MAY 2024

TEXAS
The University of Texas at Austin

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

Authors: **Asad Aali**[1], Marius Arvinte[2], Sidharth Kumar[1], Yamin Arefeen[1], Jon Tamir[1]

[1]The University of Texas at Austin

[2]Intel Labs

UT CSI Lab

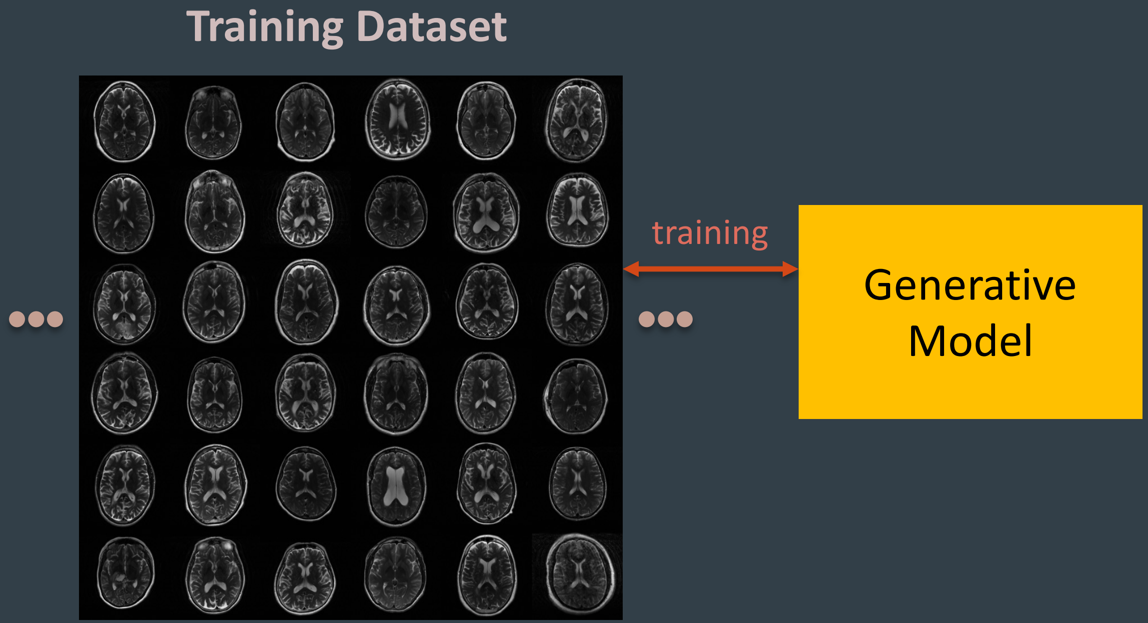
Motivation

- Deep Diffusion Probabilistic (Generative) Models are powerful tools for accelerated MRI reconstruction
    - ✓ Exploit large training databases
    - ✓ Decouples from the forward model

Song *NeurIPS* (2019), Kingma *ICLR* (2014), Goodfellow *NeurIPS (2014)*

Motivation

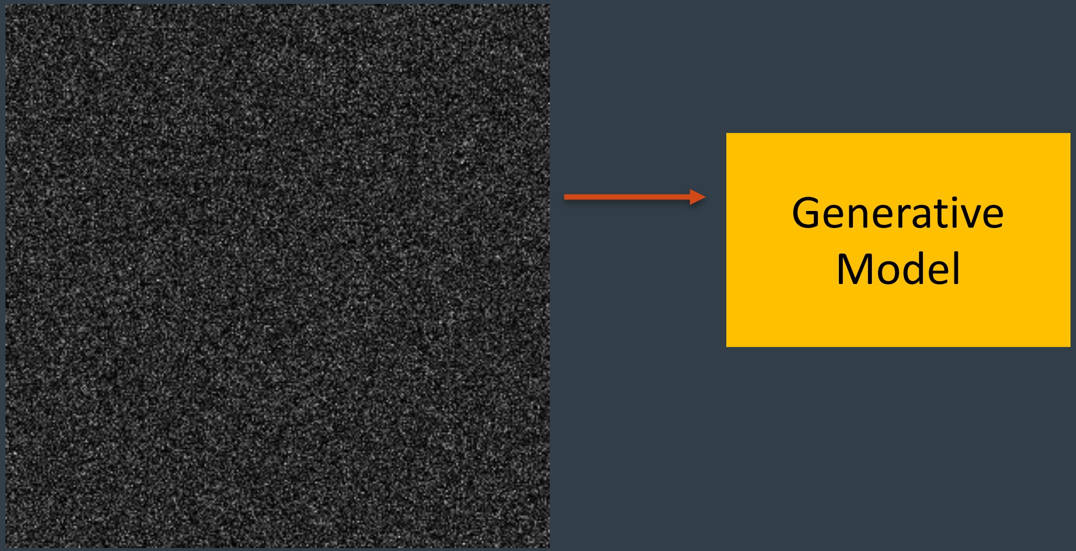
- Generative models learn priors for MR images.



Motivation

- Generative models learn priors for MR images.

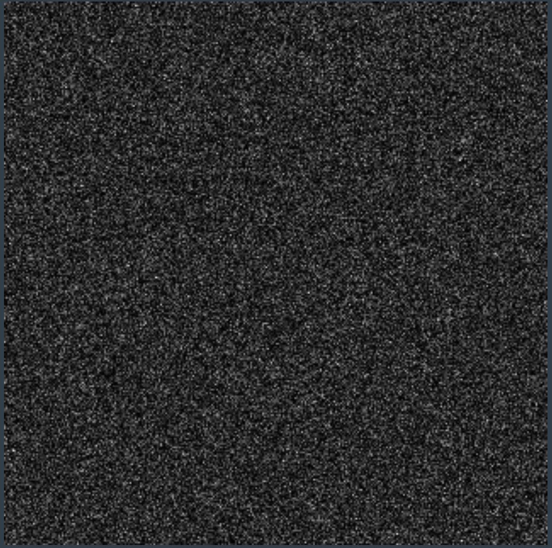
Sample from Gaussian Distribution



Motivation

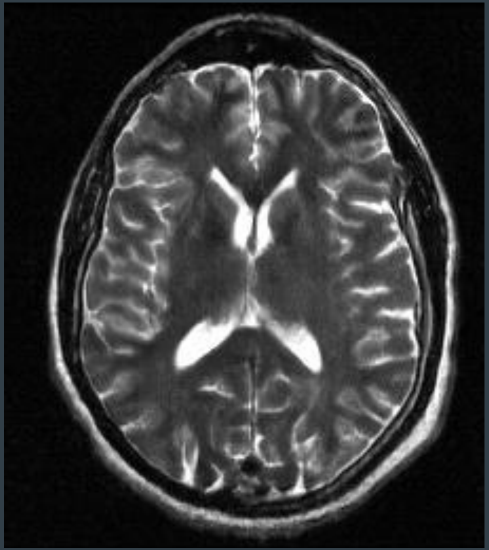
- Generative models learn priors for MR images.

Sample from Gaussian Distribution



Generative Model

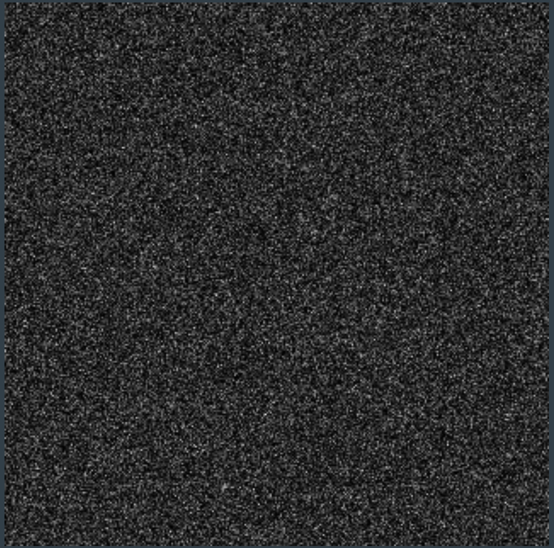
Sample from Image Distribution



Motivation

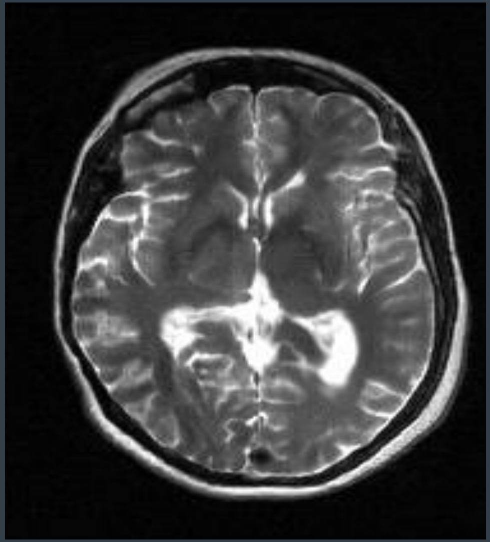
- Generative models learn priors for MR images.

Sample from Gaussian Distribution



→ Generative Model →

Sample from Image Distribution



Motivation

- Generative models learn priors for MR images.

Sample from Gaussian Distribution

Sample from Image Distribution

$$\sim \mathcal{N}(z) \longrightarrow \boxed{\text{Generative Model}} \longrightarrow \sim p(x)$$

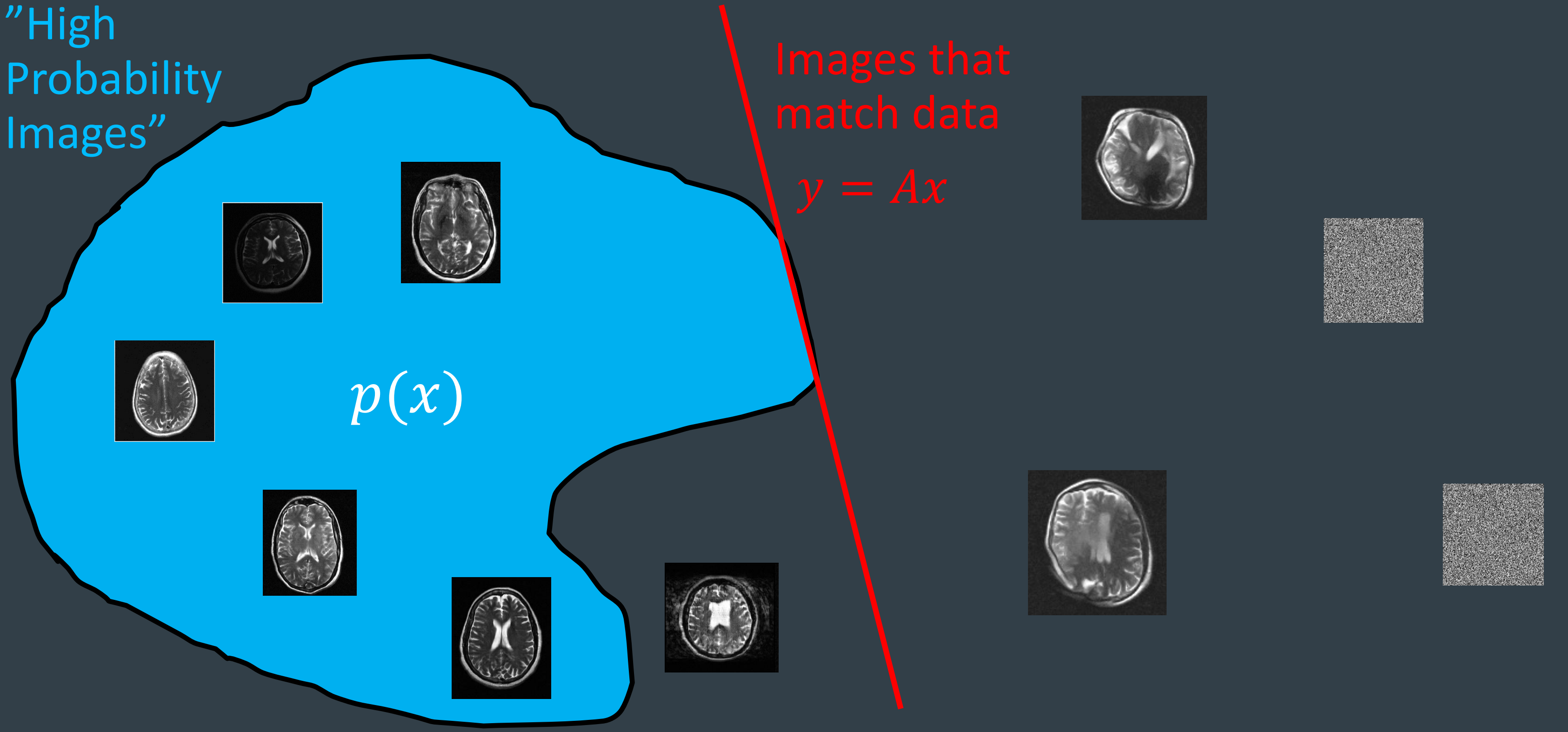
Image Prior

Motivation

- Generative Models to guide accelerated MRI reconstructions.

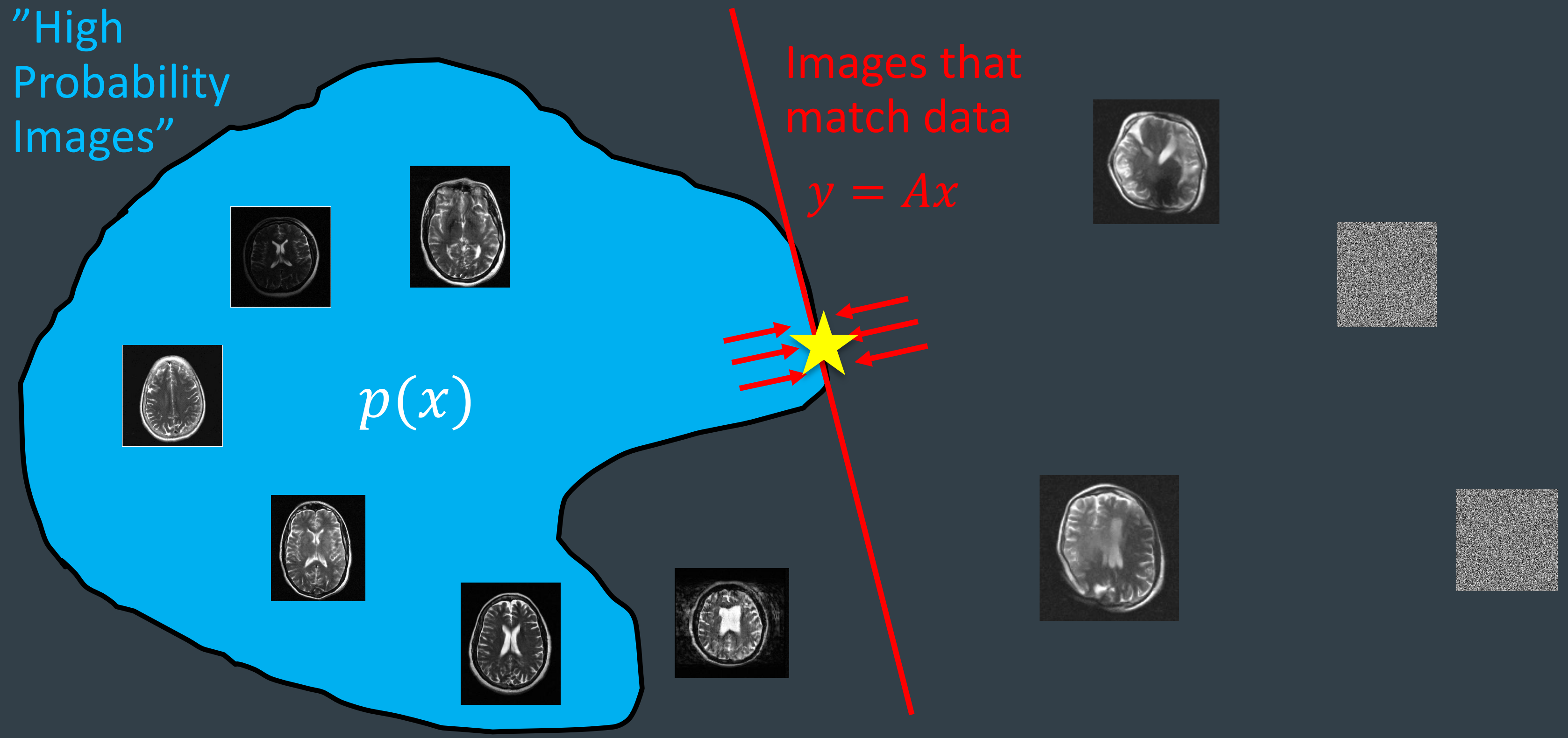
Motivation

- Generative Models to guide accelerated MRI reconstructions.



Motivation

- Generative Models to guide accelerated MRI reconstructions.

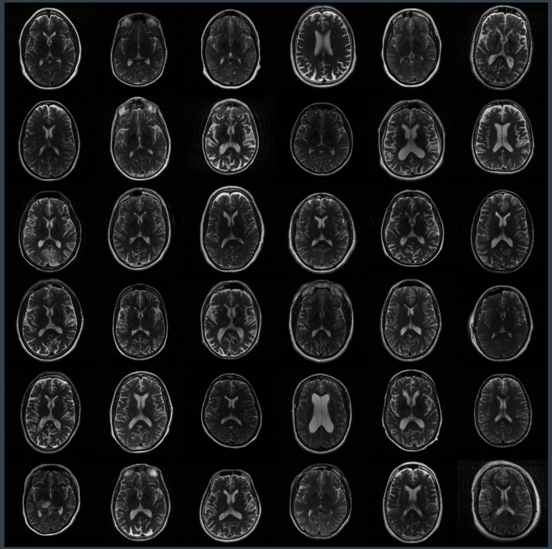


Motivation

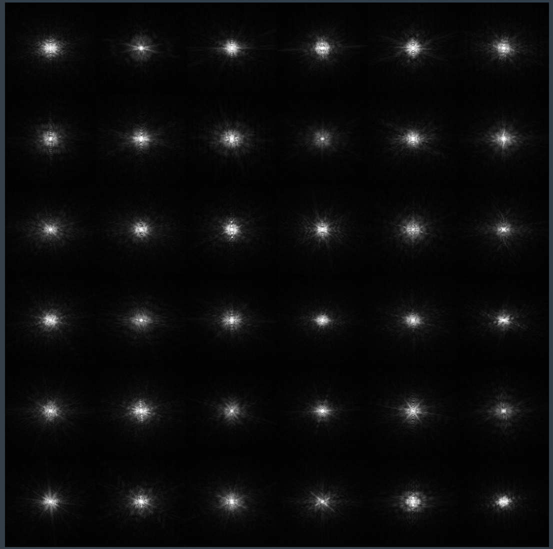
- Generative Models rely on large amounts of ***high-quality data***.
- MRI data are ***inherently noisy***[1,2], multi-coil k-space.

~~Training Dataset~~ Processed Dataset

Training Data: Multi-coil K-space



reconstruction

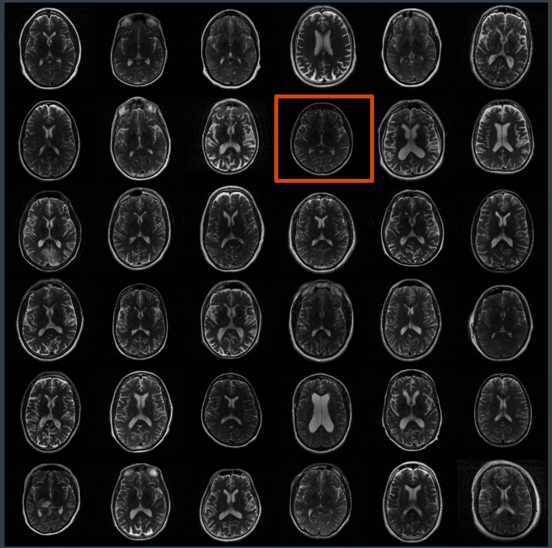


[1]FastMRI (https://fastmri.med.nyu.edu/), [2]Wang, *MRM* (2024)

Motivation

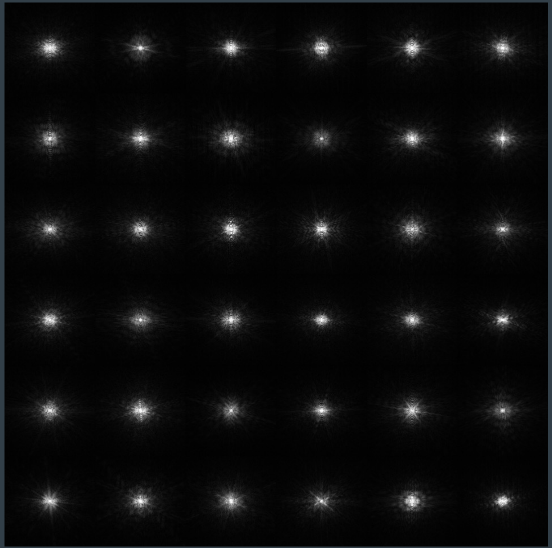
- Generative Models rely on large amounts of ***high-quality data***.
- MRI data are ***inherently noisy***[1,2], multi-coil k-space.

~~Training Dataset~~ Processed Dataset



reconstruction

Training Data: Multi-coil K-space

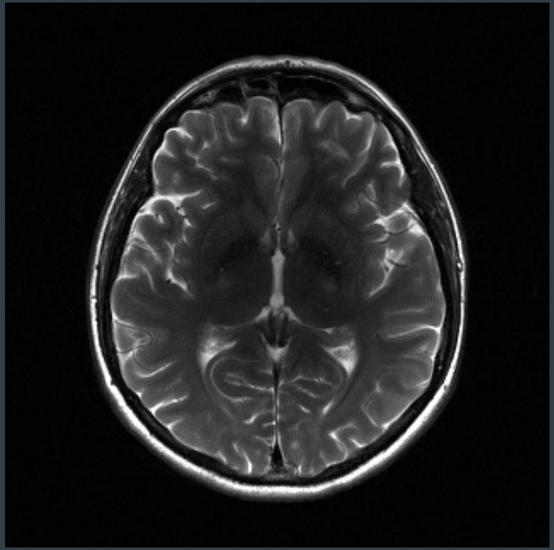


[1]FastMRI (https://fastmri.med.nyu.edu/), [2]Wang, *MRM* (2024)

Motivation

- Generative Models rely on large amounts of ***high-quality data***.
- MRI data are ***inherently noisy***[1,2], multi-coil k-space.

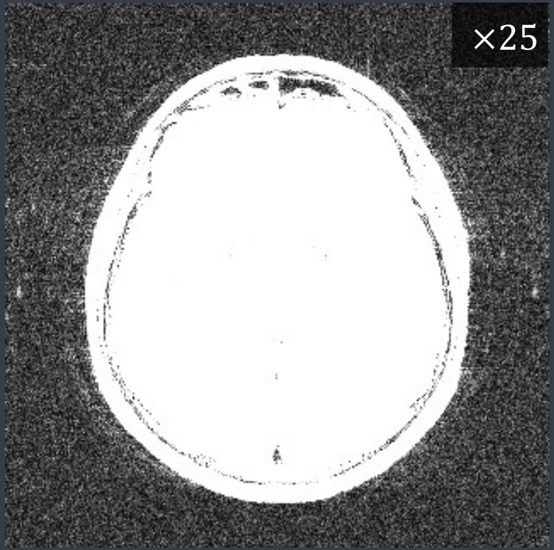
~~Training Dataset~~ Processed Dataset



Motivation

- Generative Models rely on large amounts of ***high-quality data***.
- MRI data are ***inherently noisy***[1,2], multi-coil k-space.

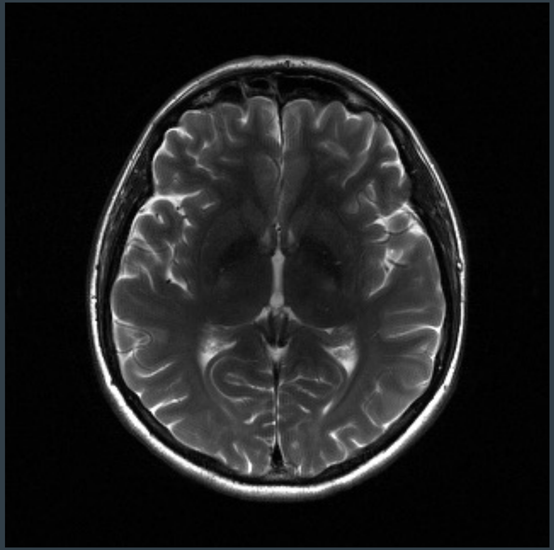
~~Training Dataset~~ Processed Dataset



Motivation

- Generative Models rely on large amounts of ***high-quality data***.
- MRI data are ***inherently noisy***[1,2], multi-coil k-space.

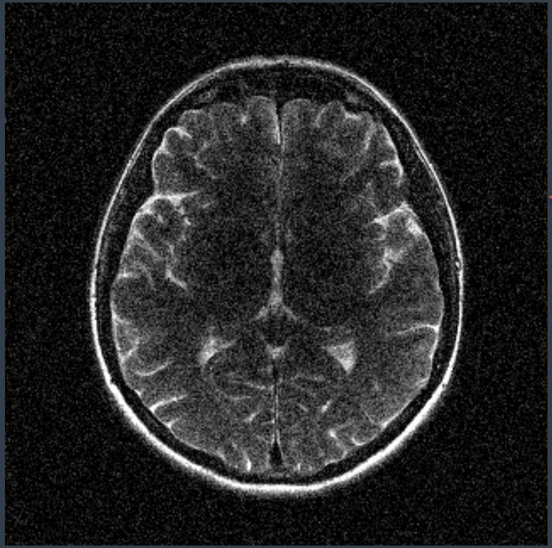
~~Training Dataset~~ Processed Dataset



Motivation

- Training generative models with noisy datasets leads to a poor prior.
- **Reconstruction performance depends on accuracy of priors**

Training Dataset

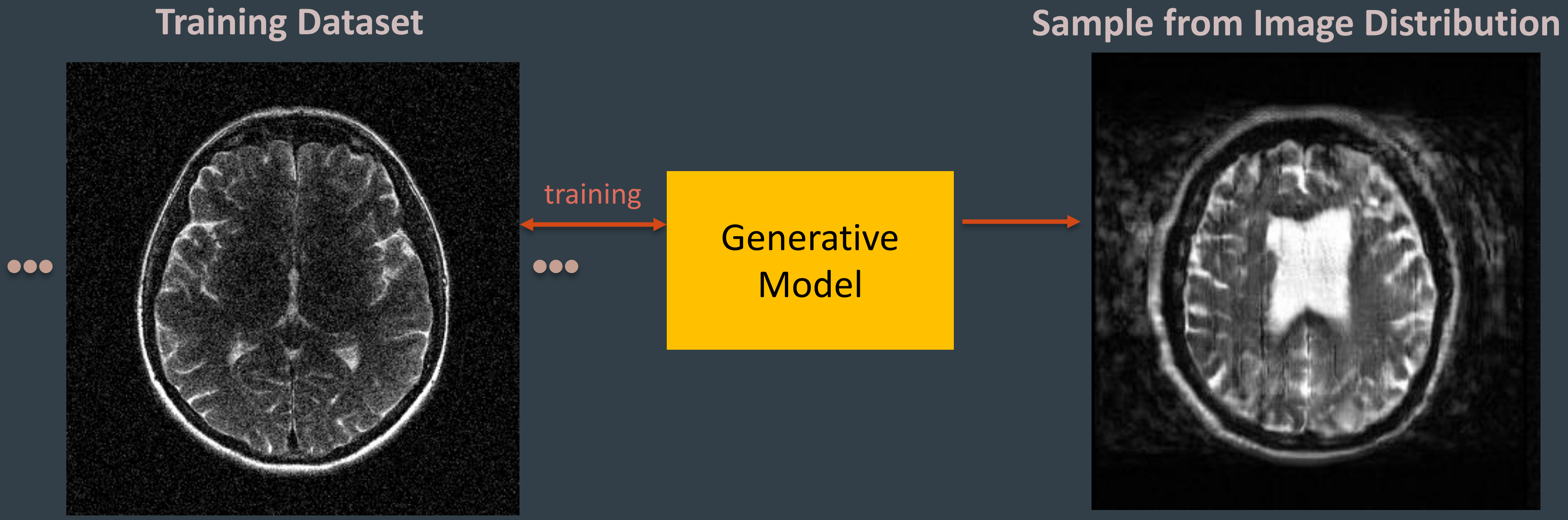


training

Generative Model

Motivation

- Training generative models with noisy datasets leads to a poor prior.
- **Reconstruction performance depends on accuracy of priors**

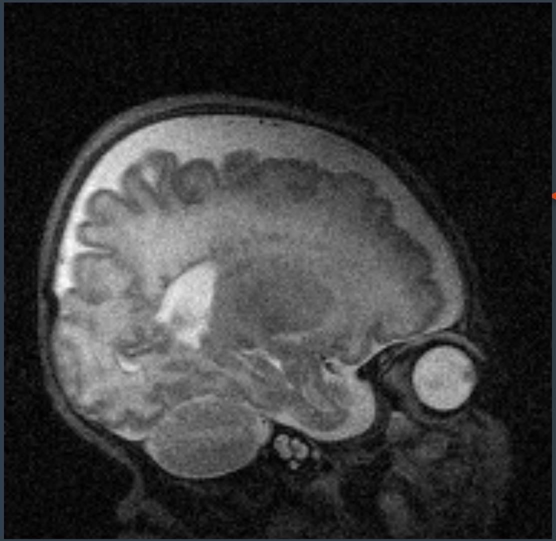


Motivation

Application in real world datasets: low field neo-natal MRI

- Training generative models with noisy datasets leads to a poor prior.
- **Reconstruction performance depends on accuracy of priors**

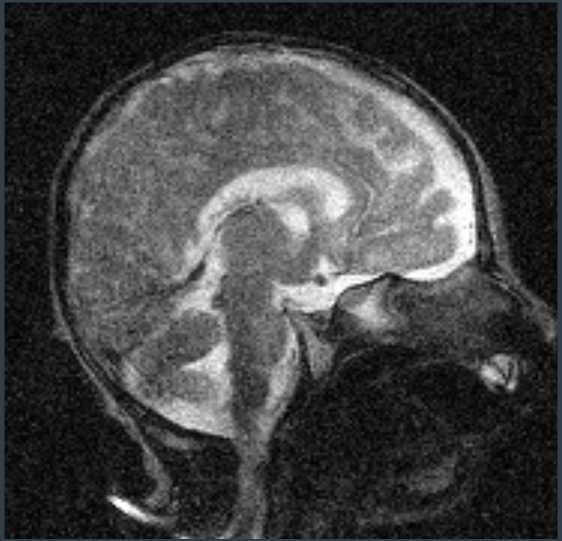
Training Dataset



training

Generative Model

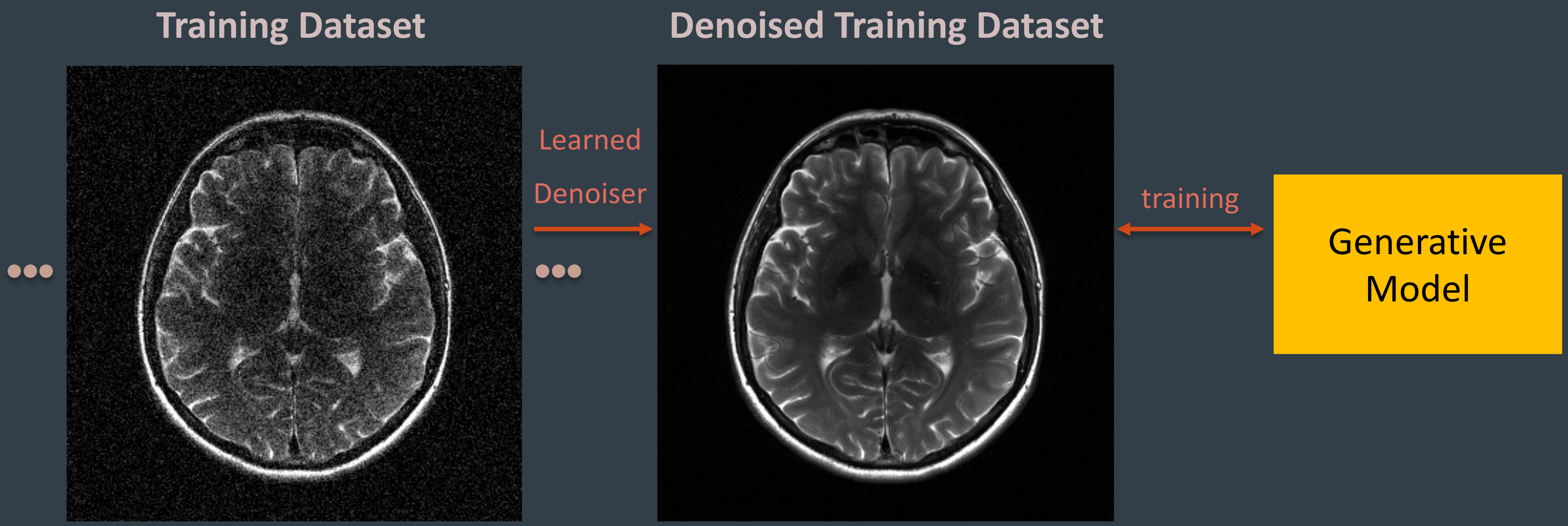
Sample from Image Distribution



*Scans courtesy of Aspect Imaging
Aspect Embrace 1T Scanner
Installed at SZMC, Israel

Purpose

- Learn model to denoise dataset before training generative models



Purpose

Training a denoiser without access clean training samples.

Investigate the **effectiveness** of self-supervised **denoising** as a pre-processing step to learning **generative priors** for accelerated MRI reconstruction

Problem Formulation

Problem Formulation

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

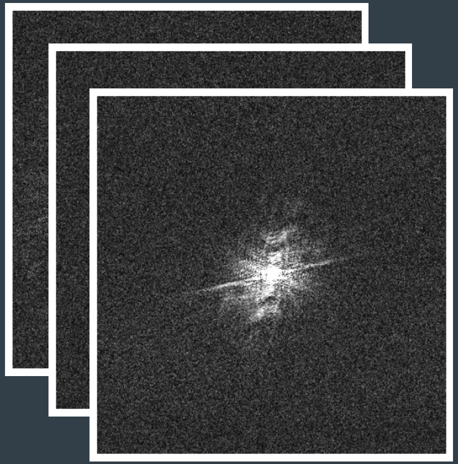
$$y = FSx + noise$$

Problem Formulation

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

$$y = FSx + noise$$

y



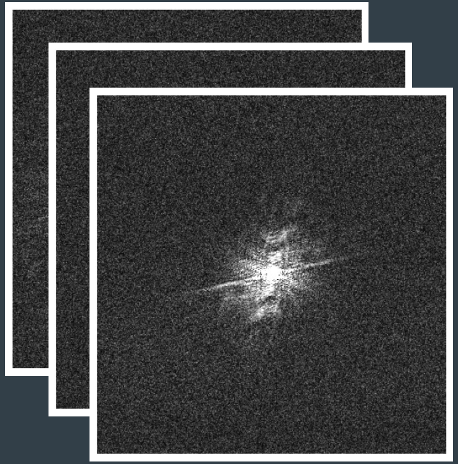
Original K-Space

Problem Formulation

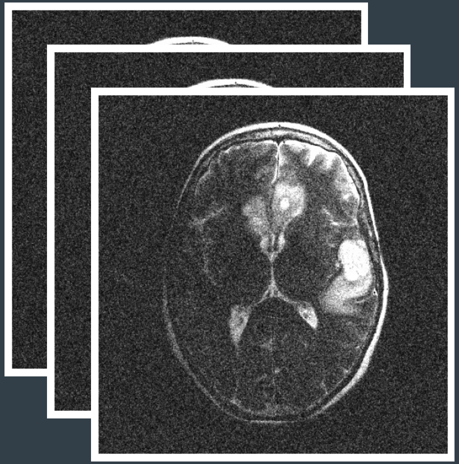
Goal is to learn the **clean distribution** using fully-sampled, multi coil *noisy* data (i.i.d Gaussian, with known power σ_w^2).

$$y = FSx + noise$$

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



Original K-Space



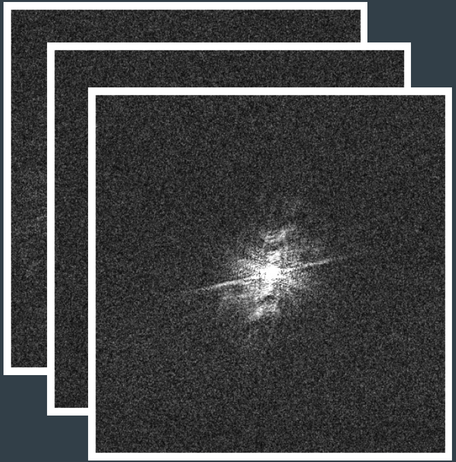
Coil Images

Problem Formulation

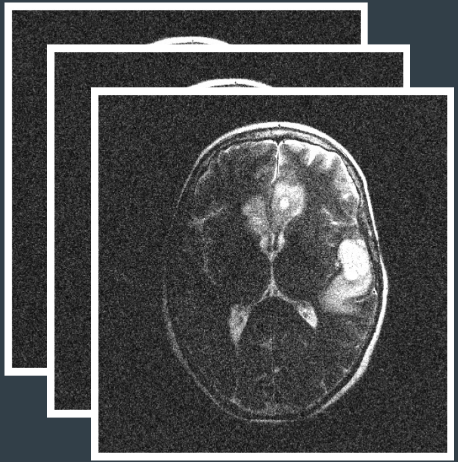
Goal is to learn the **clean distribution** using fully-sampled, multi coil *noisy* data (i.i.d Gaussian, with known power σ_w^2).

$$y = FSx + noise$$

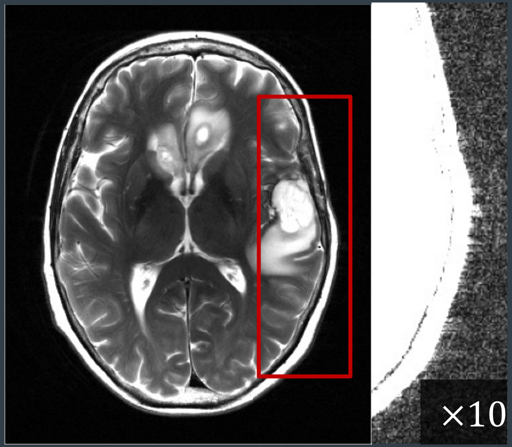
$y \longrightarrow F^{\mathrm{H}}y \longrightarrow \boxed{\hat{x}_{noisy} = A^H y}$



Original K-Space



Coil Images

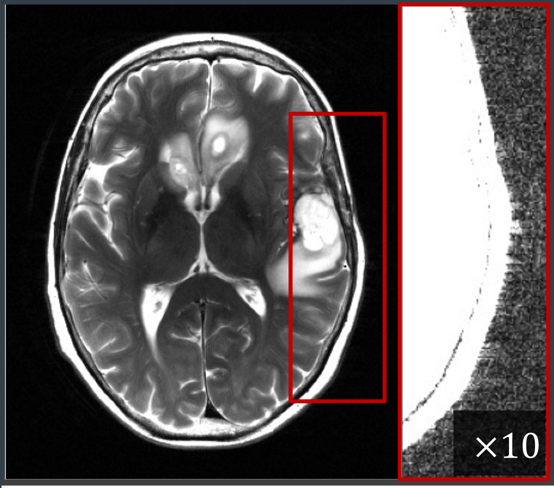


Noisy MRI Sample

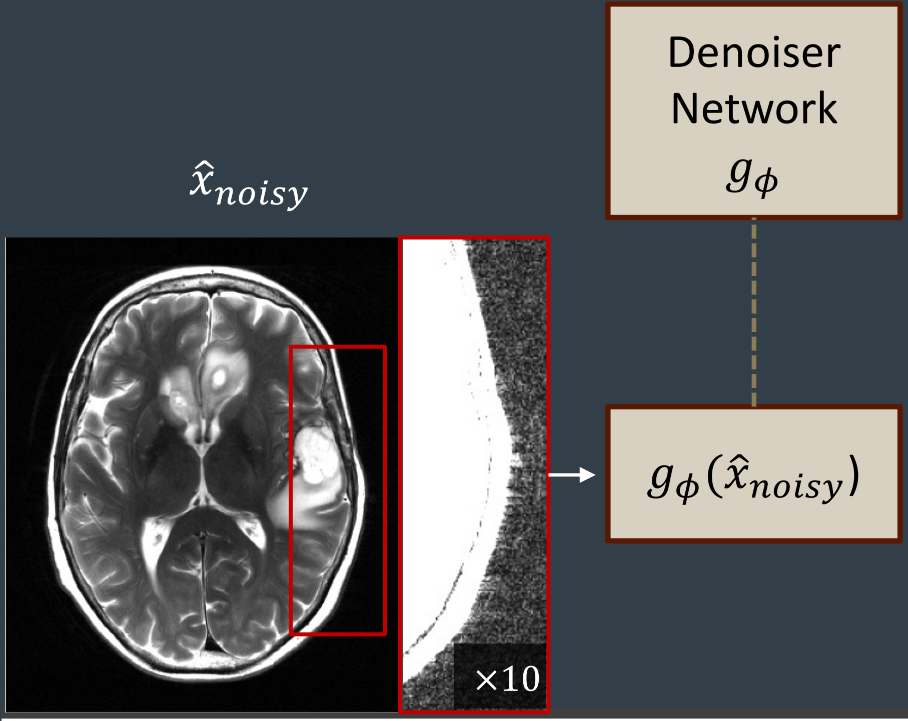
Proposed Methods

Proposed Methods

$\hat{x}_{noisy}$



Proposed Methods

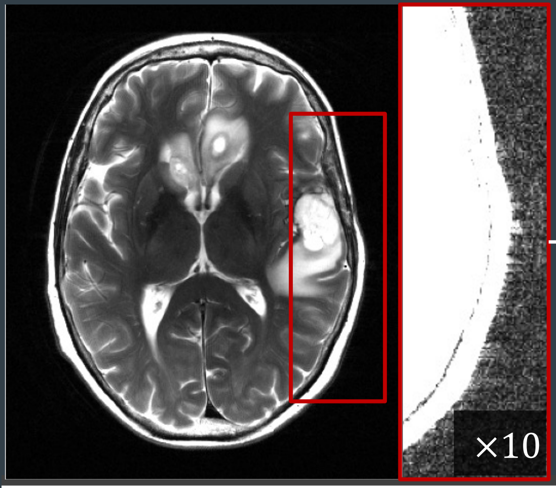


Proposed Methods

Denoiser Network

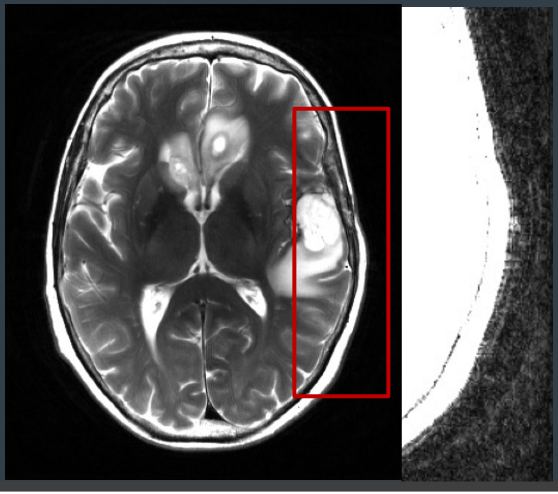
g_ϕ

$\hat{x}_{noisy}$

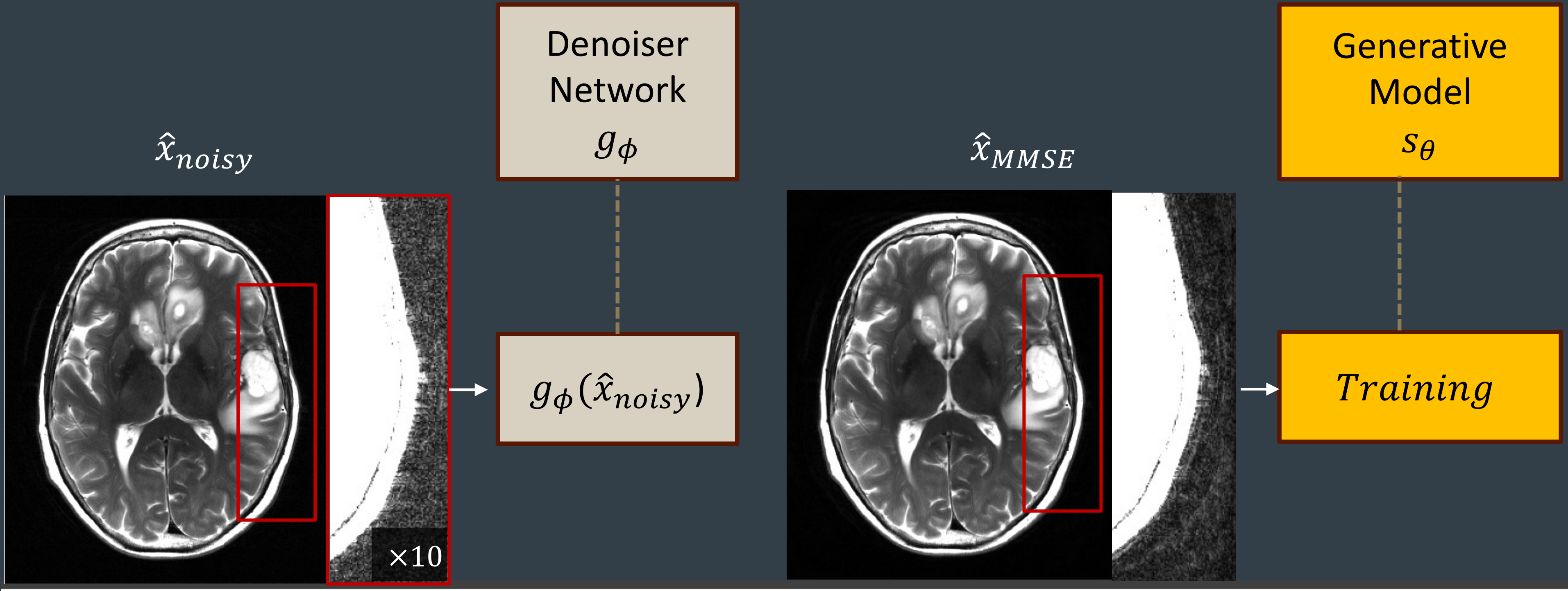


$g_\phi(\hat{x}_{noisy})$

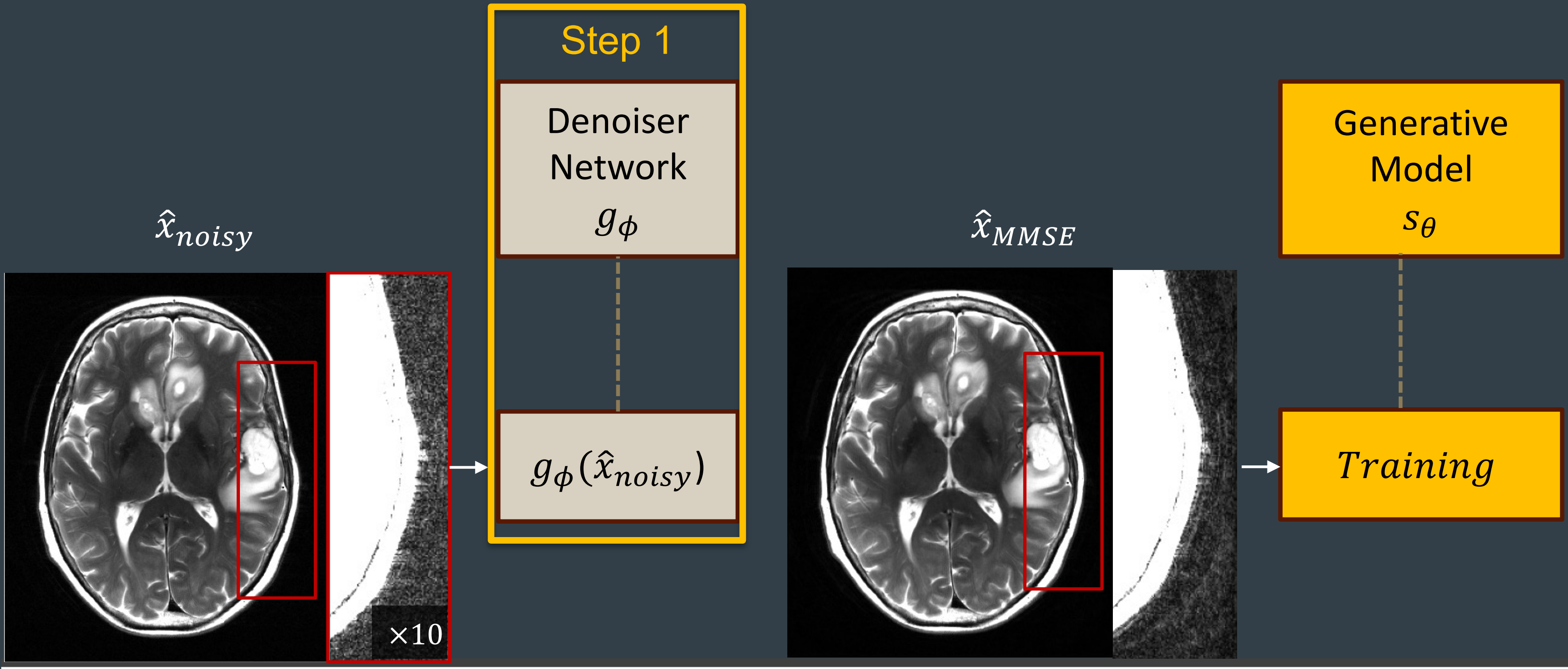
$\hat{x}_{MMSE}$



Proposed Methods



Proposed Methods



Self-Supervised Denoising

Training a denoiser with only access to noisy data

A is a Linear Forward Operator (Fully-Sampled) -> **GSURE**[1,2,3]

$$y = FSx + noise$$

[1]Soltanayev, *NeurIPS,* 2018, [2]Eldar, *IEEE Transactions on Signal Processing,* 2008, [3]Kawar, *TMLR,* 2023

Generalized SURE (GSURE) Basics

- GSURE[1]: Self-supervised denoising technique, only need access to:
  - $\hat{x}_{noisy}$ → **Noisy Samples**
  - Noise **Covariance Matrix**

- An unbiased estimate of the MSE

$$E[\mathrm{L}_{GSURE}] = E\left\| g_{\phi}\left(\hat{x}_{noisy}\right) - x \right\|$$

[1]Eldar, *IEEE Transactions on Signal Processing, 2008*

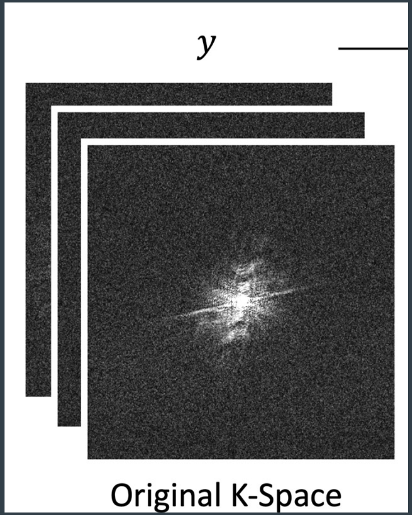
Pre-Processing Noisy Dataset

- GSURE loss requires the **noise covariance** matrix
- **Pre-whitening** (noise covariance $= I$) makes computation relatively straight-forward

Kellman *MRM* (2005)

Pre-Processing Noisy Dataset

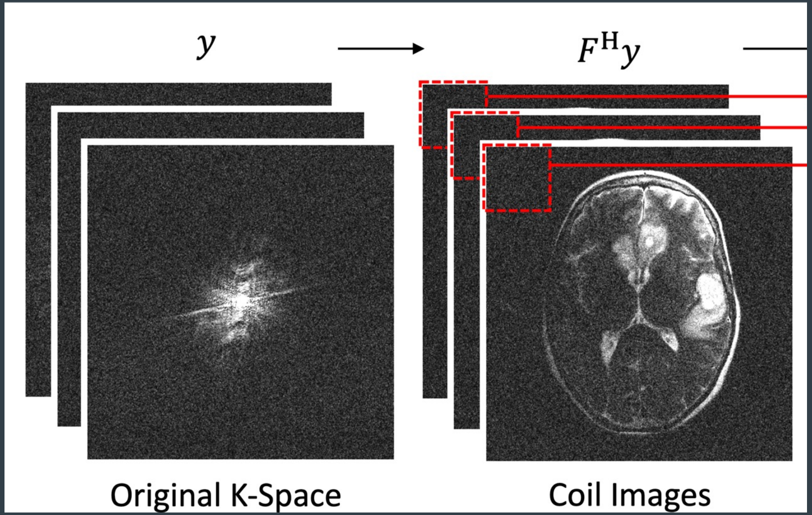
- GSURE loss requires the **noise covariance** matrix
- **Pre-whitening** (noise covariance $= I$) makes computation relatively straight-forward



Kellman *MRM* (2005)

Pre-Processing Noisy Dataset

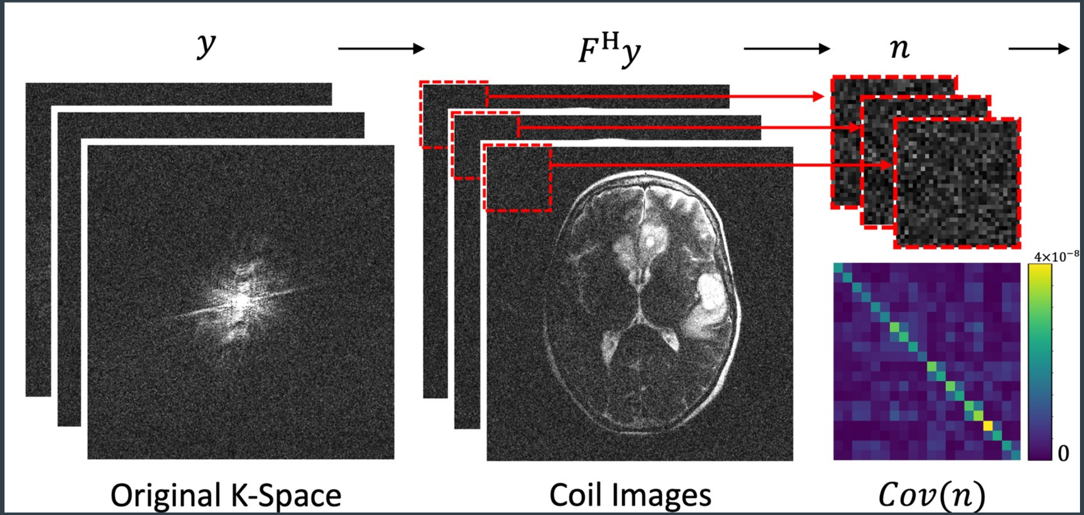
- GSURE loss requires the **noise covariance** matrix
- **Pre-whitening** (noise covariance $= I$) makes computation relatively straight-forward



Kellman *MRM* (2005)

Pre-Processing Noisy Dataset

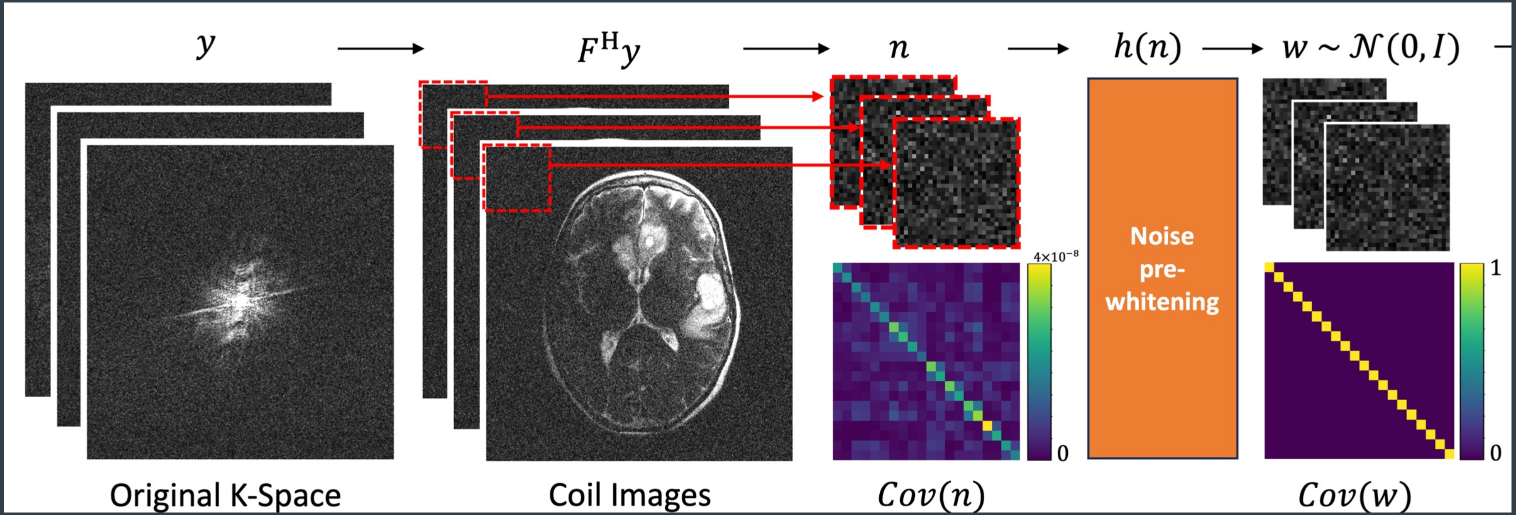
- GSURE loss requires the **noise covariance** matrix
- **Pre-whitening** (noise covariance $= I$) makes computation relatively straight-forward



Kellman *MRM* (2005)

Pre-Processing Noisy Dataset

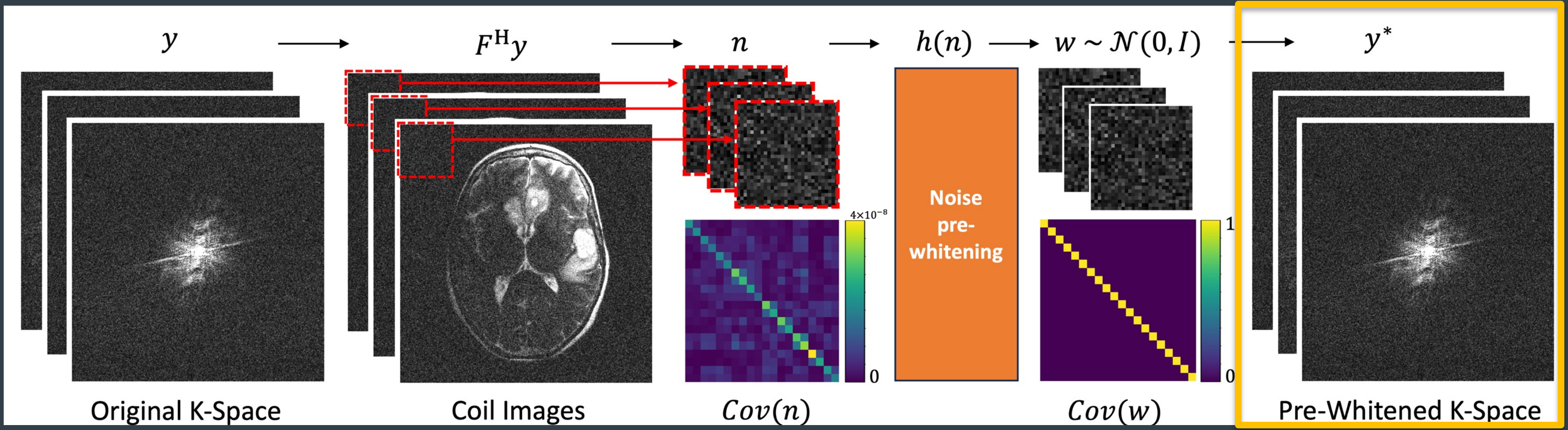
- GSURE loss requires the **noise covariance** matrix
- **Pre-whitening** (noise covariance $= I$) makes computation relatively straight-forward



Kellman *MRM* (2005)

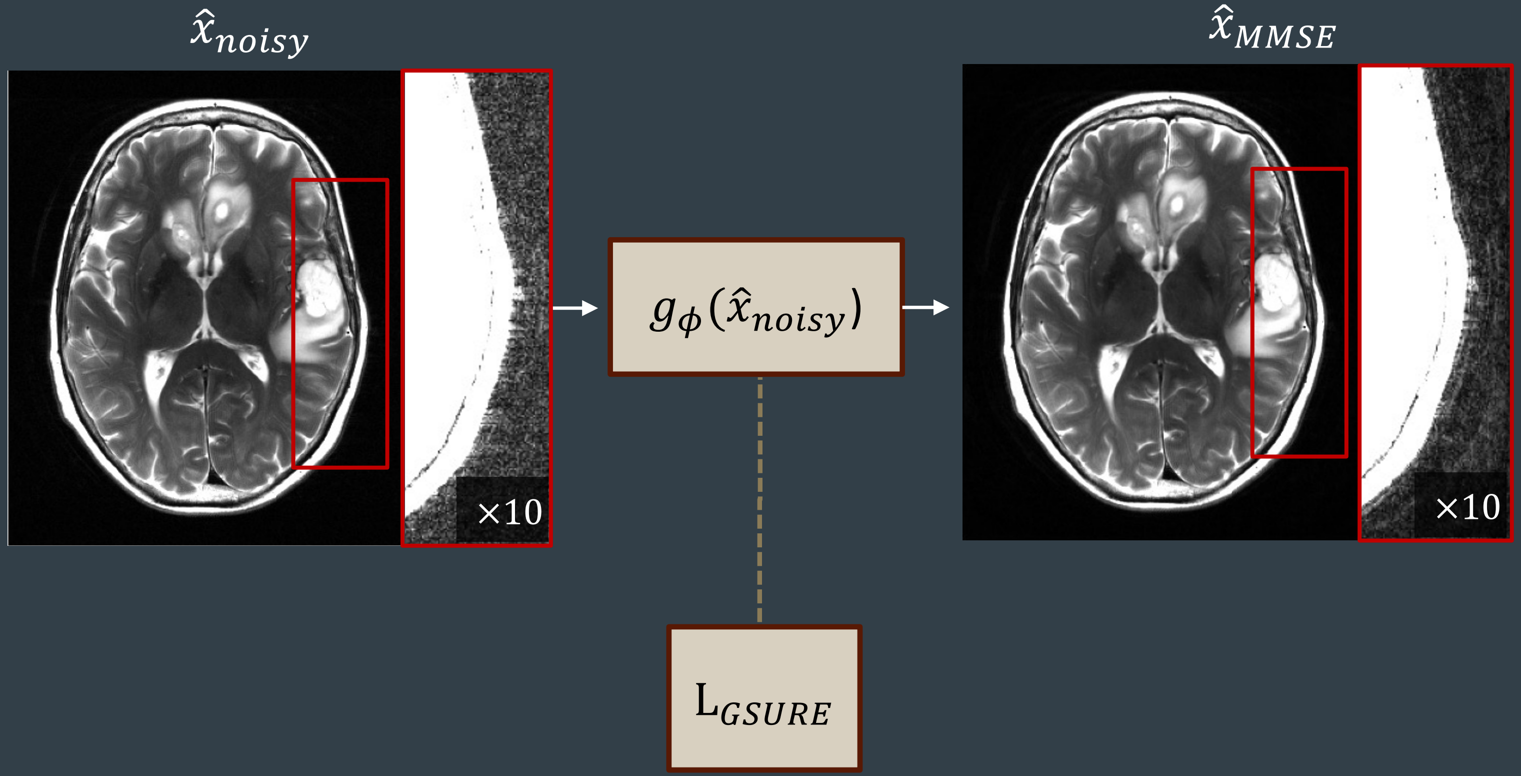
Pre-Processing Noisy Dataset

- GSURE loss requires the **noise covariance** matrix
- **Pre-whitening** (noise covariance $= I$) makes computation relatively straight-forward



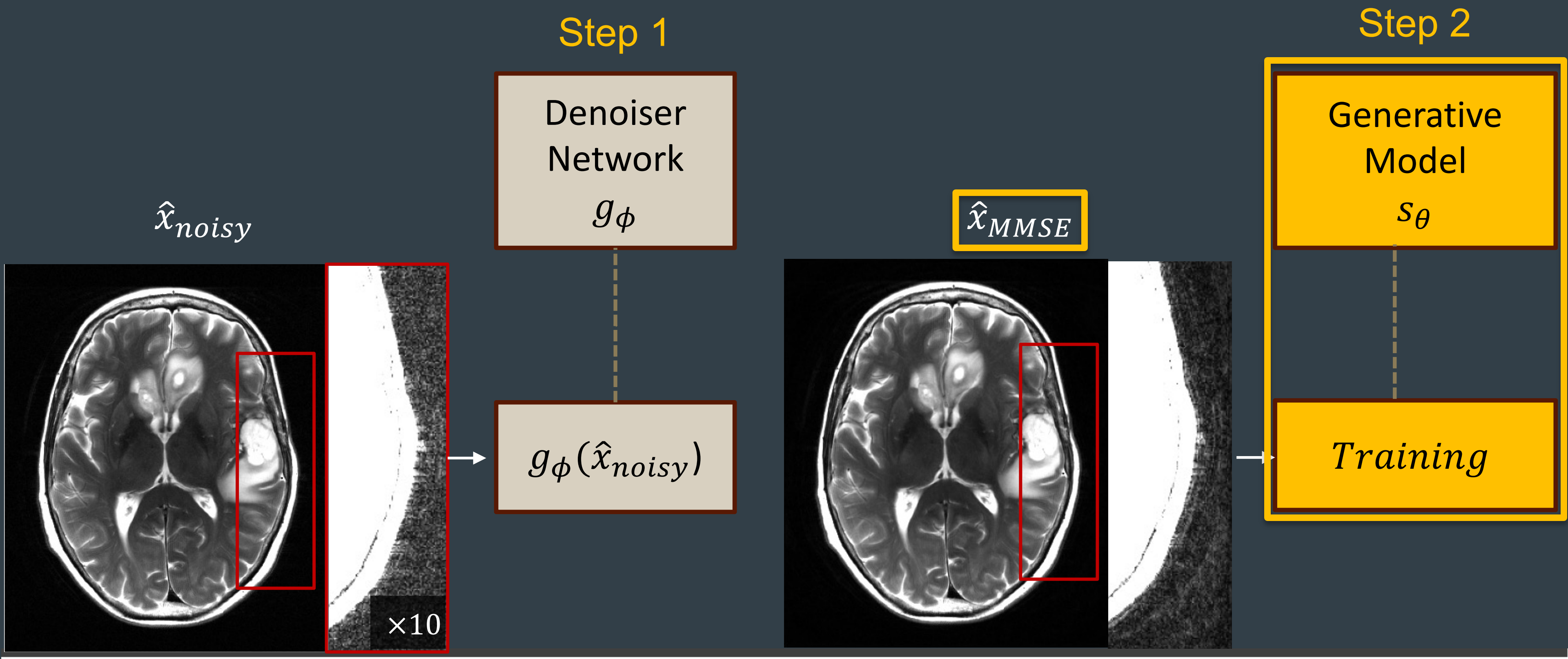
Kellman *MRM* (2005)

GSURE Denoising - Summary



GSURE Training

Proposed Methods



Diffusion Probabilistic (Generative) Model Details

- Score-based models[1]
- Trained with denoising score matching[4]
- Posterior sampling (MRI reconstruction) with annealed Langevin dynamics[6]

[1]Hyvarinen, *JMLR* 2005 [2]Song, *UAI,* 2018 [3]Vincent, *MIT Press* 2011 [4]Song, *NeurIPS* 2019 [5]Dhariwal, *NeurIPS* 2021 [6]Jalal *NeurIPS* 2021

Experiments

1. Evaluation of **Self-Supervised Denoising** (GSURE)
2. **Prior sampling** performance of score models trained on Noisy vs. GSURE Denoised data
3. **Accelerated MRI Reconstruction** performance of score models trained on Noisy vs. GSURE Denoised data

Experiments

1. Evaluation of **Self-Supervised Denoising** (GSURE)

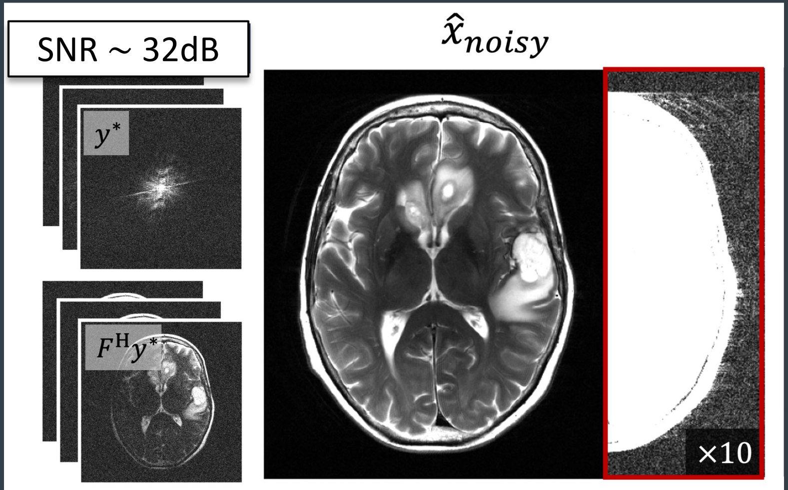
Experimental Details:

- Brain:
  - 10,000 2D T_2-weighted brain samples
- Knee:
  - 2,000 2D fat-suppressed knee

- Learned Denoiser Architecture: NCSNv2 (Song *NeurIPS 2020*)

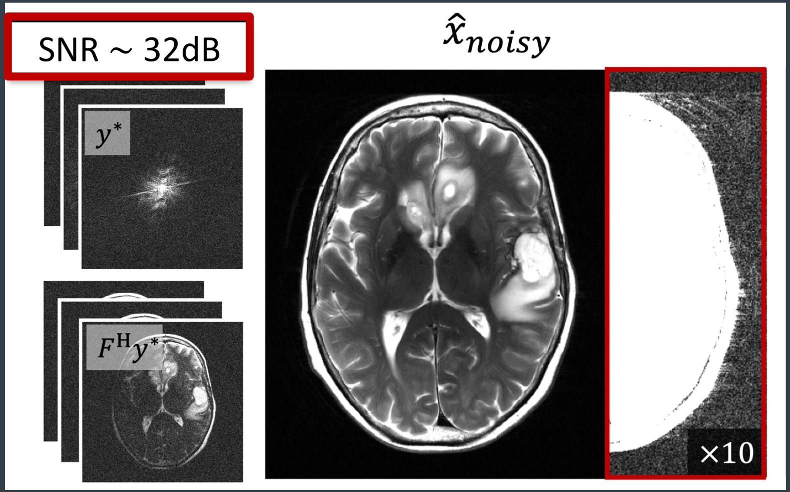
T2 Brain Scans

Original FastMRI



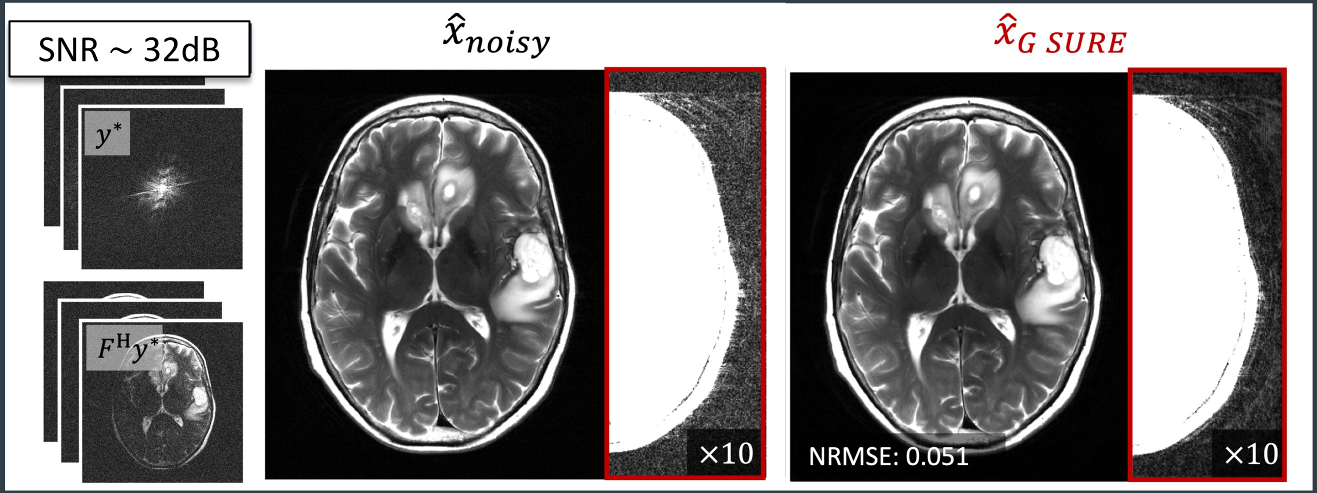
T2 Brain Scans

Original FastMRI



T2 Brain Scans

Original FastMRI



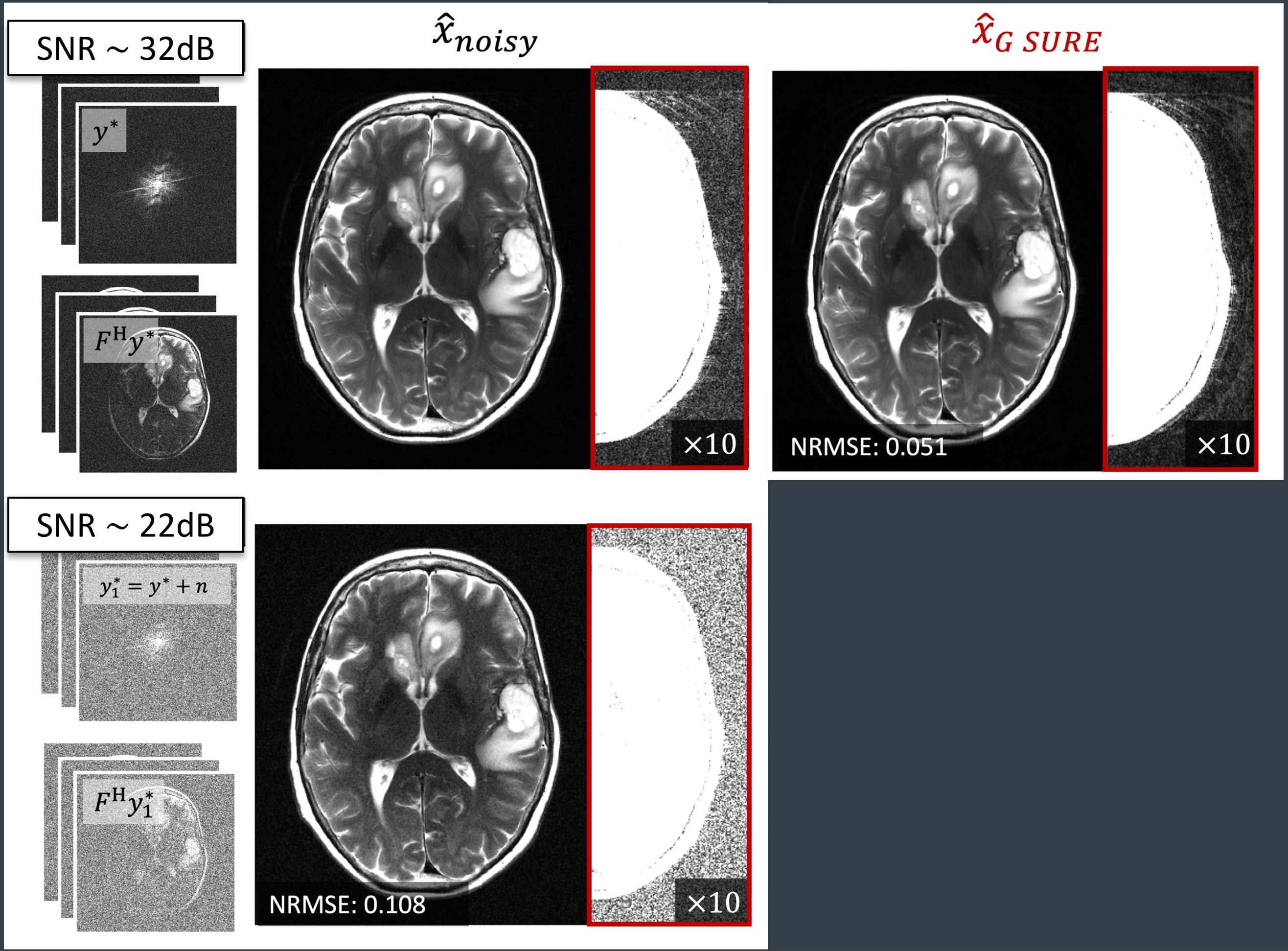
T2 Brain Scans

Original FastMRI

Original FastMRI

+

Additive Gaussian Noise



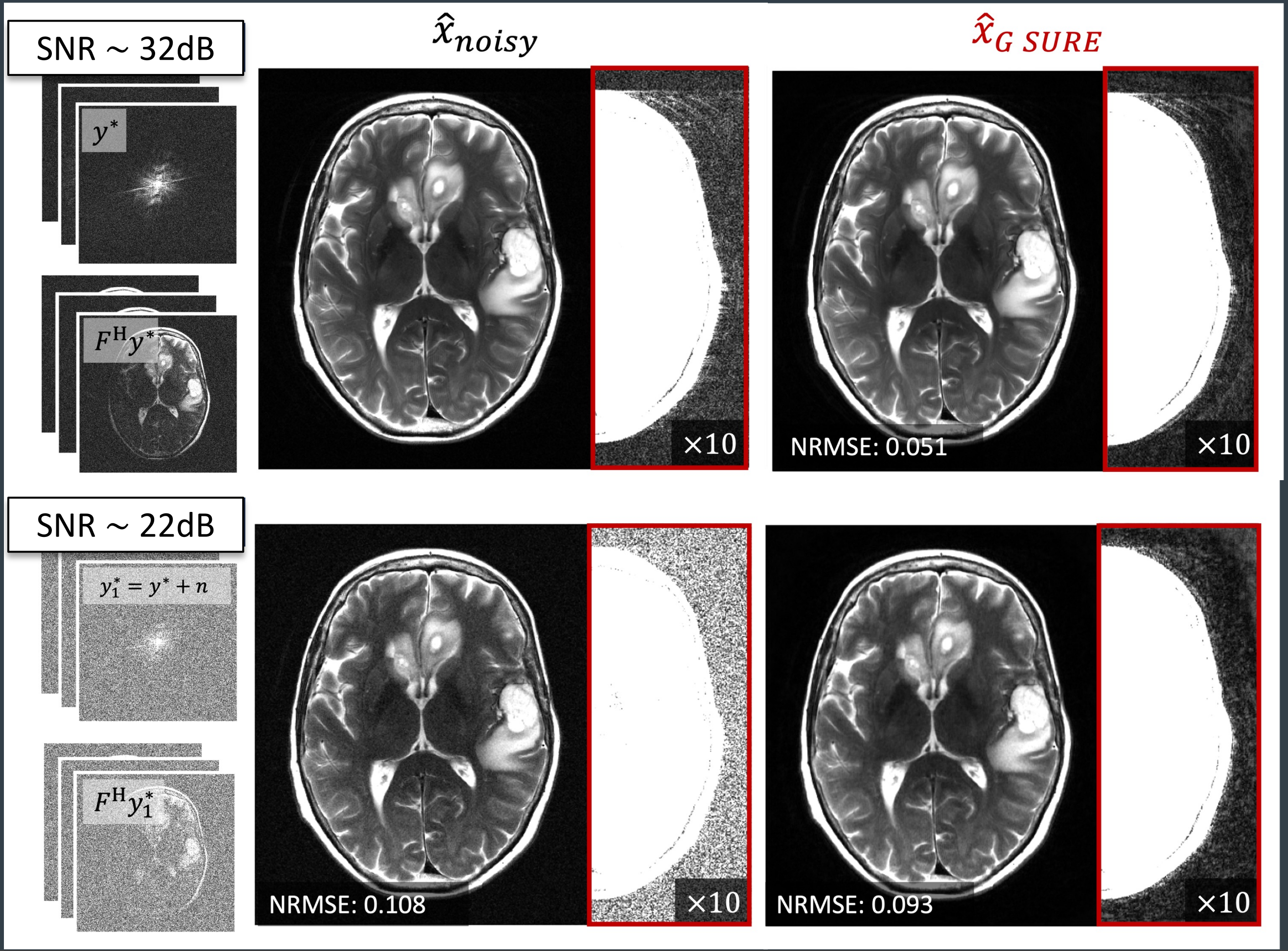
T2 Brain Scans

Original FastMRI

Original FastMRI

+

Additive Gaussian Noise



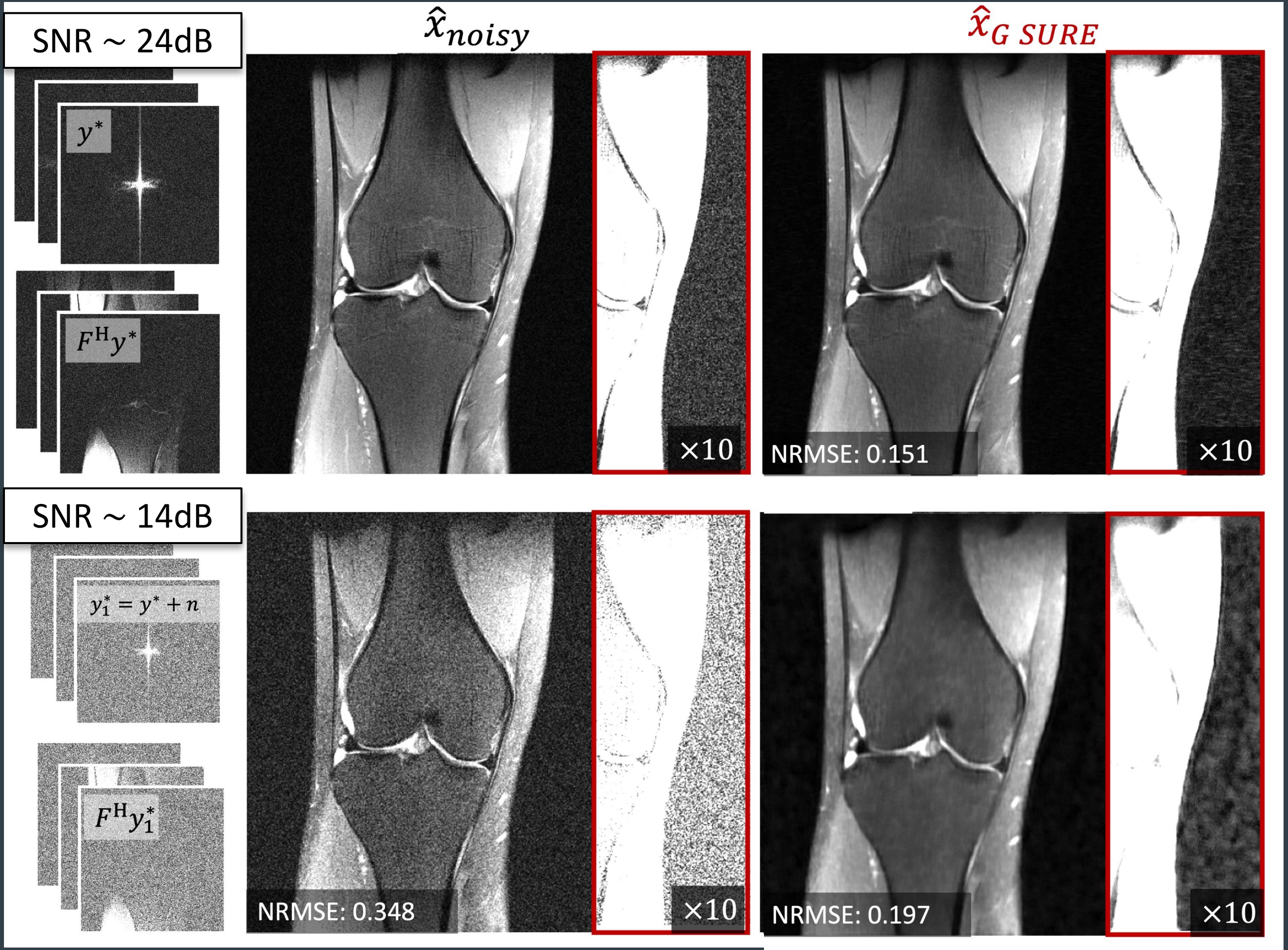
Knee Scans

Original FastMRI

Original FastMRI

+

Additive Gaussian Noise



Results

1. Evaluation of **Self-Supervised Denoising** (GSURE)
2. **Prior sampling** performance of score models trained on Noisy vs. GSURE Denoised data
3. **Accelerated MRI Reconstruction** performance of score models trained on Noisy vs. GSURE Denoised data

Results

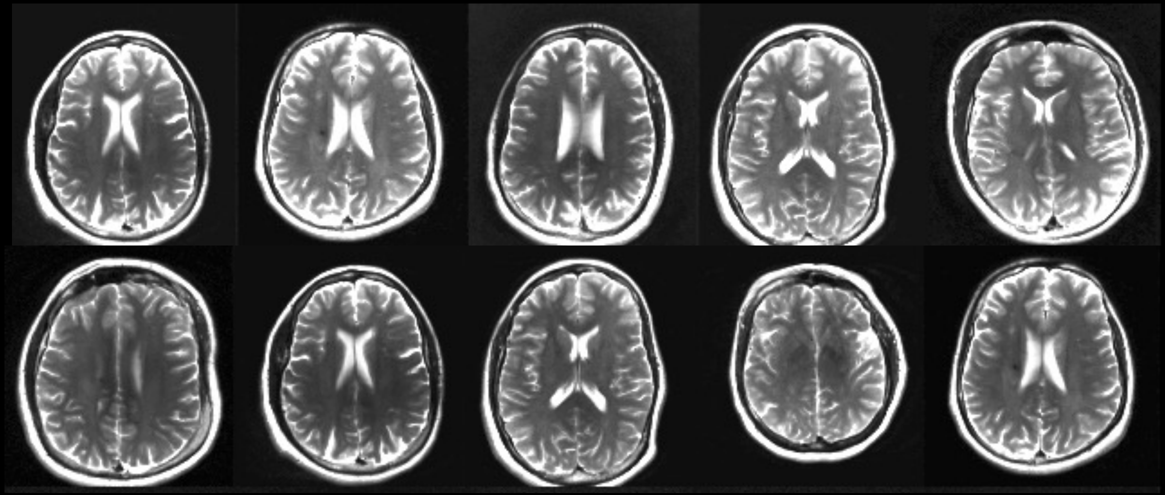
1. Evaluation of **Self-Supervised Denoising** (GSURE)
2. **Prior sampling** performance of score models trained on Noisy vs. GSURE Denoised data

Experimental Details:

- Score Model Trained on noisy and denoised versions of the 10,000 sample T_2 Brain dataset.
- Score-Model Architecture: NCSNv2 (Song *NeurIPS 2020*)

Naive Score
~ 32 dB

GSURE- Score
~ 32 dB

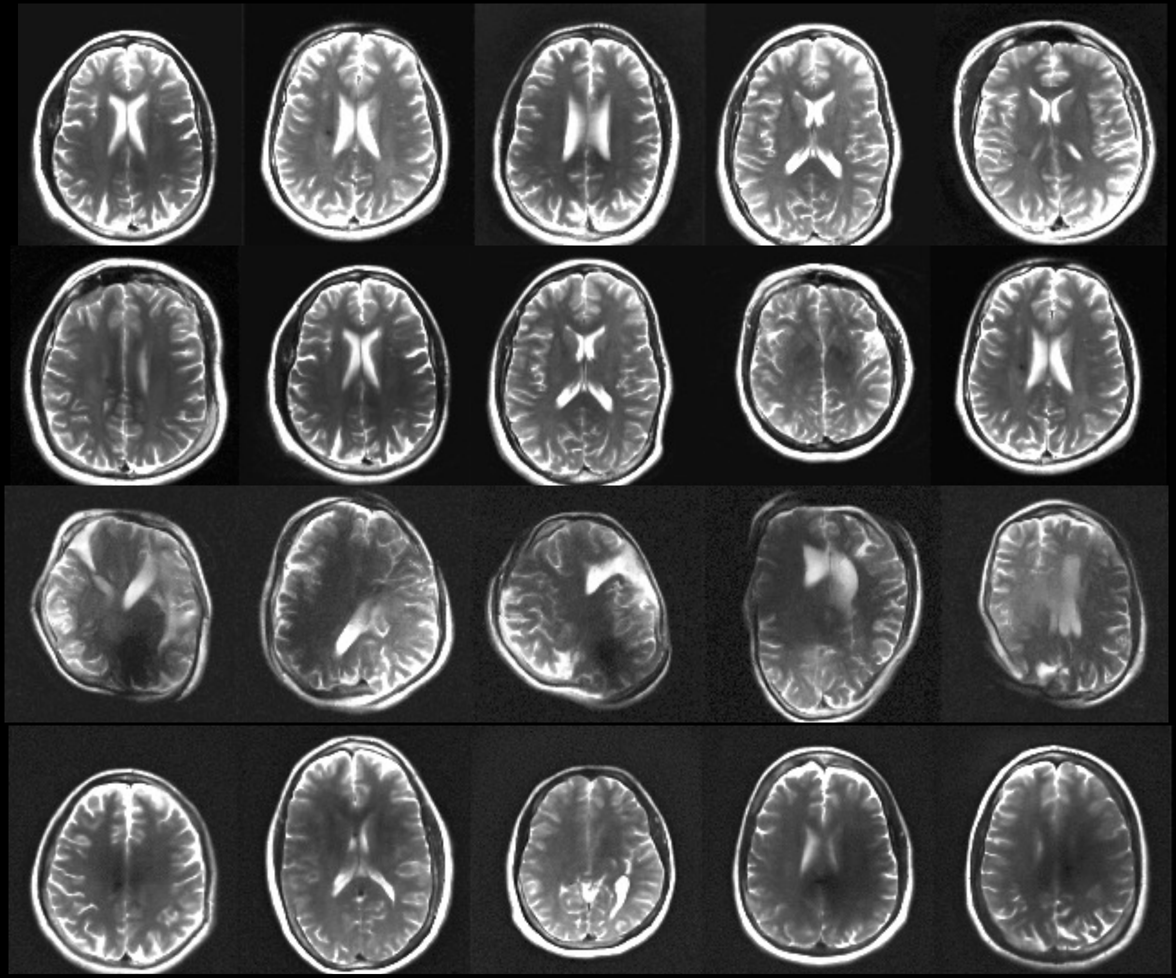


Naive Score
~ 32 dB

GSURE- Score
~ 32 dB

Naive- Score
~ 22 dB

GSURE- Score
~ 22 dB



Results

1. Evaluation of **Self-Supervised Denoising** (GSURE)
2. **Prior sampling** performance of score models trained on Noisy vs. GSURE Denoised data
3. **Accelerated MRI Reconstruction** performance of score models trained on Noisy vs. GSURE Denoised data

Results

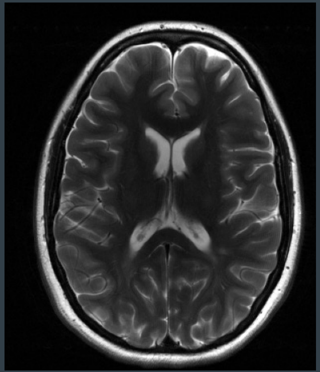
1. Evaluation of **Self-Supervised Denoising** (GSURE)
2. **Prior sampling** performance of score models trained on Noisy vs. GSURE Denoised data
3. **Accelerated MRI Reconstruction** performance of score models trained on Noisy vs. GSURE Denoised data

Experimental Details

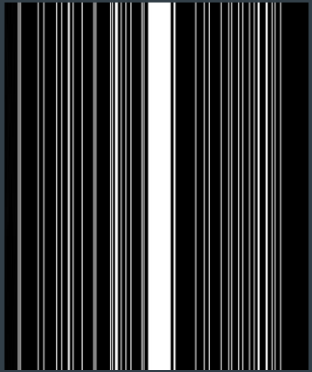
- 100 retrospectively under-sampled 2D T_2 Brain validation samples

Posterior Sampling $x \sim p(x|y)$

Fully-Sampled

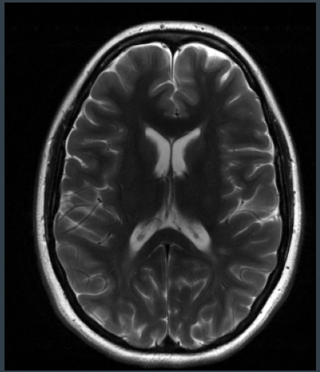


R = 5

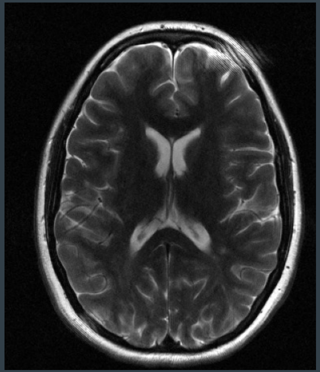


Posterior Sampling $x \sim p(x|y)$

Fully-Sampled

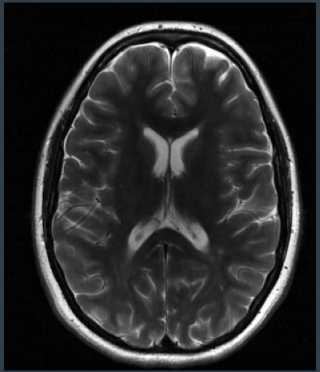


Naive Score @ 22dB



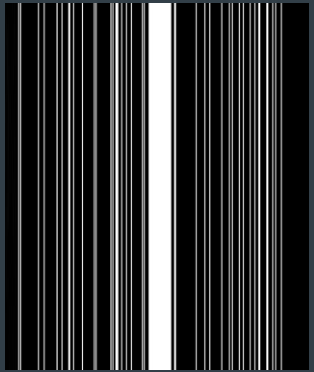
NRMSE: 0.228

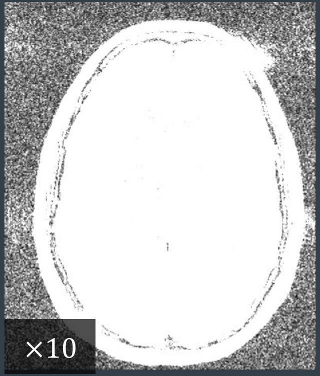
GSURE-Score @ 22dB

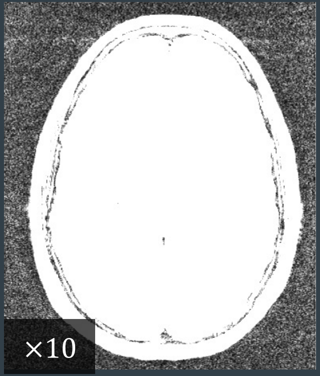


NRMSE: 0.108

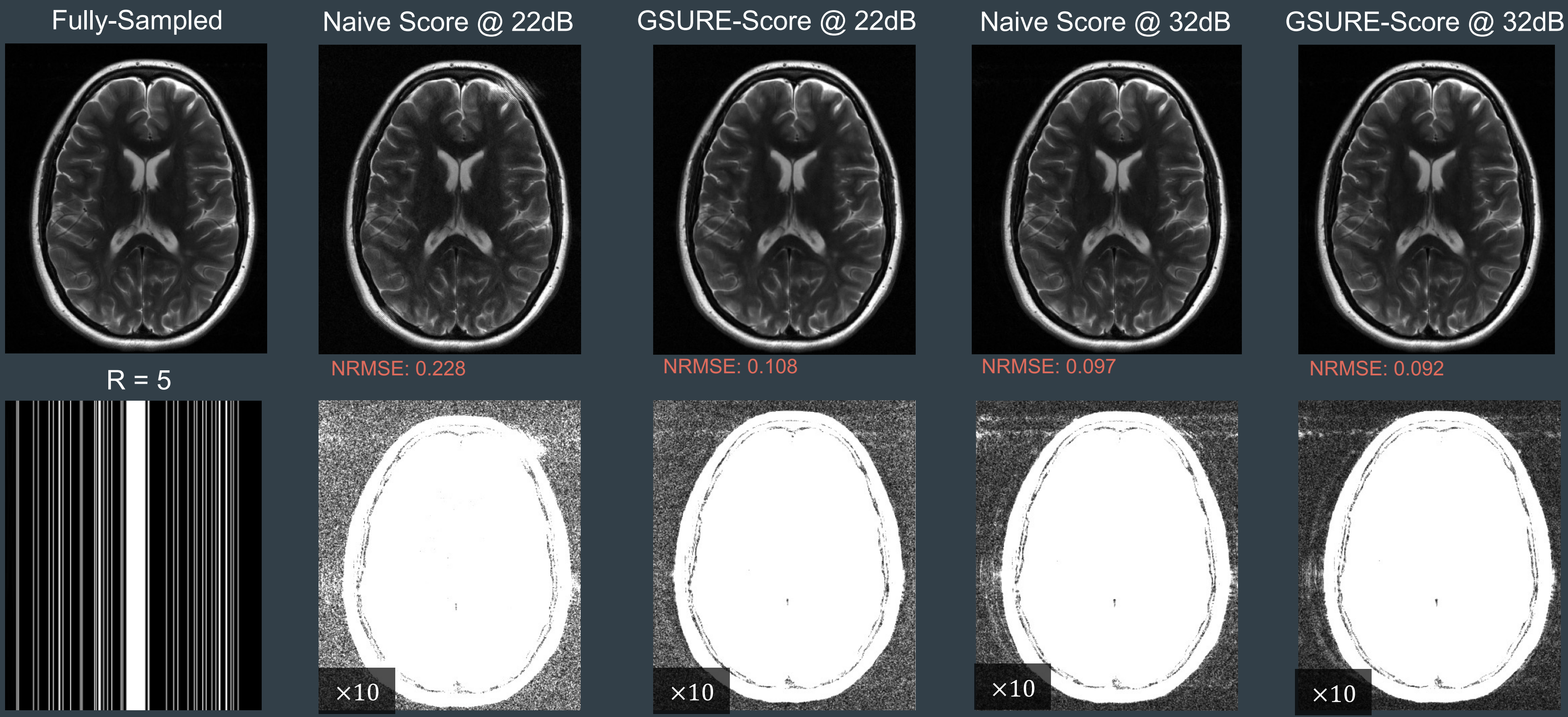
R = 5



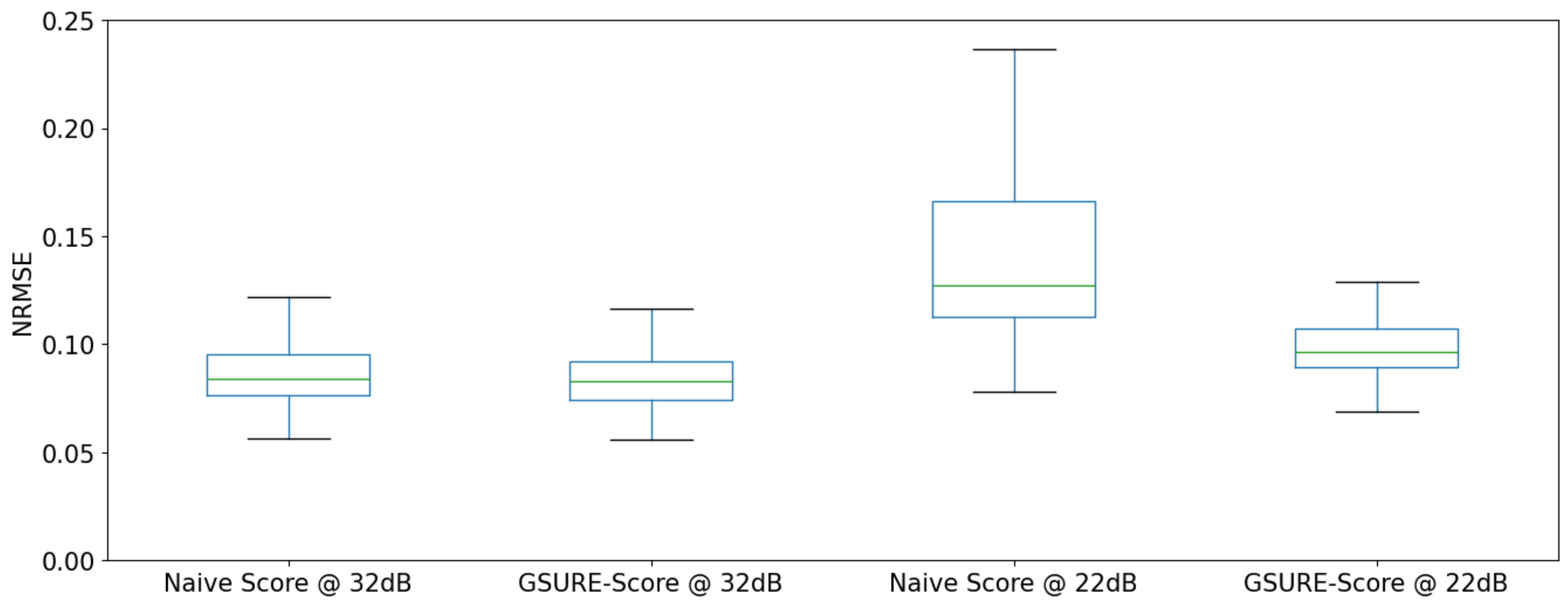




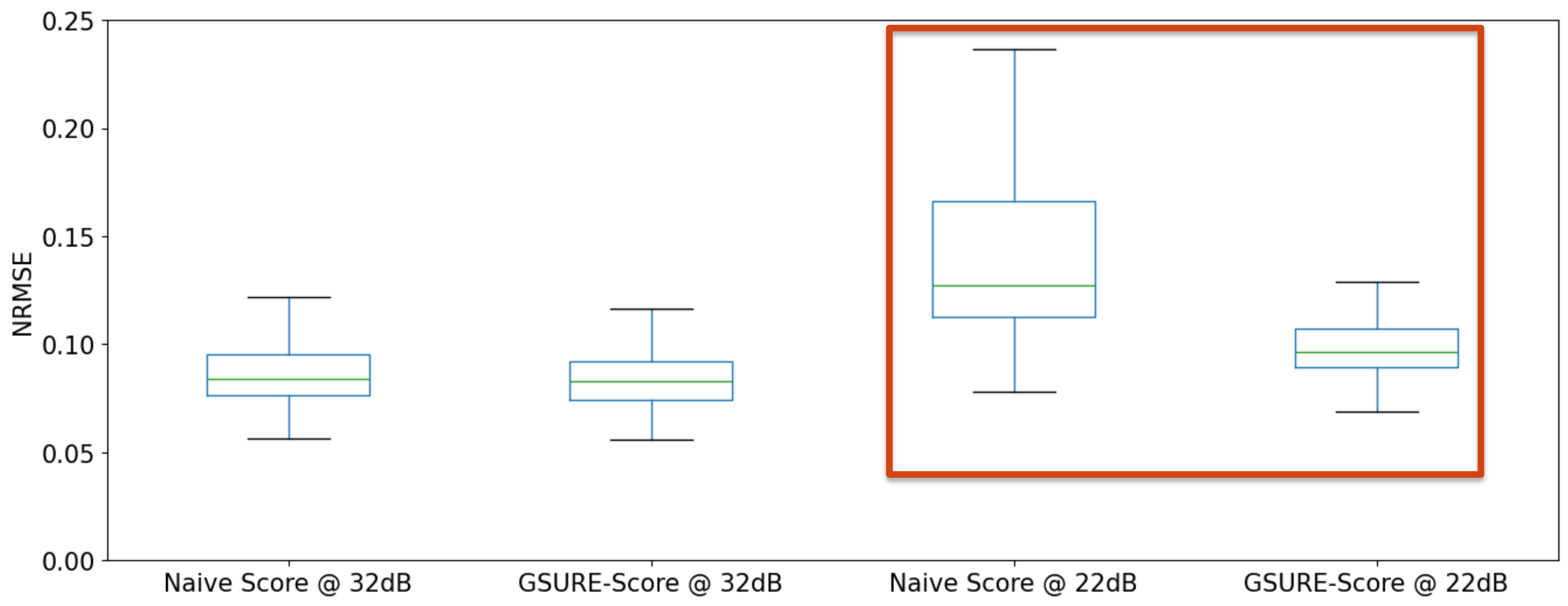
Posterior Sampling $x \sim p(x|y)$



Accelerated MRI Reconstruction with Posterior Sampling $x \sim p(x|y)$



Accelerated MRI Reconstruction with Posterior Sampling $x \sim p(x|y)$



Discussion and Conclusion

1. GSURE Denoising as a pre-processing step helps train more **accurate priors** which are better **inverse problem solvers** than naive training.

2. The benefit of denoising is more visible in **lower SNR** settings

3. Important to investigate tradeoff between noise and distortion

4. Applicable to other learning settings (e.g. end-to-end methods)

Future Works

A is a Linear Forward Operator (**Fully-Sampled**) -> GSURE[1,2,3]

$$y = FSx + noise$$

[1]Soltanayev, *NeurIPS,* 2018, [2]Eldar, *IEEE Transactions on Signal Processing,* 2008, [3]Kawar, *TMLR,* 2023, [4]Aali, AmbientDPS, *Arxiv*, 2024

Future Works

A is a Linear Forward Operator (**Fully-Sampled**) -> GSURE[1,2,3]

$$y = FSx + noise$$

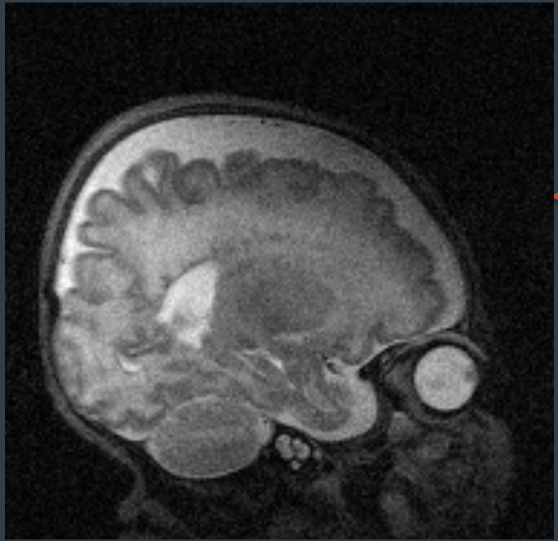
Assume A is a **Low-Rank** Forward Operator[4]

$$y = \boldsymbol{P}FSx + noise$$

[1]Soltanayev, *NeurIPS,* 2018, [2]Eldar, *IEEE Transactions on Signal Processing,* 2008, [3]Kawar, *TMLR,* 2023, [4]Aali, AmbientDPS, *Arxiv*, 2024

Application in real world datasets: low field neo-natal MRI

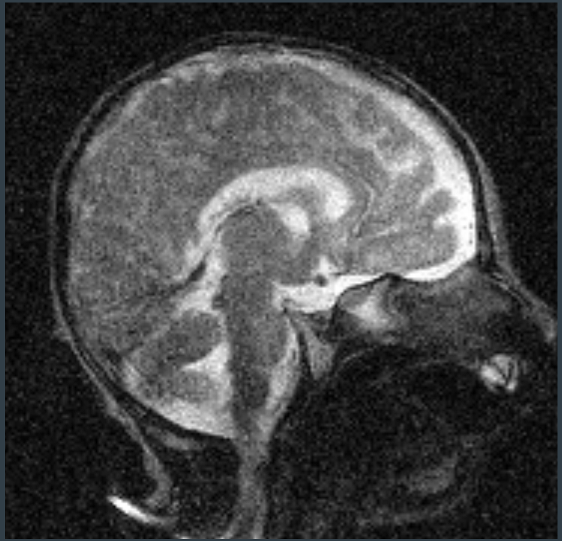
Training Dataset



training

Generative Model

Sample from Image Distribution



*Scans courtesy of Aspect Imaging
Aspect Embrace 1T Scanner
Installed at SZMC, Israel

Thank you!

Asad Aali

Email: asad.aali@utexas.edu

Website: https://asadaali.com/

MS ECE, UT Austin

Source Code: https://github.com/utcsilab/GsureScore-Diffusion.git