Multi-Contrast 3D Fast Spin-Echo T2 Shuffling Reconstruction with Score-Based Deep Generative Priors

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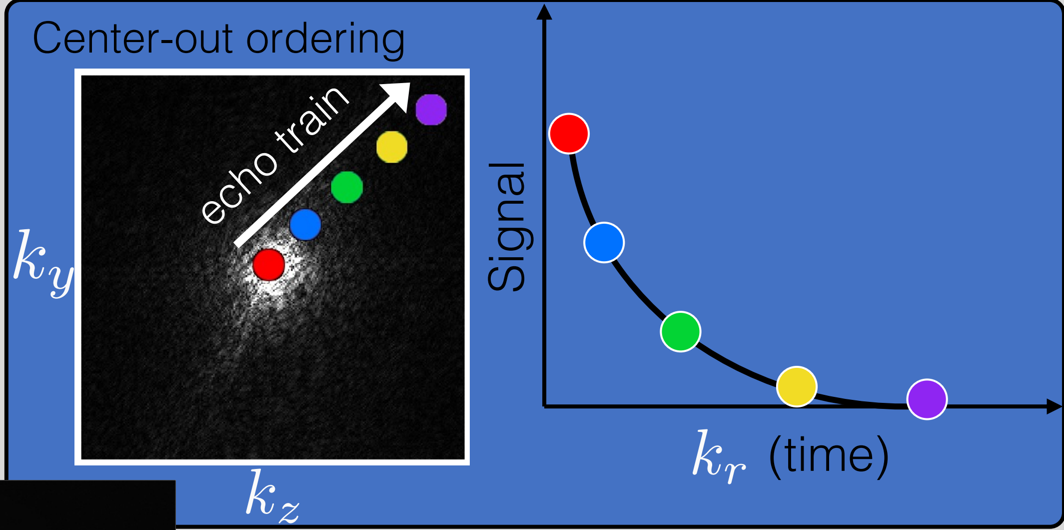
Declaration of
Financial Interests or Relationships

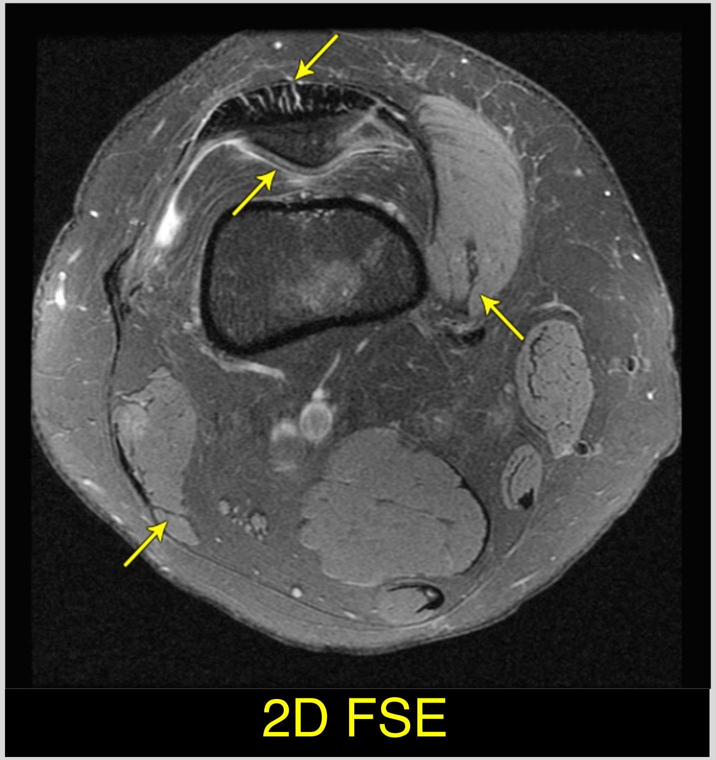
Speaker Name: Sidharth Kumar

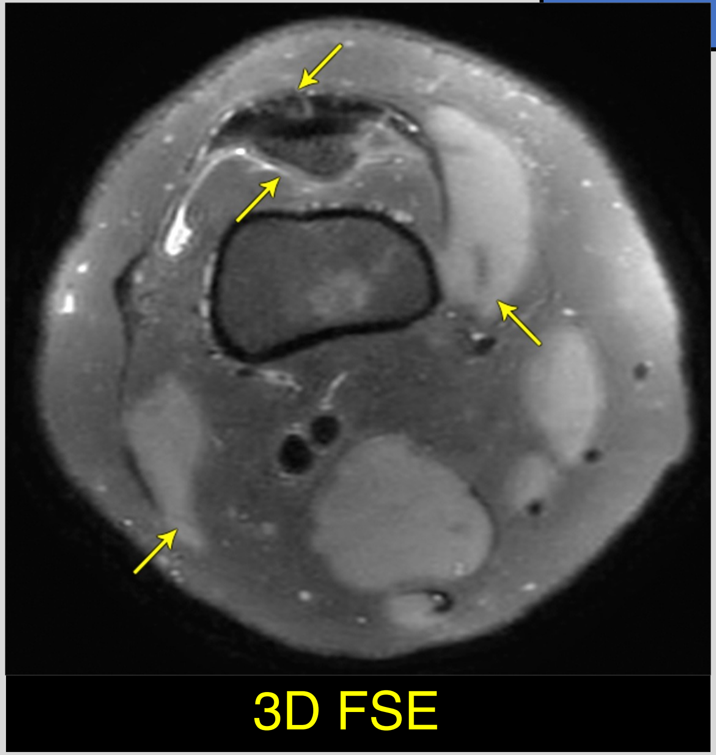
I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

Conventional 3DFSE*

- Spatial blurring due to T2 decay
- Single image contrast per scan



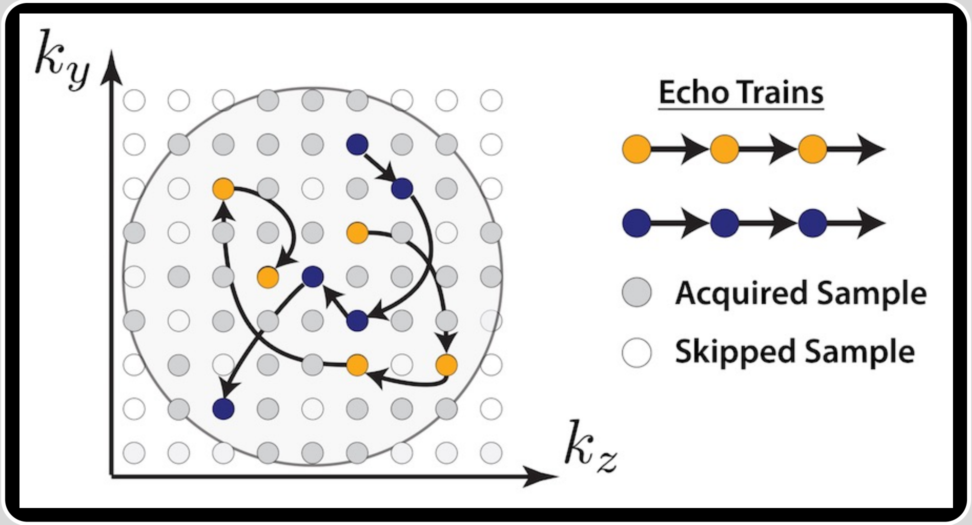




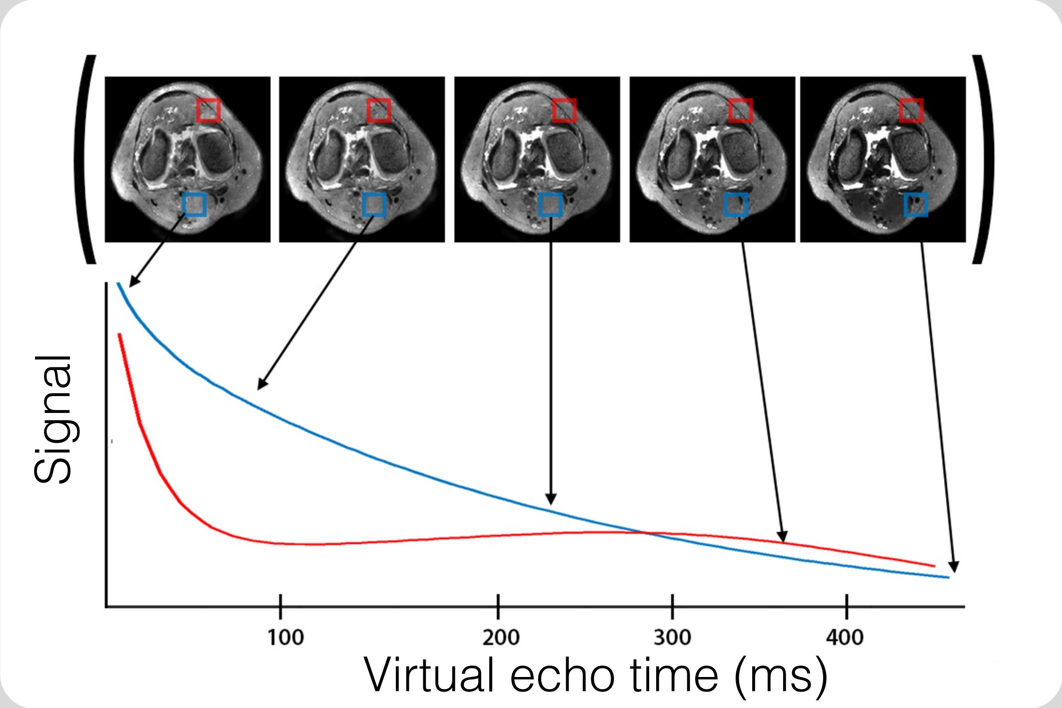
*J.P. Mugler et al., JMRI 2014. doi: 10.1002/mrm.24542
*R.F. Busse et al., MRM 2006. doi: 10.1002/mrm.20863

T2 Shuffling*

Randomly shuffled echo trains



Compressed sensing in relaxation dimension



Volumetric, multi-contrast reconstruction

- Resolves T2 relaxation curve
- Reduces image blur
- Increases scan efficiency

powered by BART

*J.I. Tamir et al., MRM 2016. doi: 10.1002/mrm.26102

T2 Shuffling*

Reconstruction*

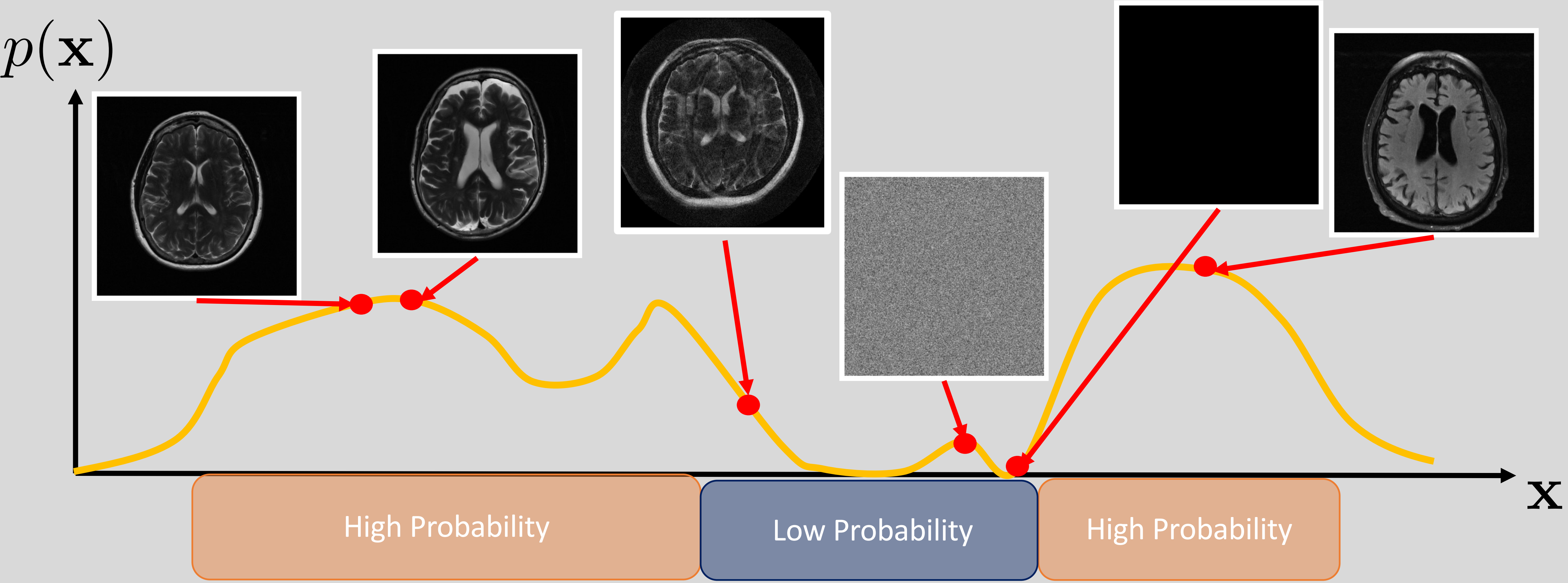
$$\min_{\alpha} \frac{1}{2}||\mathbf{y} - \mathbf{PF\Phi}_K \alpha||_2^2 + \lambda \sum_{\mathbf{r}} ||R_{\mathbf{r}}(\alpha)||_*$$

1. Low rank (handcrafted) prior

2. Limited ability to represent prior distribution

*J.I. Tamir et al., MRM 2016. doi: 10.1002/mrm.26102

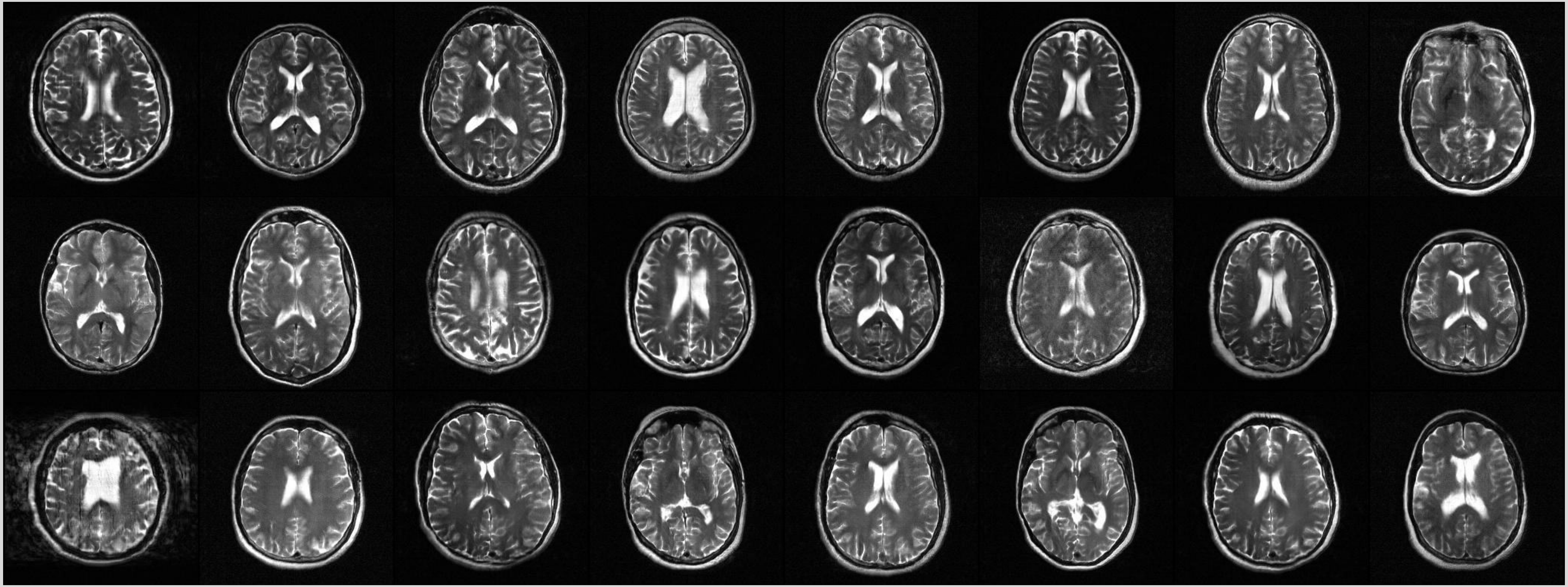
“True” Prior Distribution Over MR Images



Generative models are powerful image generators

https://thiscatdoesnotexist.com

Generative models are powerful image generators



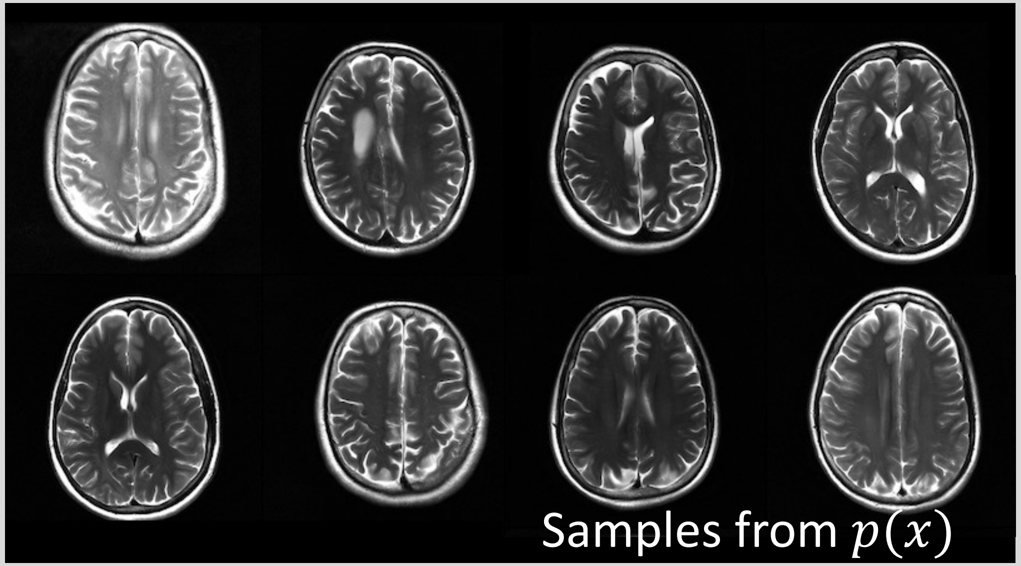
Generative model trained on FastMRI data

Purpose

Investigate the feasibility and effectiveness of score based generative models as a prior for Multi-Contrast 3D Fast Spin-Echo T2 Shuffling Reconstruction

Generative Modeling

- <u>Goal:</u> Use deep networks to learn the prior distribution



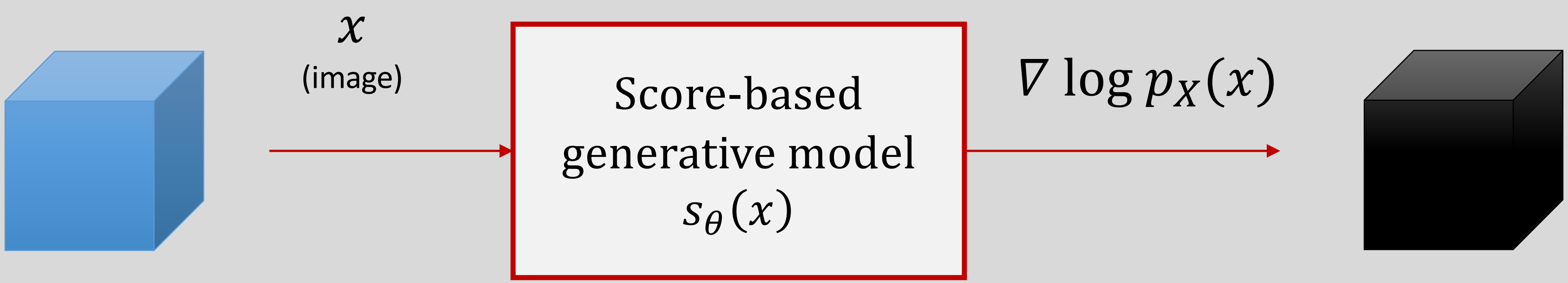
- <u>Decouple</u> statistical image prior from measurement model
- Apply Bayesian principles for reconstruction, $p(x|y)$

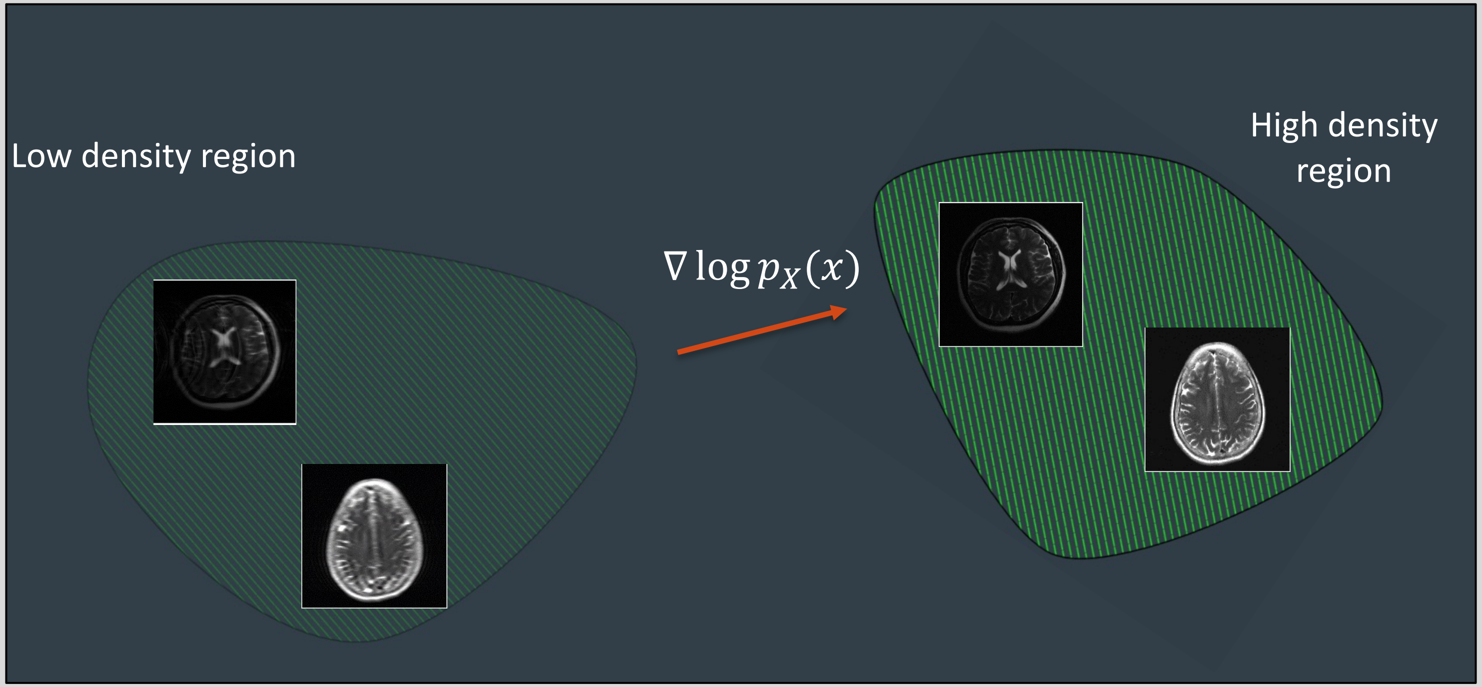
A Bora et al., ICML 2017. Y Song and S Ermon, NeurIPS 2019. P Dhariwal and A Nichol, arXiv:2105.05233. RV Marinescu et al., arXiv:2012.04567, 2021.

Proposed Approach: score-based generative models

- Don't actually need the prior, only the grad-log of it
- E.g., MAP: $$\min_{\mathbf{x}} \frac{1}{2\sigma_v^2} ||\mathbf{y} - \mathbf{A}\mathbf{x}||_2^2 - \log p(\mathbf{x})$$
- Gradient: $$\frac{\mathbf{A}^H (\mathbf{A}\mathbf{x} - \mathbf{y})}{\sigma_v^2} - \underbrace{\nabla \log p(\mathbf{x})}_{\textbf{Score function}}$$
- Idea: use deep networks to learn the score function

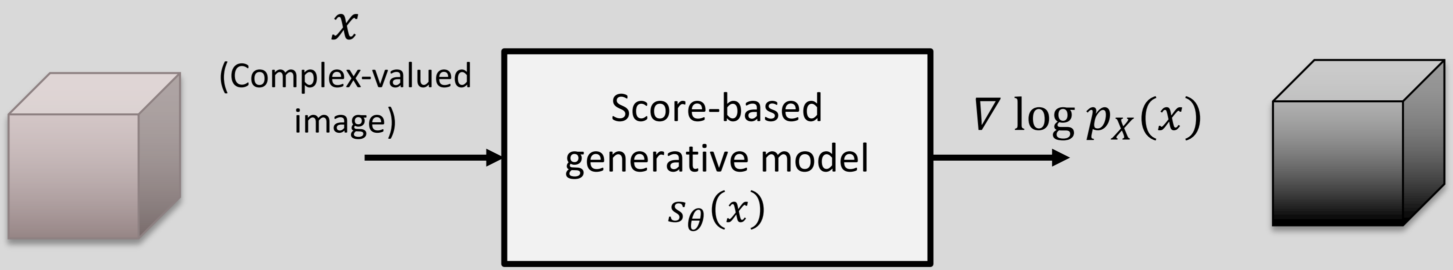
Score-based generative models





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.

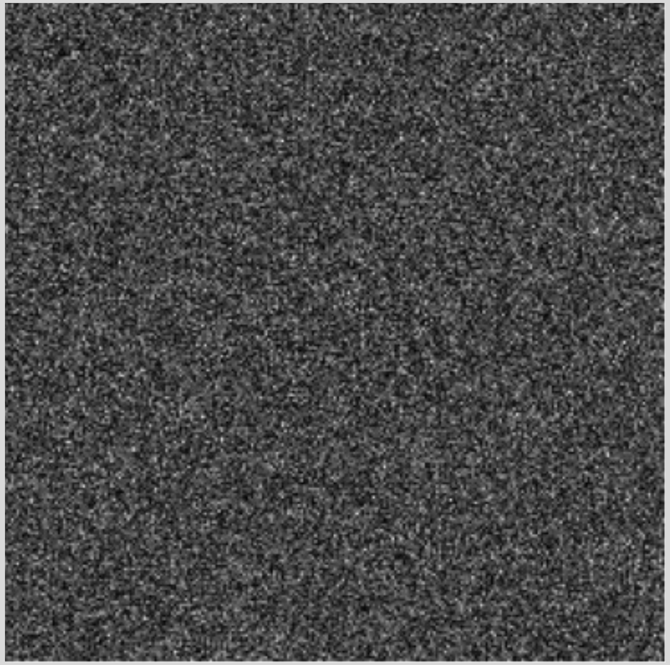
MRI recon with score-based models



Posterior sampling $x \sim p_X(x|y)$:

$$x_{t+1} \leftarrow x_t + \alpha\left(A^H(y - Ax_t) + s_\theta(x_t;\sigma_t)\right) + \sqrt{2\beta\sigma_t}\zeta_t$$

$$\zeta_t \sim N(0, I), \qquad t = 0 \ldots N$$



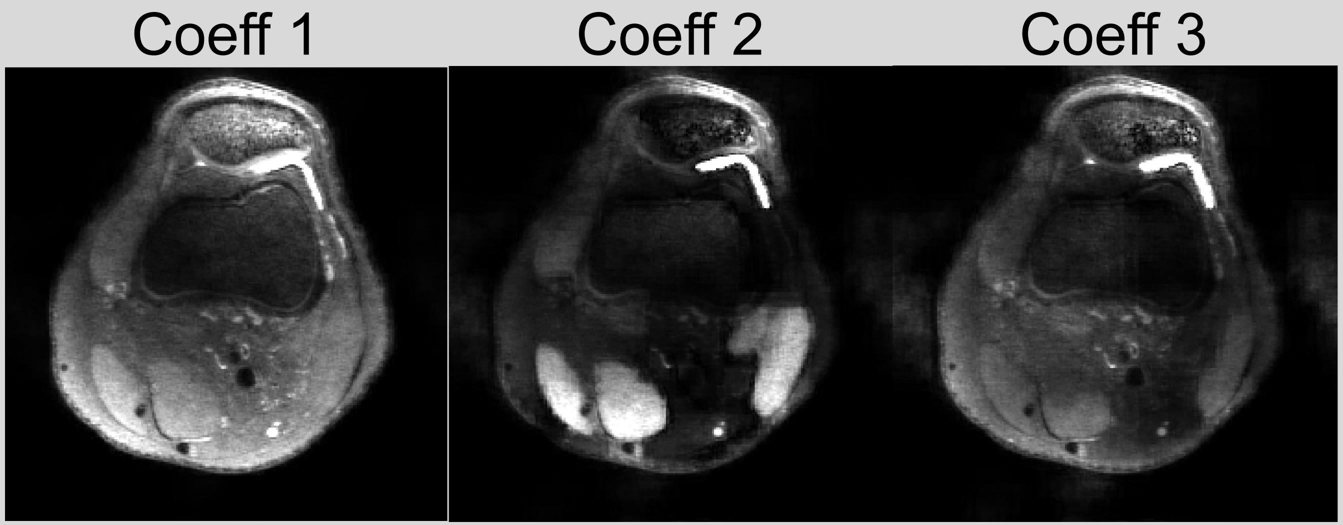
data consistency, **source prior**, **annealed noise**, hyperparameters

Y Song and S Ermon, NeurIPS 2019 , A Jalal et al, ICML 2021. A Jalal, M Arvinte, et al, NeurIPS 2021.

Challenges

1. K-space training set is highly undersampled

Only train on first coefficient image



Assume same prior for all coefficients:

$$\nabla \log p(\alpha_1, \alpha_2, \alpha_3) = \sum_i \nabla \log p(\alpha_i)$$

Methods

Data:

- MRI T2Sh basis coefficients images with IRB approval[1,2]
- Images reconstructed with Bart[3]
- Training: 50 subjects with 100 slices per subject
- Test: Separate subject, k-space data generated with forward operator[4]

Network:

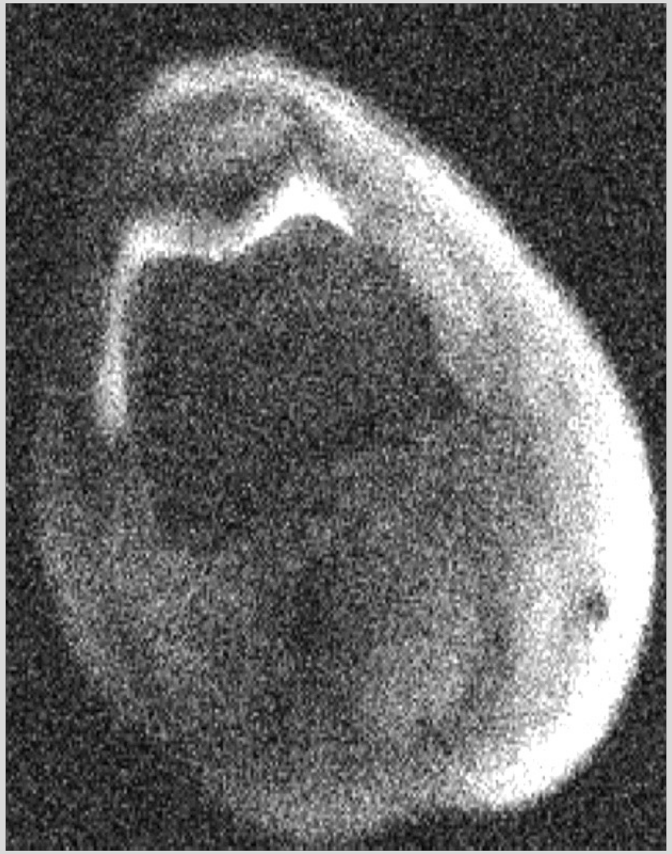
- Trained NCSNv2[5] as score prior

Evaluation:

- Compared with T2sh reconstruction acting as "ground truth"
- Metric: NRMSE and qualitative comparison

[1] J Tamir et. al, JMRI 2019. [2] S Bao et. al, JMRI 2017. [3] M Uecker, BART v0.4.04. [4] E. Shimron et. al, PNAS 2022. [5] Y Song. et. al, Neurips 2020

Results: Posterior sampling reconstruction process

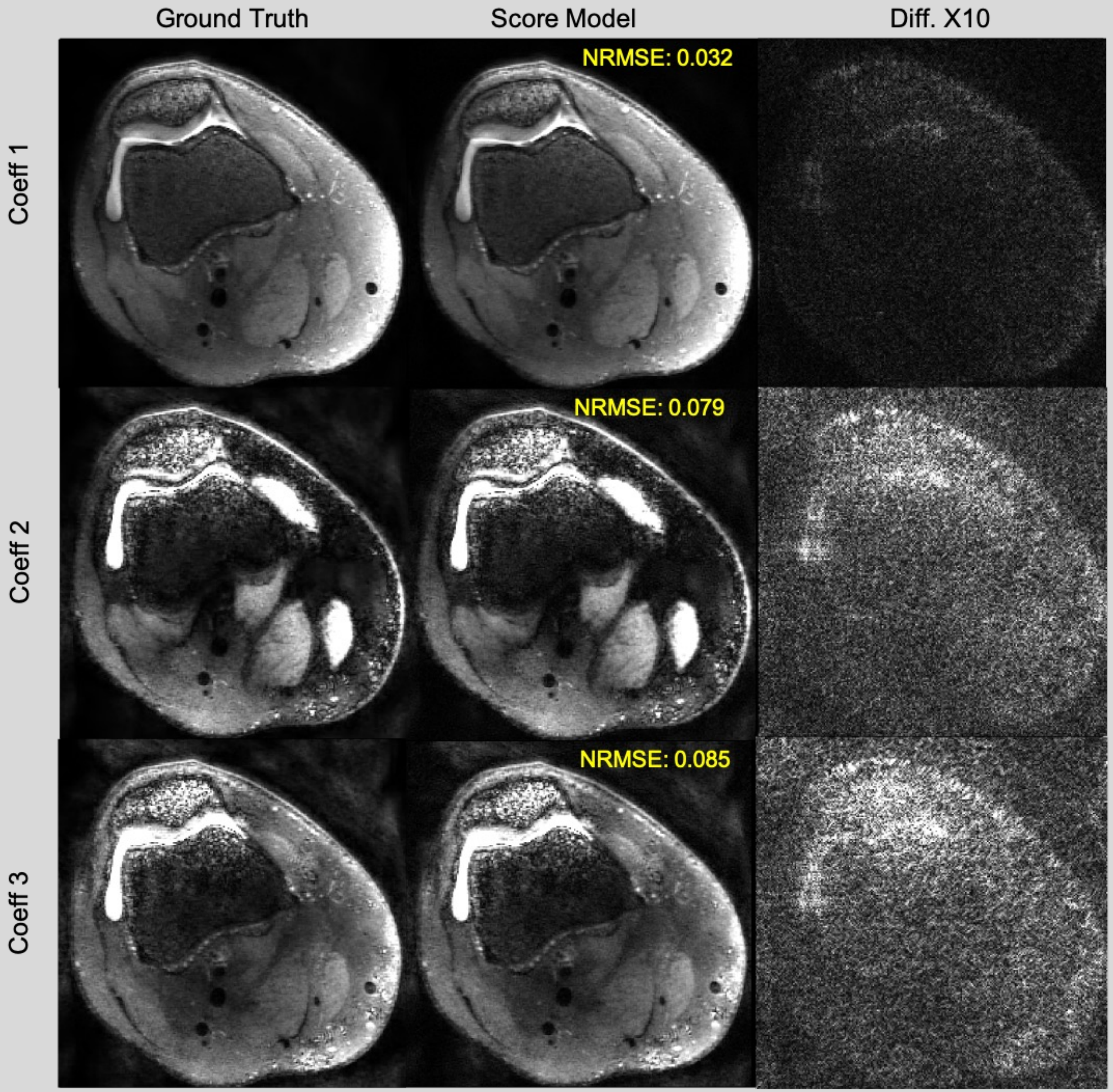


Coeff 1

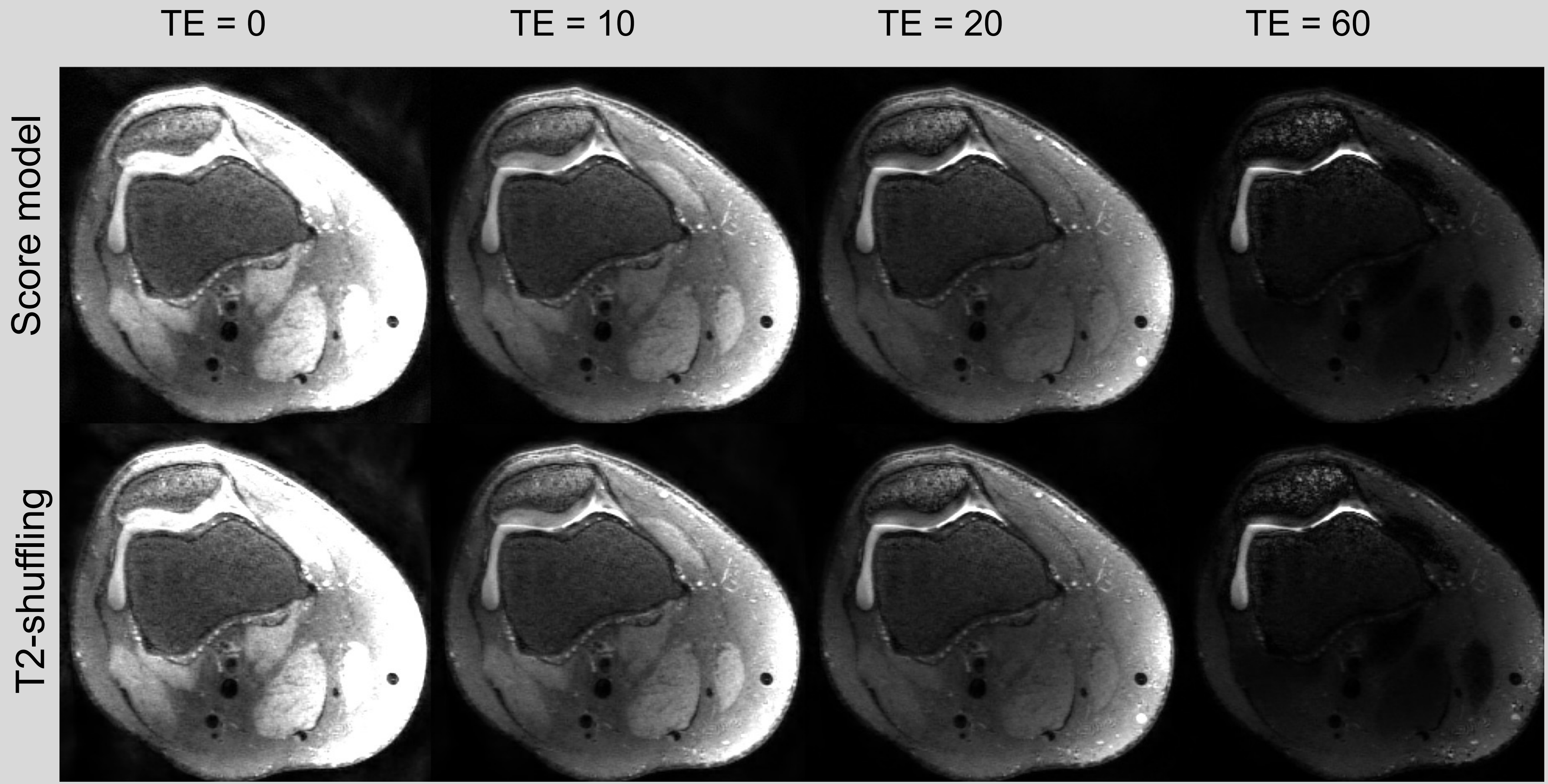
Coeff 2

Coeff 3

Results: Basis coefficient Comparison



Results: Time Series Comparison



Discussion and Conclusion

T2-Shuffling 3DFSE Acquisition:

✓ Provides sharp multi-contrast images

✗ Local low-rank prior has limited expressivity

Score-Based Deep Generative Prior:

✓ Promising approach for modeling multi-contrast sequences

✓ Provides informative prior decoupled from underlying acquisition

Next Steps:

- Refine approach for raw k-space data[1]
- Investigate image quality for higher accelerations (~5min) and resolutions (~0.5mm)

1 Kumar et al. ISMRM Sedona workshop 2023

Thanks!

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