Report

This proceedings contribution proposes a physics-guided, modular neural approach to approximate the inverse of QUBIC's forward operator for CMB map-making in the presence of ill-conditioning and partial non-invertibility. The main idea is to embed analytically known (or well-conditioned) inverse components as deterministic or dynamic layers, while modeling the remaining problematic parts with constrained learnable modules. In particular, the method introduces a dynamic layer meant to capture instrumental effects (e.g. detector time constants) through a parametric transfer function, and an operator-inspired learnable correction for the projection/unmixing stage, formulated via graph-based filtering using Chebyshev polynomials and motivated by a Neumann-series approximation. The author demonstrates the approach on simulated QUBIC time-ordered data, showing example reconstructed maps and a qualitative comparison against a preconditioned conjugate-gradient baseline, and argue that the proposed architectural constraints can improve interpretability and generalization while requiring only a small number of trainable parameters.

The paper is well motivated for a proceedings submission, as it targets the computational and numerical challenges of QUBIC CMB map-making and frames the problem naturally in terms of operator inversion. A key strength is the modular, physics-guided design: separating well-understood (invertible or well-conditioned) components from ill-conditioned/non-invertible ones yields an architecture that is more interpretable than a generic black-box network and may generalize better across configurations. The use of constrained learnable blocks (e.g. graph/Laplacian-based filtering with Chebyshev polynomials, linked to a Neumann-series viewpoint) provides a reasonable inductive bias with very few trainable parameters, and the inclusion of a dynamic, parametric layer to represent instrumental effects such as detector time constants is a promising direction for jointly improving reconstruction and instrument modeling.

I find the work very interesting, but several central claims are currently under-supported. Therefore, the author should address the following questions and comments to support publication of this proceedings contribution. Given the format constraints of a proceedings, I believe that addressing the points below with minimal additional figures/tables and clarifications would be sufficient.

1. I suggest the author provides at least one quantitative evaluation (e.g. rmse/mae per Stokes parameter, correlation, or power-spectrum residuals) aggregated over multiple simulations (mean$\pm$std over N runs), rather than only qualitative examples.

2. The author should specify the exact PCG setup (e.g residual tolerance, max iterations, etc ...) and report either runtime on stated hardware or the number of forward/adjoint operator applications, since PCG performance depends strongly on these choices and the current comparison is otherwise hard to interpret

3. Several claims in the abstract/conclusion (uncertainty propagation and learning instrumental parameters) are not demonstrated; add a minimal experiment showing recovery of the instrumental parameter(s) (e.g. τ) against ground truth and how

parameter uncertainty affects the reconstructed map (or at least map error under τ mismatch).

4. Clarify the implementation and notation of the dynamic/instrumental layer: if it is a frequency-domain transfer function (diagonal operator), explain how it is applied (elementwise multiplication in Fourier space), and how it differs from a generic dense linear layer.

5. The training setup must be specified: loss function, training targets (map domain vs harmonic domain), dataset size, simulation setup (including noise level/type), and any regularization used; this is needed to assess reproducibility.

6. For the graph-based module, the author must describe precisely how the graph is constructed (nodes, edges, etc ...) and report the computational overhead relative to PCG.

7. Typos: "constraints it" → "constrains it" in introduction; "noninvertible" → "non-invertible"; Eq. 7, the summation index k should be from 1 to 9; In Pg. 4, "cm are learnable coefficients, corresponds to ..." → should be "coefficients, correspond to ...