

Efficient and accurate inversion of multiple scattering with deep learning

Yu Sun

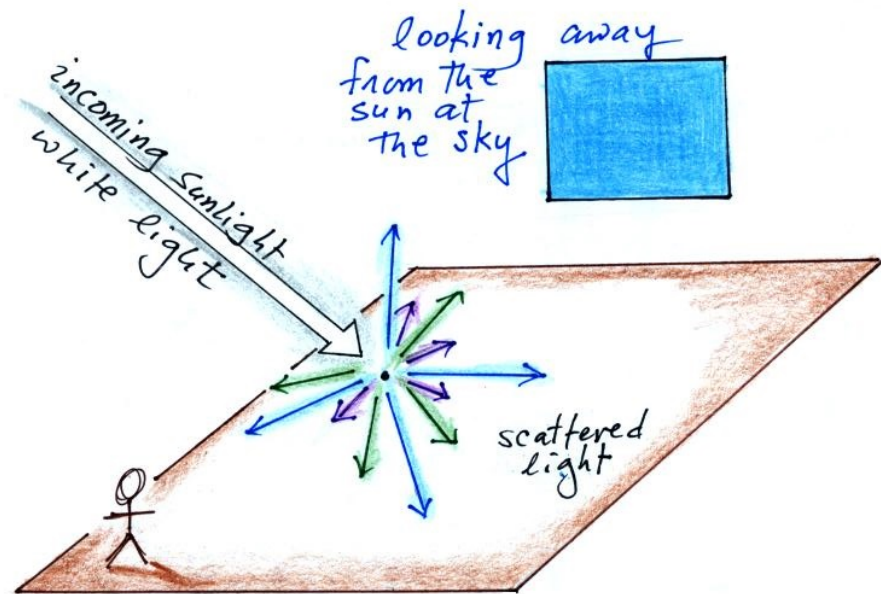


iTWIST, CIRM, Marseille, France. November, 2018

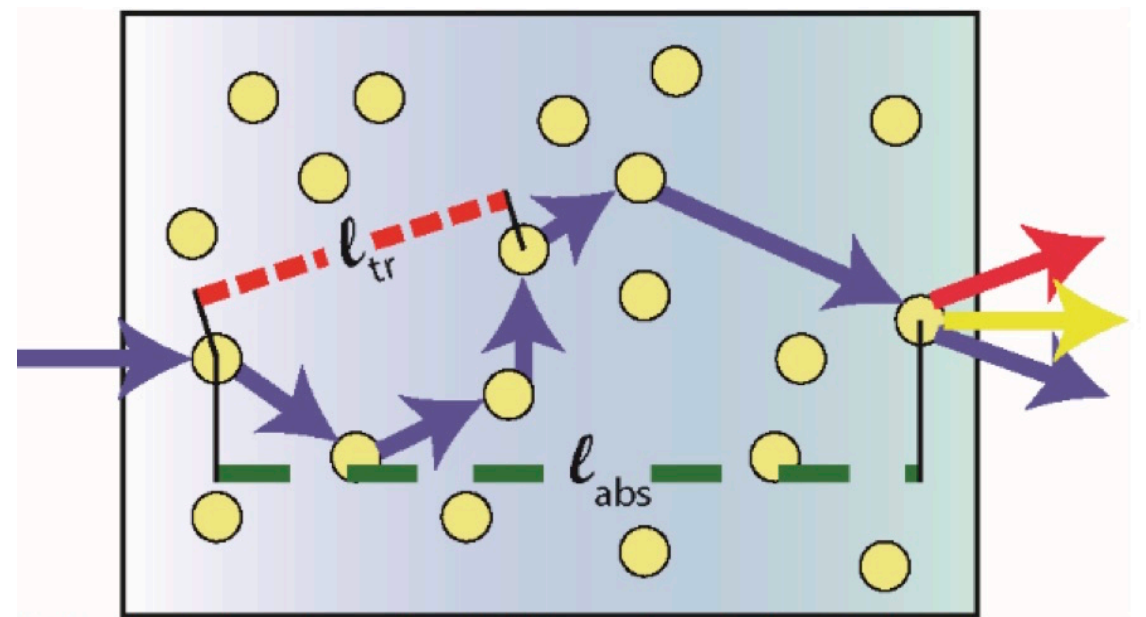
Thanks for the NSF support under grant No. 1813910.

What is multiple scattering ?

- **Interaction between wave and object**
- Related to refractive index



Single/**linear** scattering

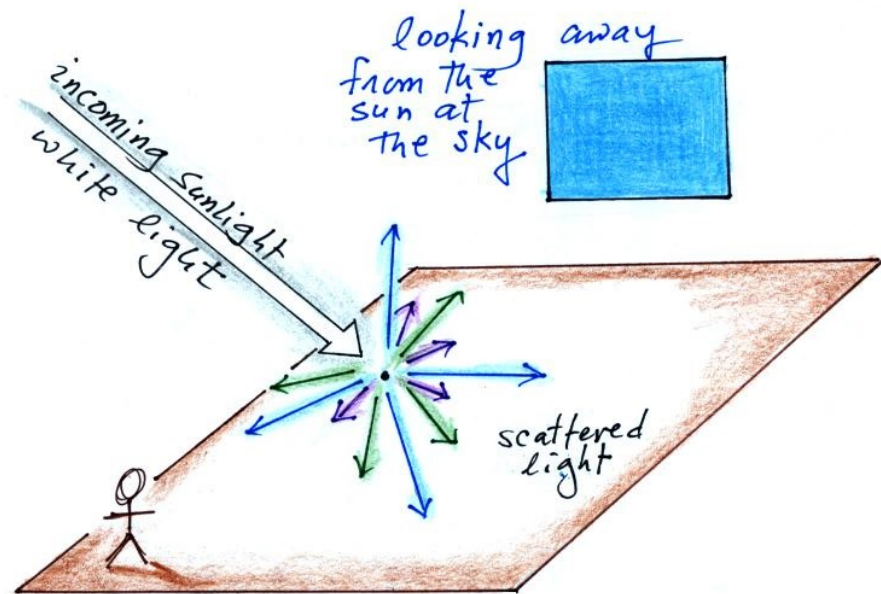


Multiple/**nonlinear** scattering

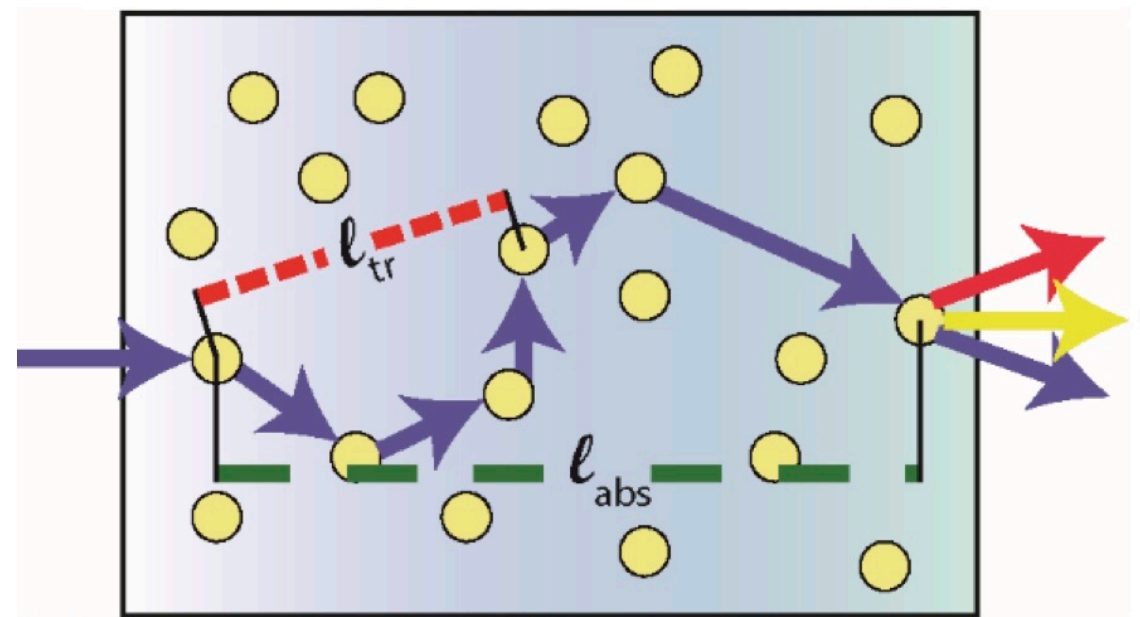
What is multiple scattering ?

- Interaction between wave and object
- **Related to refractive index**

$$f \uparrow \sim \text{Scattering strength} \uparrow$$



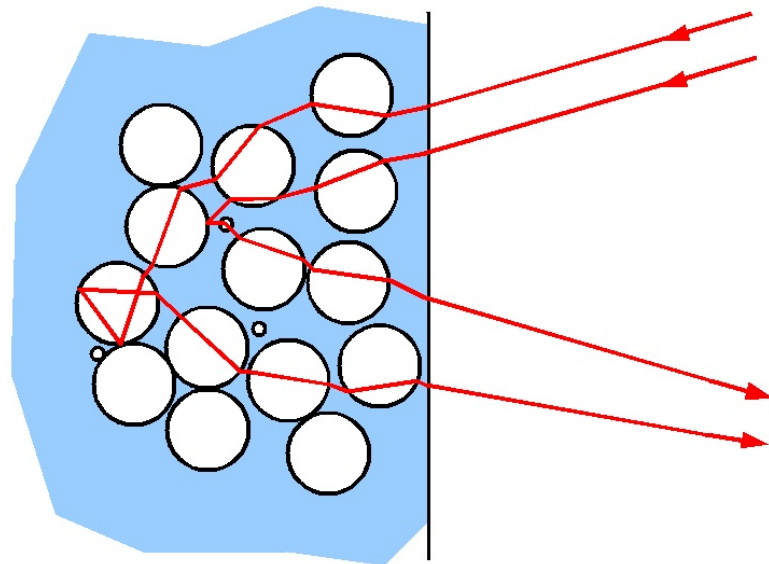
Single/**linear** scattering



Multiple/**nonlinear** scattering

Scattering exists in wave imaging

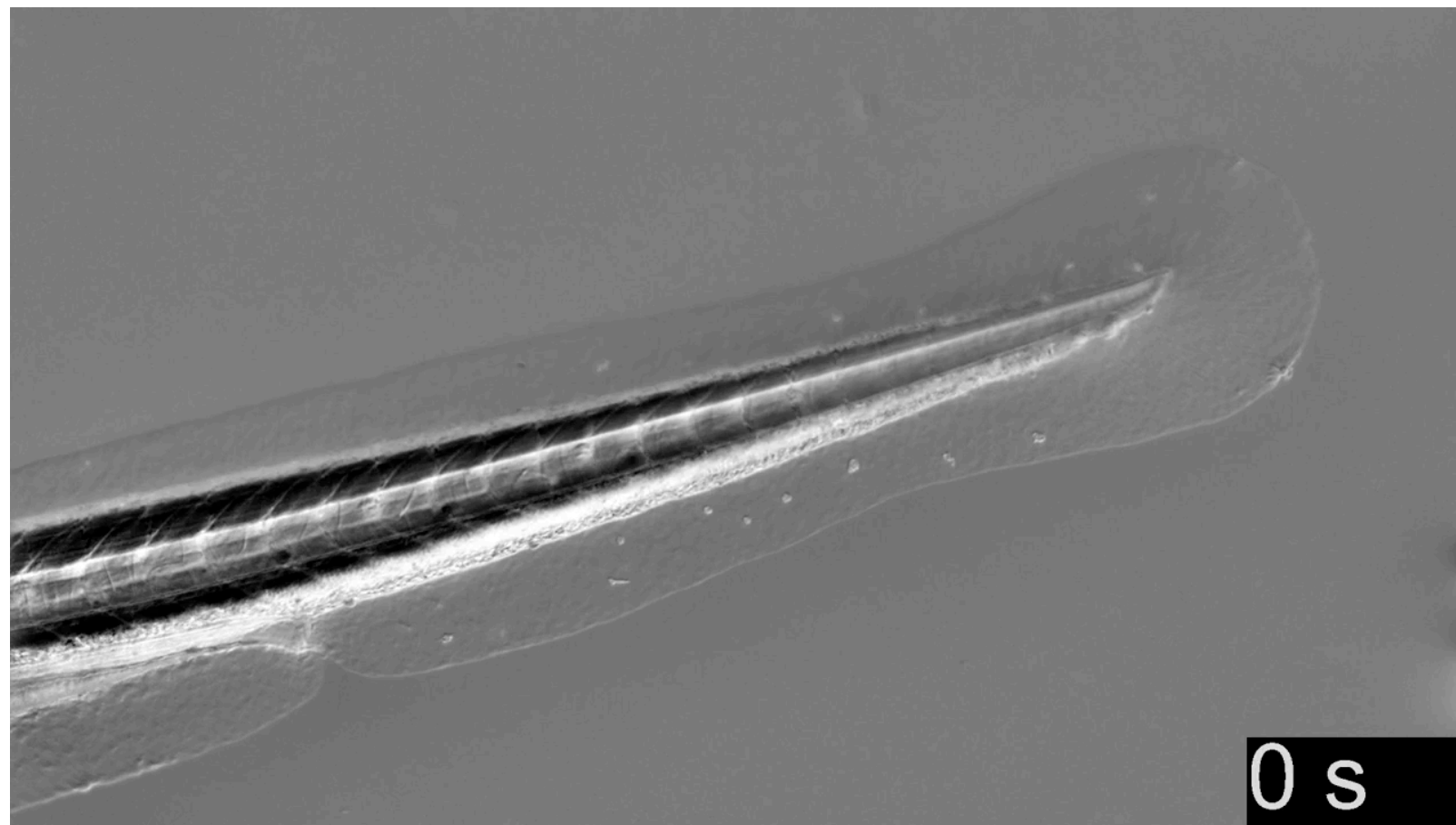
Hilarious Scattering



His brother?

Reconstruct image by inverting scattering

- Microwave imaging
- Ultrasound refraction tomography
- **Optical diffraction tomography [T. Kim et al., 2014]**
- ...

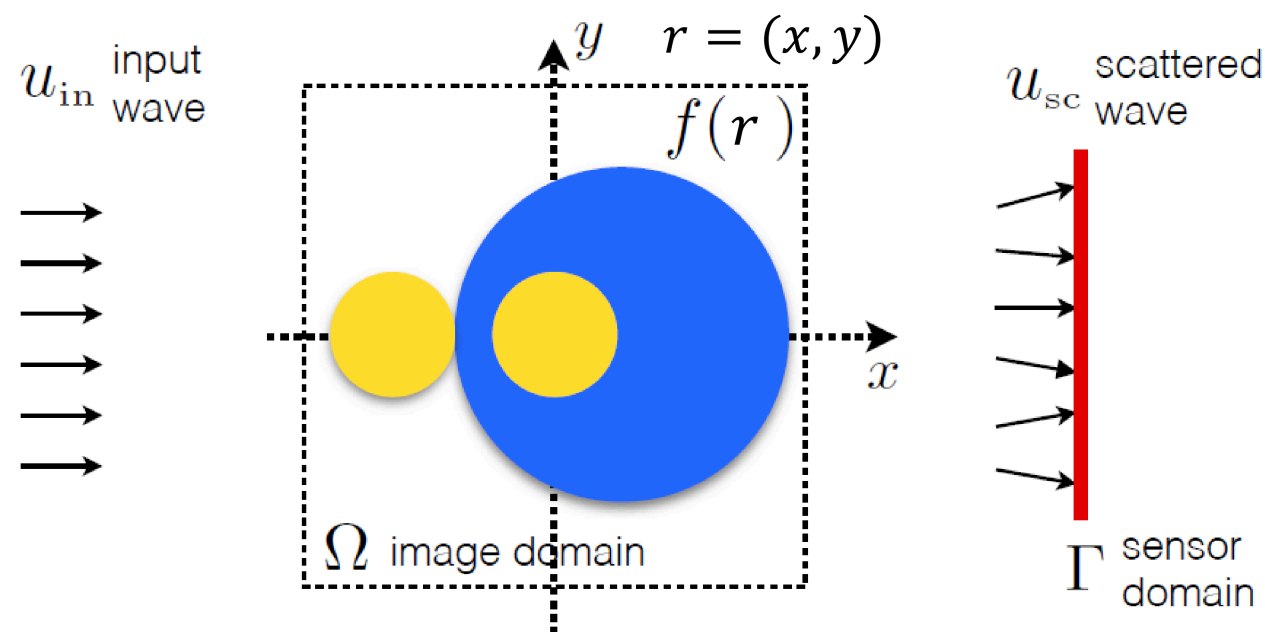


Zebra fish dynamics

Inverting scattering as inverse problem

- **Lippmann-Schwinger equation [Lippmann & Schwinger, 1950]**
- Optimization formulation
- ISTA/FISTA/ADMM
- Effective in practice

$$u(\mathbf{r}) = u_{\text{in}}(\mathbf{r}) + k^2 \int_{\Omega} g(\mathbf{r} - \mathbf{r}') u(\mathbf{r}') f(\mathbf{r}') d\mathbf{r}', \quad \forall \mathbf{r} \in \mathbb{R}^d.$$



Inverting scattering as inverse problem

- Lippmann-Schwinger equation
- **Optimization formulation**
- ISTA/FISTA/ADMM
- Effective in practice

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{f} \in \mathbb{R}^N} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{H}(\mathbf{f})\|_{\ell_2}^2 + \mathcal{R}(\mathbf{f}) \right\},$$

data-fidelity regularizer

where

$$\mathbf{H}(\mathbf{f}) = \mathbf{S} \text{diag}(\mathbf{u}(\mathbf{f})) \mathbf{f}$$

$\mathbf{u}(\mathbf{f}) = \mathbf{u}_{\text{in}}$ **linear ~ single scattering**

$\mathbf{u}(\mathbf{f}) \neq \mathbf{u}_{\text{in}}$ **nonlinear ~ multiple scattering**

Inverting scattering as inverse problem

- Lippmann-Schwinger equation
- Optimization formulation
- **ISTA/FISTA/ADMM**
- Effective in practice

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{f} \in \mathbb{R}^N} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{H}(\mathbf{f})\|_{\ell_2}^2 + \mathcal{R}(\mathbf{f}) \right\},$$

data-fidelity regularizer

where

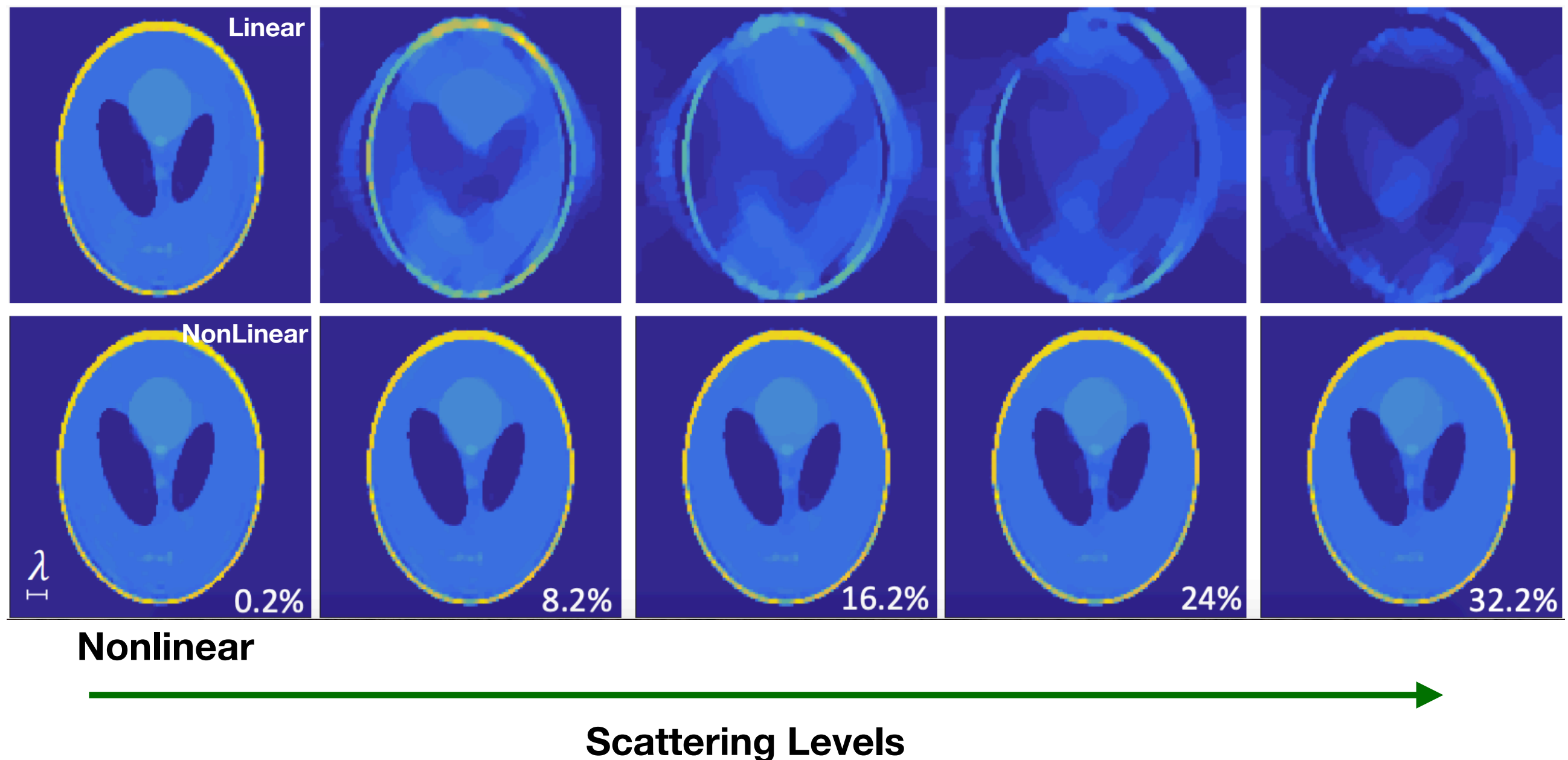
$$\mathbf{H}(\mathbf{f}) = \mathbf{S} \text{diag}(\mathbf{u}(\mathbf{f})) \mathbf{f}$$

$\mathbf{u}(\mathbf{f}) = \mathbf{u}_{\text{in}}$ linear ~ single scattering

$\mathbf{u}(\mathbf{f}) \neq \mathbf{u}_{\text{in}}$ nonlinear ~ multiple scattering

Results obtained by linear/nonlinear FISTA-TV

- Effective in practice



But, optimization-based methods have drawbacks

- **Slow reconstruction**
 - ~ hours for 1 example
- **Artifacts / inaccurate**
 - strong noise

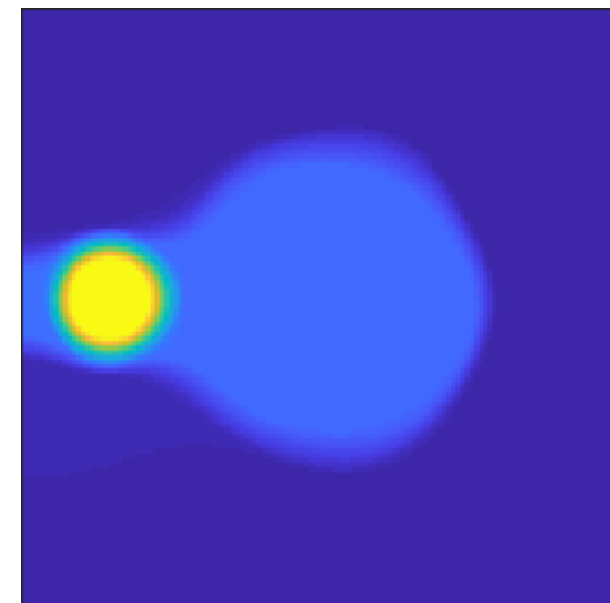
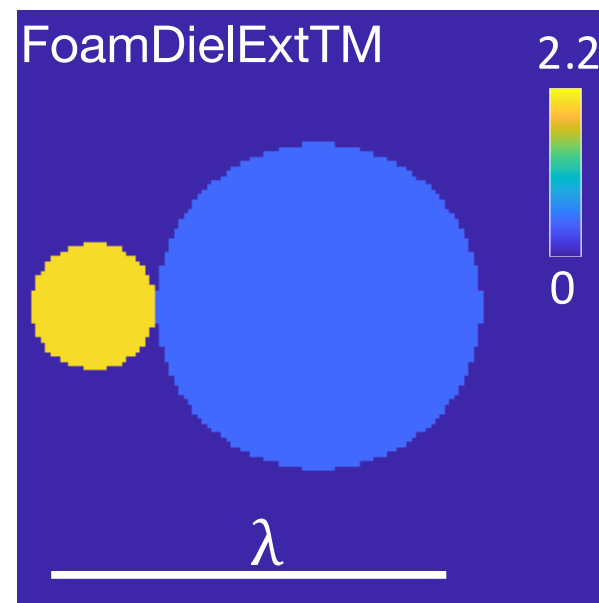
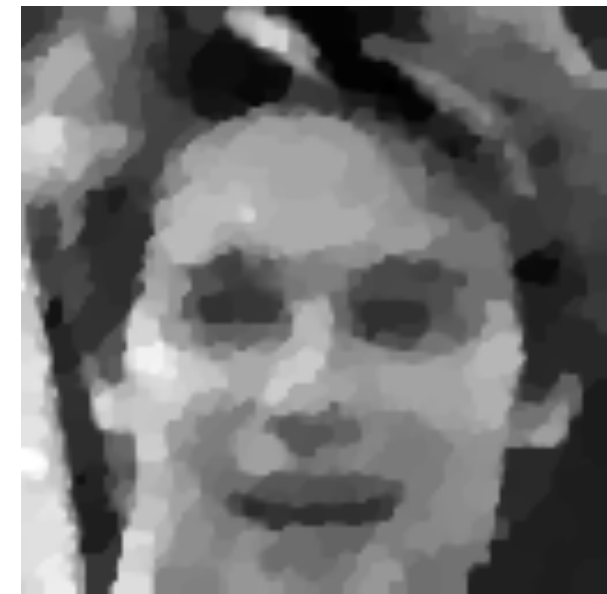
$$u(\mathbf{r}) = u_{\text{in}}(\mathbf{r}) + k^2 \int_{\Omega} g(\mathbf{r} - \mathbf{r}') u(\mathbf{r}') f(\mathbf{r}') d\mathbf{r}', \quad \forall \mathbf{r} \in \mathbb{R}^d.$$

$$\mathbf{u}^* = \underset{\mathbf{u}}{\operatorname{argmin}} \|\mathbf{A}\mathbf{u} - \mathbf{u}_{\text{in}}\|_2^2$$

$$\text{where } \mathbf{A} := \mathbf{I} - \mathbf{G}\text{diag}(\mathbf{f})$$

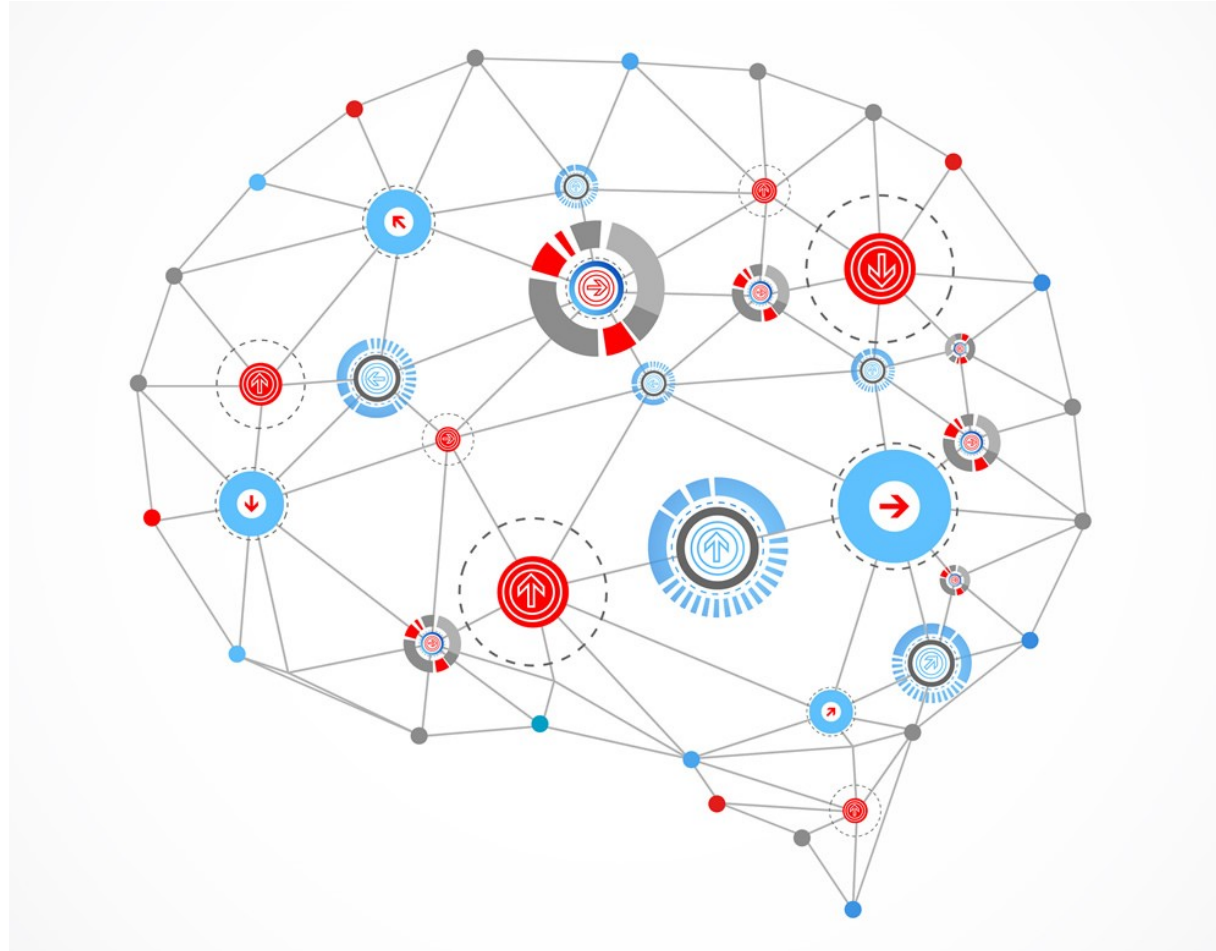
But, optimization-based methods have drawbacks

- **Slow reconstruction**
 - ~ hours for 1 example
- **Artifacts / inaccurate**
 - strong noise



FISTA-TV, Input SNR = 20 dB, Strong scattering

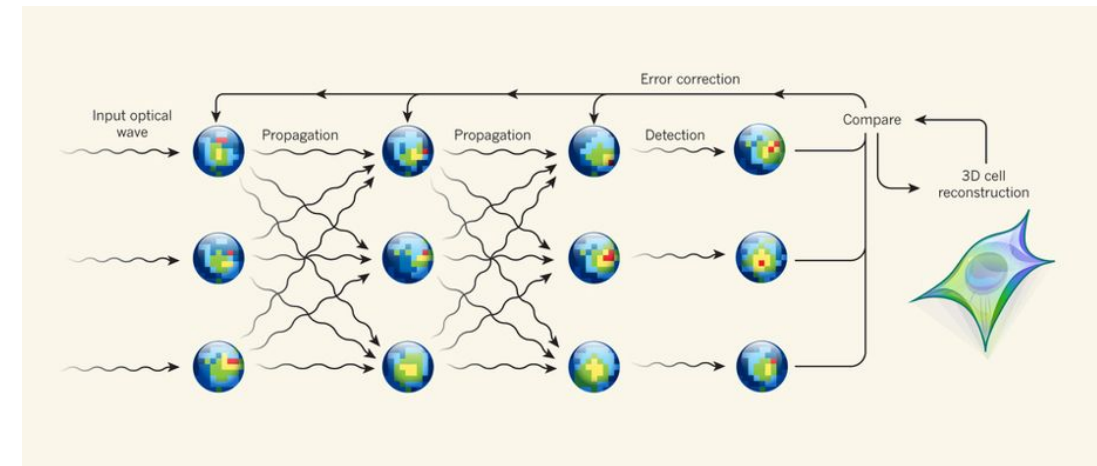
Can we do faster and more accurate simultaneously ?



Deep Learning !

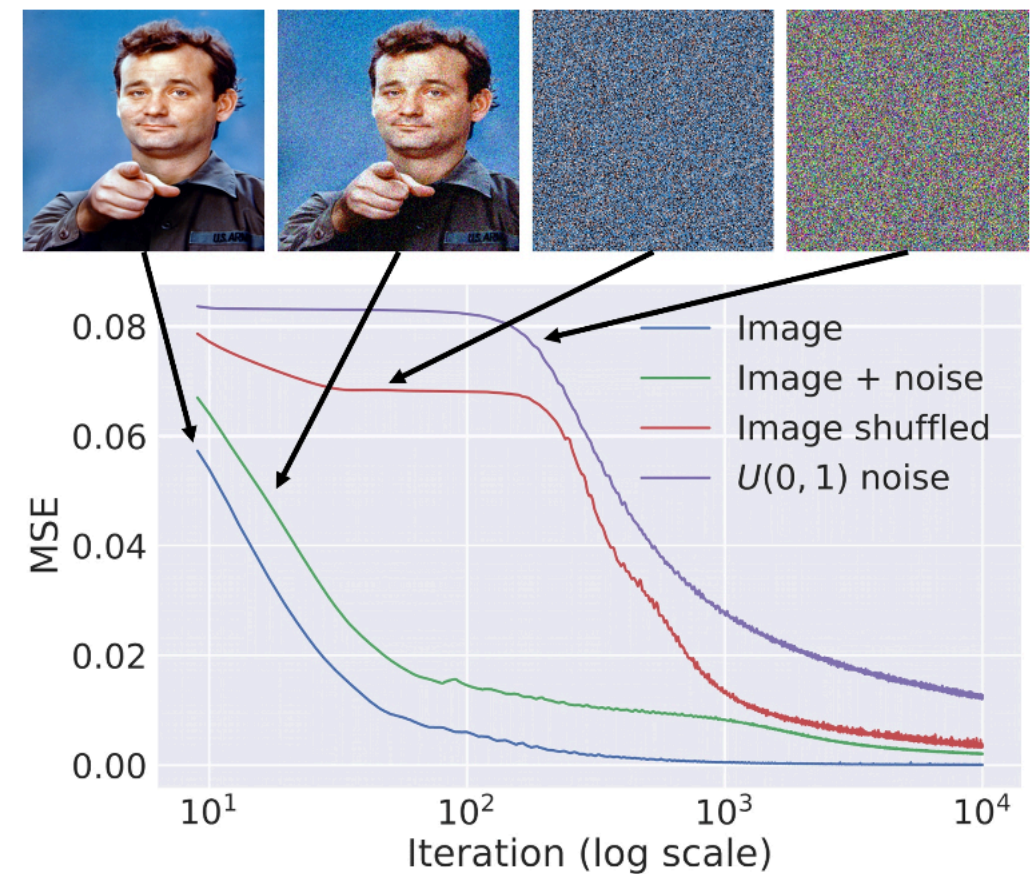
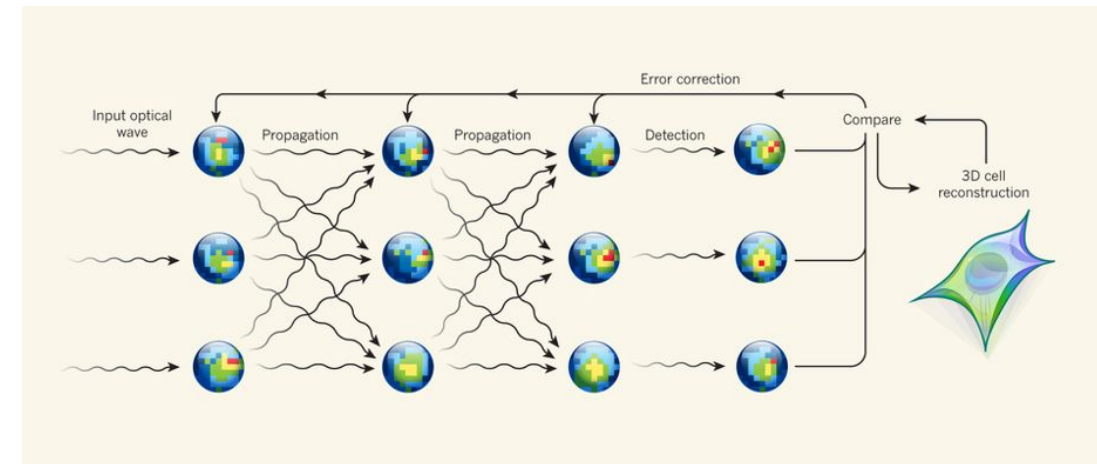
Why we consider deep learning ?

- **Multiple scattering = repeated convolutions**
 - Inverting scattering = repeated deconvolution



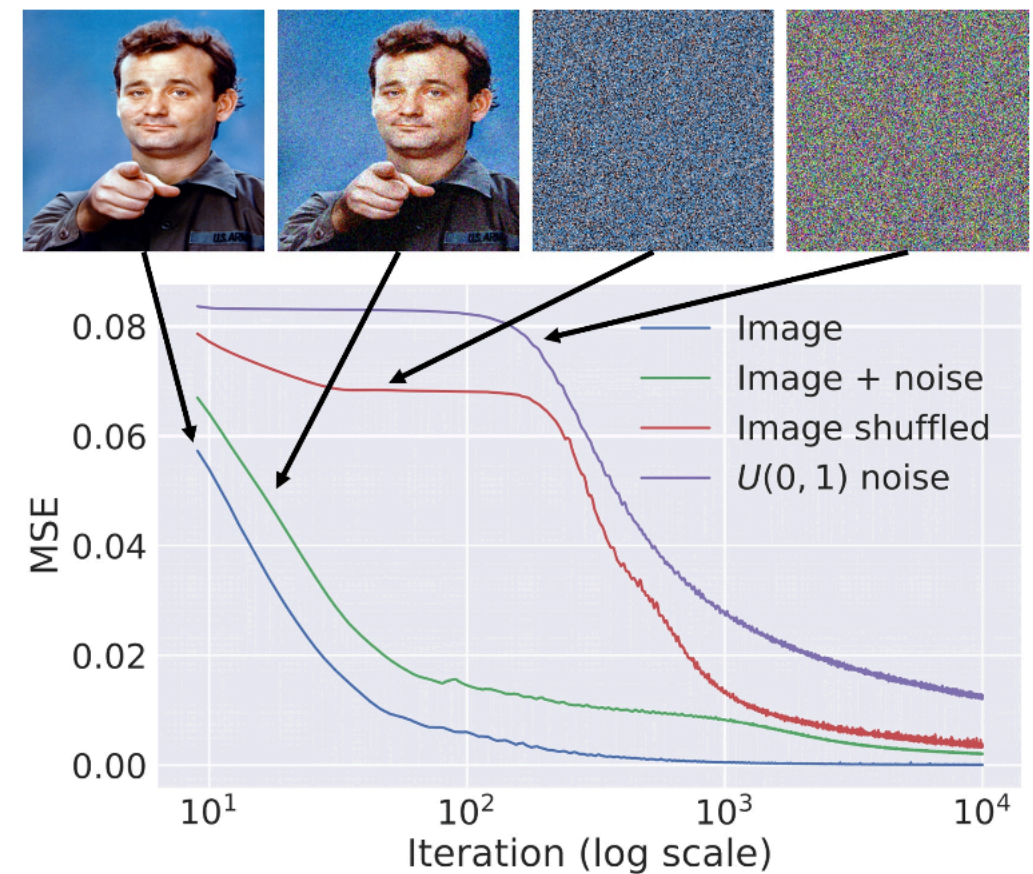
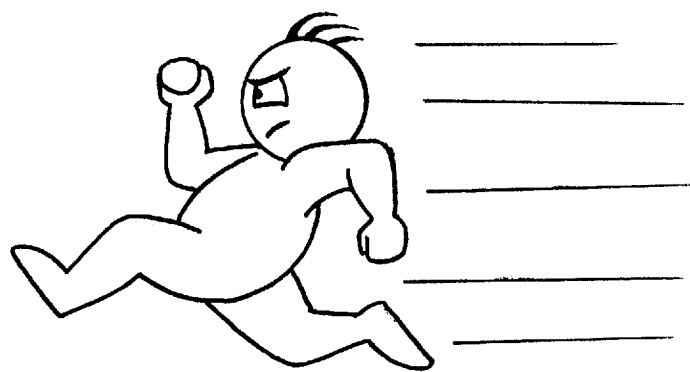
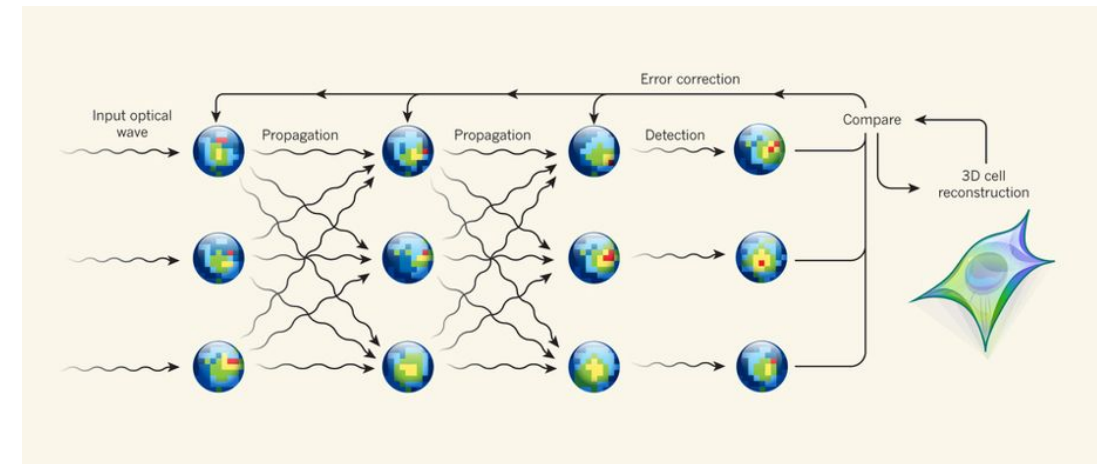
Why we consider deep learning ?

- **Multiple scattering = repeated convolutions**
 - Inverting scattering = repeated deconvolution
- **Naturally fit to image**
 - Denoising / inpainting / deblurring

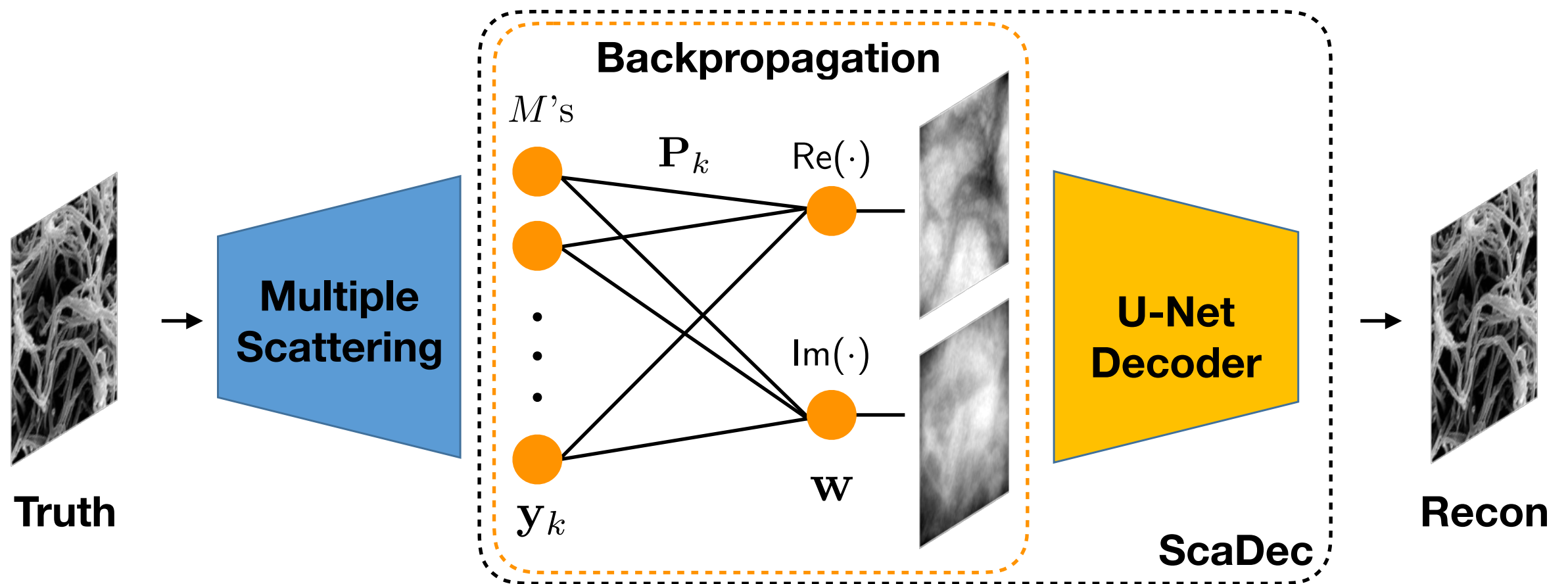


Why we consider deep learning ?

- **Multiple scattering = repeated convolutions**
 - Inverting scattering = repeated deconvolution
- **Naturally fit to image**
 - Denoising / inpainting / deblurring
- **Fast prediction**
 - Single forward propagation



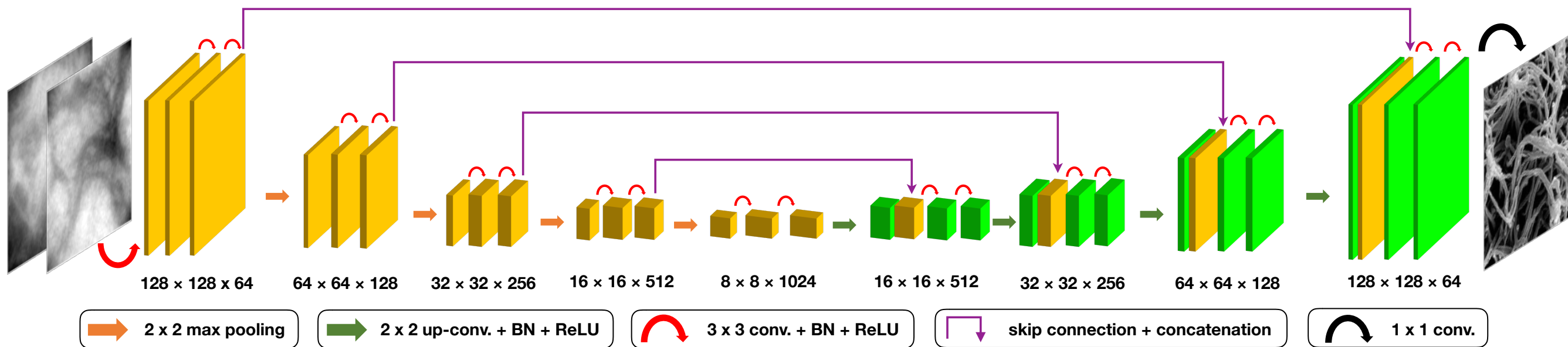
The framework of Scattering decoder (ScaDec)



$$\mathbf{z}_k = \mathbf{P}_k \mathbf{y}_k \quad \text{with} \quad \mathbf{P}_k \triangleq \text{diag}(\mathbf{u}_{in}^*) \mathbf{H}^H$$

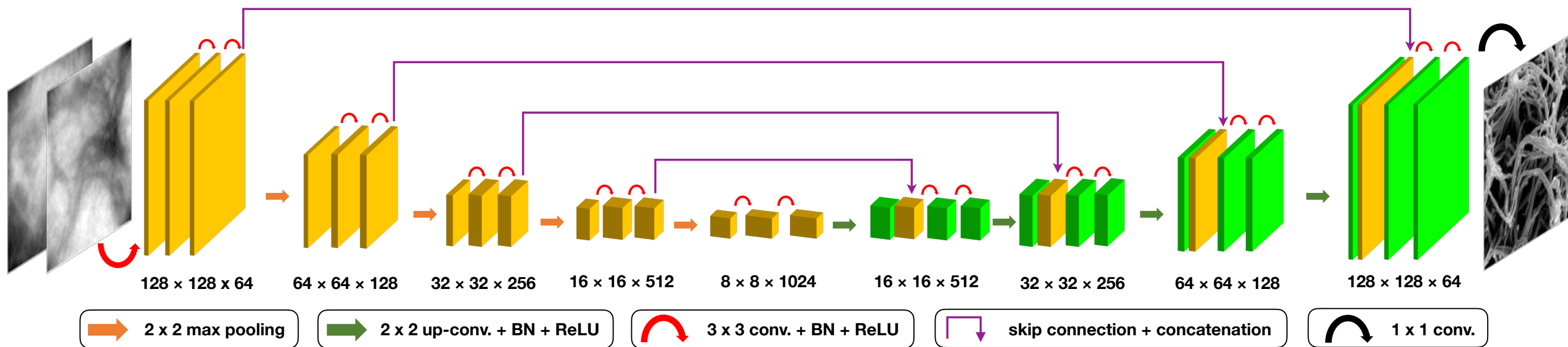
$$\mathbf{w} = \sum_{k=1}^K \mathbf{z}_k = \sum_{k=1}^K \mathbf{P}_k \mathbf{y}_k$$

We design the decoder based on U-Net

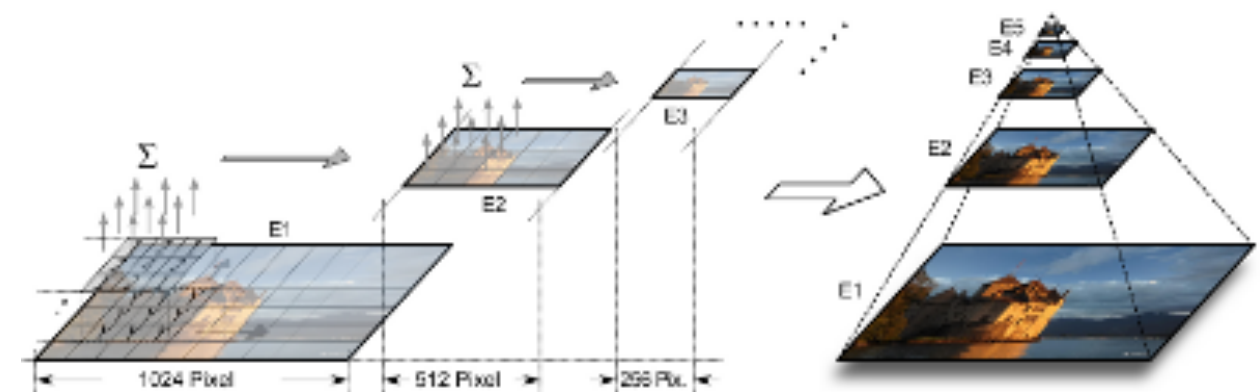


- **U-Net [Ronneberger et al., 2015]**
 - Cited by 3314

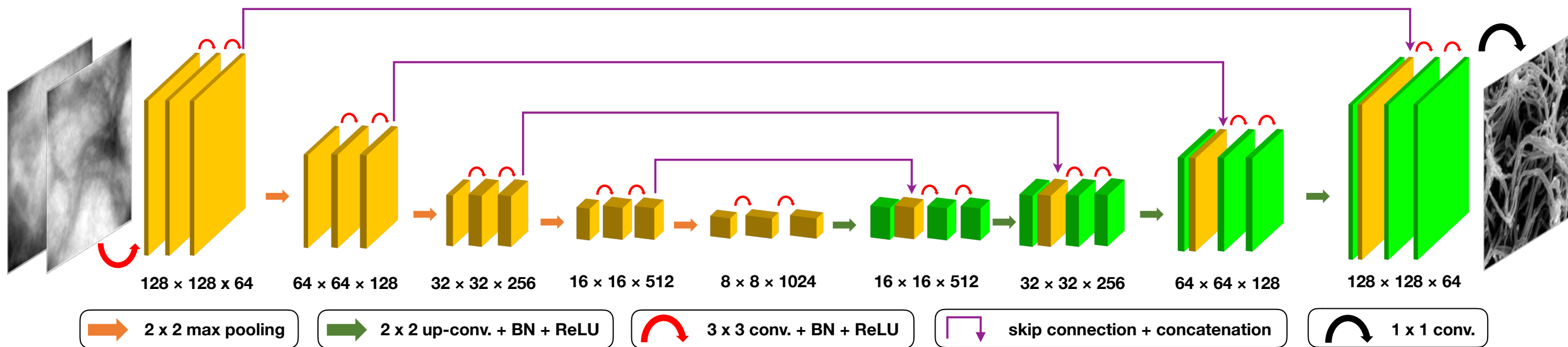
We design the decoder based on U-Net



- **U-Net [Ronneberger et al., 2015]**
 - Cited by 3314
- **Multi-resolution decomposition**
 - Increasing effective receptive field



We design the decoder based on U-Net

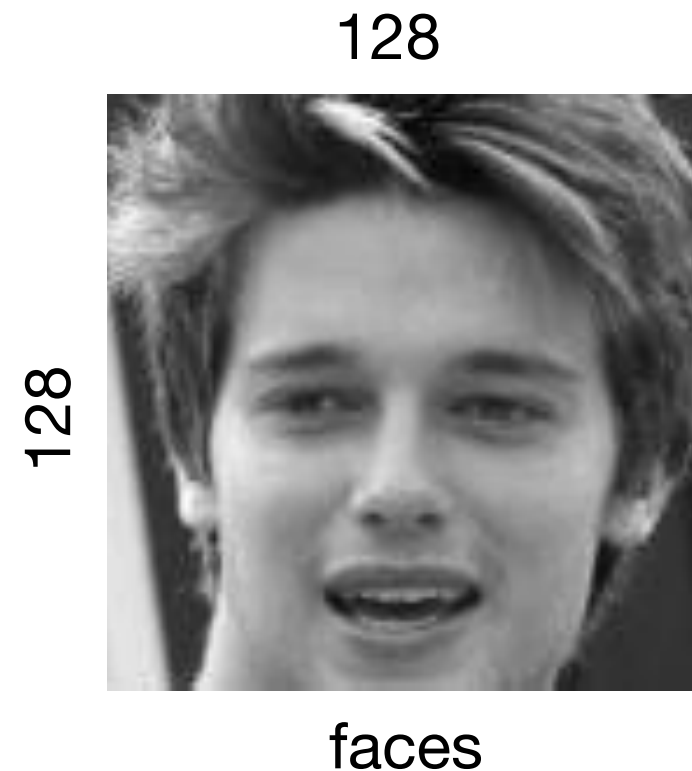
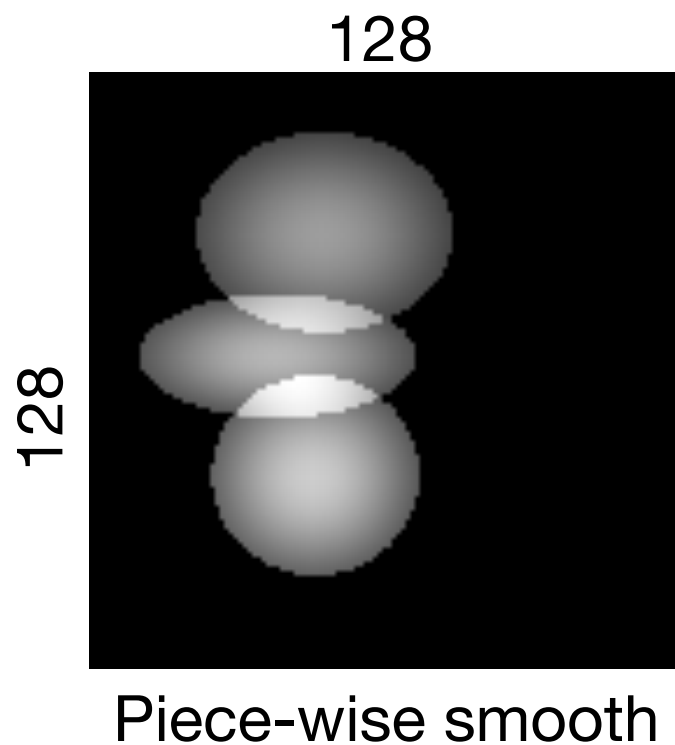


- **U-Net [Ronneberger et al., 2015]**
 - Cited by 3314
- **Multi-resolution decomposition**
 - Increasing effective receptive field
- **Local-global composition**
 - Local details + global features

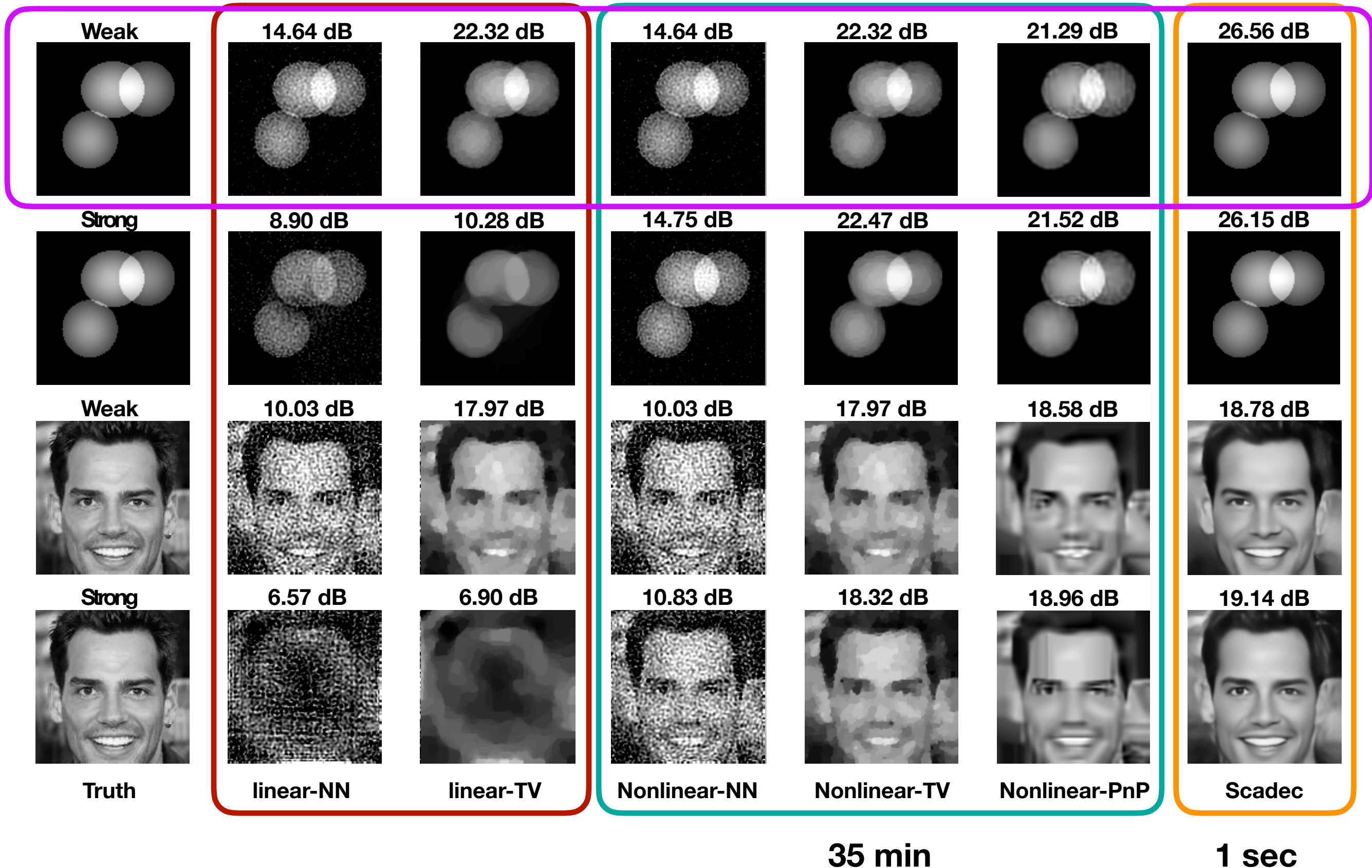
We firstly validate ScaDec on simulated datasets

Simulated data

- Piece-wise smooth & Human faces (CelebA)
- Use high fidelity model to simulate measurements
- Add noise with Input SNR = 20 dB
- Training: 1500 / Test: 24 (randomly selected)



Visual comparison on Piece-wise smooth and Faces



ScaDec is also competitive in terms of average SNR

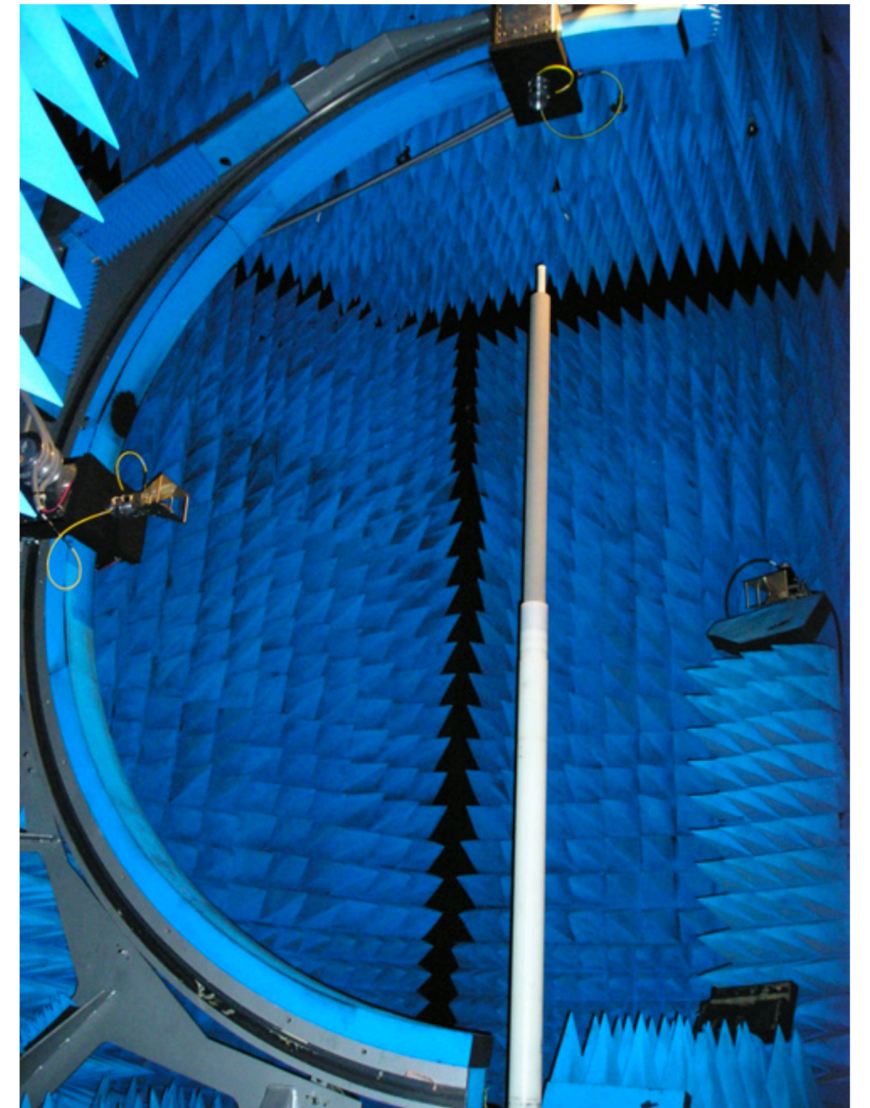
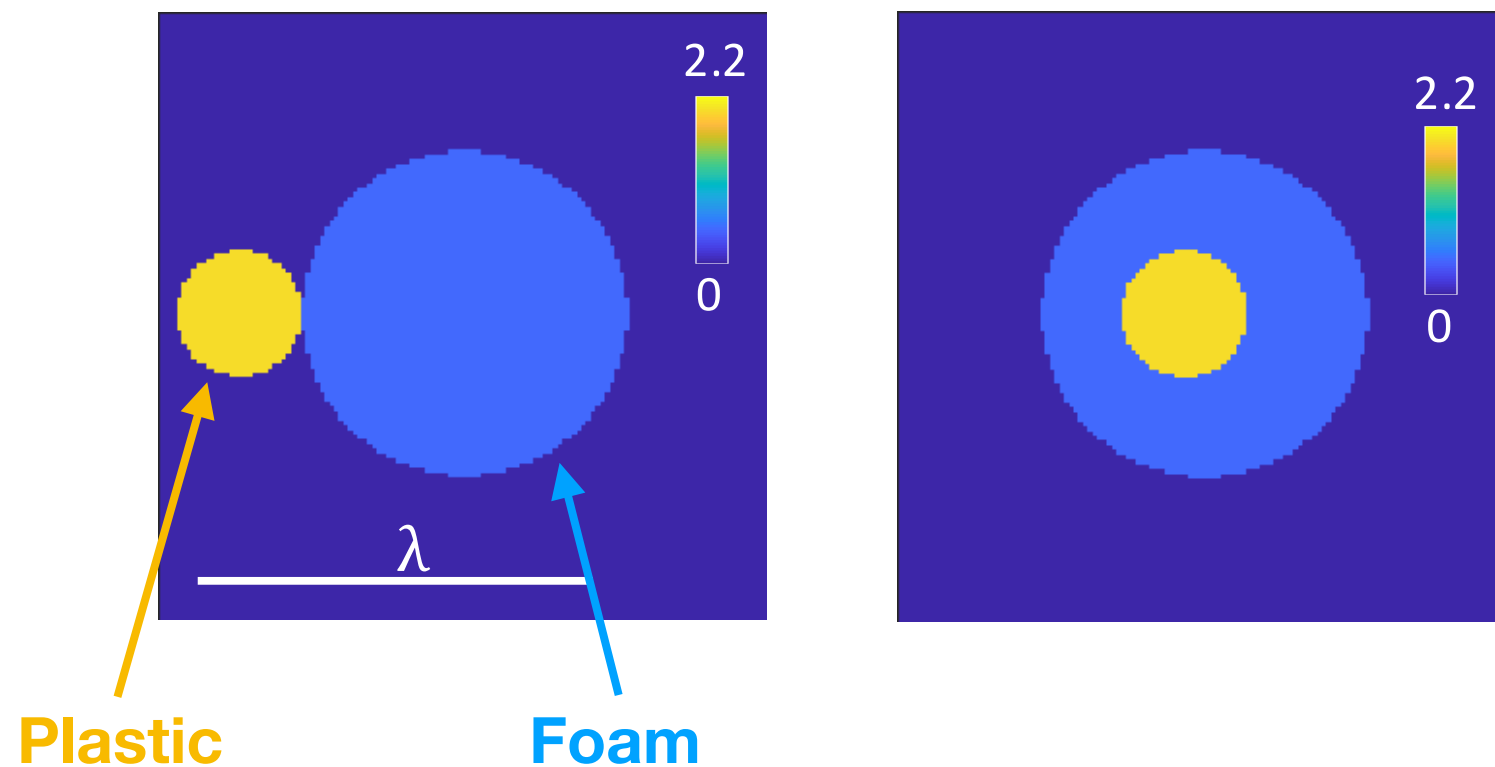
Table 1. SNR (dB) comparison of six methods on two datasets

Method	Average SNR over the dataset			
	Piecewise-smooth		Human faces	
	Weak	Strong	Weak	Strong
FB-NN	16.49	12.79	10.39	6.61
LS-NN	16.49	16.74	10.39	10.85
FB-TV	23.04	15.53	19.79	7.08
LS-TV	23.04	22.57	19.79	20.12
LS-BM3D	21.54	21.72	20.48	20.99
ScaDec	26.14	26.19	20.26	20.21

Validation on experimental microwave dataset

Experimental data

- **Plastic & foam (J.M. Geffrin, et al. 2005)**
- **Microwave / Very Noisy**
- Use 6500 synthesized data to train
- Strong prior

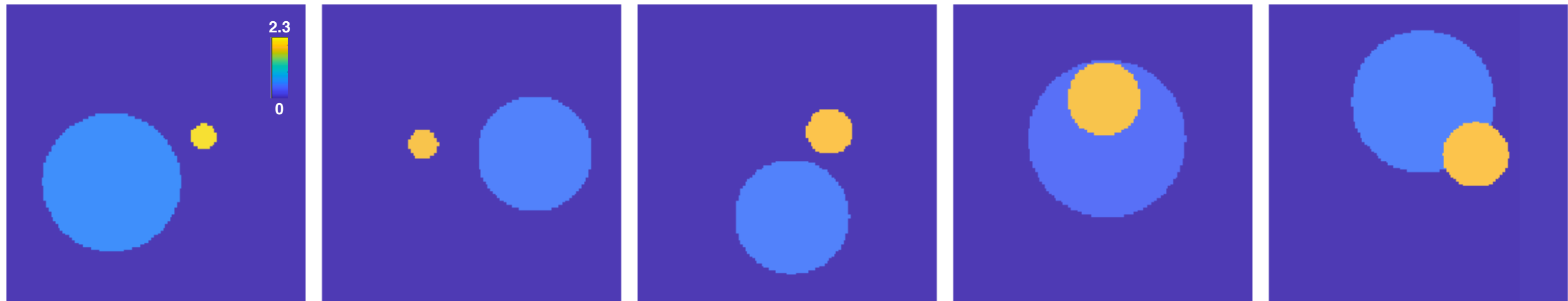


(a) Experimental setup

Examples of synthesized data for training ScaDec

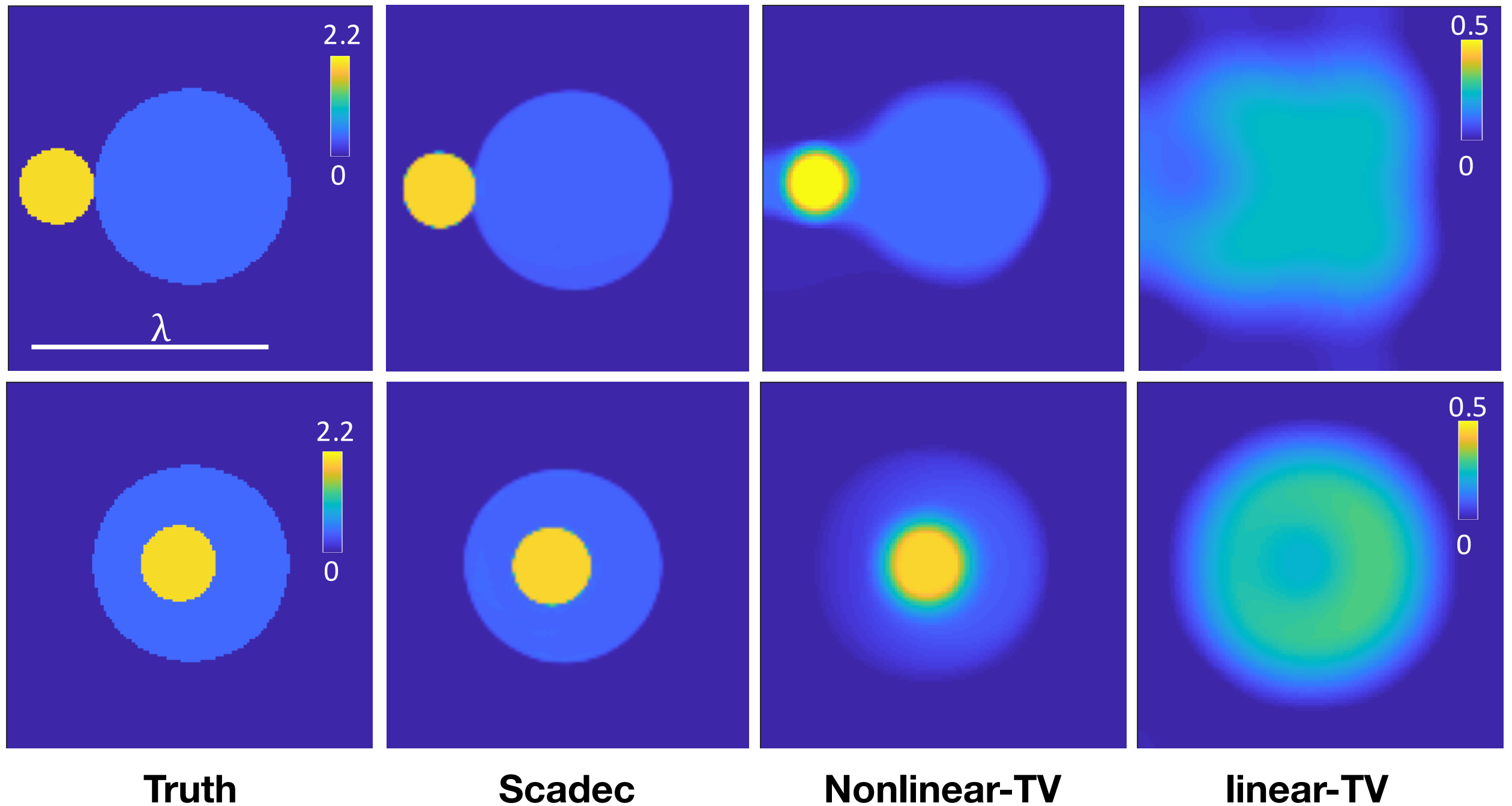
Experimental data

- Microwave data (J.M. Geffrin, et al. 2005)
- Very Noise
- **Use 6500 synthesized data to train**
- **Strong prior**



Synthesized examples

ScaDec successfully reconstructs the image from real data

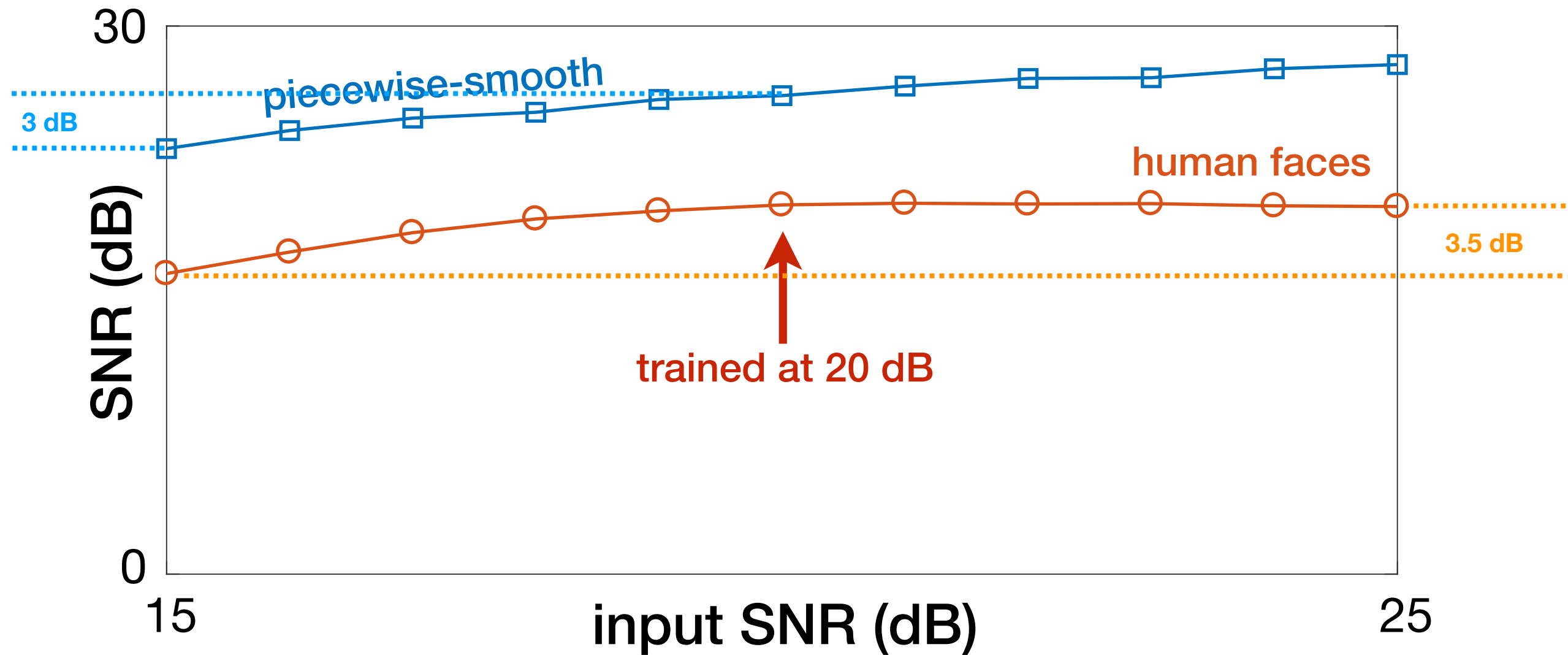


We test the stability of ScaDec with respect to noise and refractive index

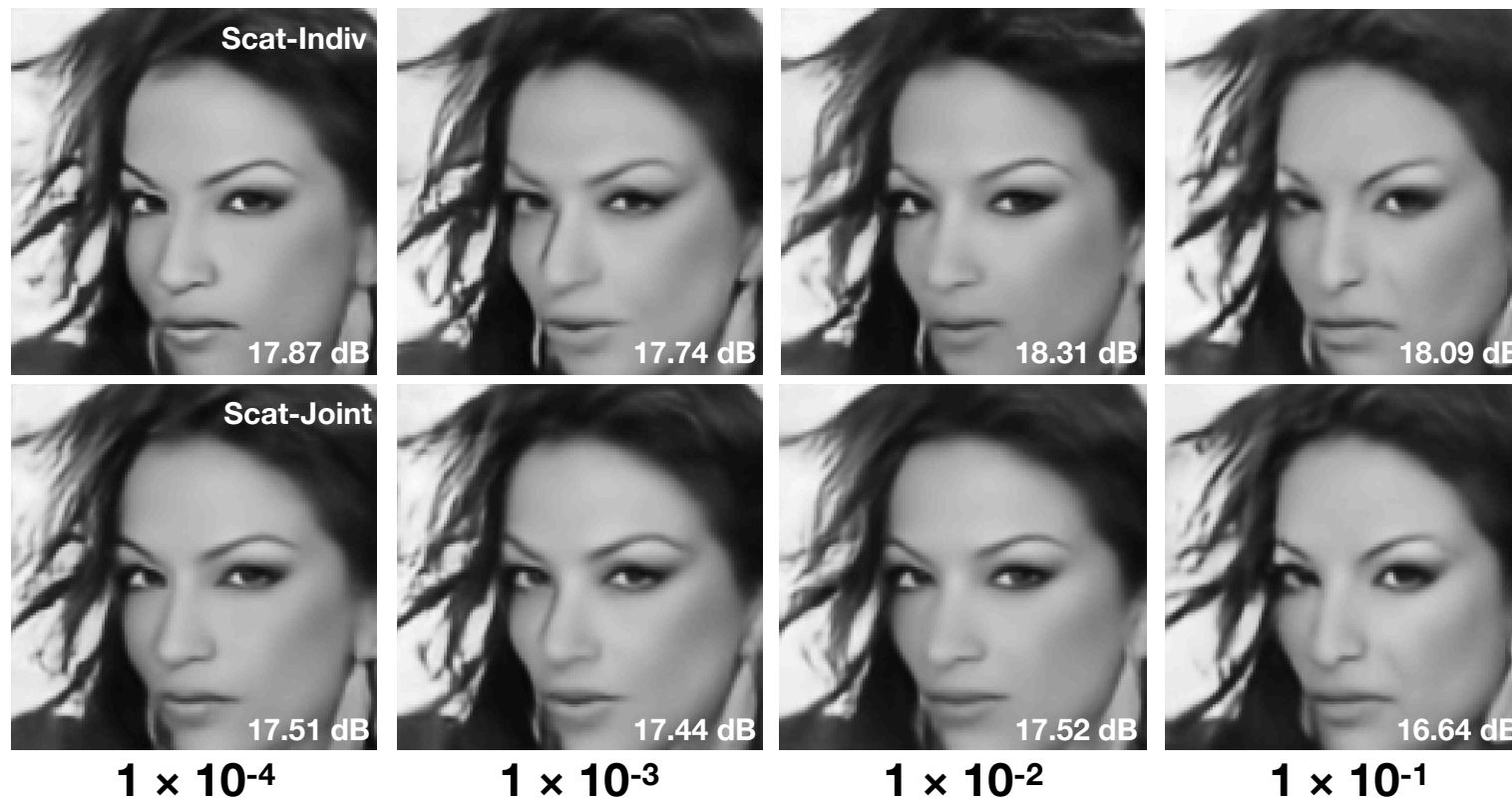
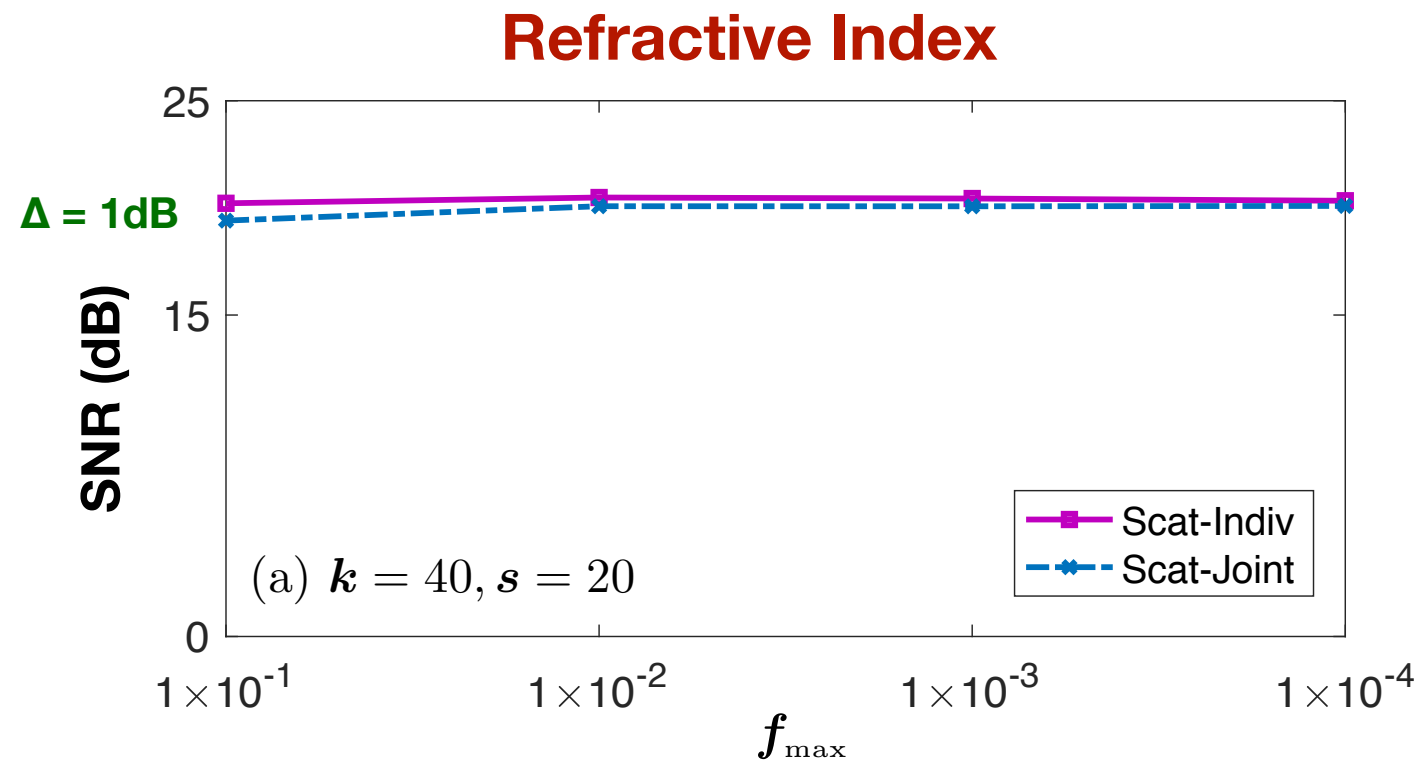
Not enough, is the model robust ?

- Learning-based
- **Input noise**
- **Refractive index**

ScaDec degrades as noise level increases



ScaDec generalizes well by training jointly



Conclusion

- Inverting Scattering is important & difficult
- ScaDec is shown to achieve fast and accurate reconstruction
- ScaDec is stable with respect to noise and scattering strength
- Code available here: <https://github.com/sunyumark/ScaDec-deep-learning-diffractive-tomography>

Hit & Follow us

