

fastMRI

Tullie Murrell, Research Engineer at Facebook AI Research (FAIR)

What is fastMRI?

- Collaborative research project between Facebook AI Research (FAIR) and NYU Langone Health
- Aims to use deep learning to improve acceleration and robustness of MRI scans
- Began early 2018

Team

FAI R

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- Anuroop Sriram
- Nafissa Yakubova
- Aaron Defazio
- Suvrat Bhooshan
- Michal Drzodzal
- Adriana Romero
- Sumana Basu
- Luis Pineda
- Patrick Mineault
- Roberto Calandra
- Mike Rabbat
- Larry Zitnick
- Mark Tygert
- Jure Zbontar
- + More

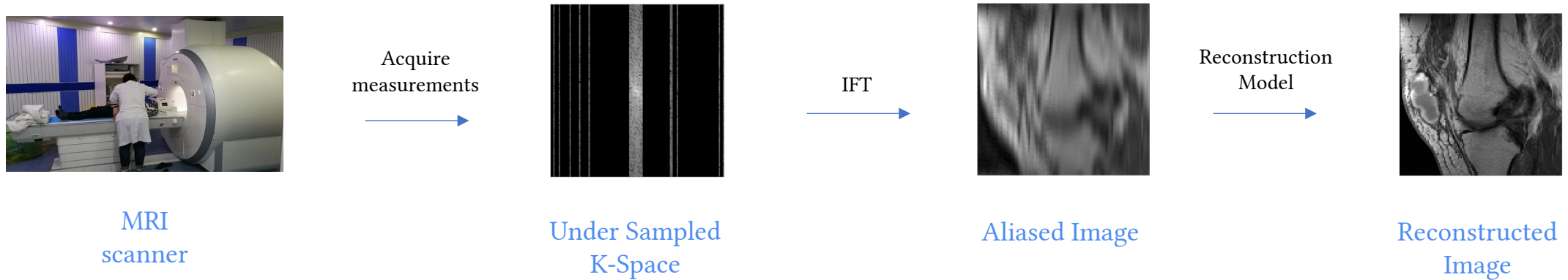
NY U

- Florian Knoll
- Matt Muckley
- Zhengnan
- Patricia Johnson
- Ruben Stern
- Krzysztof Geras
- Dan Sodickson
- Michael Recht
- Yvonne Lui
- Hersh Chandanara
- + More

Why accelerate MRI?

- MR scanning is slow: 20 minutes ~ 1 hour
- More people could access MRI
- Patients too sick to stay still or children
- Potentially replace other, more-harmful imaging types (e.g. X-rays)
- Image moving organs (heart, lung, abdomen)

MRI Reconstruction



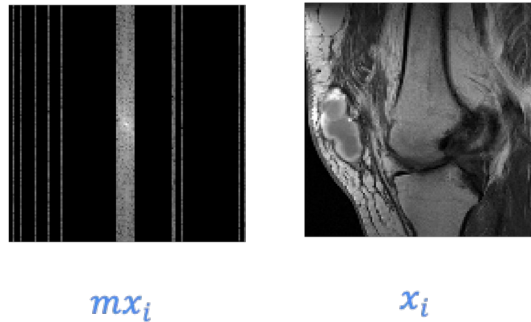
- MRI scanners acquire images in the Fourier domain (called K-space)
- K-space is acquired one line at a time
- Scan time is proportional to the number of measurements

Two approaches to acceleration

- Parallel imaging - use multiple coils
 - Grappa – k-space reconstruction
 - Sense – Image reconstruction
- Compressed sensing – use prior on the structure of image
 - Traditionally uses sparsity prior
 - Modern techniques use Machine Learning to learn the prior

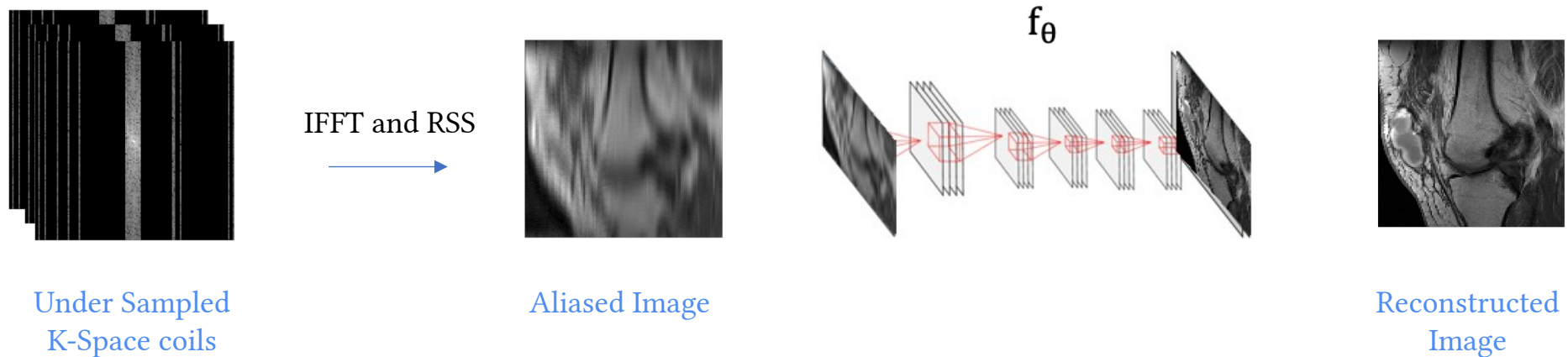
Supervised learning for MRI reconstruction

- Given a dataset of fully sampled k-space coils, X
- Use mask, m , to create pairs of masked and fully sampled coils (mx_i, x_i) , $x_i \in X$
- Find parameters θ that minimize risk $R(f_\theta) = E[L(f_\theta(mx_i), x_i)]$



Convolutional Neural Network (CNN)

- A deep learning approach to the problem is to use a CNN for f_θ
- CNNs learn hierarchical feature representation using Convolution and Pooling layers. They're commonly used on images.
- Needs large dataset to learn useful parameters



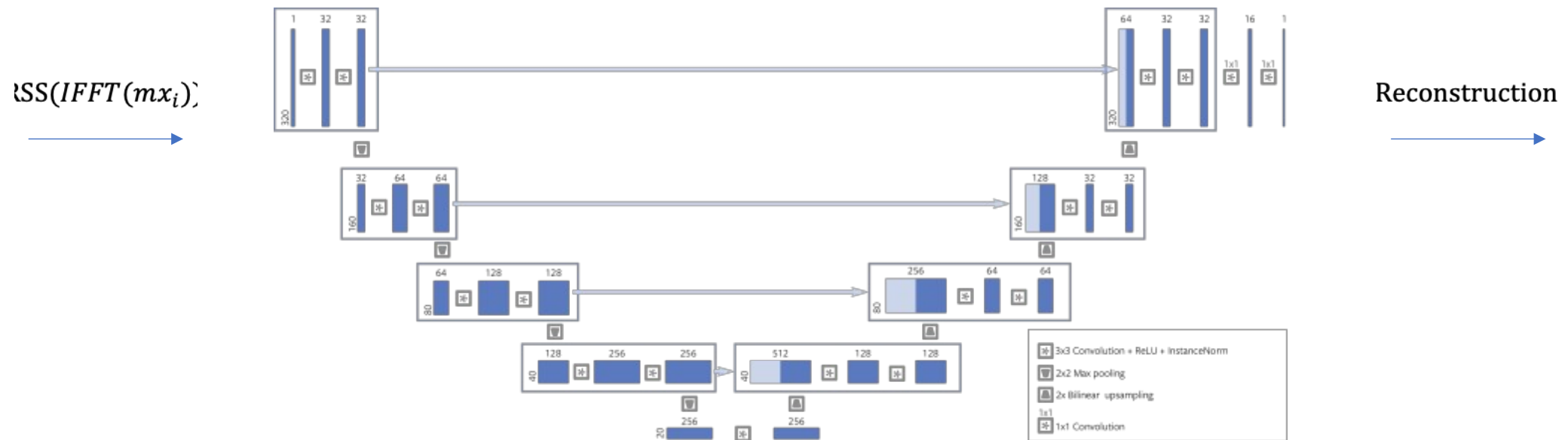
fastMRI Dataset

- Released the first version of data + baseline models + leaderboard in Nov.
- Announced at the RSNA radiology conference.
- 1.6K 3D Knee MRIs (57K images) + 1.2M additional pre-processed images
- Expected to release additional Brain and Abdomen MRIs in the near future



U-Net

- Good baseline image reconstruction model
- Handle multiple coils with Root Sum of Squares on mx_i

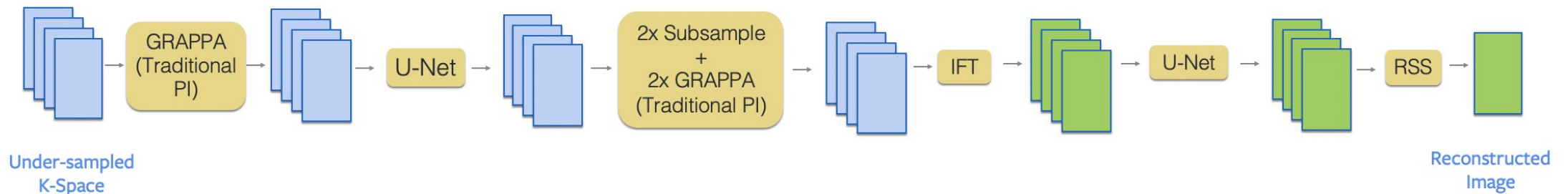


Incorporating physical properties of MRI

- GrappaNet – Grappa based
- Variational Network 2.0 – Sense based, extension of Variational Network*

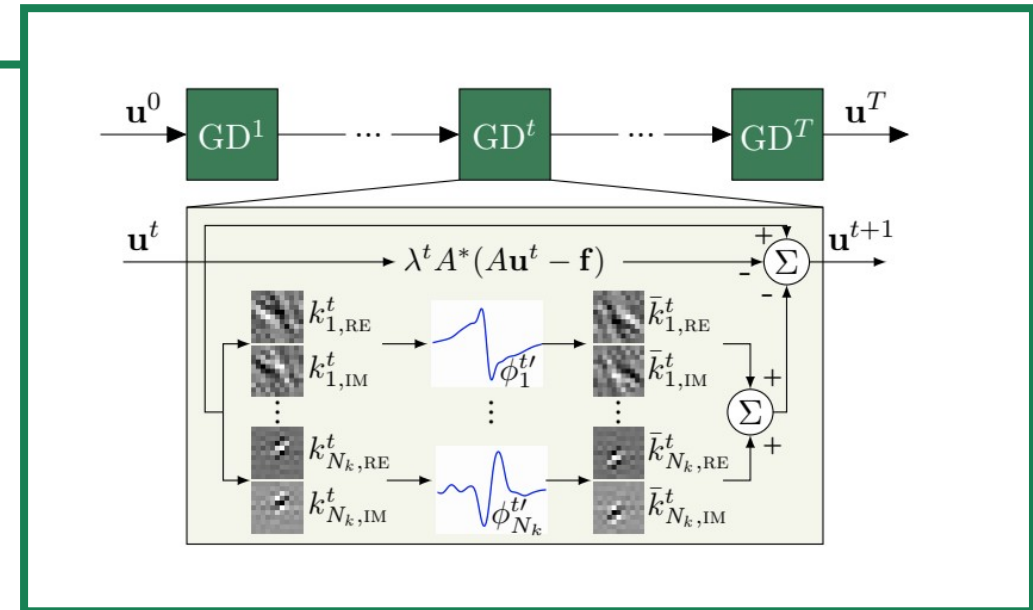
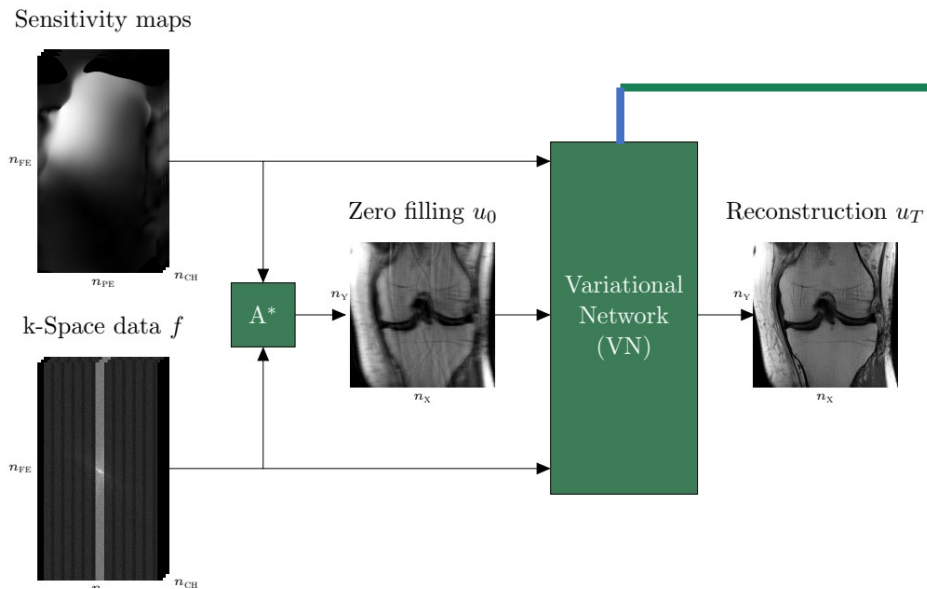
GrappaNet

- Introduces “GRAPPA layer”, which applies GRAPPA kernel at 4x and 2x accelerations between a U-Net
- Applying GRAPPA is differentiable so the entire network can be trained in end-to-end fashion using backpropagation
- Intuition: GRAPPA adapts to sensitivity profiles differences of each coil



Variational Network (Hammernik et al.)

- Data consistency layers (soft consistency)
- Relies on sensitivity estimation (e.g. precomputed with ESPIRIT)



Variational Network 2.0

- 3 main differences to Variational Network
 1. Uses U-Net for model instead of RBF Kernels
 2. Learns sensitivities with U-Net rather than precomputing with ESPIRIT
 3. Data consistency is done without sensitivities. This is achieved by computing it per coil rather than decomposing the reconstructed image

How to evaluate models?

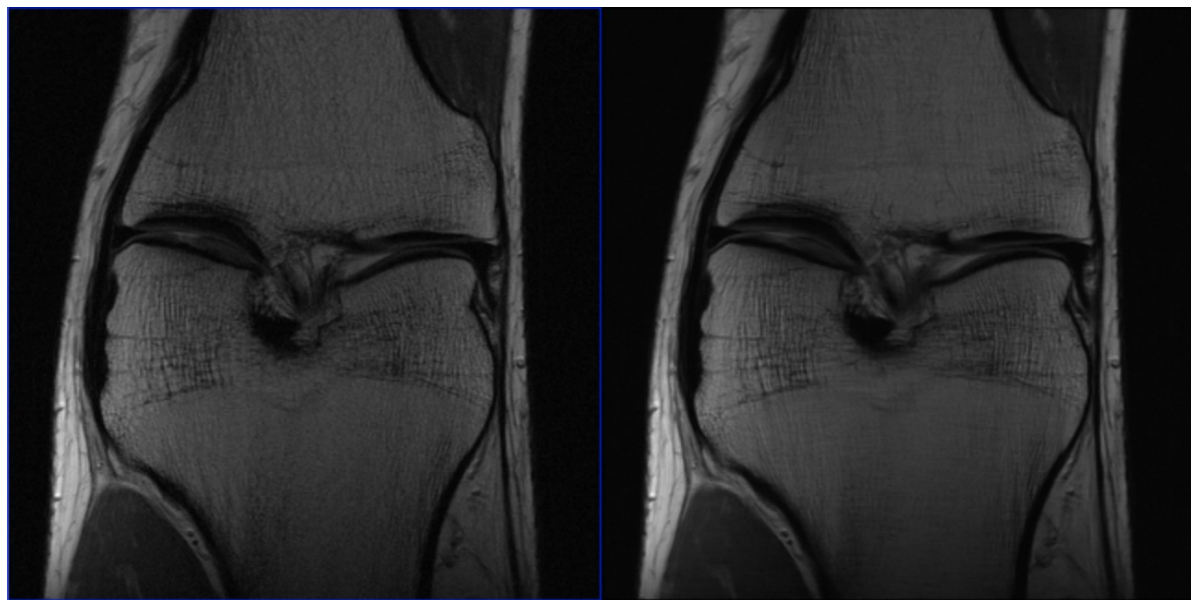
- Metrics: SSIM, MSE, PSNR
- Weekly radiologist review
- Interchangeability study
 - 1) Are reports written by radiologists with ground truth MRIs the same as reports from reconstructed MRIs?
 - 2) Do radiologist like the image quality of the reconstructed MRIs the same or better than the ground truth MRIs?

SSIM for 4x and 8x acceleration

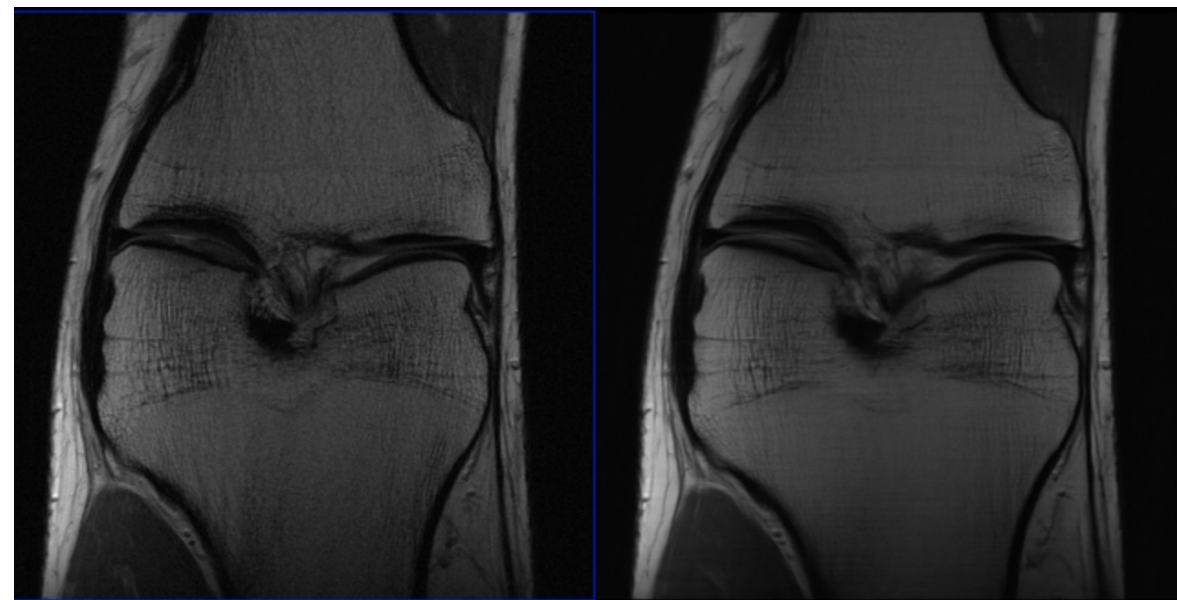
Model	SSIM 4x acceleration		SSIM 8x acceleration	
	PD	PDFS	PD	PDFS
Classical CS baseline	0.693	0.588	0.642	0.551
U-Net Baseline	0.815	0.636	0.762	0.559
Variational Net	0.919	0.855	0.788	0.675
GrappaNet	0.957	0.891	0.922	0.842
Variational Network 2.0	0.953	0.880	0.922	0.846

Sample Reconstructions

- Variational Network 2.0 images



4x acceleration



8x acceleration

fastMRI challenge

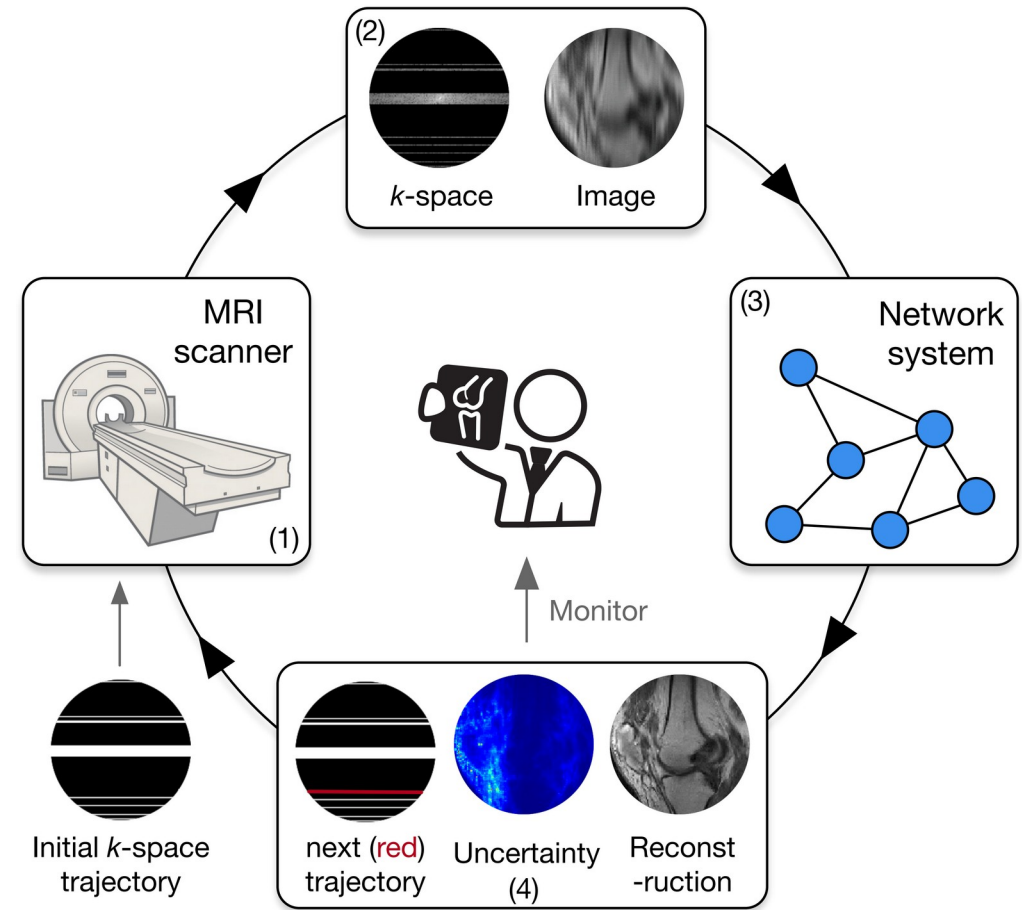
- The dataset has been released publicly and we've launched a challenge for the best 4x and 8x reconstructions
- The challenge will be part of a workshop at NeurIPS, where winners will be invited
- Details about the challenge including a leaderboard can be found at fastmri.org

Increasing acceleration further

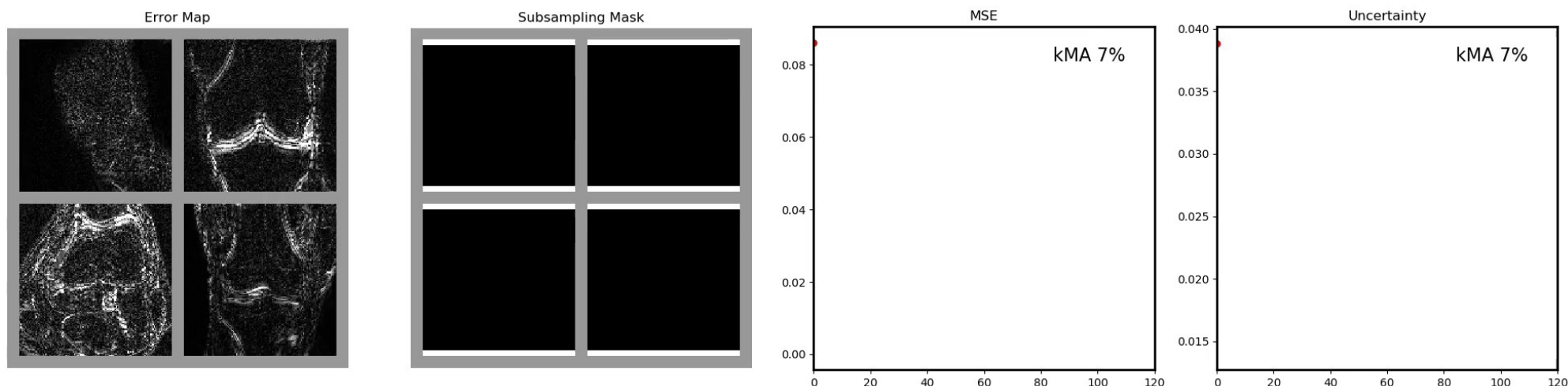
- Fixed accelerations likely not optimal
- This motivates work on active acquisition - aiming to find optimal sampling trajectory

Active acquisition for MRI Reconstruction

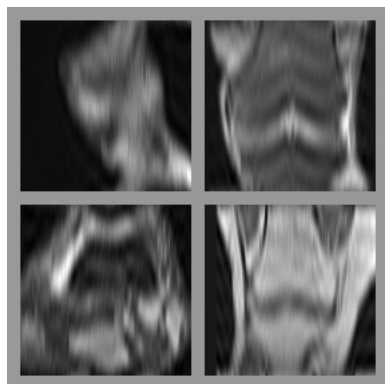
- Network system made up of:
 - Reconstruction and uncertainty model
 - Evaluator model
- Evaluator is a **Discriminator-like** architecture, trained in an **adversarial** way.
 - Evaluator estimates each measurement MSE.
 - Reconstruction network tries to make evaluator think that all measurements have an MSE of 0.
- Evaluator scores are used at inference time to perform **active acquisition**.



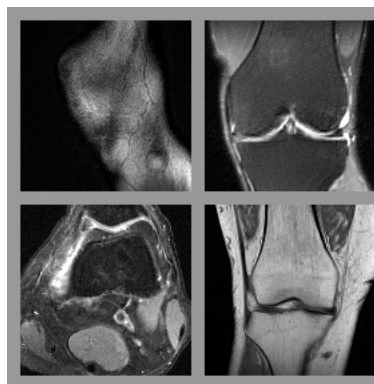
Active acquisition in action



Initial
input



Target

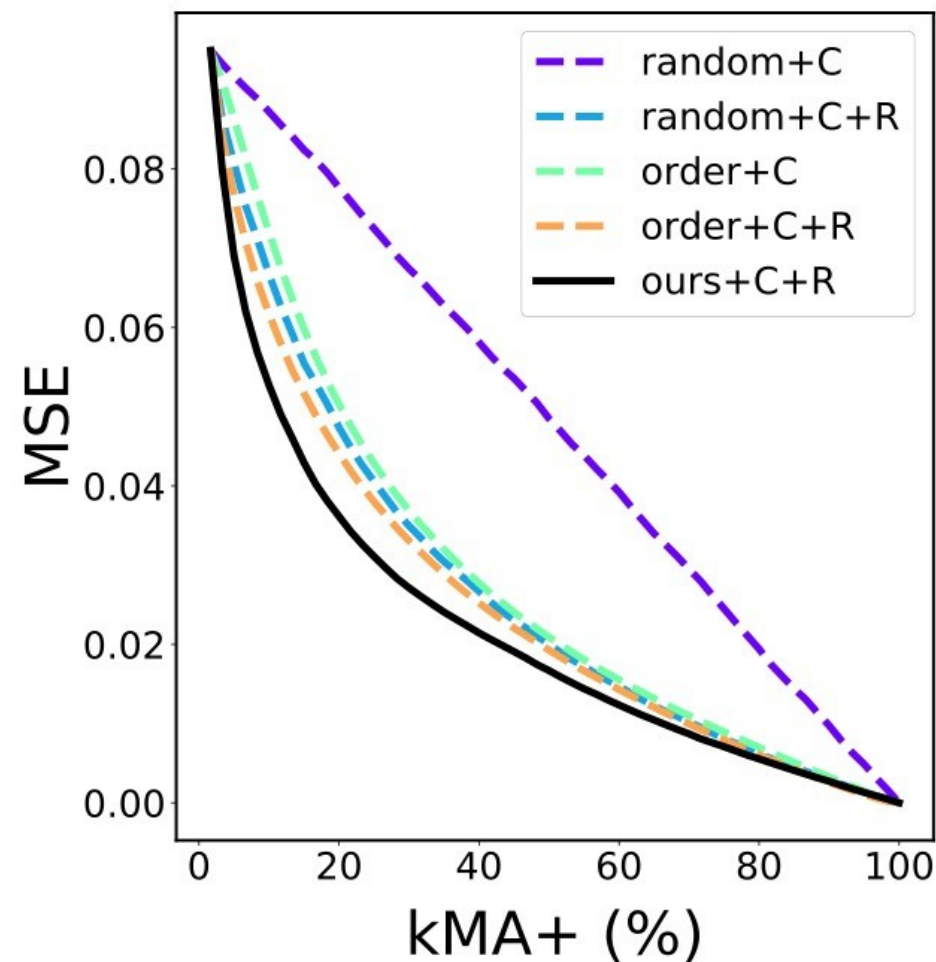


Initial subsampling ratio $10/128 = 7.8\%$
kMA
kMA: k-space Measurement Acquired (%)

Baselines vs active acquisition

Compared strategies:

1. Random
2. Random + Reconstruction
3. Order (from low freq. to high freq.)
4. Order + Reconstruction



Looking ahead

- Brain image reconstruction
- Dynamic MRI robust reconstruction, GRASP dataset
- Extensions to active sampling

Thank you