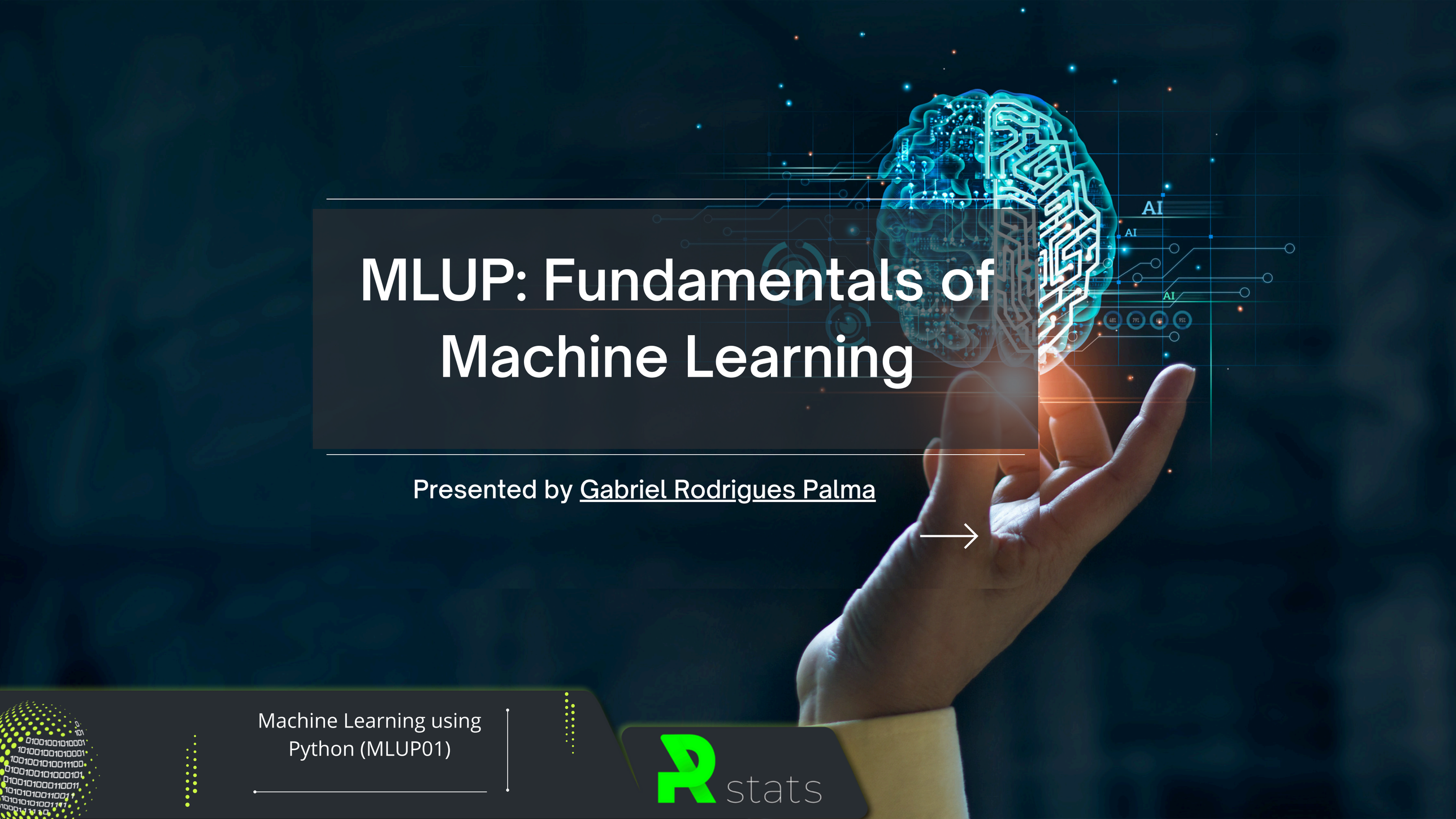
MLUP: Fundamentals of Machine Learning

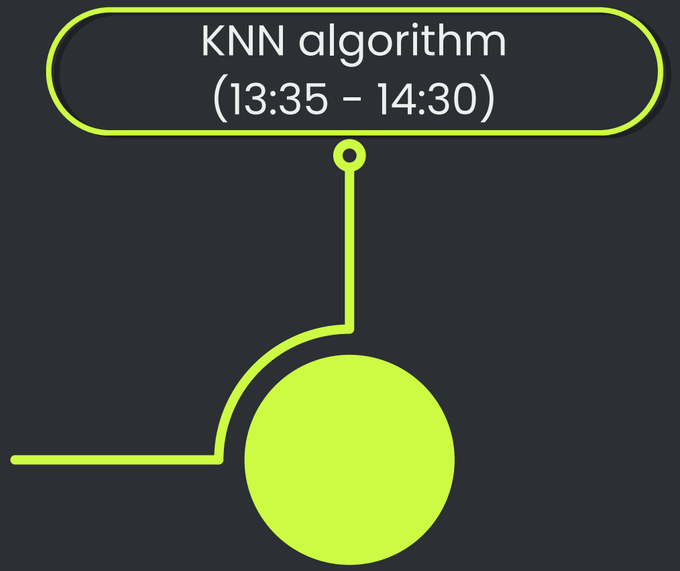
Presented by Gabriel Rodrigues Palma



Machine Learning using Python (MLUP01)

stats

Day 4 (13:30 - 17:30)



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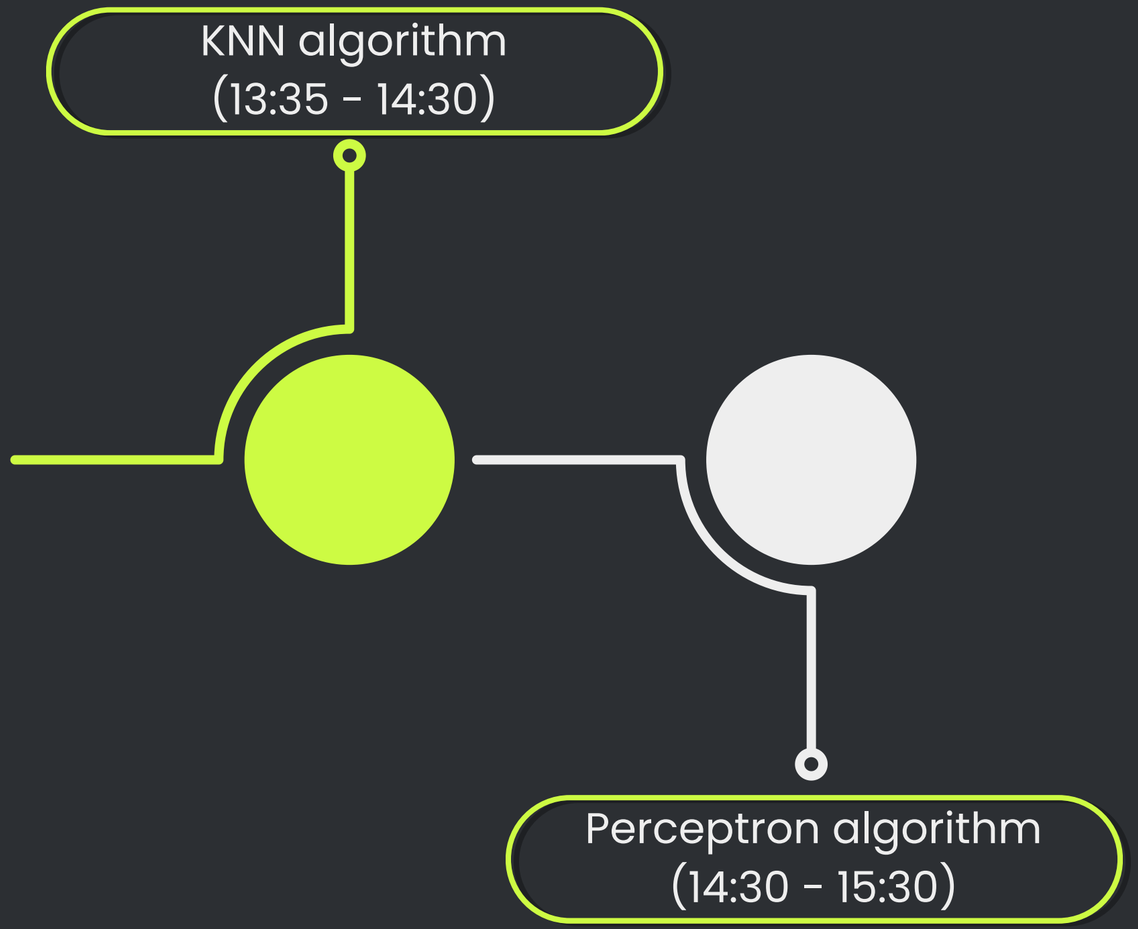

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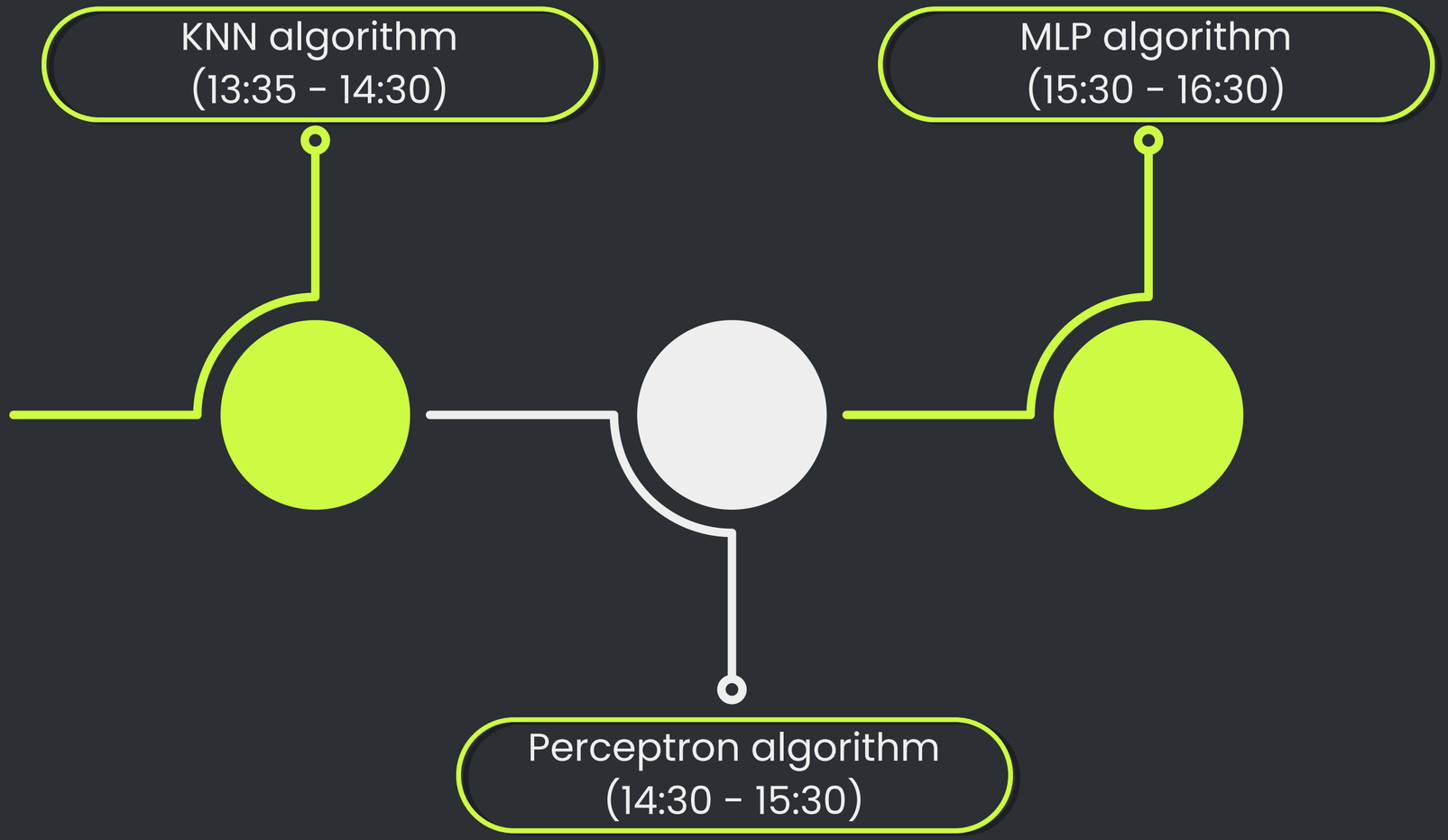

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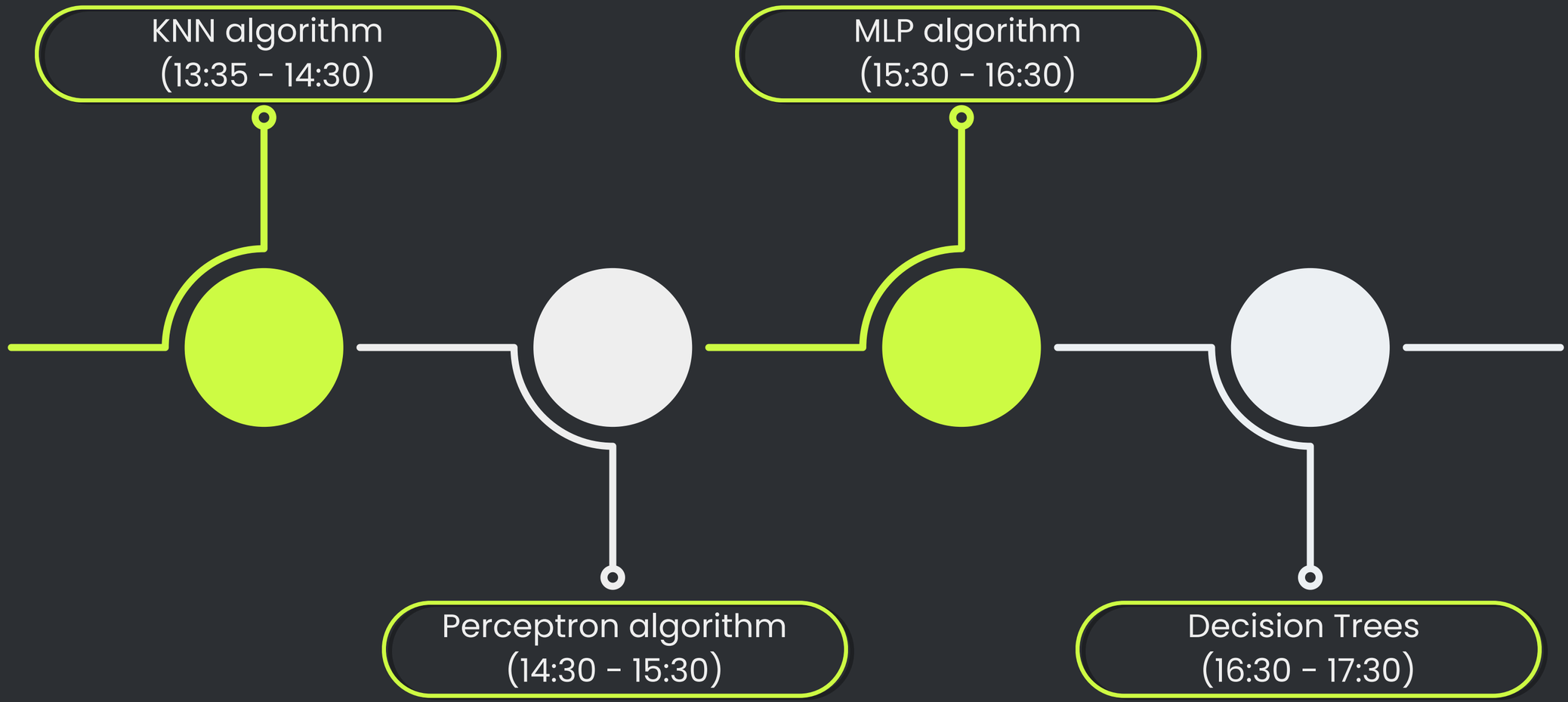

KNN algorithm

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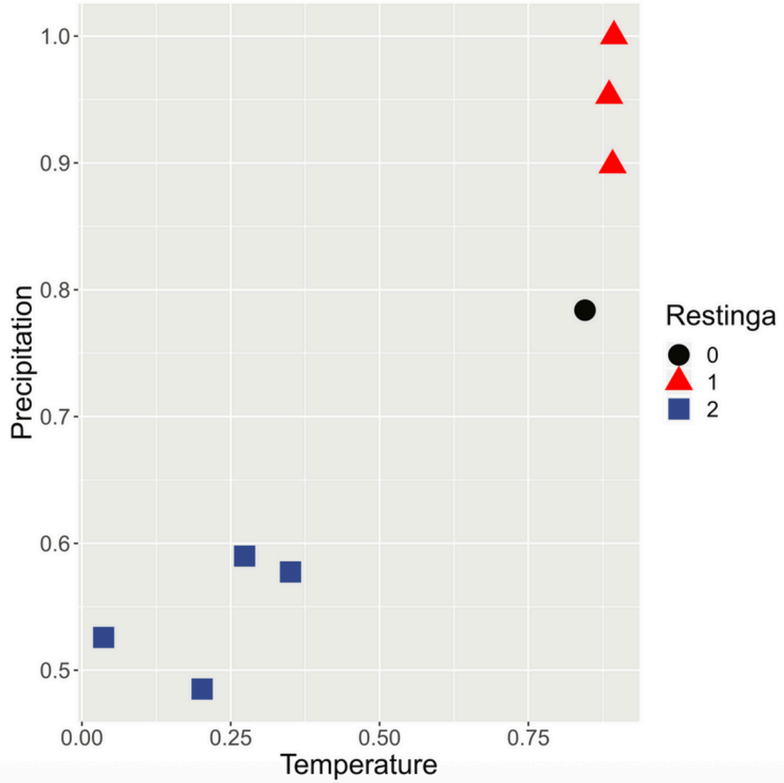
KNN algorithm

Temp. Range	Humidity	Precipitation	Atm	Wind	FAPAR	Ludwigia leptocarpa	Restinga
0.72	0.61	0.59	0.98	0.19	0.67	1	1
0.92	0.58	0.52	0.99	0.17	0.37	0	0
0.86	0.82	0.62	1.00	0.12	0.80	0	1
0.82	0.87	0.63	1.00	0.17	1.00	0	0

KNN algorithm



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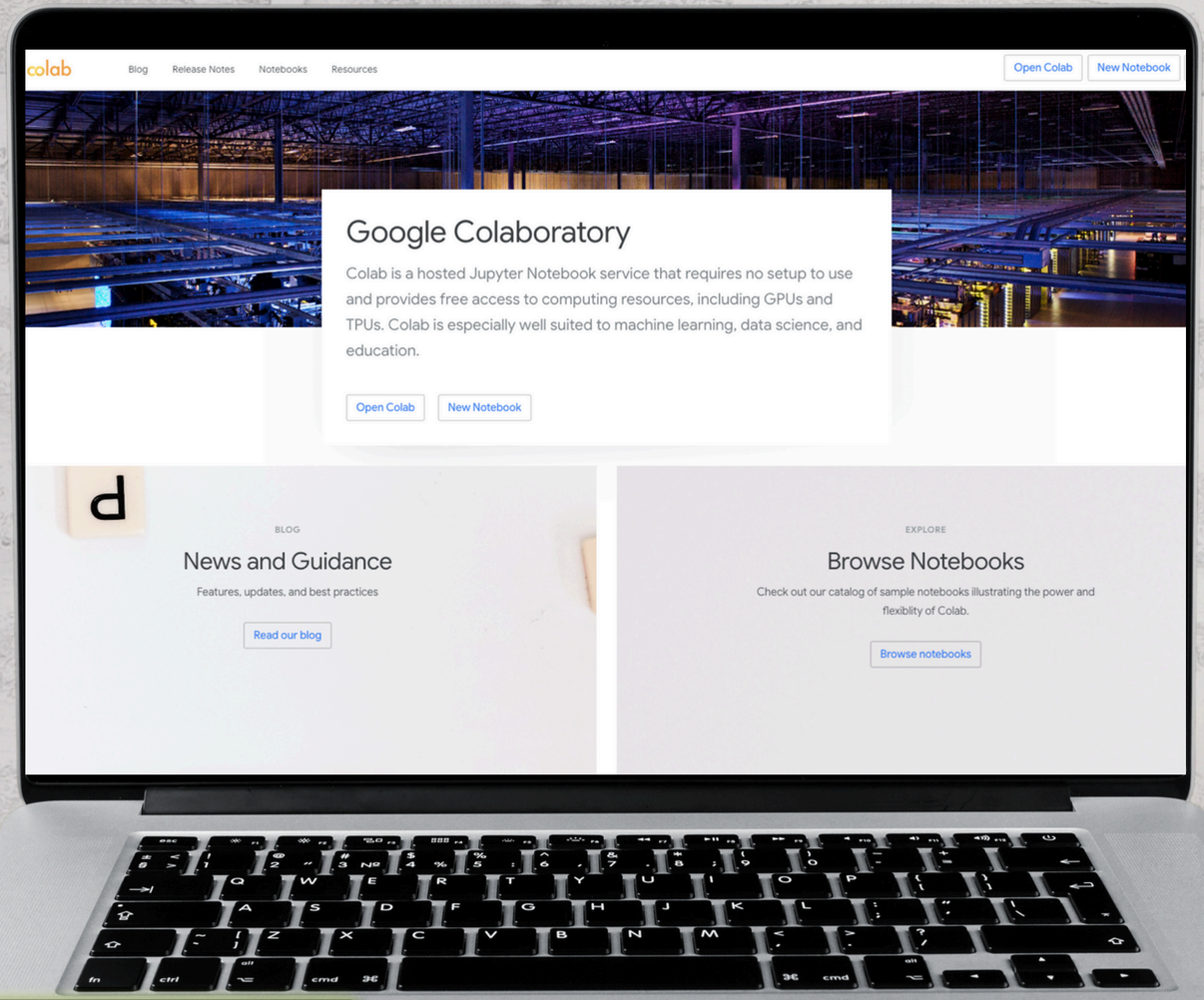

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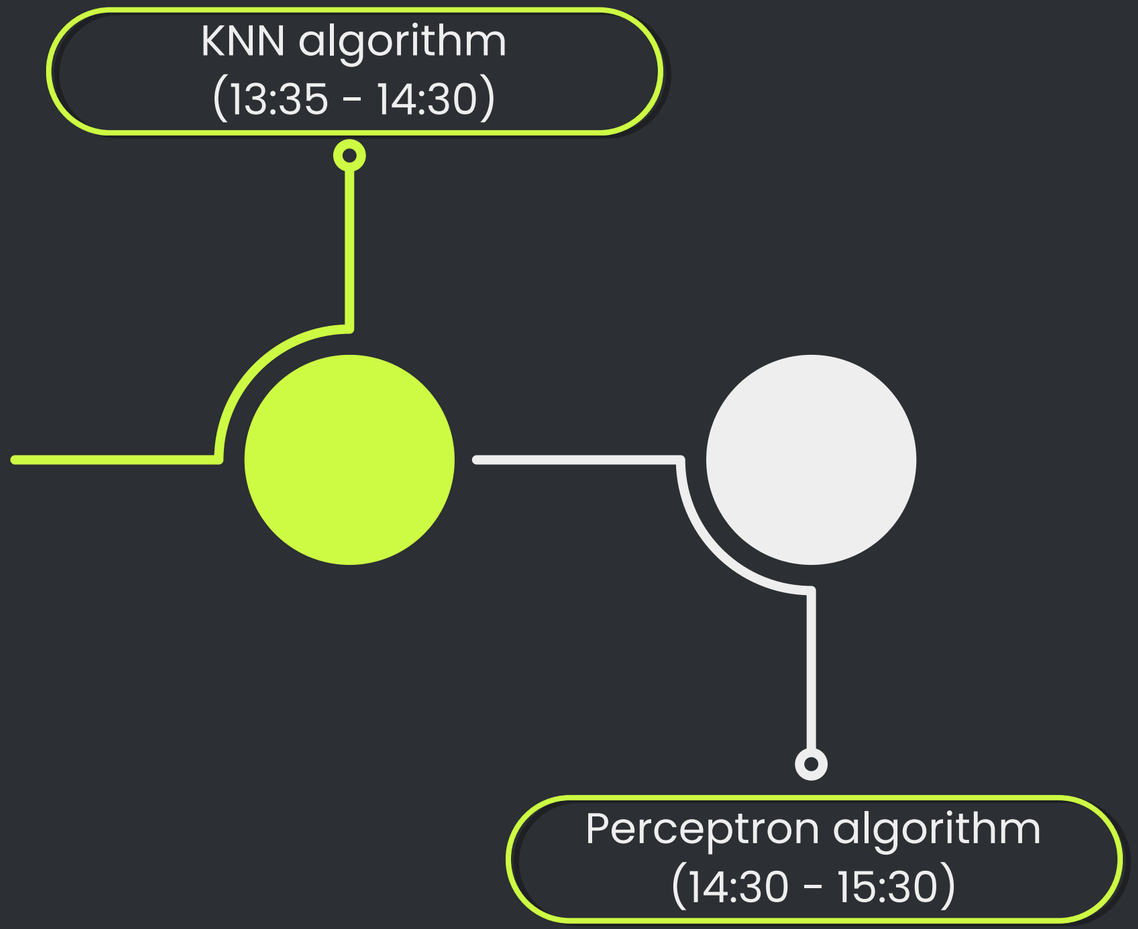
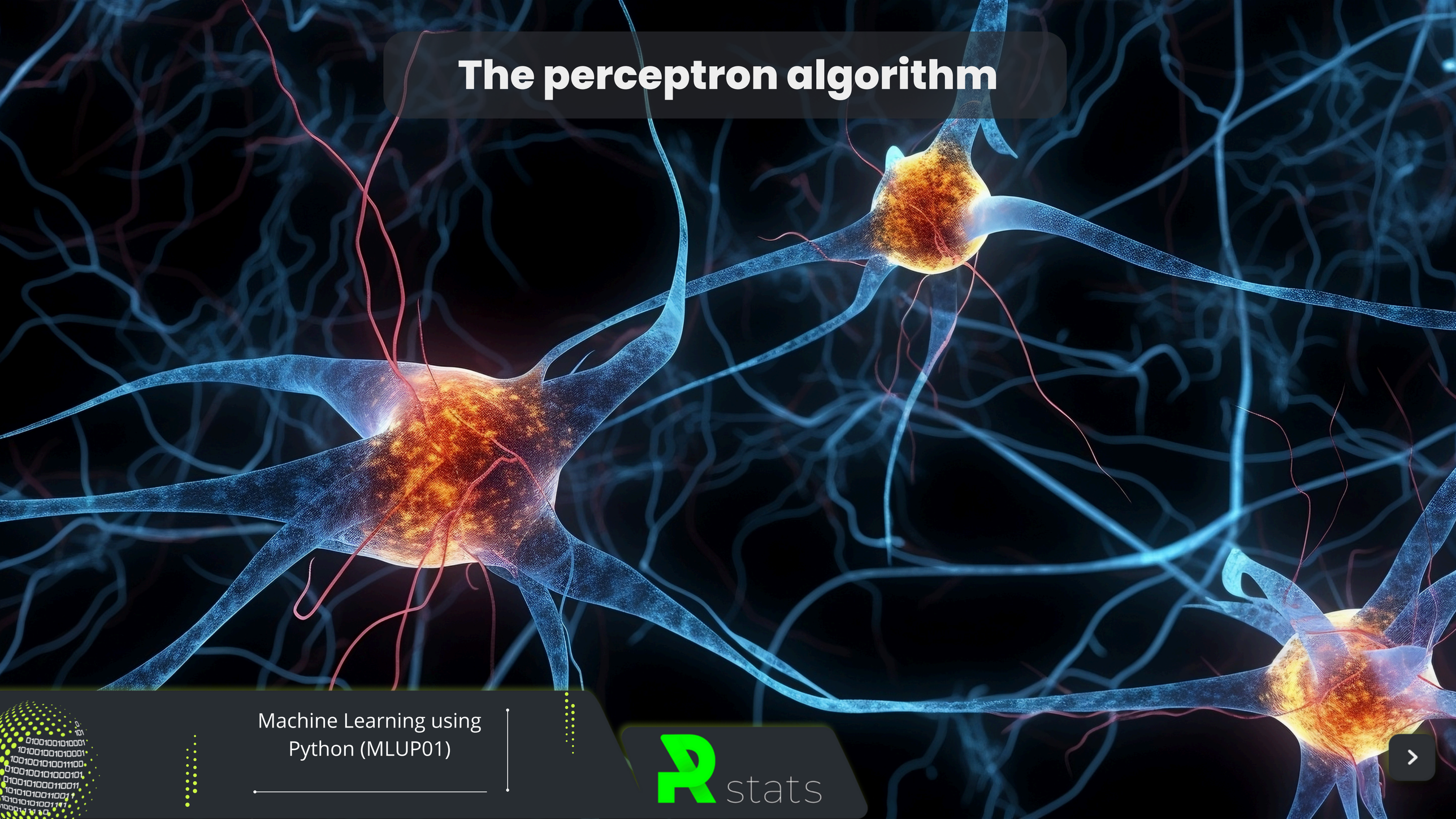


The perceptron algorithm



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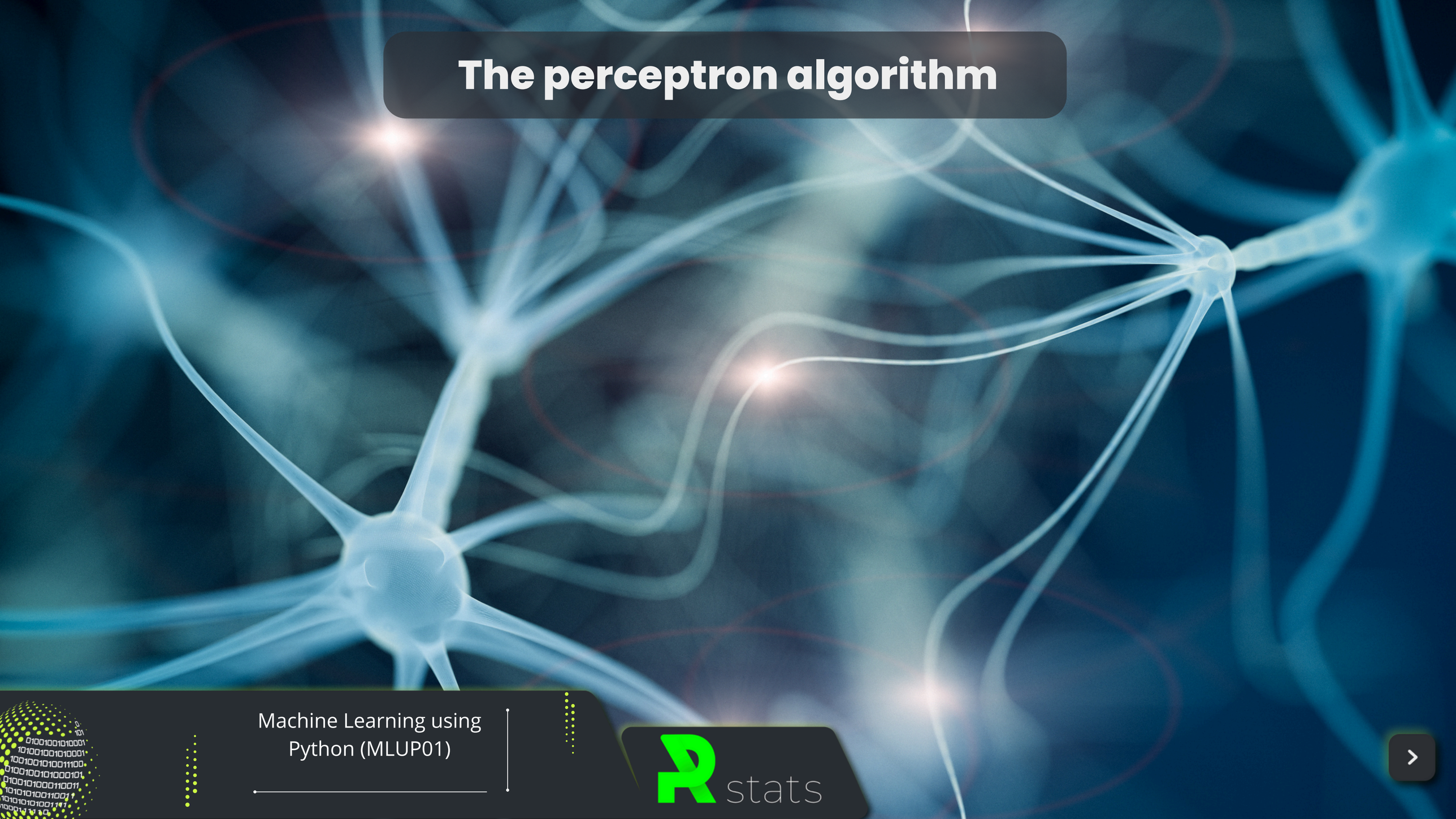

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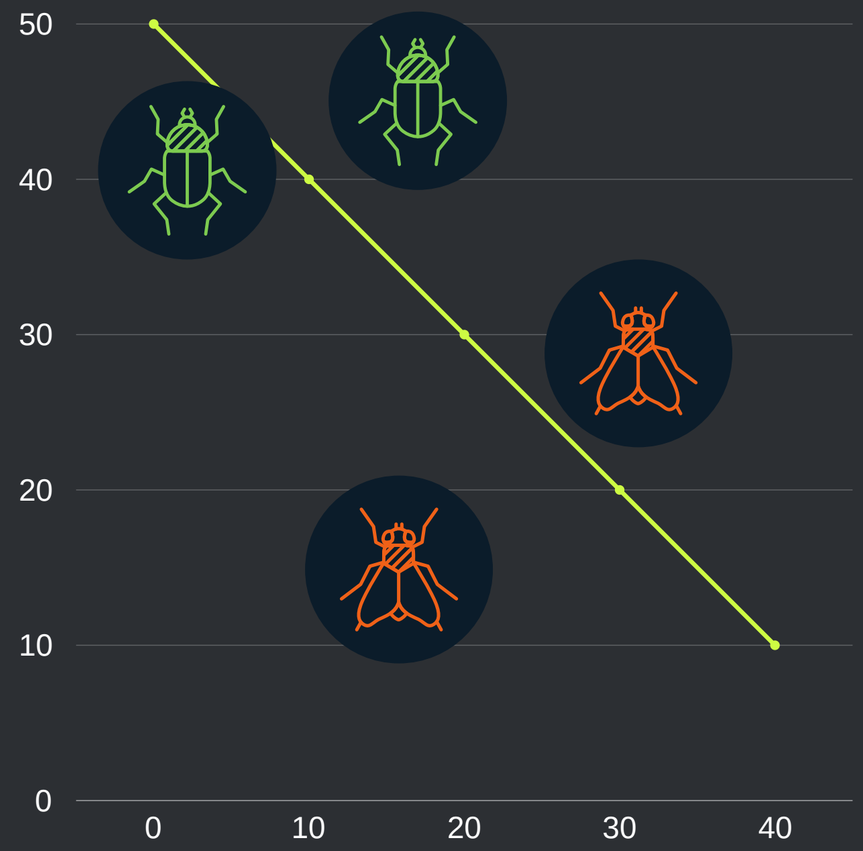

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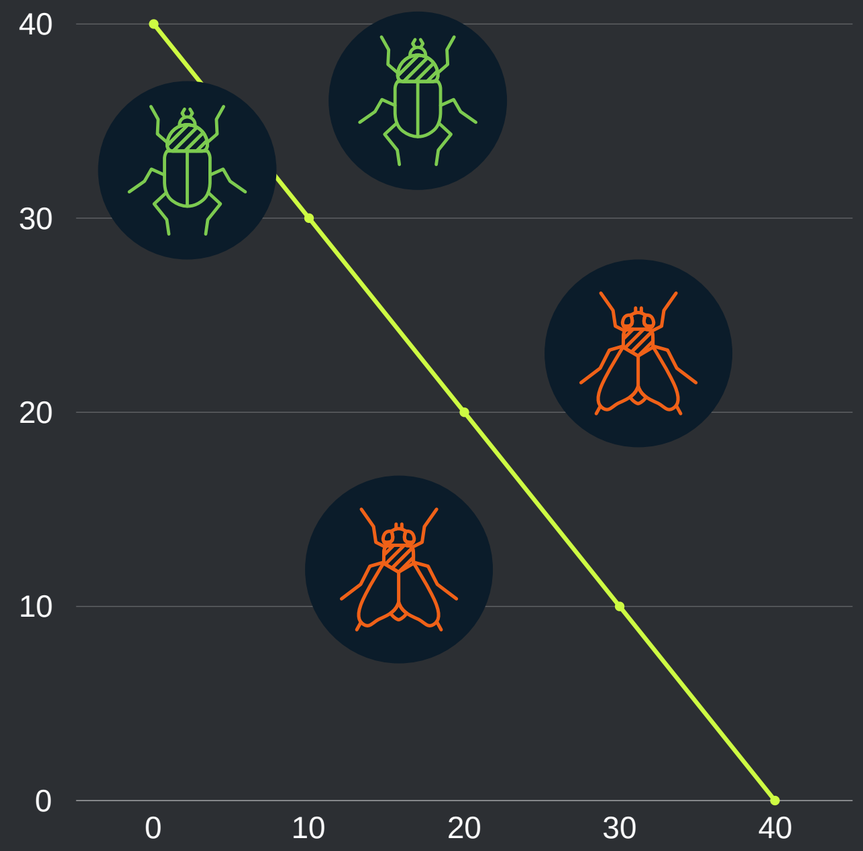

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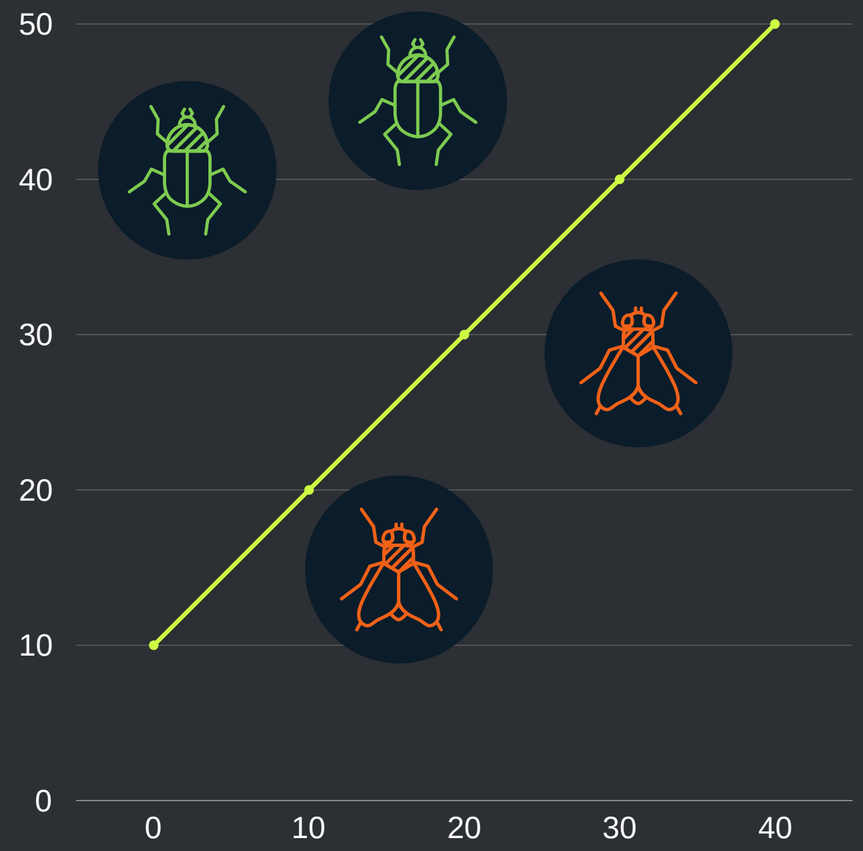

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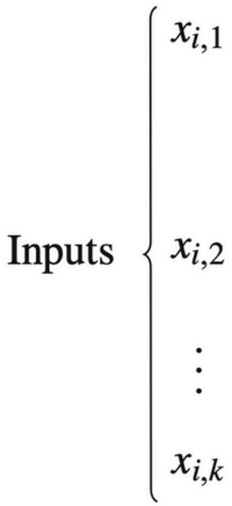

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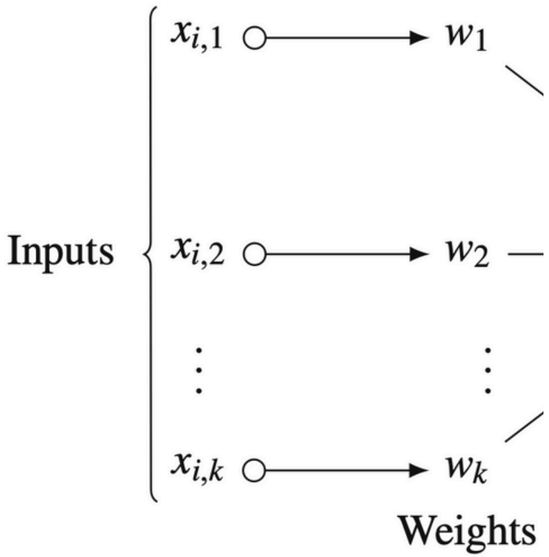

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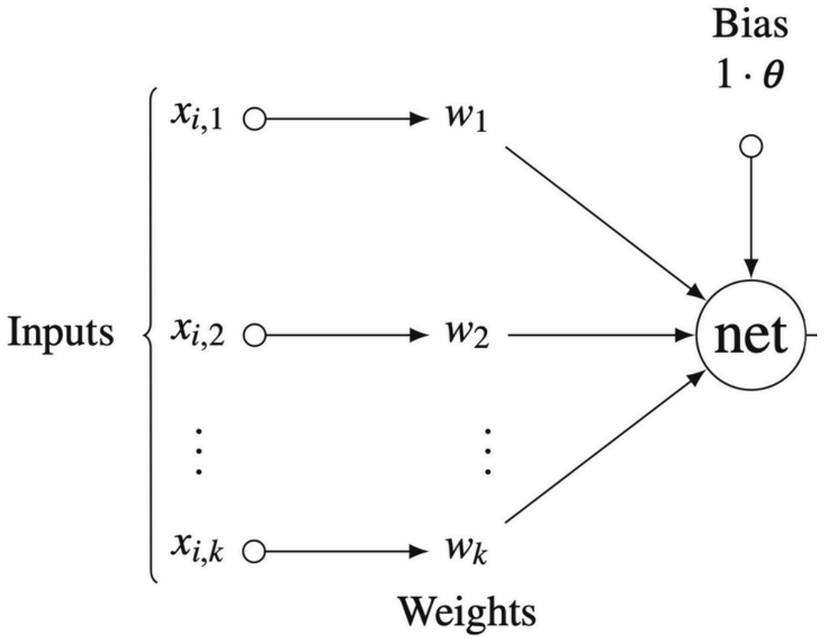

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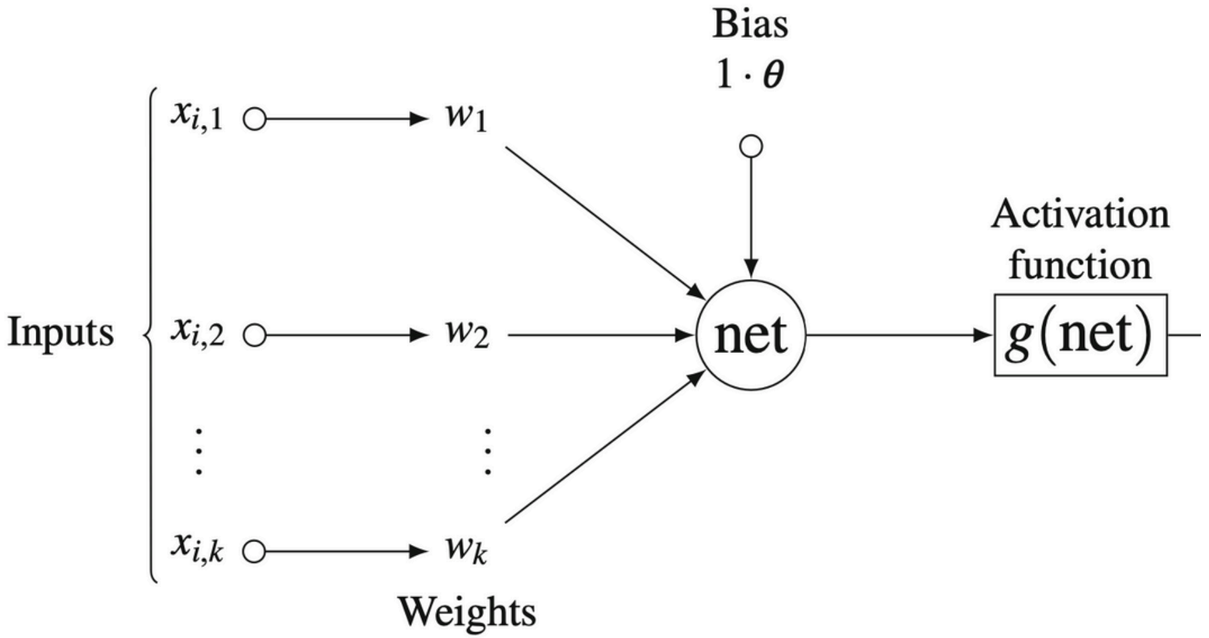

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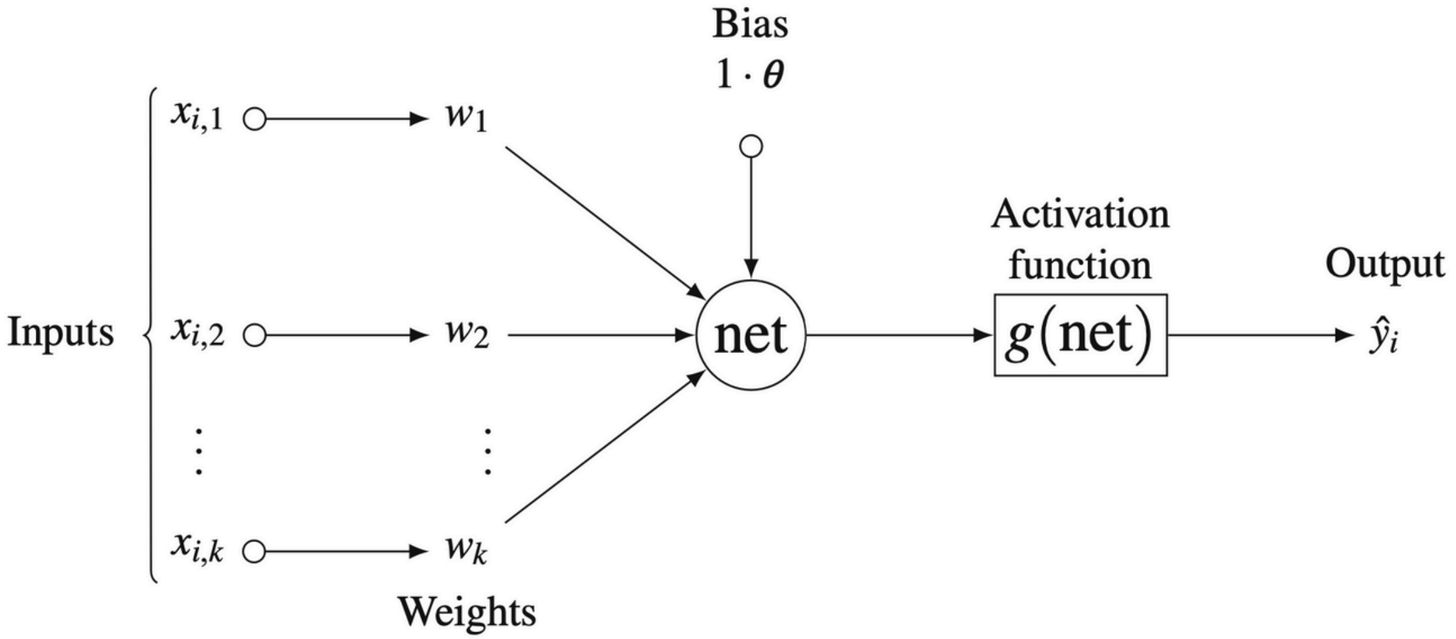

The perceptron algorithm

The Perceptron algorithm was proposed by Rosenblatt [11] in 1957. It considers an artificial neuron or unit[4] that receives an input example x_i to produce an output class y_i, as illustrated in Fig. 1.29. Such input example $x_i \in \mathbb{R}^k$, i.e. it contains a list of indexed variables $j = 1, \ldots, k$.

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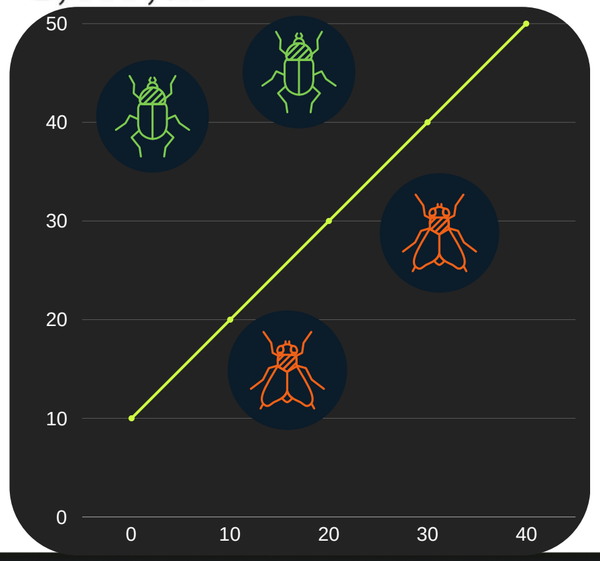

The perceptron algorithm

The neuron multiplies every input value $x_{i,j}$ by a weight w_j as well as constant 1 by the bias term[5] denoted by θ. As a next step, this algorithm computes a term $\text{net} = \sum_{j=1}^{k} x_{i,j} w_j + \theta$.

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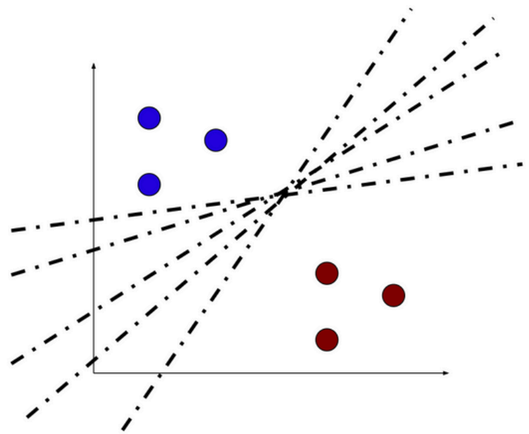

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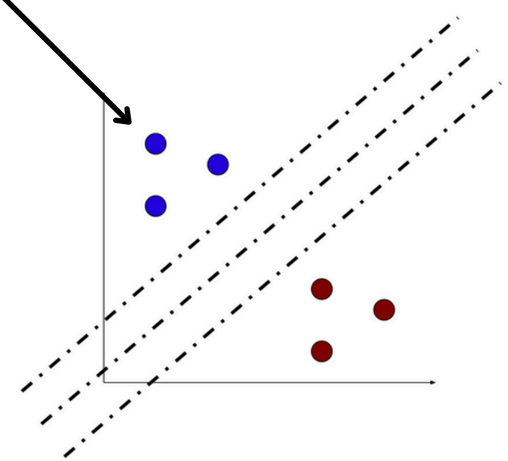

The perceptron algorithm

Next, the Perceptron applies a heaviside (or step) function $g(\text{net})$ (Eq. (1.10)), in which ϵ is a user-defined parameter, producing the output class $\hat{y}_i$ for example x_i.

$$g(\text{net}) = \begin{cases} 1, & \text{iff net} > \epsilon \\ 0, & \text{otherwise} \end{cases} \tag{1.10}$$

The perceptron algorithm

Perceptron while finding a good linear approximation function to solve this problem. The Perceptron aims to converge to the minimum of function E^2.

$$E^2 = \sum_{i=1}^{n} \ell_{\text{squared}}(x_i, y_i, g(x_i)) = \sum_{i=1}^{n} (y_i - g(x_i))^2 \tag{1.12}$$

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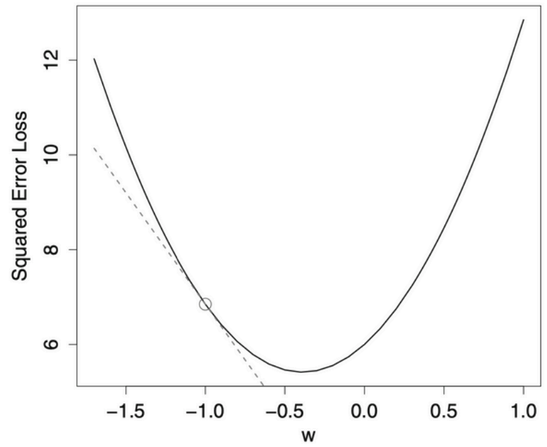

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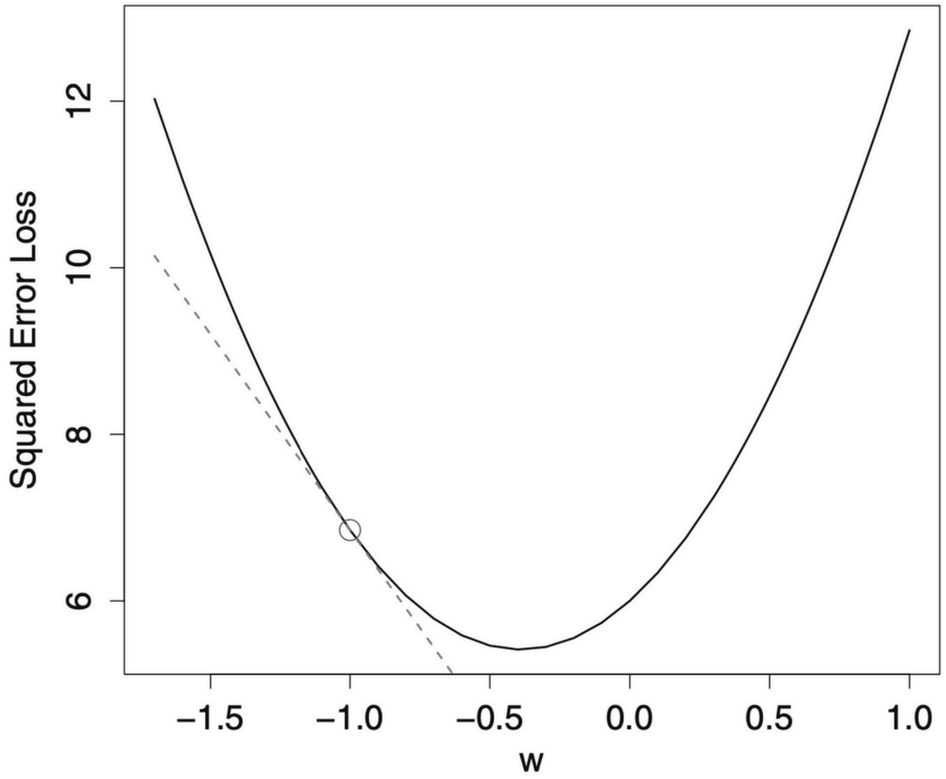

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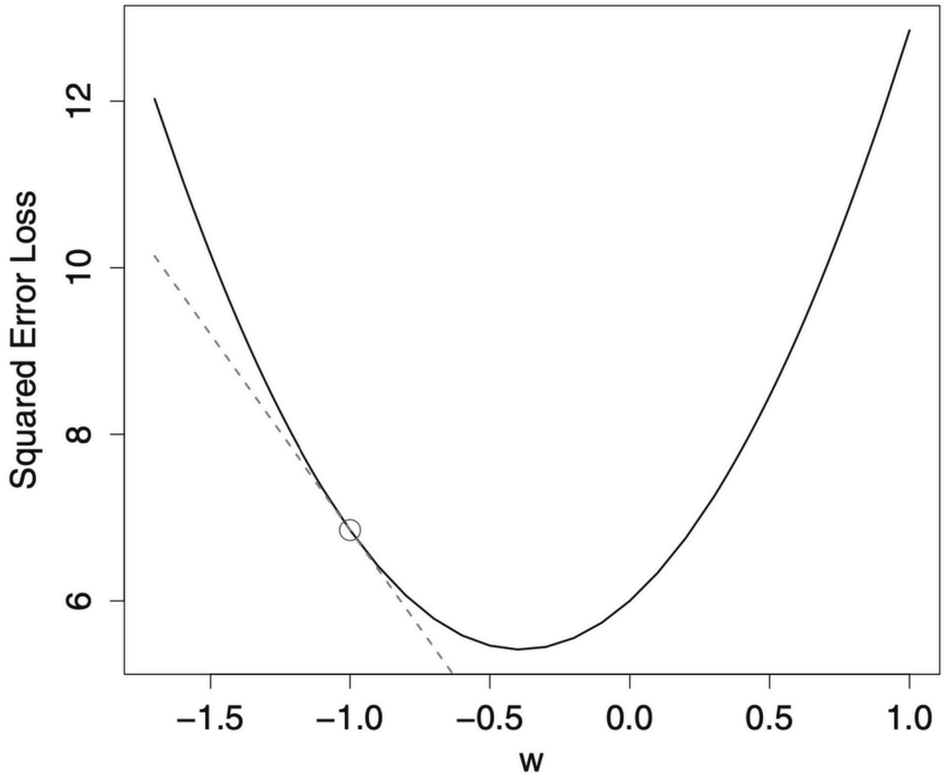

$$w_1(t+1) = w_1(t) - \eta \frac{\partial E^2}{\partial w_1}$$

The perceptron algorithm

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$$\frac{\partial E^2}{\partial \theta} = 2 \sum_{i=1}^{n} (y_i - f(x_i)) \frac{\partial [y_i - f(x_i)]}{\partial \theta}.$$

The perceptron algorithm

Recall y_i is the expected output class for example i (i.e., a label defined by some specialist), thus when differentiating it in terms of either w_1 or θ, y_i is disconsidered. Differentiating $\frac{\partial - f(x_i)}{\partial w_1}$ and $\frac{\partial - f(x_i)}{\partial \theta}$:

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The Gradient Descent method is formulated as follows:

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$$
\begin{aligned}
w_1(t+1) &= w_1(t) - \eta \frac{\partial E^2}{\partial w_1} \\
&= w_1(t) - \eta\, 2 \sum_{i=1}^{n} (y_i - f(x_i))(-x_{i,1}), \\
&= w_1(t) - \eta\, 2 \sum (y_i - [x_{i,1} w_1 + \theta])(-x_{i,1}),
\end{aligned}
$$

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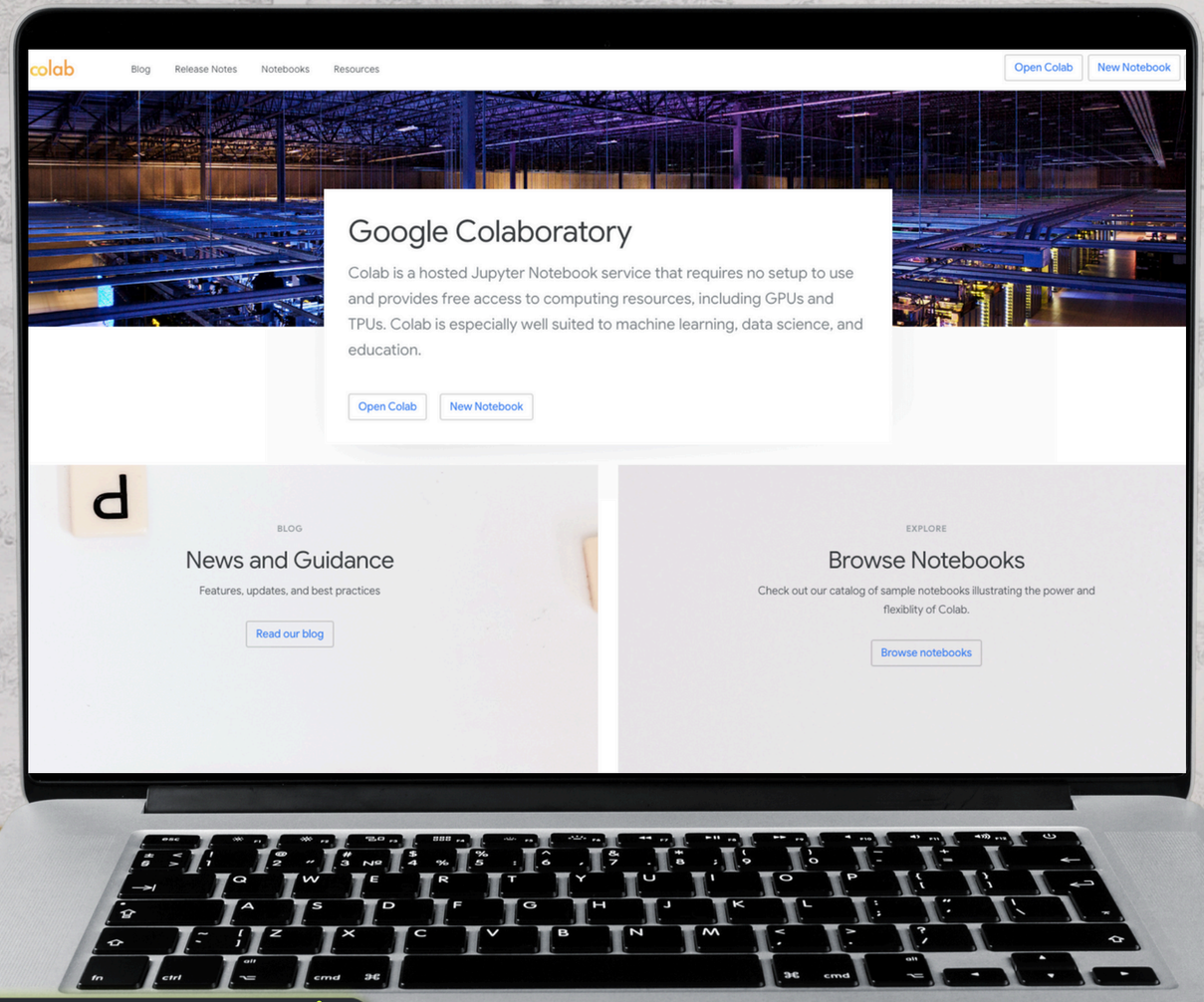

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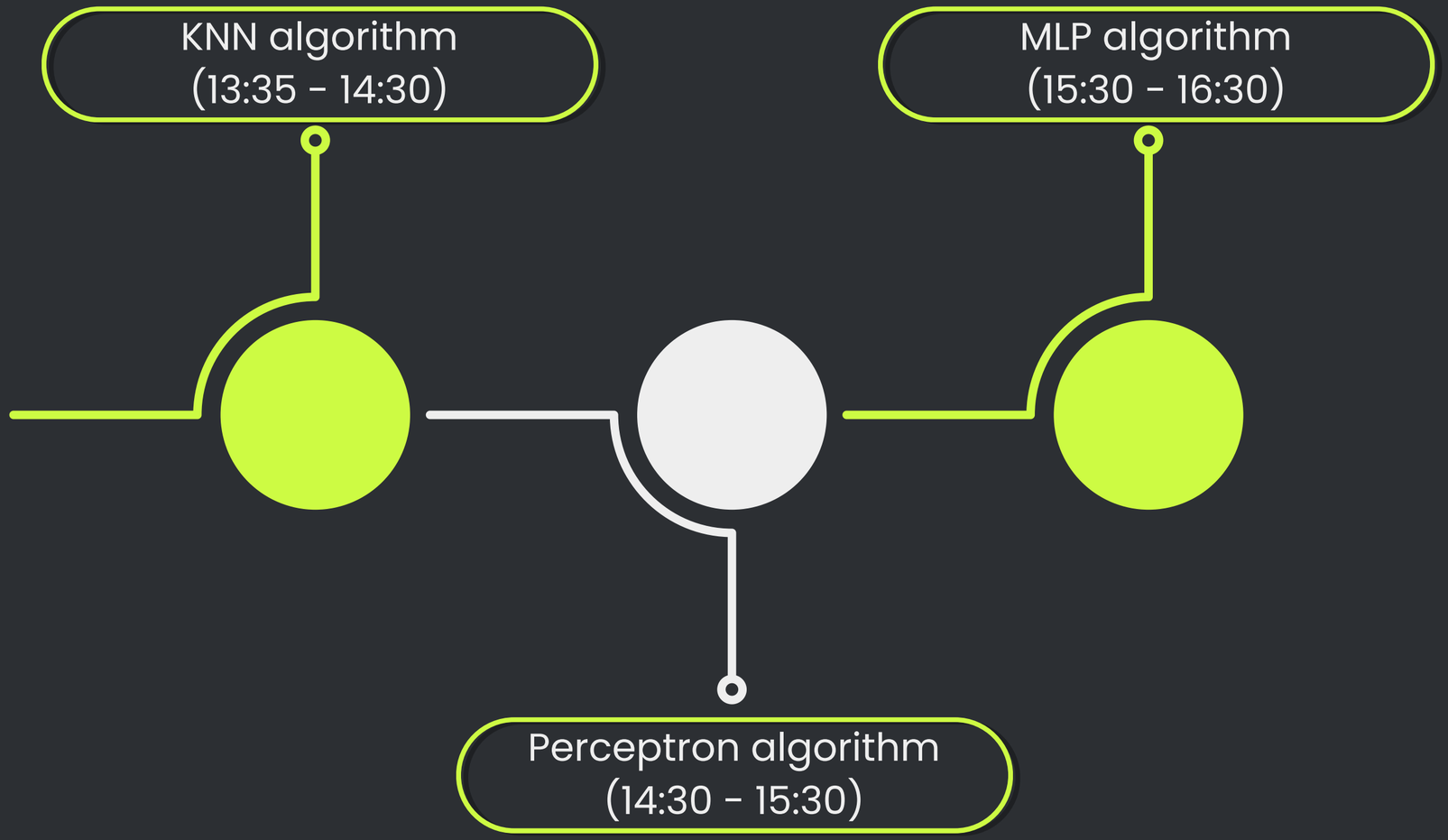
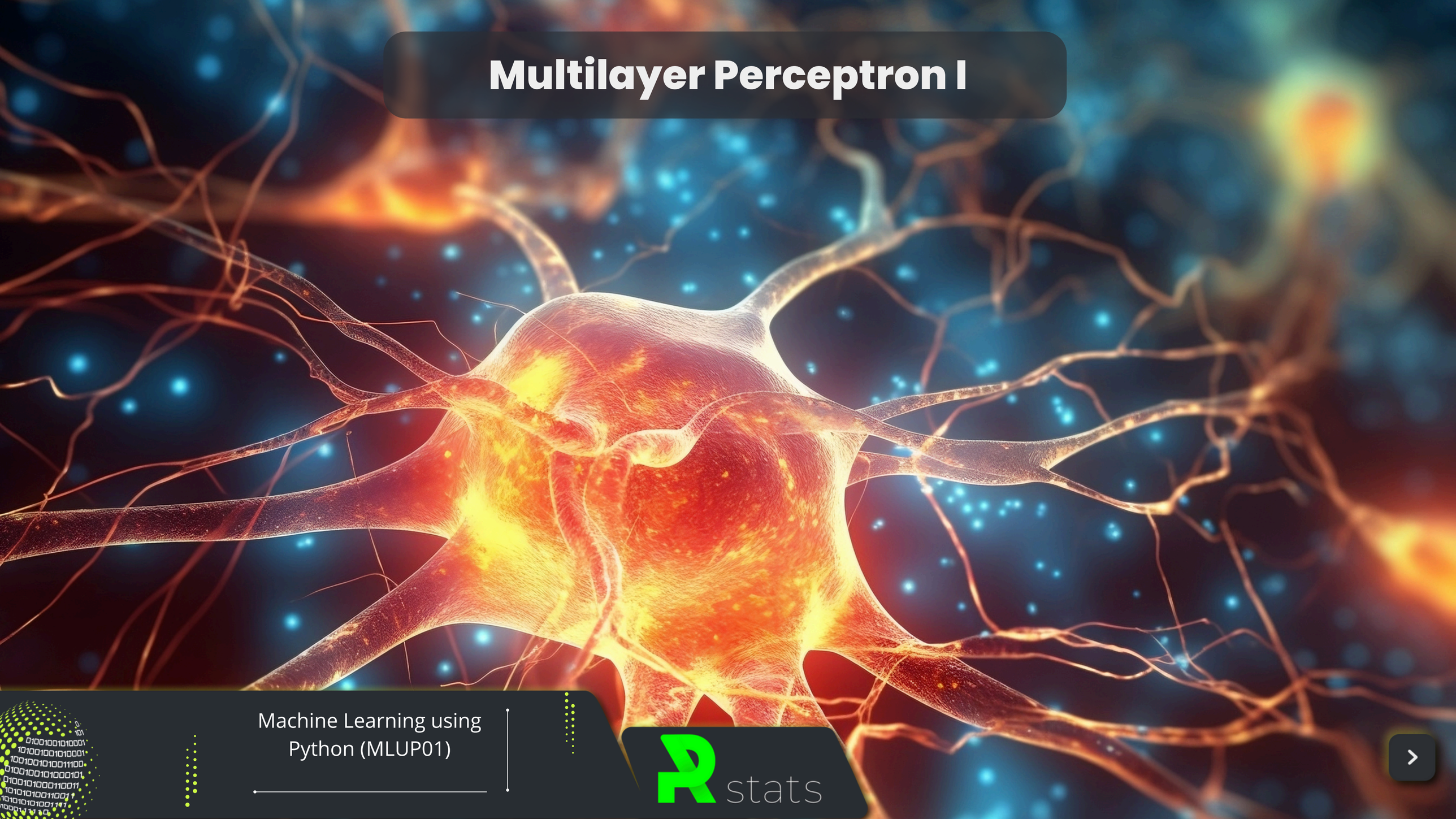


Multilayer Perceptron I



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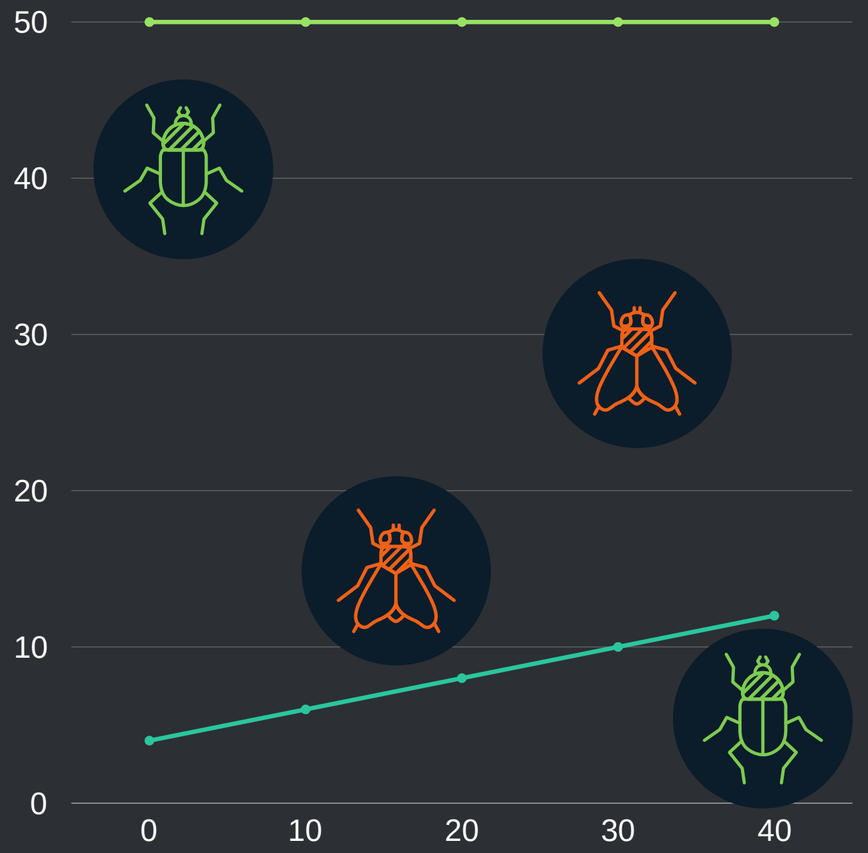

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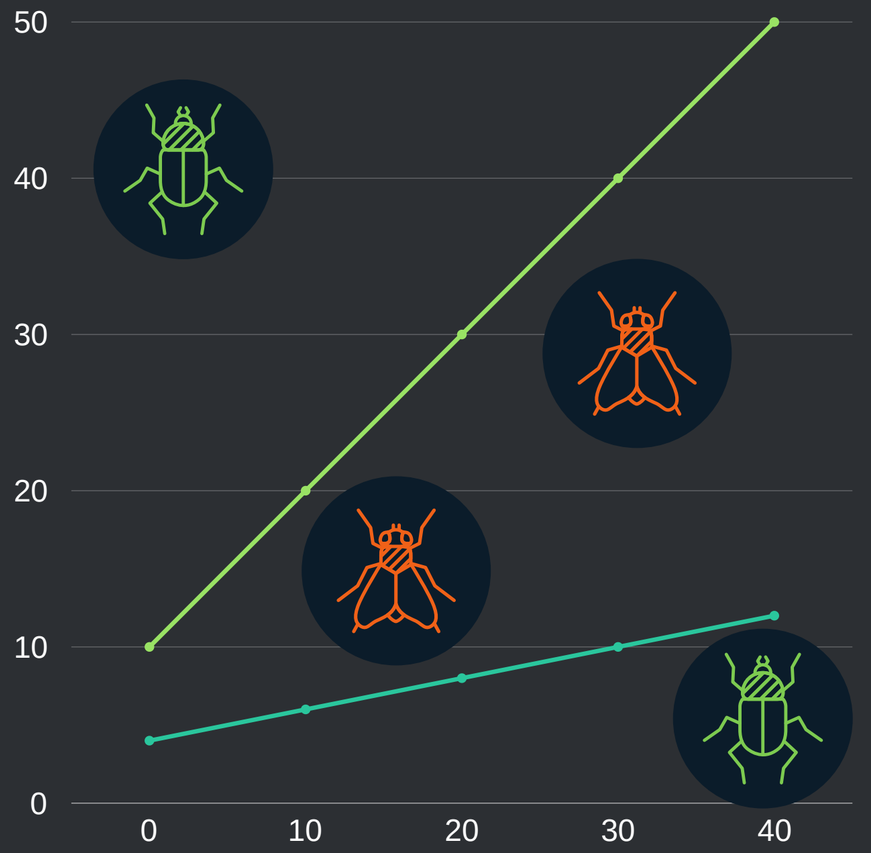

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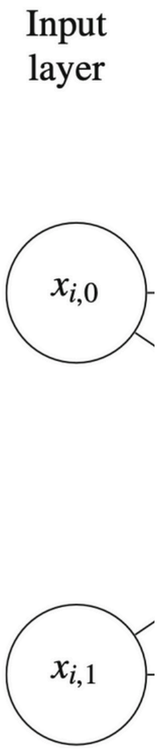

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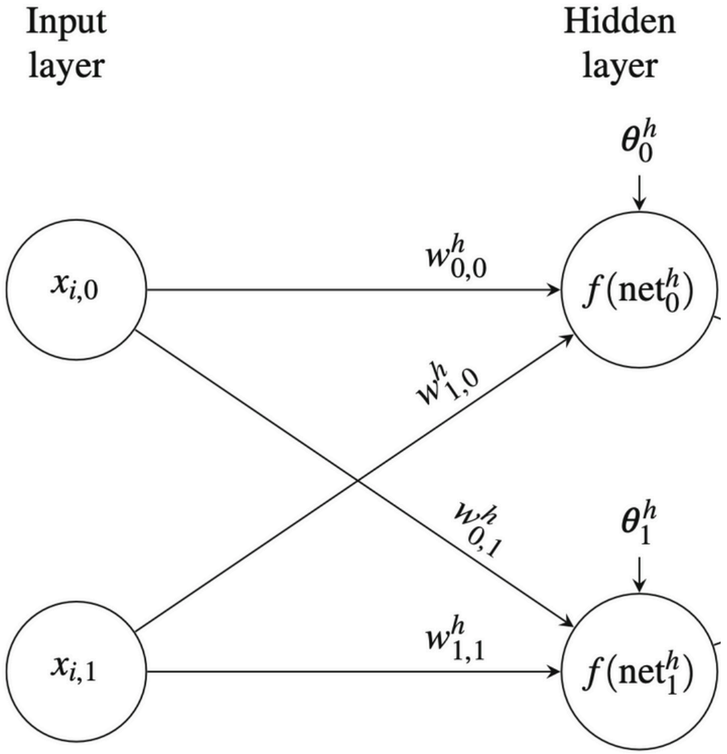

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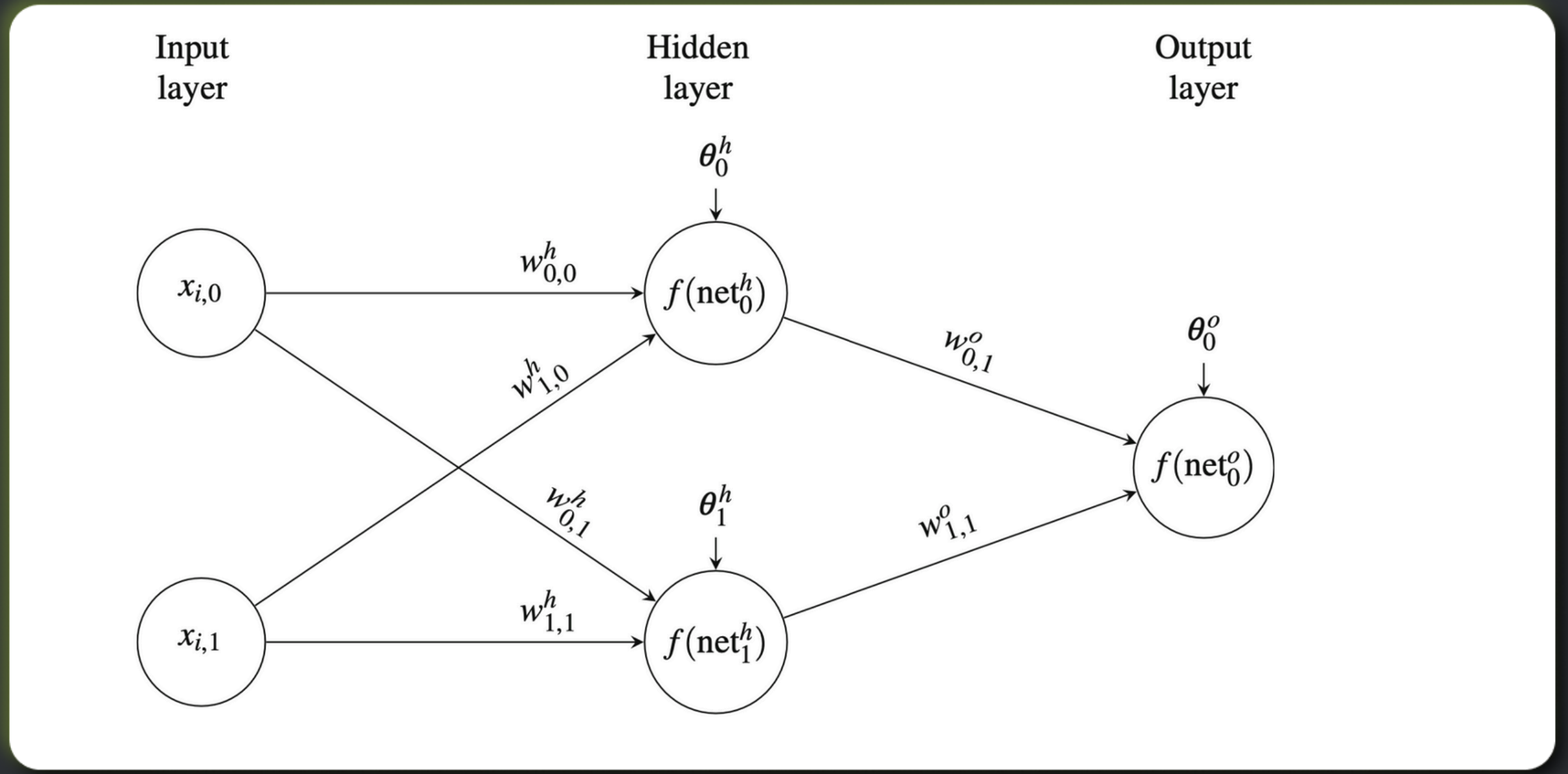

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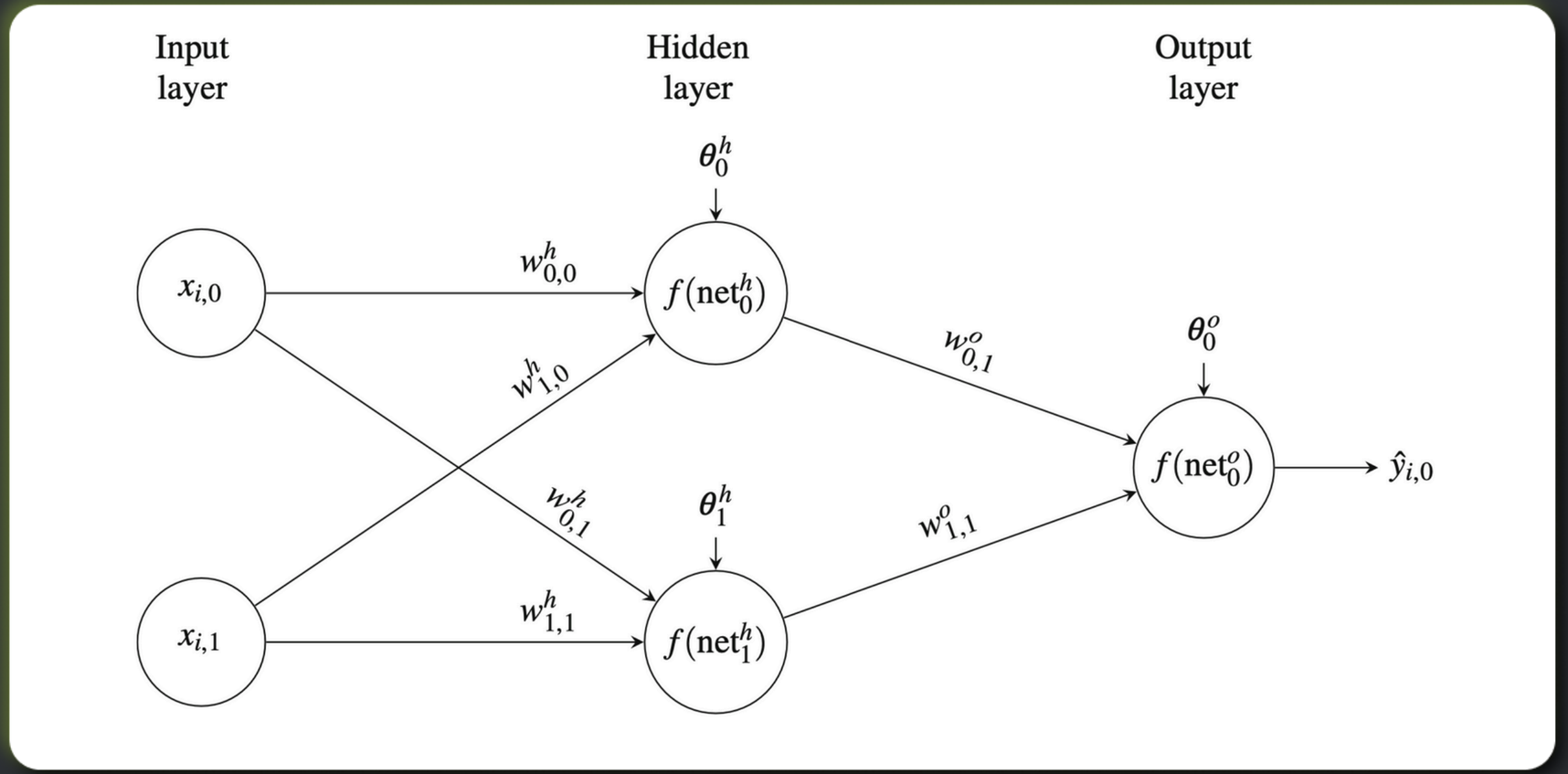

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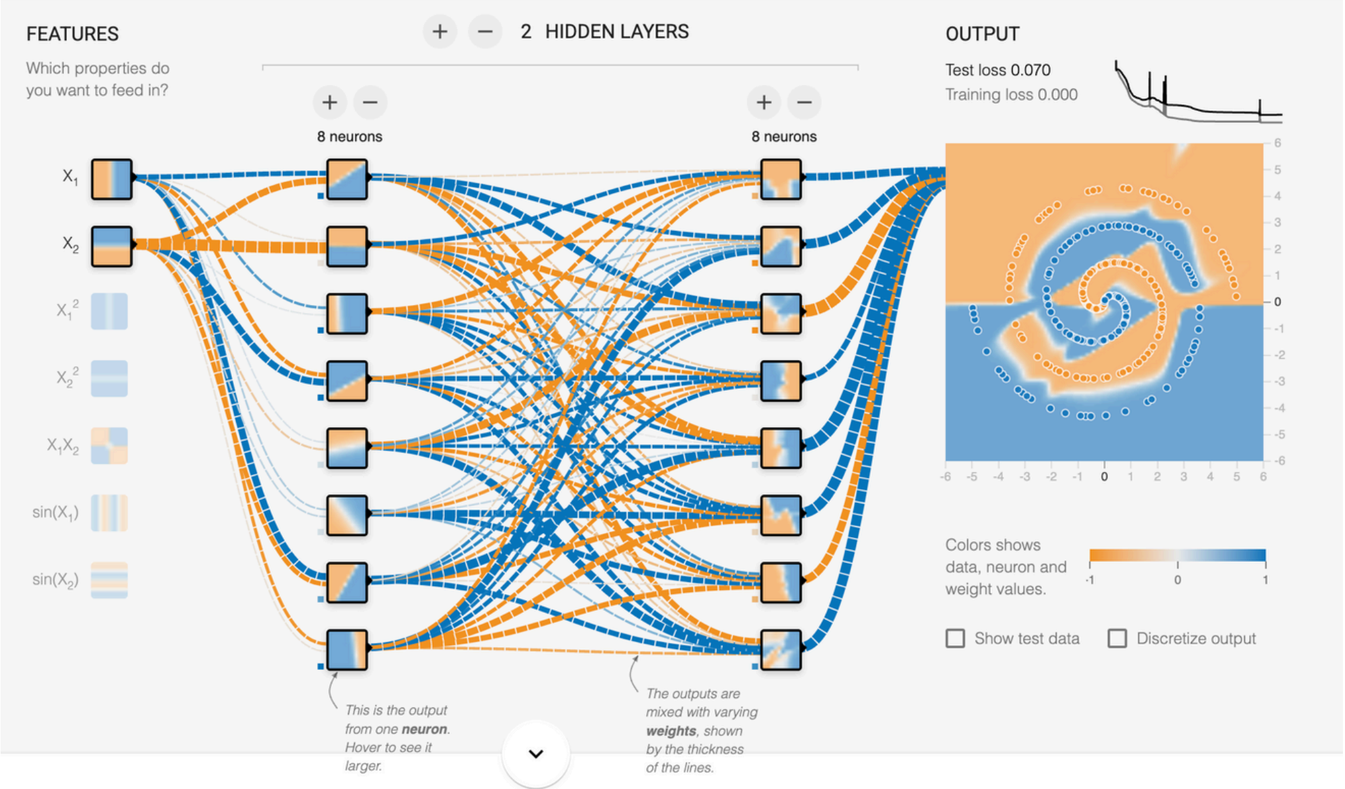
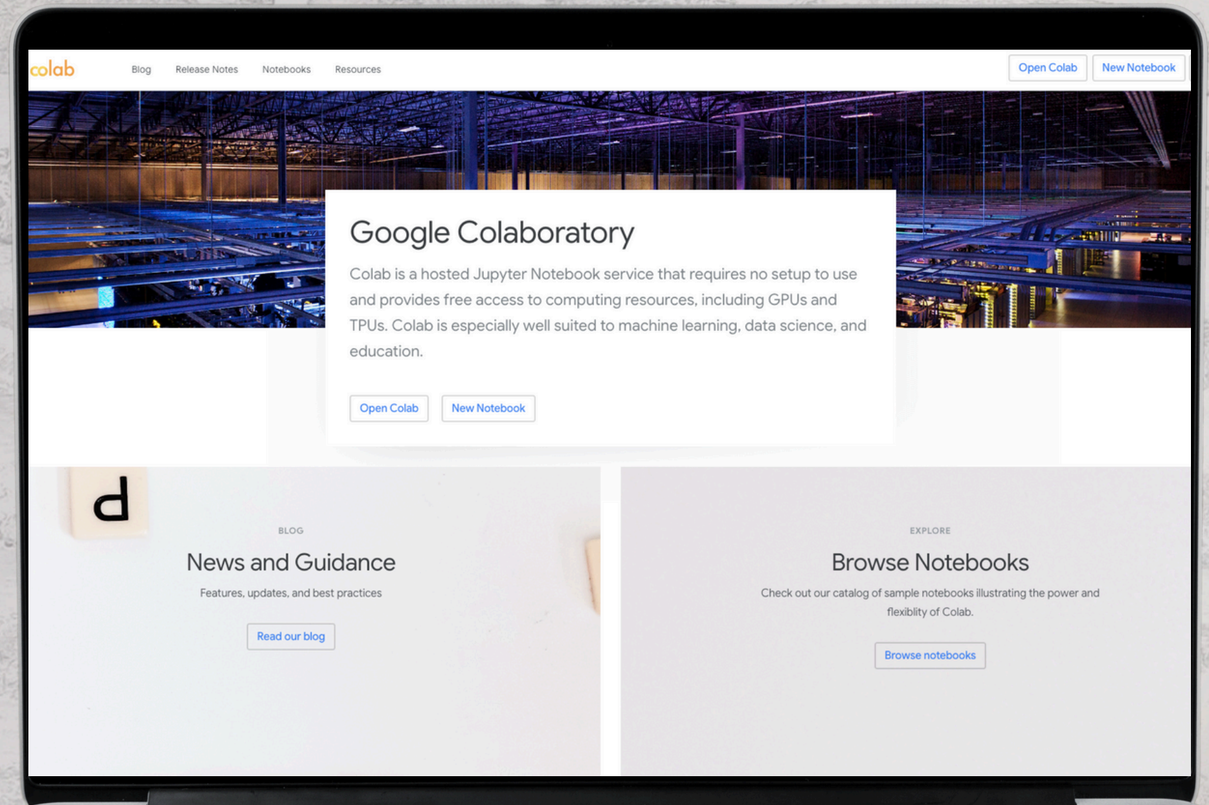


Multilayer Perceptron I



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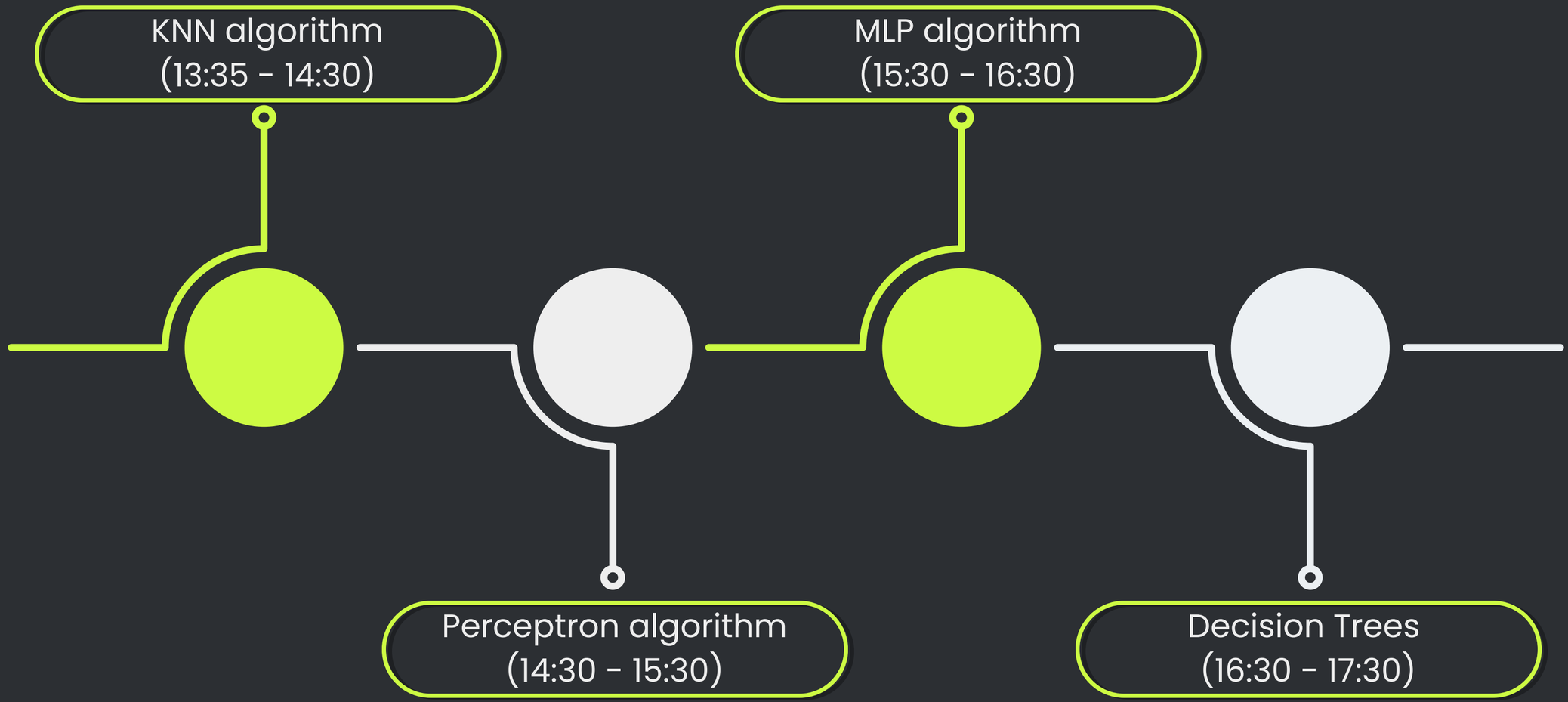
Day 4 (13:30 - 17:30)



Decision Trees

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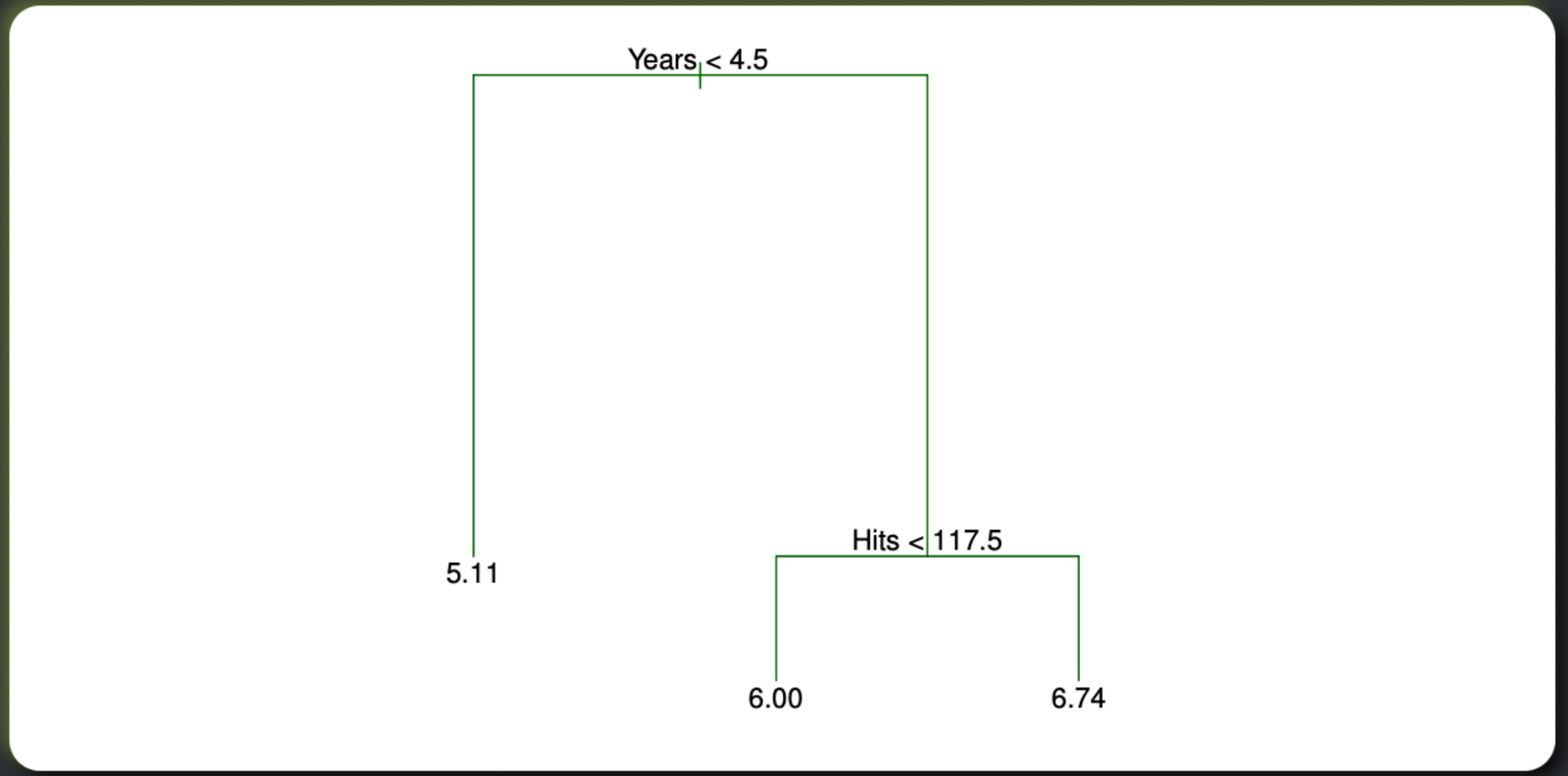
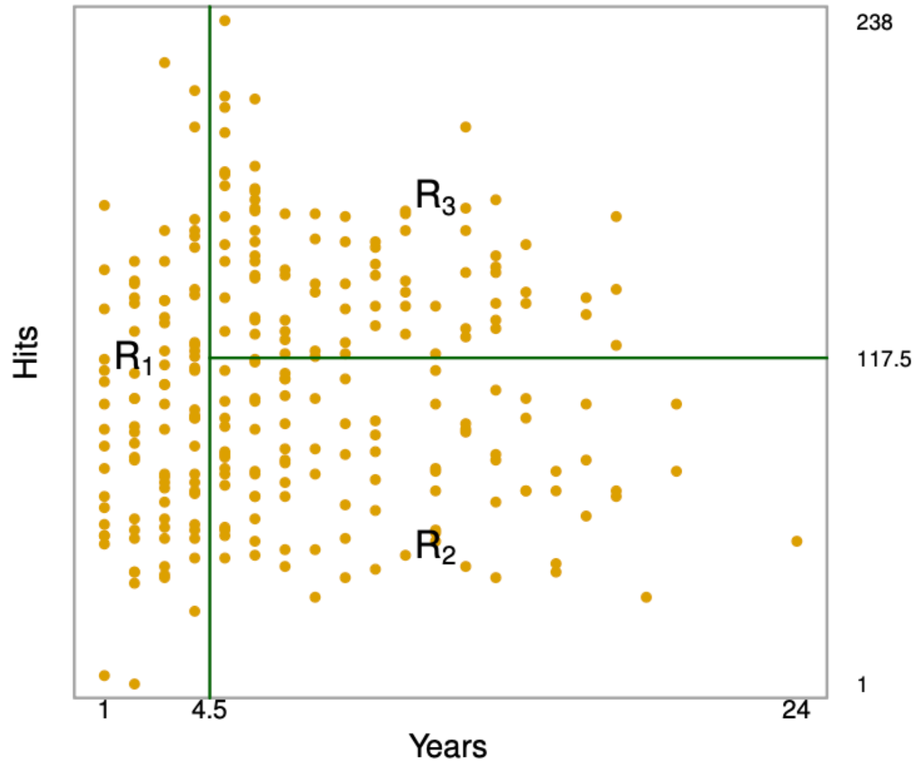
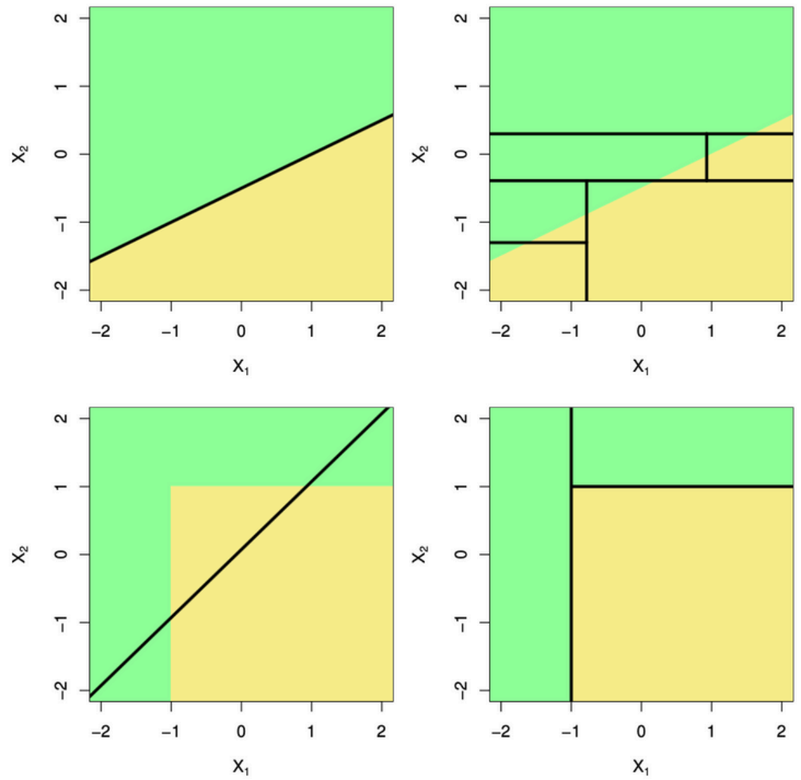
Decision Trees



Decision Trees



Decision Trees



Decision Trees

1. Use recursive binary splitting to grow a large tree on the training data, stopping only when each terminal node has fewer than some minimum number of observations.

2. Apply cost complexity pruning to the large tree in order to obtain a sequence of best subtrees, as a function of α.

3. Use K-fold cross-validation to choose α. That is, divide the training observations into K folds. For each $k = 1, \ldots, K$:

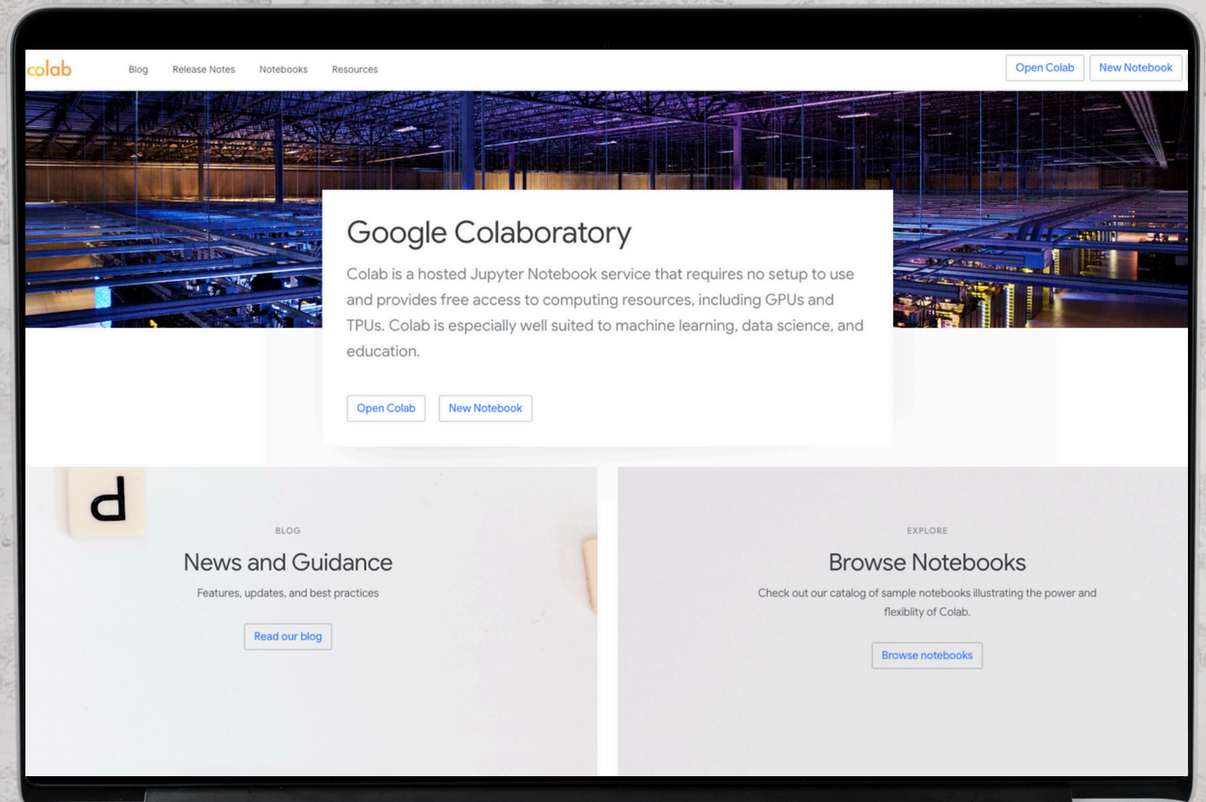
   (a) Repeat Steps 1 and 2 on all but the kth fold of the training data.

   (b) Evaluate the mean squared prediction error on the data in the left-out kth fold, as a function of α.

   Average the results for each value of α, and pick α to minimize the average error.

4. Return the subtree from Step 2 that corresponds to the chosen value of α.

Decision Trees



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