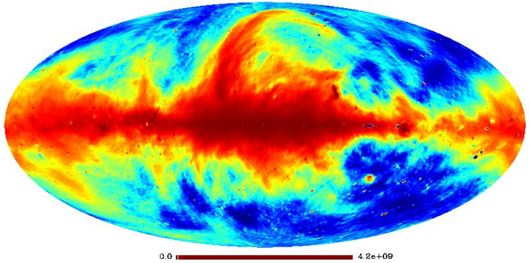
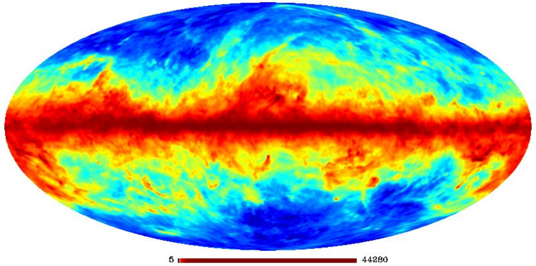
In Pursuit of Accurate CMB B-mode Angular Power Spectrum with ILC and ANN

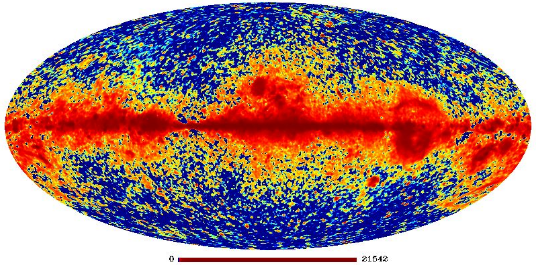
Sarvesh Kumar Yadav

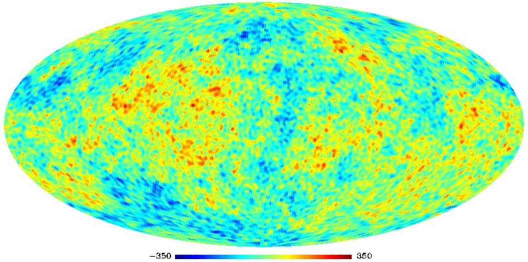
Raman Research Institute, Bangalore

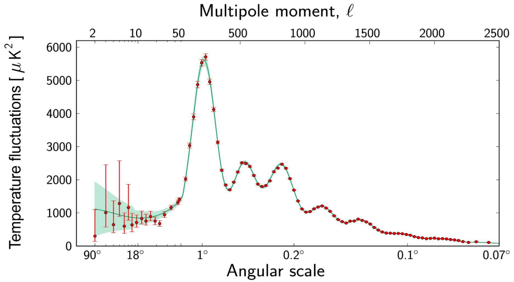
CMB Cosmology











Ω, ω_b, ω_{cdm}, Ω_Λ, H_0, A, n_s, r, τ

Internal Linear Combination Method

- The clean CMB map S can be obtained by a linear combination of n input maps :

$$S = \sum_{i=1}^{n} w_i X_i$$

- In order to calculate the w_i we minimize the variance of the output map S, assuming condition on spectral nature of the signal.

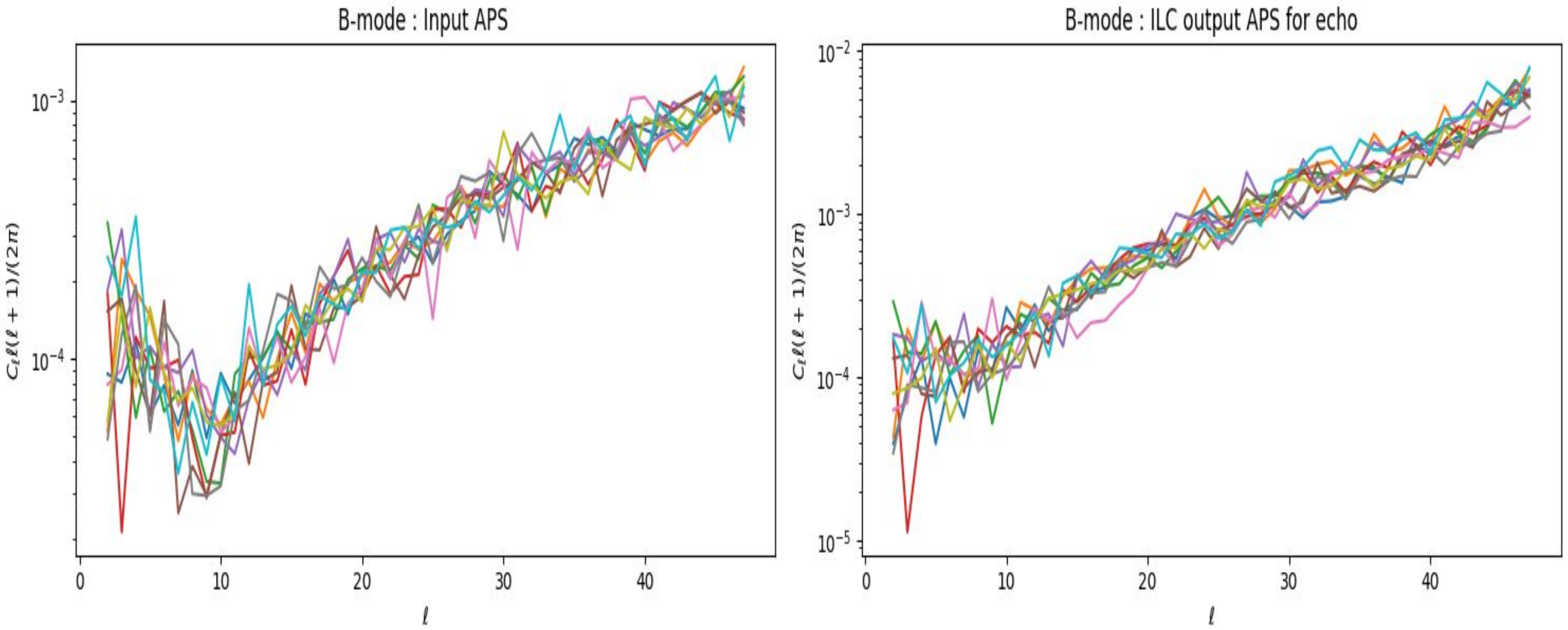
The standard ILC estimator is biased

- ILC assumes that there is no correlation between the signal of interest (CMB in this case) and other astrophysical components.

- Differences between the true emission laws and the constraints used to minimize the variance.

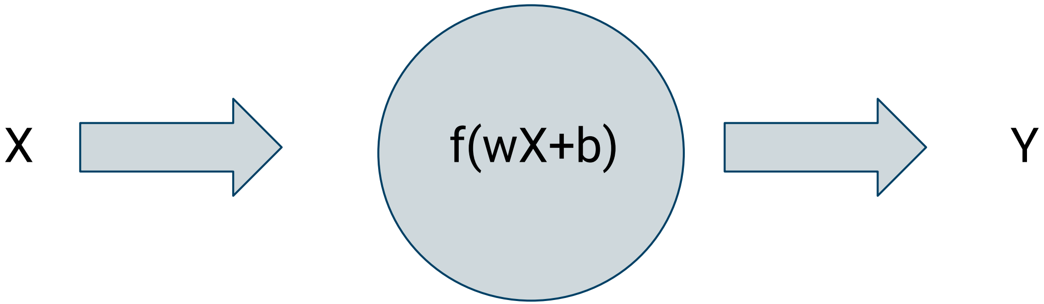
- Noise-induced correlations. (J. Delabrouille et.al)

The standard ILC estimator is biased

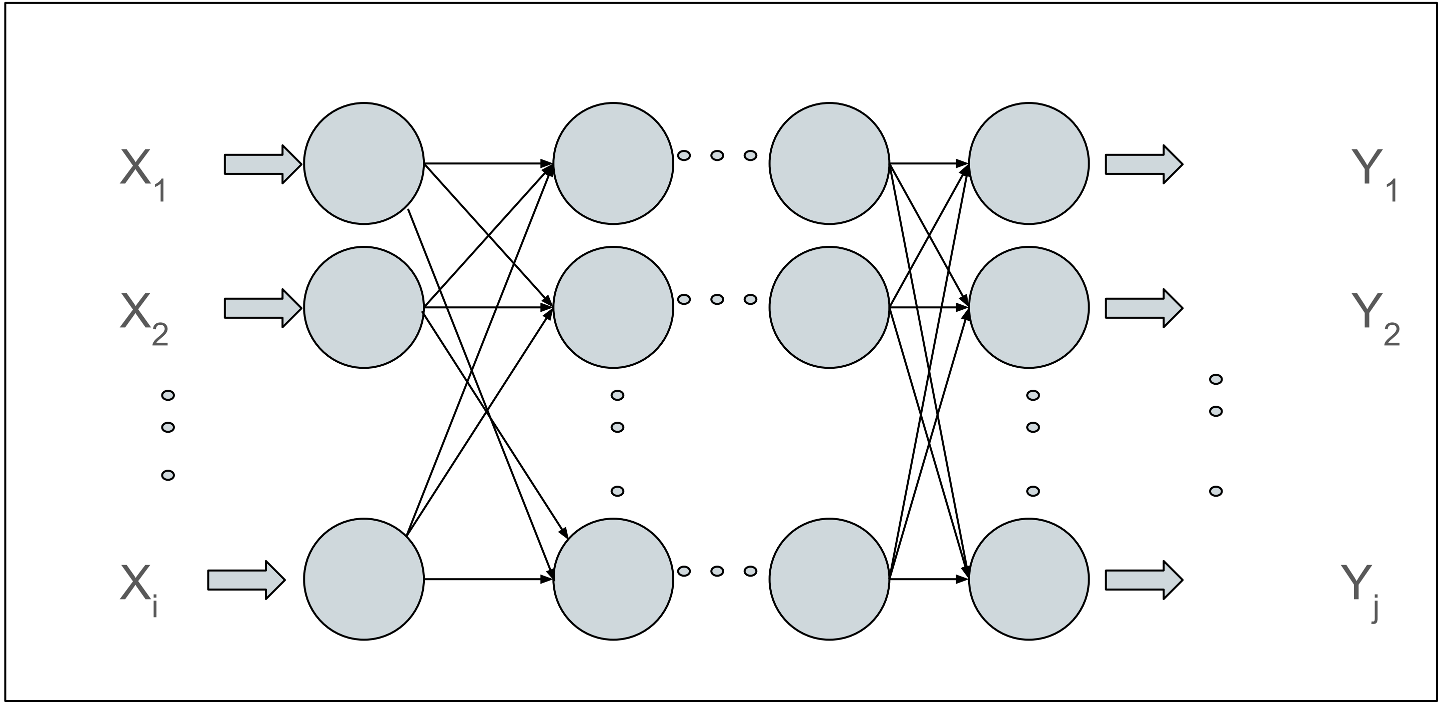


Perceptron

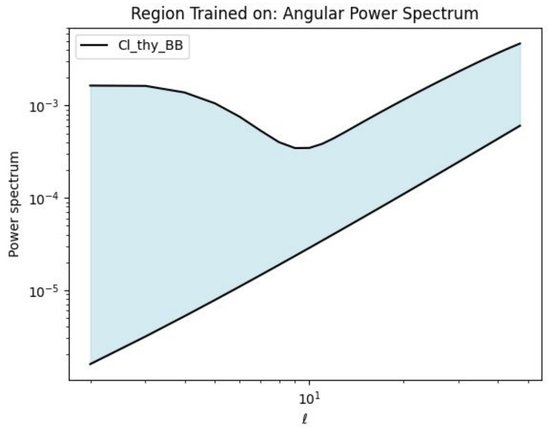
- An artificial Neuron :



Perceptron Network



Simulations



CMB B-mode Maps :

Nside =16

lmax = 47

9 degree Gaussian Beam smoothing

Cosmology LCDM + r (Tensor-to-scalar 1e-1 to 1e-6)

Noise Model :

ECHO (Exploring Cosmic History and Origins) 20 frequency channels

White noise

Simulations

Foregrounds :

Synchrotron radiation :

1) **S1:** A power law scaling is used for the synchrotron emission, with a spatially varying spectral index.

2) **S3:** A power law with a curved index.

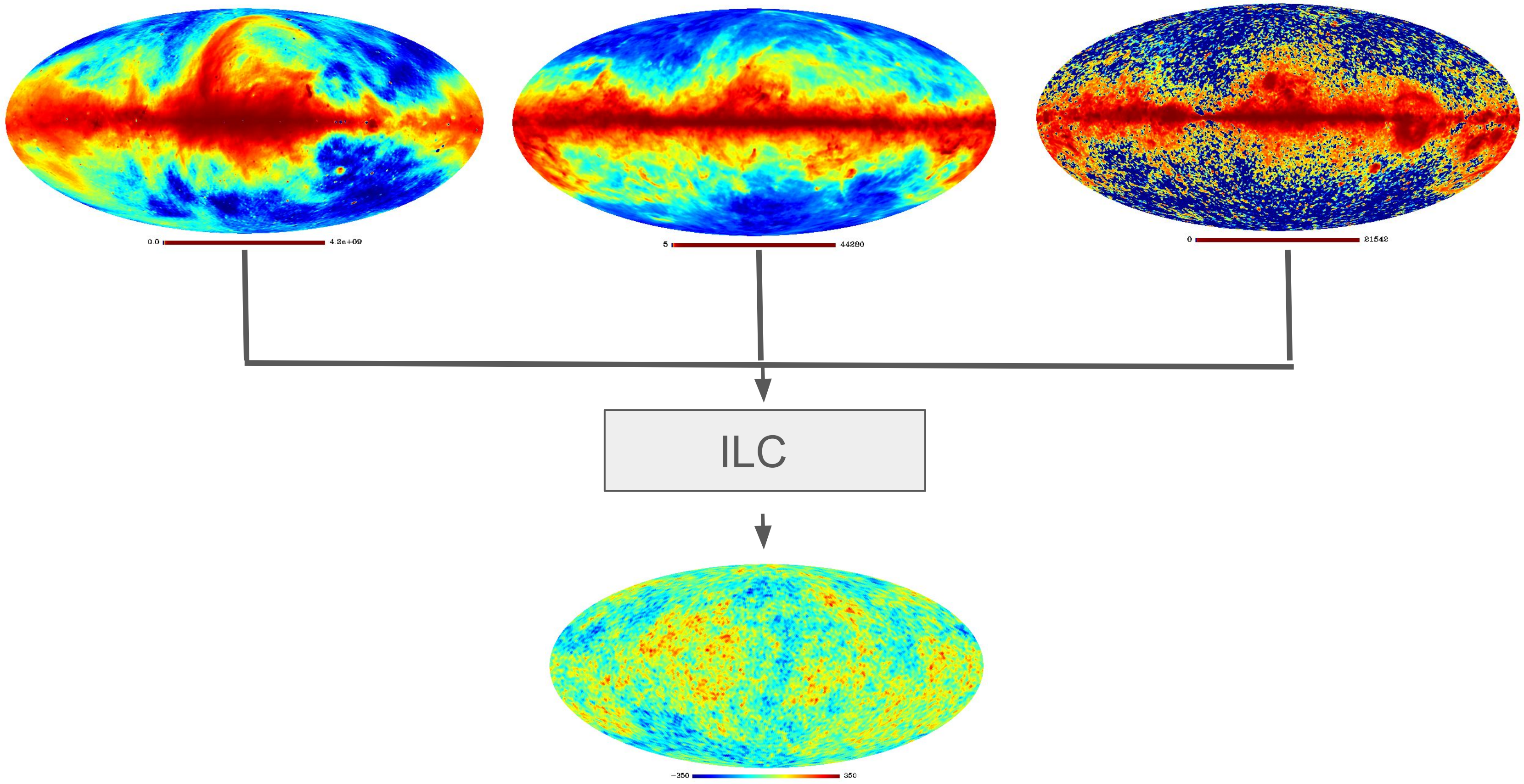
Thermal Dust :

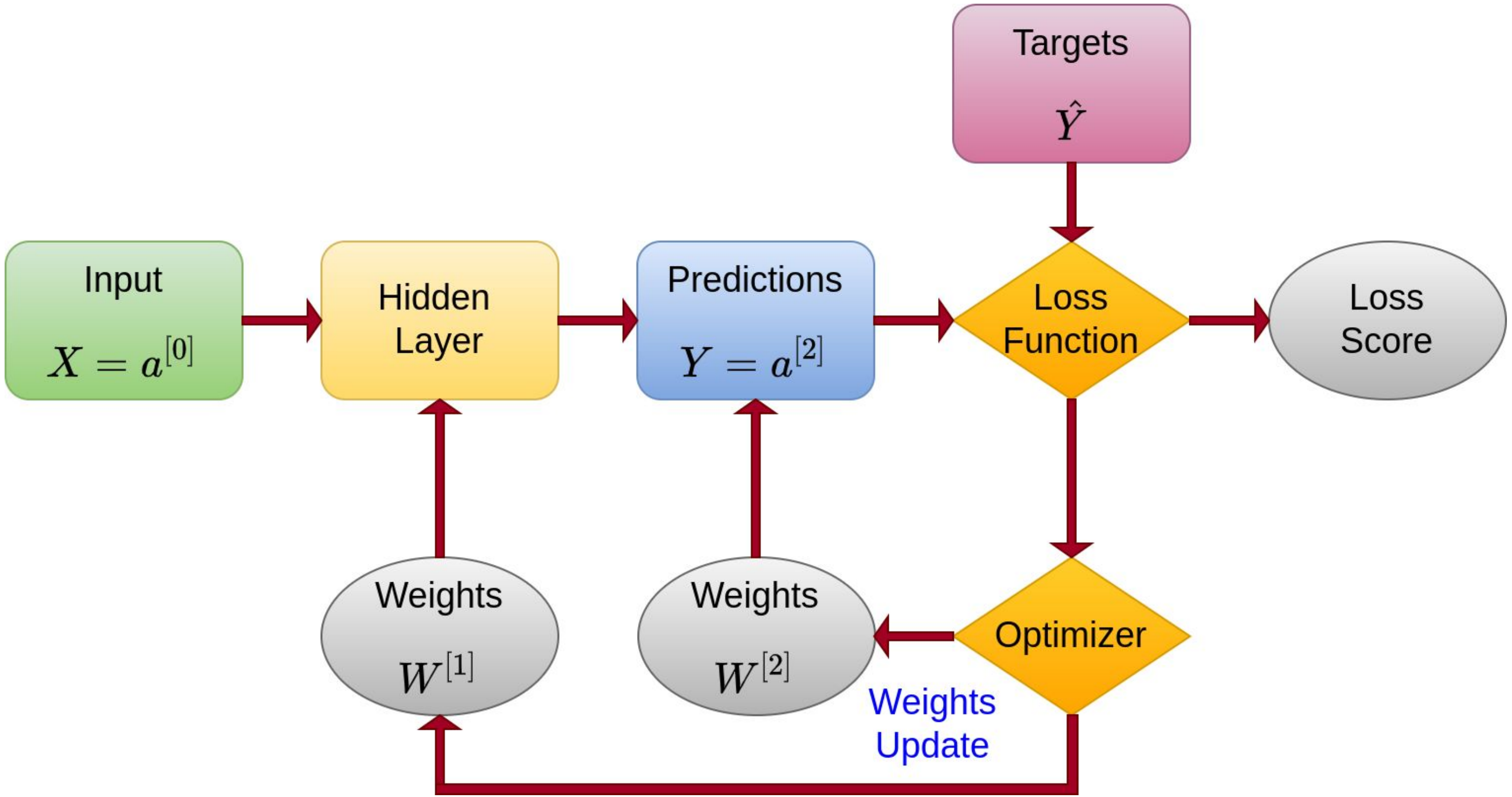
1) **D1:** Thermal dust is modelled as a single-component modified black body.

2) **D4:** A generalization of model 1 to multiple dust populations.

Anomalous microwave emission:

1) **A2:** AME has 2% polarization fraction.


0.0
4.2e+09
5
44280
0
21542
ILC
−350
350


Targets
$\hat{Y}$
Input
$X = a^{[0]}$
Hidden
Layer
Predictions
$Y = a^{[2]}$
Loss
Function
Loss
Score
Weights
$W^{[1]}$
Weights
$W^{[2]}$
Optimizer
Weights
Update

The Loss function

- The loss function:

Heteroscedastic

True value

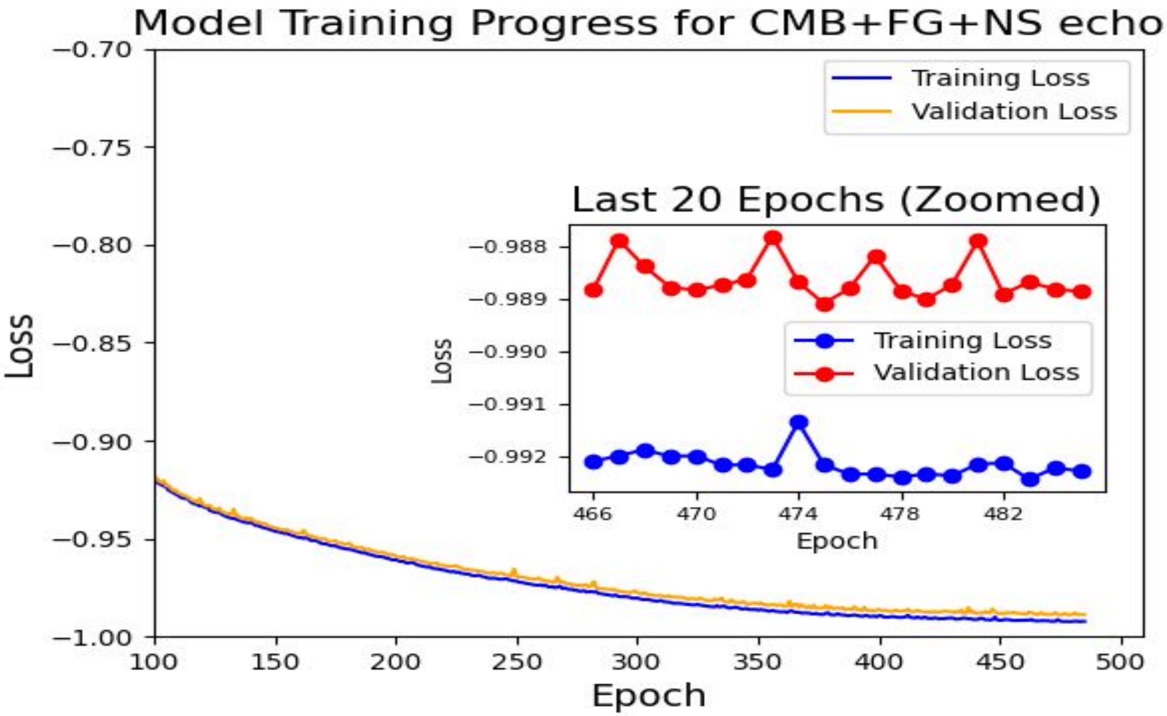
$$\mathcal{L} = \frac{1}{n_{\text{out}}} \sum_{q=1}^{n_{\text{out}}} \left[\frac{1}{2} \exp(-s_q) || y_q - \hat{y}_q ||^2 + \frac{1}{2} s_q \right]$$

Total No. of training samples

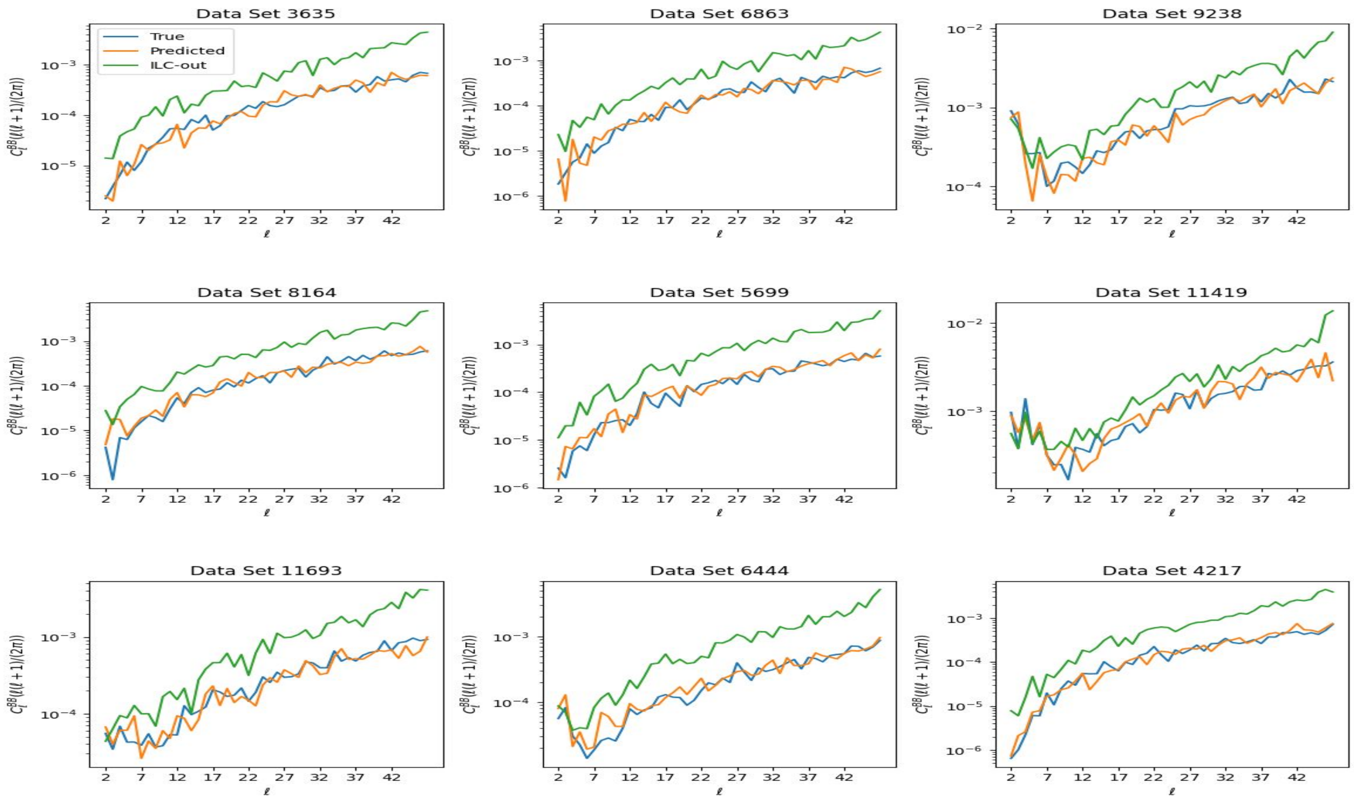
$$s_q = \log \sigma_q^2$$

Predicted value

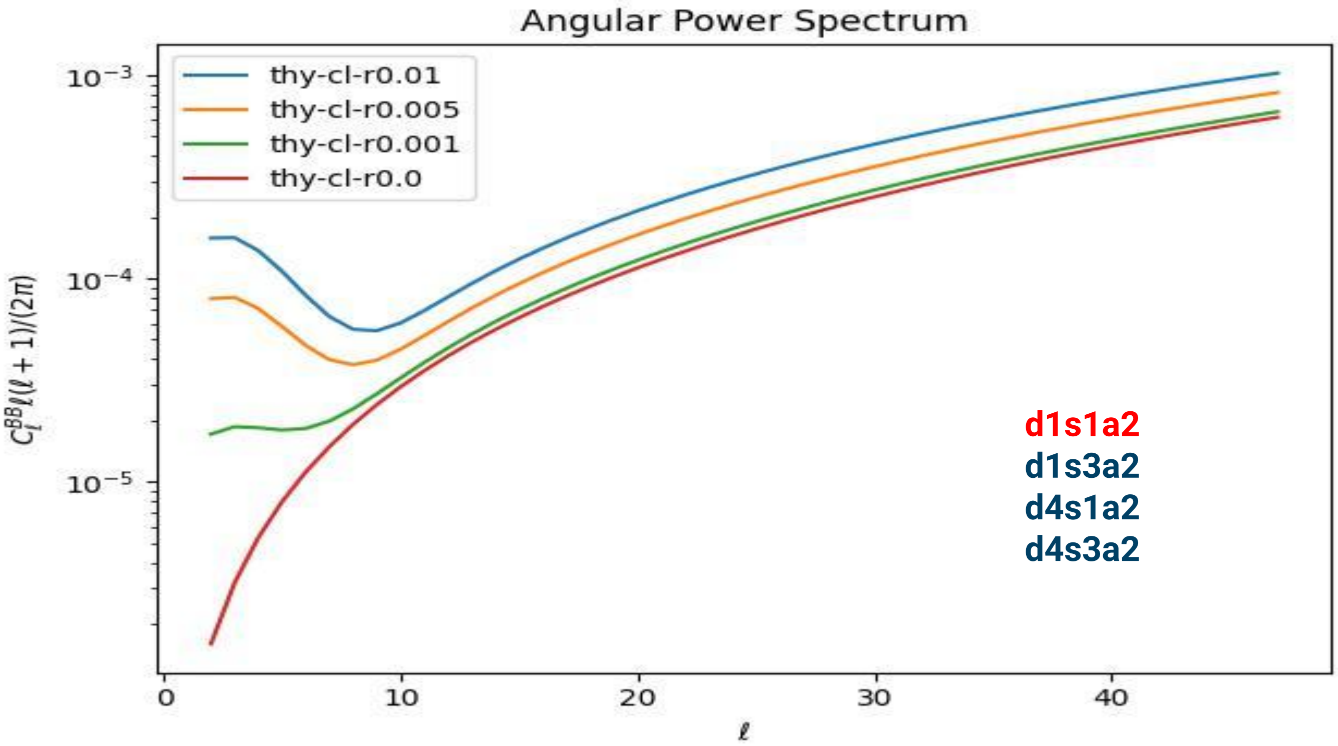
Results: No overfitting



Results: Model on random test samples

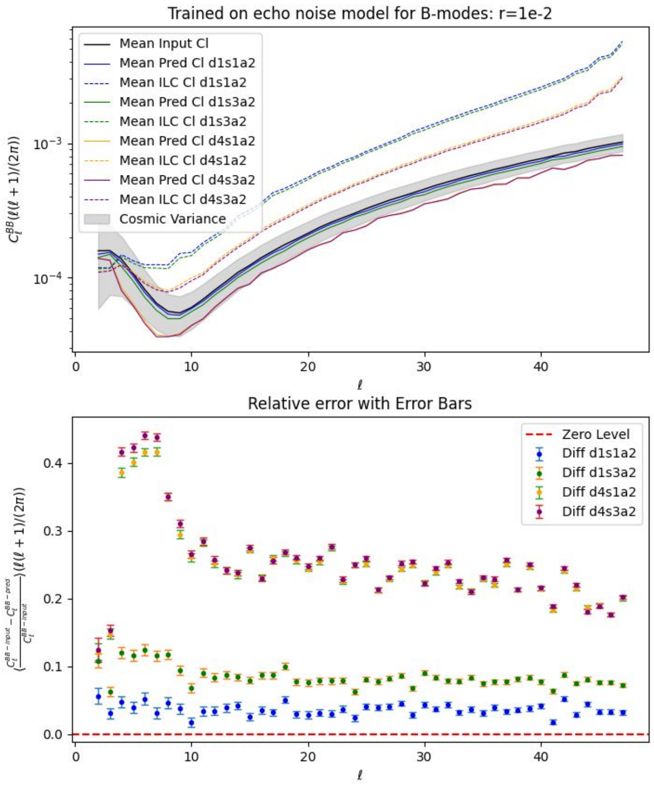


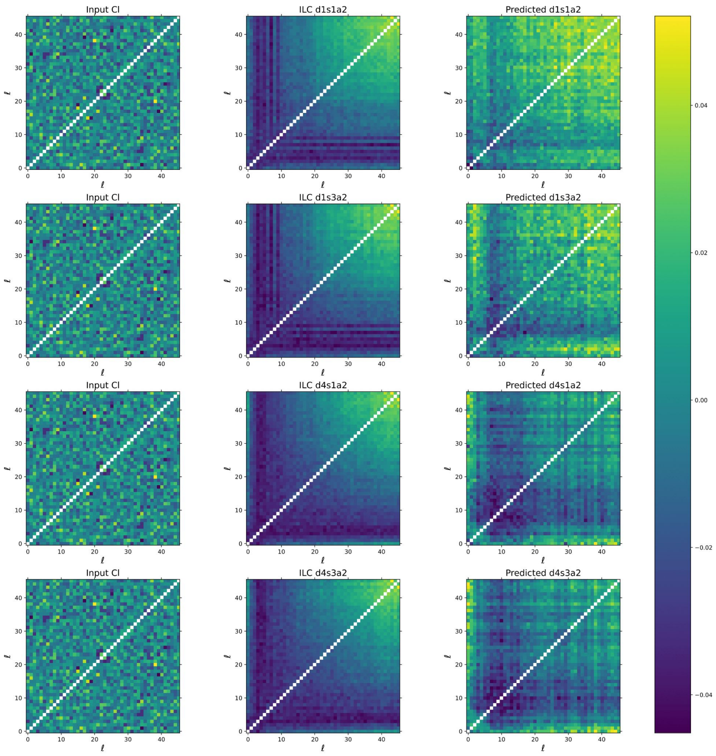
Results: Validating Model Performance with Unseen Data



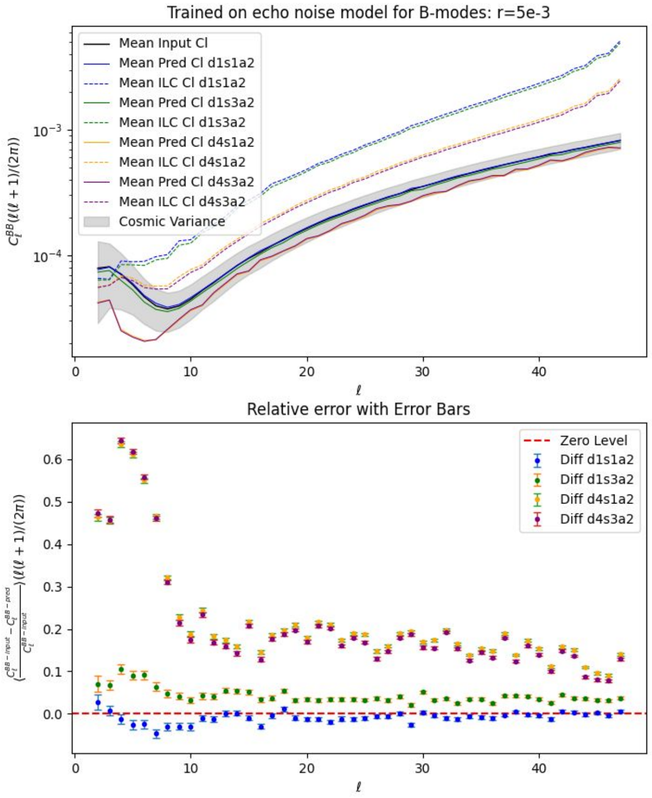
d1s1a2
d1s3a2
d4s1a2
d4s3a2

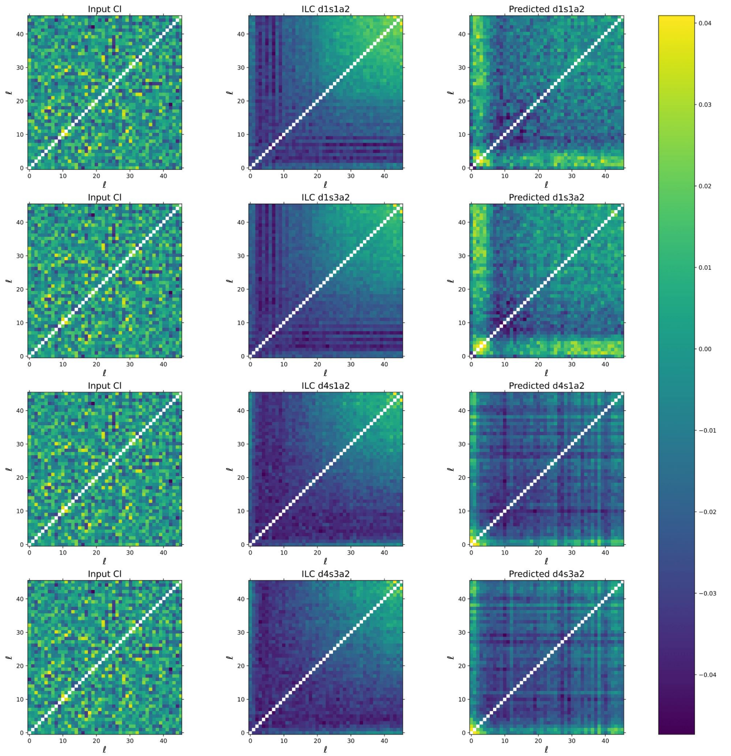
Results: Validating Model Performance with Unseen Data



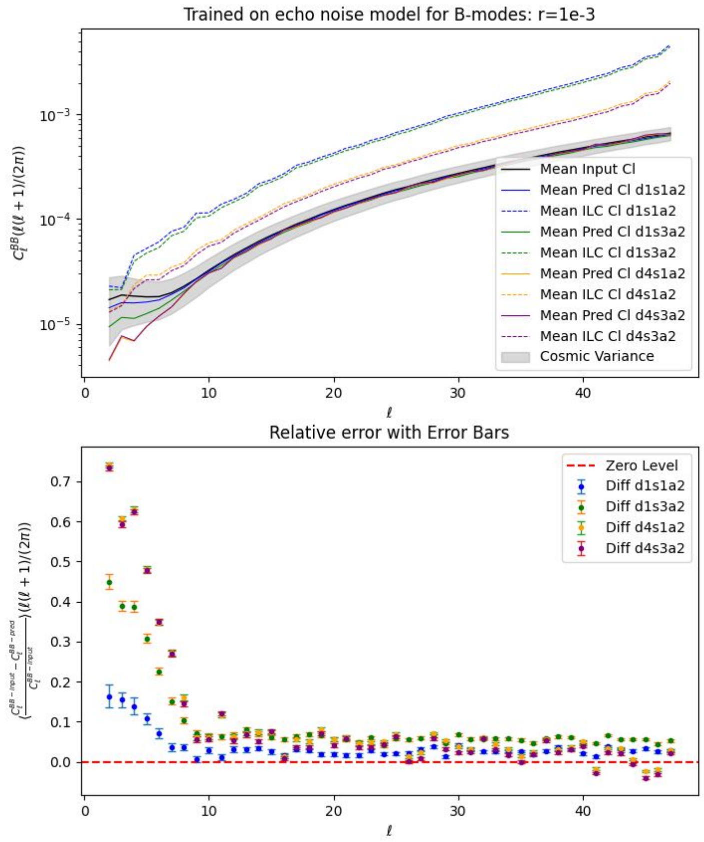


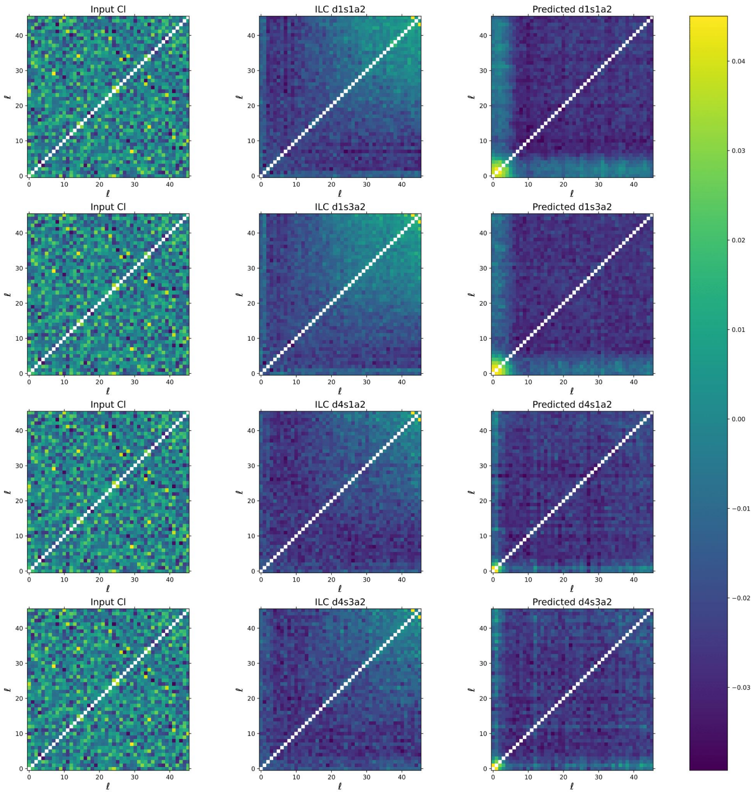
Results: Validating Model Performance with Unseen Data



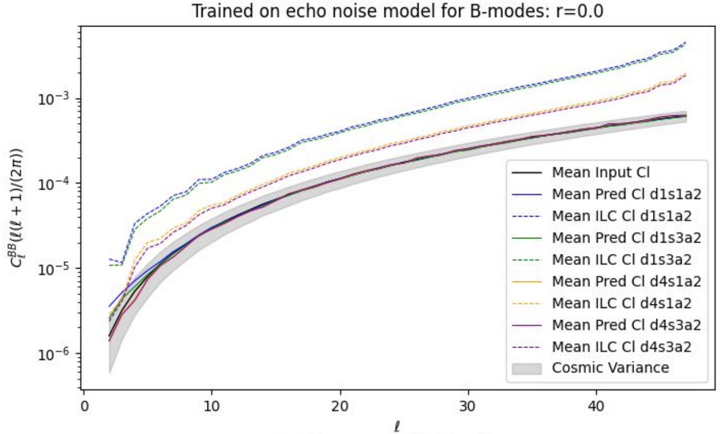


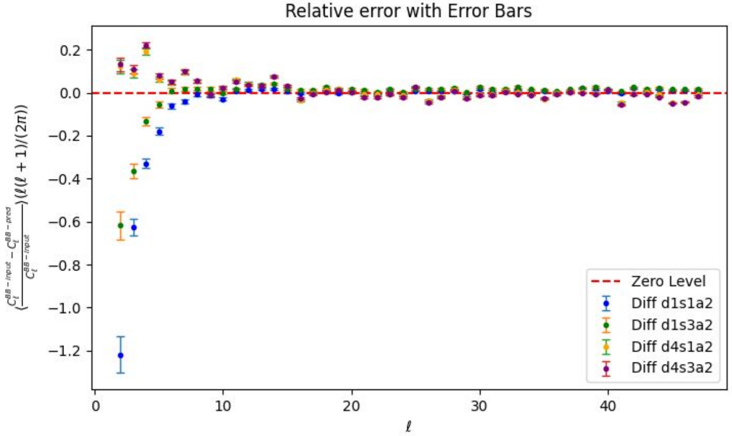
Results: Validating Model Performance with Unseen Data

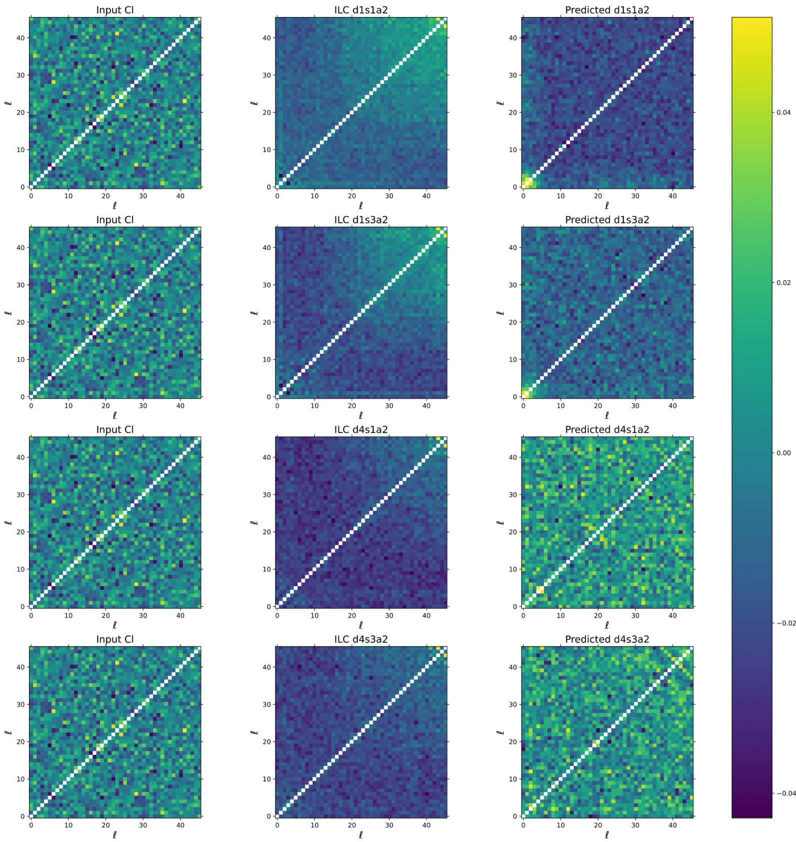




Results: Validating Model Performance with Unseen Data







Conclusion

- The method substantially reduces (~ 1 to 1.5 sigma CV) the ILC bias in the predicted angular power spectrum for various level of r and possible foregrounds other than it is trained on.
- The method accurately predicts the power spectrum for r=0 case, the samples for which was never revealed to the network during training.
- A perceptron network can be used to minimize the complex ILC bias to obtain accurate angular power spectrum, even when complex foregrounds are orders of magnitude stronger and in presence of noise.

Future Directions and Applications for CMB-S4

- In the current work, we used simulation outputs from PySM with default parameters. In future work, we will also incorporate errors associated with the foreground parameters.
- We will apply the method to a CMB-S4-like experiment, aiming to efficiently mitigate effects due to masking, atmospheric noise, inhomogeneous noise, and other issues.
- In a follow-up to the current article, we will also apply the method to debias the ILC map for a CMB-S4-like instrument.

Thank you for listening