

APRIL 2023



GENERATIVE PRIORS FOR SOLVING INVERSE PROBLEMS FROM NOISY DATA

IFML WORKSHOP 2023

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TEXAS
The University of Texas at Austin



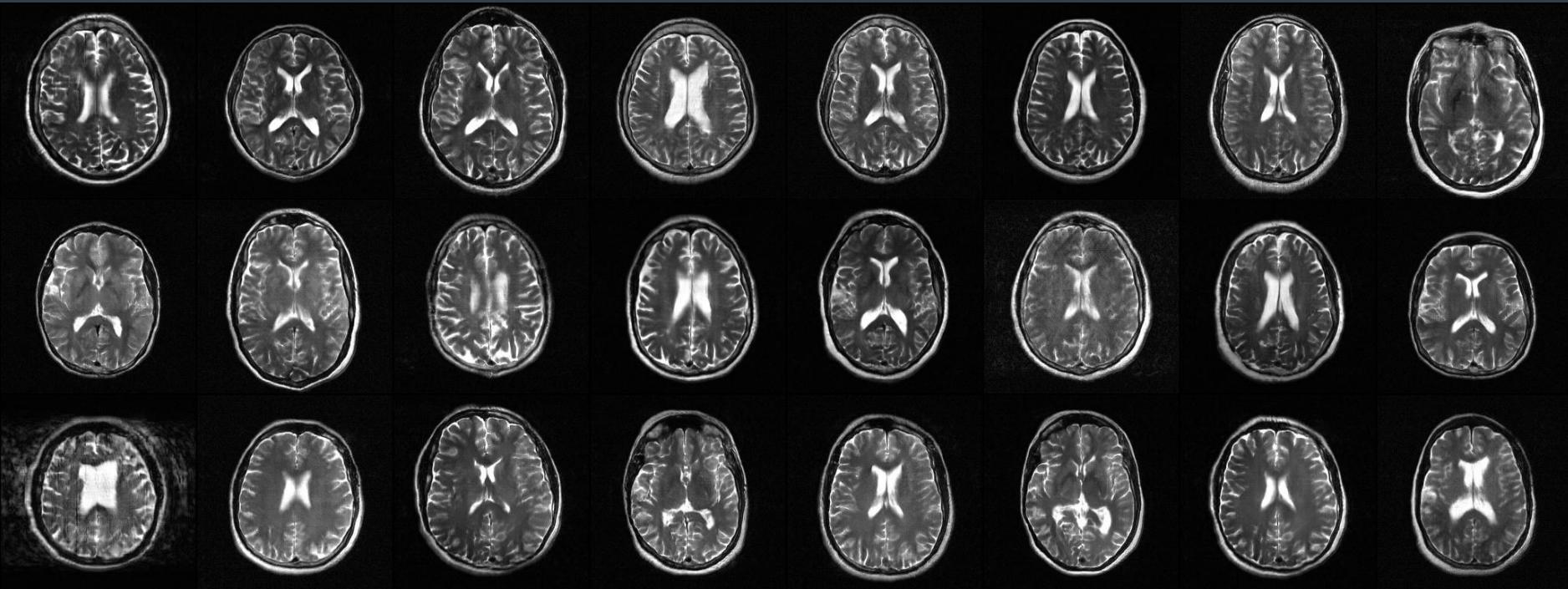
IFML

Generative models are powerful image generators



<https://thiscatdoesnotexist.com>

Generative models are powerful image generators

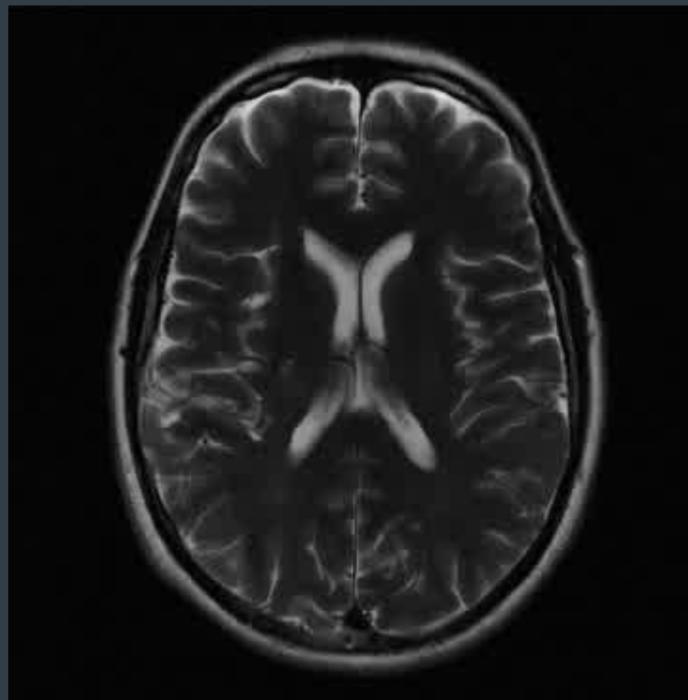


Generative model trained on FastMRI data

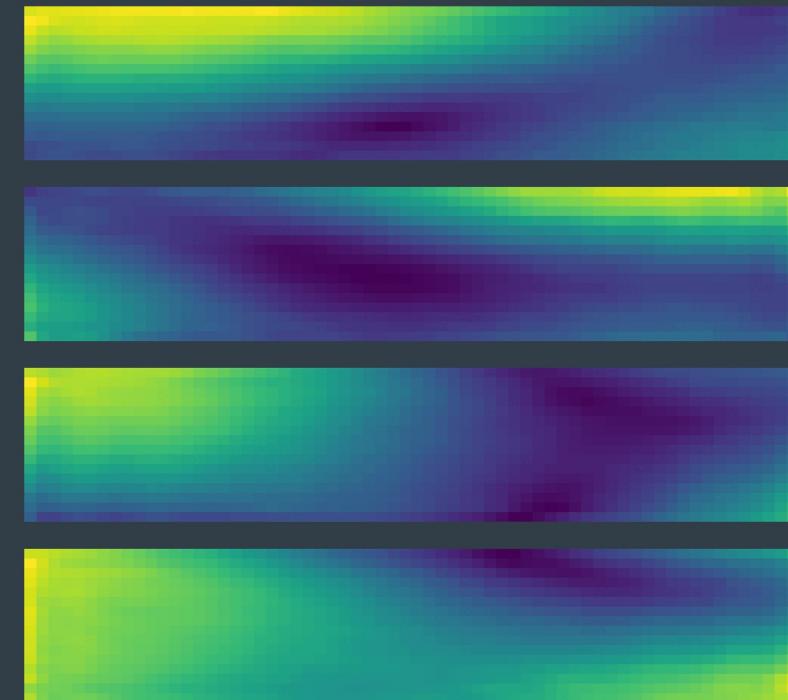
Score models for inverse problems $\rightarrow x \sim p(x|y)$

$$y = Ax + \text{noise}$$

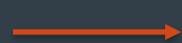
Brain FastMRI



Wireless CDL Channels

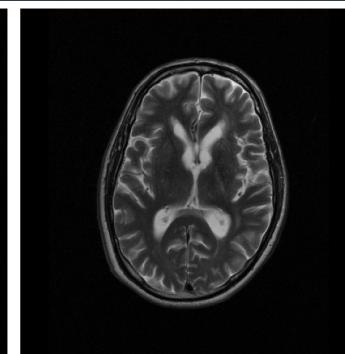
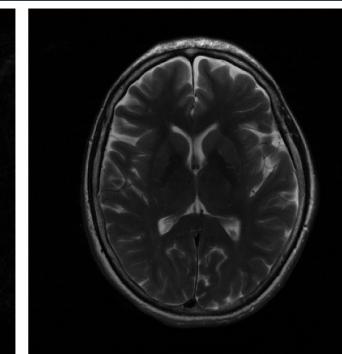
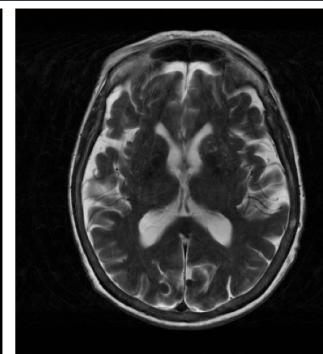
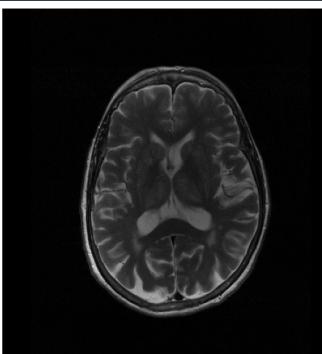
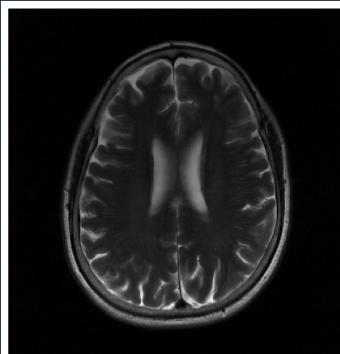


Learning from Noisy Data

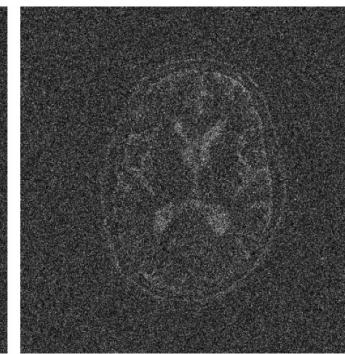
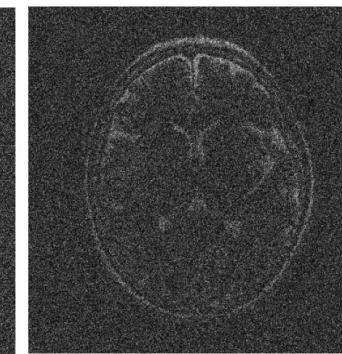
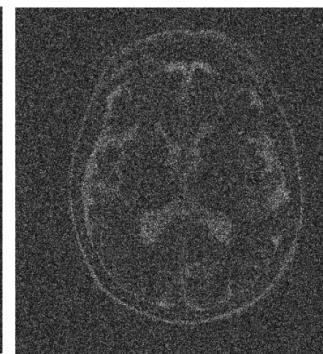
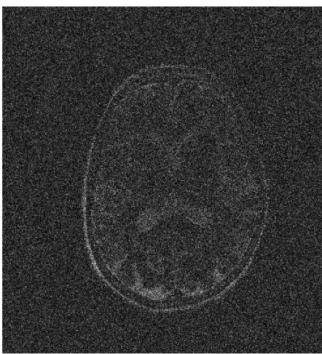
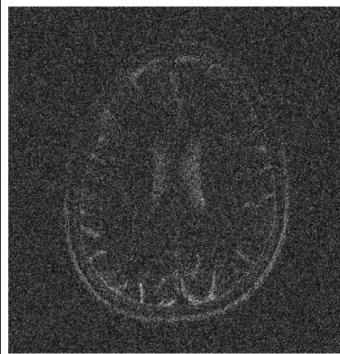


$$\tilde{x} = x + w$$
$$w \sim N(0, \sigma_w^2 I)$$

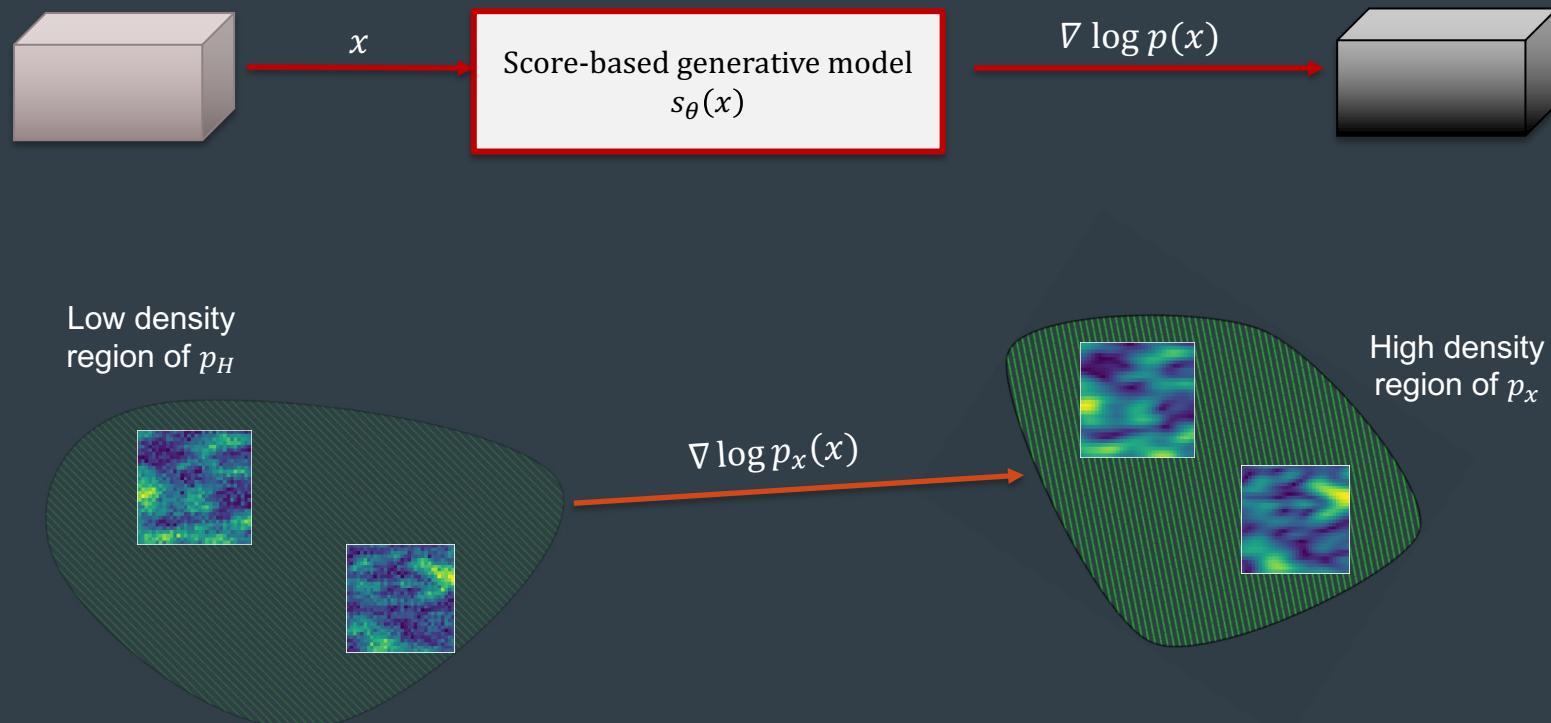
x



\tilde{x}
(0 dB)



Score-based generative models [1]



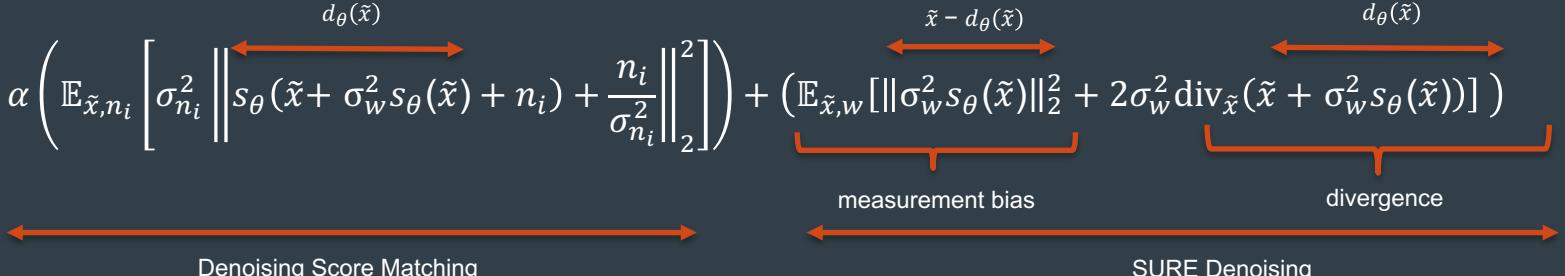
Single-Network SURE-Score – Our Proposed Method

We combine *denoising score matching* and *Stein's Unbiased Risk Estimate (SURE)*

$$\mathcal{L}(\theta) = \alpha \text{ (Denoising Score Matching)} + \text{SURE Denoising}$$

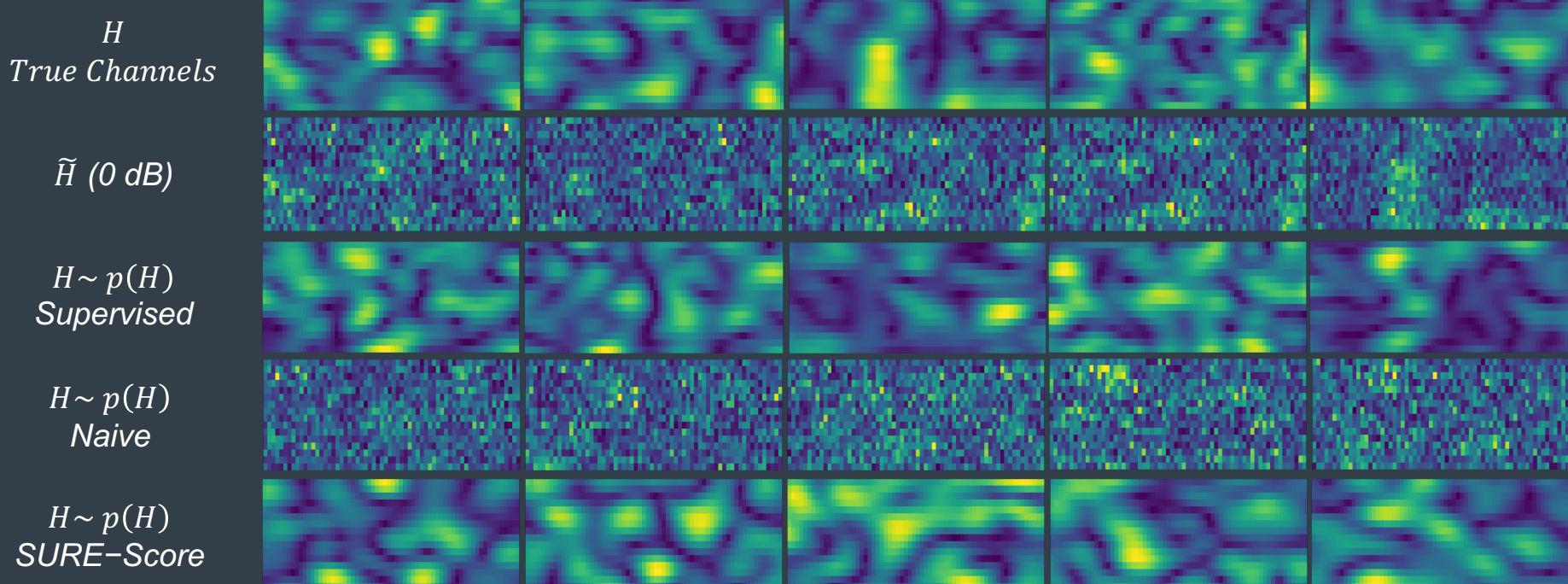
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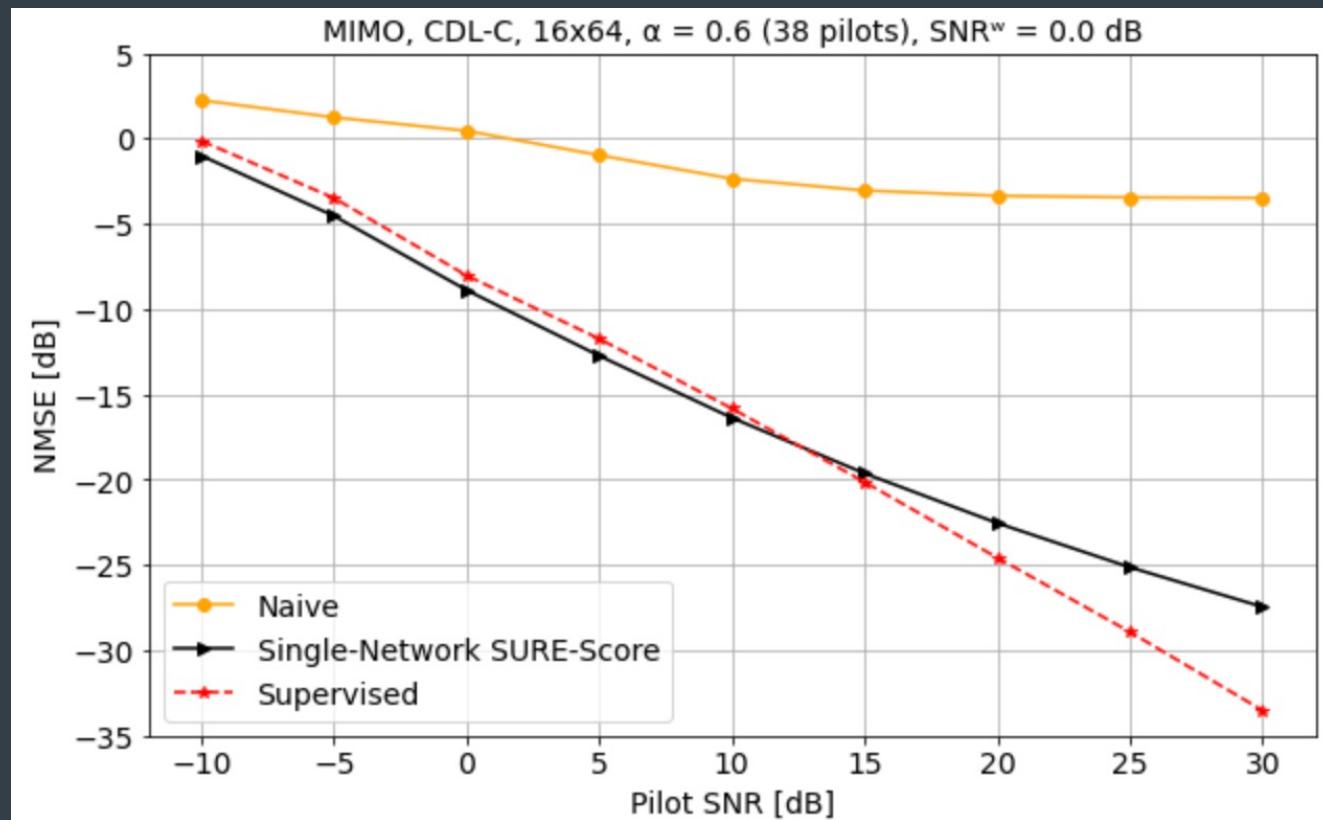
$$\mathcal{L}(\theta) = \alpha \left(\mathbb{E}_{\tilde{x}, n_i} \left[\sigma_{n_i}^2 \left\| s_\theta(\tilde{x} + \sigma_w^2 s_\theta(\tilde{x}) + n_i) + \frac{n_i}{\sigma_{n_i}^2} \right\|_2^2 \right] \right) + \left(\mathbb{E}_{\tilde{x}, w} [\| \sigma_w^2 s_\theta(\tilde{x}) \|_2^2 + 2\sigma_w^2 \text{div}_{\tilde{x}}(\tilde{x} + \sigma_w^2 s_\theta(\tilde{x}))] \right)$$


- Where $\text{div}_{\tilde{x}}(\tilde{x} + \sigma_w^2 s_\theta(\tilde{x})) = \text{tr} \left(J_{\tilde{x} + \sigma_w^2 s_\theta(\tilde{x})} \right)$
- Where α is appropriate scaling applied to score loss

Experiment 1 – Wireless MIMO CDL Prior Sampling



Experiment 2 – Wireless MIMO Posterior Reconstruction



Experiment 3 – FastMRI Posterior Reconstruction

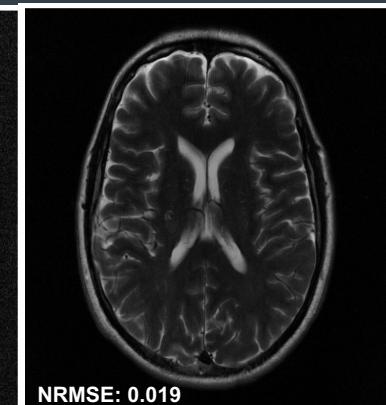
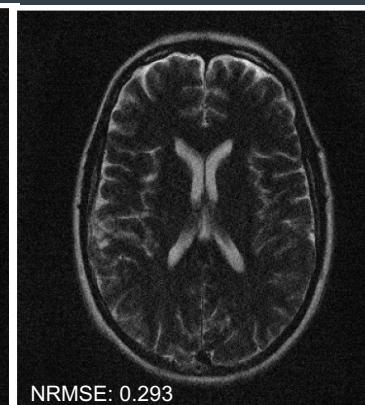
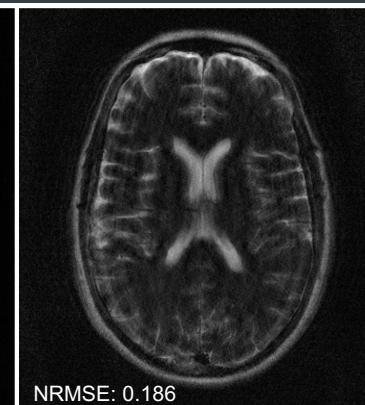
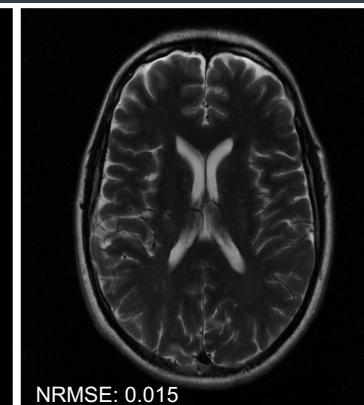
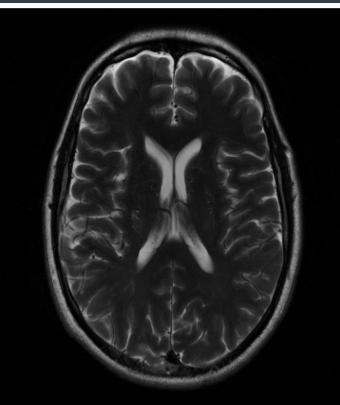
Ground Truth

Supervised Score Model

L2 Regularization

Naive

Single-Network SURE-Score



* Acceleration Factor -> 5

General Score Model Training/Sampling Pipeline

- score-diffusion-training
 - Train diffusion models for arbitrary multi-dim data
- score-diffusion-sampling

Prior, posterior sampling for arbitrary forward models

<https://github.com/utcsilab>



UT Computational Sensing and Imaging Lab

- Joint design of imaging system and software algorithms
- Focus on inverse problems and deep learning applications in MRI
- Work with clinicians to translate work to hospital



Jon Tamir

Sidharth
Kumar



Brett
Levac



Asad
Aali



Zach
Stoebner



Sofia
Kardonik

