Compressed Sensing & Artificial Intelligence

M229 Advanced Topics in MRI

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2021.05.27

Class Business

- Final project abstract / presentation
  - Abstract due on 6/4 by 5pm
  - Recorded presentation file (5-6min) due on 6/7 by 5pm
  - Final project presentation and Q&A (<5min) session on 6/8 (10-12pm)
- Office hours
  - Instructors: Fri 10-12 noon
- Online course evaluation

Today’s Topics

- Compressed sensing
  - Compressibility or sparsity
  - Incoherent measurement
  - Reconstruction
- Machine learning / artificial intelligence
  - Model evaluation
  - Model selection

Fast MRI Techniques

- Many reconstruction methods minimize aliasing artifacts by exploiting *information redundancy* (or *prior knowledge*)
  - Parallel imaging
  - Compressed sensing

Donoho, IEEE TIT, 2006
Candes et al., Inverse Problems, 2007

What is Compressed Sensing?

- CS is about acquiring a sparse signal in a most efficient way (subsampling) with the help of an incoherent projecting basis

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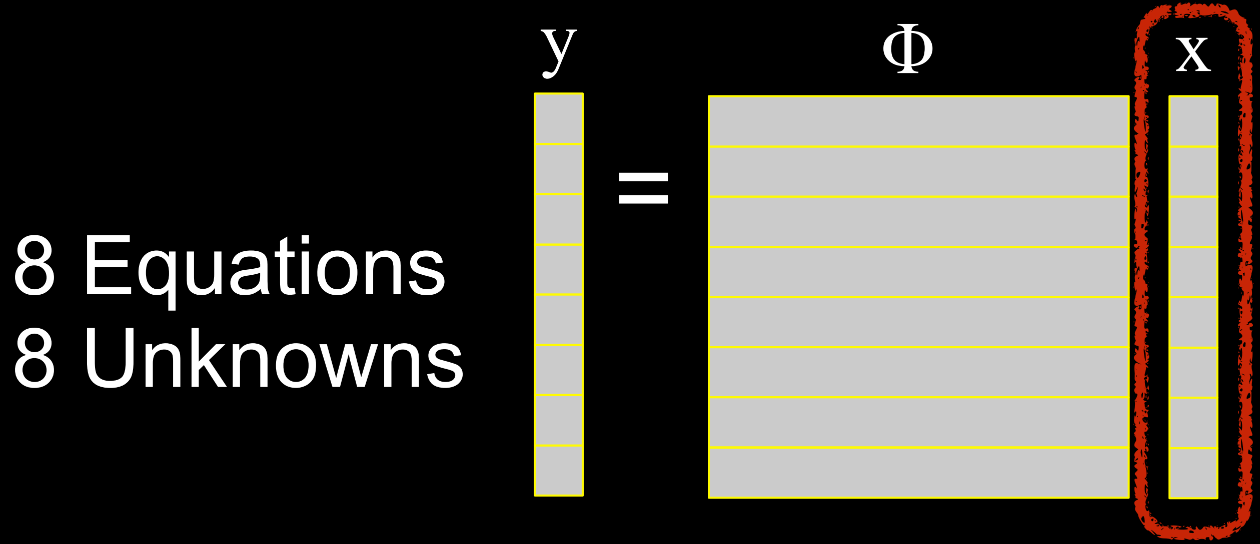
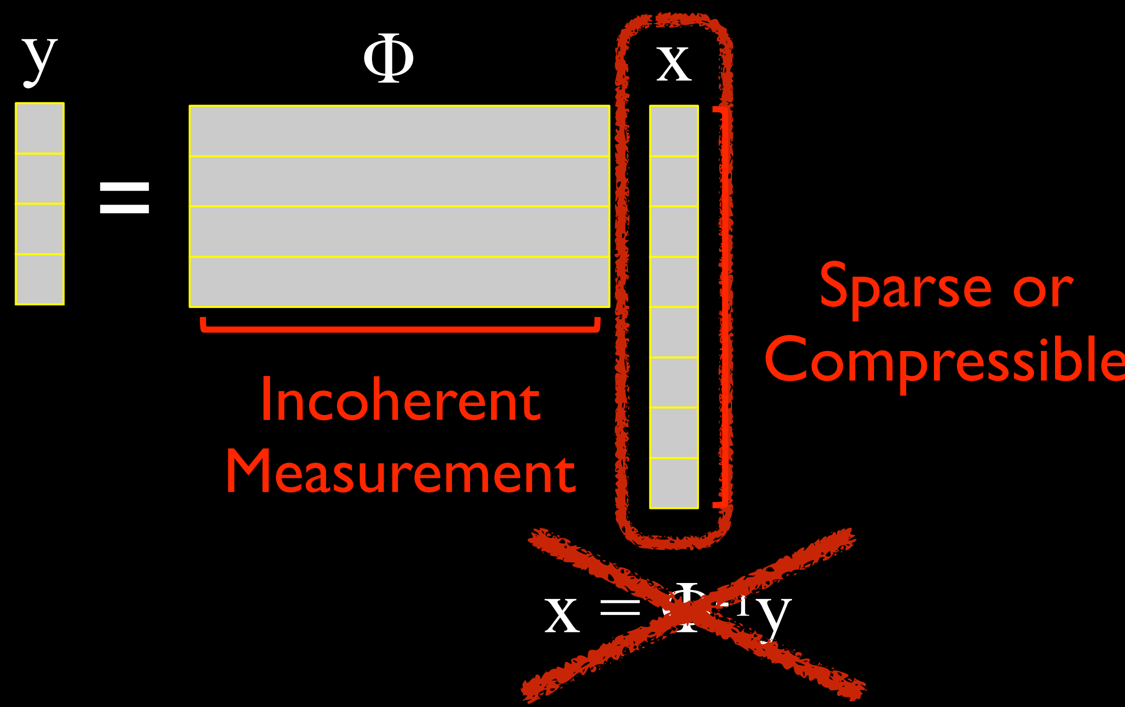


$x = \Phi^{-1} y$

What is Compressed Sensing?

- CS is about acquiring a sparse signal in a most efficient way (subsampling) with the help of an incoherent projecting basis

4 Equations
8 Unknowns



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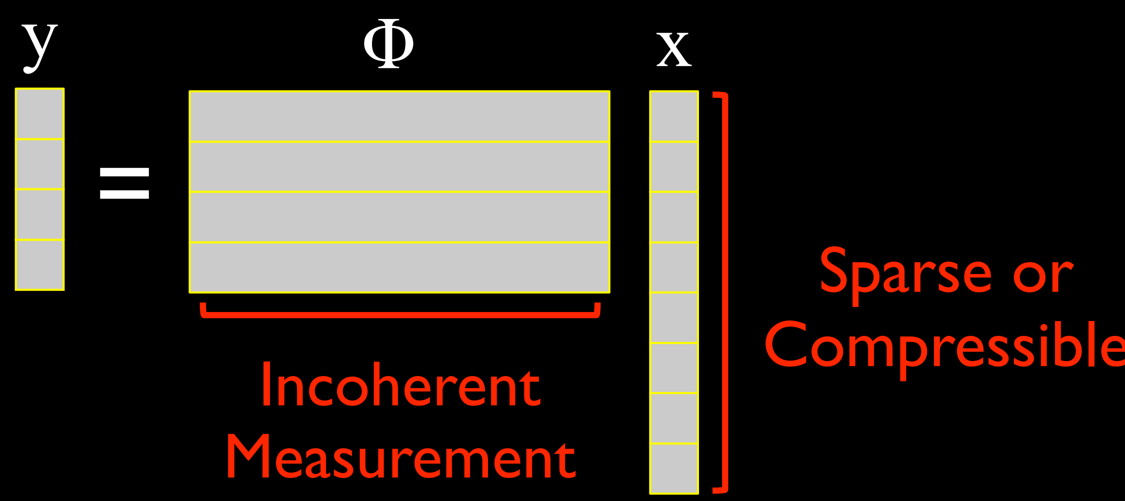
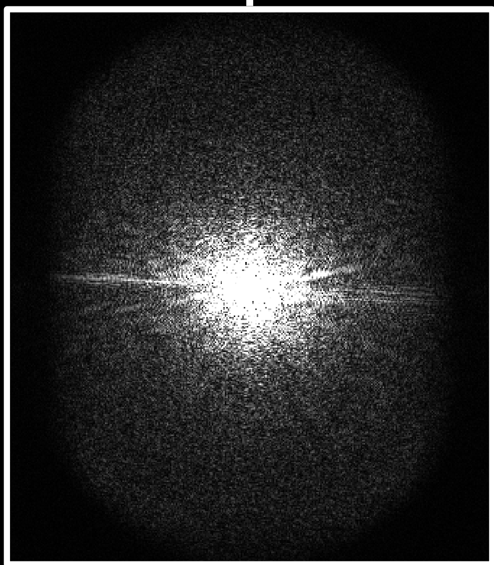


We still can find 8 unknowns!

Compressed Sensing MRI

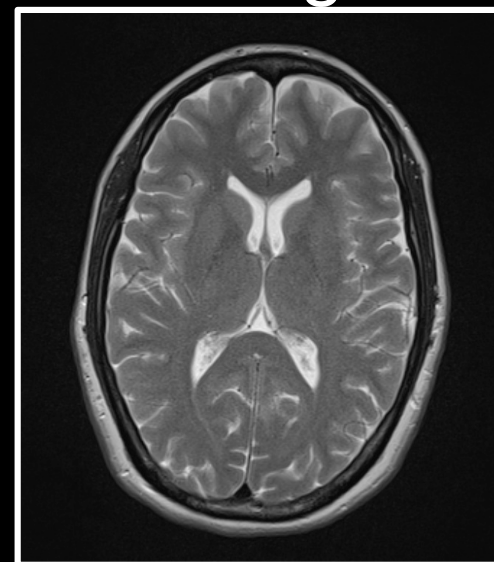
k-space



Inverse Fourier Transform Φ^{-1}

$$x = \Phi^{-1} y$$

Image



Compressed Sensing MRI

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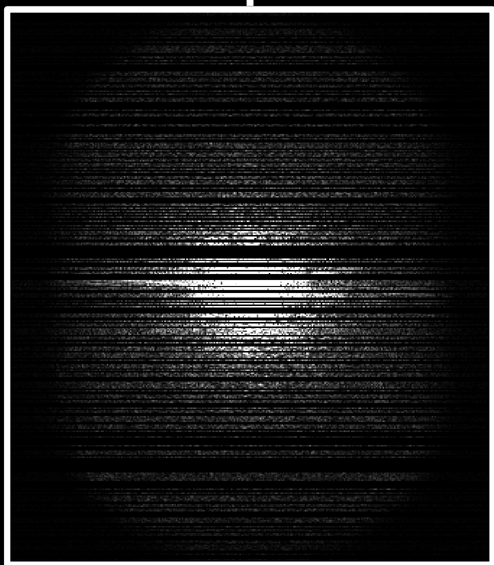
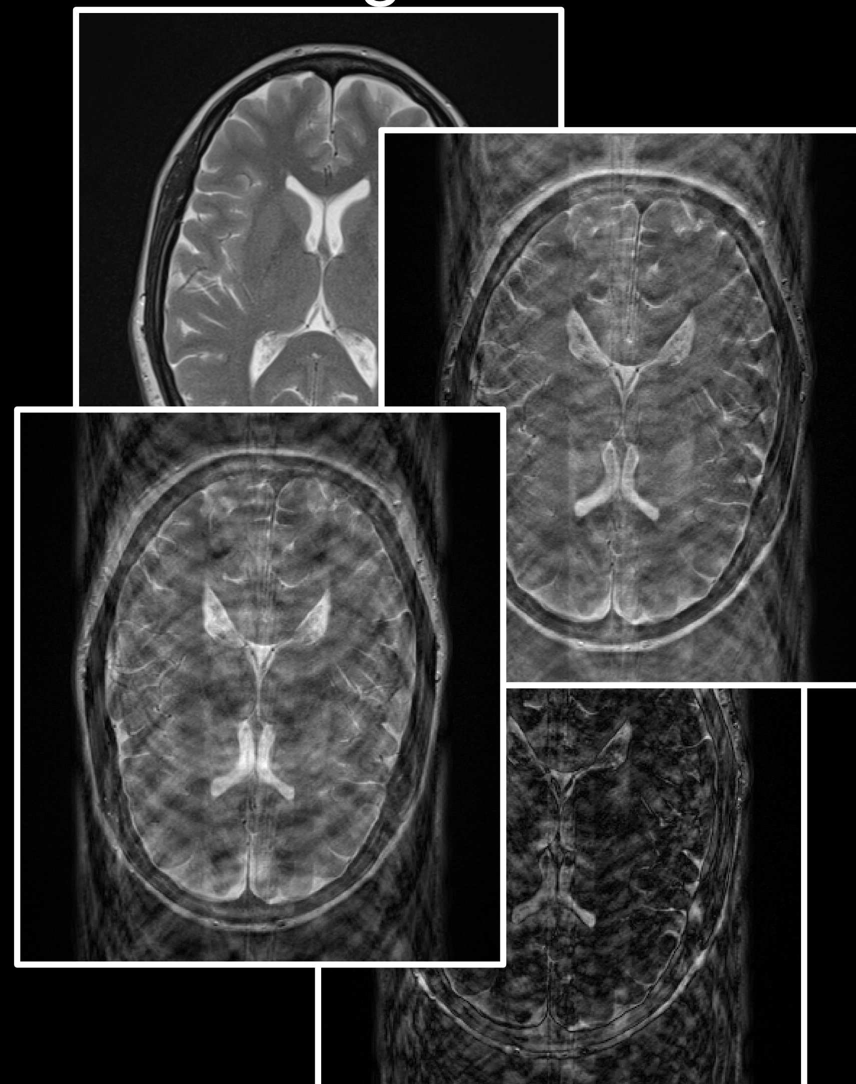


~~Inverse Fourier Transform~~ $\cancel{\Phi^{-1}}$

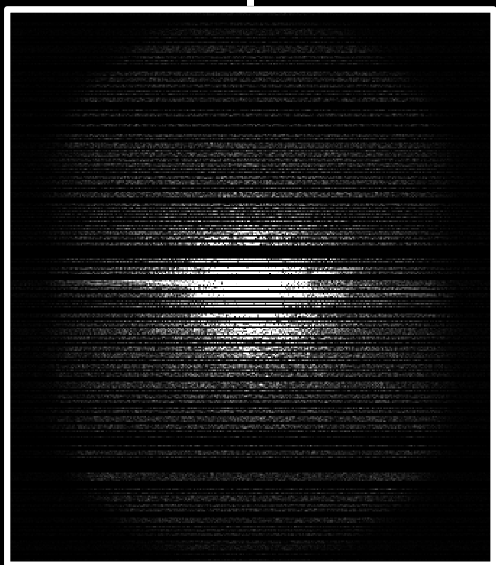
$$\cancel{x = \Phi^{-1} y}$$

Image



Compressed Sensing MRI

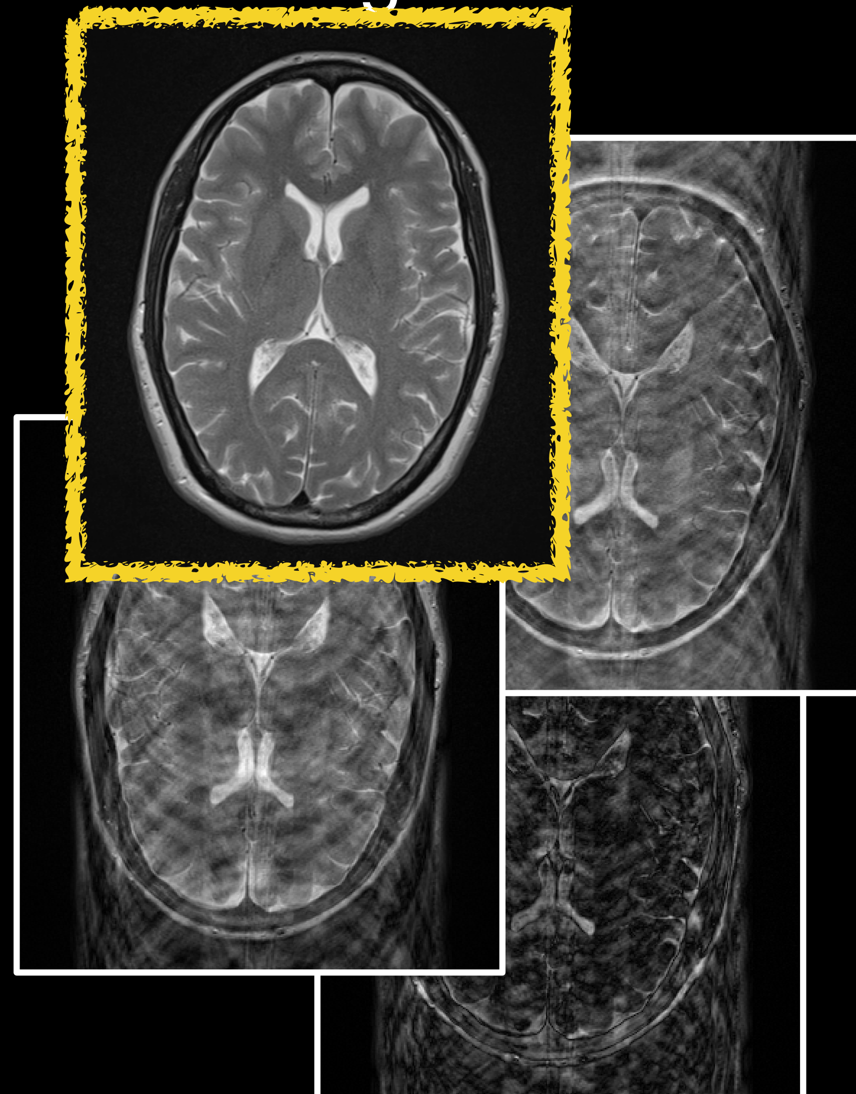
k-space



~~Inverse Fourier Transform~~ $\cancel{\Phi^{-1}}$

$$\cancel{x = \Phi^{-1} y}$$

Image



Choose the most compressible image matching data (*systematic optimization*)

Math Background

L0-norm ($|x|_0$): a number of non-zero coefficients

L1-norm ($|x|_1$): a sum of absolute values of coefficients

L2-norm ($|x|_2$): a sum of squared values of coefficients

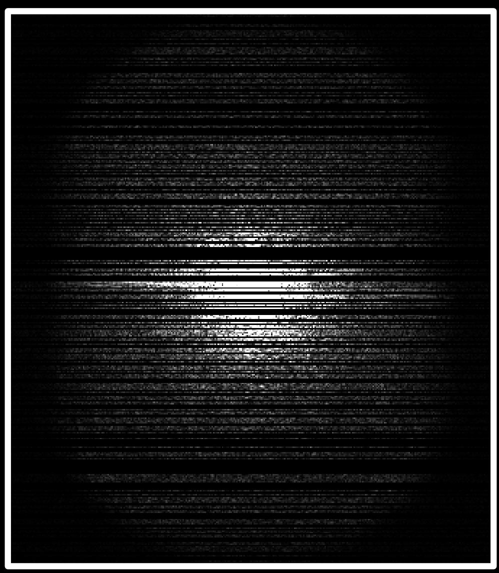
$$
\begin{array}{ccc}
x & x & x \\
\begin{bmatrix} 0 \\ 1 \\ 2 \\ 3 \end{bmatrix} & \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} & \begin{bmatrix} 1 \\ 1 \\ -2 \\ 3 \end{bmatrix}
\end{array}
$$

CS-MRI Reconstruction

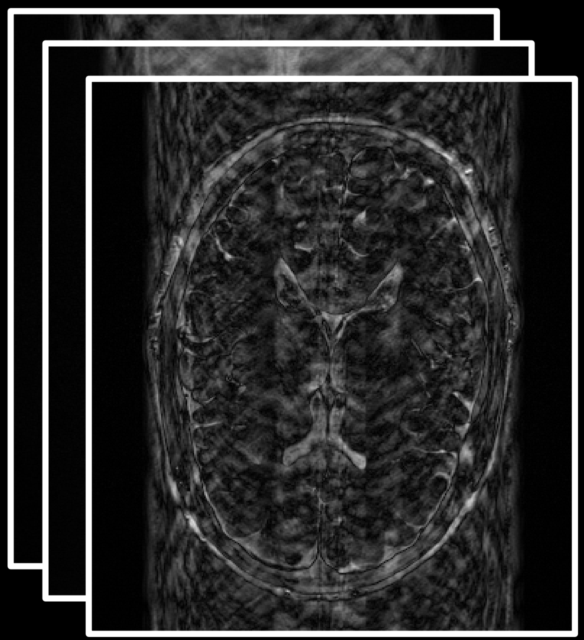
$|y - \Phi x|^2 < \varepsilon$

$w = \Psi x$

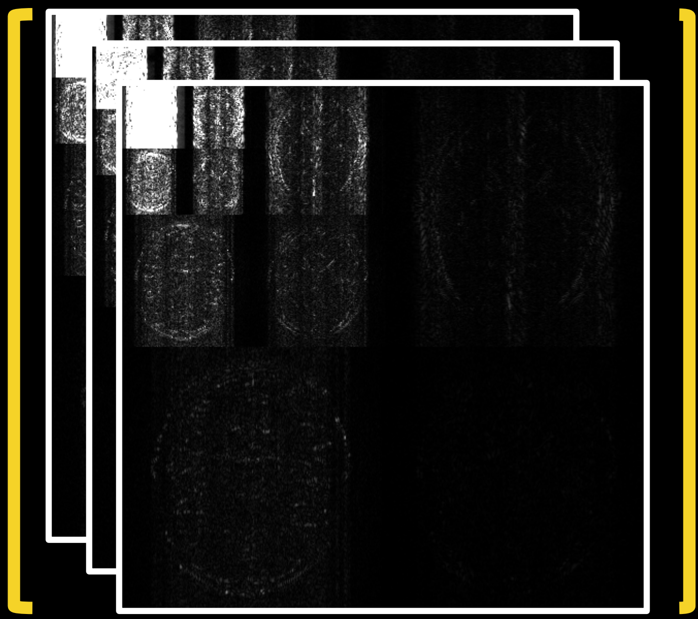
y: k-space



x: Image



w: Wavelet



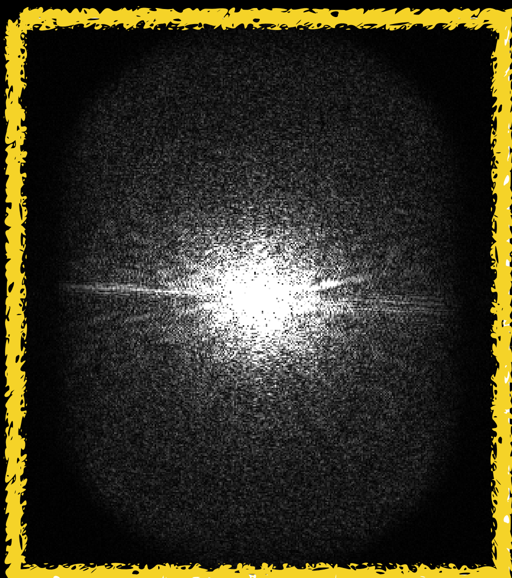
L1-norm

minimize $|\Psi x|_1$

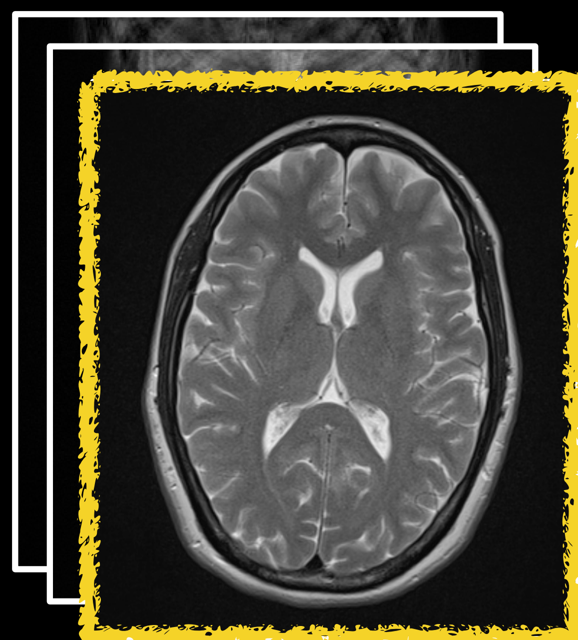
CS-MRI Reconstruction

minimize $F(x): |y - \Phi x|^2 + R(x)$

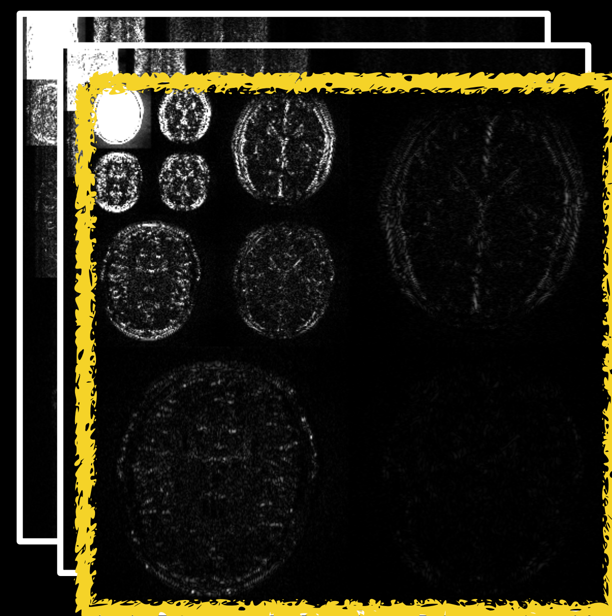
y: k-space



x: Image



w: Wavelet



$y' = \mathrm{FT}(x)$

$x = \Psi^{-1}w$

Three Tenets of CS

$$\text{minimize } F(x): \underbrace{|y - \Phi x|_2^2}_{\text{Data Consistency}} + \underbrace{R(x)}_{\text{Compressibility Constraint}}$$

- Three key elements of Compressed Sensing:

Compressibility

Incoherence

Nonlinear Reconstruction

Compressibility Constraint

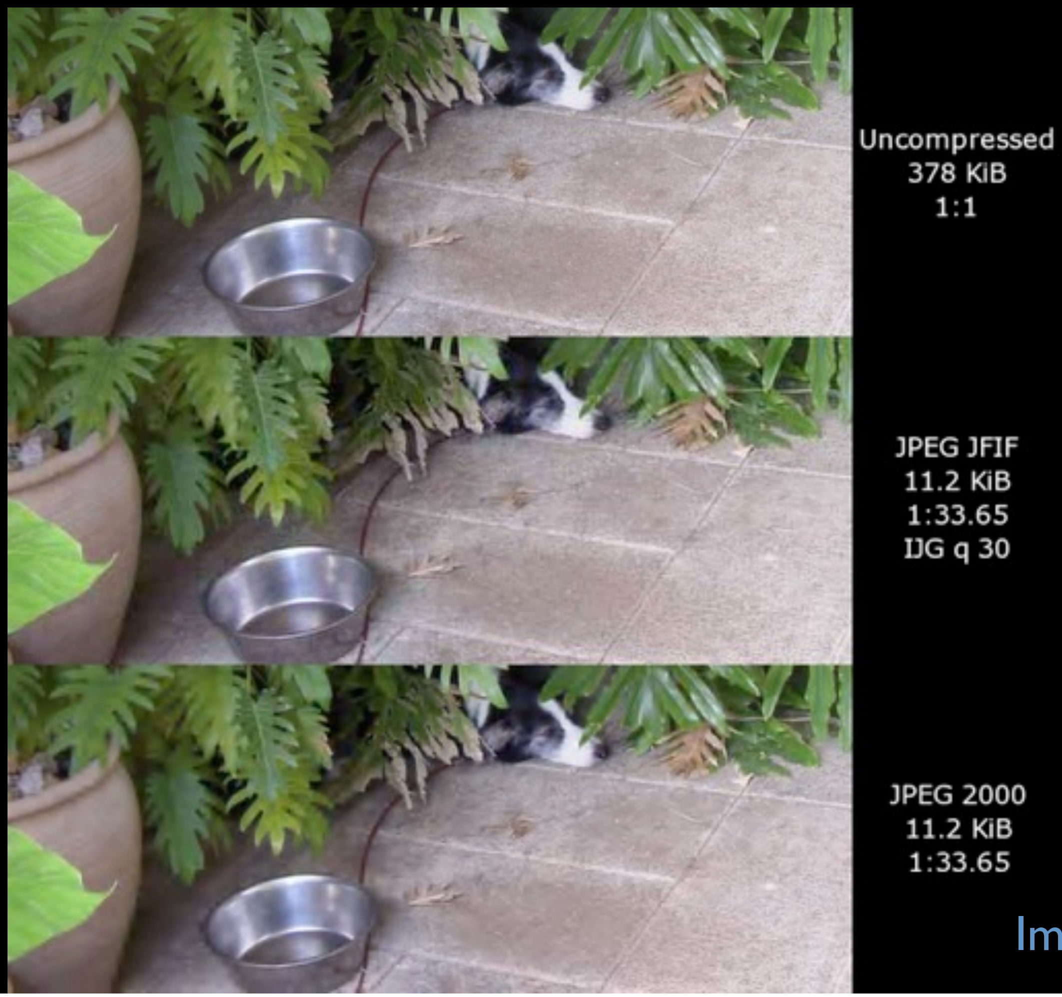
minimize $F(x): |y - \Phi x|^2_2 + \underbrace{R(x)}_{\text{Compressibility Constraint}}$

- $R(x) = \lambda|x|_1$ (*Identity Transform*)
- $R(x) = \lambda|\Psi x|_1$ (*Wavelet Transform*)
- $R(x) = \lambda H(x)$ (*Total Variation*)
- $R(x) = \lambda|x|_*$ (*Rank or Nuclear Norm*)
- Many more…

Wavelet Transform

- Natural images are compressible using wavelet transforms

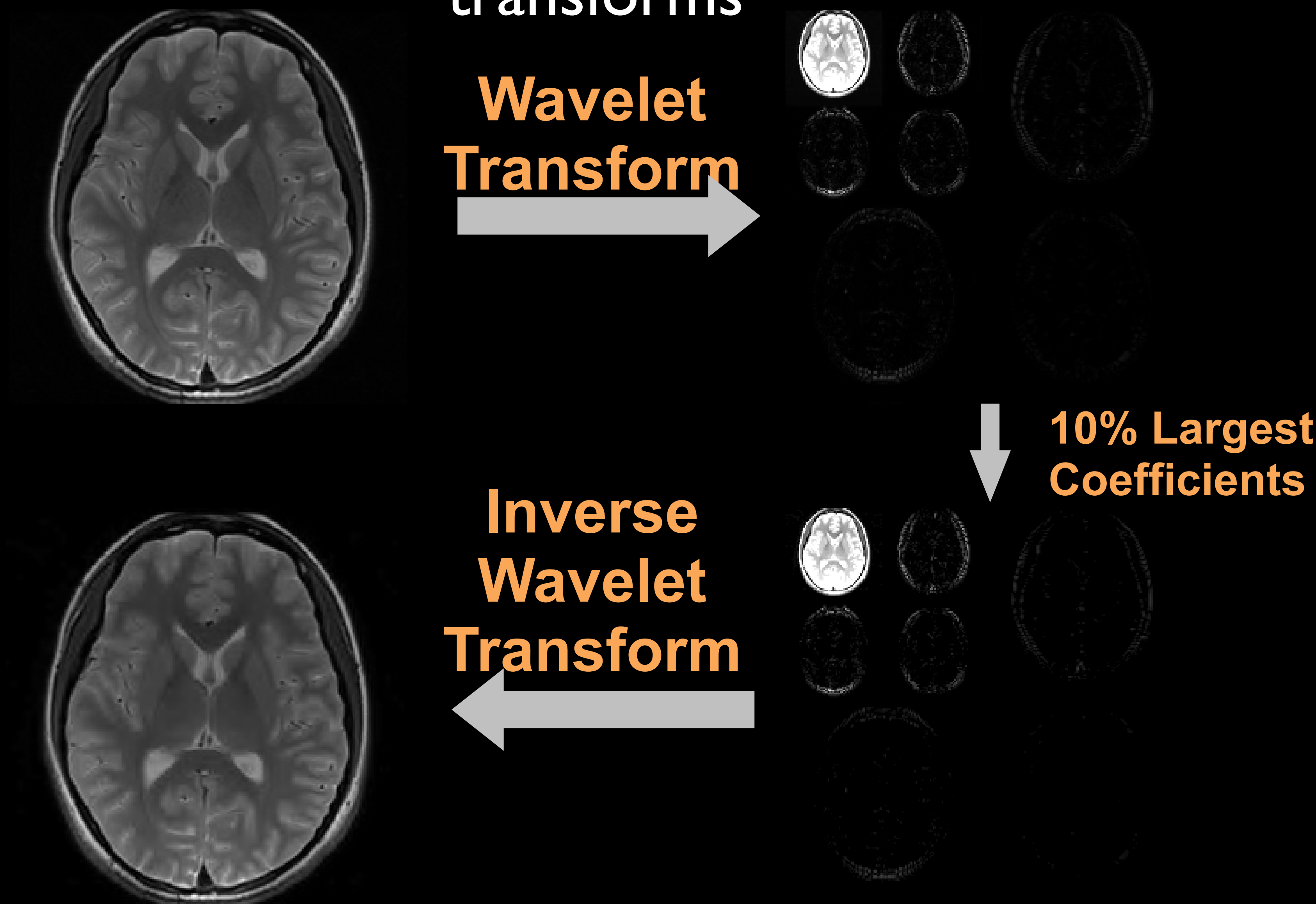
Image Compression Standard: JPEG2000



Images from Wikipedia

Wavelet Transform

MR images are mostly compressible using wavelet transforms



Wavelet Transform

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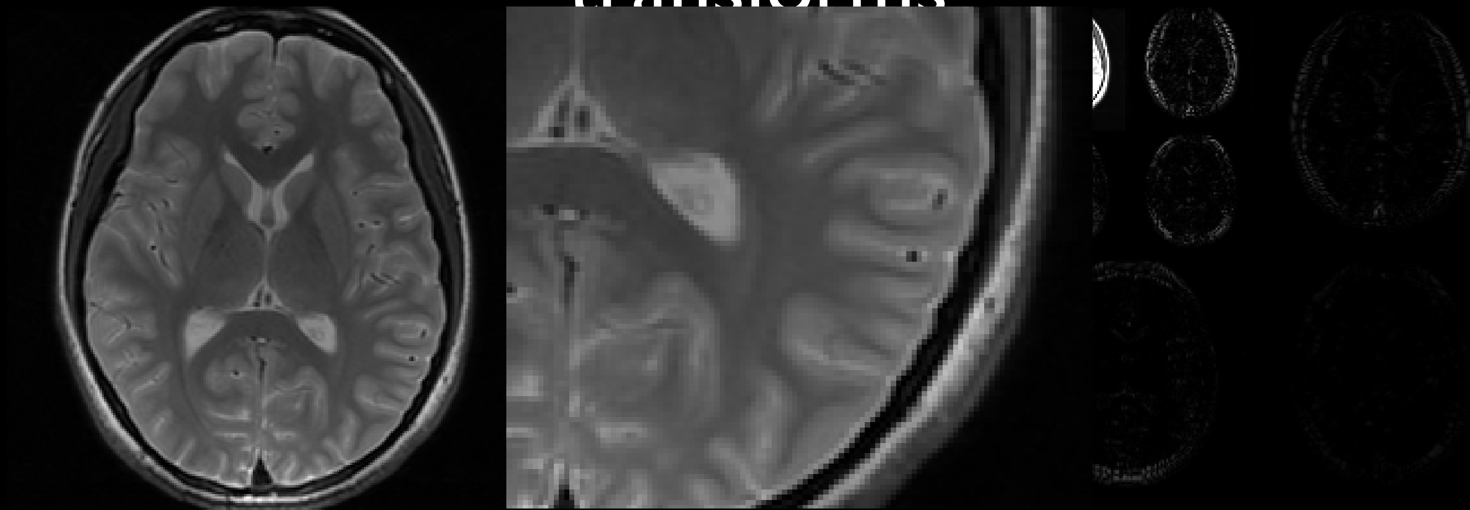
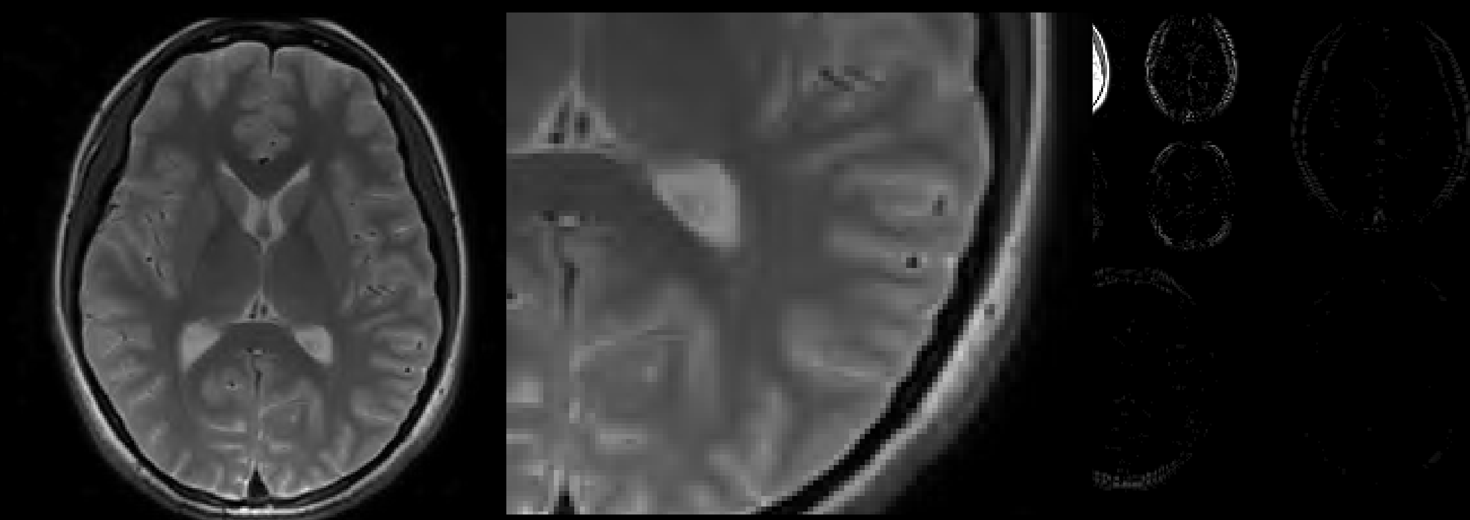
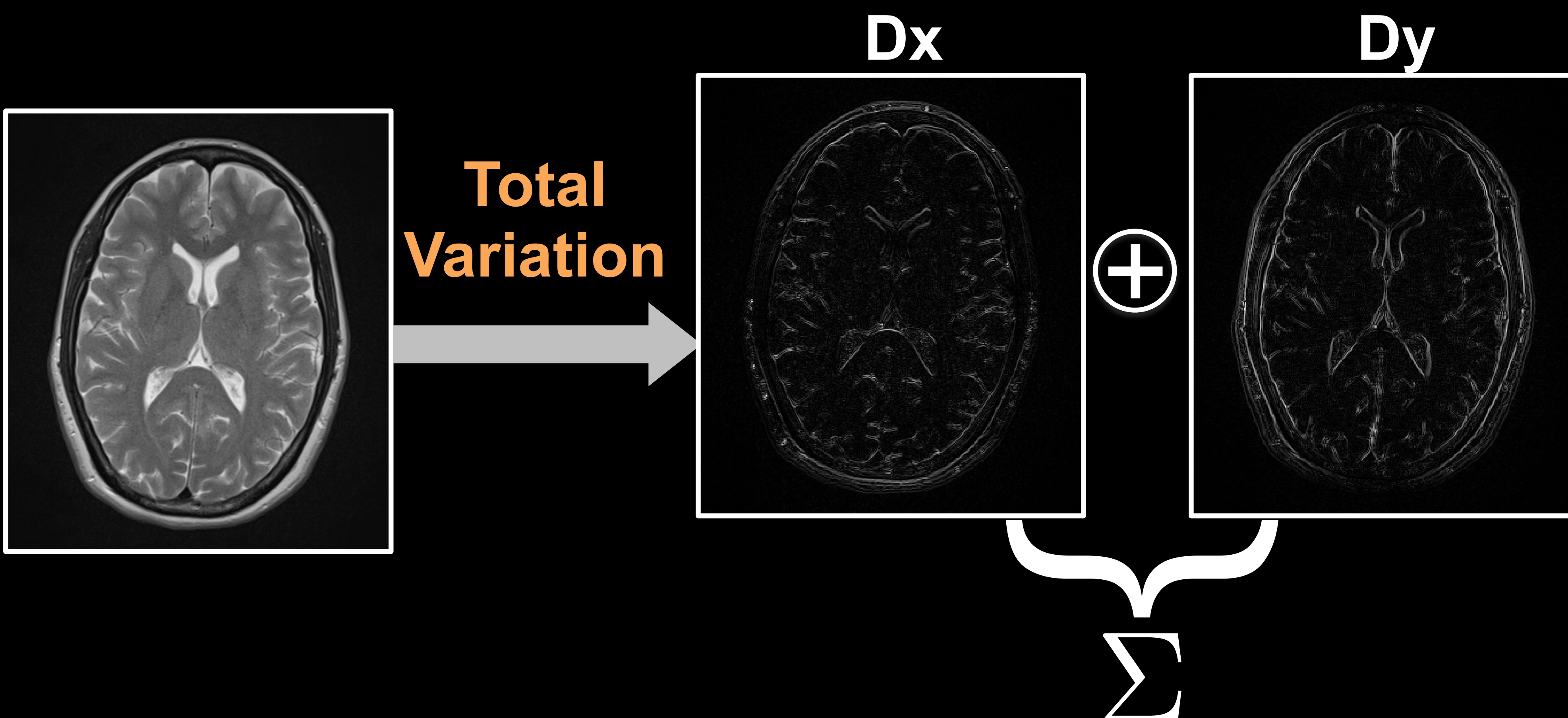


10% Largest Coefficients



Total Variation

$$H(x) = \sum_{i,j} \sqrt{\underbrace{|x_{i+1,j} - x_{i,j}|^2}_{\mathbf{Dx}} + \underbrace{|x_{i,j+1} - x_{i,j}|^2}_{\mathbf{Dy}}}$$



CS-MRI Reconstruction

minimize $F(x): |y - \Phi x|_2^2 + R(x)$

- Minimizing F(x) is non-trivial since R(x) is not <u>differentiable</u>
  - Linear programming is challenging due to high computational complexity
- Simple gradient-based algorithms have been developed:
  - Re-weighted L1 / FOCUSS
  - IST / IHT / AMP / FISTA
  - Split Bregman / ADMM

I.F. Gorodnitsky, et al., J. Electroencephalog. Clinical Neurophysiol. 1995 Daubechies I, et al. Commun. Pure Appl. Math. 2004
Elad M, et al. in Proc. SPIE 2007
T. Goldstein, S. Osher, SIAM J. Imaging Sci. 2009

State-of-the-Art CS-MRI

- Reducing possible reconstruction failure
  - Improve sparse transformations
  - Develop k-space undersampling schemes
- Integrating CS with DL/parallel imaging
  - Develop compatible undersampling patterns
  - Develop reconstruction methods

State-of-the-Art CS-MRI

- Methods to evaluate CS reconstructed images
  - RMSE / SSIM / Mutual Information
- Reducing reconstruction time
  - Reduce computational complexity
  - Parallelize reconstruction problems
- Developing stable reconstruction algorithms
  - Minimize / avoid the number of regularization parameters

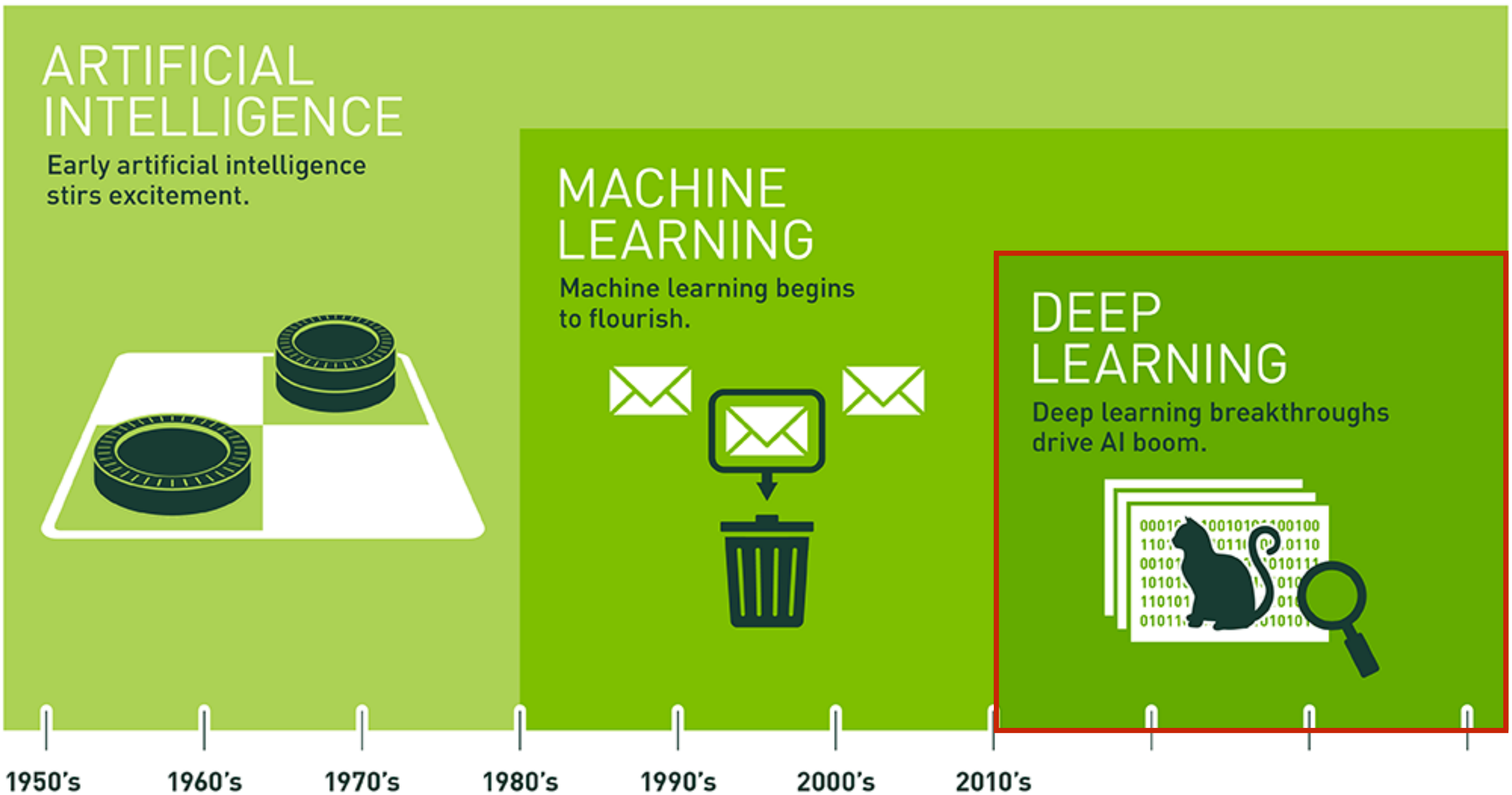
Summary So Far...

minimize $F(x)$: $\underbrace{|y - \Phi x|_2^2}_{\text{Data Consistency}} + \underbrace{R(x)}_{\text{Compressibility Constraint}}$

Compressibility Constraint

Incoherent Measurement

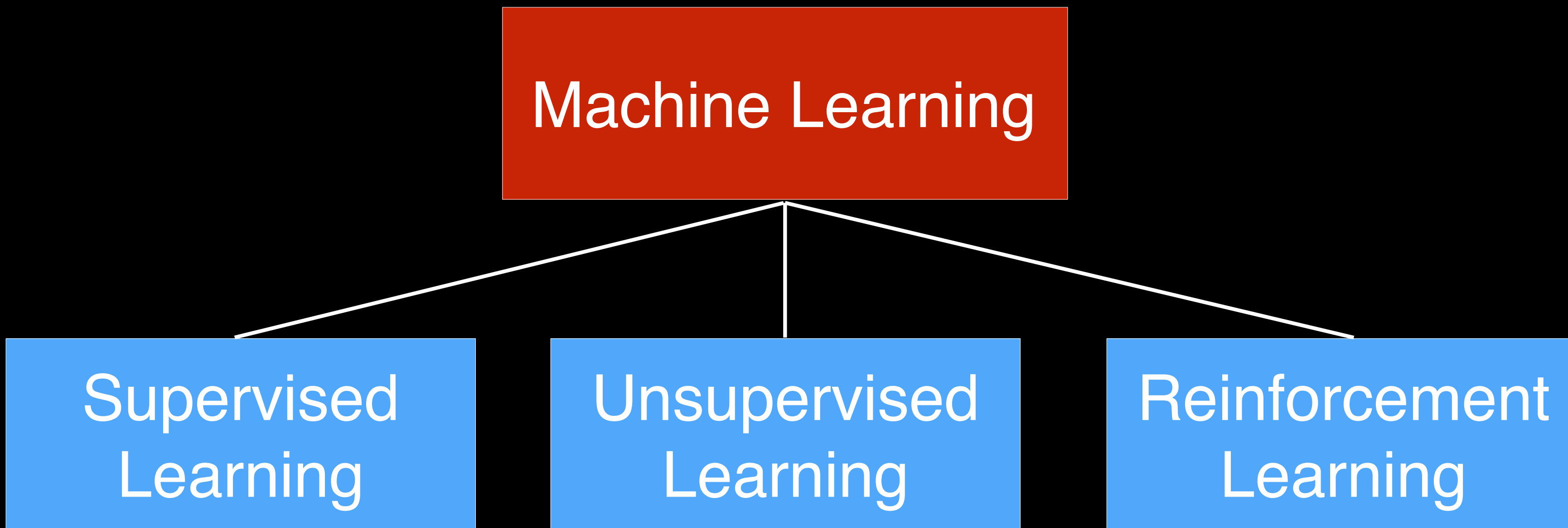
Reconstruction



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.

From nvidia.com

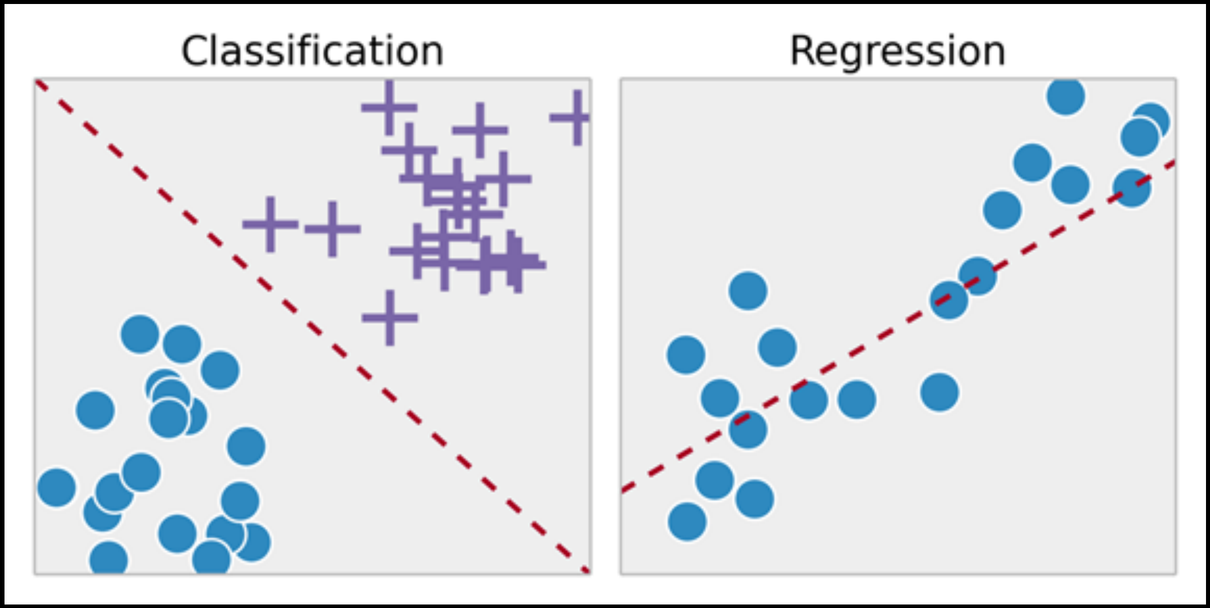
Types of Machine Learning



Task driven (Regression /Classification)	Data driven (Clustering)	Algorithm learns to react to an environment

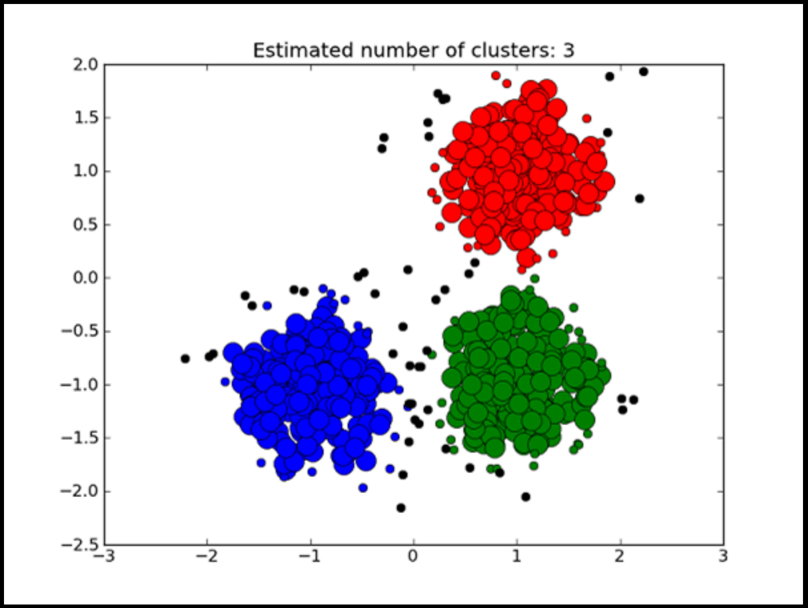
Types of Machine Learning

Supervised Learning



Discriminative Model

Unsupervised Learning



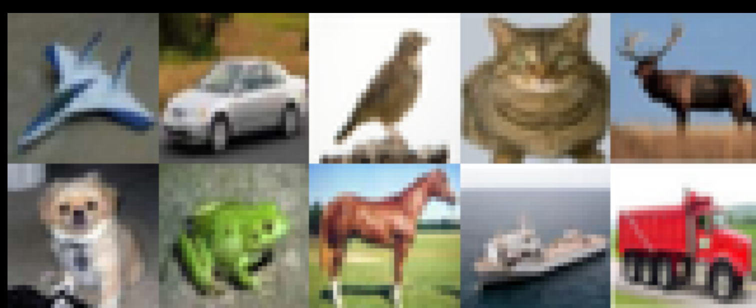
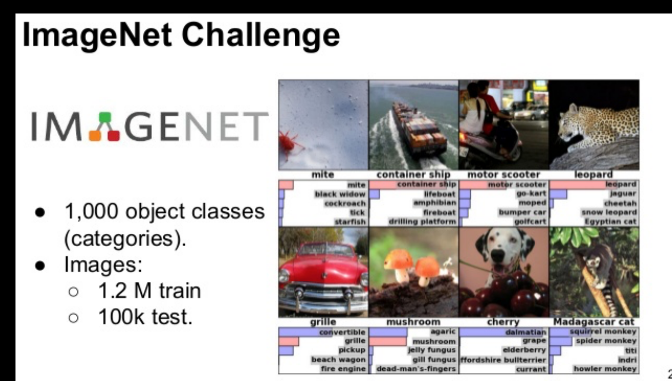
Generative Model

Common Datasets for Deep Learning

- MNIST: 60,000 images, hand writing digits (1998)
- CIFAR-10: 60,000 images 10 classes of

Not trivial to build medical imaging database with a high number of images and accurate labeling

- ImageNet: 1,300,000 high-res images, 1,000 classes of object (2012)

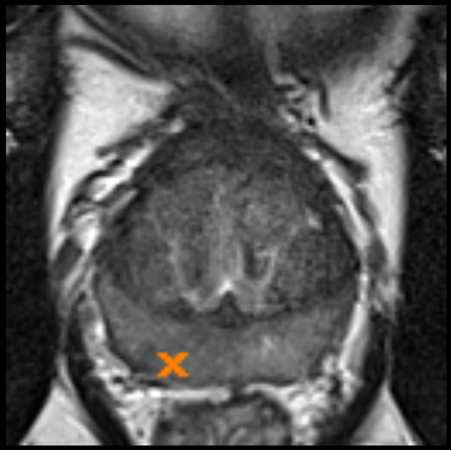




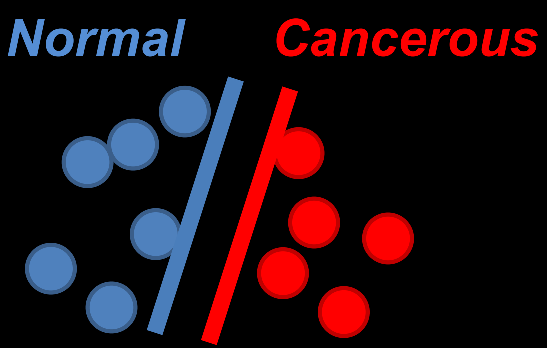
Key Design Considerations

1. Define clear clinical questions
2. Design deep learning models
   - Supervised vs. unsupervised learning
   - Descriptive vs. generative modeling
3. Consider potential limitations
   - Limited amount of training and testing data
   - Uncertainties in labeling

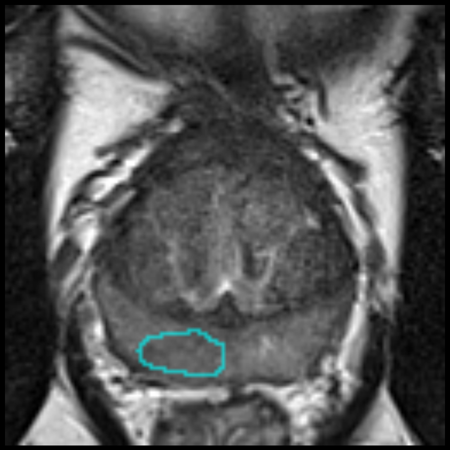
Artificial Intelligence for MRI

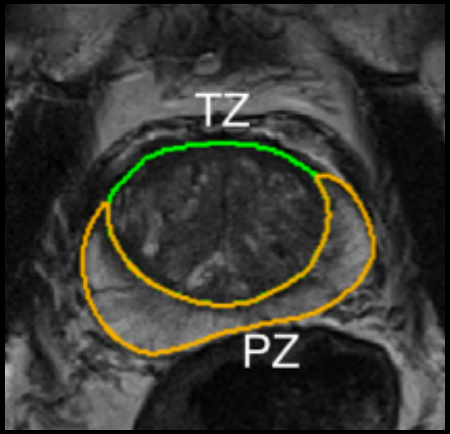
Detection



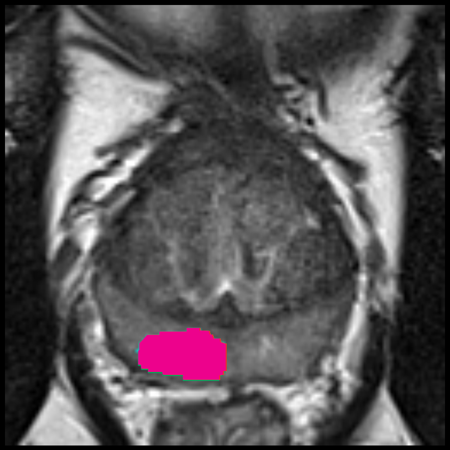


Segmentation





Classification

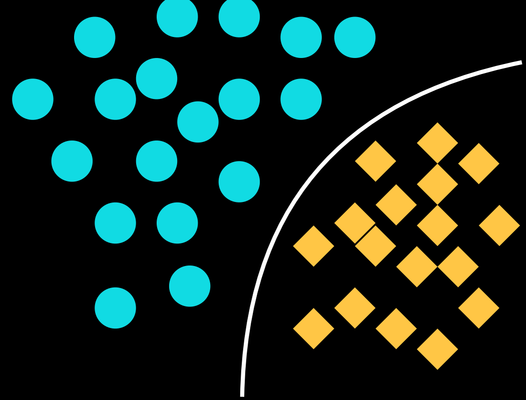


Histologic Findings

Model Evaluation, Model Selection, and Algorithm Selection

- Target function is a specific, unknown model that we want to learn or approximate
- Model is a certain function that we believe is similar to the true function, the target function that we want to model
- Learning algorithm is a set of instructions that tried to model the target function using a training dataset
- Hyperparameters are the tuning parameters of a machine learning algorithm

Target Function and Model



Target function
y = f(x)

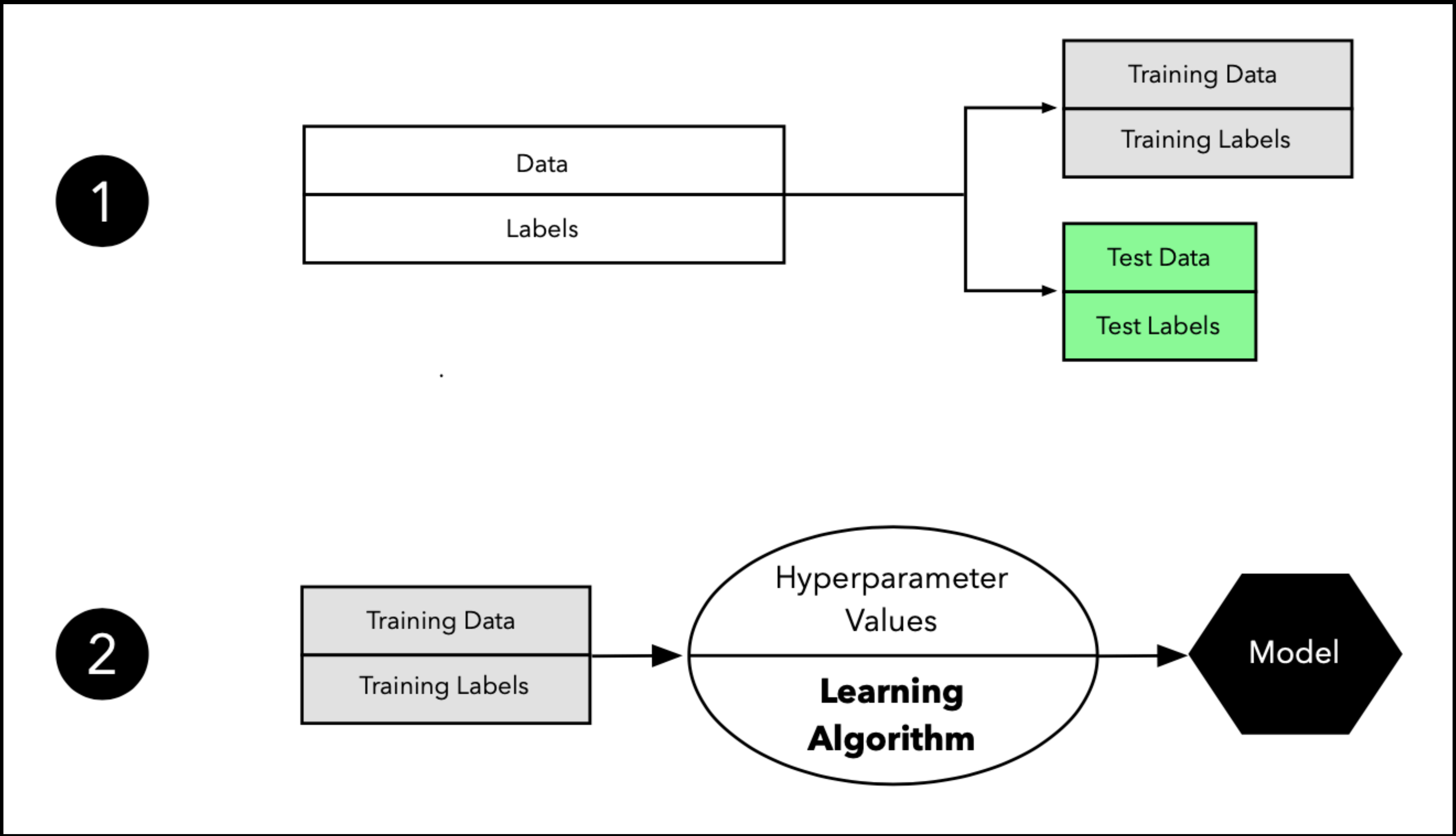
Model: y = ax + b

Model parameters: a and b

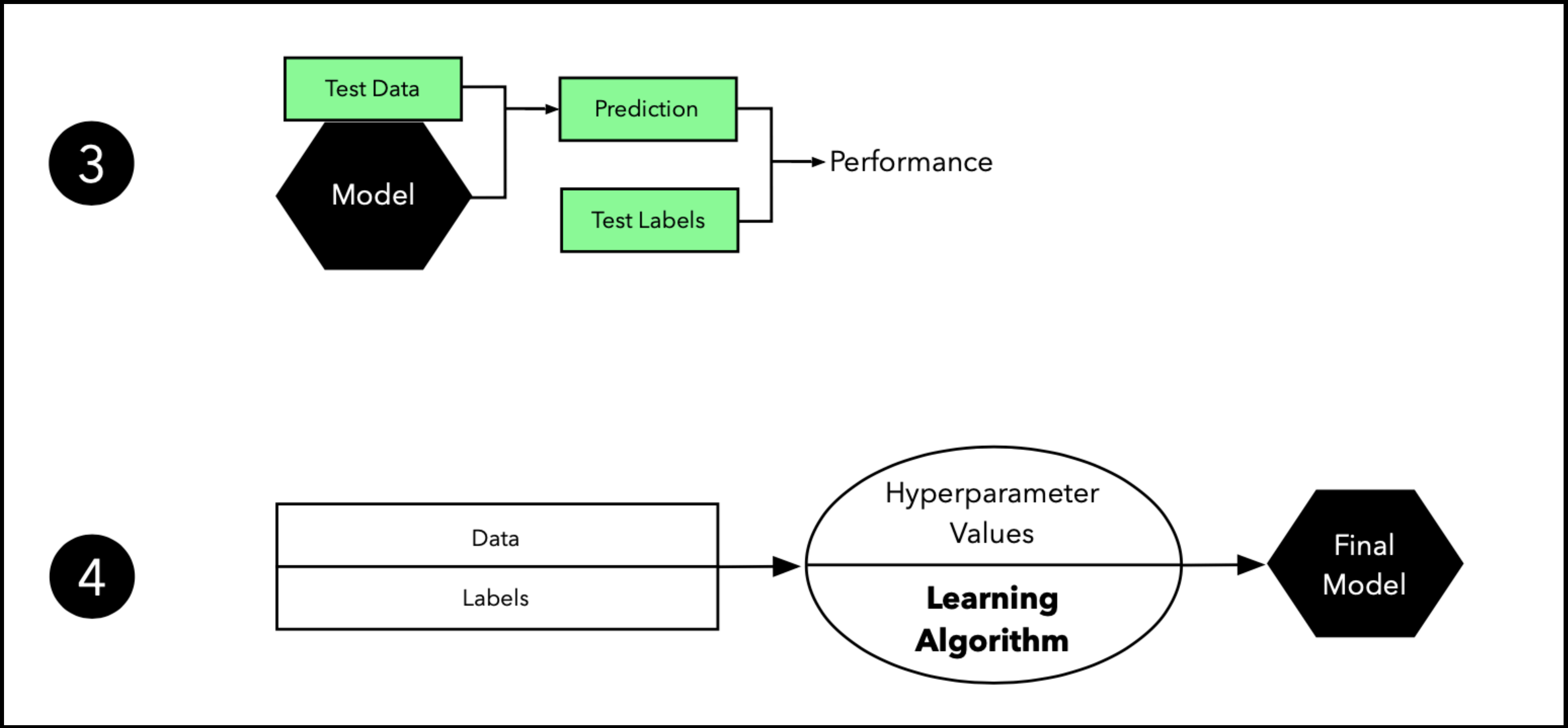
Learning Algorithm

Hyperparameters

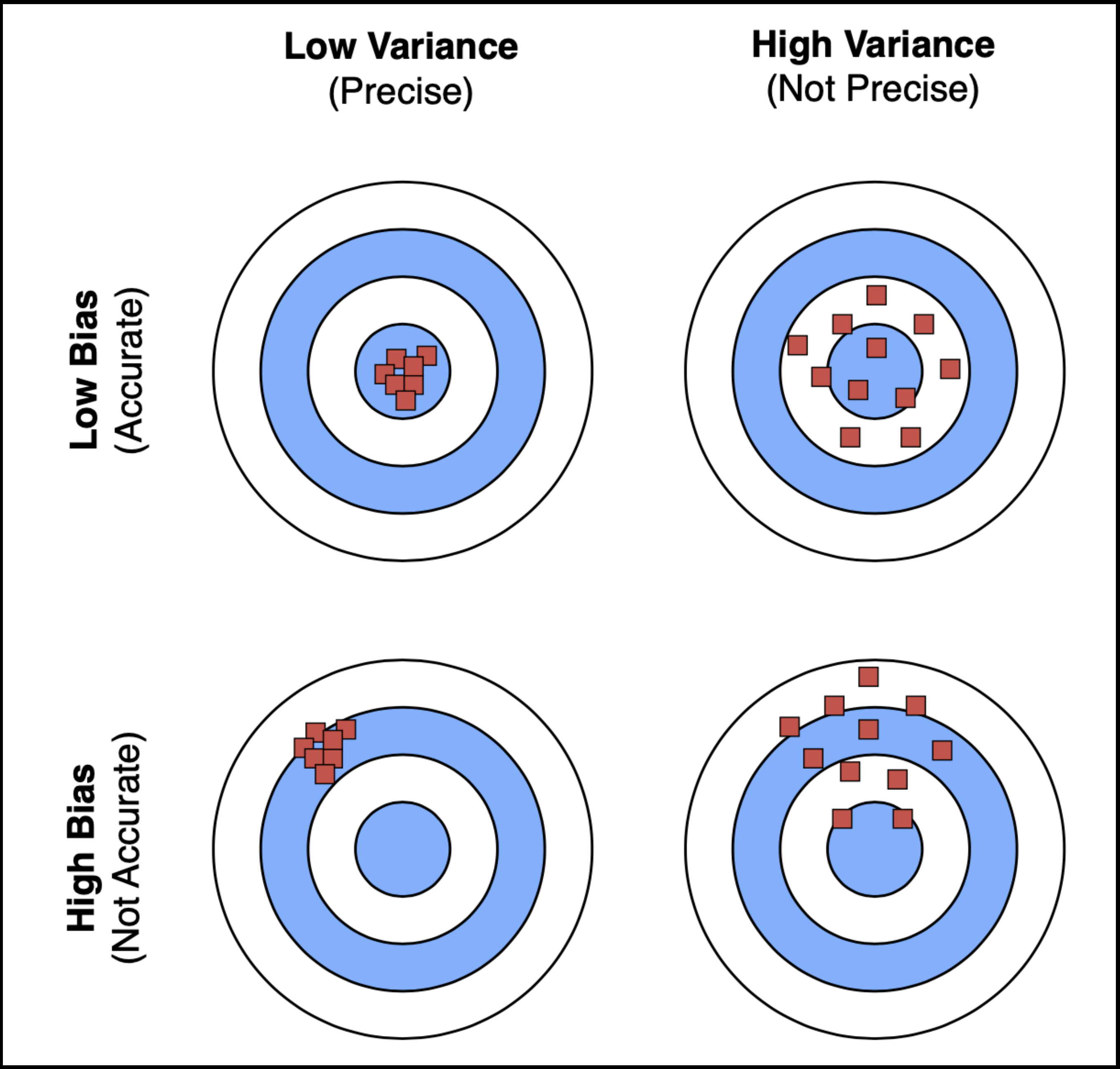
Holdout Validation Method



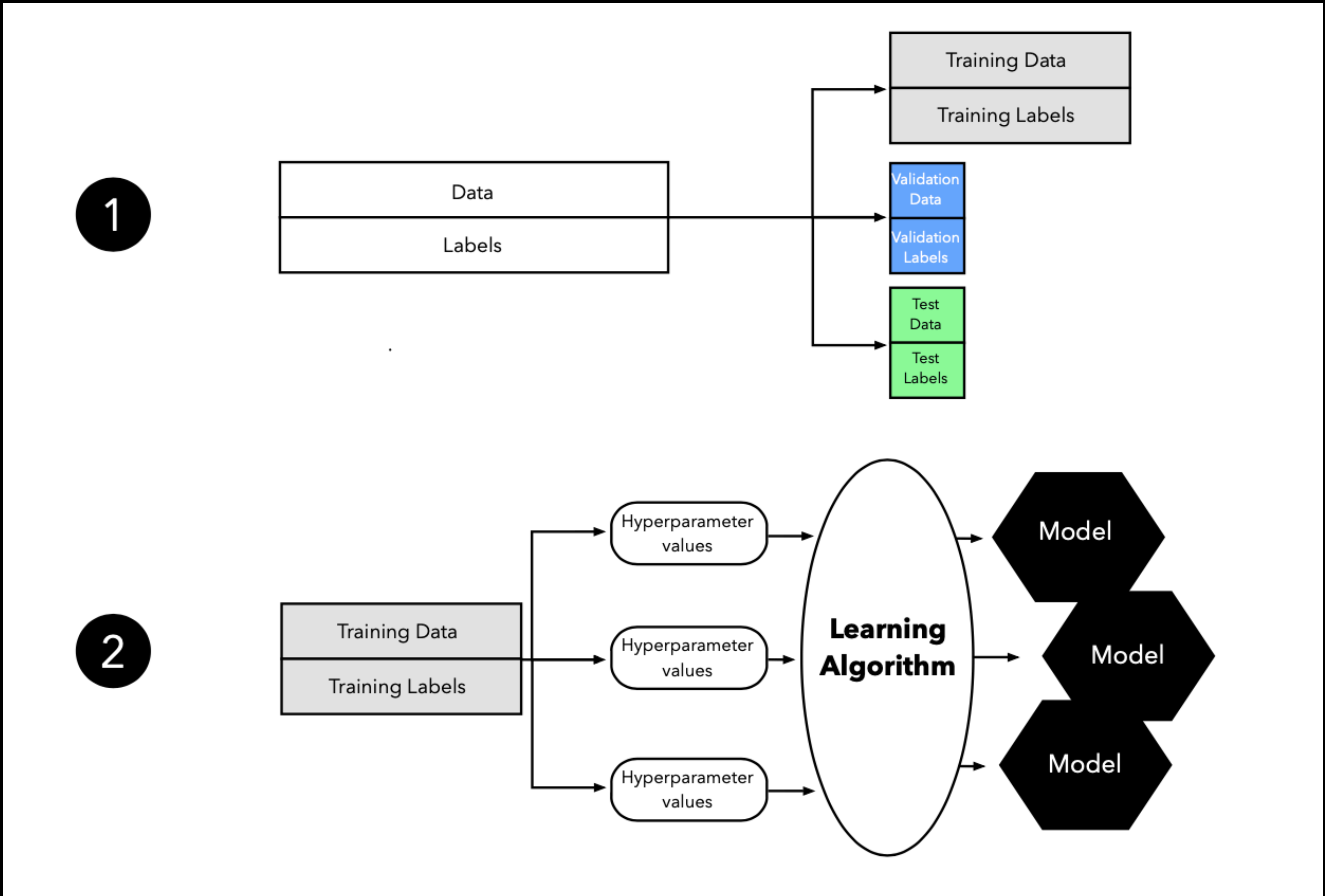
Holdout Validation



Bias and Variance



Three-way Holdout Method



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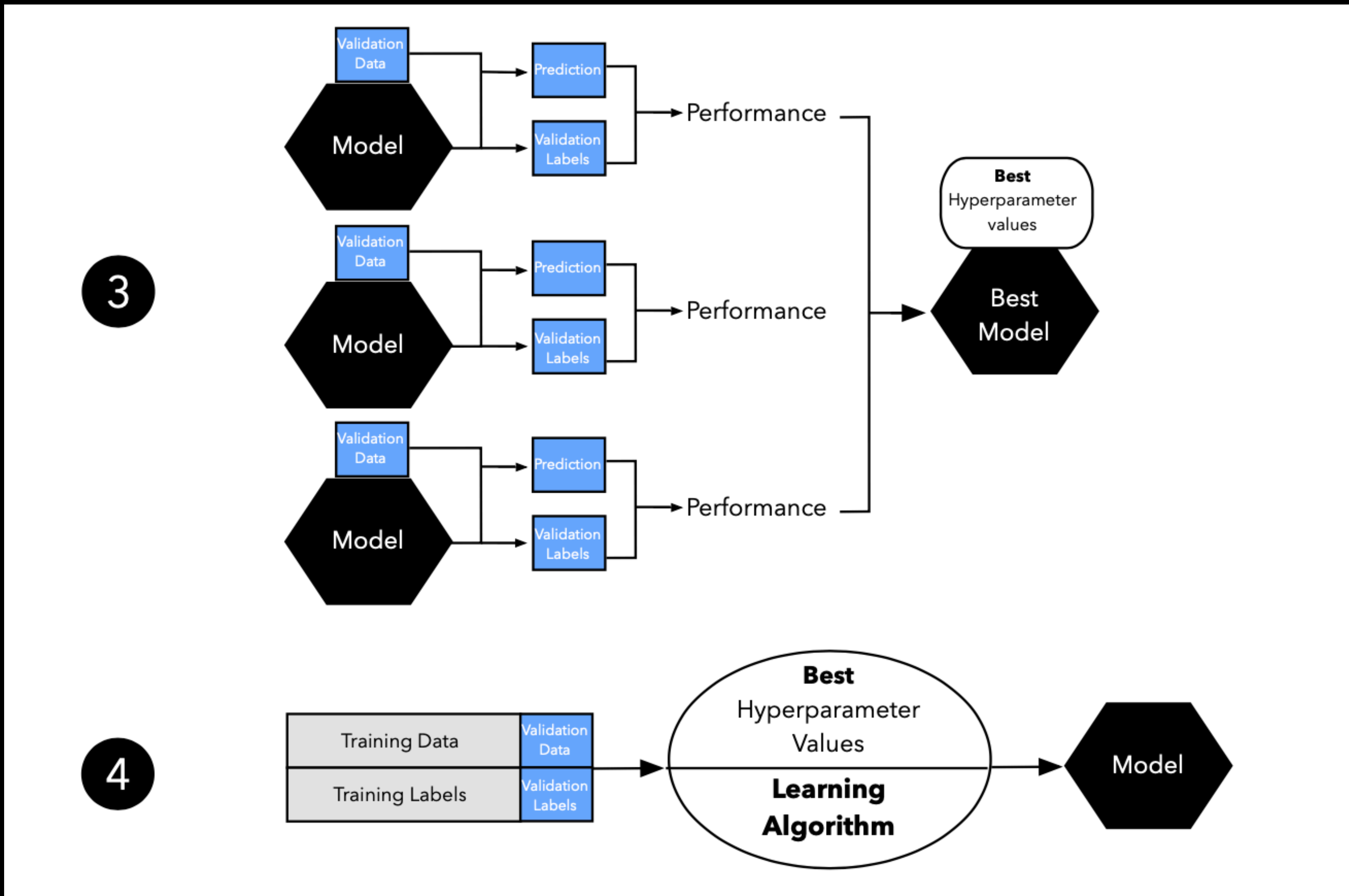
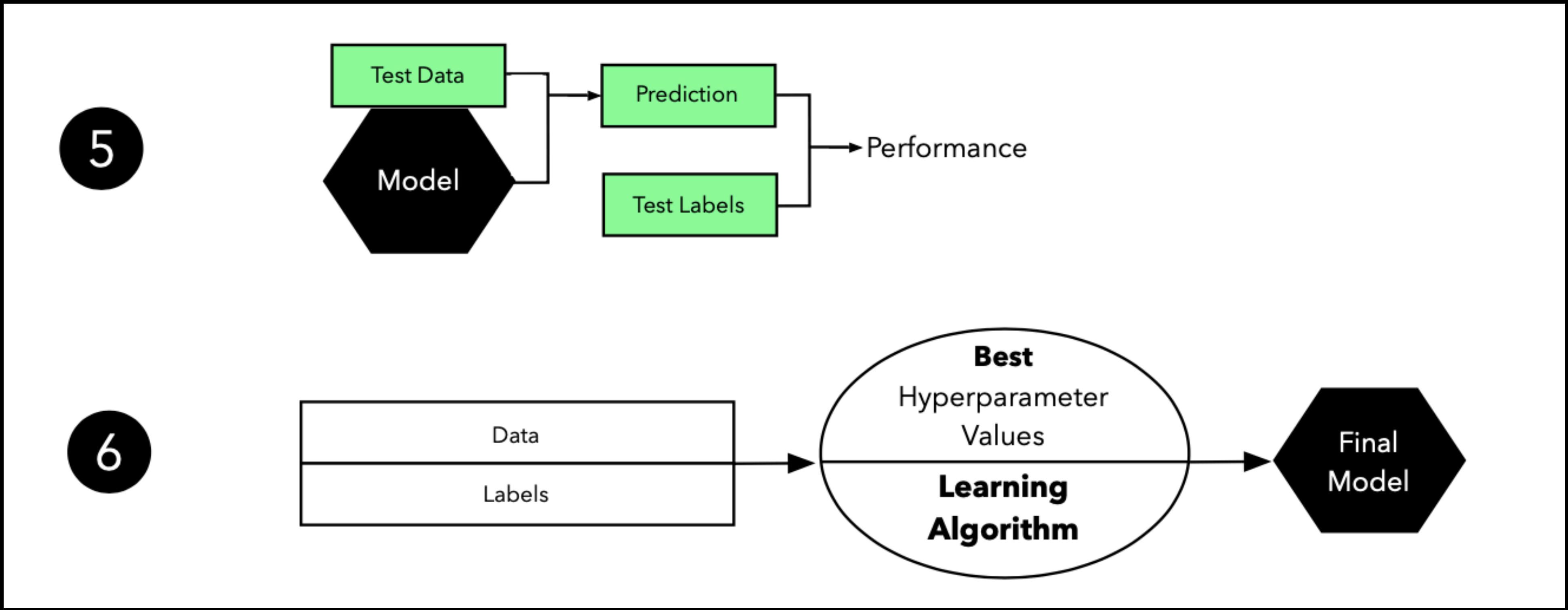
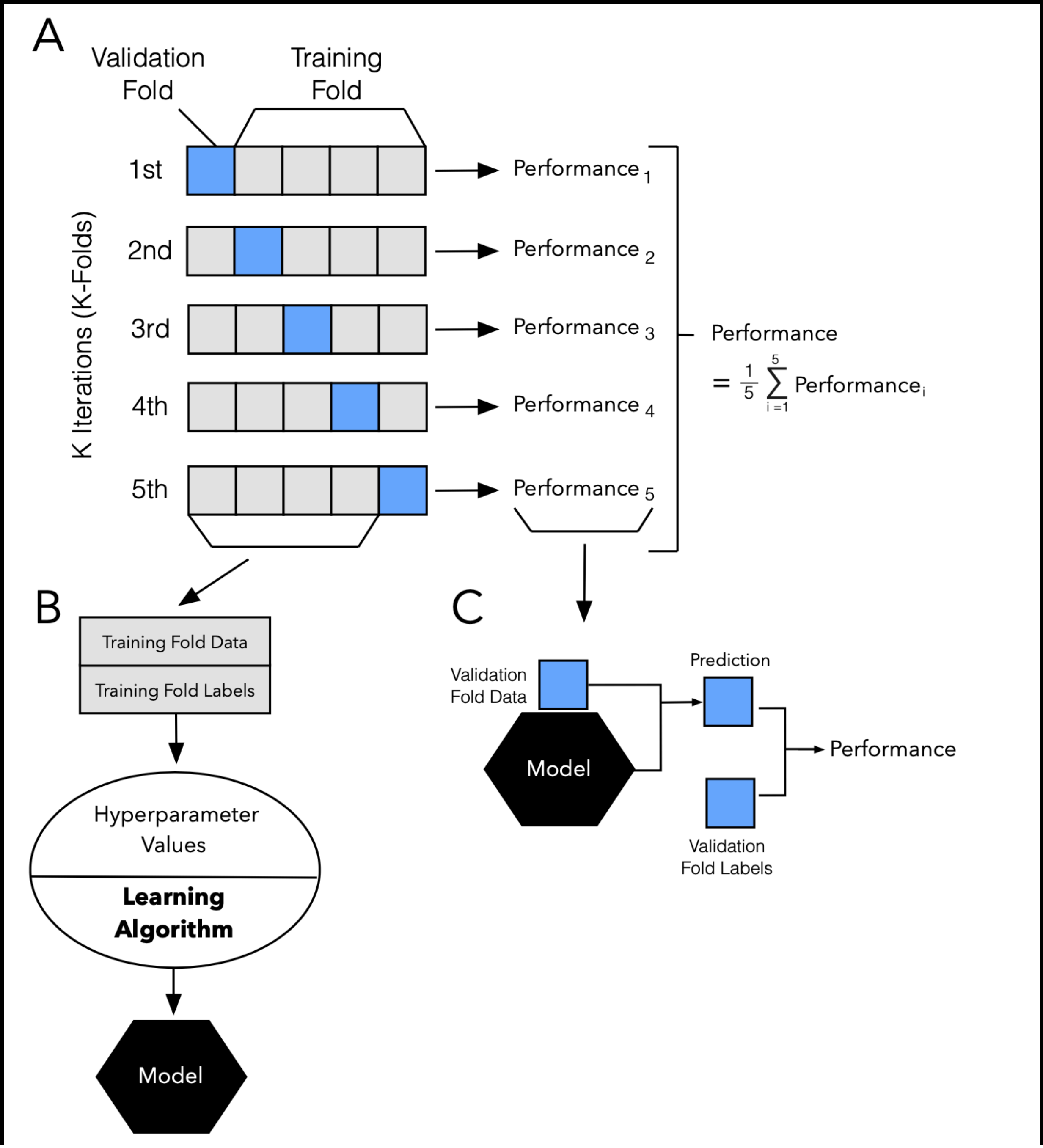


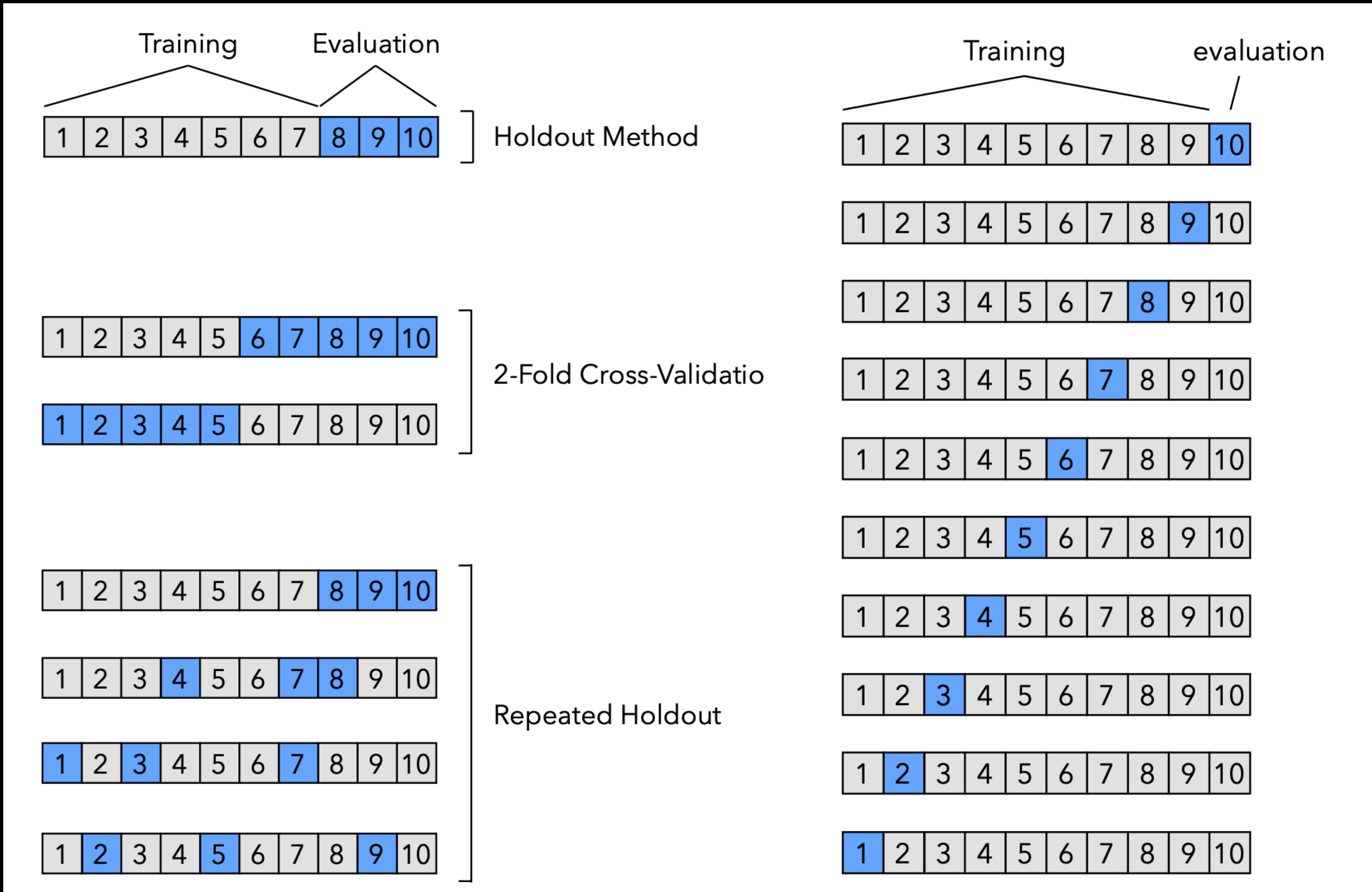
Three-way Holdout Method



k-fold Cross-Validation



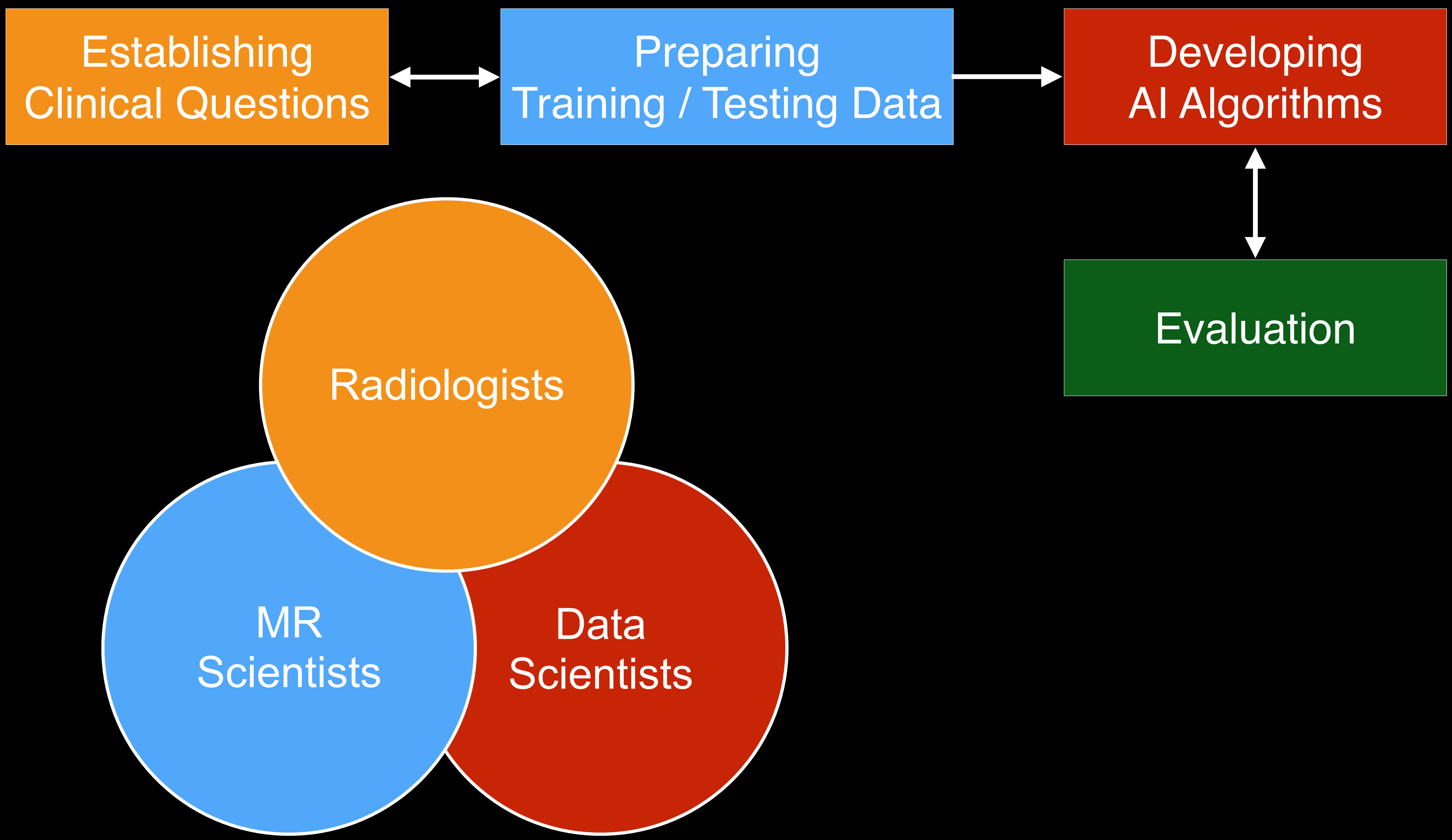
Holdout / CV / Repeated Holdout / LOOCV



Summary

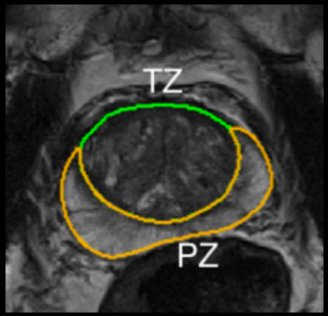
- Performance estimation
  - Large dataset
    - 2-way holdout method (train/test split)
    - Confidence interval via normal approximation
  - Small dataset
    - (Repeated) k-fold cross-validation without independent test set
    - Leave-one-out cross-validation without independent test set
    - Confidence interval via 0.632(+) bootstrap

- Model selection (hyperparameter optimization) and performance estimation
  - Large dataset
    - 3-way holdout method (train/validation/test split)
  - Small dataset
    - (Repeated) k-fold cross-validation with independent test set
    - Leave-one-out cross-validation with independent test set

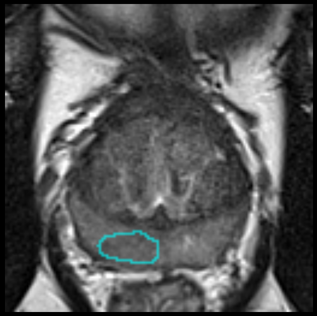

Establishing
Clinical Questions
Preparing
Training / Testing Data
Developing
AI Algorithms
Evaluation
Radiologists
MR
Scientists
Data
Scientists

On-going AI Projects

Organ segmentation



Prostate
Breast
Placenta

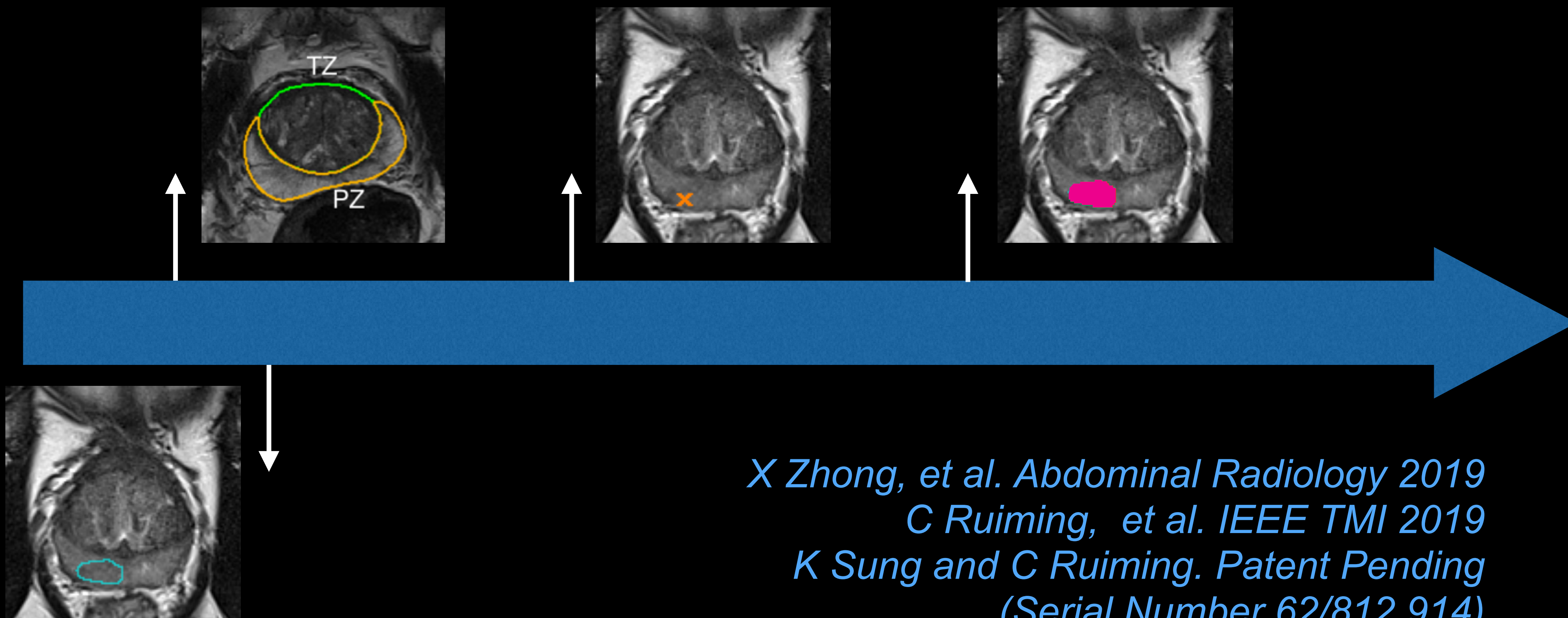


Tumor segmentation

C Ruiming, et al. IEEE ISBI 2019
(Runners-up for Best Paper Award)
Y Liu, et al. IEEE Access 2019
Y Liu, et al. ICCV 2019 Demo
Y Liu, et al. IEEE Access 2020

On-going AI Projects

Organ segmentation Cancer detection Cancer classification

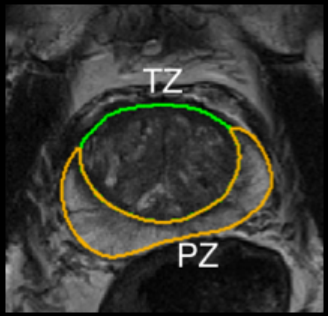


Tumor segmentation

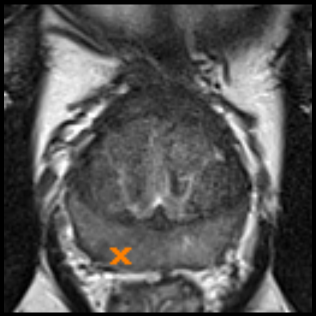
X Zhong, et al. Abdominal Radiology 2019
C Ruiming, et al. IEEE TMI 2019
K Sung and C Ruiming. Patent Pending (Serial Number 62/812,914)
K Sung, et al. US Patent# 10,939,87

On-going AI Projects

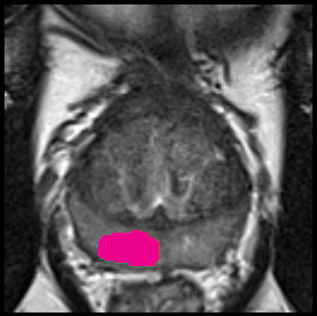
Organ segmentation

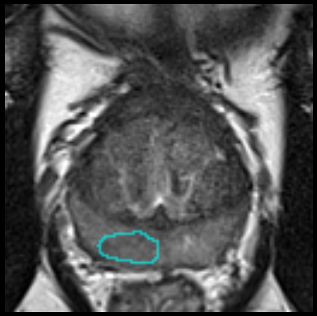


Cancer detection



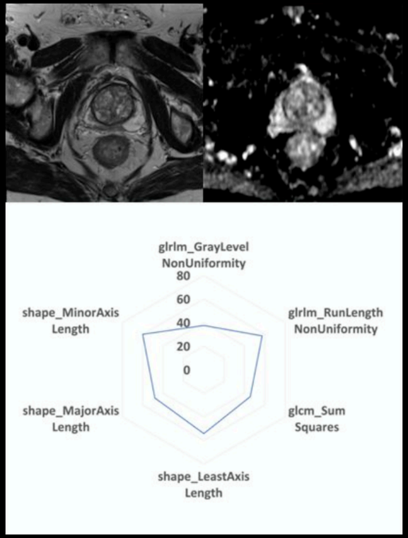
Cancer classification



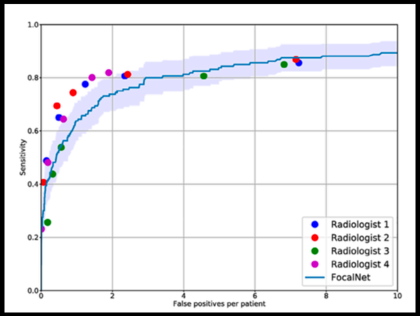


Tumor segmentation

Cancer risk stratification



Human-AI comparison



Cao, Ruiming, et al. JMRI 2021

H Zheng, et al. IEEE ISBI 2021

On-going AI Projects

Prediction of
adverse pregnancy
outcome (APO)

Predicting negative
MRI findings
and anomaly detection

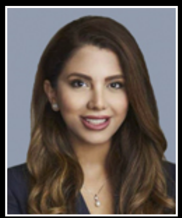
Integrative AI model
with imaging
and genomic information

Breast cancer risk
assessment
with BPE calculation

Predicting pathological
outcome for
non-mass enhancement
Breast lesions

Super-resolution MRI
via GAN

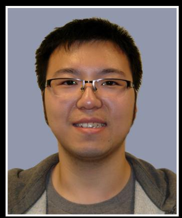

Qi Miao, M.D.


Melina Hosseiny, M.D.

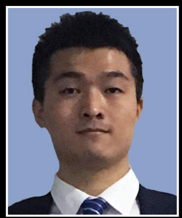

Wakana Murakami, M.D.

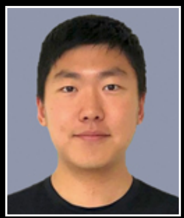

Brian Lee, M.D.

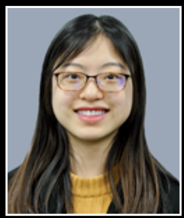

Arya Aliabadi, M.D. candidate


Jiahao Lin


Alibek Danyalov


Yongkai Liu


Haoxin Zheng


Ran Yan

Future of Prostate MRI: What is Next?

- Human-AI interaction
  - Integration of the models in the clinical workflow
  - Accessibility for non-developers
- Interpretable / explainable AI
  - ROC curves are not everything. Critical to understand which problem matters, what matters is how it is going to affect clinical practice and help save lives
- Multi-institutional validation

Further Reading

- Original Compressed Sensing
  - https://ieeexplore.ieee.org/document/1580791
  - https://ieeexplore.ieee.org/document/1614066
- Compressed Sensing MRI
  - https://ieeexplore.ieee.org/abstract/document/4472246
- ML model selection and evaluation
  - https://arxiv.org/abs/1811.12808

Thanks!

- Next time
  - Dr. Kim-Lien Nguyen (6/1)
  - Dr. Ai-Chi Chen (6/3)

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