XPDNet for brain multi-coil MRI reconstruction

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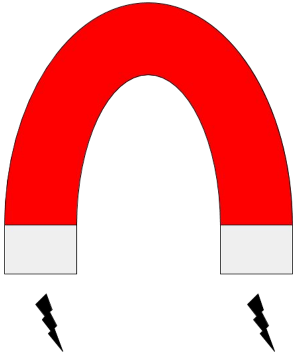
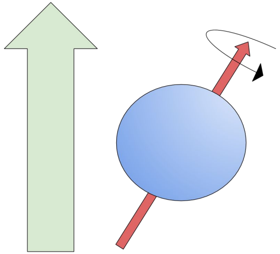
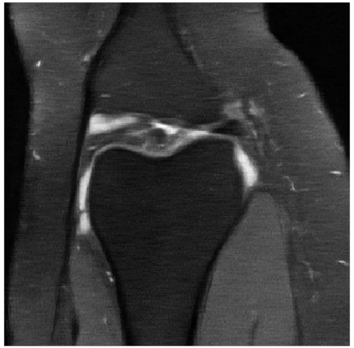
Jean-Luc Starck

What is MRI?

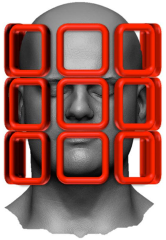
MRI = **M**agnetic **R**esonance **I**maging

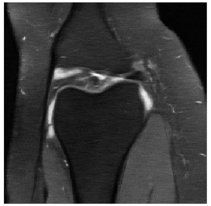


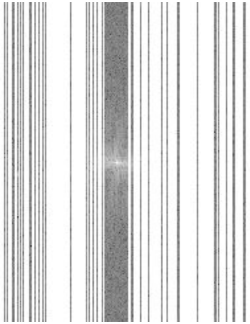




The (idealized) inverse problem







$$\forall j, \; F_{\Omega} S_j x = y_j$$

Masked 2D Fourier Transform, **well-defined** in the fastMRI case

The “periodic” mask, **known** but **specific to each acquisition**, part of the **input**

The sensitivity maps, **unknown** and **specific to each acquisition**

The anatomical image, the **output** of our reconstruction

The k-space measurements for all coils, part of the **input** to our reconstruction (complex-valued)

Where is the room for learning?

$$\underset{x \in \mathbb{C}^n}{\arg\min} \sum_j \frac{1}{2} \| y_j - F_\Omega S_j x \|_2^2 + R(x)$$

Optimization algorithm parameters, such as **step sizes** or **iterates merging**, can be learned

Noise model data consistency distance, usually set to be AWGN, we can learn the equivalent of its **gradient**

Sensitivity maps can be computed using l1-SPIRiT, but we can learn how to **refine them**

Prior term usually set by hand, we can learn the equivalent of its **proximity operator**

Outline

1. Cross domain learning
2. Measurement operator refinement
3. Proximity operator learning
4. Data consistency learning

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Cross-domain learning

Key intuitive idea: Alternate the corrections between image domain and k-space, "comparing" the original k-space measurements with the current iterate's k-space measurements.

Tool for that: unrolling optimisation algorithms.

Correction in the **k-space**

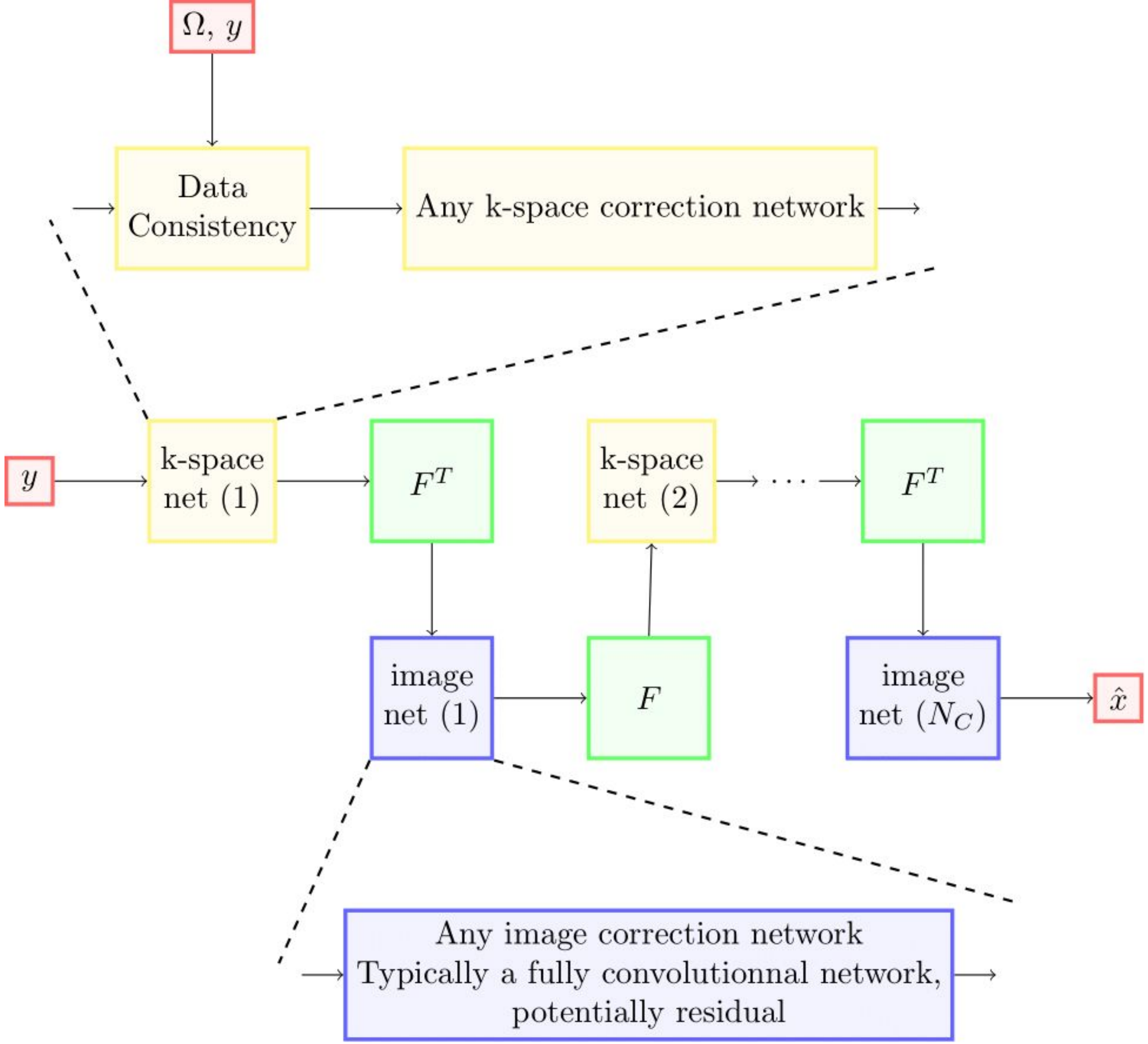
Current k-space measurements

$$x_{n+1} = x_n + \epsilon_n \, (F_\Omega S)^H (F_\Omega S \, x_n - y)$$

$$x_{n+1} = \mathrm{prox}_{\epsilon_n R}\,(x_{n+1})$$

Correction in the **image domain**

Original k-space measurements



Ω, y
Data Consistency
Any k-space correction network
y
k-space net (1)
F^T
k-space net (2)
F^T
image net (1)
F
image net (N_C)
$\hat{x}$
Any image correction network
Typically a fully convolutionnal network,
potentially residual

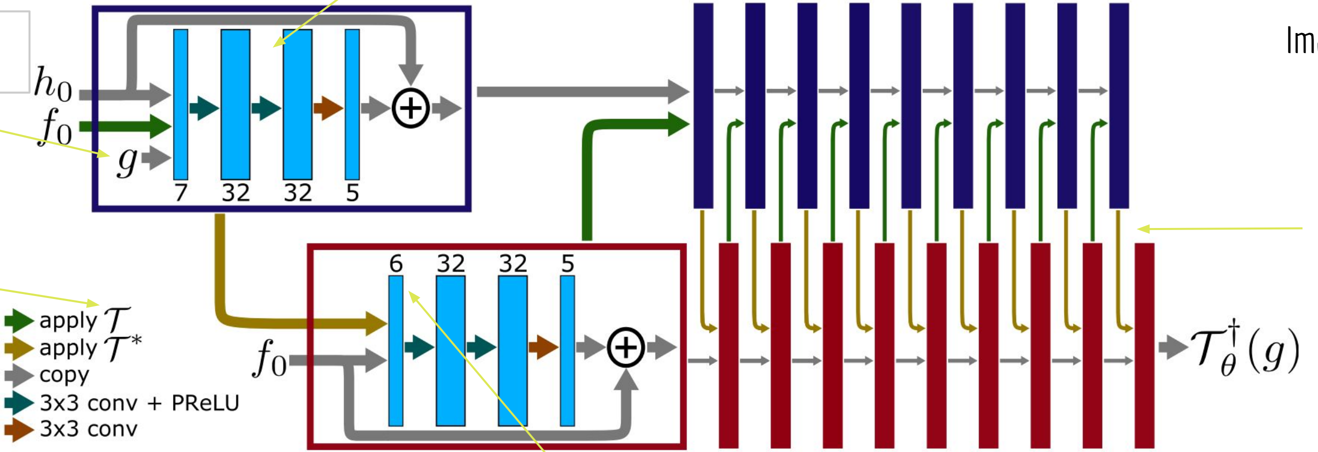
Cross-domain learning - unrolling PDHG [1]

PD-net unrolls the PDHG, where the data consistency is a (learned) residual

We don't use a k-space correction network, and just use a residual

Original measurements

Image from [1]



Masked, multicoil Fourier transform

We unroll **25** iterations

Buffers are used to learn the merging of consecutive iterates

[1] Learned Primal-Dual Reconstruction, Adler et al. 2018

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Sensitivity maps refinement [2]

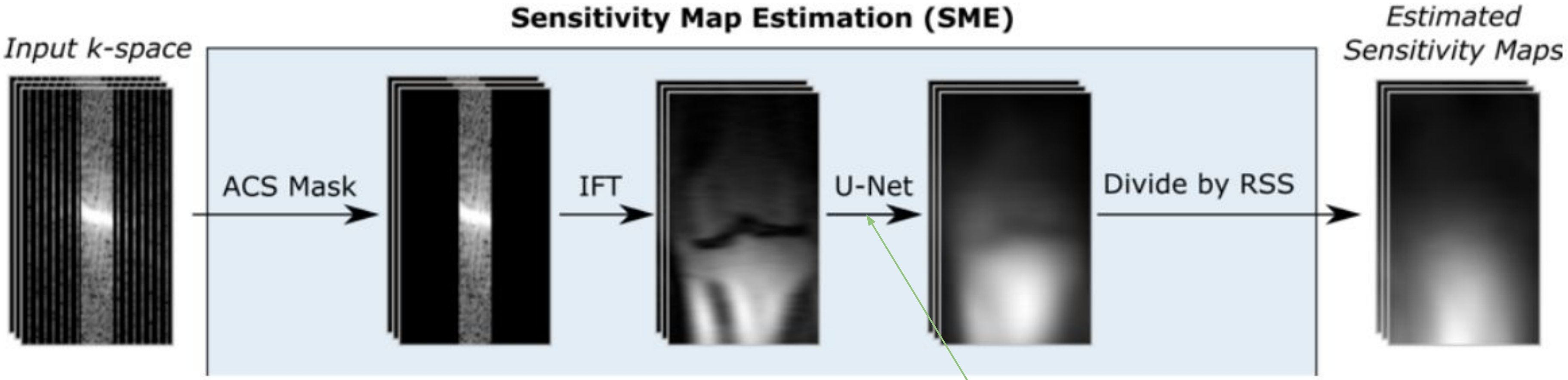

Image from [2]

The U-net is applied to all the coarse sensitivity maps with the same weights.

[2] End-to-End Variational Networks for Accelerated MRI Reconstruction, Sriram et al. 2020

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Proximity operator architecture [3]

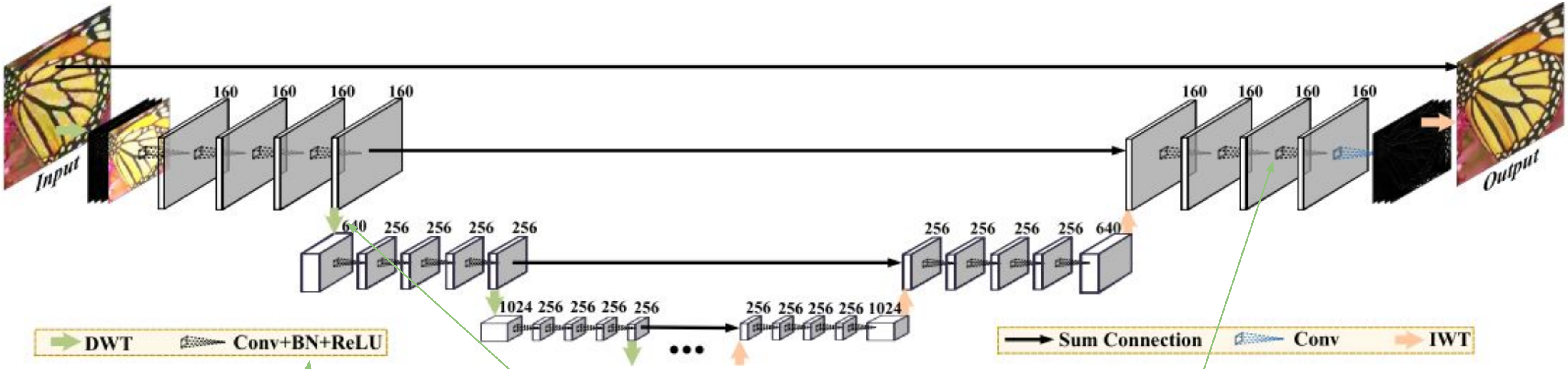

Image from [3]

Pooling is done using a simple wavelet operator (same for unpooling)

We **omit** Batch Normalisation in the architecture given the batch size is 1

To fit on a single GPU, we use **less feature channels** (64, 128, 256)

[3] Multi-level Wavelet-CNN for Image Restoration, Liu et al. 2018

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Data consistency learning

I didn't use it during the challenge... No good reason (I thought memory was going to be an issue).

Adding a CNN here

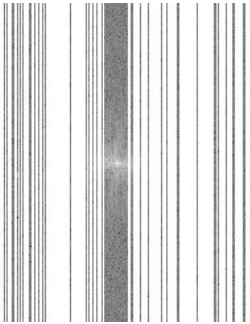
$$x_{n+1} = x_n + \epsilon_n (F_\Omega S)^H (F_\Omega S\, x_n - y)$$

$$x_{n+1} = \mathrm{prox}_{\epsilon_n R}(x_{n+1})$$

Data

We use the fastMRI dataset [4], which is composed of:

- 4469 train volumes (1.2 Tb), 1378 volumes, 558 test volumes (unknown ground truth)
- Input data is generated retrospectively



[4] fastMRI: An Open Dataset and Benchmarks for Accelerated MRI, J. Zbontar et al. 2018.

Training details

- Data scaling by 10^6 (not grid-searched)
- RAdam optimizer (with default params.), learning rate of 10^{-4} [5]
- Total number of steps 446.9k (= 100 epochs x 4469 volumes) => 1 week on V100 for 155.5M params.
- Batch size of 1 (we select one slice at random during each epoch)
- Training is done separately for Accel. factor 4 and 8, then the network is fine-tuned per-contrast
- Loss is a compound L1-MSSIM as advised in [6]

[5] On the Variance of the Adaptive Learning Rate and Beyond, Liu et al. 2020
[6] An Adaptive Intelligence Algorithm for Undersampled Knee MRI Reconstruction: Application to the 2019 fastMRI Challenge, Pezzotti et al. 2020

2020 fastMRI challenge - AF4 quantitative podium

AIRS-Net 10/15/2020	4x	0.0028	0.9640	42.2	✓
Joint-ICNet 10/15/2020	4x	0.0035	0.9599	41.2	✓
xpdnet_v2 10/15/2020	4x	0.0034	0.9589	41.3	✓

2020 fastMRI challenge - AF8 quantitative podium

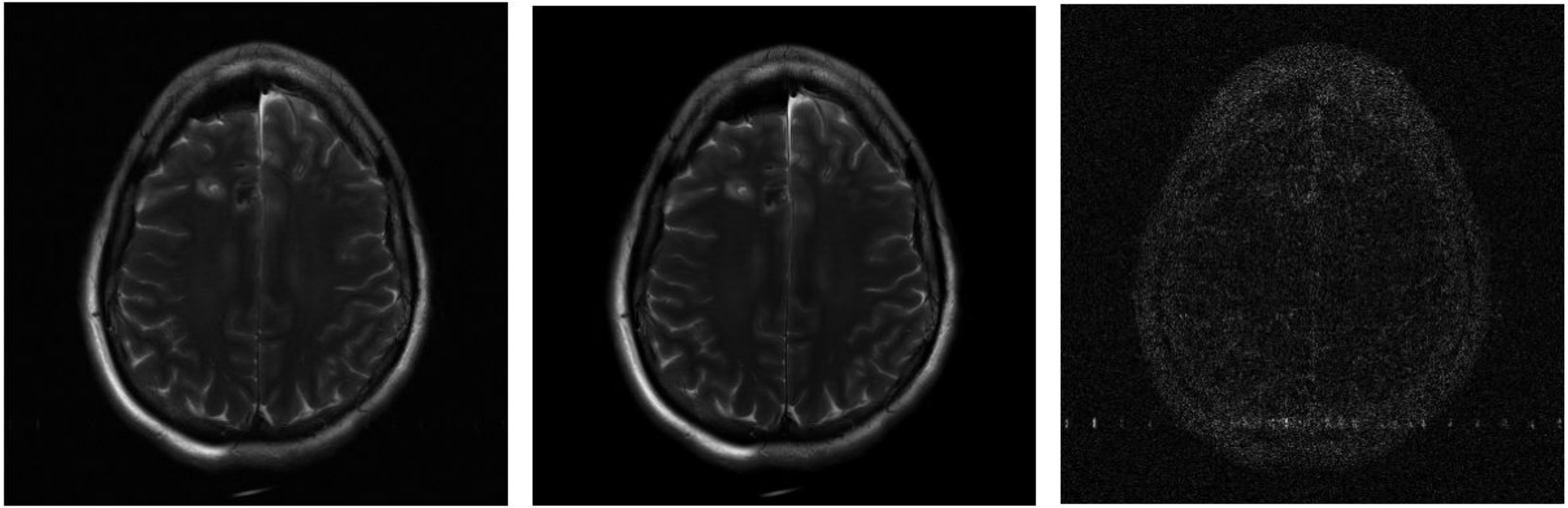
AIRS-Net 10/15/2020	8x	0.0050	0.9524	39.6	✓
Joint-ICNet 10/15/2020	8x	0.0073	0.9437	37.9	✓
xpdnet_v2 10/15/2020	8x	0.0072	0.9420	38.0	✓

2020 fastMRI challenge - qualitative podium [7]

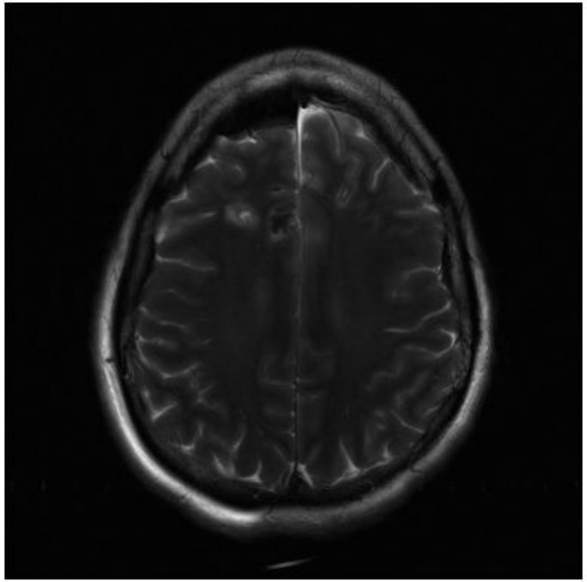
Team	Rank	Artifacts	Sharpness	CNR
4X Track				
AIRS Medical	**1.36 ± 0.64**	**1.53 ± 0.70**	**1.53 ± 0.51**	**1.53 ± 0.51**
Neurospin	1.94 ± 0.86	1.81 ± 1.01	1.72 ± 0.66	1.75 ± 0.84
ATB	2.22 ± 0.87	1.75 ± 0.97	1.97 ± 0.65	1.86 ± 0.80
8X Track				
AIRS Medical	**1.28 ± 0.64**	**1.67 ± 0.68**	**1.89 ± 0.75**	**1.94 ± 0.75**
Neurospin	2.25 ± 0.77	1.86 ± 0.83	2.72 ± 0.81	2.28 ± 0.81
ATB	2.28 ± 0.70	1.92 ± 0.94	2.56 ± 0.77	2.42 ± 0.84

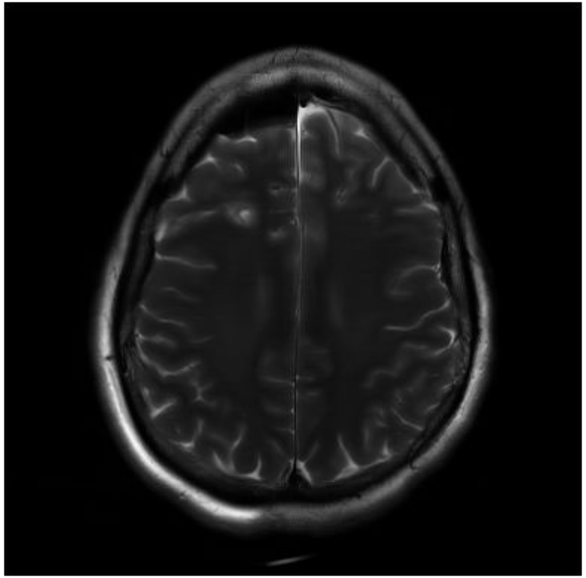
[7] State-of-the-art Machine Learning MRI Reconstruction in 2020: Results of the Second fastMRI Challenge, Mcukley et al. 2020

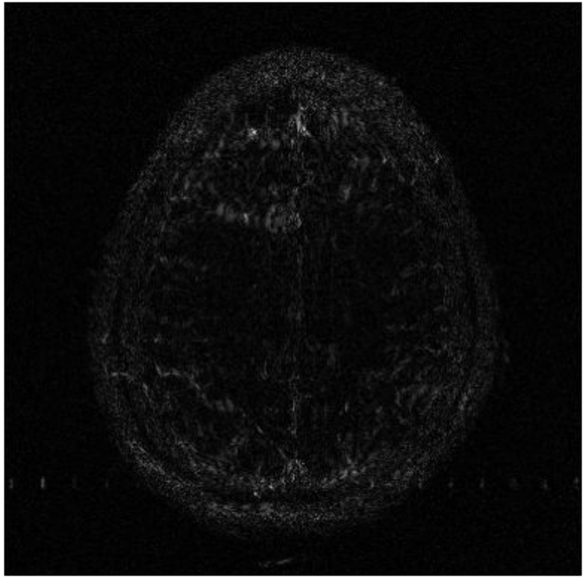
Qualitative validation results - T2 - R4



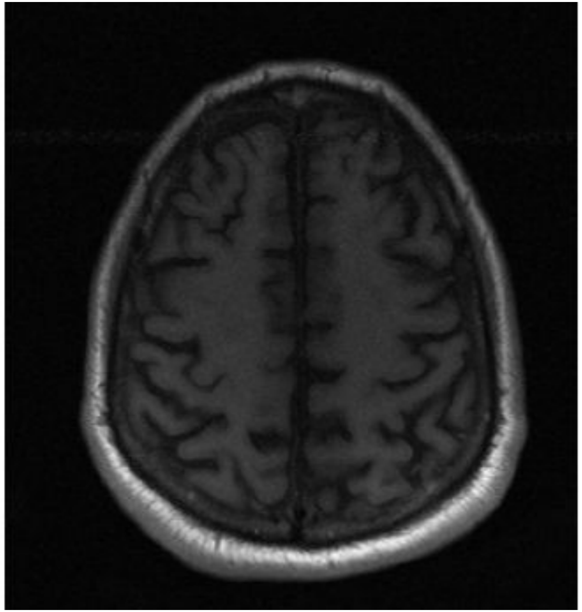
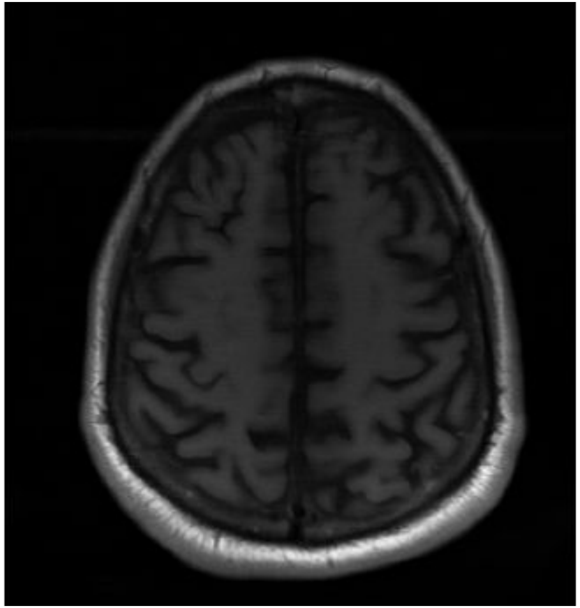
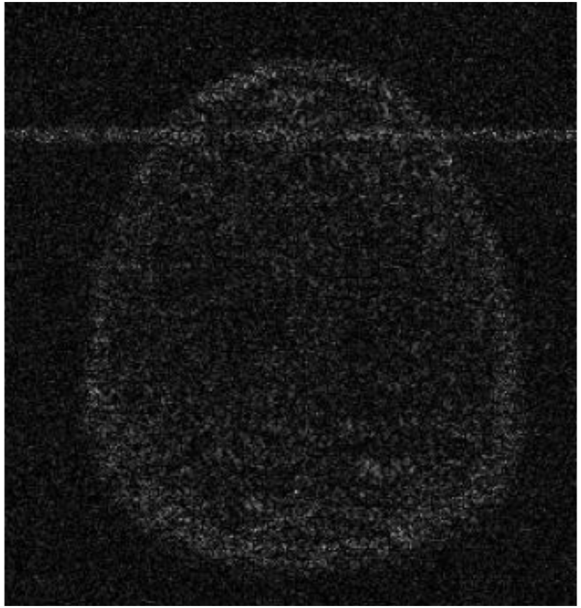
Qualitative validation results - T2 - R8



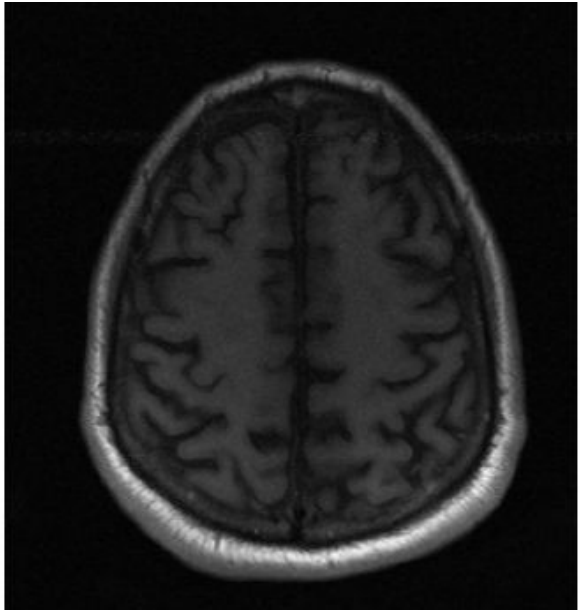


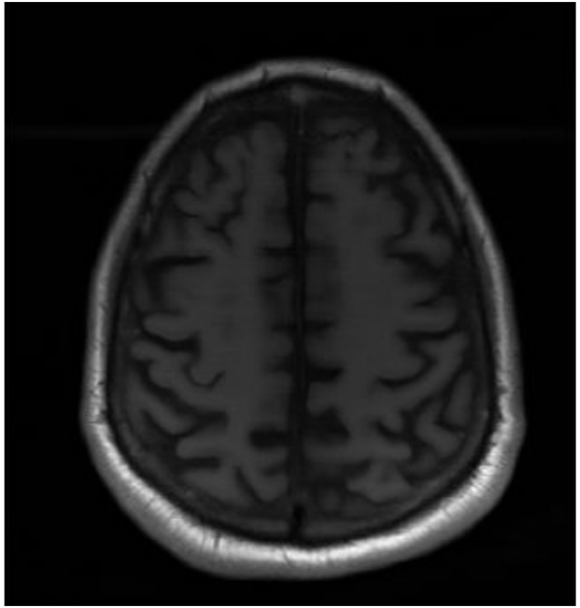


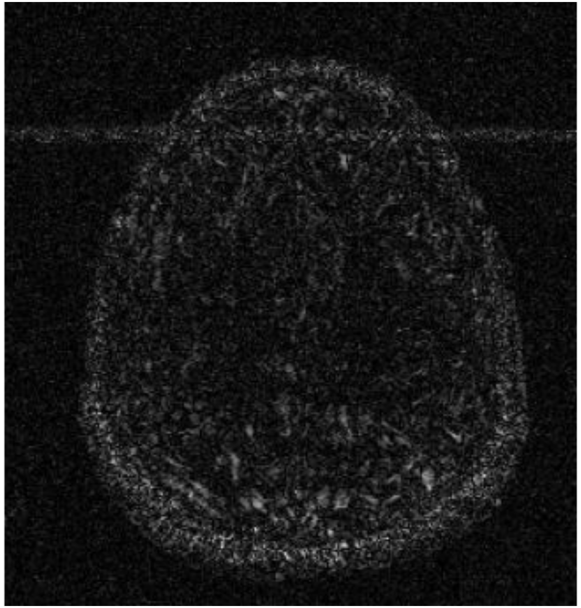
Qualitative validation results - T1 - R4

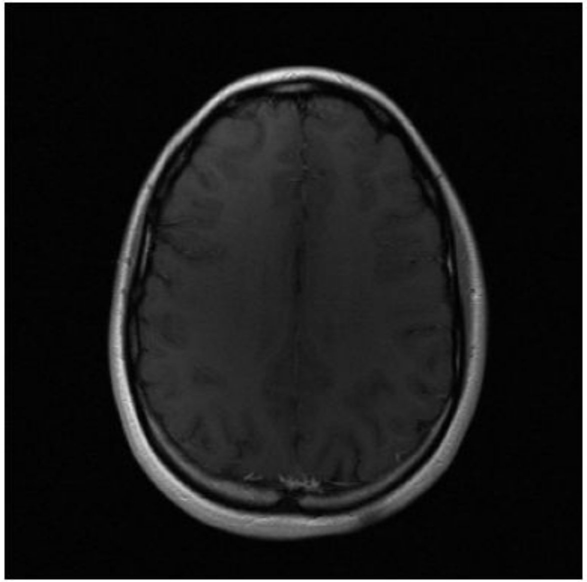
Qualitative validation results - T1 - R8

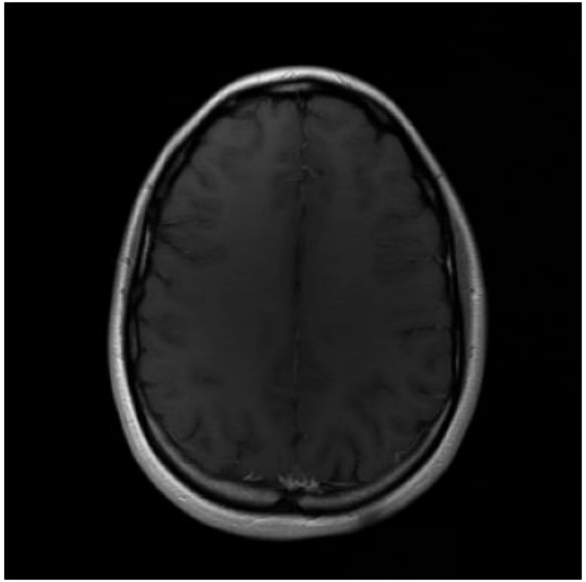


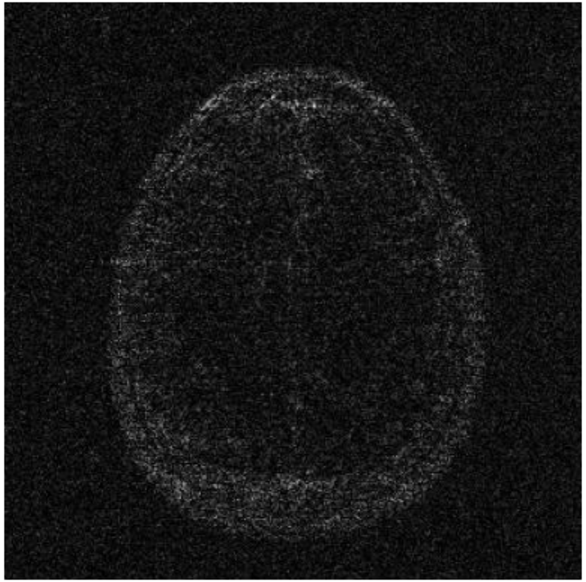




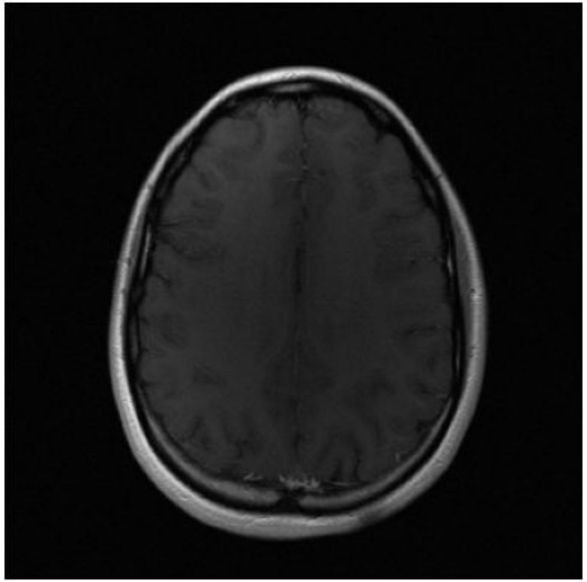
Qualitative validation results - T1POST - R4

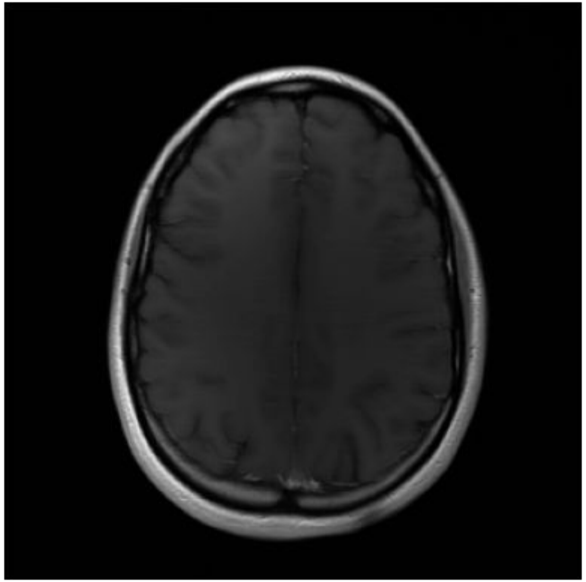


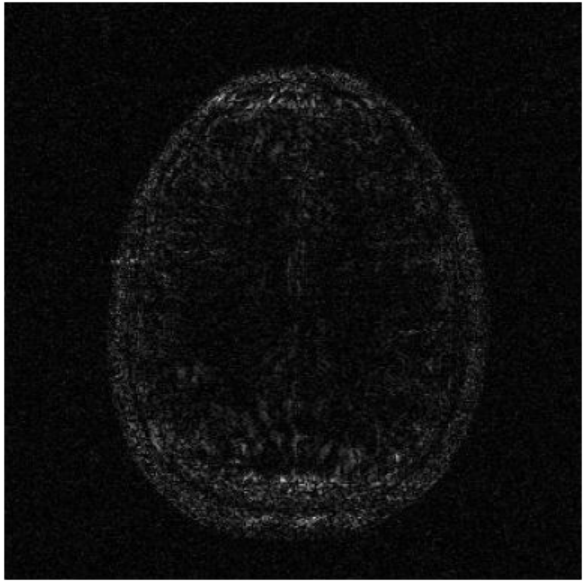




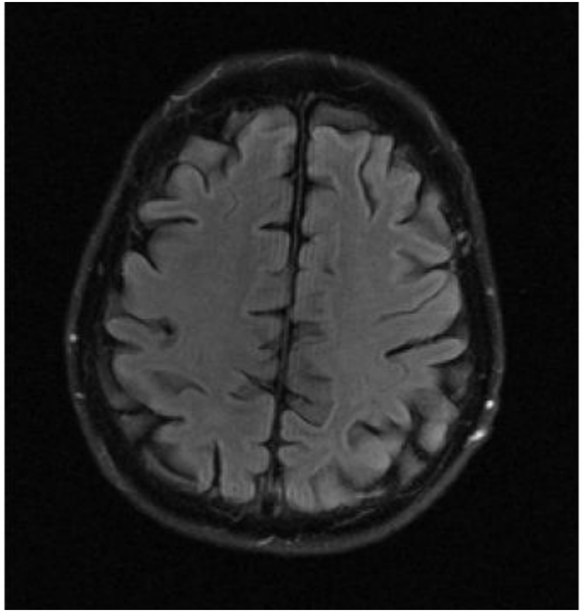
Qualitative validation results - T1POST - R8

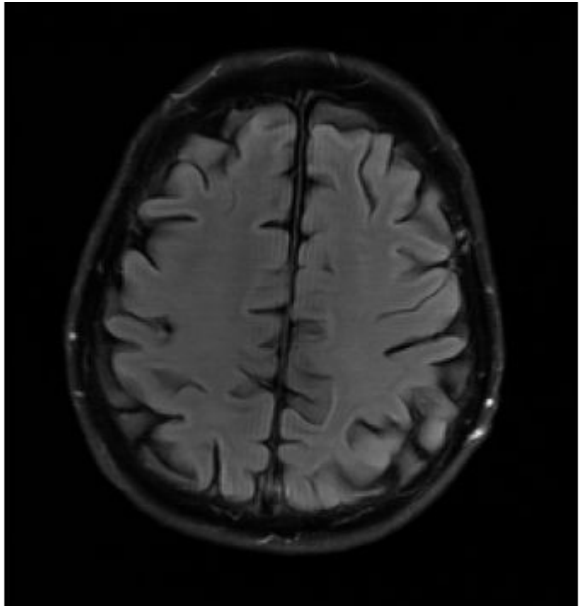


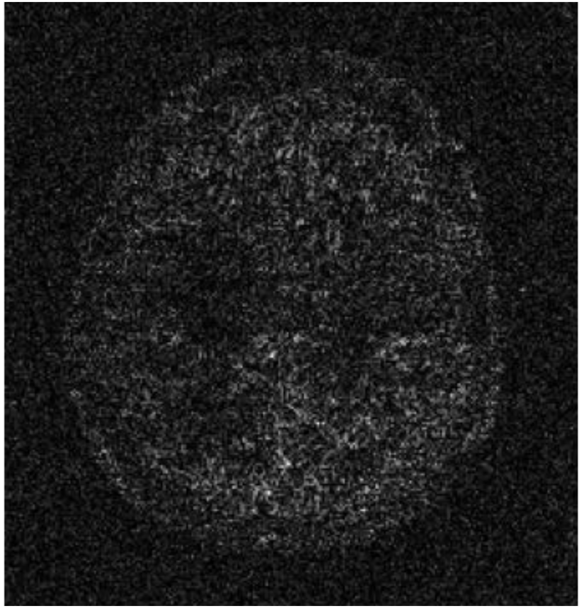




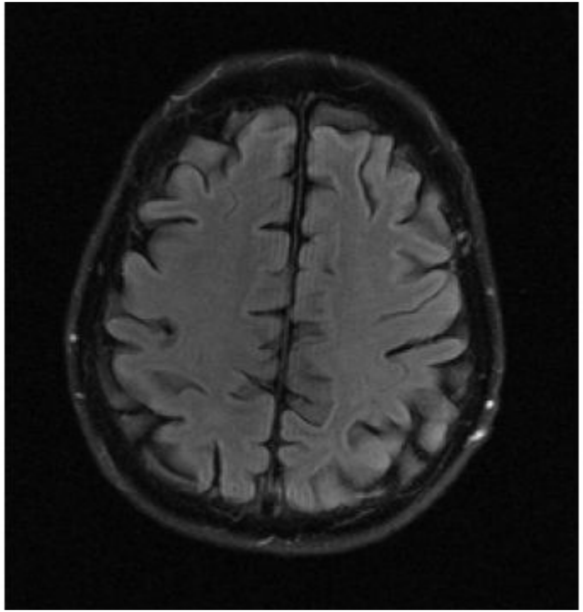
Qualitative validation results - FLAIR - R4

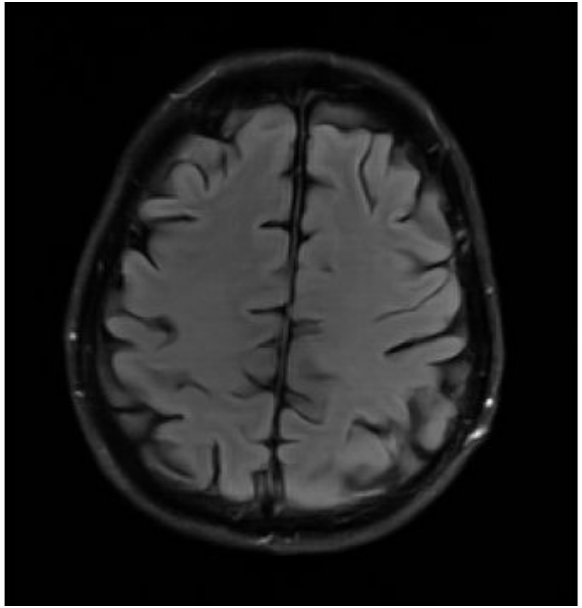


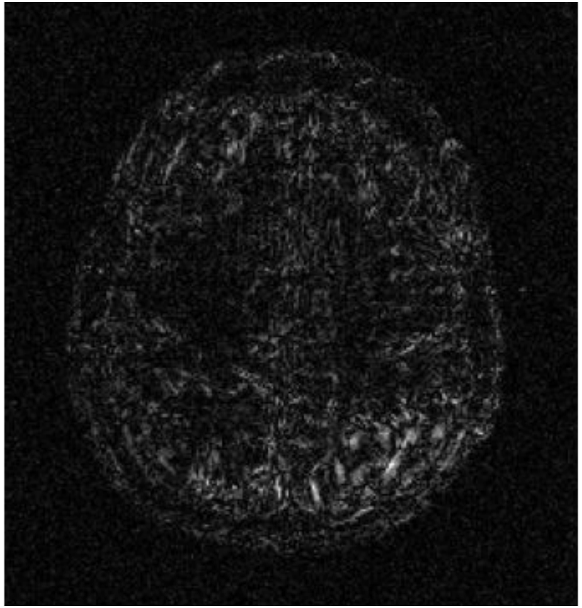




Qualitative validation results - FLAIR - R8







Why I am only second?

What winners did better than me:

- Unclear feature multi-domain learning
- 3D Post-processing (main network is 2D)
- Distributed training (4 GPUs)

Conclusion and future steps

Conclusion

- XPDNet is more than just **prior learning**: it can learn the **unrolled optim.** structure, the **measurements operator** and the **noise model**.
- Using this, we achieve 2nd spot in the fastMRI 2020 challenge.

Next steps

- Implement the missing bits (DC learning, post-processing, better/longer training, multi-domain learning)
- Full 3D using model parallelism
- Implicit Deep Learning

Acknowledgements and code

Code is available in TensorFlow on GitHub: github.com/zaccharieramzi/fastmri-reproducible-benchmark

Thanks to the French Institute of development and resources in scientific computing (IDRIS) for allowing the use of a supercluster (Jean Zay) of V100 GPUs.

Don’t hesitate to ask me questions about Jean Zay or refer to the user’s doc!

Thank you!

Questions ?

Robustness - generalization to OOD-prospective

Brain acquired on a Siemens scanner:

- different resolution
- different orientation
- different field strength
- different AF
- presents a cerebellum
- prospective acquisition