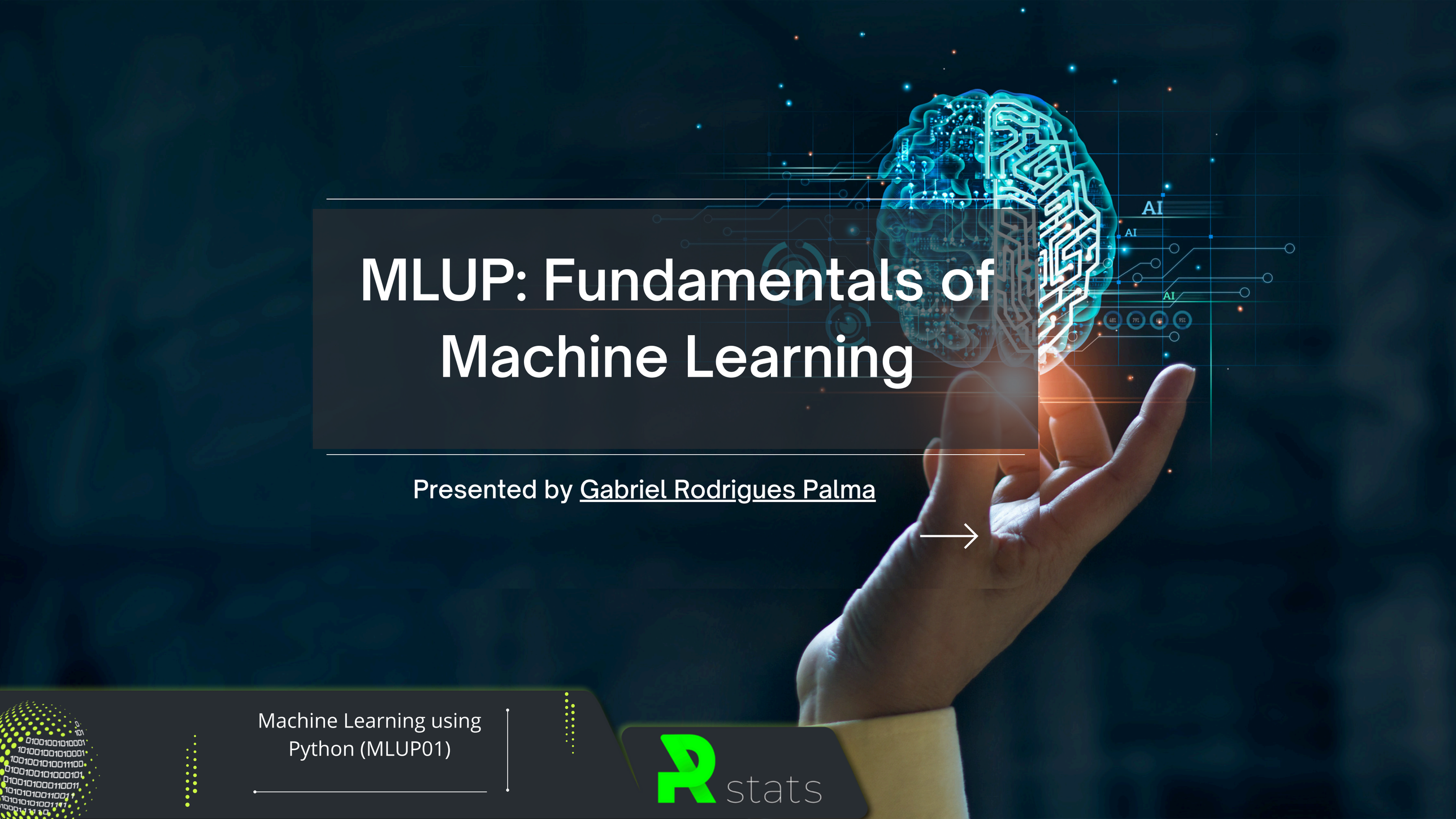
MLUP: Fundamentals of Machine Learning

Presented by Gabriel Rodrigues Palma



Machine Learning using Python (MLUP01)

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Day 3 (13:30 – 17:30)

Your First Steps into ML
(13:35 - 14:30)

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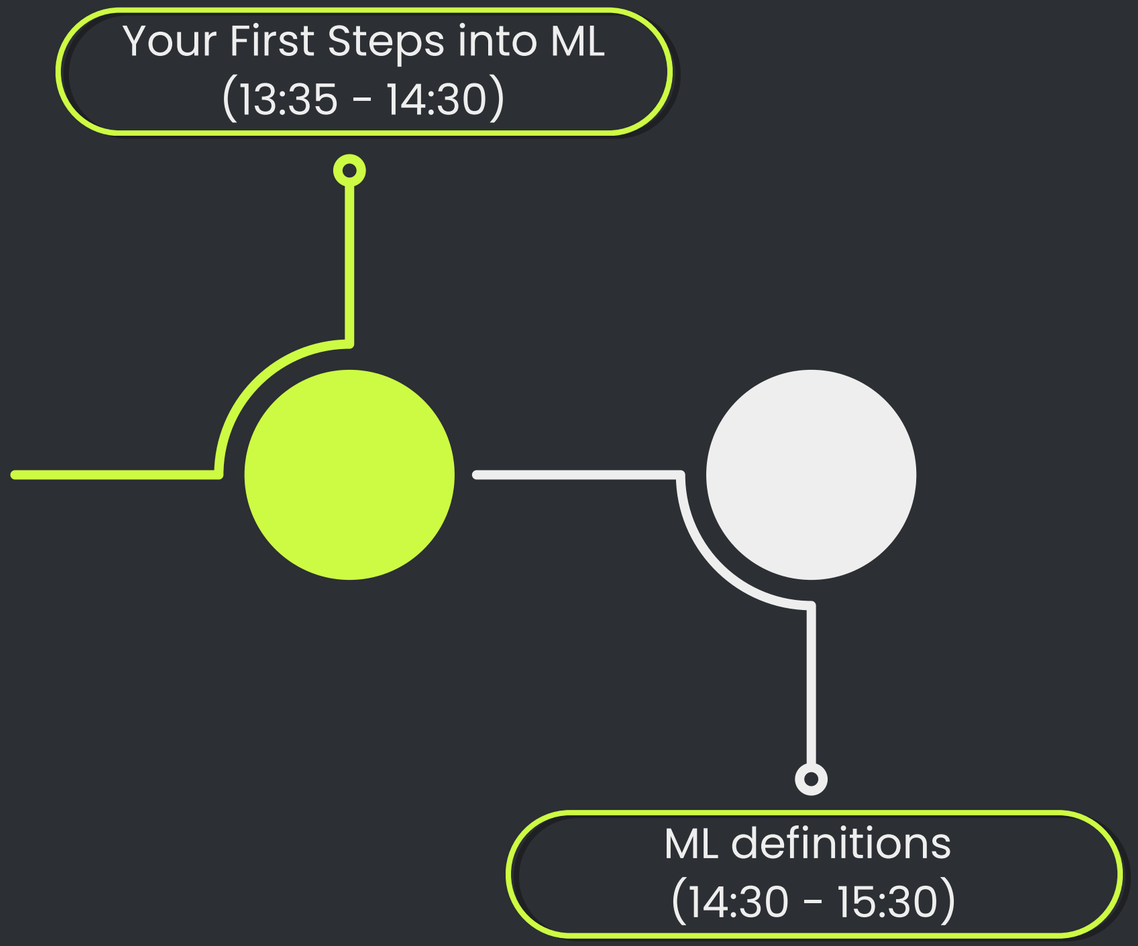

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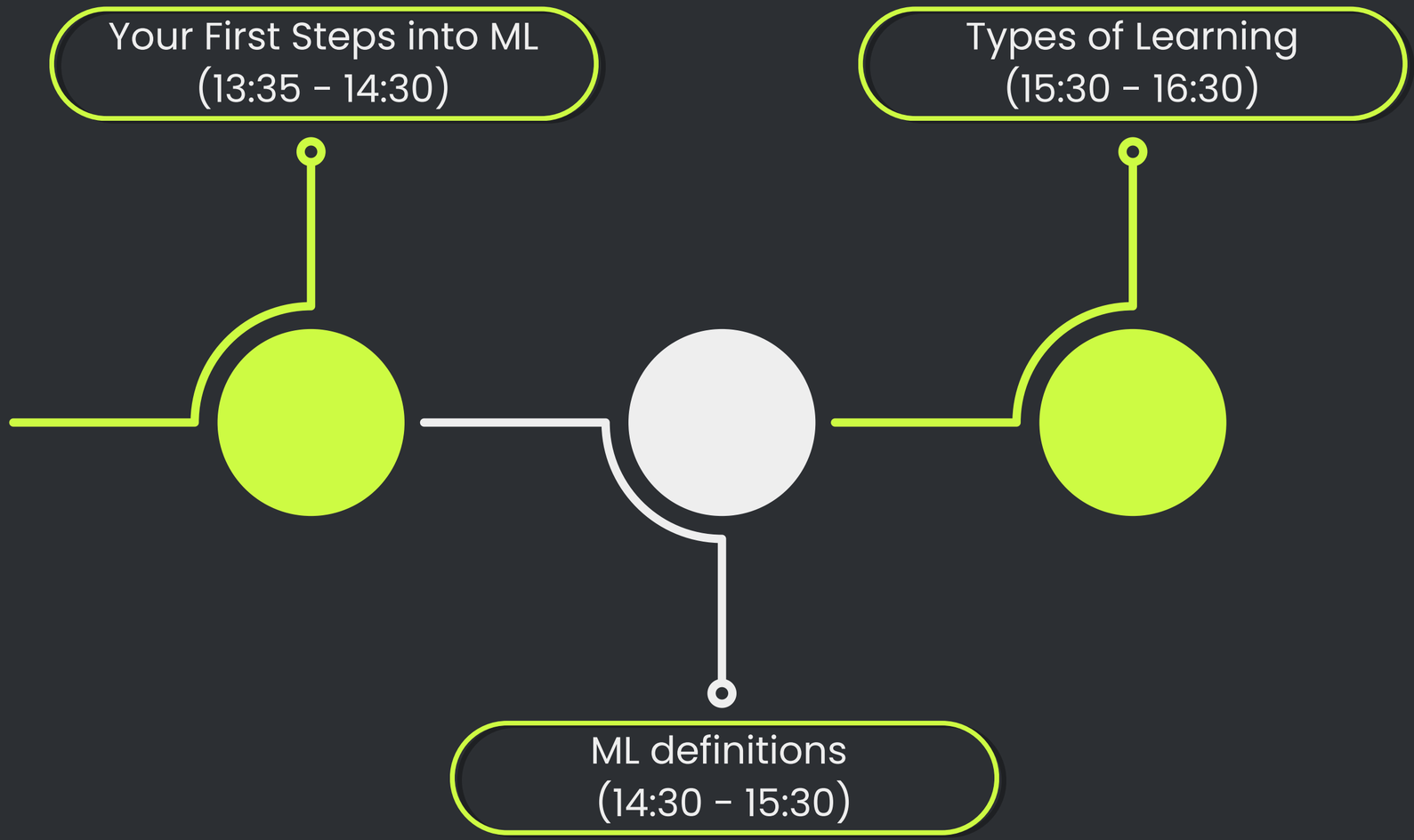

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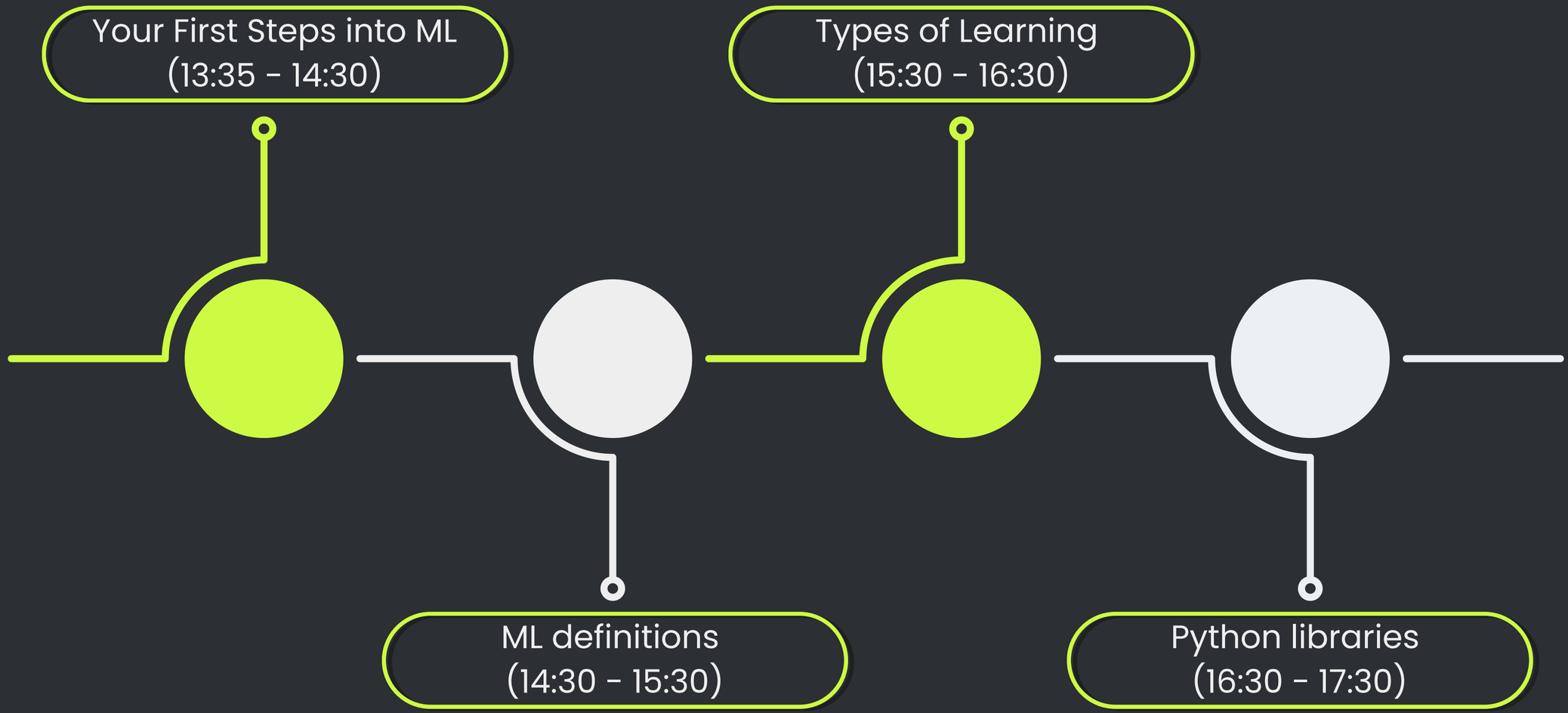

Your First Steps into ML

Machine Learning using Python (MLUP01)

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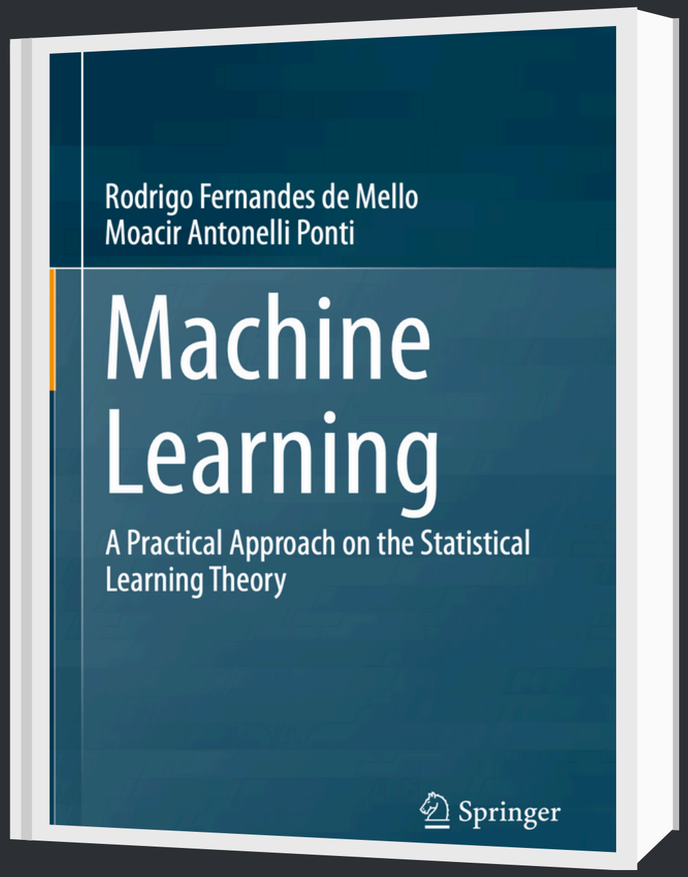

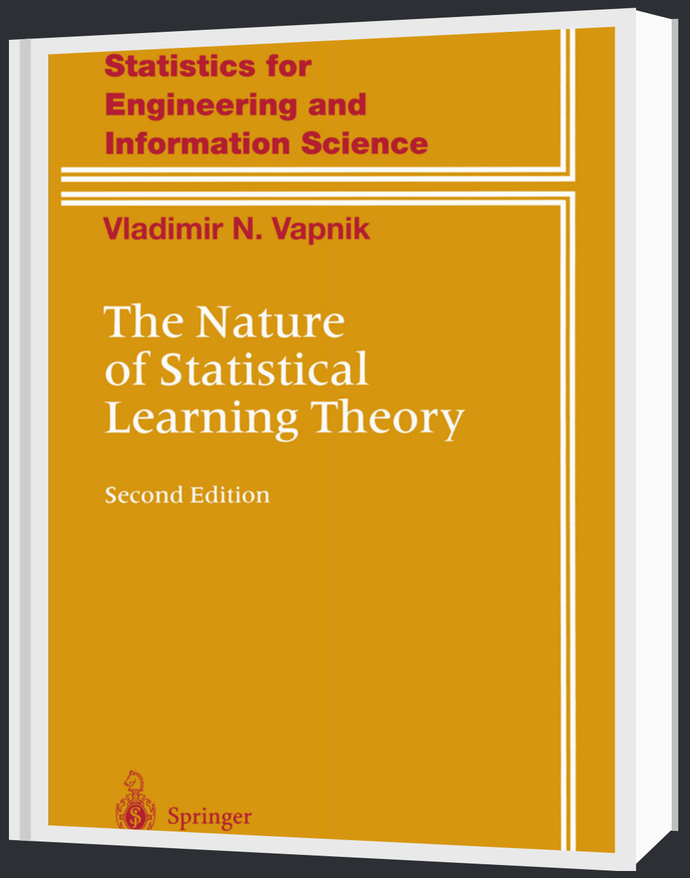

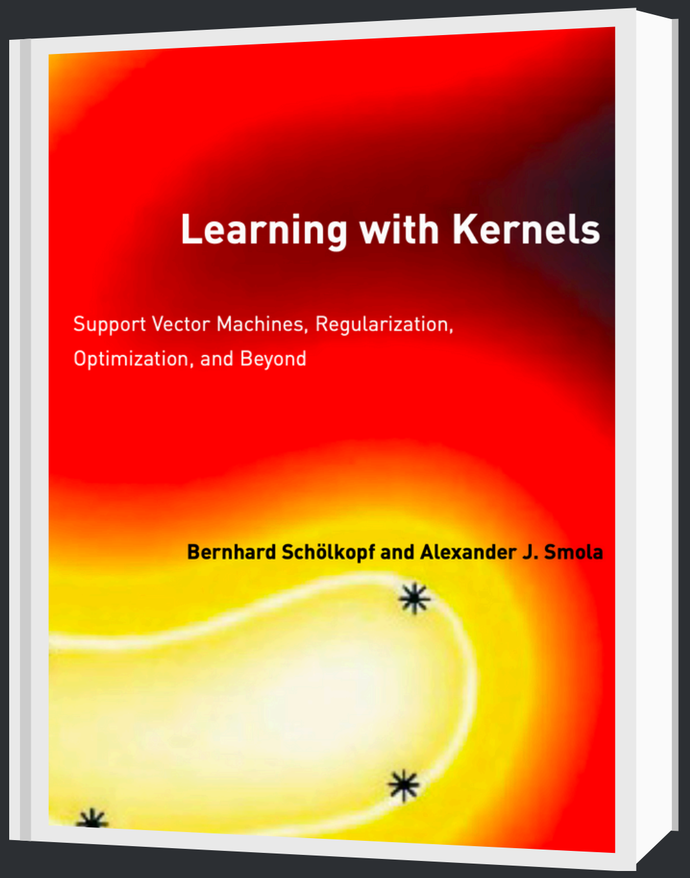

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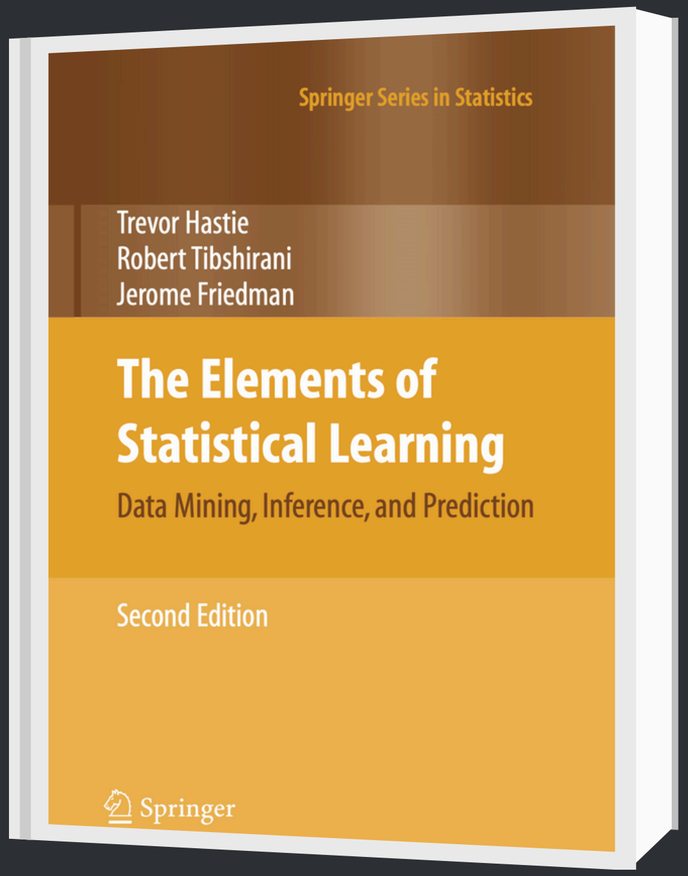

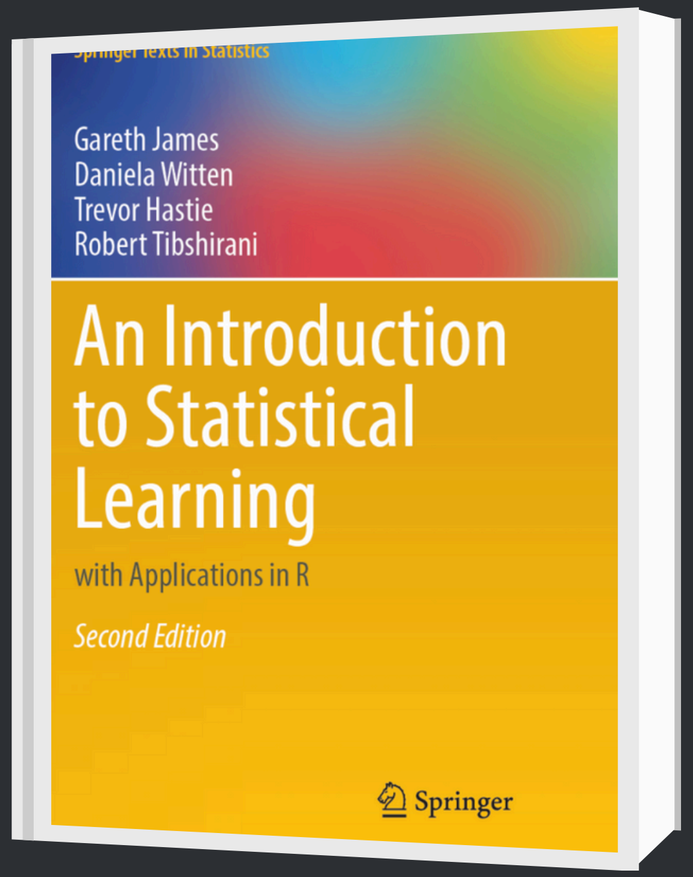

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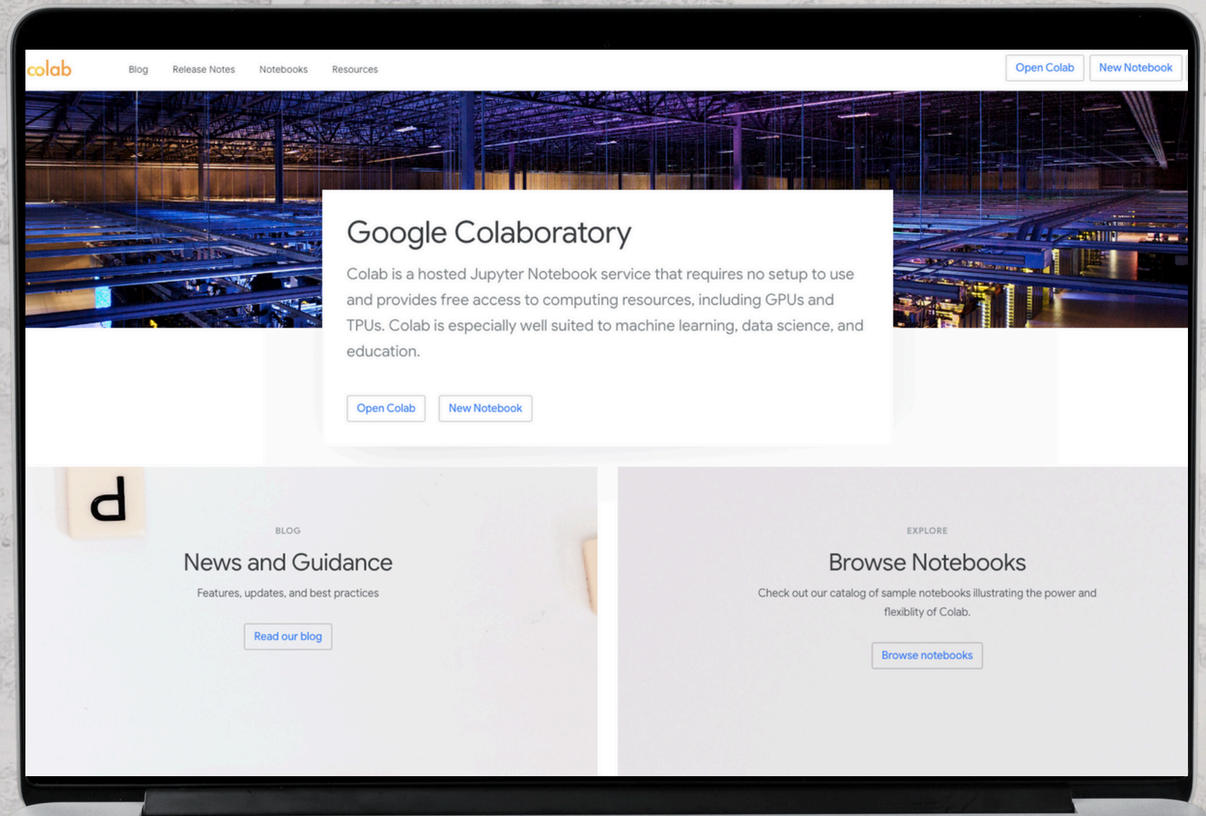

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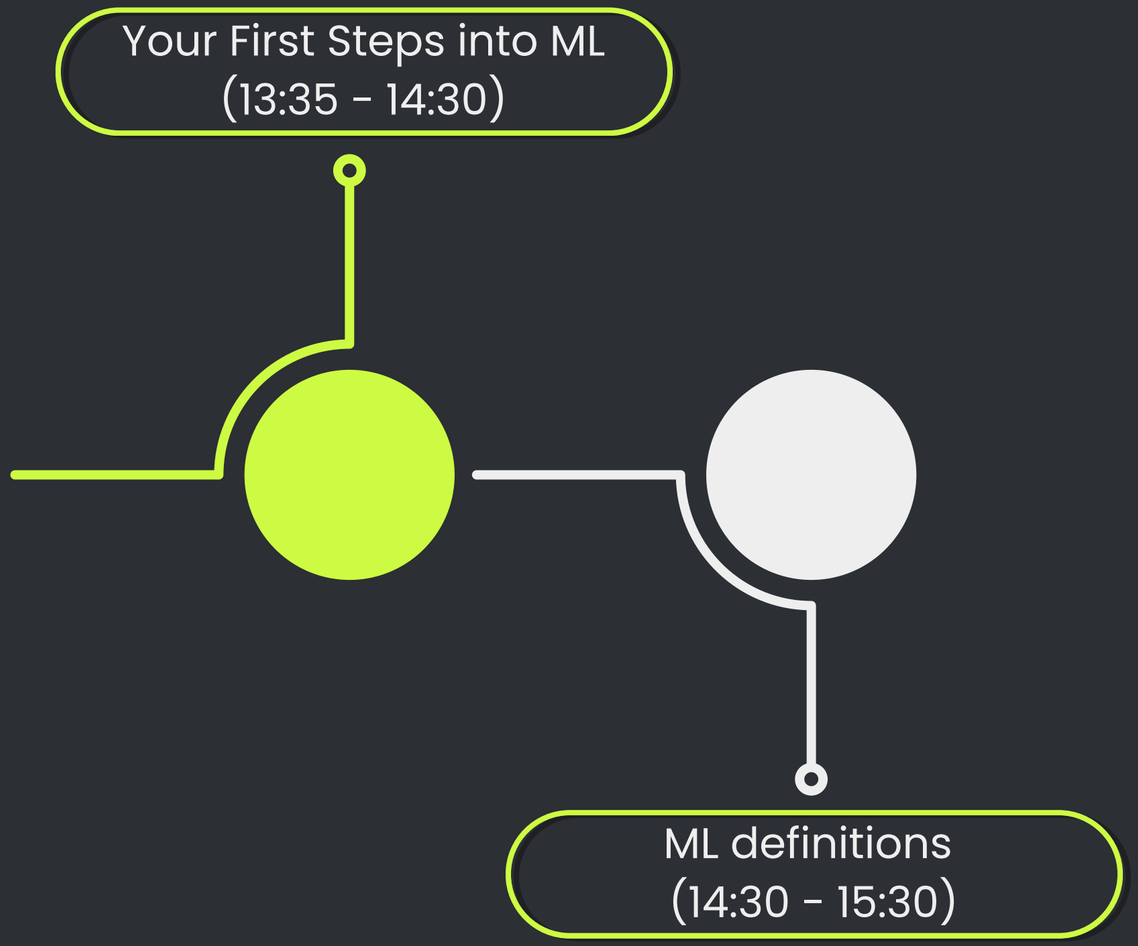

ML definitions

The area of Machine Learning (ML) is interested in answering how a computer can “learn” specific tasks

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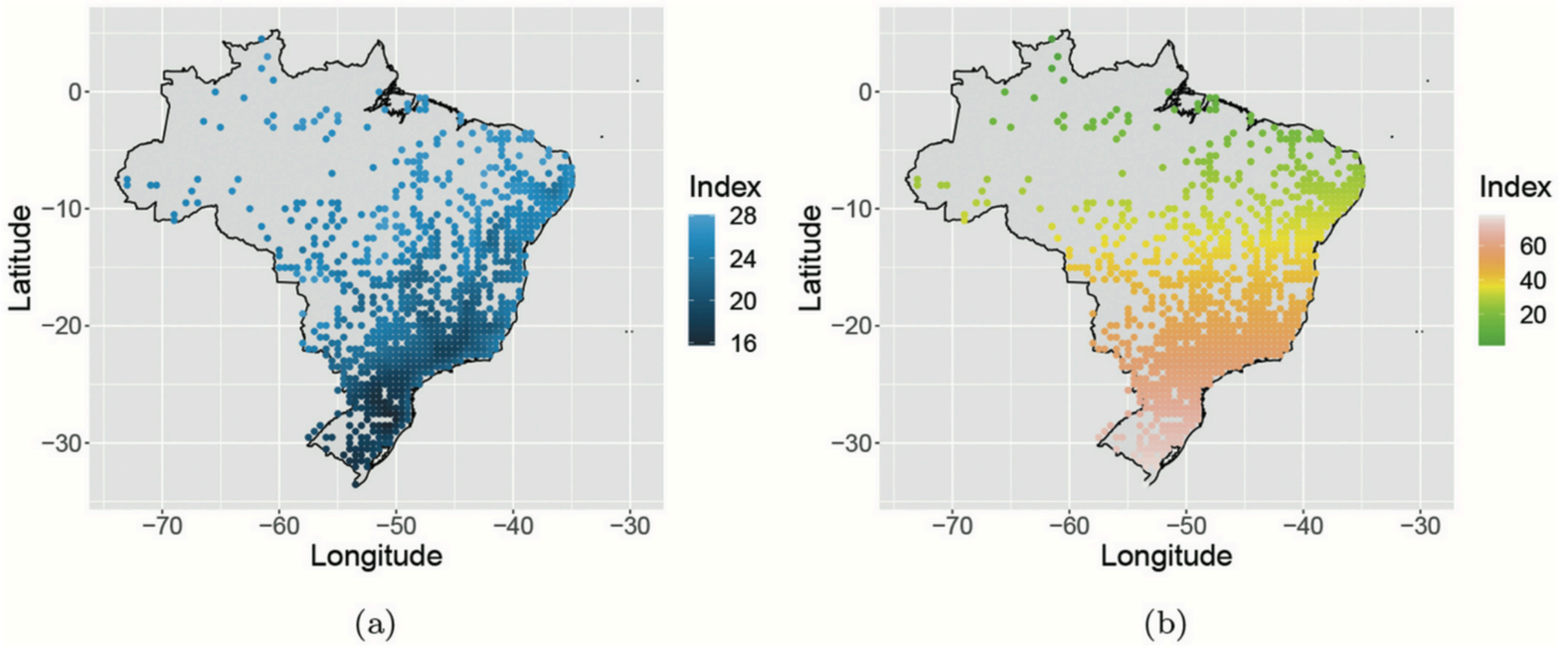
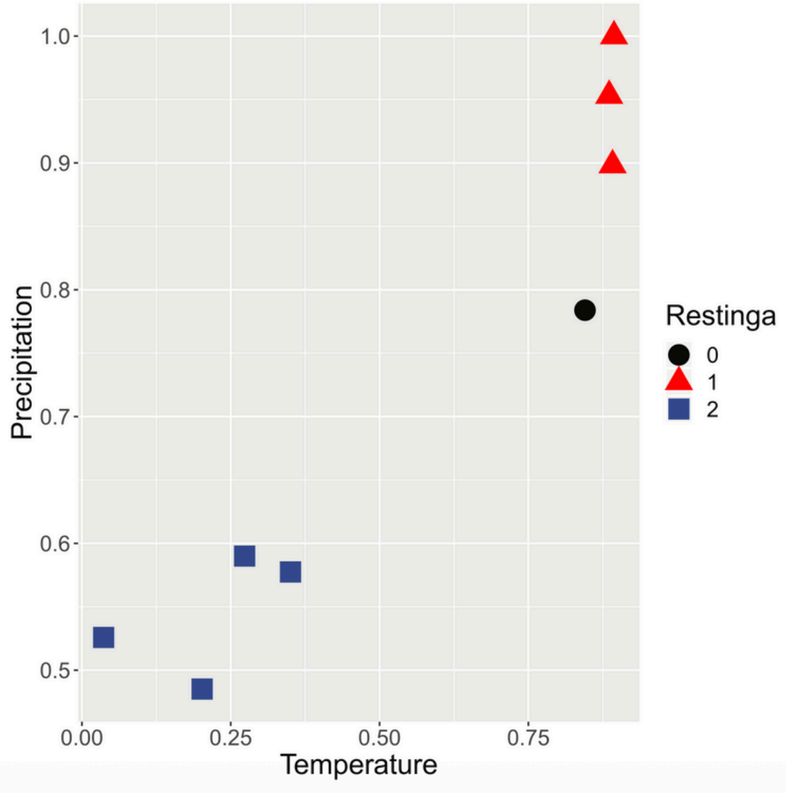


ML definitions

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

ML definitions



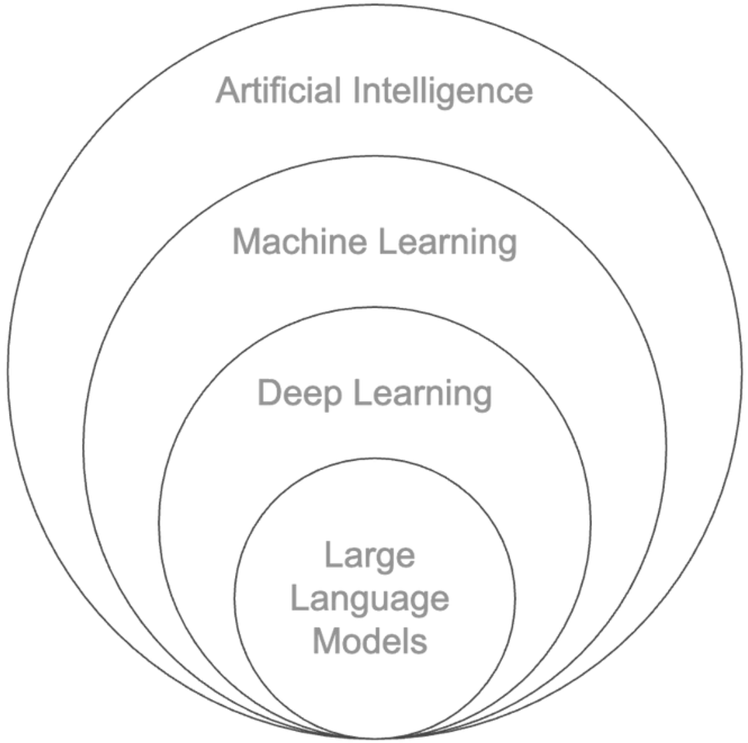
ML definitions

Broadest field of study

Subset of AI

Specialized subset of Machine Learning

Specific applications of Deep Learning



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McCulloch and Pitts (1943)

- proposed a computational model based on biological neural networks
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- psychologist, proposed the learning hypothesis based on neural plasticity mechanism
- Neural plasticity:
  - Brain's ability to remodel itself based on subject's experiences
  - Reformulation of connections according to needs and environmental factors
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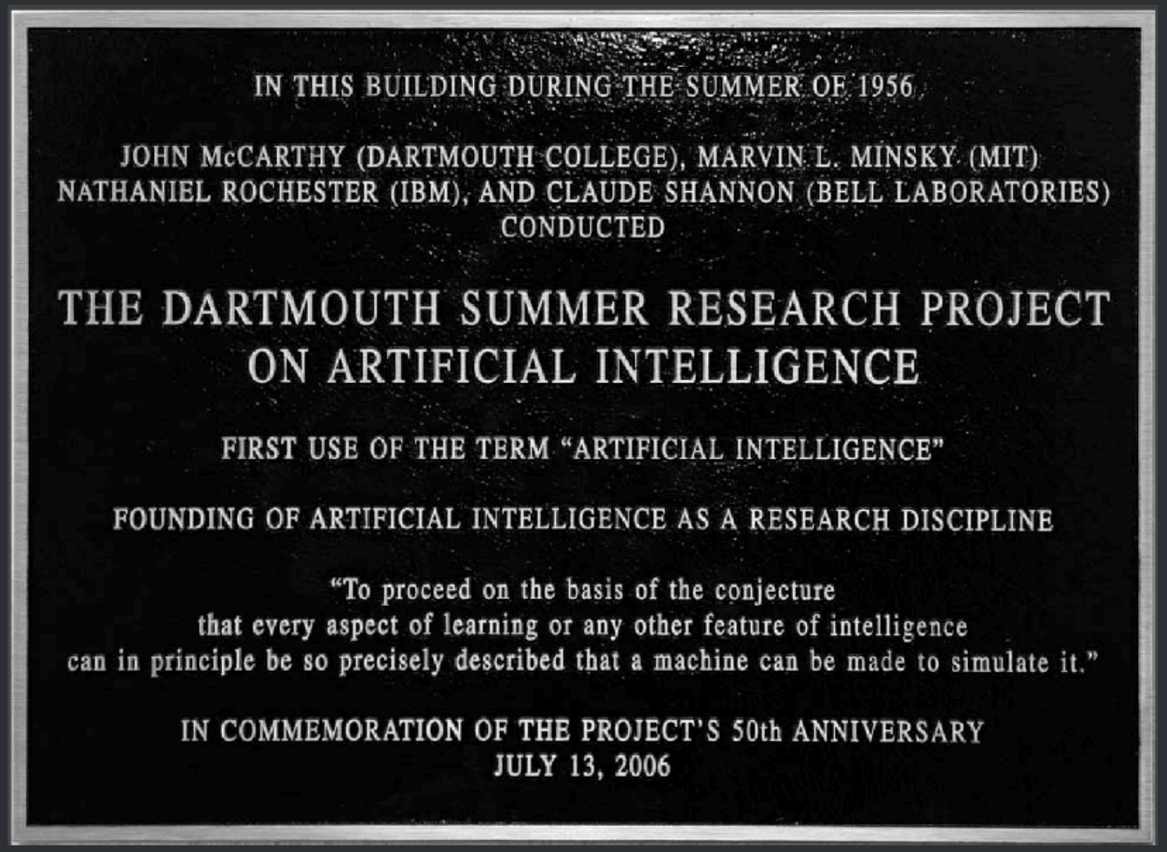
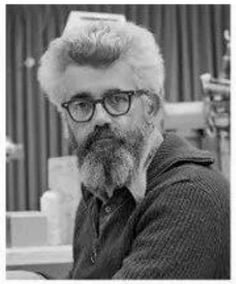
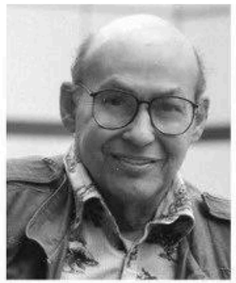
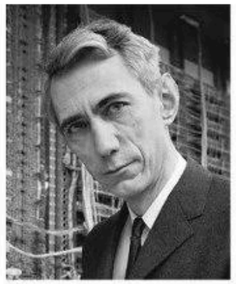


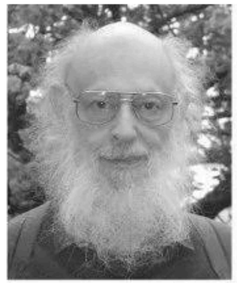
ML definitions

1956 Dartmouth Conference: The Founding Fathers of AI


John MacCarthy


Marvin Minsky

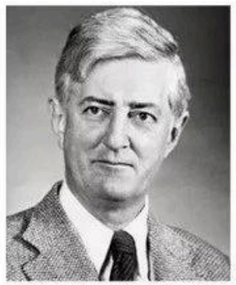

Claude Shannon


Ray Solomonoff


Alan Newell


Herbert Simon

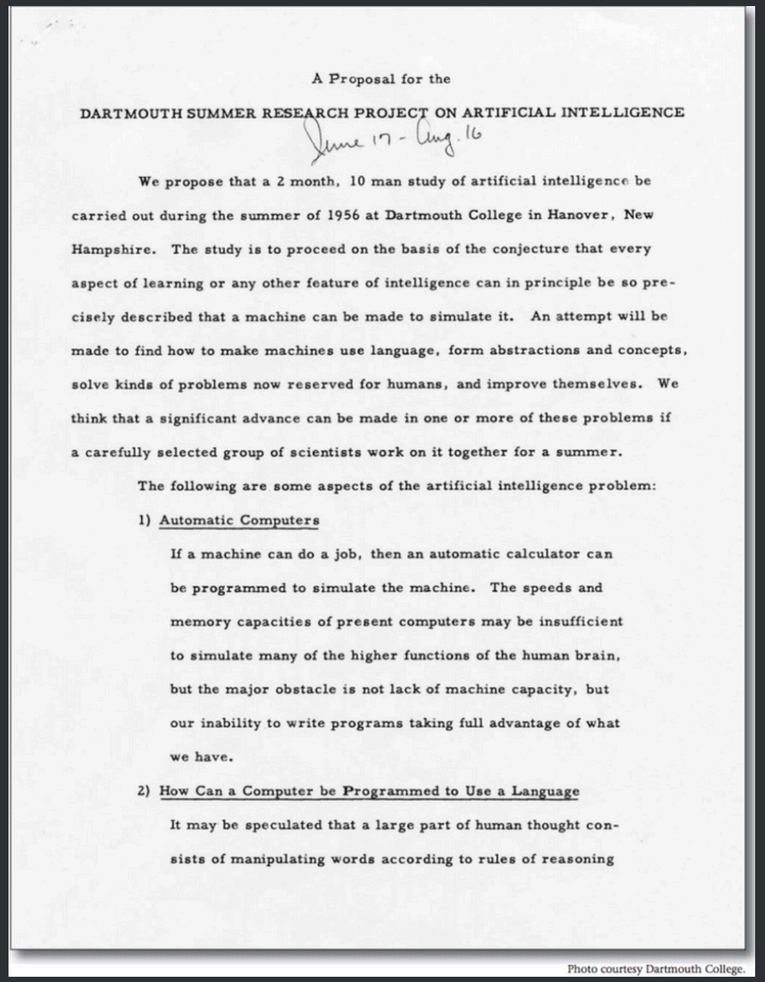

Arthur Samuel


Oliver Selfridge


Nathaniel Rochester


Trenchard More

ML definitions



A Proposal for the

DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

June 17 - Aug. 16

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

The following are some aspects of the artificial intelligence problem:

1) Automatic Computers

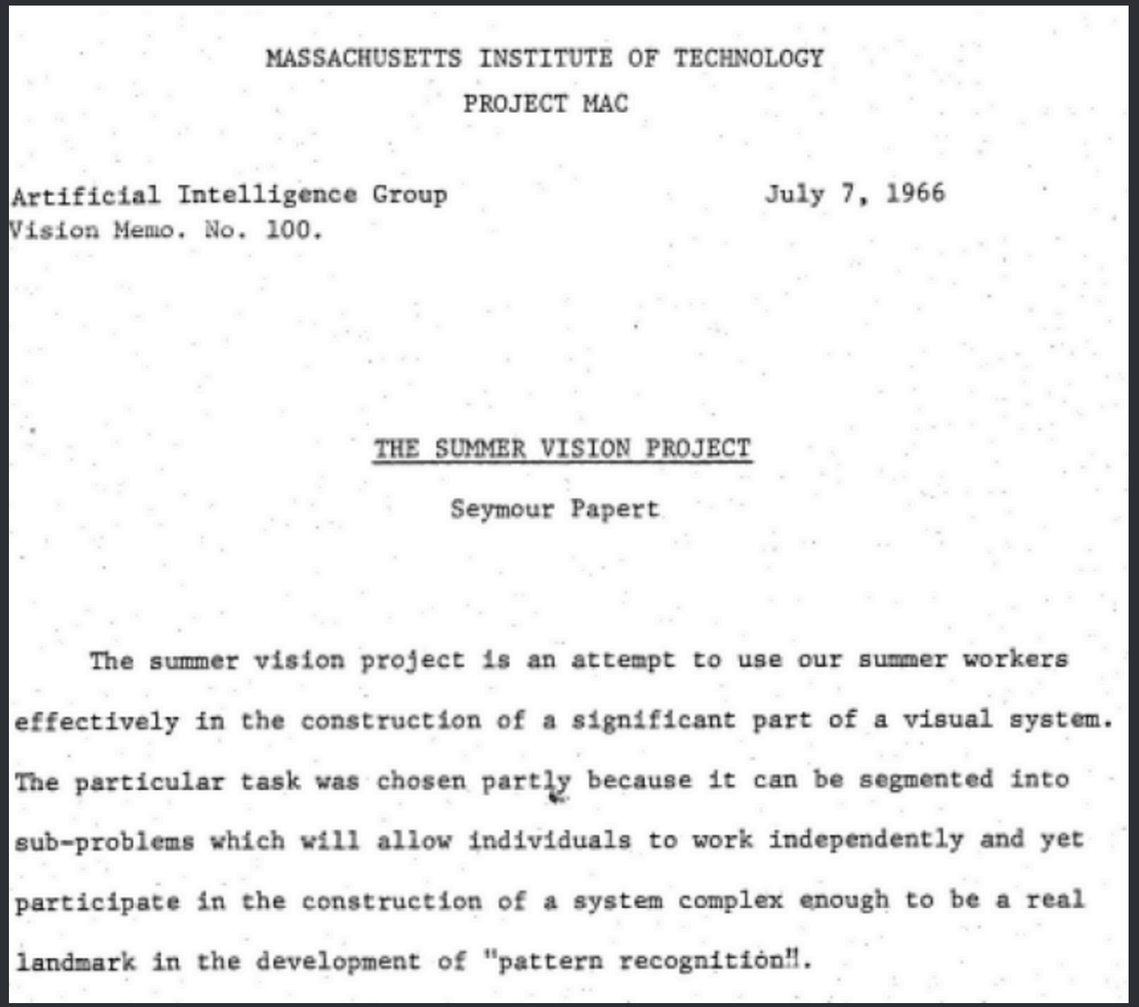
If a machine can do a job, then an automatic calculator can be programmed to simulate the machine. The speeds and memory capacities of present computers may be insufficient to simulate many of the higher functions of the human brain, but the major obstacle is not lack of machine capacity, but our inability to write programs taking full advantage of what we have.

2) How Can a Computer be Programmed to Use a Language

It may be speculated that a large part of human thought consists of manipulating words according to rules of reasoning

Photo courtesy Dartmouth College.

ML definitions



MASSACHUSETTS INSTITUTE OF TECHNOLOGY

PROJECT MAC

Artificial Intelligence Group — July 7, 1966
Vision Memo. No. 100.

THE SUMMER VISION PROJECT

Seymour Papert

The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

ML definitions

After Minsky and Papert's publication (1969), the field became stagnant because they discovered:

- That problems like Exclusive-OR could not be solved using the Perceptron
- Computers did not have sufficient capacity to process larger artificial neural networks

ML definitions

This discovery led to the first "AI winter" in neural network research, which lasted until the development and popularisation of backpropagation in the mid-1980s. The XOR problem demonstrated a fundamental limitation of single-layer perceptrons in their inability to solve non-linearly separable problems.

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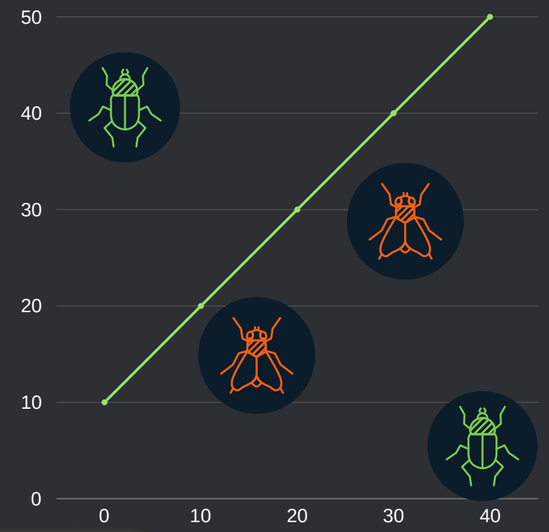
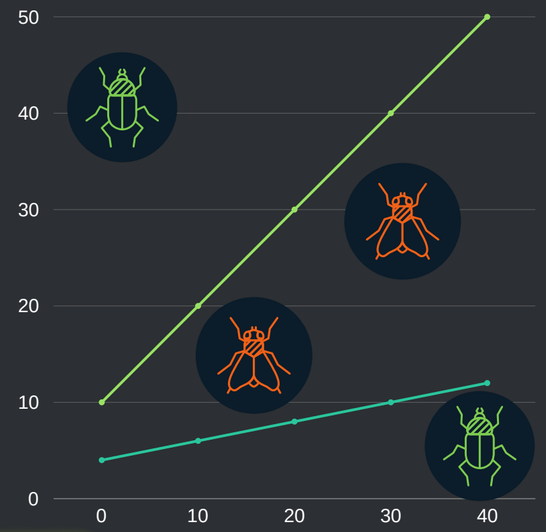


ML definitions

Research in the field resumed after the proposal of the Backpropagation algorithm (Webos 1975):

- Solved the Exclusive-OR (XOR) problem



ML definitions

In the mid-1980s, the field of parallel and distributed processing emerged under the name of connectionism:

- Due to its use in implementing Artificial Neural Networks
- "Rediscovery" of the Backpropagation algorithm through the paper "Learning Internal Representations by Error Propagation" (1986)
- Motivated adoption and popularized usage

ML definitions

Predicted	Observed	
	Yes	No
Yes	TP	FP
No	FN	TN

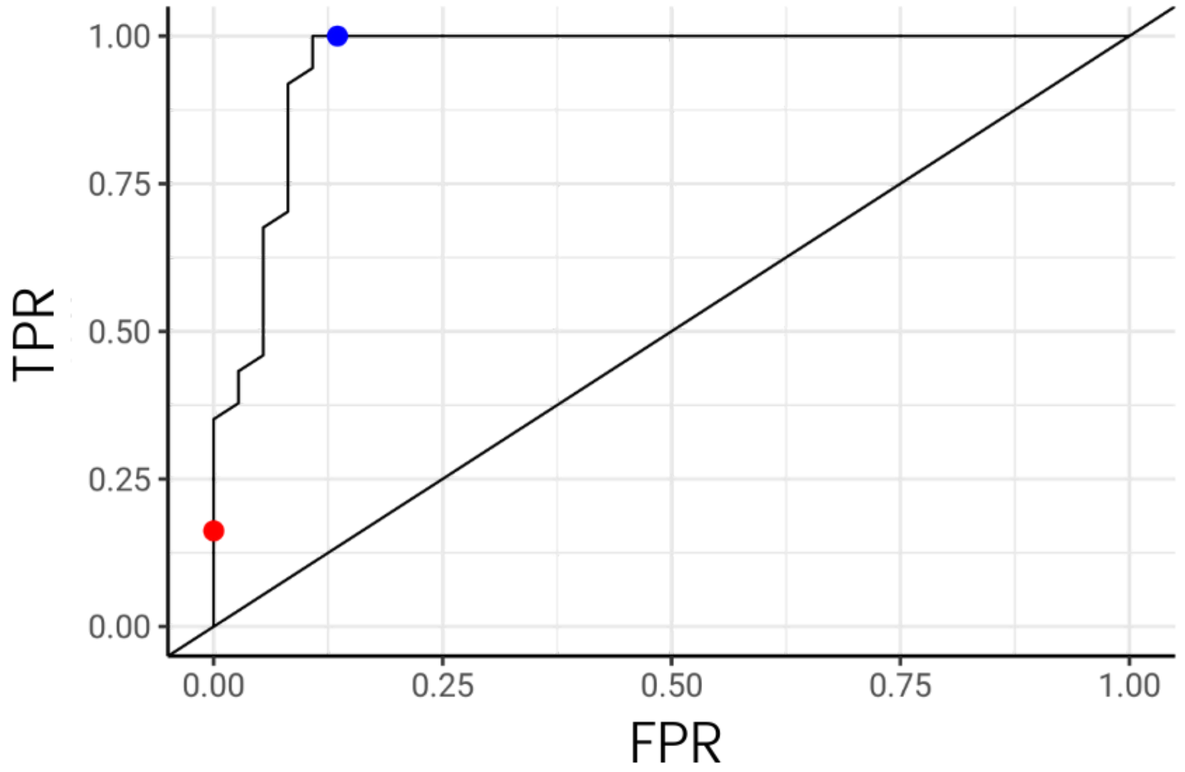
ML definitions

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}},$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN} + \mathrm{FP}},$$

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}.$$

ML definitions



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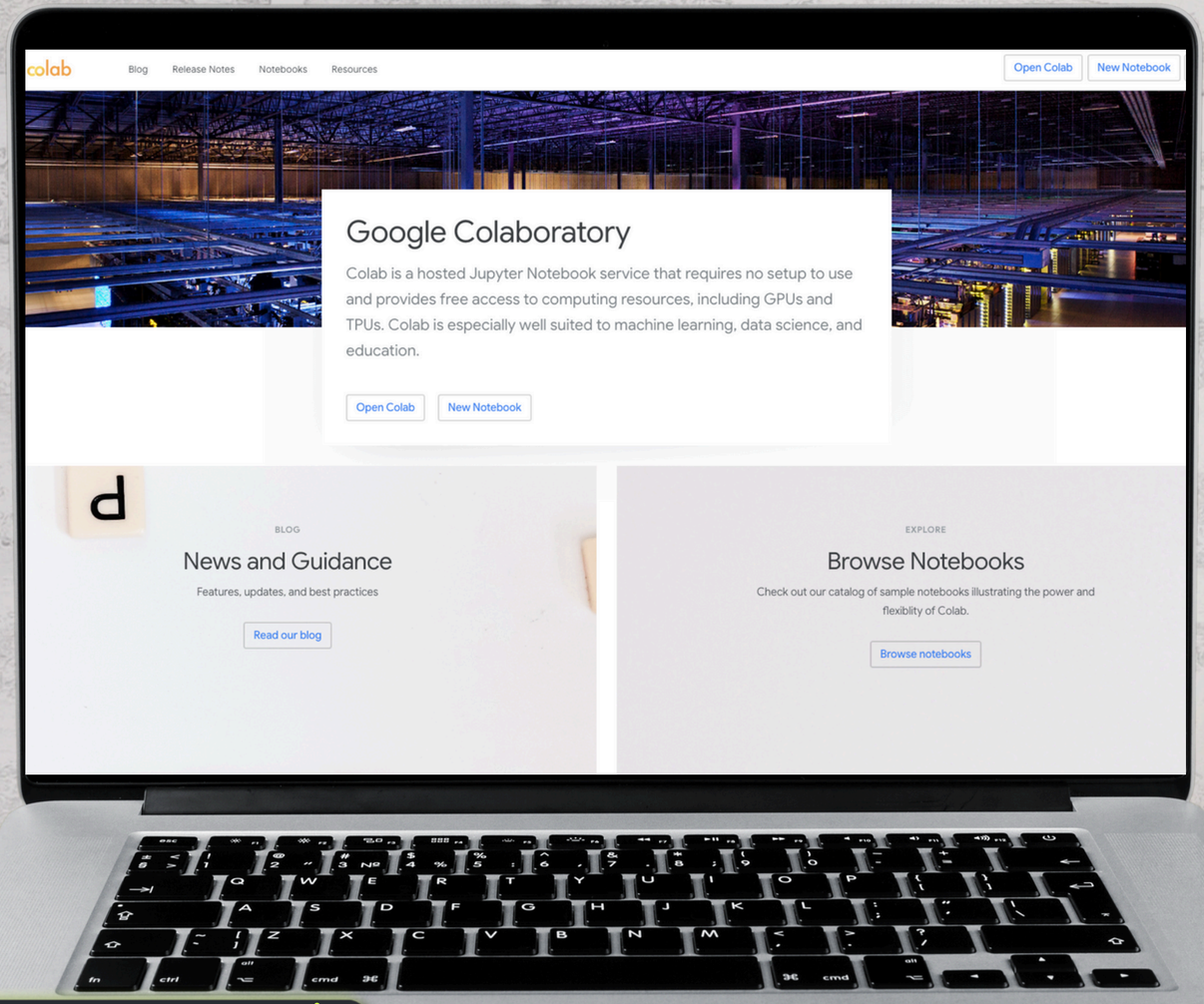

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stats

ML definitions

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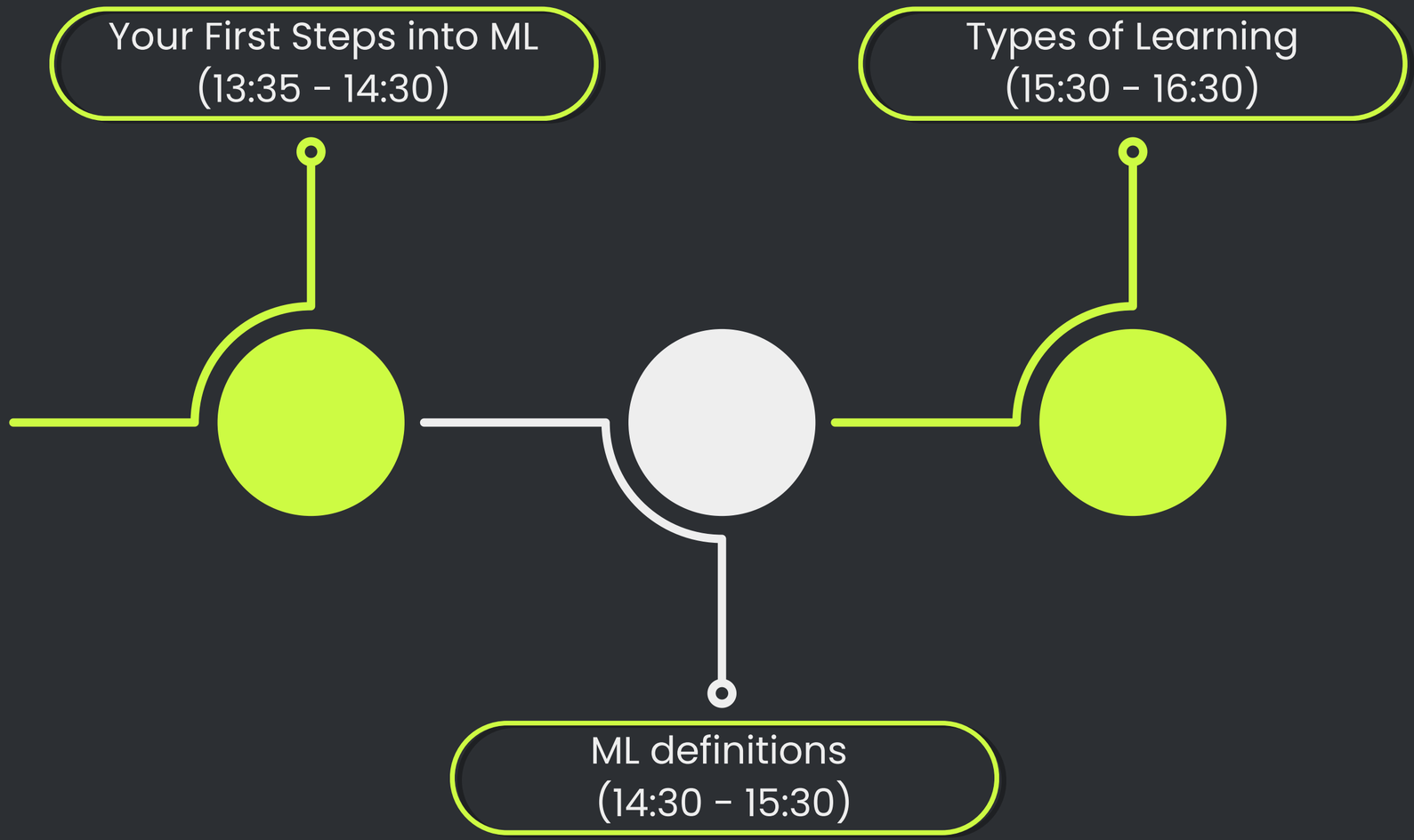

Types of Learning

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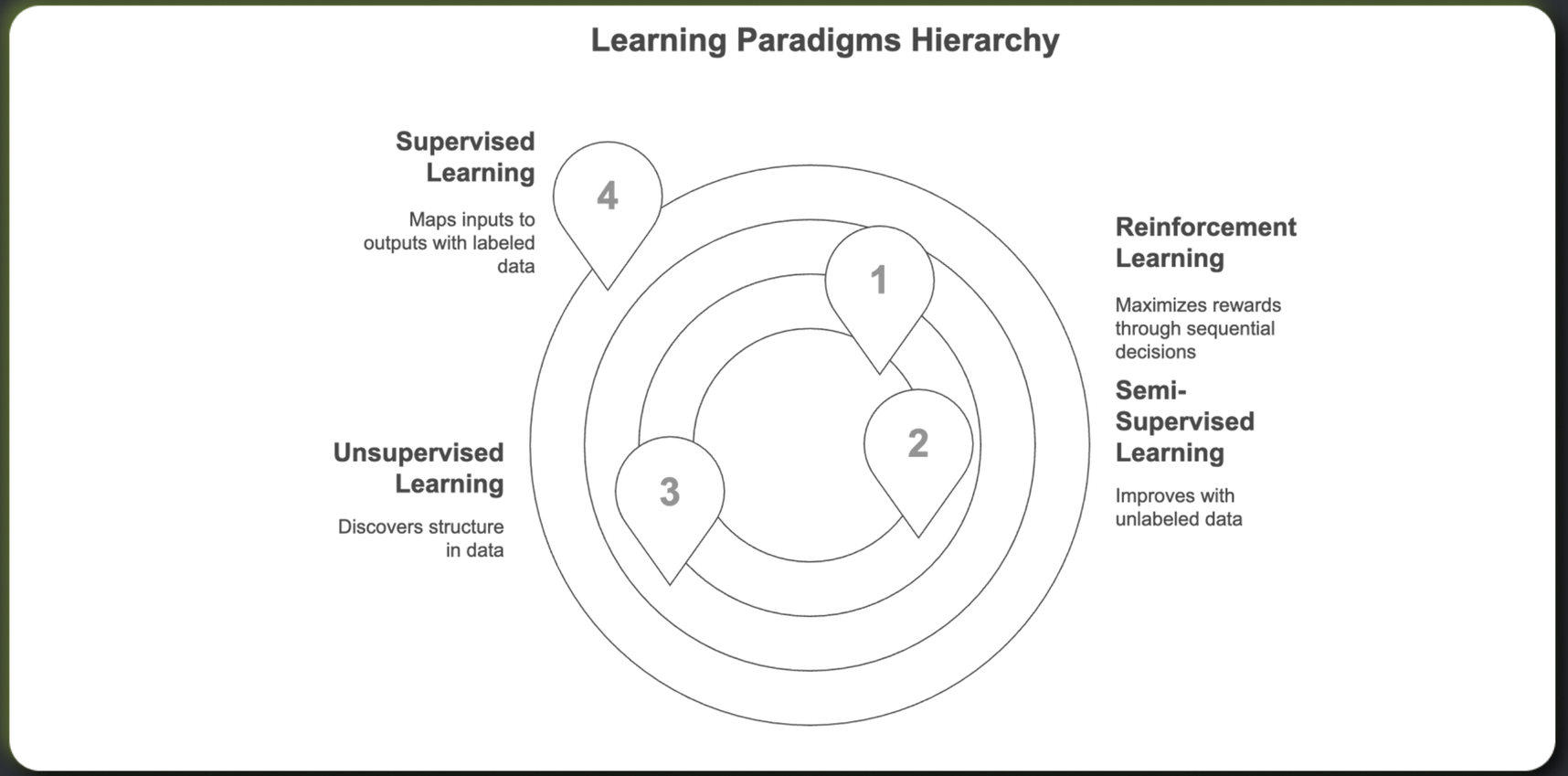

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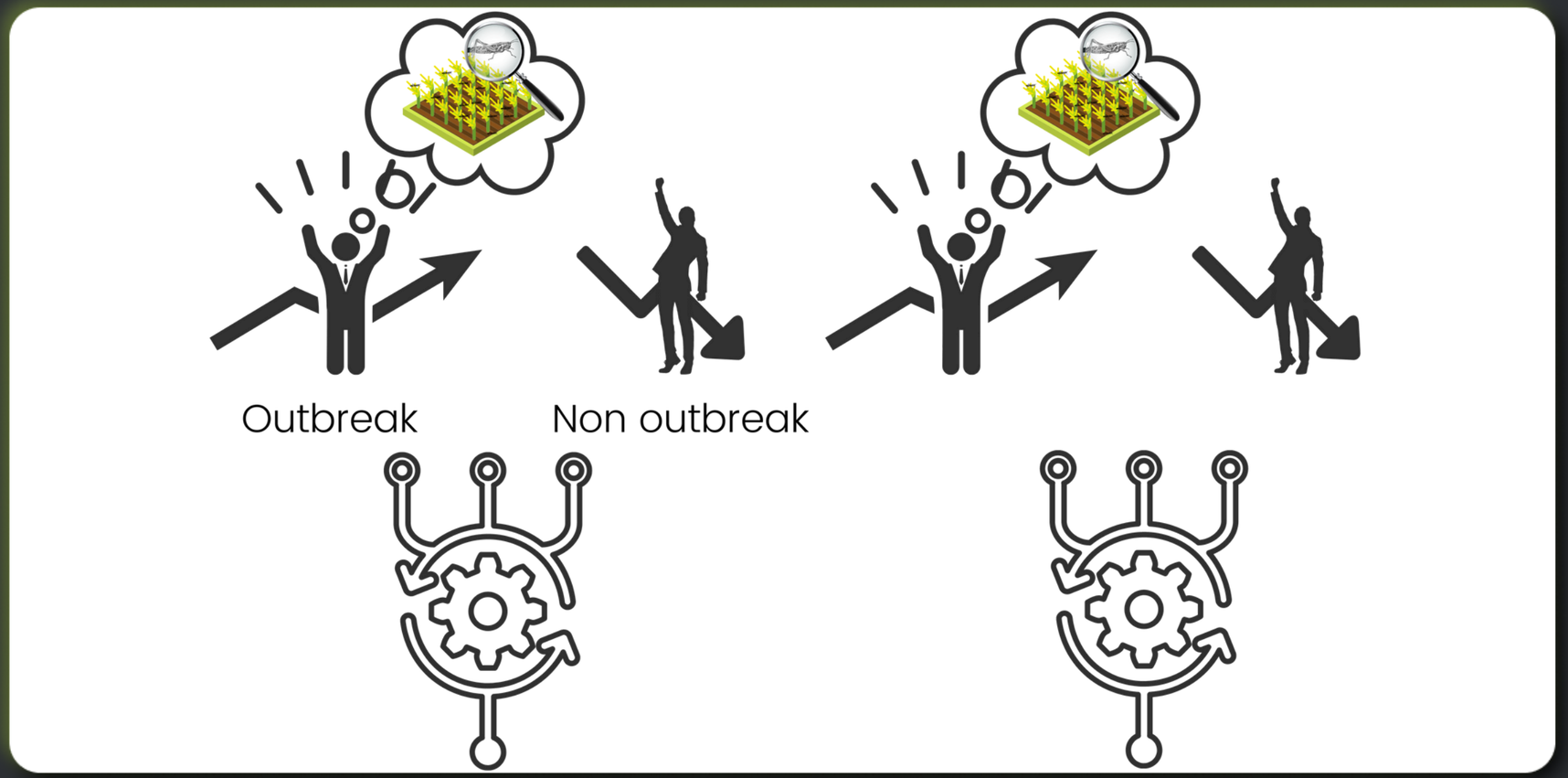

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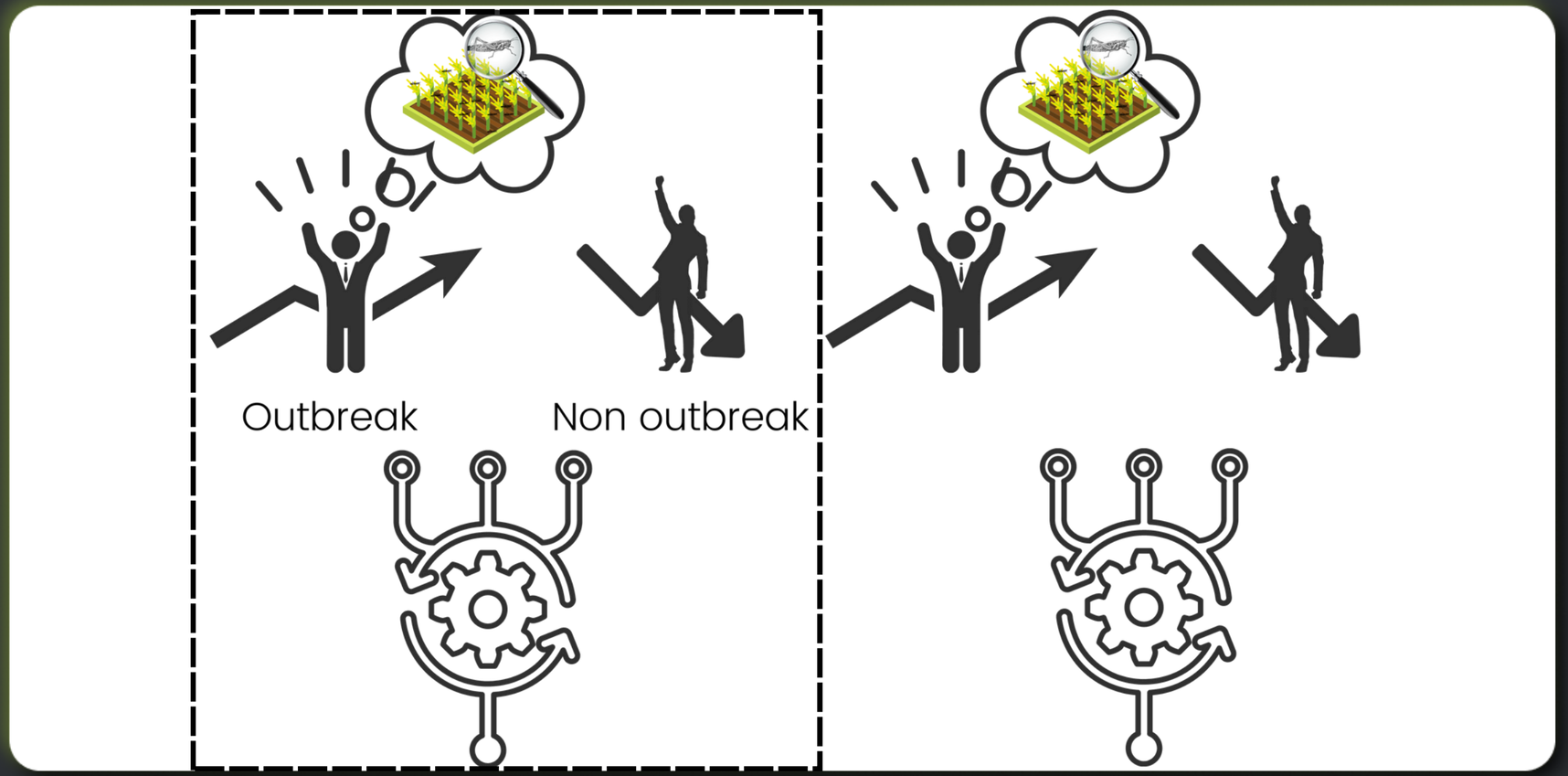

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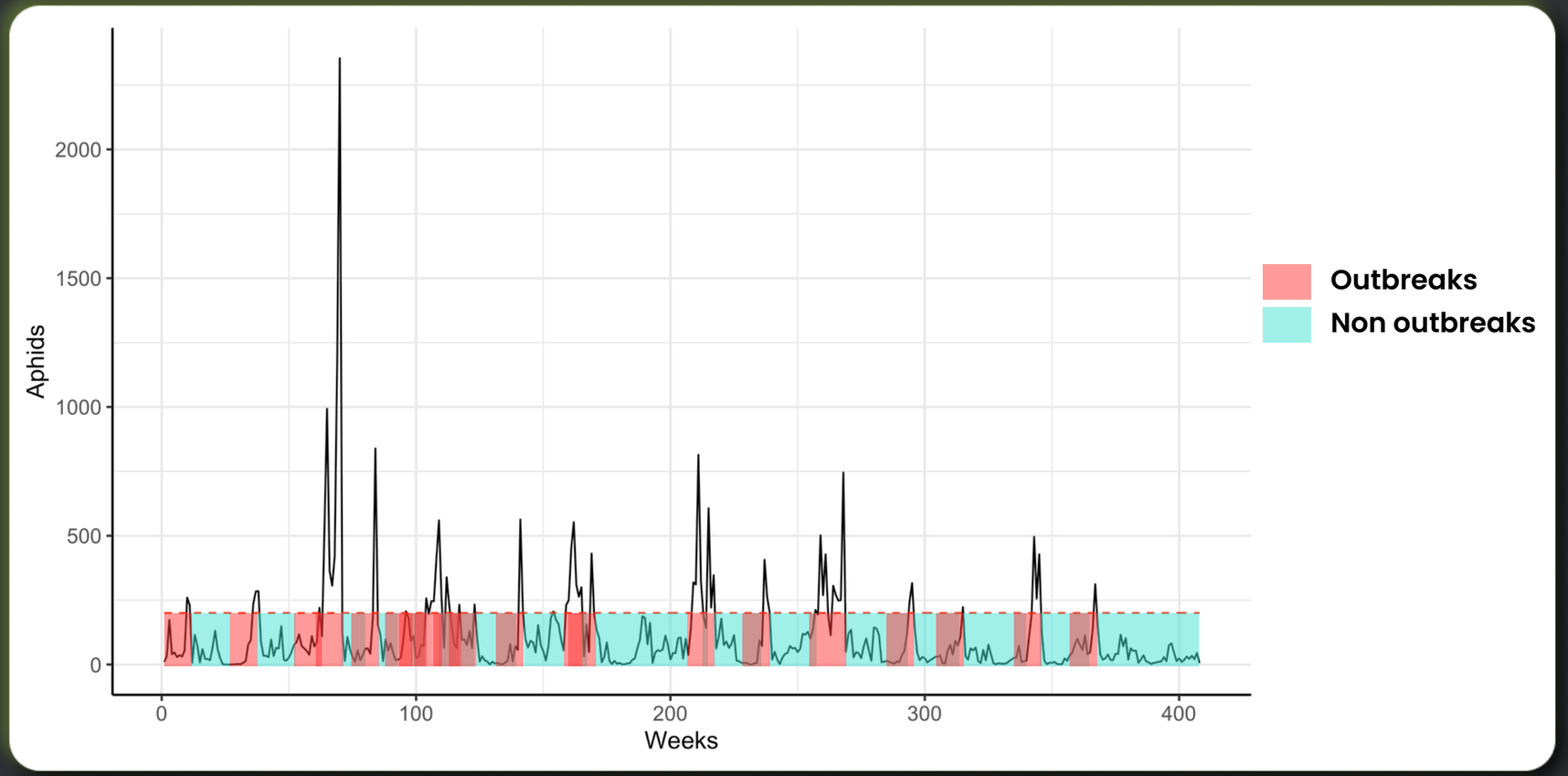

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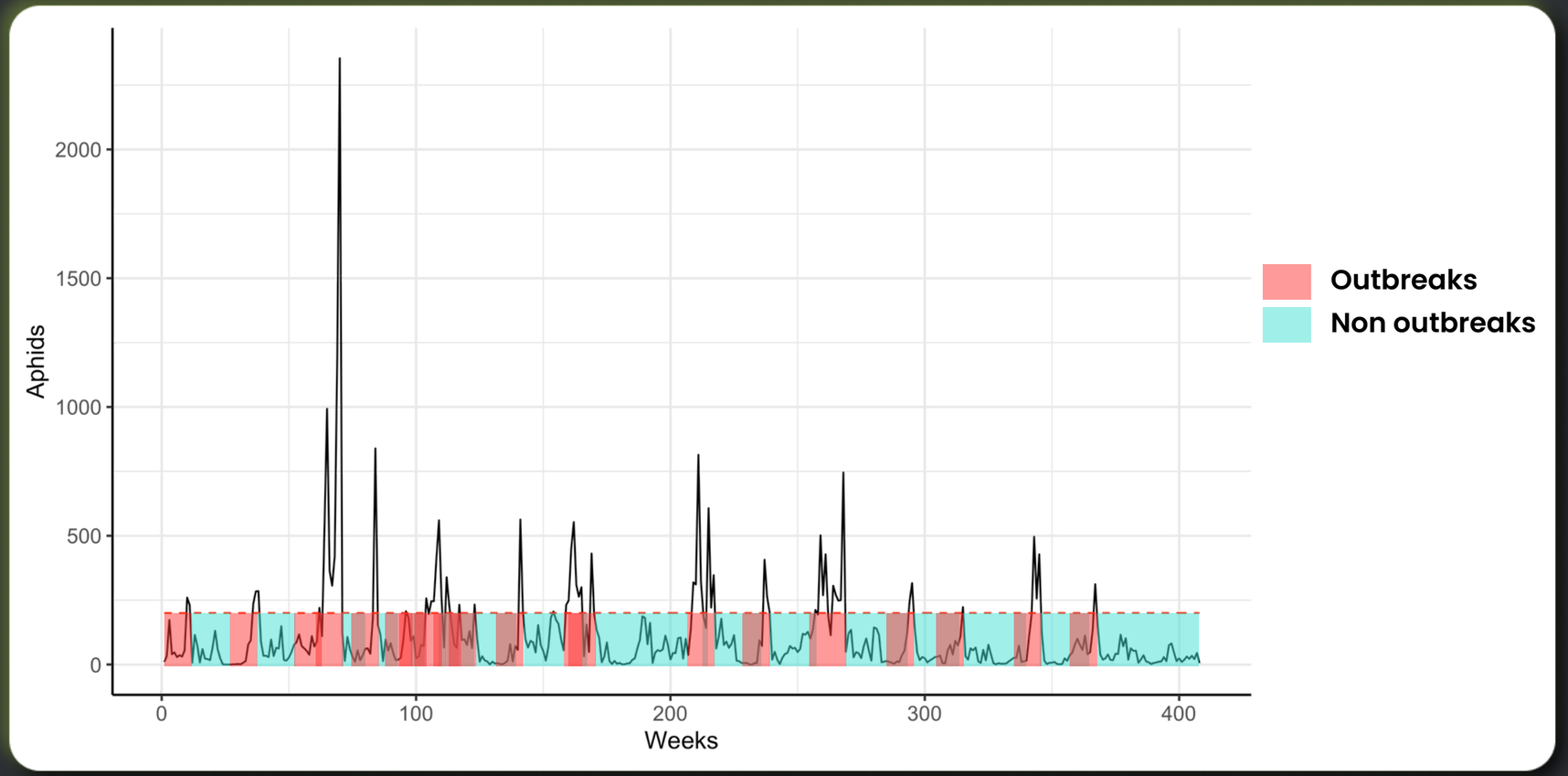

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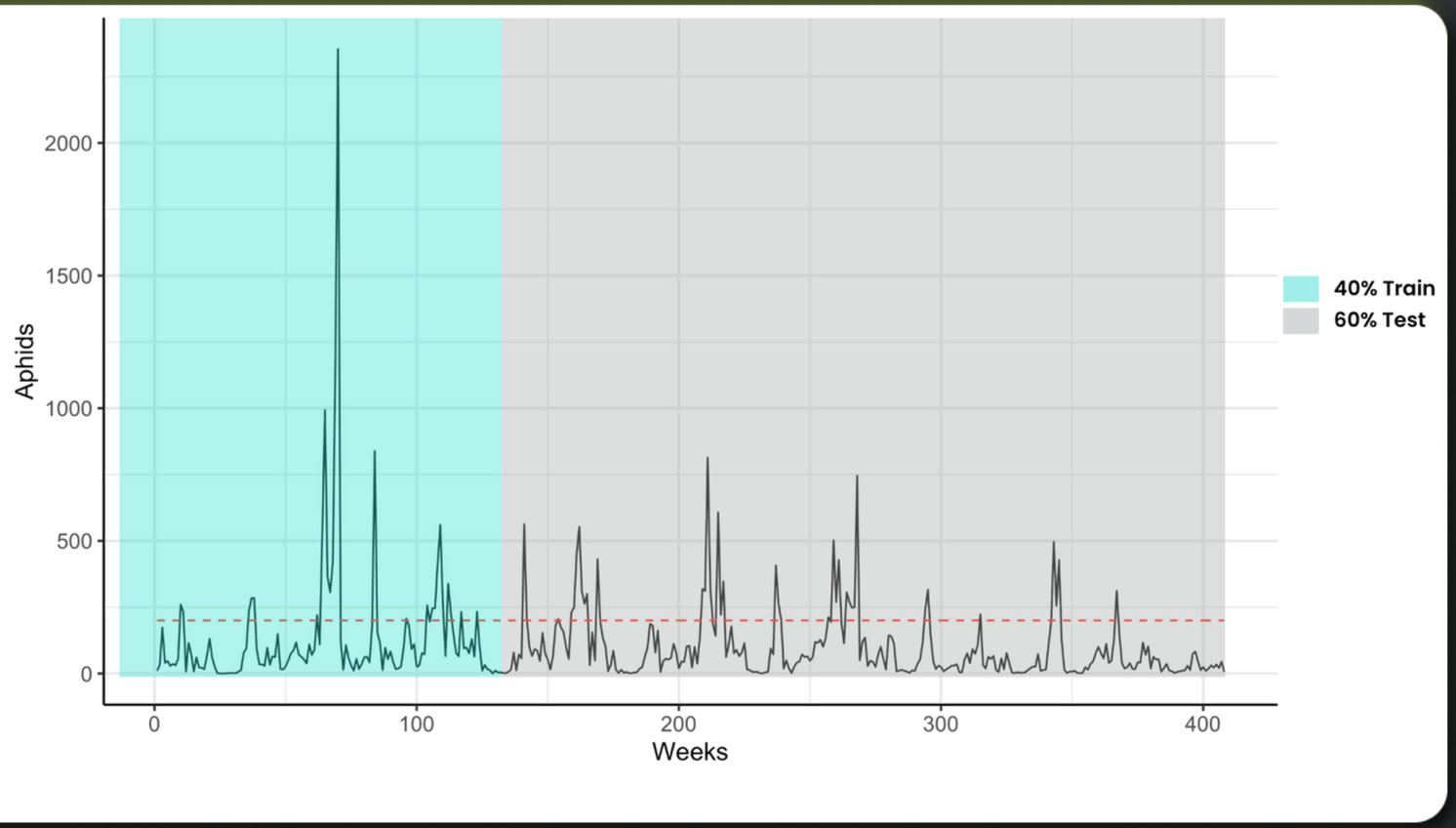

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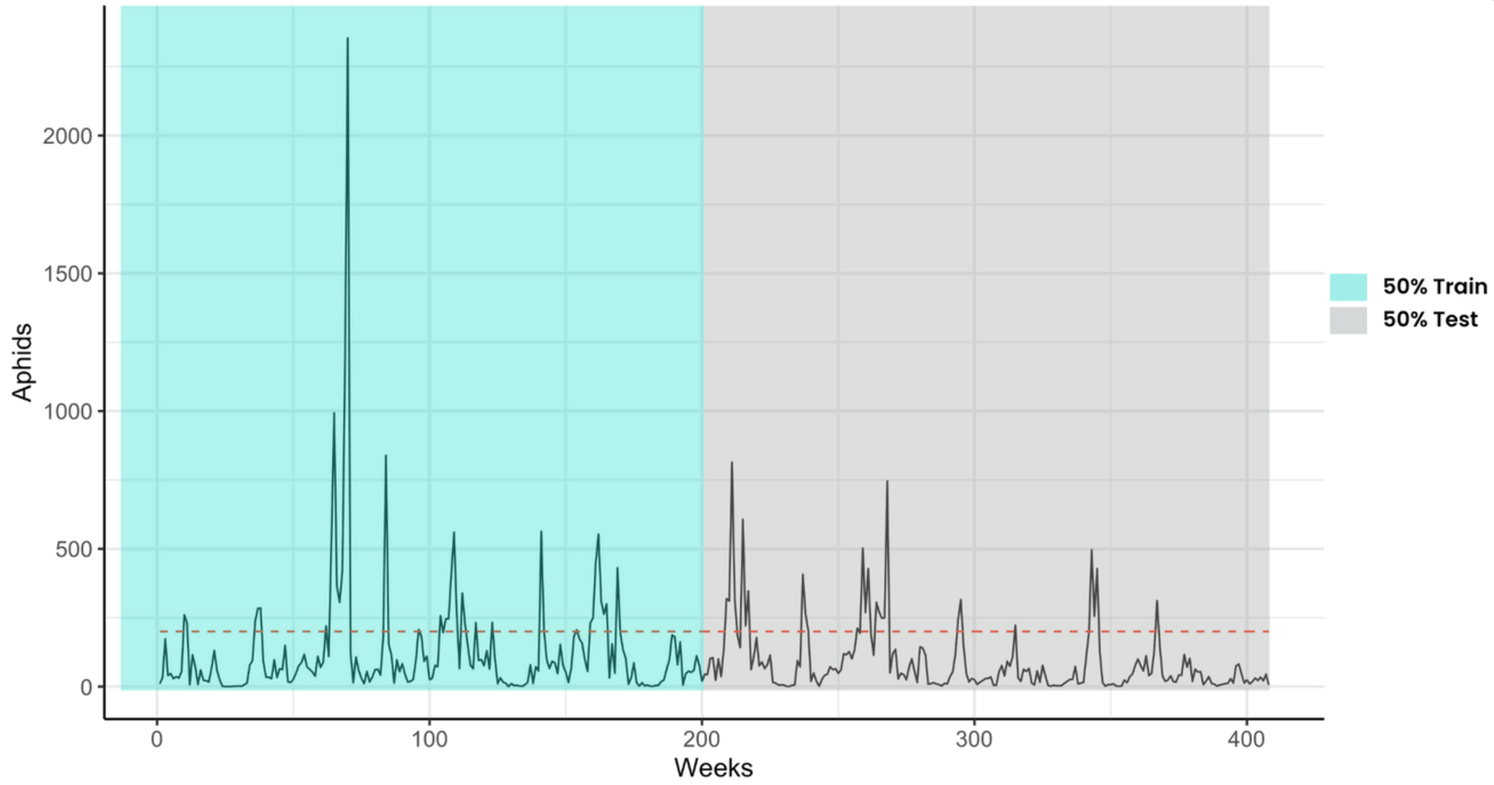

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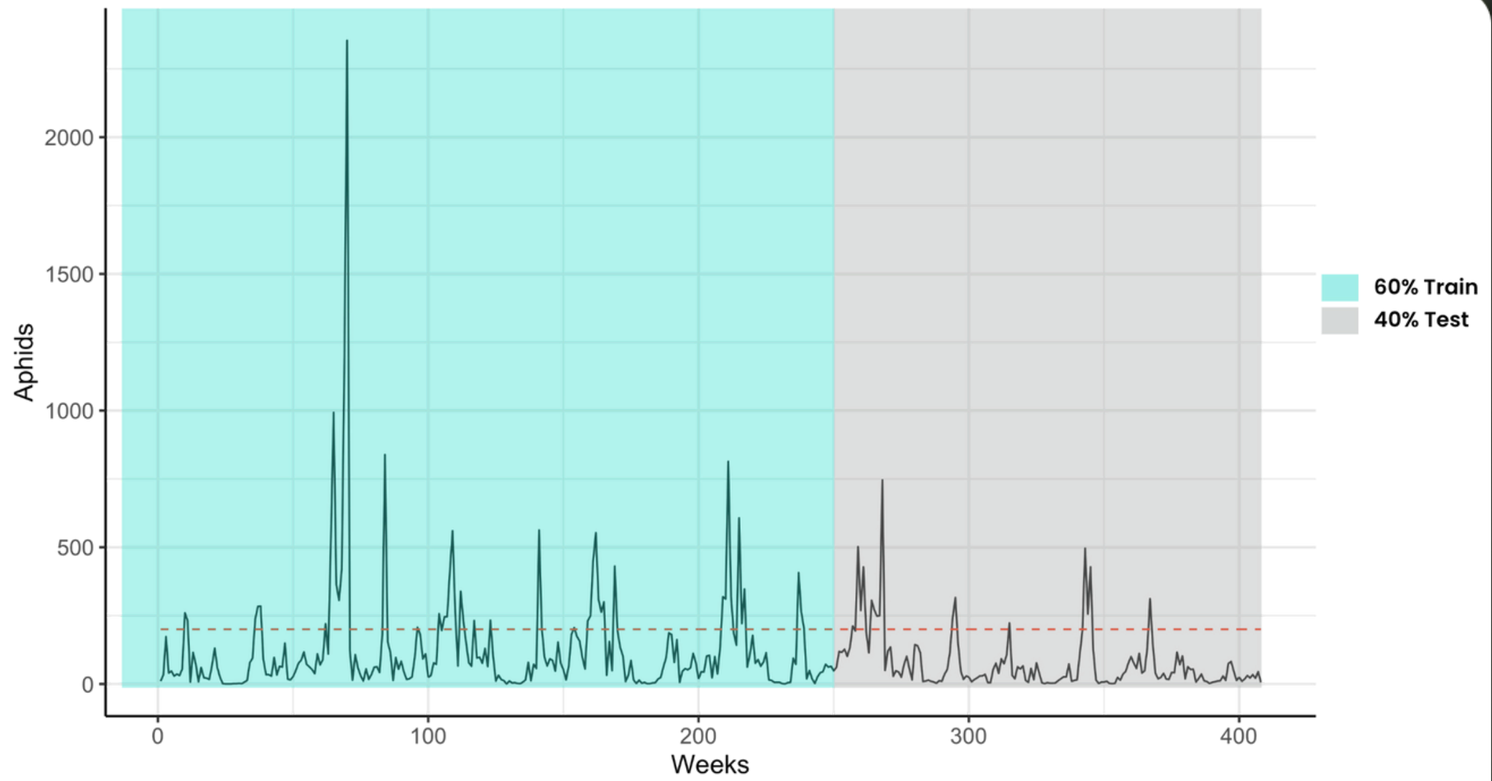

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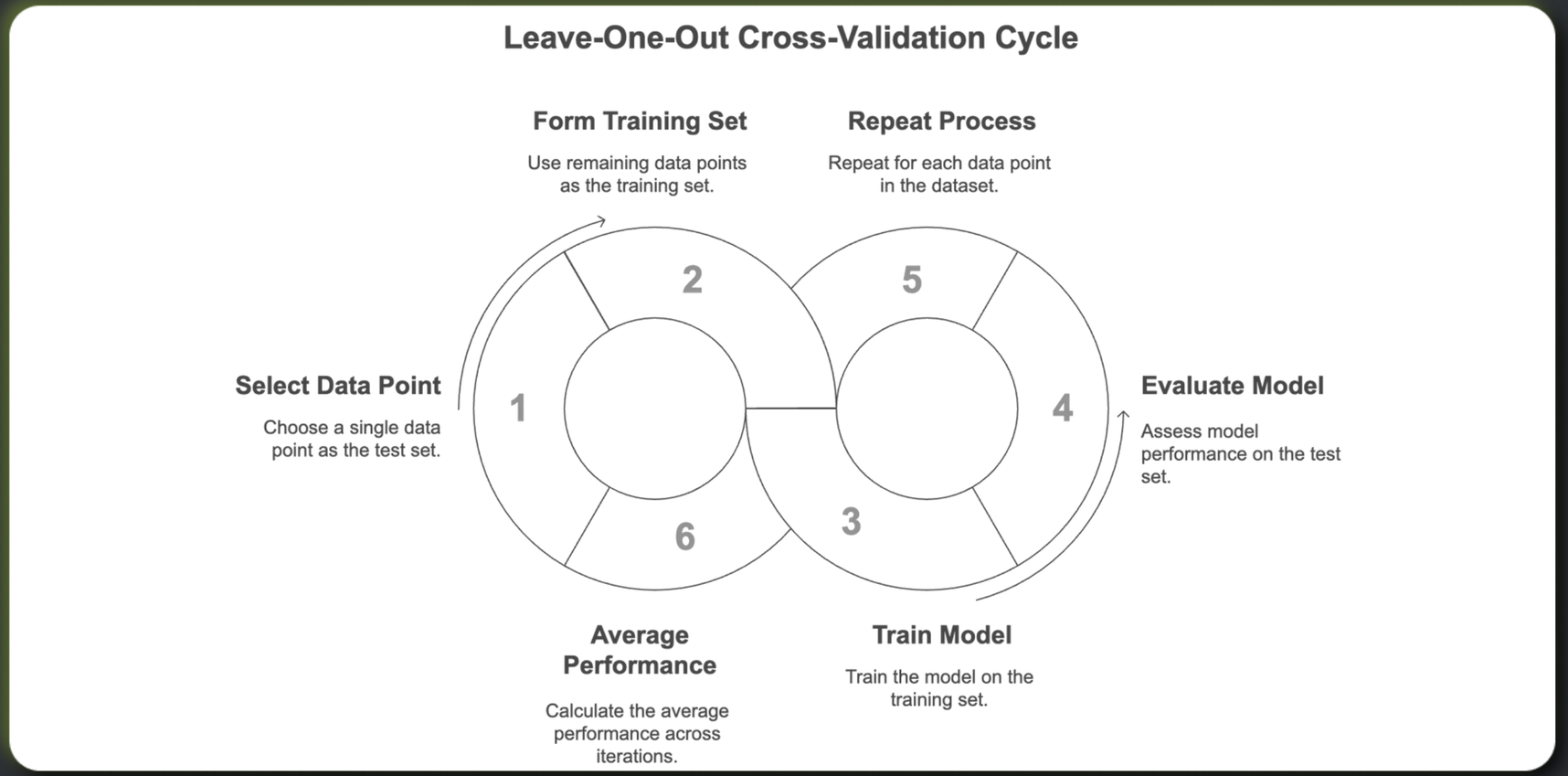

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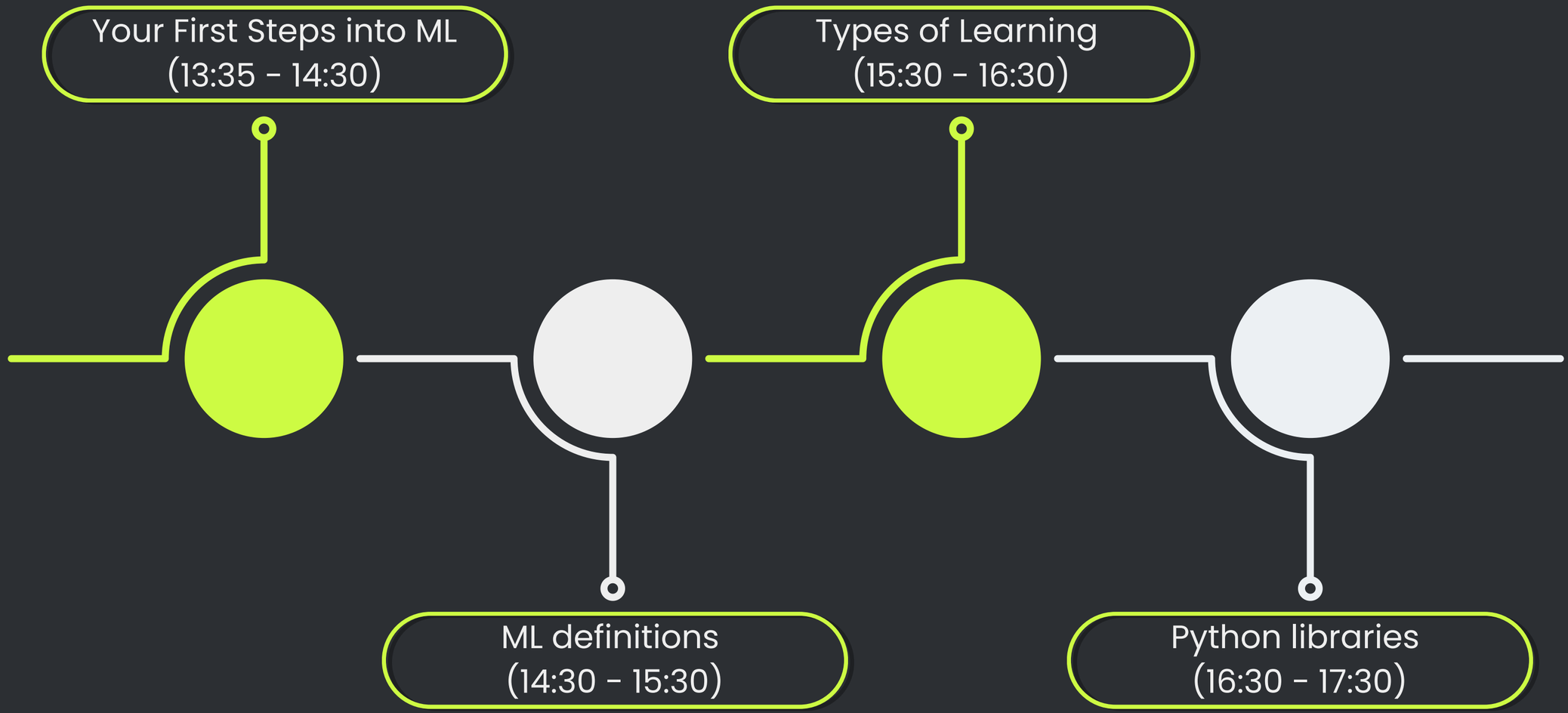

Python libraries

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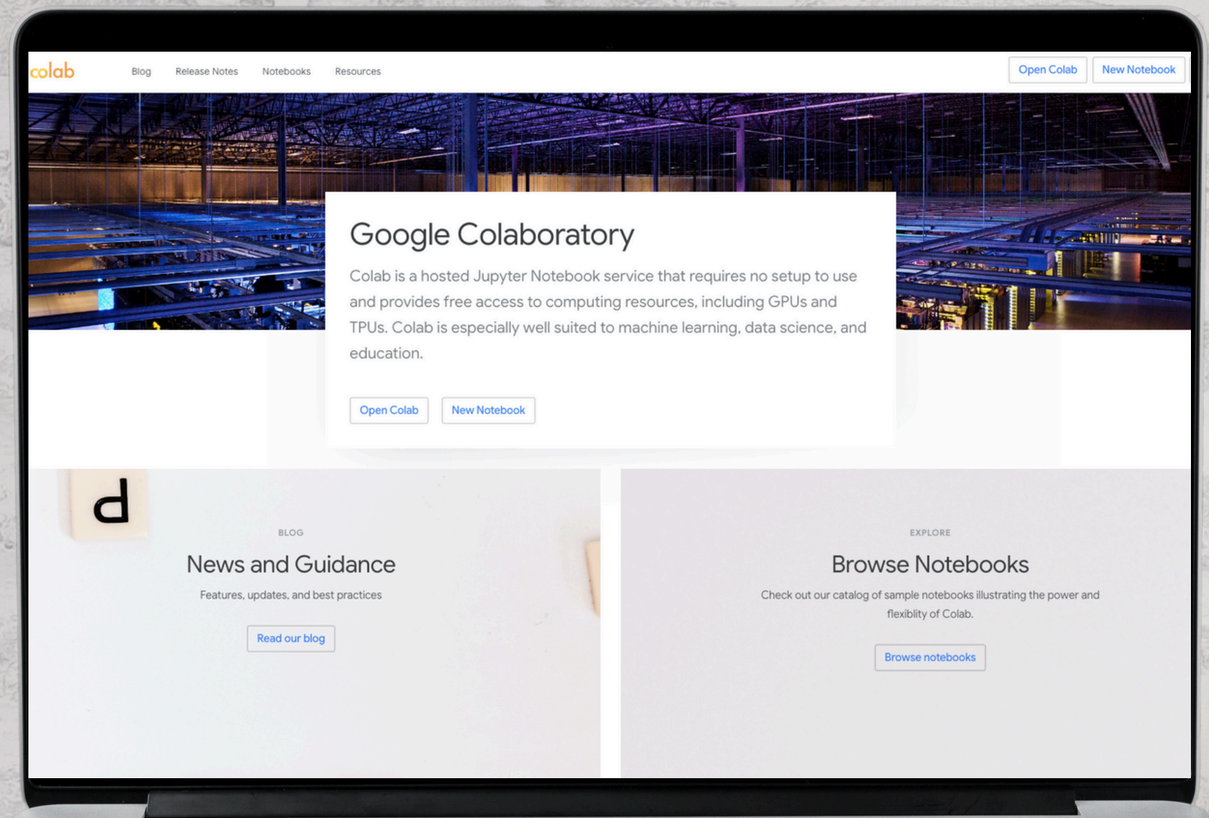

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