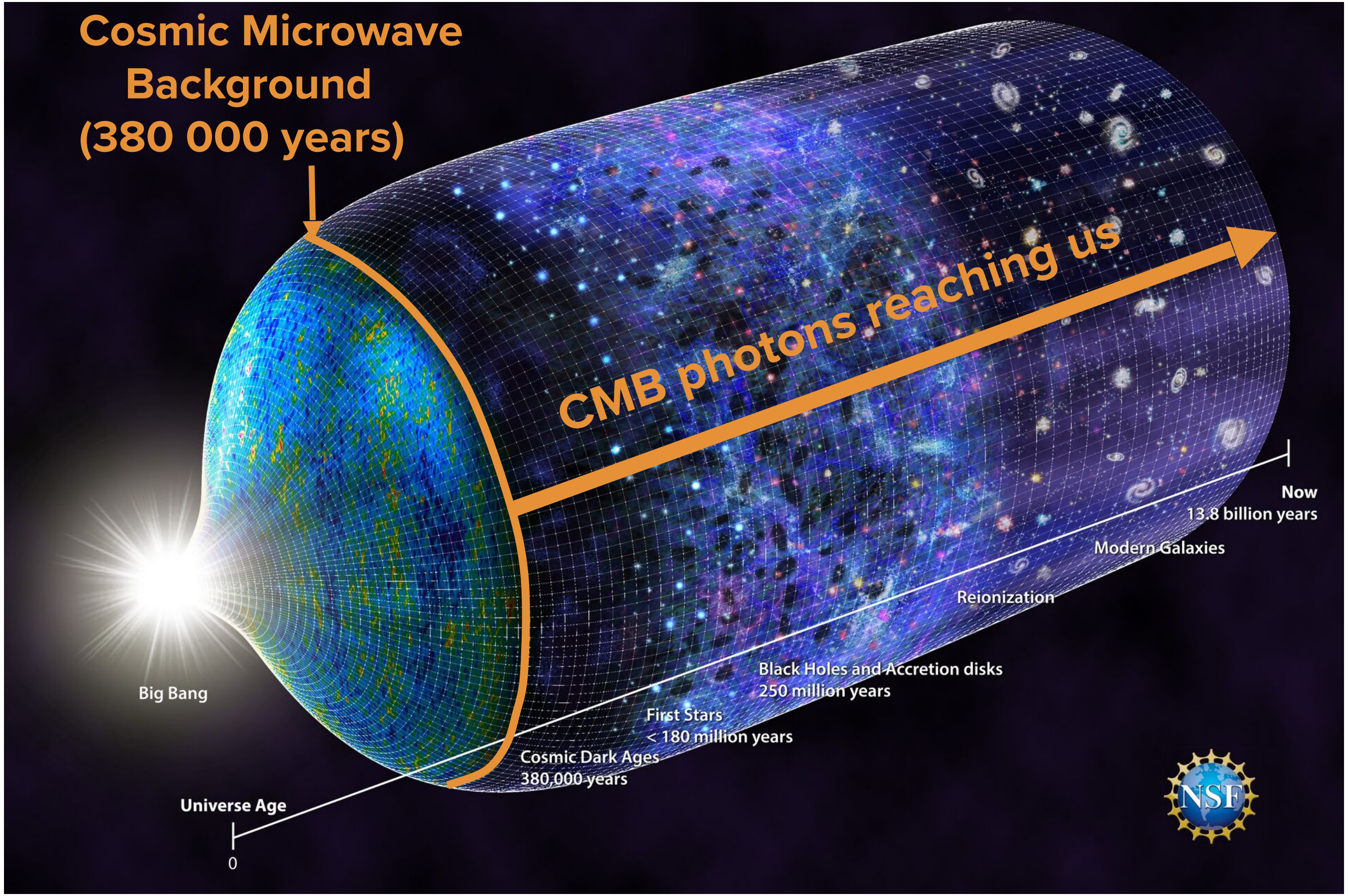

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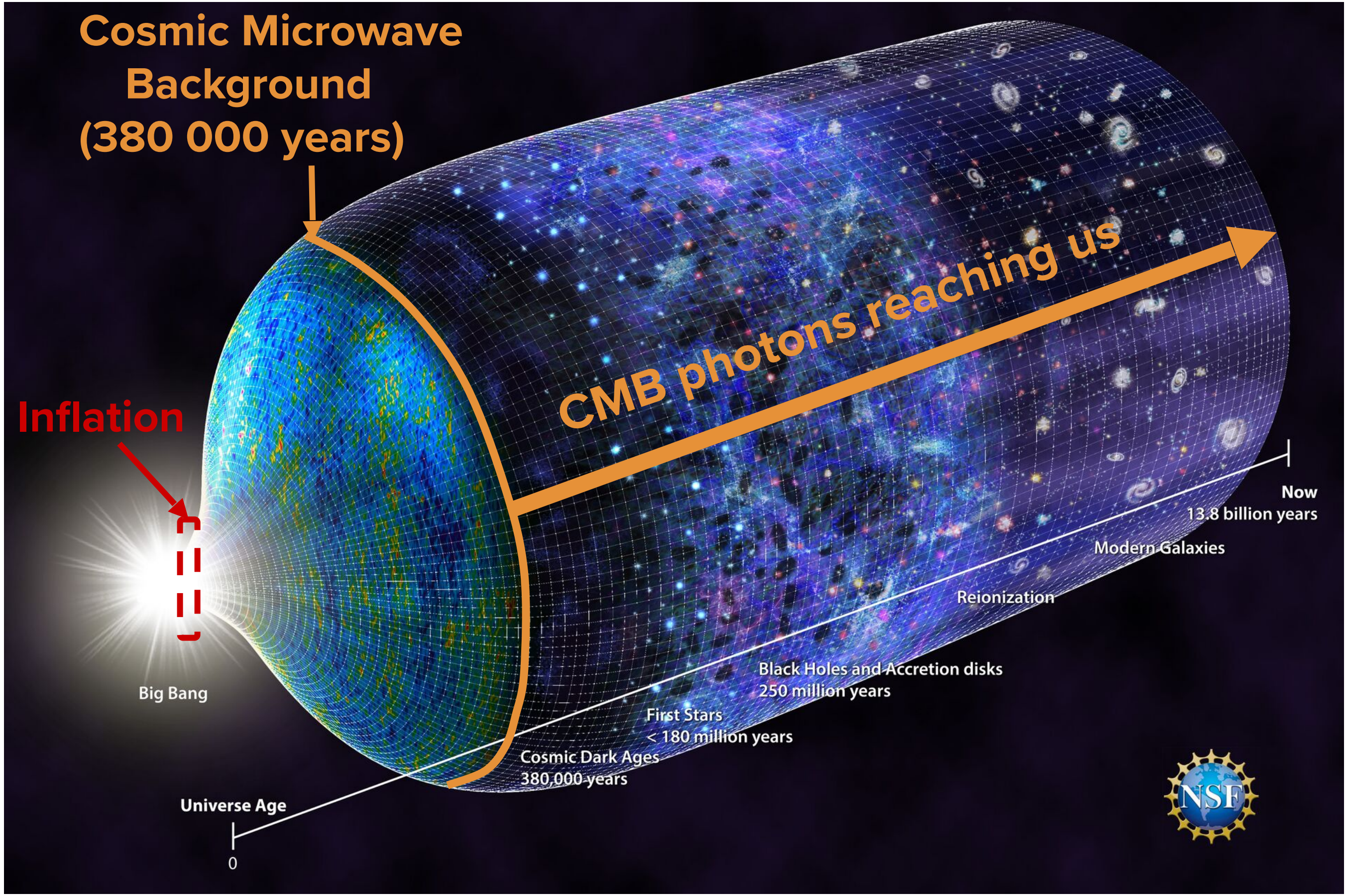

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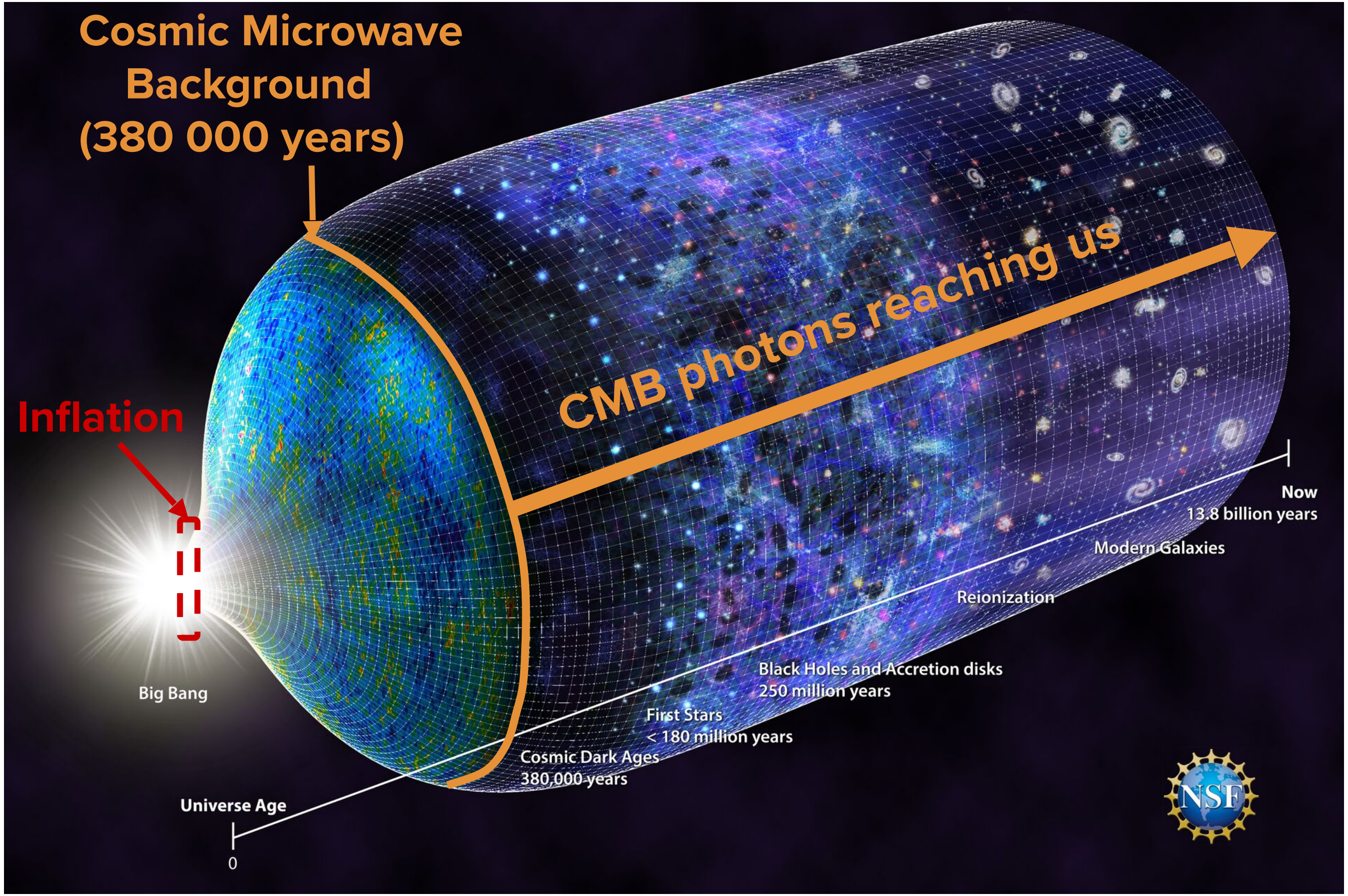

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Inflation would have generated **primordial gravitational waves**, imprinting **characteristic *B*-mode pattern** in the **CMB polarization**

→ **Tensor-to-scalar ratio r**

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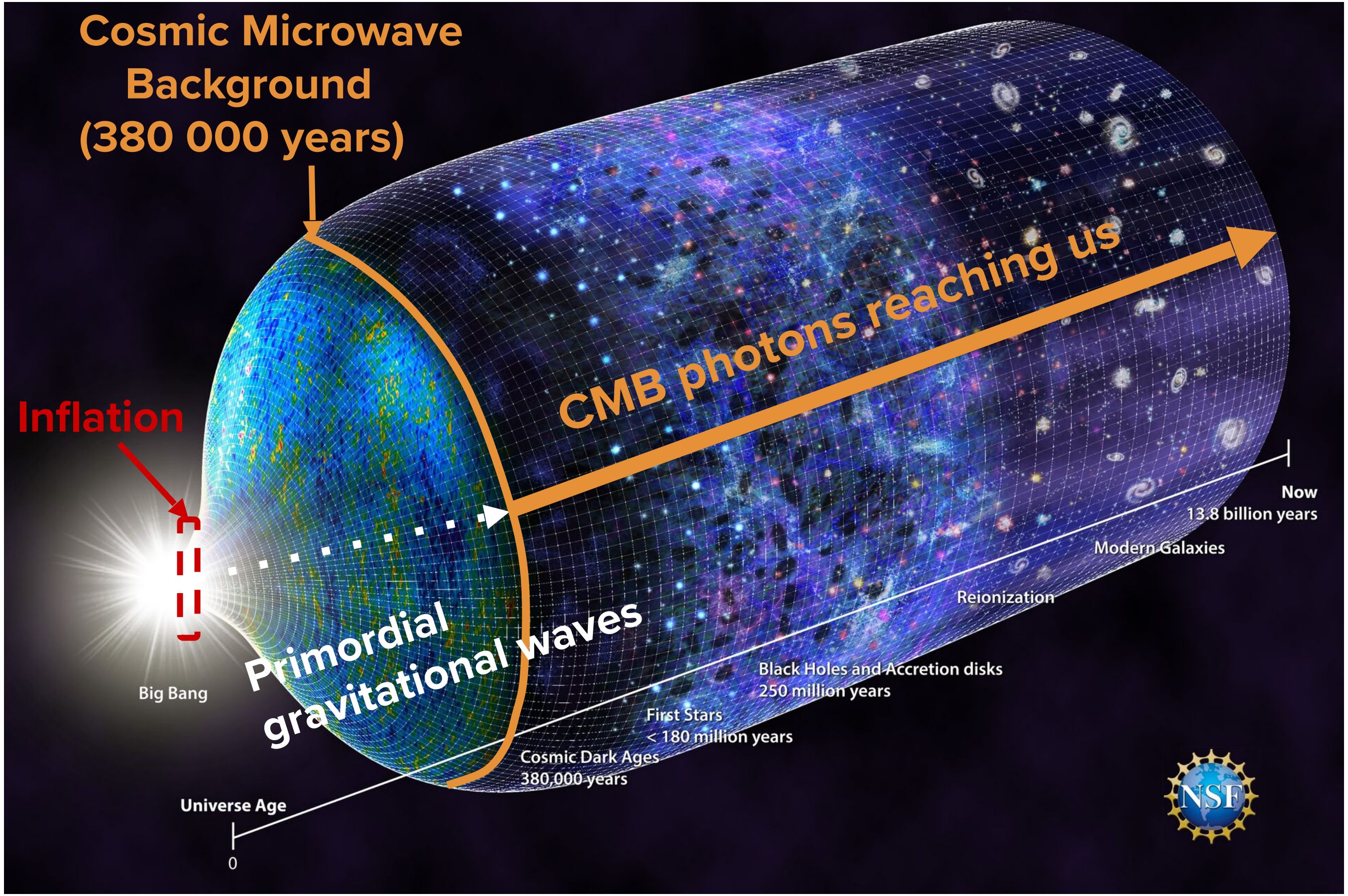

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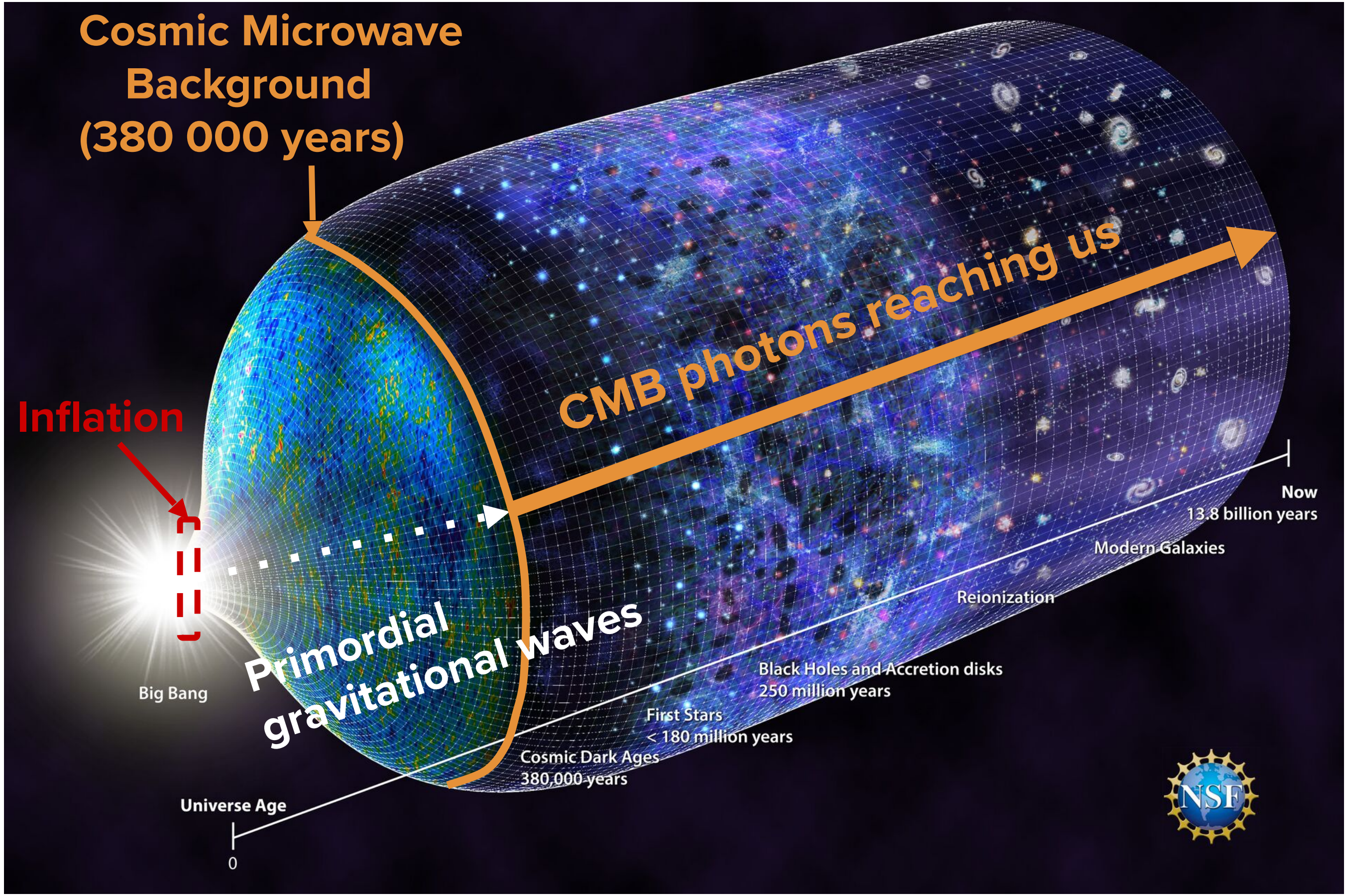

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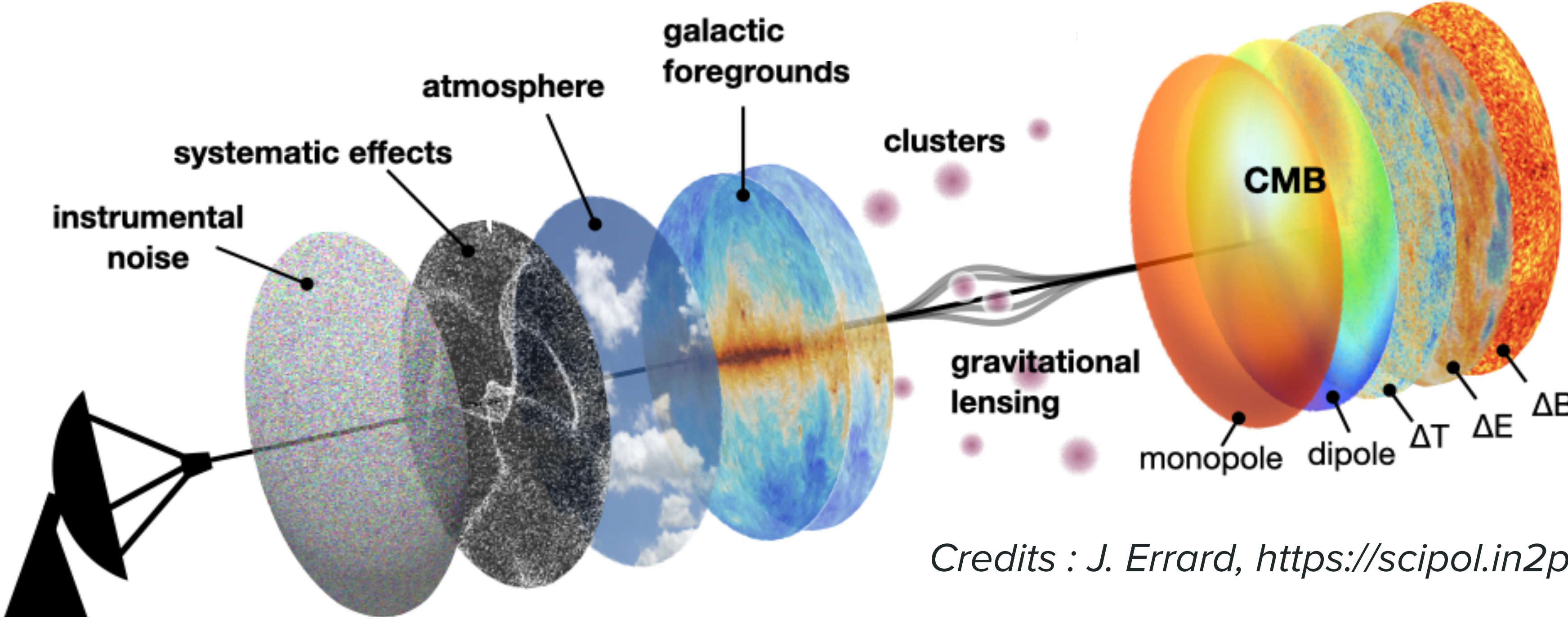
Science goal of current (**Simons Observatory,** Adrien's and Baptiste's talks!) and future (**LiteBIRD**, **CMB-S4**) CMB experiments

Component separation methods in CMB data analysis



Credits : J. Errard, https://scipol.in2p3.fr/

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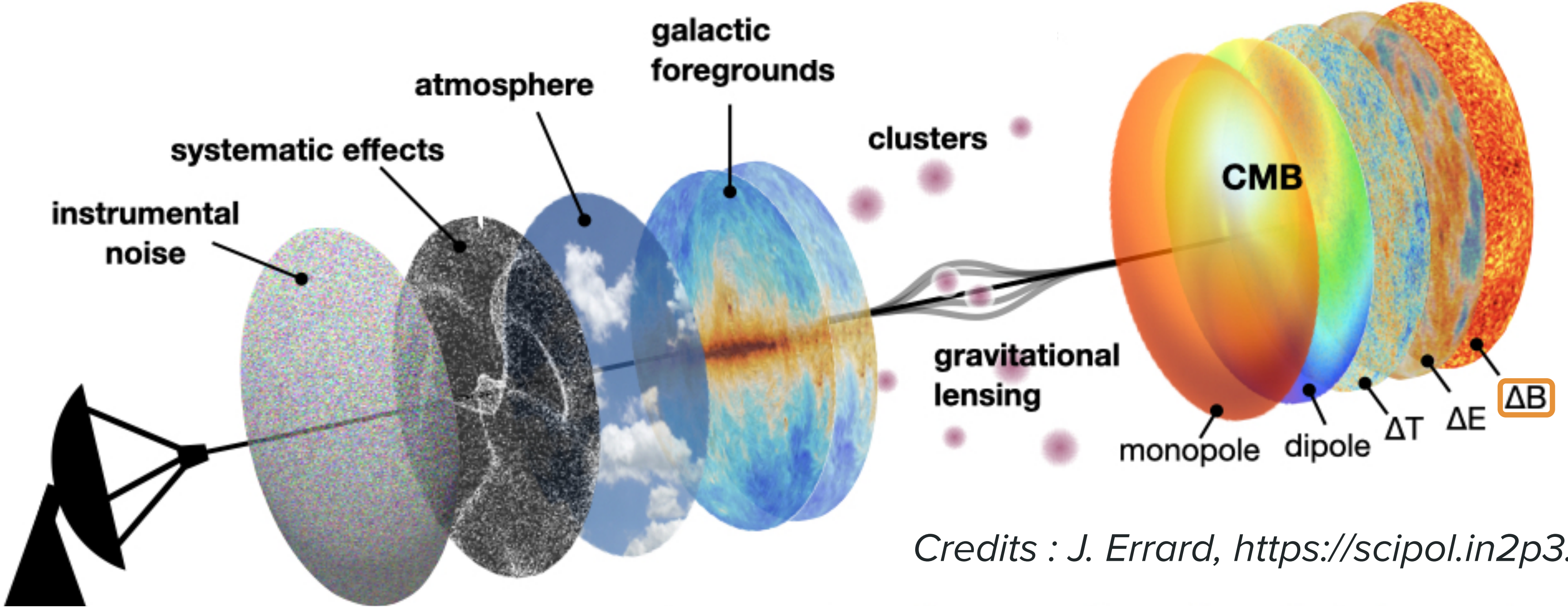

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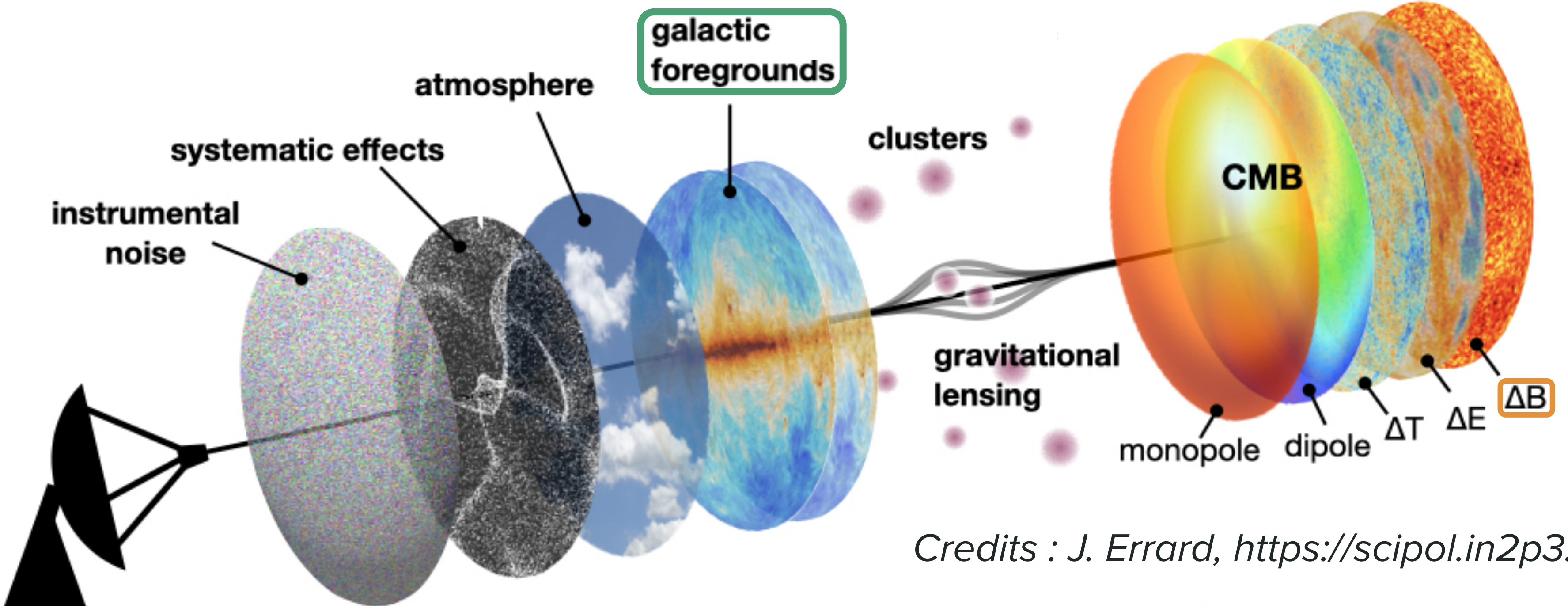

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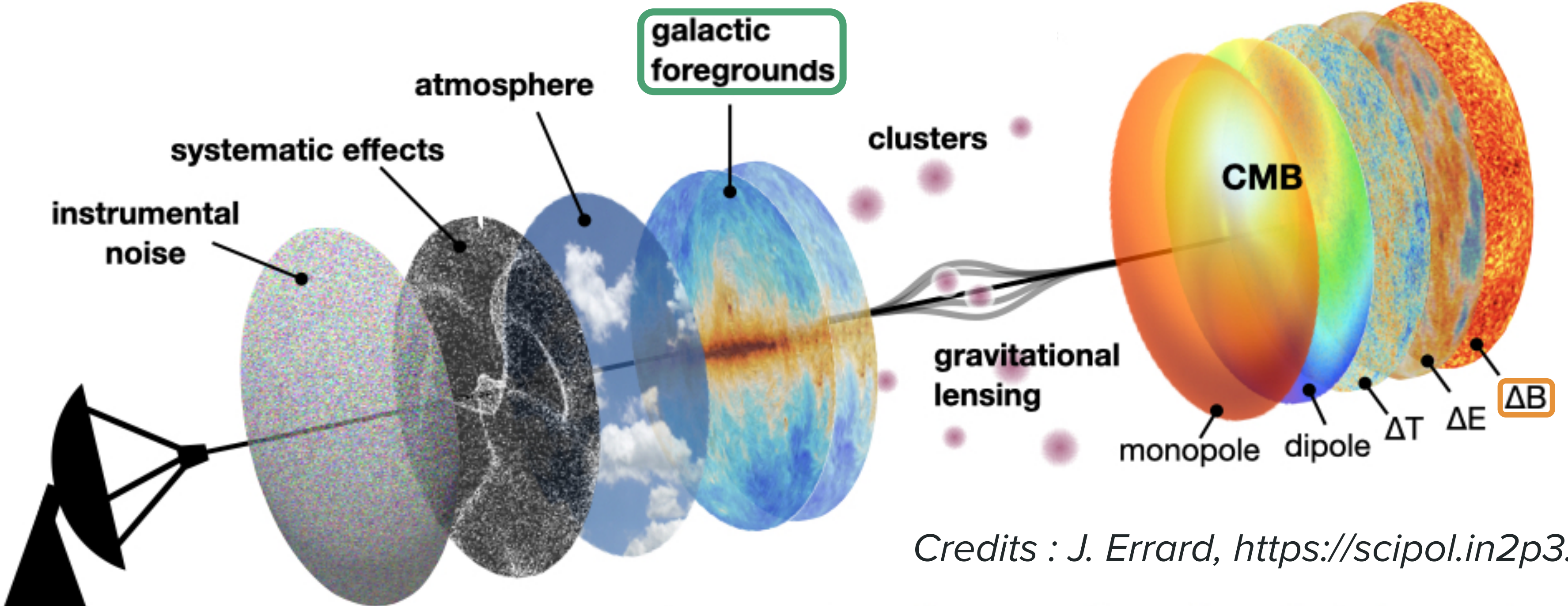

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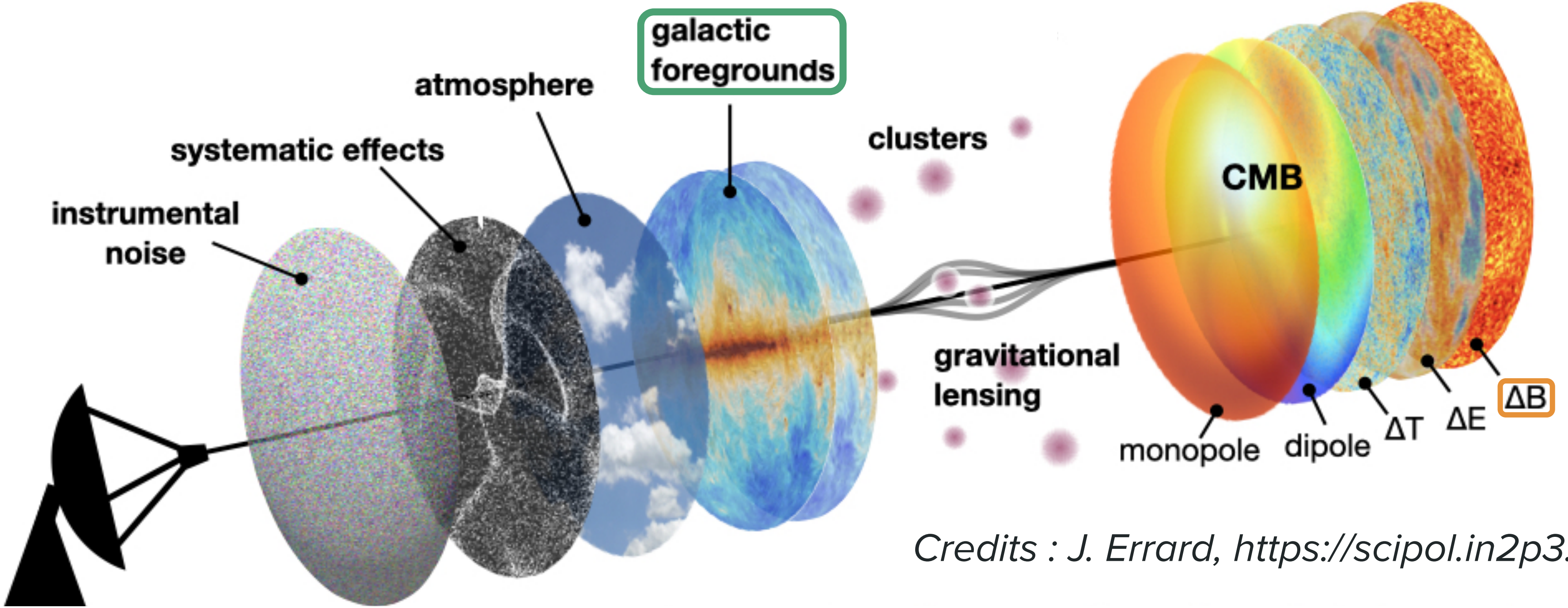

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Component separation:
Isolate **CMB** signal from foregrounds (**Galactic dust**, **Galactic synchrotron** in polarization) using their respective **spectral energy distributions** (SED)

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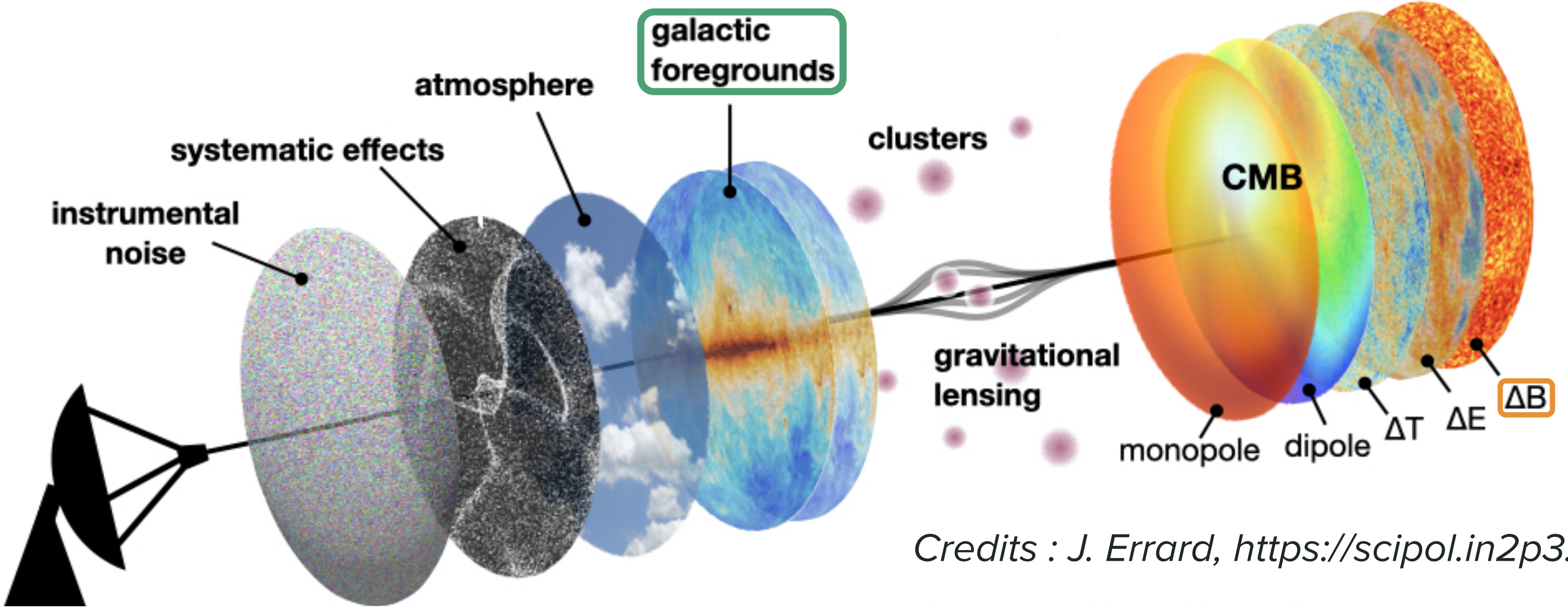

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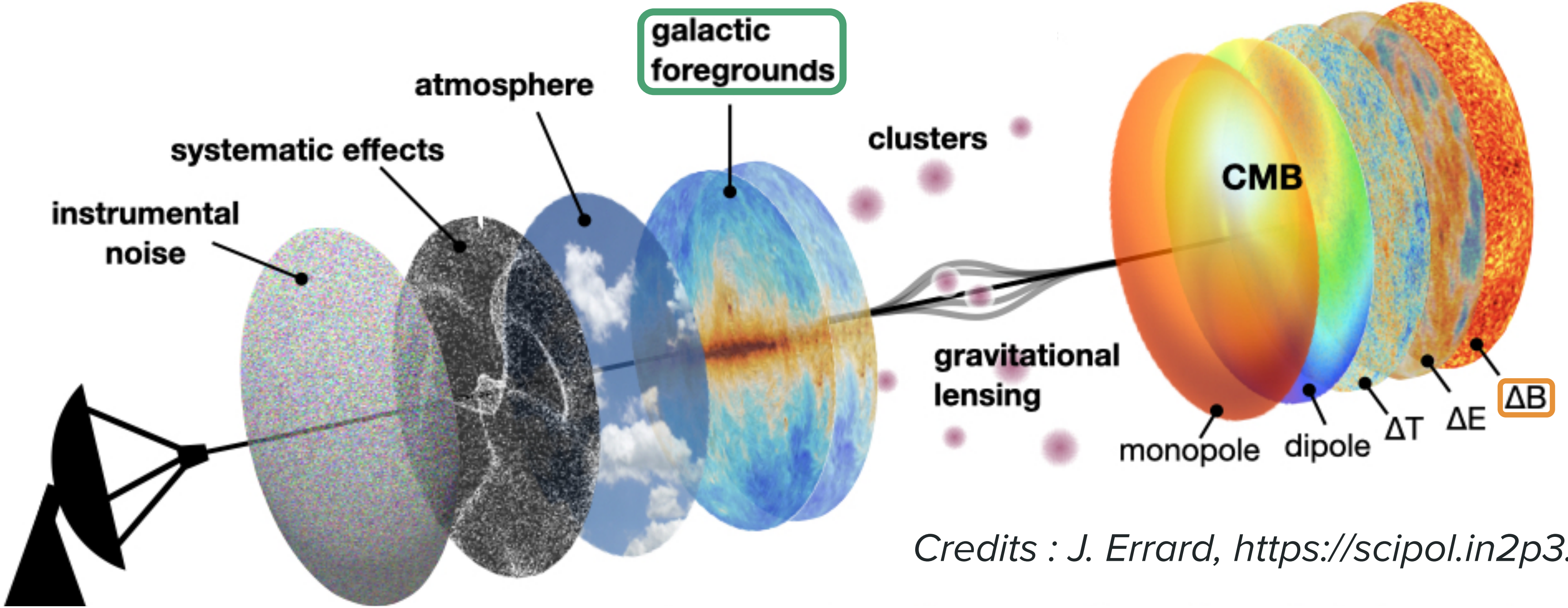

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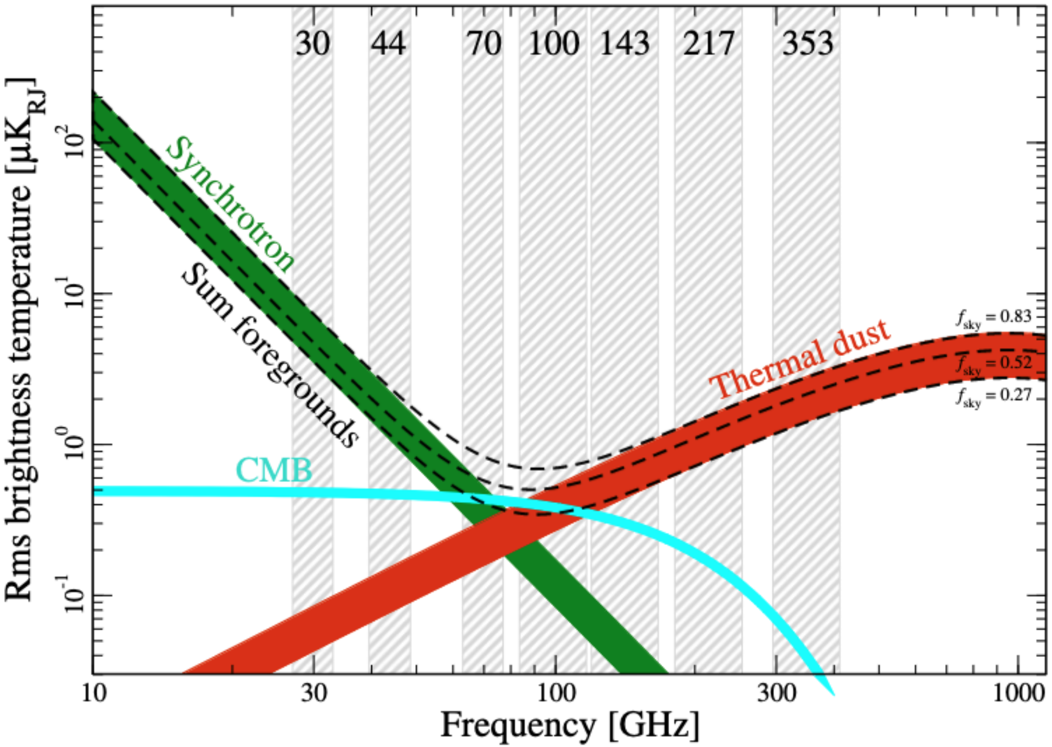
➔ **CMB** is a blackbody spectrum

➔ **Dust** SED as modified blackbody and **synchrotron** SED as power law?

Polarized foregrounds



Credits: Planck 2018 results, I

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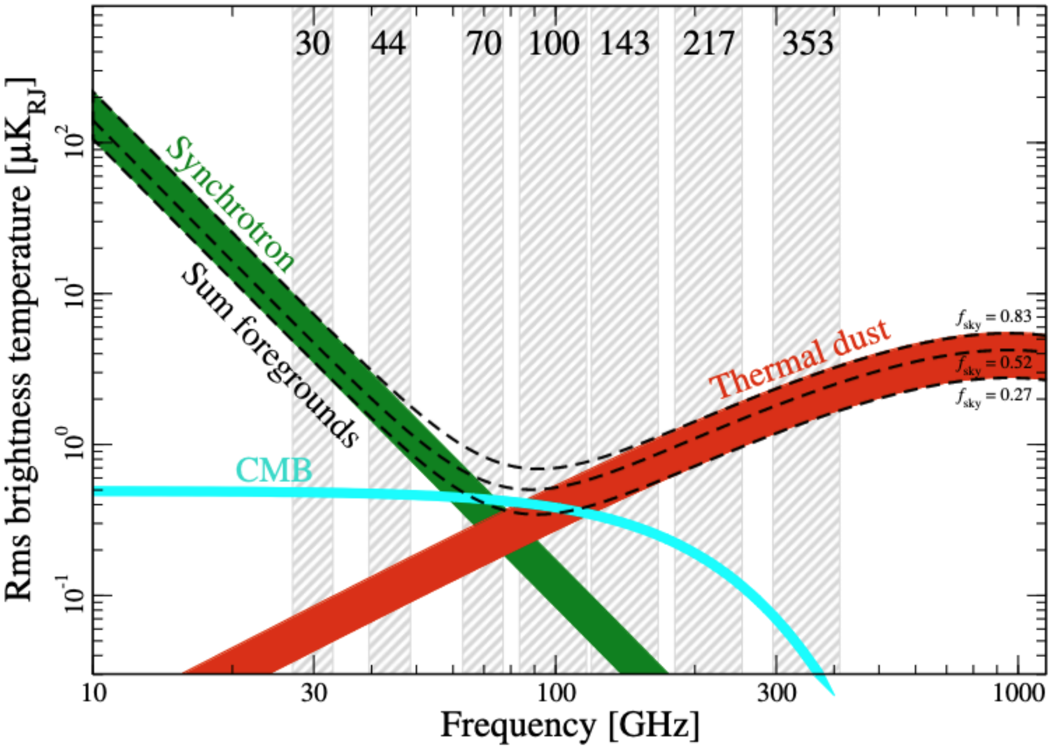

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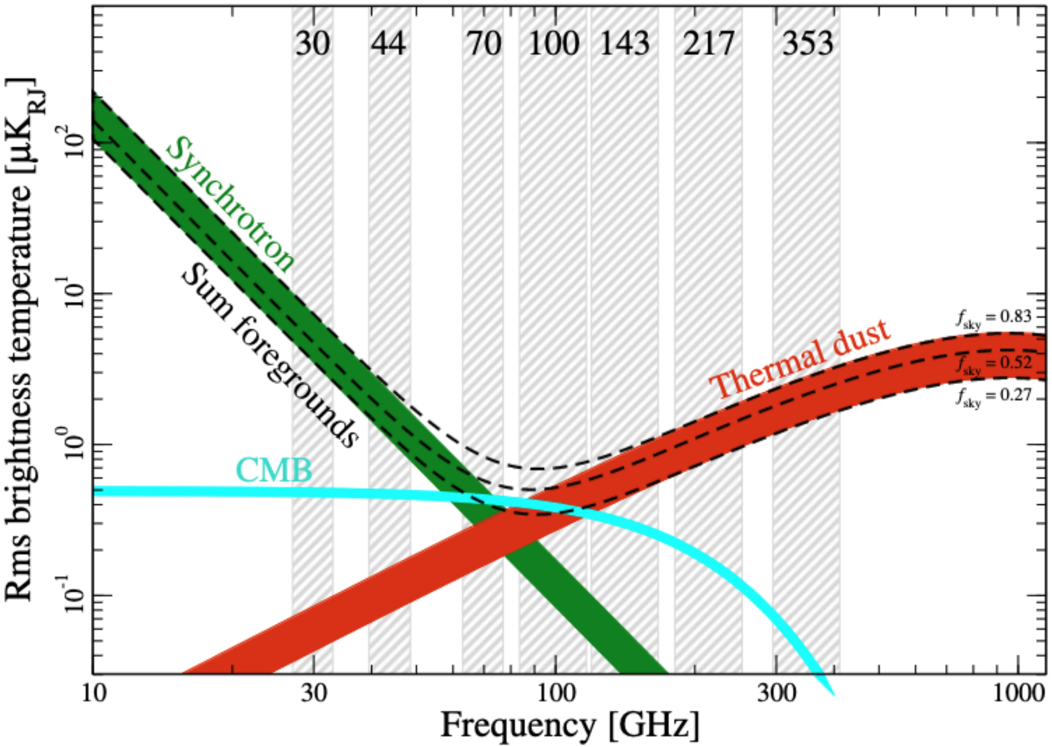

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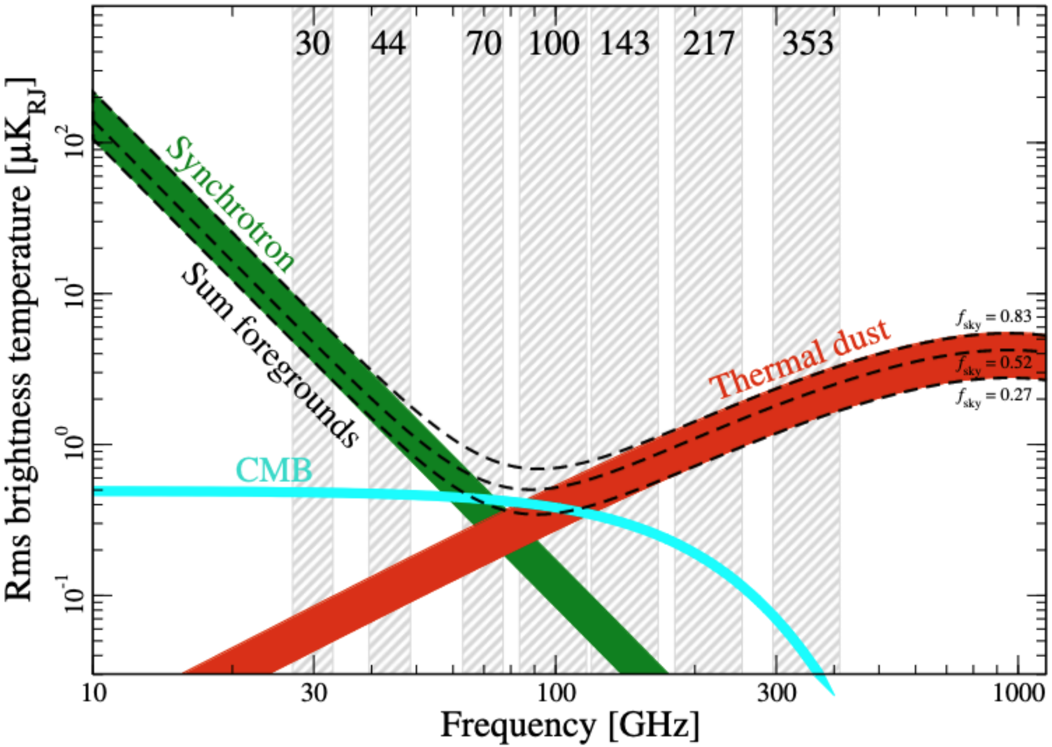

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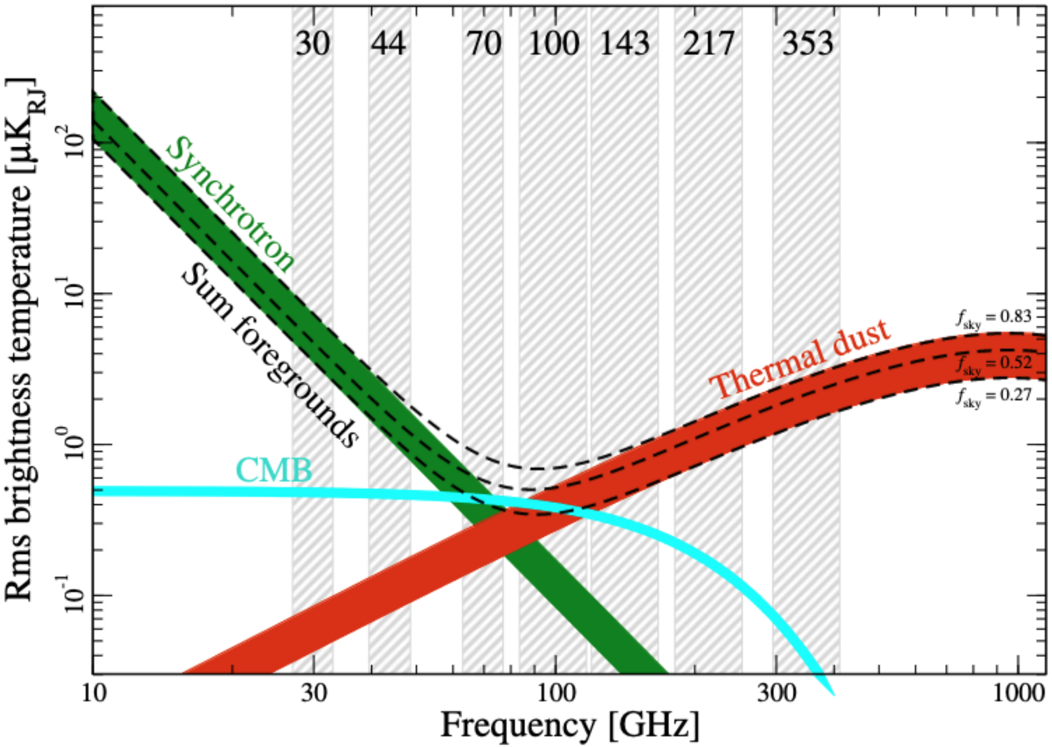

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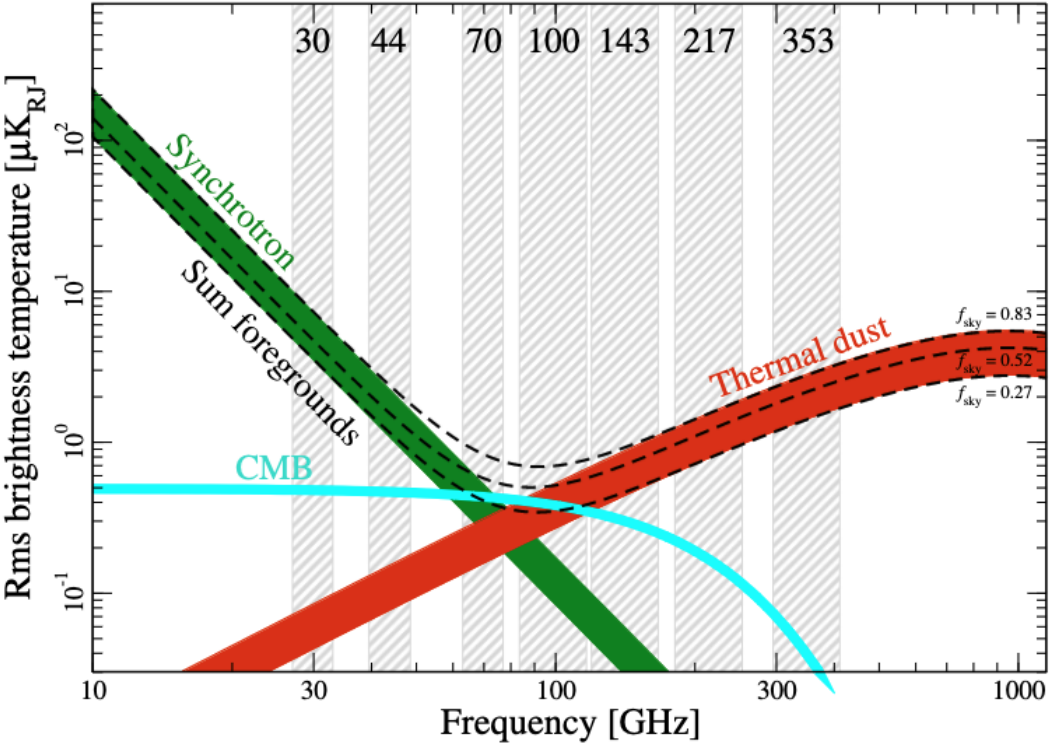

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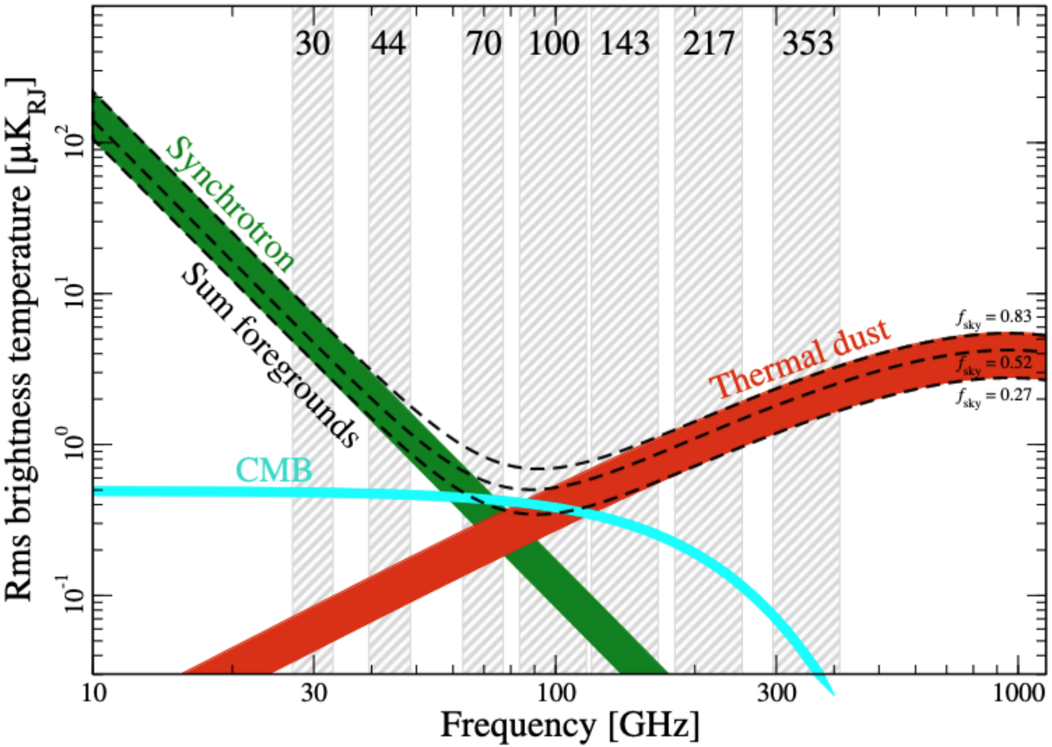

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  ➔ Possibly complex **Galactic foregrounds**

Address **assumptions on foregrounds' SEDs** and **spatial variability**?

➔ Minimally informed approach developed in **Leloup et al. 2023**

Basic assumptions of the method by Leloup et al. 2023

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Goal: Retrieve CMB signal with minimal assumptions on foregrounds

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Observed data

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Observed data

CMB *signal*

foreground components

(dust and **synchrotron**)

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Mixing matrix

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noise

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CMB signal
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Formalism:

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Mixing matrix

noise

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  ➔ Fit for amplitudes for each **foreground component** and each **frequency**
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Main feature: perform **foreground cleaning** while making assumptions on **CMB**

Novel component separation method from Leloup et al. 2023

New Maximum Likelihood method to estimate some elements of the **mixing matrix** to clean **foregrounds** while minimizing number of assumptions

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What is retrieved: **Cosmological parameter(s)** and **mixing matrix elements**

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What is retrieved: **Cosmological parameter(s)** and **mixing matrix elements**

What is shown against the equivalent **parametric component separation method** (in spherical harmonic domain):

- With simulations using **parametric scaling**
- With simulations using **non-parametric scaling**

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What is shown against the equivalent **parametric component separation method** (in spherical harmonic domain):

- With simulations using **parametric scaling**
  ➔ Performs as good
- With simulations using **non-parametric scaling**
  ➔ Performs better

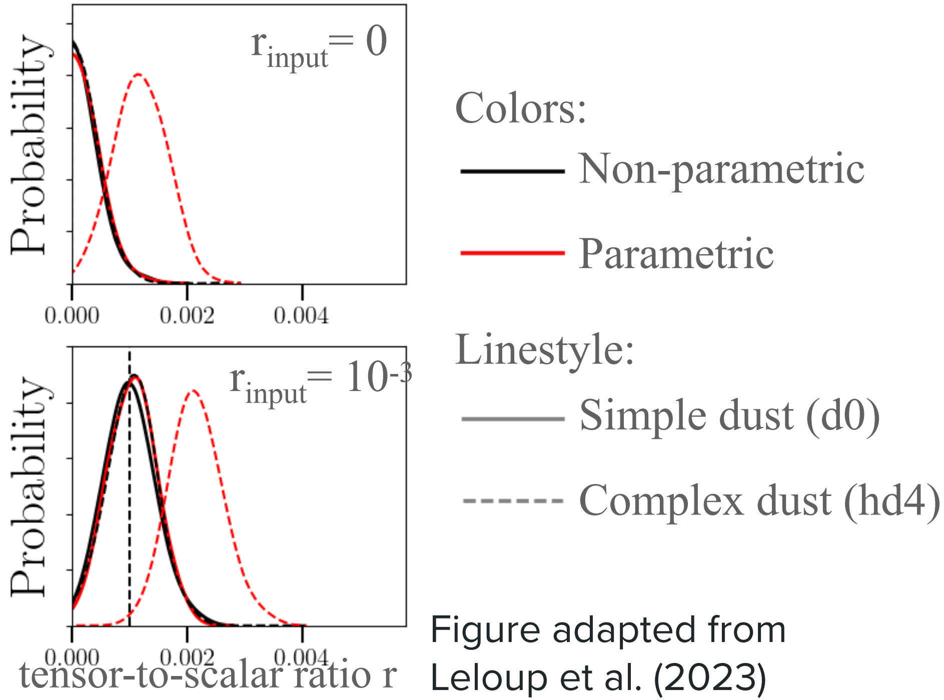

Figure adapted from Leloup et al. (2023)

Main results in harmonic domain from Leloup et al. 2023

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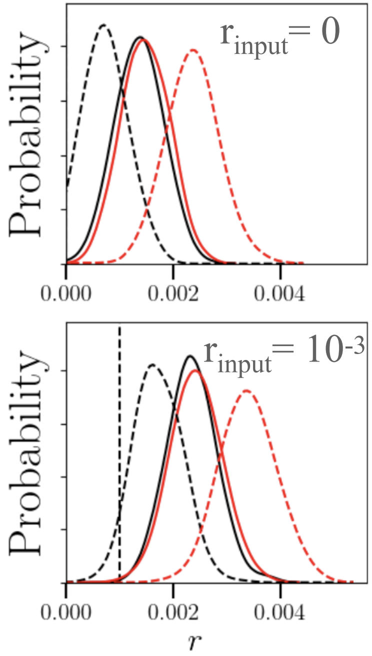

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Different models for foregrounds with **spatial variability**

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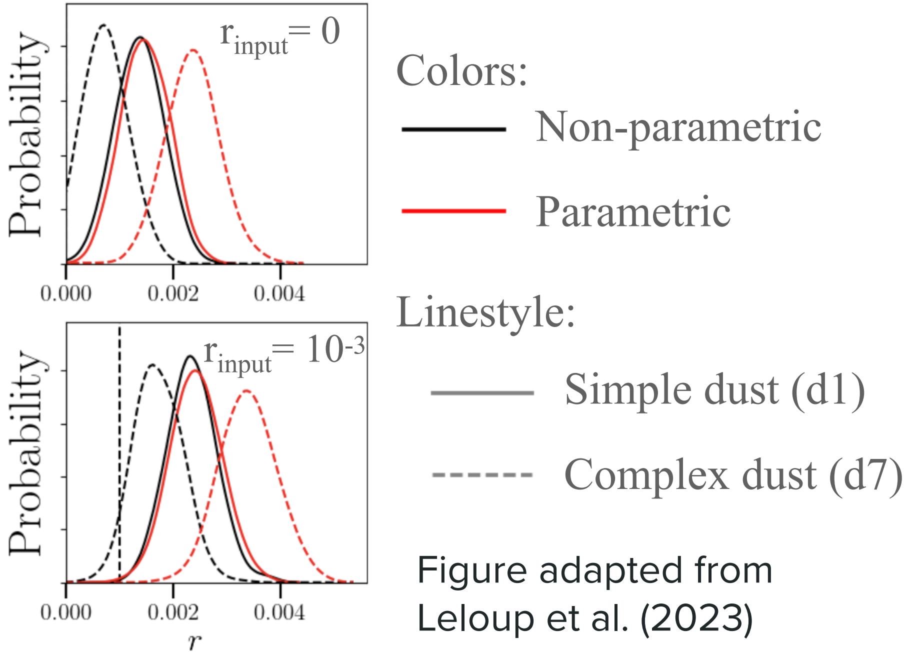

Figure adapted from Leloup et al. (2023)

Different models for foregrounds with **spatial variability**

Both methods fail when **foreground SED spatial variability** involved

➜ Calls for a **pixel domain implementation**

Pixel domain implementation

Challenges:

- Adaptation of the **likelihood** of **Leloup et al. 2023** to **pixel domain**

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$$\boxed{\mathcal{S}_{spec}^{\mathrm{corr}}(\mathbf{B}, \mathbf{C}) = \mathbf{d}^{\mathrm{T}}\,\mathbf{P}\,\mathbf{d} + \mathbf{s}_{\mathbf{c}}^{\mathbf{ML}^{\mathrm{T}}}(\mathbf{N_c} + \mathbf{C})^{-1}\,\mathbf{s}_{\mathbf{c}}^{\mathbf{ML}} + \ln|\mathbf{C} + \mathbf{N_c}| - \ln\left|\tilde{\mathbf{C}} + \mathbf{N_c}\right|}$$

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from harmonic to pixel domain

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from harmonic to pixel domain

$$\mathcal{S}^{\mathrm{corr}}_{\mathrm{prof}}\left(\mathbf{s_c},\mathbf{B},\mathbf{C},\boldsymbol{\eta}\right) \equiv \mathbf{d}^{\mathrm{T}}\,\mathbf{P}\,\mathbf{d} + \mathbf{s}_{\mathbf{c}}^{\mathbf{ML}\,\mathrm{T}}\left(\mathbf{N_c}+\mathbf{C}\right)^{-1}\mathbf{s}_{\mathbf{c}}^{\mathbf{ML}} + \left(\mathbf{s_c}-\mathbf{s}_{\mathbf{c}}^{\mathbf{WF}}\right)^{\mathrm{T}}\left(\mathbf{N}_{\mathbf{c}}^{-1}+\mathbf{C}^{-1}\right)\left(\mathbf{s_c}-\mathbf{s}_{\mathbf{c}}^{\mathbf{WF}}\right) + \ln\left|\mathbf{C}\right| + \boldsymbol{\eta}^{\mathrm{T}}\left(\tilde{\mathbf{C}}^{1/2}\left(\tilde{\mathbf{C}}^{-1}+\mathbf{N}_{\mathbf{c}}^{-1}\right)\tilde{\mathbf{C}}^{1/2}\right)^{-1}\boldsymbol{\eta}.$$

pixel domain likelihood

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pixel domain likelihood

$$+\ln\left|\underline{\mathbf{C}}\right| + \boldsymbol{\eta}^{\mathrm{T}}\left(\underline{\tilde{\mathbf{C}}}^{1/2}\left(\underline{\tilde{\mathbf{C}}}^{-1}+\mathbf{N}_{\mathbf{c}}^{-1}\right)\underline{\tilde{\mathbf{C}}}^{1/2}\right)^{-1}\boldsymbol{\eta}.$$

harmonic domain covariances

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from harmonic to pixel domain

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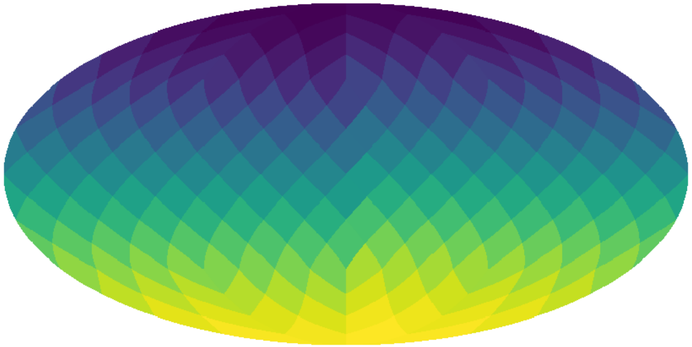
pixel domain likelihood

$$+ \ln\left|\underline{\mathbf{C}}\right| + \boldsymbol{\eta}^{\mathrm{T}}\left(\underline{\tilde{\mathbf{C}}}^{1/2}\left(\underline{\tilde{\mathbf{C}}}^{-1}+\mathbf{N}_{\mathbf{c}}^{-1}\right)\underline{\tilde{\mathbf{C}}}^{1/2}\right)^{-1}\boldsymbol{\eta}.$$

harmonic domain covariances

- Account for **foreground SED spatial variability**

➜ Use of **multipatch approach**: mixing matrix with pixel dependence (divided in patches instead of the full sky)



➜ Makes the likelihood more complex

Minimally Informed CMB MAp foreground Cleaning: MICMAC

New formalism described in ***MM et al.*** *(2024) [arXiv:2405.18365]*

New package in pixel domain: github.com/CMBSciPol/MICMAC

Credits: Ema Tsang King Sang

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M I C M A C

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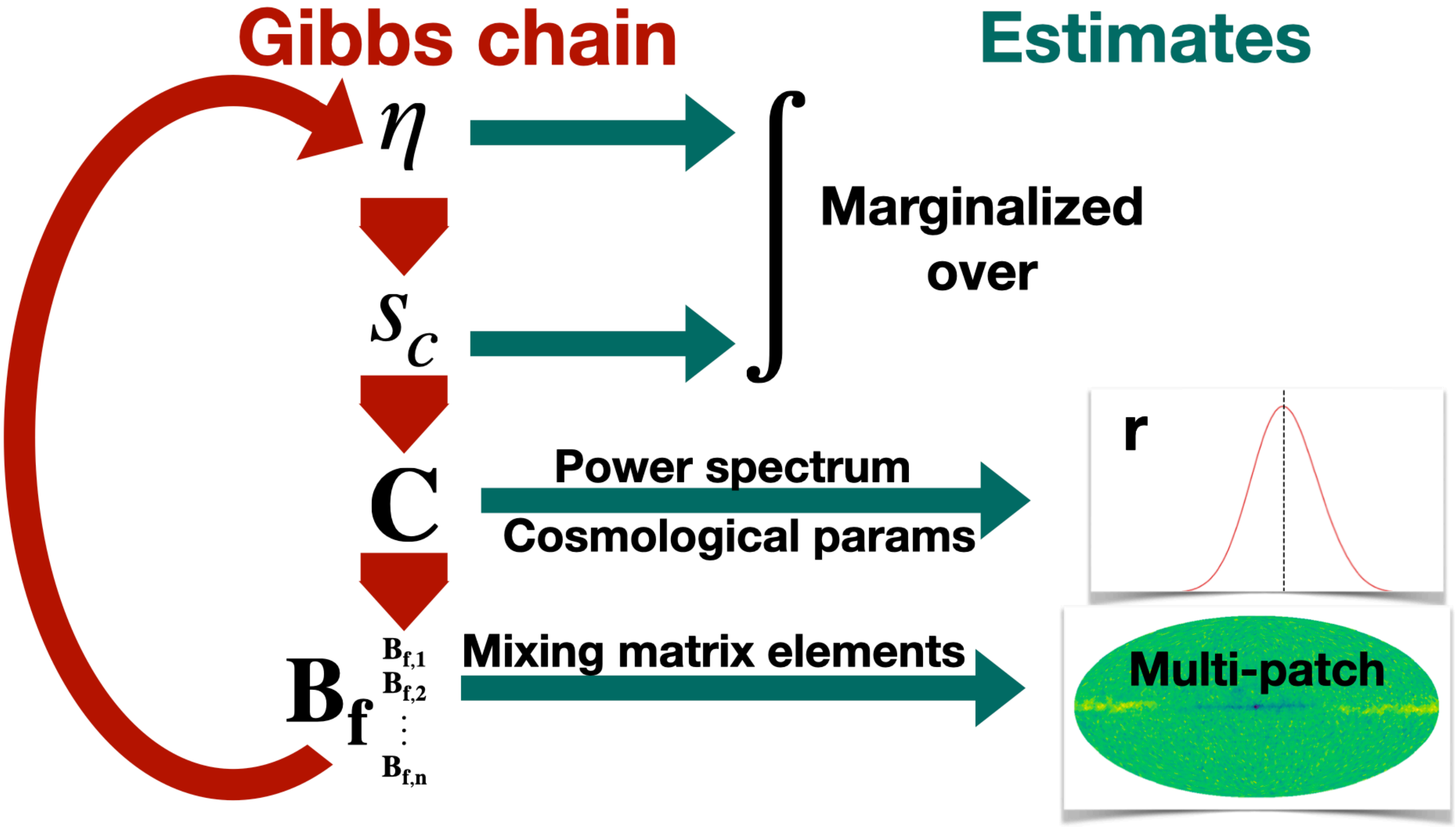
Use of the package (documentation available here):

- **No major assumptions on the foregrounds**, few "tuning" parameters
- Start from frequency maps to estimate:
  - **CMB power spectrum /cosmological parameters** $\boxed{\mathbf{C}}$
  - **Redefined mixing matrix elements (pixel)** $\boxed{\mathbf{B_f}}$
- Possibility to have a different patch distribution for each mixing matrix element

Minimally Informed CMB MAp foreground Cleaning: MICMAC

Gibbs Sampling divided in four steps:



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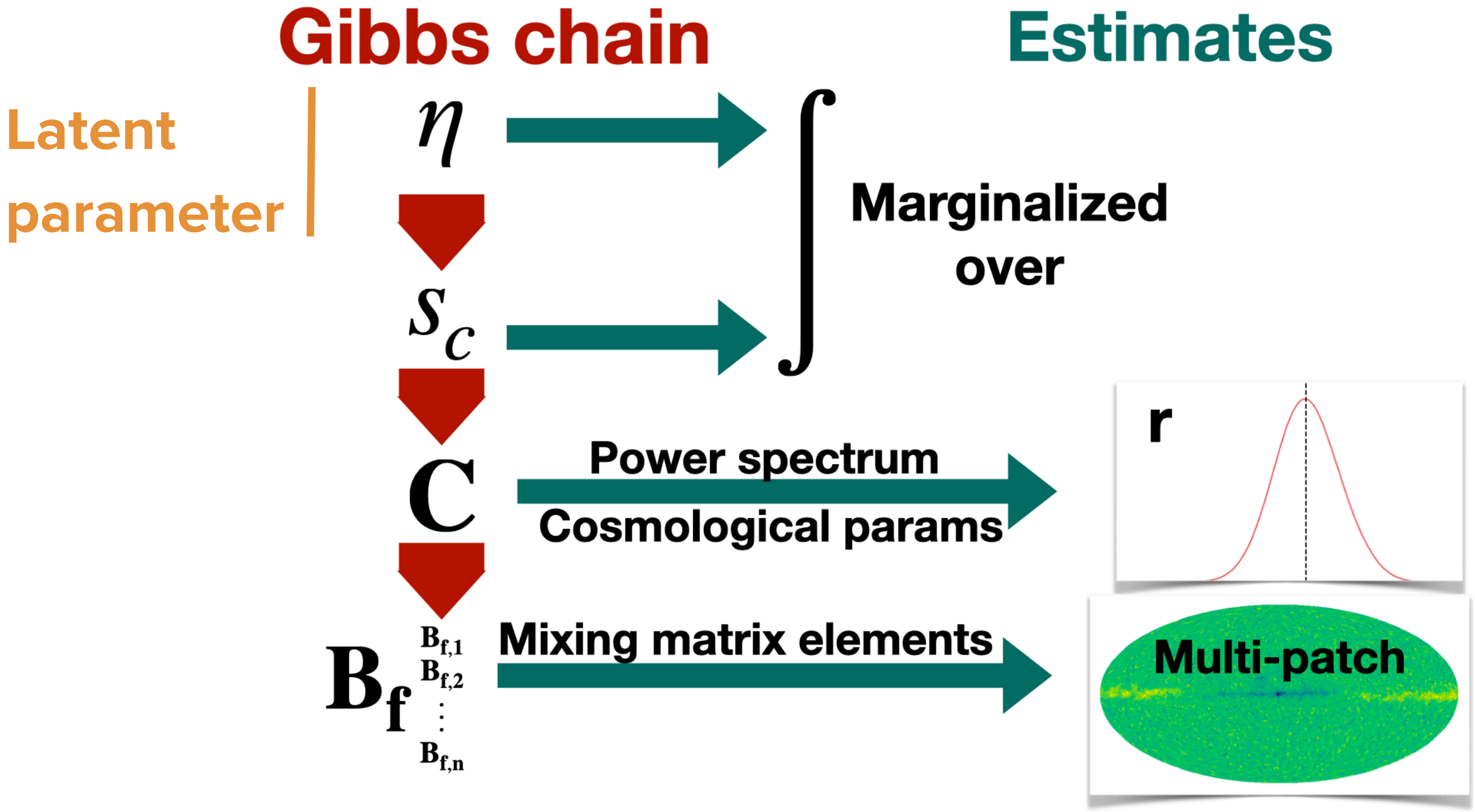

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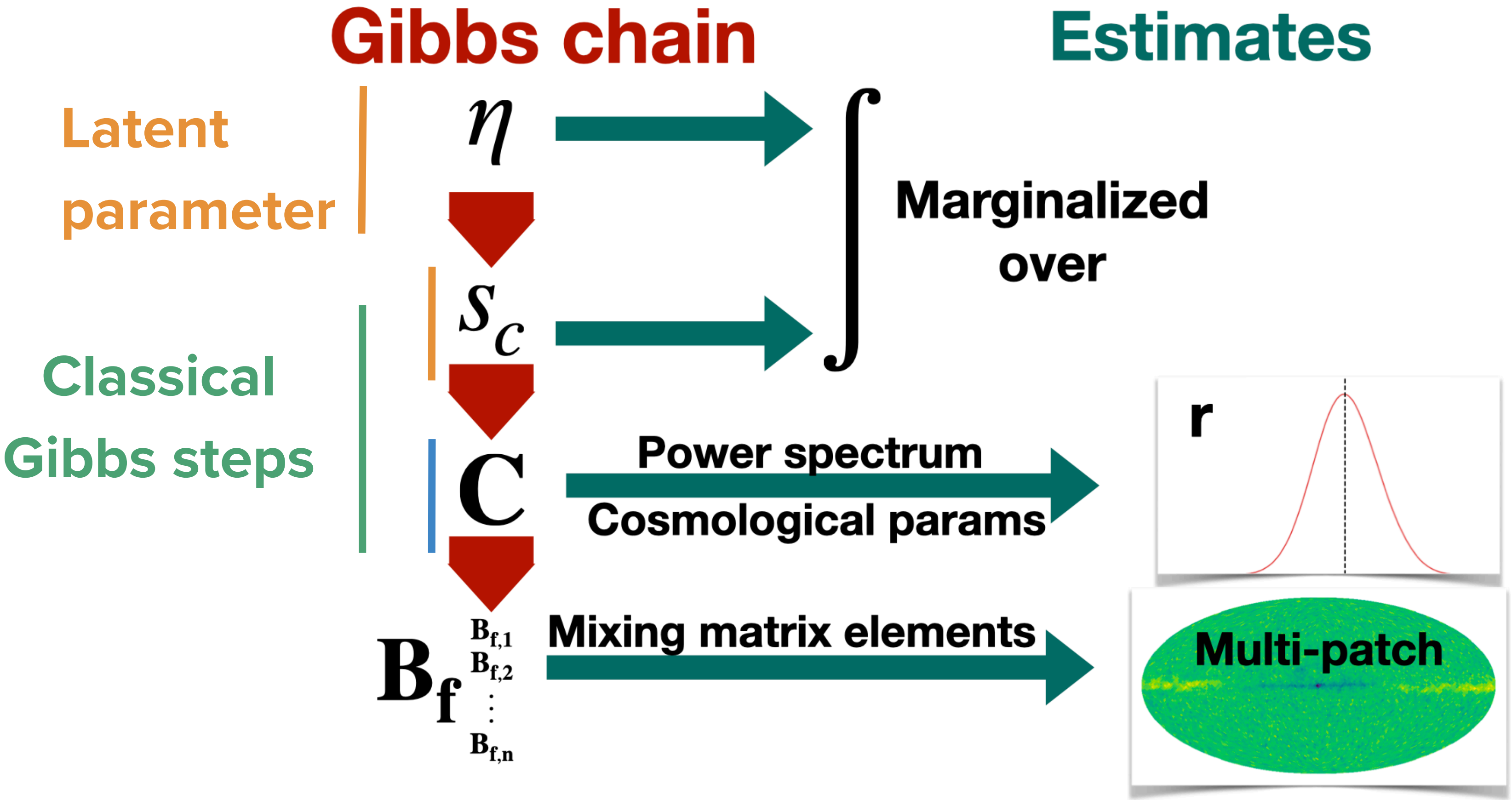

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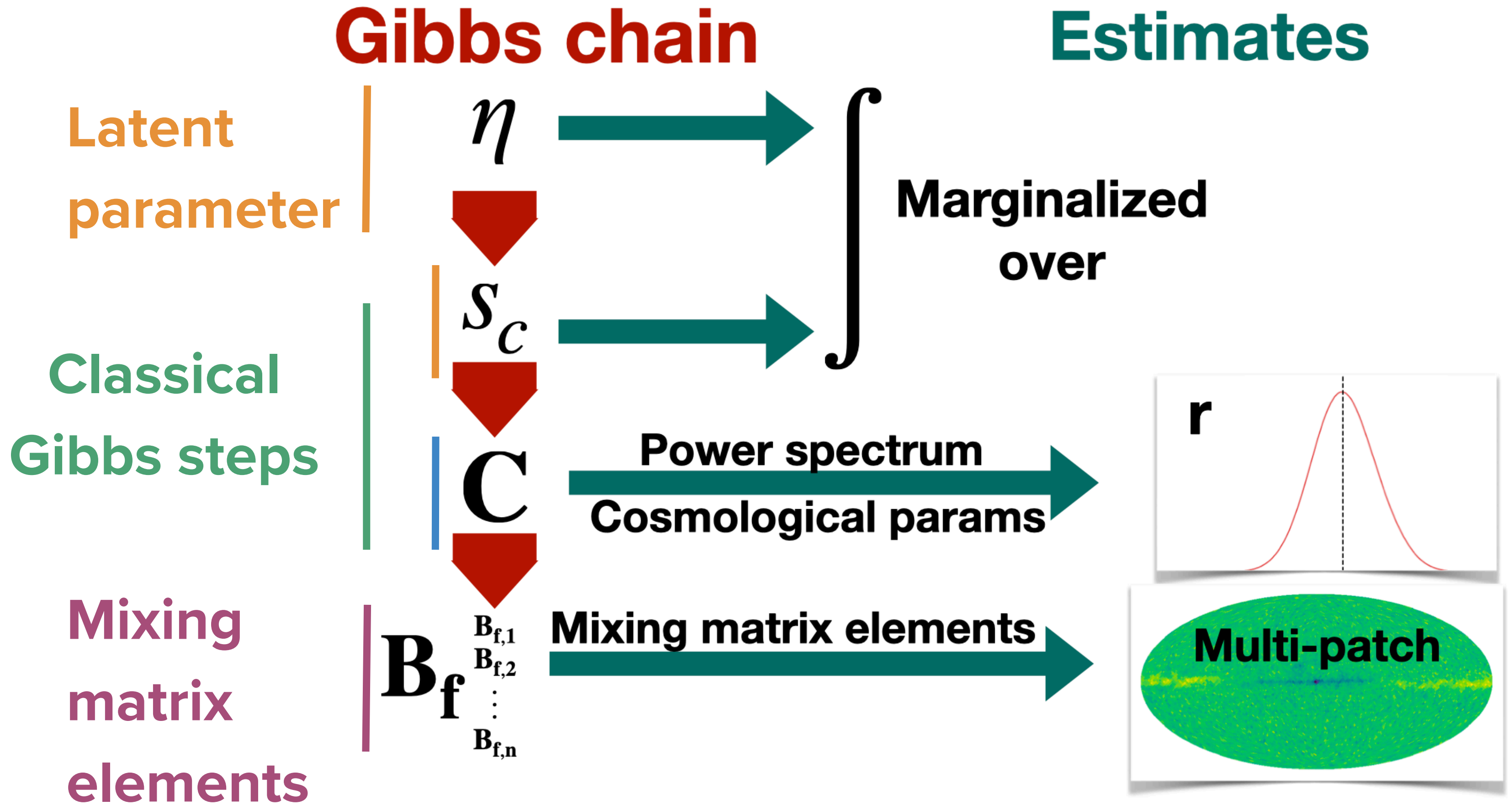

Minimally Informed CMB MAp foreground Cleaning: MICMAC

Gibbs chain

Latent parameter

η

Gaussian

$$\mathcal{P}(\eta|....) \propto \eta^t \, \tilde{\mathbf{C}}^{-1/2} \, (\tilde{\mathbf{C}}^{-1} + \mathbf{N_c}^{-1})^{-1} \tilde{\mathbf{C}}^{-1/2} \, \eta$$

Classical Gibbs steps

s_c

Gaussian (Wiener-filter)

$$\mathcal{P}(\mathbf{s_c}|....) \propto (\mathbf{s_c} - \mathbf{s_{c,WF}})^t \, (\mathbf{C}^{-1} + \mathbf{N_c}^{-1}) \, (\mathbf{s_c} - \mathbf{s_{c,WF}})$$

$\mathbf{C}$

Inverse Wishart (or r through **MwG**)

$$\mathcal{P}(\mathbf{C}|....) \propto \mathbf{s_c}^t \mathbf{C}^{-1} \mathbf{s_c} + \ln|\mathbf{C}|$$

Mixing matrix elements

$\mathbf{B_f}$: $\mathbf{B_{f,1}}$, $\mathbf{B_{f,2}}$, $\vdots$, $\mathbf{B_{f,n}}$

Metropolis-within-Gibbs

$$\mathcal{P}(\mathbf{B_f}|....) \propto -(\mathbf{d} - \mathbf{B_c s_c})^t \mathbf{N}^{-1} \mathbf{B_f} (\mathbf{B_f^t} \mathbf{N}^{-1} \mathbf{B_f})^{-1} \mathbf{B_f^t} \mathbf{N}^{-1} (\mathbf{d} - \mathbf{B_c s_c}) + \eta^t \, \tilde{\mathbf{C}}^{-1/2} \, (\tilde{\mathbf{C}}^{-1} + \mathbf{N_c}^{-1})^{-1} \tilde{\mathbf{C}}^{-1/2} \, \eta$$

Minimally Informed CMB MAp foreground Cleaning: MICMAC

Gaussian

$$\mathcal{P}(\eta|....) \propto \eta^t\, \tilde{\mathbf{C}}^{-1/2}\, (\tilde{\mathbf{C}}^{-1} + \mathbf{N_c}^{-1})^{-1} \tilde{\mathbf{C}}^{-1/2}\, \eta$$

Gaussian (Wiener-filter)

$$\mathcal{P}(\mathbf{s_c}|....) \propto (\mathbf{s_c} - \mathbf{s_{c,WF}})^t\, (\mathbf{C}^{-1} + \mathbf{N_c}^{-1})\, (\mathbf{s_c} - \mathbf{s_{c,WF}})$$

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Minimally Informed CMB MAp foreground Cleaning: MICMAC

harmonic ↔ pixel

(harmonic + pixel)$^{-1}$ with **Conjugate Gradient method**

Careful **multipatch** memory handling

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Careful **multipatch** memory handling

→ Numerically expensive code (choice of JAX)

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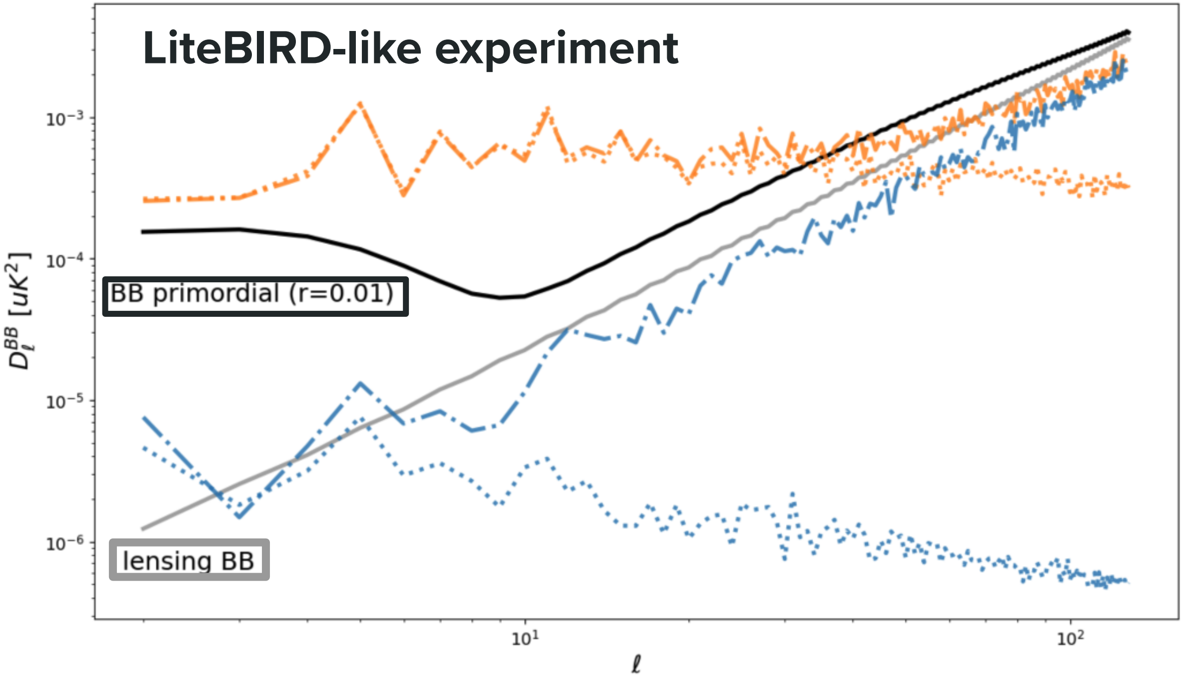
Minimally Informed CMB MAp foreground Cleaning: MICMAC

Residual validation of **MICMAC** against ***customized model d7s1*** with **foregrounds spatial variability** downgraded to 12 patches

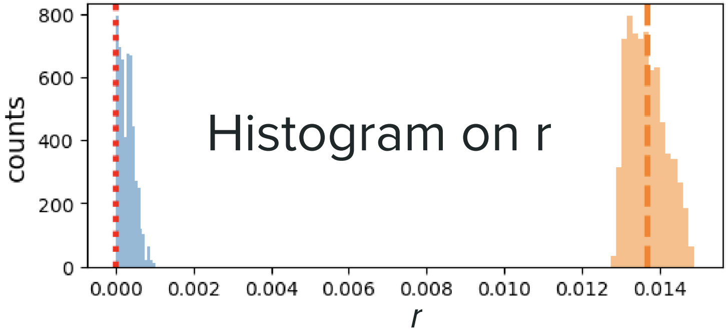


Total and foreground residuals of the analysis

Two configurations tested:

- **"ns=1":** 12 patches
- **"ns=0":** 1 patch

Total residuals include noise!



Posteriors on tensor-to-scalar ratio *r*

MM et al. *(2024)*

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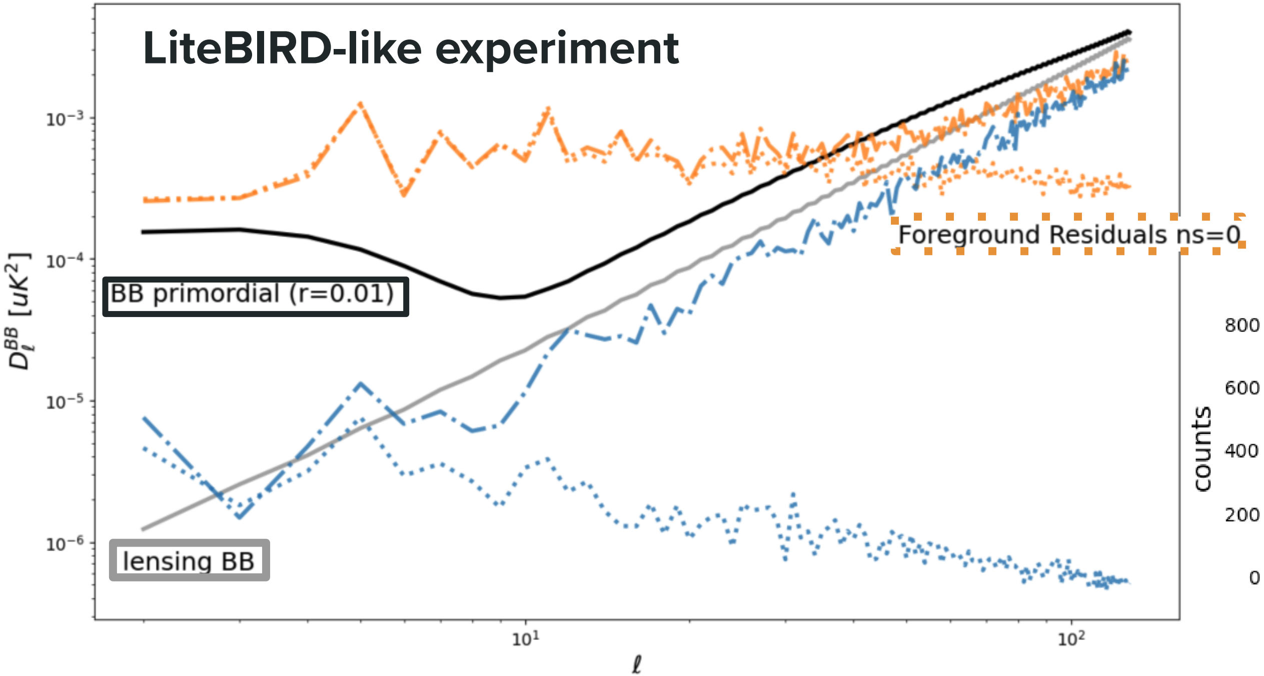

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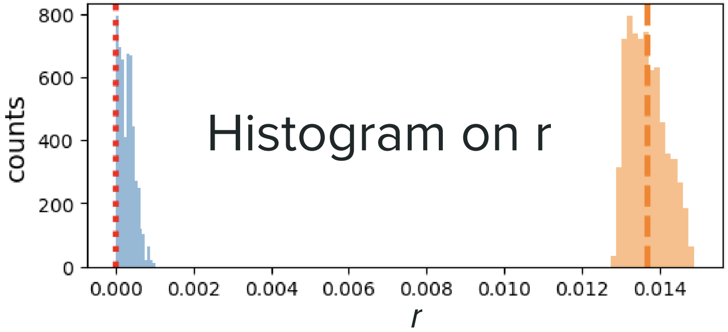

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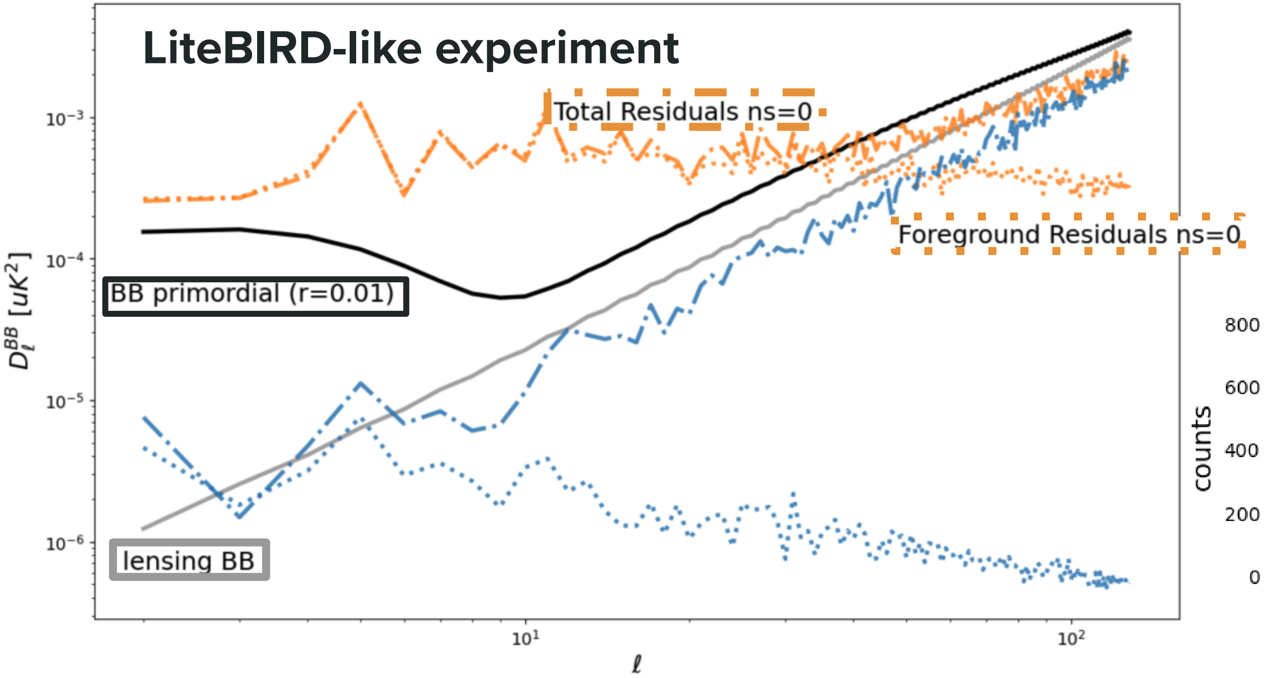

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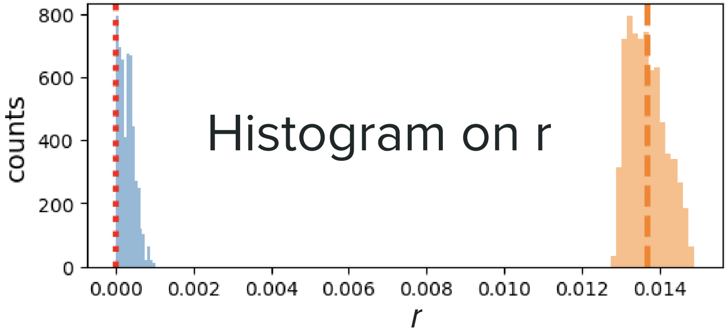

Posteriors on tensor-to-scalar ratio r

MM et al. *(2024)*

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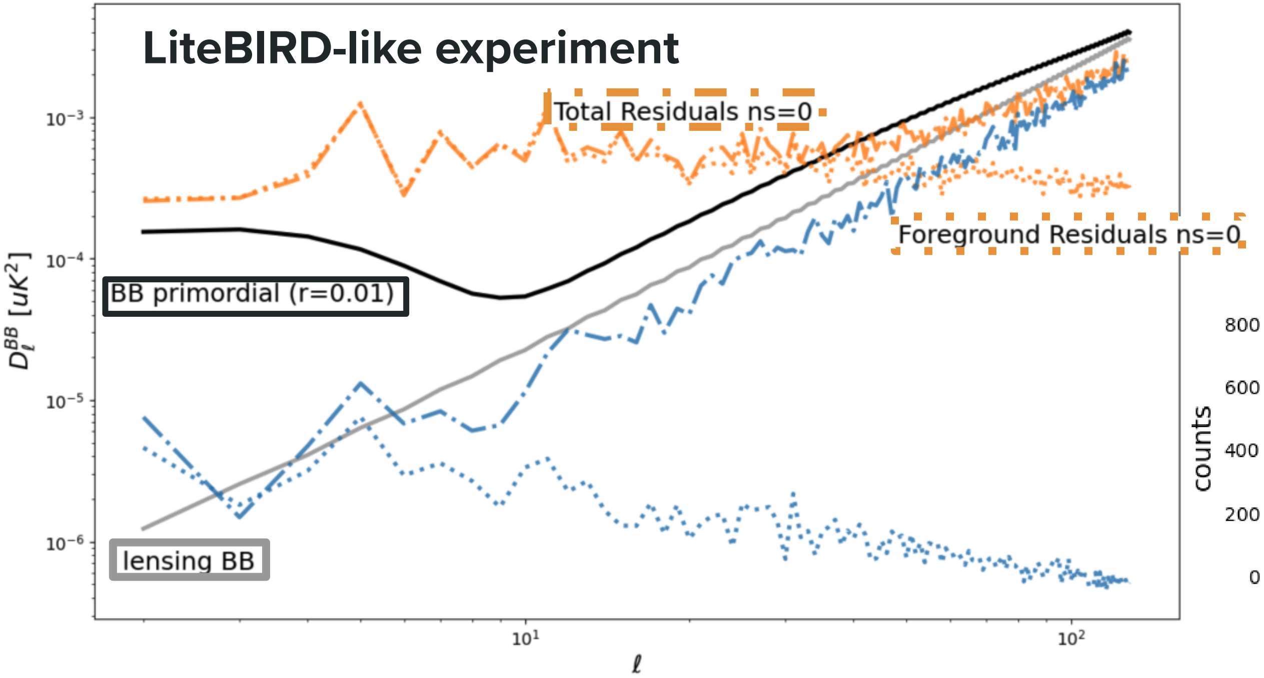

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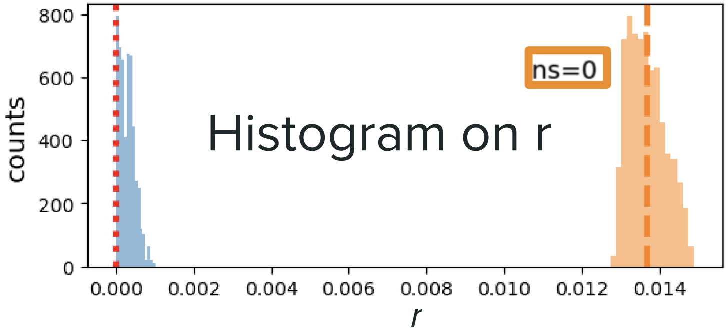

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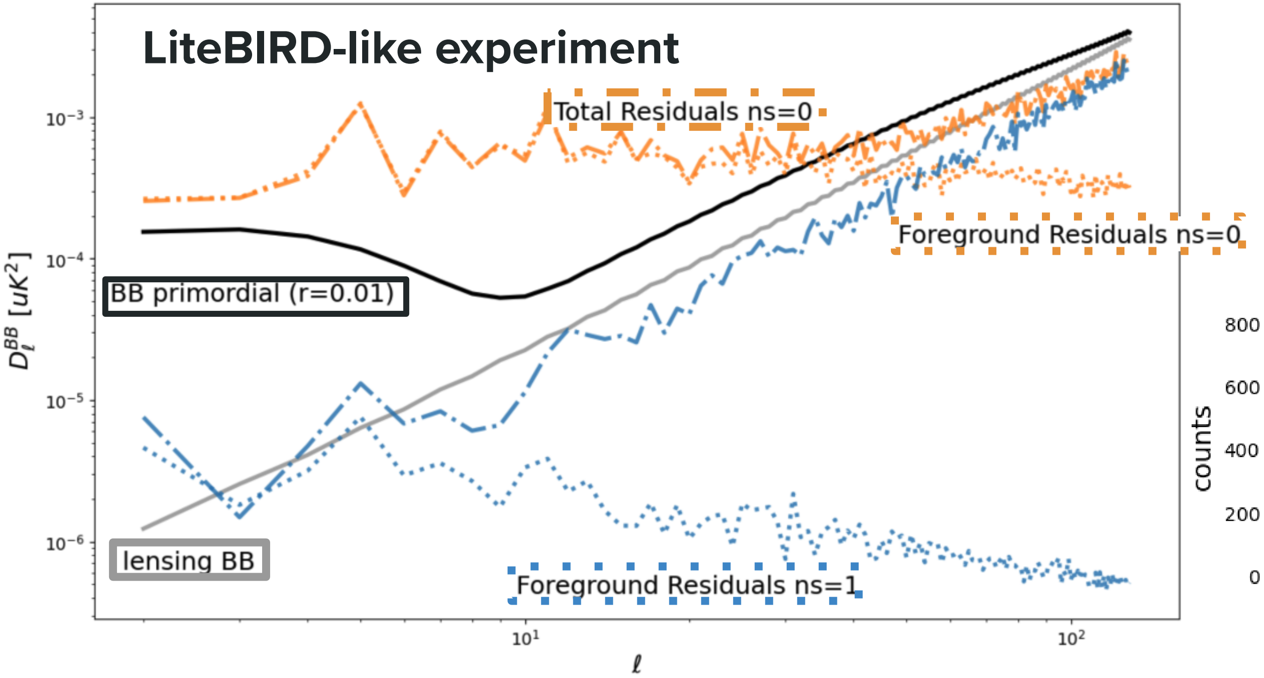

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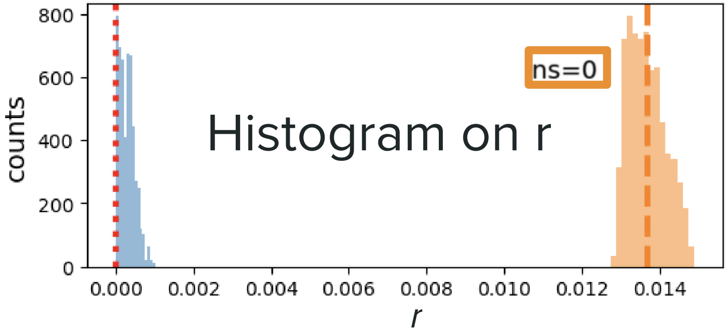

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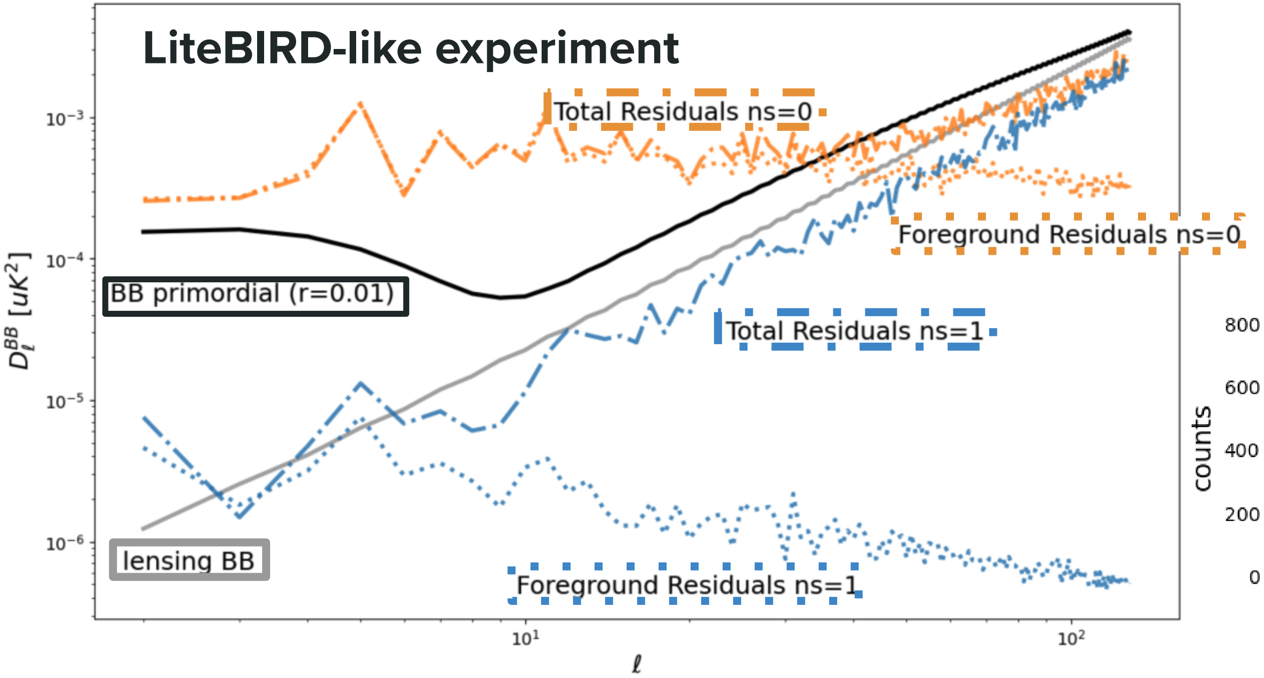

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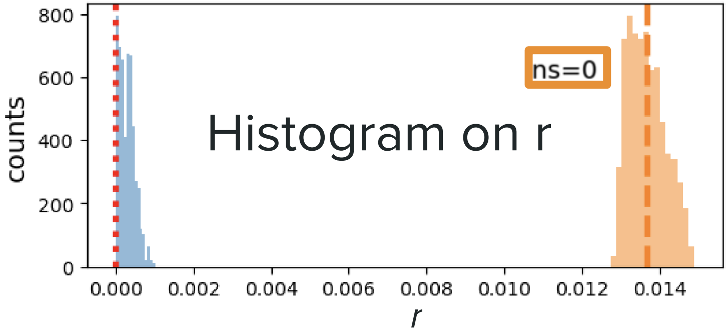

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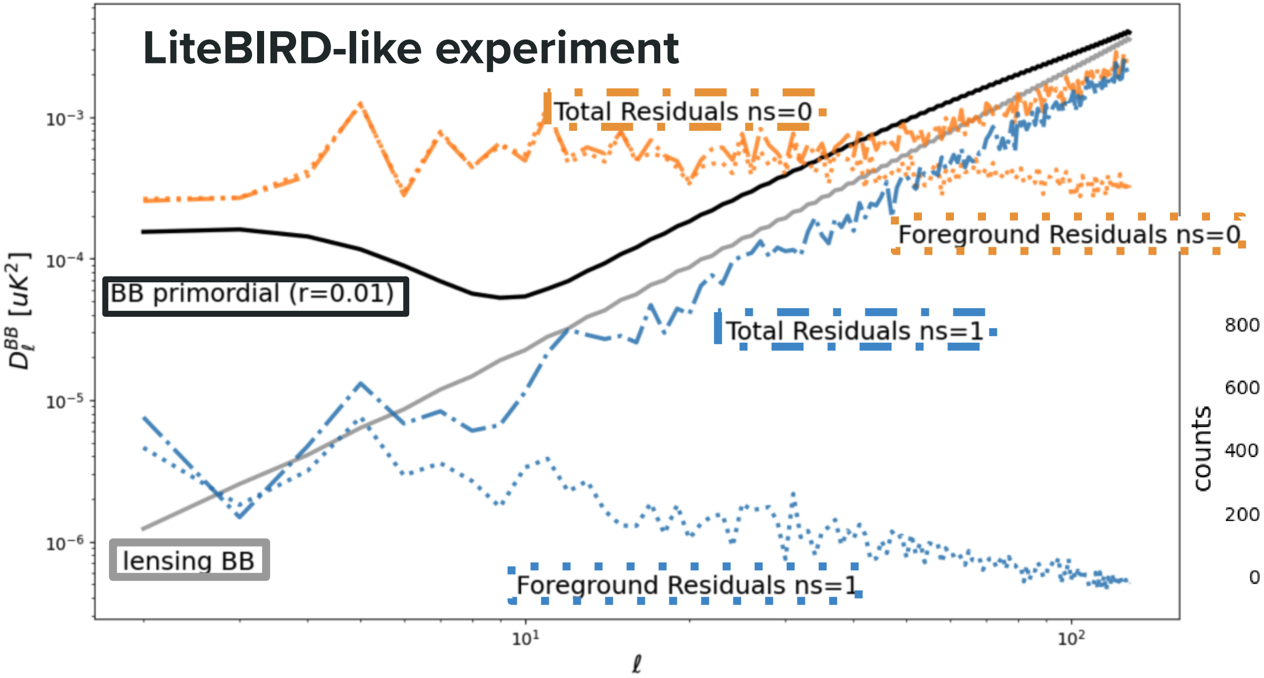

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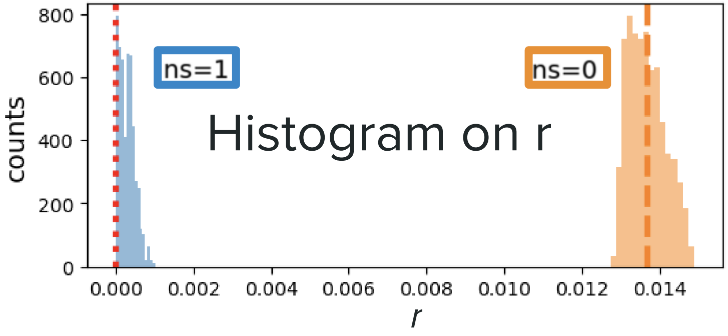

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MEGATOP

Consistency tests for Simons Observatory

Schematics of **Pipeline C** (parametric)

Estimation of spectral emission laws

↓ spectral parameters

Estimation of the component separated sky maps

↓

Computation of angular power spectra of each sky component, as well as the noise covariance

↓

Sampling of the cosmological likelihood to estimate r, A_{lens} (with an optional marginalization over A_{dust})

Credits: Wolz et al. (2024), *arXiv:2302.04276*

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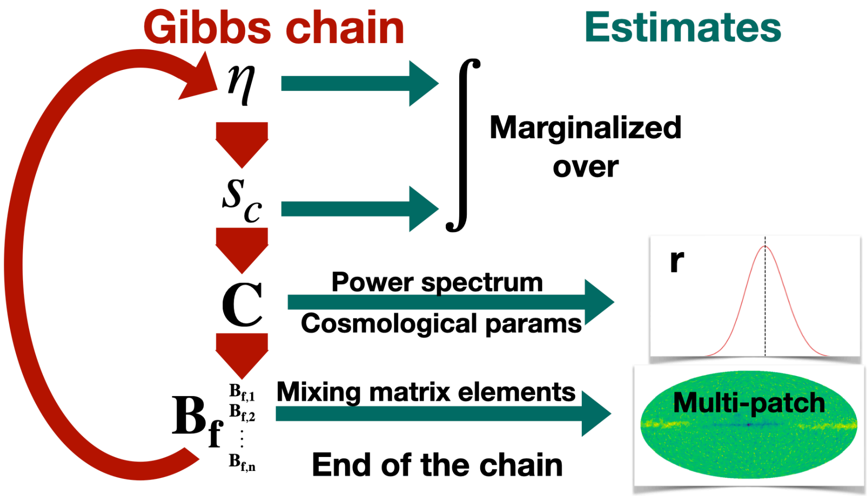

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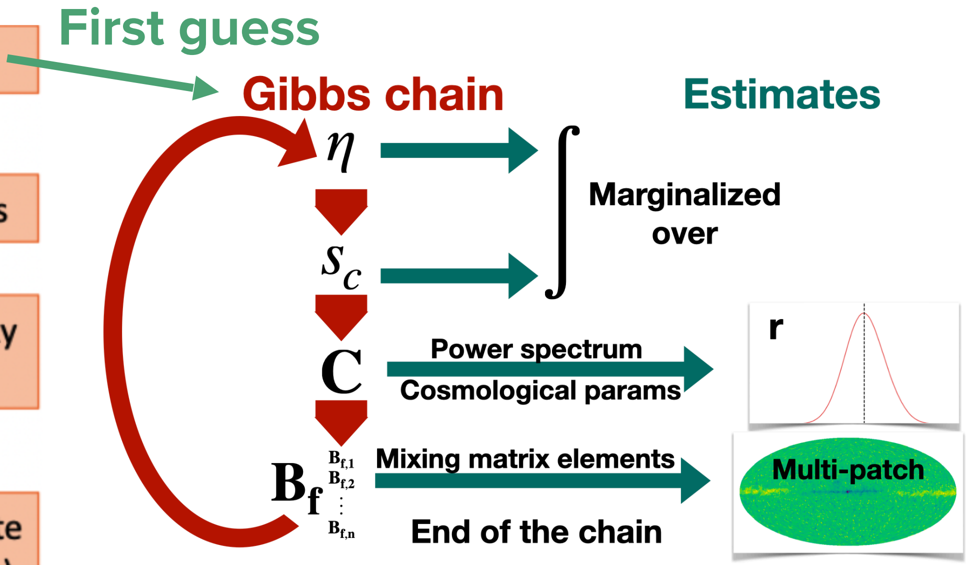

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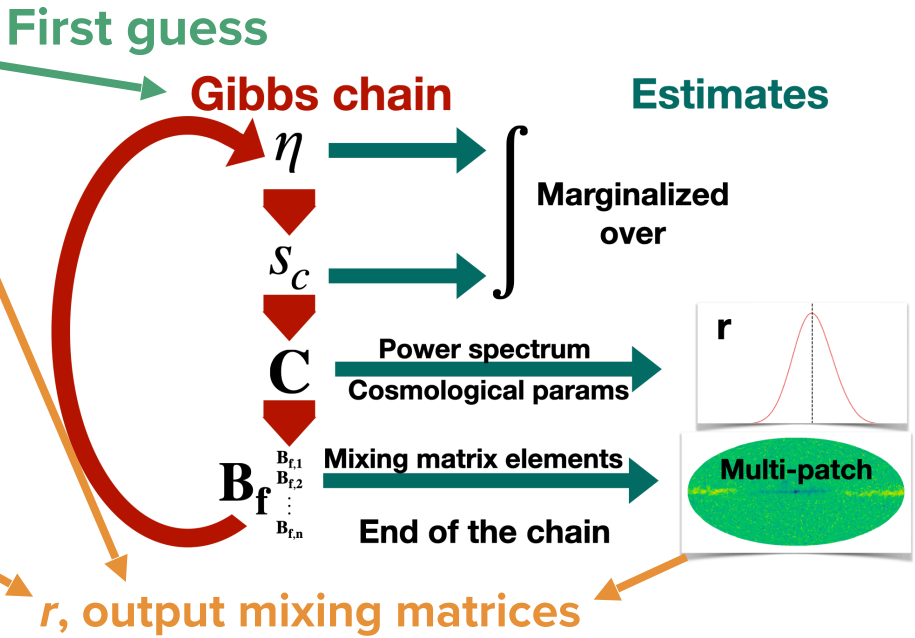

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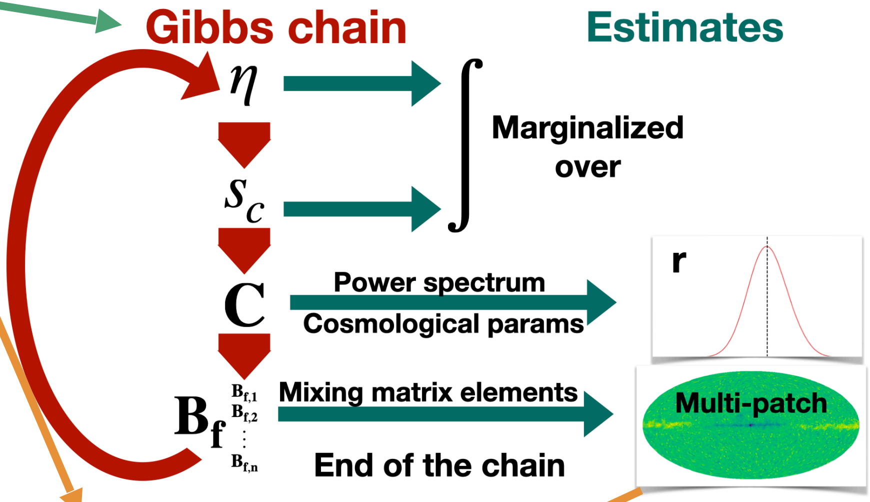
MICMAC

First guess



r, output mixing matrices

Credits: Wolz et al. (2024), *arXiv:2302.04276*

Consistency between pixel-based parametric and non-parametric component separation

New forecasting tool – Leloup, MM et al. *(in prep)*

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To assess the impact of a given parameterization choice on:

- Bias on ***r***
- Uncertainty on ***r***

Forecasting tool based on the Hessian of the likelihood (à la *Xforecast,* **Stompor et al. 2016**), currently implemented in harmonic domain and focused on the fixed CMB estimate

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➔ Preliminary results favor **good margin in the choice of the fixed CMB estimate**

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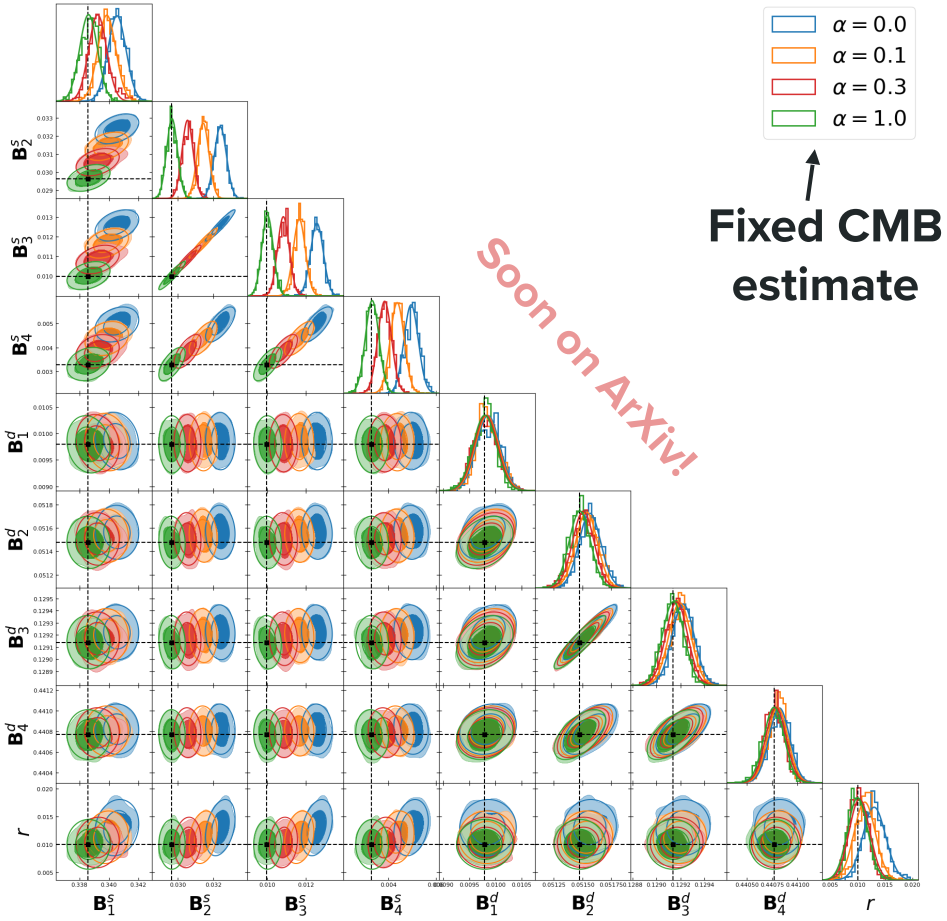

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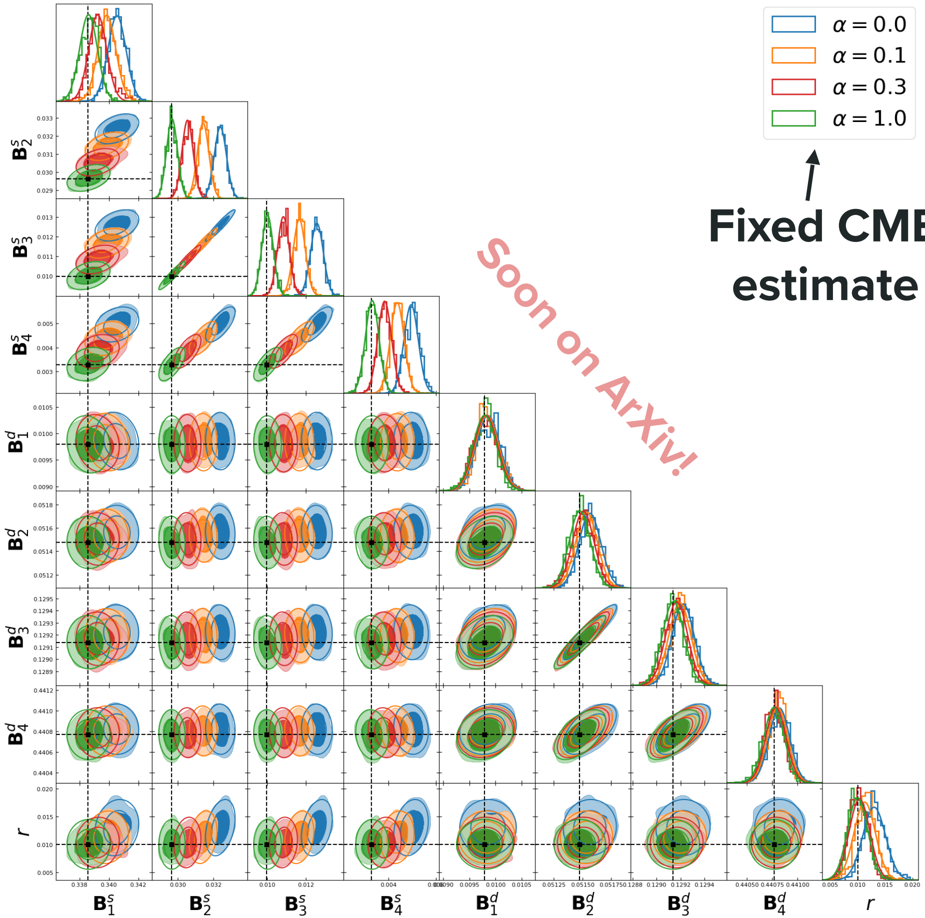
→ Preliminary results favor **good margin in the choice of the fixed CMB estimate**

→ Prospects for the future: assess systematic mitigation impact



Fixed CMB estimate

Soon on ArXiv!

Conclusion

- Several challenges for component separation methods, to robustly retrieve **CMB** signal with future generation experiments
- New pixel domain method (**MICMAC**) based on **Leloup et al. 2023**:
    - No assumption on **foregrounds SED modeling** (except for the multi-patch)
    - Relies on **Gibbs sampling**
    - Current implementation able to handle:
        - **Spatial variability of the foregrounds**, inhomogeneous noise
    - Formalism explained and validated in **MM et al. 2024**
- Ongoing project(s):
    - Forecasting tool in **Leloup et al. [in prep]**
    - Performances of **MICMAC** with complex foregrounds (lead by A. Rizzieri)
    - Inclusion of beams and filtering for MEGATOP (Baptiste's talk!)

INFN

Istituto Nazionale di Fisica Nucleare

Extensions and first applications of the minimally informed component separation approach, MICMAC and MICS

CMB-France #6

Institut Henri Poincarré

2024, December 18-19th

Magdy MORSHED
postdoc at INFN Ferrara (Italy)