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

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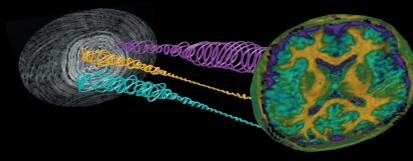
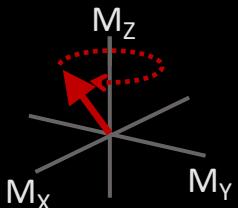
- Joint design of imaging system and software
- Particular focus on application to MRI
- Work with clinicians to translate work to hospital



Jon Tamir, PhD
Assistant Professor, ECE, UT Austin
<http://www.jtsense.com/> <https://github.com/utcsilab>

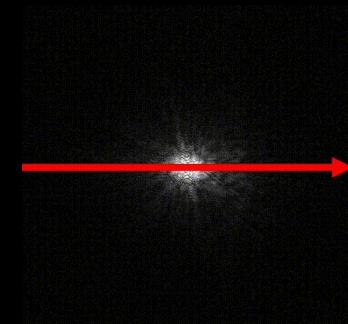
Computational MRI

Imaging physics

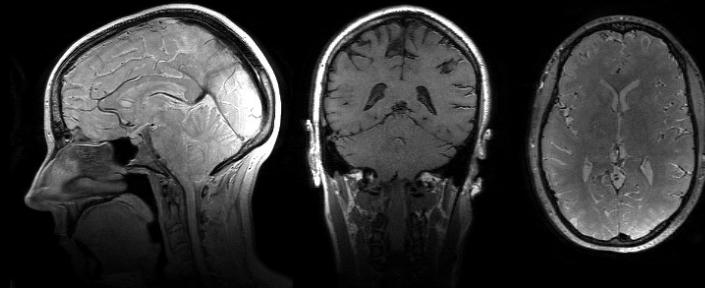


Prior knowledge

Acquisition

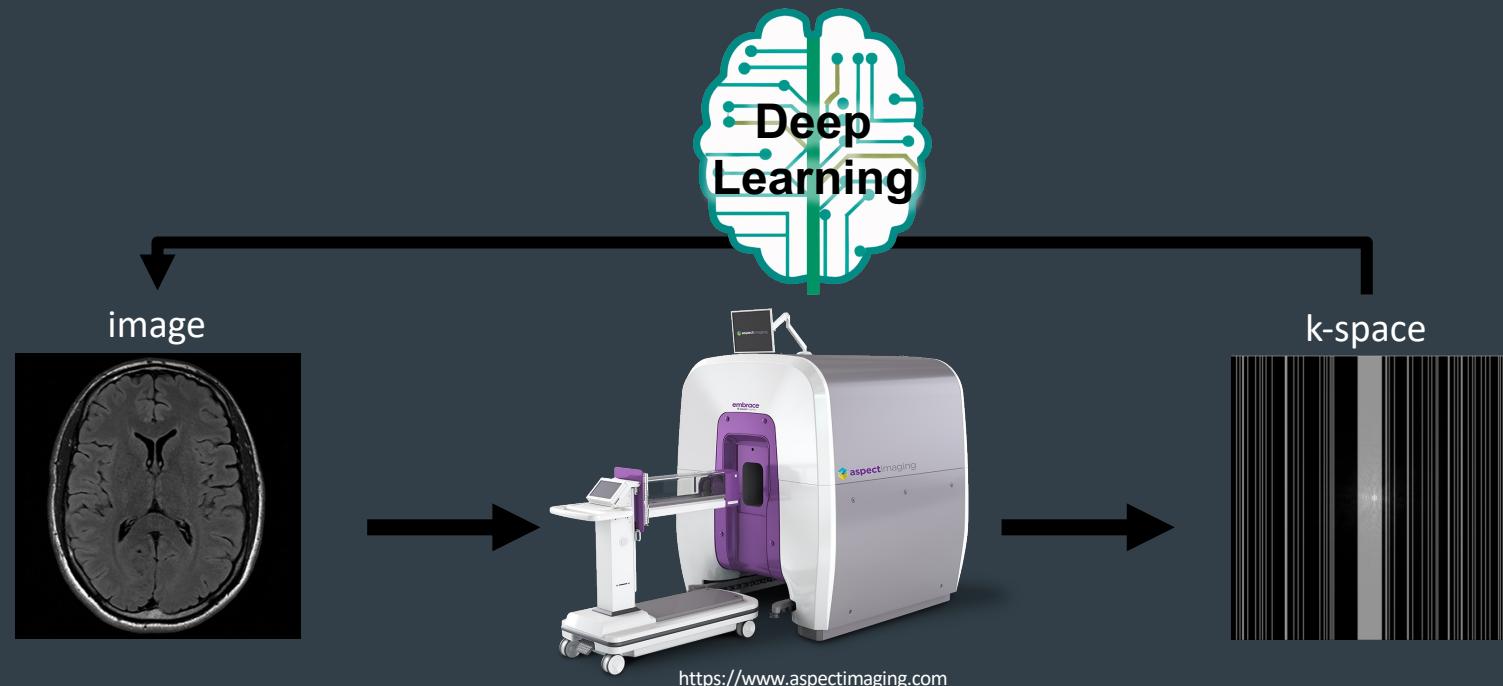


Reconstruction



Deep learning inversion for MRI

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



Generative models are powerful image generators

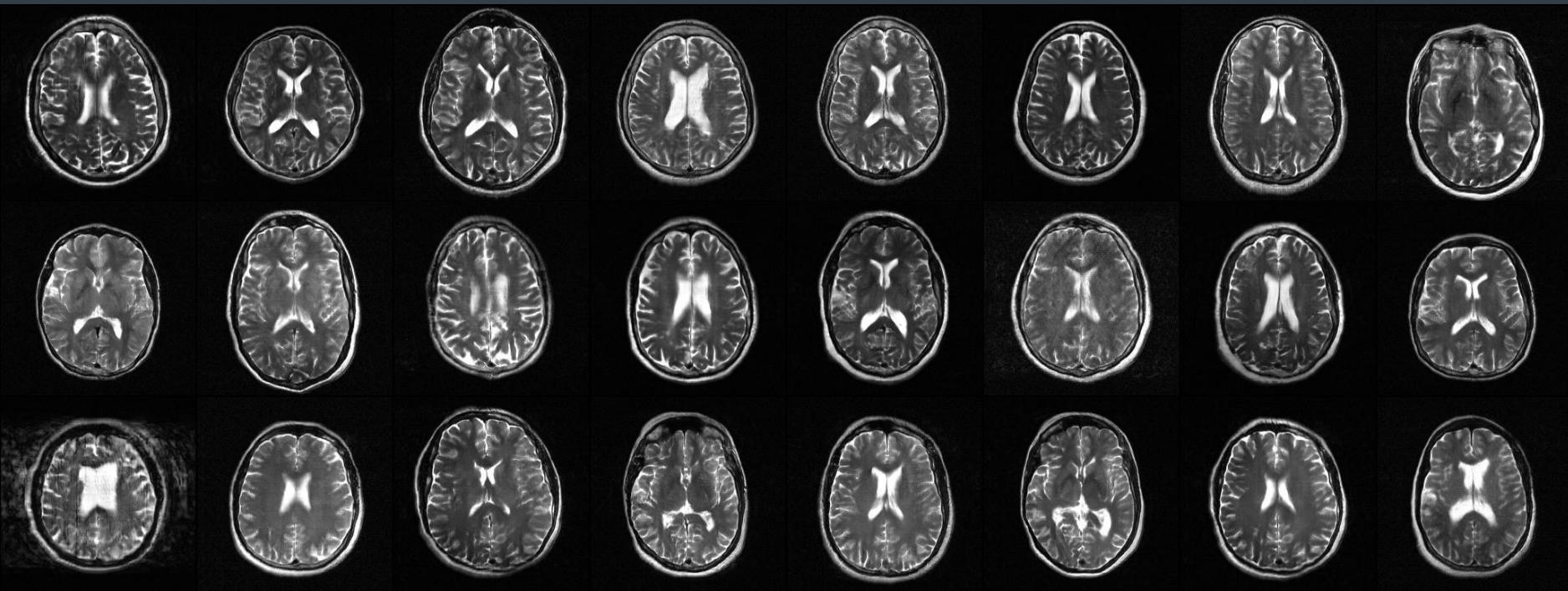


Generative models are powerful image generators



<https://thiscatdoesnotexist.com/>

Generative models are powerful image generators

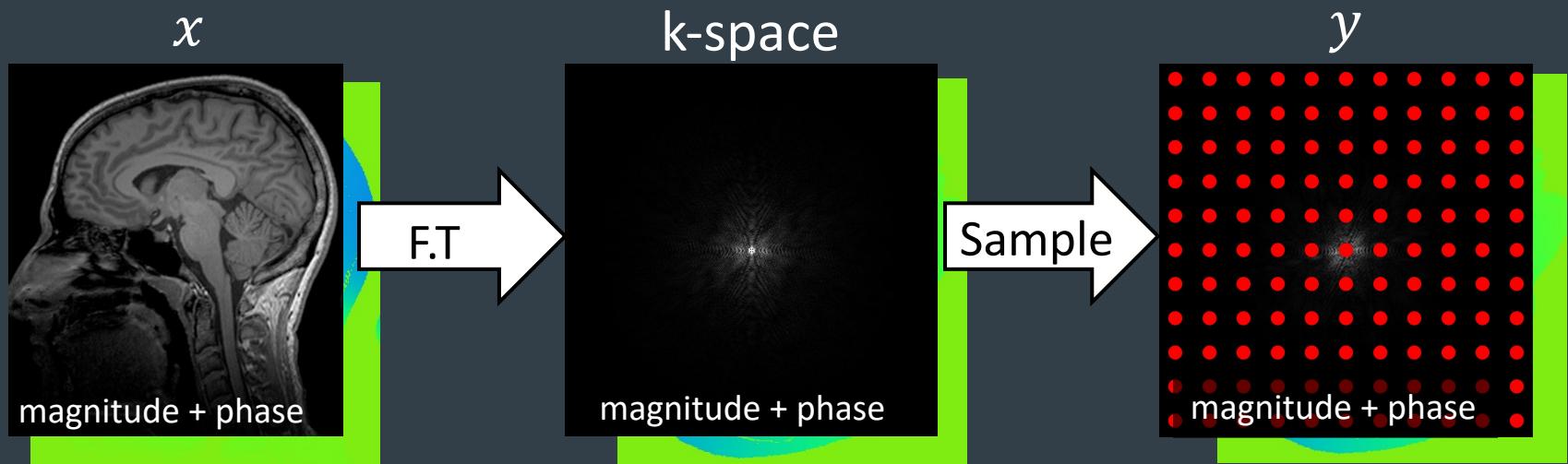


Generative model trained on FastMRI data

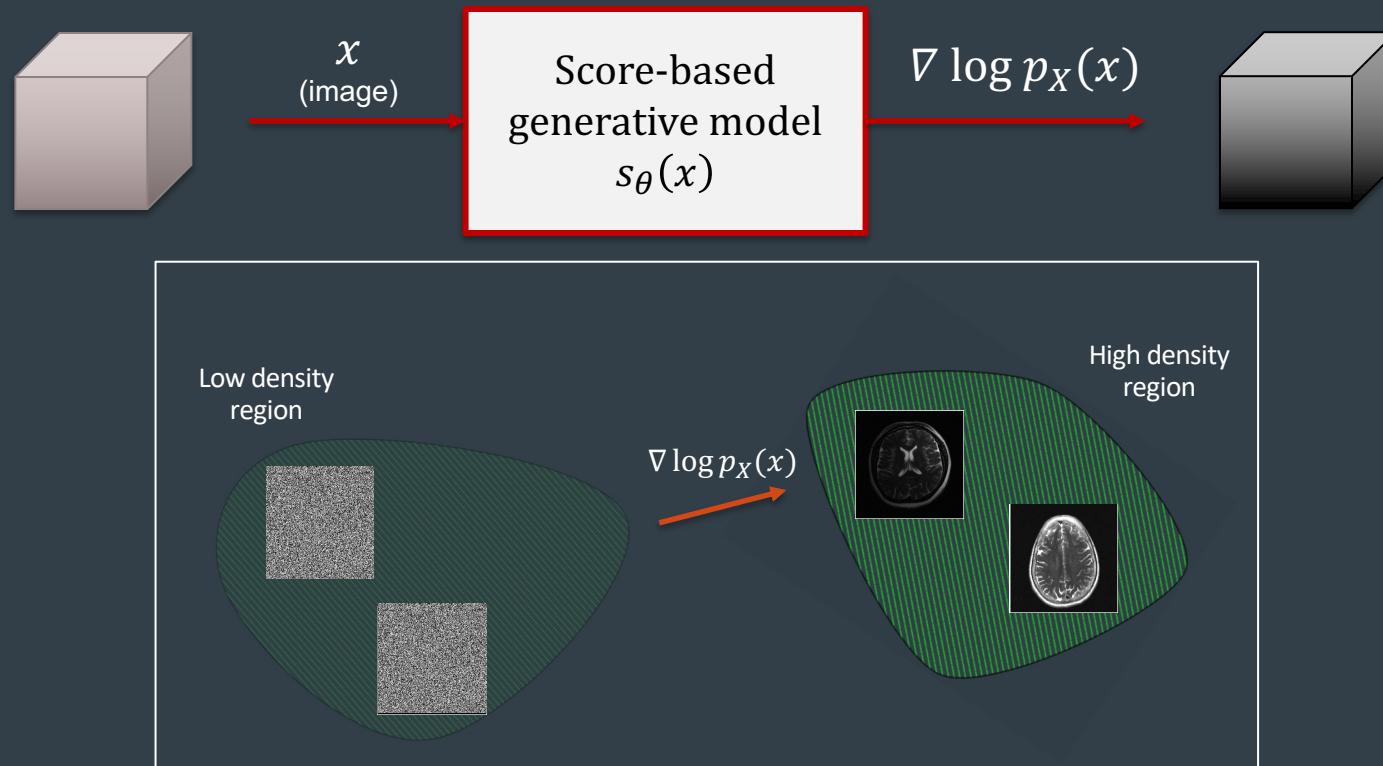
MRI: Problem Formulation

Signal is the Fourier transform of the image

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



Score-based generative models

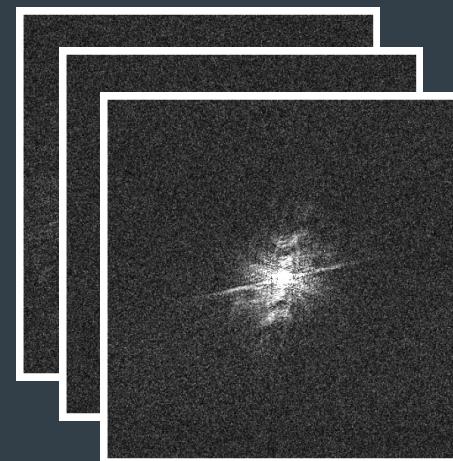


MRI Samples are inherently noisy

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

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

y

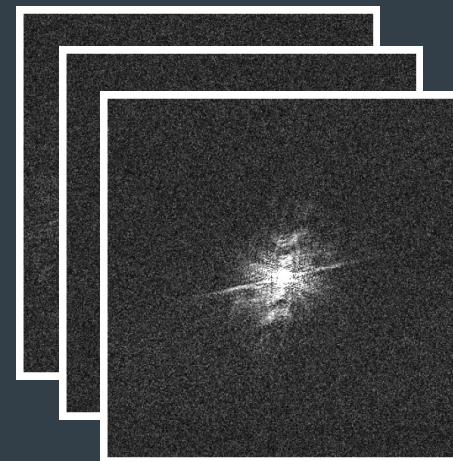


Original K-Space

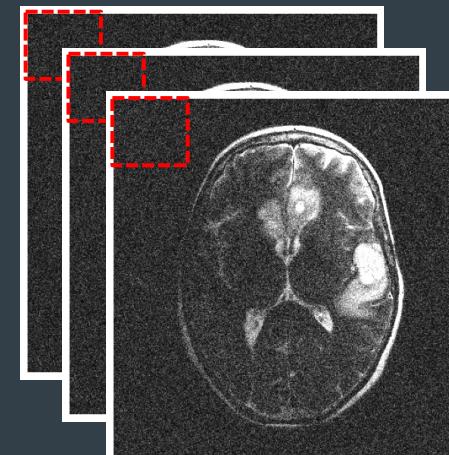
MRI Samples are inherently noisy

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

 y  $F^H y$ 

Original K-Space

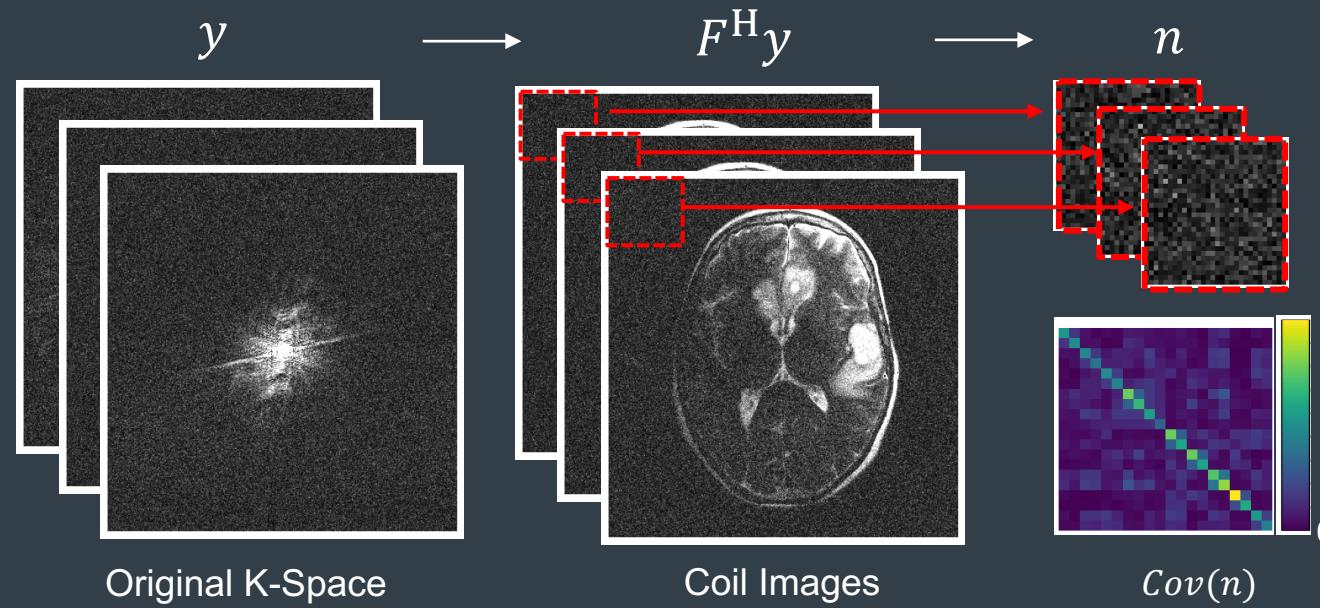


Coil Images

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).

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

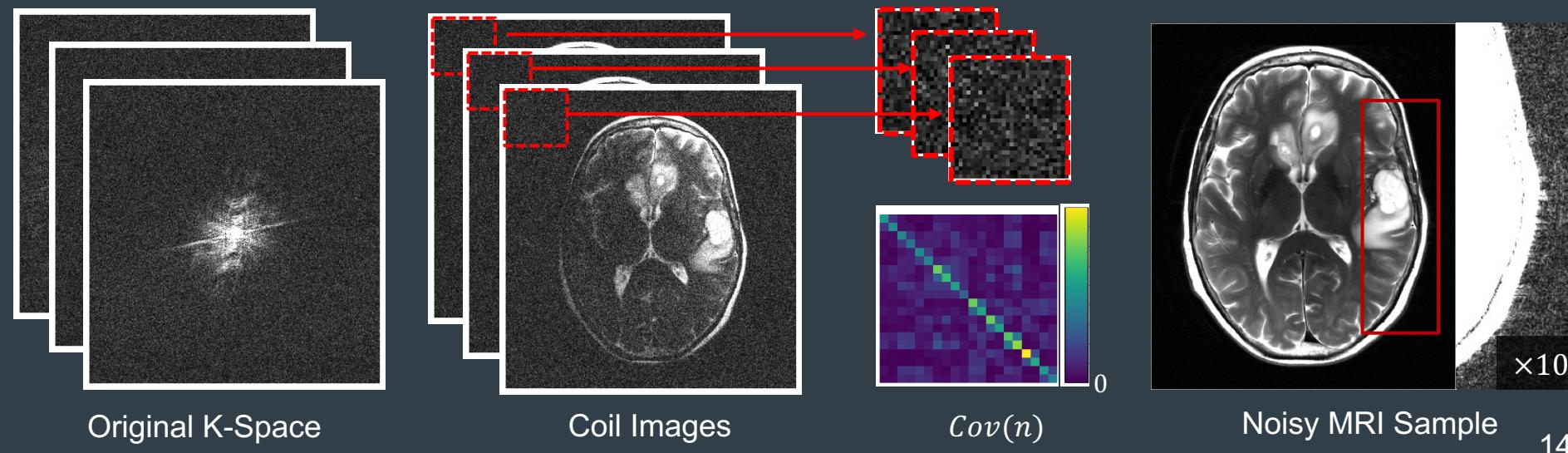


MRI Samples are inherently noisy

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

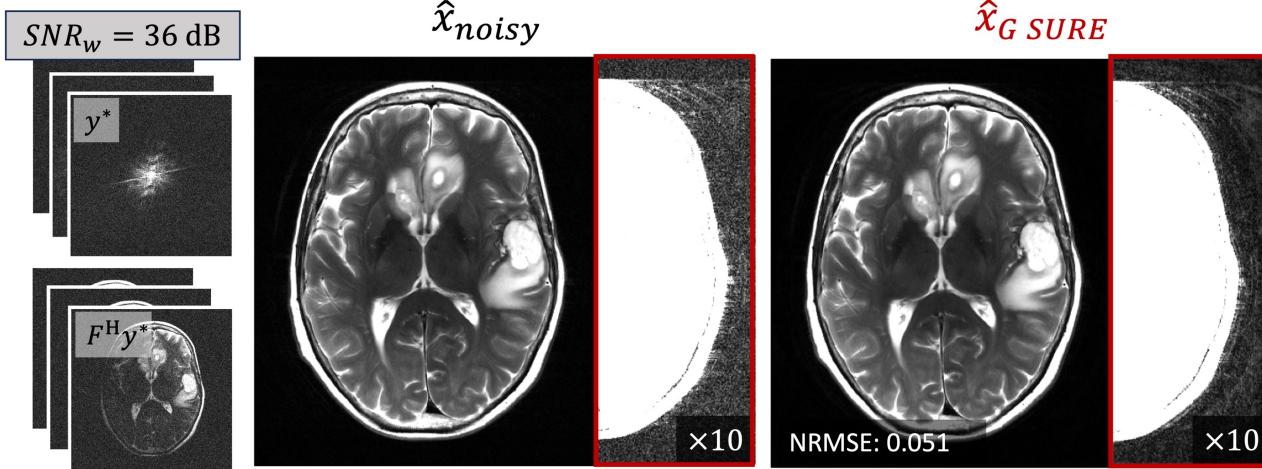
$$y = Ax + \text{noise}$$

$$y \longrightarrow F^H y \longrightarrow n \longrightarrow \hat{x}_{\text{noisy}} = A^H y^*$$



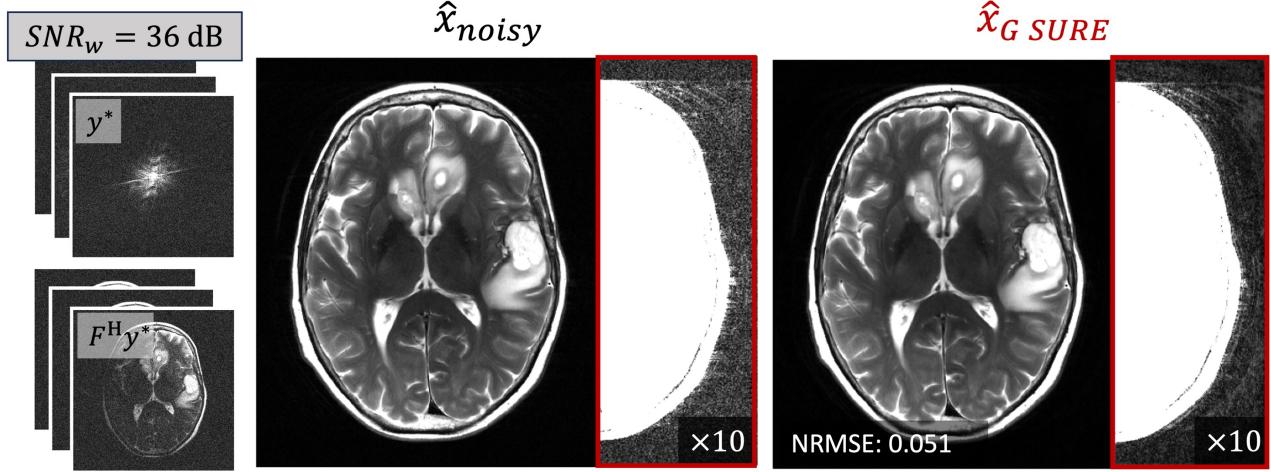
Denoising with GSURE

Original FastMRI



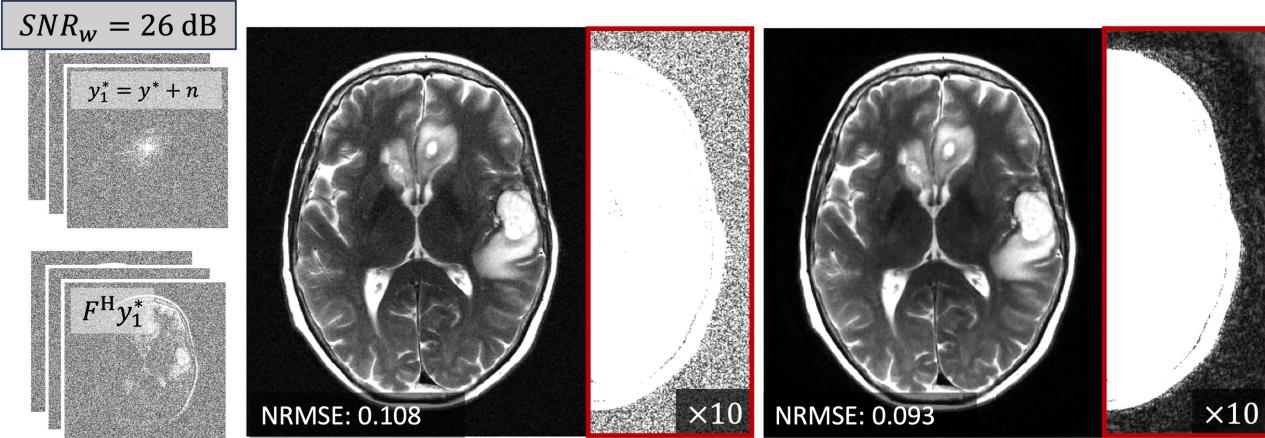
Denoising with GSURE

Original FastMRI



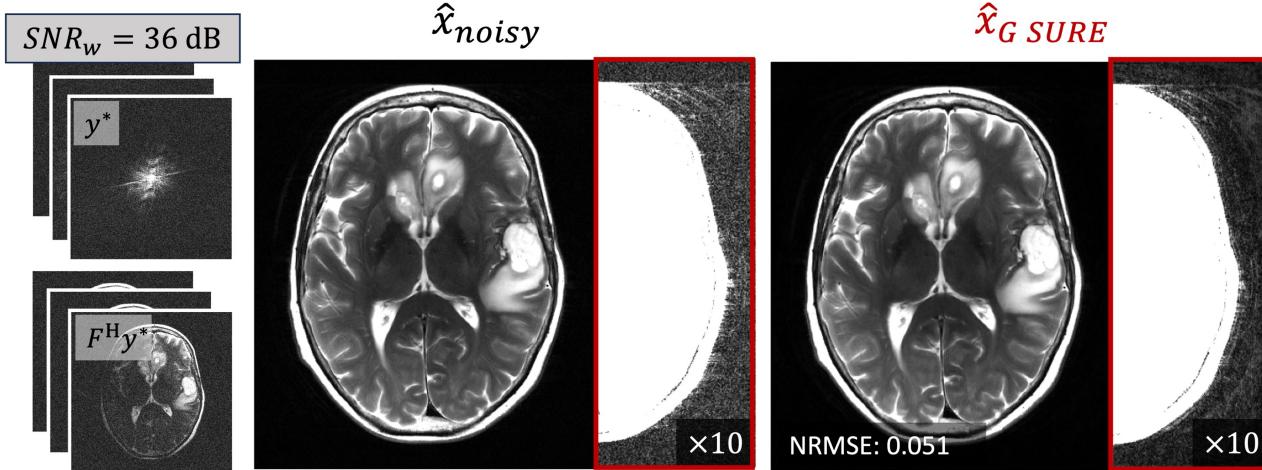
Original FastMRI

+
Additive Gaussian Noise



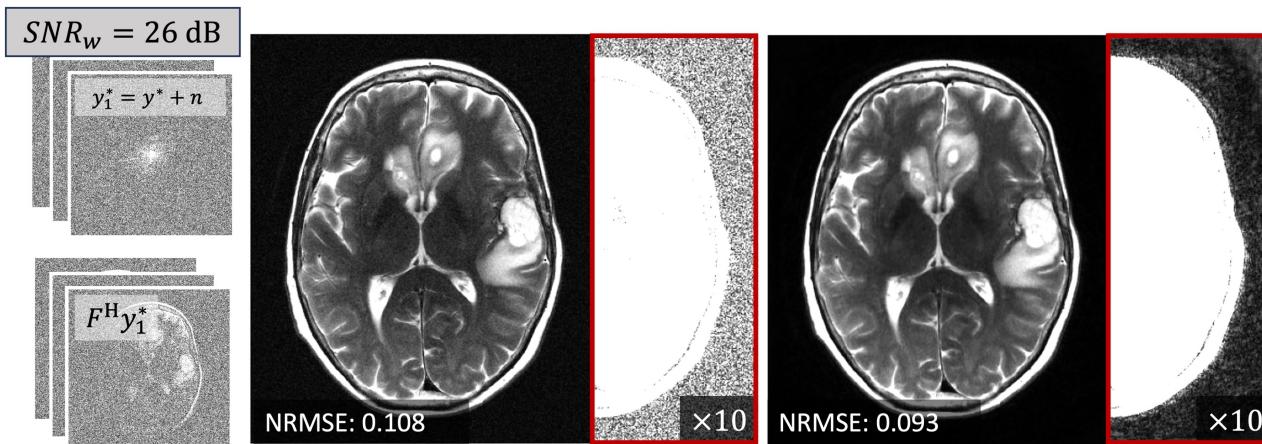
Denoising with GSURE

Original FastMRI



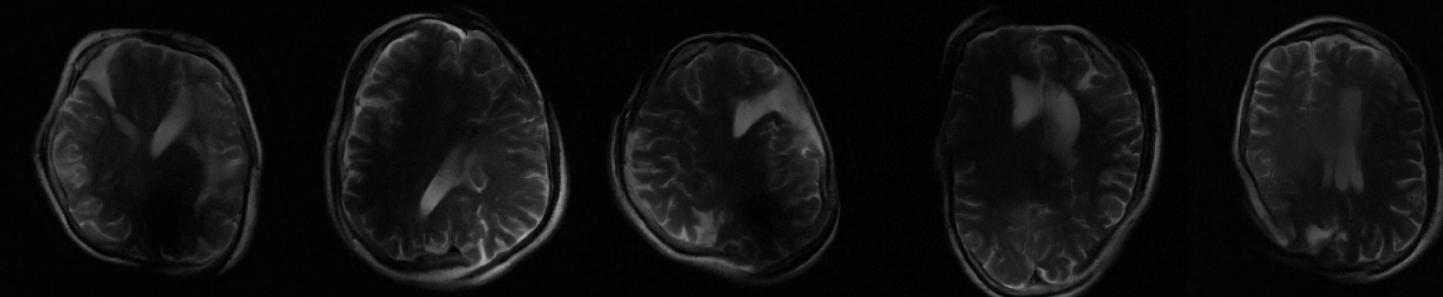
Original FastMRI

+
Additive Gaussian Noise



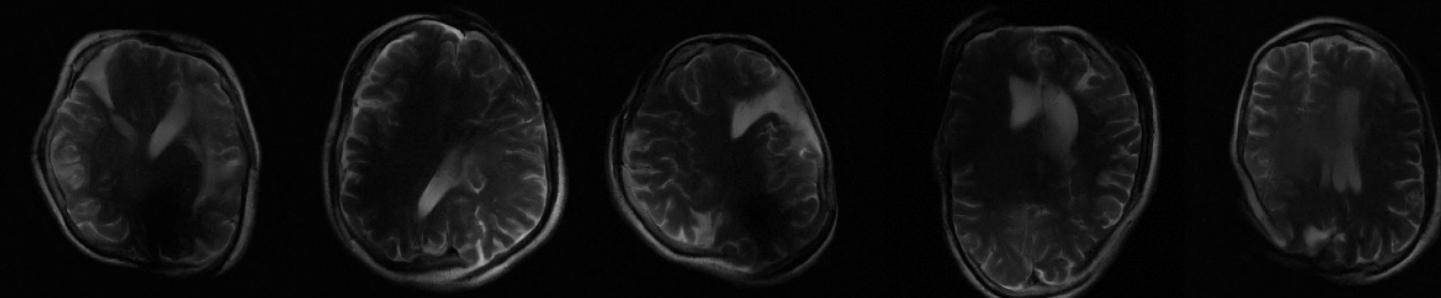
Learning Priors using Generative Models – $p(x)$

Naive Score

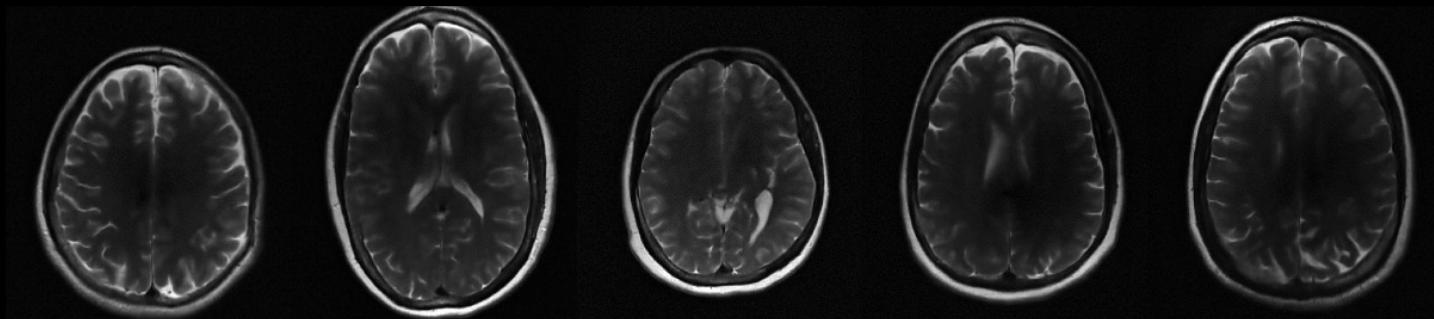


Learning Priors using Generative Models – $p(x)$

Naive Score

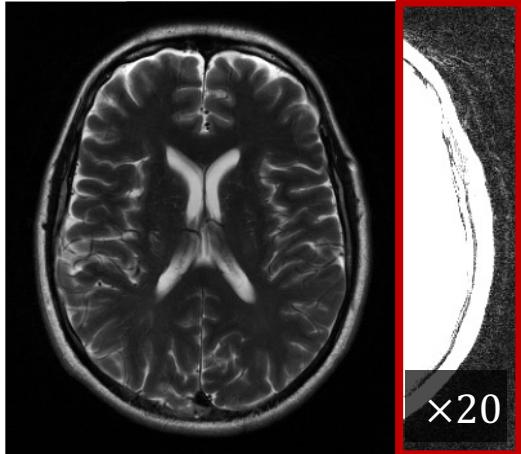


GSURE-Score

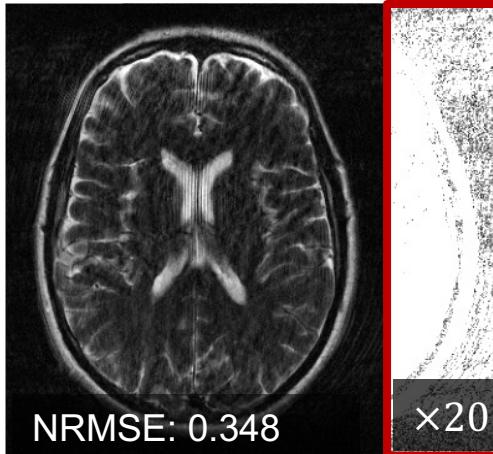


Inverse Problems using Generative Models $x \sim p(x|y)$

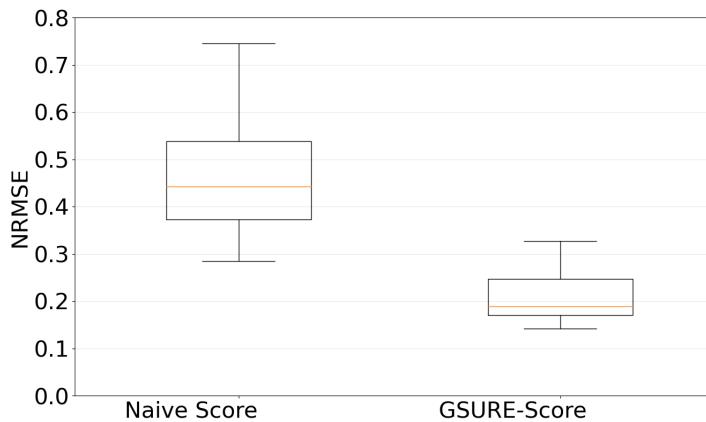
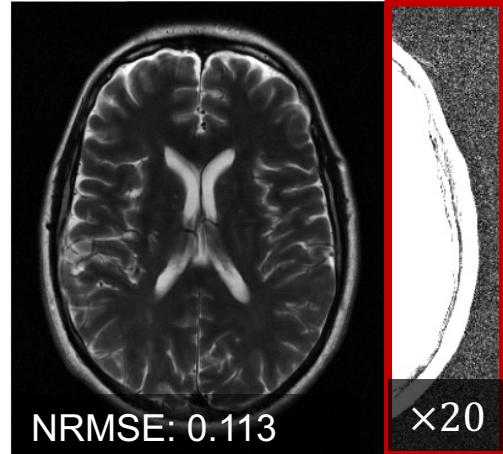
Fully Sampled



Naive Score



GSURE-Score



Conclusions

1. MRI samples are inherently noisy
2. Self-supervised techniques like GSURE can successfully remove noise
3. Denoising as a pre-processing step, severely improves the quality of generative priors
4. Priors trained on denoised FastMRI are better inverse problem solvers than naive training

Thank you!

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