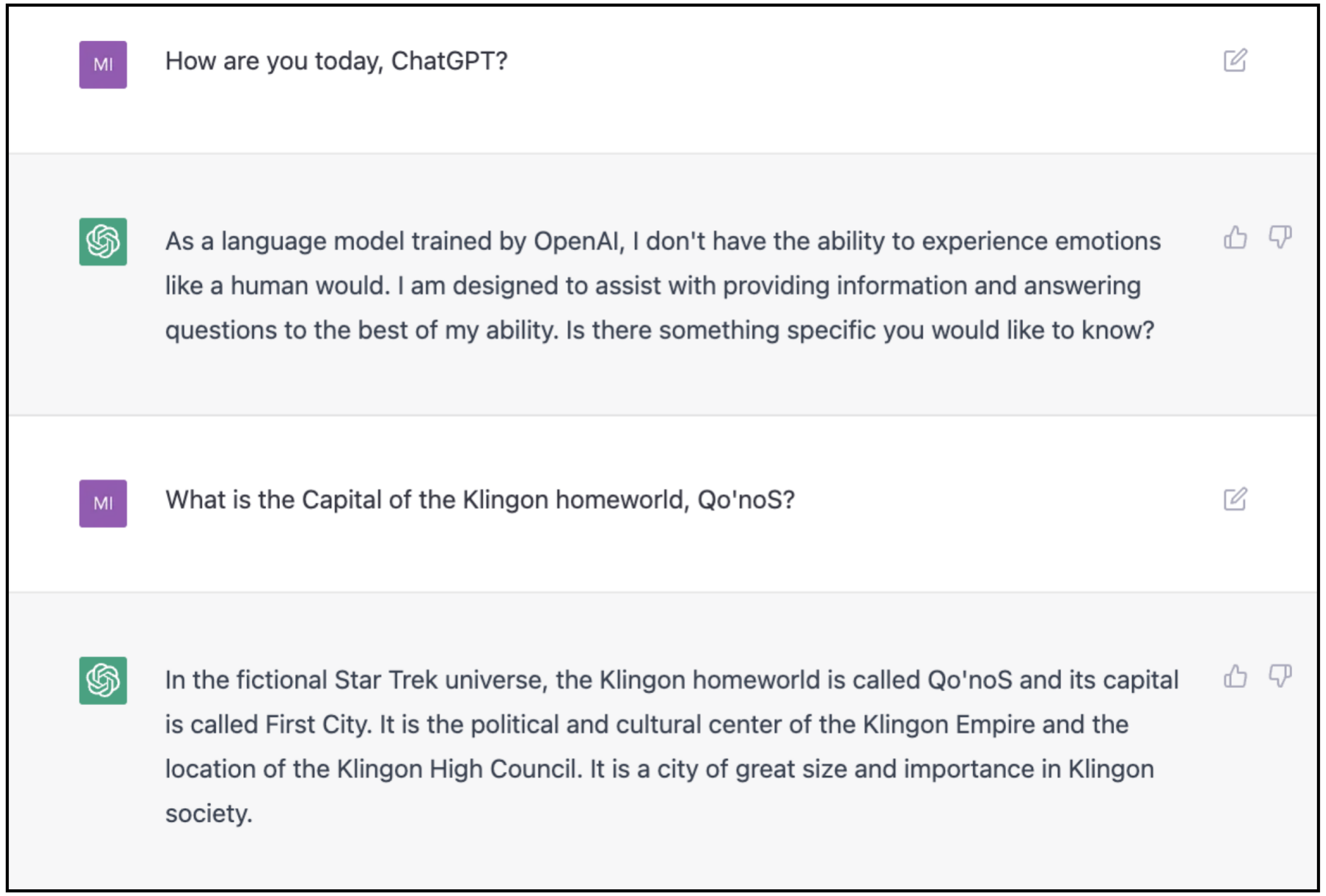
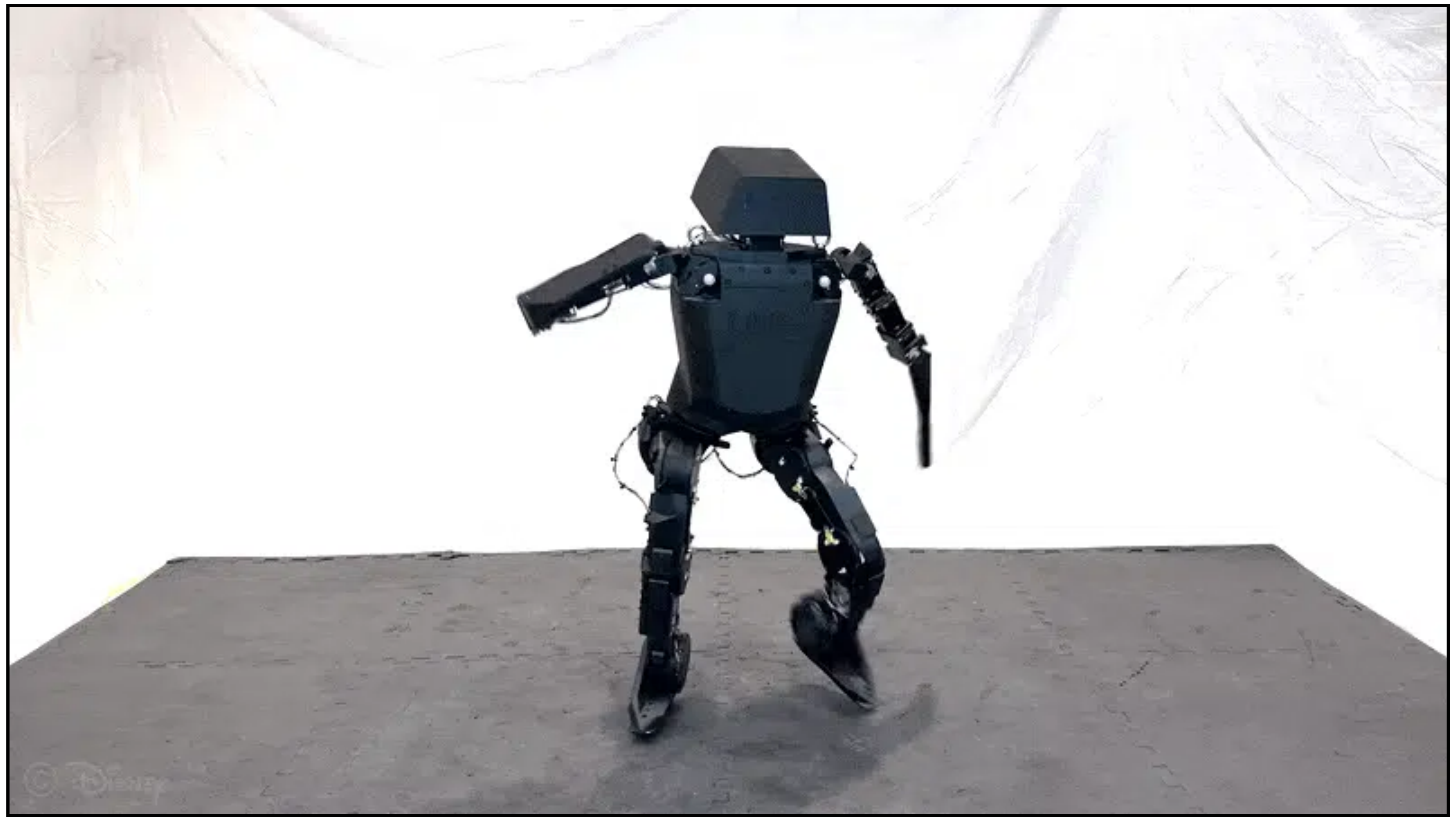
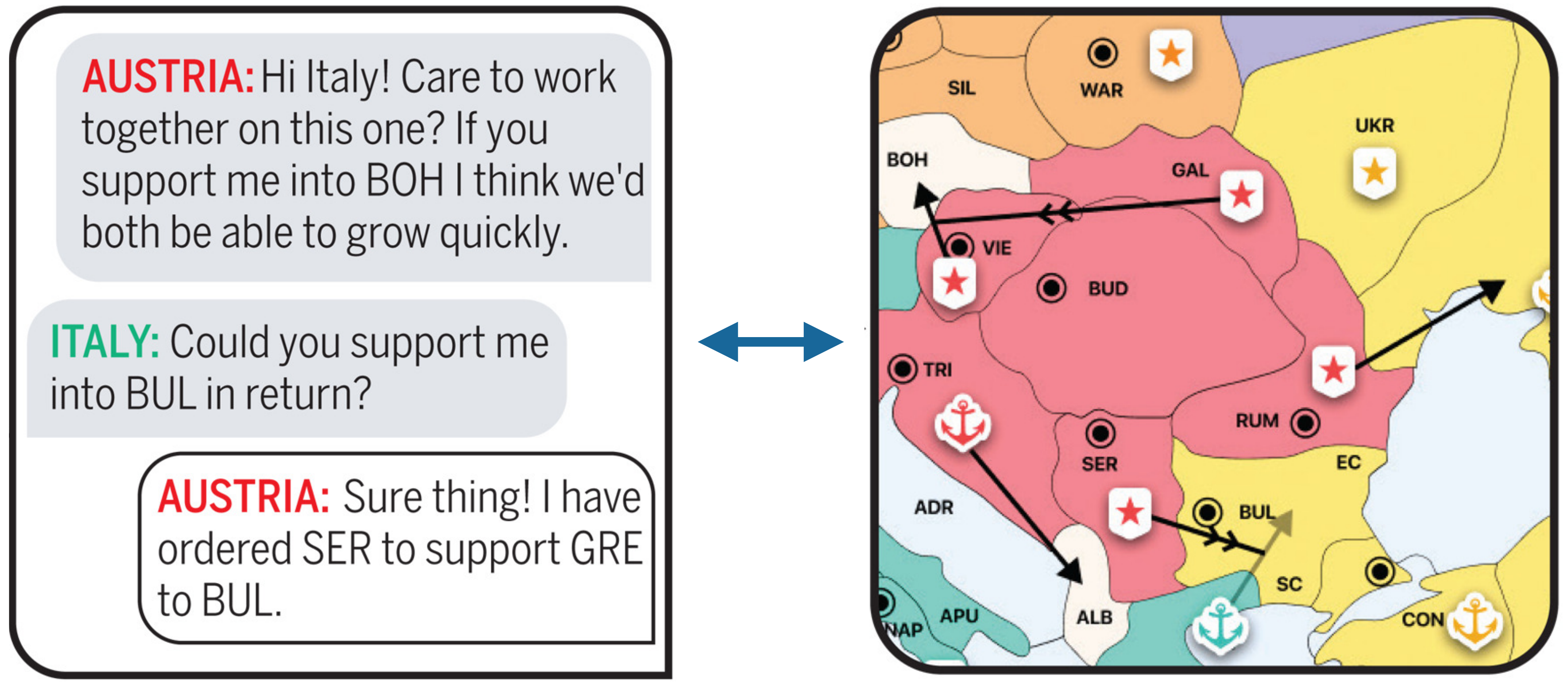
Introduction to machine learning



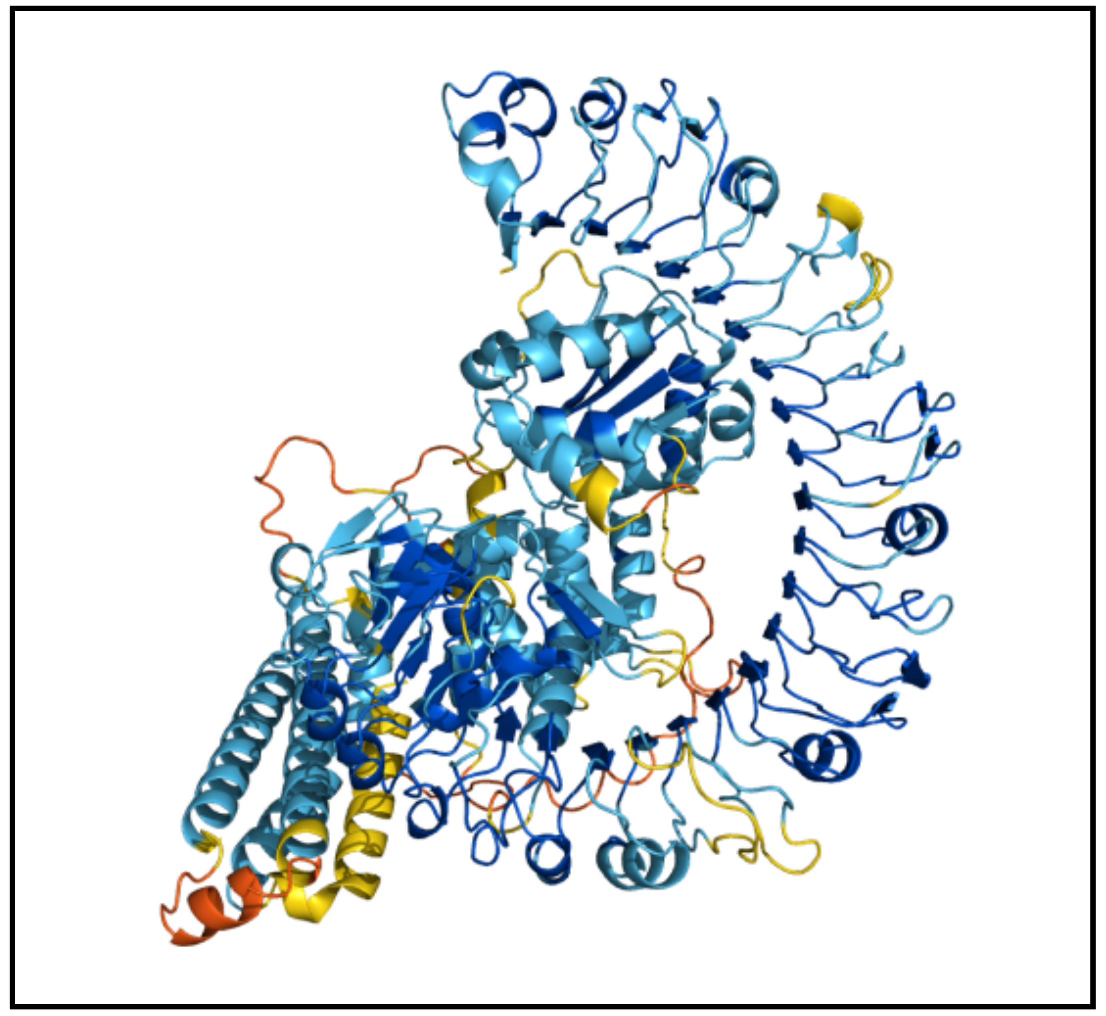
ChatGPT


Disney Research



Cicero


DALLE-2


AlphaFold

Roadmap

- What is machine learning?
- Machine learning paradigms
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
- Perceptron
  - Example: Golden retriever vs. Doberman
  - Perceptron model
  - Training via update rule
  - Testing
- Multi-layer Perceptron (MLP)
- Multi-class Perceptron

Reminder: Policy on generative AI tools in COS 126

Executive summary.

- Do not use generative AI tools for any purpose for graded assessments (unless explicitly allowed).

Reasons not to use generative AI (unless permitted):

- Enhance your critical thinking and problem-solving skills.
- Establish a strong foundation in programming (syntax, semantics, design, debugging, data structures, algorithms, performance, and theoretical principles).
- Will use generative AI more effectively in the future by learning to critically evaluate its output.
- Relying on AI-generated code without understanding how it works can lead to significant technical and ethical issues.
- We routinely detect the use of generative AI on assignments and refer these cases to the CoD.

Full details. See course syllabus.

ML data ⇔ related fields

Player	Minutes	Points	Rebounds	Assists
A	41	20	6	5
B	30	29	7	6
C	22	7	7	2
D	26	3	3	9

Tabular

Visual

ML data ⇔ related fields

Player	Minutes	Points	Rebounds	Assists
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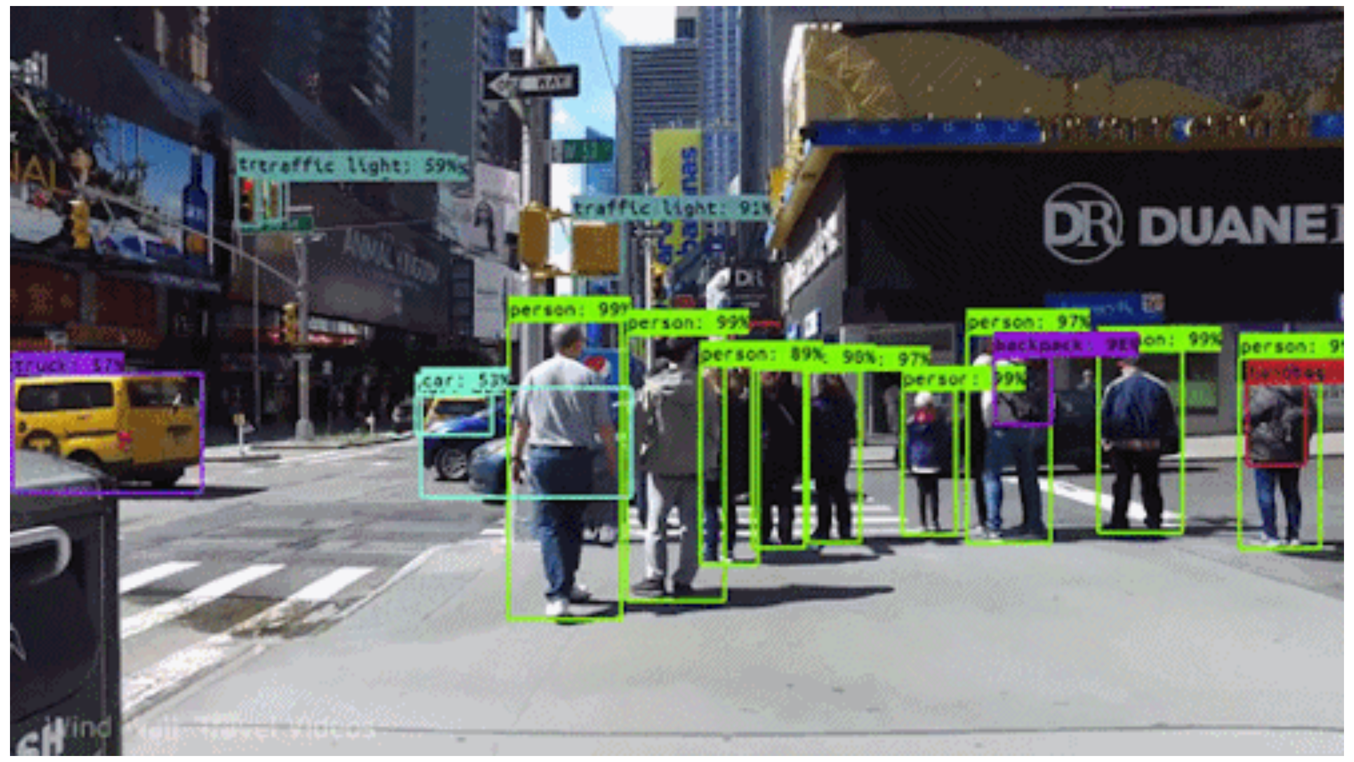
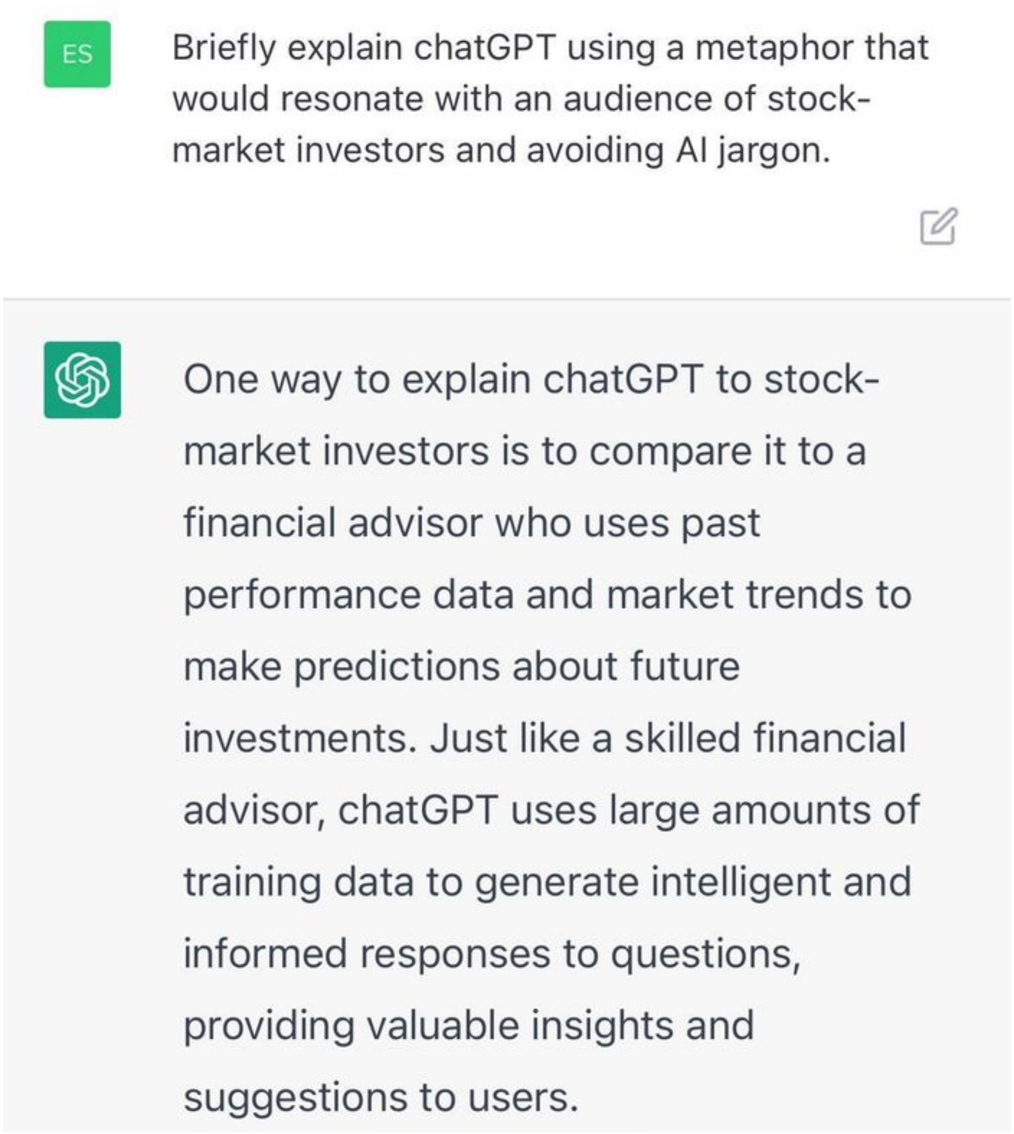
Tabular

Machine learning



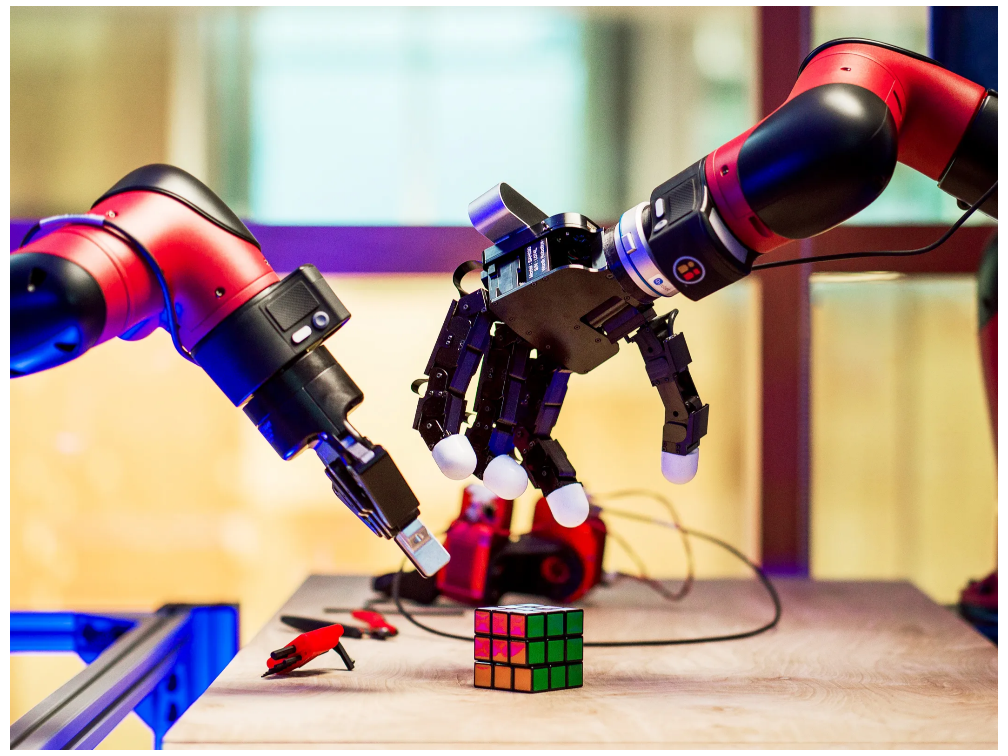
Visual

Computer vision



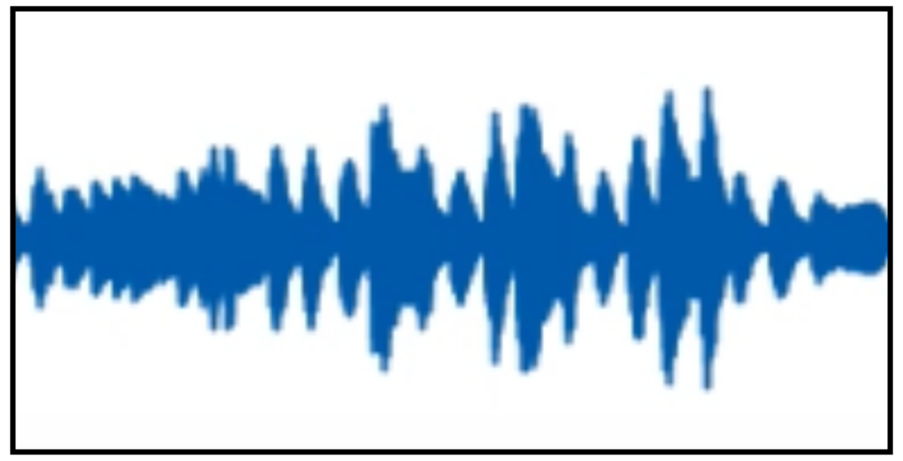
Text

Natural language processing (NLP)



Real manipulation

Robotics



Audio

Audio processing

What is machine learning?

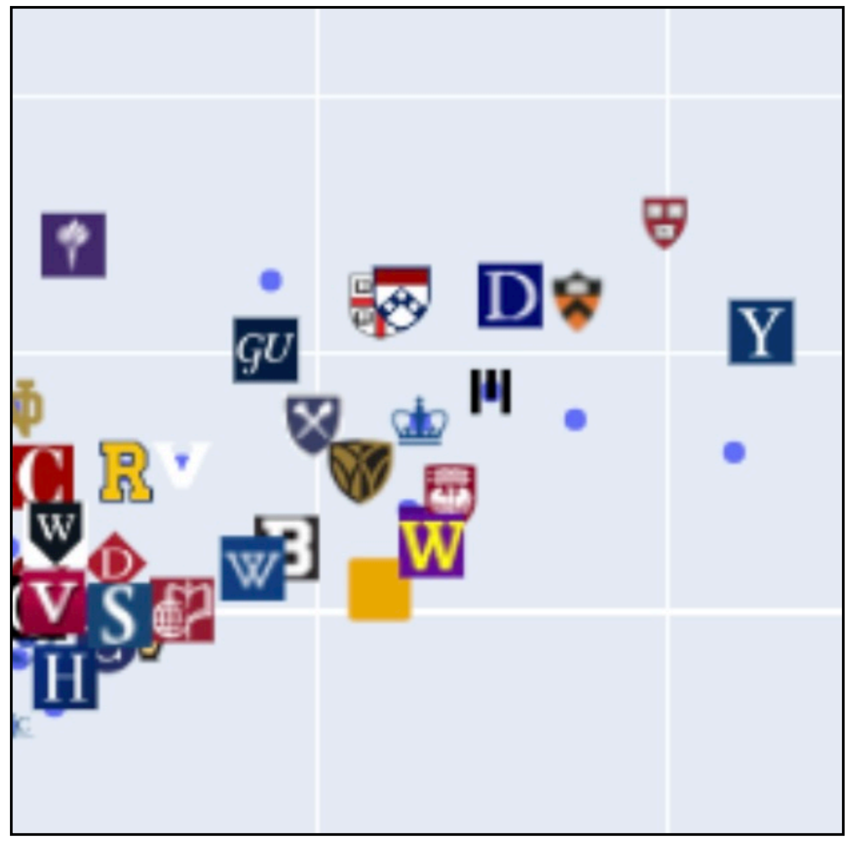
Machine learning (ML):
Algorithms that improve automatically using data or repeated experience.

Notes:

- This is **not** true for the programs that you have written so far in COS126 (i.e. your programs = explicit instructions for the computer).
- There are many non-ML algorithms in computer vision, NLP, robotics, etc.

Machine learning paradigms

1. Supervised learning: learn to **predict** an output from an input.
2. Unsupervised learning: learn **patterns** from data.
3. Reinforcement learning: learn by **interacting** with an environment (i.e. **trial-and-error**).



Supervised learning

Given (input, output) pairs, **predict** an output from its input.

$\text{input}_1 \rightarrow \text{output}_1$
$\text{input}_2 \rightarrow \text{output}_2$
$\text{input}_3 \rightarrow \text{output}_3$

Supervised learning

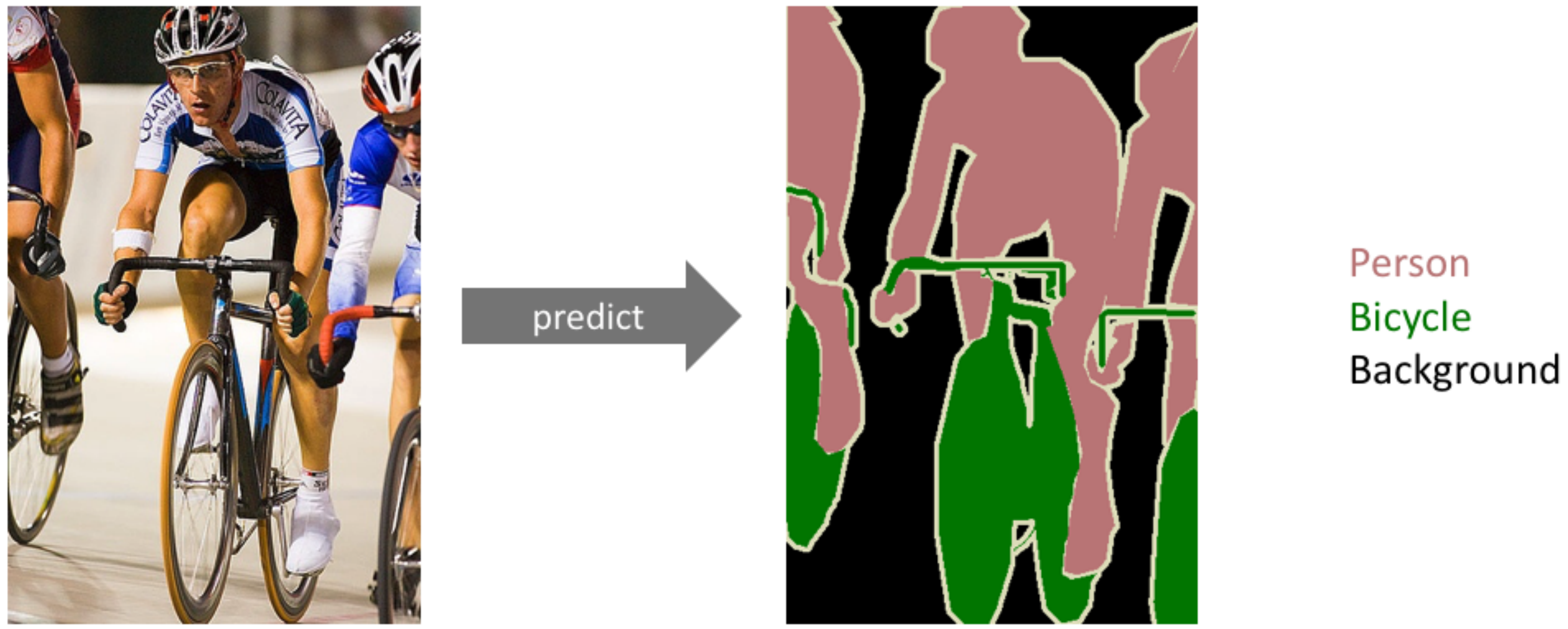
Medicine

- Input: medical information (i.e. age, body mass index [BMI], blood sugar levels, etc.)
- Output: blood pressure (in mm Hg)

Supervised learning

Computer vision: segmentation

- Input: an image
- Output: segmentation map of objects

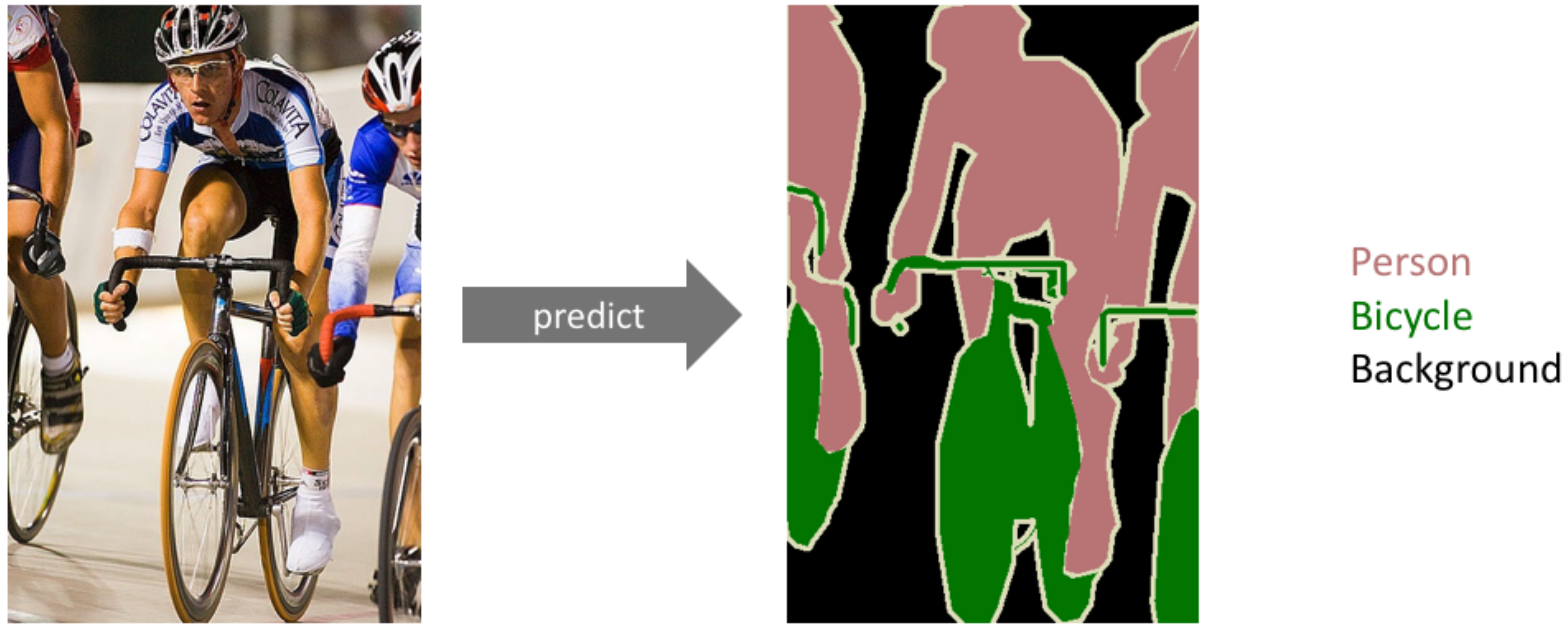


Pascal VOC dataset
http://host.robots.ox.ac.uk/pascal/VOC/voc2012/

Supervised learning

Computer vision: segmentation

- Input: an image
- Output: segmentation map of objects
- **Application: self-driving cars**



Pascal VOC dataset
http://host.robots.ox.ac.uk/pascal/VOC/voc2012/

https://github.com/meetps/pytorch-semseg

Supervised learning

NLP: Machine translation

- Input: a sentence in English
- Output: its translation in Spanish
- **Application: Google Translate**

Gender Bias in Machine Translation: https://towardsdatascience.com/gender-bias-in-machine-translation-819ddce2c452

"That river is dangerous to swim in." → "Es peligroso nadar en ese río."

"The baby is playing with some toys." → "El bebé juega con algunos juguetes."

Anki Tab-Delimited Bilingual Sentence Pairs
https://www.manythings.org/anki/

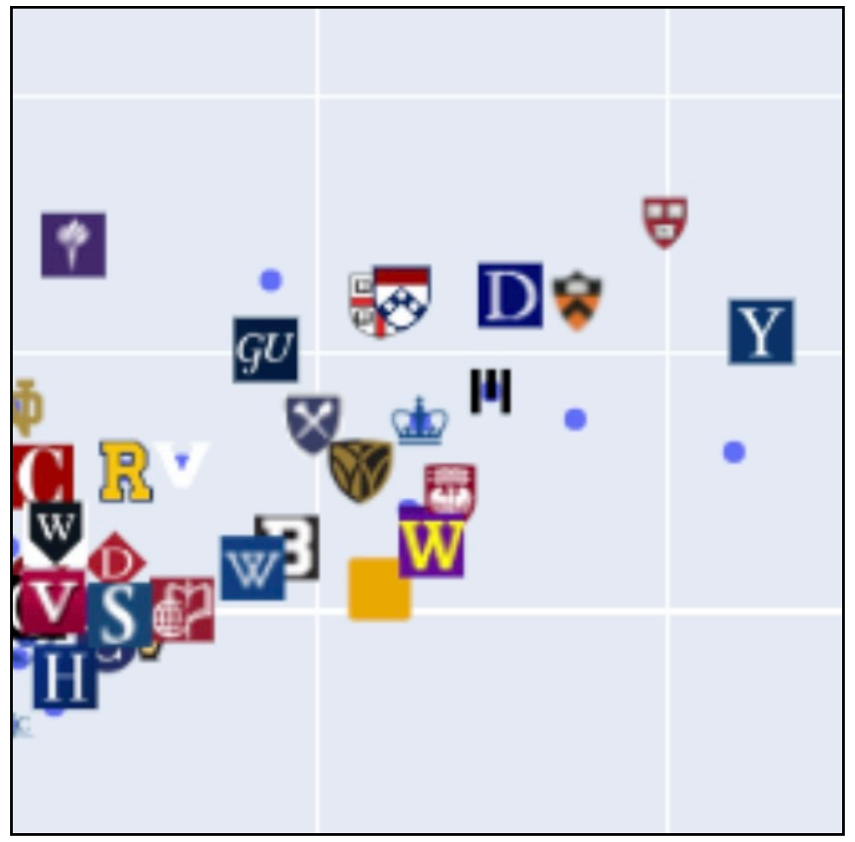
Supervised learning

Other applications

- Spam filtering: email text → {spam, not spam}
- Speech recognition: audio clip → text transcription
- Medical imaging: CT scan of COVID patients → severity of COVID symptoms
- …

If you can create a dataset of (input, output) pairs, you can use supervised learning.

Unsupervised learning



Learn **patterns** from unlabelled data (i.e. no input-output pairs).

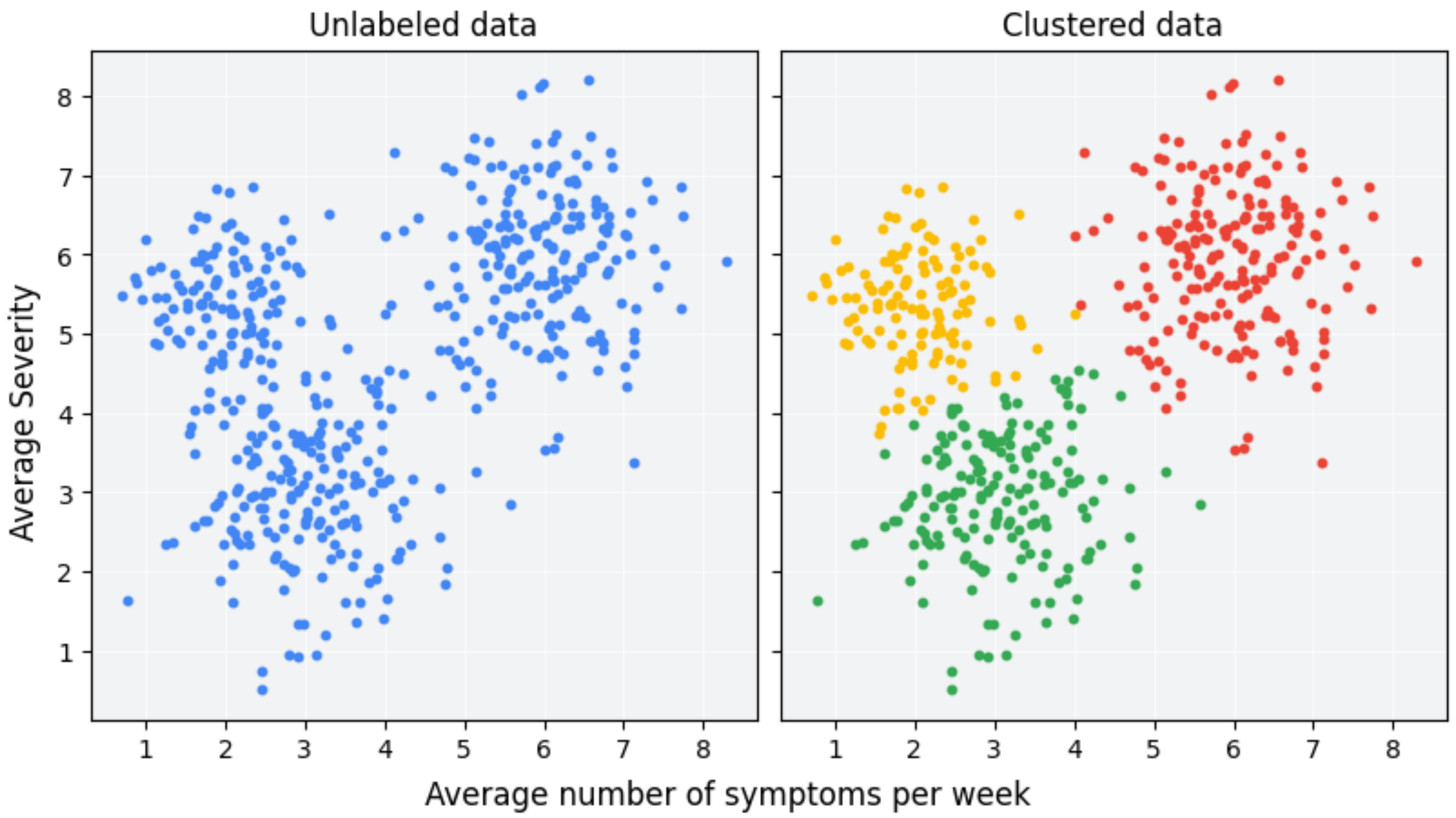
Examples:

- Clustering
- Dimensionality reduction
- Anomaly detection
- Generative modeling
- …

Unsupervised learning

Clustering

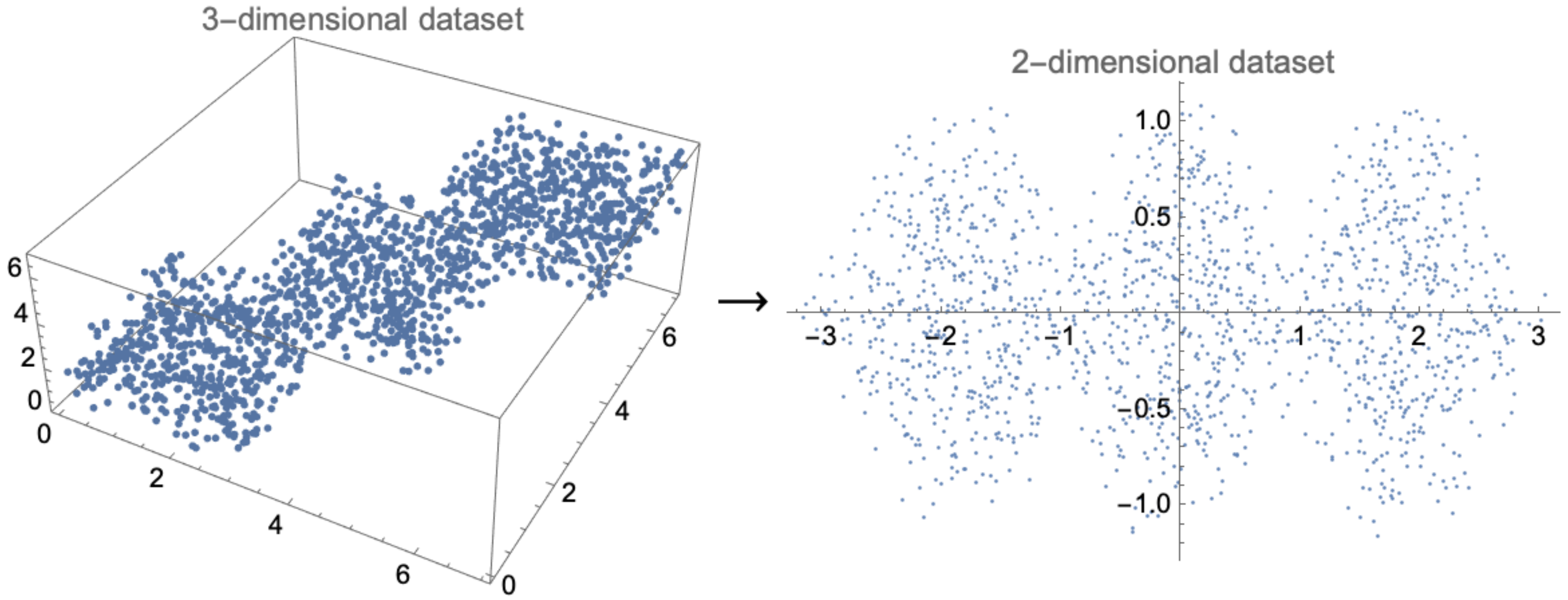
- Goal: Given a data point, categorize it into one of k clusters.
- Unlike supervised learning, there are no output labels! i.e. no (data point, cluster) pairs
- Application in medicine: What types of cancers are similar to each other?



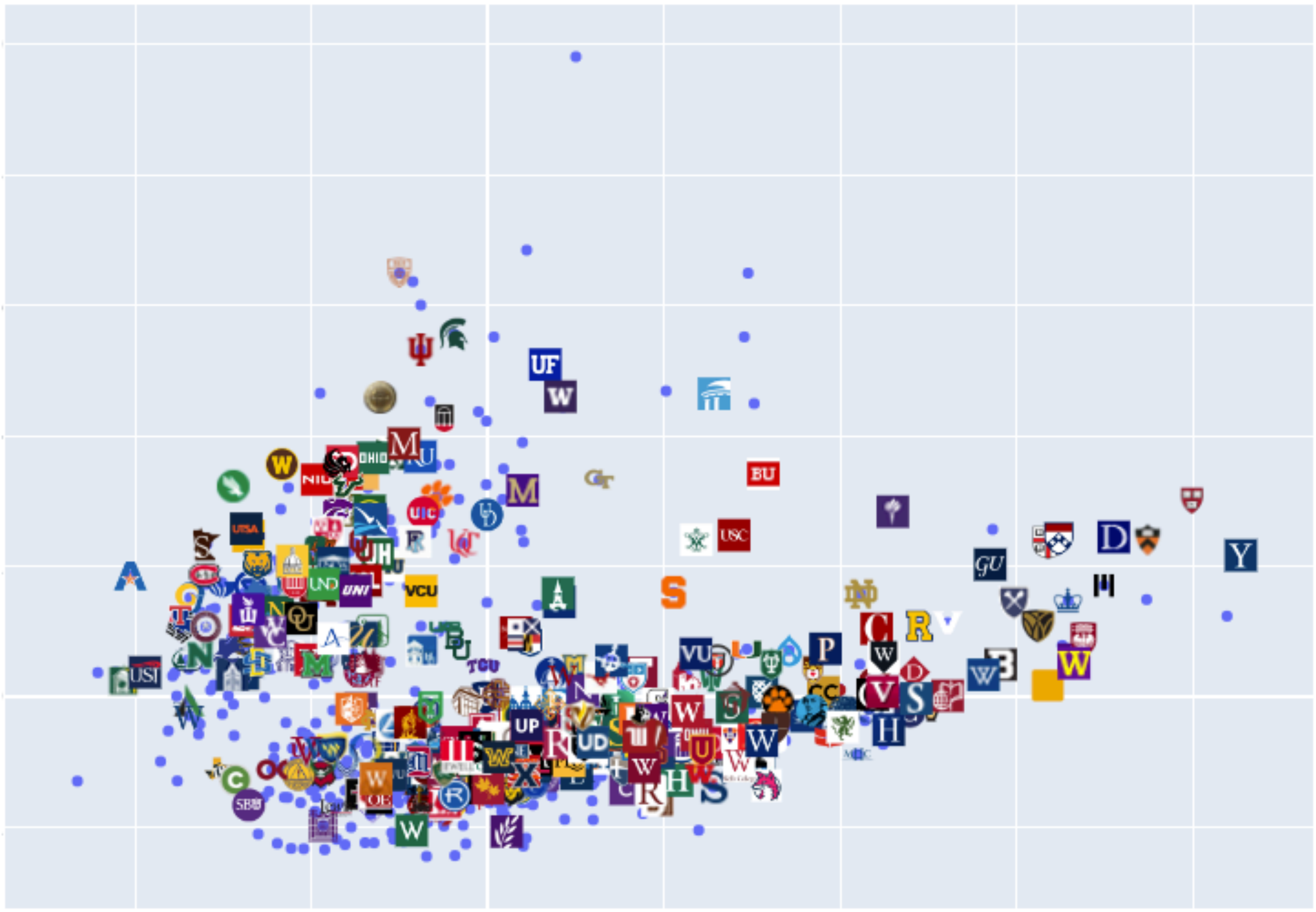
Unsupervised learning

Dimensionality reduction

- Goal: Reduce number of variables while preserving patterns (e.g. distances between points)
- Uses:
  - Compression
  - Visualization
  - …



PCA example of colleges dataset

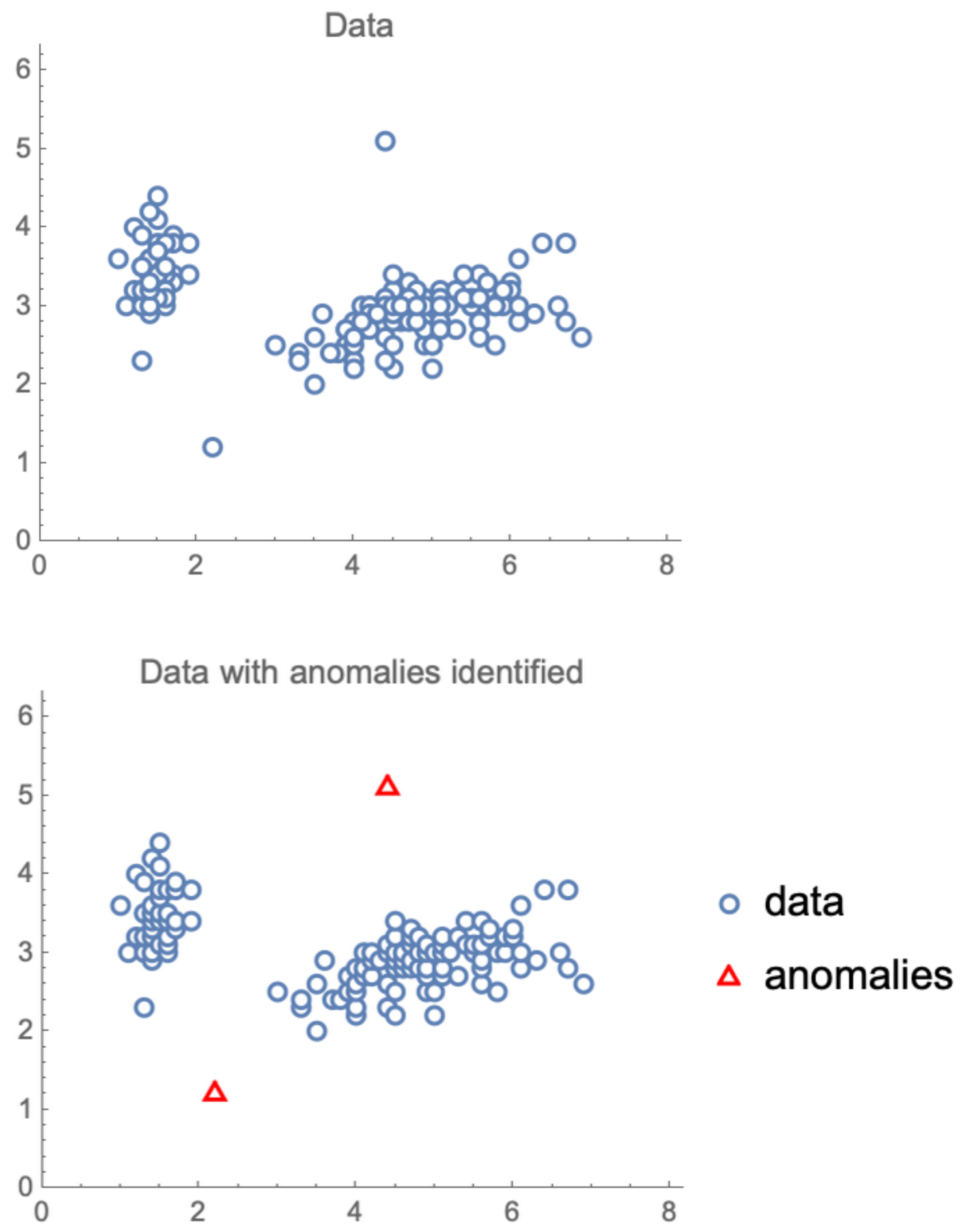


https://www.ruthfong.com/cos324/pca_colleges.html

Unsupervised learning

Anomaly detection

- Goal: Identify anomalies (outliers)
- Applications:
  - Credit card fraud
  - Medical diagnosis
  - …



Unsupervised learning

Generative model

- Goal: Create synthetic examples that look realistic.
- Applications:
  - Computer vision:
    Given a dataset of portraits, generate realistic looking faces.
  - NLP:
    Given Shakespeare's sonnets, generate a realistic sounding, Shakespearean sonnet.

Generated by StyleGAN
(Karras, et al., CVPR 2019)

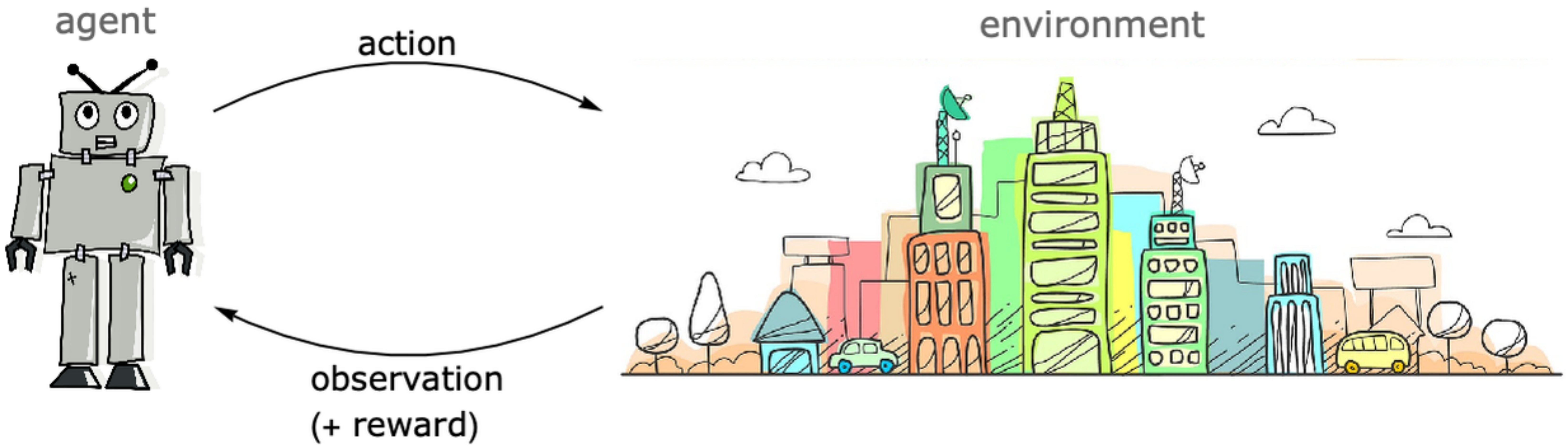
*"am of my faults thy sweet self dost deceive:
they look into the beauty of thy deeds
nativity, once in the chronicle of wasted time
not from the thing they see"*

Generated by Markov Chains
https://rpubs.com/malcolmbarrett/shakespeare

Reinforcement learning

Learn by **interacting** (i.e. **trial-and-error**) with an *environment.*

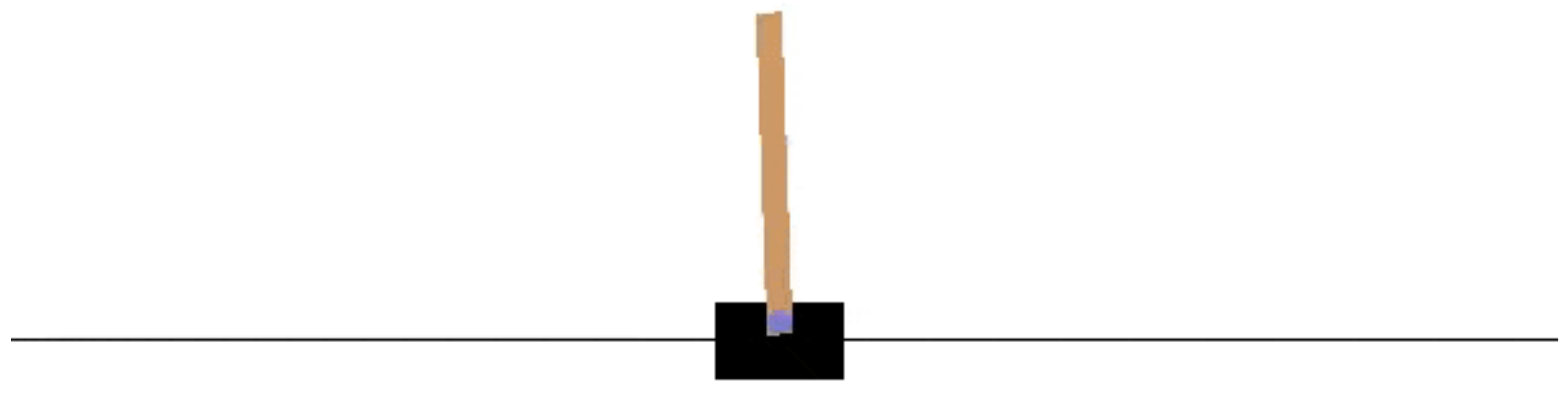
- An *agent* interacts with an *environment* by performing *actions* and then gathers *observations* (and sometimes *rewards*) that occur in response to its actions
- Interactions generate data (i.e. no fixed dataset).
- Goal: Learn *agent* to maximize *reward*.



Reinforcement learning

CartPole

- Goal: Balance a pole on a cart by moving it left and right.
- Actions: {left, right}
- Reward: +1, for each step the pole is upright.
- Learn over many attempts (i.e. episodes).



https://gymnasium.farama.org/environments/classic_control/cart_pole/

Reinforcement learning

CartPole

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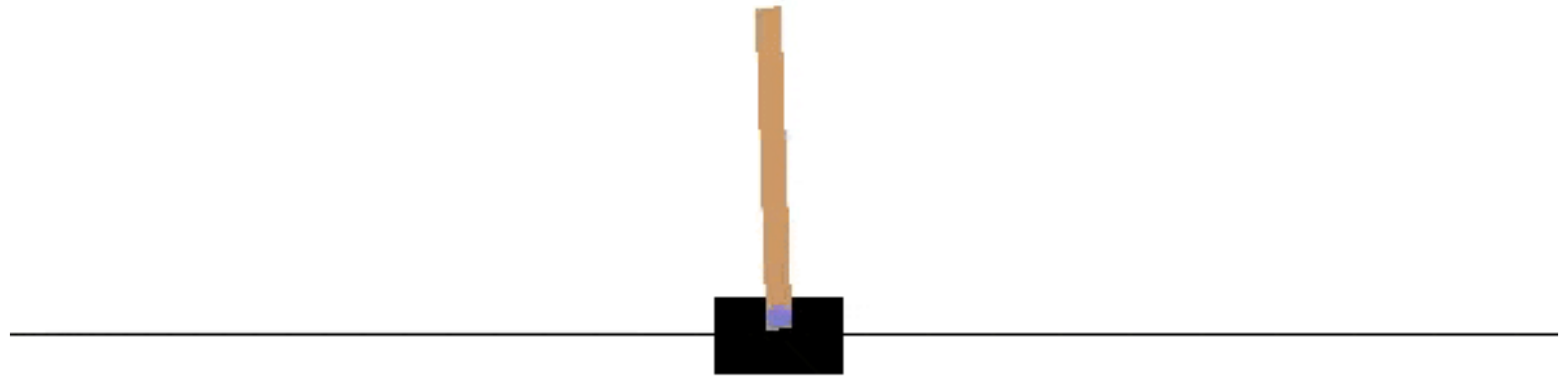
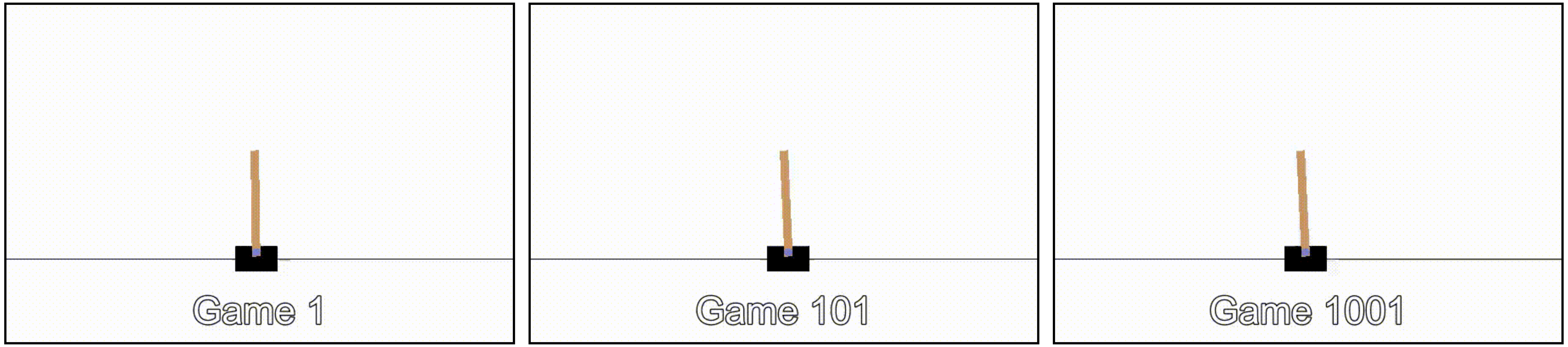


https://gymnasium.farama.org/environments/classic_control/cart_pole/

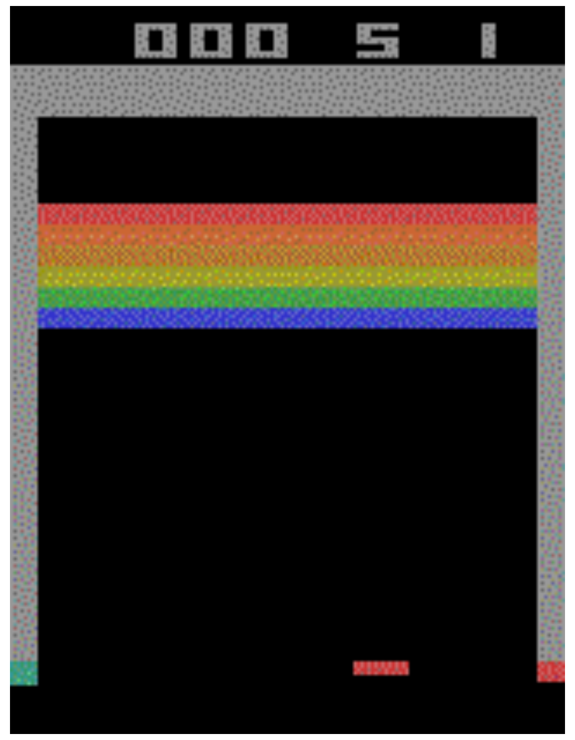


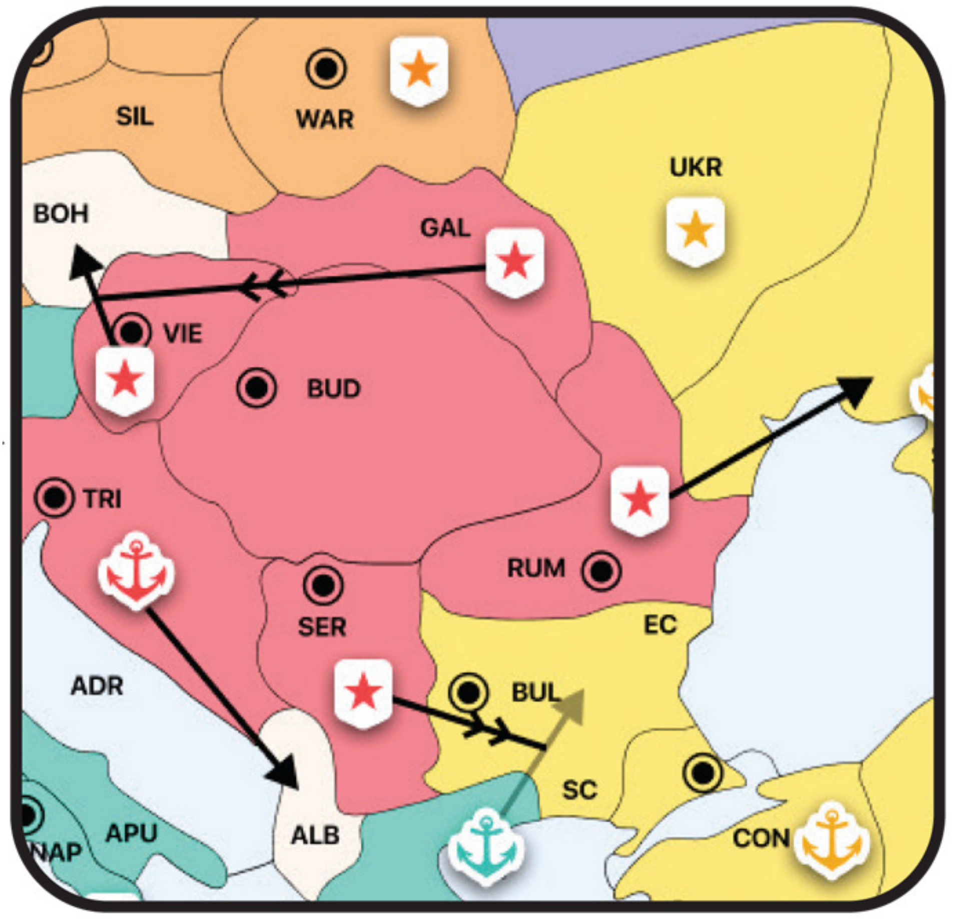
https://blog.ml6.eu/importance-of-data-visualization-for-ml-936239c355d0

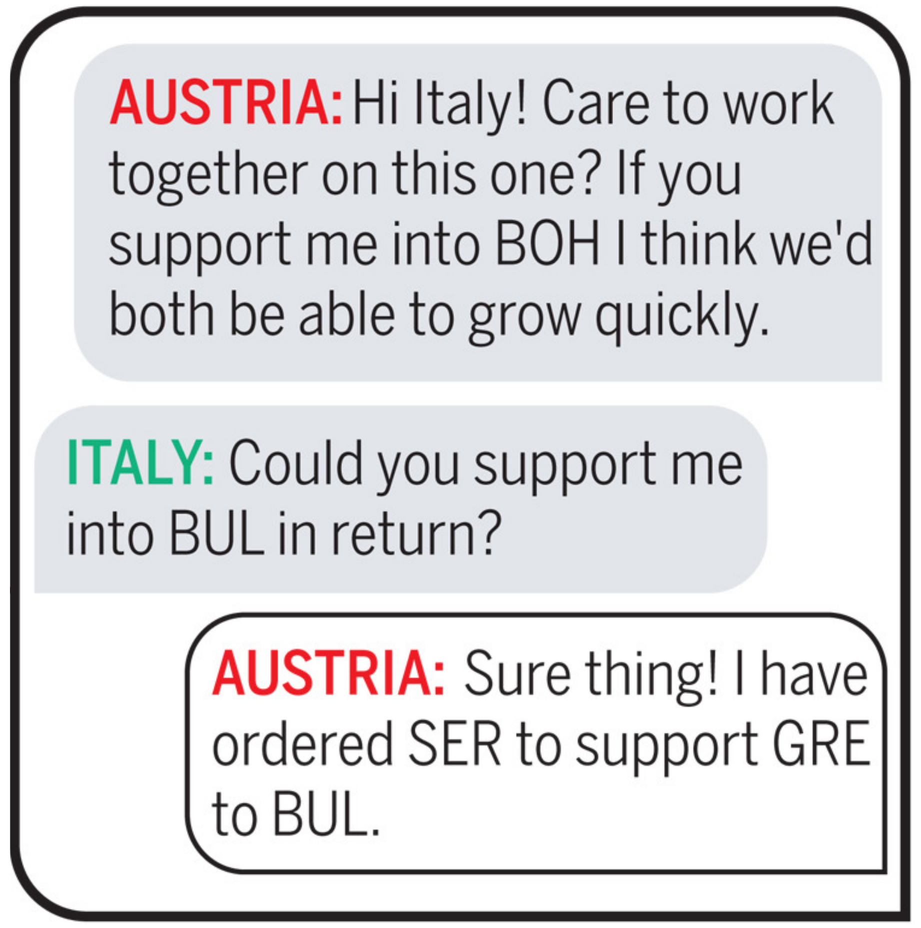
Reinforcement learning

Application: Games

- Atari (2015): DeepMind
- Go (2016): AlphaGo from DeepMind
- Poker (2017, 2019):
  Libratus and Pluribus from CMU
- Diplomacy (2022): Cicero from Meta AI



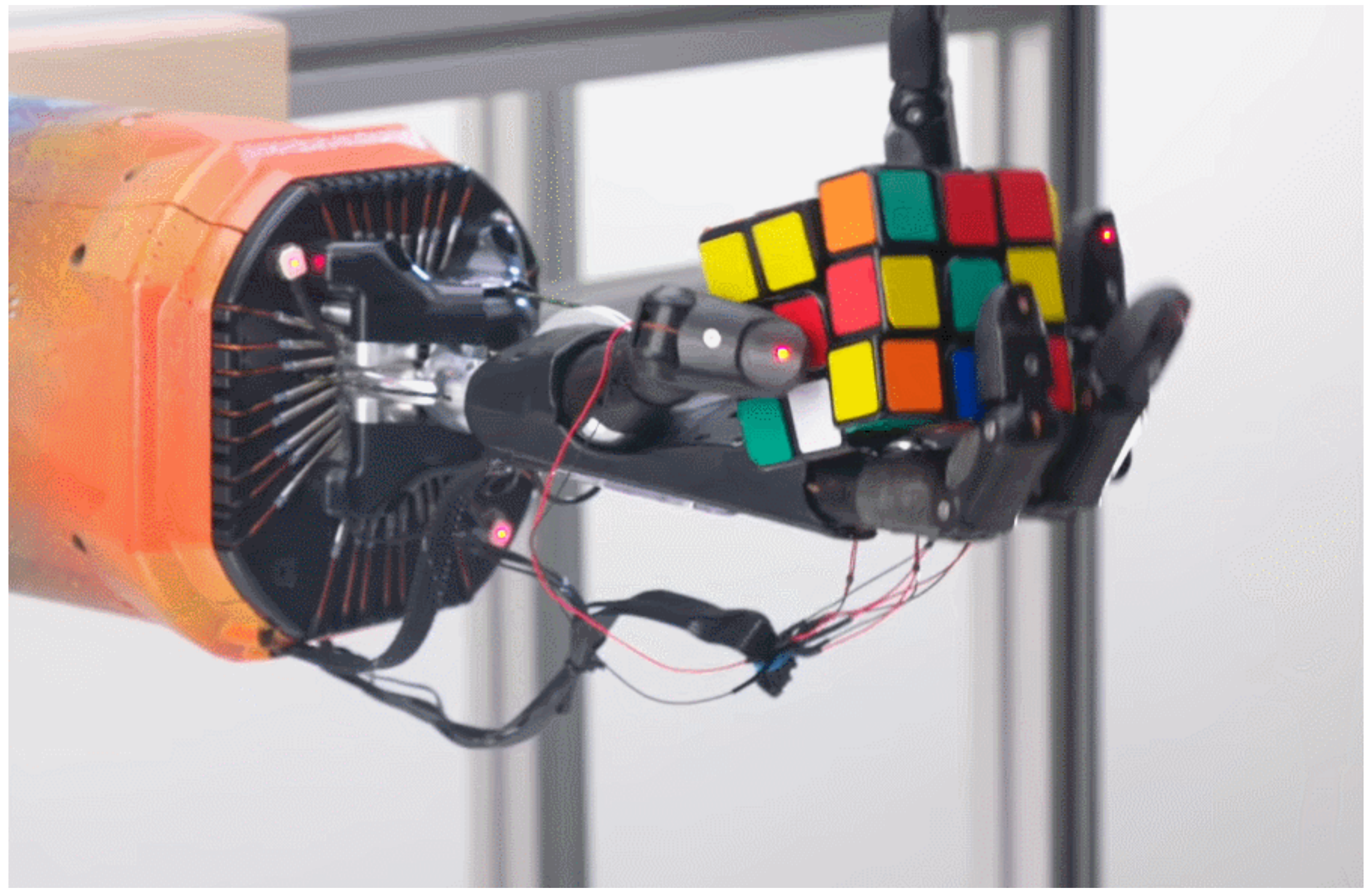




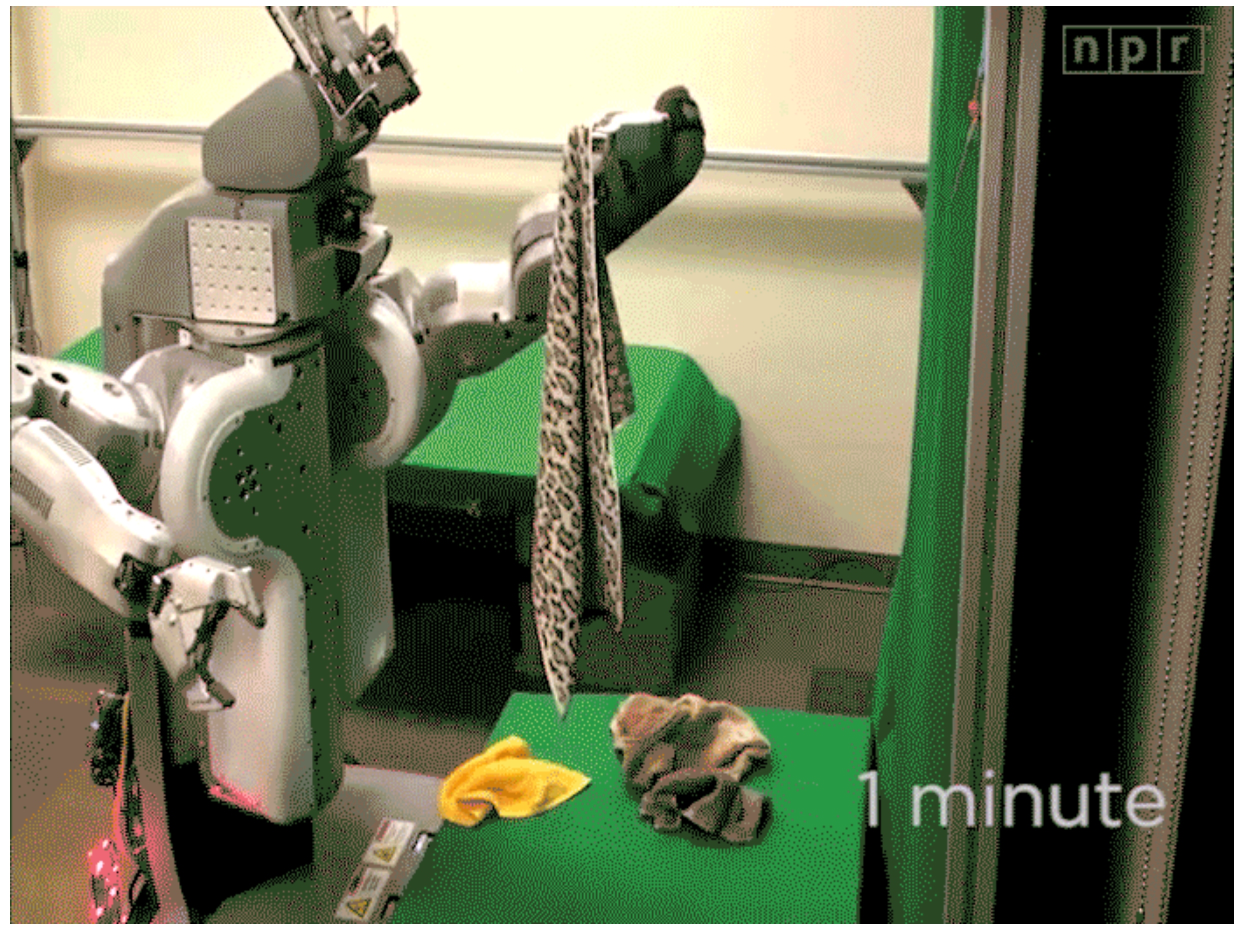
Reinforcement learning

Application: Robotics

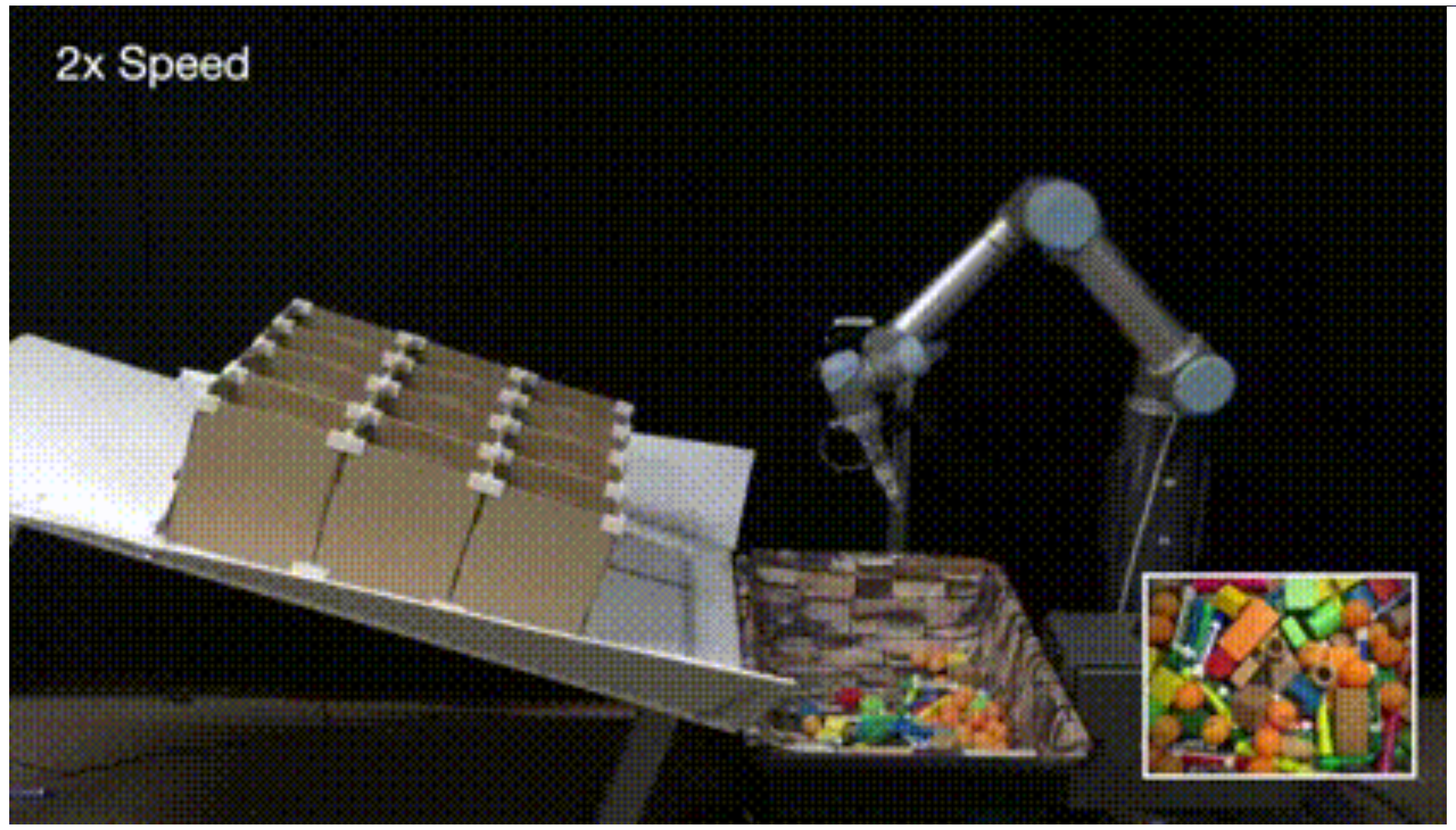
- Solving a Rubik's cube
- Manipulating objects
  (e.g. grasp, throw, etc.)
- Laundry folding



OpenAI's ADR (2019)



Berkeley's BRETT (2015)



Princeton+Google's TossingBot (2019)

Poll

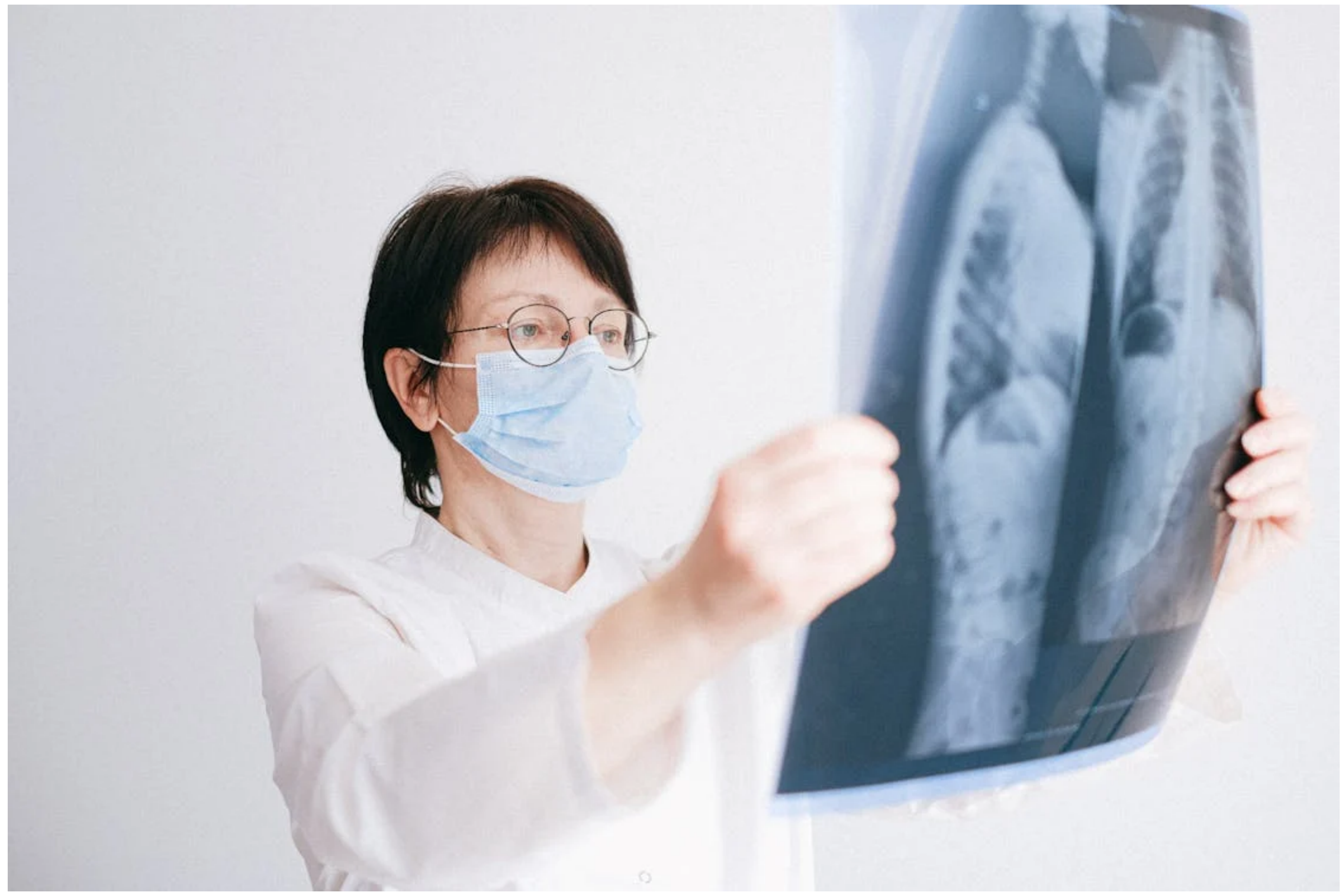
Predict if a patient's lung scan is abnormal based on a huge dataset of lung scans.

What kind of machine learning problem is this?

A. Supervised learning

B. Unsupervised learning

C. Reinforcement learning



https://www.pexels.com/photo/doctor-looking-at-lung-scans-she-is-holding-4225926/

Machine learning paradigms

1. Supervised learning: learn to **predict** an output from an input.
2. Unsupervised learning: learn **patterns** from data.
3. Reinforcement learning: learn by **interacting** with an environment (i.e. **trial-and-error**).

Other paradigms:

- *Self-supervised learning*
- *Semi-supervised learning*
- *Transfer learning*
- *Online learning*
- *…*

Ingredients of ML

1. **Data.** Can be labelled, unlabelled, or from experience.
2. **Model.** A model maps from datapoint to a desired answer or output.
3. **Model parameters**. Internal parameters of model that are learnable.
4. **Training.** Given datapoints, find good model parameters.
5. **Testing.** Evaluate the performance of learned model
   ... on new, previously unseen data (i.e. test set).

Perceptron

Supervised learning

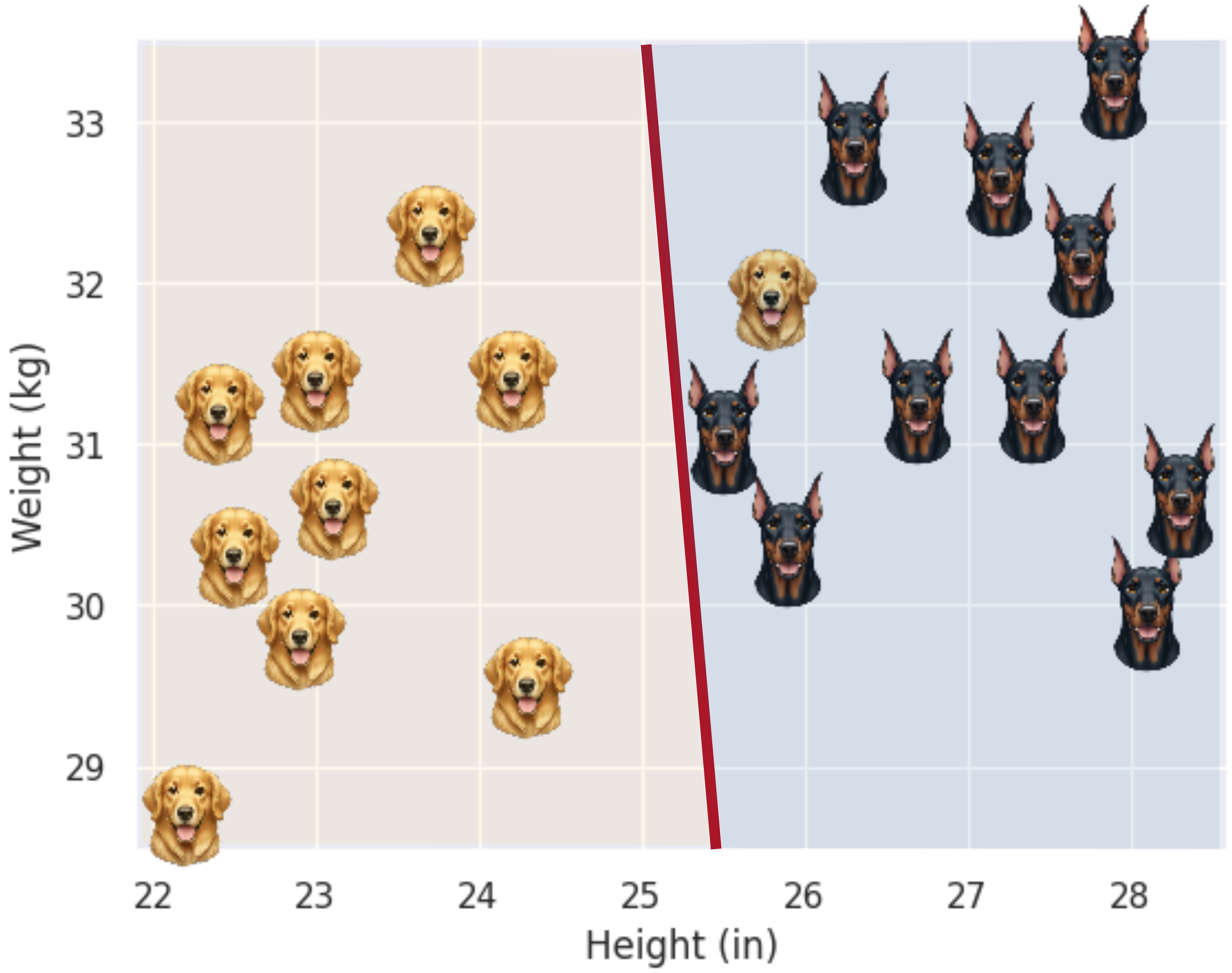
Given (input, output) pairs, **predict** an output from its input.

$\text{input}_1 \rightarrow \text{output}_1$
$\text{input}_2 \rightarrow \text{output}_2$
$\text{input}_3 \rightarrow \text{output}_3$

Basic problems described by output type:

- **Regression**: Predict a continuous value (e.g. number).
- **Classification**: Predict a discrete category (i.e. classes).
  - **Binary classification**: Predict one of **two** classes.
  - **Multi-class classification**: Predict one of **k** classes (k > 2).

Binary classification



Data is nearly **linearly separable**.

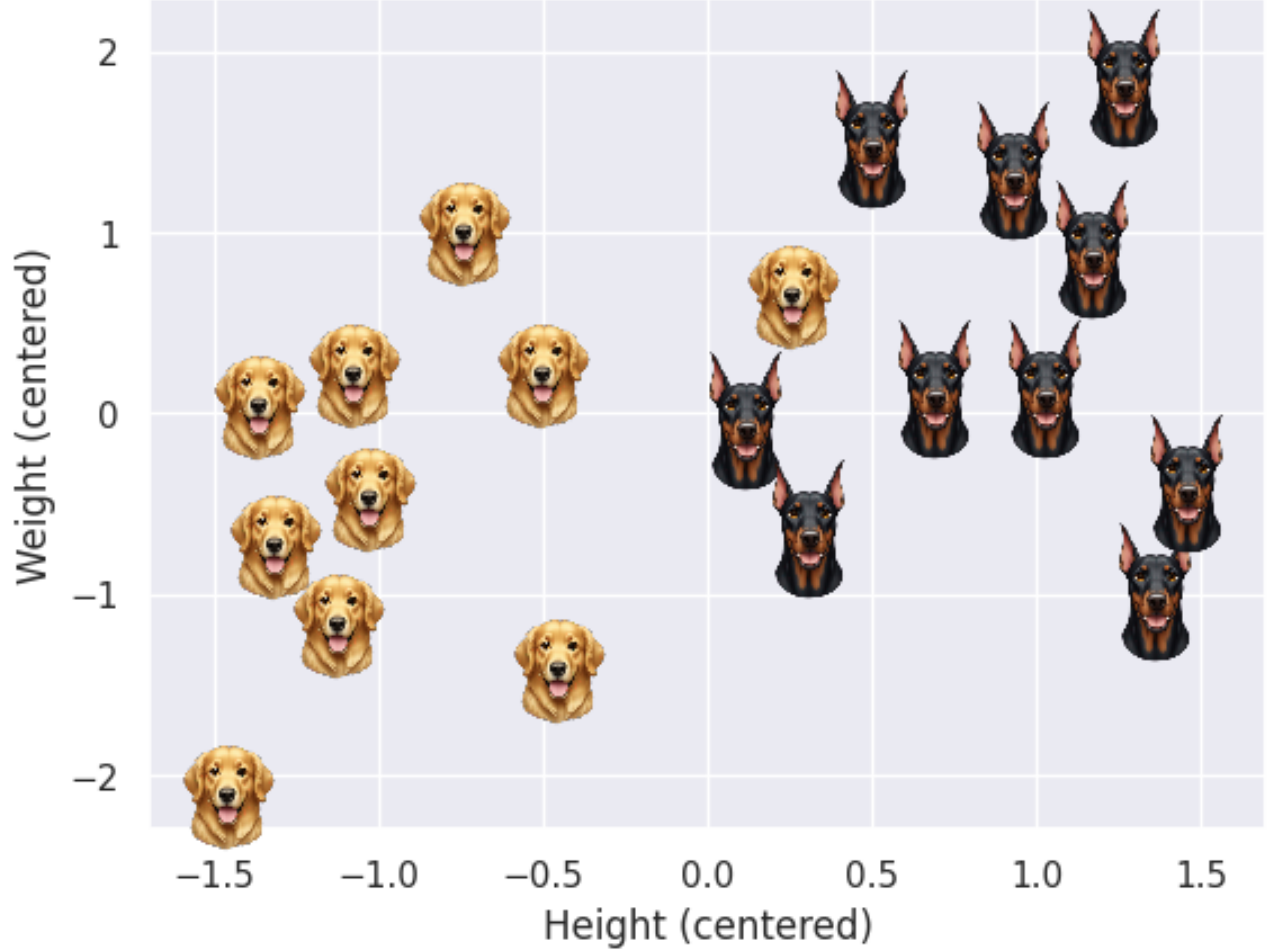
Binary classification

Predict dog species

- Input (centered*)
  - Height
  - Weight
- Output
  - Golden Retriever: $+1$
  - Doberman Pinscher: -1

= "Golden Retriever detector"

* Input centered to have
mean = 0 and standard deviation = 1.

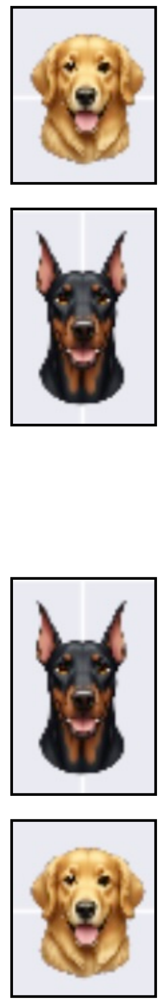


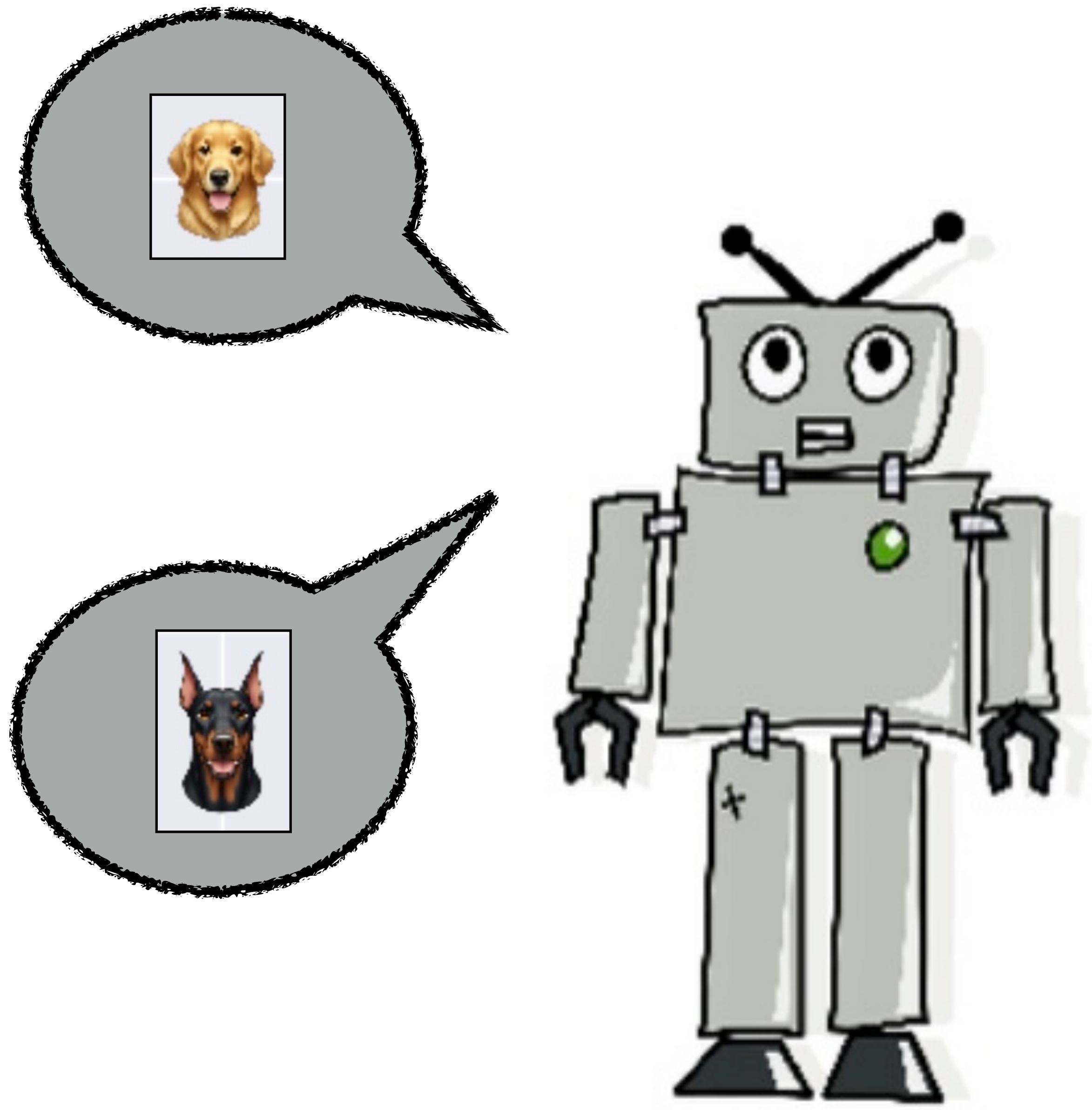
True/False Positive/Negative

Ways to get the answer right or wrong:

- True Positive
- False Positive

- True Negative
- False Negative

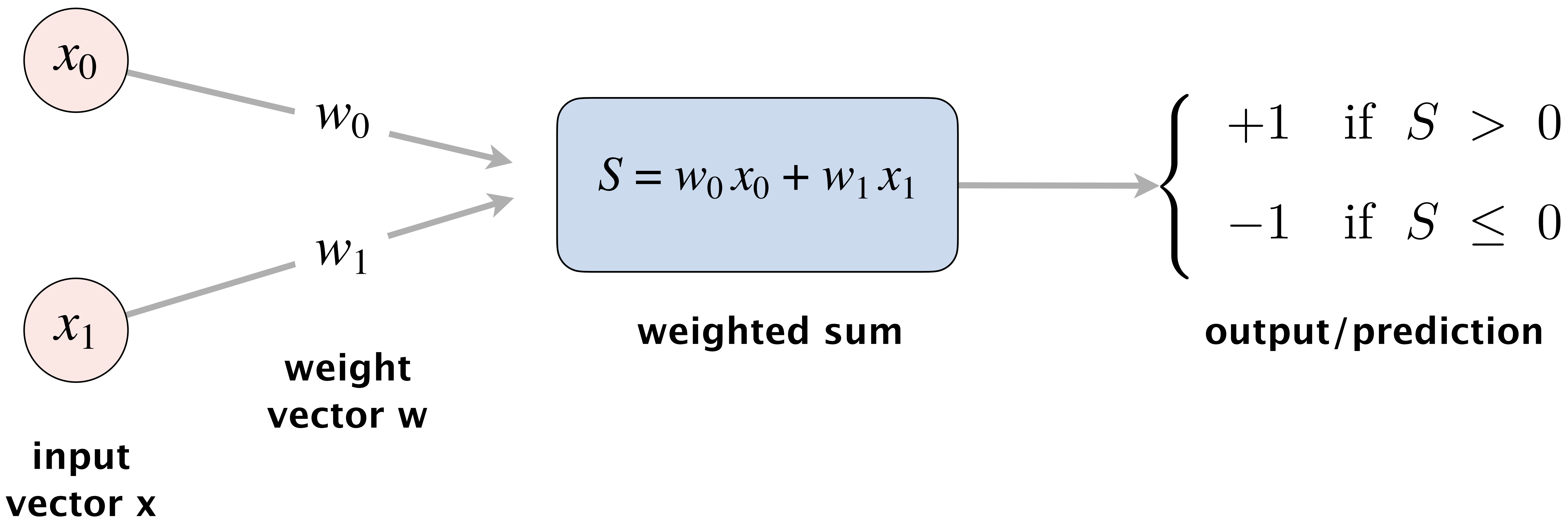




Perceptron

Algorithm that takes several inputs and produces a single, binary output.

- Inputs: x_0, x_1 (i.e. height, weight)
- Compute weighted sum
  $S = w_0 x_0 + w_1 x_1$
- Output
  $\text{sign}(S) = +1$ if $S > 0$
  $= -1$ if $S \leq 0$



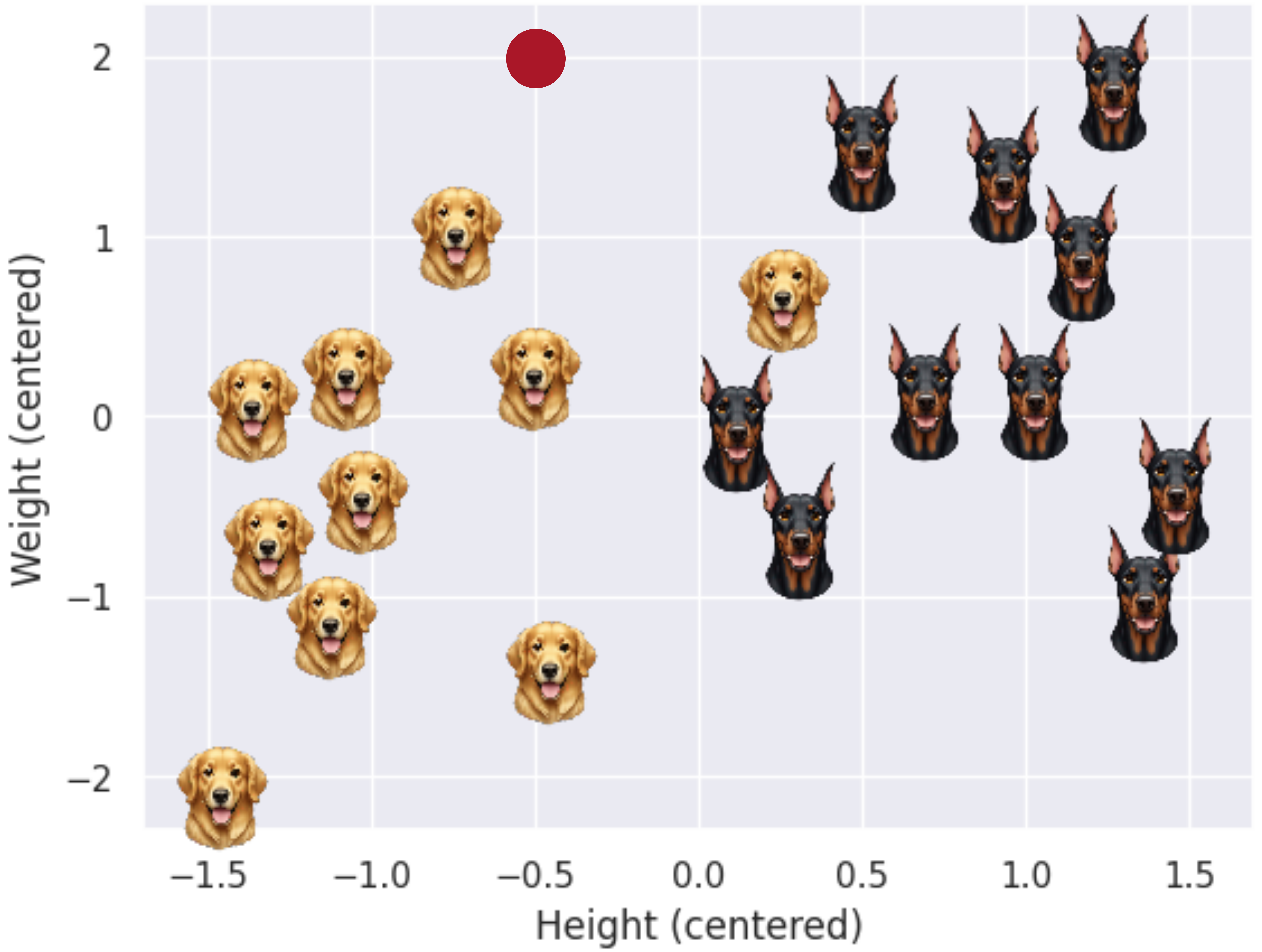
Poll

- Inputs: $x_0 = -0.5,\ x_1 = 2$
- Weights: $w_0 = -2,\ w_1 = -0.1$
- Compute weighted sum
  $S = w_0 x_0 + w_1 x_1$
- Output
  $\text{sign}(S) = +1$ if $S > 0$
  $= -1$ if $S \leq 0$

What is the weighted sum S?

A. -1.2 C. 0.8

B. -0.2 D. 1.0



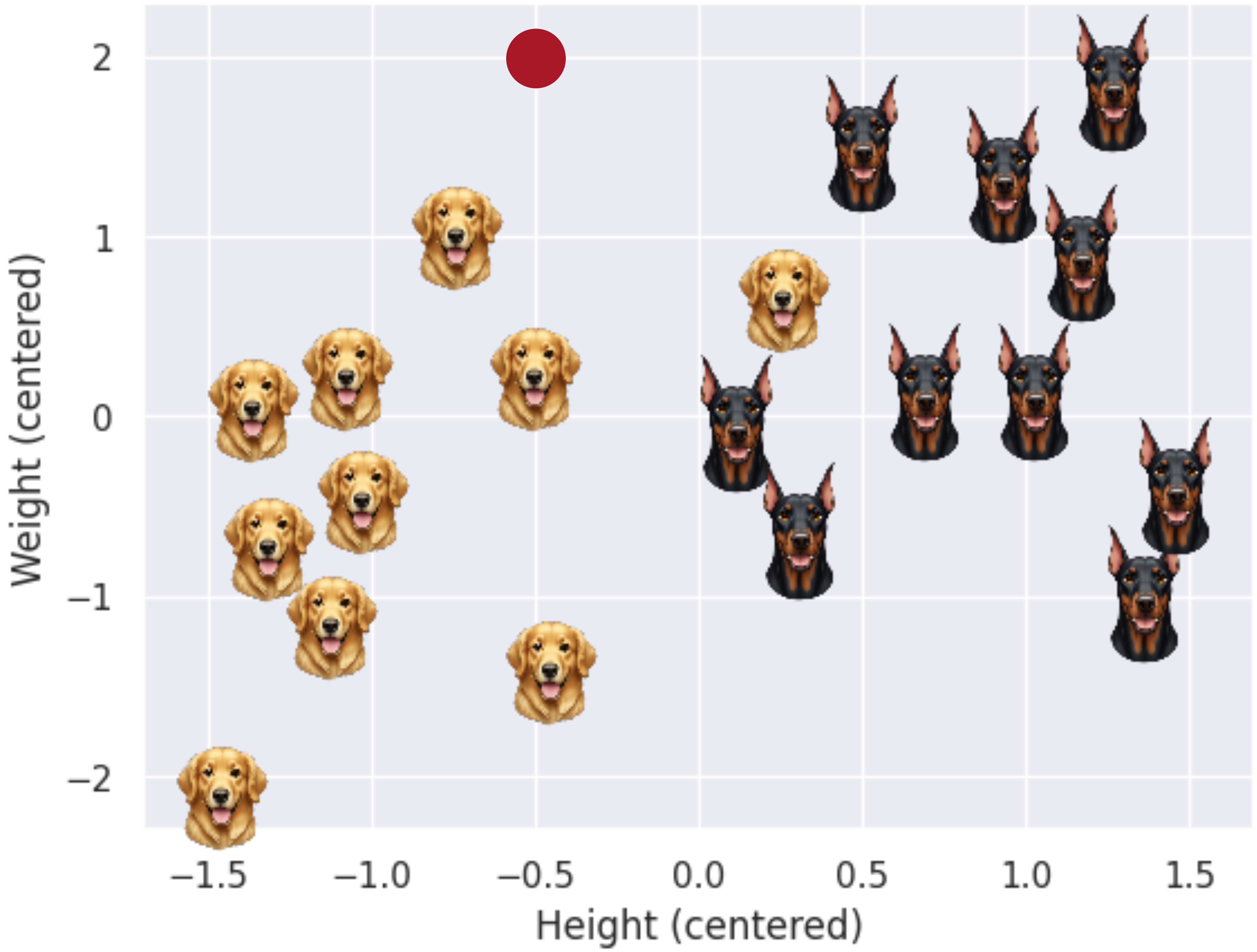
Golden retriever: +1, Doberman -1

Perceptron

- Inputs: $x_0 = -0.5,\ x_1 = 2$
- Weights: $w_0 = -2,\ w_1 = -0.1$
- Compute weighted sum
  $S = w_0 x_0 + w_1 x_1$
- Output
  $\text{sign}(S) = +1$ if $S > 0$
  $\qquad\qquad = -1$ if $S \leq 0$

$$S = w_0 x_0 + w_1 x_1$$
$$= (-2) \cdot (-0.5) + (-0.1) \cdot 2$$
$$= 1 + (-0.2) = 0.8$$

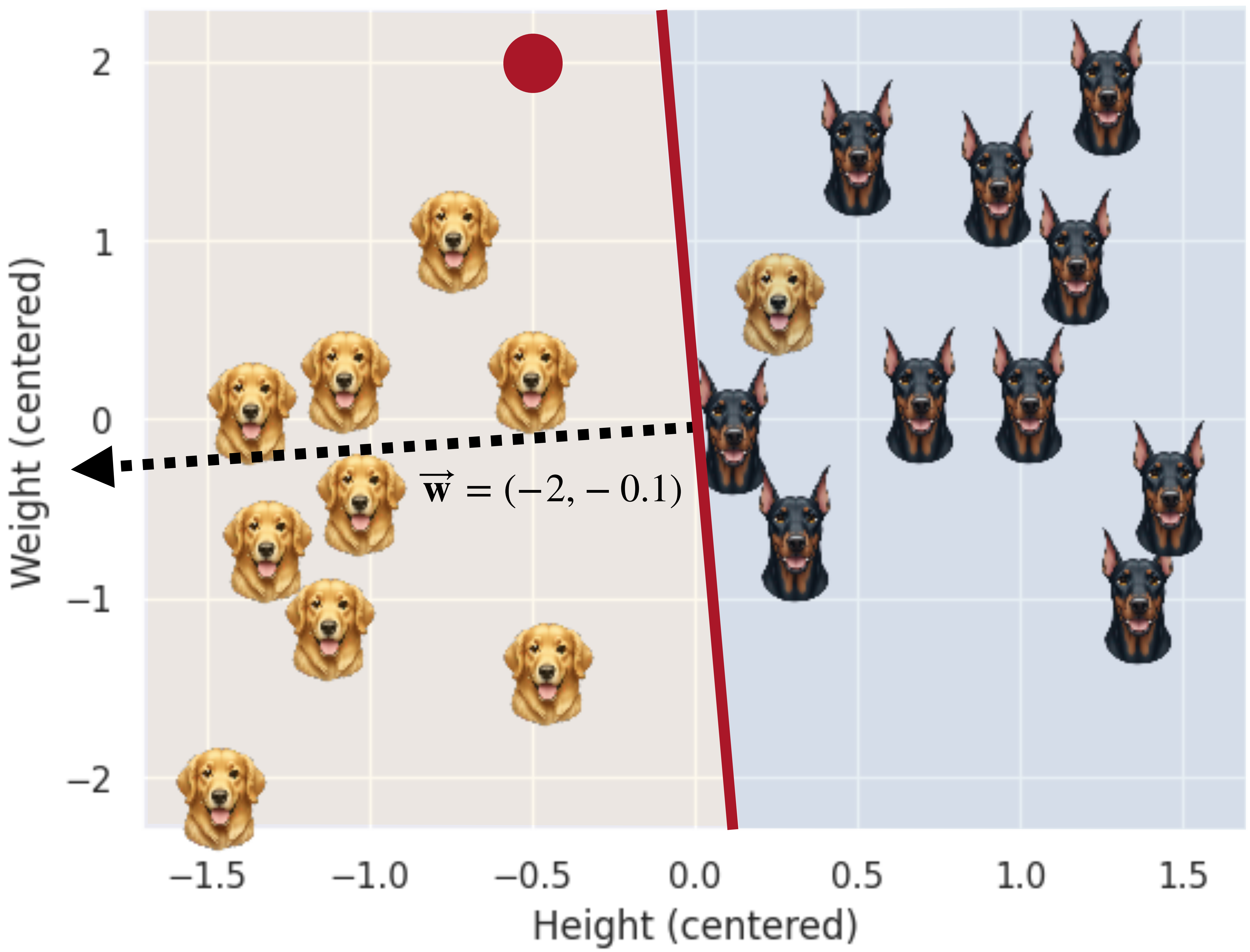
$\text{sign}(S) = \text{sign}(0.8) = +1$



Golden retriever: +1, Doberman -1

Perceptron: Geometric Perspective

- Inputs: $x_0 = -0.5,\ x_1 = 2$
- Weights: $w_0 = -2,\ w_1 = -0.1$
- Compute weighted sum
  $S = w_0 x_0 + w_1 x_1 = 0.8$
- Output
  $\text{sign}(S) = +1$
- Weight vector $\vec{\mathbf{w}}$ is **perpendicular** to linear decision boundary.
- Datapoints on the "side" with weight vector $\vec{\mathbf{w}}$ are predicted as $+1$; those on the "opposite site" as -1.



Golden retriever: +1, Doberman -1

Ingredients of ML

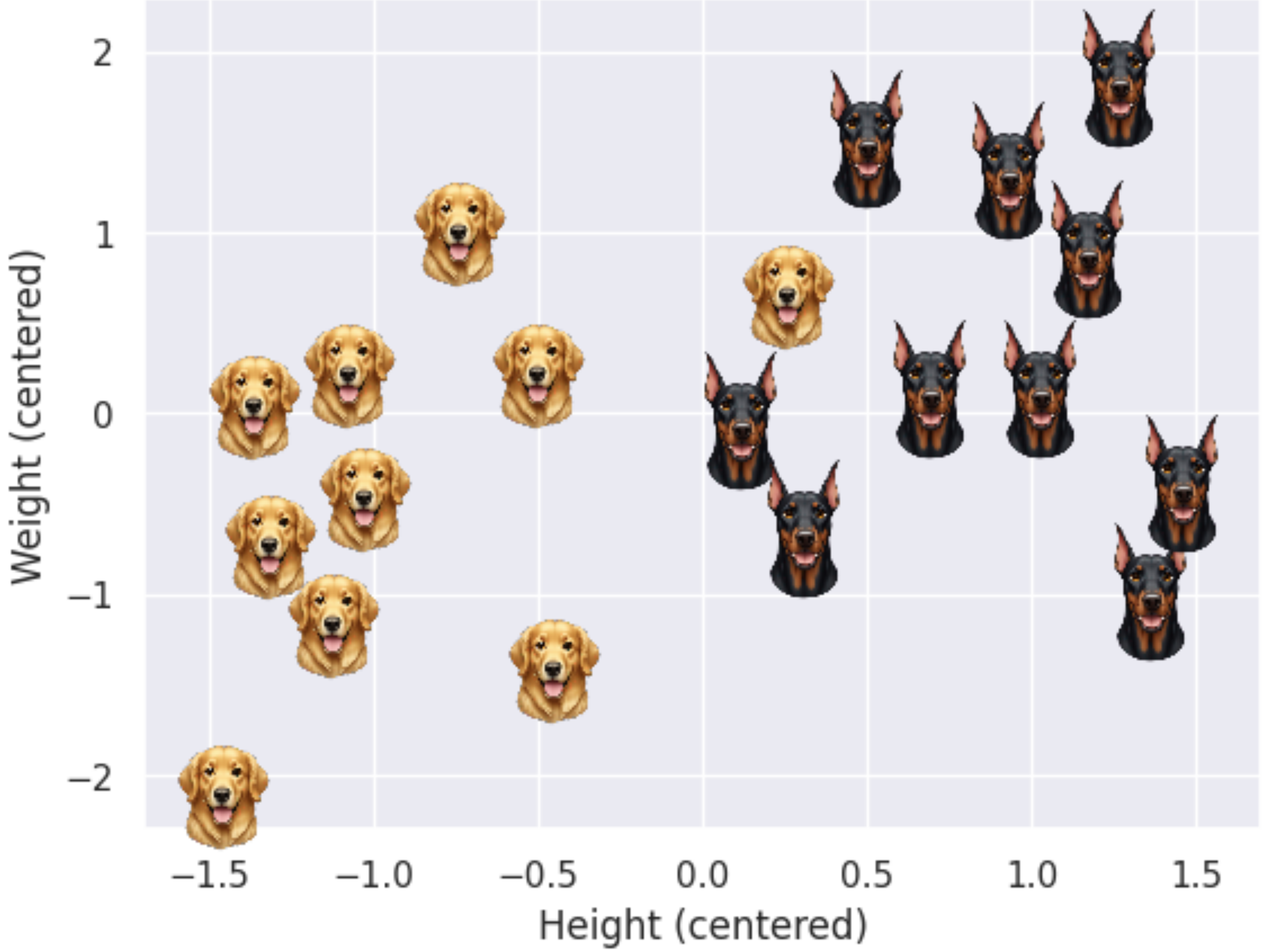
1. **Data.** Height and weight (x_0, x_1)
   and label $y \in \{+1, -1\}$ for Golden Retriever or Doberman.
2. **Model.** Perceptron model.
3. **Model parameters**. Weight vector $\vec{\mathbf{w}} = (w_0, w_1)$.
4. **Training.** Given datapoints, find good model parameters.
5. **Testing.** Evaluate the performance of learned model on new, previously unseen data (i.e. test set).

Perceptron: Training

Initialize all weights to 0.

For each training example with label $y \in \{+1, -1\}$:

- Compute predicted output $\hat{y} = \text{sign}(S)$
- Update weights if incorrect (i.e. $\hat{y} \neq y$)

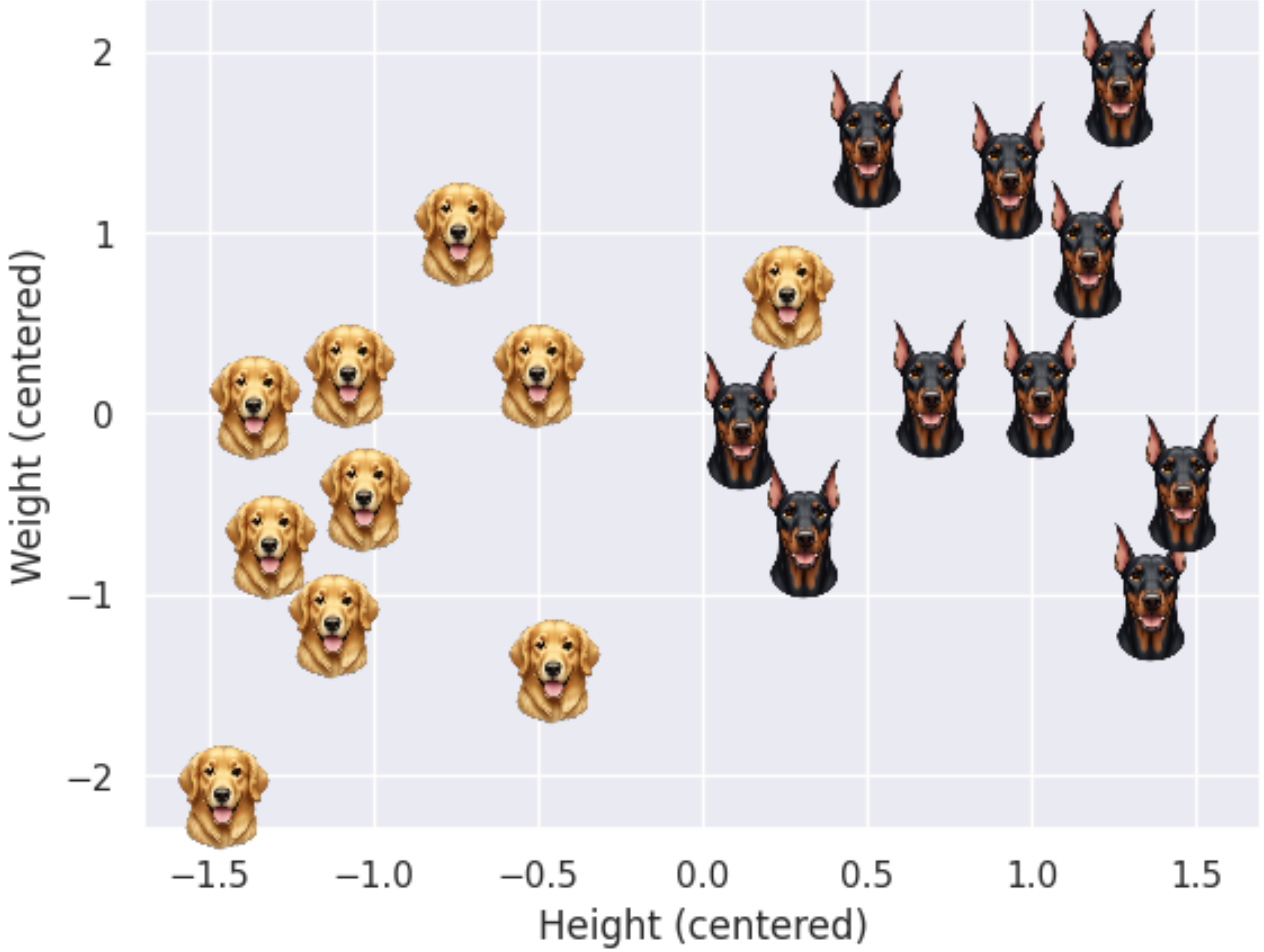


Golden retriever: +1, Doberman -1

Perceptron: Update Rule

For each training example with label $y \in \{+1, -1\}$:

- Compute predicted output
  $S = w_0 x_0 + w_1 x_1$
  $\hat{y} = \text{sign}(S) = +1$ if $S > 0$
  $= -1$ if $S \leq 0$
- If correct ($y = \hat{y}$), do nothing.
- If false positive ($y = -1,\ \hat{y} = +1$):
  $w_j' = w_j - x_j$
- If false negative ($y = +1,\ \hat{y} = -1$):
  $w_j' = w_j + x_j$



Golden retriever: +1, Doberman -1

Poll

- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- Weights: $w_0 = -2,\ w_1 = -0.1$
- Compute predicted output

$$S = w_0 x_0 + w_1 x_1$$

$$\hat{y} = \text{sign}(S) = +1 \text{ if } S > 0$$

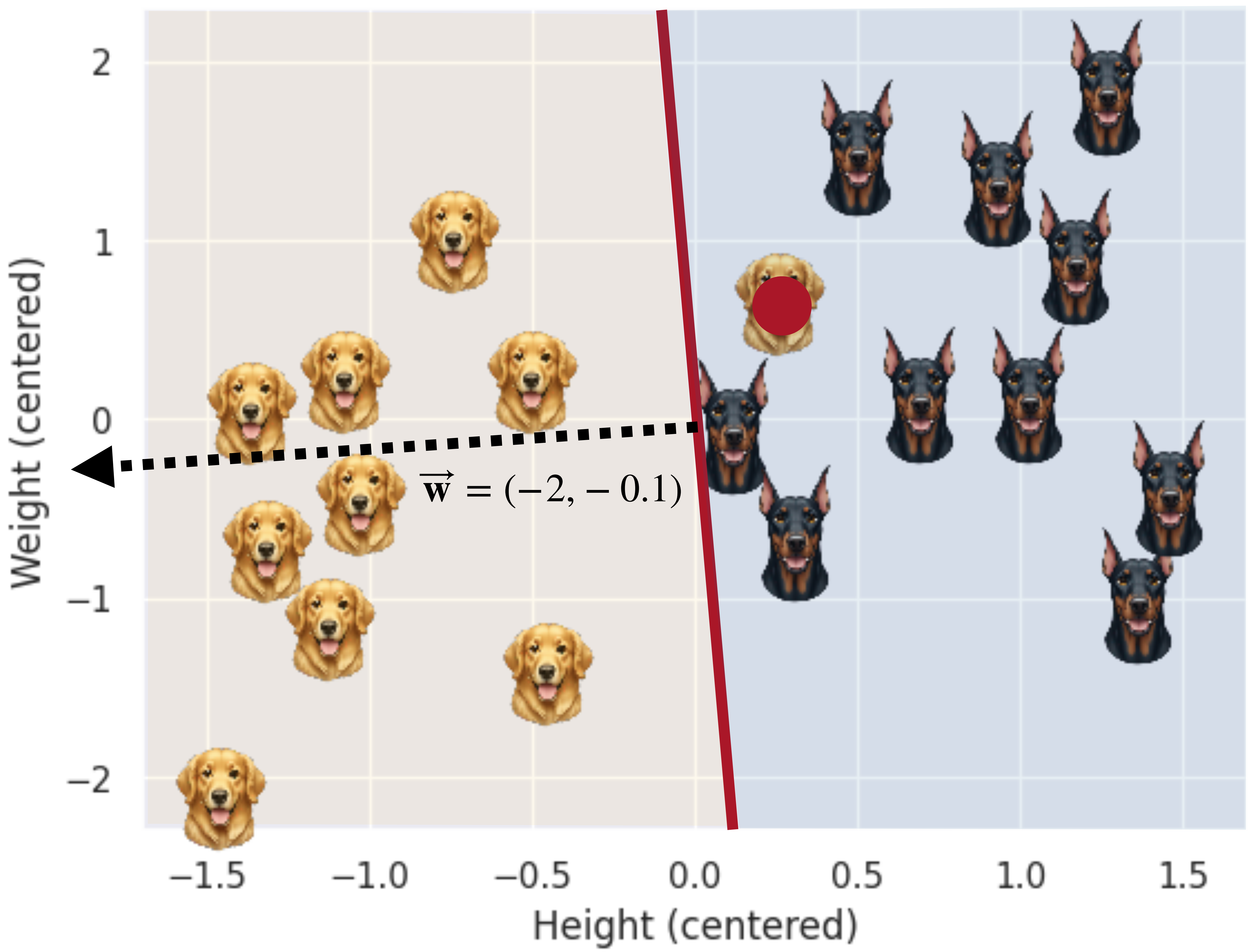
$$= -1 \text{ if } S \leq 0$$

Which scenario is true?

A. Correct prediction ($y = \hat{y}$)

B. False positive ($y = -1,\ \hat{y} = +1$)

C. False negative ($y = +1,\ \hat{y} = -1$)



Golden retriever: +1, Doberman -1

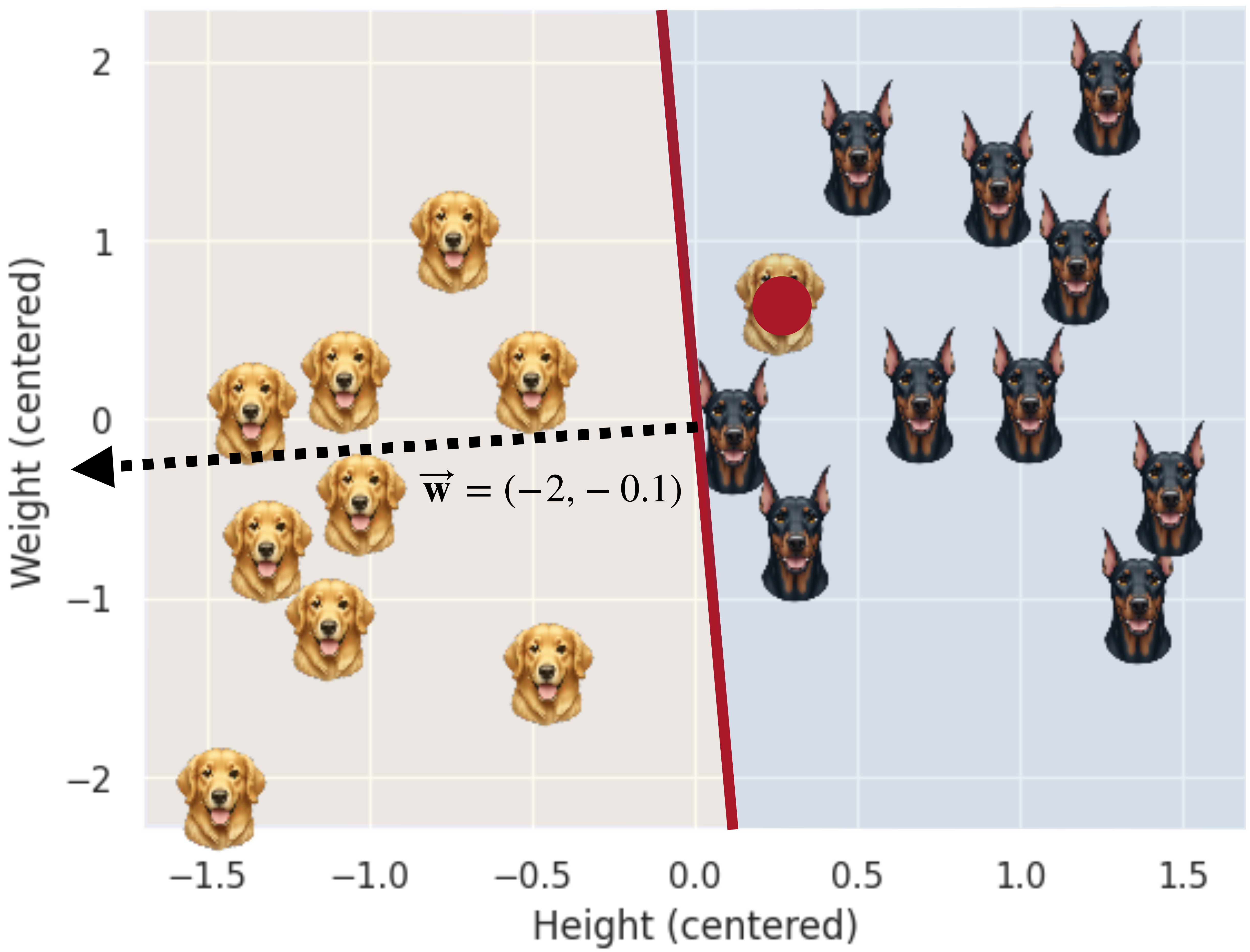
Poll

- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- Weights: $w_0 = -2,\ w_1 = -0.1$

$$S = w_0 x_0 + w_1 x_1$$
$$= (-2) \cdot 0.3 + (-0.1) \cdot 0.6$$
$$= -0.6 + (-0.06) = -0.66$$

$$\hat{y} = \text{sign}(S) = -1$$

Which scenario is true?



Golden retriever: +1, Doberman -1

Perceptron: Update Rule

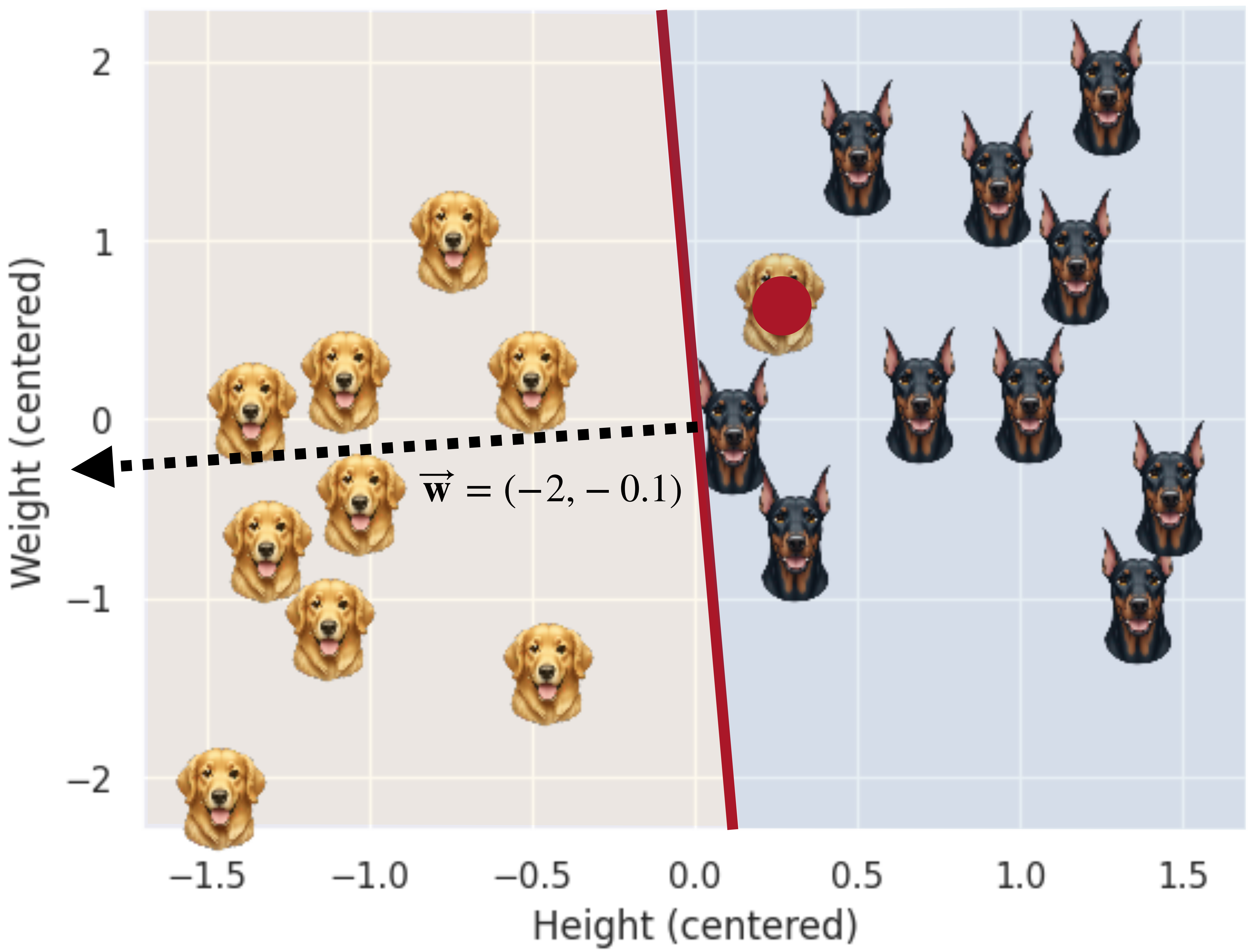
- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- Weights: $w_0 = -2,\ w_1 = -0.1$

$S = w_0 x_0 + w_1 x_1 = -0.66$

$\hat{y} = \text{sign}(S) = -1$

Update rules:

- If correct ($y = \hat{y}$), do nothing.
- If false positive ($y = -1,\ \hat{y} = +1$):
  $w_j' = w_j - x_j$
- If false negative ($y = +1,\ \hat{y} = -1$):
  $w_j' = w_j + x_j$



Perceptron: Update Rule

- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
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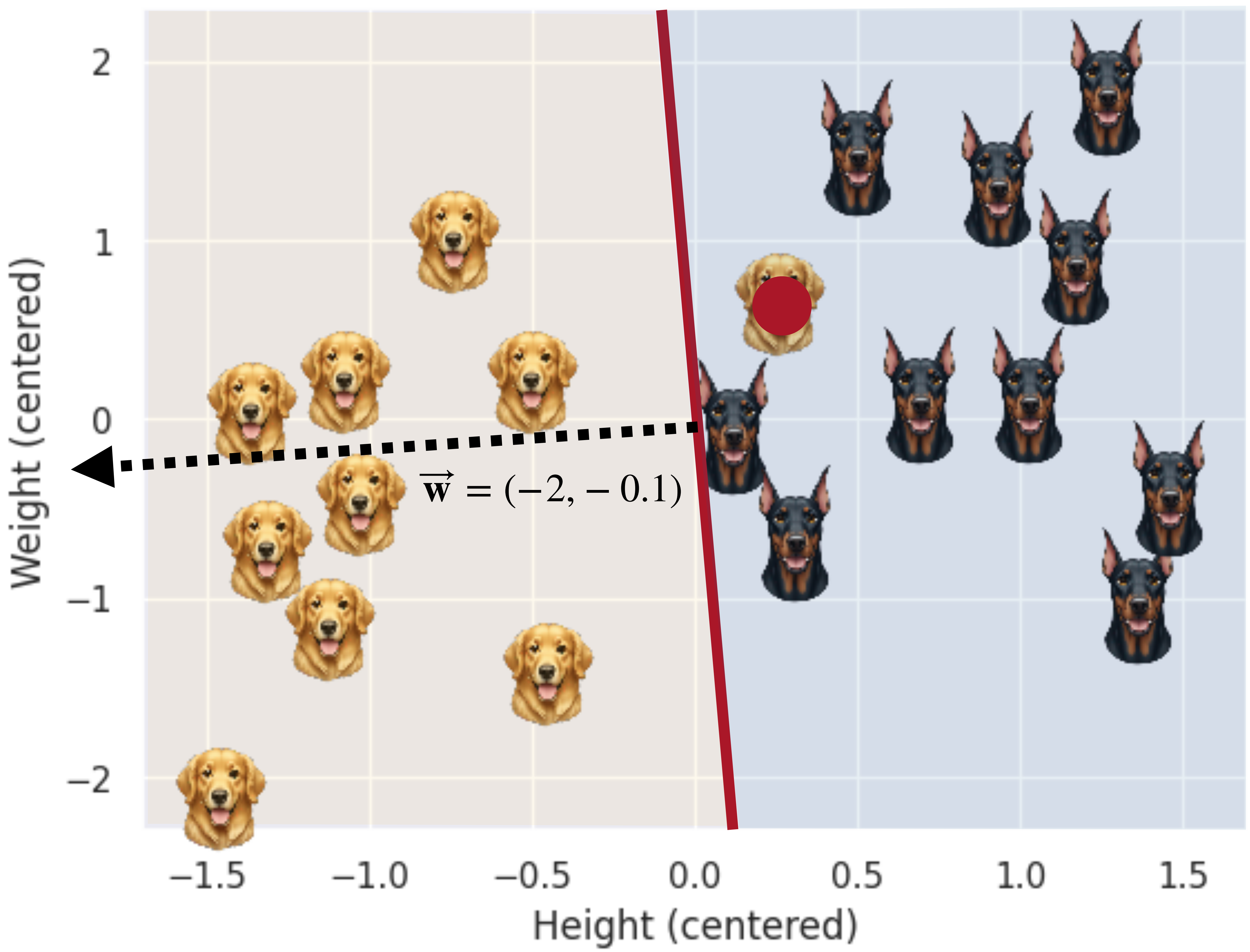
$S = w_0 x_0 + w_1 x_1 = -0.66$

$\hat{y} = \text{sign}(S) = -1$



Update rules:

- If correct ($y = \hat{y}$), do nothing.
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  $w_j' = w_j - x_j$
- **If false negative ($y = +1,\ \hat{y} = -1$):**
  $w_j' = w_j + x_j$

Perceptron: Update Rule

- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- Weights: $w_0 = -2,\ w_1 = -0.1$

$S = w_0x_0 + w_1x_1 = -0.66$

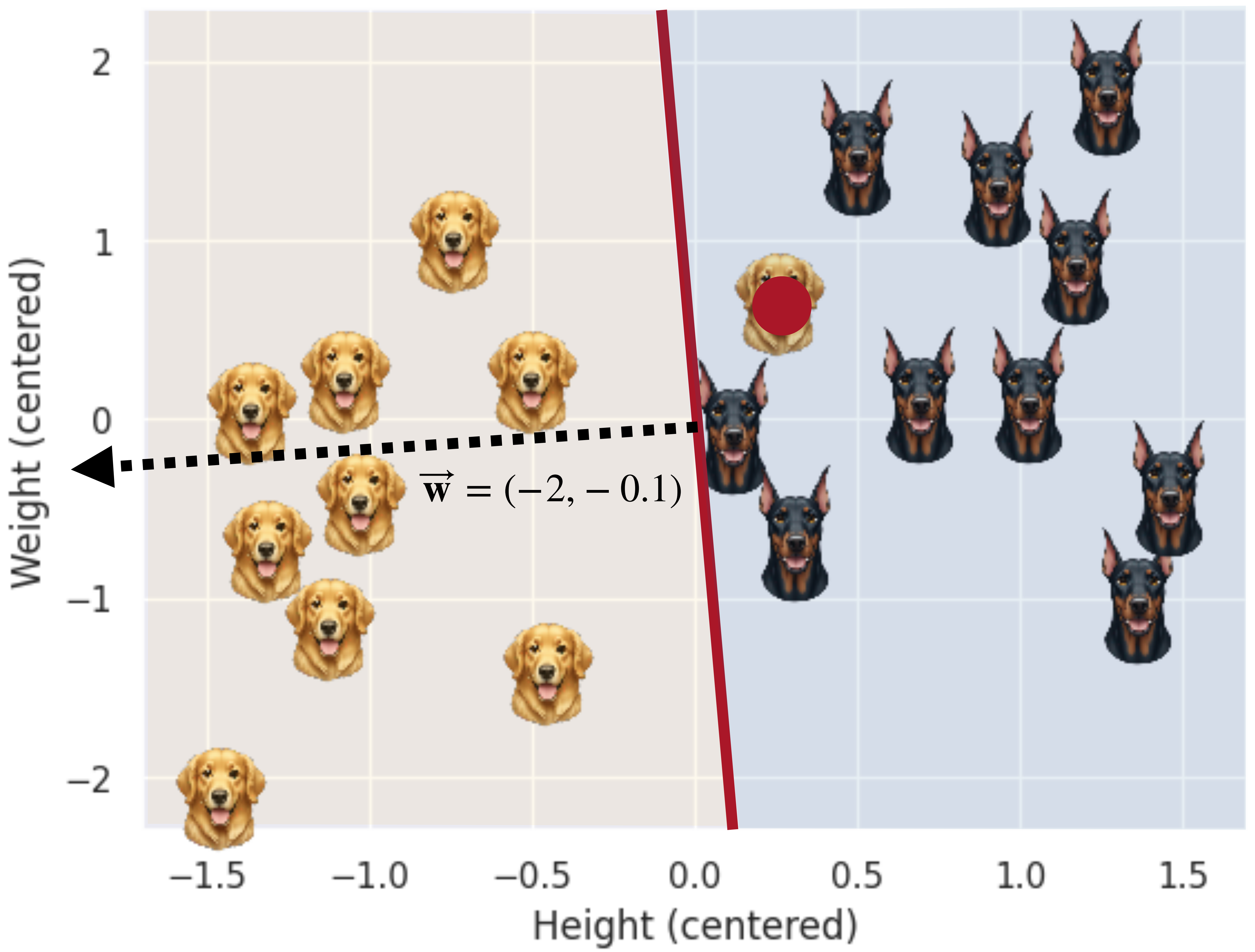
$\hat{y} = \text{sign}(S) = -1$

If false negative ($y = +1,\ \hat{y} = -1$):

$w_j' = w_j + x_j$

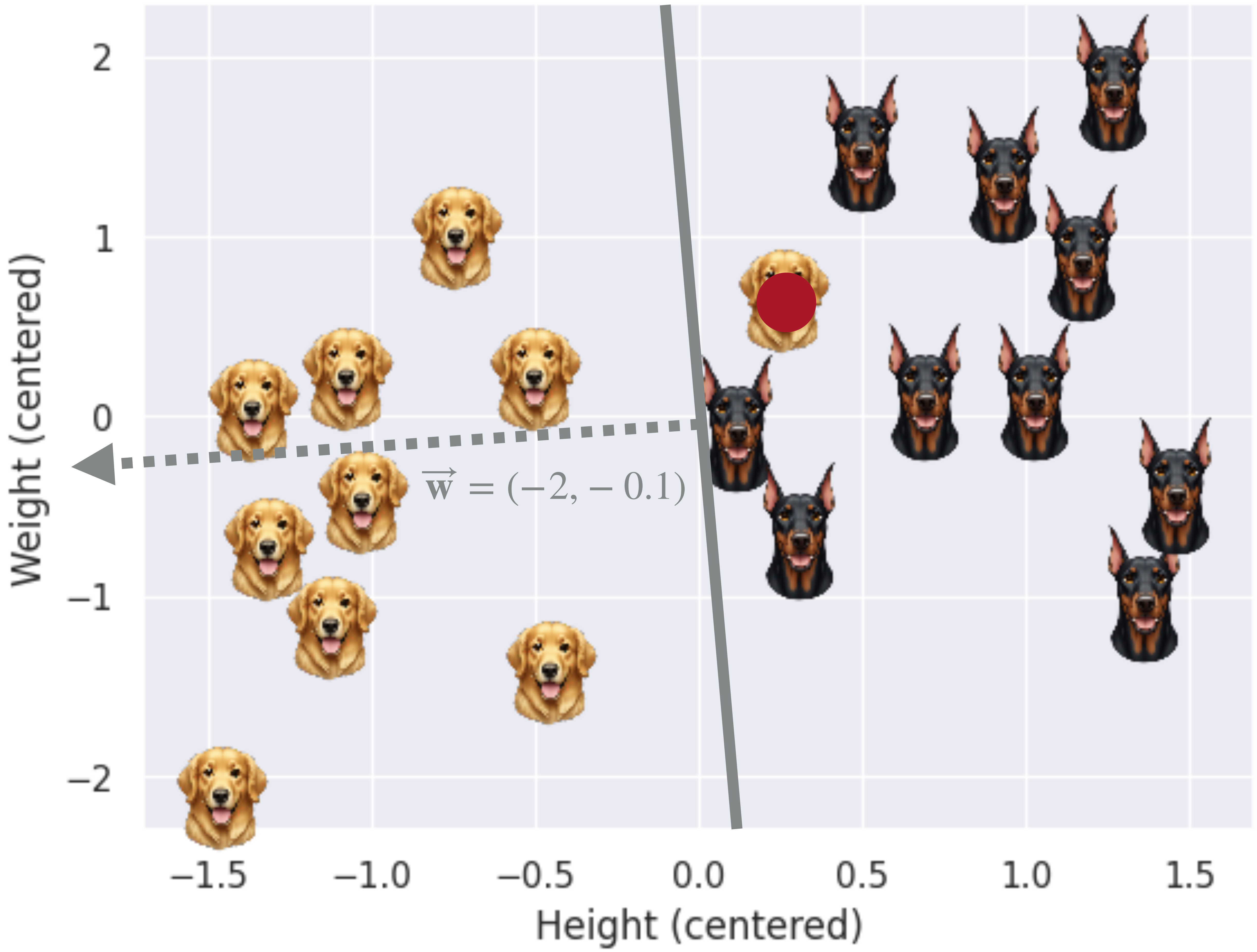
$w_0' = w_0 + x_0 = -2 + 0.3 = -1.7$

$w_1' = w_1 + x_1 = -0.1 + 0.6 = 0.5$



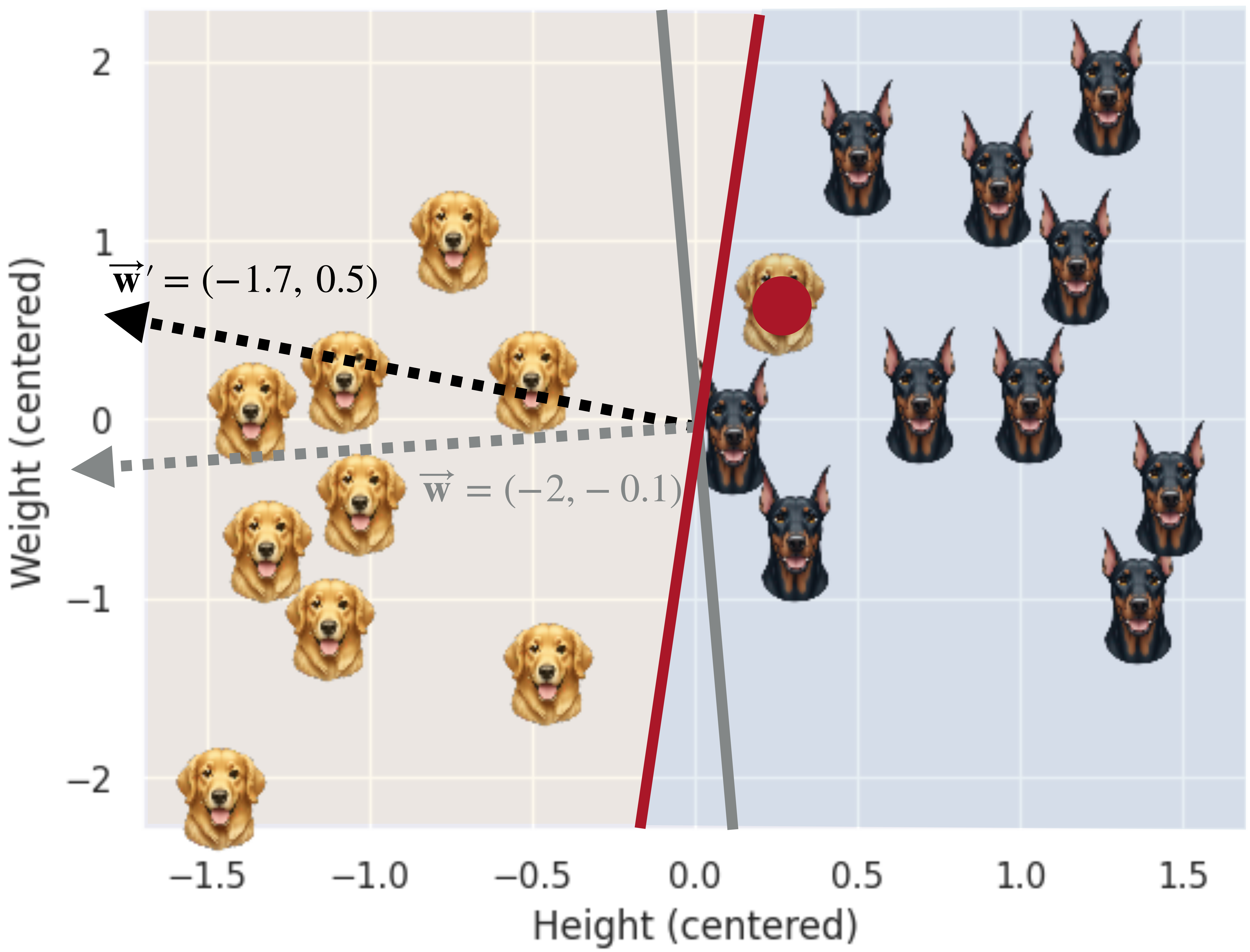
Perceptron: Update Rule

- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- Old weights: $w_0 = -2,\ w_1 = -0.1$



Perceptron: Update Rule

- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- Old weights: $w_0 = -2,\ w_1 = -0.1$
- New weights: $w_0' = -1.7,\ w_1' = 0.5$



Perceptron: Update Rule

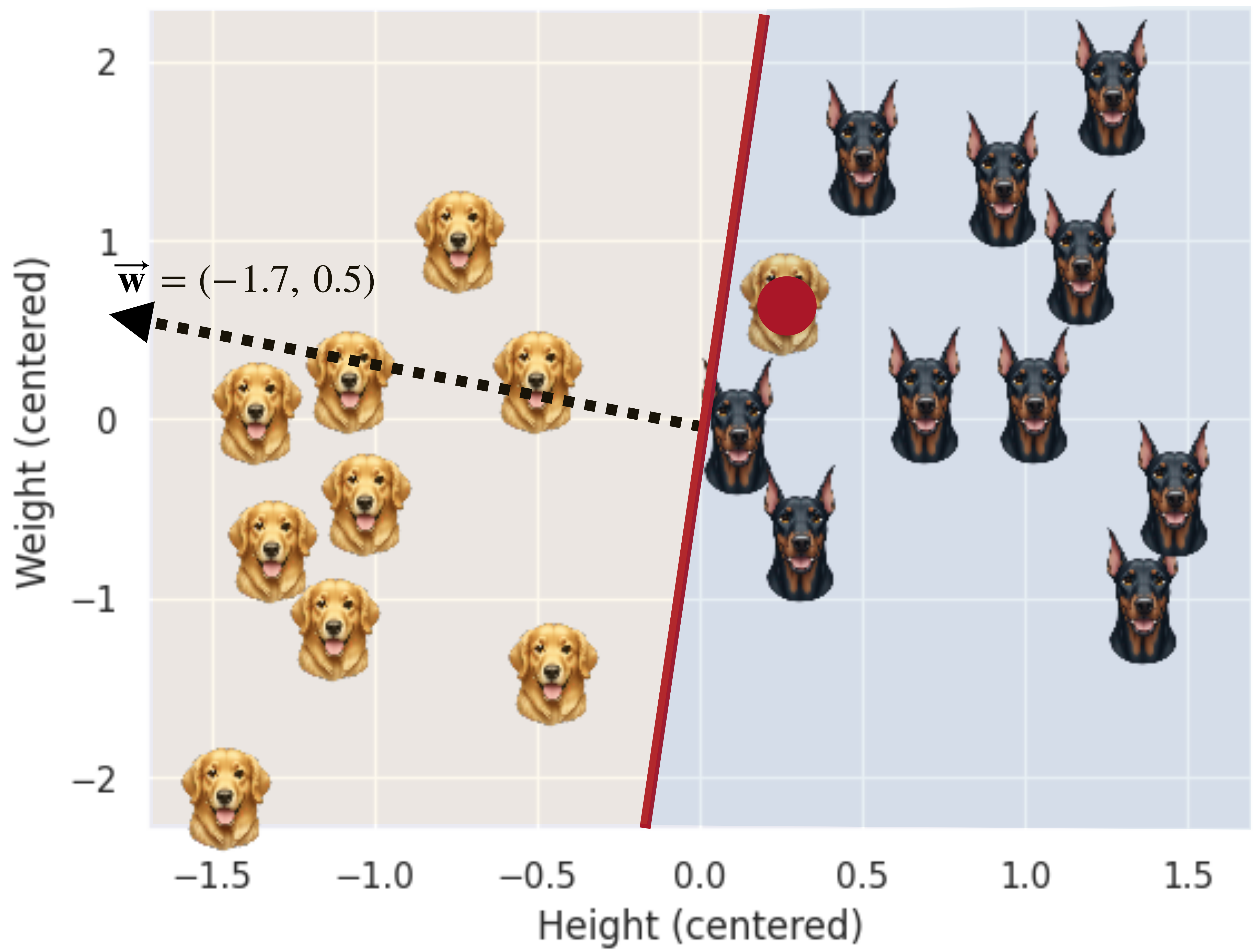
- Inputs: $x_0 = 0.3,\ x_1 = 0.6,\ y = +1$
- New weights: $w_0 = -1.7,\ w_1 = 0.5$

$S = w_0 x_0 + w_1 x_1 = -0.21$

$\hat{y} = \text{sign}(S) = -1$

Still false negative, but closer to boundary.

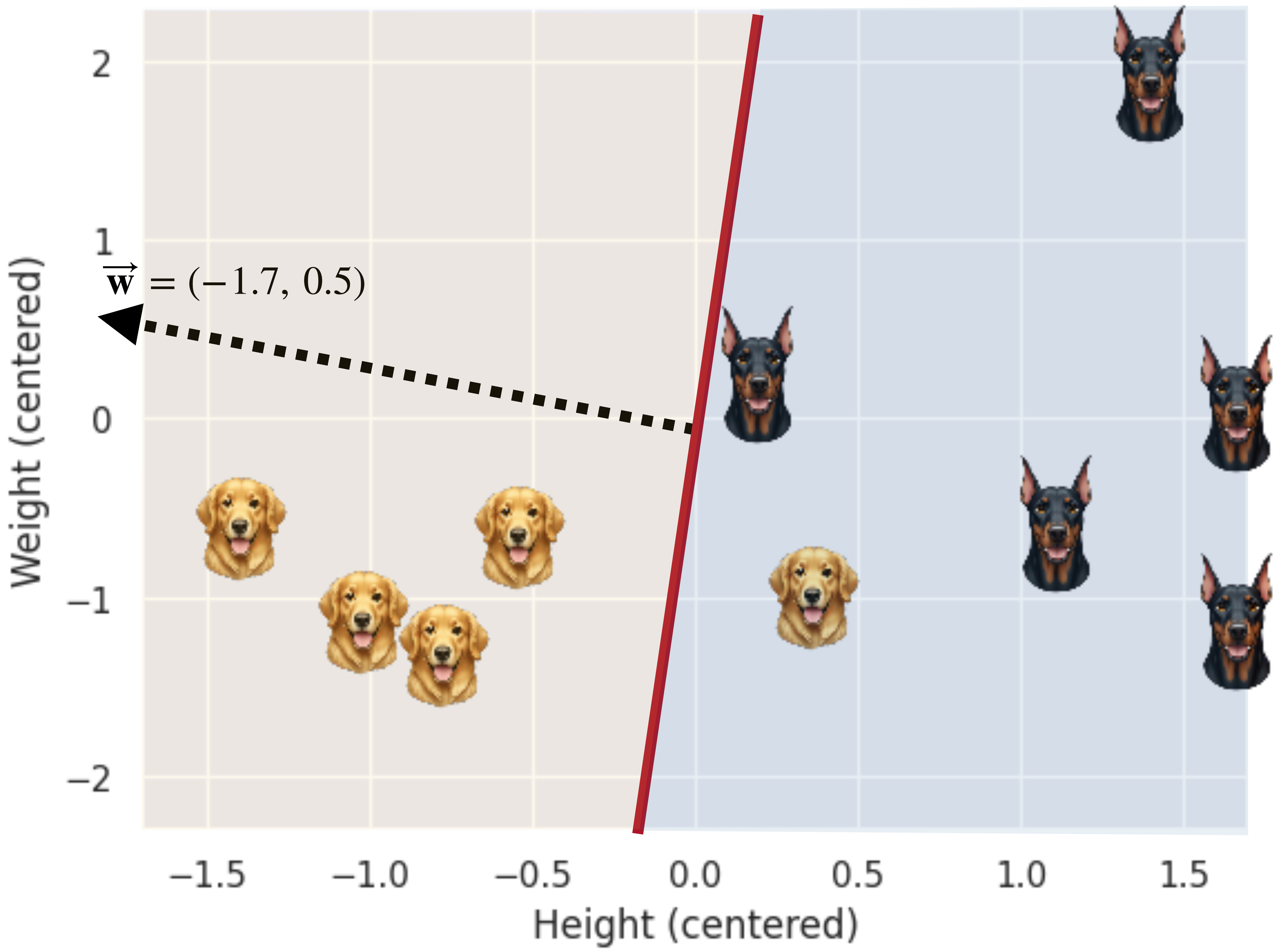
Intuition: Update rule moves decision boundary to be better for the current training example.



Perceptron: Testing

Evaluate performance using an evaluation metric on an unseen set of examples (e.g. test examples).

$$\text{Error rate} = \frac{\#\ \text{incorrect}}{\#\ \text{total}}$$



Poll

Evaluate performance using an evaluation metric on an unseen set of examples (e.g. test examples).

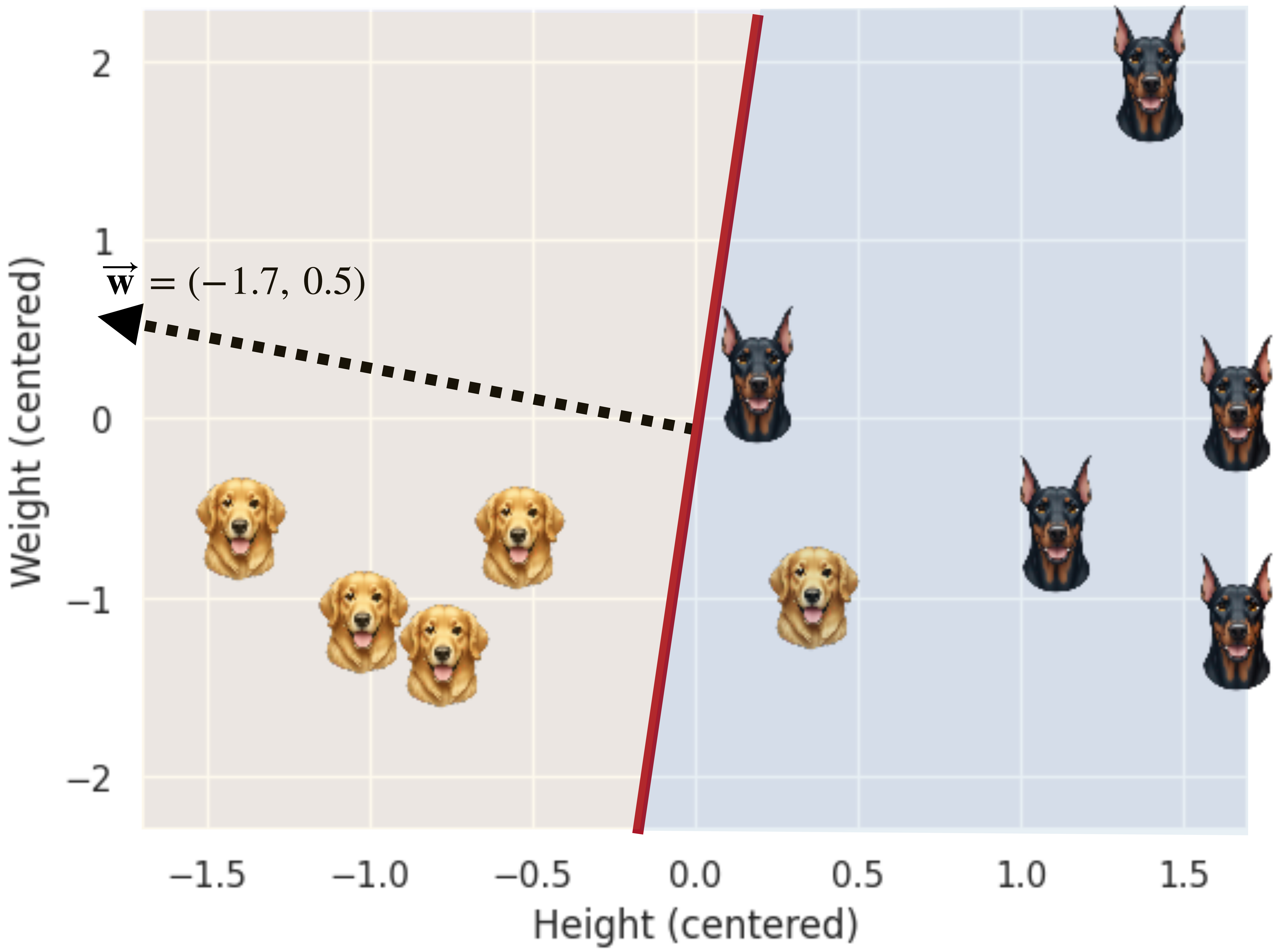
$$\text{Error rate} = \frac{\#\text{ incorrect}}{\#\text{ total}}$$

Consider the following unseen examples (5 Golden Retrievers, 5 Dobermans) and the given Perceptron model.

What is the error rate on test set?

A. $0/10$ C. $2/10$

B. $1/10$ D. $9/10$



Poll

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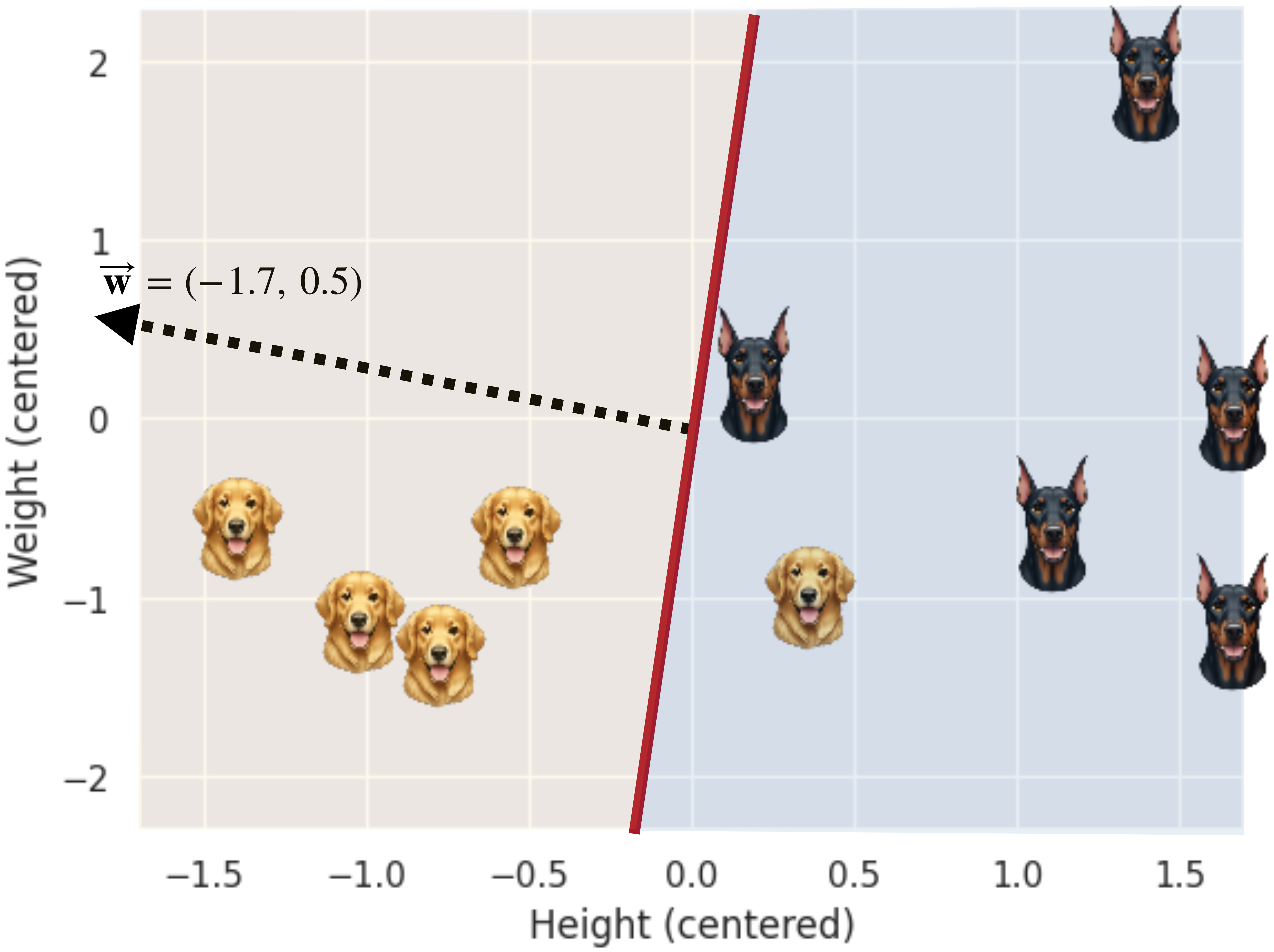
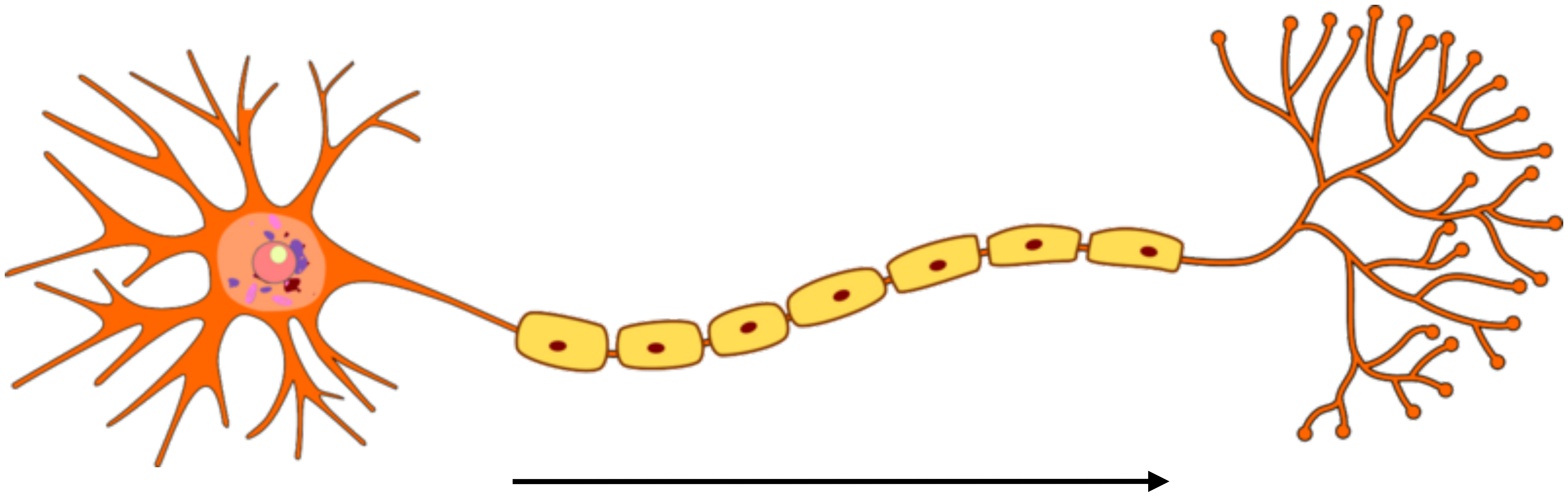


Ingredients of ML

1. **Data.** Height and weight (x_0, x_1) and label $y \in \{+1, -1\}$ for Golden Retriever or Doberman.
2. **Model.** Perceptron model.
3. **Model parameters**. Weight vector $\vec{\mathbf{w}} = (w_0, w_1)$.
4. **Training.** Use the Perceptron update rule to train on training examples.
5. **Testing.** Compute error rate on new, previously unseen data (i.e. test set).

Multi-layer Perceptron

Biological Neuron



Dendrites

Receive information from other neurons

Action potential

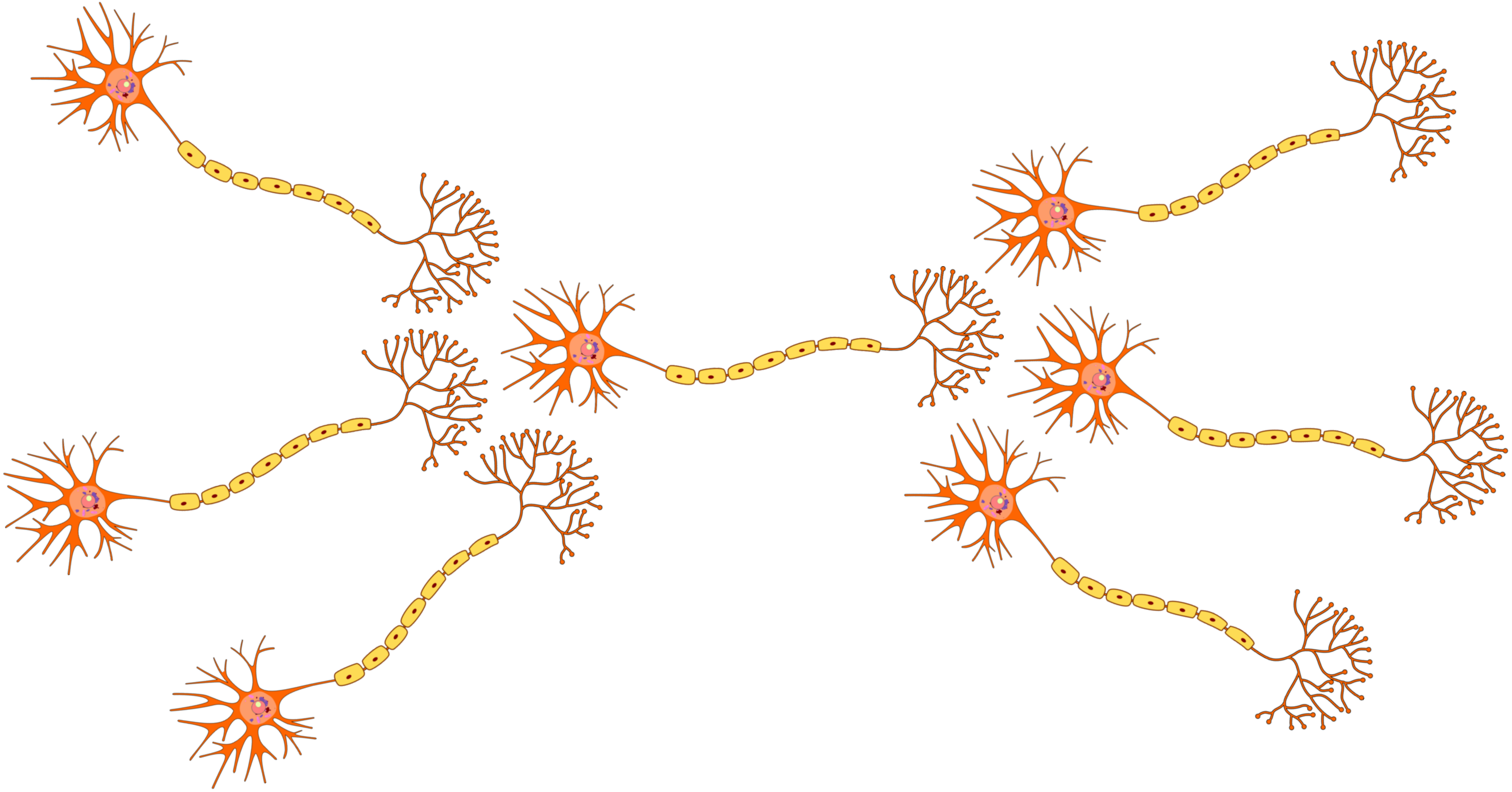
Neuron "fires" based on received information

Synaptic terminals

Relay "firing" to other neurons

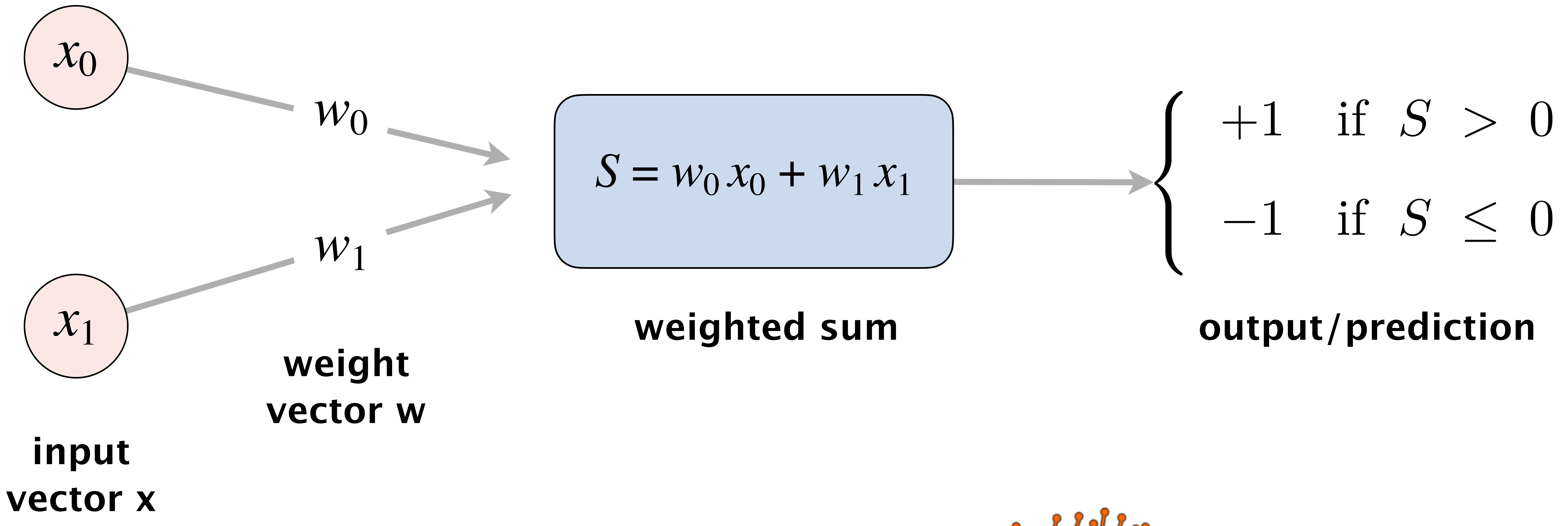
Neuron firing (or not) is a binary output.

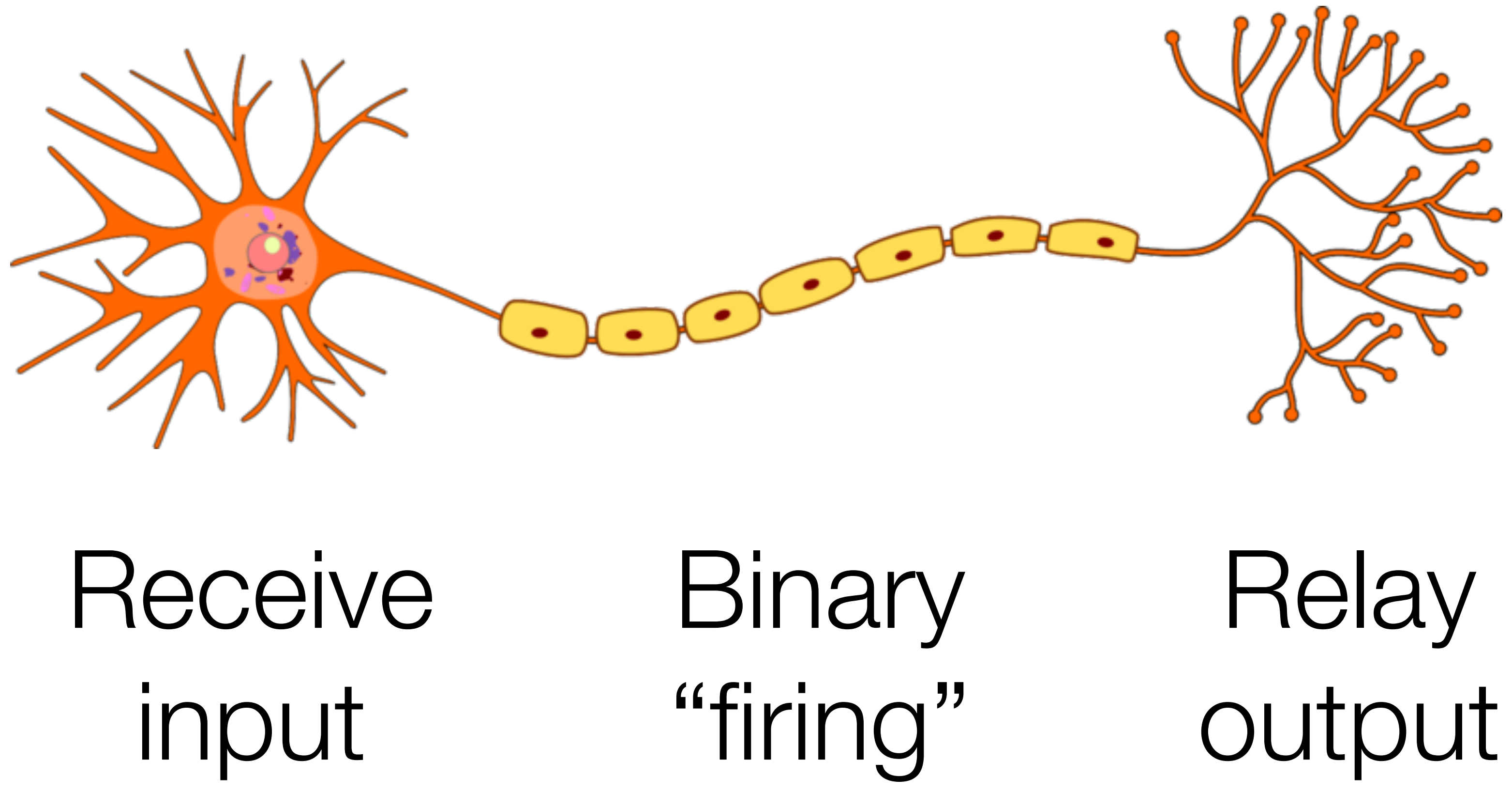
Biological Neuron



Perceptron

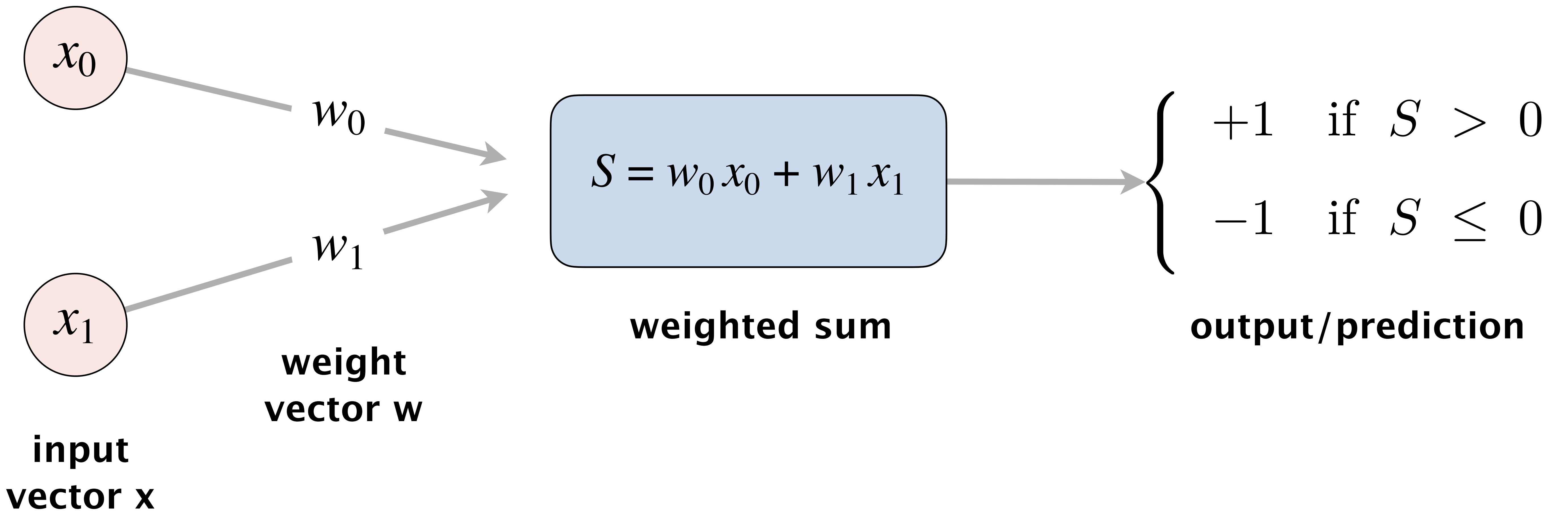
Takes several inputs and produces a single binary output.

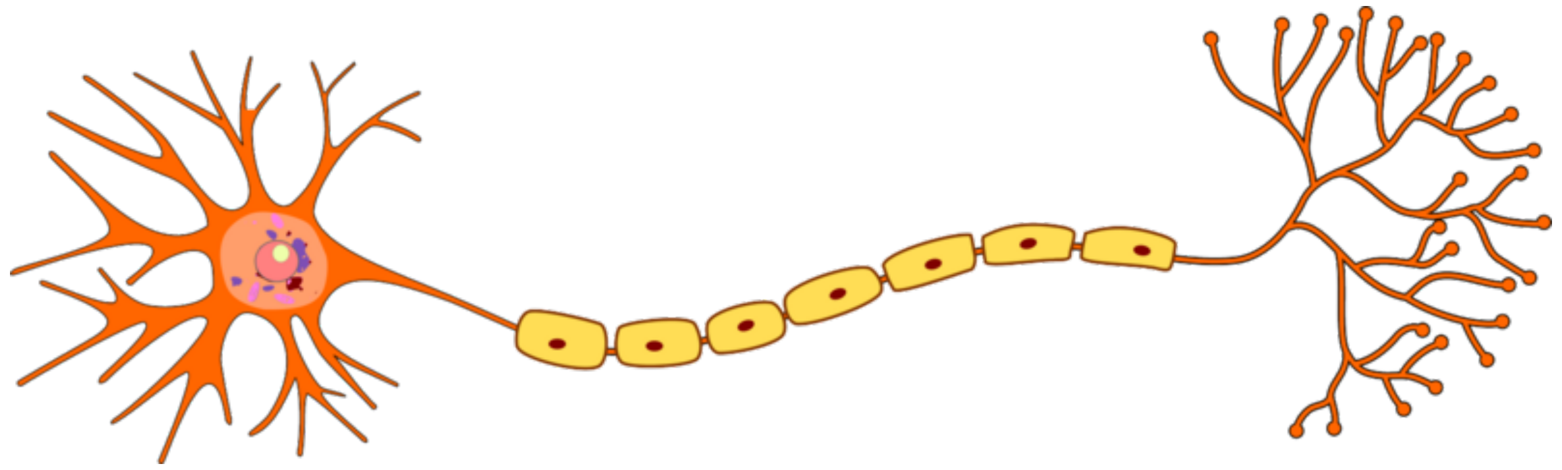


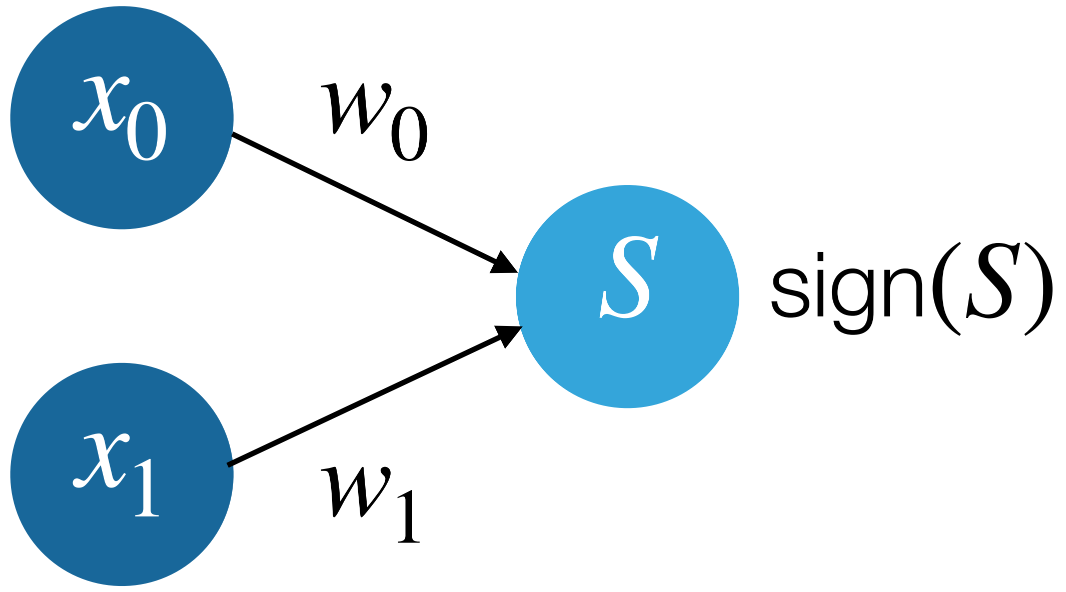


Perceptron

Takes several inputs and produces a single binary output.



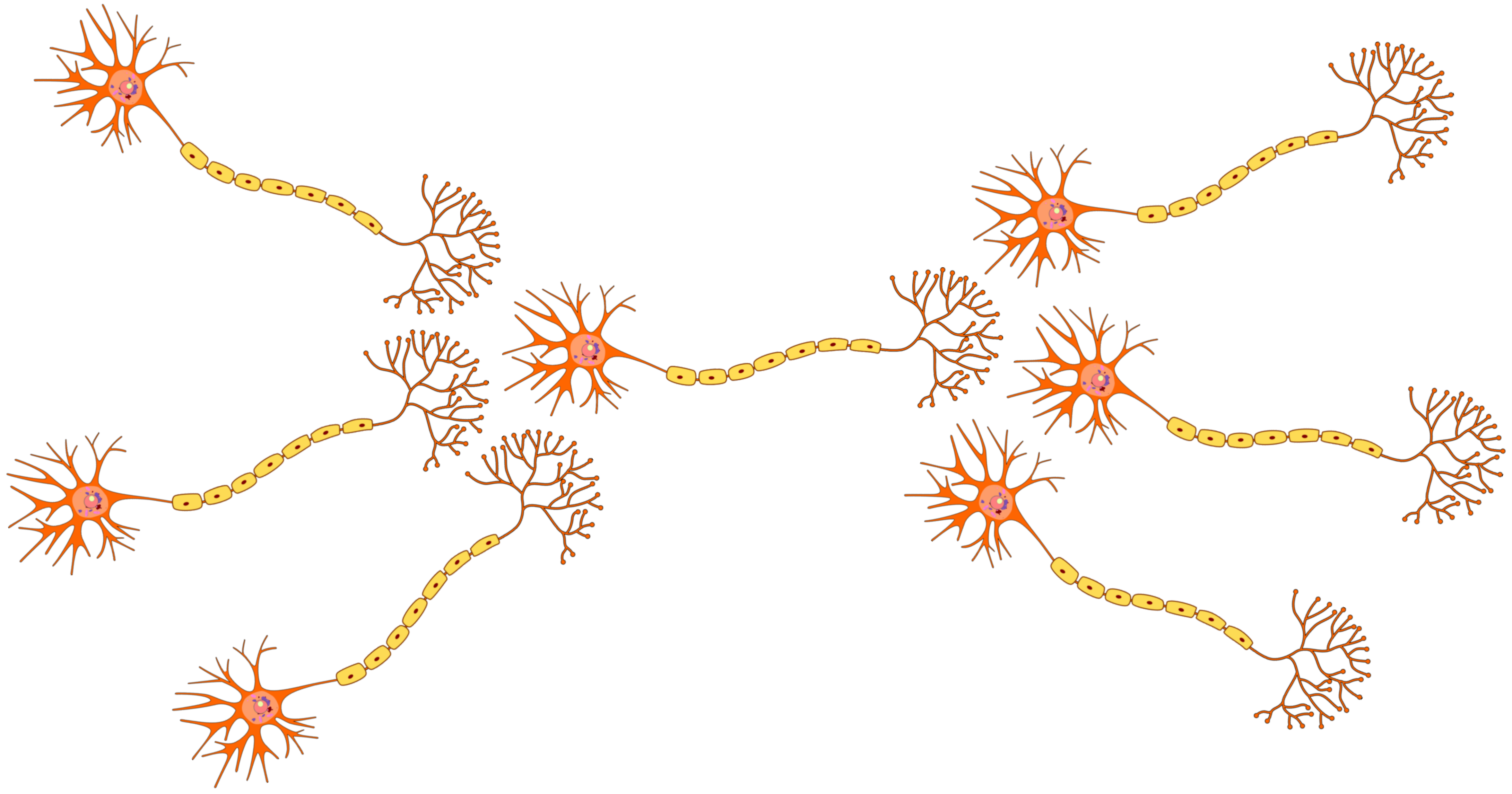


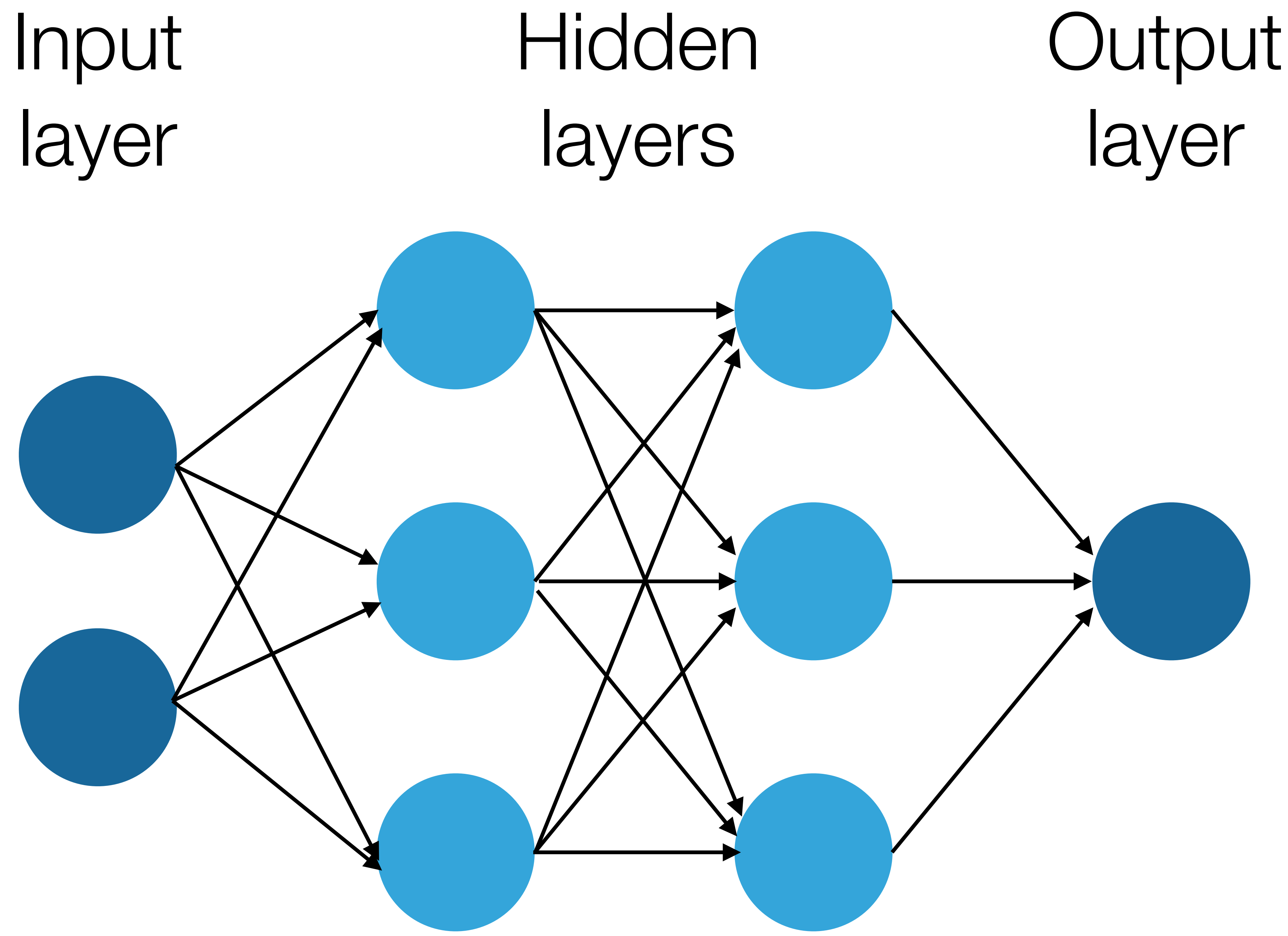


Multi-Layer Perceptron (MLP)

Composed of multiple layers of perceptron neurons, where each neuron is connected to all neurons in the next layer (i.e. fully-connected).

MLPs are an example of a deep neural network.



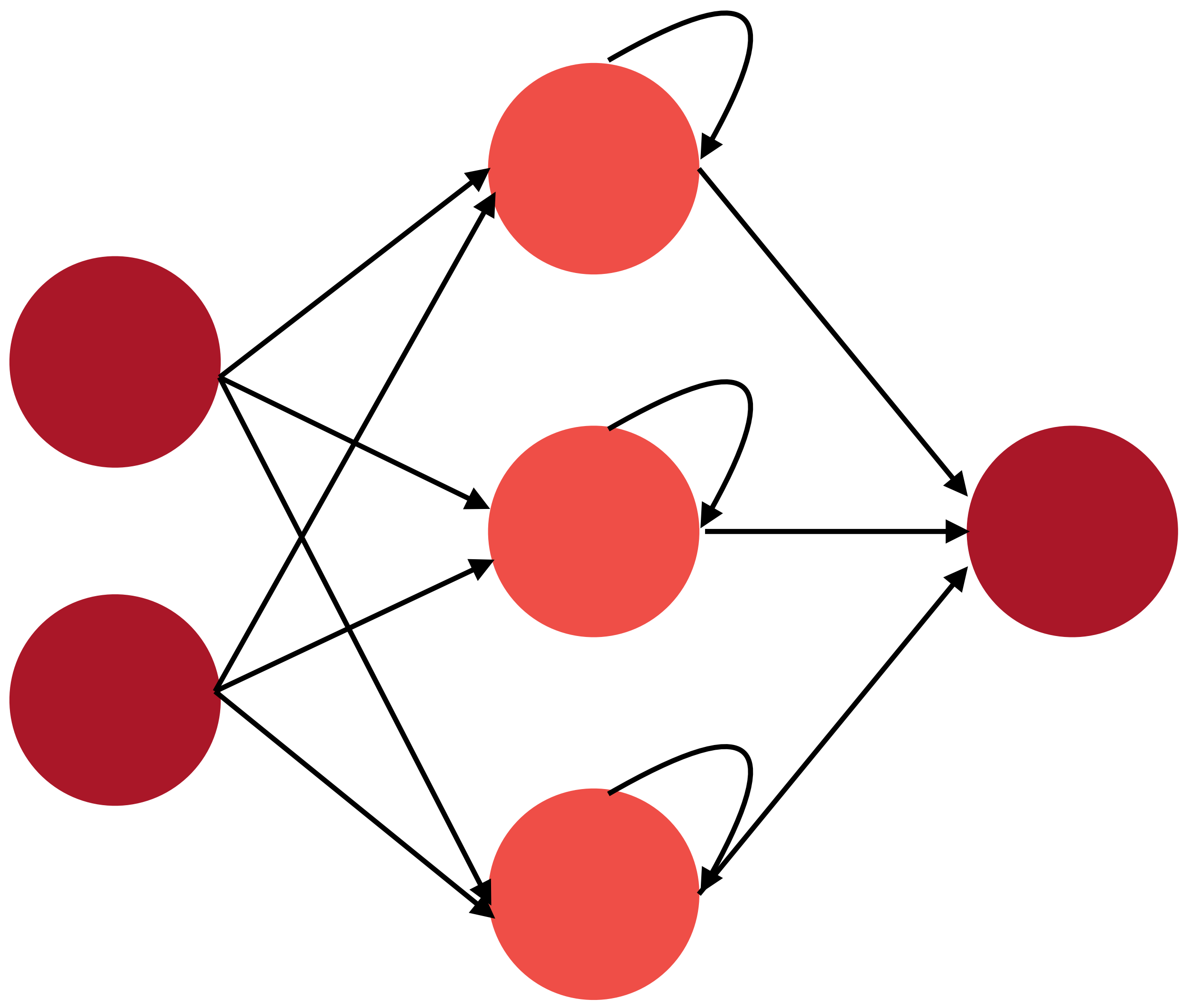


Deep Learning

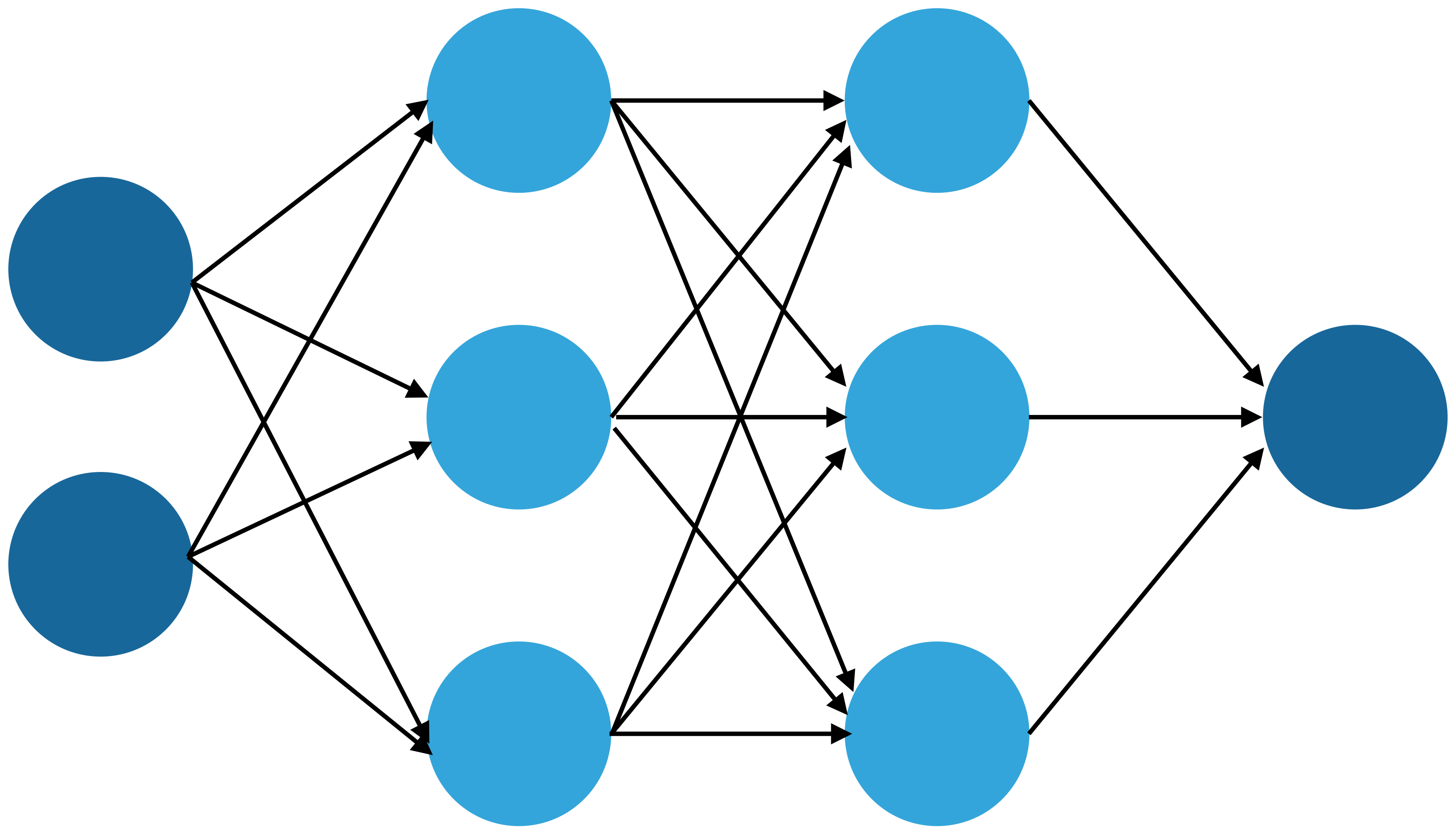
Refers to ML models that use deep neural networks.

Popular neural network architectures:

- Recurrent neural networks
- Convolutional neural networks
- Transformers



Recurrent NN



Fully-connected NN

Multi-class Perceptron

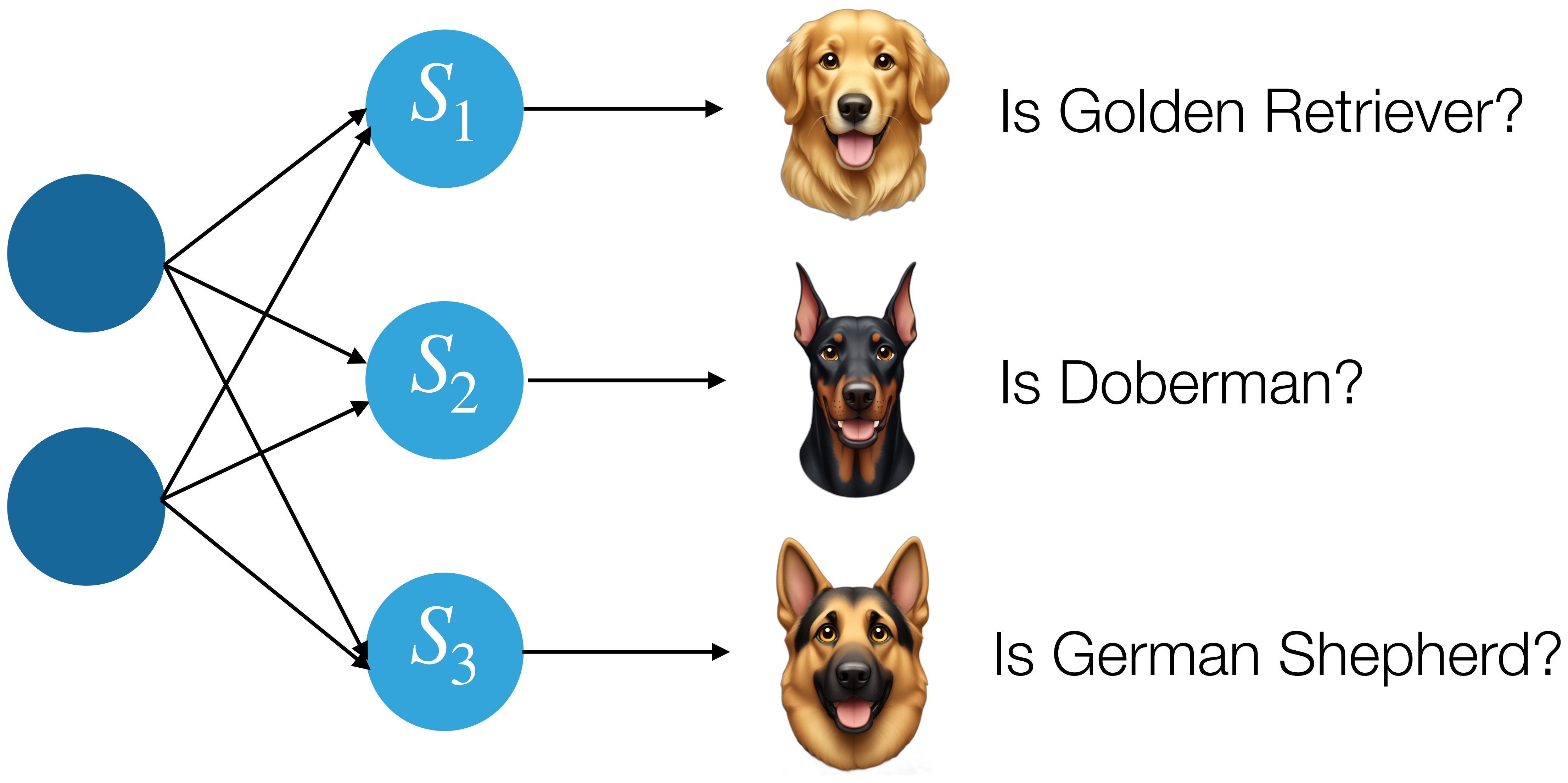
Multi-class Classification

Predict one of **k** classes (k > 2).

Suppose we have **k = 3** dog species we are trying to classify.

Train **k = 3** binary Perceptron models and compute **3** weighted sums: S_1, S_2, S_3.

Final prediction is the class with the largest weighted sum.



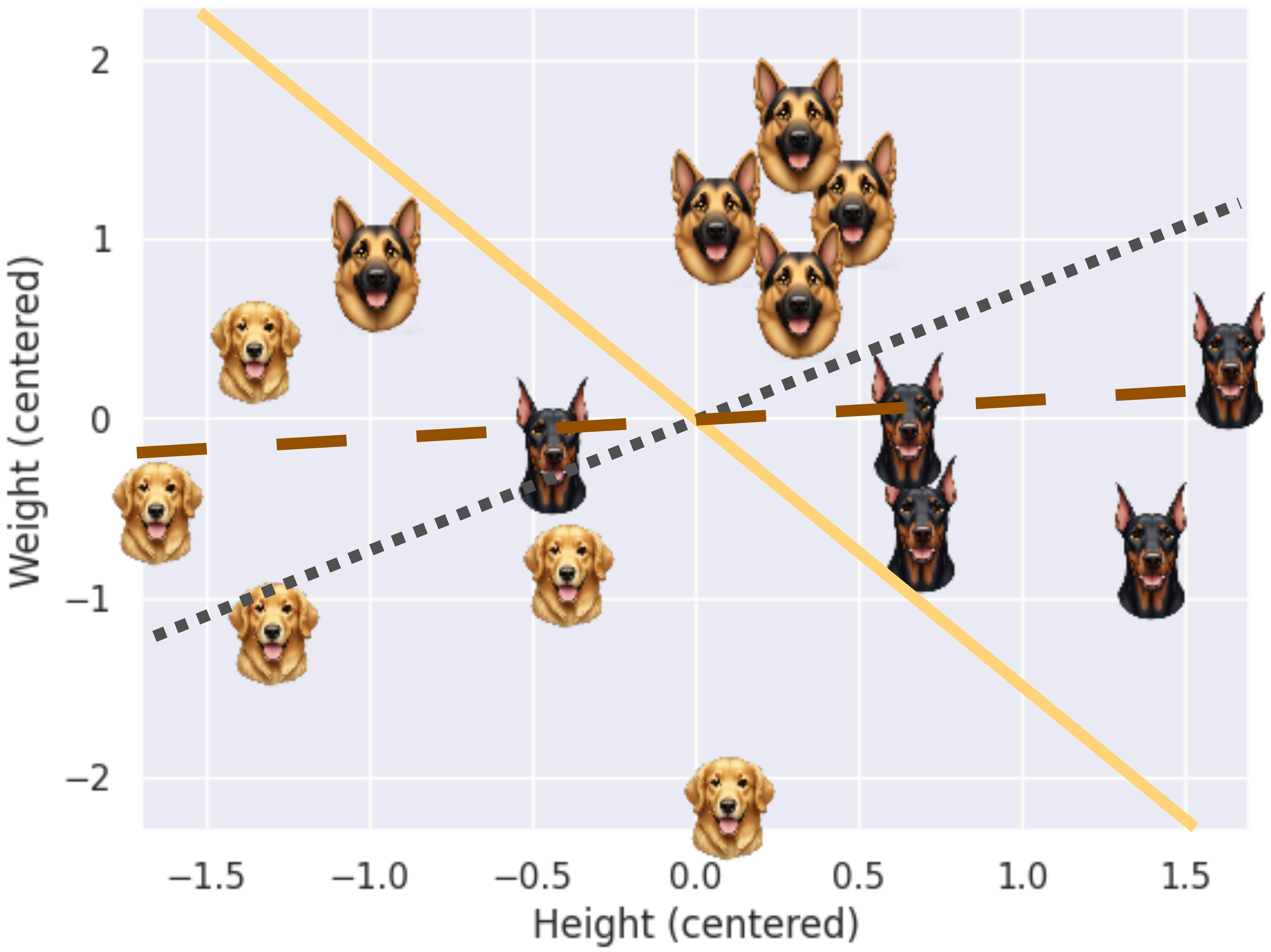
Multi-class Classification: Geometric Perspective

Predict one of **k** classes (k > 2).

Suppose we have **k = 3** dog species we are trying to classify.

Train **k = 3** binary Perceptron models and compute **3** weighted sums: S_1, S_2, S_3.

Final prediction is the class with the largest weighted sum.



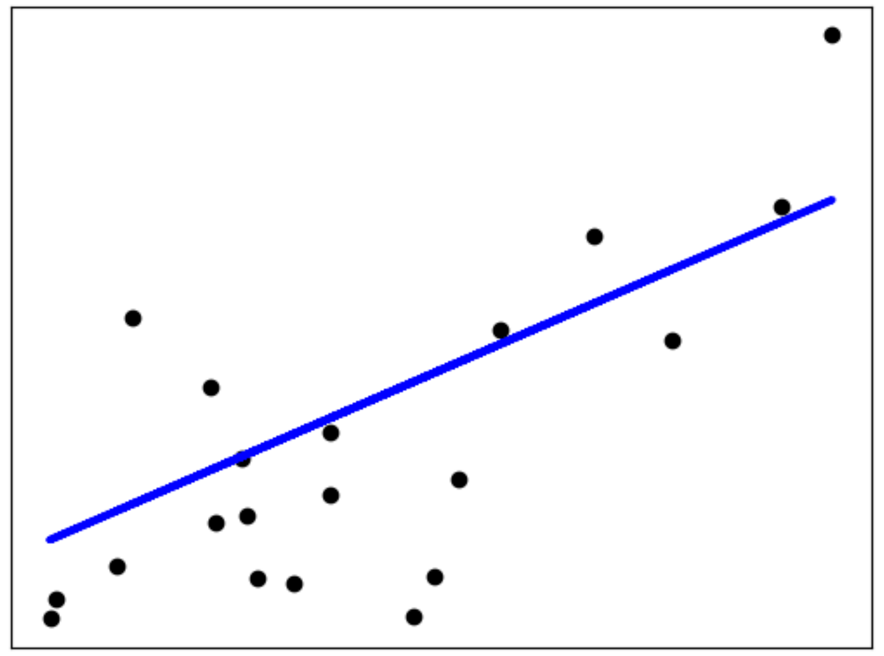
Machine learning models

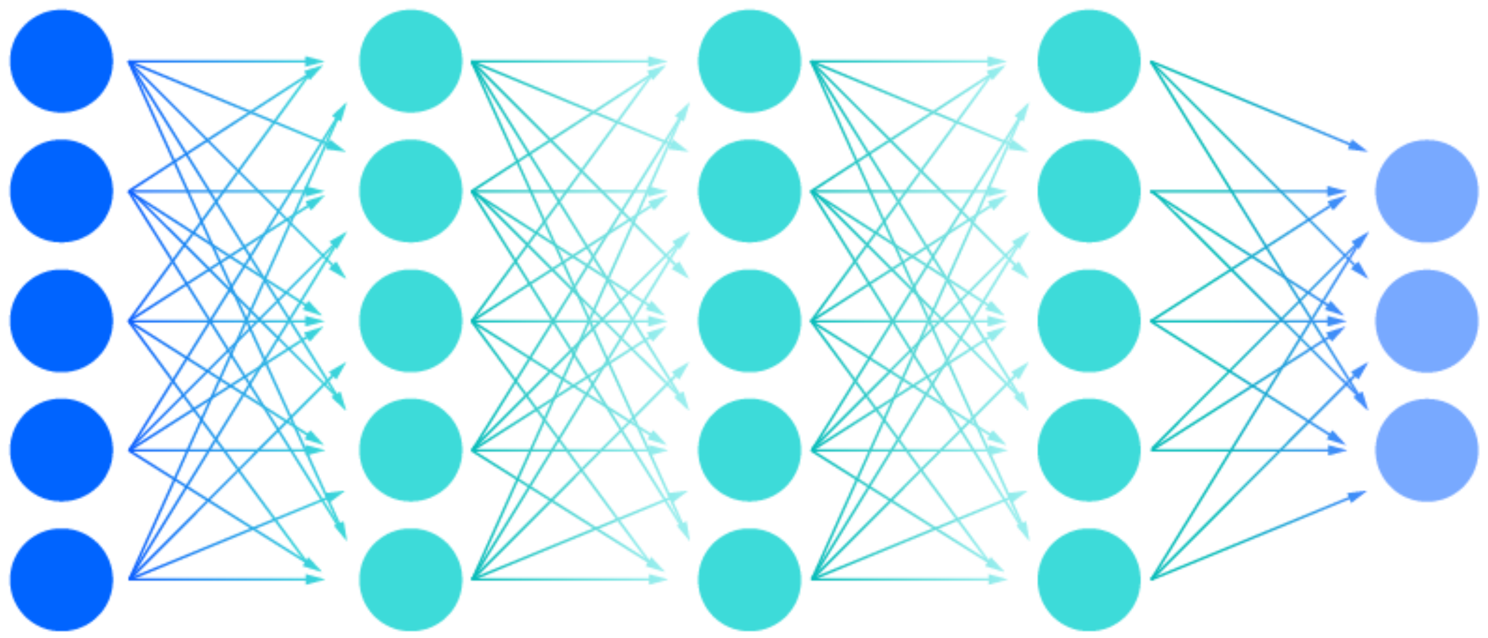
ML model: an algorithm used to perform a task.

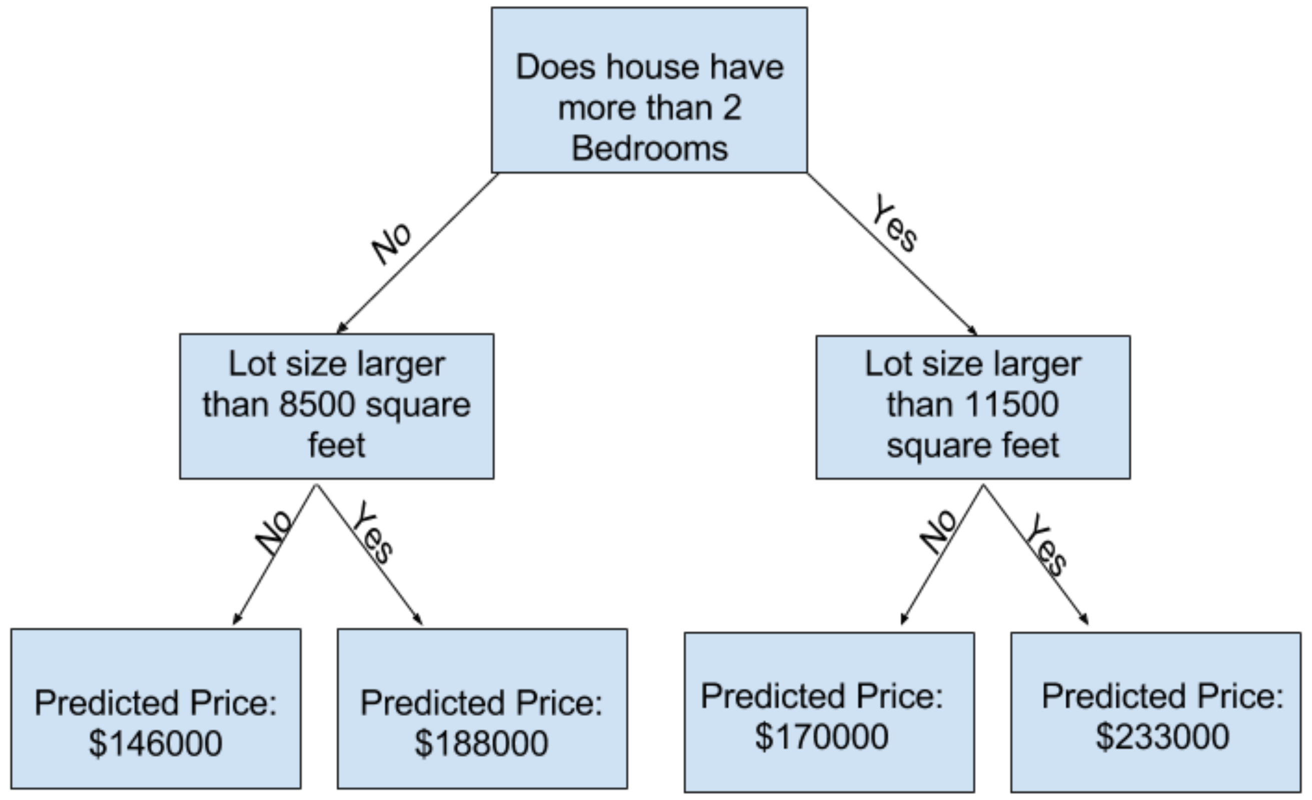
Supervised ML models:

- Linear models (e.g. perceptron)
- Deep neural networks*
  (e.g. multi-layer perceptron)
- Decision trees
- Ensembles (e.g. random forests)
- …

*also for unsupervised and
reinforcement learning







Credits

Lecture contents based on the following:

- COS 126 lecture on Introduction to Machine Learning by Ruth Fong
- COS 324 instructors and lectures
- Etienne Bernard, Wolfram. Introduction to Machine Learning: Machine Learning Paradigms. https://www.wolfram.com/language/introduction-machine-learning/machine-learning-paradigms/
- Shree Nayar. Perceptron | Neural Networks. https://youtu.be/OFbnpY_k7js?si=wrWOvNXE3UVCq-7Z

Credits

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CartPole	Gymnasium	
Cart Pole Games	Andreas De Neve	
Atari Breakout	OpenAI Gym	
AlphaGo	New Yorker	
Rubik's Cube robot arm	OpenAI	
TossingBot	Google Research	

Credits

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Doberman	Emojis.sh	
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Deep neural network	IBM	
Decision tree	Kaggle	