Evaluation of Supervision in Deep Learning networks for accelerated-MRI reconstruction

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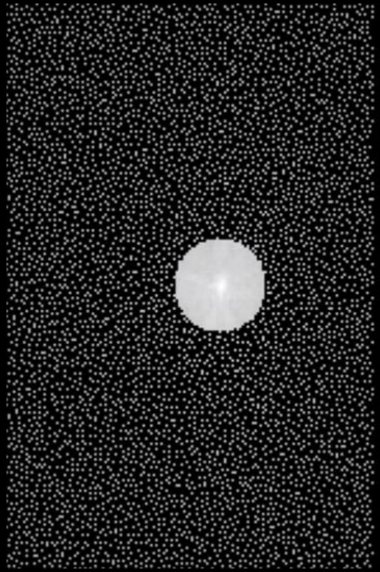

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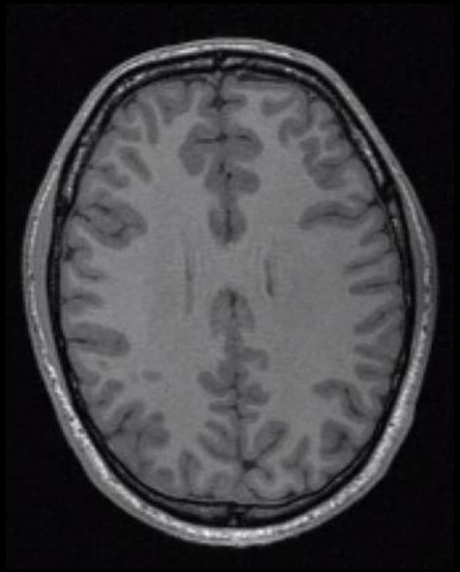
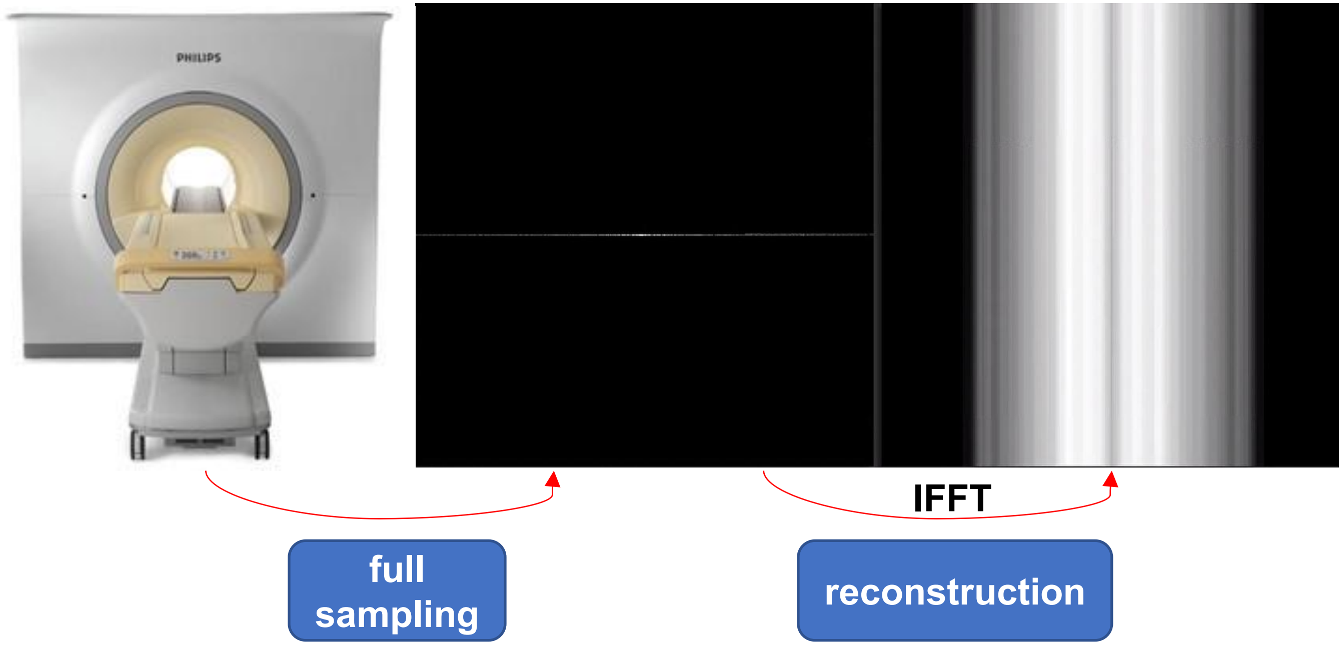


About me

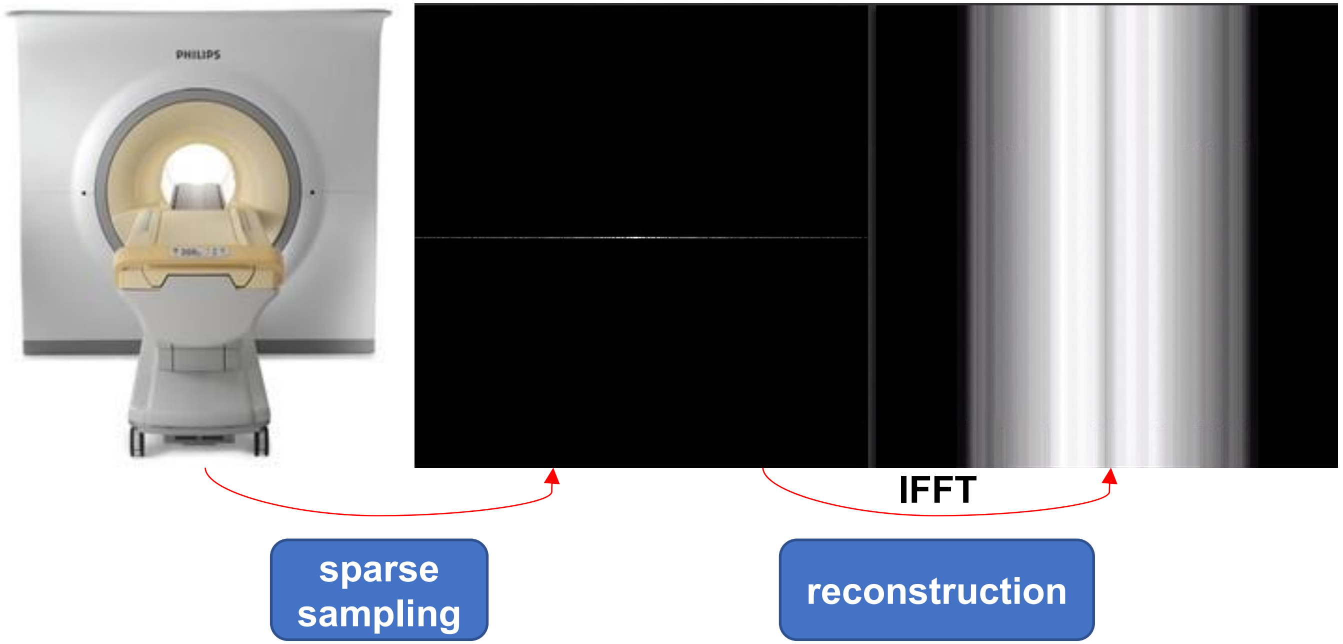
- BSc & MSc in Informatics & Computer Engineering, University of West Attica, Athens
- Undergraduate Thesis: “Deep Learning and Explainable Artificial Intelligence techniques for Alzheimer’s disease detection on magnetic resonance images”
- Previous Experience: Machine Learning Engineer Intern at HOMLI
- Started my Internship at Amsterdam UMC in mid-October 2022

MRI Acquisition



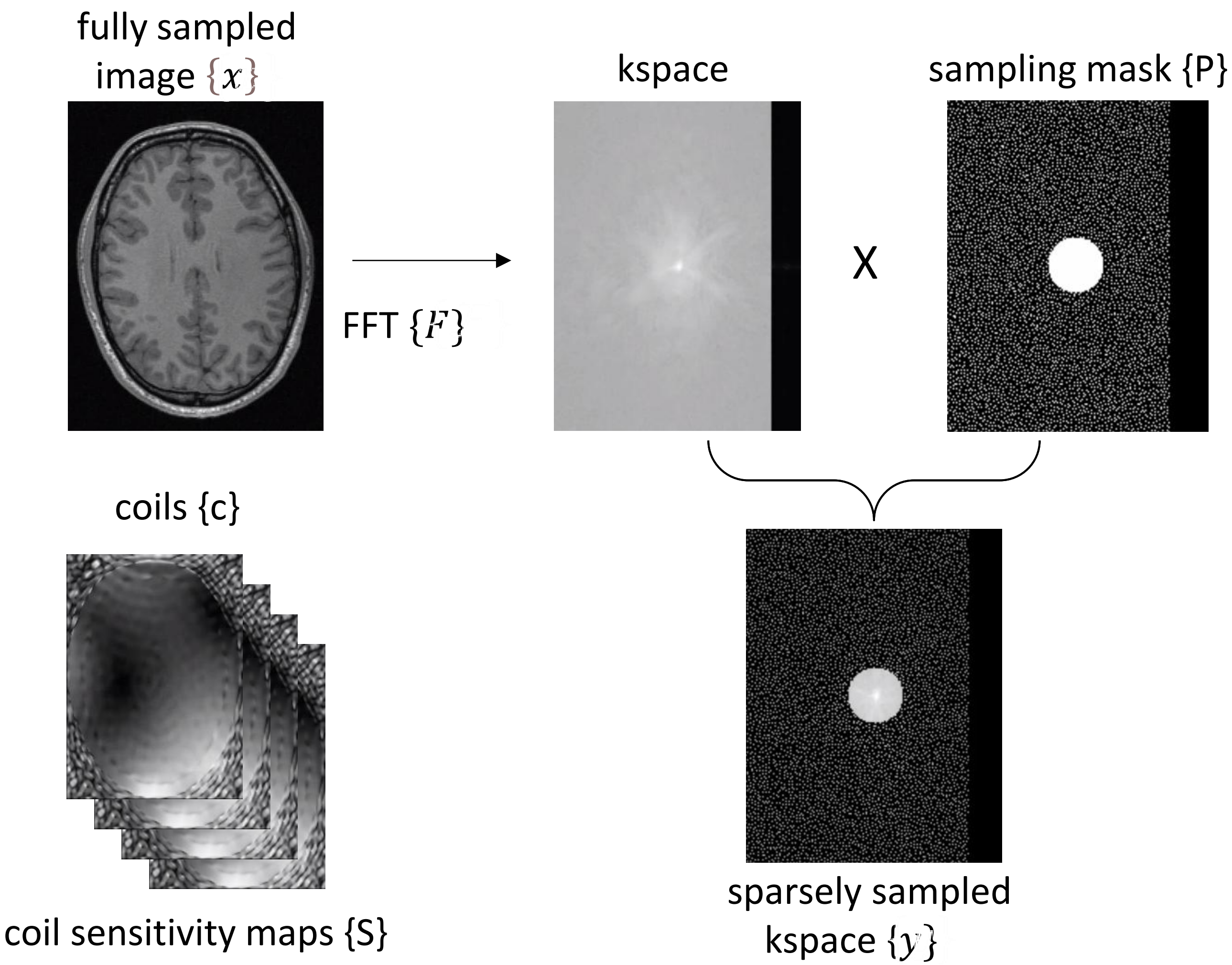
Fully sampling the k-space gives the best image quality, but is slow.

Sparse sampling



Sparsely sampling the k-space is faster, but introduces aliasing, noise etc.

The forward model of Accelerated-MRI acquisition



<u>Prior knowledge</u>

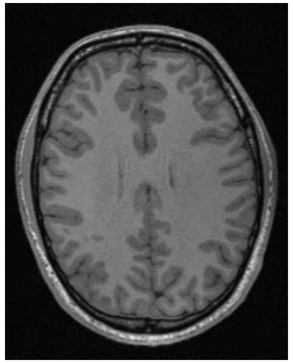
$$y = PFS_i^H x + n_i, \quad i = 1, \ldots, c$$

Accelerated MRI Reconstruction

Prior knowledge

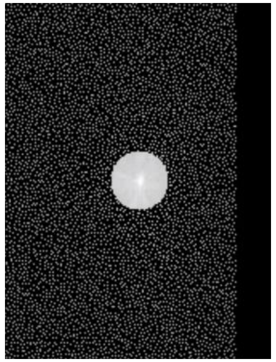
$$y = PFS_i^H x + n_i, \quad i = 1, \ldots, c$$

fully sampled image $\{x\}$



Inverse transform ?

sparsely sampled
kspace $\{y\}$



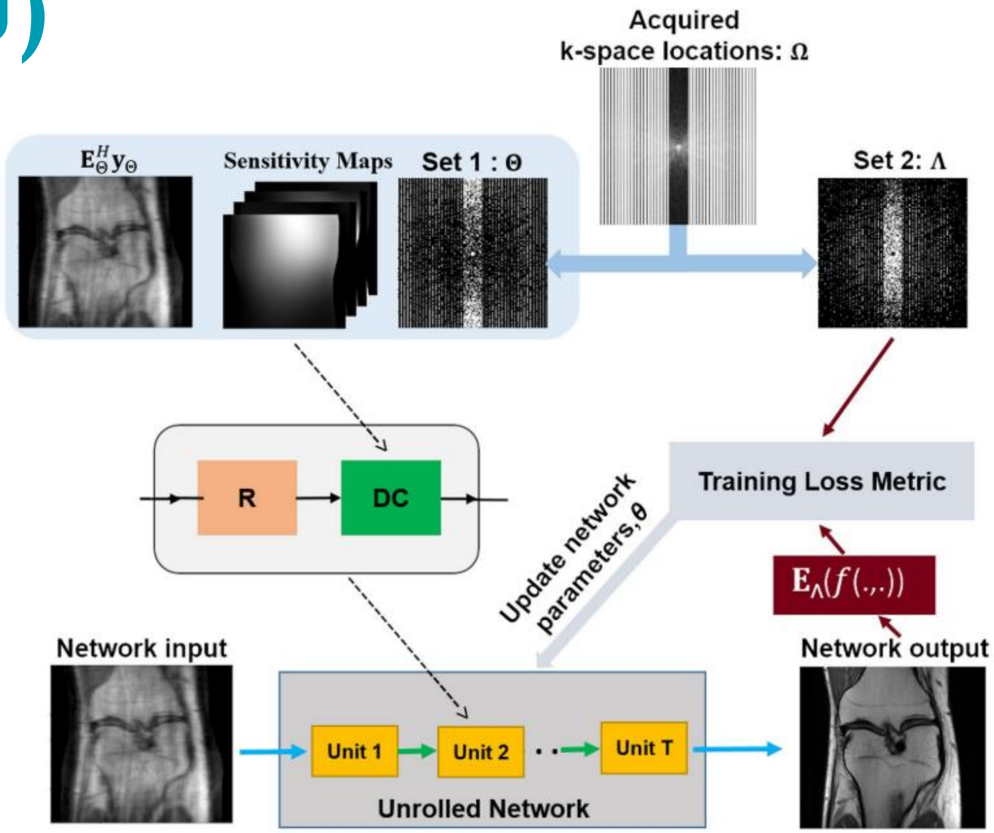
- In MRI Reconstruction we are trying to find the inverse transform that approximates the fully sampled image from a sparsely sampled k-space.

In this study

- We compared various MRI reconstruction methods, including both supervised and self-supervised techniques
- We systematically evaluated and compared these methods to identify the contribution of supervision to MRI reconstruction
- Our main hypothesis was that a well-trained pre-trained model would be able to perform equally or even better than the self-supervised approaches

Self-supervised learning via data undersampling (SSDU)

- The acquired subsampled k-space measurements, Ω, are split into two disjoint sets, Θ and Λ.
- Θ used for predictions
- Λ used in loss function
- ResNet was used as the regularizer
- Proximal Gradient was used in the Data Consistency (DC) Block
- DC ensures that the predictions space is close to the latent space of the input

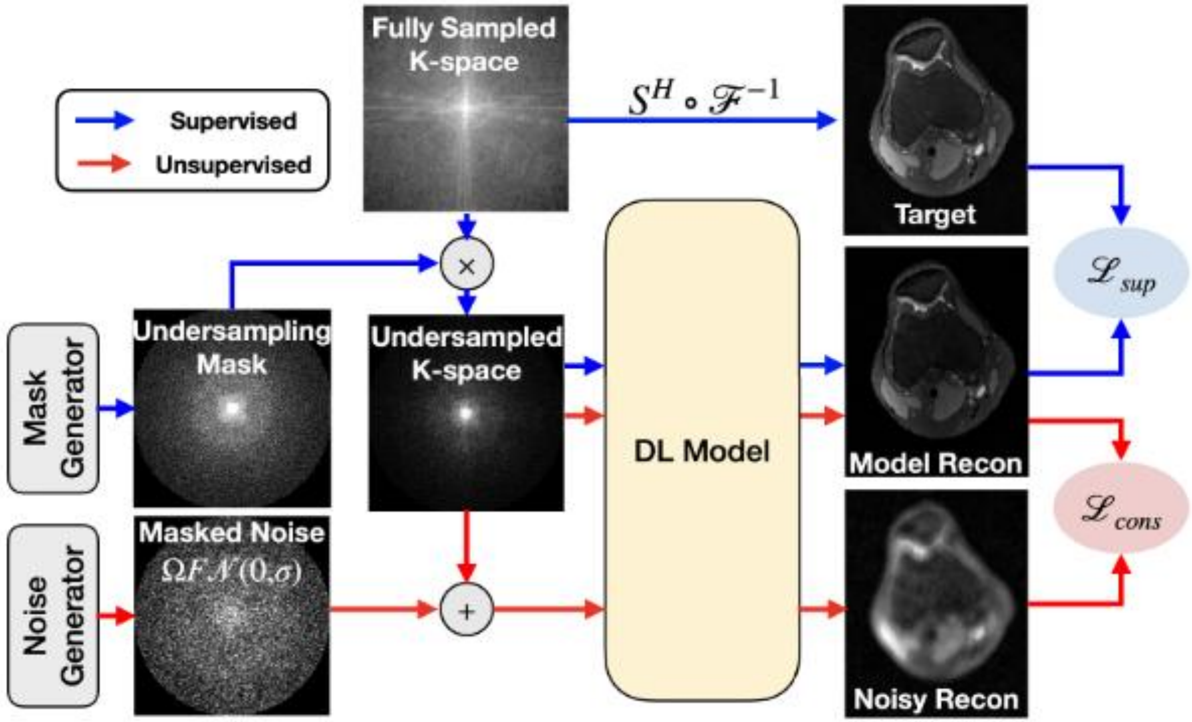


Benefits

- This framework allows training of physics-guided DL-MRI reconstruction without requiring fully sampled data

Yaman et. al (2020).
Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data. *Magnetic Resonance in Medicine*, *84*(6), 3172–3191.

Noise2Recon



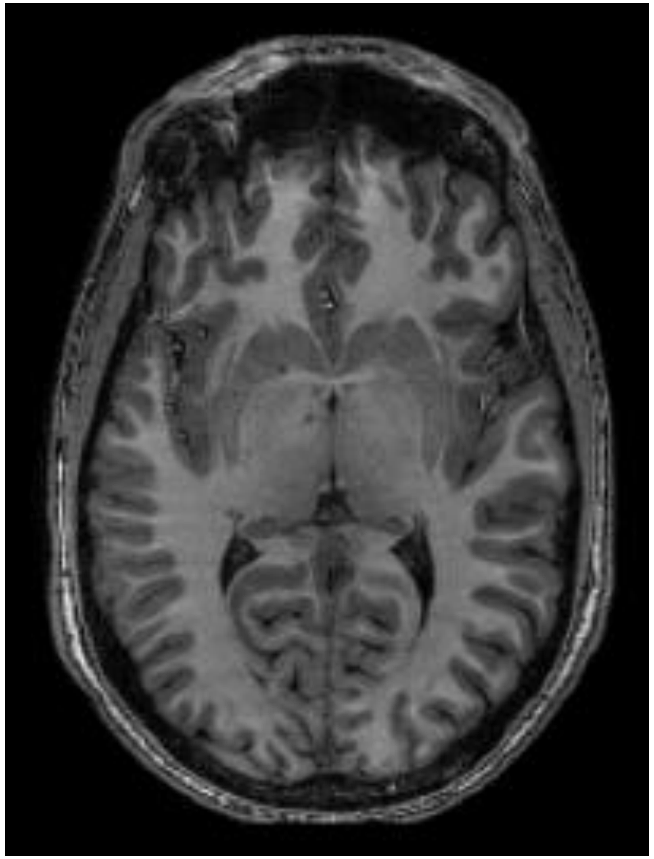
- The same model reconstructs both the non-augmented and augmented scans.
- The total loss is a weighted sum of the supervised and consistency losses: $L_{total} = L_{sup} + \lambda L_{cons}$
- U-Net was used as the backbone model

Benefits

- Can utilize both fully-sampled and undersampled scans to simultaneously enable reconstruction in label-limited settings and to increase robustness to noise.
- Is model-agnostic and can be extended to unsupervised settings, where no fully-sampled references are available

Desai et al. (2021).
Noise2Recon: A Semi-Supervised Framework for Joint MRI Reconstruction and Denoising. http://arxiv.org/abs/2110.00075

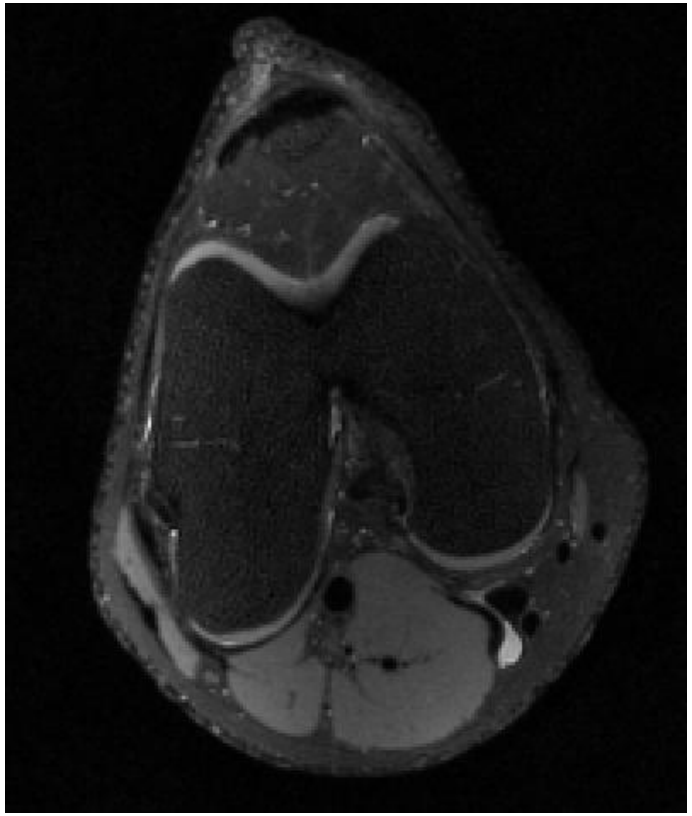
Datasets (1/2)



In-house 3T T1 3D Brains dataset

- Used for pre-training the supervised models
- 11 subjects total
- Training: 10 subjects (~3000 slices)
- Validation: 1 subject (~300 slices)
- Sampling Mask: 2D Gaussian 12x

Datasets (2/2)



Stanford 3D fast-spin echo knee

- Used for training the rest of the models
- Used for evaluating all methods
- 19 subjects total
- Training: 14 subject(4480 slices)
- Validation: 2 subjects (640 slices)
- Test: 3 subjects (960 slices)
- Sampling Mask: 2D Poisson Disc 12x

Evaluation Metrics

- Structural Similarity Index (SSIM)
- Peak Signal-to-Noise Ratio (PSNR)
- Mean Squared Error (MSE)
- Normalized Mean Square Error (NMSE)

All metrics were calculated and reported per volume

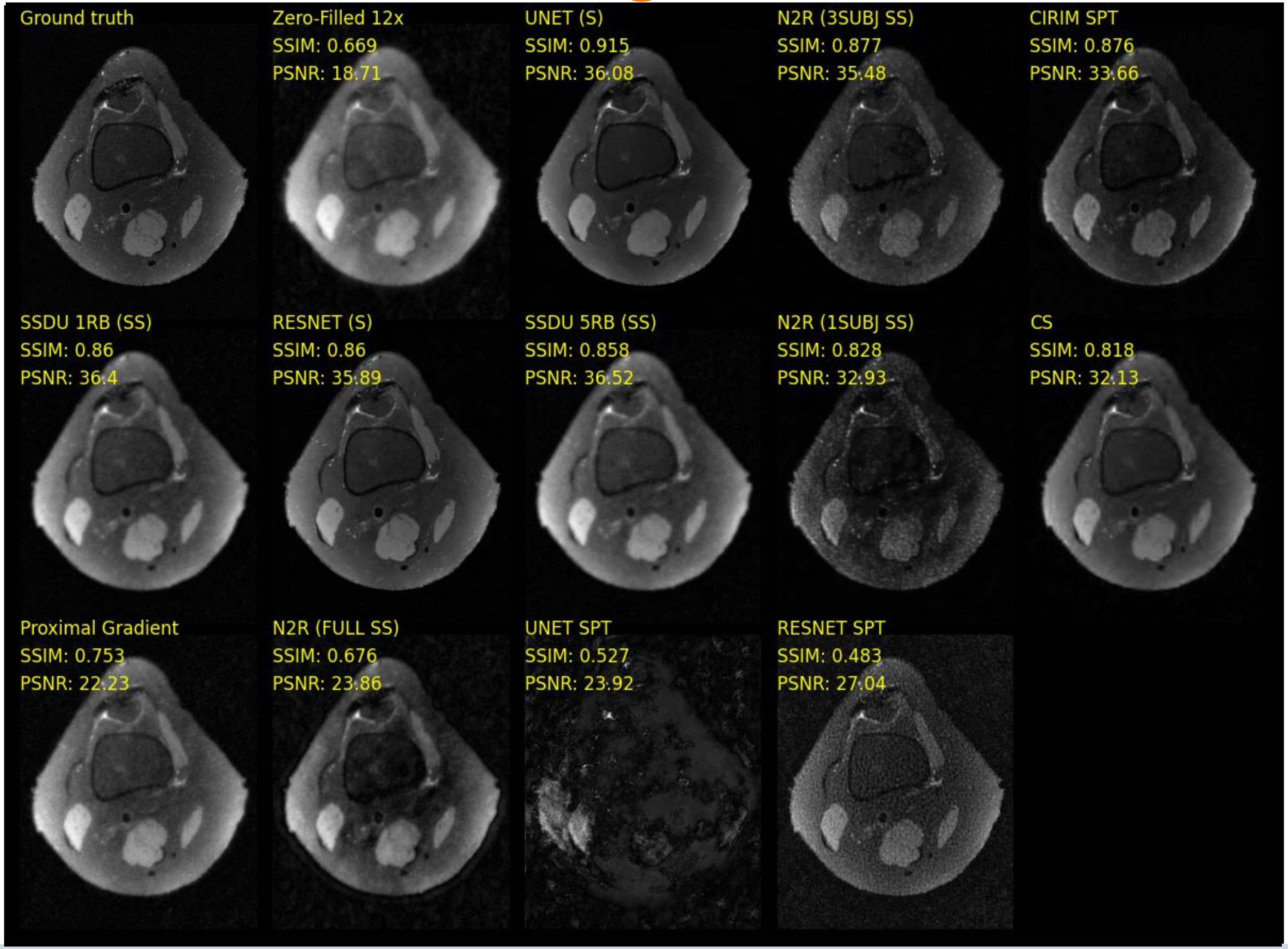
Experiments

Self-Supervised (SS)	Supervised Pre-trained (SPT)	Supervised (S)	Traditional
SSDU with 1 residual block (SSDU1RB)	Cascades of Independent Recurrent Inference Machines (CIRIM)	U-NET	Compressed Sensing (CS)
SSDU with 5 residual blocks (SSDU5RB)	U-NET	ResNet	Proximal Gradient
Noise2Recon fully self-supervised (N2R FULLSS)	ResNet		
Noise2Recon with 3 supervised subjects (N2R 3SUBJ)			
Noise2Recon with 1 supervised subject (N2R 1SUBJ)			

Results

Method	SSIM↑	PSNR↑	MSE↓	NMSE↓
UNET (S)	**0.853 ± 0.049**	28.41 ± 4.26	0.002 ± 0.002	0.251 ± 0.232
N2R 3SUBJ (SS)	0.846 ± 0.037	29.03 ± 3.52	**0.001 ± 0.001**	0.212 ± 0.156
RESNET (S)	0.838 ± 0.045	27.02 ± 4.56	0.002 ± 0.003	0.350 ± 0.360
CIRIM (SPT)	0.822 ± 0.048	28.25 ± 3.39	0.002 ± 0.001	0.253 ± 0.172
N2R 1SUBJ (SS)	0.814 ± 0.045	**29.15 ± 3.42**	**0.001 ± 0.001**	**0.207 ± 0.153**
CS	0.793 ± 0.051	26.15 ± 4.07	0.003 ± 0.002	0.418 ± 0.350
SSDU 5RB (SS)	0.792 ± 0.130	24.58 ± 8.10	0.004 ± 0.006	0.717 ± 0.912
SSDU 1RB (SS)	0.791 ± 0.139	24.72 ± 8.61	0.004 ± 0.006	0.710 ± 0.940
Proximal Gradient	0.662 ± 0.026	20.45 ± 1.84	0.009 ± 0.004	1.482 ± 0.482
N2R FULLSS (SS)	0.629 ± 0.026	22.34 ± 1.99	0.006 ± 0.003	0.960 ± 0.323
Zero-Filled SENSE	0.603 ± 0.041	18.00 ± 0.56	0.016 ± 0.002	2.590 ± 0.435
UNET (SPT)	0.574 ± 0.036	25.90 ± 0.82	0.003 ± 0.000	0.419 ± 0.021
RESNET(SPT)	0.449 ± 0.008	23.42 ± 2.63	0.005 ± 0.003	0.758 ± 0.401

Reconstructions



Conclusions

- Well-trained CIRIM generalized well on the unseen dataset given a strong prior knowledge from the 3T T1 3D Brains dataset
- Pretrained networks without MR physics knowledge didn't manage to generalize well
- High SNR acquisitions are more important than the structure in building strong prior knowledge for the physics-based model

Future work

- Train all models until full convergence
- Experiment with different datasets for pre-training the supervised models
- Use another dataset for evaluating all models to see how they generalize

Thank you!

Q&A

Acknowledgments

Dimitris Karkalousos

Matthan Caan