Artificial Intelligence and Deep Learning in Healthcare

Case studies:
(1) Cardiac resynchronization therapy (CRT)
(2) Knee Total Joint Arthroplasty Research

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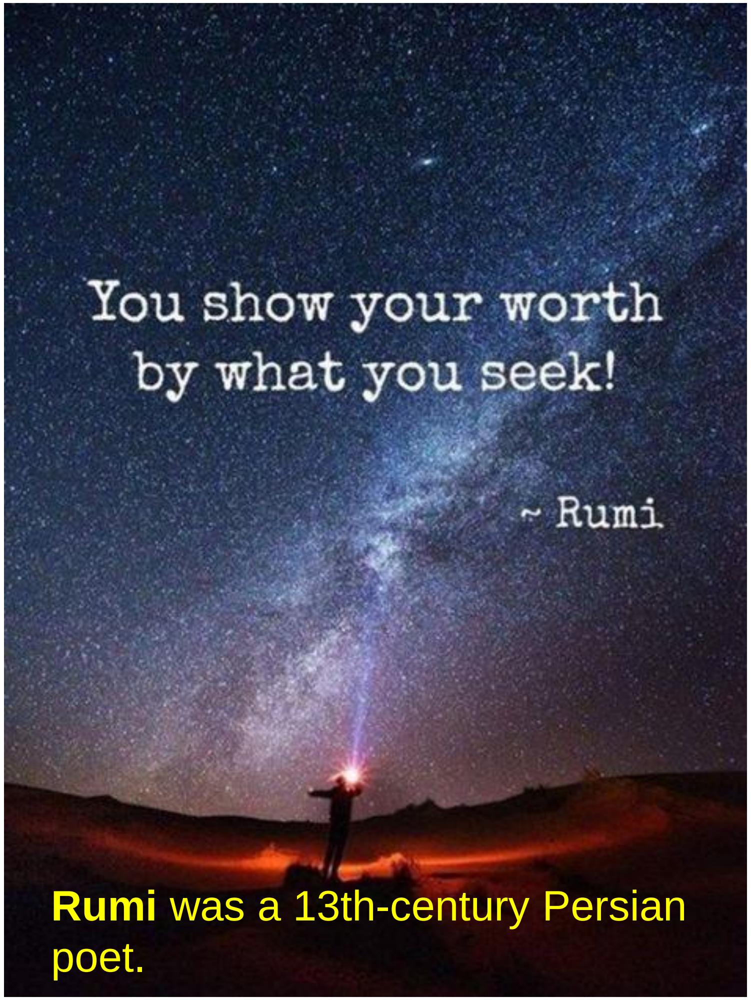
http://aptafti.github.io

WHO AM I?

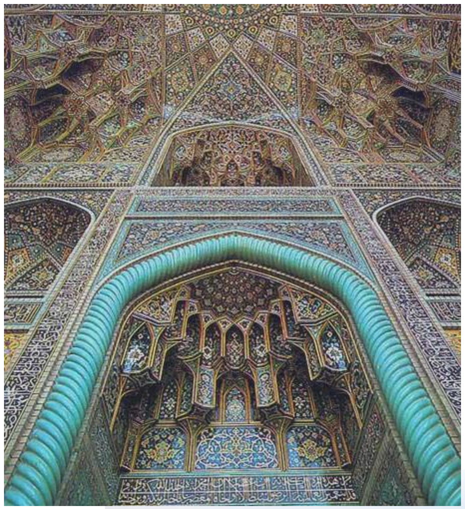


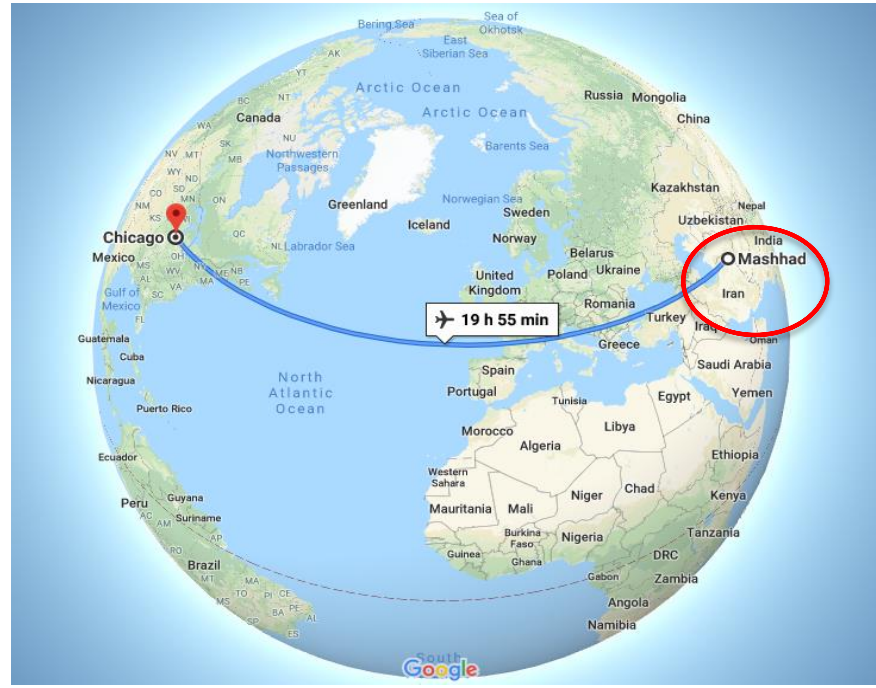
Rumi was a 13th-century Persian poet.

https://www.pinterest.com/pin/336855247124113773/
https://en.wikipedia.org/wiki/Rumi

MAYO CLINIC

WHERE AM I COMING FROM?





https://www.google.com/maps

Mashhad

Population: ~ 6,000,000 with over 25 million tourists per year

https://en.wikipedia.org/wiki/Mashhad

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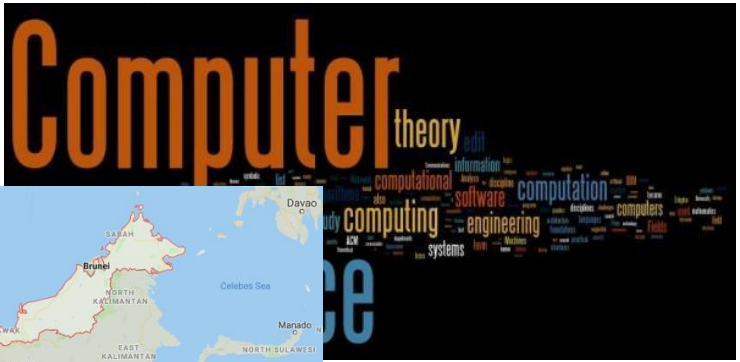
WHAT/WHERE DID I STUDY?



cademics-and-
grams/computer-science

TEXAS
The University of Texas at Austin

https://brand.utexas.edu/identity/logos/

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https://uwm.edu/

UNIVERSITY of WISCONSIN
UWMILWAUKEE

A LITTLE BIT ABOUT MY FAMILY…

Elham (Ellie) Sagheb
Informatics Specialist
Division of Digital Health Sciences
Mayo Clinic

Sara, 2017

Elham (Ellie) and Ahmad, 2018

Sara, 2019

Sara, 2018

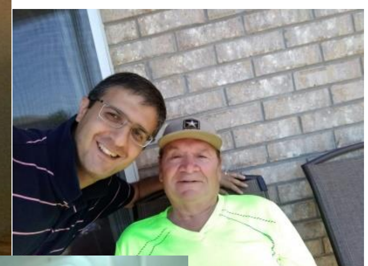
Sara, 2019

What do I like to do?

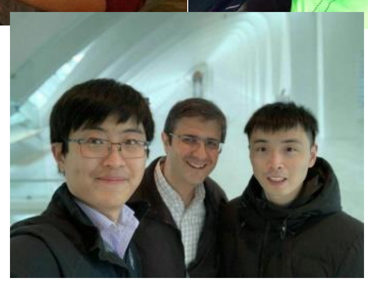


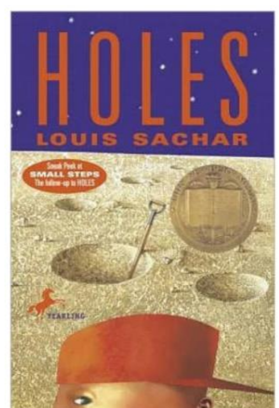








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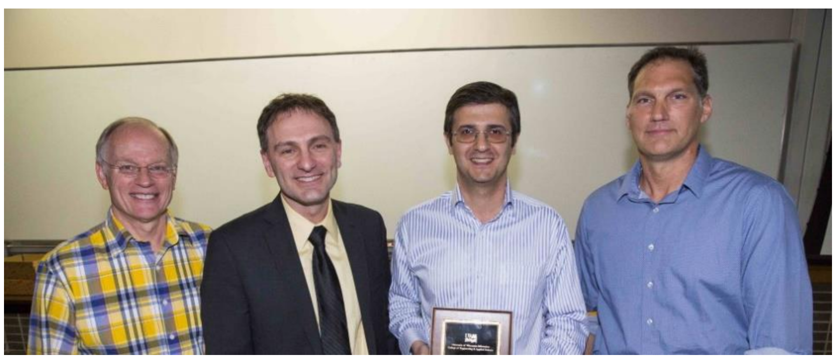
I DO LIKE PARTICIPATING SCIENTIFIC COMMUNITIES



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MAIN COLLABORATORS/BIG BOSSES

Nilay Shah, PhD
Chair, Division of Health Care Policy & Research
Department of Health Sciences Research
Mayo Clinic, Rochester, MN

Hongfang Liu, PhD
Chair, Division of Digital Health Sciences
Department of Health Sciences Research
Mayo Clinic, Rochester, MN

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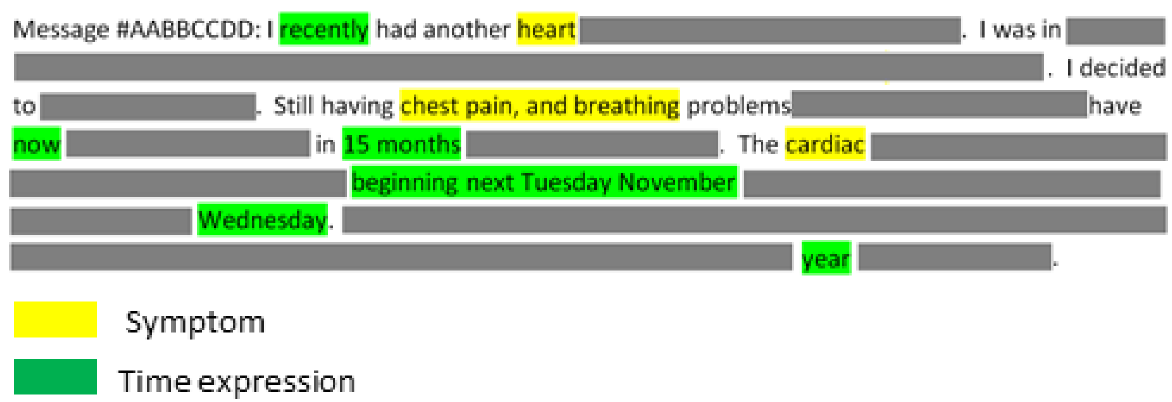
I am pretty much interested in utilizing **AI** to:

- Computationally interpret **medical images** (e.g., X-rays, CTs, MRIs, US)
- Computationally interpret **medical text data** (e.g., clinical notes, radiology reports, patient portal messages)

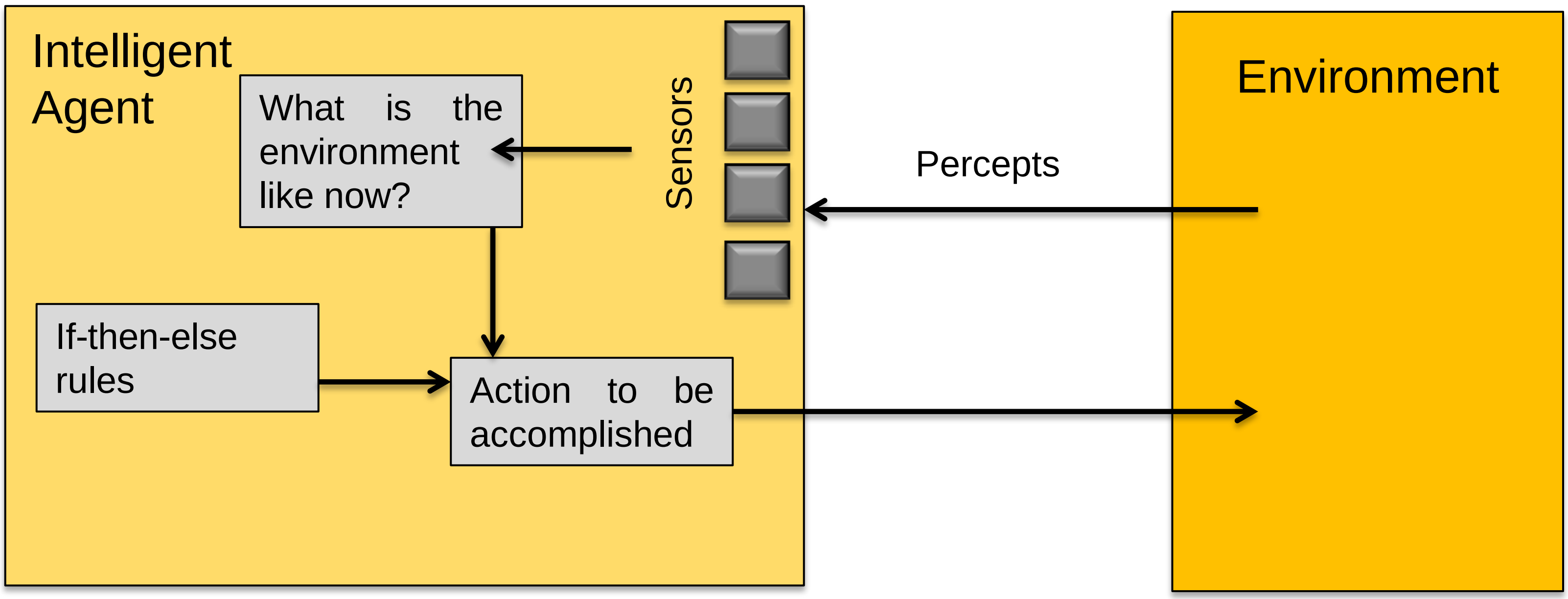


OUTLINE

- Artificial Intelligence; What and Why?
- Deep Learning; What and Why?
- Deep Learning Computational Vision; What and Why?
- AI Adoption in Healthcare
- Deep Learning to Advance Cardiac Resynchronization Therapy (CRT)
- Deep Learning Computational Vision to Advance Knee Osteoarthritis (OA) and Knee Total Joint Arthroplasty (TJA) Research

ARTIFICIAL INTELLIGENCE; WHAT AND WHY?

- **AI** is a computer system that can **sense its environment**, **think**, **learn**, and **take action** in response to what it is sensing and its objectives.



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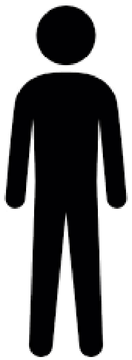
ARTIFICIAL INTELLIGENCE; WHAT AND WHY?

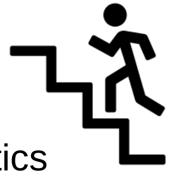


Speech Recognition

NLP

Computer Vision

Image Processing



Robotics

Pattern Recognition

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RULE-BASED VERSUS LEARNING-BASED AI

Step

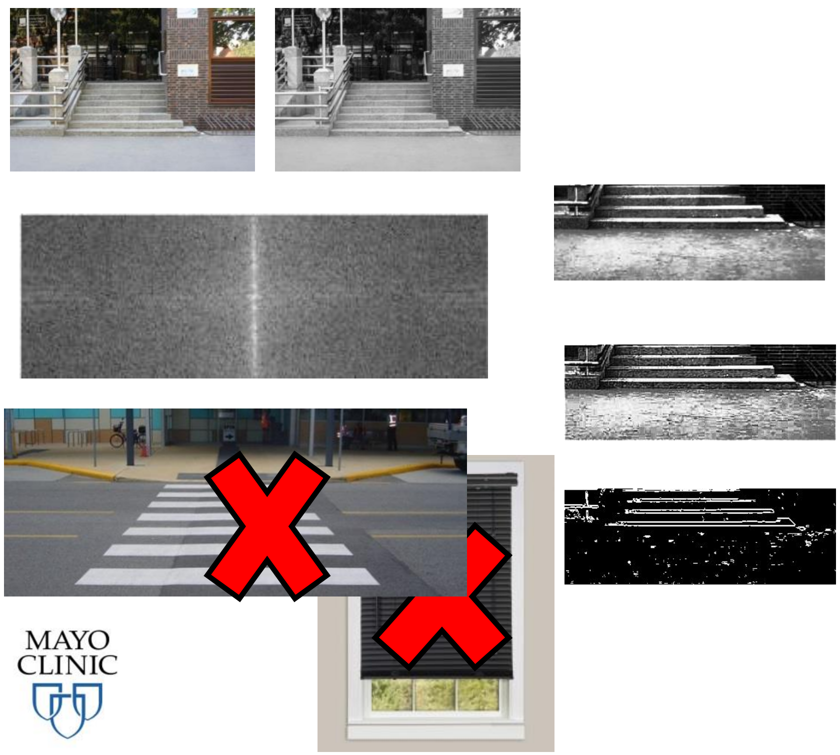
Door

How to implement **singularities**???

Rule-based algorithms | Learning-based algorithms

Deep and machine learning strategies vs. **Traditional** (rule-based) methods

Traditional (there is no any learning technique)	Deep and machine learning techniques



We train computers at recognizing doors from steps by showing them a **large amount** of:

(object_type, picture) pairs.

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Machine Learning Strategies

Machine Learning Tasks

Descriptive Machine Learning Algorithms (<u>What happened?</u>)

- **Clustering:** Grouping of samples (instances) given un-labeled data.
- **Summarization:** Finding a compact description for a data set.
- **Association Rules:** Discovering interesting relations between variables in a large DB.

Predictive Machine Learning Algorithms (<u>What will be happened?</u>)

- **Regression:** Attempting to predict a continuous attribute.
- **Classification:** Predicting the sample (instance) class from pre-labeled samples.

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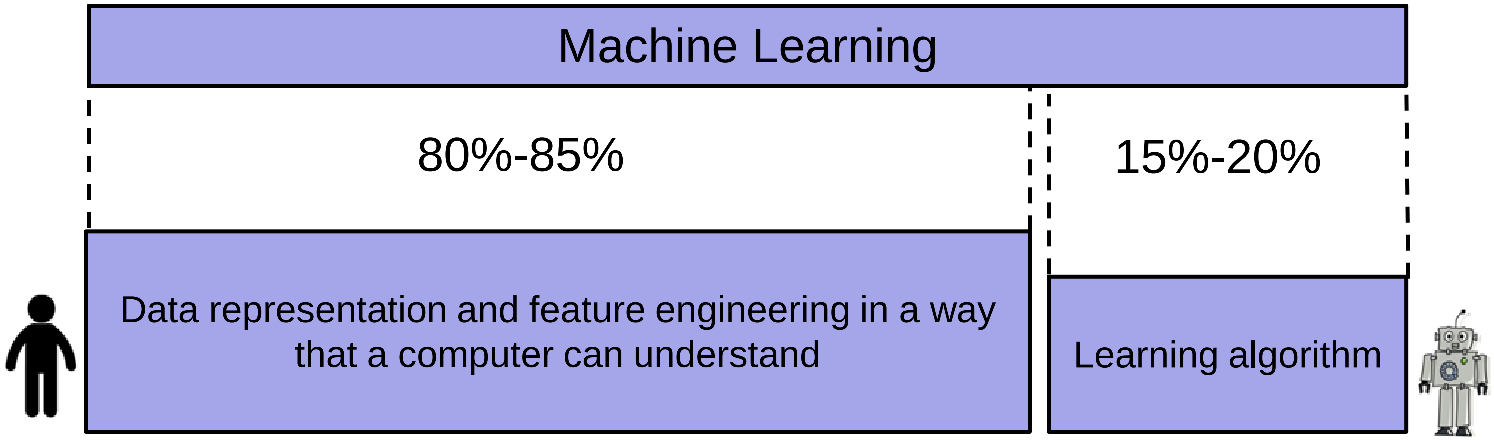
What is the problem with Machine learning?

- Most **machine learning** methods work well because of **human-designed representation** and **input features**.
- **Machine learning** becomes **just optimizing weights** to best make a final prediction.



- Problem: **Manually designed features** are often **over-specified**, **incomplete**, and take a **long time** to **design** and **validate**.

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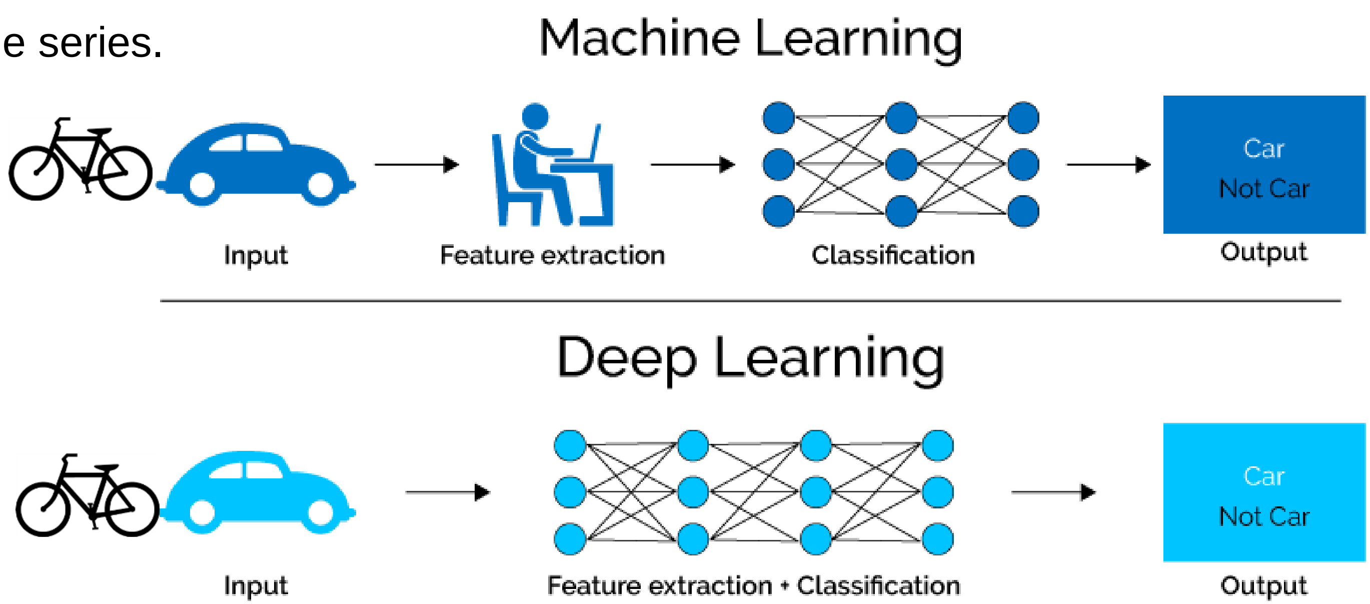
What is Deep Learning?

- **Deep Learning algorithms** attempt to **automatically learn good features** or **representation**.
- **Deep Learning** provides a very **flexible** and **universal** learnable framework for representing a variety of data types, such as visual data, linguistics, audio streams, and time series.



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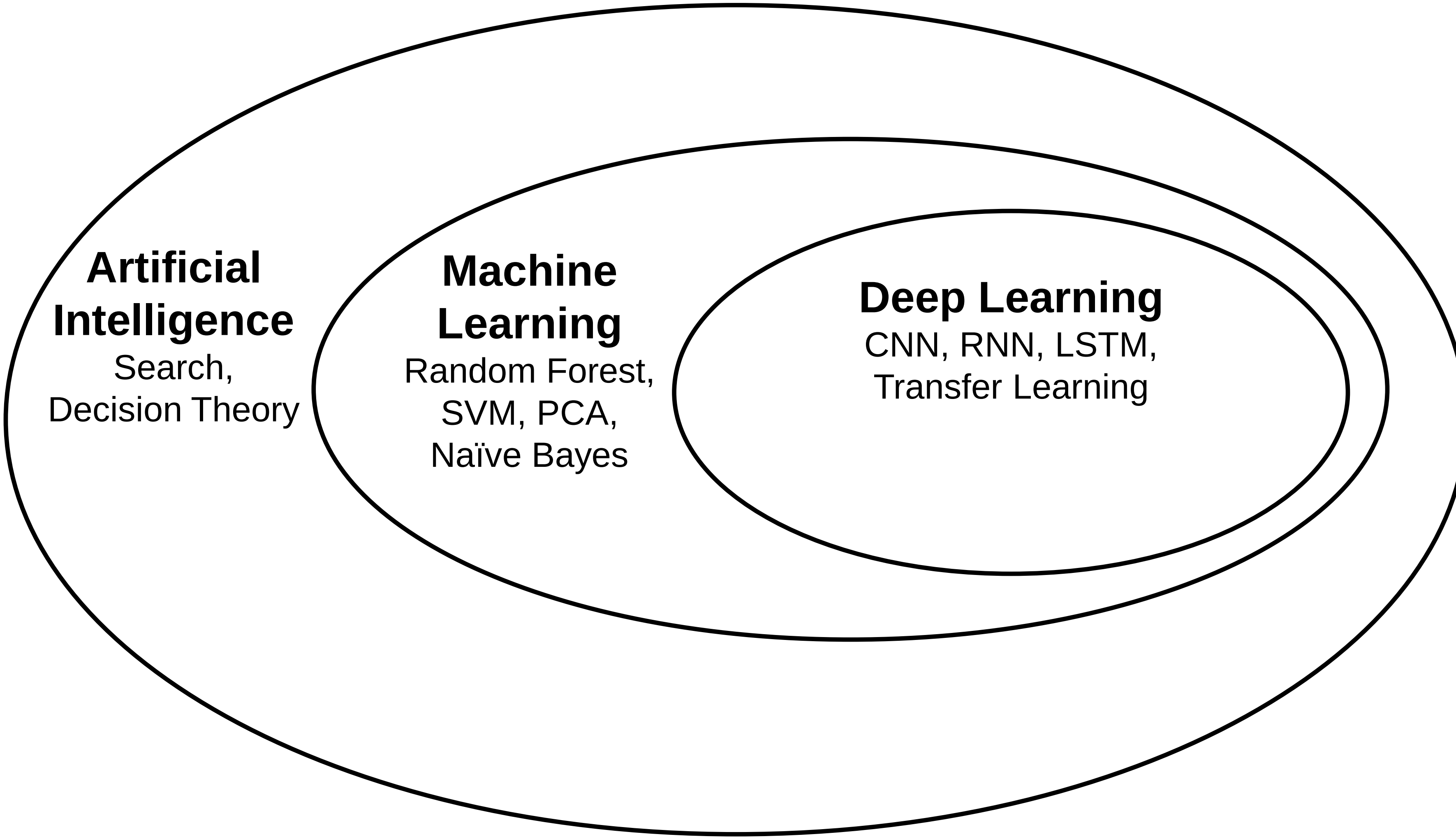
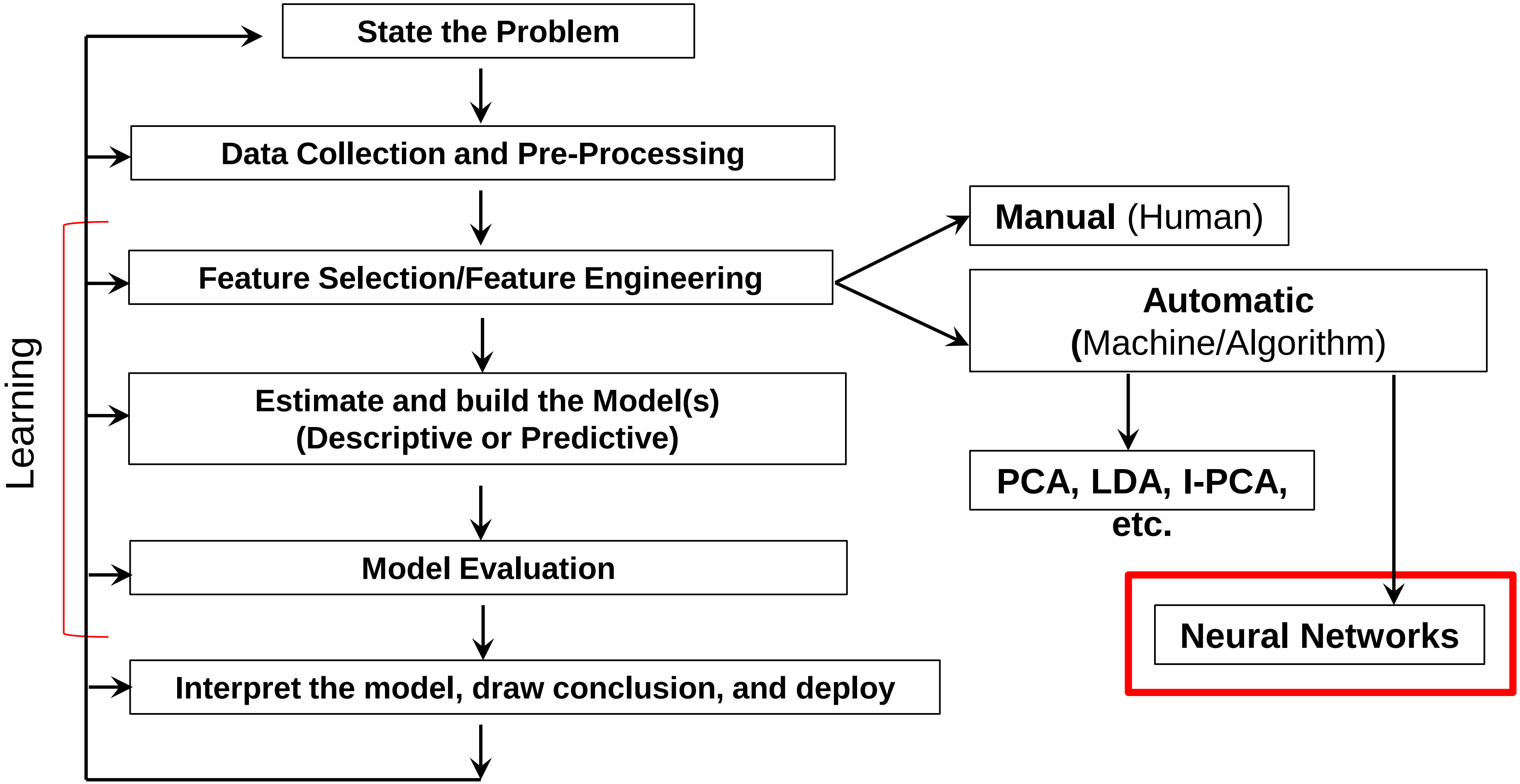
DEEP LEARNING; WHAT AND WHY?



MACHINE LEARNING PIPELINE AND FEATURE SELECTION



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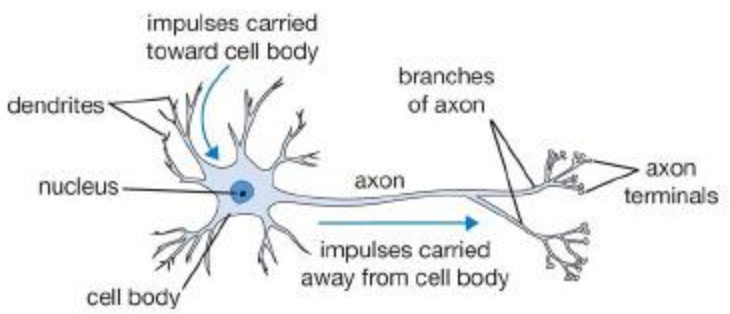
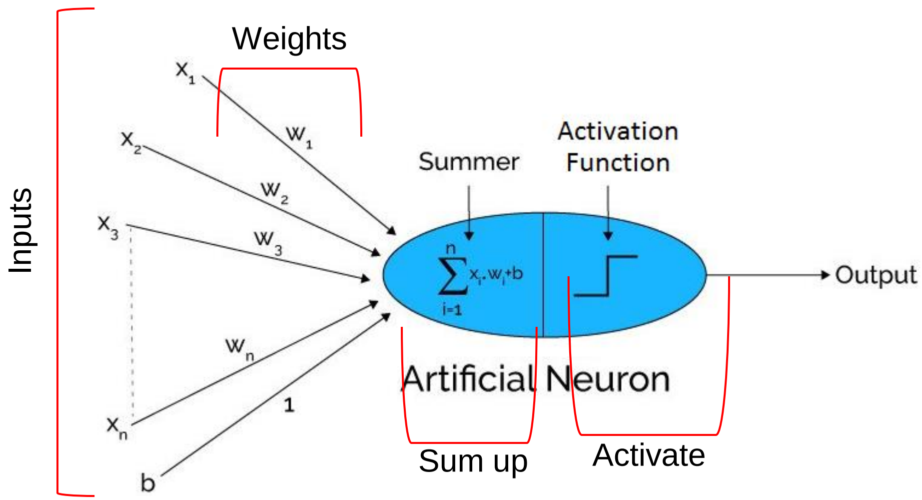
NEURAL NETWORKS



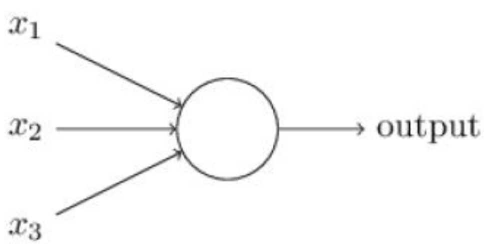


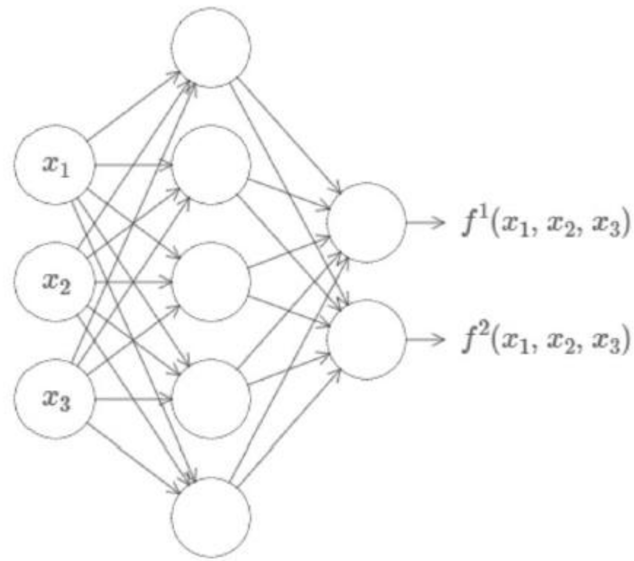
Neuron: Computational building block for the "Brain"
Human Brain: ~100 to 1000 trillion synapses

Artificial Neuron: Computational building block for the "Neural Networks"
Neural Network: ~1 to 10 billion synapses

1 0 0
1 1 1 0 0 0 0 0 0
1 1 0 0 0 0

NEURAL NETWORKS ARE AMAZING

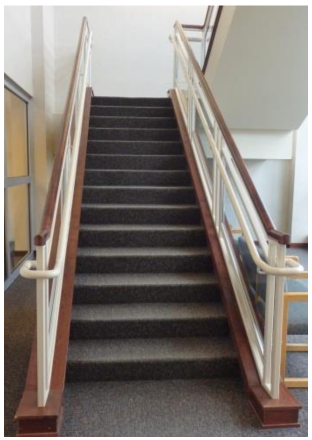




Universality: for any arbitrary function f(x), there exists a neural network that closely approximates it for any input x.

Universality is an incredible property to neural networks, and it holds for just 1 hidden layer.

LINEAR CLASSIFICATIONS USING NEURAL NETWORKS



[40 * 60 * 3]

Input image

Parameters

$$f\,(x, W) = W\,x + b$$

Stair: 5.4

Door: -3.7

Sign: 2.9

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Bashiri FS, LaRose E, Peissig P, **Tafti AP**. MCIndoor20000: A fully-labeled image dataset to advance indoor objects detection. Data in brief. 2018 Apr 1;17:71-5.

LINEAR CLASSIFICATIONS USING NEURAL NETWORKS

3 Classes AND 4 Features

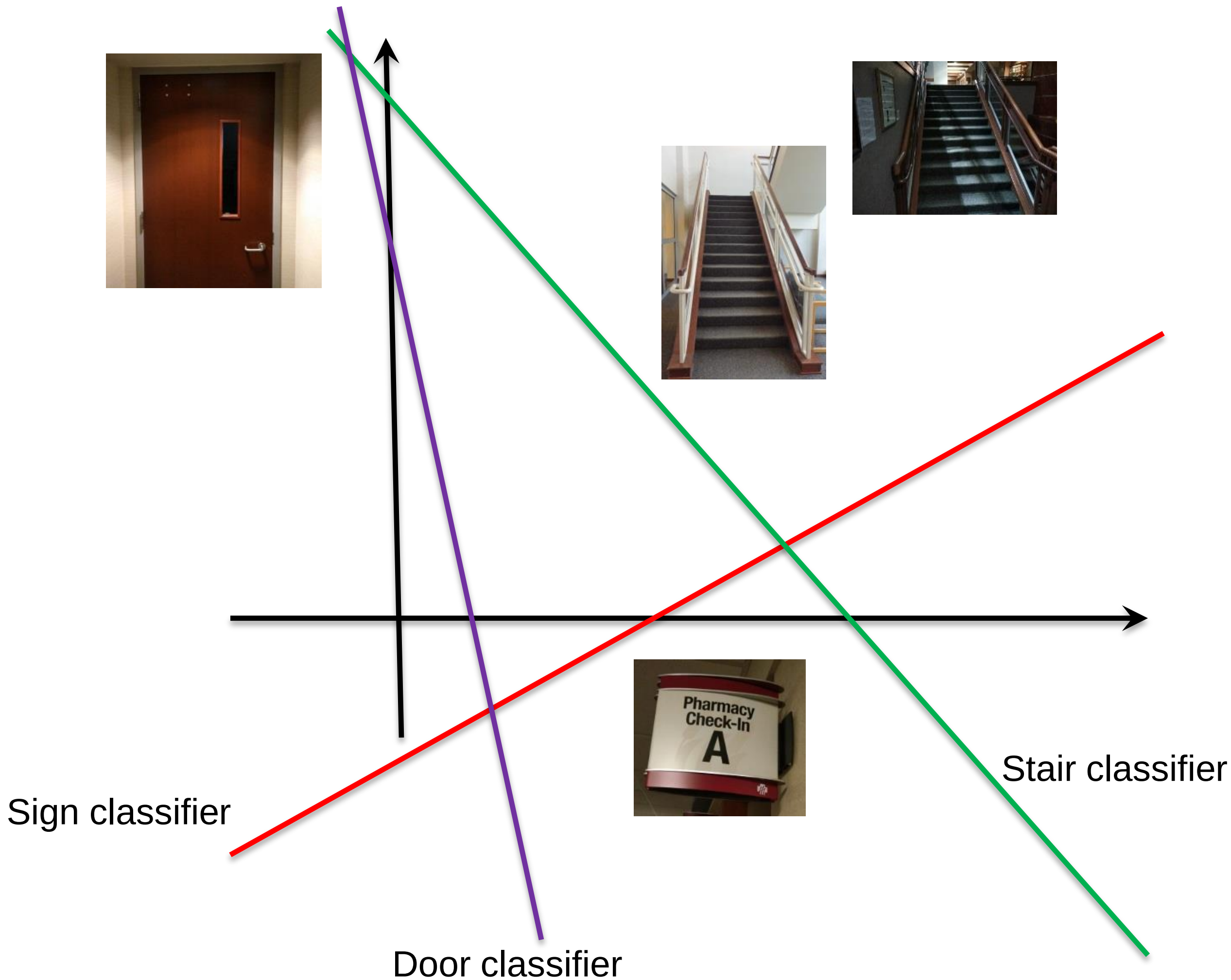
Input Image

$$\underset{W}{\begin{bmatrix} 0.2 & -0.5 & 1 & 2.0 \\ 1.5 & 1.3 & 2.1 & 0.0 \\ 0.0 & 0.25 & 0.2 & -0.3 \end{bmatrix}} * \underset{x_i}{\begin{bmatrix} 56 \\ 231 \\ 24 \\ 2 \end{bmatrix}} + \underset{b}{\begin{bmatrix} 1.1 \\ 3.2 \\ -1.2 \end{bmatrix}} \rightarrow \underset{f\,(x_i;\, W,\, b)}{\begin{bmatrix} -75.2 \\ \mathbf{437.9} \\ 60.75 \end{bmatrix}} \begin{matrix} \text{Stair} \\ \text{Door} \\ \text{Sign} \end{matrix}$$

Bashiri FS, LaRose E, Peissig P, **Tafti AP**. MCIndoor20000: A fully-labeled image dataset to advance indoor objects detection. Data in brief. 2018 Apr 1;17:71-5.

Linear Classifications using Neural Networks

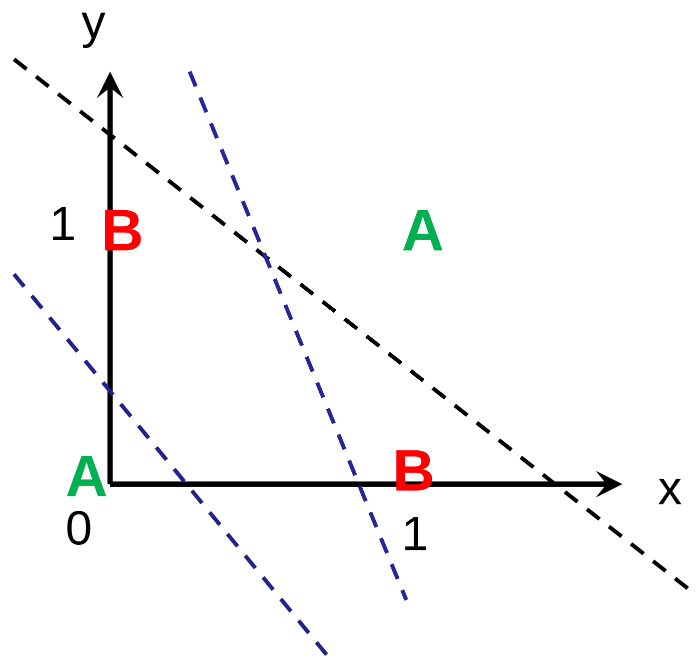
$$f(x_i; W, b) = Wx_i + b$$

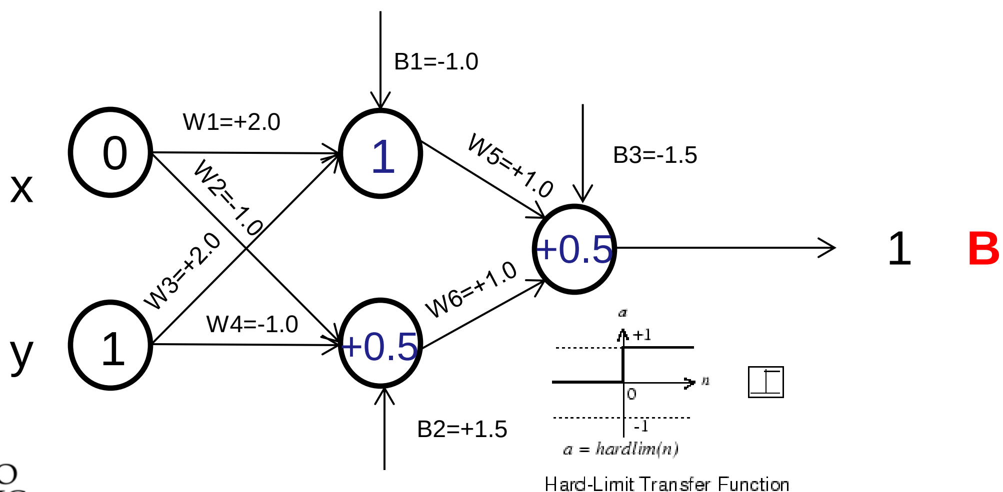


Bashiri FS, LaRose E, Peissig P, **Tafti AP**. MCIndoor20000: A fully-labeled image dataset to advance indoor objects detection. Data in brief. 2018 Apr 1;17:71-5.

NON-LINEAR CLASSIFICATIONS USING NEURAL NETWORKS

x	y	x XOR y	Class
0	0	0	A
0	1	1	B
1	0	1	B
1	1	0	A





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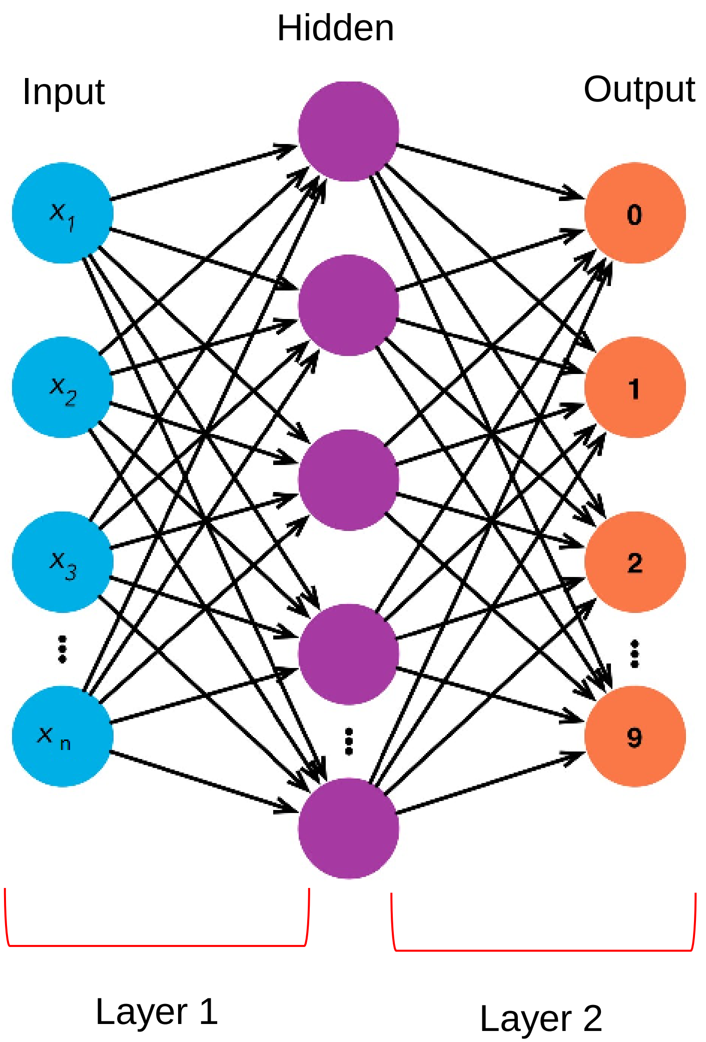
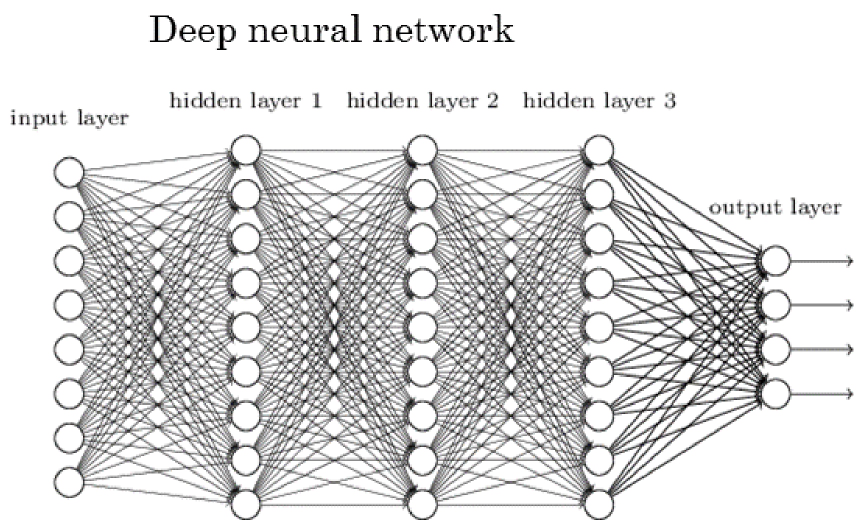
SHALLOW NEURAL NETWORK





https://datawarrior.wordpress.com/2016/04/16/relevance-and-deep-learning/

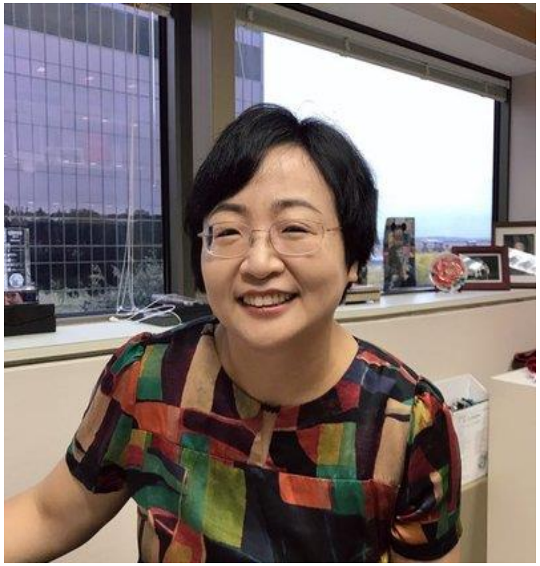
CONVOLUTIONAL NEURAL NETWORKS: WHY?

- Why do shallow fully connected neural networks not work when the input is an image?

- There are two main reasons:

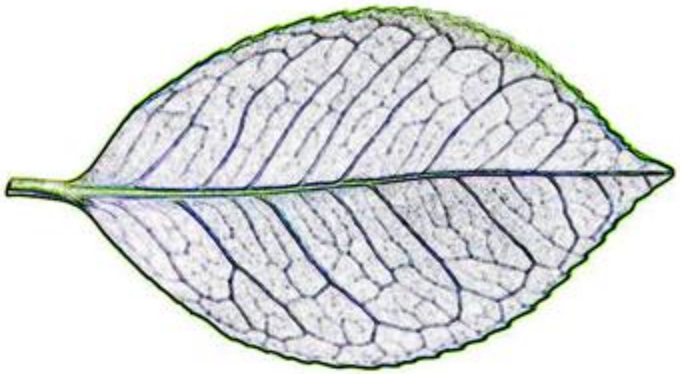
(1) The input consists of 3,000,000 numbers, therefore many weights are needed for each node in the hidden Layer. Saying 100 nodes in the first layer, this corresponds to 300,000,000 weight parameters required to define only this layer. More **parameters** mean **more training data** is needed to prevent **overfitting**. This leads to more time required to train the model.

(2) Processing by Fully Connected Deep Feed Forward Networks requires that the image data be transformed into a linear 1-D vector. This results in a **loss of structural information**, including correlation between pixel values in 2-D.



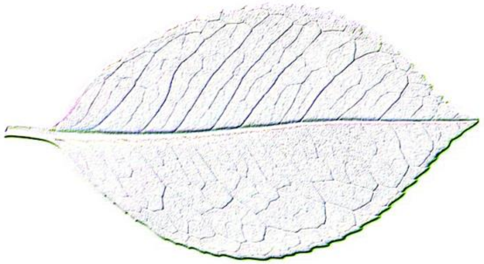
[1000 * 1000 * 3] = 3,000,000

CONVOLUTIONAL NEURAL NETWORKS: WHY?



CONVOLUTIONAL LAYER

-1	**-1**	**-1**
-1	**8**	**-1**
-1	**-1**	**-1**



Convolution of an image (left) with an edge detector convolution kernel (middle). Right is the output.

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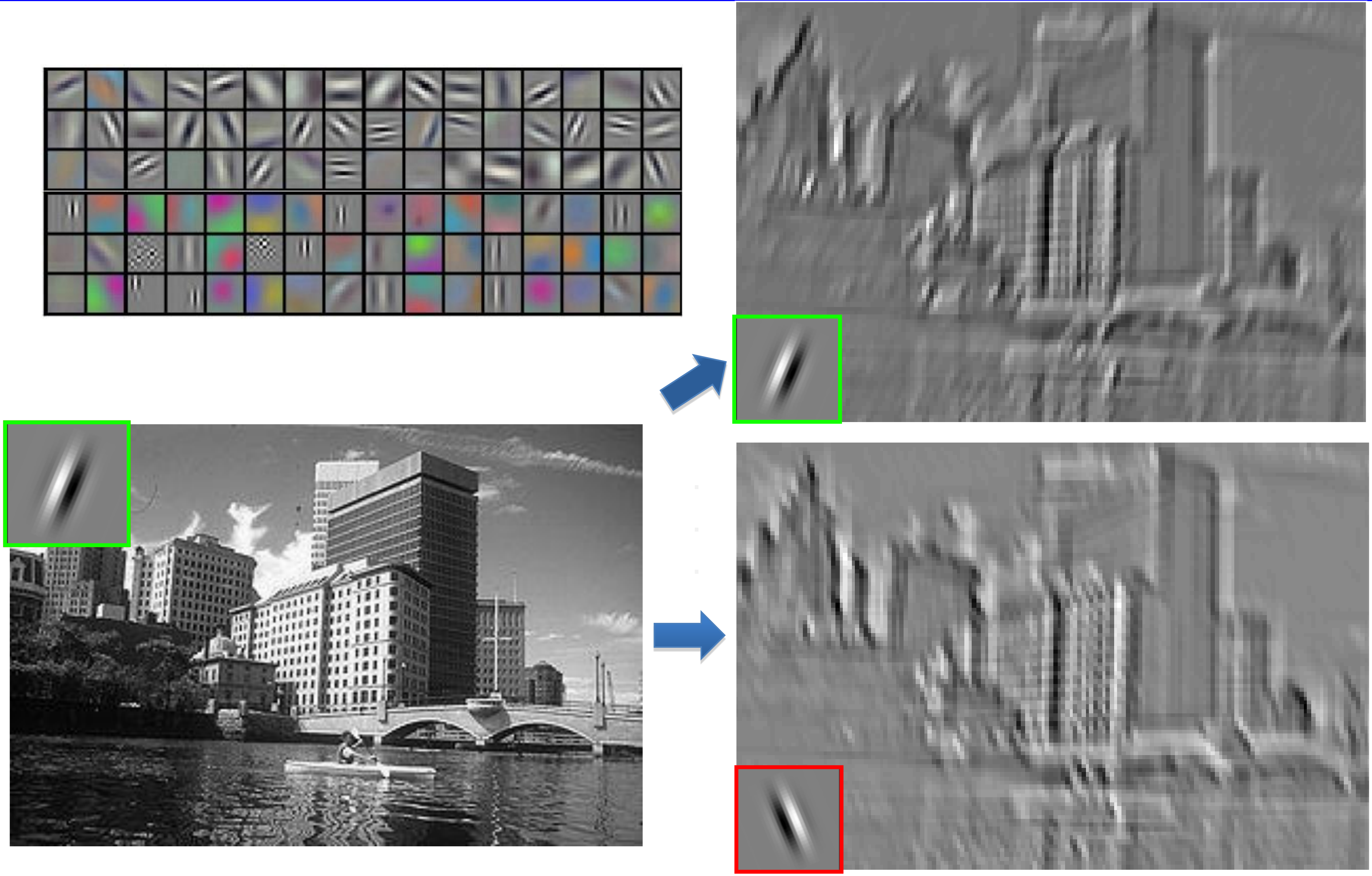

The convolution operation (slide adopted from [1])

1. Fergus, R., el al. (2012) *Deep learning methods for vision*. In: CVPR http://cs.nyu.edu/~fergus/tutorials/deep_learning_cvpr12/

CNNs: A BIT OF HISTORY

Fukushima-1980

The first **CNN**, LeNet, to read and understand hand-written checks in the US.

1993

The first **RNN**

1997

Deep Learning stagnation and inactivity.
Reasons:
- Lack of large-scale training data
- Lack of high performance computational resources
- Difficulties to train Deep Neural Networks
- Availability of highly accurate and easy-to-use ML methods, such as SVM, Naïve Bayes

……………………..…..

Hinton, G.E., Osindero, S. and Teh, Y.W., 2006. A fast learning algorithm for deep belief nets. *Neural computation*, *18*(7), pp.1527-1554.

2006

CNN (AlexNet, ZFNet, VGG) won several competitions in Image Classification, Object Recognition.

ResNet (2015): Error ~ 3.57

2012-2015

http://yann.lecun.com/exdb/lenet/

IMAGENET

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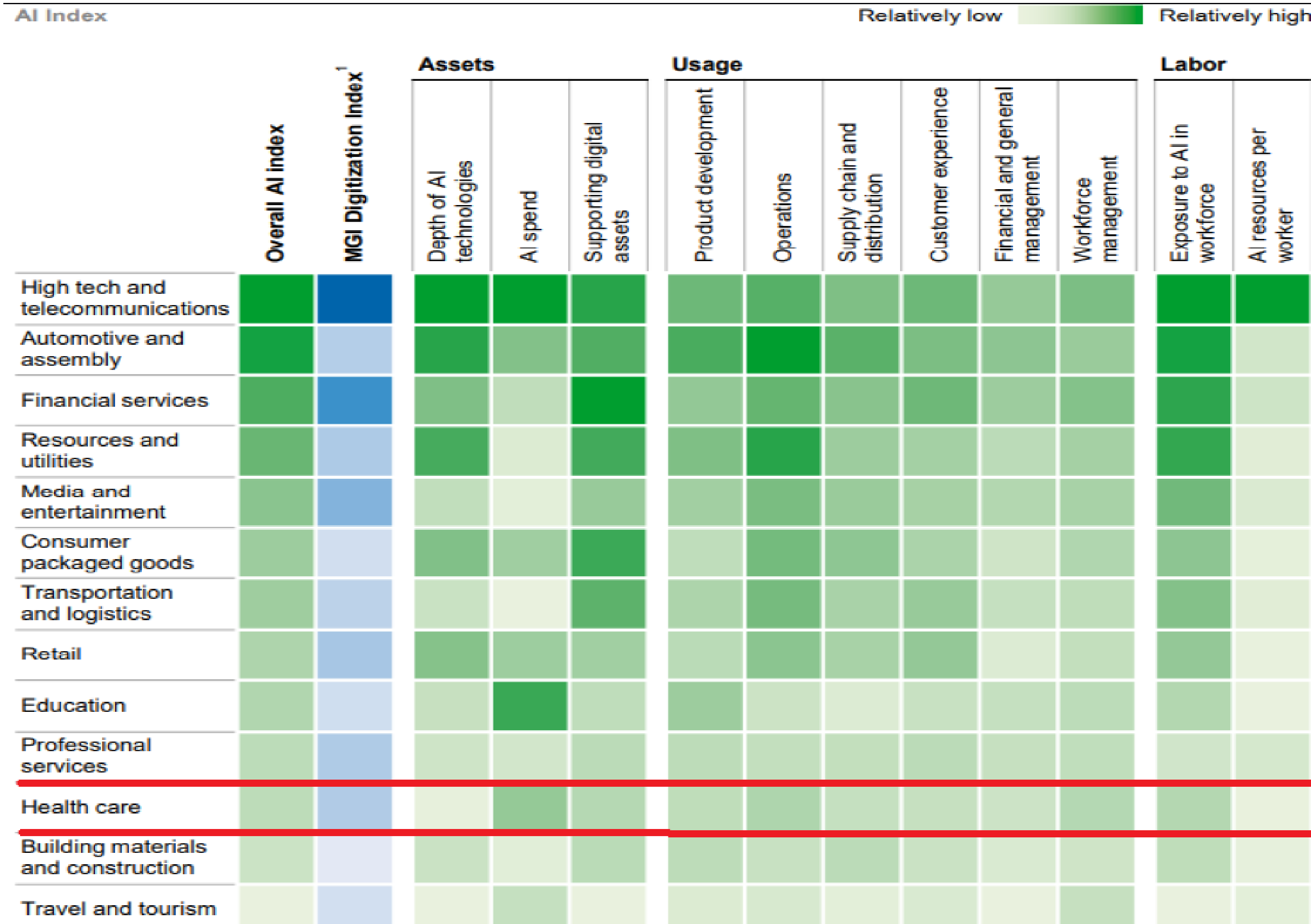
Advantages	Disadvantages
Automatic feature extraction: It reduces the need for feature engineering, one of the most time-consuming parts of machine learning practice	It requires a large amount of data. If we only have thousands of examples, deep learning is unlikely to outperform other approaches
Multi-layer feature representation/learning	It is extremely computationally expensive to train. Complex models take weeks to train. We do need GPUs to speed up the process
More accurate learning methods	Deep learning algorithms do not have much in the way of strong theoretical foundation
Can be adapted to new problems relatively easily	What is learned is not easy to comprehend. Other classifiers (e.g. decision trees, logistic regression, etc.) make it much easier to understand what’s going on

AI Adoption in Healthcare



1 The MGI Digitization Index is GDP weighted average of Europe and United States. See Appendix B for full list of metrics and explanation of methodology.

SOURCE: McKinsey Global Institute AI adoption and use survey; *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June

AI ADOPTION IN HEALTHCARE

Challenges of AI in Healthcare

- Inadequate understanding of what a given type of AI technology can or can't do
- Shortage of trained workforce
- Difficulty in deployment
- Ambiguous regulatory guidelines
- Concerns regarding privacy and security

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10 Promising AI Applications in Healthcare

APPLICATION	POTENTIAL ANNUAL VALUE BY 2026	KEY DRIVERS FOR ADOPTION
Robot-assisted surgery	$40B	Technological advances in robotic solutions for more types of surgery
Virtual nursing assistants	20	Increasing pressure caused by medical labor shortage
Administrative workflow	18	Easier integration with existing technology infrastructure
Fraud detection	17	Need to address increasingly complex service and payment fraud attempts
Dosage error reduction	16	Prevalence of medical errors, which leads to tangible penalties
Connected machines	14	Proliferation of connected machines/devices
Clinical trial participation	13	Patent cliff; plethora of data; outcomes-driven approach
Preliminary diagnosis	5	Interoperability/data architecture to enhance accuracy
Automated image diagnosis	3	Storage capacity; greater trust in AI technology
Cybersecurity	2	Increase in breaches; pressure to protect health data

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Source: Harvard Business Review, Kalis, Collier, Fu, 2018

PREDICTING CRT RESPONDERS: ENSEMBLE OF ENSEMBLE MACHINE LEARNING METHODS

Yong-Mei Cha, M.D.

Che Ngufor, PhD

Hongfang Liu, Ph.D.

Ahmad P. Tafti, PhD

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PROBLEM STATEMENT

- Cardiac resynchronization therapy (CRT) efficacy has been widely studied in the medical literature; however, about 30% of candidates still continue to fail to respond to this highly effective treatment strategy.

- We will be exploring the use of ensemble of ensemble machine learning methods combined with multiple clinical data to implement a risk stratification tool for patients implanted with a cardiac resynchronization device.

- Risk stratification tool for patients implanted with a cardiac resynchronization device can enable precise understanding of the phenotypes of responders and measures of response to CRT.

AIM

- To build a machine learning-based predictive model to predict CRT responders using multiple clinical data.

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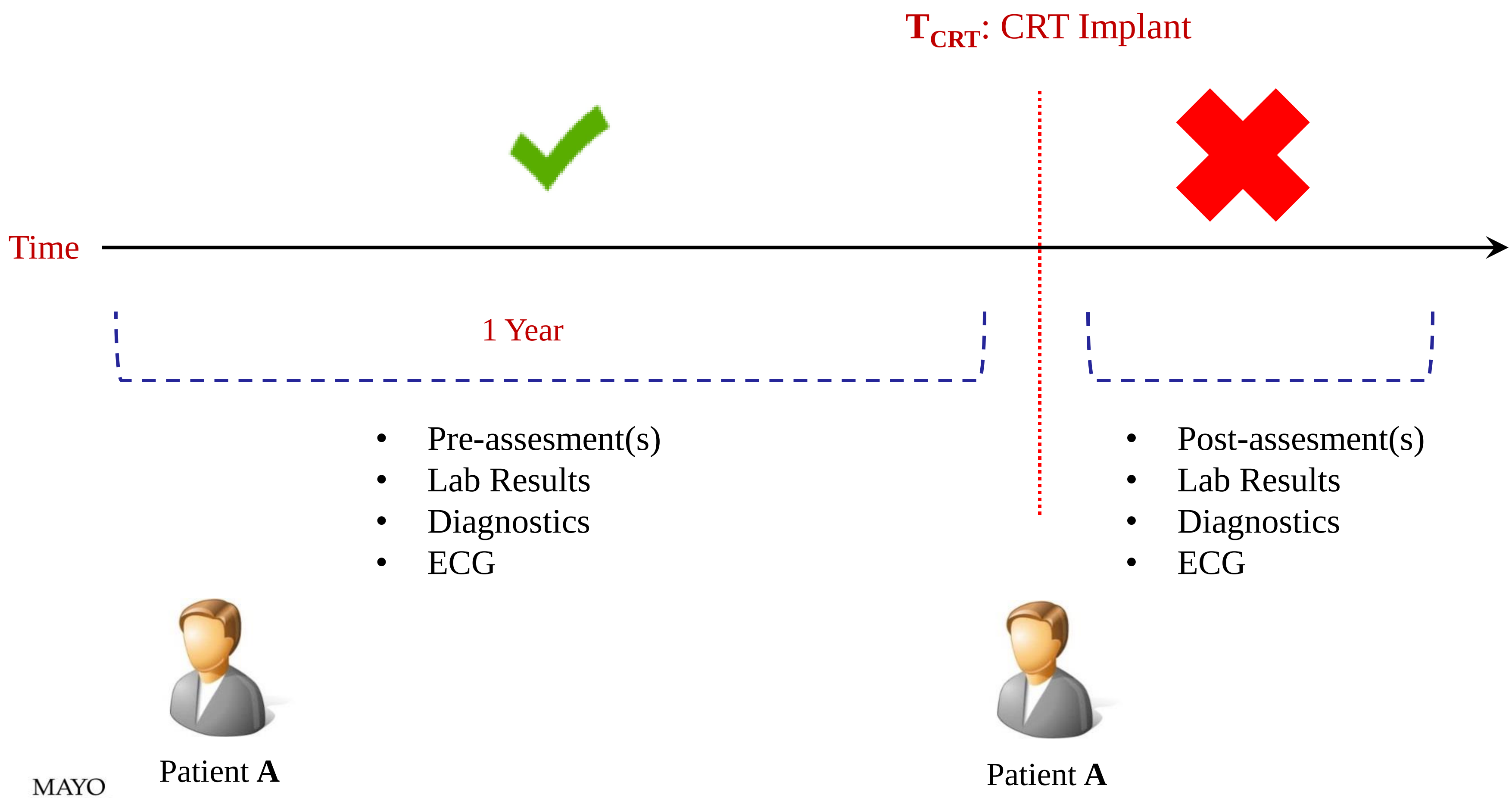
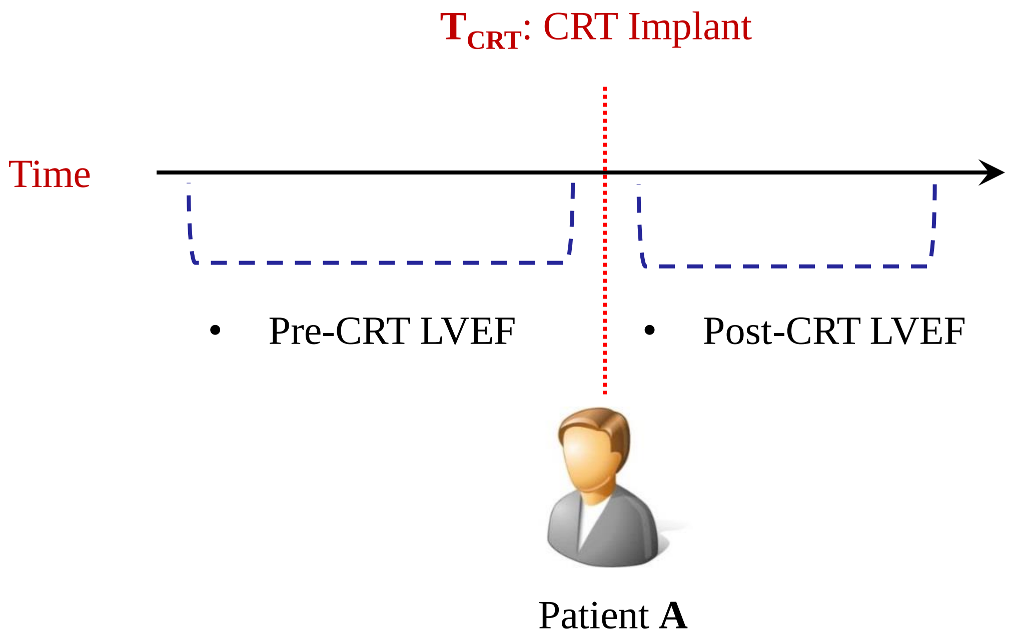
How We Processed the Data?

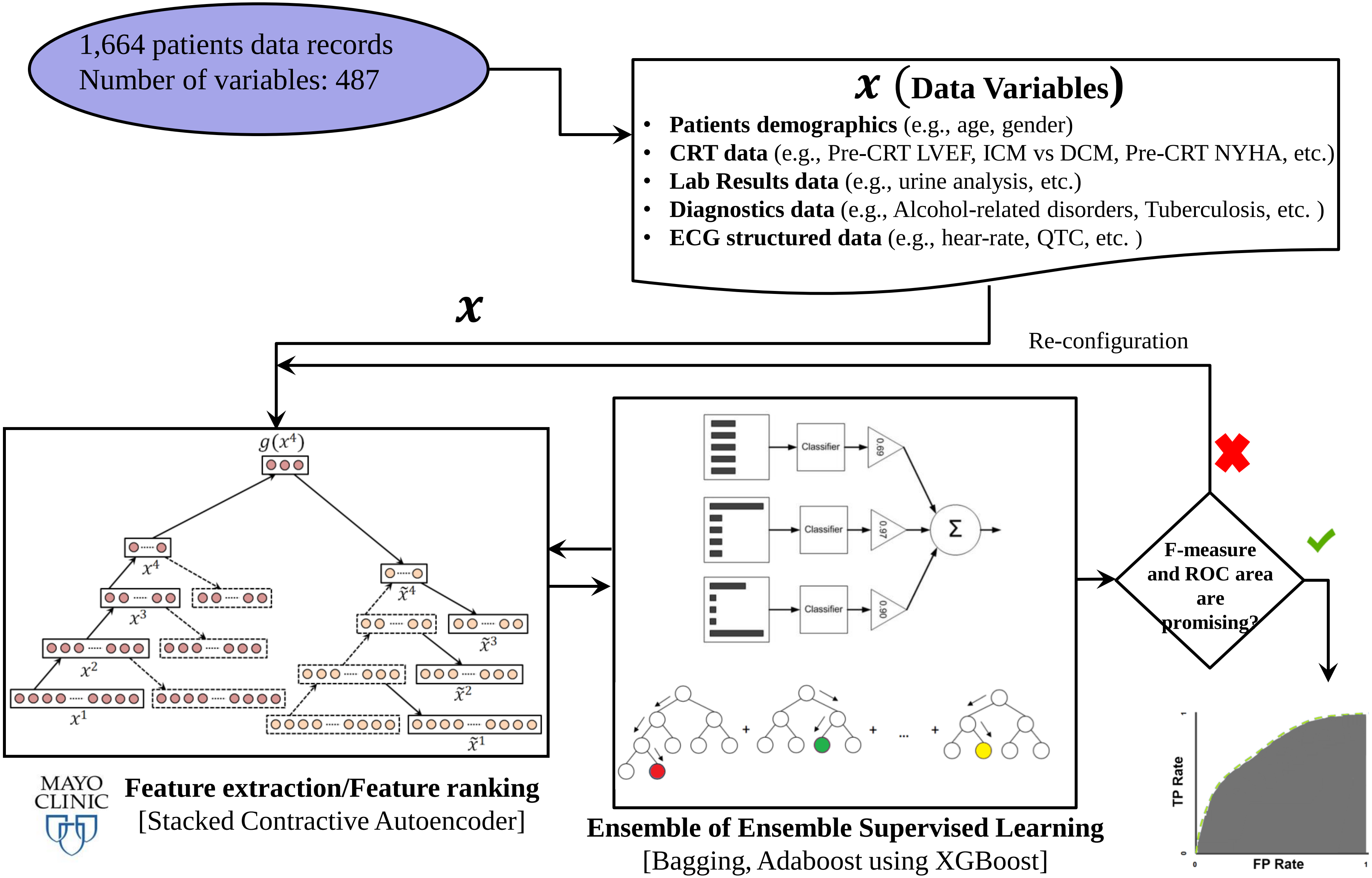


Who Is a CRT Responder?



$$Post_{CRT}LVEF - Pre_{CRT}LVEF > 10\%$$

Ensemble of Ensemble Machine Learning Methods



Results (Summary) (Contd.)

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0.739	0.261	0.721	0.739	0.734	0.758

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Results (Summary)

Top Relevant Features:

1) Pre_CRT LVEF
2) Pre-CRT MR grade
3) Pre-CRT LV end-diastolic dimension
4) Pre-CRT LVEDV
5) % paced at time of follow up (3 months)
6) QRS (0=None/normal, 1-LBBB…)
7) ACE/ARB
8) Upgrade from device (0= PM 1= ICD2=GR 9= no prev device)
9) Pre-CRT size
10) ICM vs DCM
11) 2002-ROCLIS_last_observation (Erythrocytes)
12) 2373-ROCLIS_last_observation (Bilirubin, Total, S)
13) 5423-ROCLIS_last_observation (Appearance.....)
14) 2794-ROCLIS_last_observation (Bicarbonate, P/S,)
15) 5428-ROCLIS_last_observation (Protein)
16) 6579-ROCLIS_last_observation (Protein/Osmolality)
17) 80198-ROCLIS_last_observation (LDL, Calculated)
18) 81793-ROCLIS_last_observation (BUN (Bld Urea Nitrogen))
19) 8476-ROCLIS_last_observation (Glucose(P))
20) 9236-ROCLIS_last_observation (Prothrombin Time(P))
21) 2093-ROCLIS_median (Monocytes..)
22) 2097-ROCLIS_median (Platelet Count)
23) 81793-ROCLIS_median (BUN (Bld Urea Nitrogen))
24) 9236-ROCLIS_median (Prothrombin Time(P))
25) CCS_Code_2616 (E Codes: Adverse effect of medical care)
26) CCS_Code_57 (Immunity DX)
27) CCS-Code-149 (Biliary Disease)
28) CCS_Code_660 (Alcohol-related disorder)
29) Number_of_times_ECG_occurred_before_CRT_implanted
30) Last_PR_WAVE_NBR

Baseline CRT data + Demographics

Lab results

Diagnostics

ECG structured data

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DEEP LEARNING COMPUTATIONAL VISION ADOPTION IN KNEE TJA RESEARCH

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Michael J. Taunton, M.D.
Orthopedic Surgeon

David G. Lewallen, M.D.
Orthopedic Surgeon

Sunghwan Sohn, Ph.D.

Hongfang Liu, Ph.D.

Ahmad P. Tafti, Ph.D.

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PROBLEM STATEMENT

- Osteoarthritis (OA) is the most common joint disease across the world, and knee OA takes more than 80% of the disease which influences at least 23% of Americans. Unfortunately, there are no effective treatment strategies for knee OA except the Total Joint Arthroplasty (TJA).
- After a TJA surgery, boneless, infection and other complications can happen around prosthesis.
- Currently, knee OA severity and TJA follow-up are diagnosed by examining the symptomatic joint and X-ray radiographic.
- However, the radiologist and surgeons are facing with an overwhelming amount of X-ray images in a daily basis. That being said, the increasing prevalence of knee OA and knee TJA as a serious consequence, means there is a pressing need to develop effective artificial intelligence-enabled mechanisms to help the radiologist and clinicians make the diagnosis more efficient and choose a precious treatment paln in a timely fashion.

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AIMS

- Establishing a knee TJA cohort, and computationally assemble an intensive fully-annotated radiographic dataset through the institutional TJA registry.
- Develop, train, validate, and test advanced deep learning computational vision algorithms for autonomous detection (presence-absence), localization (zone, location), and characterization (fractures, lucency, implant loosening, infection) of selected TJA complications in total knee arthroplasty radiographs.
- Assess the validity of automated deep learning-enabled radiographic markers as surrogates of revision surgery.

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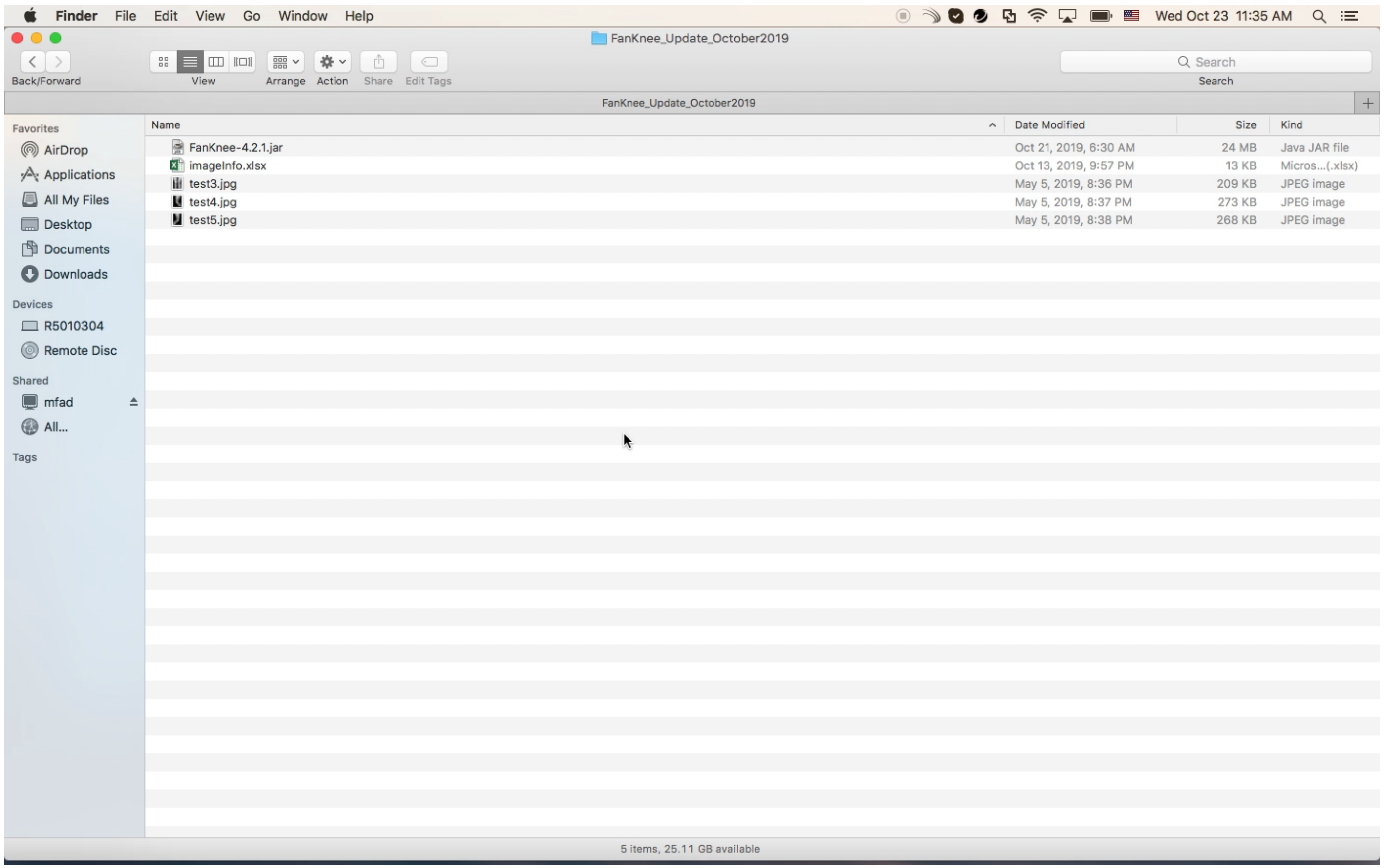
OUR SO FAR CONTRIBUTIONS: FANKNEE

FanKnee: **an open-source toolkit to make fully-annotated datasets using plain radiographs**



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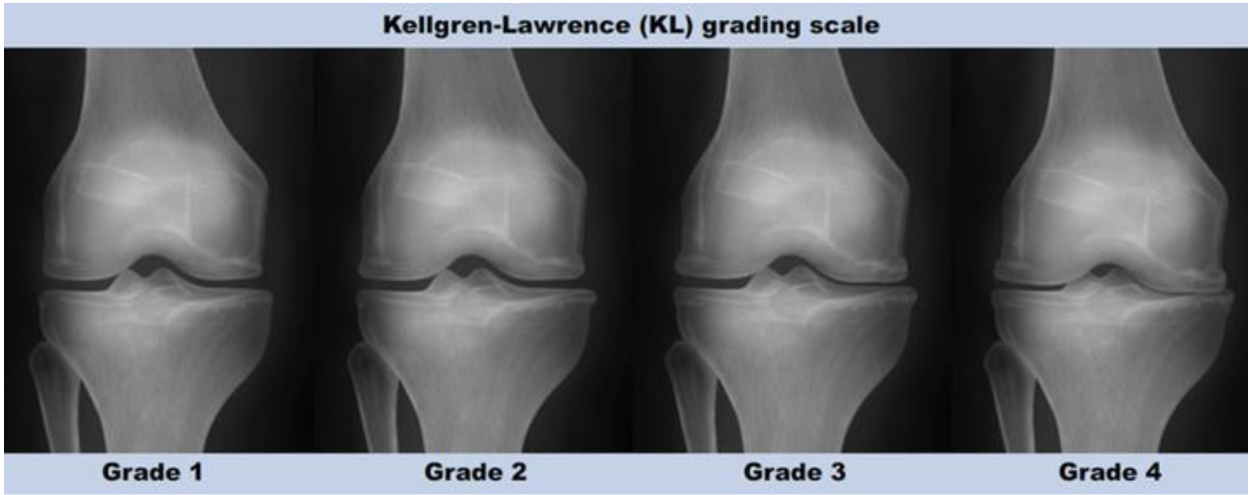
OUR SO FAR CONTRIBUTIONS: DEEPFUSEDKNEE

- Task
  - Quantify the severity of knee OA
  - Understanding it as a 5 classes classification task



- Data Source
  - Osteoarthritis Initiative (OAI) + Mayo Clinic Data
  - About 4000 patients

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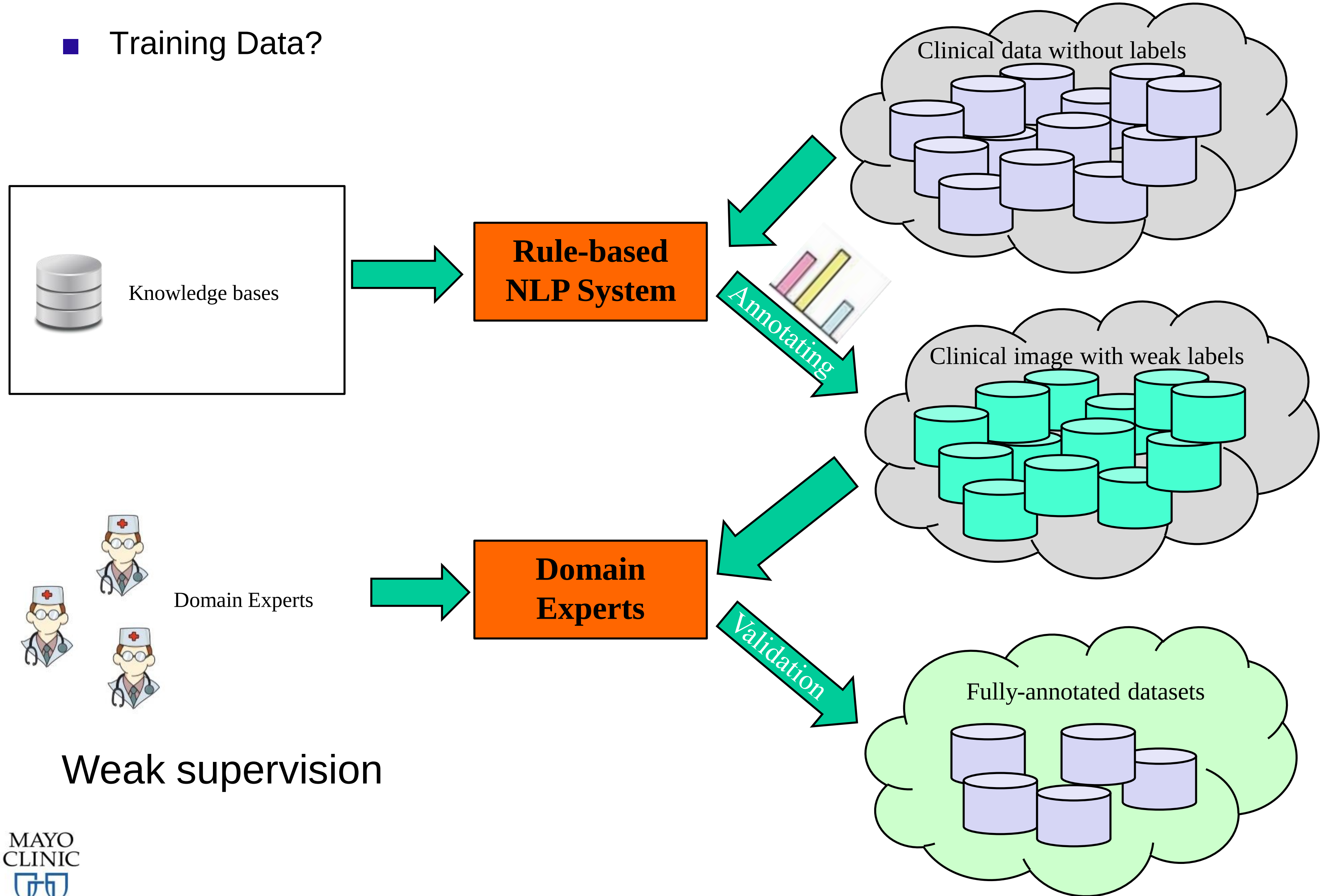
OUR SO FAR CONTRIBUTIONS: DEEPFUSEDKNEE

- Training Data?



Weak supervision

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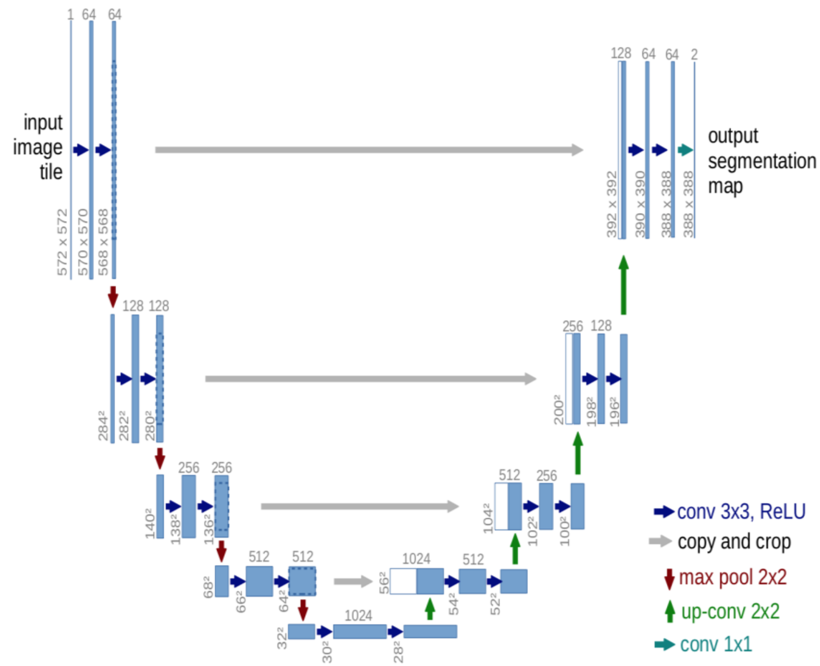
OUR SO FAR CONTRIBUTIONS: DEEPFUSEDKNEE

Knee joint space localization using plain radiographs: a deep learning method

U-Net Architecture
- Contains set of down-sampling layers

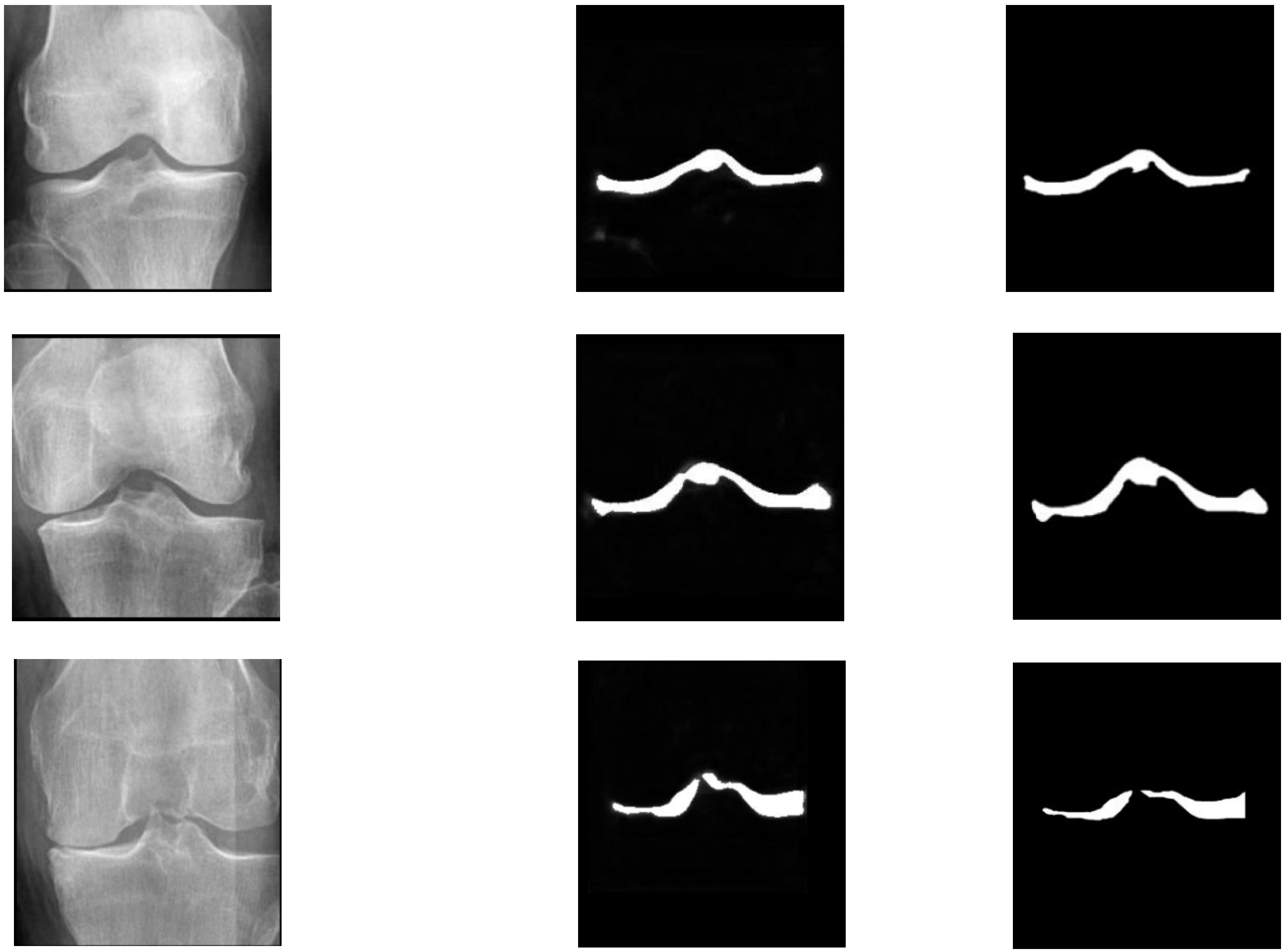
Training details:
- Overall 9,093 images
- 6,200 for training
- ~2,900 for validation



https://arxiv.org/pdf/1505.04597.pdf

RESULTS

X-ray Image | Prediction | Ground Truth



IOU Score= 0.97

IOU Score= 0.94

IOU Score= 0.93

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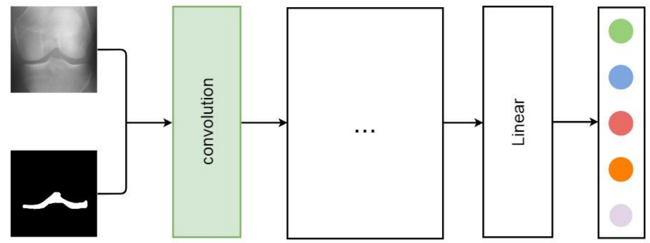
Our so far contributions: DeepFusedKnee

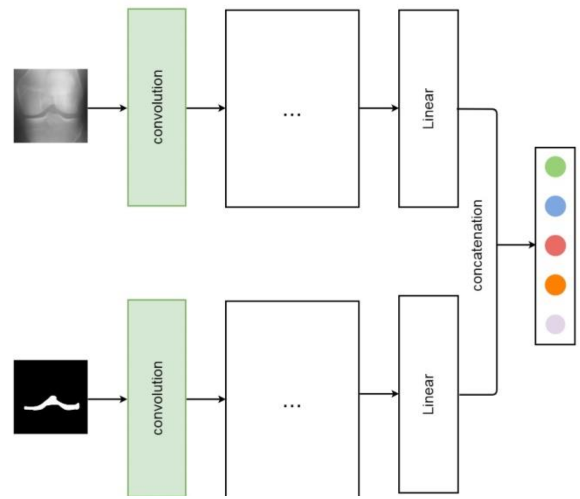
Early fusion strategy:

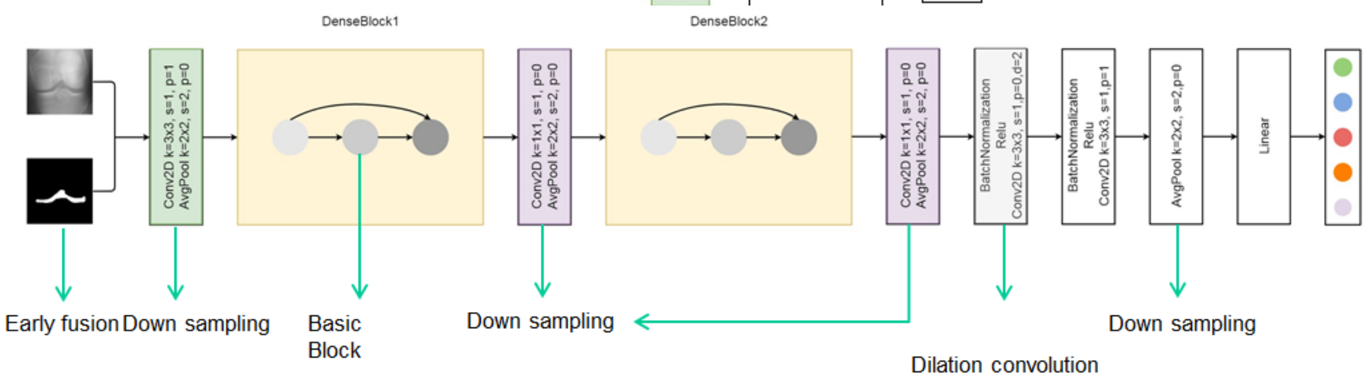
If the original image resolution is 256*256 *3, after early fusion, you will have 256*256*6



Late fusion strategy:

Feed images into two same pipeline, then concatenate the linear layer.





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OUR SO FAR CONTRIBUTIONS: DEEPFUSEDKNEE

– We split the data by patient ID with the ratio 70%:15%:15%

Class	Accuracy	Precision	Recall	F1 Score
1	88.25%	0.75	0.79	0.77
2	84.5%	0.67	0.75	0.71
3	86.25%	0.75	0.68	0.71
4	90.5%	0.84	0.77	0.80

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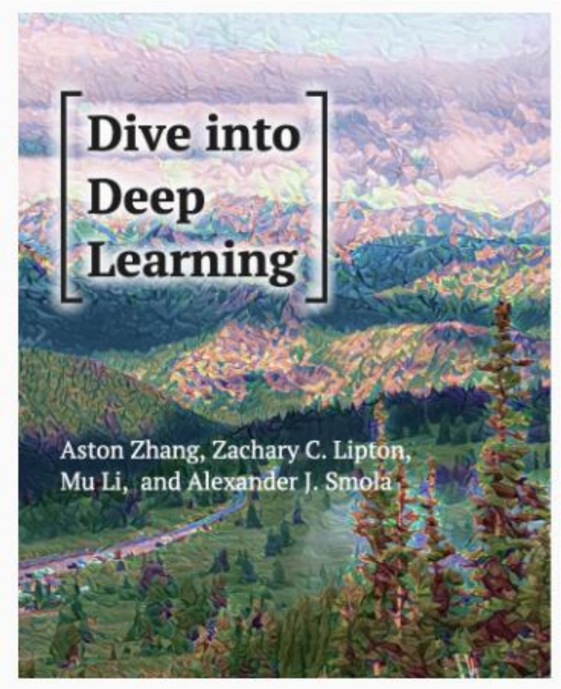
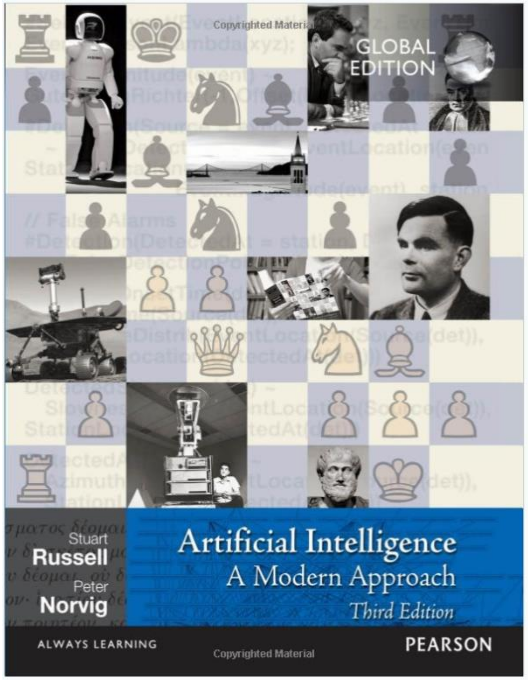
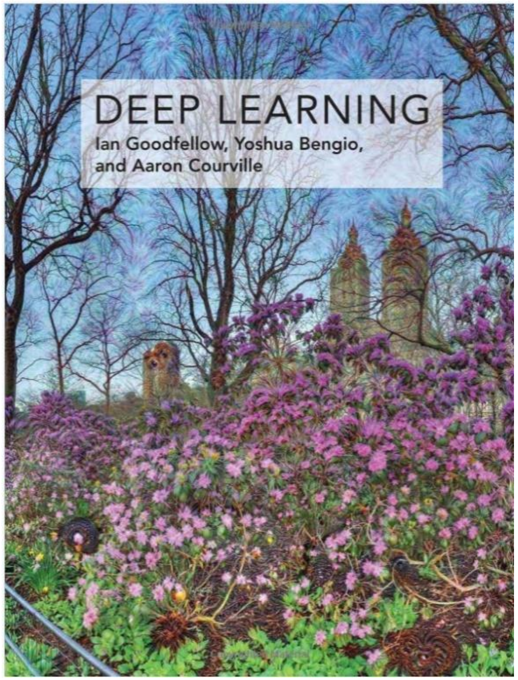
MORE READINGS







Thank You!

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