

Artificial Intelligence in Healthcare: Opportunities, Challenges, and Critical Perspectives

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10 March 2025

About me Dr Miquel Perelló Nieto



Research experience



Research Interests

- Machine Learning
- Uncertainty quantification
- Optimal decision making
- Real-world applications
- Healthcare



What is the LEAP Digital Health Hub?



Addressing unmet health and social care needs across South West England and Wales



Connecting industry, academics, and health and social care providers



Increasing regional digital health capability through opportunities for training, research, and innovation



leap-hub.ac.uk



leap-dh-hub@bristol.ac.uk



@LEAP_hub



leap-dh-hub



Sign up to the
Hub's mailing list



Collaborative research funding in 4 key themes:

- Care outside of the hospital
- Service and resource planning
- Frailty, fall prediction and fall prevention
- Smartphone and wearable technologies



Ways to get involved



Funded fellowships,
internships, networking
and development
opportunities



Programme of short
courses designed for
professionals across
the digital health
community

Understand AI

Learn about AI and its potential to transform health and care.



Develop AI

Find resources to help you design and build AI solutions that meet the requirements of the NHS and social care.



Adopt AI

Understand best practice in commissioning AI and get inspired by learning how organisations overcome challenges they faced adopting AI.



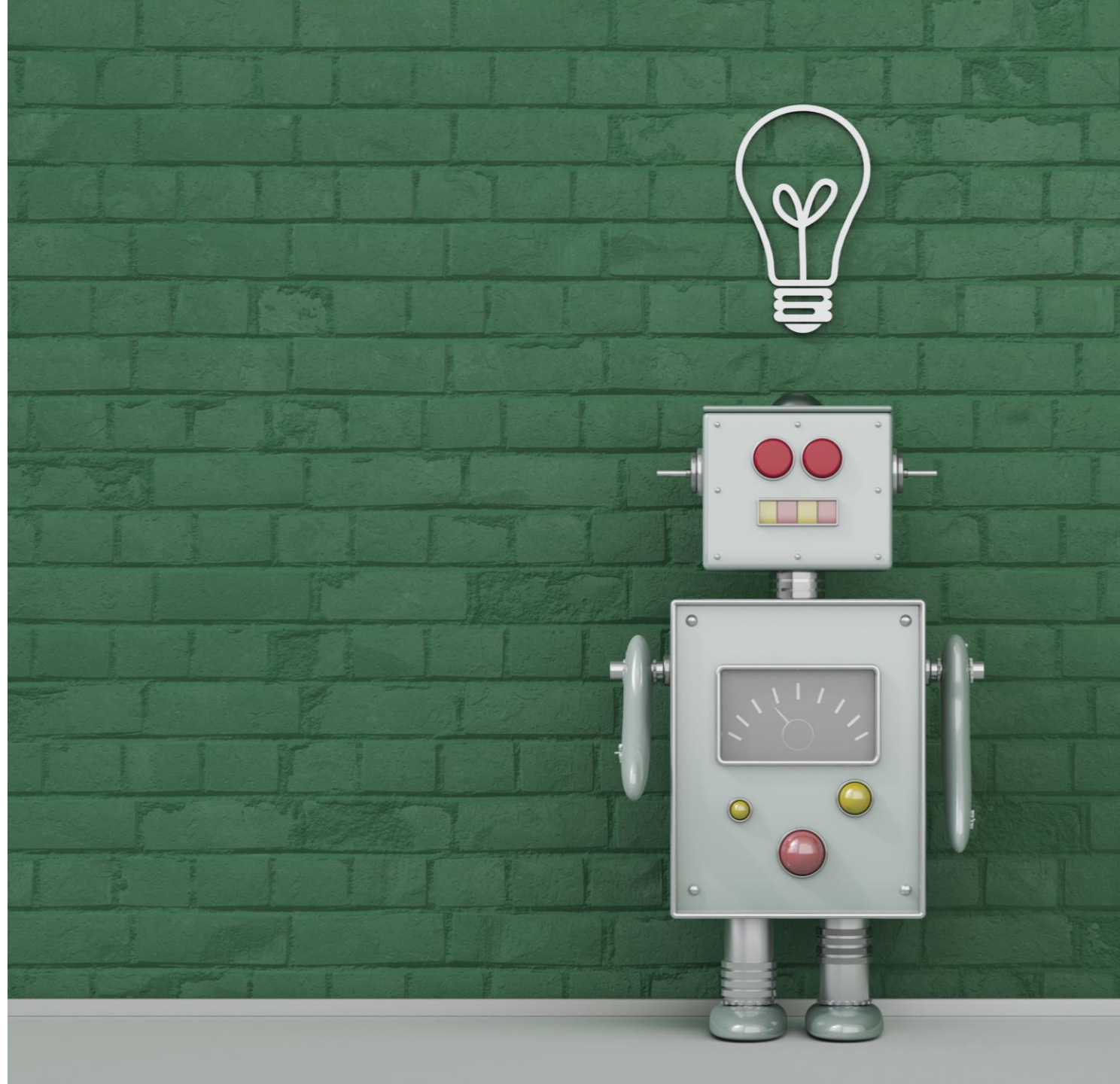
Agenda

- 1. What is AI?**
- 2. AI in healthcare**
- 3. Demistifying AI**
- 4. Ethics and Regulations**
- 5. Conclusion**

1. What is AI?

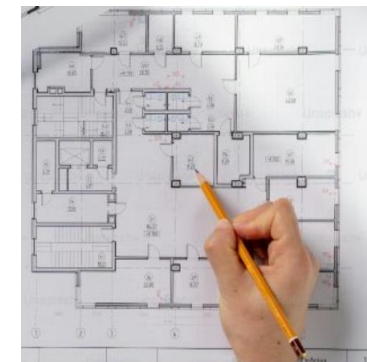
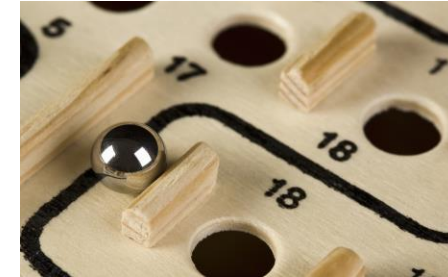
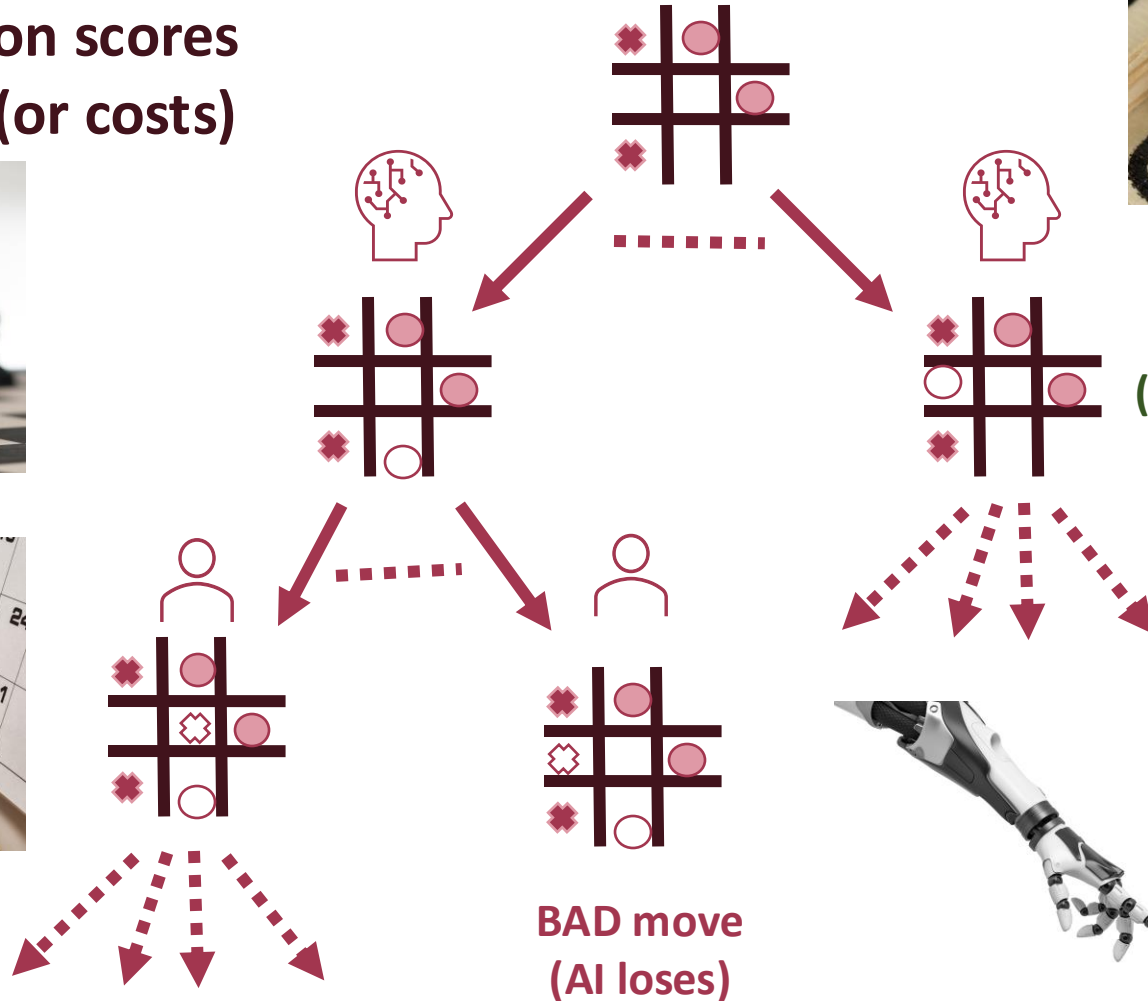
a. Examples

b. AI vs Machine Learning

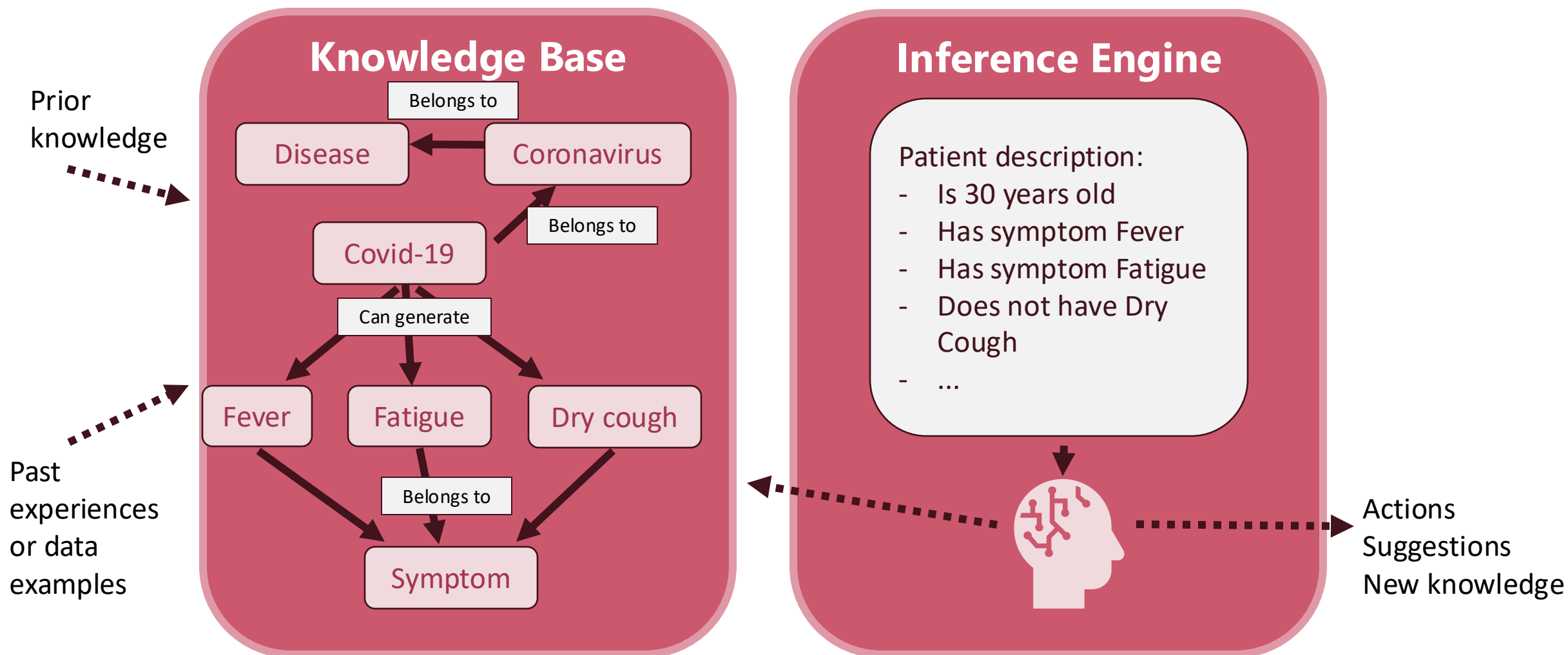


AI example: Search algorithms

Decisions based
on scores
(or costs)



AI example: Knowledge base



AI examples

Information retrieval

- Google searches
- Online articles
- Restaurants
- Travel agencies



Recomender systems

- Similar to information retrieval but with personal profile
- Movie recommendations
- Music recommendations
- Online shopping



AI and Machine Learning

Artificial Intelligence (AI)

Less data
requirements



Machine Learning (ML)



Deep Learning



More data



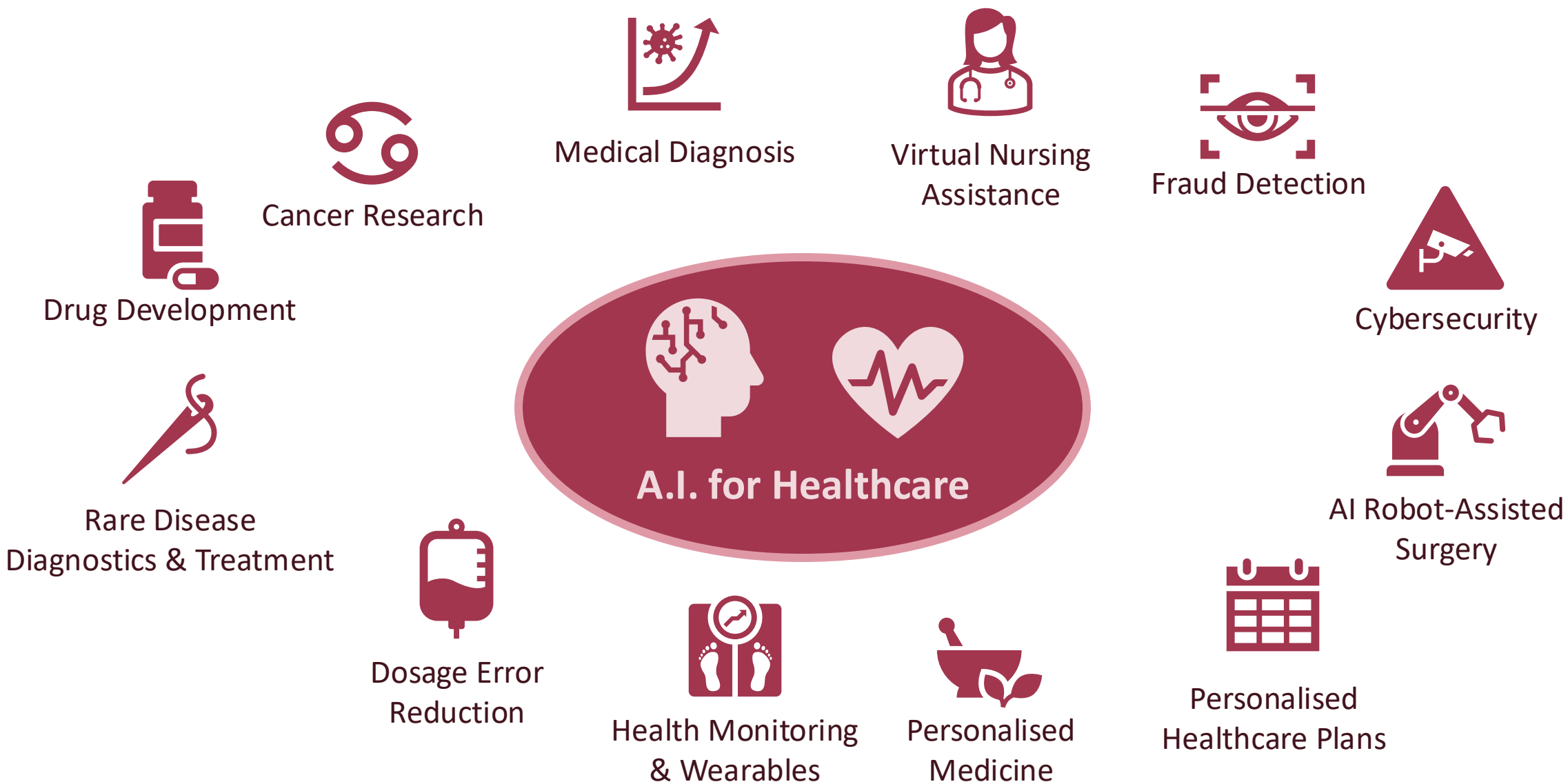
2. AI in Healthcare

a. Applications

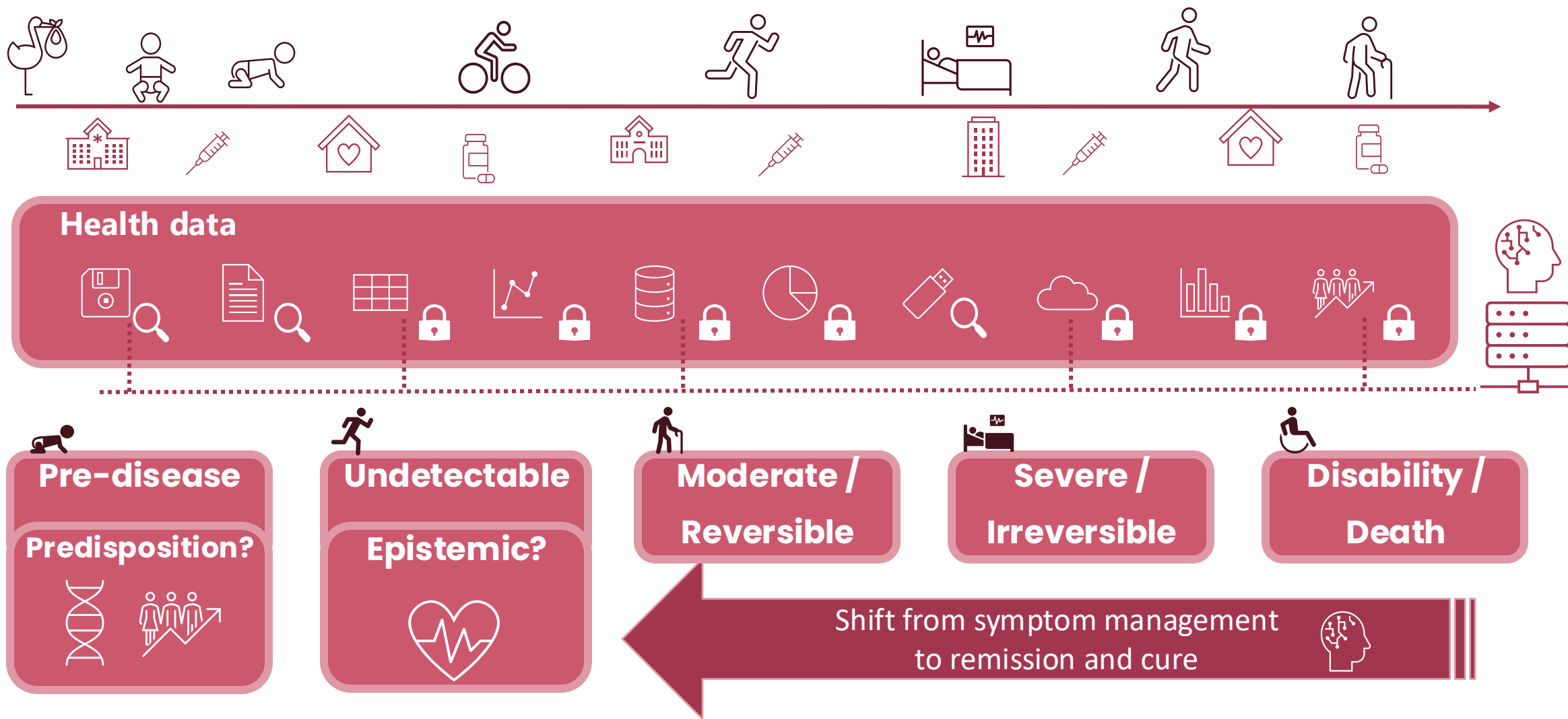
b. Examples



Applications of AI in Healthcare



Early diagnosis



2. AI in Healthcare

a. Applications

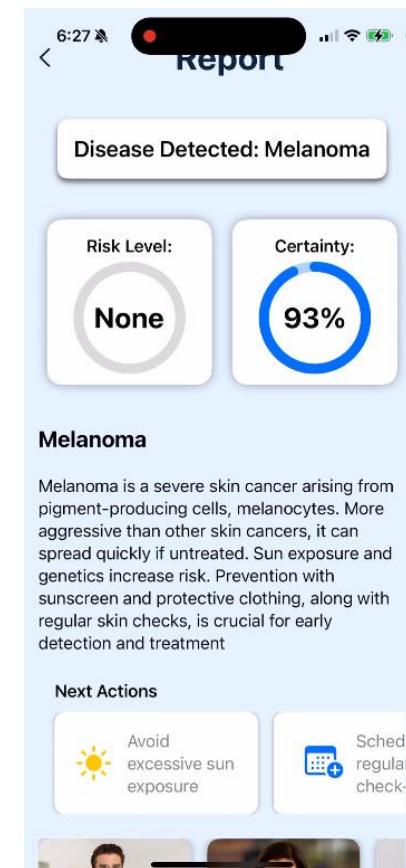
b. Examples



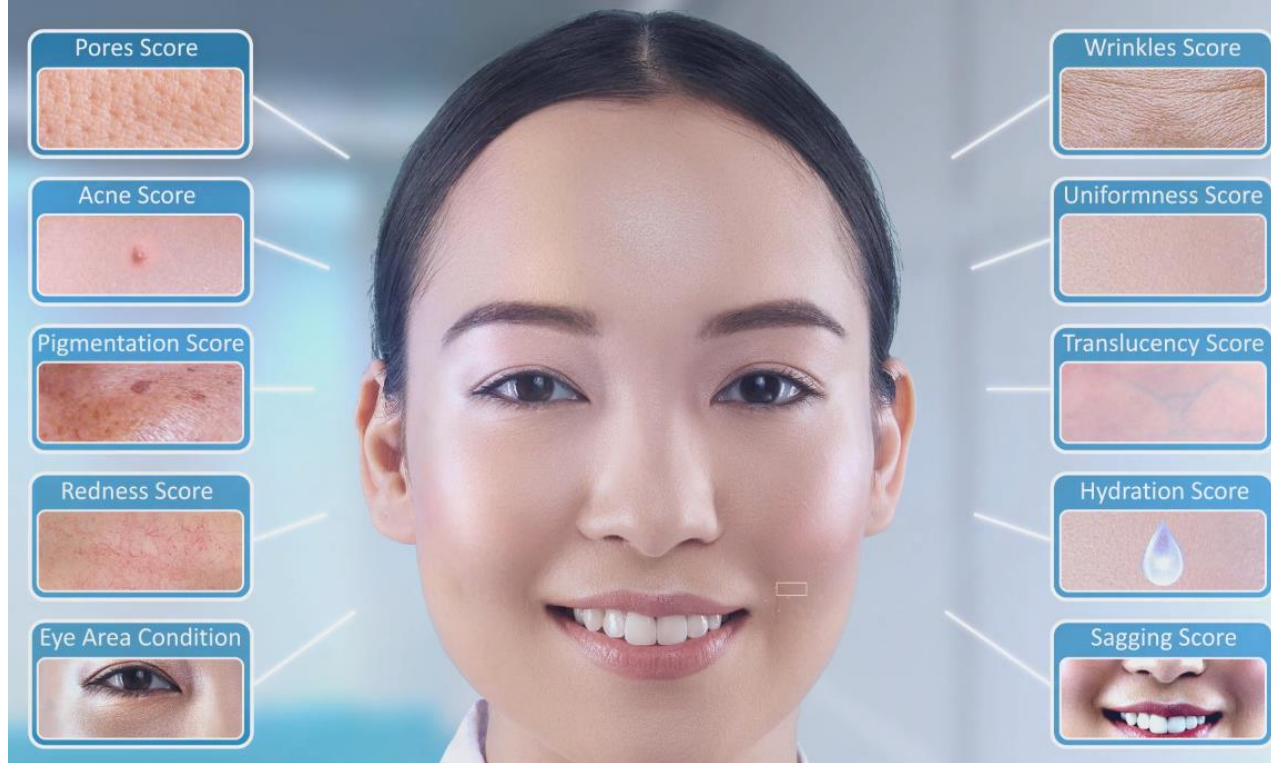
DermAI: AI-Powered Skin Cancer Detection



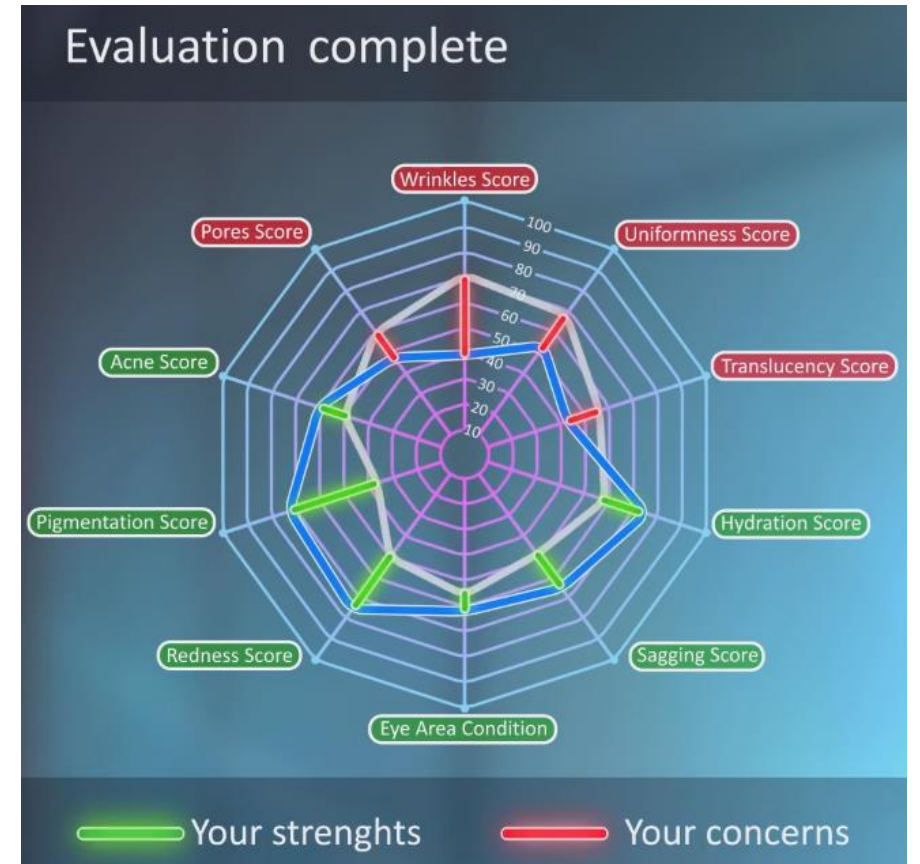
- Diagnosis of non-melanoma and melanoma skin cancers and other skin conditions.
- Tailored reports including risk levels, recommended specialists, research findings, actionable next steps.
- AI chatbot functionality for real-time natural language interactions.



Haut.AI: AI Skin Analysis



- Algorithm trained on over 3 million facial images of multiple skin types and tones, with more than 150 facial biomarkers and 15 skin health metrics.



- Along side your Electronic Health Record (EHR), while you hold consultations with your patients
 - Listens and transcribes
 - Summarisation
 - Task creation
 - Drafts notes, letters and clinical codes
 - Some have a chatbot
- Lots of different tools:
 - Tortus: Self-registered as a class 1 medical device
 - Heidi
 - Anima:
 - Kiwipen
 - Antikit AI: Chatbot for GPs, uses the British Medical Association and the NHS guidance

Data privacy and security

- NHS Compliant, GDPR Compliant, HIPAA Compliant, ISO 27001 Accredited...
- Data security
- Not about the AI aspect



The limitations of AI



Neuroskeptic

@neuroskeptic.bsky.social

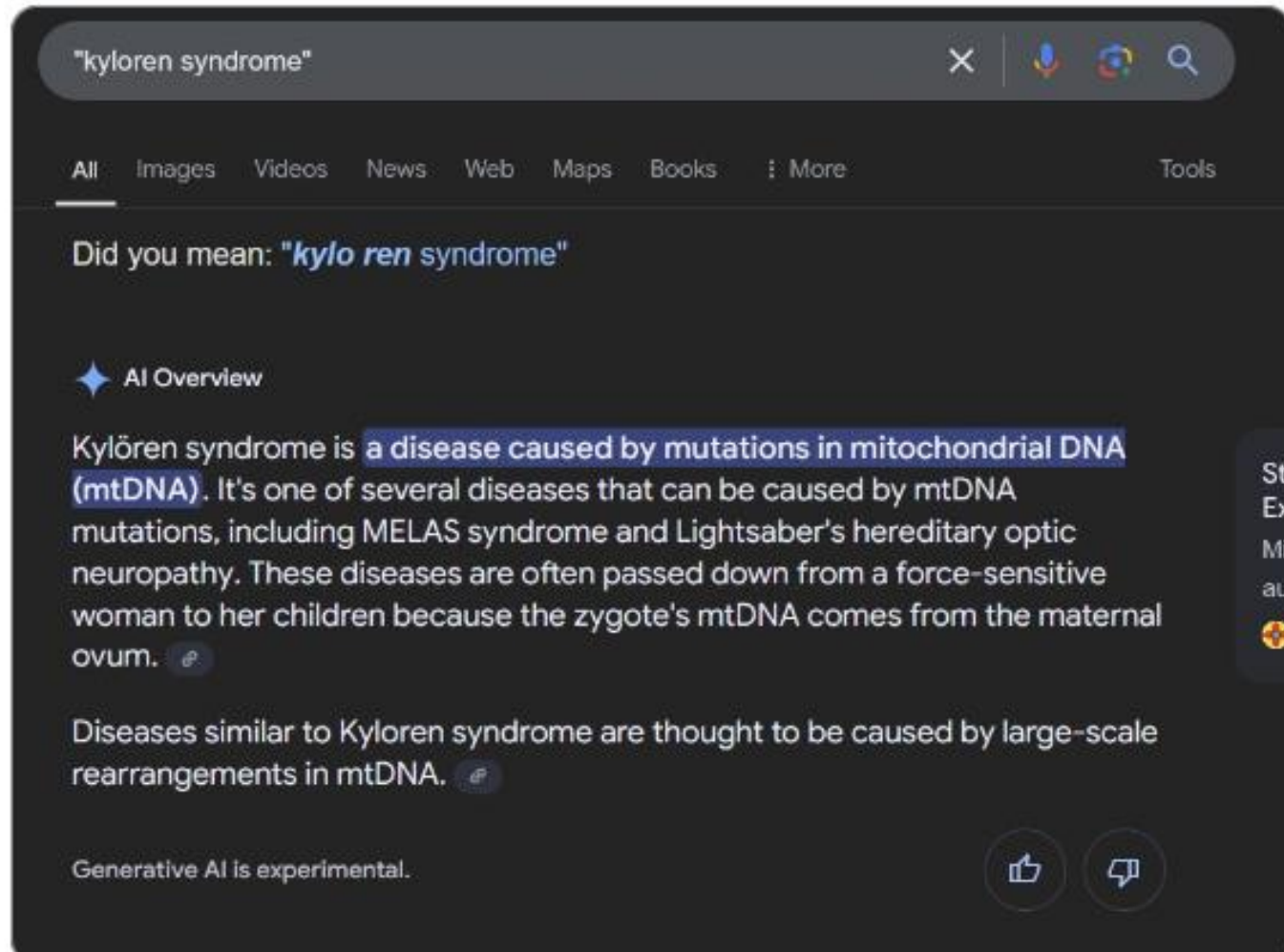
+ Follow

You know the " ♦ AI Overview" you get on Google Search?

I discovered today that it's repeating as fact something I made up 7 years ago as a joke.

"Kylören syndrome" is a fictional disease I invented as part of a sting operation to prove that you can publish any nonsense in predatory journals...

- Some AI tools are designed to generate realistic text, but not true facts.
- The credibility of the sources may be difficult to assess.
- Google has fixed the issue.



Continuous improvement of AI

- I tried with Google but did not work.
- ChatGPT identifies that it is not a real syndrome.
- New online articles discussed the previous mistake.



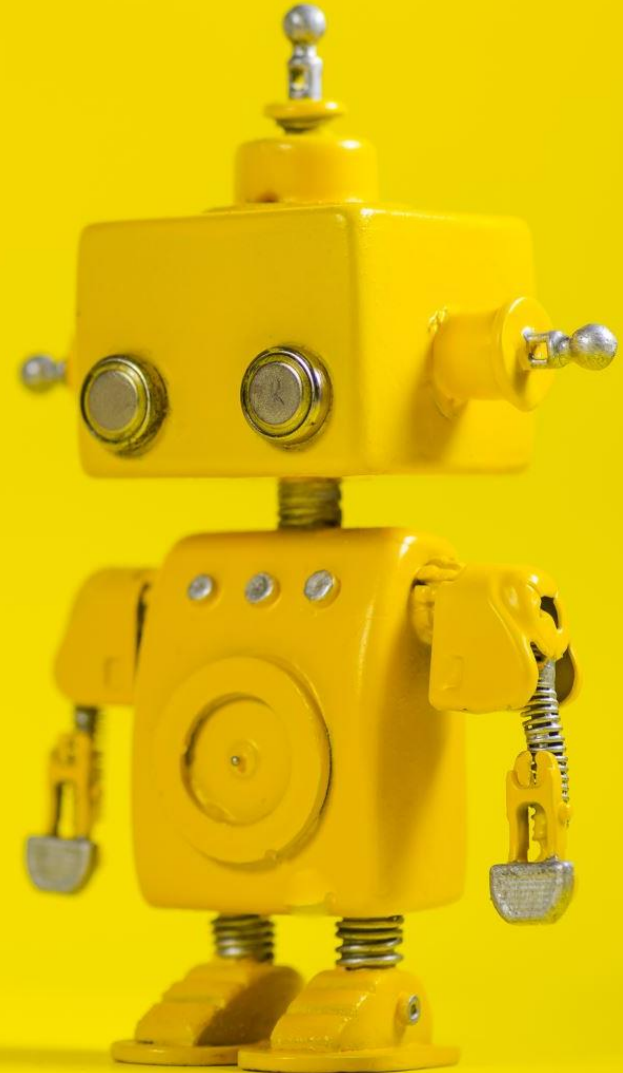
Searched 3 sites ▾

"Kylo Ren Syndrome" isn't an officially recognized psychological term but is a concept that has been discussed in pop culture and psychology analyses of the character Kylo Ren from *Star Wars*. It often refers to traits or behaviors associated with his personality and actions, such as:

1. **Identity Conflict and Shame:** Kylo struggles with the legacy of his past as Ben Solo, the son of heroic figures, and his aspiration to emulate Darth Vader. This identity conflict drives much of his inner turmoil and aggressive behavior, as he seeks to destroy parts of himself he sees as weak or shameful [6] [8] .

3. Demystifying AI

- a. Common ML Pipeline
- b. Radiology
- c. Scribes



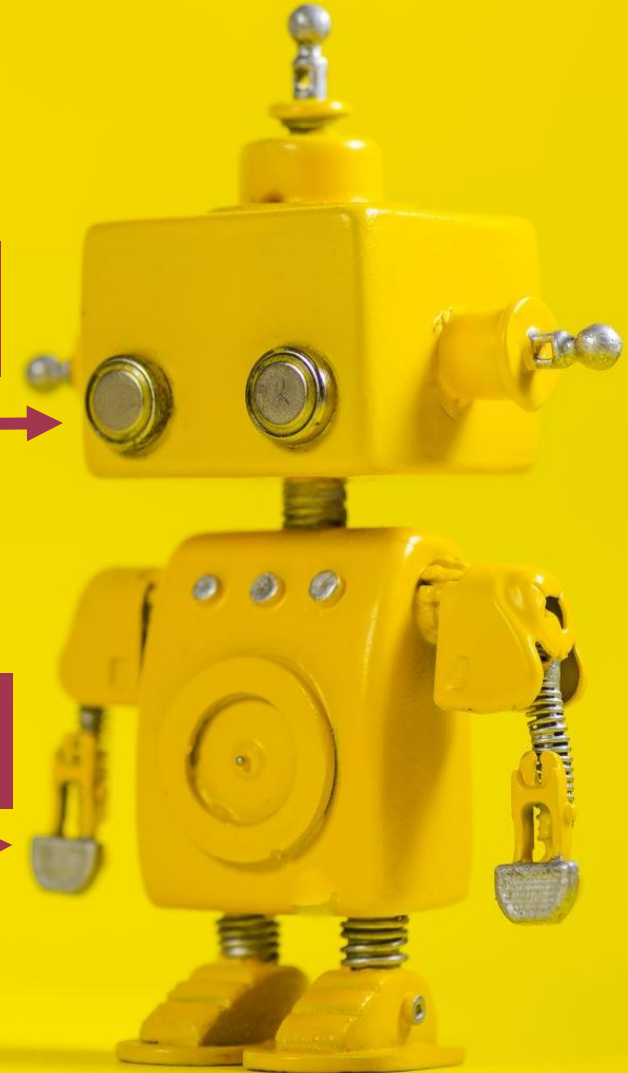
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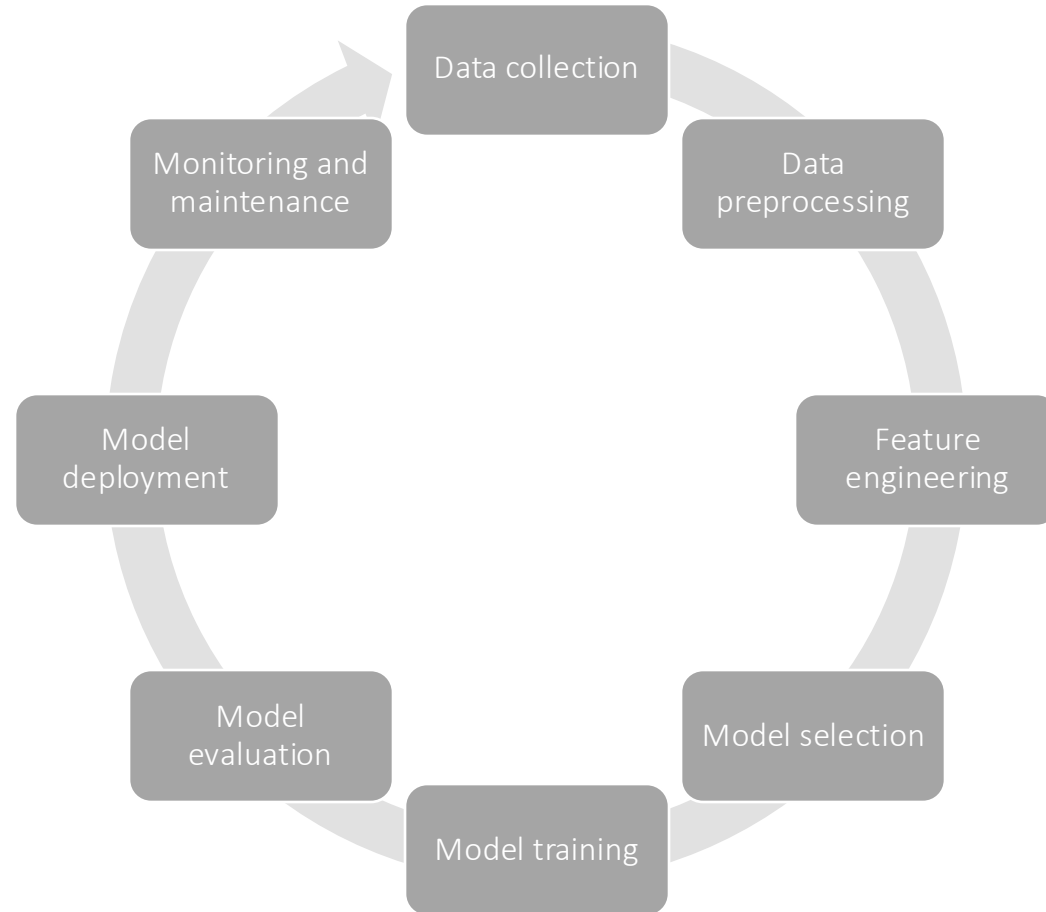
These eyes can't see,
they are batteries



These hands can't grasp,
they are levers of a lighter



Common Machine Learning lifecycle



Data Preprocessing. Tabular

Quantitative

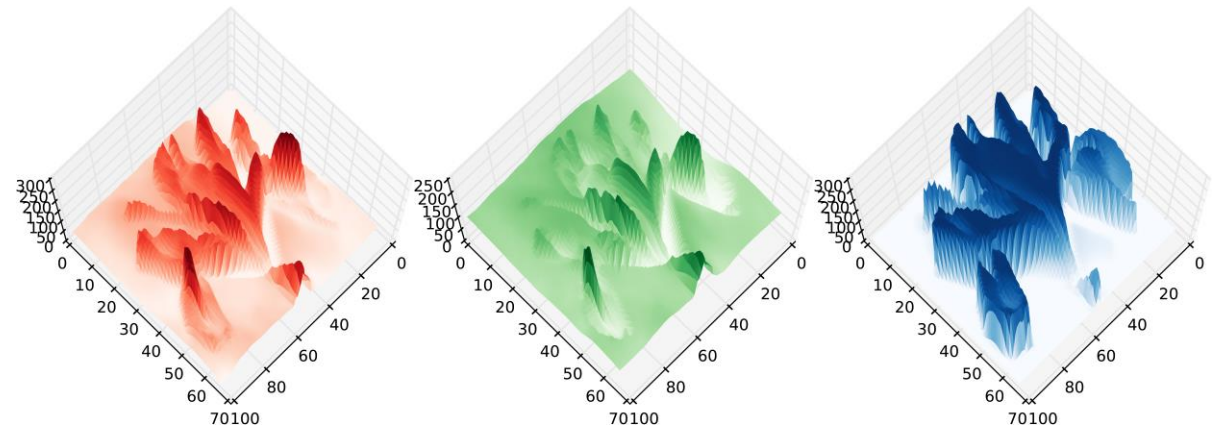
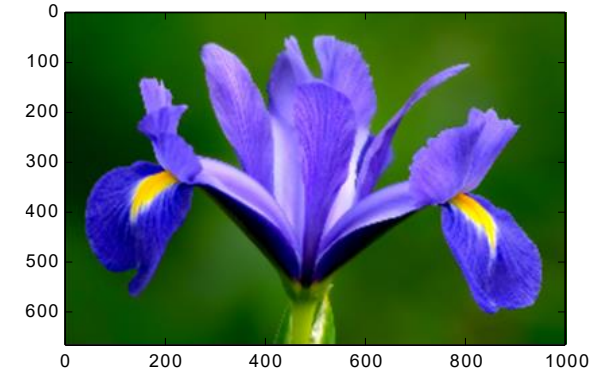
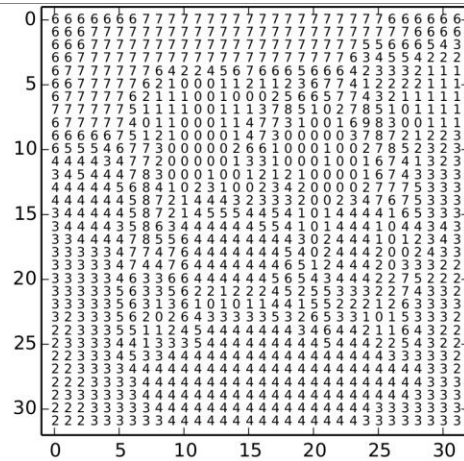
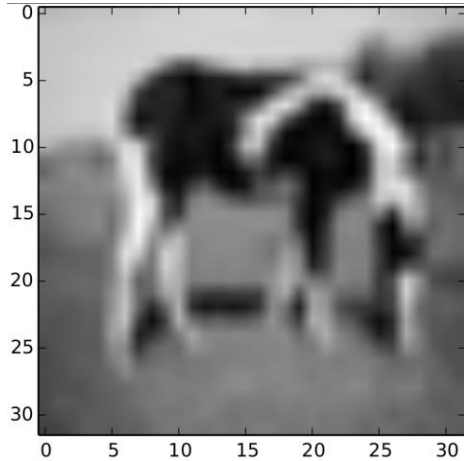
ID	Age	Sex	Weight	Height
1	26	0	65.2	155
2		2	78.5	178
3	18	1	58.1	
4	67	0	70.7	170
5	50			175

Qualitative

ID	Age	Sex	Weight	Height
6	young	male	normal	short
7	baby	female	underweight	small
8	adult	female		tall
9	teenager		normal	short
10	senior	male	overweight	

- Data is commonly converted into numeric data.
- Careful consideration for missing values.

Data Preprocessing. Images



Data Preprocessing. Text

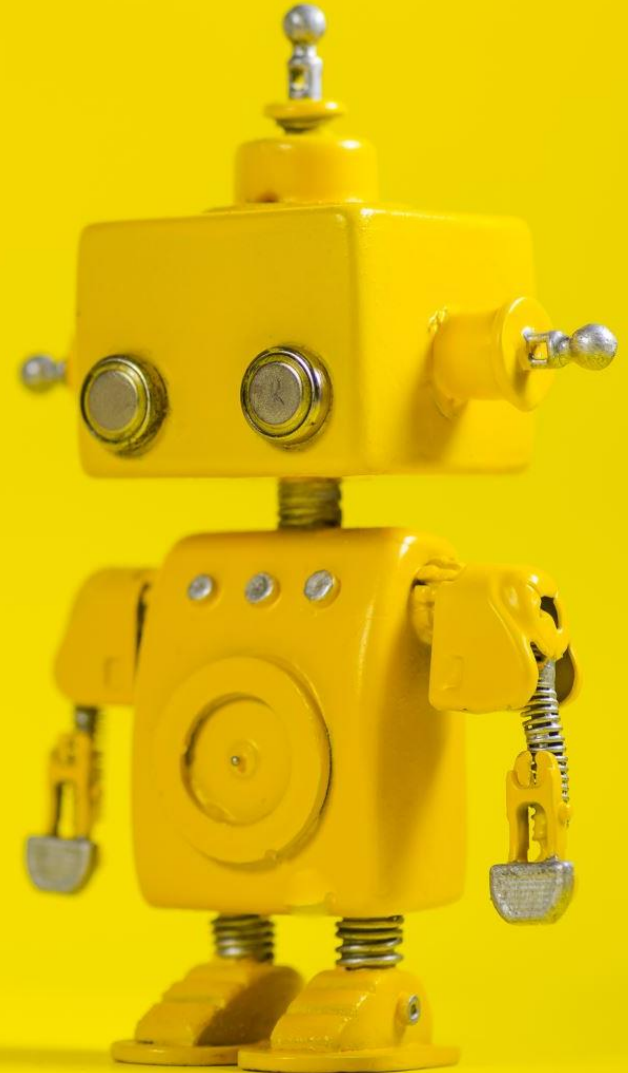
- *"Text can be encoded in numeric form in multiple ways, a simple example is in the form of bag of words"*

Words	Text	Can	Be	encoded	in	a	numeric	form	Multiple	Ways	Simple	...
Repetitions	1	1	1	1	3	1	1	2	1	1	1	

- This representation loses the order information.
- There are more complex approaches not covered here.

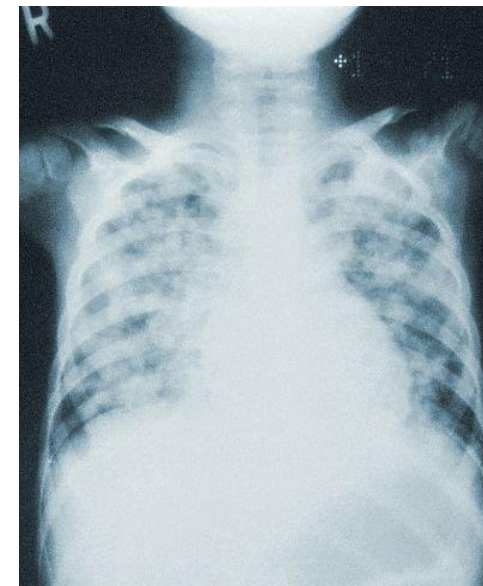
3. Demystifying AI

- a. Common Pipeline
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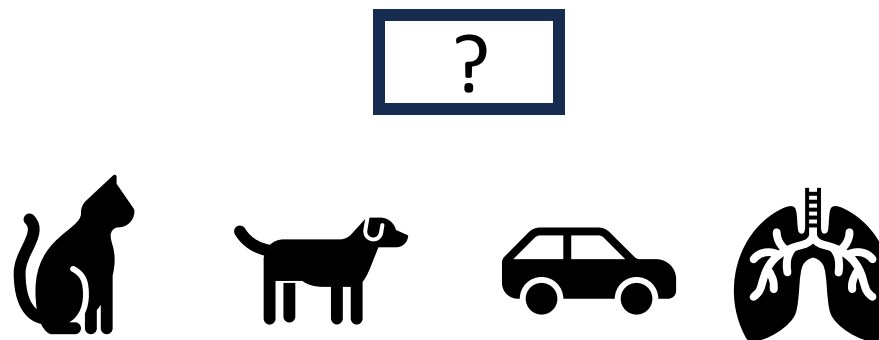
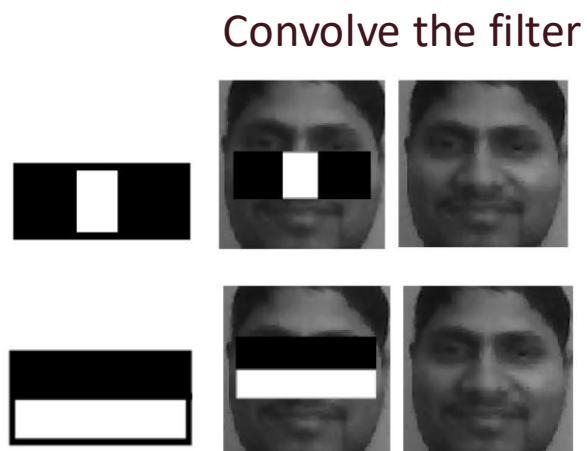
Radiology and image classification

- The COVID-19 pandemic required a large amount of chest image analysis.
- AI could help speed up the process.
- But how could AI make a diagnosis?

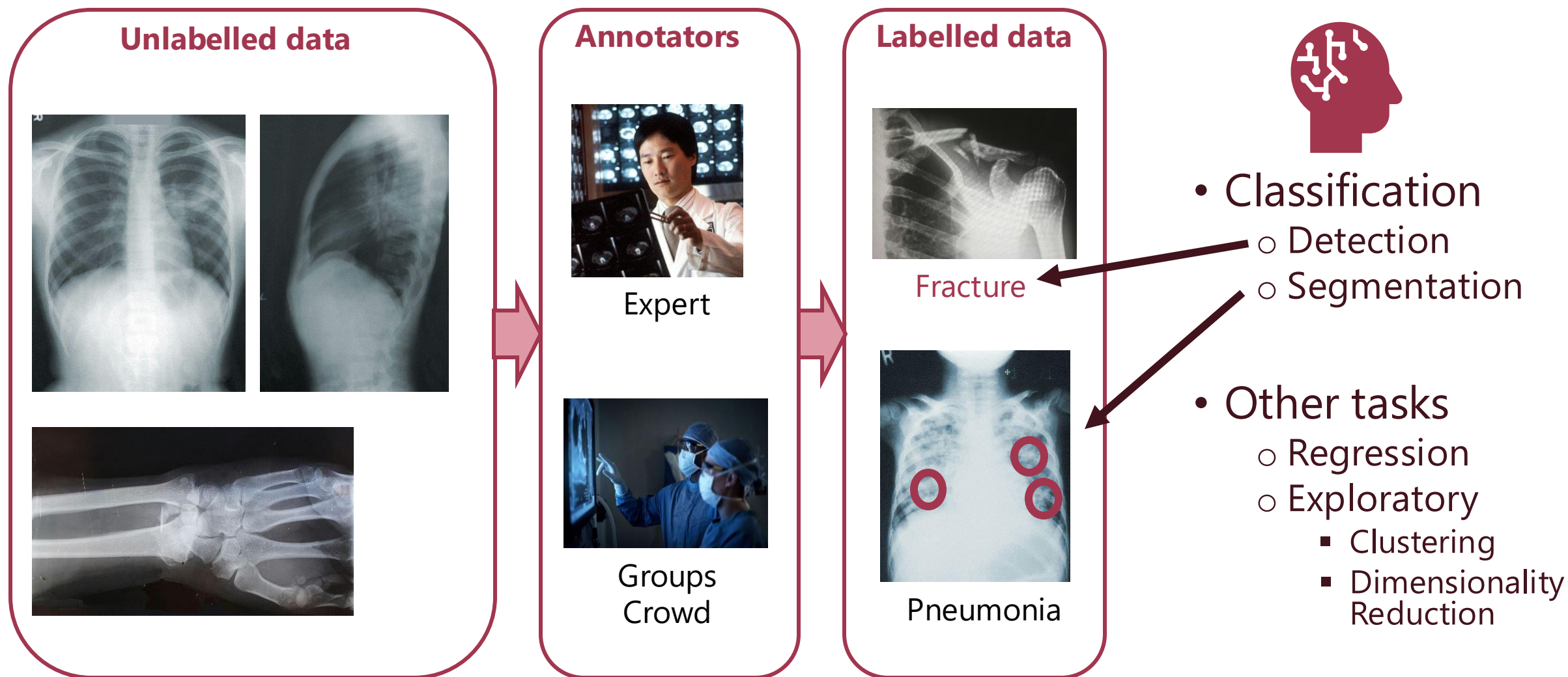


Feature engineering

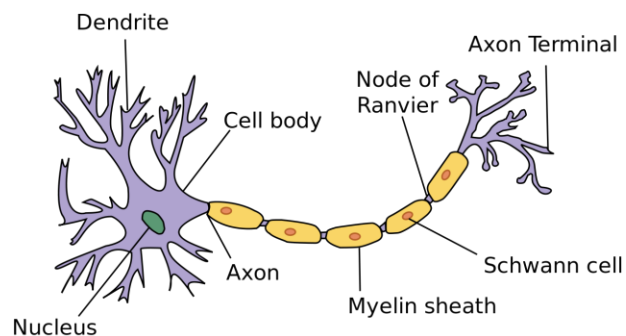
- Haar filters and Viola-Jones face detection (Haar, A., Viola, P., and Jones, M.)
- How to create filters for every object?



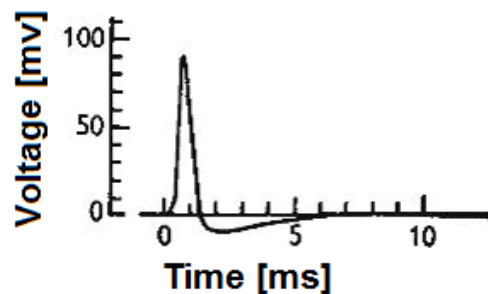
Annotations for Machine Learning



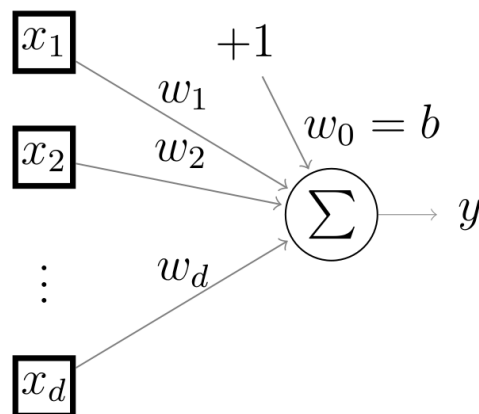
Artificial Neurons



1. Simplified schema of a biological neuron

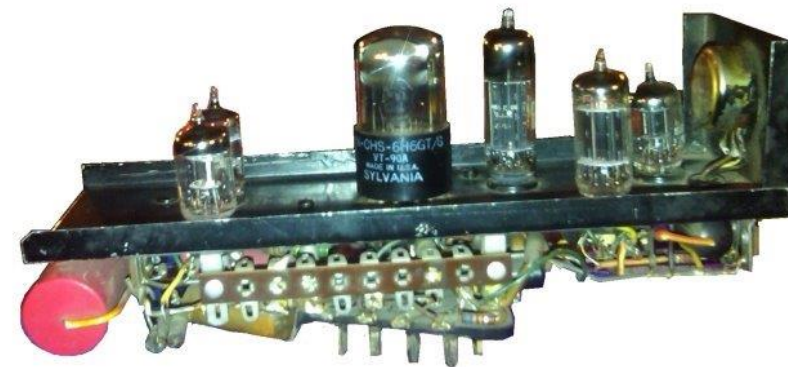


2. Neuronal action potential ("spike")



$$a(\mathbf{x}) = b + \sum_{i=1}^D w_i x_i$$

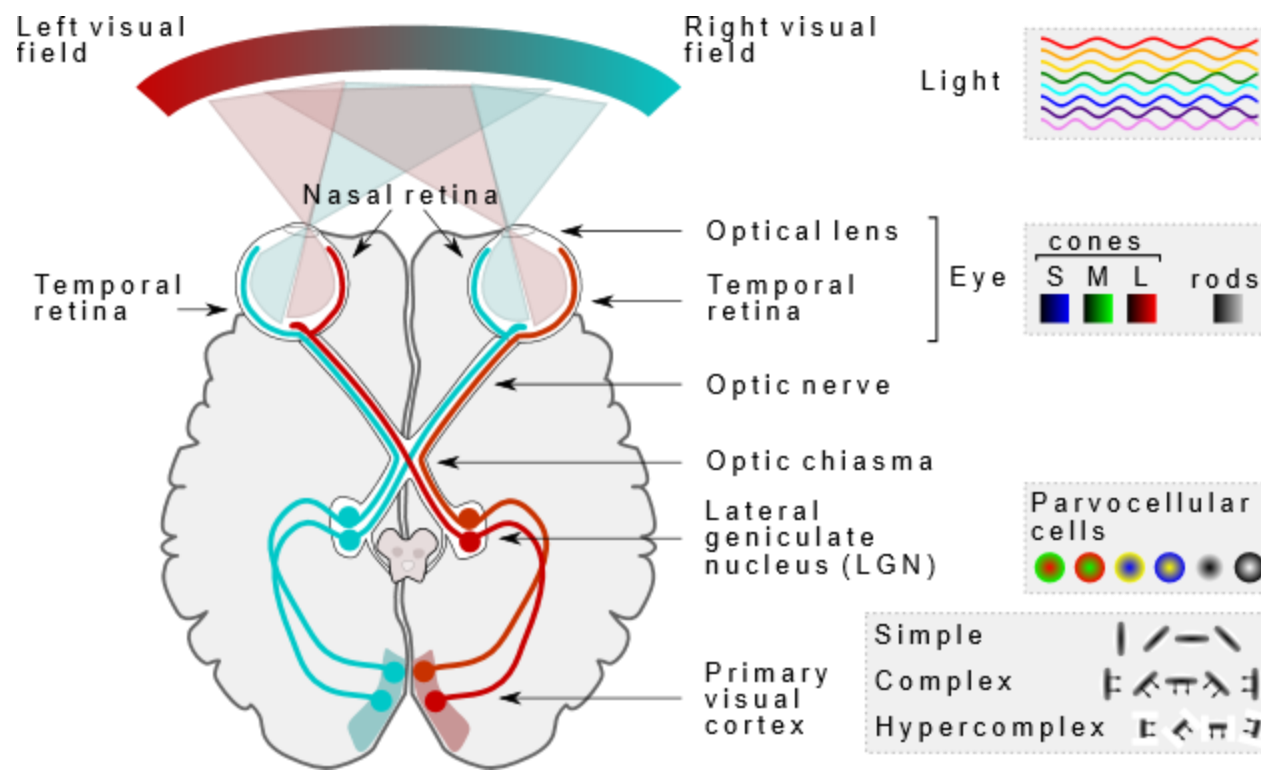
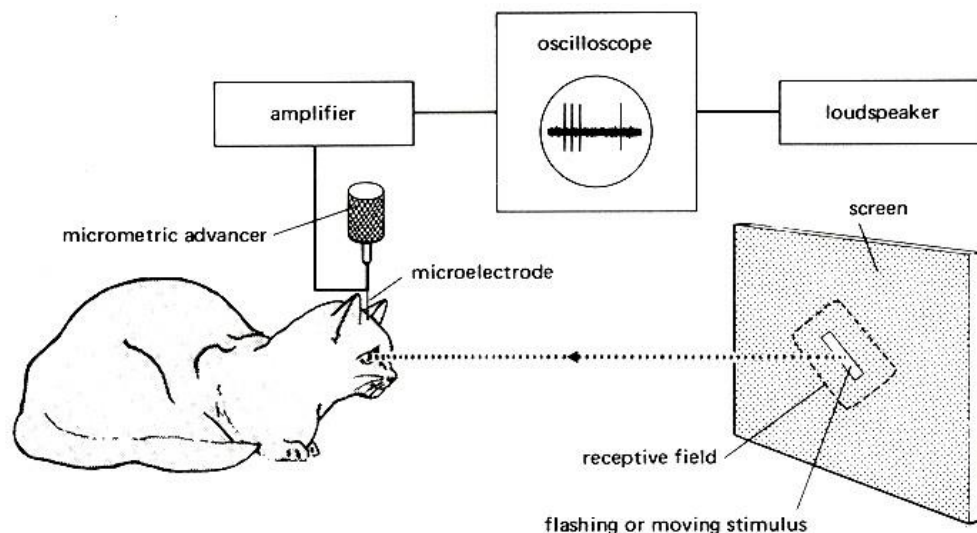
Mathematical
simplification of a neuron
as a weighted sum



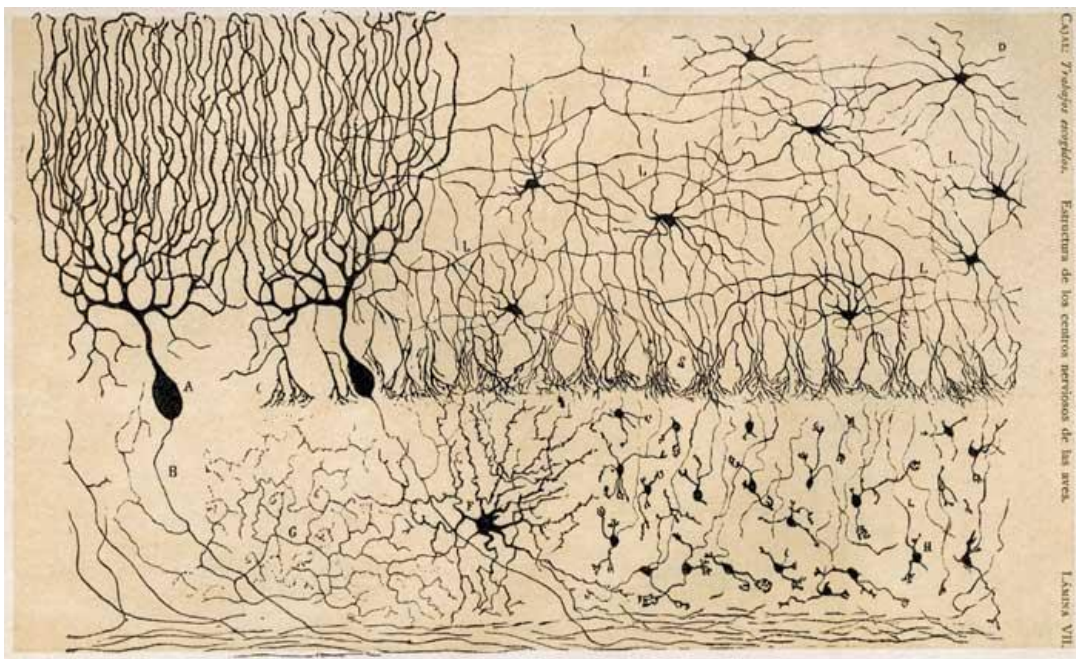
Neuron from the SNARC (Stochastic Neural Analog Reinforcement Calculator) designed by Marvin Lee Minsky ~ 1951

1. Originally Neuron.jpg taken from the US Federal (public domain) (Nerve Tissue, retrieved March 2007), redrawn by User:Dhp1080 in Illustrator. Source: "Anatomy and Physiology" by the US National Cancer Institute's Surveillance, Epidemiology and End Results (SEER) Program.
2. By Nir.nossenson - Own work, CC BY-SA 4.0, <https://commons.wikimedia.org/w/index.php?curid=48019779>

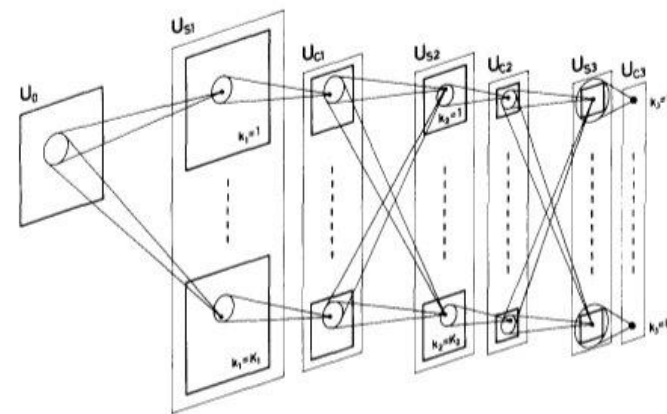
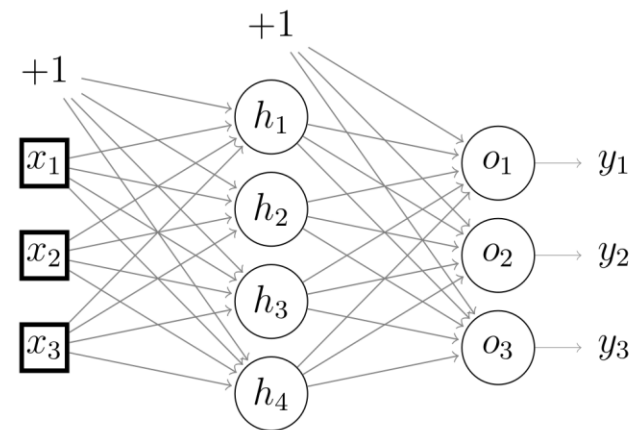
Cat's visual cortex (1962)



Artificial Neural Networks

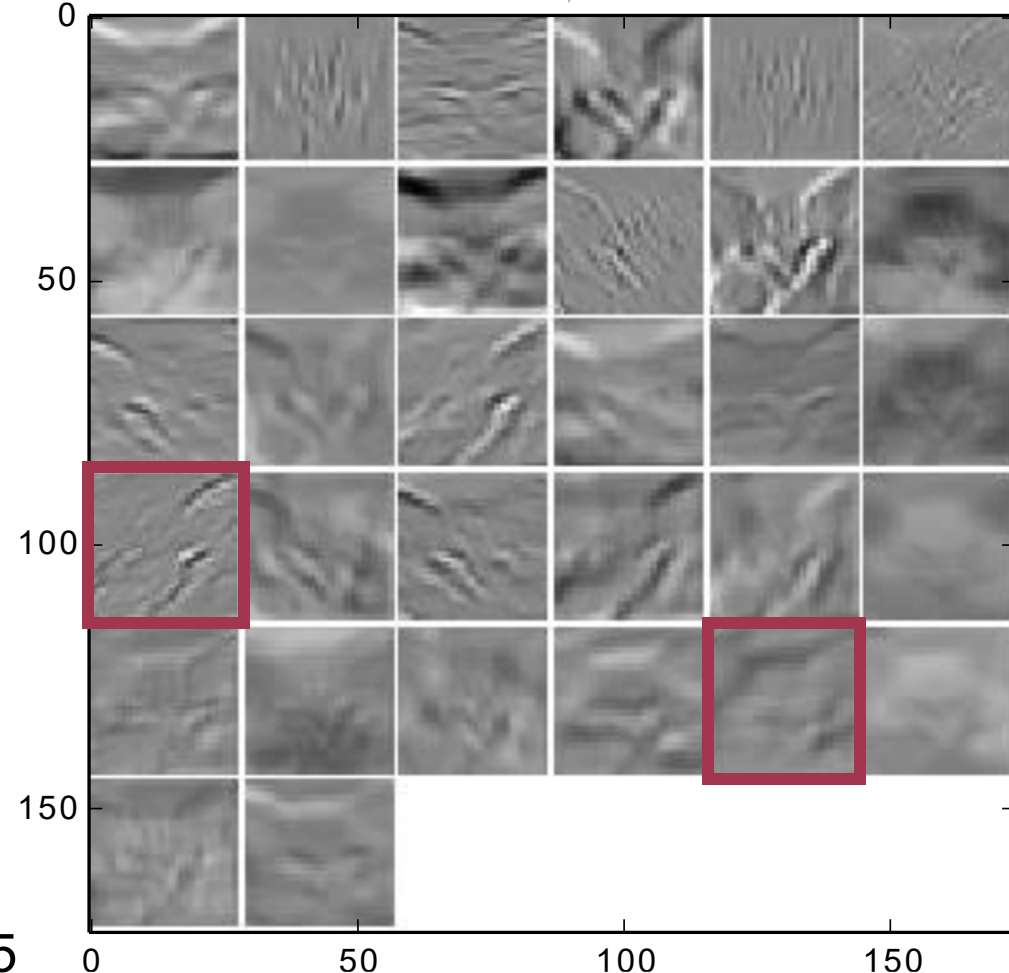
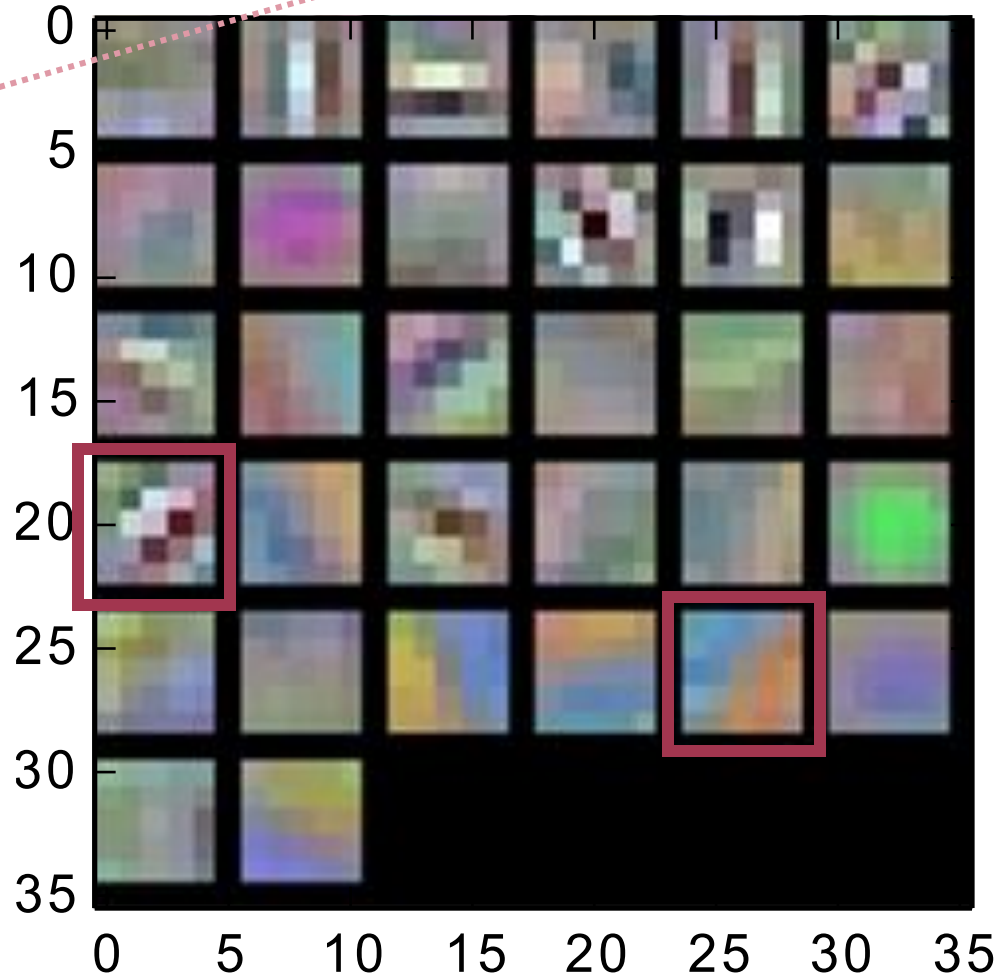
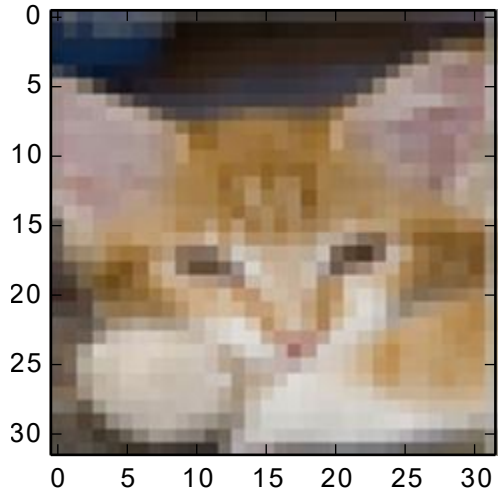
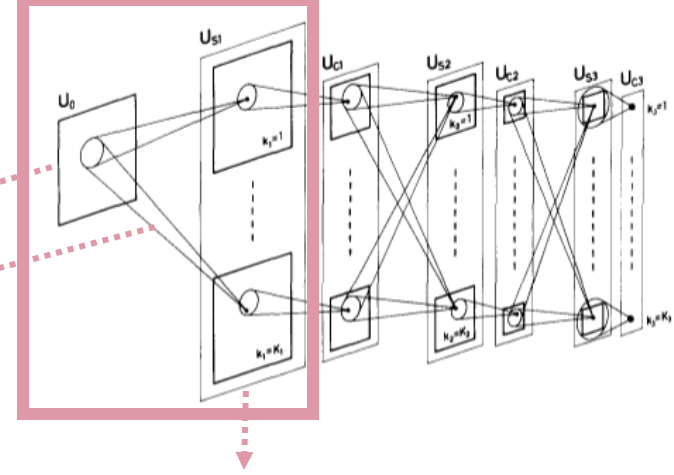


Drawing of neurons by Santiago Ramón y Cajal
(around 1890s)

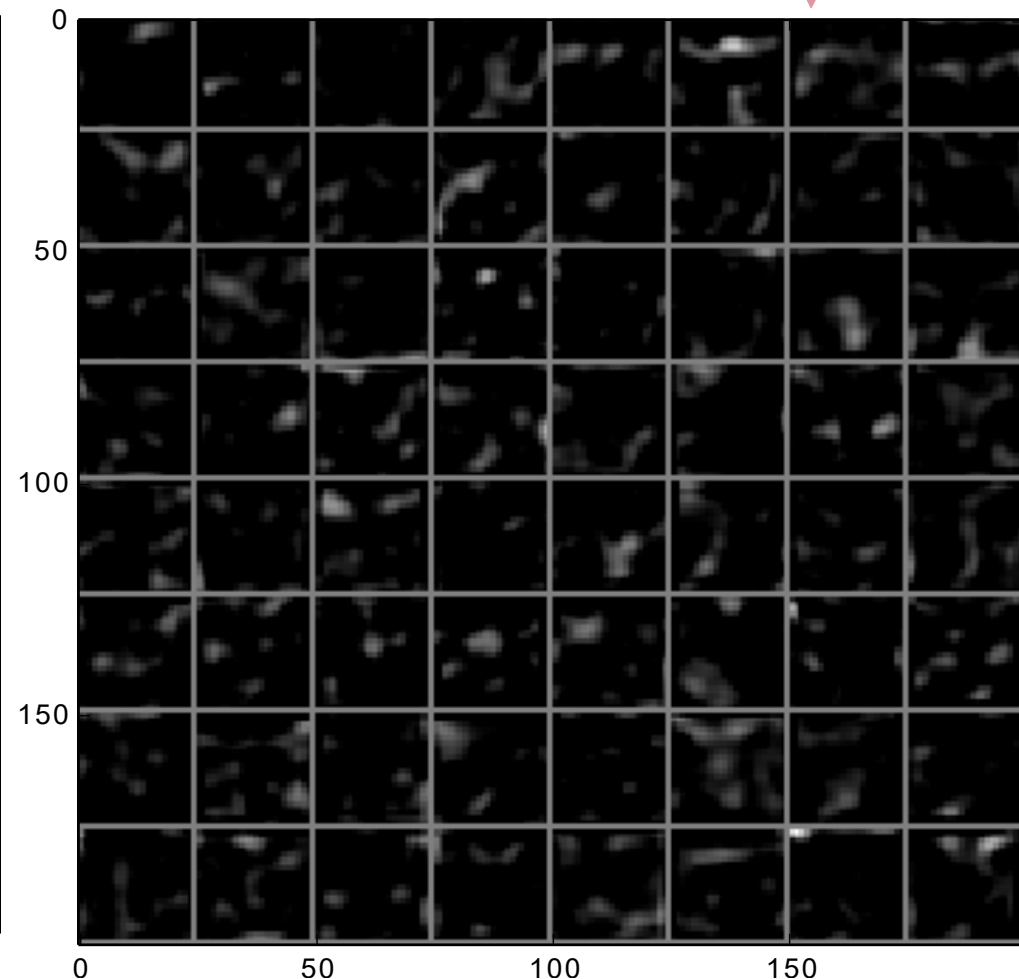
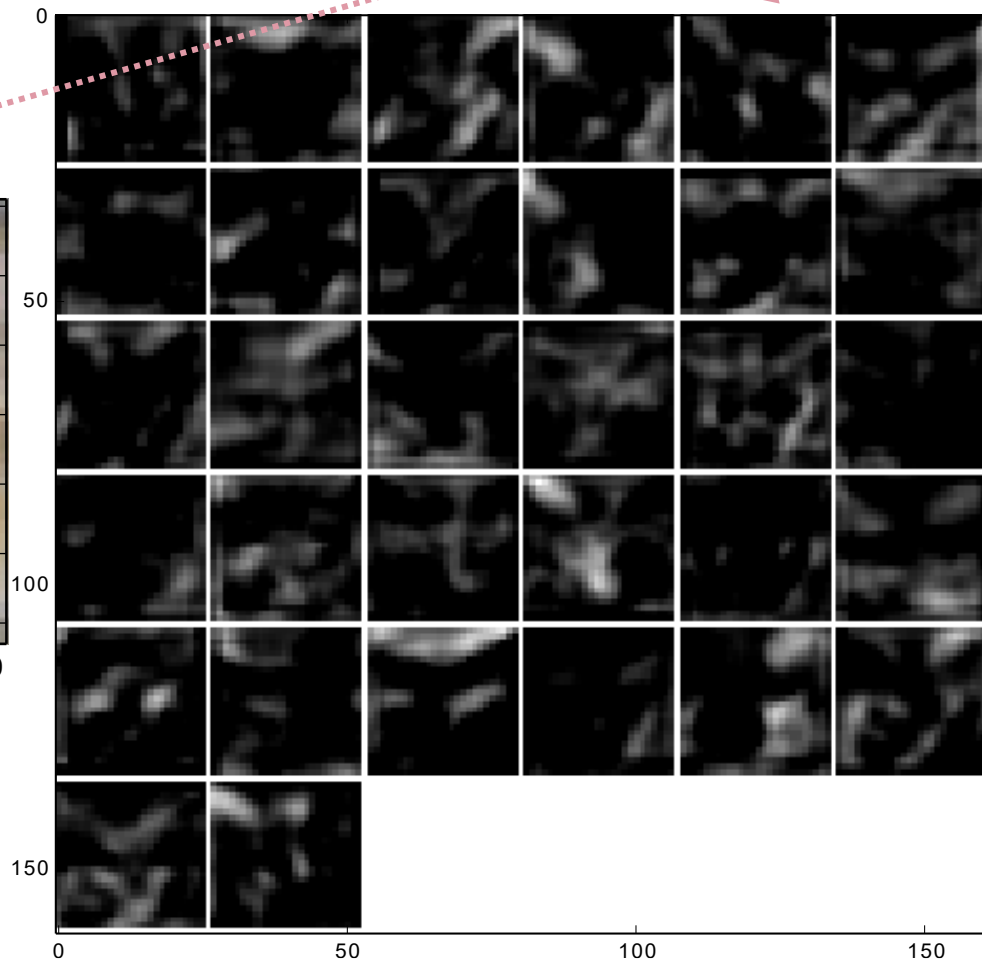
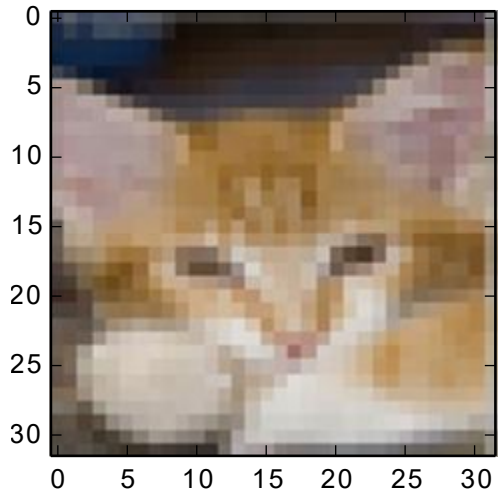
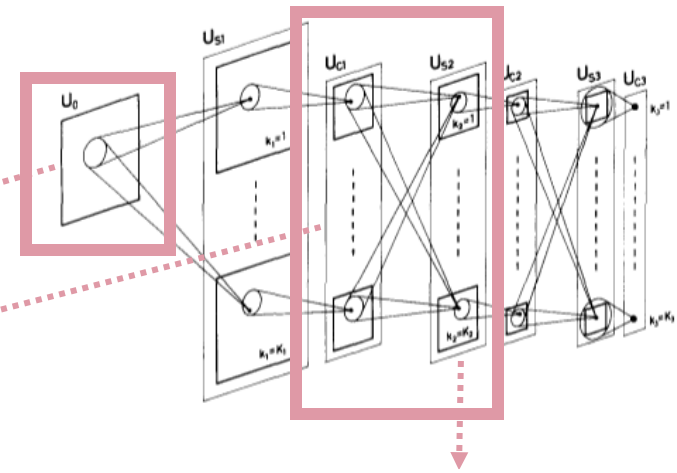


Neocognitron schematic diagram illustrating the
interconnections between multiple layers [Fukushima, 1980]

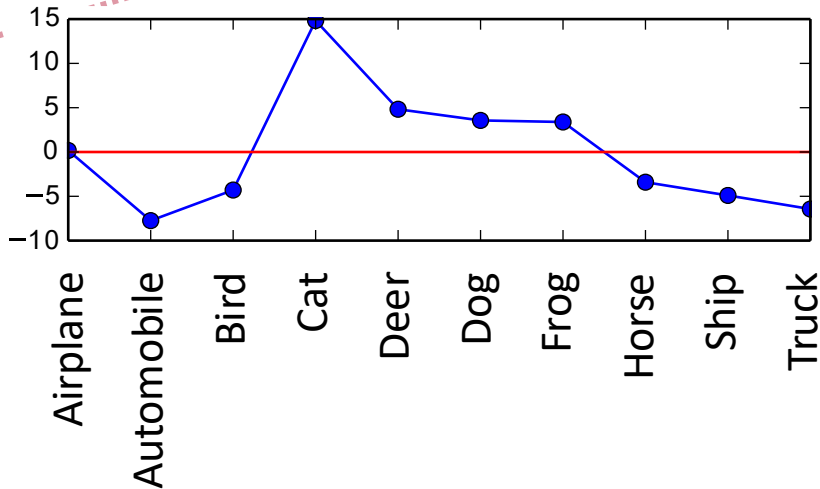
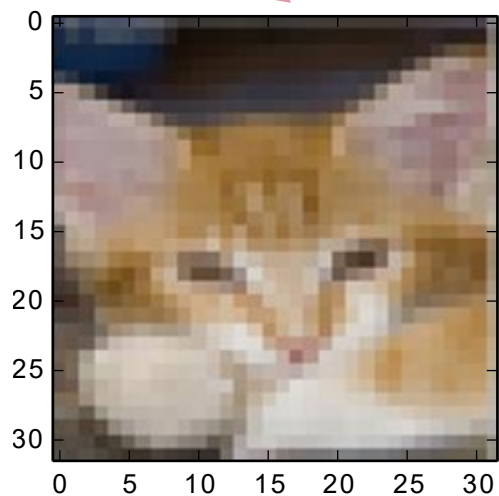
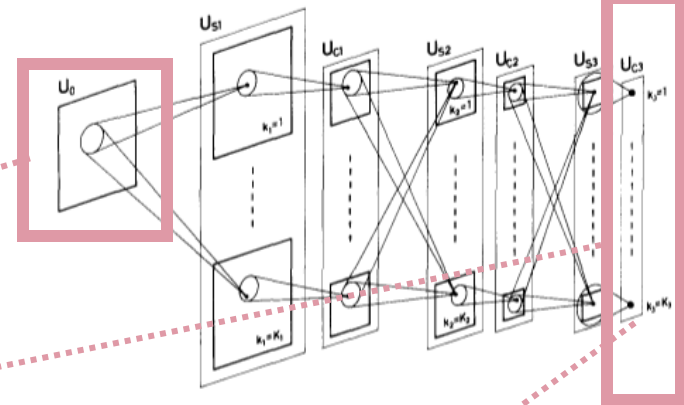
Learned filters



More complex features

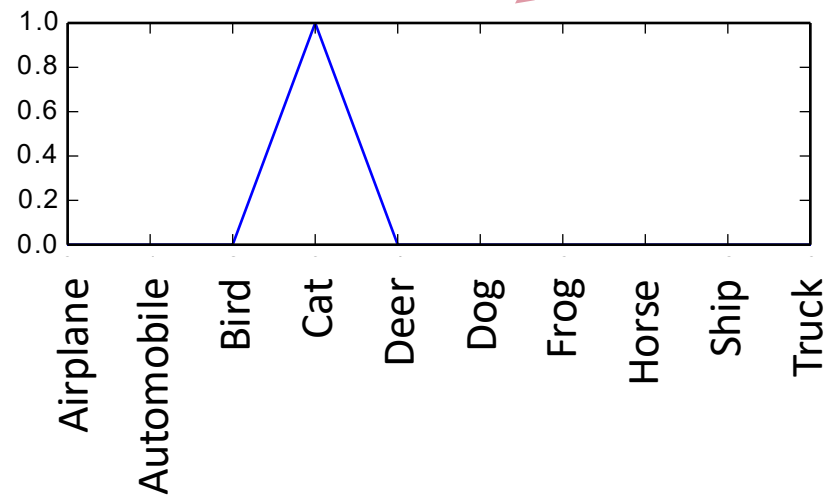


Final prediction

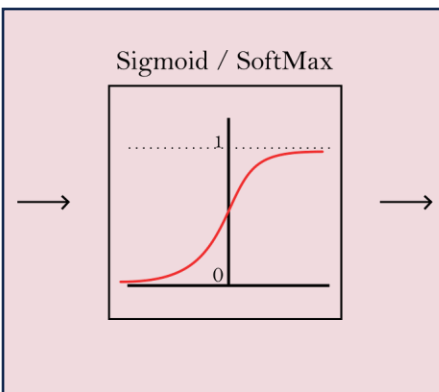


SoftMax

$$s(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}}$$



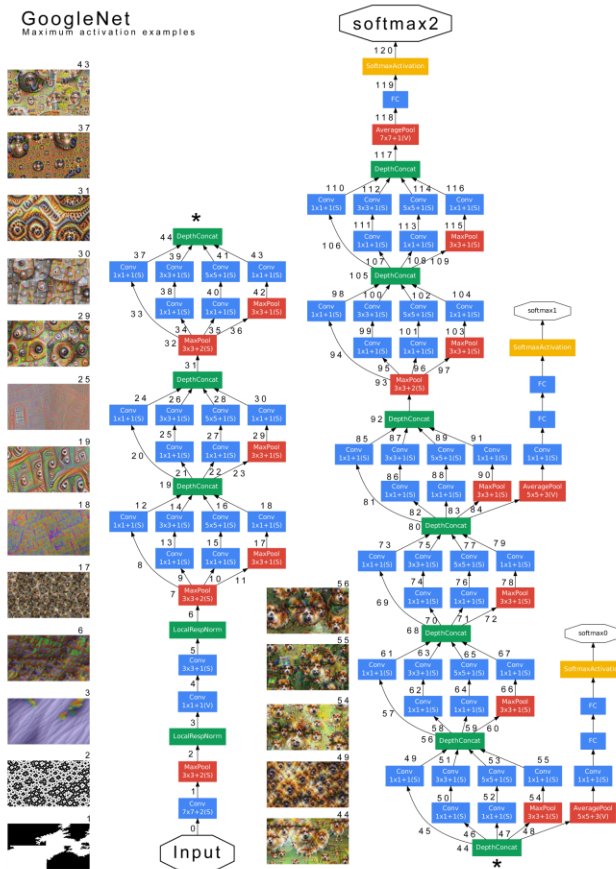
Input
 $X \in \mathbb{R}$



Output

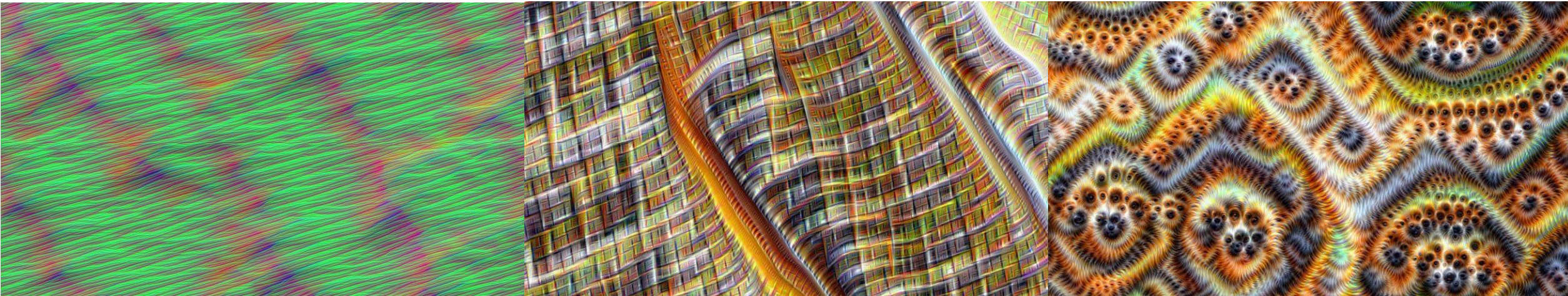
$P(Y=k | X) \in [0,1]$

Deep Neural Network



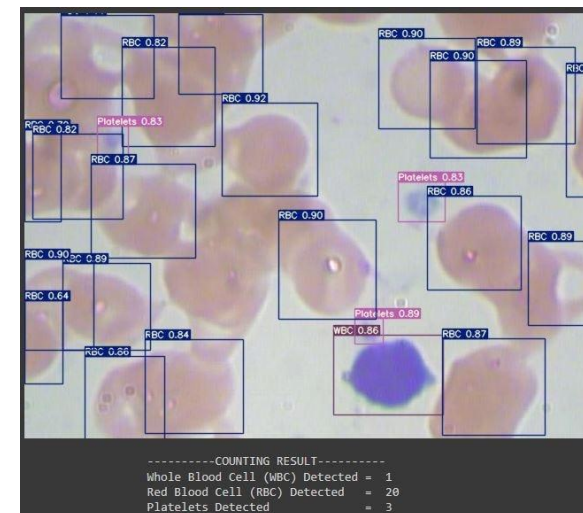
- VGG-16: 16 layers
- GoogleNet: 22 layers DNN [Szegedy et al., 2014]
- ResNet: 34 layers
- ResNet-50: 50 layers
- ...

What different layers represent



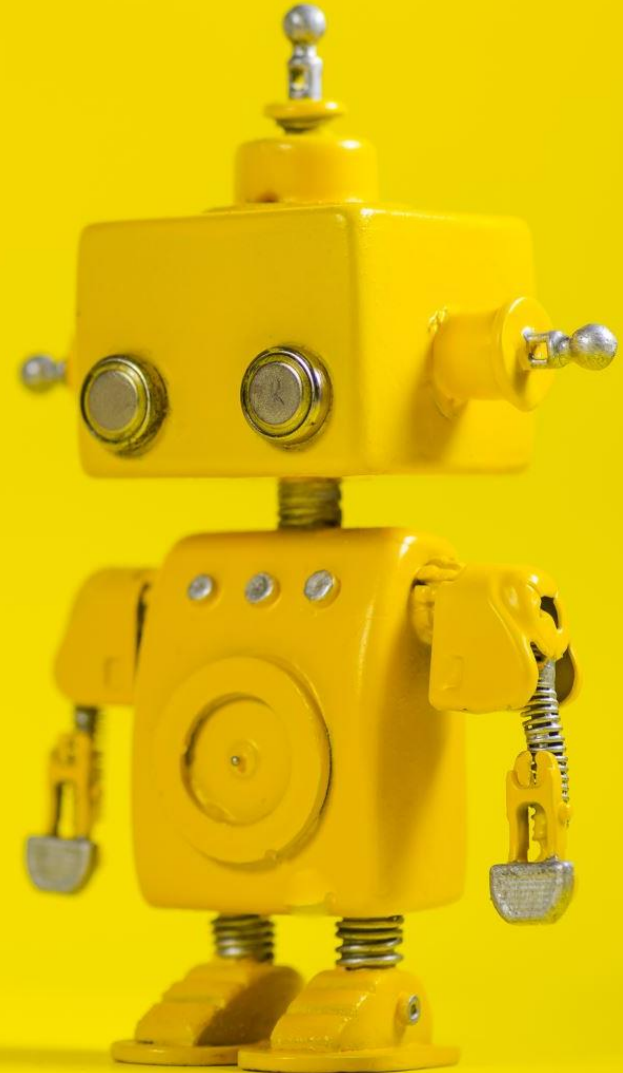
Radiology and other image predictions

- Plenty of AI methods for image analysis
- Each with its own drawbacks
- AI should support experts
- Constant monitoring is necessary
- Provide explanations under request



3. Demystifying AI

- a. Common Pipeline
- b. Radiology
- c. **Scribes**



- Voice to text in real time
- Summarisation of the text
- Use of additional text information (e.g., EHR)
- Help writing a reference letter
- Sometimes Chat functionalities

Most parts probably done with Large Language Models with prompt engineering

Large Language Models (Chat GPT)

- **Generative:** Designed to **g**enerate the next "word".
- **Pre-trained:** **P**re-trained with bast amounts of text.
- **Transformer:** A **T**ransformer architecture to iteratively assign importance to the "words" in the text.

Data Preprocessing. Text

- "Text can be encoded in numeric form in multiple ways, a simple example is in the form of bag of words"

Words	Text	Can	Be	encoded	in	a	numeric	form	Multiple	Ways	Simple	...
Repetitions	1	1	1	1	3	1	1	2	1	1	1	

- N-gram: sequences of n adjacent symbols (words).

1-gram	Rep.
text	1
can	1
be	1
encoded	1
in	3
...	...

2-gram	Rep.
Text can	1
Can be	1
Be encoded	1
Encoded in	1
In numeric	1
...	...

3-gram	Rep.
Text can be	1
Can be encoded	1
Be encoded in	1
Encoded in numeric	1
In numeric form	1
...	...

Can we predict the new word in the sentence

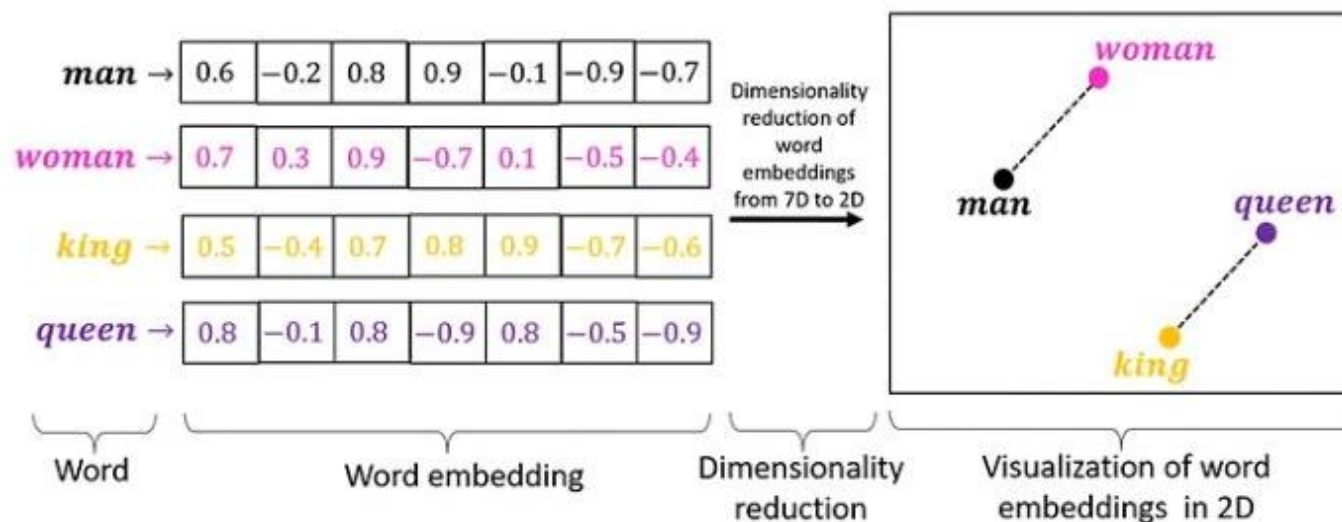
A simple ...

And the next one?

In ...

Learning the meaning of words

- Training the model to predict the new word with limited information forces the model to learn a representation of the meaning of words



$\text{king} - \text{man} + \text{woman} \approx \text{queen}$

$\text{sushi} - \text{japan} + \text{germany} \approx \text{bratwurst}$

Text generation

- The huge amount of training has a multitude of context
- Prompts provide a context to "reduce the search area"
- In any particular context the text generation will be different
- It does not need to find exact matches, as it has learned the "meaning" of words
- What it generates looks like natural language, but it is debatable if there is any type of thought process

4. Ethics and Regulations

- a. **Regulations**
- b. Privacy
- c. Explainability
- d. Fairness
- e. Accountability
- f. Contestability



Healthcare regulations affecting AI

- Market regulations:
 - EU AI Act
 - EU Digital Services Act
 - EU Digital Markets Act
 - EU Cyber Resilience Act
- Biopharma regulations:
 - European Health Data Space
 - General Pharmaceutical Legislation
 - Clinical Trial Regulations
- Data regulations:
 - GDPR (General Data Protection Regulation)
 - Data Act
 - Data Governance Act

AI ethics and regulations

- Five key principles for regulatory use of AI for medical products

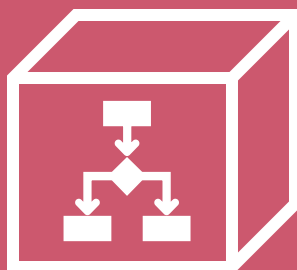
1

**Safety,
security and
robustness**



2

**Transparency
and
explainability**



3

Fairness



4

**Accountability
and
governance**



5

**Contestability
and
redress**

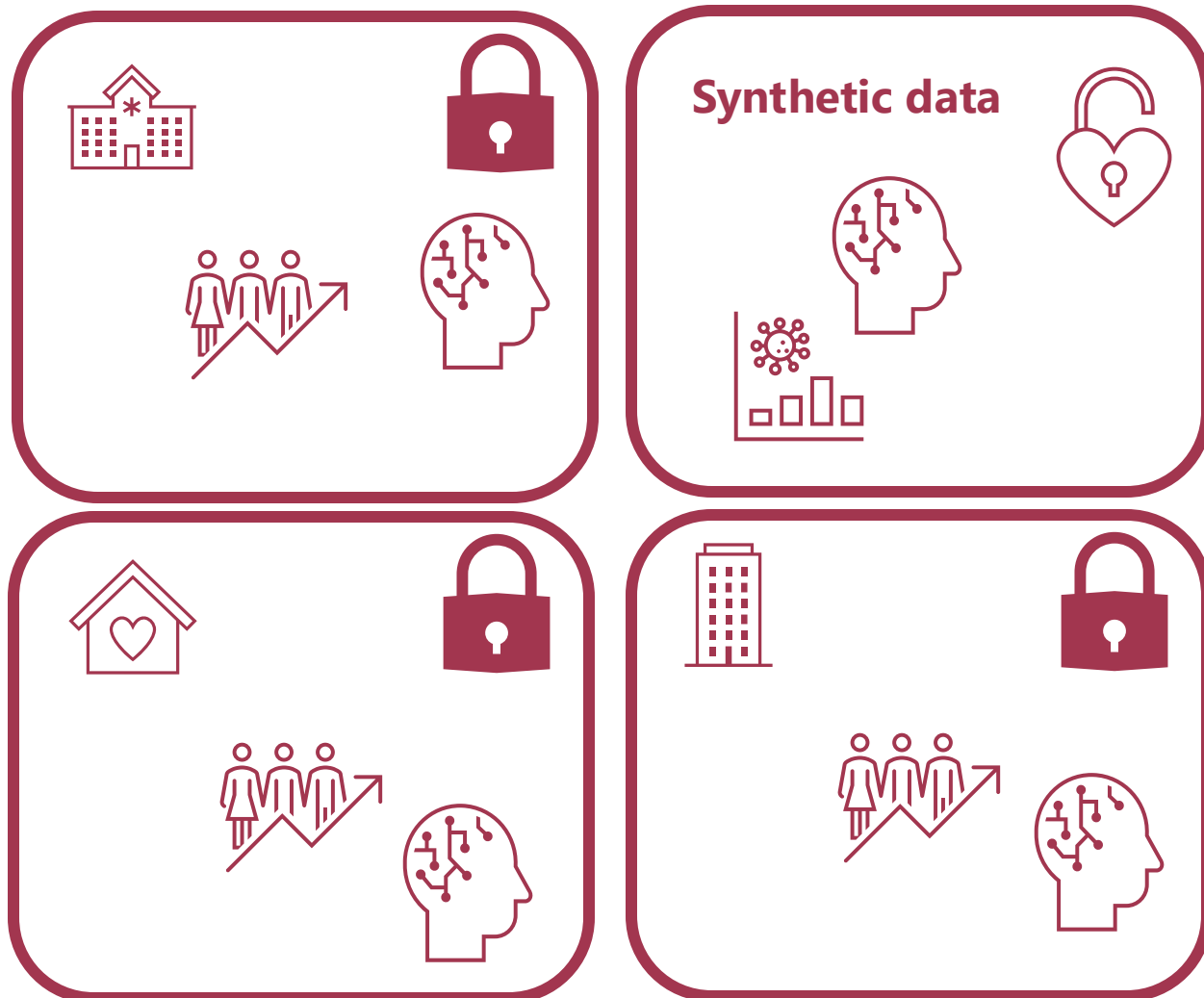


4. Ethics and Regulations

- a. Regulations
- b. Privacy**
- c. Explainability
- d. Fairness
- e. Accountability
- f. Contestability



Safety and security



- Federated learning
- Synthetic data
- Foundation models
- Differential privacy

Requirements:

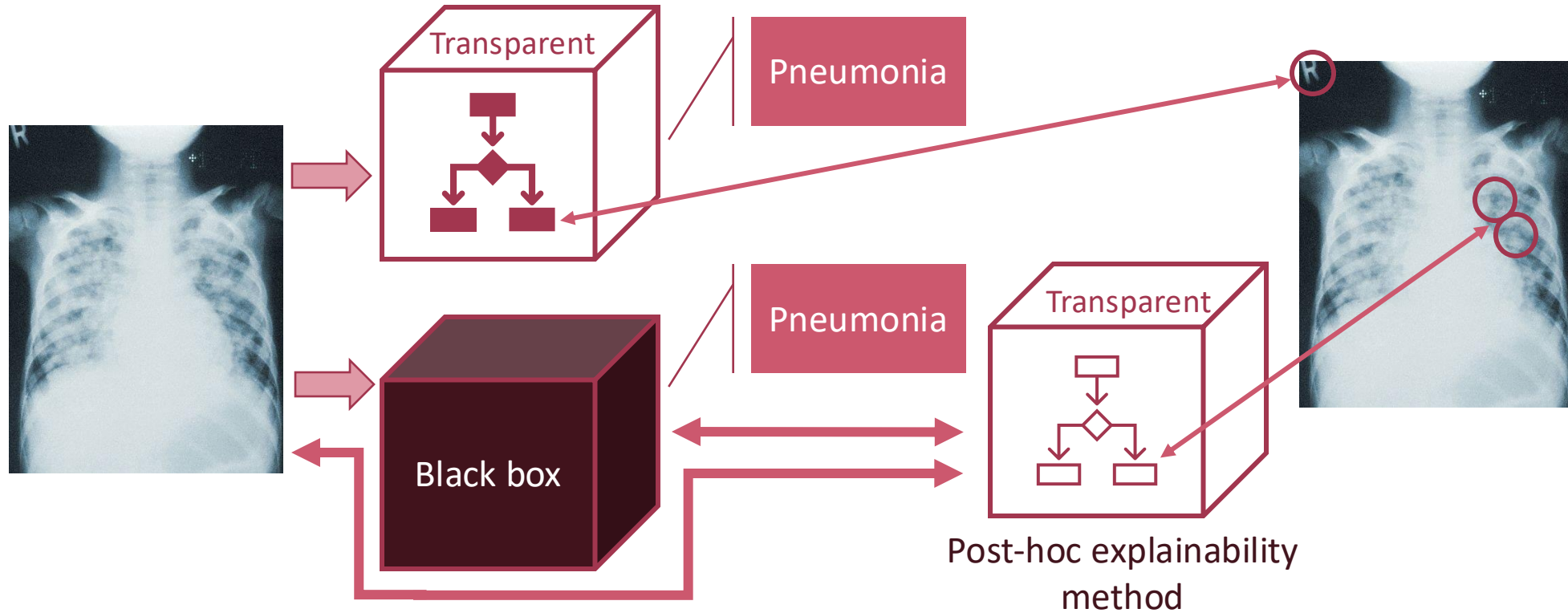
- Standardisation
- Infrastructure

4. Ethics and Regulations

- a. Regulations
- b. Privacy
- c. **Explainability**
- d. Fairness
- e. Accountability
- f. Contestability



Transparency and explainability



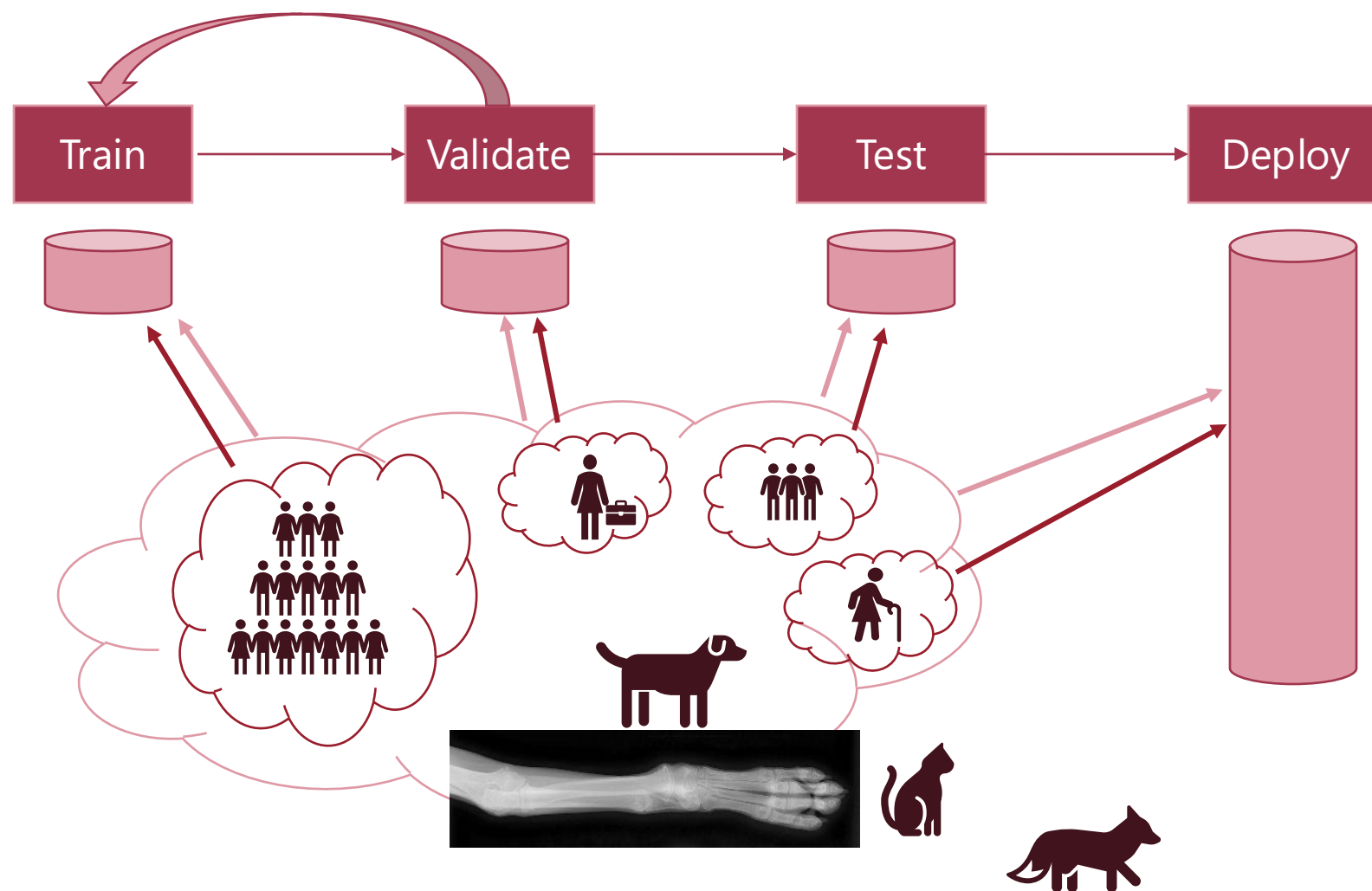
- Identify dataset biases, or model problems
- Model complexity vs transparency vs performance

4. Ethics and Regulations

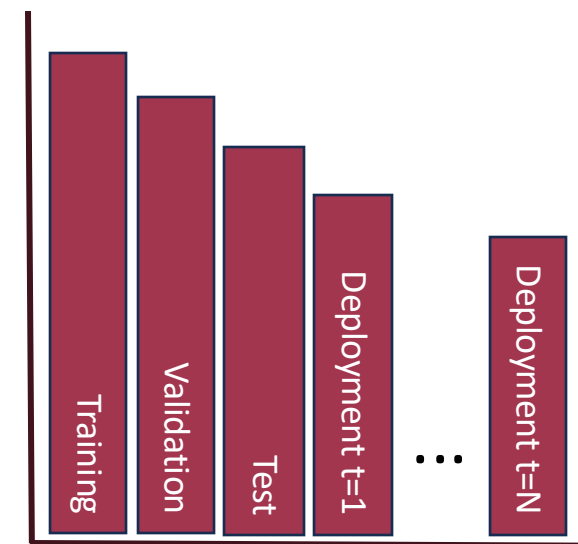
- a. Regulations
- b. Privacy
- c. Explainability
- d. Fairness**
- e. Accountability
- f. Contestability



Fairness and robustness



Performance



Requires
constant
monitoring

MailOnline Science

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Is this soap dispenser RACIST? Controversy as Facebook employee shares video of machine that only responds to white skin

- A Facebook employee tweeted a soap dispenser that only works for white hands
- It's likely because the infrared sensor was not designed to detect darker skin
- Critics say tech's diversity problem causes this and other racist technology

By [SAGE LAZZARO FOR DAILYMMAIL.COM](#)

PUBLISHED: 18:54, 17 August 2017 | UPDATED: 19:32, 18 August 2017

The New York Times

[Does Your Teen Recognize A.I.?](#) | [Art World Takes On A.I.](#) | [Putting A.I. in Charge](#) | [A.I. and Hollywood](#)

Google's Photo App Still Can't Find Gorillas. And Neither Can Apple's.



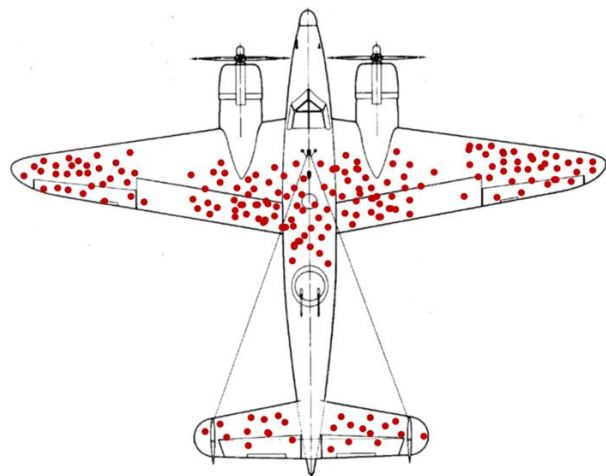
Desiree Rios/The New York Times

Eight years after a controversy over Black people being mislabeled as gorillas by image analysis software — and despite big advances in computer vision — tech giants still fear repeating the mistake.

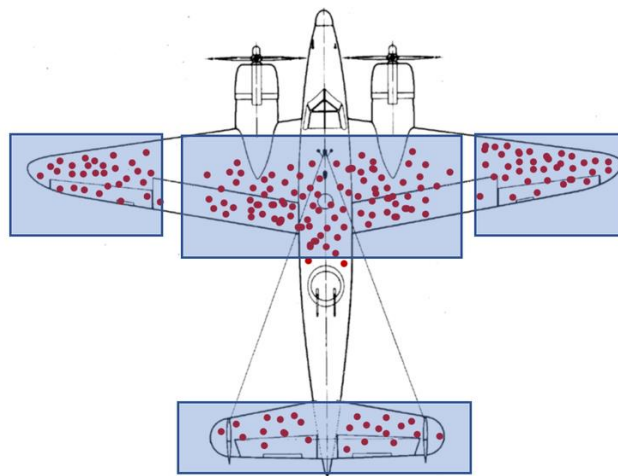
By [Nico Grant](#) and [Kashmir Hill](#)

May 22, 2023

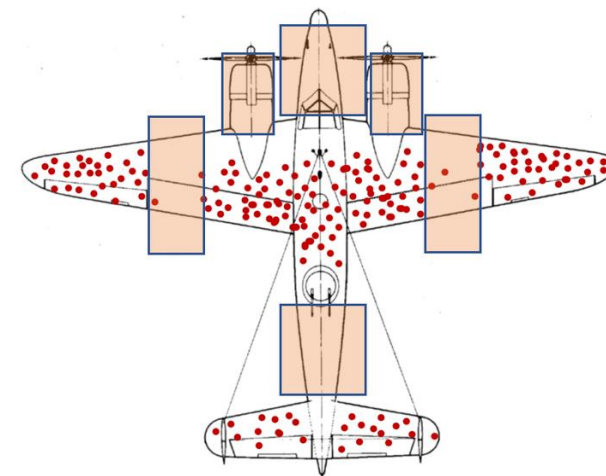
The survivorship bias



Our data if only from returning flights. Here we is a visualization of the places that bullet holes were observed.

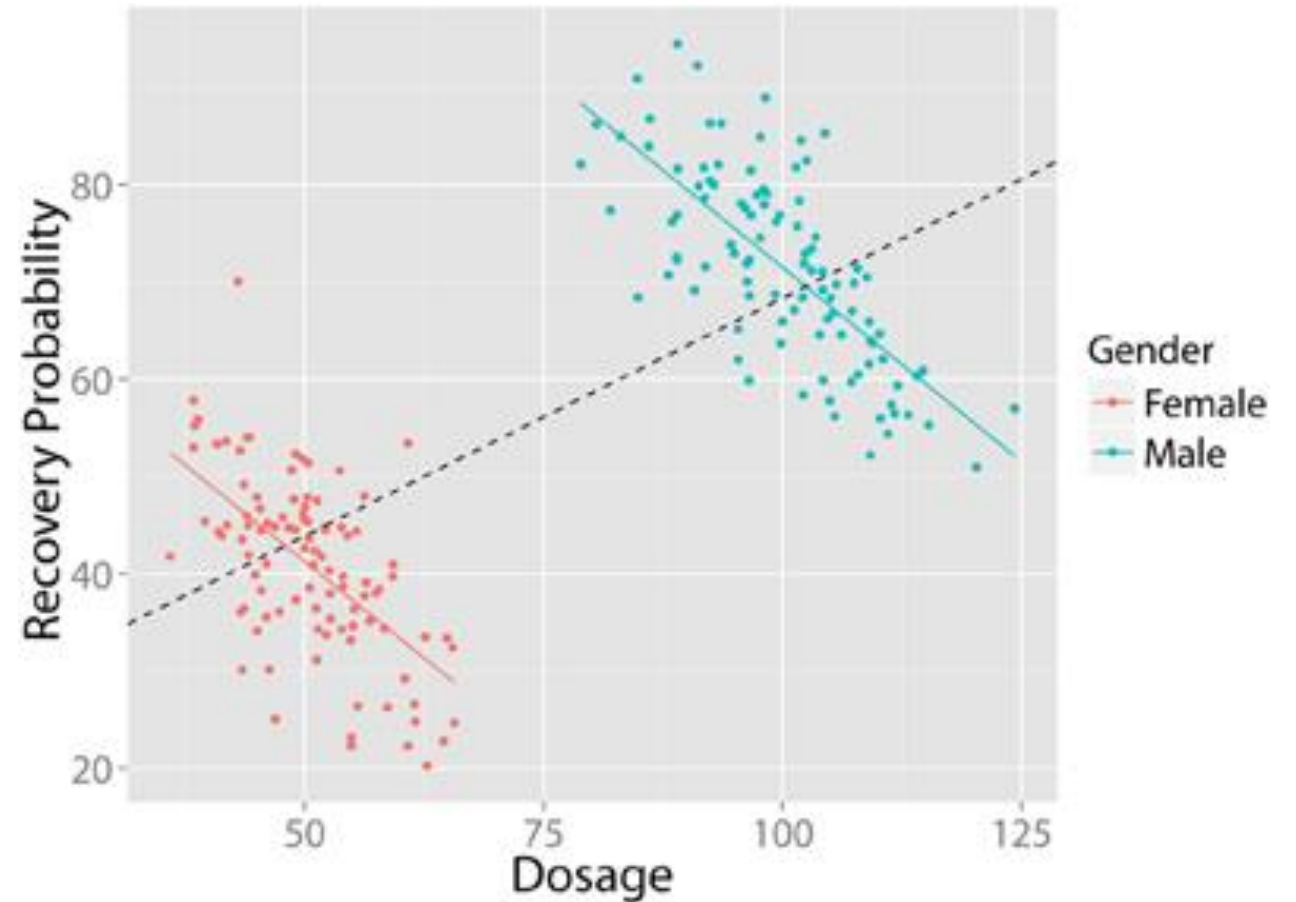


And initial guess at how to fix this might be to apply additional armor platting to the parts of the plane with the most holes...



.... However this is where planes that *returned* had bullet holes. The planes we want to protect are the ones that did *not* return, so we should place armor there.

The Simpson's paradox



4. Ethics and Regulations

- a. Regulations
- b. Privacy
- c. Explainability
- d. Fairness
- e. **Accountability**
- f. Contestability



Accountability and Governance

- Effective oversight of the use of AI.
- Clear lines of accountability across the AI life cycle.
- Trustworthiness auditing

4. Ethics and Regulations

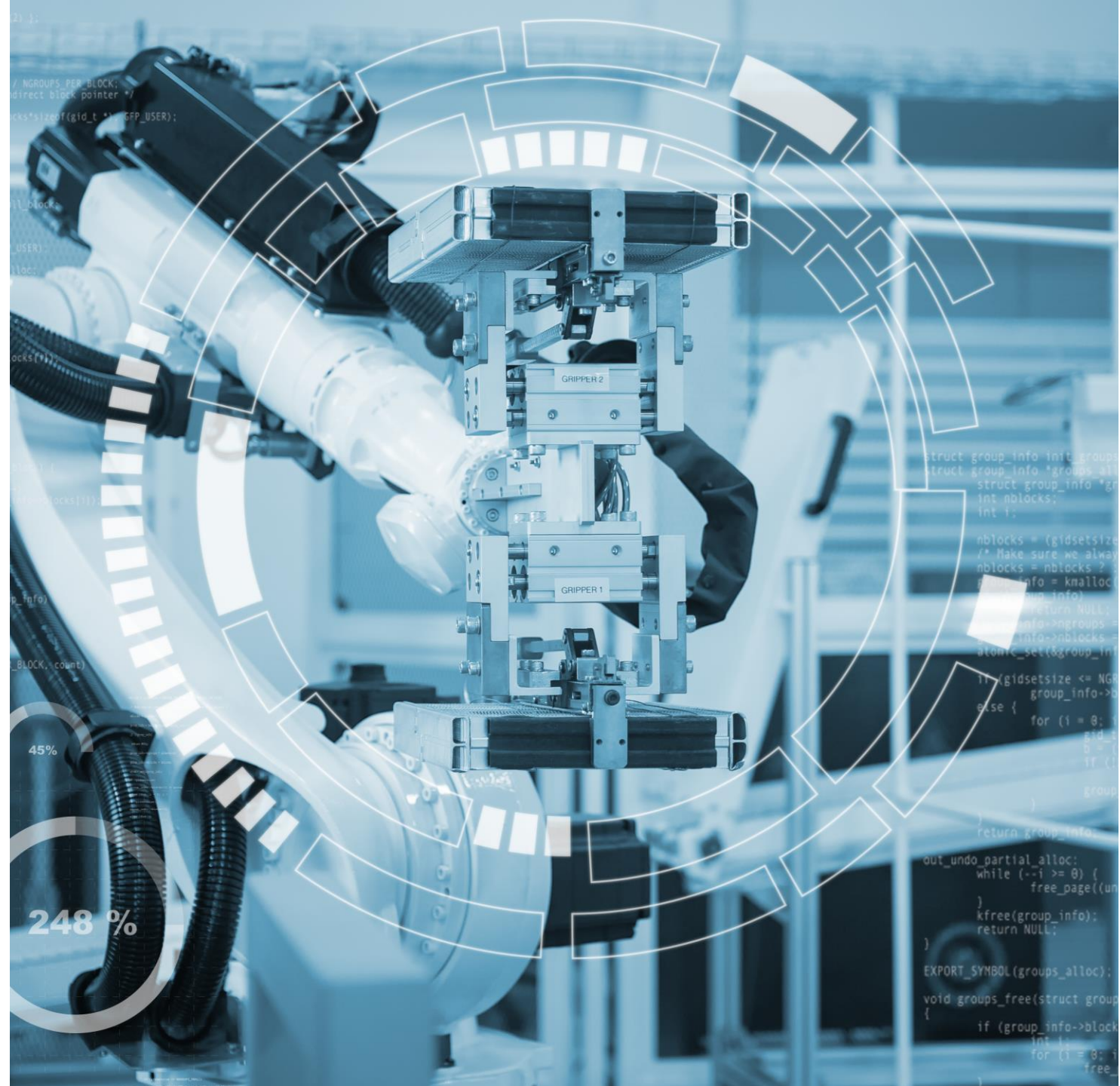
- a. Regulations
- b. Privacy
- c. Explainability
- d. Fairness
- e. Accountability
- f. **Contestability**



Contestability and redress

- A person affected by the outcomes or a decision from an AI should be able to contest the AI.
- How to rectify and address any harm resulting from an AI decision

5. Conclusion



Conclusion

- It is not easy to validate an AI technology for critical applications.
- A governmental organization should investigate the transparency and understanding of such technologies.
- The data used for training may have unexpected consequences (e.g., bias, discrimination).

Q&A and Discussion

Artificial Intelligence in
Healthcare:
Opportunities, Challenges,
and Critical Perspectives

Presenter:
Dr Miquel Perelló Nieto

