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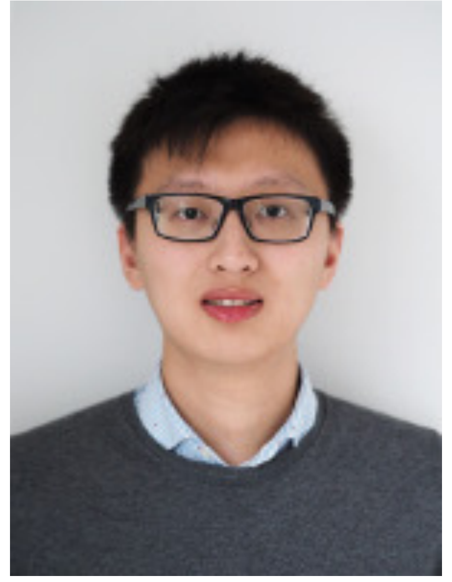
JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Neural Fourier Filter Bank

Zhijie Wu

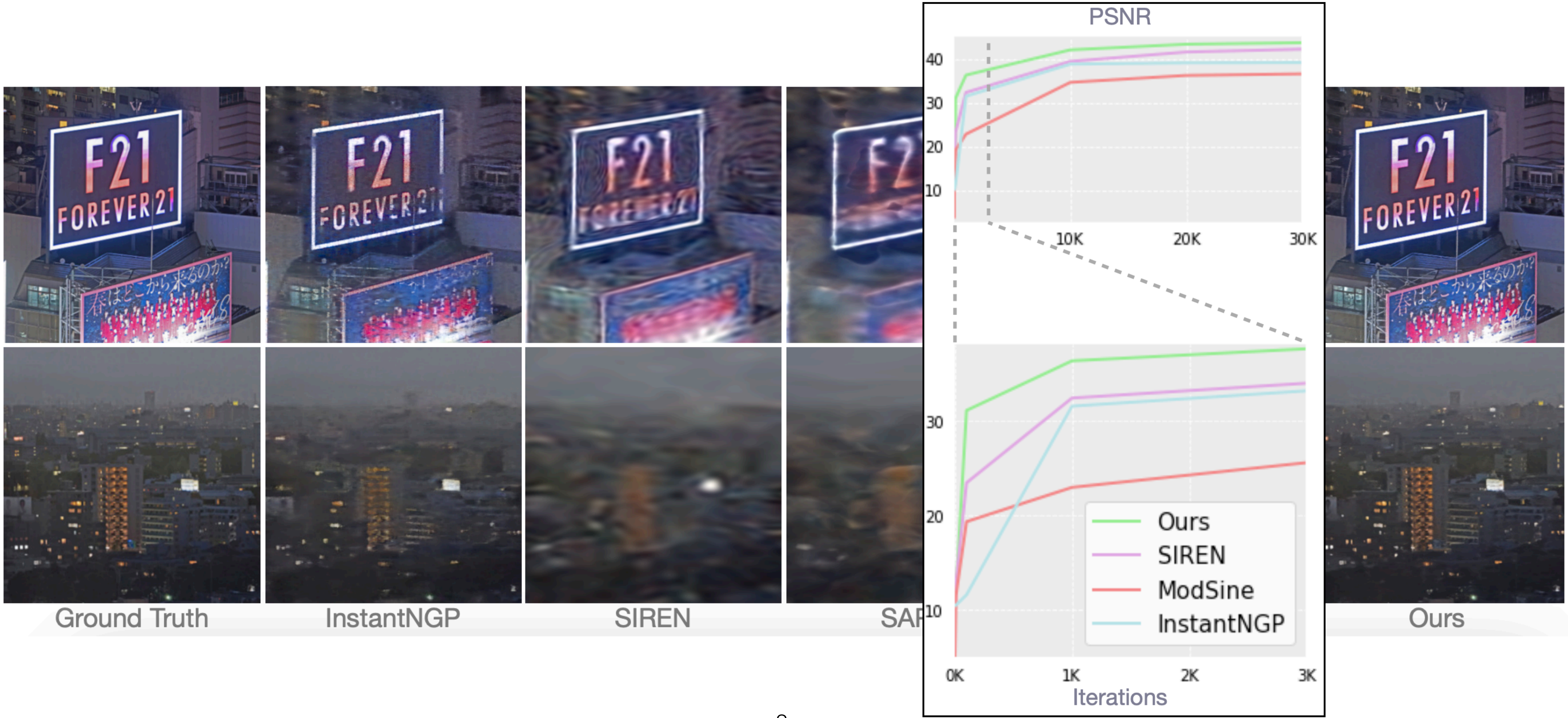


Yuhe Jin

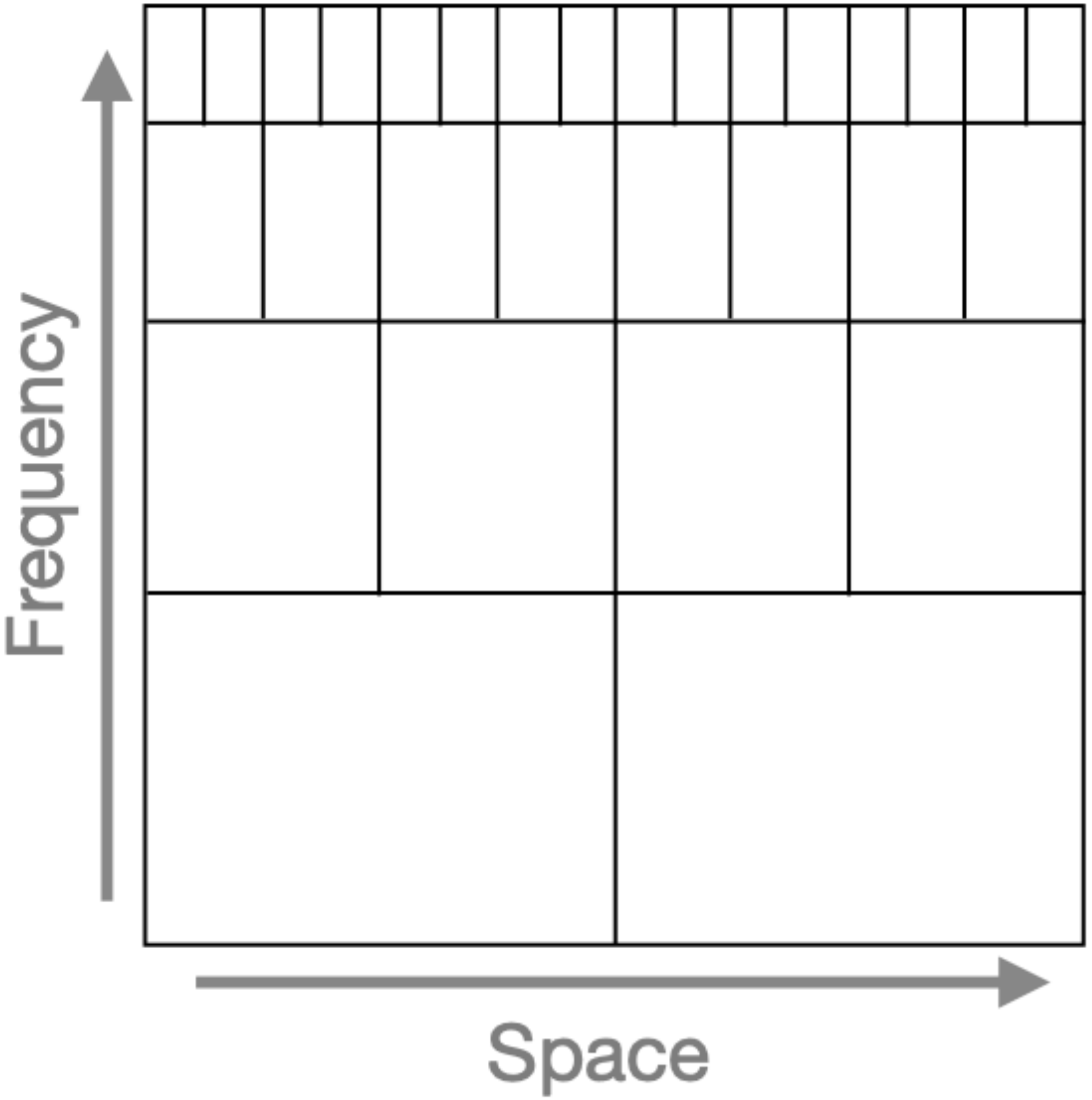
Kwang Moo Yi

WED-PM-172

Reconstruction quality↑ + compute↓



Considering both space and frequency



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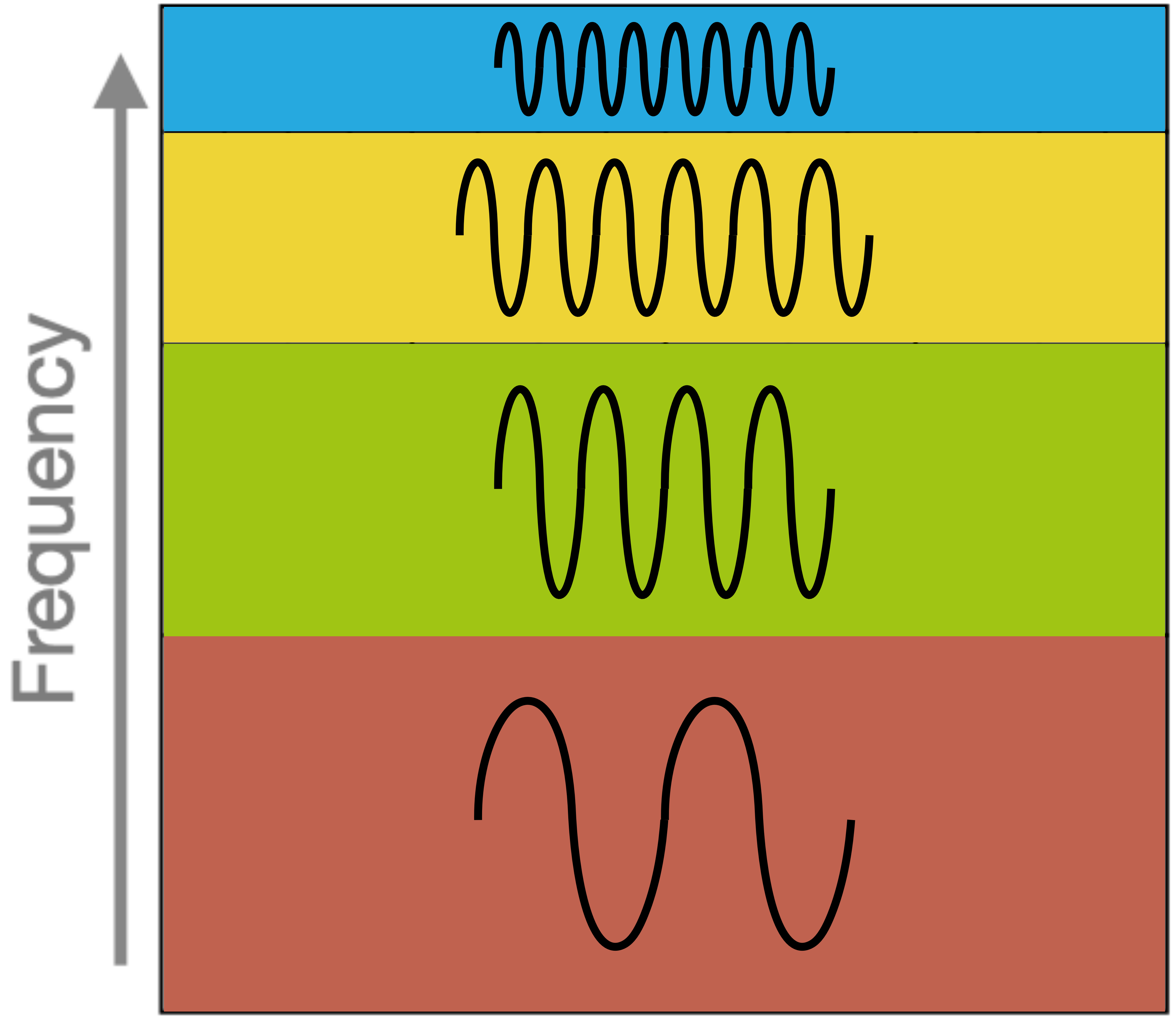

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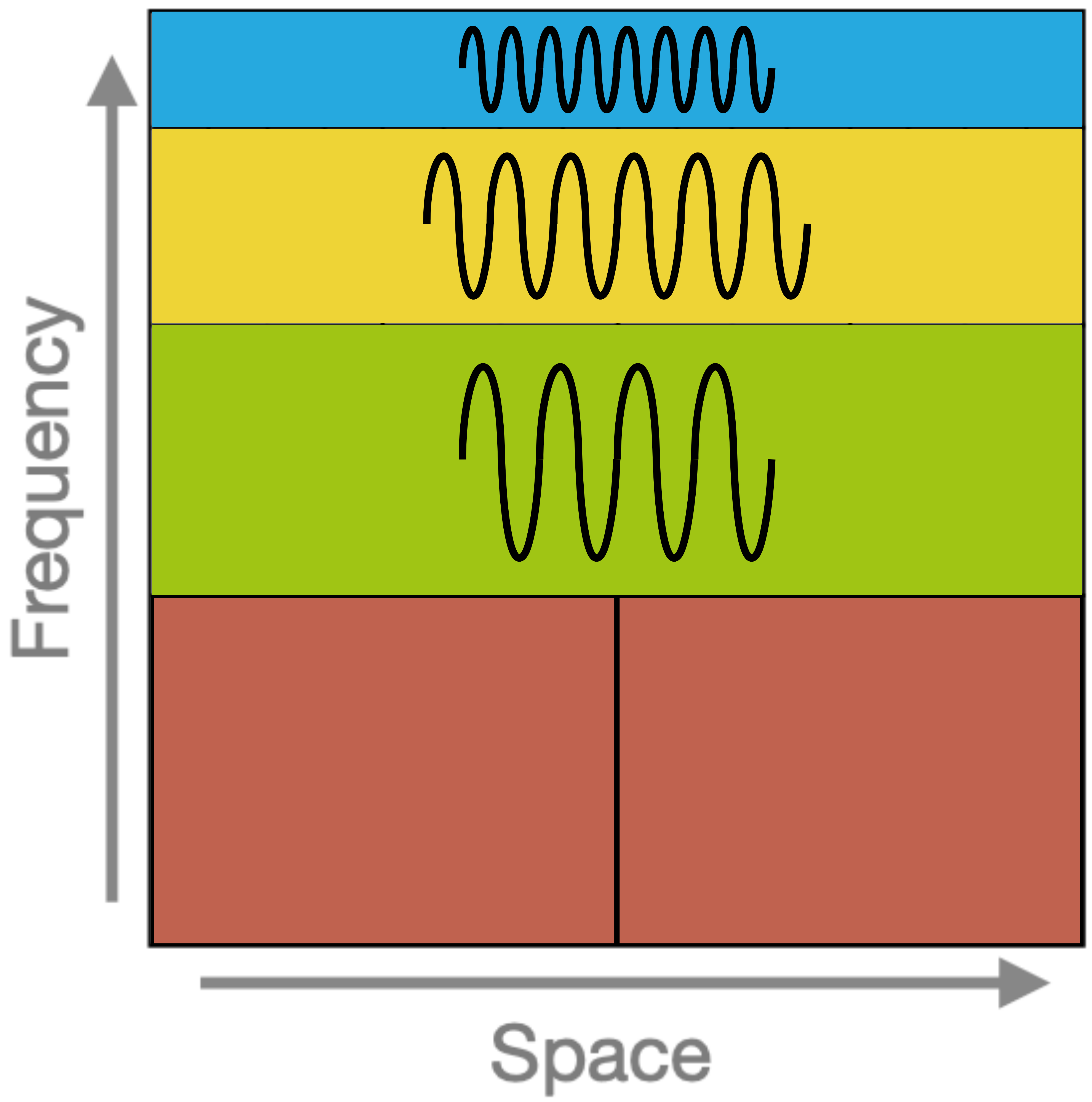

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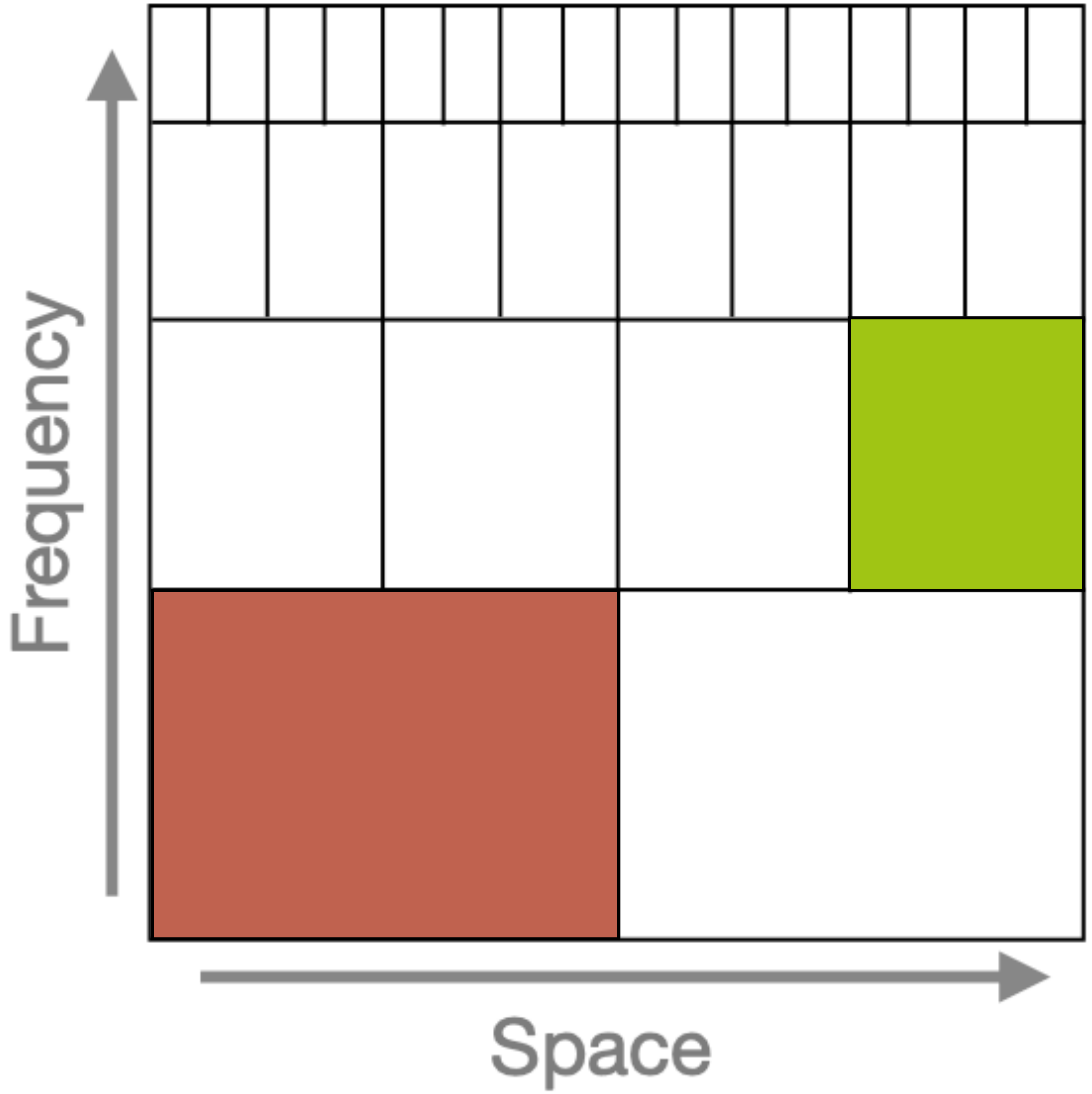

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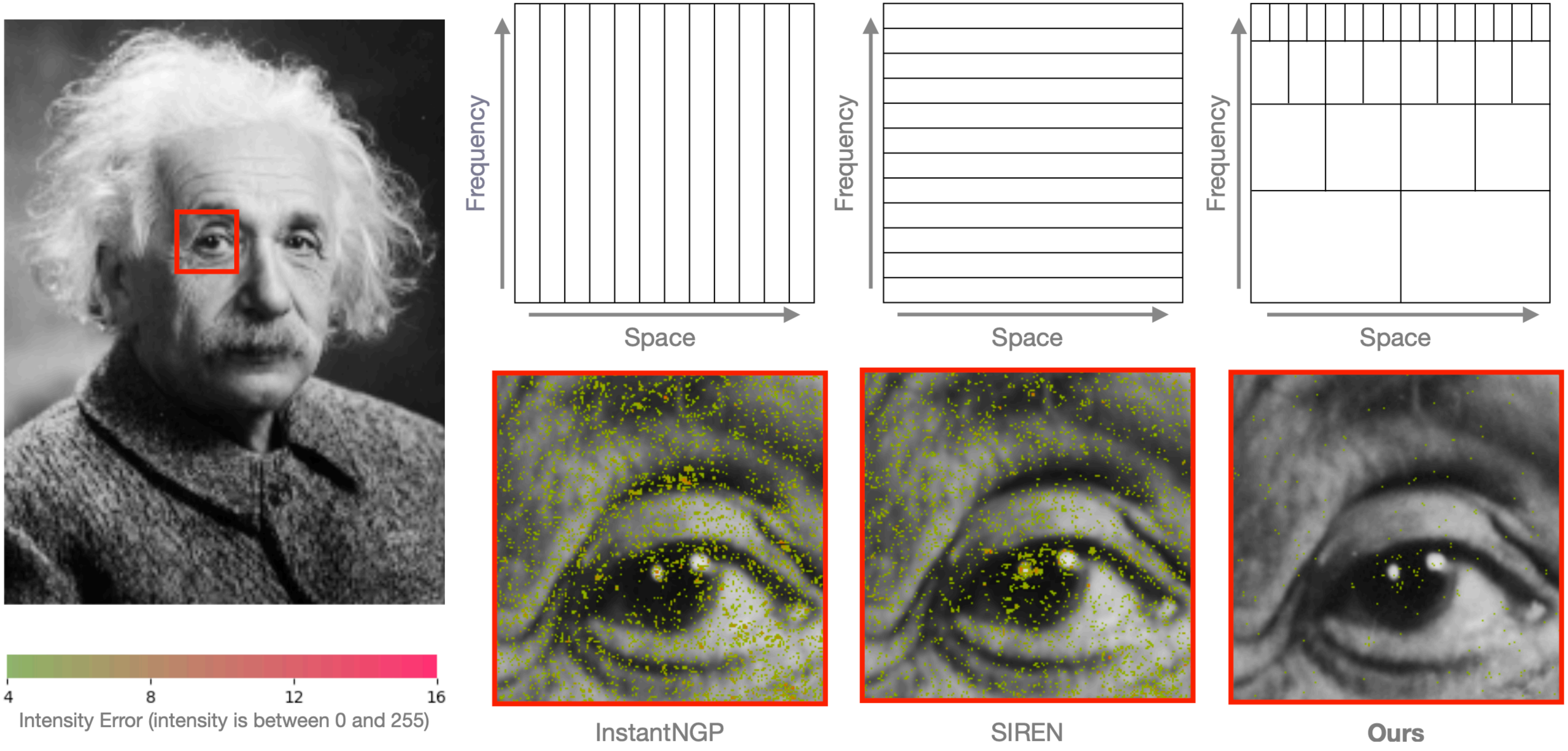

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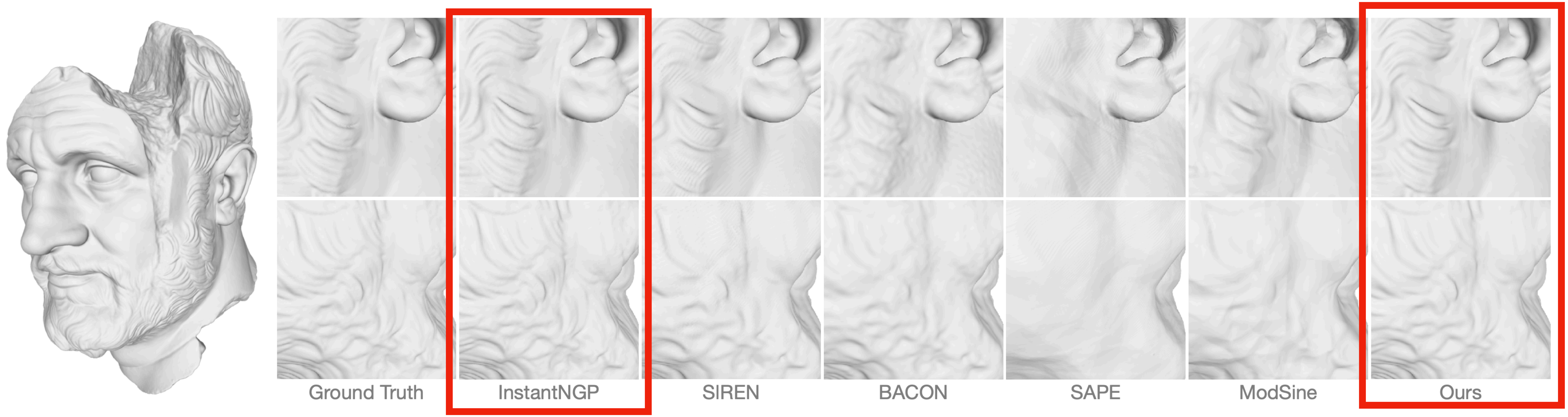
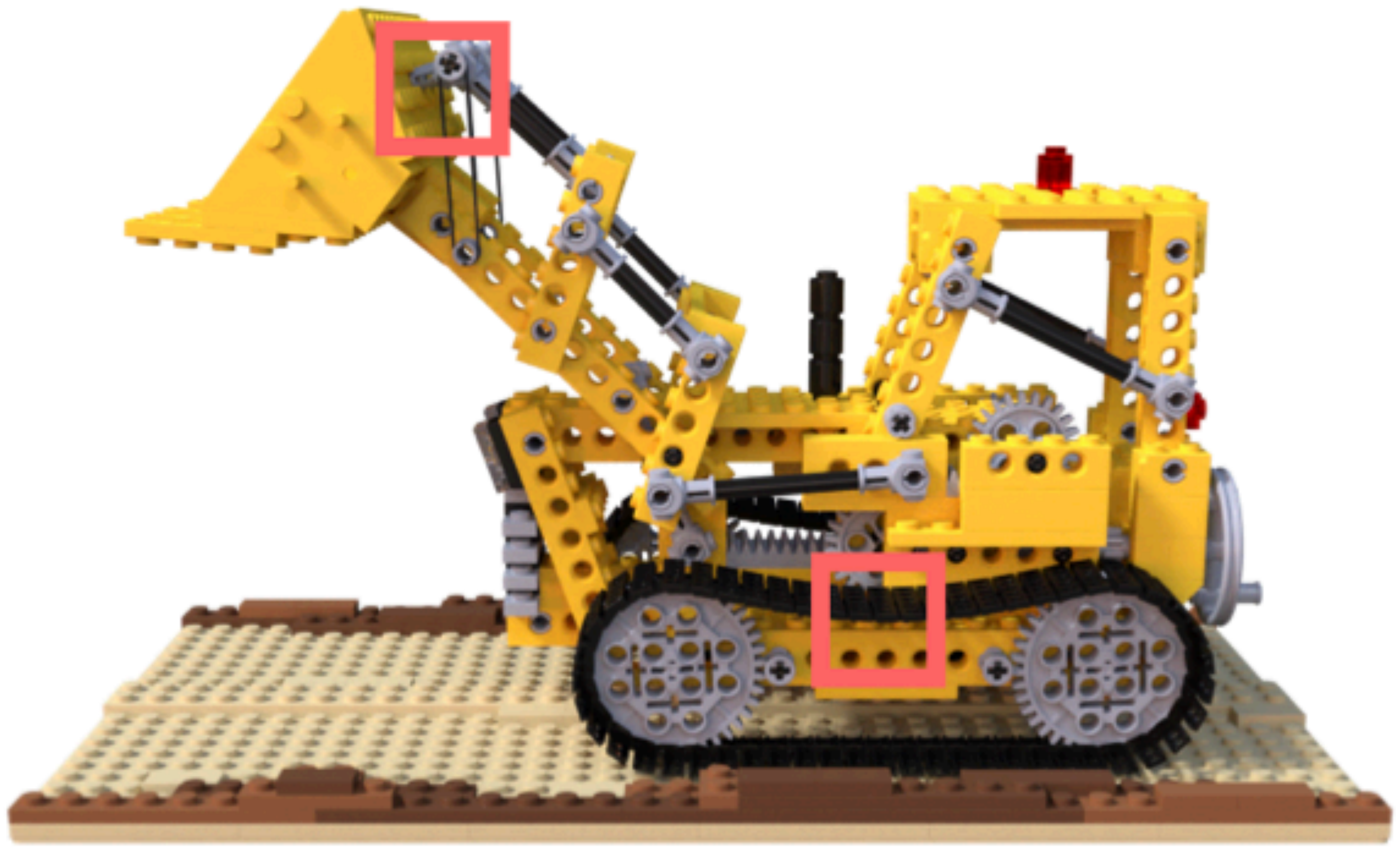
Results — 2D image fitting

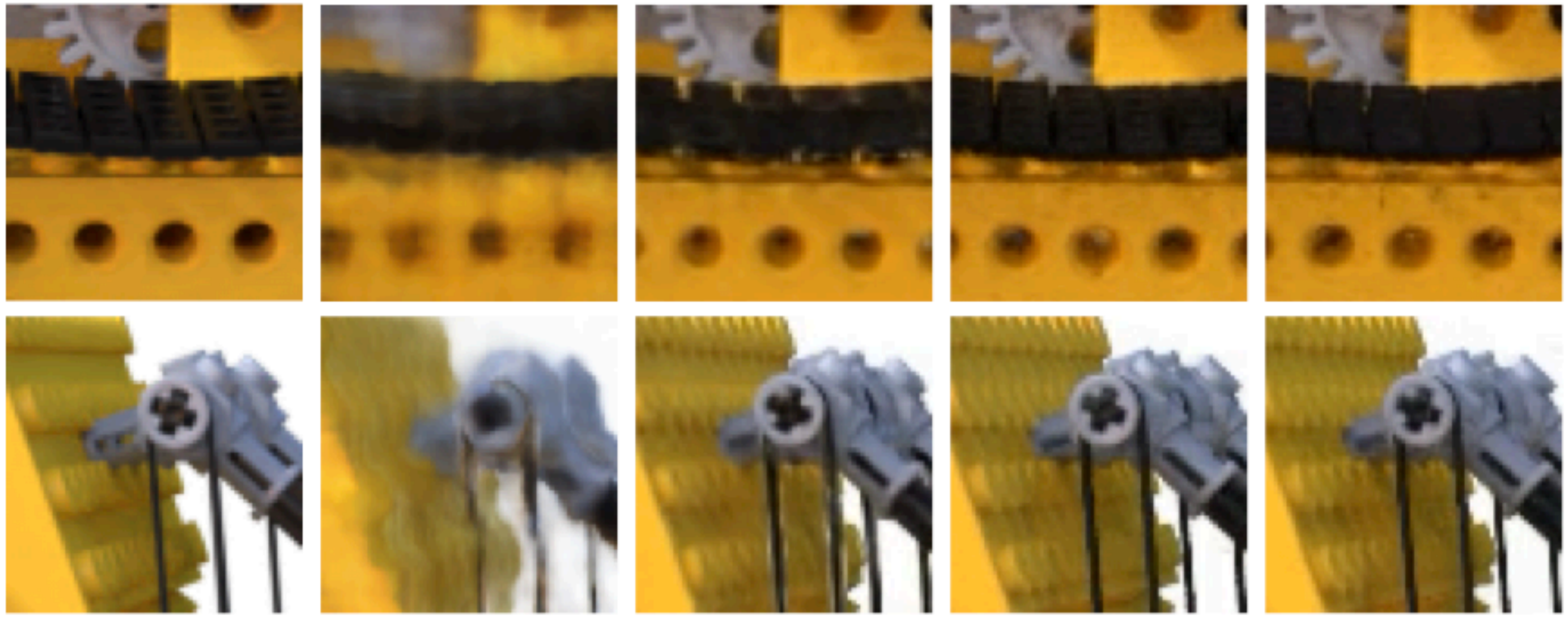
Ground Truth | InstantNGP | SIREN | SAPE | ModSine | Ours

Results — 3D shape fitting



Results — Novel View Synthesis





Neural Fields

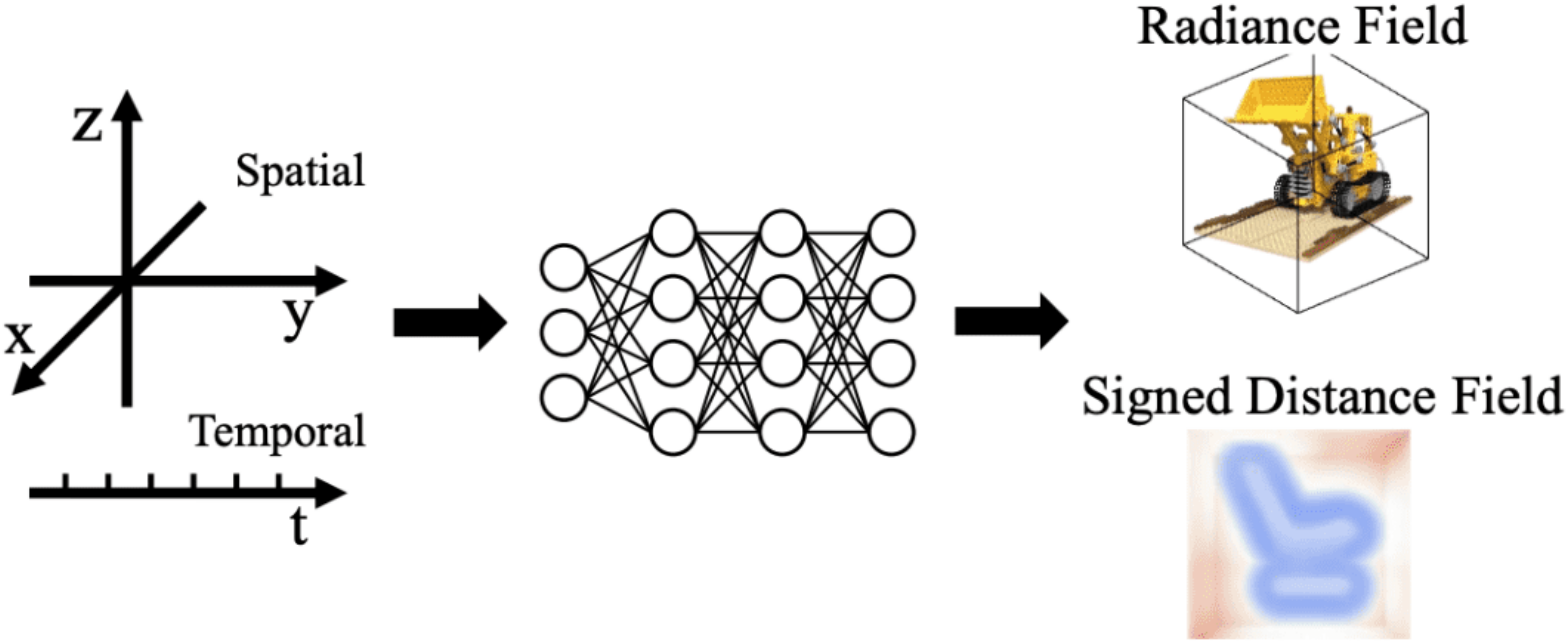
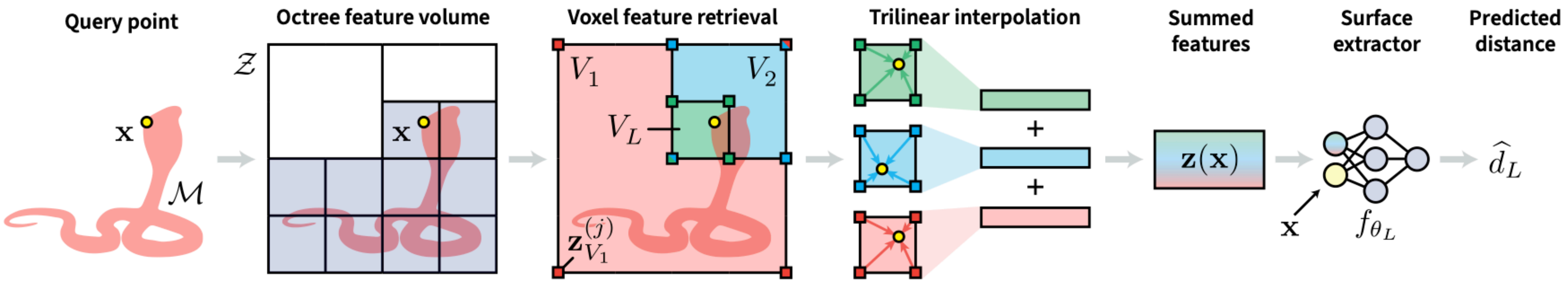
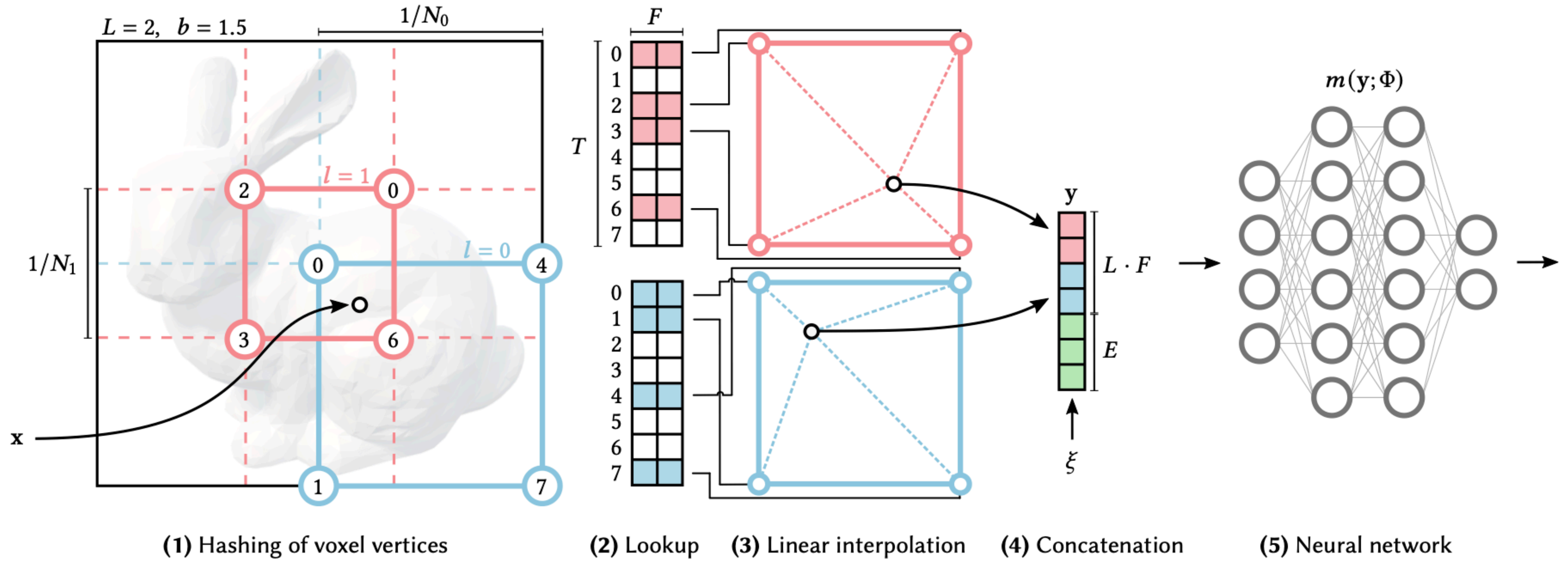


Image from Xie et al., 2022, reproduced for educational use.

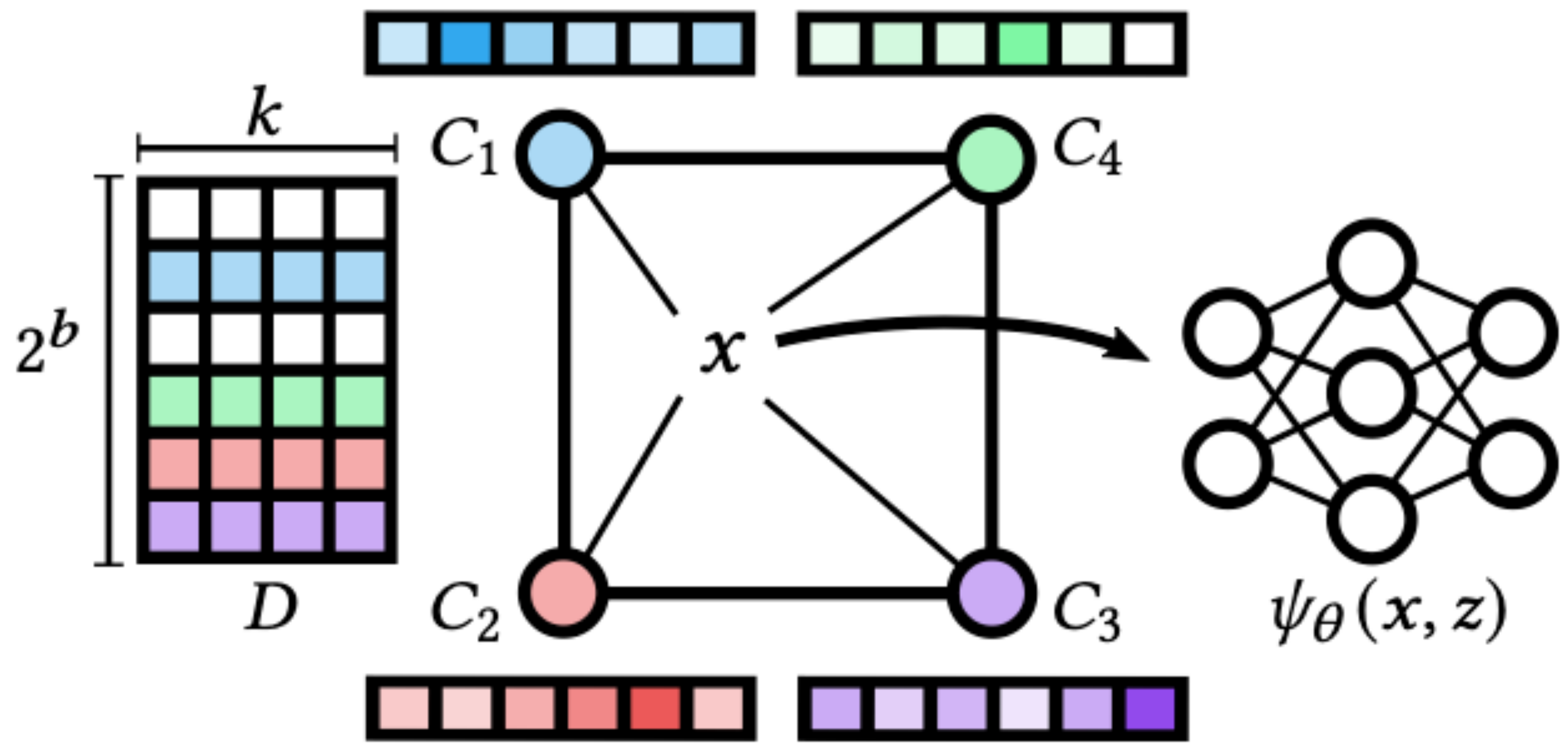
State-Of-The-Art Methods



[Takikawa et al., 2021]



[Müller et al., 2022]

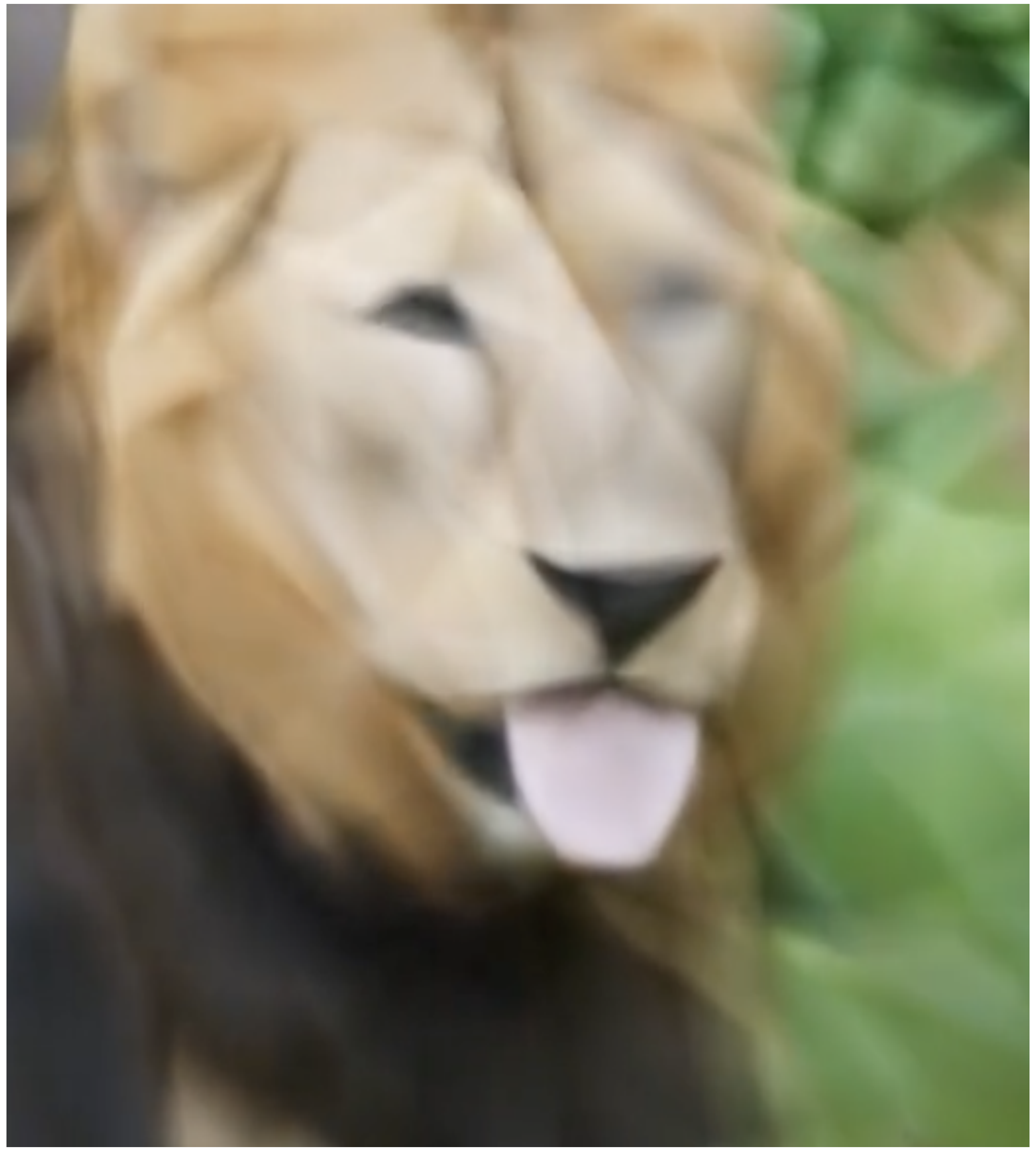


[Takikawa et al., 2022]

A missing component

[Muller et al., 2022]

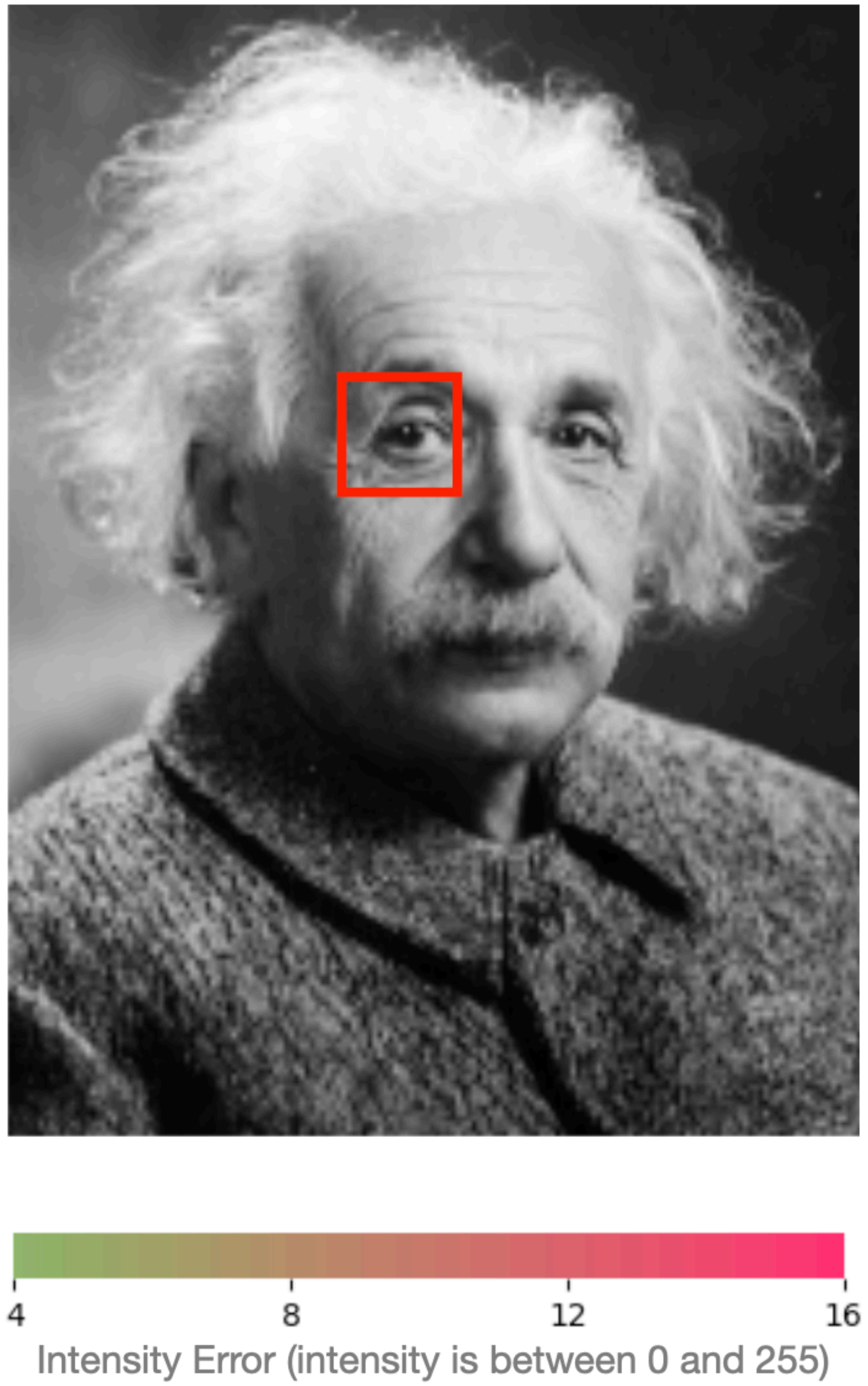
Extremely fast training via hash grids



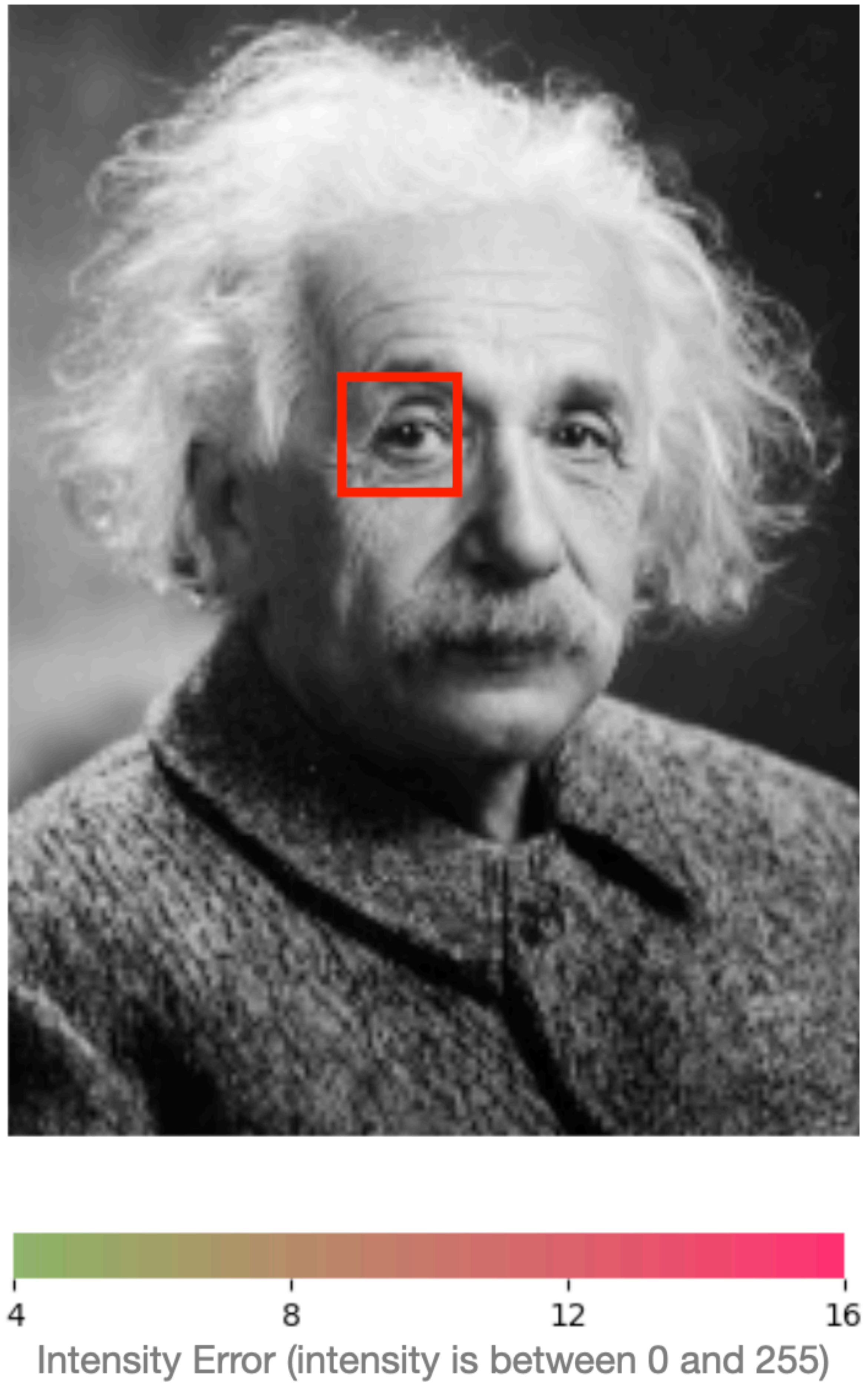
[Mildenhall et al., 2020]

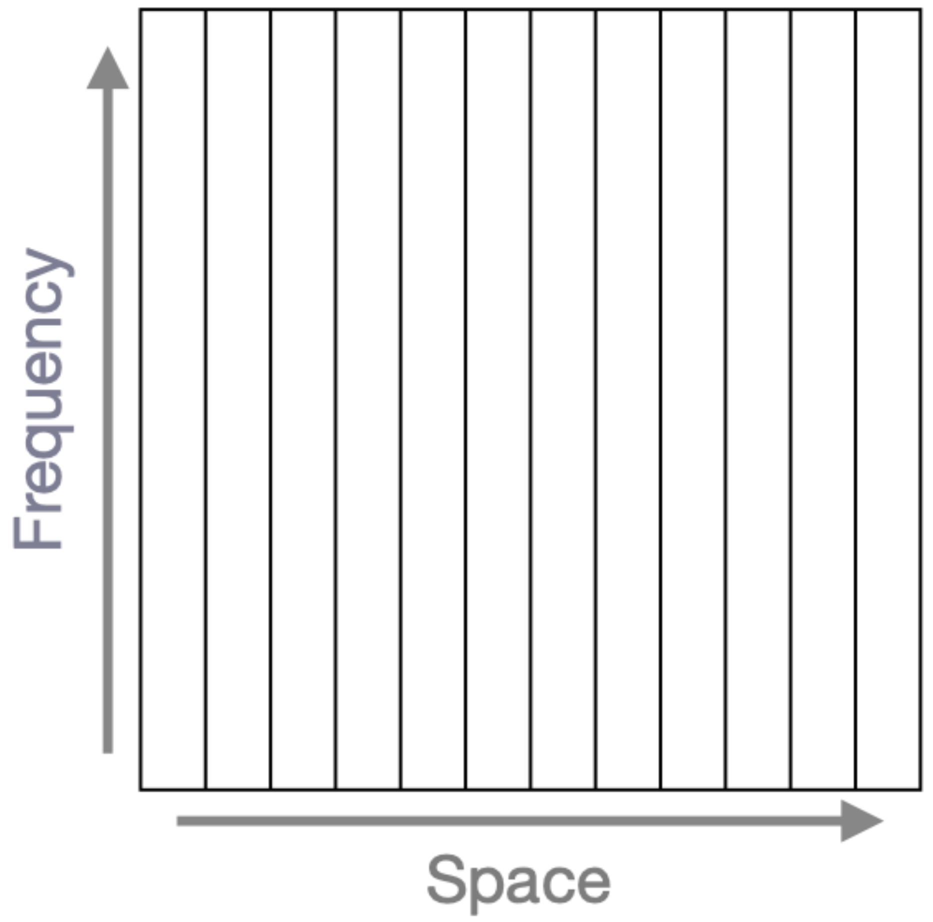
Frequency is important

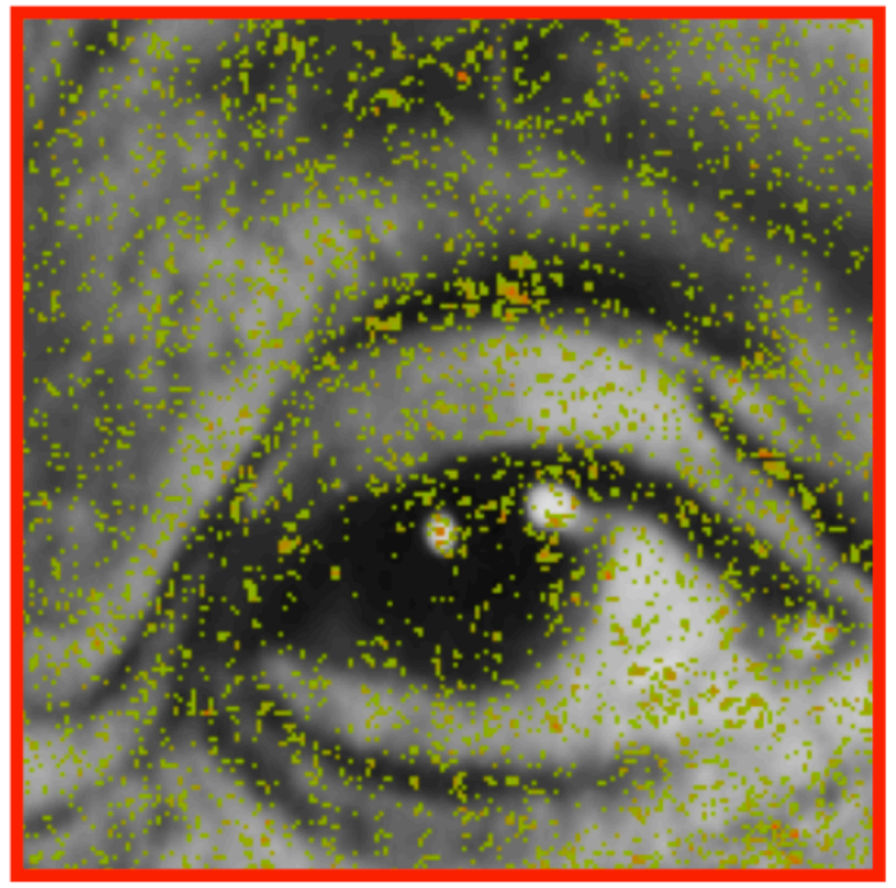
Considering both space and frequency



Considering both space and frequency



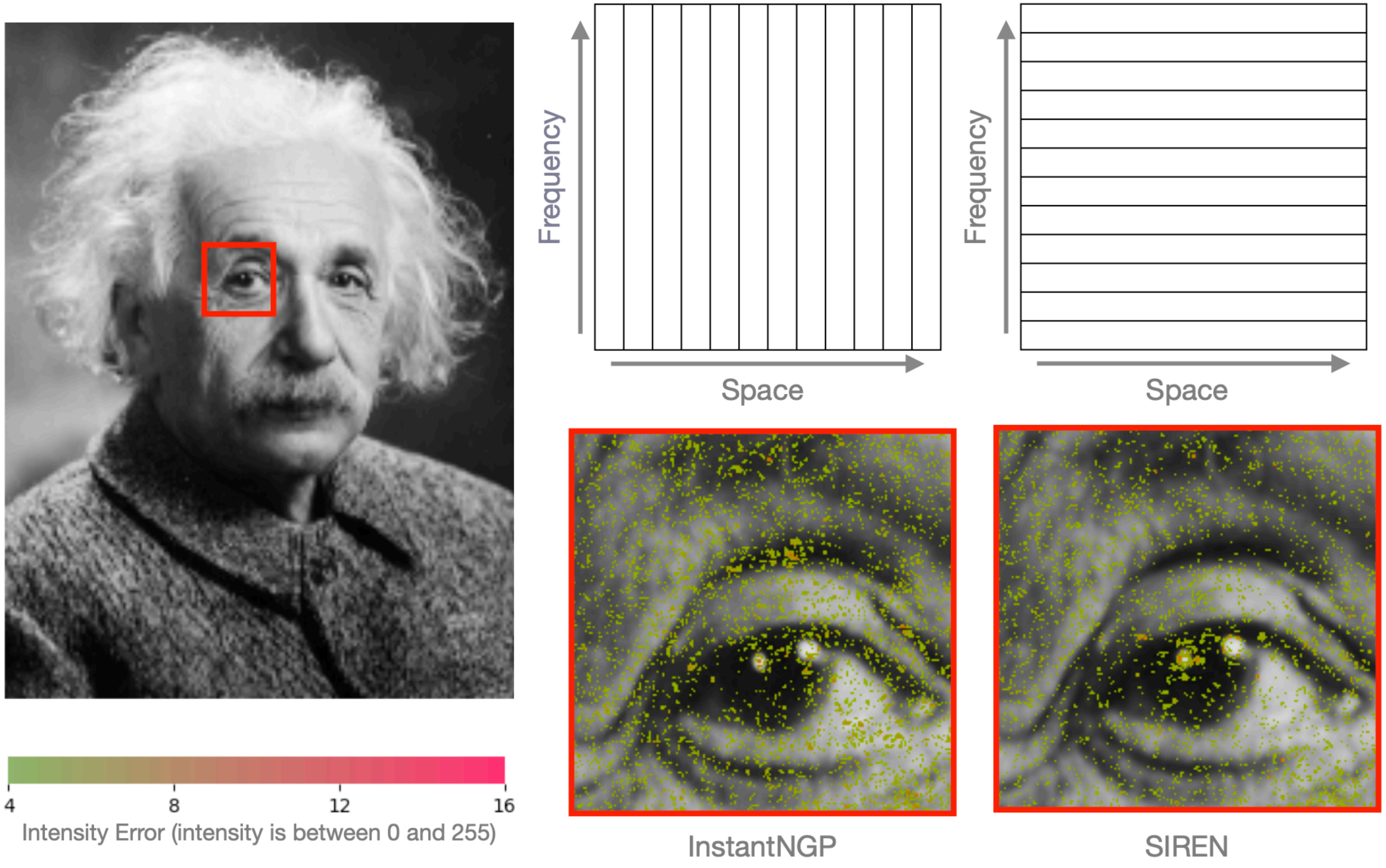




InstantNGP

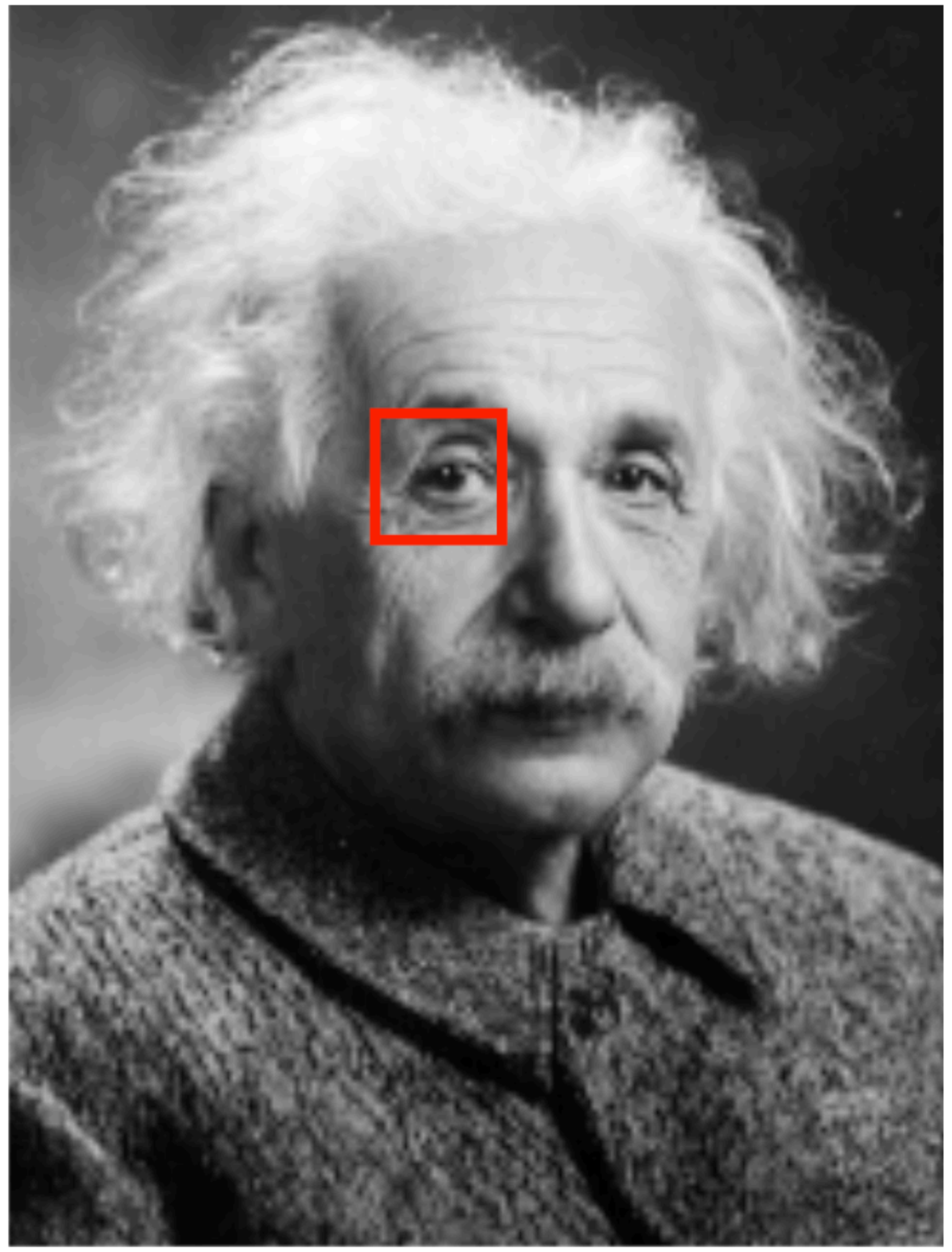
Use <u>hashgrid</u> to divide space into local regions and speed up training

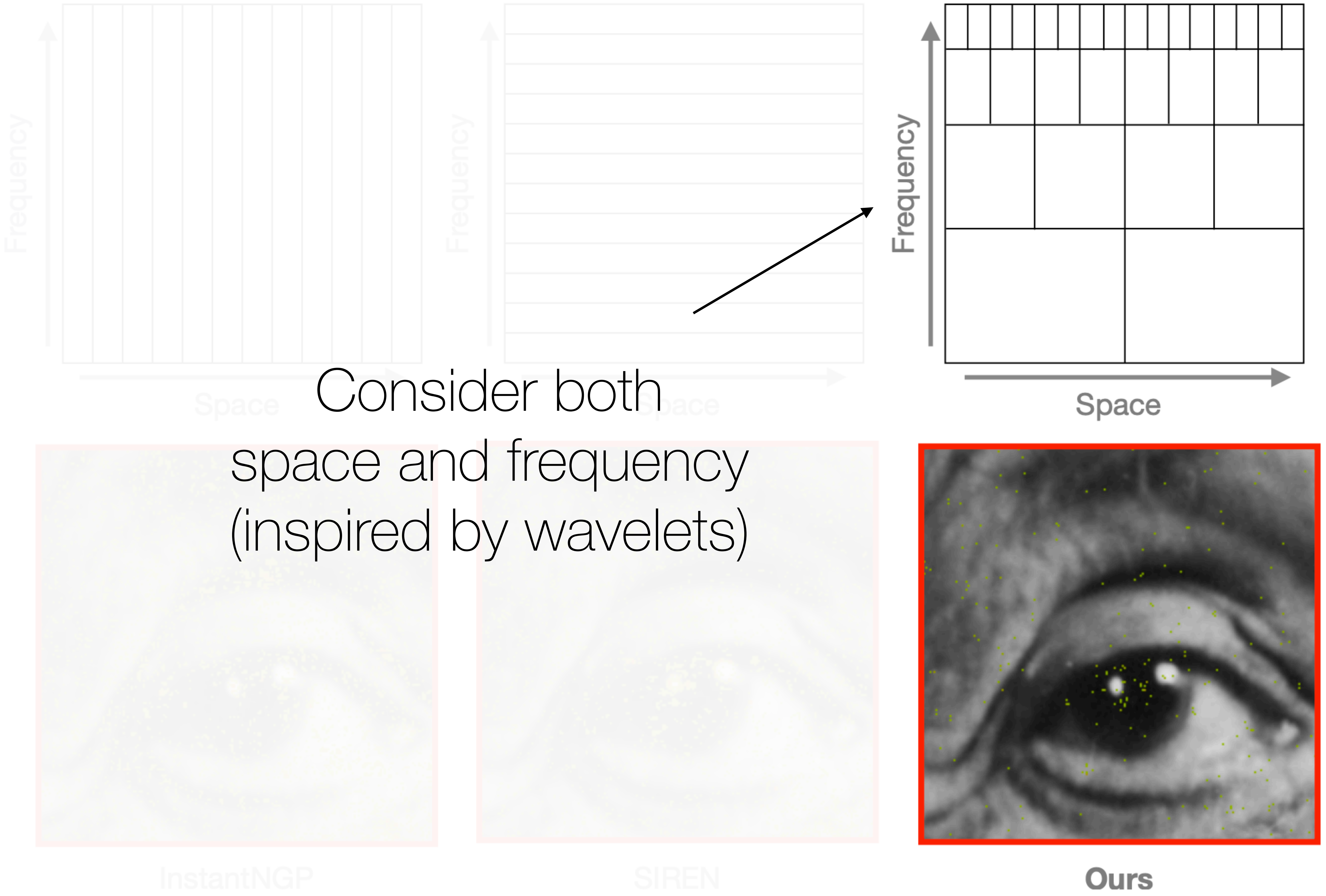
Considering both space and frequency



Analogous to neurons operating in the frequency domain via <u>sine activations</u>

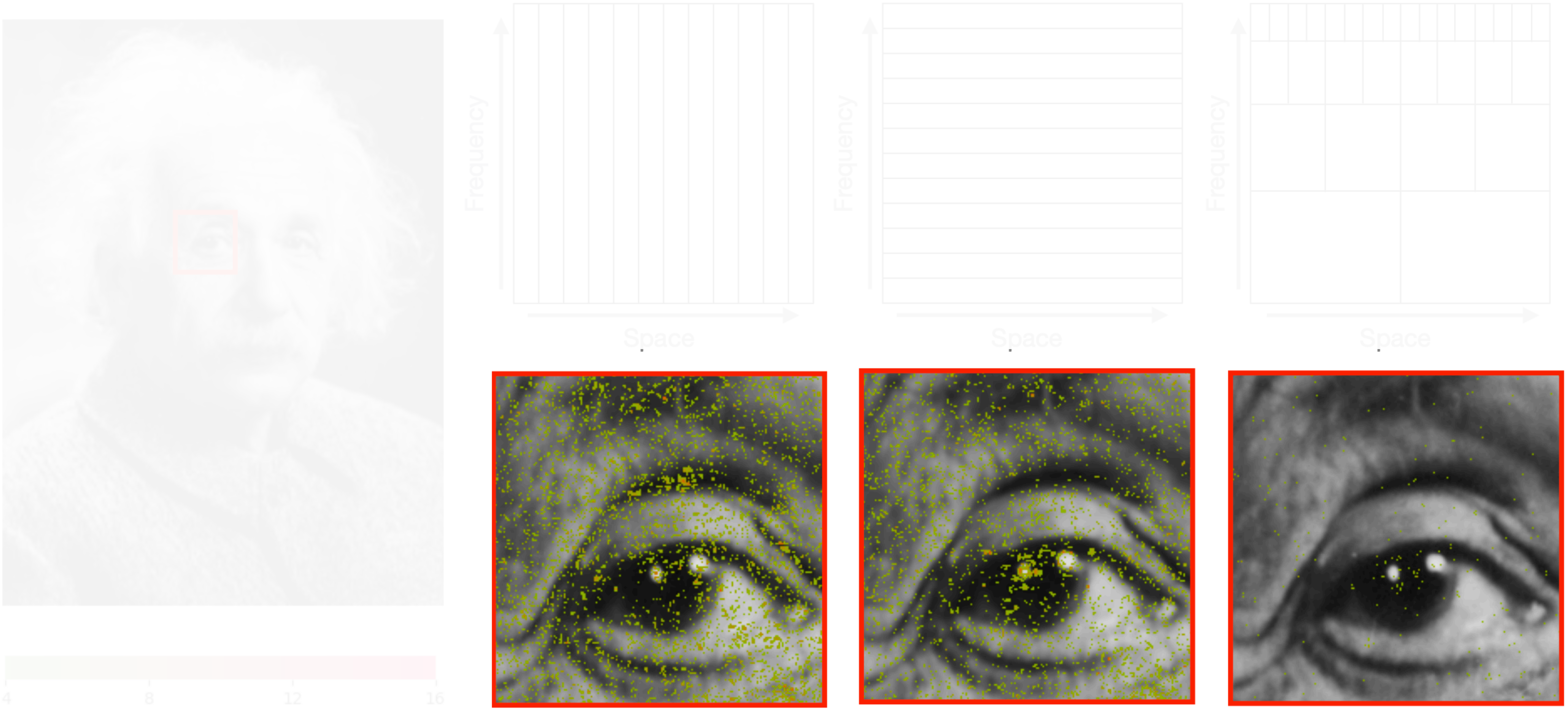
Considering both space and frequency





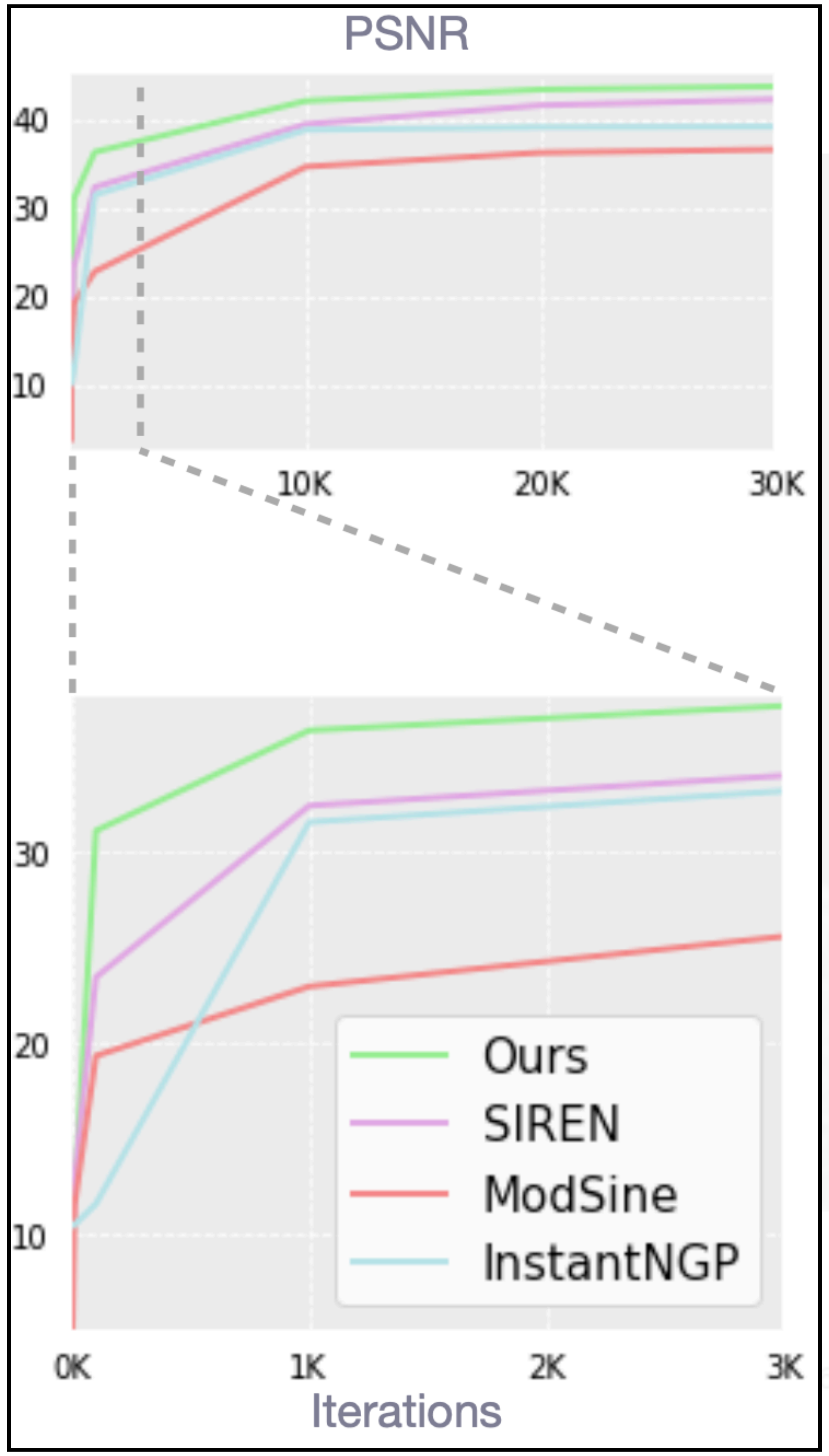
Consider both
space and frequency
(inspired by wavelets)

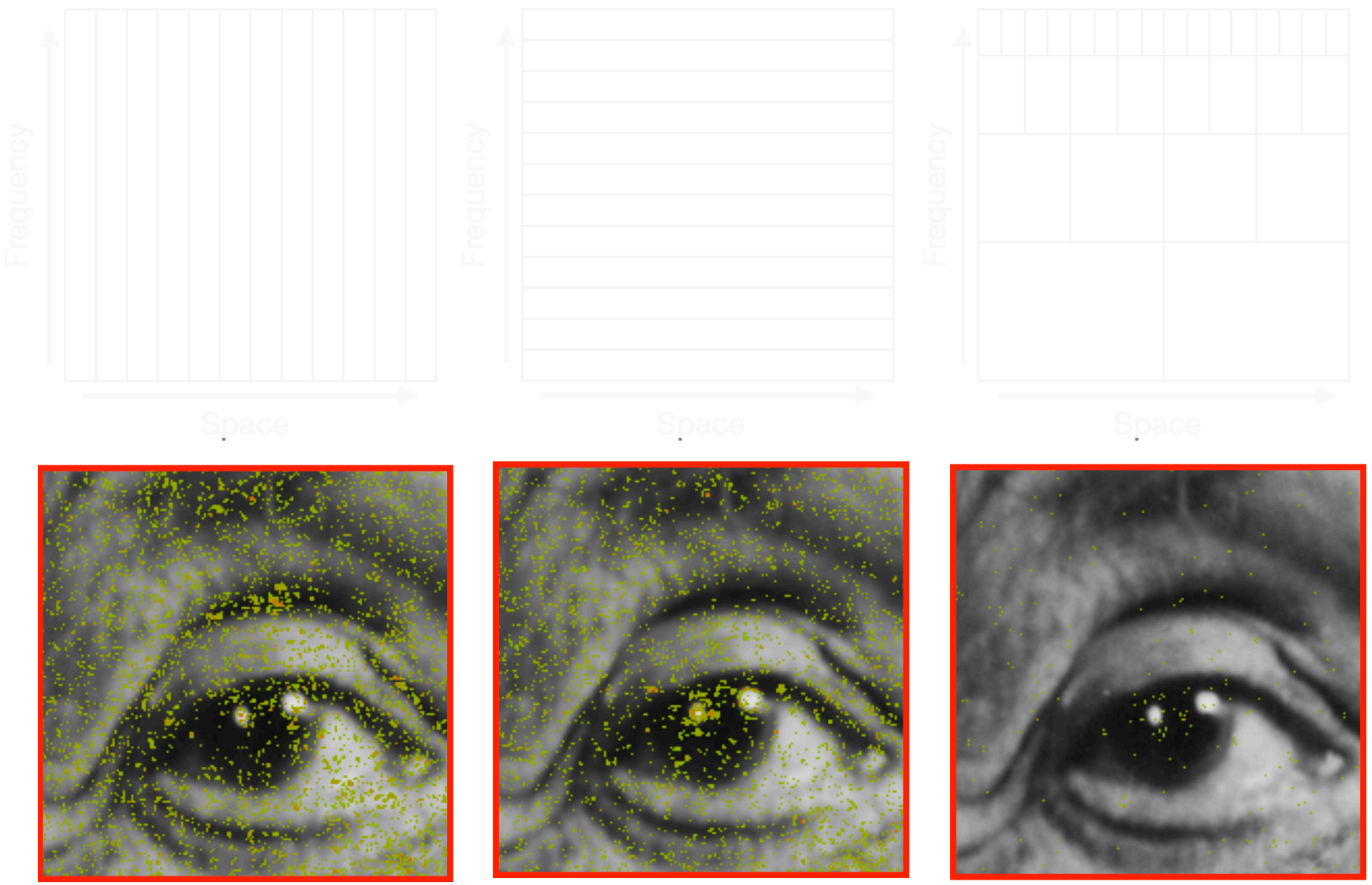
Considering both space and frequency



InstantNGP SIREN **Ours**

Considering both space and frequency

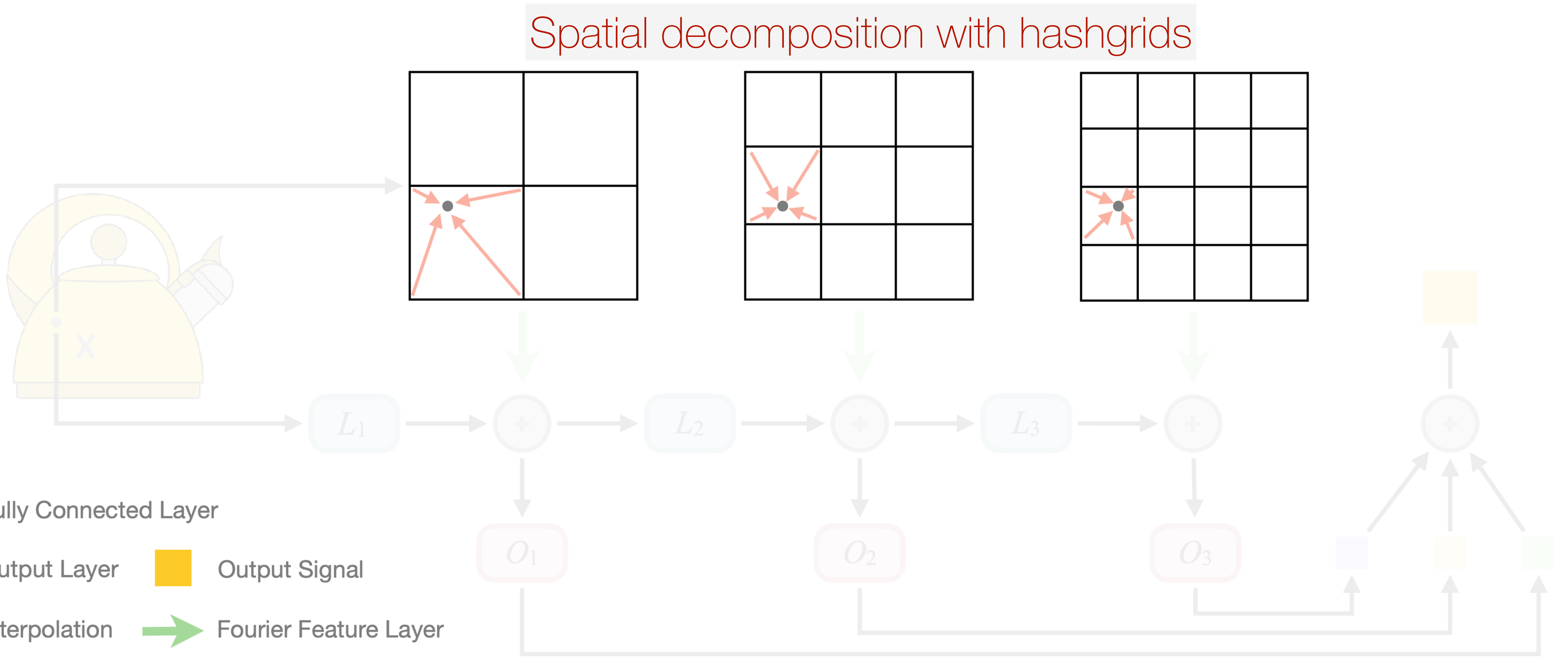




InstantNGP SIREN **Ours**

Implementing the idea as an architecture

Implementing the idea as an architecture



L Fully Connected Layer

O Output Layer

Output Signal

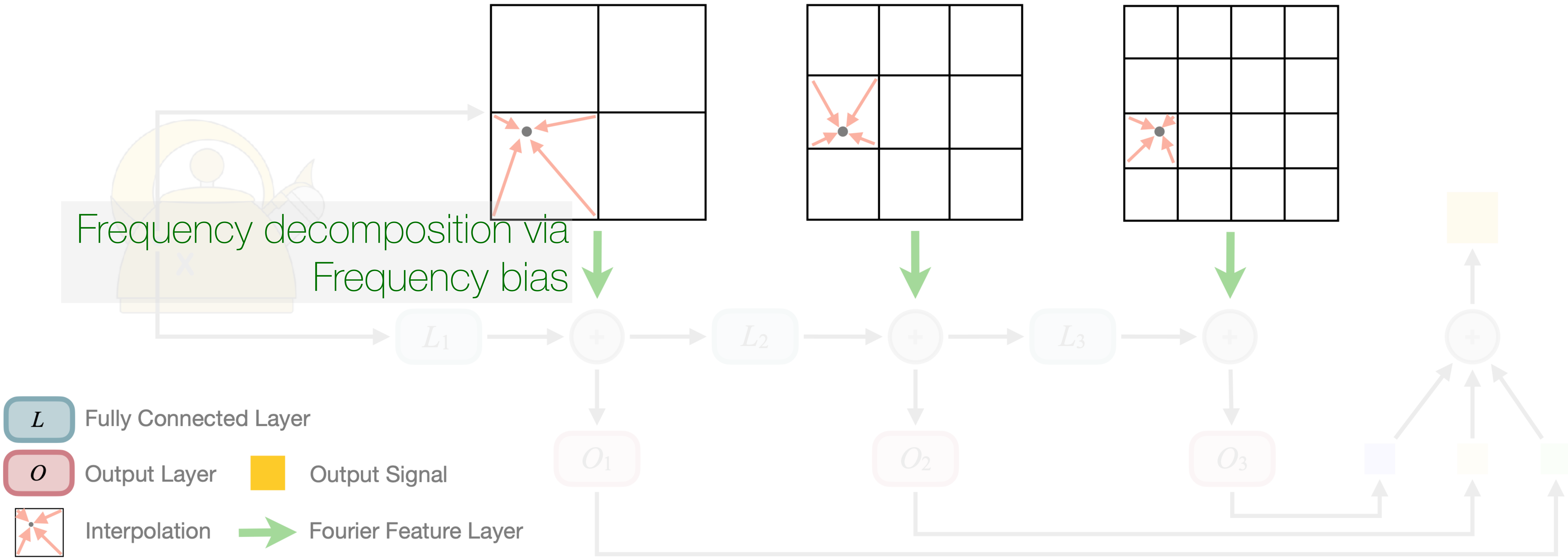
Interpolation

Fourier Feature Layer

Implementing the idea as an architecture

Spatial decomposition with hashgrids

Frequency decomposition via
Frequency bias



Implementing the idea as an architecture

Results — 2D image fitting

Ground Truth | InstantNGP | SIREN | SAPE | ModSine | Ours

Results — 2D image fitting

	Tokyo				Albert			
	Size (MB)↓	PSNR↑	SSIM↑	LPIPS↓	Size (MB)↓	PSNR↑	SSIM↑	LPIPS↓
InstantNGP [33]	36.0	33.38	0.9452	0.201	3.7	41.61	0.9623	0.152
SIREN [41]	5.2	28.52	0.8921	0.474	5.0	42.51	0.9661	0.478
SAPE [15]	**3.2**	21.64	0.5357	0.745	**3.2**	34.26	0.9219	0.399
ModSine [30]	3.5	23.23	0.7587	0.607	4.2	36.74	0.9184	0.438
Ours	4.1	31.57	0.9403	0.187	-	-	-	-
Ours	10.0	**33.62**	**0.9555**	**0.141**	3.7	**43.83**	**0.9763**	**0.142**

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Best quality among similar #params

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Improved quality with <1/3 #param

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Results — 2D image fitting

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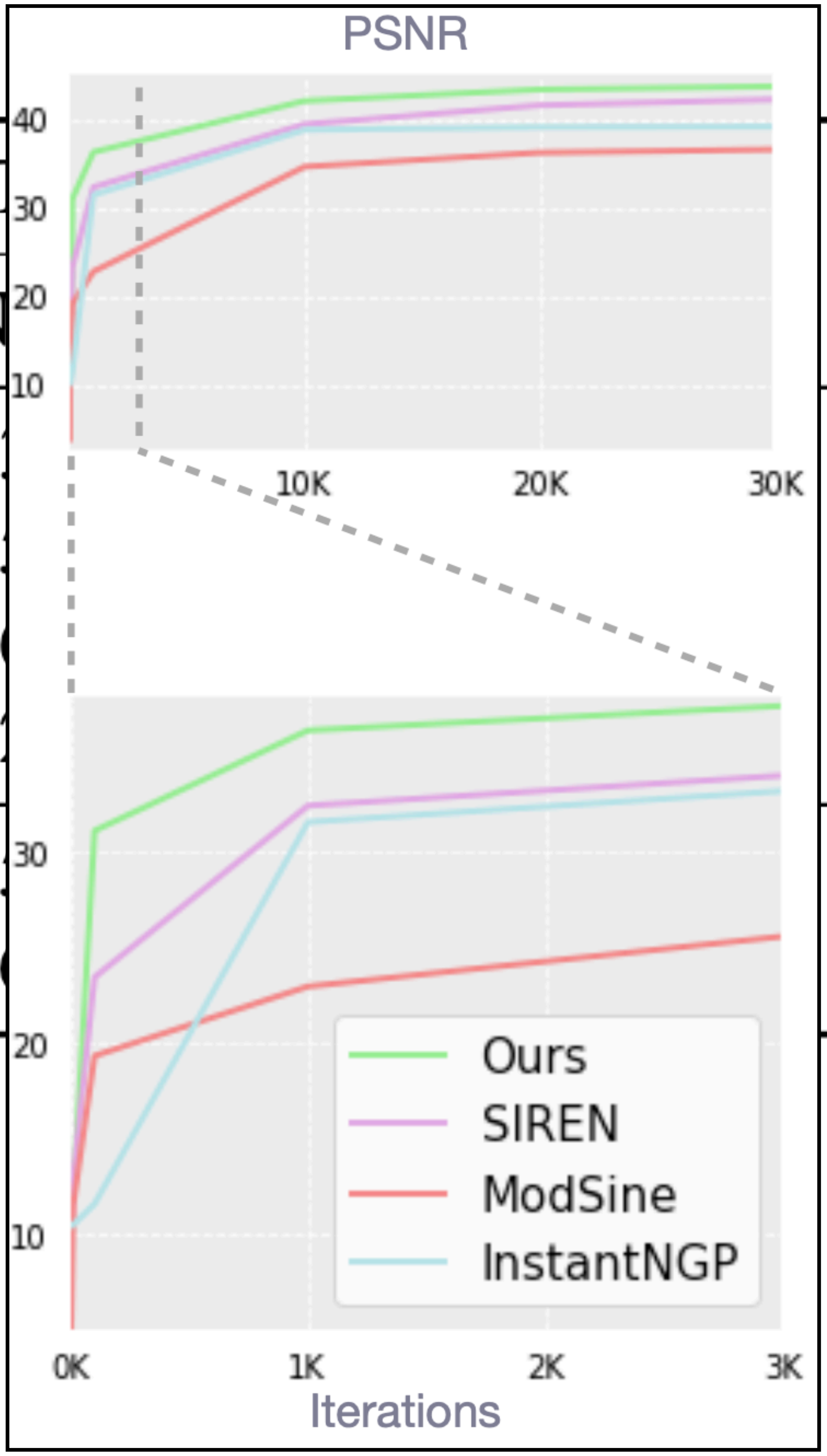


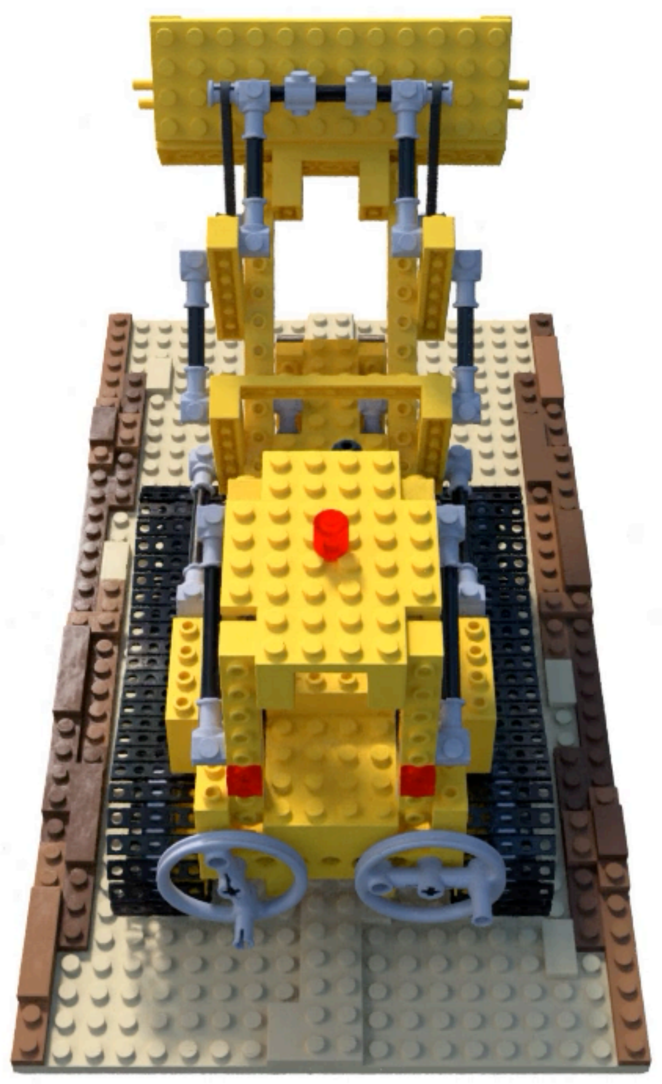
Best result with faster convergence

Results — 3D shape fitting

On par, but with 1/40 #params

	Size (MB)↓	Asian Dragon			Beard Man		
		F-score↑	IoU↑	Cham dist↓	F-score↑	IoU↑	Cham dist↓
InstantNGP [33]	46.5	0.8714	**1.0**	0.00191	**0.999**	0.9970	**0.00272**
Ours	**1.4**	0.8717	**1.0**	**0.00189**	**0.999**	**0.9985**	**0.00272**

Results — NeRF

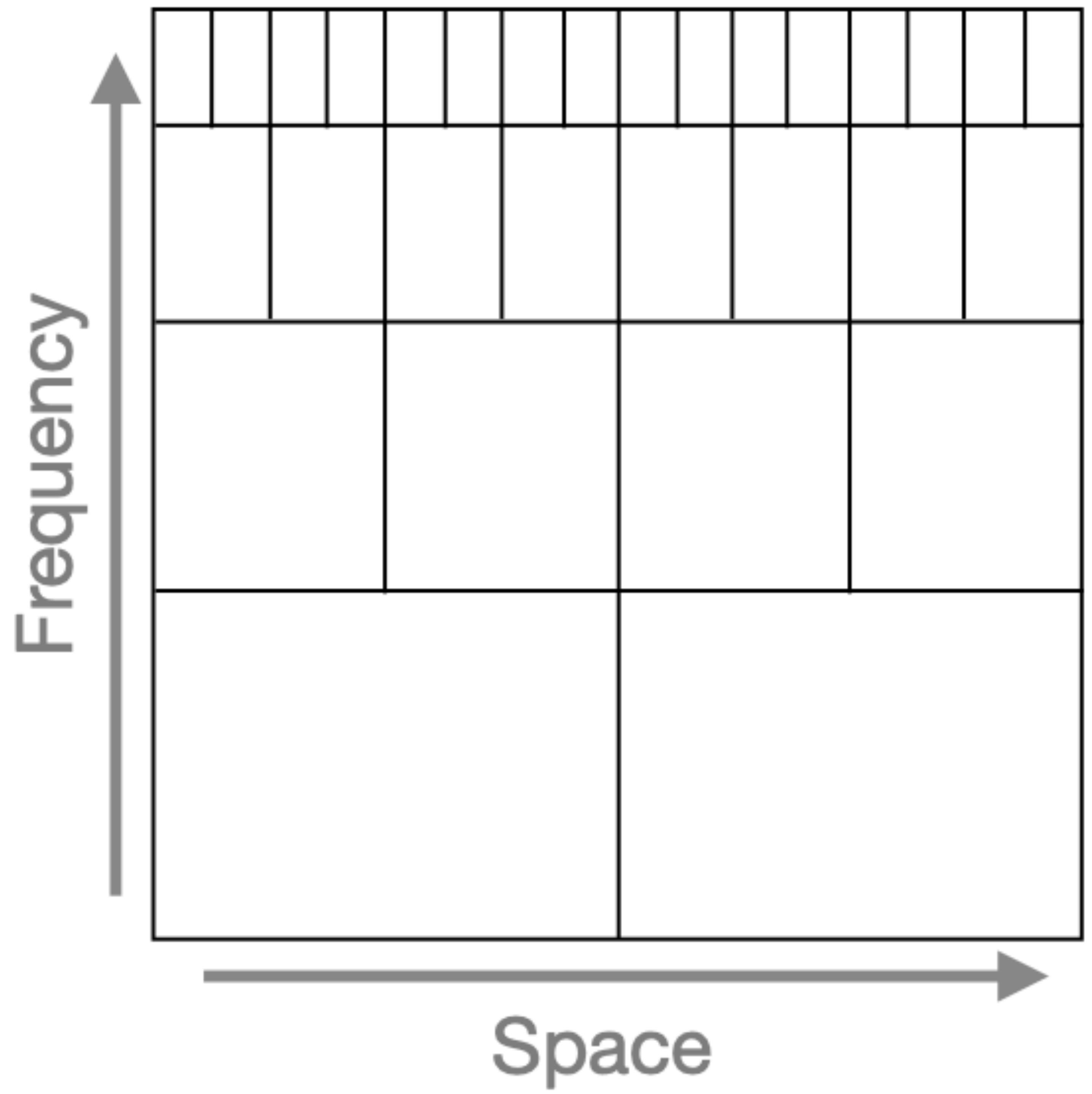


	Steps	Size (MB) ↓	Time ↓	PSNR ↑	SSIM ↑
NeRF [36]	300k	5.0	> 30h	31.01	0.947
Plenoxels [45]	128k	778.1	11.4m	31.71	0.958
DVGO [50]	30k	612.1	15m	31.95	0.957
InstantNGP [37]	30k	46.6	3.4m	32.08	0.955
Ours	30k	14.7	13.1m	32.04	0.955

Similar performance but with less #param and fewer steps

Summary

- We propose a novel framework that decomposes the modeled signal both spatially and frequency-wise
- Our method achieves better trade-off between result quality and network complexity on three tasks



Summary

- We propose a novel framework that decomposes the modeled signal both spatially and frequency-wise
- Our method achieves better trade-off between result quality and network complexity on three tasks

- Released codes & Implementation details: https://github.com/ubc-vision/NFFB
- Project webpage: https://zhijiew94.github.io/NFFB