

Outline

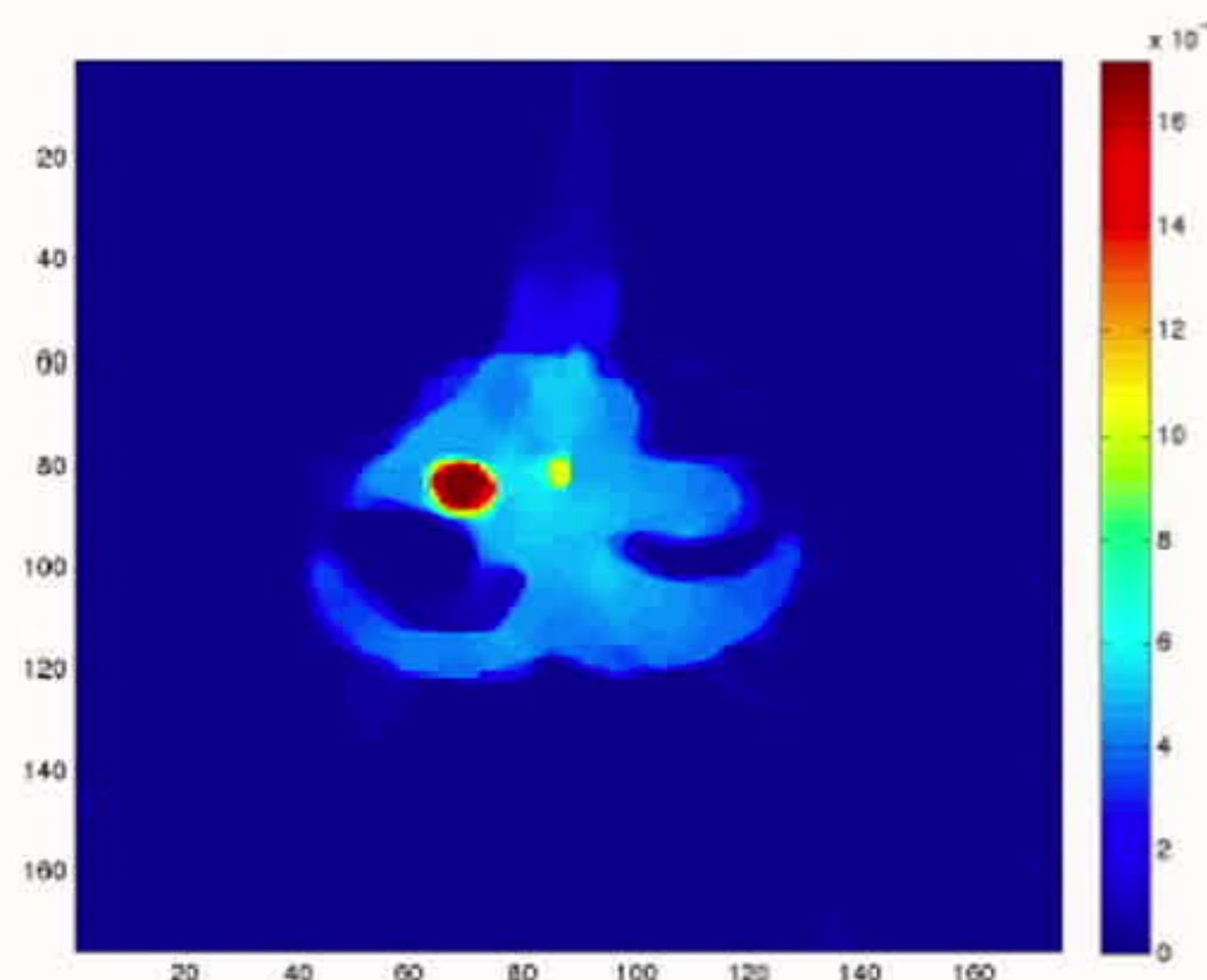
- 1 Knowledge-driven inversion
- 2 Data-driven inversion
- 3 Deeply learned inversion
 - Learning a regularizer

What is an inverse imaging problem?

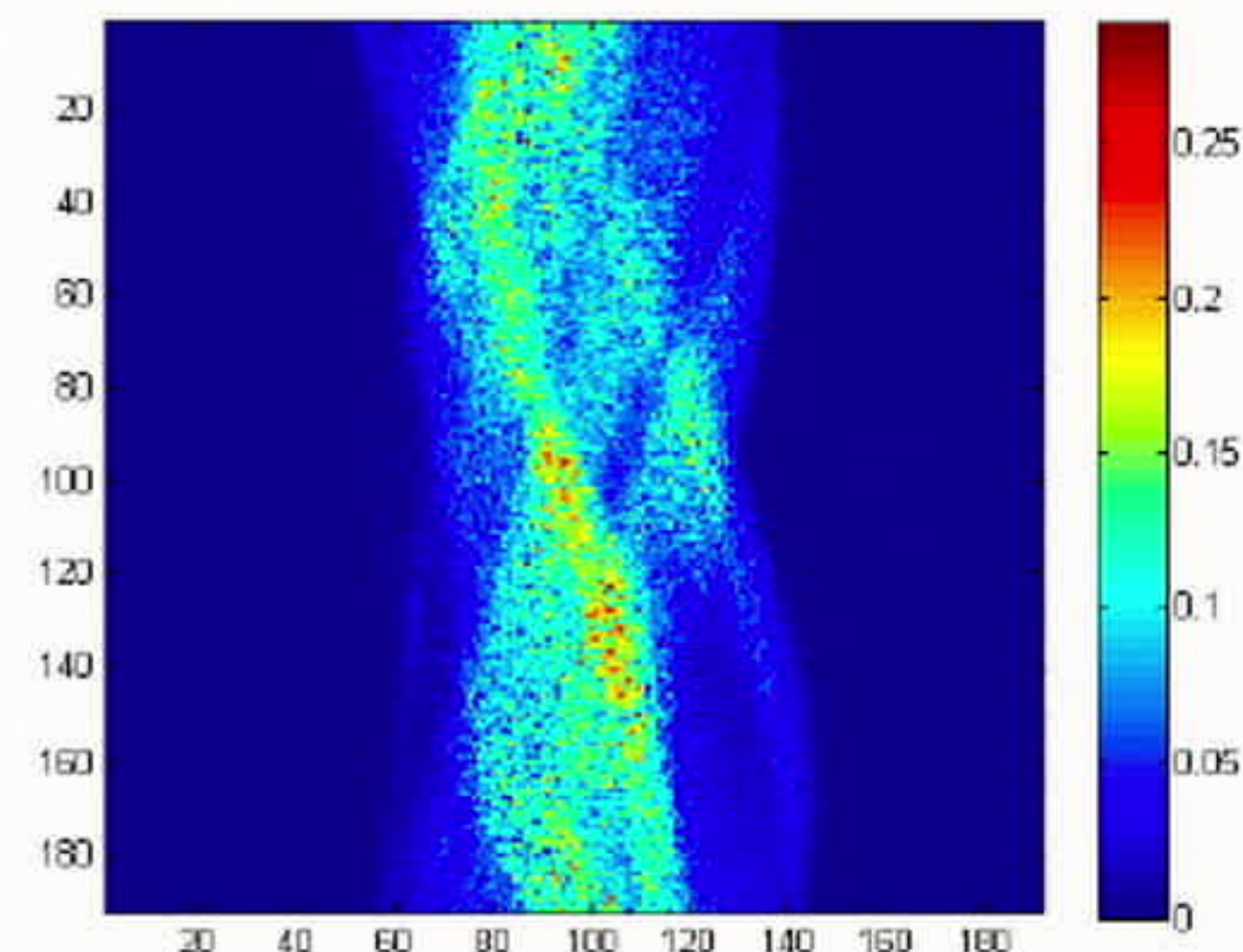
Forward problem: knowing physical quantity compute the measurements

Inverse problem: measuring the datum compute the physical quantity.

Physical quantity
(trazer accumulation)



Measurements
(sinogram)

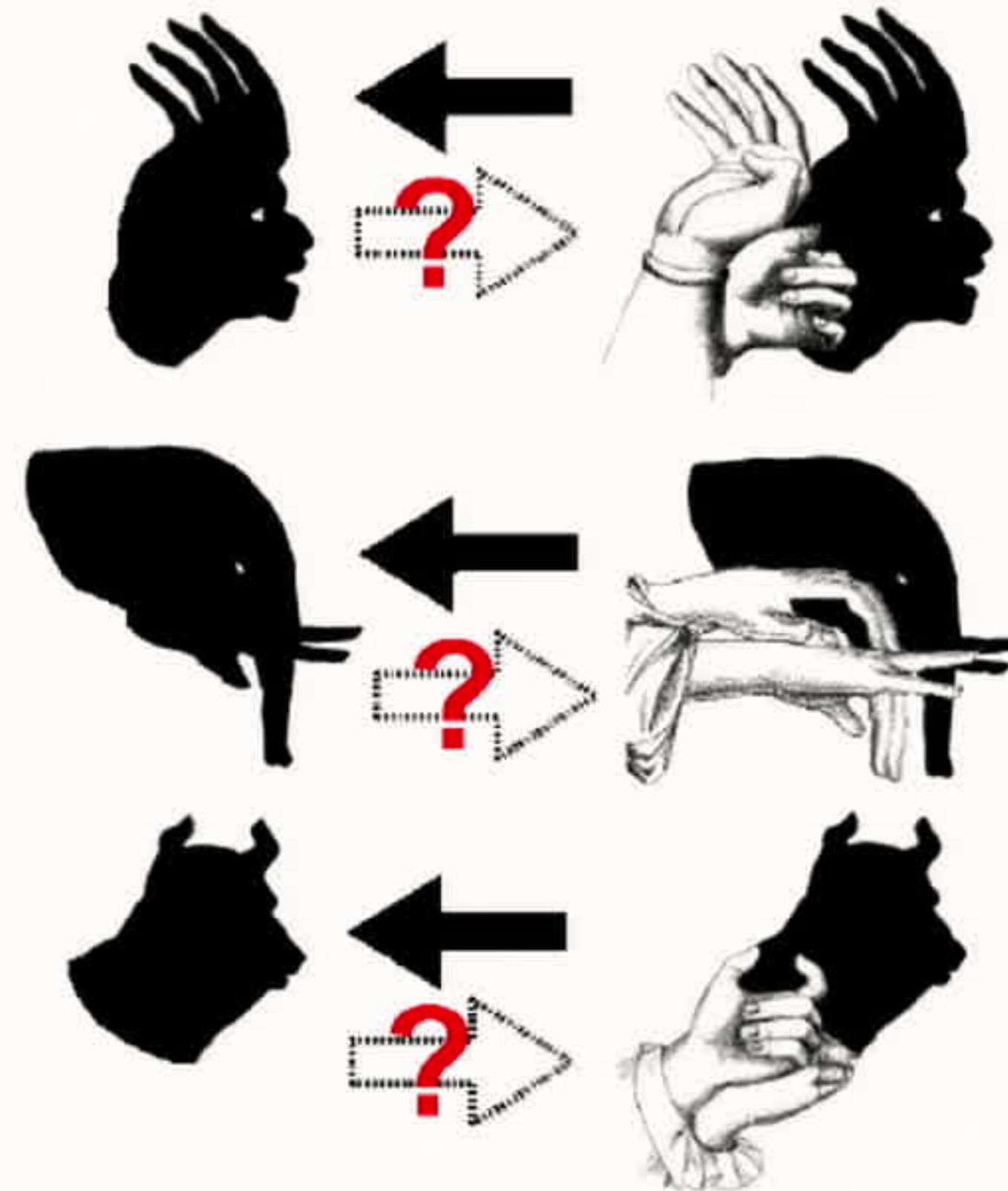


Mathematically: compute $u \in X$ from $Y \ni f = T(u) + n$, X, Y normed vector spaces.

Ill-posedness

Reasons: unbounded or discontinuous inverse (examples are compact forward operators with infinite range), underdetermined data (subsampling), noise, ...

Consequences: instabilities (solution is not continuously dependent on input data), non-uniqueness, ...



The variational approach

General task: **restore** u from an **observed datum** f where

$$f = \underbrace{T(u)}_{\text{forward model}} + \underbrace{n}_{\text{noise}}.$$

Variational approach: Compute u as a minimizer of

$$\mathcal{J}(u) = \alpha \underbrace{R(u)}_{\text{regularization}} + \underbrace{D(T(u), f)}_{\text{data fidelity}} \rightarrow \min_{u \in X}$$

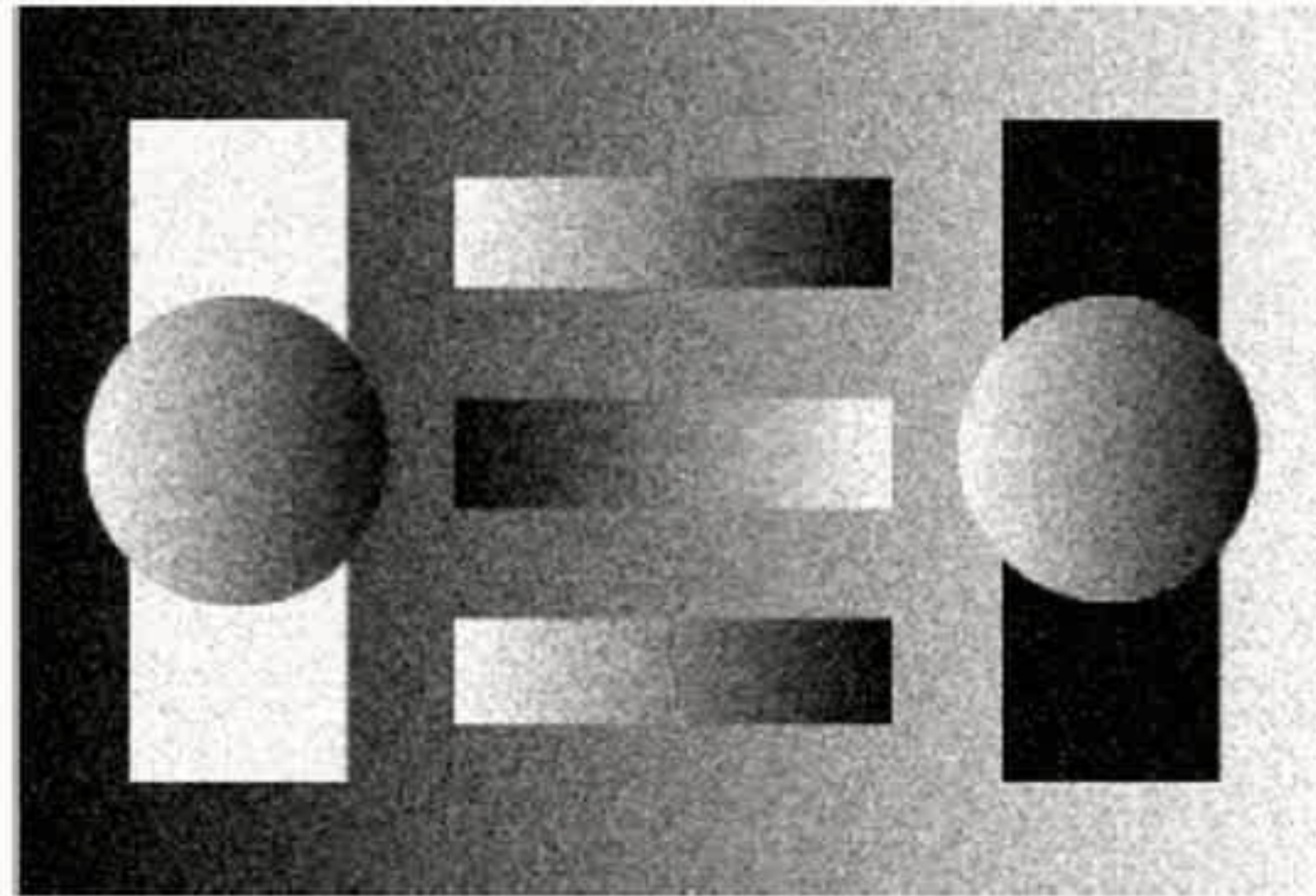
where

- $R(u)$ is a prior/regularizer that models a-priori information on u weighted by positive α , e.g., $R(u) = \|\nabla u\|_1$ (in infinite dimensions $|Du|(\Omega)$)
- $D(\cdot, \cdot)$ is a distance function, e.g. $D(Tu, g) = \|Tu - g\|_2^2$ and B suitable Banach space, e.g., $X = BV(\Omega)$.

Engl, Hanke, Neubauer '96; Rudin, Osher, Fatemi, Physica D '92; Natterer, Wübbeling '01;
Candes, Romberg, Tao, IEEE Trans Inf Theory '06; Kaltenbacher, Neubauer, Scherzer '08;
Schuster, Kaltenbacher, Hofmann, Kazimierski '12

What is the right sparsity?

$$\min_u \left\{ \min_w \left\{ \alpha_1 \|\nabla u - w\|_1 + \alpha_2 \|Ew\| \right\} + \|u - f\|_2^2 \right\}$$



Noisy image

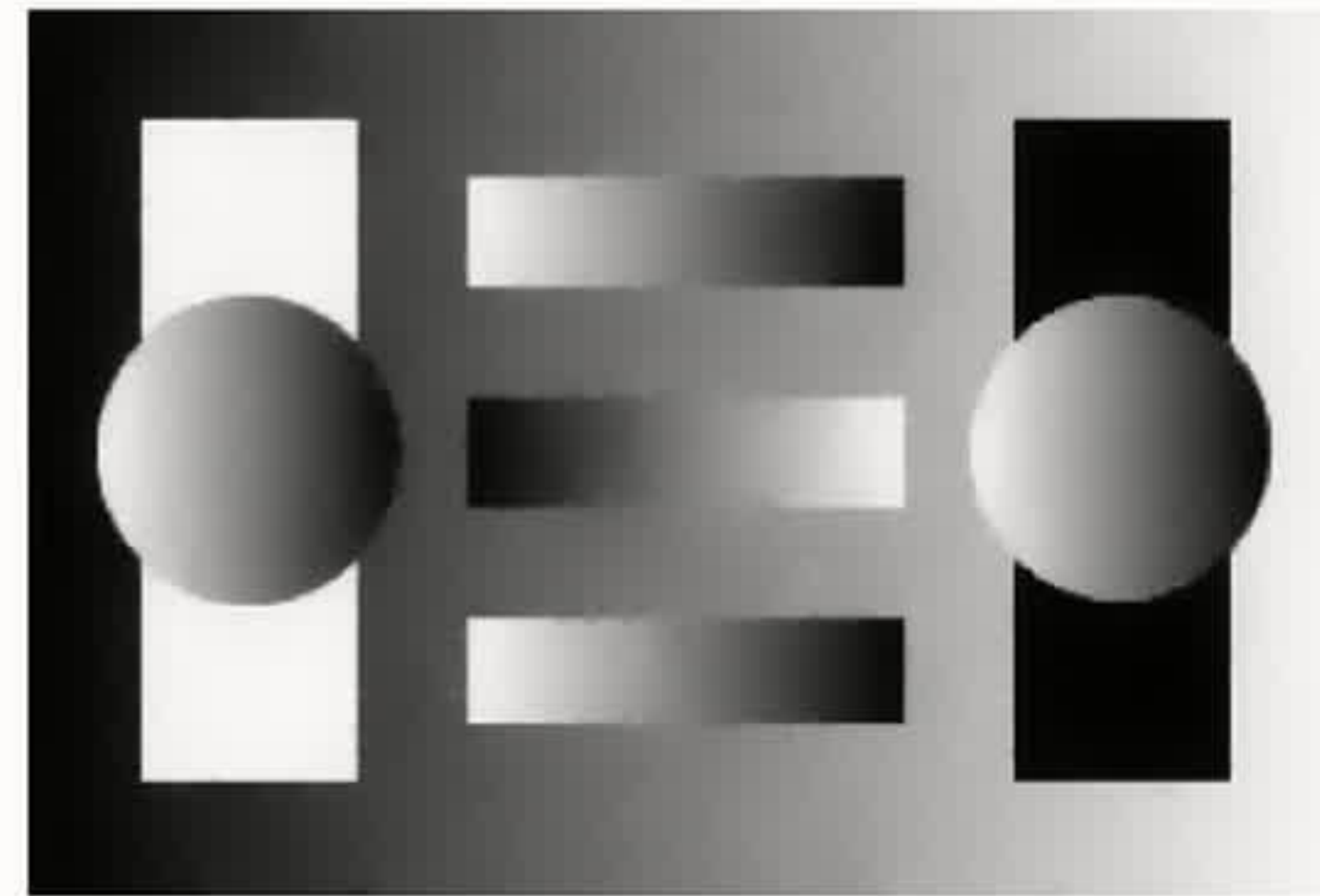
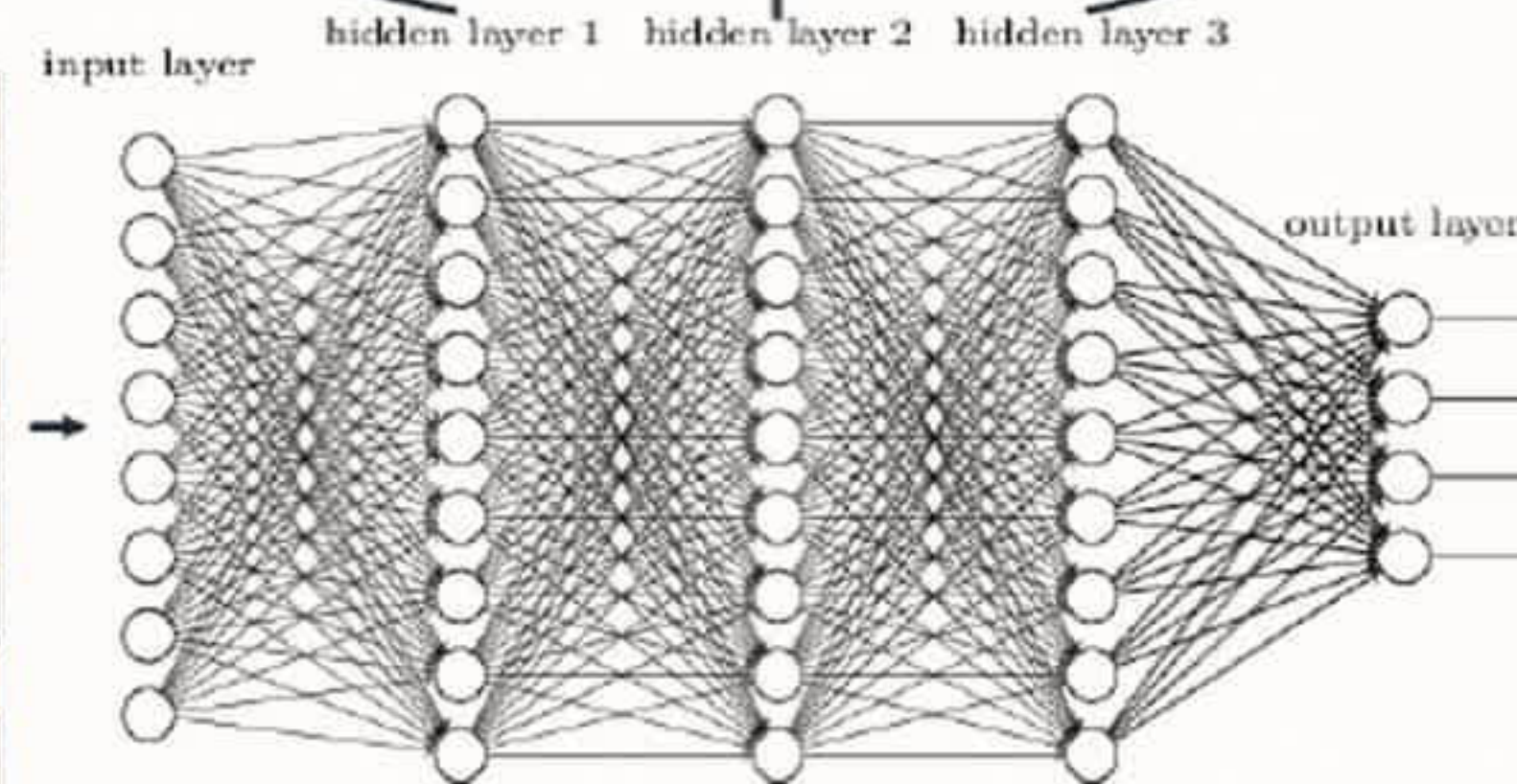
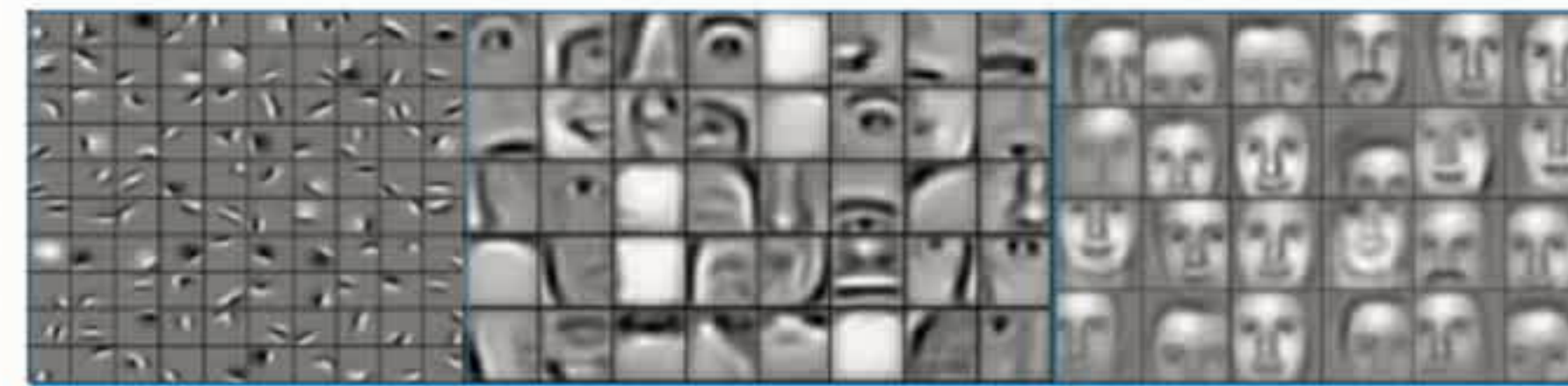
TGV² denoised image

Image courtesy of K. Papafitsoros

References: Rudin, Osher, Fatemi '92; Hinterberger, Scherzer, Computing '06; Bredies, Kunisch, Pock, SIAM Imaging '10; Papafitsoros, CBS, J. Math. Imaging & Vision, '13 ...

Deep image processing

Deep neural networks learn hierarchical feature representations



Picture from strong analytics. [LeCun, Y., Bengio, Y., & Hinton, G. \(2015\). Deep learning. Nature, 521\(7553\), 436-444.](#)

Basic model for deep learning

$$\min_{\Theta} F(u_{\Theta}^K) \quad \text{s.t.} \quad \begin{aligned} &u^0 \in \mathbb{R}^n \\ &u^1 = \psi(A_{\Theta}^0 u^0 + b_{\Theta}^0) \\ &\vdots \\ &u^k = \psi(A_{\Theta}^{k-1} u^{k-1} + b_{\Theta}^{k-1}) \\ &\vdots \\ &u_{\Theta}^K = \psi(A_{\Theta}^{K-1} u^{K-1} + b_{\Theta}^{K-1}) \end{aligned}$$



Learning from ex-
amples

Deep learning for inverse imaging

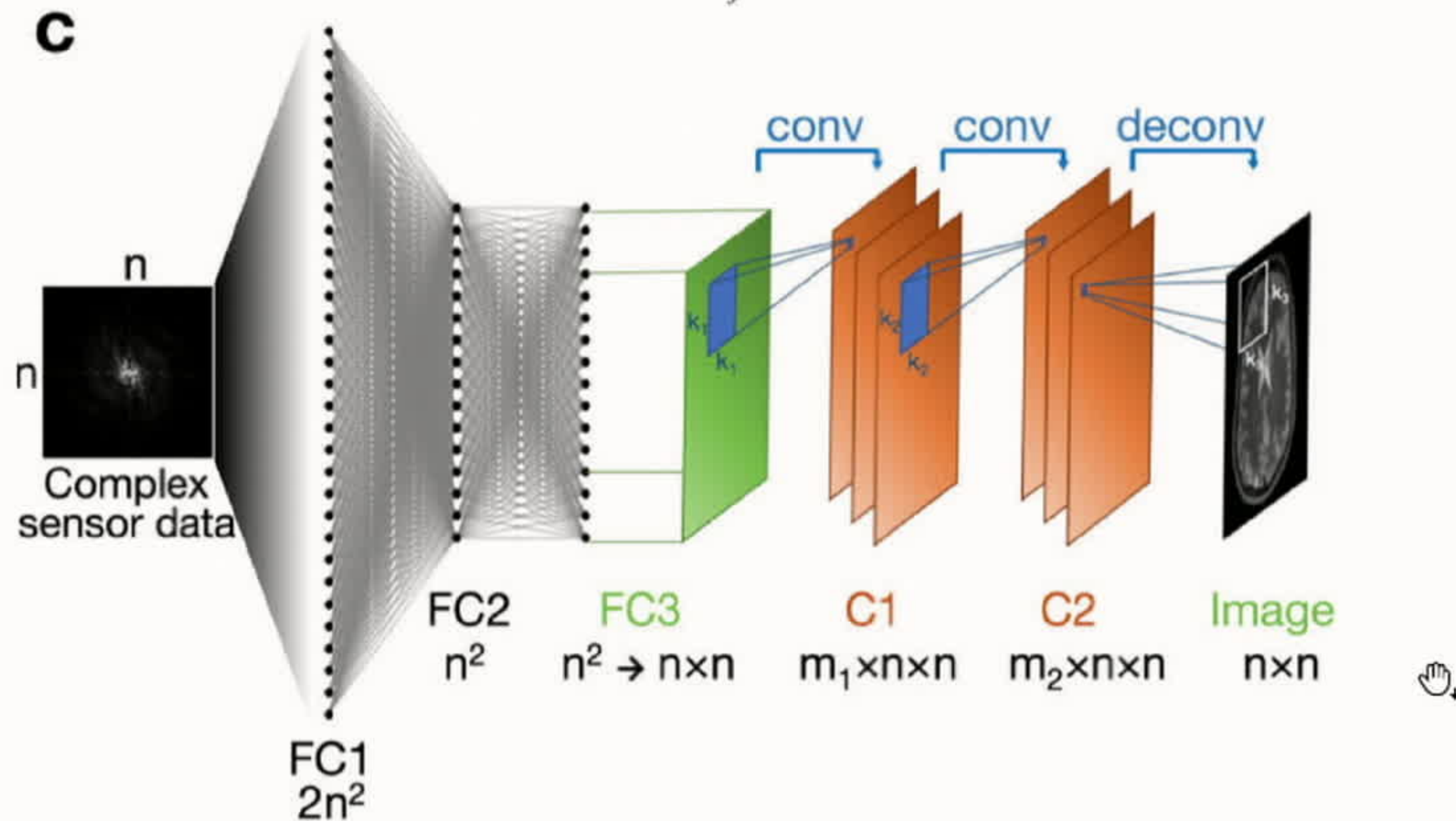
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Recent reviews: McCann, Jin, Unser, IEEE Signal Processing Magazine, 34(6), 85-95, '17; Arridge, Maass, Öktem, CBS, Acta Numerica '19

Fully learned model

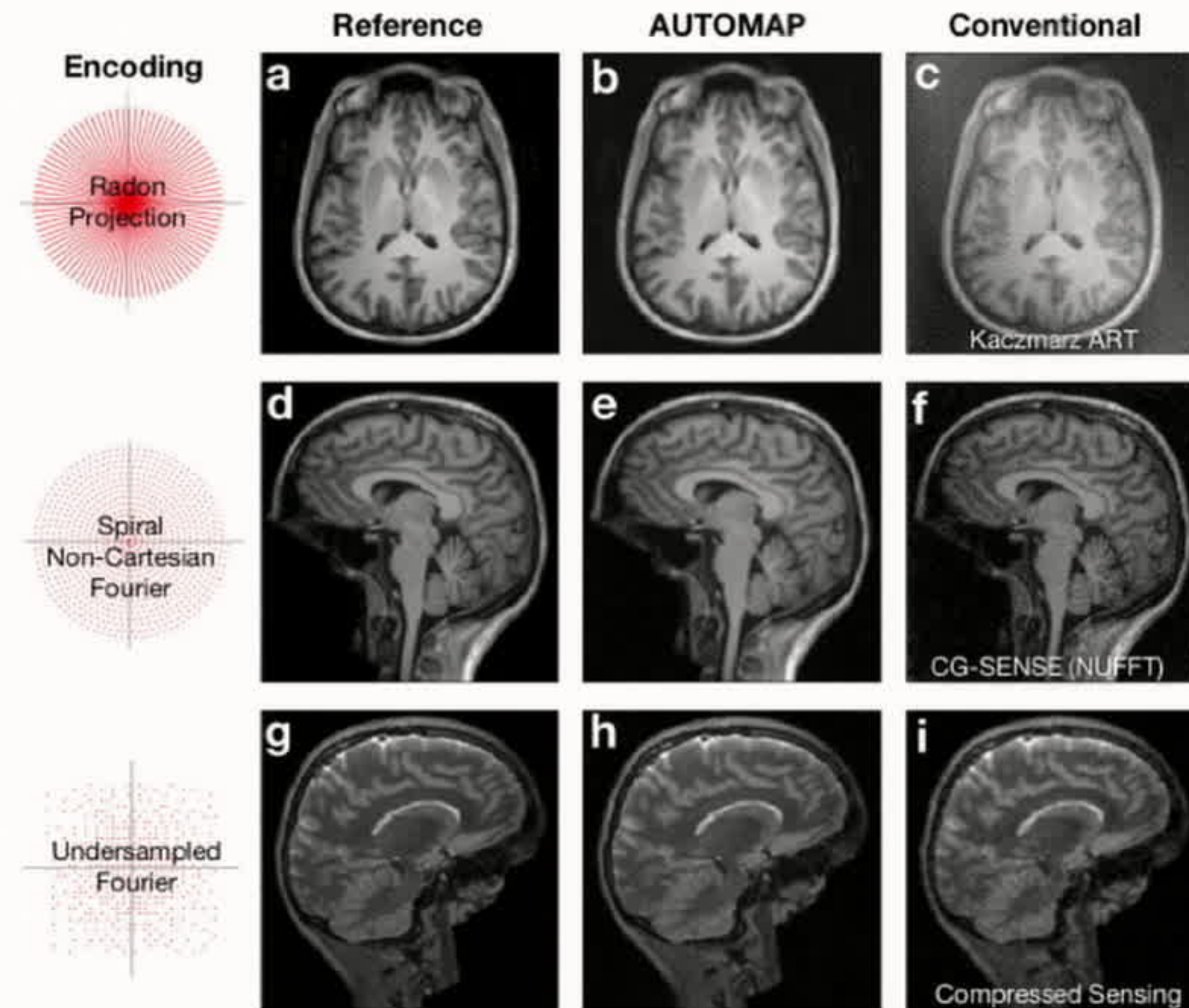
Example: AUTOMAP [Zhu, Bo, Liu, Cauley, Rosen, Rosen, Nature '18.](#)



Training with dataset of 50,000 brain images.

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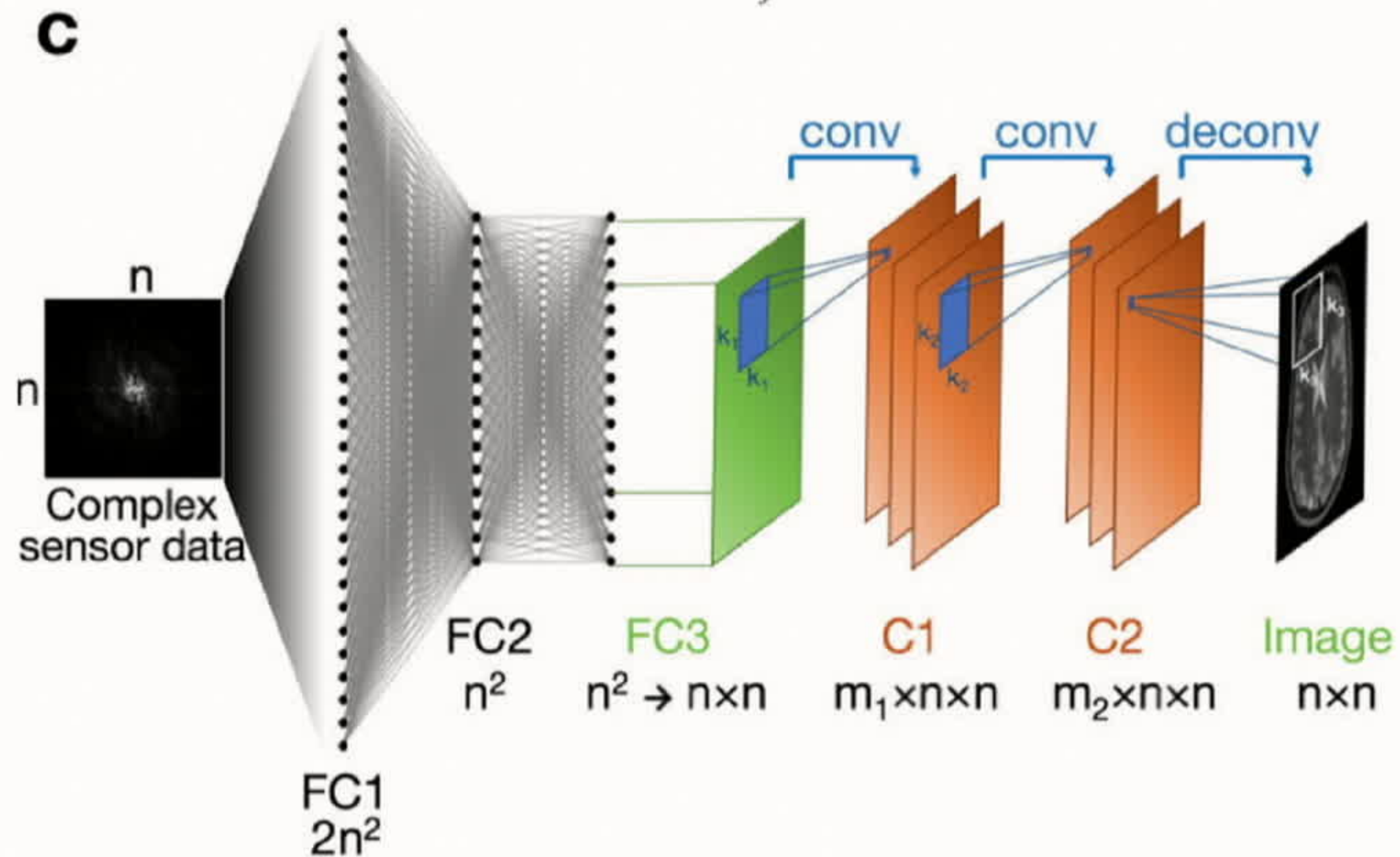
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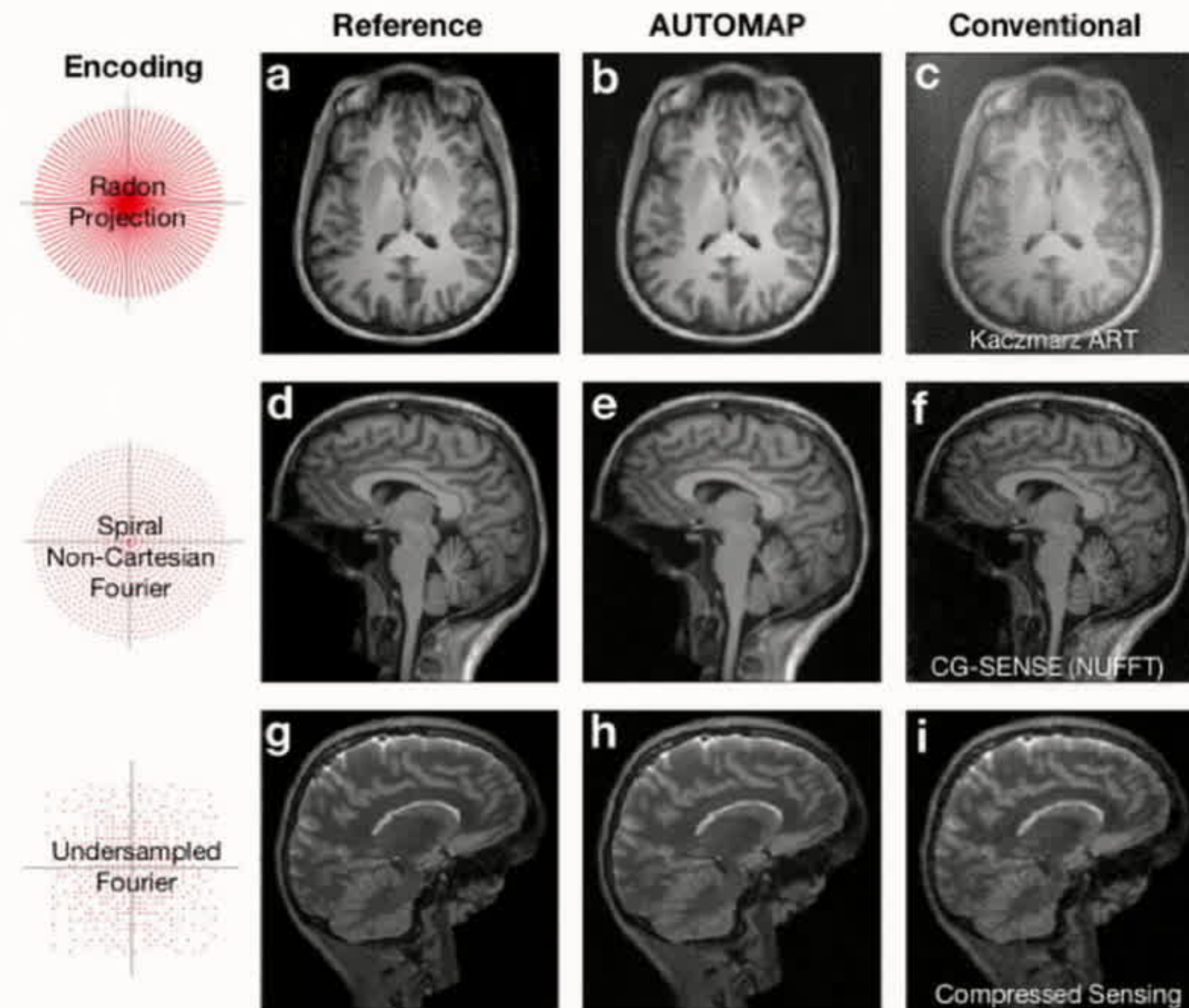
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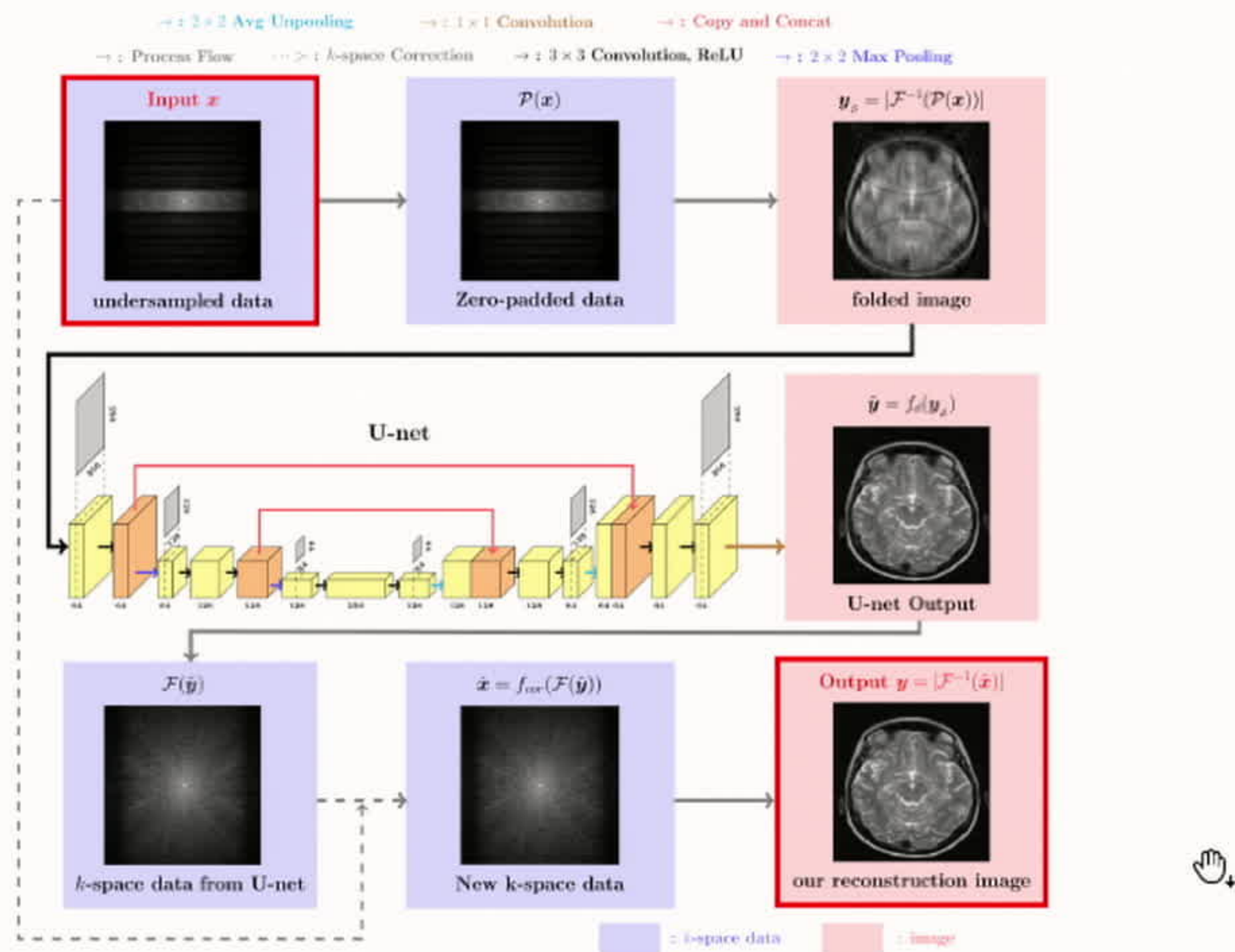
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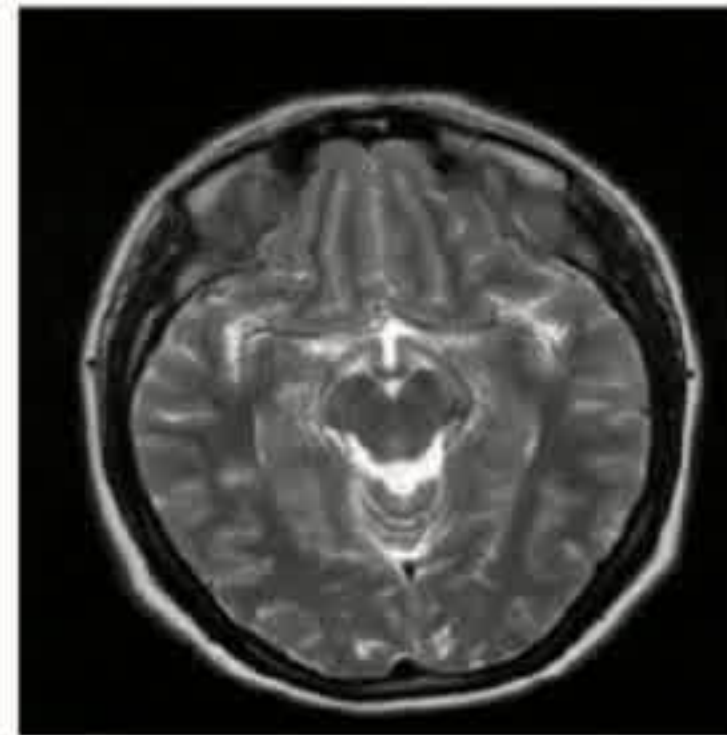
Learned post processing



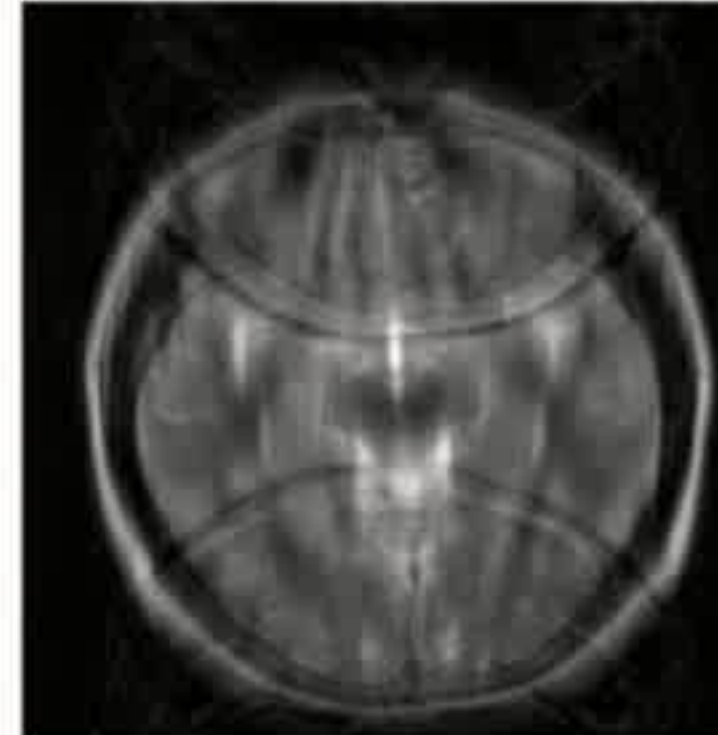
Chang Min Hyun et al 2018 Phys. Med. Biol. 63 135007. From Jin Keun Seo's group.

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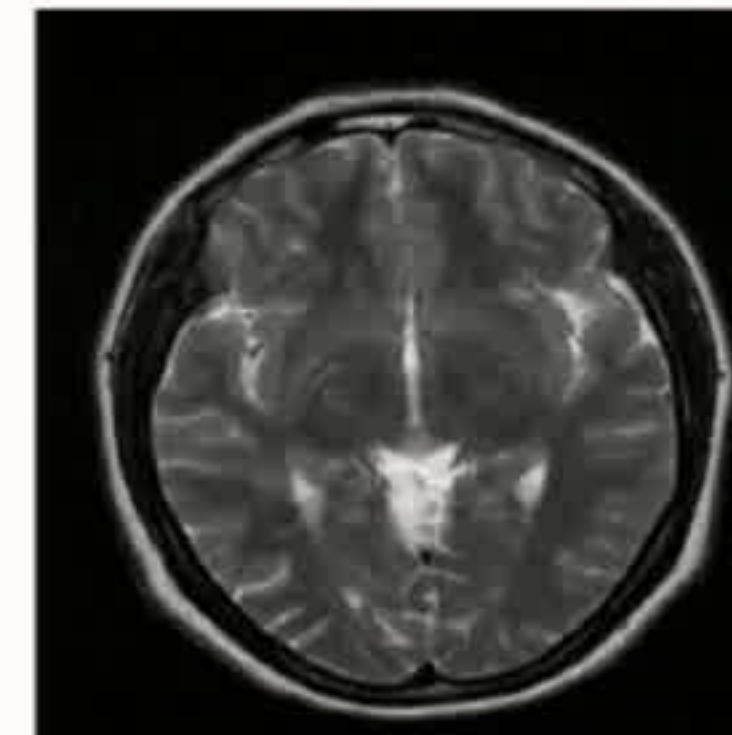
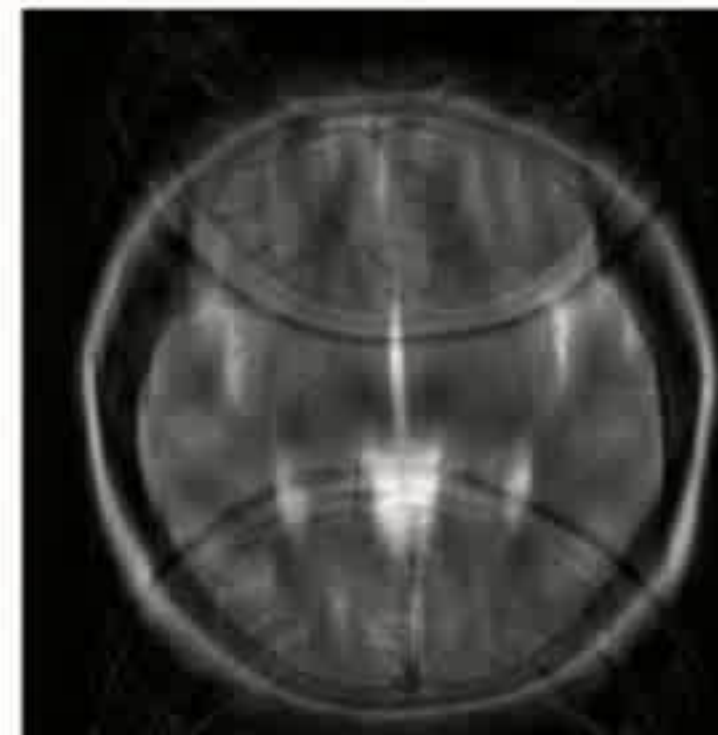
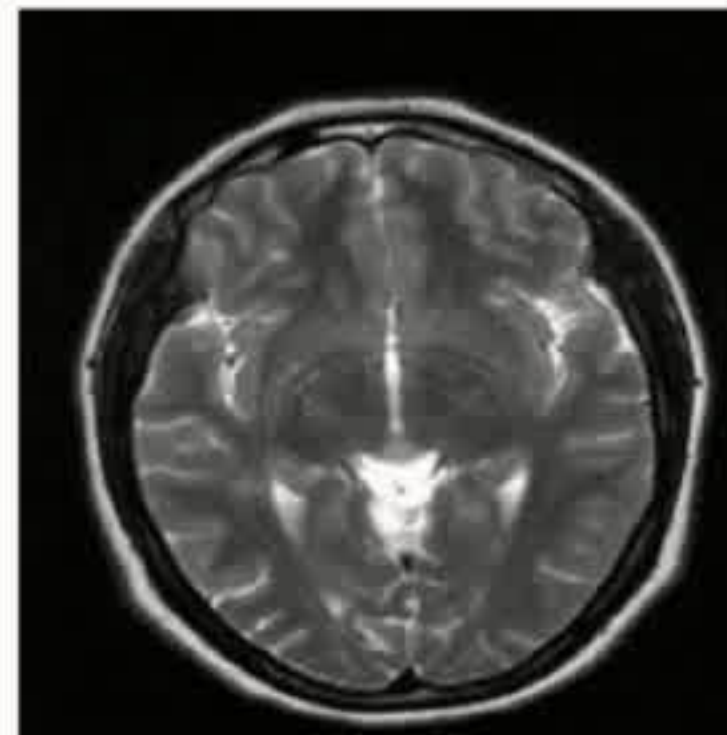
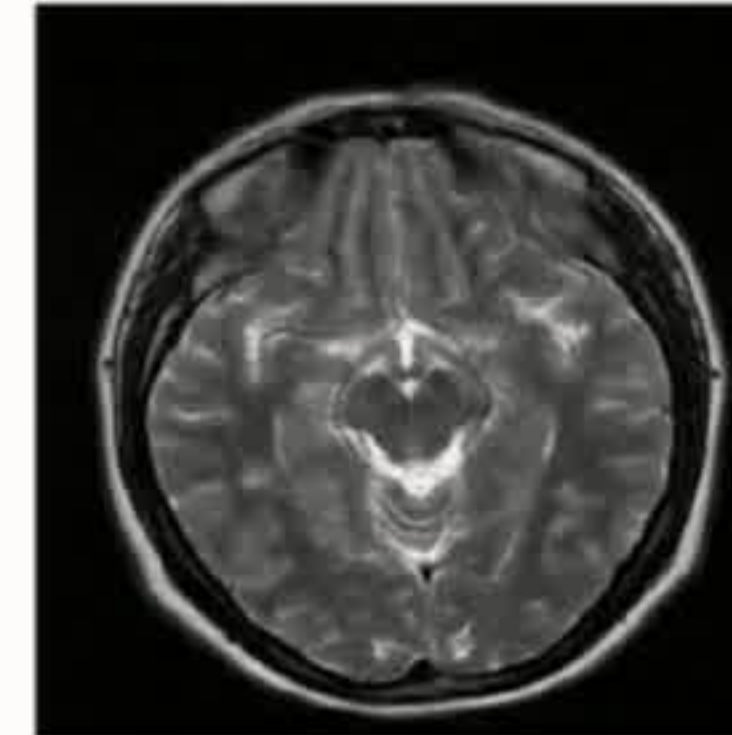
Ground Truth



Aliased Image



Corrected Image



Reconstruction from only 29% of Fourier samples. Trained on 1400 images.

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Learned iterative reconstruction

Learning to reconstruct

- ▶ Variational regularization:
Iterative schemes
- ▶ Learned operators
- ▶ Data in \rightarrow reconstruction out

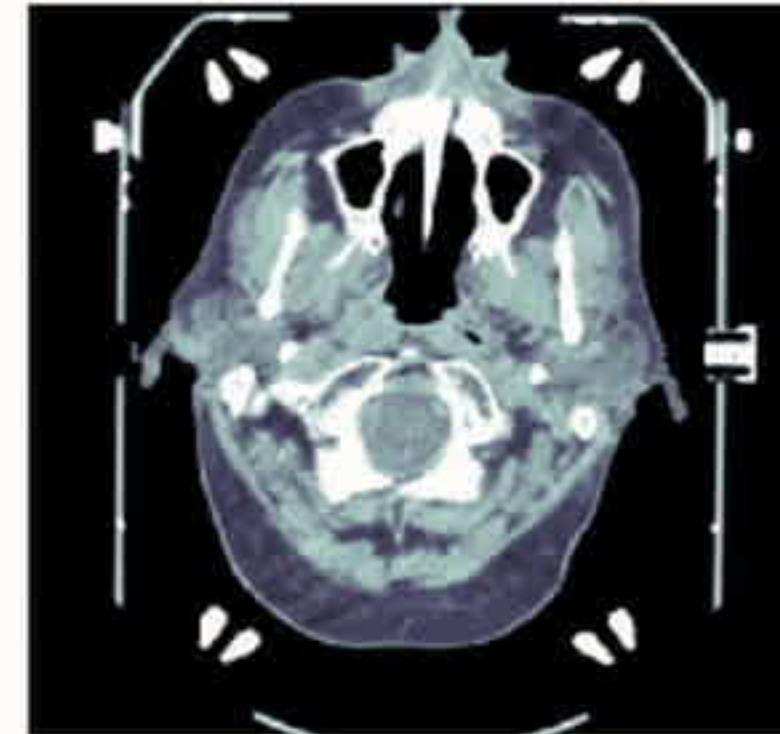
Algorithm 1 Learned Gradient

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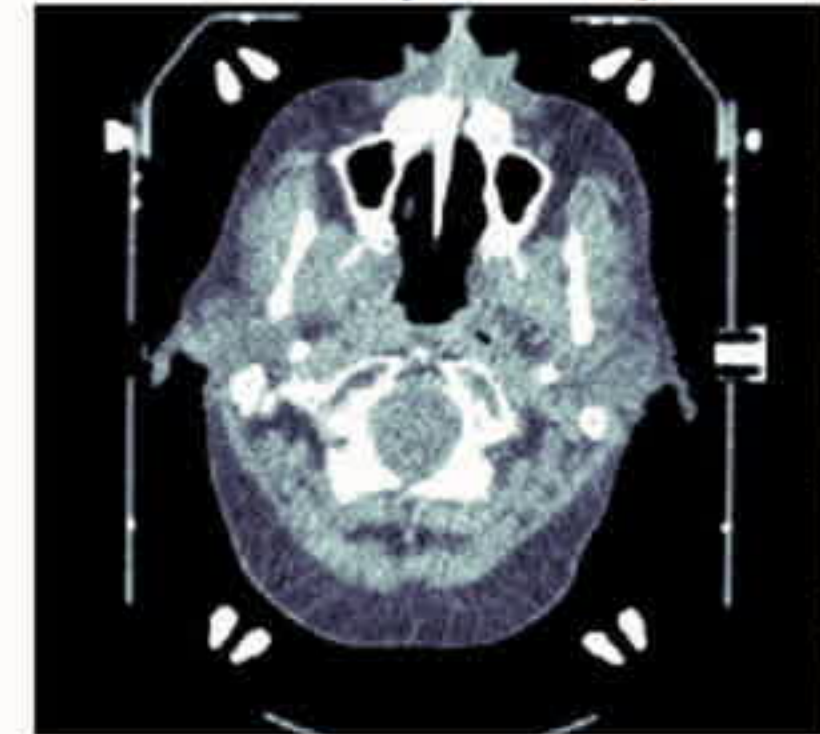
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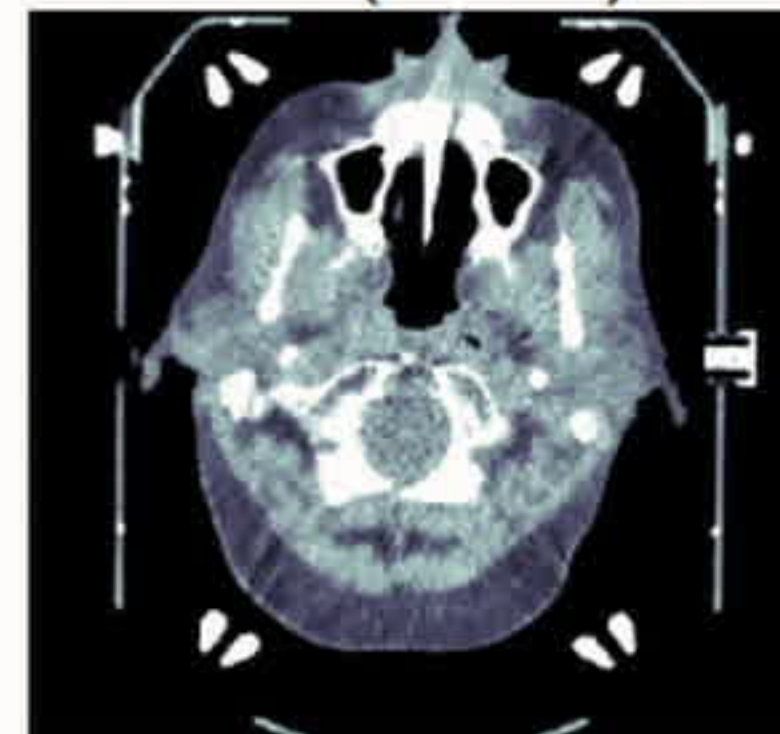
Ground truth



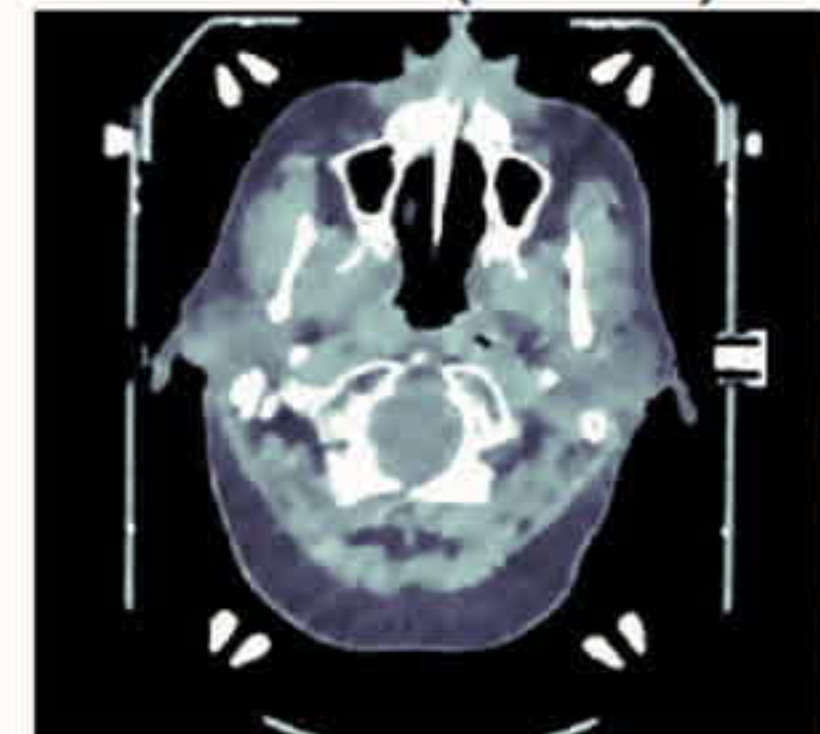
FBP (36 dB)



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Learned (44 dB)



J. Adler and O. Öktem, *Solving ill-posed inverse problems using iterative deep neural networks*, *Inverse Problems* '17. See also M. Unser et al. 2017; Hammernick et al. 2018; J. Adler, S. Lutz, O. Verdier, CBS, O. Öktem 2018

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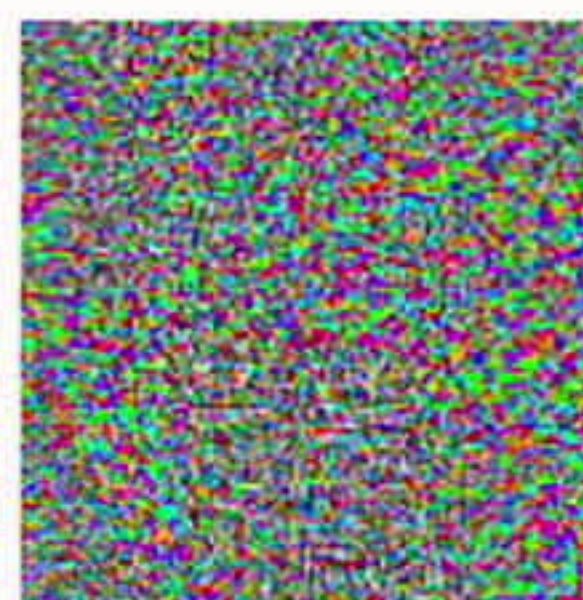
Deep Fool

 \mathbf{x}

"panda"

57.7% confidence

+ .007 ×

 $\text{sign}(\nabla_{\mathbf{x}} J(\boldsymbol{\theta}, \mathbf{x}, y))$

"nematode"

8.2% confidence

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Perturbed examples - visually indistinguishable but they break network performance.

Goodfellow I, Shlens J, Szegedy C., CoRR 2015; Nguyen A, Yosinski J, Clune J. In Computer Vision and Pattern Recognition (CVPR '15), IEEE, 2015; Szegedy, Zaremba, Sutskever, Bruna, Erhan, Goodfellow, Fergus, arXiv:1312.6199; Antun, Renna, Poon, Adcock, Hansen, arXiv:1902.05300

How to stabilise? Haber, Ruthotto, Inverse Problems '17; Chaudhari, Oberman, Osher, Soatto, Carlier, Research in the Mathematical Sciences, '18

Outline

- 1 Knowledge-driven inversion
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 - Learning a regularizer

Deep neural networks as regularizers

Joint work with Sebastian Lunz and Ozan Öktem



S. Lunz, O. Öktem, CBS, Adversarial Regularizers in Inverse Problems, in NeurIPS 2018

Conclusion

Philosophy: **learning structured but adaptive imaging models with guarantees**

See also forthcoming **Acta Numerica 2019**.

And several minisymposia this week, e.g. **MS35, MS54, MS108, MS109, MS110, MS113, MS133, MS141-143, MS146, ..., MS266, ...**

Cambridge Image Analysis

- Dr Angelica Aviles-Rivero
- Dr Noemie Debroux
- Dr Yury Korolev
- Dr Lukas Lang
- Dr Pan Liu
- Dr Jingwei Liang
- Dr Matt Thorpe
- Thomas Buddenkotte
- Veronica Corona
- Tamara Grossmann
- Sebastian Lunz
- Lisa Kreusser
- Simone Parisotto
- Erlend Riis
- Philip Sellars
- Ferdia Sherry
- Rob Tovey
- Jon Williams

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Wanted: image processing researcher



Researcher for project *Scalable image enhancement for light-sheet microscopy: space varying deconvolution and image fusion*.

Collaboration between CAIC, CIA, LMB, SLCU.



Limit of tenure is 2 years. Start date: June 2019

More details: <http://www.jobs.cam.ac.uk/job/20474/> or
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Thank you very much for your attention!



More information see:

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Variational regularisation

Consider the inverse problem associated to operator $T : X \rightarrow Y$, X and Y Banach spaces

$$y = Tx + n$$

Variational regularisation model under Gaussian white noise model is given by

$$\arg \min_x \|Tx - y\|_2^2 + \lambda R(x)$$

Aim: parametrise regulariser and optimise it over appropriate 'data'.

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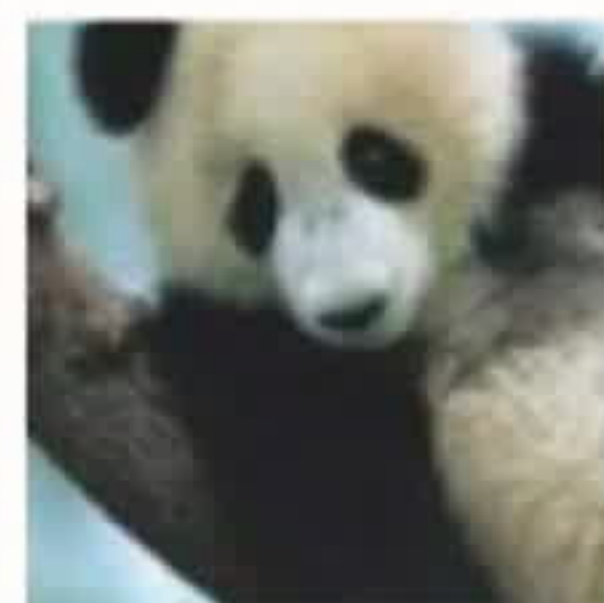
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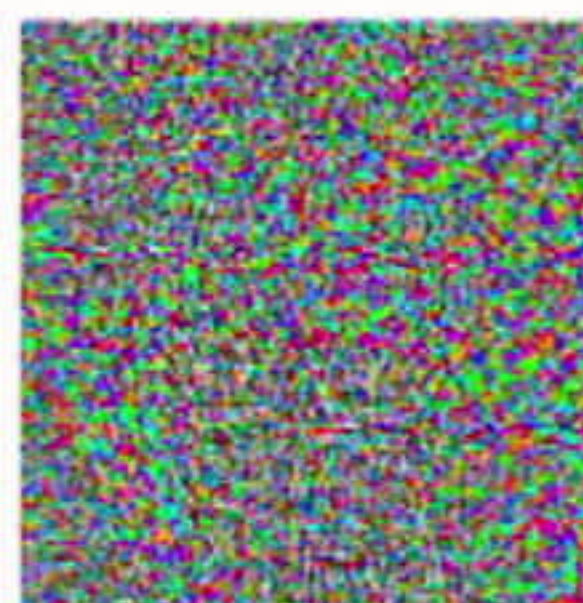
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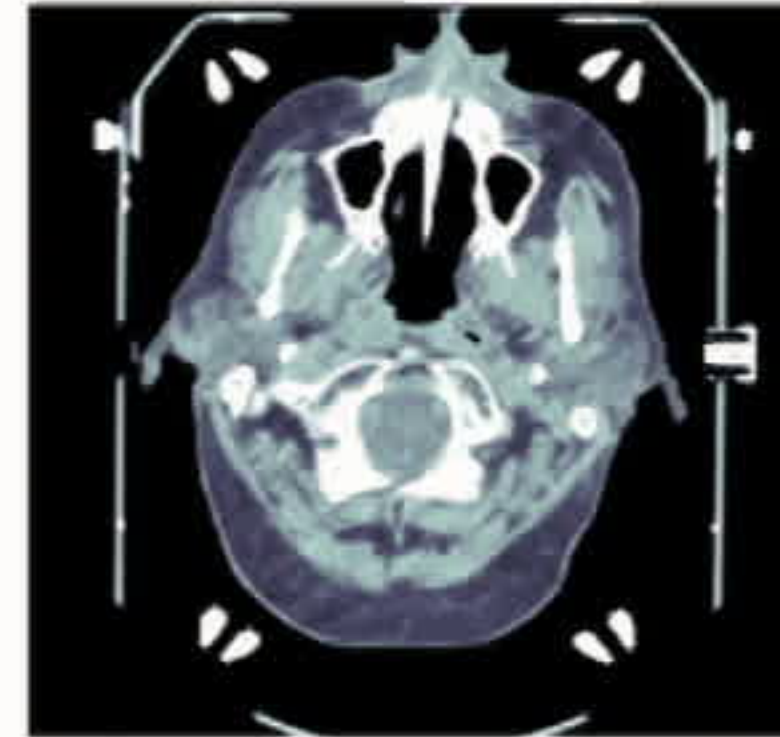
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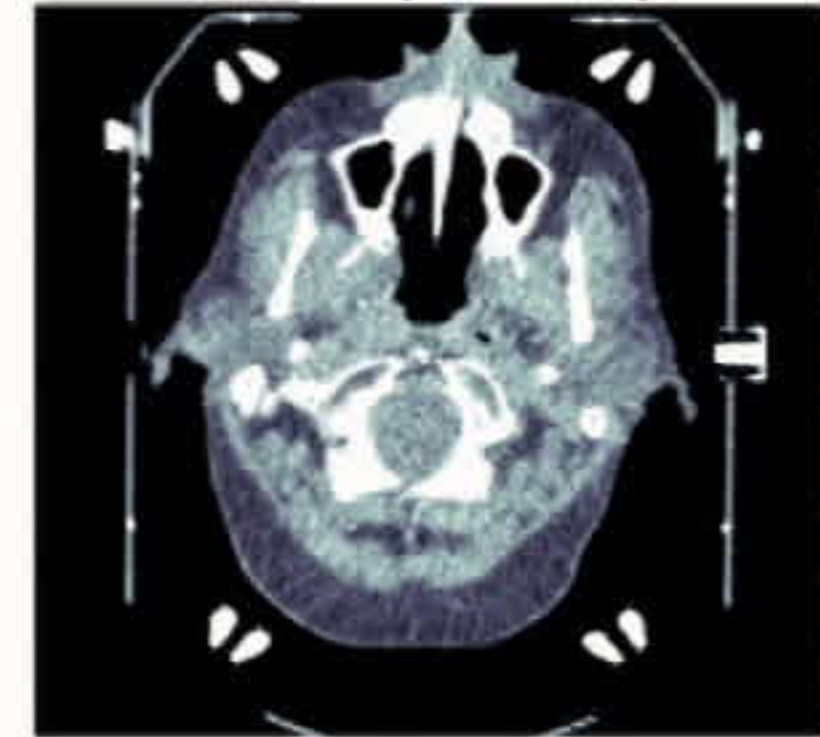
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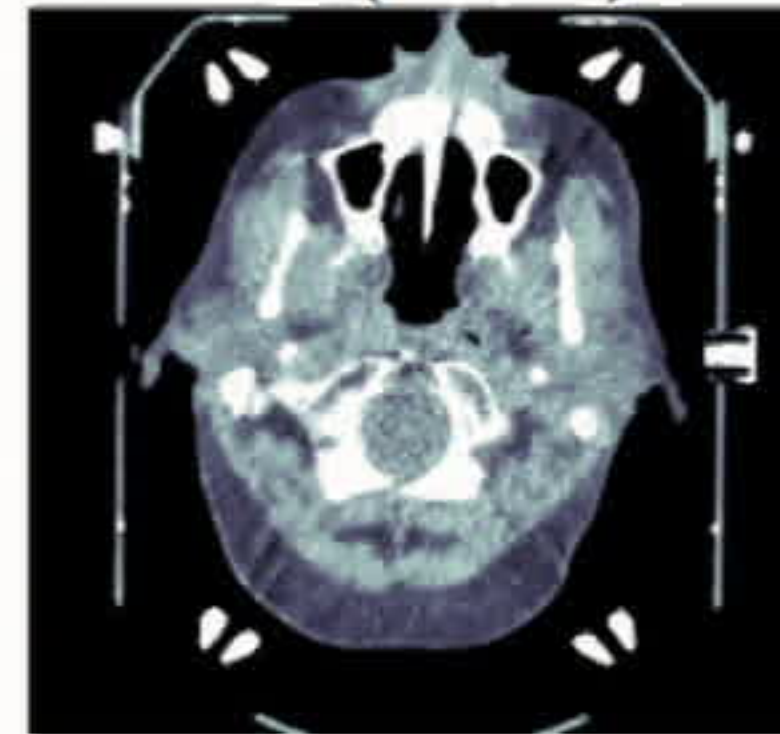
Ground truth



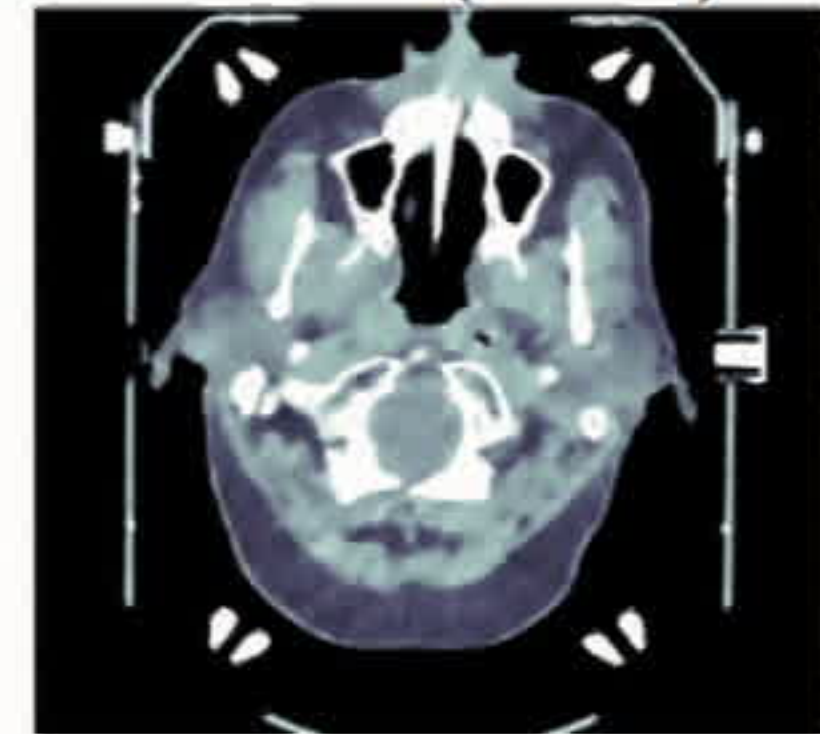
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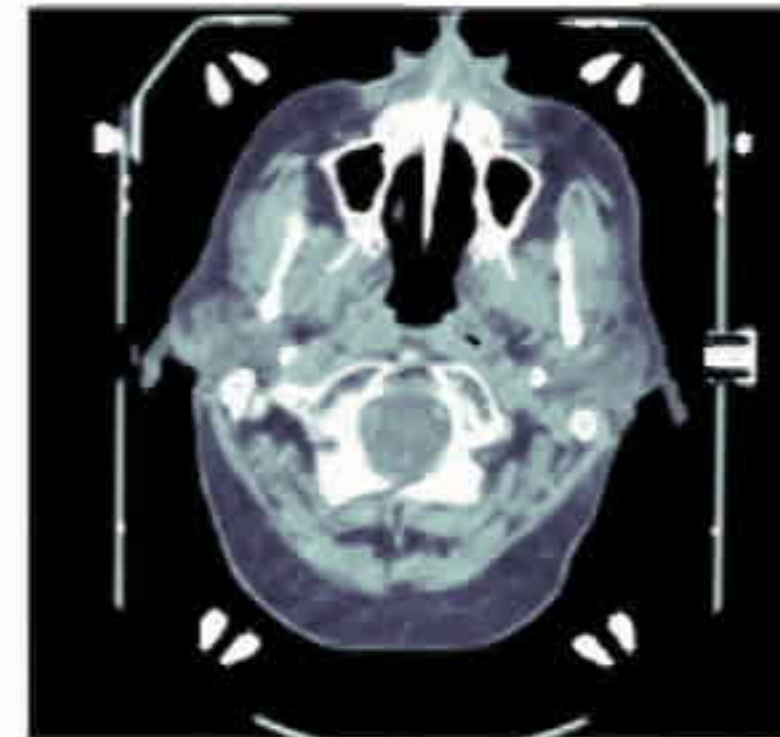
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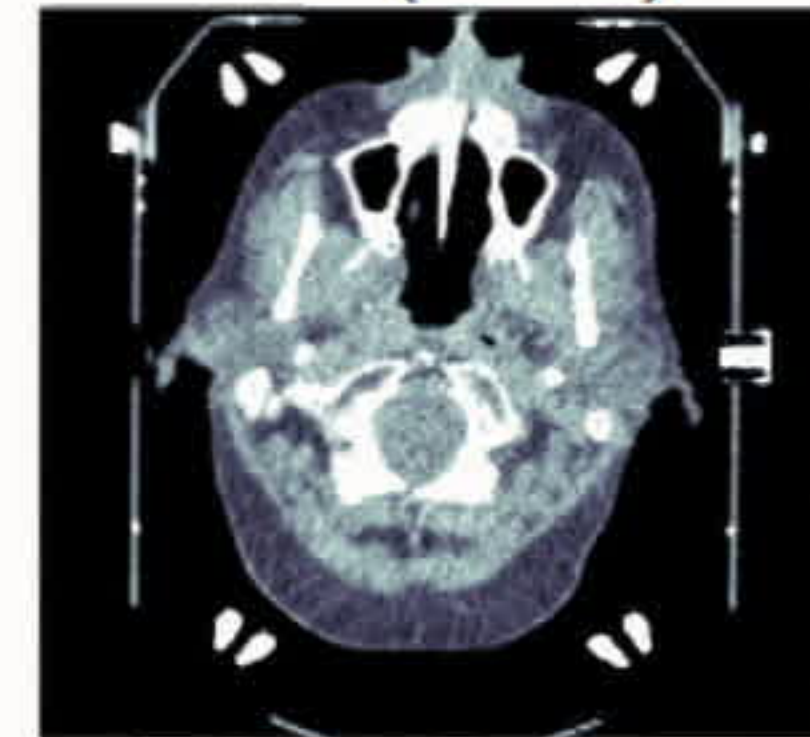
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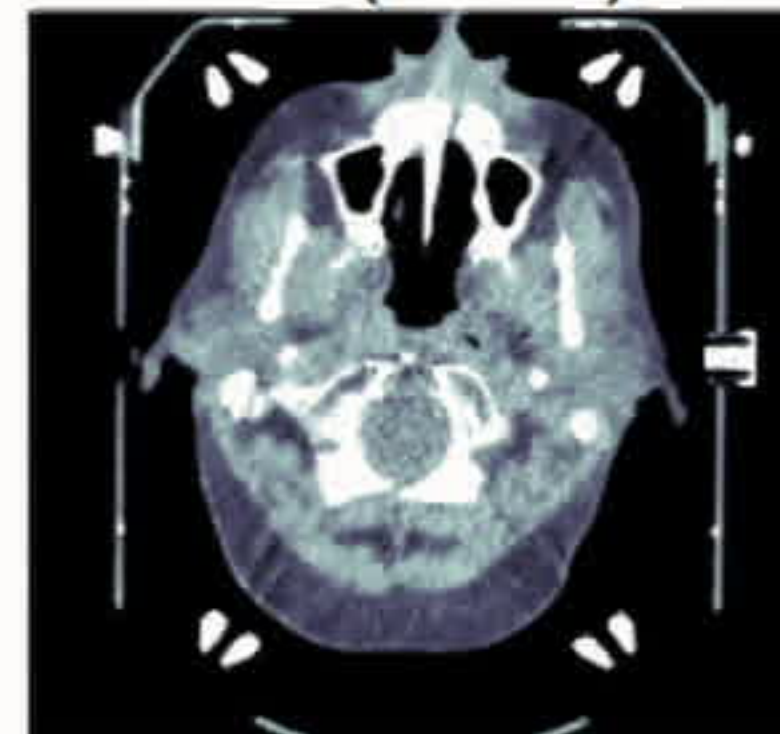
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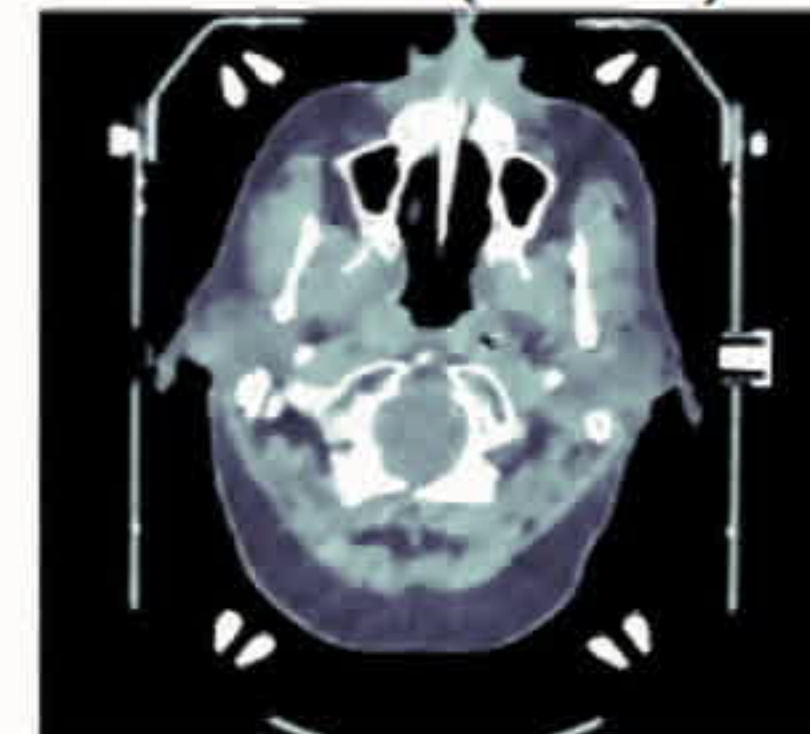
FBP (36 dB)



TV (38 dB)

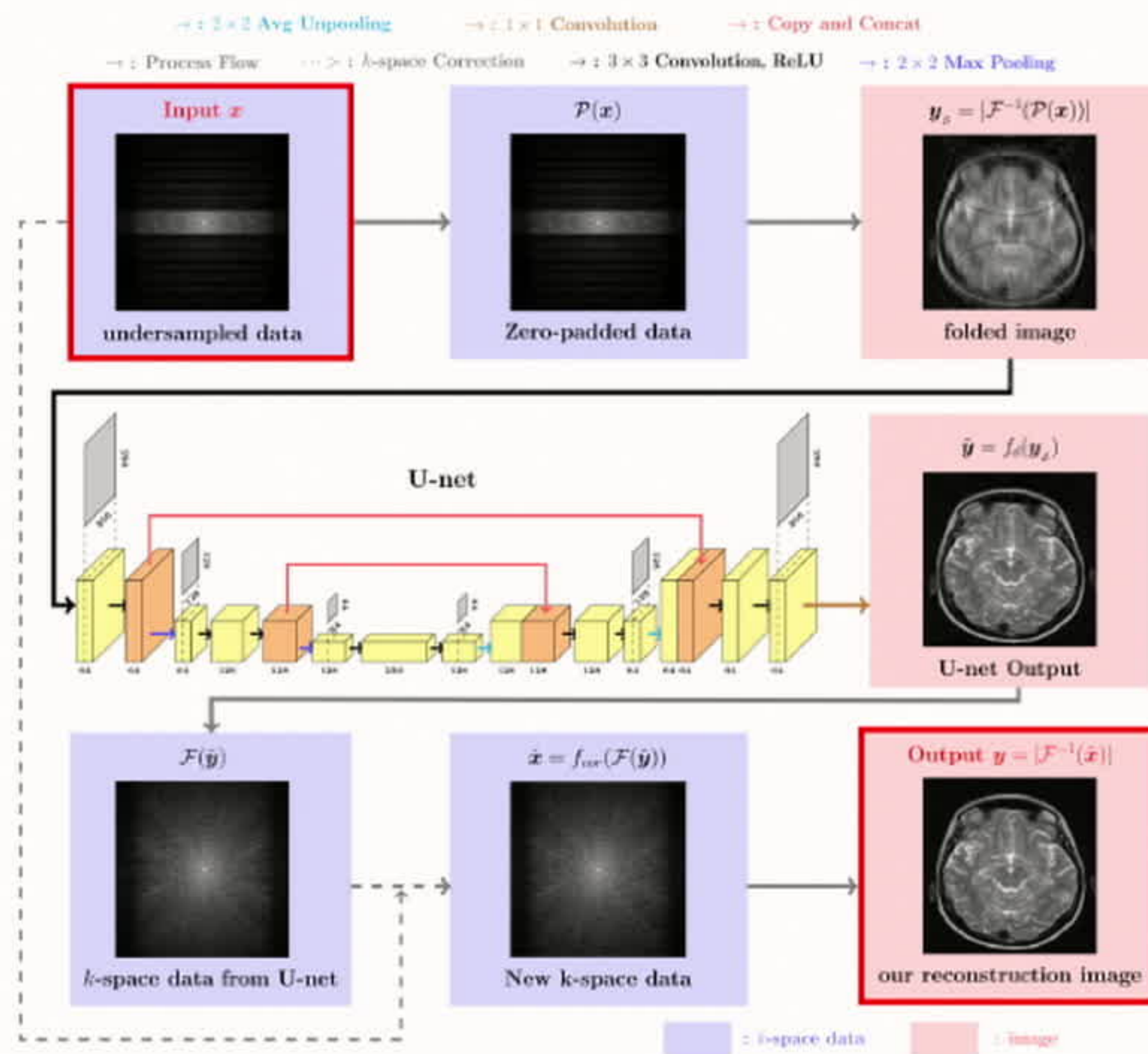


Learned (44 dB)



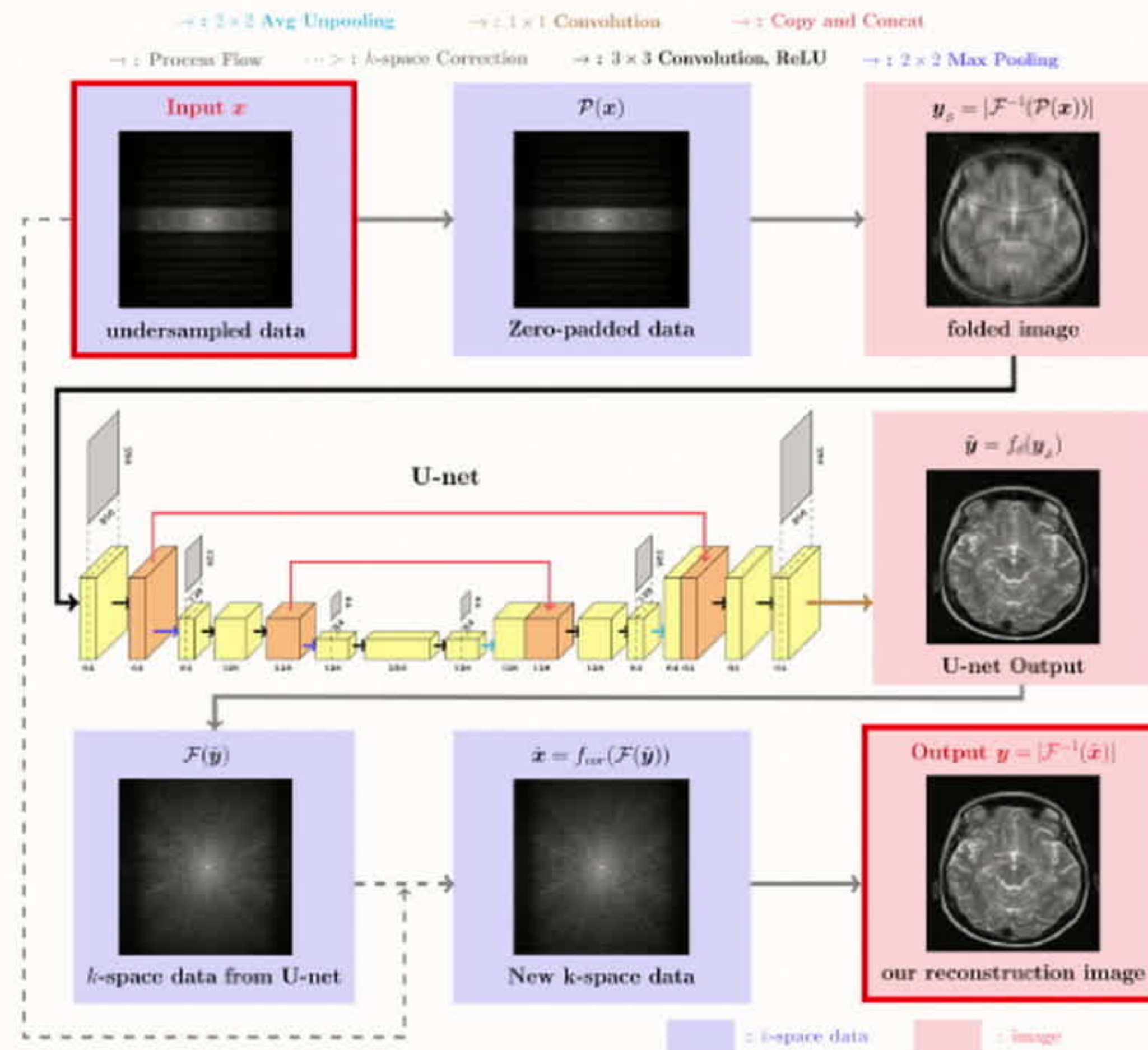
J. Adler and O. Öktem, *Solving ill-posed inverse problems using iterative deep neural networks*, *Inverse Problems* '17. See also M. Unser et al. 2017; Hammernick et al. 2018; J. Adler, S. Lutz, O. Verdier, CBS, O. Öktem 2018

Learned post processing



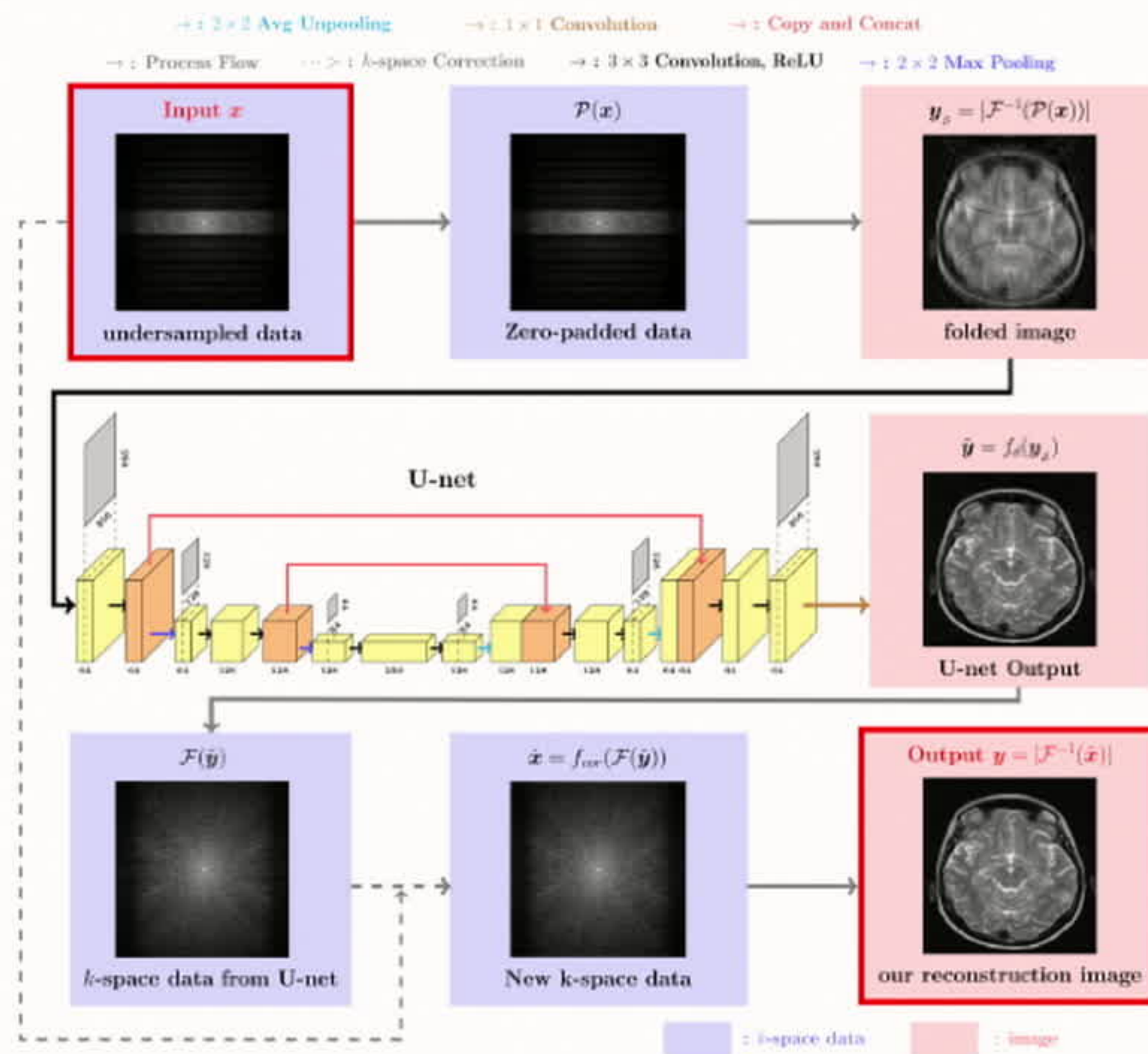
Chang Min Hyun et al 2018 Phys. Med. Biol. 63 135007. From Jin Keun Seo's group.

Learned post processing



Chang Min Hyun et al 2018 Phys. Med. Biol. 63 135007. From Jin Keun Seo's group.

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Deep learning for inverse imaging

Main existing approaches

- Fully Learned Models Zhu, Bo, Liu, Cauley, Rosen, Rosen, Nature '18.
- Learned Post Processing Jin, McCann, Froustey, Unser, IEEE Transactions on Image Processing, '17; Kang, Min, Ye, Medical Physics '17.
- **Learned Iterative Schemes** Yang, Sun, Li, Xu, In Advances in Neural Information Processing Systems '16; Meinhardt, Moeller Hazirbas, Cremers, ICCV '17; Putzky, Welling, ArXiv 1706.04008; Adler, Öktem, Inverse Problems '17; Adler, Öktem, IEEE transactions on medical imaging '18; Hammernik, Klatzer, Kobler, Recht, Sodickson, Pock, Knoll; Magnetic resonance in medicine, '18; Adler, Lunz, Verdier, CBS, Öktem, In NIPS 2018 meets medical imaging, ArXiv 1809.00948; Hauptmann, Lucka, Betcke, Huynh, Adler, Cox, Beard, Ourselin, Arridge, IEEE Transactions on Medical Imaging, 2019.
- Learning the regulariser Li, Schwab, Antholzer, Haltmeier, '18; Lunz, Öktem, CBS, NeurIPS '18; Ye, Ravishankar, Long, Fessler, IEEE Transactions on Medical Imaging '18.

Recent reviews: McCann, Jin, Unser, IEEE Signal Processing Magazine, 34(6), 85-95, '17; Arridge, Maass, Öktem, CBS, Acta Numerica '19

Learned iterative reconstruction

Learning to reconstruct

- ▶ Variational regularization:
Iterative schemes
- ▶ Learned operators
- ▶ Data in \rightarrow reconstruction out

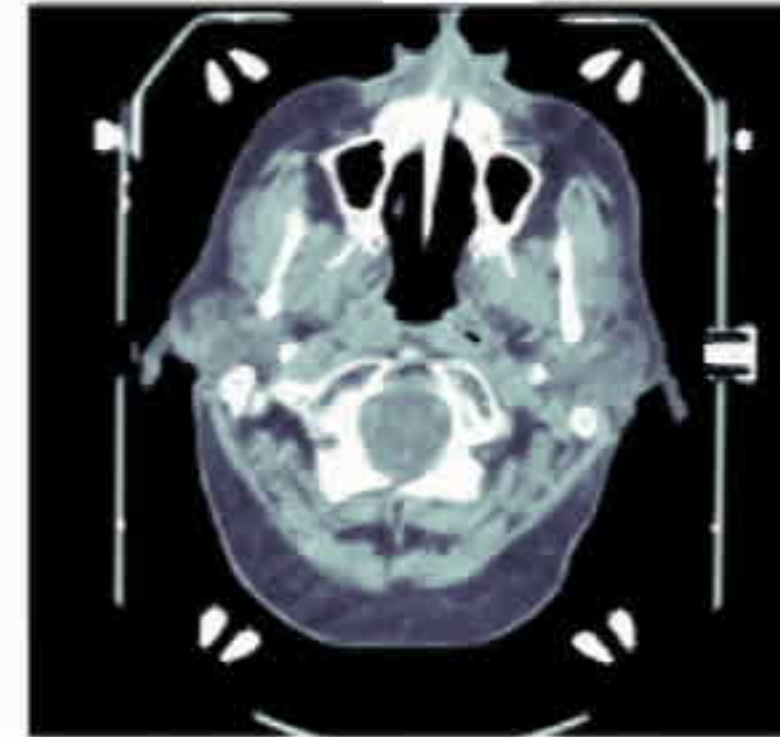
Algorithm 1 Learned Gradient

```

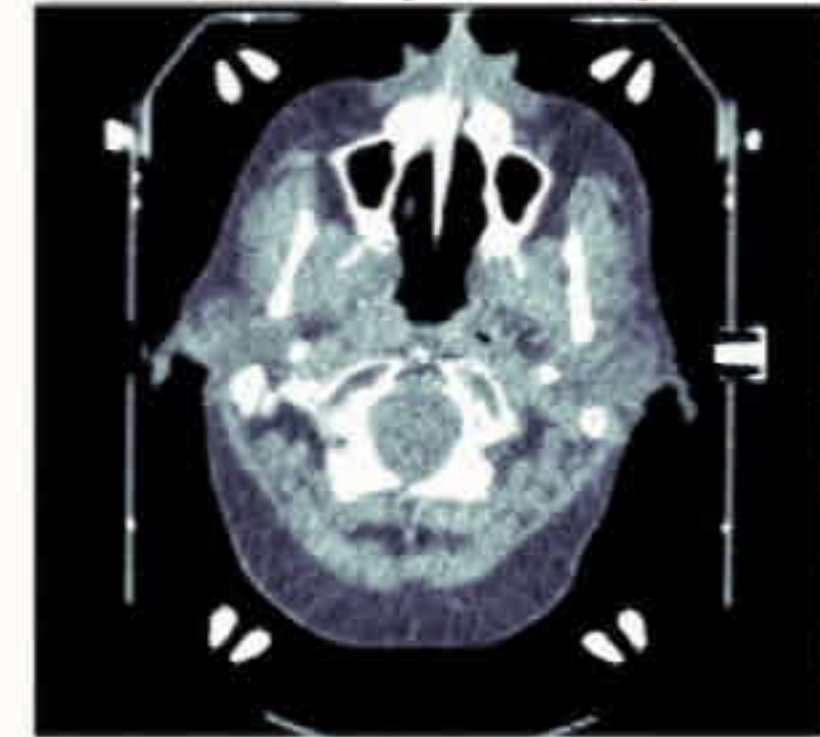
1: for  $i = 1, \dots$  do
2:    $\Delta f_i \leftarrow \Lambda_{\Theta}(f_i, \nabla [\mathcal{L}(\mathcal{T}(\cdot), g)](f_{i-1}))$ 
3:    $f_i \leftarrow f_{i-1} + \Delta f_i$ 

```

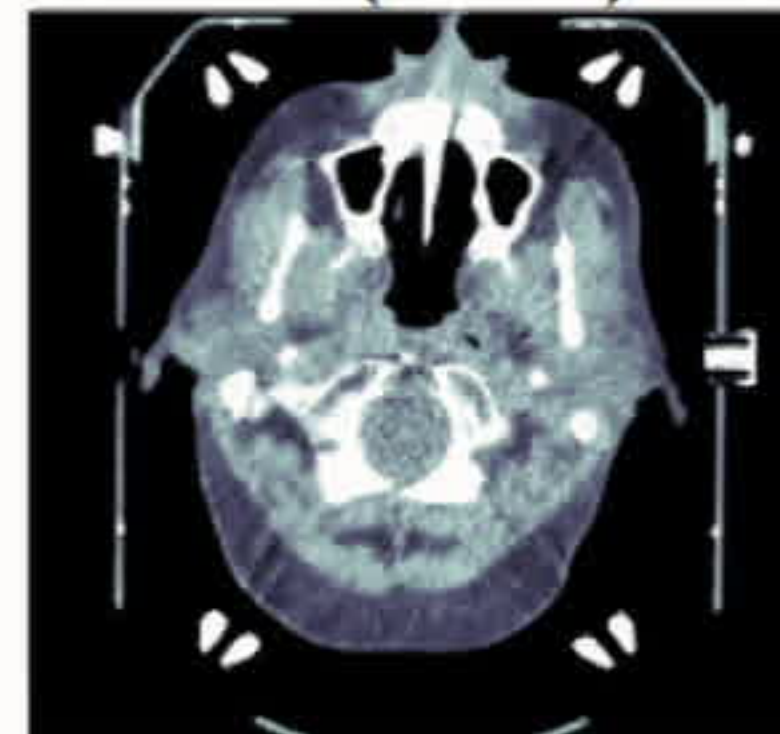
Ground truth



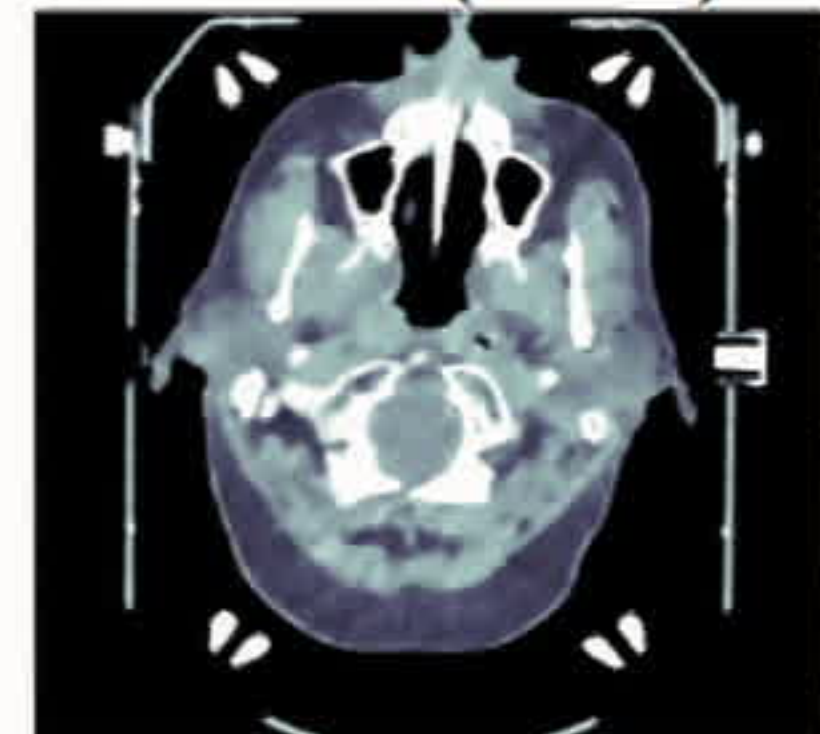
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Outline


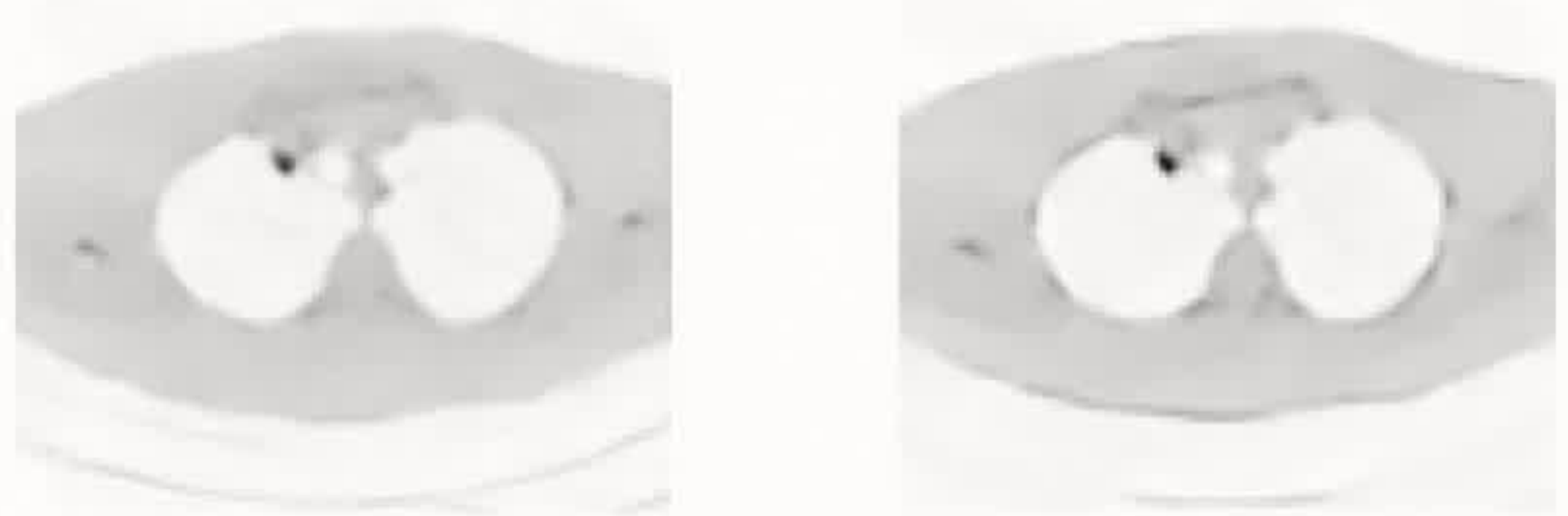
- 1 Knowledge-driven inversion
- 2 Data-driven inversion
- 3 Deeply learned inversion**
 - Learning a regularizer

Bookmarks

- Knowledge-driven inversion
- Data-driven inversion
- Deeply learned inversion
 - Learning a regularizer

Deeply learned inversion

CT reconstruction on LIDC data

(a) Post-Processing (b) Adversarial Reg.

Figure: Reconstruction from simulated CT measurements on LIDC

Schönlieb (DAMTP) Deep learning inversion SIAM CSE - 25/02/2019

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