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TEXAS
The University of Texas at Austin

GSURE Denoising enables training of higher quality generative priors for accelerated Multi-Coil MRI Reconstruction

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Electrical & Computer Engineering
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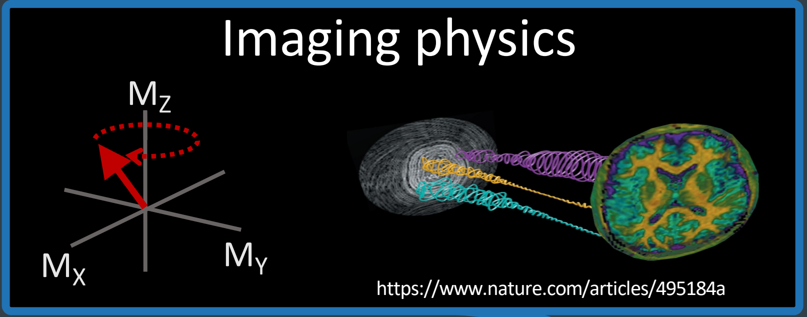
UT Computational Sensing and Imaging Lab

- Joint design of imaging system and software
- Particular focus on application to MRI
- Work with clinicians to translate work to hospital

Jon Tamir, PhD
Assistant Professor, ECE, UT Austin
http://www.jtsense.com/

https://github.com/utcsilab

Computational MRI



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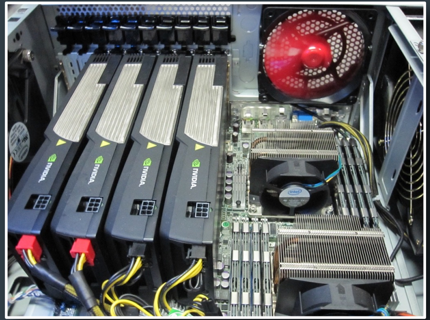
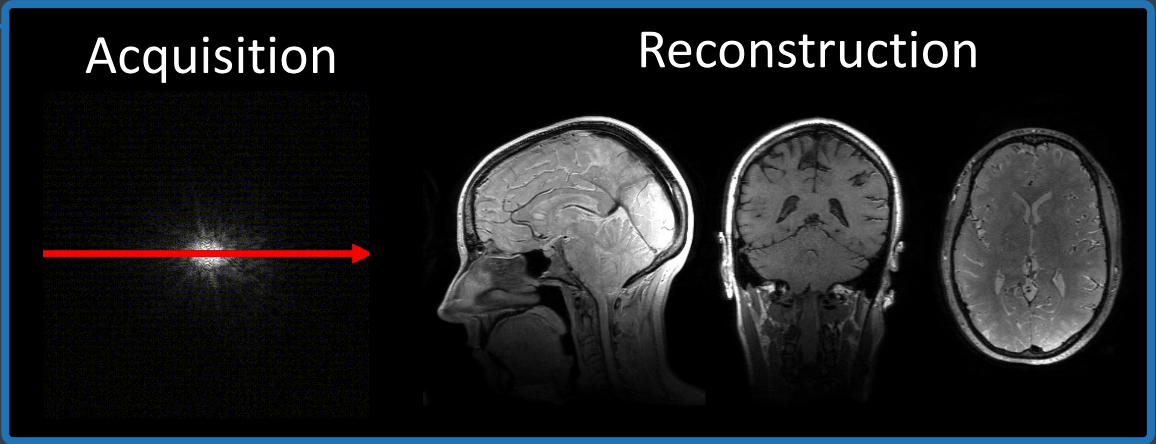
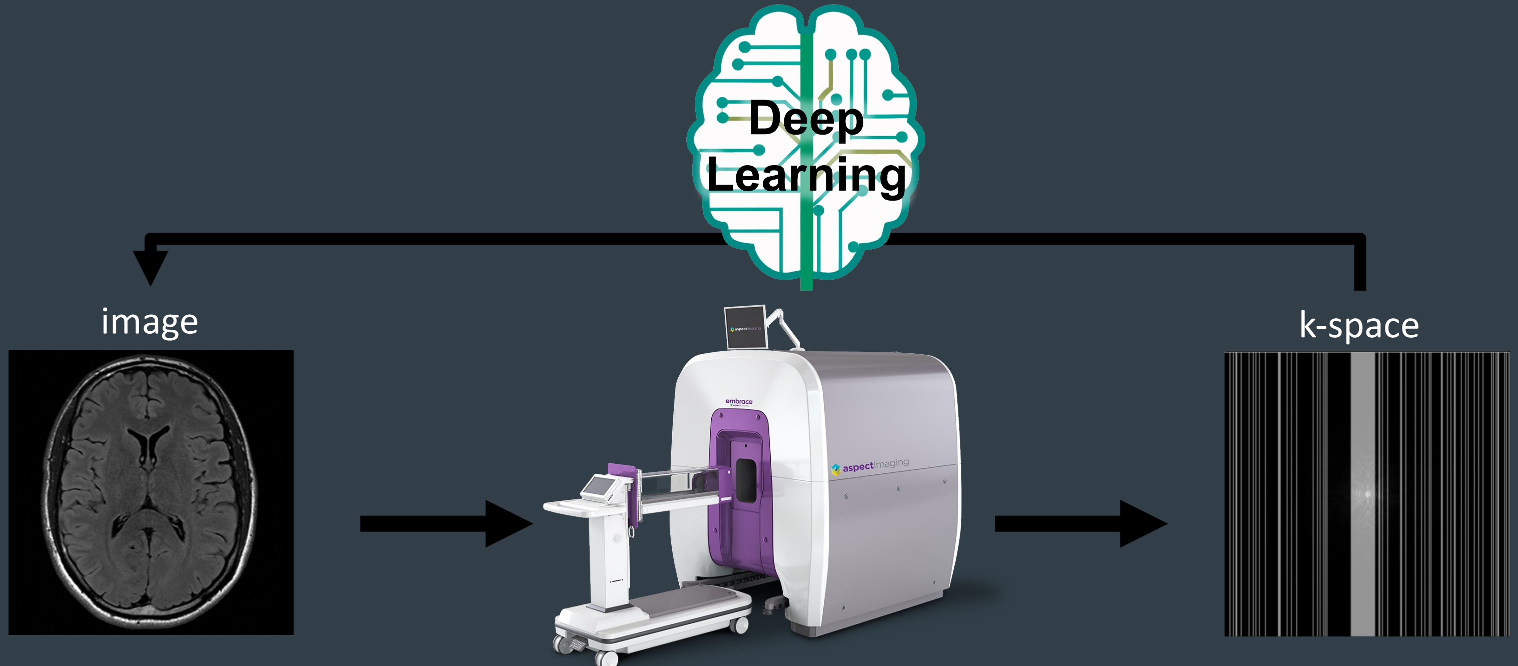




Deep learning inversion for MRI

1. End-to-end supervised training
2. Distribution learning / generative modeling



https://www.aspectimaging.com

Generative models are powerful image generators

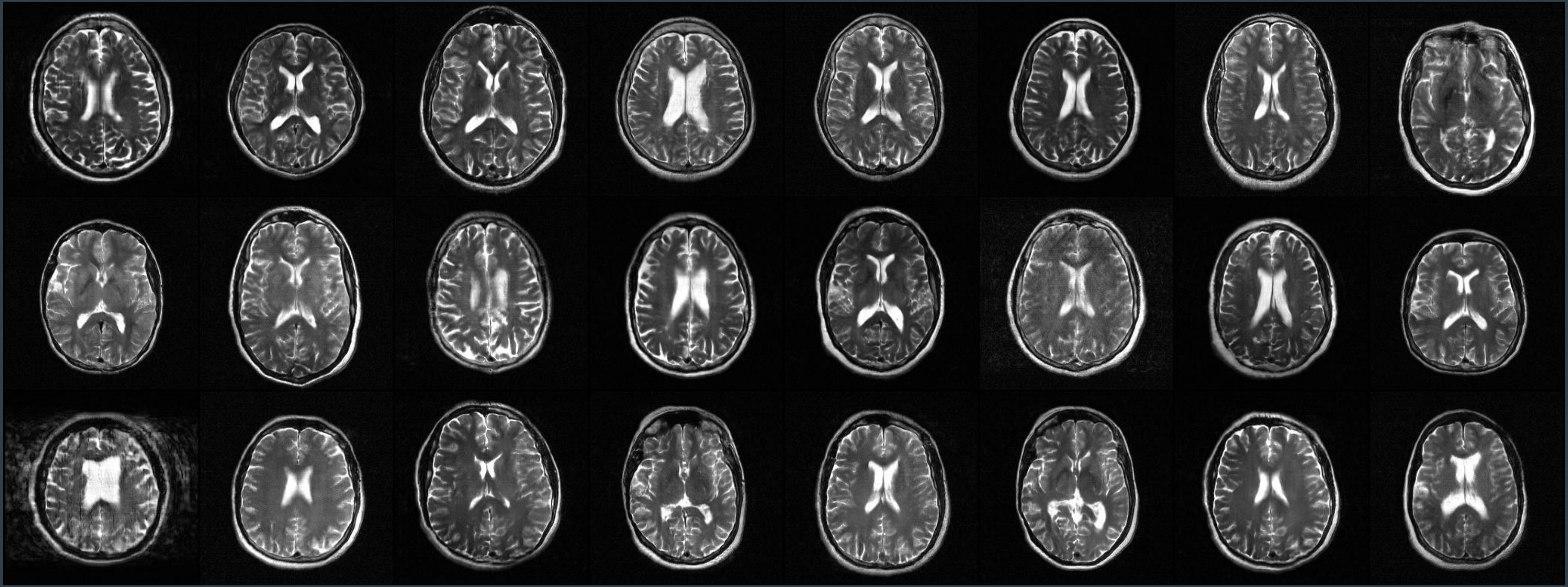
T Karras et al., CVPR 2020

Y Song et al., ICLR 2021

Generative models are powerful image generators

https://thiscatdoesnotexist.com/

Generative models are powerful image generators

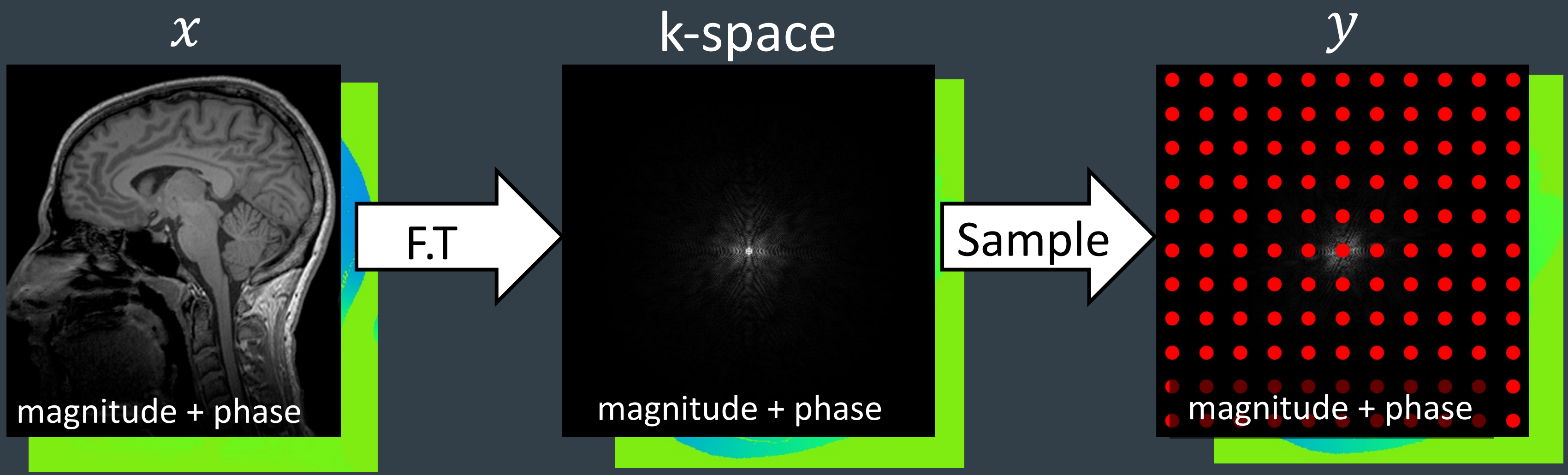


Generative model trained on FastMRI data

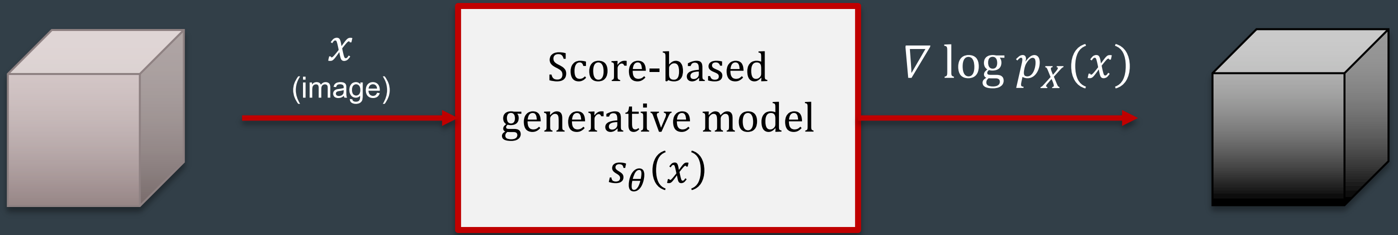
MRI: Problem Formulation

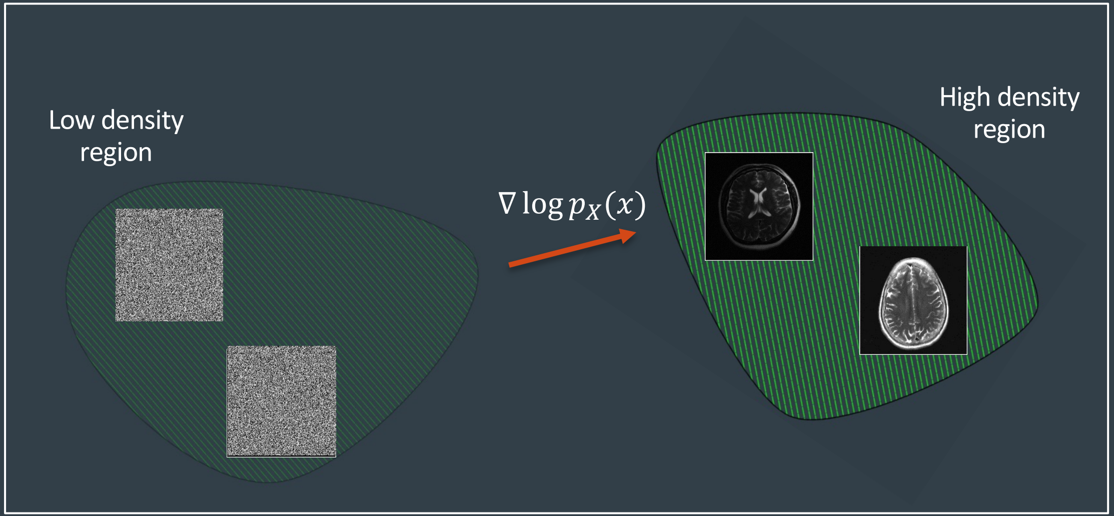
Signal is the Fourier transform of the image

$$y = Ax + noise$$



Score-based generative models





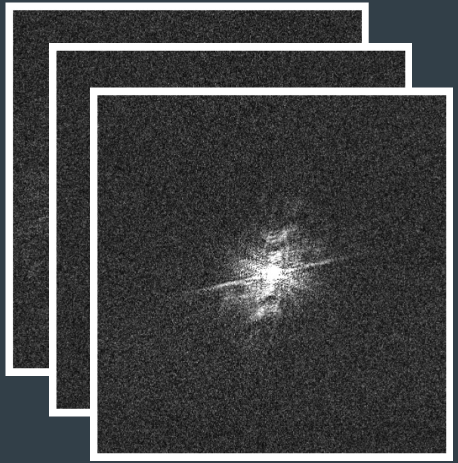
A Hyvarinen, JMLR 2005, Y Song et al., UAI 2018, Vincent et al., MIT Press 2011, Y Song et al., NeurIPS 2019. P Dhariwal et al,. NeurIPS 2021.

MRI Samples are inherently noisy

Goal is to learn the **clean distribution** using *noisy* data (i.i.d Gaussian, with known power σ_w^2).

$$y = Ax + noise$$

y



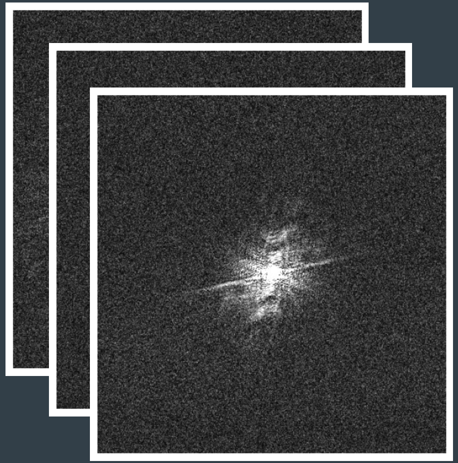
Original K-Space

MRI Samples are inherently noisy

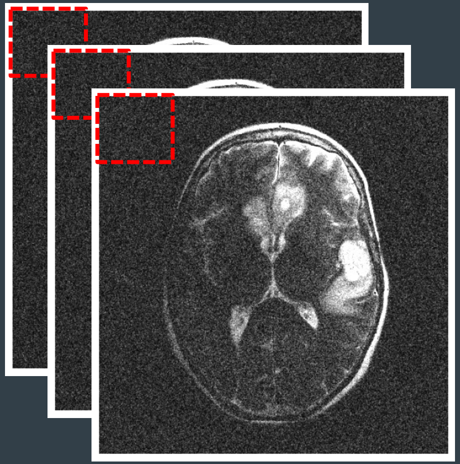
Goal is to learn the **clean distribution** using *noisy* data (i.i.d Gaussian, with known power σ_w^2).

$$y = Ax + noise$$

$y \longrightarrow F^{\mathrm{H}}y$



Original K-Space

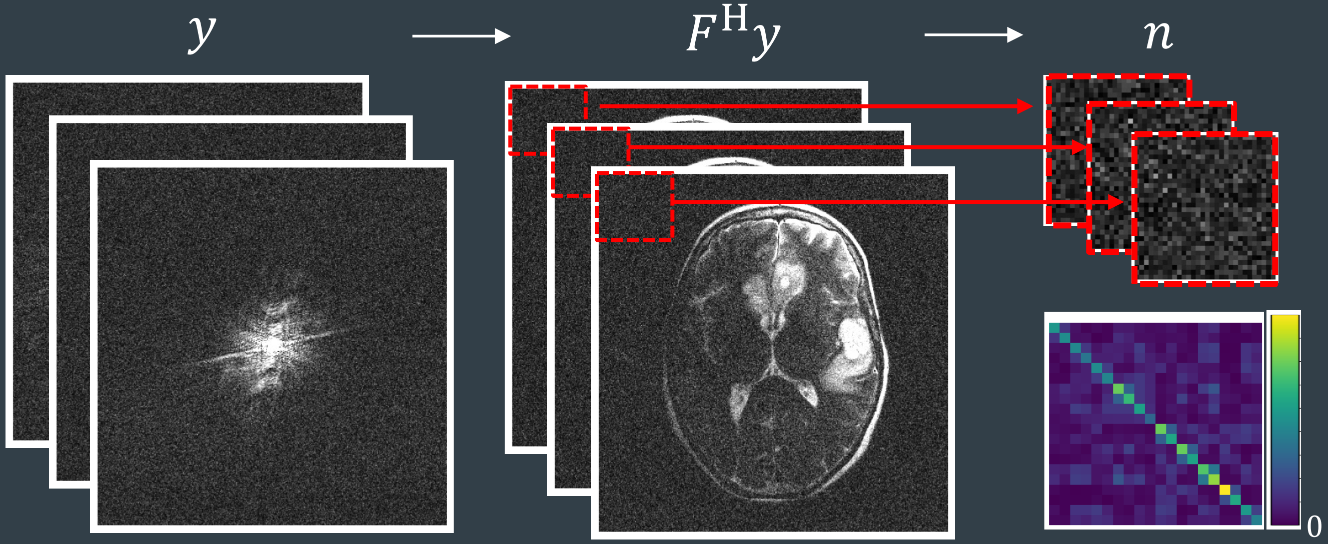


Coil Images

MRI Samples are inherently noisy

Goal is to learn the **clean distribution** using *noisy* data (i.i.d Gaussian, with known power σ_w^2).

$$y = Ax + noise$$

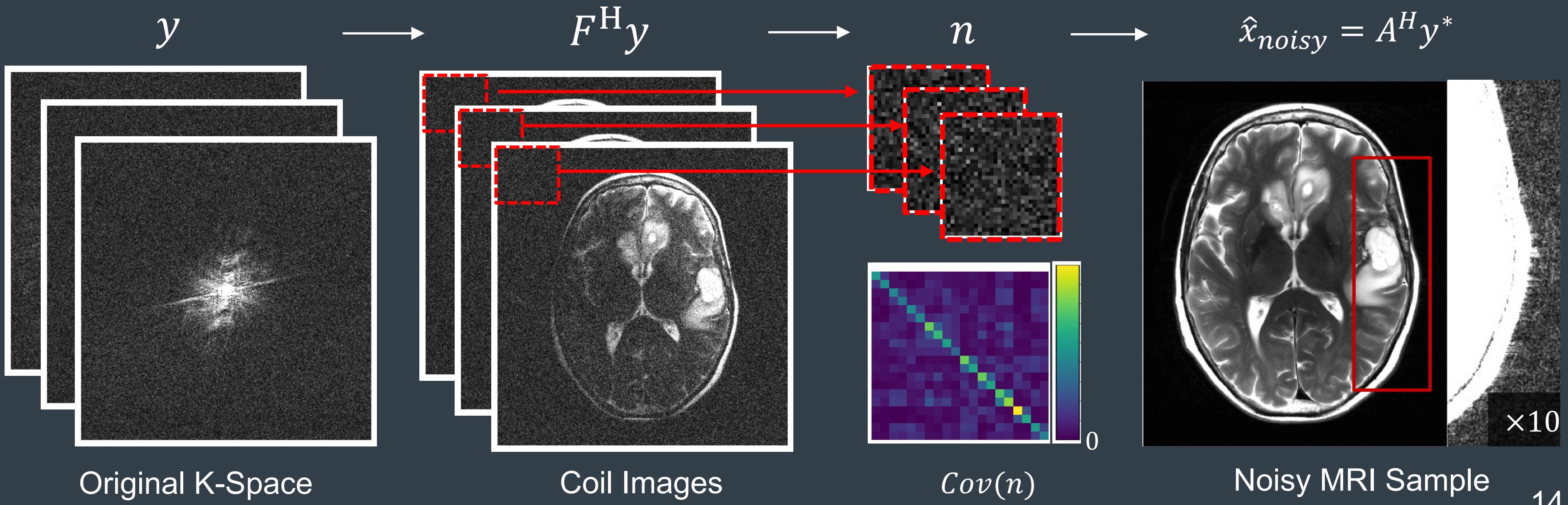


Original K-Space Coil Images $Cov(n)$

MRI Samples are inherently noisy

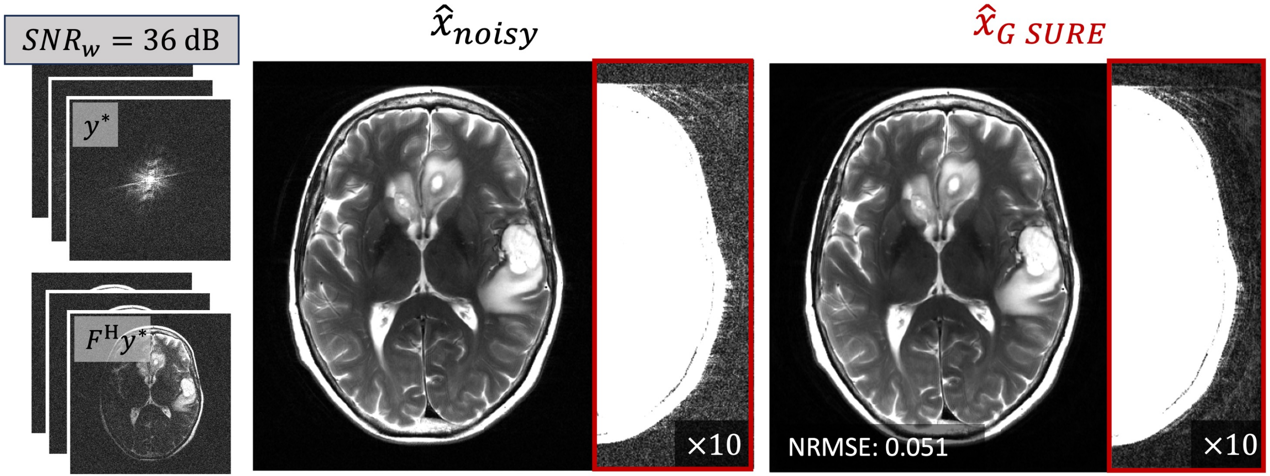
Goal is to learn the **clean distribution** using *noisy* data (i.i.d Gaussian, with known power σ_w^2).

$$y = Ax + noise$$



Denoising with GSURE

Original FastMRI



Denoising with GSURE

Original FastMRI

Original FastMRI

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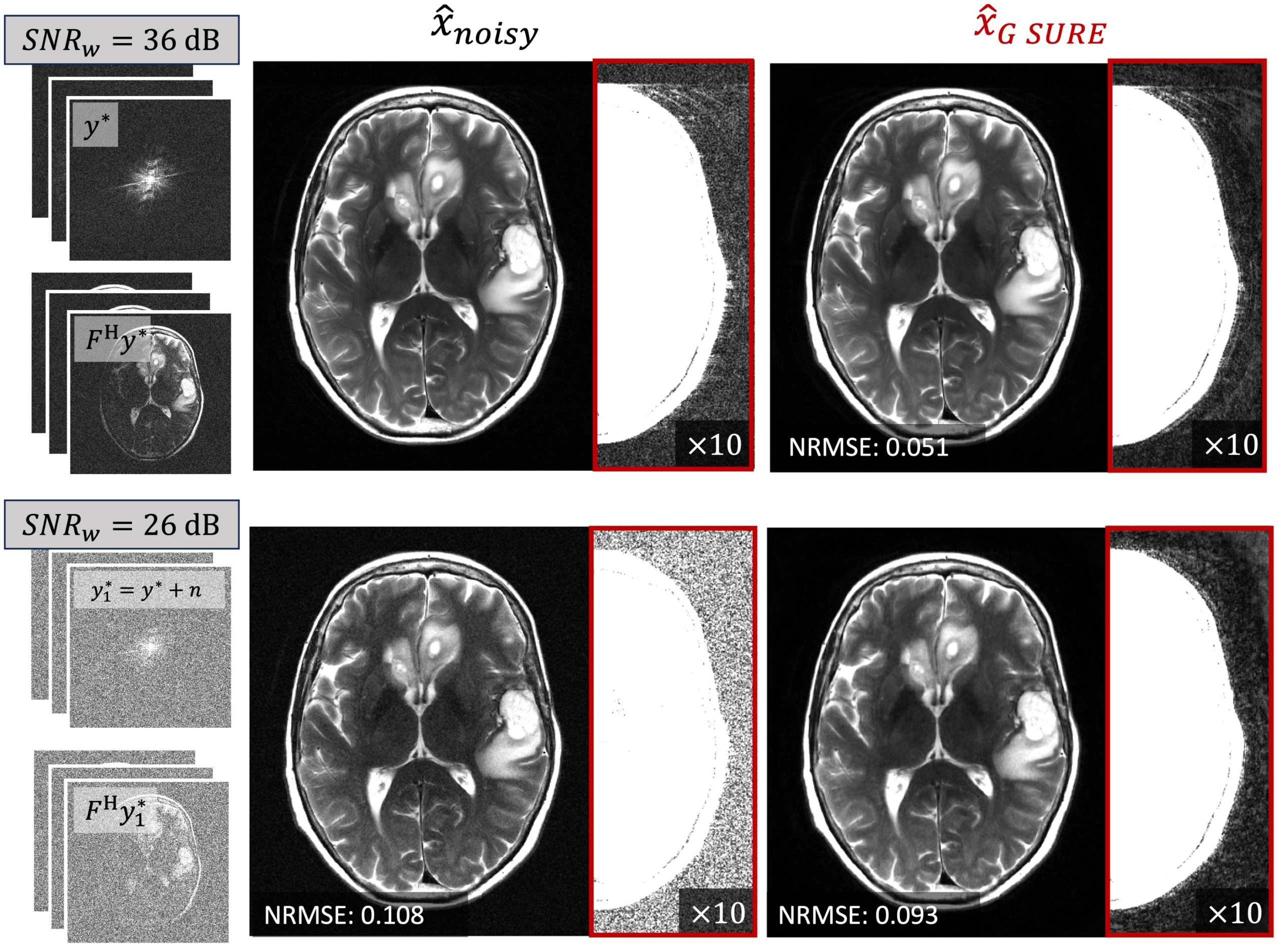
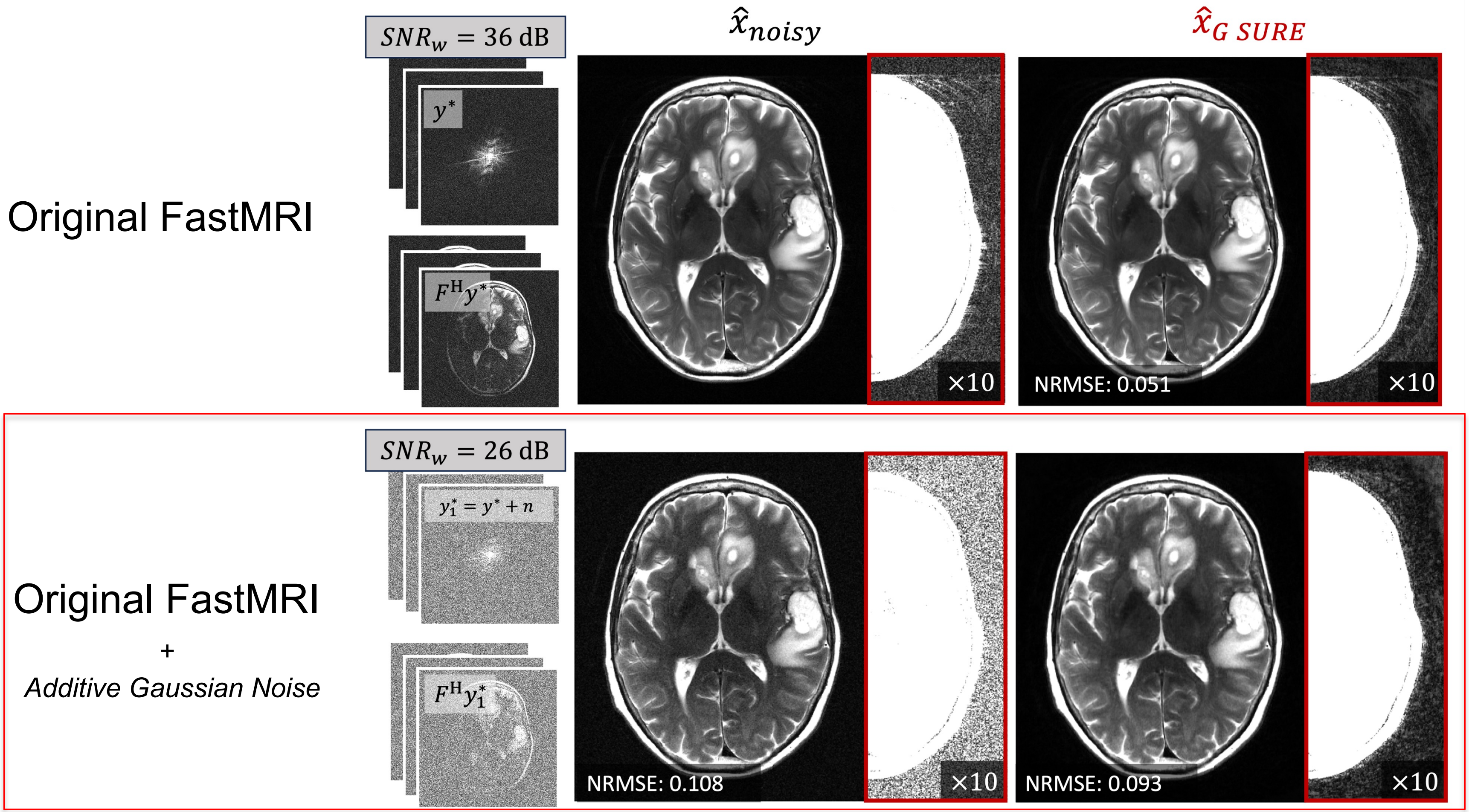
Additive Gaussian Noise

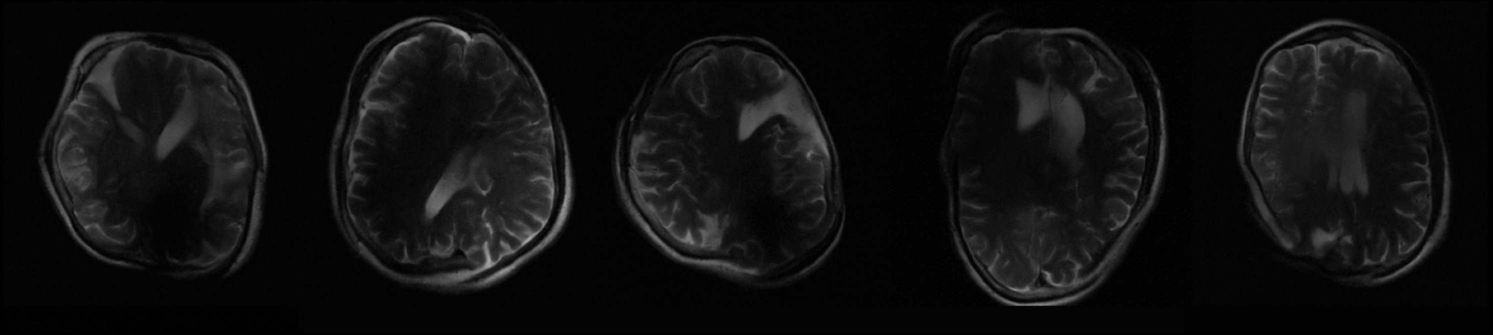


Denoising with GSURE



Learning Priors using Generative Models – $p(x)$

Naive Score



Learning Priors using Generative Models – $p(x)$

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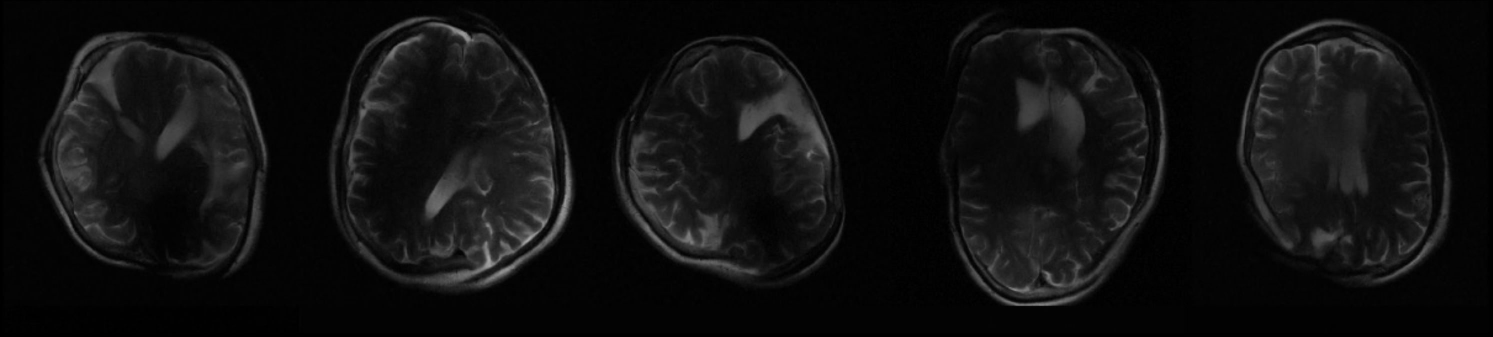
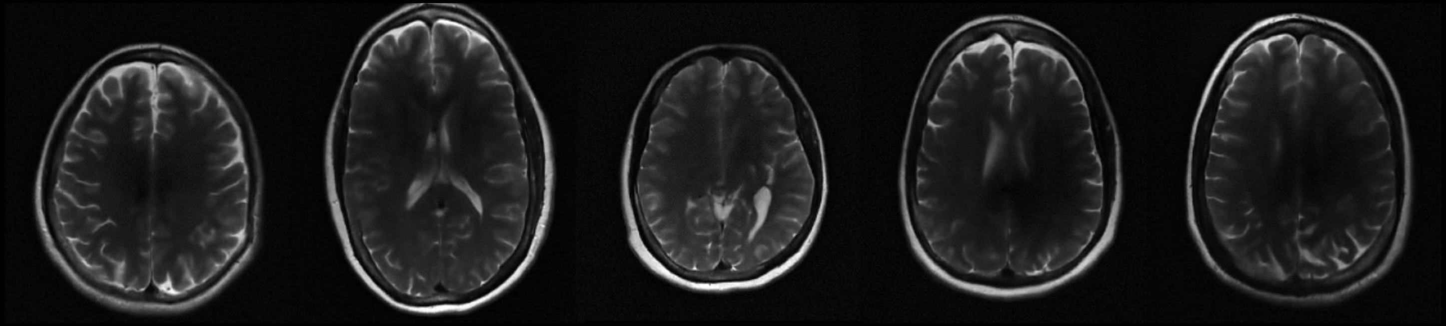
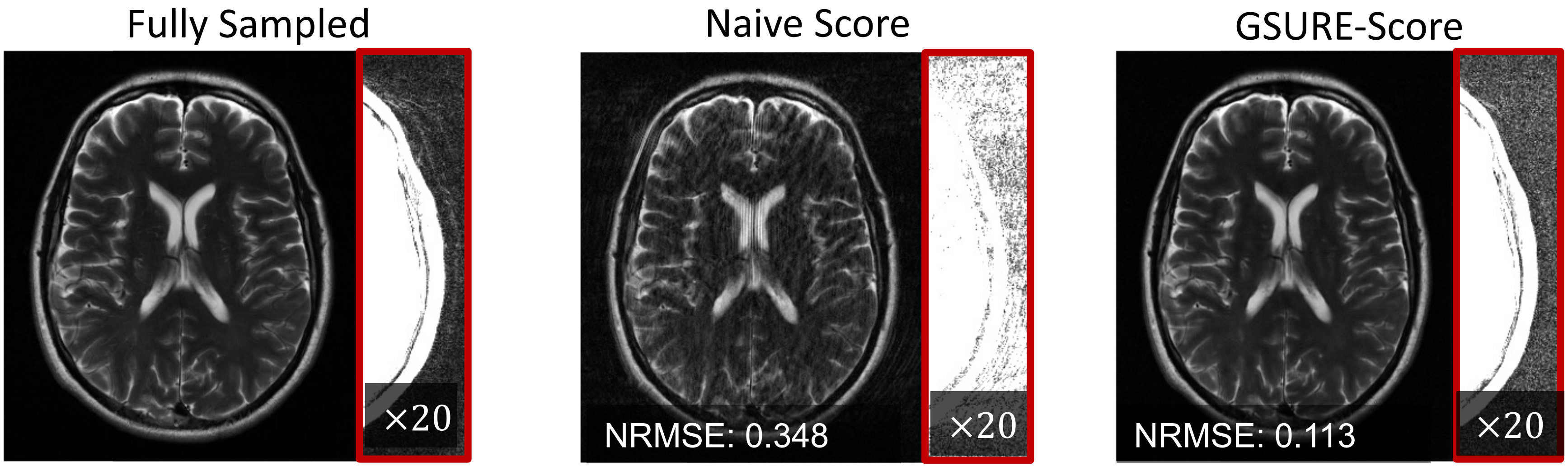
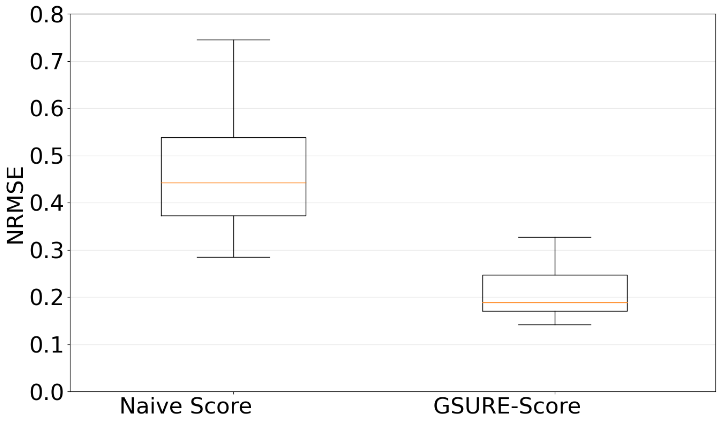


GSURE-Score



Inverse Problems using Generative Models $x \sim p(x|y)$





Conclusions

1. Self-supervised techniques like GSURE can successfully remove noise

2. Denoising as a pre-processing step, severely improves the quality of generative priors

3. Priors trained on denoised FastMRI are better inverse problem solvers than naive training

Thank you!

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