Recovering the CMB signal with neural networks

“2nd International Conference on Machine Learning for Astrophysics (ML4ASTRO2)”

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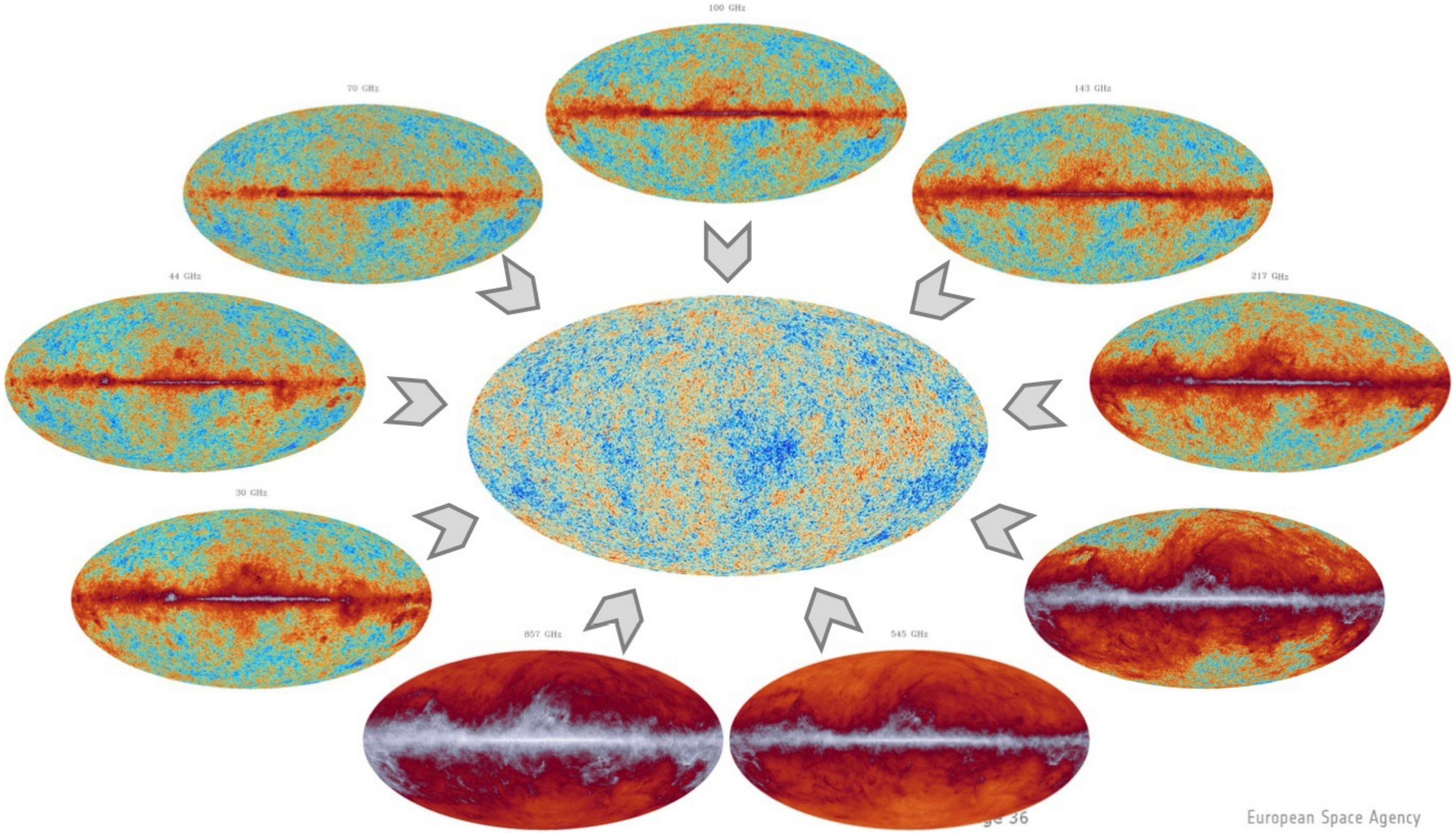
Introduction – Component Separation



ESA image

Parametric methods

- Commander (Eriksen+2008)
- FGBuster (Puglisi+2022)
- Moment Expansion (Chluba+2017)
- B-SeCRET (de la Hoz+2020)

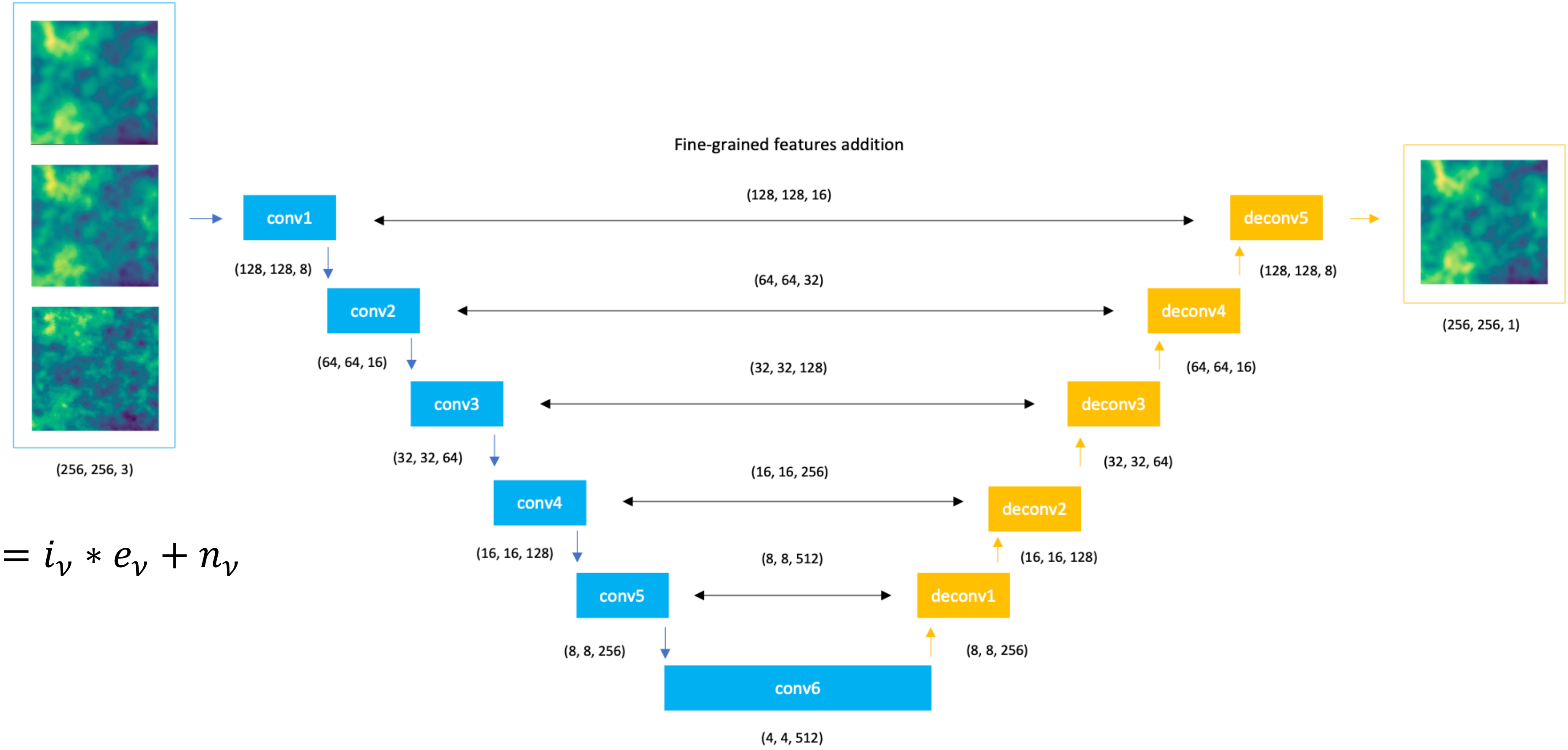
(Semi) blind methods

- NILC (Delabrouille+2009)
- cMILC (Remazeilles+2021)
- GNILC (Remazeilles+2011b)

and … Machine learning ?

Contents

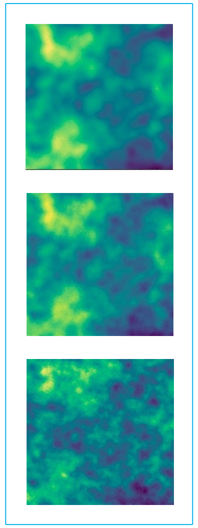
Methodology - CENN architecture

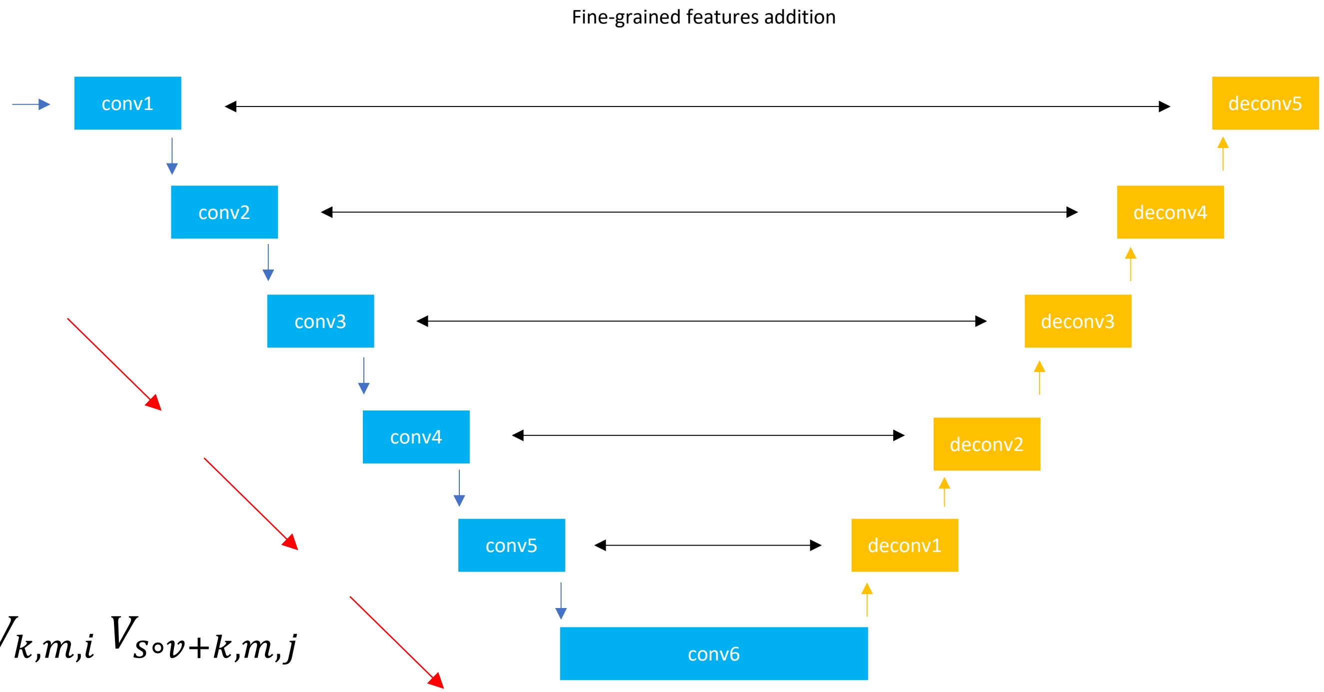


$$x_\nu = i_\nu * e_\nu + n_\nu$$

Casas+2022b, A&A, 666, A89

Methodology - CENN convolutions

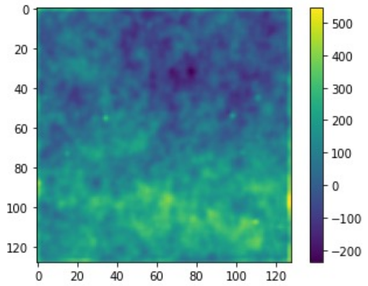




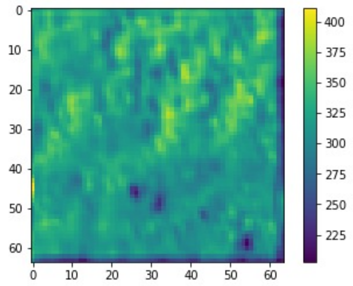
$$H_{v,i,j} = \sum_{k,m} W_{k,m,i} \, V_{s \circ v+k,m,j}$$

Methodology – CENN convolutions

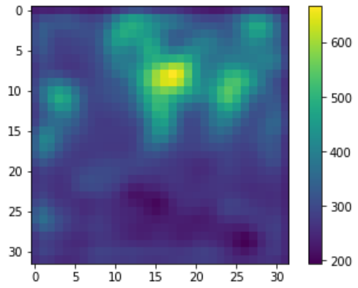
conv1



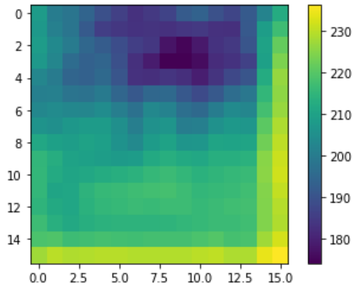
conv2



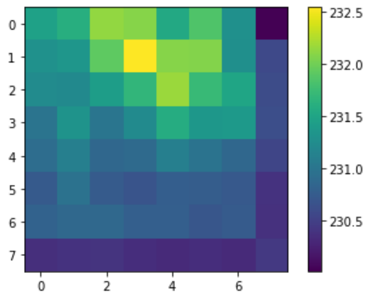
conv3



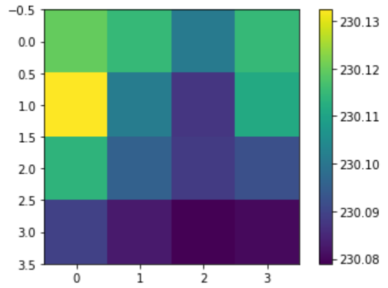
conv4



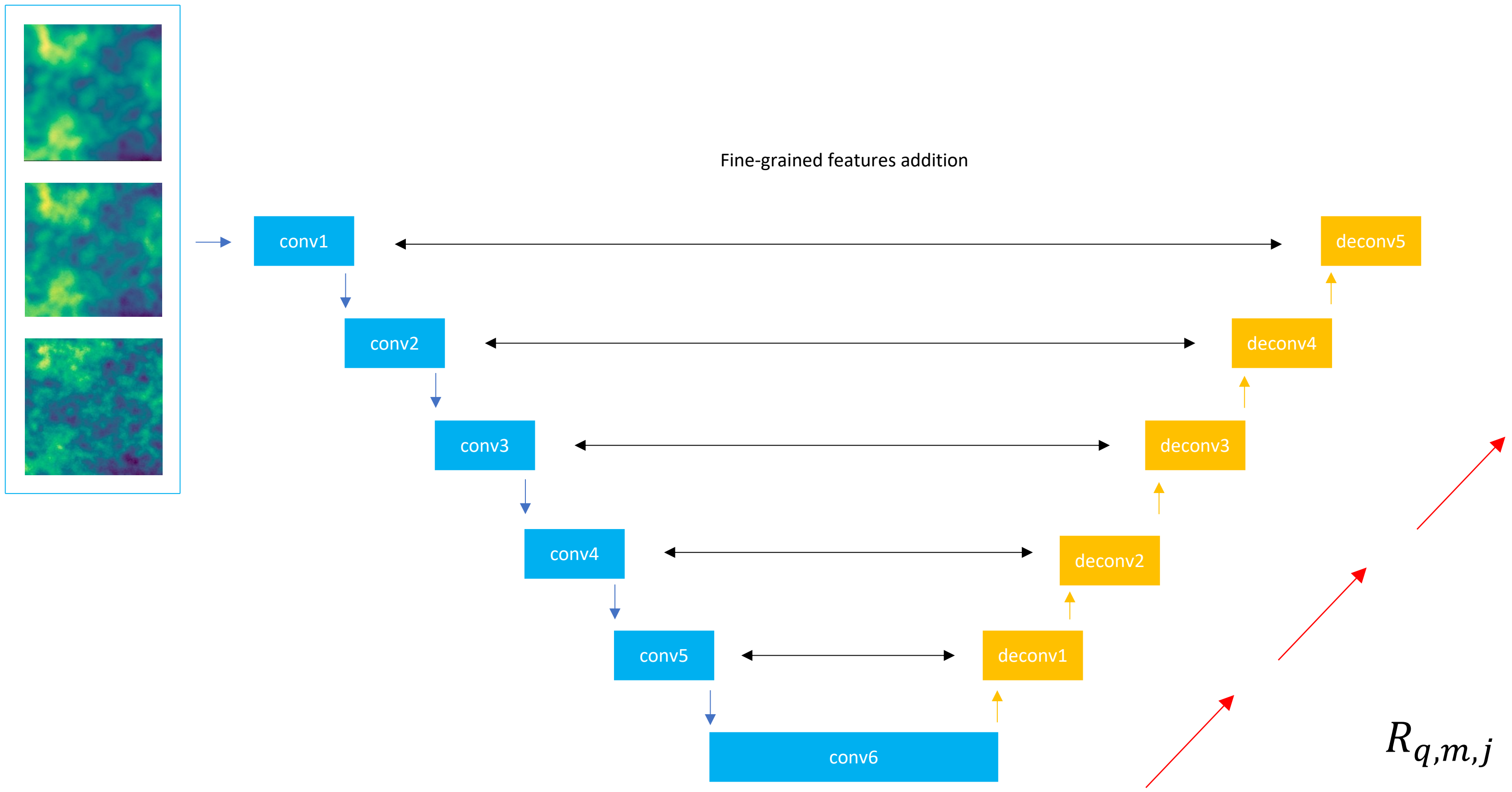
conv5



conv6



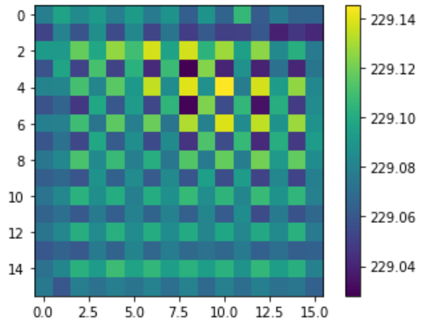
Methodology - CENN deconvolutions



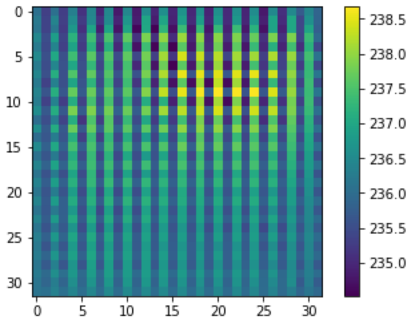
$$R_{q,m,j} = \sum_{v,k|s \circ v+k=q} \sum_{i} W_{k,m,i} H_{v,i,j}$$

Methodology – CENN deconvolutions

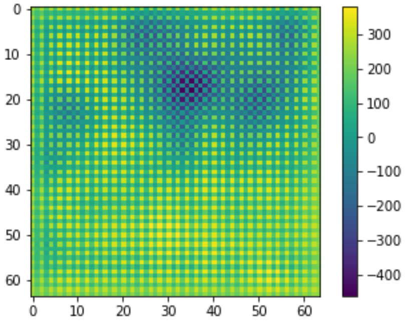
deconv1



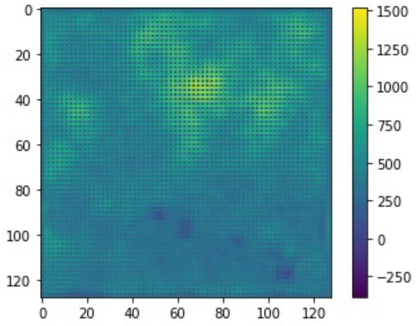
deconv2



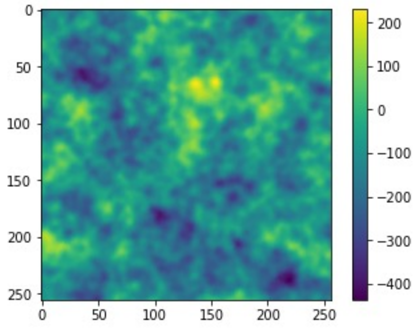
deconv3



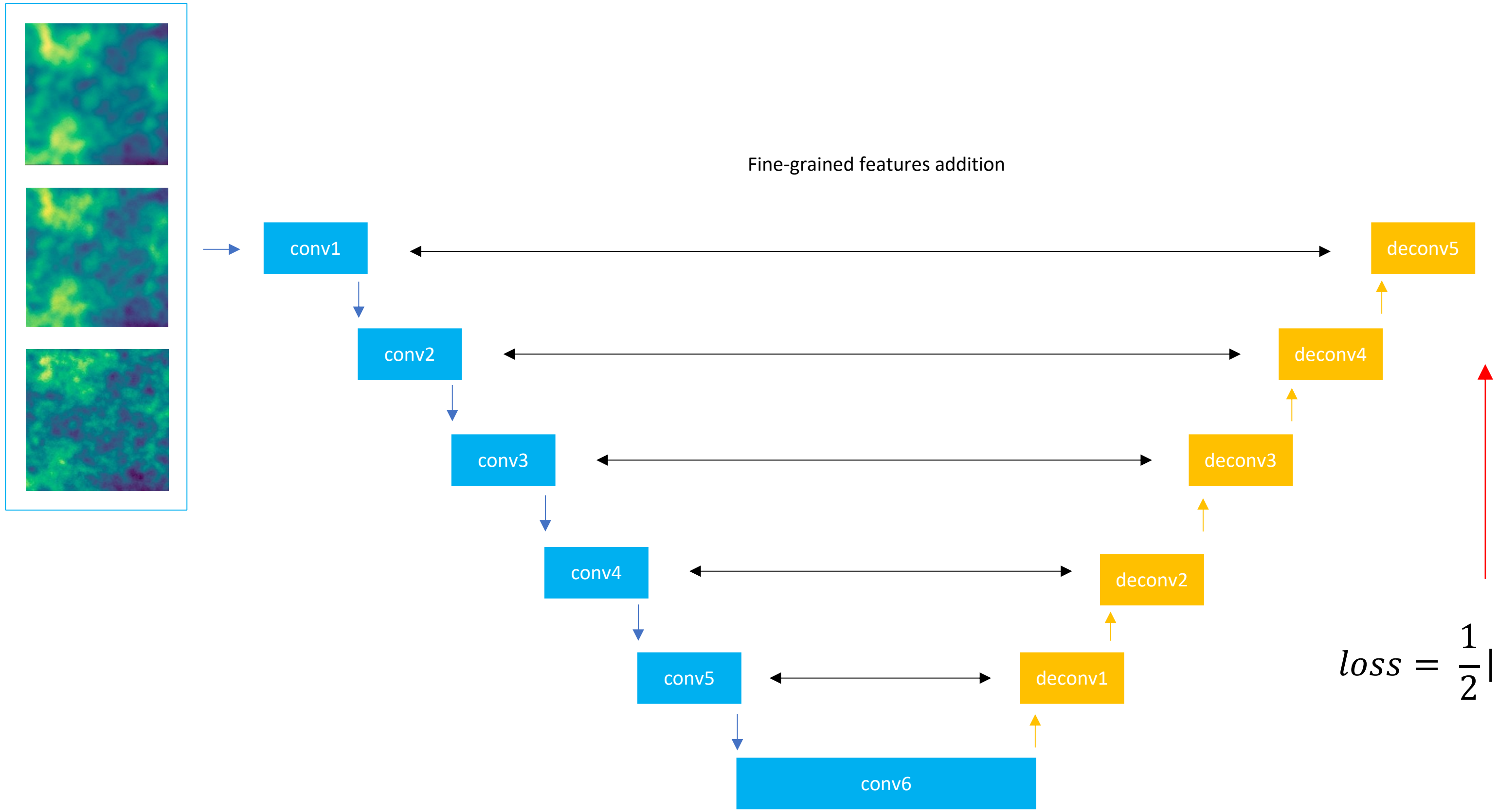
deconv4



deconv5



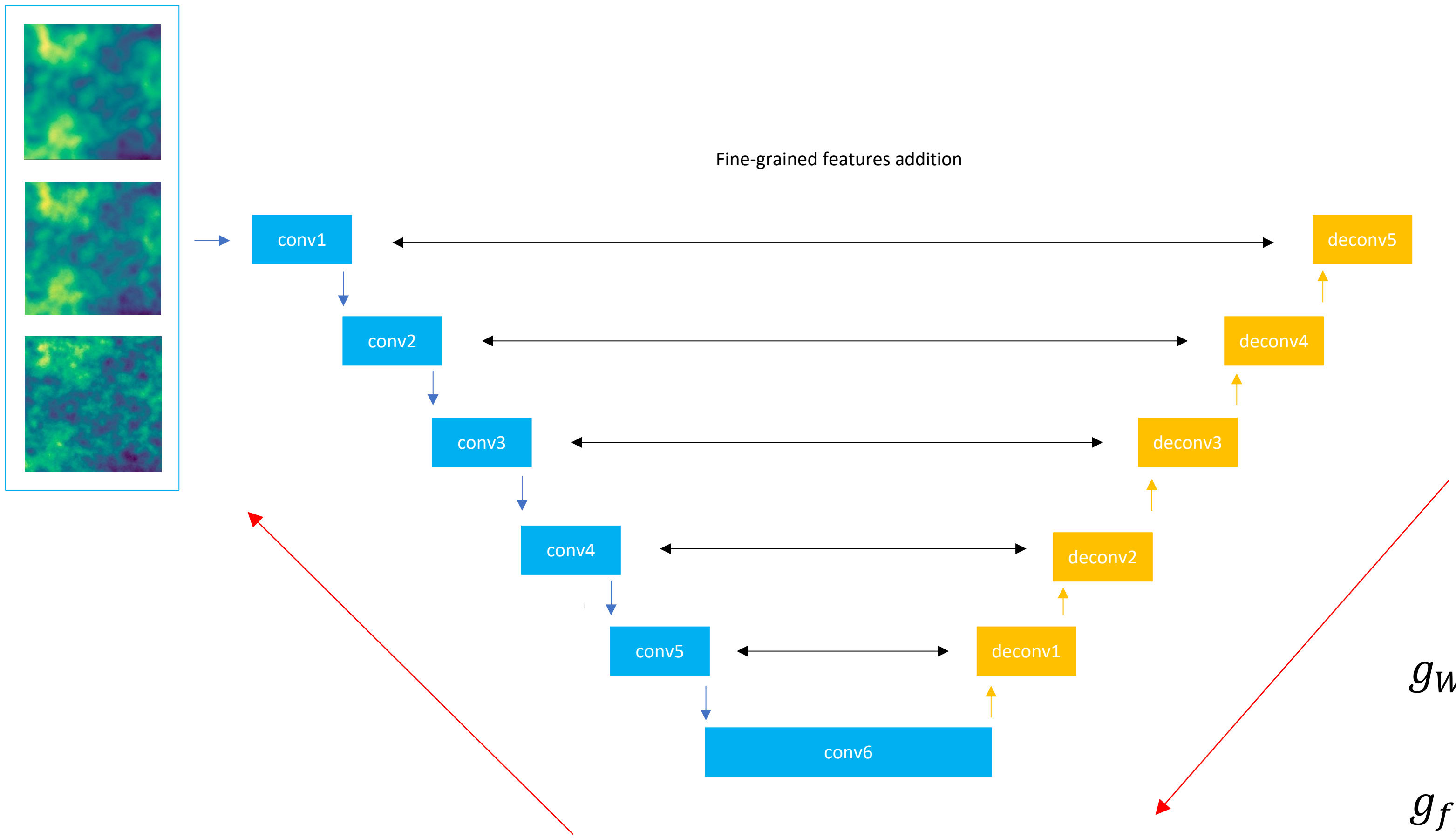
Methodology - CENN learning process



$$loss = \frac{1}{2}|output - label|^2$$

$$g = \frac{\partial\ loss}{\partial\ output\ patch}$$

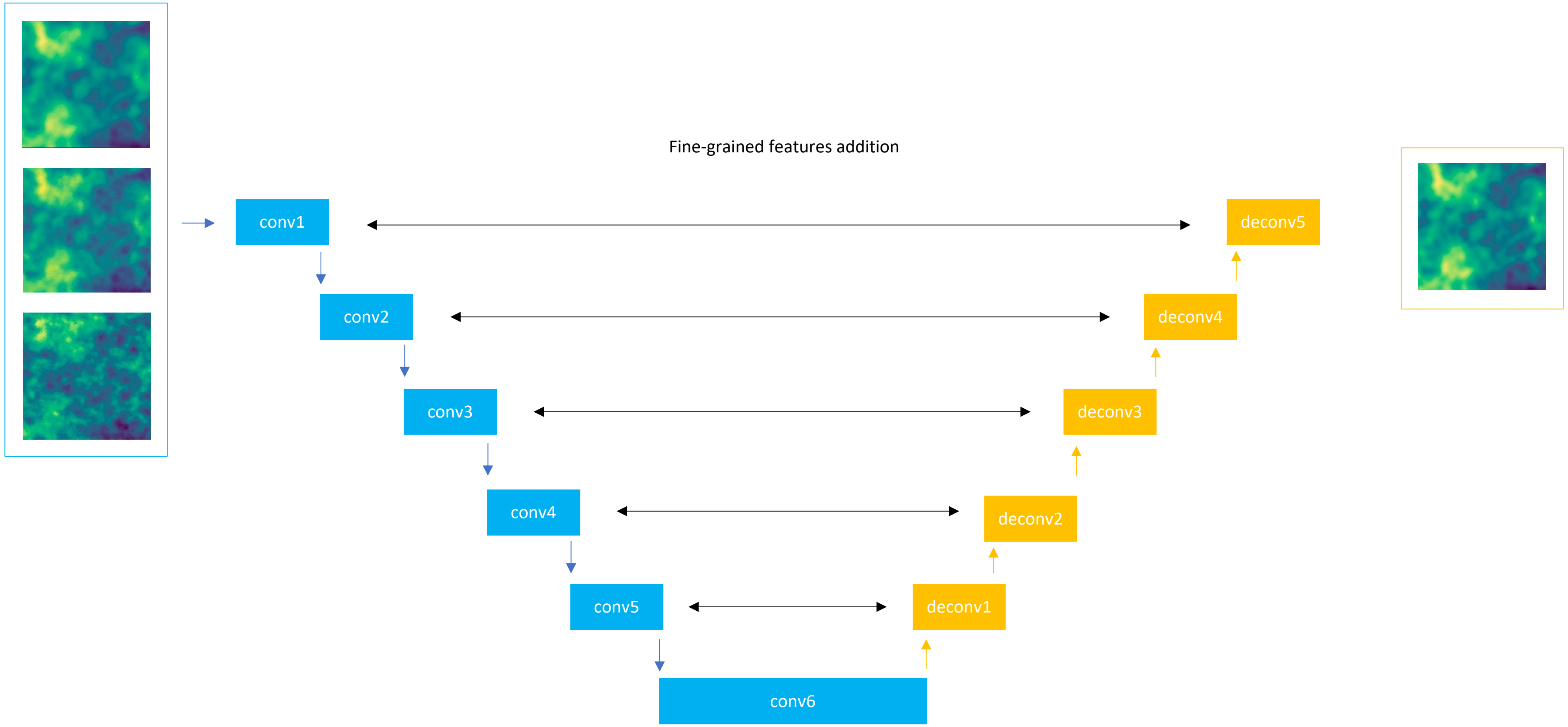
Methodology - CENN learning process



$$g_{W_B} = \frac{\partial O_B}{\partial W_{B-1}} = \frac{\partial O_B}{\partial O_{B-1}} \frac{\partial O_{B-1}}{\partial W_{B-1}} = g_B f_{B-1}$$

$$g_{f_B} = \frac{\partial O_B}{\partial W_{B-1}} = \frac{\partial O_B}{\partial O_{B-1}} \frac{\partial O_{B-1}}{\partial f_{B-1}} = g_B W_{B-1}$$

Methodology - CENN prediction



$$\tilde{x} = i_{\nu_0} * e_{CMB,\nu_0} + \tilde{n}$$

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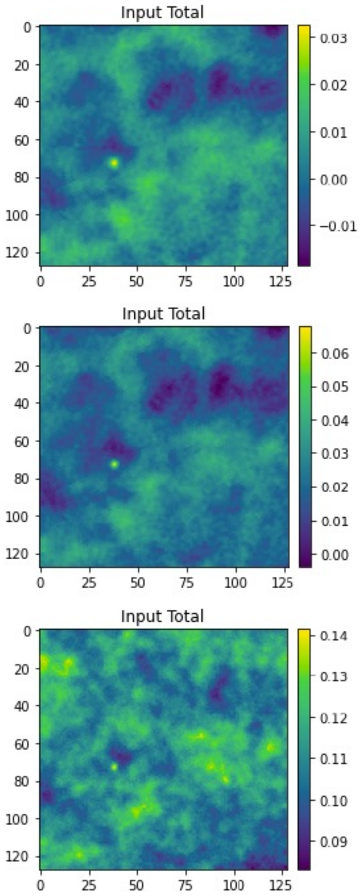
Datasets - Training and testing the neural network



Q, U simulations

CMB + Dust + Synchrotron + PS + Noise + SZ + CIB

I simulations

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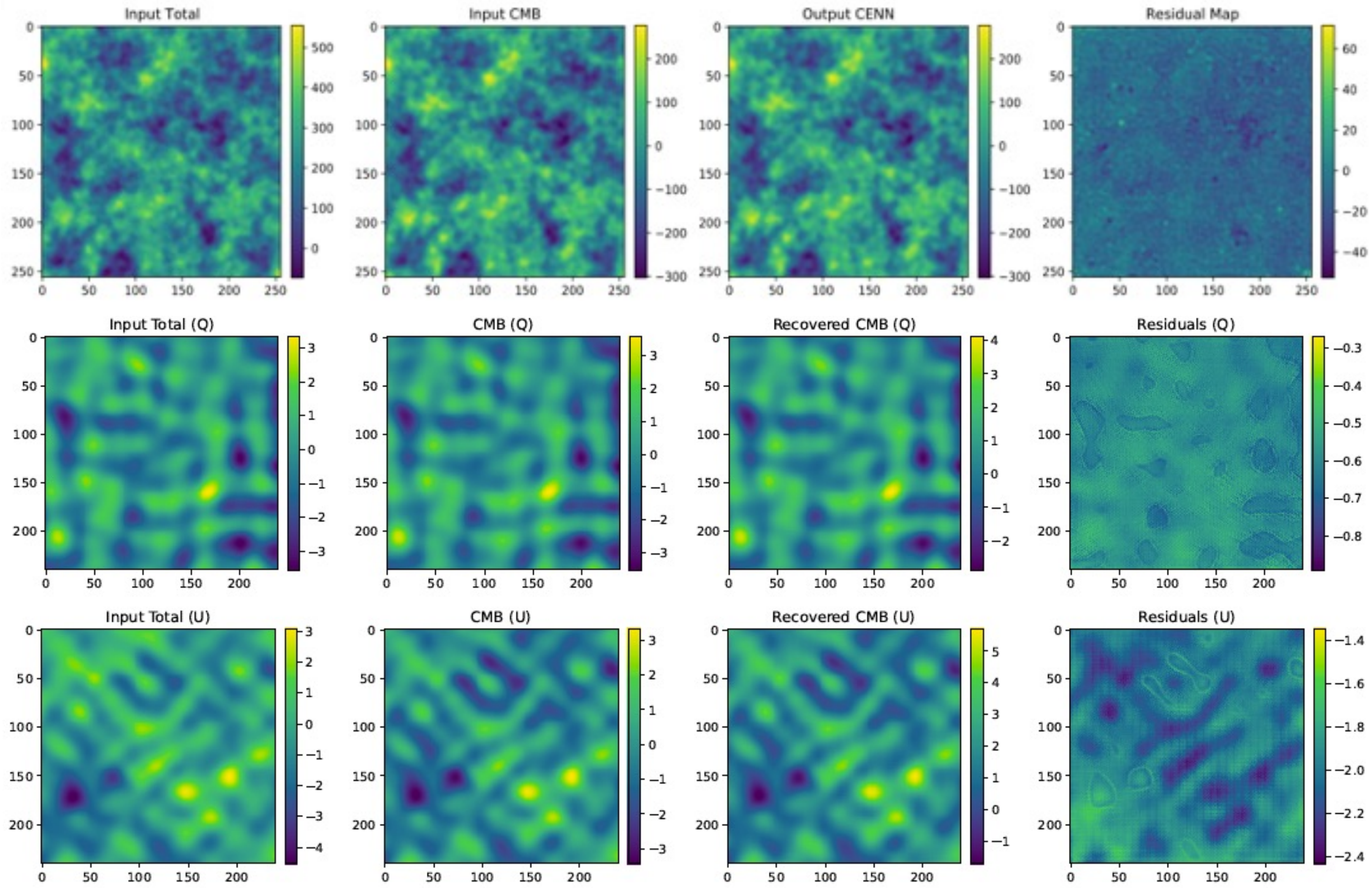
Results – Output patches

Input Total | Input CMB | Output CENN | Residuals

I

Q

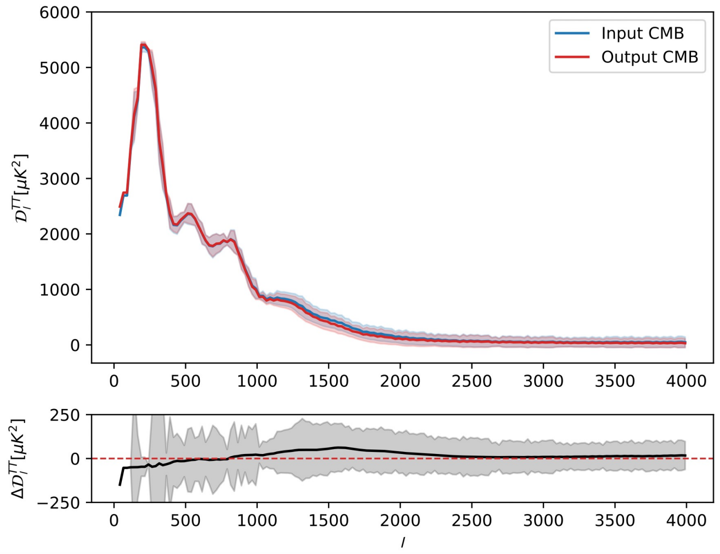
U



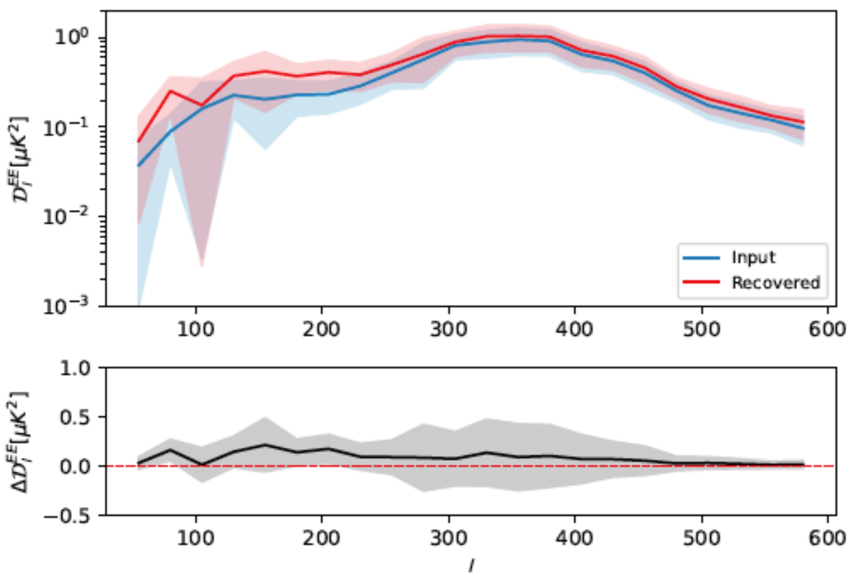
Casas+2022b, A&A, 666, A89 Casas+2024, Submitted to A&A, arXiv:2310.07590

Results – TT, EE & BB Power Spectrum

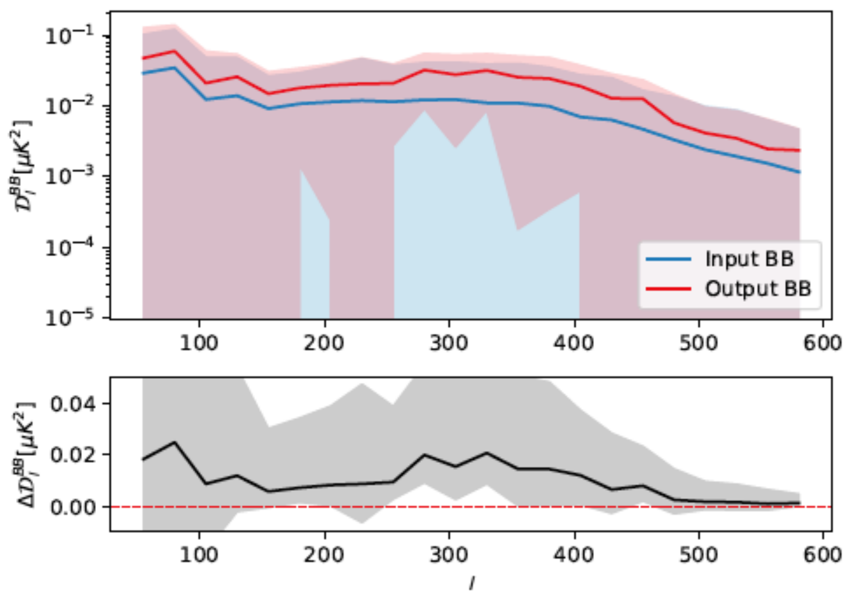
TT



EE



BB



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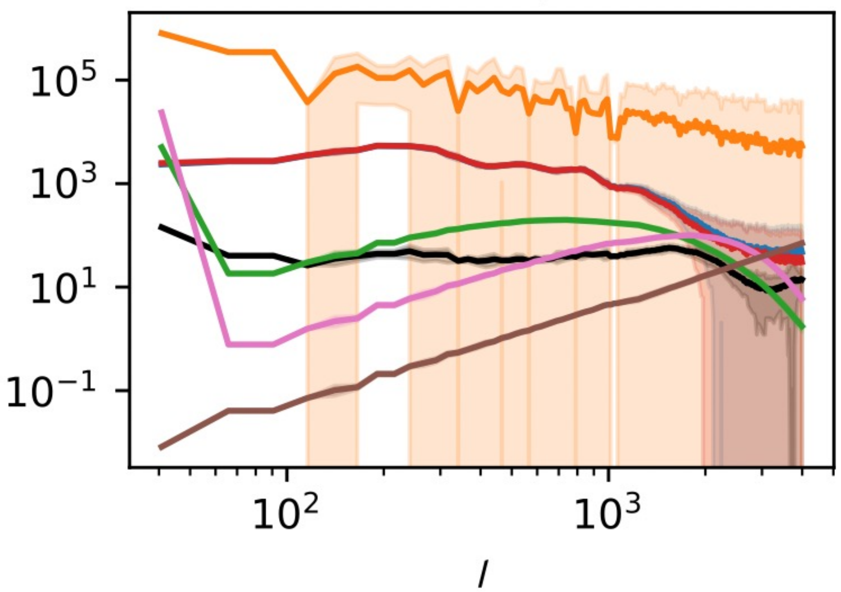
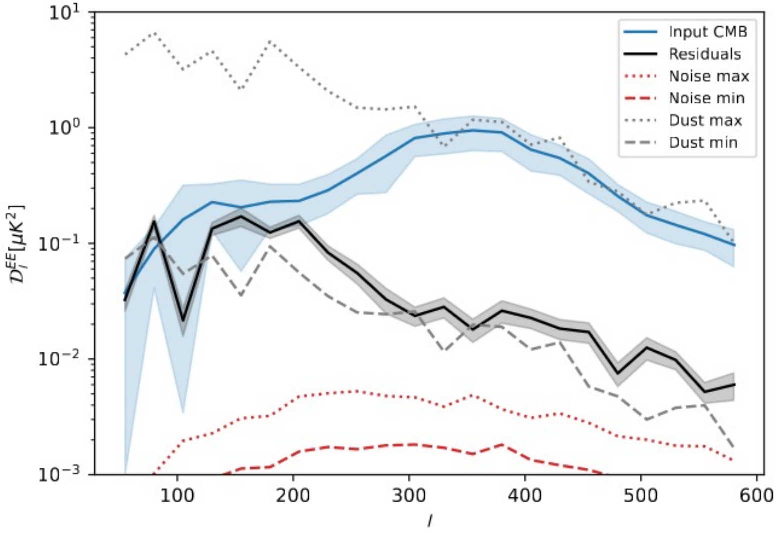
Casas+2024, Submitted to A&A, arXiv:2310.07590

Results – TT, EE & BB Residuals

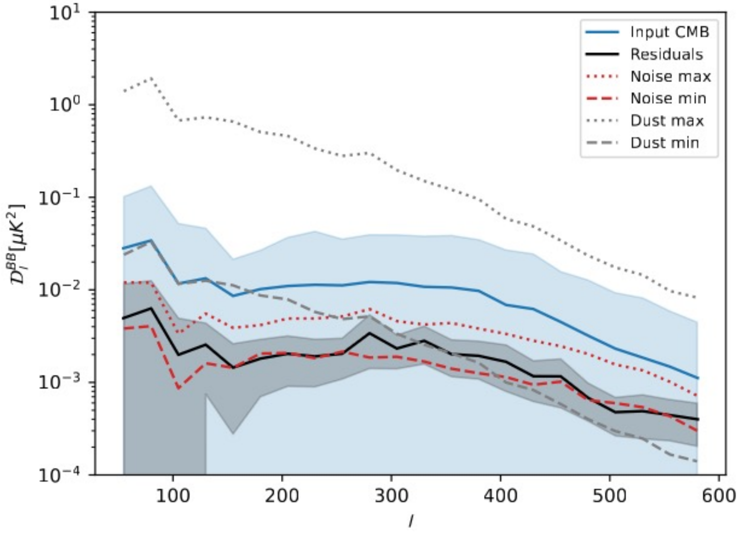
TT



EE



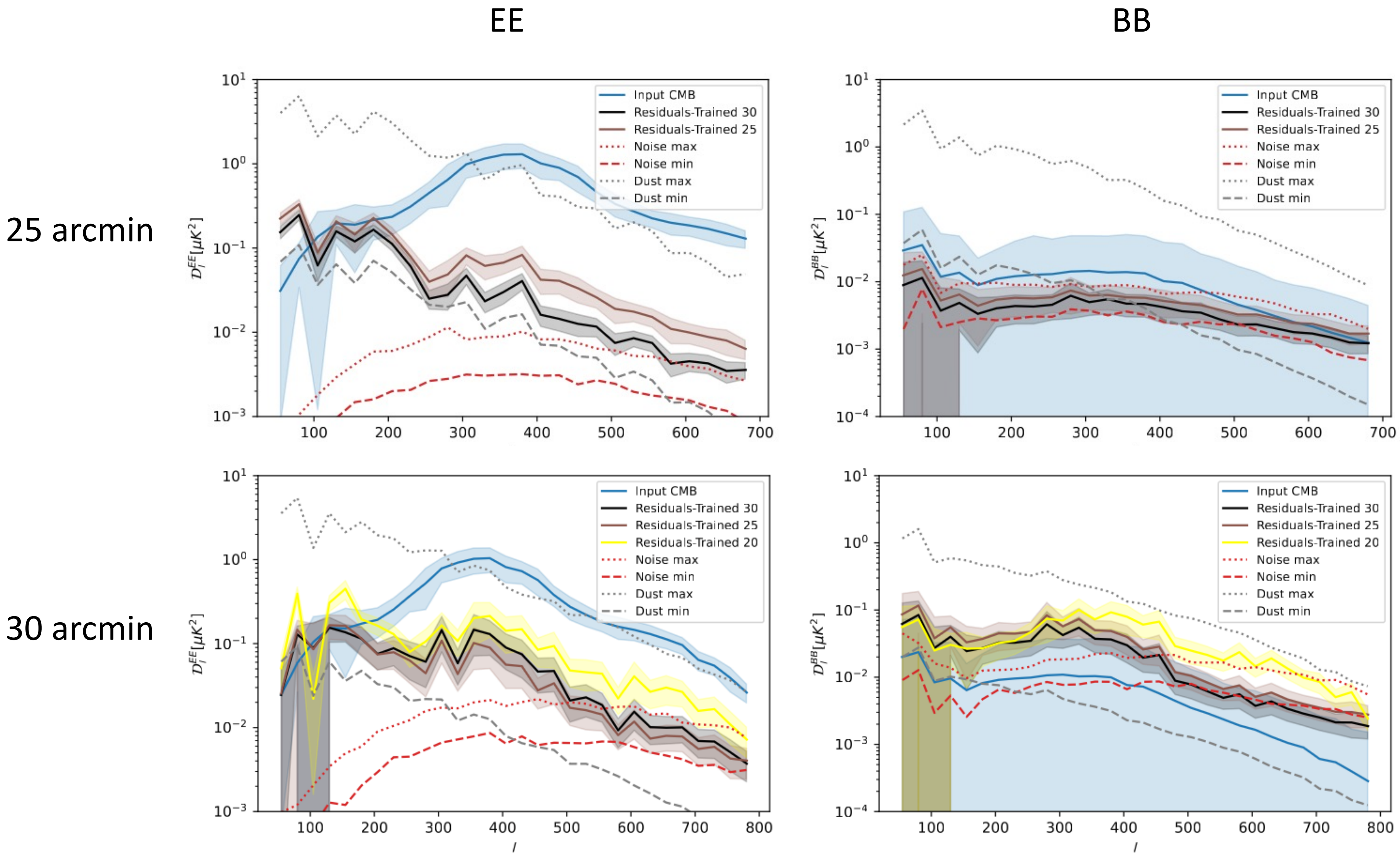
BB



Casas+2022b, A&A, 666, A89

Casas+2024, Submitted to A&A, arXiv:2310.07590

Results – Testing different noise levels/resolution

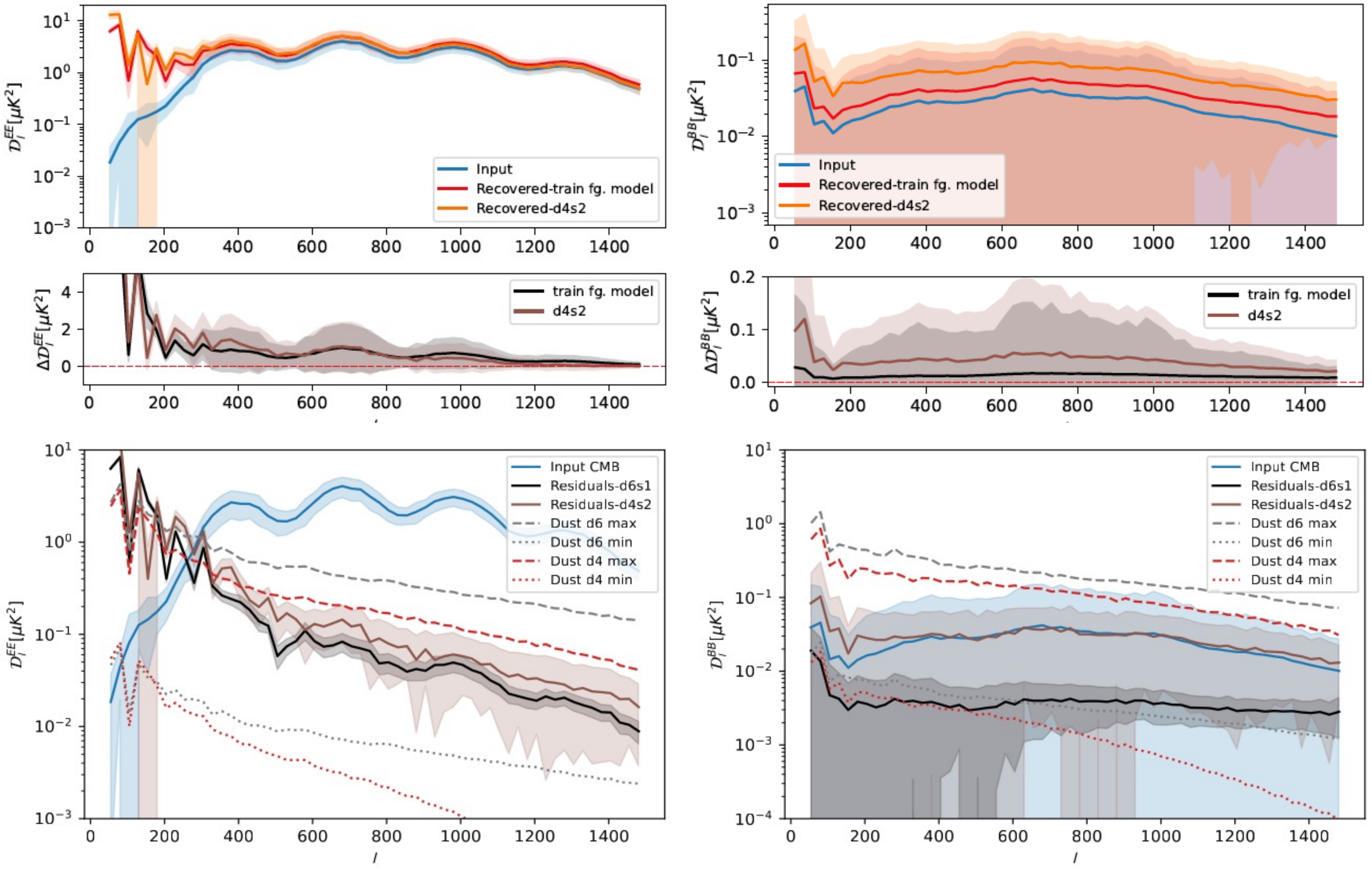


Casas+ 2024, Submitted to A&A, arXiv:2310.07590

Results – Using a different foreground model

EE BB

5 arcmin



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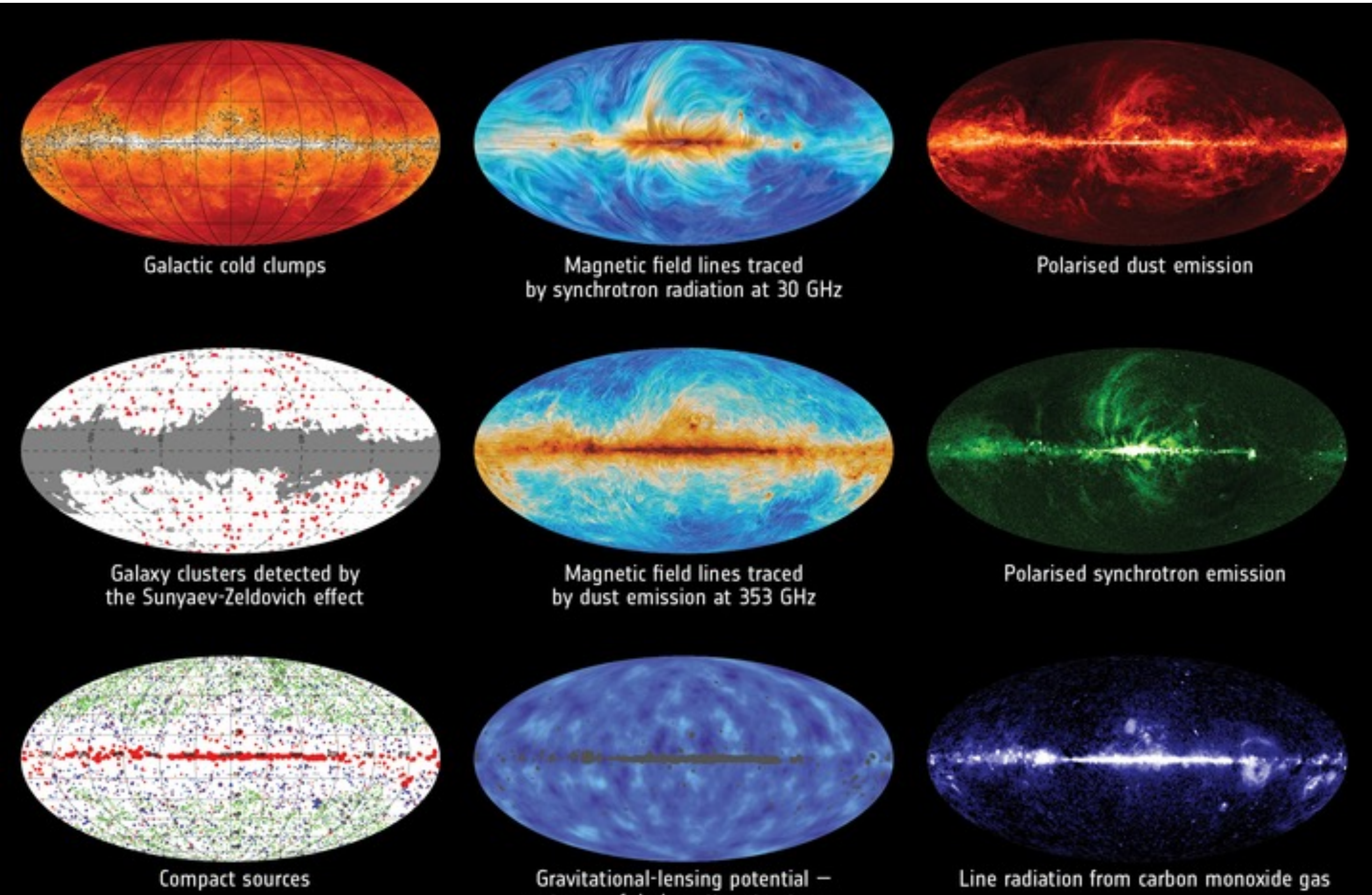
Conclusions & Ongoing work

- Promising results recovering the CMB in realistic temperature and polarization simulations
- Neural networks seem to be more reliable when training with low noise levels
- Training with the proper sky is crucial for B-mode detection

- Testing with real data
- Characterizing synchrotron and dust emissions

Thank you for your attention!



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