MBA em Artificial Intelligence & Machine Learning

MBA+

Introdução a Inteligência Artificial

Prof . Vinicius Soares
vinicius@mais.ai

2018

CONTEÚDO DA DISCIPLINA

- ~~A.I. e a 4ª Revolução Industrial~~
- ~~Definições~~
- ~~Revolução das Interfaces~~
- ~~Cenários Utópicos~~
- ~~Estudos de Caso de Sucesso~~
- ~~Ferramentas de A.I.~~
- ~~Ética no Desenvolvimento de A.I.~~
- ~~Cenários Distópicos~~
- ~~Riscos / Desafios / Caminhos~~
- ~~Taxonomia de Falhas~~
- ~~AI Fails: Estudos de Caso de Fracasso~~
- A.I. para negócios
- Conceito de aprendizagem
- Aprendizagem Supervisionada
- Aprendizagem não Supervisionada
- Aprendizagem por Reforço
- Áreas / subáreas da A.I.
- Intenção & Entidade
- Assistentes pessoais

MCKINSEY GLOBAL INSTITUTE

ARTIFICIAL INTELLIGENCE:

THE NEXT DIGITAL FRONTIER?

MGI AI adoption and use survey sample overview

% of respondents (n = 3,073)

Geography

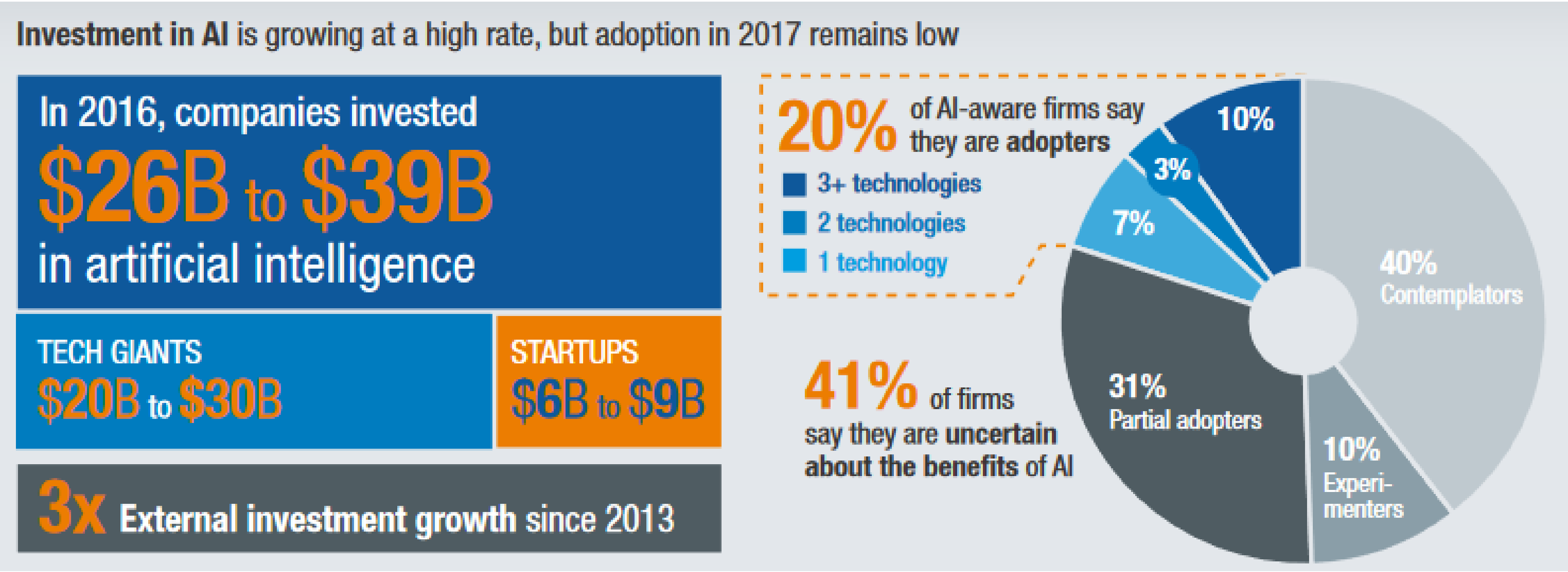
Sweden	5
South Korea	9
China	10
Germany	10
Japan	10
Italy	11
Canada	11
France	11
United States	11
United Kingdom	12

Company size

>10,000	7
5,000–10,000	6
1,000–5,000	15
500–1,000	10
250–500	10
50–250	11
10–50	14
<10	27

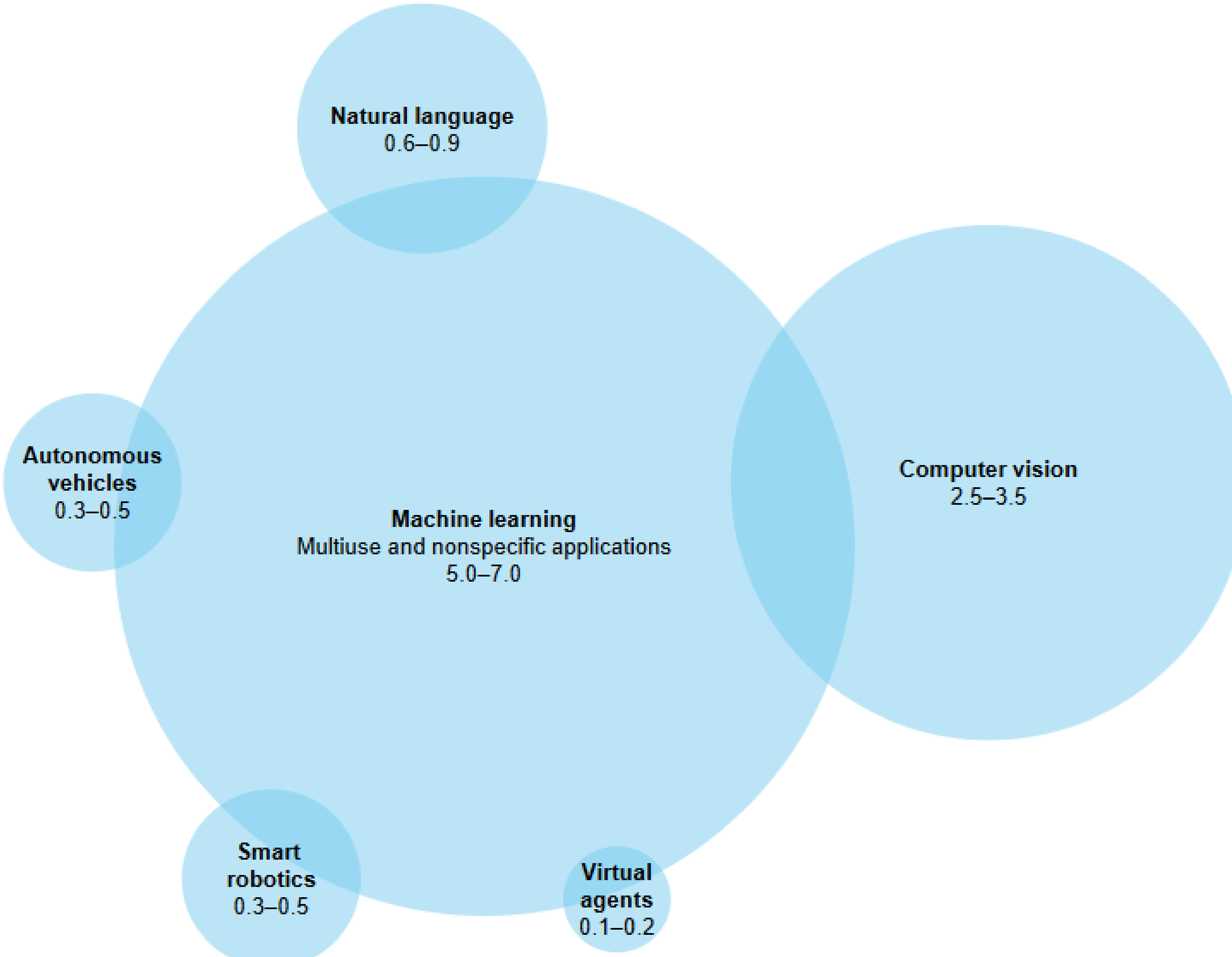
Sector

Other	12
Energy and resources	3
Travel and tourism	4
Automotive and assembly	4
Transportation and logistics	4
Telecommunications	5
Consumer packaged goods	5
Education	5
Media and entertainment	5
Financial services	5
Health-care systems and services	7
Construction	8
Retail	8
High tech	10
Professional services	14



Investment in AI is growing at a high rate, but adoption in 2017 remains low
In 2016, companies invested
$26B to $39B
in artificial intelligence
TECH GIANTS
$20B to $30B
STARTUPS
$6B to $9B
3x External investment growth since 2013
20% of AI-aware firms say they are adopters
3+ technologies
2 technologies
1 technology
10%
3%
7%
40% Contemplators
31% Partial adopters
10% Experi-menters
41% of firms say they are uncertain about the benefits of AI

External investment in AI-focused companies by technology category, 2016[1]
$ billion



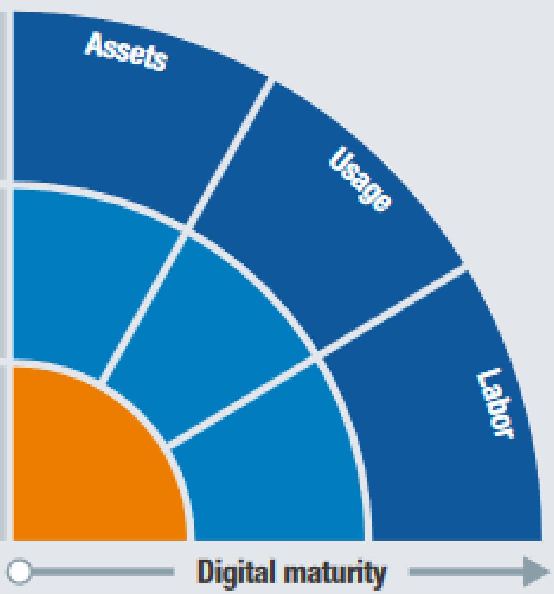
1 Estimates consist of annual VC investment in AI-focused companies, PE investment in AI-related companies, and M&A by corporations. Includes only disclosed data available in databases, and assumes that all registered deals were completed within the year of transaction.

SOURCE: Capital IQ; Pitchbook; Dealogic; McKinsey Global Institute analysis

How companies are adopting AI

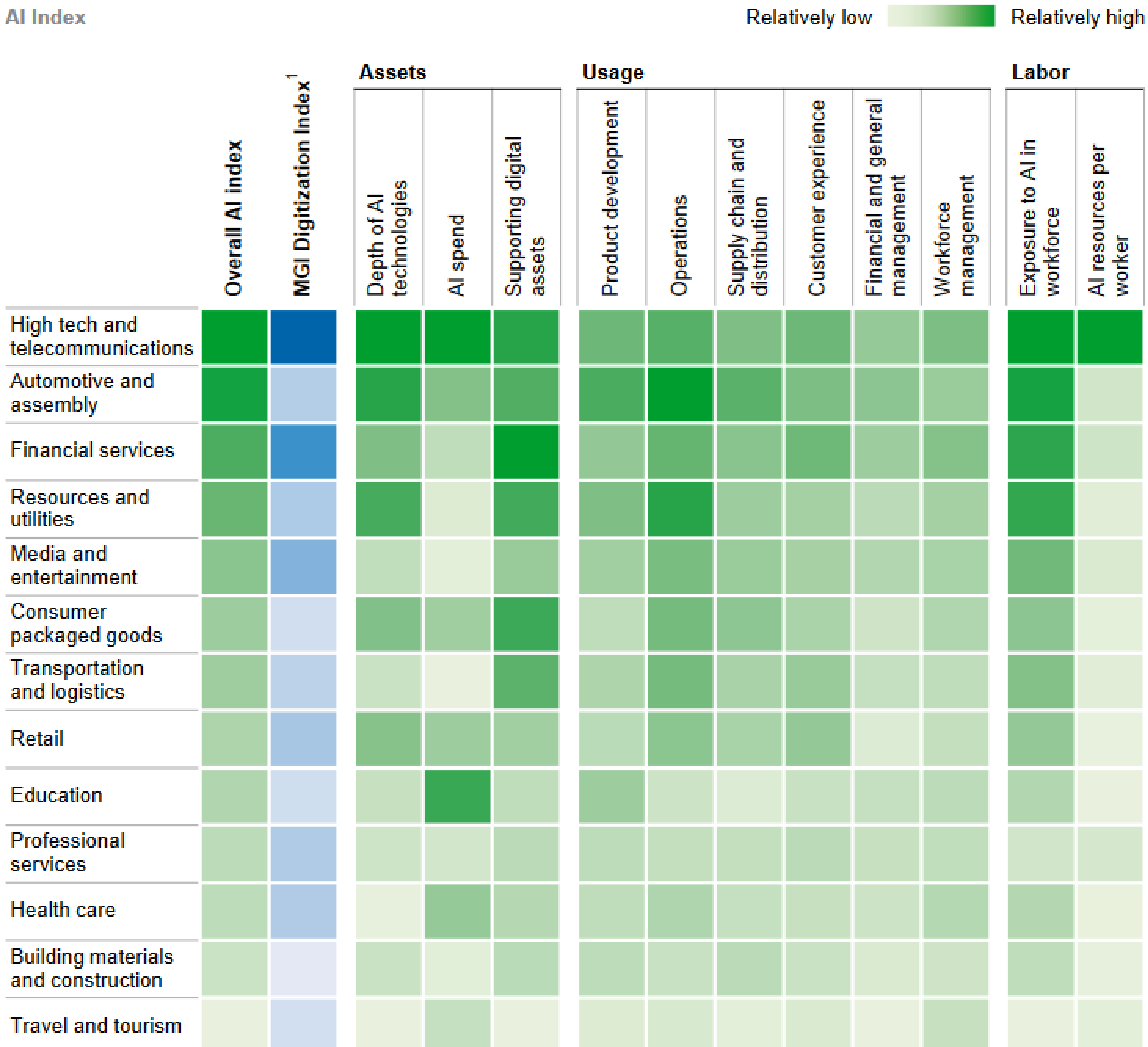
AI adoption is greatest in sectors that are already **strong digital adopters**

High AI adoption	• High tech / telecom • Automotive / assembly • Financial services
Medium AI adoption	• Retail • Media / entertainment • CPG
Low AI adoption	• Education • Health care • Travel / tourism



Six characteristics of early AI adopters

- Digitally mature
- Larger businesses
- Adopt AI in core activities
- Adopt multiple technologies
- Focus on growth over savings
- C-level support for AI

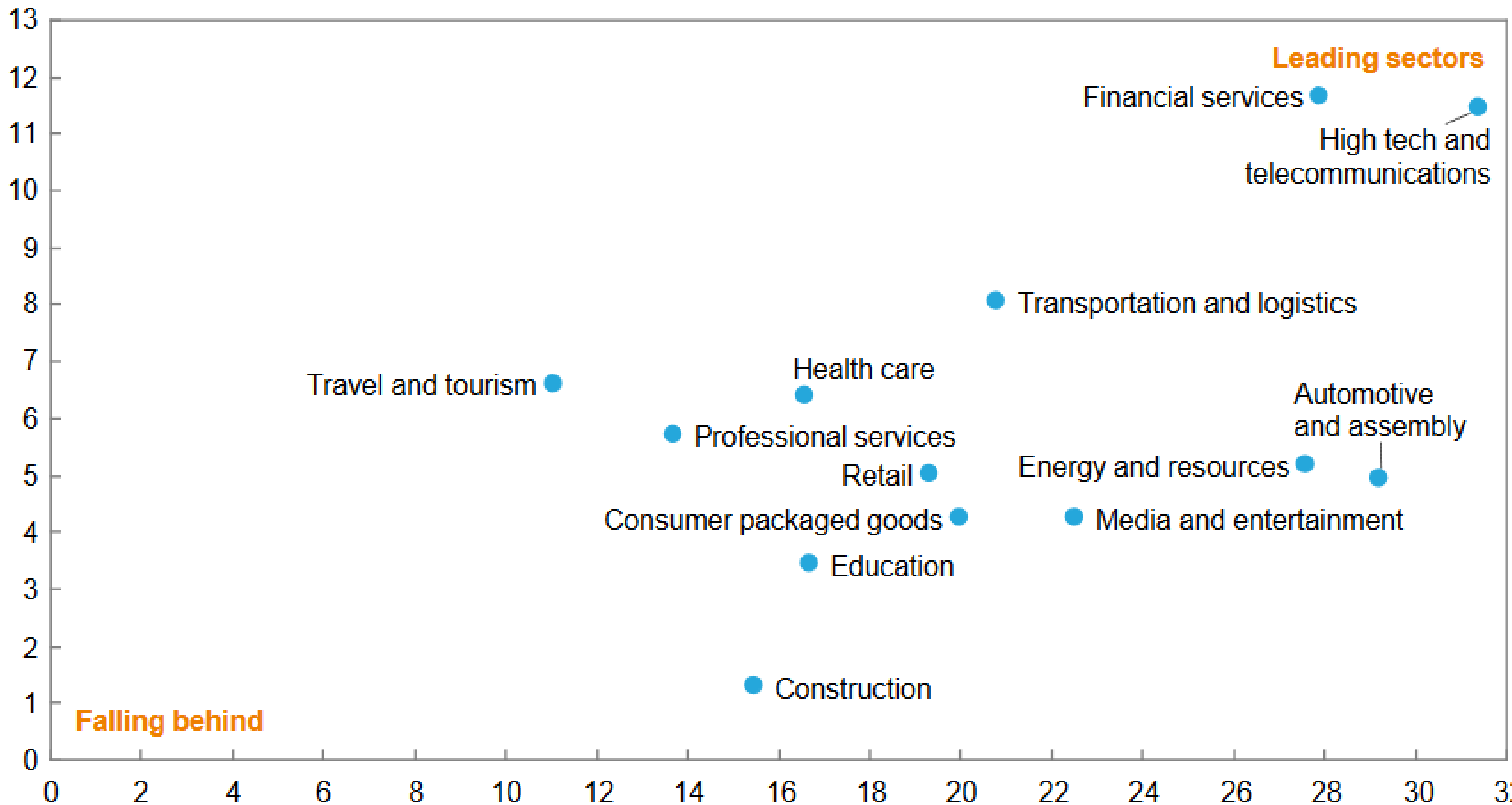


1. The MGI Digitization Index is GDP weighted average of Europe and United States. See Appendix B for full list of metrics and explanation of methodology.

Metric			Description
Assets	**Depth of AI technologies**		Average number of AI technologies adopted at scale or in core part of business per company
	AI spend		Average AI spend as share of total annual investment[1]
	Supporting digital assets		Percentage of firms using cloud and big data
Usage	**Product development**	**An entirely new product or service**	Percentage of firms in sector using AI for entirely new product or service
		Research and development	Percentage of firms in sector using AI in R&D
	Operations		Percentage of firms in sector using AI in operations
	Supply chain and distribution	**Supply chain management**	Percentage of firms in sector using AI in supply chain management
		Distribution	Percentage of firms in sector using AI in distribution
	Customer experience	**Customer services**	Percentage of firms in sector using AI in customer services
		Sales and marketing	Percentage of firms in sector using AI in sales and marketing
	Financial and general management	**Executive management**	Percentage of firms in sector using AI in executive management
		Financial and risk management	Percentage of firms in sector using AI in financial and risk management
	Workforce management	**Management of operational staff**	Percentage of firms in sector using AI in operational staff management
		HR	Percentage of firms in sector using AI in HR
Labor	**Exposure to AI in workforce**		Percentage of workforce in firms adopting AI at scale or in core part of business
	AI resources per worker		Average AI spend per employee (€ thousand)

Sectors leading in AI adoption today also intend to grow their investment the most

Future AI demand trajectory[1]
Average estimated % change in AI spending, next 3 years, weighted by firm size[2]

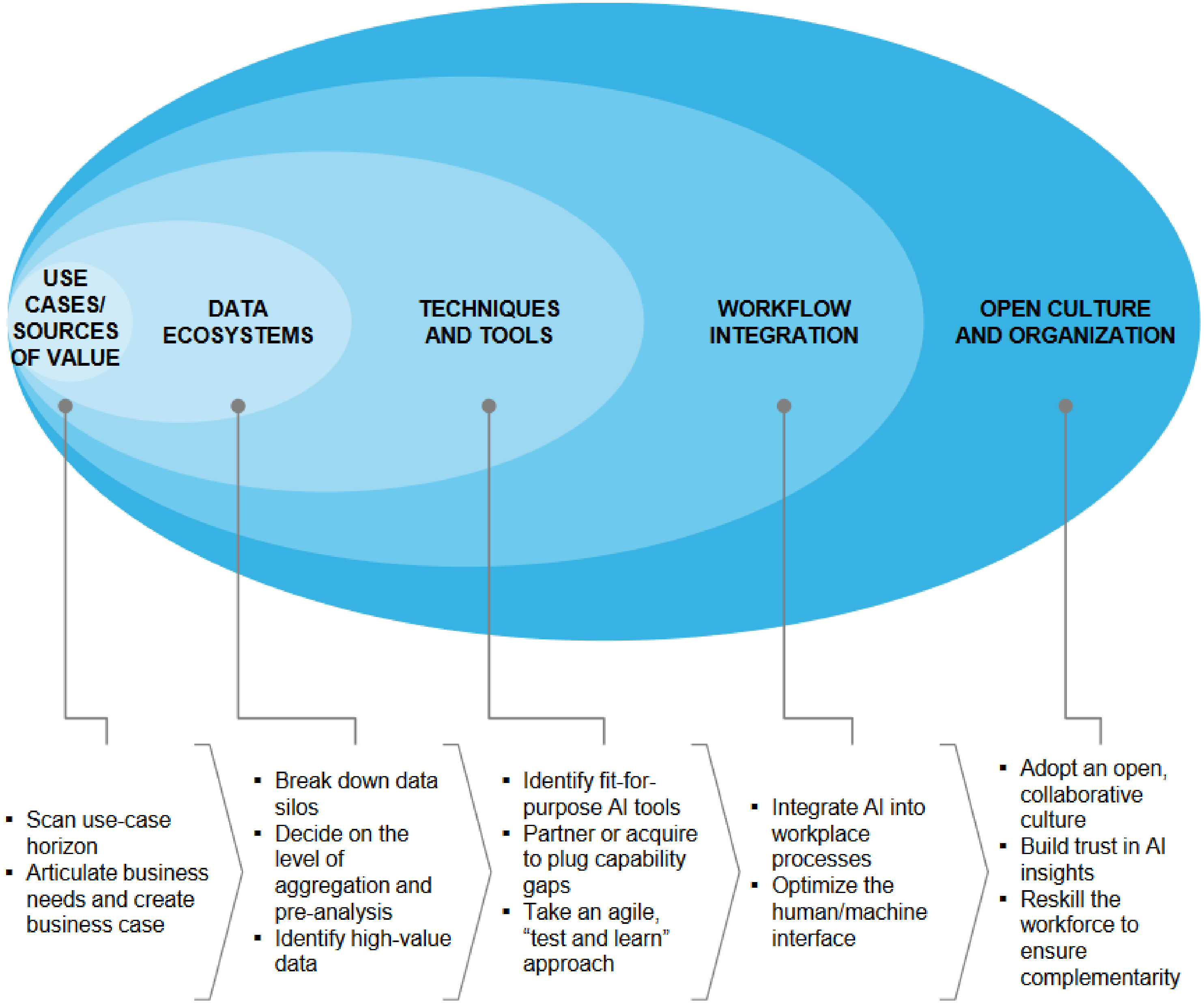


Current AI adoption
% of firms adopting one or more AI technology at scale or in a core part of their business, weighted by firm size[2]

1 Based on the midpoint of the range selected by the survey respondent.
2 Results are weighted by firm size. See Appendix B for an explanation of the weighting methodology.

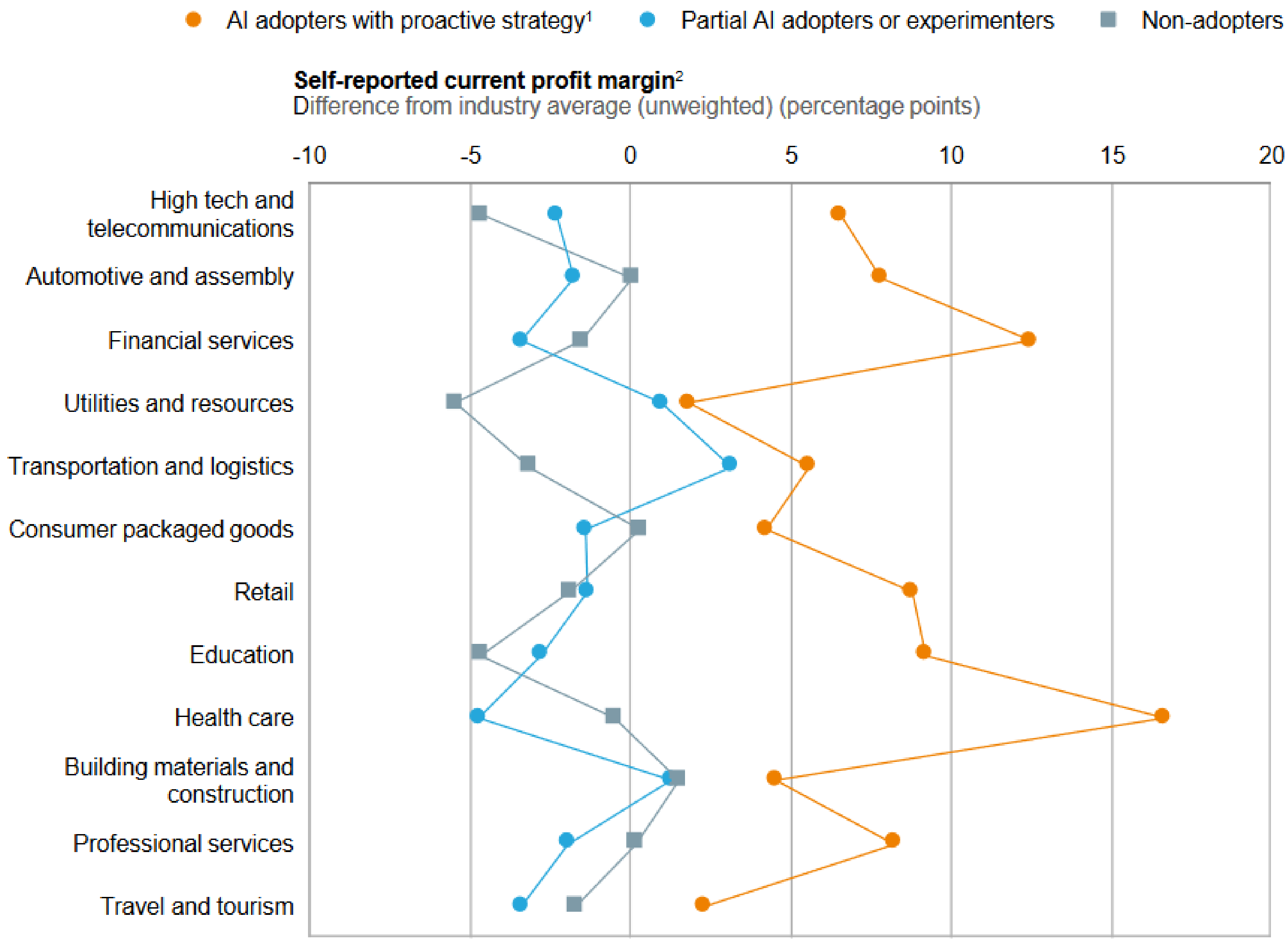
SOURCE: McKinsey Global Institute AI adoption and use survey; McKinsey Global Institute analysis

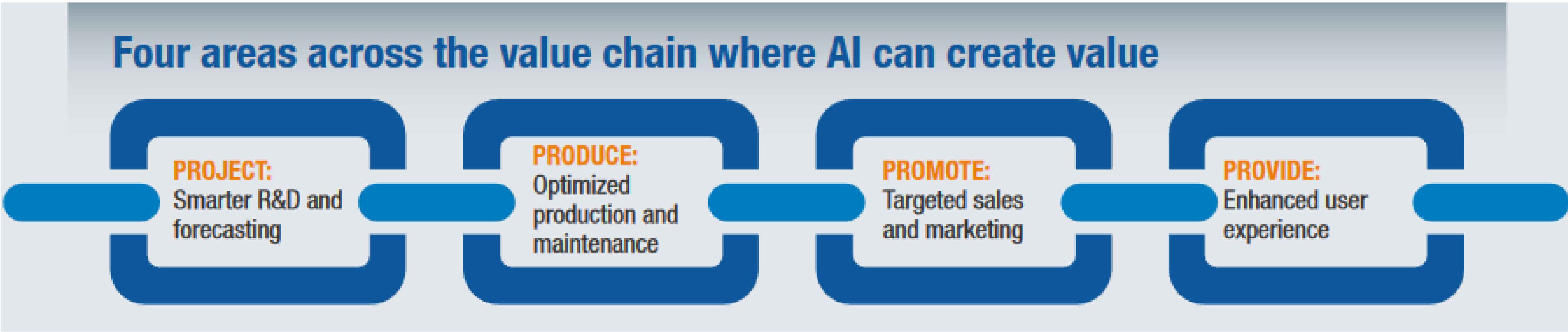
“Se você automatizar um processo ruim, só vai fazer a coisa errada mais rapidamente.”



SOURCE: *The age of analytics: Competing in a data-driven world*, McKinsey Global Institute, December 2016; McKinsey Global Institute analysis

AI adopters with a proactive strategy have significantly higher profit margins




Four areas across the value chain where AI can create value
PROJECT:
Smarter R&D and forecasting
PRODUCE:
Optimized production and maintenance
PROMOTE:
Targeted sales and marketing
PROVIDE:
Enhanced user experience

	Project	Produce	Promote	Provide
	Accurate demand forecasting, smart sourcing, and enlightened R&D	**Higher productivity and minimized maintenance and repairs**	**Products and services at the right price, with the right message, to the right targets**	**Enriched, tailored, and convenient user experience**
Retail	▪ **1–2% EBIT[1] improvement** using machine learning to anticipate fruit and vegetable sales ▪ **20% stock reduction** using deep learning to predict e-commerce purchases ▪ **2 million** fewer product returns per year	▪ **30% reduction of stocking time** using autonomous vehicles in warehouses	▪ **50% improvement of assortment efficiency** ▪ **4–6% sales increase** using geospatial modeling to improve micromarket attractiveness ▪ **30% online sales increase** by using dynamic pricing and personalization	
Electric utilities	▪ Objective to **cut 10% in national electricity usage** by using deep learning to predict power demand and supply	▪ **20% energy production increase** using machine learning and smart sensors to optimize assets' yield ▪ **10–20% EBIT improvement** by using machine learning to enhance predictive maintenance, automate fault prediction, and increase capital productivity		▪ **$10–$30 savings on monthly bills** by using machine learning to automatically switch electricity supply deals

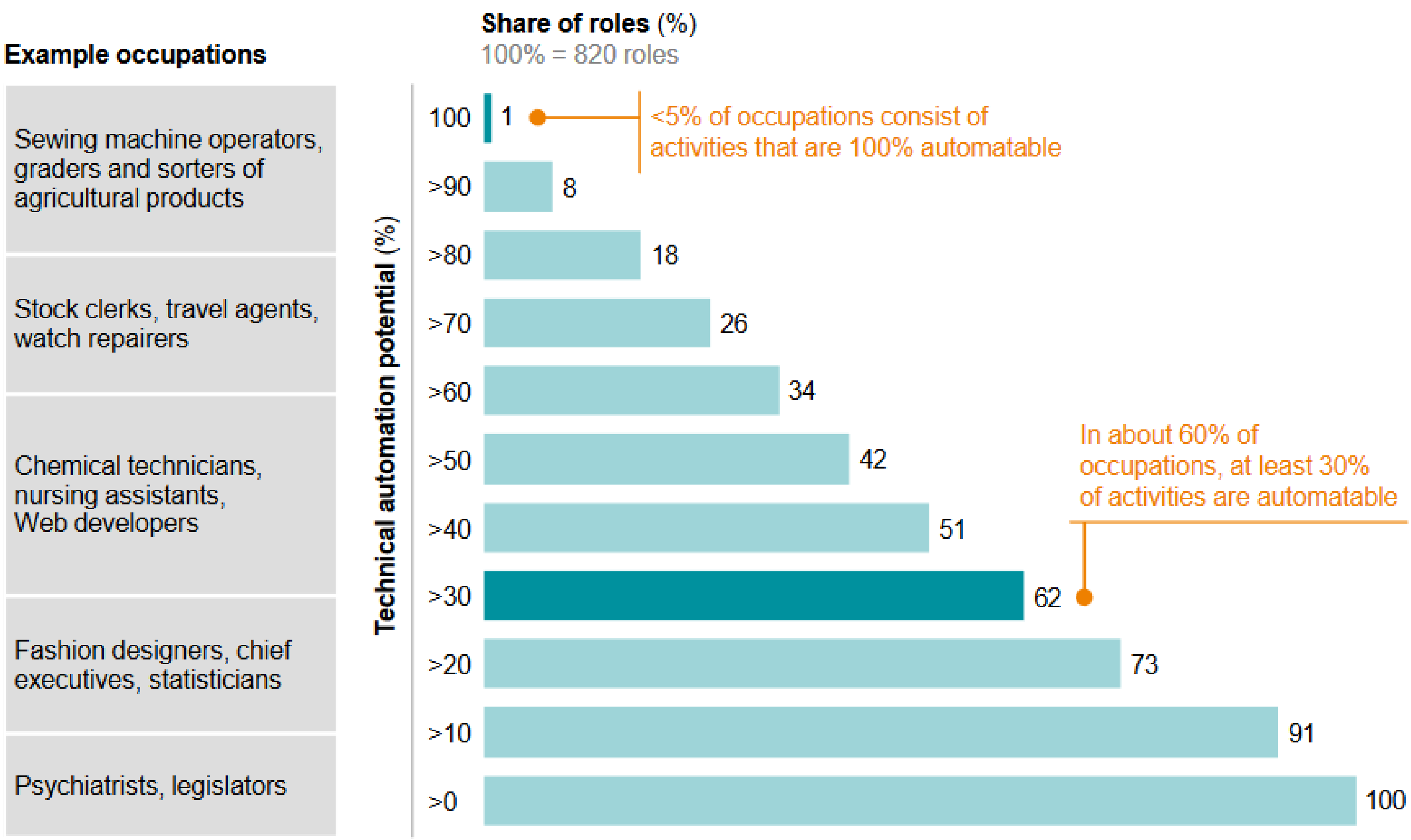
SOURCE: McKinsey Global Institute analysis

	Project	Produce	Promote	Provide
	Accurate demand forecasting, smart sourcing, and enlightened R&D	**Higher productivity and minimized maintenance and repairs**	**Products and services at the right price, with the right message, to the right targets**	**Enriched, tailored, and convenient user experience**
Manufac-turing	▪ **10% yield improvement** for integrated-circuit products using AI to improve R&D process ▪ **39% IT staff reduction** by using AI to fully automate procurement processes	▪ **30% increase of material delivery time** using machine learning to determine timing of goods' transfer ▪ 3–5% production yield improvement	▪ **13% EBIT improvement** by using machine learning to predict sources of servicing revenues and optimize sales efforts	▪ **12% fuel savings** for manufacturers' customers, airlines, by using machine learning to optimize flight routes
Health care	▪ **$300 billion possible savings** in the United States using machine learning tools for population health forecasting ▪ **£3.3 billion possible savings** in the United Kingdom using AI to provide preventive care and reduce nonelective hospital admissions	▪ **30–50% productivity improvement** for nurses supported by AI tools ▪ Up to **2% GDP savings** for operational efficiencies in developed countries	▪ **5–9% health expenditure reduction** by using machine learning to tailor treatments and keep patients engaged	▪ **$2 trillion–$10 trillion savings** globally by tailoring drugs and treatments ▪ **0.2–1.3 additional years** of average life expectancy
Education		▪ Virtual teaching assistants can **answer 40% of students' routine questions**	▪ **1% increase in enrollment** by using a virtual assistant to follow up with applicants	▪ **85% match with human grading**, using machine learning and predictive modelling

SOURCE: McKinsey Global Institute analysis

E OS EMPREGOS?

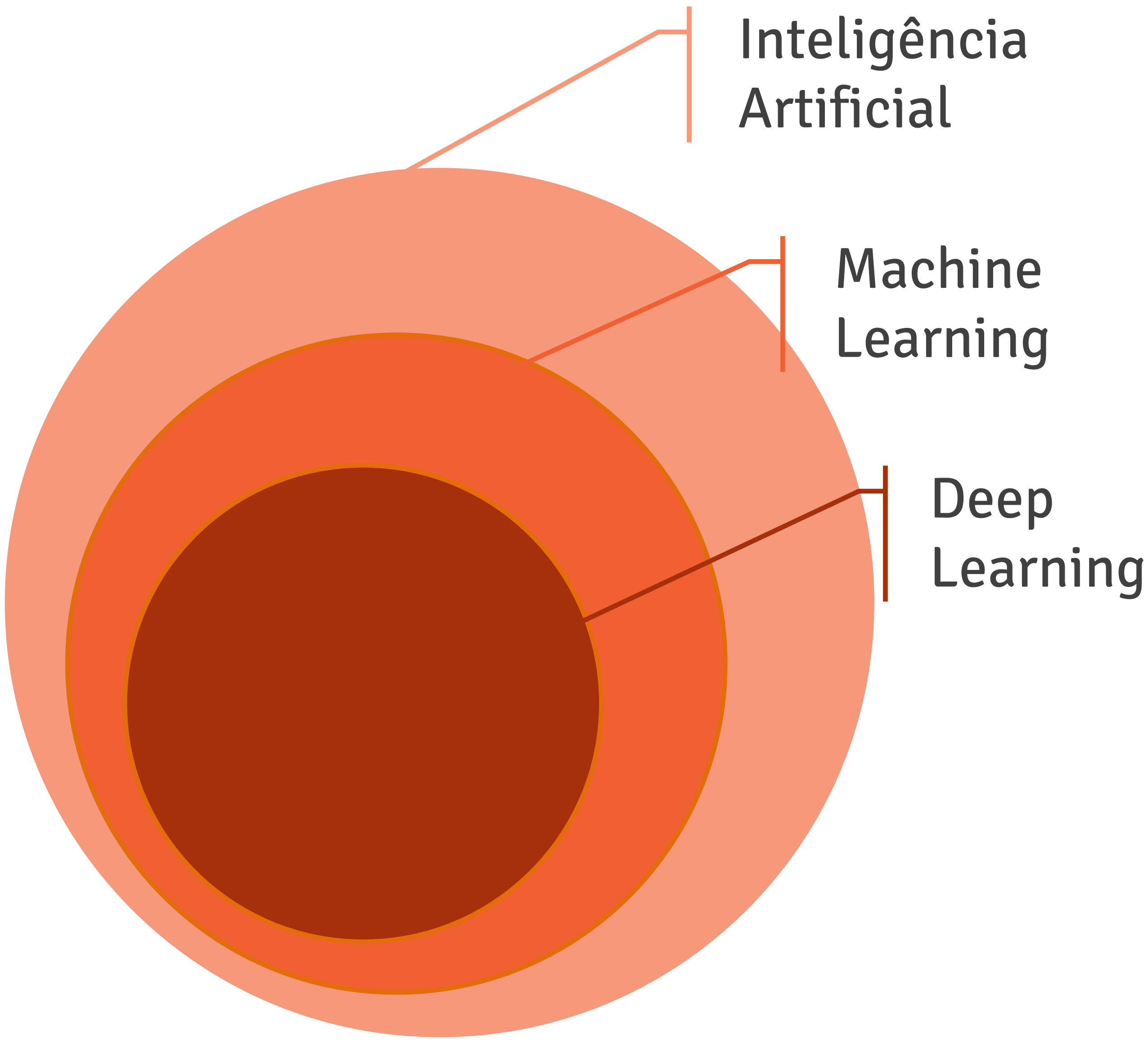
Automation potential based on demonstrated technology of occupation titles in the United States (cumulative)[1]



1 We define automation potential according to the work activities that can be automated by adapting currently demonstrated technology.

SOURCE: US Bureau of Labor Statistics; *A future that works: Automation, employment and productivity*, McKinsey Global Institute, January 2017; McKinsey Global Institute analysis

CONCEITOS DE APRENDIZAGEM


Inteligência
Artificial
Machine
Learning
Deep
Learning

TIPOS DE APRENDIZAGEM

SUPERVISIONADO Com histórico

Classificação, Regressão

NÃO - SUPERVISIONADO Sem histórico

Agrupamento, Associação, Sumarização

POR REFORÇO Interação com o ambiente

Aplicações

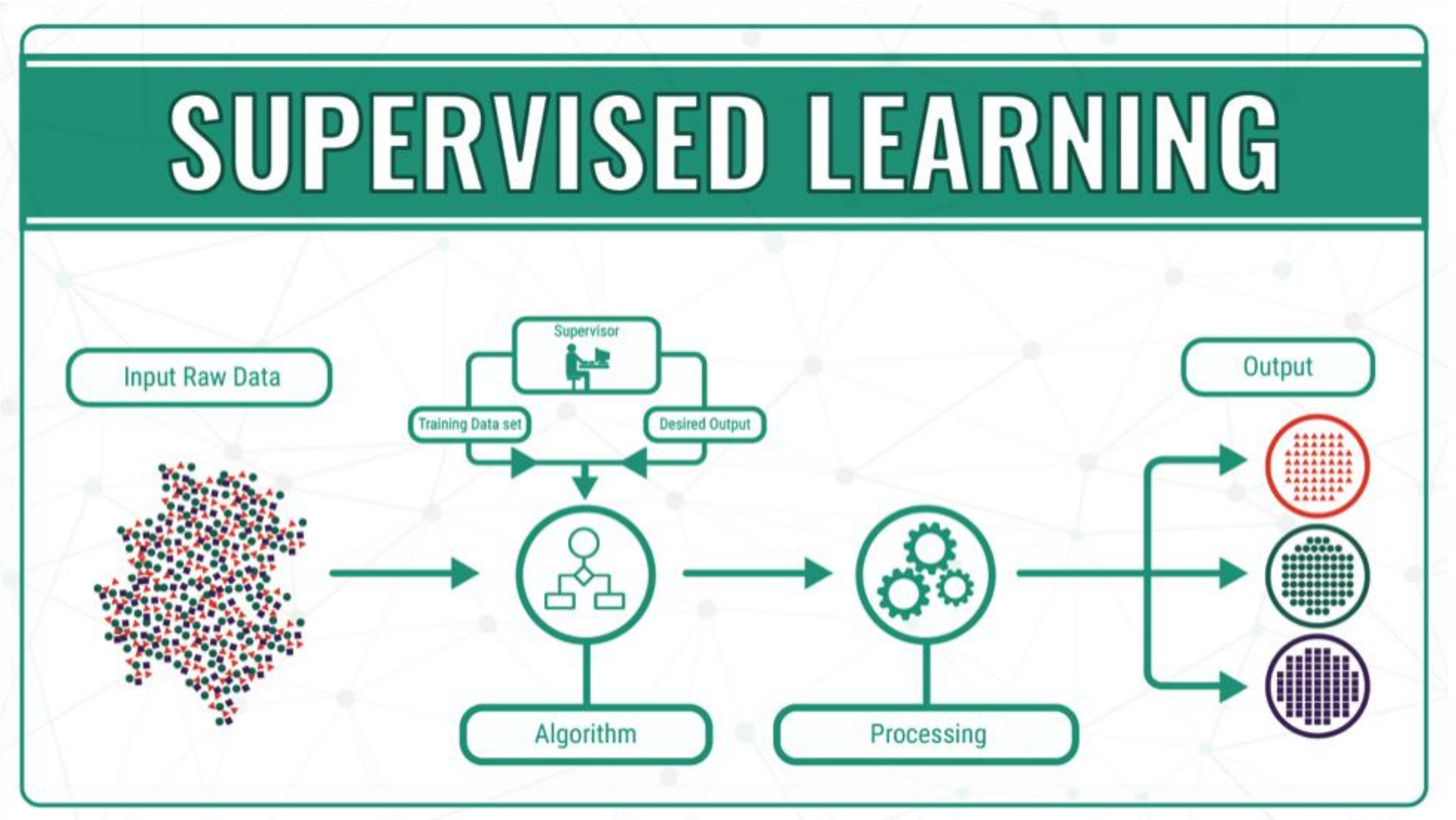
FIAP

Machine Learning Use Cases

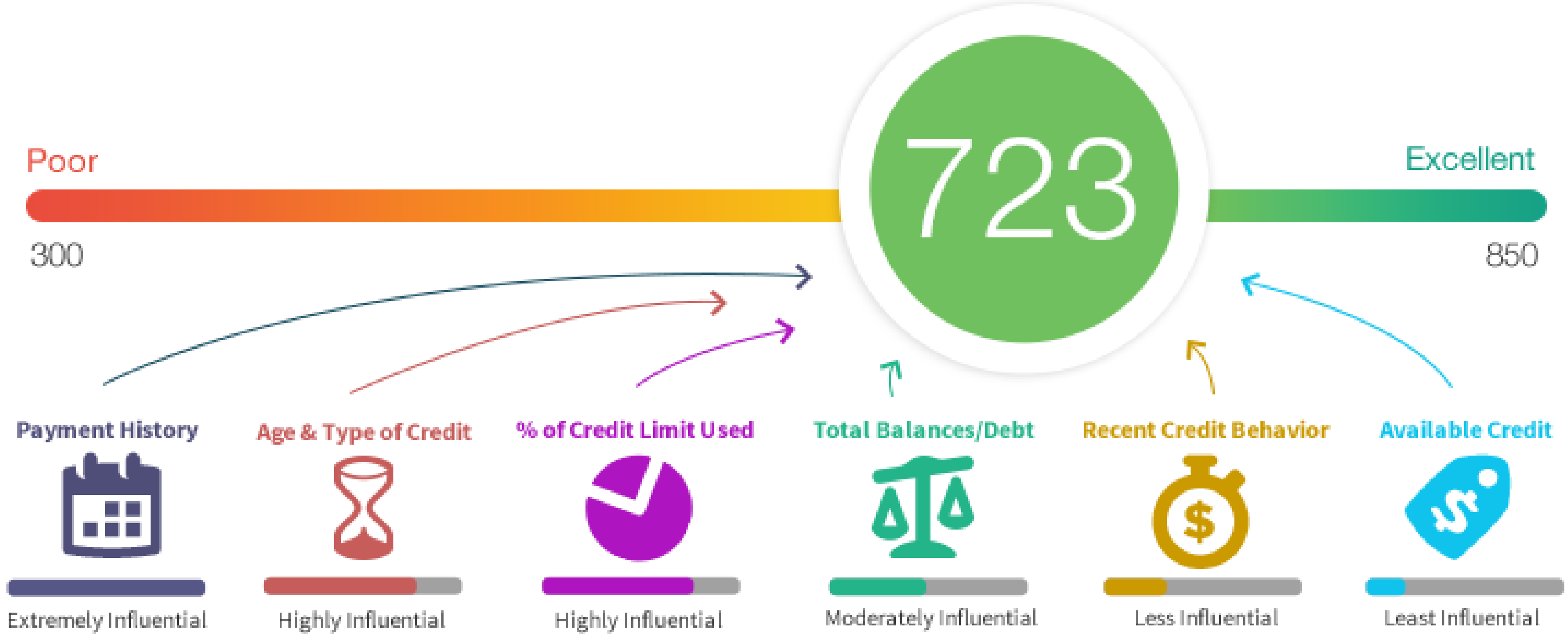
	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Banking	**Predict credit worthiness of credit card holders**: Build a machine learning model to look for delinquency attributes by providing it with data on delinquent and non-delinquent customers	**Segment customers by behavioral characteristics**: Survey prospects and customers to develop multiple segments using clustering	**Create a 'next best offer' model for the call center group**: Build a predictive model that learns over time as users accept or reject offers made by the sales staff
Healthcare	**Predict patient readmission rates**: Build a regression model by providing data on the patients' treatment regime and readmissions to show variables that best correlate with readmissions	**Categorize MRI data by normal or abnormal images**: Use deep learning techniques to build a model that learns different features of images to recognize different patterns	**Allocate scarce medical resources to handle different types of ER cases**: Build a Markov Decision Process that learns treatment strategies for each type of ER case
Retail	**Analyze products customers buy together**: Build a supervised learning model to identify frequent item sets and association rules from transactional data	**Recommend products to customers based on past purchases**: Build a collaborative filtering model based on past purchases by "customers like them"	**Reduce excess stock with dynamic pricing**: Build a dynamic pricing model that adjusts the price based on customer response to offers

APRENDIZAGEM SUPERVISIONADA

Aprendizagem Supervisionada



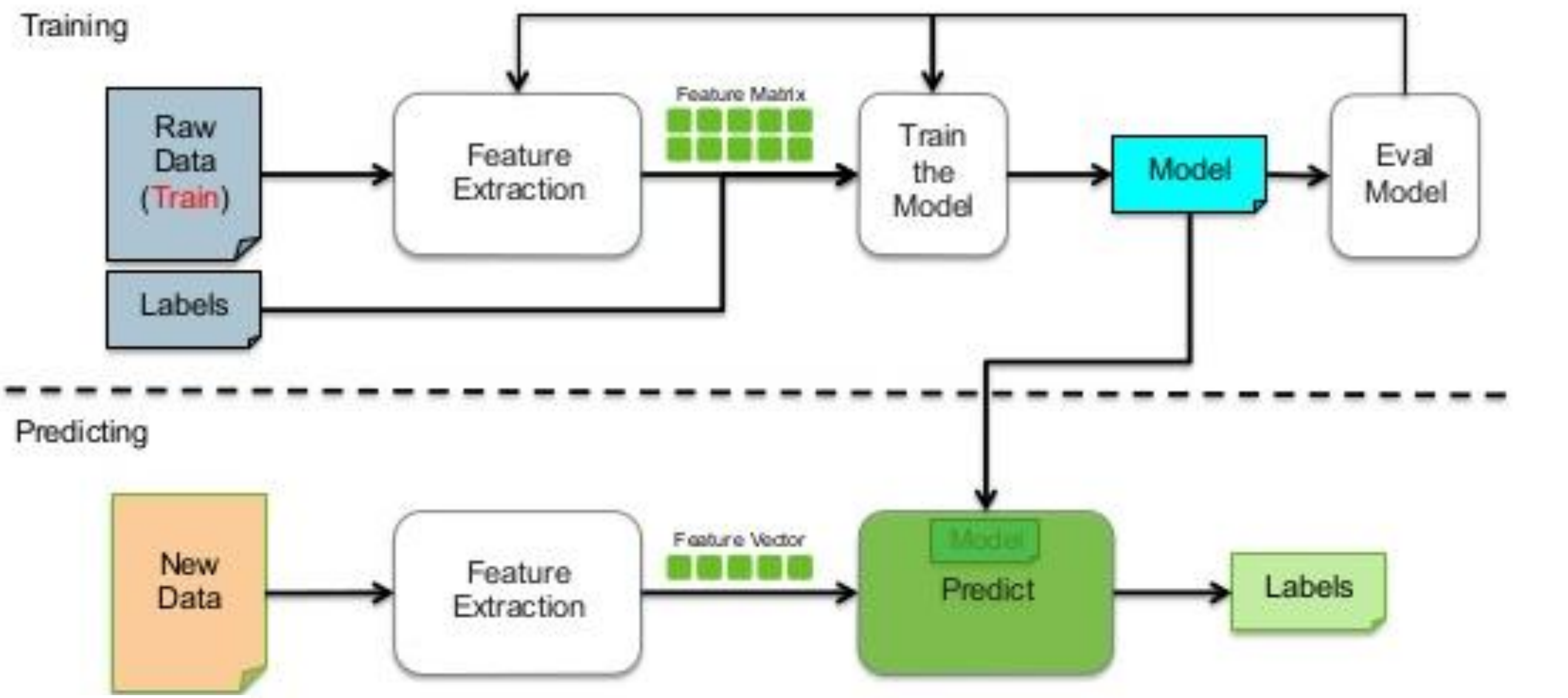
Aplicações



Poor
Excellent
723
300
850
Payment History
Extremely Influential
Age & Type of Credit
Highly Influential
% of Credit Limit Used
Highly Influential
Total Balances/Debt
Moderately Influential
Recent Credit Behavior
Less Influential
Available Credit
Least Influential

Fluxo da Aprendizagem Supervisionada

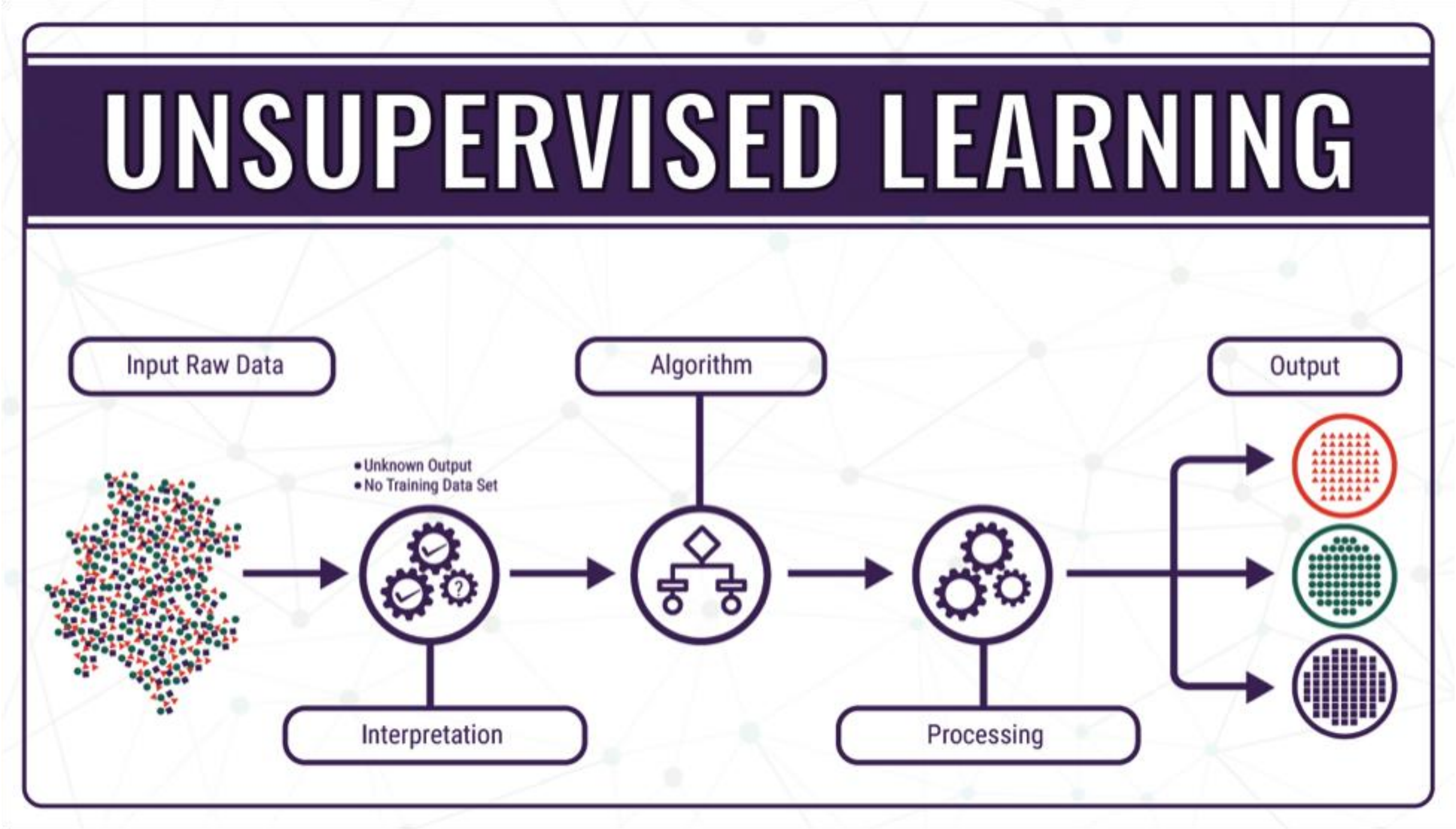
FIAP



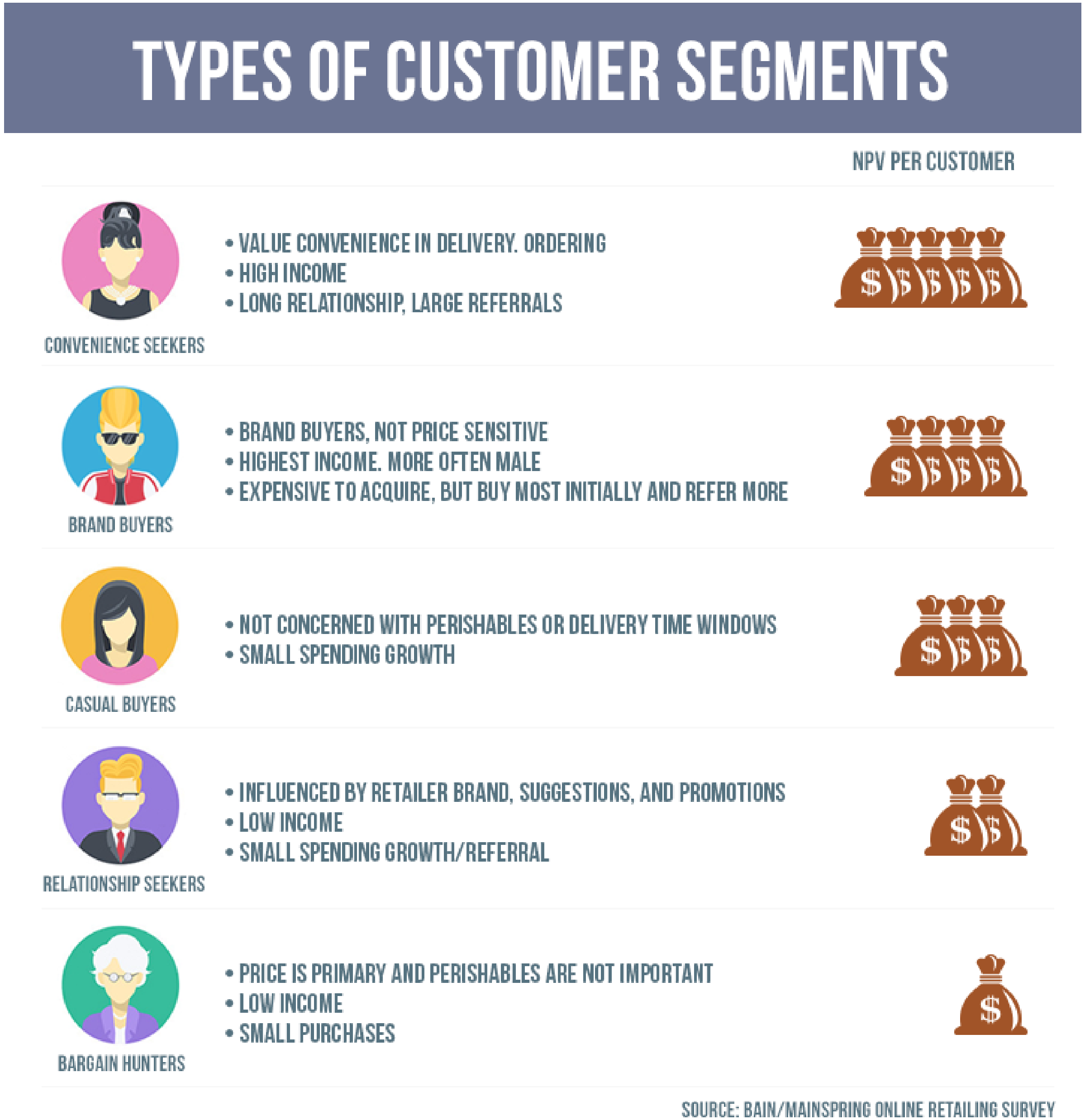
Predict credit worthiness of credit card holders: Build a machine learning model to look for delinquency attributes by providing it with data on delinquent and non-delinquent customers

APRENDIZAGEM NÃO-SUPERVISIONADA

Aprendizagem não Supervisionada

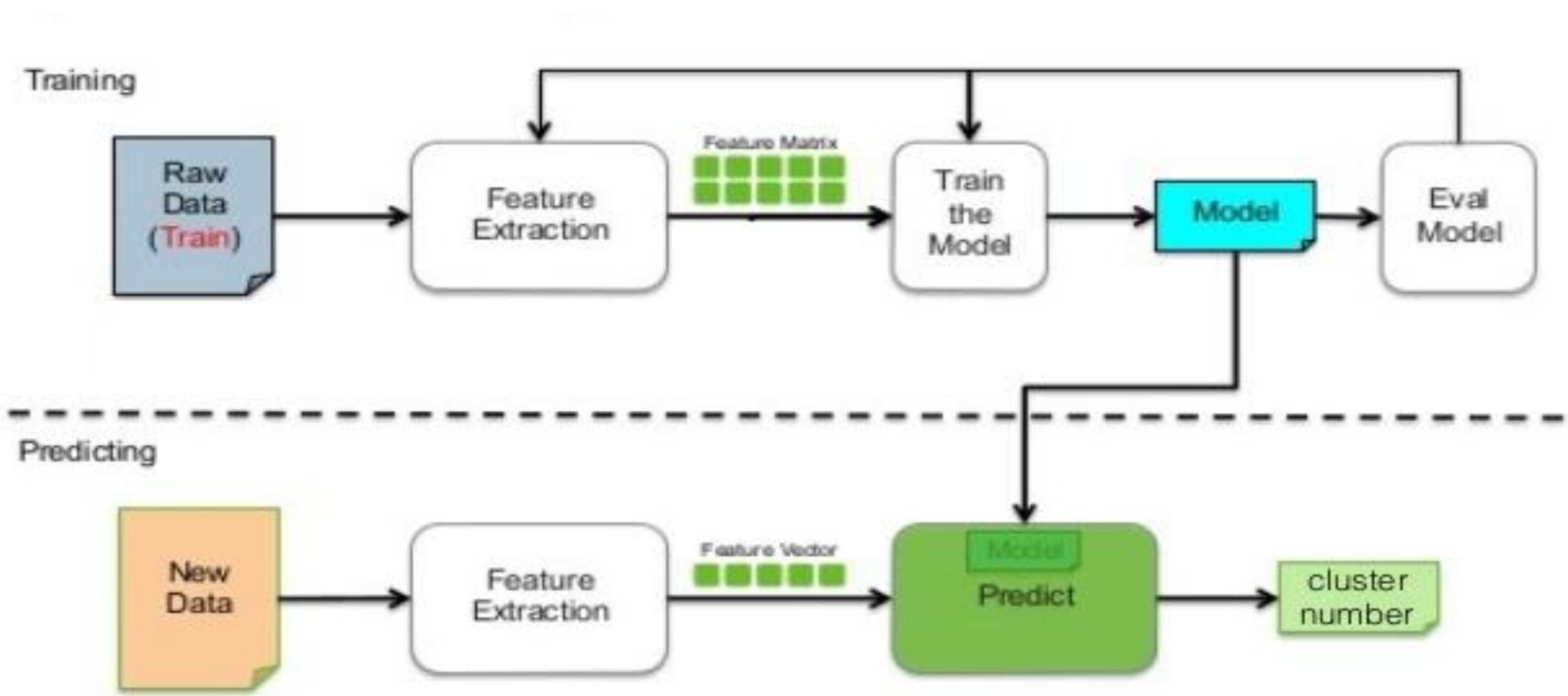


Aplicações



TYPES OF CUSTOMER SEGMENTS
NPV PER CUSTOMER
• VALUE CONVENIENCE IN DELIVERY. ORDERING
• HIGH INCOME
• LONG RELATIONSHIP, LARGE REFERRALS
CONVENIENCE SEEKERS
• BRAND BUYERS, NOT PRICE SENSITIVE
• HIGHEST INCOME. MORE OFTEN MALE
• EXPENSIVE TO ACQUIRE, BUT BUY MOST INITIALLY AND REFER MORE
BRAND BUYERS
• NOT CONCERNED WITH PERISHABLES OR DELIVERY TIME WINDOWS
• SMALL SPENDING GROWTH
CASUAL BUYERS
• INFLUENCED BY RETAILER BRAND, SUGGESTIONS, AND PROMOTIONS
• LOW INCOME
• SMALL SPENDING GROWTH/REFERRAL
RELATIONSHIP SEEKERS
• PRICE IS PRIMARY AND PERISHABLES ARE NOT IMPORTANT
• LOW INCOME
• SMALL PURCHASES
BARGAIN HUNTERS
SOURCE: BAIN/MAINSPRING ONLINE RETAILING SURVEY

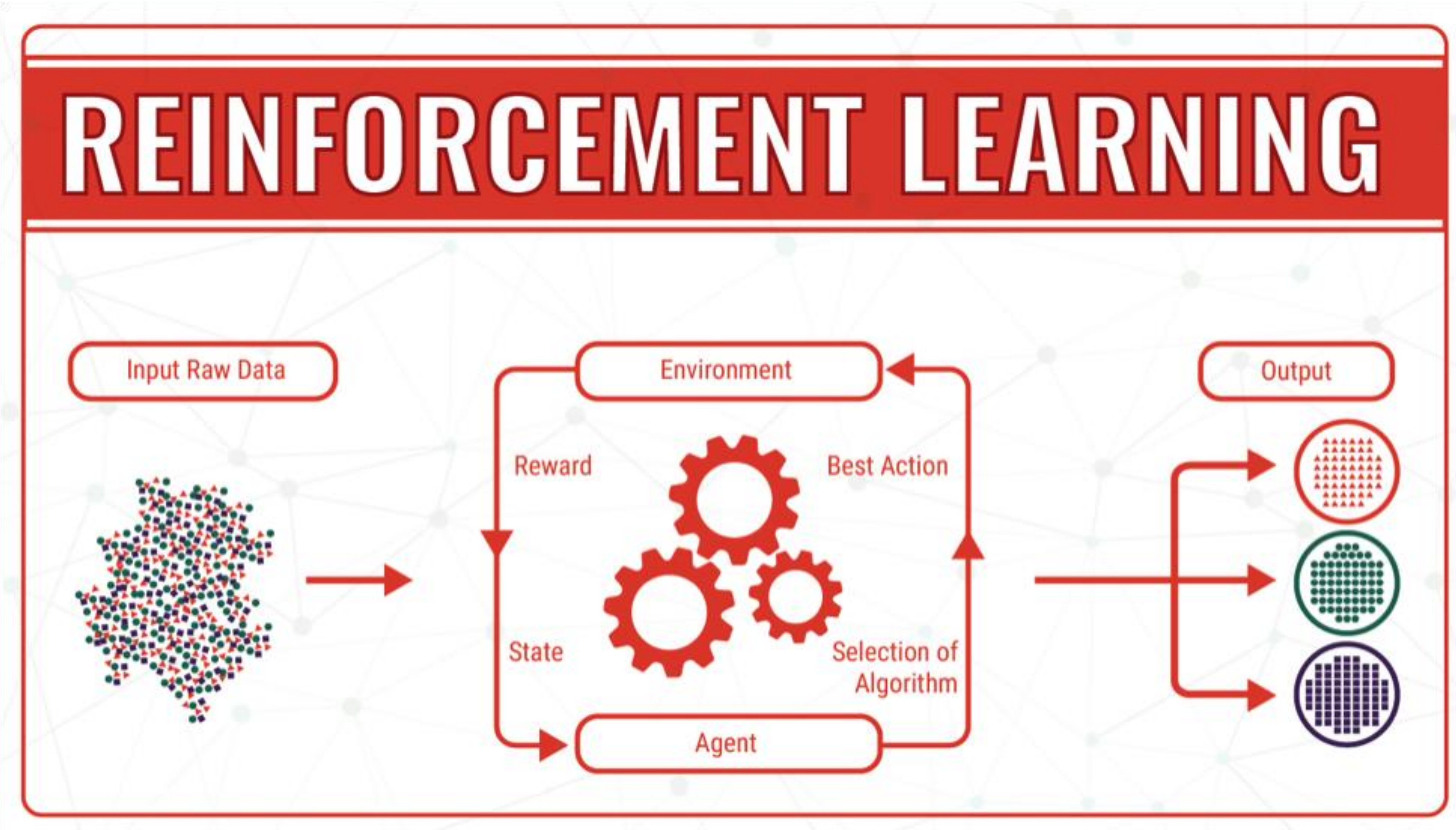
Fluxo da
Aprendizagem Não Supervisionada



Segment customers by behavioral characteristics: Survey prospects and customers to develop multiple segments using clustering

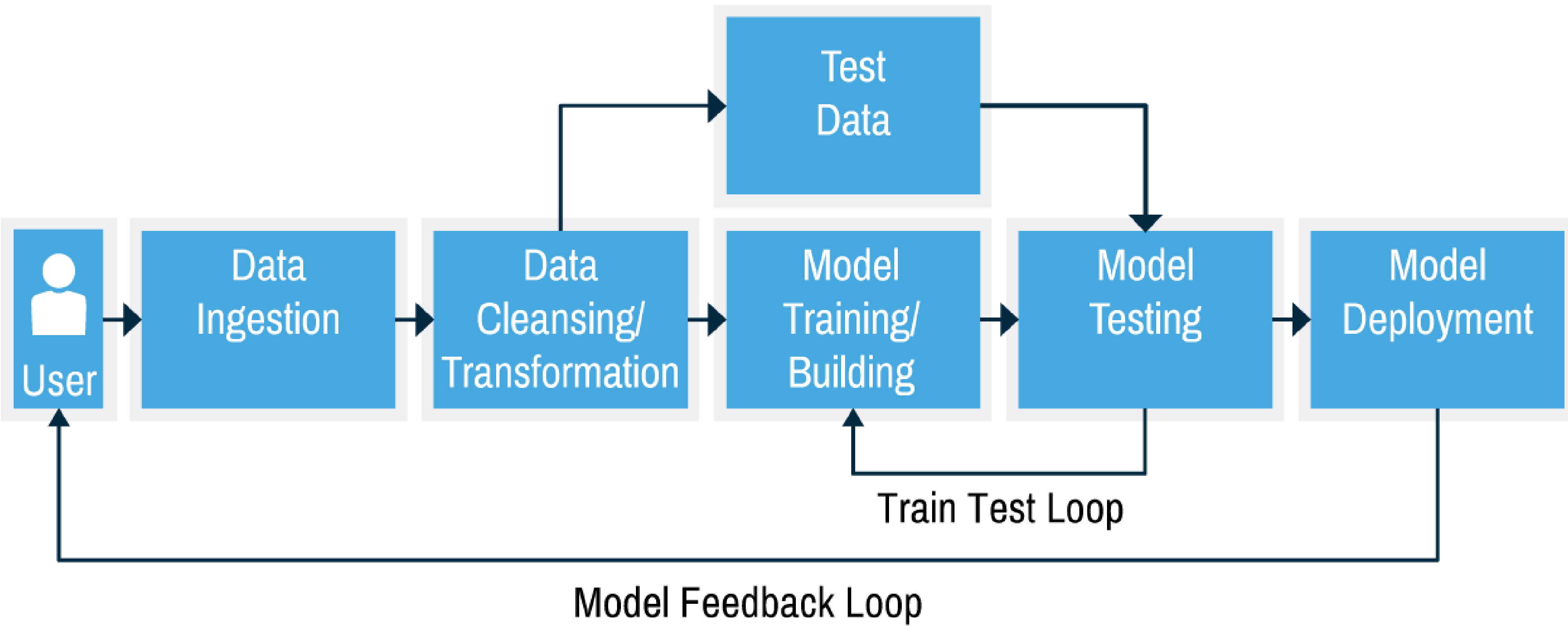
APRENDIZAGEM POR REFORÇO

Aprendizagem por Reforço



Aplicações

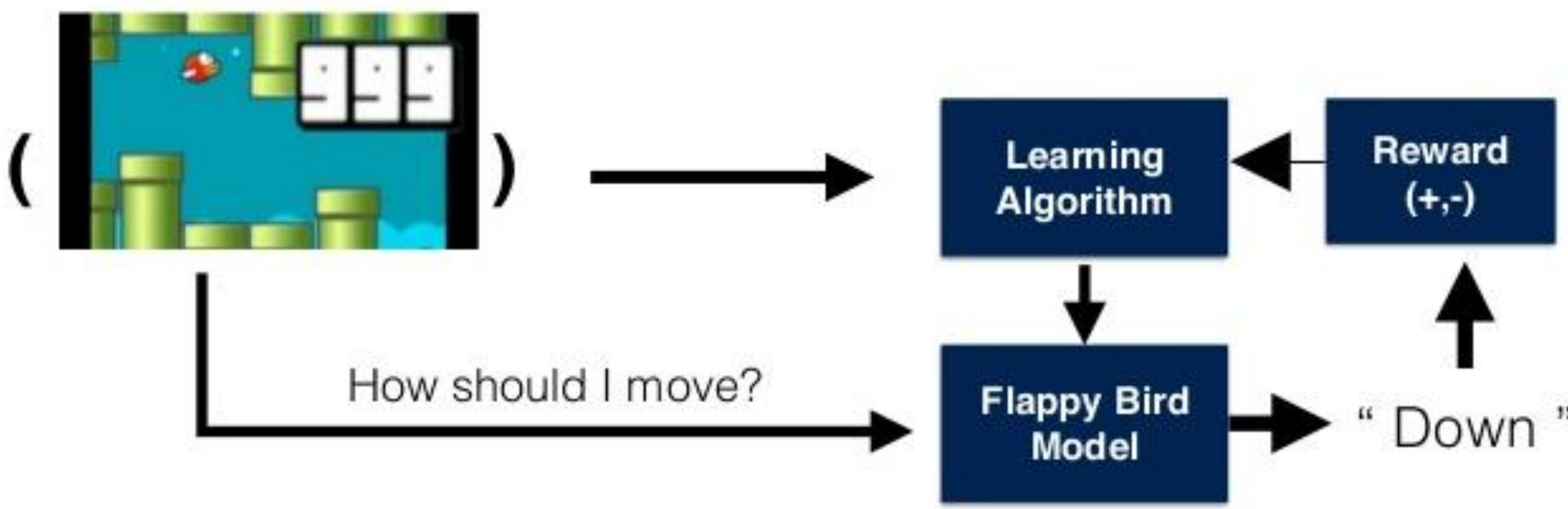
Fluxo da Aprendizagem por Reforço



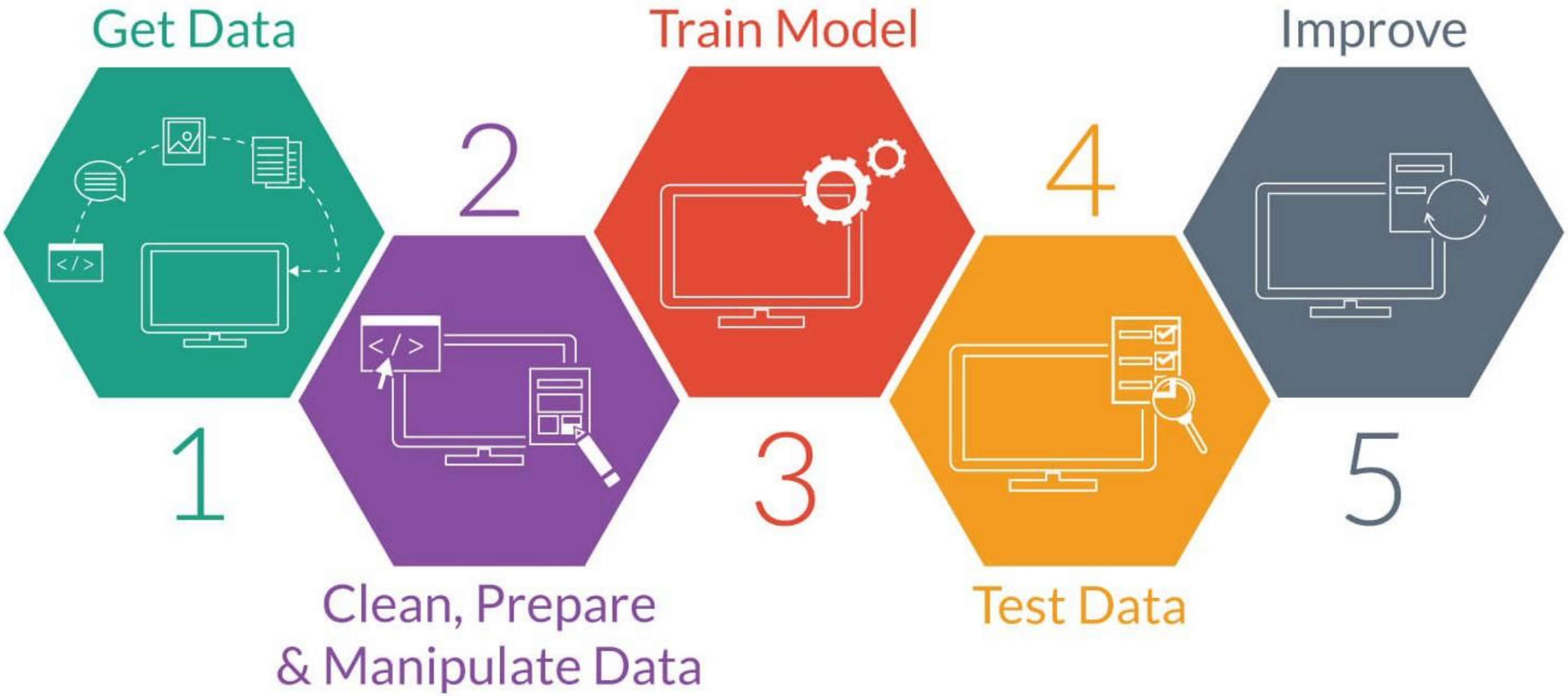
Create a 'next best offer' model for the call center group: Build a predictive model that learns over time as users accept or reject offers made by the sales staff

Fluxo de Trabalho

Reinforcement Learning



Resumo - Fluxos de Trabalho



ALGORITMOS

Tipos de Algoritmos

Regressão: ***Previsão de valores***

Se quisermos prever números antes que eles ocorram, os métodos de regressão são adequados. A regressão linear é um dos métodos de regressão e é um dos mais populares em aprendizado de máquina.

Classificação: ***Previsão de Categorias***

Se houver a necessidade de classificar objetos ou categorias com base em suas classificações e atributos históricos, serão usados métodos de classificação, como árvores de decisão (DT também pode ser Regressão).

Clusterização: ***Agrupamento em categorias desconhecidas***

Se não tivermos idéia sobre os dados e quisermos dividí-los em subgrupos para entender seu comportamento coletivo, a clusterização é um dos métodos de referência.

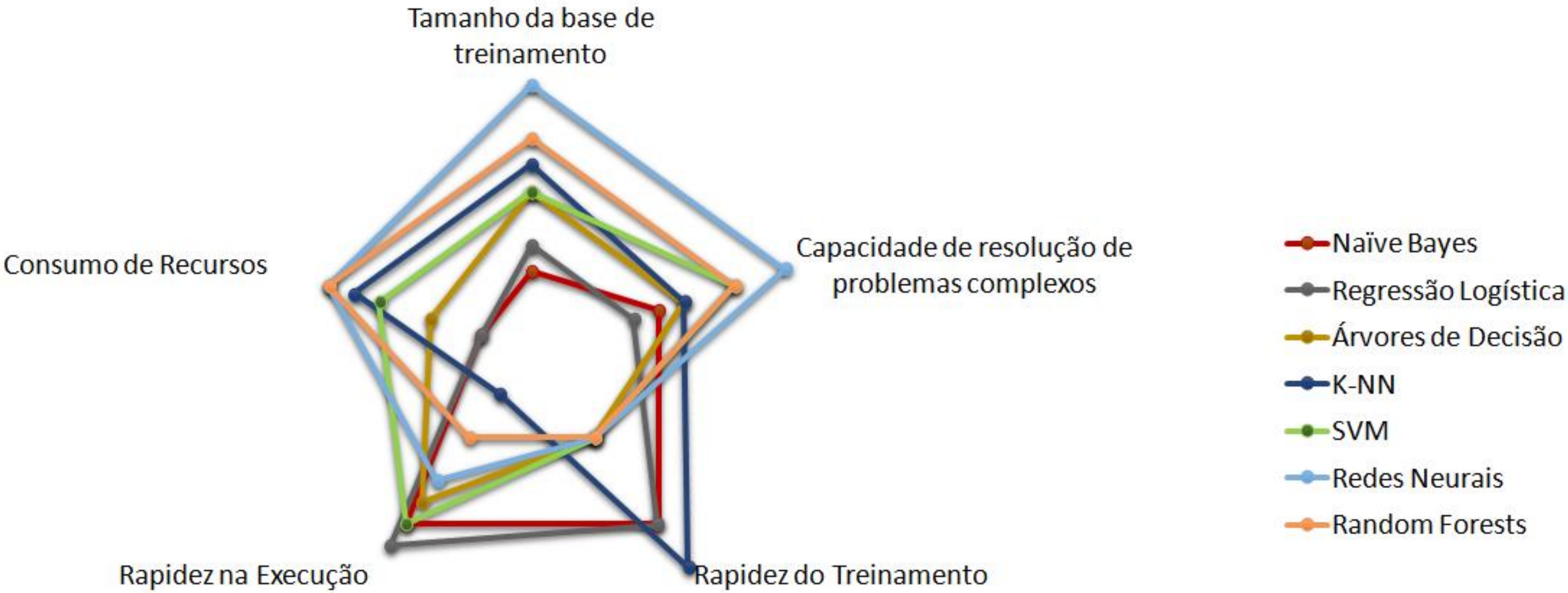
ALGORITMOS DE CLASSIFICAÇÃO

Classificação

Se o valor da predição tende a ser uma categoria como sim/não, positivo/negativo etc, ele se caracteriza como um problema de classificação em Machine Learning.

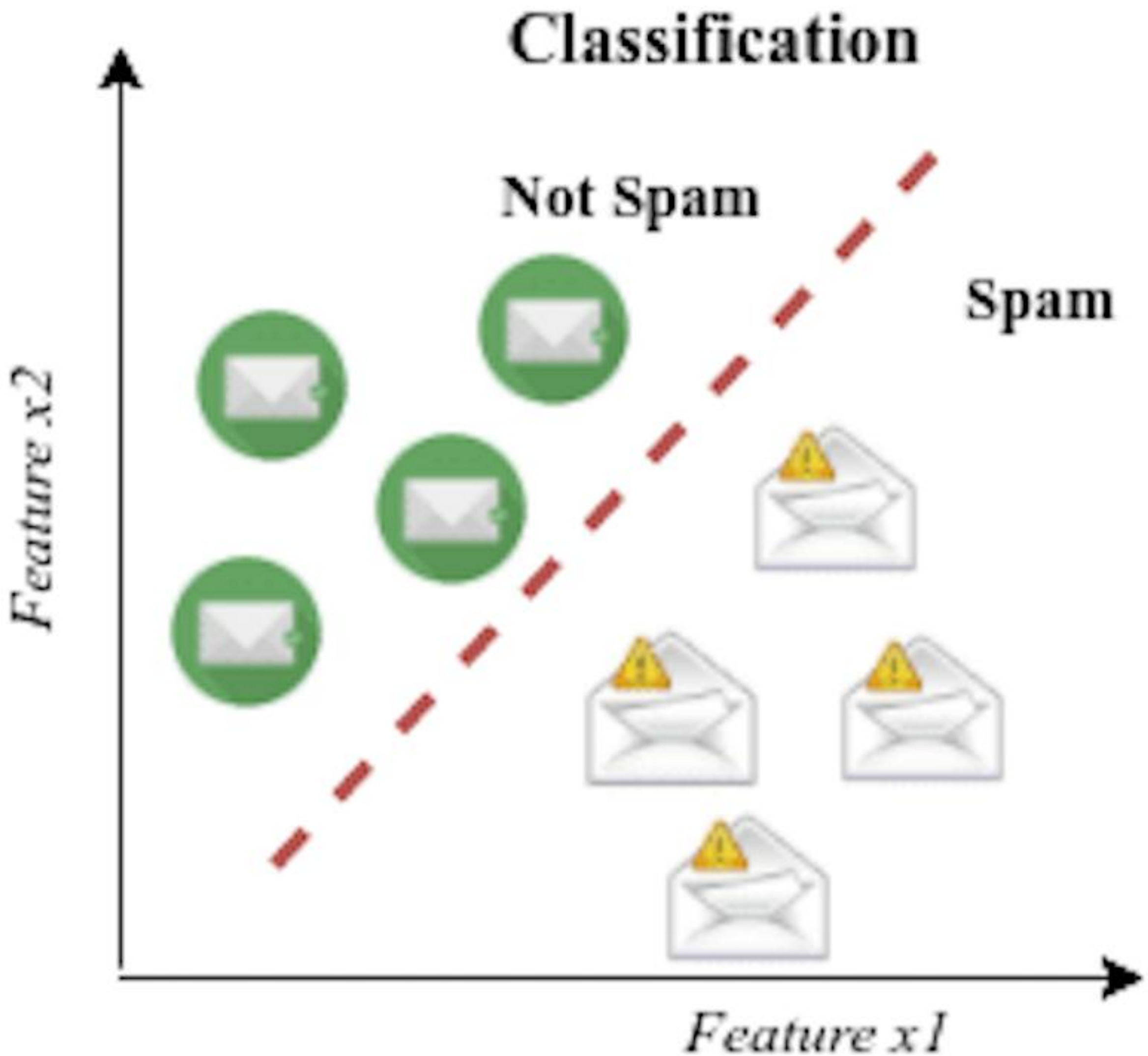
Exemplo: Dada uma frase, prever se é um review negativo ou positivo.

Classificação

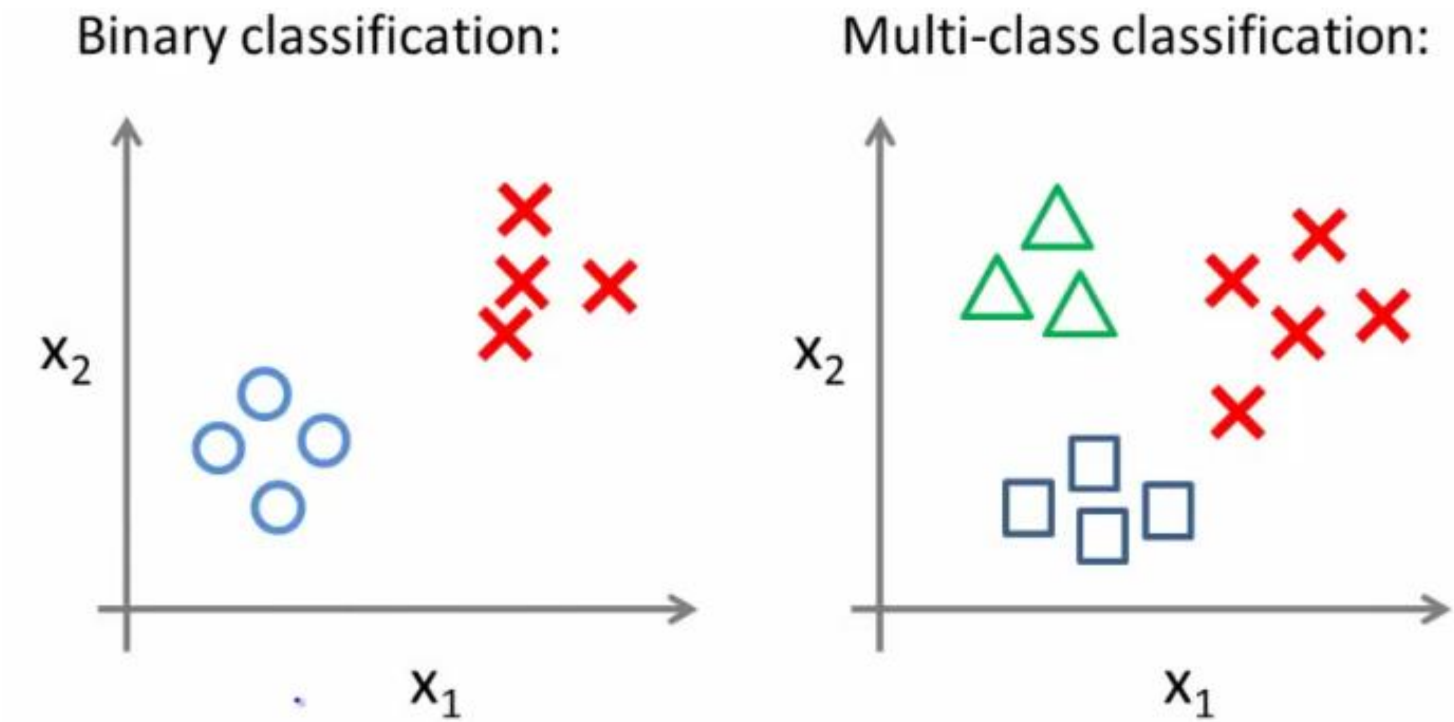


Fonte: Flávio A. Rezende Calado

Classificação



Classificação



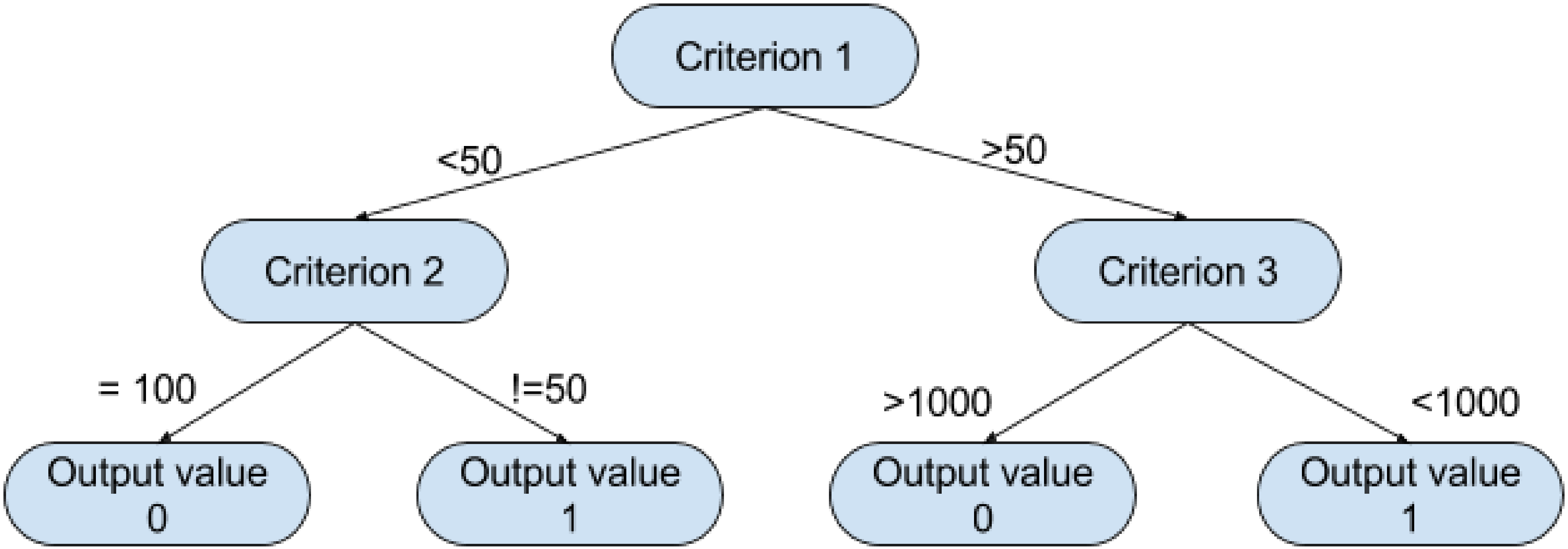
TOMATO SORTING

https://www.youtube.com/watch?v=Lz88nsWL4kw

UBER – ATENÇÃO NA ESTRADA

https://www.youtube.com/watch?v=iMOD9TYRtr8

CLASSIFICAÇÃO COM ÁRVORE DE DECISÃO



ÁRVORE DE DECISÃO

Eficiência Computacional

- Modelo de classificação *in-memory*
- Pouco acesso a base de dados
- Baixo custo computacional

ÁRVORE DE DECISÃO

Compreensão e transparência

- Muito utilizados por bancos pela extrema transparência na decisão baseada em regras.

ÁRVORE DE DECISÃO

Qualidade dos dados

- São capazes de lidar com bases de dados com erros e valores faltantes.

ÁRVORE DE DECISÃO

Error Rates

- Apresentam taxas de erros relativamente altas, mas não tão altas quanto a regressão linear.

ÁRVORE DE DECISÃO

Compatibilidade de dados

- Árvores de decisão podem manipular dados com atributos numéricos ou nominais.

ÁRVORE DE DECISÃO

Impacto do número de atributos

- Estes algoritmos tendem a producir resultados errados se fatores complexos ou intangíveis estiverem presentes, como no caso de segmentação de clientes, por exemplo.

ALGORITMOS DE REGRESSÃO

Regressão

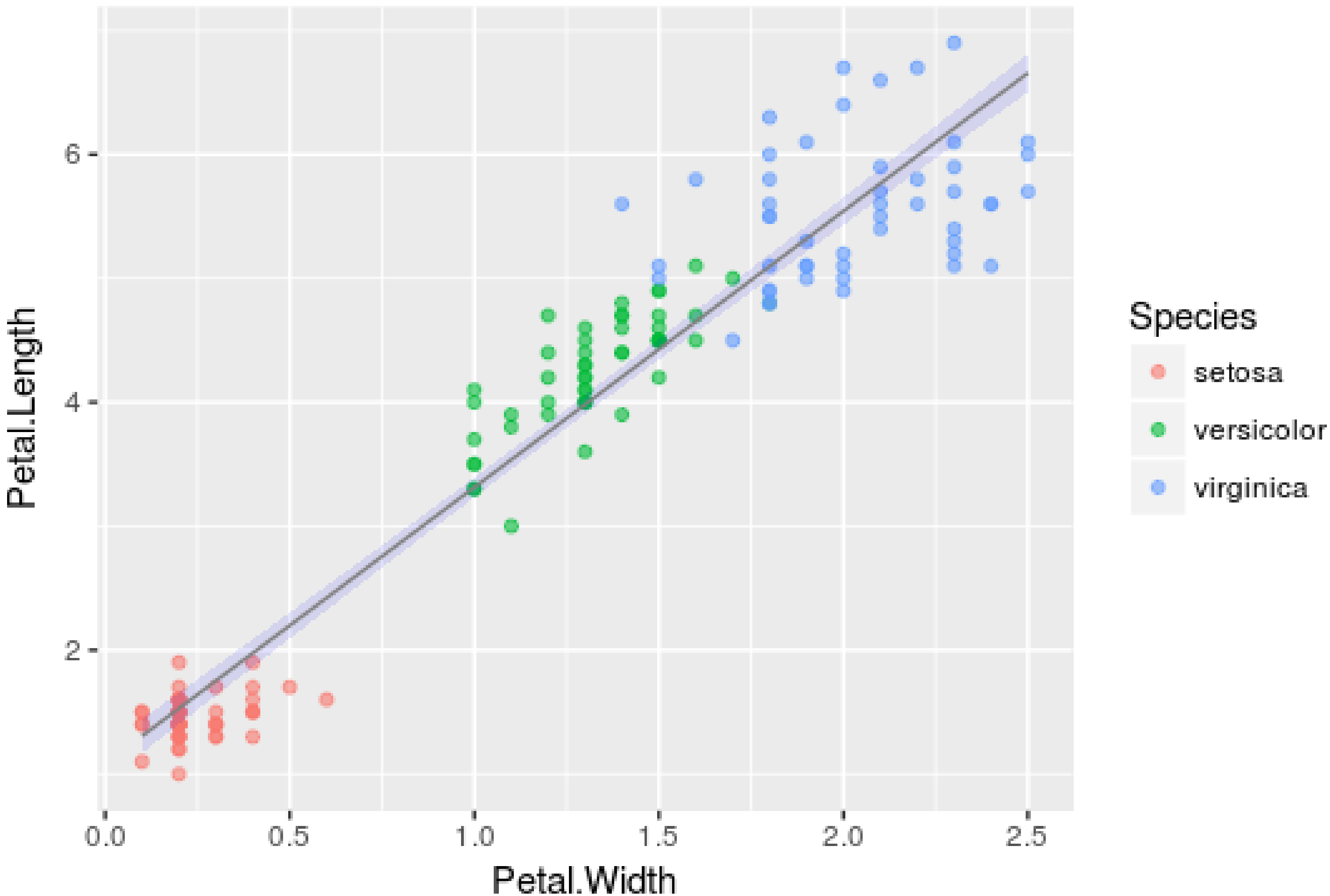
Se o valor a ser previsto tende a ser contínuo ele se caracteriza como um problema de Regressão em Machine Learning.

Exemplo: Em função da região, tamanho do terreno etc, prever o custo de um terreno.

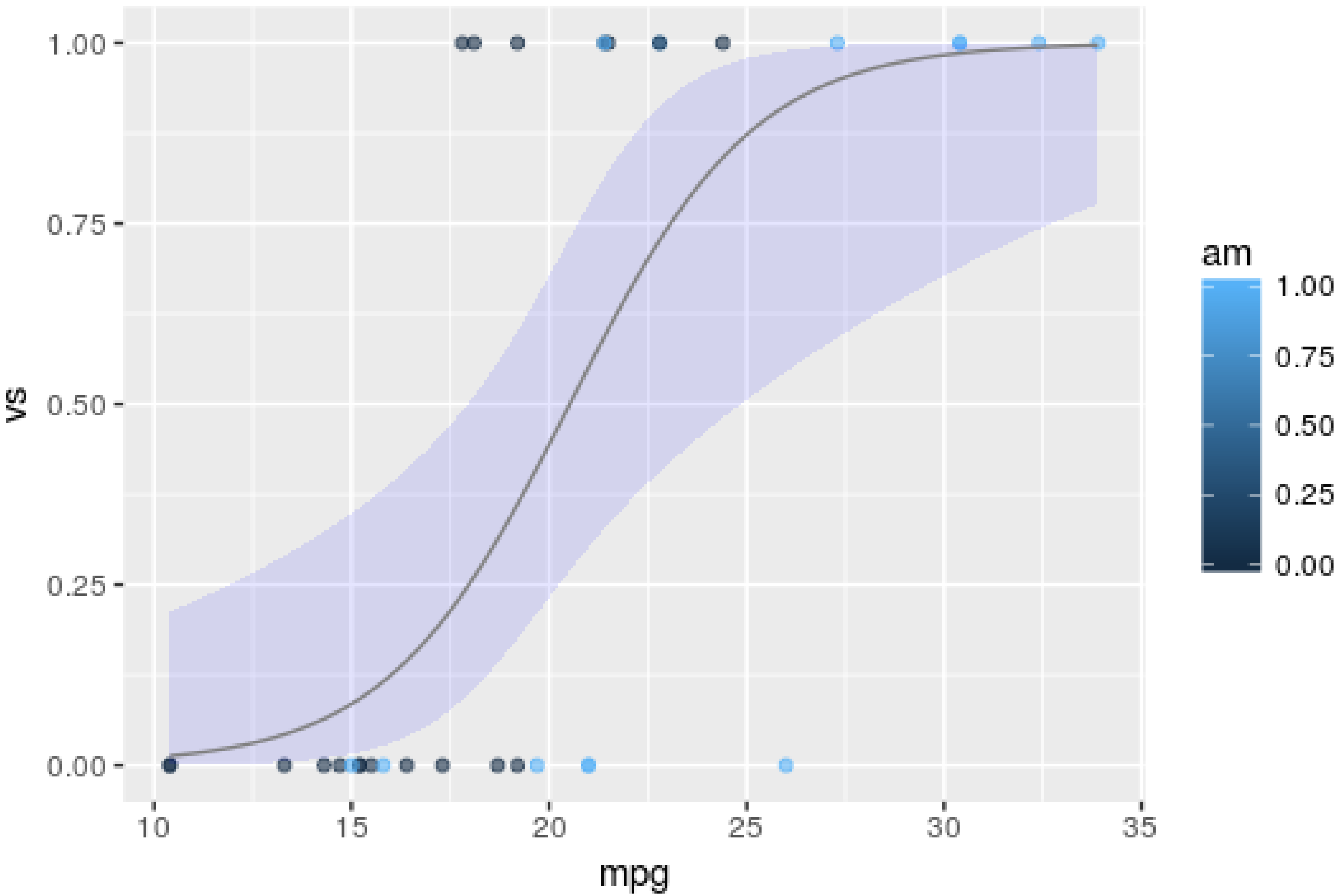
Regressão Linear

- Método mais tradicional
- Utilizado em aplicações práticas
- $Y=f(X)$

REGRESSÃO LINEAR



REGRESSÃO LOGÍSTICA



REGRESSÃO LINEAR

Capacidade para classificação:

- Prevê um valor contínuo.
- Não adequado para classificação

REGRESSÃO LINEAR

Taxa de erro

- Mais fraco que outros algoritmos no aspecto redução da taxa de erro

REGRESSÃO LINEAR

Compatibilidade de dados

- Depende de dados contínuos (numéricos)

REGRESSÃO LINEAR

Qualidade dos dados

- Cada valor faltante prejudica a otimização
- Outliers podem corromper significativamente a saída

REGRESSÃO LINEAR

Complexidade Computacional

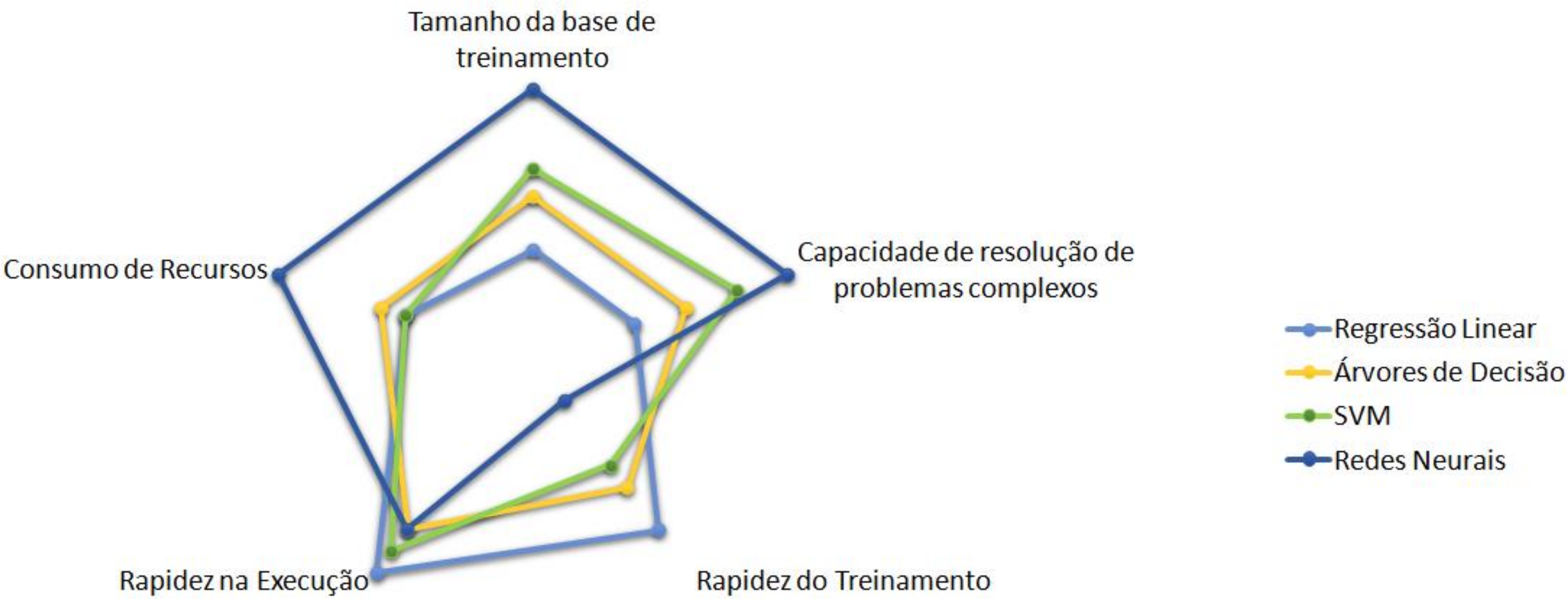
- Comparado a árvores de decisão e clusterização, não é custosa computacionalmente.

REGRESSÃO LINEAR

Compreensão e transparência

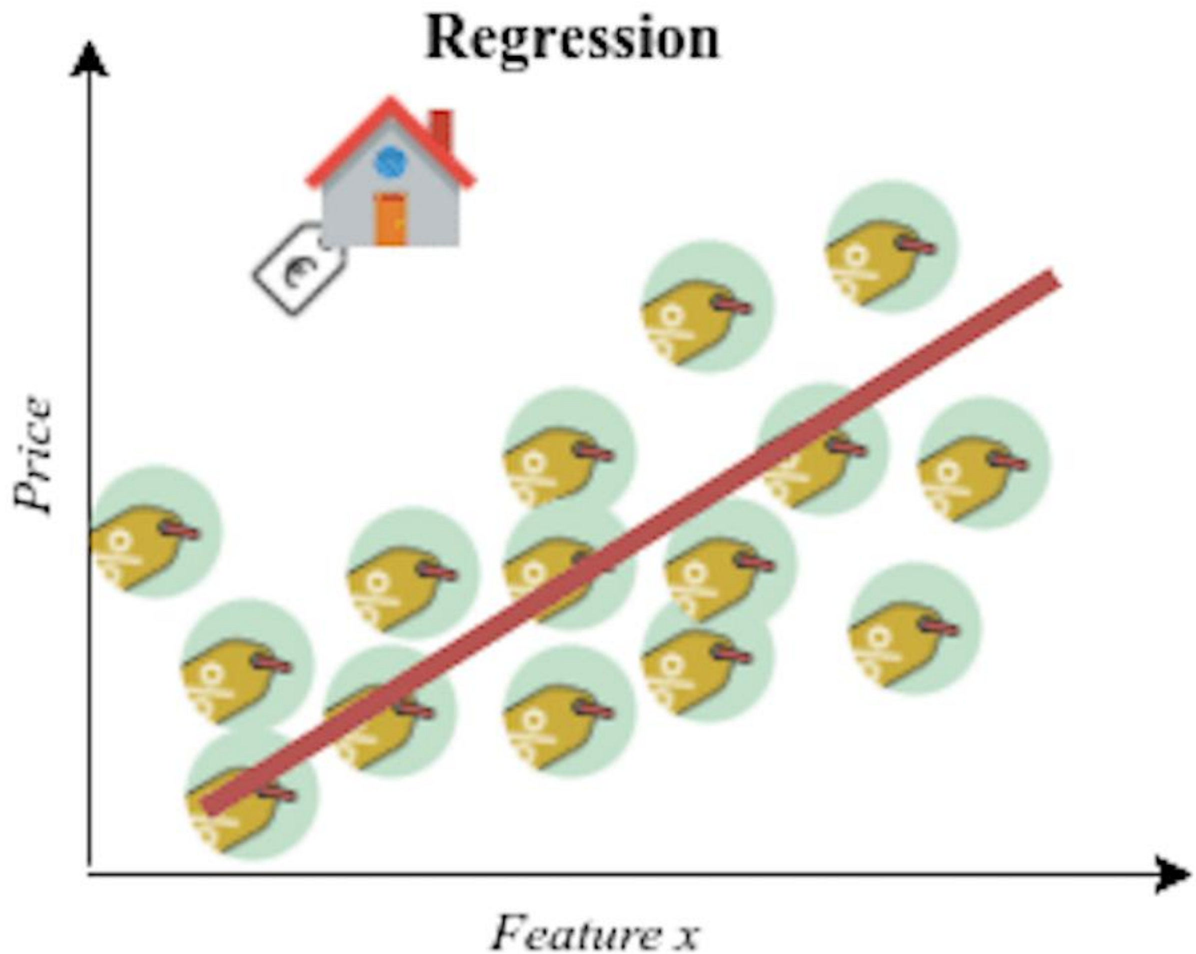
- Facilmente compreensível através de notação matemática

REGRESSÃO



Fonte: Flávio A. Rezende Calado

Regressão



ALGORITMOS DE CLUSTERIZAÇÃO

Clusterização

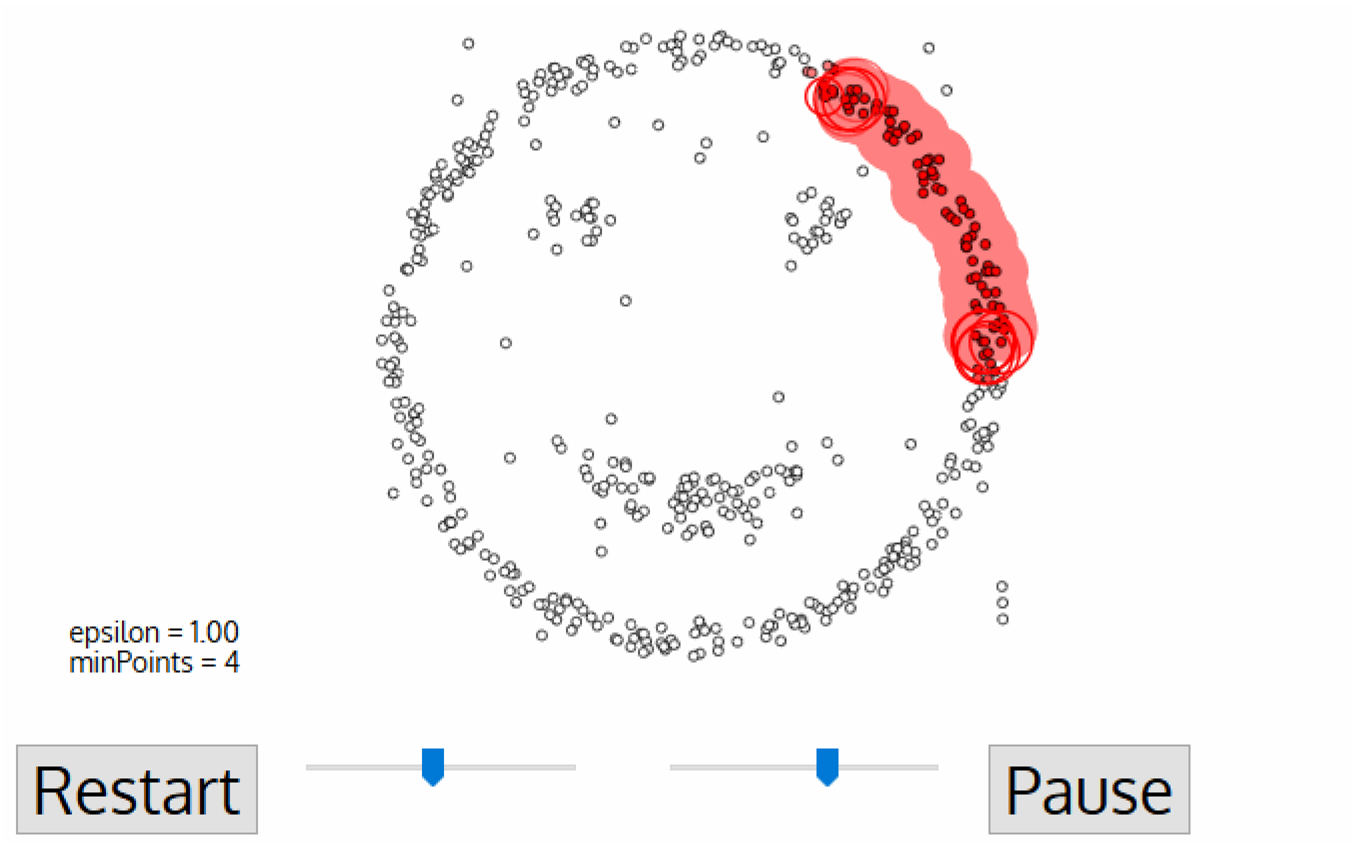
Agrupamento de um conjunto de pontos em um determinado número de clusters.

Exemplo: Dados os números 3, 4, 8 e 9, e uma quantidade de clusters igual a 2, o algoritmo deve dividir em dois clusters (3, 4) e (8, 9).

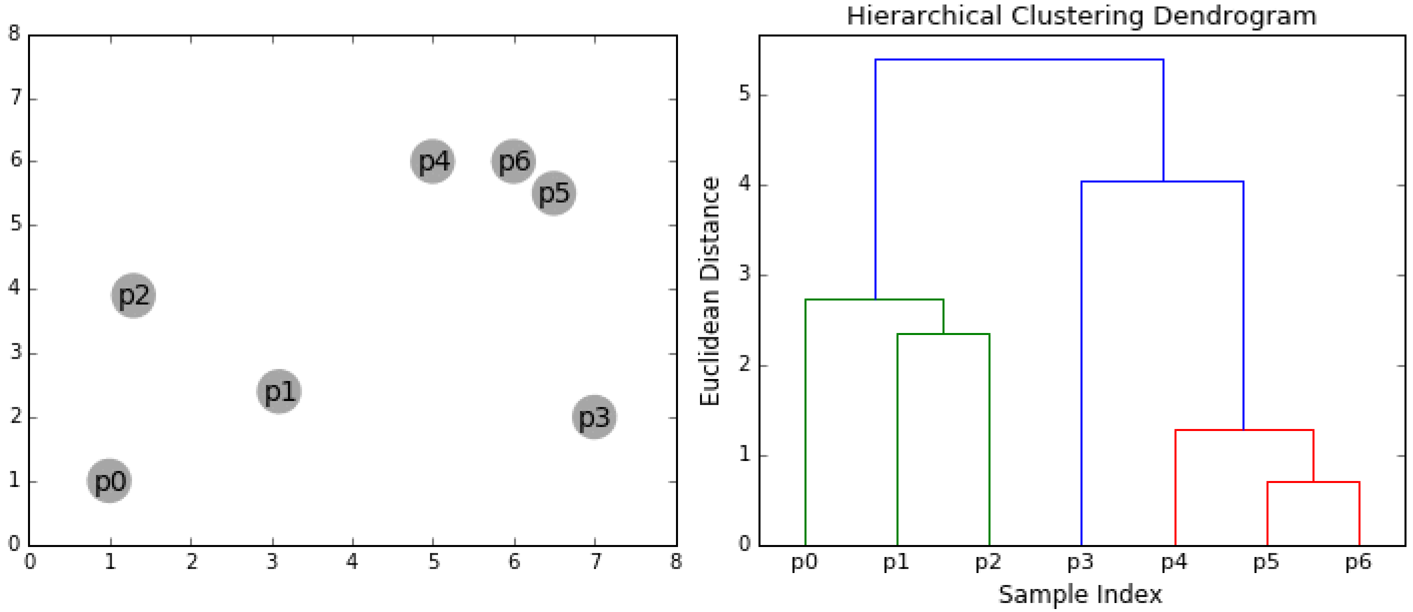
CLUSTERIZAÇÃO

Agrupamento em segmentos com características similares.

Aprendizagem não supervisionada, busca padrões na própria estrutura dos dados sob análise



Density-Based Spatial Clustering of Applications with Noise (DBSCAN)



Agglomerative Hierarchical Clustering

CLUSTERIZAÇÃO

Capacidade de manipulação de dados

- Compatível com a maioria dos tipos de dados e ignora dados faltantes.

CLUSTERIZAÇÃO

Qualidade dos dados

- Funciona bem com dados contínuos ou fatoriais

CLUSTERIZAÇÃO

Compreensibilidade e Transparência

- Requer explicações no nível da implementação, não compreensíveis diretamente por leigos.

CLUSTERIZAÇÃO

Eficiência Computacional

- São algoritmos custosos computacionalmente, pois requerem frequentes consulta à base de dados.

CLUSTERIZAÇÃO

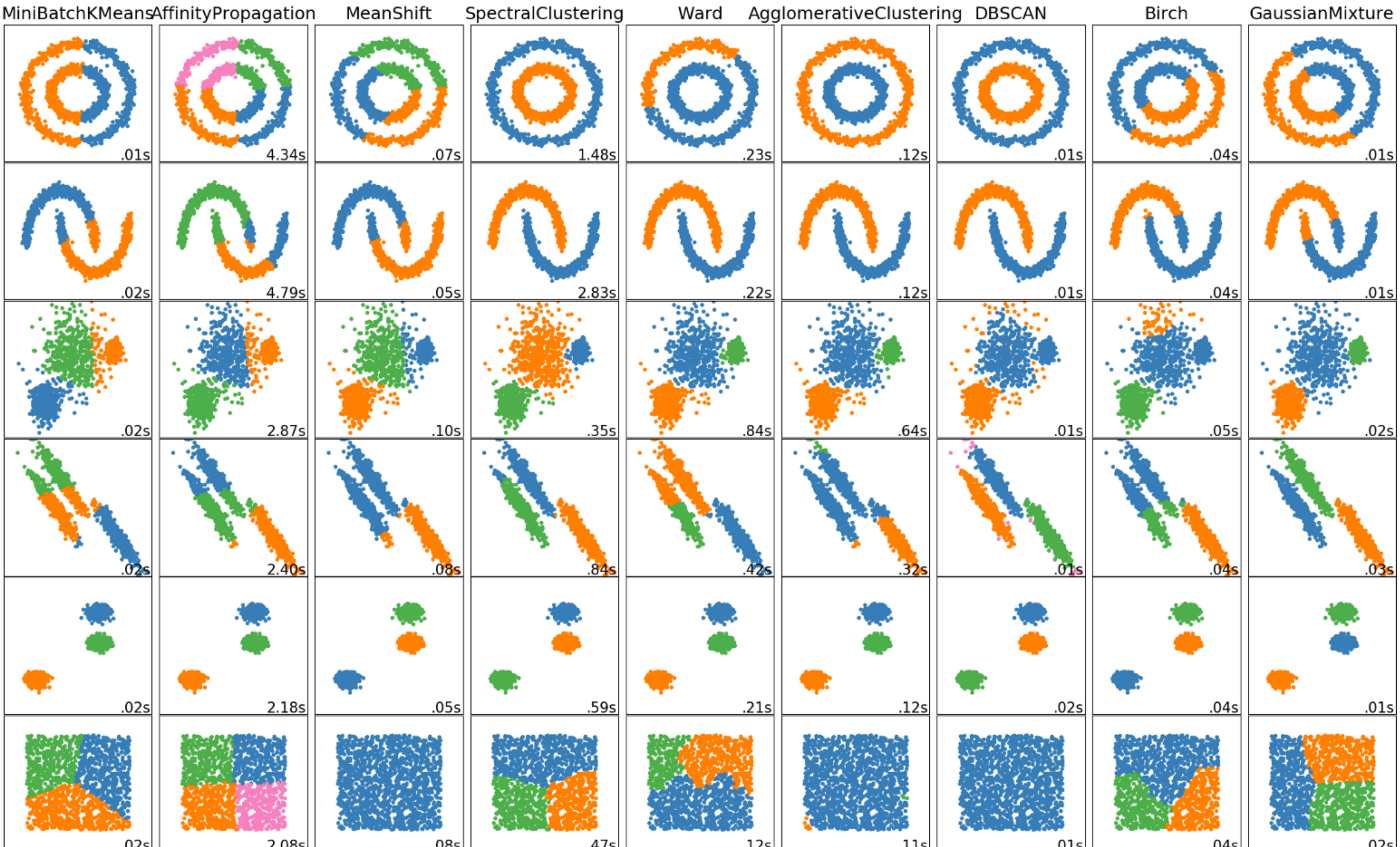
Taxa de erros

- Semelhante aos classificadores bayesianos (baixa)

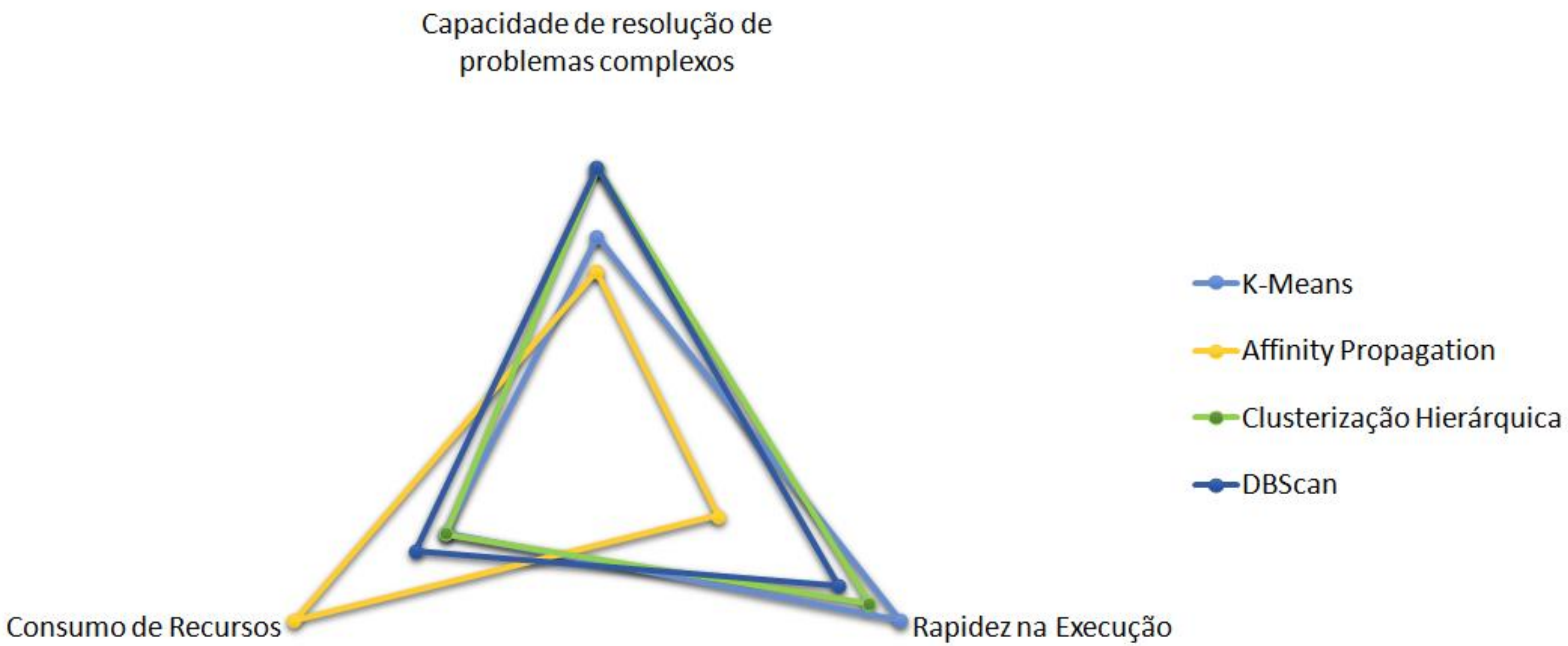
CLUSTERIZAÇÃO

Impacto do número de atributos

- Capazes de manipular múltiplos atributos e interações complexas.

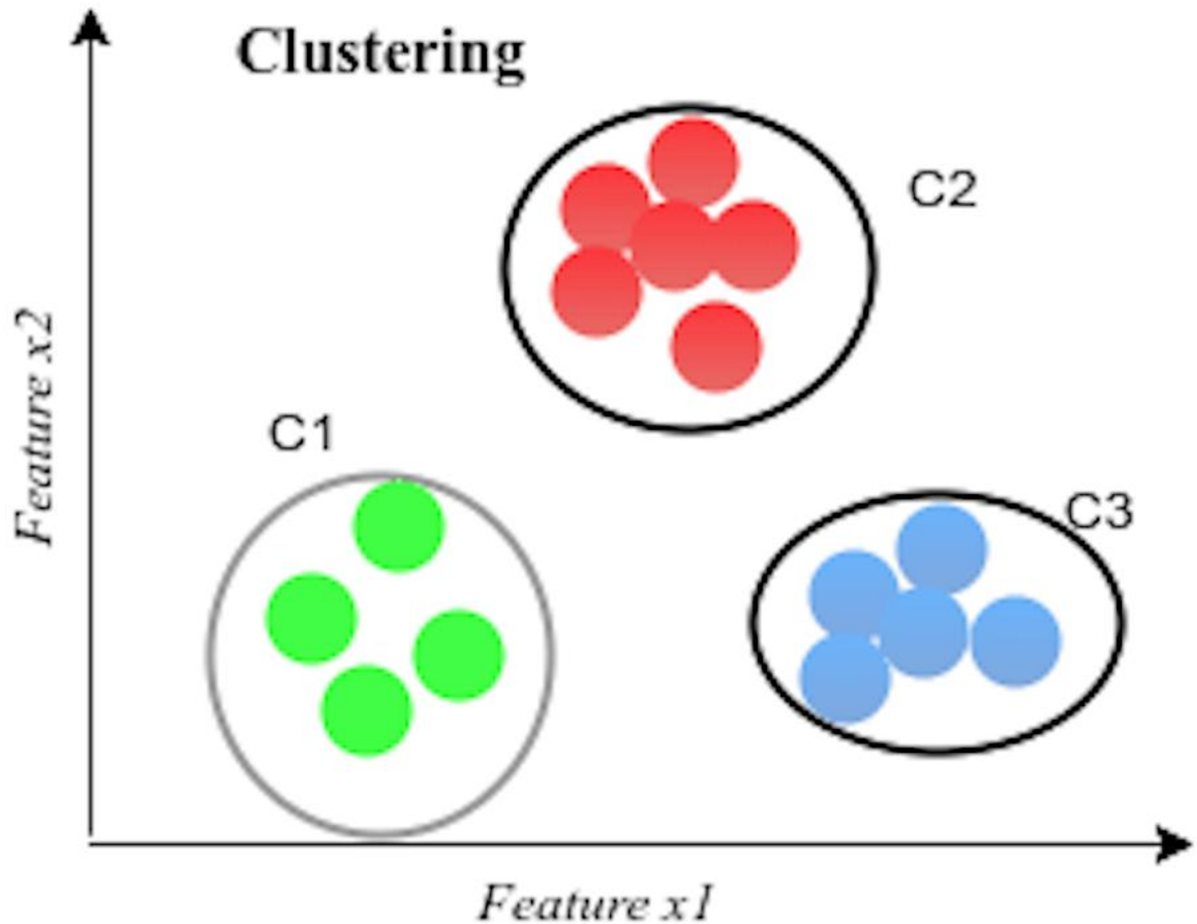

MiniBatchKMeans
AffinityPropagation
MeanShift
SpectralClustering
Ward
AgglomerativeClustering
DBSCAN
Birch
GaussianMixture
.01s
4.34s
.07s
1.48s
.23s
.12s
.01s
.04s
.01s
.02s
4.79s
.05s
2.83s
.22s
.12s
.01s
.04s
.01s
.02s
2.87s
.10s
.35s
.84s
.64s
.01s
.05s
.02s
.02s
2.40s
.08s
.84s
.42s
.32s
.01s
.04s
.03s
.02s
2.18s
.05s
.59s
.21s
.12s
.02s
.04s
.01s
.02s
2.08s
.08s
.47s
.12s
.11s
.01s
.04s
.02s

Clusterização

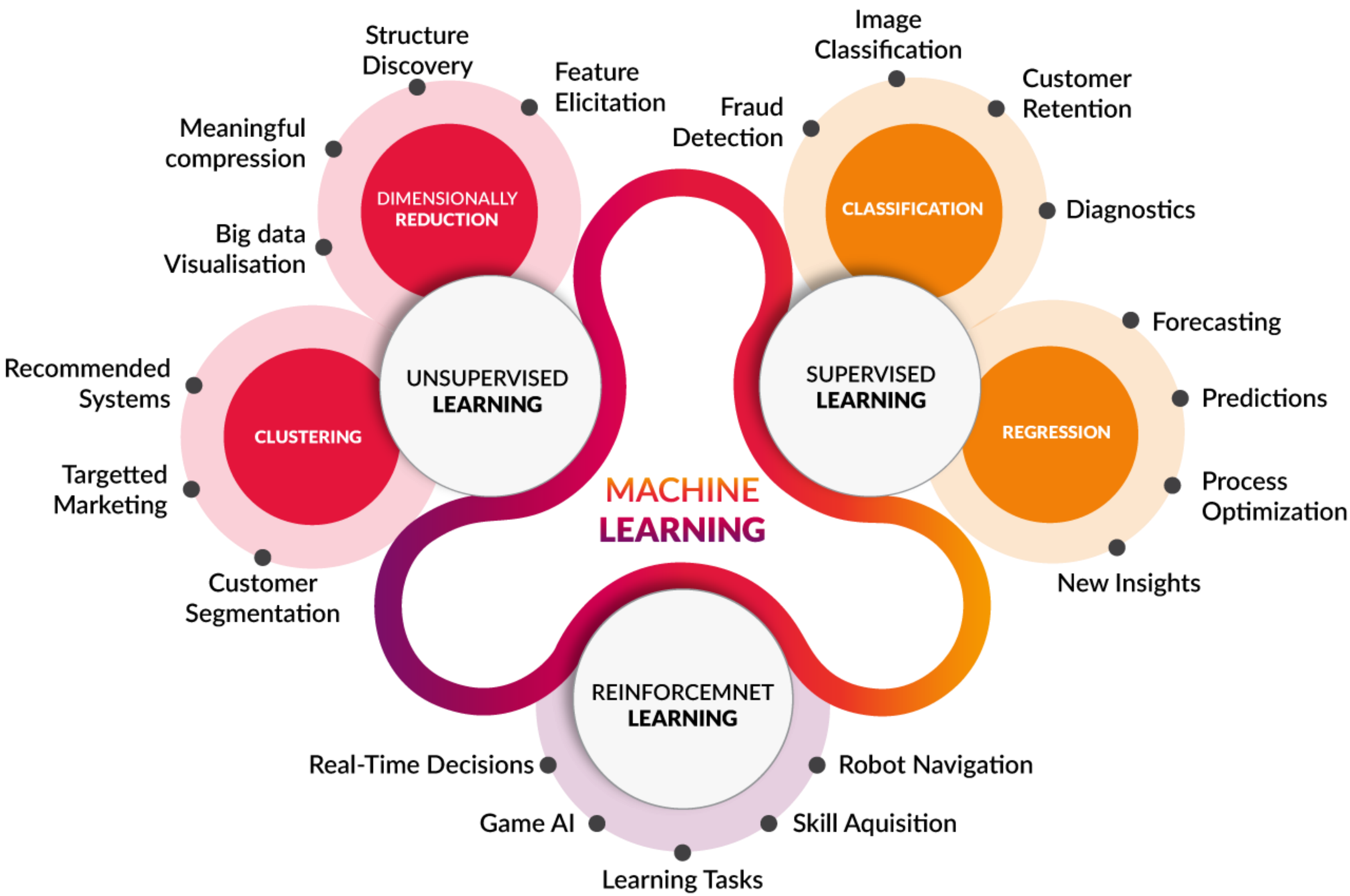


Fonte: Flávio A. Rezende Calado

CLUSTERIZAÇÃO



Aplicações


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

ALGORITMOS PRONTOS E APIs

Ferramentas Python

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, ... — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, ... — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples

http://scikit-learn.org/stable/

IBM

- Conversation
- Translation
- Classifier
- NLU
- Personality Insights
- Speech to text / Text to speech
- Tone Analyser
- Visual Recognition
- Voice Agent (labs)
- Data Kits (labs)
- IBM Cloud

https://console.bluemix.net/catalog/

MICROSOFT

- NLP/NLU
- Text Analytics (sentimentos e assuntos)
- Azure
- Bot Framework

https://dev.botframework.com/

https://azure.microsoft.com/pt-br/services/cognitive-services/

FIAP

GOOGLE

- Infra - Cloud TPUs
- Tensor Flow
- AutoML
- Job Search and Discovery
- DialogFlow
- Video Analysis
- Image Analysis
- Speech Recognition
- Text Analysis
- Translation

https://ai.google/tools

https://cloud.google.com/apis/

AMAZON

- Lex - ASR NLU
- Polly - TTS
- Rekognition - Imagem
- Infra

https://aws.amazon.com/pt/amazon-ai/

FACEBOOK

- Detectron
- AR/VR
- Data Science
- NLP / Speech
- Caffe2
- Faiss
- Torch

https://research.fb.com/downloads/

OPEN SOURCE

- Open Cog
- Open AI
- Open CV

https://opencog.org/ https://openai.com/ https://opencv.org/

TRABALHO

ESCOLHA UM PROBLEMA RELEVANTE

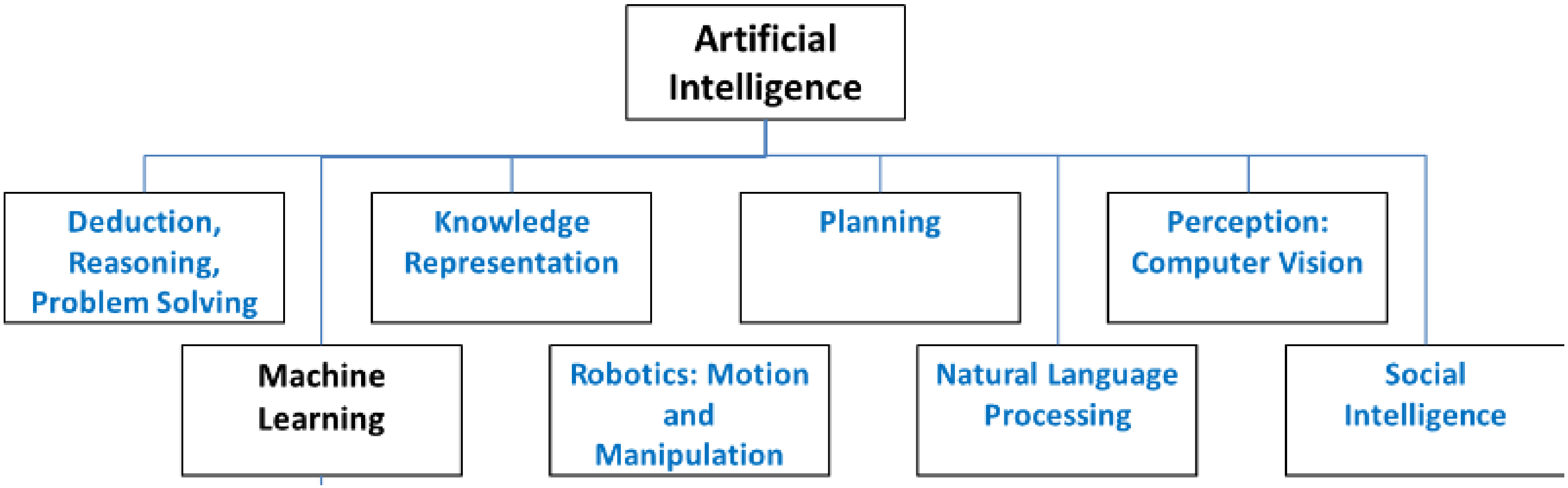
Trabalho Final – Pontos Importantes

- Introdução e Problemática;
- Motivação e Objetivo;
- Possível Ferramental e (ou) Técnicas;
- Considerações e Potencial.

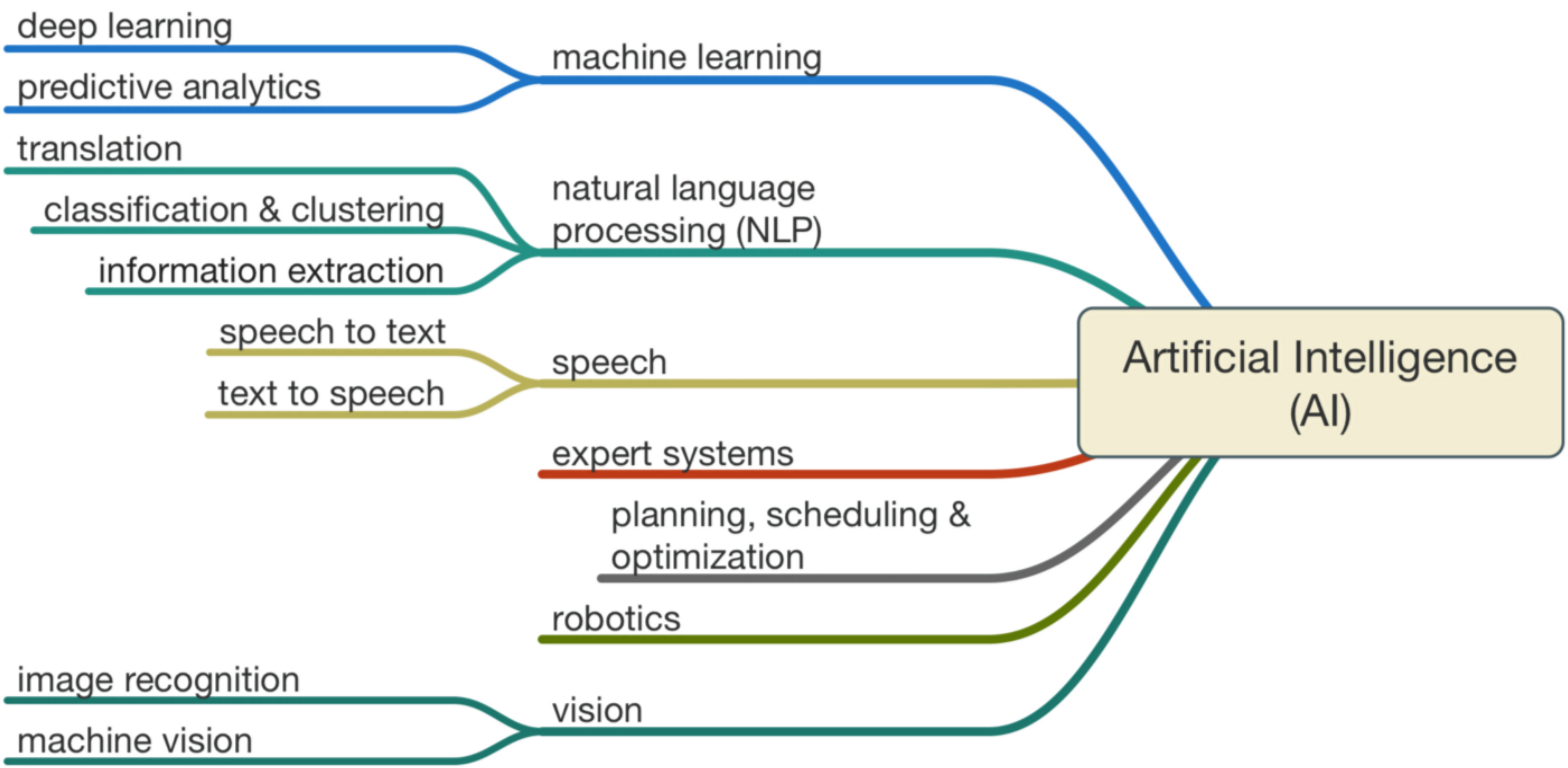
- **Avaliação:**

    - Aderência aos pontos;
    - Participação de todos os alunos;
    - Originalidade, “*fit*”para com o perfil do curso/alunos e “*doability*”.

Perspectiva 1



Perspectiva 2



Perspectiva 3

NLP

NLU

STT

TTS

Tradução

Visão Computacional

1.: Análise de Tom

2.: Análise de Tom para Engajamento

1.: Personalidade PT-BR

2.: Personalidade EN