DE LA RECHERCHE À L'INDUSTRIE

Apprentissage profond pour la reconstruction d'images IRM acquises sous forme comprimée

L'imagerie médicale à l'heure de l'IA : défis et opportunités

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23 avril 2019
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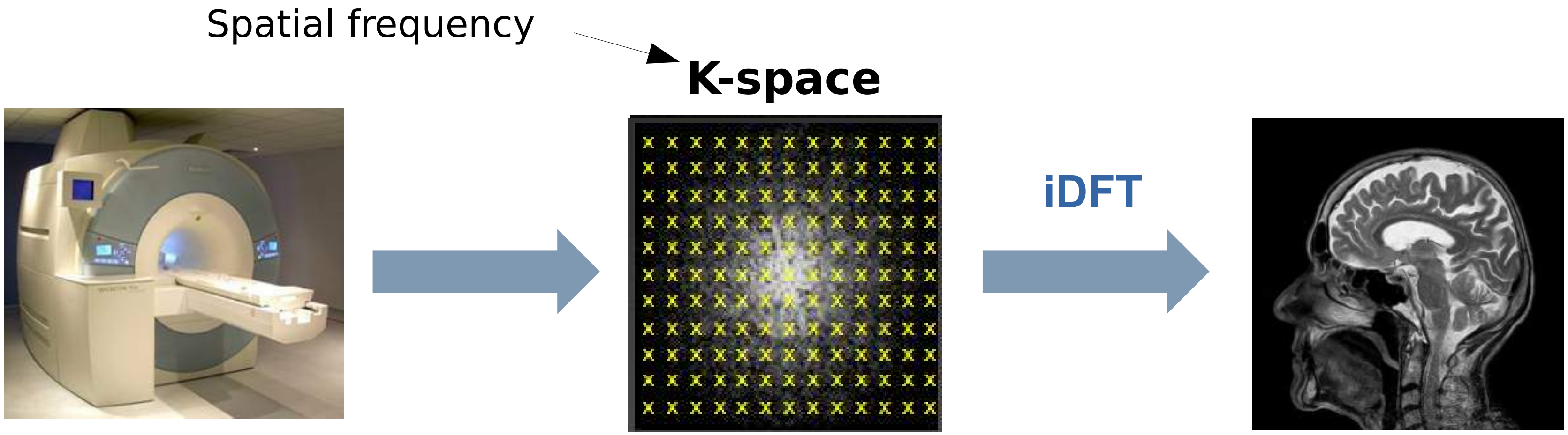
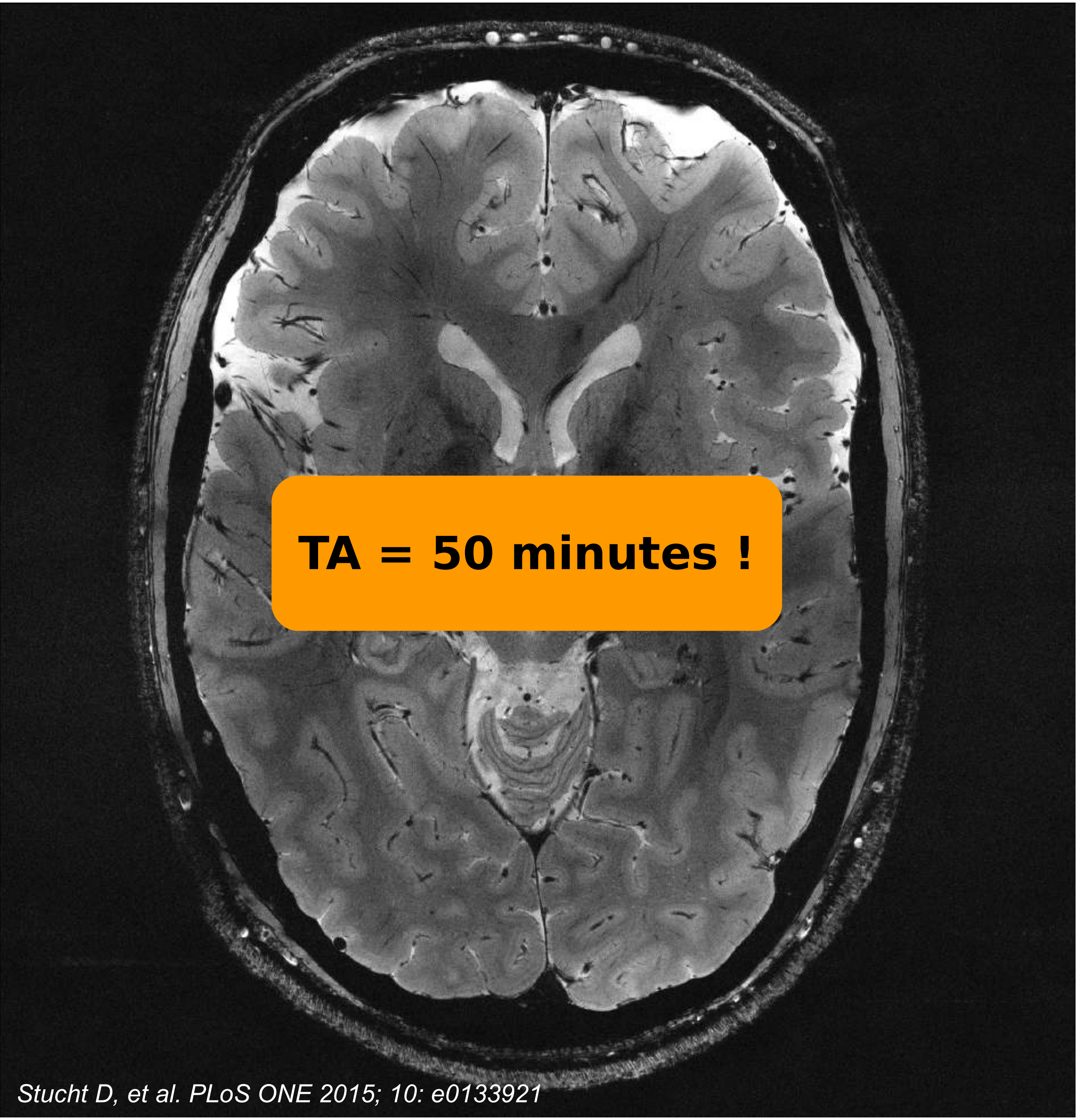
Sampling in MRI



Perfect reconstruction of an object would require measurement of *all* locations in k-space (infinite!)

Data is acquired **point-by-point** in k-space (sampling) along **curves** parametrized by **time**.

Long acquisition time



Stucht D, et al. PLoS ONE 2015; 10: e0133921

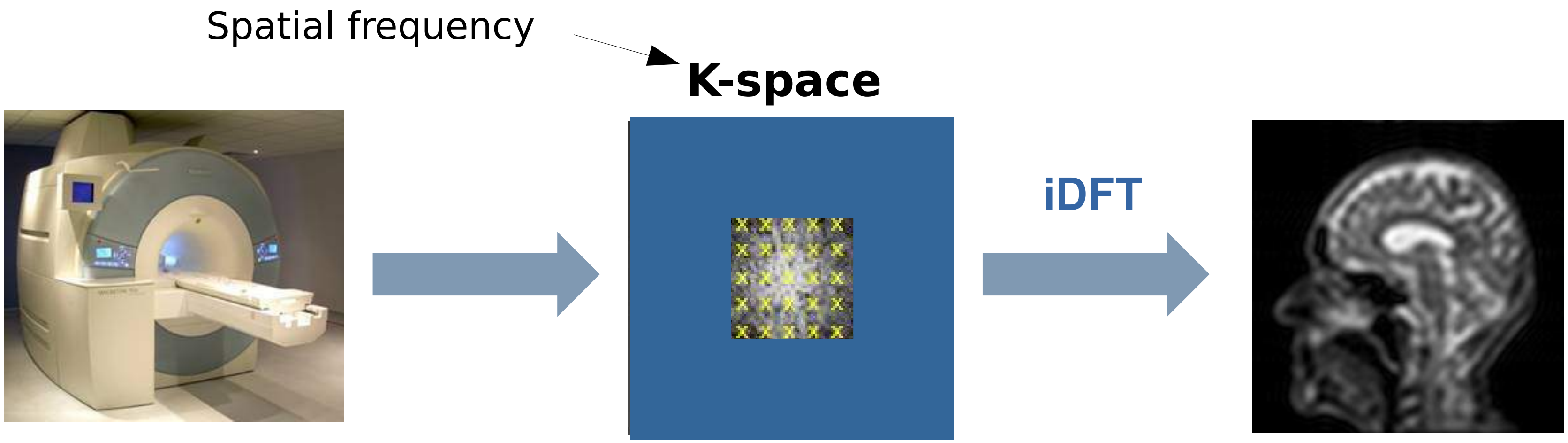
2D T2*w axial whole-brain

120x120x600 µm^3

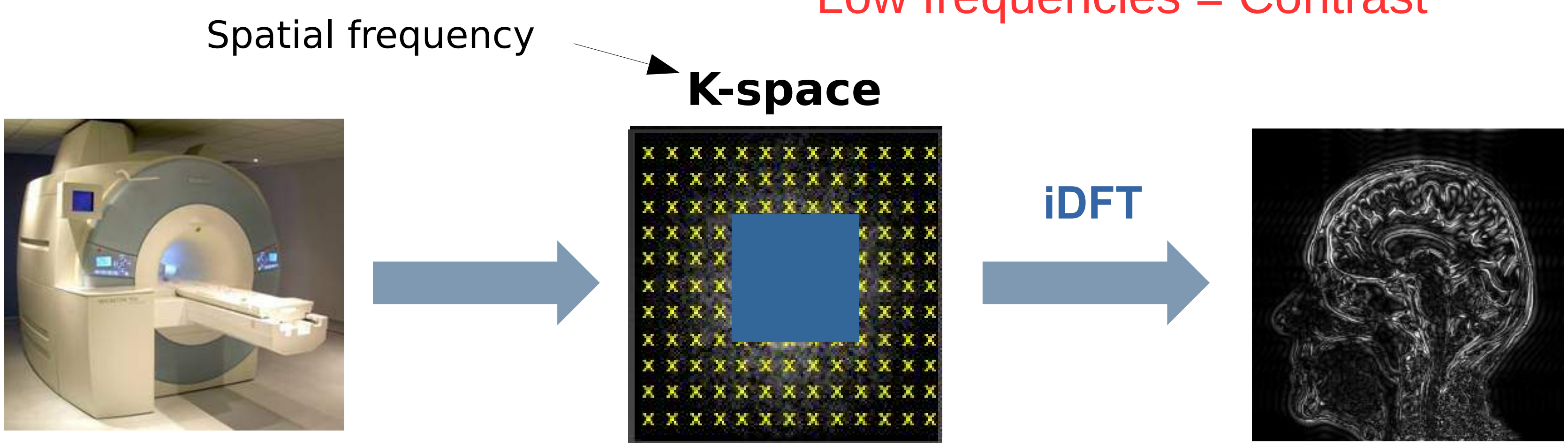
NEX=2

How can we speed up the acquisition?

Under-sampling in MRI



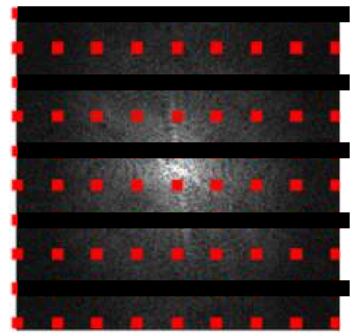
Low frequencies = Contrast



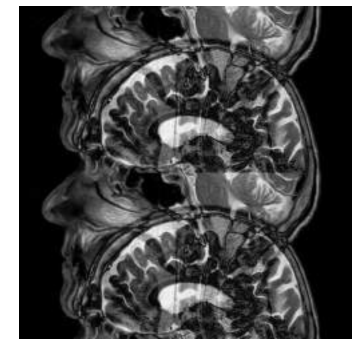
High frequencies = boundaries/edges

Under-sampling in MRI

K-space



iDFT

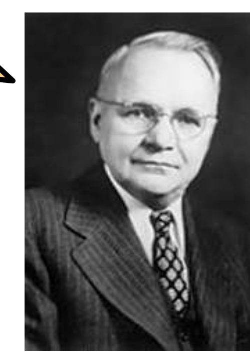


Nyquist-Shannon theory

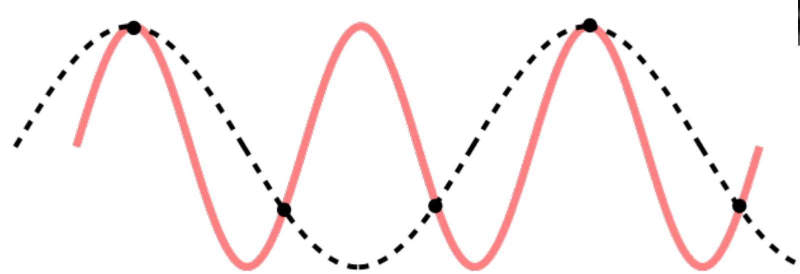
$\uparrow$ resolution $\Rightarrow$ $\uparrow$ #samples

Long acquisition times

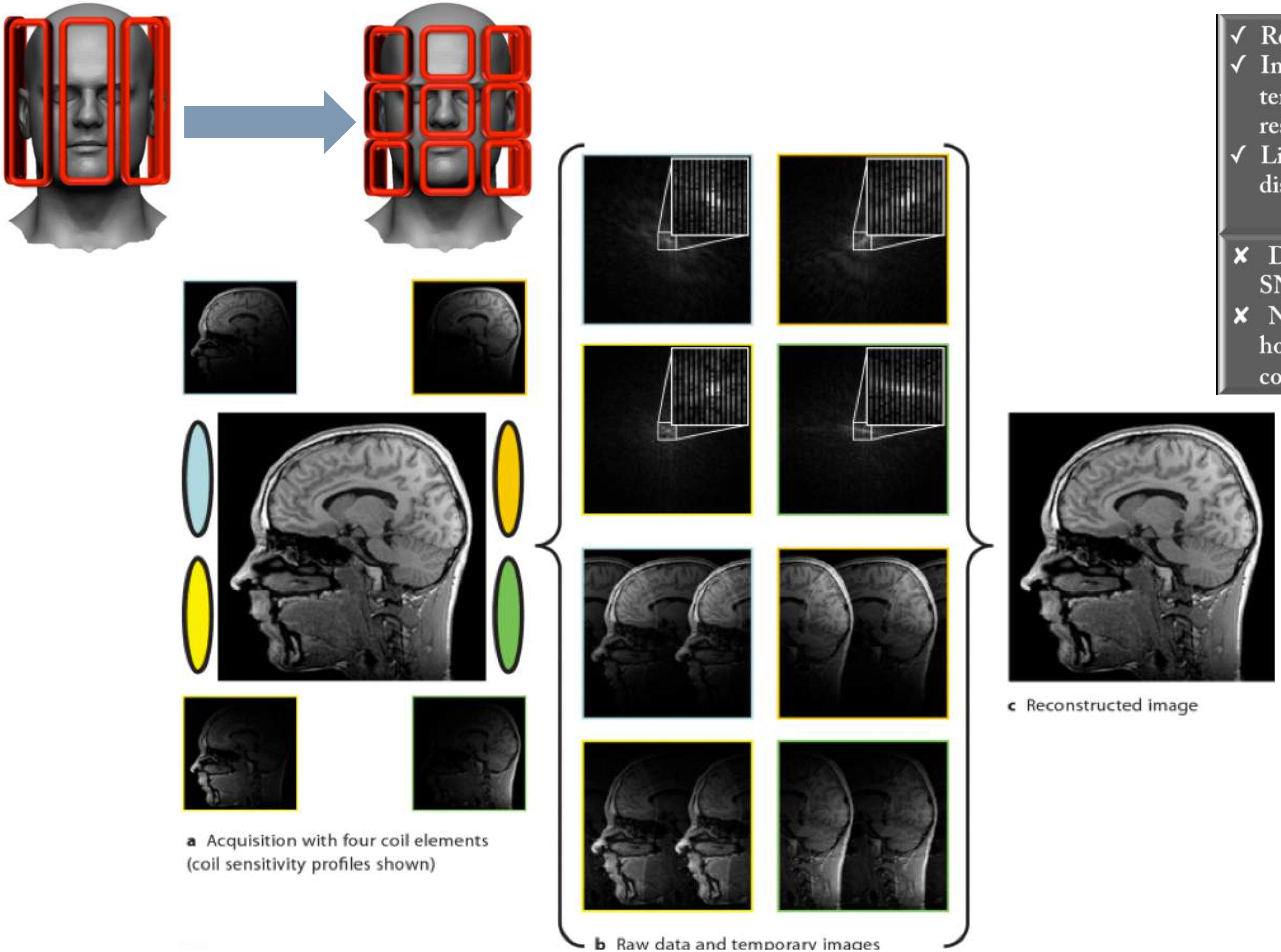
The sampling frequency should be at least twice the highest frequency contained in the signal



Harry Nyquist



Accelerated MRI using Parallel Imaging



- ✓ Reduce scan time
- ✓ Improve spatial / temporal resolution
- ✓ Limit geometric distorsions

- ✗ Decrease the SNR
- ✗ Non-homogeneous coils

Outline

Part I: Compressed Sensing in MRI

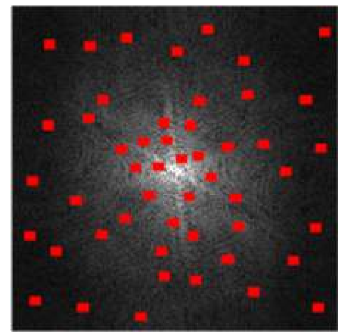
- Standard CS acquisition
- Standard CS reconstruction
- SPARKLING

Part II: Deep learning for MR Image reconstruction

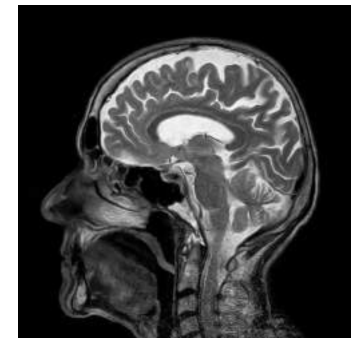
- Motivations
- A recent breakthrough
- From single to double-domain denoising
- Where to contribute?

Compressed Sensing in MRI

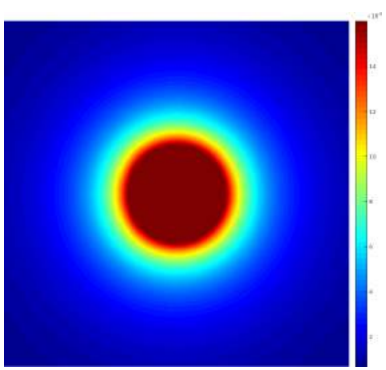
K-space



Nonlinear reconstructions

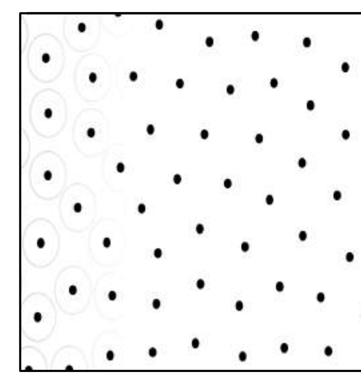


Subsampling with guarantees of image recovery
if these two criteria are fulfilled :



i. Variable-density sampling

ii. Locally uniform coverage

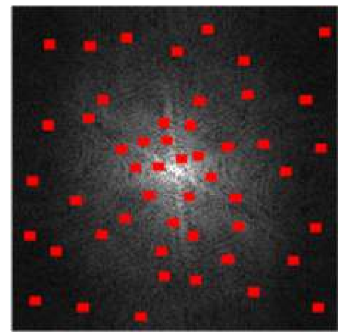


Emmanuel Candes and Yaniv Plan.
A probabilistic and ripless theory of compressed sensing.
Information Theory, IEEE Transactions on, 57(11):7235–7254, 2011.

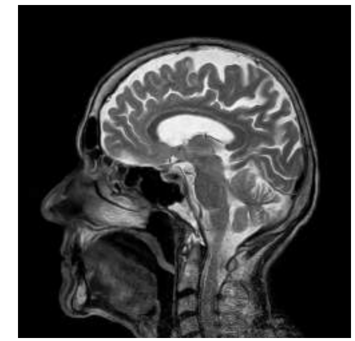
Ben Adcock, Anders C. Hansen, Clarice Poon, and Bogdan Roman.
Breaking the coherence barrier: A new theory for compressed sensing.
arXiv preprint arXiv:1302.0561, 2013.

Usual undersampling strategies for CS-MRI

K-space



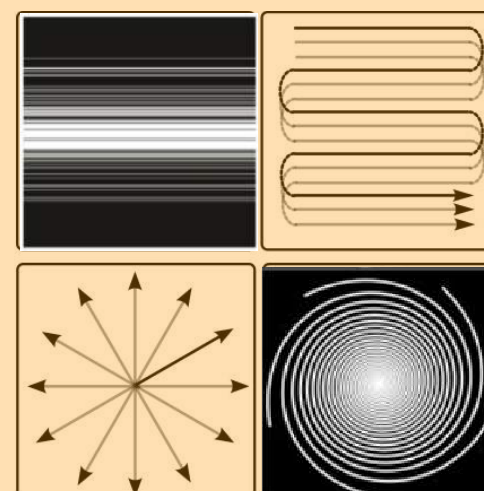
Nonlinear reconstructions



Sampling in MRI: $k(t) = k(0) + \gamma \int_0^t G(\tau) d\tau$

- **Segmented acquisition**:
  Scan time proportional to number of shots

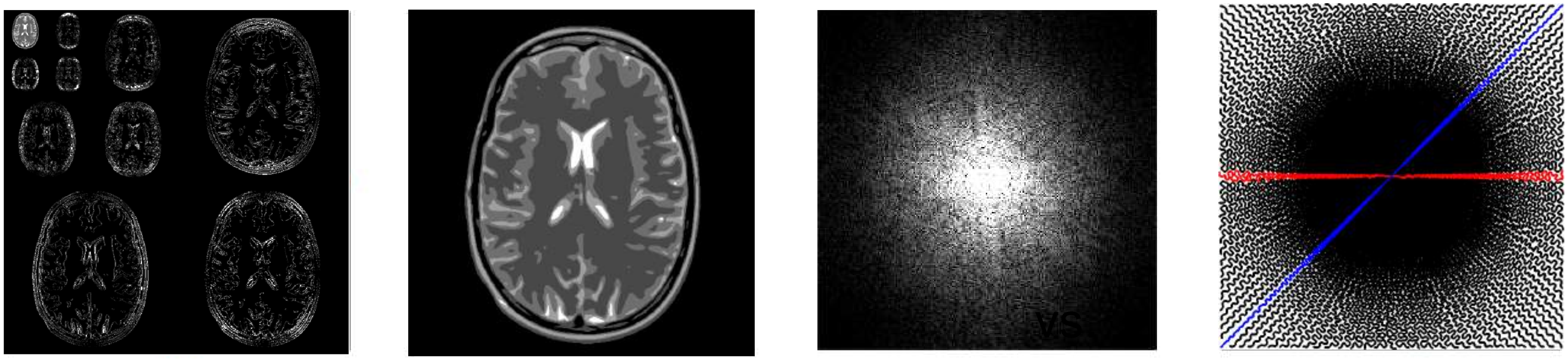
- **Hardware constraints on gradients**:
  $G_{max} < 40$ mT/m ; $S_{max} < 200$ T/m/s
  → bounded velocity and acceleration



$$\mathcal{S}_{\mathrm{MRI}} = \left\{ \boldsymbol{k} : [0, T] \mapsto \mathbb{R}^2, \|\dot{\boldsymbol{k}}\|_{2,\infty} \leqslant \gamma G_{\max}, \|\ddot{\boldsymbol{k}}\|_{2,\infty} \leqslant \gamma S_{\max} \right\}$$

Compressed Sensing MR Image reconstruction

$\boldsymbol{z}$ $\quad$ $\boldsymbol{x} = \boldsymbol{\Psi} \boldsymbol{z}$ $\quad$ $\boldsymbol{F}^* \boldsymbol{\Psi} \boldsymbol{z} = \boldsymbol{A} \boldsymbol{z}$ $\quad$ $\boldsymbol{A}_\Omega \boldsymbol{z}$



Sparsity: Let $S = \{i, z_i \neq 0\}$ denote the support of $\boldsymbol{z}$.

We assume that: $|S| = s \ll n$

ℓ_1 reconstruction (analysis formulation, e.g. ADMM):

$$\widehat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x} \in \mathbb{C}^n} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{F}_\Omega^* \boldsymbol{x}\|_2^2 + \lambda \|\boldsymbol{\Psi} \boldsymbol{x}\|_1$$

CS on the market

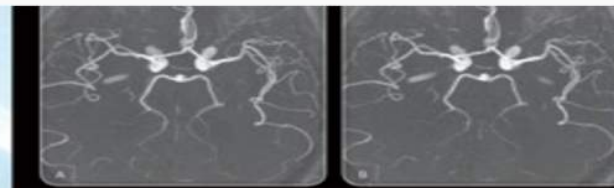
FDA Clears Compressed Sensing MRI Acceleration Technology From Siemens Healthineers

SIEMENS Healthineers

Siemens Healthineers has announced that the Food and Drug Administration (FDA) has cleared the company's revolutionary Compressed Sensing technology, which slashes the long acquisition times associated with magnetic

HyperSense Enables Shorter Scan Times Without Compromising Image Quality

by Kevin King, Senior Scientist, GE Healthcare



The improvement in scan efficiency from CS can be applied in three ways: reduce scan time, increase spatial resolution, or increase volume coverage. Compressed sensing techniques can also have a benefit of "denoising" images, but it can introduce blurring if too much acceleration is used or the image is not sufficiently compressible. While CS is a powerful technique, the acceleration needs to be tailored for specific applications. Intrinsically sparse acquisitions such as MRCP, fat

reducing the overall scan time without appreciably compromising spatial resolution or image quality. HyperSense is not dependent on coil geometry and is less sensitive to image artifacts or SNR loss at higher accelerations when compared to conventional parallel imaging techniques.

Martin J. Graves, PhD, Head of MR Physics at Cambridge University Hospitals NHS Foundation Trust, and co-author of the award-winning textbook: MRI: *From Picture to Proton*

been refined over the last few years, and using ASSET and ARC we can obtain very good results. However, there is a limitation in how far you can push these conventional techniques."

HyperSense opens up new opportunities to further reduce scan time without a substantial impact on image quality, he adds.

Dr. Graves also acknowledges that the benefit of CS varies by application. For example, for morphological

Compressed SENSE

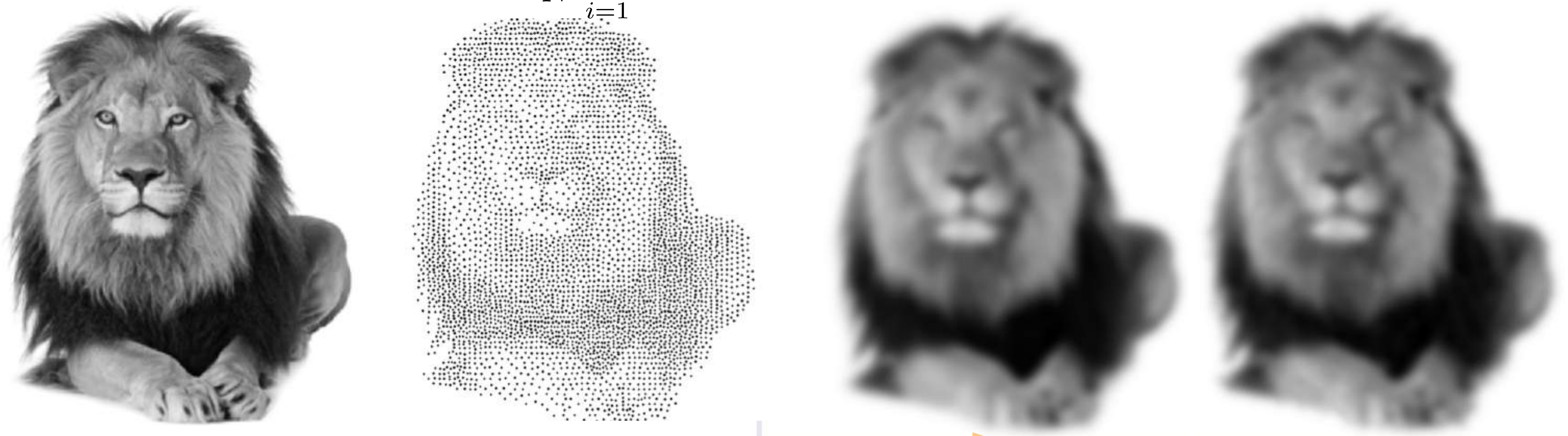
PHILIPS Healthcare

Speed done right. Every time.

Liesbeth Geerts-Ossevoort, PhD; Elwin de Weerdt, PhD; Adri Duijndam, PhD; Gert van IJperen, PhD; Hans Peeters, PhD; Mariya Doneva, PhD; Marco Nijenhuis; Alan Huang, PhD

Approximation Theory: Application to Computer Graphics

π $\quad \nu(\boldsymbol{k}) = \frac{1}{N}\sum_{i=1}^{N} \delta_{k_i}$ $\quad h_\sigma \star \pi$ $\quad h_\sigma \star \nu(\boldsymbol{k})$



Convolution with a smoothing kernel

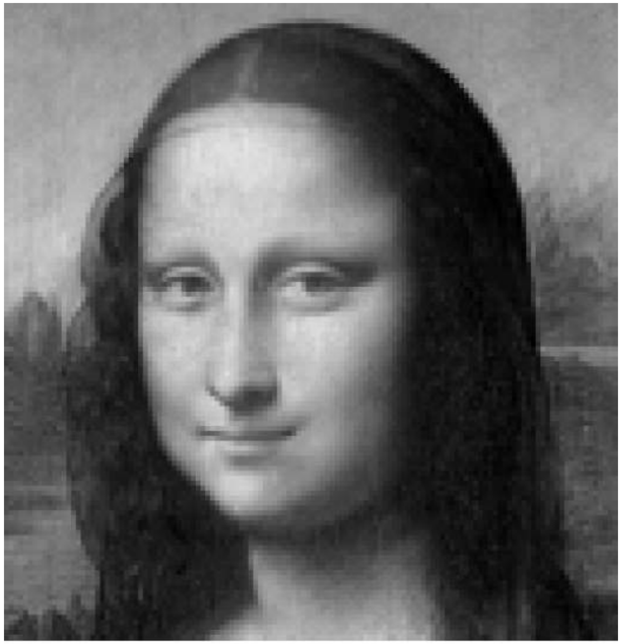
$$\min_{\boldsymbol{k}\in\Omega^N} dist(\pi, \nu(\boldsymbol{k})) = \frac{1}{2}\|h \star \nu(\boldsymbol{k}) - h \star \pi\|_2^2$$

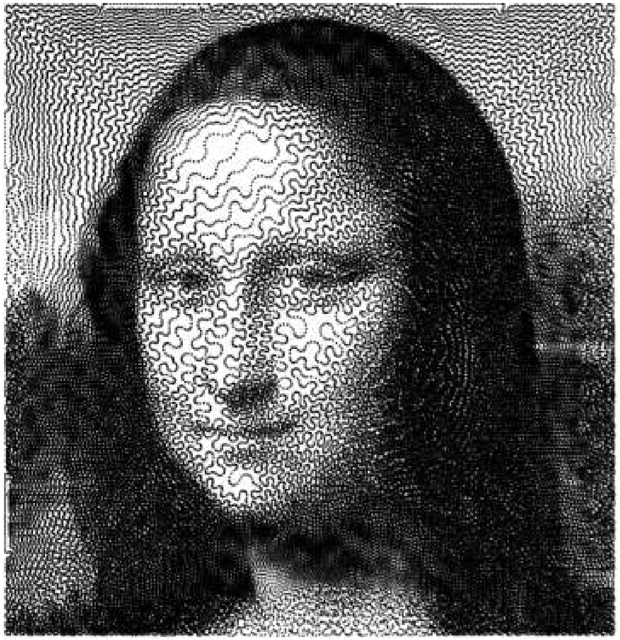
[Chauffert et al, Construct Approx 2017]

Approximation Theory: Application to Computer Graphics

π

$$\nu(\boldsymbol{k}) = \frac{1}{N}\sum_{i=1}^{N} \delta_{k_i}, \quad \text{with} \quad \boldsymbol{k} \in \mathcal{S}_{\mathrm{MRI}}$$



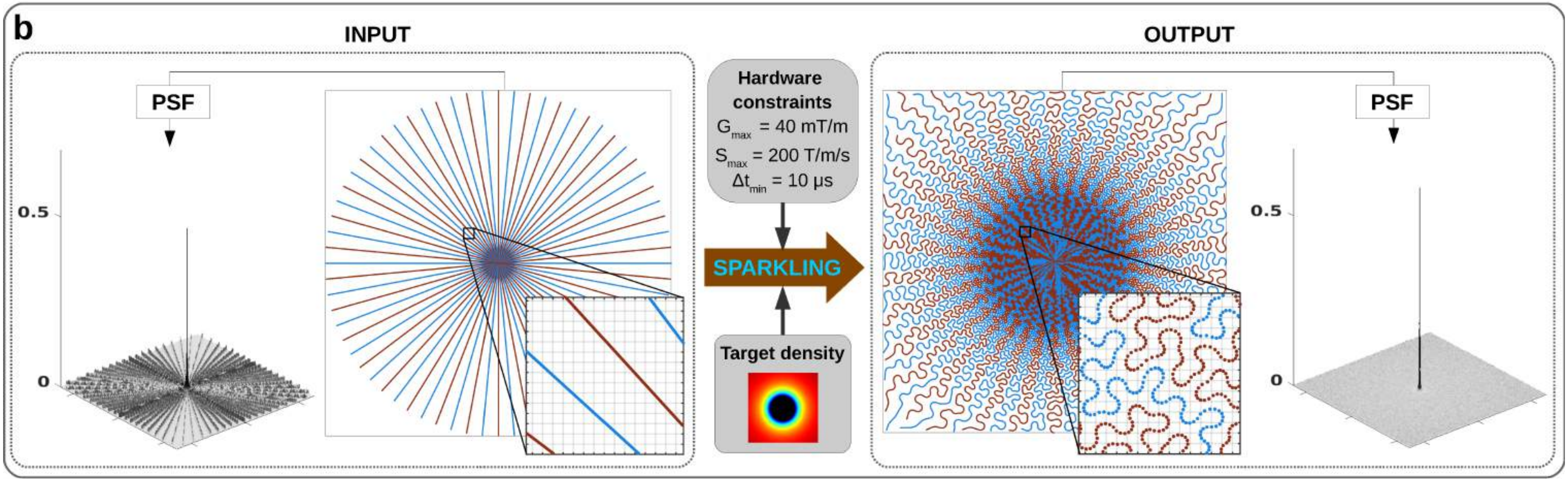


$$\min_{\boldsymbol{k}\in\mathcal{S}_{\mathrm{MRI}}} dist(\pi, \nu(\boldsymbol{k})) = \frac{1}{2}\|h \star \nu(\boldsymbol{k}) - h \star \pi\|_2^2$$

[Chauffert et al, Construct Approx 2017, Chauffert et al, IEEE TMI 2016]

SPARKLING

Spreading Projection Algorithm for Rapid K-space sampLING

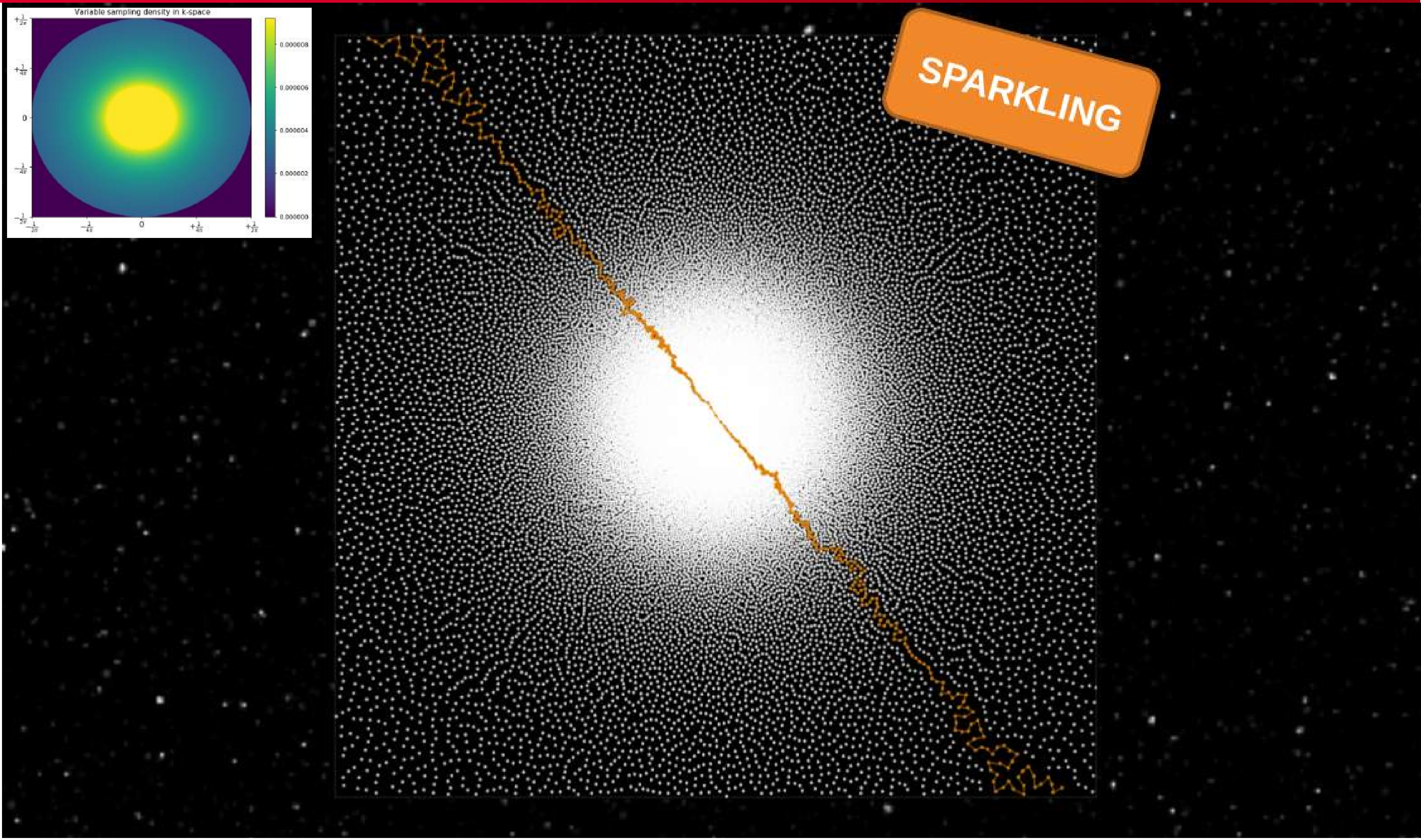


SPARKLING: A perfect point spread function

[Lazarus et al, ISMRM 2017, 2018, 2019 and MRM 2019; Patent accepted in Jan 2019]

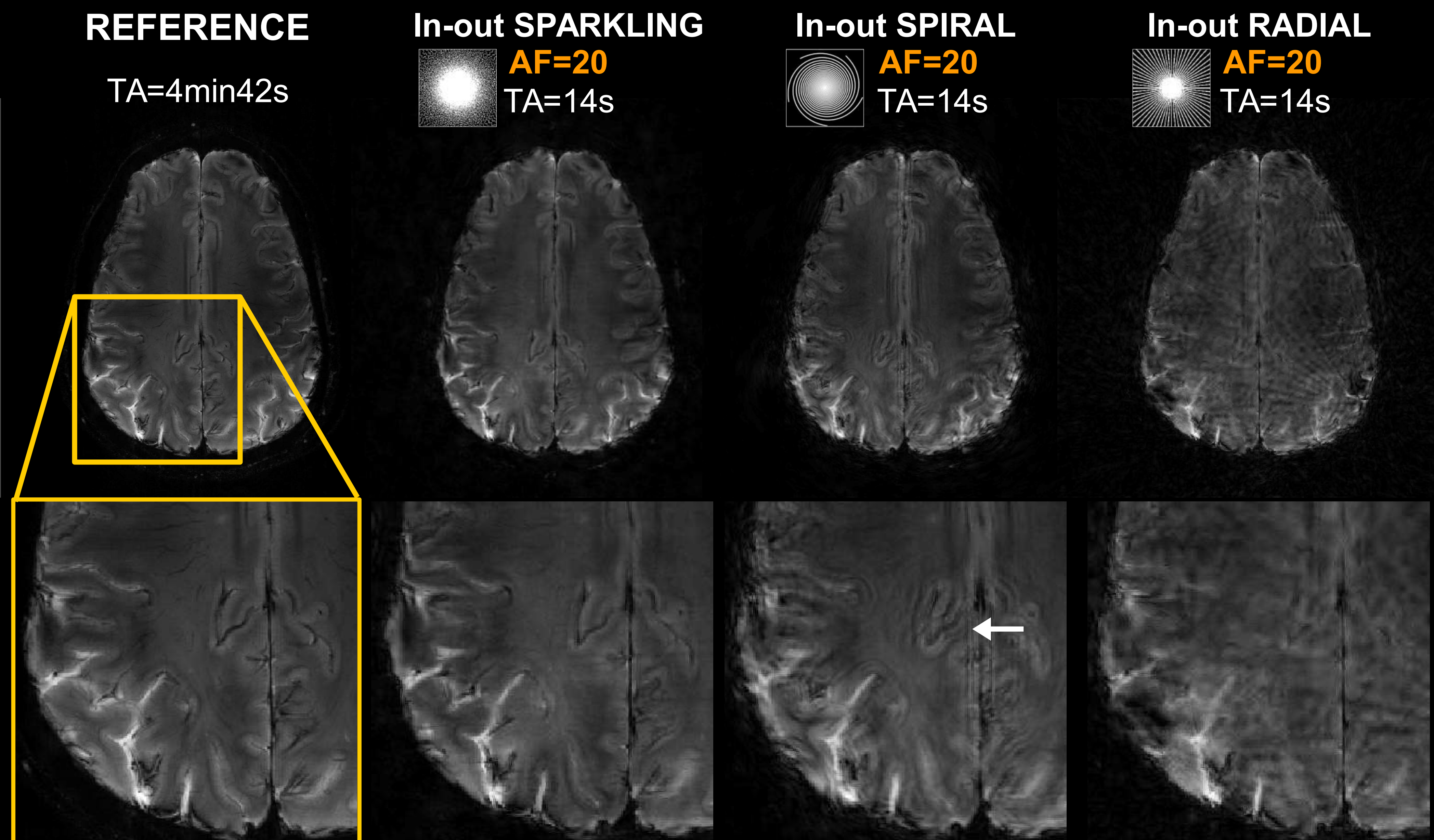
SPARKLING

Spreading Projection Algorithm for Rapid K-space sampLING



[Lazarus et al, ISMRM 2017, 2018, 2019 and MRM 2019]

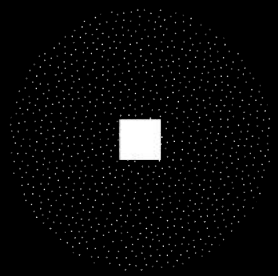
In vivo results at 0.39mm resolution
26 shots – 11 slices



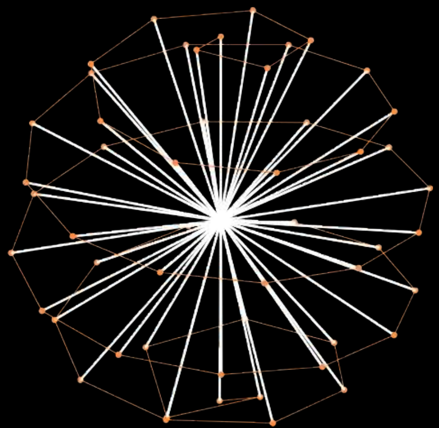
[Lazarus et al, ISMRM 2017, 2018, 2019 and MRM 2019]

Ex vivo comparison with other strategies

T2* contrast
Isotropic resolution of 0.6 mm
TA=45s

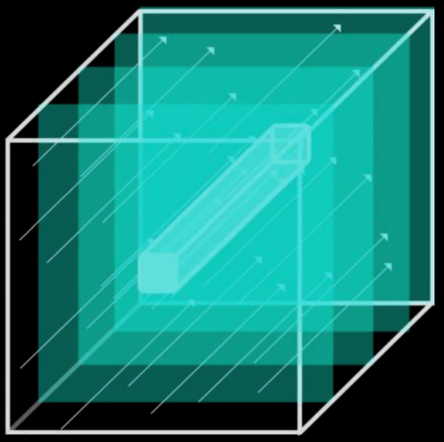


vs.



Larson et al. 2007

vs.

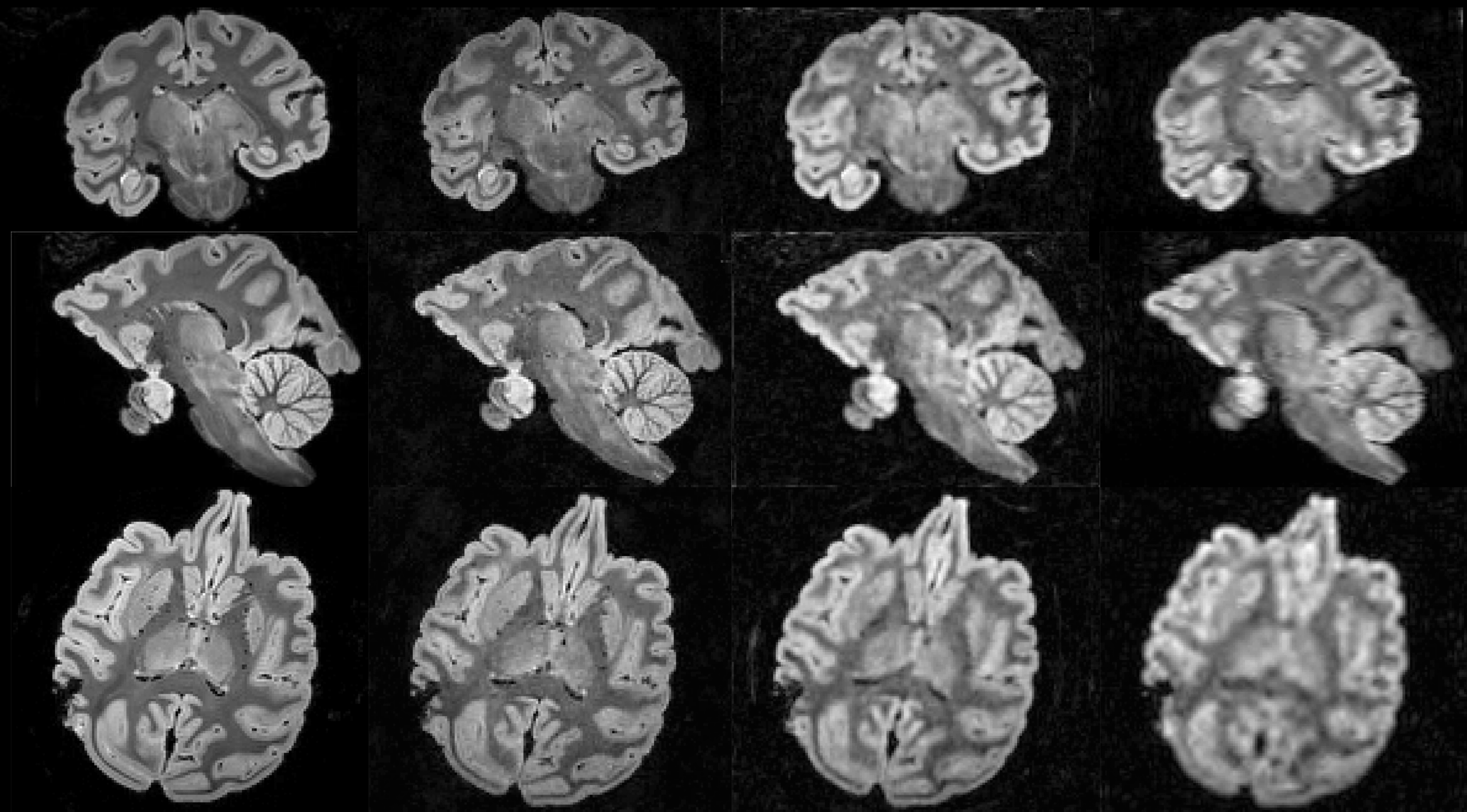


Lustig et al. 2008

[Lazarus et al , sub. to NMR Biomed 2019]

SPARKLING vs. other strategies
1140 shots - AF=69

IPAT 4	SPARKLING	RADIAL	Poisson disk lines
TA=14min31s	TA=45s	TA=45s	TA=45s
	SSIM=0.86	SSIM=0.72	SSIM=0.58



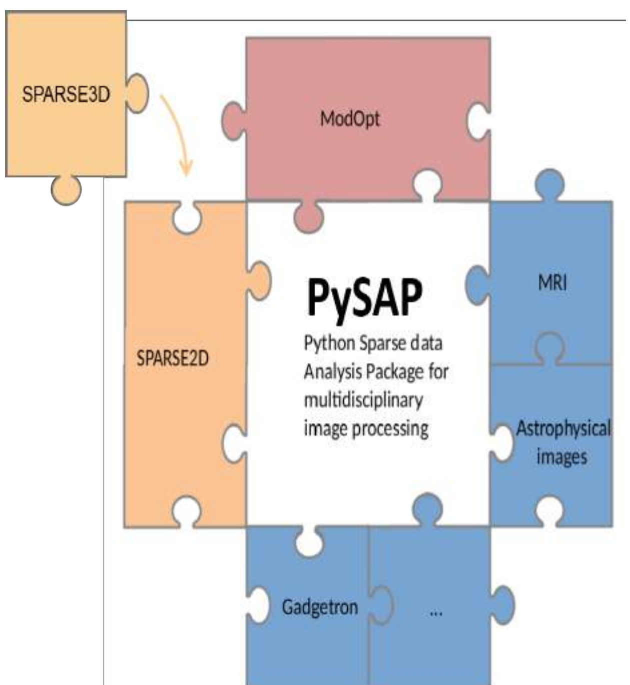
Open Source MRI recon Software

COSMIC Project: 2016-2019 CEA/DRF impulsion funding (https://cosmic.cosmostat.org)

Jean-Luc Starck

Tools:

- **PySAP: P**ython **S**parse data **A**nalysis **P**ackage : **MR & Astronomical image reconstruction from under-sampled data**.

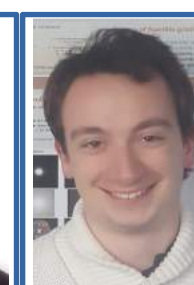


PySAP developers team:

Loubna El Gueddari

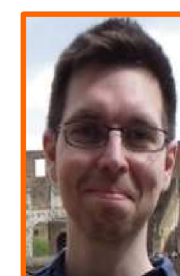
Zaccharie Ramzi

Hamza Cherkaoui



Benoît Sarthou

Antoine Grigis

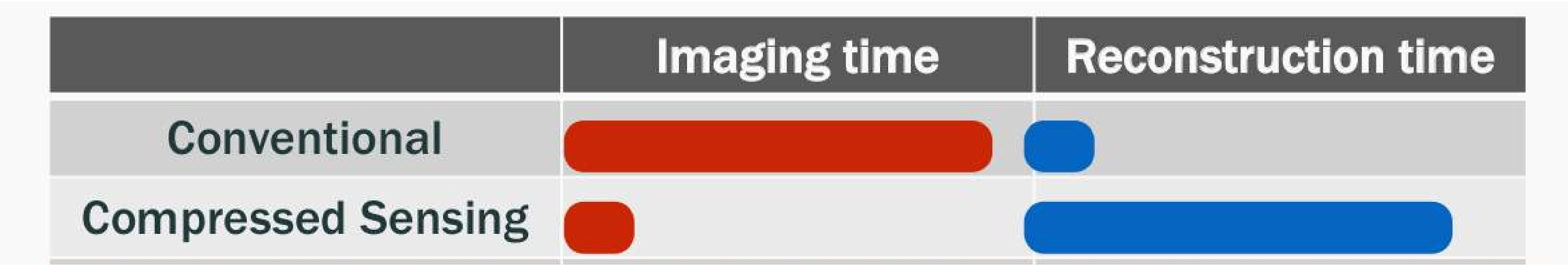


Samuel Farrens

https://github.com/CEA-COSMIC/pysap

[Cherkaoui et al, EUSIPCO 2018; El Gueddari et al, ISBI 2018, 2019; Ramzi et al, submitted to SPARS 2019]

Main CS limitations



- **Long reconstruction times**
- **Fixed sparsifying transform (e.g., wavelets, Total Variation, etc.)**
- **Require hyperparameter setting**

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- Standard CS reconstruction
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Part II: Deep learning for MR Image reconstruction

- Motivations
- A recent breakthrough
- From single to double-domain denoising
- Where to contribute?

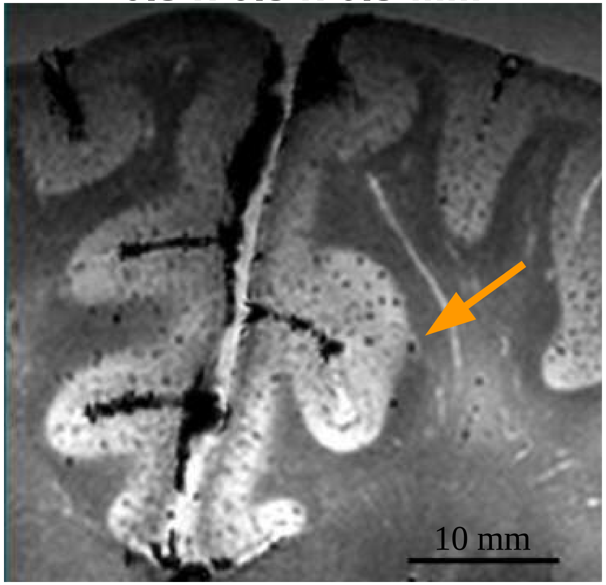
Unmet needs in MRI

- **MRI is an essential tool for diagnosis especially in high-resolution**

  Example:

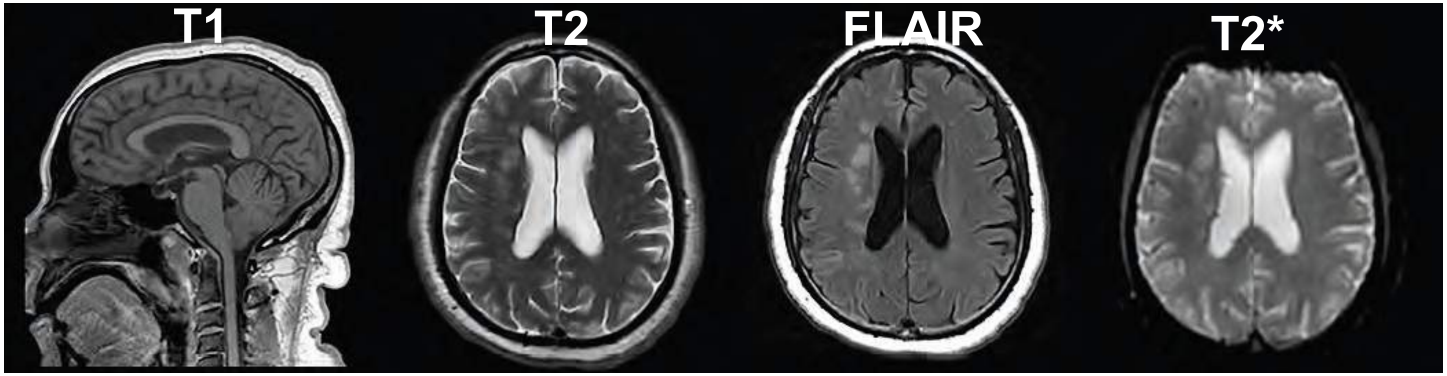
  Alzheimer's Disease and amyloid plaques

0.3 x 0.3 x 0.3 mm



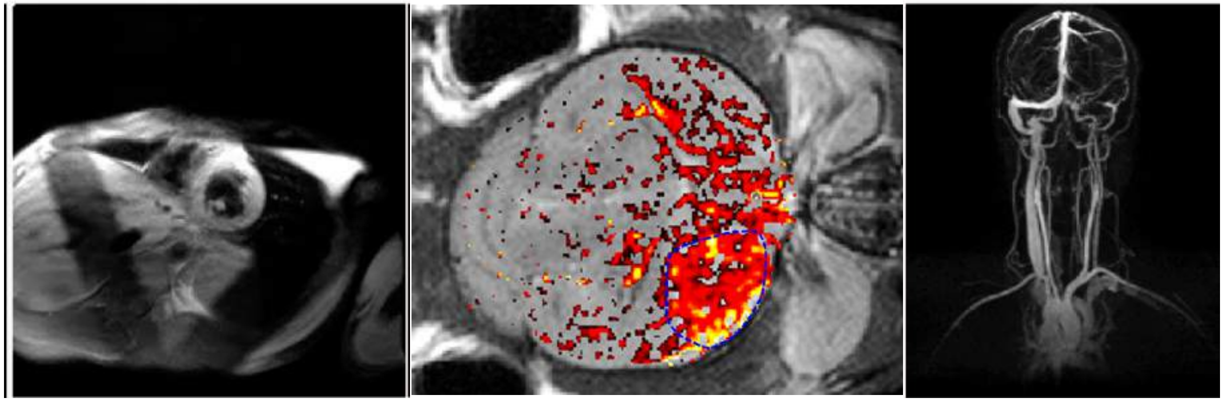
Van Rooden et al. 2009.

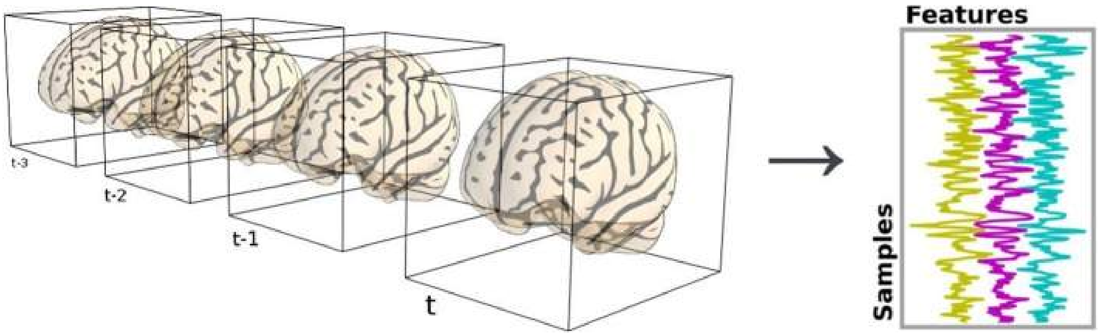
- **Multi-contrast weighted**



Unmet needs in MRI

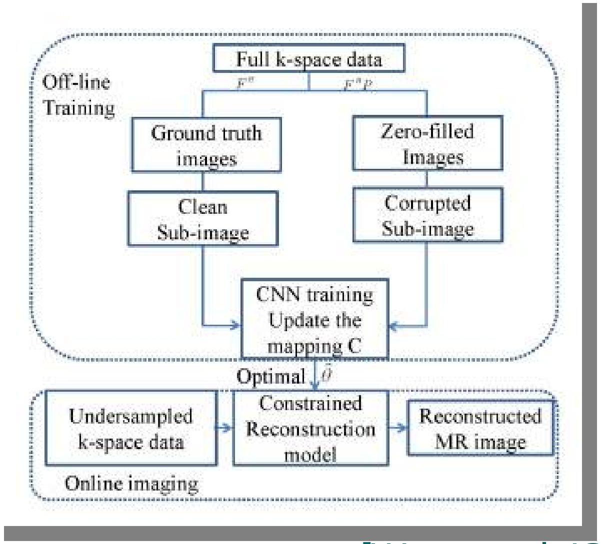
- **MR exam protocol may last 30 – 60 min/patient**
  - DL reconstruction should increase the throughput of MR scanning
- **Dynamic MRI : cardiac imaging, functional brain imaging, DCE-MRI, dynamic MRA**
  - Should improve temporal resolution too





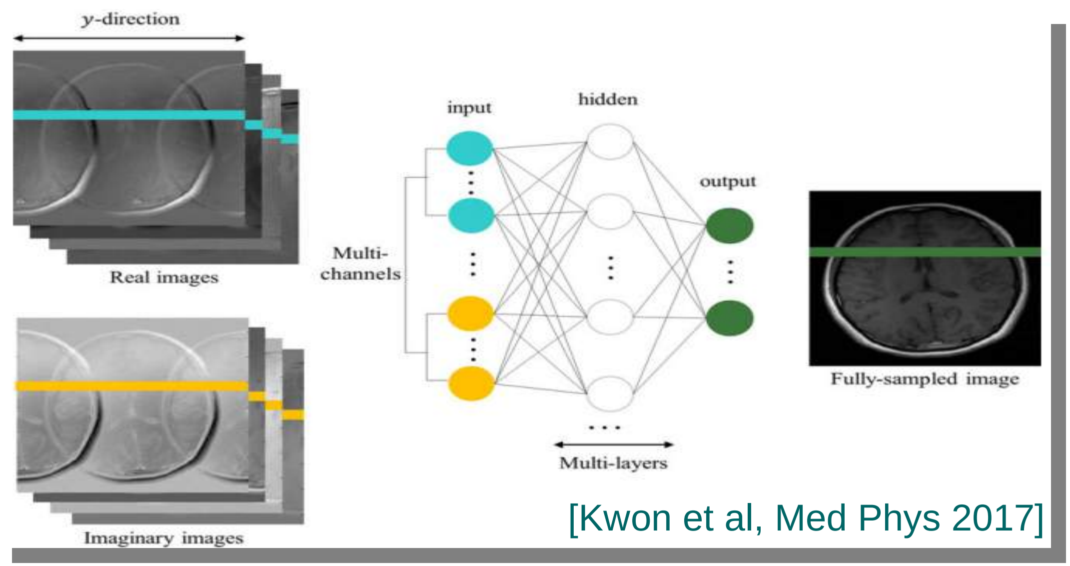
2016-18: Deep Learning Breakthrough in MR

Fully end-to-end CNN



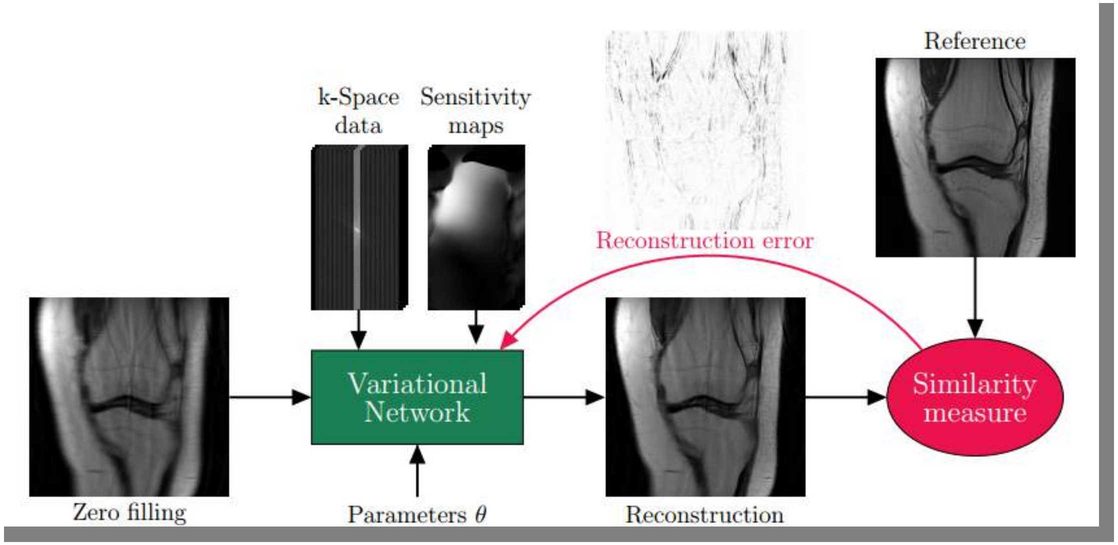
[Wang et al, ISBI 2016

Multilayer perceptron



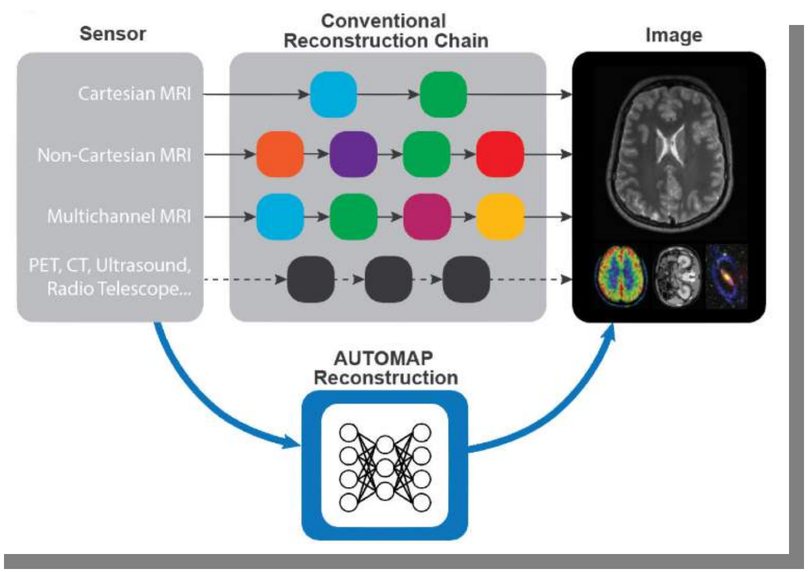
[Kwon et al, Med Phys 2017]

Variational network



[Hammernik et al, MRM 2018]

Fully connected DNN



[Zhu et al, Nature 2018]

Different Deep Learning Approaches

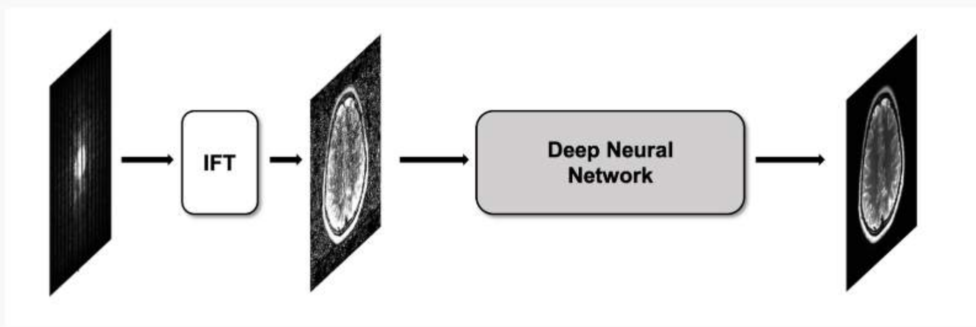
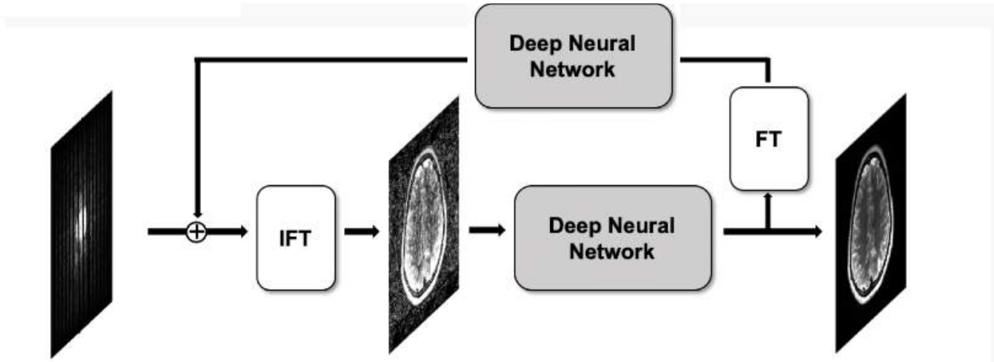
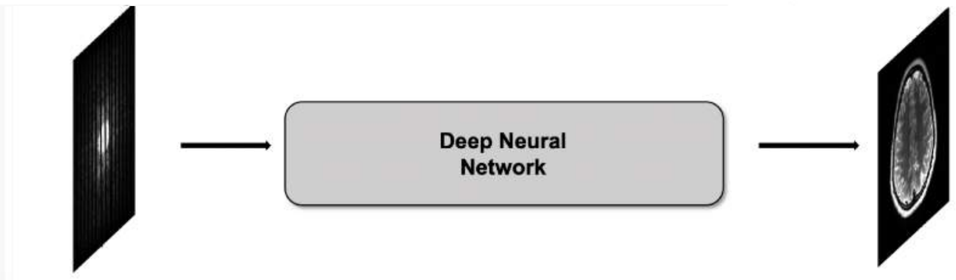


Image-domain learning

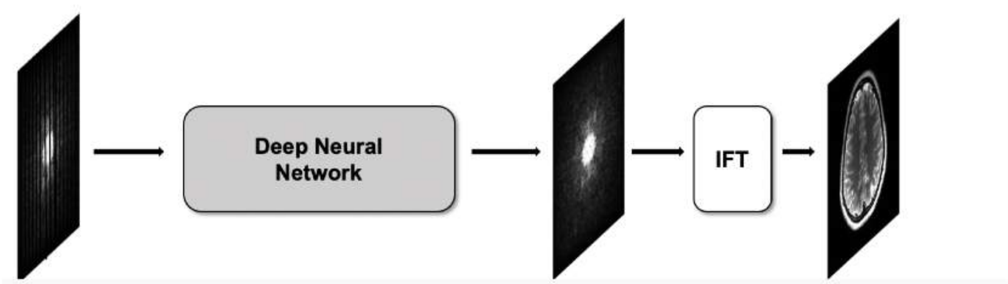
Hybrid-domain learning



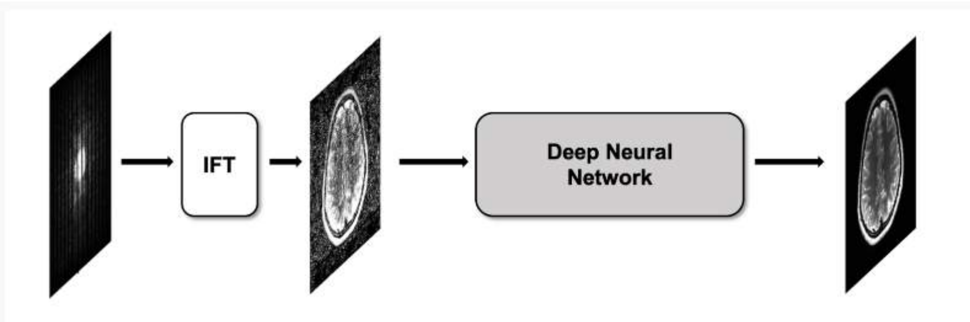


Domain-transform learning

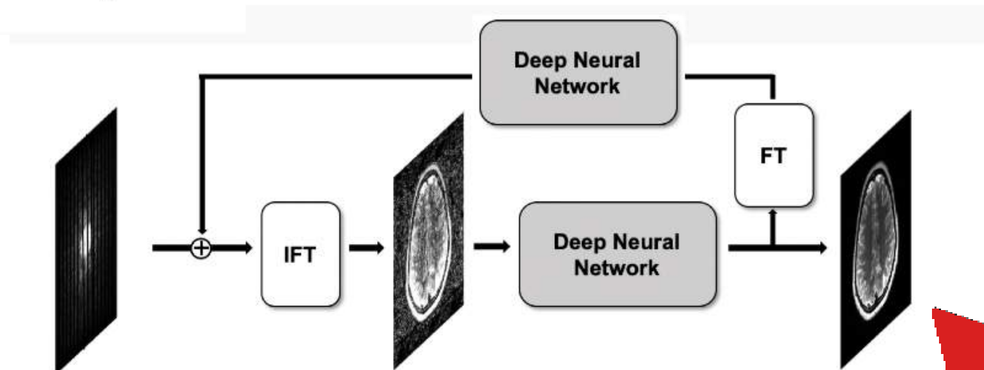
Sensor-domain learning

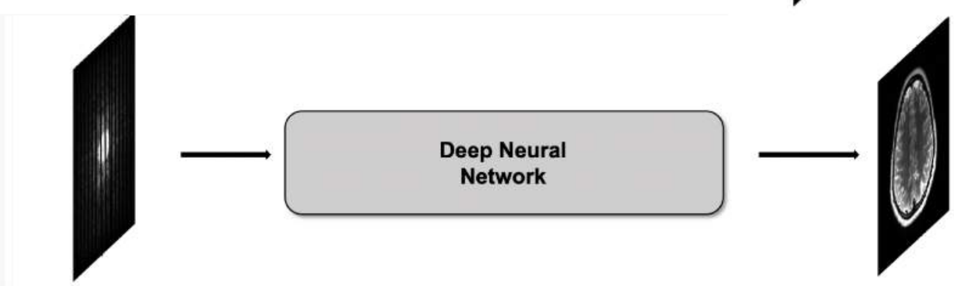


Different Deep Learning Approaches



Data-driven learning





Model-based learning

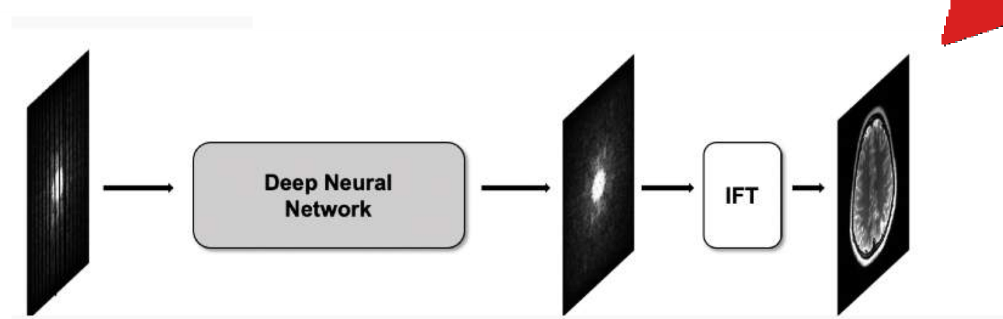
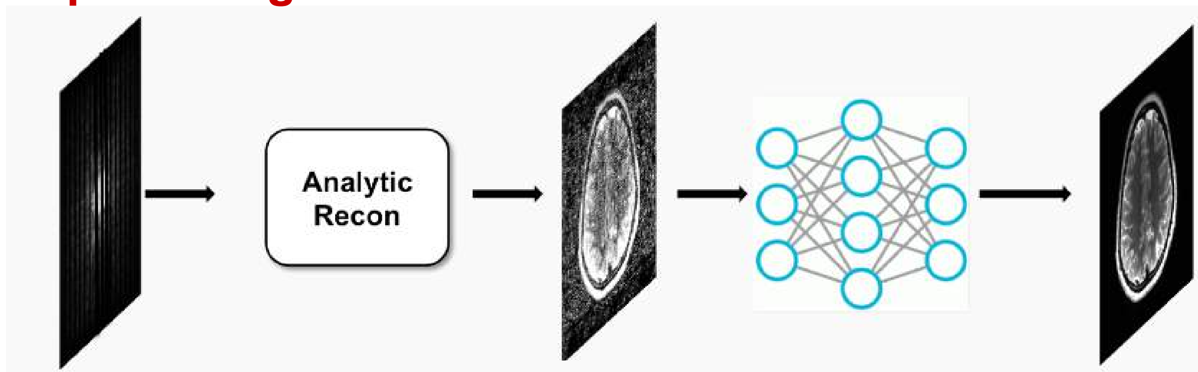


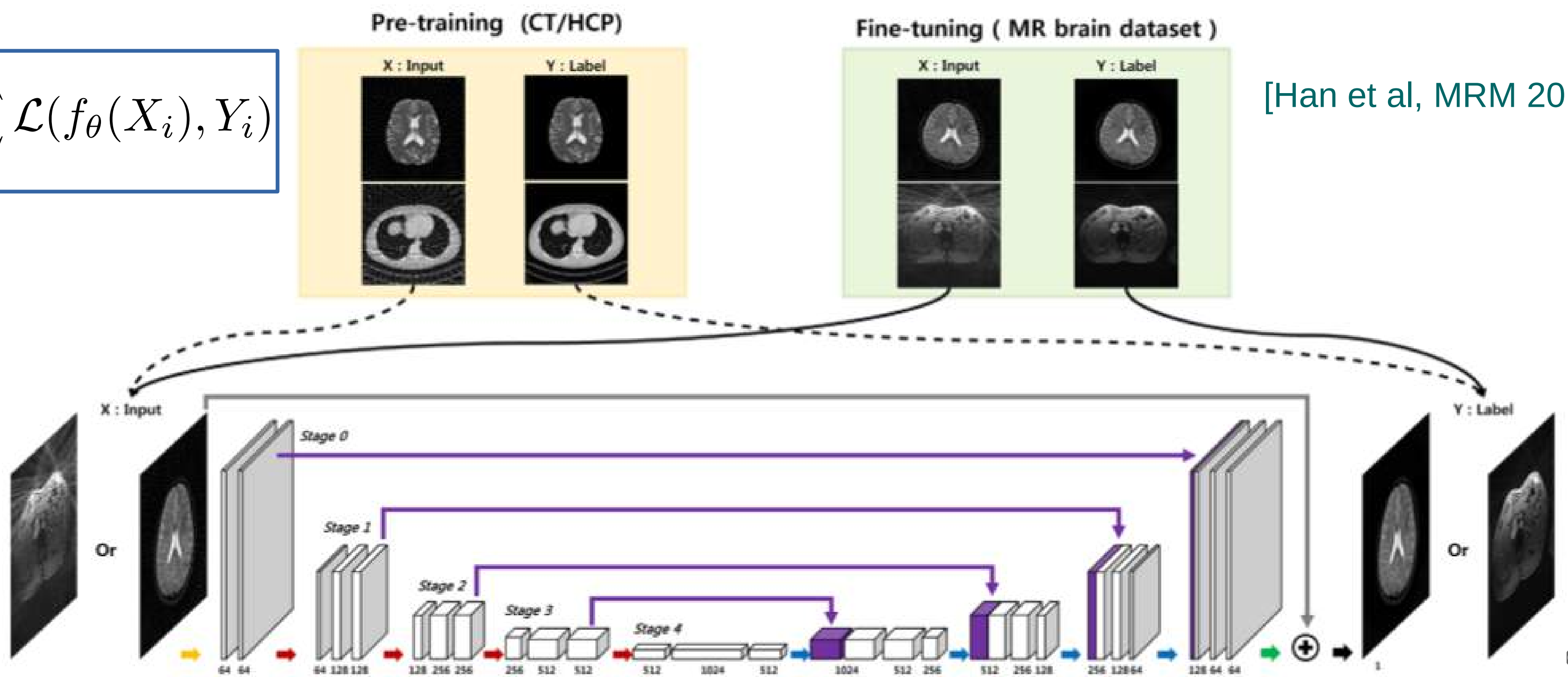
Image-Domain Learning

- **Data-driven deep learning for fast MRI reconstruction**



Domain adaptation network

$$\arg\min_{\theta} \sum_{i=1}^{N} \mathcal{L}(f_\theta(X_i), Y_i)$$

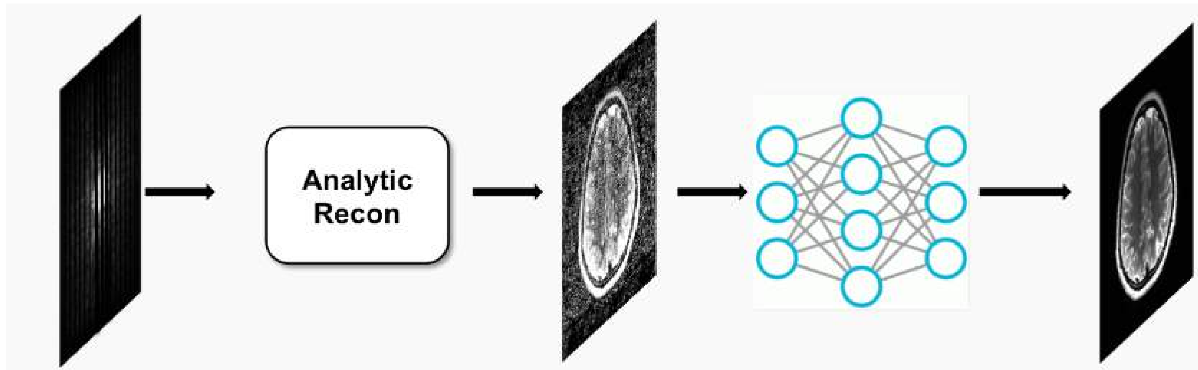


[Han et al, MRM 2018]

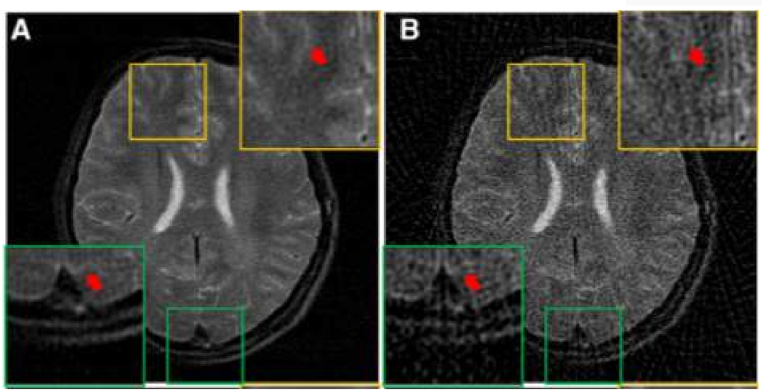
[Hanneberger et al, MICCAI 2015]

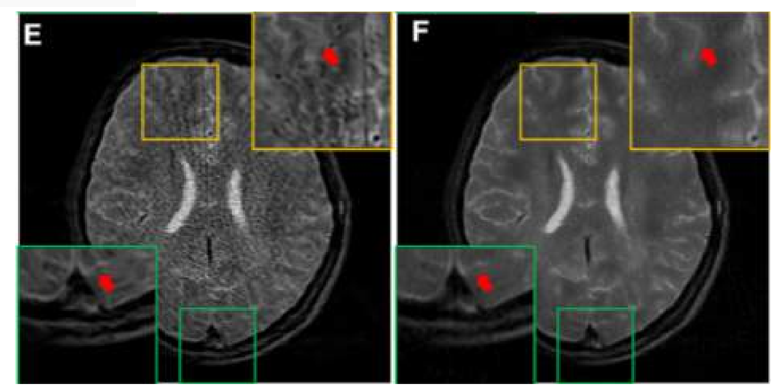
Image-Domain Learning

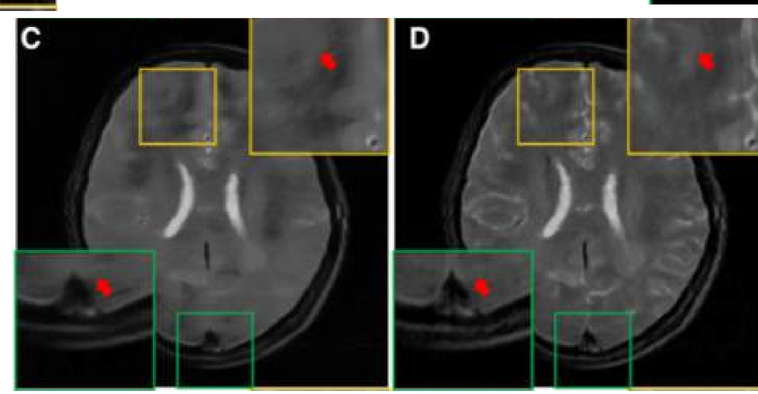
- **Data-driven deep learning for fast MRI reconstruction**



Domain adaptation network



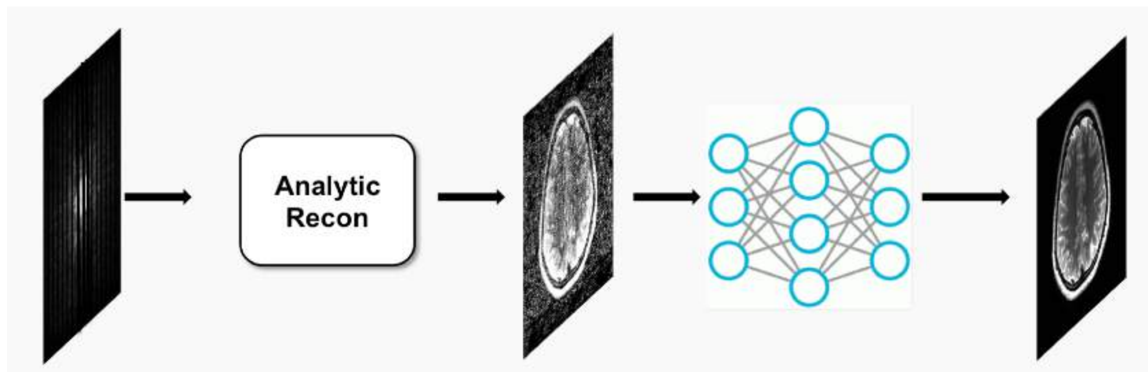




[Han et al, MRM 2018]

Image-Domain Learning

- **Data-driven deep learning: Generative Adversarial Networks for CS**

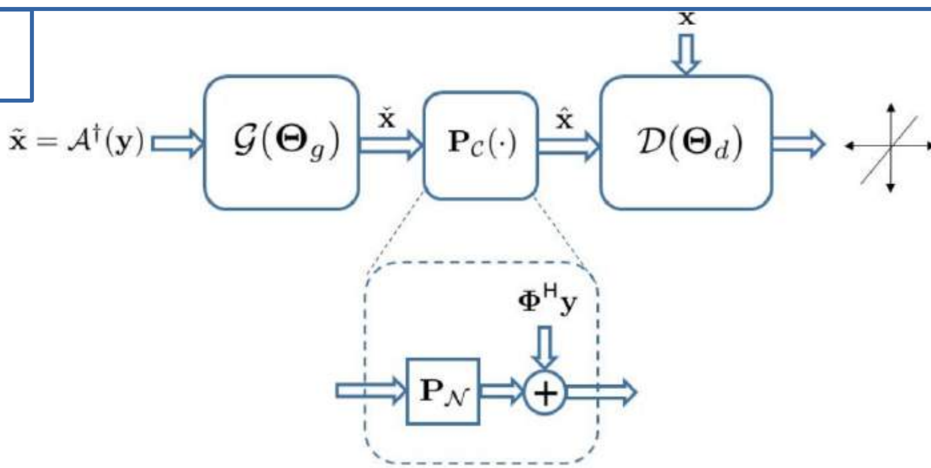


GANCS

$$\arg\min_{\mathbf{\Theta}_d} \frac{1}{N}\sum_{i=1}^{N}(1-\mathcal{D}(X_i;\mathbf{\Theta}_d))^2+\sum_{i=1}^{N}\Big(\mathcal{D}(\mathcal{G}(\tilde{X}_i;\mathbf{\Theta}_g);\mathbf{\Theta}_d)\Big)^2$$

$$\tilde{X}_i = \boldsymbol{A}^{\dagger}Y_i$$

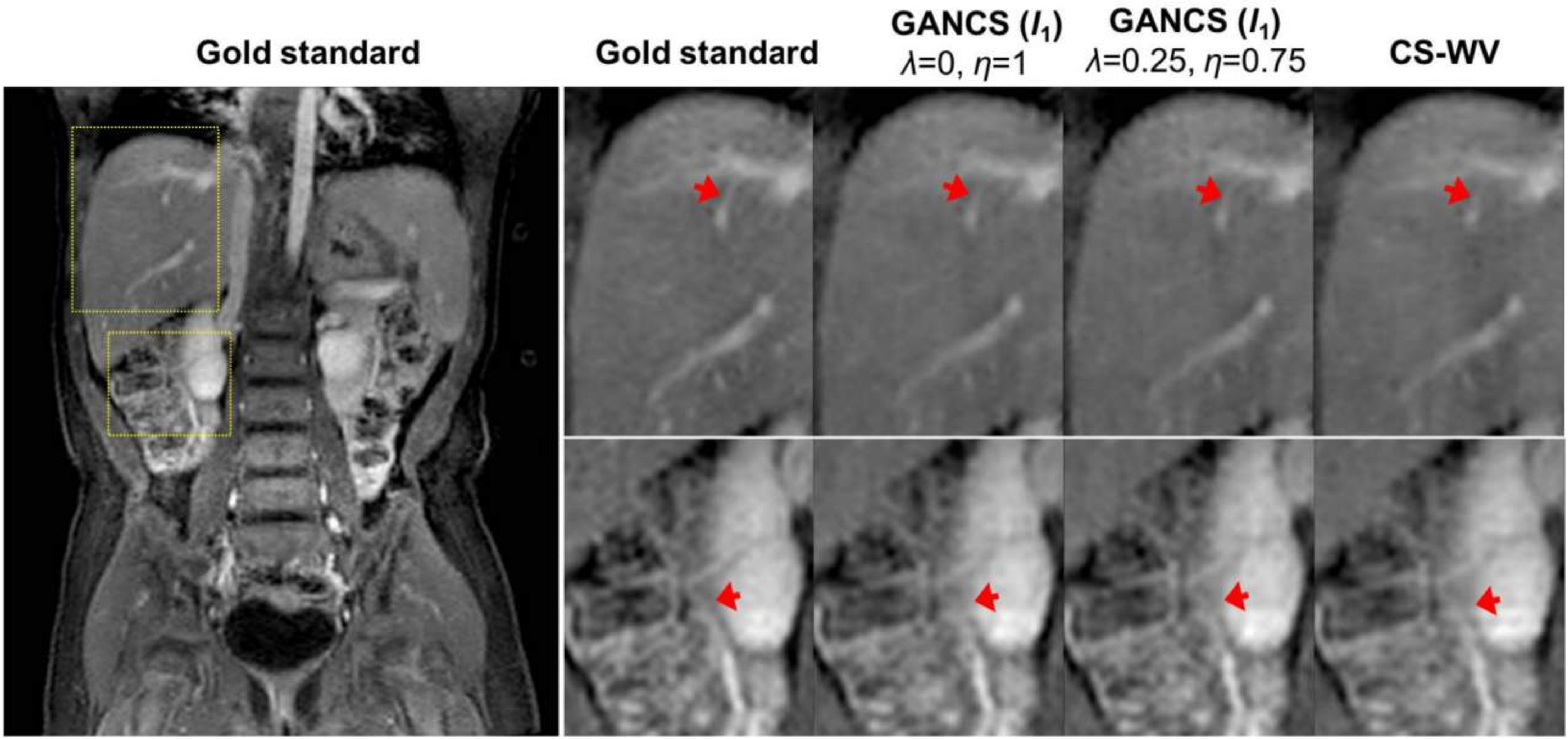
$$\arg\min_{\mathbf{\Theta}_g}\frac{1}{N}\sum_{i=1}^{N}\|Y_i-\boldsymbol{A}\mathcal{G}(\tilde{X}_i;\mathbf{\Theta}_g)\|^2 +\eta\sum_{i,j=1}^{N}\|X_i-\mathcal{G}(\tilde{X}_j;\mathbf{\Theta}_g)\|_{1,2} +\lambda\sum_{i=1}^{N}\Big(1-\mathcal{D}(\mathcal{G}(\tilde{X}_i;\mathbf{\Theta}_g);\mathbf{\Theta}_d)\Big)^2$$



$$\boldsymbol{P}_{\mathcal{N}} = (\boldsymbol{I}-\boldsymbol{A}^{\dagger}\boldsymbol{A})$$

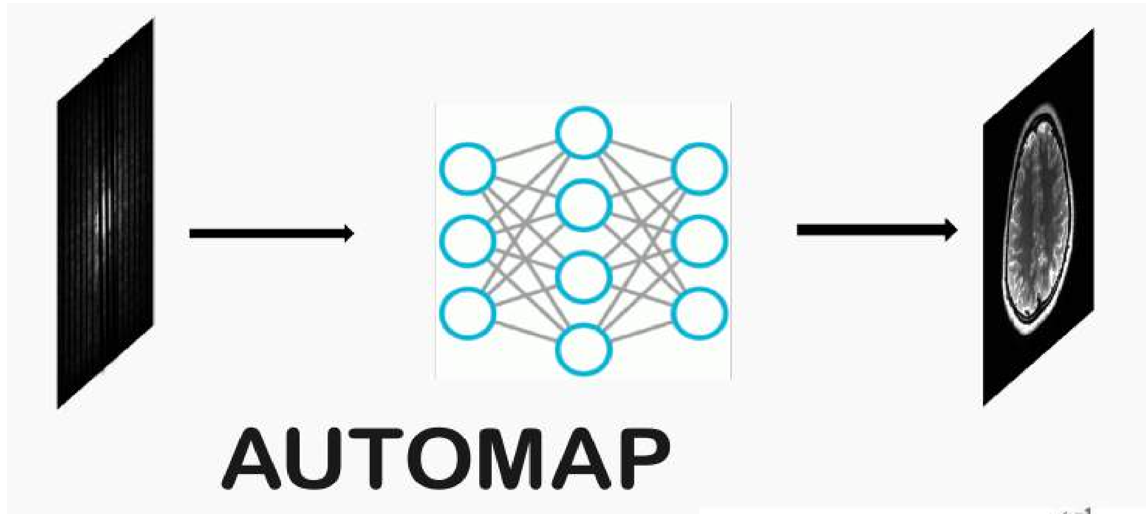
[Mardani et al, TMI 2019]

GANCS Results

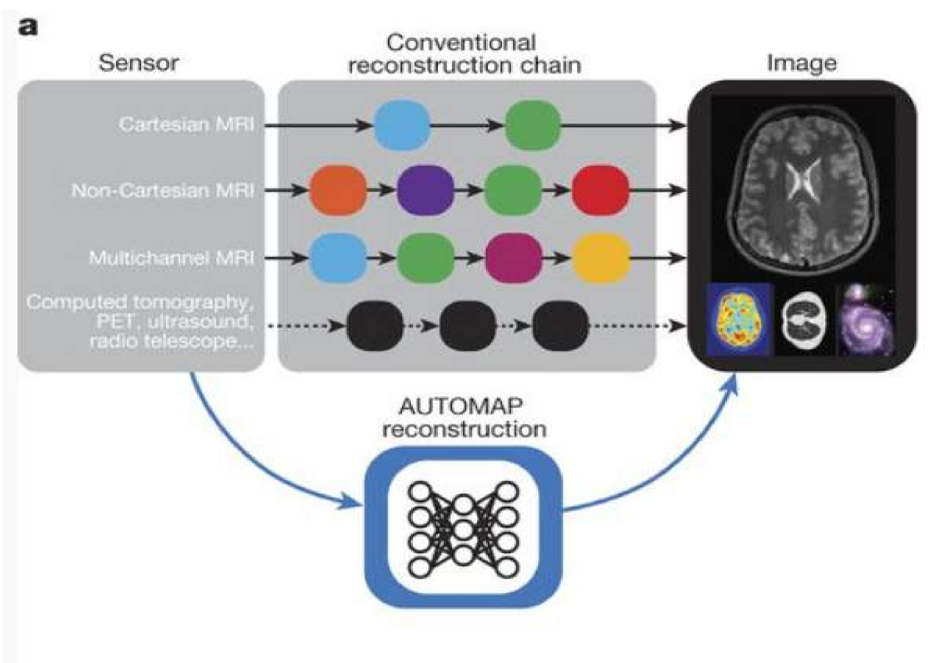


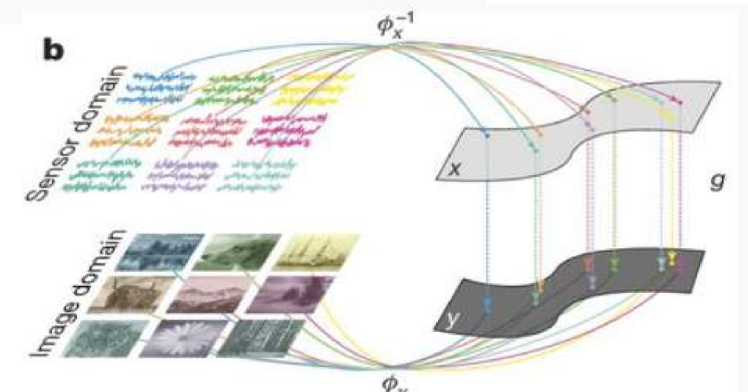
[Mardani et al, IEEE TMI 2019]

Domain-transform Learning: AUTOMAP

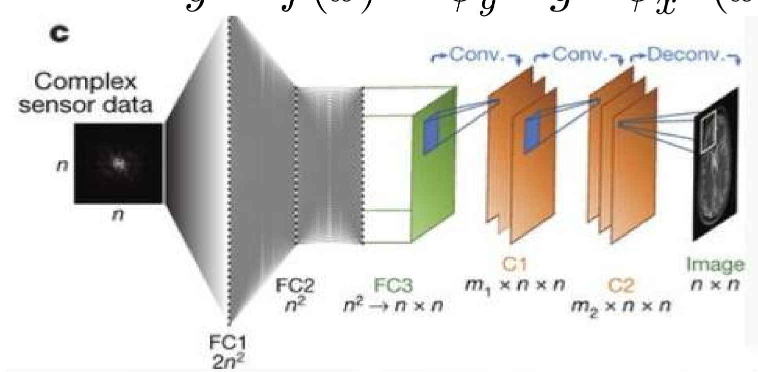


$$\arg\min_{Q} \mathcal{D}_{\mathrm{KL}}\left(P(Y,X,\widetilde{X}) \| Q_{(f,p)}(Y,X,\widetilde{X})\right)$$



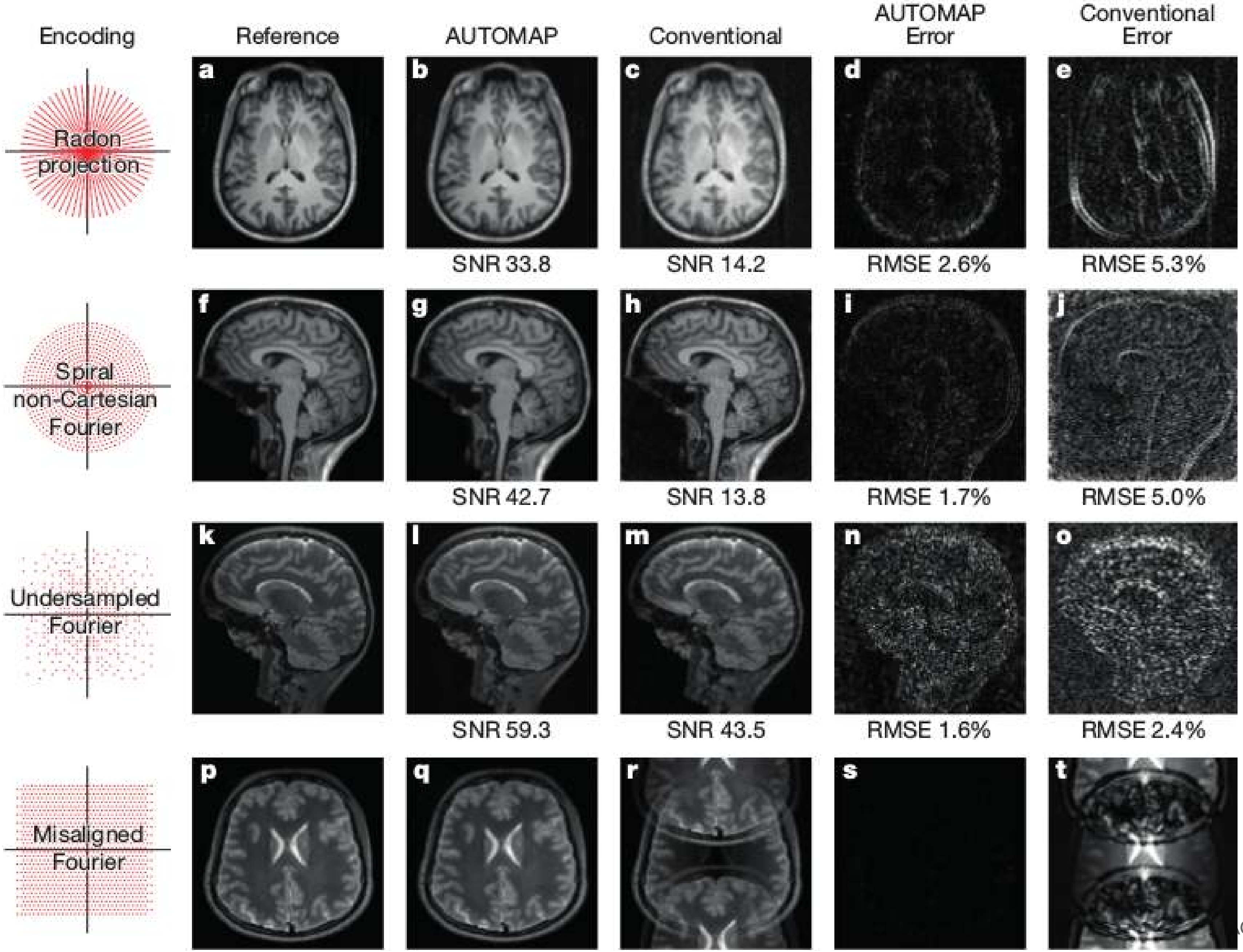


$$y = f(x) = \phi_y \circ g \circ \phi_x^{-1}(x)$$



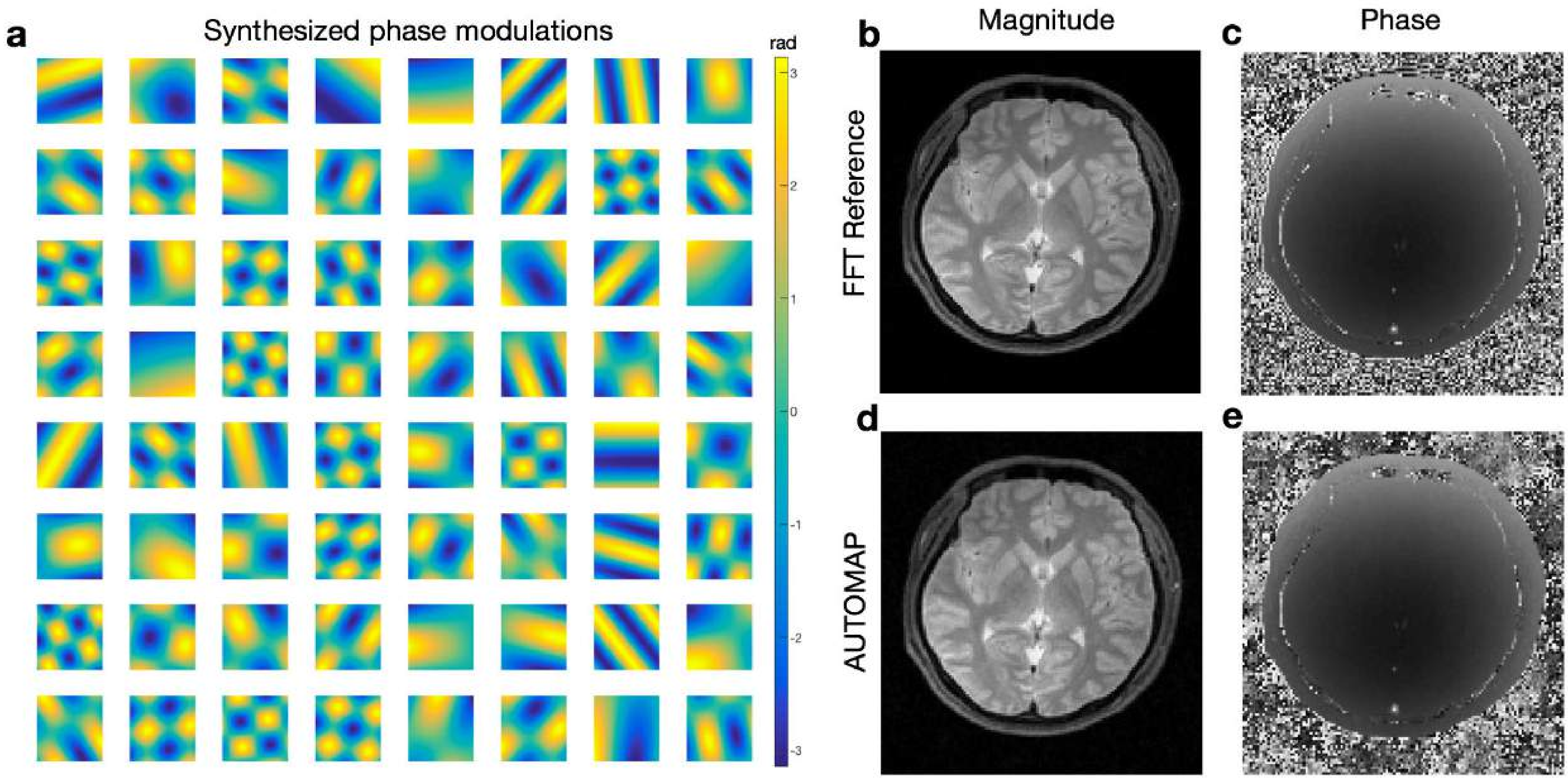
[Zhu et al, Nature 2018]

AUTOMAP Results (Magnitude)



[Zhu et al, Nature 2018]

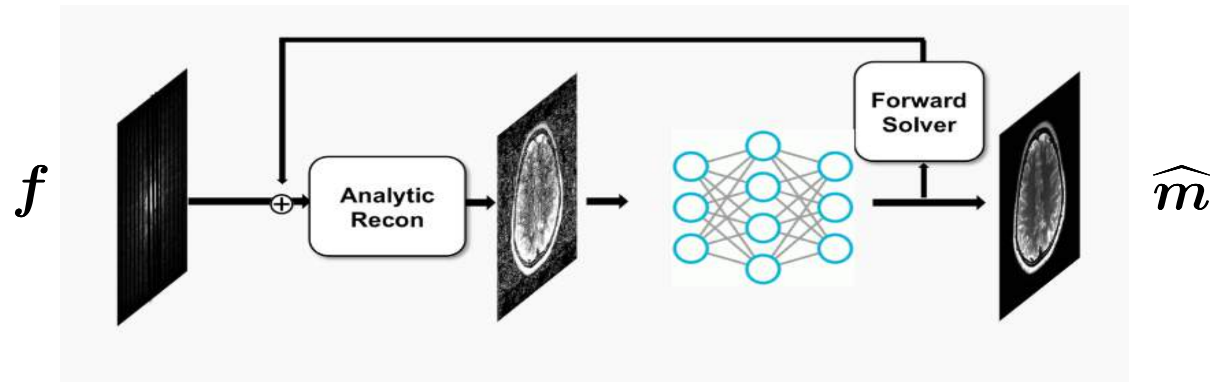
AUTOMAP Results (Phase)



[Zhu et al, Nature 2018]

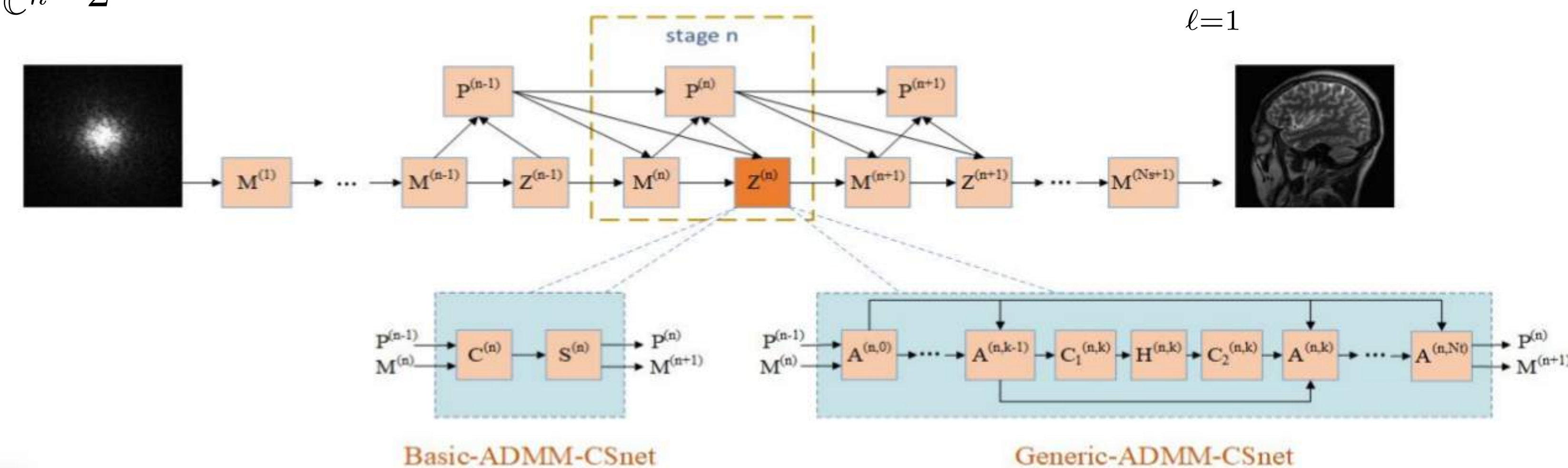
Single-Net Hybrid-Domain Learning

- Unroll iterative optimization algorithms: ADMM-Csnet, ISTA-net, ...



$$\widehat{\boldsymbol m} = \arg\min_{\boldsymbol m \in \mathbb{C}^n} \frac{1}{2} \|\boldsymbol{A}\boldsymbol{m} - \boldsymbol f\|_2^2 + G(\boldsymbol m)$$

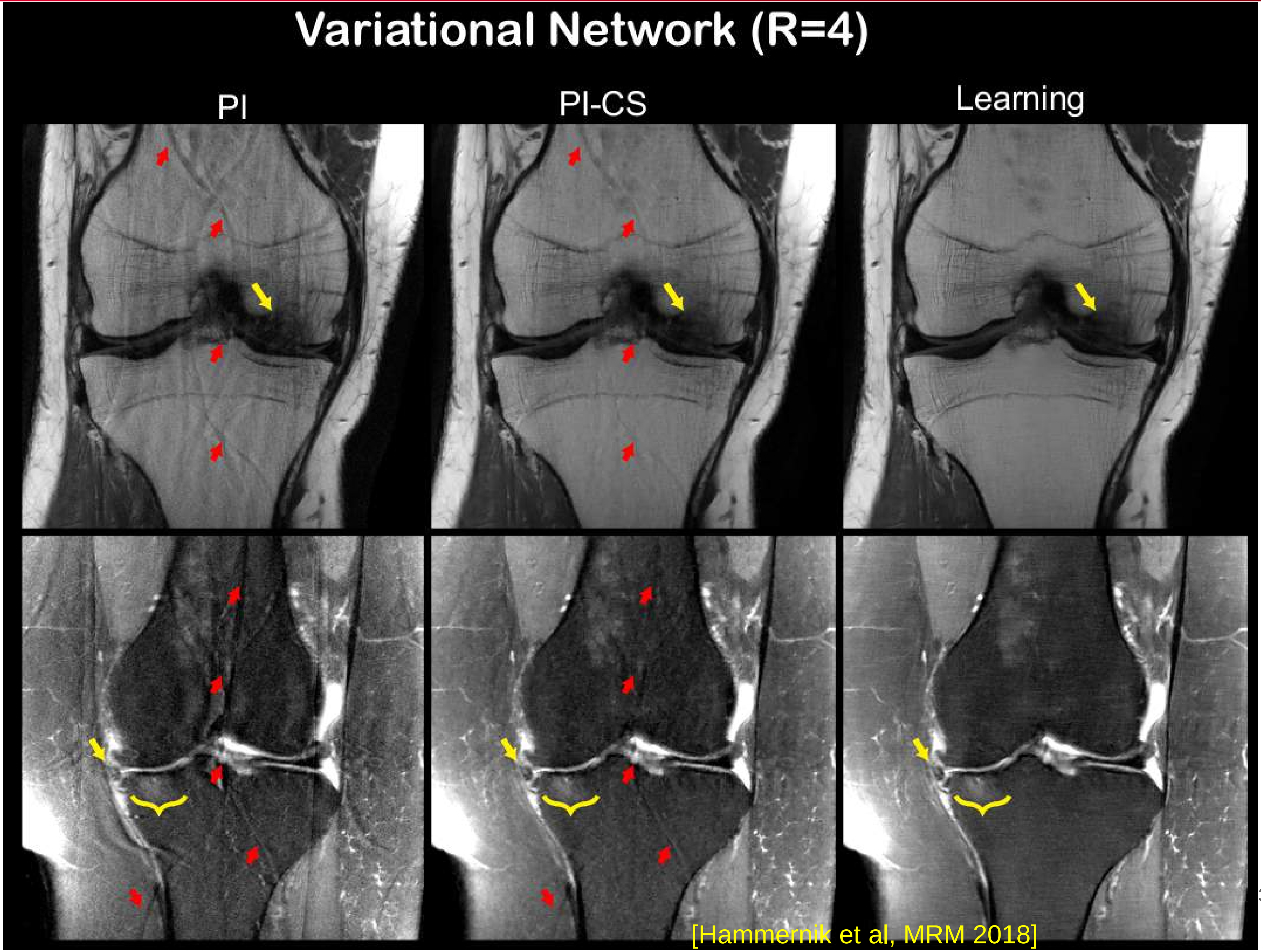
$$G(\boldsymbol m) = \sum_{\ell=1}^{L} \lambda_\ell g(\boldsymbol D_\ell \boldsymbol m)$$



$$\begin{cases} \boldsymbol M^{(n)}: & \boldsymbol m^{(n)} = \dfrac{\boldsymbol A^H \boldsymbol f + \sum_{\ell=1}^{L} \rho_\ell \boldsymbol D_\ell^T (\boldsymbol z_\ell^{(n-1)} - \beta_\ell^{(n-1)})}{\boldsymbol A^H \boldsymbol A + \sum_{\ell=1}^{L} \rho_\ell \boldsymbol D_\ell^{t} (\boldsymbol z_\ell^{(n-1)} - \beta_\ell^{(n-1)})} \\ \boldsymbol Z^{(n)}: & \boldsymbol z^{(n)} = \boldsymbol S(\boldsymbol D_\ell \boldsymbol m^{(n)} + \beta_\ell^{(n-1)}; \lambda_\ell / \rho_\ell) \\ \boldsymbol P^{(n)}: & \beta_\ell^{(n)} = \beta_\ell^{(n-1)} + \eta_\ell (\boldsymbol D_\ell \boldsymbol m^{(n)} - \boldsymbol z_\ell^{(n)}) \end{cases}$$

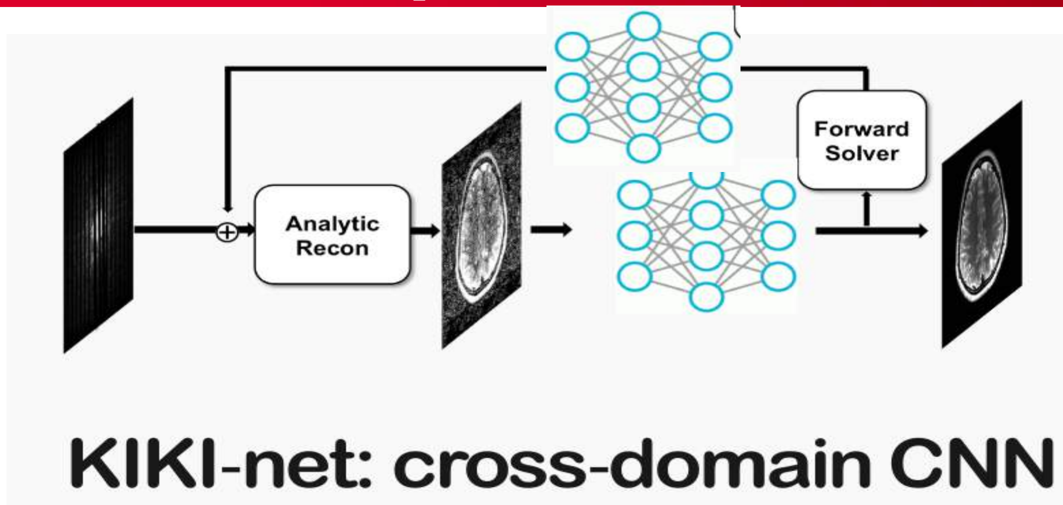
[Yang et al, NIPS 2016, Yang et al, IEEE PAMI 2018]

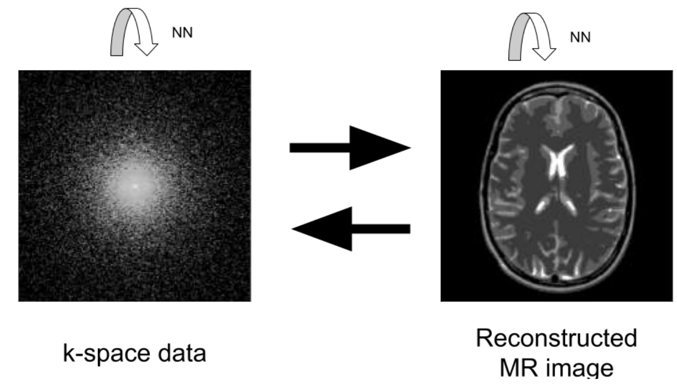
Variational-net Extension

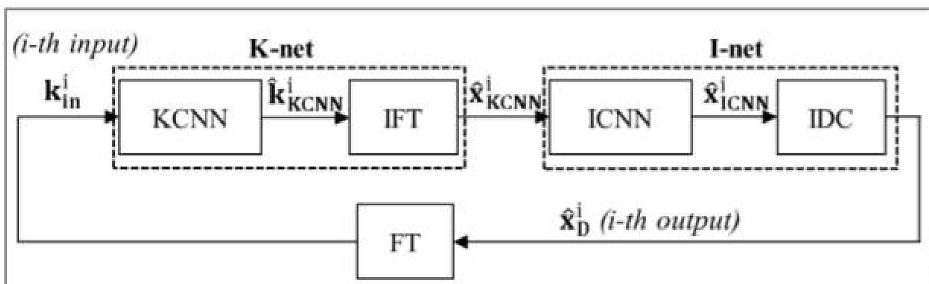


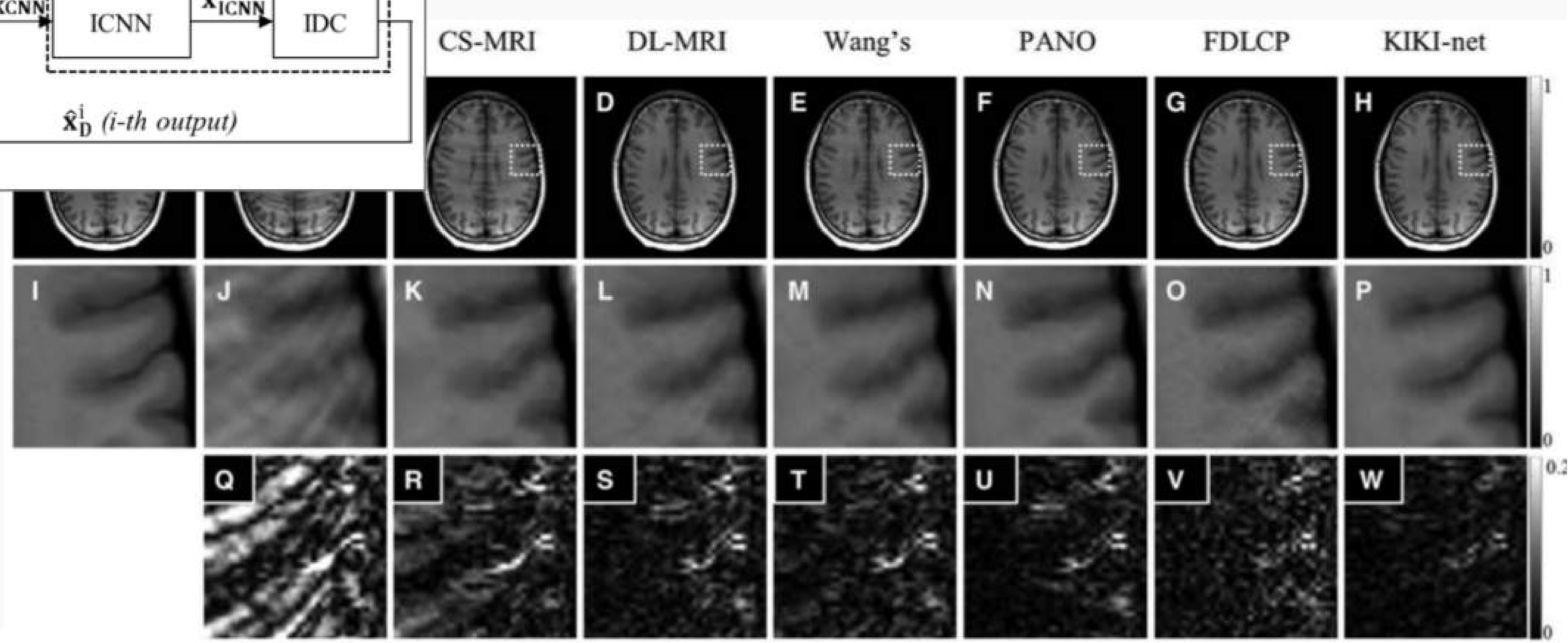
[Hammernik et al, MRM 2018]

Double-Net Hybrid-Domain Learning (DN-HDL)









[Eo et al, MRM 2018]

Current Investigation in DN-HDL

Optimization algorithm

Algorithm 1 Non-linear primal dual hybrid gradient

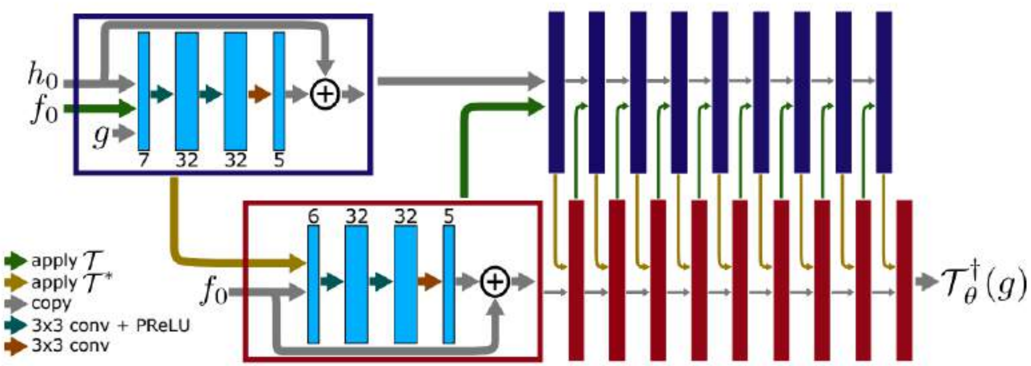
1: Given: $\sigma, \tau > 0$ s.t. $\sigma\tau\|\mathcal{K}\|^2 < 1$, $\gamma \in [0,1]$ and $f_0 \in X$, $h_0 \in U$.
2: **for** $i = 1, \ldots$ **do**
3: $\quad h_{i+1} \leftarrow \operatorname{prox}_{\sigma\mathcal{F}^*}(h_i + \sigma\mathcal{K}(\bar{f}_i))$
4: $\quad f_{i+1} \leftarrow \operatorname{prox}_{\tau\mathcal{G}}(f_i - \tau[\partial\mathcal{K}(f_i)]^*(h_{i+1}))$
5: $\quad \bar{f}_{i+1} \leftarrow f_{i+1} + \gamma(f_{i+1} - f_i)$

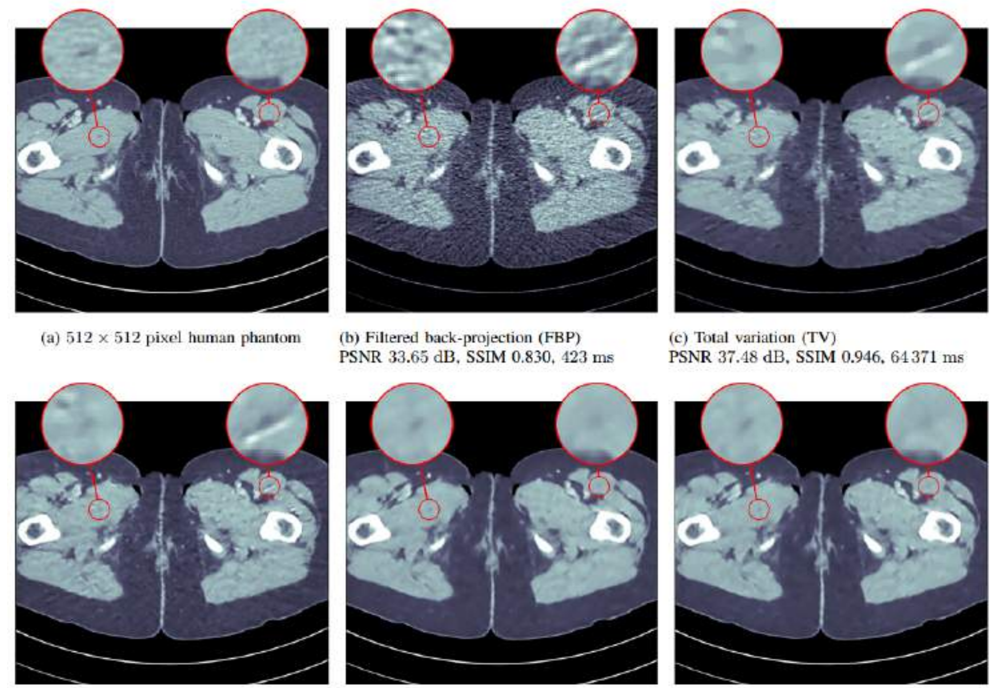
Learned version with DNN

Algorithm 3 Learned Primal-Dual

1: Initialize $f_0 \in X^{N_{\text{primal}}}$, $h_0 \in U^{N_{\text{dual}}}$
2: **for** $i = 1, \ldots, I$ **do**
3: $\quad h_i \leftarrow \Gamma_{\theta_i^d}(h_{i-1}, \mathcal{K}(f_{i-1}^{(2)}), g)$
4: $\quad f_i \leftarrow \Lambda_{\theta_i^p}(f_{i-1}, [\partial\mathcal{K}(f_{i-1}^{(1)})]^*(h_i^{(1)}))$
5: **return** $f_I^{(1)}$

[Adler et al, IEEE TMI 2018]





(a) 512 × 512 pixel human phantom

(b) Filtered back-projection (FBP) PSNR 33.65 dB, SSIM 0.830, 423 ms

(c) Total variation (TV) PSNR 37.48 dB, SSIM 0.946, 64371 ms

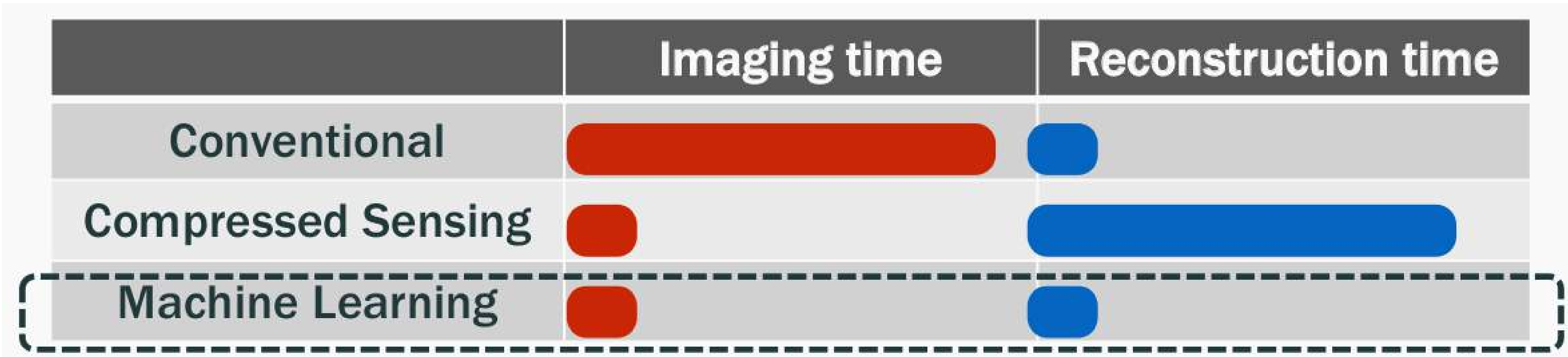
(d) FBP + U-Net denoising PSNR 41.92 dB, SSIM 0.941, 463 ms

(e) Primal-Dual, linear PSNR 44.10 dB, SSIM 0.969, 620 ms

(f) Primal-Dual, non-linear PSNR 43.91 dB, SSIM 0.969, 670 ms

- **Extension to NFFT & B0 inhomogeneities**
- **Parallel Imaging**

What Deep Learning enables?



- **High quality image reconstruction: better than CS**
- **After training, fast reconstruction on unseen data**
- **Interpretable models**

Conclusion & Outlook

- **Save time for MR acquisition especially for high-resolution imaging**
  - SPARKLING: adaptive sampling strategy to any MR system & imaging contrast
  - Ongoing extensions for 4D imaging (multi-contrast 3D & 3D+time)
  - Ability to perform anisotropic sampling!

- **Save time for MR image reconstruction using deep learning**
  - Scalability of CNN for high-resolution imaging (large dimensions)
  - Scalability of CNN for 5D image reconstruction in the pMRI context
  - Best trade-off between the **size of the training set** vs the **diagnosis precision**
  -

- **Joint DL for fast MR Acquisition & Image reconstruction**
  - Optimize the acquisition/reconstruction pair in various imaging scenarios

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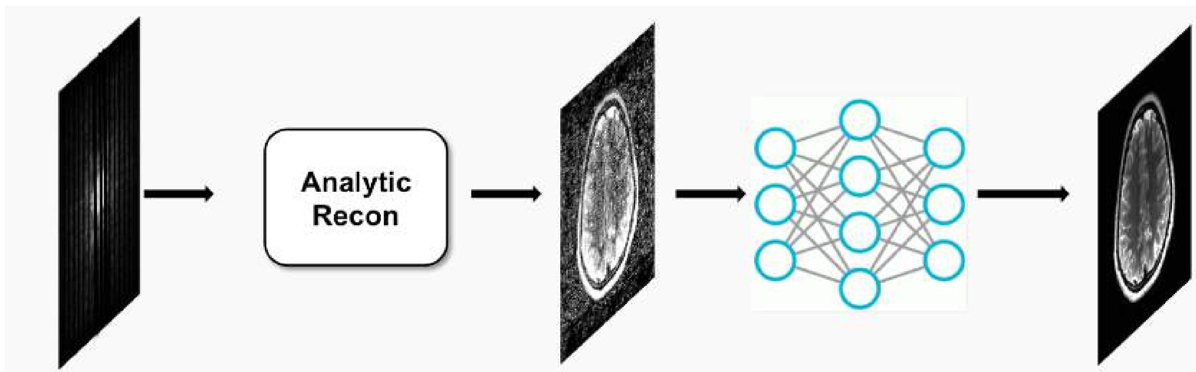
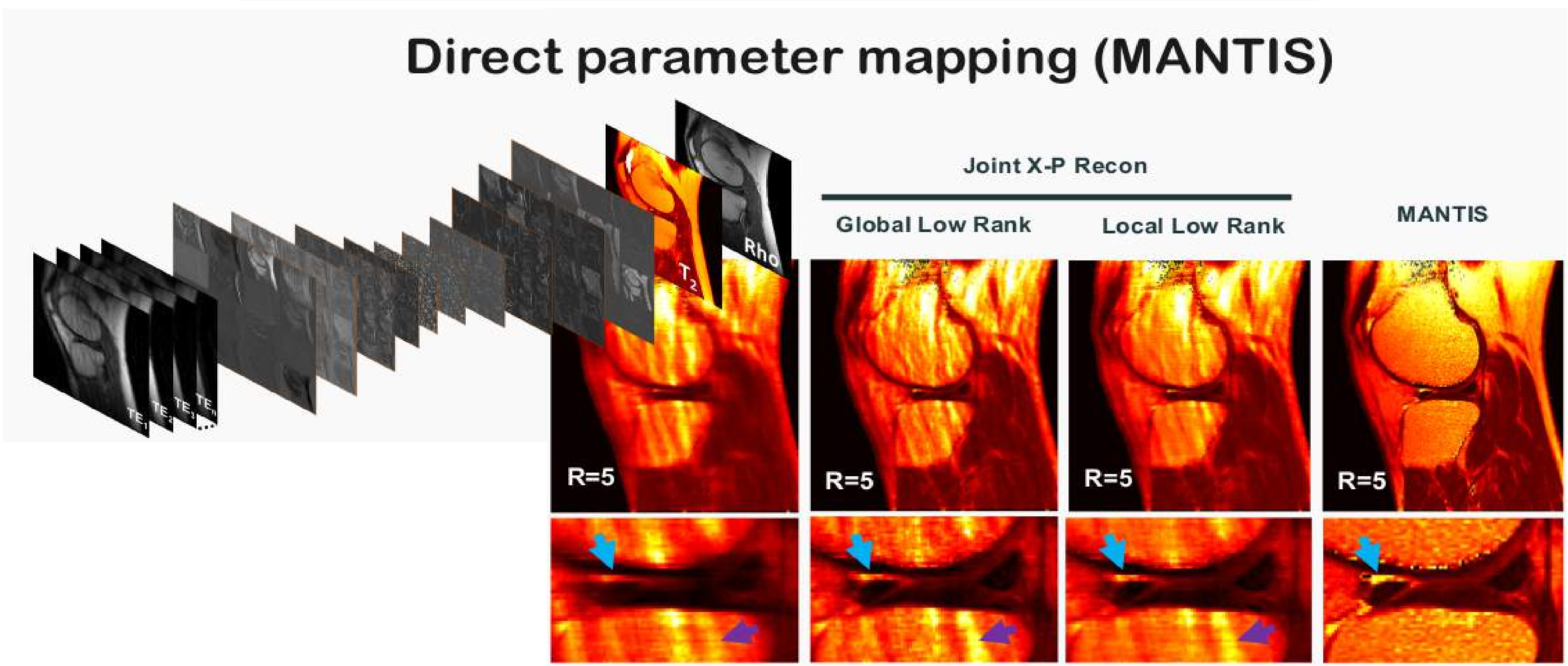
Olivier Grisel
Bertrand Thirion

Siemens Healthineers:
Franck Mauconduit

Image-Domain Learning

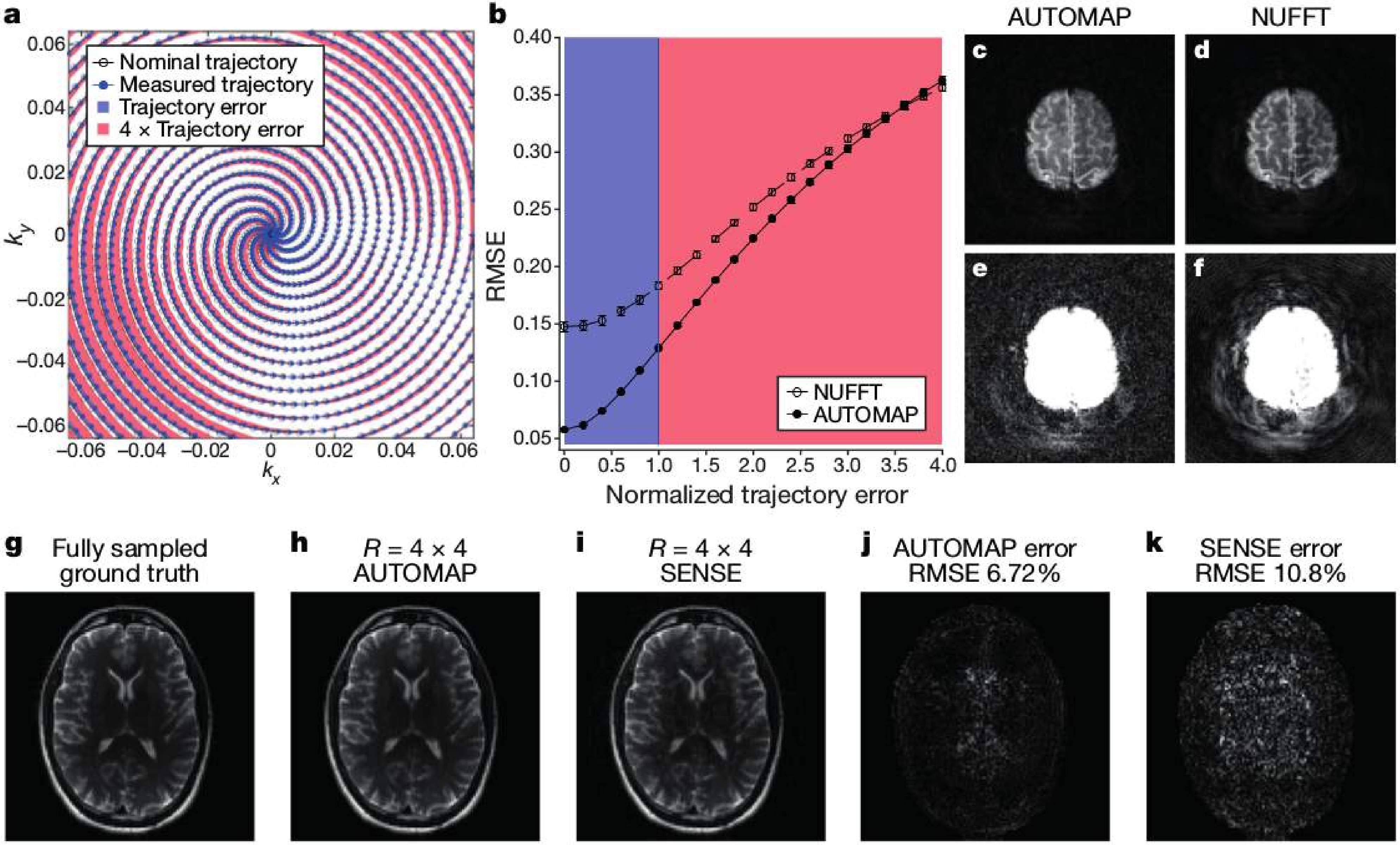
- **Data-driven deep learning for fast MRI reconstruction**





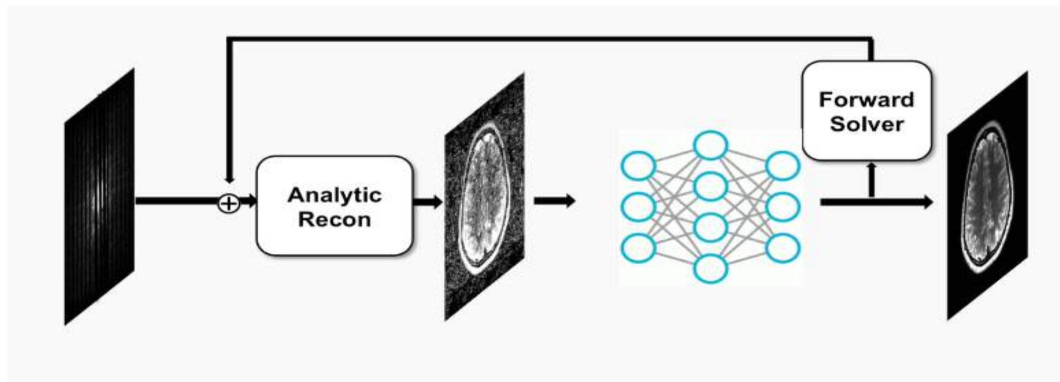
[Yoon et al, neuroImage 2018]

AUTOMAP results in spiral imaging

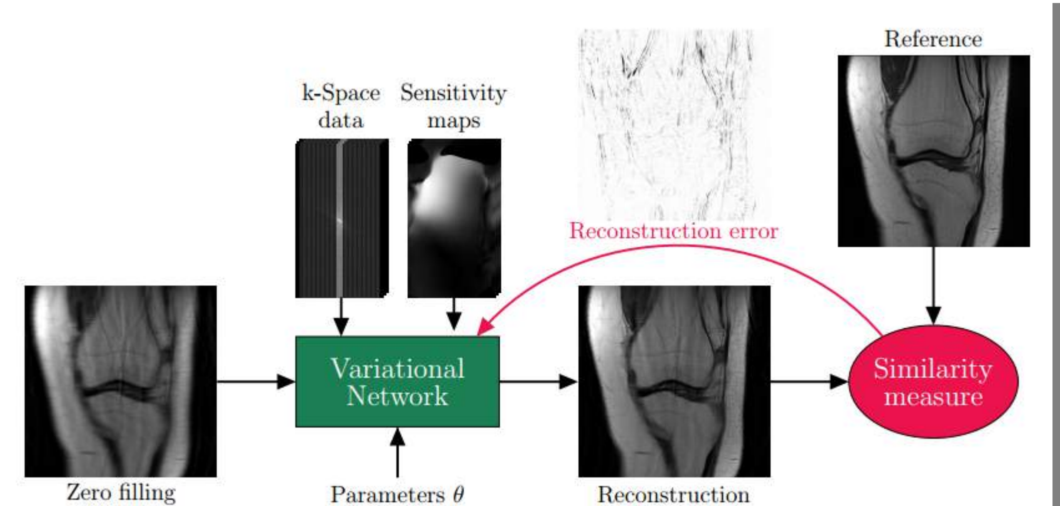


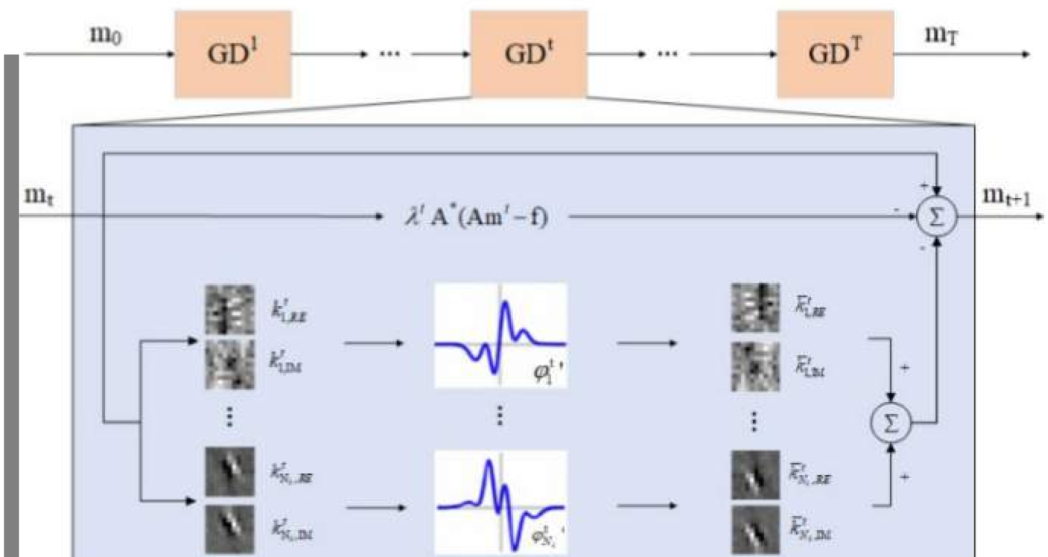
Single-Net Hybrid-Domain Learning

- Variational Network for parallel imaging using a single CNN



$$\widehat{\boldsymbol{m}} = \underset{\boldsymbol{m}\in\mathbb{C}^n}{\arg\min}\ \frac{1}{2}\|\boldsymbol{A}\boldsymbol{m} - \boldsymbol{f}\|_2^2 + G(\boldsymbol{m}) \longrightarrow G(\boldsymbol{m}) = \sum_{i=1}^{N_k} \langle \Phi_i(\boldsymbol{K}_i\boldsymbol{m}), \boldsymbol{1}\rangle$$



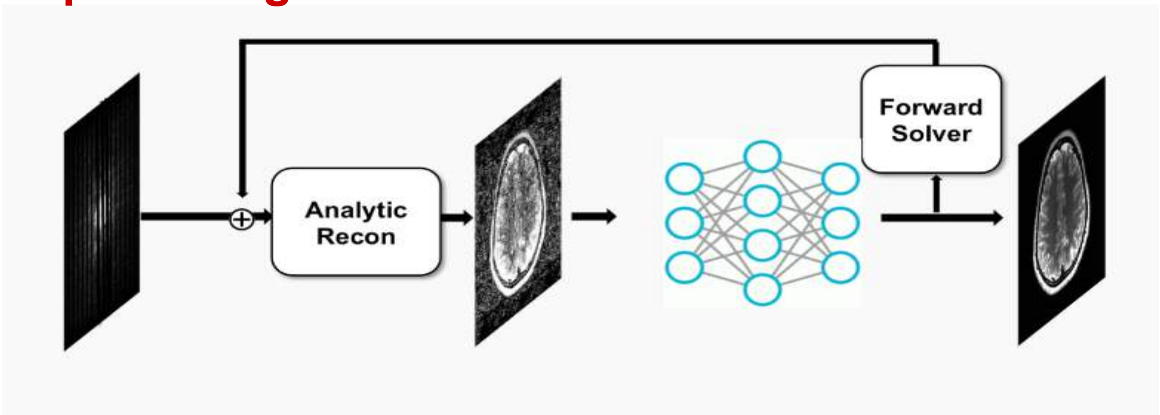


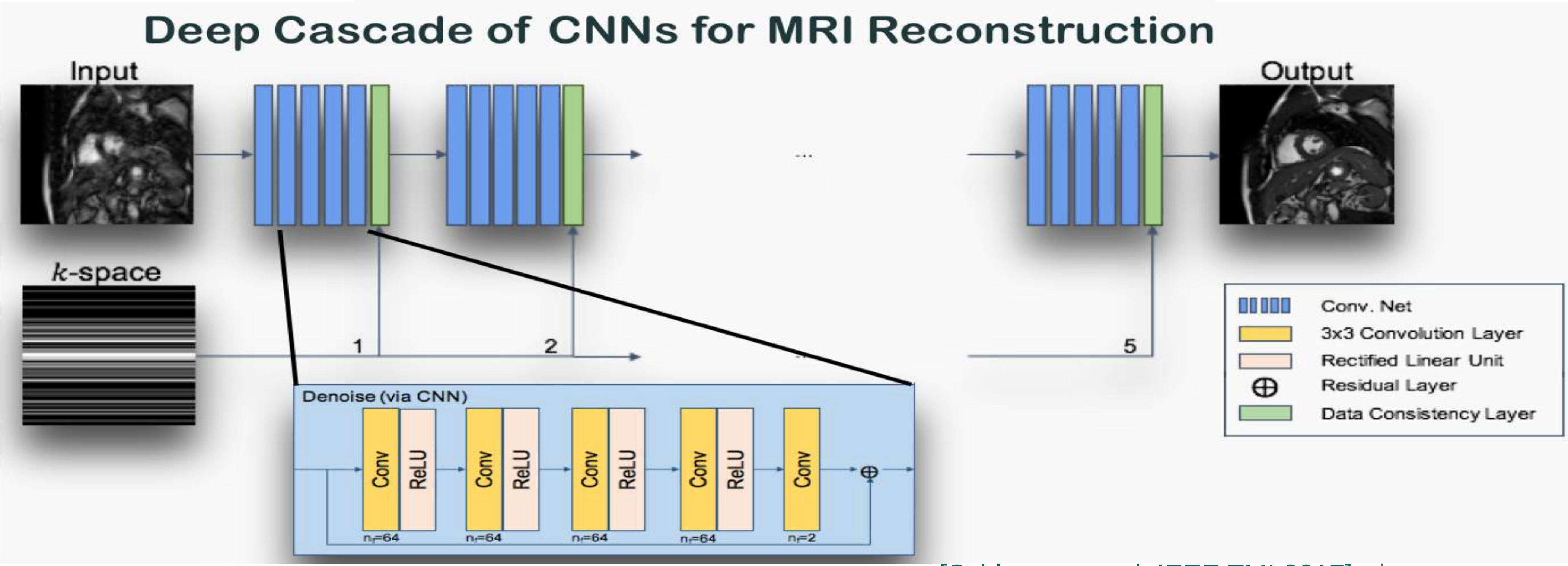
$$\boldsymbol{m}^{(t+1)} = \boldsymbol{m}^{(t)} - \sum_{i=1}^{N_k} (\boldsymbol{K}_i^{(t)})^T \boldsymbol{\Phi}_i^{(t)\prime}(\boldsymbol{K}_i^{(t)}\boldsymbol{m}^{(t)}) - \lambda \boldsymbol{A}^H(\boldsymbol{A}\boldsymbol{m}^{(t)} - f)$$

[Hammernik et al, MRM 2018]

Hybrid-Domain Learning

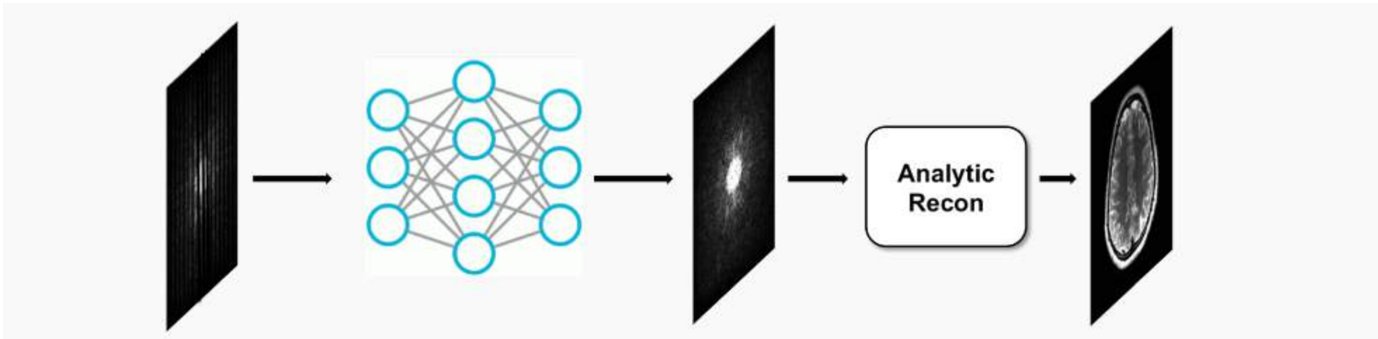
- **Model-based deep learning for fast MRI reconstruction**



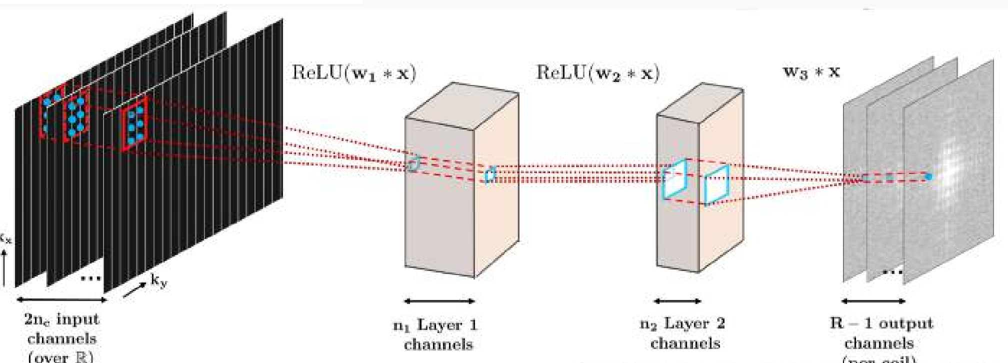


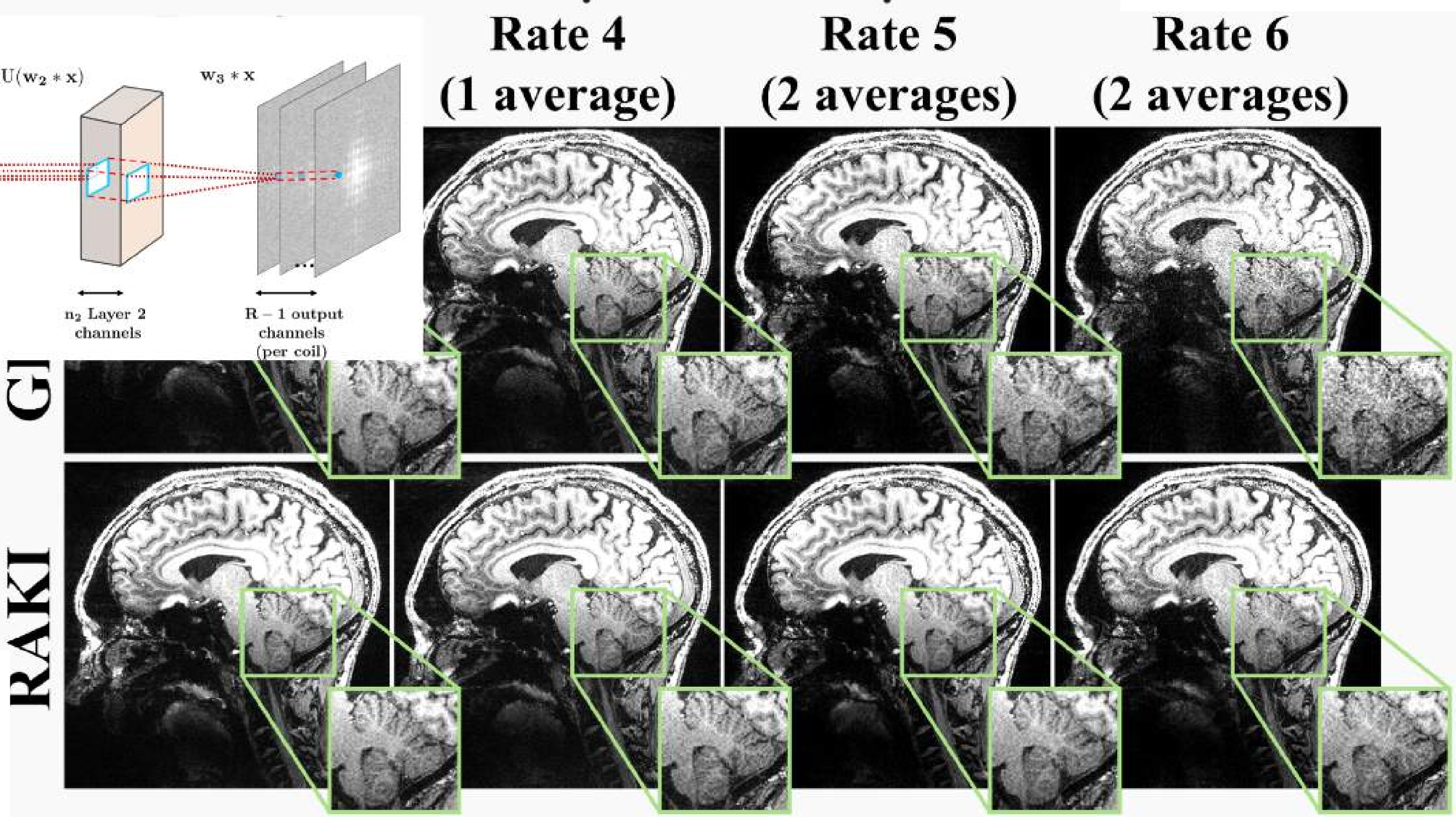
[Schlemper et al, IEEE TMI 2017]

Sensor domain Learning



RAKI: Robust ANN for k-space Interpolation





[Akçakaya et al, MRM 2019]