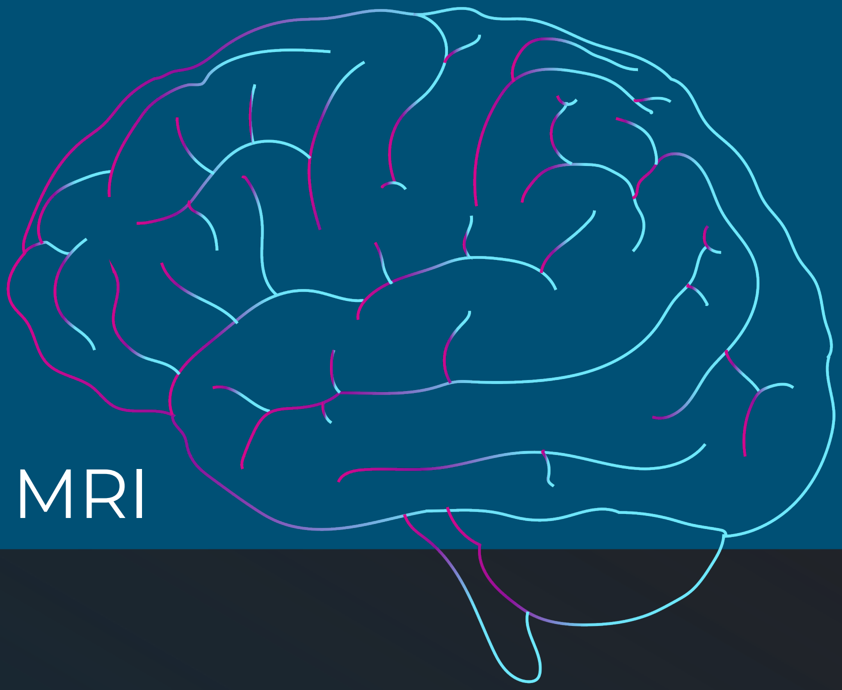
BIOMEDICAL IMAGING & ANALYTICS

Seminar 4. Image reconstruction and MRI



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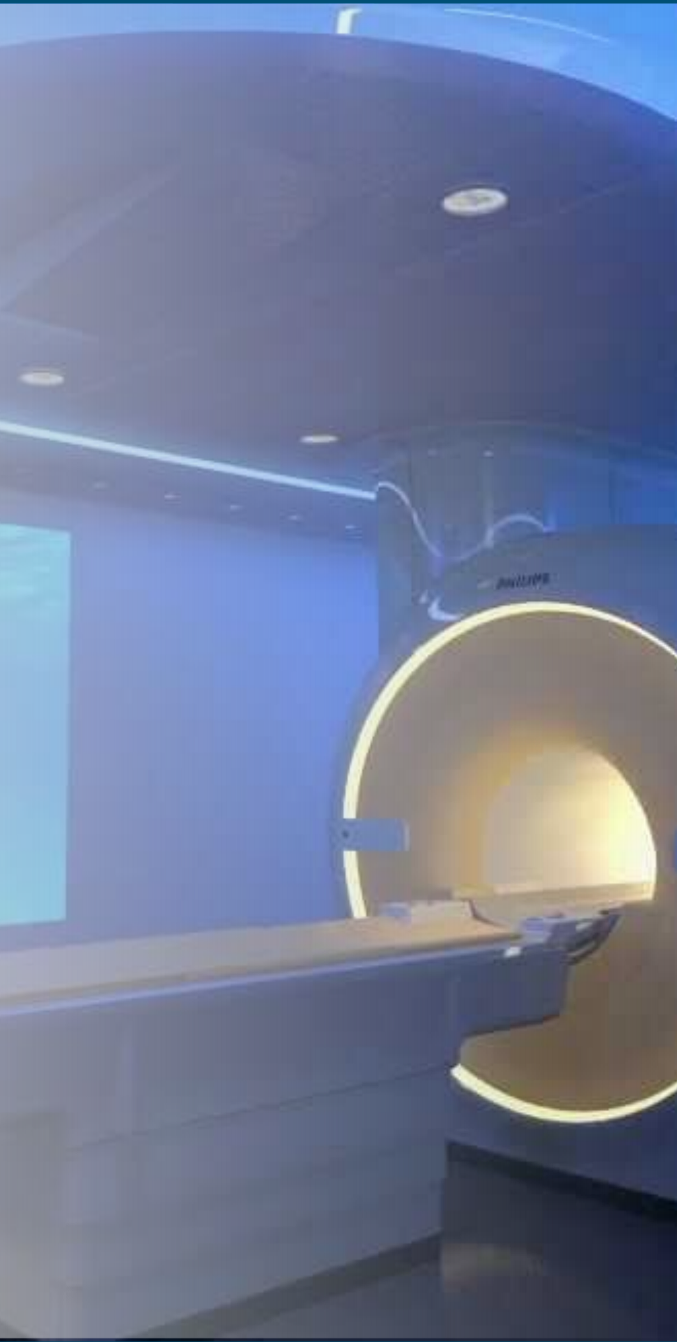
Research Scientist at Philips Research

What is MRI?

- Non-invasive medical imaging technique with **excellent soft-tissue contrast**
- Does **not involve X-rays** or the use ionizing **radiation**, which makes it harmless (just keep magnetizable objects aside)

- Fun fact: MRI was initially called NMRI (nuclear magnetic resonance imaging) but “nuclear” was dropped to avoid negative associations



How to get an MRI image?

In the **simplest** case we need to:

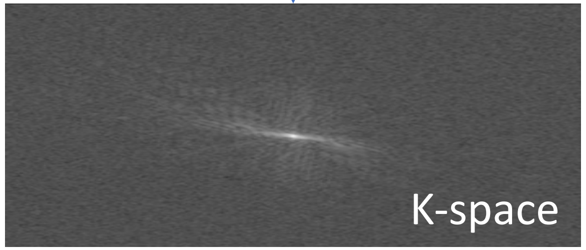
1. Place a patient in the scanner

How to get an MRI image?

In the **simplest** case we need to:

1. Place a patient in the scanner
2. Acquire raw data – **k-space** (wait and do not move)

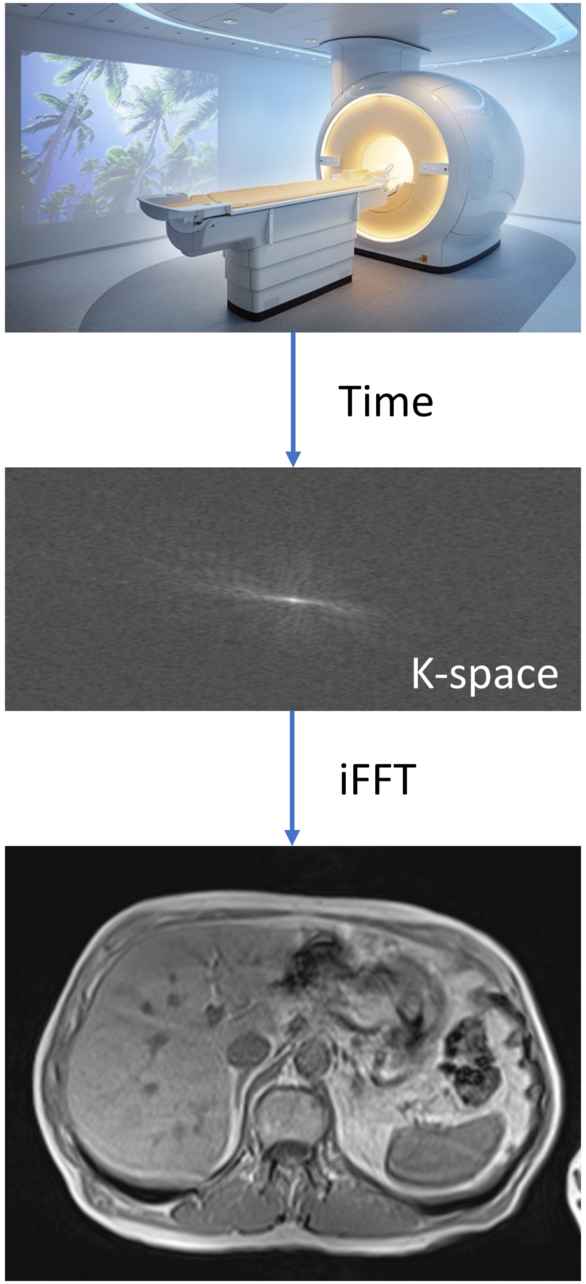
Time



How to get an MRI image?

In the **simplest** case we need to:

1. Place a patient in the scanner
2. Acquire raw data – **k-space** (wait and do not move)
3. Reconstruct an image using inverse **Fast Fourier Transform (iFFT)**



How to get an MRI image?

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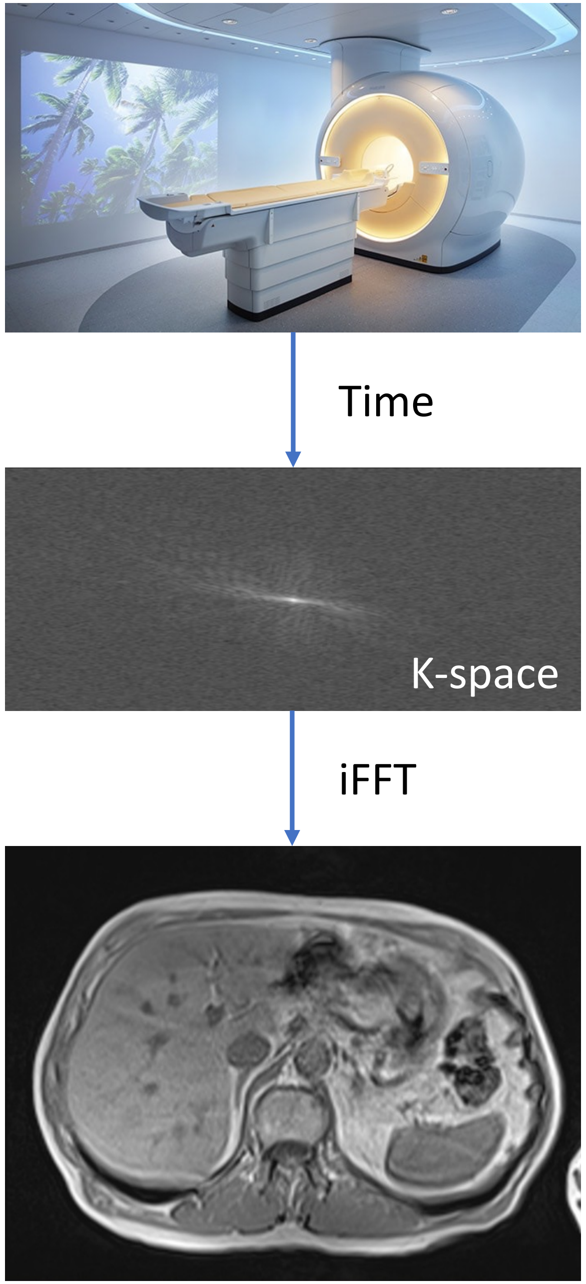
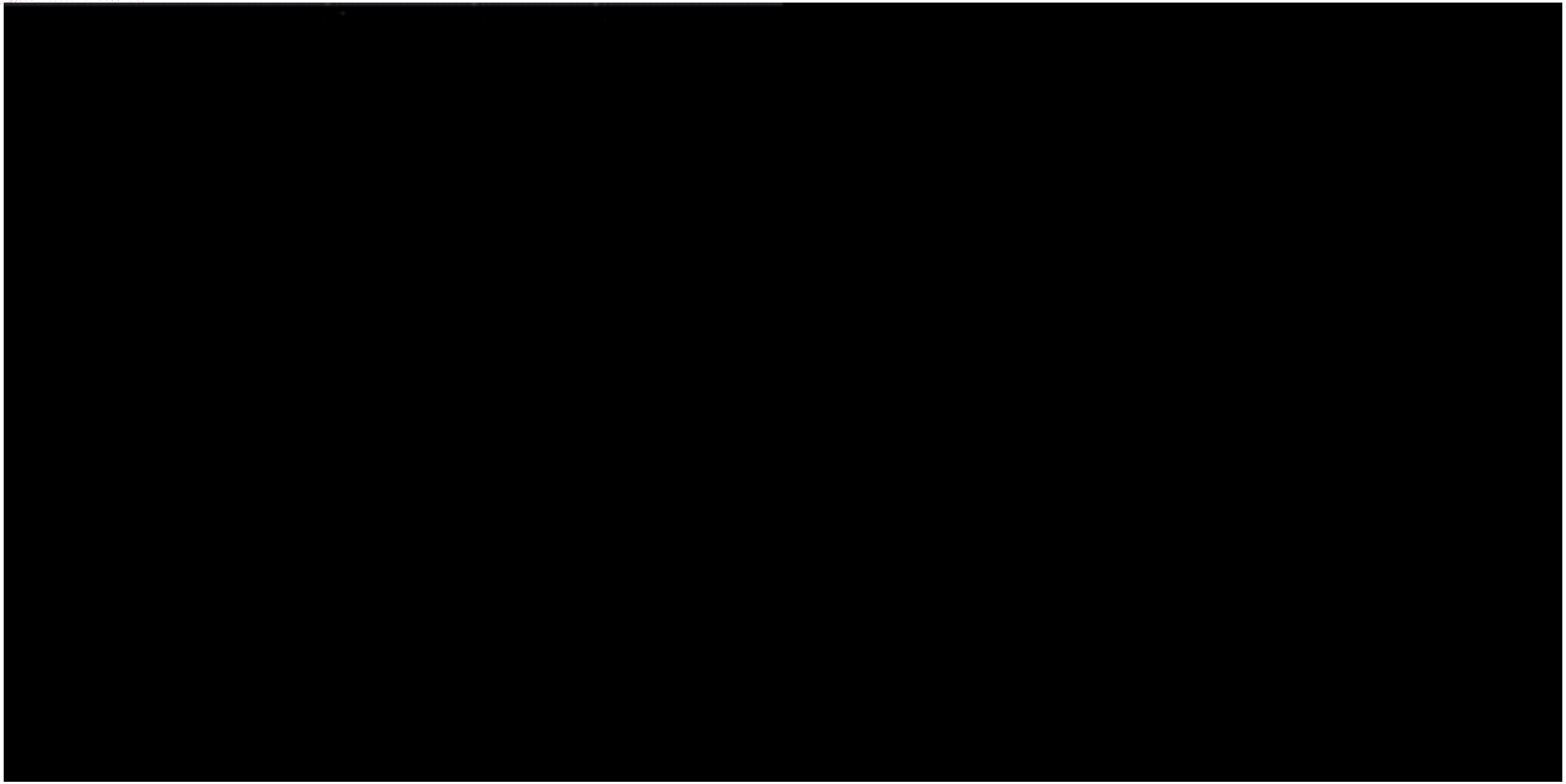


Problem

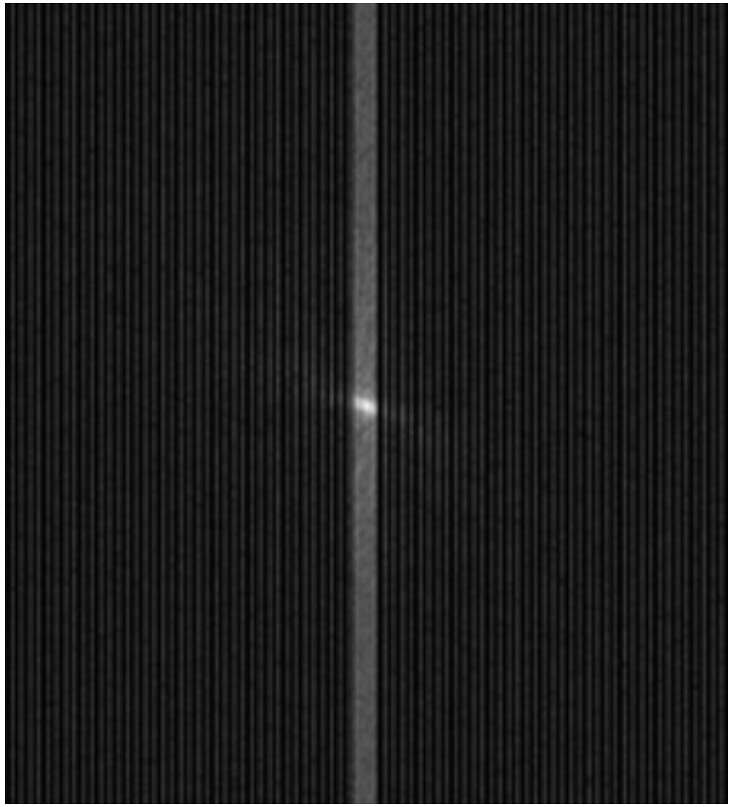
Data acquisition takes **a lot of time**: typically, from 20 to 60 min

Why so long?



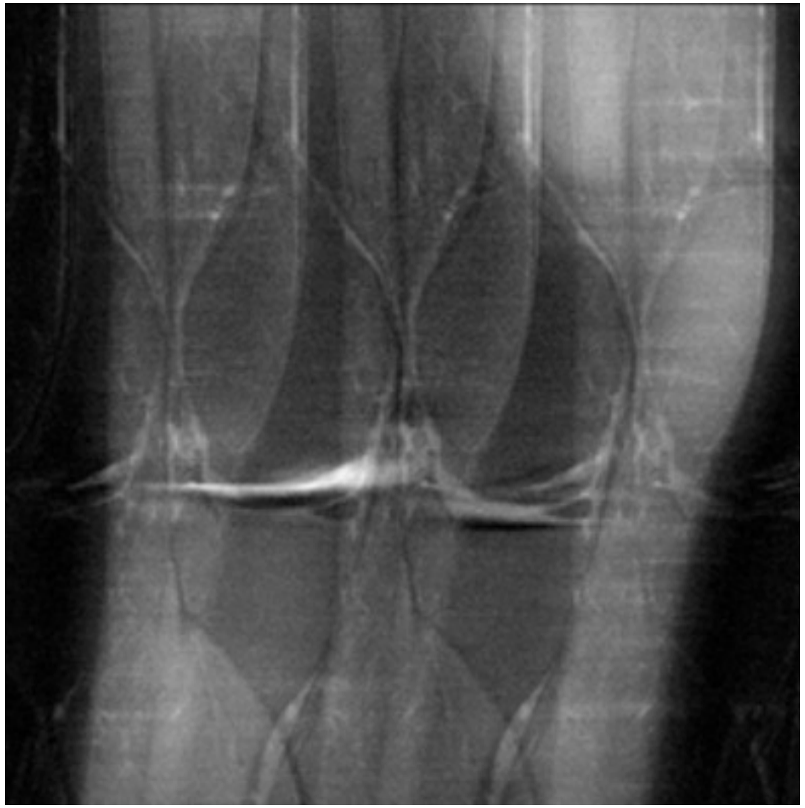
Standard sequential Certesian filling of k-space (Courtesy of Brian Hargreaves)

Problem statement



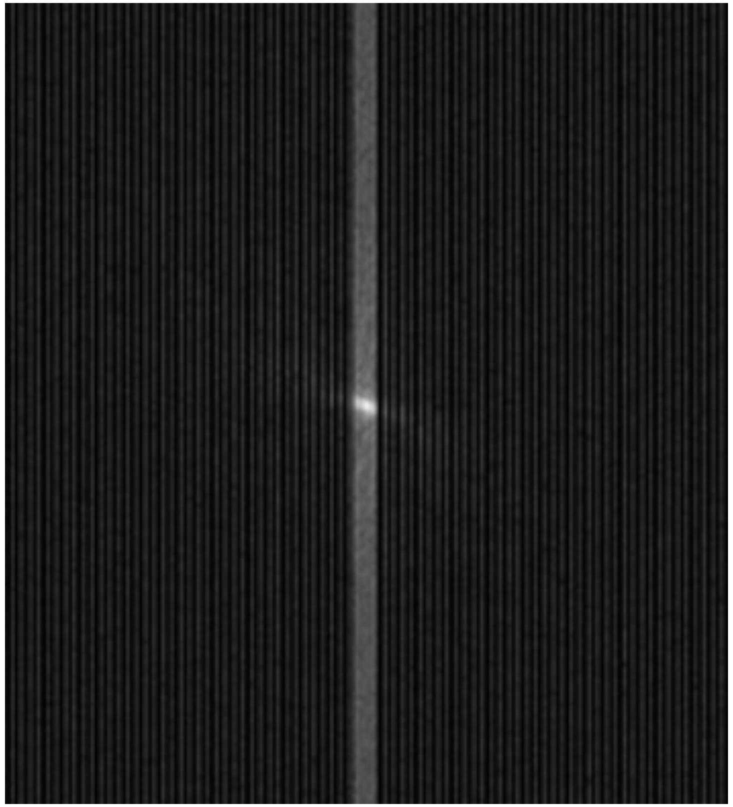
k-space

Standard reconstruction



Reconstructed image

Problem statement

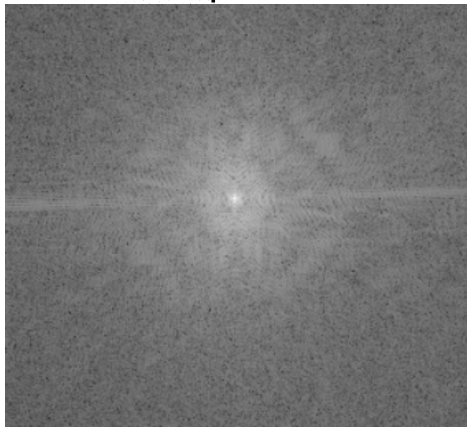


k-space

Reconstructed image

Accelerating Magnetic Resonance Imaging

k-space

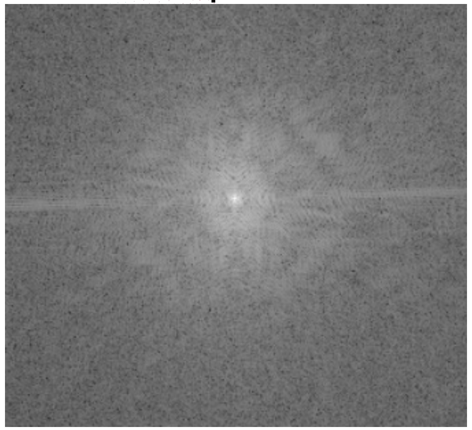


iFFT

Fully-Sampled recon

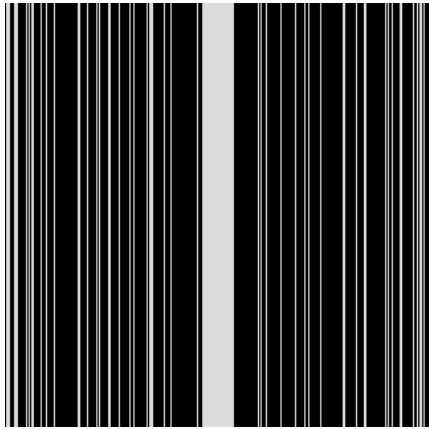
Accelerating Magnetic Resonance Imaging

k-space



X

Sampling mask



iFFT

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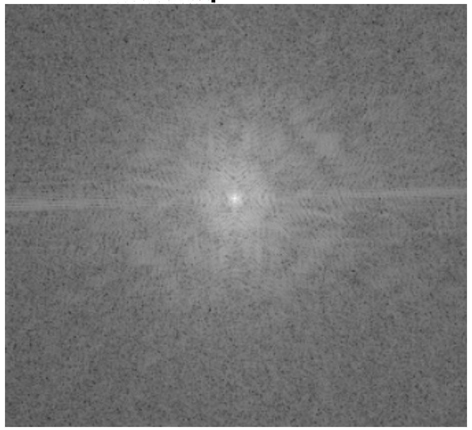
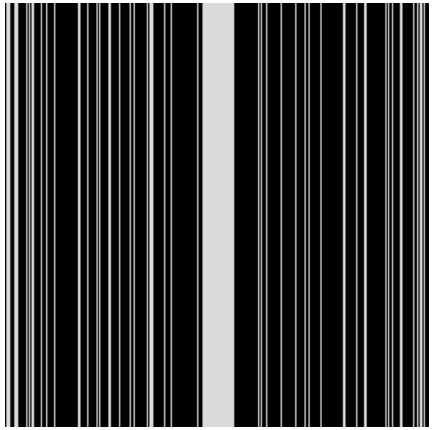
Accelerating Magnetic Resonance Imaging

k-space



x

Sampling mask



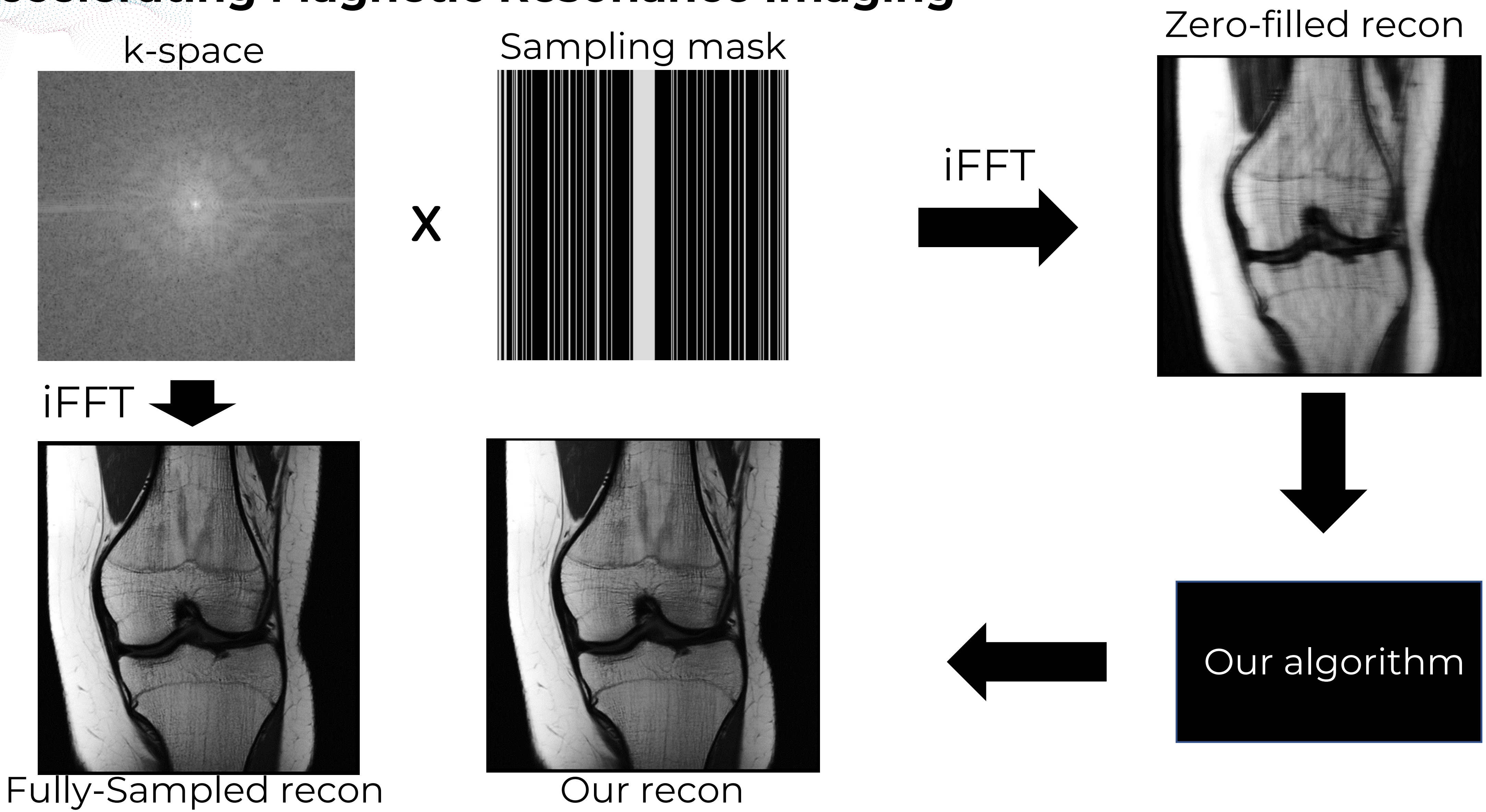
iFFT

Zero-filled recon

iFFT

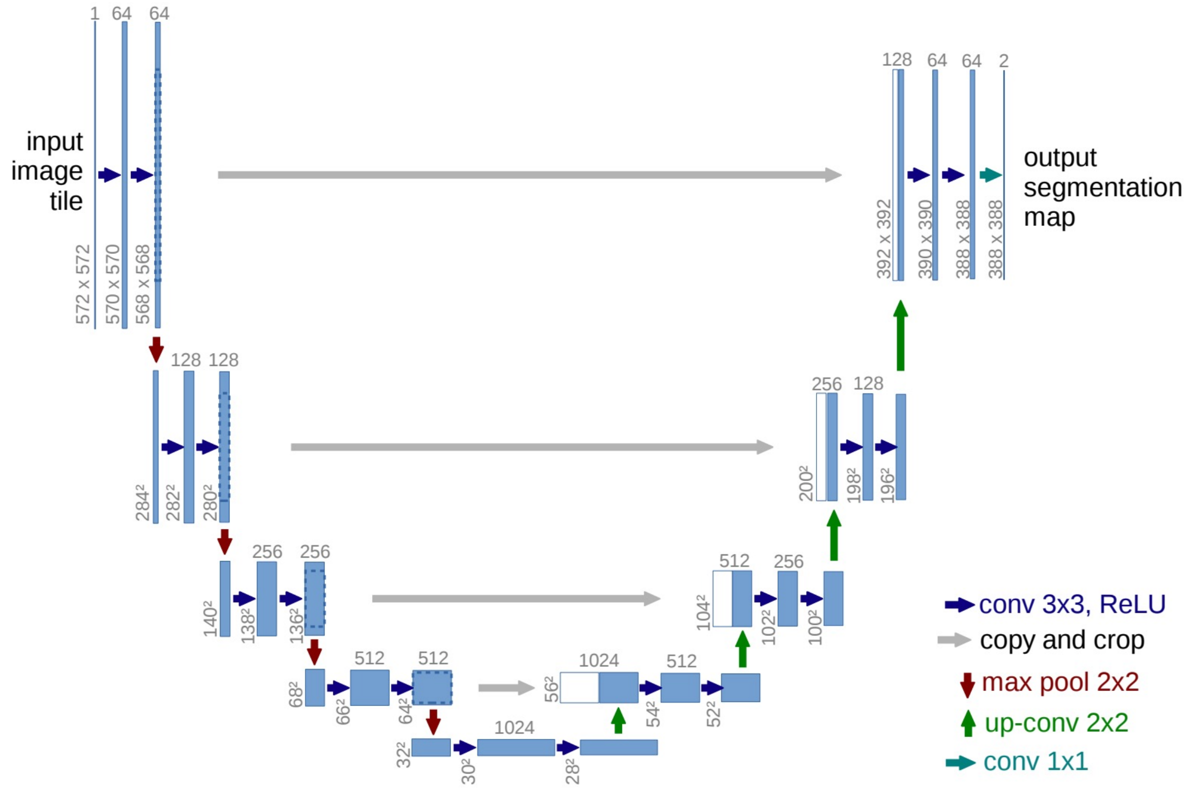
Fully-Sampled recon

Accelerating Magnetic Resonance Imaging



What algorithm to choose? A baseline approach

- U-Net [1] architecture is an easy first candidate for virtually any image-to-image task
- Copy-pasted between codebases since 2015
- No one remembers why U-Net, but still use it
- Initially proposed for medical image segmentation but can be adapted for virtually any task by changing a couple of first layers



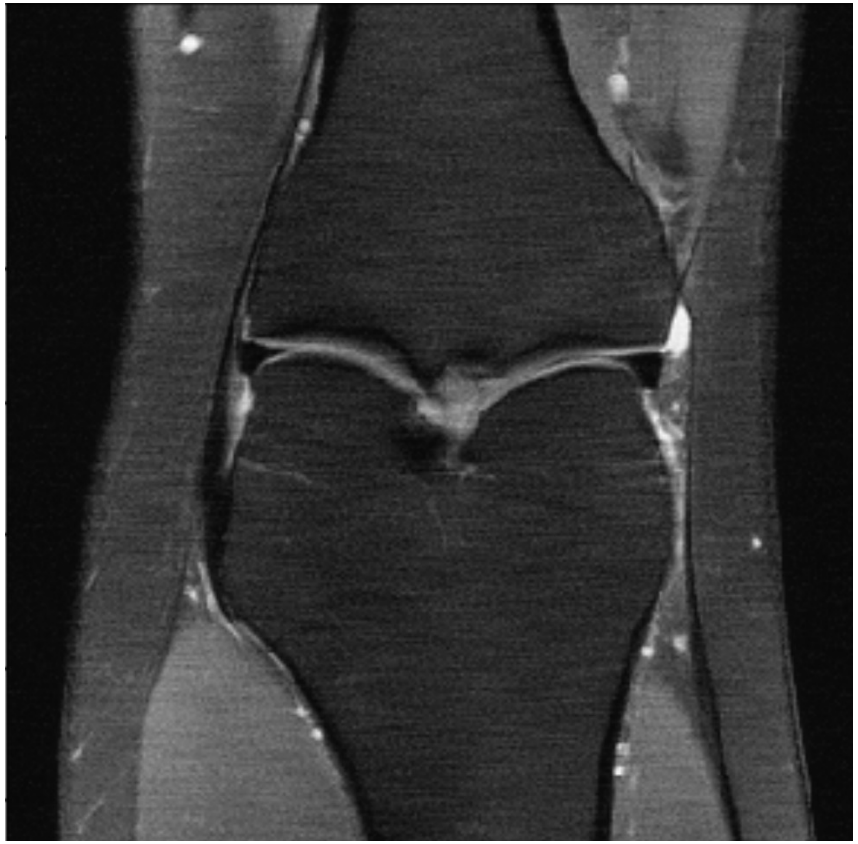
Demo 1 – Baseline approaches

Find the code in the S4_Image_reconstruction_and_MRI_basic.ipynb file in the BIA course repository

Everyone uses U-Net, it should be enough, right?

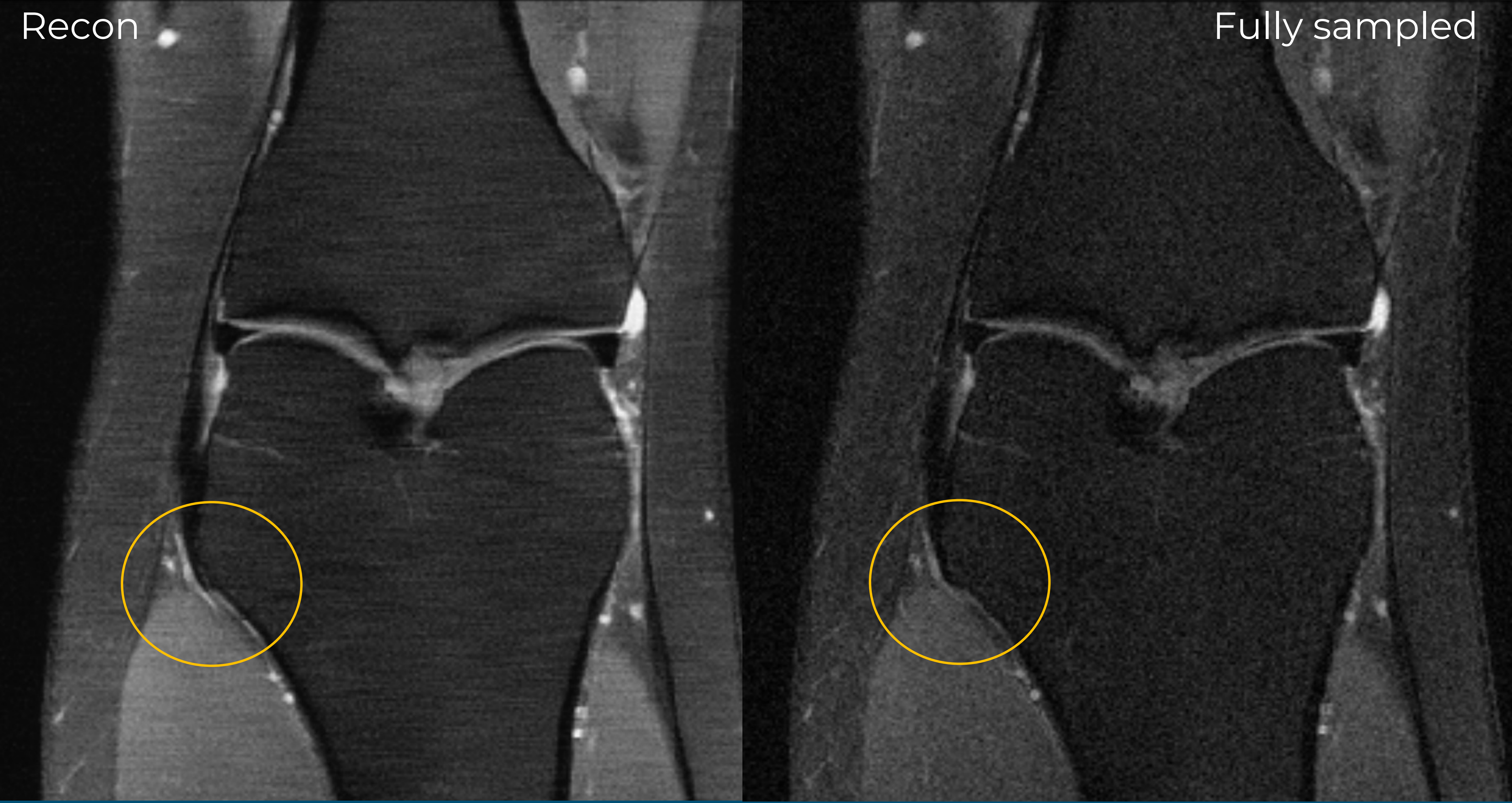
Images from Demo 1

Zero-filled R=4



Recon

Fully sampled


Recon
Fully sampled

OK, let us use GANs then!

The original paper [2] (2015) on Generative Adversarial Networks (GANs) introduced the following objective

$$\min_G \max_D V(D, G) = \mathbb{E}_{\boldsymbol{x} \in p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \in p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}))] \tag{1}$$

Equation 1 can be simplified as follows:

$$\begin{aligned} V(D, G) &= \int_{\boldsymbol{x}} p_{\text{data}}(\boldsymbol{x}) \log(D(\boldsymbol{x})) d\boldsymbol{x} + \int_{z} p_{\boldsymbol{z}}(\boldsymbol{z}) \log(1 - D(G(\boldsymbol{z})) d\boldsymbol{z} \\ &= \int_{\boldsymbol{x}} p_{\text{data}}(\boldsymbol{x}) \log(D(\boldsymbol{x})) + p_g(\boldsymbol{x}) \log(1 - D(\boldsymbol{x})) d\boldsymbol{x} \end{aligned} \tag{2}$$

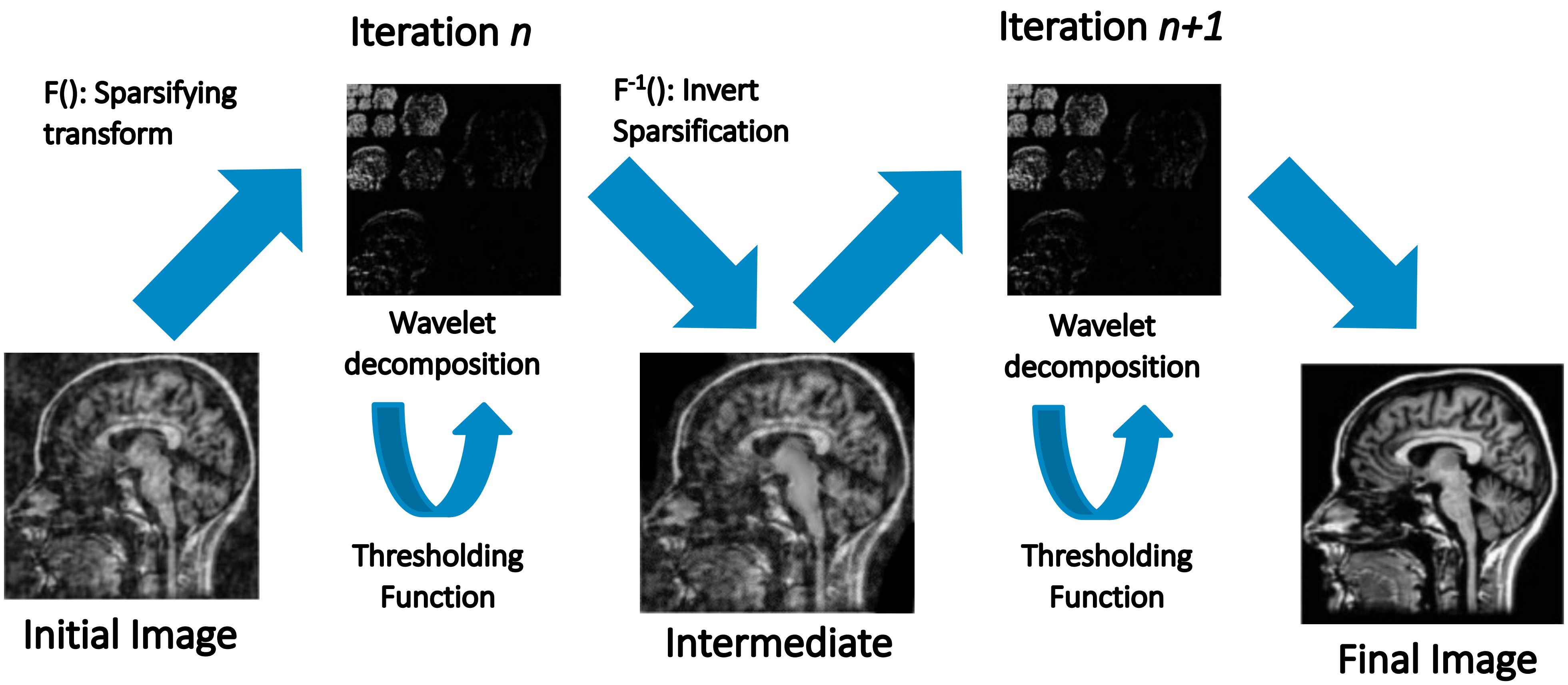
Hence, the optimal discriminator is:

$$D_G^*(\boldsymbol{x}) = \frac{p_{\text{data}}(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})} \tag{3}$$

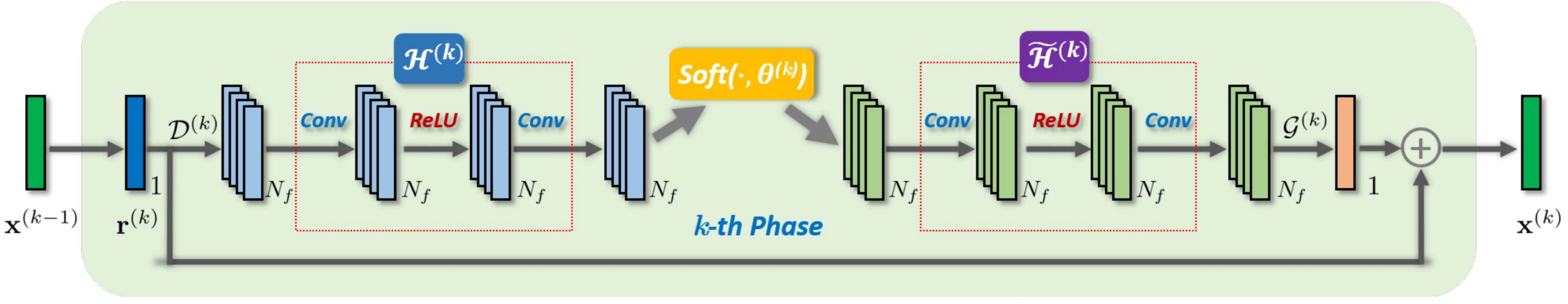
But that is **not** what we want.

We want to achieve the **best reconstruction quality** but **not make it similar** to images from train set!

Compressed Sensing for MR reconstruction (commercial SOTA)



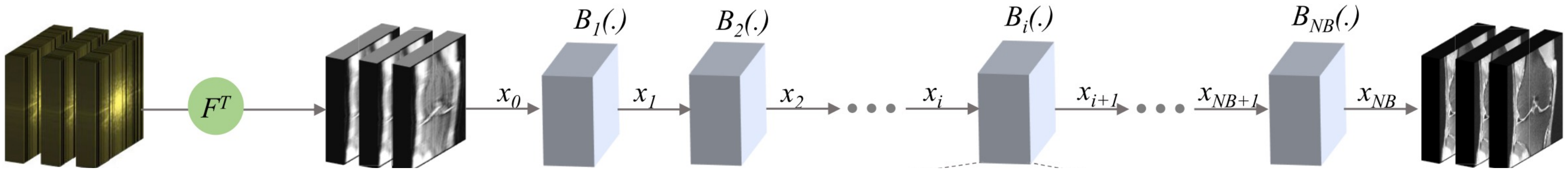
ISTA-Net



- **ISTA-Net** [3] introduced in 2017 but did not gain a lot of popularity
- **ISTA** stands for **Iterative Shrinkage-Thresholding Algorithm**
- Natural extension of iterative approaches, using **learned** blocks (convolutional layers) instead of **deterministic** (e.g., wavelet) functions
- Applies soft thresholding – threshold values are learnable parameters
- There is an extension called ISTA-Net^{+} (same authors, same paper) , where residual computations are adopted

Adaptive CS-Net [4] Architecture

Winner of the 2019 fastMRI challenge [5] in 2 out of 3 most clinically-relevant tracks



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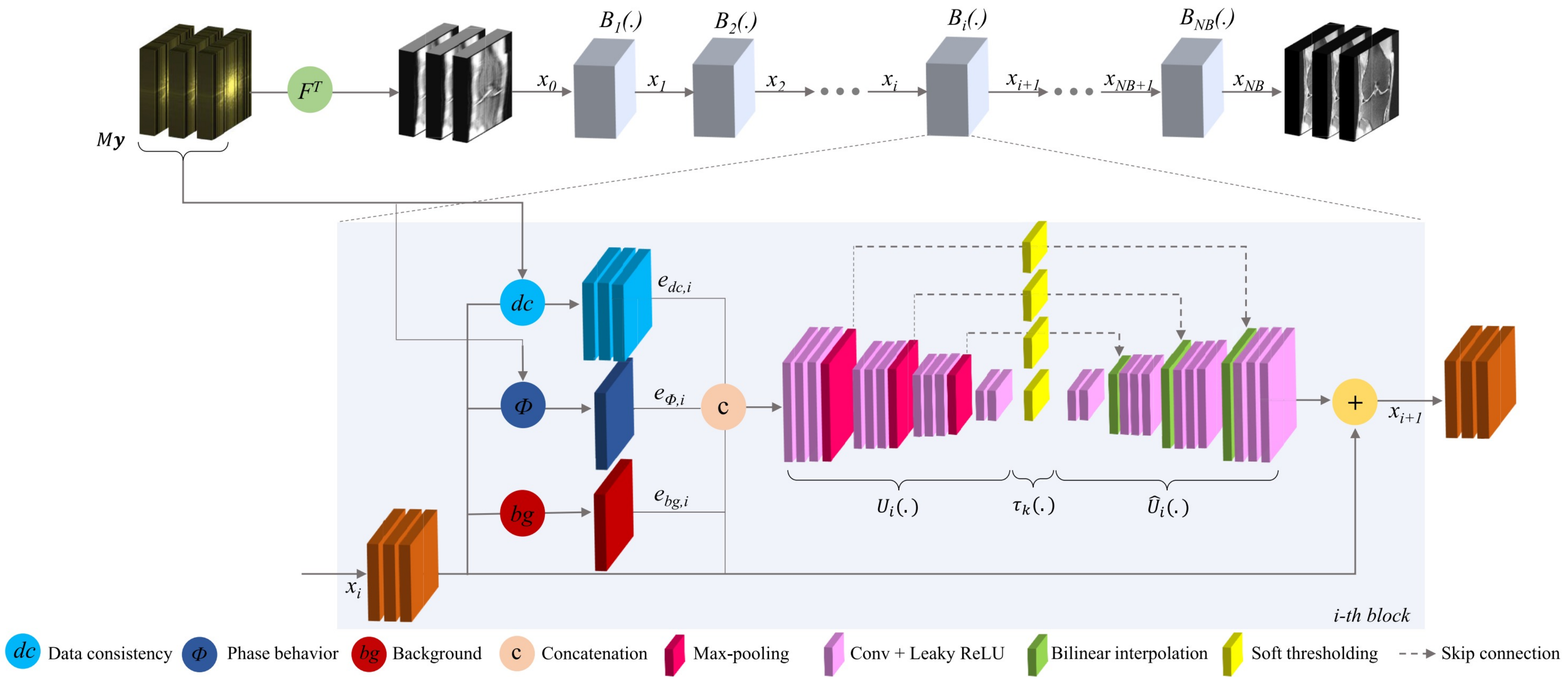
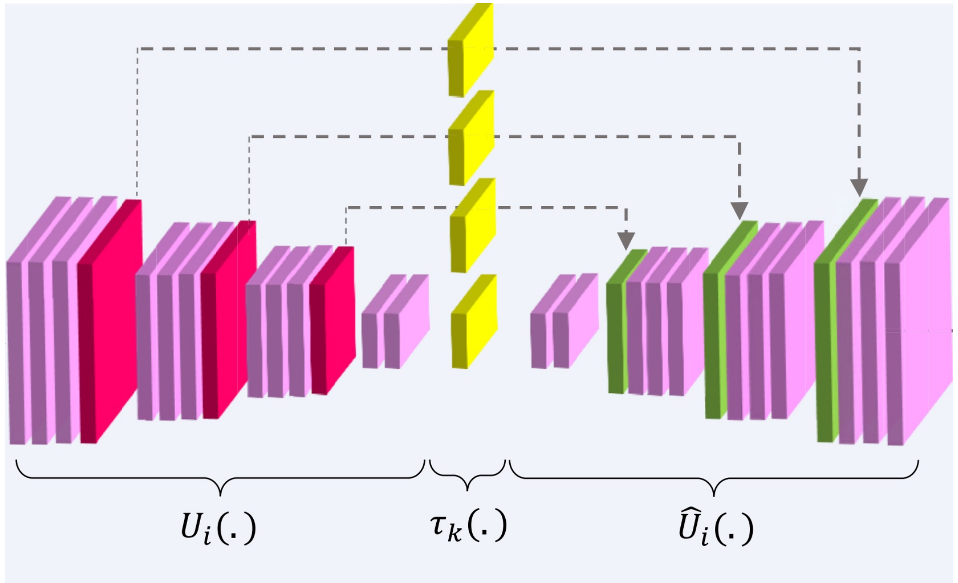
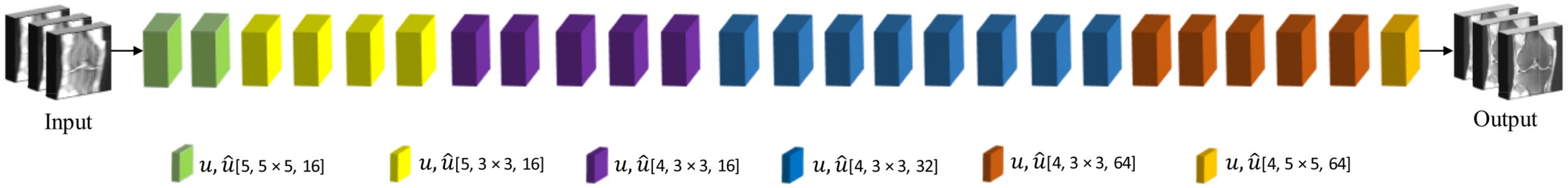


Adaptive CS-Net [4] Building Blocks

U-Net – like architecture of fully convolutional blocks:

- Each feature map is filtered
- Only basic Deep Learning operations to retain control
  - 2D convolutions without bias term
  - Leaky ReLu
  - Max Pooling
  - Interpolation 2D
- 2.5D convolutions – loss applied to the central slice only

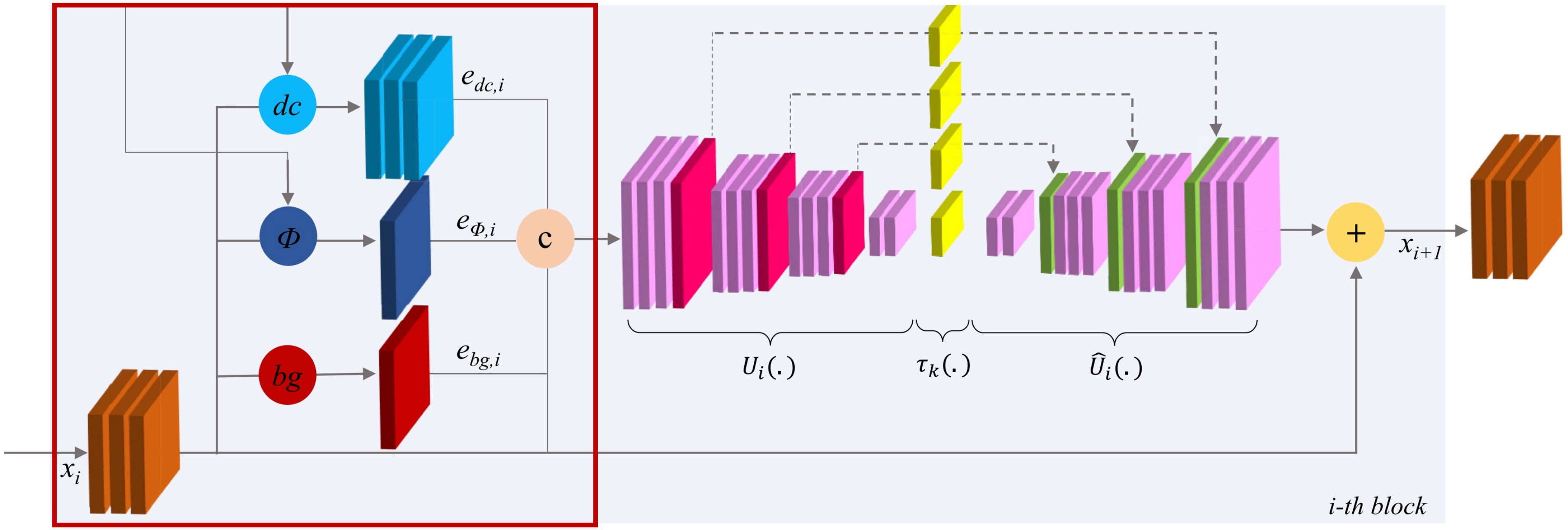




MR-specific knowledge

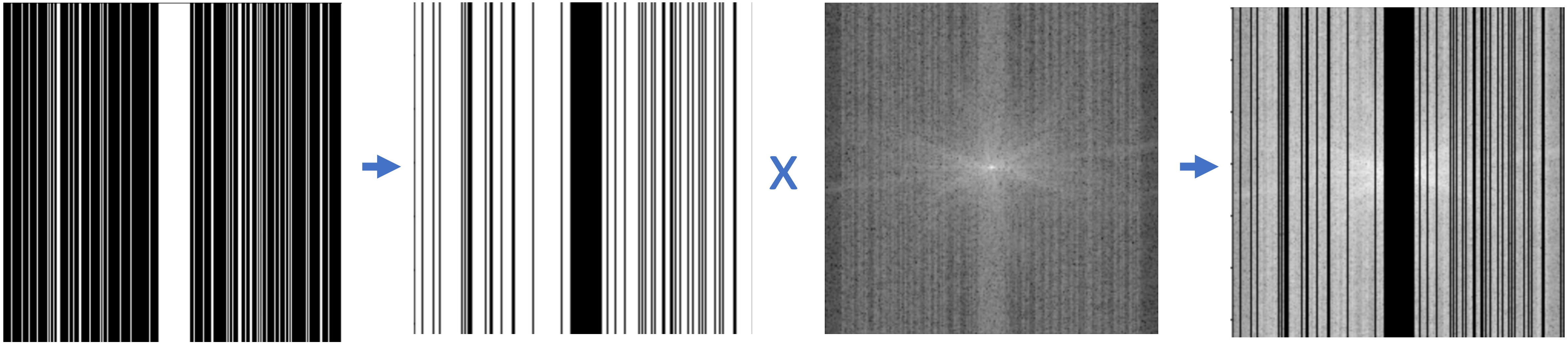
The following soft priors capture some properties on an MR image that cannot be easily learned due to the limited size of the receptive field:

- Soft data consistency
- Phase behavior
- Background information



Soft data consistency $e_{dc,i}$

- Our algorithms **do not know** what they should fix and what not
- Data consistency is a way to “undo” **unnecessary** corrections of our algorithm



Sampling mask

Inverted Sampling mask

Recon k-space

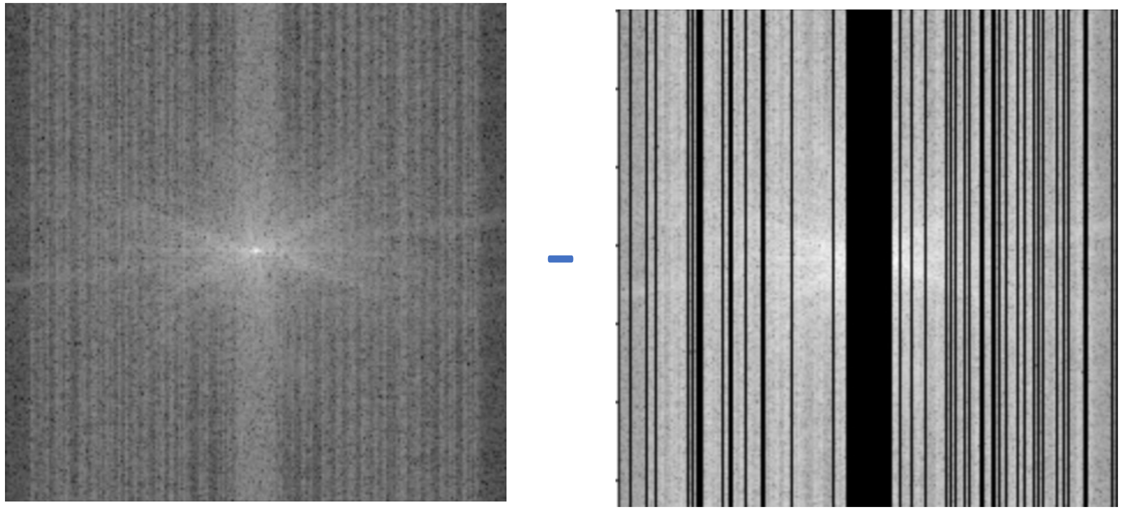
Unnecessary corrections

Soft data consistency $e_{dc,i}$

- **Data consistency**
  Subtract unnecessary corrections from the recon k-space to get implement data consistency

- **Soft data consistency**
  Provide unnecessary corrections as an additional input for reconstruction module to let the network learn to evaluate reliability of the acquired data and potentially compensate

Data consistency



Recon k-space

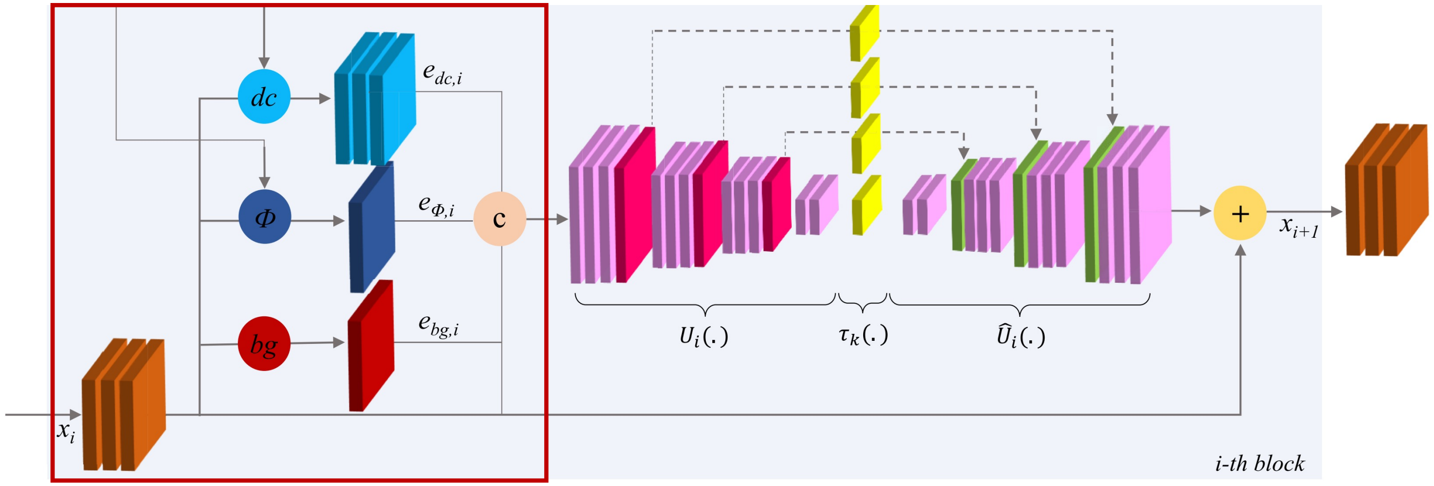
Unnecessary corrections

Phase behavior $e_{\Phi,i}$

- Theoretically, spin-echo sequences have zero phase everywhere in the image
- In practice, slow varying phase will occur only in low frequencies due to hardware and acquisition imperfections
- It means that final recon image should be real-valued after removing this component

$$\mathbf{e}_{\phi,i} = \left\{ \mathbf{x}_i \cdot \frac{\mathbf{x}^*_{i,\mathrm{lpf}}}{\|\mathbf{x}_{i,\mathrm{lpf}}\|_2} \right\}_{imag},$$

where lpf refers to low pass filtering.



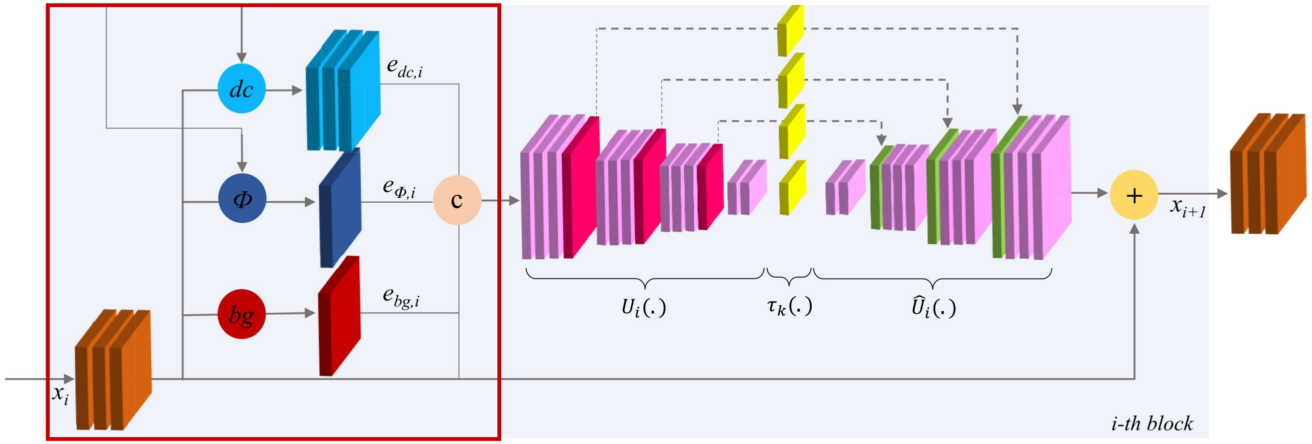
Background information $e_{bg,i}$

- Estimate the location in the $\mathbf{x}_i$ where the background is found

$$\mathbf{e}_{\mathrm{bg},i} = \frac{\mathbf{x}_i}{\|\mathbf{x}_{i,\mathrm{lpf}}\|_2}.$$

- This prior penalize estimated signal content where $||\mathbf{x}_{i,\,\mathrm{lpf}}||$ is low, i.e., within the background

- Note that last two priors are commonly used techniques applied in parallel imaging. However, in our demo we used artificial single-coil data for simplicity, which has different properties.

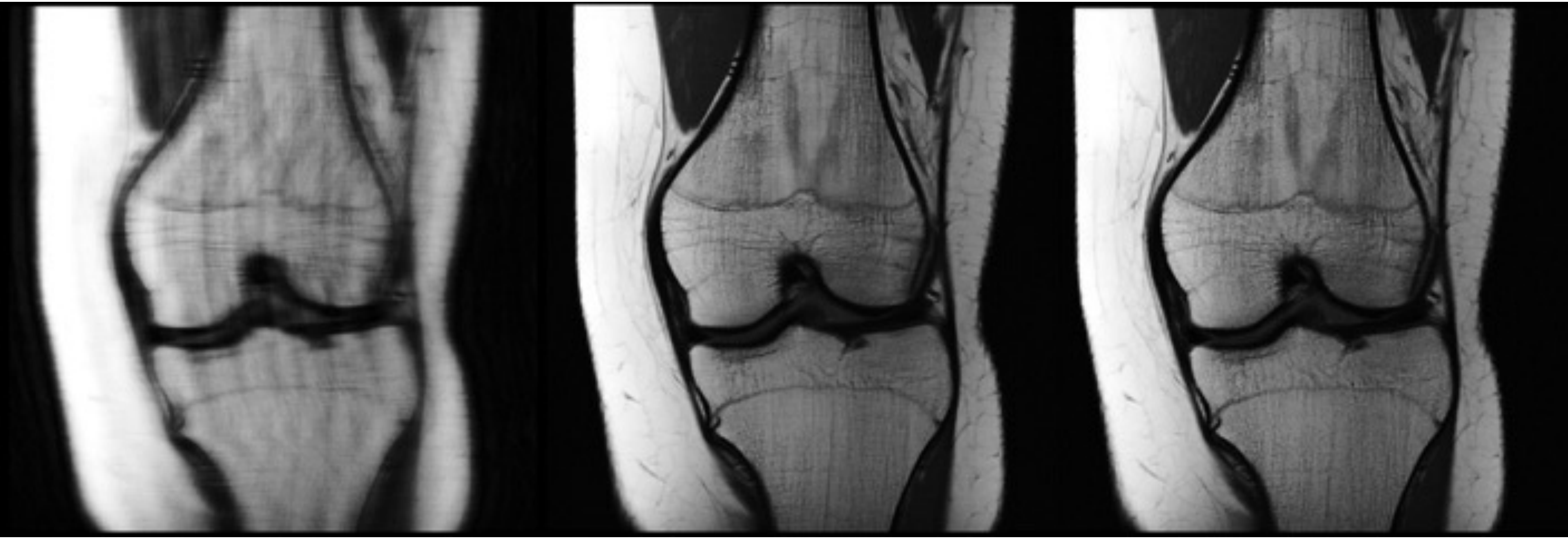


Demo 2 – Data consistency

Find the code in the S4_Image_reconstruction_and_MRI_advanced.ipynb file in the BIA course repository.

Is it worth it? – Results from the 2019 fastMRI challenge

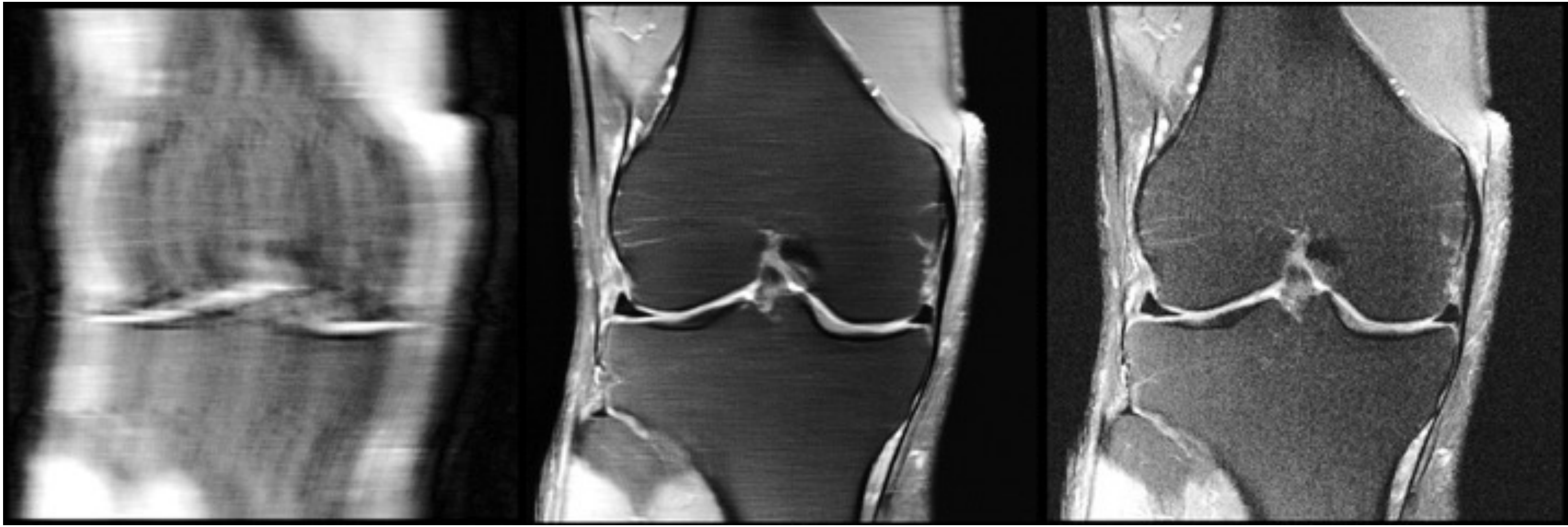
Effective acceleration: 3.64x – SSIM: 0.9885



Zero-filled | Recon | Fully sampled

Is it worth it? - Results from the 2019 fastMRI challenge

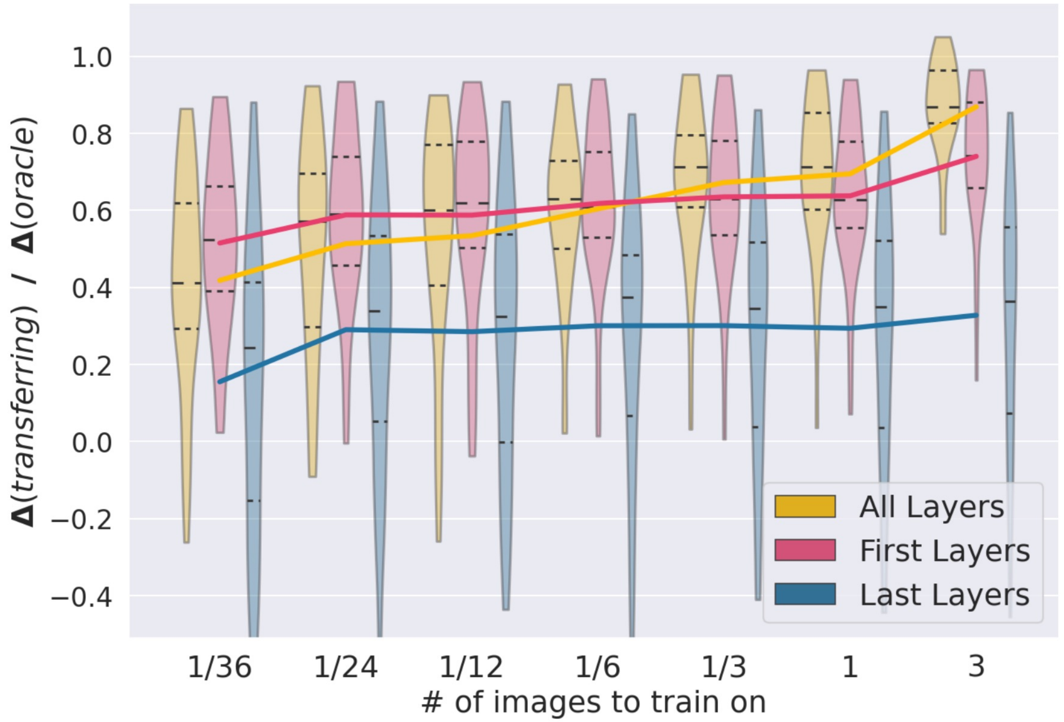
Effective acceleration: 9.68x – SSIM: 0.8254



Zero-filled Recon Fully sampled

Ongoing work - vendor/domain adaptation

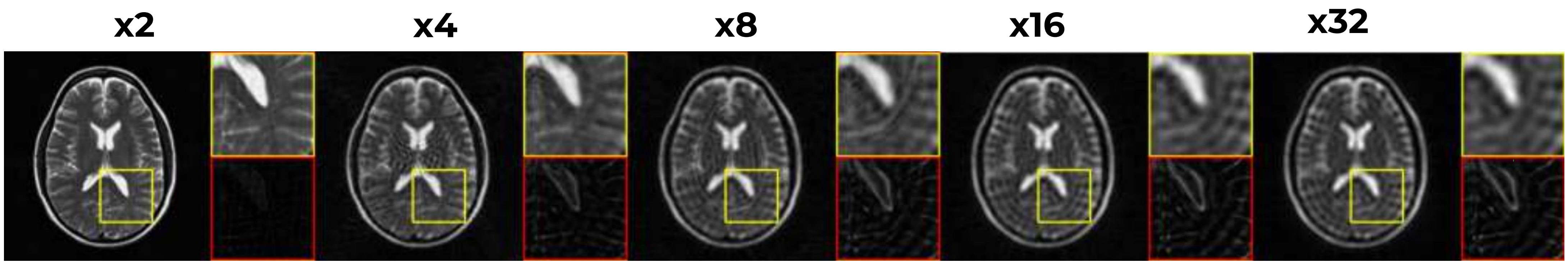
- Major vendors of MRI systems (Philips, GE, Siemens) have **proprietary implementations**, which causes **domain shift** between their data
- Domain adaptation between vendor data remains **ongoing work** with **high commercial interest** for all involved parties (patients, vendors, clinics, third parties)
- FastMRI challenge 2020 had a special track for cross-vendor domain adaptation
- The problem reveals new **theoretical insights**. For instance, recent work from Shirokikh, Zakazov et. al. [6] (2020) shows that **first** U-Net layers contain more domain-specific information than the **last ones**



Dependence of the relative Surface Dice improvement (y-axis) on the target domain data availability

Ongoing work – generative models for scan acceleration

- Recent work from Belov, Stadelmann, Kastryulin and Dylov [7] (2021) experiments with generative models for reconstruction from **extremely undersampled** k-spaces (acceleration up to x64)
- Experiments show that:
  - GANs **cannot** produce reliable diagnostic quality (confirm previous discussions)
  - Generated images can be applied for **different MRI applications** such as computer-assisted surgery or radiation planning

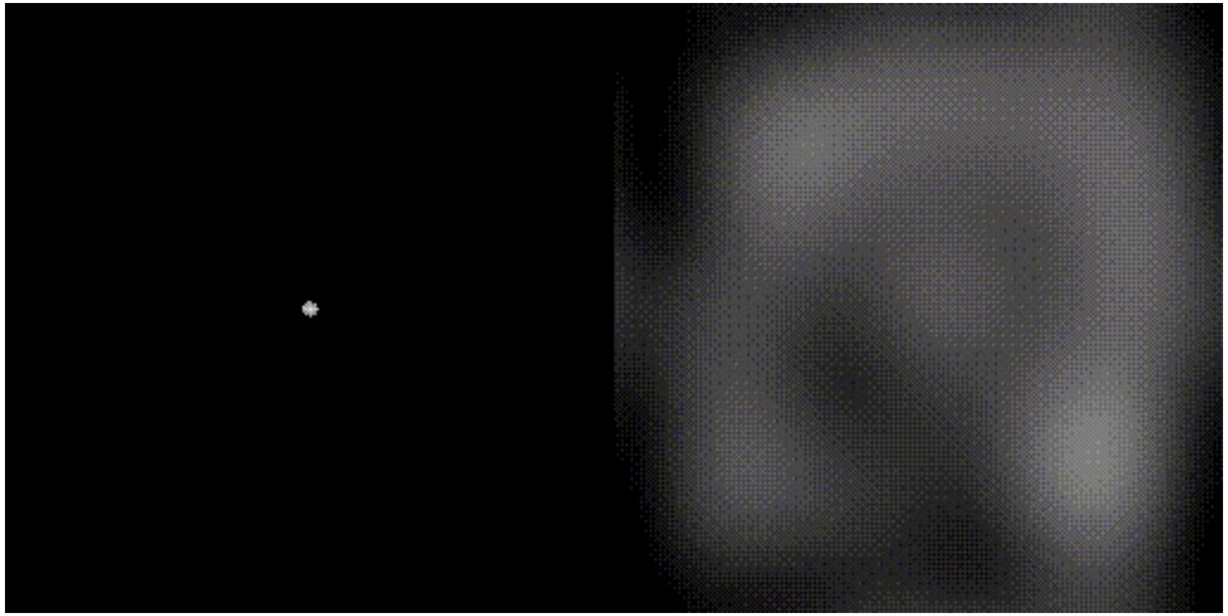


Examples of images obtained using different acceleration factors.
The red crop shows the absolute difference between the ground truth and the undersampled images.

Ongoing work – sampling patterns

- As we saw, **sampling** pattern play a **huge** role in accelerated image formation
- **Cartesian** sampling (the one that we discussed on the seminar) is the **most widespread** technique for sampling of **2D** MR data
- It is possible to find **optimal parameters** of Cartesian sampling w.r.t. **subsequent reconstruction** model
- **Other** sampling techniques exist, and their verification and application is a **hot research topic**

Outward radial ordering of k-space



Courtesy of Brian Hargreaves

Find better sampling pattern

- As we discussed, sampling heavily influences the quality of resulting images
- In Demo 1 we achieved SSIM scores close to 0.61 for $R = 4$ and 0.53 for $R = 8$ (in the single-coil track)
- Find sampling pattern that would beat the baseline SSIM score
    - Target $R = 4$: SSIM > 0.7
    - Target $R = 8$: SSIM > 0.6

<Solution>

- **Code….**

© Credits

- **Slide |7, 34|** http://mri-q.com/k-space-trajectories.html animations are courtesy of Brian Hargreaves

Resources

1. Olaf Ronneberger et. al, U-Net: Convolutional Networks for Biomedical Image Segmentation, 2015, arXiv:1505.04597
2. Ian Goodfellow et. al., Generative Adversarial Networks, 2014, arXiv:1406.2661
3. Jian Zhang and Bernard Ghanem, ISTA-Net: Interpretable Optimization-Inspired Deep Network for Image Compressive Sensing, 2017, arXiv:1706.07929
4. Pezzotti, ..., **Kastryulin** et. al, An Adaptive Intelligence Algorithm for Undersampled Knee MRI Reconstruction, 2021, doi: 10.1109/ACCESS.2020.3034287
5. Jure Zbontar et. al., FastMRI: An Open Dataset and Benchmarks for Accelerated MRI, 2018, arXiv:1811.08839
6. Boris Shirokikh, Ivan Zakazov et. al., First U-Net Layers Contain More Domain Specific Information Than The Last Ones, 2020, arXiv:2008.07357
7. Belov, Stadelmann, **Kastryulin**, **Dylov**, Towards Ultrafast MRI via Extreme k-Space Undersampling and Superresolution, 2021, arXiv:2103.02940