BSS and deep learning Victor Bonjean

Joint ARGOS-TITAN-TOSCA workshop - 6th/7th June 2024







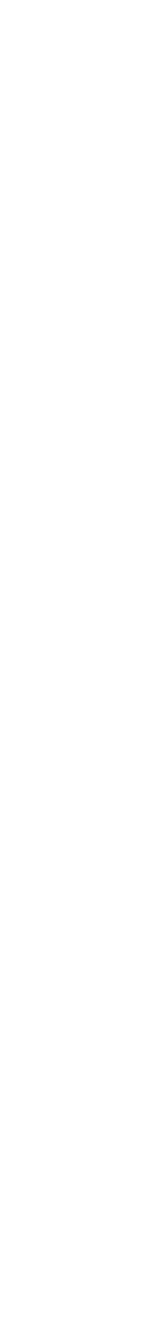








Funded by the European Union



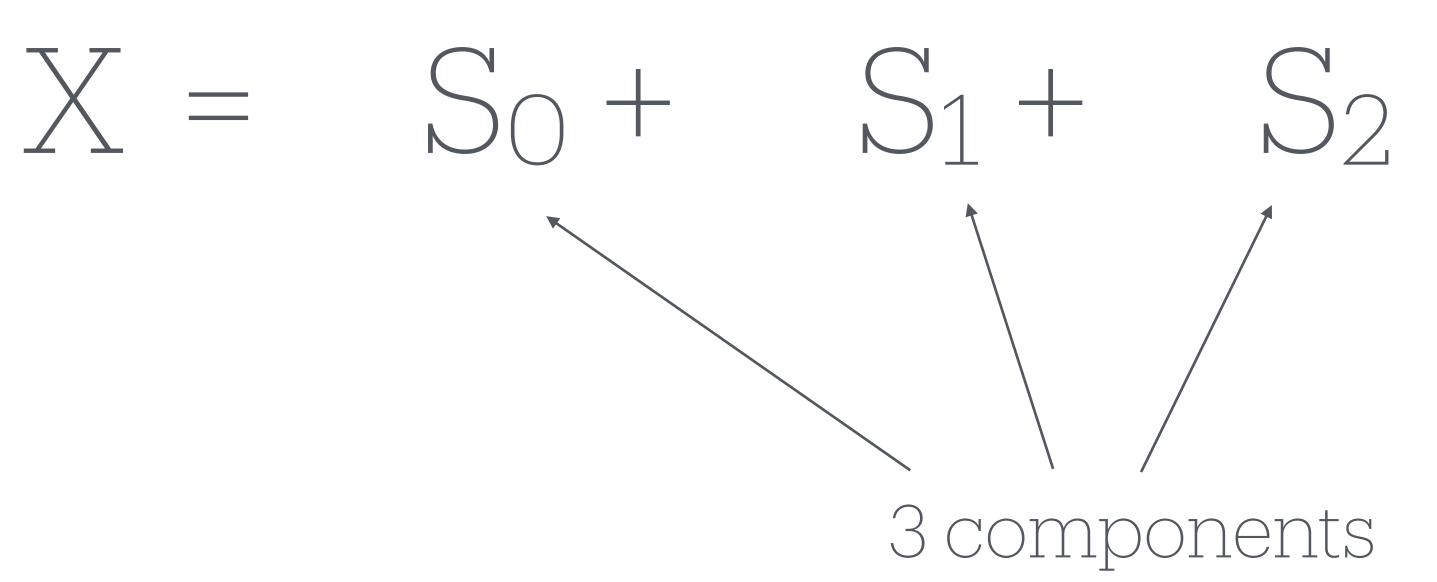




Observation

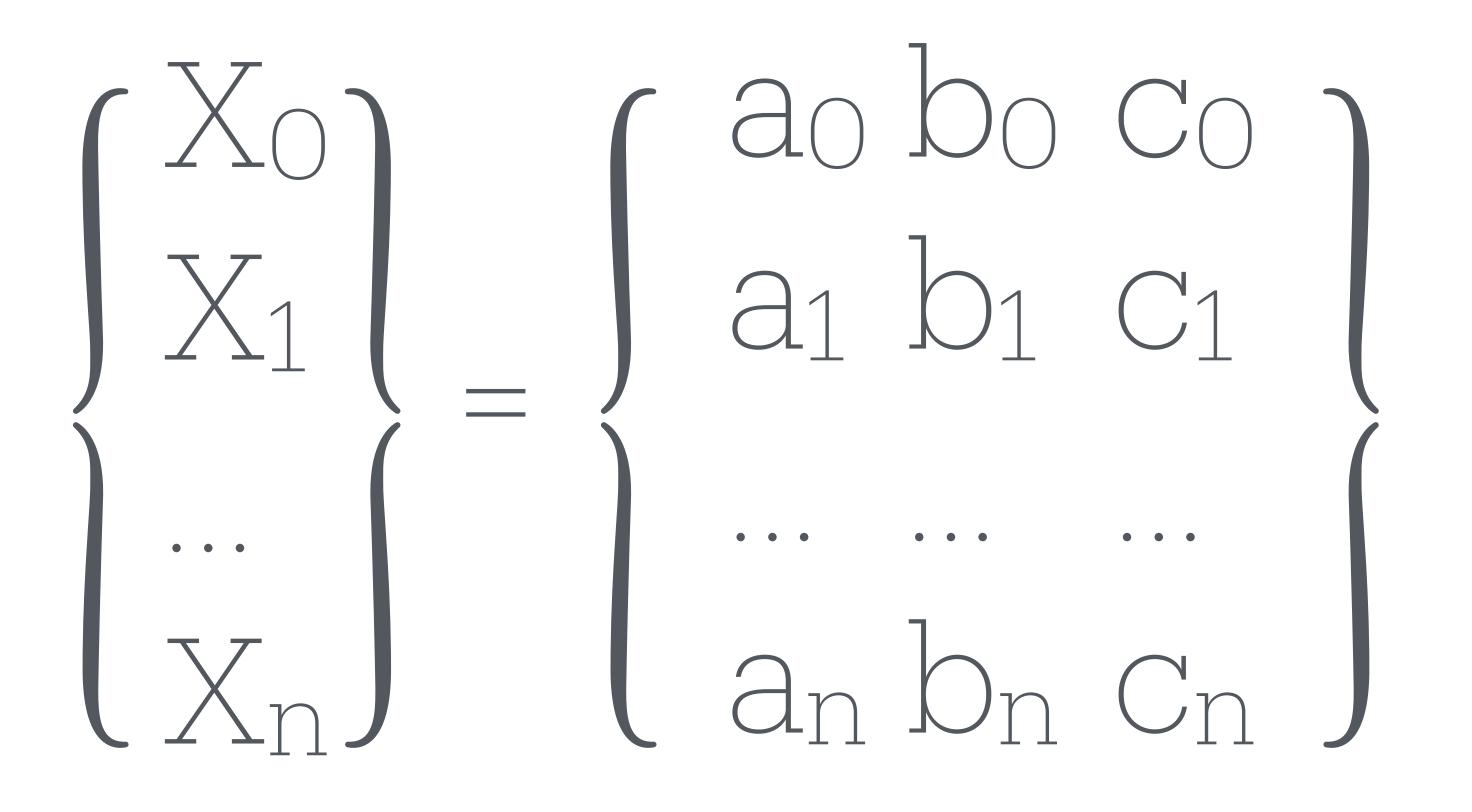


Observation



Observation

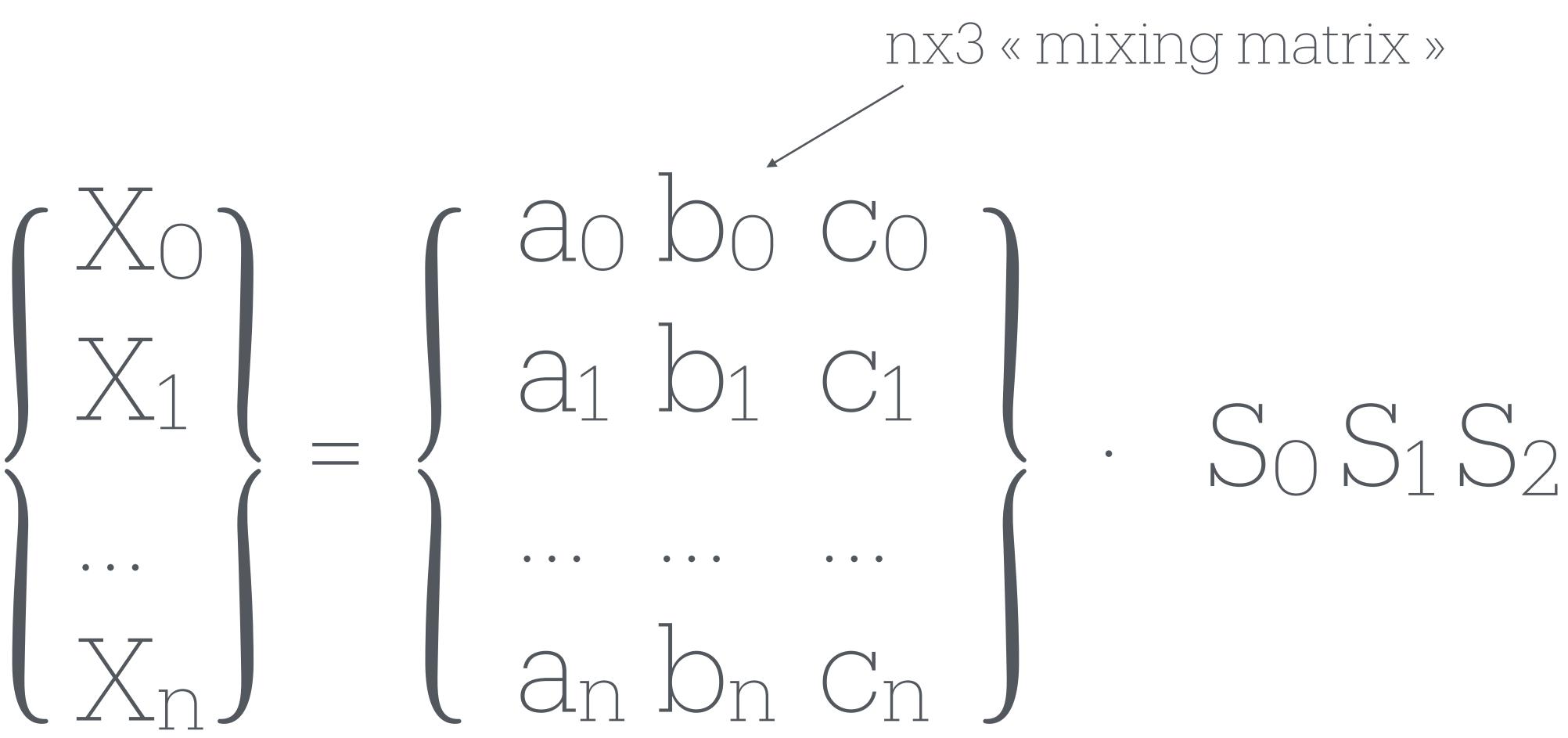
Multiple frequencies $X_{i} = a_{i}S_{0} + b_{i}S_{1} + c_{i}S_{2}$ 3 com onents



$) S_1 S_2$

n frequencies





n frequencies



 $\mathbf{X} = \mathbf{A} \cdot \mathbf{S}$

X = A S

1. We know A

«No problem» $S = A^{-1}X$

• Never the case



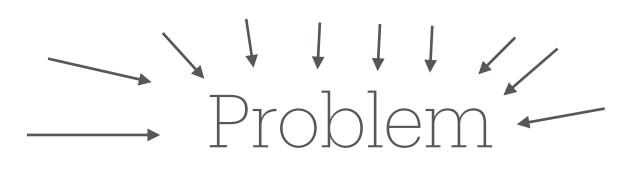
X = AS + NBlind Source Separation (BSS)

1. We know A

«No problem» $S = A^{-1}X$

• Never the case

2. We don't know A



- FastICA _____ Prior on S
- GMCA
- Unsupervised Learning





1. We know A

«No problem» $S = A^{-1} X$

• Never the case

1.5. We know a bit of A

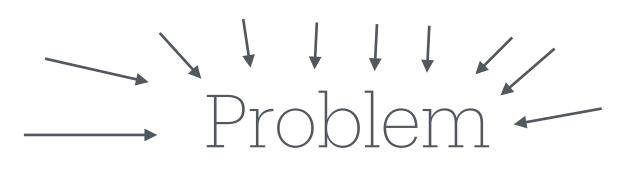
Problem

- ILC
- GMCA
- Self-supervised Learning
- Template based fitting

----- Prior on A

X = AS + NBlind Source Separation (BSS)

2. We don't know A



- FastICA \longrightarrow Prior on S
- GMCA
- Unsupervised Learning





1. We know A

«No problem» $S = A^{-1} X$

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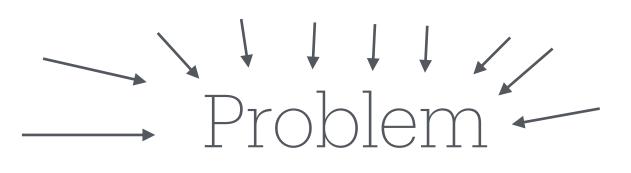
1.5. We know a bit of A

Problem

- ILC
- GMCA
- Self-supervised Learning
- Template based fitting
 - ----- Prior on A

X = AS + NBlind Source Separation (BSS)

2. We don't know A



- FastICA _____ Prior on S
- GMCA
- Unsupervised Learning





1. We know A

«No problem» $S = A^{-1}X$

• Never the case

X = AS + NBlind Source Separation (BSS) 1.5. We know a bit of A 2. We don't know A 1.75 My work - Problem Problem • ILC GMCA • FastICA _____ Prior on S • Self-supervised GMCA Learning Unsupervised • Template based fitting Learning

- - ----- Prior on A





Encoder

(a) Blind source separation training procedure.

Anything you want (fitted mixing matrix, **non linear model**...)

Decoder

Webster et al, 2023





Single channel mixture:

Webster et al, 2023

Single Mixed Image Separation



Application: deraining

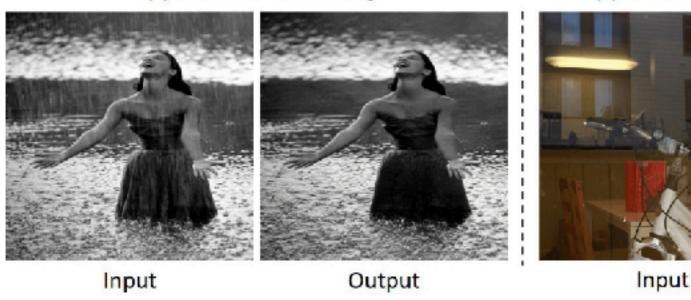
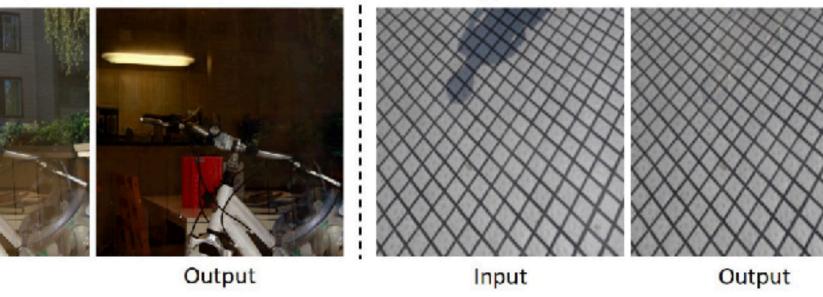


Figure 1: We propose a unified framework for single mixed image separation under an adversarial training paradigm. Our method can be applied to a variety of real-world tasks, including image deraining, photo reflection removal, image shadow removal, etc.

Single Mixed Image Separation

Application: photo reflection removal

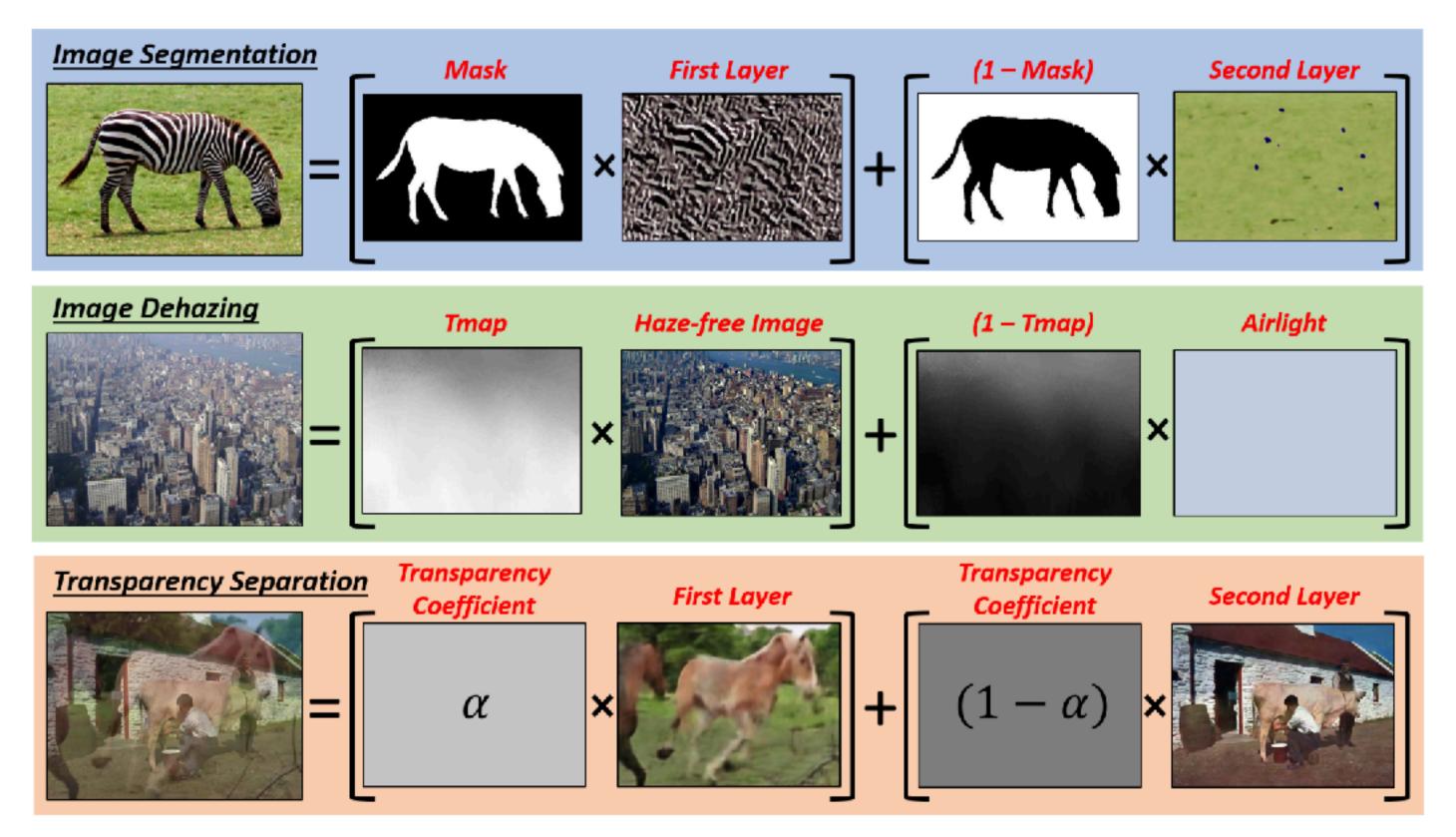
Application: shadow removal



(+ regularization term on (non) correlation)



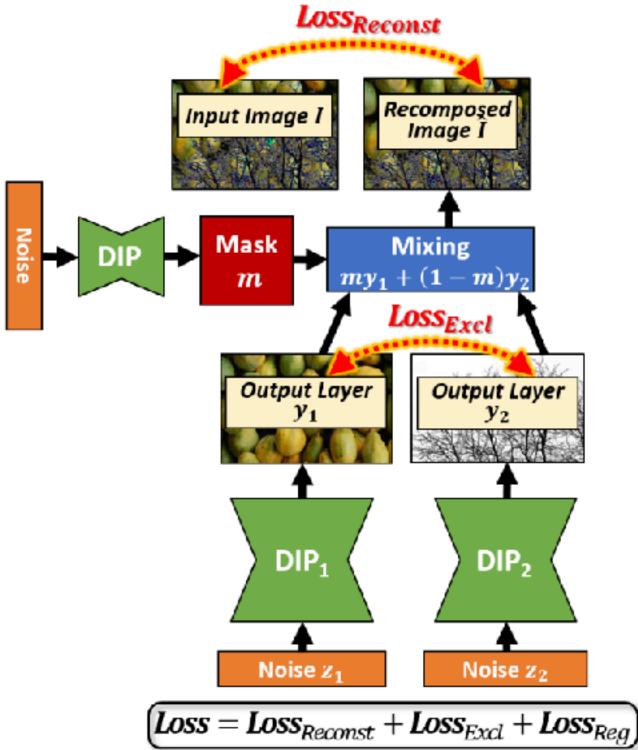
« Double-DIP »



segmentation, dehazing, transparency separation). Such a decomposition can be achieved using "Double-DIP".

Figure 1: A unified framework for image decomposition. An image can be viewed as a mixture of "simpler" layers. Decomposing an image into such layers provides a unified framework for many seemingly unrelated vision tasks (e.g.,

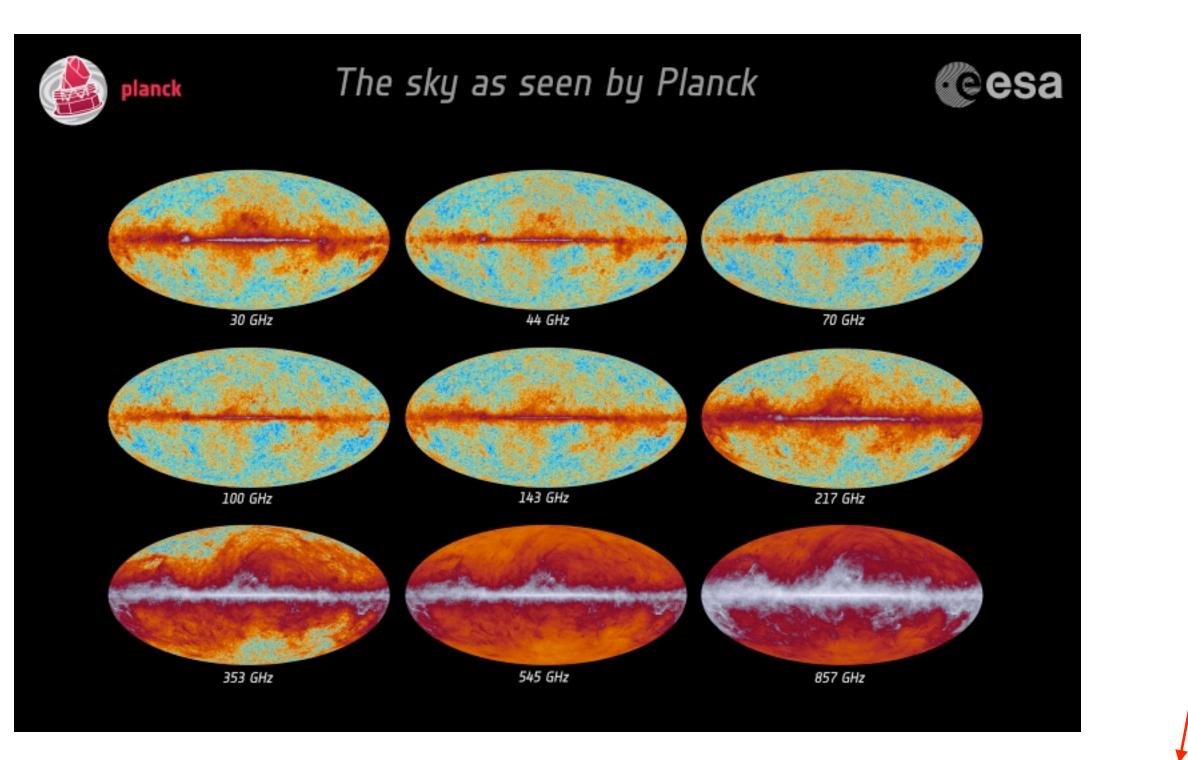
Gandelsman et al, 2018



« Double-DIP »

Figure 2: Double-DIP Framework. Two Deep-Image-Prior networks (DIP₁ & DIP₂) jointly decompose an input image I into its layers ($y_1 \& y_2$). Mixing those layers back according to a learned mask m, reconstructs an image $\hat{I} \approx I$.

Gandelsman et al, 2018

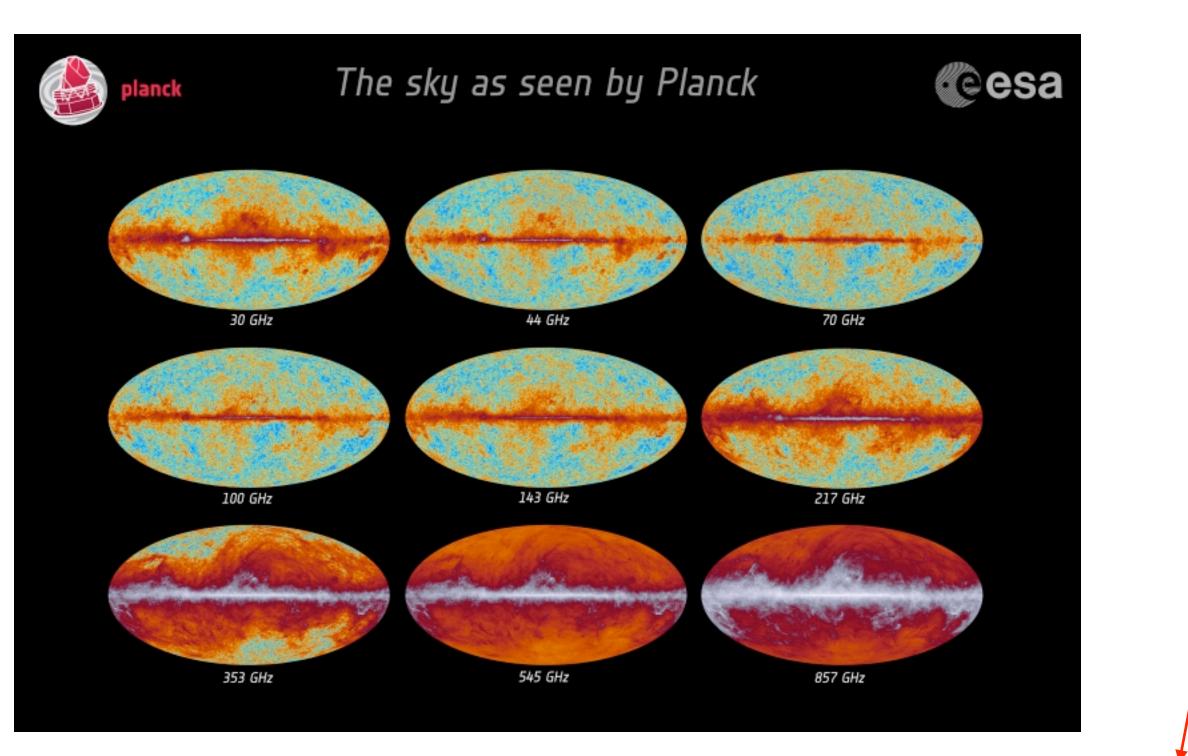


- CMB
- CIB
- tSZ
- Noise
- Beam
- kSZ
- Radio

constant weights approximated weights known weights known known constant weights freq. > 90GHz

- Foregrounds (CO + dust + radio)
- Major issue





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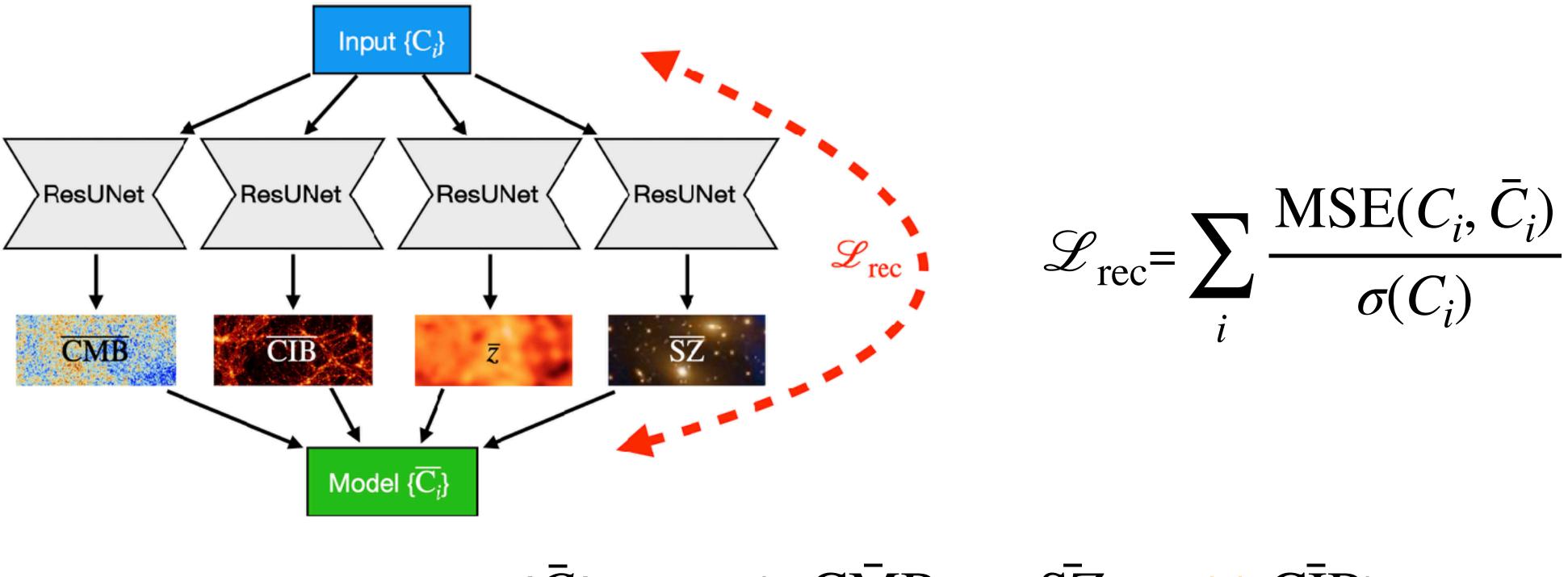
- constant weights approximated weights known weights known known constant weights freq. > 90GHz
- Foregrounds (CO + dust + radio)

Not statistically independent $\longrightarrow \{C_i\} = \text{Bio}(1^*(\text{CMB}+\text{kSZ}) + \text{fi}^*\text{SZ} + \text{CIBi}) + \text{Ni}$ Non linear









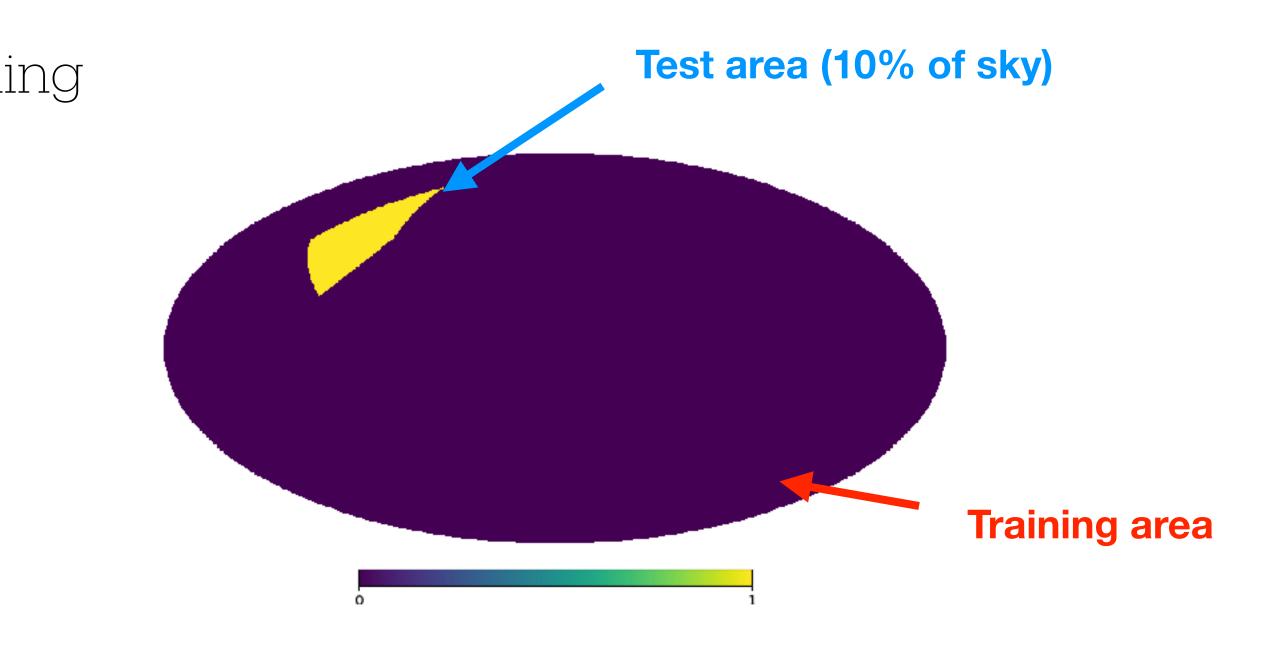
 \rightarrow { C_i } = Bi o (1*CMB + fi*SZ + CIBi) + Ni

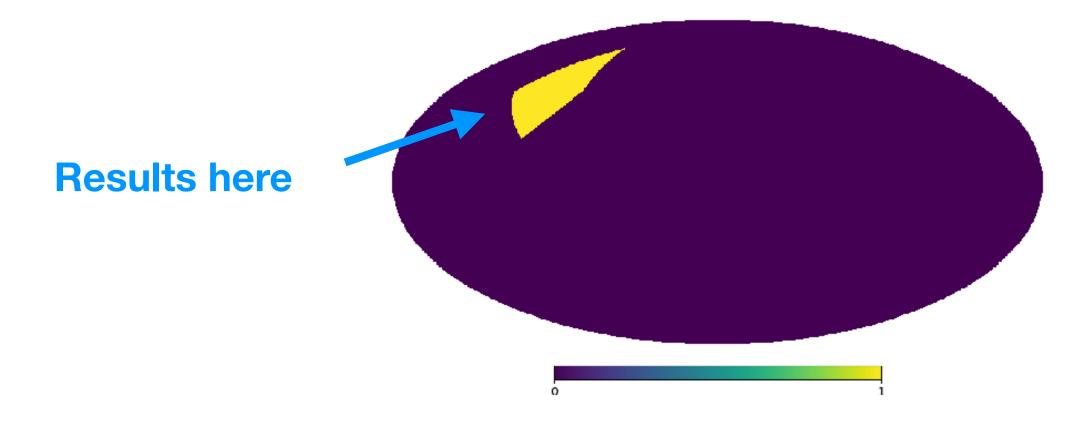
$\longrightarrow \{\overline{C}_i\} = Bi \circ (1*CMB + fi*SZ + gi(\overline{z})*CIB)$

(gi -> Greybody)

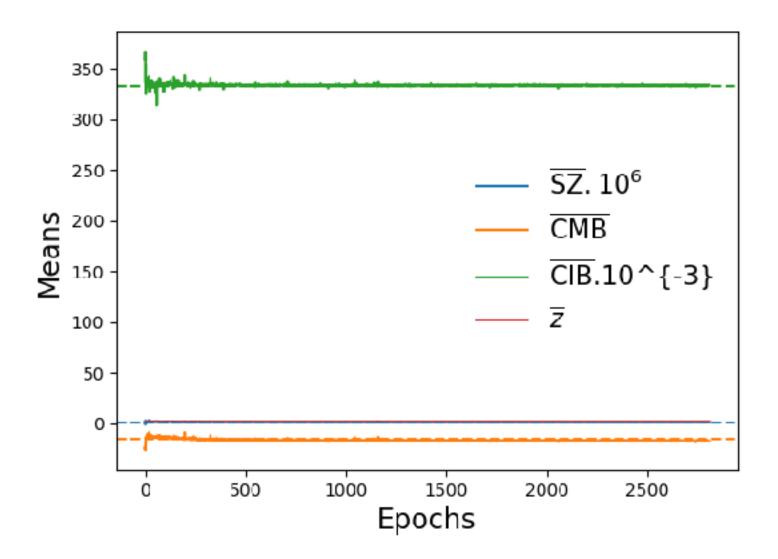
Healpix maps from WebSky numerical simulations (Stein et al., 2020):

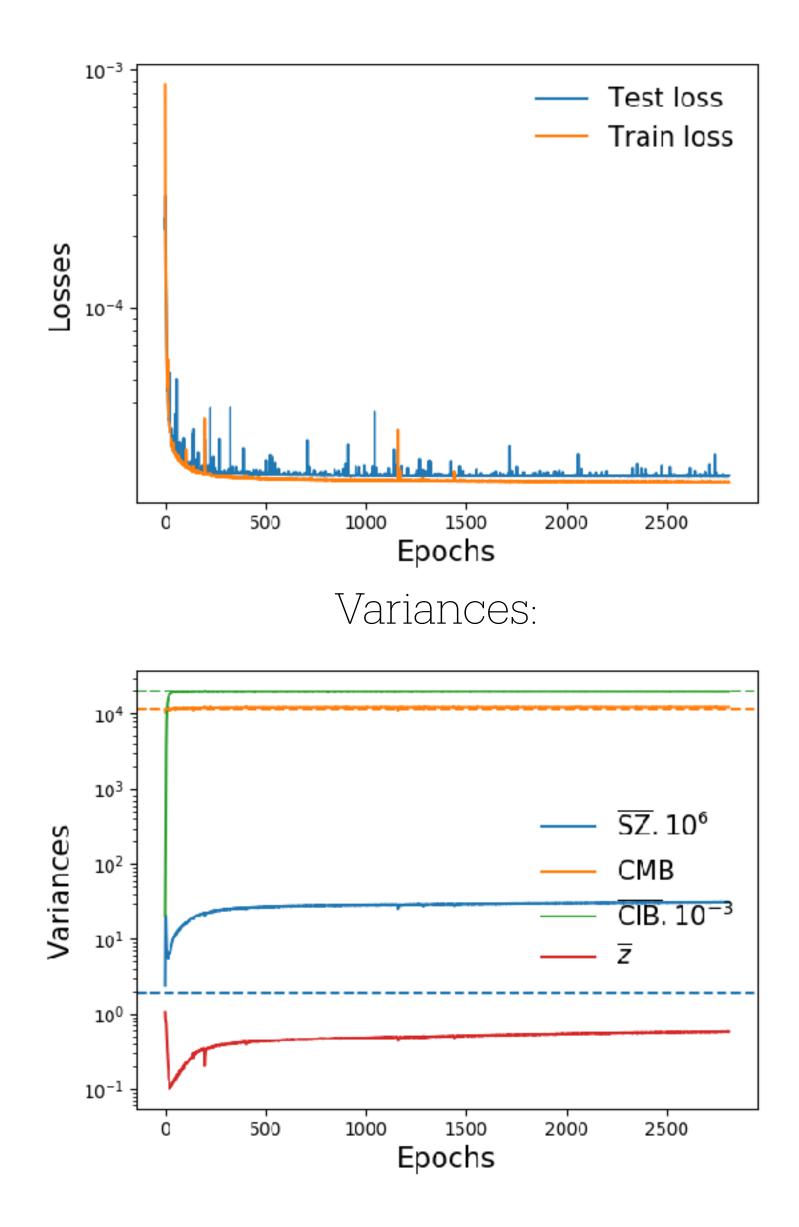
- 90, 100, 143, 145, 217, 225, 280, 353, 545 GHz (Planck and SO)
- Healpix nside=4096
- CMB, CIB (all dust IR emission including point sources), SZ
- No noise, no beams
- 100,000 patches of 64x64 pixels $(0.8^{\circ} \times 0.8^{\circ})$



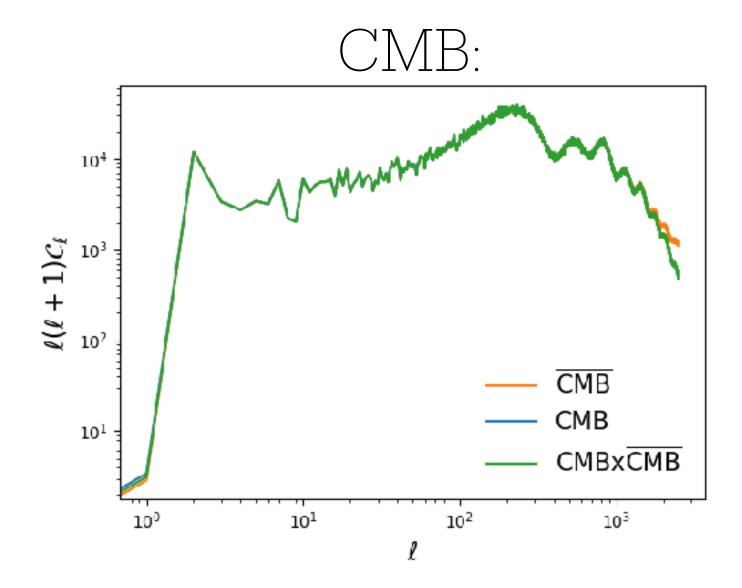


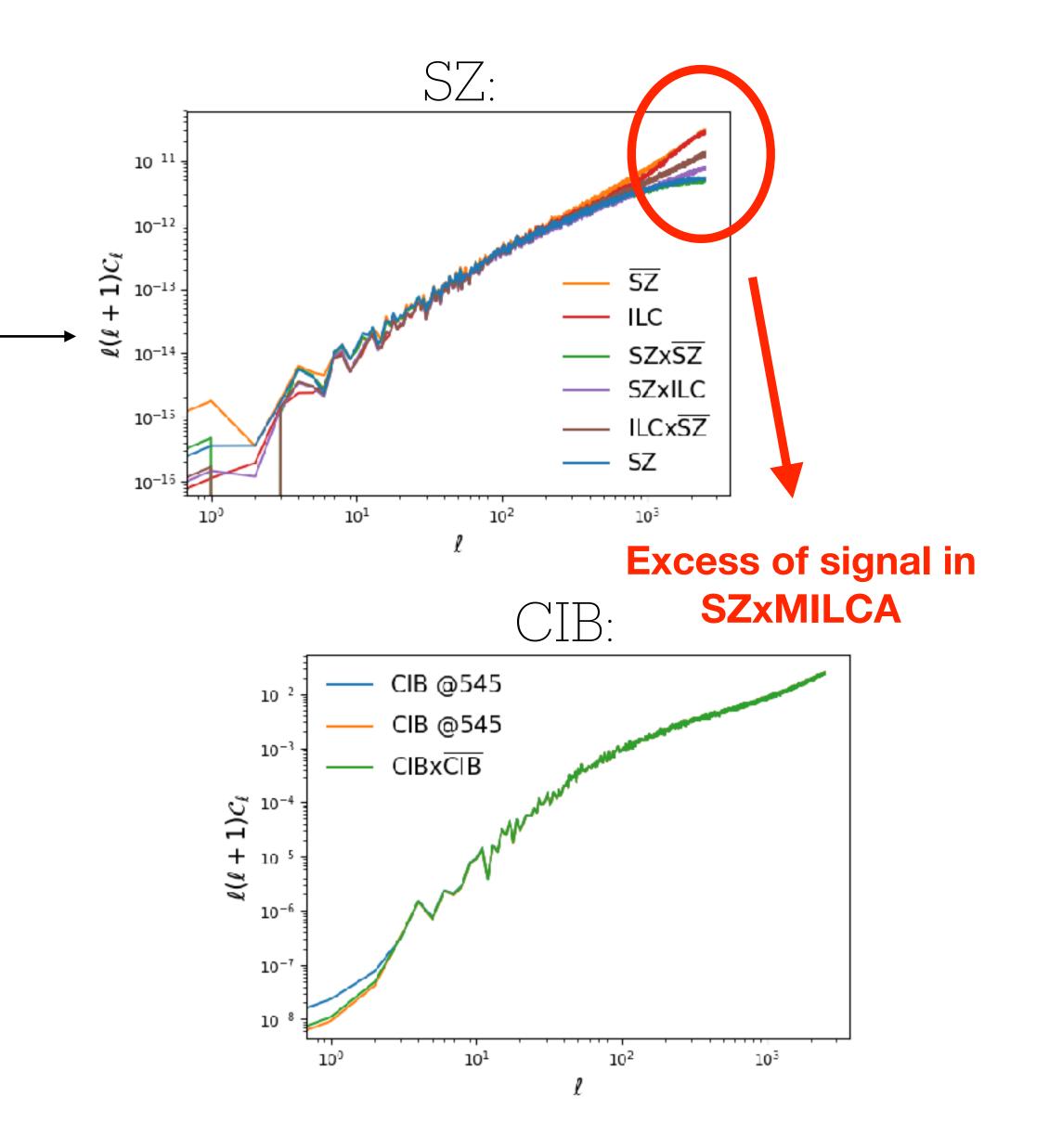
Means:





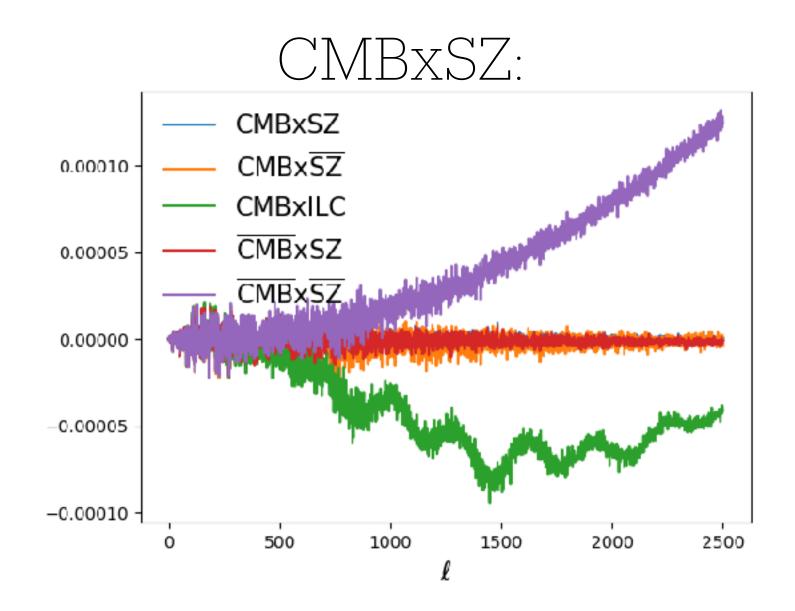
Power-spectra:

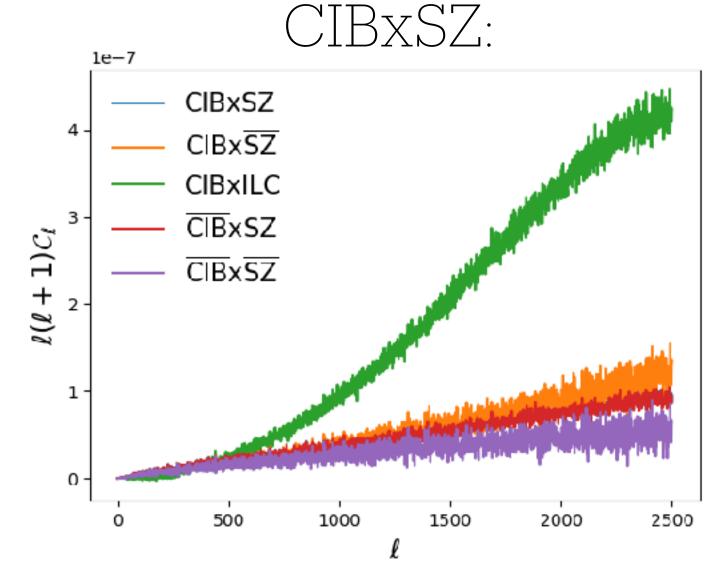


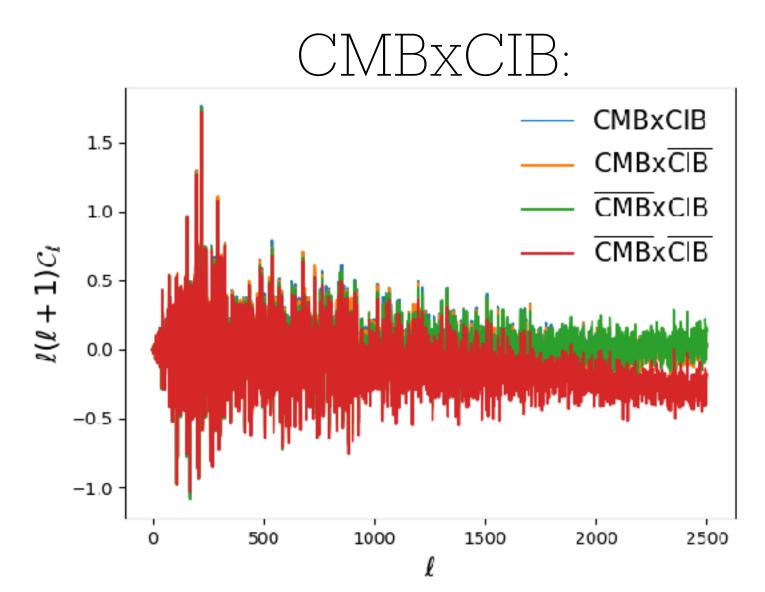


Cross-spectra:

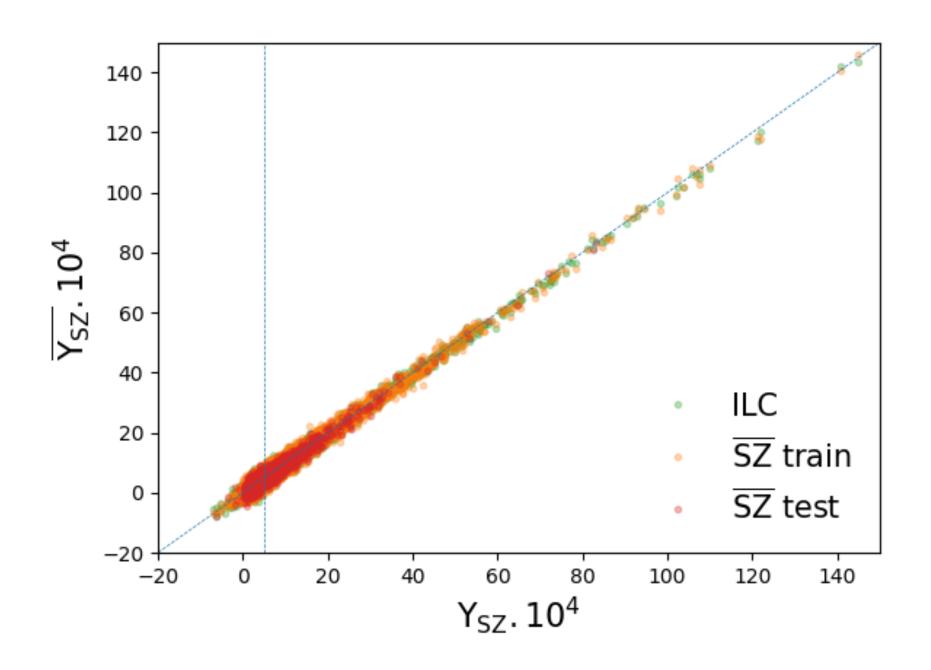
SZ map less contaminated by other components

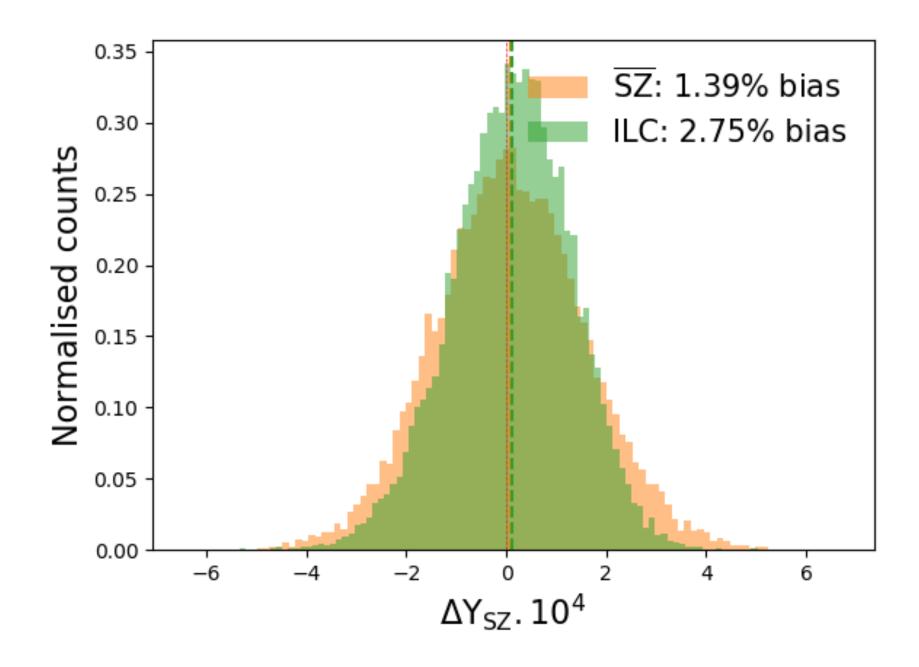






Focus on SZ fluxes around clusters:





Future applications

- CIB removal for CO/CII studies (Sia's talk)
- Single Channel Mixture for CO/CII separation?
- Foreground removal in radio (SKA) for HI and/or EoR?