

Accelerate Magnetic Resonance Imaging (MRI) Using Compressed Sensing and Deep Learning

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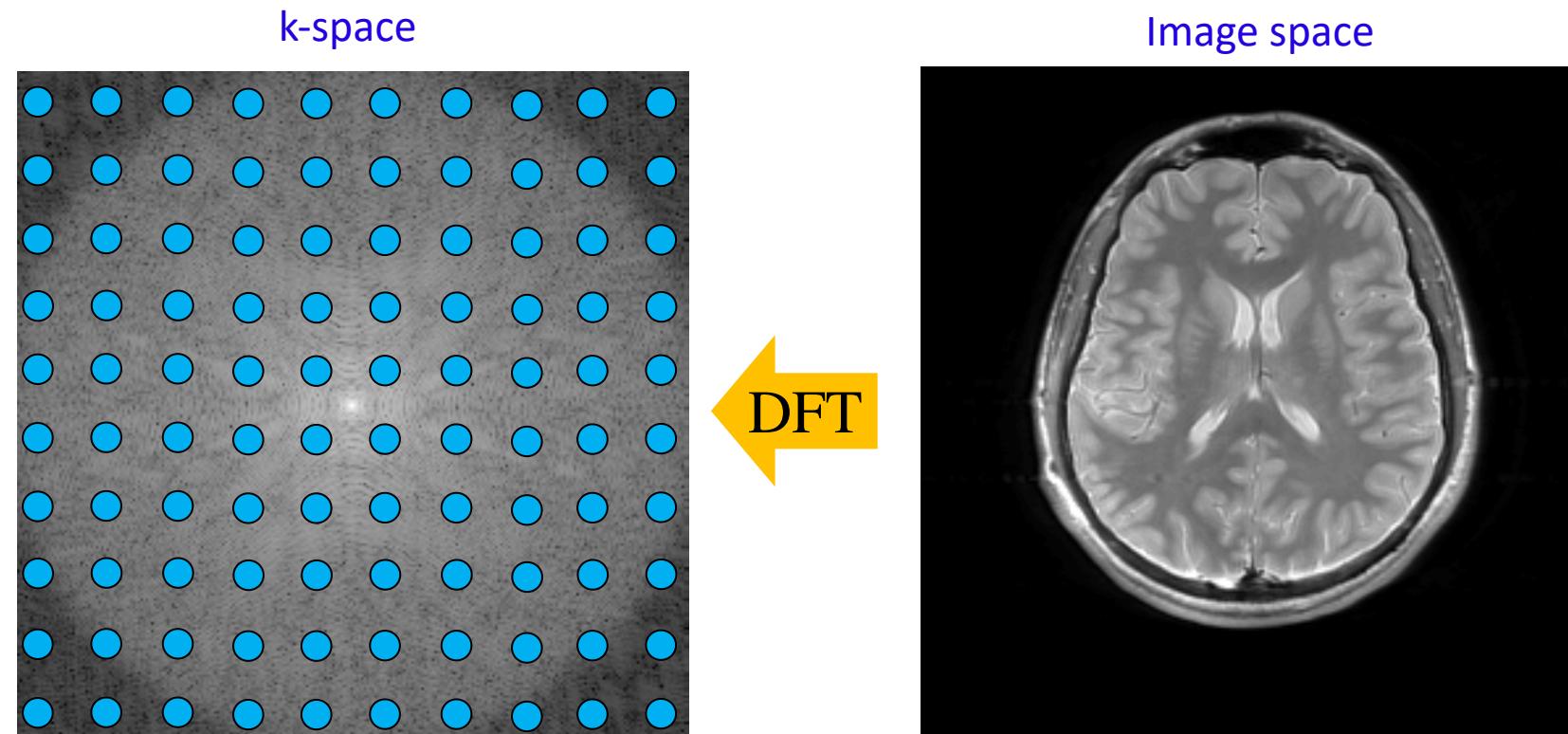
January 29, 2023

Outline

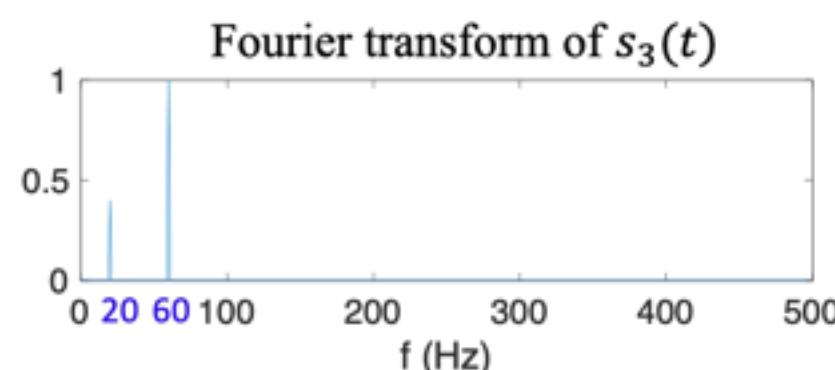
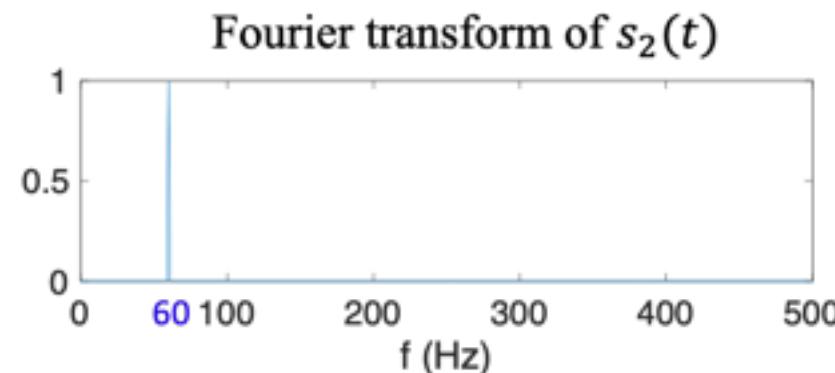
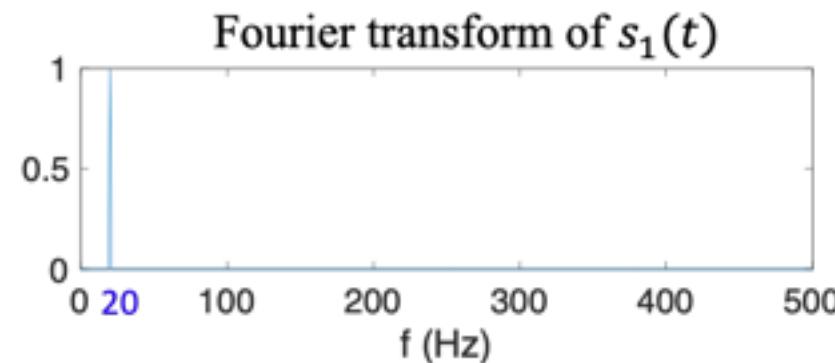
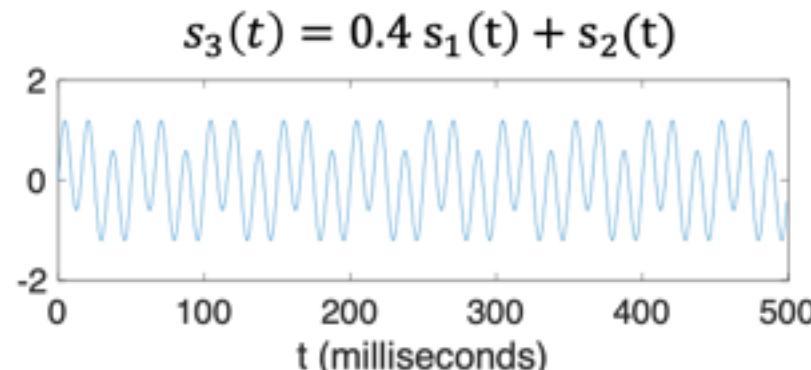
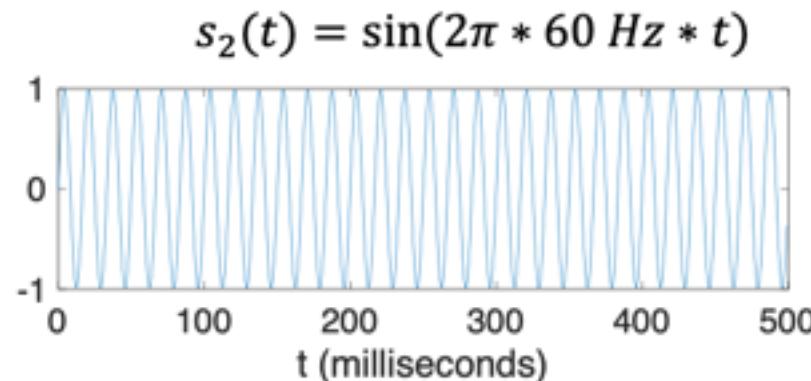
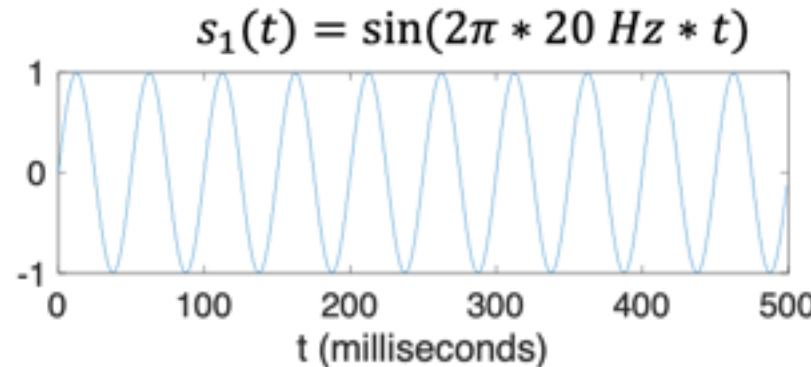
- **MR Image Acquisition and Reconstruction**
 - Imaging parameters
 - Reconstruction from accelerated scans
- Deep Learning for Accelerated MRI
 - Supervised learning
 - Experimental Results
- Recent Advances

MR Image Acquisition and Reconstruction

- Raw data are collected in the Fourier domain (k-space)
 - The acquired data are the discrete Fourier transform (DFT) samples of the object being imaged
 - Using the conventional 2DFT acquisition, each line of k-space is acquired one after the other (one per **repetition time (TR)** of the readout sequence)

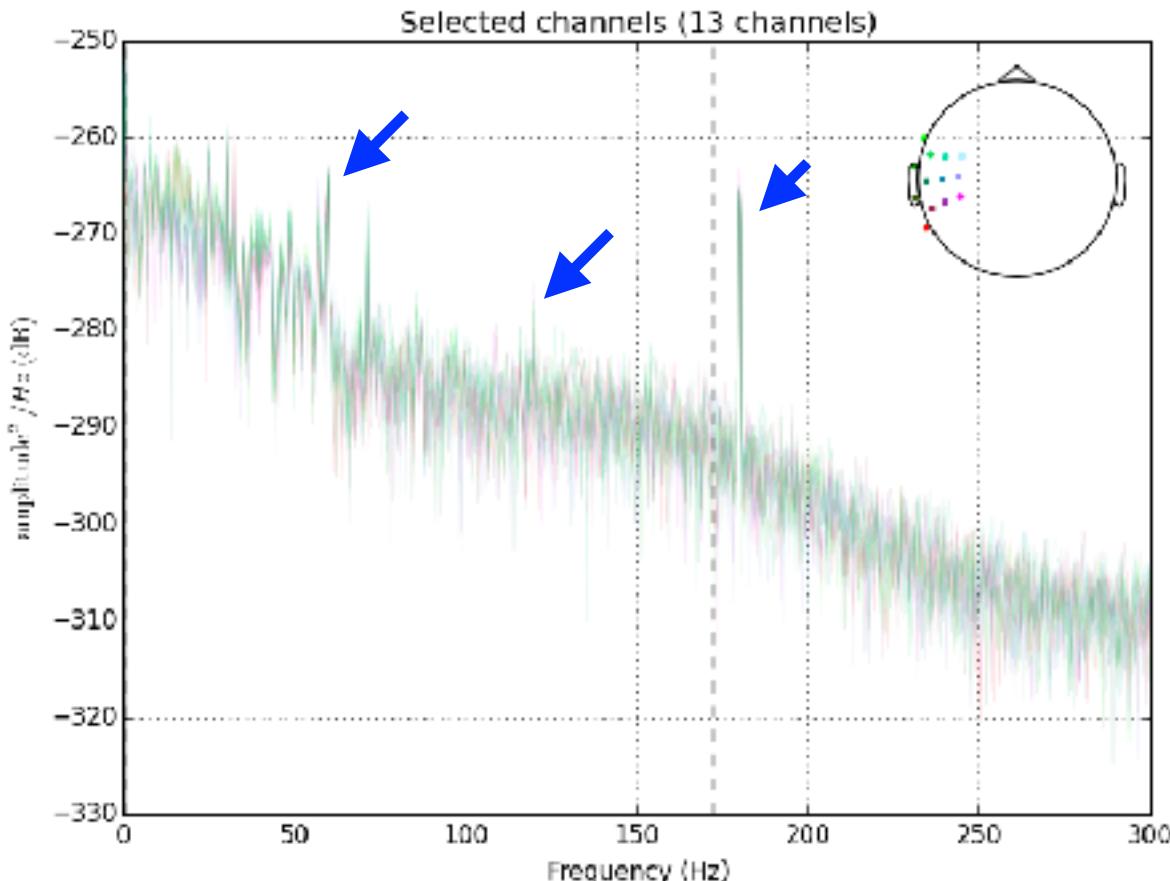


Review: Fourier Transform

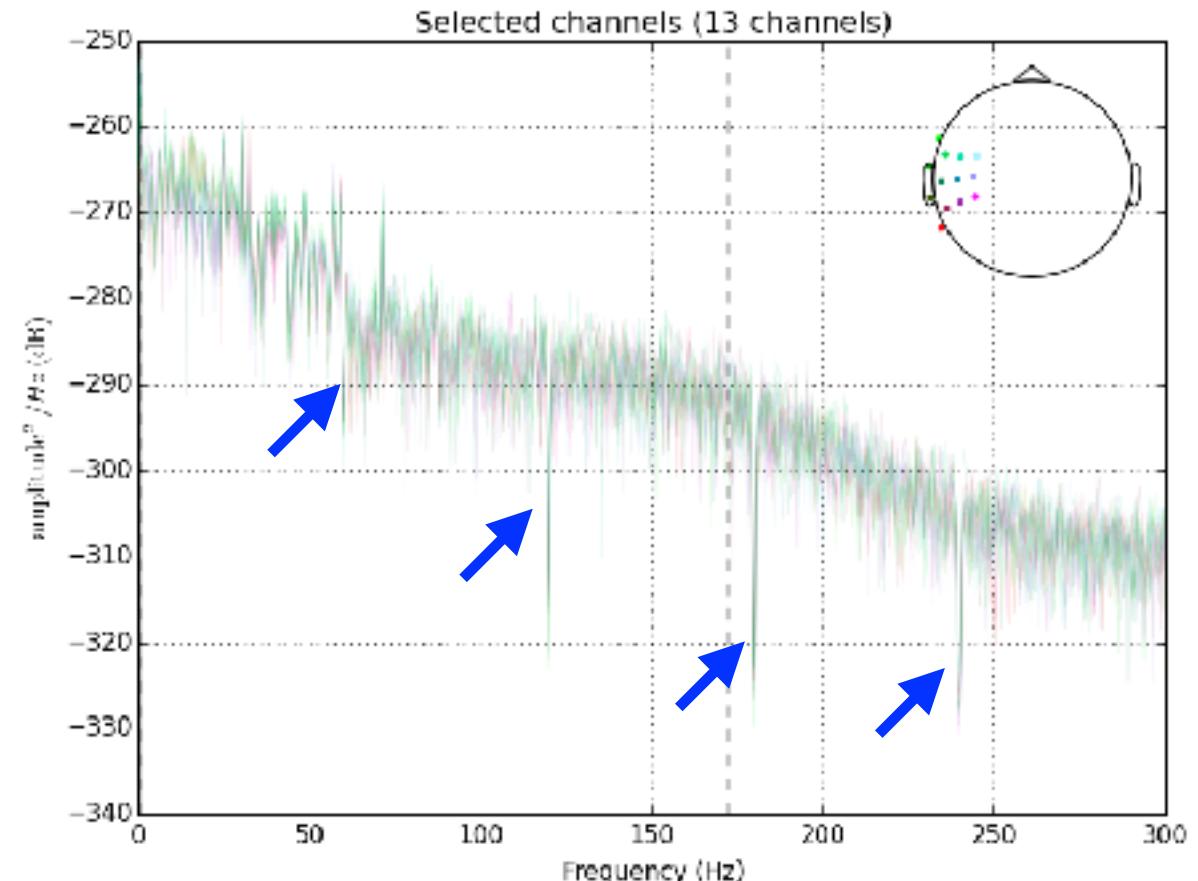


Review: Application of Fourier Transform to EEG

The Fourier transform of the acquired EEG signals



The filtered signals at the integer multiples of 60 Hz

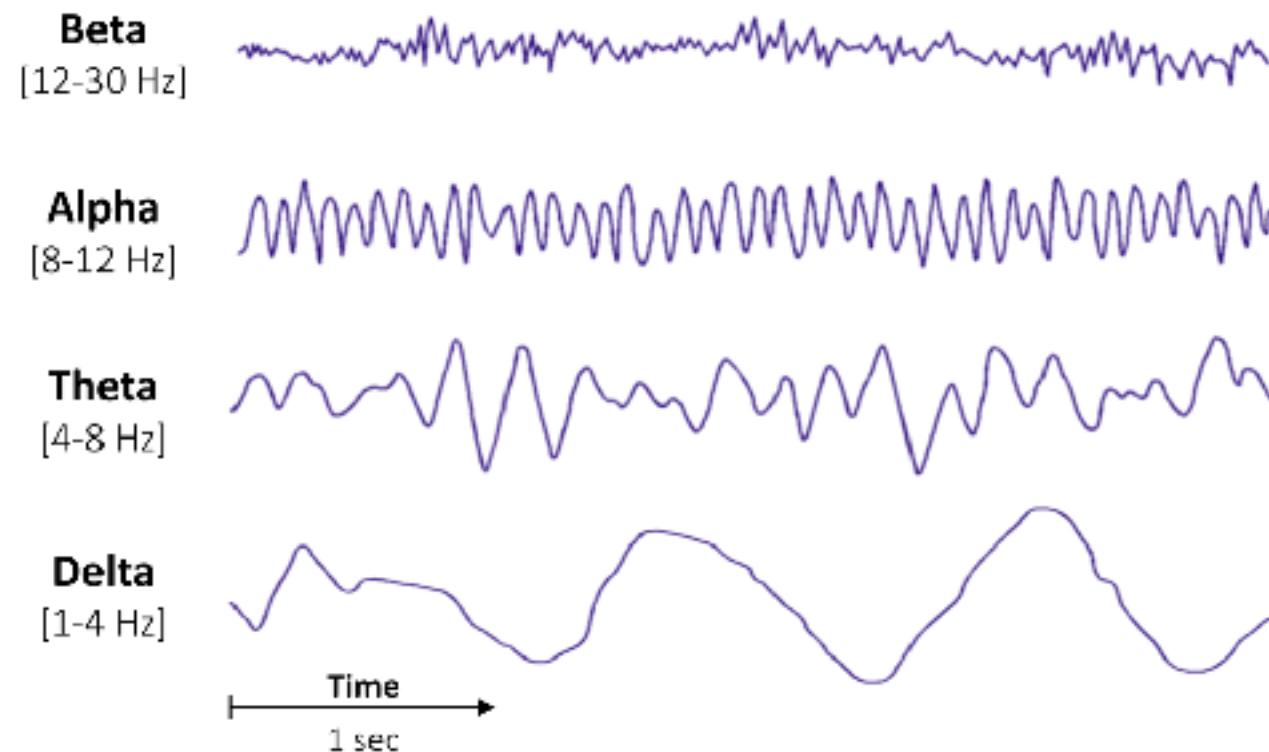


Power-line noise: potentially at the harmonic frequencies of 60 Hz (or 50 Hz)

MNE's Filtering and resampling data

Review: Application of Fourier Transform to EEG

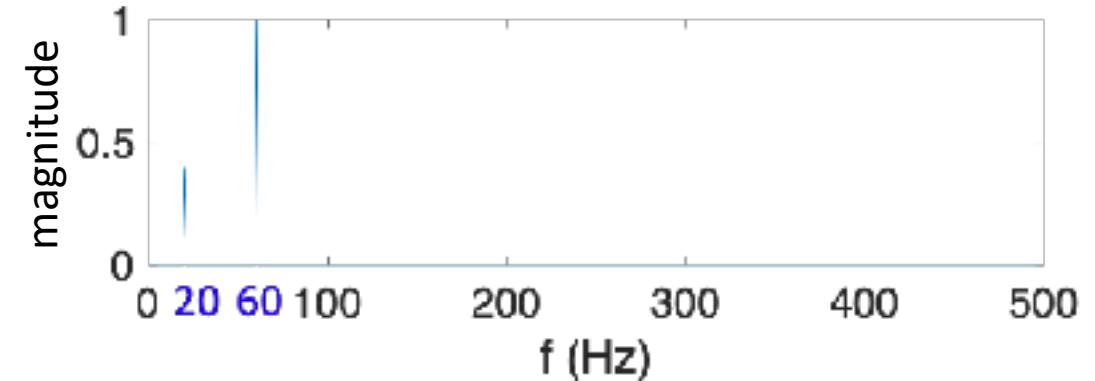
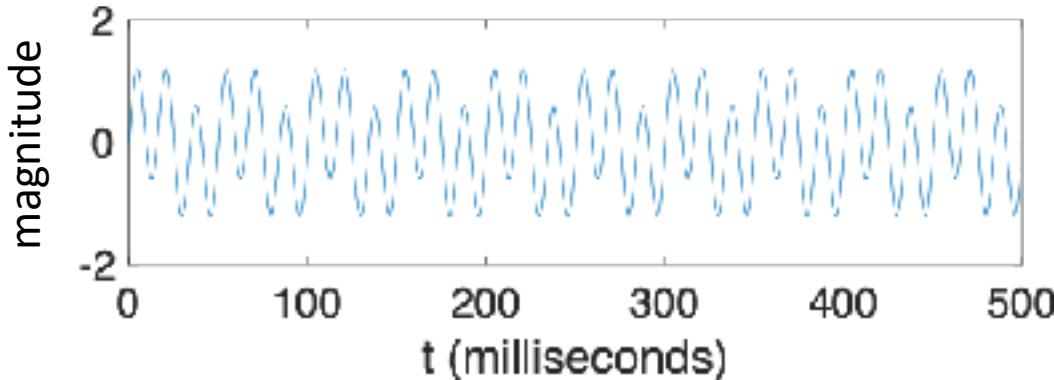
Example of brain rhythm frequency bands associated with cognitive processes



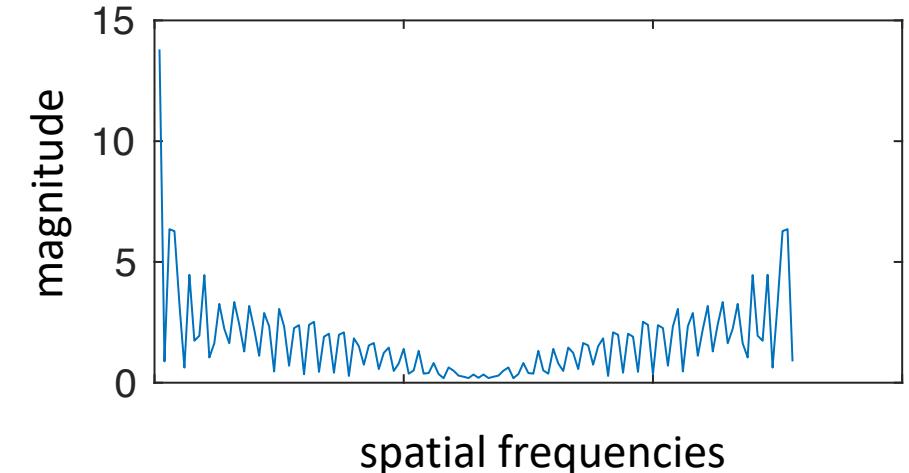
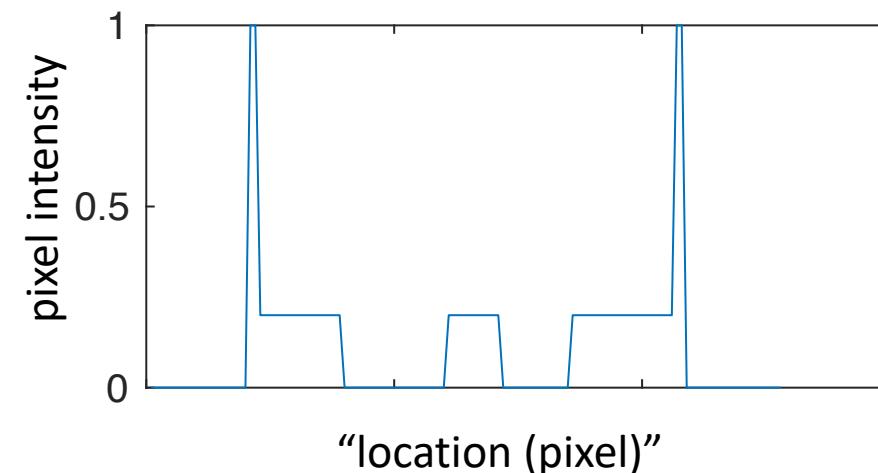
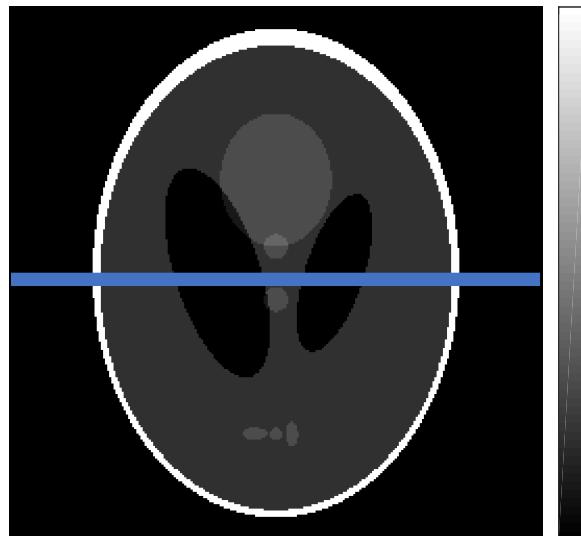
Compute the average bandpower of an EEG signal

Review: Application of Fourier Transform to images

Fourier transform: time \leftrightarrow frequency

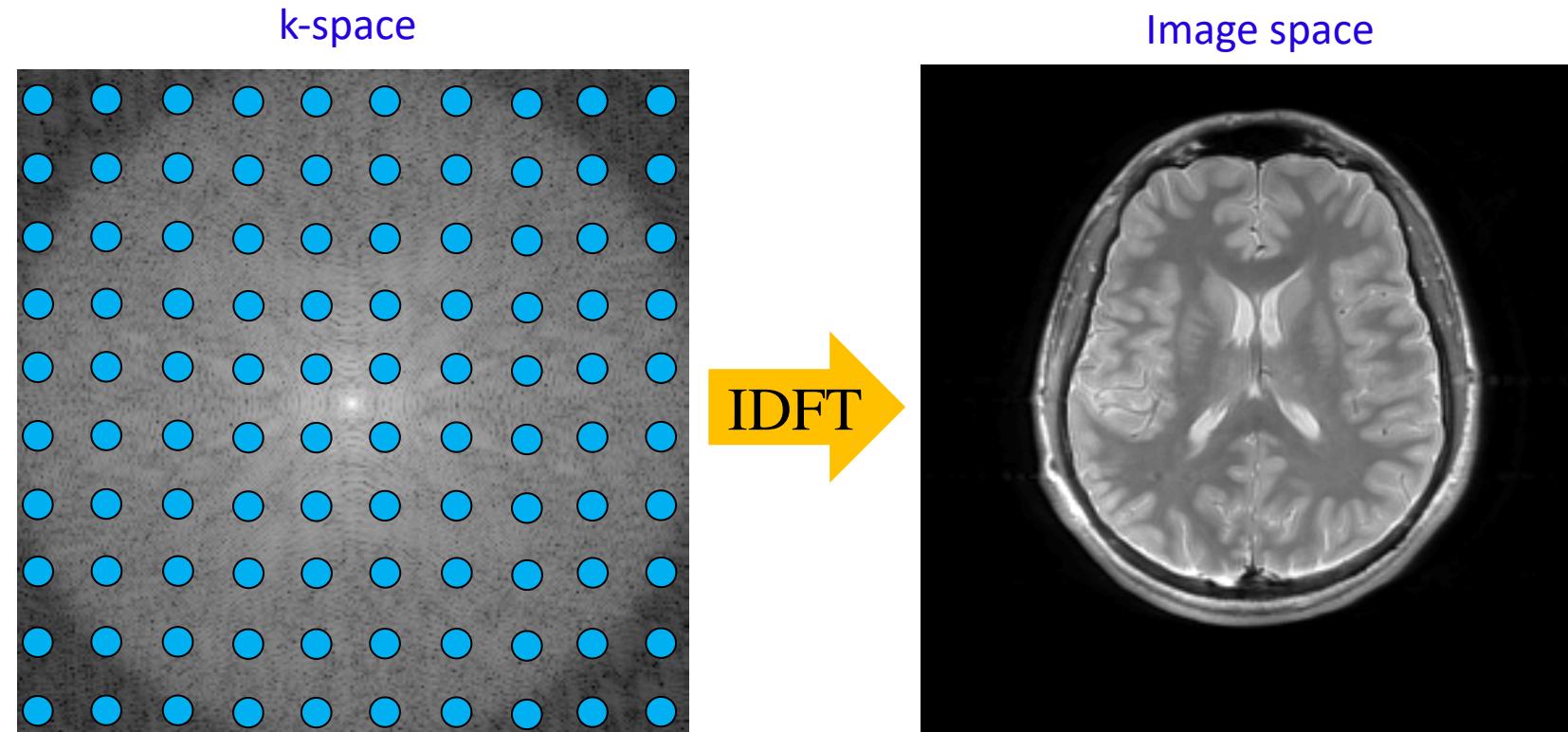


Fourier transform: location \leftrightarrow spatial frequency



MR Image Acquisition and Reconstruction

- Raw data are collected in the Fourier domain (k-space)
 - The acquired data are the discrete Fourier transform (DFT) samples of the object being imaged
 - Using the conventional 2DFT acquisition, each line of k-space is acquired one after the other (one per **repetition time (TR)** of the readout sequence)
- If the sampling rate is high enough (“Nyquist”), the image can be reconstructed by applying the inverse DFT to the k-space data



k-space

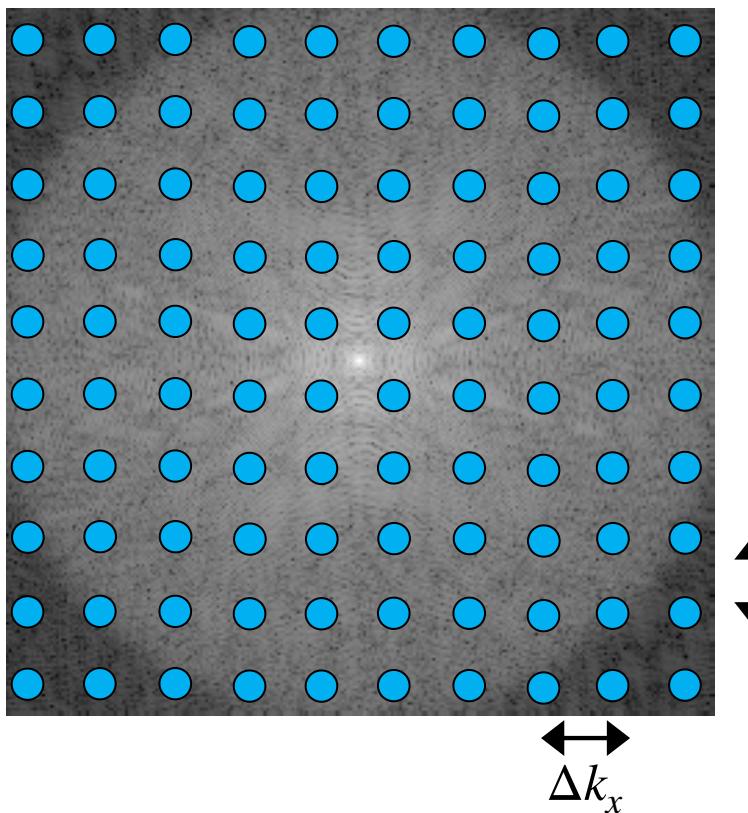
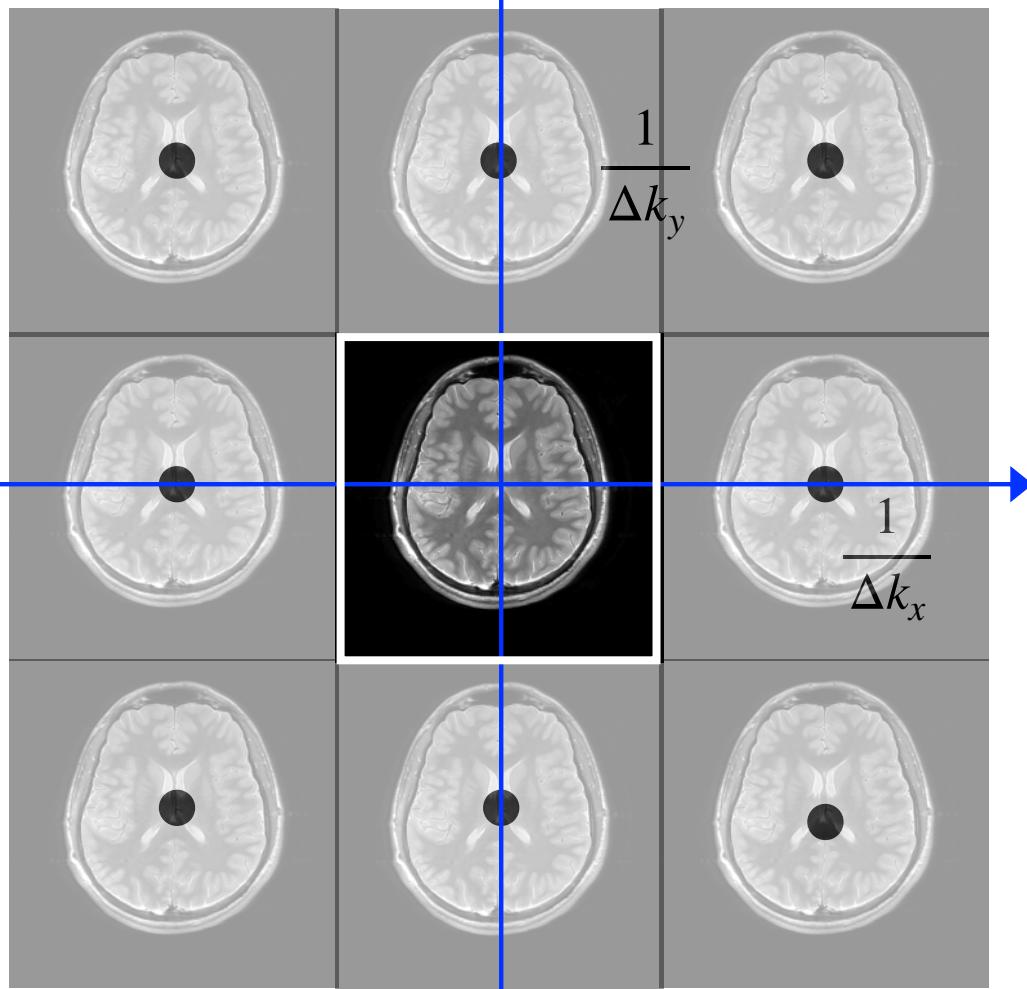
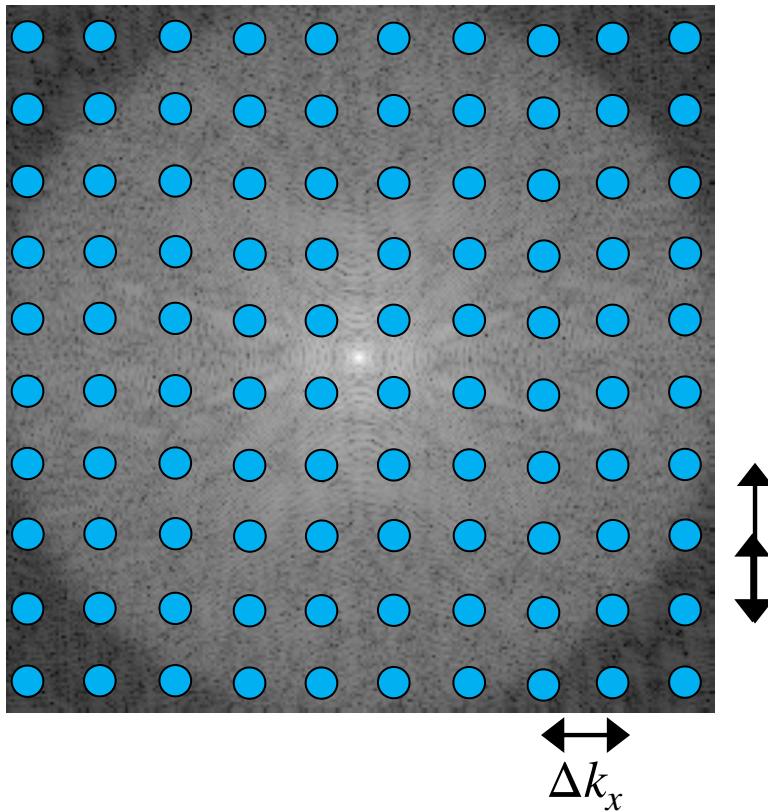


Image space



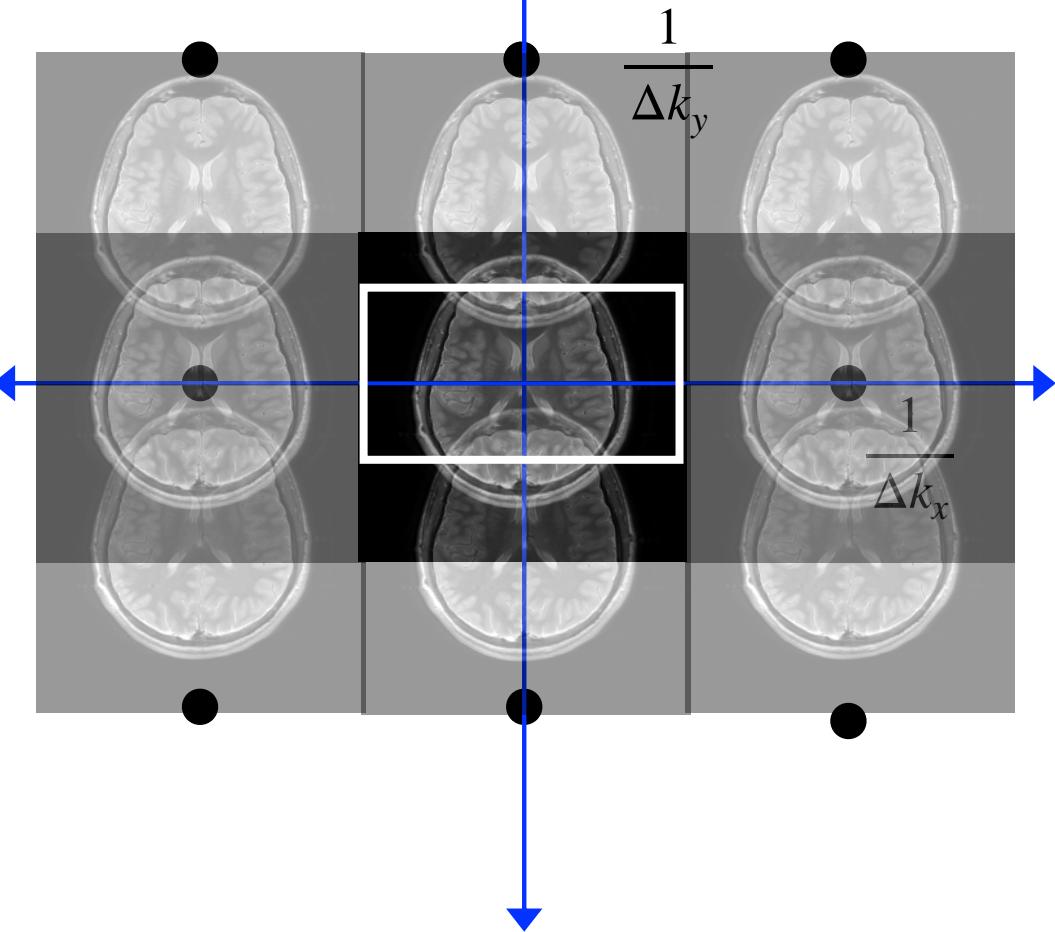
$$FOV_x = \frac{1}{\Delta k_x}$$

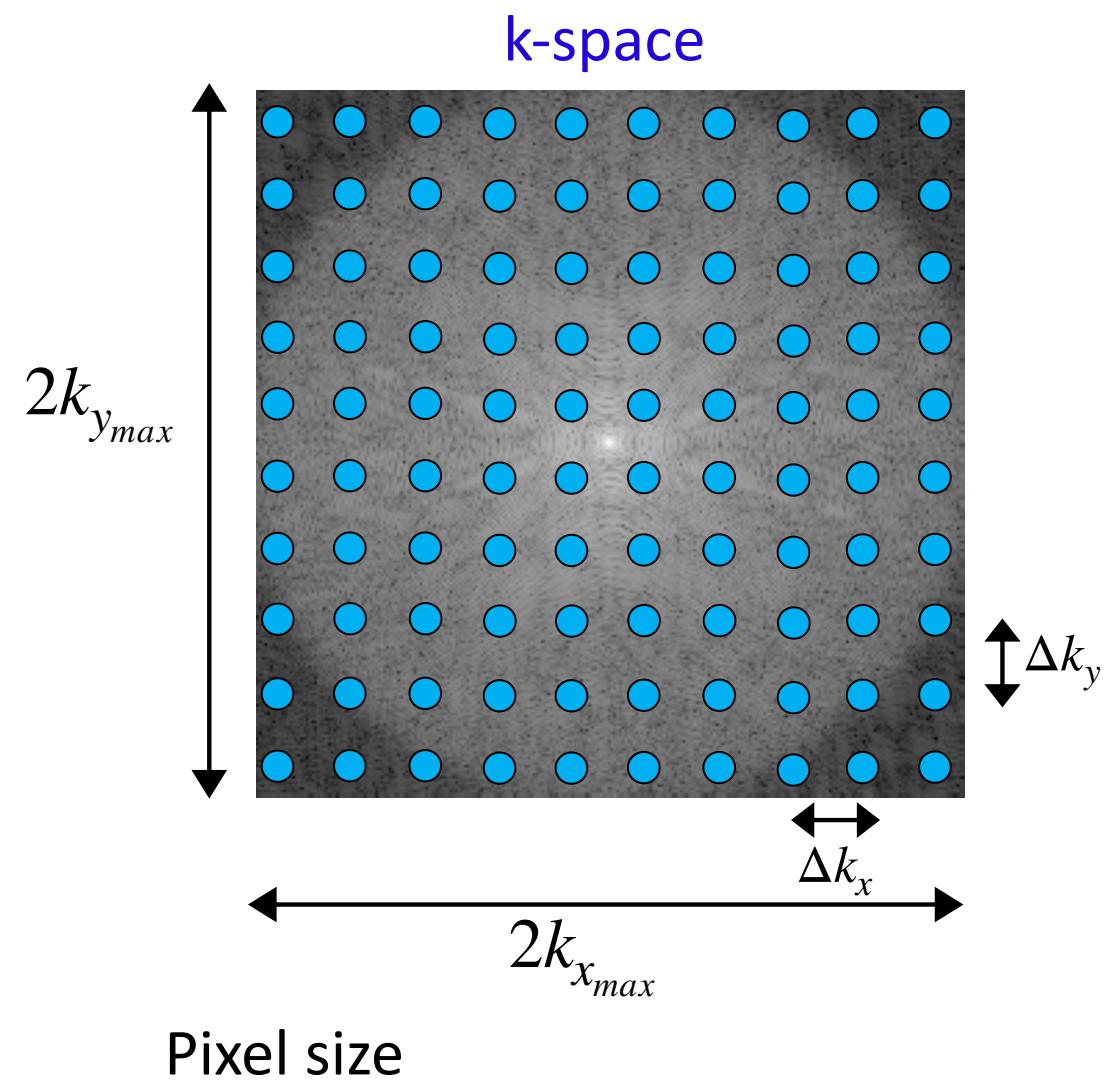
k-space



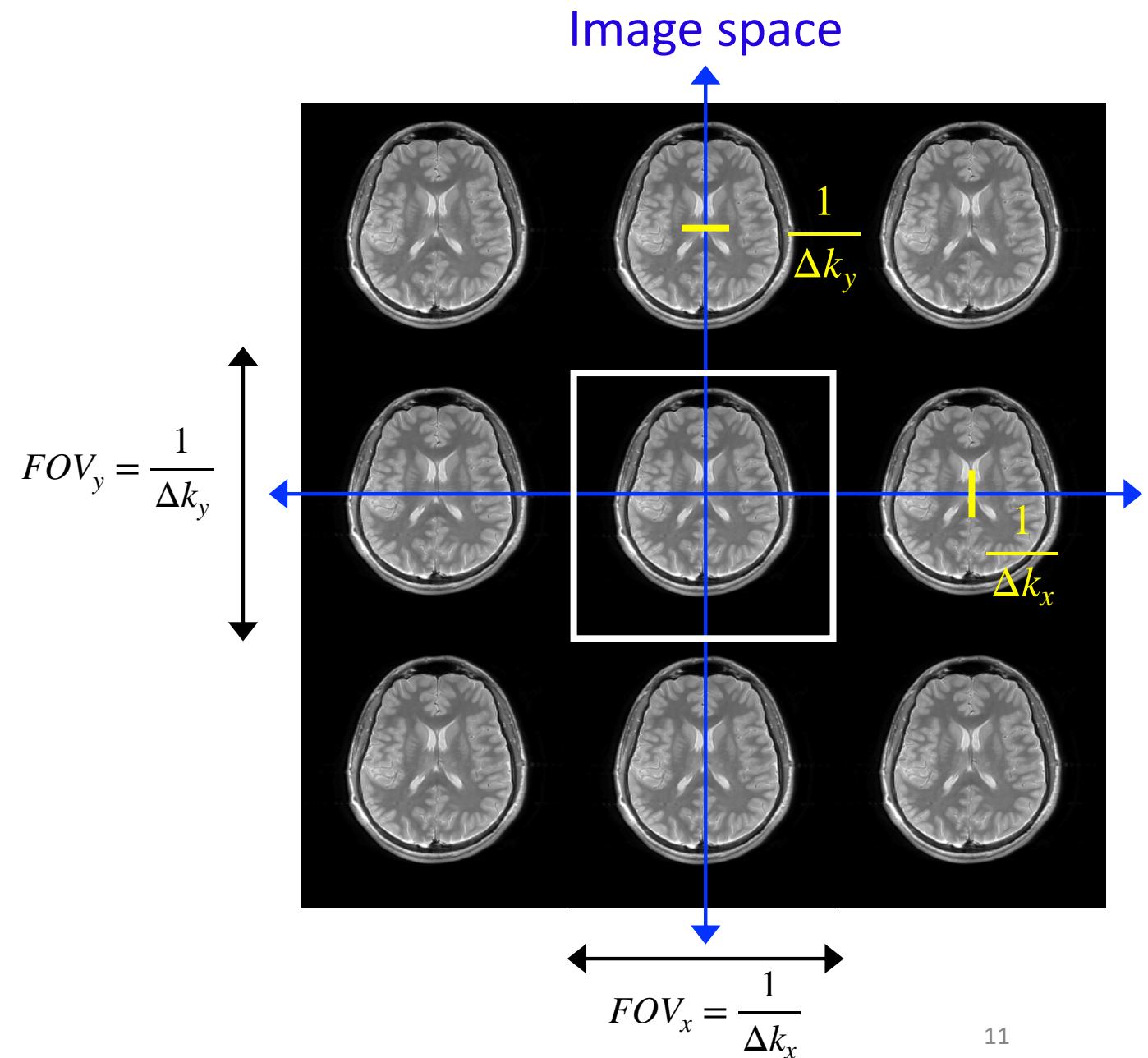
$$FOV_y = \frac{1}{\Delta k_y}$$

Image space



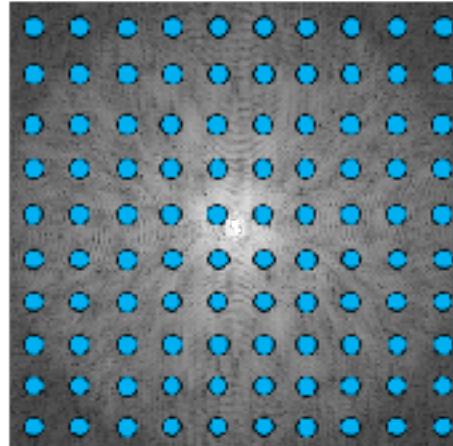


$$\Delta x \approx \frac{1}{2k_{x_{max}}} \quad \Delta y \approx \frac{1}{2k_{y_{max}}}$$

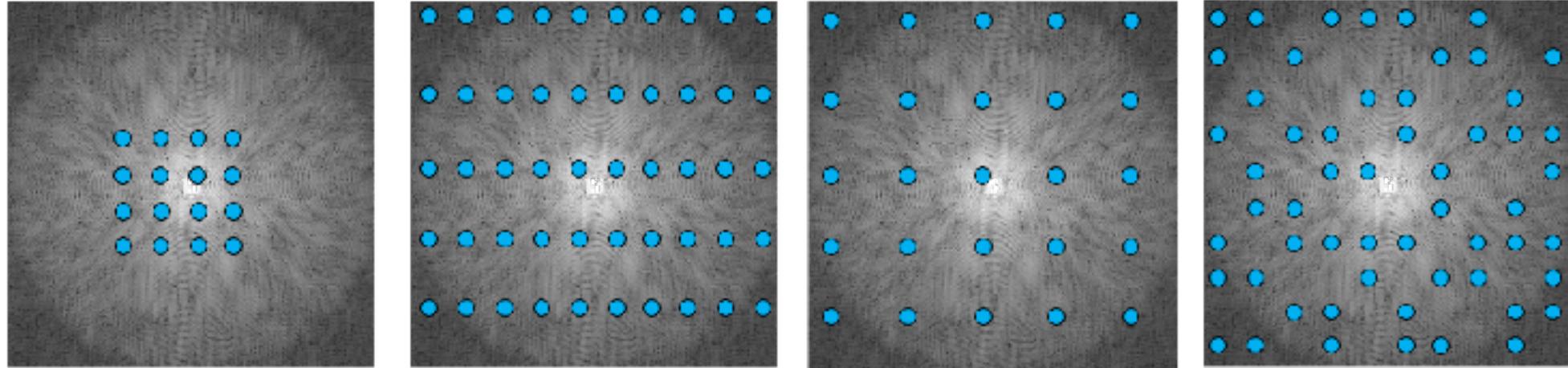


Accelerated MRI – Collect fewer k-space samples

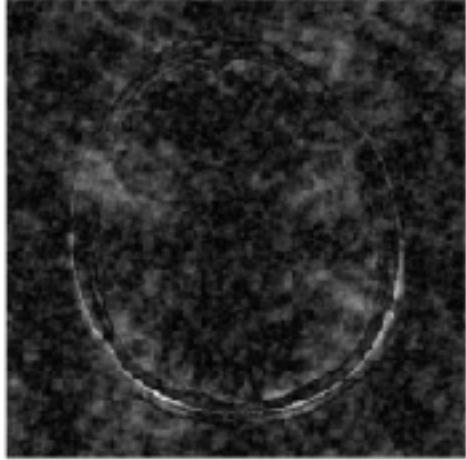
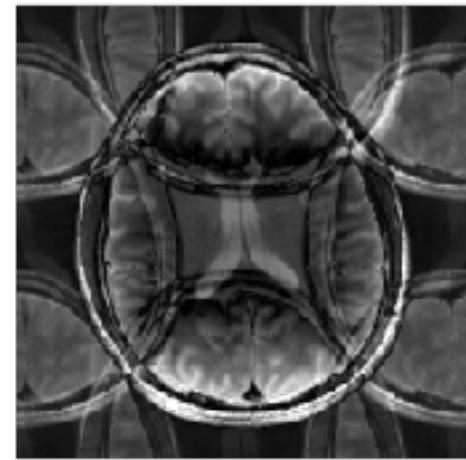
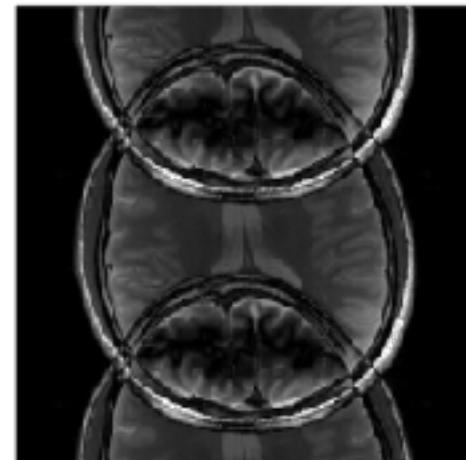
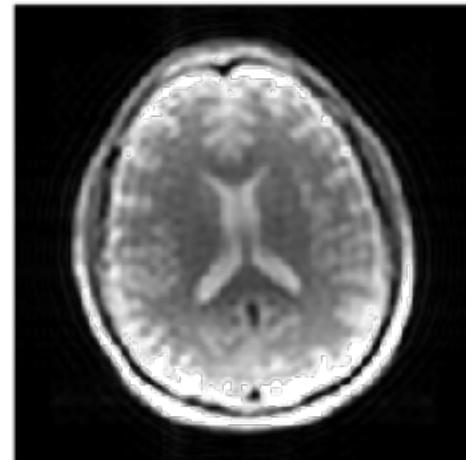
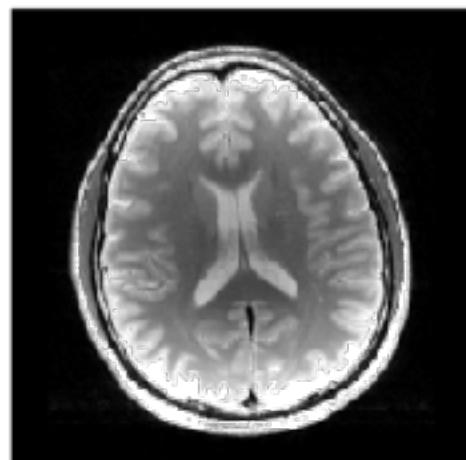
Fully sampled acquisition



Accelerated acquisition



Direct application of 2D inverse Fourier transform to the acquired data



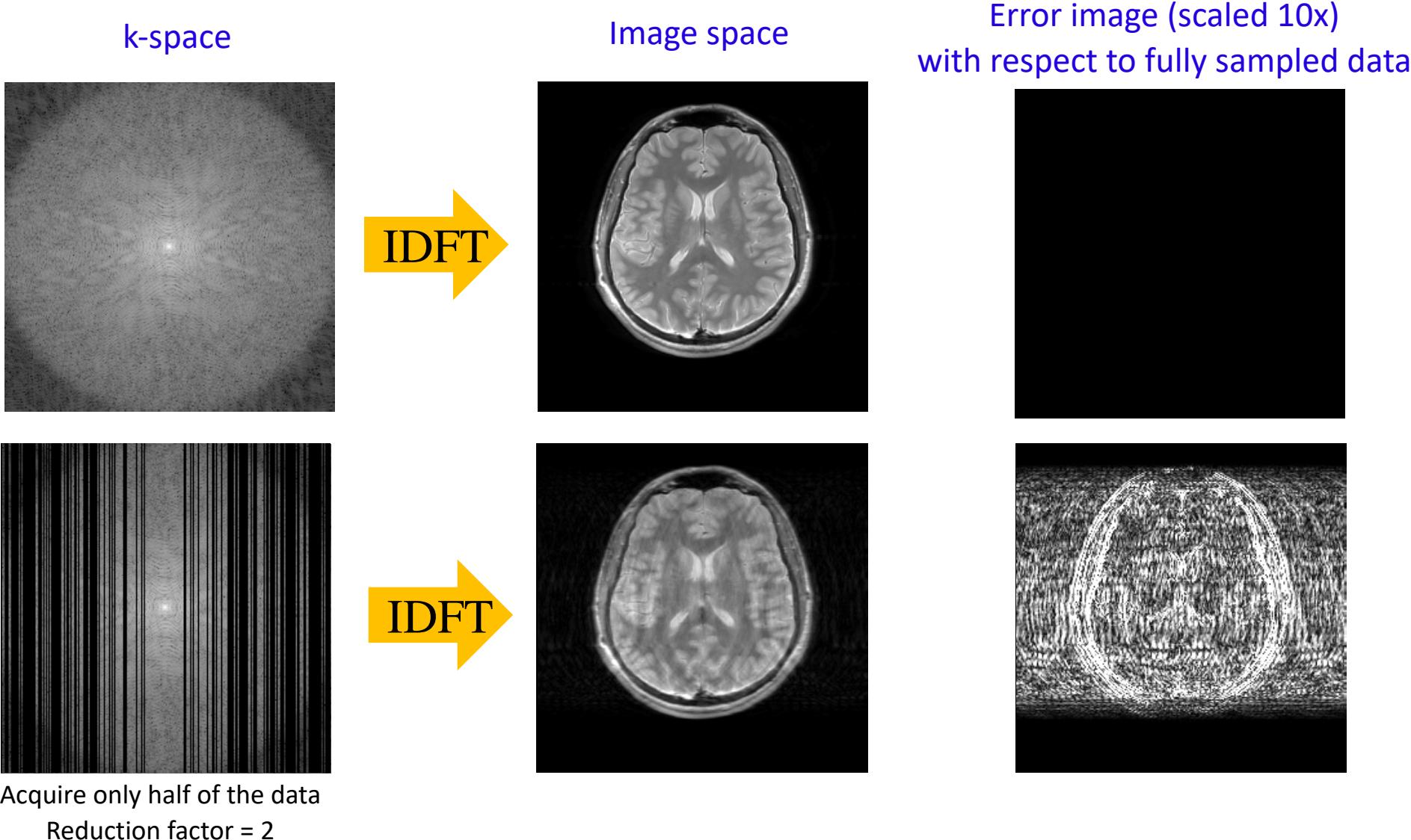
blurry

Artifact (one direction)

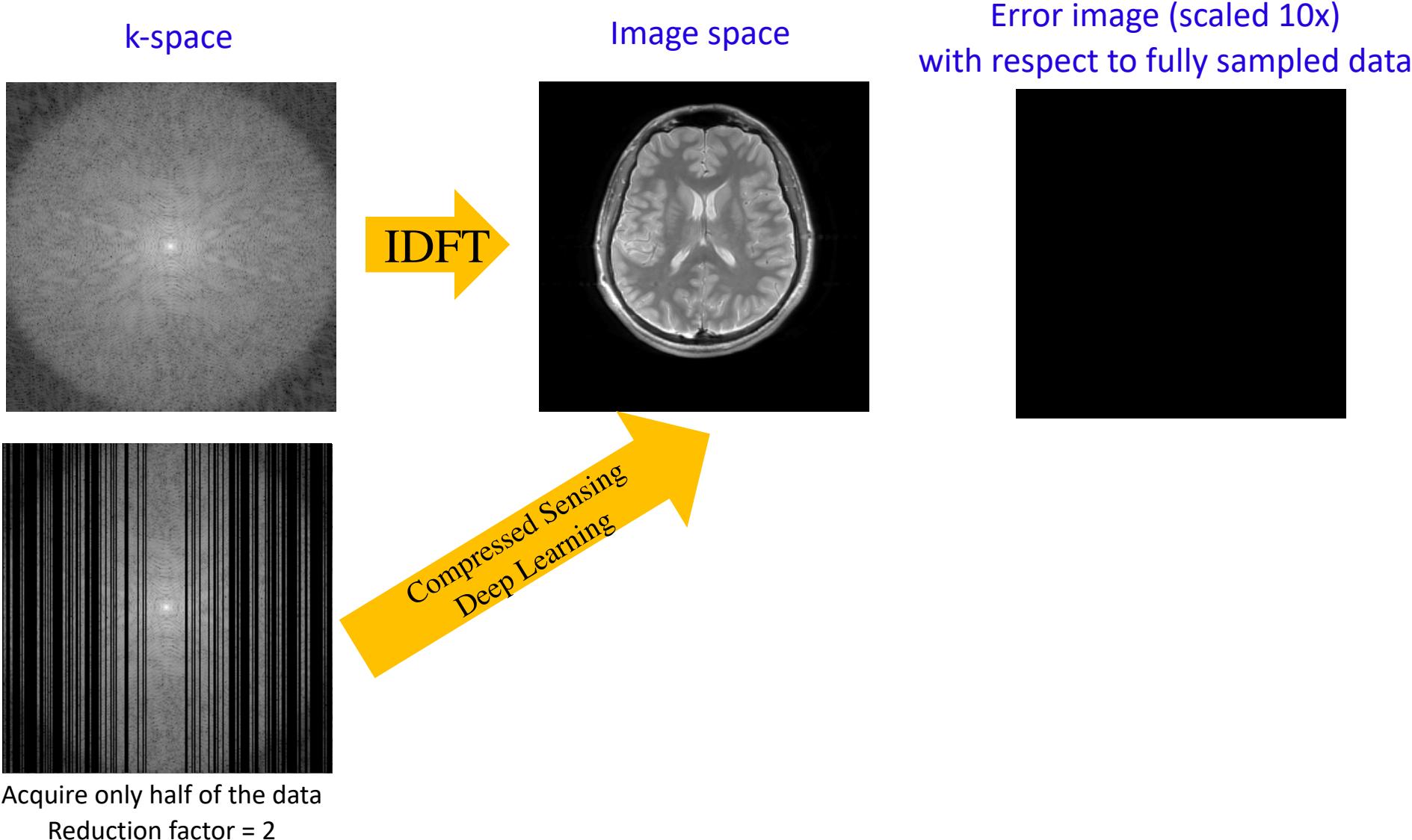
Artifact (two directions)

Noise-like artifact

MR Image Reconstruction from Accelerated Scans



MR Image Reconstruction from Accelerated Scans



Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|f(x) - y\|_2^2 + \lambda R(x)$$

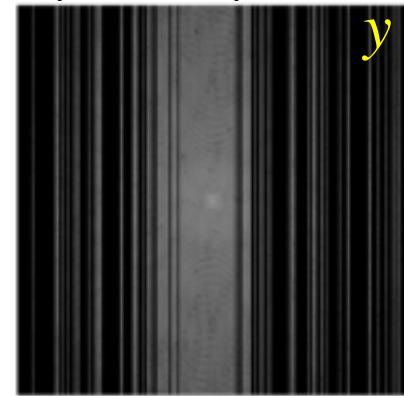
x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|f(x) - \mathbf{y}\|_2^2 + \lambda R(x)$$

Acquired k-space data



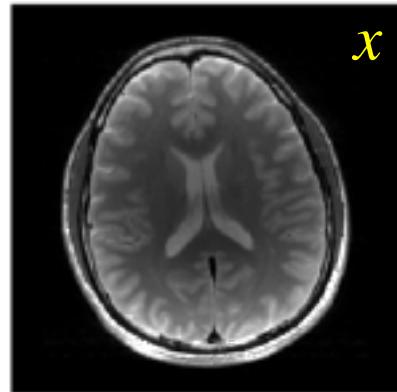
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Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|f(\mathbf{x}) - y\|_2^2 + \lambda R(x)$$

What you want to reconstruct



x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
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Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|f(x) - y\|_2^2 + \lambda R(x)$$

Our hand-designed
function to approximate
the acquisition process

x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|MFx - y\|_2^2 + \lambda R(x)$$

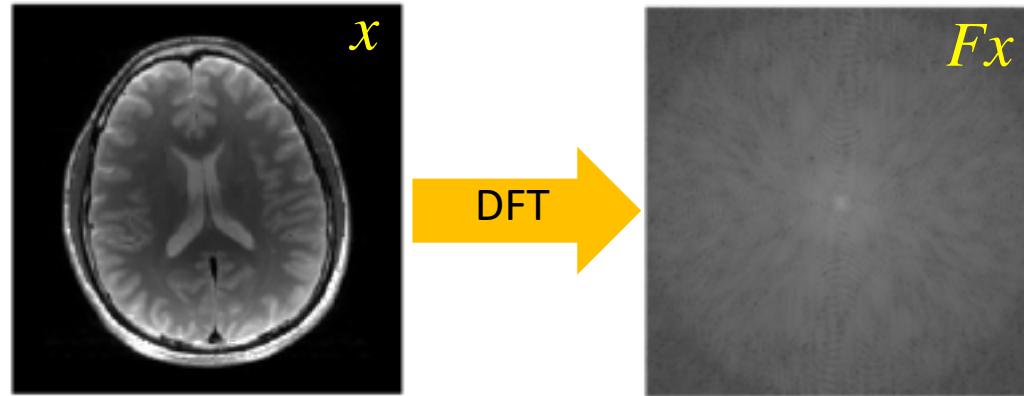
Our hand-designed
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x	: Image
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M	: Undersampling mask
y	: Observed k-space data
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λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|M\mathbf{F}x - y\|_2^2 + \lambda R(x)$$



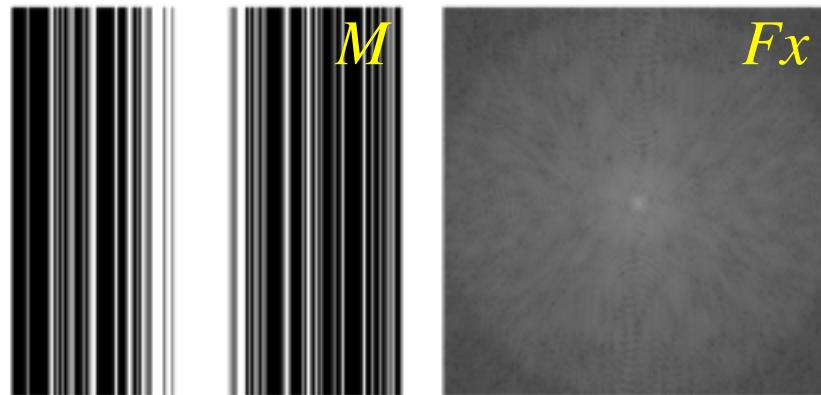
x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \| \mathbf{M} \mathbf{F} x - y \|_2^2 + \lambda R(x)$$

Pixel-wise multiplication



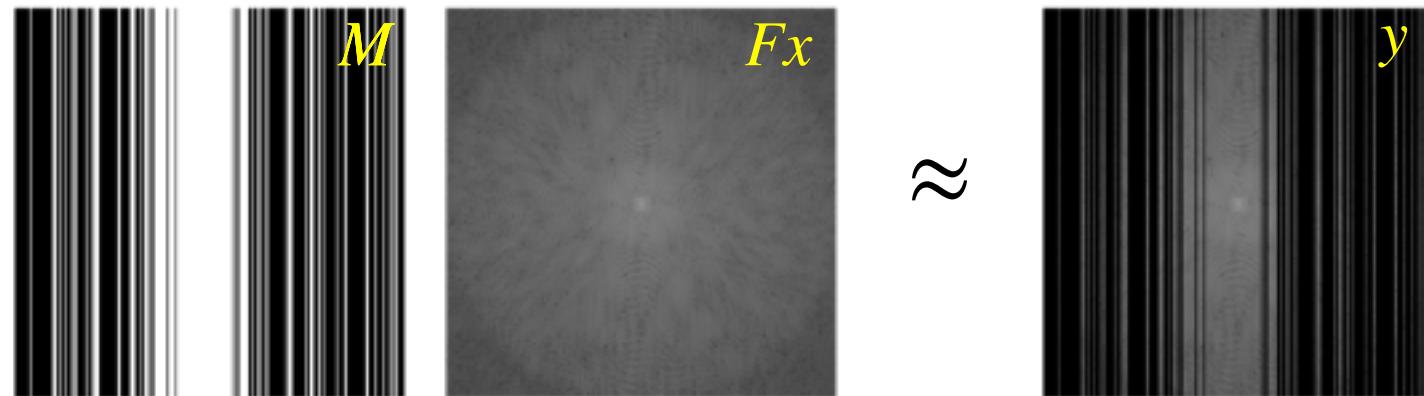
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Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|MFx - y\|_2^2 + \lambda R(x)$$

Data consistency → keep improving x until you get $MFx \approx y$



x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|MFx - y\|_2^2 + \lambda R(x)$$

Regularization

Incorporate prior knowledge on x

x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
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Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|MFx - y\|_2^2 + \lambda R(x)$$

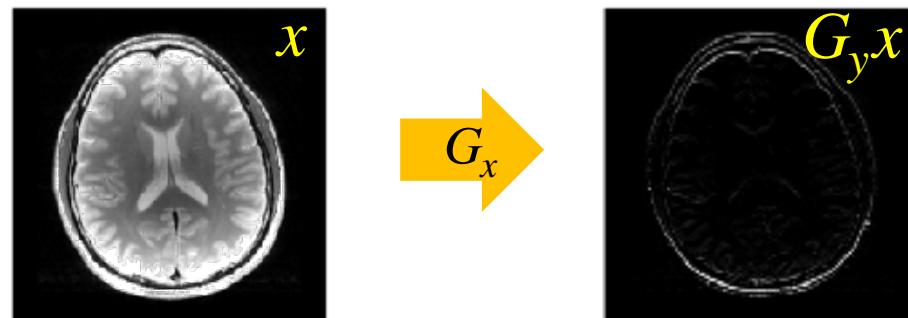
x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

$$\hat{x} = \arg \min_x \frac{1}{2} \|Mx - y\|_2^2 + \lambda \|Gx\|_1$$

G : Gradient operator discretized using finite differences



x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

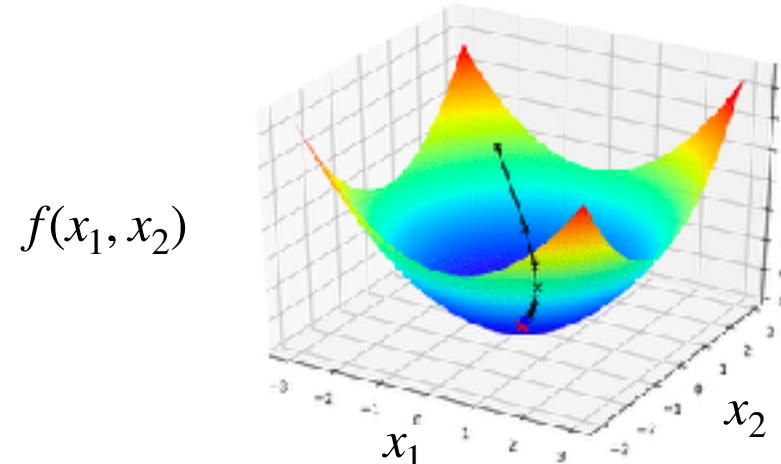
$$\min_x \frac{1}{2} \|Mx - y\|_2^2 + \lambda \|Gx\|_1$$

- Gradient descent (an iterative method)

$$x = \arg \min_x f(x)$$

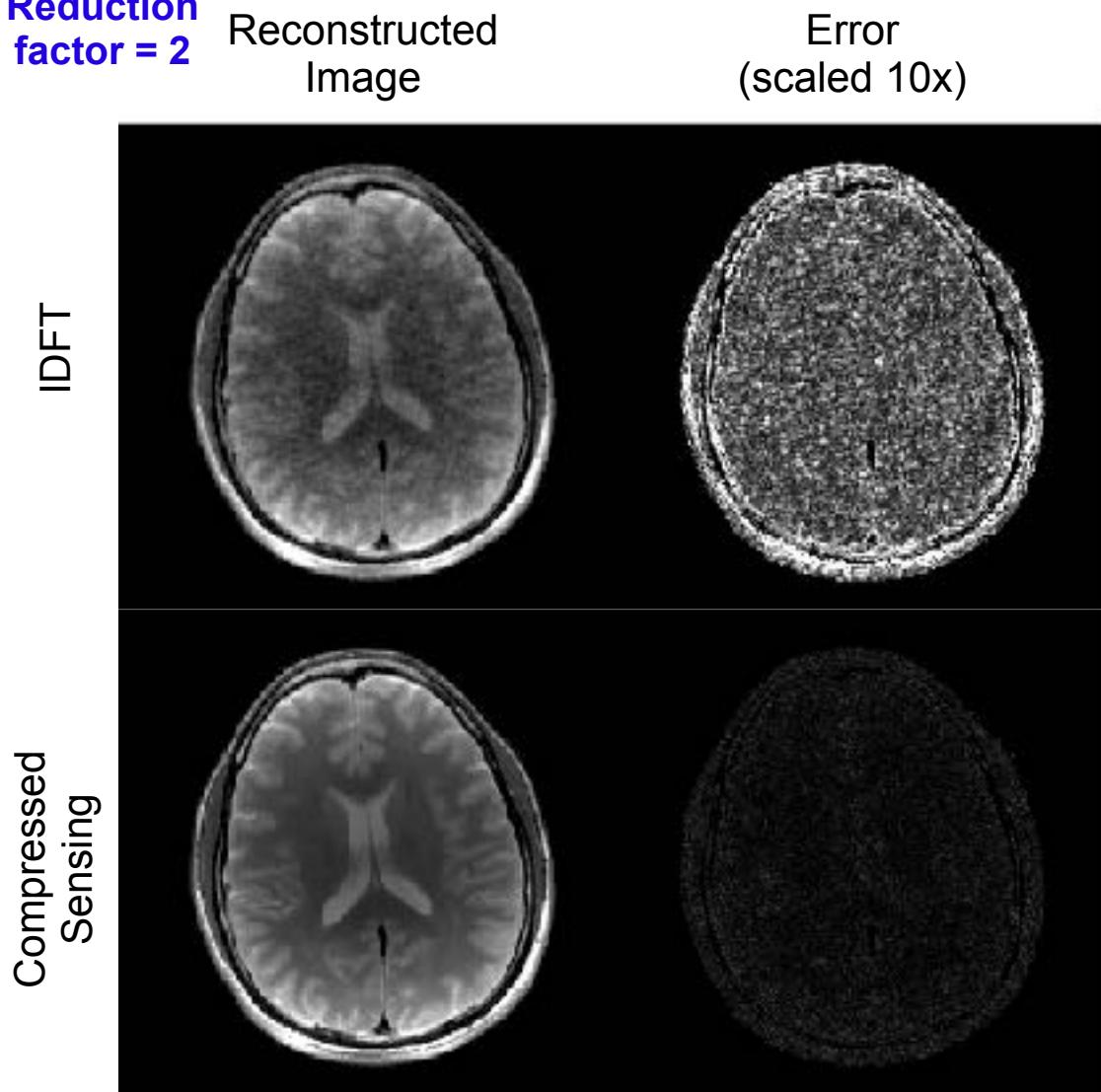
- Update equation for iteration k

$$x_{k+1} = x_k - \alpha \nabla f(x_k)$$

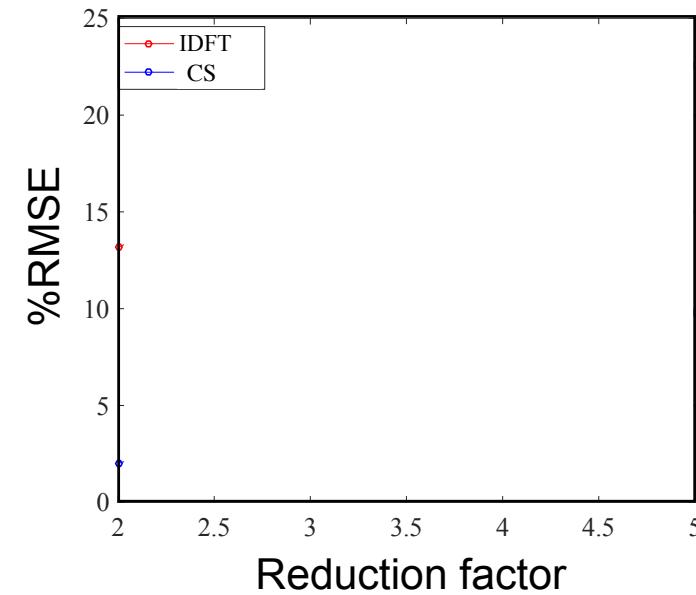


Compressed Sensing

Reduction factor = 2

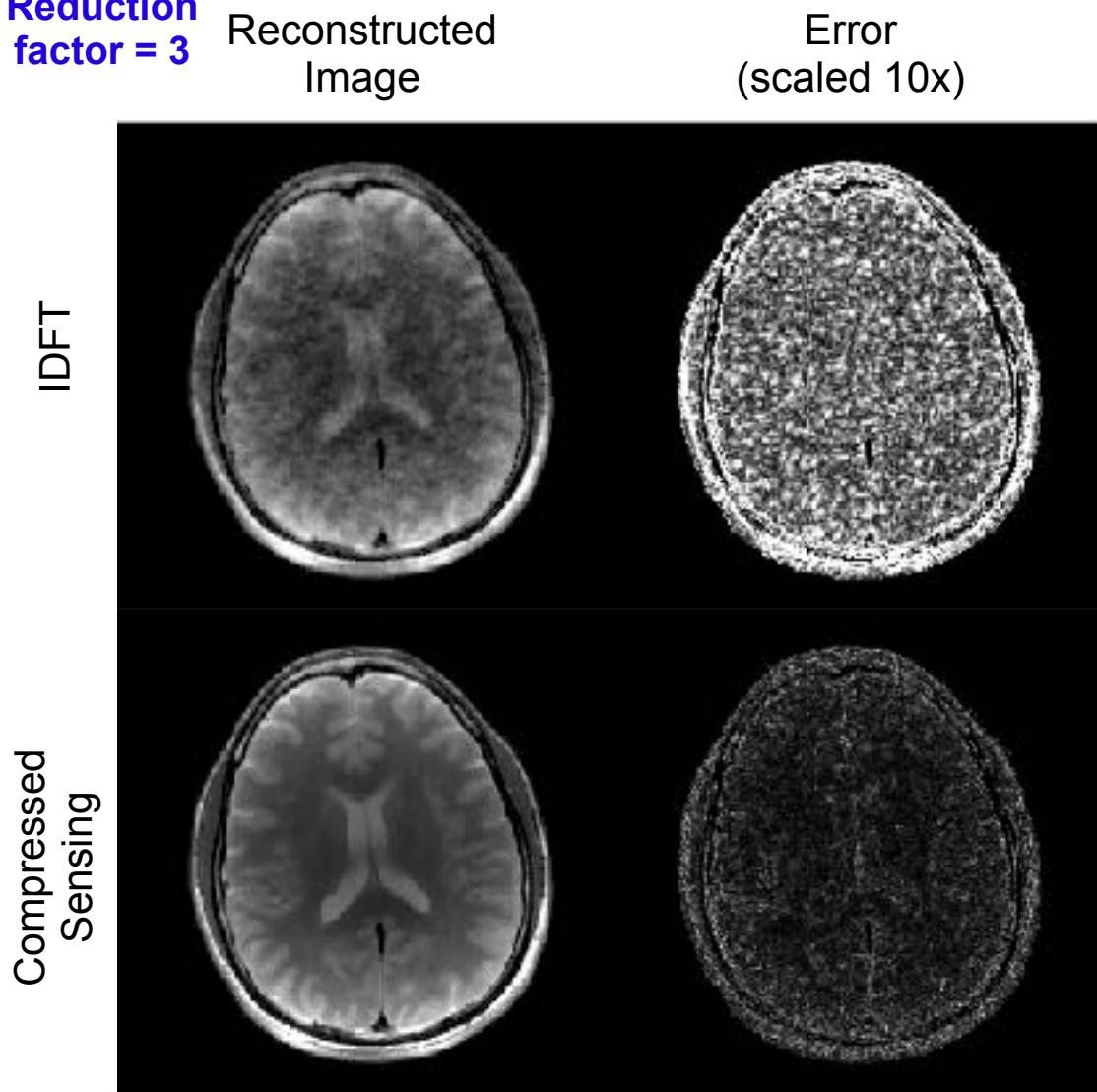


$$\hat{x} = \arg \min_x \frac{1}{2} \|M\hat{F}x - y\|_2^2 + \lambda \|Gx\|_1$$

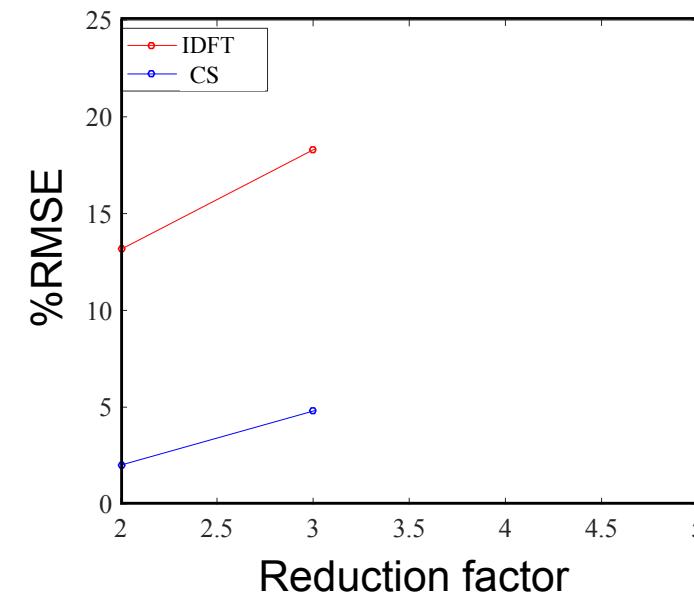


Compressed Sensing

Reduction factor = 3

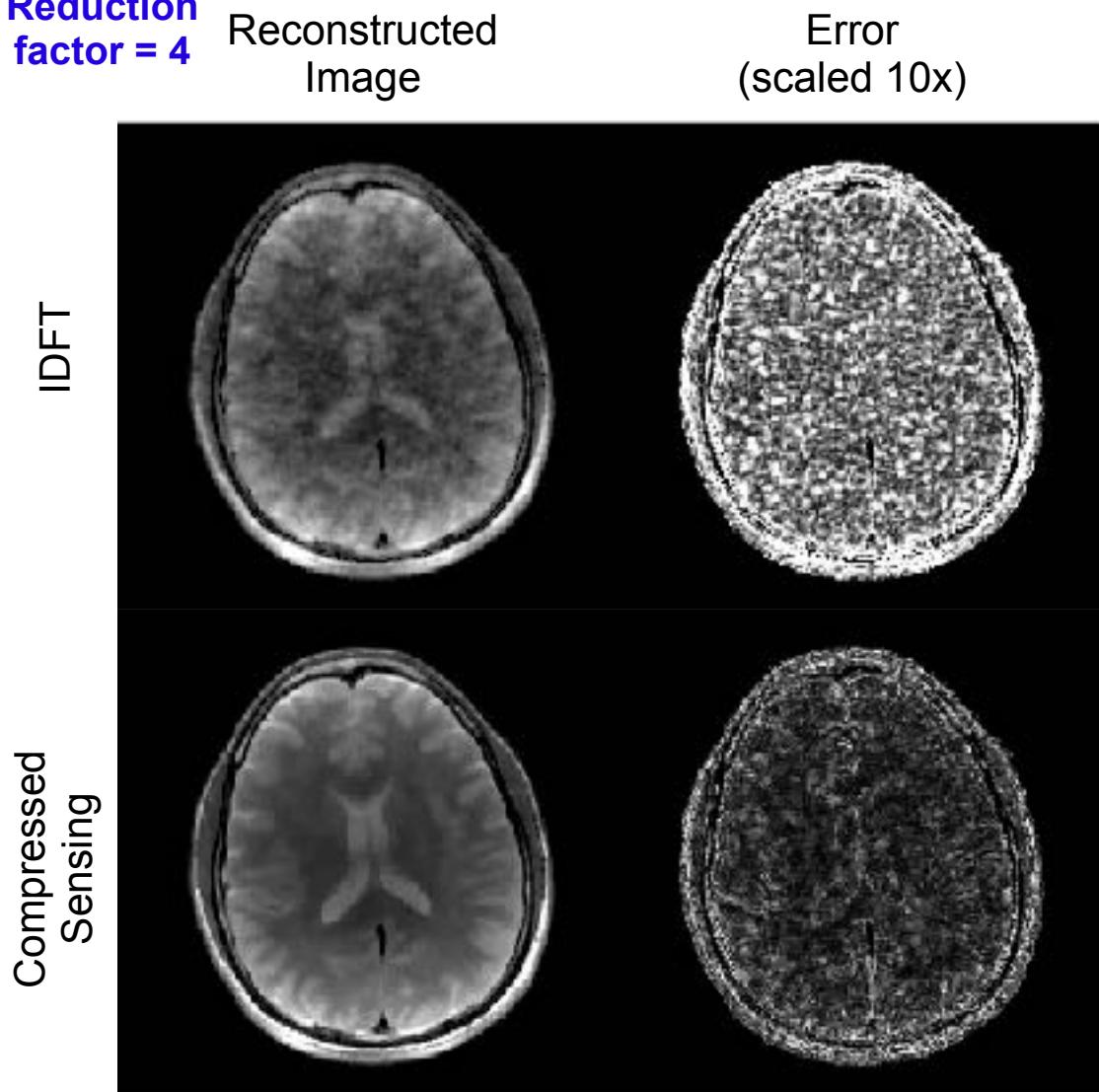


$$\hat{x} = \arg \min_x \frac{1}{2} \|M\hat{F}x - y\|_2^2 + \lambda \|Gx\|_1$$

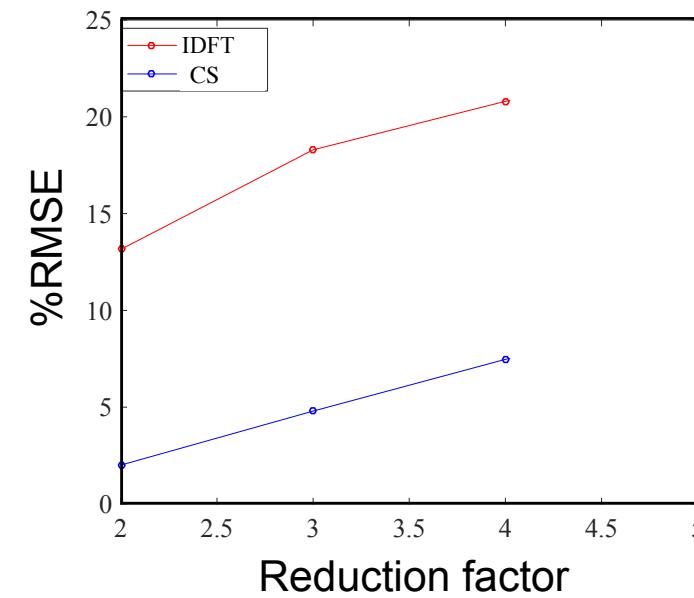


Compressed Sensing

Reduction
factor = 4

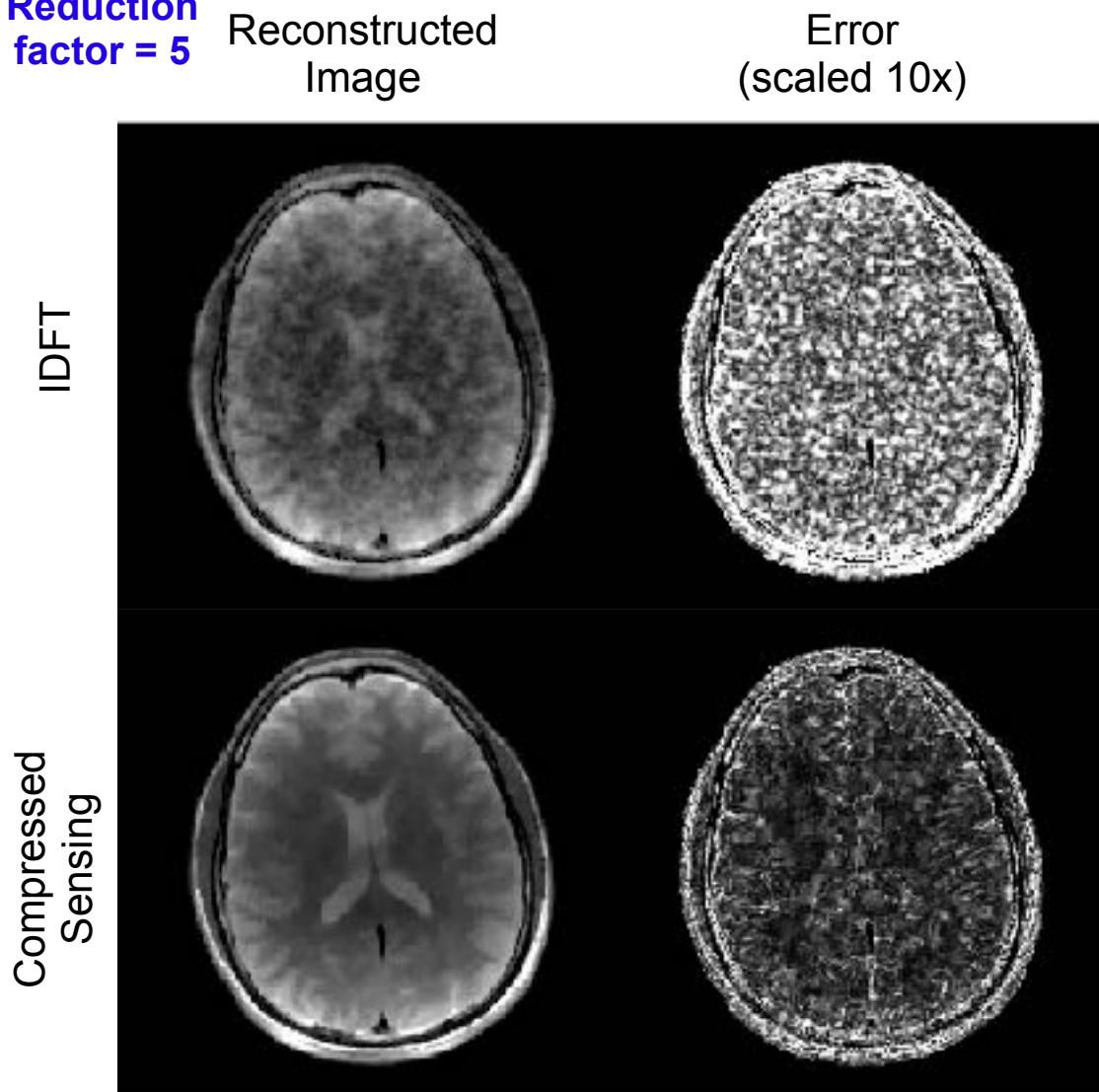


$$\hat{x} = \arg \min_x \frac{1}{2} \|M\hat{F}x - y\|_2^2 + \lambda \|Gx\|_1$$

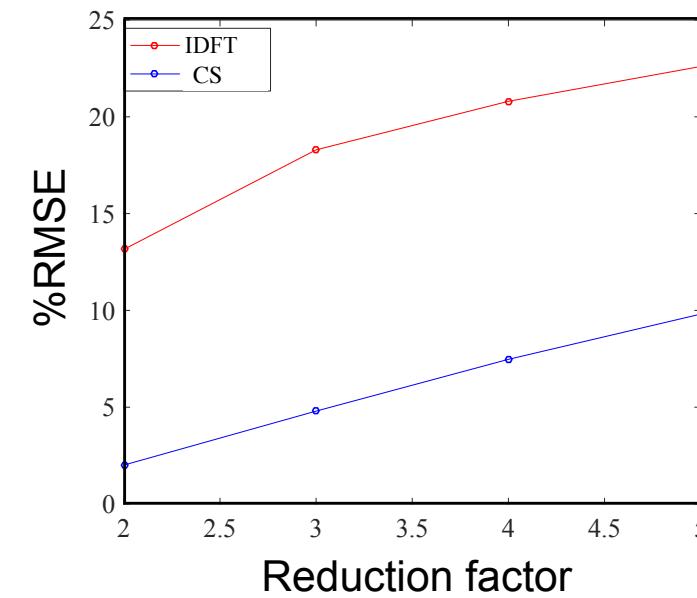


Compressed Sensing

Reduction factor = 5



$$\hat{x} = \arg \min_x \frac{1}{2} \|M\hat{F}x - y\|_2^2 + \lambda \|Gx\|_1$$



Compressed Sensing

$$\hat{x} = \arg \min_x \frac{1}{2} \|M F x - y\|_2^2 + \lambda \|G x\|_1$$

Reduction factor = 1

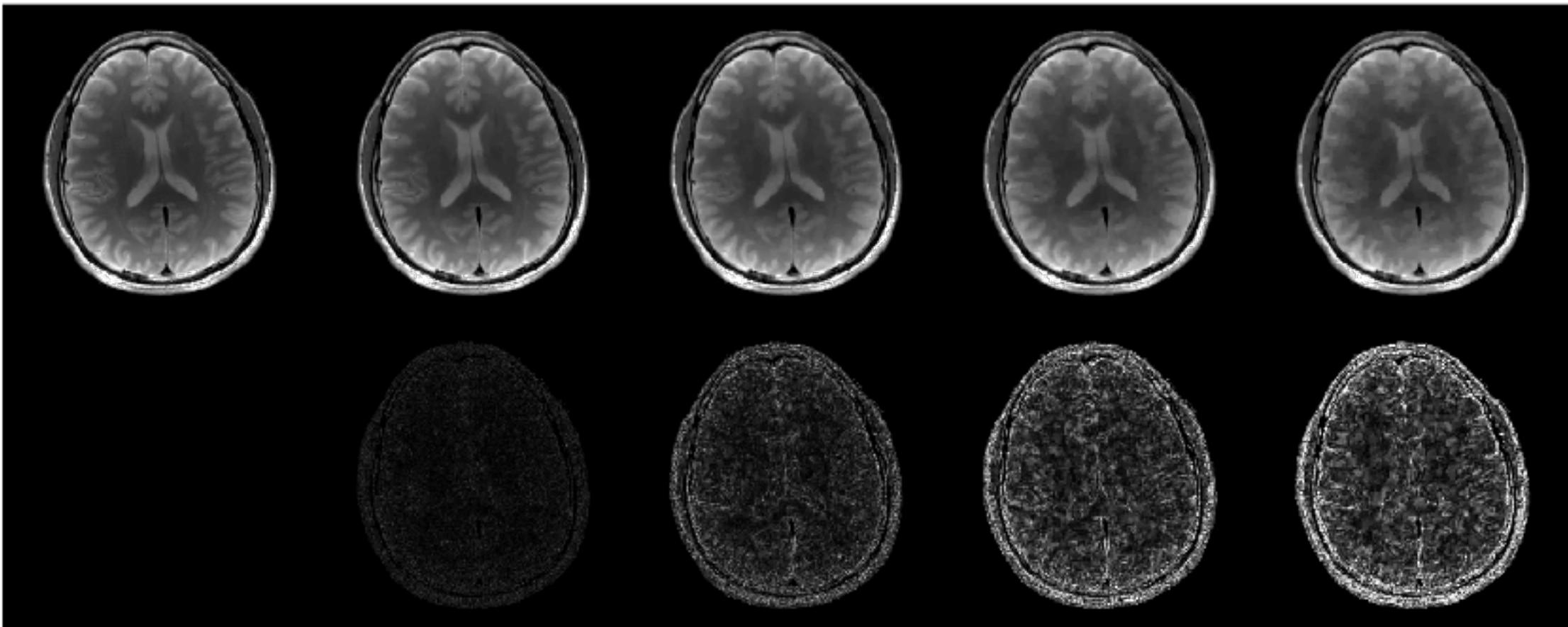
Reduction factor = 2

Reduction factor = 3

Reduction factor = 4

Reduction factor = 5

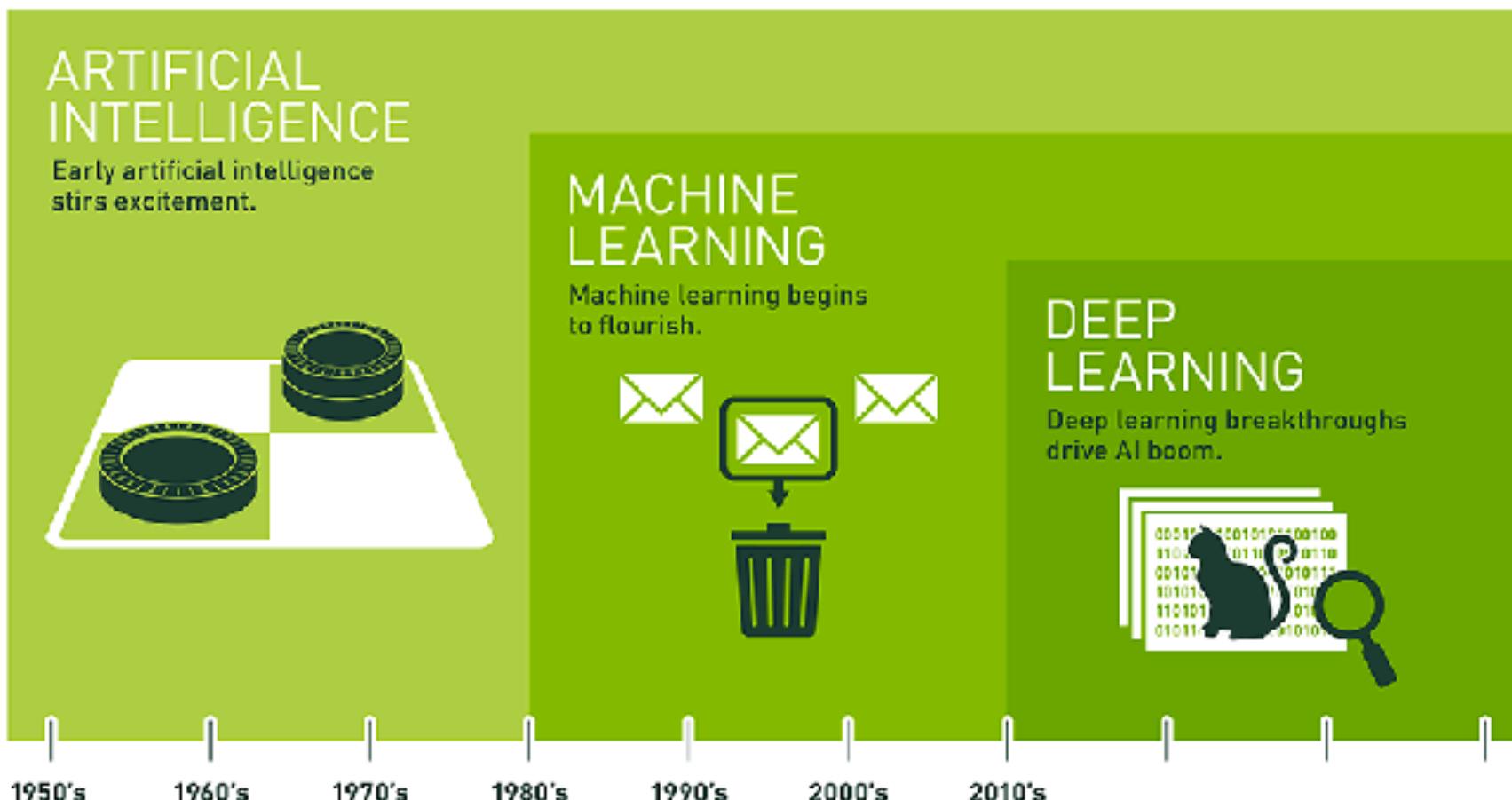
Reconstructed Image



Outline

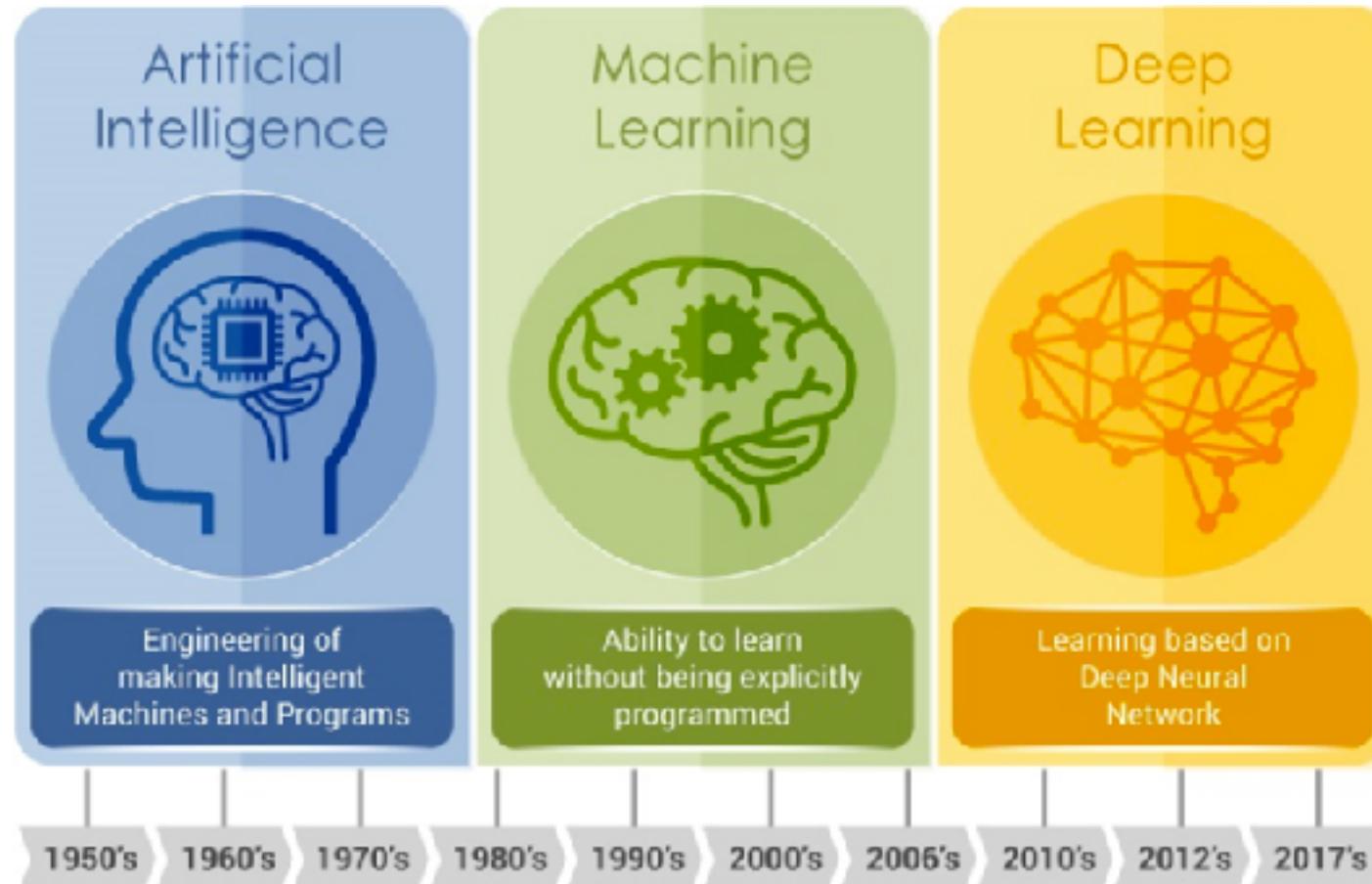
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Deep Learning



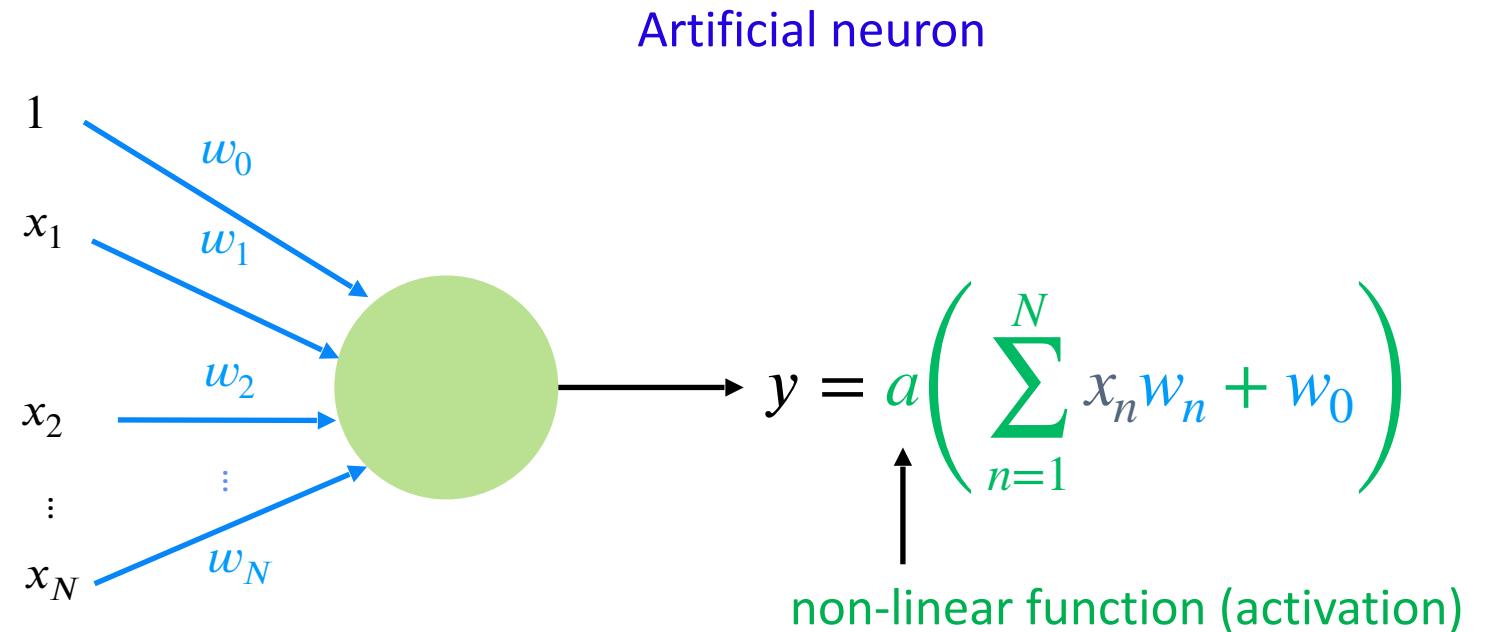
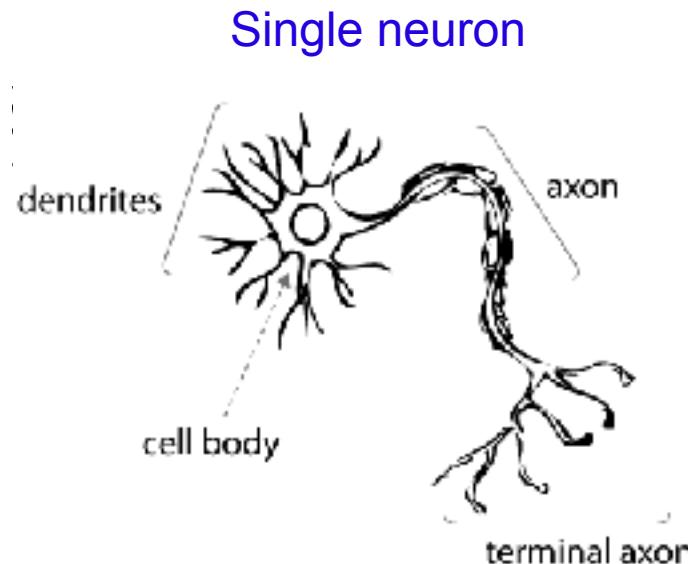
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Deep Learning



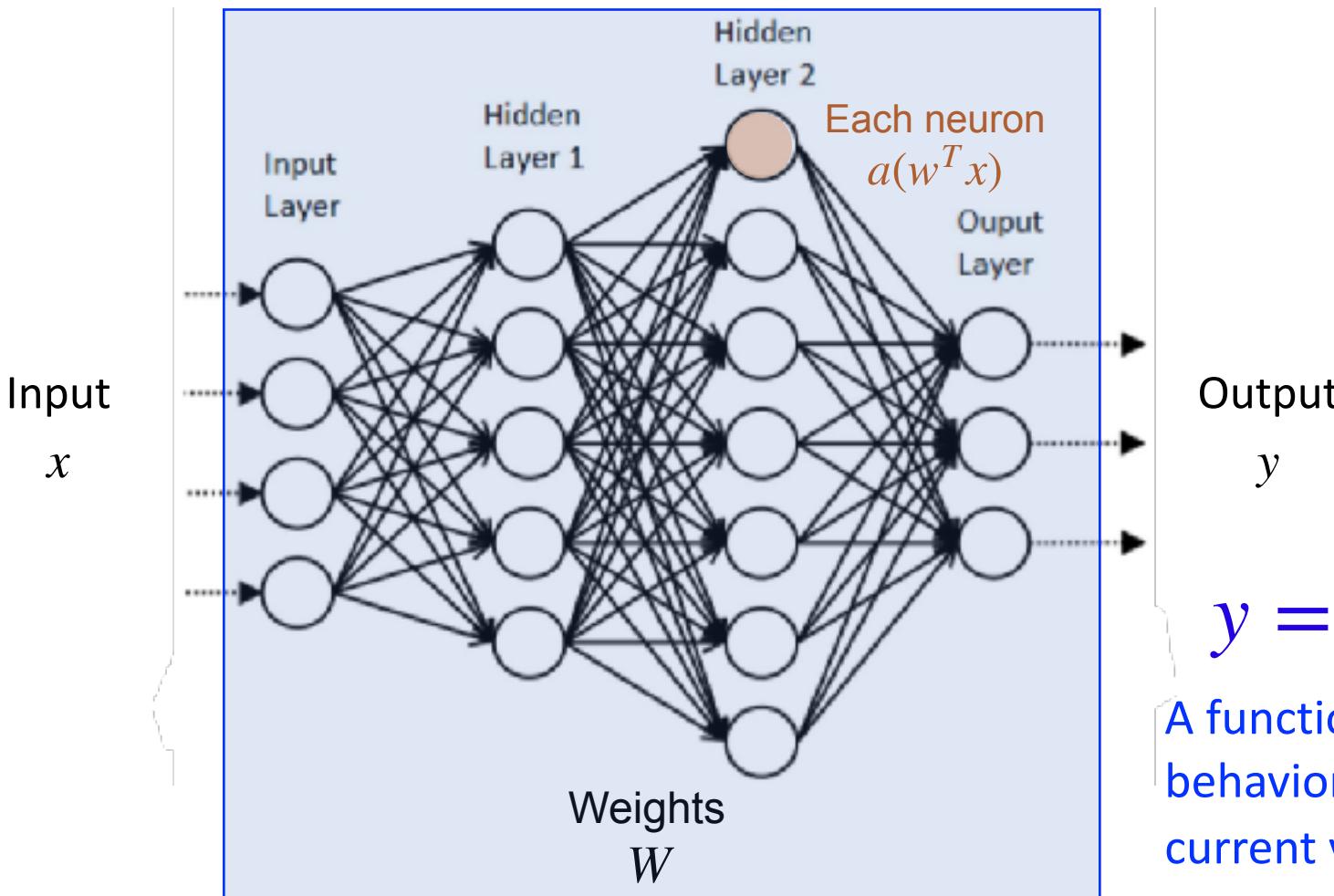
Deep Learning

- Deep learning is a subfield of machine learning that stems from artificial neural networks (ANN)



Deep Learning

- An artificial neural network with **many hidden layers** is called a **deep** artificial neural network (ANN)



A function that can change
behavior depending on the
current values of W

Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
 - MRI reconstruction function



- MRI segmentation function

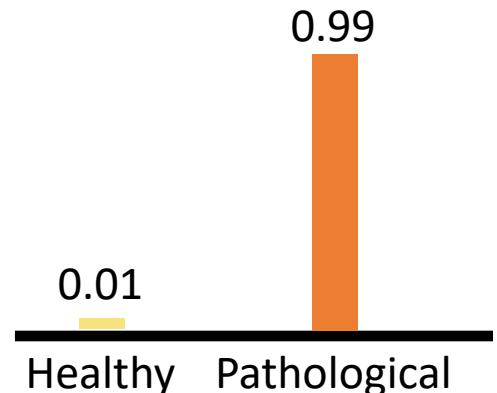
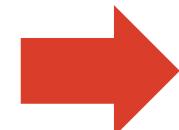


- MRI super-resolution function

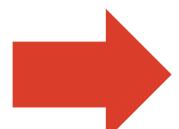
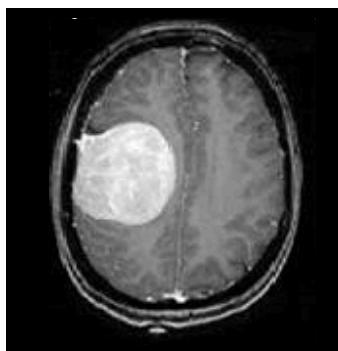
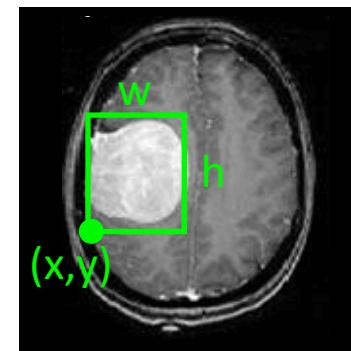
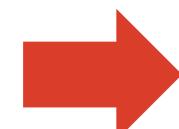


Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
 - MR image classification function

 $f_{classif, W}$ 

- Detection function

 $f_{detection, W}$ 

A mostly complete chart of

Neural Networks

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- Backfed Input Cell
- Input Cell
- △ Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- △ Spiking Hidden Cell
- Output Cell
- Match Input/Output Cell
- Recurrent Cell
- Memory Cell
- △ Different Memory Cell
- Kernel
- Convolution or Pool

MC



HNN



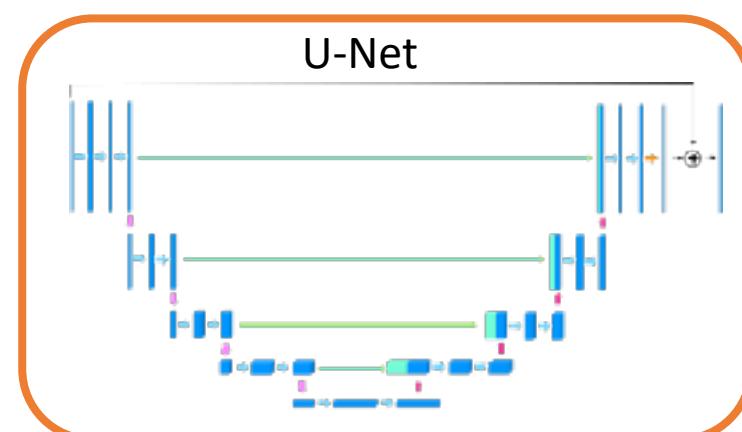
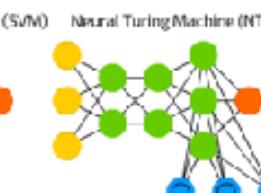
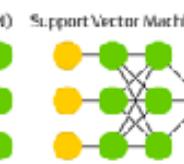
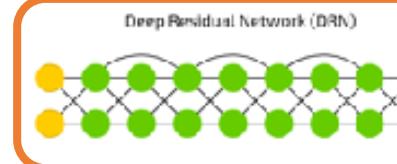
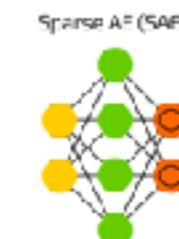
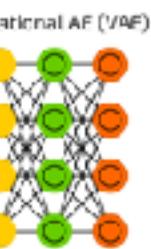
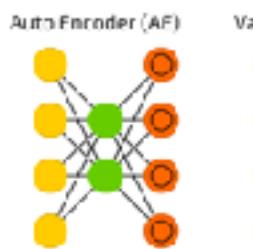
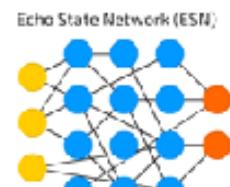
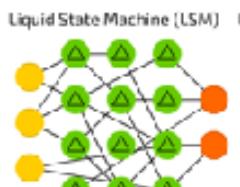
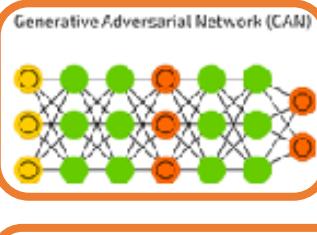
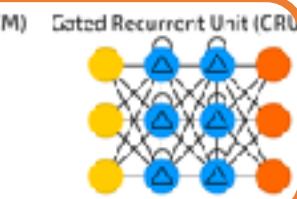
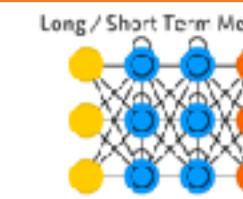
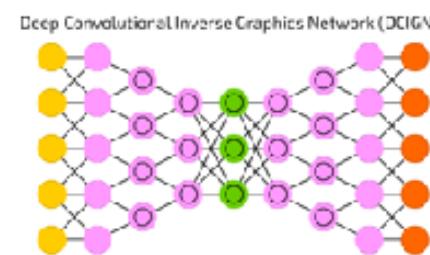
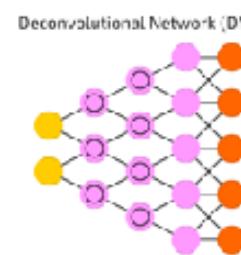
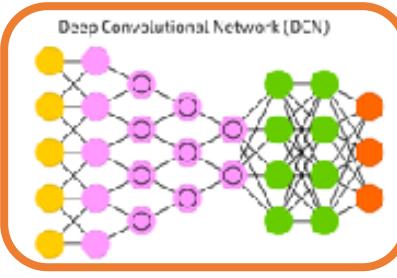
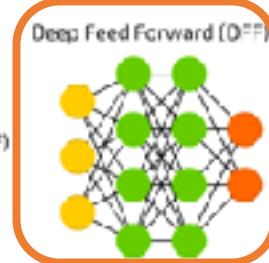
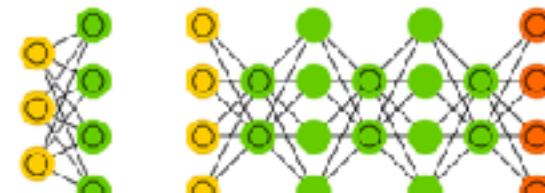
DM



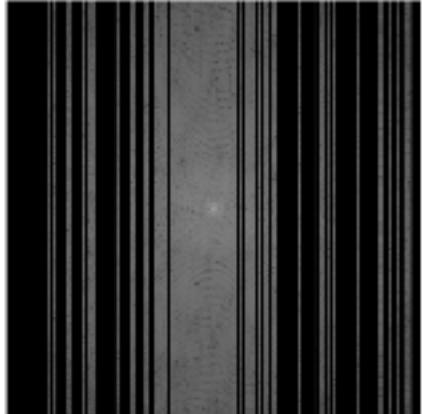
RDM



Deep Belief Network (DBN)



Deep Learning for MR Image Reconstruction

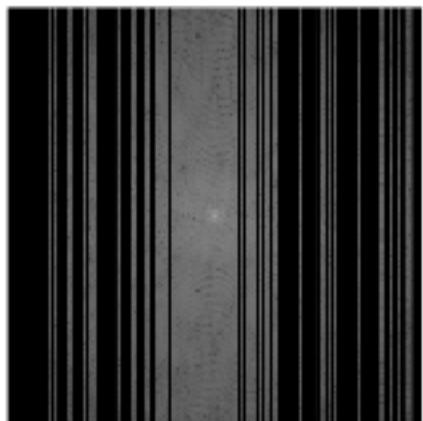
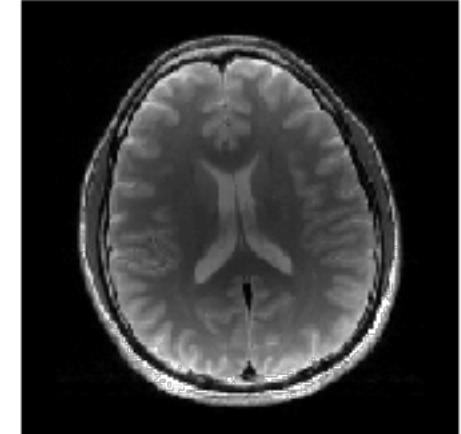


Underlying Process

g_{recon}

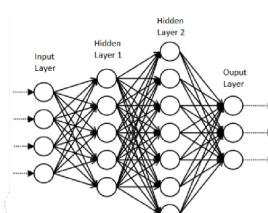
An *unknown* highly complicated function that includes (but not limited to)

- Inverse Fourier transform
- Artifact removal
- Magnetic field map correction

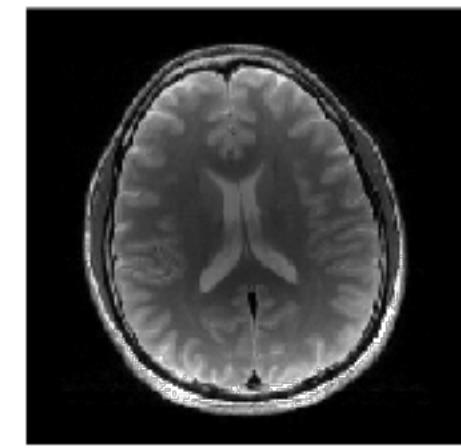


Deep Learning

f_W

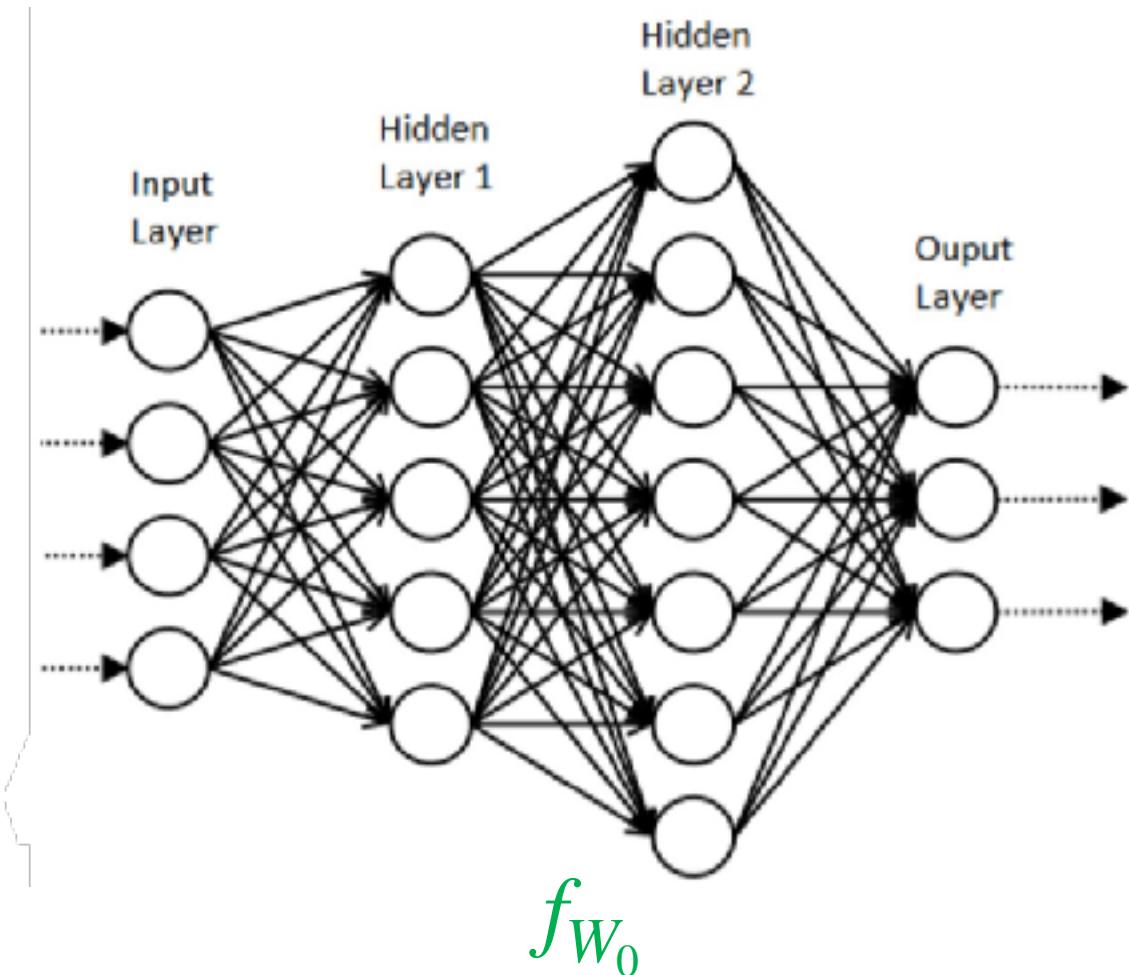


With model training, we could obtain
 $f_W \approx g_{recon}$



Supervised Model Training

Step 1: Create a neural network with some initial weight f_{W_0}

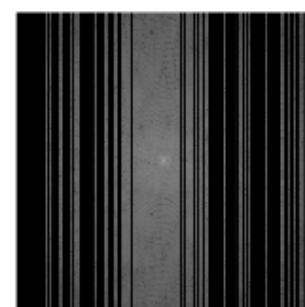
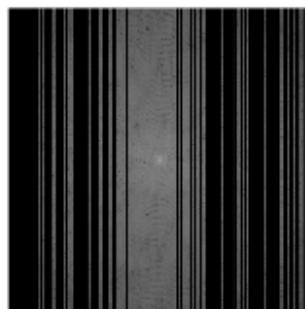
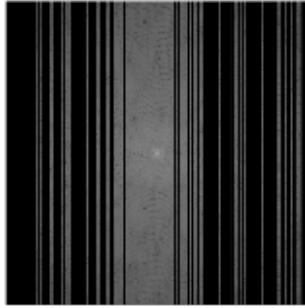


Keywords: dataset preparation, target, labels, ground truth, true, input-output pairs

Supervised Model Training

Prepared input

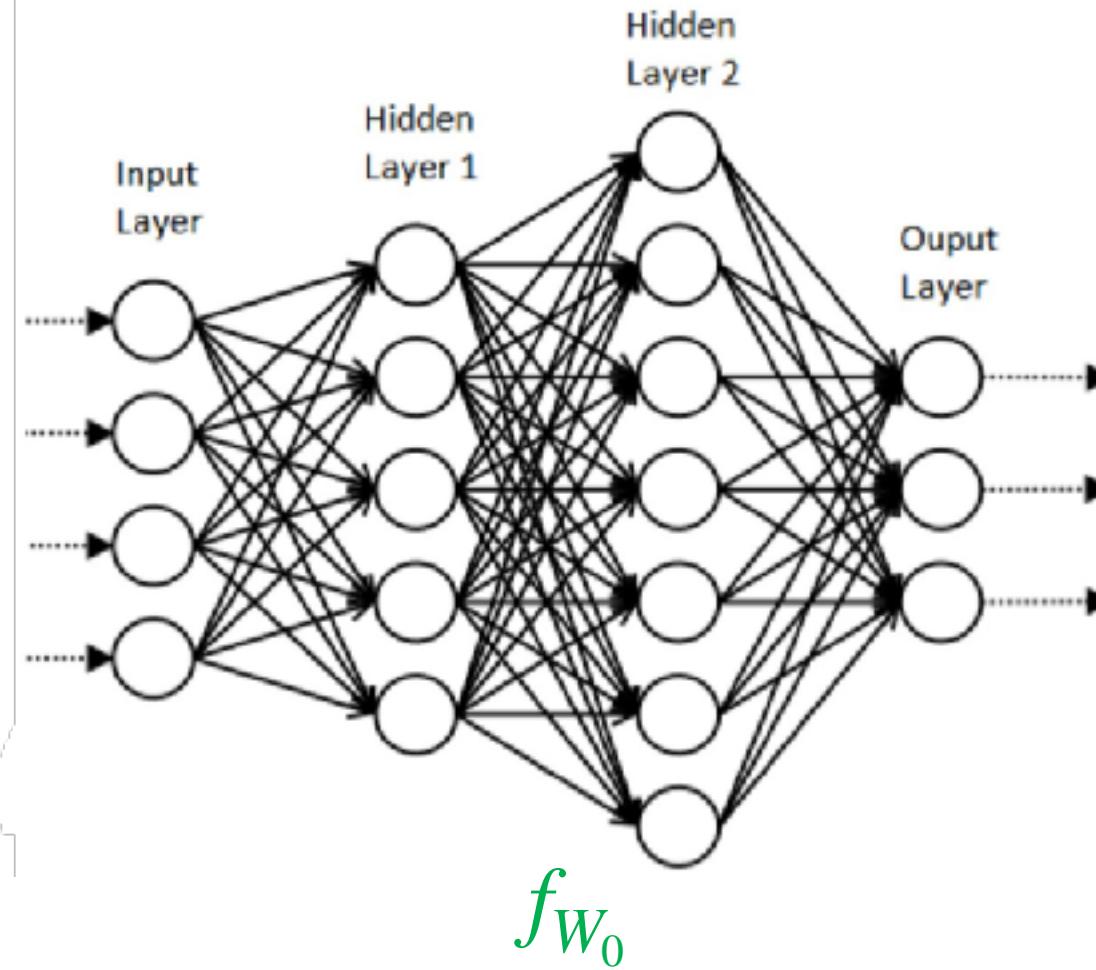
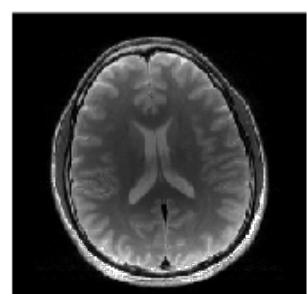
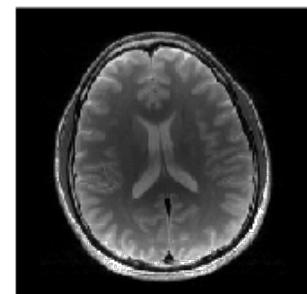
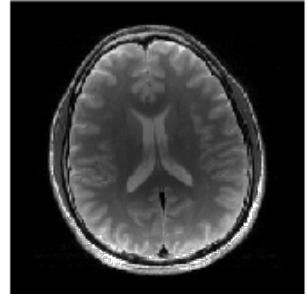
x



Step 2: Prepare a dataset which is a collection of input-output pairs

Prepared output

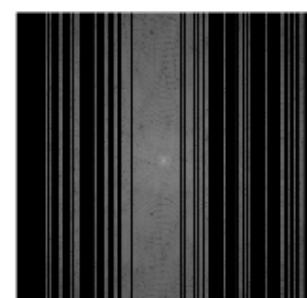
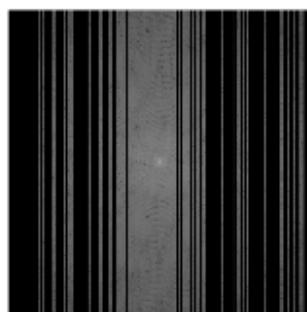
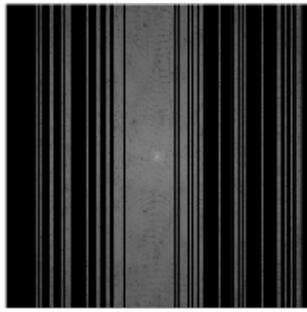
y



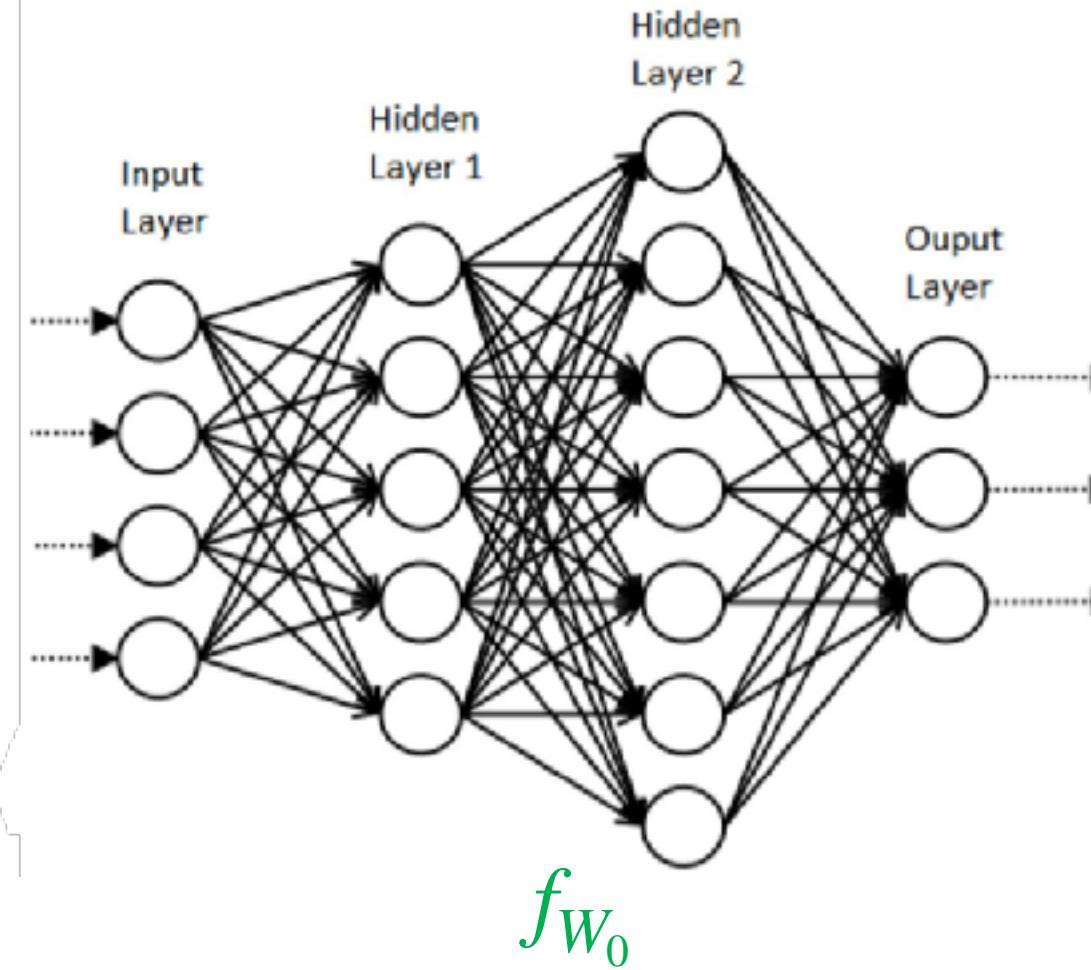
Supervised Model Training

Prepared input

x

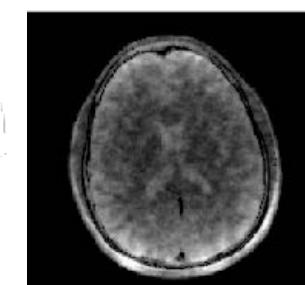
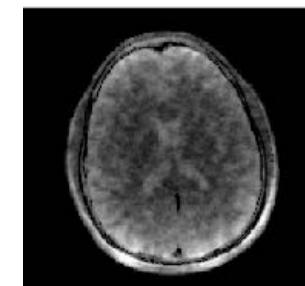
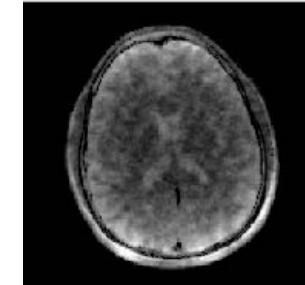


Step 3: Pass the prepared input to the network



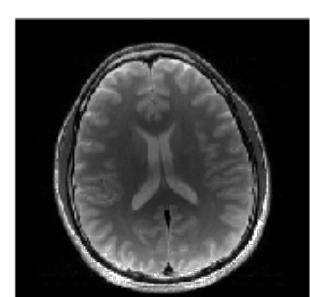
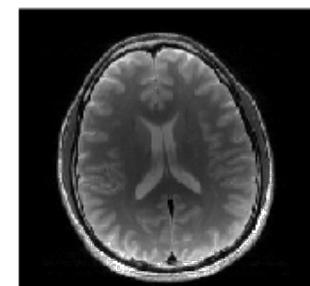
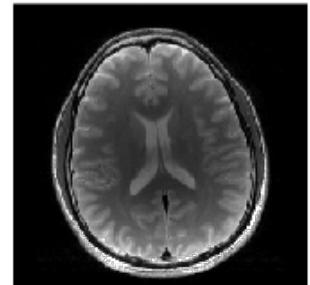
Estimated output

$$\hat{y} = f(x)$$



Prepared output

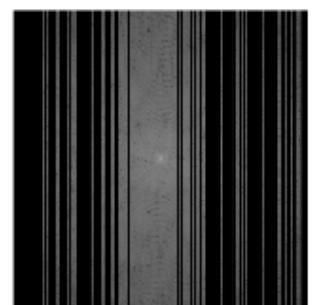
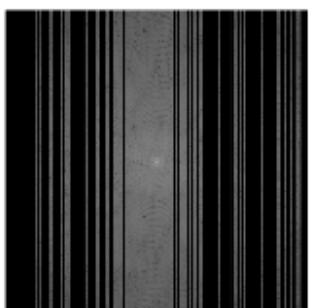
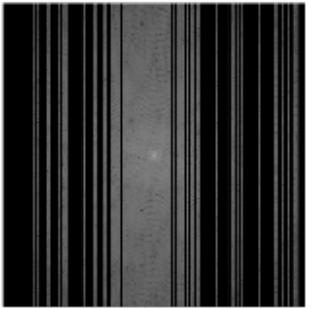
y



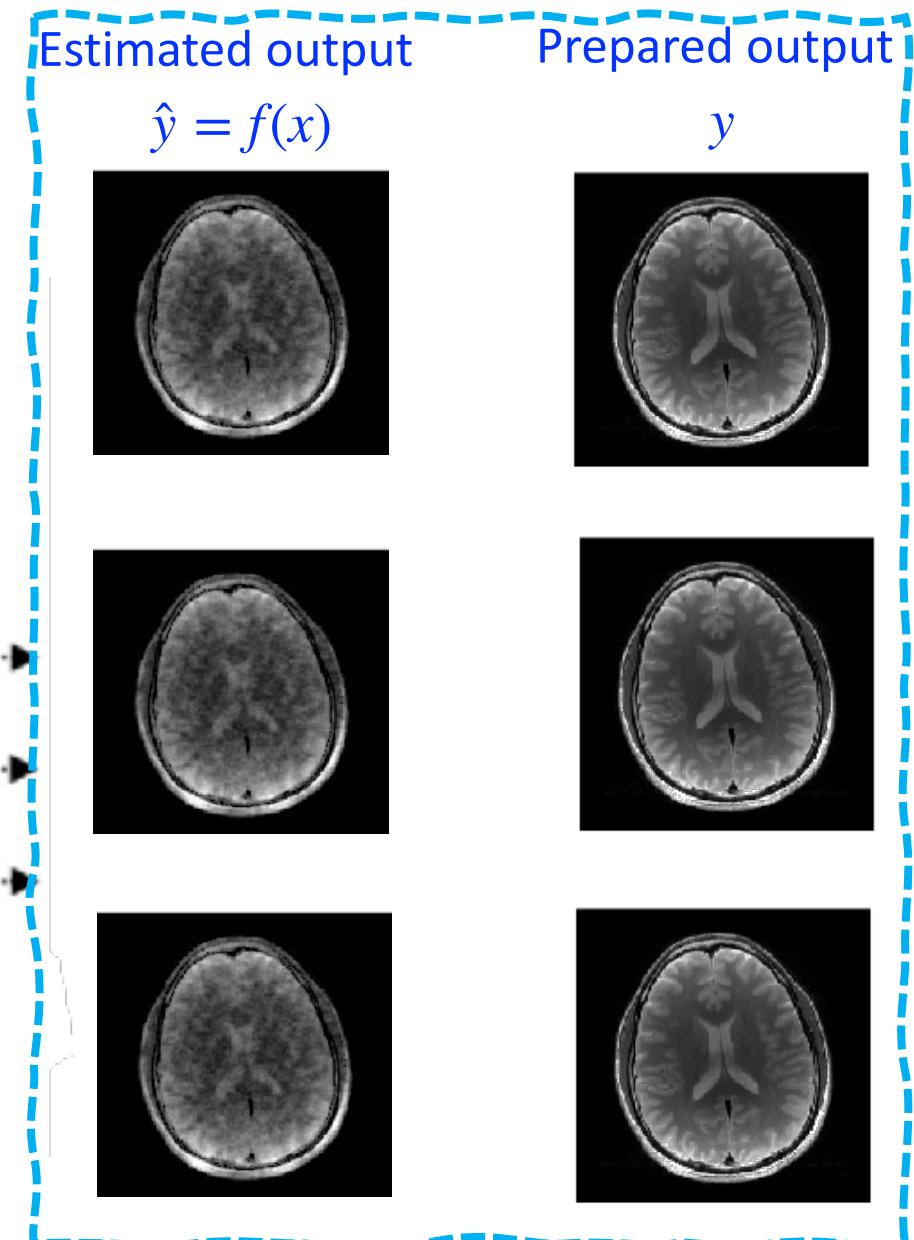
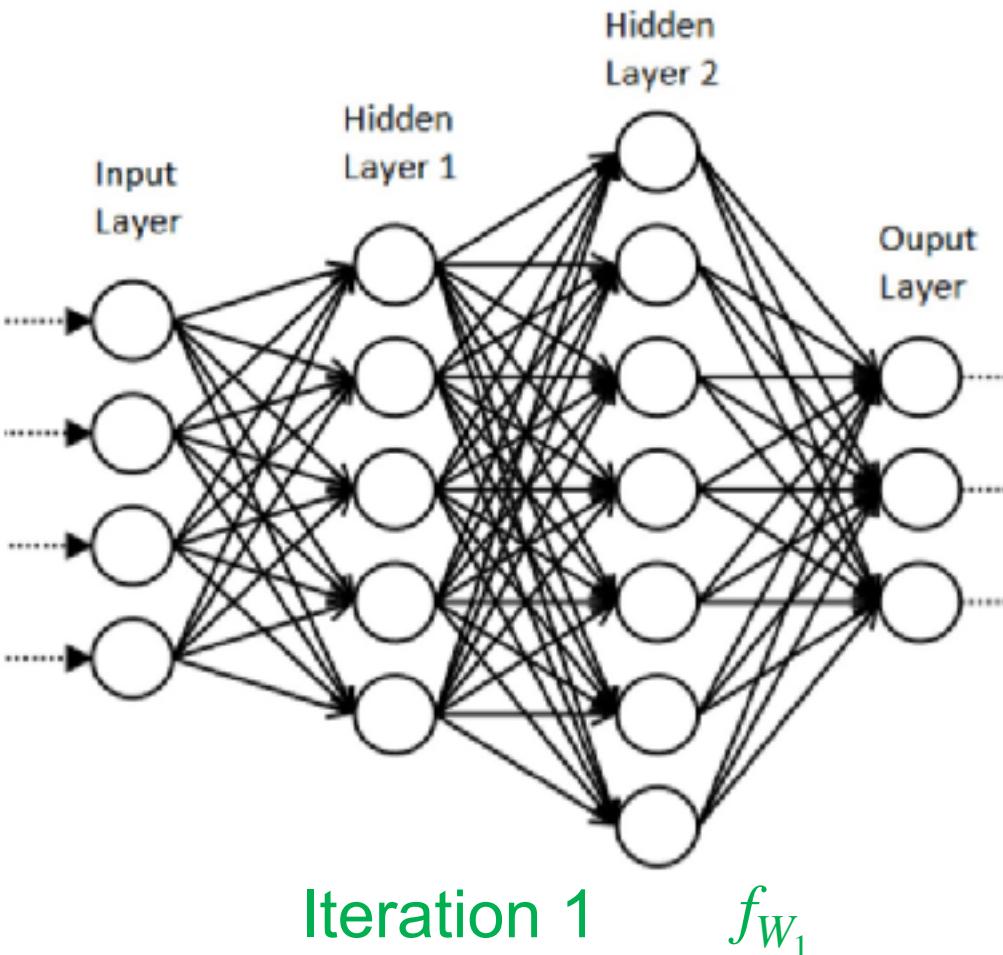
Supervised Model Training

Prepared input

x



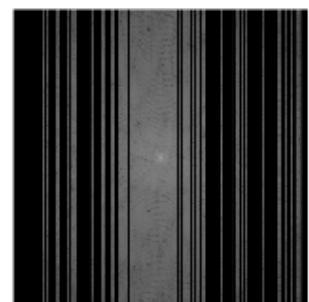
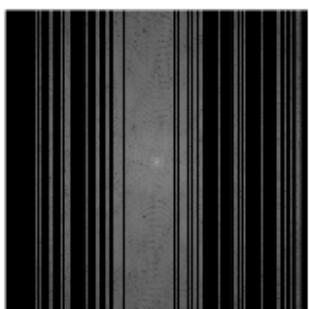
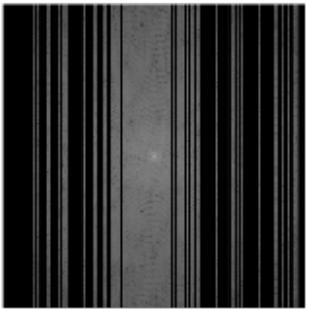
Step 4: Compare \hat{y} to y and modify the weights of the neural network to make \hat{y} approach y using the backpropagation algorithm



Supervised Model Training

Prepared input

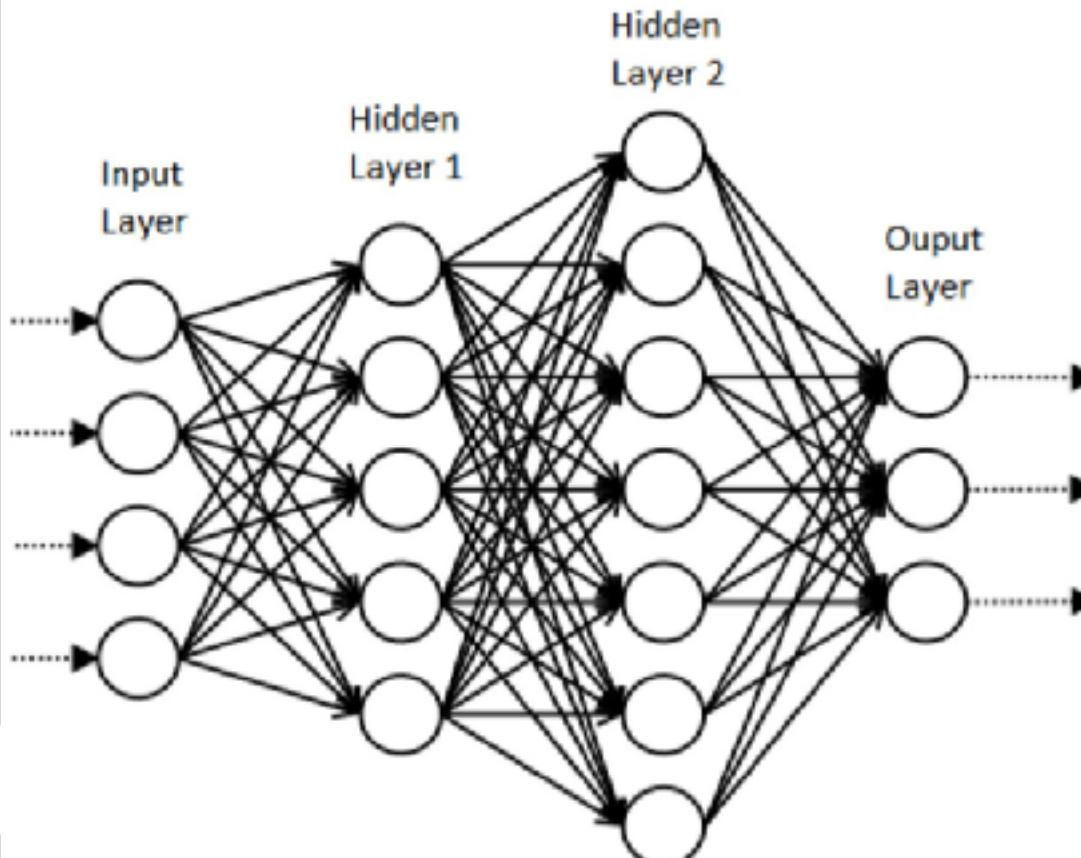
x



Repeat steps 3 and 4 to continuously
improve the weights of the neural network

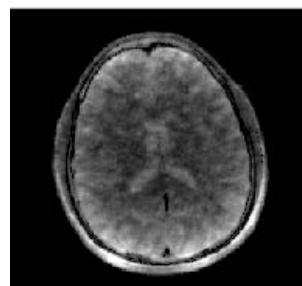
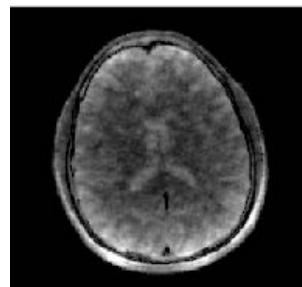
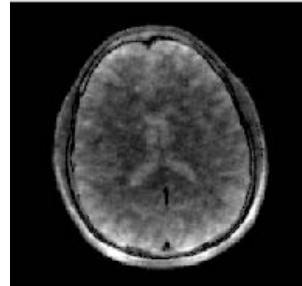
Iteration 2

f_{W_2}



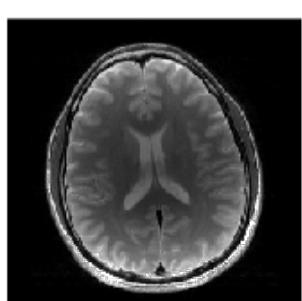
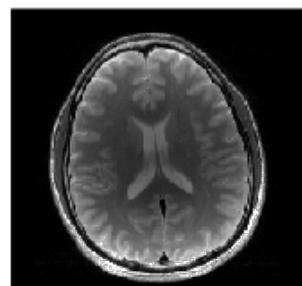
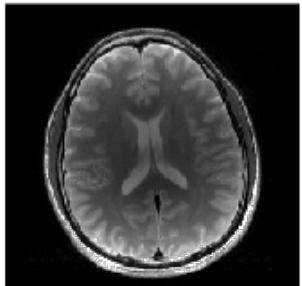
Estimated output

$$\hat{y} = f(x)$$



Prepared output

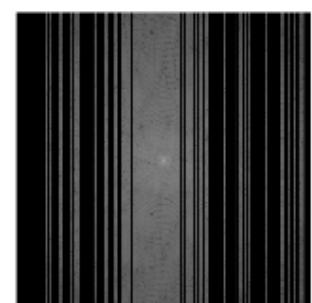
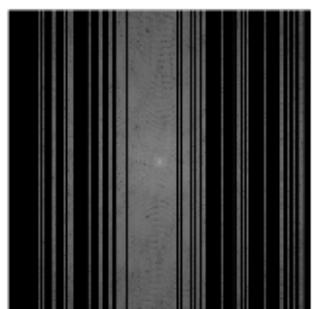
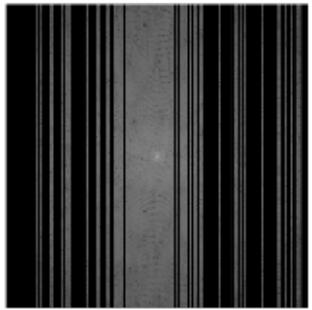
y



Supervised Model Training

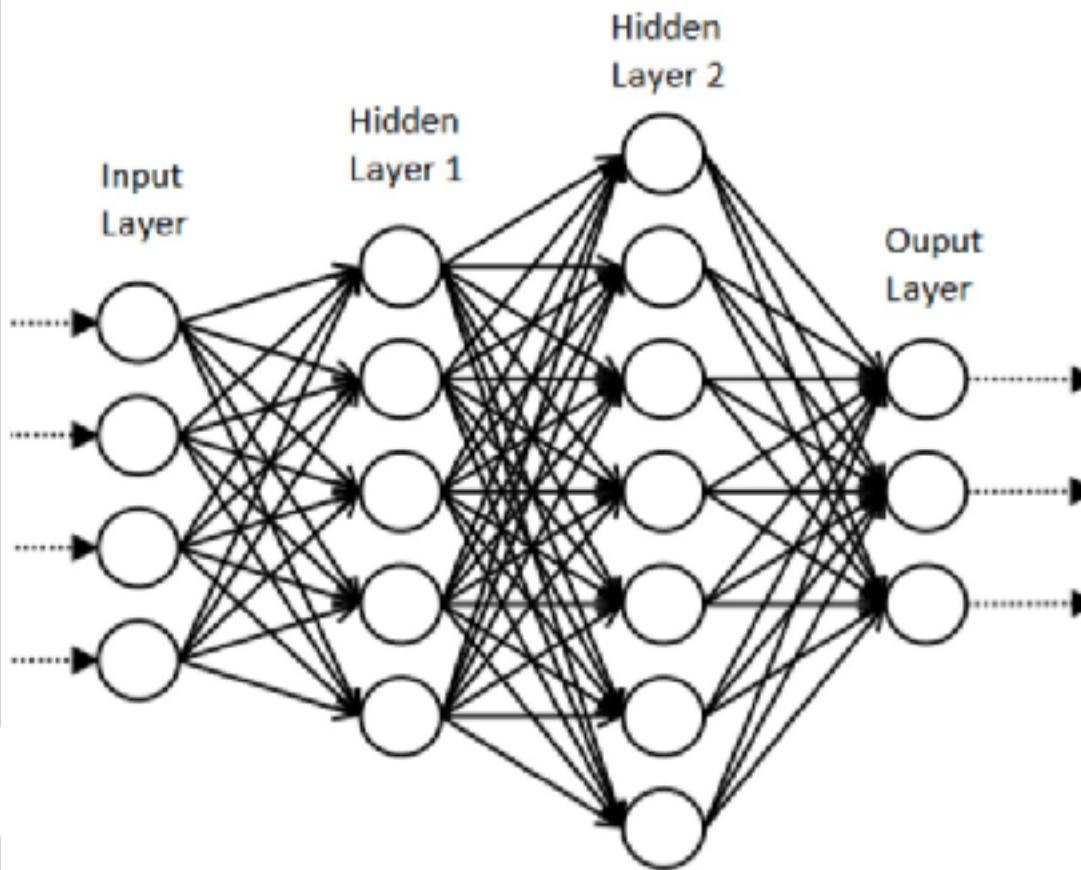
Prepared input

x



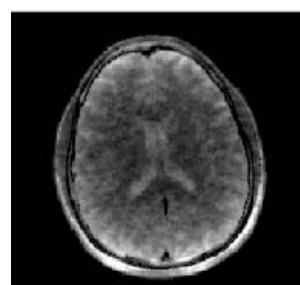
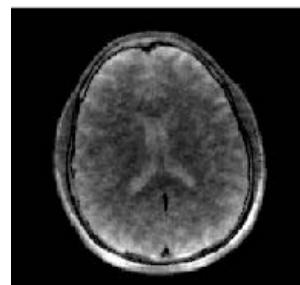
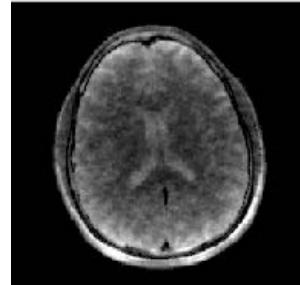
Repeat steps 3 and 4 to continuously
improve the weights of the neural network

Iteration 20 f_{W_20}



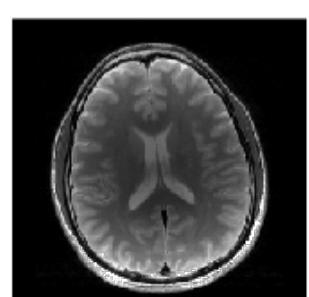
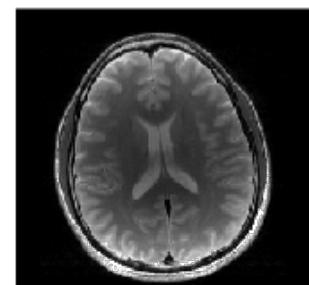
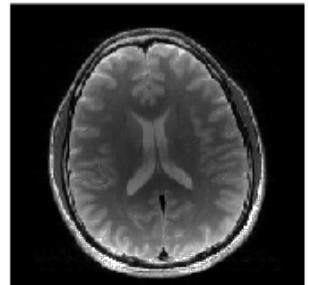
Estimated output

$$\hat{y} = f(x)$$



Prepared output

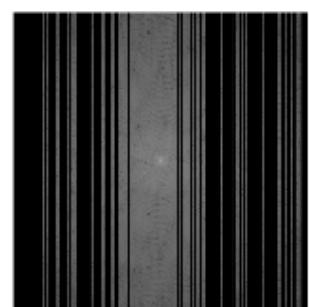
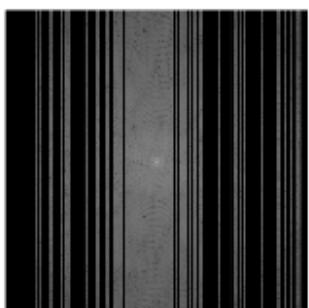
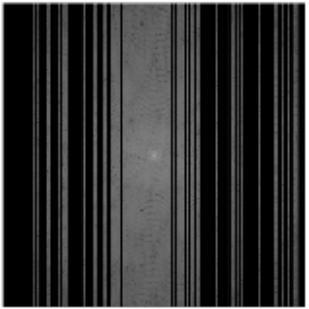
y



Supervised Model Training

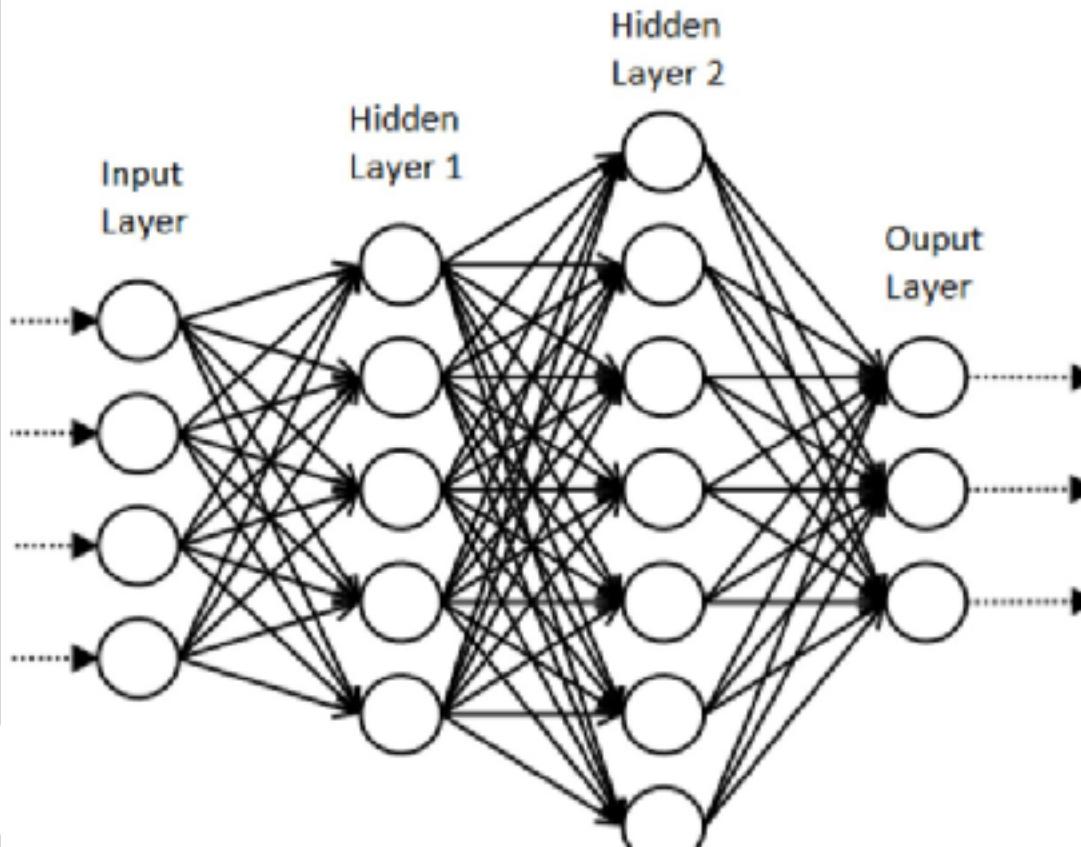
Prepared input

x



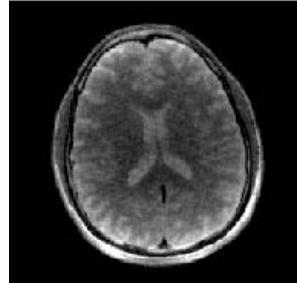
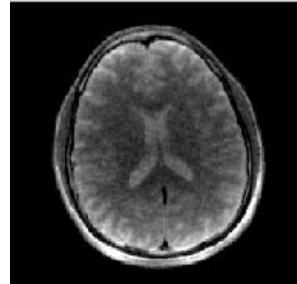
Repeat steps 3 and 4 to continuously
improve the weights of the neural network

Iteration 30 $f_{W_{30}}$



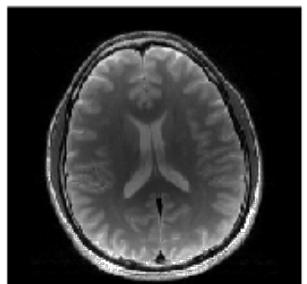
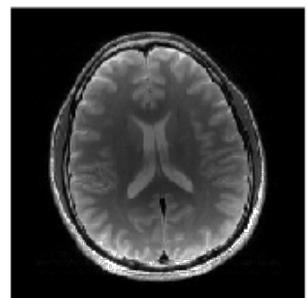
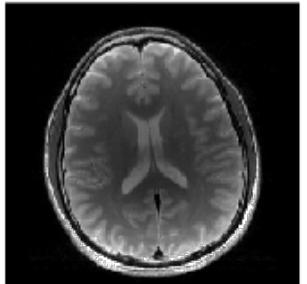
Estimated output

$$\hat{y} = f(x)$$



Prepared output

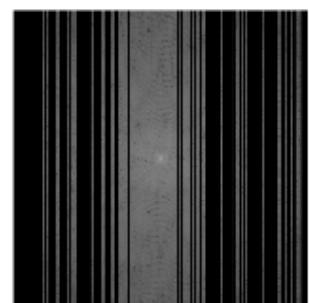
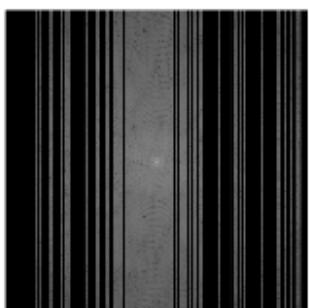
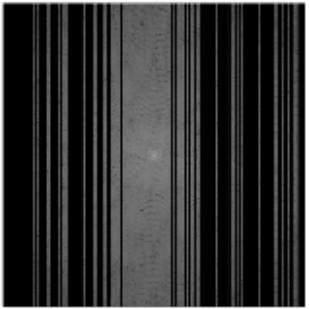
y



Supervised Model Training

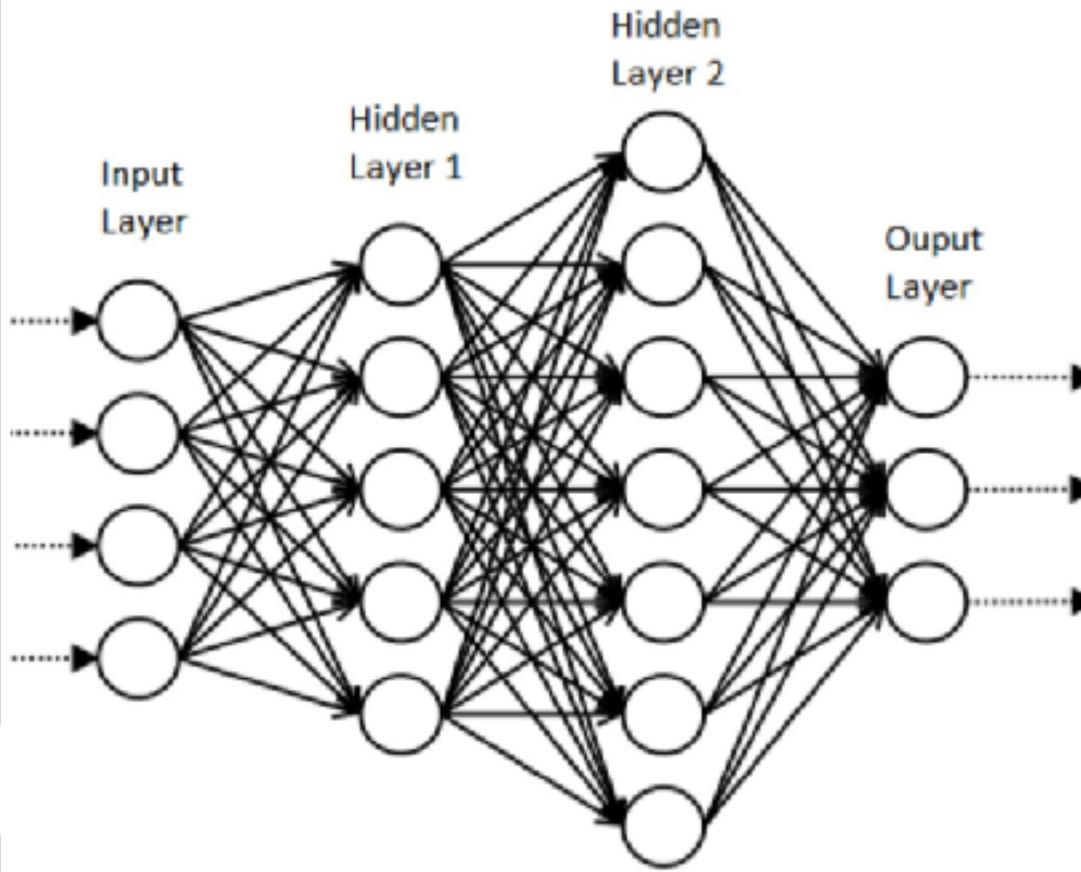
Prepared input

x



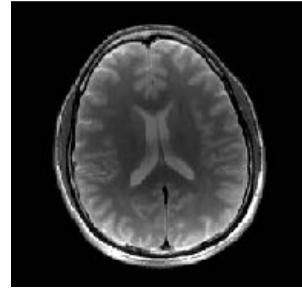
Repeat steps 3 and 4 to continuously
improve the weights of the neural network

Iteration 100 $f_{W_{100}}$

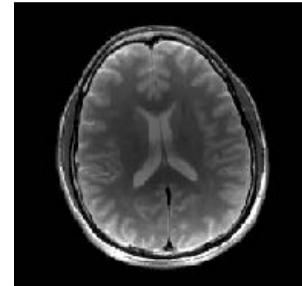


Estimated output

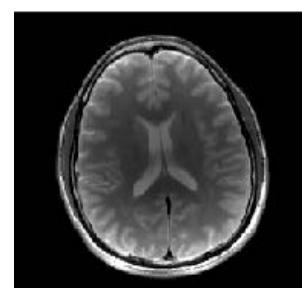
$$\hat{y} = f(x)$$



\approx



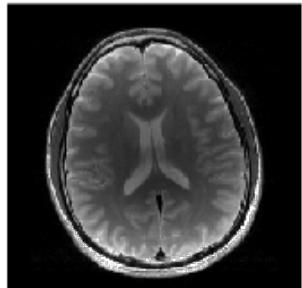
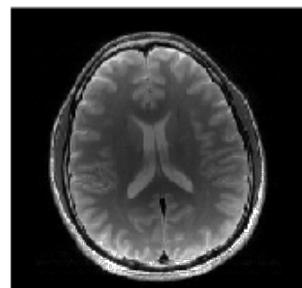
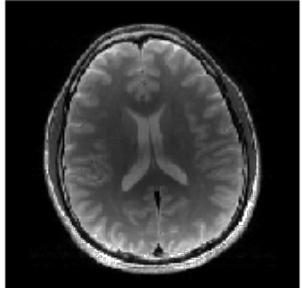
\approx



\approx

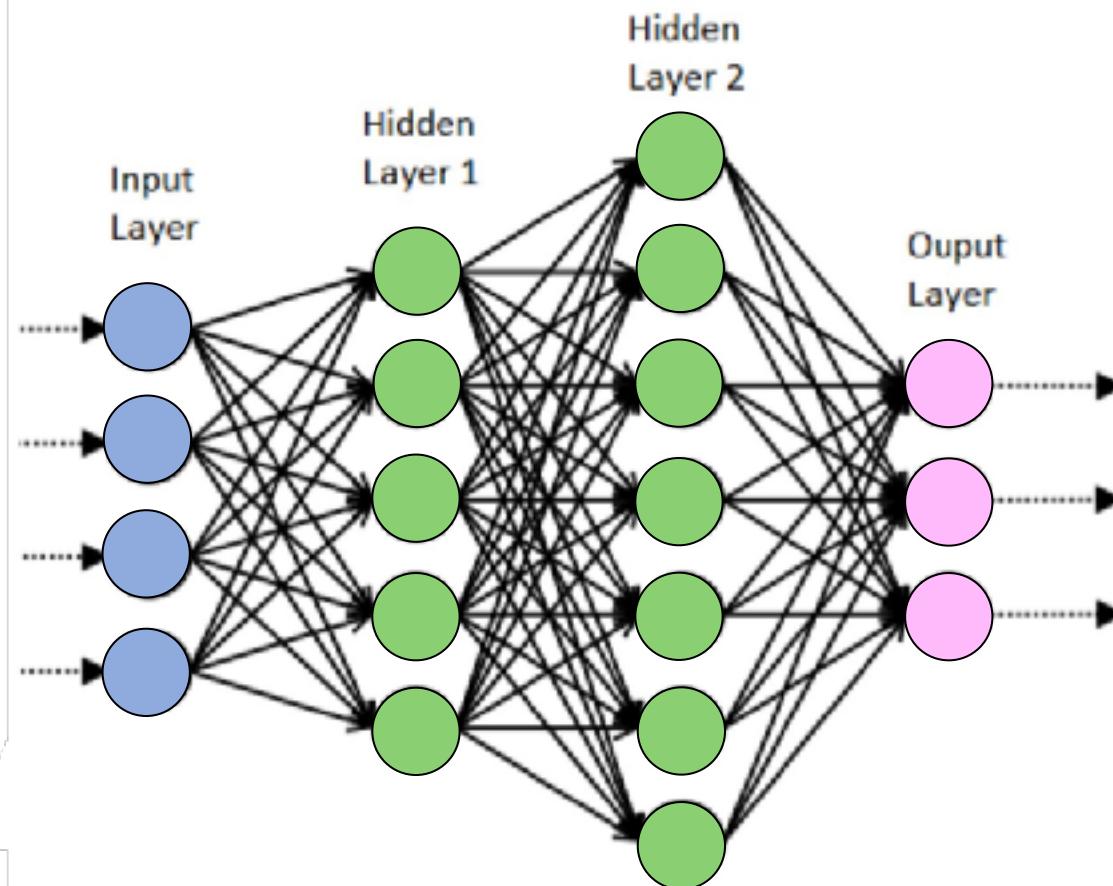
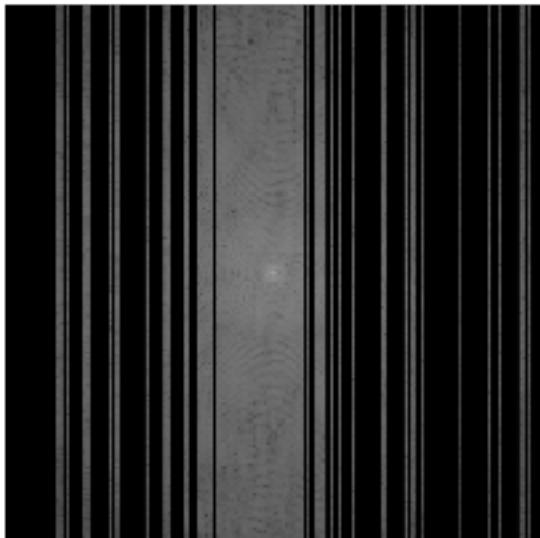
Prepared output

y



Test the Trained Model

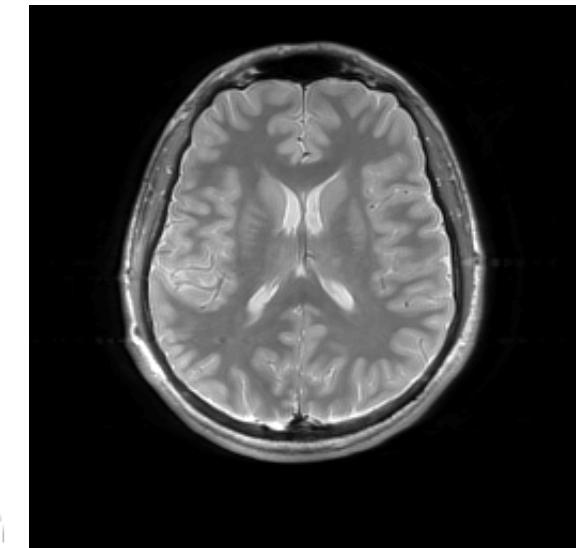
Acquired undersampled k-space data that you wish to reconstruct



Trained model

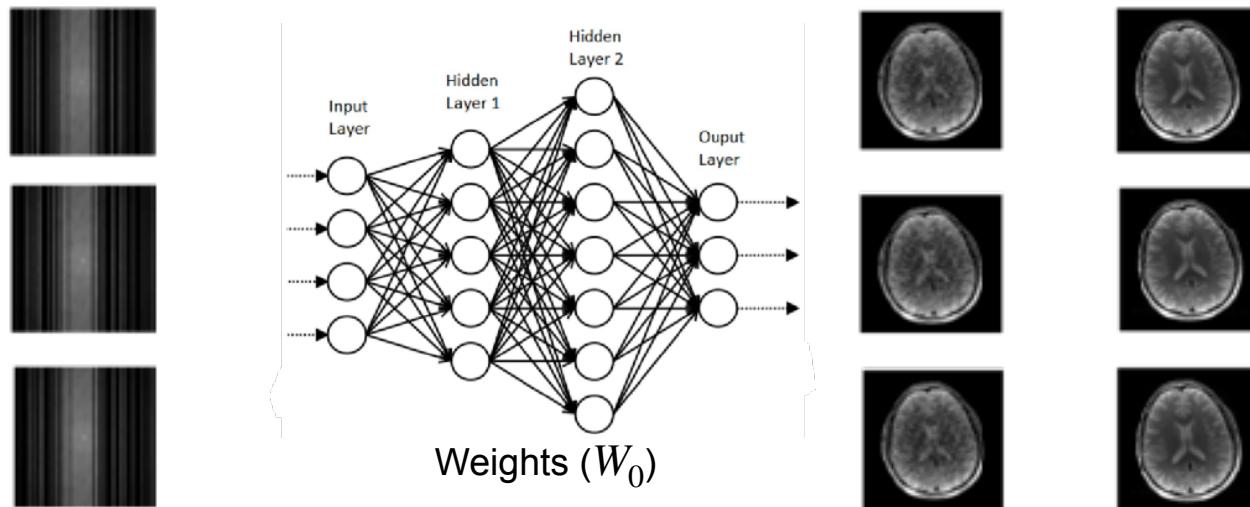
$$f_{W^*}$$

Reconstructed image

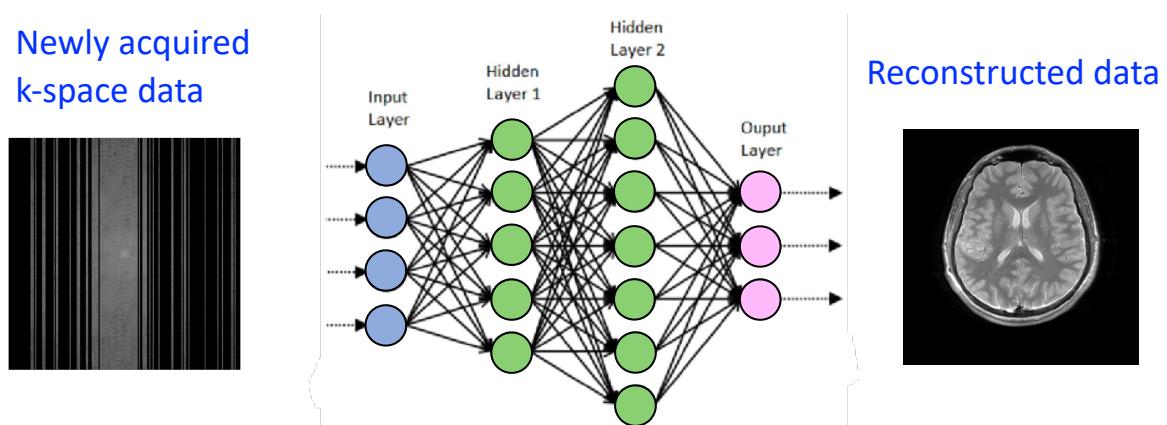


Accelerated MRI Using Deep Learning

- Training phase: Optimize the weights of a deep neural network

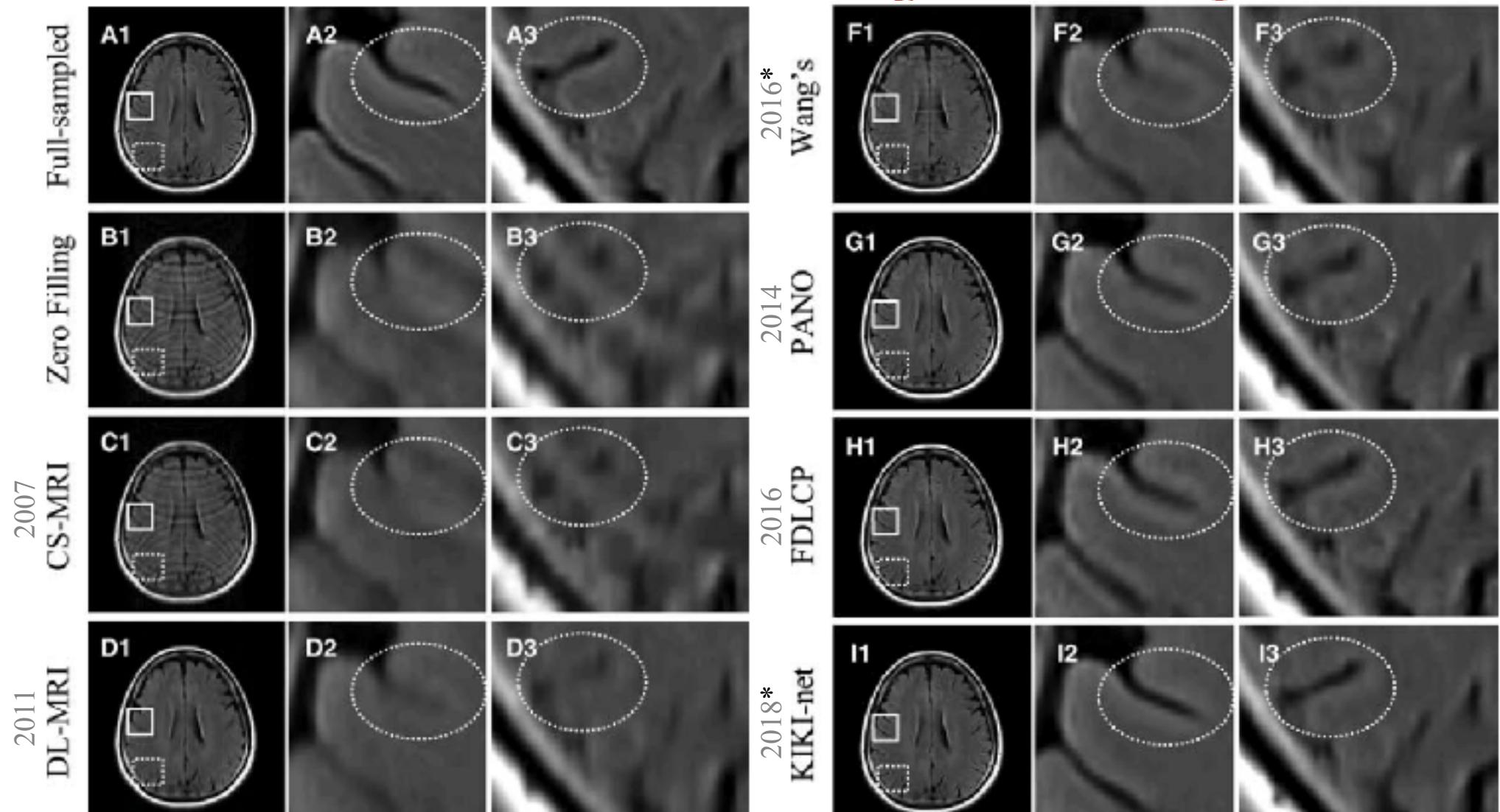
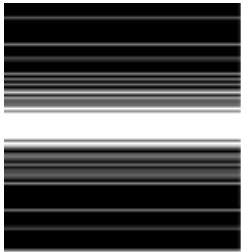


- Test phase: Reconstruct new data using the trained deep neural network



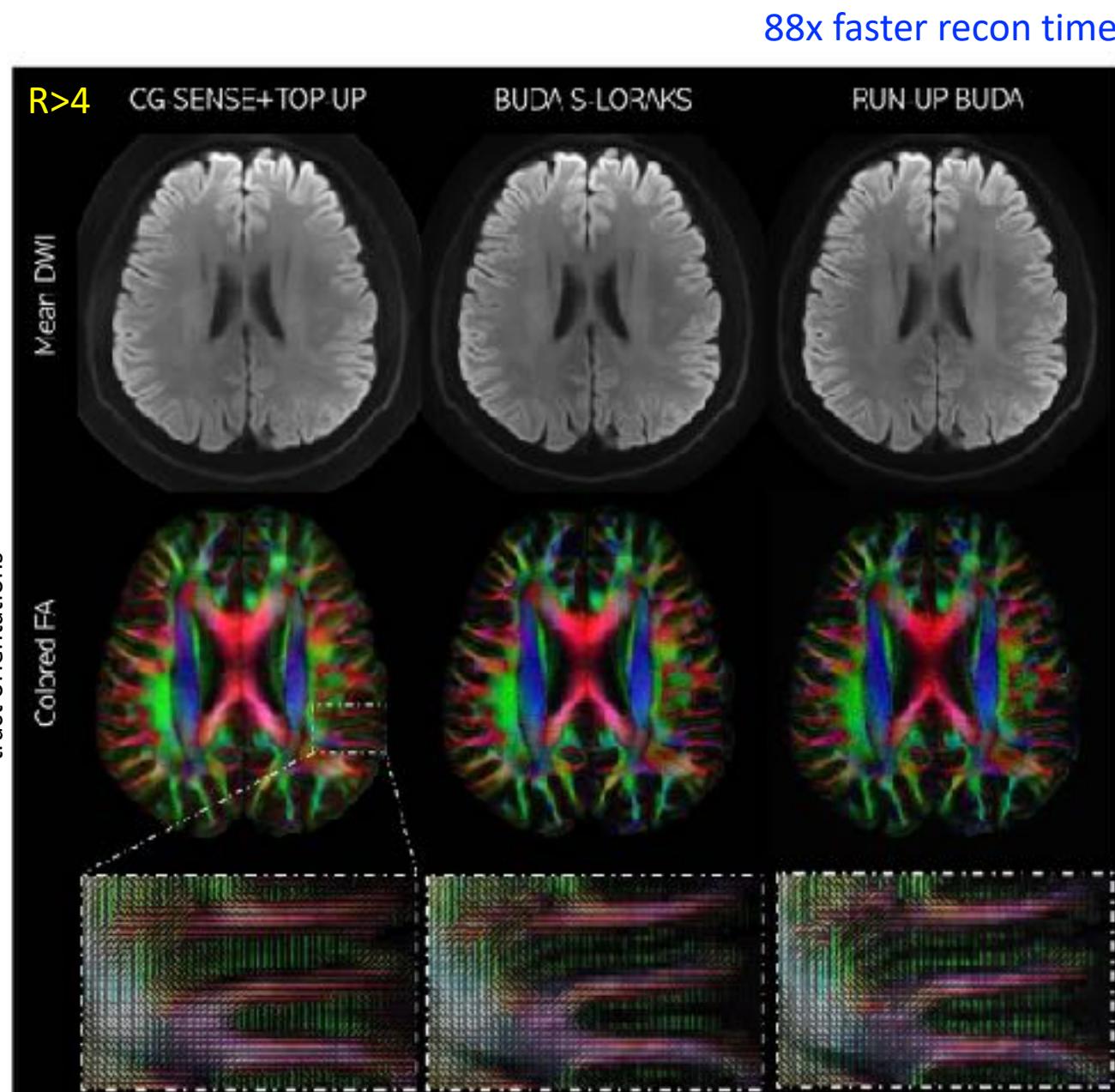
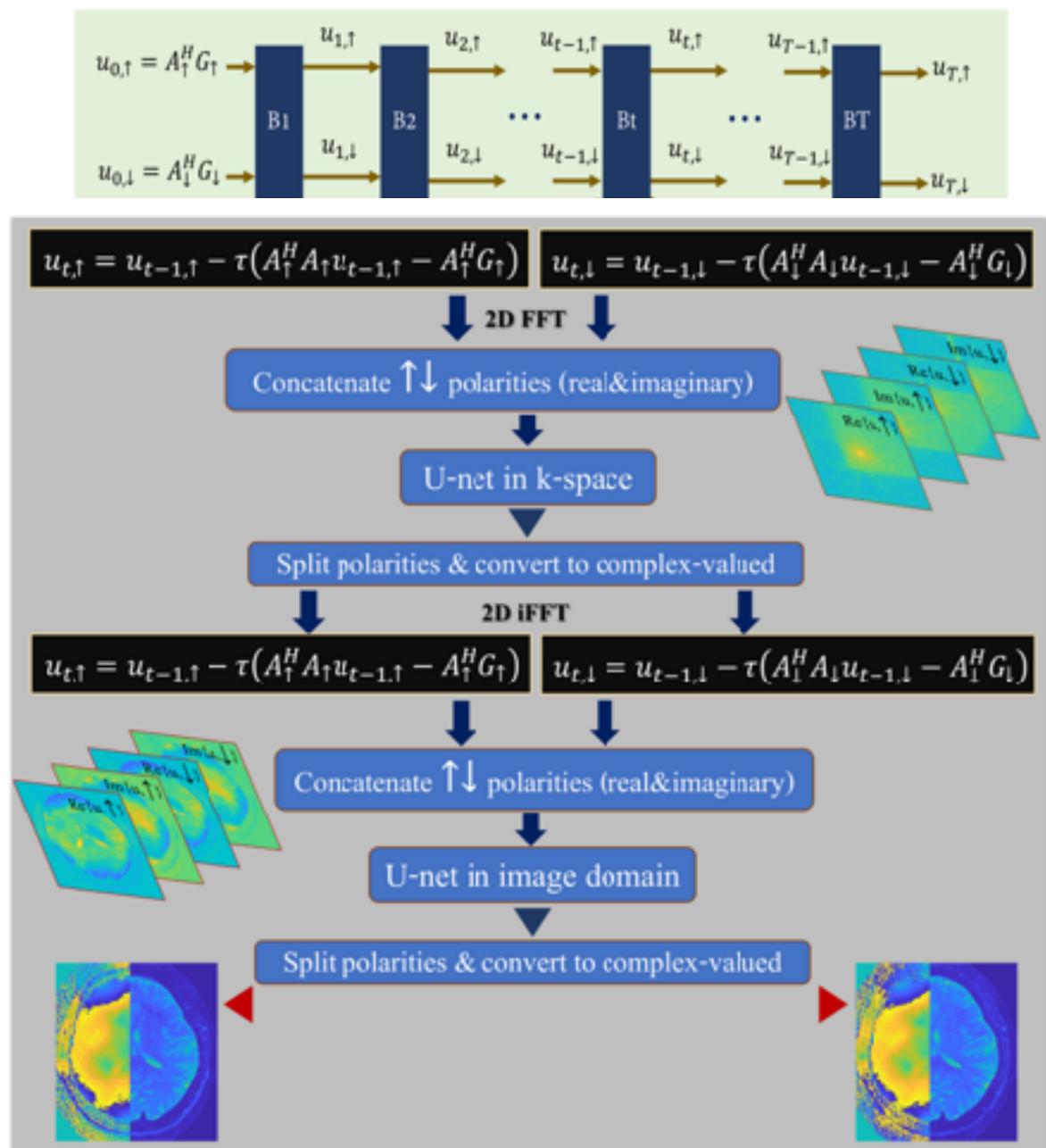
Cross-domain CNNs for Reconstructing Undersampled MRI

T_2 -FLAIR
(R=4)



Eo, Taejoon, et al. "KIKI-net: cross-domain convolutional neural networks for reconstructing undersampled magnetic resonance images." Magnetic resonance in medicine 80.5 (2018): 2188-2201.

*deep learning
based methods



Yarach, Utén et al. "Rapid reconstruction of Blip up-down circular EPI (BUDA-cEPI) for distortion-free dMRI using an Unrolled Network with U-Net as Priors." Proceedings of the 30th Scientific Meeting of ISMRM. Online Conference. 2022.

Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
 - MRI reconstruction function



- MRI segmentation function

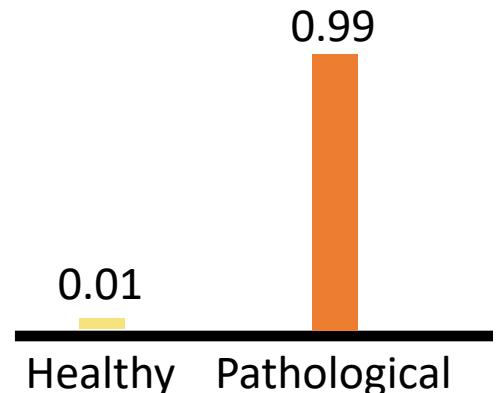


- MRI super-resolution function

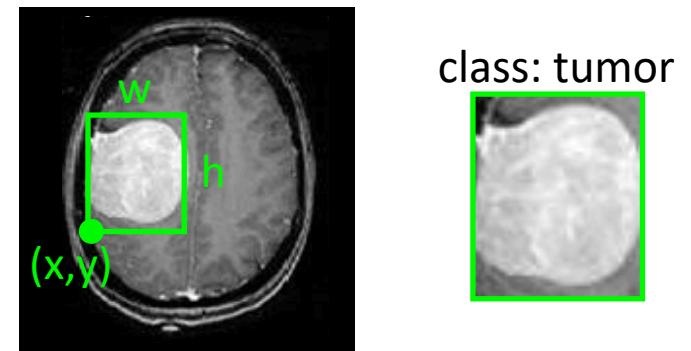
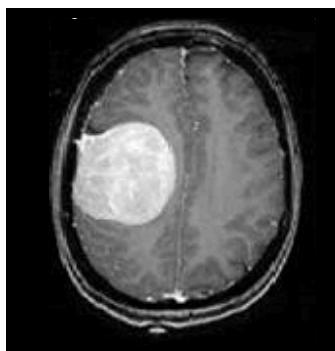


Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
 - MR image classification function



- Detection function



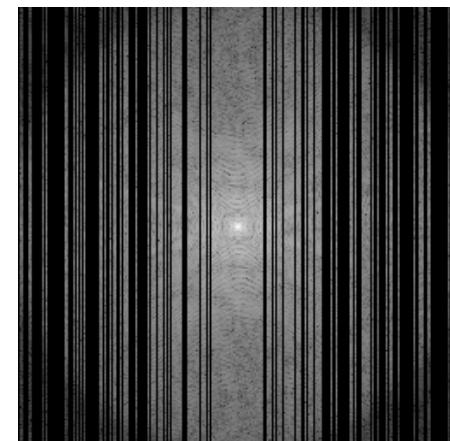
Alam, Sadia, et al. "An efficient image processing technique for brain tumor detection from MRI images." 2019 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE). IEEE, 2019.

Summary

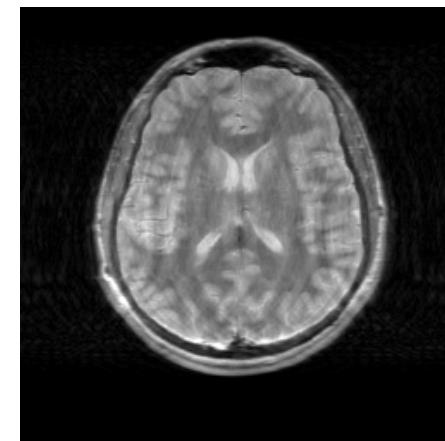
- **Magnetic Resonance Imaging (MRI)**

- Data acquired in the Fourier transform domain (k-space)
 - If the sampling rate is high enough, the inverse DFT can be directly applied to recover the data
- Data acquisition time can be reduced by collecting fewer k-space samples
 - Applying the inverse DFT to the undersampled k-space data leads to reconstruction with artifacts
 - Need more sophisticated approaches to reconstruct data: compressed sensing and deep learning

2x faster acquisition



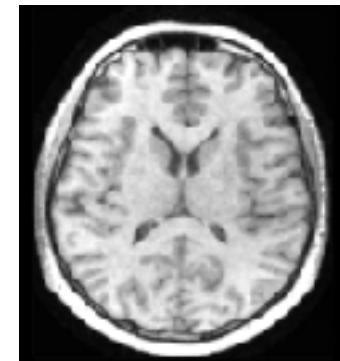
IDFT



Summary

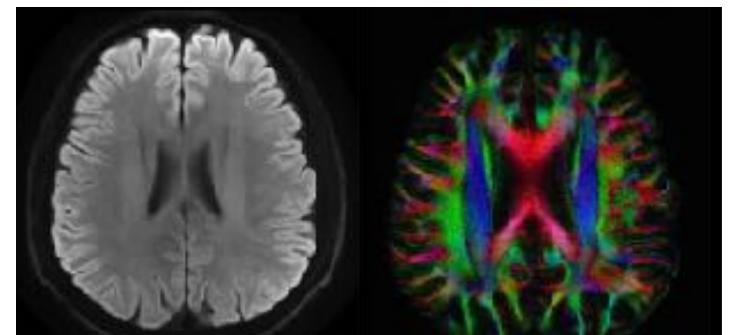
- Deep Learning for MRI
 - With lots of training data, supervised deep learning is an attractive approach for MR image reconstruction, analysis, quantification, and diagnosis
 - Other types of learning have recently gained in importance
- Current Challenges
 - Robustness
 - Uncontrollable factors
 - Adversarial attack
 - How to use data more efficiently
 - Explainable models

9x faster acquisition



Cho, Jaejin, et al.
ISMRM (2021)

88x faster reconstruction



Yarach, Uten, et
al. ISMRM (2022)



Acknowledgments



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GENERAL HOSPITAL



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