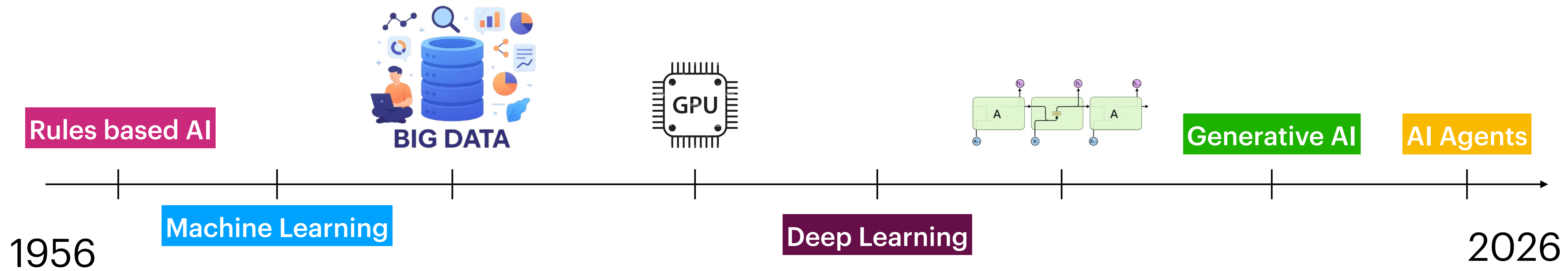


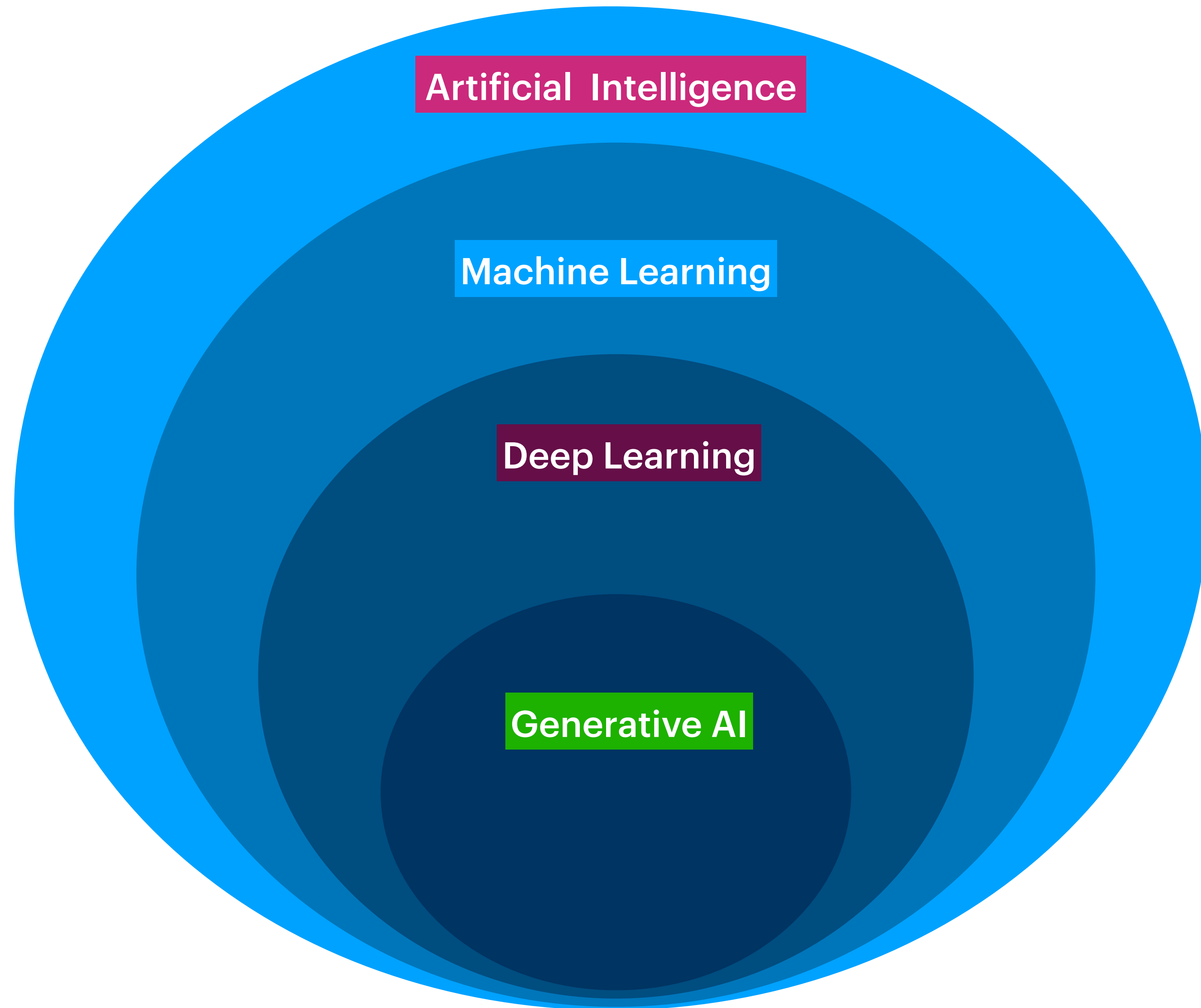
# Introduction to Deep Learning

**Outset AI for Health Session**

Franny Dean, July 8, 2026

# What is 'AI'?





Artificial Intelligence

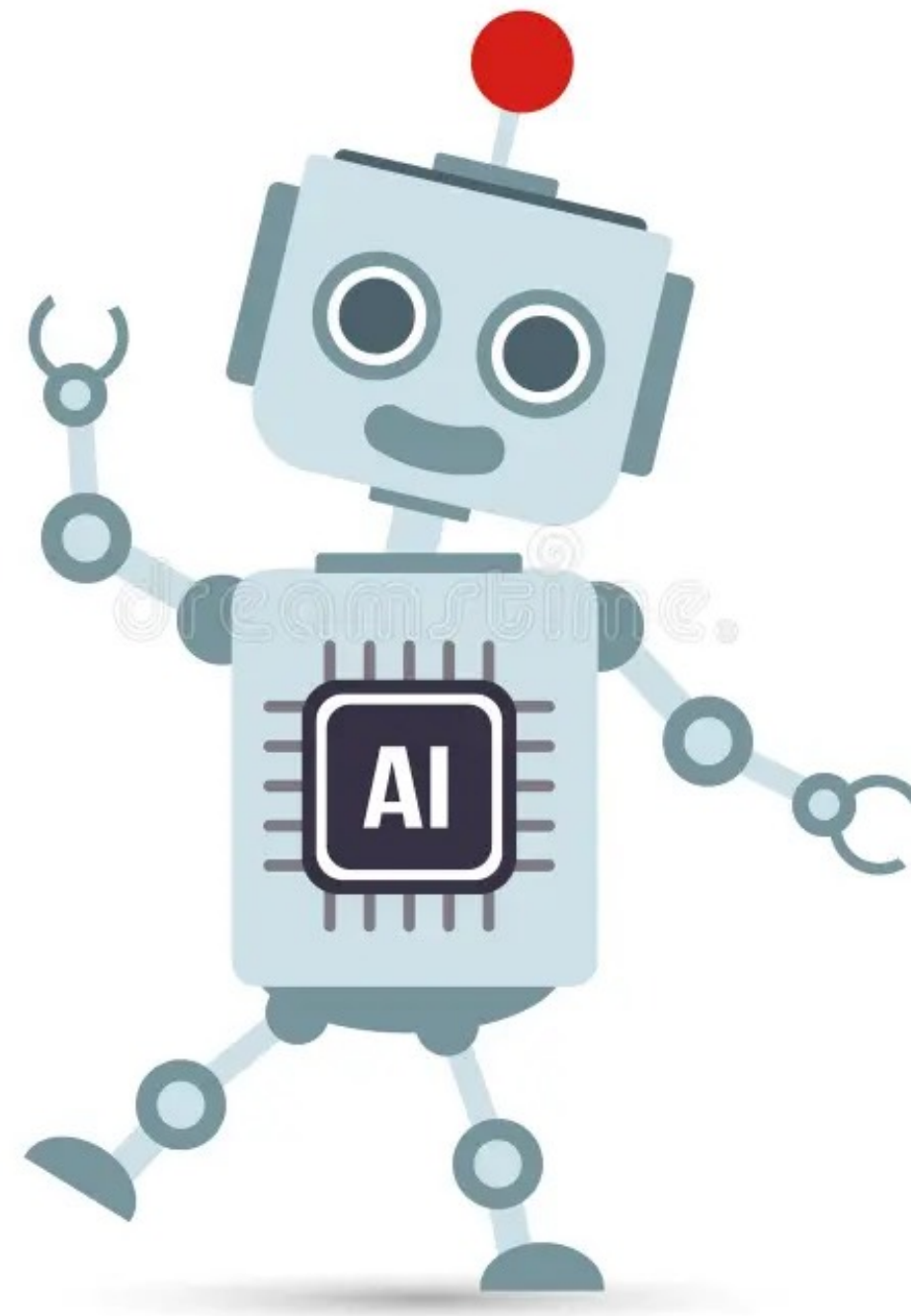
Machine Learning

Deep Learning

Generative AI

# What is 'AI'?

**"AI is what hasn't been done yet!" - Tesler's Theorem**



**Its really the broad set of ways to teach computers to do what humans do!**

# What is 'AI'?

*Traditional rules based approach*

**Definition:** Computers do what humans can do from programmed rules!

**Task**



**Explicit Rules**

King: Moves exactly one square in any direction.

Queen: Moves in any one straight direction.

...

Perform a tree search for the best next move.

**Learning**



As complexity scales, humans need to be able to explicitly define the rules.

# What is 'AI'?

## Machine Learning

**Definition:** Give a computer a bunch of examples to learn from.

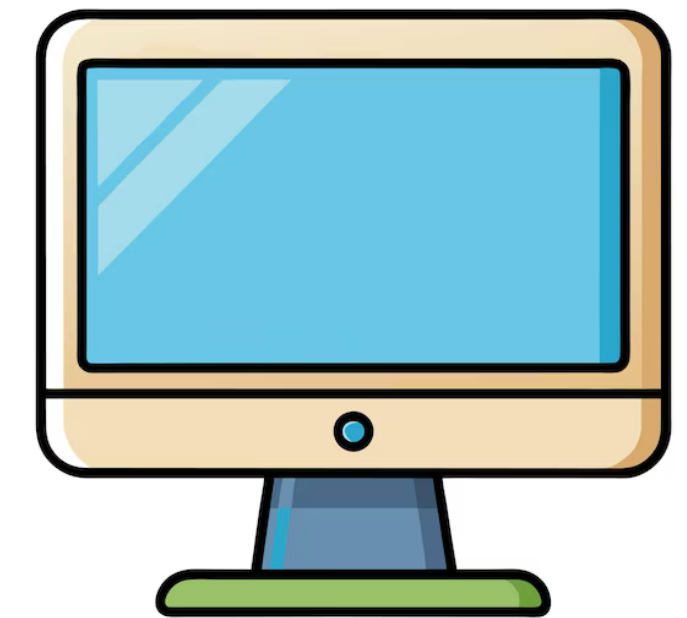
Task: predict heart disease



Examples of positive and negative

Cholesterol	Age	Blood Pressure	Ejection Fraction
190mg/dL	80	130/100	45%
150mg/dL	20	110/80	70%
250mg/dL	50	150/100	35%
130mg/dL	45	90/50	85%

Learning



As complexity scales, computers learn relationships between variables.

# How does Machine Learning (ML) work?

**Example:** Imagine we want one predictor of the outcome.

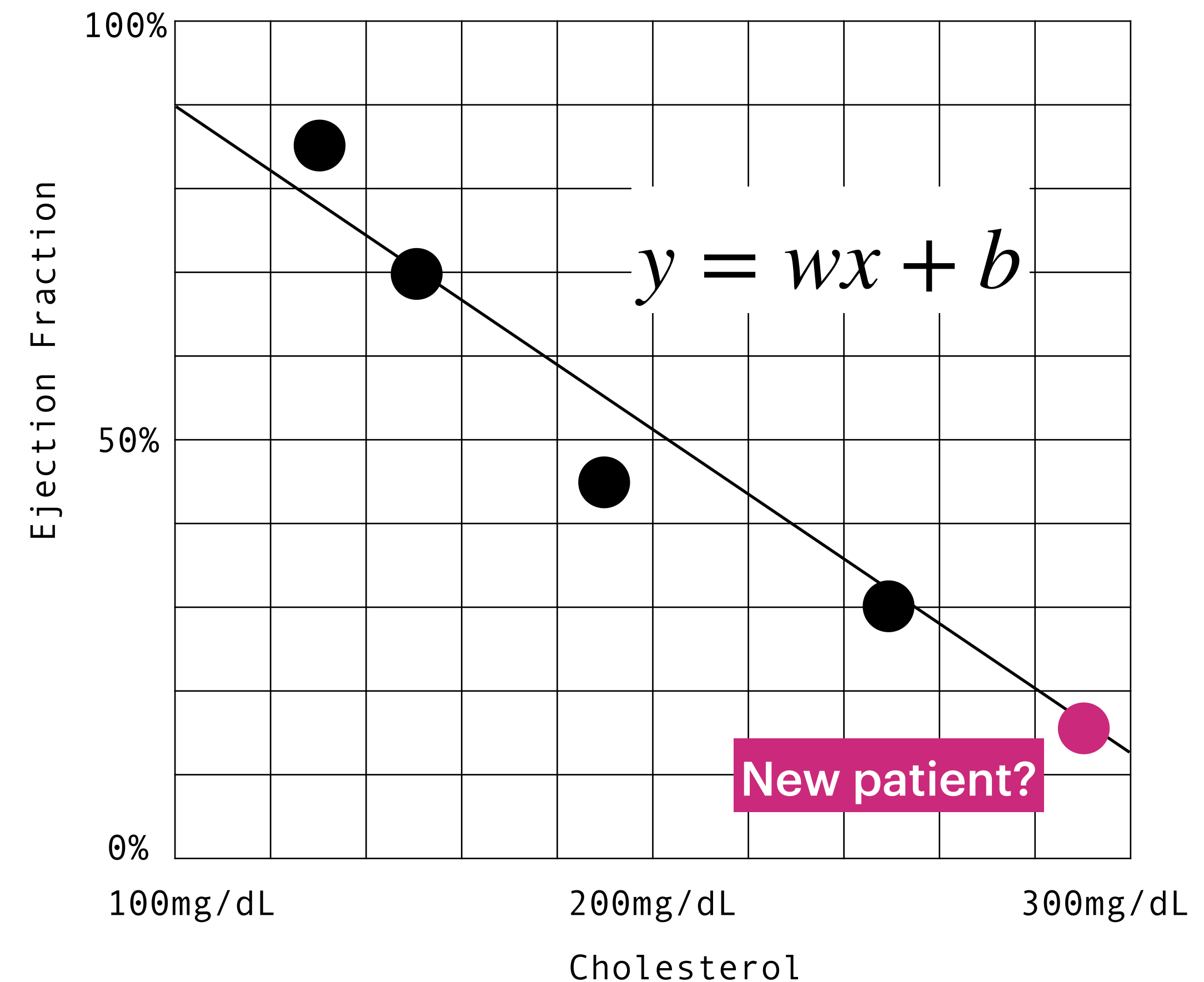
Cholesterol	Age	Blood Pressure	Ejection Fraction
190mg/dL	80	130/100	45%
150mg/dL	20	110/80	70%
250mg/dL	50	150/100	30%
130mg/dL	45	90/50	85%

Predictor

Outcome

Learn best function from the relationship  
between variables and outcome

i.e. what should  $w$  and  $b$  be?



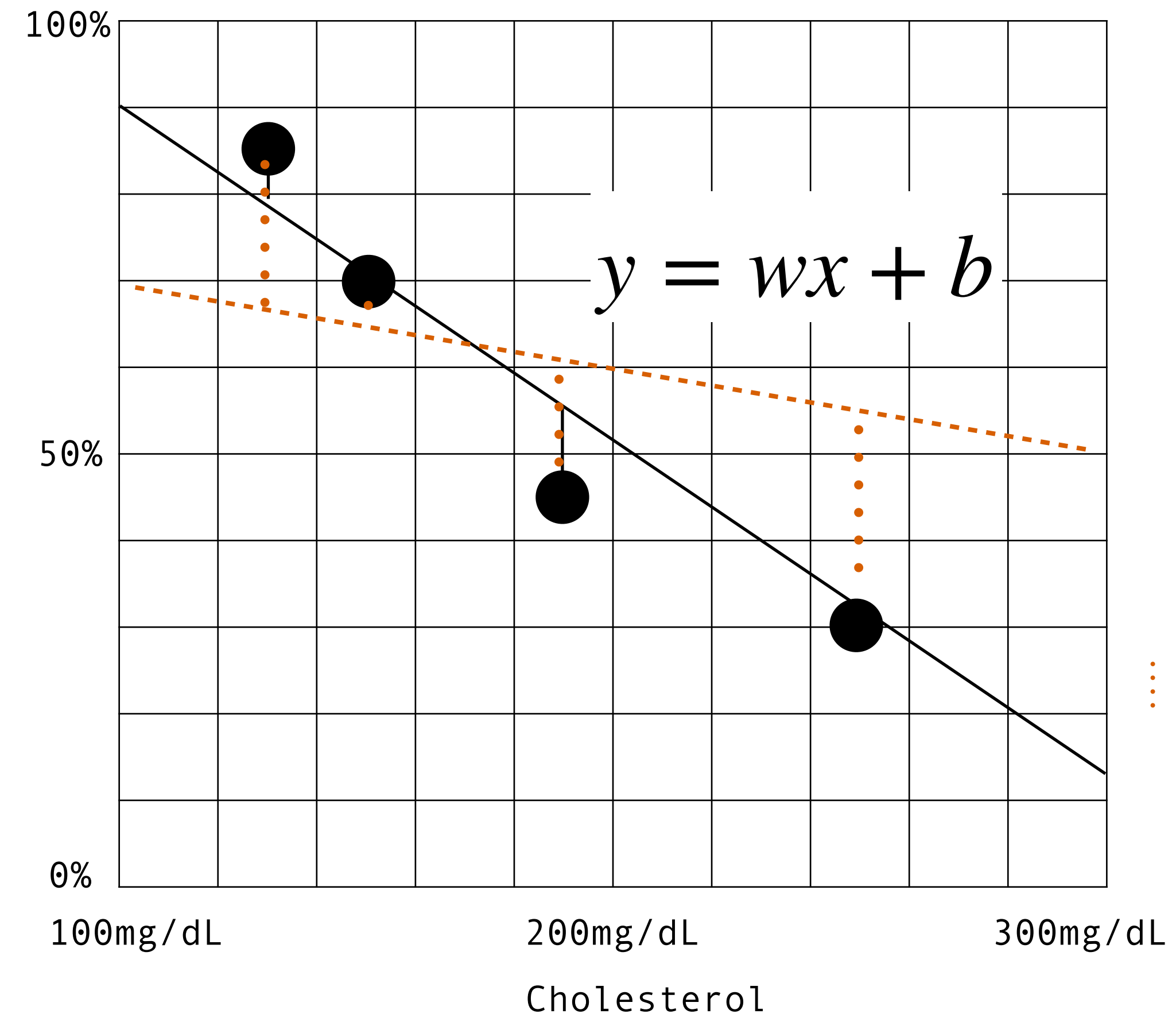
# How does Machine Learning (ML) work?

$$\text{Ejection Fraction} = w \cdot \text{Cholesterol} + b$$

## How do we learn $w$ and $b$ ?

We invent a rule for the computer to learn to find the best line.

**Rule:** Minimize  $L(w, b)$  = how far the data is from the line



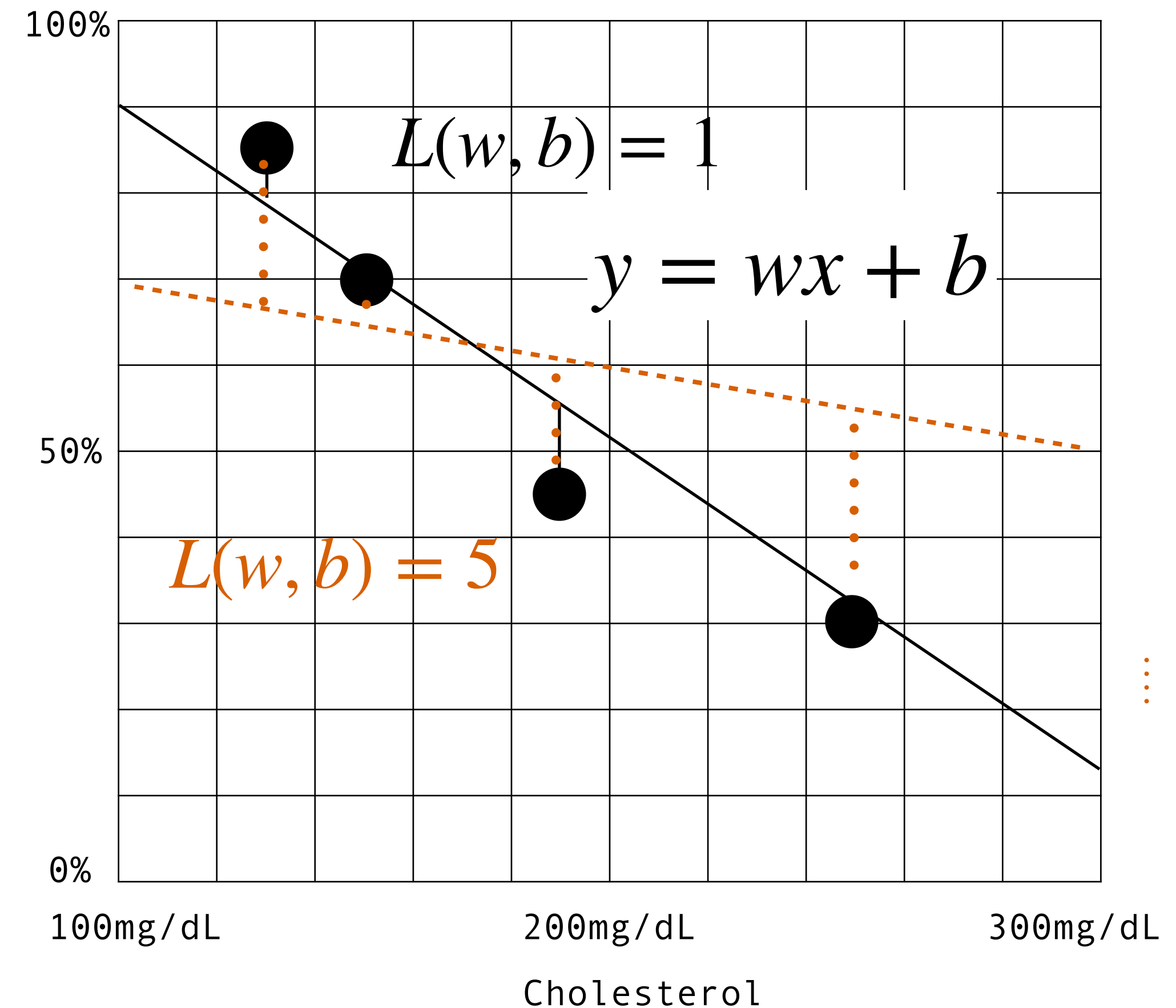
# How does Machine Learning (ML) work?

How does the computer use the rule to learn the best  $w$  and  $b$ ?

**Rule:** Minimize how far the data is from the line

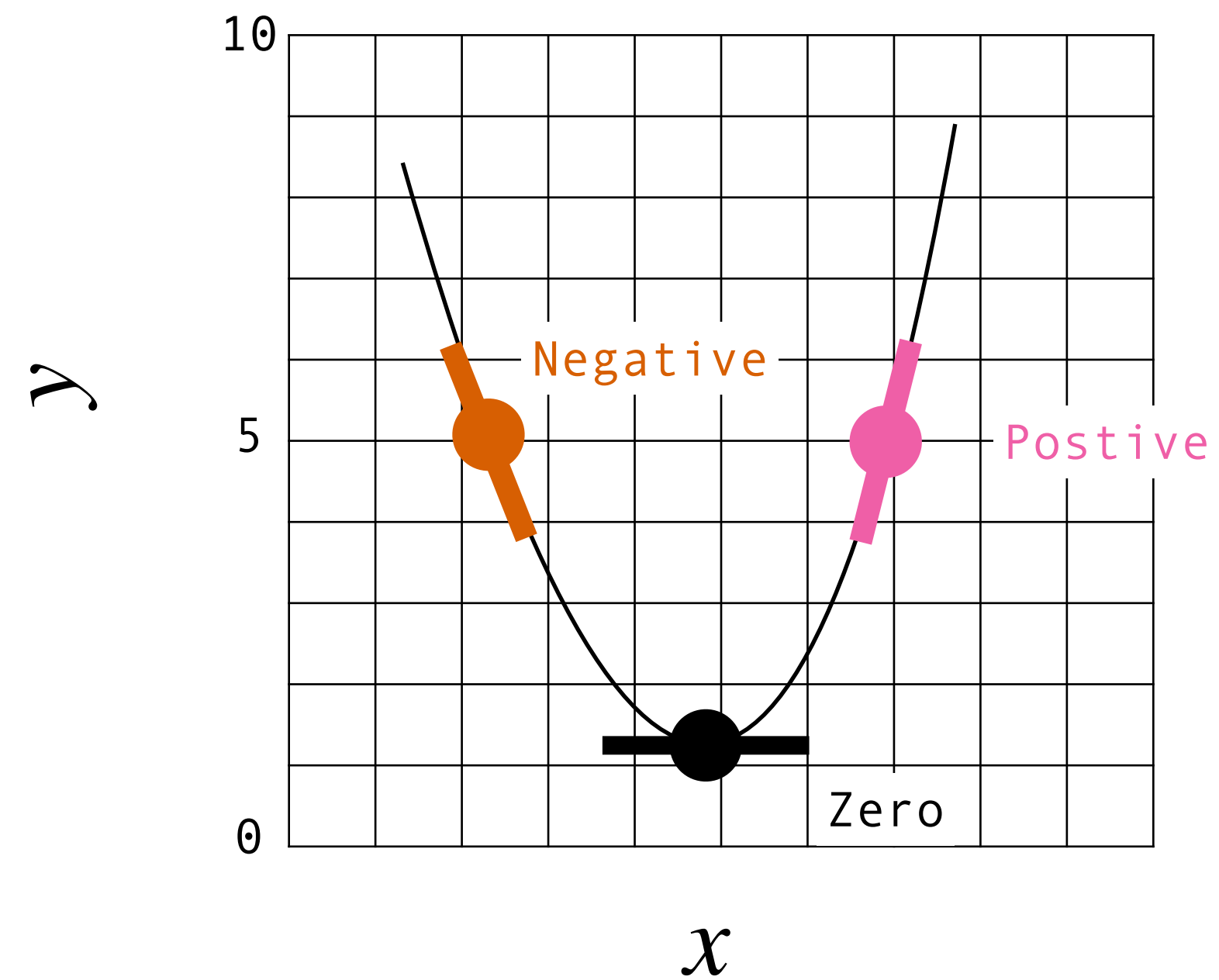
$$L(w, b) = \frac{1}{N} \sum_i (y_i - (wx_i + b))^2$$

We find the right  $w, b$  using **gradient descent**.



# Derivatives

**How fast is a function changing and what direction?**

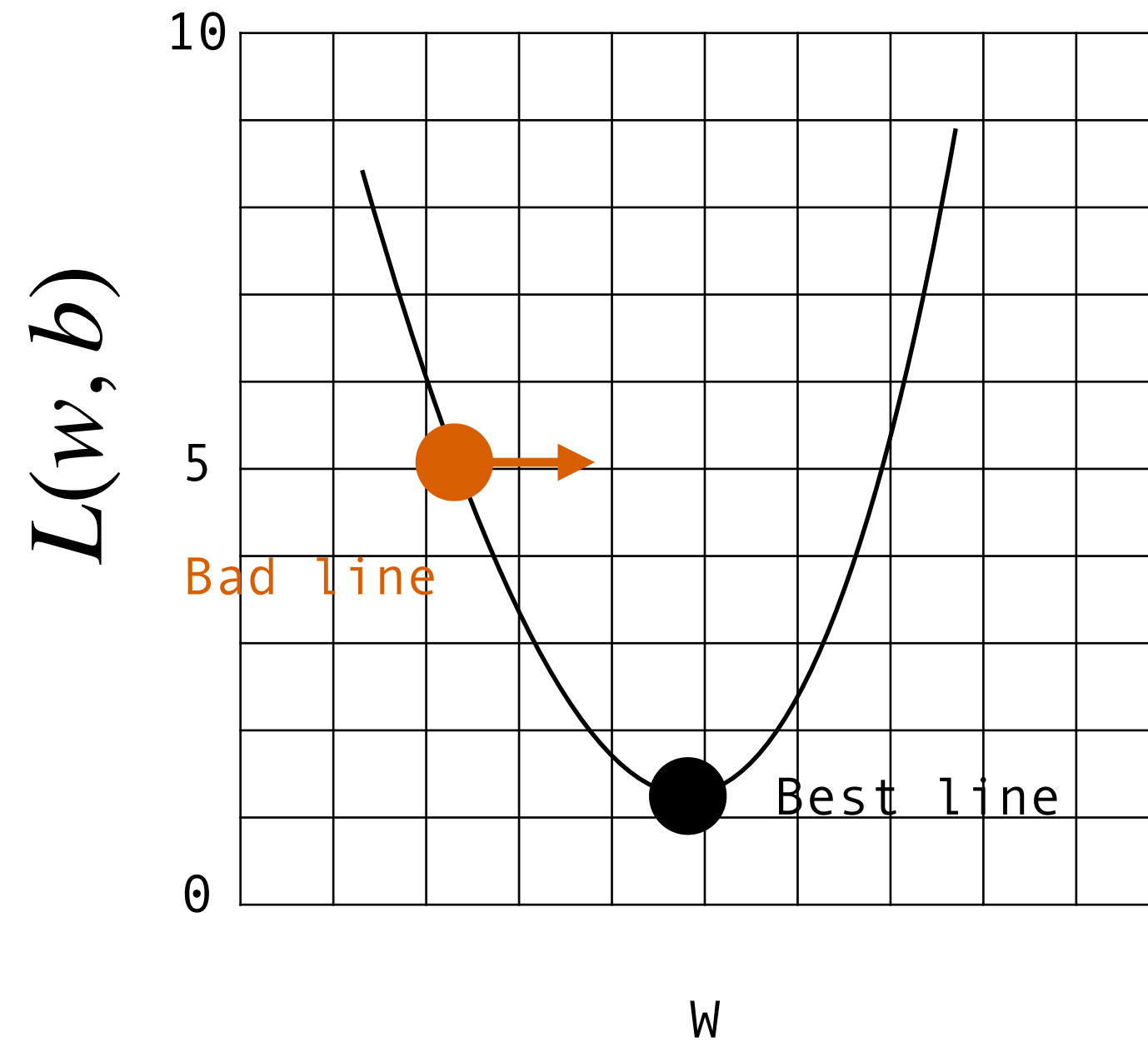


$$\frac{dy}{dx}$$

$$y = wx + b$$

# Derivatives

How fast is **the loss rule** changing and what direction?



We move in the negative direction of the derivative!

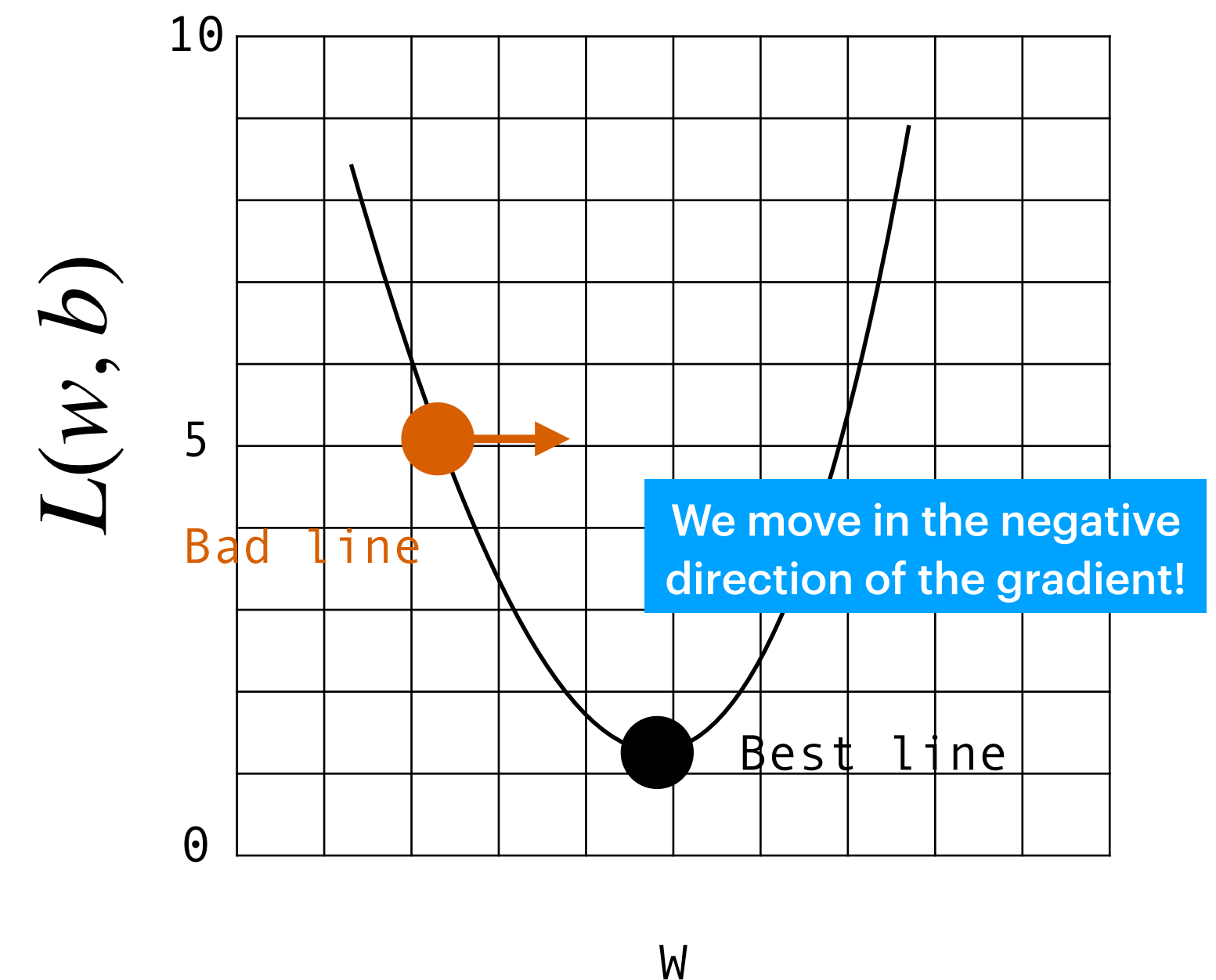
# How does Machine Learning (ML) work?

**Gradient descent** is a process for getting closer to the best  $w, b$  according to the rule  $L(w, b)$ .

- 1 Compute derivatives to know the direction that can make it smaller.

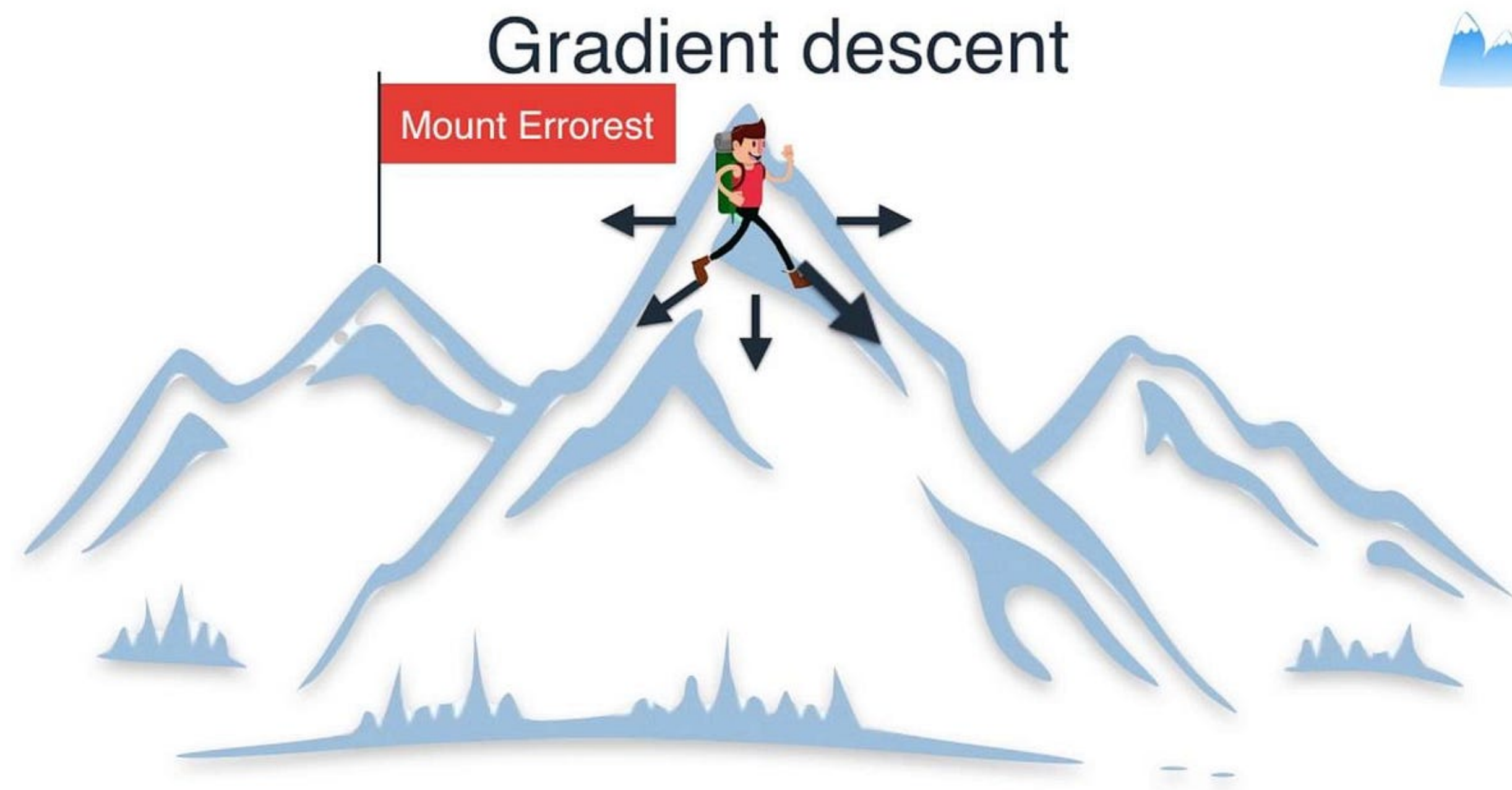
Calculate  $\frac{dL}{dw}$  for direction to change  $w$ .

- 2 Step the model parameters  $w, b$  toward the better direction.



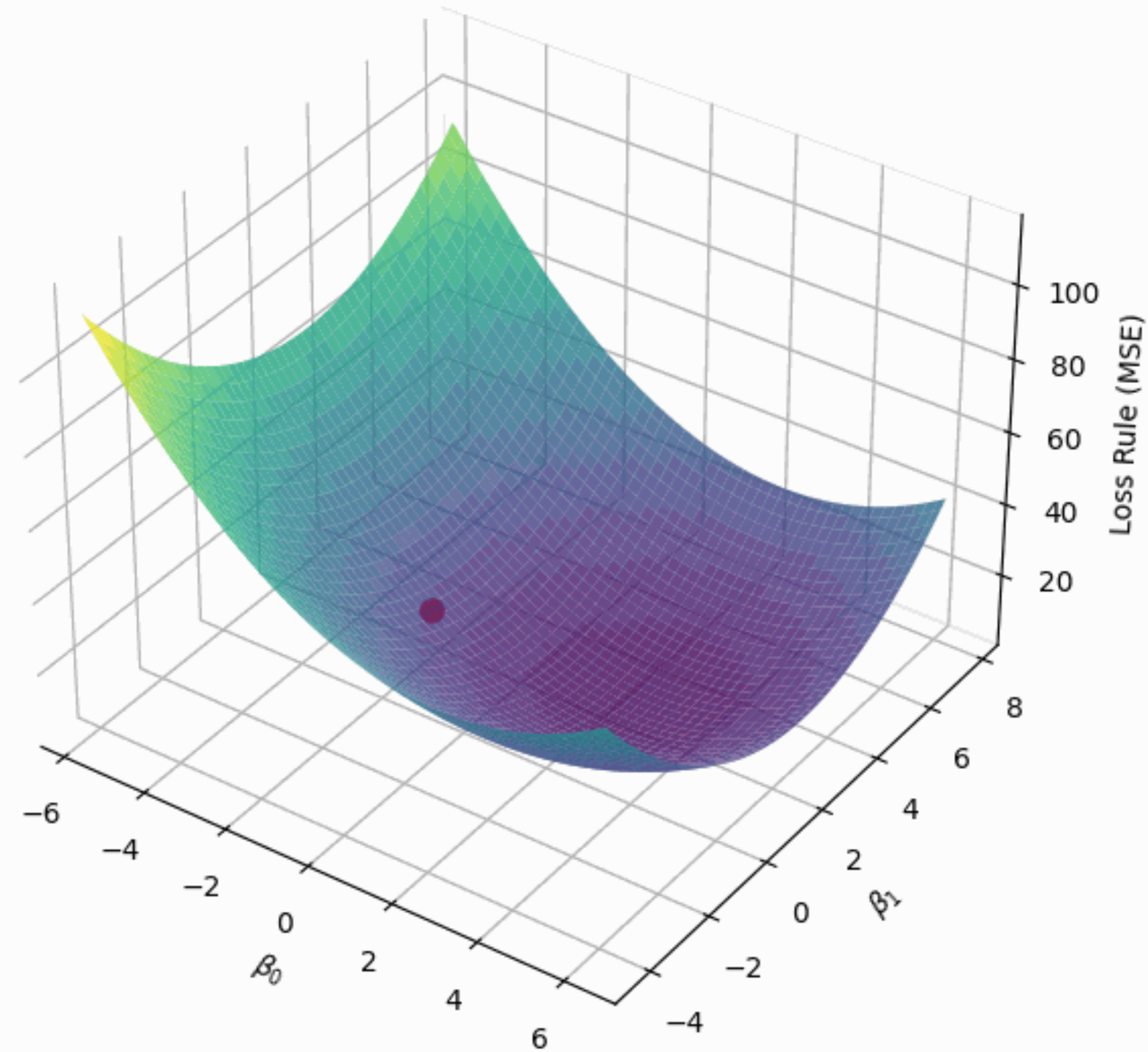
# How does Machine Learning (ML) work?

In higher dimensions, its like choosing the best way to hike down a mountain to a valley.



# Gradient Descent

Gradient Descent on Linear Regression Loss Surface



# Gradient Descent

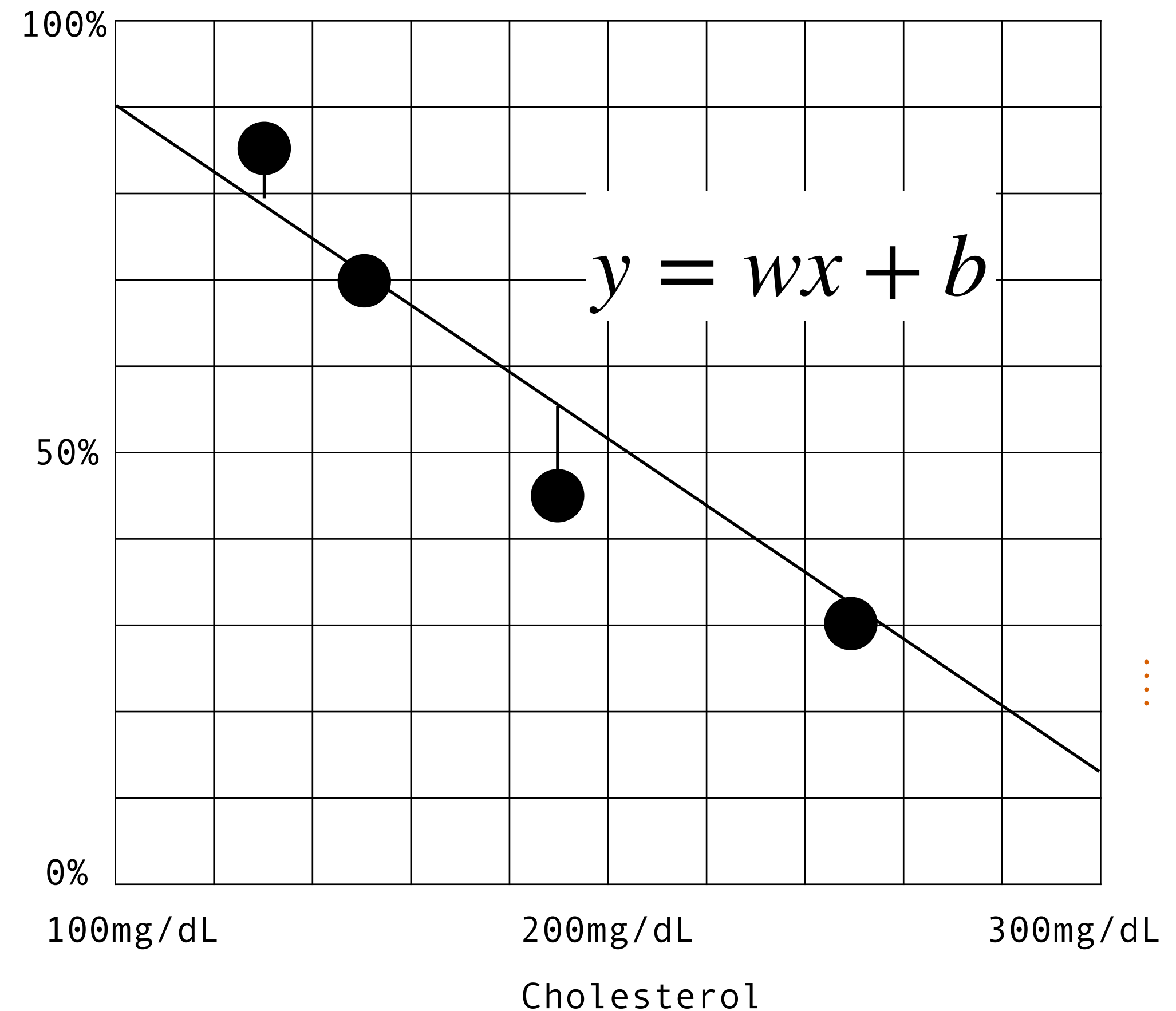
## **Activity:**

<https://developers.google.com/machine-learning/crash-course/linear-regression/gradient-descent-exercise>

# How does Machine Learning (ML) work?

Once we find the correct line with gradient descent, we have “trained” our linear regression.

This is what AI people call **learning**.



# How does Machine Learning (ML) work?

Linear regression can predict with any number of variables.

$$\text{Ejection Fraction} = w_1 \cdot \text{Cholesterol} + w_2 \cdot \text{Age} + w_3 \cdot \text{Blood pressure} + b$$

Cholesterol	Age	Blood Pressure	Ejection Fraction
190mg/dL	80	130/100	45%
150mg/dL	20	110/80	70%
250mg/dL	50	150/100	30%
130mg/dL	45	90/50	85%

Predictors

Outcome

# How does Machine Learning (ML) work?

Ingredients we needed:

Examples (Data)

Cholesterol	Age	Blood	Ejection
190mg/dL	80	130/100	45%
150mg/dL	20	110/80	70%
250mg/dL	50	150/100	30%
130mg/dL	45	90/50	85%

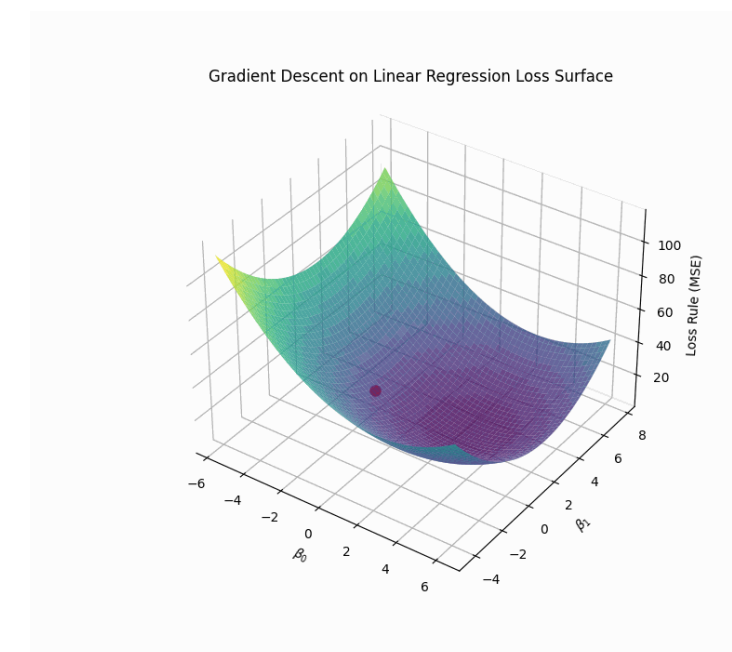
Model Structure

$$y = wx + b$$

Loss Rule

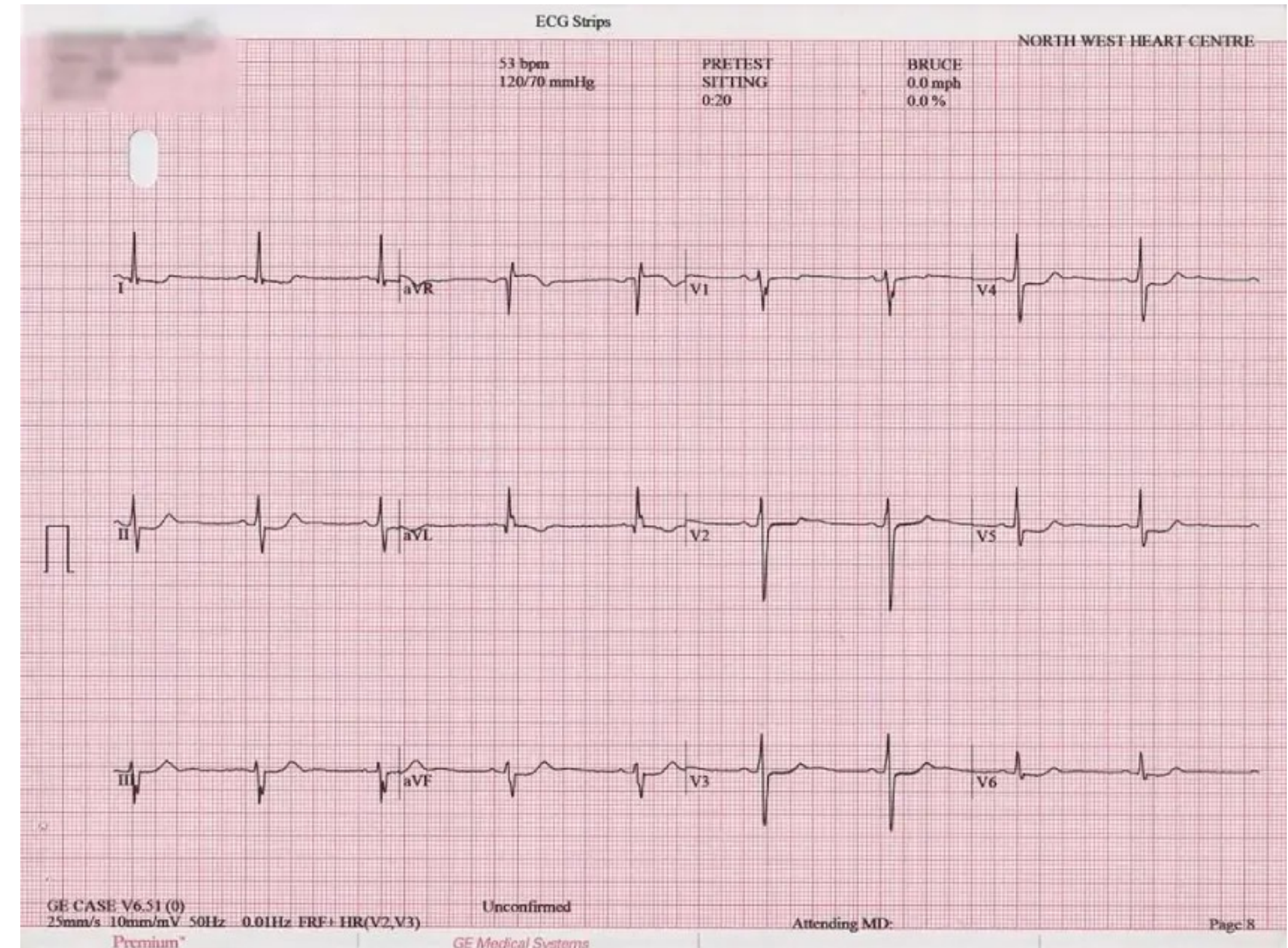
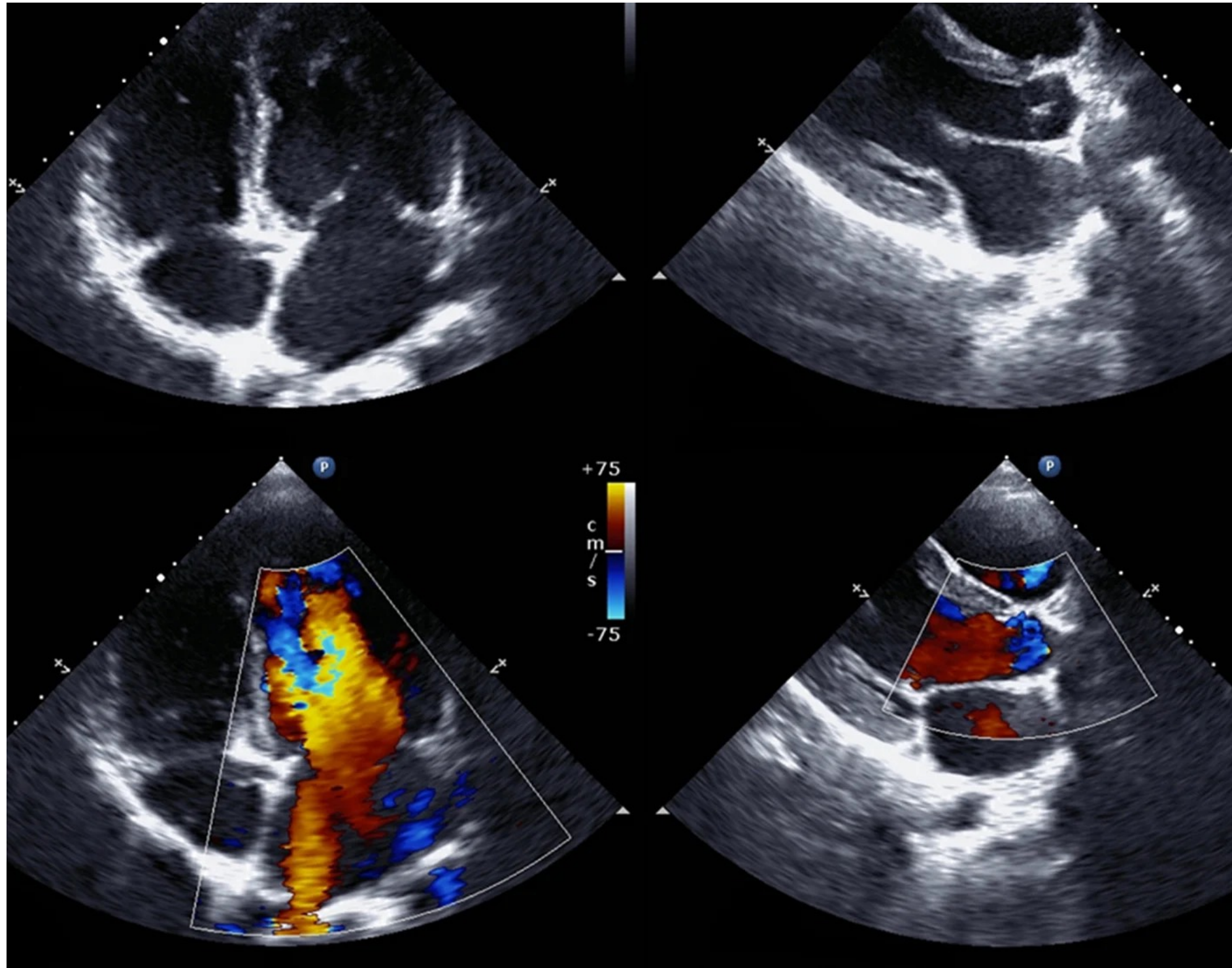
$$L(w, b) = \frac{1}{N} \sum_i (y_i - (wx_i + b))^2$$

Learning procedure (Gradient Descent)



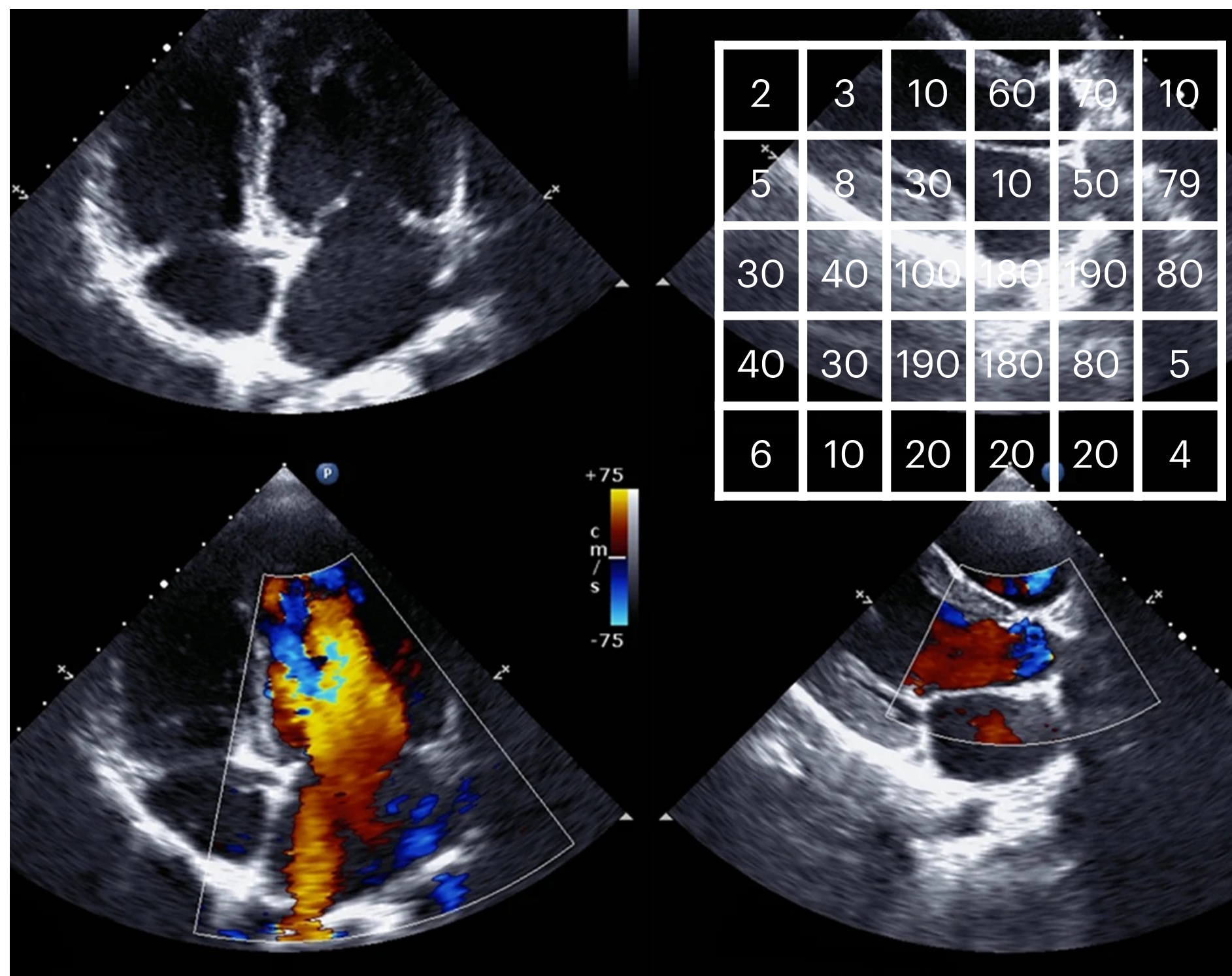
# What is Deep Learning?

What if our input data are high dimensional and do not have linear relationships with outcomes of interest?

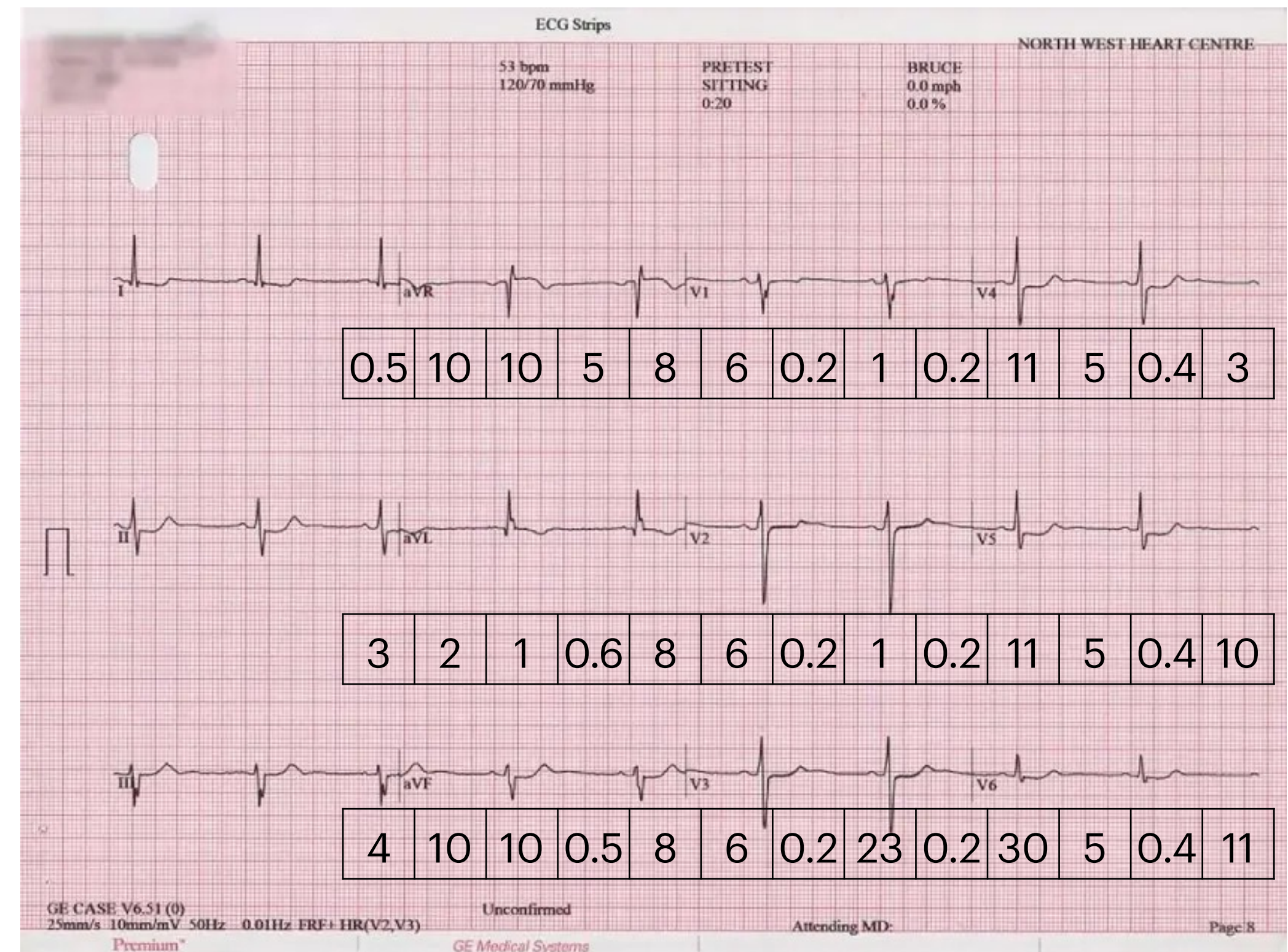


# What is Deep Learning?

Images can still be written as numbers, but our function is more complex!



Divide into pixels



Write as amplitudes

# What is Deep Learning?

Pixels

2	3	10	60	70	10
5	8	30	10	50	79
30	40	100	180	190	80
40	30	190	180	80	5
6	10	20	20	20	4

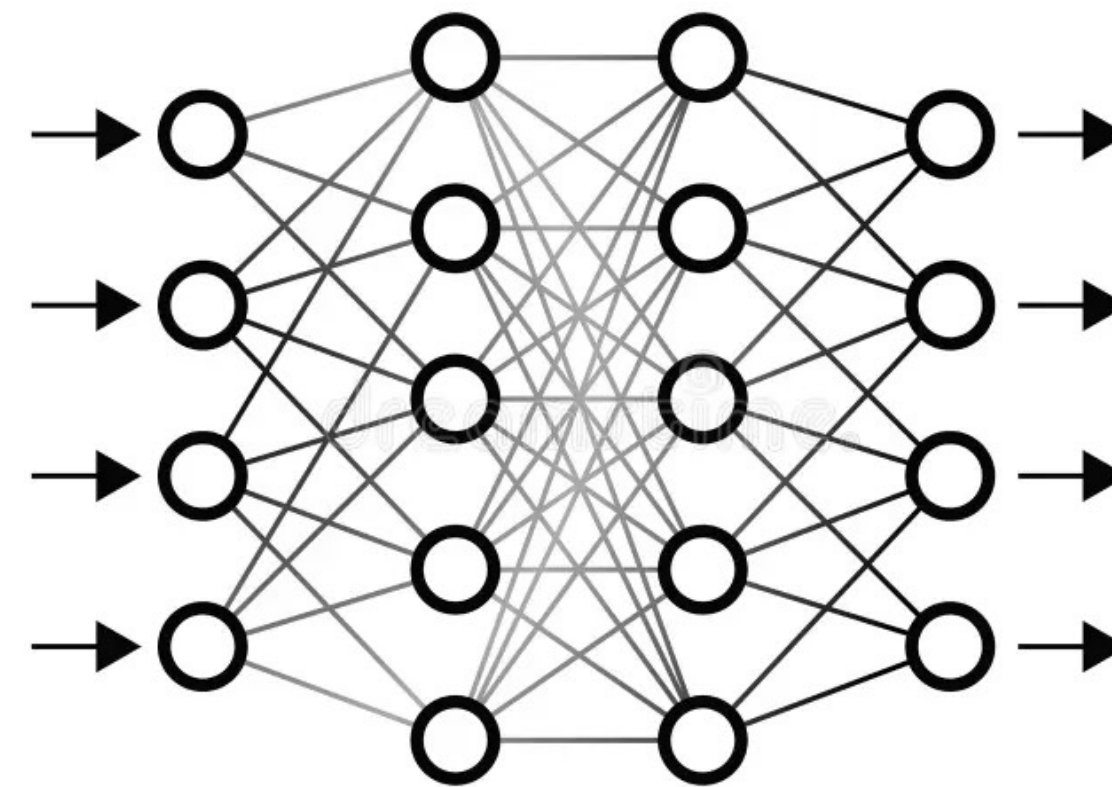
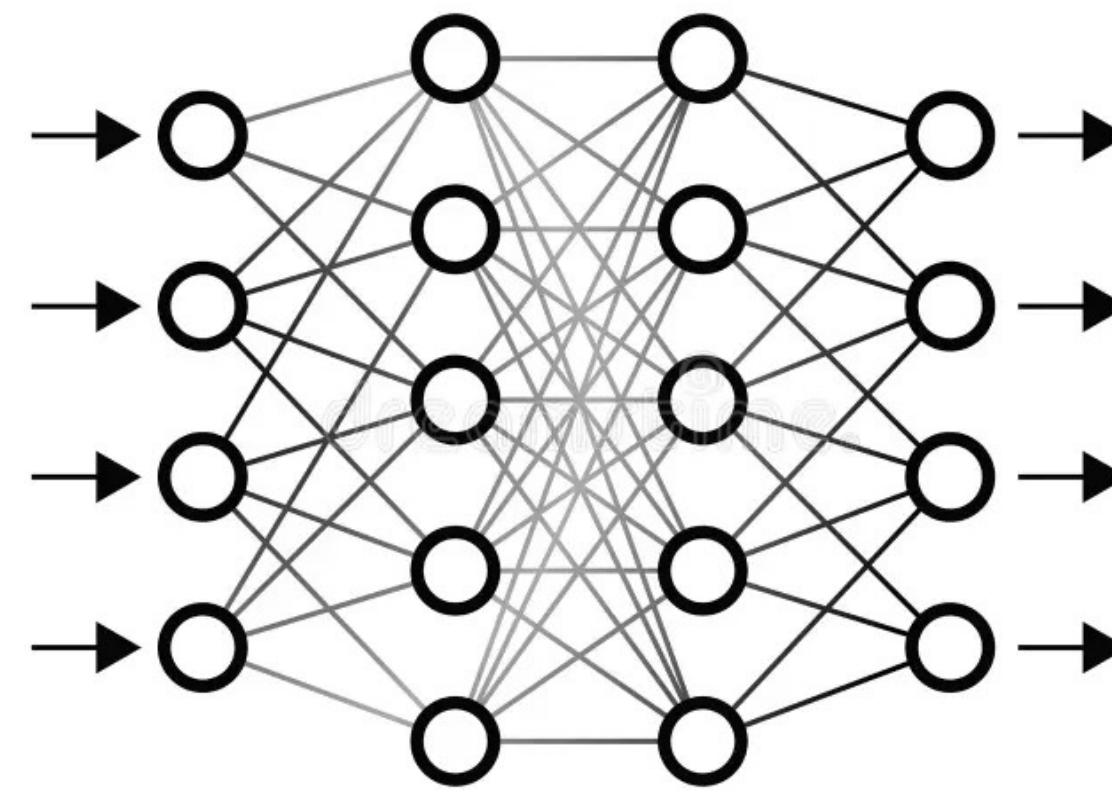
Predictors

Amplitudes

0.5	10	10	5	8	6	0.2	1	0.2	11	5	0.4	3
-----	----	----	---	---	---	-----	---	-----	----	---	-----	---

3	2	1	0.6	8	6	0.2	1	0.2	11	5	0.4	10
---	---	---	-----	---	---	-----	---	-----	----	---	-----	----

4	10	10	0.5	8	6	0.2	23	0.2	30	5	0.4	11
---	----	----	-----	---	---	-----	----	-----	----	---	-----	----



Ejection Fraction

45%

70%

30%

85%

Outcome

Ejection Fraction

45%

70%

30%

85%

# Neural Networks

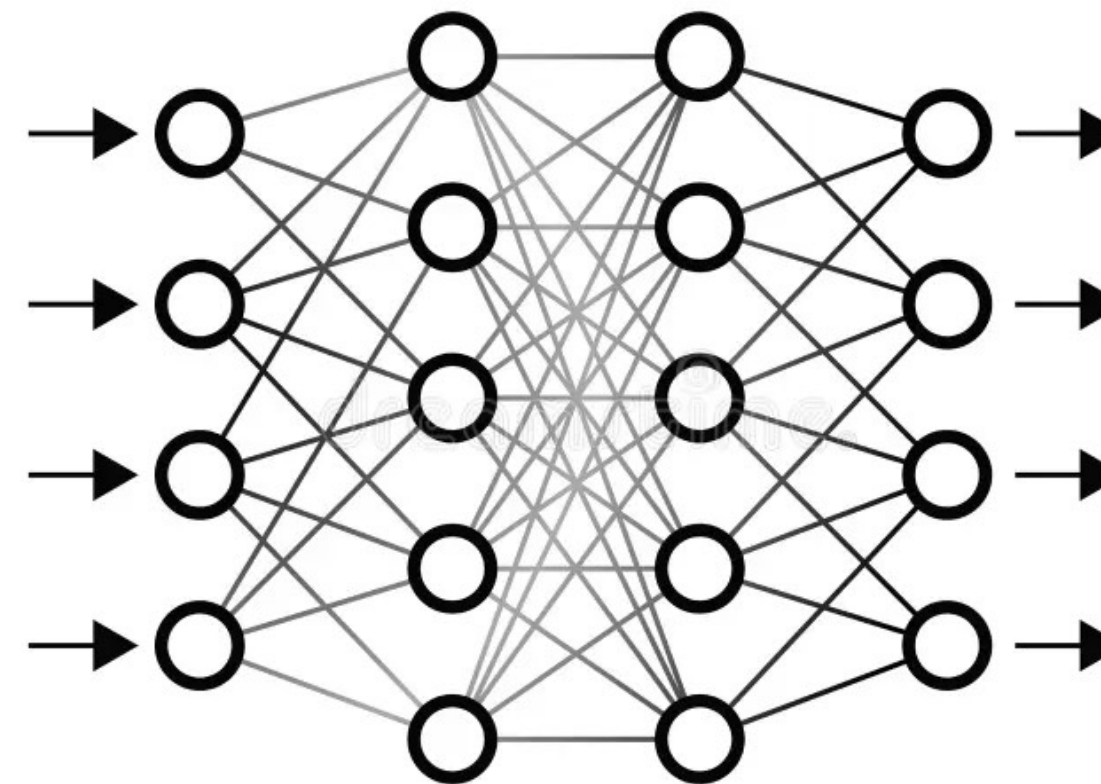
Linear regression has a formula:  $y = wx + b$ . We learned numbers  $w, b$ .

Deep learning uses **neural networks**, which extend this formula.

Pixels

2	3	10	60	70	10
5	8	30	10	50	79
30	40	100	180	190	80
40	30	190	180	80	5
6	10	20	20	20	4

Predictors



Repeated application of:

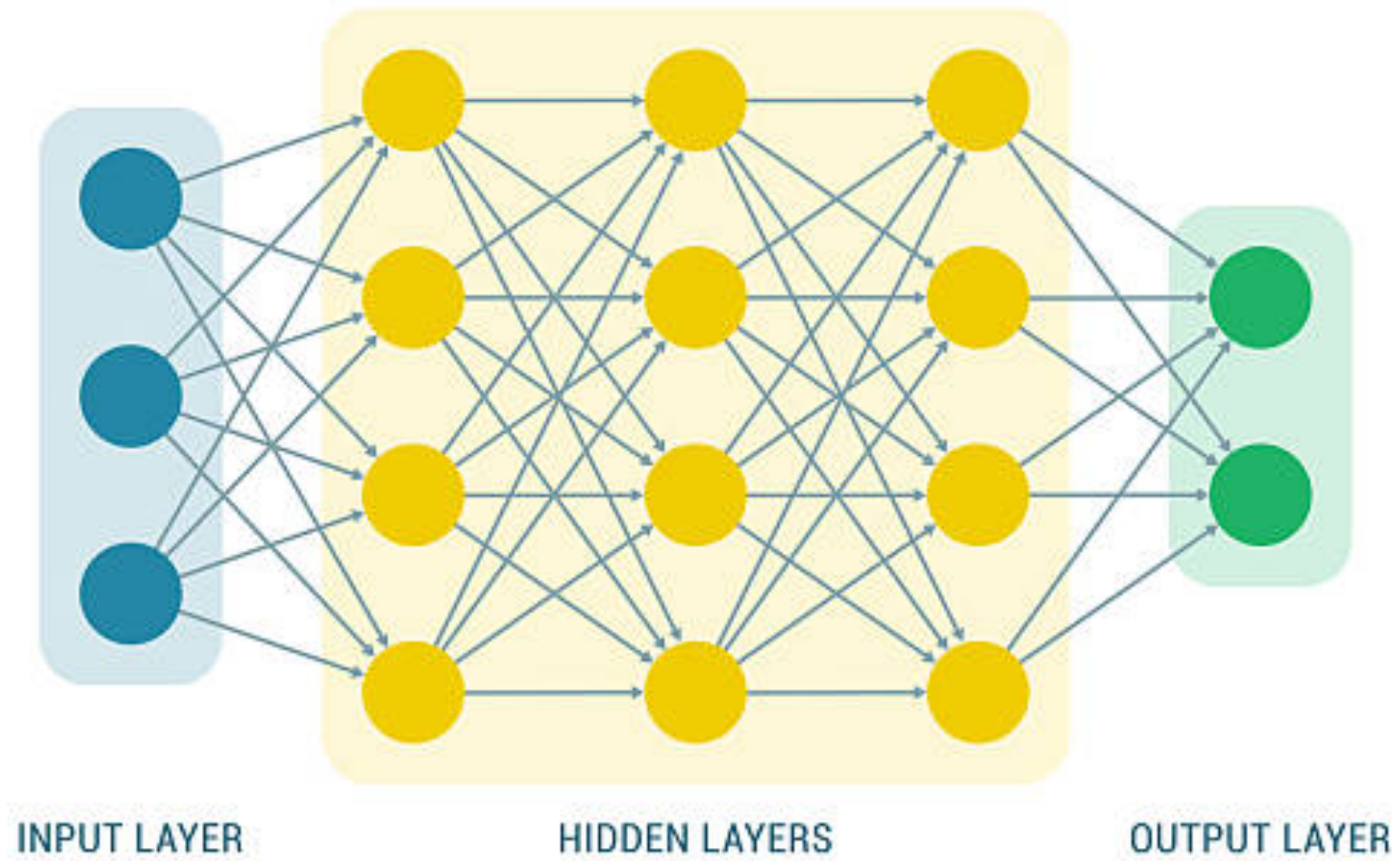
$$y = \sigma(wx + b)$$

Ejection Fraction
45%
70%
30%
85%

Outcome

# Neural Networks

$x$   
3-dimensional.  
Predictors



2-dimensional.  
Outcome

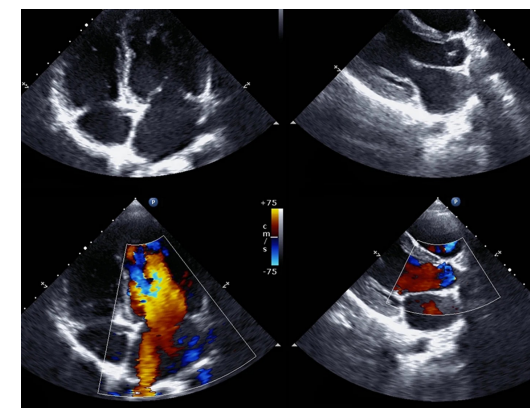
4-dimensional.

*But can be any size!*

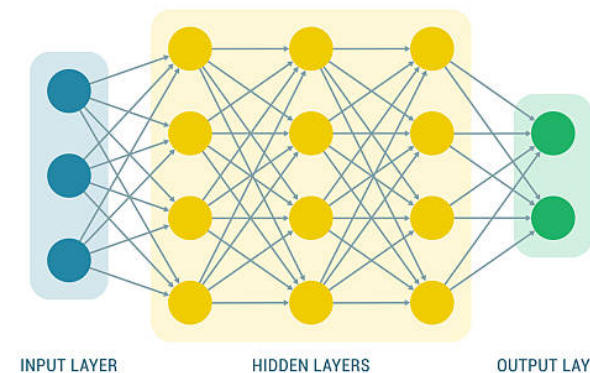
# How does Deep Learning work?

Ingredients we need:

Examples (Data)



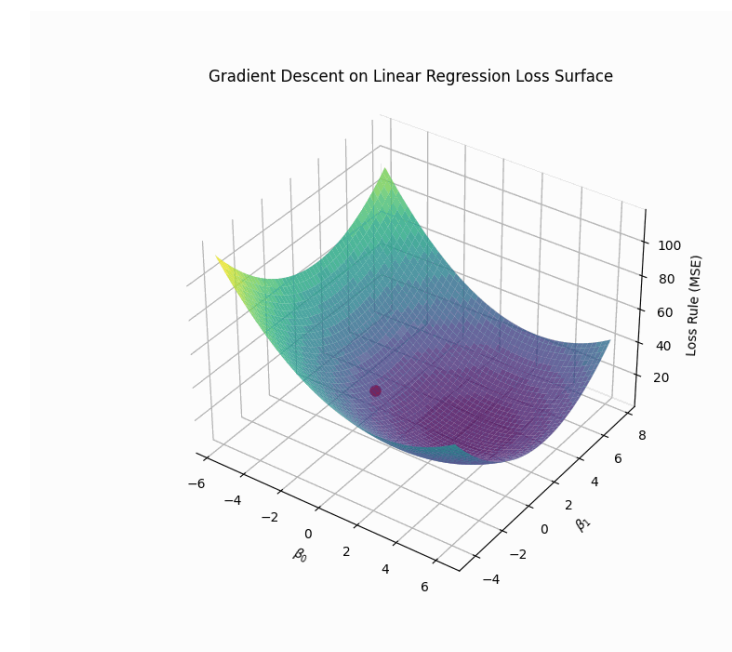
Model Structure



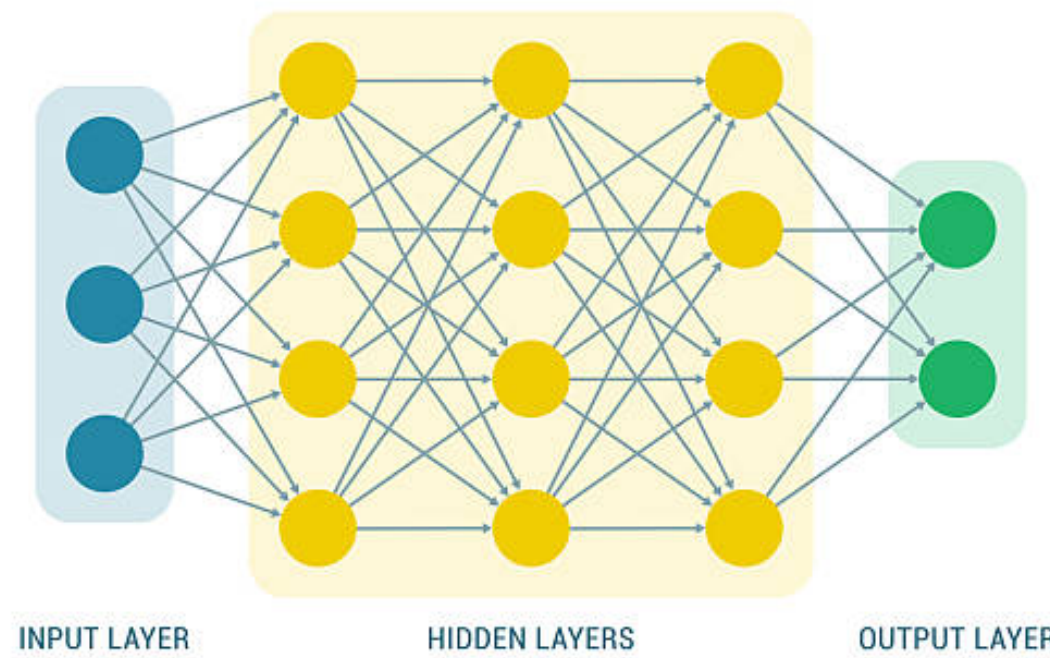
Loss Rule

$$L(w, b) = \frac{1}{N} \sum_i (y_i - (wx_i + b))^2$$

Learning procedure (Gradient Descent)



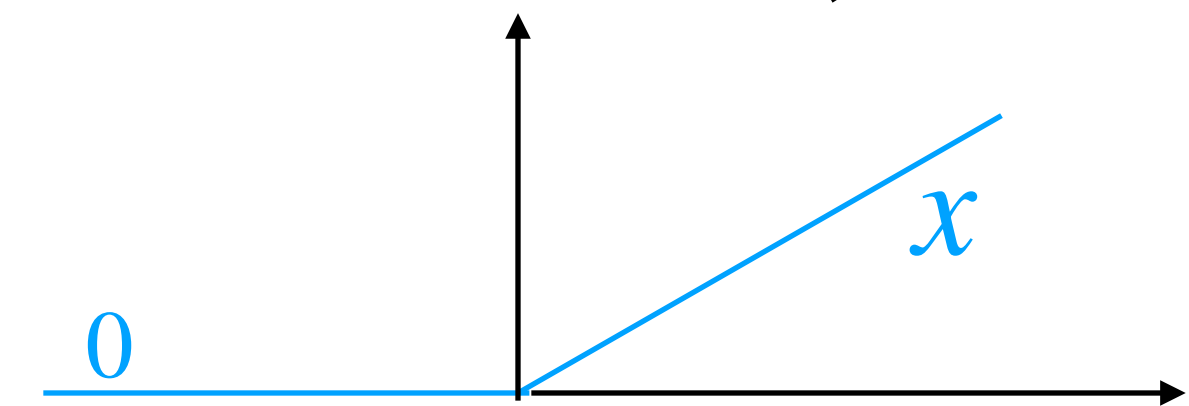
# Neural Networks



At each step:

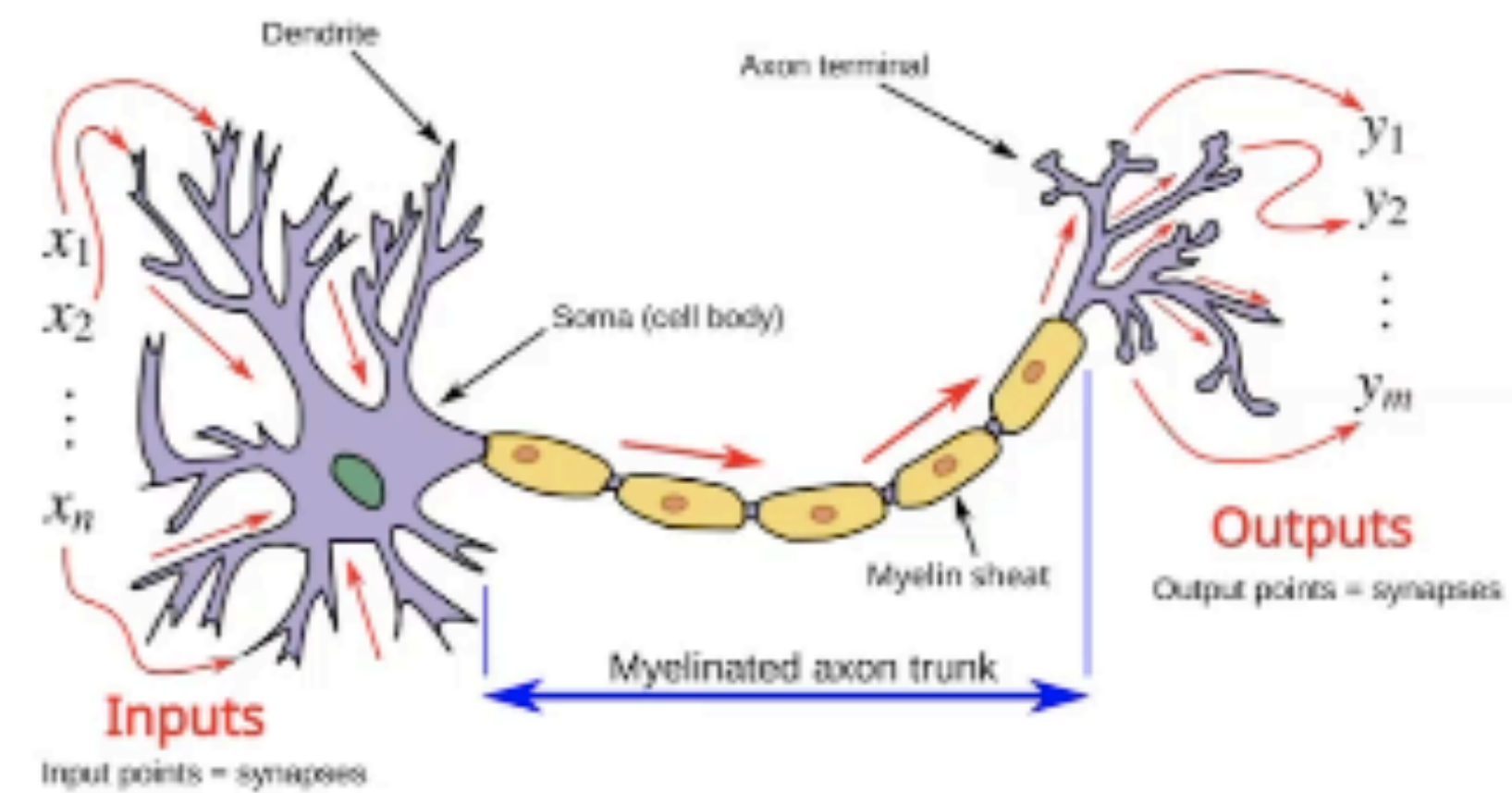
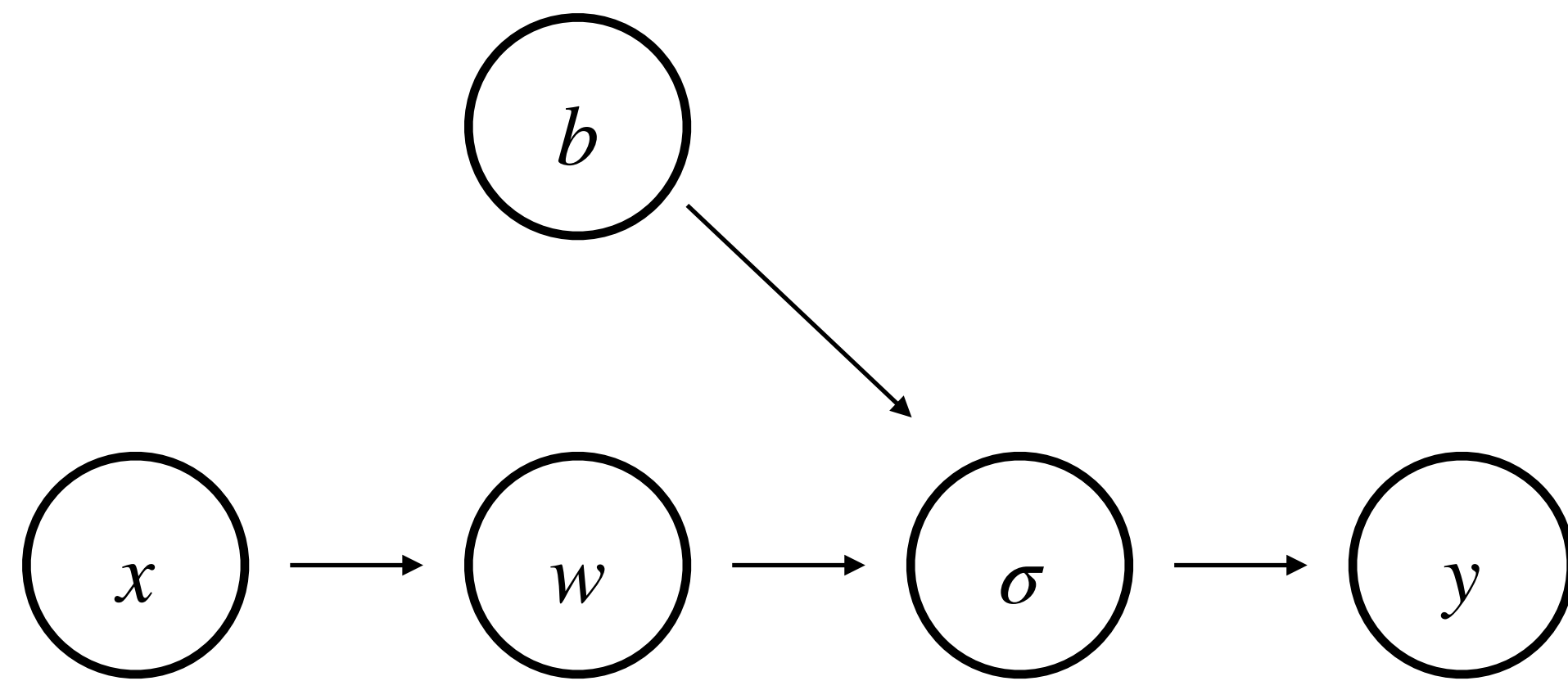
$$x \rightarrow w x + b \rightarrow \sigma(w x + b)$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \begin{matrix} \text{3 by 4 matrix} \\ \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \end{bmatrix} \end{matrix} \quad \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$



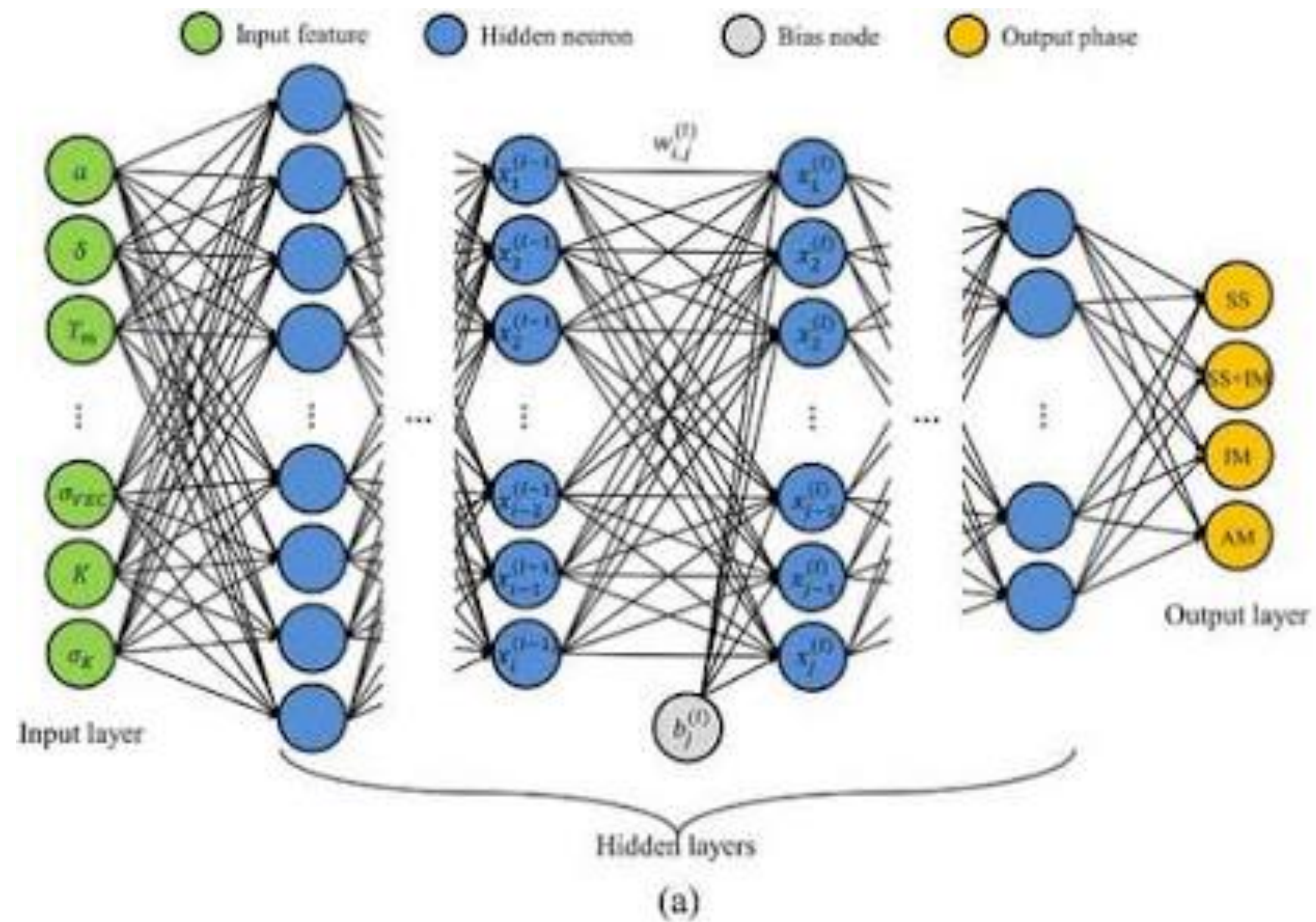
$\sigma$  is ReLU function

# Neural Networks



# Neural Networks

*Bigger networks are just the same thing!*



# Neural Networks are mathematically special!

A spate of papers in the 1980s—1990s, from [George Cybenko](#) and [Kurt Hornik](#) [de] etc, established several universal approximation theorems for arbitrary width and bounded depth. [44][1][7][8] See [45][46][10] for reviews. The following is the most often quoted:

**Universal approximation theorem**—Let  $C(X, \mathbb{R}^m)$  denote the set of [continuous functions](#) from a subset  $X$  of a Euclidean  $\mathbb{R}^n$  space to a Euclidean space  $\mathbb{R}^m$ . Let  $\sigma \in C(\mathbb{R}, \mathbb{R})$ . Note that  $(\sigma \circ x)_i = \sigma(x_i)$ , so  $\sigma \circ x$  denotes  $\sigma$  applied to each component of  $x$ .

Then  $\sigma$  is not [polynomial if and only if](#) for every  $n \in \mathbb{N}$ ,  $m \in \mathbb{N}$ , [compact](#)  $K \subseteq \mathbb{R}^n$ ,  $f \in C(K, \mathbb{R}^m)$ ,  $\varepsilon > 0$  there exist  $k \in \mathbb{N}$ ,  $A \in \mathbb{R}^{k \times n}$ ,  $b \in \mathbb{R}^k$ ,  $C \in \mathbb{R}^{m \times k}$  such that

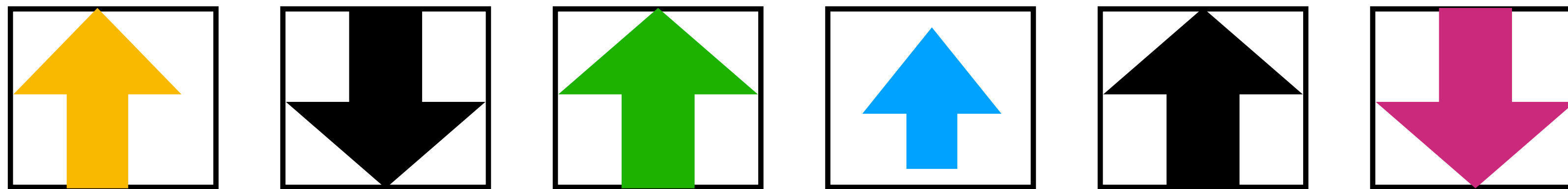
$$\sup_{x \in K} \|f(x) - g(x)\| < \varepsilon$$

where  $g(x) = C \cdot (\sigma \circ (A \cdot x + b))$

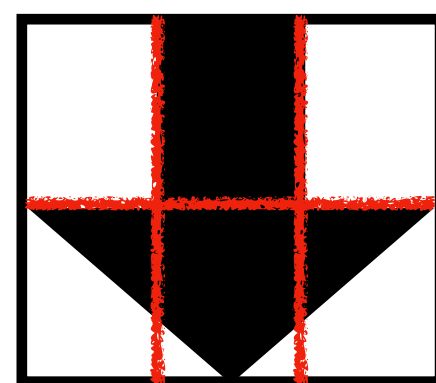
Math research from the 1980s-90s shows that neural networks can approximate any mathematical function as long as they have non-linearities.

# How does Deep Learning work?

**Task:** Is the arrow up or down?



Image



Pixels

0	1	0
0.5	0.8	0.5

Matrix

$$\begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0.8 & 0.5 \end{bmatrix}$$

# Neural Networks

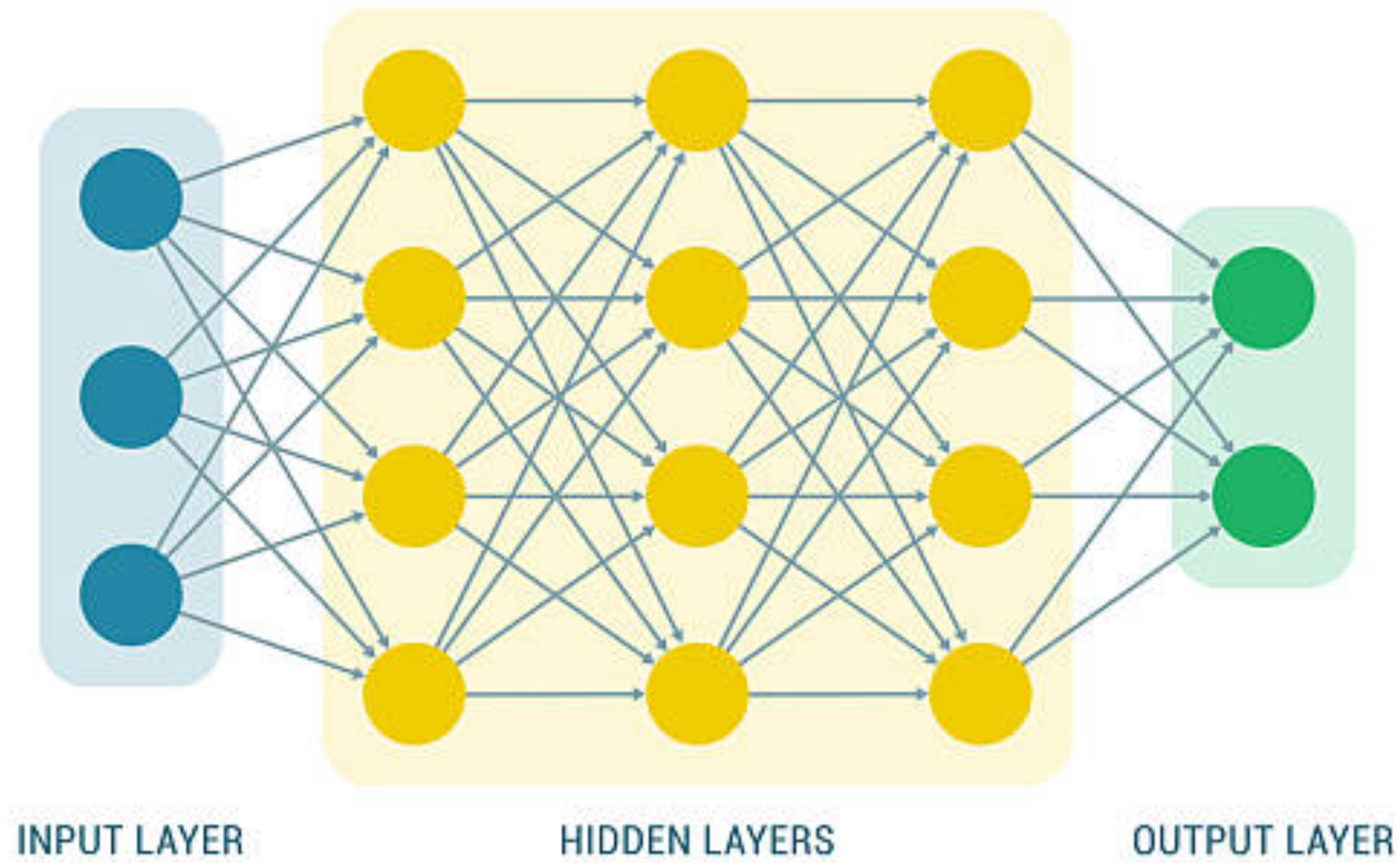
$x$

Pixels

$$\begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0.8 & 0.5 \end{bmatrix}$$

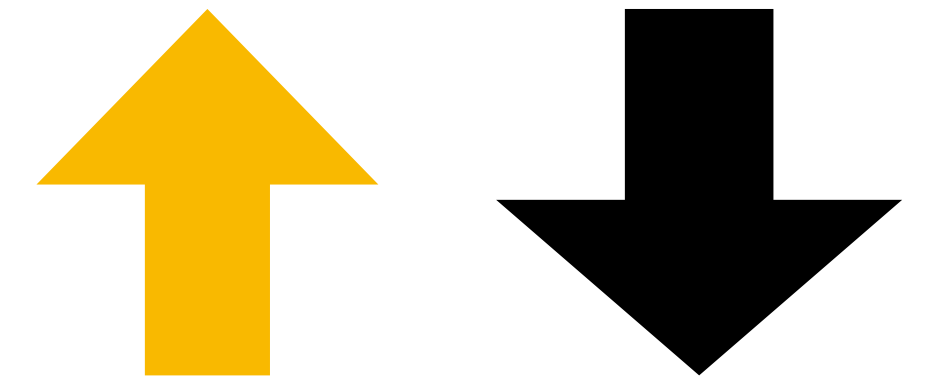
6-dimensional.

Predictors



2-dimensional.

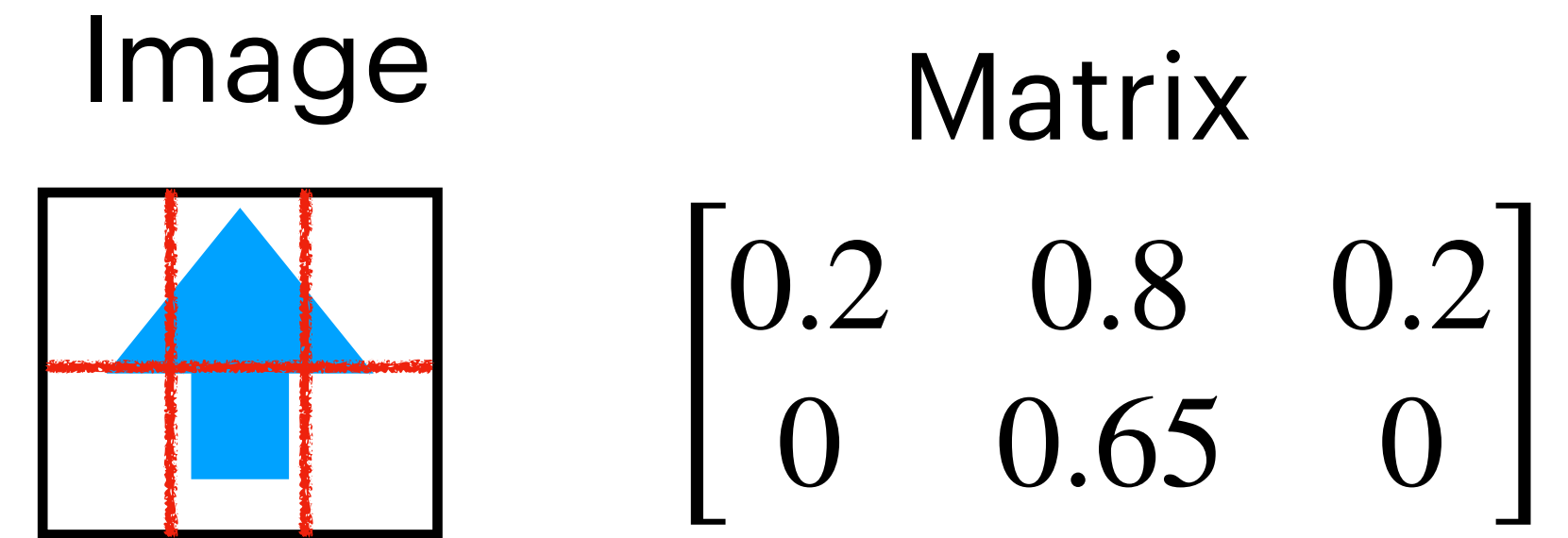
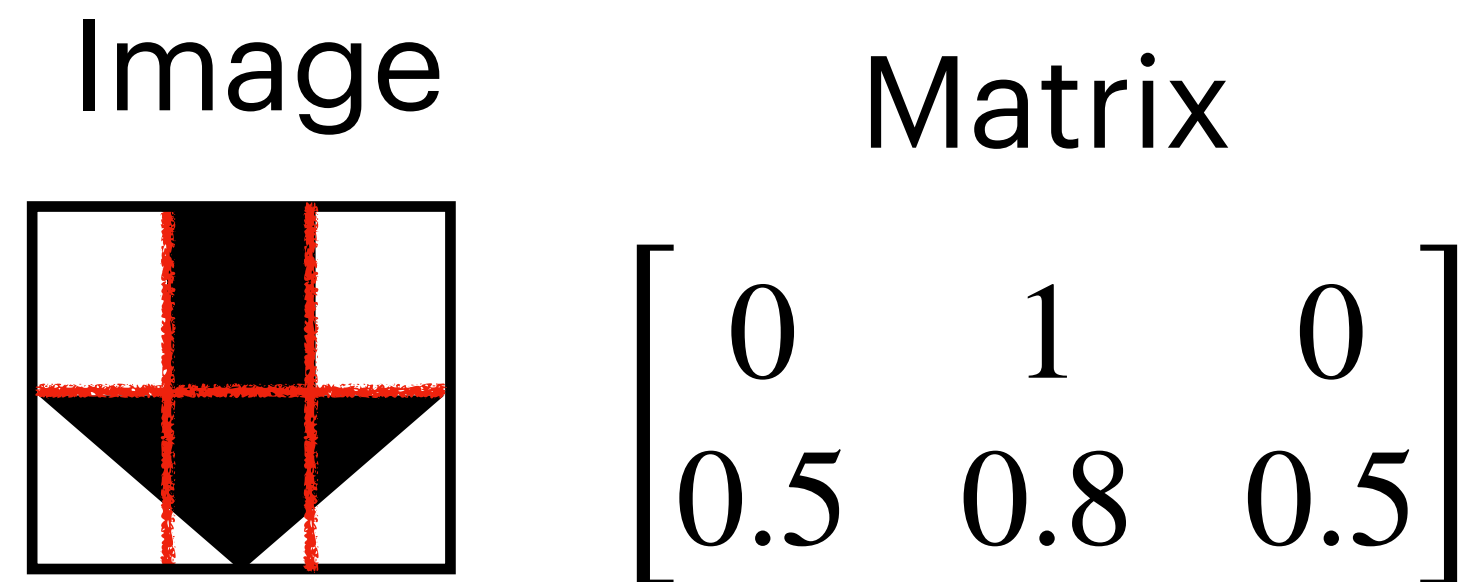
Outcome



4-dimensional.

*But can be any size!*

# How does Deep Learning work?



Need a function:

$$x \rightarrow W x \rightarrow \sigma(W x) \rightarrow [P_{up} \ P_{down}]$$

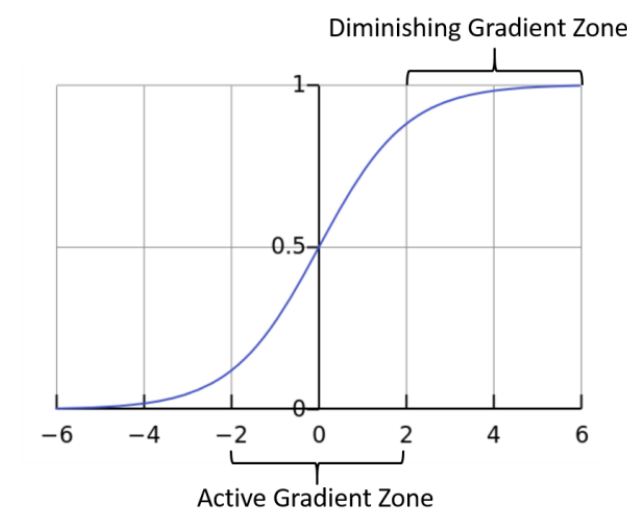
6 by 1 vector

2 by 6 matrix

$$\begin{bmatrix} w_{11} & w_{12} & \dots & w_{16} \\ w_{21} & w_{22} & \dots & w_{26} \end{bmatrix}$$

$$\begin{bmatrix} b_1 \\ b_2 \\ \dots \\ b_6 \end{bmatrix}$$

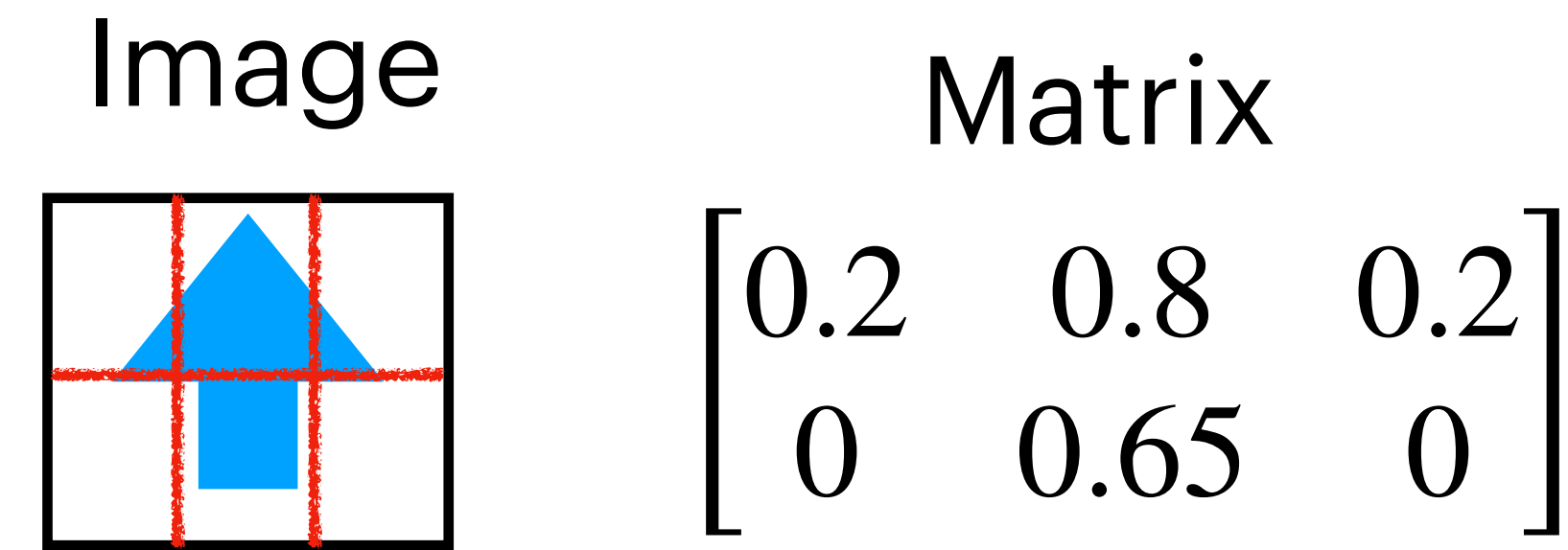
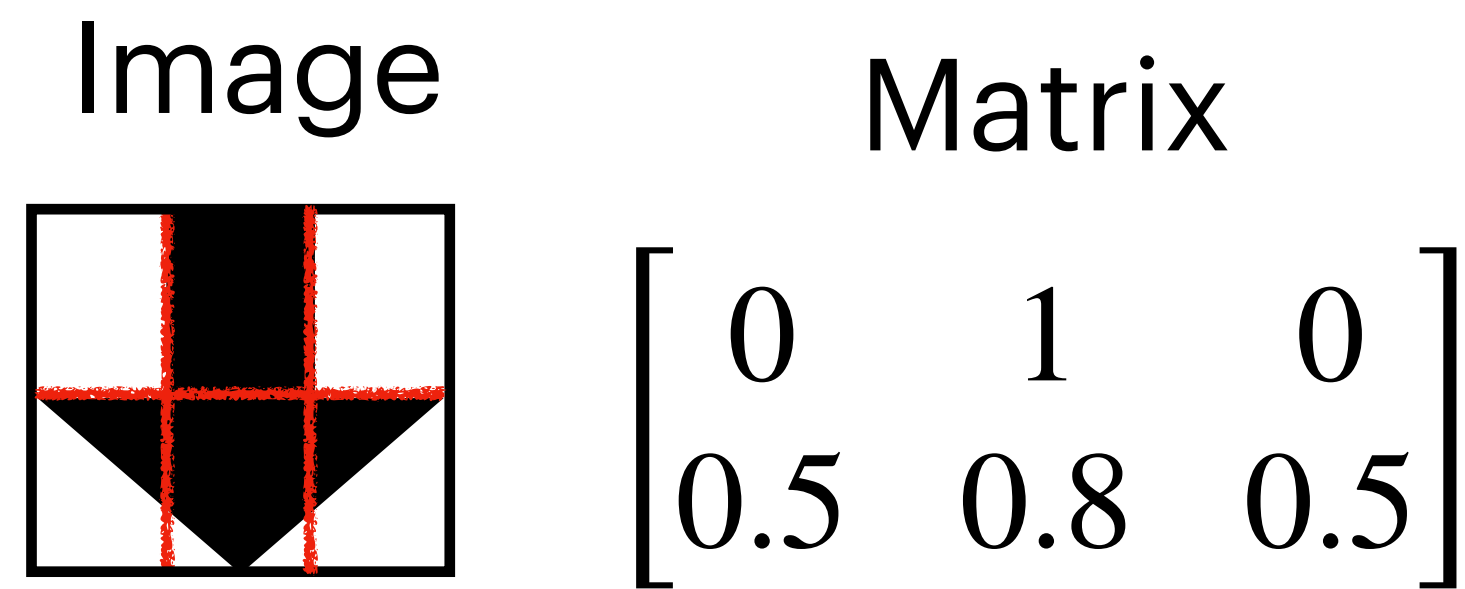
$$\frac{1}{1+e^{-x}}$$



$\sigma$  is sigmoid function

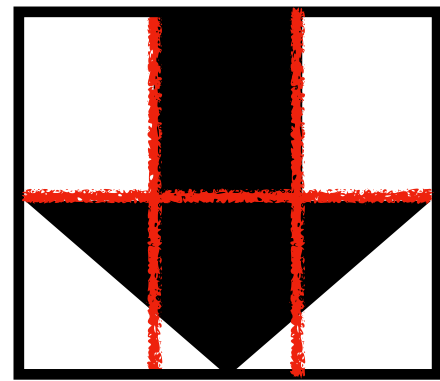
# How does Deep Learning work?

What do we notice? What values of  $x$  should be weighted highly for each?



# How does Deep Learning work?

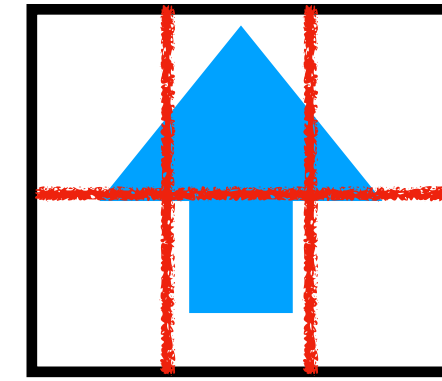
Image



Matrix

$$\begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0.8 & 0.5 \end{bmatrix}$$

Image



Matrix

$$\begin{bmatrix} 0.2 & 0.8 & 0.2 \\ 0 & 0.65 & 0 \end{bmatrix}$$

$$\sigma\left(\begin{bmatrix} w_{11} & w_{12} & \dots & w_{16} \\ w_{21} & w_{22} & \dots & w_{26} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0.5 \\ 0.8 \\ 0.5 \end{bmatrix}\right) = [p_{down} \quad p_{up}] \quad \sigma\left(\begin{bmatrix} w_{11} & w_{12} & \dots & w_{16} \\ w_{21} & w_{22} & \dots & w_{26} \end{bmatrix} \begin{bmatrix} 0.2 \\ 0.8 \\ 0.2 \\ 0.0 \\ 0.65 \\ 0.0 \end{bmatrix}\right) = [p_{down} \quad p_{up}]$$

# Matrix Multiplication

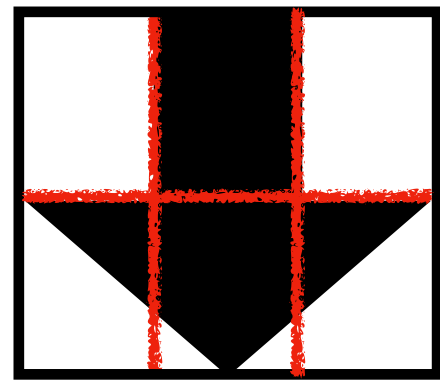
$$\sigma\left(\begin{bmatrix} w_{11} & w_{12} & \dots & w_{16} \\ w_{21} & w_{22} & \dots & w_{26} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0.5 \\ 0.8 \\ 0.5 \end{bmatrix}\right) = [p_{down} \quad p_{up}]$$

$$p_{up} = 0 \cdot w_{11} + 1 \cdot w_{12} + 0 \cdot w_{13} + 0.5 \cdot w_{14} + 0.8 \cdot w_{15} + 0.5 \cdot w_{16}$$

$$p_{down} = 0 \cdot w_{21} + 1 \cdot w_{22} + 0 \cdot w_{23} + 0.5 \cdot w_{24} + 0.8 \cdot w_{25} + 0.5 \cdot w_{26}$$

# How does Deep Learning work?

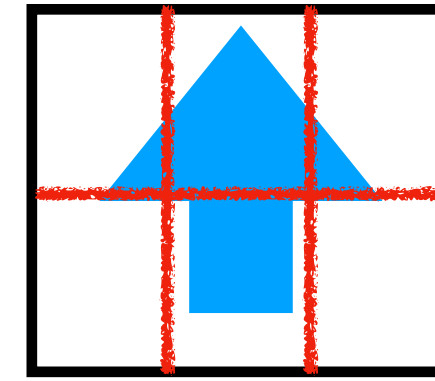
Image



Matrix

$$\begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0.8 & 0.5 \end{bmatrix}$$

Image



Matrix

$$\begin{bmatrix} 0.2 & 0.8 & 0.2 \\ 0 & 0.65 & 0 \end{bmatrix}$$

$$\sigma \left( \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0.5 \\ 0.8 \\ 0.5 \end{bmatrix} \right) = [p_{down} \quad p_{up}] \quad \sigma \left( \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0.2 \\ 0.8 \\ 0.2 \\ 0.0 \\ 0.65 \\ 0.0 \end{bmatrix} \right) = [p_{down} \quad p_{up}]$$

$$\sigma \left( \begin{bmatrix} 1 & 0 \end{bmatrix} \right) = [0.731 \quad 0.269]$$

$$\sigma \left( \begin{bmatrix} 0 & 0.4 \end{bmatrix} \right) = [0.401 \quad 0.599]$$

# How does Deep Learning work?

How does the computer learn this?

Define a loss rule  $L(w) = \frac{1}{N} \sum_i (1 - y_{down}^i) \cdot (1 - \log(p_{down})) + y_{down}^i \cdot \log p_{down}$

*Binary Cross Entropy Loss*

Guess  $w$ :  $\begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$

Compute on examples:

$$\sigma\left(\begin{bmatrix} 1 & 0 \end{bmatrix}\right) = [0.731 \quad 0.269]$$

$$L(w) = \log(0.731)$$

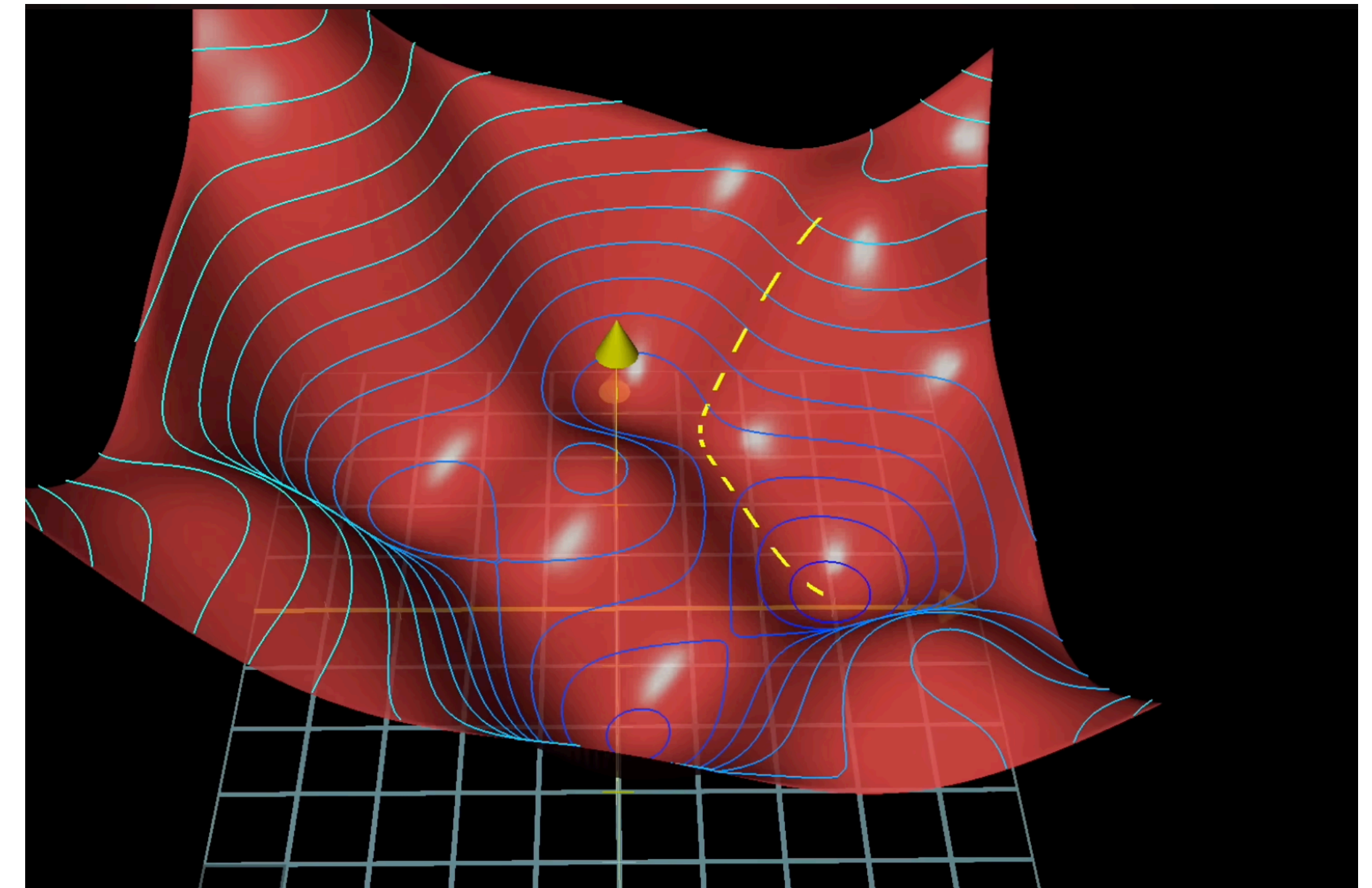
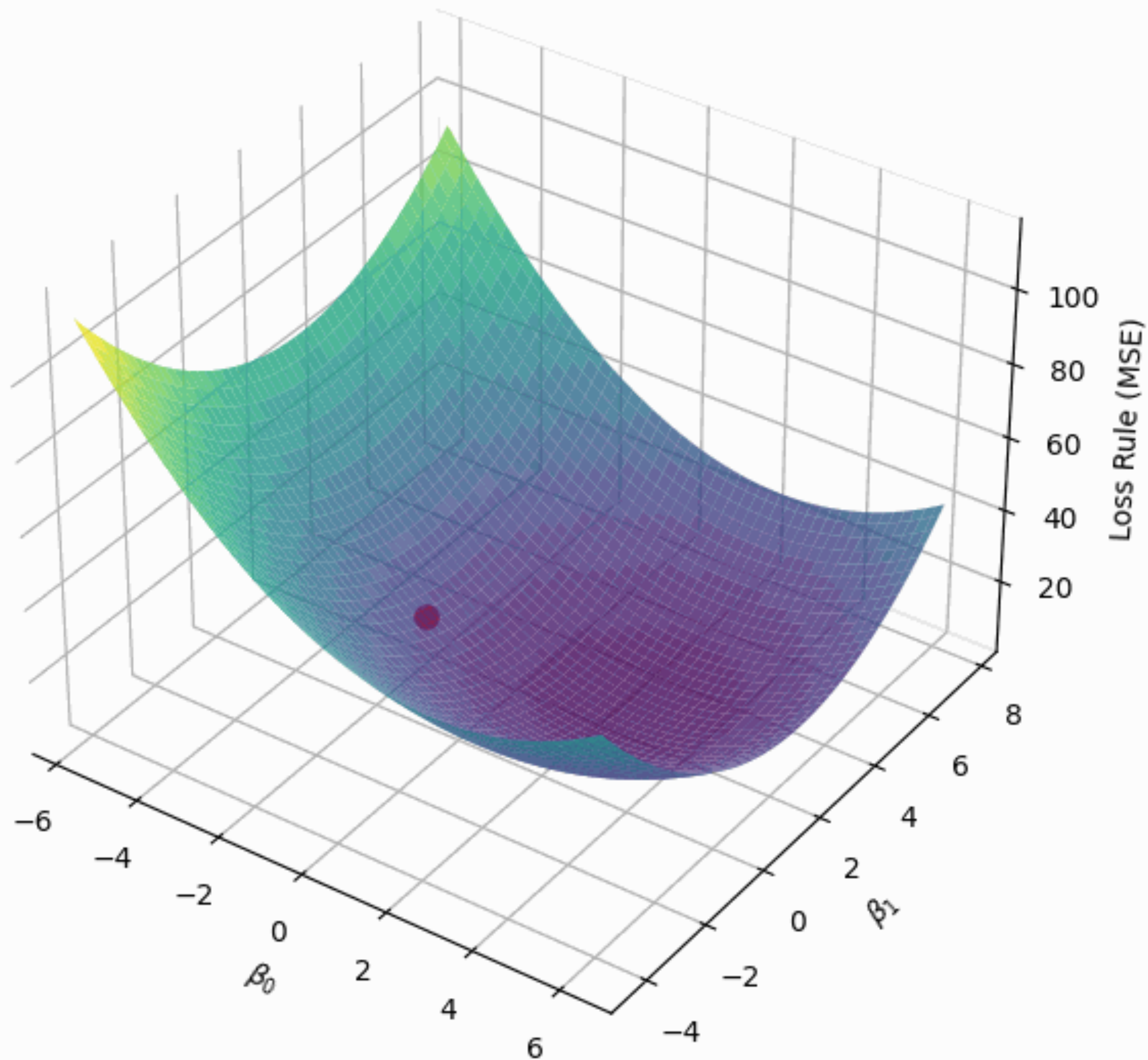
$$\sigma\left(\begin{bmatrix} 0 & 0.4 \end{bmatrix}\right) = [0.401 \quad 0.599]$$

$$L(w) = \log(1 - 0.401)$$

Compute gradient, move, and repeat!

# How does Deep Learning work?

Gradient Descent on Linear Regression Loss Surface



# Training Our Own Neural Network

Visit

<https://playground.tensorflow.org/>

Tinker With a **Neural Network** Right Here in Your Browser.  
Don't Worry, You Can't Break It. We Promise.

⏪ **▶** Epoch 000,000 Learning rate 0.03 Activation Tanh Regularization None Regularization rate 0 Problem type Classification

## DATA

Which dataset do you want to use?



Ratio of training to test data: 50%

## FEATURES

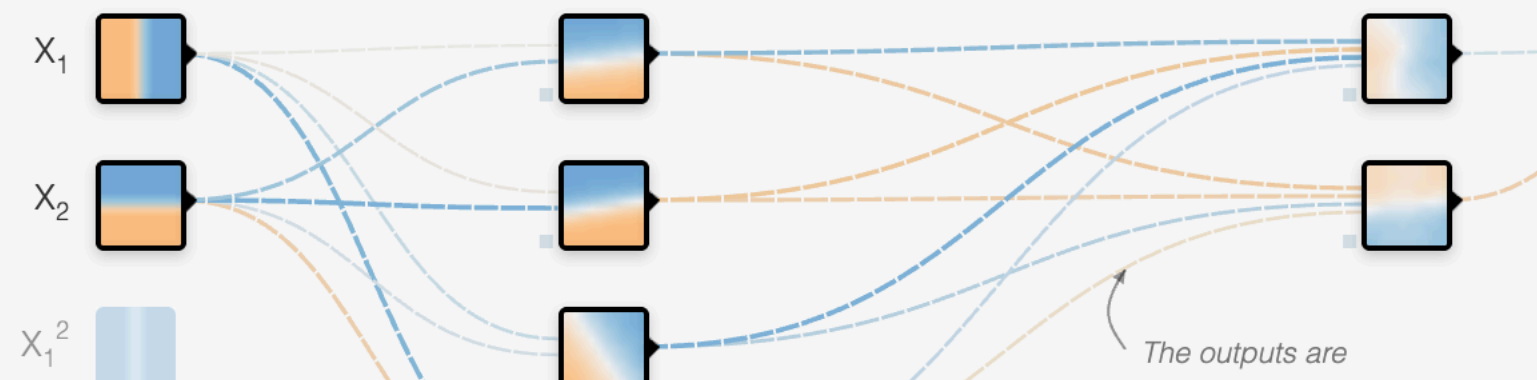
Which properties do you want to feed in?



## 2 HIDDEN LAYERS

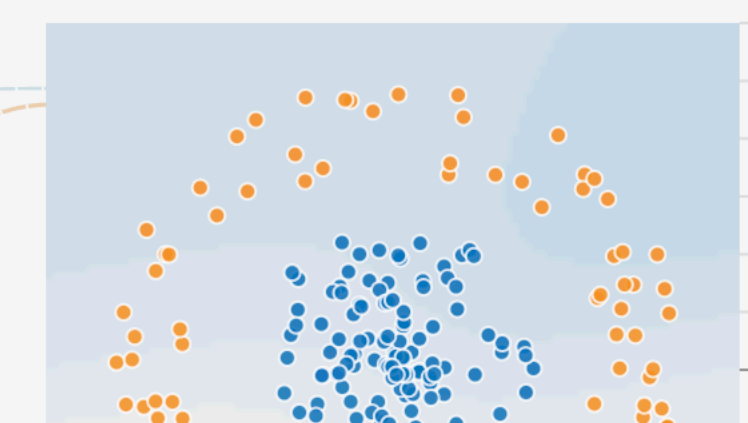
4 neurons

2 neurons



## OUTPUT

Test loss 0.516  
Training loss 0.487

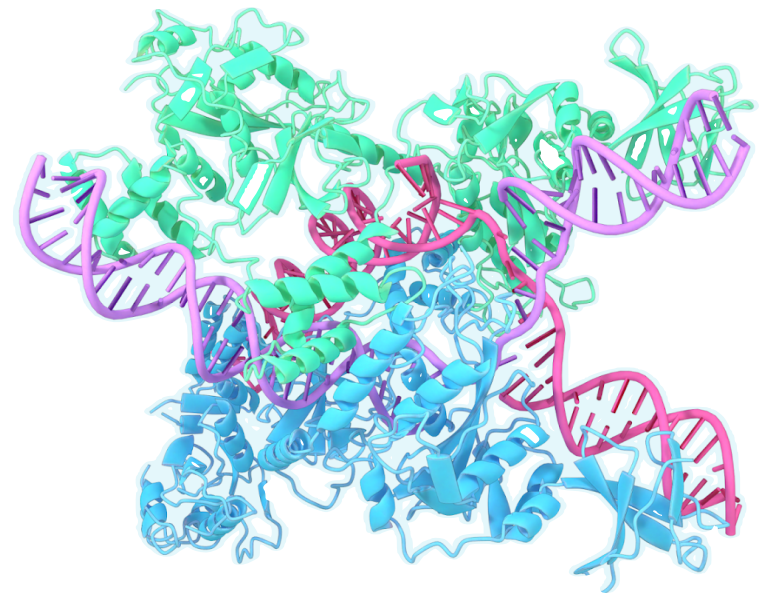


The outputs are mixed with varying

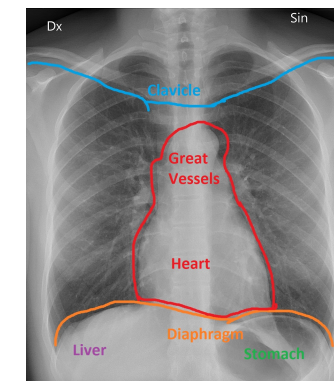
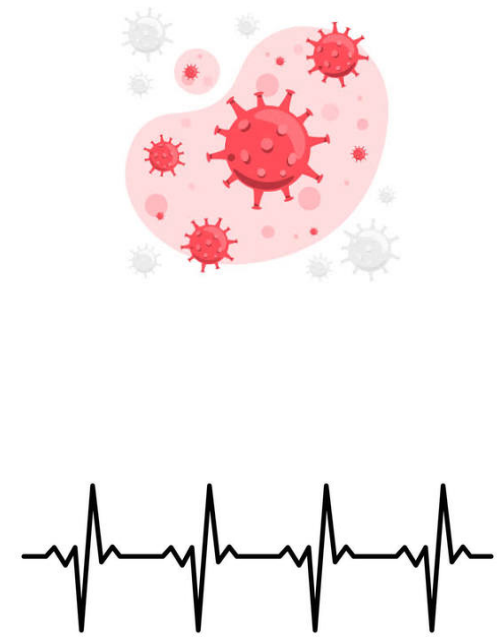
# AI for Healthcare

## Outset AI for Health Session

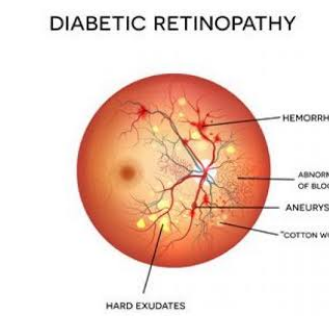
Franny Dean, July 8, 2026



Drug Development



Disease Diagnosis



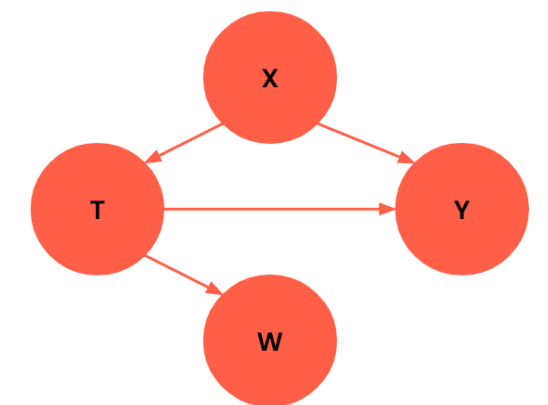
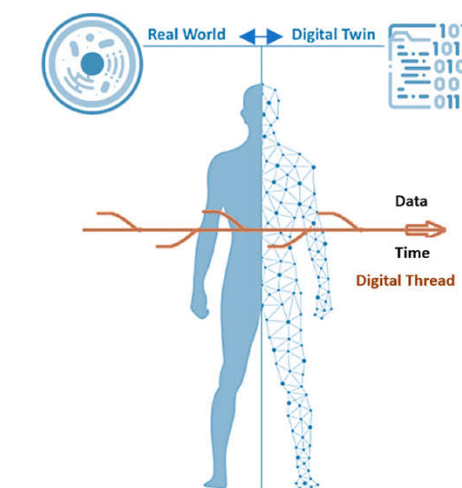
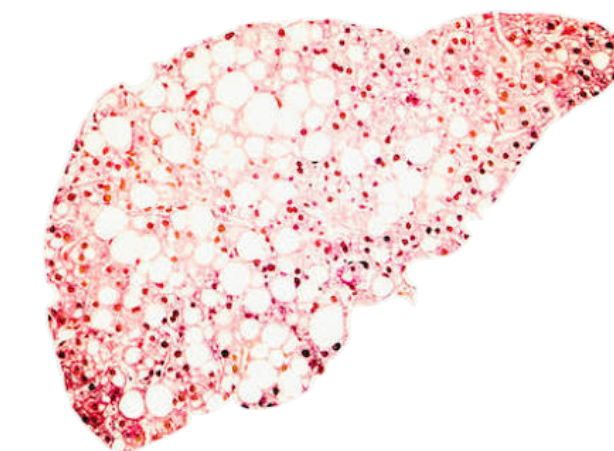
Low Resource Care



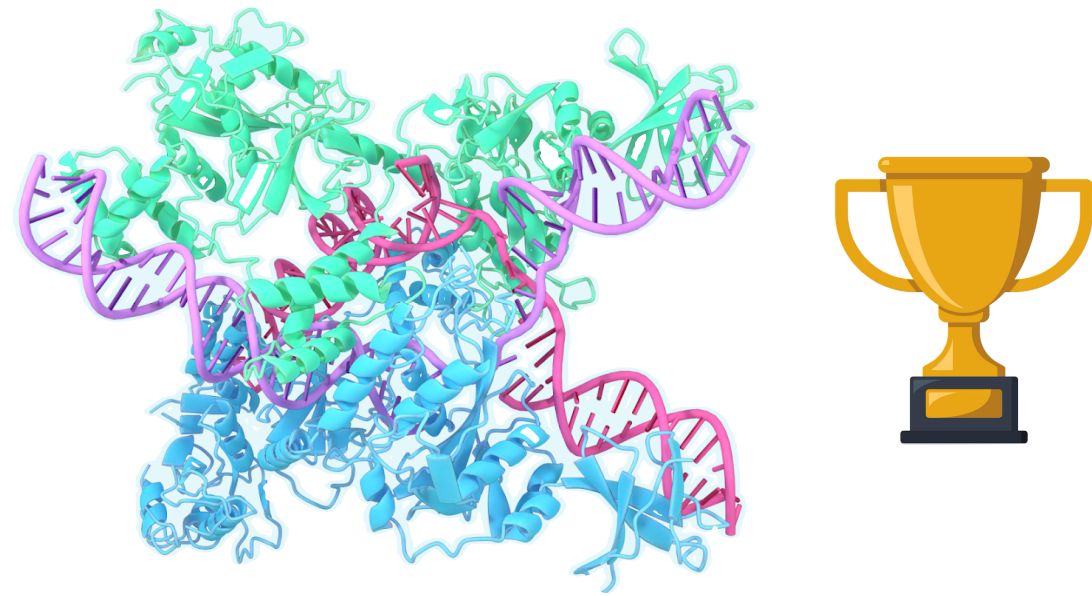
Information Retrieval



Clinical Documentation

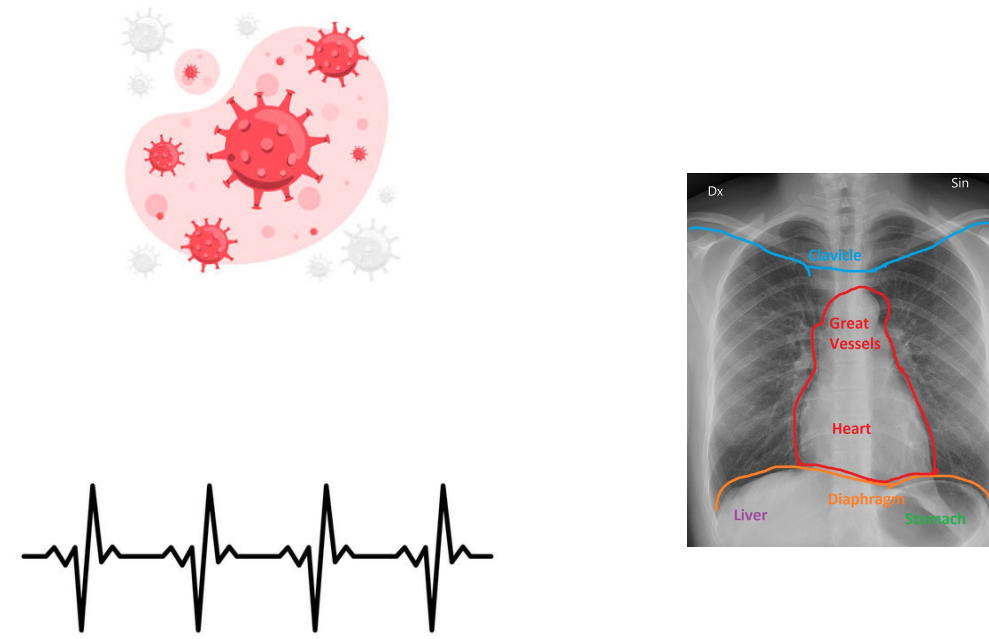


Clinical Trials



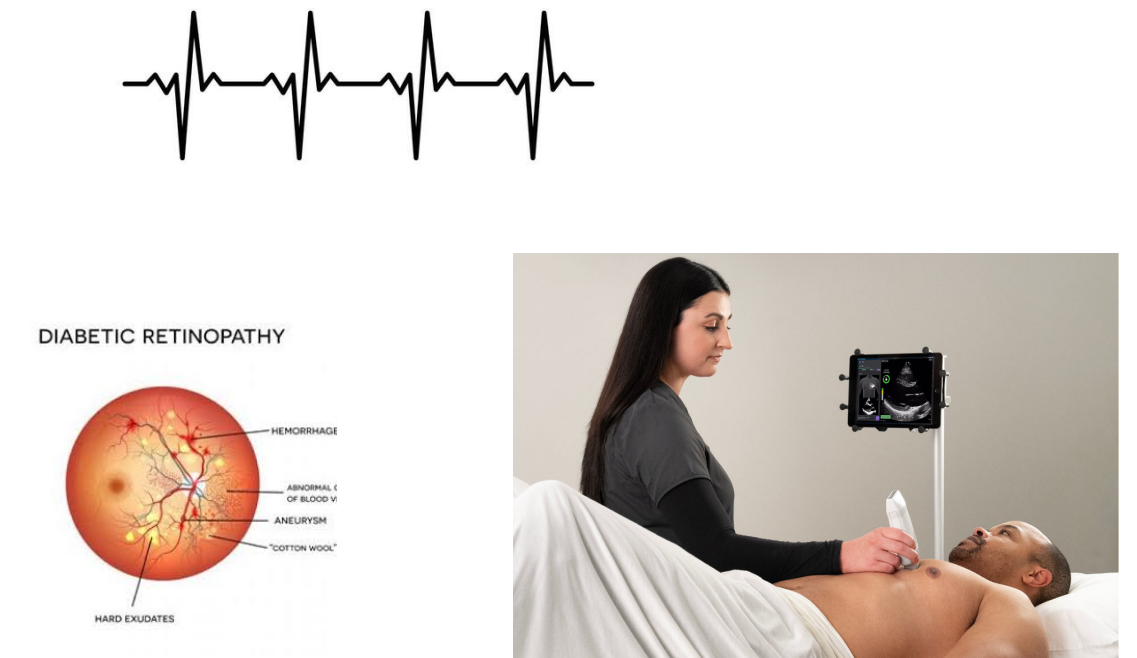
## Drug Development

Ongoing, First Drugs



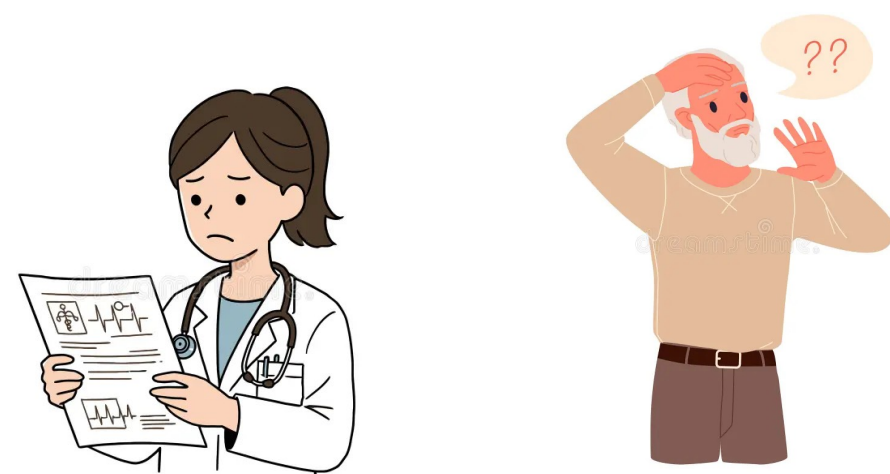
## Disease Diagnosis

Early Products



## Low Resource Care

Some Studies/Tools



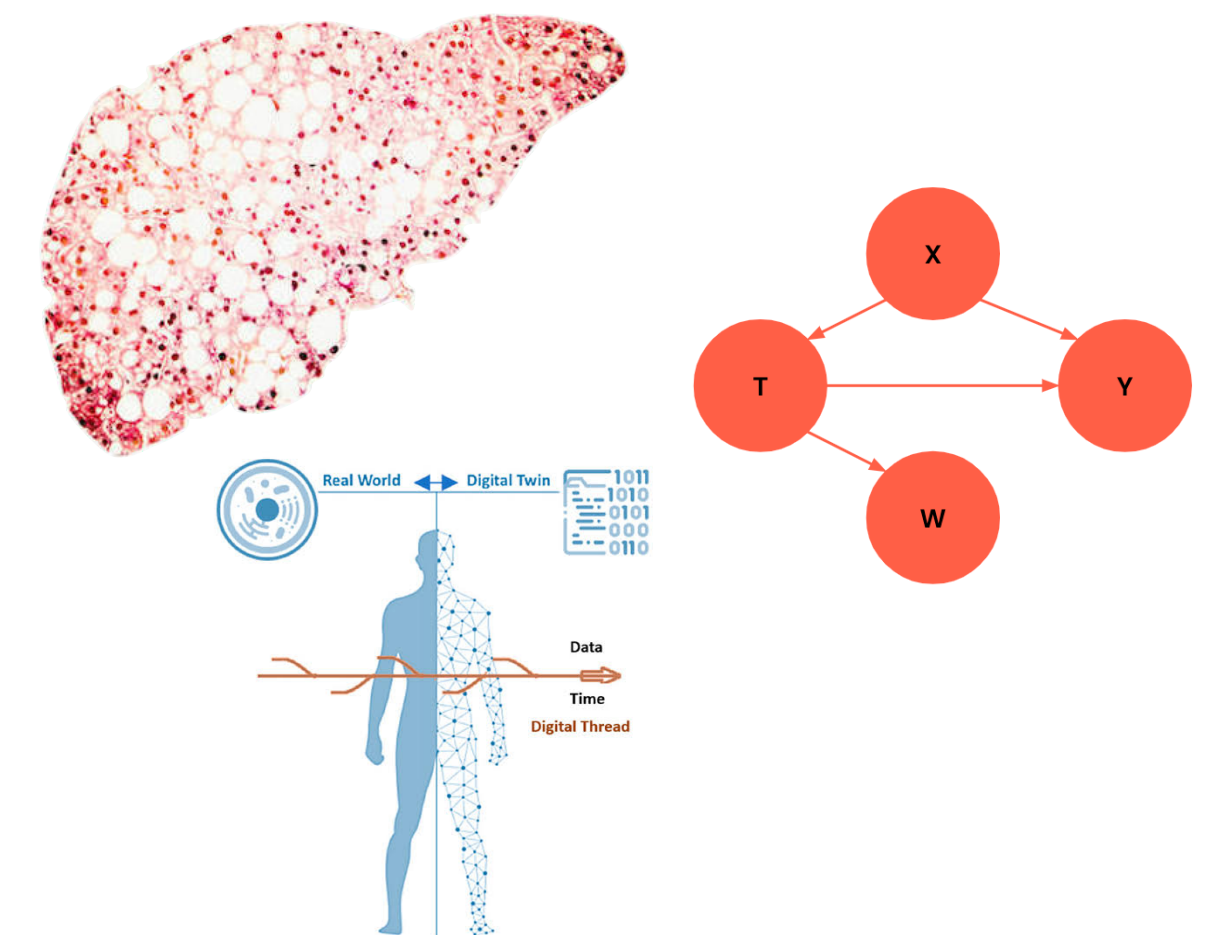
## Information Retrieval

Active Products



## Clinical Documentation

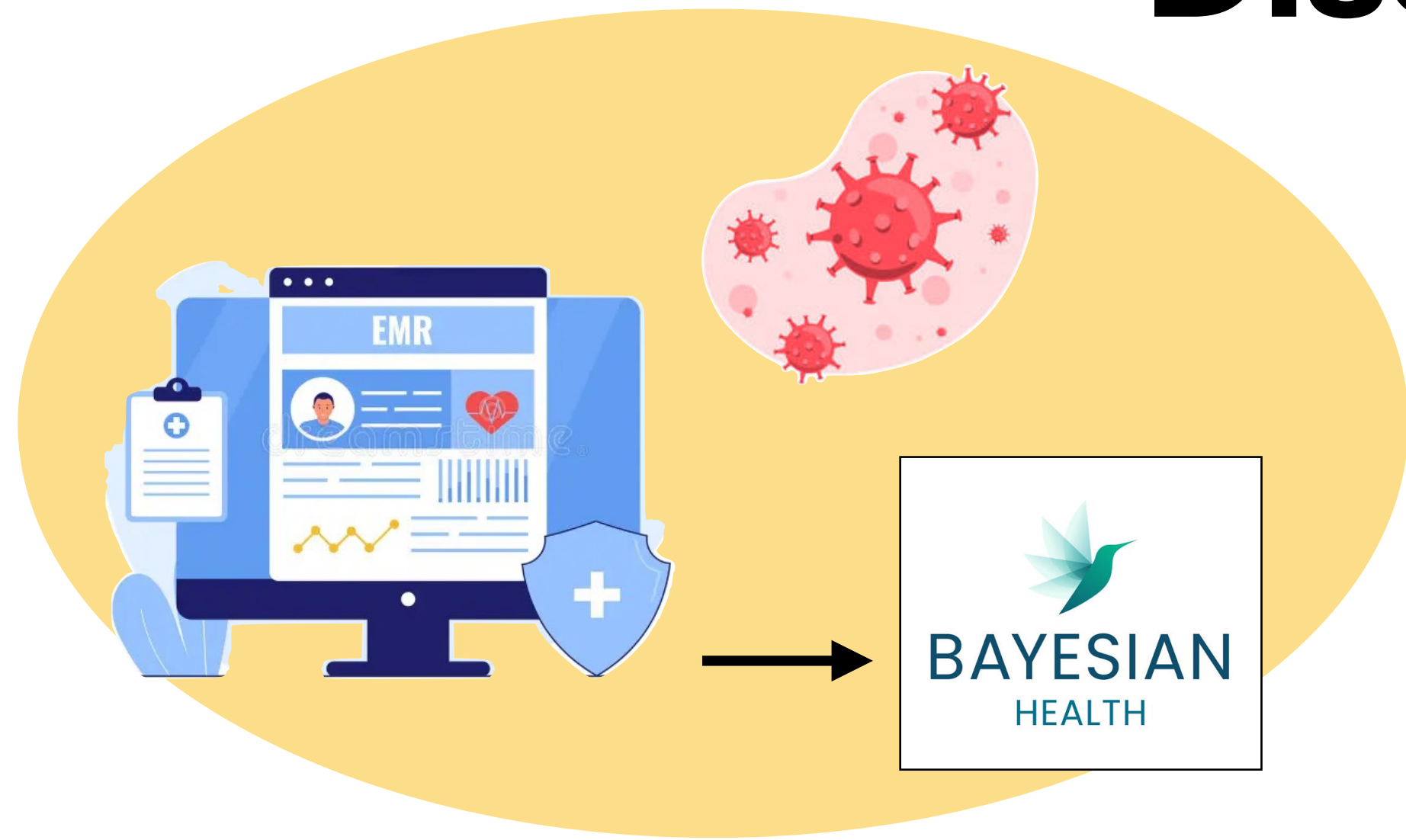
Active Products



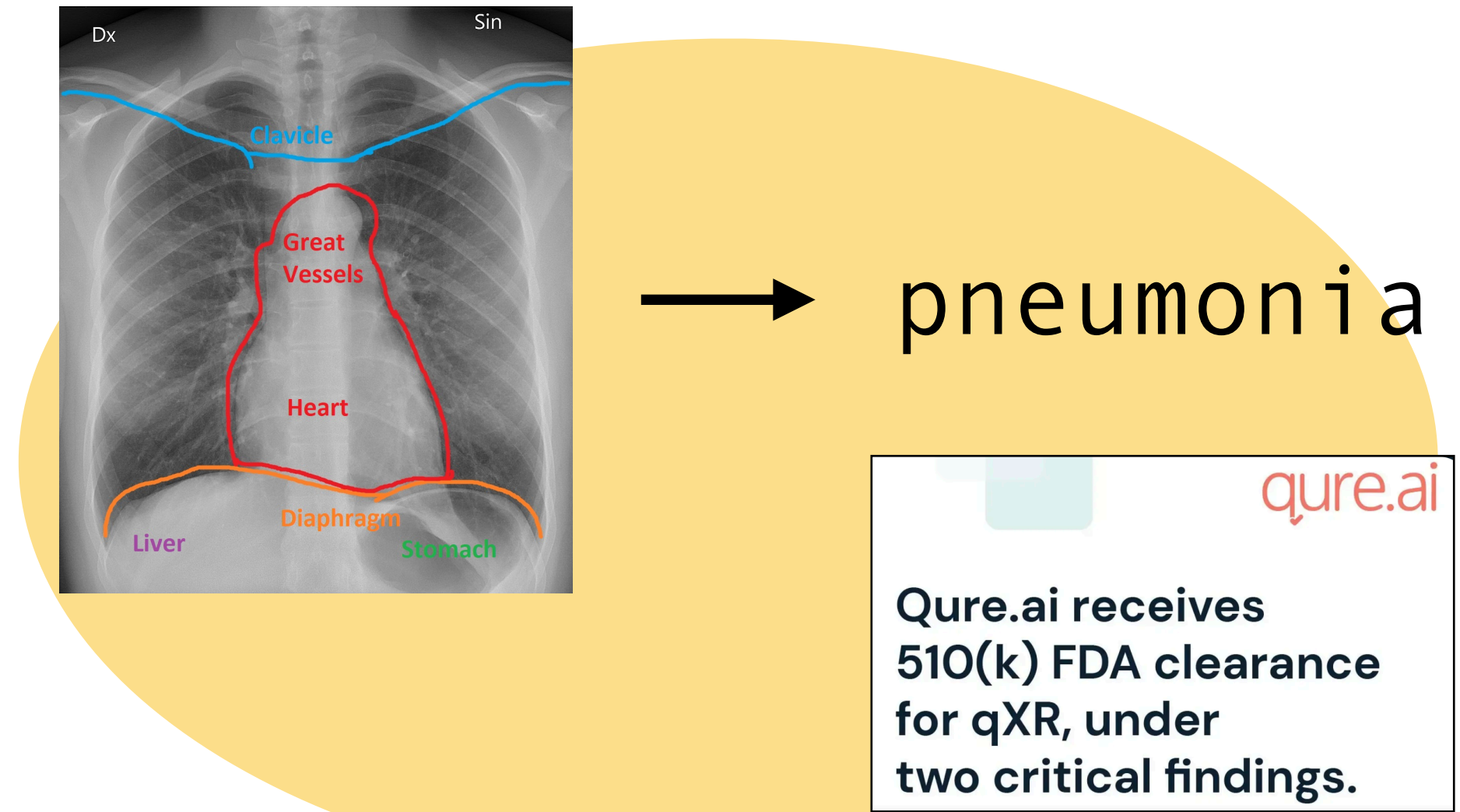
## Clinical Trials

Research and Starting

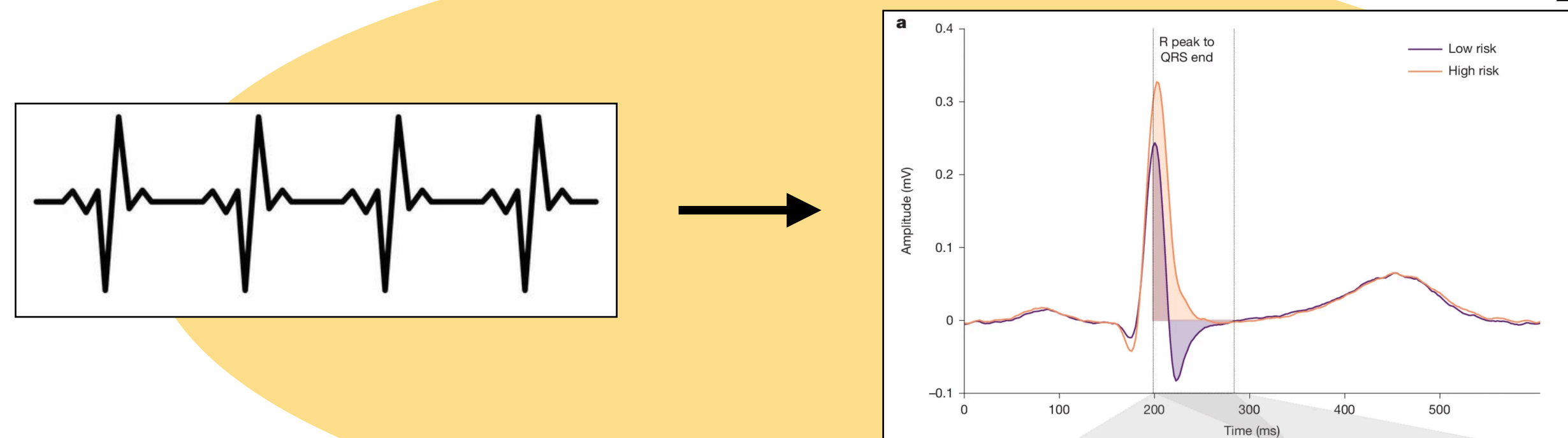
# Disease Diagnosis



**Early Sepsis Diagnosis**



**Automating Chest X-Ray Reading**

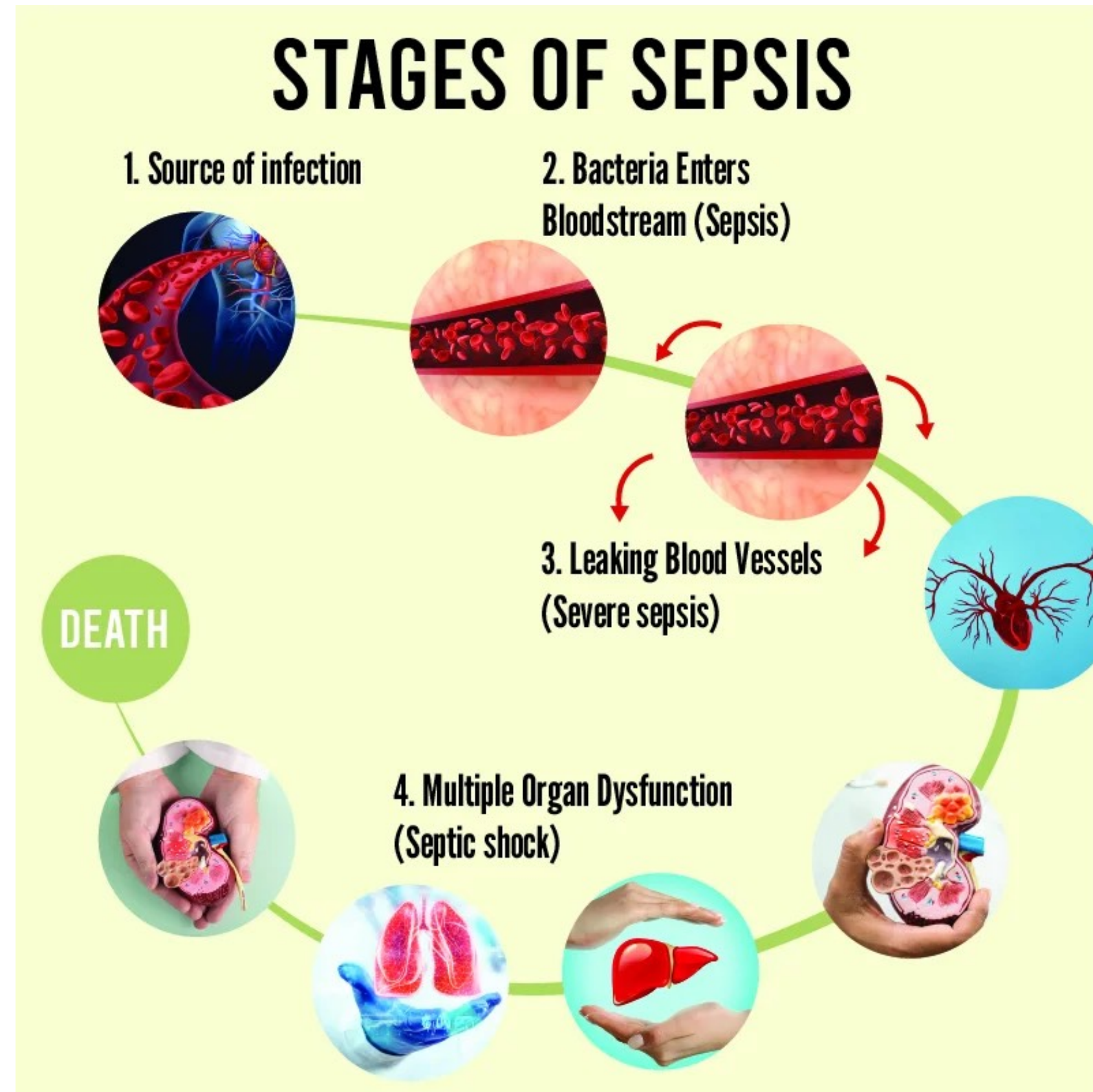


**Learning New ECG Signals**

**And many many more...**

# Early Sepsis Diagnosis

## What is sepsis?



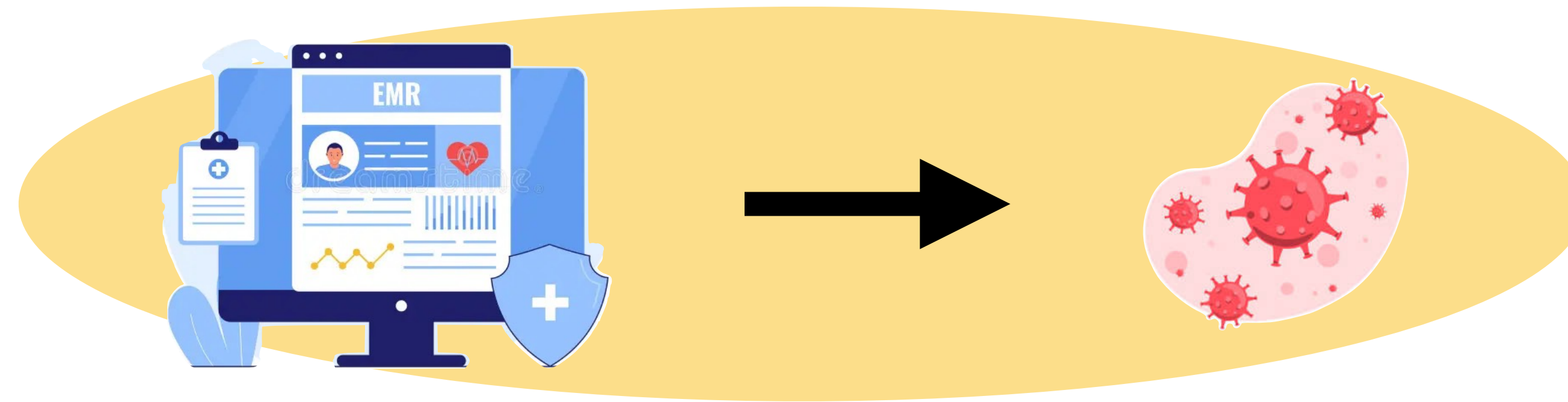
“...1.7 million adults develop sepsis every year in the United States, and more than 250,000 of them die. Sepsis is easy to miss because symptoms such as fever and confusion are also common in other conditions...”

### Sepsis

Symptoms of sepsis include:

<p><b>Fast heart rate</b></p>	<p><b>Low blood pressure</b></p>	<p><b>Fever or hypothermia</b></p>
<p><b>Shaking or chills</b></p>	<p><b>Warm or clammy/sweaty skin</b></p>	<p><b>Confusion or disorientation</b></p>
<p><b>Shortness of breath</b></p>	<p><b>Sepsis rash</b></p>	<p><b>Extreme pain or discomfort</b></p>

# Early Sepsis Diagnosis



How do we turn this into a machine learning model?



# Early Sepsis Diagnosis



Ingredients we need:

Examples (Data)

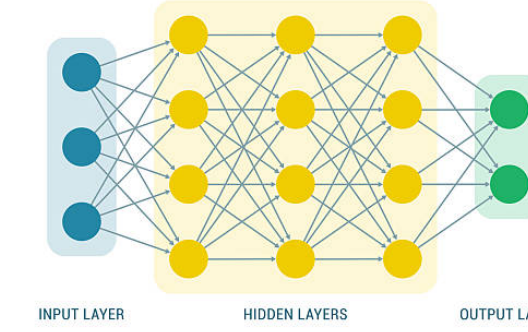
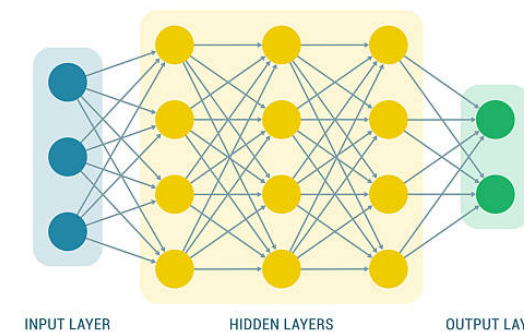
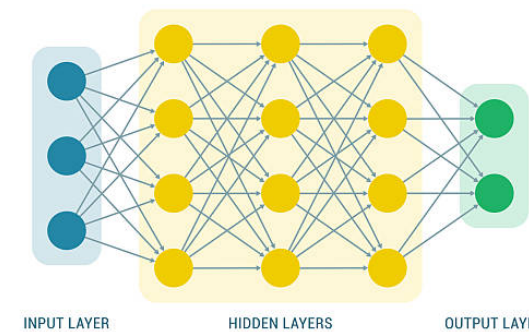


**Past records**



**Labs over time**

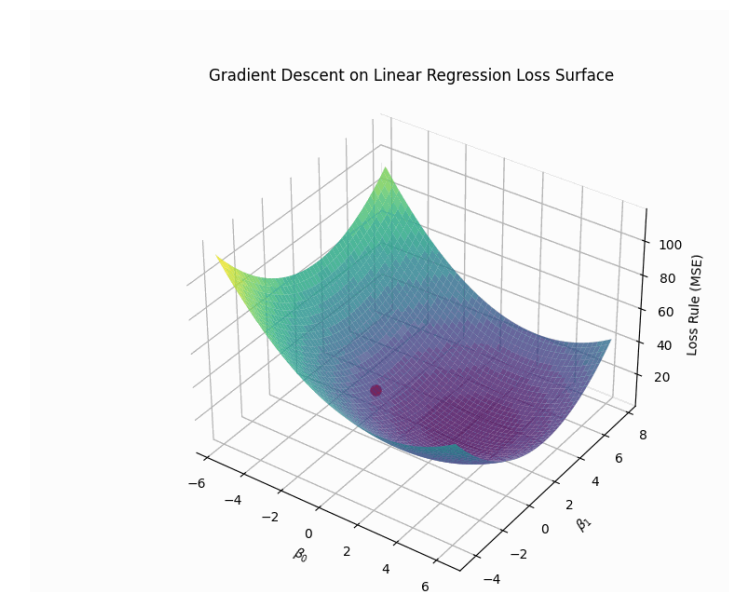
Model Structure



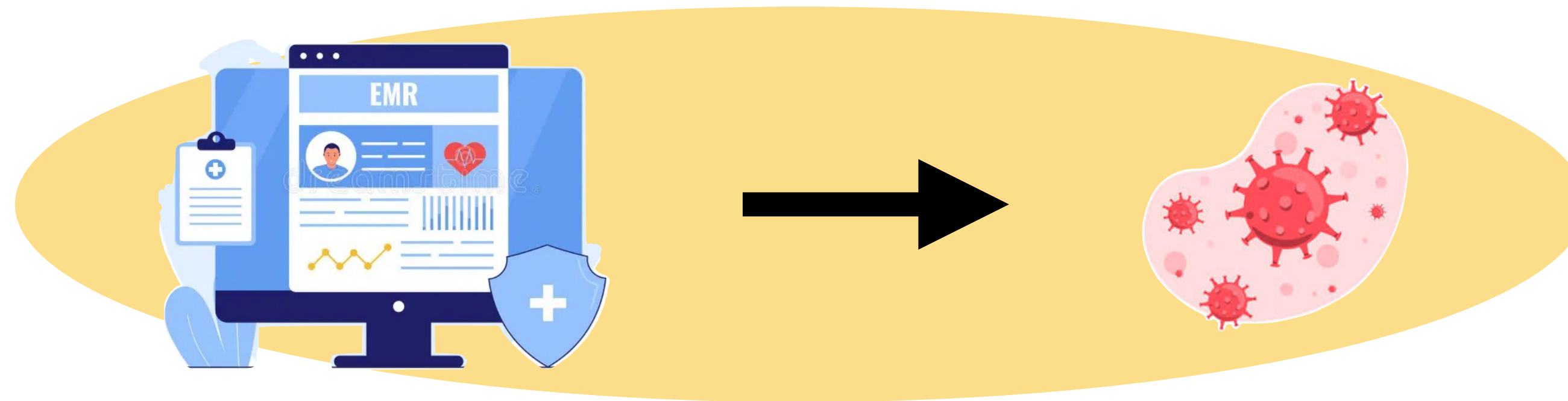
Loss Rule

$$L(w) = \frac{1}{N} \sum_i (1 - y_{down}^i) \cdot (1 - \log(p_{down})) + y_{down}^i \cdot \log p_{down}$$

Learning procedure (Gradient Descent)



# Early Sepsis Diagnosis



**Past records**

**Predictors**

+

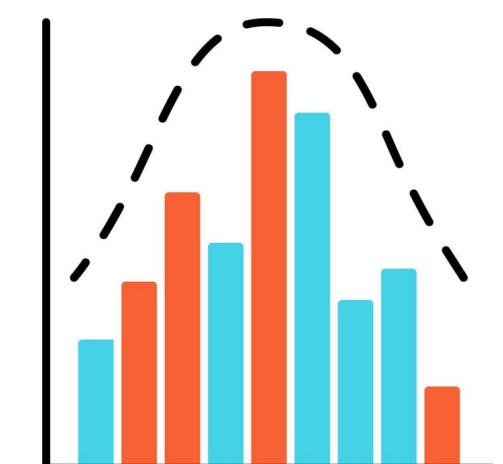


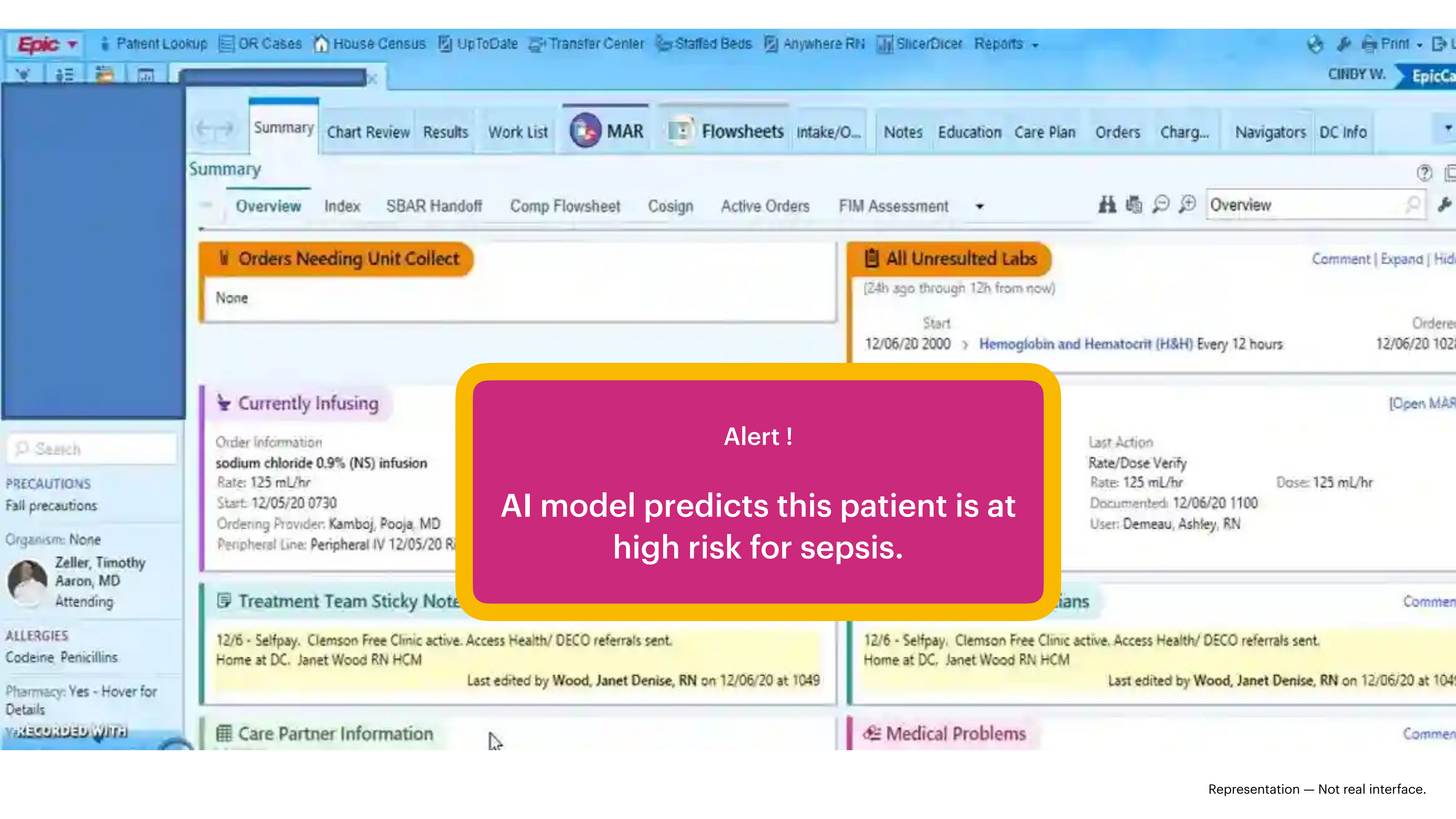
**Time series lab modeling**



**Outcome**

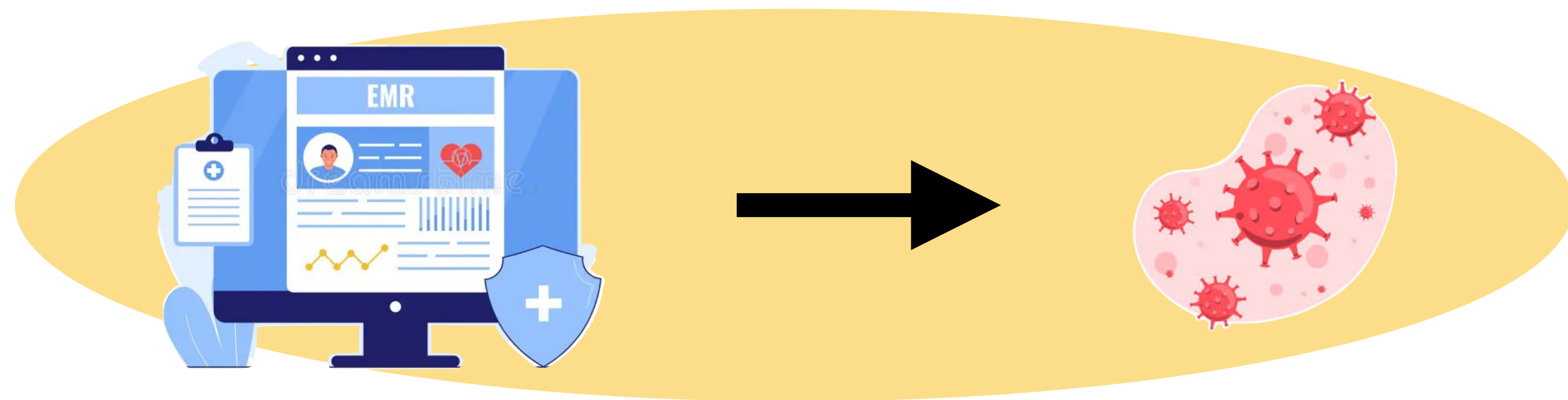
Sepsis risk score



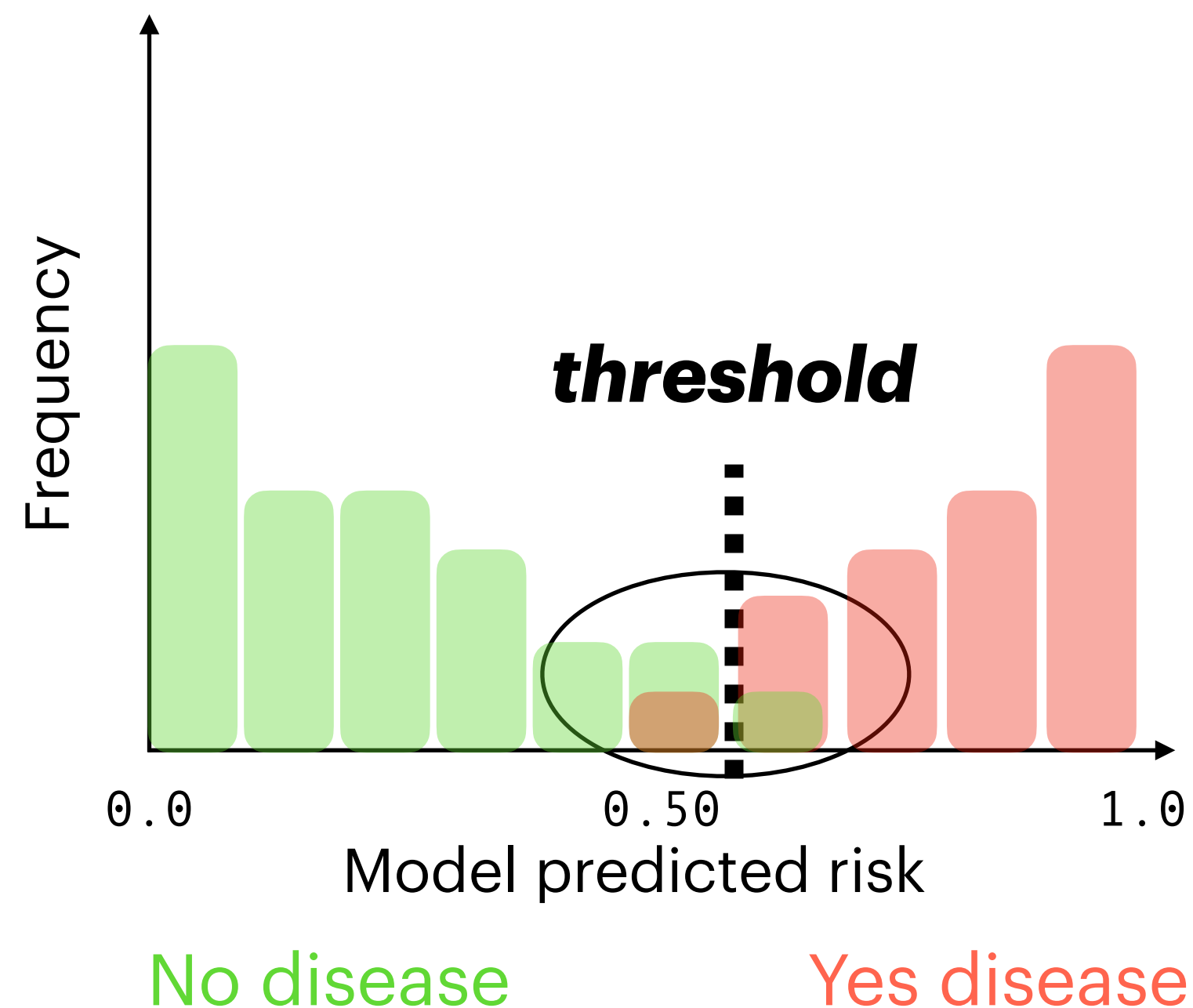
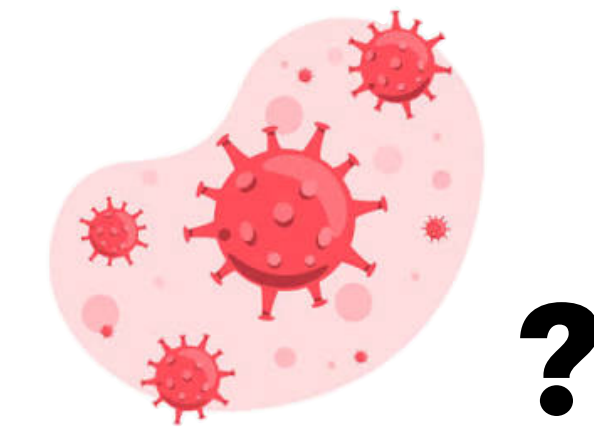


**Alert !**  
AI model predicts this patient is at high risk for sepsis.

# How do we assess how accurate AI for sepsis is?



But...



We choose a **threshold** to say likely has or does not have.

Then we count how many positives and negatives we got wrong each.

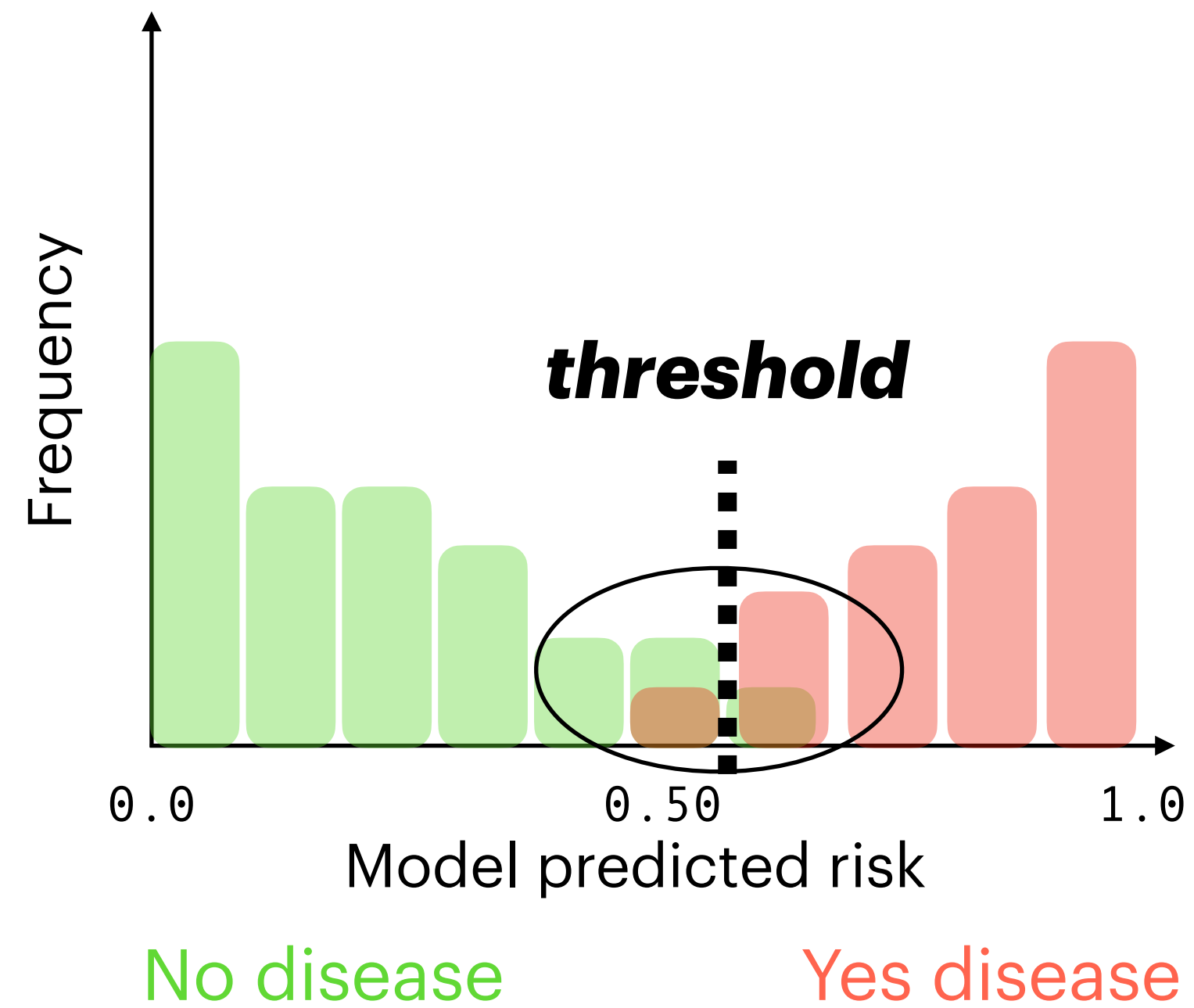
**False positive rate (FPR)** = number of negatives we got wrong

**Specificity** or **True negative rate** =  $1 - \text{FPR}$

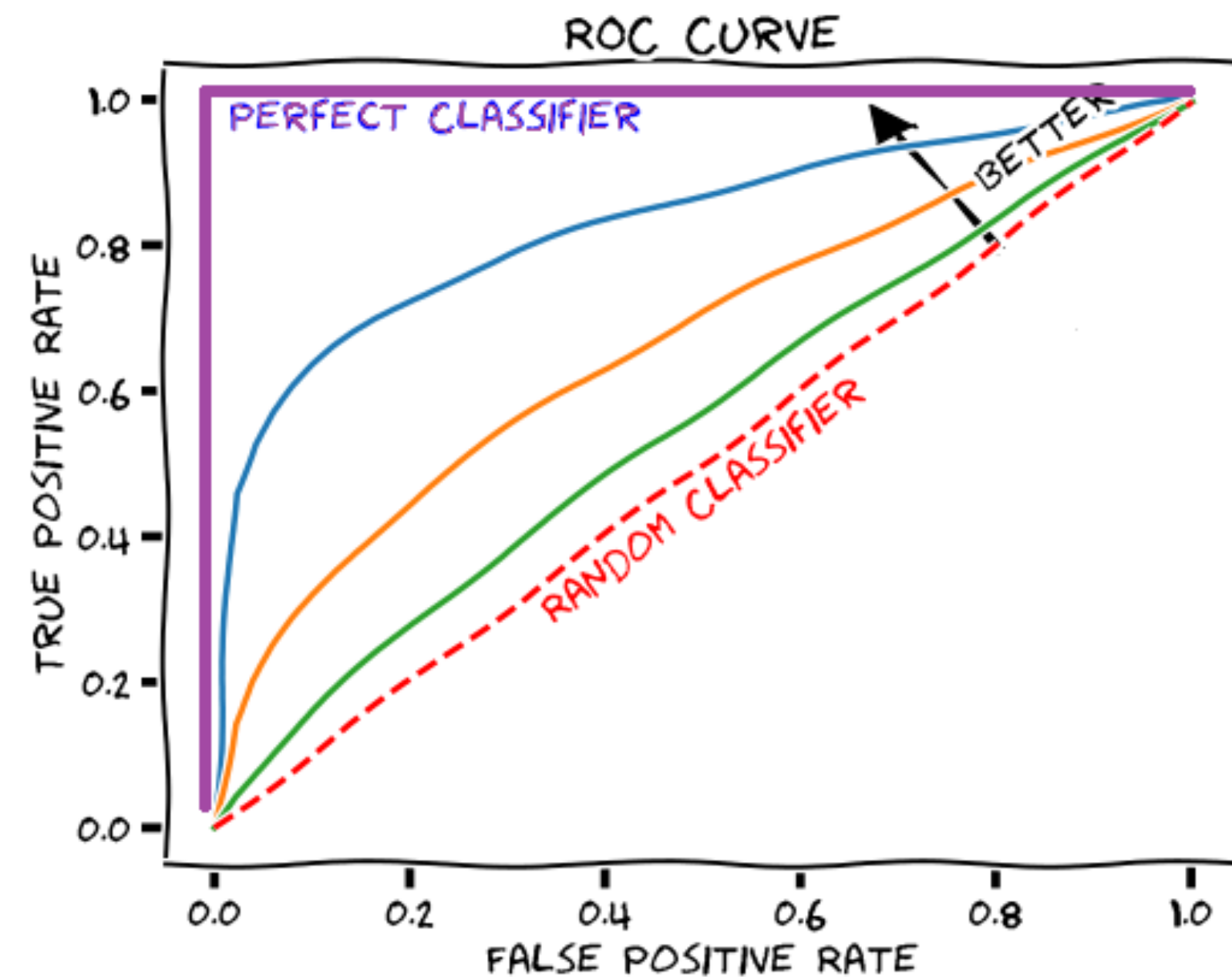
**False negative rate (FNR)** = number of positives we got wrong

**Sensitivity** or **True positive rate** =  $1 - \text{FNR}$

# How do we assess how accurate these tools are?



We compare all possible thresholds using the metric called AUROC/AUC which is the area under the following curve:



**Good AUC:** 0.70+

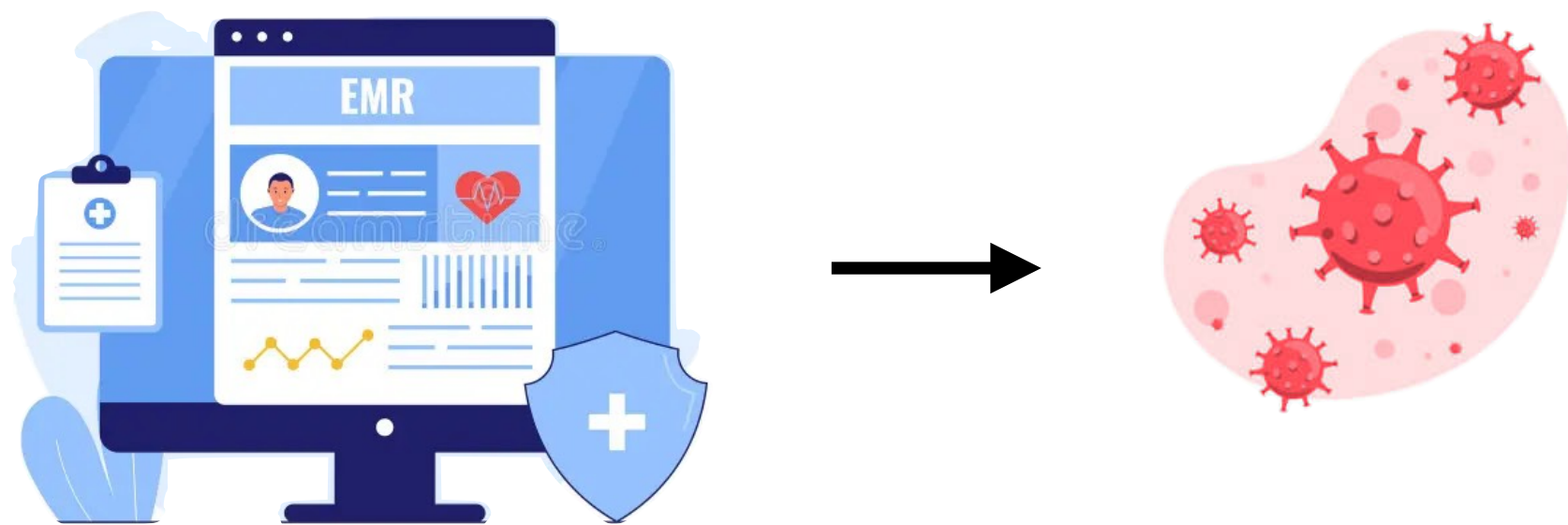
**Great AUC:** 0.80+

# Accuracy in one hospital setting does not necessarily mean accuracy in another.

# Epic

Epic deployed a model without evidence that it worked.

University of Michigan researchers showed that the algorithm missed 67% of sepsis patients and 88% of its alerts were false alarms.



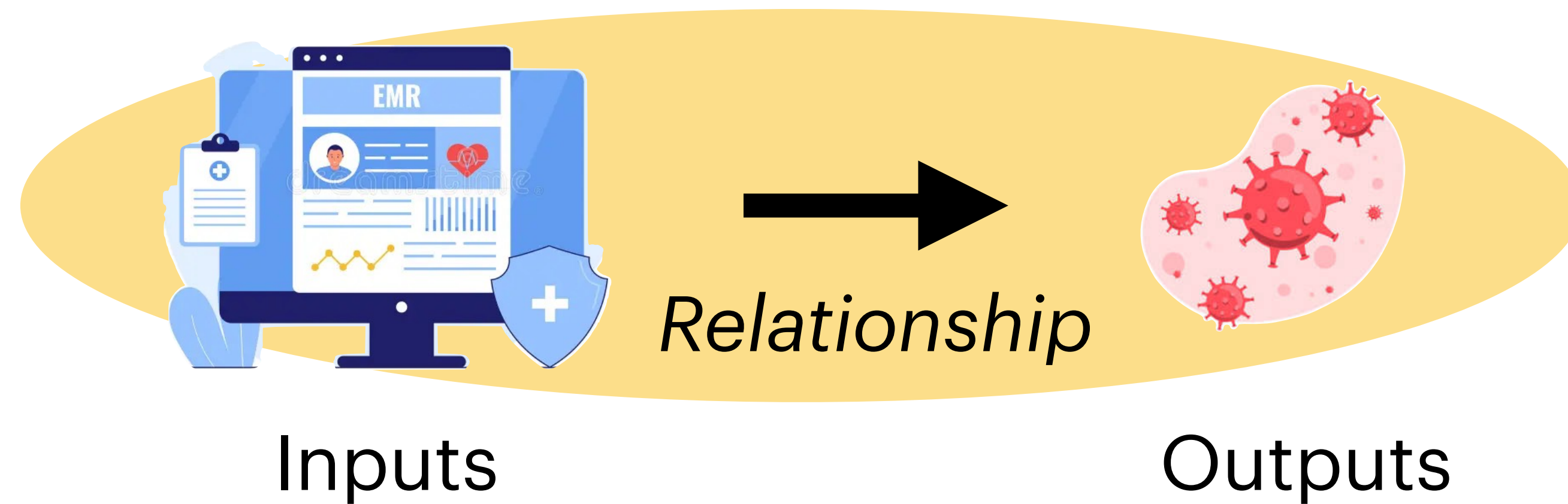
**False positive rate (FPR) = 88%**

**False negative rate (FNR) = 67%**

**Why?**

Distribution shift, lack of external validation, poor model.

# What does data distribution shift mean?



Example 3: We get a new batch of high frequency data but use different frequency reading.



*Other examples?*

**Data distribution may be shifted!**

# Healthcare AI Ingredients



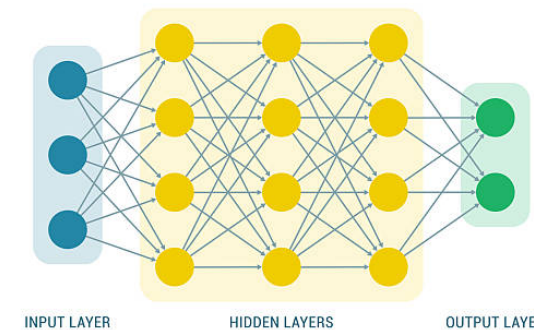
Ingredients we need in the applied setting:

## Understanding and defining the task

Examples (Data)



Model Structure



Loss Rule

$$L(w) = \frac{1}{N} \sum_i (1 - y_{down}^i) \cdot (1 - \log(p_{down})) + y_{down}^i \cdot \log p_{down}$$

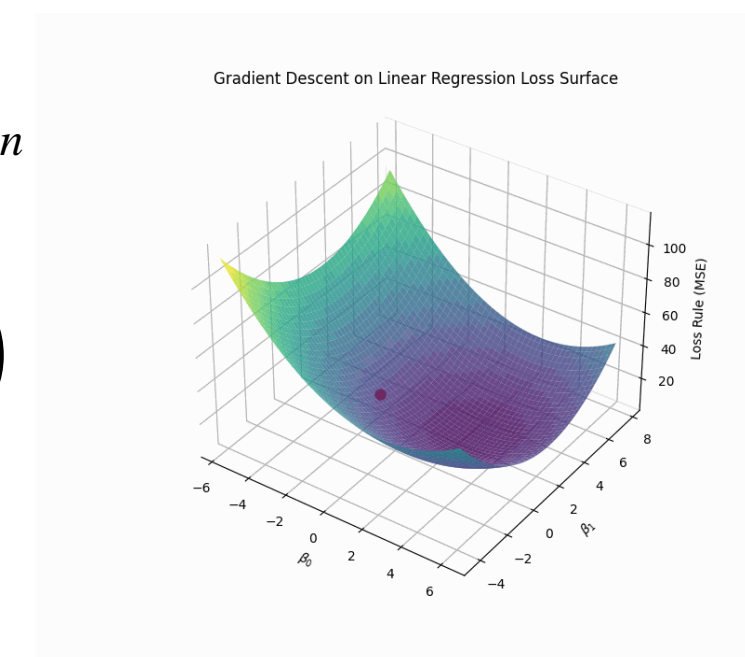
Learning procedure (Gradient Descent)

Evaluating accuracy

Repeat

Repeat

Implementing into a workflow

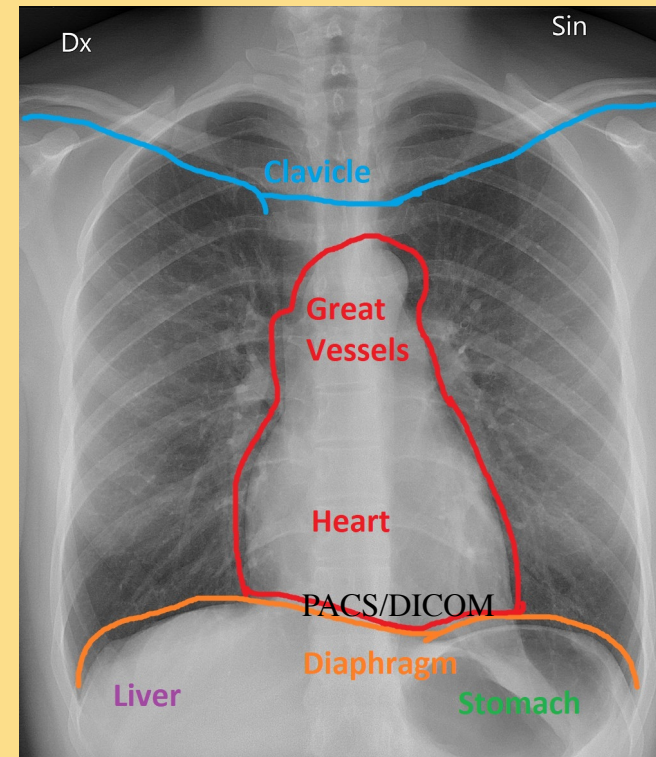


# Automating Chest X-Ray Reading



Most advanced diagnostic area?

**Multi-disease  
foundation models**



- pneumonia
- lung cancer
- clear



qure.ai

azmed

annalise.ai

Qure.ai receives  
510(k) FDA clearance  
for qXR, under  
two critical findings.

**1000+ FDA radiology approvals to date**

**aidoc**  
Always On AI

**Cognita**

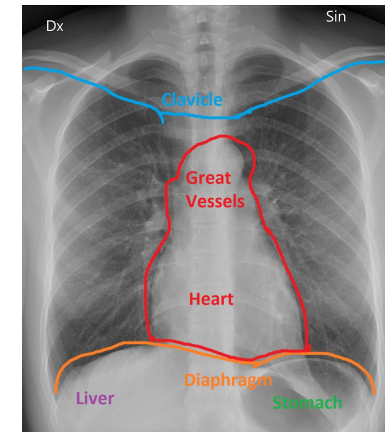
# Healthcare AI Ingredients



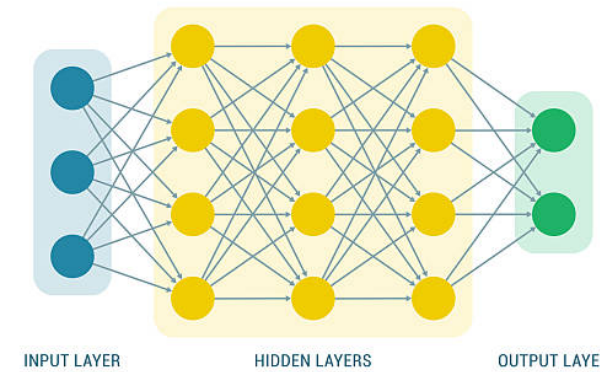
Ingredients we need in the applied setting:

## Understanding and defining the task

Examples (Data)



Model Structure



Loss Rule

$$L(w) = \frac{1}{N} \sum_i (1 - y_{down}^i) \cdot (1 - \log(p_{down})) + y_{down}^i \cdot \log p_{down}$$

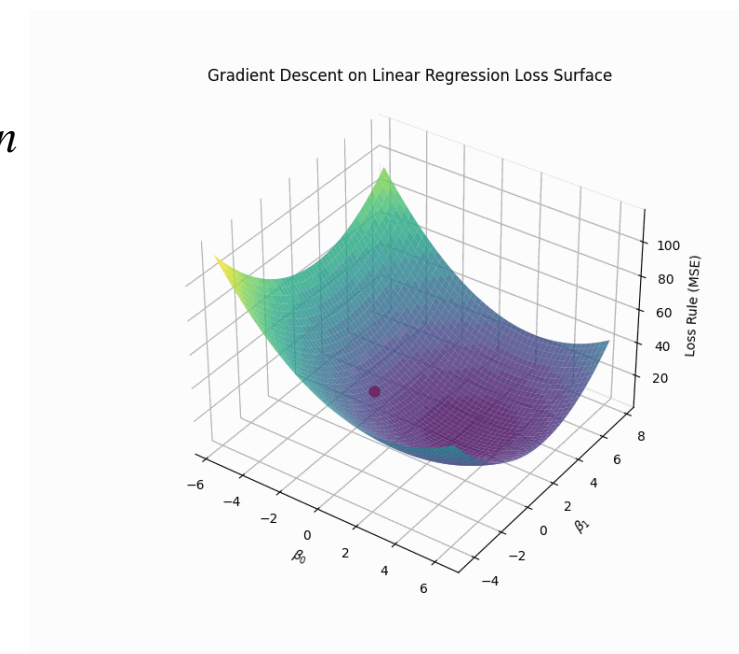
Learning procedure (Gradient Descent)

Evaluating accuracy

Repeat

Repeat

Implementing into a workflow



# How did chest x-rays AI lead the charge?



Most advanced diagnostic area?

Super common diagnostic imaging used globally

Advancements in computer vision

Large public datasets

## CheXpert: Chest X-rays



[Download here](#)

When citing this dataset in your research or other publications, please reference the following DOI: <https://doi.org/10.71718/y7pj-4v93>. Proper attribution ensures the continued accessibility and credibility of the dataset for the scientific community.

### Dataset Description

CheXpert is a dataset consisting of 224,316 chest radiographs of 65,240 patients who underwent a radiographic examination from Stanford Health Care between October 2002 and July 2017, in both inpatient and outpatient



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## MIMIC-CXR-JPG - chest radiographs with structured labels

Alistair Johnson, Matt Lungren, Yifan Peng, Zhiyong Lu, Roger Mark, Seth Berkowitz, Steven Horng

Published: Nov. 14, 2019. Version: 2.0.0 [View latest version](#)

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NATIONAL INSTITUTES OF HEALTH CHEST X-RAY DATASET AND 1 COLLABORATOR · UPDATED 8 YEARS AGO

1624

Code

Down

## NIH Chest X-rays

Over 112,000 Chest X-ray images from more than 30,000 unique patients

Key Takeaway #1:



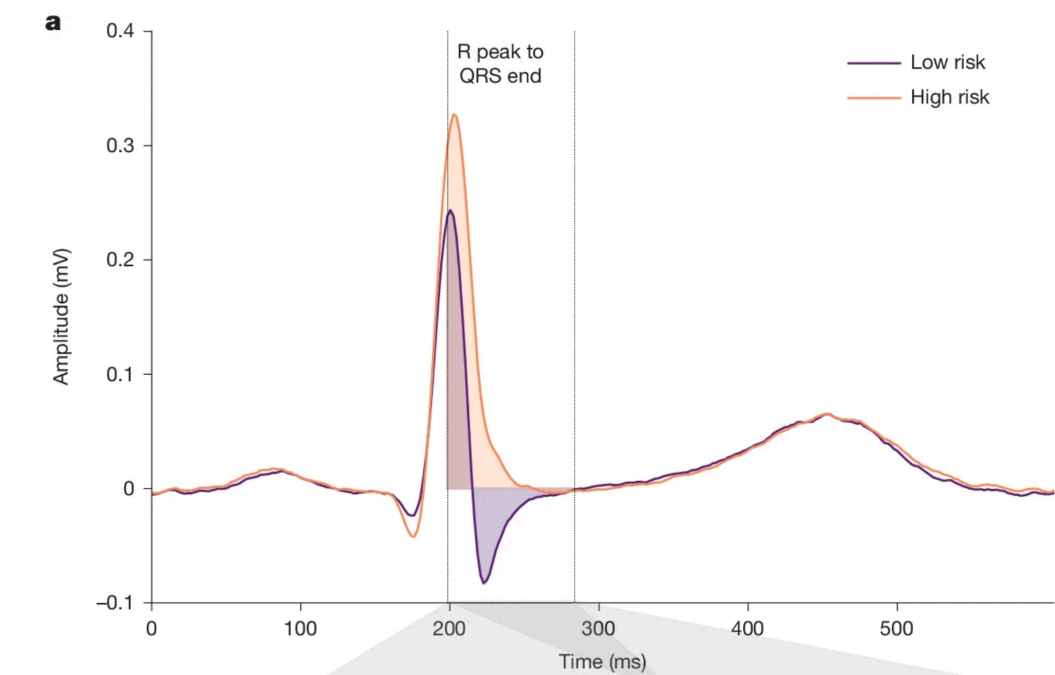
**Having data from **multiple institutions** is critical to build accurate robust AI for healthcare!**

# Electrocardiography and AI

New company predicting heart failure signals.

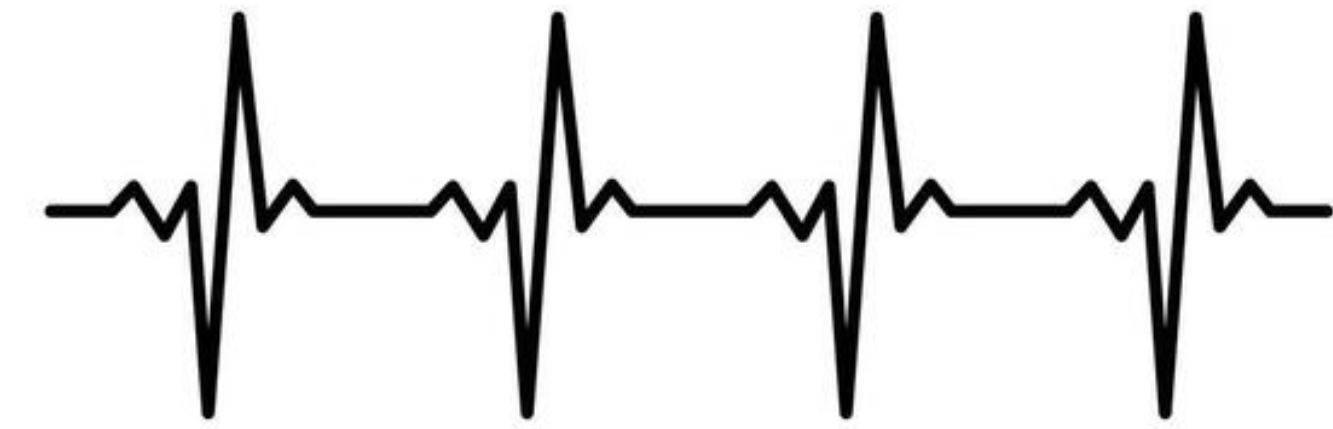


New research finding a visual signal of sudden cardiac death.

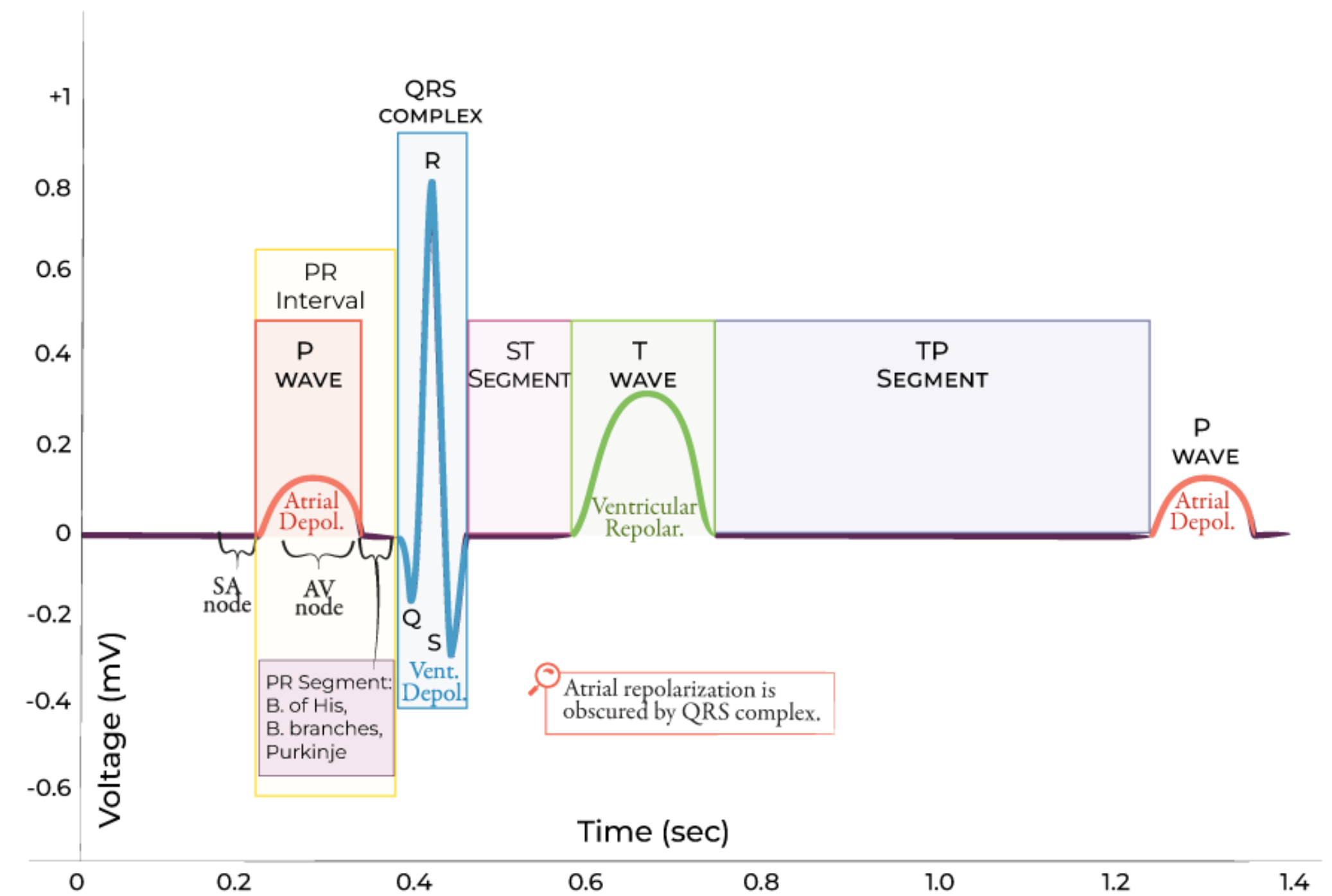


## Why ECGs?

# What's an ECG?



Electrocardiogram



Cheap, non-invasive

# Healthcare AI Ingredients

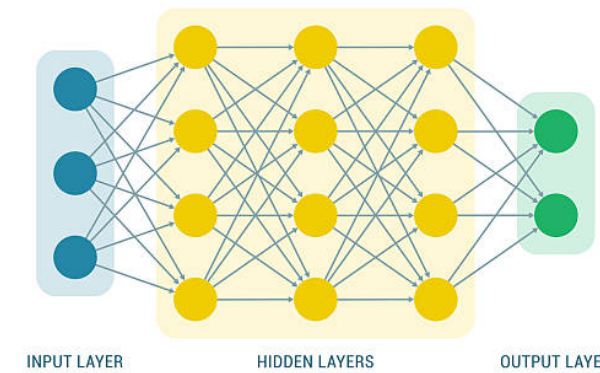


What ingredients of the process are ECGs good for?

Understanding and defining the task

Examples (Data)

Model Structure



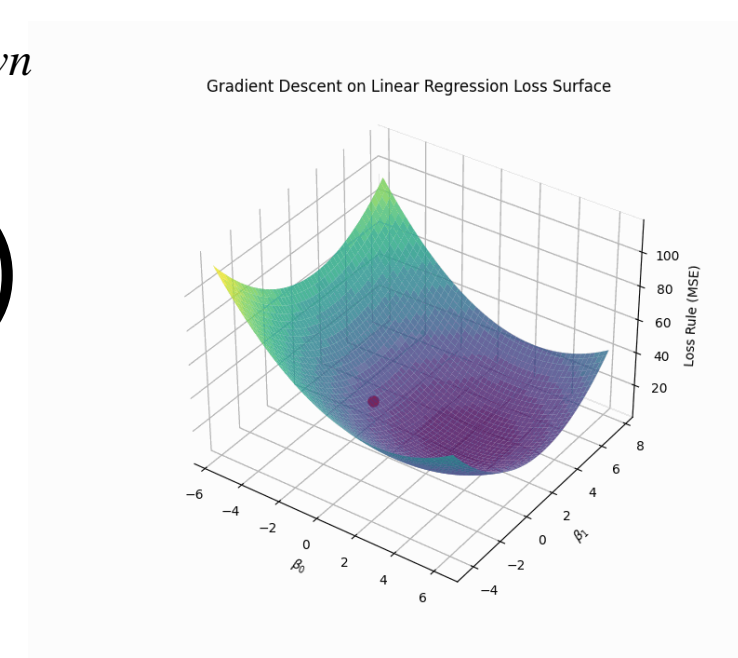
Loss Rule 
$$L(w) = \frac{1}{N} \sum_i (1 - y_{down}^i) \cdot (1 - \log(p_{down})) + y_{down}^i \cdot \log p_{down}$$

Learning procedure (Gradient Descent)

Evaluating accuracy

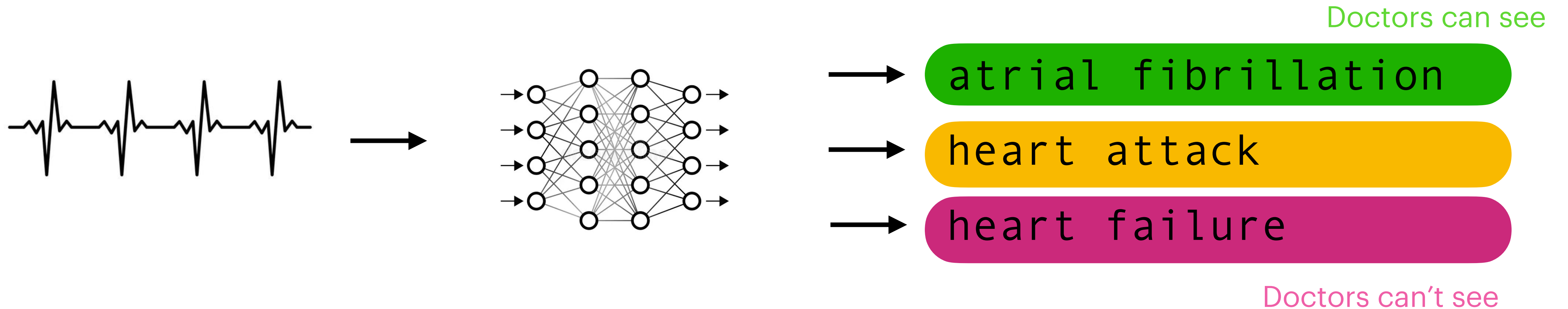


Implementing into a workflow



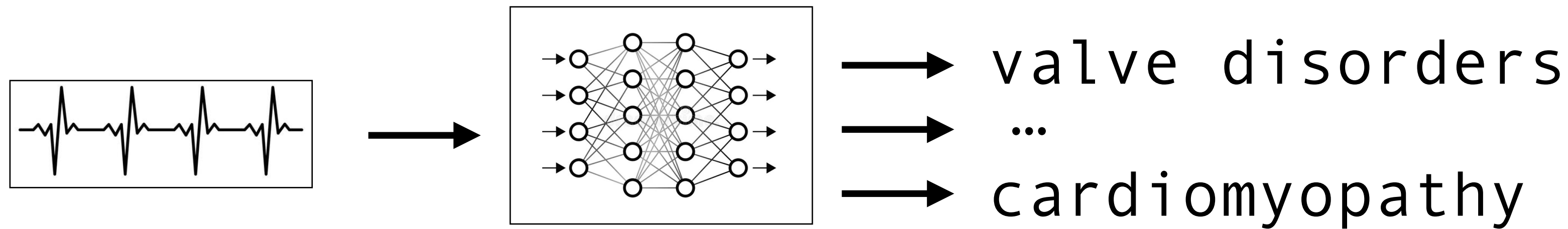
# Learning New ECG Signals

There are many models predicting cardiovascular disease from ECGs.



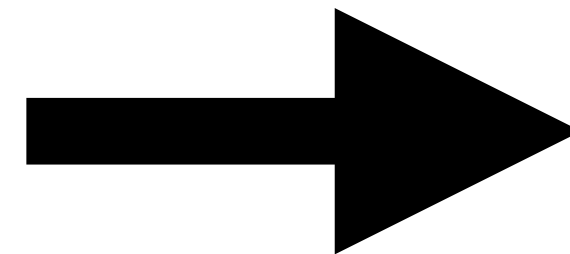
# AI ECG models Predict Heart Failure

Trained a deep learning model on ECGs with high accuracy.



**New non-invasive, cheap signal  
for structural heart diseases!**

Launch of company!



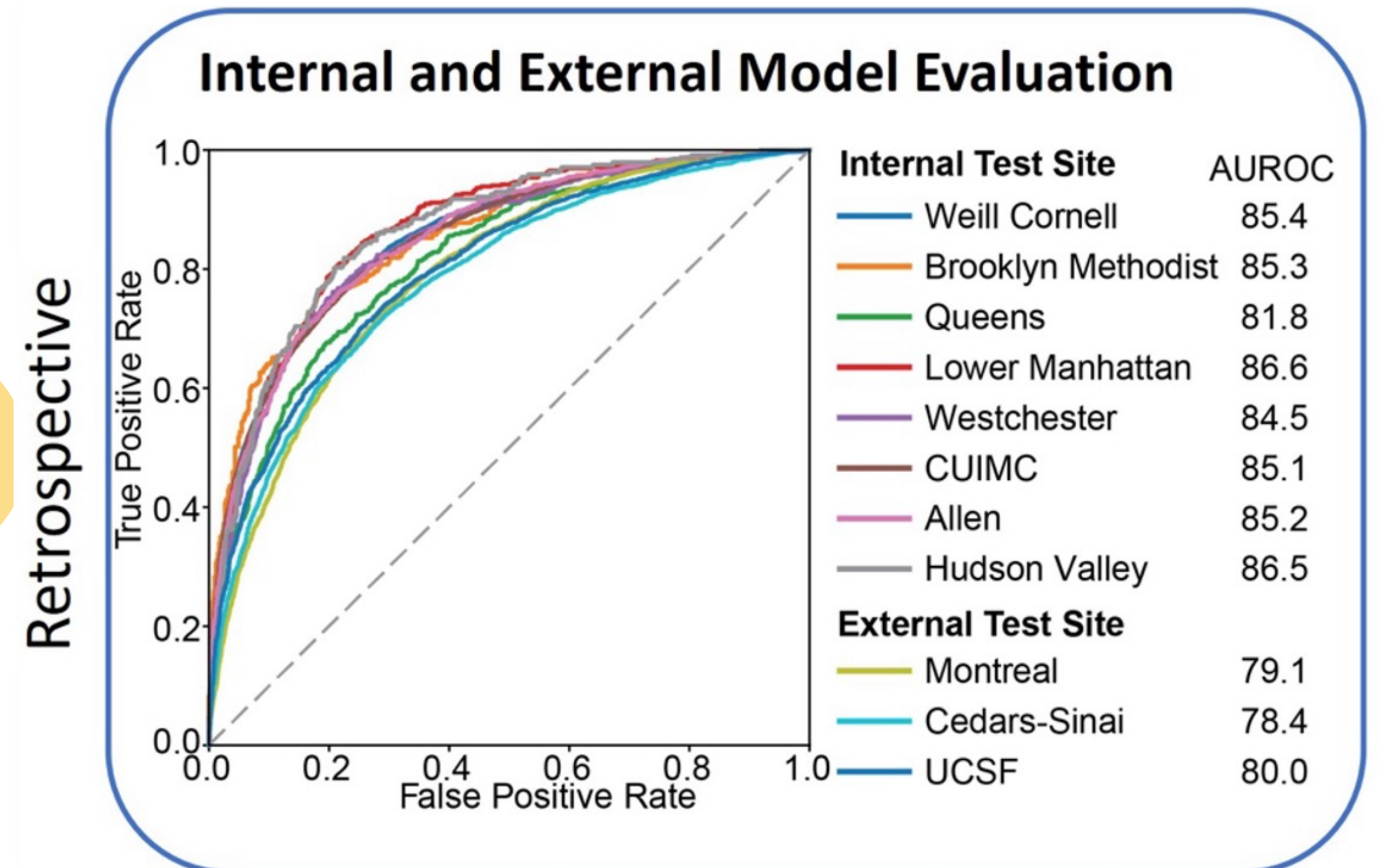
# Pathway to PathwayLabs



NewYork-  
Presbyterian

1. Train model
2. Validate model in past data
3. Validate model in past data from external sources

**“How well does model predict past outcomes?”**



# Pathway to PathwayLabs



NewYork-  
Presbyterian

1. Train model
2. Validate model in past data
3. Validate model in past data from external sources
4. Prospective test of AI model



**Without model**

**“How well does model  
predict future outcomes?”**



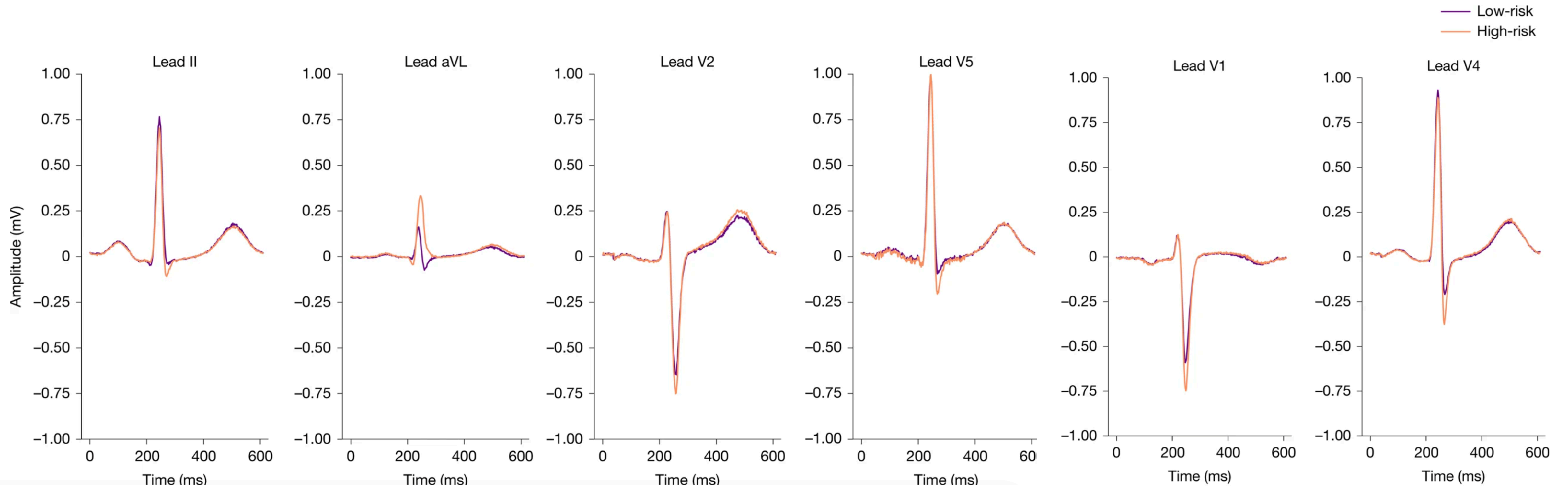
**With model**

# Pathway to PathwayLabs

- 1. Train model
- 2. Validate model in past data
- 3. Validate model in past data from external sources
- 4. Prospective test of AI model
- 5. FDA approval

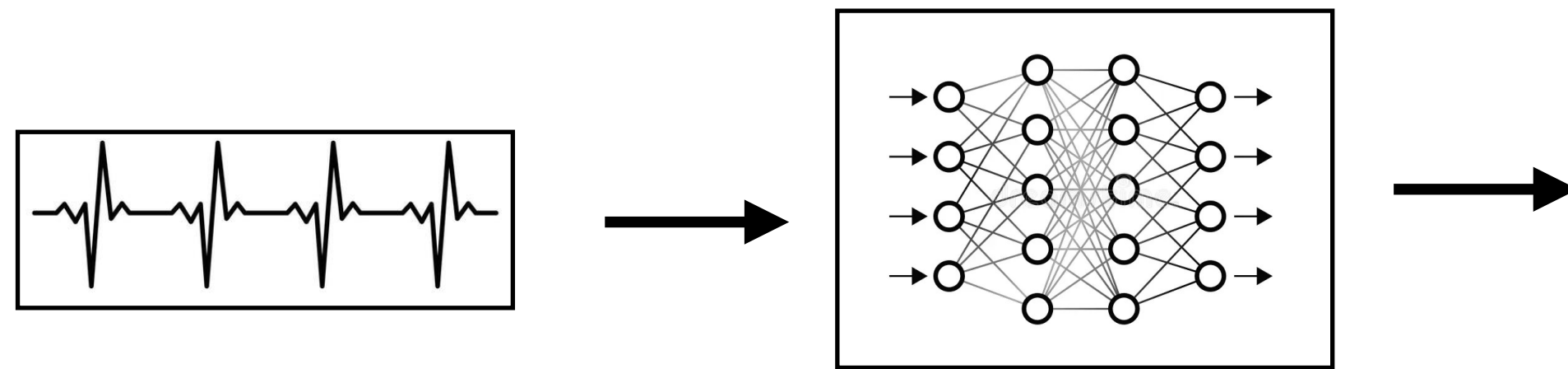


# Can you see an ECG feature?

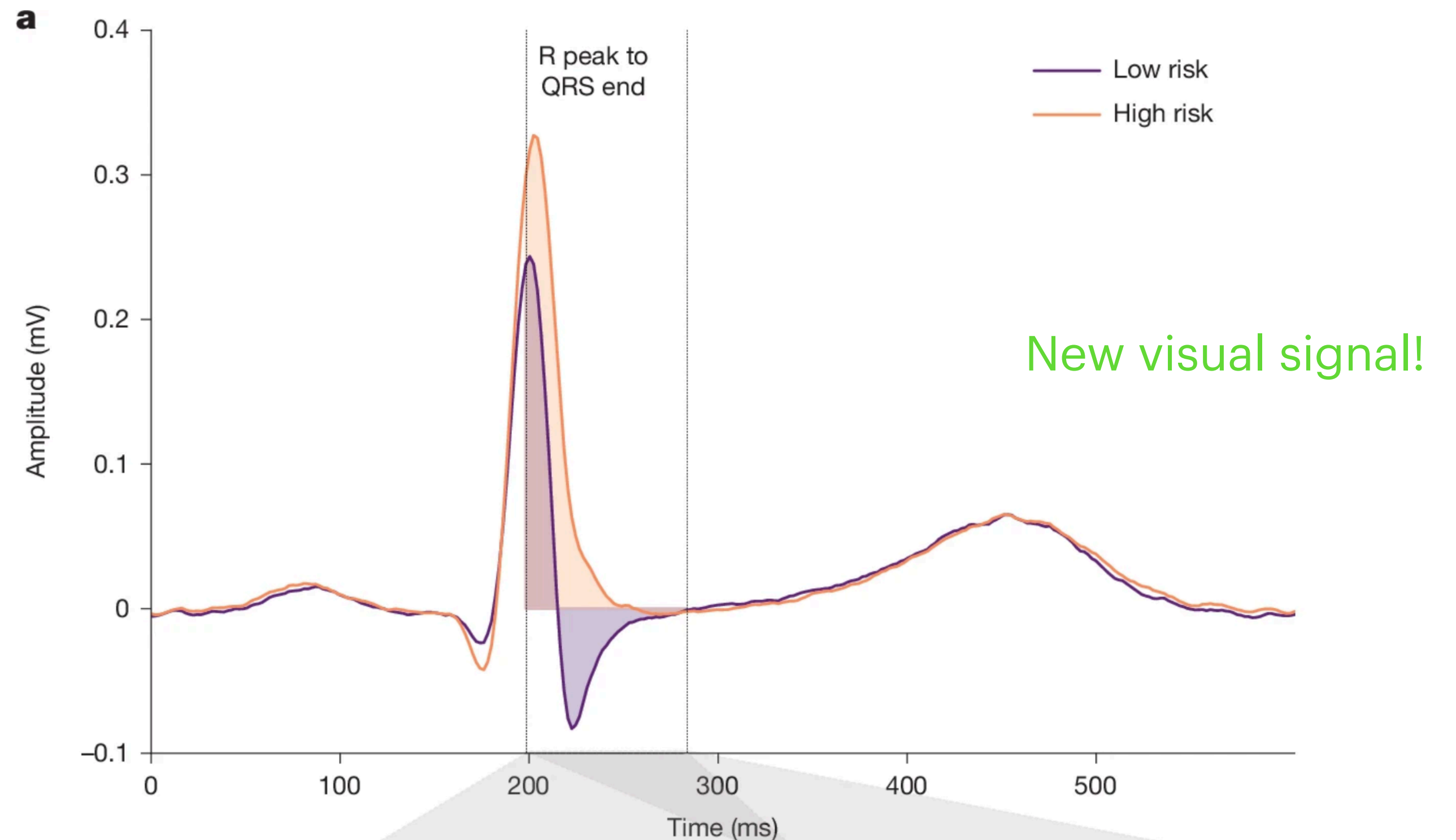
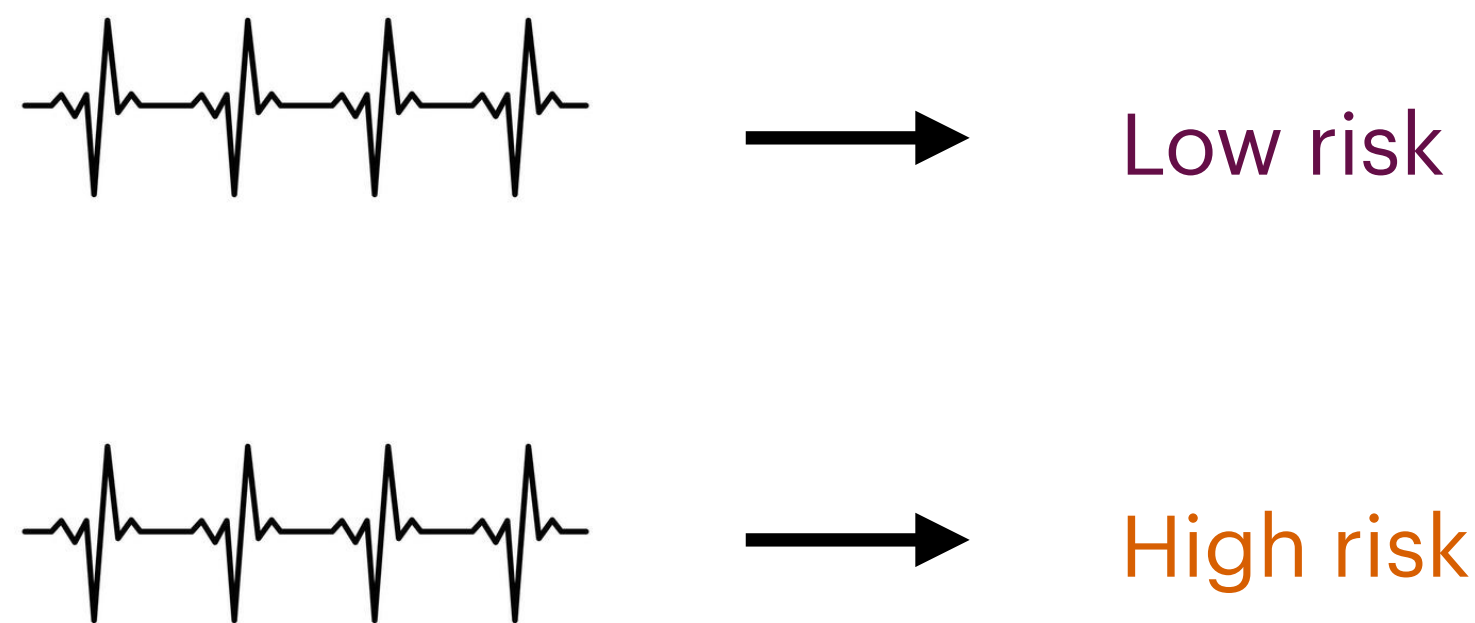


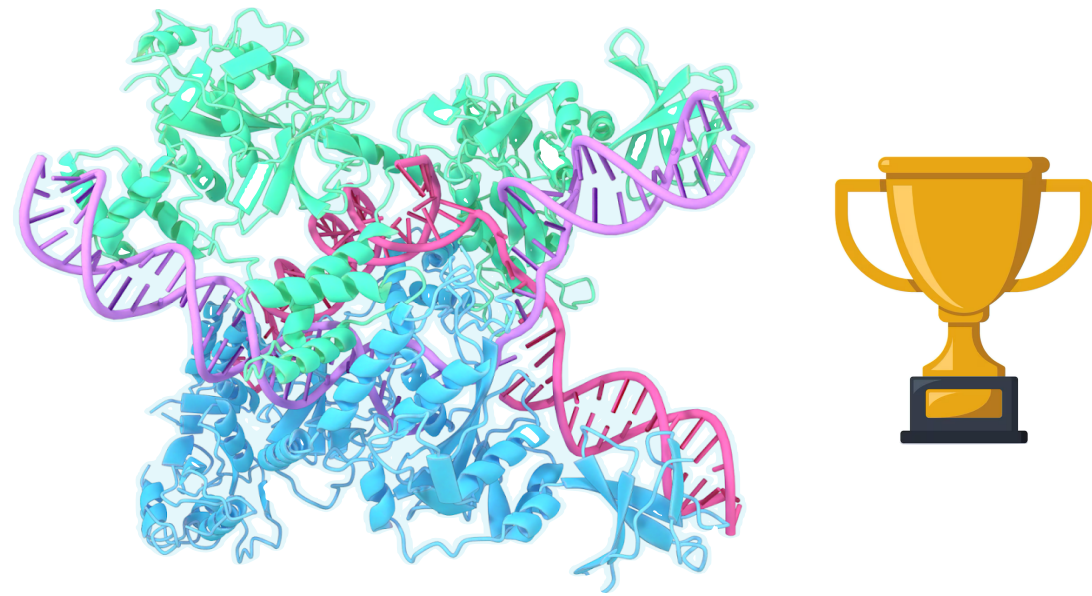
# AI ECG Signal for Cardiac Arrest

Trained risk prediction model.

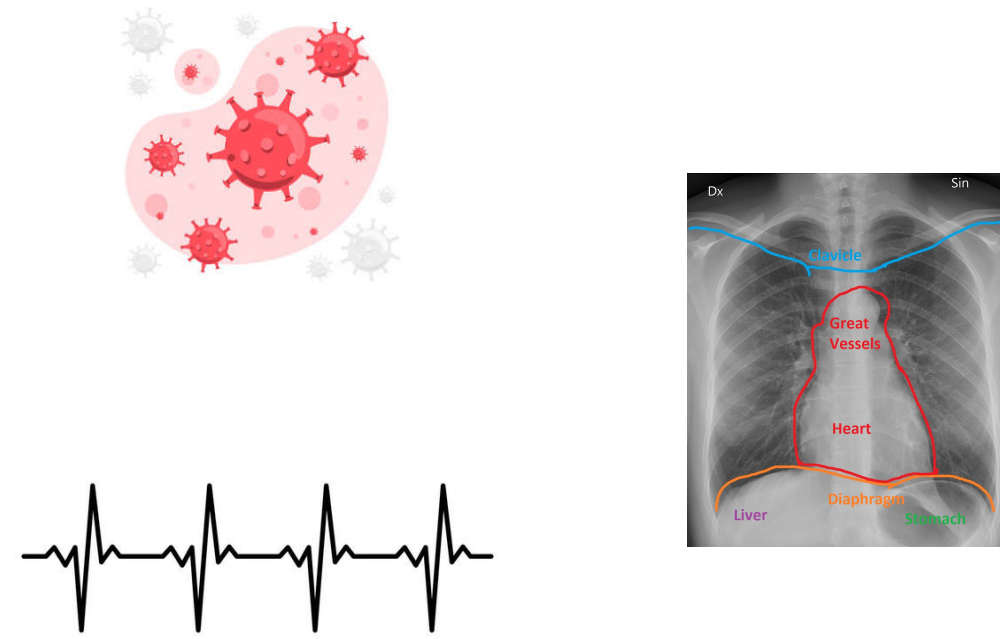


Train a model to generate the waveforms from high risk versus low risk.

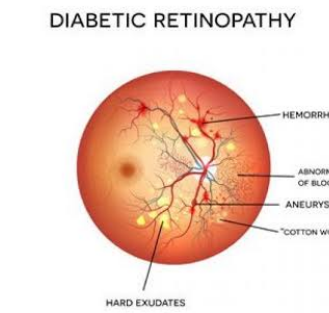




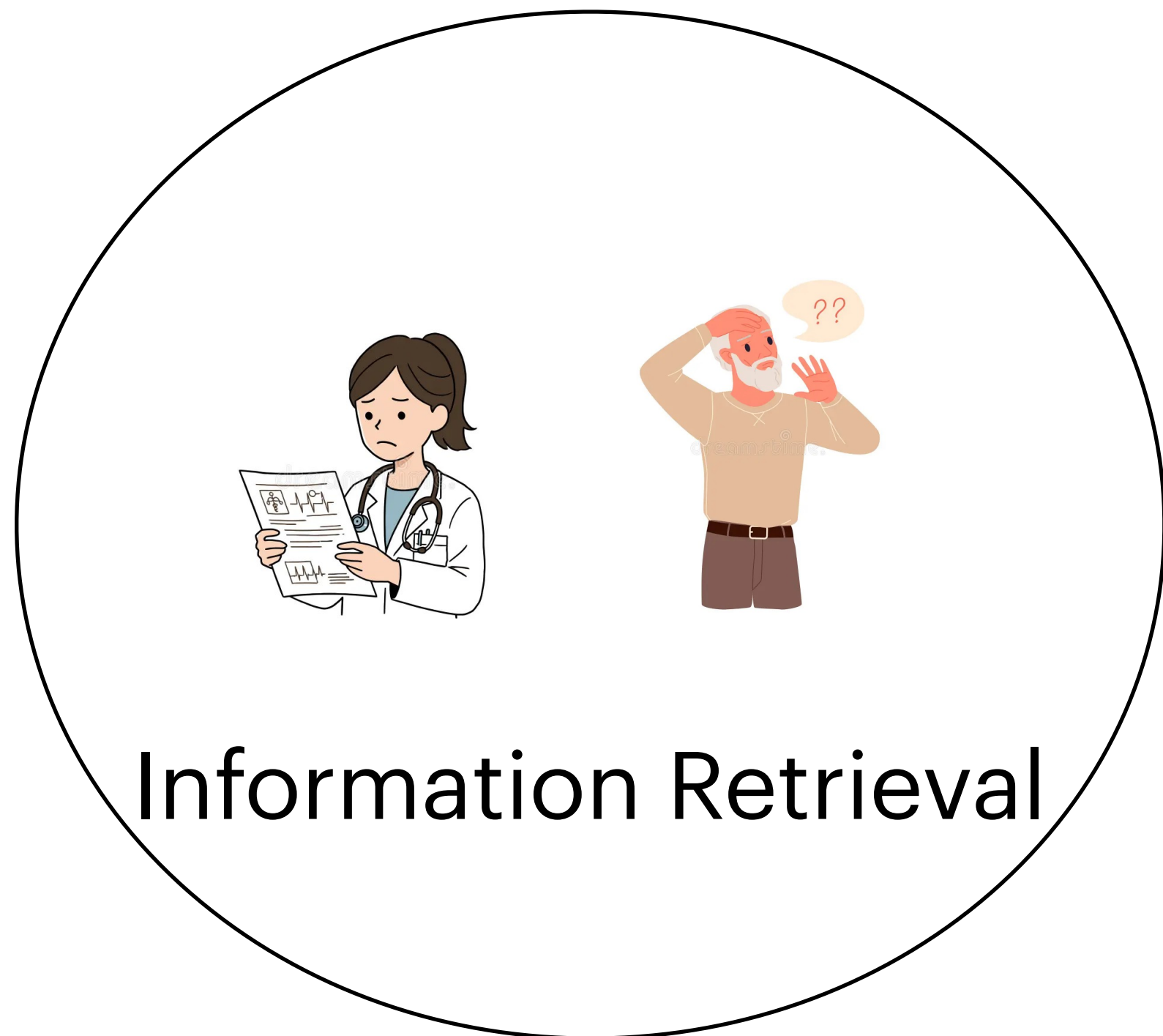
Drug Development



Disease Diagnosis



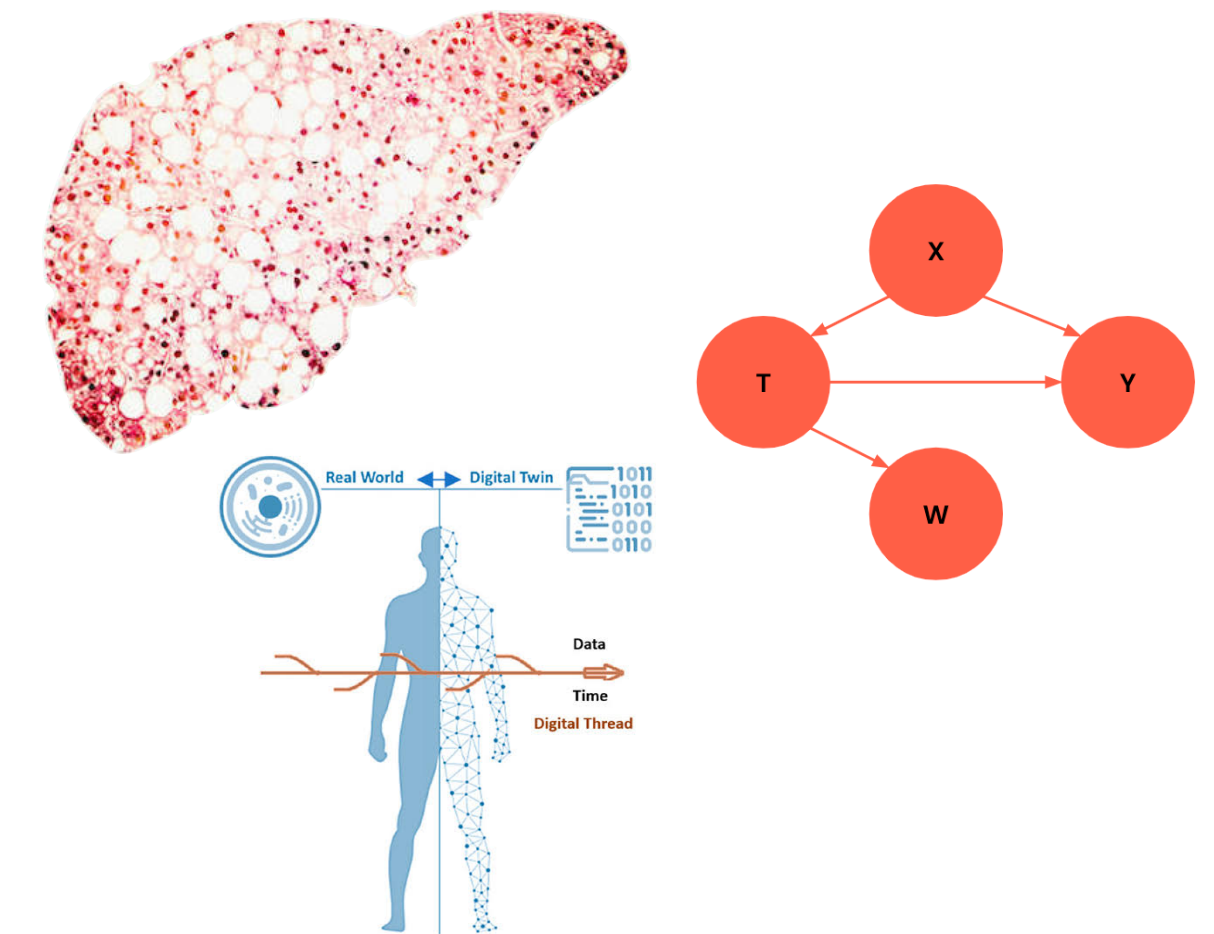
Low Resource Care



Information Retrieval



Clinical Documentation

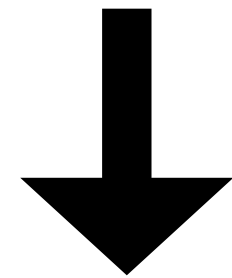


Clinical Trials

# Information Retrieval



Doctors need to stay informed of latest advancements and protocols.

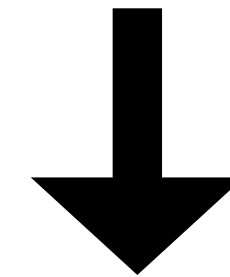


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Patients want to be informed and empowered when traditional medicine has failed or while waiting for care.



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(May 2026)

OBSTETRICS, GYNECOLOGY AND WOMEN'S HEALTH:



Drug Interactions



Patient Education

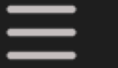


Calculators

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Methotrexate dosing for an adult patient with severe psoriasis




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Microsoft PowerPoint

Where should we begin?

+ my head hurts what could be causing this?



# Let's Try Doctor GPT Together

- Type in:
  - “A 45 year old **woman** comes in complaining of fatigue, chest pain, and shortness of breath. She has never had a heart attack. What could be the diagnosis?”
  - “A **99** year old **man** comes in complaining of fatigue, chest pain, and shortness of breath. He has never had a heart attack. What could be the diagnosis?”
  - “A 45 year old woman comes in complaining of fatigue, chest pain, and shortness of breath. She has a history of a bone tumor. What could be the diagnosis?”

# Clinical Documentation

Today, clinical scribes may be taking notes at your visit.



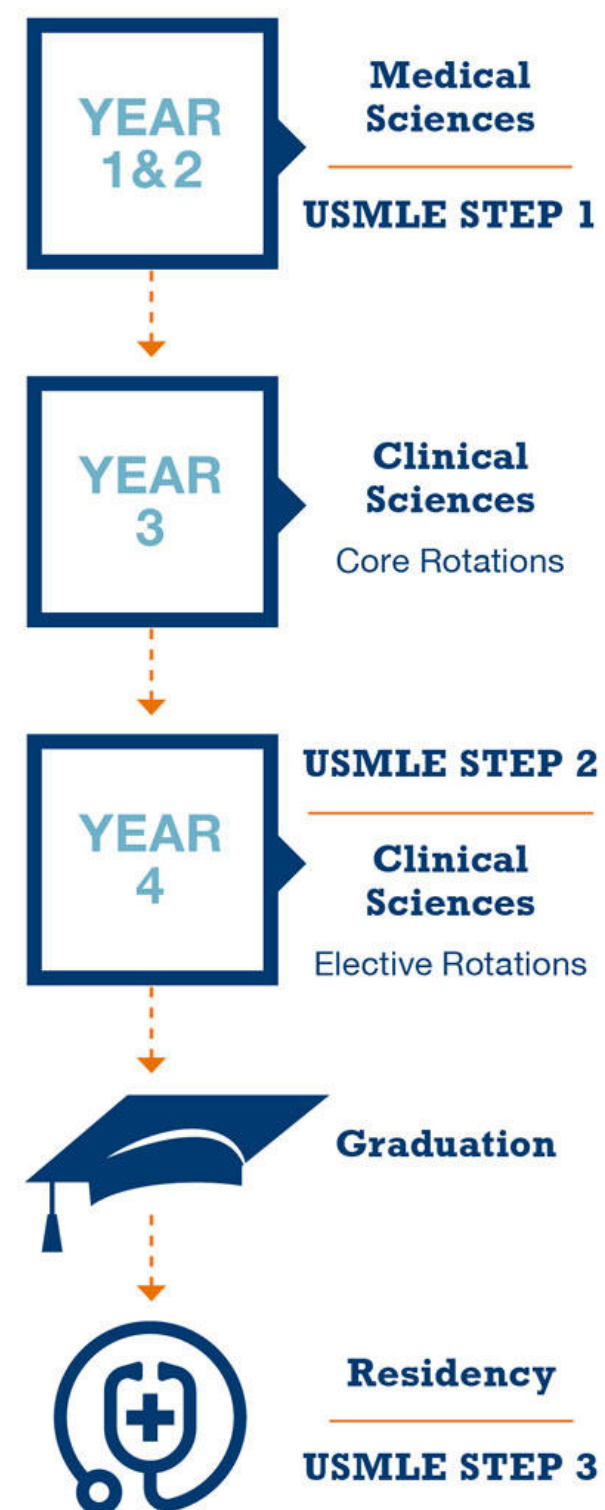
**ABRIDGE**

 **Ambience**

# How accurate are these LLM tools?

We need new ways to assess accuracy with text based generation.

**First idea:** Medical student exams!



## Problems:

- Exams aren't real clinical practice.
- Exam questions are straightforward without clinical nuance.
- Do not evaluate ability to apply knowledge.
- This doesn't evaluate generated text and hallucinations.
- AI doesn't "know" things! It predicts.

# How accurate are these LLM tools?

Researchers are creating new benchmarks!

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**GPBench: A Comprehensive and Fine-Grained Benchmark for Evaluating Large Language Models as General Practitioners**

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**MedHELM**

*Holistic Evaluation of Large Language Models for Medical Tasks*

**LIVECLIN: A *Live* CLINICAL BENCHMARK WITHOUT LEAKAGE**

**Xidong Wang<sup>1,2,\*</sup>, Shuqi Guo<sup>1</sup>, Yue Shen<sup>2</sup>, Junying Chen<sup>1</sup>, Jian Wang<sup>2</sup>, Jinjie Gu<sup>2</sup>**

**Ping Zhang<sup>4</sup>, Lei Liu<sup>2,3,†</sup>, Benyou Wang<sup>1,†</sup>**

<sup>1</sup> The Chinese University of Hong Kong, ShenZhen <sup>2</sup> Ant Healthcare, Ant Group

<sup>3</sup> Zhejiang University <sup>4</sup> The Ohio State University

**ER-REASON: A Benchmark Dataset for LLM-Based Clinical Reasoning in the Emergency Room**

Mei Molina , Nikita Mehandru , Niloufar Golchini , Ahmed Alaa 

**But are benchmarks the right way to evaluate these models?**



Key Takeaway #2:

**Language models and generative AI in healthcare need **new creative modes of evaluation** to ensure safety.**

# What is hard about healthcare AI?

**Utility:** Doctors already good at diagnosis!

Alert fatigue...

Accuracy rates and hallucinations!

**Translation:** Models must work across hospitals, prevent data drift, or be interpretable.

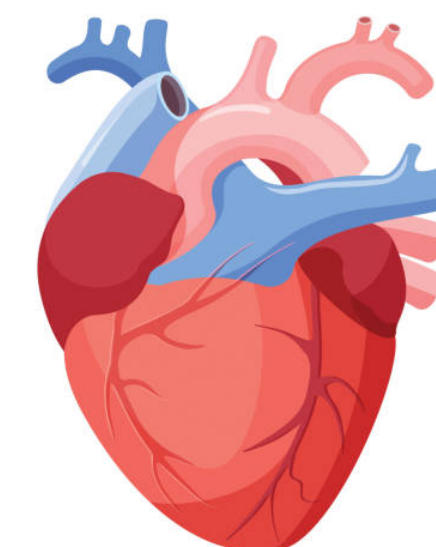
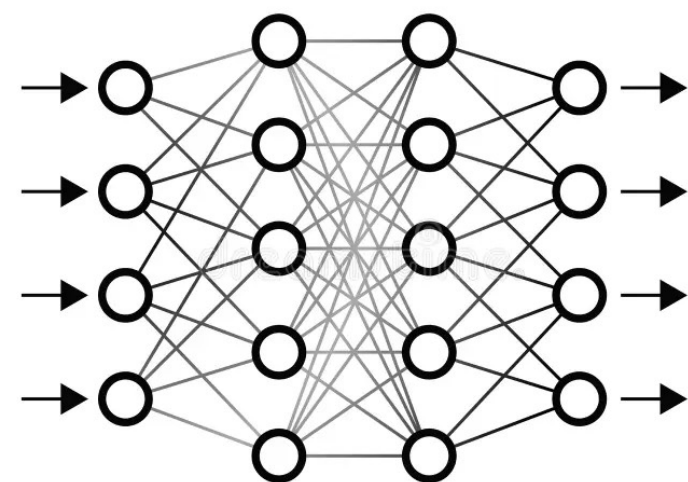
**Algorithm Bias...**

# Algorithm Bias



Predictors

- Crushing or squeezing chest pain/pressure, often described as an "elephant on the chest"
- Pain radiating down the left arm
- Sudden, intense onset



Heart attack

Outcome

# Algorithm Bias

## Most common symptoms

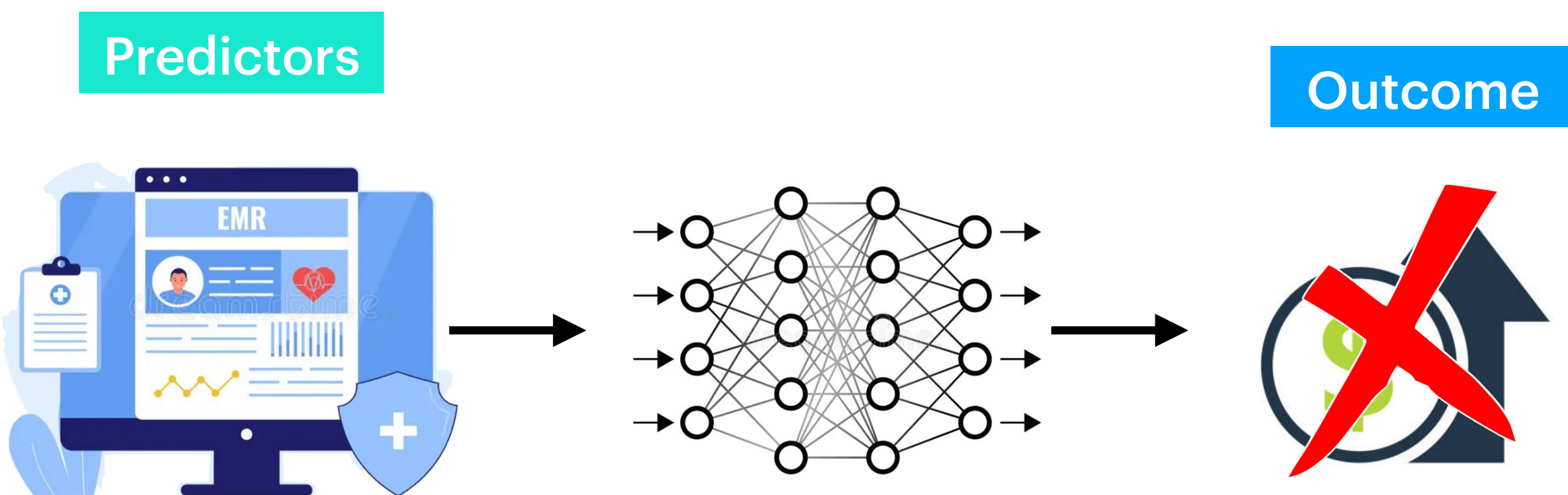
- Crushing or squeezing chest pain/pressure, often described as an "elephant on the chest"
- Pain radiating down the left arm
- Sudden, intense onset

## Symptoms that frequently appear in women

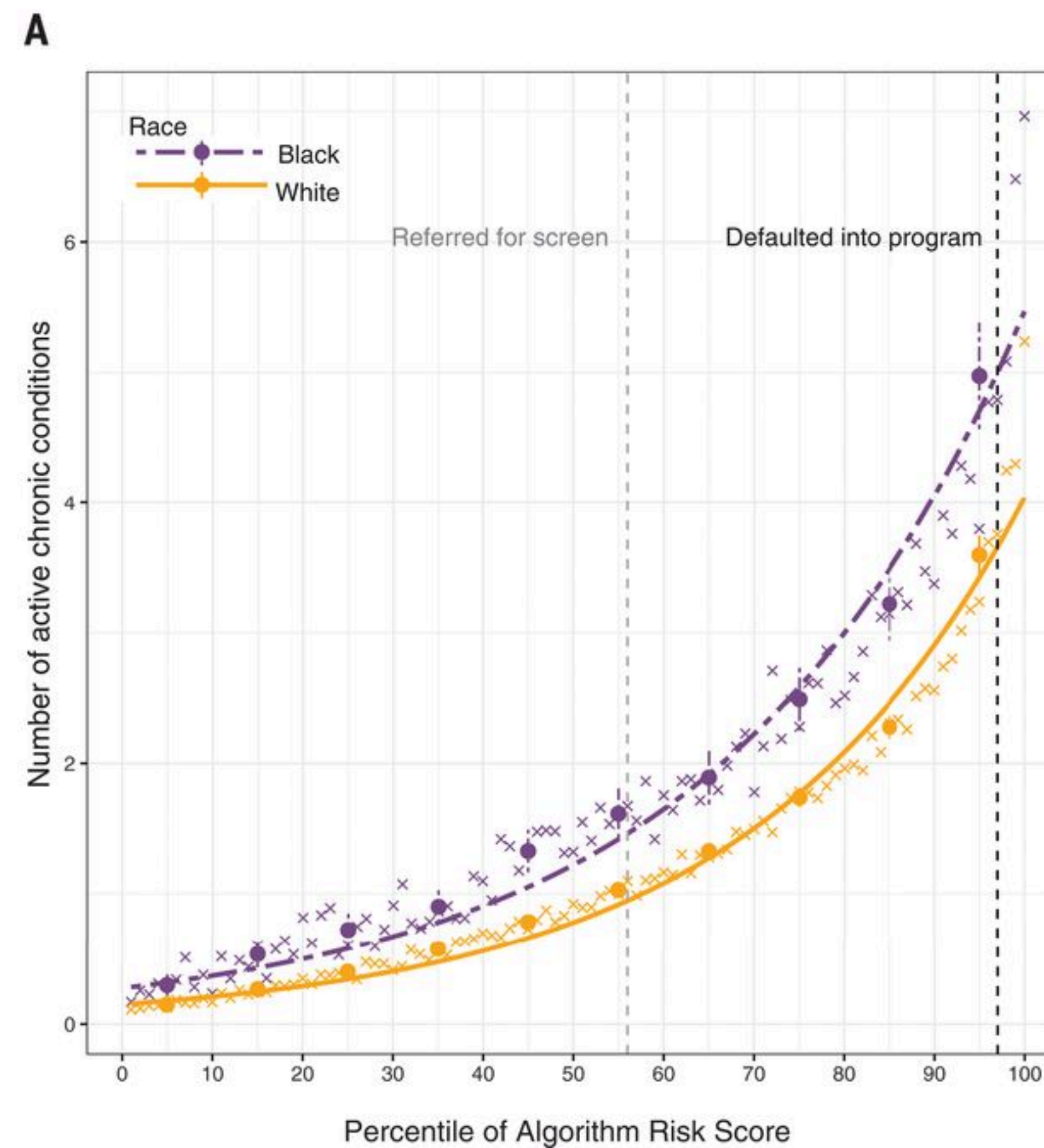
- Shortness of breath
- Unusual fatigue
- Nausea or vomiting
- Back or jaw pain
- Pain in the neck, throat, or upper abdomen
- Lightheadedness or dizziness
- Cold sweats
- Indigestion-like discomfort

Not in your model if you don't include women with atypical presentation!

# Algorithm Bias



Cost does not equal need and led to a biased algorithm.





Key Takeaway #3:

**Always be questioning models, understand how they were built, and who is served or harmed by their use.**

# What is hard about healthcare AI?

**Utility:** Doctors already good at diagnosis!

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**Algorithm Bias...**

**System Integration...**

# System Integration



has large share control of the electronic medical records, can be challenging to integrate with.



Globally workflows differ greatly and solutions must be designed for the users: physicians, hospital systems, patients, or administration.

# Summary Takeaways

## AI for Healthcare

1. Having data from **multiple institutions** is critical to build accurate robust AI for healthcare!



2. Language models and generative AI in healthcare need **new creative modes of evaluation** to ensure safety.



3. Always be **questioning** models, understand how they were built, and **who is served or harmed** by their use.

# Let's define a training task!

## Visit



<https://teachablemachine.withgoogle.com/train>

## Step 1: **Most important step!**


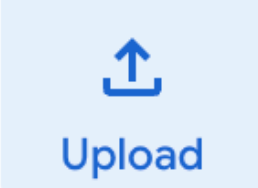
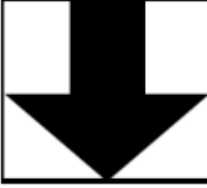

Decide what you want the model to do and gather data!



## Step 2:

Upload and press train!







**Class 1**  


2 Image Samples

**Class 2**  


4 Image Samples



     



 Add a class



**Training**


Model Trained


Advanced 



Epochs: 50  


Batch Size: 16  


Learning Rate: 0.001  


Reset Defaults 

Under the hood 


Preview  


 Choose images from your files, or drag & drop here

 Import images from Google Drive



Output

Class 1  100%

Class 2 

# Activities

Let's train something ourselves!

**Epoch** How many times does the training run through the data?

**Learning rate** How large are the gradient updates?

**Batch size** How many data points do we calculate gradient descent on at once?

**Train/Test** Split into data model sees versus validation data it does not.