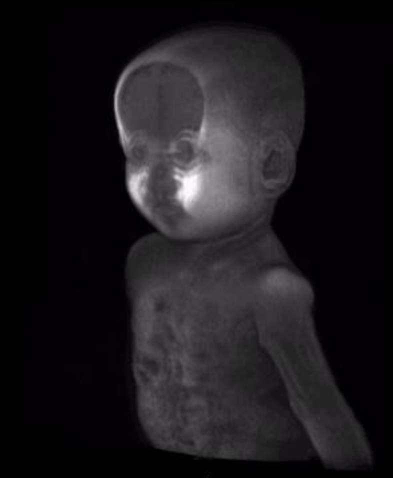
Technion
Israel Institute of Technology

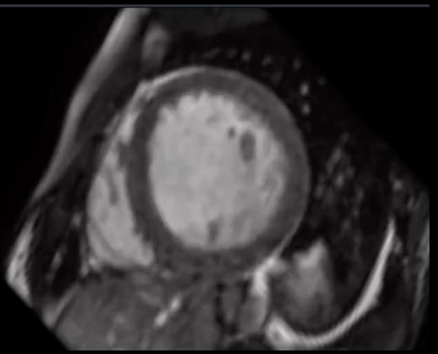
MRI reconstruction methods:
Compressed sensing, model-based and machine learning methods

Efrat Shimron

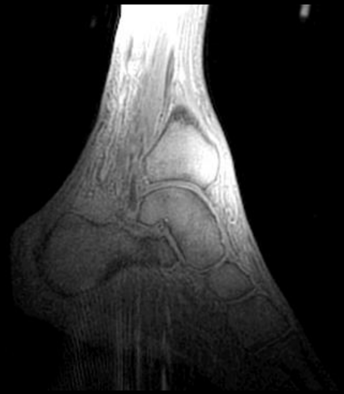
MRI



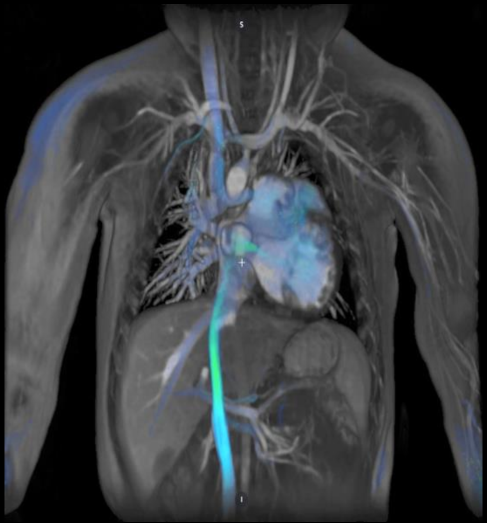
Courtesy of Lustig Lab



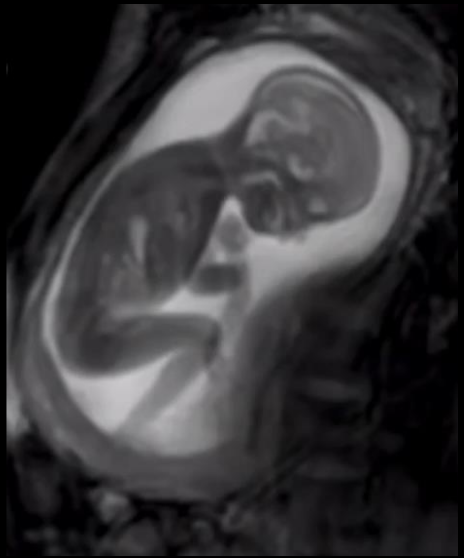
Courtesy of Lustig lab



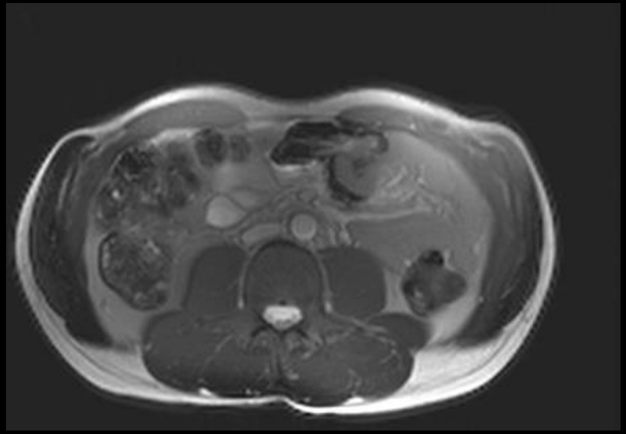
Courtesy of Lustig lab



Courtesy of Joseph Cheng/Stanford



www.youtube.com/user/channelmum

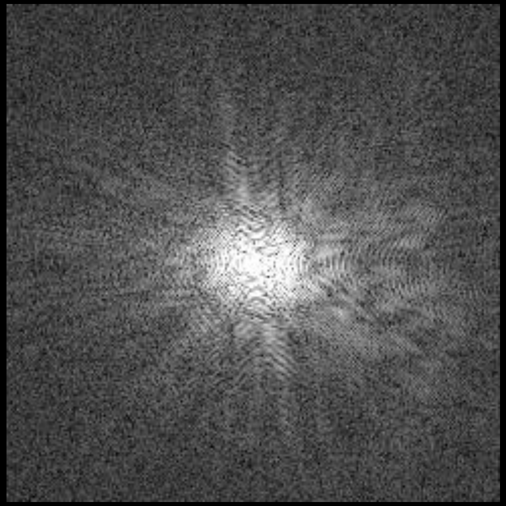


Courtesy of Lustig lab

MRI: from sampling to images

MRI

Fourier domain
k-space



MRI: from sampling to images

MRI

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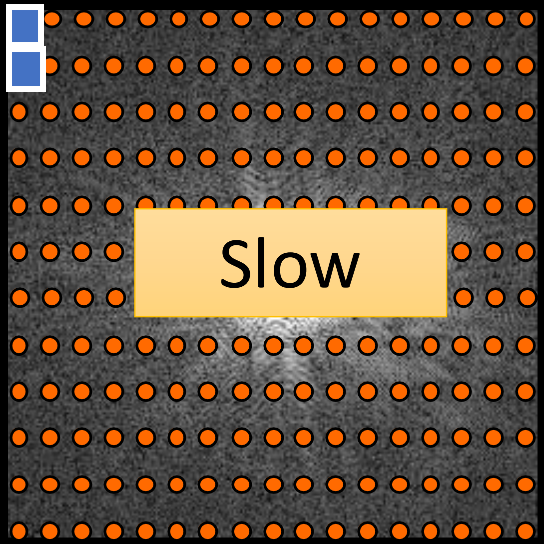
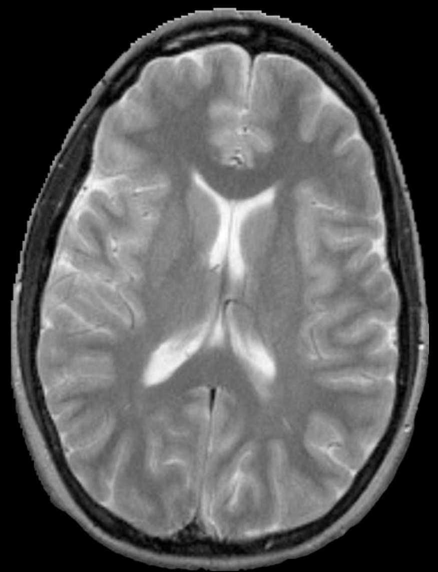


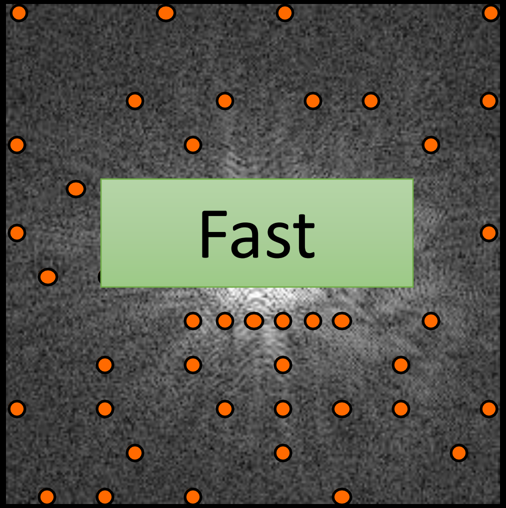
IFFT



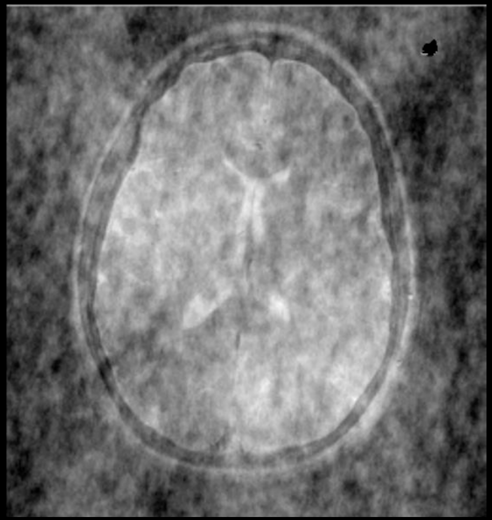
MRI: from sampling to images

MRI

Fourier domain
k-space



IFFT



MRI: from sampling to images

MRI

Fourier domain
k-space

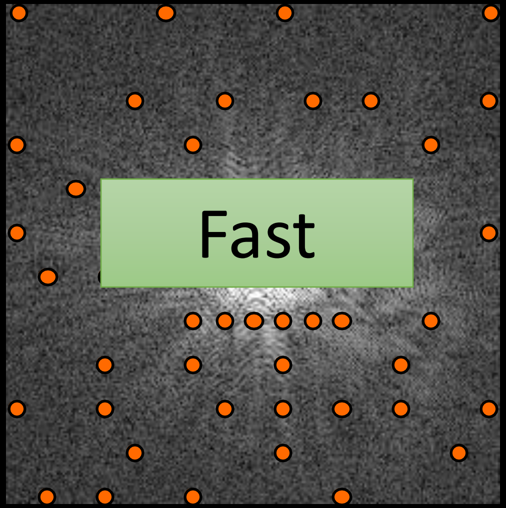
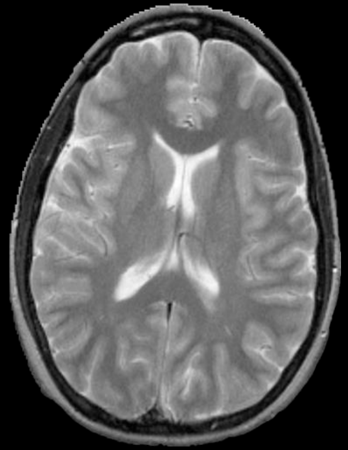


Image reconstruction algorithm



The MRI inverse problem

Measurement model: $y = Ax + n$

acquired data

forward operator

image (unknown)

noise

Aim: estimate x from y

Under-sampling → ill-posed problem

Fessler, IEEE Signal Processing 2010

The MRI inverse problem

Measurement model: $y = Ax + n$

Image reconstruction - least-squares problem:

$$\min_x \|y - Ax\|_2$$

Closed form solution

$$\hat{x} = (A^H A)^{-1} A^H y$$

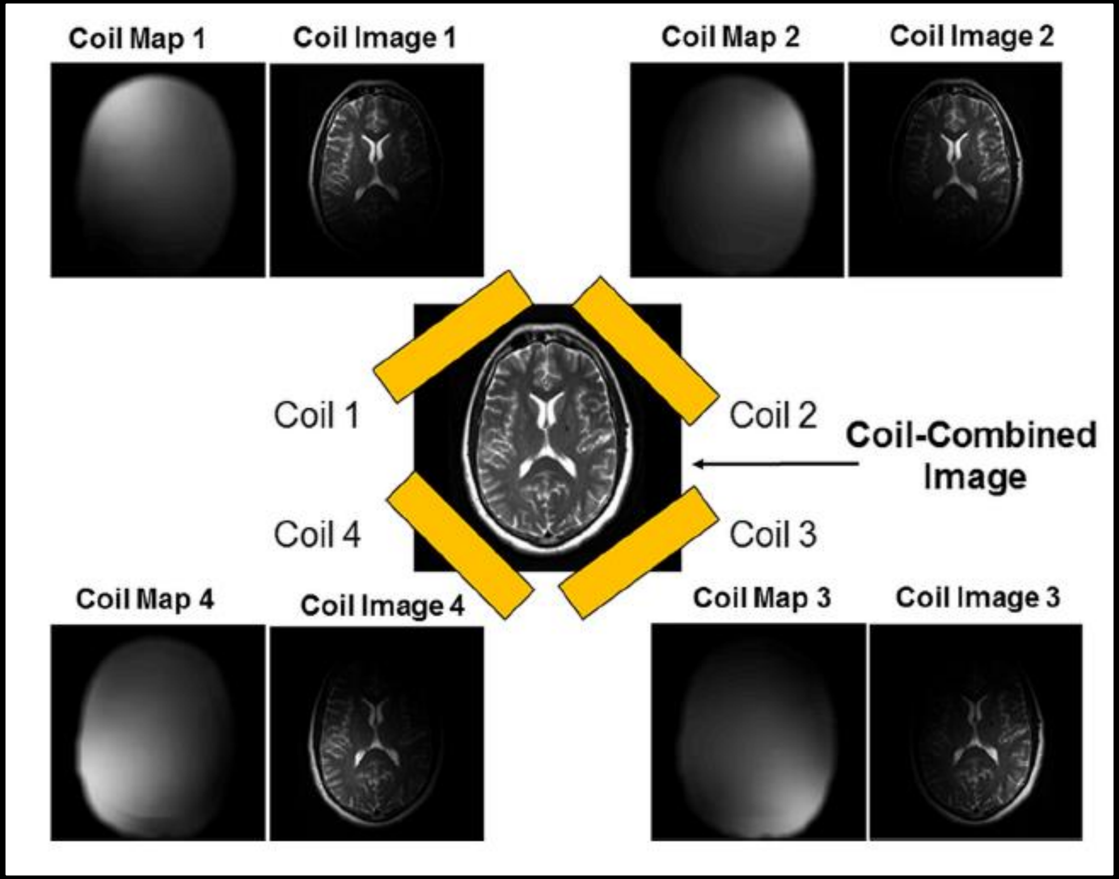
Reviews: Fessler, IEEE Signal Processing 2010

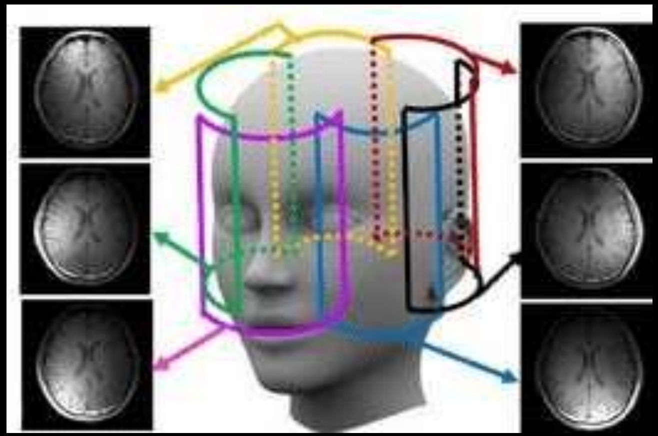
Hammernik et al., “Physics-based deep learning..” IEEE Sig Proc Magazine 2023

Parallel Imaging

Parallel MRI

Imaging with multi-coil arrays





Parallel Imaging Illustration
Mardani et al. arxiv

Pruessman et al., 1999, MRM; Griswold et al., 2002, MRM; Sodickson et al 2000; Hamilton et al. (2017) Prog Nucl Mag Res Sp

Parallel MRI

SENSE

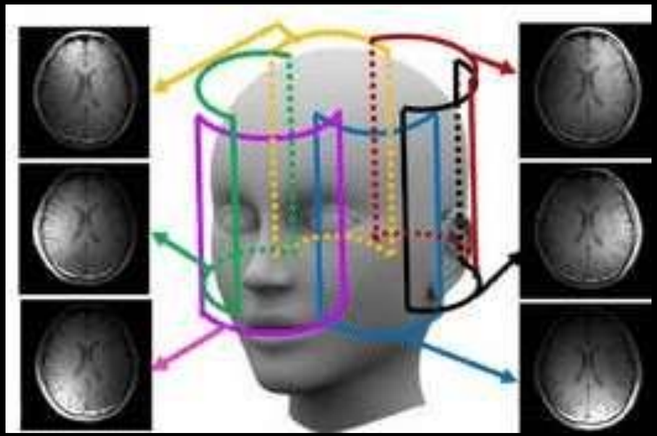
GRAPPA

Advantages:

- Linear computations
- High SNR
- Clinical applications

Limitations:

- modest acceleration (2-4)



Parallel Imaging Illustration
Mardani et al. arxiv

How can we do better?

Pruessman et al., 1999, MRM; Griswold et al., 2002, MRM; Sodickson et al 2000; Hamilton et al. (2017) Prog Nucl Mag Res Sp

The MRI inverse problem

A *regularized* least-squares problem:

$$\min_{x} ||y - Ax||_2 \ + \lambda R(x)$$

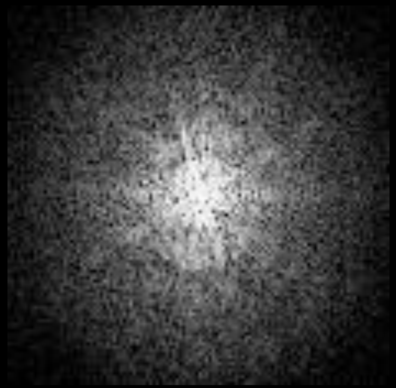
Types of regularization:

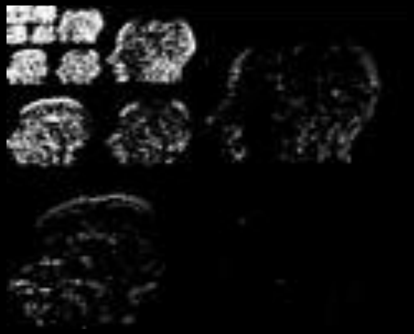
- Tikhonov: $R(x) = ||x||^2$
- Compressed sensing - promotes sparsity

ledge

Fessler, IEEE Signal Processing 2010

Compressed Sensing





Compressed Sensing

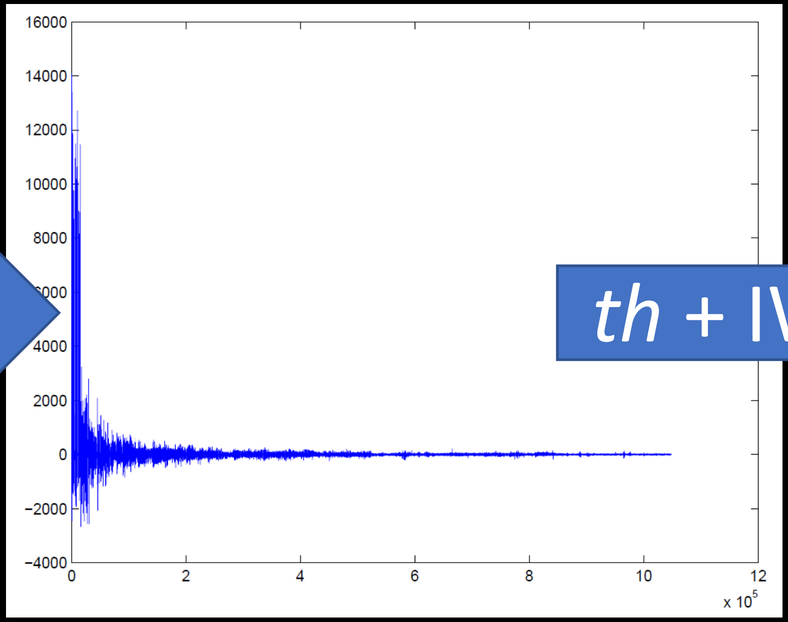
Sparsity

An image is **sparse** if it has very few ‘strong’ coefficients

Full data

100% coeffs.

WT



th + IWT

Rec. Image

7% coeffs.

Lustig, Donoho, Pauly (2007); Candés, Romberg, Tao (2006); Donoho (2006)

Compressed Sensing

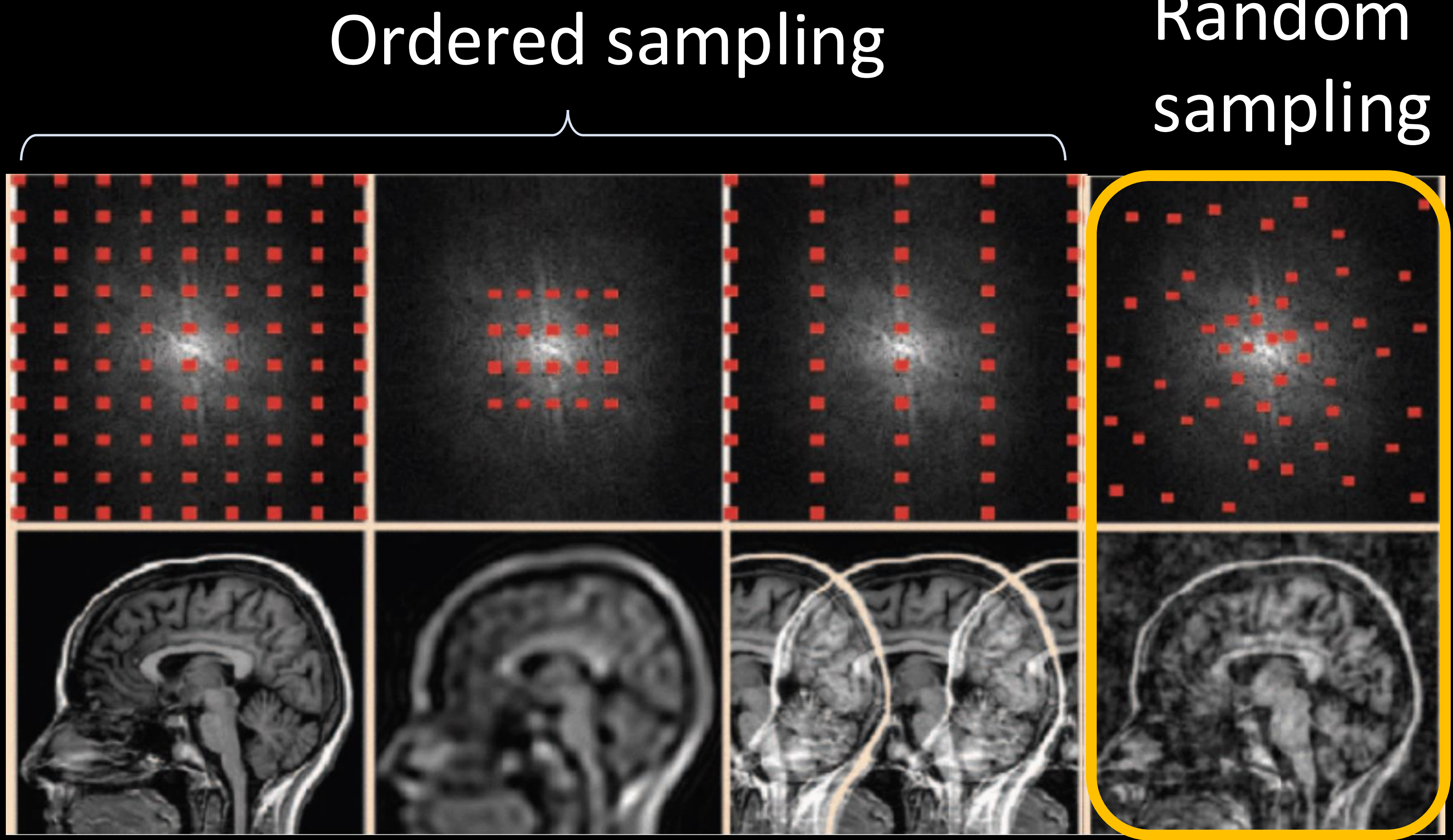
$$\min_x \underbrace{\|y - Ax\|_2}_{\text{Data consistency}} + \lambda \underbrace{|\Psi x|_1}_{\text{Sparisty promoting regularization}}$$

CS methods:

- Recover a **sparse** solution in the Ψ domain
- Introduce non-linearity
- Require *incoherent* undersampling artifacts

Lustig, Donoho, Pauly (2007); Candés, Romberg, Tao (2006); Donoho (2006)

Compressed Sensing



incoherent
“noise-like”
artifacts

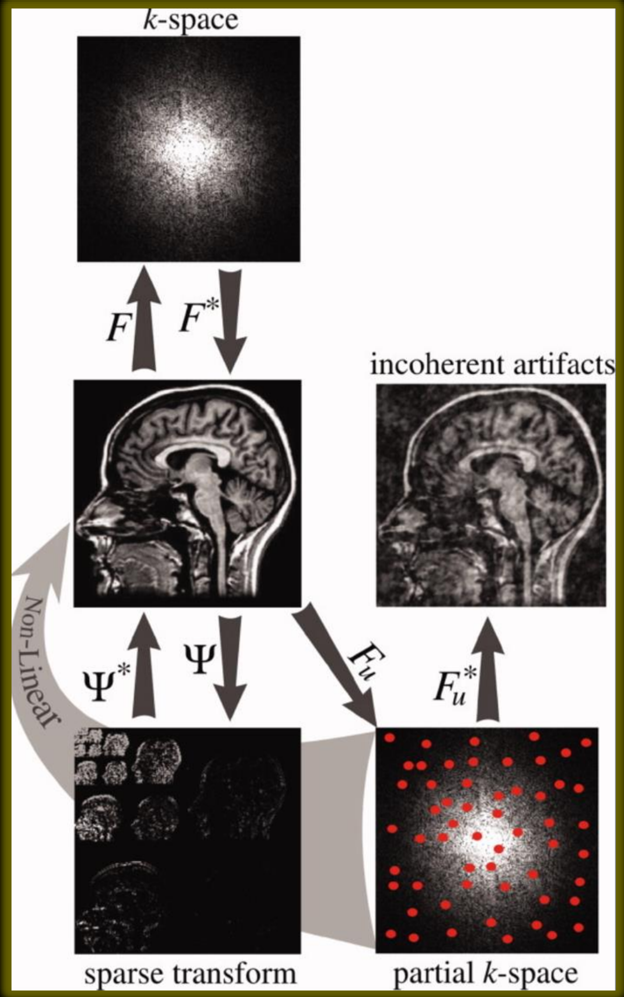
Lustig, Donoho, Pauly (2007); IEEE Sig Proc Magazine; Feng et al., JMRI 2016

Compressed Sensing

Iterative reconstruction

Optimization algorithms:

- Iterative soft thresholding algorithm (ISTA)
- Proximal methods

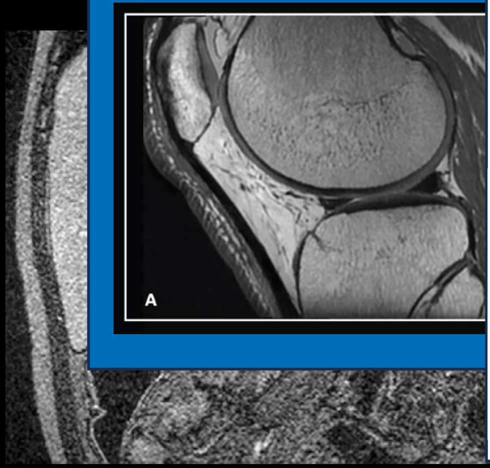


Fessler, J. "Optimization methods for MR image reconstruction" *arXiv* (2019)

Lustig, Donoho, Pauly (2007); IEEE Sig Proc Magazine; Feng et al., JMRI 2016

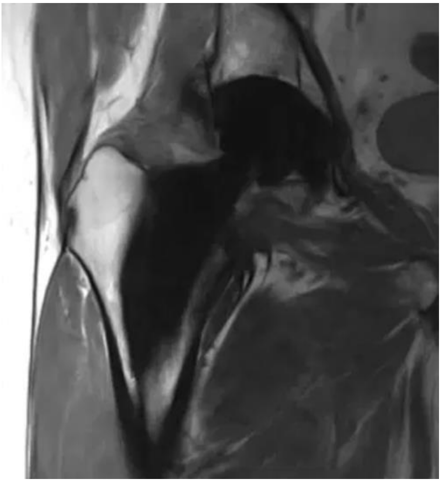
Compressed Sensing

HyperSense



SIEMENS
Healthineers

Compressed Sensing SEMAC



Vasanawala et al., Radiology 2(

PHILIPS

Compressed SENSE

Lustig, Donoho, Pauly (2007); Candés, Romberg, Tao (2006); Donoho (2006)
Feng et al. MRI 2017;

Compressed Sensing

$$\min_{x} \underbrace{\|y - Ax\|_2}_{\text{Data consistency}} + \lambda \underbrace{|\Psi x|_1}_{\text{Sparisty-promoting Regularization}}$$

Advantages:
- High acceleration (R)
- Convex optimization

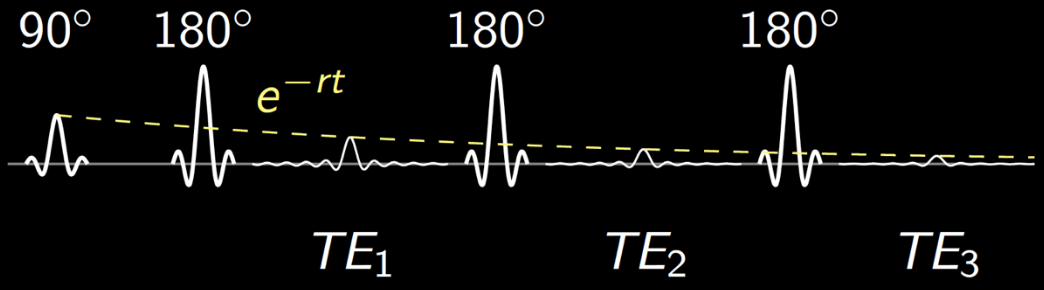
Limitations:
- Heavy iterative computations
- Sensitivity to parameter tuning

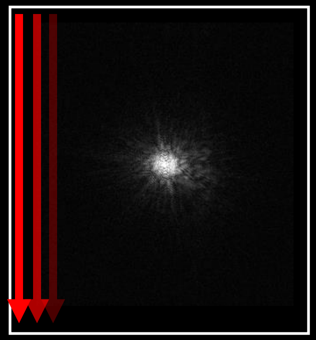
Lustig, Donoho, Pauly (2007); Candés, Romberg, Tao (2006); Donoho (2006)

Model-based reconstruction

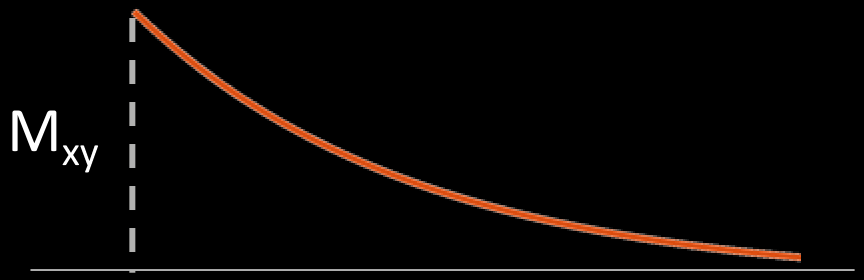
Adding *physics* to the optimization

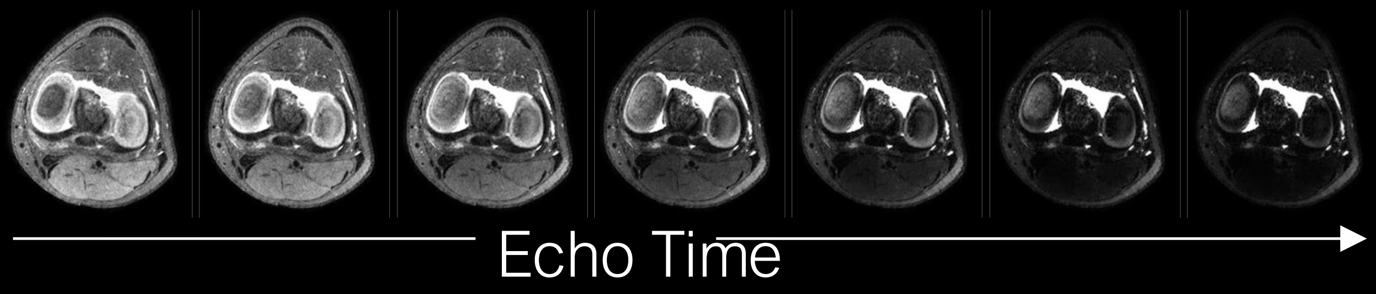
Fast Spin-Echo





- Fast
- But - T2 blurring effect - the signal decays during sampling

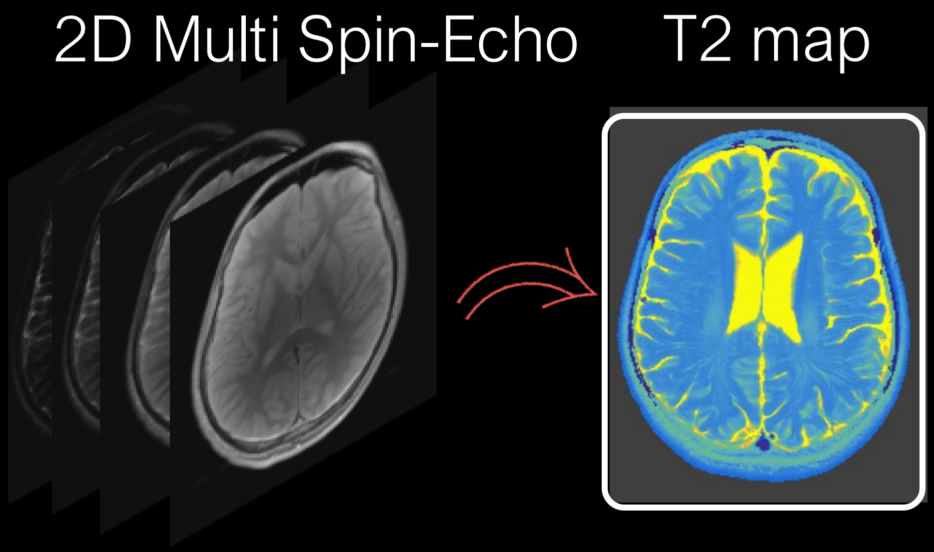




Figures from Jonathan Tamir

Fast Spin-Echo

Quantitative imaging, e.g. T2 mapping, requires estimating a series of images – long scans



Figures from Jonathan Tamir

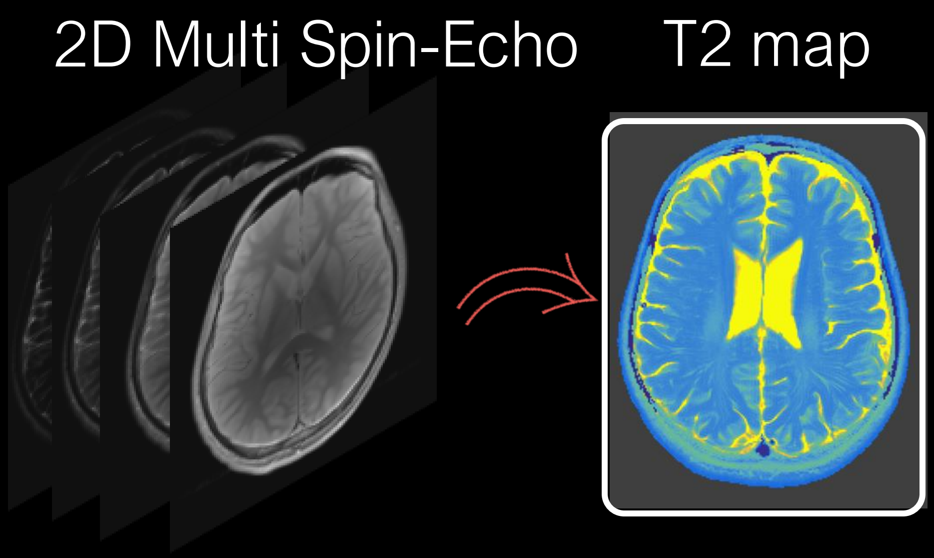
Model-based reconstruction

Signal decay is known – Bloch equations

We solve directly for parameter naps (T2, T1 maps)

Advantages:

- Dimensionality reduction
- We can synthesize images as any time



Figures from Jonathan Tamir

Model-based reconstruction

- The forward model now includes *relaxation* – it's *nonlinear*
- We solve directly for tissue relaxation maps $\mathrm{Q}(\vec{x})$ (e.g., T2 map)
- We can also solve for the image simultaneously (ρ, spin density)

$$\min_{\rho,q} \|y - \mathcal{M}(\rho, q)\|_2 + R(x)$$

Forward model:

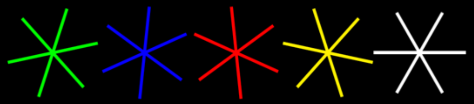
$$\mathcal{M}: (\rho, q) \rightarrow \int d\vec{x} \rho \vec{x} e^{-Q(\vec{x})} e^{-i\vec{k}(t)\vec{x}}$$

Requires algorithms for non-linear optimization, e.g. conjugate gradient

Block et al., IEEE TMI 2009; Fessler, IEEE Sig Proc Mag, 2010; Tamir et al, IEEE Sig Proc Mag 2020;
Wang et al., Philosophical Transactions of the Royal Society 2021

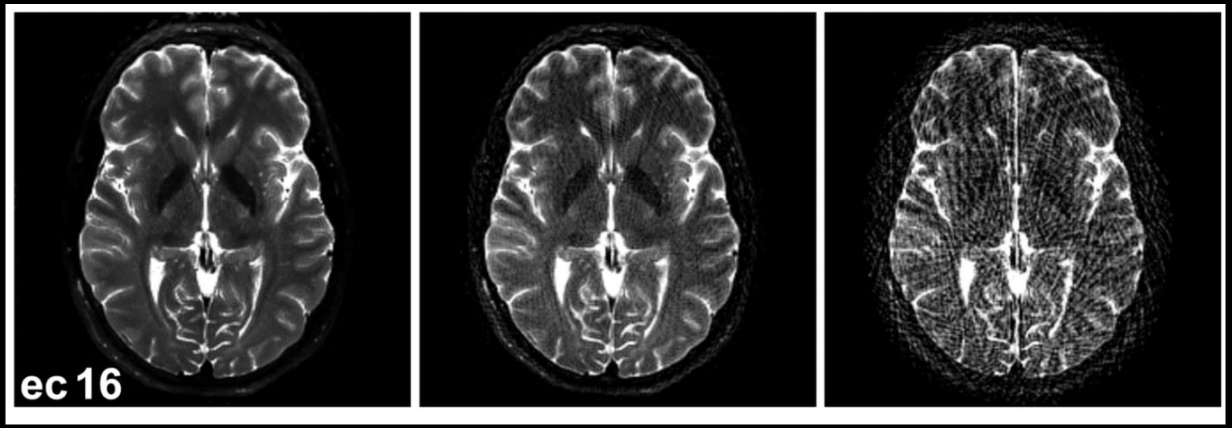
Model-based reconstruction

Example: solve directly for tissue relaxation map and image from radial spokes [Block et al., IEEE TMI 2009]

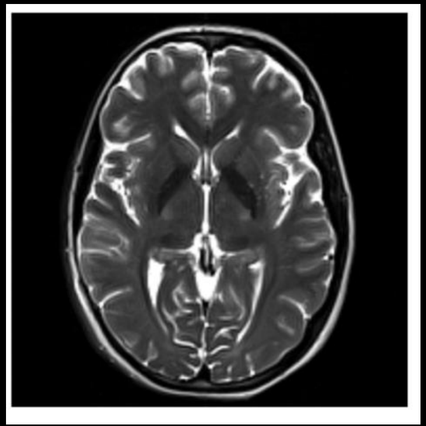


echos

Model-based kwic method gridding



Cartesian fully sampled (much longer)



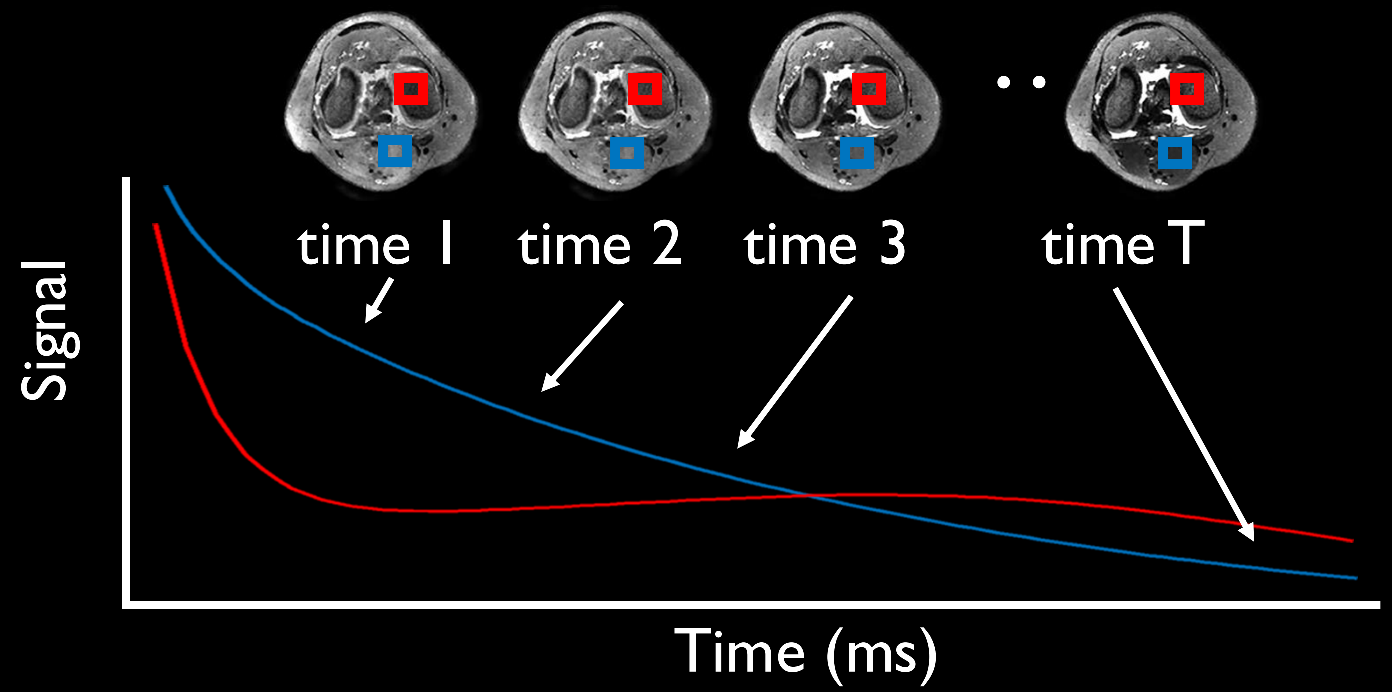
How can we do better?

Block et al., IEEE TMI 2009

Subspace-constrained reconstruction

Relaxation of different tissues is highly correlated

→ lower dimensional space



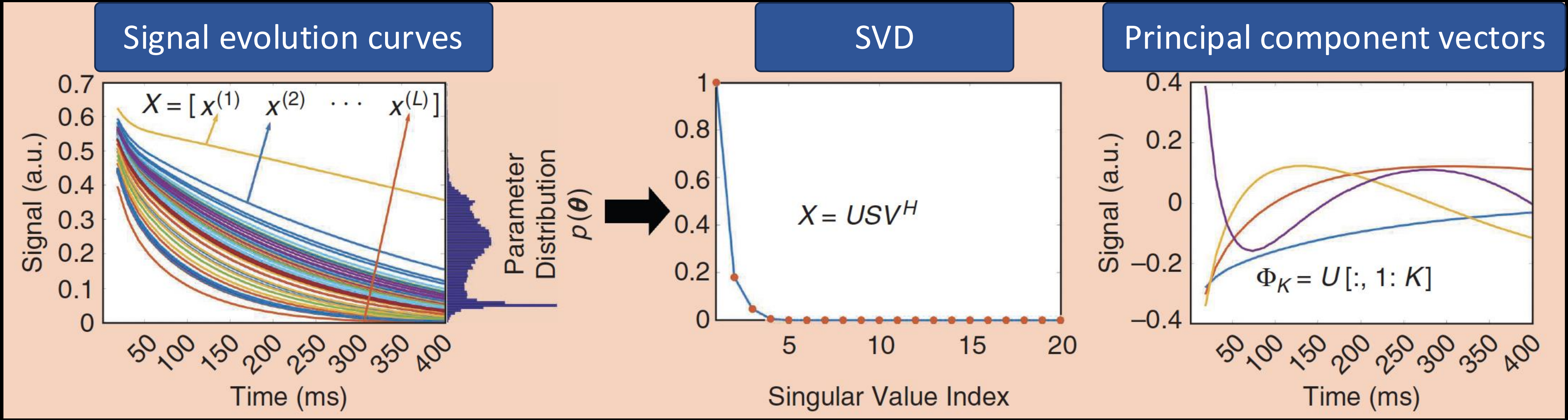
Subspace-constrained recon exploits the lower dimensionality

Figures from Jonathan Tamir

Tamir et al., ”T2 shuffling”, MRM (2017); Tamir et al, IEEE Sig Proc Mag 2020;

Subspace-constrained reconstruction

Plot signal curves → SVD → the main components (K largest values) → use this to regularize the optimization problem



Tamir et al., "T2 shuffling", MRM (2017); Tamir et al, IEEE Sig Proc Mag 2020;

Subspace-constrained reconstruction

Plot signal curves → SVD → the main components (K largest values) → use this to regularize the optimization problem

$$\underbrace{\min_x \|y - Ax\|_2}_{\text{Data consistency}} + \underbrace{\lambda_1 \left\| x - \Phi_K \Phi_K^H \right\|_2^2}_{\text{Subspace-constrained regularization}} + \underbrace{\lambda_2 R(x)}_{\text{Other regulariztaion}}$$

Implemented in BART!
Comping up – hands-on tutorial by Martin's & Julia

Tamir et al., "T2 shuffling", MRM (2017); Tamir et al, IEEE S

How can we do better?

Deep learning

Deep Learning

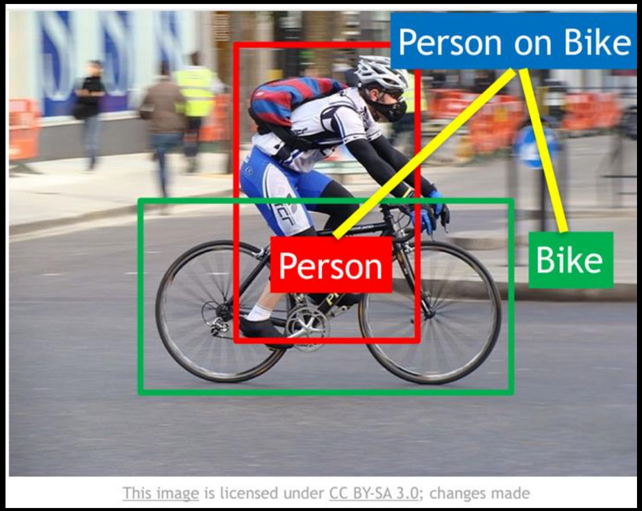
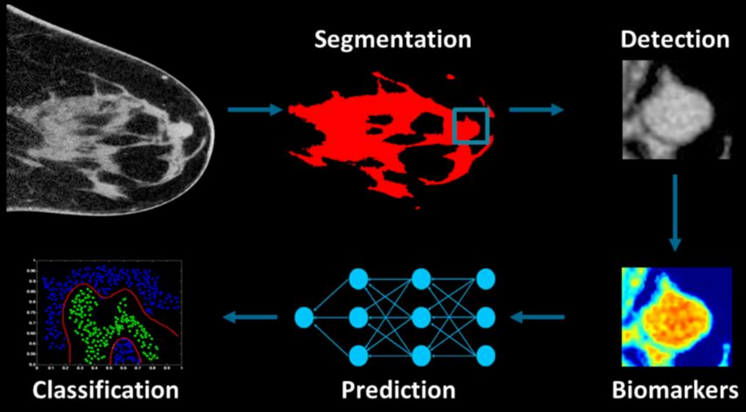
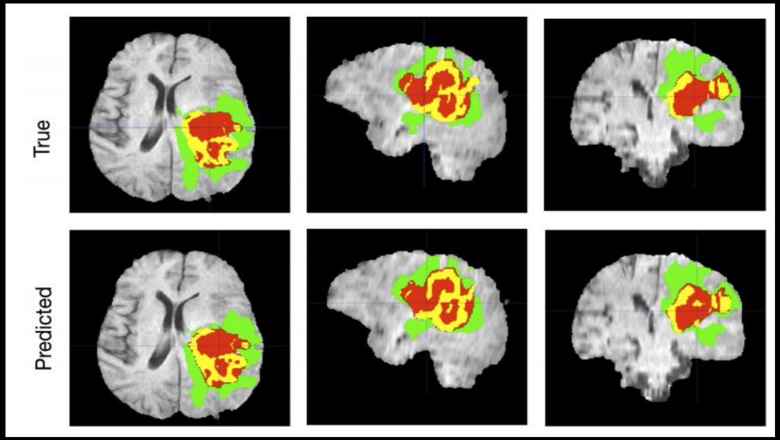


Image by Jin Clyde Monge

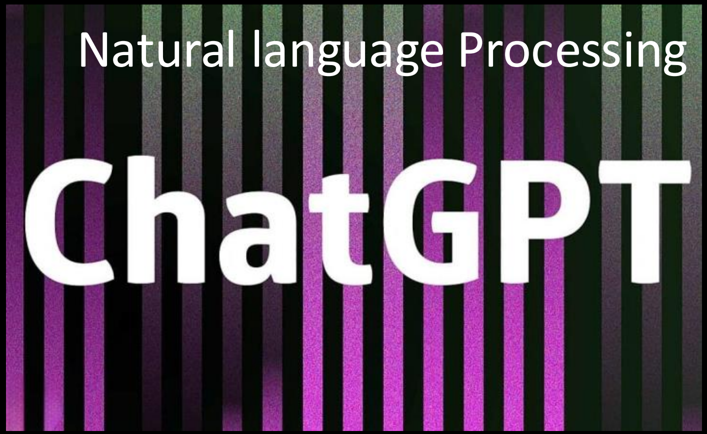
Mindy-support.com



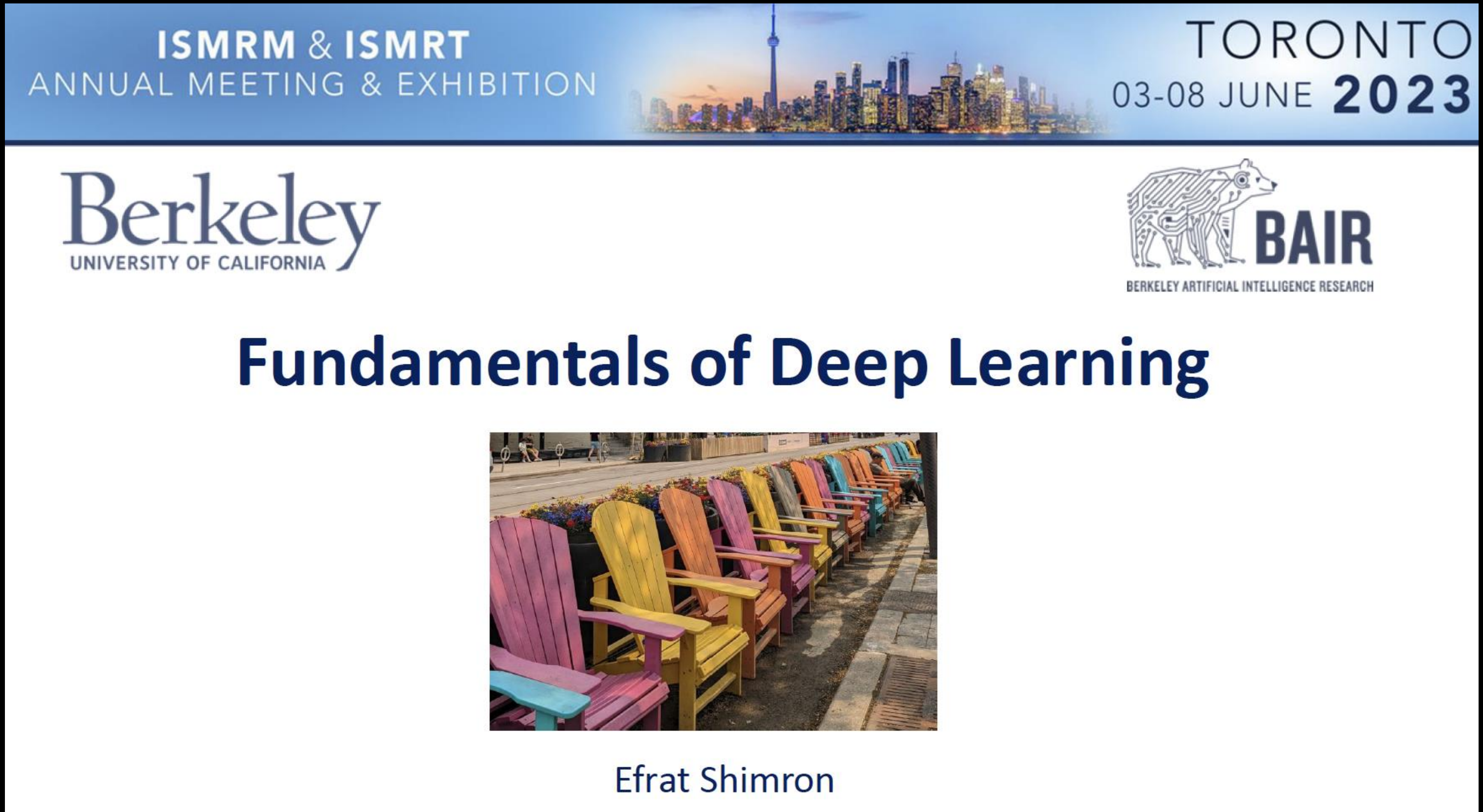
http://axti.radboudimaging.nl/



Nvidia.com



Deep Learning



Slides here:

Review paper here:

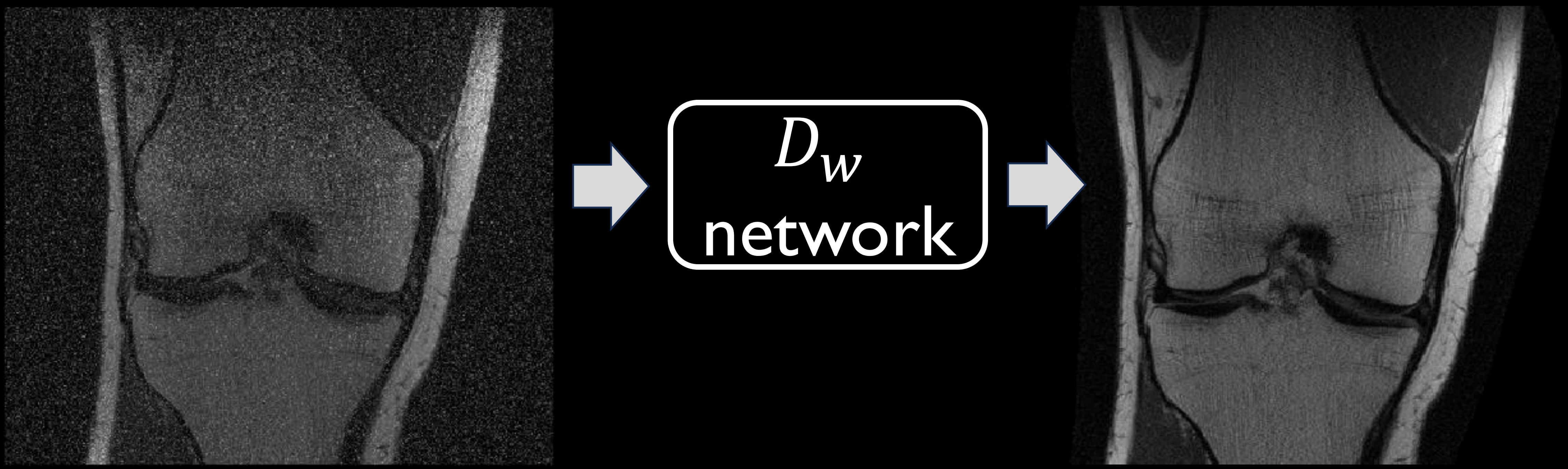
Review paper

[Deep learning for accelerated and robust MRI reconstruction]

Reinhard Heckel, Mathews Jacob, Akshay Chaudhari, Or Perlman, Efrat Shimron, (MAGMA 2024)

Deep Learning

$x_0 = F^{-1}(y)$ $\quad$ $\mathrm{x} = D_w(x_0)$



Figures from Jonathan Tamir

Deep Learning

First deep-learning papers – data driven approach:
Learn the mapping from zero-filled images to reconstructed images

ACCELERATING MAGNETIC RESONANCE IMAGING VIA DEEP LEARNING

Shanshan Wang[1], Zhenghang Su[2], Leslie Ying[3], Xi Peng[1], Shun Zhu[1]
Feng Liang[4], Dagan Feng[5] and Dong Liang[1]

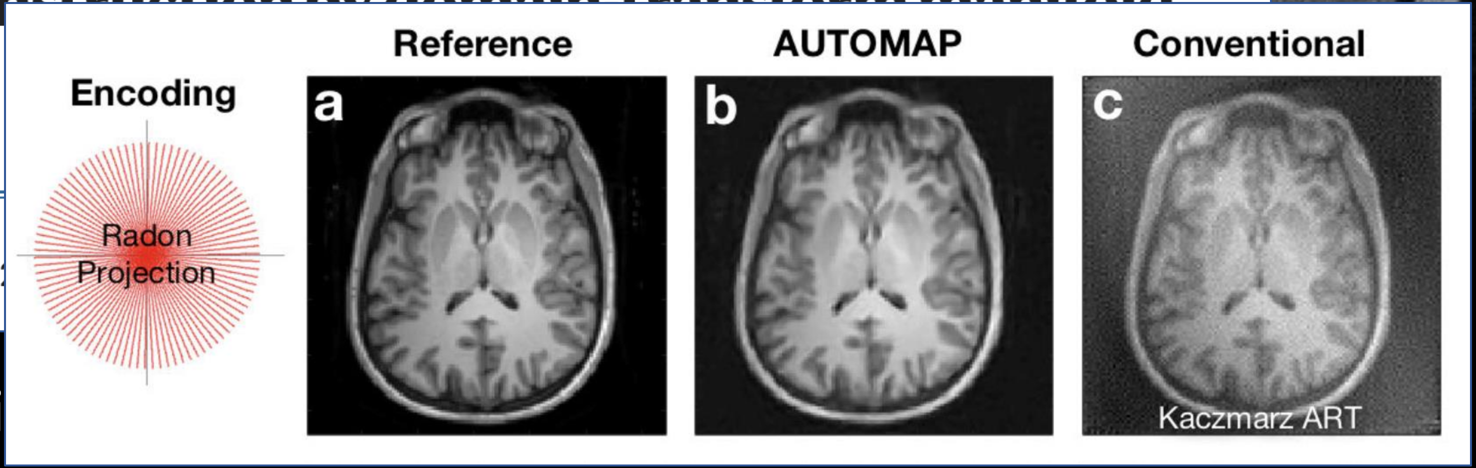
nature

Letter | Published: 22 March 2018

Image recon... learning

Bo Zhu, Jeremiah Z. L...

Nature **555**, 487–49...



Figures from Jonathan Tami...

Deep Learning

$$\min_x \underbrace{\cancel{\|y - Ax\|_2}}_{\text{Data consistency}} + \underbrace{\lambda R(x)}_{\text{Regularization}}$$

Early deep learning methods:

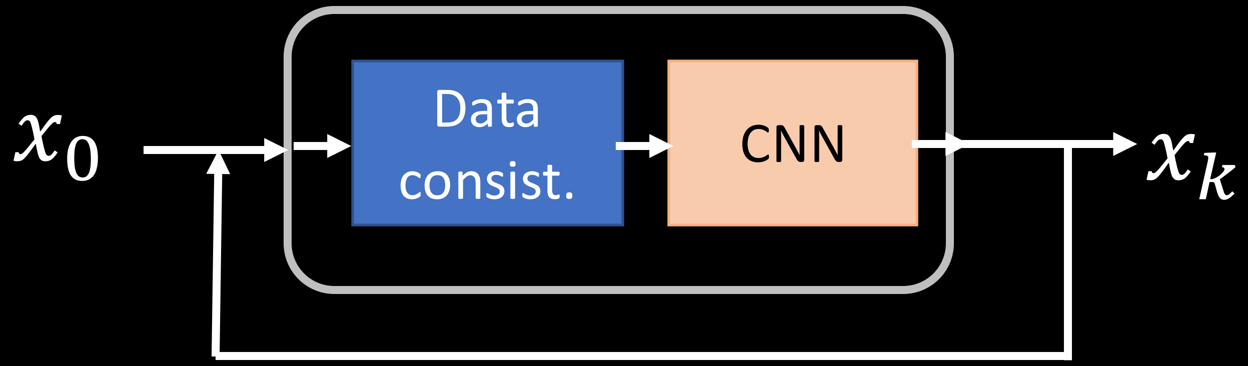
$$x = D_w(x_0)$$

- Data driven
- Replace hand-crafted regularizers with *learned* ones
- No data consistency

Deep Learning

Iterative (unrolled) deep learning - the best of both worlds!

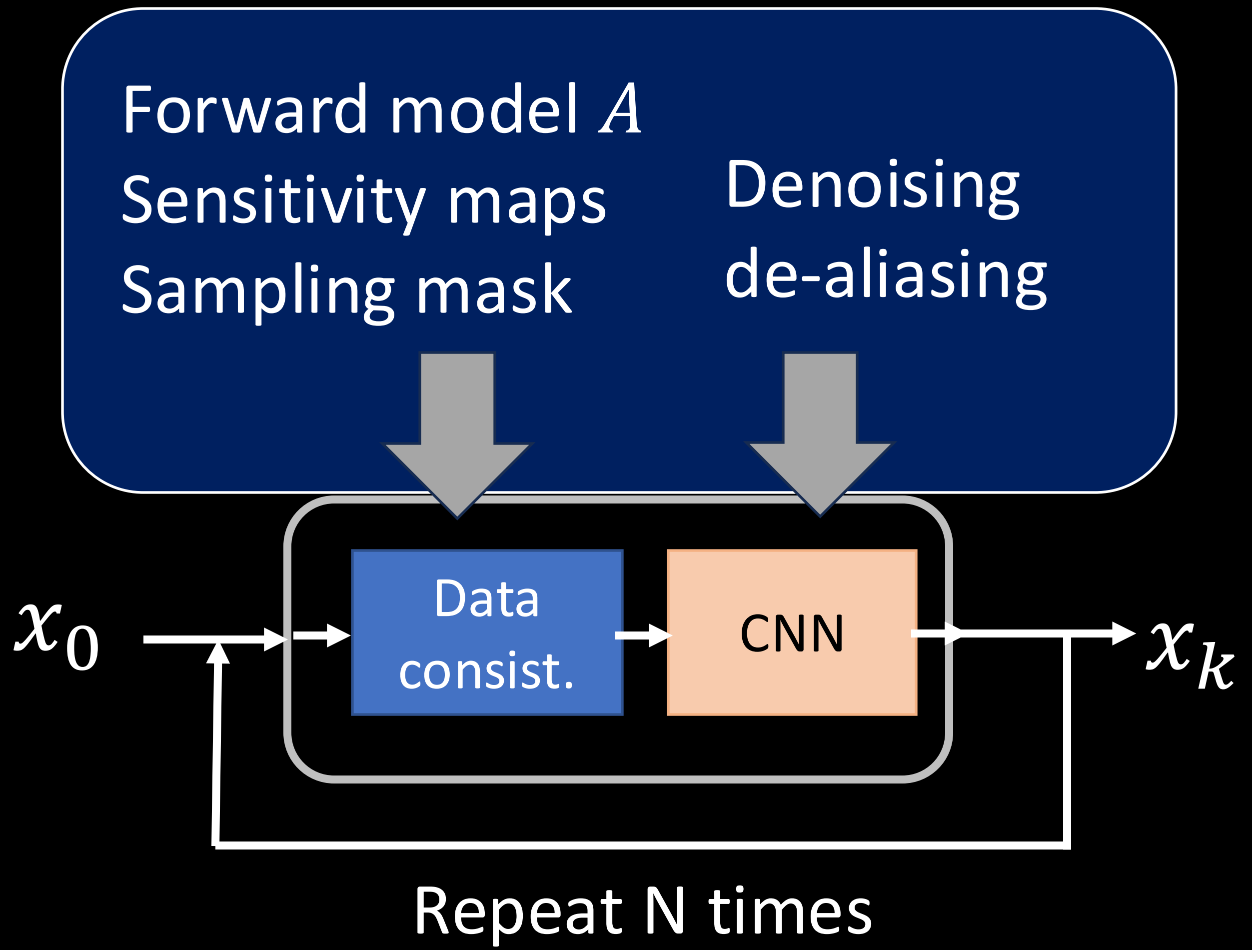
$$\min_{x} \underbrace{\|y - Ax\|_2}_{\text{Data consistency}} + \underbrace{D_w(x_0)}_{\text{Deep-learning regularization}}$$



Repeat N times

Deep Learning

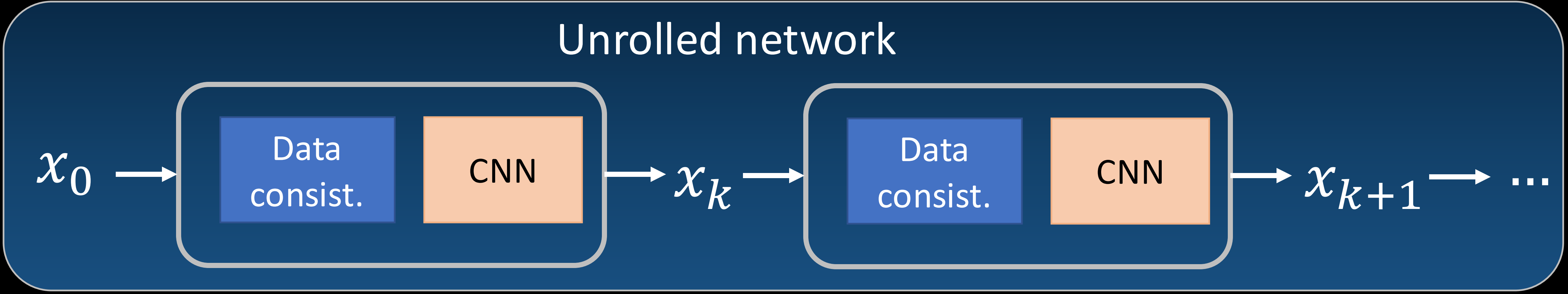
Iterative (unrolled) deep learning - the best of both worlds!



Deep Learning

Iterative deep learning - the best of both worlds!

$$\min_{x} \underbrace{\|y - Ax\|_2}_{\text{Data consistency}} + \underbrace{D_w(x_0)}_{\text{Deep-learning regularization}}$$



Magnetic Resonance in Medicine | ISMRM | ONE Community for Clinicians and Scientists

Full Paper | Free Access

Learning a variational network for reconstruction of accelerated MRI data

Kerstin Hammernik, Teresa Klatzer, Erich Kobler, Michael P. Recht, Daniel K. Sodickson, Thomas Pock, Florian Knoll

...f both worlds!

Journals & Magazines > IEEE Transactions on Medical ... > Volume: 38 Issue: 2

MoDL: Model-Based Deep Learning Architecture for Inverse Problems

Publisher: IEEE

Cite This | PDF

Hemant K. Aggarwal ; Merry P. Mani ; Mathews Jacob ; All Authors

$x_0 \rightarrow$ Data consist. | C... ...

EMB | IEEE NPSS | IEEE Signal Processing Society | UFFC

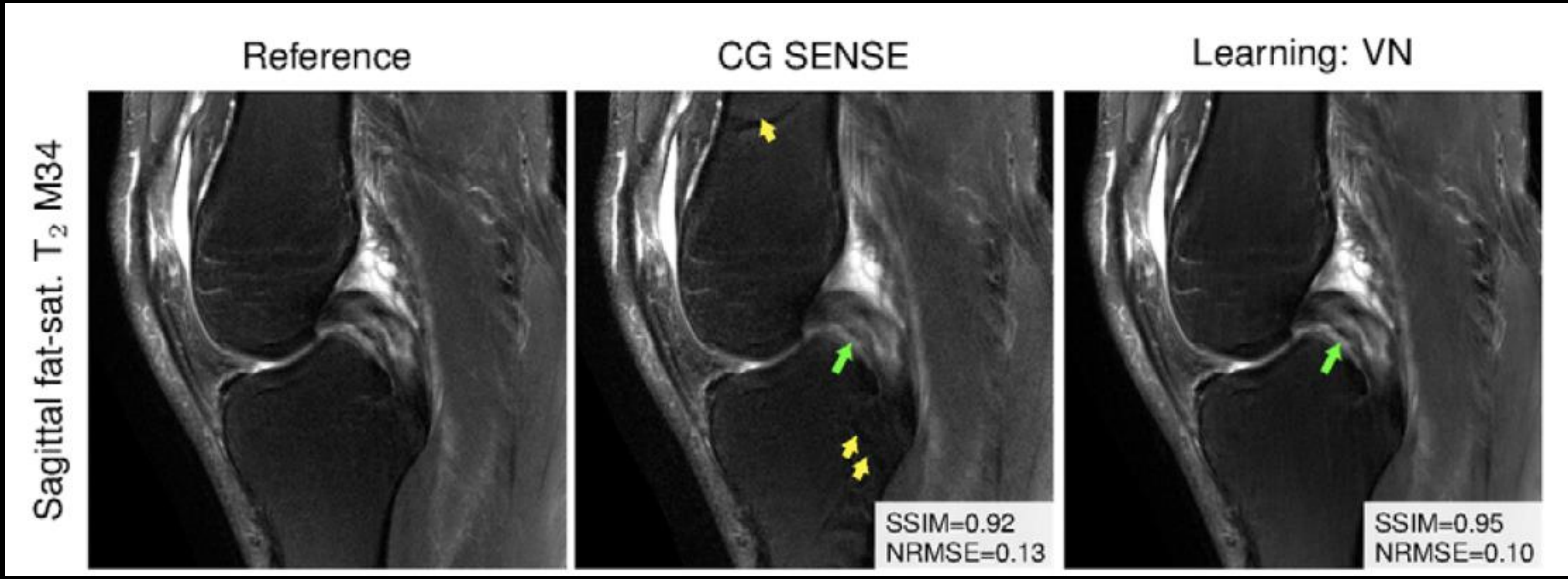
IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 37, NO. 2, FEBRUARY 2018 491

A Deep Cascade of Convolutional Neural Networks for Dynamic MR Image Reconstruction

Jo Schlemper, Jose Caballero, Joseph V. Hajnal, Anthony N. Price, and Daniel Rueckert, *Fellow, IEEE*

Deep Learning

Iterative deep learning - the best of both worlds!

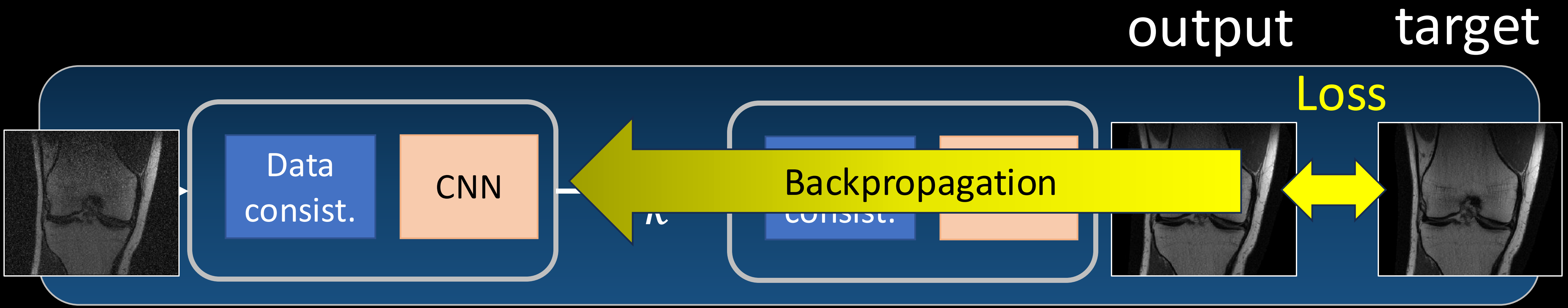


Hammernik et al., MRM 2018

Deep Learning

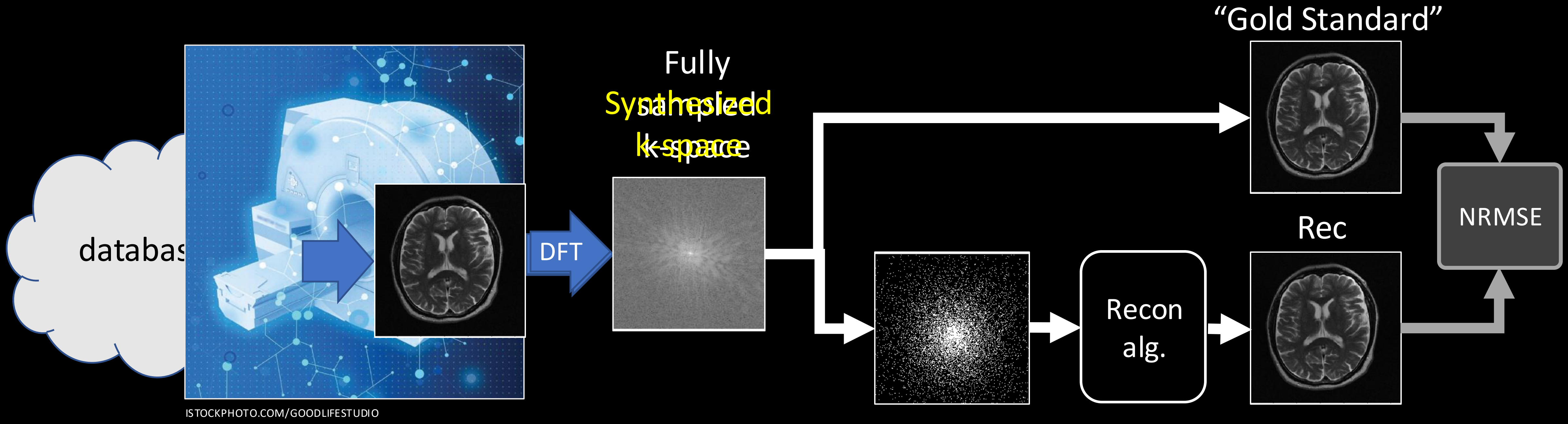
Training - Supervised learning:

Training data?



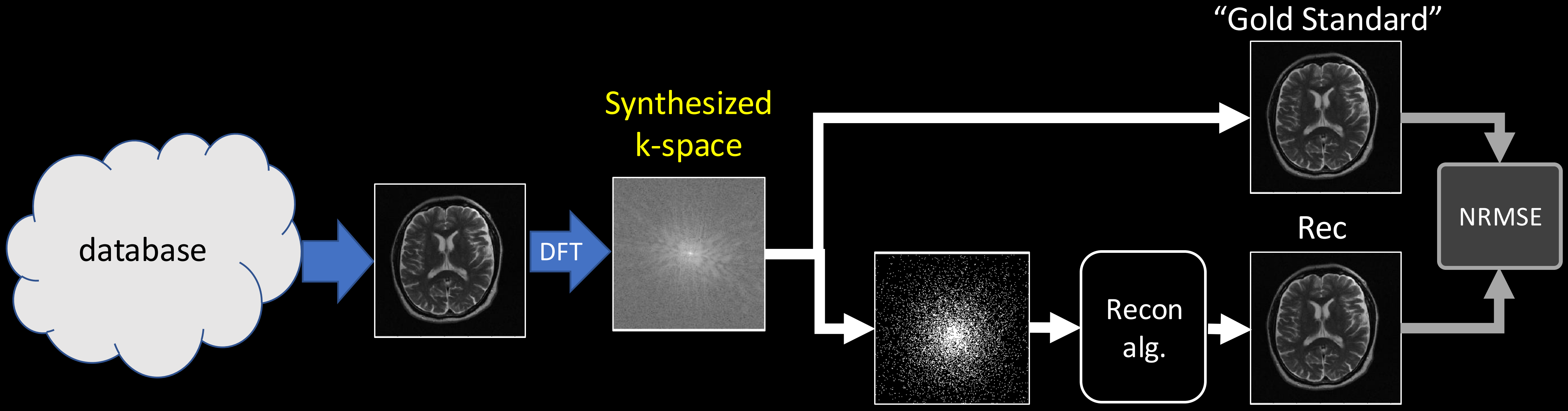
Data Crimes

A Common Research Pipeline



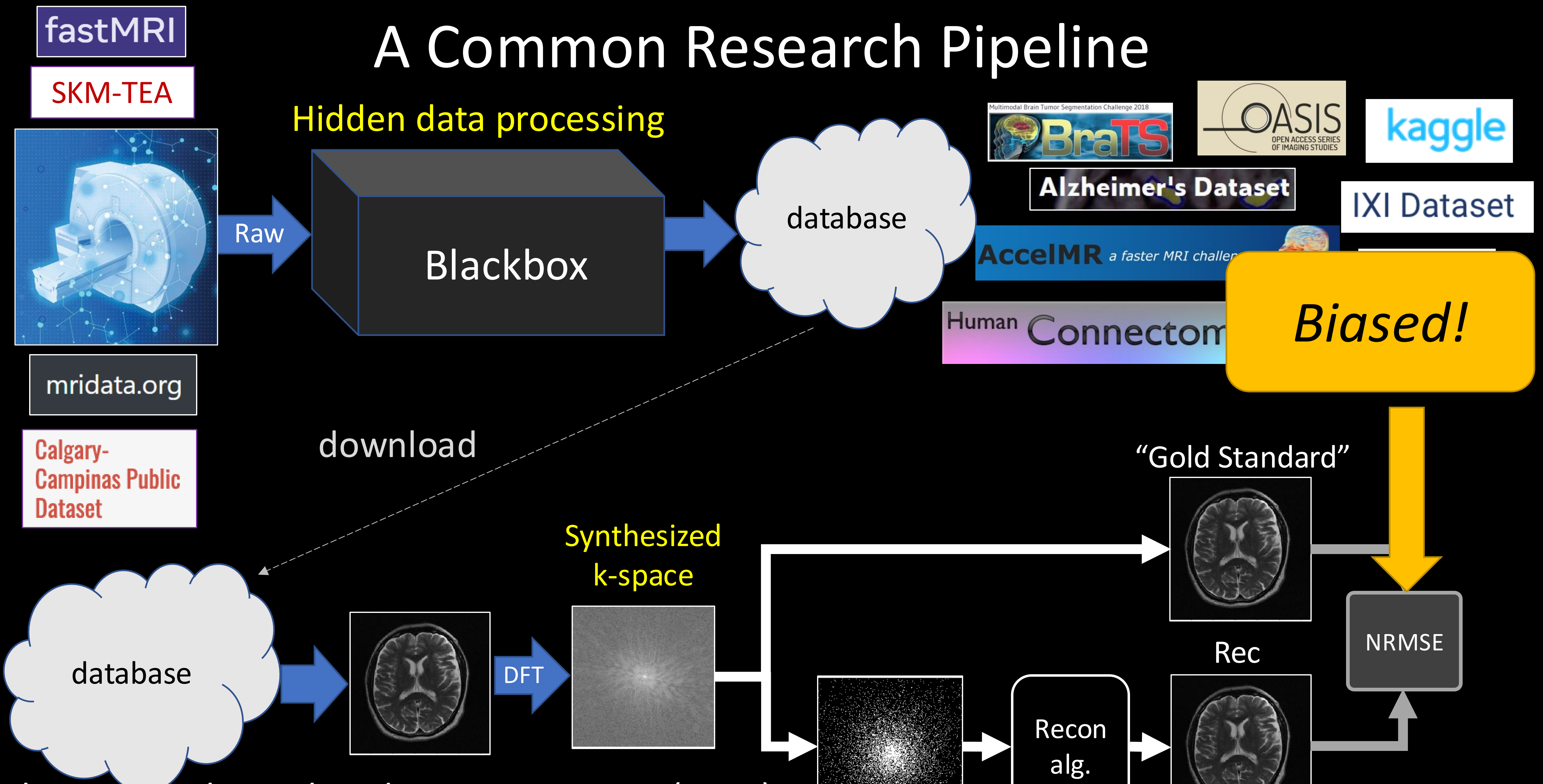
Shimron et al., *Implicit data crimes,* PNAS (2022)

A Common Research Pipeline



Shimron et al., *Implicit data crimes,* PNAS (2022)

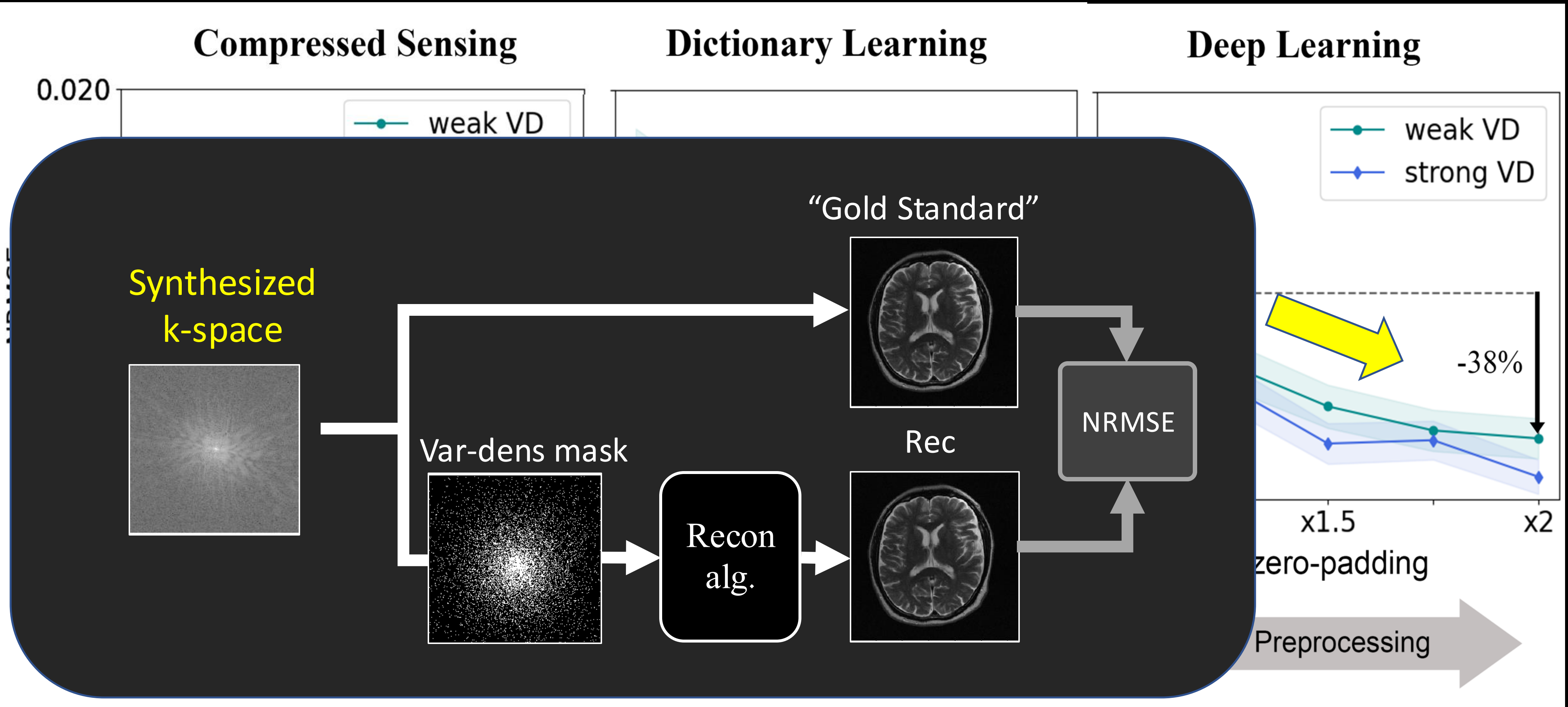
A Common Research Pipeline



Shimron et al., *Implicit data crimes*, PNAS (2022)

Data Crimes

FastMRI Data



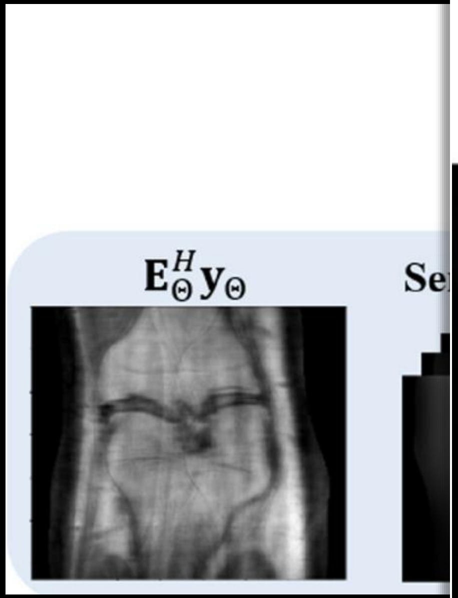
✗ Naïve use of Big Data can lead to biased results

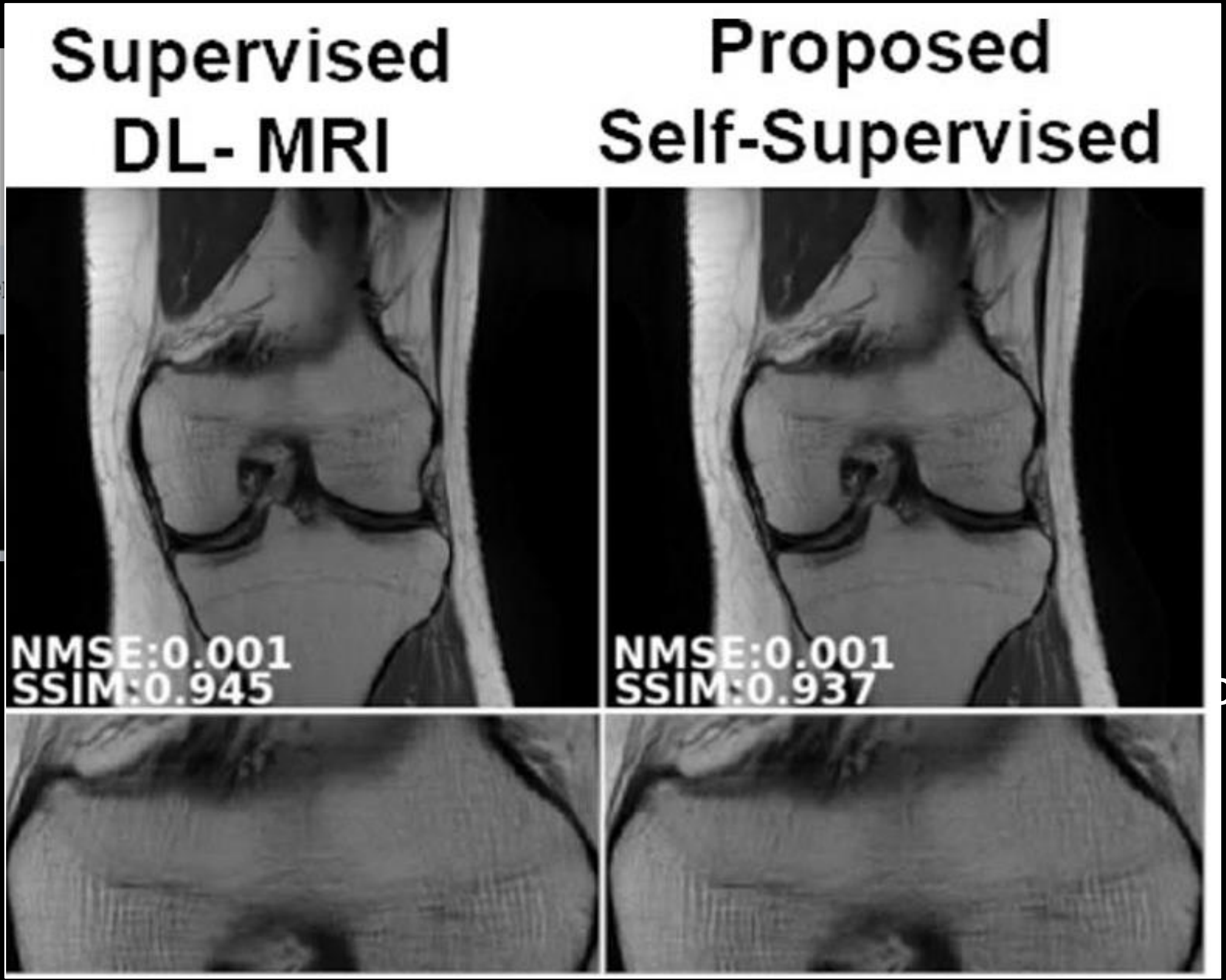
✗ Error metrics - *blind* to the preprocessing

Shimron et al., *Implicit data crimes,* PNAS (2022)

Self-supervised MRI reconstruction

Deep learning: Self-supervised training

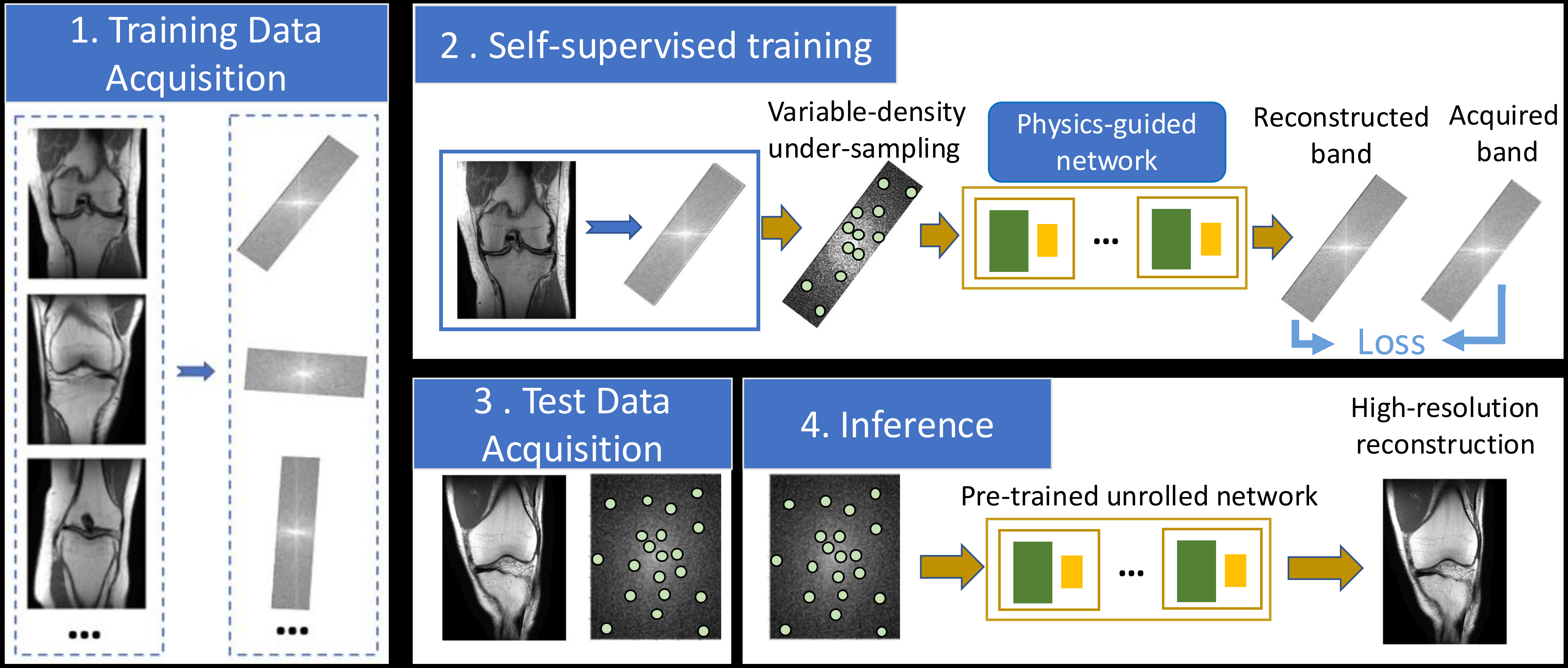




oss)

Yaman et al., MRM 2020

K-band: Fast Acquisition & Self-supervised Reconstruction

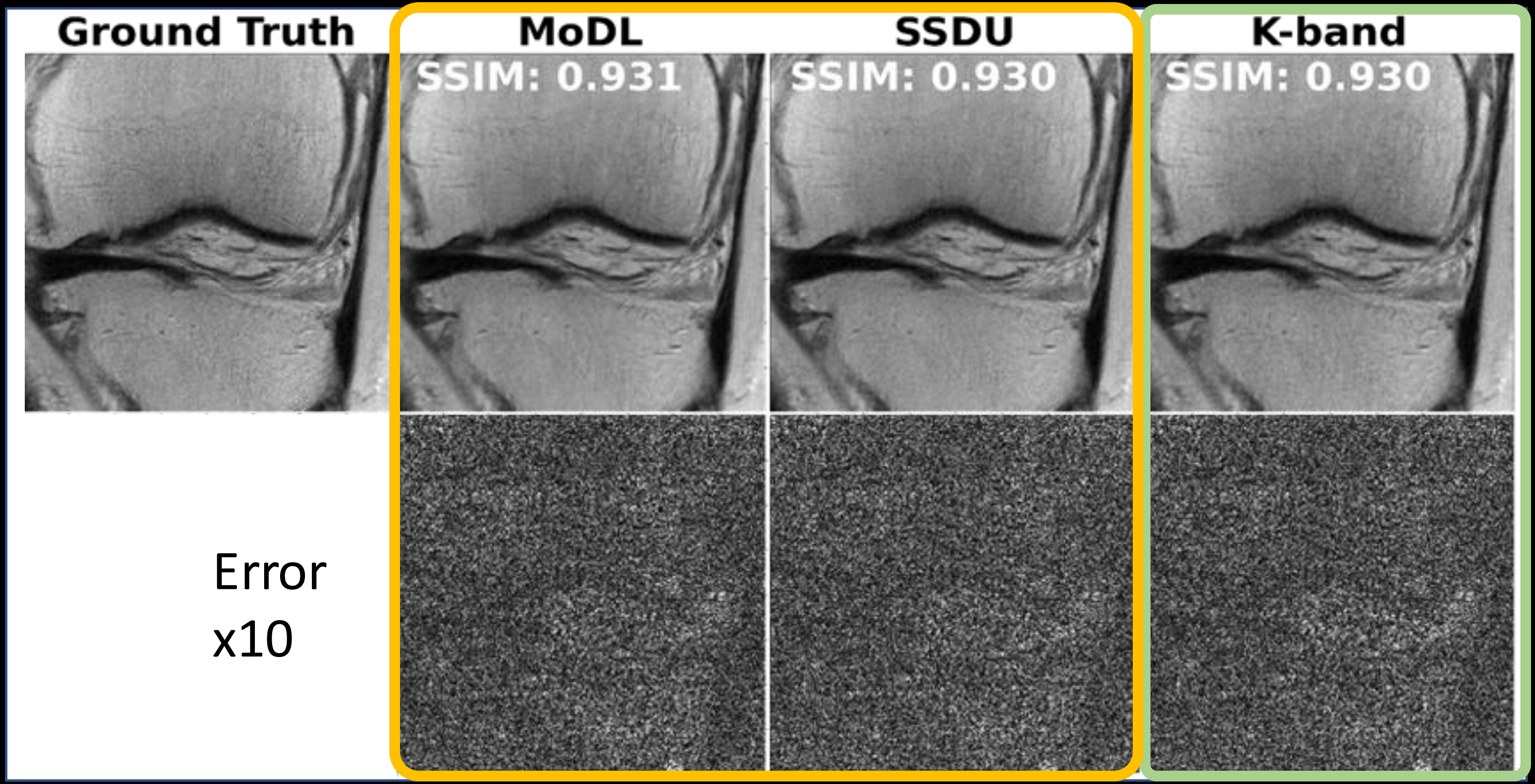


Wang et al., arXiv 2023, “k-band: self-supervised MRI reconstruction”

K-band: Fast Acquisition & Self-supervised Reconstruction

Trained on high-res data

Trained on data with 4x lower resolution



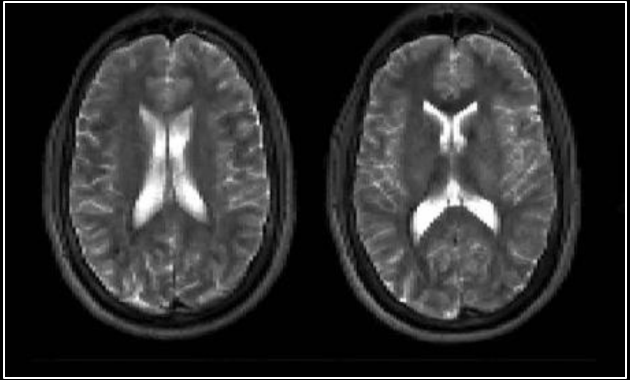
Mathematical convergence proof – in the paper

Wang et al., arXiv 2023, "k-band: self-supervised MRI reconstruction"

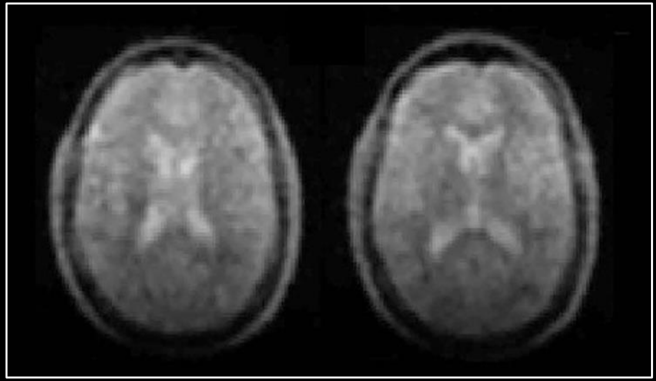
Reconstruction for low-field MRI

Low-field MRI

High-field MRI



Low-field MRI

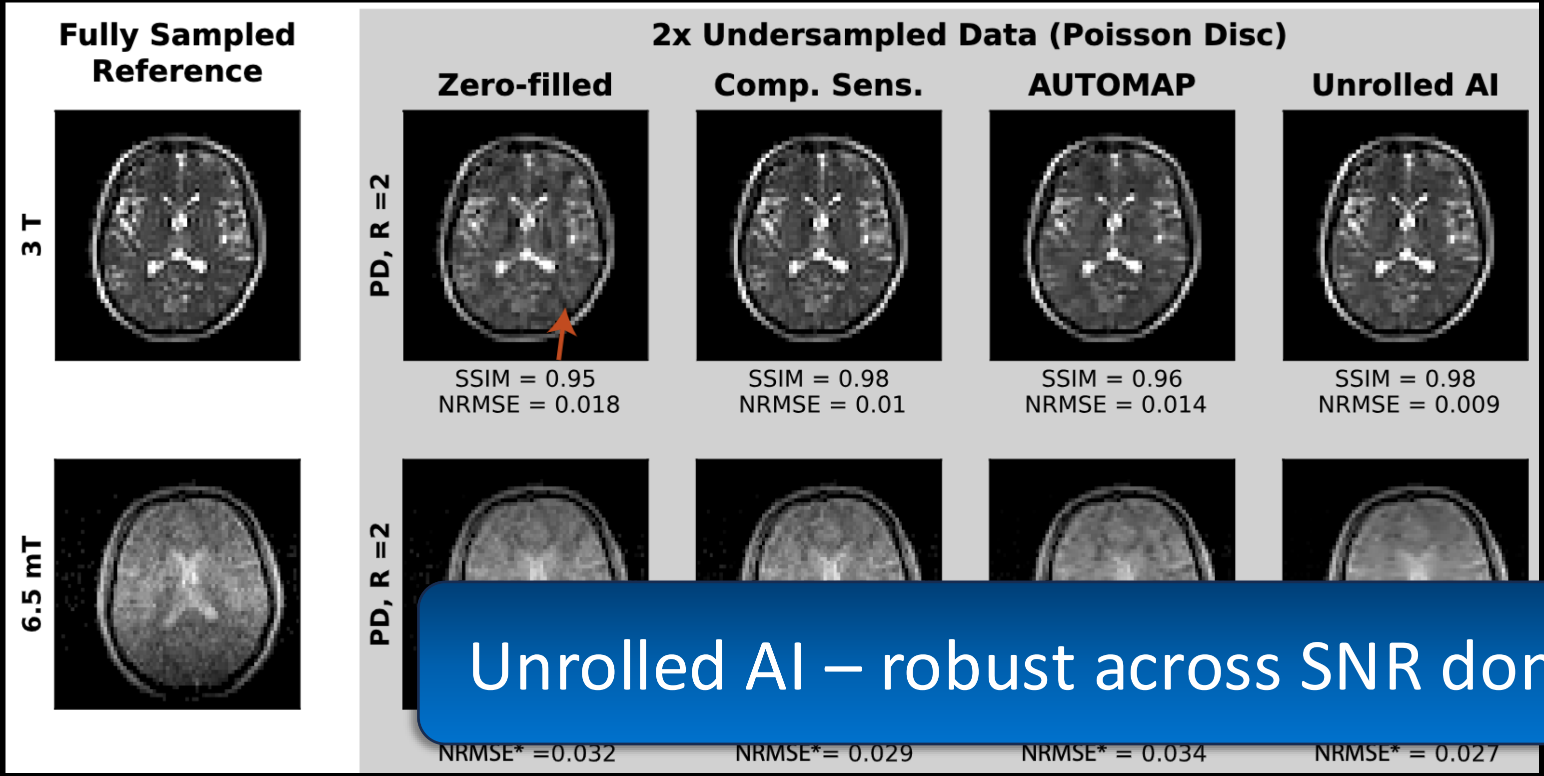


Low SNR

AI for low-field MRI

Coming soon on arXiv

Unrolled networks provide high-quality recons

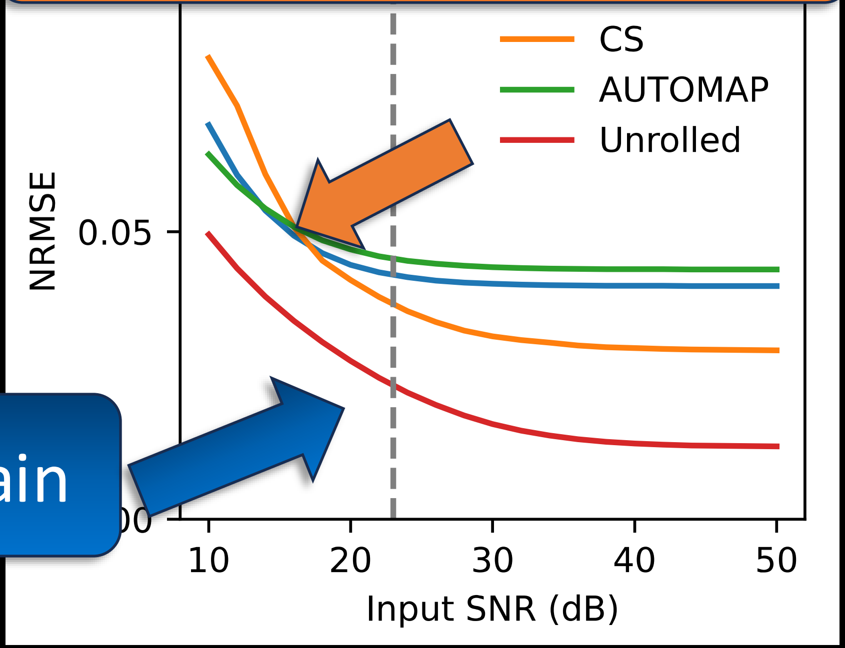


Unrolled AI – robust across SNR domain

David Waddington

Matthew Rosen

CS & AUTOMAP switch places



Waddington, Shimron, et al., ISMRM 2023

Open positions - Med AI & MRI lab

Technion

May-Blum-Dahl
TecH MRC
Technion Human MRI Research Center

Team

Join us

Thank You