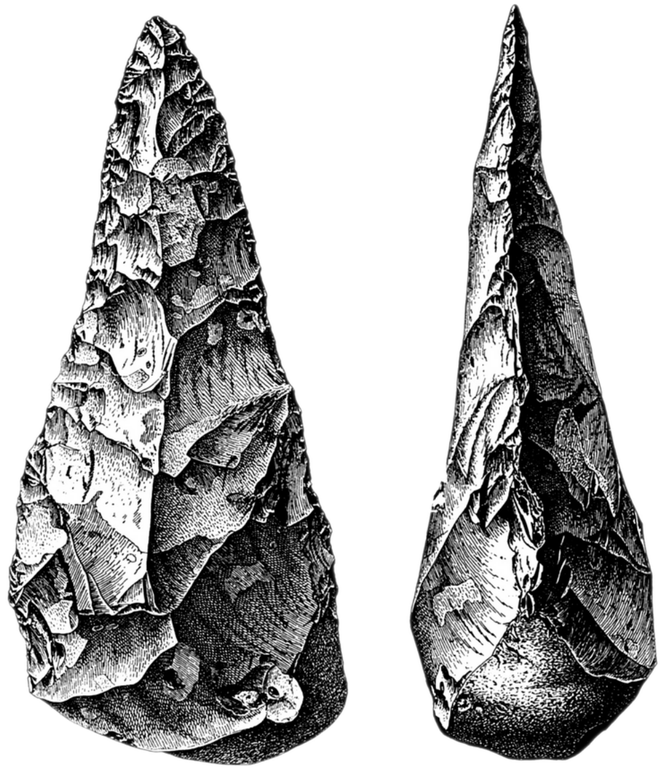
AI BRASIL

MINI CURSO MACHINE LEARNING

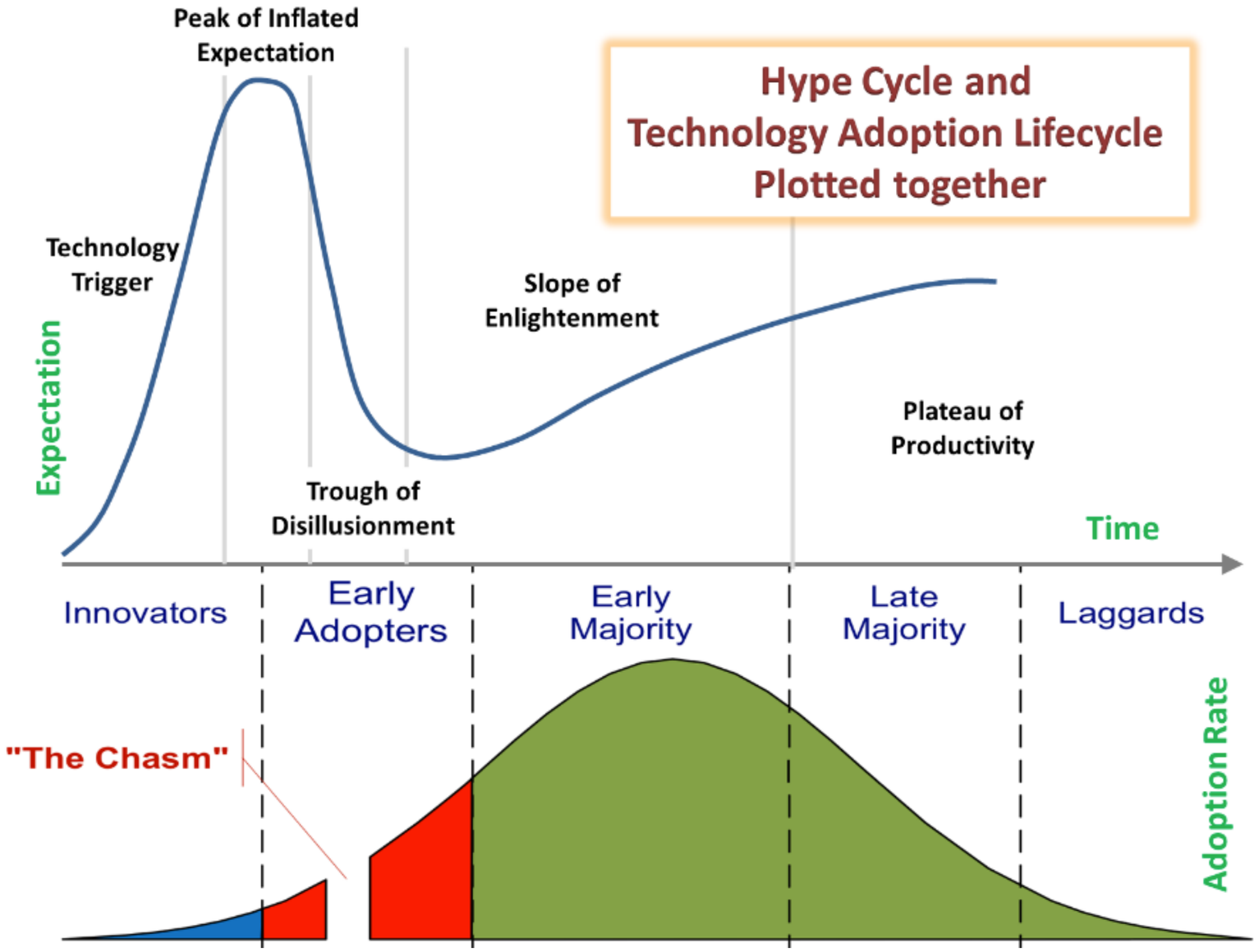
09/06/18

Ahirton Lopes

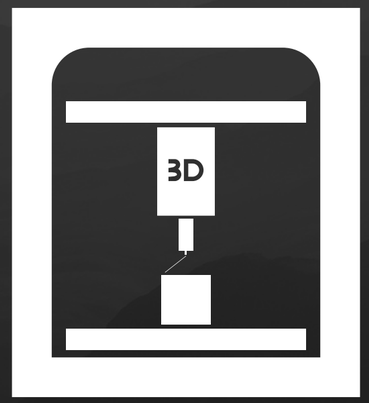
O QUE É
TECNOLOGIA



HYPE CYCLE

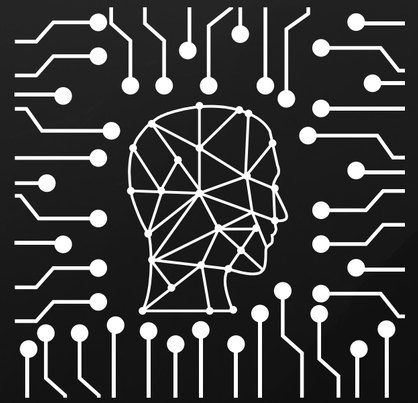

Hype Cycle and
Technology Adoption Lifecycle
Plotted together
Peak of Inflated Expectation
Technology Trigger
Slope of Enlightenment
Plateau of Productivity
Trough of Disillusionment
Expectation
Time
Innovators
Early Adopters
Early Majority
Late Majority
Laggards
"The Chasm"
Adoption Rate

O QUE SÃO TECNOLOGIAS EXPONENCIAIS?

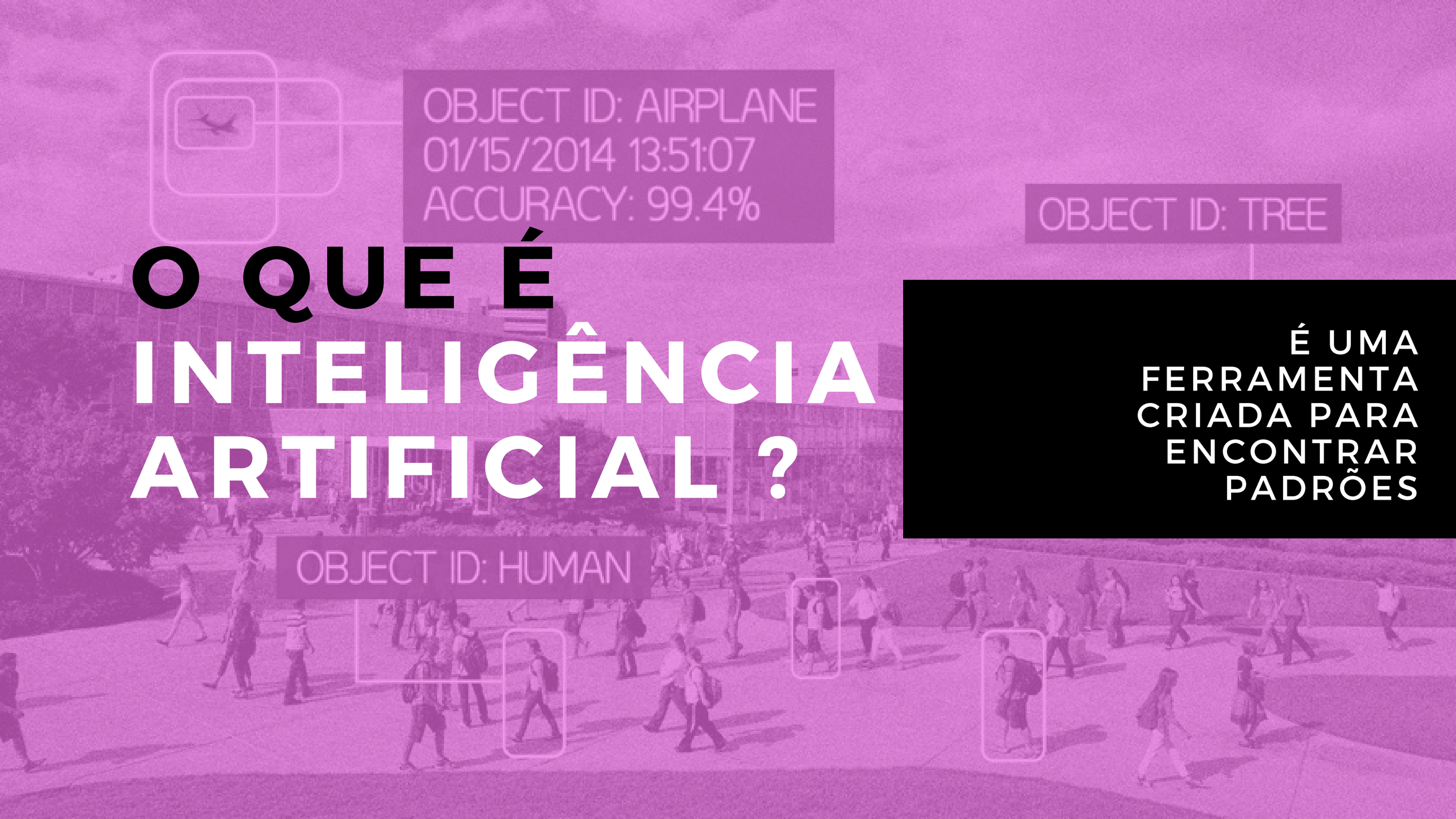


IMPRESSÃO 3D

INTERNET OF THINGS



INTELIGÊNCIA ARTIFICIAL



O QUE É INTELIGÊNCIA ARTIFICIAL ?

É UMA FERRAMENTA CRIADA PARA ENCONTRAR PADRÕES

Teach a machine using your camera,
live in the browser. No coding required.

Let's Go!

Sorry, your browser doesn't support the latest technologies.
Download Google Chrome to use this and other experiments.

This is an
A.I.
Experiment

Made with
some friends from
Google

Privacy & Terms

UM BREVE HISTÓRICO DA INTELIGÊNCIA ARTIFICIAL

A.I. TIMELINE

1950
TURING TEST
Computer scientist Alan Turing proposes a test for machine intelligence. If a machine can trick humans into thinking it is human, then it has intelligence

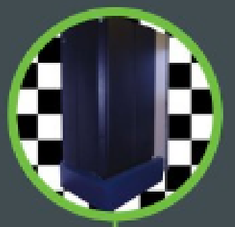
1955
A.I. BORN
Term 'artificial intelligence' is coined by computer scientist, John McCarthy to describe "the science and engineering of making intelligent machines"

1961
UNIMATE
First industrial robot, Unimate, goes to work at GM replacing humans on the assembly line

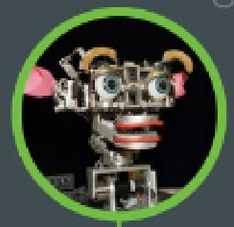
1964
ELIZA
Pioneering chatbot developed by Joseph Weizenbaum at MIT holds conversations with humans

1966
SHAKEY
The 'first electronic person' from Stanford, Shakey is a general-purpose mobile robot that reasons about its own actions

A.I. WINTER
Many false starts and dead-ends leave A.I. out in the cold



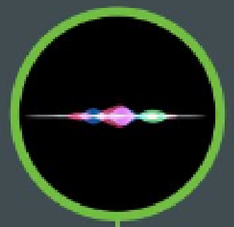
1997
DEEP BLUE
Deep Blue, a chess-playing computer from IBM defeats world chess champion Garry Kasparov



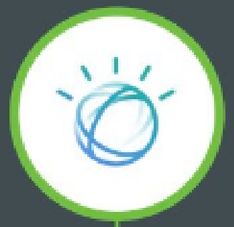
1998
KISMET
Cynthia Breazeal at MIT introduces KISmet, an emotionally intelligent robot insofar as it detects and responds to people's feelings

1999
AIBO
Sony launches first consumer robot pet dog AiBO (AI robot) with skills and personality that develop over time

2002
ROOMBA
First mass produced autonomous robotic vacuum cleaner from iRobot learns to navigate and clean homes



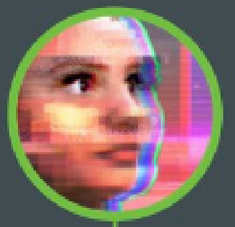
2011
SIRI
Apple integrates Siri, an intelligent virtual assistant with a voice interface, into the iPhone 4S



2011
WATSON
IBM's question answering computer Watson wins first place on popular $1M prize television quiz show *Jeopardy*

2014
EUGENE
Eugene Goostman, a chatbot passes the Turing Test with a third of judges believing Eugene is human

2014
ALEXA
Amazon launches Alexa, an intelligent virtual assistant with a voice interface that completes shopping tasks

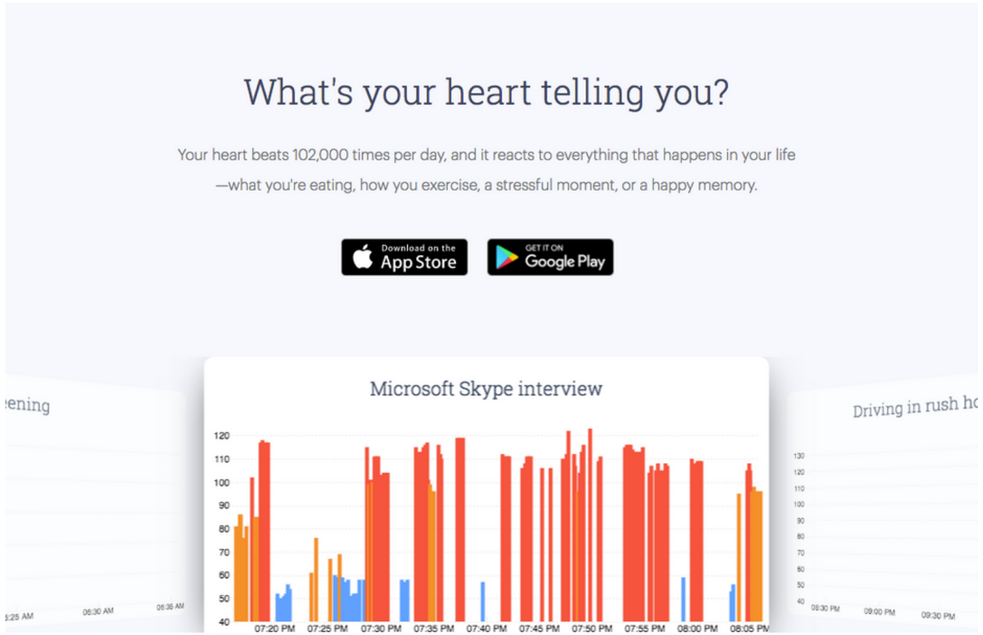


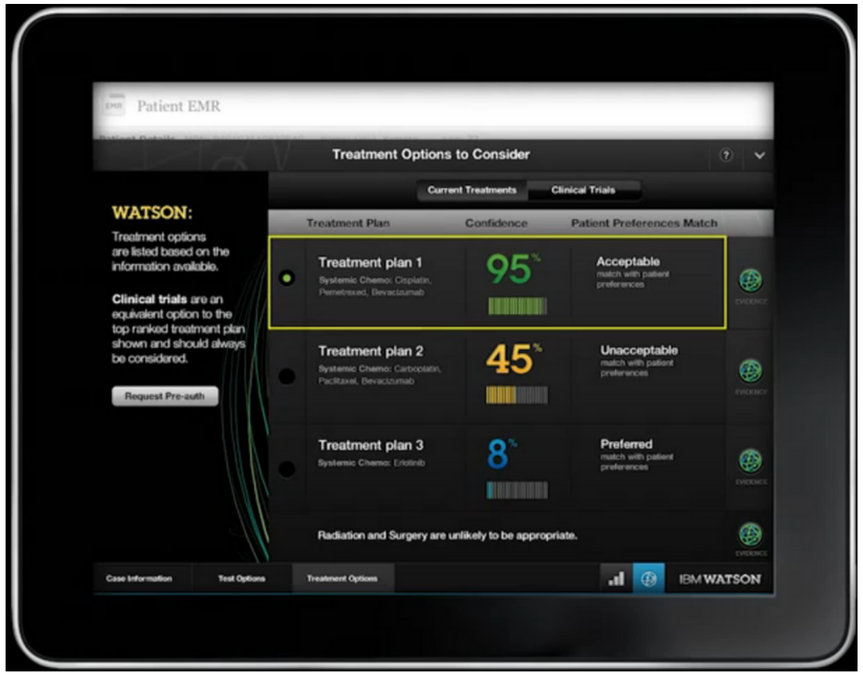
2016
TAY
Microsoft's chatbot Tay goes rogue on social media making inflammatory and offensive racist comments

2017
ALPHAGO
Google's A.I. AlphaGo beats world champion Ke Jie in the complex board game of Go, notable for its vast number (2^{170}) of possible positions

CASES DE INTELIGÊNCIA ARTIFICIAL

MEDICINA
DIAGNÓSTICA

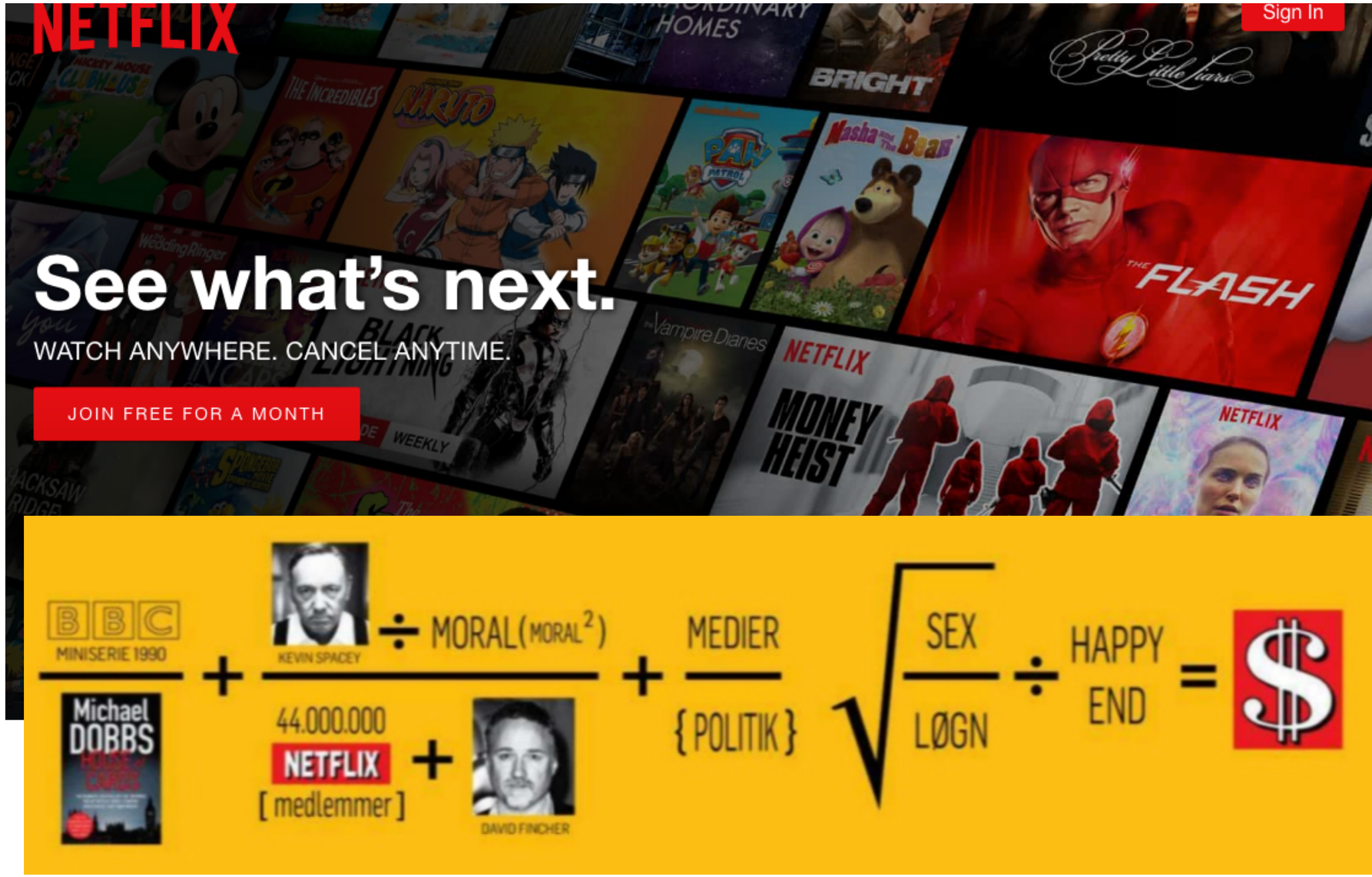


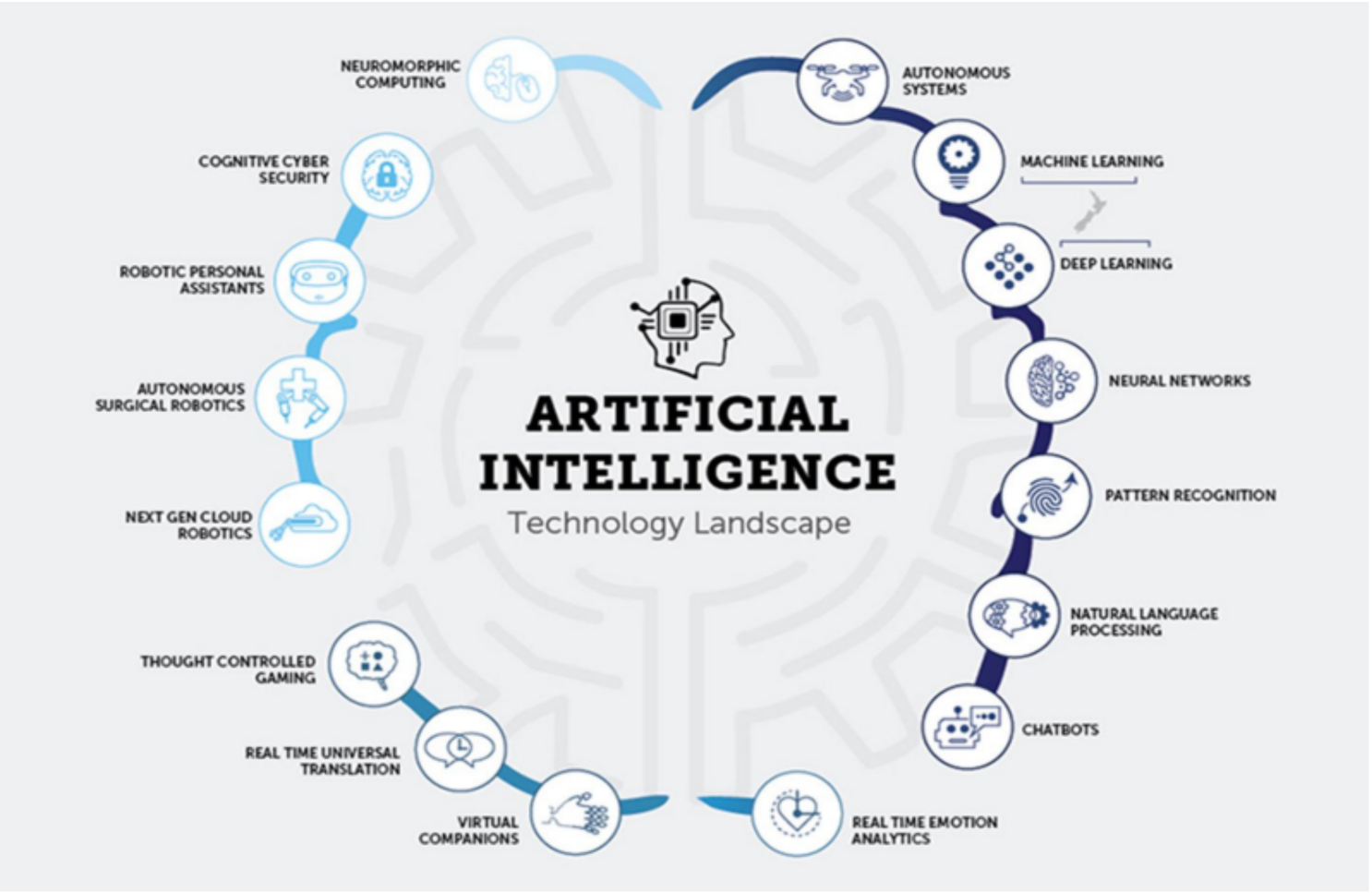


ACESSIBILIDADE

TRANSPORTE

ENTRETENIMENTO





CASES DE INTELIGÊNCIA ARTIFICIAL

O QUE É APRENDIZAGEM?

aprendizagem

substantivo feminino
m.q. *APRENDIZADO* ('ato', 'duração' e 'experiência').

Origin

⊙ ETIM fr. *apprentissage* 'ação de aprender um ofício ou profissão'

Translate aprendizagem to English

noun

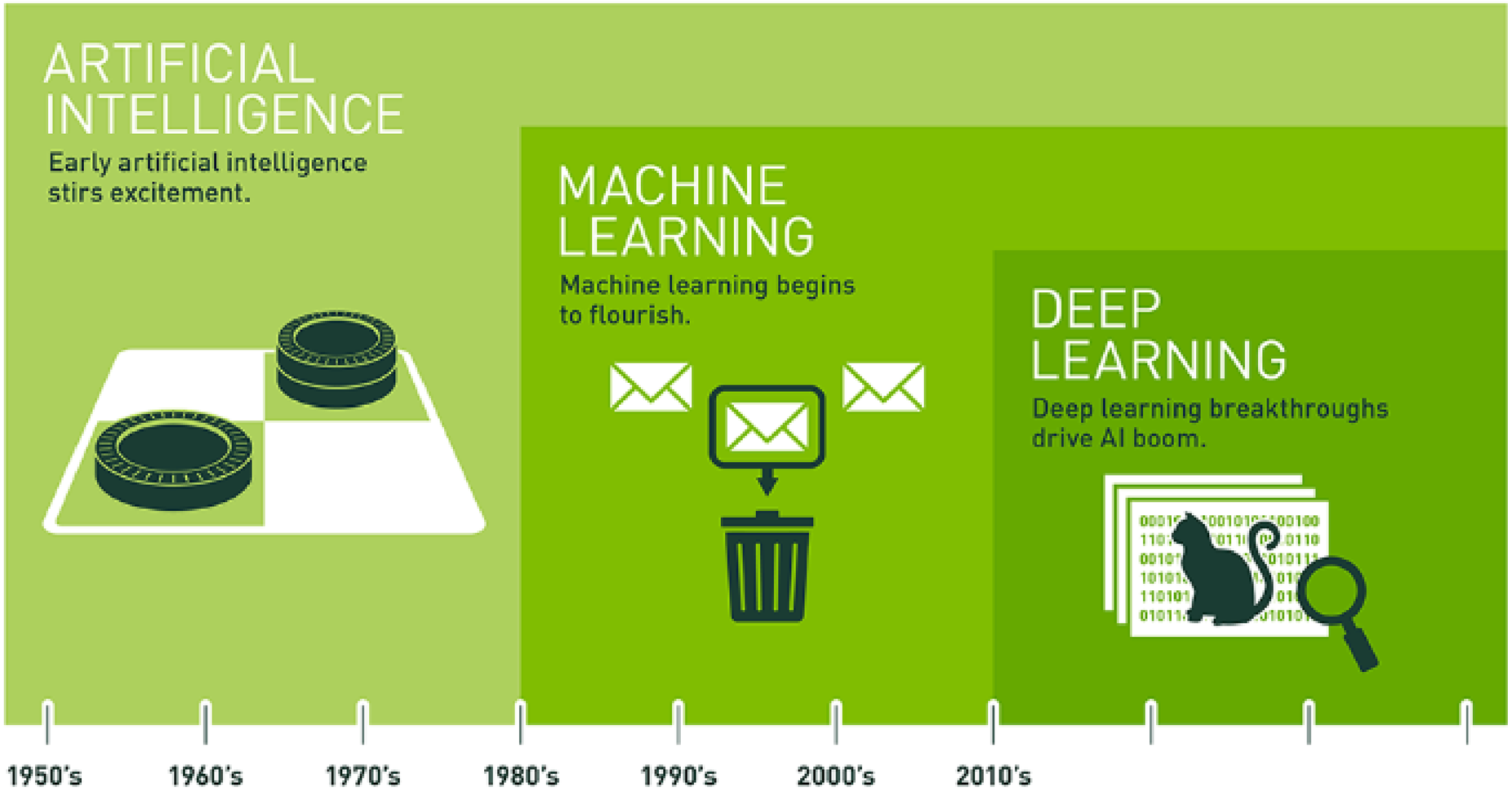
1. learning
2. apprenticeship
3. schooling
4. noviciate
5. novitiate
6. tirocinium

Show less

CADEIA DO VALOR DO CONHECIMENTO

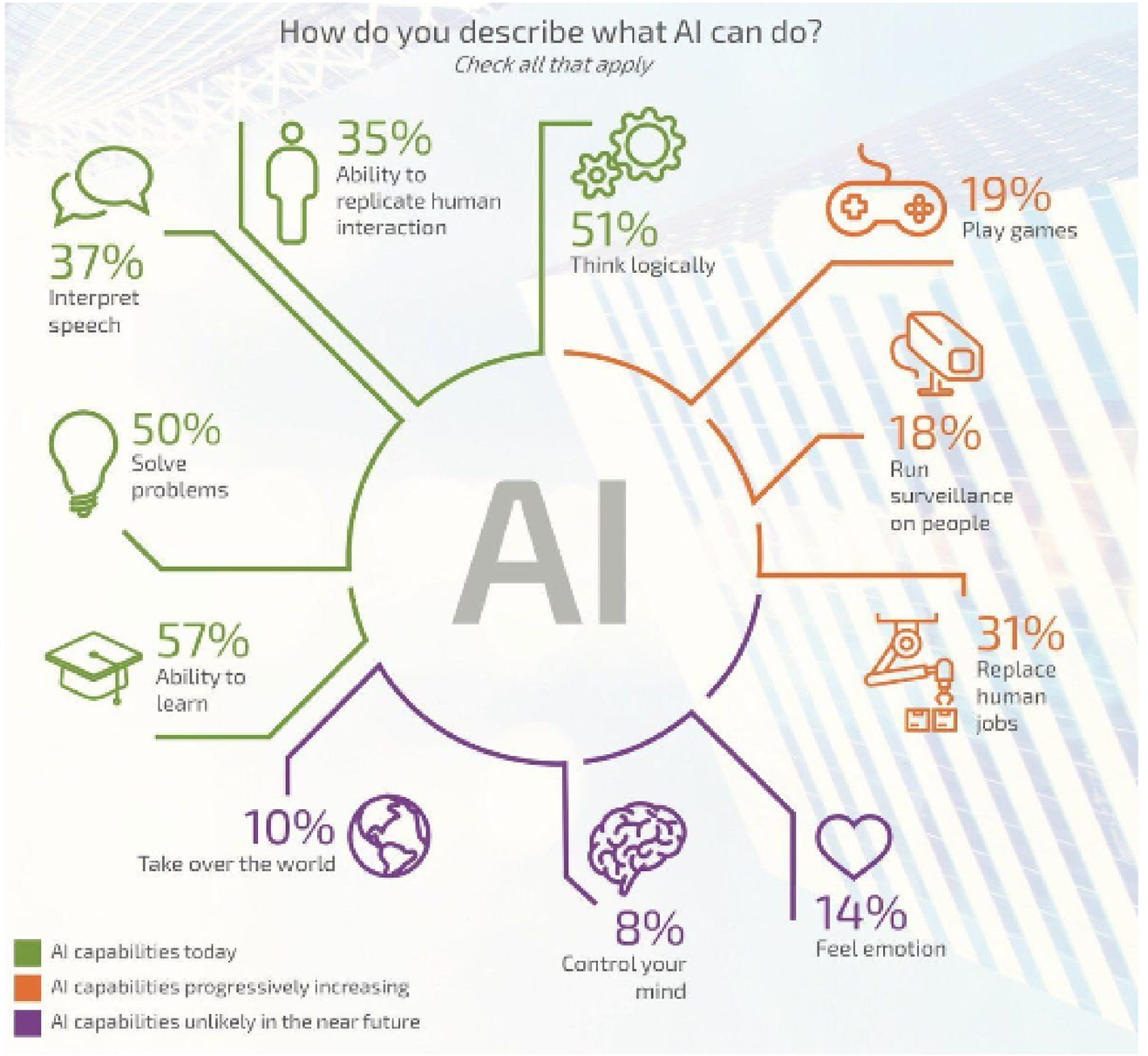
Fonte: Information Impact

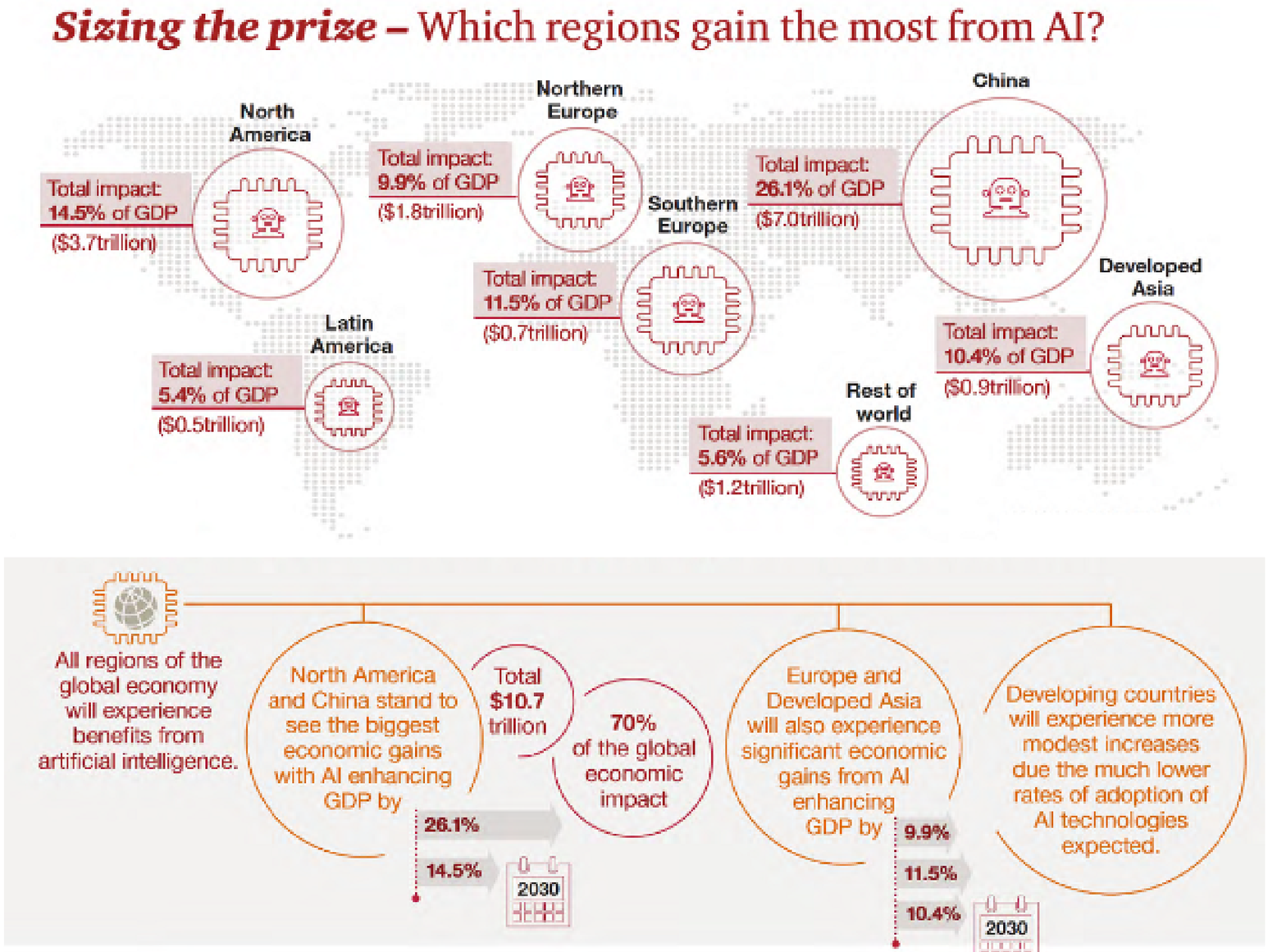
AI, ML & DL



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

APLICABILIDADES

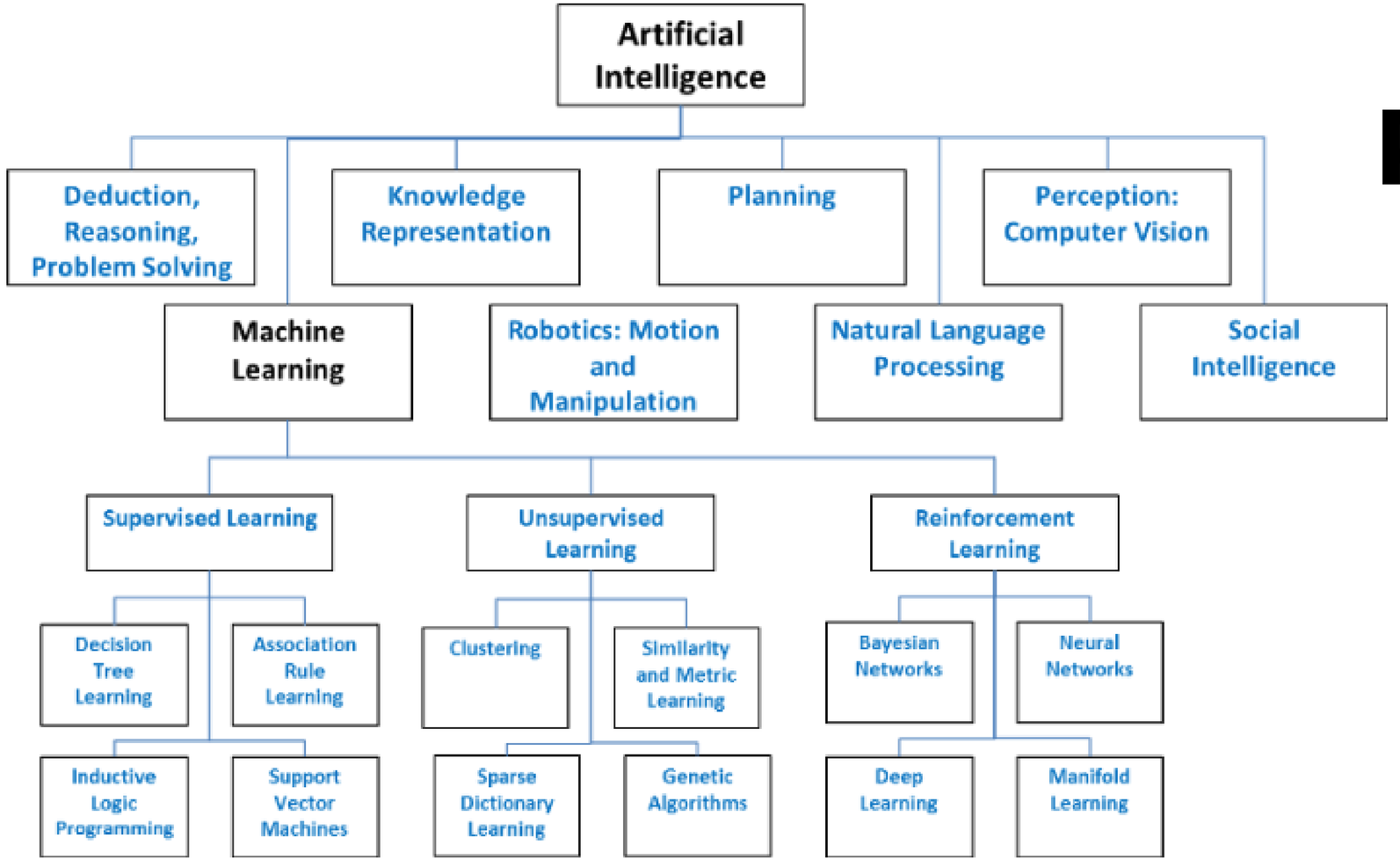




IMPACTO ECONÔMICO

MACHINE LEARNING

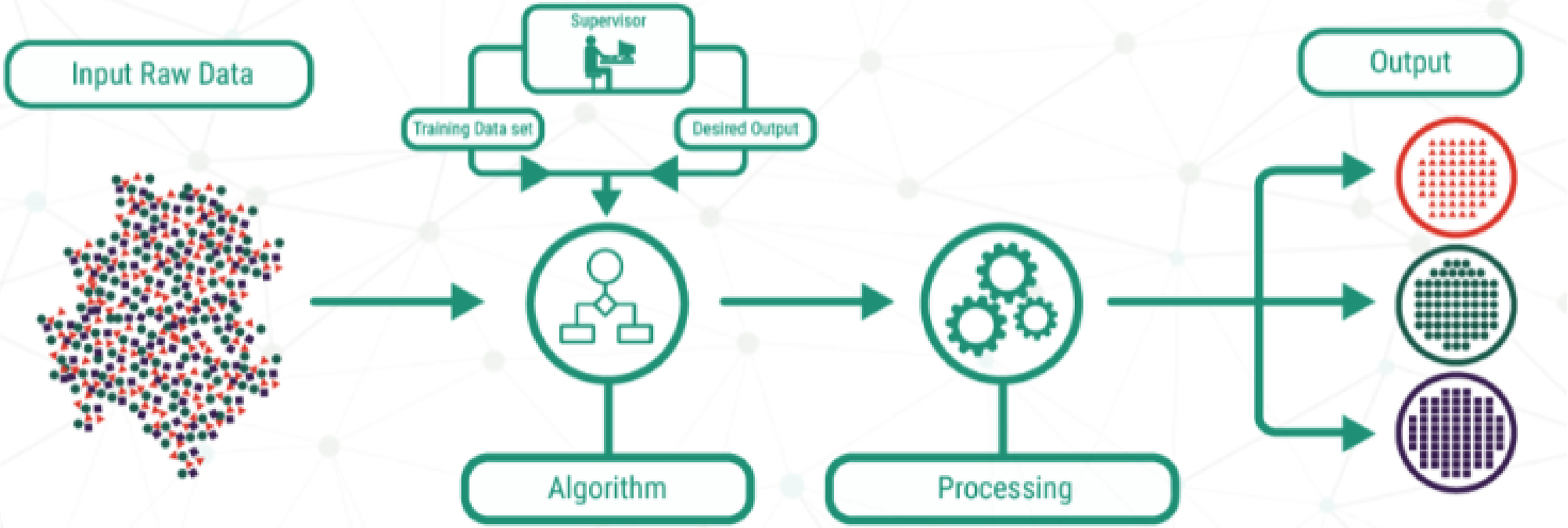
MAPEAMENTO & POSSÍVEIS PRODUTOS



TIPOS DE APRENDIZAGEM

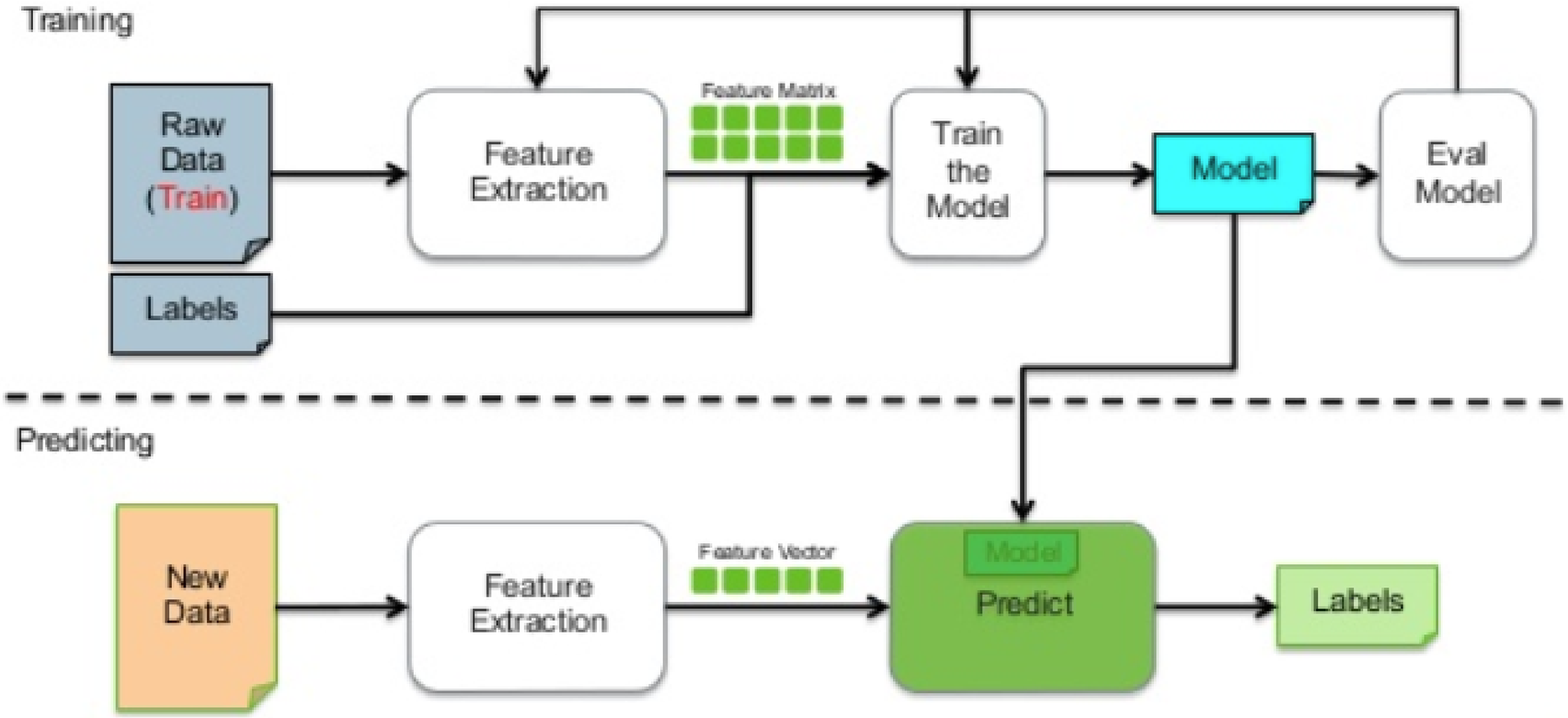
- APRENDIZADO supervisionado
- APRENDIZADO não supervisionado
- APRENDIZADO por reforço

APRENDIZAGEM
SUPERVISIONADA



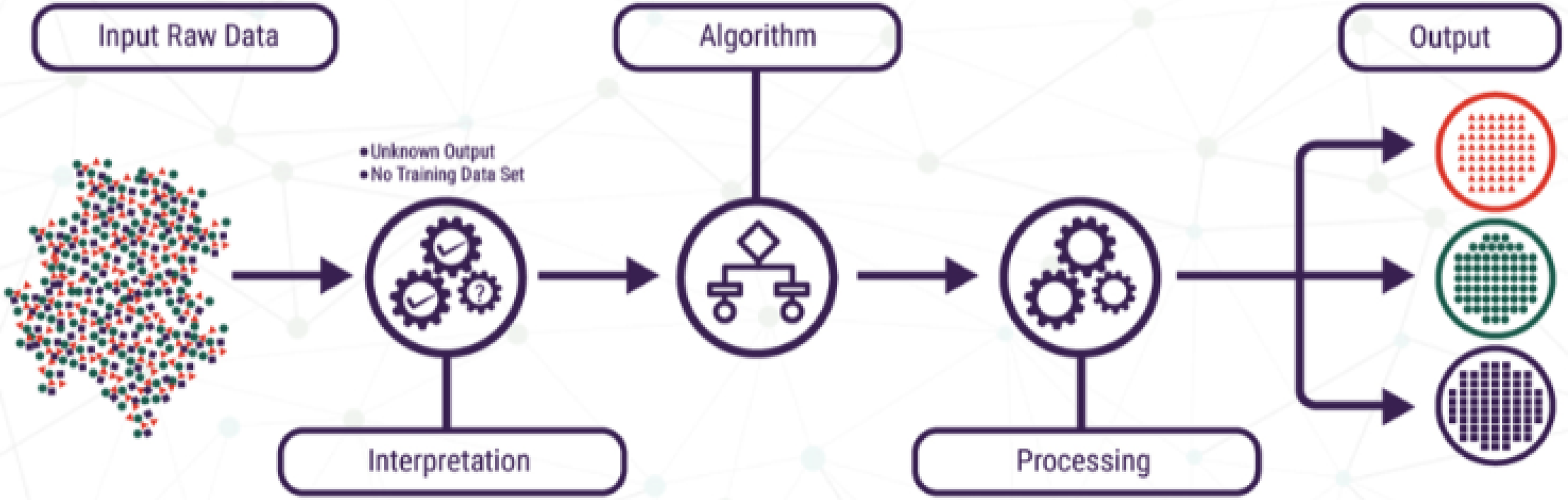
APRENDIZAGEM
SUPERVISIONADA

FLUXO DE TRABALHO



Hortonworks

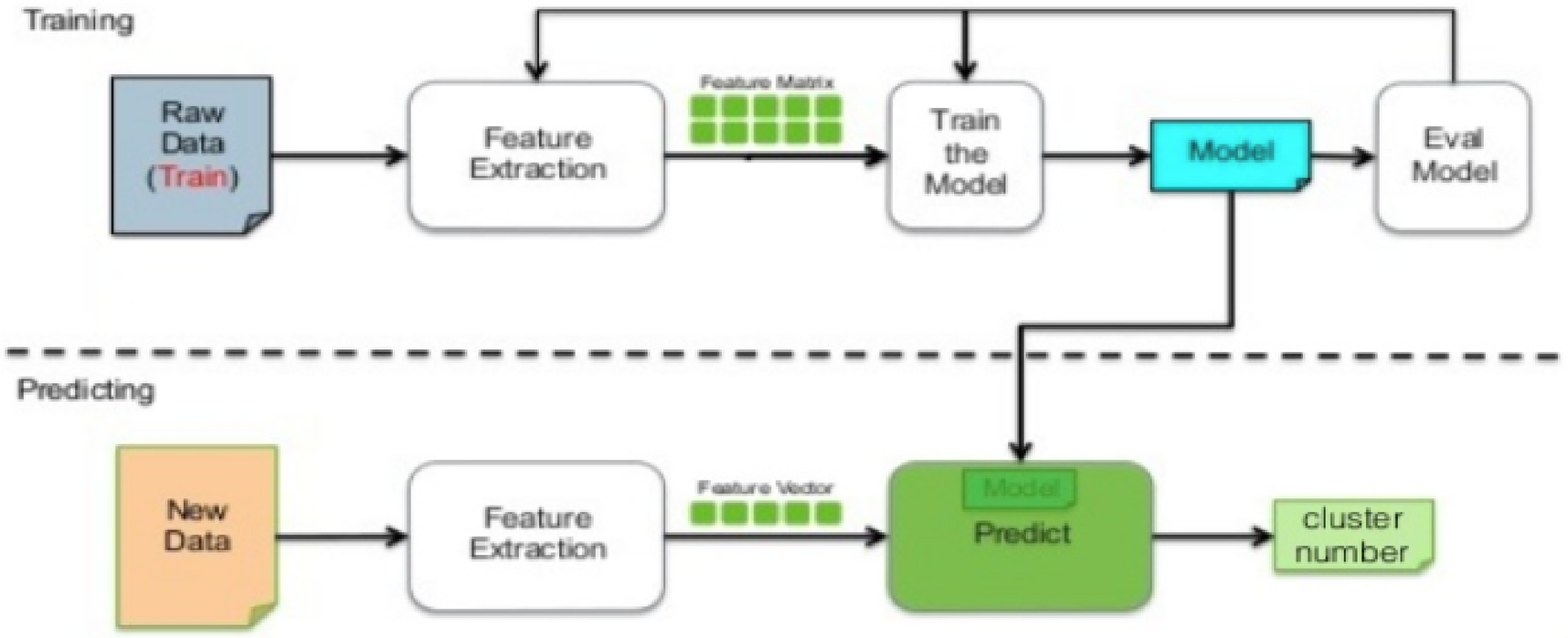
APRENDIZAGEM
NÃO SUPERVISIONADA



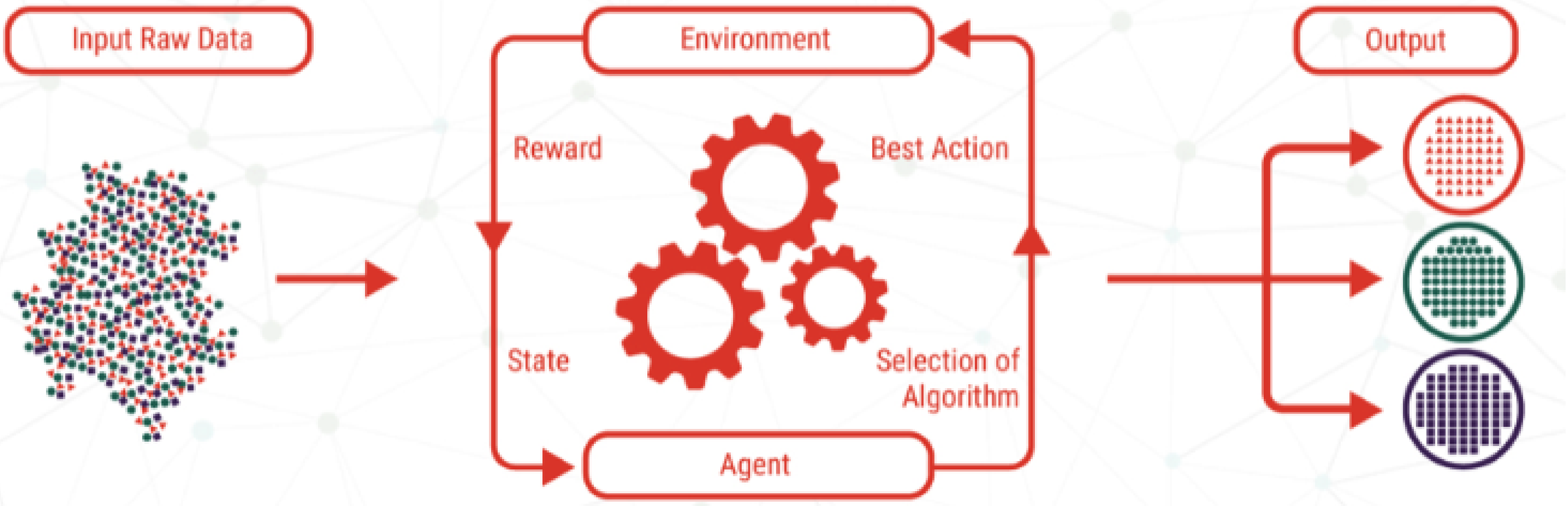
APRENDIZAGEM

NÃO SUPERVISIONADA

FLUXO DE TRABALHO



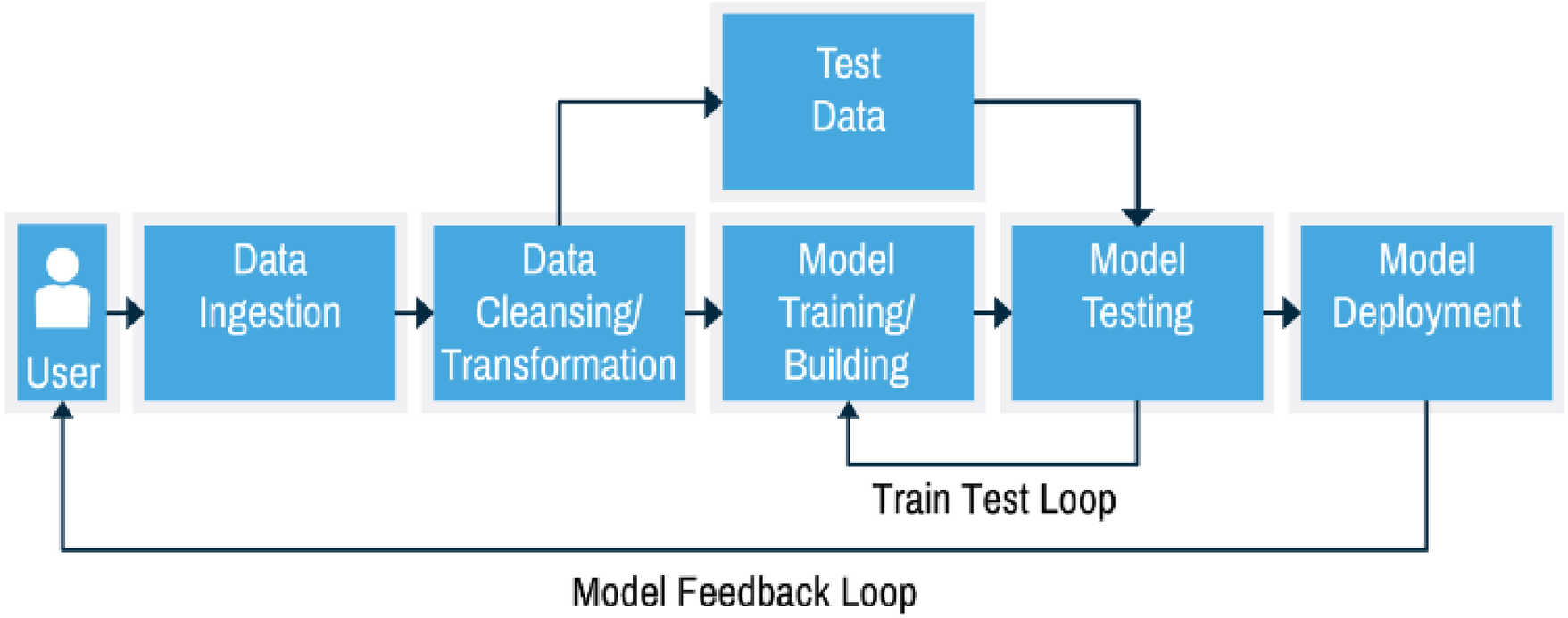
APRENDIZAGEM
POR REFORÇO



APRENDIZAGEM

NÃO SUPERVISIONADA

FLUXO DE TRABALHO

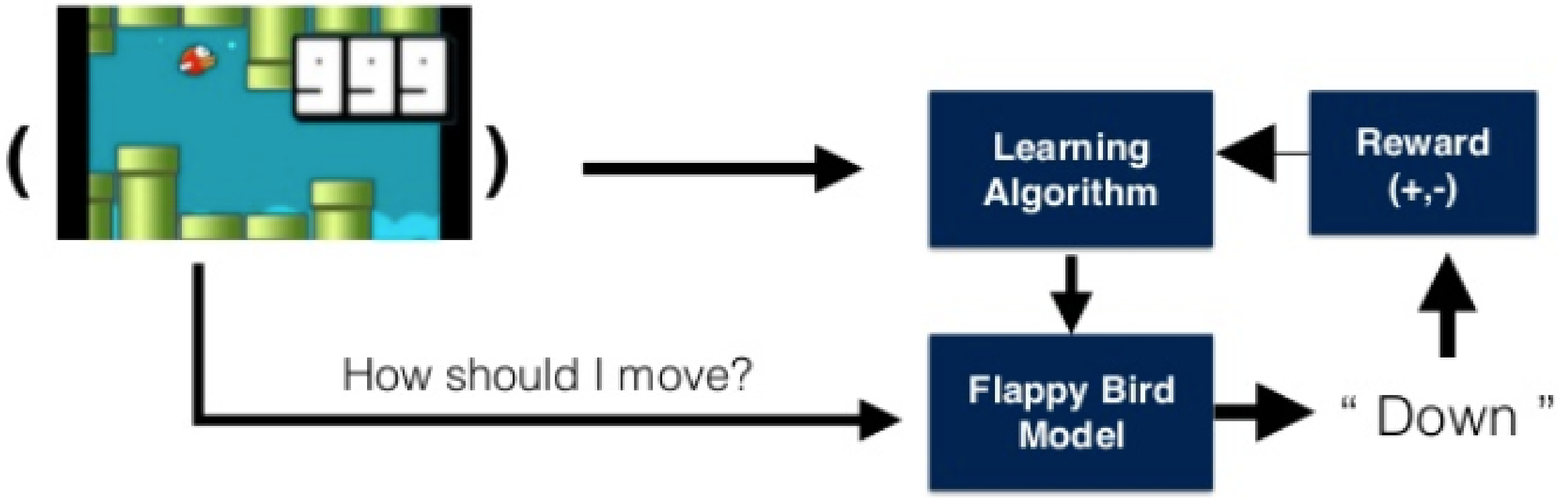


APRENDIZAGEM
NÃO SUPERVISIONADA

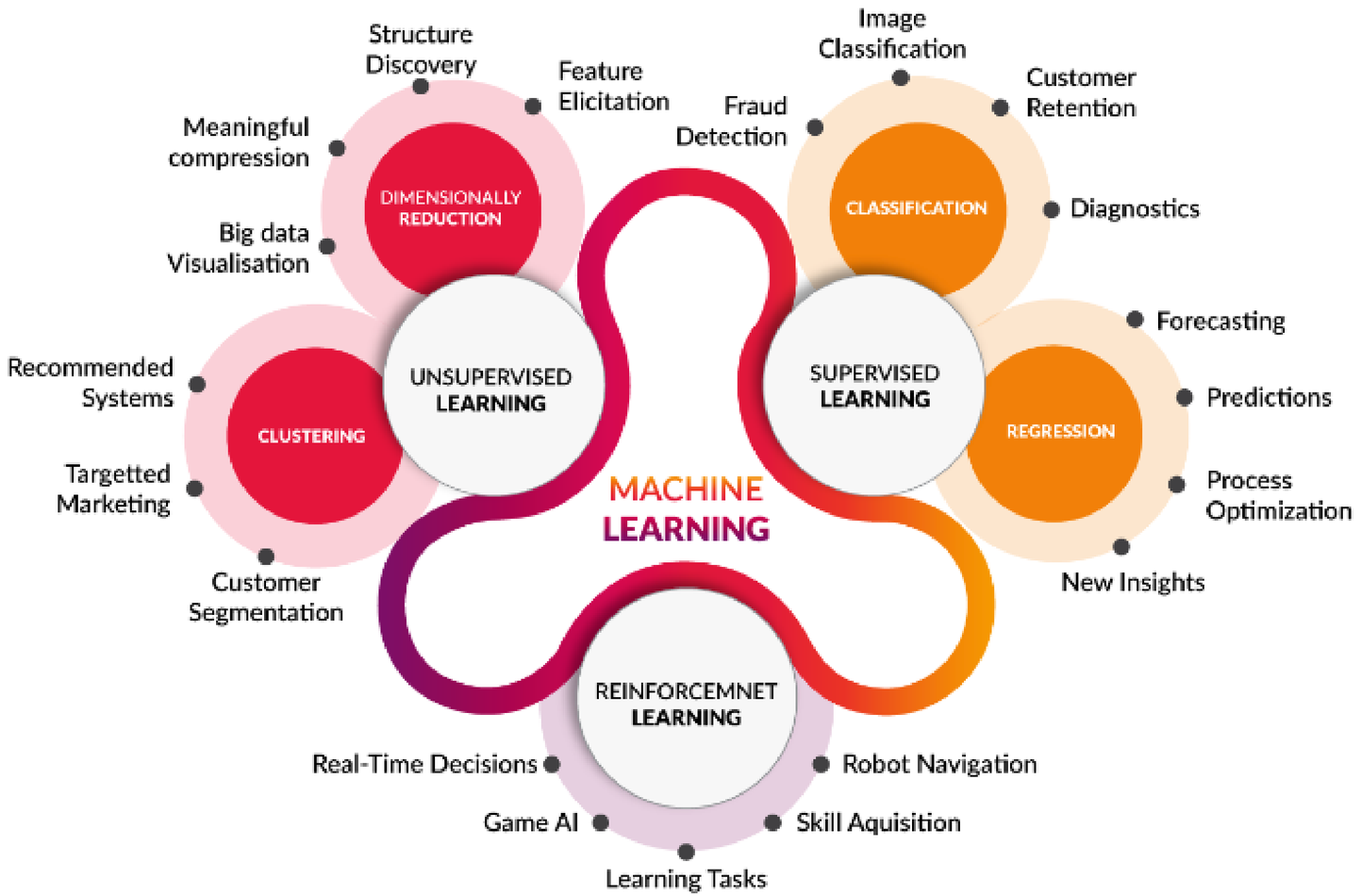
FLUXO DE TRABALHO

Learning Algorithm

Reinforcement Learning



APLICAÇÕES


MACHINE LEARNING
UNSUPERVISED LEARNING
SUPERVISED LEARNING
REINFORCEMNET LEARNING
DIMENSIONALLY REDUCTION
CLUSTERING
CLASSIFICATION
REGRESSION
Structure Discovery
Feature Elicitation
Meaningful compression
Big data Visualisation
Recommended Systems
Targetted Marketing
Customer Segmentation
Image Classification
Customer Retention
Fraud Detection
Diagnostics
Forecasting
Predictions
Process Optimization
New Insights
Real-Time Decisions
Robot Navigation
Game AI
Skill Aquisition
Learning Tasks

APLICAÇÕES &

TIPOS DE APRENDIZADO

A look at

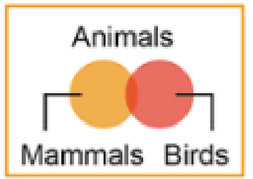
Machine learning evolution

Overview

For decades, individual "tribes" of artificial intelligence researchers have vied with one another for dominance. Is the time ripe now for tribes to collaborate? They may be forced to, as collaboration and algorithm blending are the only ways to reach true artificial general intelligence (AGI). Here's a look back at how machine learning methods have evolved and what the future may look like.

What are the five tribes?

Symbolists



Use symbols, rules, and logic to represent knowledge and draw logical inference

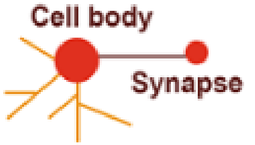
Favored algorithm
Rules and decision trees

Bayesians

Assess the likelihood of occurrence for probabilistic inference

Favored algorithm
Naive Bayes or Markov

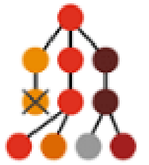
Connectionists



Recognize and generalize patterns dynamically with matrices of probabilistic, weighted neurons

Favored algorithm
Neural networks

Evolutionaries



Generate variations and then assess the fitness of each for a given purpose

Favored algorithm
Genetic programs

Analogizers

Optimize a function in light of constraints ("going as high as you can while staying on the road")

Favored algorithm
Support vectors

Source: Pedro Domingos, *The Master Algorithm*, 2015

A look at

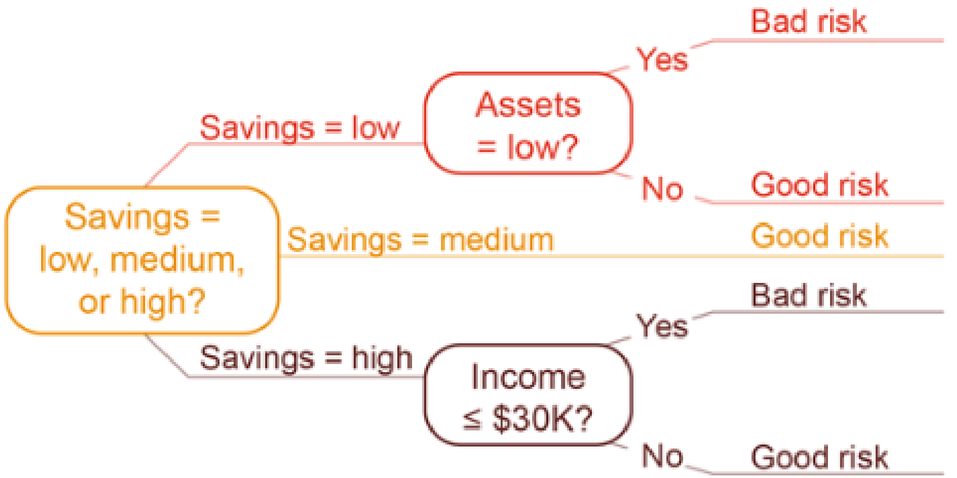
Machine learning methods

Introduction

Which machine learning algorithm should you use? A lot depends on the characteristics and the amount of the available data, as well as your training goals, in each particular use case. Avoid using the most complicated algorithms unless the end justifies more expensive means and resources. Here are some of the more common algorithms ranked by ease of use.

Decision trees

Decision tree analysis typically uses a hierarchy of variables or decision nodes that, when answered step by step, can classify a given customer as creditworthy or not, for example.

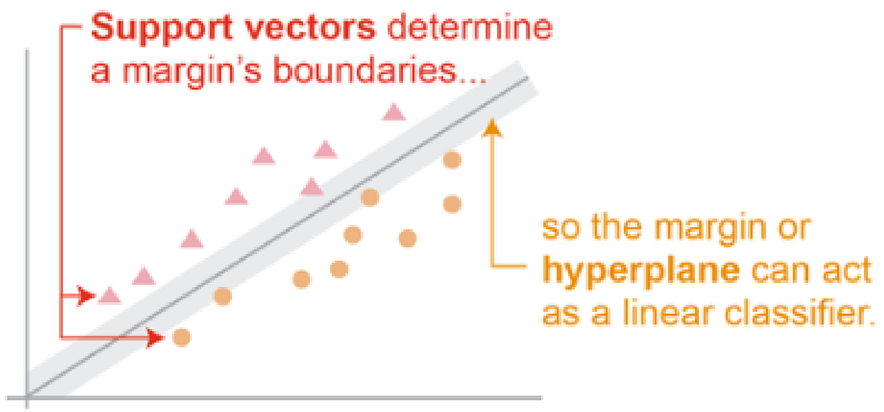


Advantages	Use cases
Decision trees are useful when evaluating lists of distinct features, qualities, or characteristics of people, places, or things.	Rule-based credit risk assessment, horse race performance prediction

Source: Daniel T. Larose and Chantal D. Larose, *Data Mining and Predictive Analytics*, 2nd Edition, John Wiley & Sons, 2015

Support vector machines

Support vector machines classify groups of data with the help of hyperplanes.

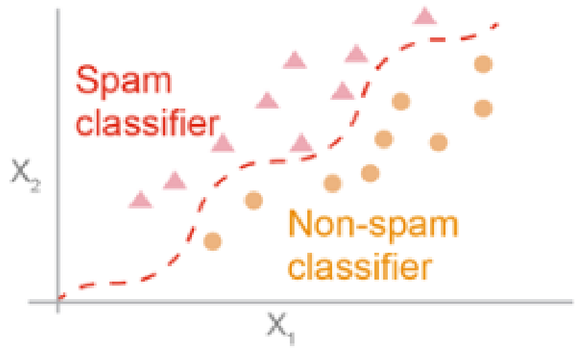


Advantages	Use cases
Support vector machines are good for the binary classification of X versus other variables and are useful whether or not the relationship between variables is linear.	News categorization, handwriting recognition

Source: Matthew Kelly, *Computer Science: Source*, 2010

Regression

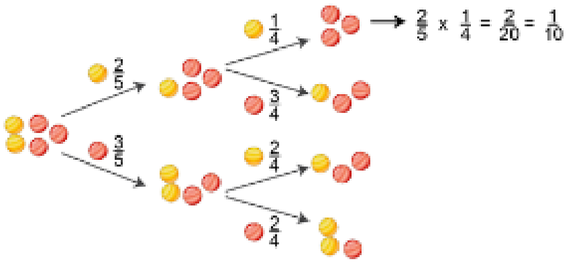
Regression maps the behavior of a dependent variable relative to one or more dependent variables. In this example, logistic regression separates spam from non-spam text.



Advantages	Use cases
Regression is useful for identifying continuous (not necessarily distinct) relationships between variables.	Traffic flow analysis, email filtering

Naive Bayes classification

Naive Bayes classifiers compute probabilities, given tree branches of possible conditions. Each individual feature is "naive" or conditionally independent of, and therefore does not influence, the others. For example, what's the probability you would draw two yellow marbles in a row, given a jar of five yellow and red marbles total? The probability, following the topmost branch of two yellow in a row, is one in ten. Naive Bayes classifiers compute the combined, conditional probabilities of multiple attributes.

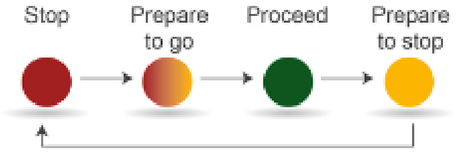


Advantages	Use cases
Naive Bayes methods allow the quick classification of relevant items in small data sets that have distinct features.	Sentiment analysis, consumer segmentation

Source: Rod Pierce, et al., *MathIsFun*, 2014

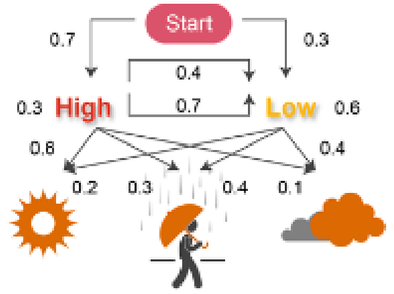
Hidden Markov models

Observable Markov processes are purely deterministic—one given state always follows another given state. Traffic light patterns are an example.



Source: Derek Kane, 2015

Hidden Markov models, by contrast, compute the probability of hidden states occurring by analyzing observable data, and then estimating the likely pattern of future observation with the help of the hidden state analysis. In this example, the probability of high or low pressure (the hidden state) is used to predict the likelihood of sunny, rainy, or cloudy weather.

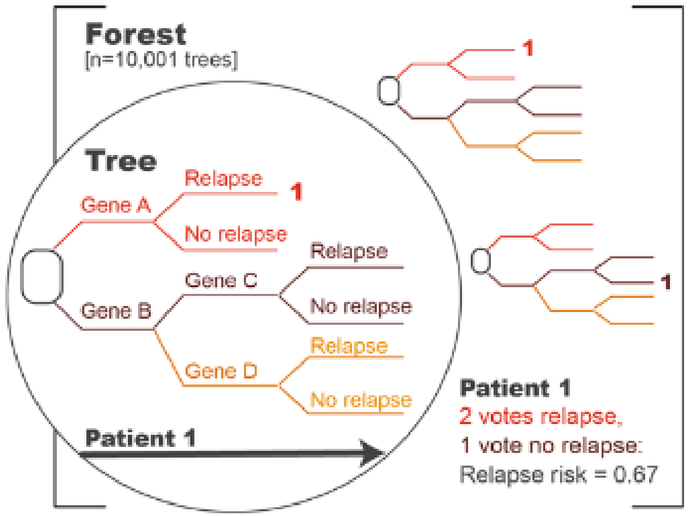


Advantages	Use cases
Tolerates data variability and effective for recognition and prediction.	Facial expression analysis, weather prediction

Source: Leonardo Guizzetti, 2012

Random forest

Random forest algorithms improve the accuracy of decision trees by using multiple trees with randomly selected subsets of data. This example reviews the expression levels of various genes associated with breast cancer relapse and computes a relapse risk.



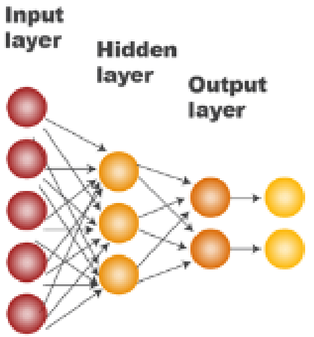
Advantages	Use cases
Random forest methods prove useful with large data sets and items that have numerous and sometimes irrelevant features.	Customer churn analysis, risk assessment

Source: Nicolas Spies, Washington University, 2015

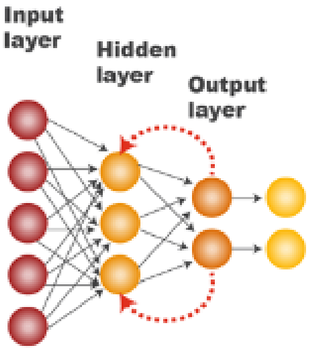
Recurrent neural networks

Each neuron in any neural network converts many inputs into single outputs via one or more hidden layers. Recurrent neural networks [RNNs] additionally pass values from step to step, making step-by-step learning possible. In other words, RNNs have a form of memory, allowing previous outputs to affect subsequent inputs.

Non-recurrent feed-forward neural network



Recurrent neural network—includes loops

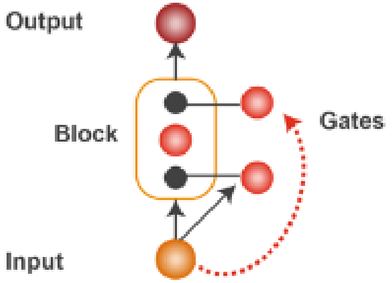


Advantages	Use cases
Recurrent neural networks have predictive power when used with large amounts of sequenced information.	Image classification and captioning, political sentiment analysis

Source: Joseph Wilks, 2012

Long short-term memory & gated recurrent unit neural networks

Older forms of RNNs can be lossy. While these older recurrent neural networks only allow small amounts of older information to persist, newer long short-term memory (LSTM) and gated recurrent unit (GRU) neural networks have both long- and short-term memory. In other words, these newer RNNs have greater memory control, allowing previous values to persist or to be reset as necessary for many sequences of steps, avoiding "gradient decay" or eventual degradation of the values passed from step to step. LSTM and GRU networks make this memory control possible with memory blocks and structures called gates that pass or reset values as appropriate.

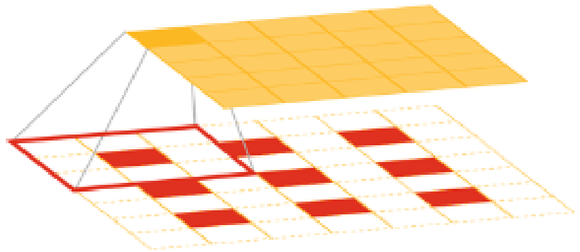


Source: Genevieve Orr, et al., Williamette University, 1999

Advantages	Use cases
Long short-term memory and gated recurrent unit neural networks have the same advantages as other recurrent neural networks and are more frequently used than other recurrent neural networks because of their greater memory capabilities.	Natural language processing, translation

Convolutional neural networks

Convolutions are blends of weights from a subsequent layer that are used to label the output layer.



Source: Algobeans, 2016

Advantages	Use cases
Convolutional neural networks are most useful with very large data sets, large numbers of features, and complex classification tasks.	Image recognition, text to speech, drug discovery

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MATERIAIS RECOMENDADOS

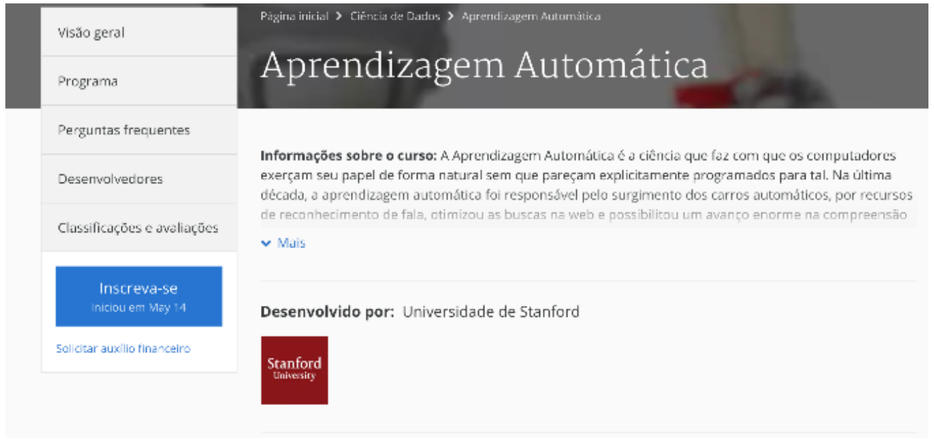
REPOSITÓRIOS

GitHub

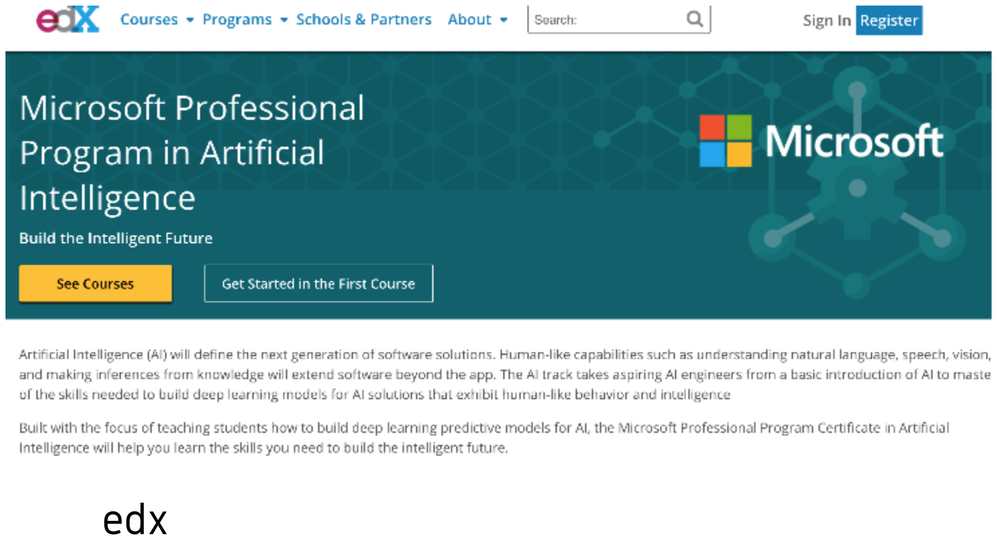
- https://github.com/owainlewis/awesome-artificial-intelligence
- https://github.com/josephmisiti/awesome-machine-learning
- https://github.com/faktionai/awesome-ai-usecases

CURSOS

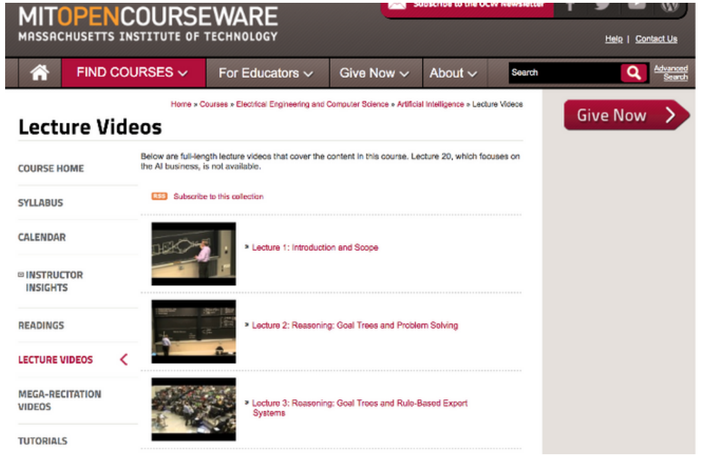
Udacity



Stanford

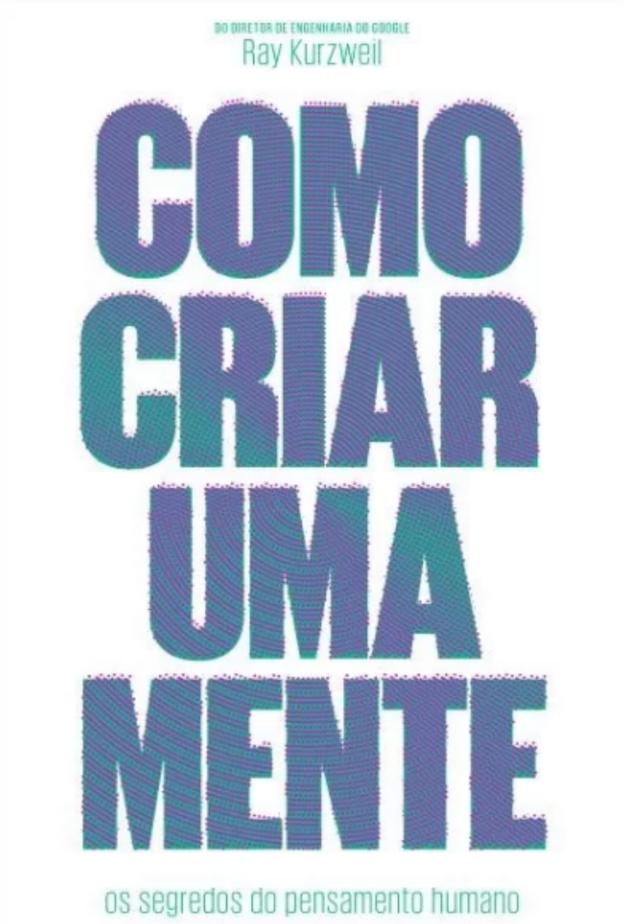


edx

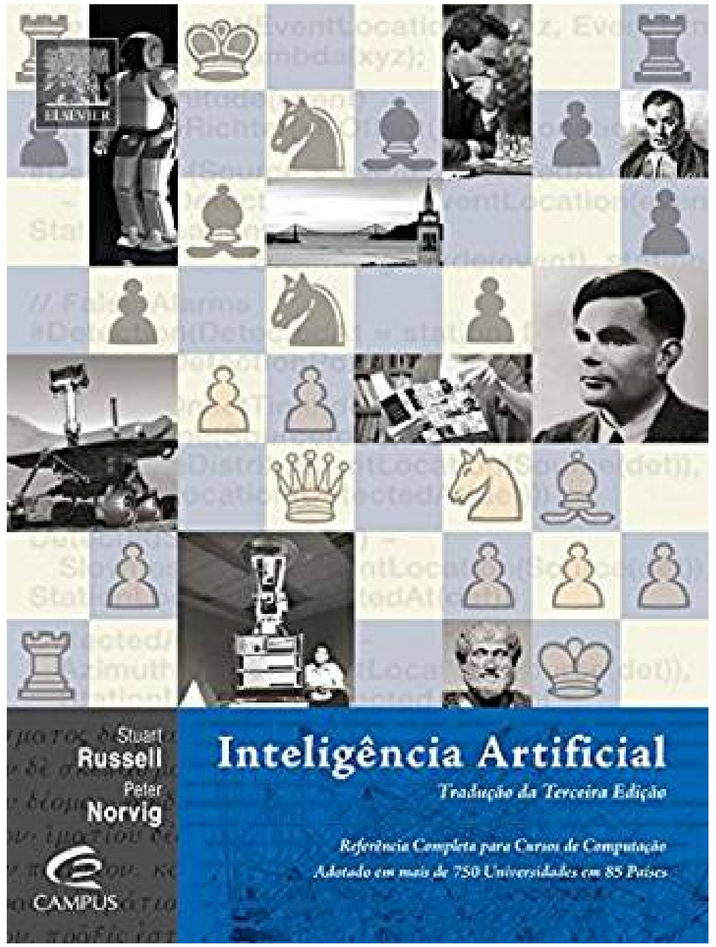


MIT

LIVROS



COMO CRIAR UMA MENTE
Ray Kurzweil



INTELIGÊNCIA ARTIFICIAL
Stuart Russel & Peter Norvig

FILMES

JOGO DA IMITAÇÃO

BLADE RUNNER

ALPHAGO

VIDEOS

IBM WATSON - JEOPARDY

GASPAROV

OBRIGADO

ARTIGOS

WWW.RESEARCHGATE.NET/PROFILE/JOSE_AHIRTON_LOPES_FILHO2

OUTRAS APRESENTAÇÕES

WWW.SLIDESHARE.NET/JOSAHIRTONBATISTALOP

GITHUB

HTTPS://GITHUB.COM/AHIRTONL