# Artificial Intelligence in General Practice

Alastair Droop, 2023-11-29

# What is Artificial Intelligence?

*"The capacity of computers or other machines to exhibit or simulate intelligent behaviour; the field of study concerned with this."*

OED, `https://www.oed.com/viewdictionaryentry/Entry/271625`

# Common Uses for AI

- Credit card fraud detection
- Identity recognition
- Fitness monitoring
- Self-driving cars
- Natural Language Processing → Language processing, Spam email detection, Sentiment analysis, Chatbots, Summarisation
- Image Recognition → Image Classification, Facial recognition, Video tracking, Handwriting recognition, Deepfaking, Anomaly detection

Artificial Intelligence is all around us, for both good and bad

Natural Language Processing (NLP) attempts to use computers to make sense of human language

Image recognition techniques attempt to extract meaningful data from images

# Some Terminology…

| | |
|---|---|
| input | The inputs to an AI process can be pretty much anything we can measure |
| ↓ select relevant features | Features are the things (called variables) that we want to measure (eg. Blood pressure, disease status, *etc…*) |
| ↓ convert features into numbers | We encode features into numbers so we can use maths to process them. Different kinds of features will use different encodings to do this |
| ↓ maybe apply transformations | Transformations change the values of the features in defined ways to make them easier to use. Whatever transformations we do, we're changing all the values in the same way |
| ↓ Maths! | We input the transformed input features into a mathematical function (an algorithm) that generates the outputs for us |
| ↓ output numbers | The AI function generates numerical values as outputs |
| ↓ interpret outputs | We need to interpret the numerical values to work out what the AI has told us |

# Encoding Data

Encoding data changes the labels to make it easier for computers to work with

- Encodings need to be unambiguous, consistent and (as much as possible) complete

For example, encoding a patient's "sex" is more complicated than many people realise:

- Chromosomal sex (karyotype), physical sex, gender, and perceived sex are all different (what about mosaicism?)

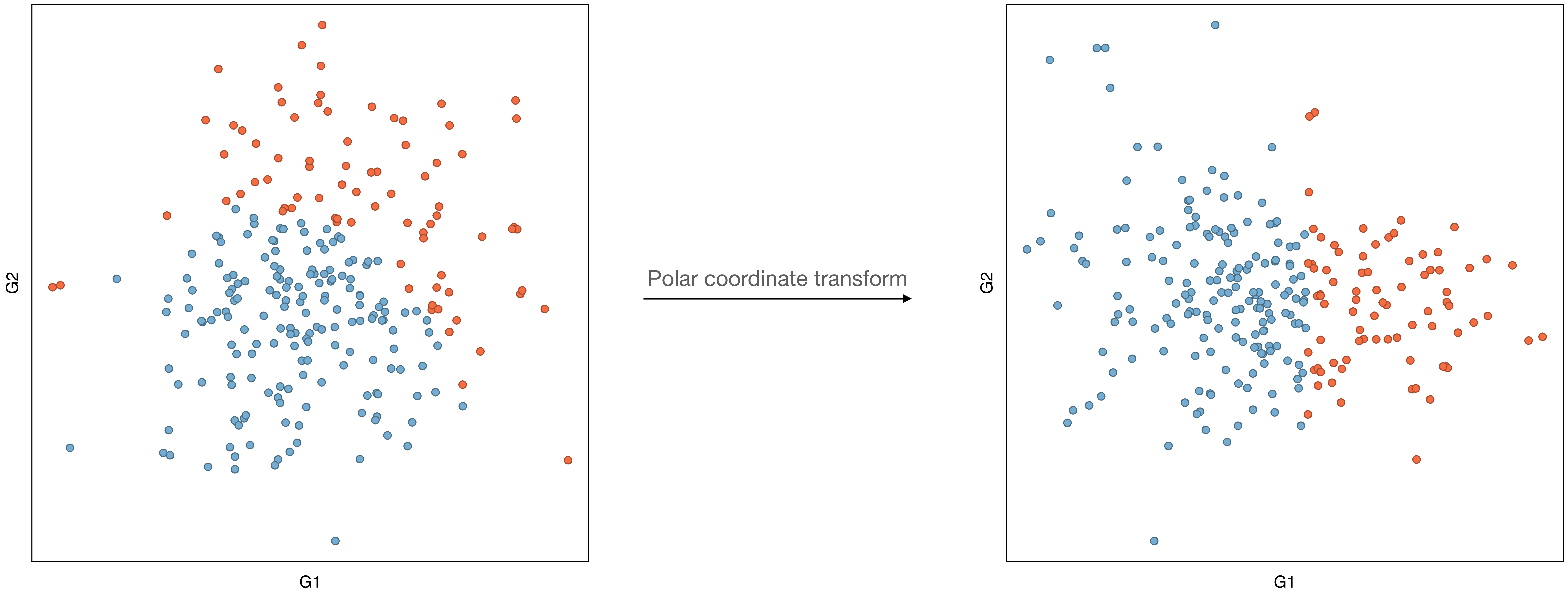
| Karyotype | Name | Incidence (live births) | Encoding |
|---|---|---|---|
| XX | Female | 1 in 2 | 1 |
| XY | Male | 1 in 2 | 2 |
| X | Turner syndrome | 1 in 4,000 | 3 |
| XXX | Trisomy X | 1 in 2,000 | 4 |
| XXY | Klinefelter syndrome | 1 in 1,320 | 5 |
| XYY | Jacobs syndrome | 1 in 1,000 | 6 |
| XXXY | 48,XXXY syndrome | 1 in 100,000 | 7 |
| XXYY | 48,XXYY syndrome | 1 in 80,000 | 8 |
| XXXXY | 49,XXXXY syndrome | 1 in 200,000 | 9 |
| other | – | – | 10 |
| unknown | – | – | 0 |

https://medlineplus.gov/genetics/condition

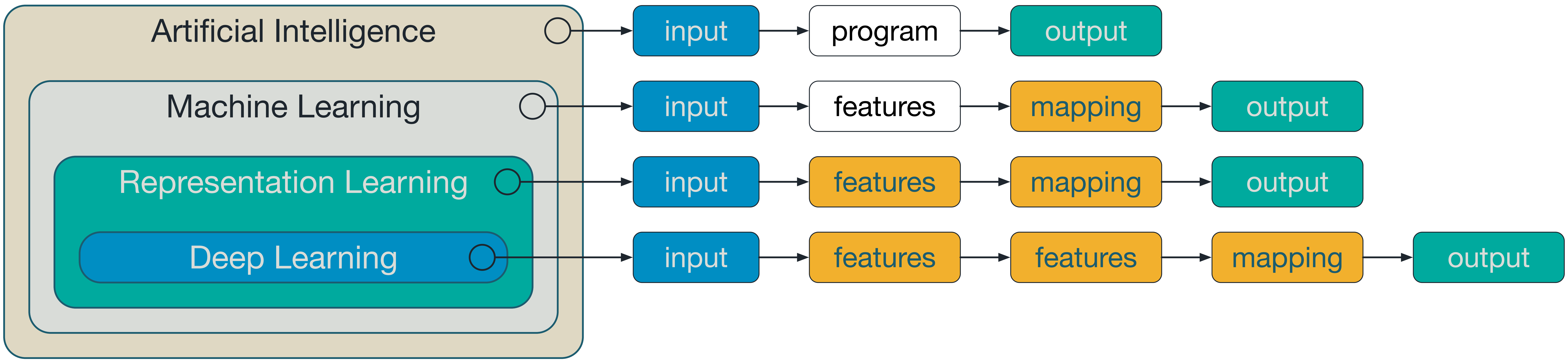
# Transforming Data

We can transform our data before starting to analyse it to make the maths easier

This is done after feature selection



# Types of AI

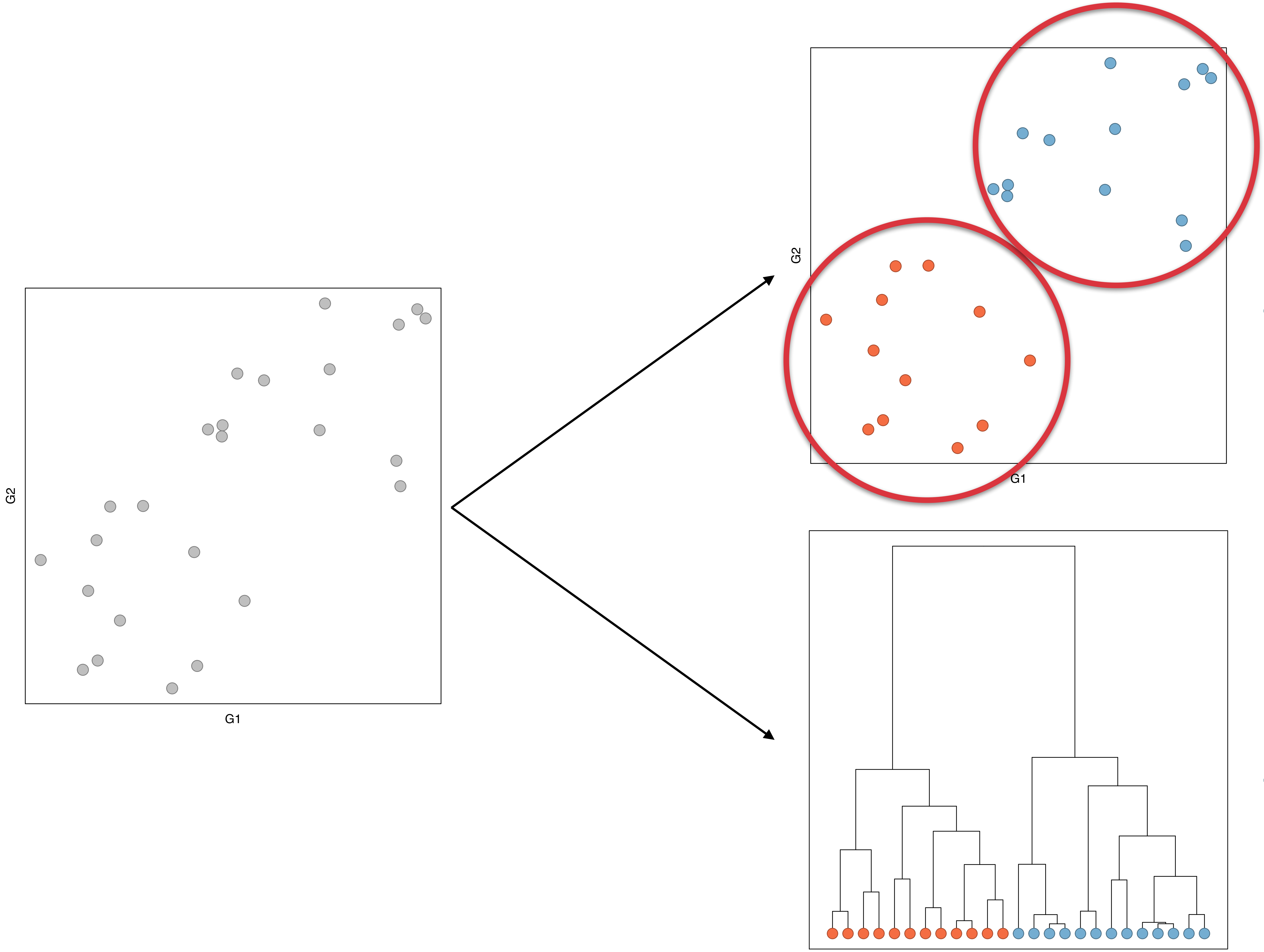



The boxes in yellow are where we allow the computer to learn

Machine learning allows the computer to learn how to modify & combine (*ie*. map) the inputs to make the outputs

Representation learning allows the computer to learn the features to extract as well as the mappings

# Classification Methods




Group by distance into fixed number of groups

This is called k-means clustering

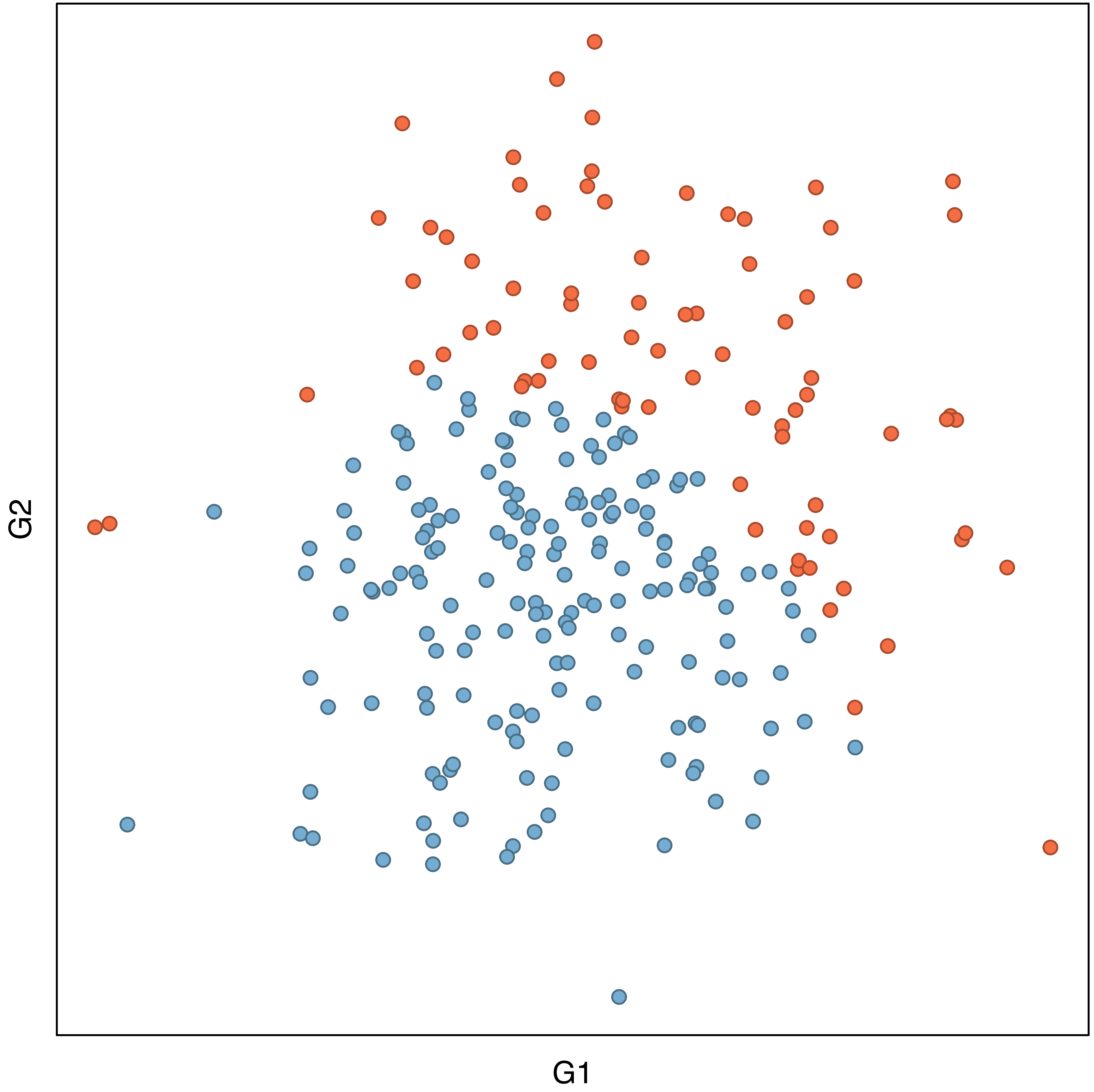
Group by distance then decide the grouping after

This is called hierarchical clustering

Many problems in biology are not this simple, so we can’t use the simple methods above

How could we do this?

- We could alter (i.e. transform) the features to some other (easier to learn) format
- Or, we could use a more complex technique

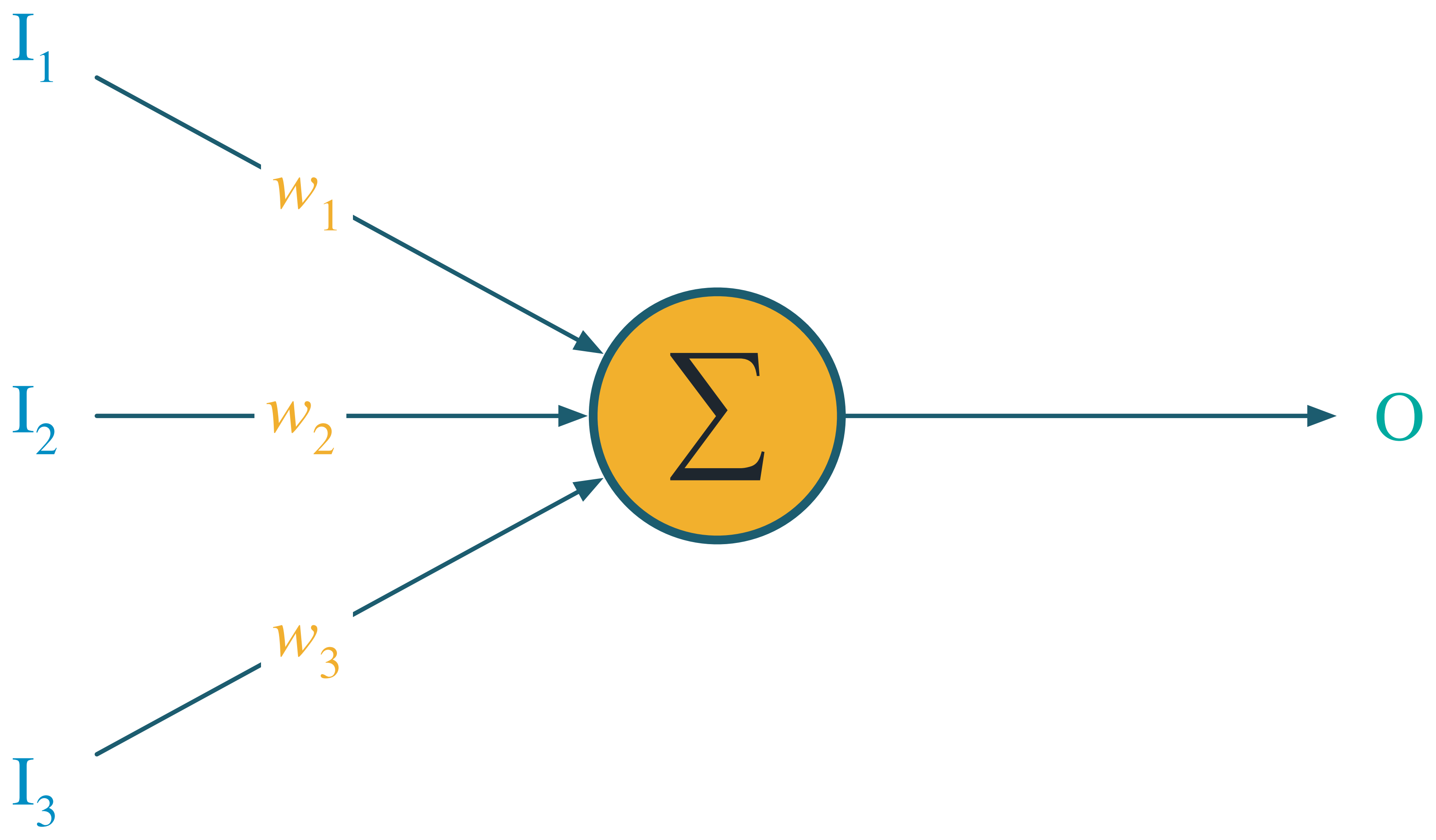


# Neural Networks

Neural Networks are made up of many perceptrons

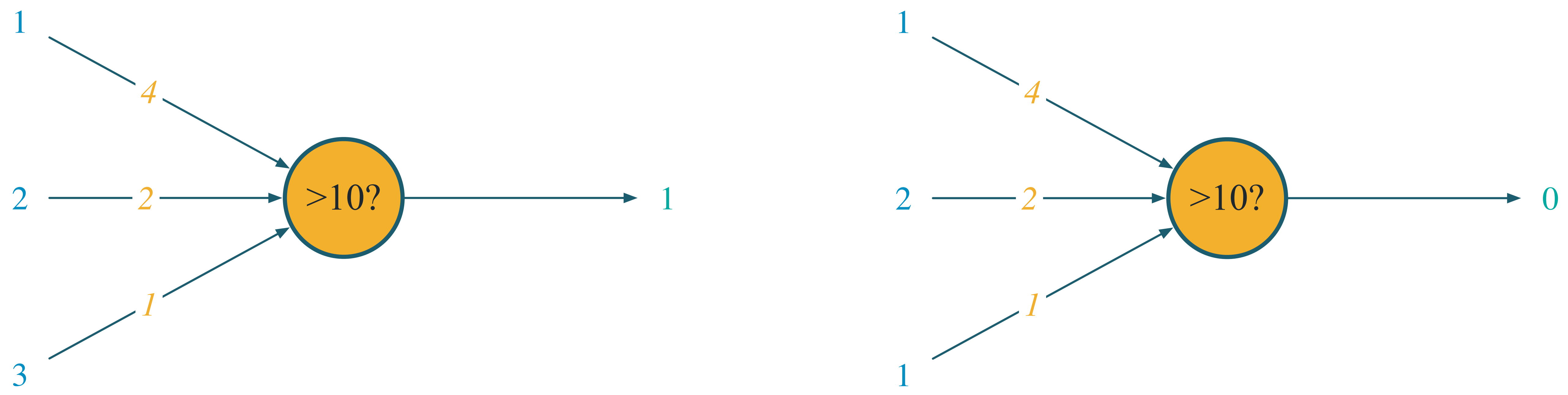
Each perceptron is simply a mathematical sum that adds up its weighted inputs and returns a result if the sum is above a specified number

Perceptrons can have any number of inputs and outputs

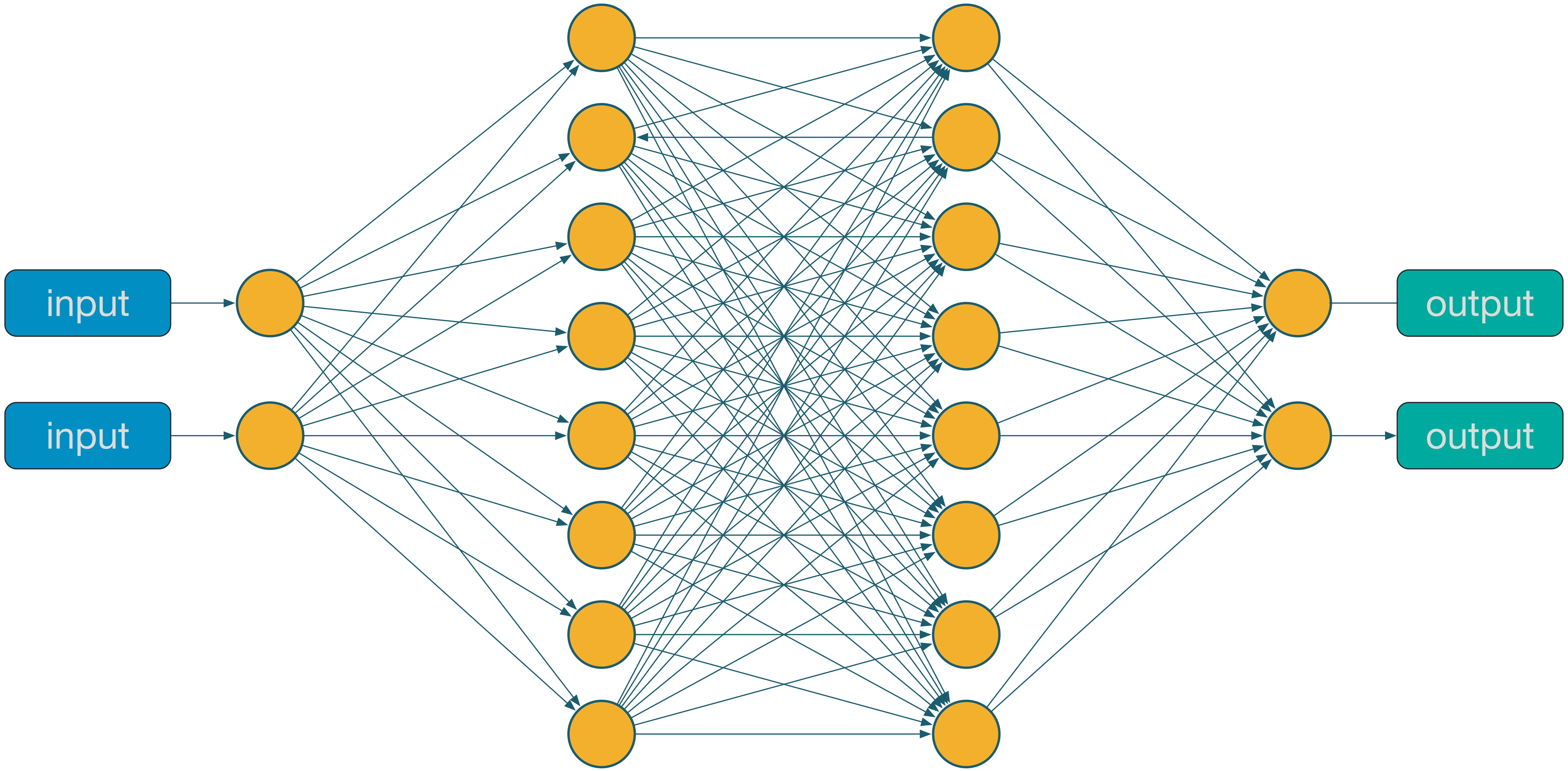



$$(w_1 \times I_1) + (w_2 \times I_2) + (w_3 \times I_3) \geq 1$$

Two examples with real values. In both cases, the perceptron checks if its weighted inputs sum to 10 or more.




**NB**: This is a bit simplified. Talk to me afterwards for more maths if you want.

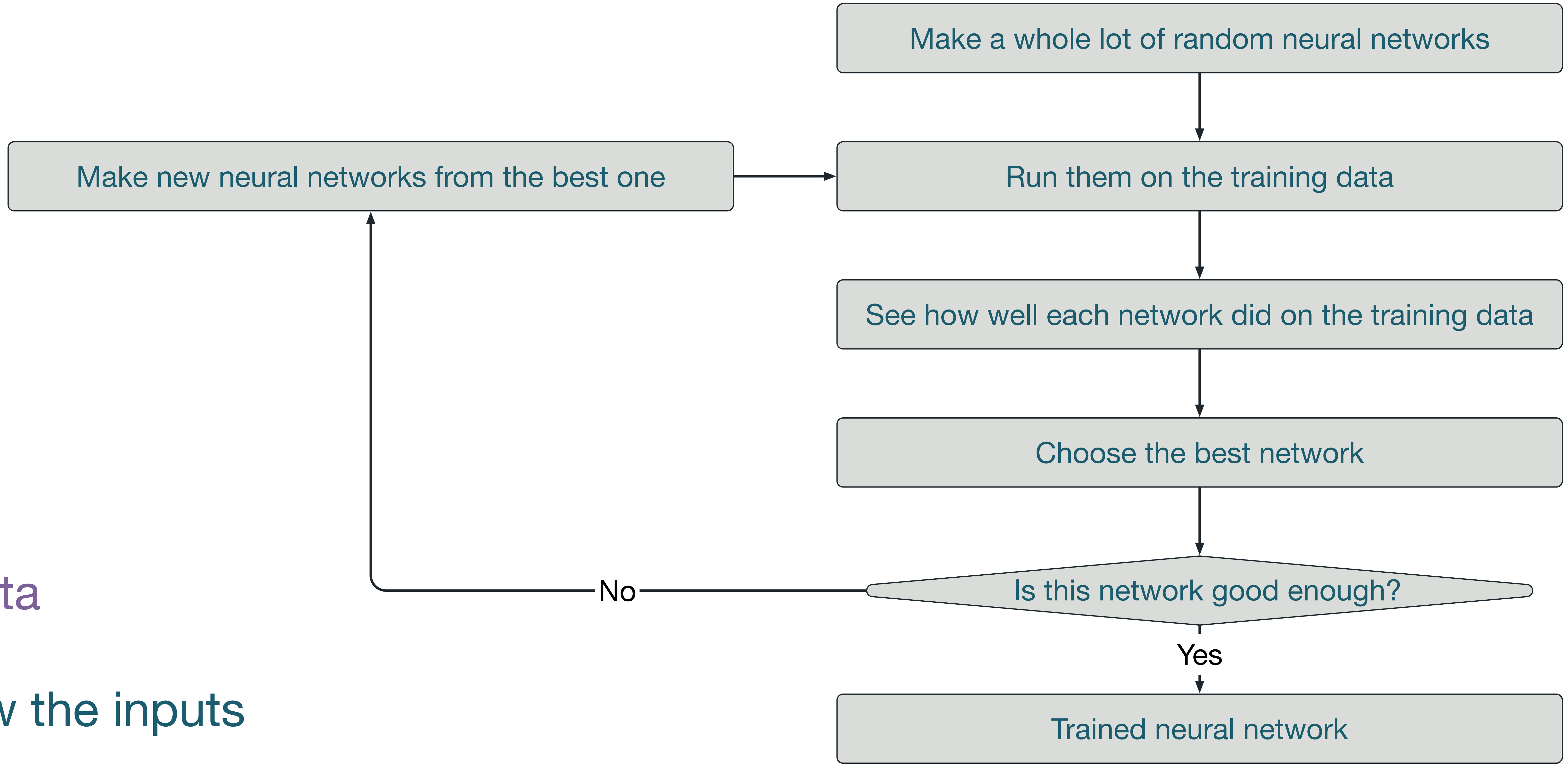



A neural network (NN) is made up of many perceptrons connected together

The encoded inputs are fed into to the input layer; the encoded outputs are read out of the output layer

This network has two hidden layers connecting the inputs and outputs. This makes it a deep neural network (DNN)

# Training Neural Networks 1




To train a neural network, we use training data

Training data are simply data where we know the inputs and also the outputs we want to get

Training involves randomly changing weights and then hoping the new weights are better than the old ones

There is a risk of overfitting

# Training Neural Networks 2

Training a neural network simply involves tweaking the perceptron weights until it gives the right answer

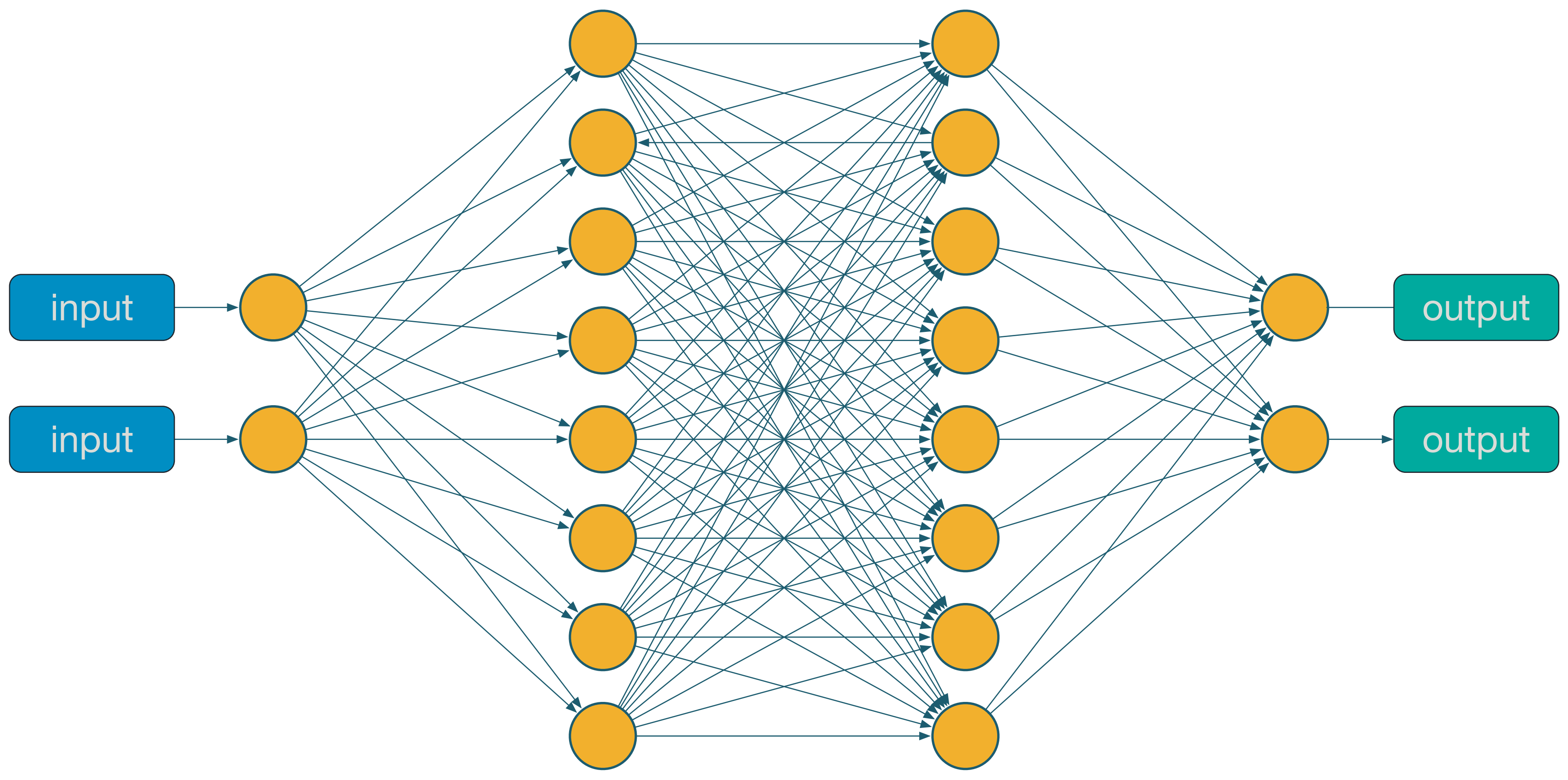
The trouble is, there are *a lot of weights*

In our example before, there are 96 different weights, each of which can be any number

As we don't control what the neural network decides to learn, it is crucial that we:

- Use appropriate training data
- Use enough (lots) training data

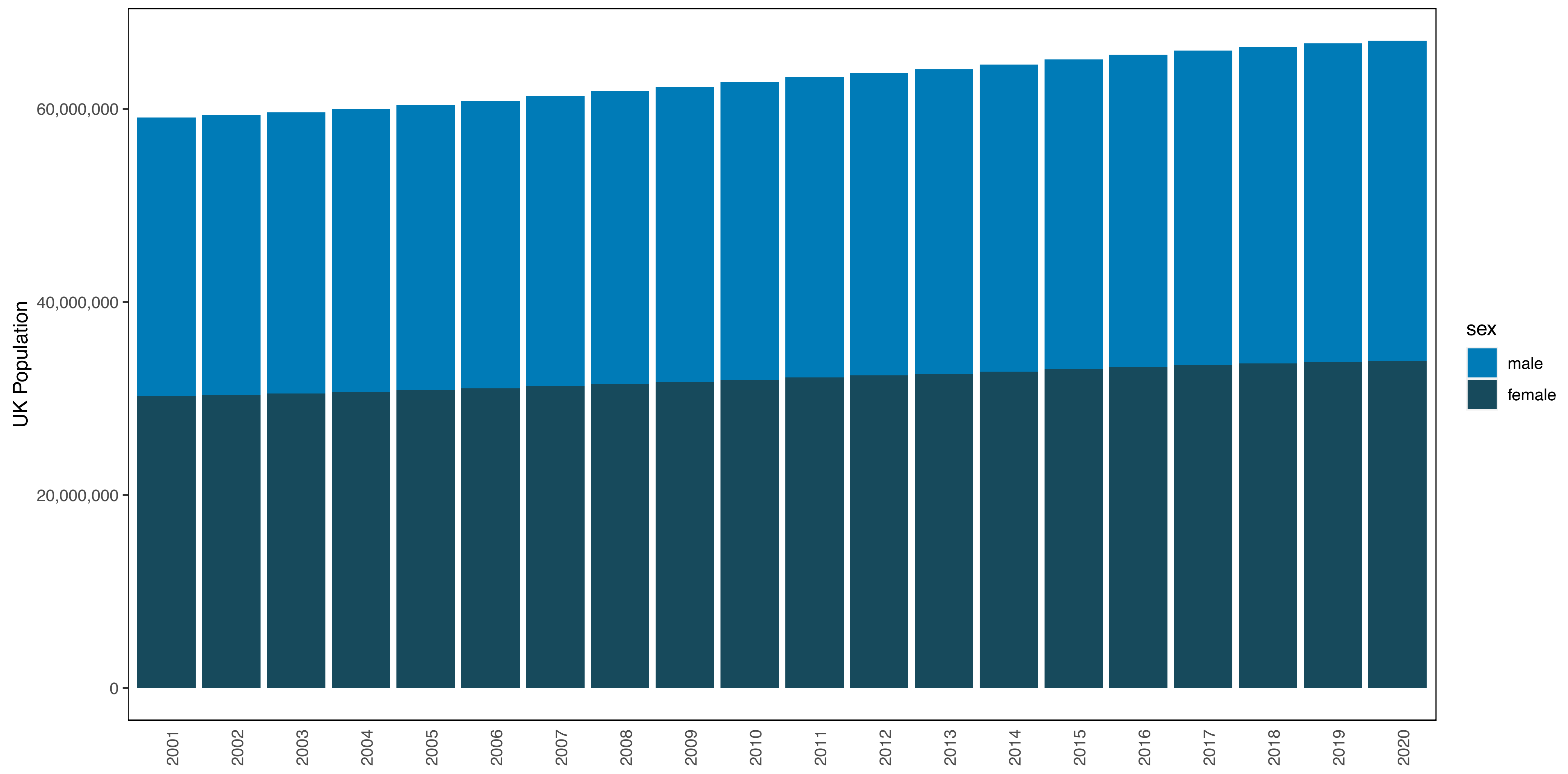
It is very easy to underestimate how many training data points we need

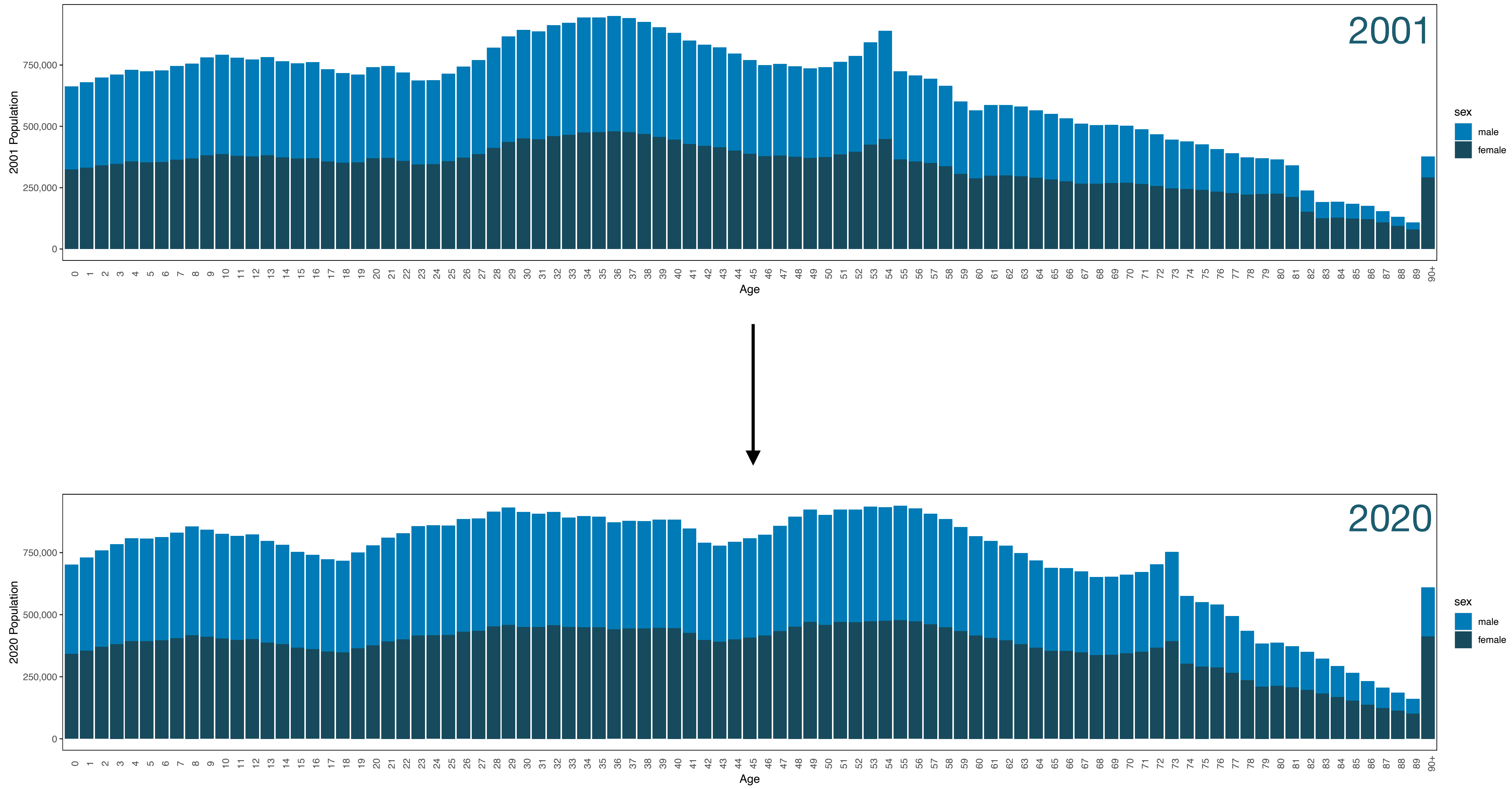



We train our neural network on 10,000 training points, then make it guess on our real data

After all that, it still gets two points wrong!

# The UK Population is Growing and Getting Older




More people to interact with the NHS

Older people have on average more complex and expensive medical requirements

https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2020

# Diagnosis is Becoming More Difficult

More data are being collected for diagnosis

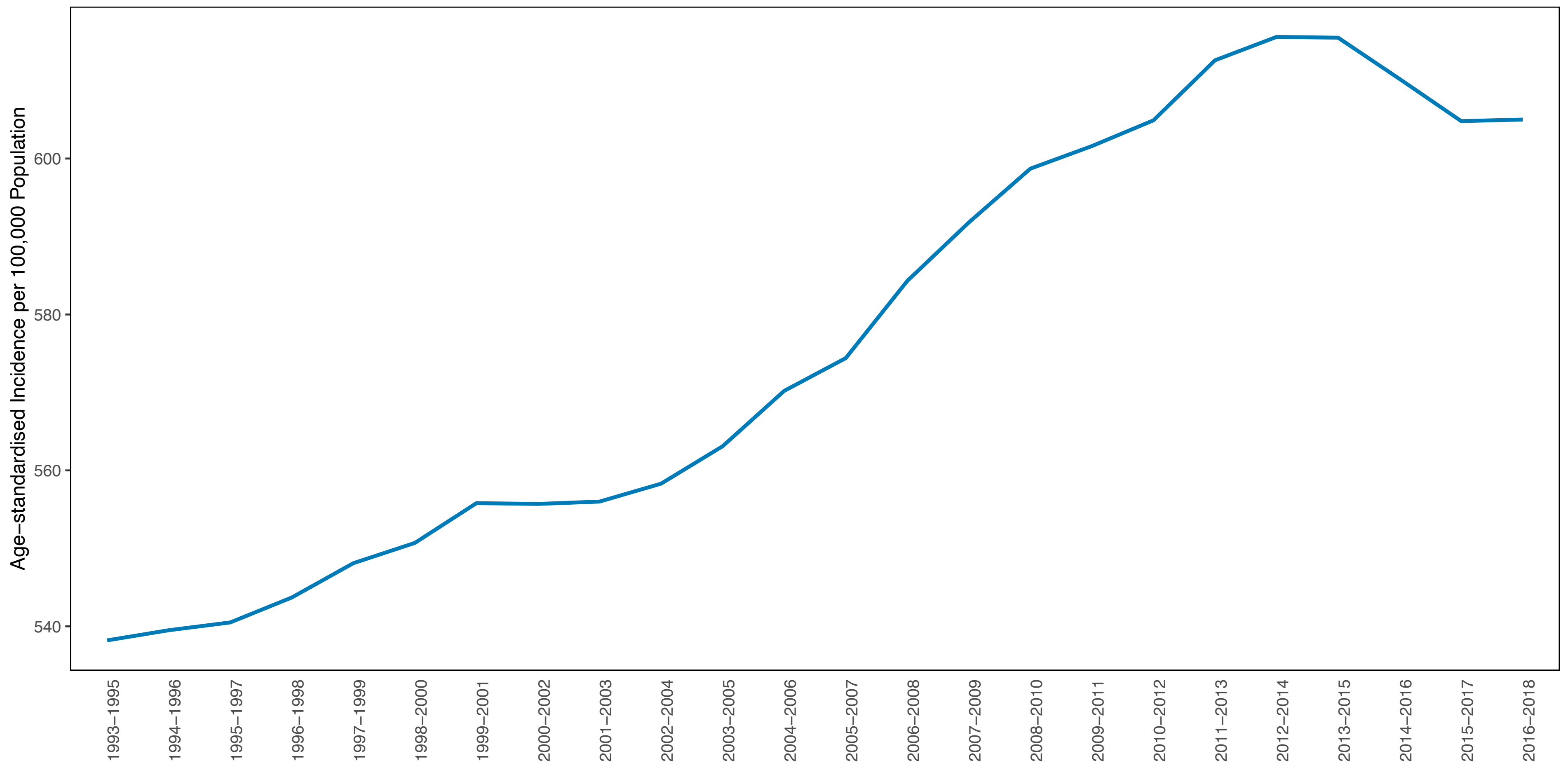
Annual imaging and radiological examinations in England increased 164% from 1995 to 2014

As well as increasing numbers of images, the complexity of each image is increasing

- Higher resolution
- More image types

Increasing rates of chronic diseases

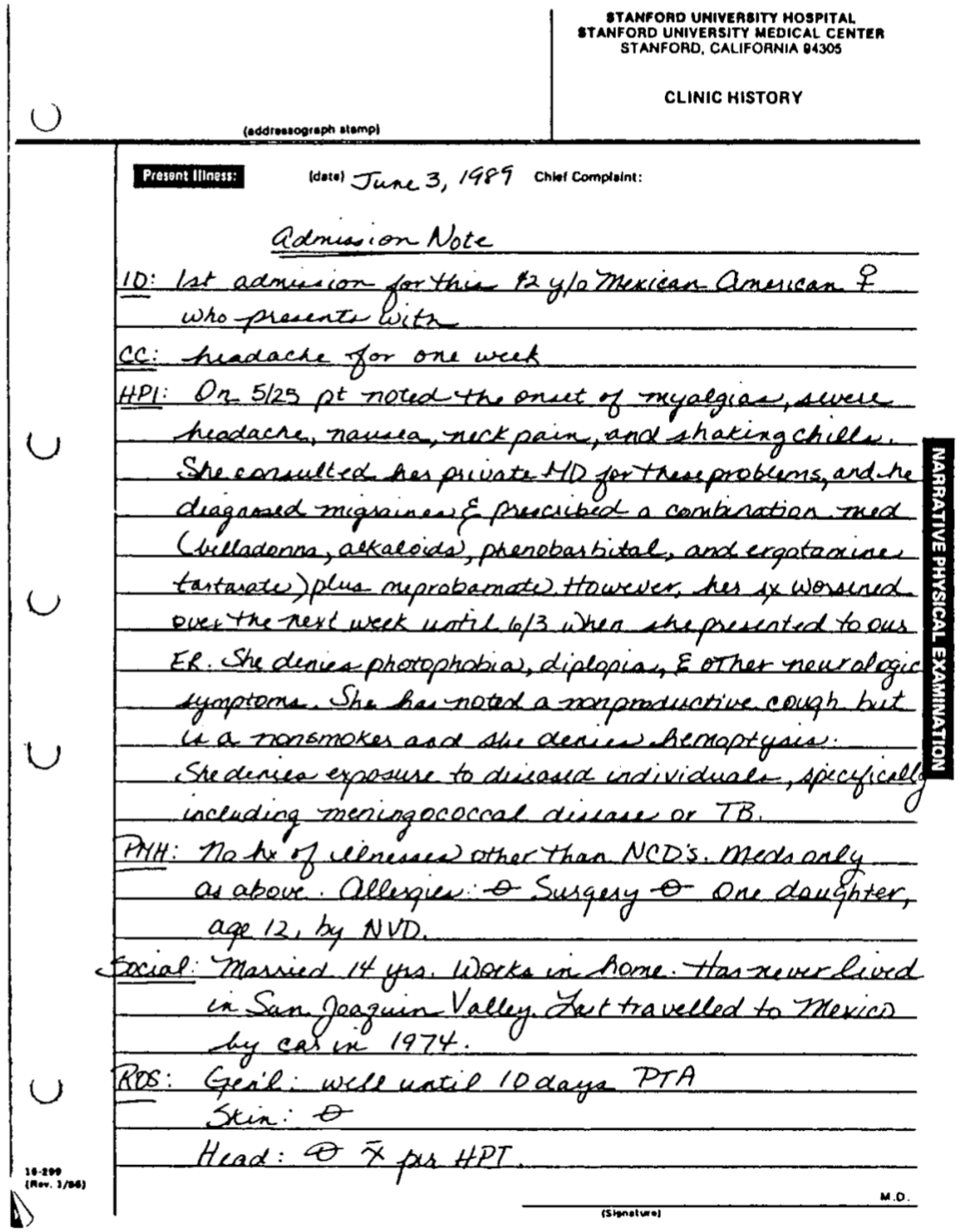
- (diabetes, obesity, cardiac disease, cancer)




https://www.england.nhs.uk/statistics/statistical-work-areas/diagnostics-waiting-times-and-activity/imaging-and-radiodiagnostics-annual-data

https://www.cancerresearchuk.org/health-professional/cancer-statistics/incidence/all-cancers-combined

# Doctors Have Really Bad Handwriting



STANFORD UNIVERSITY HOSPITAL
STANFORD UNIVERSITY MEDICAL CENTER
STANFORD, CALIFORNIA 94305

CLINIC HISTORY

(addressograph stamp)

Present Illness: (date) June 3, 1989 Chief Complaint:

Admission Note

ID: 1st admission for this 42 y/o Mexican American ♀ who presents with

CC: headache for one week

HPI: On 5/25 pt noted the onset of myalgias, severe headache, nausea, neck pain, and shaking chills. She consulted her private MD for these problems, and he diagnosed migraines & prescribed a combination med (belladonna, alkaloids), phenobarbital, and ergotamine tartrate) plus meprobamate. However, her sx worsened over the next week until 6/3 when she presented to our ER. She denies photophobia, diplopia, & other neurologic symptoms. She has noted a nonproductive cough but is a nonsmoker and she denies hemoptysis. She denies exposure to diseased individuals, specifically including meningococcal disease or TB.

PMH: No hx of illnesses other than NCD's. Meds only as above. Allergies: ⊖ Surgery ⊖ One daughter, age 12, by NVD.

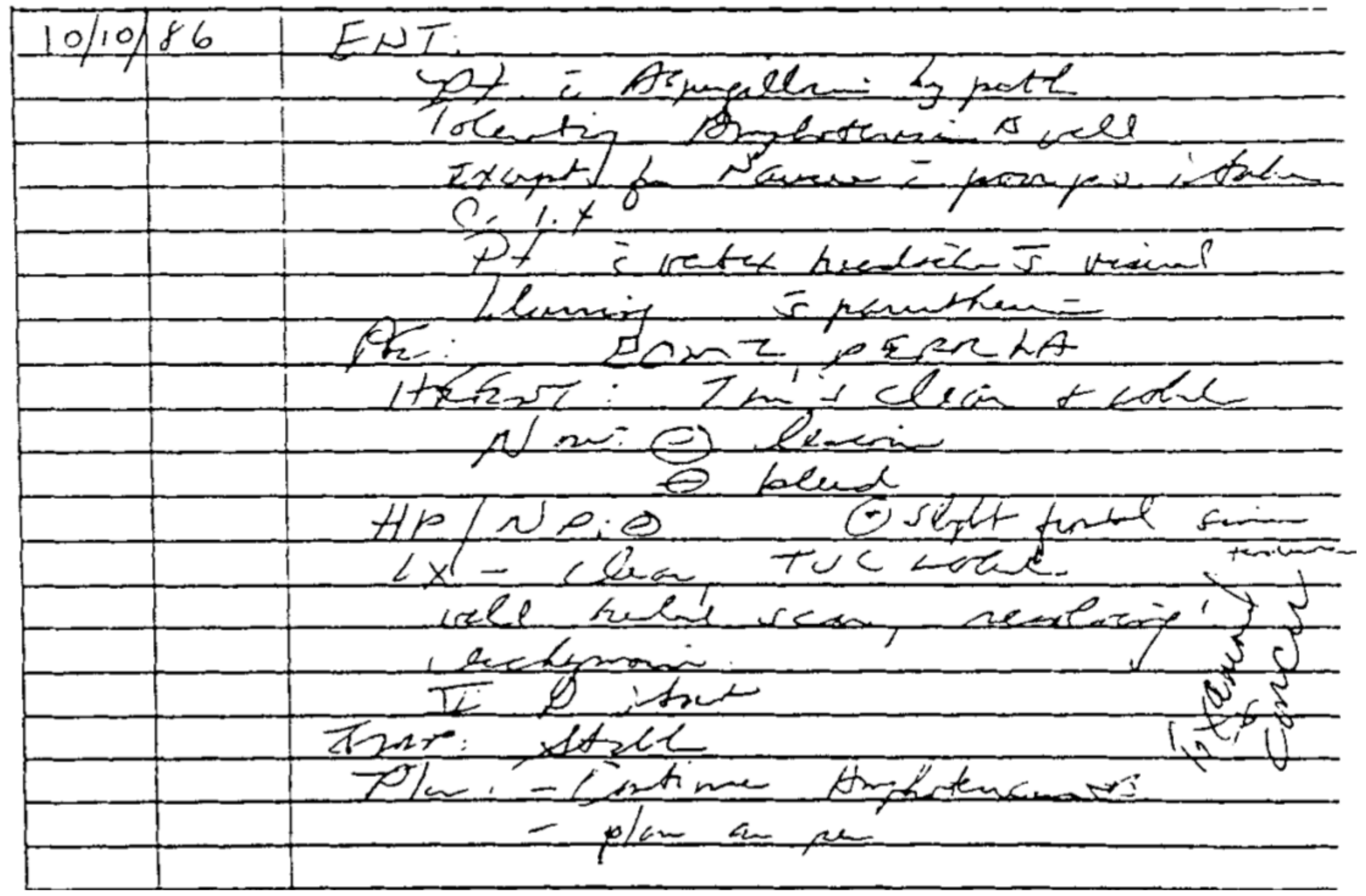
Social: Married 14 yrs. Works in home. Has never lived in San Joaquin Valley. Last travelled to Mexico by car in 1974.

ROS: Gen'l: well until 10 days PTA
Skin: ⊖
Head: ⊖ x per HPI.

NARRATIVE PHYSICAL EXAMINATION

15-299 (Rev. 3/86)

M.D.
(Signature)



10/10/86 ENT:

# How Can AI Help – Detecting Cardiac Arrhythmia

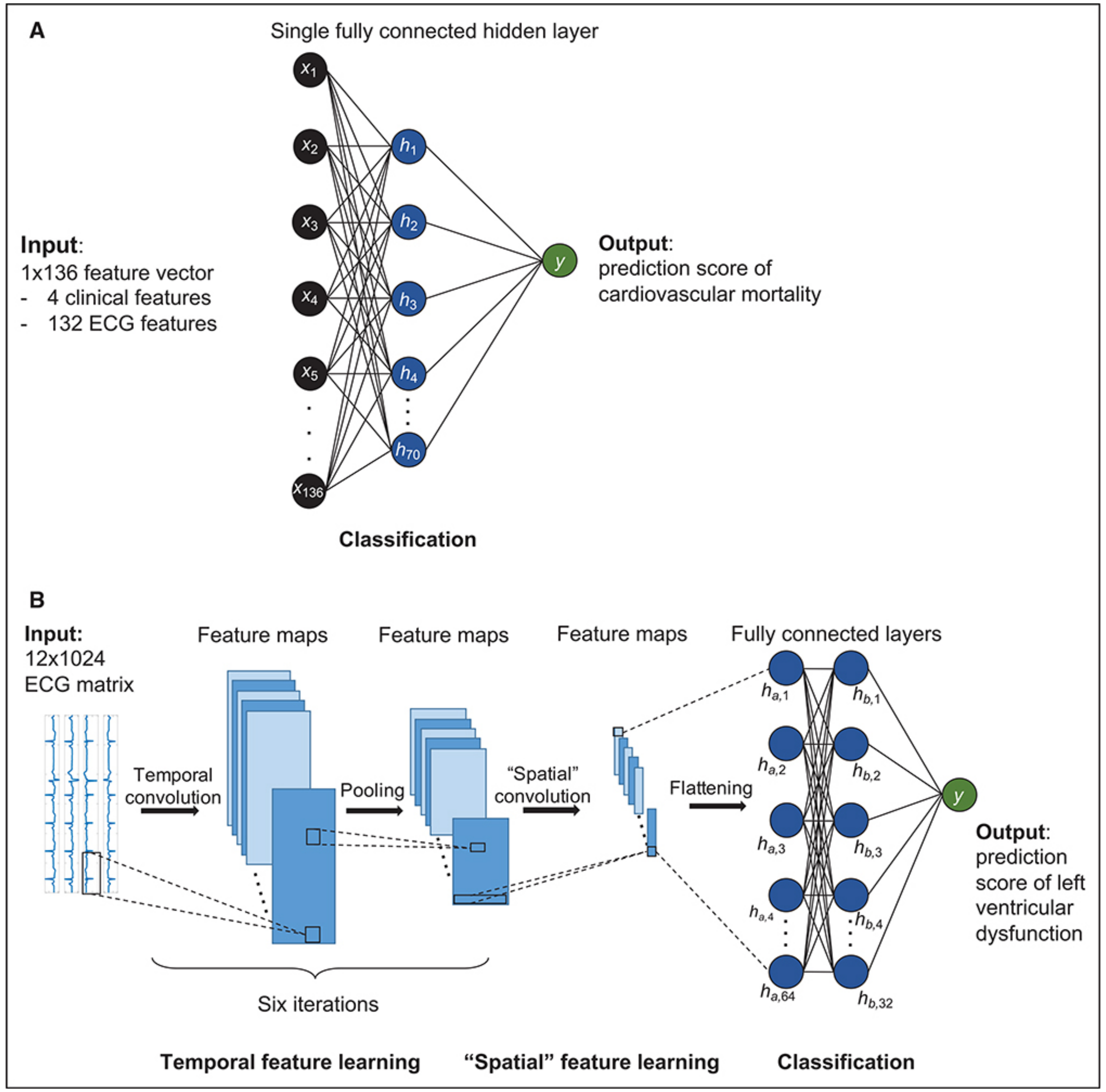
Input features are ECG traces

Image processing step to generate features

136 inputs features:

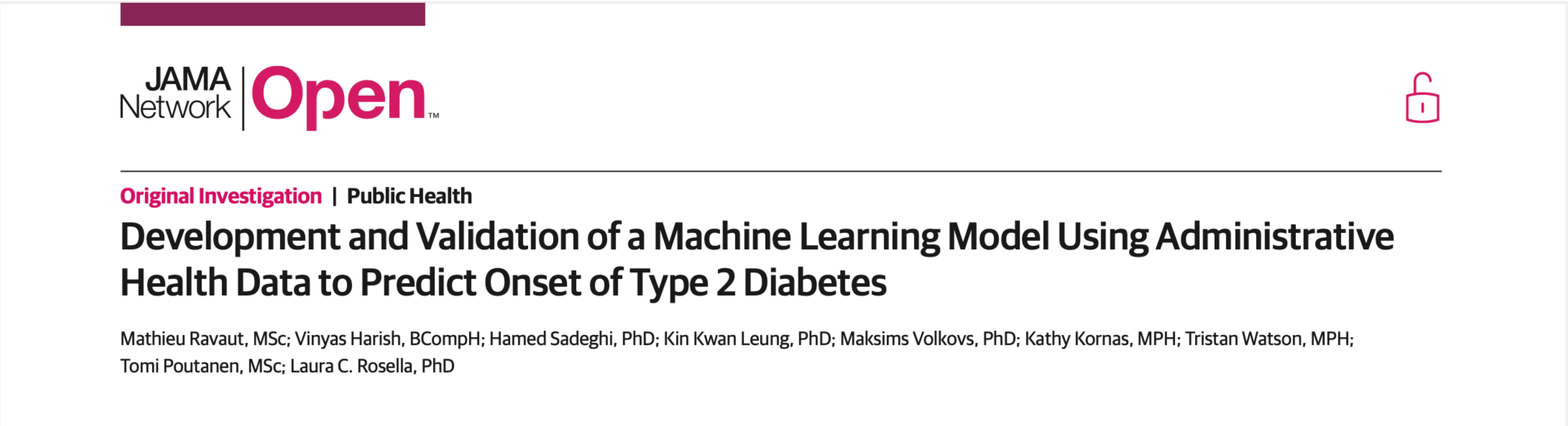
- 132 ECG trace features
- 4 clinical features

Output is prediction of cardiovascular mortality




Feeny *et al* (2020) "Artificial Intelligence and Machine Learning in Arrhythmias and Cardiac Electrophysiology" *Circ Arrhythm Electrophysiol*. **13**(8):e007952. `https://doi.org/10.1161/circep.119.007952`

# How Can AI Help – Predicting Type 2 Diabetes


JAMA Network Open

Original Investigation | Public Health

Development and Validation of a Machine Learning Model Using Administrative Health Data to Predict Onset of Type 2 Diabetes

Mathieu Ravaut, MSc; Vinyas Harish, BCompH; Hamed Sadeghi, PhD; Kin Kwan Leung, PhD; Maksims Volkovs, PhD; Kathy Kornas, MPH; Tristan Watson, MPH; Tomi Poutanen, MSc; Laura C. Rosella, PhD

A different type of AI model (a gradient boosting decision tree model)

>300 features (demographic information, laboratory measurements, drug benefits, health care system interactions, social determinants of health, and ambulatory care and hospitalisation records)

Trained on 1,657,395 patients

Rafvaut *et al* (2021) Development and Validation of a Machine Learning Model Using Administrative Health Data to Predict Onset of Type 2 Diabetes. JAMA Netw Open. **4**(5):e2111315

# How Can AI Help – Electronic Health Records

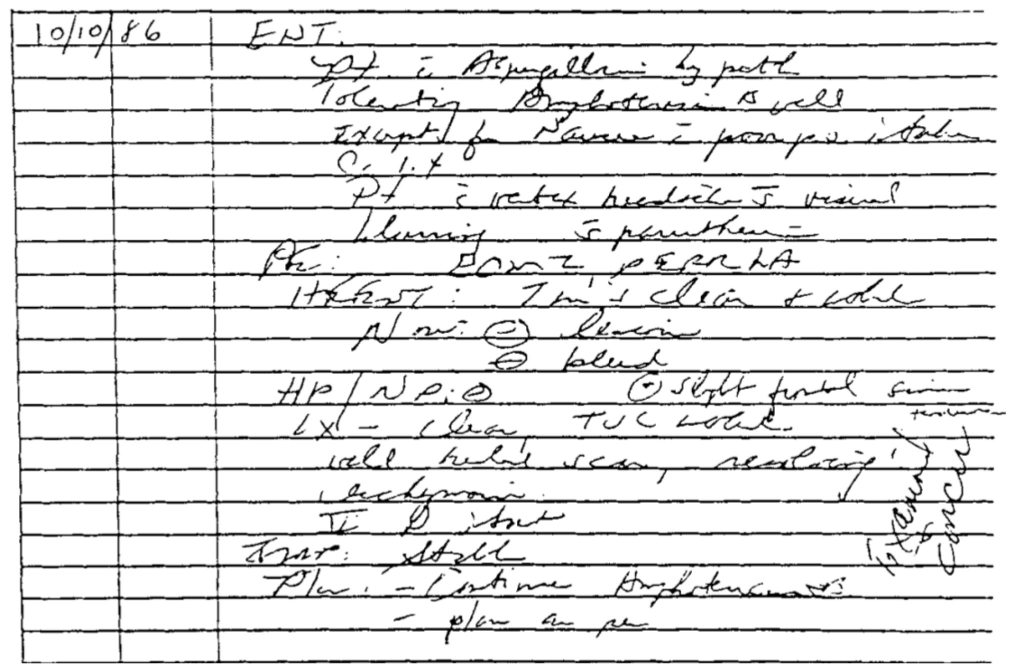
No digital system can make full use of Electronic Health Records (EHRs) until they are digitised

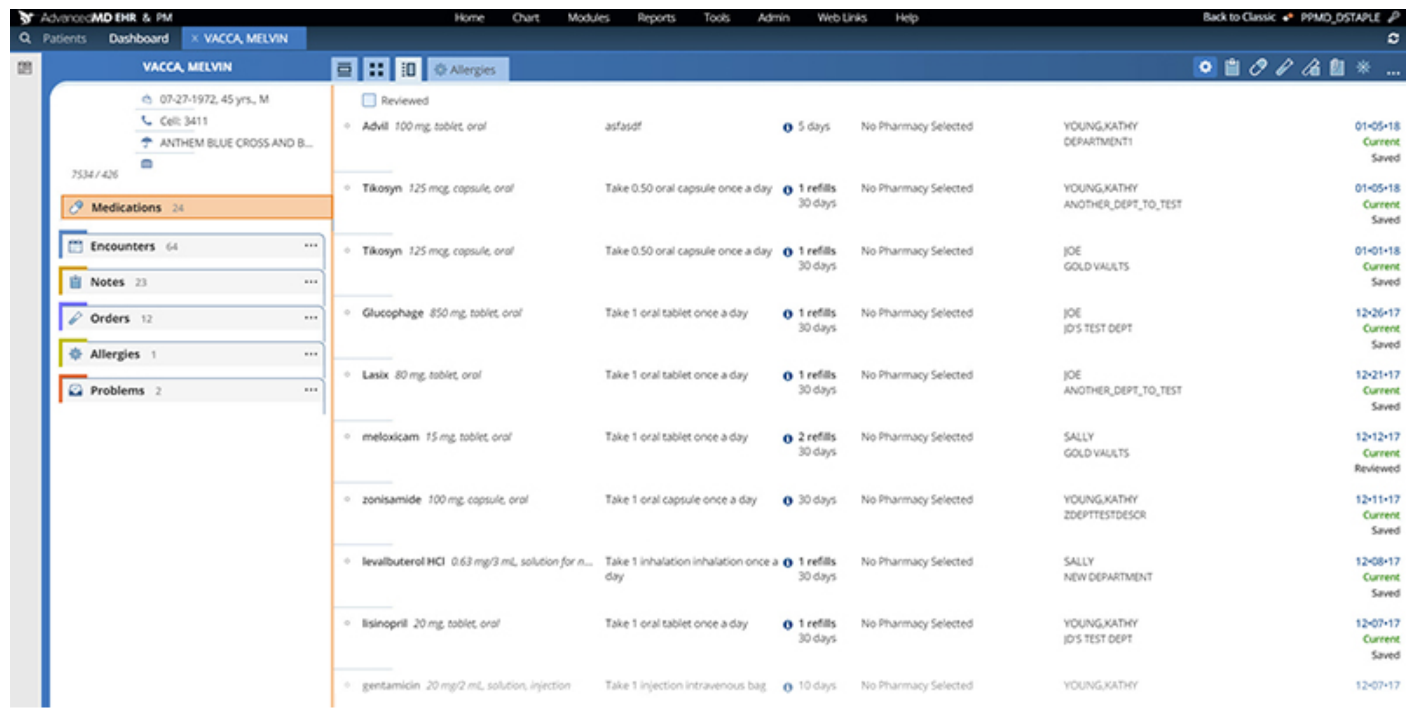
Step 1 is to *scan* all patient records

- Allows rapid retrieval of records
- Allows patient access to their own records

Step 2 is to *digitise* the records

- Use text recognition to pull out the information in the records





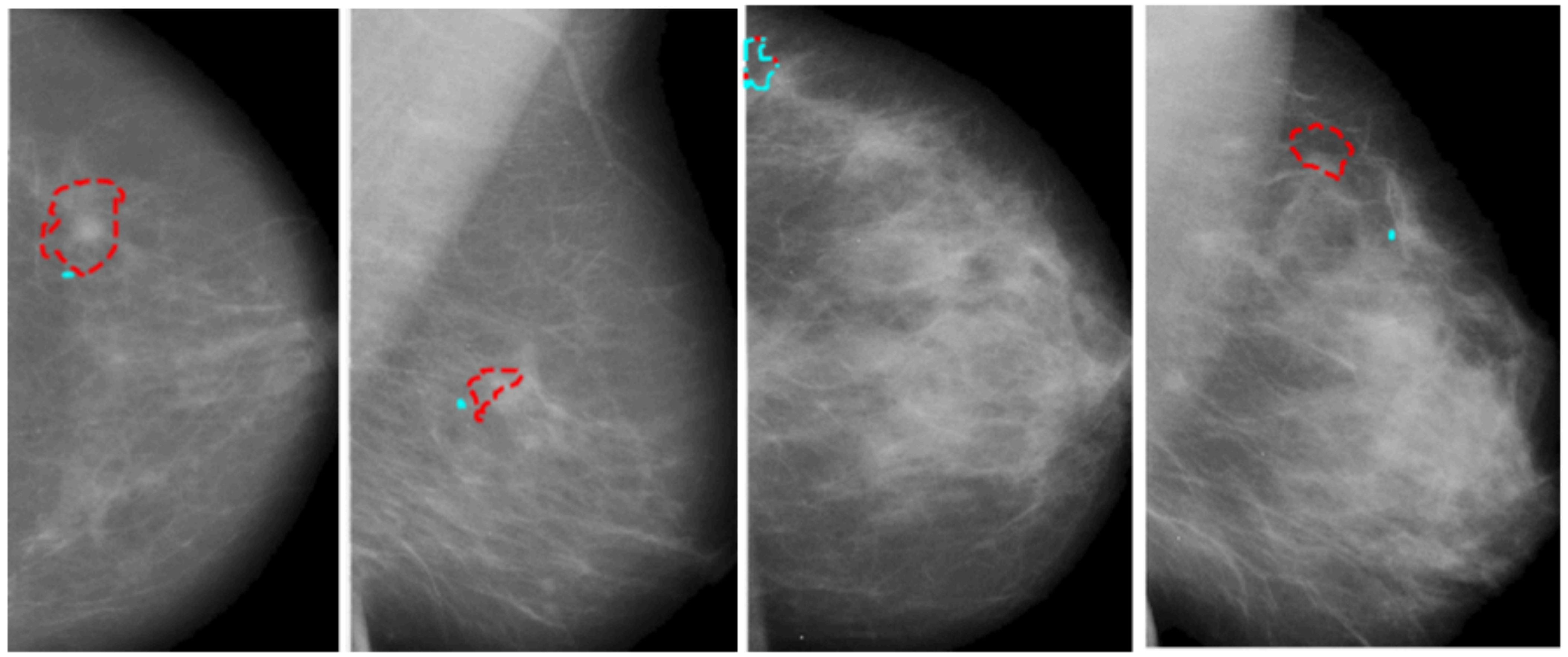
https://www.advancedmd.com/emr-ehr-software/patient-cards/

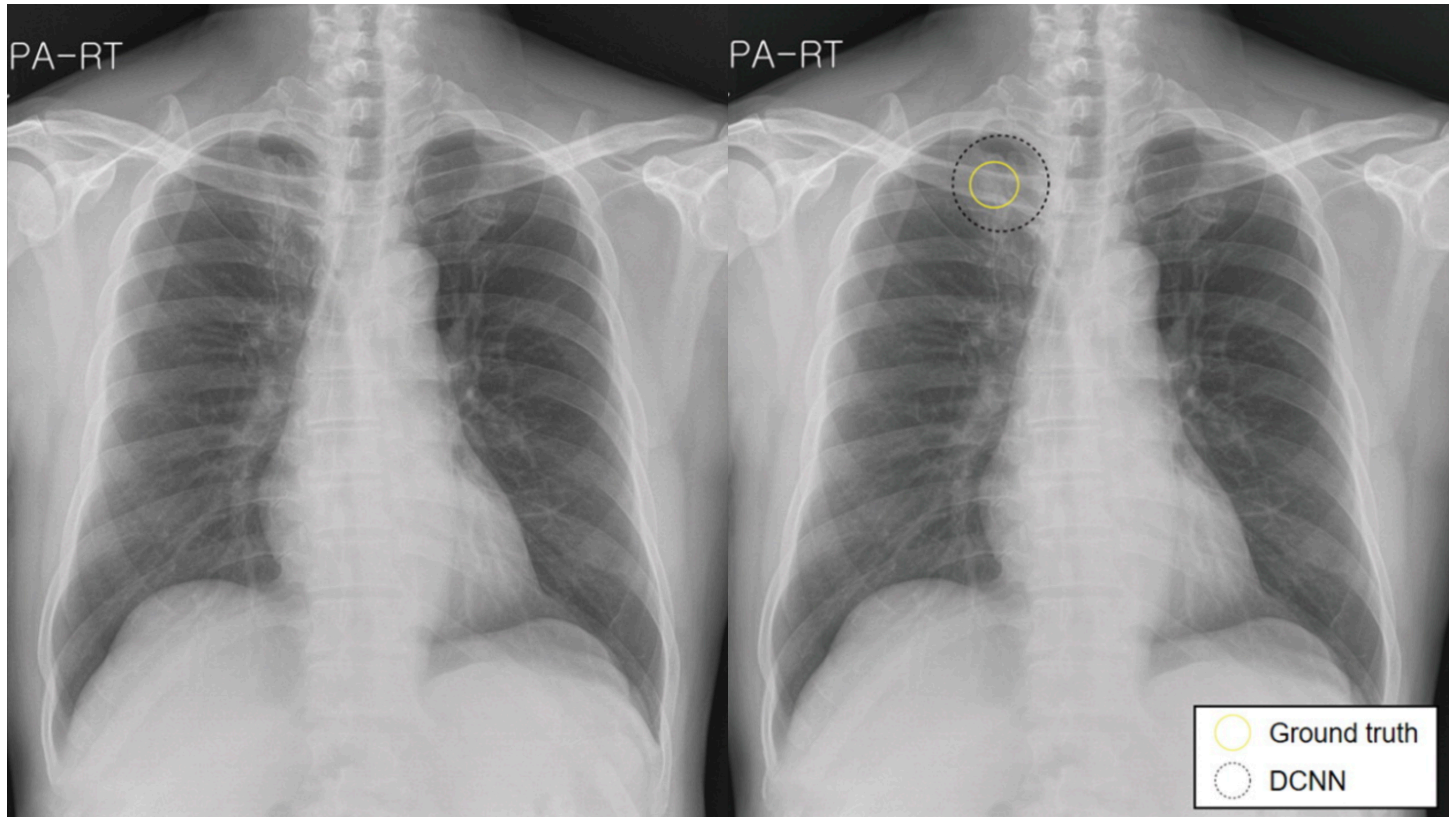
# How Can AI Help – Image Analysis

Image Recognition is *very* hard, even for trained specialists

Recognising pathological features in an image is slow, and often error-prone

Neural Networks are being used to detect pathologies in medical images






Yongsik *et al* (2019) *Radiology* **294**(1) `https://doi.org/10.1148/radiol.2019182465`

Perek, Hazan, Barkan & Akselrod-Ballin (2018) “Mammography Dual View Mass Correspondence” `https://doi.org/10.48550/arXiv.1807.00637`

# Issues with AI In Health Data – Anonymity

We need lots of data about patients to train a DNN, but each datapoint must be anonymous

How can we keep our health data anonymous?

- Does your age (year + month of birth) identify you?
- My date of birth is May 1980 and I'm alive. Does this identify me?
- OK; I'm alive and my birthday is March 1907. How about now?

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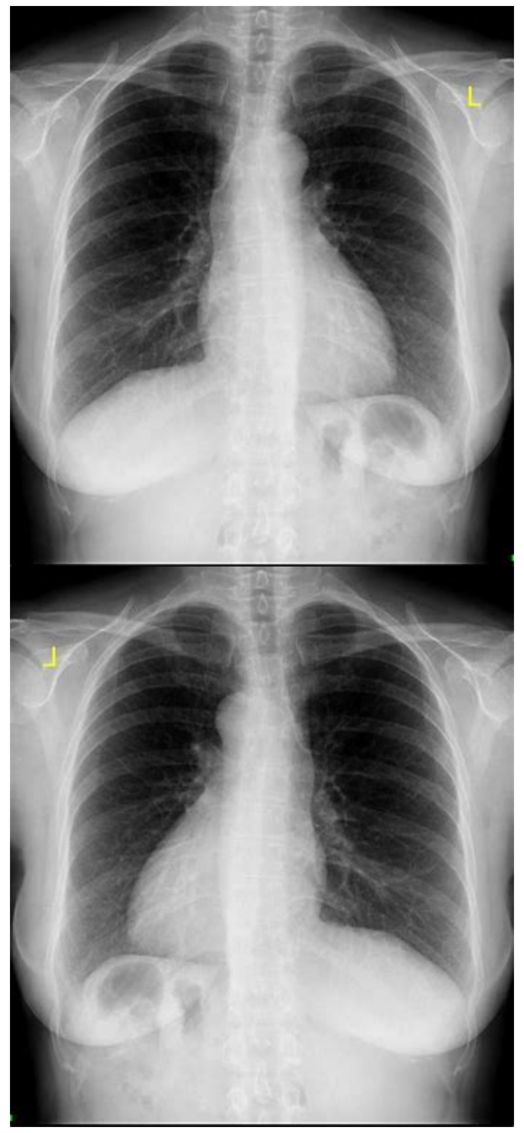
https://www.catalannews.com/society-science/item/catalonias-maria-branyas-becomes-oldest-living-person-on-earth-at-11

# Issues with AI In Health Data – Input Fragility



Normal
67.30%

Pneumonia
54.06%

https://share.streamlit.io/smarthardik10/xray-classifier/main/webapp.py

# Issues with AI In Health Data – Input Fragility

Normal
67.30%

Pneumonia
54.06%

Normal
98.64%

Normal
71.12%

Pneumonia
96.06%

https://share.streamlit.io/smarthardik10/xray-classifier/main/webapp.py

# Issues with AI In Health Data – Input Fragility

Normal
67.30%

Pneumonia
54.06%

Normal
98.64%

Normal
71.12%

Pneumonia
96.06%

Pneumonia
69.92%

https://share.streamlit.io/smarthardik10/xray-classifier/main/webapp.py

# Issues with AI In Health Data – Input Fragility

Normal
67.30%

Pneumonia
54.06%

Normal
98.64%

Normal
71.12%

Pneumonia
96.06%

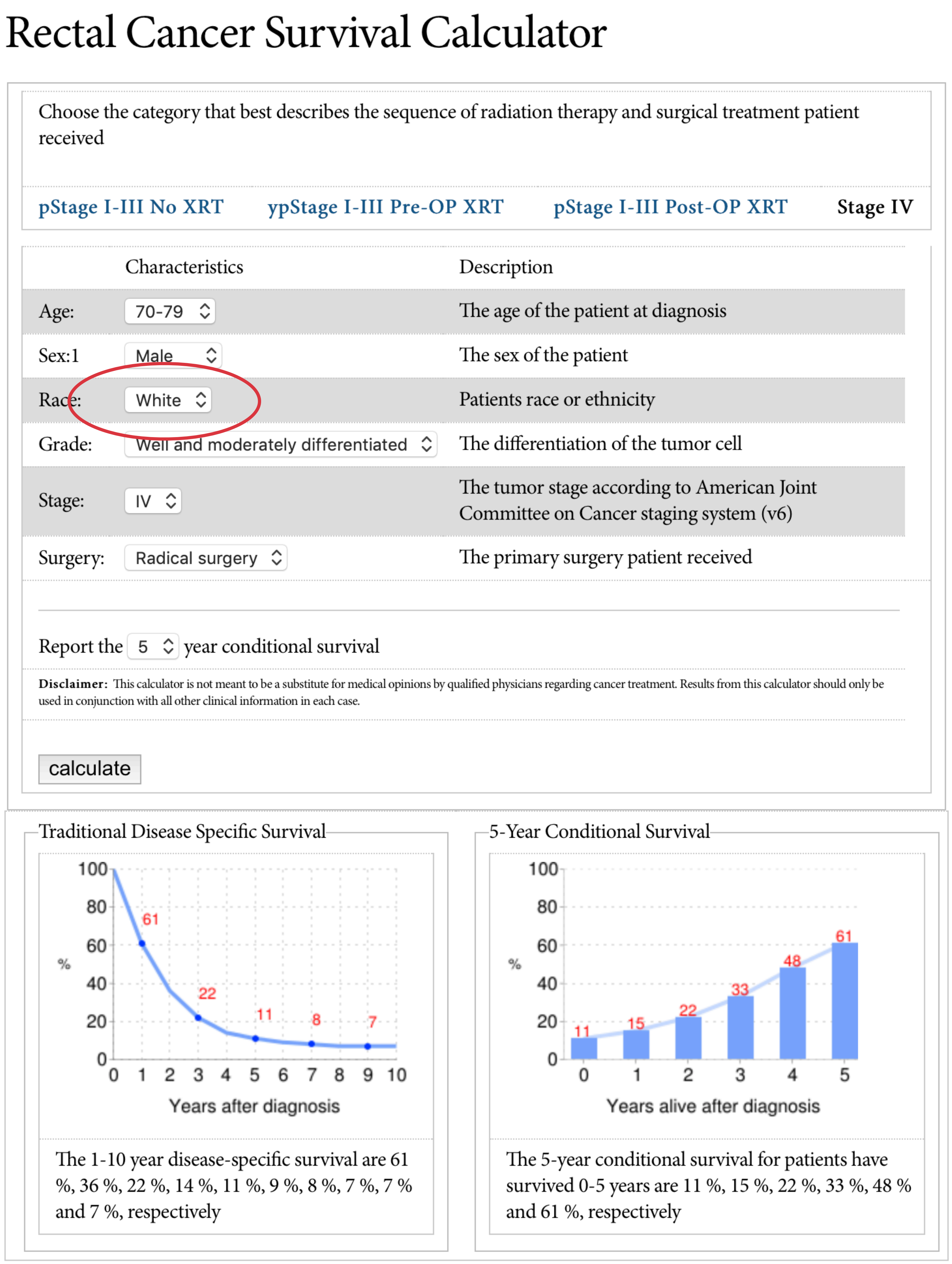
Pneumonia
69.92%

Given this, how can we trust that this classification is correct?

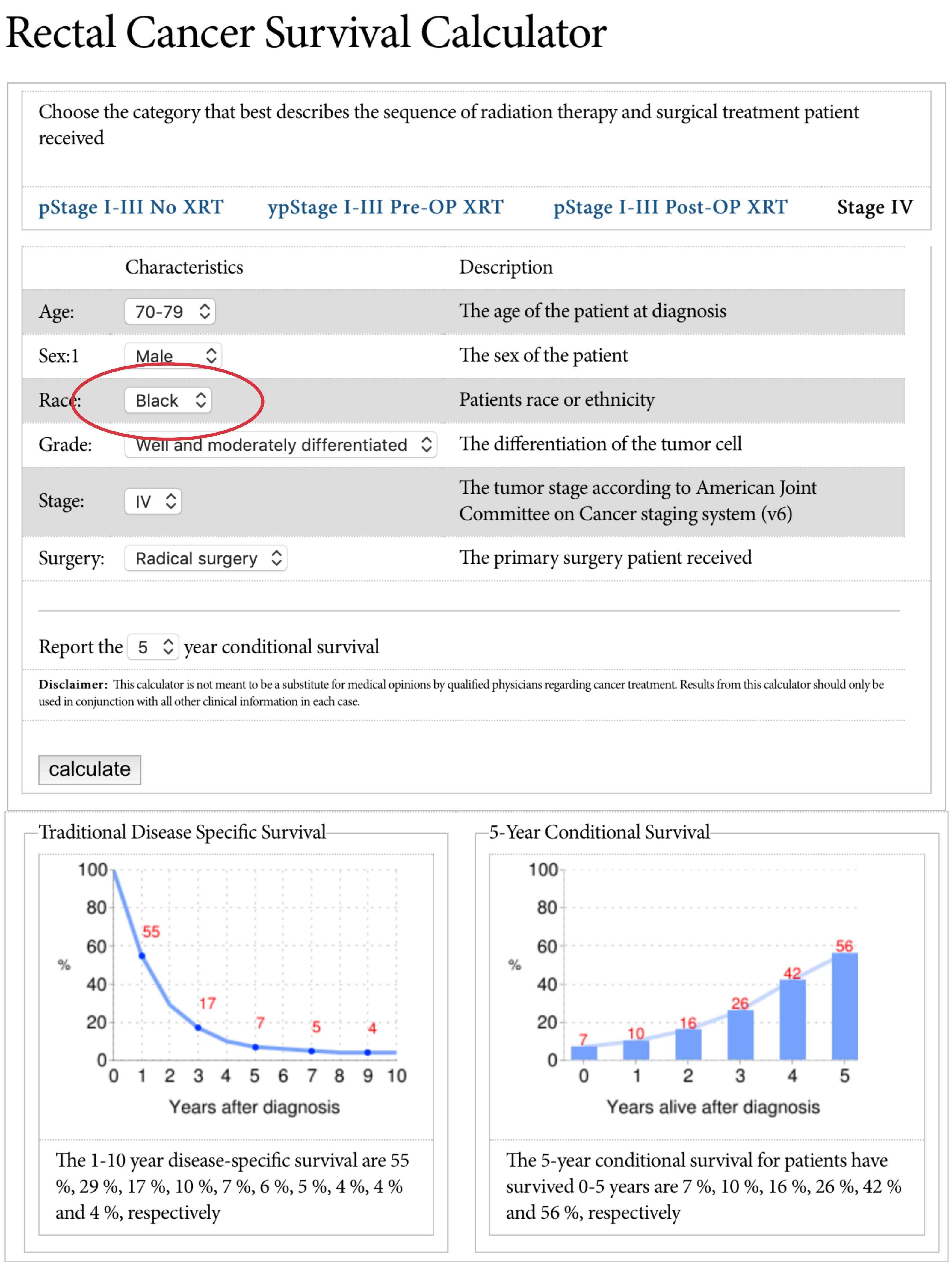

Pneumonia
86.46%

https://share.streamlit.io/smarthardik10/xray-classifier/main/webapp.py

# Issues with AI In Health Data – Implicit Bias




VS




http://www3.mdanderson.org/app/medcalc/index.cfm?pagename=rectumcancer

# Issues with AI In Health Data – Incorrect Data

**Liam Thorp** 💙
@LiamThorpECHO

So I'm not getting a vaccine next week - was feeling weird about why I'd been selected ahead of others so rang GP to check. Turns out they had my height as 6.2cm rather than 6 ft 2, giving me a BMI of 28,000 😂

8:43 AM · Feb 17, 2021

220.7K    See the latest COVID-19 information on Twitter

# Issues with AI In Health Data – Adversarial Classification


| | |
|---|---|
| Recognised as **STOP** | 100% |
| Recognised as **45mph** | 0% |

Eykholt et al (2018) "Robust Physical-World Attacks on Deep Learning Visual Classification" in IEEE CVPR 2018

# Issues with AI In Health Data – Adversarial Classification


| | |
|---|---|
| Recognised as **STOP** | 100% |
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Eykholt et al (2018) "Robust Physical-World Attacks on Deep Learning Visual Classification" in IEEE CVPR 2018

# Issues with AI In Health Data – Adversarial Classification


| | | |
|---|---|---|
| Recognised as **STOP** | 100% | < 3% |
| Recognised as **45mph** | 0% | 86% |

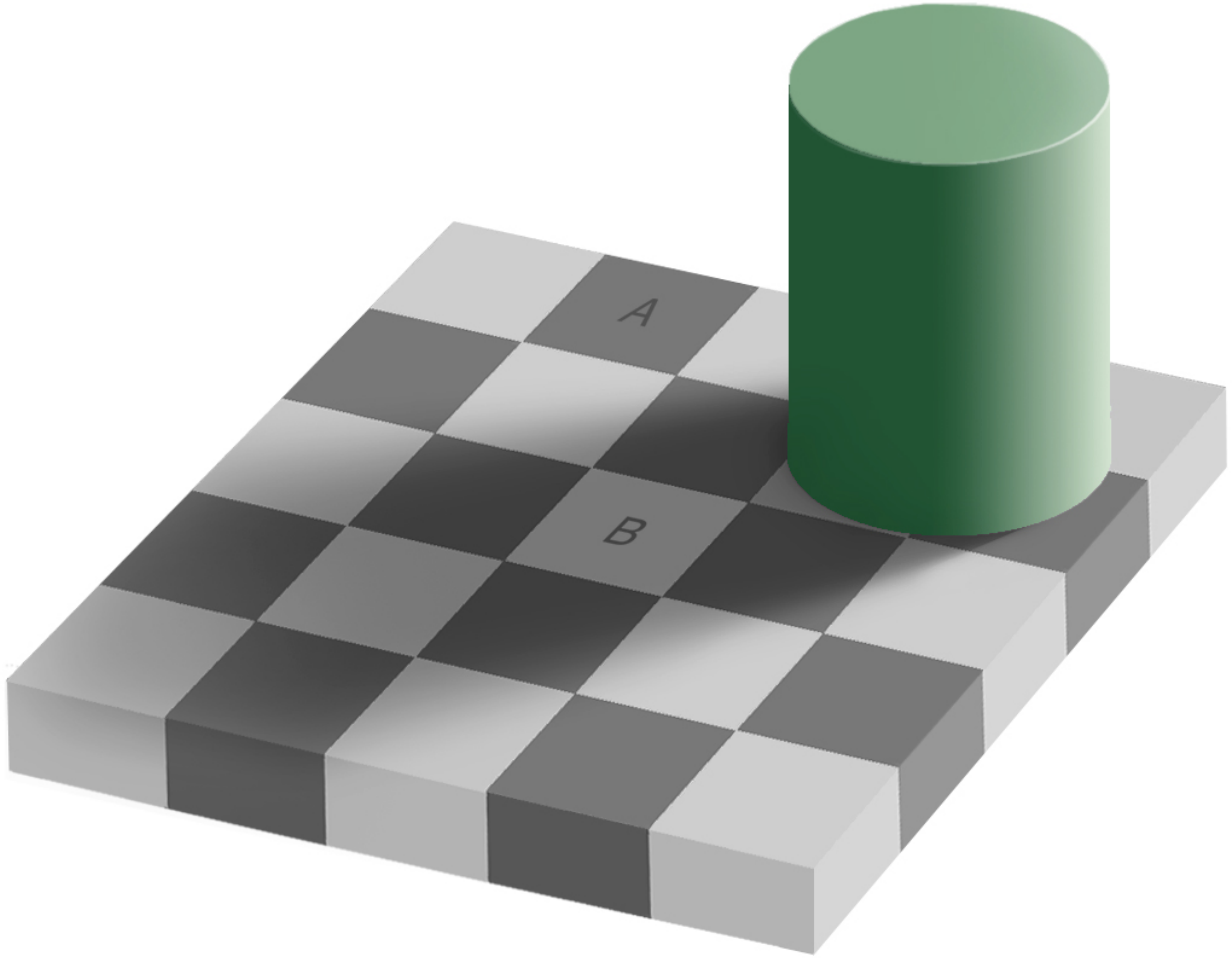
Eykholt et al (2018) “Robust Physical-World Attacks on Deep Learning Visual Classification” in IEEE CVPR 2018

# Issues with AI In Health Data – Adversarial Classification


| | | | |
|---|---|---|---|
| Recognised as **STOP** | 100% | < 3% | 40% |
| Recognised as **45mph** | 0% | 86% | 27% |

Eykholt et al (2018) “Robust Physical-World Attacks on Deep Learning Visual Classification” in IEEE CVPR 2018

# It Gets Worse…



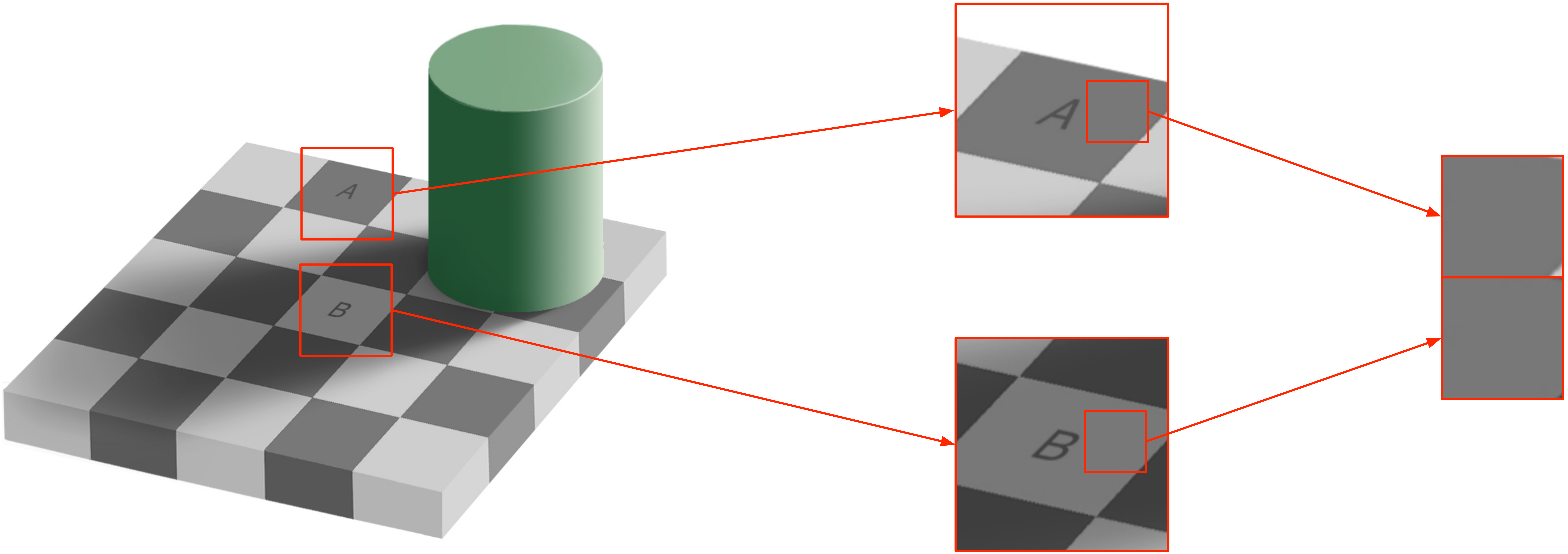

Are the squares A & B the same colour?

Why do they seem so?

Do you think we *could* ever teach this to a computer?

*Should* we teach computer to think like this?

Edward H. Adelson (1995) Dept. of Brain and Cognitive Sciences MIT (`http://persci.mit.edu/gallery/checkershadow`)


A
B
A
B