Exploring the limitations of deep learning for MR image reconstruction

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Declaration of Financial Interests or Relationships

Speaker Name: Florian Knoll

I have the following financial interest or relationship(s) to disclose with regard to the subject matter of this presentation:

- Patent royalties for AI image reconstruction: Siemens Healthineers
- Research support: Siemens Healthineers
- Scientific advisory board: Imaginostics
- Stock options: Subtle Medical

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Patricia Johnson
Gene Kim (now Cornell)
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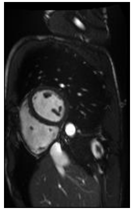

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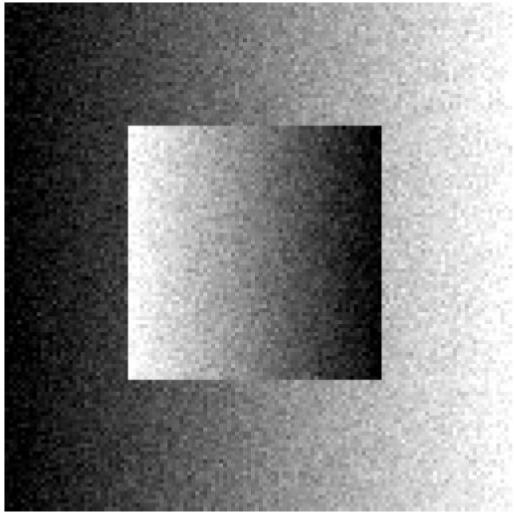
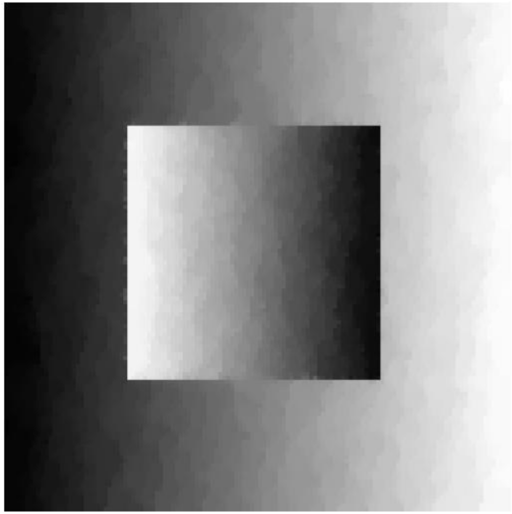
Image reconstruction 2011

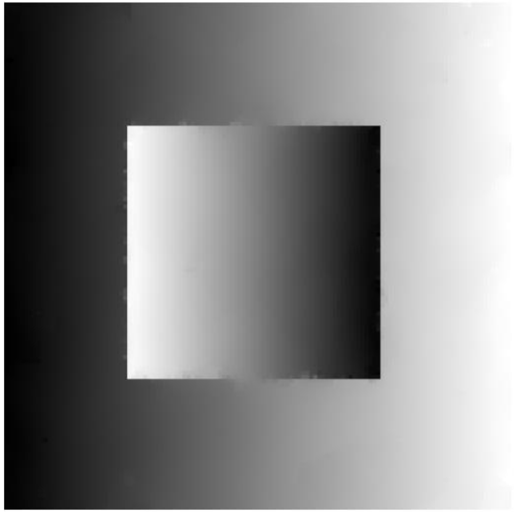
Noisy



TV



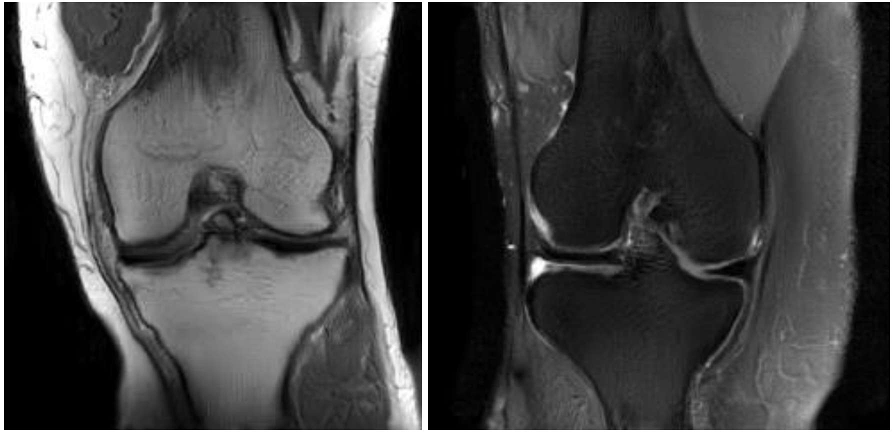
TGV^2



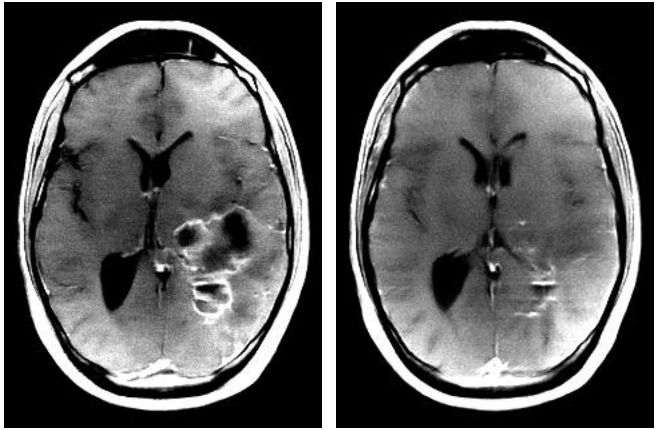
Knoll MRM 2011

Image reconstruction 2026

AI generated knee MRI



Two recons same patient



Narnhofer SPIE 2019
Radmanesh Radiology AI 2022

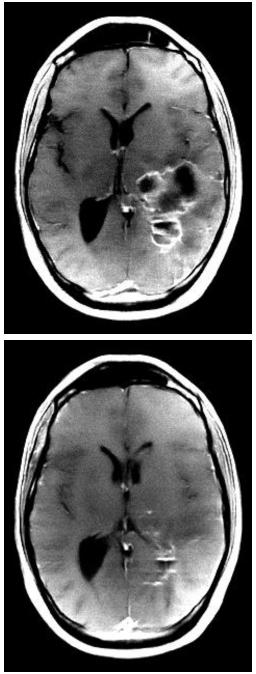
Roadmap

When does DL recon go wrong?

How does it go wrong?

What is the reason it goes wrong?

Can you recognize when it goes wrong?



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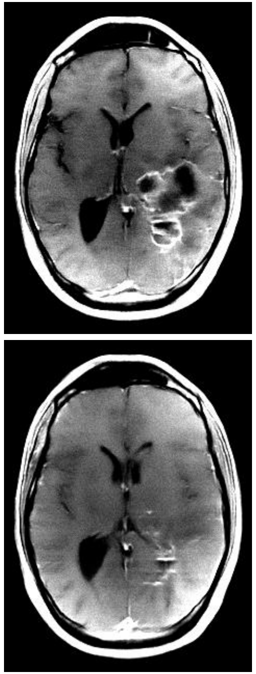
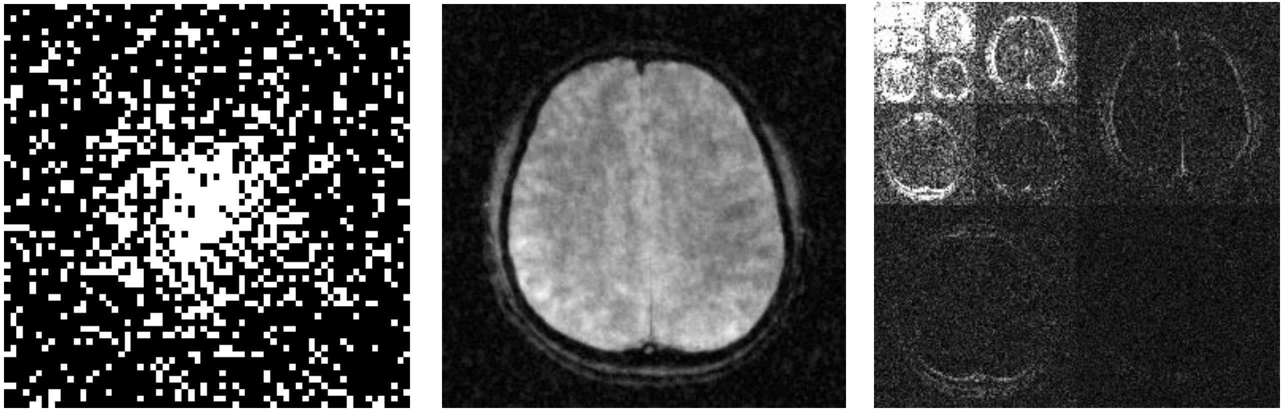


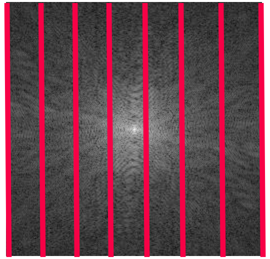
MR image reconstruction as inverse problem

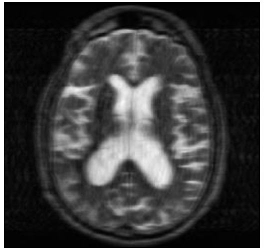


$$\min_u \frac{\lambda}{2}||Au - f||_2^2 + \mathcal{R}(u)$$

Lustig MRM 2007

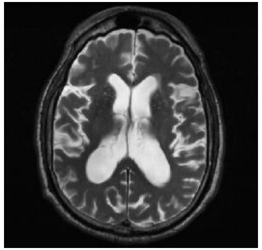
Learned unrolled iterations

f 

u_0 

input

$\longrightarrow GD_1 \; [DC \mid \mathcal{R}] \longrightarrow GD_t \; [DC \mid \mathcal{R}] \longrightarrow GD_T \; [DC \mid \mathcal{R}] \xrightarrow{u_T}$

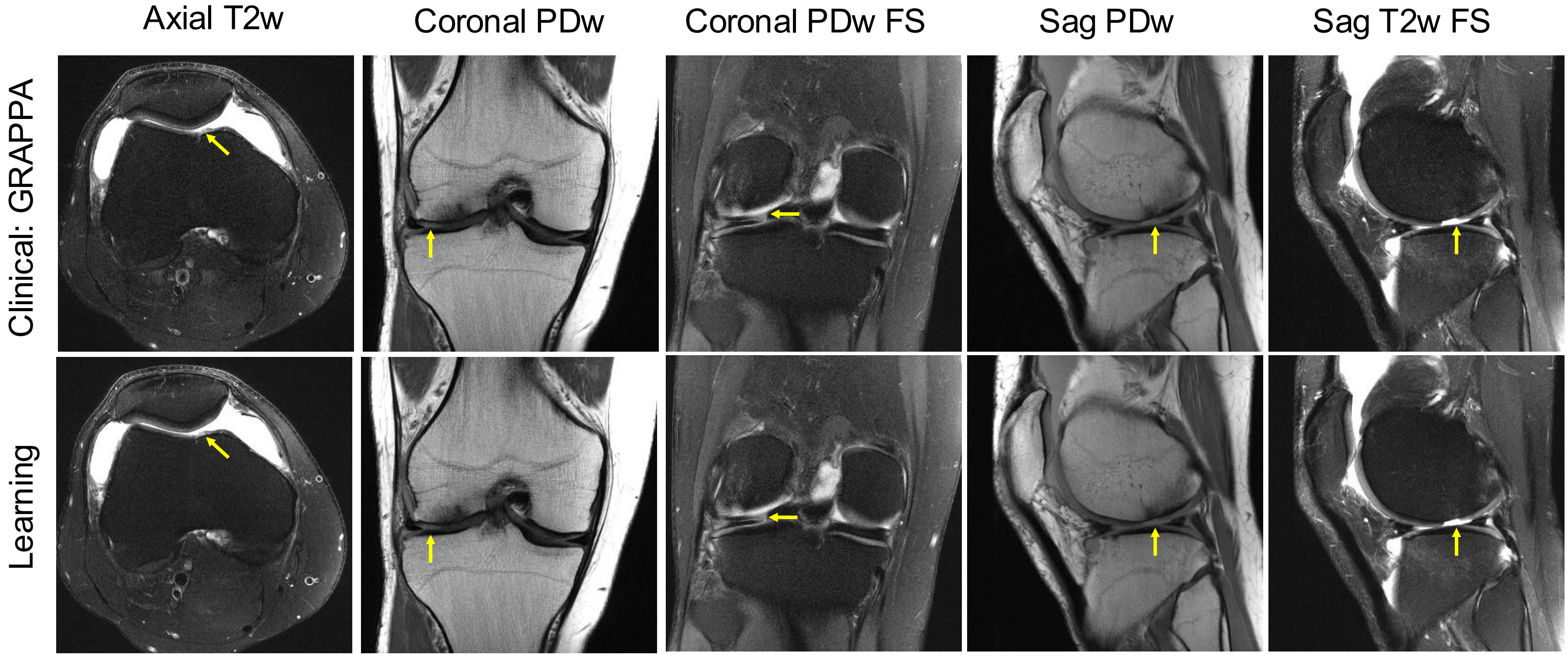


reconstruction

$$u_t = u_{t-1} - \frac{\partial}{\partial u}\left(\frac{\lambda}{2}||Au_{t-1} - f||_2^2 + \mathcal{R}(u_{t-1})\right)$$

Hammernik MRM 2018

Clinical study 170 patients



Protocol time: 5min 52s

Johnson Radiology 2023

Clinical study 170 patients

Anatomical area	Type	Readers Agree Conventional Only	Readers Agree Different Protocols
Cartilage abnorm	LFC	85.5%	84.4%
Cartilage abnorm	LTP	85.8%	84.9%
Cartilage abnorm	MFC	85.1%	83.6%
Cartilage abnorm	MTP	86.9%	85.9%
Cartilage abnorm	Patella	90.9%	89.4%
Cartilage abnorm	Trochlea	89.3%	88.5%
Ligament tears	ACL	98.0%	97.5%
Ligament tears	LCL	99.6%	99.5%
Ligament tears	MCL	98.2%	97.9%
Ligament tears	PCL	99.8%	99.5%
Ligament tears	Ext Mech	98.5%	98.6%
Meniscal tears	LM	92.3%	90.6%
Meniscal tears	MM	90.9%	90.8%
Marrow abnorm	LFC	96.1%	95.4%
Marrow abnorm	LTP	91.3%	89.8%
Marrow abnorm	MFC	93.0%	92.9%
Marrow abnorm	MTP	89.6%	89.2%
Marrow abnorm	Patella	95.3%	95.5%
Marrow abnorm	Trochlea	92.4%	91.8%

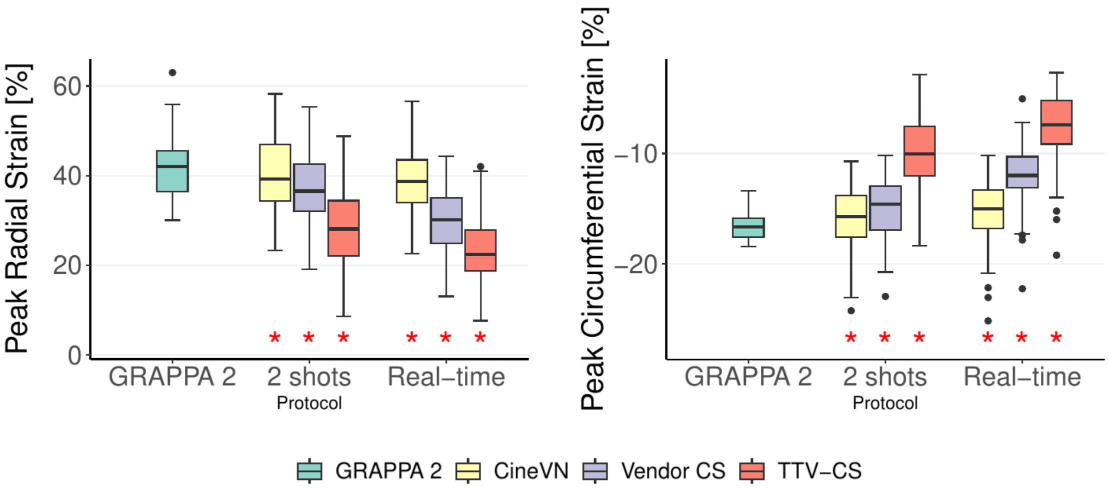
Data 170 patients: 94 female/76 male, age 18 to 76

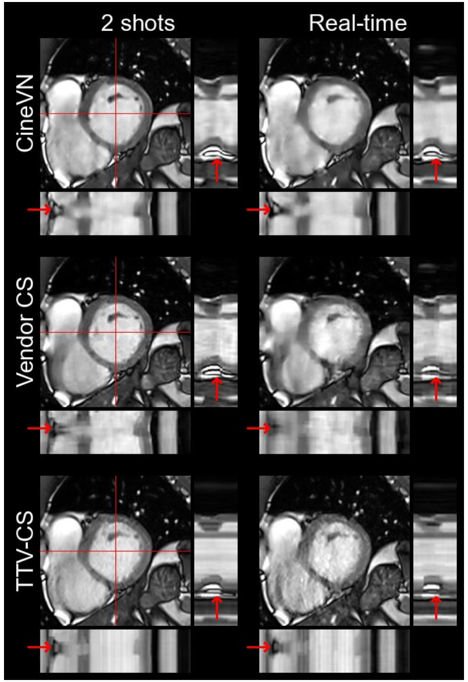
Johnson Radiology 2023

Validation beyond images: Cardiac function

Prospective evaluation, 18 Subjects

Strain, EF, volumes, …

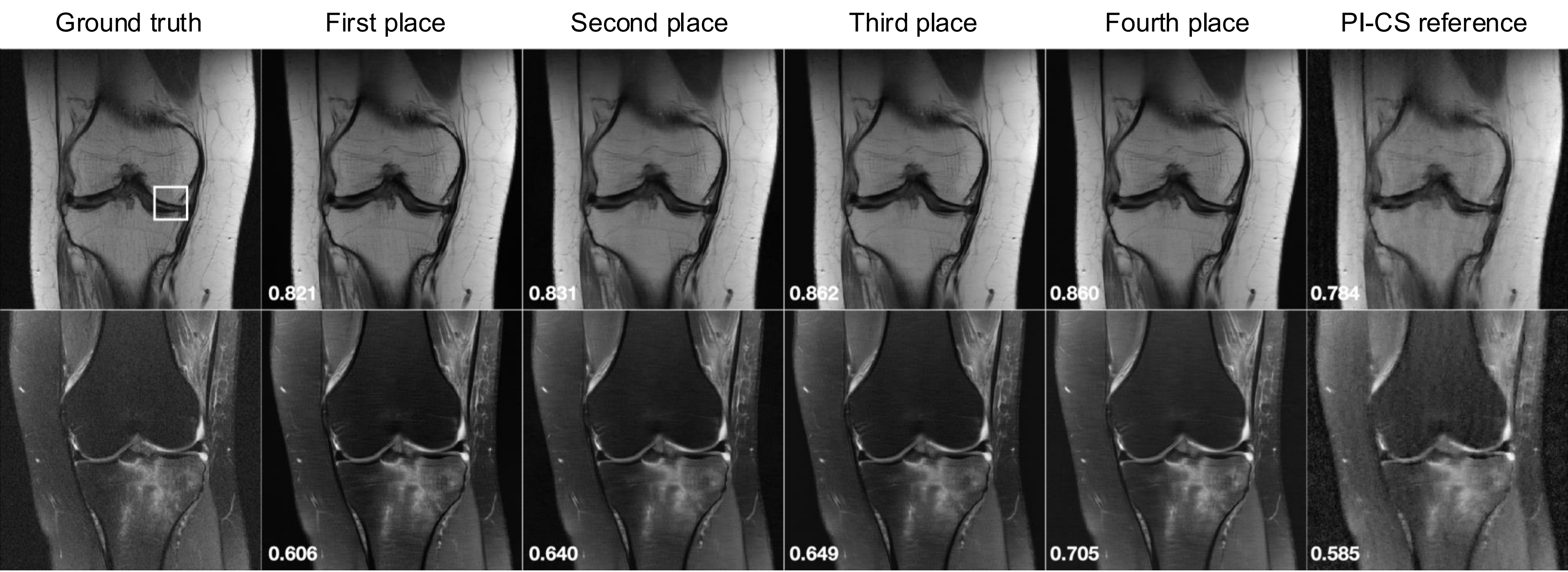




1.6 mm^2 isotropic spatial resolution
<46ms temporal resolution

Vornehm MRM 2025

fastMRI 2019 R=4 results



Knoll MRM 2020

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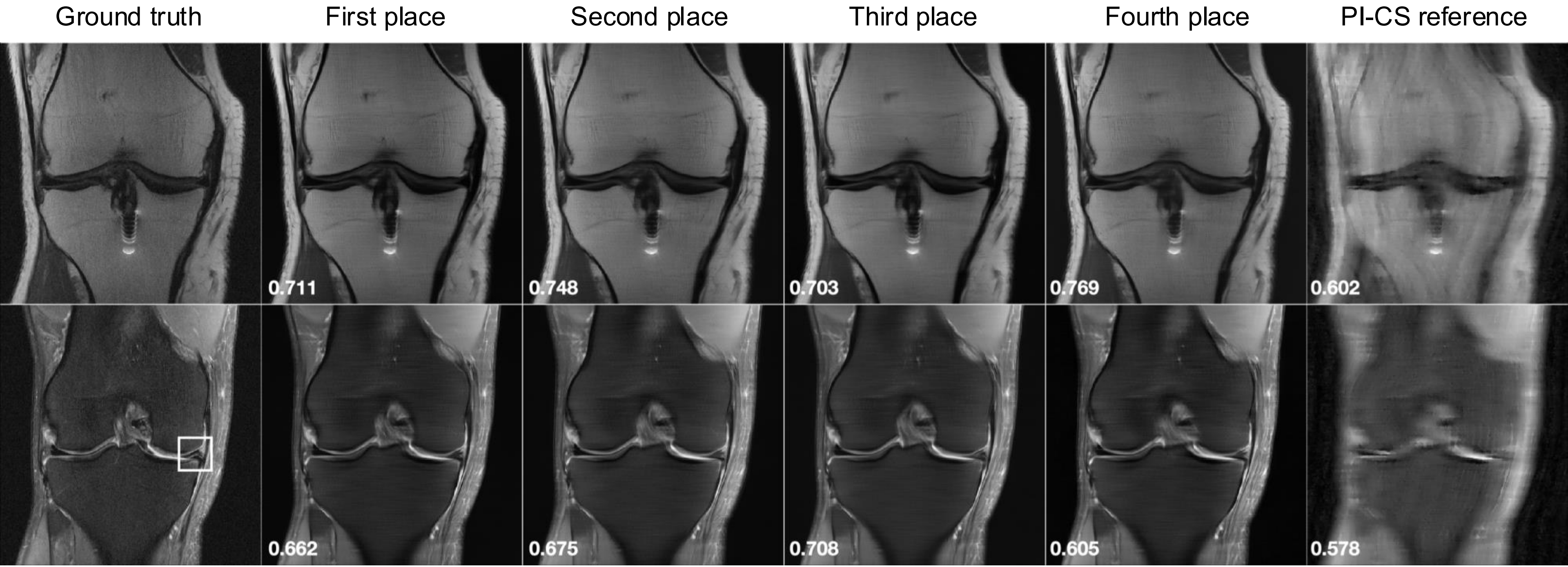
Artificial Intelligence Research

fastMRI 2019 R=8 results



Knoll MRM 2020

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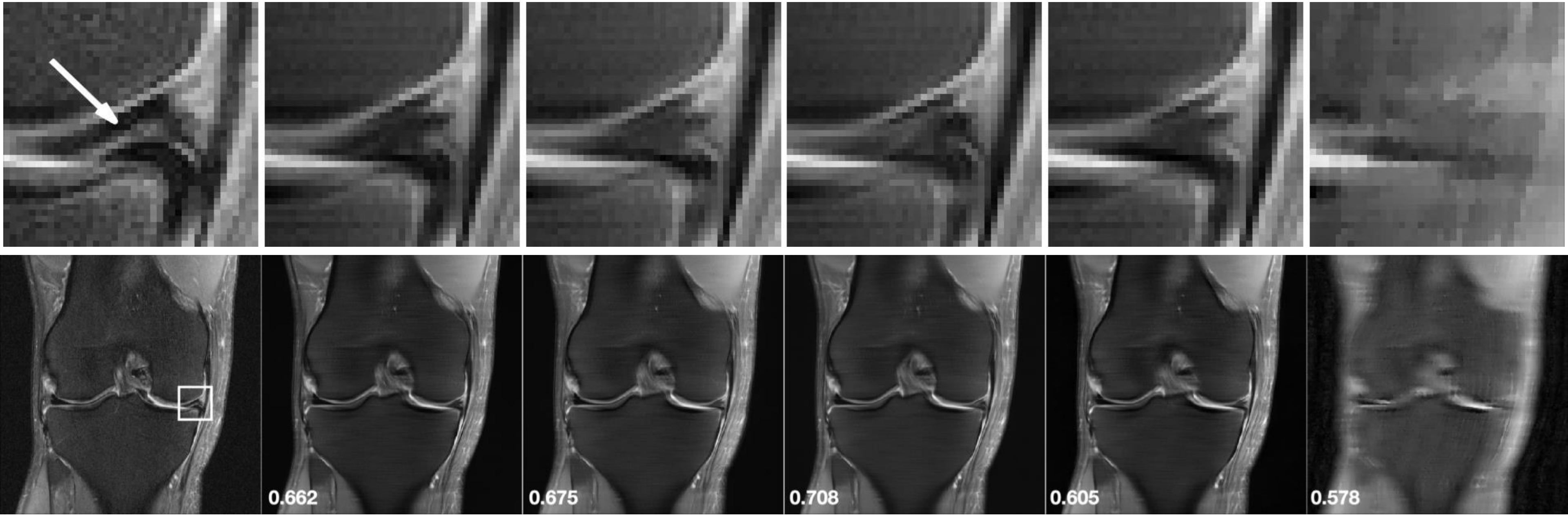
R=8 results: Pathology

Ground truth | First place | Second place | Third place | Fourth place | PI-CS reference



Knoll MRM 2020

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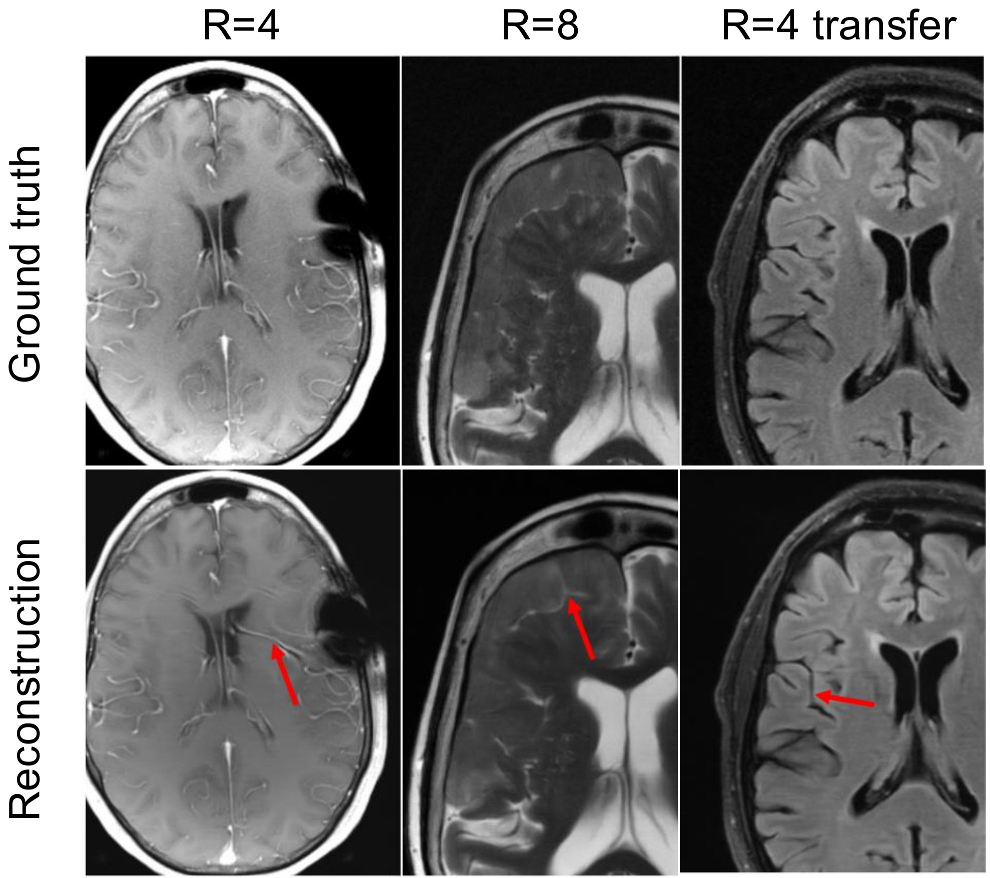
2020 fastMRI challenge results: hallucinations



Muckley TMI 2021

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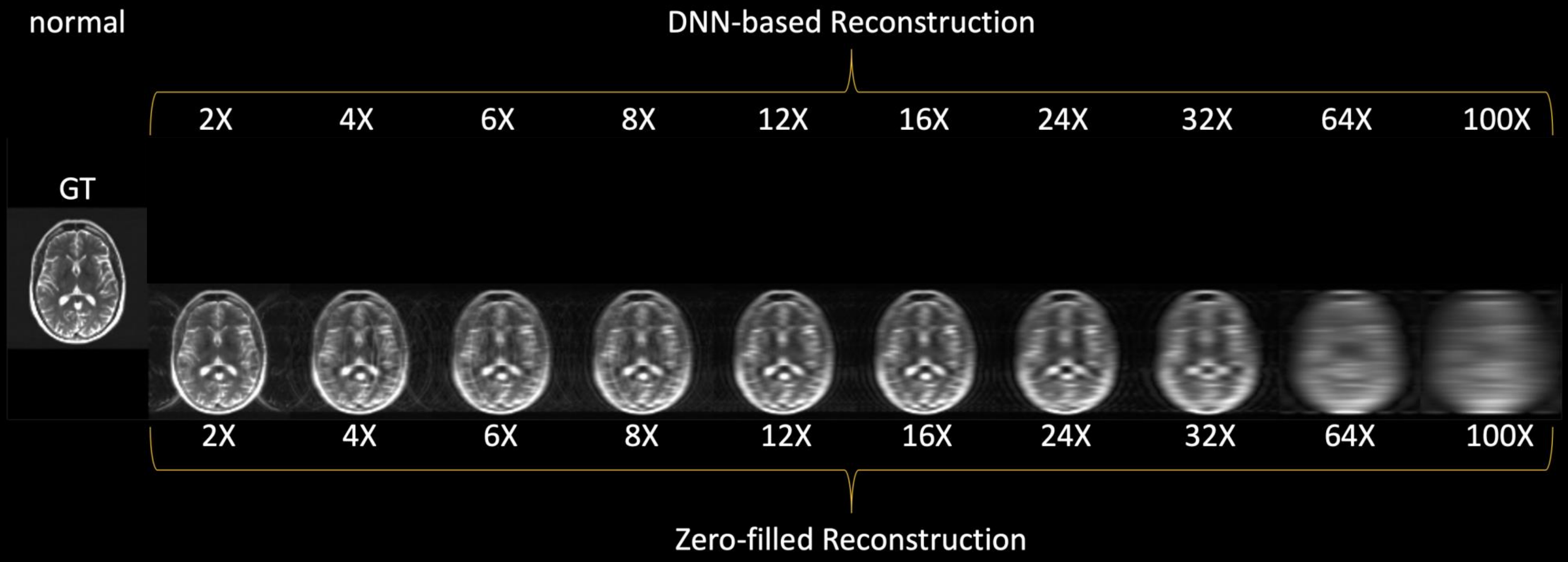
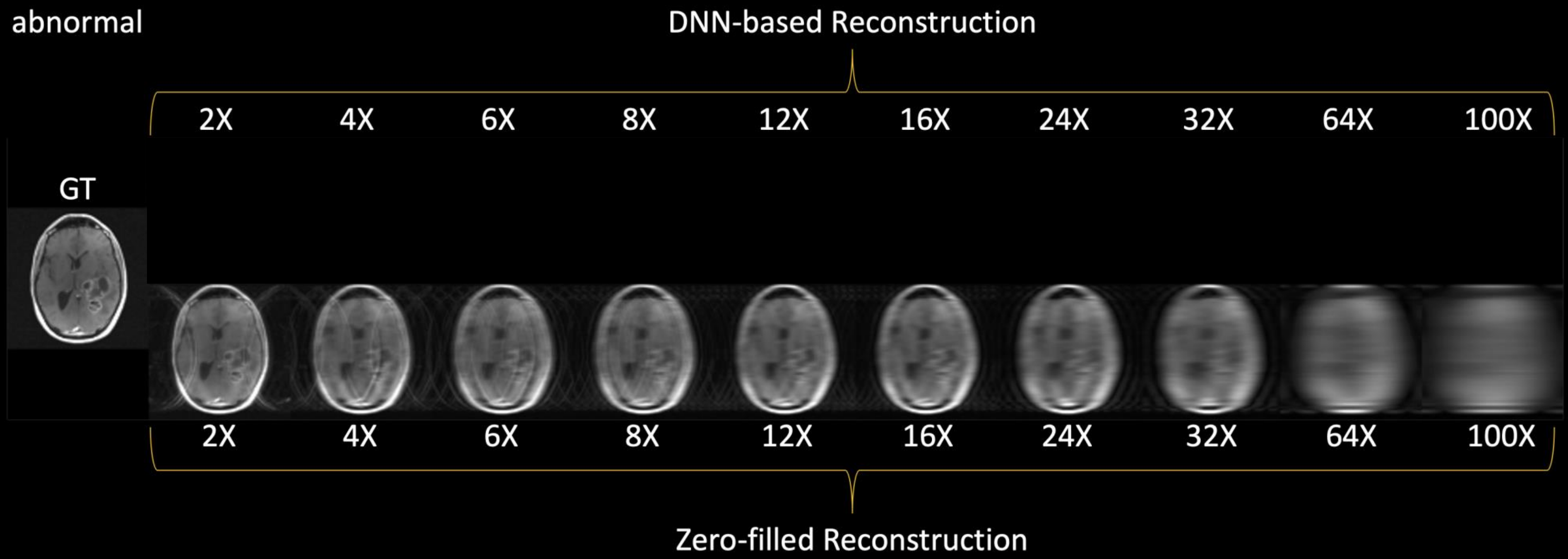
Performance at progressive acceleration



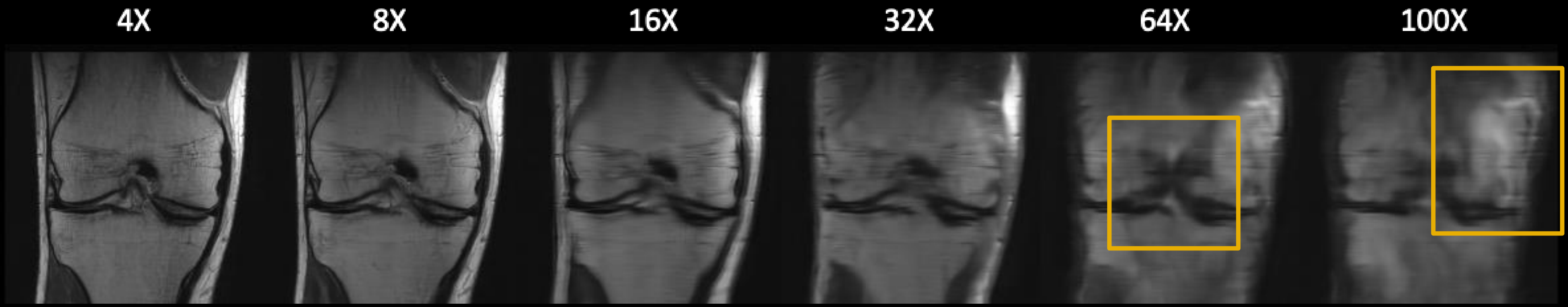
Radmanesh Radiology AI 2022

Performance at progressive acceleration



Radmanesh Radiology AI 2022

Out of domain data



Radmanesh Radiology AI 2022

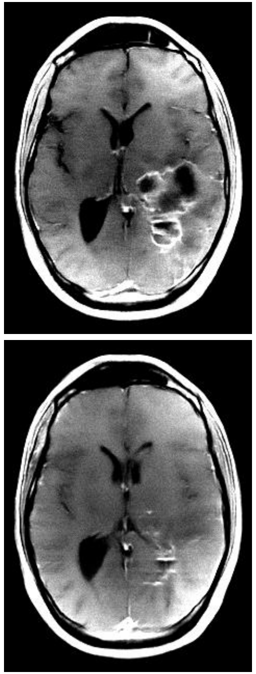
Roadmap

When does DL recon go wrong?

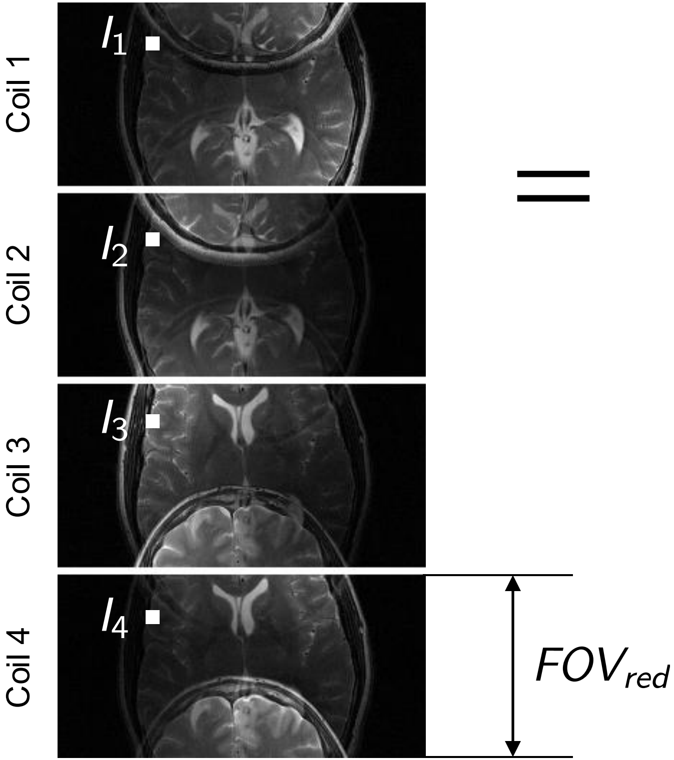
How does it go wrong?

What is the reason it goes wrong?

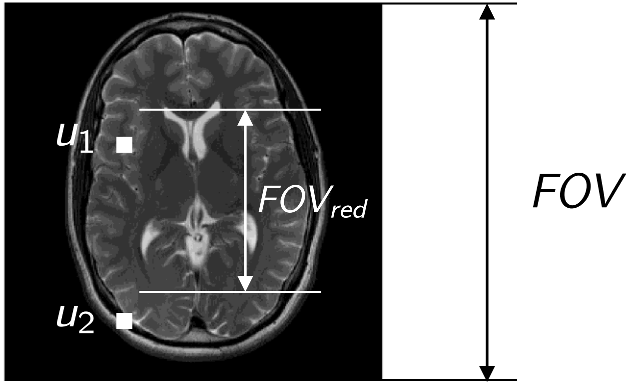
Can you recognize when it goes wrong?



SENSE R=2



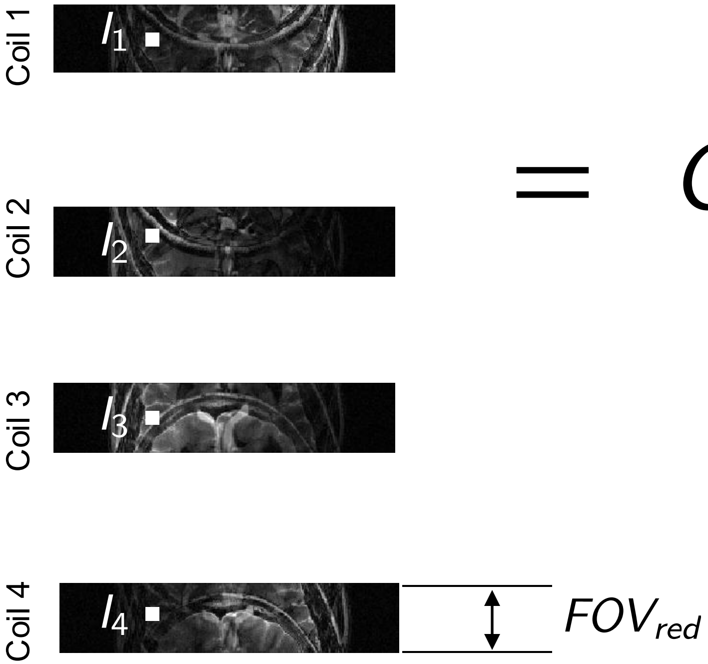
$$= C_{ij} \cdot$$



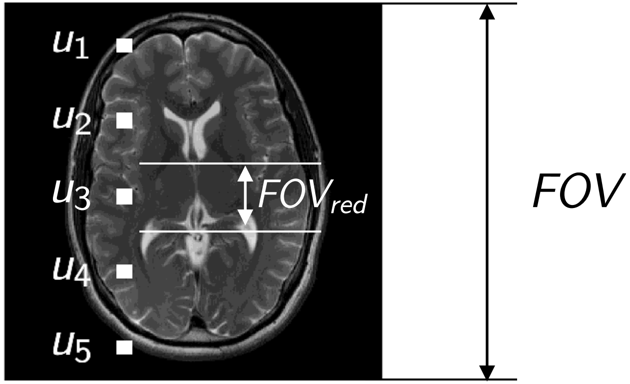
$$\begin{pmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \\ C_{31} & C_{32} \\ C_{41} & C_{42} \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}$$

Pruessmann MRM 1999

SENSE R=5



$$= \quad C_{ij} \quad \cdot$$



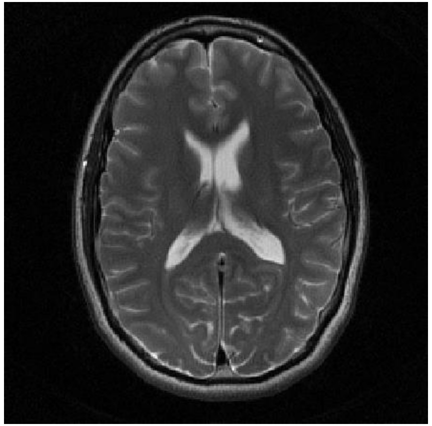
$$\begin{pmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} & C_{15} \\ C_{21} & C_{22} & C_{23} & C_{24} & C_{25} \\ C_{31} & C_{32} & C_{33} & C_{34} & C_{35} \\ C_{41} & C_{42} & C_{43} & C_{44} & C_{45} \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{pmatrix}$$

Pruessmann MRM 1999

Constrained reconstruction

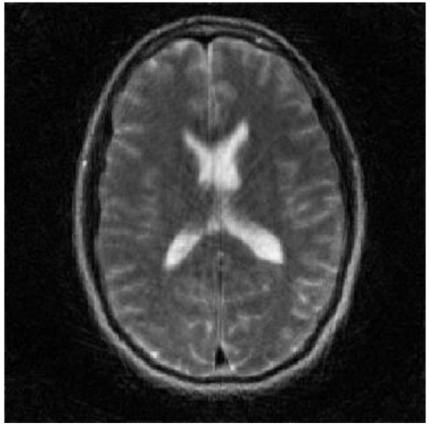
$$\min_u \frac{\lambda}{2}||Au - f||_2^2 + \mathcal{R}(u)$$

R≈3, $\lambda = 10^{-4}$



Knoll MRM 2011

R≈10, $\lambda = 10^{-4}$

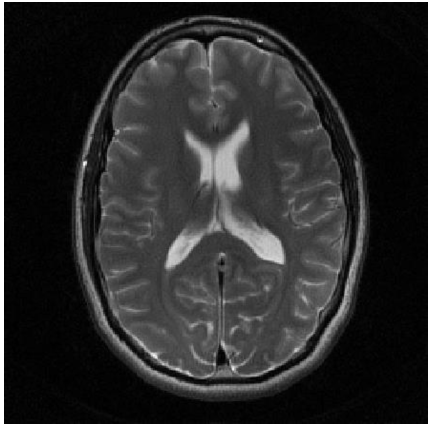


Weak prior

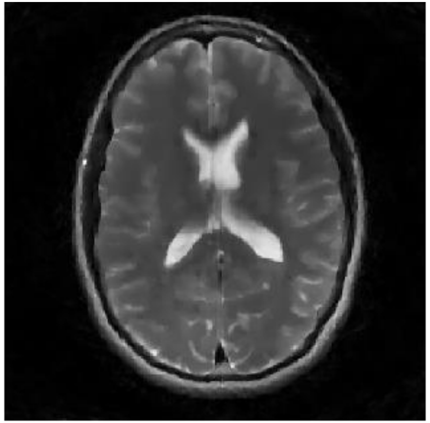
Constrained reconstruction

$$\min_u \frac{\lambda}{2}||Au - f||_2^2 + \mathcal{R}(u)$$

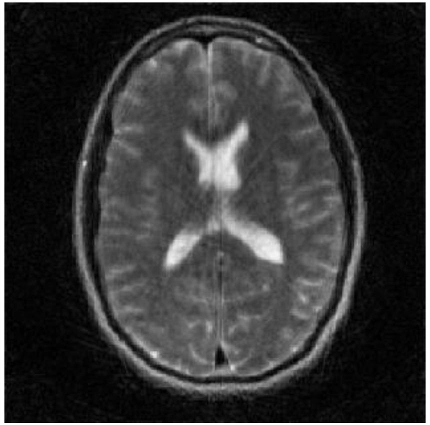
R≈3, $\lambda = 10^{-4}$



R≈10, $\lambda = 10^{-8}$



R≈10, $\lambda = 10^{-4}$



Strong prior ⟷ Weak prior

Knoll MRM 2011

Spaceflight: Let’s add redundancy

NASA TECH BRIEF
Manned Spacecraft Center

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Dual Redundant Core Memory Systems

PREFERRED RELIABILITY PRACTICES

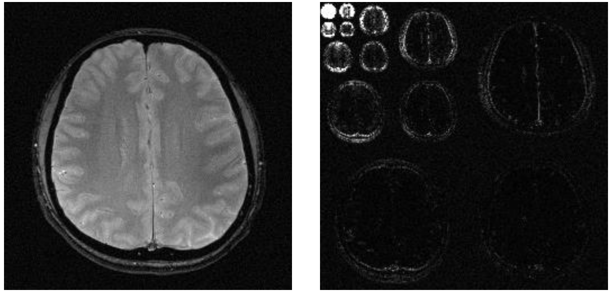
REDUNDANCY IN CRITICAL MECHANICAL SYSTEMS

Practice:

The careful use of redundancy in Critical Kennedy Space Center (KSC) Ground Support Equipment (GSE) Mechanical Systems ensures reliable operation.

NASA Tech-Brief 19720000261 1972
NASA practice No. GSE-3003 1995

Accelerated imaging: Let’s get rid of redundancy



$$\min_u \frac{\lambda}{2}||Au - f||_2^2 + \mathcal{R}(u)$$

Lustig MRM 2007

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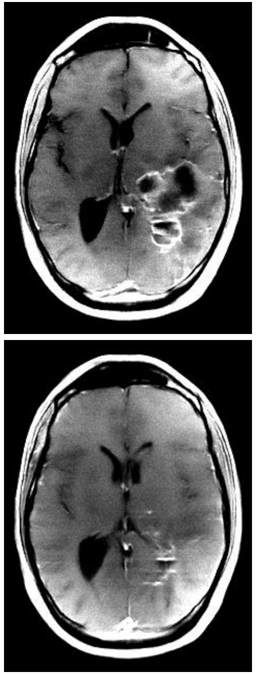
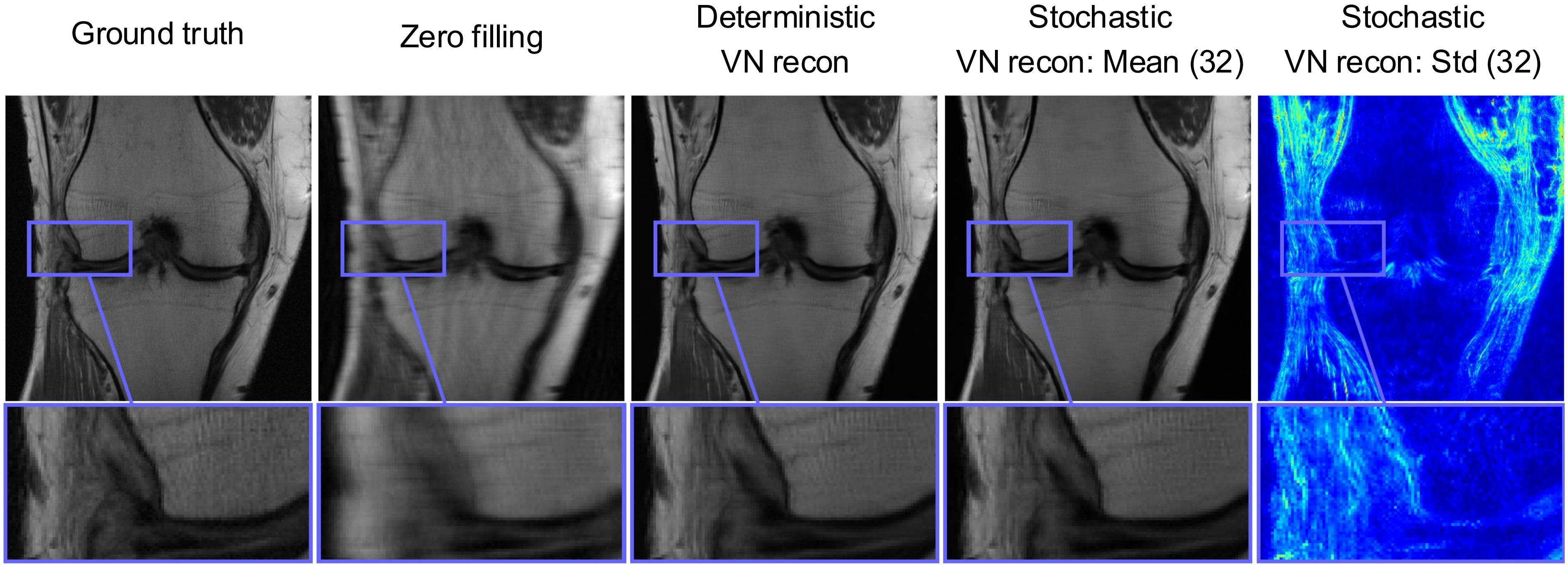
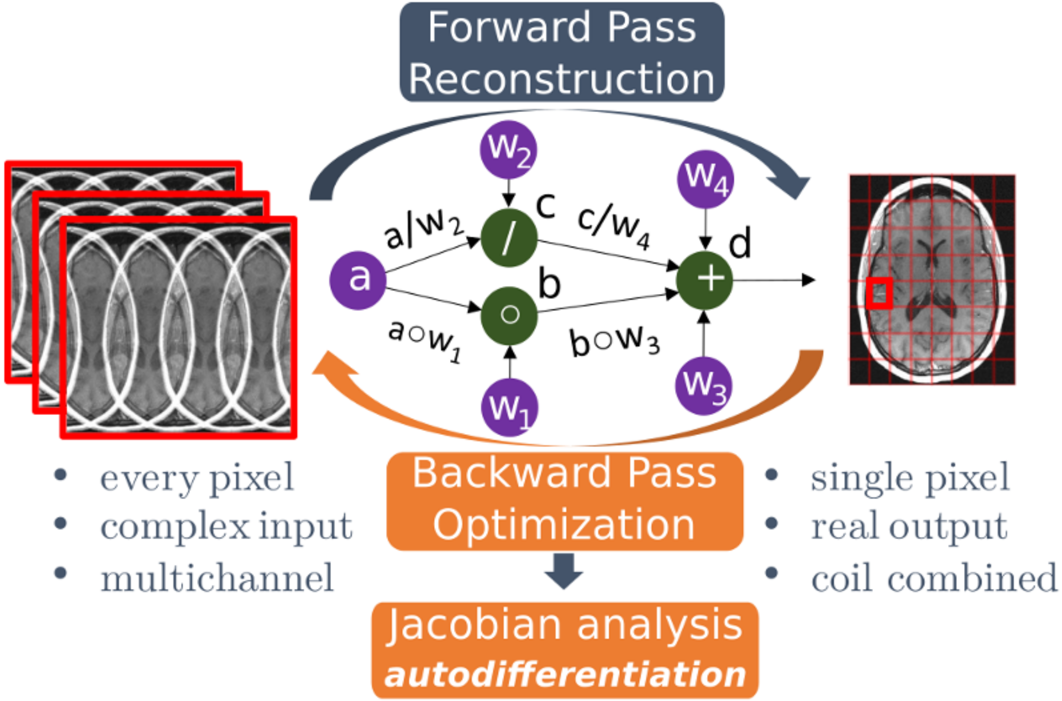


Bayesian Uncertainty Estimation



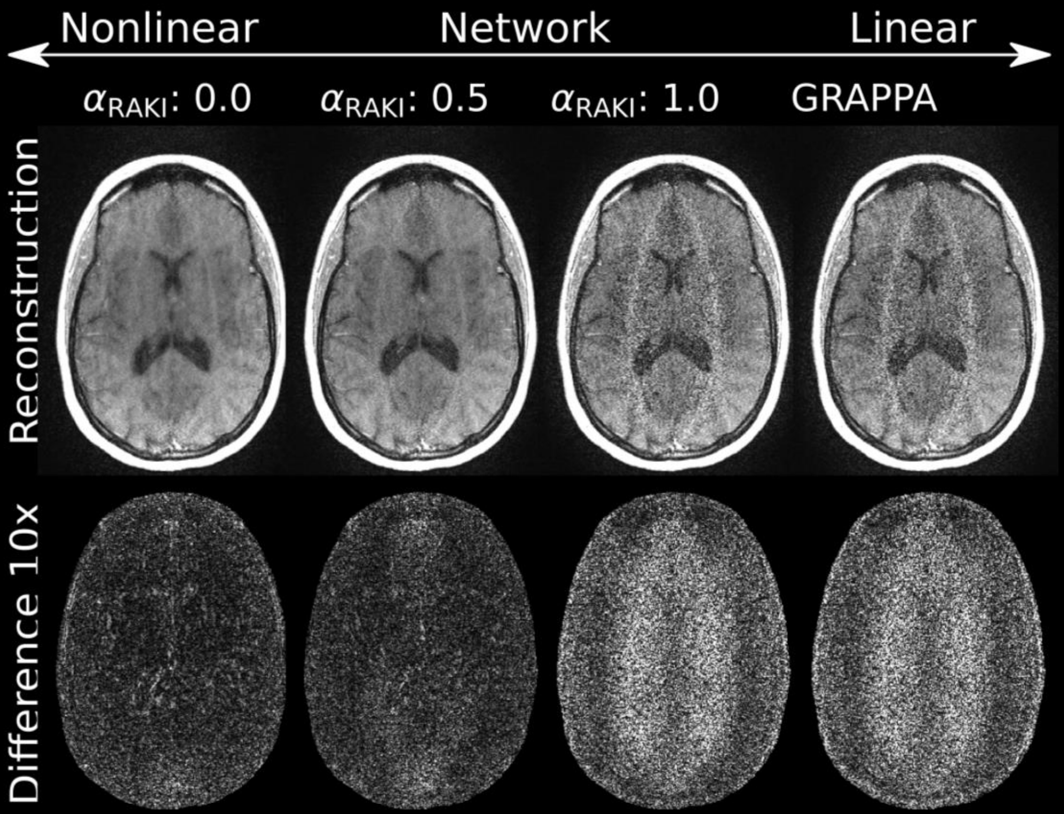
Narnhofer IEEE TMI 2021

Pixel-level variance analysis using backpropagation



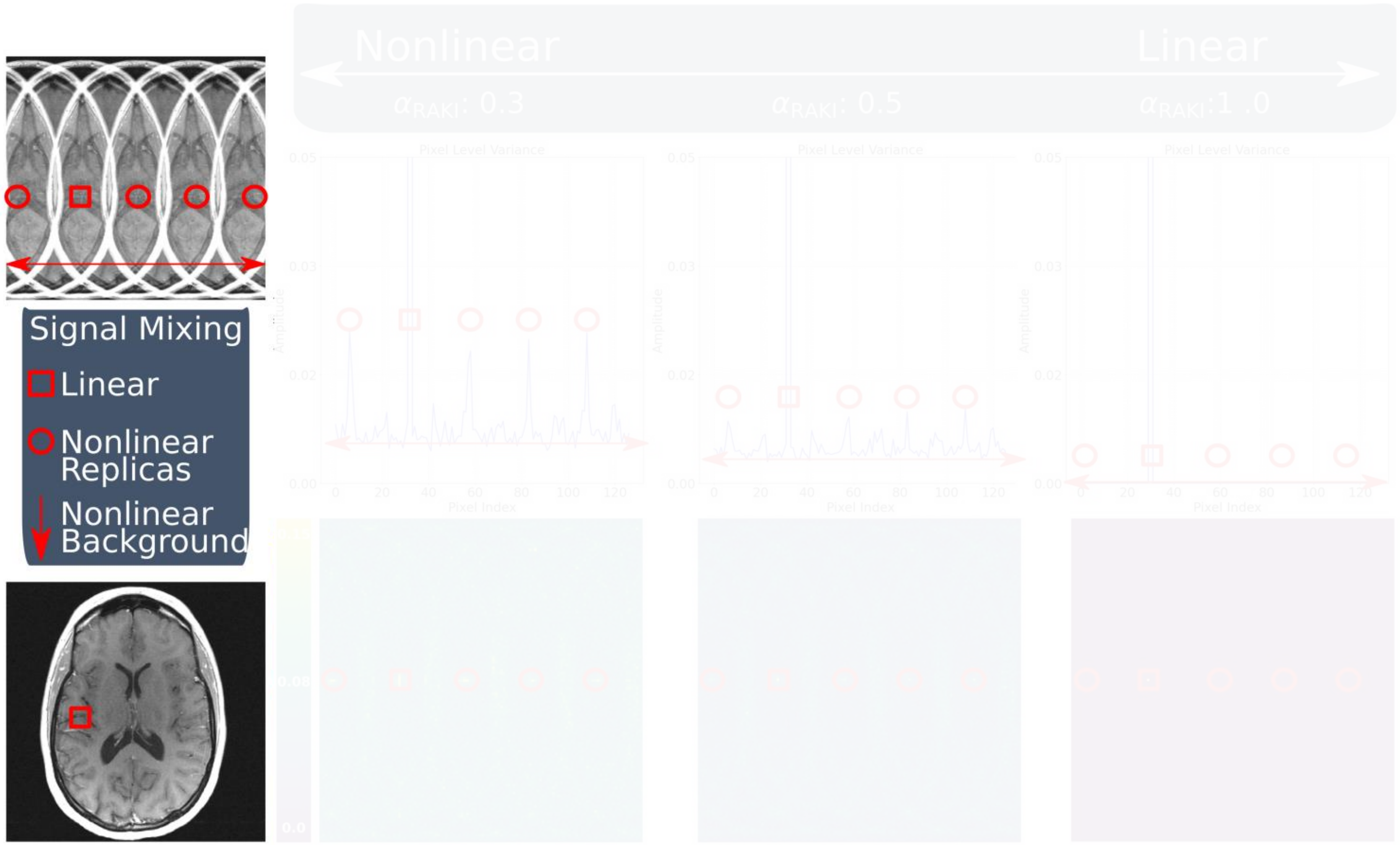
Wang ISMRM 2022
Homolya arXiv 2025

DL: Influence of degree of nonlinearity (RAKI)



Akcakaya MRM 2019
Homolya arXiv 2025

Network gradient flow analysis using backward pass



Homolya arXiv 2025

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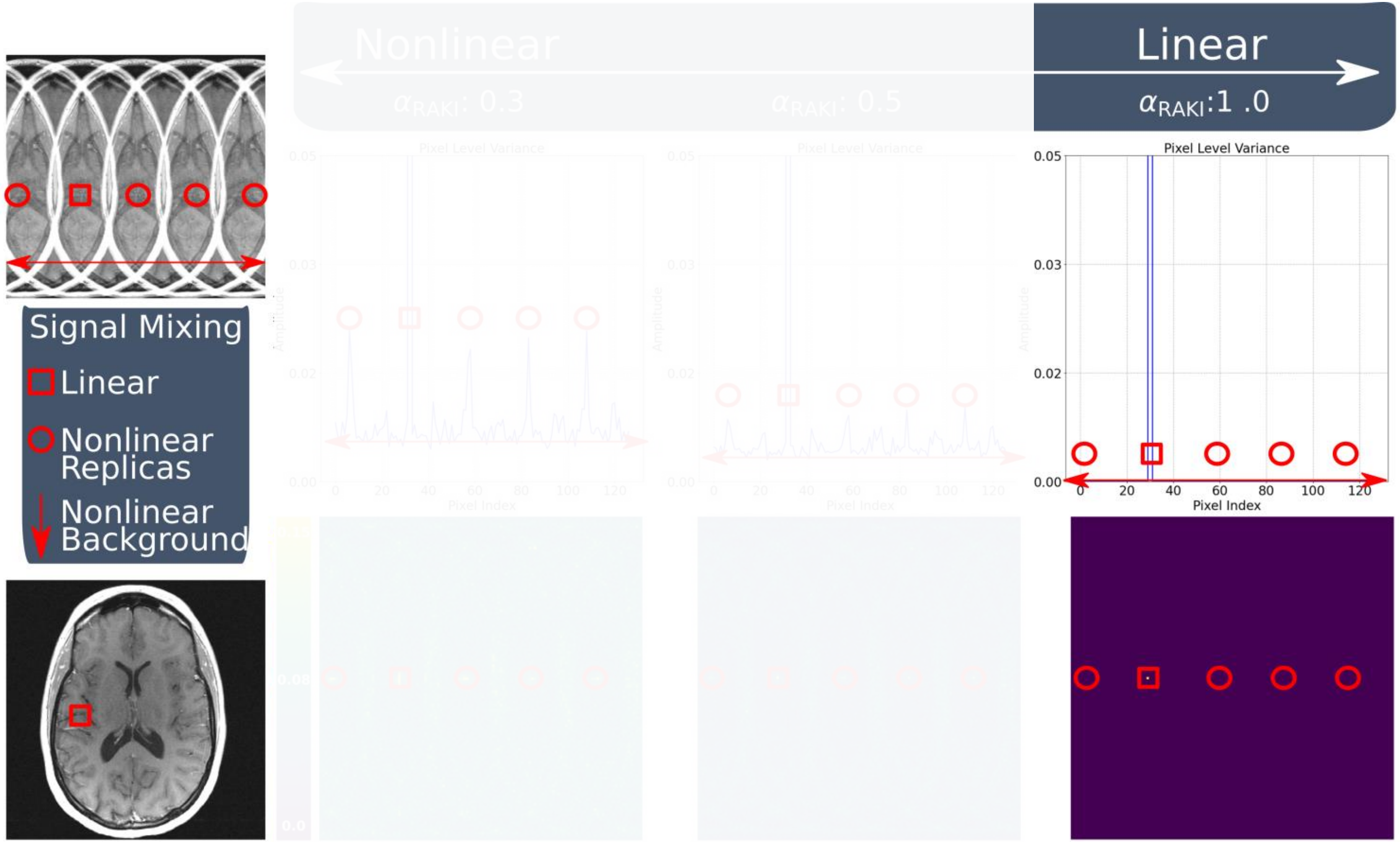

Homolya arXiv 2025

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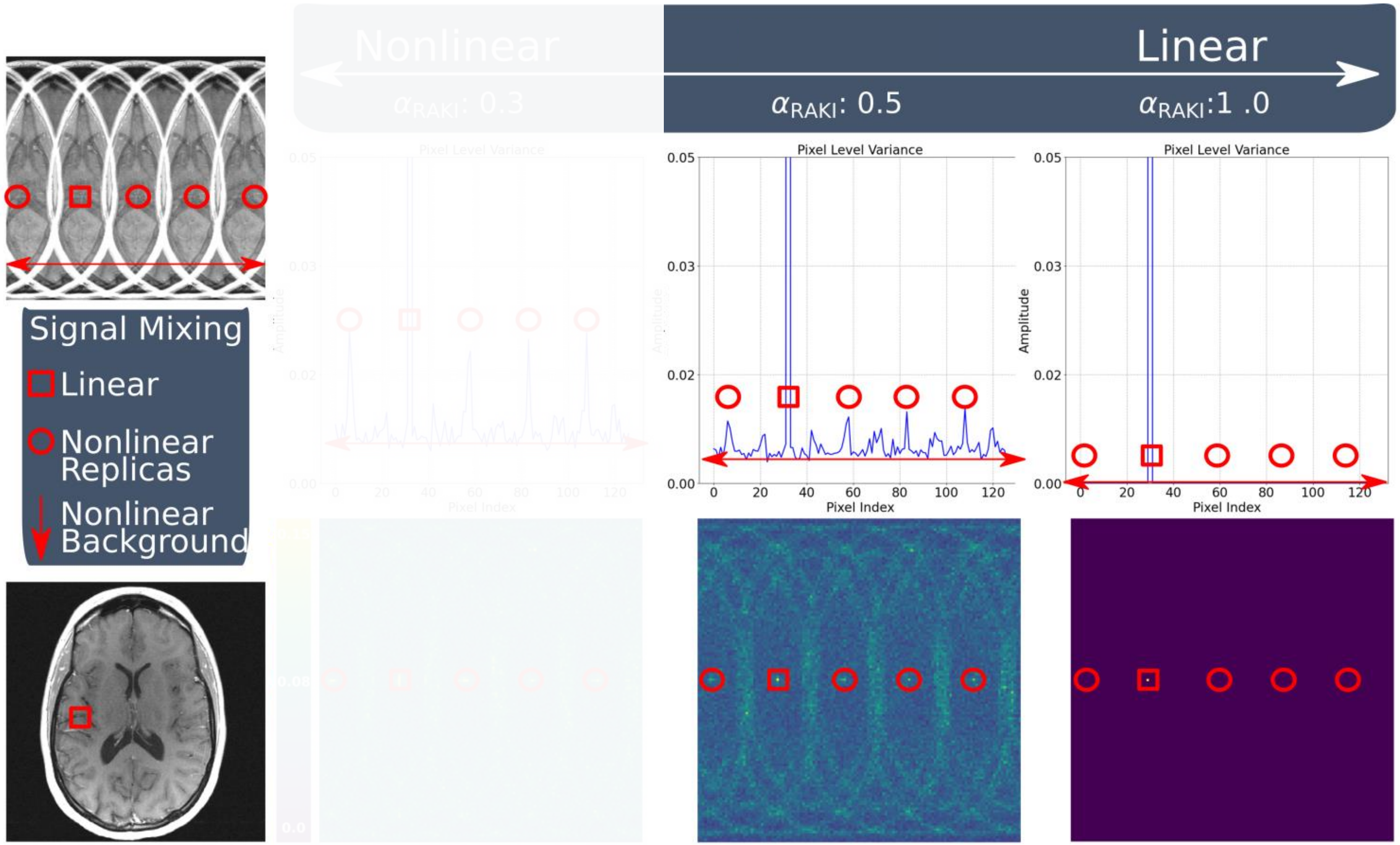

Homolya arXiv 2025

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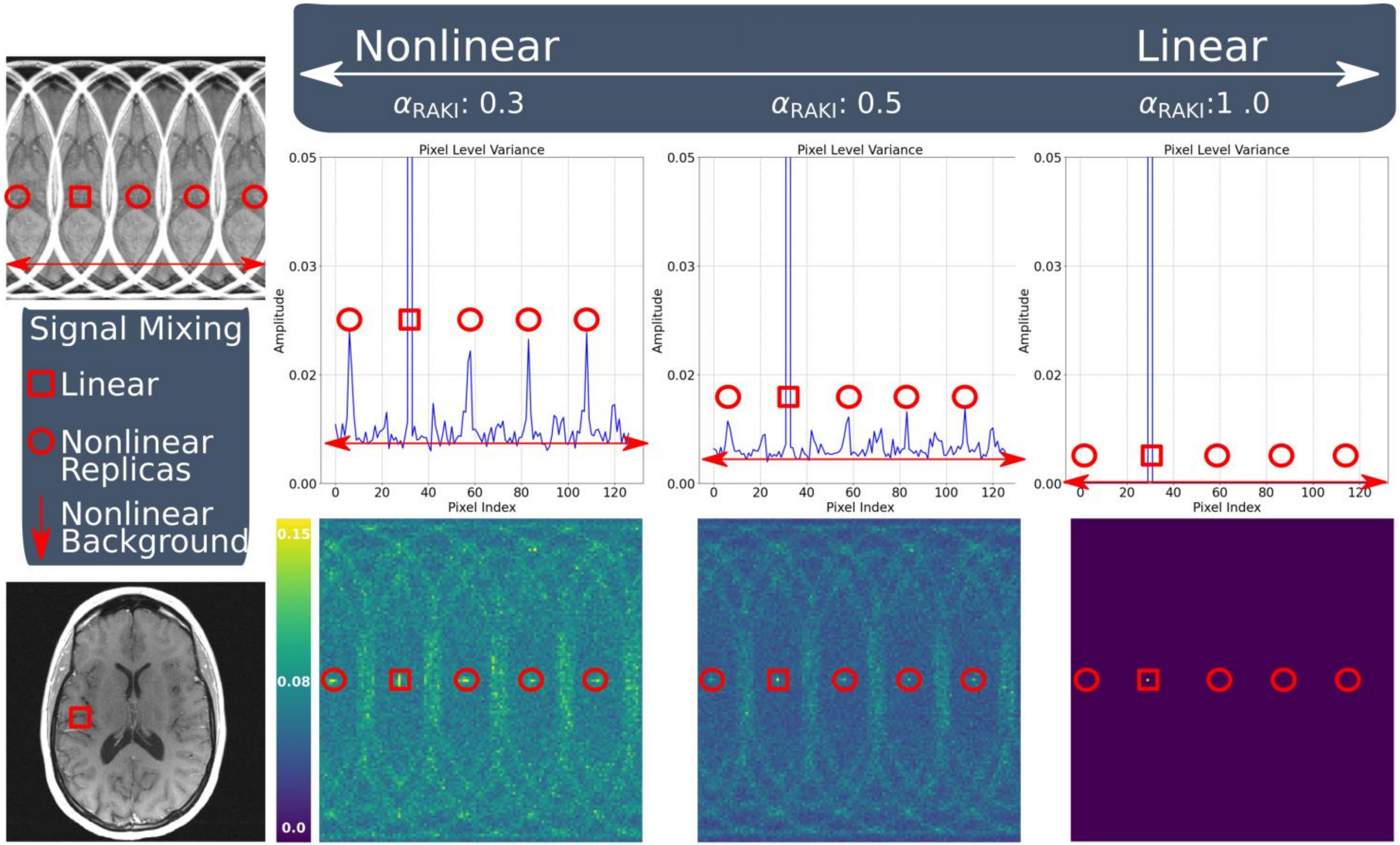
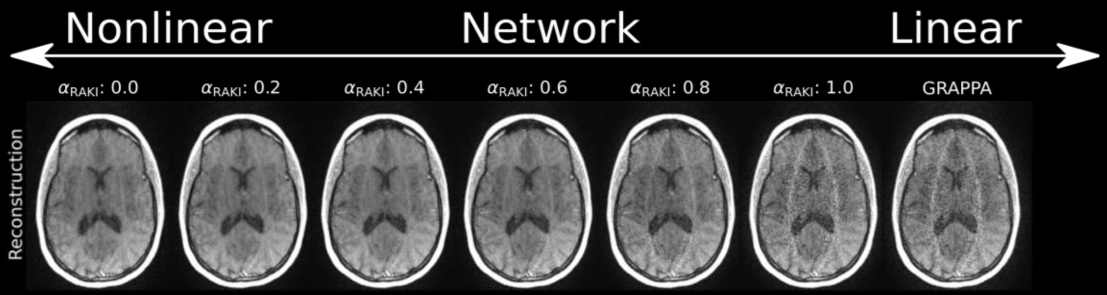
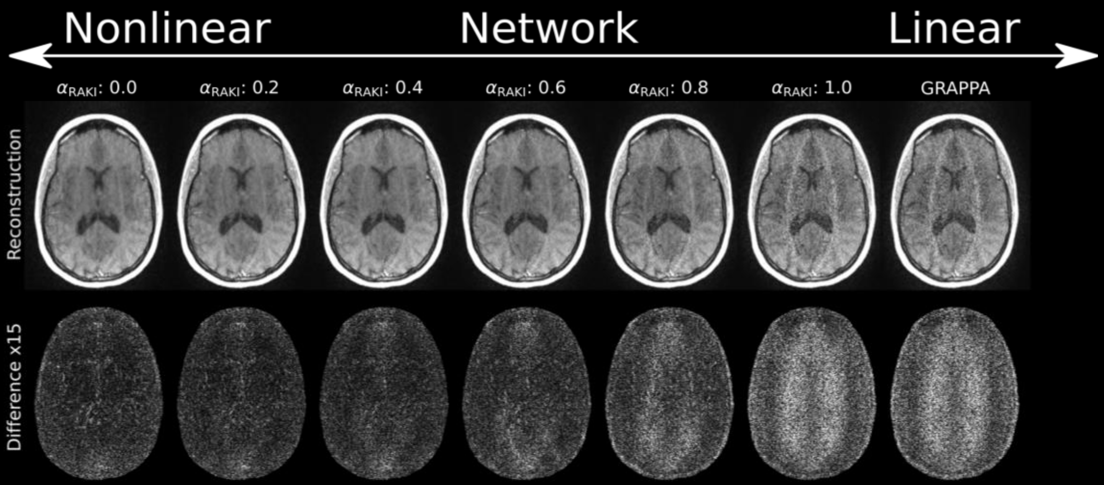


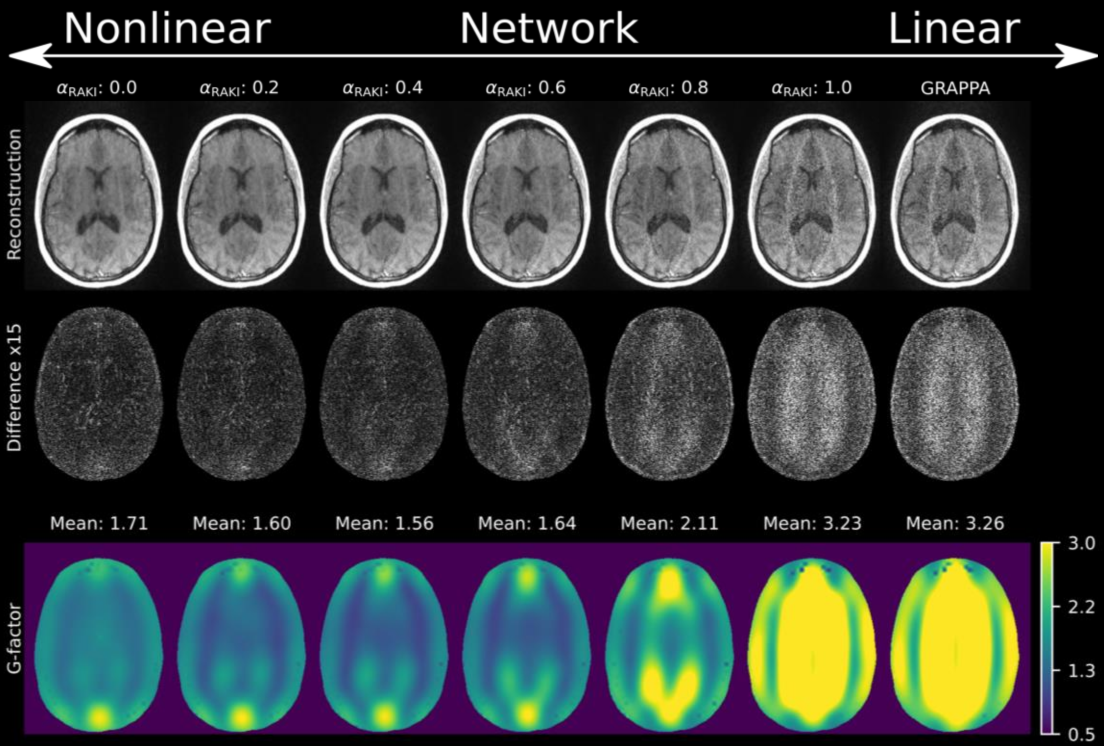
Homolya arXiv 2025



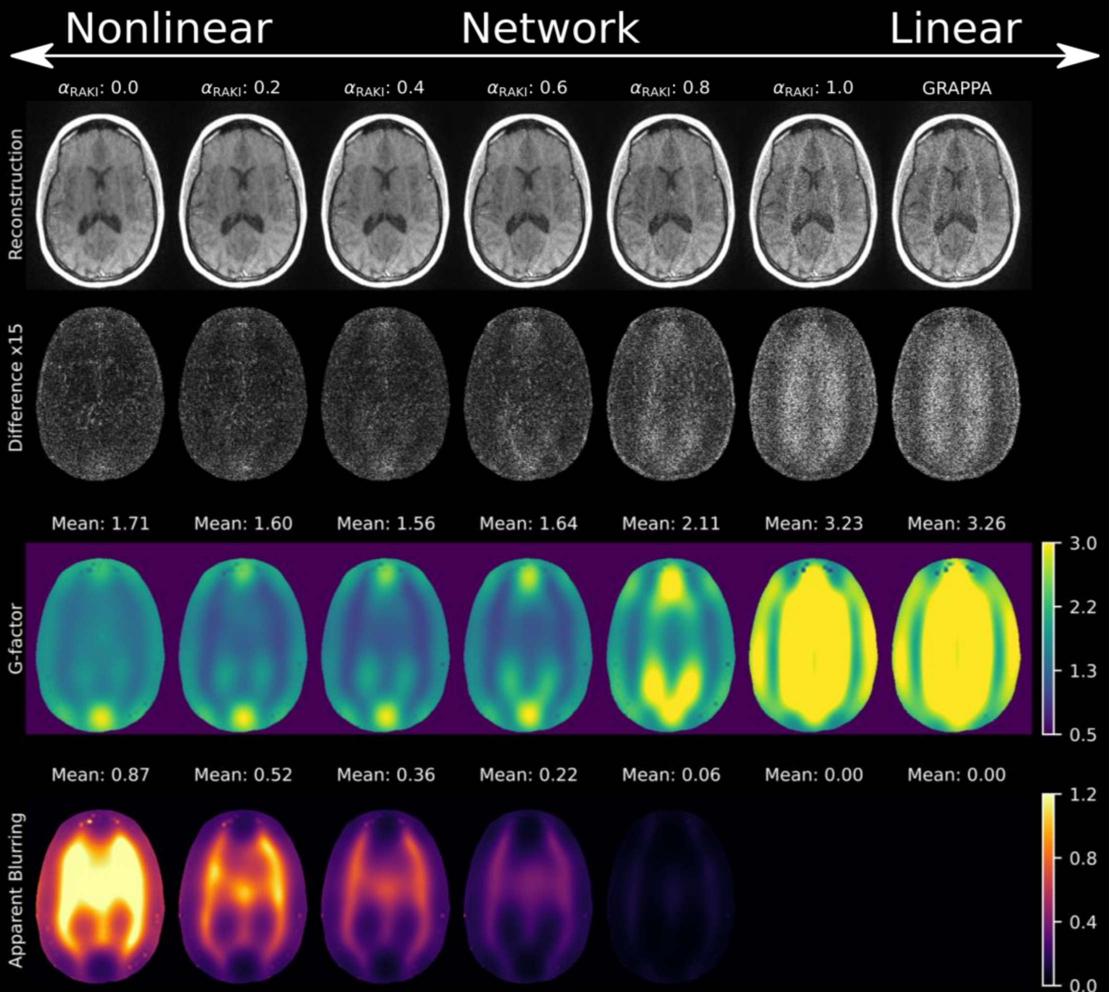
Homolya arXiv 2025



Homolya arXiv 2025

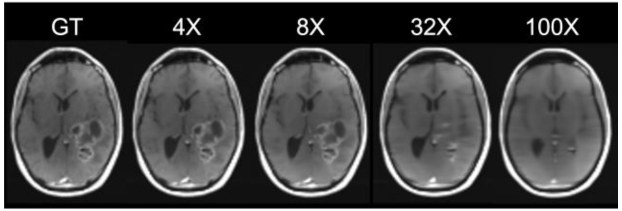


Homolya arXiv 2025

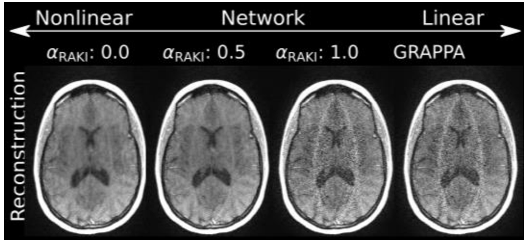


Homolya arXiv 2025

When does DL recon go wrong?

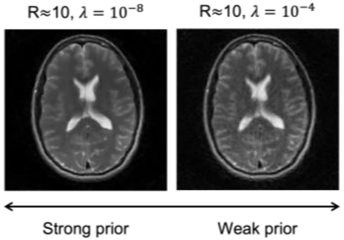


How does it go wrong?



What is the reason it goes wrong?

$$\begin{pmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} & C_{15} \\ C_{21} & C_{22} & C_{23} & C_{24} & C_{25} \\ C_{31} & C_{32} & C_{33} & C_{34} & C_{35} \\ C_{41} & C_{42} & C_{43} & C_{44} & C_{45} \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{pmatrix}$$



Can you recognize when it goes wrong?