



# Introduction to AI

Kickstarting your data-driven and medical AI projects

November 28<sup>th</sup>, 2024



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- Research Affairs, Faculty of Medicine, Chulalongkorn University
- Computational Molecular Biology Group (CMB)
- Center for Artificial Intelligence in Medicine (CU-AIM)

# About myself

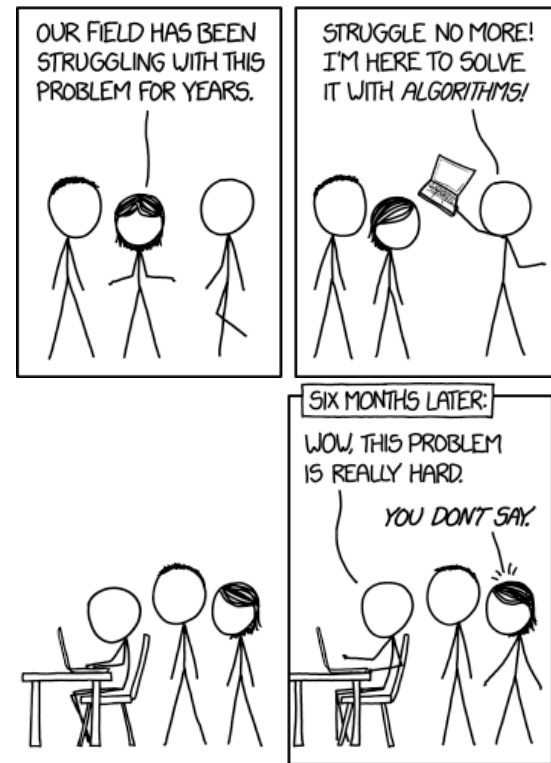
Background in **computational biology**: mathematics, computer sciences, and molecular biology

Learned but never use ML/AI until 2017



Form Computational Molecular Biology and AI in Medicine Centers at Chula

Like to apply computational thinking to any problem



# Talk plan



- Day 1
  - Introduction to AI
  - Roles of medical practitioner in the AI era
  - Federated learning workshop
- Day 2
  - How to become an AI-ready hospital?
  - Practical experiences on AI-assisted CXR workflow



# What is AI?

# Natural vs artificial intelligence

- AI is the result of **computer algorithms mimicking the natural learning process**
- Measure of intelligence
  - Ability to generalize to unseen data
  - Ability to create things
  - Ability to reason with cause and effect

## Single cortical neurons as deep artificial neural networks

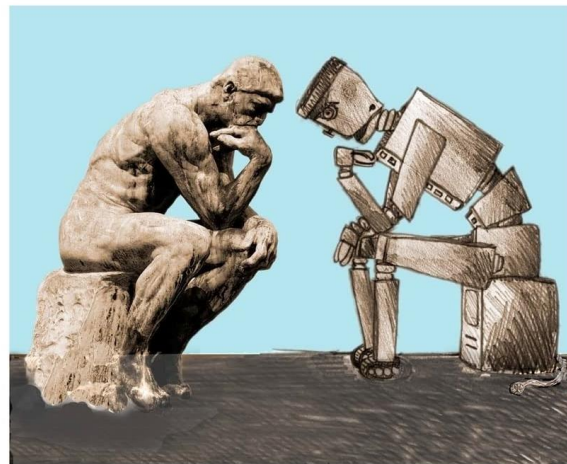
David Beniaguev,<sup>1,3,\*</sup> Idan Segev,<sup>1,2</sup> and Michael London<sup>1,2</sup>

<sup>1</sup>Edmond and Lily Safra Center for Brain Sciences (ELSC), The Hebrew University of Jerusalem, Jerusalem 91904, Israel

<sup>2</sup>Department of Neurobiology, The Hebrew University of Jerusalem, Jerusalem 91904, Israel

## UNDERSTANDING UNDERSTANDING

NATURAL AND ARTIFICIAL  
INTELLIGENCE



ROBERT K. LINDSAY

# Mechanism of learning



	Human	Machine
Memorization	✓	✓✓✓
Pattern recognition	✓	✓
Trial and error	✓	✓
Generalization/Reasoning	✓✓✓	x
Information compression	?	✓✓✓

# Memorization and information compression



# Pattern recognition

## Human vs Machine: Pneumonia

Chest X-Rays image the lungs, heart, blood vessels, and bones. AI has been used to read and understand them.

Example:  
Pneumonia

Computers:  
Score: 0.371

Doctors:  
0/15 Detected



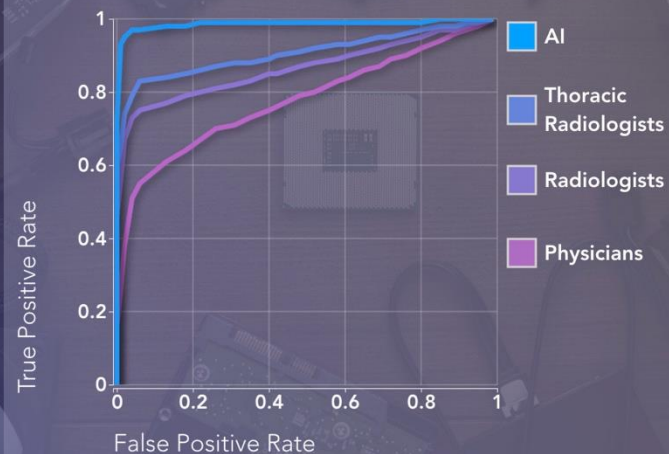
Clearvue Health

Hwang et al

## AI vs Doctors: Chest X-Rays

AI was significantly more accurate and precise than radiologists and physicians in diagnosing chest x-rays.

AUC-ROC: Human vs Computer

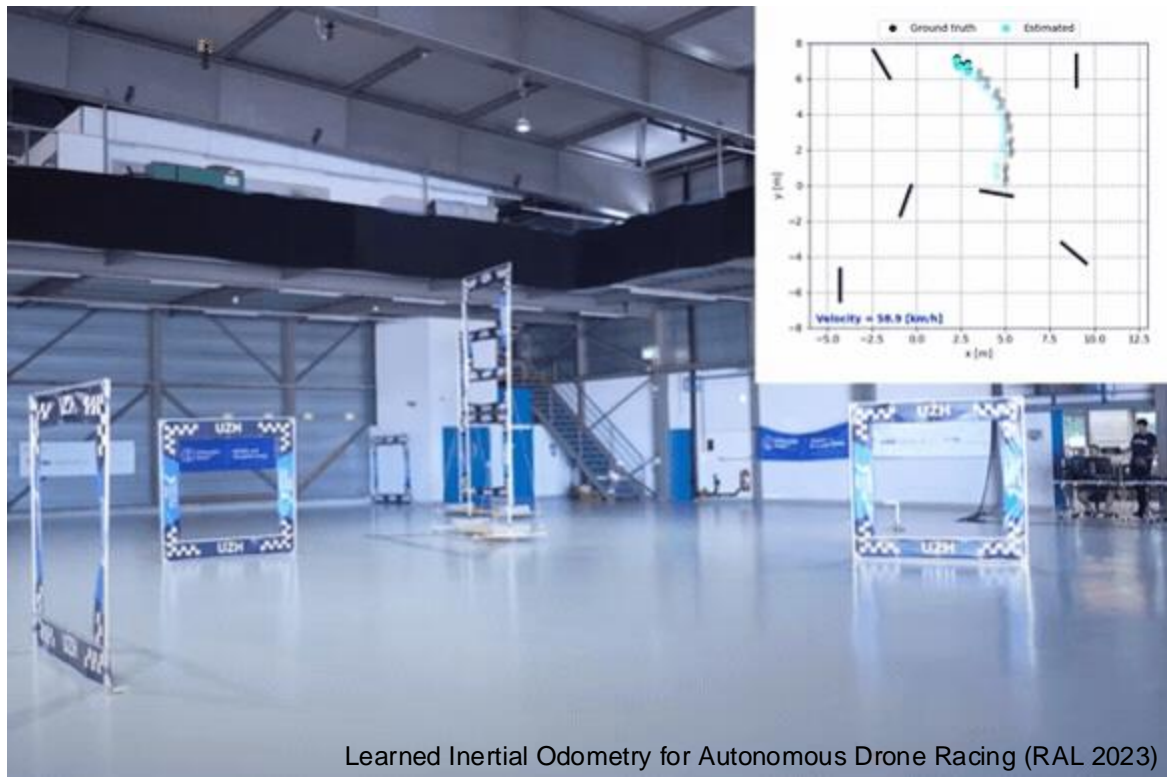


Clearvue Health

Hwang et al



# Trial and error



Google DeepMind's AlphaGo computer beats top player Lee Sedol for third time to sweep competition



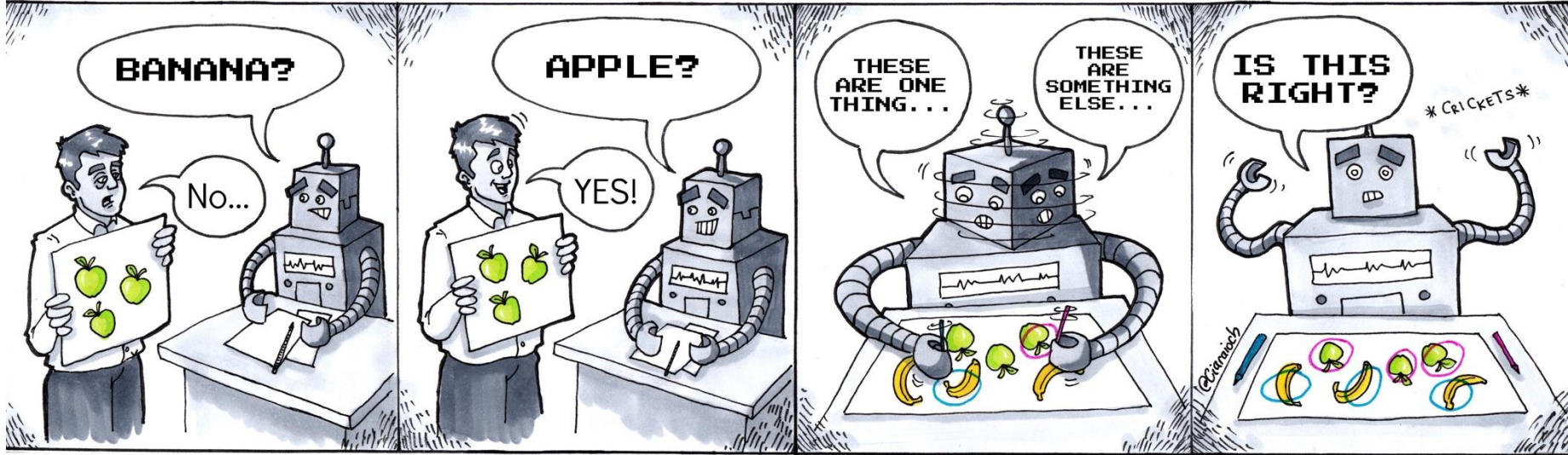


# **Machine learning (ML), the engine behind modern AI**

# Internet search: AI without ML



# Supervised and unsupervised learning



## Supervised Learning

Find decision functions with high accuracy

## Unsupervised Learning

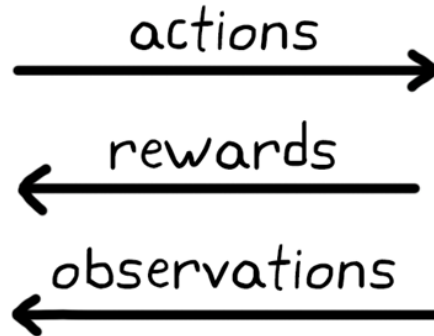
Find patterns and similarities among data

# Reinforcement learning

Supervised learning with dynamic,  
on-the-fly data generation

Find action strategies with high rewards

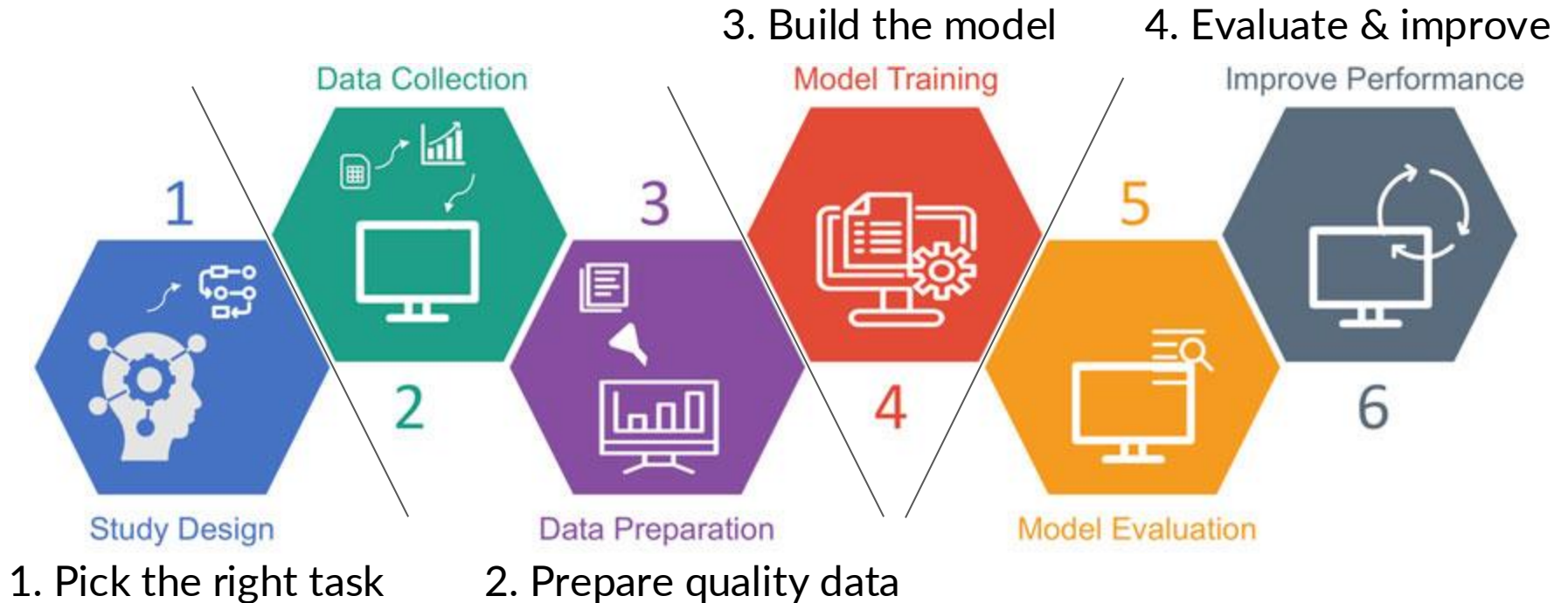
agent



environment



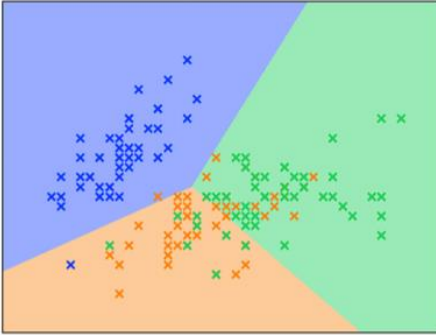
# Supervised learning framework



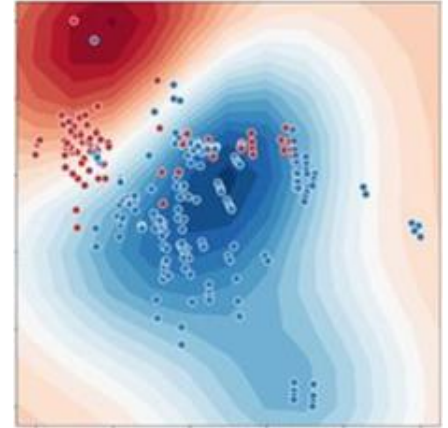
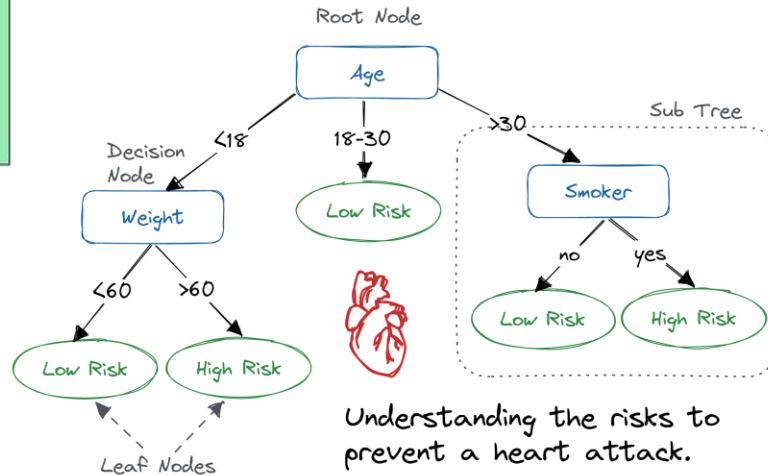


# Some classical ML models

**Linear:**  $\text{Score} = (\text{input}_1 \times w_1) + \dots + (\text{input}_n \times w_n)$

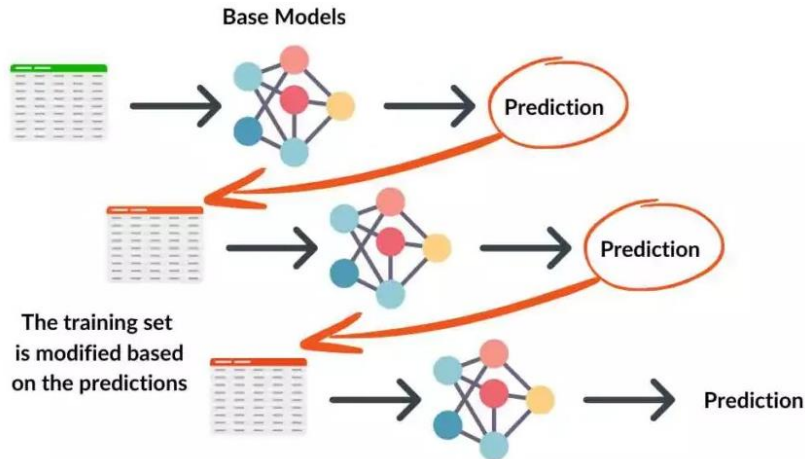


**Tree:** Collection of decisions



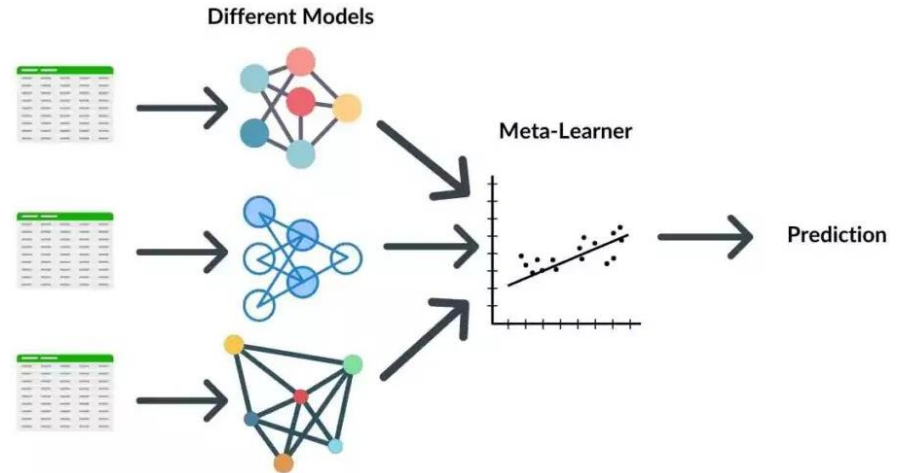
**Neighbor-based:**  
Predict using similarity to past observations

# Ensemble approaches



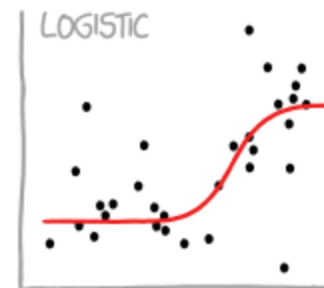
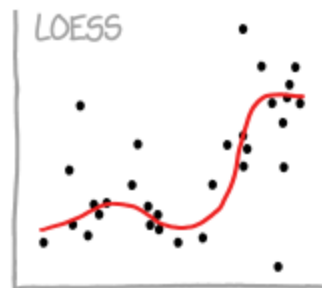
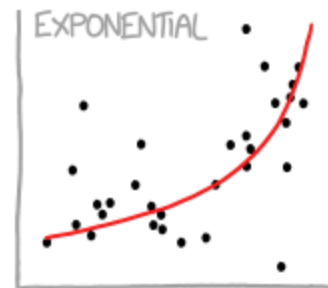
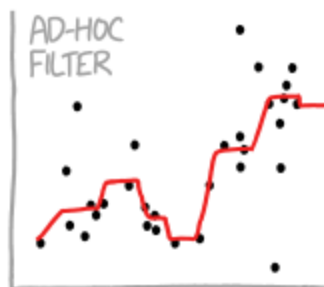
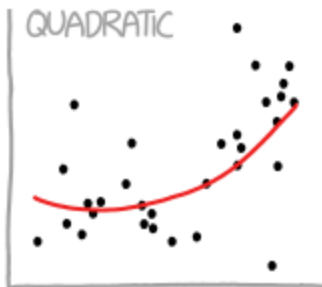
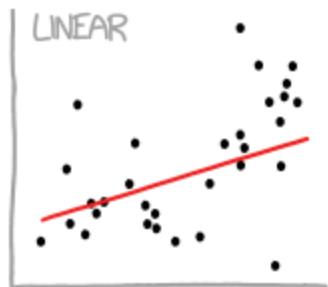
**Boosting:** Iterative improvement with additional models

**Stacking:** Combine multiple models with different capabilities

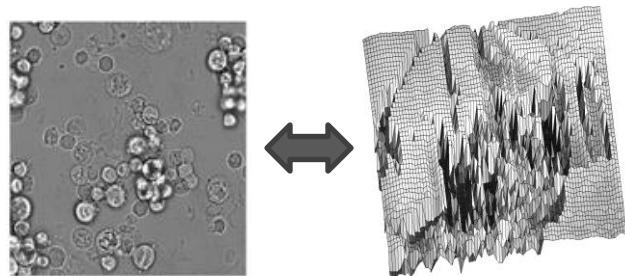




# Limitation of classical ML



- Unable to fit complex relationships
- Unable to handle raw data like text or image



# Naïve representation is not useful

	1	2	3	4	5	6	7	8	9
man	1	0	0	0	0	0	0	0	0
woman	0	1	0	0	0	0	0	0	0
boy	0	0	1	0	0	0	0	0	0
girl	0	0	0	1	0	0	0	0	0
prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

Image from hackermoon.com

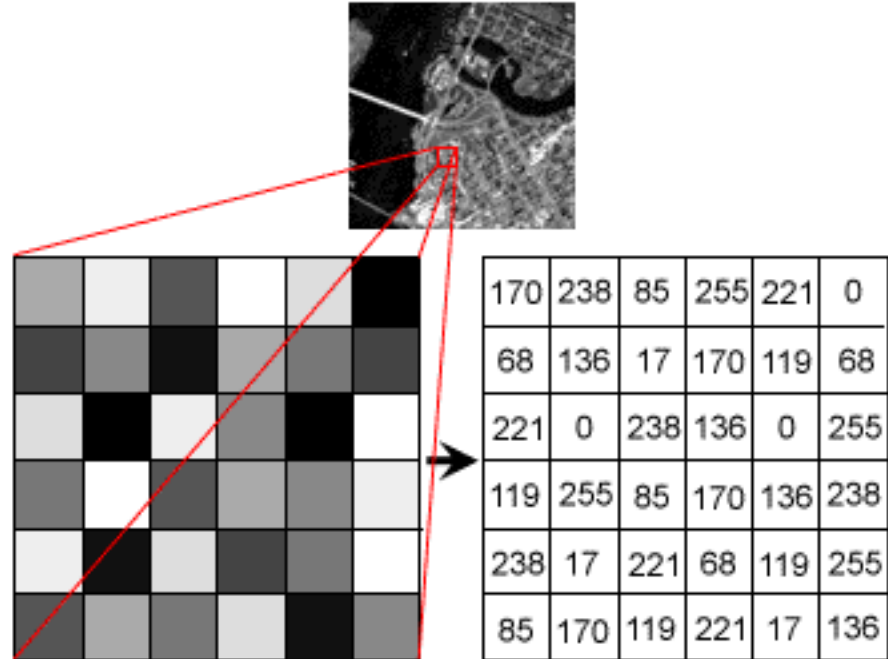
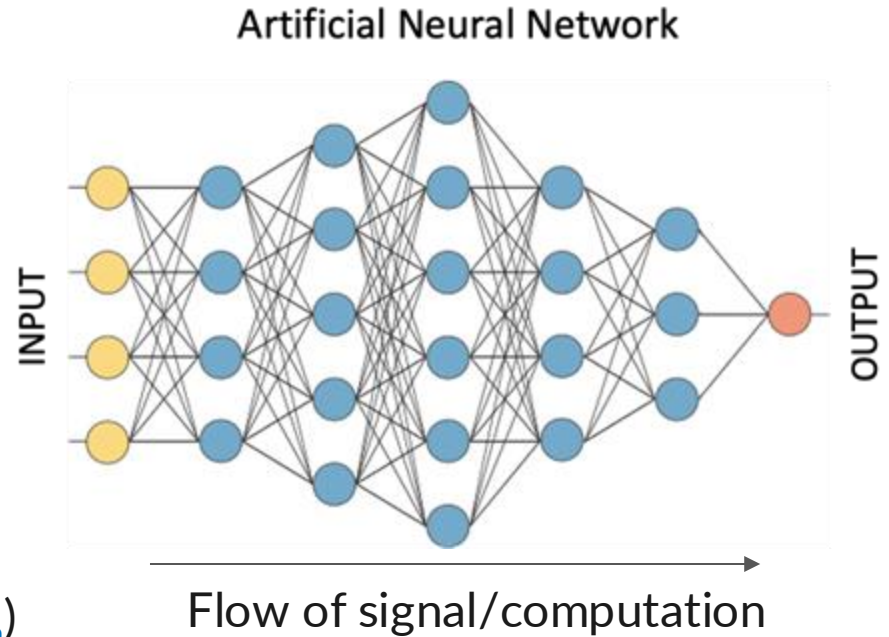
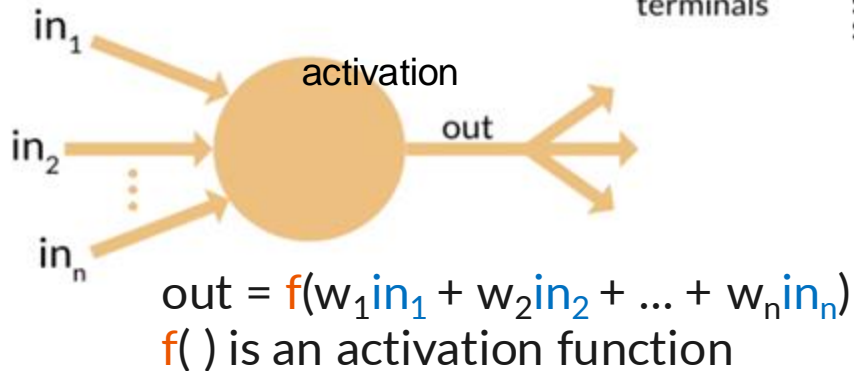
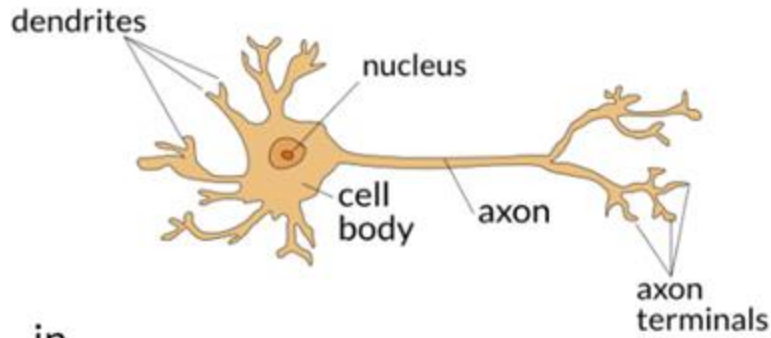


Image from naushardsblog.wordpress.com



# Artificial neural network (ANN)

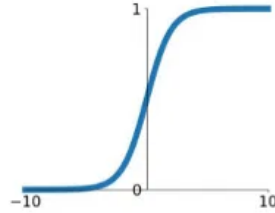
# Inspired by biological neurons



# Activation function

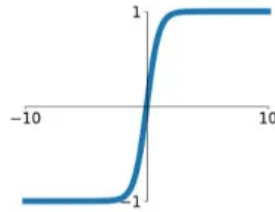
## Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



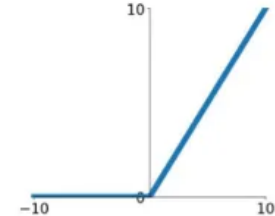
## tanh

$$\tanh(x)$$



## ReLU

$$\max(0, x)$$



- Simple, non-linear function
- Mimic the activation of a biological neuron
- Without non-linear activation function, ANN is just a linear regression

# Universal approximation theorem (Cybenko 1989)

**Universal Approximation Theorem:** Fix a continuous function  $\sigma : \mathbb{R} \rightarrow \mathbb{R}$  (activation function) and positive integers  $d, D$ . The function  $\sigma$  is not a polynomial if and only if, for every **continuous** function  $f : \mathbb{R}^d \rightarrow \mathbb{R}^D$  (target function), every **compact** subset  $K$  of  $\mathbb{R}^d$ , and every  $\epsilon > 0$  there exists a continuous function  $f_\epsilon : \mathbb{R}^d \rightarrow \mathbb{R}^D$  (the layer output) with representation

$$f_\epsilon = W_2 \circ \sigma \circ W_1,$$

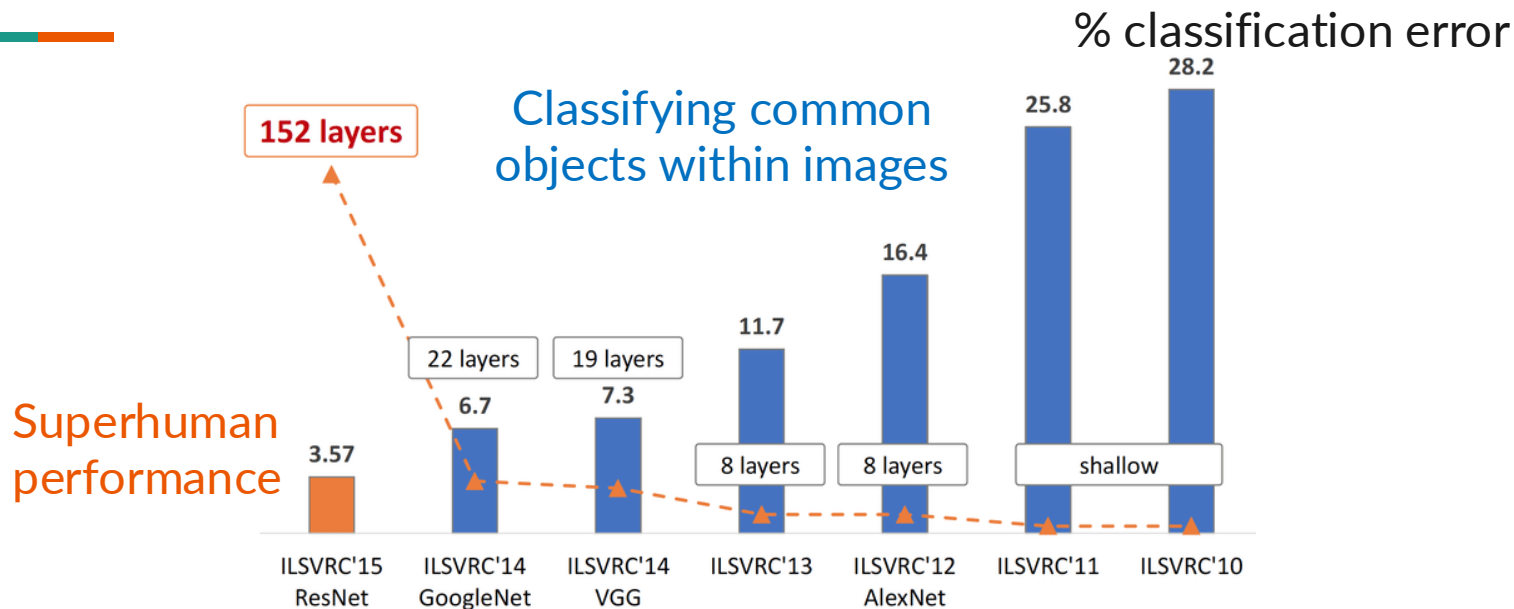
where  $W_2, W_1$  are **composable affine maps** and  $\circ$  denotes component-wise composition, such that the approximation bound

$$\sup_{x \in K} \|f(x) - f_\epsilon(x)\| < \epsilon$$

holds for any  $\epsilon$  arbitrarily small (distance from  $f$  to  $f_\epsilon$  can be infinitely small).

- ANN with just one layer of neurons and a non-polynomial activation function can capture any continuous mathematical relationship

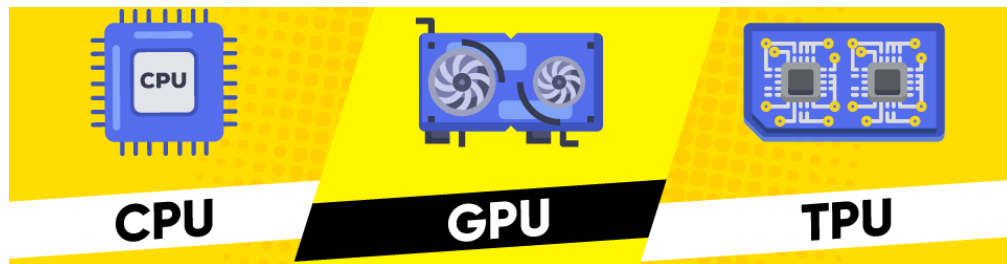
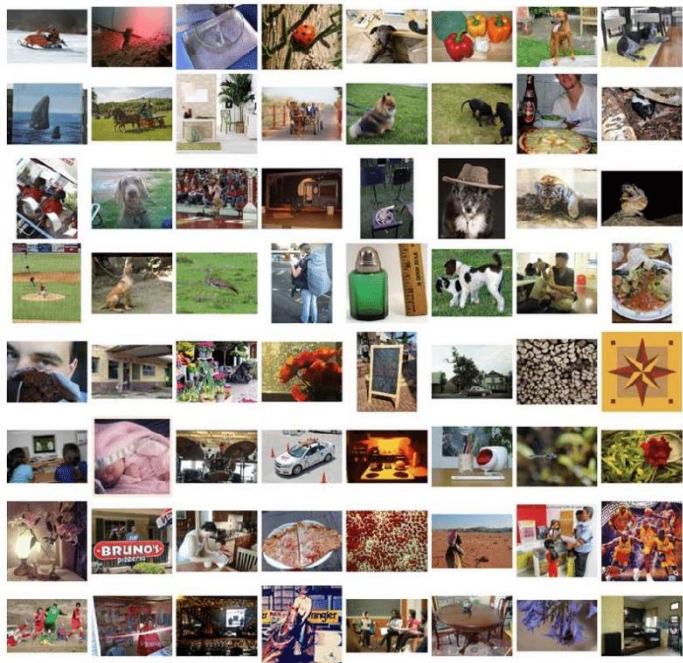
# The rise of ANN



- During 2010-2015, ANN suddenly improved from 28% error to superhuman performance. **Why?**

# Data and computing resources

## ImageNet



<https://serverguy.com/cpu-vs-gpu-vs-tpu/>

- **Data:** Internet and digital technology
- **Compute:** Faster, more optimized for ANN training (GPU and TPU)





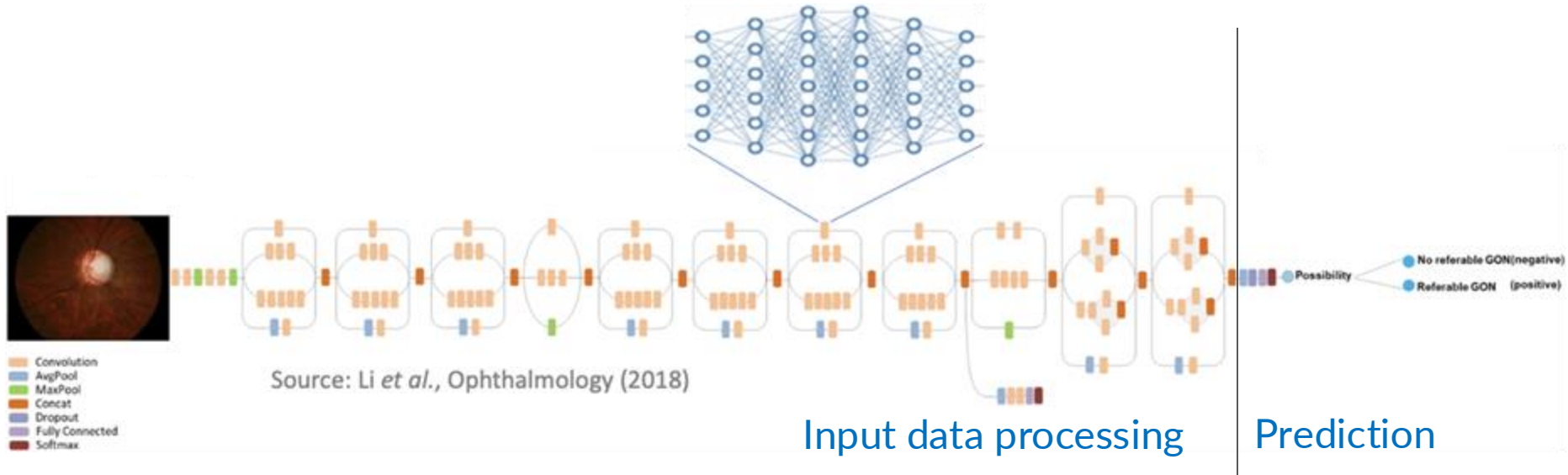
# Deep learning

A close-up shot of Leonardo DiCaprio in a dark suit and white shirt. He is looking down and slightly to his right with a serious, intense expression. The lighting is dramatic, with strong highlights and shadows. The background is blurred, showing what appears to be an office or indoor setting.

**THAT'S NOT ENOUGH**

**WE HAVE TO GO DEEPER**

# Deep ANN is needed to process raw input data



- Millions to billions of parameters
- **Deep learning** = ML techniques for deep ANN

# Extracting information from image (pixel data)



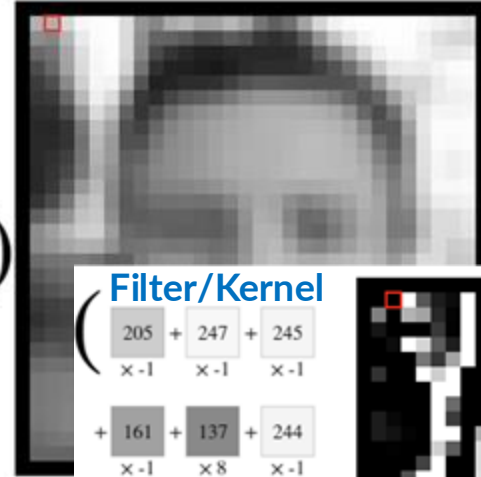
input image

**Filter/Kernel**

$$\begin{pmatrix} 205 & 247 & 245 \\ \times 0.0625 & \times 0.125 & \times 0.0625 \\ + & 161 & 137 & + & 244 \\ \times 0.125 & \times 0.25 & \times 0.125 \\ + & 154 & 75 & + & 200 \\ \times 0.0625 & \times 0.125 & \times 0.0625 \end{pmatrix}$$

= 175

kernel: blur



**Filter/Kernel**

$$\begin{pmatrix} 205 & 247 & 245 \\ \times -1 & \times -1 & \times -1 \\ + & 161 & 137 & + & 244 \\ \times -1 & \times 8 & \times -1 \\ + & 154 & 75 & + & 200 \\ \times -1 & \times -1 & \times -1 \end{pmatrix}$$

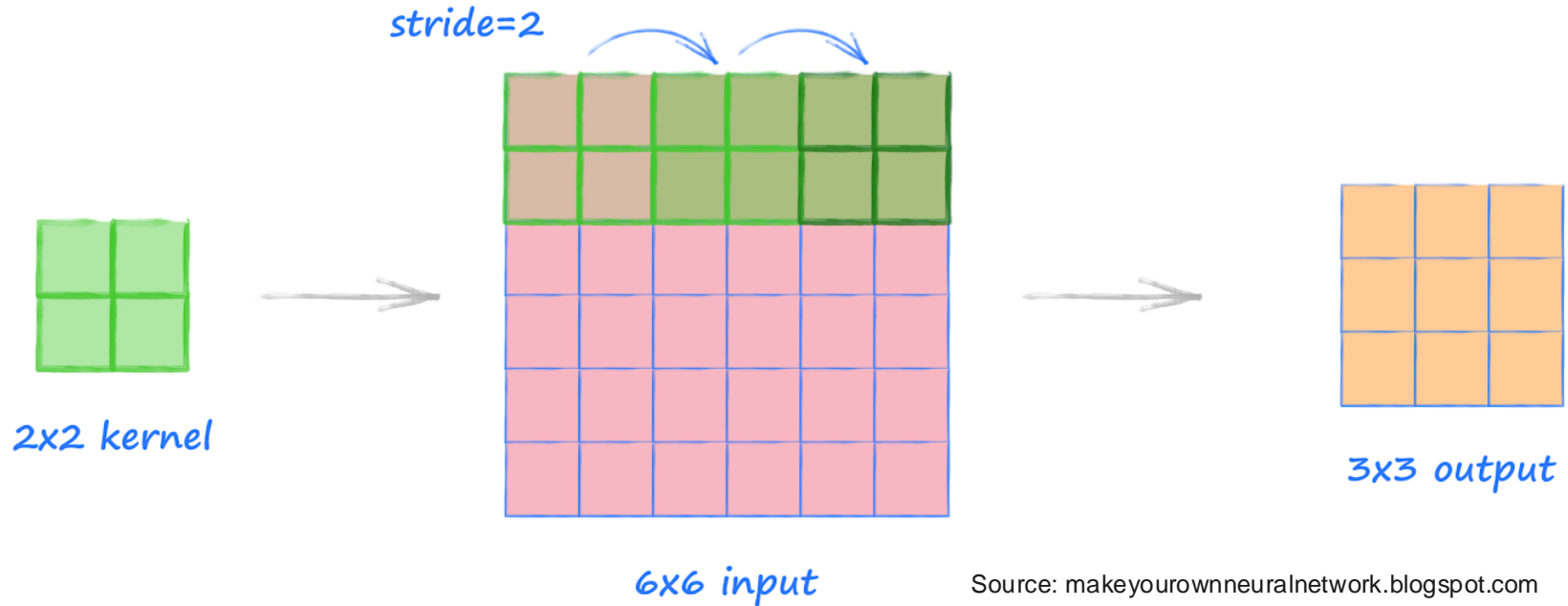
= -435

kernel: outline



output image

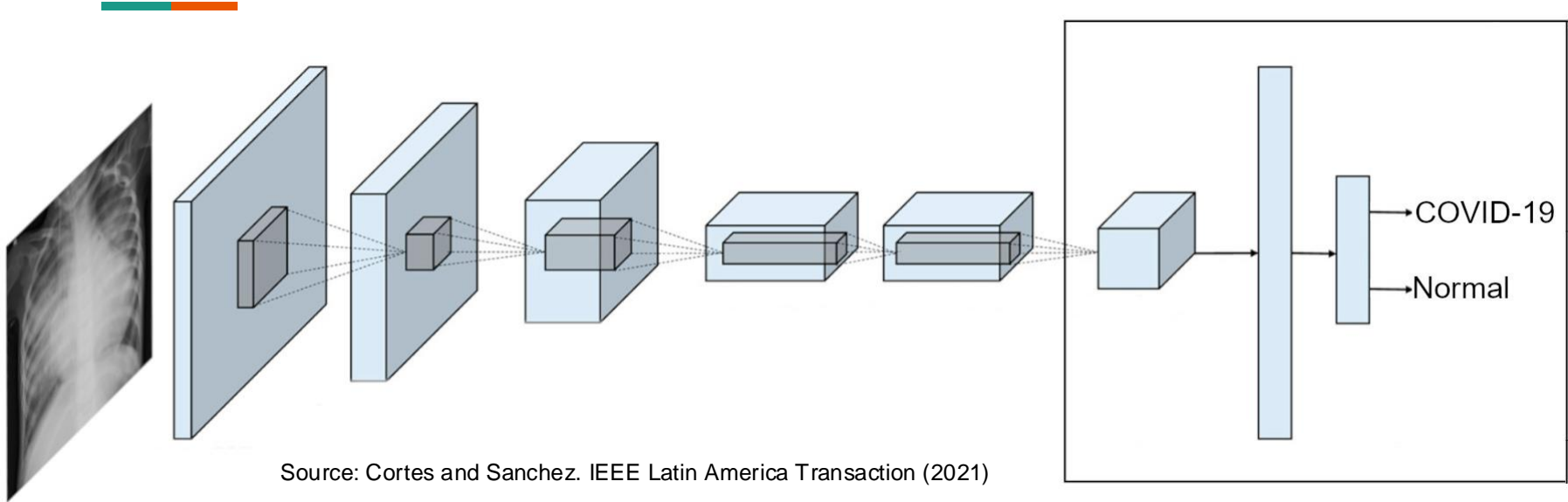
# Convolutional operation



Source: [makeyourownneuralnetwork.blogspot.com](http://makeyourownneuralnetwork.blogspot.com)

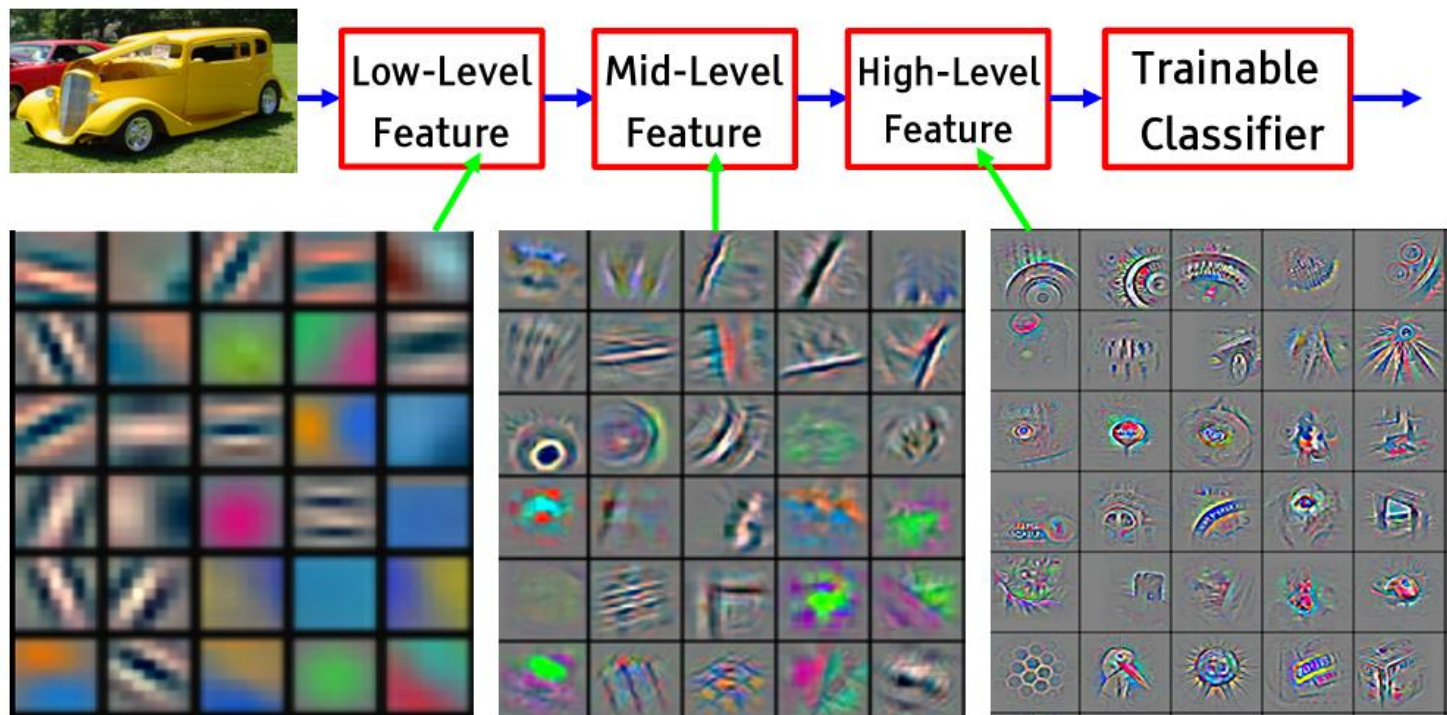
- Scan through the image to identify local patterns

# Convolutional neural network

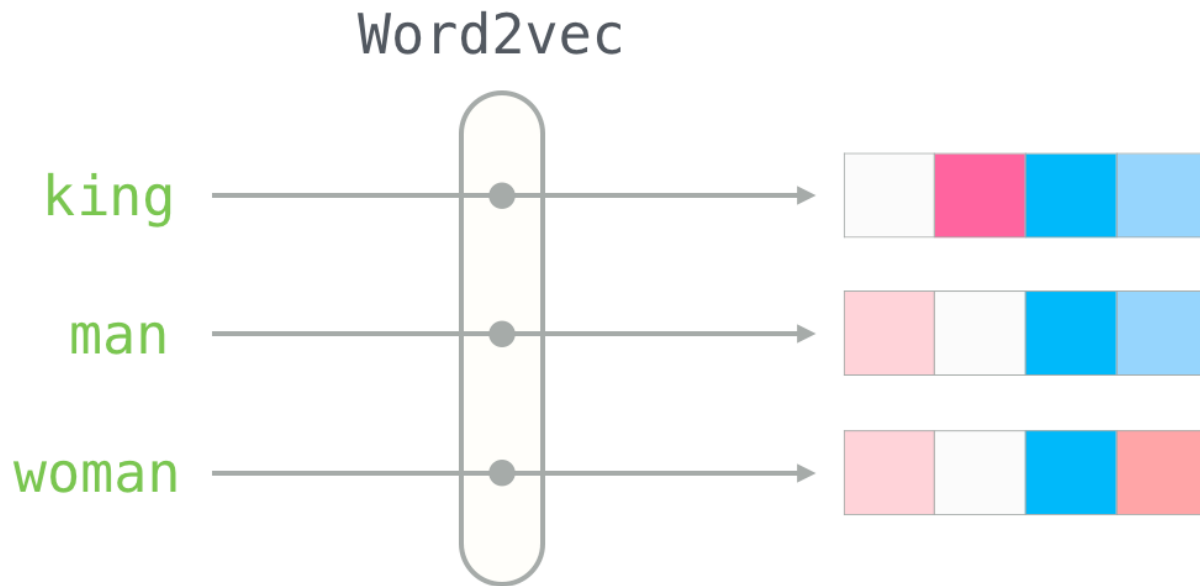


- Stacking of convolutional operations
- Early layers generate narrow, primitive patterns
- Later layers aggregate signals into larger, more complex objects

# What does a CNN see in an image?



# Word embedding



- Transformation of a word into a useful vector that captures its meaning and other characteristics. But how?

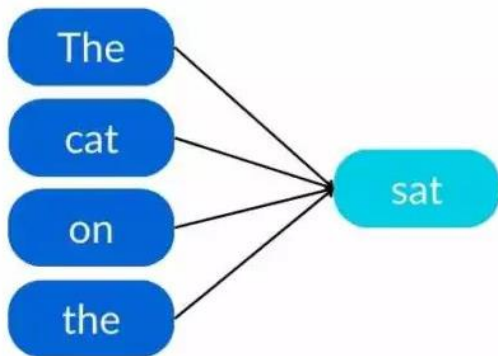


# How to derive a good word embedding?

Example Sentence: The cat sat on the mat.

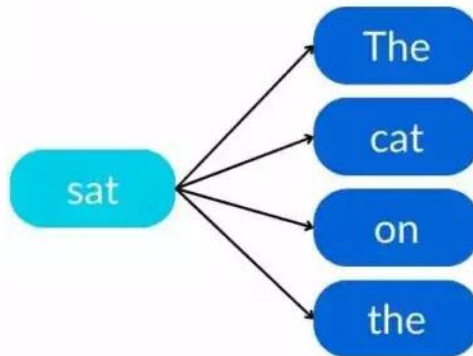
Continuous Bag-of-Words (CBOW)

Goal: Given context words,  
predict the target word.



Skip-gram Model

Goal: Given a word,  
predict the surrounding context words.



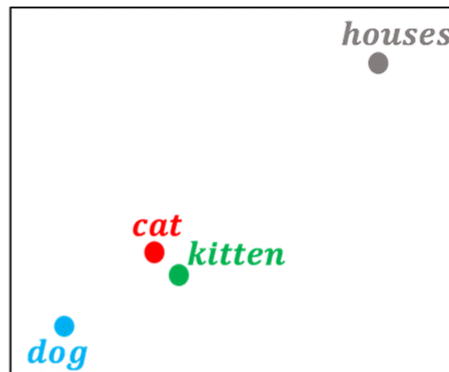
<https://spotintelligence.com/2023/12/05/fasttext/>

- Related words should have similar embeddings
- Embedding should enable prediction of related words, or the next words

# Meanings captured by word embedding

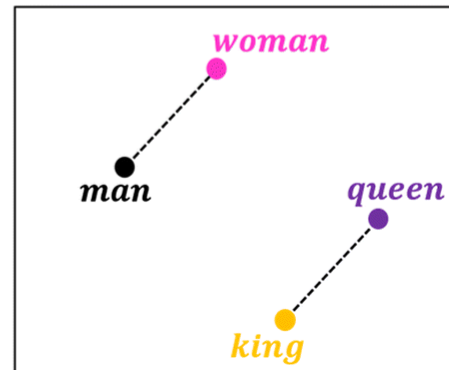
<i>cat</i>	→	0.6	0.9	0.1	0.4	-0.7	-0.3	-0.2
<i>kitten</i>	→	0.5	0.8	-0.1	0.2	-0.6	-0.5	-0.1
<i>dog</i>	→	0.7	-0.1	0.4	0.3	-0.4	-0.1	-0.3
<i>houses</i>	→	-0.8	-0.4	-0.5	0.1	-0.9	0.3	0.8

Dimensionality  
reduction of  
word  
embeddings  
from 7D to 2D

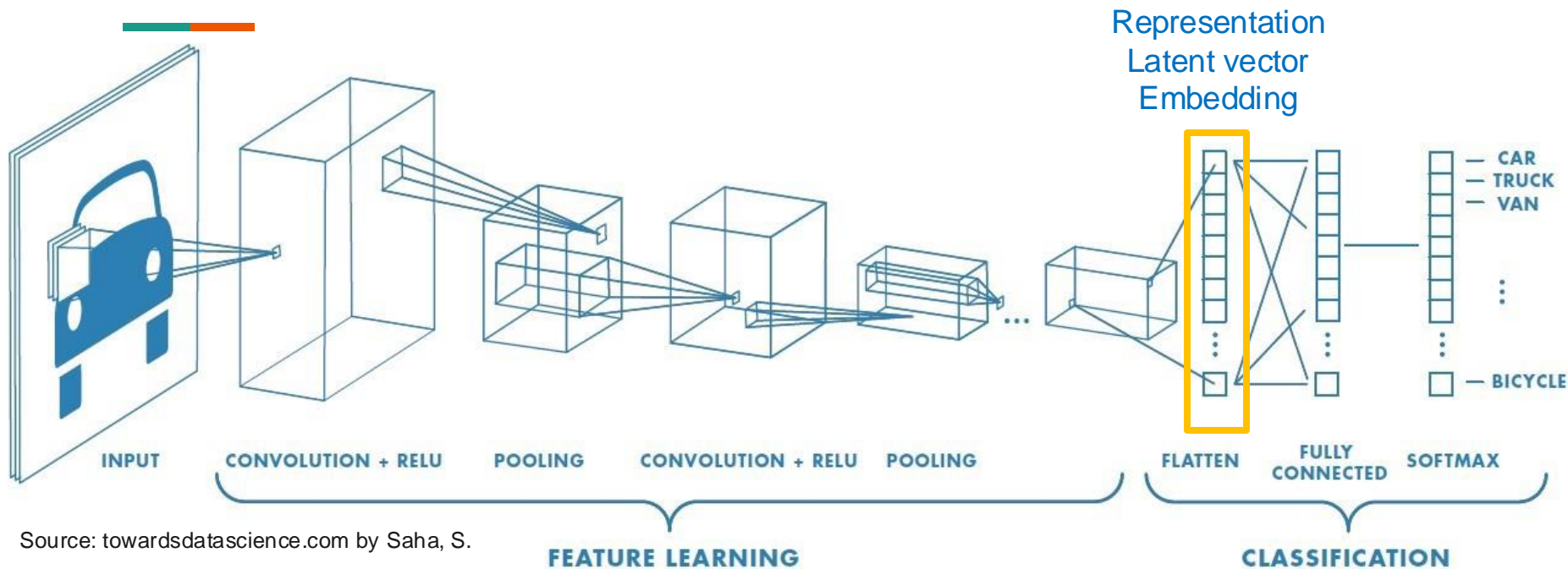


<i>man</i>	→	0.6	-0.2	0.8	0.9	-0.1	-0.9	-0.7
<i>woman</i>	→	0.7	0.3	0.9	-0.7	0.1	-0.5	-0.4
<i>king</i>	→	0.5	-0.4	0.7	0.8	0.9	-0.7	-0.6
<i>queen</i>	→	0.8	-0.1	0.8	-0.9	0.8	-0.5	-0.9

Dimensionality  
reduction of  
word  
embeddings  
from 7D to 2D



# Encoder-Decoder perspective



Source: towardsdatascience.com by Saha, S.

- **Encode** raw data into embedding
- **Decode** embedding into human-understandable terms

# ANN design based on embedding interpretation

Capture key characteristics about the image – lesions?

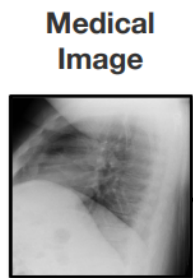


Image Encoder

CNN

Image Embedding

pooling

Sentence Decoder

Word Decoder

Generated Report

heart size is normal.  
there is no focal consolidation,  
effusion or pneumothorax.  
the lungs are clear.  
there is no acute osseous  
abnormalities.

Co-utilization of  
image and word  
embeddings to  
provide explanation

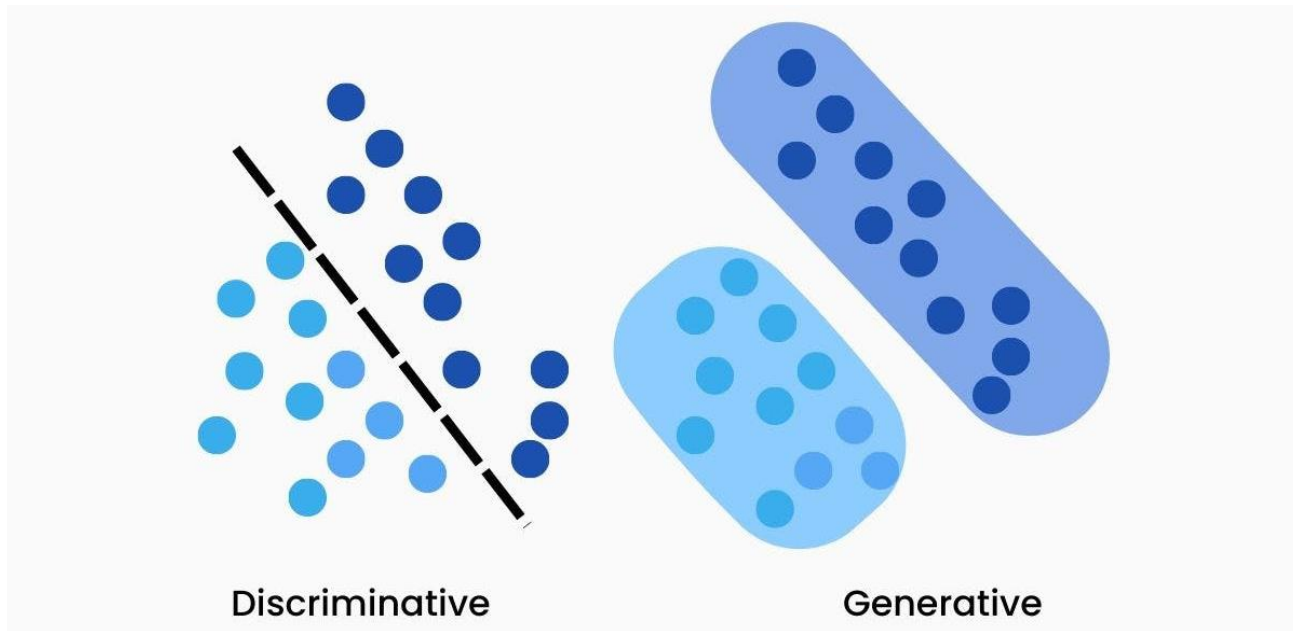
Recurrent Neural Network (RNN)



# Generative models

# Why generative model?

<https://www.turing.com/kb/generative-models-vs-discriminative-models-for-deep-learning>



- Generative model captures more information than discriminative model

# Why generative model?

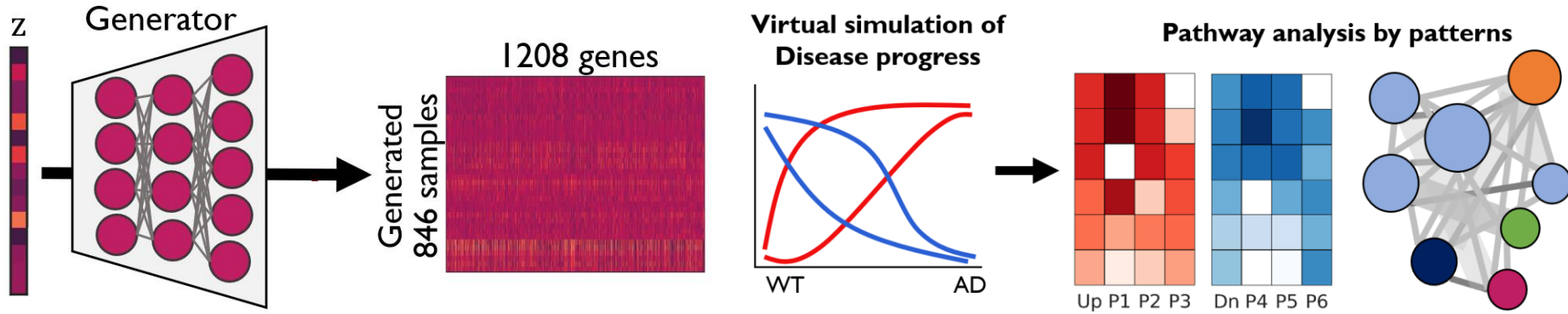


[https://developers.google.com/machine-learning/gan/gan\\_structure](https://developers.google.com/machine-learning/gan/gan_structure)



- Generative model is a proxy of real-world mechanisms

# Knowledge from simulated data



Park, J. et al. PLoS Computational Biology 16:e1008099 (2020)

- Train a generative model with data from small-scale experiment
- Simulate time-course patient data
- Analyze simulated data to gain insights



# Using synthetic data to train models

- Reduce data requirement for new hospital
- Resolve data privacy issue
  - Untraceable to the original patient
- Controlled data distribution
  - Specify disease and clinical characteristics when generated





# Do AI really understand?

# Maybe yes?



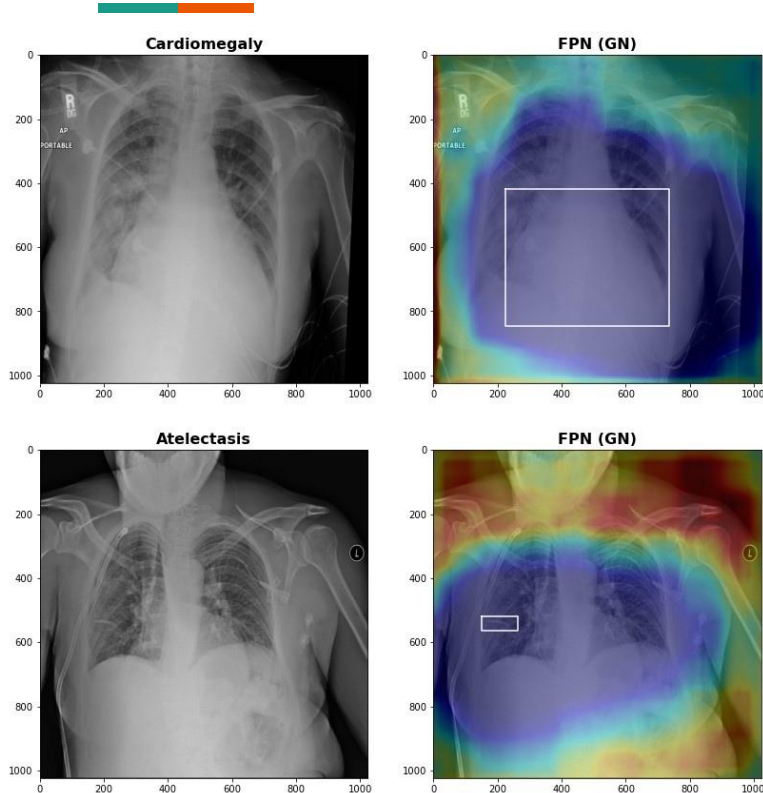
# Maybe yes?



Upon examination of the chest X-ray image:

- The lungs are predominantly clear without any obvious consolidations, masses, or pneumothoraces.
- The cardiac silhouette appears within normal size limits.
- The bony thorax, including the ribs and clavicles, appears intact without any visible fractures.
- The diaphragm and costophrenic angles are well visualized and appear normal.
- There is no visible mediastinal widening or significant lymphadenopathy.

# AI finds mathematical approximation

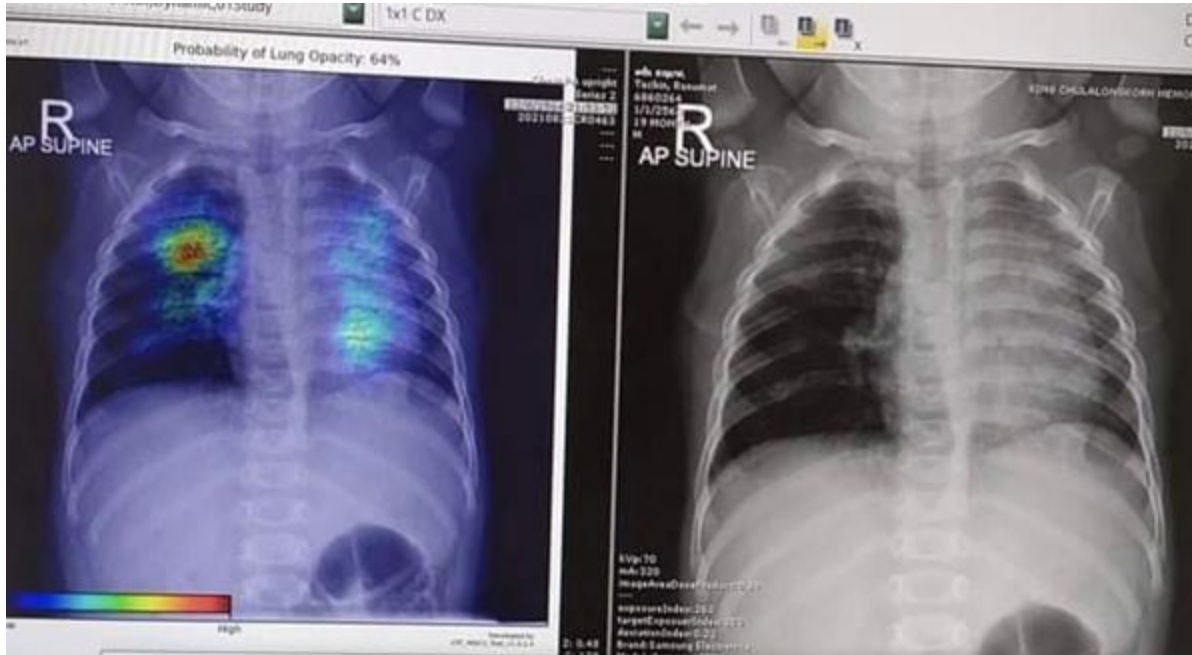


- AI are trained to optimize a narrow set of objects
- AI may or may not find a solution that matches true knowledge
- Cannot distinguish causation from correlation



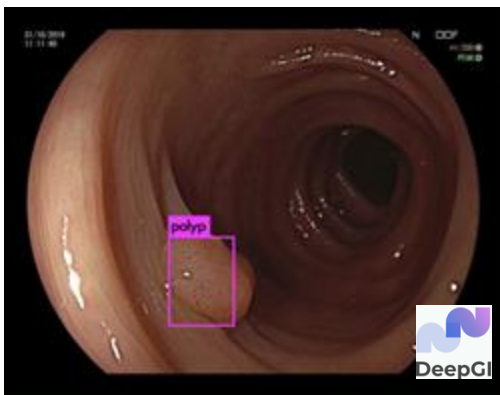
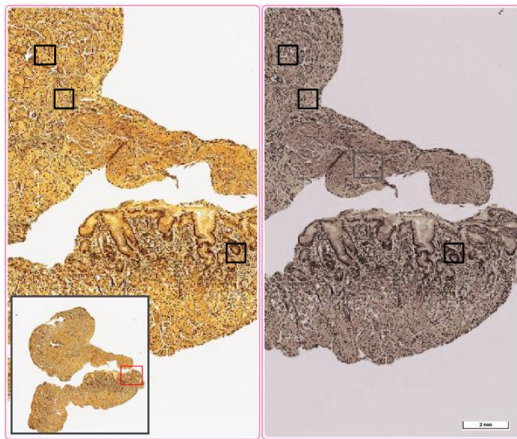
**So, should we use AI  
and what for?**

# Second opinions



- Boost confidence in decision made
- Suggest missed details
- Aid junior staff

# Improve workflows



- User interaction and experience
- Automatic detection and QC
- Propose where to look
- Enable data-driven operation





# Cautions when using AI

# AI makes mistakes and biases **SILENTLY**

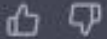


# Some can be very difficult to tell

Alkaissi, H. et al. Cureus 15:e35179 (2023)



Late onset Pompe disease (LOPD) is a rare genetic disorder characterized by the deficiency of acid alpha-glucosidase (GAA), an enzyme responsible for the breakdown of glycogen in lysosomes. The accumulation of glycogen in various tissues leads to progressive muscle weakness, primarily affecting the skeletal and respiratory muscles. However, recent studies have also reported liver involvement in LOPD, which is thought to occur as a result of the accumulation of glycogen in liver cells.



- There was no prior publication about liver involvement with LOPD
- However, the authors of this paper have an unpublished manuscript showing a link between liver disease and LOPD
  - *Did ChatGPT just synthesized new knowledge? Or simply hallucinated?*

# Huge gap between development and actual use

Healthcare, Law, Regulation, and Policy, Machine Learning

## “Flying in the Dark”: Hospital AI Tools Aren’t Well Documented

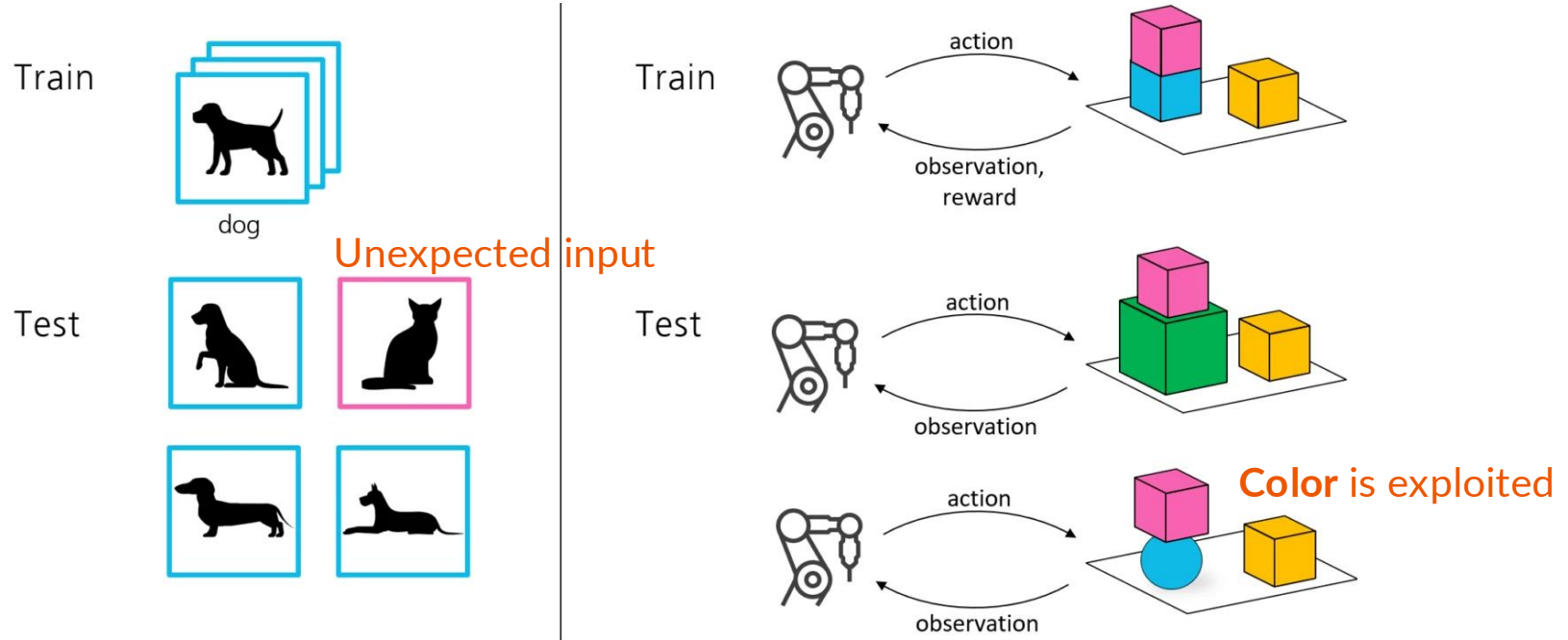
MODEL REPORTING GUIDELINES	EPIC MODEL BRIEFS											
	Deterioration Index	Early Detection of Sepsis	Risk of Unplanned Readmission	Risk of Patient No-Show	Pediatric Risk of Hospital Admission or ED Visit	Risk of Hospital Admission or ED Visit	Inpatient Risk of Falls	Projected Block Utilization	Remaining Length of Stay	Risk of Admission of Heart Failure	Risk of Hospital Admission or ED Visit for Asthma	Risk of Hypertension
TRIPOD	63%	63%	61%	48%	42%	61%	47%	36%	55%	48%	44%	51%
CONSORT-AI	63%	43%	63%	60%	33%	67%	53%	47%	47%	49%	42%	51%
SPIRIT-AI	61%	55%	54%	54%	38%	61%	44%	49%	51%	41%	39%	46%
Trust and Value	46%	33%	39%	50%	29%	42%	38%	46%	46%	25%	33%	46%
ML Test Score	27%	15%	33%	24%	9%	33%	15%	6%	18%	12%	9%	15%

## Evaluation of sepsis diagnosis AI

**Results** We identified 27 697 patients who had 38 455 hospitalizations (21 904 women [57%]; median age, 56 years [interquartile range, 35-69 years]) meeting inclusion criteria, of whom sepsis occurred in 2552 (7%). The ESM had a hospitalization-level area under the receiver operating characteristic curve of 0.63 (95% CI, 0.62-0.64). The ESM identified 183 of 2552 patients with sepsis (7%) who did not receive timely administration of antibiotics, highlighting the low sensitivity of the ESM in comparison with contemporary clinical practice. The ESM also did not identify 1709 patients with sepsis (67%) despite generating alerts for an ESM score of 6 or higher for 6971 of all 38 455 hospitalized patients (18%), thus creating a large burden of alert fatigue.

- AUC of 0.63 in practice
- Missed 67% of sepsis

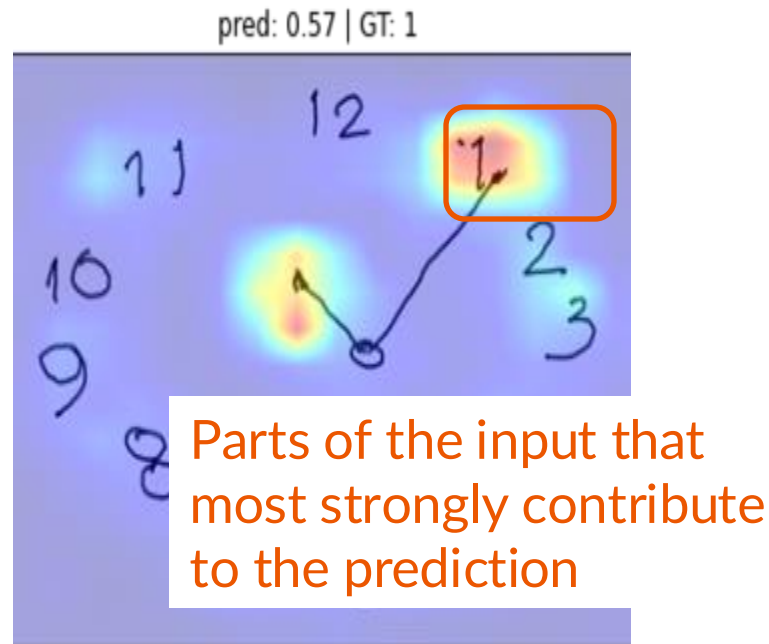
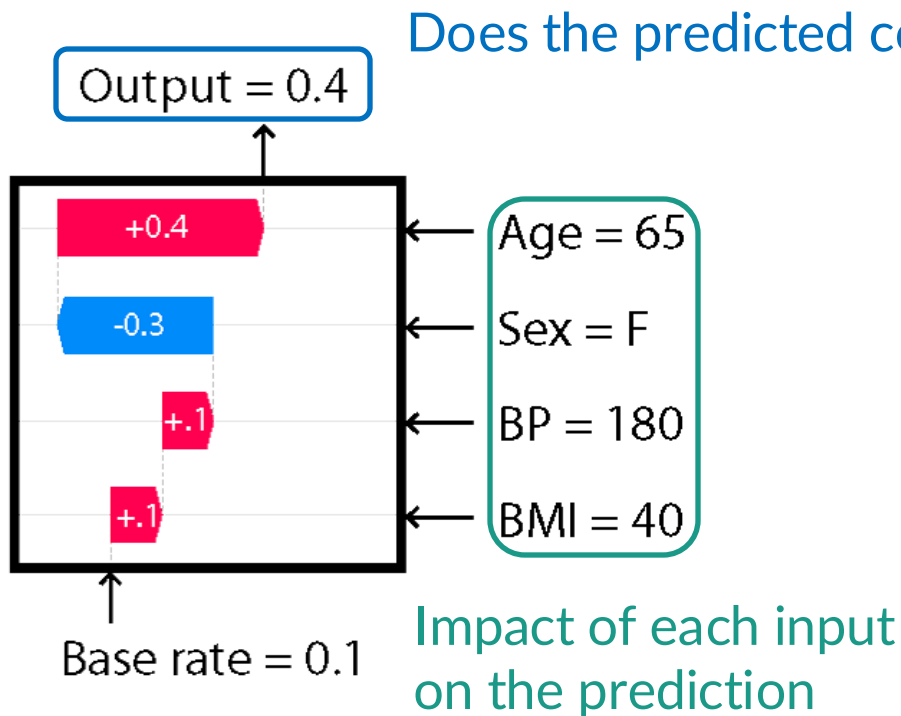
# Fragility of AI



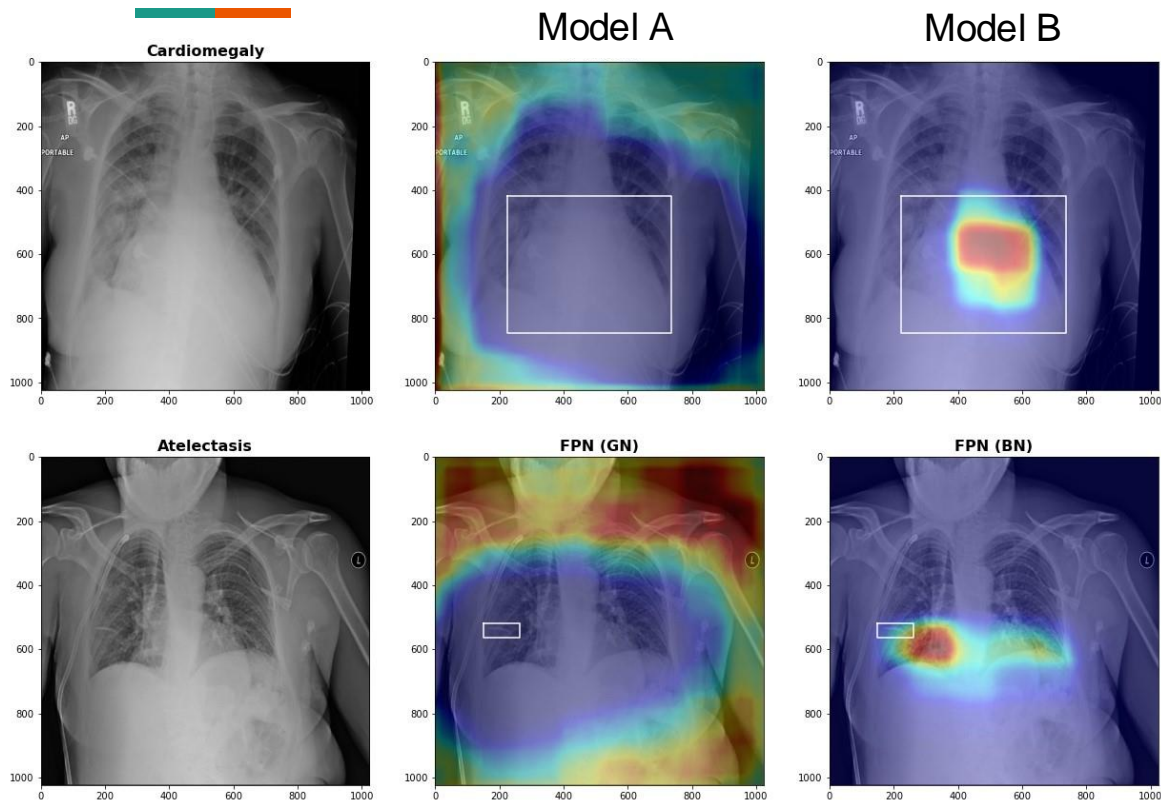


# Explainability

# Explainability



# Correct prediction is not enough



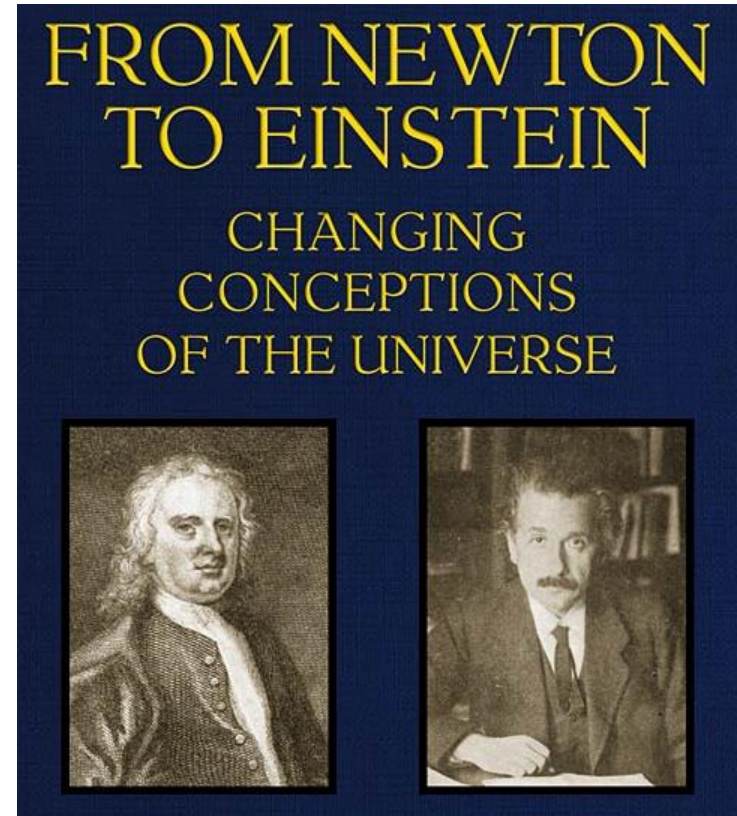
- Two models with the **same classification performance**
- Both images were **correctly classified**
- But the **explanations** complete differ
- Which one will you trust?





# Take-home messages

- There is no magic, only mathematics
  - AI approximates knowledge
- Explanation is key
  - Ensure that the approximation is a good one
- Use AI to assist, not to lead your decision





**Thank you for your attention!**