EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE
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Physics-guided Machine Learning Methods in QUBIC

Analytical solution with NN corrections and uncertainties

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The problem

- The acquisition process is given with $d = Hx + n$
- Acquisition is done through an interferometer
- The solution is ill-conditioned $\hat{x} = (H^\top N^{-1} H)^{-1} H^\top N^{-1} d$
- We dont want to rely on forward modeling $H^\top N^{-1} H\, x = H^\top N^{-1} d$

(slow, contains residual mixing at edges – nondiagonal elements not considered)

- We dont want to rely on Deep Learning – instant results, no **interpretability,** difficult **uncertainty propagation**
- We will go a step further from Physics-Informed Neural Networks (PINNs)

Our attempt

Find the analytical solution by breaking the problem into a chain of operators, and approaching them individually.

Use NN layers to imitate the approximations:

The **neural network is informed through the architecture** that approximates the inverse – not through the loss!

The solution

Interpretable, physically guided solution with uncertainty propagation – providing results in one forward pass

For a problem defined with multiple operations

$$d = B\,I\,D\,L\,\mathrm{HW}\,P\,F\,A\,T\,U\,s + n$$

we break its inverse into physically interpretable components

$$s = U^{-1}T^{-1}A^{-1}F^{-1}P^{-1}HW^{-1}L^{-1}D^{-1}I^{-1}B^{-1}d$$

and use the infrastructure of NN to imitate each.

$$[B_\tau x](t) = \int_0^\infty \frac{1}{\tau} e^{-u/\tau}\, x(t-u)\, du \iff B_\tau(f) = \frac{1}{1+2\pi i f\tau}$$

$$\hat{x}(t) = \mathcal{F}^{-1}\Big[(1+2\pi i f\tau)\,\mathcal{F}\{y(t)\}\Big]$$

Bolometer decay

$$\frac{1}{\prod T\eta} == nn.Linear\Big(\prod \Theta_T^{-1}\Theta_\eta^{-1}\Big)$$

Detector transmission

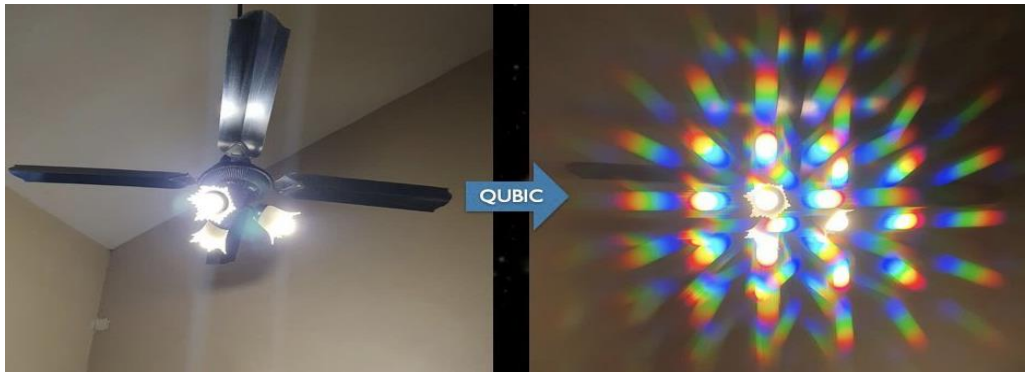
➡ SOLUTION IS CONSTRAINED BY FUNCTIONS, NOT BY THE LOSS

Results

- **Interpretable**: Weight == physical parameters
- **Fast**: one forward pass (~ms)
- **Data-efficient**: training needs only *dirty* vs *clean* maps, no sky priors
- **Modular**: swap, retrain, or Bayesian-wrap layers independently

++ add Pyro on any trainable parameter --> directly infer **uncertainty** on real physical properties!

Projection

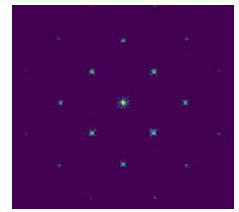


$$(I+\alpha L)\,s = b$$

$$(I+\alpha L)^{-1} = I - \alpha L + \alpha^2 L^2 - \alpha^3 L^3 + \cdots$$

$$(I+\alpha L)^{-1} = \sum_{k=0}^{\infty} (-\alpha)^k L^k$$

$$h(L) = \sum_{k=0}^{K} c_k\, T_k(\tilde{L})$$



QUBIC syntesized beam

backprojection

$$s = b \Rightarrow \alpha L b + \alpha^2 L^2 b - \alpha^3 L^3 b + \cdots$$

$$b = \frac{P^T N^{-1} d}{\mathrm{diag}(P^T N^{-1} P)}$$

$$(D+O)^{-1} = D^{-1} - D^{-1}OD^{-1} + D^{-1}OD^{-1}OD^{-1} - \cdots$$