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

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Outline

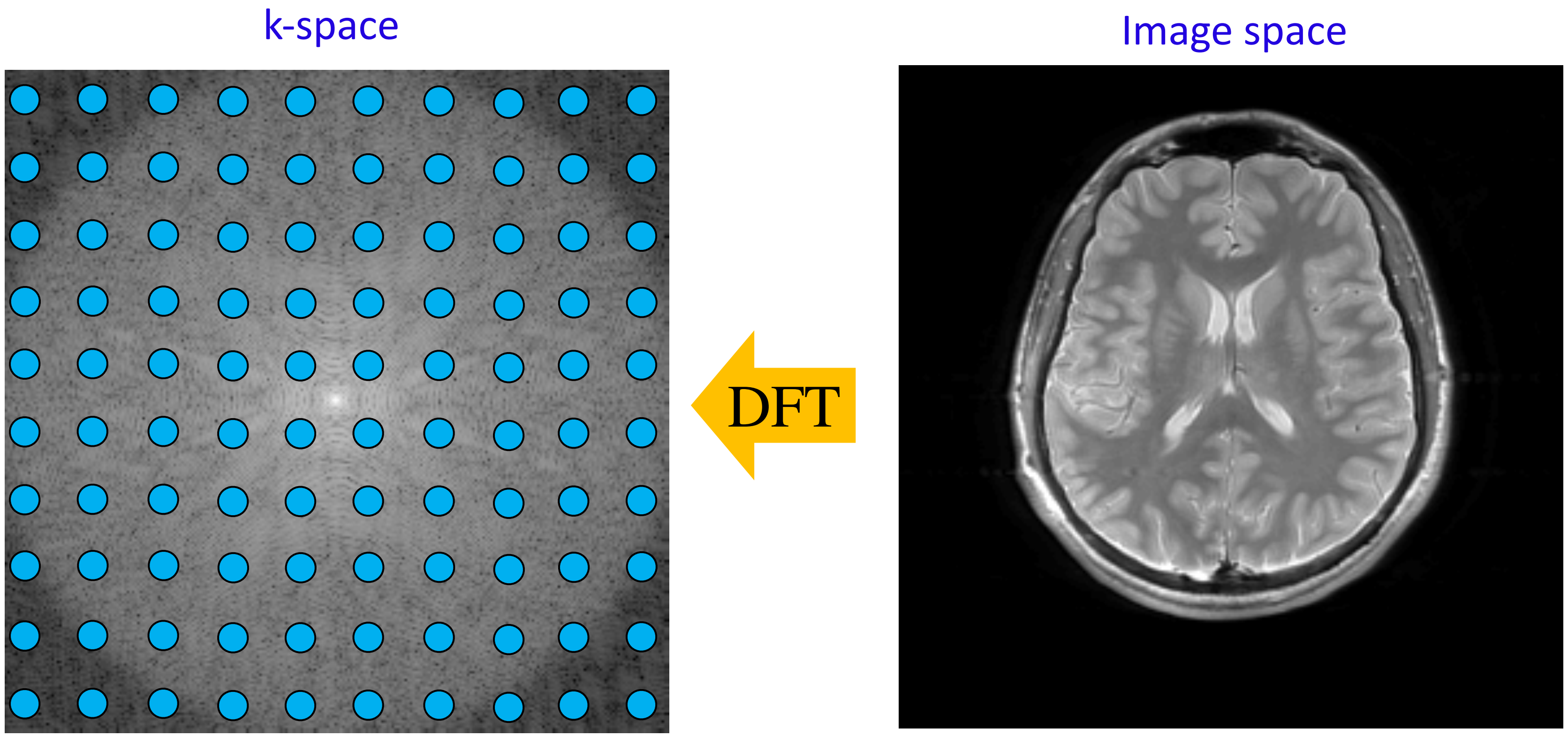
- MR Image Acquisition and Reconstruction
  - Imaging parameters
  - Reconstruction from accelerated scans
- Deep Learning for Accelerated MRI
  - Supervised learning
  - Experimental Results

Outline

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

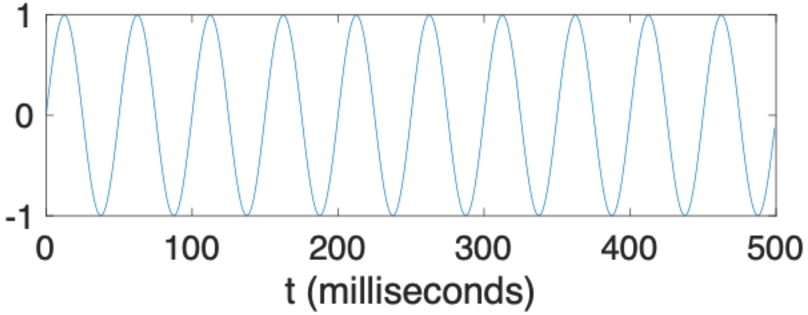
MR Image Acquisition and Reconstruction

- 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)

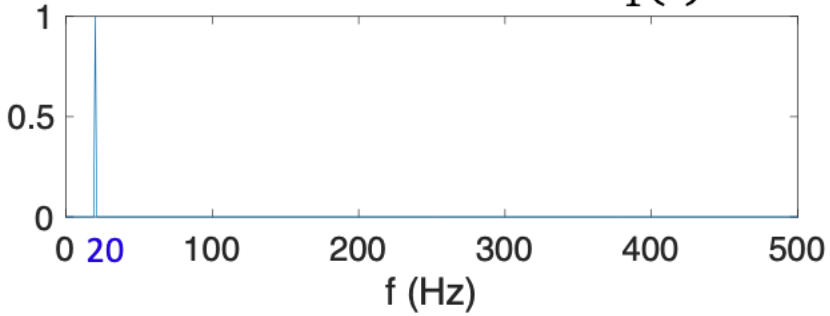


Review: Fourier Transform

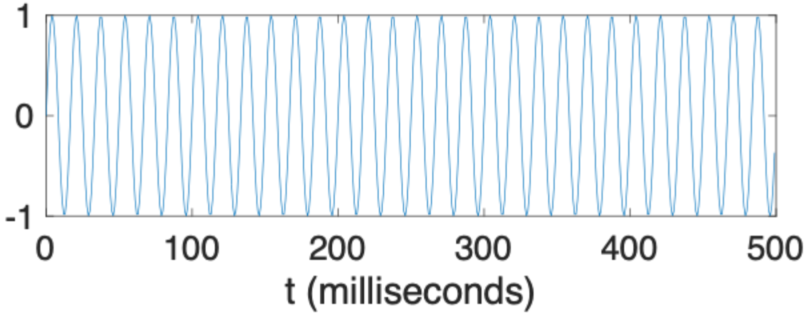
$s_1(t) = \sin(2\pi * 20\ Hz * t)$



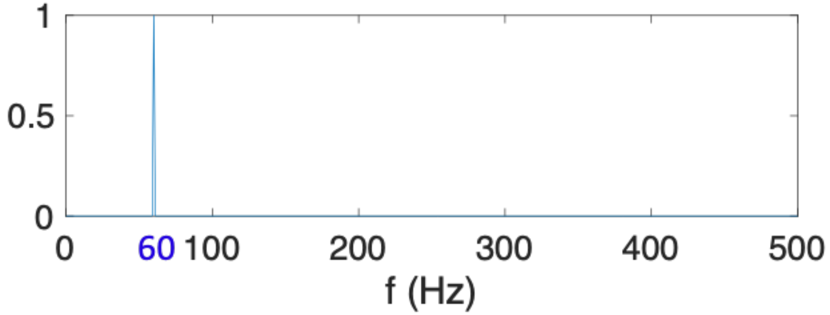
Fourier transform of $s_1(t)$



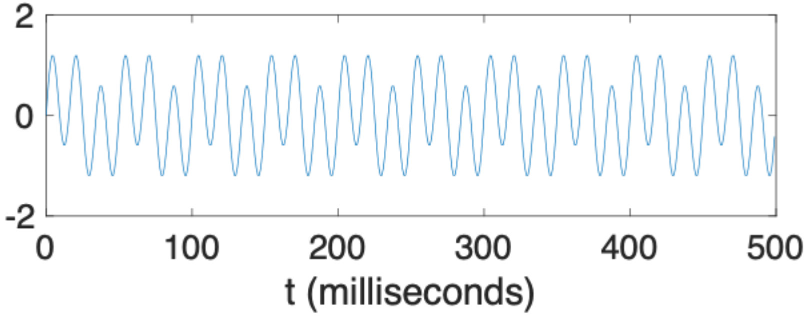
$s_2(t) = \sin(2\pi * 60\ Hz * t)$



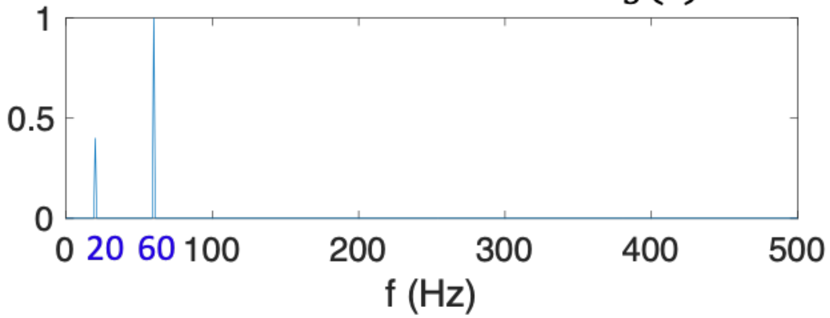
Fourier transform of $s_2(t)$



$s_3(t) = 0.4\ s_1(\mathrm{t}) + s_2(\mathrm{t})$

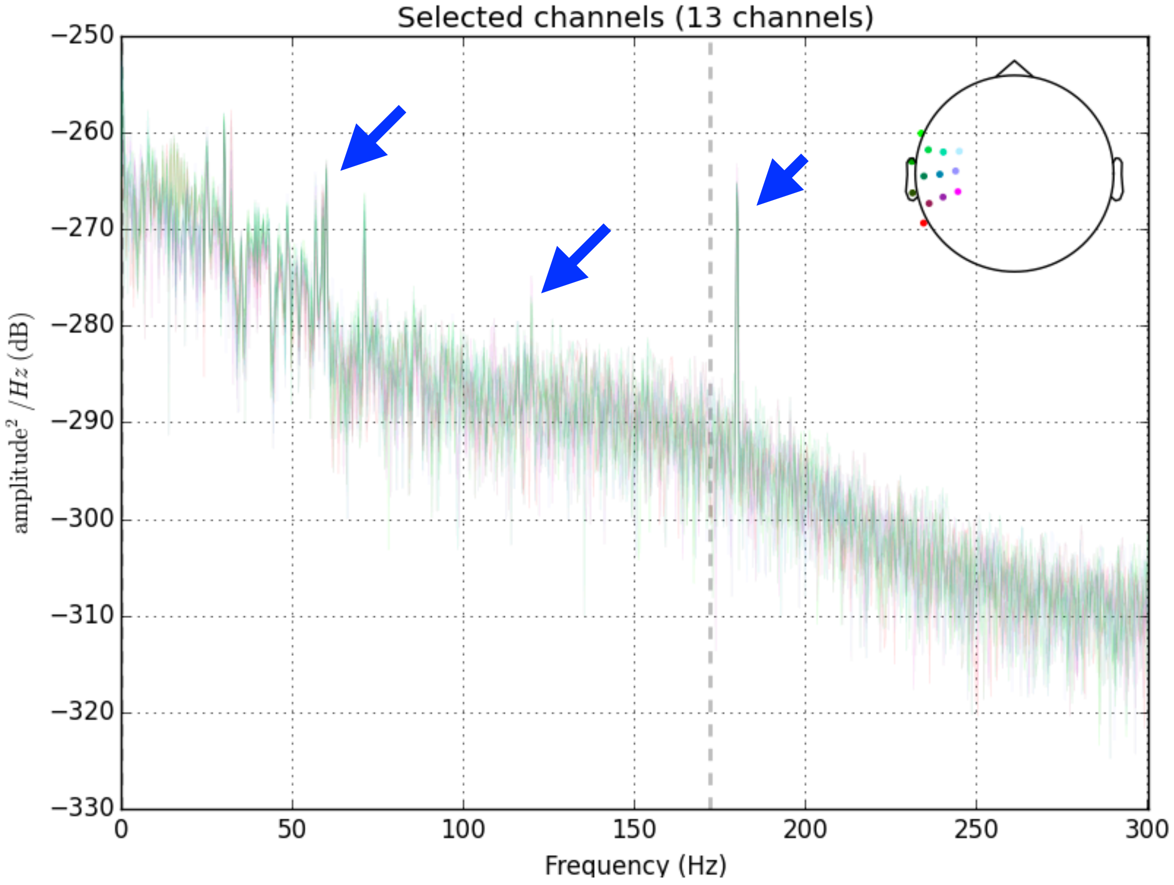


Fourier transform of $s_3(t)$

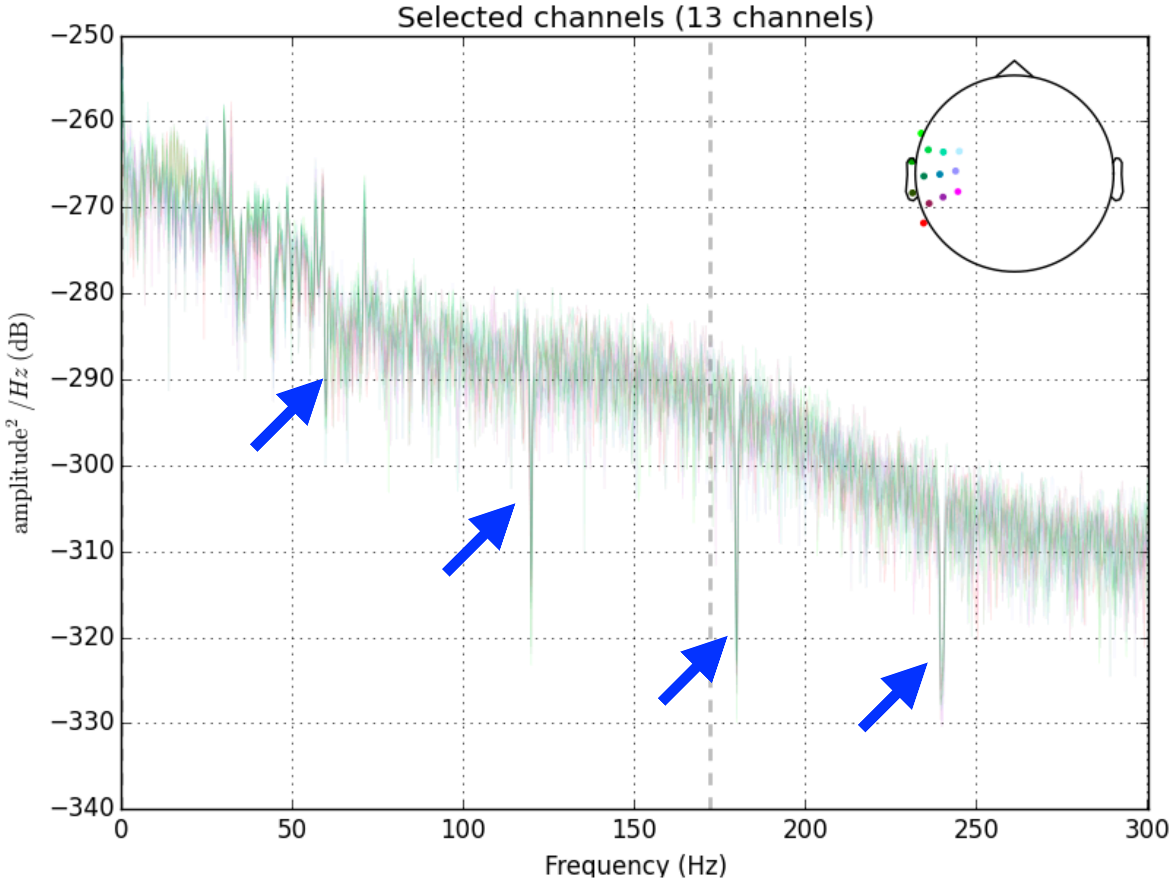


Review: Application of Fourier Transform to EEG

The Fourier transform of the acquired EEG signals



The filtered signals at the integer multiples of 60 Hz

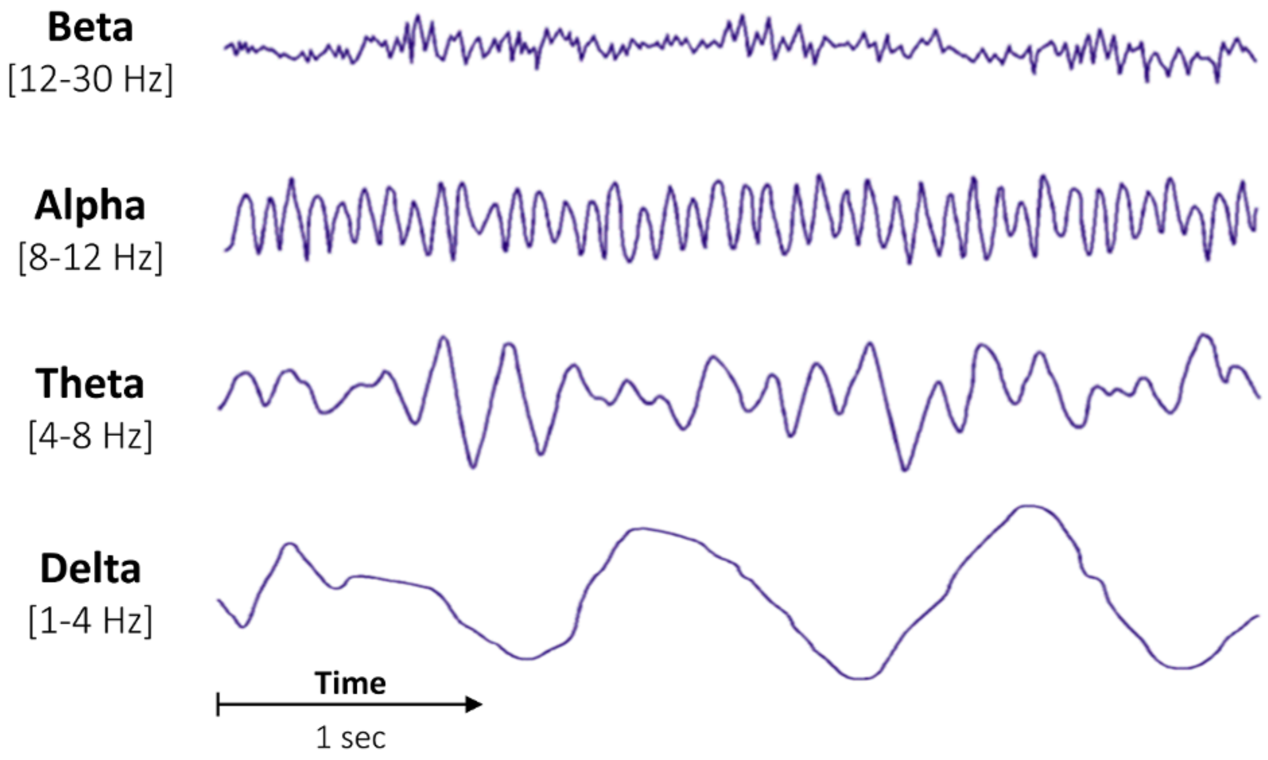


Power-line noise: potentially at the harmonic frequencies of 60 Hz (or 50 Hz)

MNE's Filtering and resampling data

Review: Application of Fourier Transform to EEG

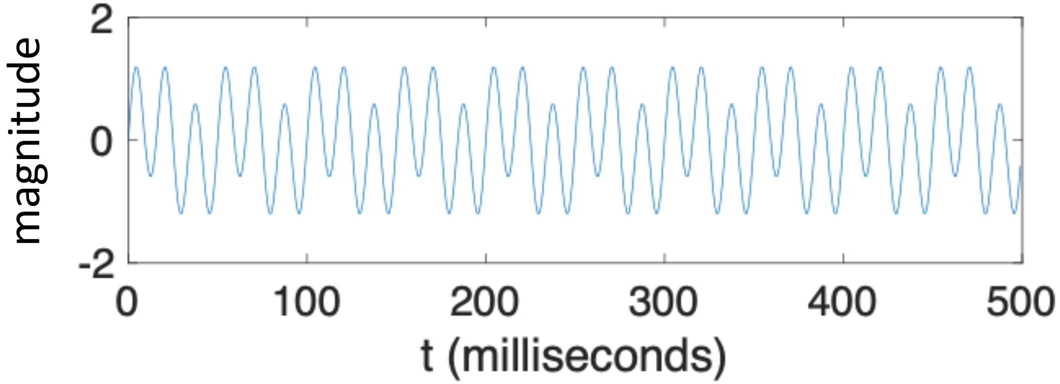
Example of brain rhythm frequency bands associated with cognitive processes

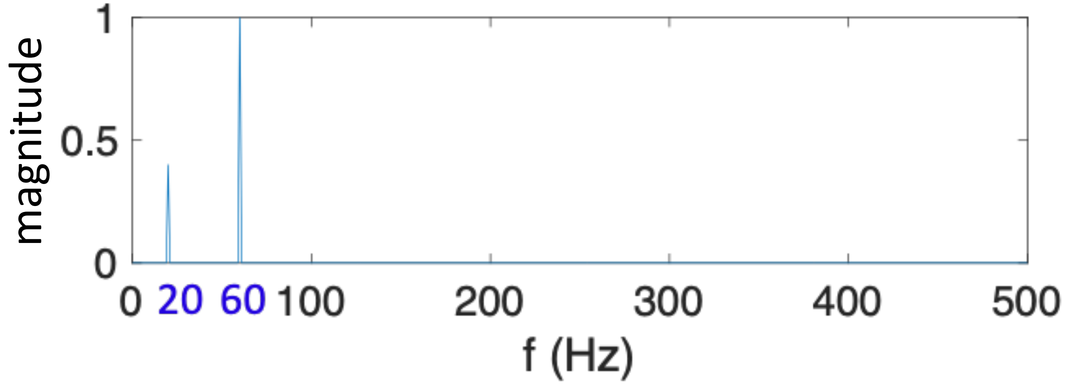


[Compute the average bandpower of an EEG signal]

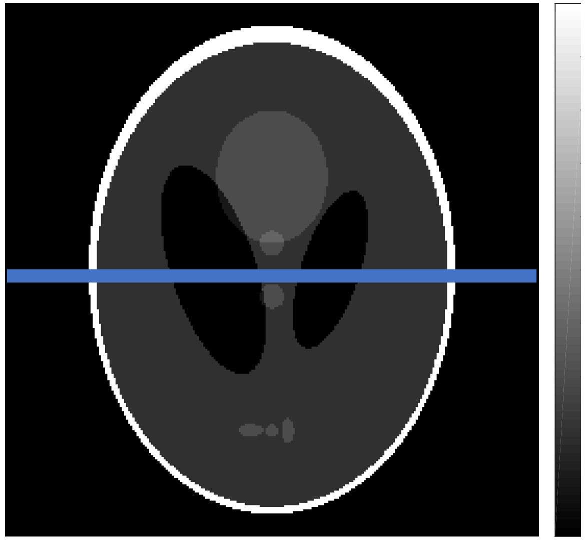
Review: Application of Fourier Transform to images

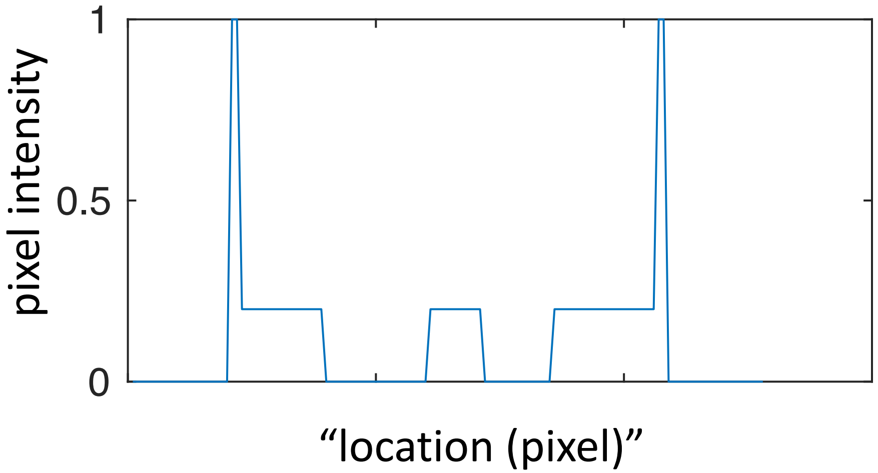
Fourier transform: time ↔ frequency

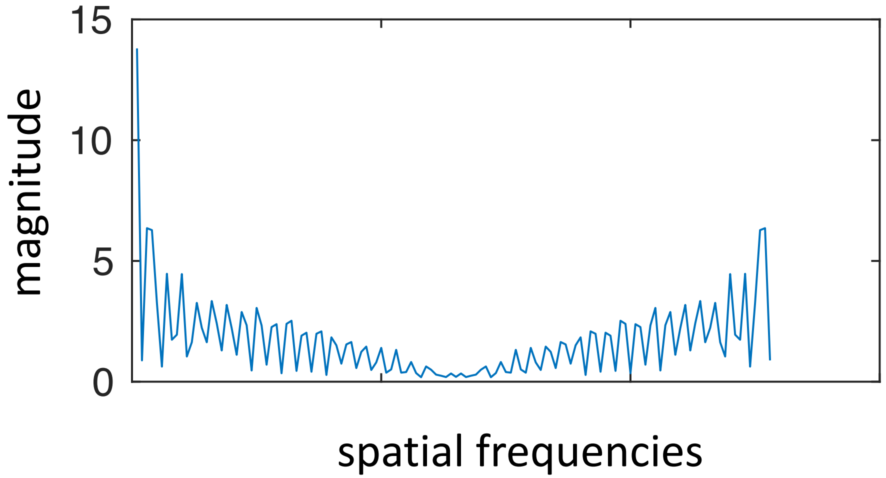




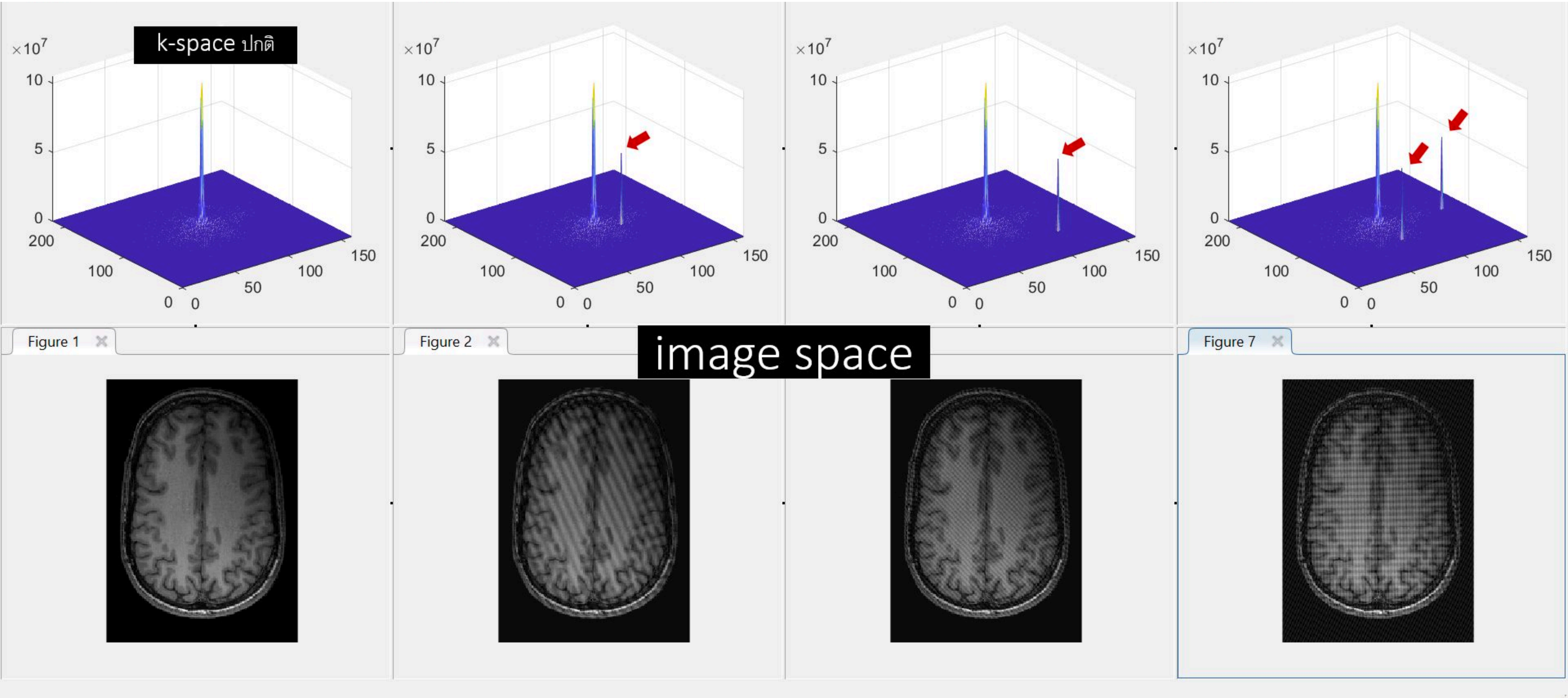
Fourier transform: location ↔ spatial frequency







Review: Application of Fourier Transform to images

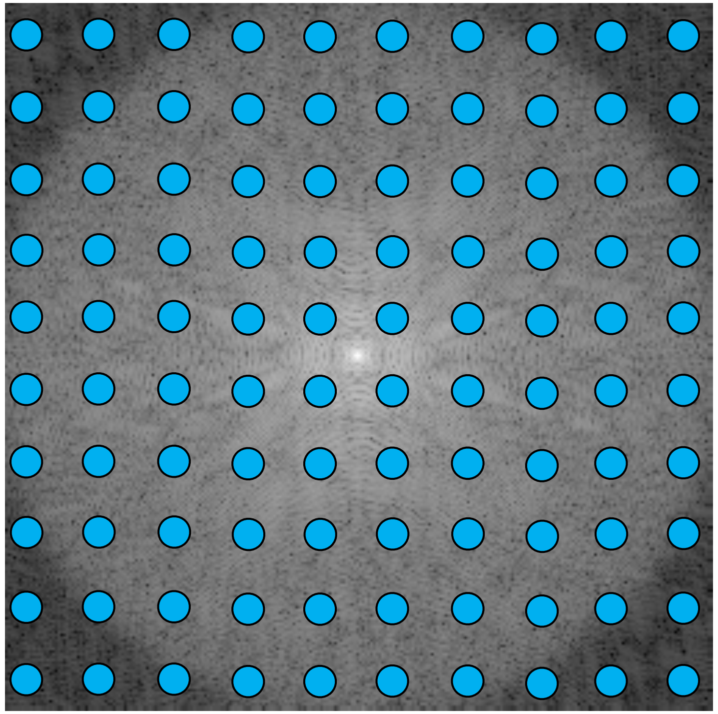


Source: Prof. Uten Yarach

MR Image Acquisition and Reconstruction

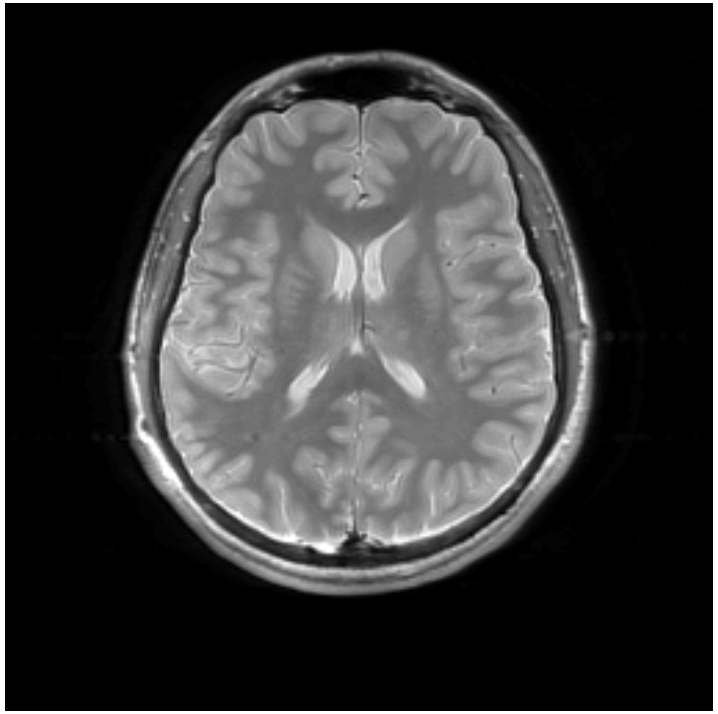
- Raw data are collected in the Fourier domain (k-space)
  - The acquired data are the discrete Fourier transform (DFT) samples of the object being imaged
  - Using the conventional 2DFT acquisition, each line of k-space is acquired one after the other (one per repetition time (TR) of the readout sequence)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



IDFT

Image space



k-space

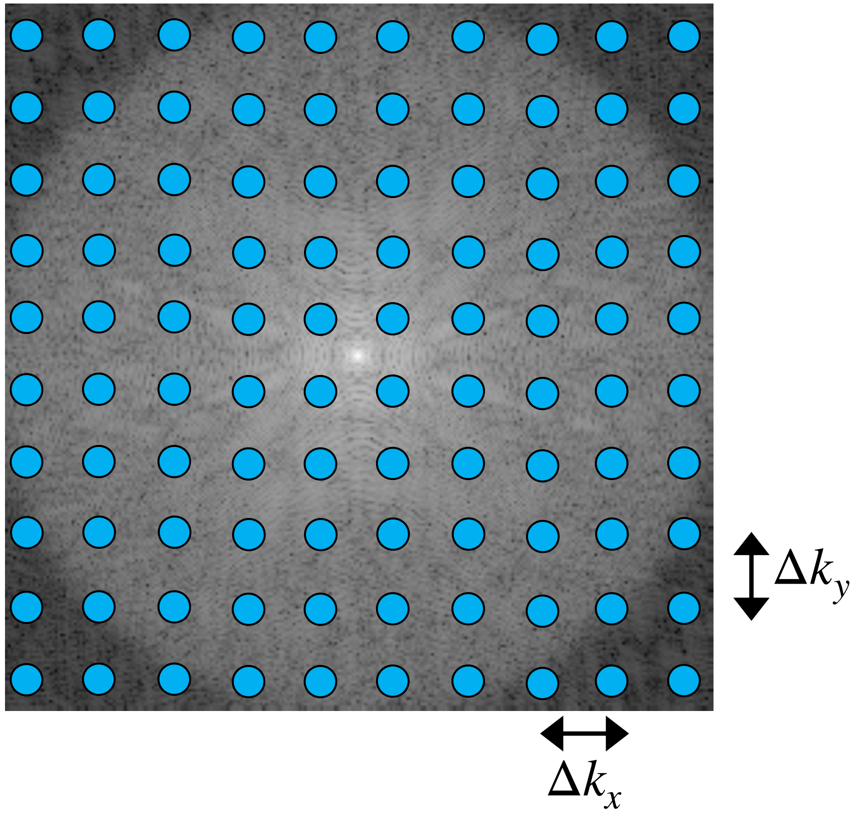
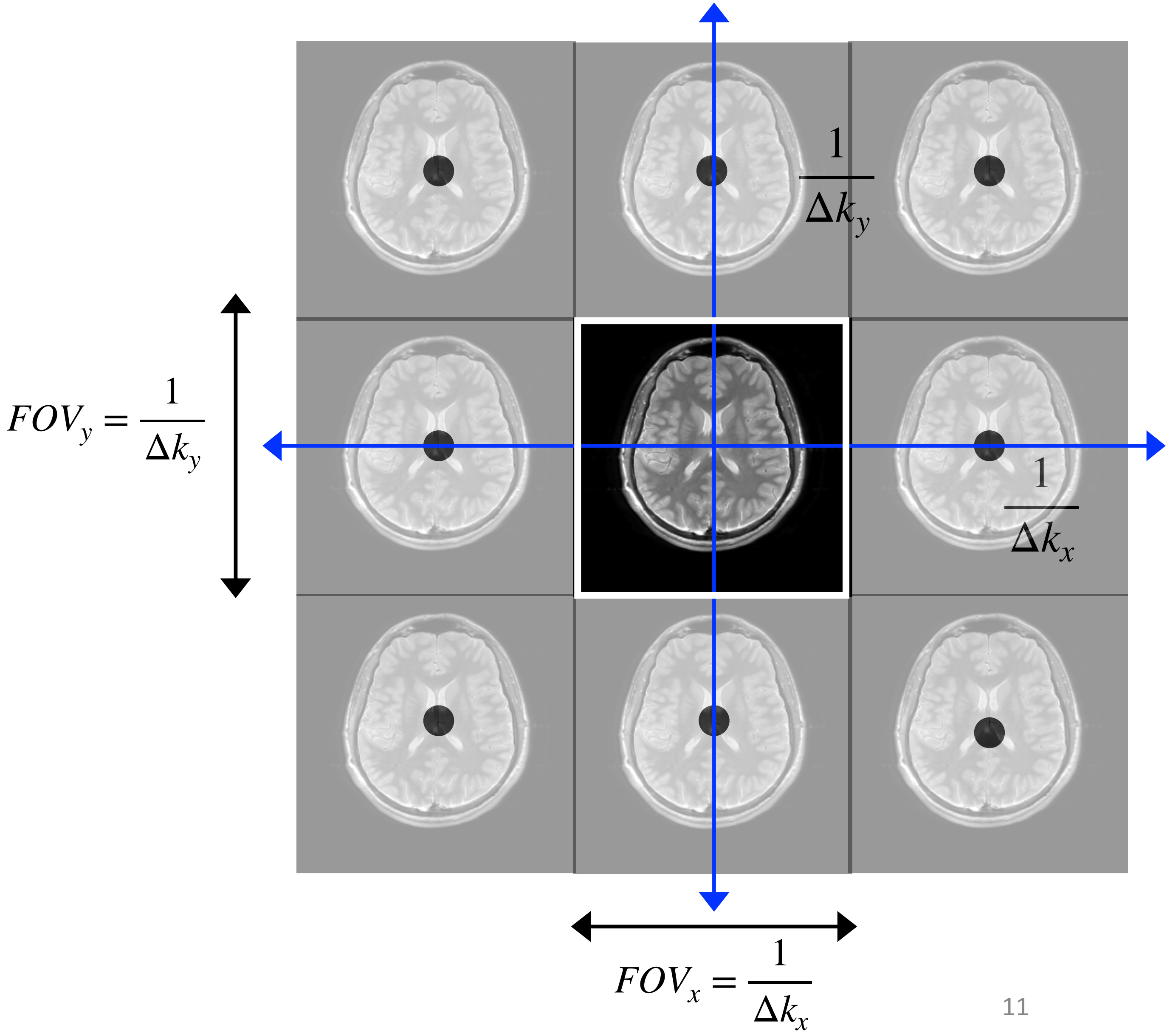
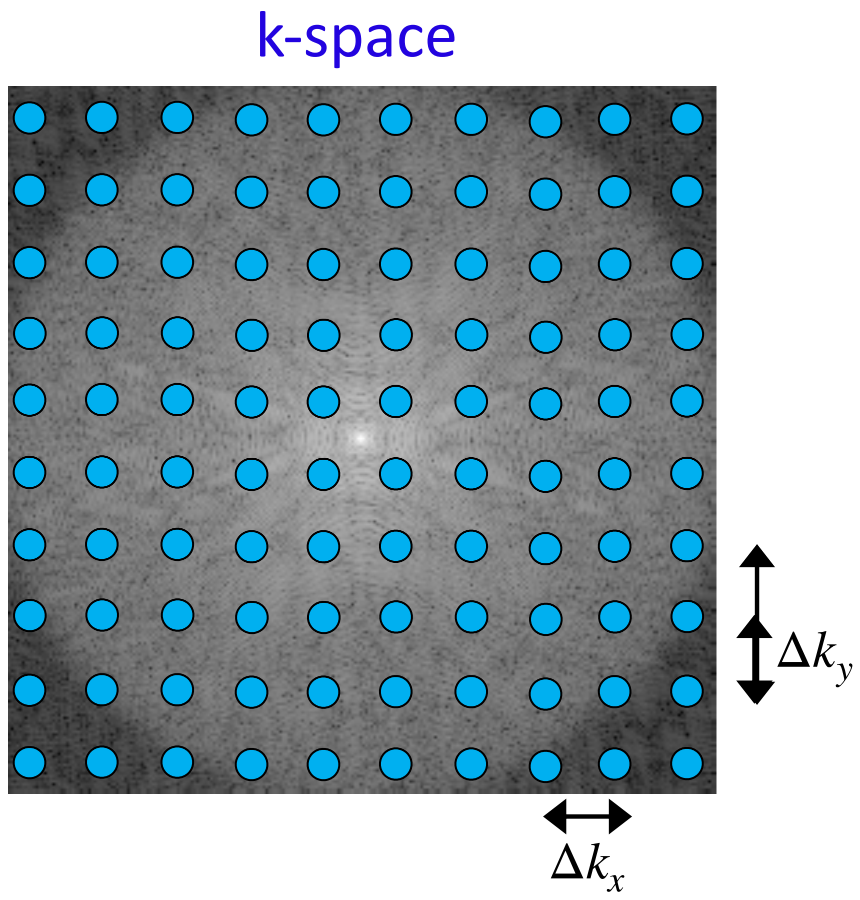
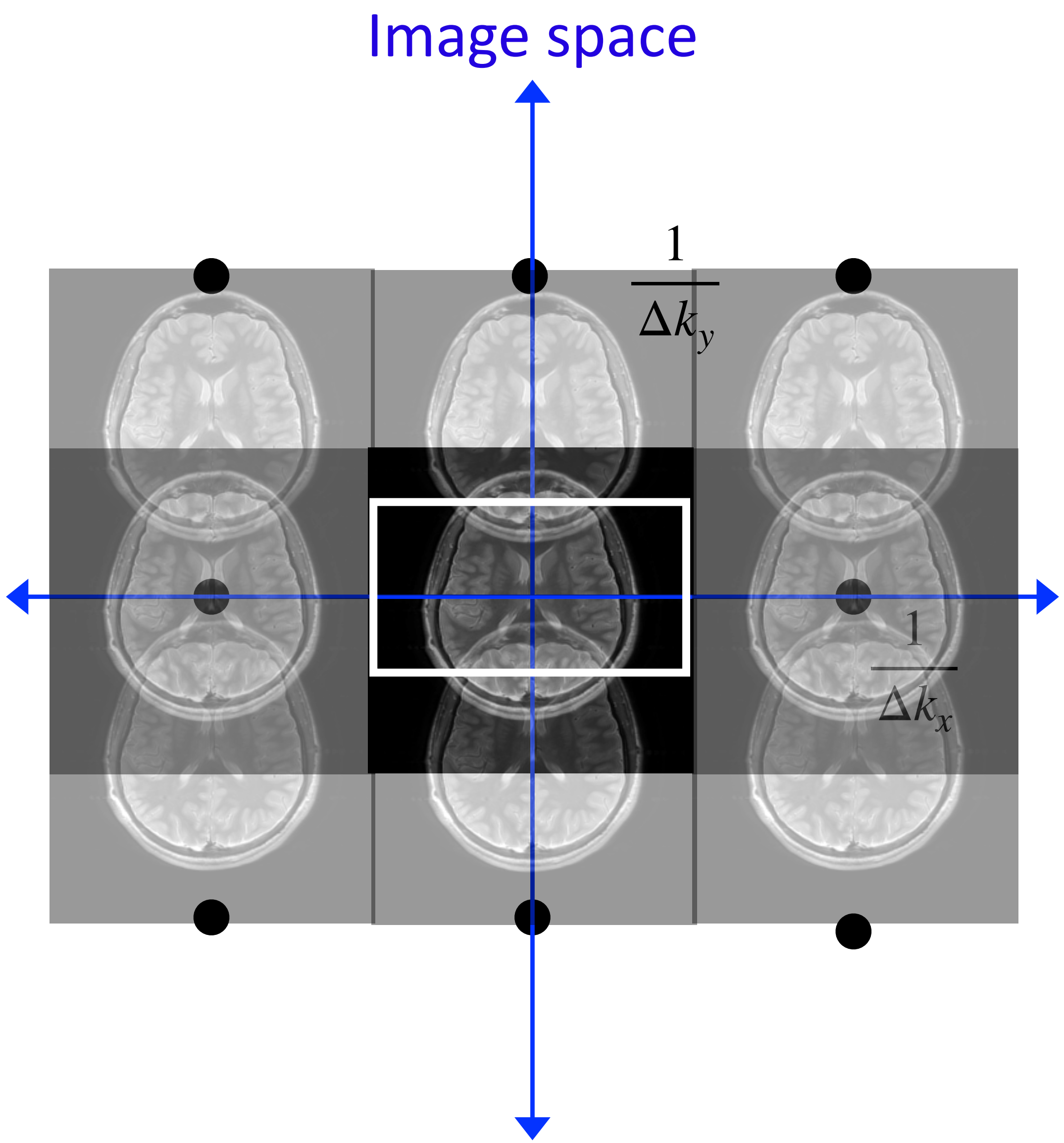


Image space





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



k-space

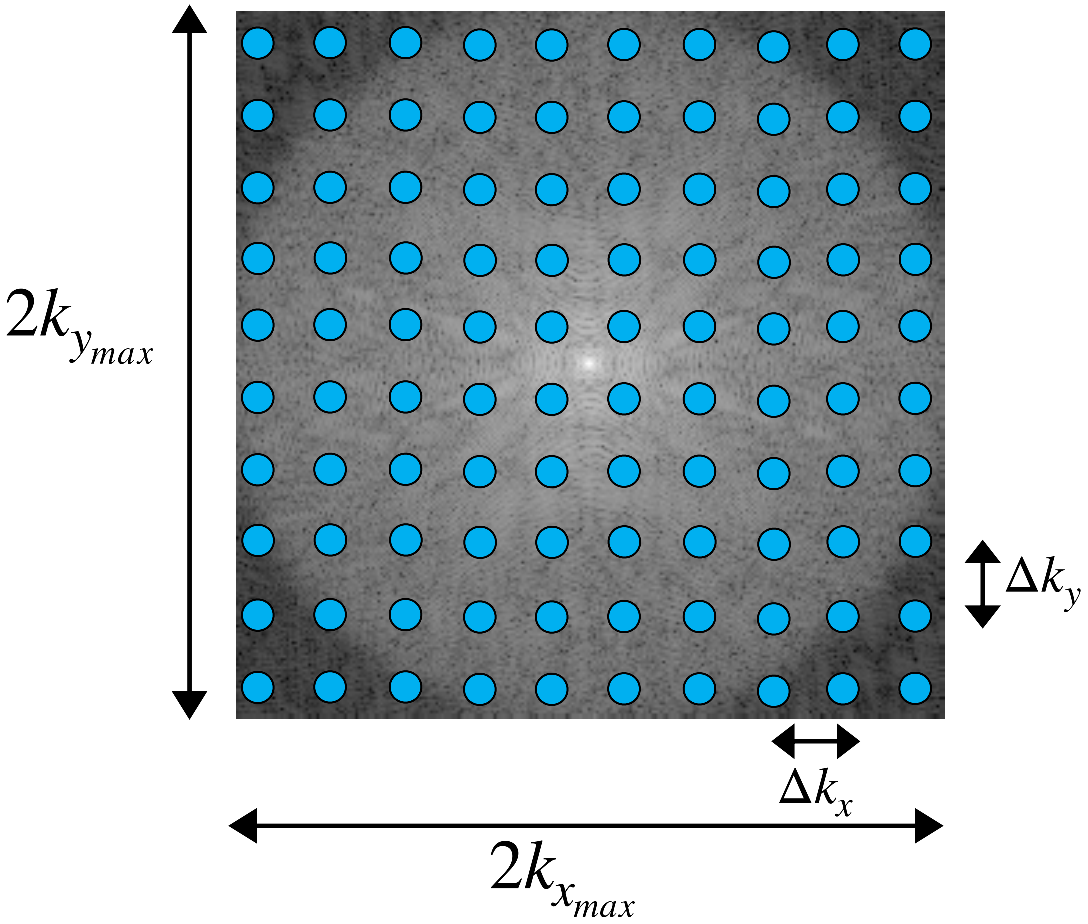
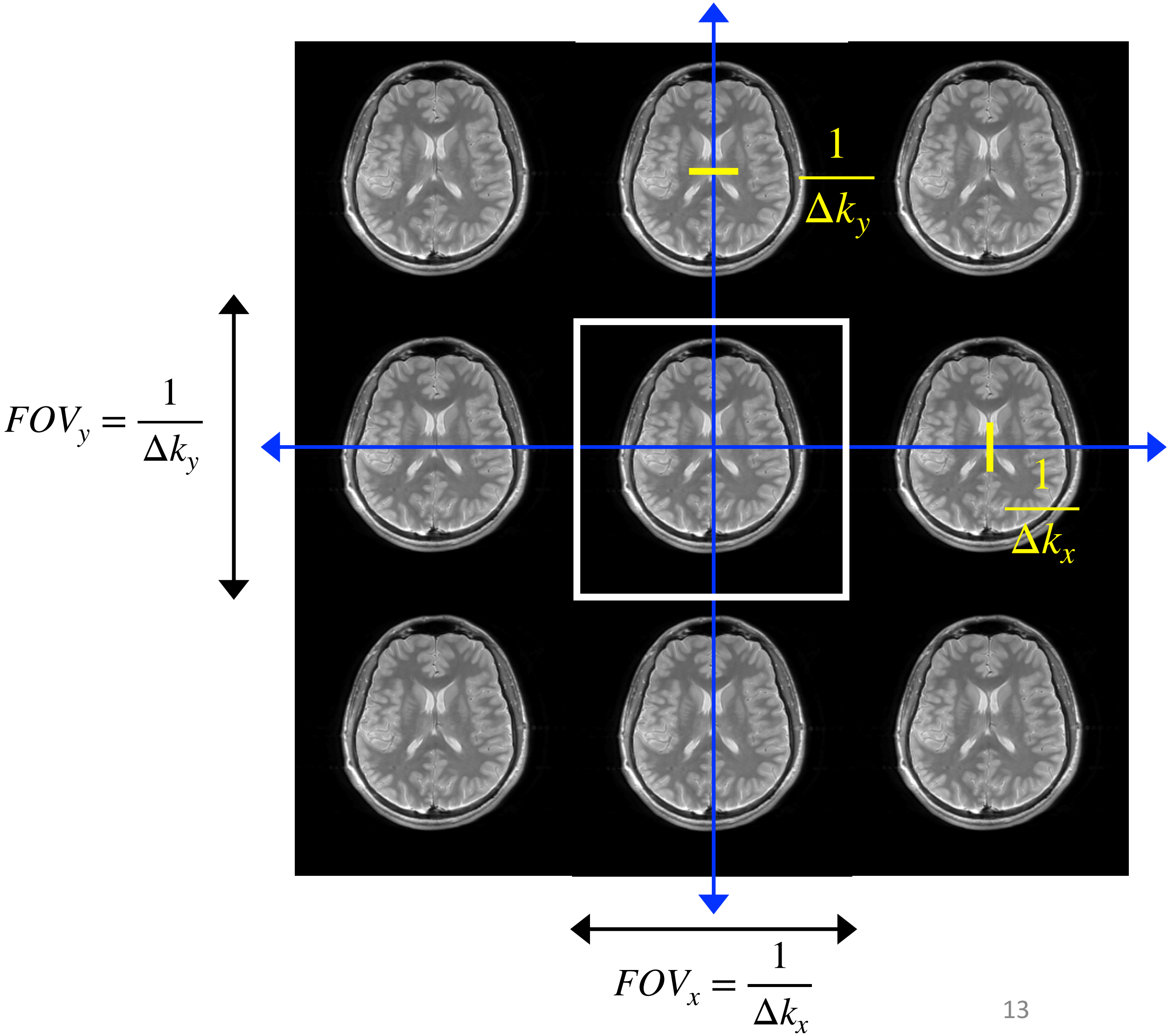


Image space

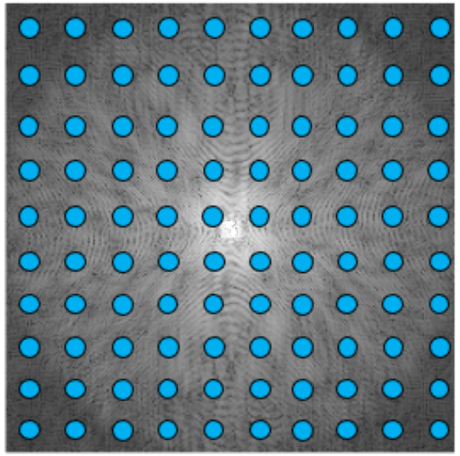


Pixel size

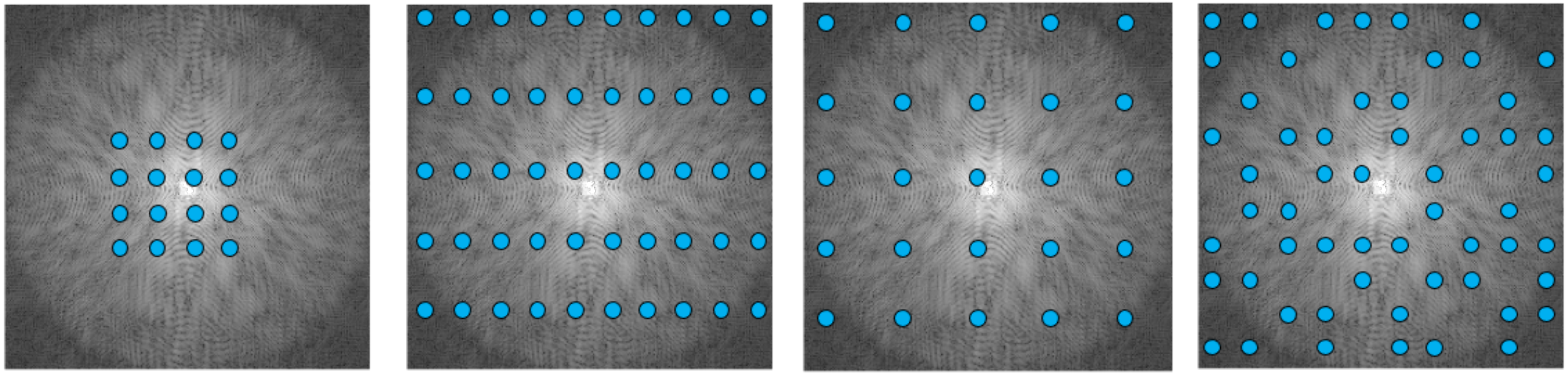
$$\Delta x \approx \frac{1}{2k_{x_{max}}} \qquad \Delta y \approx \frac{1}{2k_{y_{max}}}$$

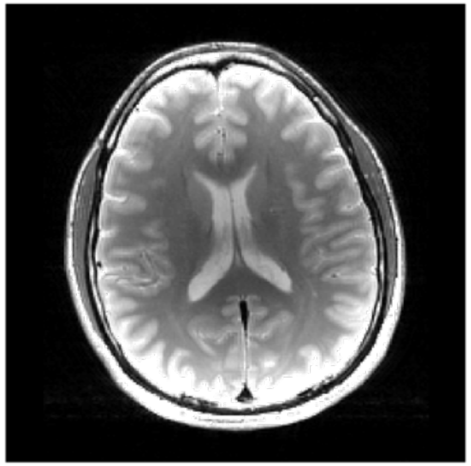
Accelerated MRI – Collect fewer k-space samples

Fully sampled acquisition

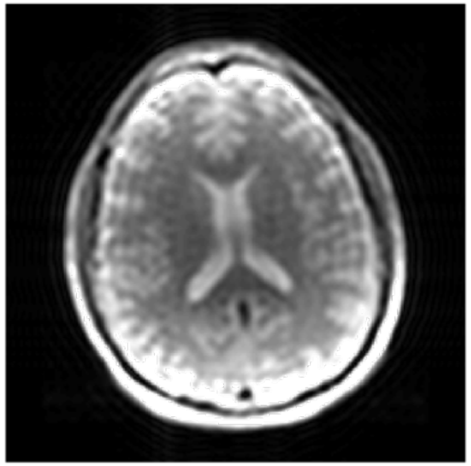


Accelerated acquisition

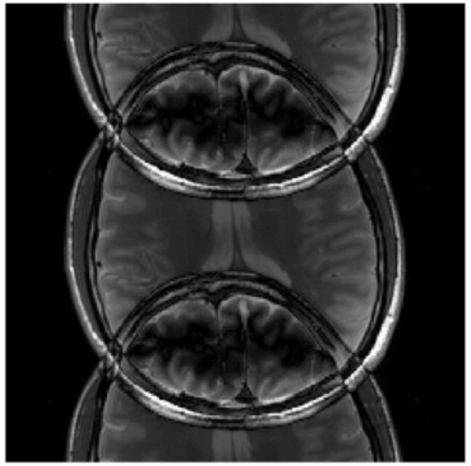




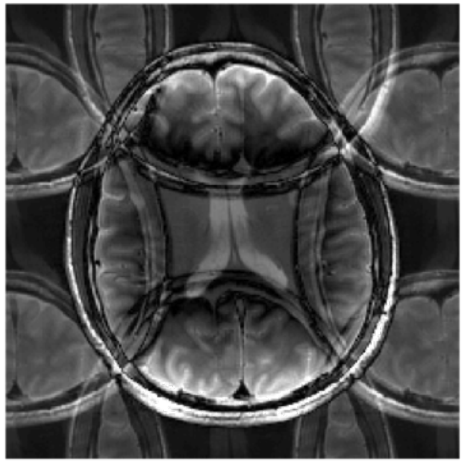
Direct application of 2D inverse Fourier transform to the acquired data



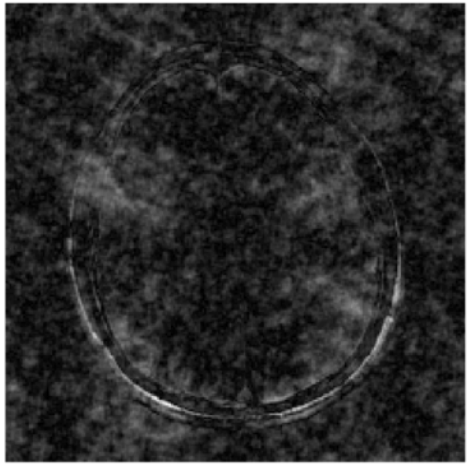
blurry



Artifact (one direction)



Artifact (two directions)



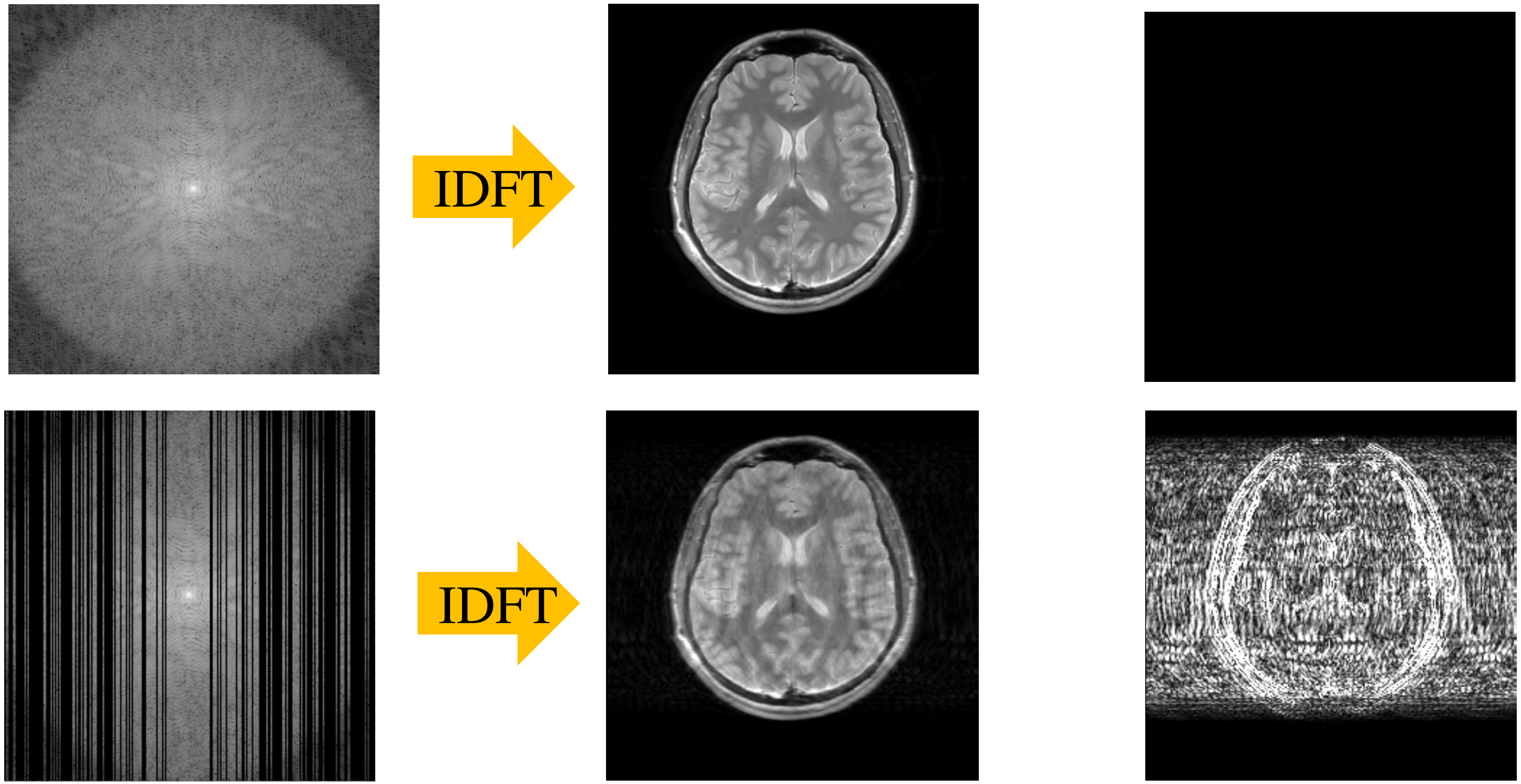
Noise-like artifact

MR Image Reconstruction from Accelerated Scans

k-space

Image space

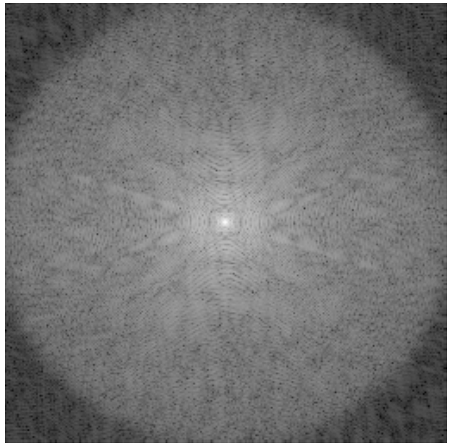
Error image (scaled 10x)
with respect to fully sampled data



Acquire only half of the data
Reduction factor = 2

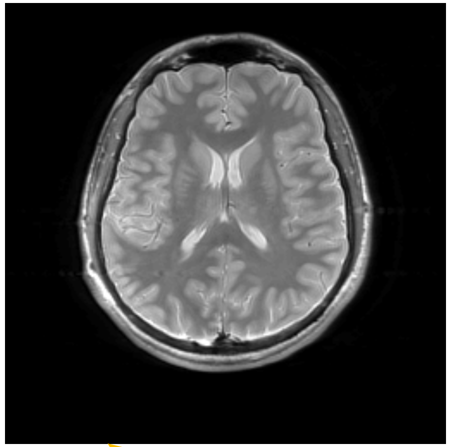
MR Image Reconstruction from Accelerated Scans

k-space

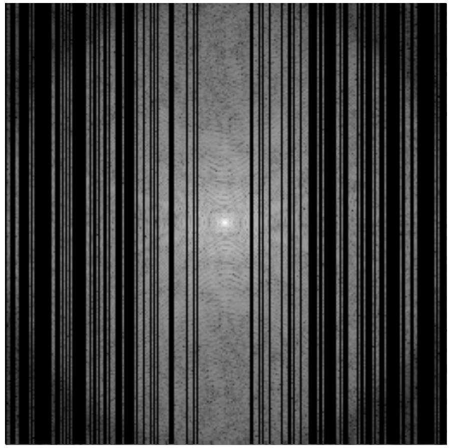


IDFT

Image space



Error image (scaled 10x)
with respect to fully sampled data



Acquire only half of the data
Reduction factor = 2

Compressed Sensing
Deep Learning

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

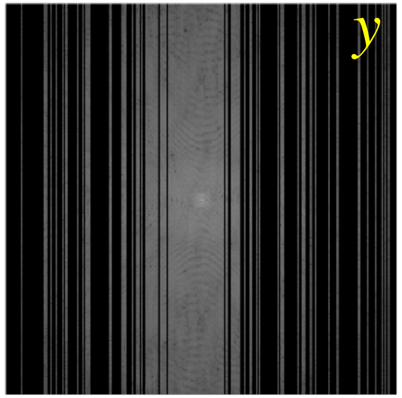
x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
R	: Regularization term
λ	: Regularization parameter

Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

Acquired k-space data



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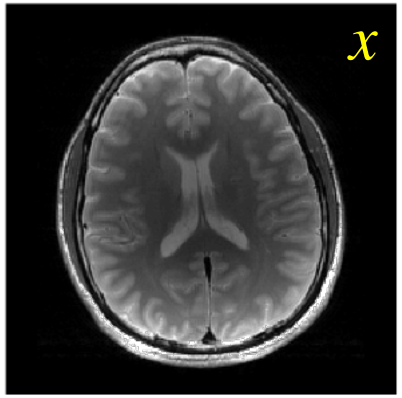
Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

What you want to reconstruct



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

- Solve the following optimization problem to reconstruct the data

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

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
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Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

Our hand-designed
function to approximate
the acquisition process

x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
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Compressed Sensing

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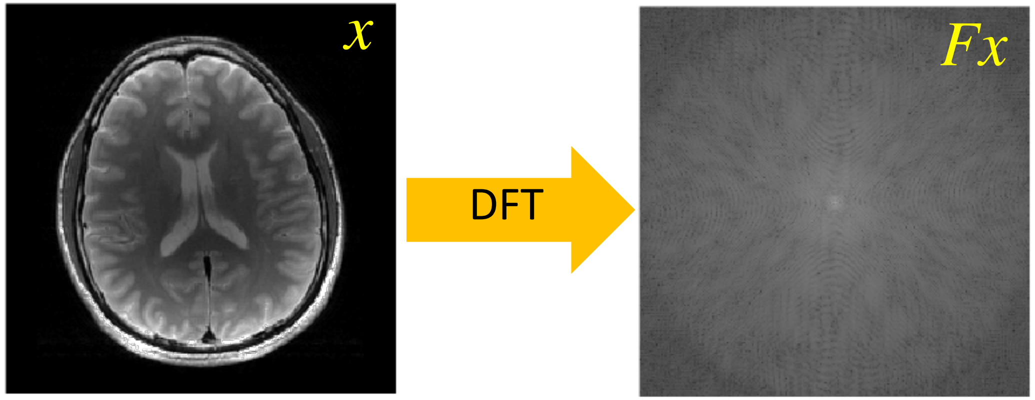

x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
M	: Undersampling mask
y	: Observed k-space data
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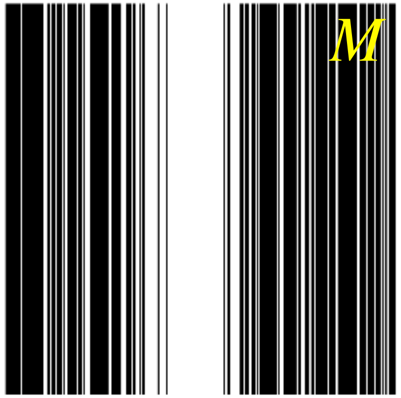
λ	: Regularization parameter

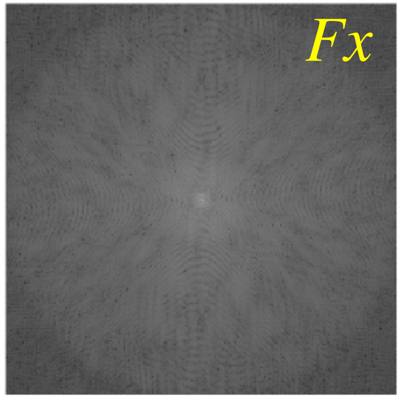
Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

Pixel-wise multiplication





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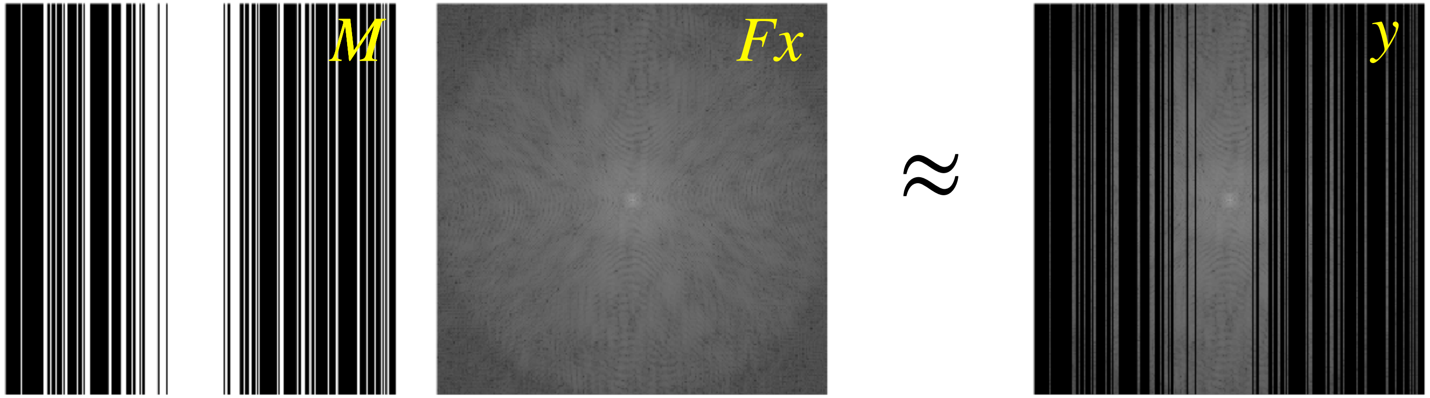
Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

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



x	: Image
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Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

Regularization

Incorporate prior knowledge on x

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

- Solve the following optimization problem to reconstruct the data

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

x	: Image
F	: Fully sampled discrete Fourier transform (DFT)
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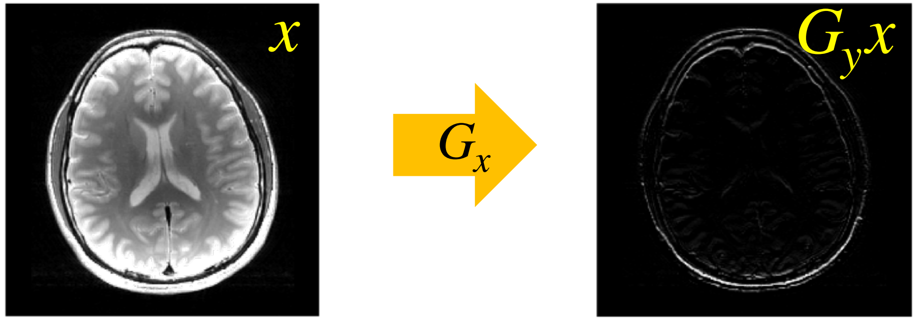
Compressed Sensing

- Solve the following optimization problem to reconstruct the data

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

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

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

- Gradient descent (an iterative method)

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

  - Update equation for iteration k

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

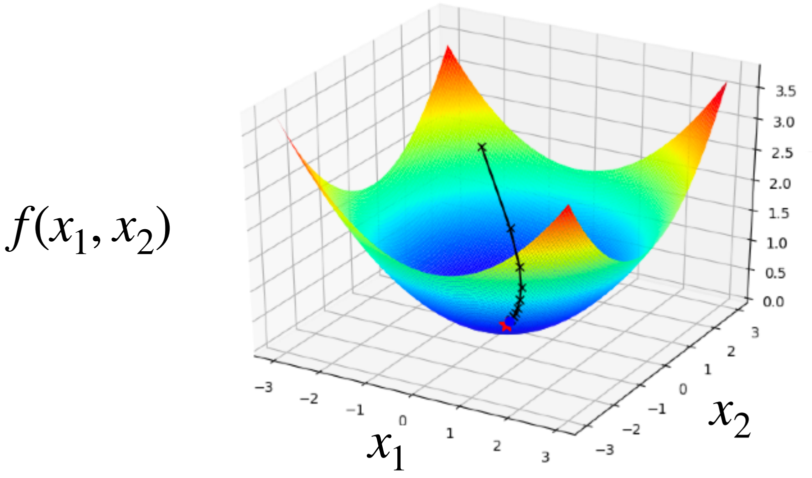


Photo credit: [Neural Network Demystified Part III – Gradient Descent and Backpropagation]

Compressed Sensing

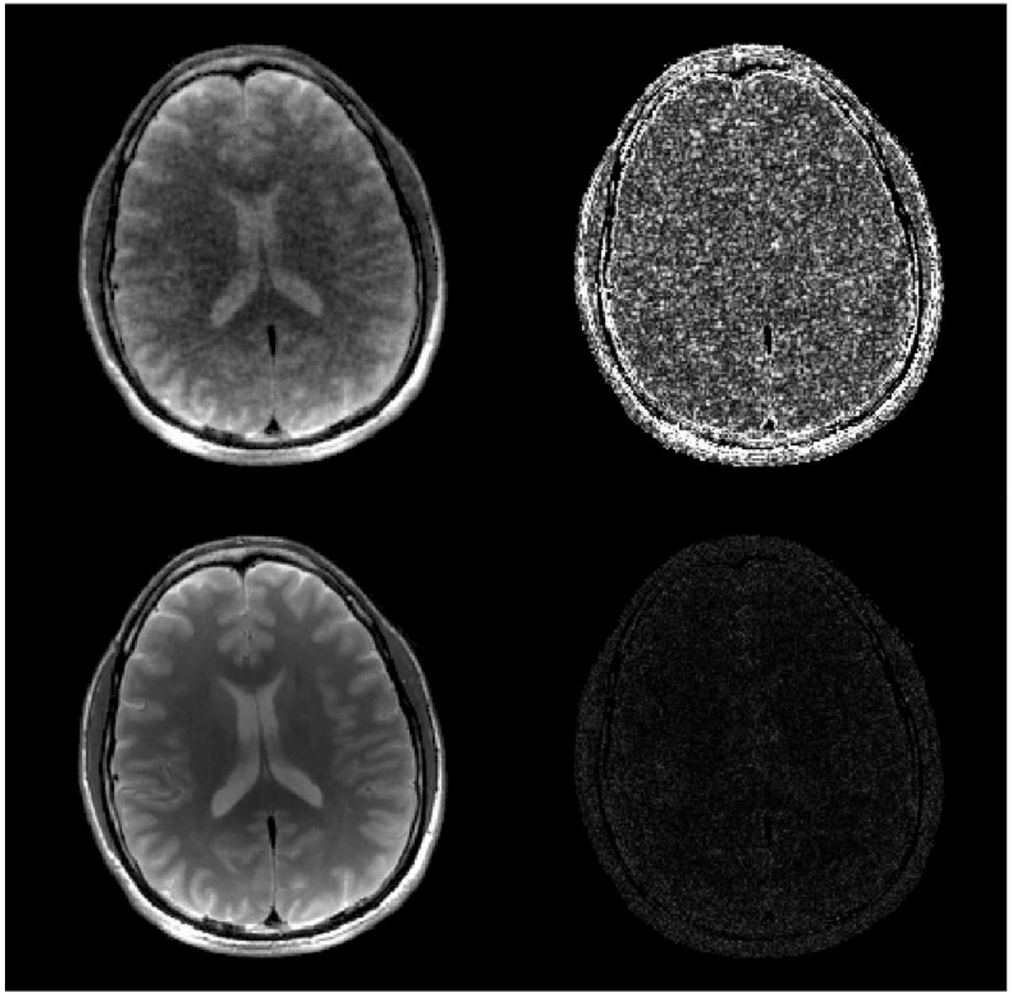
Reduction factor = 2

Reconstructed Image

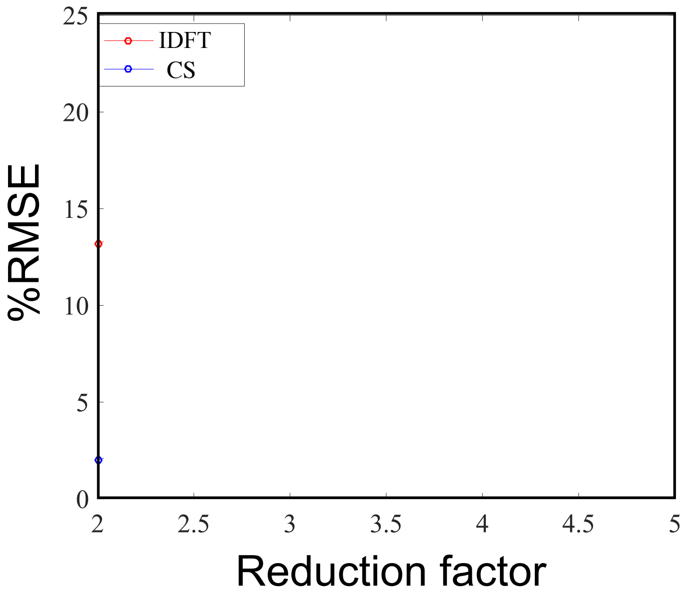
Error (scaled 10x)

IDFT

Compressed Sensing

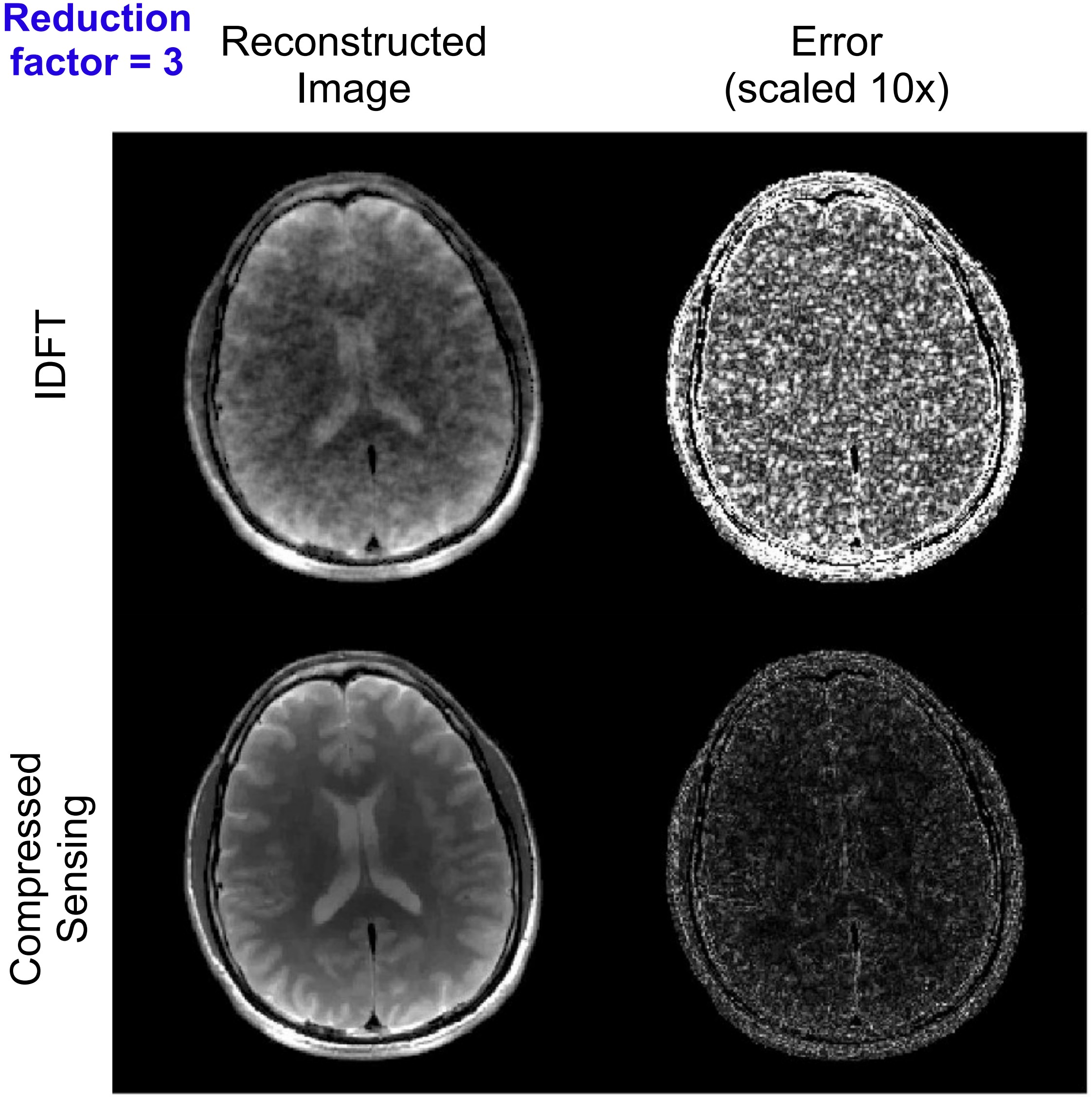


$$\hat{x} = \arg\min_{x} \frac{1}{2} \|MFx - y\|_2^2 + \lambda \|Gx\|_1$$

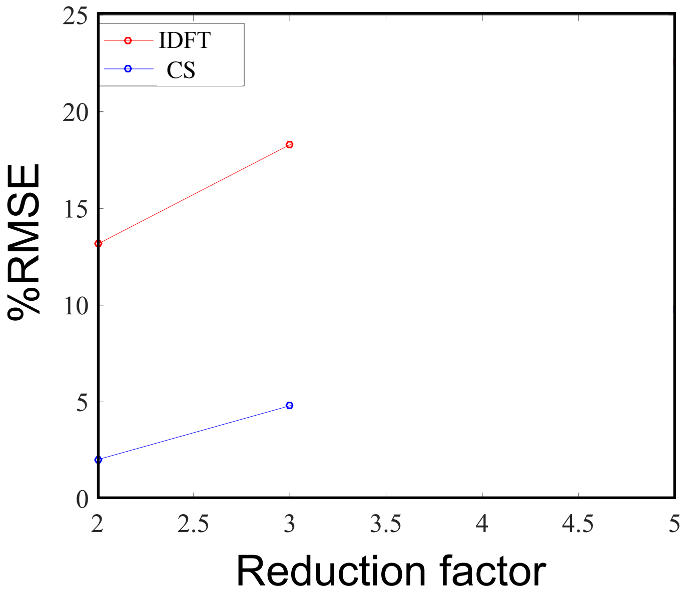


Compressed Sensing

Reduction factor = 3

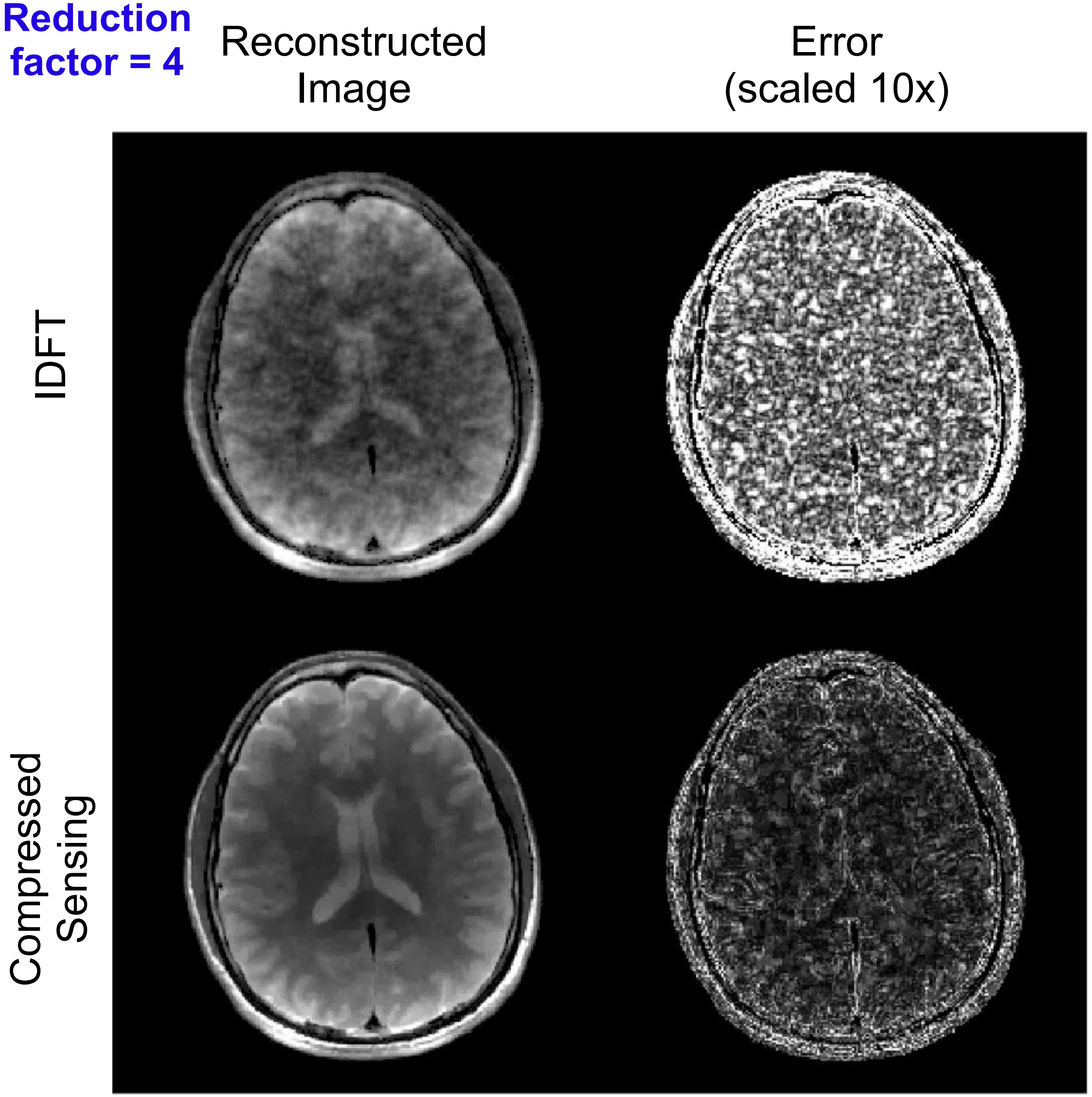


$$\hat{x} = \arg\min_{x} \frac{1}{2} \|MFx - y\|_2^2 + \lambda \|Gx\|_1$$

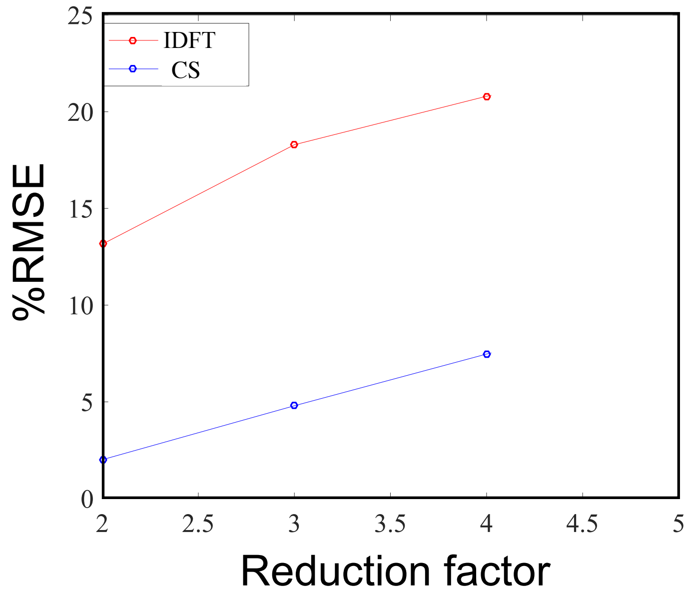


Compressed Sensing

Reduction factor = 4



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



Compressed Sensing

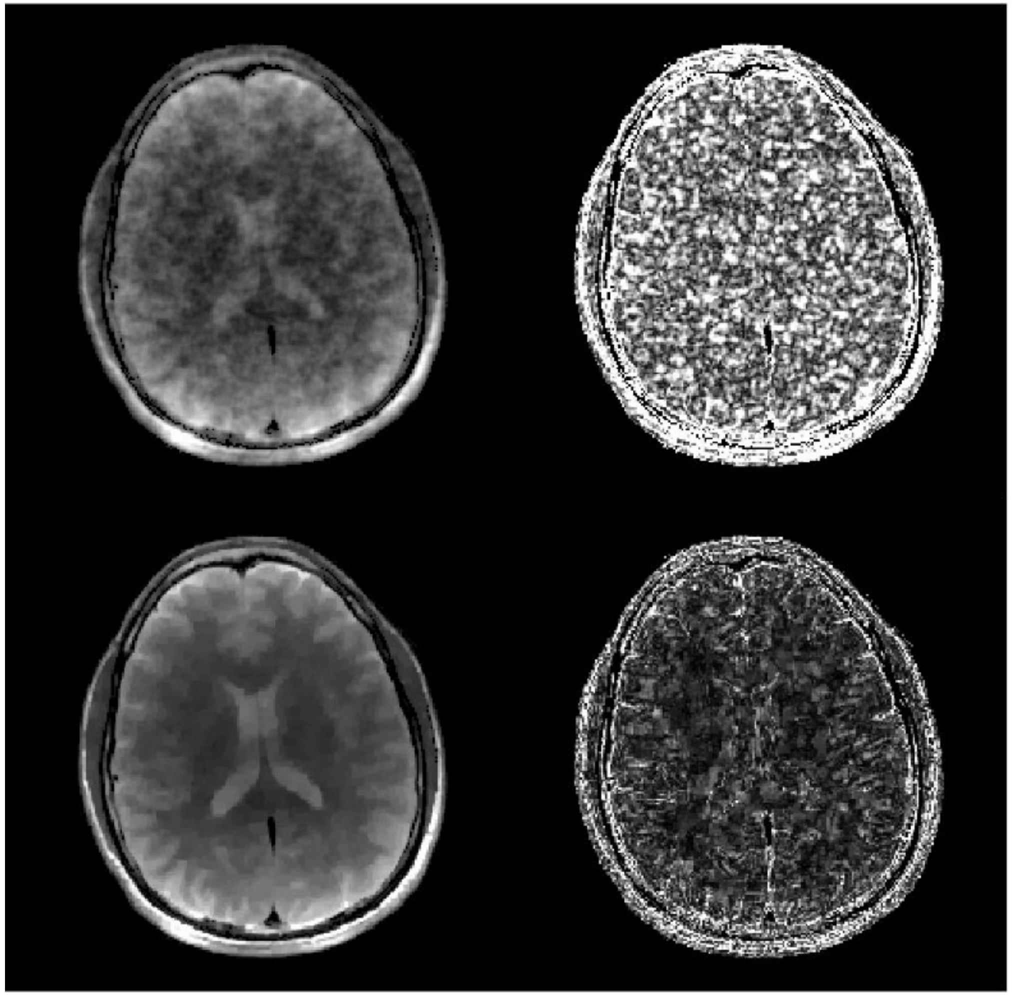
Reduction factor = 5

Reconstructed Image

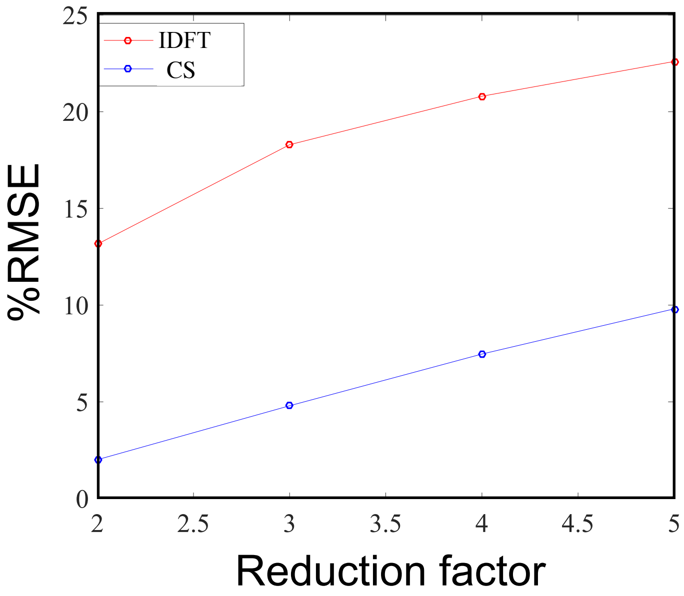
Error (scaled 10x)

IDFT

Compressed Sensing

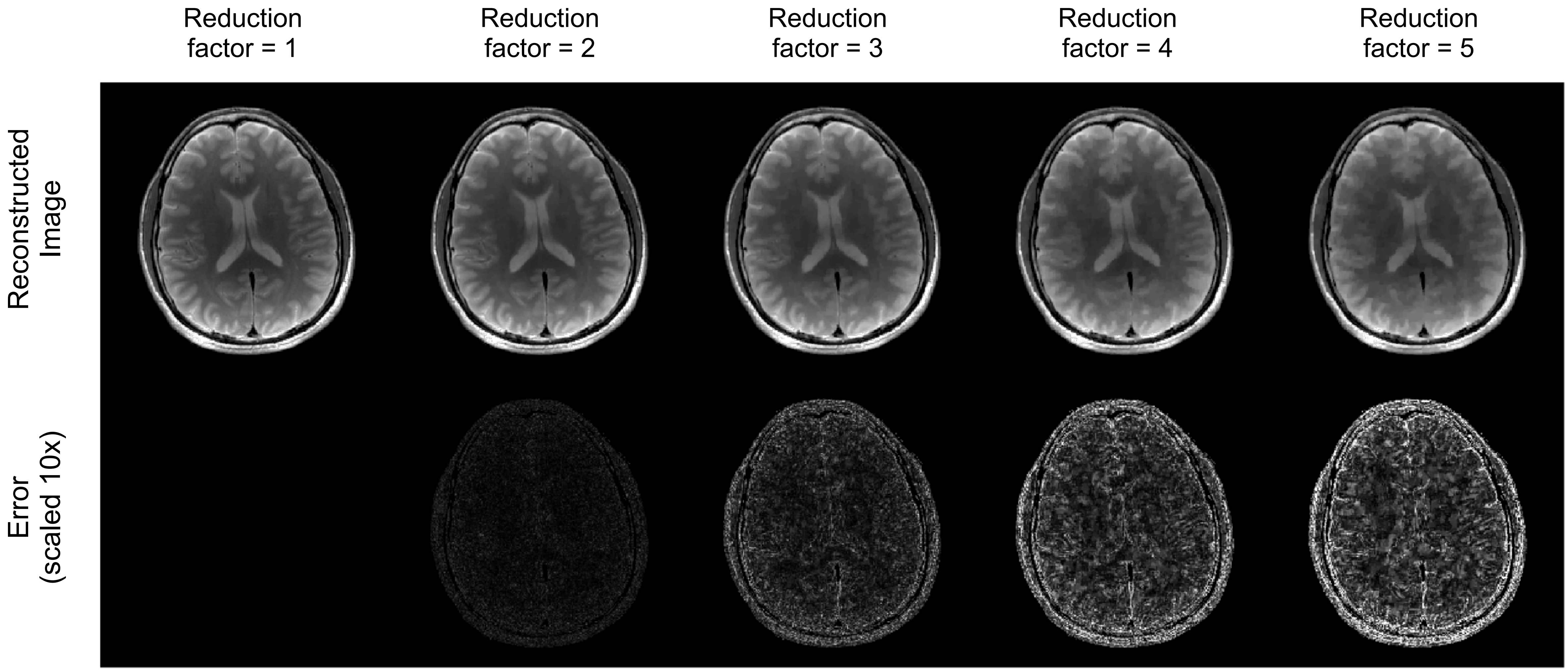


$$\hat{x} = \arg\min_{x} \frac{1}{2}\|MFx - y\|_2^2 + \lambda\|Gx\|_1$$



Compressed Sensing

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



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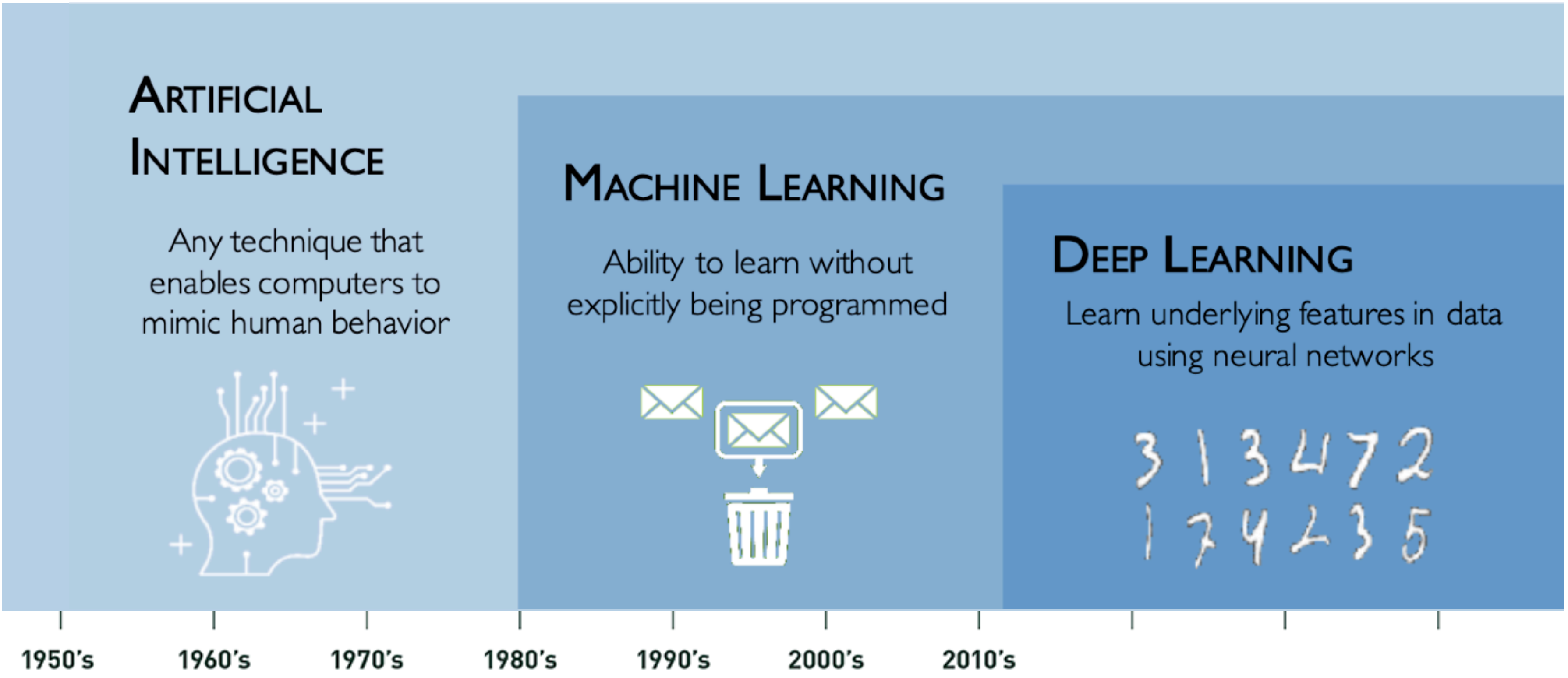
  - Supervised learning
  - Experimental Results



Fasting blood sugar test

x mg/dL

normal if $x < 100$

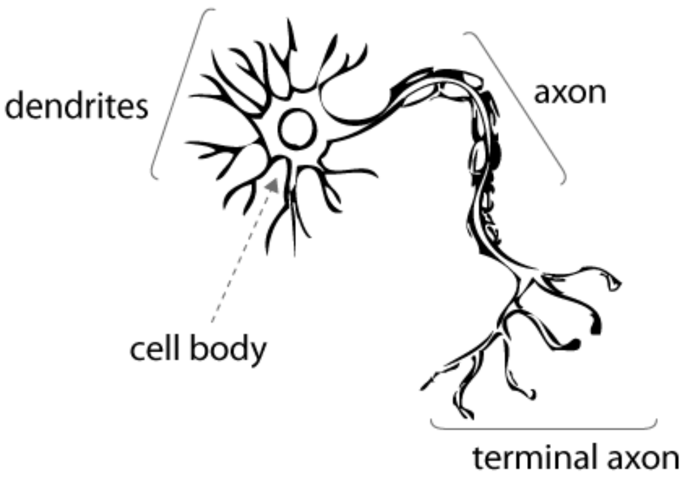
prediabetes if $100 \leq x \leq 125$

diabetes if $125 < x$

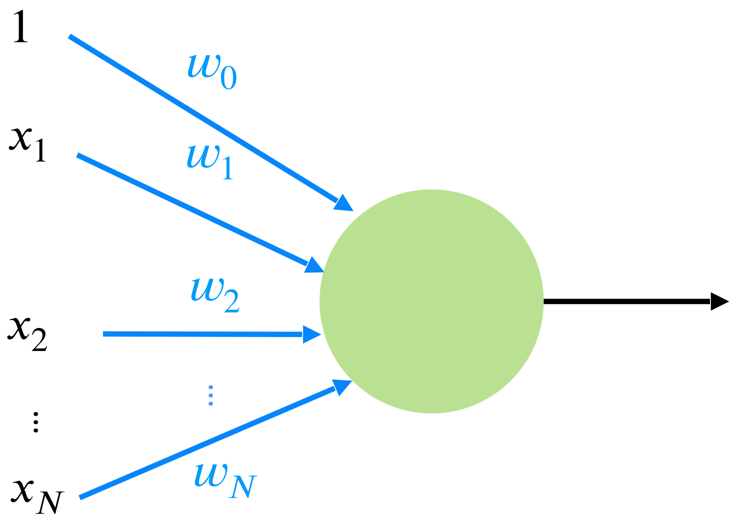
Deep Learning

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

Single neuron

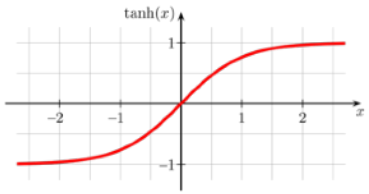


Artificial neuron



$$y = a\left(\sum_{n=1}^{N} x_n w_n + w_0\right)$$

non-linear function (activation)

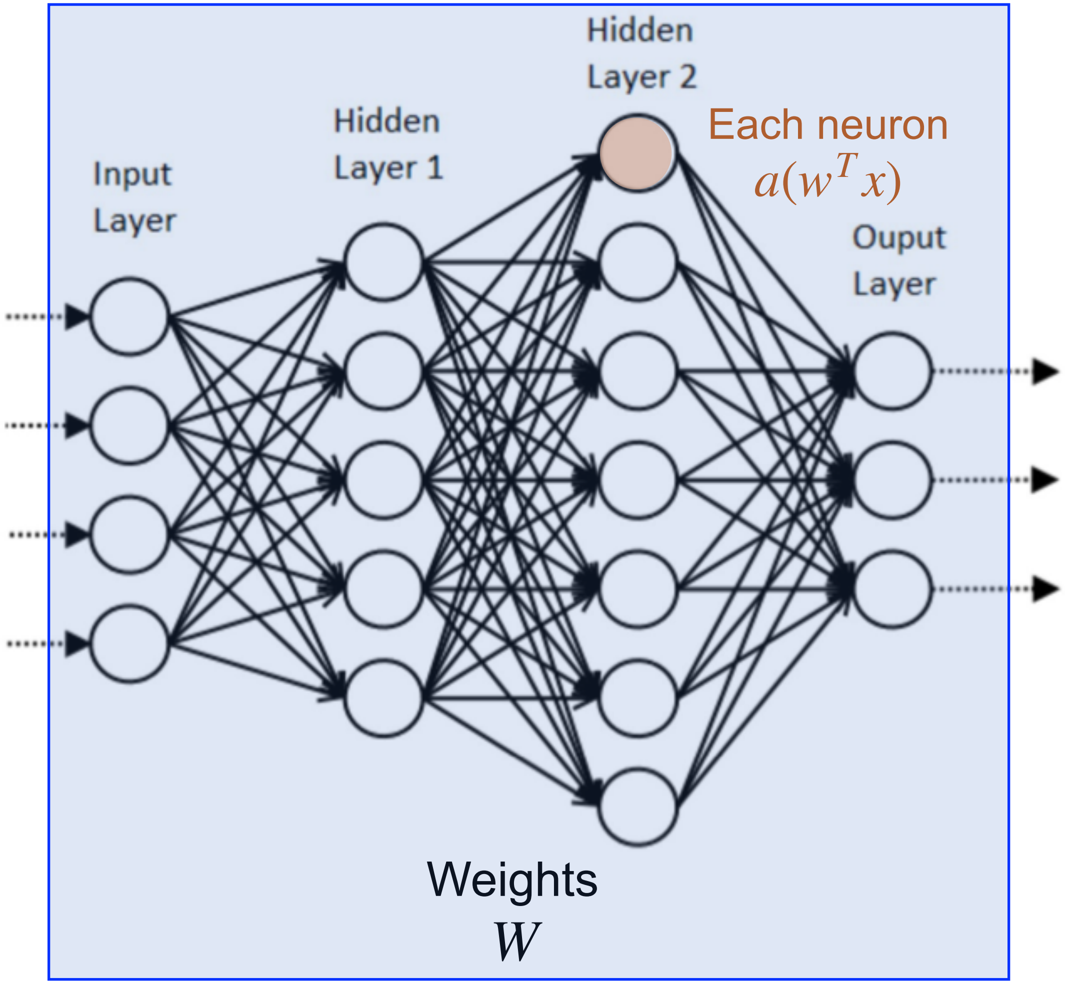


https://medium.com/@ivanliljeqvist/the-essence-of-artificial-neural-networks-5de300c995d6

Deep Learning

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

Input
x



Output
y

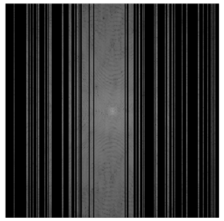
$$y = f_W(x)$$

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

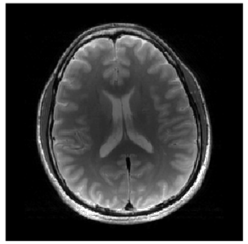
Deep Learning

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

k-space data



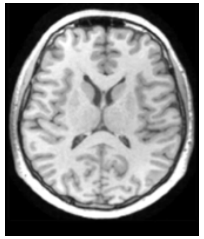
$f_{recon,W}$



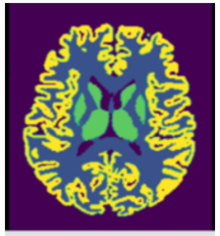
Reconstructed image

  - MRI segmentation function

Image-space data



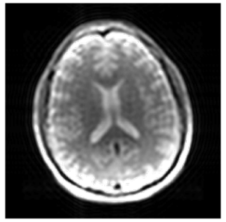
$f_{segment,W}$



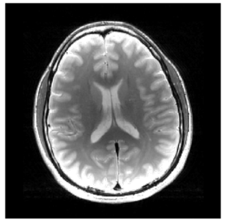
Segmentation map

  - MRI super-resolution function

Low-resolution image-space data



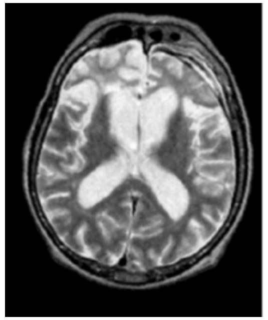
$f_{sr,W}$



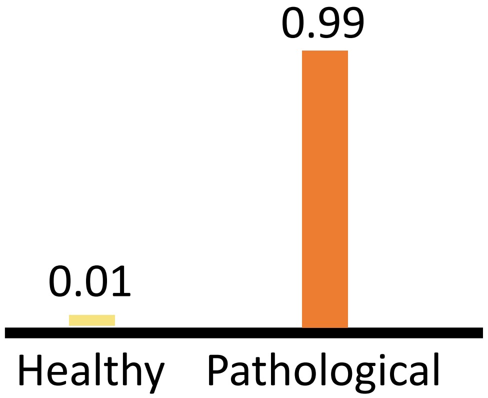
High-resolution image-space data

Deep Learning

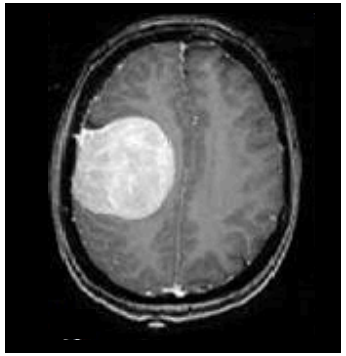
- We can use a deep artificial neural network to approximate any functions by modifying its weight
  - MR image classification function



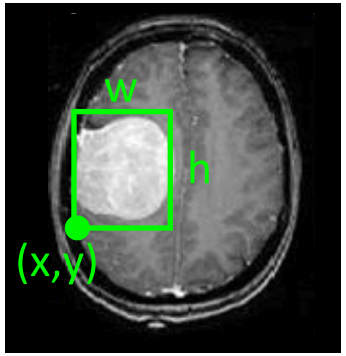
$f_{classif,W}$



  - Detection function

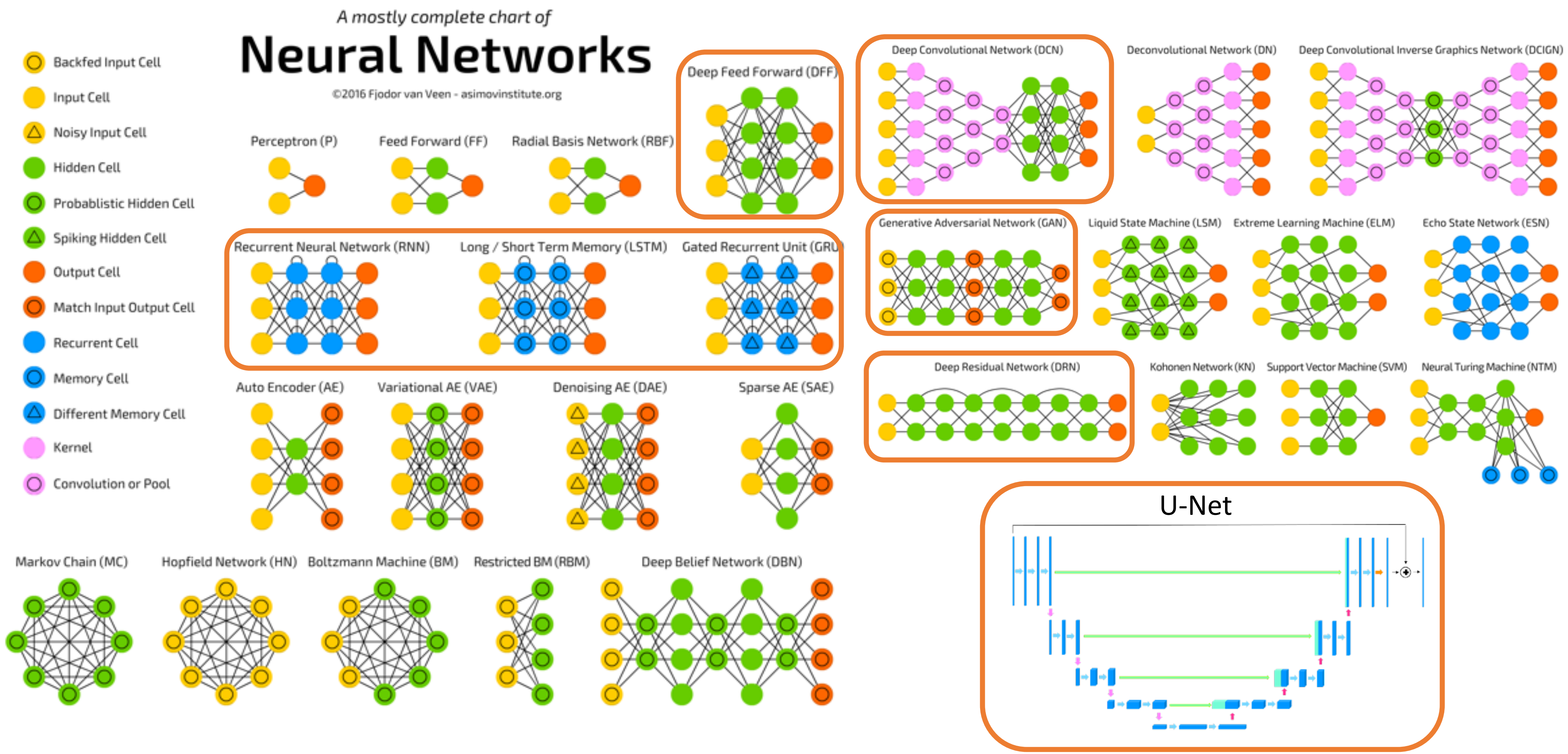


$f_{detection,W}$



class: tumor

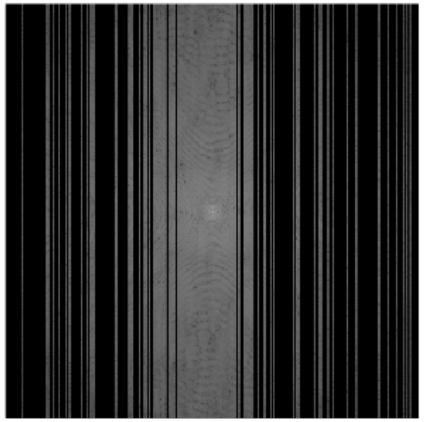
Alam, Sadia, et al. "An efficient image processing technique for brain tumor detection from MRI images." 2019 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE). IEEE, 2019.



The Mostly Complete Chart of Neural Networks by the team at the [Asimov Institute]

Deep Learning for MR Image Reconstruction

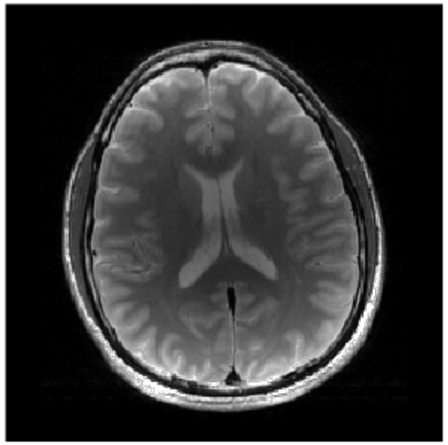
Underlying Process



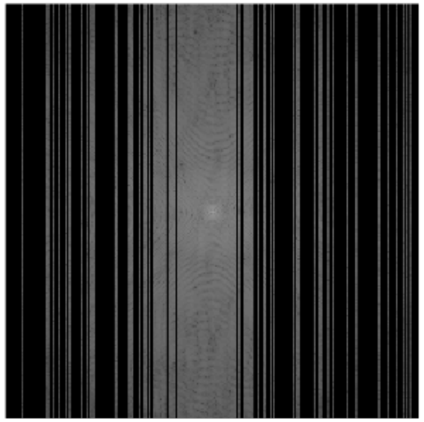
g_{recon}

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

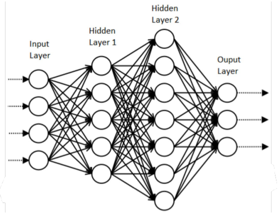
- Inverse Fourier transform
- Artifact removal
- Magnetic field map correction



Deep Learning

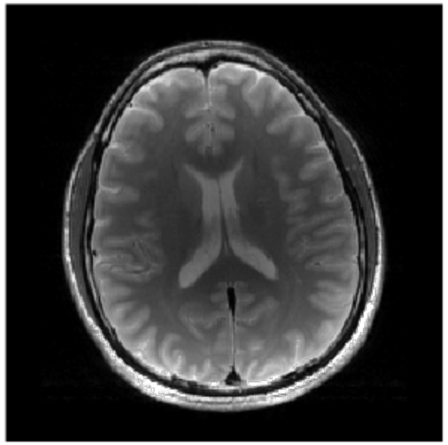


f_W



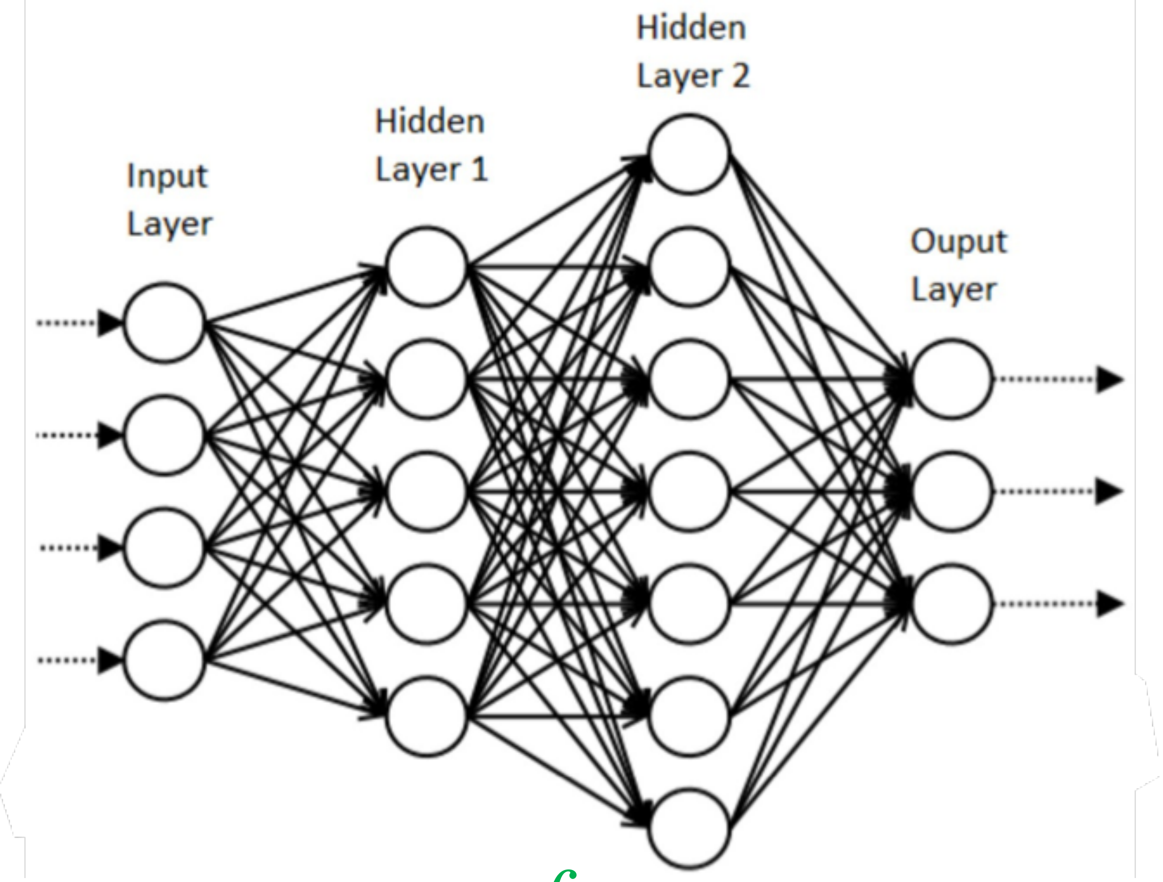
With model training, we could obtain

$f_W \approx g_{recon}$



Supervised Model Training

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



f_{W_0}

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

Supervised Model Training

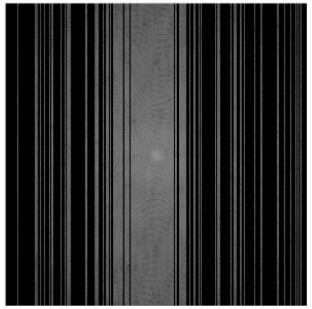
Prepared input

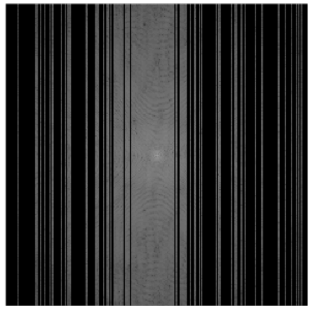
x

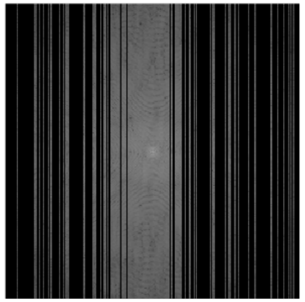
Step 2: Prepare a dataset which is a collection of input-output pairs

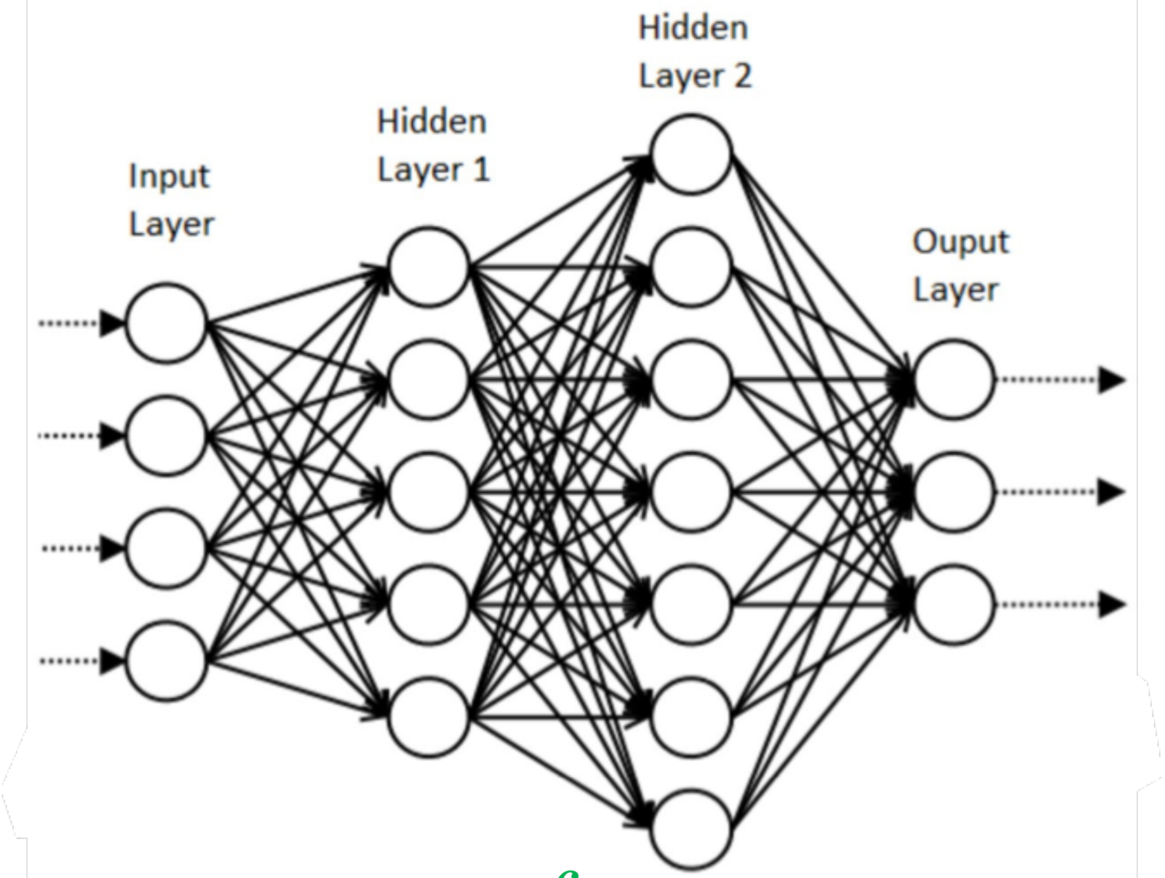
Prepared output

y

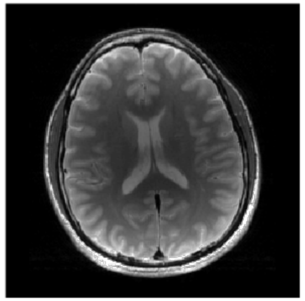


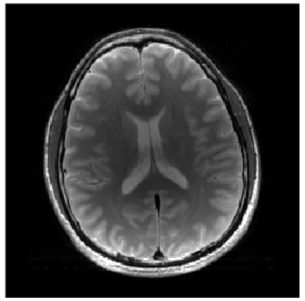


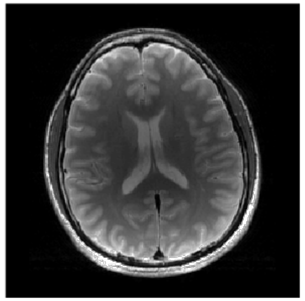




f_{W_0}



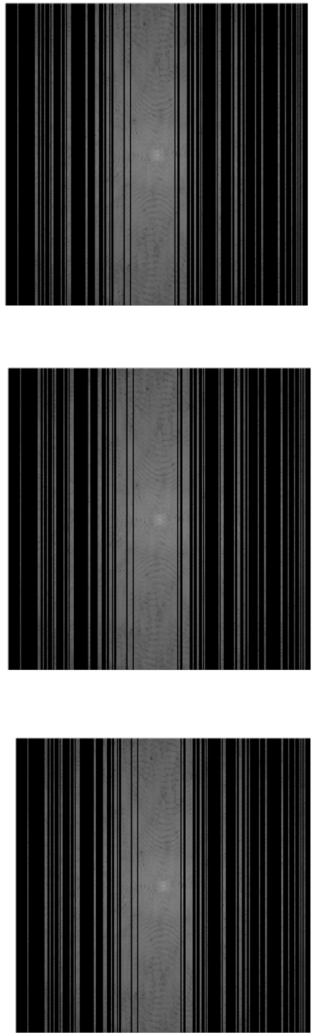




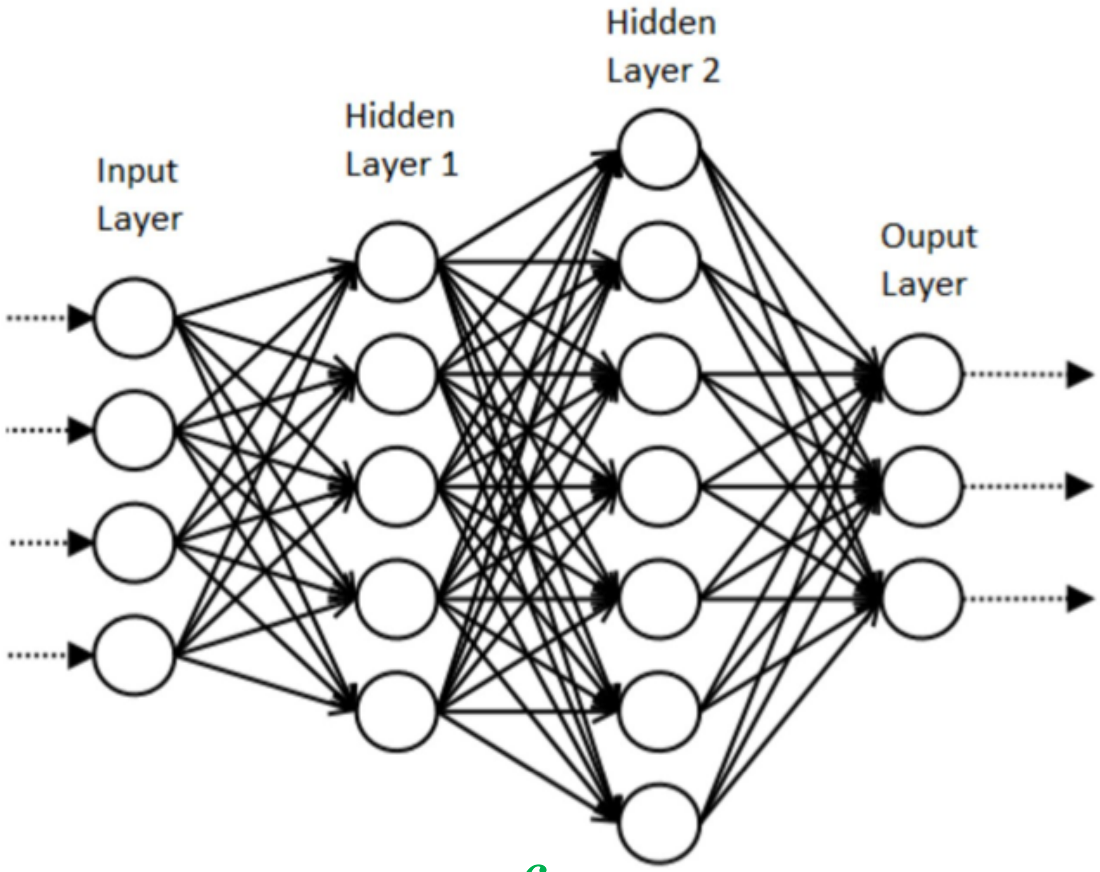
Supervised Model Training

Prepared input

x



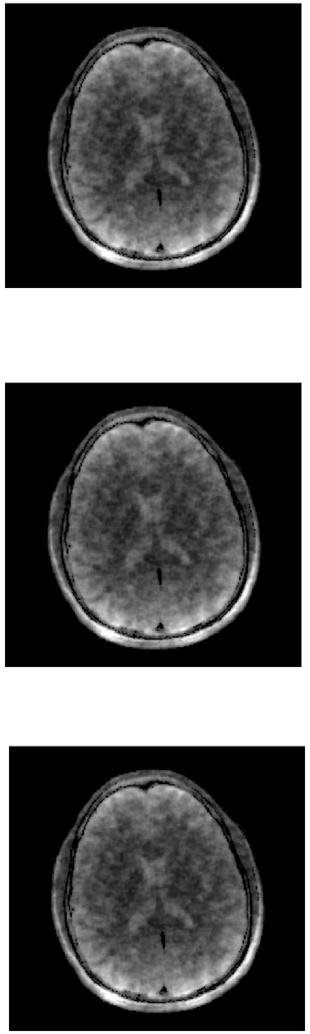
Step 3: Pass the prepared input to the network



f_{W_0}

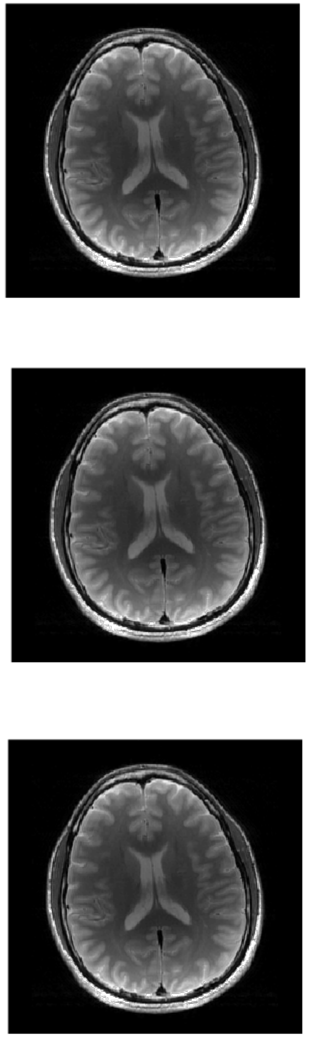
Estimated output

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



Prepared output

y

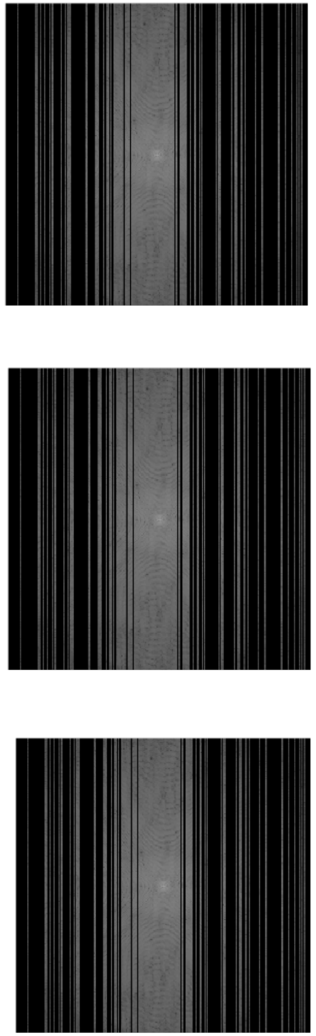


Keywords: loss function, backpropagation

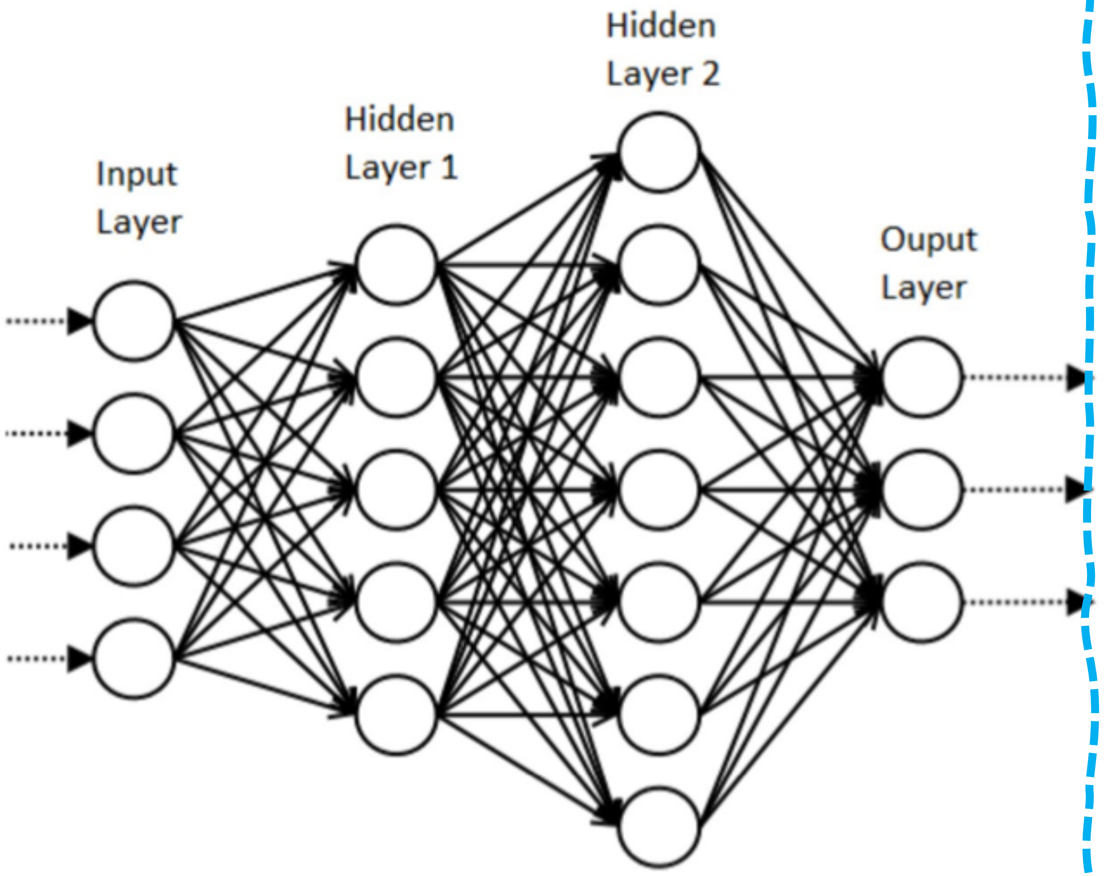
Supervised Model Training

Prepared input

x



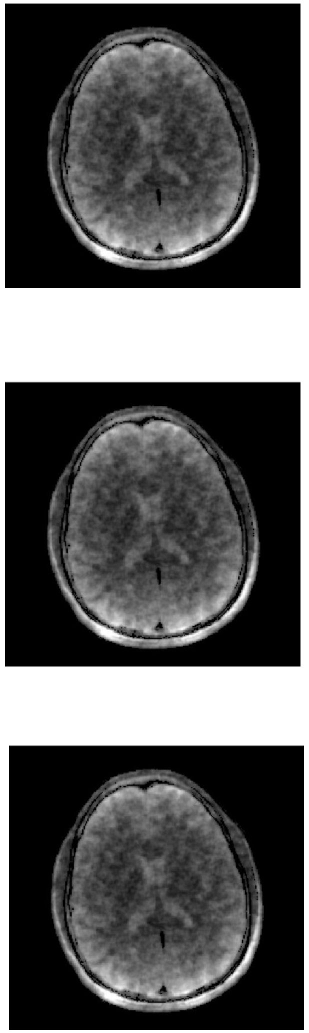
Step 4: Compare $\hat{y}$ to y and modify the weights of the neural network to make $\hat{y}$ approach y using the backpropagation algorithm



Iteration 1 f_{W_1}

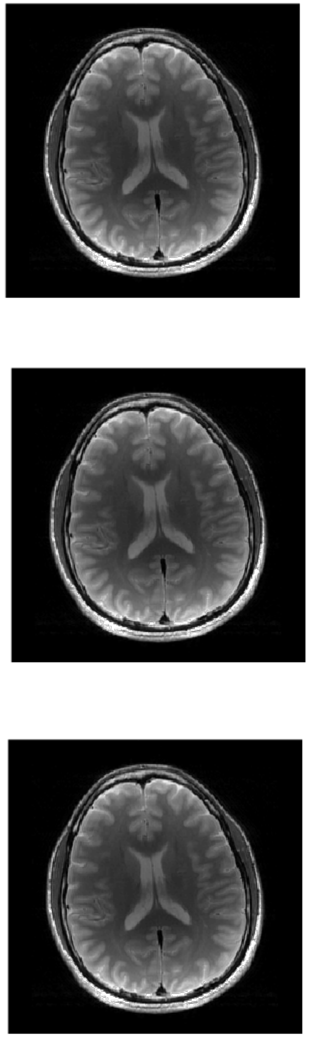
Estimated output

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



Prepared output

y

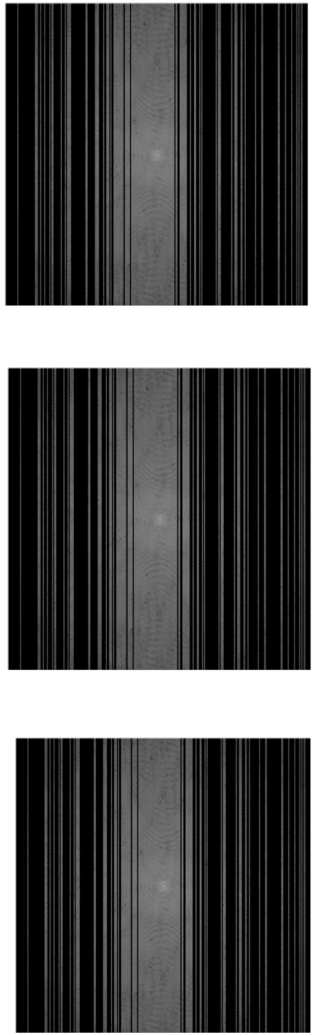


Keywords: loss function, backpropagation

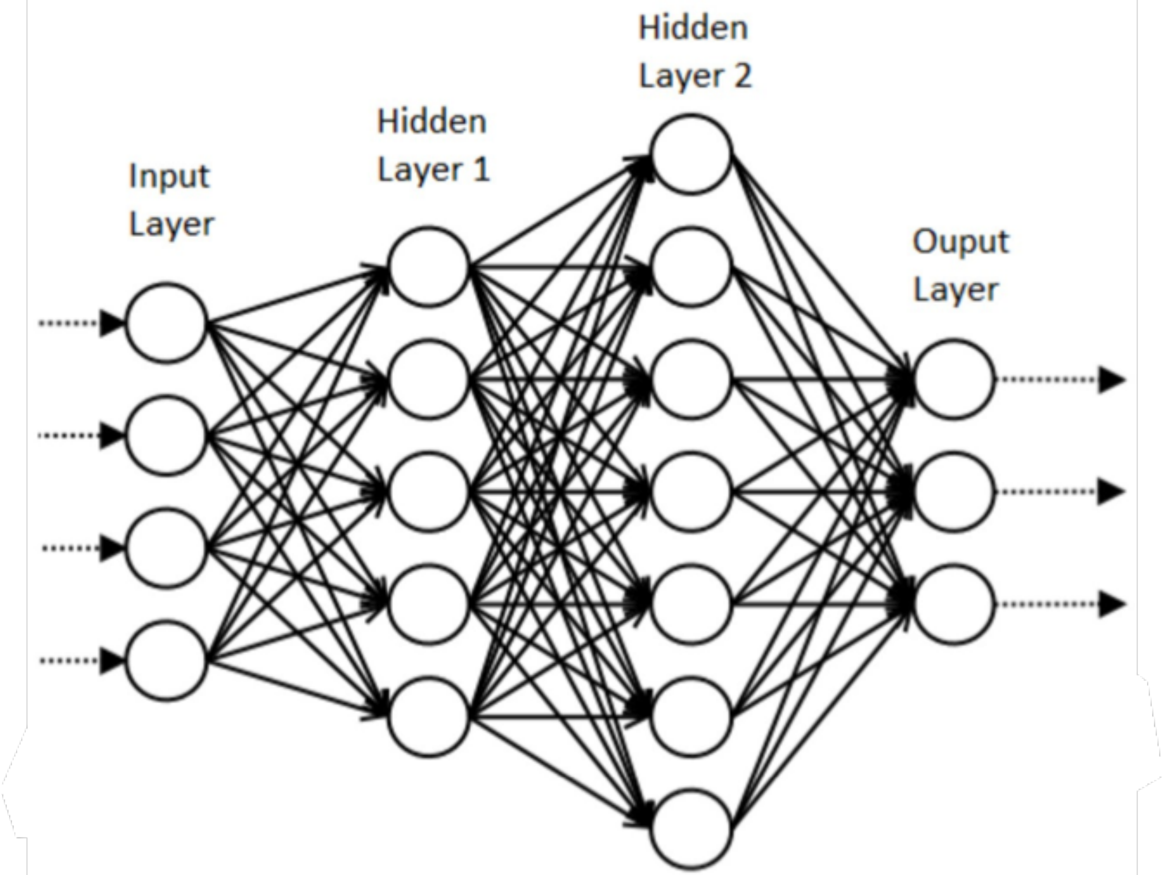
Supervised Model Training

Prepared input

x



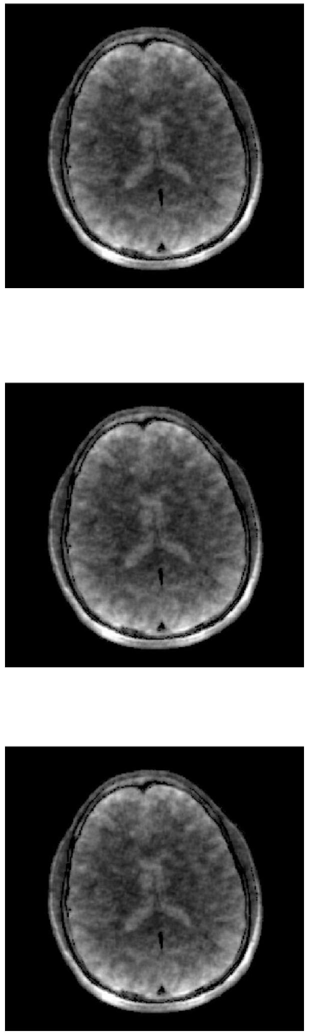
Repeat steps 3 and 4 to continuously improve the weights of the neural network



Iteration 2 f_{W_2}

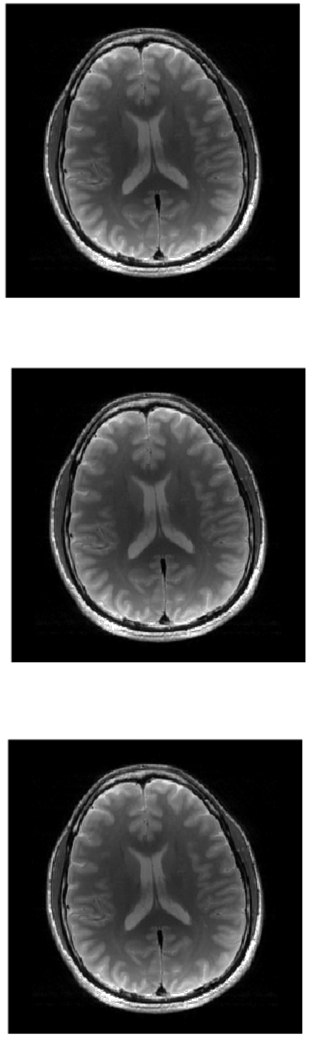
Estimated output

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



Prepared output

y

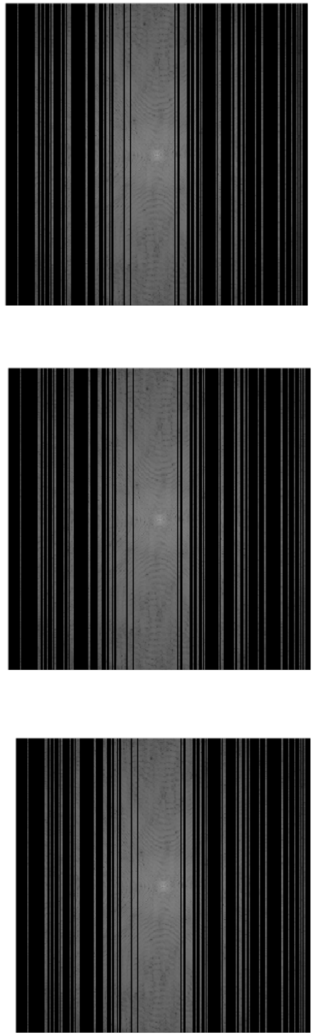


Keywords: loss function, backpropagation

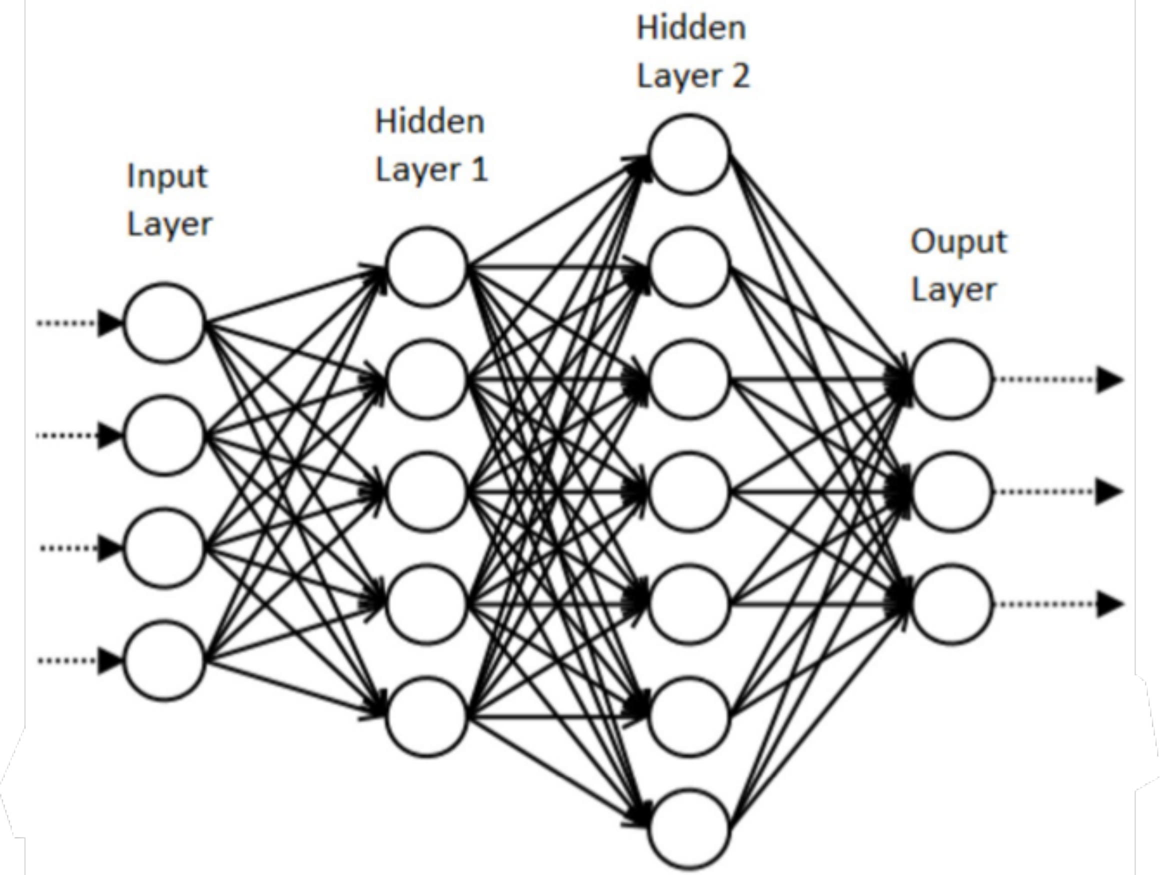
Supervised Model Training

Prepared input

x



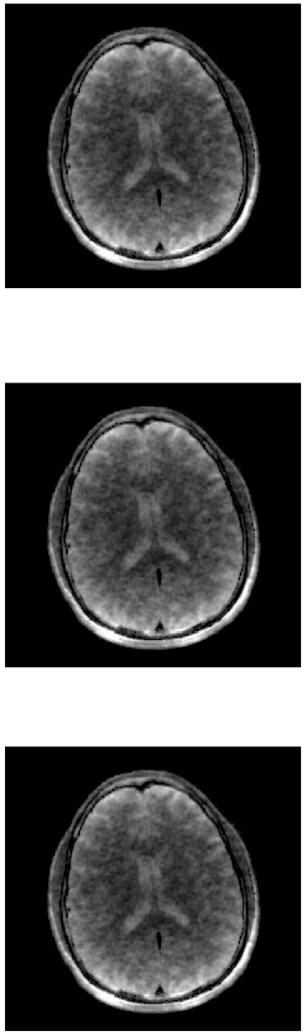
Repeat steps 3 and 4 to continuously improve the weights of the neural network



Iteration 20 $f_{W_{20}}$

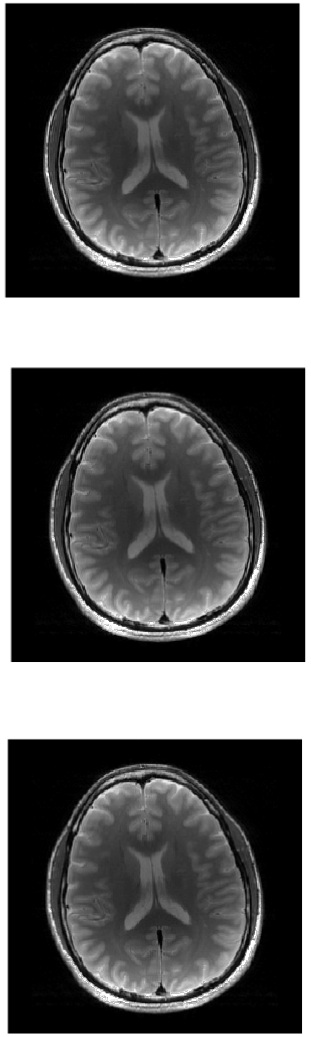
Estimated output

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



Prepared output

y

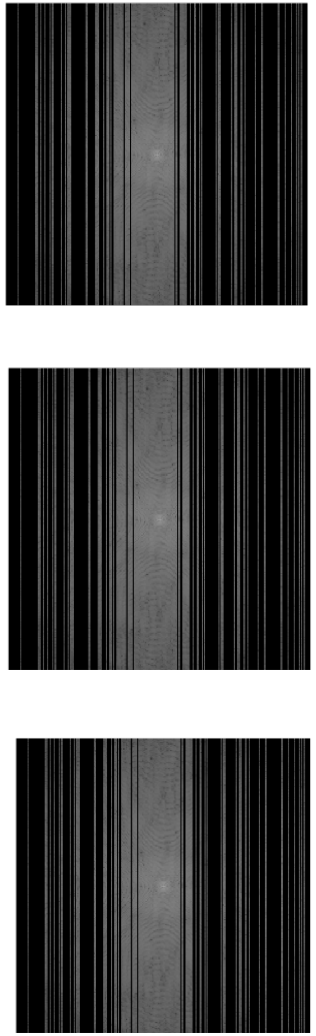


Keywords: loss function, backpropagation

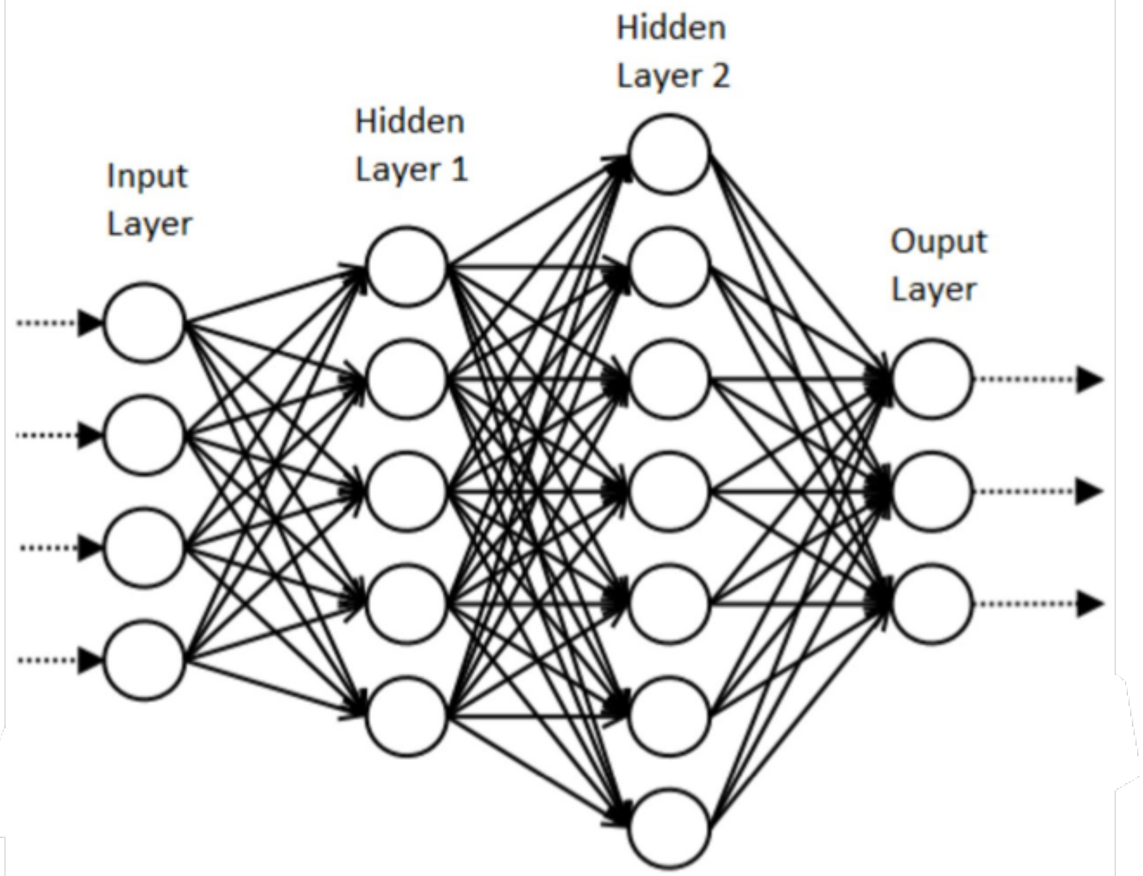
Supervised Model Training

Prepared input

x



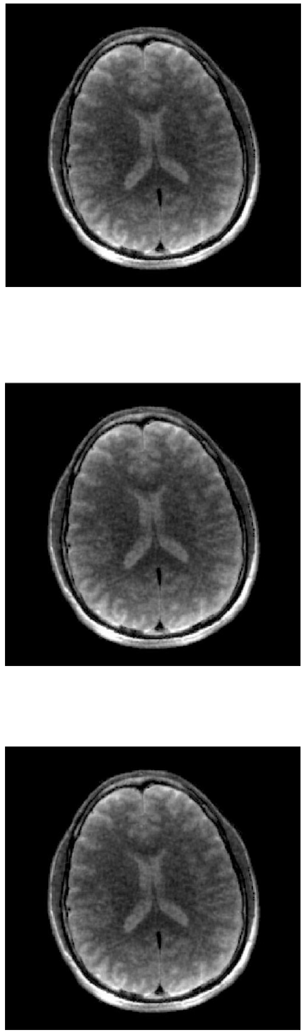
Repeat steps 3 and 4 to continuously improve the weights of the neural network



Iteration 30 $f_{W_{30}}$

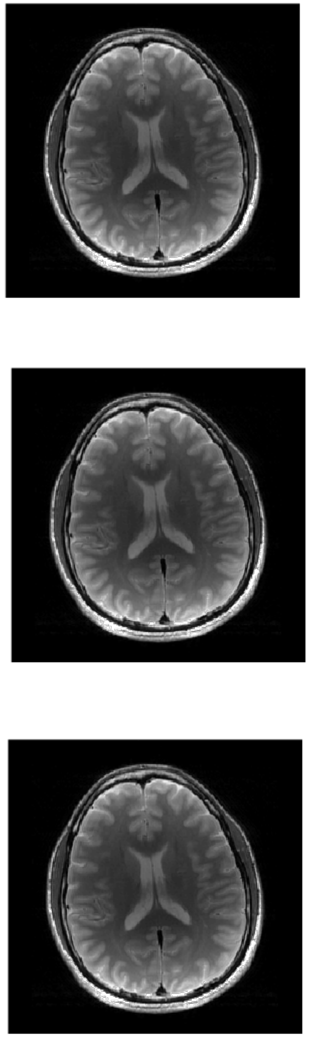
Estimated output

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



Prepared output

y



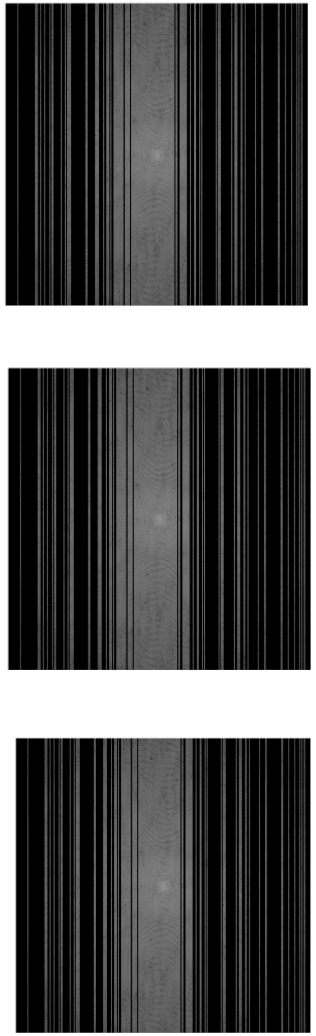
Keywords: loss function, backpropagation

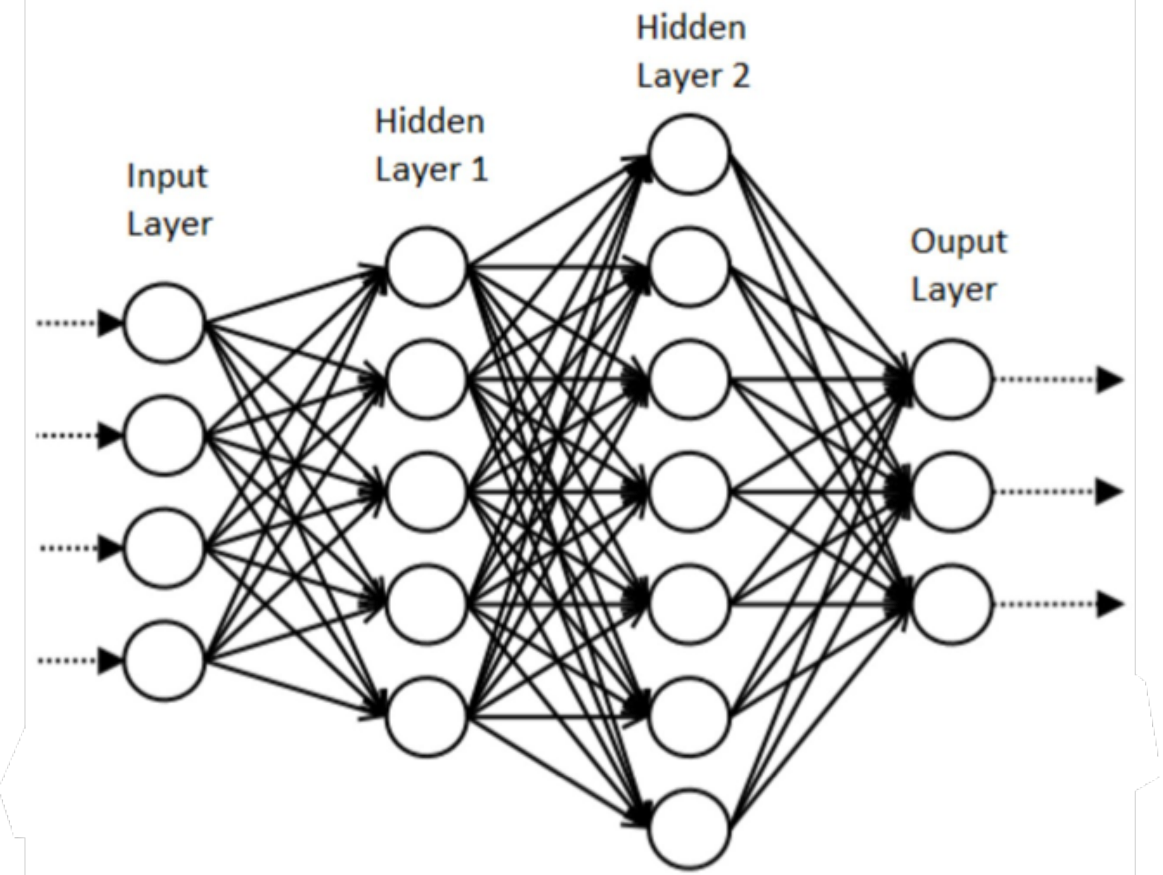
Supervised Model Training

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

Prepared input

x

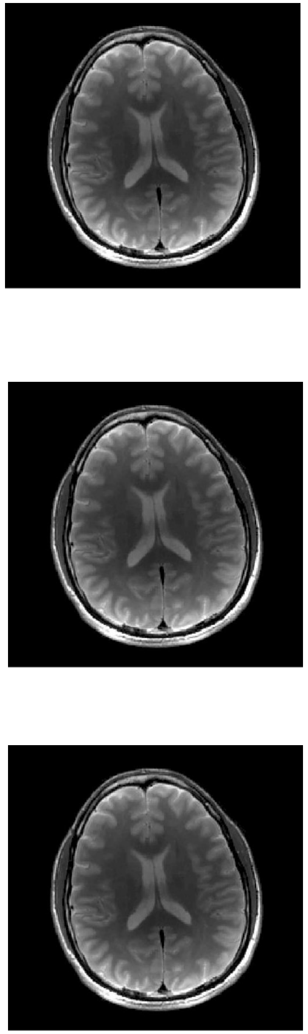




Iteration 100 $f_{W_{100}}$

Estimated output

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



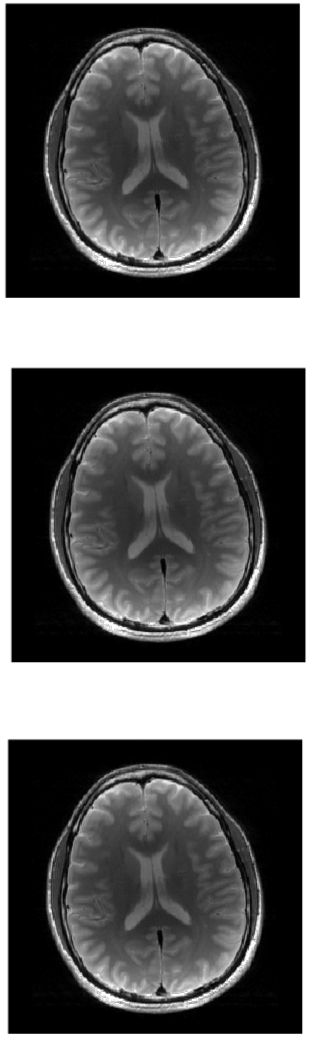
$\approx$

$\approx$

$\approx$

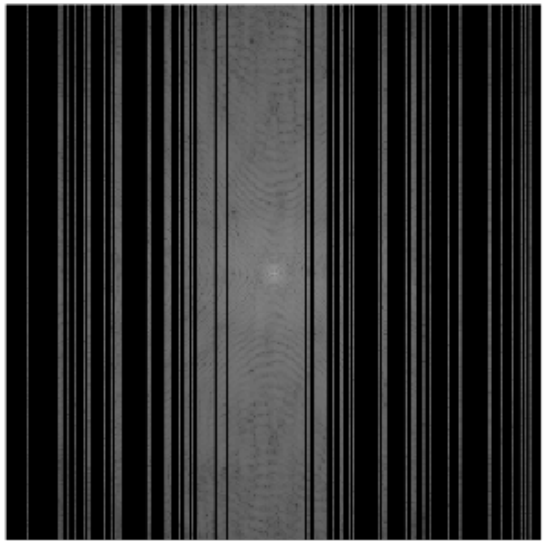
Prepared output

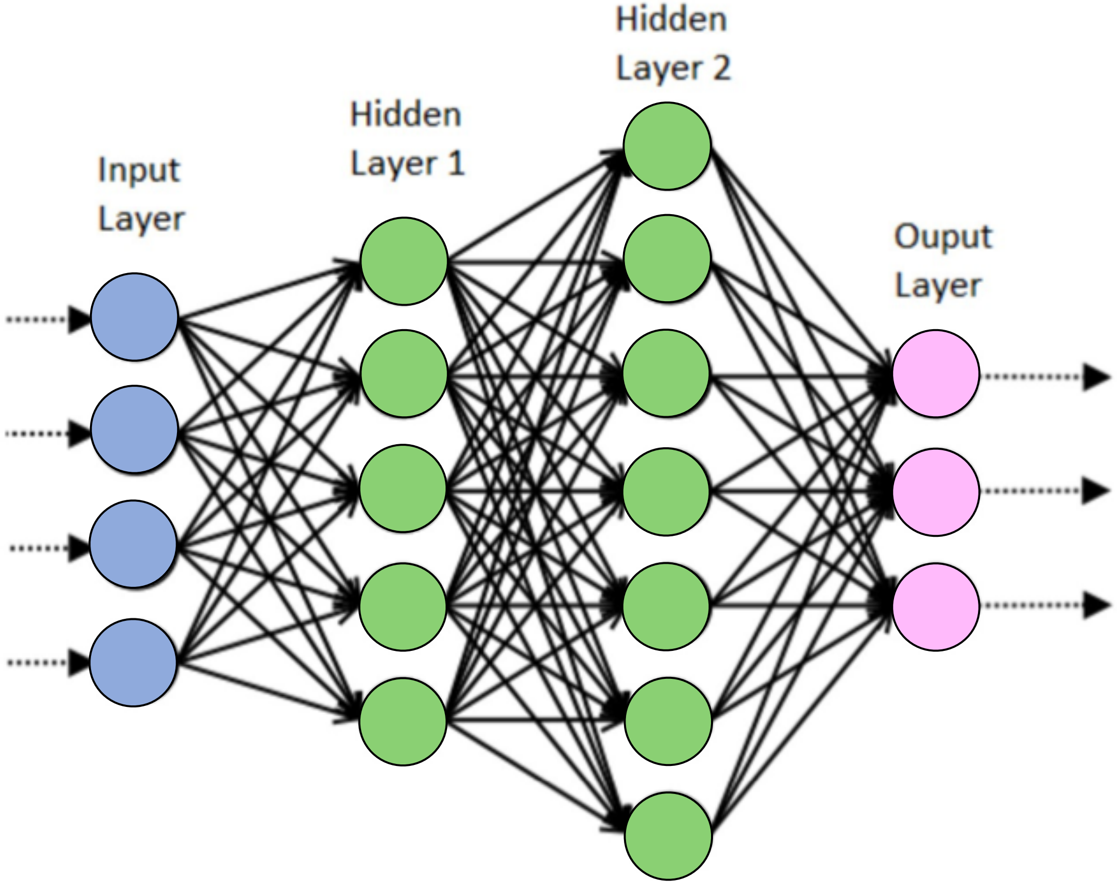
y



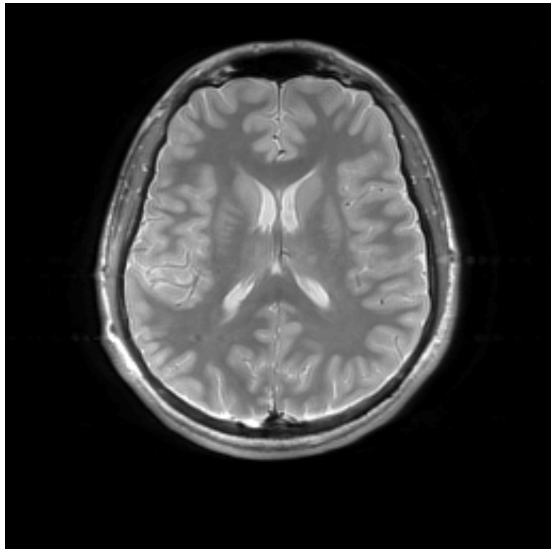
Test the Trained Model

Acquired undersampled k-space data that you wish to reconstruct





Reconstructed image



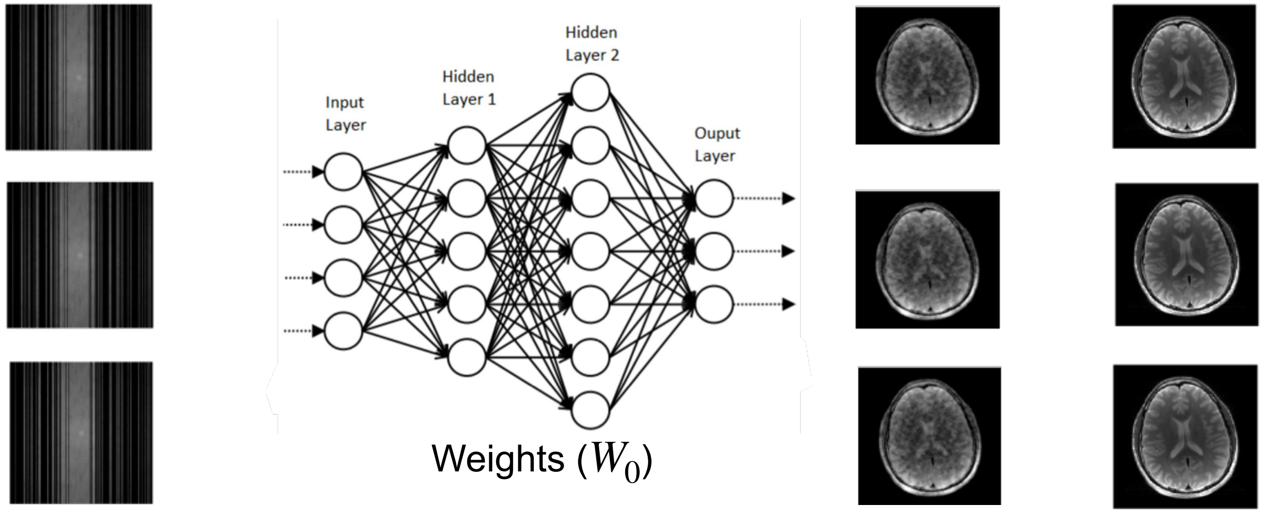
Trained model

$$f_{W^*}$$

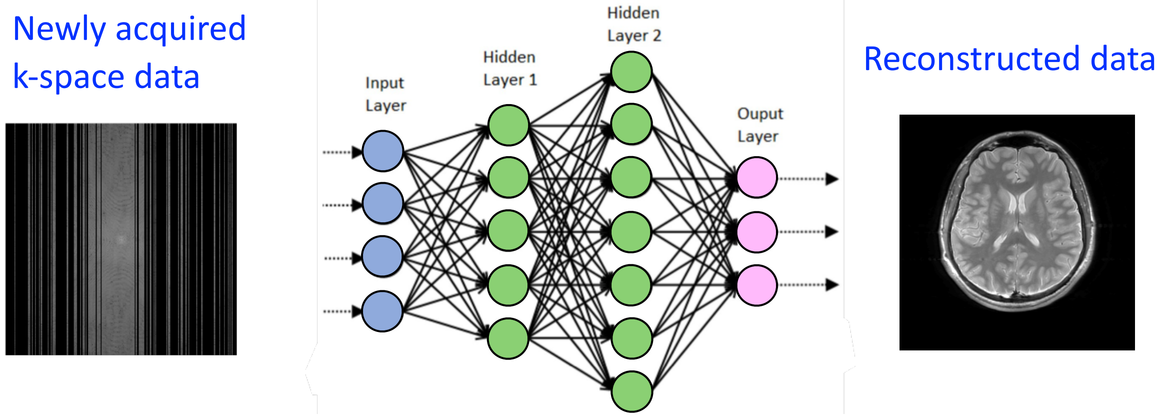
Keywords: training/validation/test data, overfitting, regularization, early stopping, data augmentation

Accelerated MRI Using Deep Learning

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

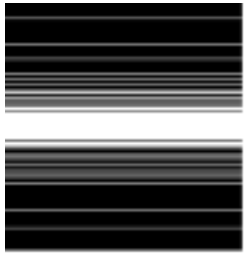


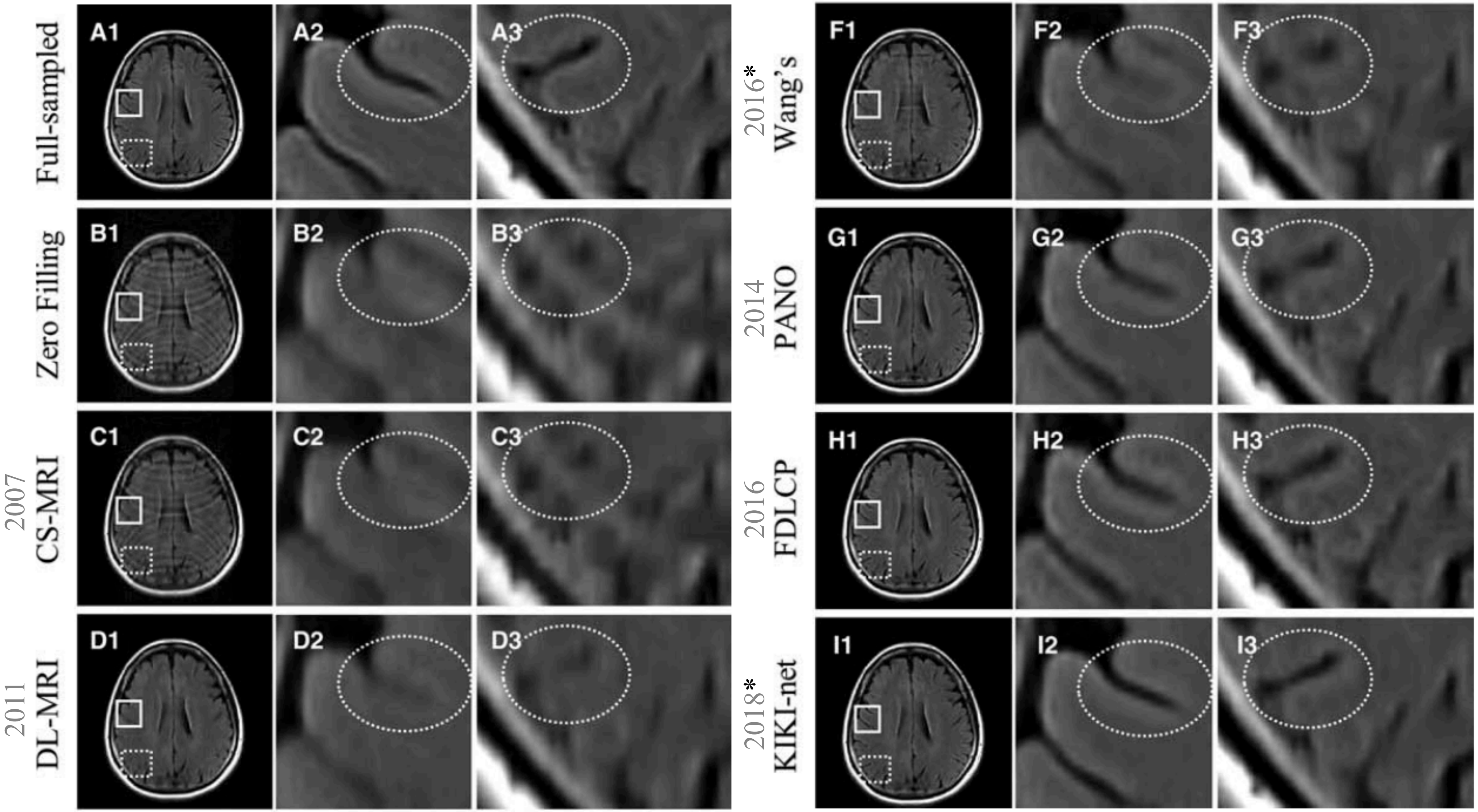
- Test phase: Reconstruct new data using the trained deep neural network



Cross-domain CNNs for Reconstructing Undersampled MRI

T_2-FLAIR
(R=4)

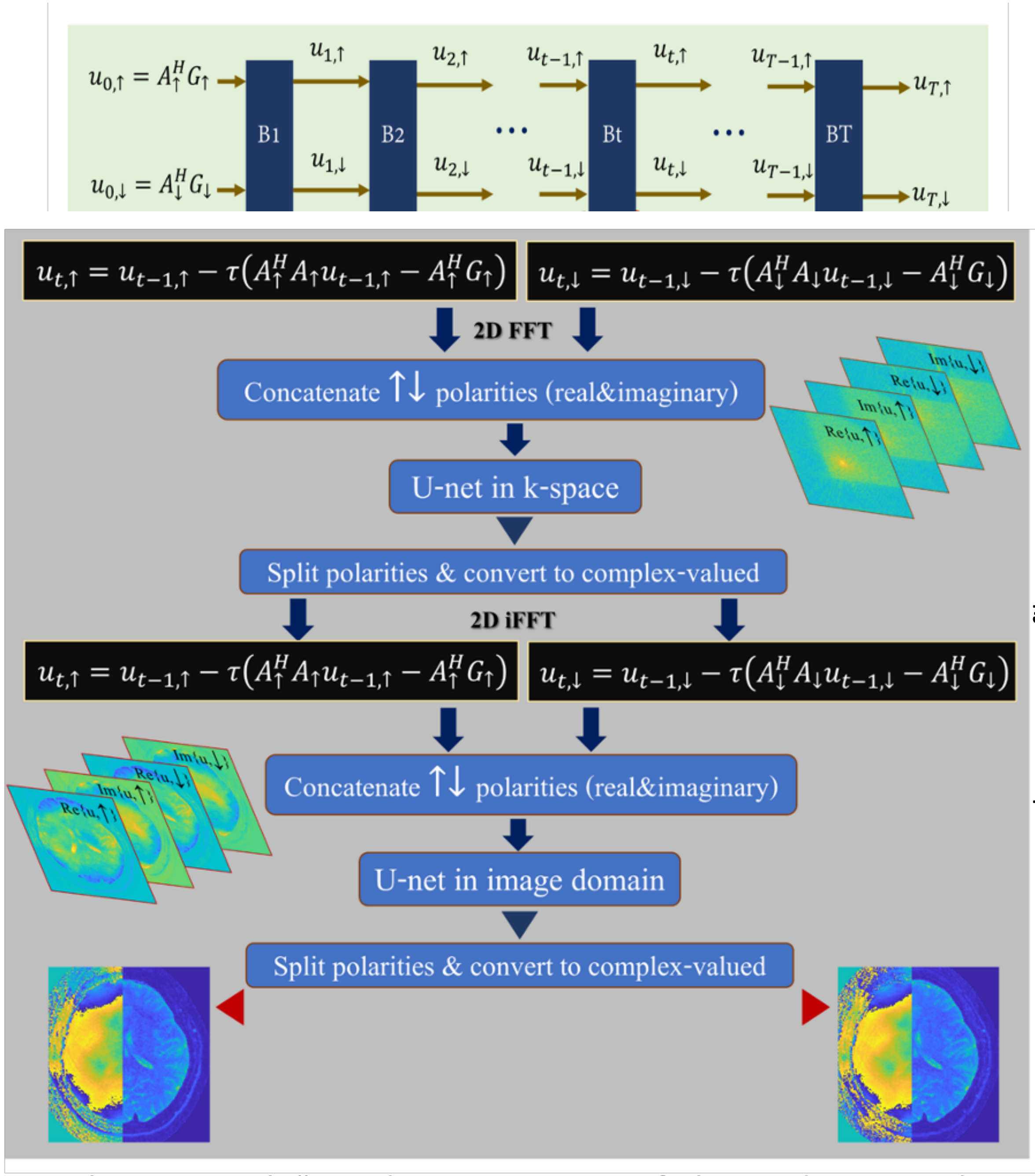




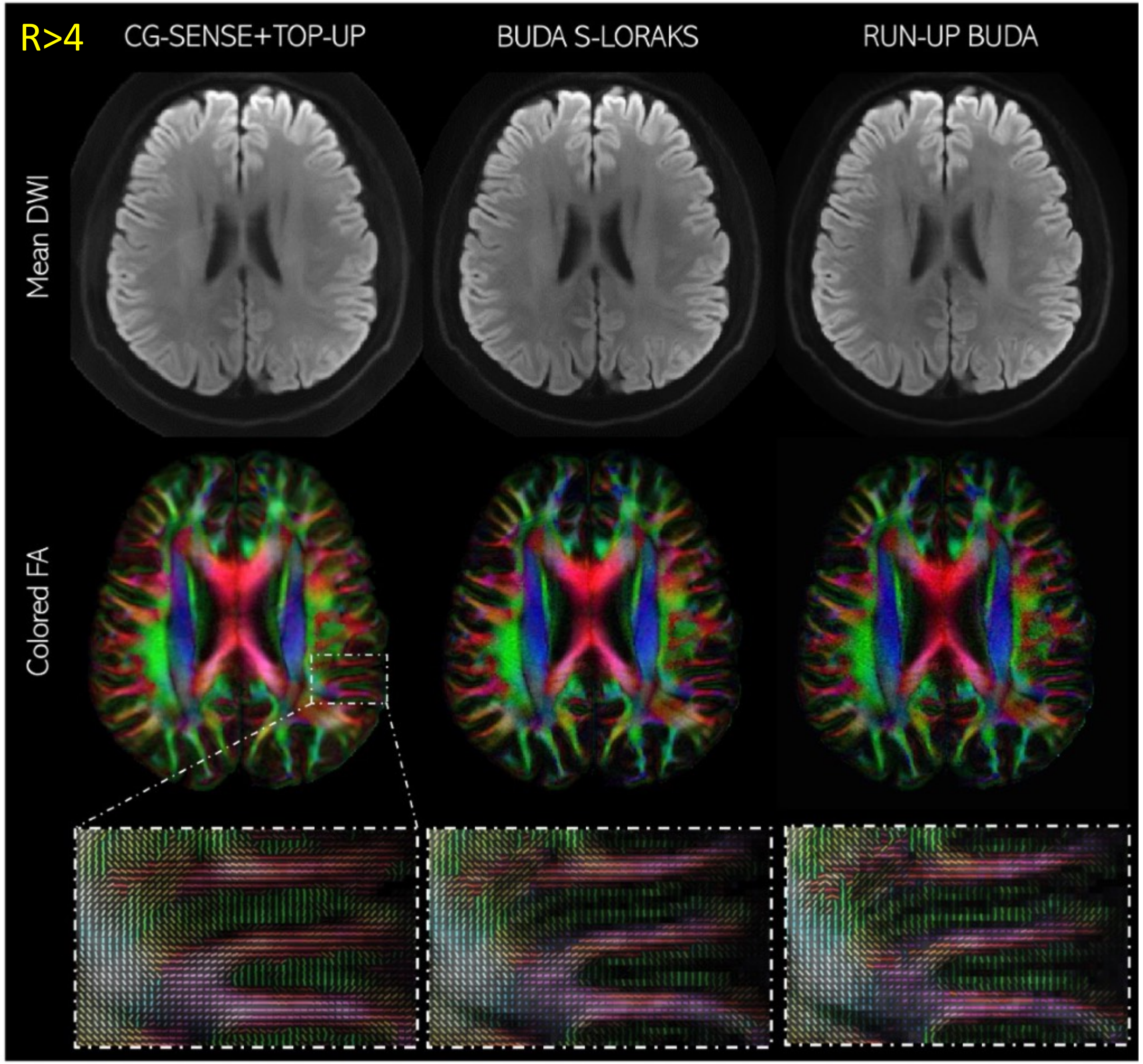
Eo, Taejoon, et al. "KIKI-net: cross-domain convolutional neural networks for reconstructing undersampled magnetic resonance images." Magnetic resonance in medicine 80.5 (2018): 2188-2201.

*deep learning based methods

88x faster recon time



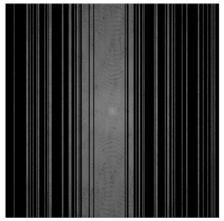
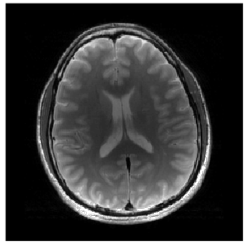
colors represent fiber tract orientations



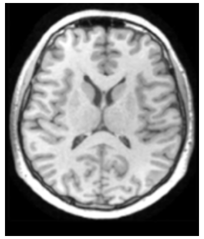
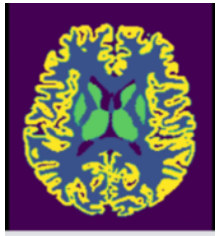
Yarach, Uten et al. “Rapid reconstruction of Blip up-down circular EPI (BUDA-cEPI) for distortion-free dMRI using an Unrolled Network with U-Net as Priors.” Proceedings of the 30th Scientific Meeting of ISMRM. Online Conference. 2022.

Deep Learning

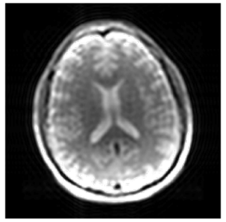
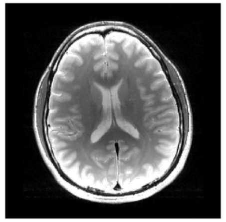
- We can use a deep artificial neural network to approximate any functions by modifying its weight
  - MRI reconstruction function

k-space data  $f_{recon,W}$  Reconstructed image

  - MRI segmentation function

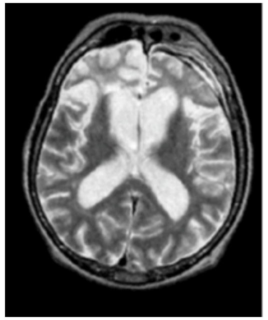
Image-space data  $f_{segment,W}$  Segmentation map

  - MRI super-resolution function

Low-resolution image-space data  $f_{sr,W}$  High-resolution image-space data

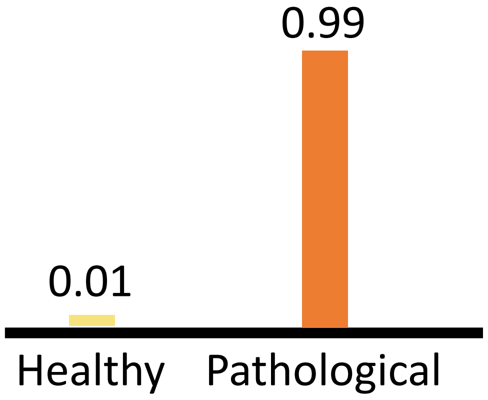
Deep Learning

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

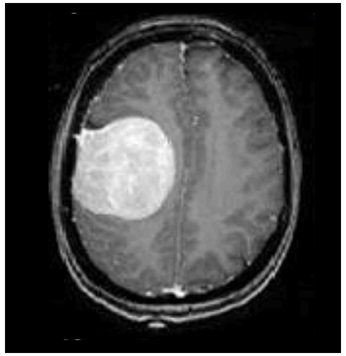


Doesn’t require hand-crafted features

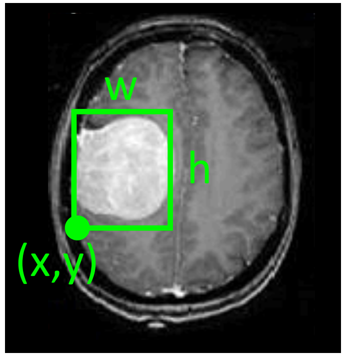
$f_{classif,W}$



  - Detection function



$f_{detection,W}$



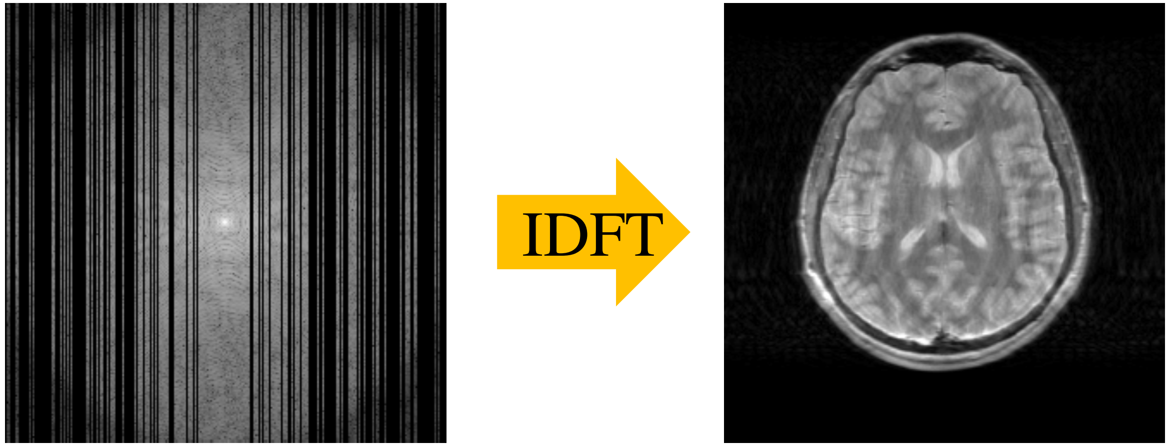
class: tumor

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



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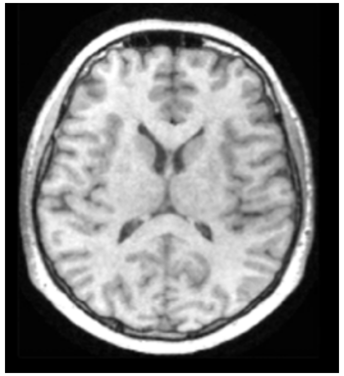
Summary

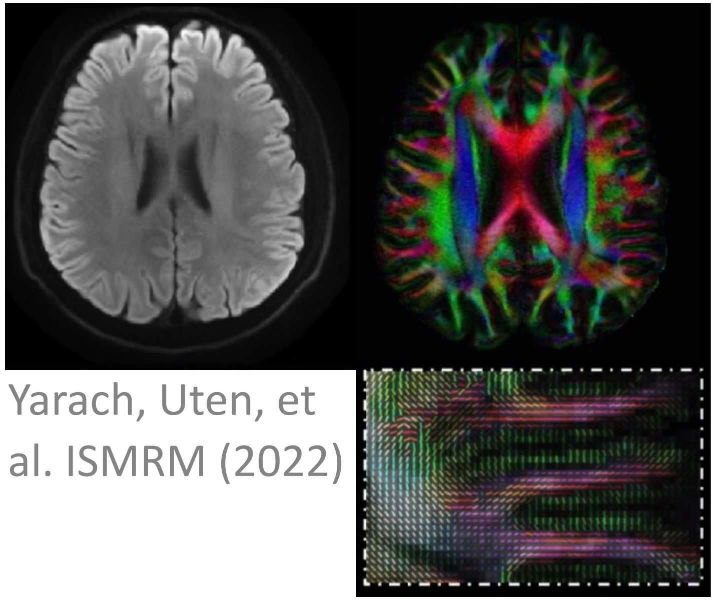
- Deep Learning for MRI
  - With lots of training data, supervised deep learning is an attractive approach for MR image reconstruction, analysis, quantification, and diagnosis
  - Other types of learning have recently gained in importance
- Current Challenges
  - Robustness
    - Uncontrollable factors
    - 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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1891

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