



# DATA SCIENCE

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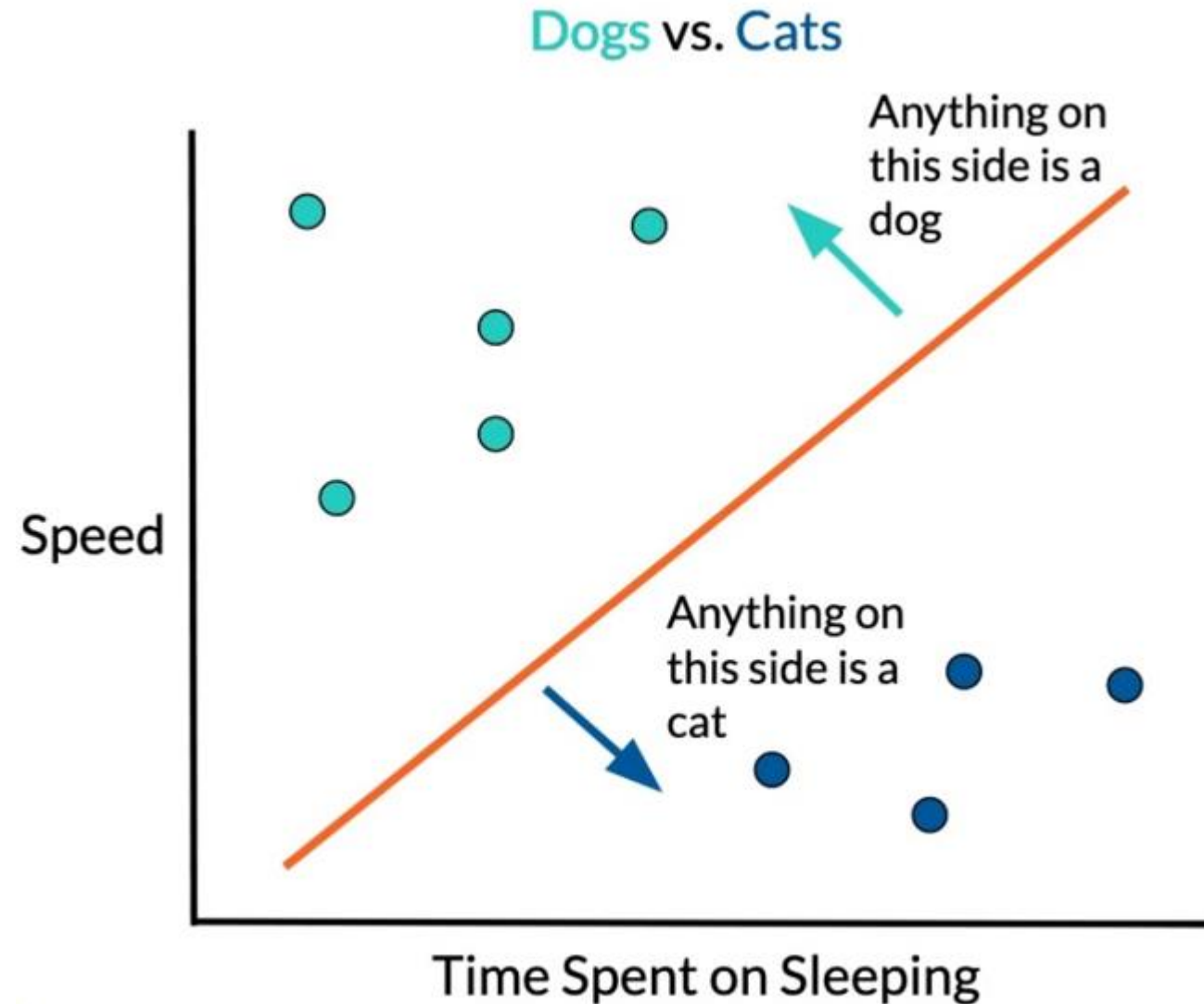


# Perceptron

- Designed to mimic the neurons in the human brain
- A single perceptron is a **linear classifier** – it separates two groups using a line.
- The perceptron learns by readjusting itself based on points it **misclassified** (points on the wrong side of the line) at every time step.



# Perceptron





# Perceptron Learning Algorithm (PLA)

- Distance from a point to the line

To write an algorithm that finds a line that separates the two groups, we must first find a way to figure out whether a given point is above or below the line.

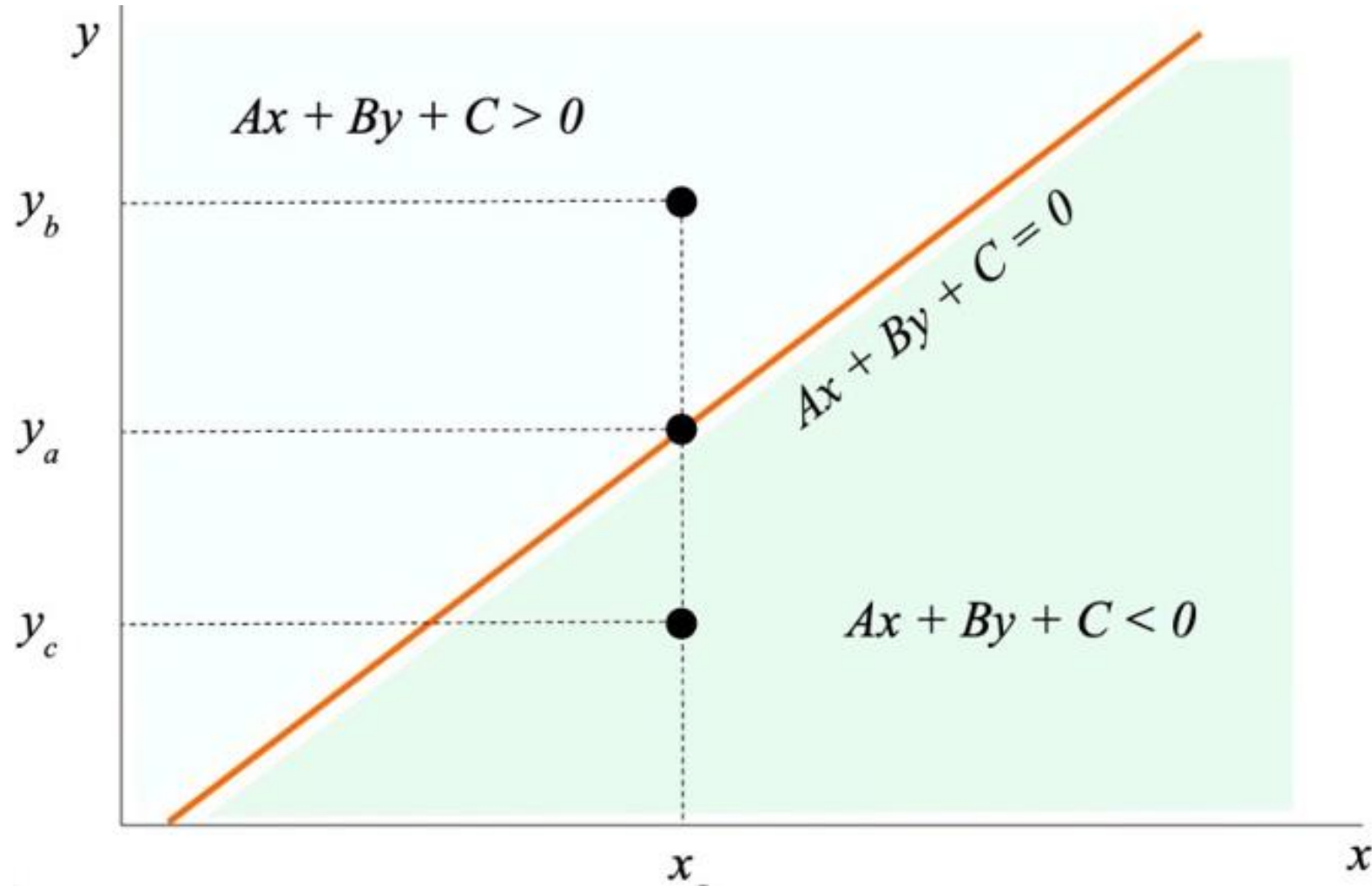
$$Ax + By + C = 0 \text{ is}$$

$$d = \frac{Ax_a + By_a + C}{\sqrt{A^2 + B^2}}.$$



# Perceptron Learning Algorithm (PLA)

- Distance from a point to the line





# Perceptron Learning Algorithm (PLA)

- Misclassified points

In summary, we can make a prediction for a point  $(x_a, y_a)$  by computing

$$\text{sgn}(Ax_a + By_b + C),$$

where the value of 1 denotes the point is part of one group and a value of  $-1$  denotes the point is part of the other.

💡 The  $\text{sgn}$  function computes the sign of the input. It is defined as follows:

$$\text{sgn}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

Given a training dataset – set of points  $(x, y, a)$  where  $x$  and  $y$  are coordinates and  $a$  is 1 or  $-1$  depending on which group the point is part of – we can find misclassified points by finding points whose  $a$  value is different from the prediction.



# Perceptron Learning Algorithm (PLA)

There are two fundamental assumptions about PLA:

1. The data is linearly separable. In other words, a hyperplane (a linear decision boundary) can completely separate the instances of the two classes in the feature space. This hyperplane is the line where the algorithm aims to find an optimal position during training.
2. The algorithm is designed for binary classification problems, where the goal is to separate data points into two classes. For instance, in a medical scenario, the algorithm could be used to predict whether a person has breast cancer or not, where the two classes are “positive” (having breast cancer) and “negative” (not having breast cancer).



# Perceptron Learning Algorithm (PLA)

- The “learning” in perceptron learning

This algorithm will **update** the line  $Ax+By+C=0$  to have new **coefficients (weights)** that ideally separate the two groups in the data.

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## Algorithm 1 2D Perceptron Learning Algorithm (sketch)

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```
1: procedure LEARN( $A, B, C, samples$ )
2:   for each datapoint  $(x, y, a)$  in  $samples$  do //  $a$  is 1 or  $-1$  depending on which group
      datapoint belongs to
3:     if datapoint is misclassified then
4:        $A \leftarrow A + a \cdot x$ 
5:        $B \leftarrow B + a \cdot y$ 
6:        $C \leftarrow C + a \cdot 1$ 
7:     end if
8:   end for
9: end procedure
```

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# Perceptron Learning Algorithm (PLA)

- Learning Rate in perceptron learning

The learning rate, “ $r$ ”, scales how much we correct our perceptron for each misclassified point.

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## Algorithm 1 2D Perceptron Learning Algorithm (with learning rate)

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```
1: procedure LEARN( $A, B, C, samples$ )
2:   for each datapoint  $(x, y, a)$  in  $samples$  do //  $a$  is 1 or  $-1$  depending on which group
      datapoint belongs to
3:     if datapoint is misclassified then
4:        $A \leftarrow A + r \cdot a \cdot x$  //  $r$  is the learning rate
5:        $B \leftarrow B + r \cdot a \cdot y$ 
6:        $C \leftarrow C + r \cdot a \cdot 1$ 
7:     end if
8:   end for
9: end procedure
```

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# Perceptron Learning Algorithm (PLA)

- Perceptron in Vectors

So far all of the calculations have been done on 2-D space – each point has two coordinates  $x$  and  $y$  (in 3D space we add a  $z$  coordinate to it). But if we switch out the notation from

$$A \leftarrow A + a \cdot x$$

$$B \leftarrow B + a \cdot y$$

$$C \leftarrow C + a \cdot 1$$

to

$$w_0 \leftarrow w_0 + a \cdot 1$$

$$w_1 \leftarrow w_1 + a \cdot x_1$$

$$w_2 \leftarrow w_2 + a \cdot x_2$$

we can then see a clear pattern. Expressed as vectors, we can instead write these updates as

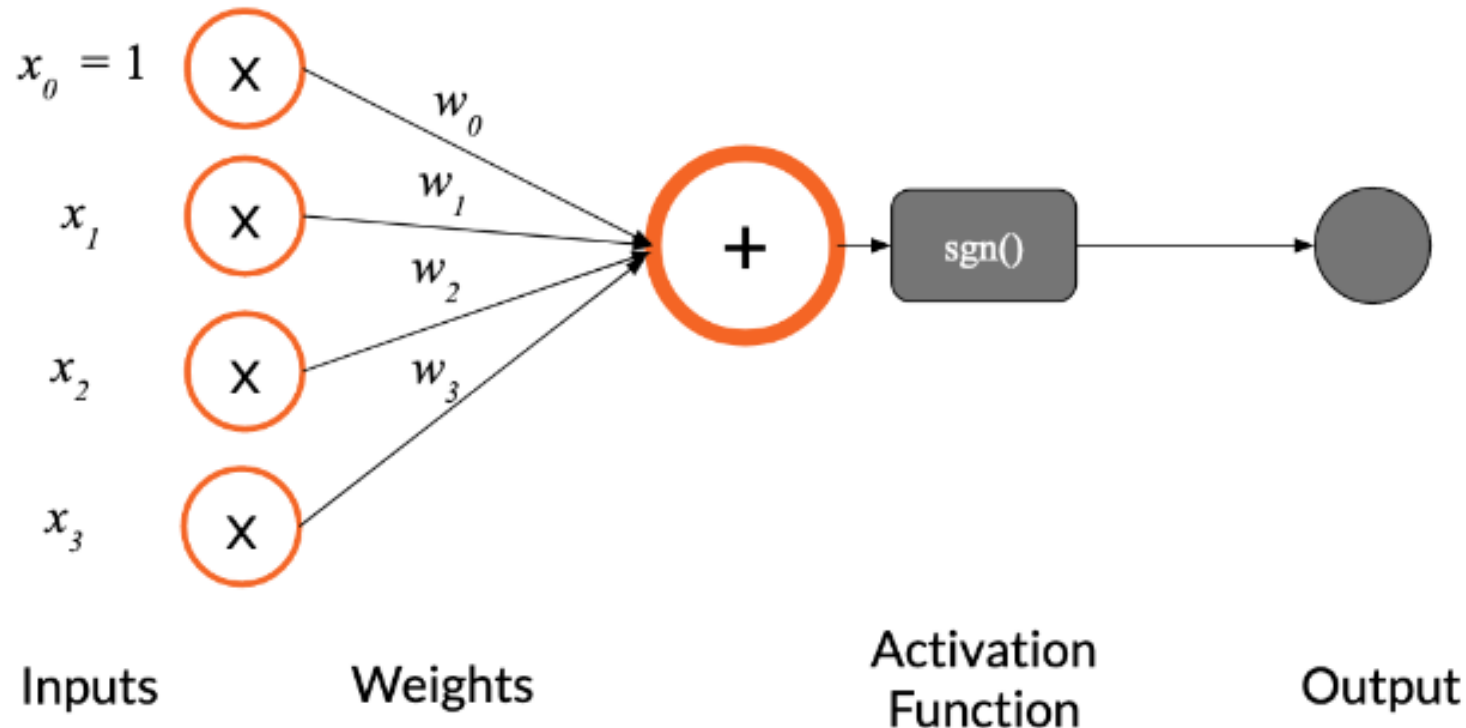
$$\vec{w} \leftarrow \vec{w} + a \cdot \vec{x}.$$



# Perceptron Learning Algorithm (PLA)

- Anatomy of a Perceptron

the algorithm requires that the data is **linearly separable**, If the data is not linearly separable, the line will end up bouncing around, never halting

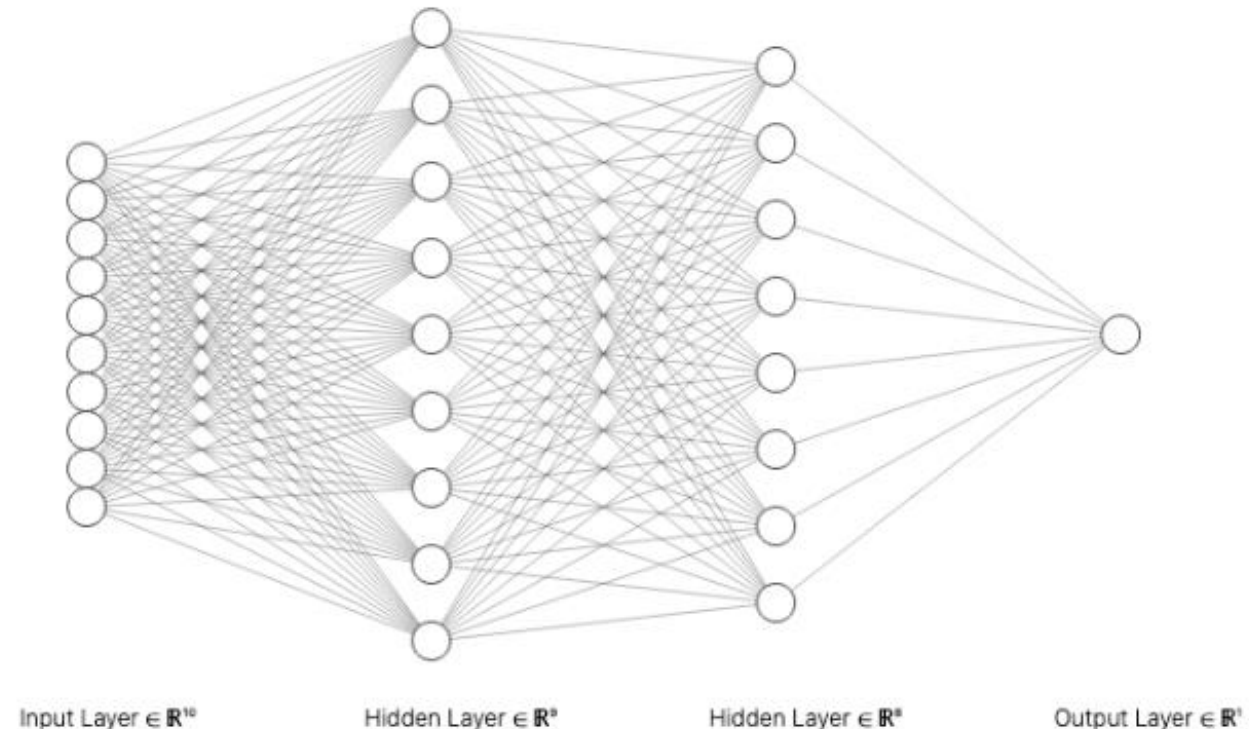




# Perceptron Learning Algorithm (PLA)

- **Multi-layered Perceptrons**

are sets of perceptrons linked together to form more complex models. These perceptrons have **non-linear activation functions**, allowing the model to be able to handle data that are **not linearly separable**



The image features a blue-tinted background showing silhouettes of several groups of business professionals in a modern office environment. They are standing on a reflective floor, and a city skyline is visible in the background. The text "Thank You" is centered in the middle of the image.

Thank You