XII ESCOLA DO CBPF

22 de julho a 02 de agosto de 2019

Inteligência Artificial utilizando *Deep Learning* e Aplicações em Física

Márcio Portes de Albuquerque
(CBPF)

Clécio R. De Bom
(CBPF/CEFET-RJ)

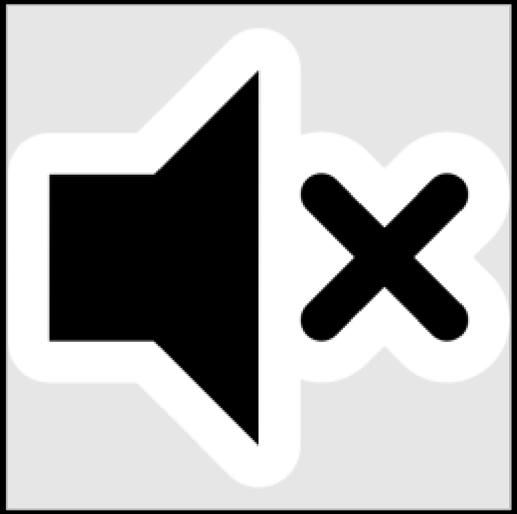
Elisangela L. Faria
(CBPF)

Uma introdução conceitual de aprendizado de máquina e uma abordagem prática em aplicações de redes neurais profundas com foco em aplicações cientificas e tecnológicas.

CBPF 70 ANOS
1949 - 2019

XII ESCOLA DO CBPF

22 de julho a 02 de agosto de 2019



Para um melhor aproveitamento do conteúdo ministrado, recomendamos à audiência que mantenha os aparelhos eletrônicos (celulares, laptops) Desligados ou mudos durante as aulas.

Comissão Organizadora
XII Escola do CBPF

XII ESCOLA DO CBPF

22 de julho a 02 de agosto de 2019

login: XII-Escola-CBPF
senha: escolacbpf2019

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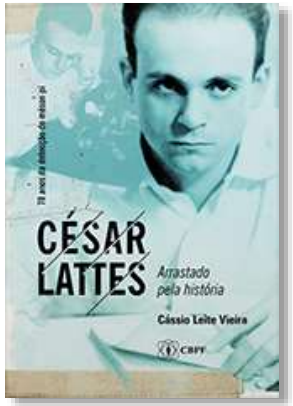
www.cbpf.br

CBPF 70 ANOS

1949 - 2019

CELEBRANDO
O PASSADO
REALIZANDO
O PRESENTE
CONSTRUINDO
O FUTURO



https://portal.cbpf.br/pt-br/livros/cesar-lattes-arrastado-pela-historia

Ministry of
Science, Technology, Innovations and Communications

MCTIC

History

Founded in 1949 (70 years in 2019)
Contributed to the creation of groups of excellence and Research Institutes

Our mission

…s and develop its
…preparing human
…cal development.

…gram (CAPES 7)

…most traditional
…Physics in Brazil)
…Instrumentation

…nnovation

…, Innovation and
…- NIT-Rio/MCTIC

…International Collaborations

HEP-Network (CERN, FERMILAB), CLAF, TWAS, CNRS, CONACYT, NSF, DAAD, SFI
Projetos: Auger/Lattes, CTA and Dark Energy Survey

A **história do CBPF** está permeada de iniciativas, que estão na base da criação de instituições que formam hoje a **espinha dorsal da Ciência no Brasil**

CNPq CLAF impa LNCC LNLS


C. Lattes


J.L. Lopes


G. Beck


J. Tiomno

CBPF 70 ANOS

Mission of Research Institutes

- ***Research***

  Push forward the frontiers of knowledge

- ***Innovation***

  Develop new, cutting-edge technologies

- ***Education***

  Train scientists and engineers of tomorrow

- ***Outreach***

  Promote Science in Society

RedeRio de computadores FAPERJ CLAF LABNANO CBPF/MCTI CERN Fermilab PIERRE AUGER OBSERVATORY

Mission of Research Institutes

- ***Research***

  Push forward the frontiers of knowledge

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  Develop new, cutting-edge technologies

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  Train scientists and engineers of tomorrow

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  Promote Science in Society

À Rio, un graffiti pour la science

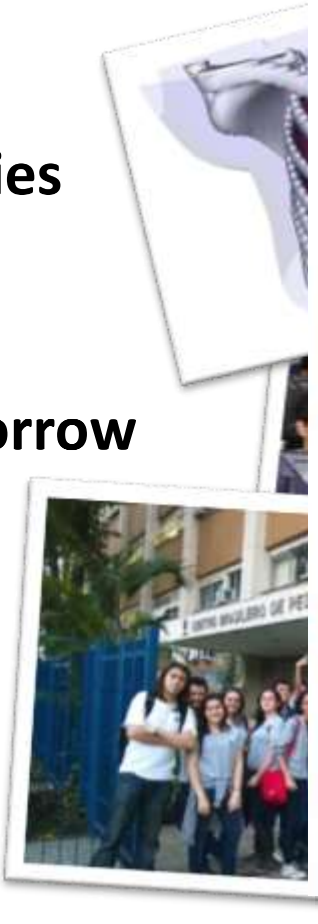
16.08.2018, par Olivier Fudym

CNRS LE JOURNAL

Le 8 juin, à Rio de Janeiro, le Centre brésilien de recherches physiques a inauguré un graffiti couvrant 240 mètres carrés d'un mur entièrement dédié aux sciences, aux technologies et à l'innovation. Unique dans le monde par sa taille et sa thématique, cette œuvre d'art urbain, qui s'inscrit dans le cadre de la promotion de la science au Brésil, invite la jeunesse du pays à embrasser une carrière scientifique.

Retrouvez toutes les informations sur ce projet soutenu par le CNRS sur le site : http://www.science-graffiti.cbpf.br/

#grafitedaciencia



RedeRio de computadores FAPERJ

CLAF

LABNANO CBPF/MCTI

Fermilab

PIERRE AUGER OBSERVATORY

CBPF – R&D Areas

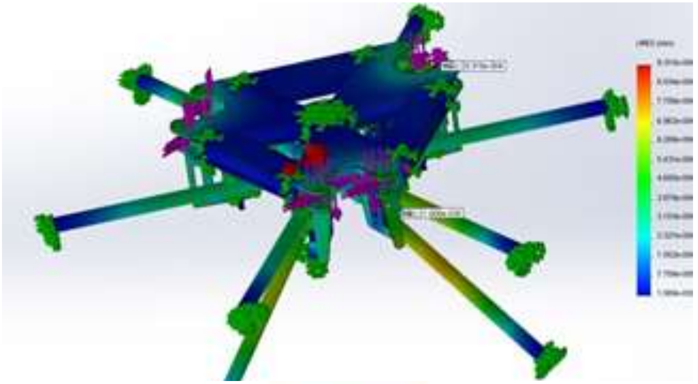
Experimental, Theoretical and Applied Physics

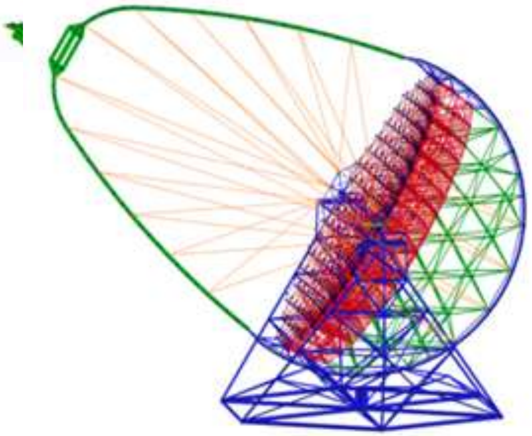
- High Energy and Astroparticle Physics
- Condensed Matter & Materials
- Nanoscience and Nanotechnology
- Biophysics & Biomaterials
- Statistical Mechanics and Complex Systems
- Quantum information
- Cosmology and Gravitation
- Signal Processing and Computing for Science
- Scientific and Technological Instrumentation

International Collaboration - Cherenkov Telescope Array

cta cherenkov telescope array

Exploring the Universe at the Highest Energies





Laboratórios

Laboratórios

CBPF

MCTIC

SisNANO
Sistema Nacional de Laboratórios em Nanotecnologias

Formação Científica

Coordenação de Formação Científica

Pós-graduação

Extensão

Doutorado e Mestrado em Física

Mestrado em Instrumentação Científica

ntos
&T

Programa de Desenvolvimen

- Publico alvo: físicos e engenhe
- Formação de recursos humano desenvolvimento tecnológico

O Programa de Pós-Graduação do CBPF completou, em 2012, seu 50º aniversário, um marco da história da Física no Brasil

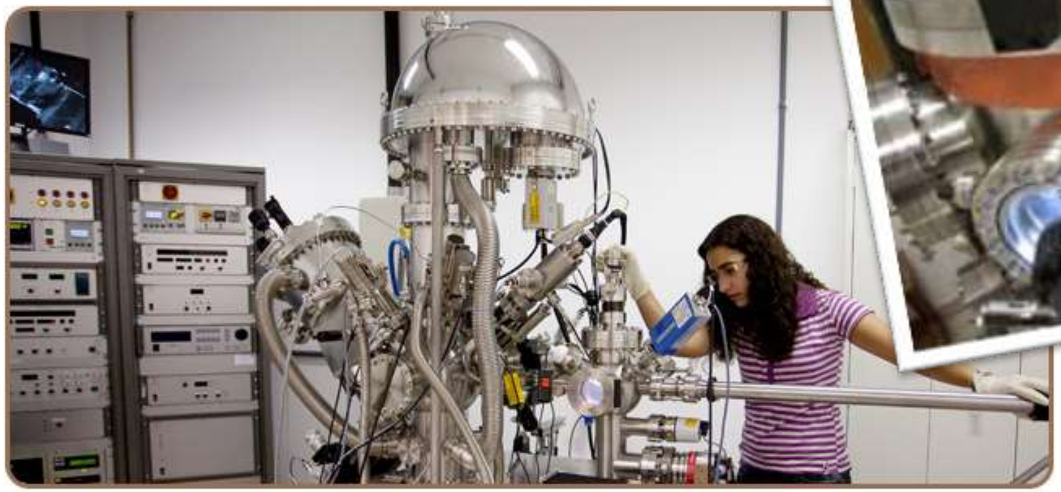
71ª REUNIÃO ANUAL DA SBPC
Sociedade Brasileira para o Progresso da Ciência

(CBPF – programa de excelência)
CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior)

CBPF in Numbers

- **Headquarters of the National High Energy Physics Network (RENAFAE)**
- **Headquarters of National Science and Technology Institute for Complex Systems and Quantum Information**
- **Headquarters of Rio de Janeiro Nanotechnology Network (LABNANO/CBPF is the main facility)**
  Strategic Lab under SisNANO network

inct-sc



LHC
Open Network Environment
(Tier1s - Tier2s)

WLCG
Worldwide LHC Computing Grid
Science DMZ

RedeRio de computadores FAPERJ

FAPERJ Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro

CBPF is the technical and operational segment of the Rio de Janeiro NREN (Advanced Research and Educ. Network)- support for 160 research, academic and governmental Institutions.

Rede de Ensino e Pesquisa (CBPF)

100 Acadêmicos
34 Prefeitura
31 Metro
2 Supervia

Total: 167

≈ 400 Km de Fibras Ópticas

CBPF & Industry

- NMR for Petrophysics;
- Quantitative Imaging techniques for characterization of high-resolution images in geological reservoirs;
- Rock plugs with controlled porosity
- Nanotechnology for O&G industry

- New materials and techniques for medical implants

- Magnetic Resonance at the micro and nanoscale

- Material Science, Nanotechnology and Magnetics Devices

- Cherenkov Telescope Array

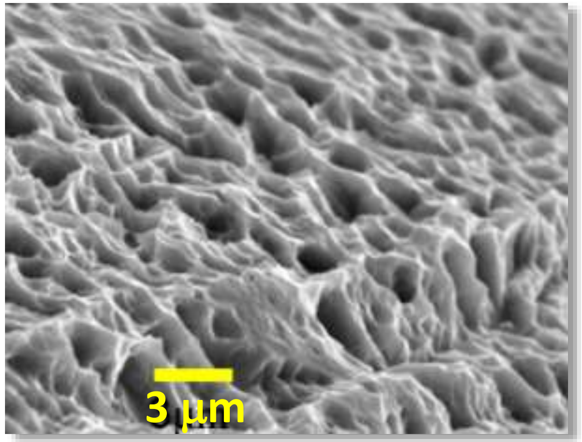
- Surface Science

Group of Surfaces and Nanostructures

Biocompatible Coatings

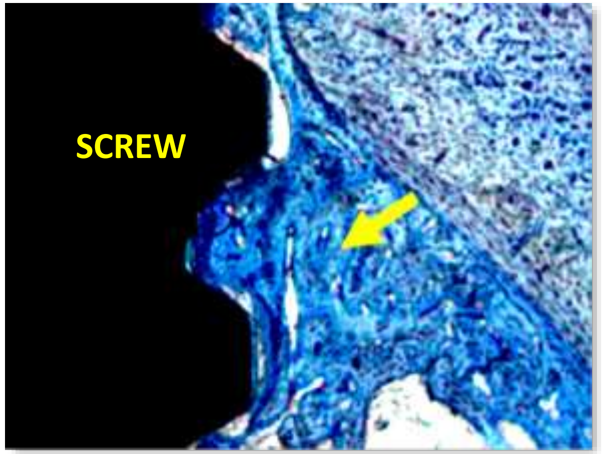
- Instrument for Crystalline and biocompatible nanometer coatings of Calcium-Phosphates produced at room temperatures.
- Pre-clinical studies in dogs and rabbits indicated high adhesion and proliferation of bone tissue around titanium implants
- Improves clinical behaviour and push up values to medical metallic implants, saving loading time and solving rejections

Commercial titanium screw with nanosized hydroxyapatite coating (100 nm)



Metal implant surface with micrometric roughness for mechanical bonding and homogeneous coating

Preclinical tests with strong adhesion and bone growth (in blue) to screw coated HAPnano (black)

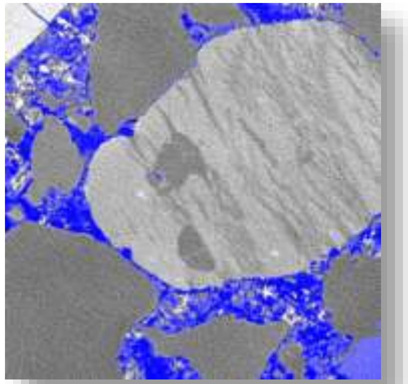


LABNANO
CBPF/MCTI

Image/Signal: Emerging techniques

Exploring multimodal imaging protocols in association with powerful imaging processing techniques

- **X rays quantitative imaging**
  - Dual Energy / Multispectral µCT / Synchrotron based techniques
- **Signal and image processing**
  - Advanced approaches for enhancement and segmentation
  - Machine learning / Deep Learning
- **Complexity and statistical physics**
  - Porous media characterization through information theory and fractal geometry



Characterization of Borehole Profile

Clustering and facies classification
texture segmentation

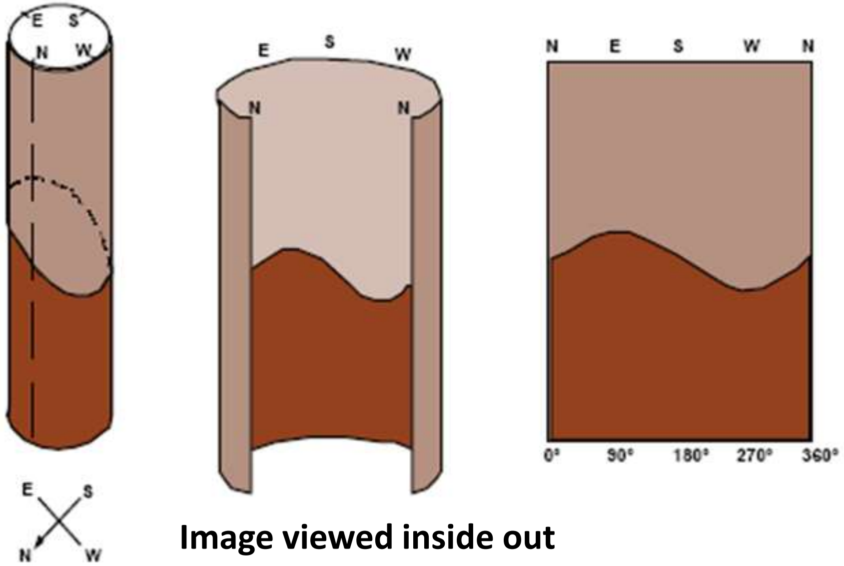
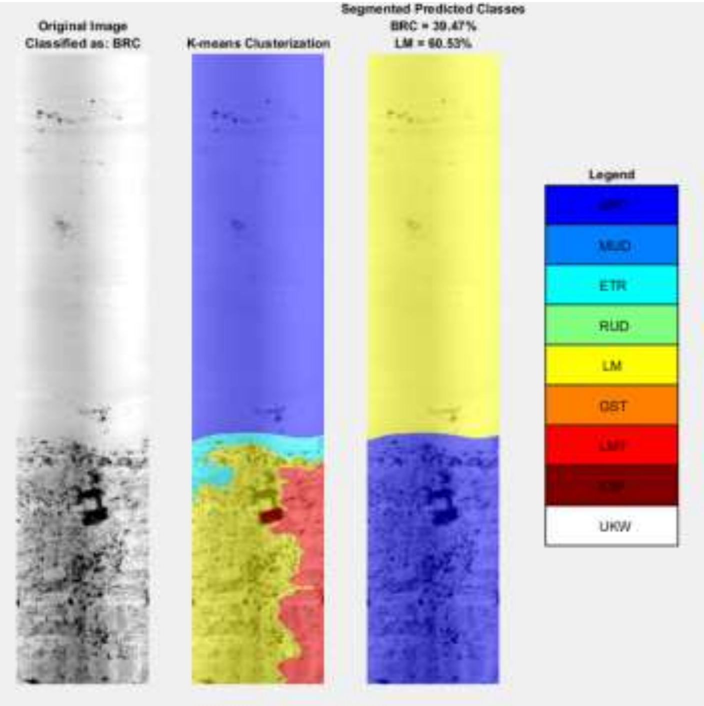


Image viewed inside out

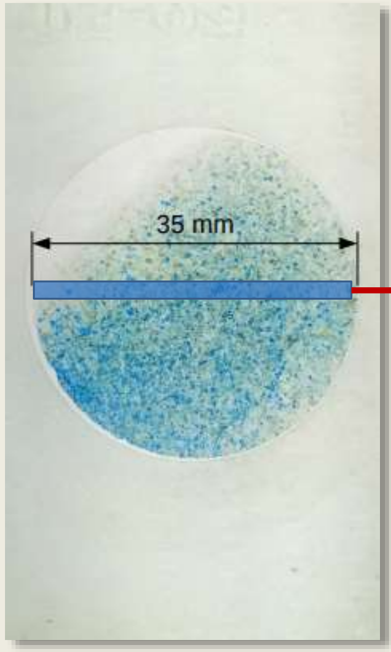


Facies classification

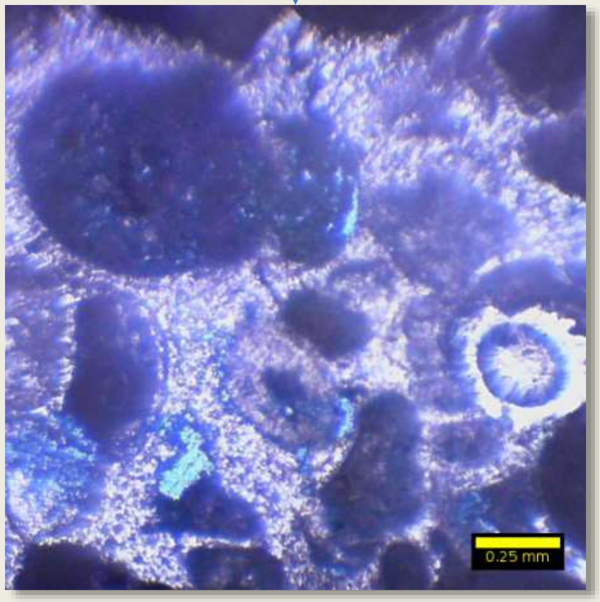
Instrumentos avançados & tecnologias de medidas

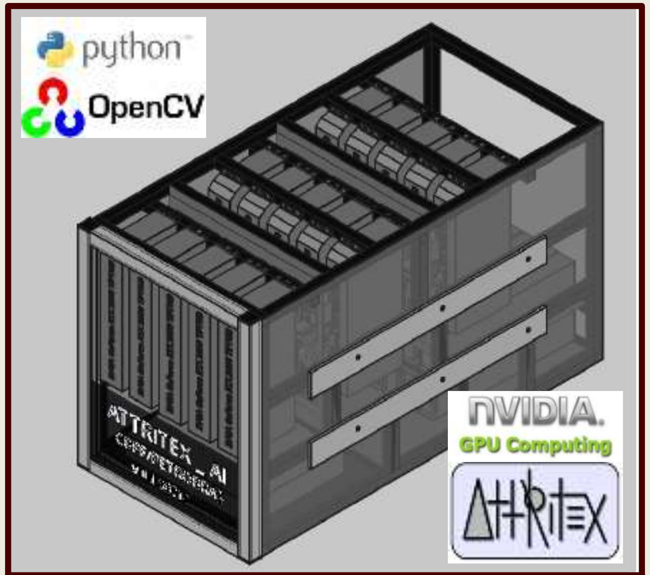
óptica aplicada | **computação científica** | **eletrônica** | **mecânica**

Imagem de alta resolução (11567 pixels)



Lâmina Petrográfica





Desenvolvimento do Sistema Computacional

Laboratório de Redes e Sistemas (LARS)

36x RTX 2080Ti
6x Quadro K6000
6x 1080Ti
13x 1050Ti

- **32 CPU cores, 128 GB RAM (expansível até 1TB),**
- **26112 CUDA cores, 84 Teraflops, 66GB VRAM,**
- **4xWaterCoolers - completo silêncio,**
- **1632 Tmus unid. de texturas e 528 ROps unid. para renderização**
- **4TB HD/backup Enterprise e 500 GB SSD/OS, 2 fontes 1600W**

NVIDIA
GPU Computing

CBPF
SciMining
6.RTX2080TI

GPGPU – General Purpose GPU

(processador da placa de vídeo)

As GPU foram originalmente usadas para renderização de imagens em jogos 3D.

Essa capacidade de processamento está sendo aproveitada de forma mais ampla para acelerar o processamento computacional em áreas como pesquisa científica, processamento de sinais/imagens, algebra linear, estatística, reconstrução 3D, modelagem financeira, exploração de petróleo e gás....

NVIDIA
GPU Computing

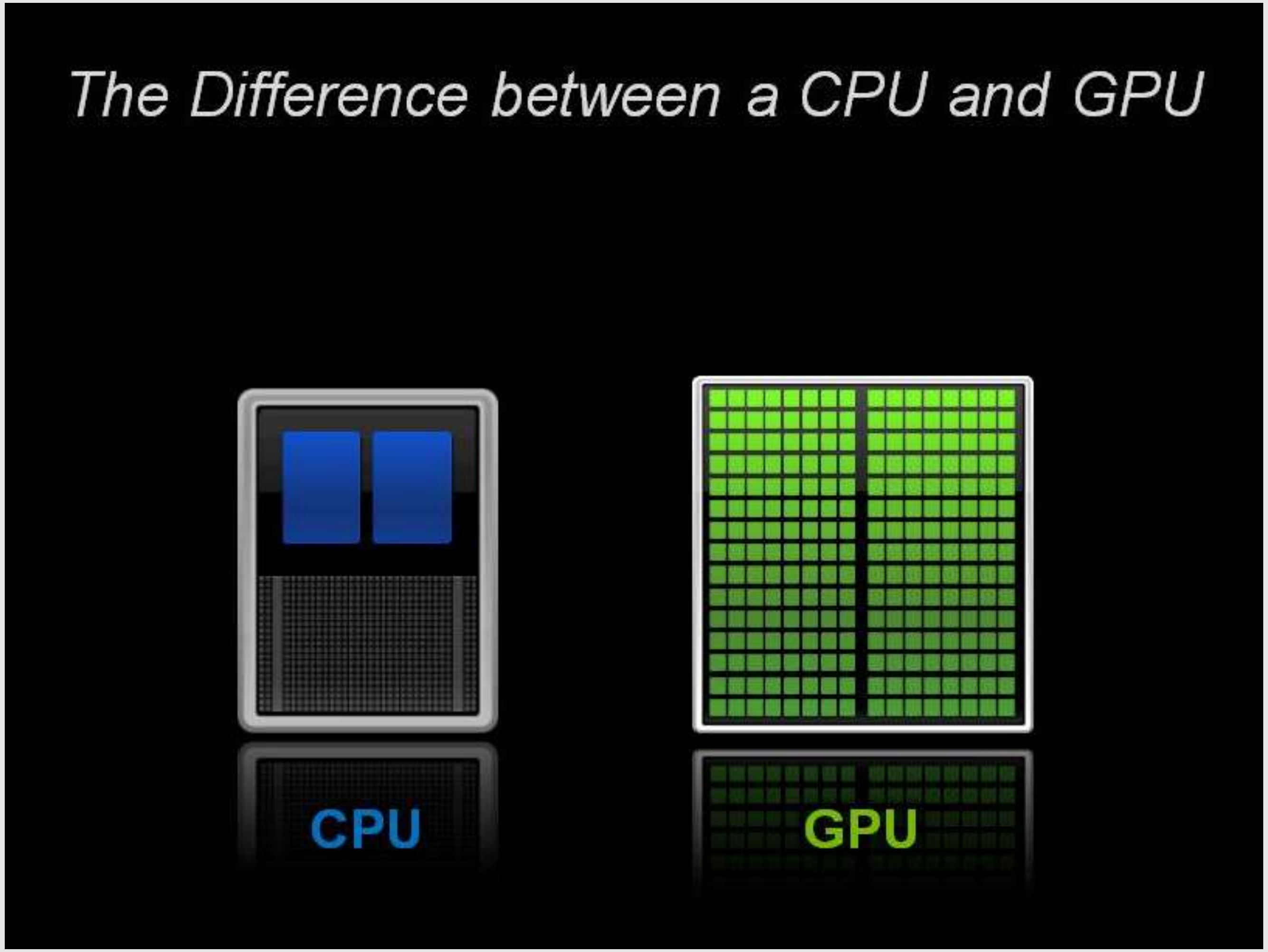
CBPF
SciMining
6.RTX2080TI

GPU – Unidade de Processamento Gráfico

(processador da placa de vídeo)

A GPU é responsável pelos cálculos de processamento de vetores, texturas, projeções das imagens em um sistema de vídeo do computador.

Libera a CPU para fazer outras tarefas (de outra complexidade).



P&D: Proc. de Imagens & Inteligência Artificial

- Processamento de sinais e imagens
- Inteligência artificial
- Instrumentação cientifica / tecnológica
- Simulações

Márcio Marcelo Clécio Elisangela Jorge Maury

André Manuel Luciana Juliana Patrick Marcos Paulo Athos Pedro

Coordenação de Desenvolvimento Tecnológico

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PETROBRAS BR

MCTIC PCI

FACC

Ementa - Roteiro

AULA 1: Apresentações iniciais, Redes Neurais Artificiais, Aprendizado de máquina, Algoritmos/Termos; Redes Perceptron de Várias Camadas.

AULA 2: Rede Neural Convolucional: Resnet e Inception.

AULA 3: Autoencoders e aprendizagem não supervisionada.
- Redes Geradoras Adversariais (GAN).

AULA 4: Redes Neurais Convolucionais Baseadas em Região (R-CNN).

AULA 5: Redes Neurais Bayesianas

Exemplos / Demonstrações

Pré-requisitos:
Recomenda-se o domínio da linguagem de programação Python
Porém é possível o uso de C ou MATLAB.

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22 de julho a 02 de agosto de 2019

You will need:

→ Python (anaconda3)

→ Keras

→ Tensorflow

→ matplotlib

→ numpy

For the examples you will also need:

→ astropy (Aulas Clécio)

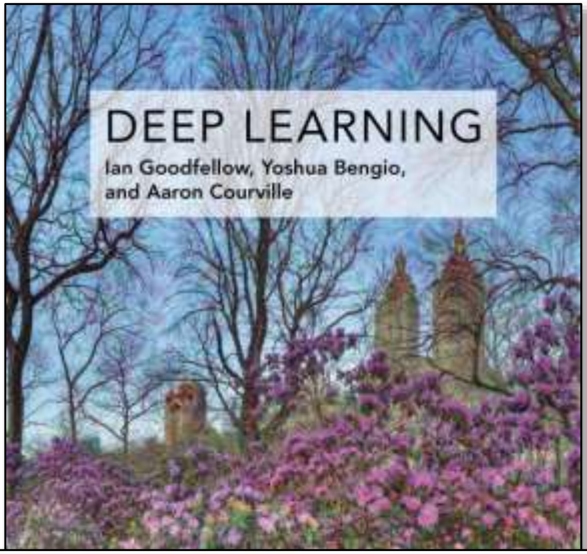
Google Colab (on-line)

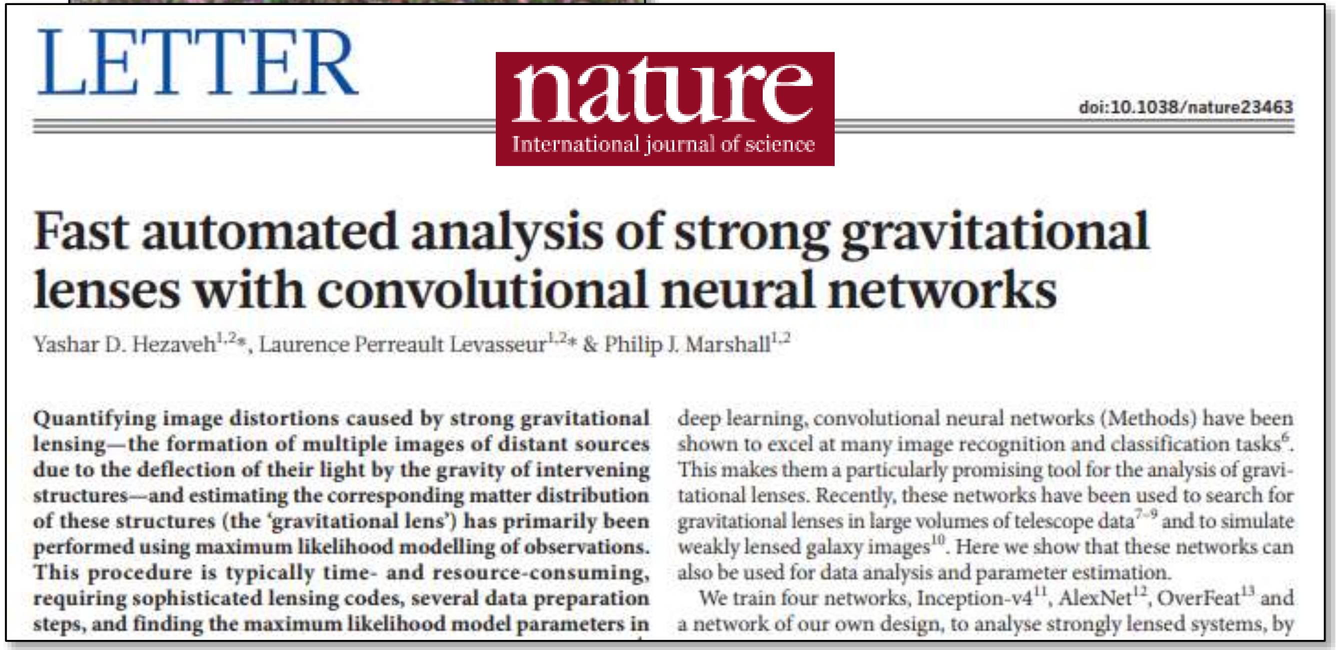
We will have several examples in Google Colabs or in Python notebooks. The examples and datasets required can be downloaded in

clearnightsrthebest.com

Bibliografia

- Cobb, A. D., Roberts, S. J., Gal, Y., "*Loss-Calibrated Approximate Inference in Bayesian Neural Networks*", 2018 arXiv:1805.03901
- Goodfellow, I., et al., "*Deep Learning*", 2016. MIT press. http://www.deeplearningbook.org.
- Hezaveh, Y. D., et al. "*Fast automated analysis of strong gravitational lenses with convolutional neural networks*." Nature 548.7669 (2017): 555.
- Krizhevsky, A., Sutskever, I. and Hinton, G. E. *ImageNet Classification with Deep Convolutional Neural Networks*. NIPS 2012: Neural Information Processing Systems, Lake Tahoe, Nevada.
- LeCun, Y., Bengio, Y. and Hinton, G., "*Deep learning*." Nature 521.7553 (2015): 436.




LETTER

nature
International journal of science

doi:10.1038/nature23463

Fast automated analysis of strong gravitational lenses with convolutional neural networks

Yashar D. Hezaveh[1,2]*, Laurence Perreault Levasseur[1,2]* & Philip J. Marshall[1,2]

Quantifying image distortions caused by strong gravitational lensing—the formation of multiple images of distant sources due to the deflection of their light by the gravity of intervening structures—and estimating the corresponding matter distribution of these structures (the 'gravitational lens') has primarily been performed using maximum likelihood modelling of observations. This procedure is typically time- and resource-consuming, requiring sophisticated lensing codes, several data preparation steps, and finding the maximum likelihood model parameters in deep learning, convolutional neural networks (Methods) have been shown to excel at many image recognition and classification tasks[6]. This makes them a particularly promising tool for the analysis of gravitational lenses. Recently, these networks have been used to search for gravitational lenses in large volumes of telescope data[7–9] and to simulate weakly lensed galaxy images[10]. Here we show that these networks can also be used for data analysis and parameter estimation.

We train four networks, Inception-v4[11], AlexNet[12], OverFeat[13] and a network of our own design, to analyse strongly lensed systems, by

- Schawinski, K., et al., "*Generative adversarial networks recover features in astrophysical images of galaxies beyond the deconvolution limit*", Monthly Notices of the Royal Astronomical Society: Letters, Volume 467, Issue 1, p.L110-L114.
- Wu, J., "Introduction to convolutional neural networks." National Key Lab for Novel Software Technology, Nanjing University. China (2017).

Alguns termos importantes

- É o termo de TIC que trata sobre a manipulação de grandes quantidades de dados que precisam ser processados, transferidos e/ou armazenados.

- O conceito de “grande” é sempre relativo. Um conjunto de dados que é considerado grande hoje quase certamente será considerado pequeno amanhã.

- Big data representa a condição no qual existem mais dados dos que as técnicas tradicionais podem processar.

- Alguns projetos definem que o “Big data” não é uma função da quantidade de dados, mas da sua complexidade. Consequentemente, é o grau de relacionamento no conjunto de dados que define o que é Big Data.

- Outra definição → Big-Data e os 3Vs: Volume, Velocidade e Variedade;
  +V (4Vs): Veracidade, (confiança e incerteza).

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MIT Technology Review

https://www.technologyreview.com/s/519851/the-big-data-conundrum-how-to-define-it/

Alguns termos importantes

- É o termo de TIC que trata sobre a manipulação de grandes quantidades de dados que precisam ser processados, transferidos e/ou armazenados.

considerado

s

https://www.technologyreview.com/s/519851/the-big-data-conundrum-how-to-define-it/

Data Science

- Estatística é a ciência capaz de fazer inferências e tomar decisões onde existe alguma incerteza. É uma ferramenta cada vez mais relevante devido à ampla quantidade e disponibilidade de dados e dos recursos computacionais atuais.

- A necessidade de processar e gerenciar grandes quantidades de dados tornou-se uma característica fundamental das ferramentas estatísticas modernas e é comumente chamada de Ciência de Dados.

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Alguns termos importantes

Inteligência

?

QI → Inteligência

- **Qualidade Mental**
  - **Aprender a partir de alguma experiência anterior**
  - **Resolver problemas**
  - **Se adaptar a situações novas**

Inteligências Múltiplas (R. Sternberg – psicólogo)

Analítica:
Habilidade para pensar de forma abstrata e resolver problemas
Criativa/Sintética:
Habilidade se adaptar a alguma nova situação ou gerar novas ideias
Prática:
Habilidade contextual ou de adaptação as condições do ambiente

Emocional:
Habilidade de perceber, entender, gerenciar e usar emoções em suas interações com os outros

Sternberg, R. J. (1985). *Beyond IQ: A triarchic theory of human intelligence*. New York: Cambridge University Press.

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Alguns termos importantes

Inteligência

?

QI → Inteligência

Inteligências Múltiplas (R. Sternberg – psicólogo)

Analítica:

Habilidade para pensar de forma abstrata e resolver problemas

Criativa/Sintética:

Fluída:

Habilidade abstração → ***capacidade de raciocínio***

Habilidade contextual ou de adaptação as condições do ambiente

Cristalizada:

Habilidade em acumular conhecimento, habilidades verbais

Habilidade de perceber, entender, gerenciar e usar emoções em suas interações com os outros

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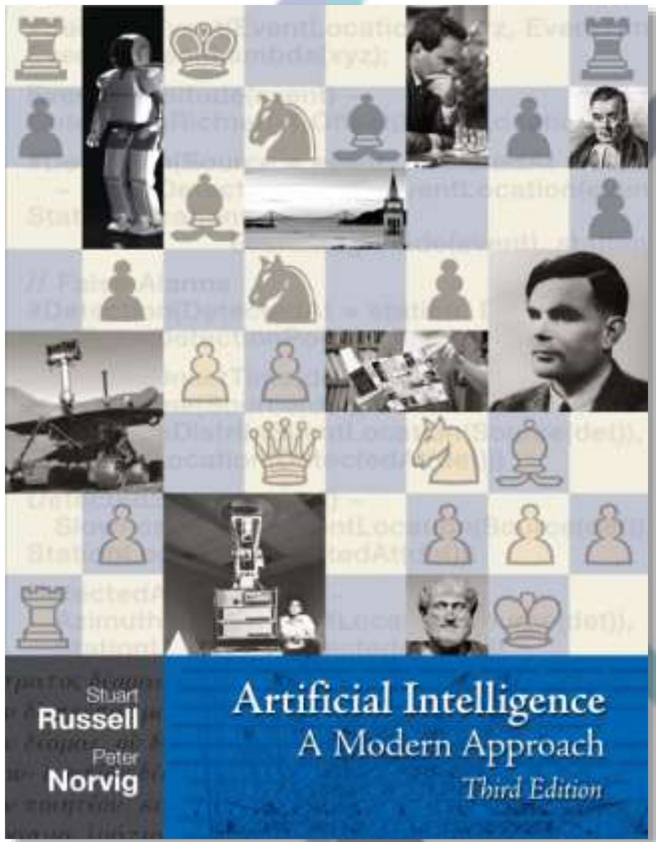
IA – Inteligência Artificial

- Inteligência Artificial (IA) é o termo frequentemente usado para descrever máquinas ou computadores que imitam funções cognitivas de seres humanos, que estão associados a *mente humana*, como “aprendizado” ou a capacidade de “resolver problemas”.

1996



http://aima.cs.berkeley.edu/

2009

A convergência entre Big Data e IA

- Em vez de depender de dados representativos, os "Cientistas de Dados" têm atuados cada vez mais a partir dos dados reais. É devido a essa característica que muitas instituições passaram de uma abordagem baseada em hipóteses para uma abordagem/decisão baseada em "dados reais".
- O processamento de grande quantidades de dados auxiliam na tomada de decisão das instituições. A análise de grandes quantidades de dados (Big Data) incentiva a <u>descoberta de padrões por meio de algoritmos iterativos</u>. Como resultado, as instituições podem rapidamente, experimentar mais e aprender mais.

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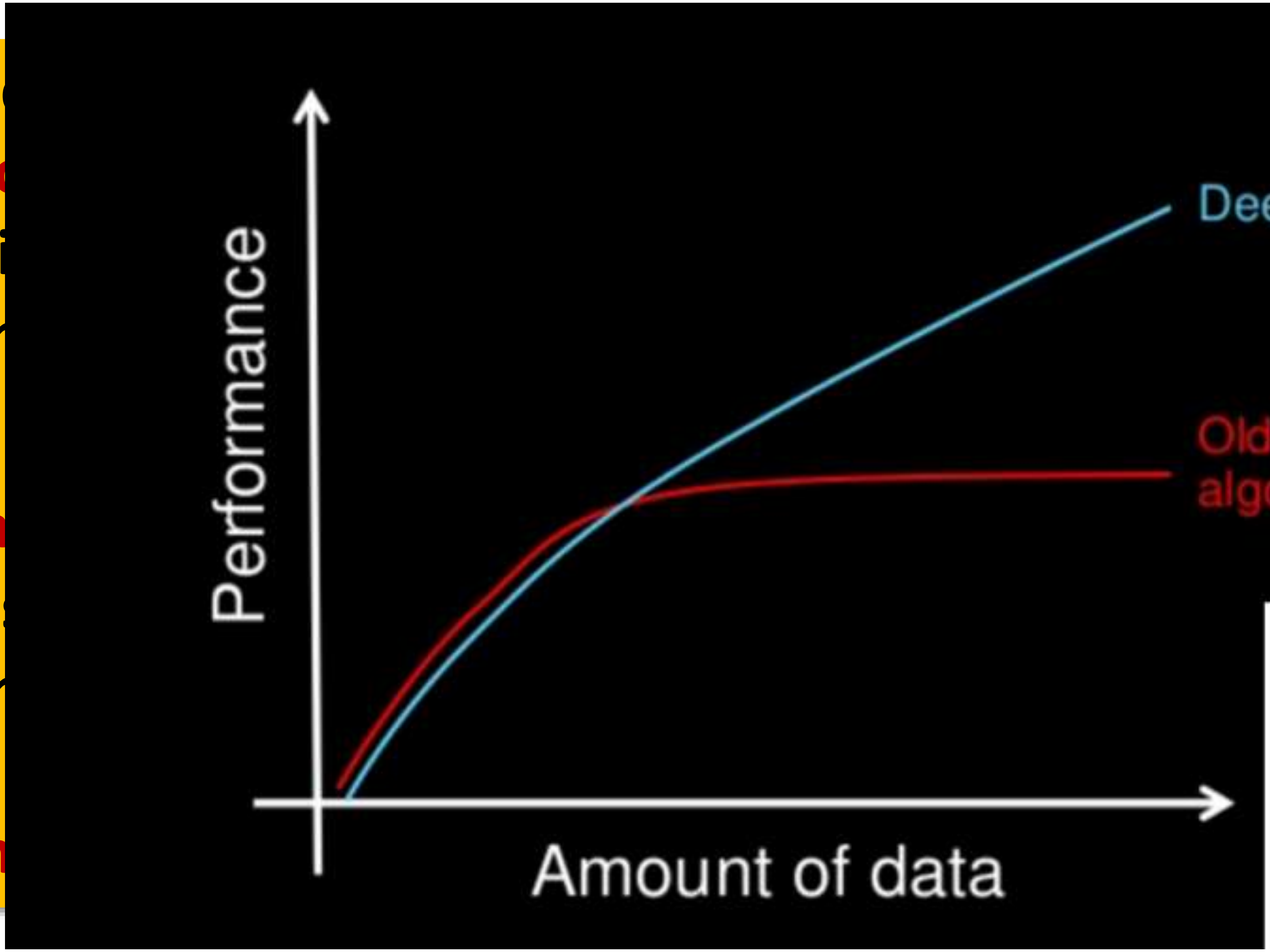
https://sloanreview.mit.edu/article/how-big-data-is-empowering-ai-and-machine-learning-at-scale/

A convergência entre Big Data e IA

- Em vez de … s"
  têm atuad…
  característi…
  baseada e… dos
  reais".

- O processa… la de
  decisão da… Big
  Data) incen… tivos.
  Como resu… ais e
  aprender n…



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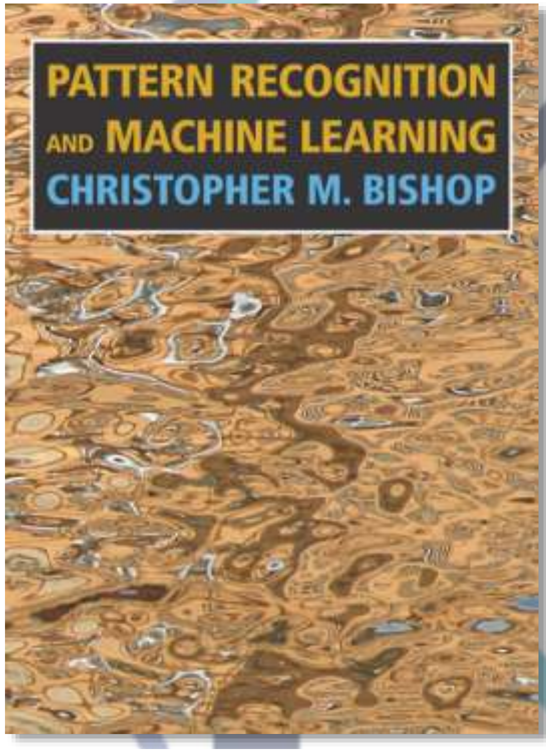
https://sloanreview.mit.edu/article/how-big-data-is-empowering-ai-and-machine-learning-at-scale/

Aprendizado de Máquina

- **Machine learning (ML):** estudo científico de algoritmos e modelos estatísticos por meio de sistemas computacionais para executar uma tarefa específica de maneira eficaz, sem usar instruções explícitas, confiando em padrões e inferências. É uma área da IA.

- **Algoritmos de ML constroem um modelo matemático** baseado em um conjunto amostra, conhecido como "dados de treinamento", para fazer previsões ou permitir decisões sem ser explicitamente programado para executar a tarefa.



https://www.springer.com/gp/book/9780387310732

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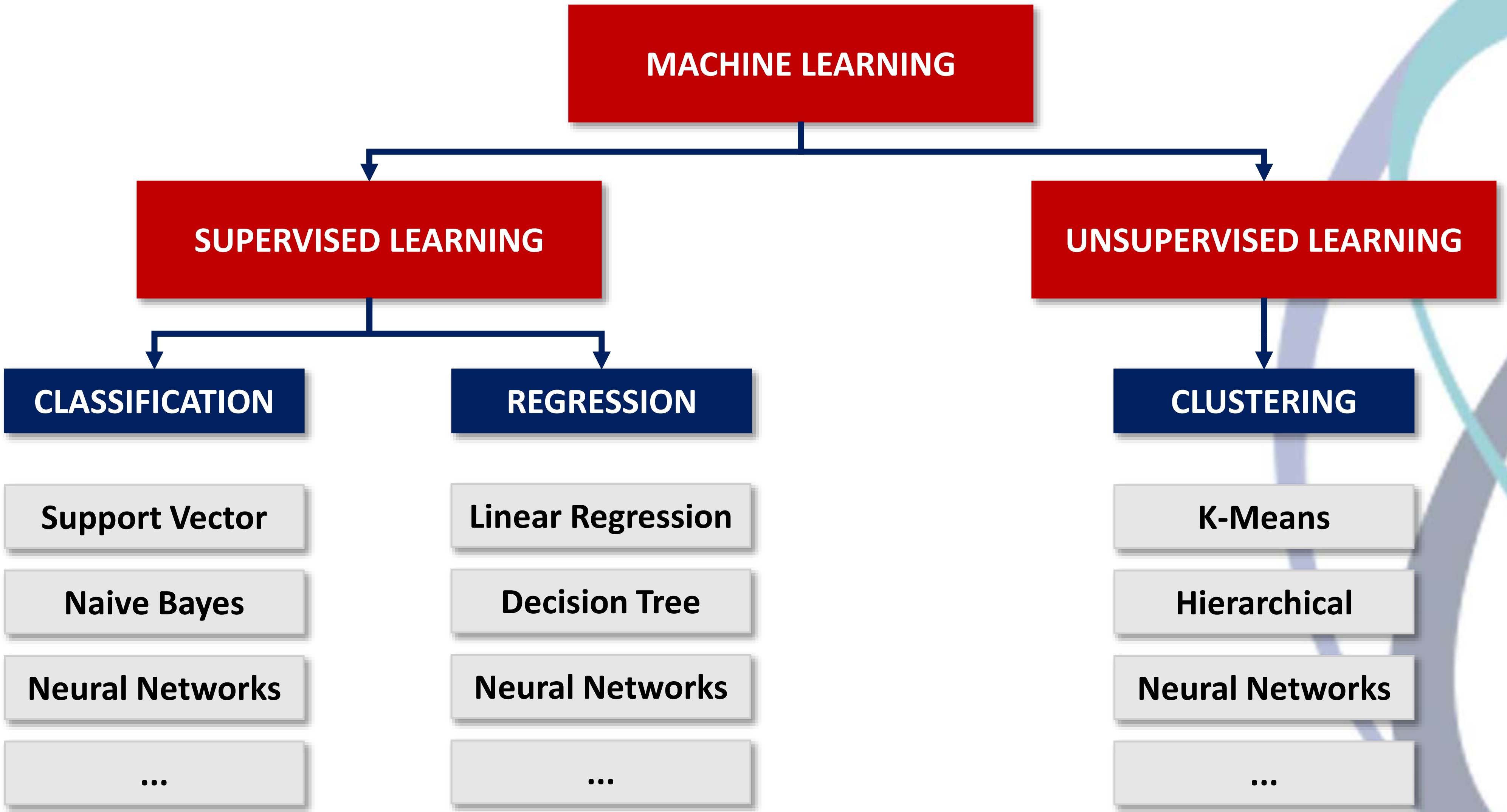
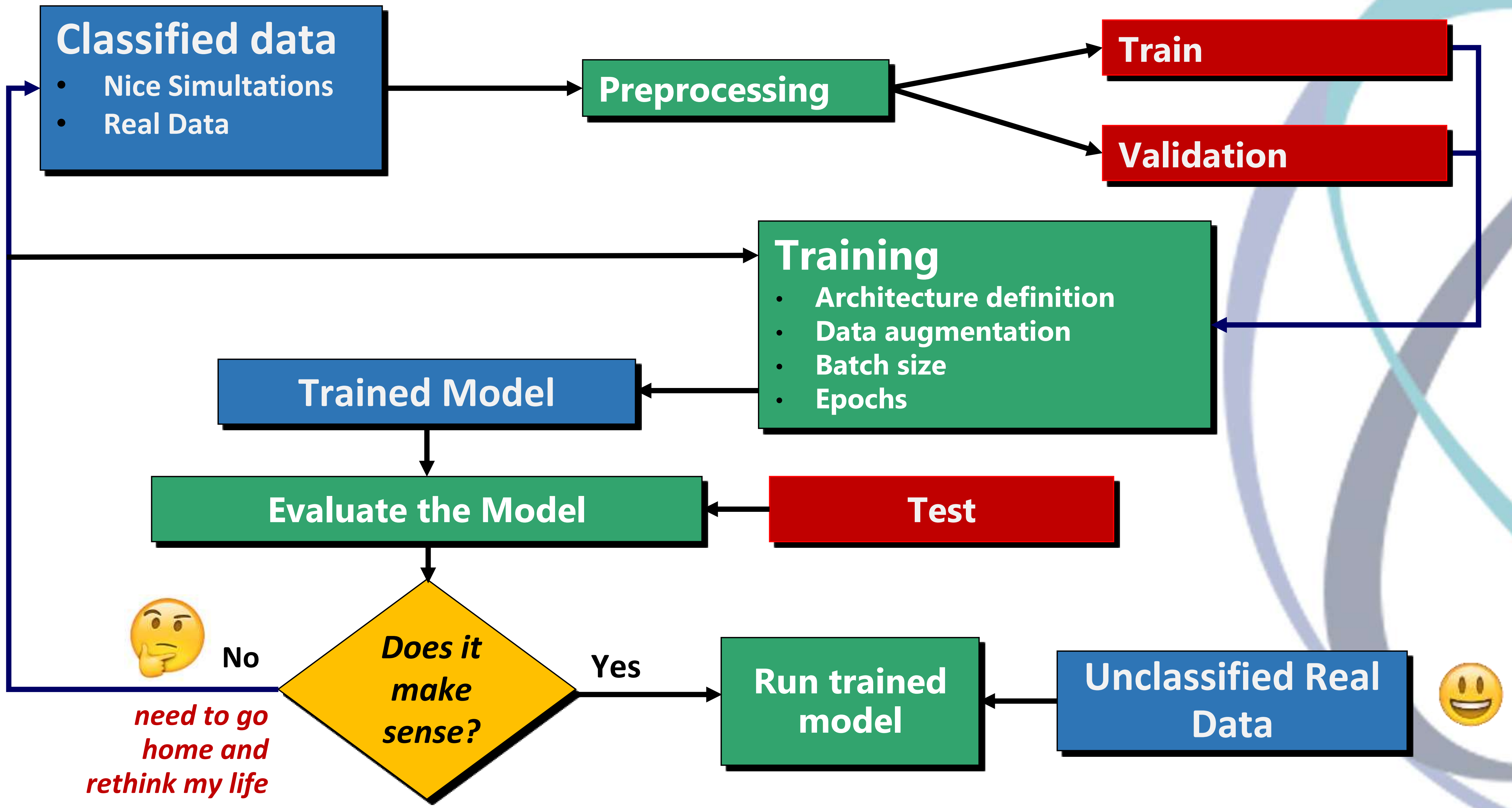
ML: Supervised & Unsupervised

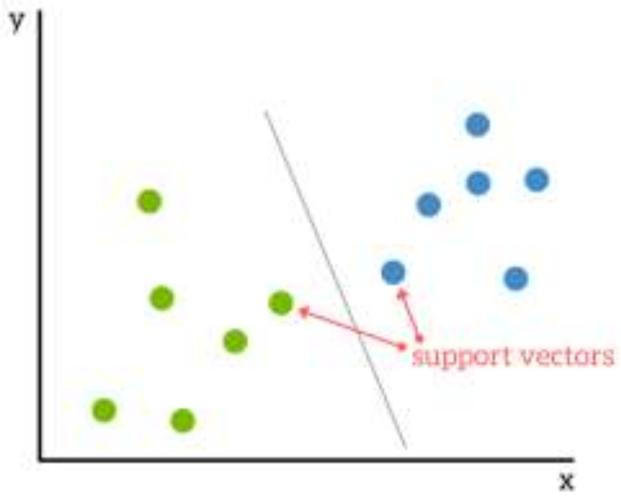


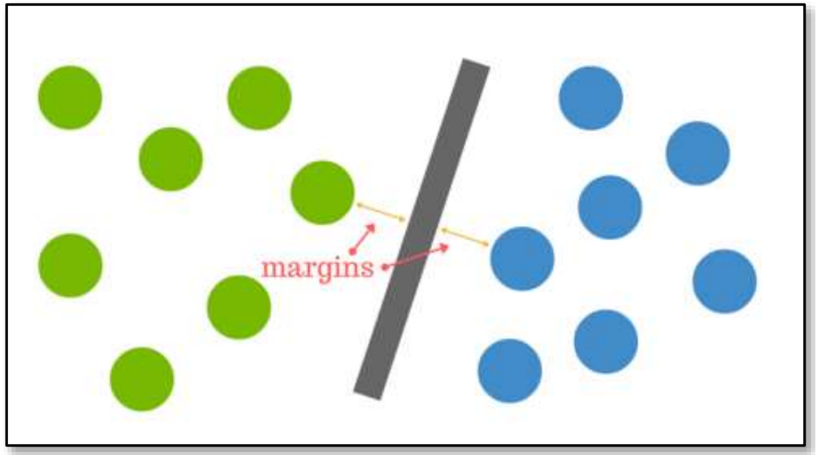
ML: Workflow Supervised

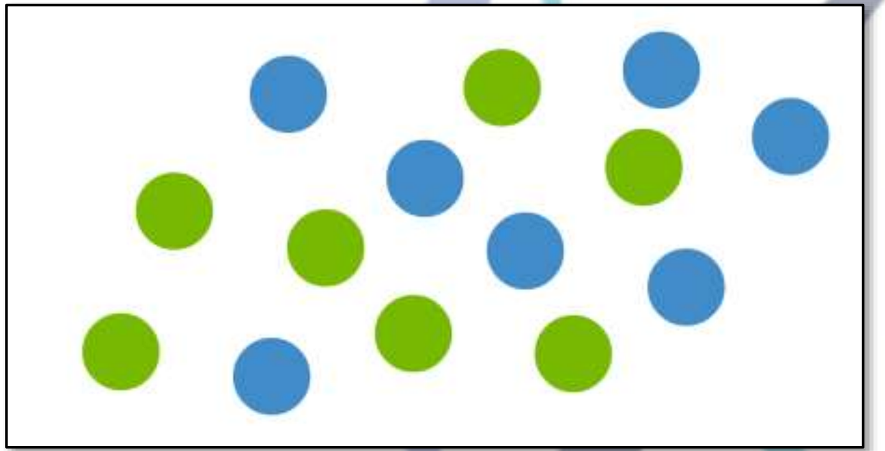


ML: Support Vector Machines - SVM

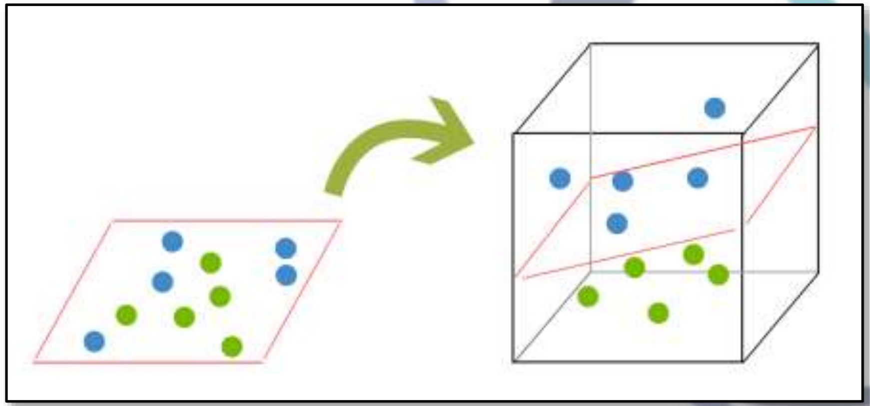
SVMs are based on the idea of finding a hyperplane that best divides a dataset into two classes.







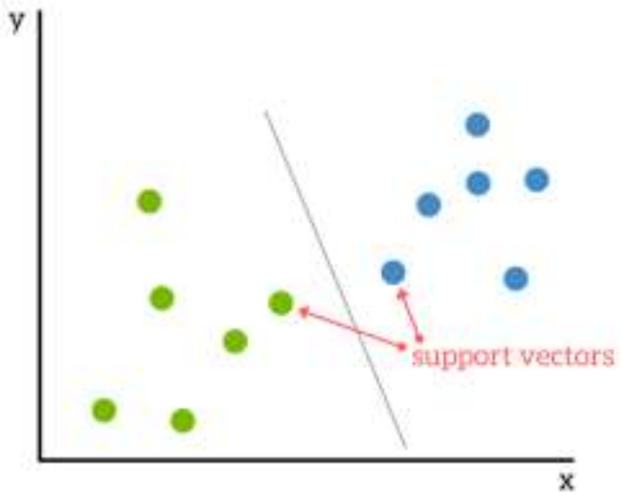
The goal is to choose a hyperplane with the greatest possible margin between the hyperplane and any point within the training set, giving a greater chance of new data being classified correctly.

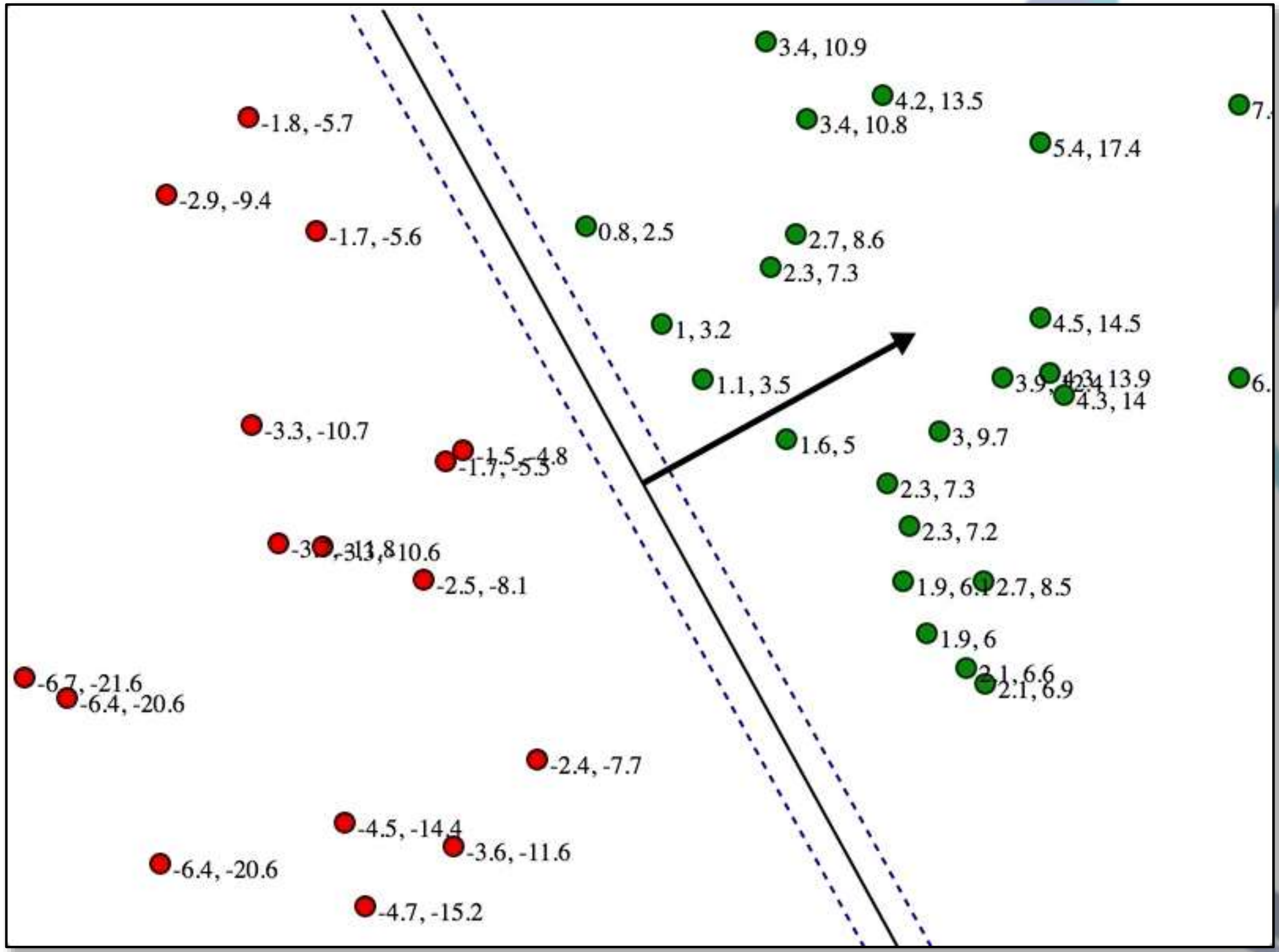


CBPF 70 ANOS

ML: Support Vector Machines - SVM

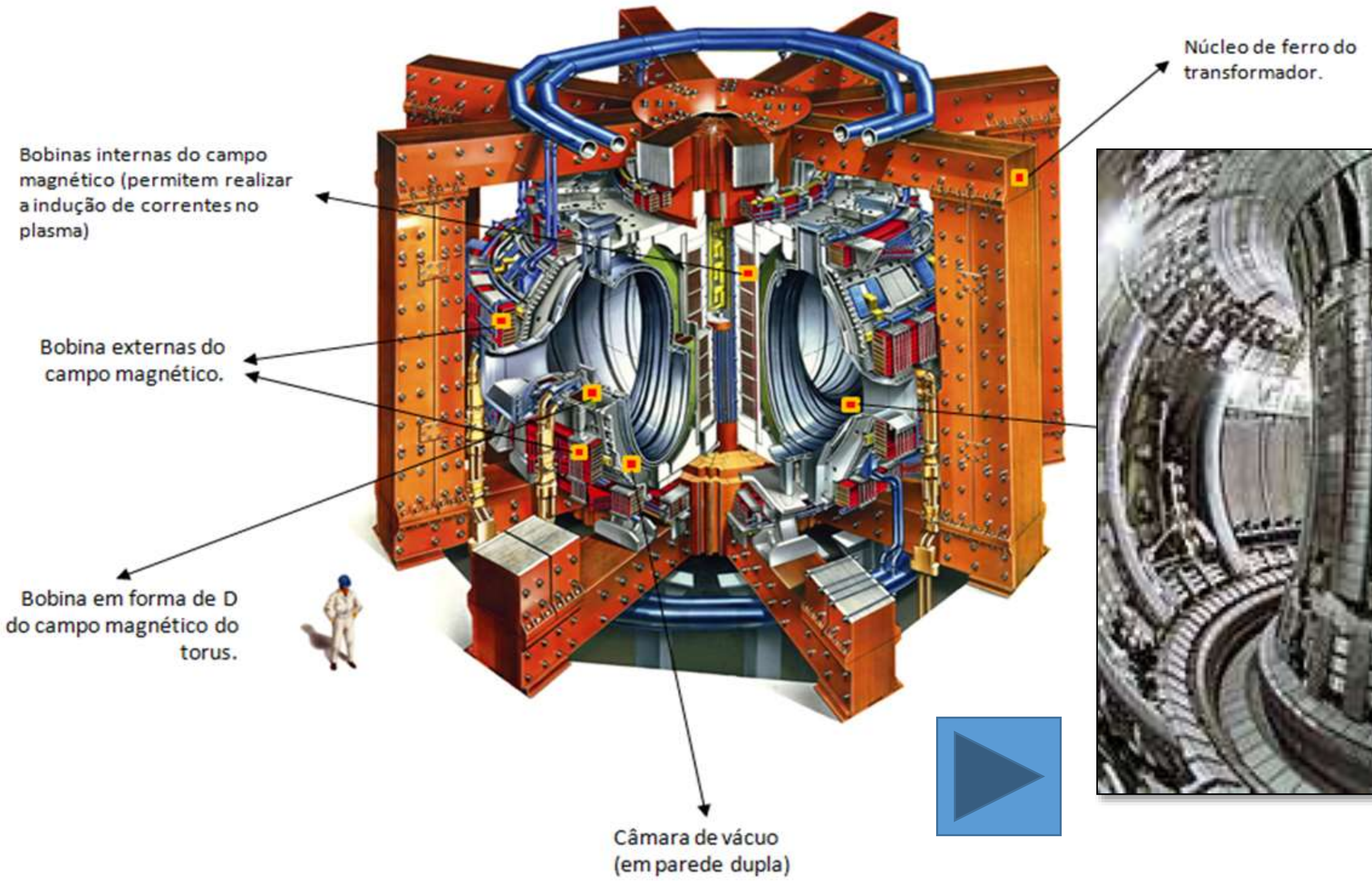
SVMs are based on the idea of finding a hyperplane that best divides a dataset into two classes.

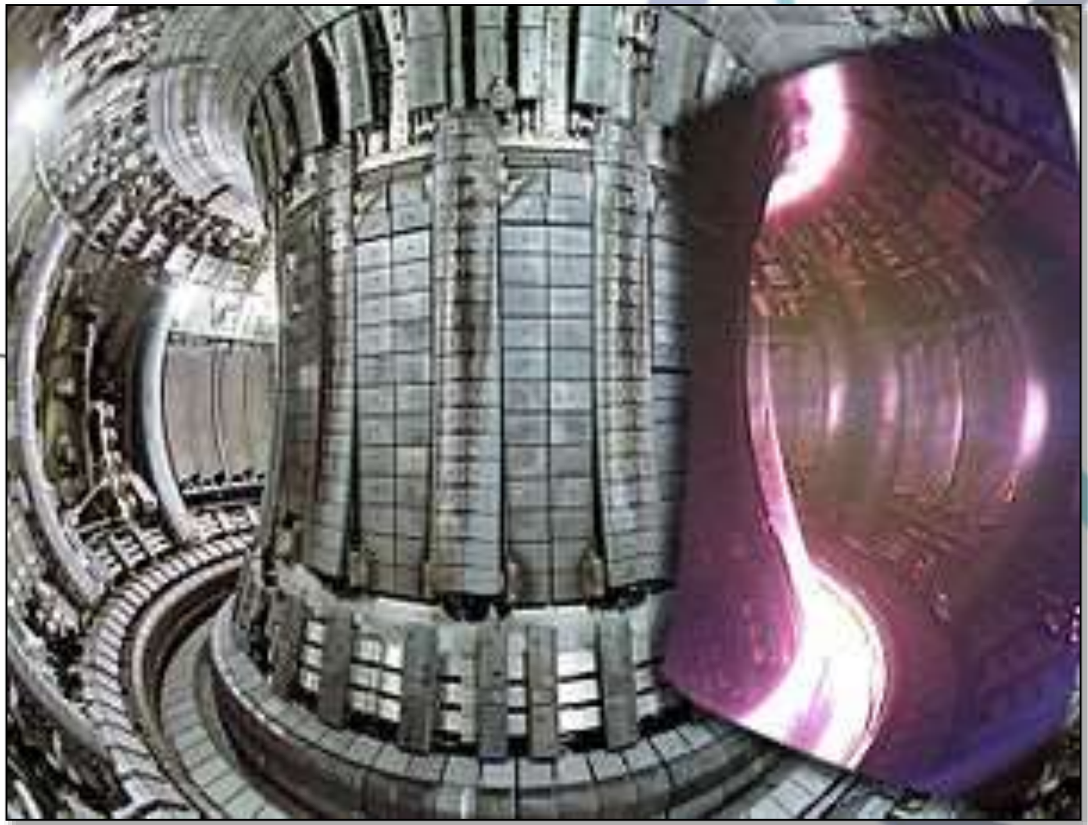




ML: Support Vector Machines – SVM (MARFE)

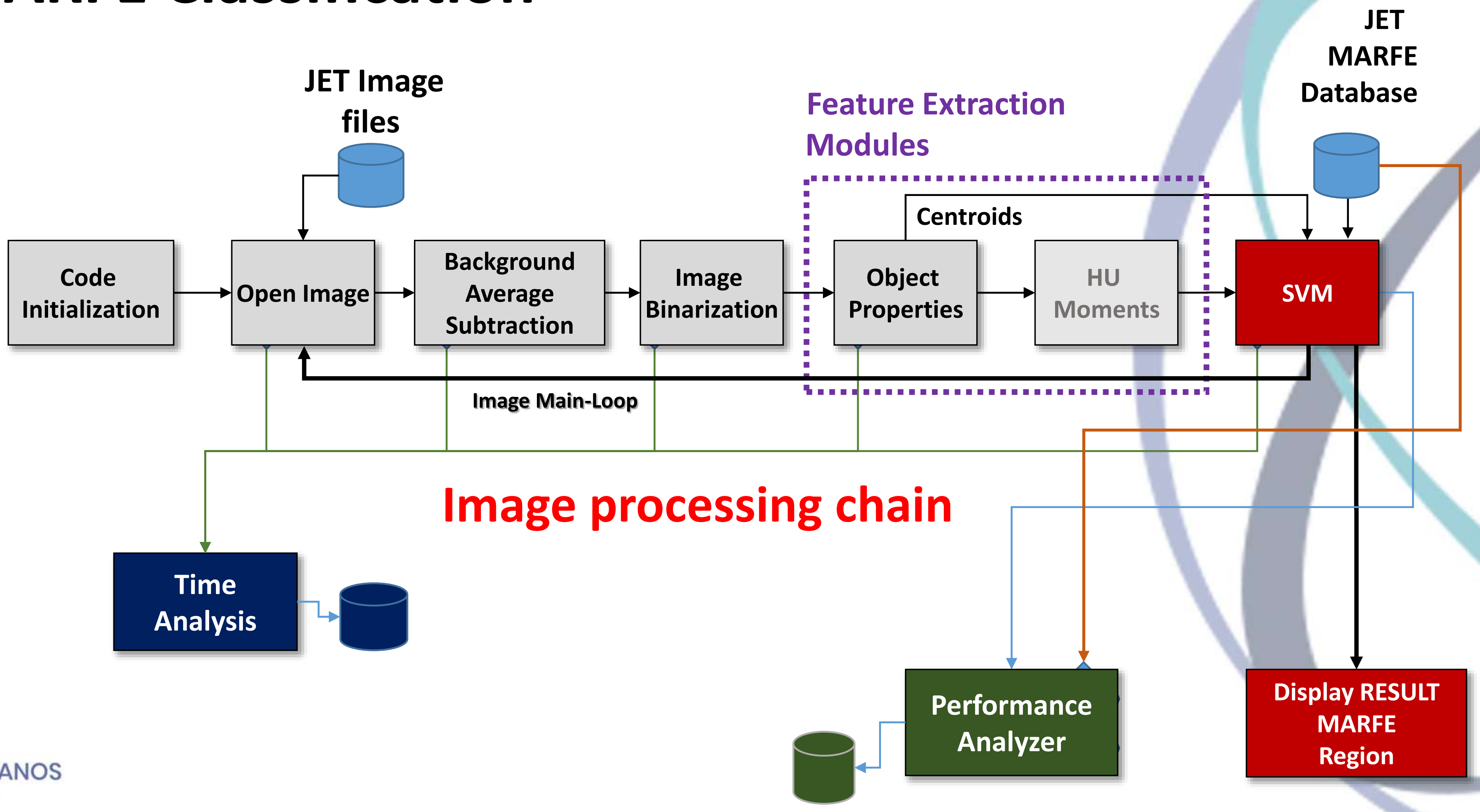
SVM – MARFE Classification



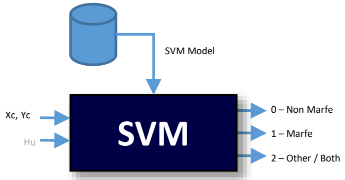


ML: Support Vector Machines – SVM (MARFE)

SVM – MARFE Classification

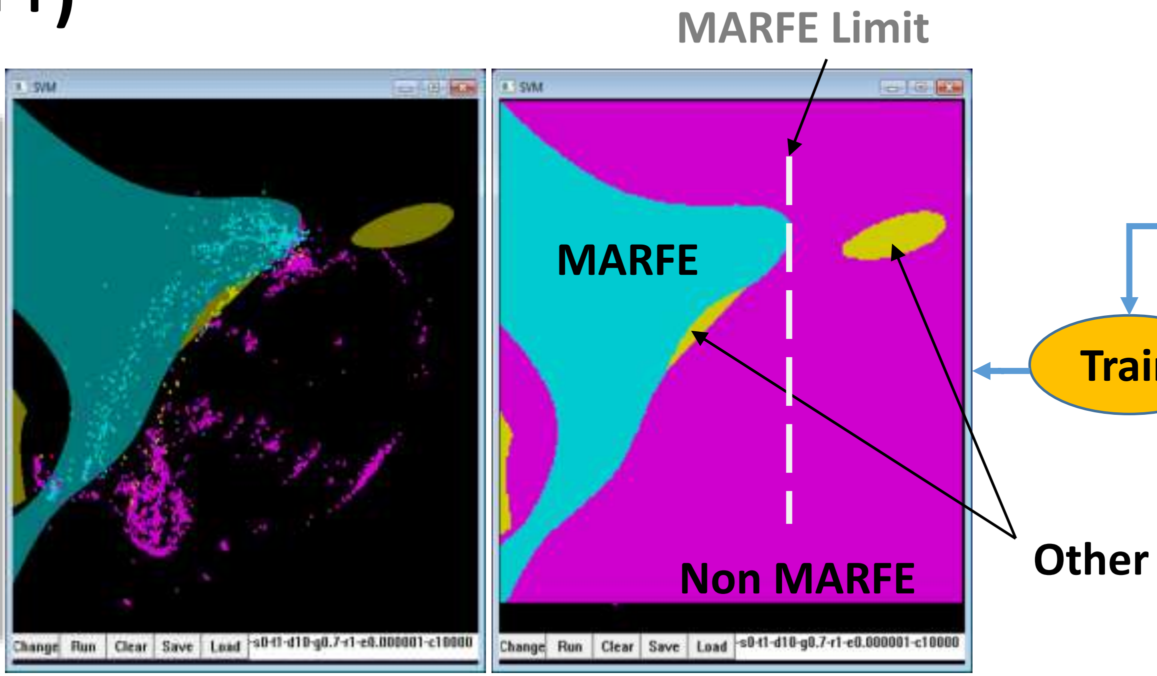


ML: Support Vector Machines – SVM (MARFE)

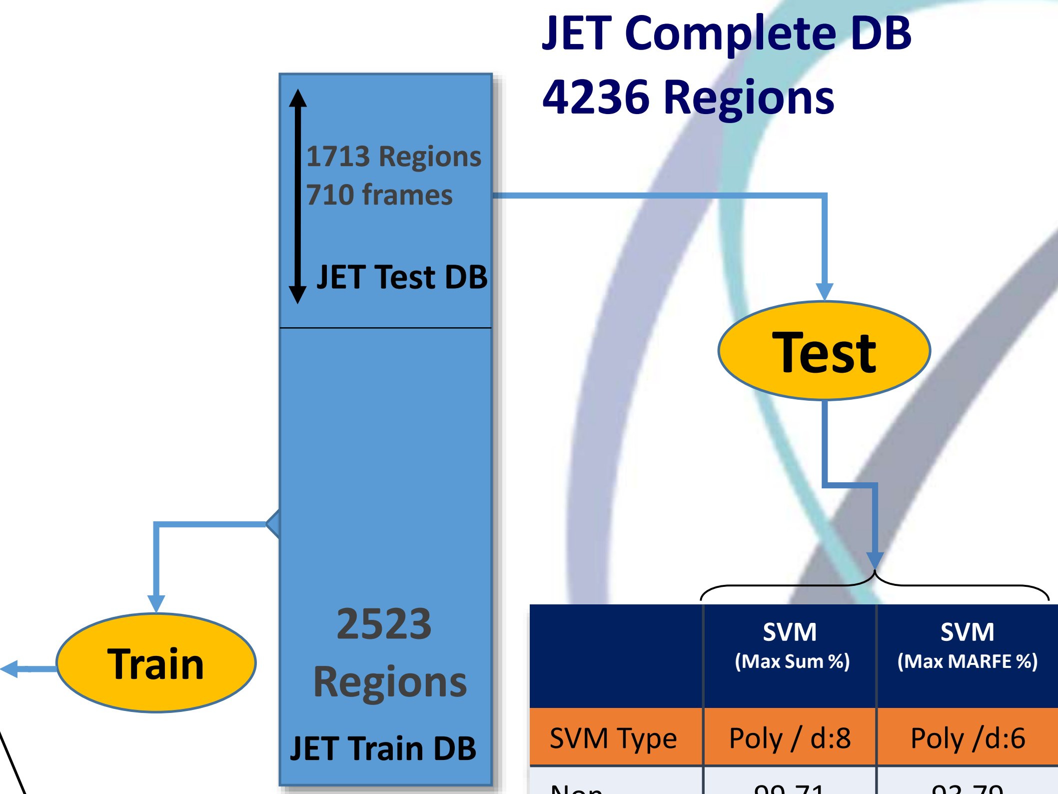


SVM Module

- LibSVM (in C++)



SVM decision



	SVM (Max Sum %)	SVM (Max MARFE %)
SVM Type	Poly / d:8	Poly /d:6
Non Marfe	99,71	93,79
Marfe	93,79	94,14
Other	25,45	14,55
Sum	96,32	96,15

Kernel type: polynomial

Evaluation test for different degree: 6, 8, 10 and 12.

(11018 SVM models were evaluated)

ML: Support Vector Machines – SVM (MARFE)

Xc, Yc

Hu

IEEE TRANSACTIONS ON PLASMA SCIENCE, VOL. 41, NO. 2, FEBRUARY 2013 341

A 10 000-Image-per-Second Parallel Algorithm for Real-Time Detection of MARFEs on JET

Márcio Portes de Albuquerque, Andrea Murari, M. Giovani, Nilton Alves, Jr., Marcelo Portes de Albuquerque, and JET-EFDA Contributors

Abstract—This paper presents a very high-speed image processing algorithm applied to multi-faceted asymmetric radiation from the edge (MARFE) detection on the Joint European Torus. The algorithm was built in serial and parallel versions and written in C/C+ using OpenCV, cvBlob, and LibSVM libraries. The code implemented was characterized by its accuracy and run-time performance. The final result of the parallel version achieves a correct detection rate of 97.6% for MARFE identification and an image processing rate of more than 10 000 frame per second. The parallel version divides the image processing chain into two groups and seven tasks. One group is responsible for Background Image Estimation and Image Binarization modules, and the other is responsible for region Feature Extraction and Pattern Classification. At the same time and to maximize the workload distribution, the parallel code uses data parallelism and pipeline strategies for these two groups, respectively. A master thread is responsible for opening, signaling, and transferring images between both groups. The algorithm has been tested in a dedicated Intel symmetric-multiprocessing computer architecture with a Linux operating system.

an entire and complex processing chain. Although parallelism depends on the problem, the low cost and the easy availability of multicore systems and parallel software make it much more attractive than in years past. On the other hand, the FPGA is still an interesting option, but its adoption in high-performance tasks is currently limited by the complexity of the FPGA design compared with the conventional software.

Magnetic confinement nuclear fusion is one of the recent fields in which digital image processing has become a fundamental tool in scientific instrumentation. Indeed, image processing is nowadays very important not only for the interpretation of the experiments but also for pattern retrieval in large databases [1], [2]. In the Joint European Torus (JET), about 30 new cameras have been installed for the current experiments with the new metallic wall. One of the most challenging characteristics of cameras as scientific instruments is the large amount of data that they produce. For example, JET global image

IEEE TRANSACTIONS ON PLASMA SCIENCE, VOL. 41, NO. 2, FEBRUARY 2013 341

SVM (Max MARFE %)
Poly /d:6
93,79
94,14
14,55
96,15

Evaluation test for different degree: 6, 8, 10 and 12.

(11018 SVM models were evaluated)

ML: K-Means (Unsupervised)

- K-Means partition the space into K classes.
- Each point belongs to the cluster with the nearest mean
- Here “nearest” is based on some norm (e.g. Euclidean norm)

4 Classes

dx.doi.org/10.7437/NT2236-7640/2016.01.003
Notas Técnicas, v. 6, n. 1, p. 19–27, 2016

Segmentação Textural de Imagens de Rocha por Microtomografia

Segmentation of Microtomography images of rocks using texture filter

Luciana Olivia Dias*
Centro Brasileiro de Pesquisas Físicas - Rua Dr. Xavier Sigaud 150, Rio de Janeiro, RJ 22290-180, Brasil

Clécio R. De Bom†
Centro Federal de Educação, Tecnológica Celso Suckow da Fonseca, Rodovia Mário Covas, lote J2, quadra J - 23810-000 Distrito Industrial de Itaguaí, Itaguaí, RJ e Centro Brasileiro de Pesquisas Físicas - Rua Dr. Xavier Sigaud 150, Rio de Janeiro, RJ 22290-180, Brasil

Heitor Guimarães,‡ Elisângela L. Faria,§ Márcio P. de Albuquerque,¶ e Marcelo P. de Albuquerque**
Centro Brasileiro de Pesquisas Físicas - Rua Dr. Xavier Sigaud 150, Rio de Janeiro, RJ 22290-180, Brasil

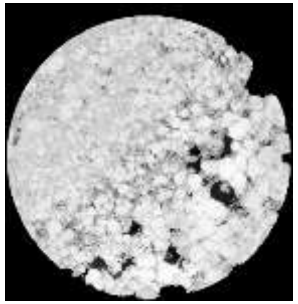
Maury D. Correia†† e Rodrigo Surmas‡‡
Centro de Pesquisas e Desenvolvimento Leopoldo Américo Miguez de Mello - CENPES PETROBRAS, Av. Horácio Macedo, 950, Cidade Universitária, Rio de Janeiro, RJ - 21941-915, Brasil

Submetido: 29/09/2015 Aceito: 10/05/2106

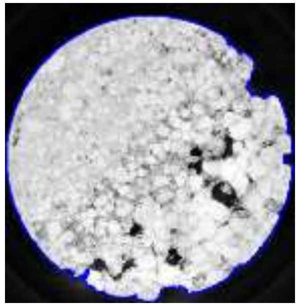
Resumo: A segmentação, realizada de maneira robusta, automatizada e eficiente, de diferentes fases em imagens de microtomografia é um fator crítico e limitador na área de Petrofísica de Rocha Digital. Abordamos a questão partindo de um algoritmo com técnicas baseadas em filtros, obtendo a maximização da Entropia Local para definir um limiar entre fundo e objeto. Validamos a qualidade da segmentação a partir de imagens de amostras de microesferas de vidro, recuperamos o raio das esferas e comparamos a técnica proposta com outros dois algoritmos de segmentação.

AttriTex

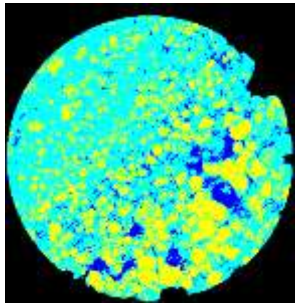
Kmeans with Automatic Contour ROI



Input Image

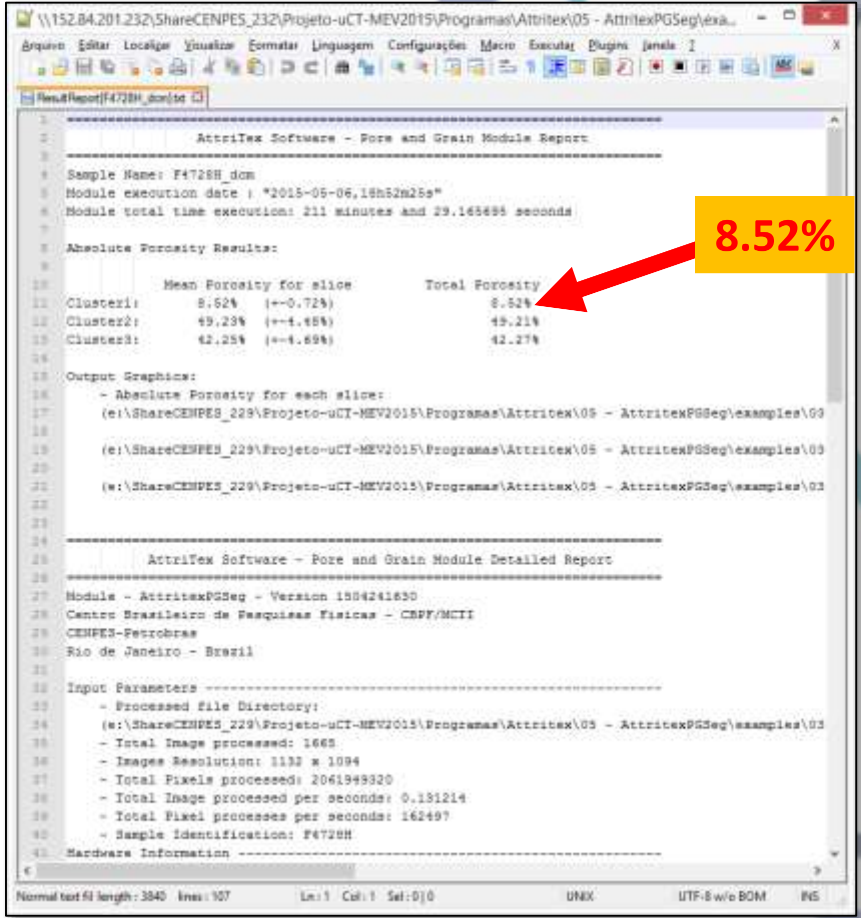


ROI Automatic Contour



3 Clusters Image

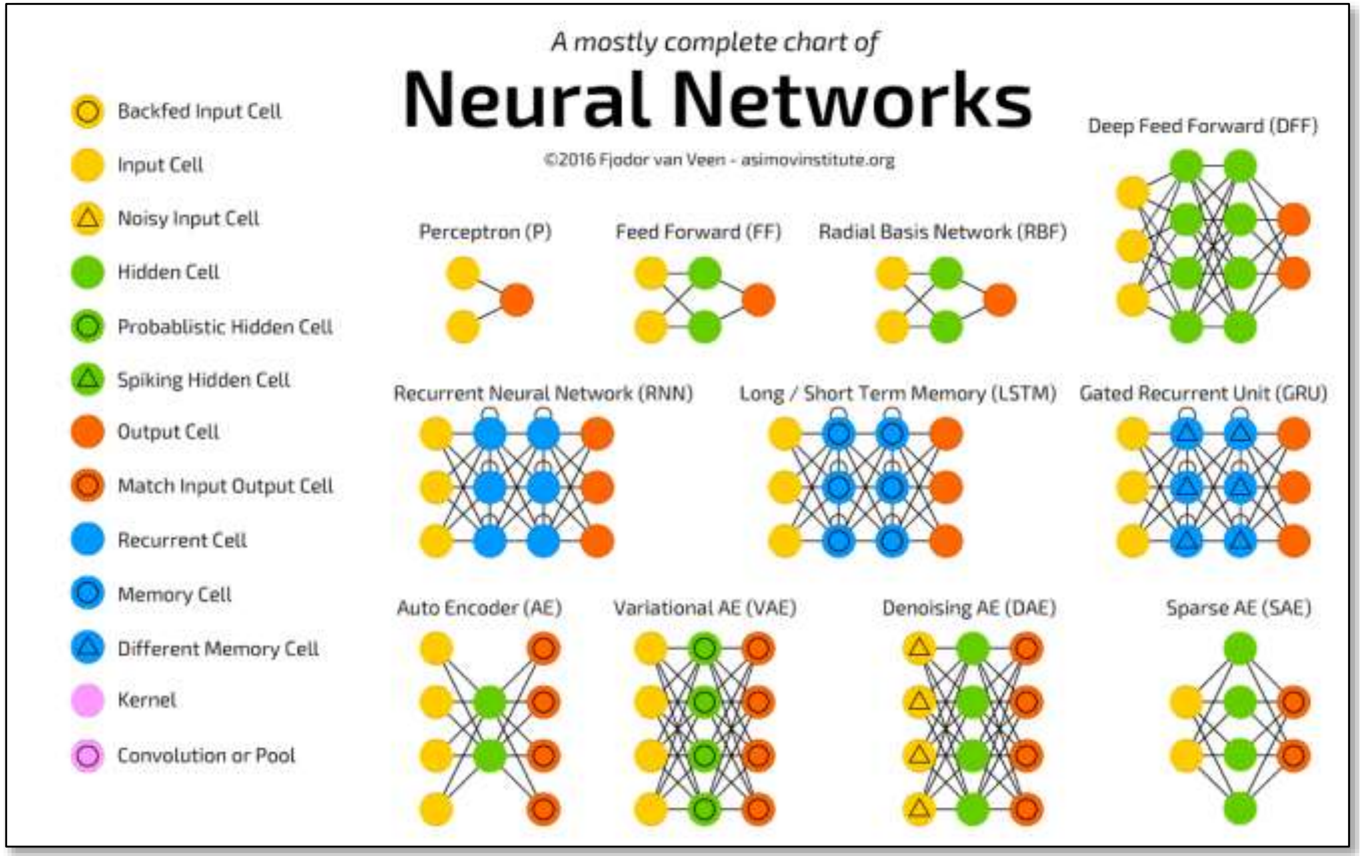
- INPUT Image: F4728H (1665 DCM Images) = 1132x1094
- Expected mean porosity by Porosimeter: 8.5%
- ROI – Automatic Contour
- Kmeans with 3 Clusters

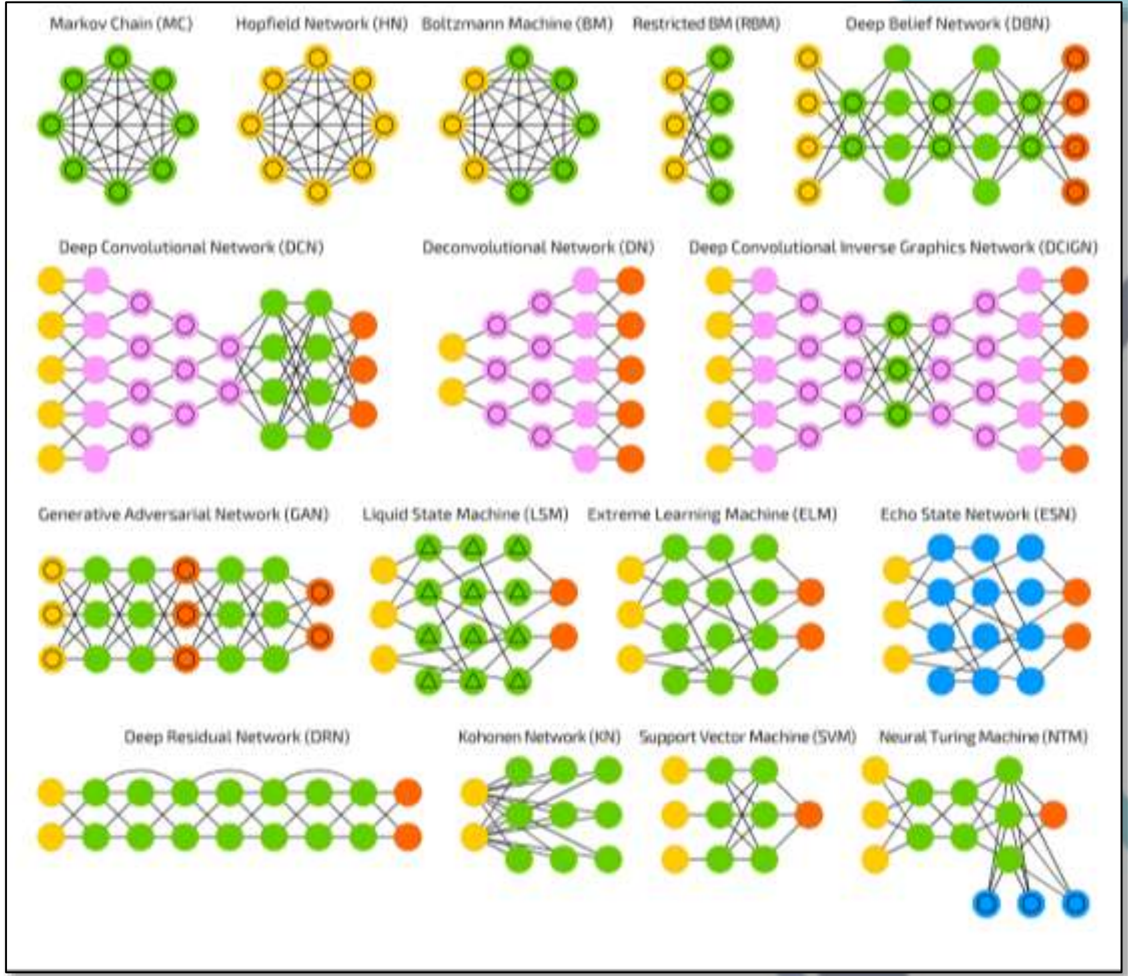


8.52%

CBPF ANOS

Alguns termos importantes

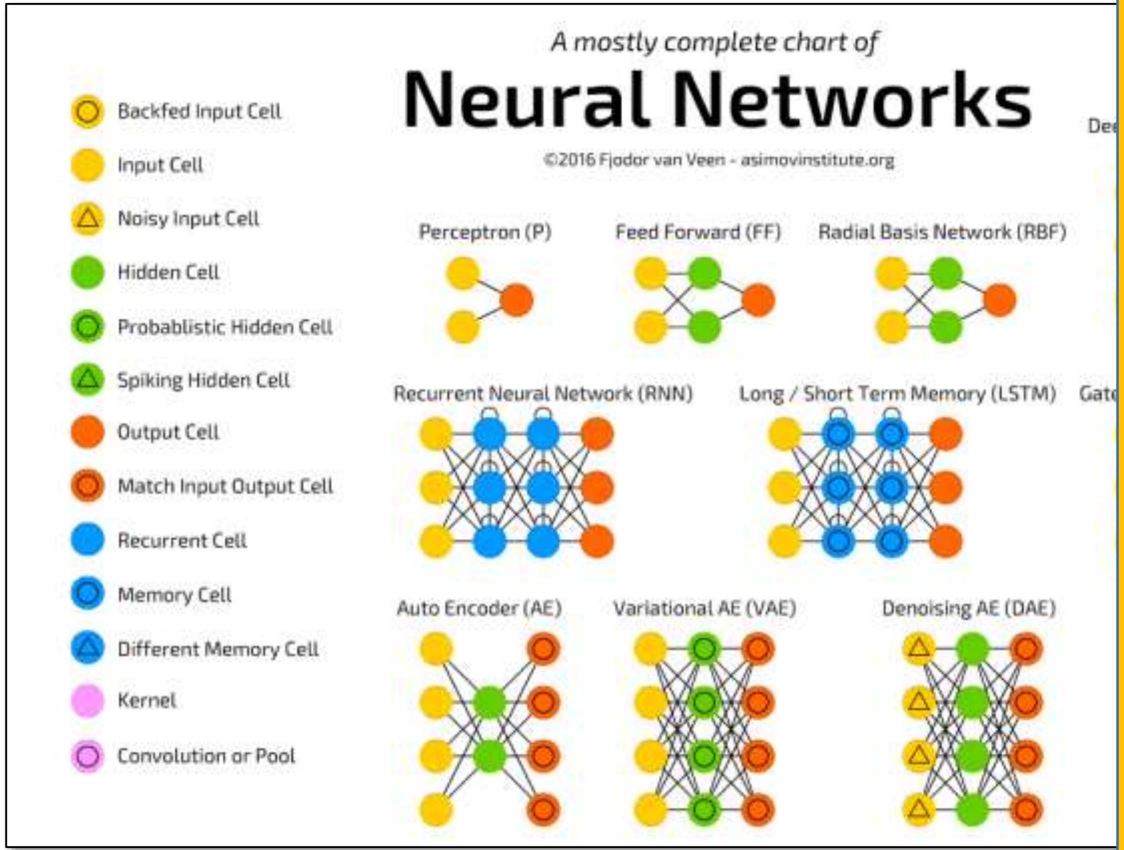




Asimov Institute
http://www.asimovinstitute.org/neural-network-zoo/

Redes Neurais Artificiais (RNAs) são modelos computacionais inspirados pelo sistema nervoso central de um animal (em particular o cérebro) e são capazes de realizar o "aprendizado de máquina" bem como "identificar padrões".

Alguns termos importantes



Asimov Institute
http://www.asimovinstitute.org/neural-network-zoo/

Alguns termos básicos

<u>Deep Learning</u> é uma Rede Neural Artificial
<u>Deep Learning</u> é uma área de Machine Learning

Alguns Termos de Redes Neurais Artificiais

- **MLP: Multi-layer Perceptron**
- **DNN: Deep Neural Networks**
- **RNN: Recurrent Neural Networks**
  - **LSTM: Long Short-Term Memory**
- **CNN ou ConvNet: Convolution Neural Network**
- **DBN: Deep Delief Networks**

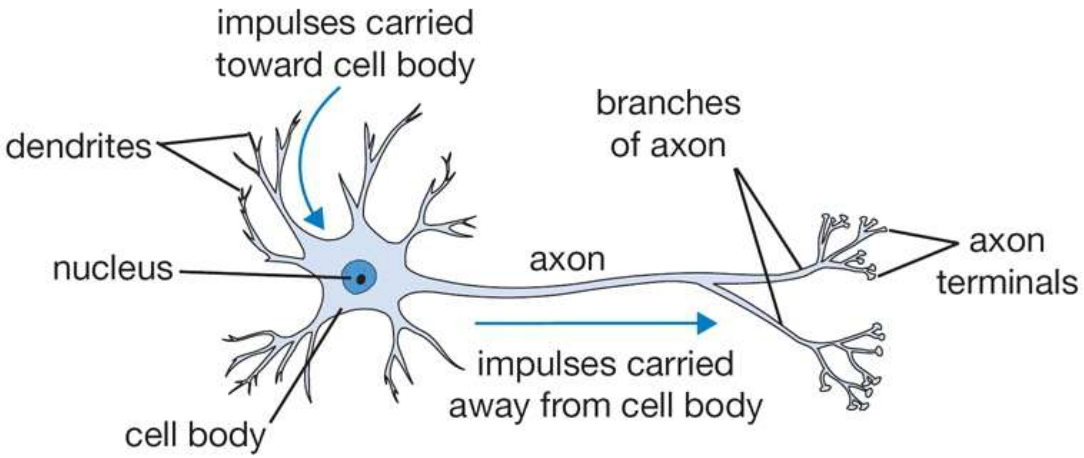
Operações das Redes Neurais Artificiais

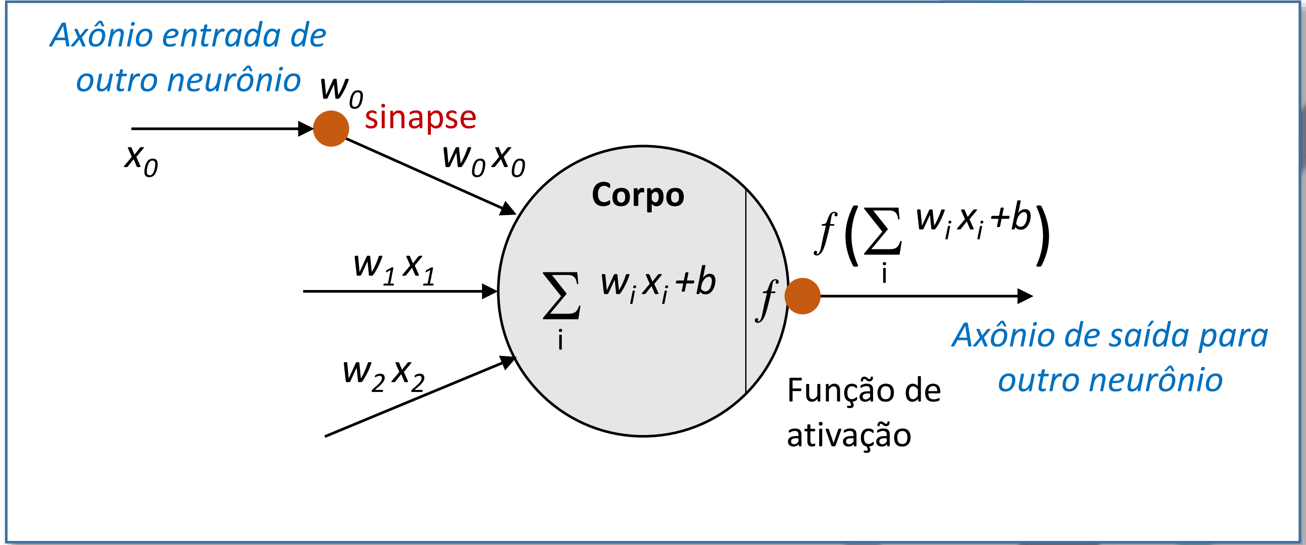
- **Convolução**
- **Pooling**
- **Função de Ativação**
- **Backpropagation**

Redes Neurais Artificiais (RNAs) são modelos comput
particular o cérebro) e são capazes de realizar o "aprendizado de máquina" bem como "identificar padrões".

Neurônio

Computação (Neurônio Artificial) → Inspiração na Biologia





Neurônio Biológico: bloco computacional de processamento do cérebro.

Cérebro Humano: ~100 – 1.000 trilhões de sinapses

10.000 x

Neurônio Artificial: bloco computacional de processamento das Redes Neurais Artificiais.

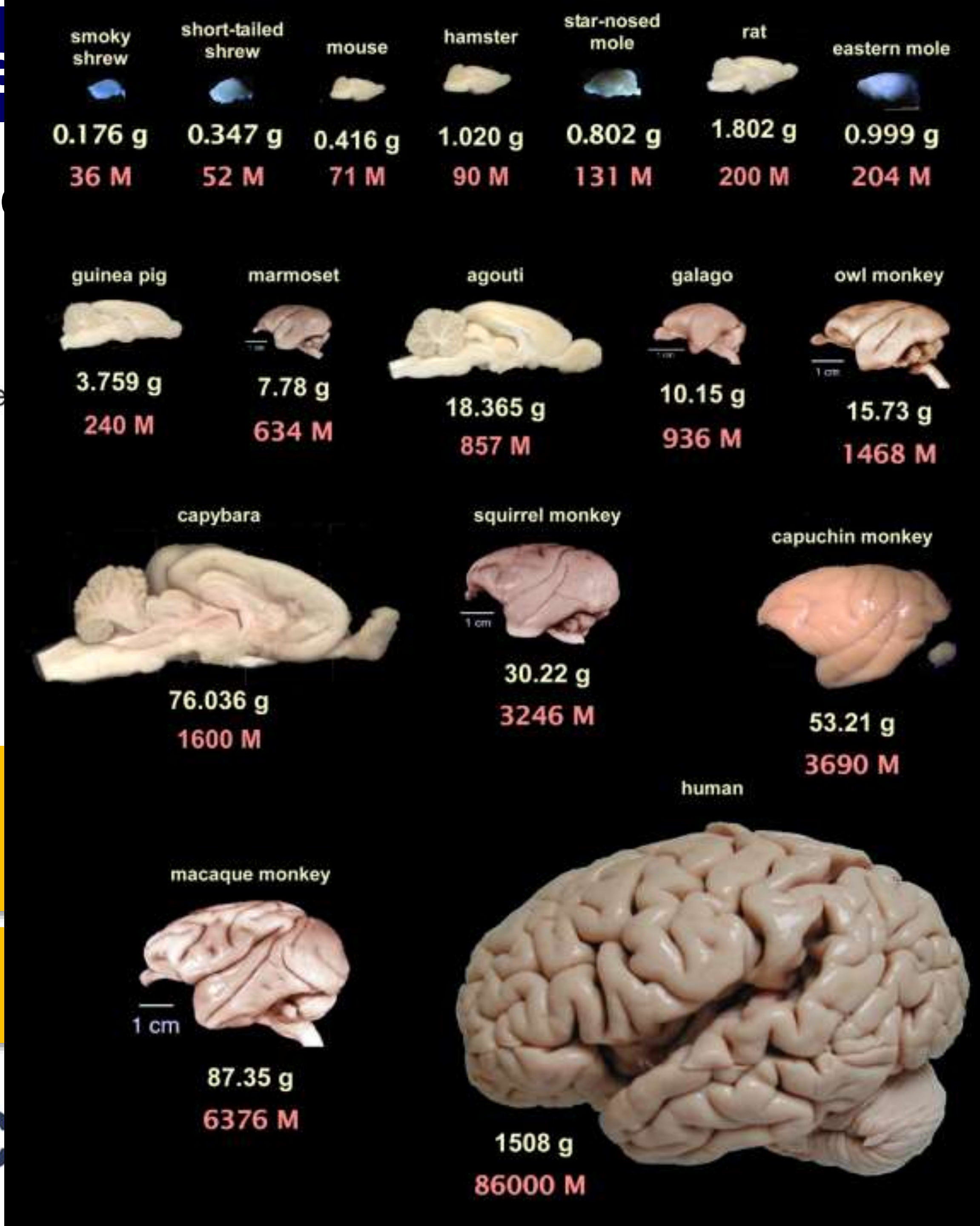
Rede Neural Artificial : ~1 – 10 bilhões de sinapses.

Ne

C

de

Brain mass and total number of neurons for the mammalian species



frontiers in Human Neuroscience

saída para
eurônio

s.

S. Herculano-Houzel

Front. Hum. Neurosci., November/2009

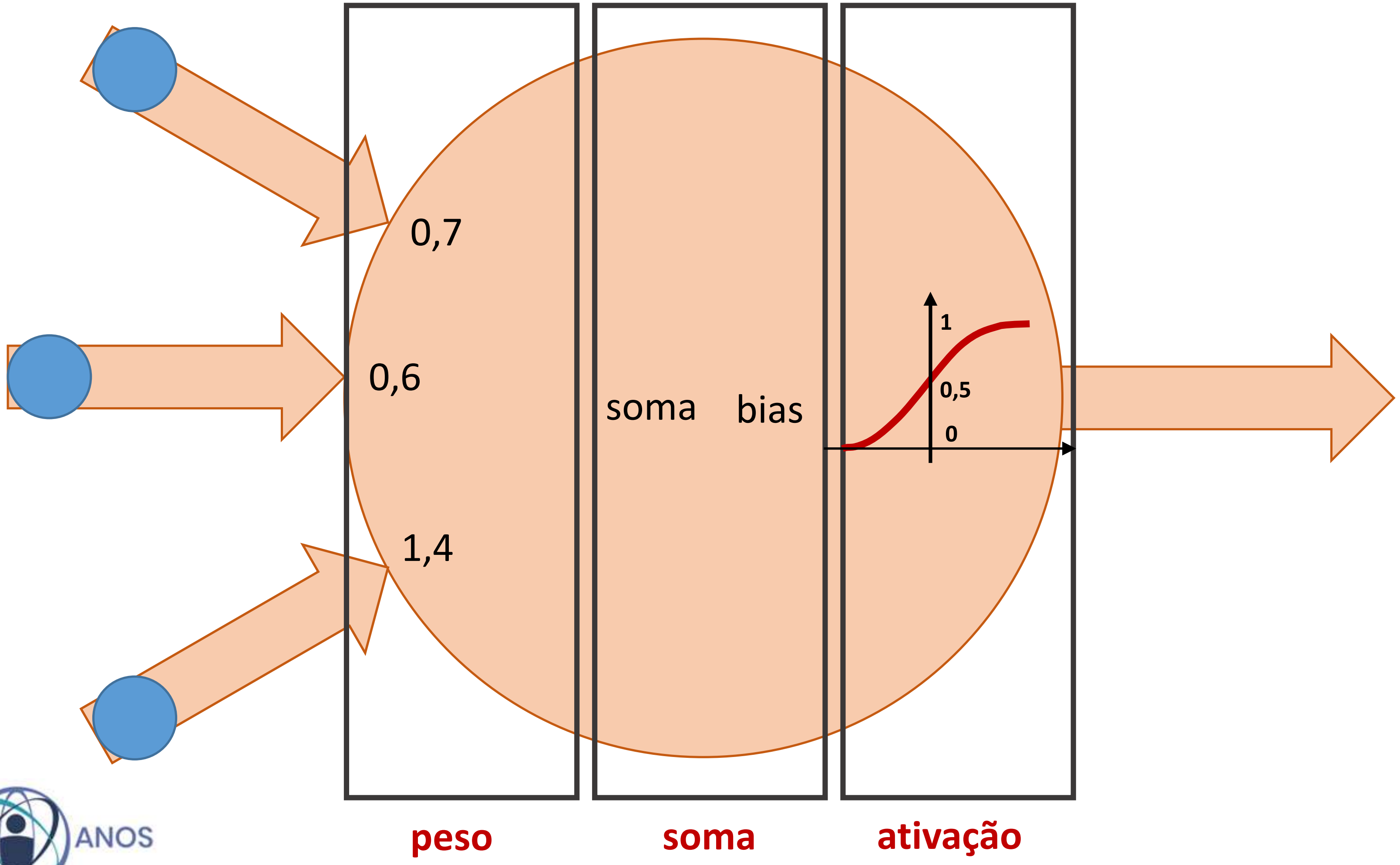
doi.org/10.3389/neuro.09.031.2009

The human brain in numbers: a linearly scaled-up primate brain

Rede Neural Artificial

Perceptron

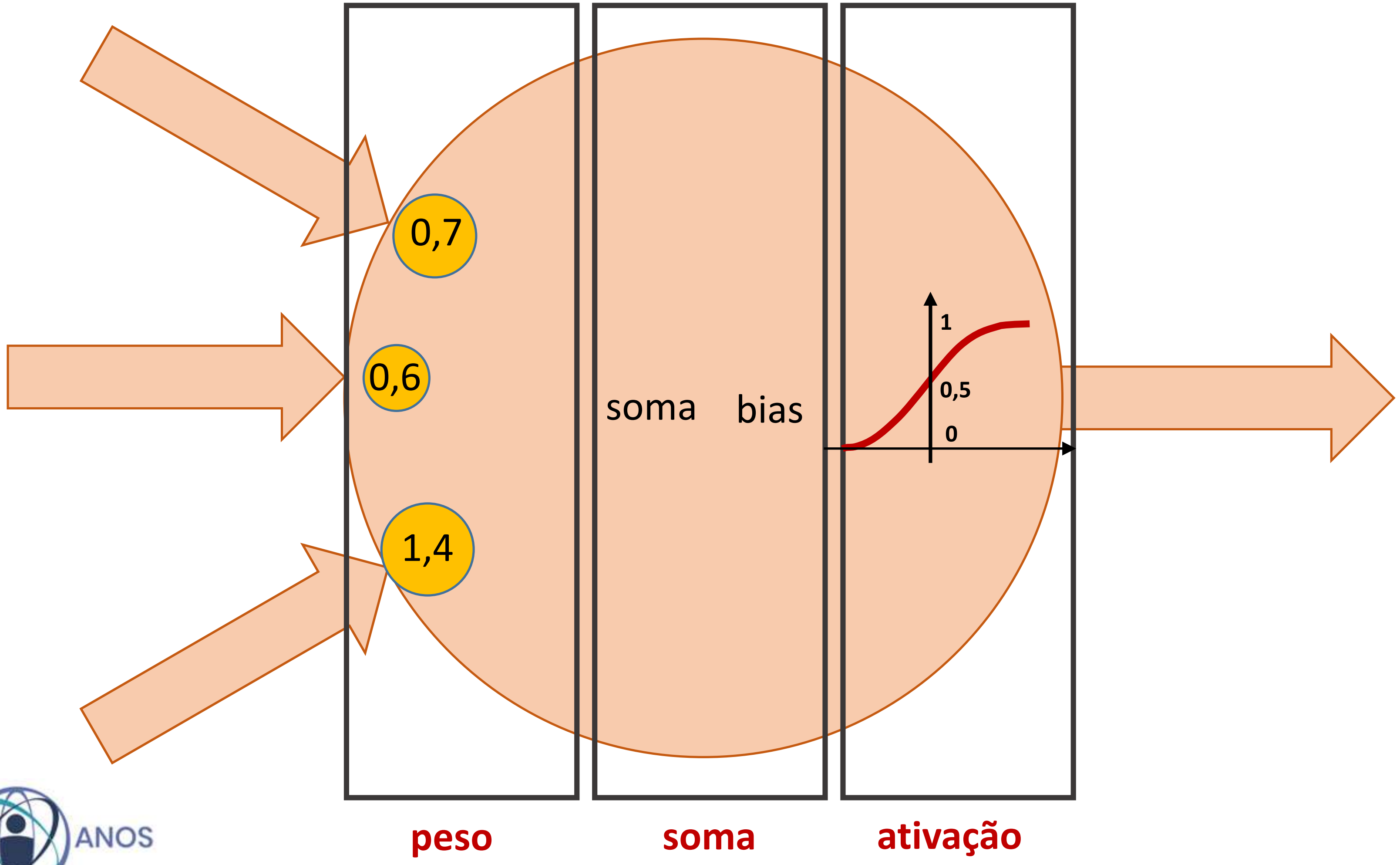
Frank Rosenblatt (1957)



Rede Neural Artificial

Perceptron

Frank Rosenblatt (1957)

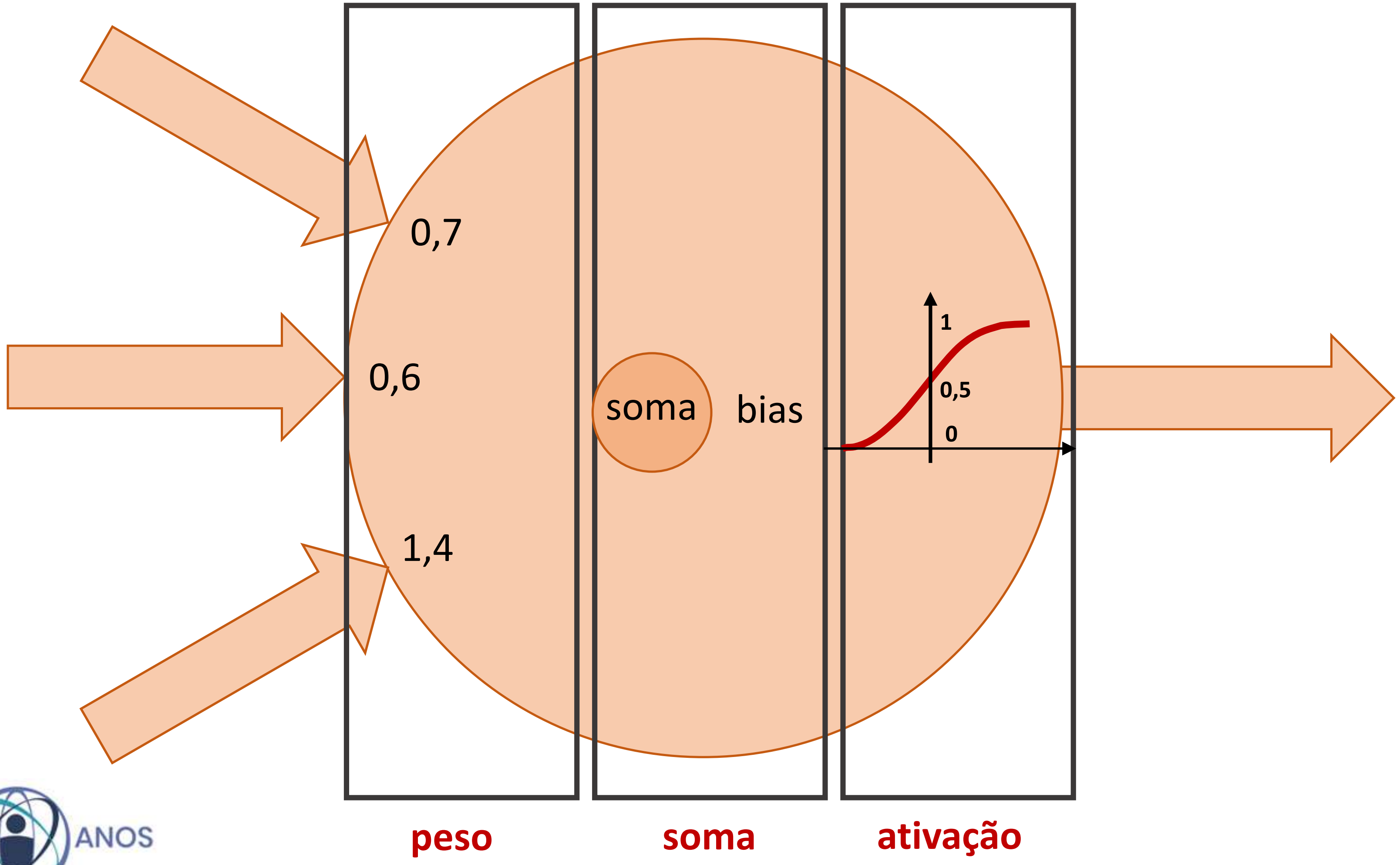


CBPF 70 ANOS

Rede Neural Artificial

Perceptron

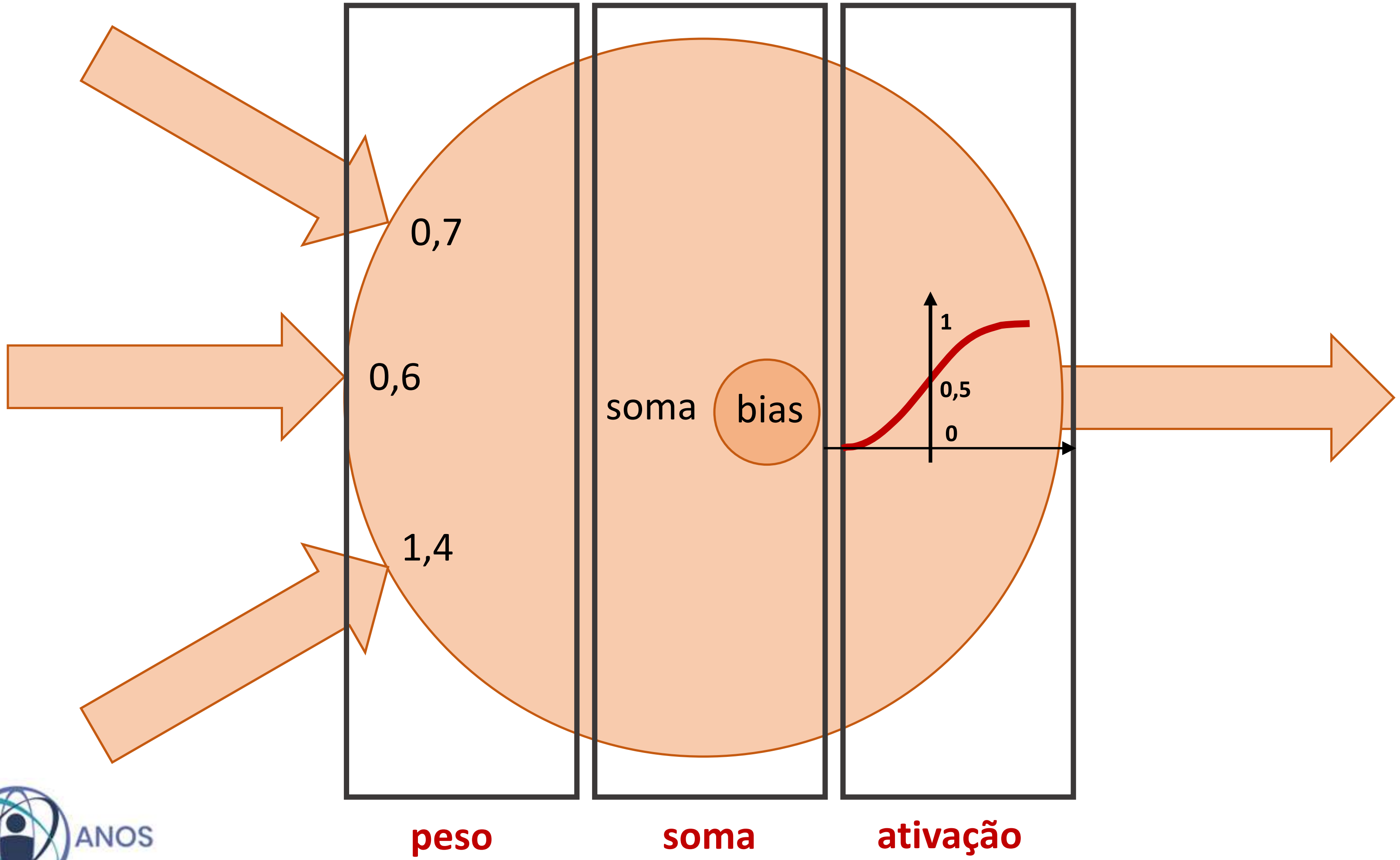
Frank Rosenblatt (1957)



Rede Neural Artificial

Perceptron

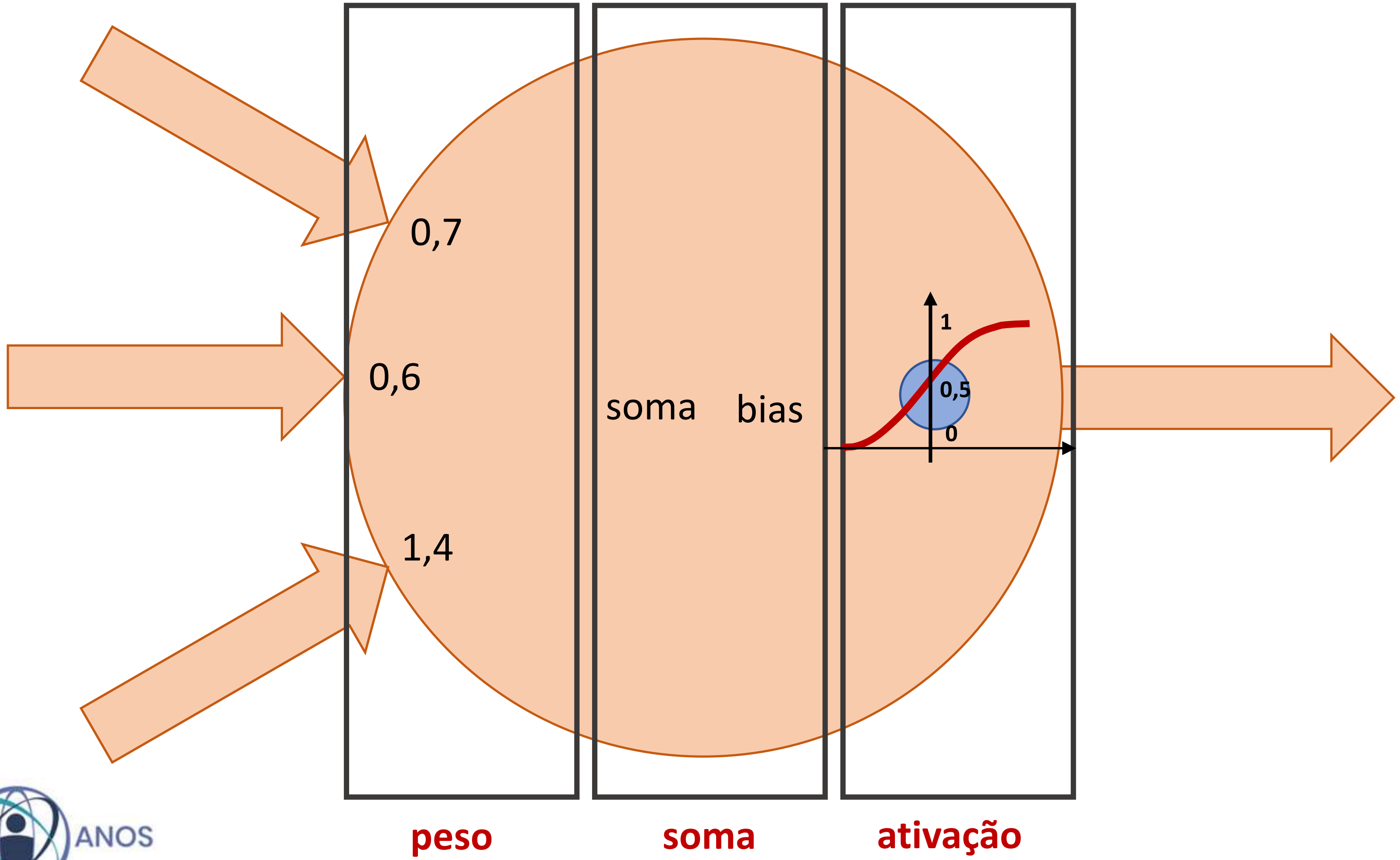
Frank Rosenblatt (1957)



CBPF 70 ANOS

Perceptron

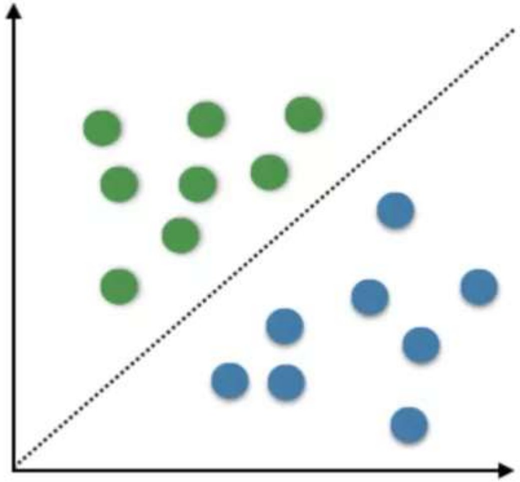
Frank Rosenblatt (1957)

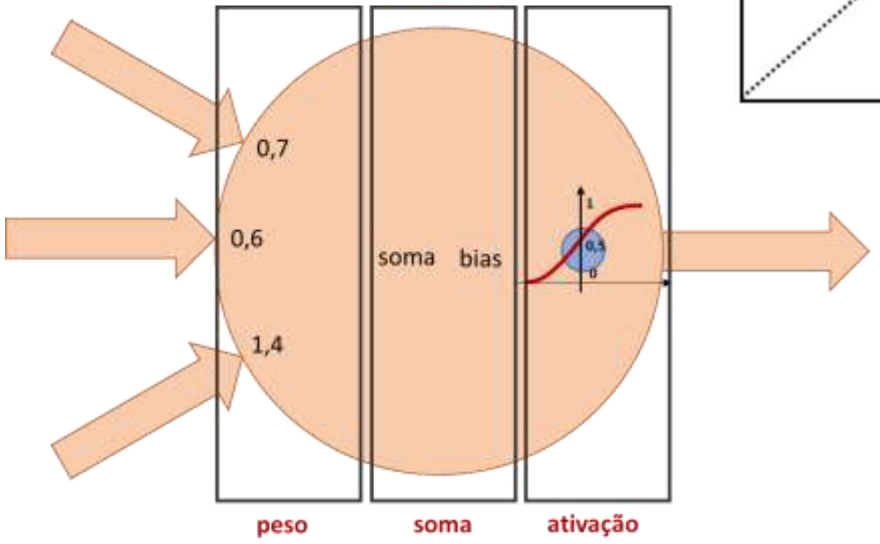


Rede Neural Artificial

Perceptron

Frank Rosenblatt (1957)

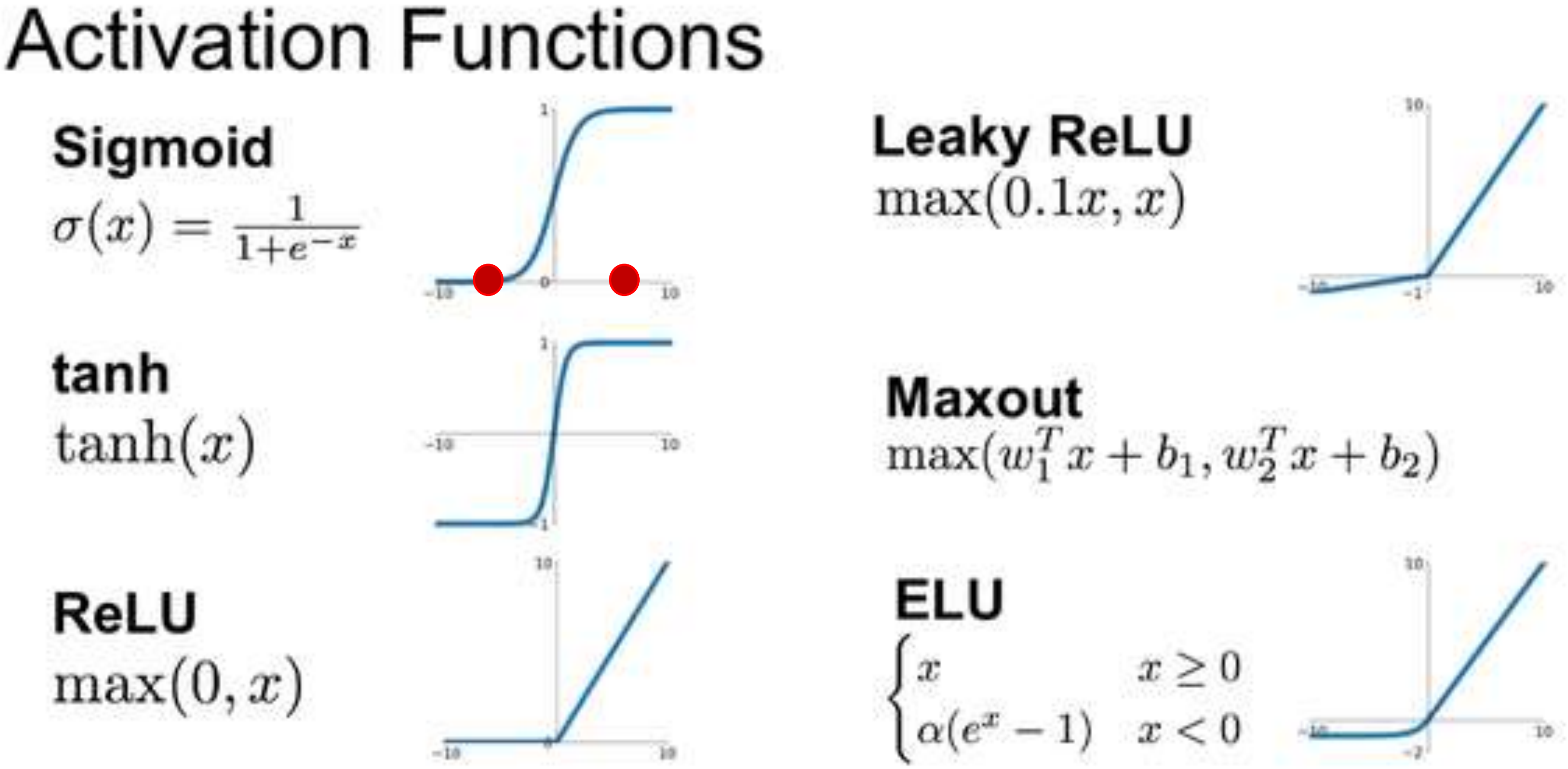




Algoritmo

- **Inicialize a rede Perceptron com pesos (w) aleatórios;**
- **Para uma data entrada, processe a saída da rede;**
- **Se a saída da rede não for igual a saída desejada, então a rede deve ser alterada, trocando os valores dos pesos (w) das sinapses;**
- **Repita esse procedimento com todos os dados de treinamento até a rede Perceptron não apresentar mais erros.**

Função de Ativação



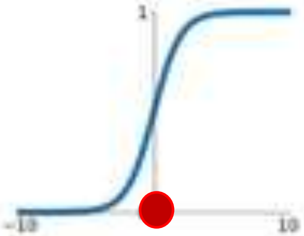
Não lineares

CBPF 70 ANOS

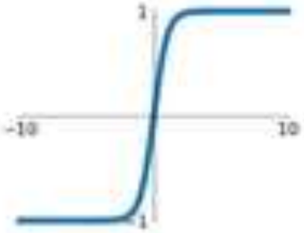
Função de Ativação

Activation Functions

Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$



tanh
$\tanh(x)$

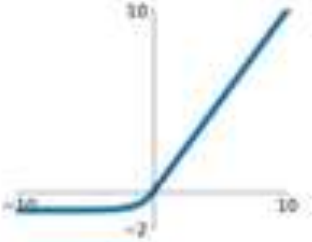


ReLU
$\max(0, x)$

Leaky ReLU
$\max(0.1x, x)$

Maxout
$\max(w_1^T x + b_1, w_2^T x + b_2)$

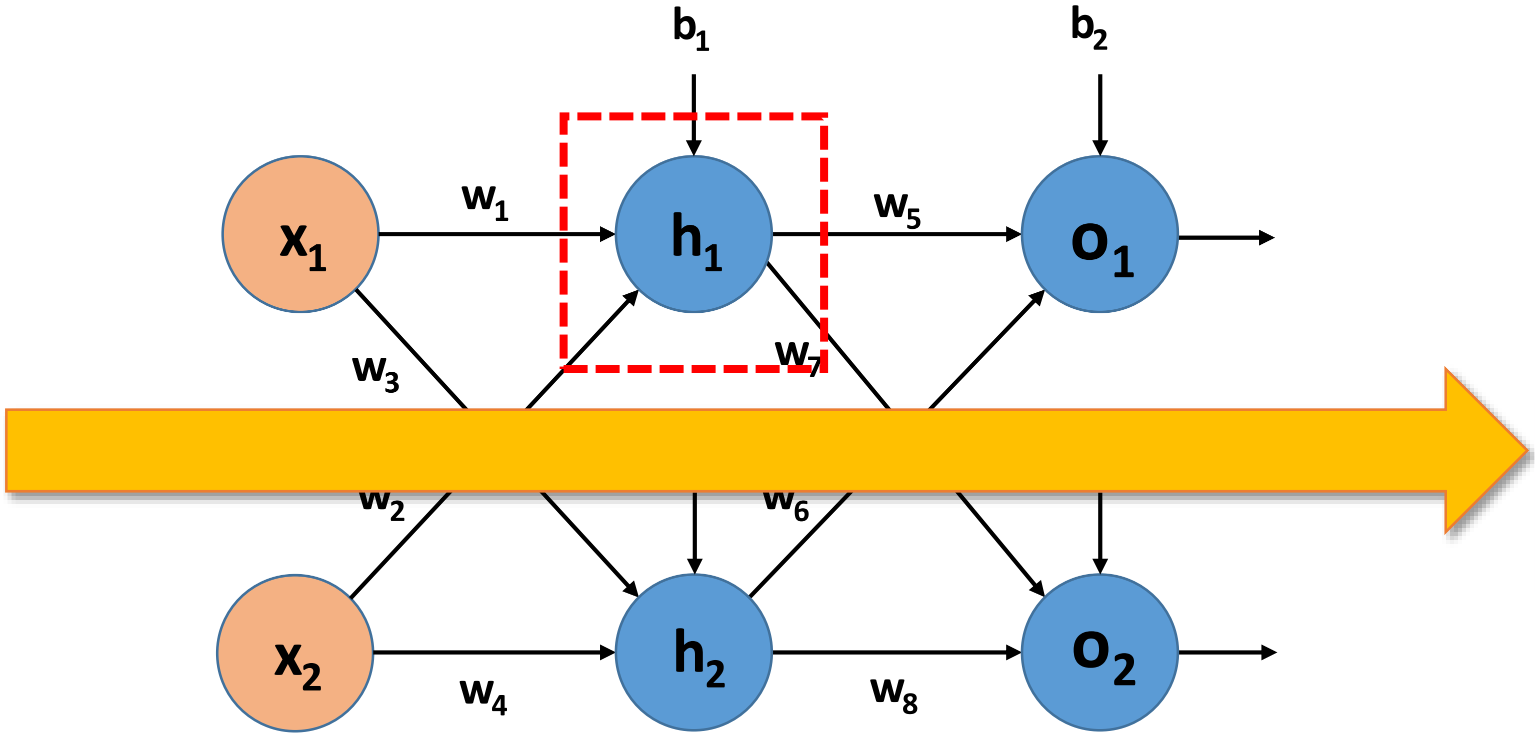
ELU
$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$



Não lineares

Feedforward and Backpropagation

Fase 1
Propagação



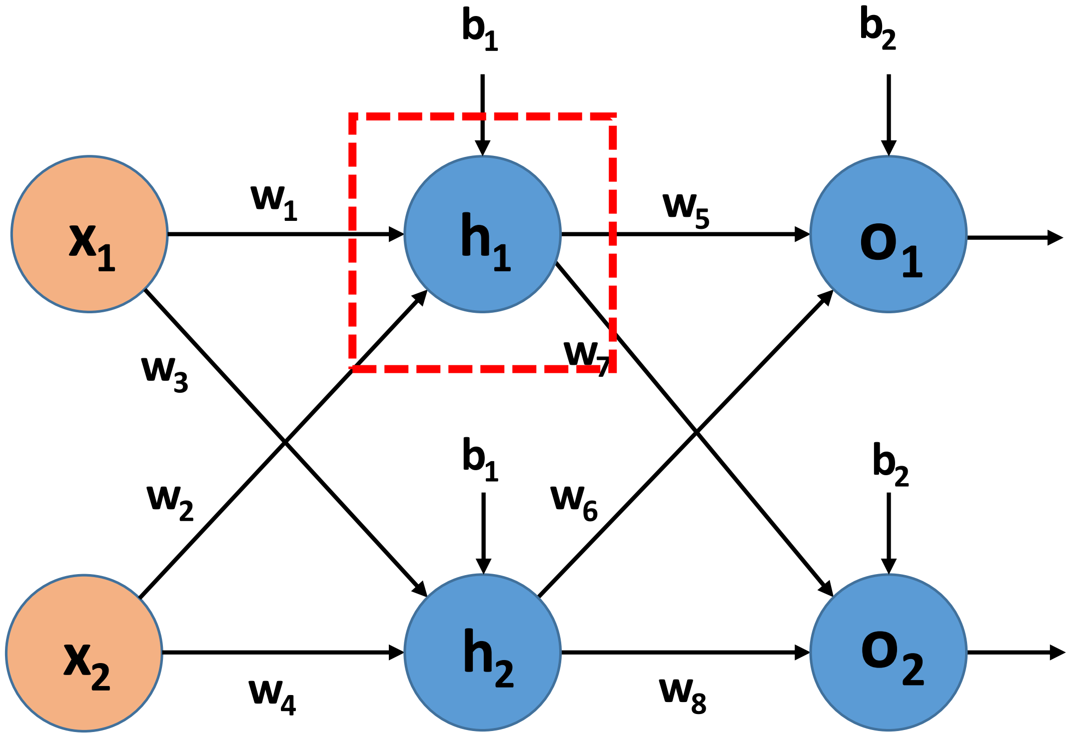
$$uh_1 = x_1 * w_1 + x_2 * w_2 + b_1 * 1$$

$$\mathrm{g}(h_1) = \mathrm{g}(uh_1) = \frac{1}{1+e^{-uh_1}}$$

CBPF ANOS

Feedforward and Backpropagation

Fase 1
Propagação



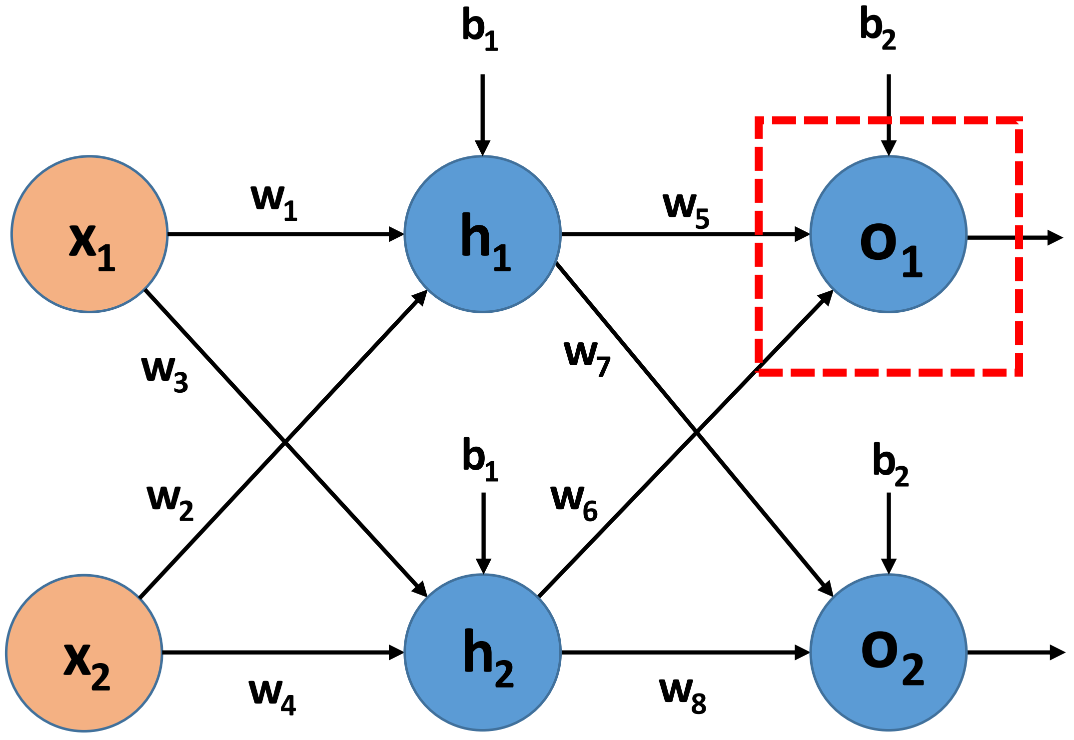
$$uh_2 = x_1 * w_3 + x_2 * w_4 + b_1 * 1$$

$$\mathrm{g}(h_2) = \mathrm{g}(uh_2) = \frac{1}{1+e^{-uh_2}}$$

CBPF 70 ANOS

Feedforward and Backpropagation

Fase 1
Propagação



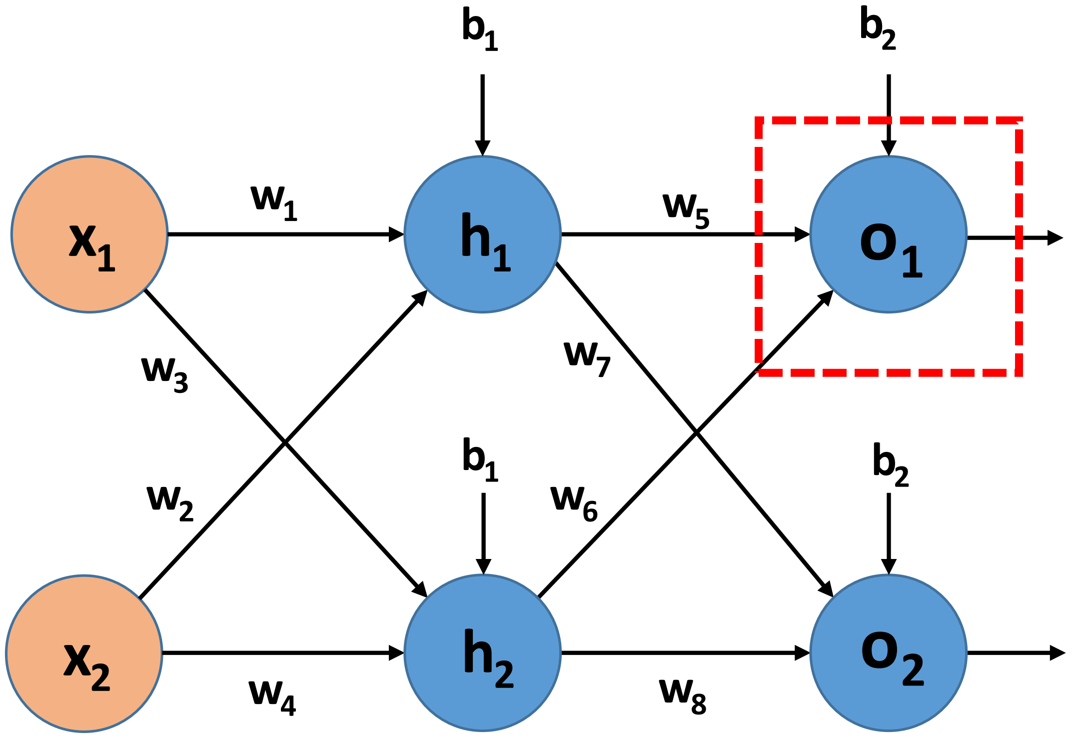
$$uo_1 = g(h_1) * w_5 + g(h_2) * w_6 + b_2 * 1$$

$$\hat{y}_1 = g(o_1) = g(uo_1) = \frac{1}{1+e^{-uo_1}}$$

CBPF 70 ANOS

Feedforward and Backpropagation

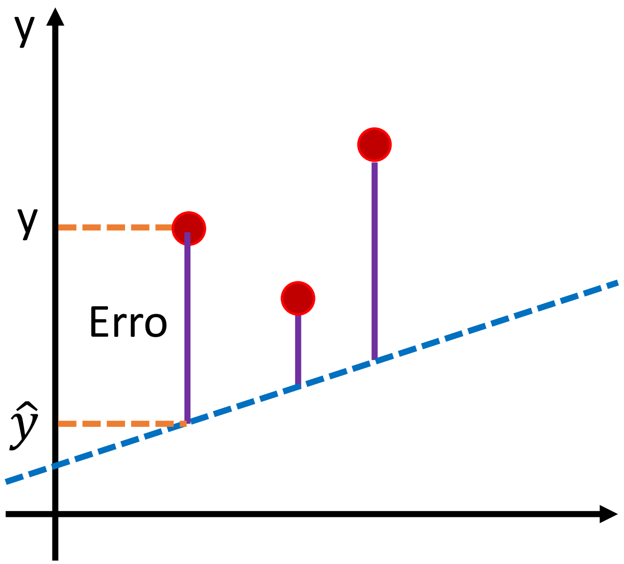
Fase 1
Propagação



$$uo_2 = g(h_1) * w_7 + g(h_2) * w_8 + b_2 * 1$$

$$\hat{y}_2 = g(o_2) = g(uo_2) = \frac{1}{1+e^{-uo_2}}$$

Rede Neural Artificial: Erro/Custo



y = valor original

$\hat{y}$ = valor predito

$$\hat{y}_n = g(o_n) = g(uo_n) = \frac{1}{1+e^{-uo_n}}$$

$$J(w_n) = \frac{\sum_{i=1}^{m}(\hat{y}_i - y_i)^2}{m}$$

CUSTO

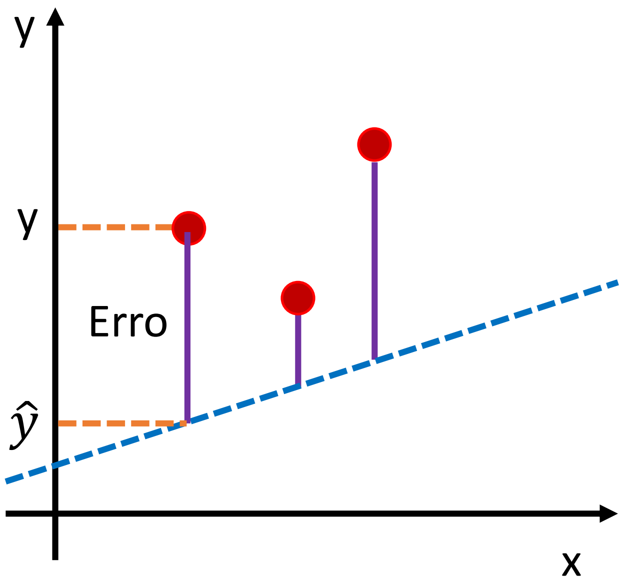
COST

(média)

MSE (*Mean Square Error* – Erro quadrático médio)

CBPF 70 ANOS

Rede Neural Artificial: Erro/Custo



y = valor original

$\hat{y}$ = valor predito

$$\hat{y}_n = g(o_n) = g(uo_n) = \frac{1}{1+e^{-uo_n}}$$

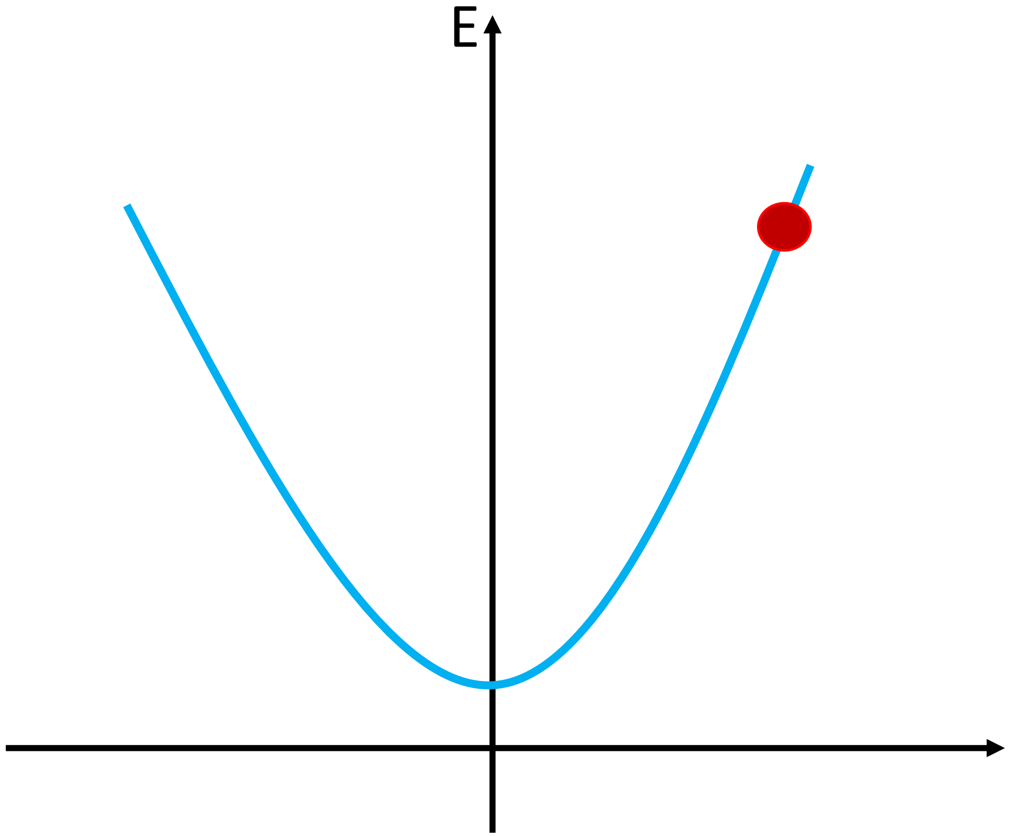
$$J(w_n) = \frac{\mathbf{1}}{\mathbf{2m}} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2$$

MSE (*Mean Square Error* – Erro quadrático médio)

Como reduzir o custo? $\min_{(w)} J(w_n)$

CBPF 70 ANOS

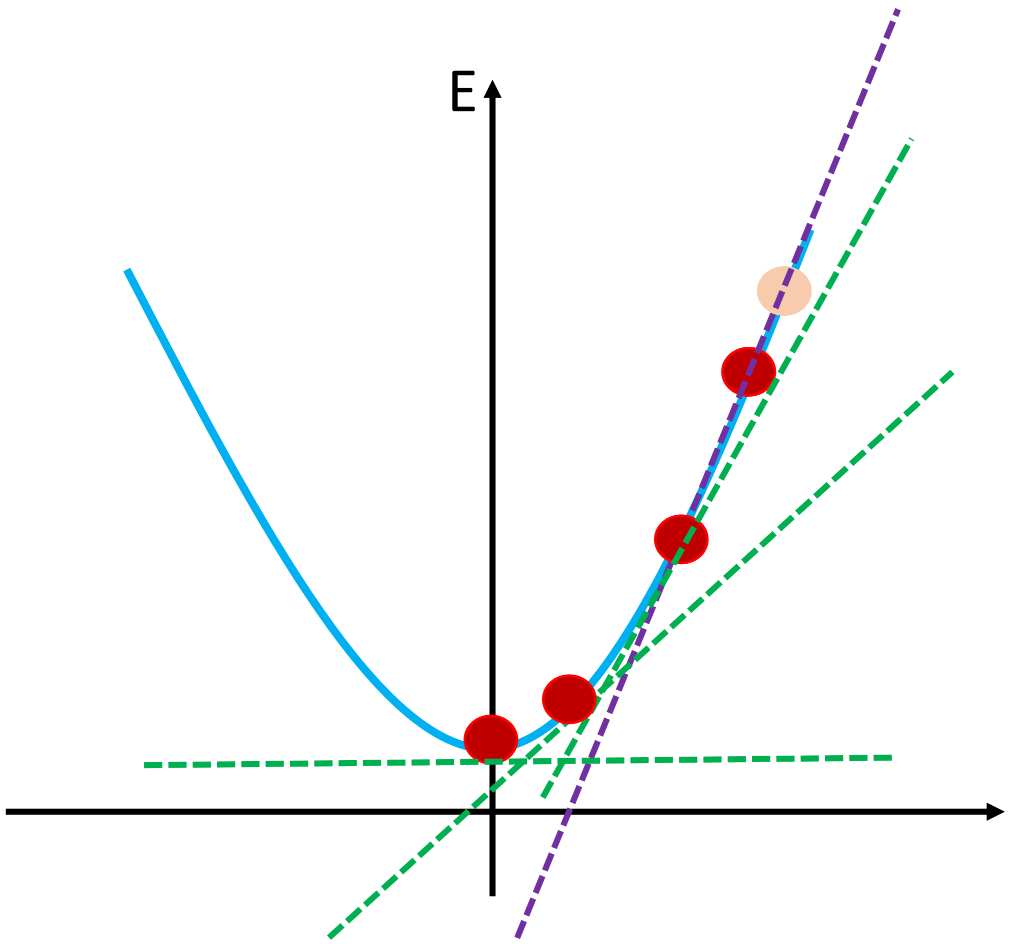
Rede Neural Artificial: Otimização



Função quadrática

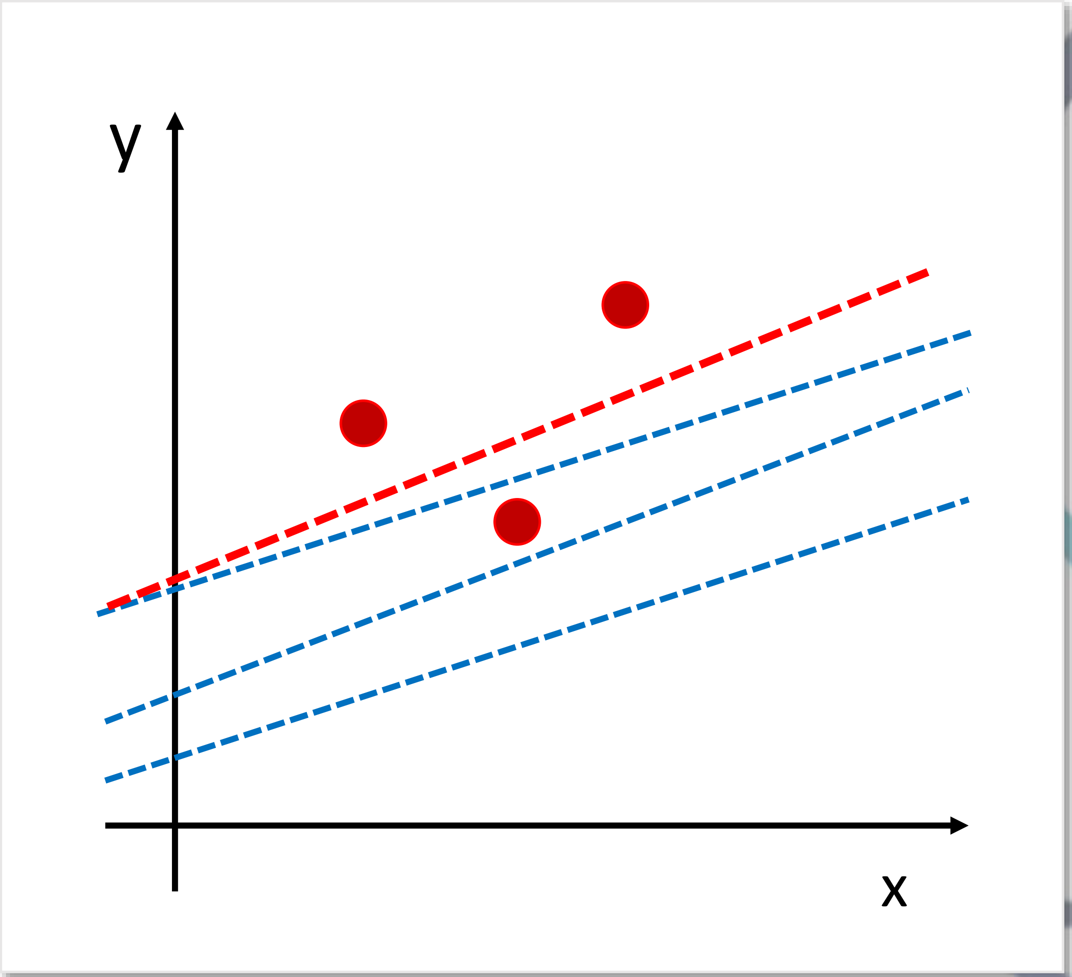
$$(\hat{y}_i - y_i)^2$$

Rede Neural Artificial: Otimização

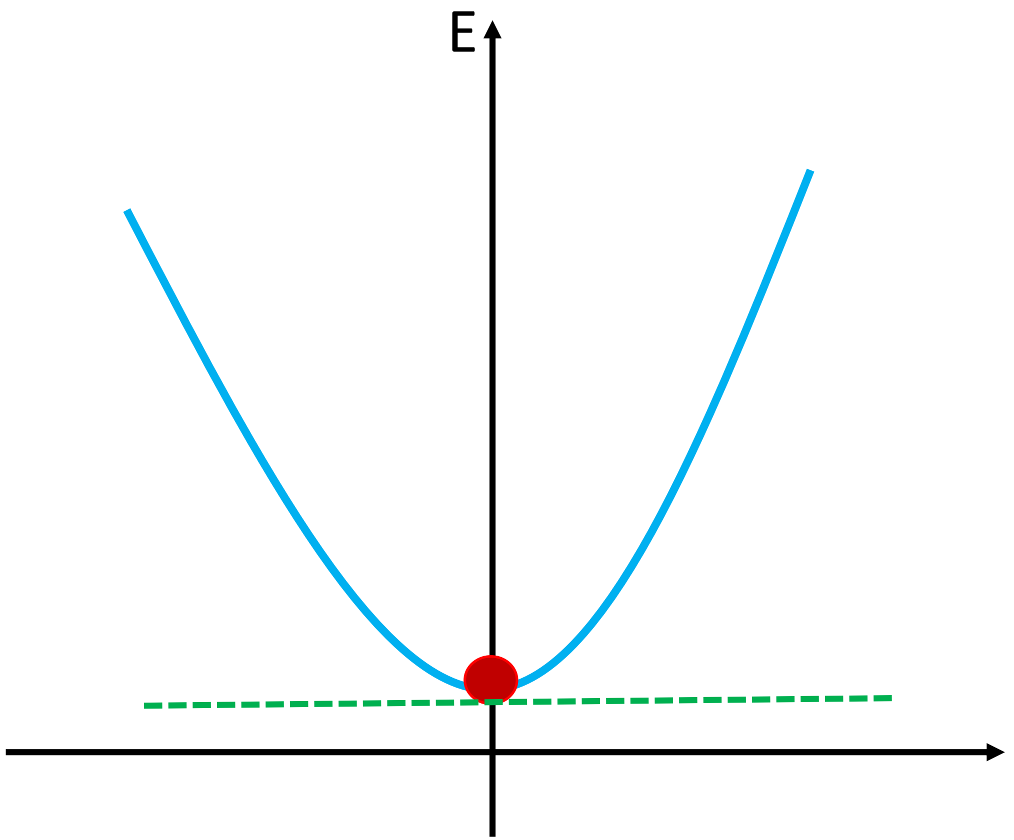


Função quadrática

$$(\hat{y}_i - y_i)^2$$

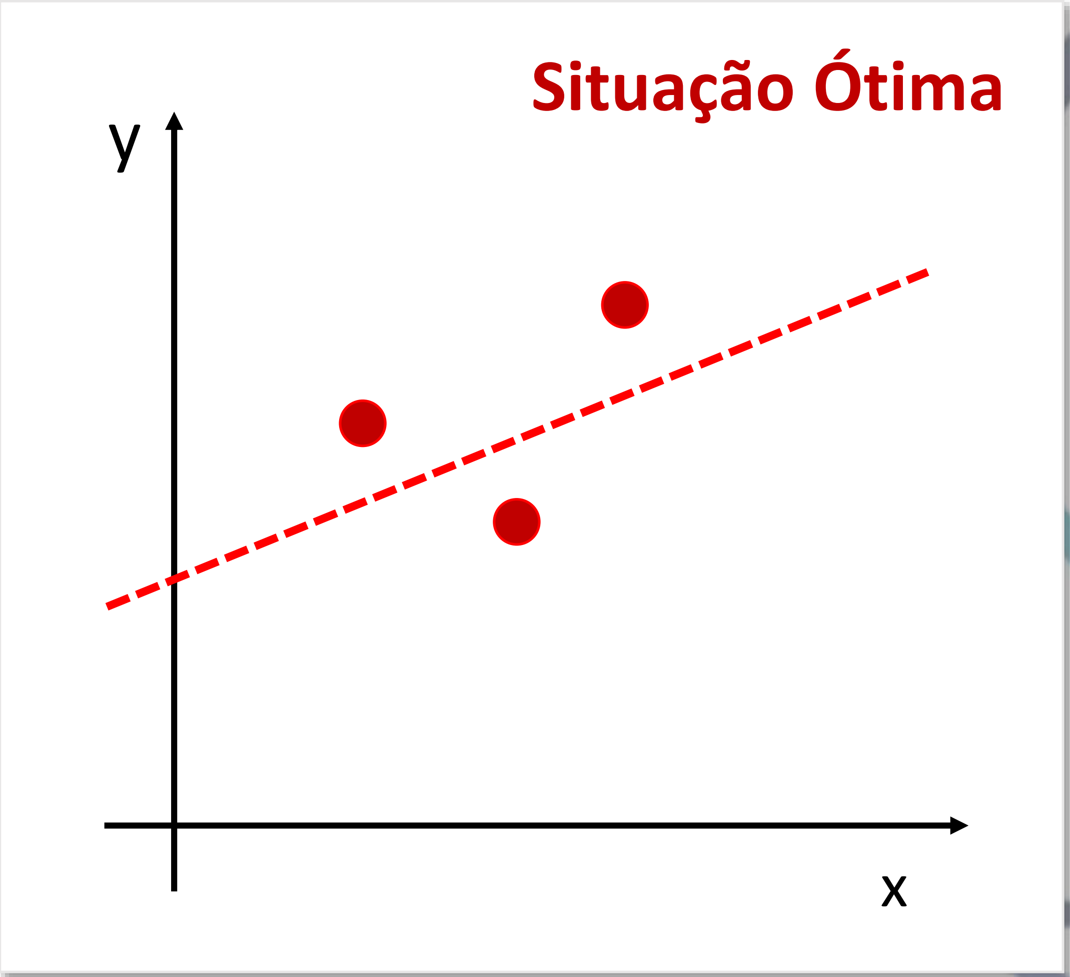


Rede Neural Artificial: Otimização



Função quadrática

$$(\hat{y}_i - y_i)^2$$



Loss function (função custo)

Loss functions in Machine Learning serve as ways to measure the distance or difference between a model's predicted output Y_{out} and the ground truth label Y in order to train our model effectively

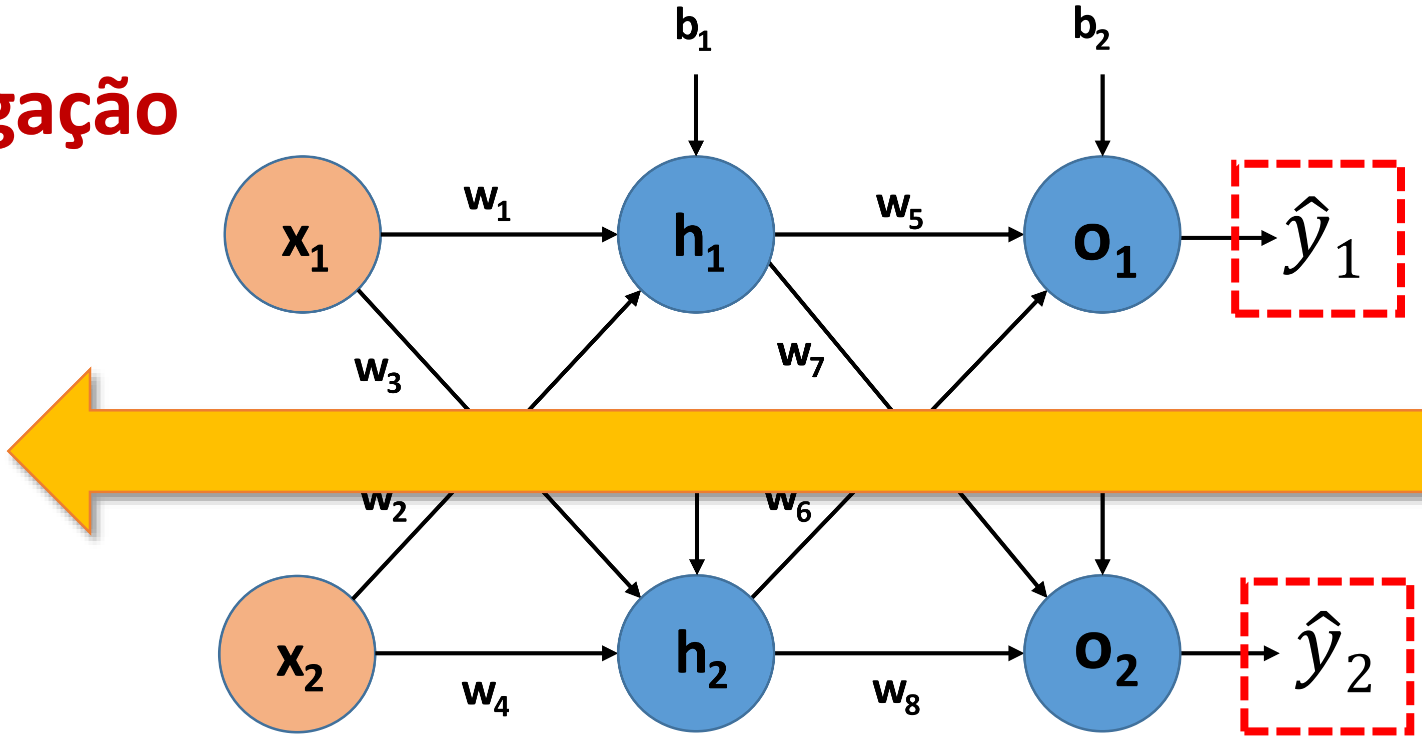
- **L2 Norm loss/ Euclidean loss function:** $L2 = \left(Y_{true} - Y_{pred}\right)^2$

- **Cross entropy Loss:**

$$H(p,q) = -\sum_i p_i log q_i \ = -y\ log\hat{y} - (1-y)\log(1-\hat{y})$$

Feedforward and Backpropagation

Fase 1
Retropropagação

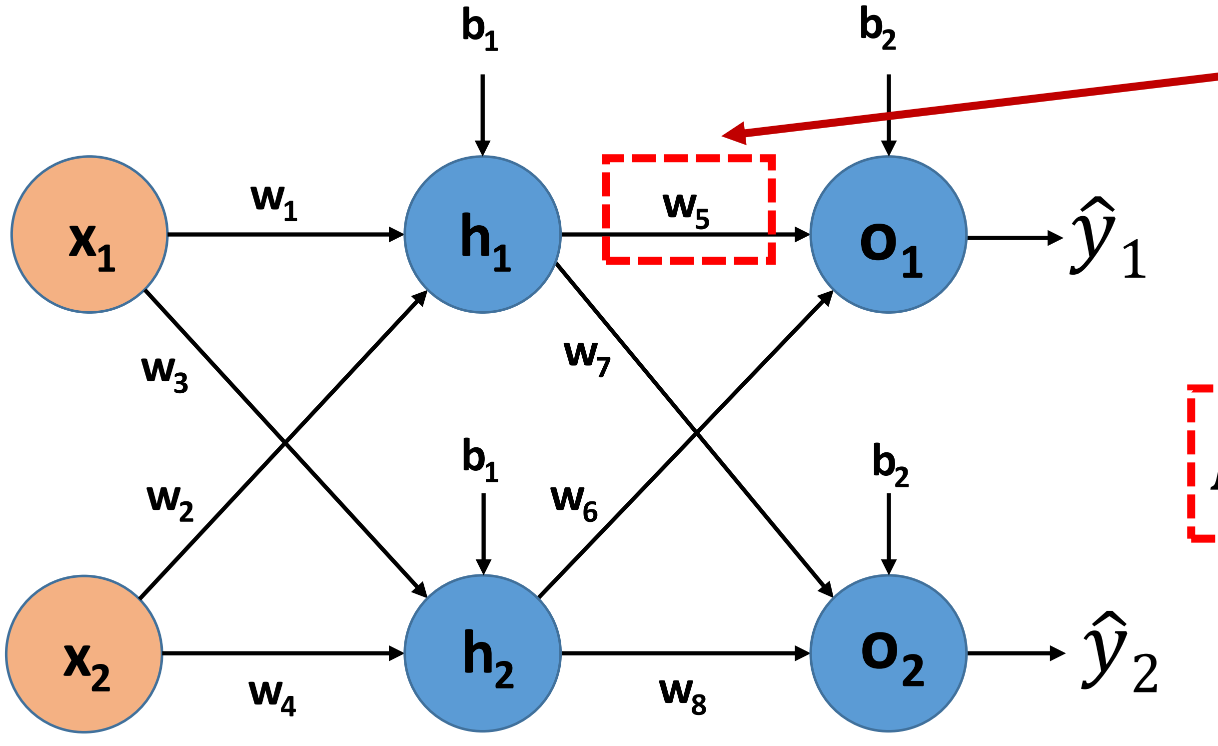


$$E_{total} = \frac{1}{2}\sum_{k=1}^{N}(\hat{y}_k - yk)^2 = E_{o1} + E_{o2}$$

Feedforward and Backpropagation

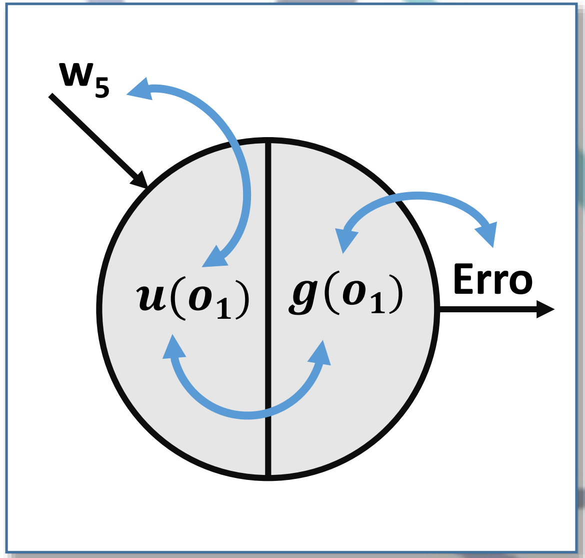
Fase 1
Retropropagação

Correção de w5: Queremos estimar quanto w5 afeta o Erro total



$$\frac{\partial E_{total}}{\partial w_5} = gradiente\ em\ relação\ a\ w_5$$

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial go_1} * \frac{\partial go_1}{\partial uo_1} * \frac{\partial uo_1}{\partial w_5}$$



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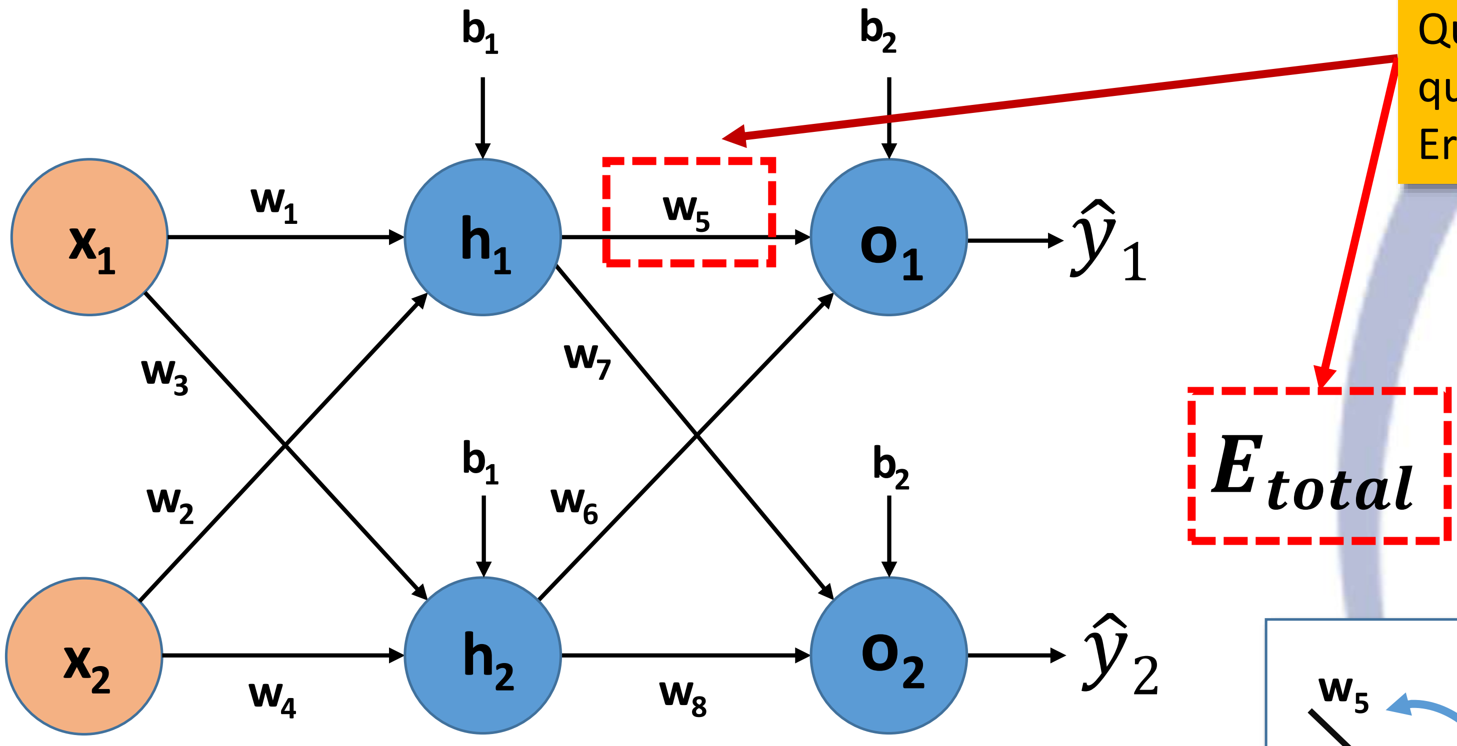
Feedforward and Backpropagation

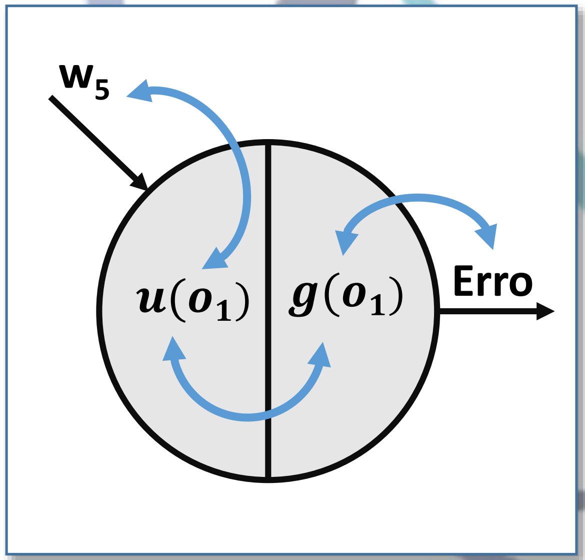
Fase 1

Retropropagação

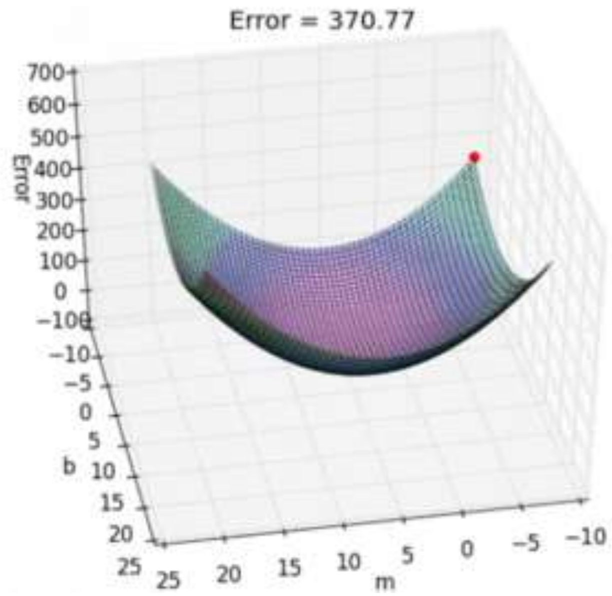


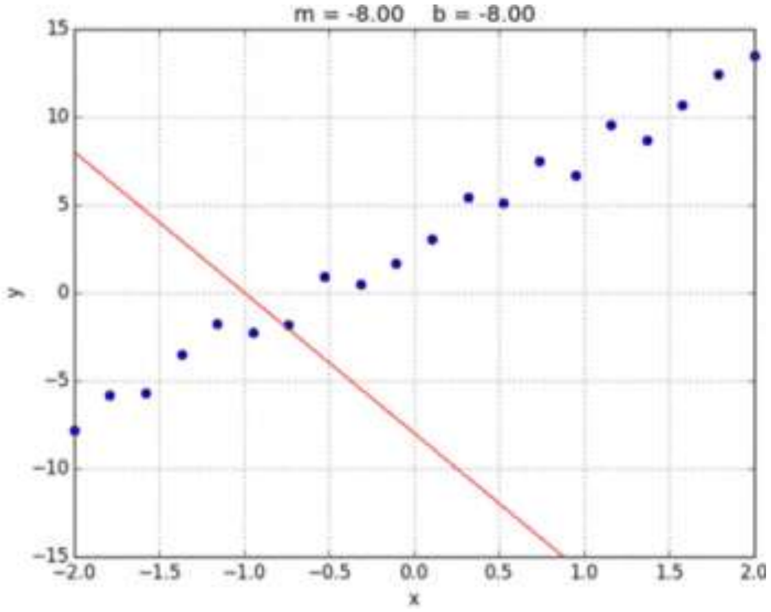
Correção de w5:
Queremos estimar quanto w5 afeta o Erro total

$$w_5(t+1) = w_5(t) - \eta \frac{\partial E_{total}}{\partial w_5}$$

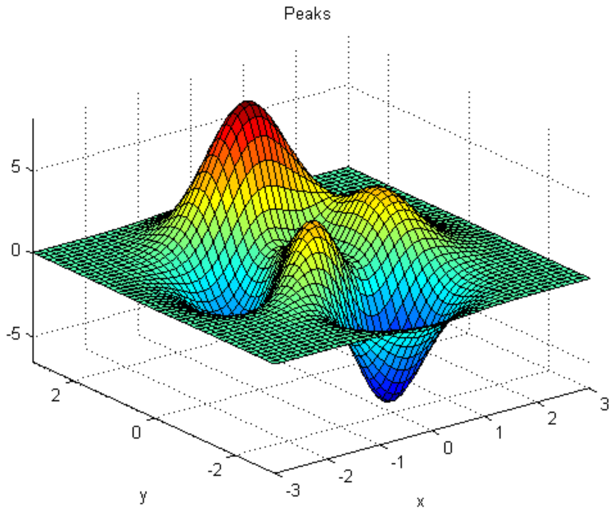


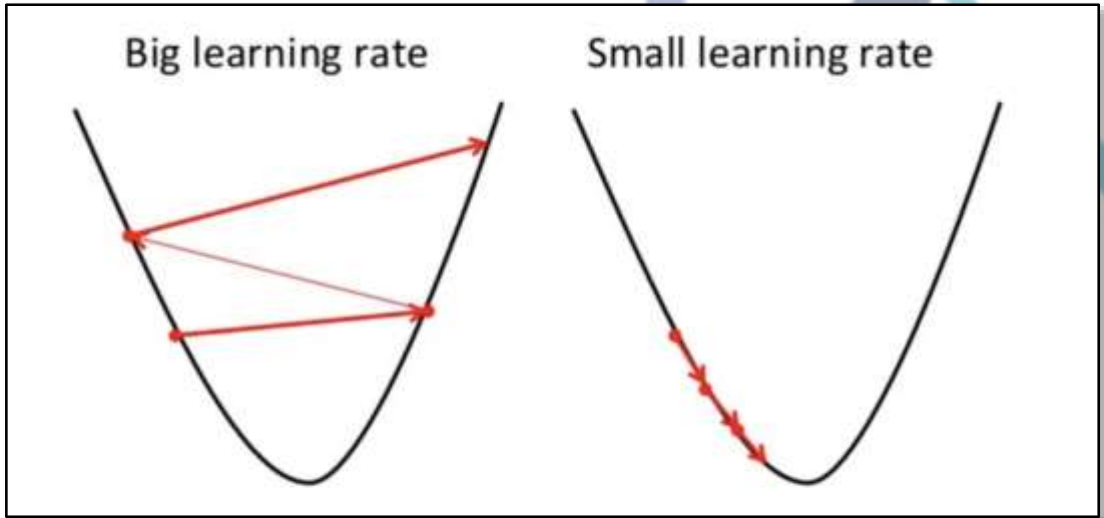
Rede Neural Artificial: Stochastic Gradient Descent - Algorithm





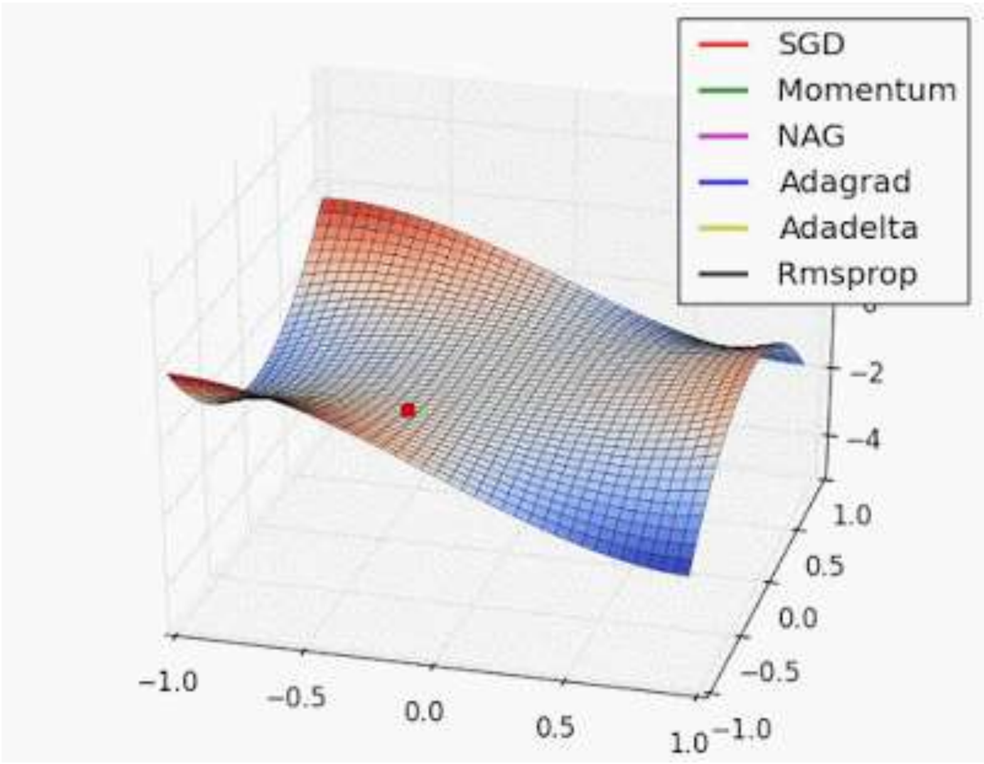
$$w_5(t+1) = w_5(t) - \eta \frac{\partial E_{total}}{\partial w_5}$$

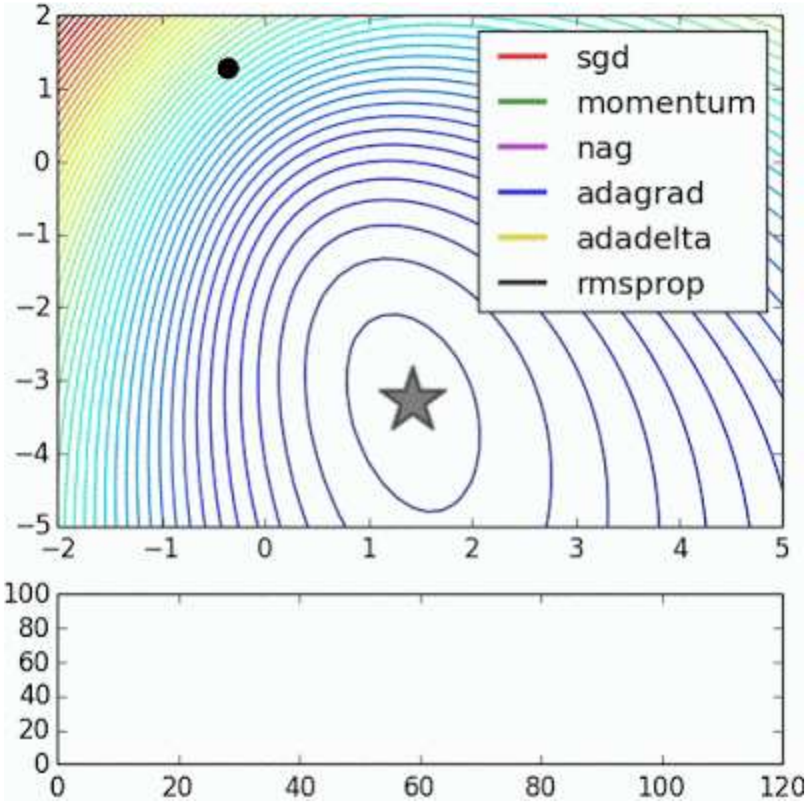




https://towardsdatascience.com/a-look-at-gradient-descent-and-rmsprop-optimizers-f77d483ef08b

Artificial Neural Network: Optimization Algorithms



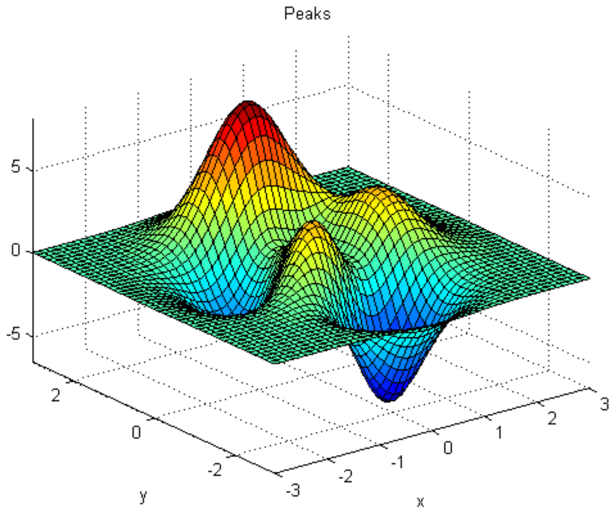


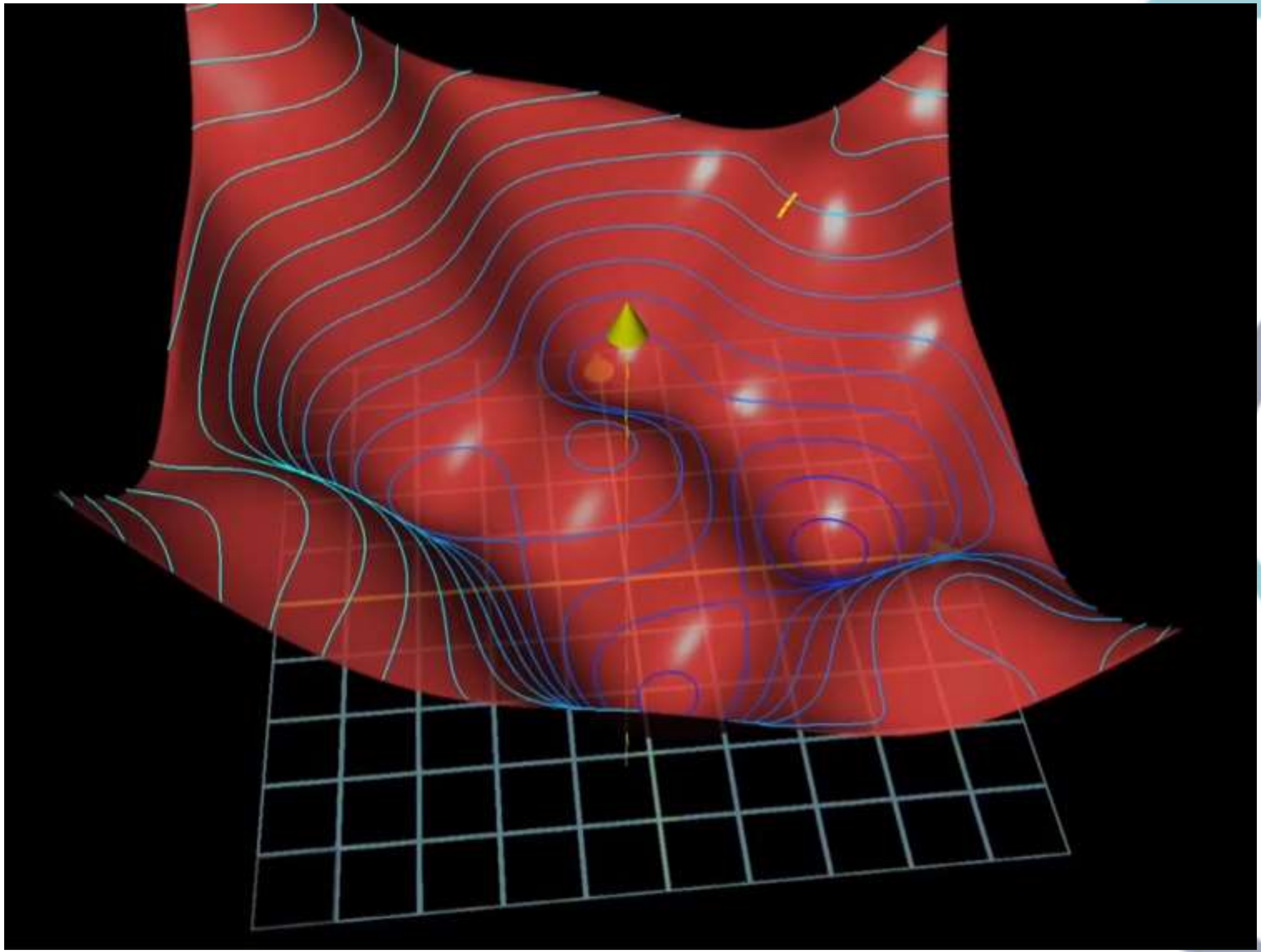
SGD: Stochastic Gradient Descent
ADAGRAD: Adaptive Gradient
ADADELTA: Adaptive Learning Rate Method
RMSPROP: Root Mean Square Propagation

Gradient depends on the average of the magnitudes of squares of previous gradients.

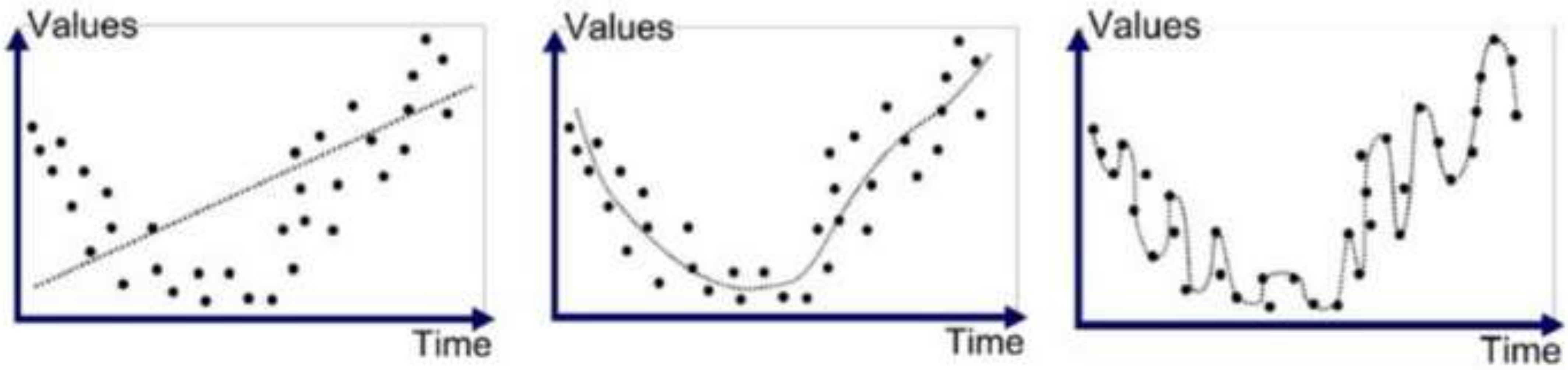
http://www.denizyuret.com/2015/03/alec-radfords-animations-for.html

Rede Neural Artificial: Stochastic Gradient Descent - Algorithm





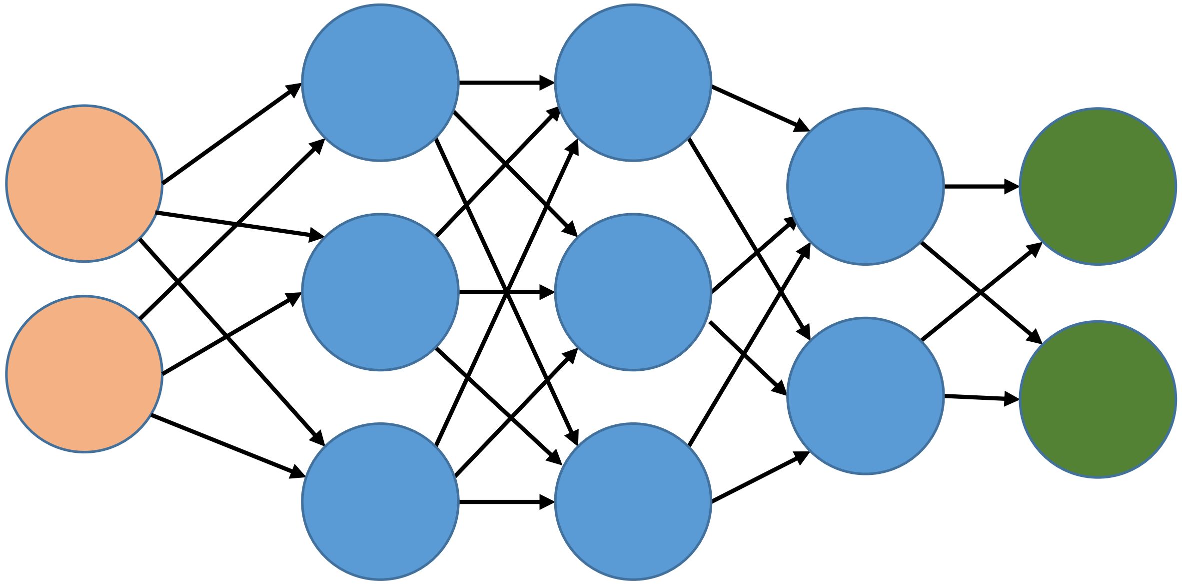
Artificial Neural Network: Overfitting



Underfitted | Good Fit/Robust | Overfitted

O **overfitting** (*sobreajuste*) é um termo para descrever quando um modelo se ajusta muito bem ao conjunto de dados, mas se mostra ineficaz para prever novos resultados.

Artificial Neural Network: DROPOUT



Dropout is a technique where randomly selected neurons are ignored during training. They are “dropped-out” randomly.

Durante o processo de treinamento devemos escolher uma probabilidade de retirada de neurônios.

A Simple Way to Prevent Neural Networks from Overfitting.

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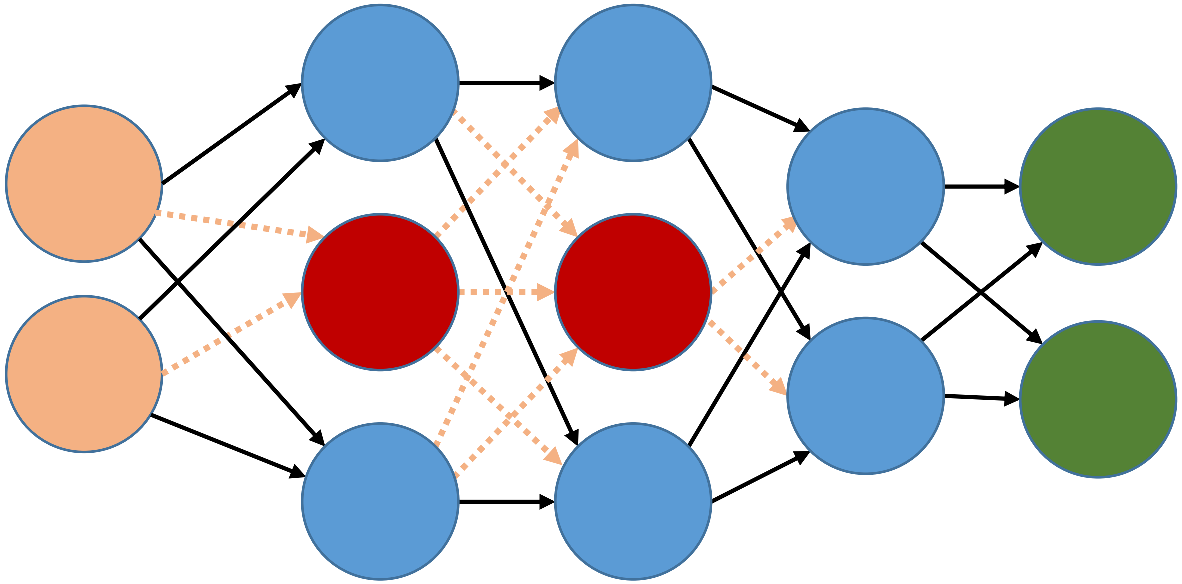
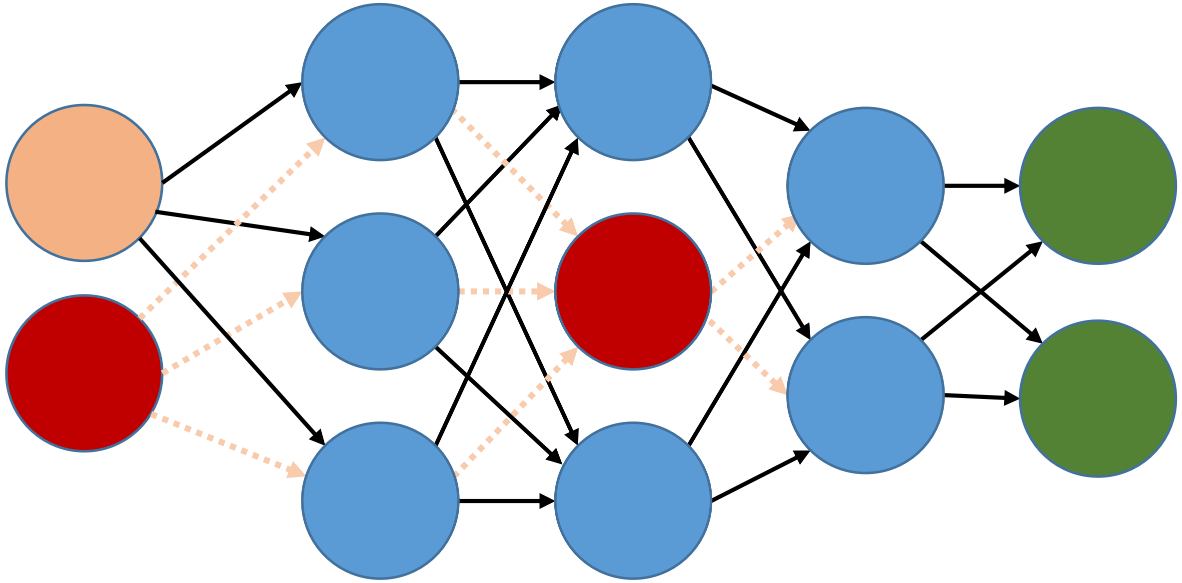
Artificial Neural Network: DROPOUT



Dropout is a technique where randomly selected neurons are ignored during training. They are “dropped-out” randomly.

A Simple Way to Prevent Neural Networks from Overfitting.

Artificial Neural Network: DROPOUT



Dropout is a technique where randomly selected neurons are ignored during training. They are “dropped-out” randomly.

A Simple Way to Prevent Neural Networks from Overfitting.

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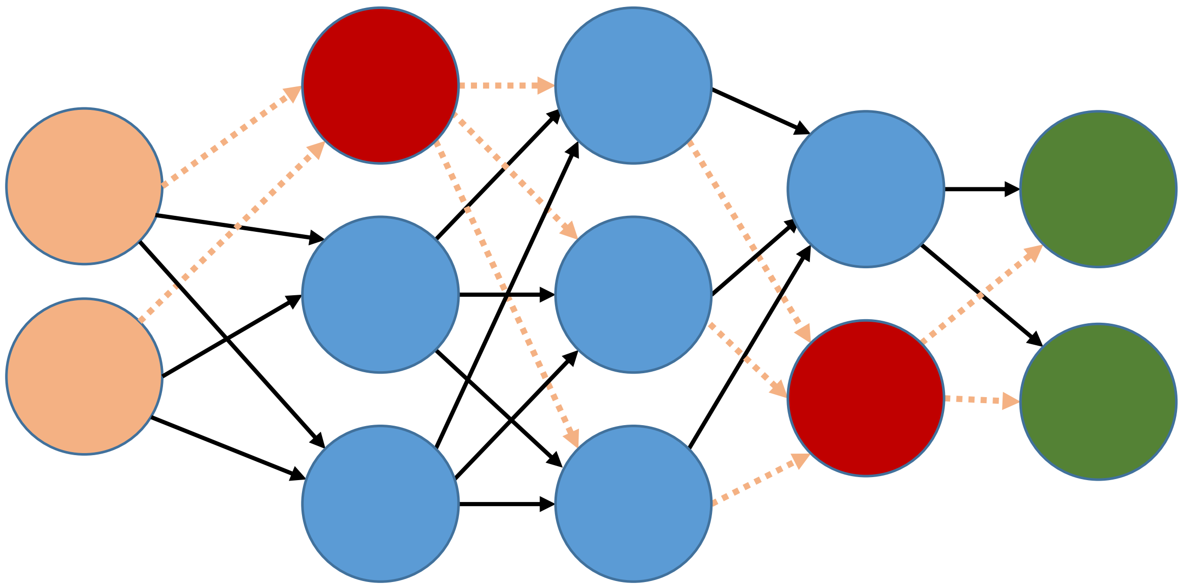
Artificial Neural Network: DROPOUT

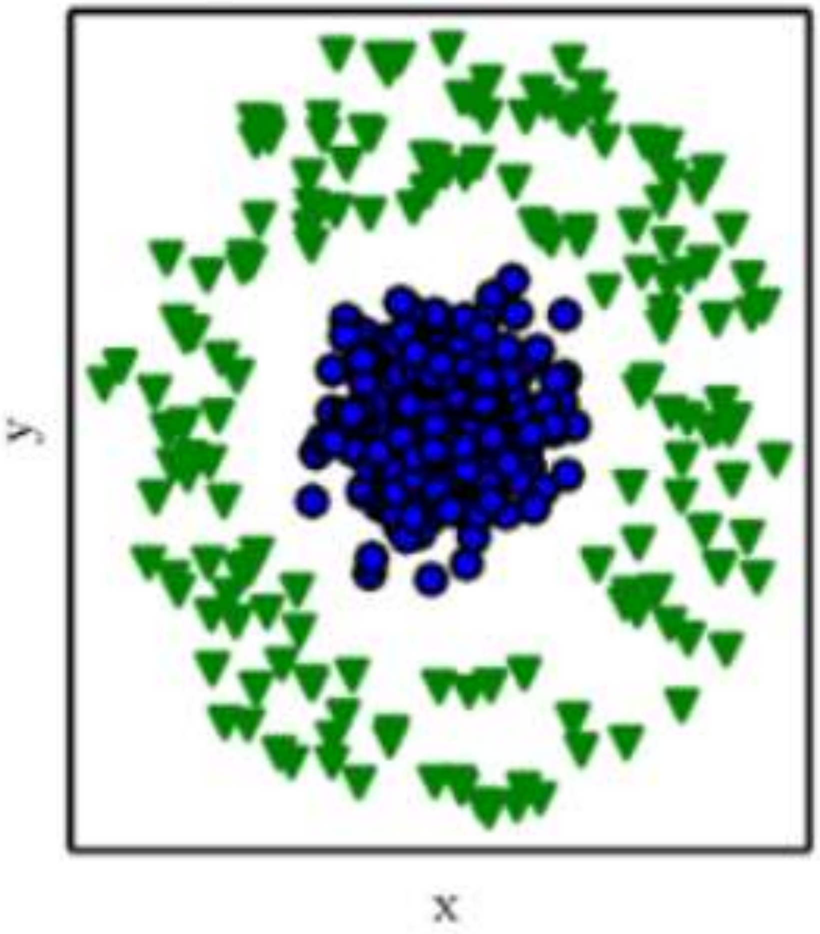


Dropout is a technique where randomly selected neurons are ignored during training. They are “dropped-out” randomly.

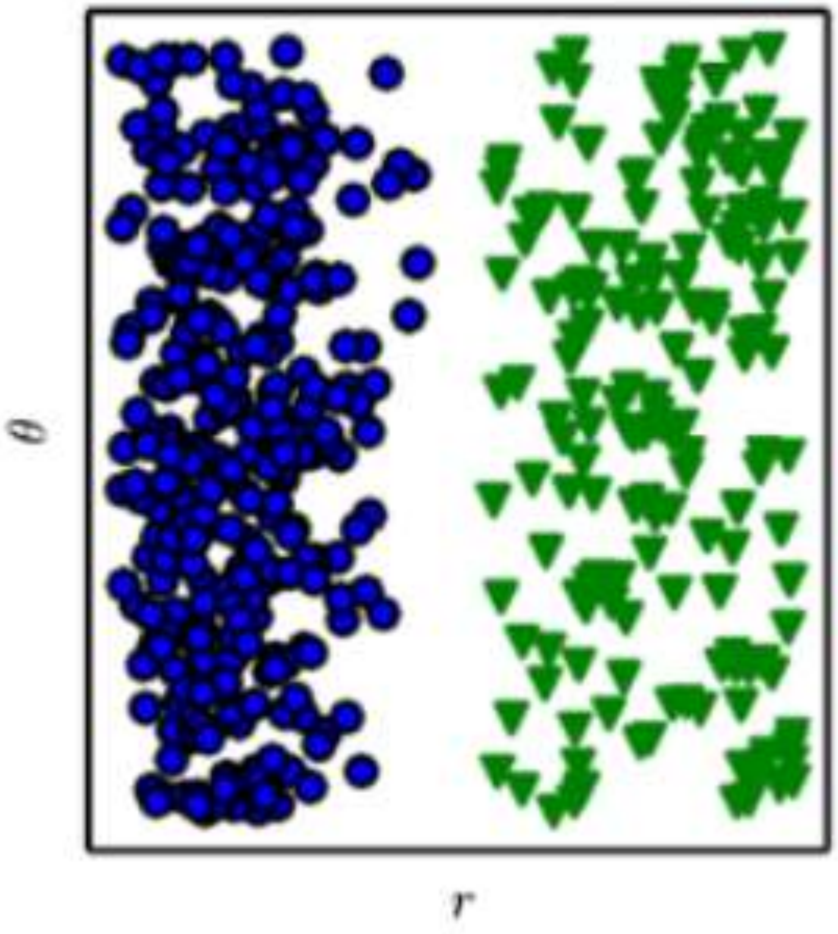
A Simple Way to Prevent Neural Networks from Overfitting.

A Representação dos dados é importante

Coordenadas Cartesianas



Coordenadas Polares



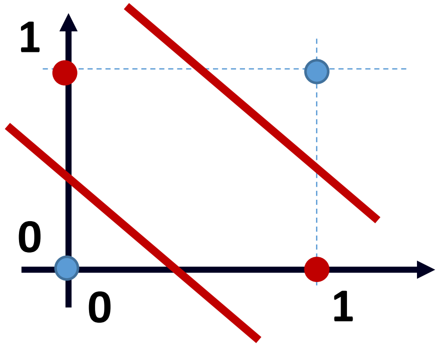
David Warde-Farley, Goodfellow et al. 2017

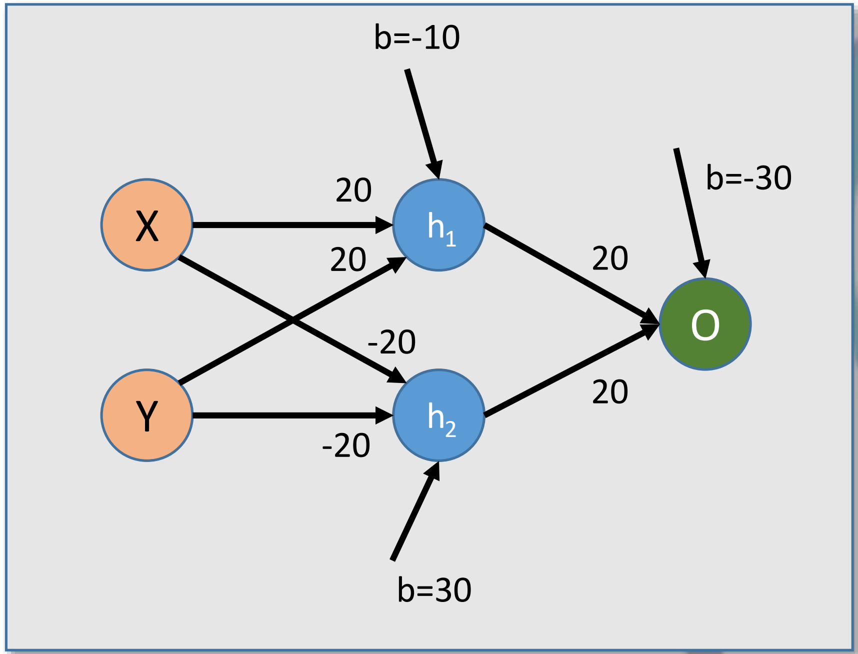
Rede Neural Artificial: O problema do OU Exclusivo

Multi-Layer Perceptron

XOR

X	Y	S
0	0	0
0	1	1
1	0	1
1	1	0





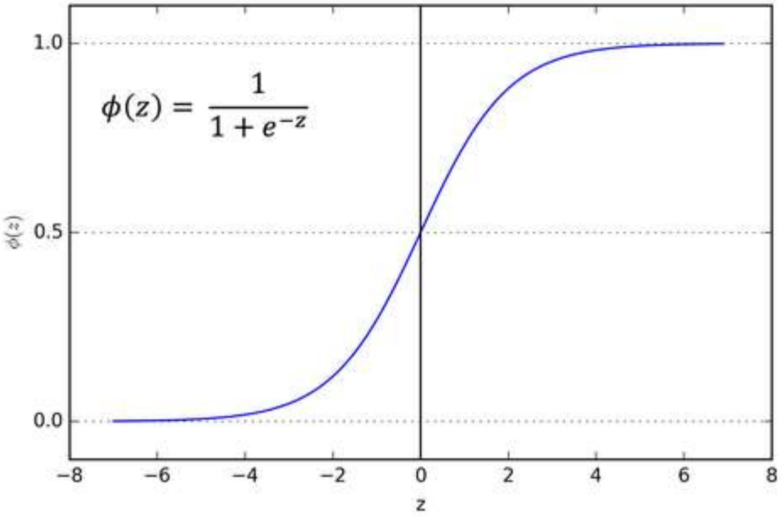


Fig: Sigmoid Function

[0 0] = ϕ(20*0 + 20*0 -10) ≈ 0 ϕ(-20*0 -20*0 +30) ≈ 1 ϕ(20*0 +20*1 -30) ≈ 0
[0 1] = ϕ(20*0 + 20*1 -10) ≈ 1 ϕ(-20*0 -20*1 +30) ≈ 1 ϕ(20*1 +20*1 -30) ≈ 1
[1 0] = ϕ(20*1 + 20*0 -10) ≈ 1 ϕ(-20*1 -20*0 +30) ≈ 1 ϕ(20*1 +20*1 -30) ≈ 1
[1 1] = ϕ(20*1 + 20*1 -10) ≈ 1 ϕ(-20*1 -20*1 +30) ≈ 0 ϕ(20*1 +20*0 -30) ≈ 0

RNA: Estruturas e Tipos de Regiões de Decisão

An Introduction to Computing with Neural Nets

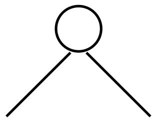
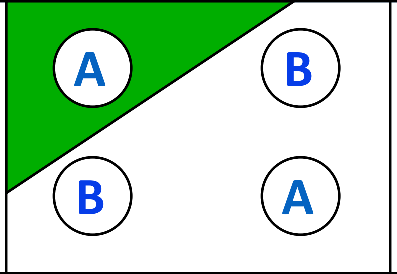
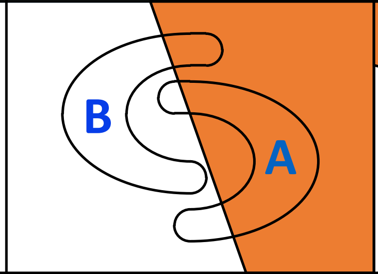
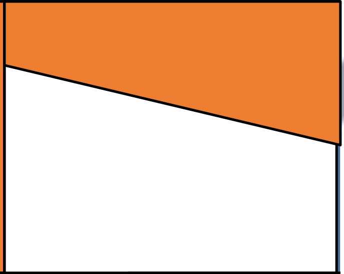
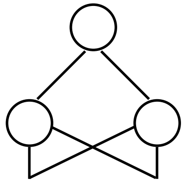
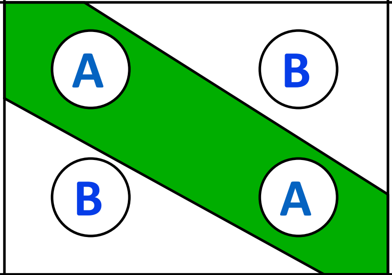
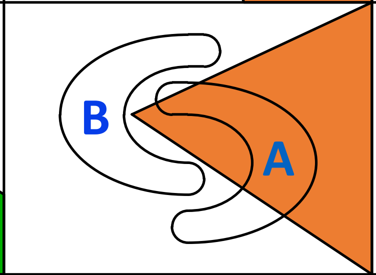
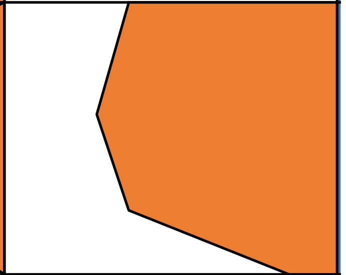
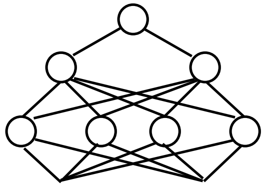
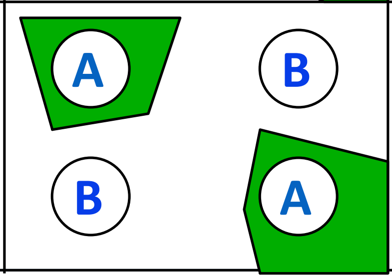
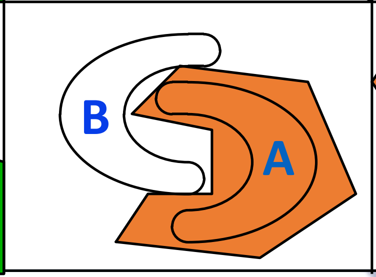
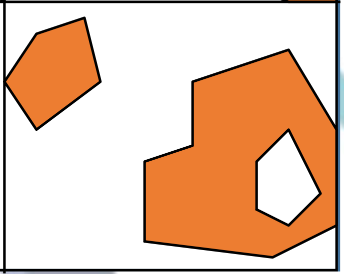
Richard P. Lippmann

Abstract

Artificial neural net models have been studied for many years in the hope of achieving human-like performance in the fields of speech and image recognition. These models are composed of many nonlinear computational elements operating in parallel and arranged in patterns reminiscent of biological neural nets. Computational elements or nodes are connected via weights that are typically adapted during use to improve performance. There has been a recent resurgence in the field of artificial neural nets caused by new net topologies and algorithms, analog VLSI implementation techniques, and the belief that massive parallelism is essential for high performance speech and image recognition. This paper provides an introduction to the field of artificial neural nets by reviewing six important neural net models that can be used for pattern classification. These nets are highly parallel building blocks that illustrate neural-net components and design principles and can be used to construct more complex systems. In addition to describing these nets, a major emphasis is placed on exploring how some existing classification and clustering algorithms can be performed using simple neuron-like components. Single-layer nets can implement algorithms required by Gaussian maximum-likelihood classifiers and optimum minimum-error classifiers for binary patterns corrupted by noise. More generally, the decision regions required by any classification algorithm can be generated in a straightforward manner by three-layer feed-forward nets.

INTRODUCTION

4 IEEE ASSP MAGAZINE APRIL 1987

Structure	*Types of Decision Regions*	*Exclusive-OR Problem*	*Classes with Meshed regions*	*Most General Region Shapes*
Single-Layer 	*Half Plane Bounded By Hyperplane*			
Two-Layer 	*Convex Open Or Closed Regions*			
Three-Layer 	Abitrary (Complexity Limited by No. of Nodes)			

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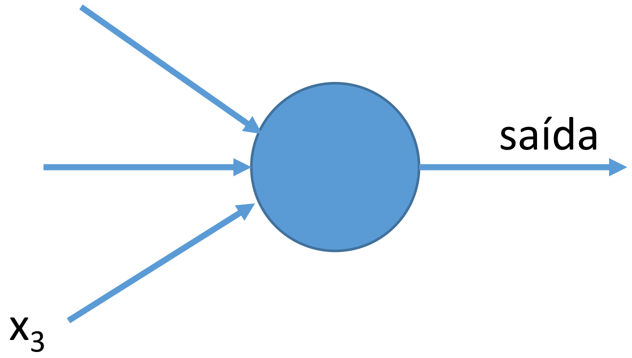
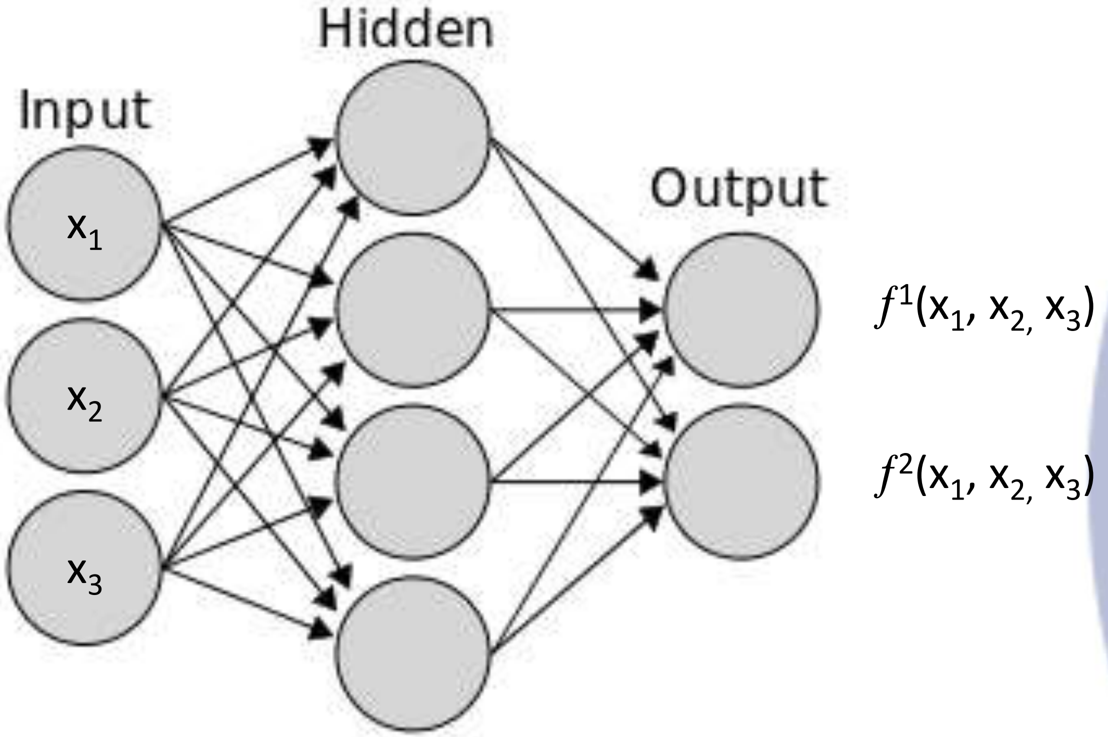
R. Lippmann, "*An introduction to computing with neural nets*“, IEEE ASSP Magazine, vol. 4, no. 2, pp. 4-22, Apr/1987.- doi: 10.1109/MASSP.1987.1165576

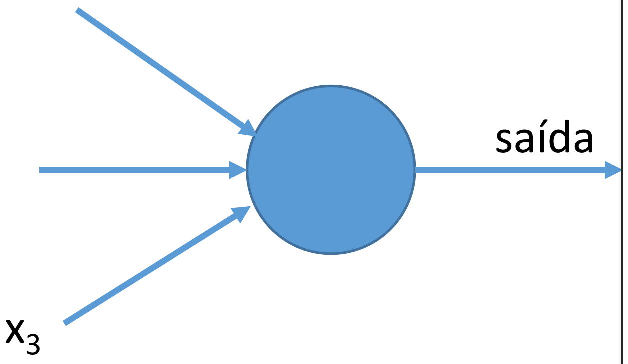
Rede Neural Artificial:

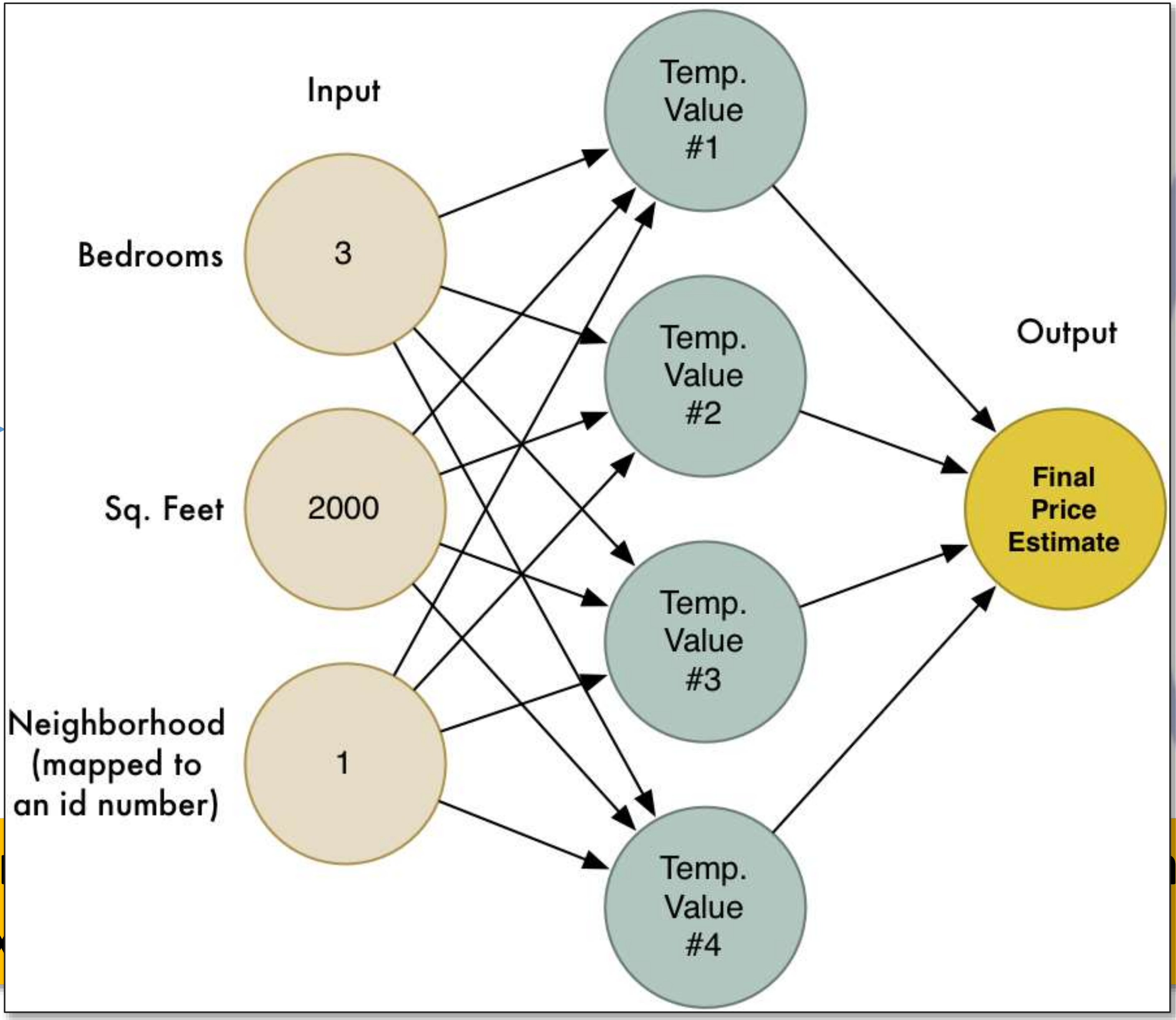




Universalidade: para qualquer função arbitrária f (x), existe uma rede neural que a aproxima.

Rede Neural Artificial:





U f (x),
ex

Rede Neural Artificial: DEEP LEARNING

DEEP LEARNING = APRENDIZADO PROFUNDO

- **SISTEMAS COMPUTACIONAIS**
  - CPUs, GPUs, ASICs
  - MEMÓRIA

- **BANCO DE DADOS ESTRUTURADOS**
  - Imagenet

- **P&D (CONCEITOS e ALGORITMOS)**
  - CNN, RCNN, BACKPROP, LSTM, ...

- **INFRAESTRUTURA DE SOFTWARE**
  - Git, AWS, AMAZON MECHANICAL TURK, GOOGLE TENSORFLOW

- **INTERESSE COMERCIAL E FINANCIAMENTO POR GRANDES COMPANHIAS**
  - Google, Facebook, Amazon, ...

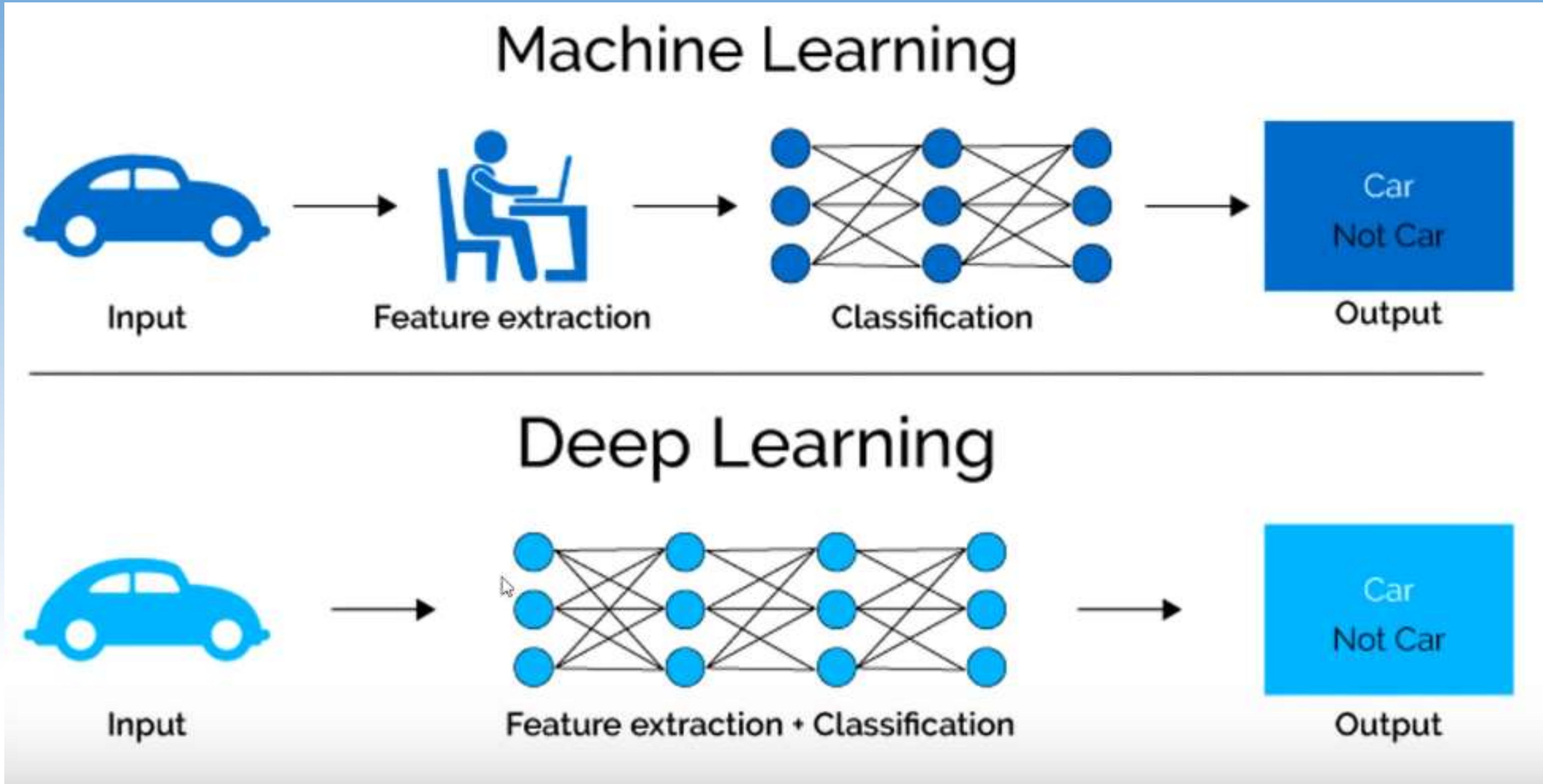
CBPF 70 ANOS

Rede Neural Artificial: DEEP LEARNING

DEE

FEATURE EXTRACTION

Extração de Características



CB

Rede Neural Artificial: DEEP LEARNING

DEEP LEARNING = APRENDIZADO PROFUNDO

Going Deeper with Convolutions

Christian Szegedy[1], Wei Liu[2], Yangqing Jia[1], Pierre Sermanet[1], Scott Reed[3],
Dragomir Anguelov[1], Dumitru Erhan[1], Vincent Vanhoucke[1], Andrew Rabinovich[4]
[1]Google Inc. [2]University of North Carolina, Chapel Hill
[3]University of Michigan, Ann Arbor [4]Magic Leap Inc.
[1]{szegedy, jiayq, sermanet, dragomir, dumitru, vanhoucke}@google.com
[2]wliu@cs.unc.edu, [3]reedscott@umich.edu, [4]arabinovich@magicleap.com

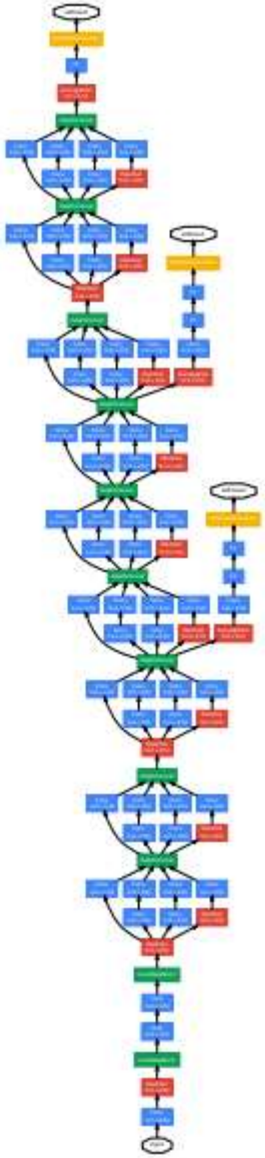
Abstract

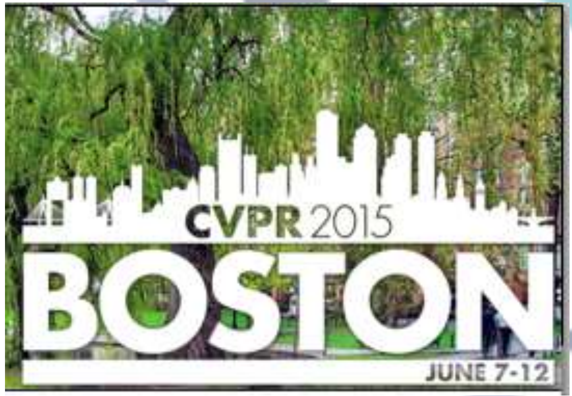
We propose a deep convolutional neural network architecture codenamed Inception that achieves the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). The main hallmark of this architecture is the improved utilization of the computing resources inside the network. By a carefully crafted design, we increased the depth and width of the network while keeping the computational budget constant. To optimize quality, the architectural decisions were based on the Hebbian principle and the intuition of multi-scale processing. One particular incarnation used in our submission for ILSVRC14 is called GoogLeNet, a 22 layers deep network, the quality of which is assessed in the context of classification and detection.

ger and bigger deep networks, but from the synergy of deep architectures and classical computer vision, like the R-CNN algorithm by Girshick et al [6].

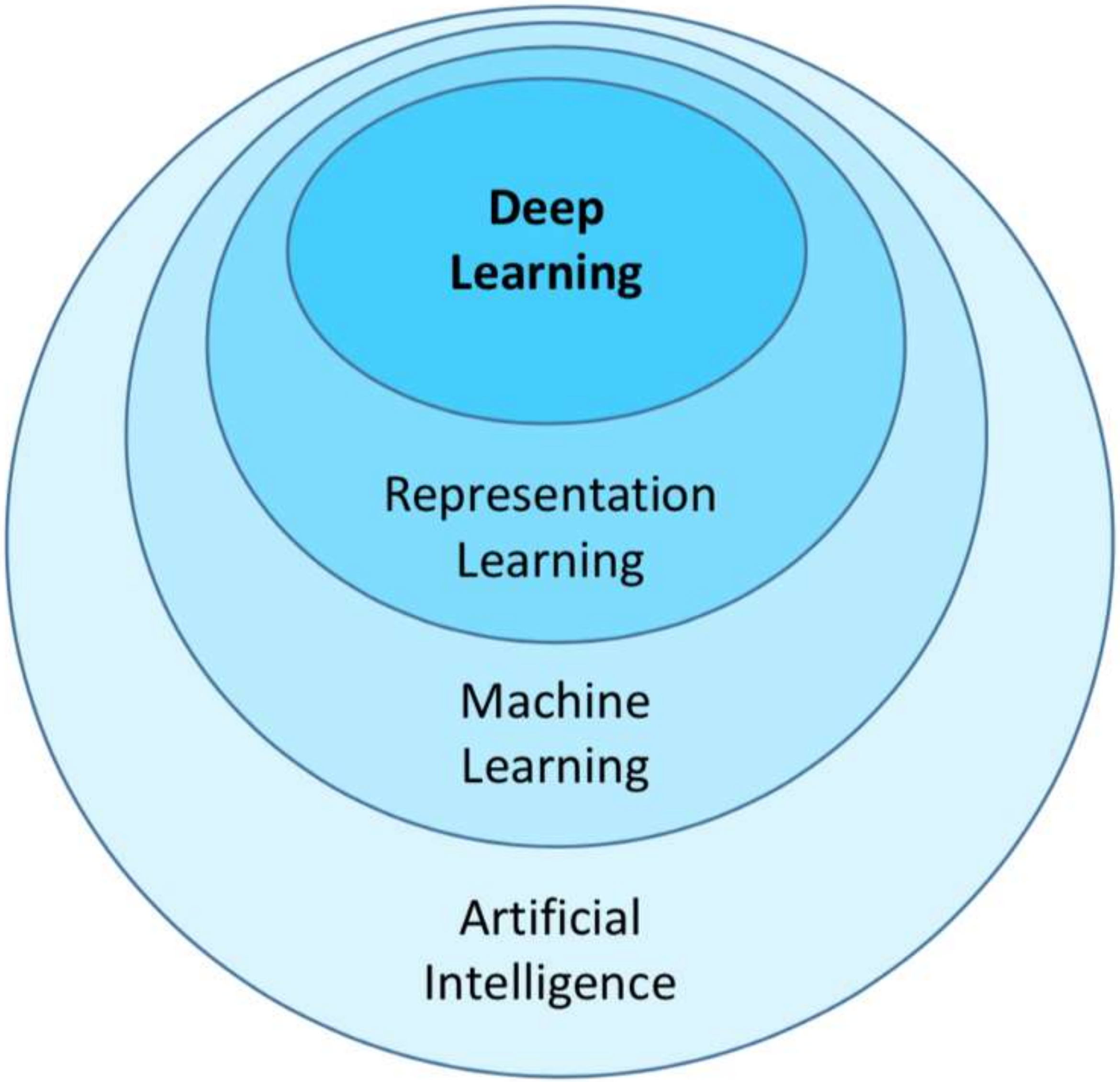
Another notable factor is that with the ongoing traction of mobile and embedded computing, the efficiency of our algorithms – especially their power and memory use – gains importance. It is noteworthy that the considerations leading to the design of the deep architecture presented in this paper included this factor rather than having a sheer fixation on accuracy numbers. For most of the experiments, the models were designed to keep a computational budget of 1.5 billion multiply-adds at inference time, so that the they do not end up to be a purely academic curiosity, but could be put to real world use, even on large datasets, at a reasonable cost.

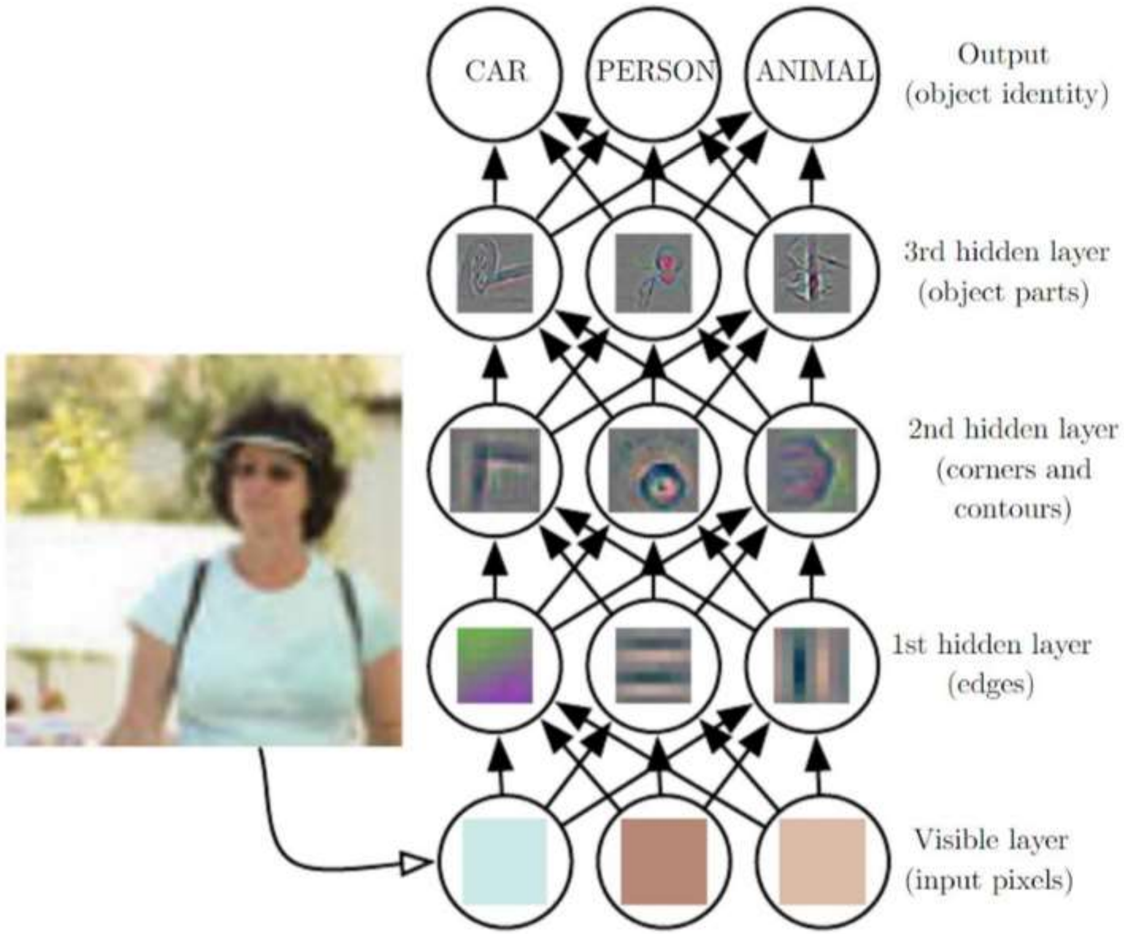
In this paper, we will focus on an efficient deep neural network architecture for computer vision, codenamed Inception, which derives its name from the Network in network paper by Lin et al [12] in conjunction with the famous





Rede Neural Artificial: DEEP LEARNING

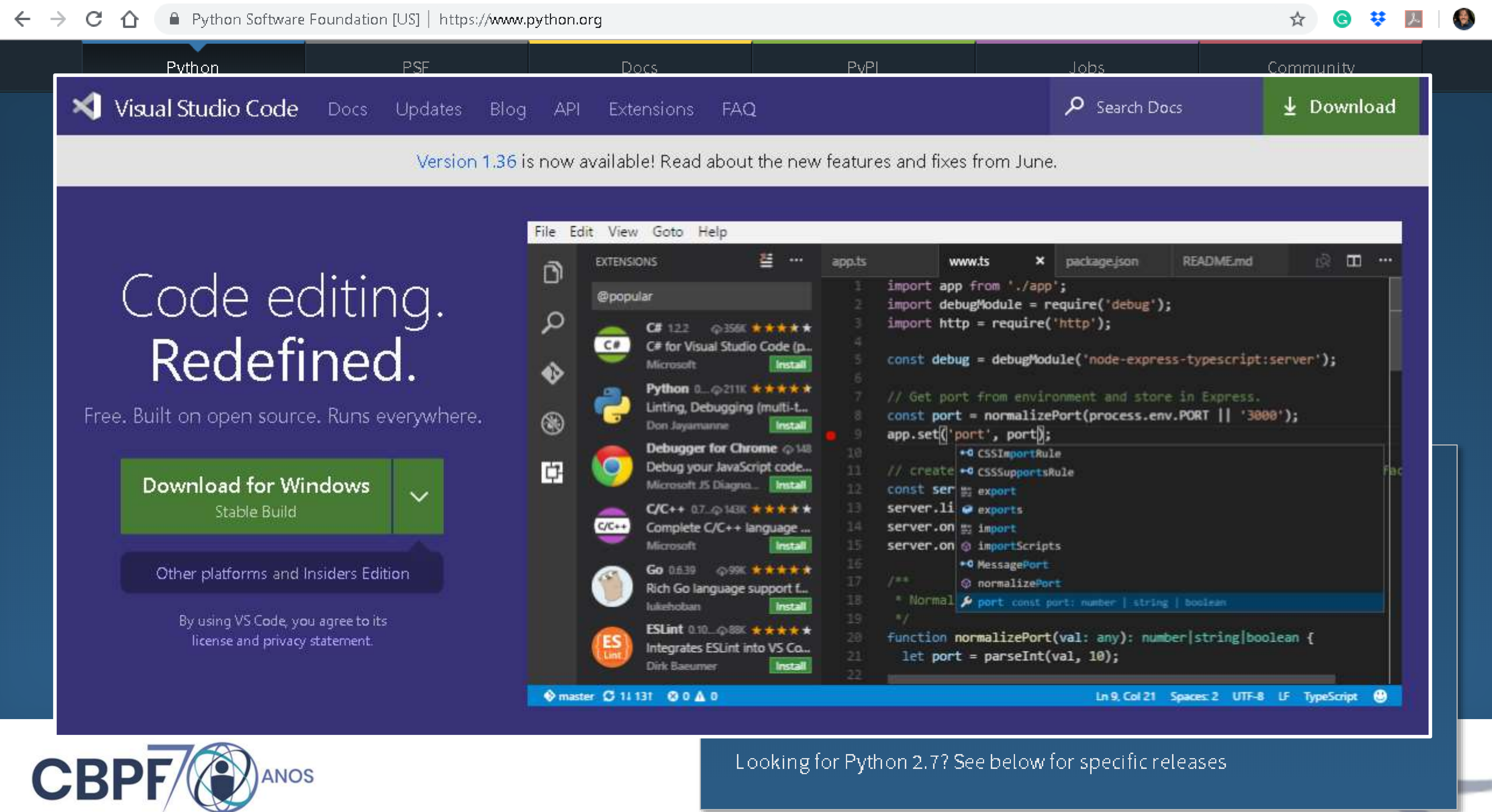




L. Fridman - MIT

Indo para a prática

...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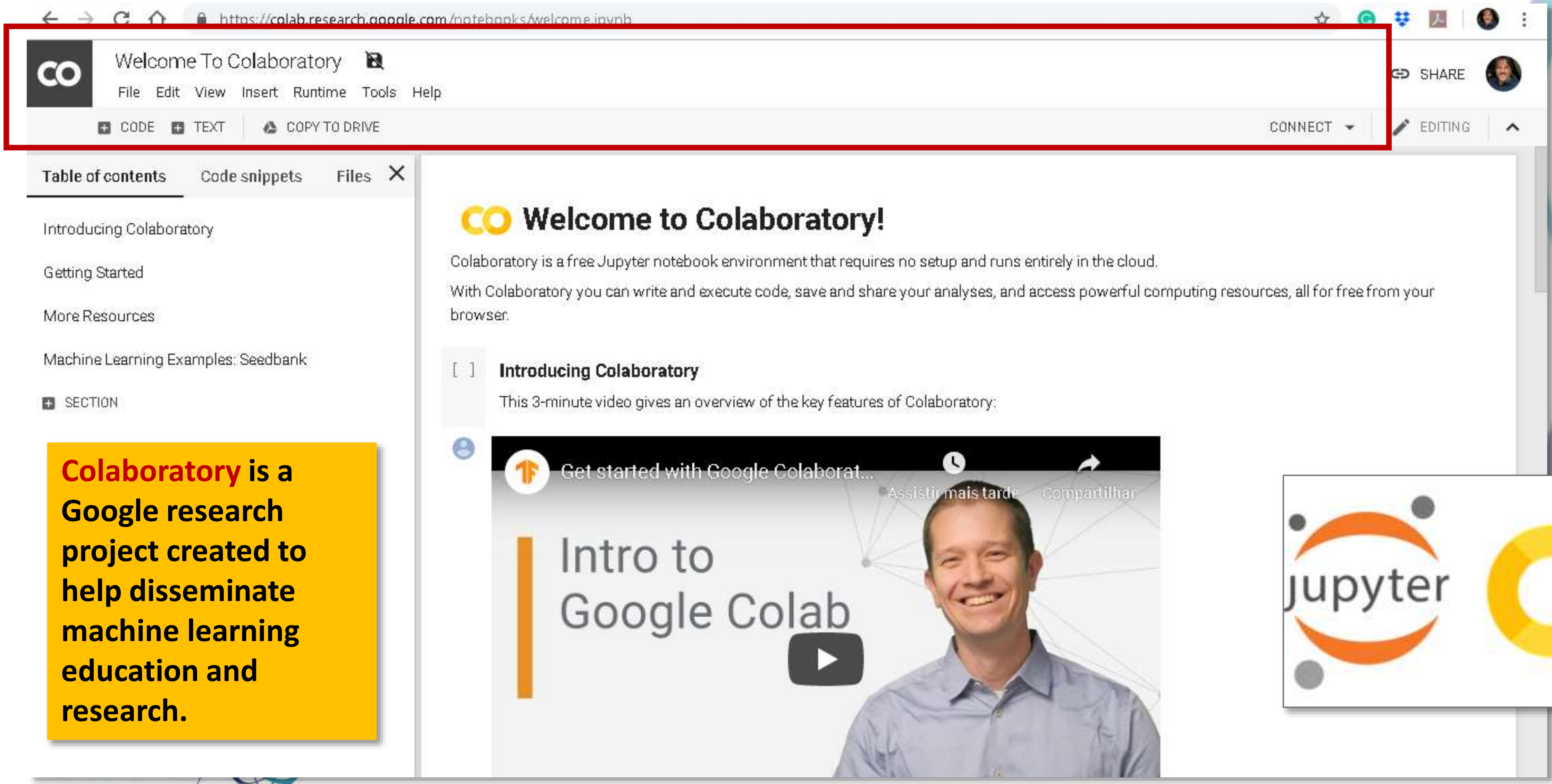
C# for Visual Studio Code (p...
Python
Linting, Debugging (multi-t...
Debugger for Chrome
Debug your JavaScript code...
C/C++
Complete C/C++ language ...
Go
Rich Go language support f...
ESLint
Integrates ESLint into VS Co...
app.ts
www.ts
package.json
README.md
import app from './app';
import debugModule = require('debug');
import http = require('http');
const debug = debugModule('node-express-typescript:server');
// Get port from environment and store in Express.
const port = normalizePort(process.env.PORT || '3000');
app.set('port', port);
function normalizePort(val: any): number|string|boolean {
let port = parseInt(val, 10);
master
Ln 9, Col 21
Spaces: 2
UTF-8
LF
TypeScript
Looking for Python 2.7? See below for specific releases

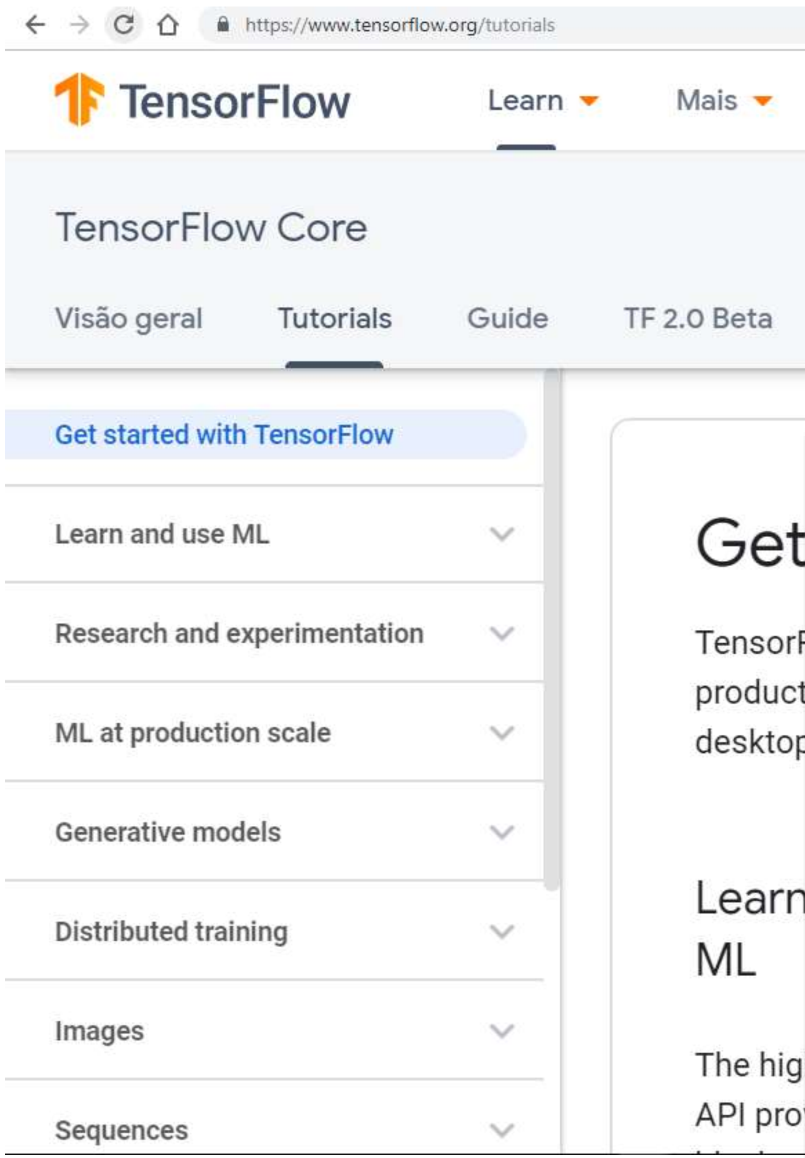
Ambientes de Desenvolvimento

https://colab.research.google.com



Google Drive

Colaboratory is a Google research project created to help disseminate machine learning education and research.



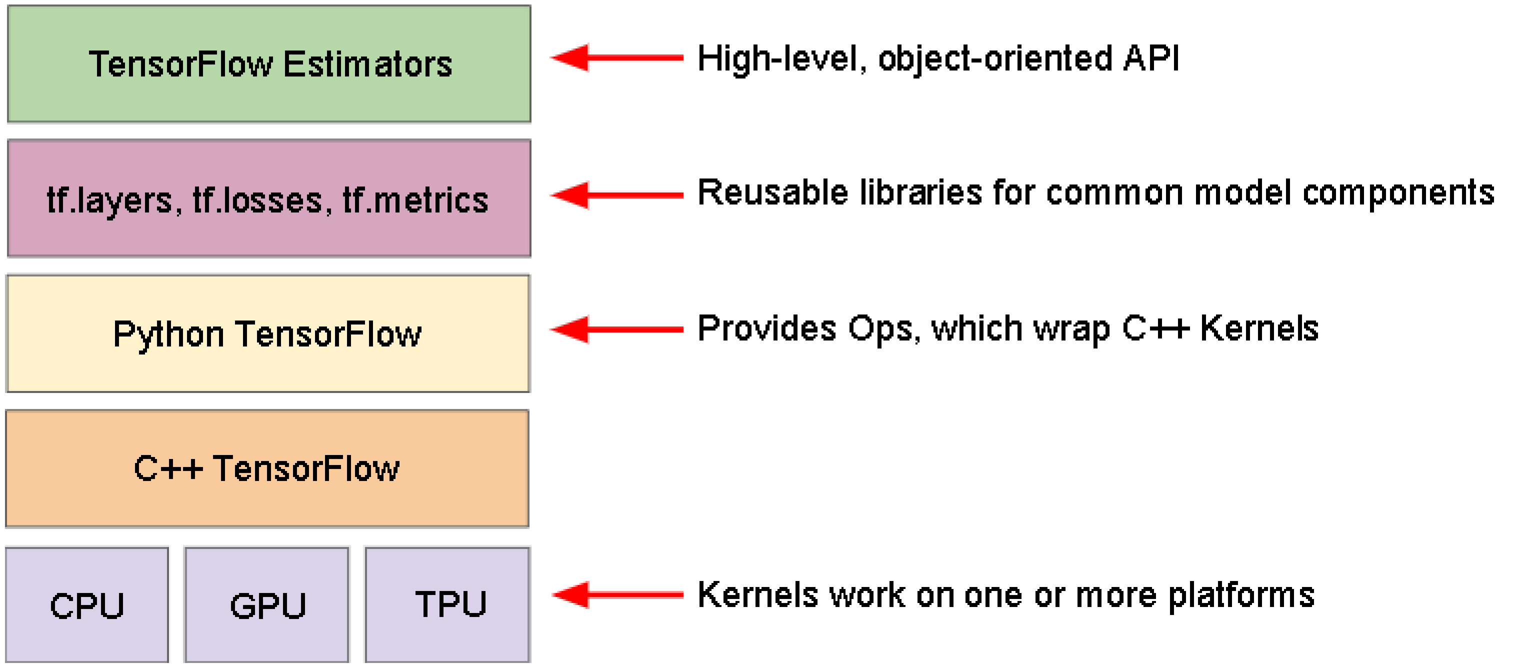


Figure 1. TensorFlow toolkit hierarchy.

Ambientes de Desenvolvimento

https://keras.io

Keras Documentation

Search docs

⊟ Home

- You have just found Keras.
- Guiding principles
- Getting started: 30 seconds to Keras
- Installation
- Configuring your Keras backend
- Support
- Why this name, Keras?

Why use Keras

GETTING STARTED

- Guide to the Sequential model
- Guide to the Functional API
- FAQ

MODELS

- About Keras models
- Sequential
- Model (functional API)

GitHub   Next »

Docs » Home   Edit on GitHub

Keras: The Python Deep Learning library

Keras

You have just found Keras.

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation. *Being able to go from idea to result with the least possible delay is key to doing good research.*

Use Keras if you need a deep learning library that:

- Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility).
- Supports both convolutional networks and recurrent networks, as well as combinations of the two.
- Runs seamlessly on CPU and GPU.

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano.

API - "Application Programming - "Interface" - Interface para Programação de Aplicativos".

Neural network terminology

one epoch: one forward pass and one backward pass of all the training examples

batch: the number of training examples in one forward/backward pass. The higher the batch size, the more memory space you'll need.

number of iterations: number of passes, each pass using [batch size] number of examples. To be clear, one pass = one forward pass + one backward pass (we do not count the forward pass and backward pass as two different passes).

Example: if you have 1000 training examples, and your batch size is 500, then it will take 2 iterations to complete 1 epoch.

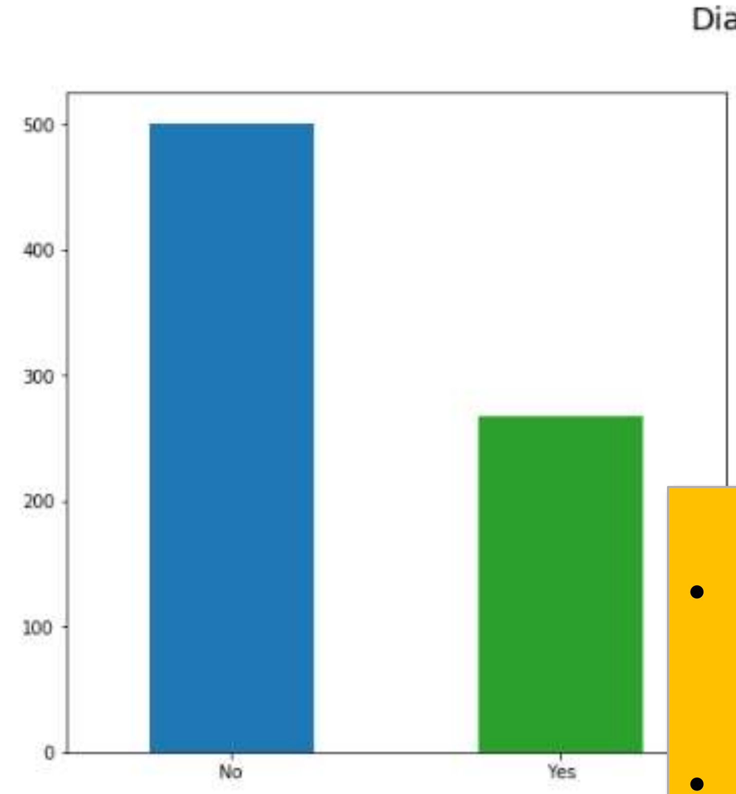
kaggle **Pima Indians Diabetes Database**

EXEMPLO 1

CLASSIFI

REDE NE

Data Visualization



age	diabetes
50	1
31	0
32	1
21	0
33	1
30	0
26	1
29	0
53	1
54	1

11	138	76
9	102	76
2	90	68

```
6,148,72,35,0,33.6,0.627,50,1
1,85,66,29,0,26.6,0.351,31,0
8,183,64,0,0,23.3,0.672,32,1
1,89,66,23,94,28.1,0.167,21,0
0,137,40,35,168,43.1,2.288,33,1
5,116,74,0,0,25.6,0.201,30,0
3,78,50,32,88,31.0,0.248,26,1
...
0,118,84,47,230,45.8,0.551,31,1
```

768 l

- **As 10 ultimas linhas foram separadas para o grupo de teste**
- **As 758 linhas restantes serão divididas em grupo de treinamento, validação**

CSV “ Comma Separeted values” file

CBPF 70 ANOS

Diabetes.py

TensorFlow python

Importa Bibliotecas

Leitura dos Dados

Ajustes dos Dados

Separa Dados de Treinamento (80% - 606) e Validação (20% - 152)

Definição da RN/

Compila o Model

Treina (FIT) a RN/

Plota a evolução da Prec
Função Custo

Apresenta os Dados de

Grupo de Teste

pregnancies	glucose	diastolic	triceps	insulin	bmi	dpf	age	diabetes
1	106	76	0	0	37.5	0.197	26	0
6	190	92	0	0	35.5	0.278	66	1
2	88	58	26	16	28.4	0.766	22	0
9	170	74	31	0	44.0	0.403	43	1
9	89	62	0	0	22.5	0.142	33	0
10	101	76	48	180	32.9	0.171	63	0
2	122	70	27	0	36.8	0.340	27	0
5	121	72	23	112	26.2	0.245	30	0
1	126	60	0	0	30.1	0.349	47	1
1	93	70	31	0	30.4	0.315	23	0

- **Camada de Saída: 1 neurônio**

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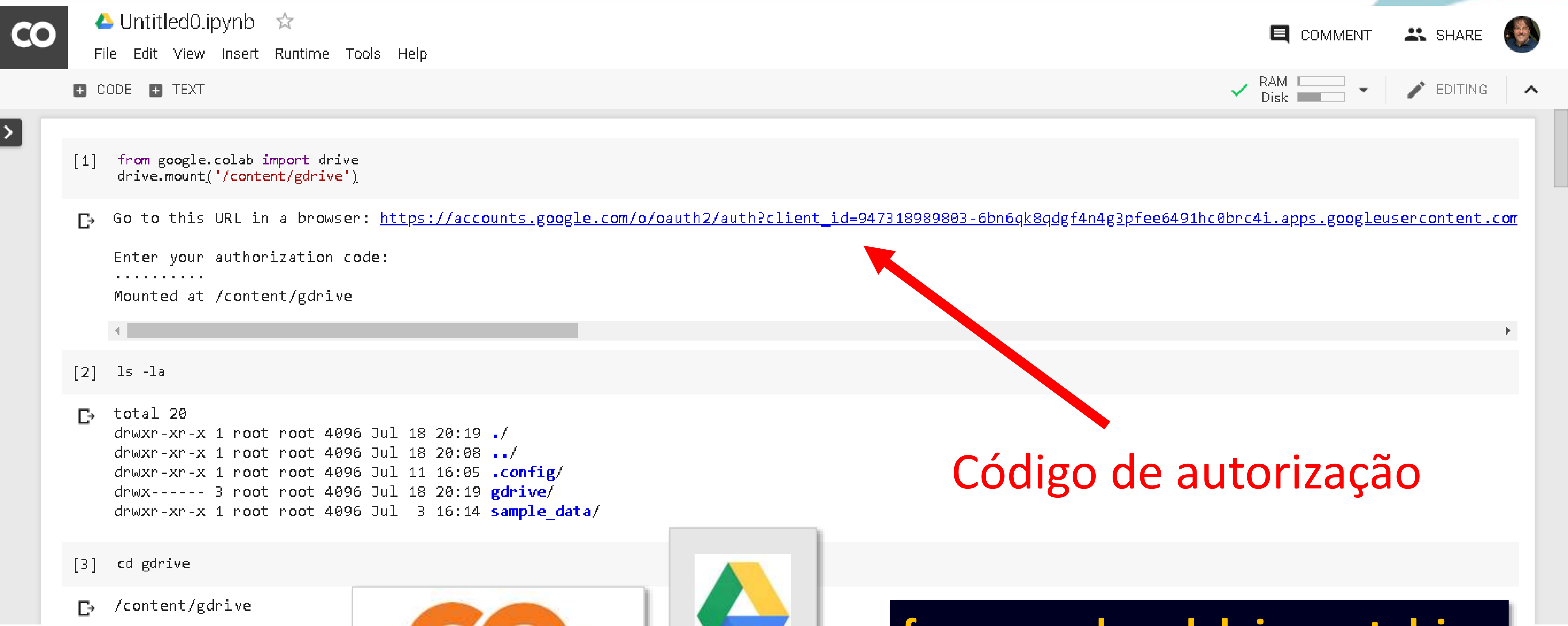
1. Acesse o link google drive para compartilhamento:

https://drive.google.com/drive/folders/1Vodmo0ayZ0tdx_DJEb5n2hFudxJF0ay9?usp=sharing



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the collaboratory

Google Drive

```
from google.colab import drive
drive.mount('/content/gdrive')
```

EXEMPLO 2

RECONHECIMENTO DE CARACTERES MANUSCRITOS

REDE NEURAL MULTI-LAYER

Sobre Imagem Digital

- Imagem é um **sinal digital (2D)** de suporte a informação (Teoria de Sinais)
- Uma imagem digital é uma função discreta de posição (2D ou 3D, tempo e banda espectral) e níveis de cinza. Cada **coordenada** da imagem contem uma informação de **luminância** (ou crominância).

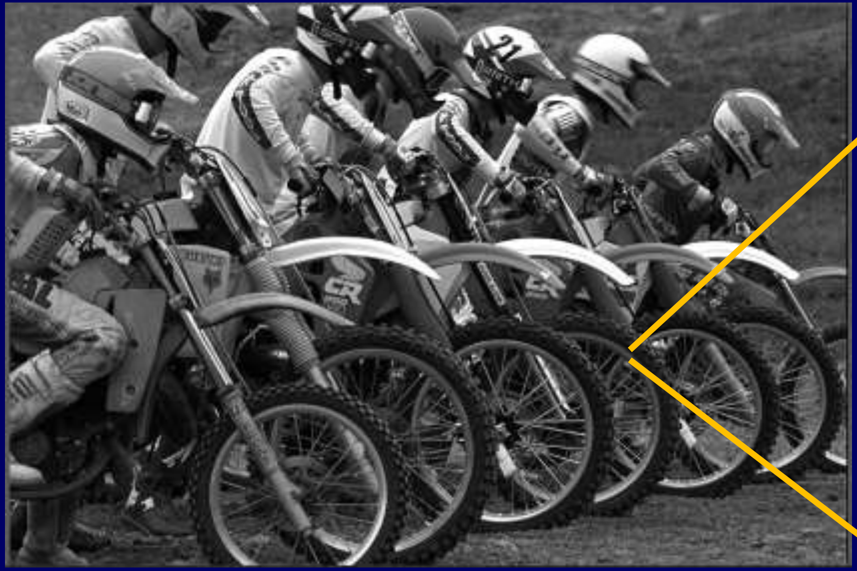
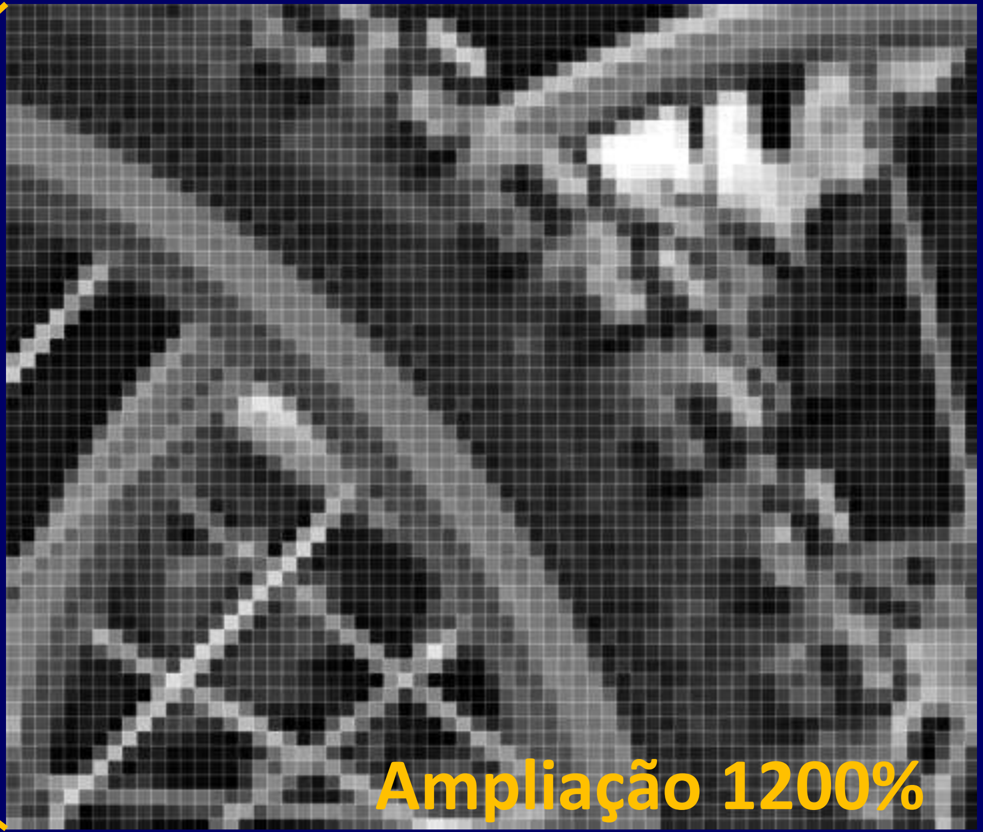
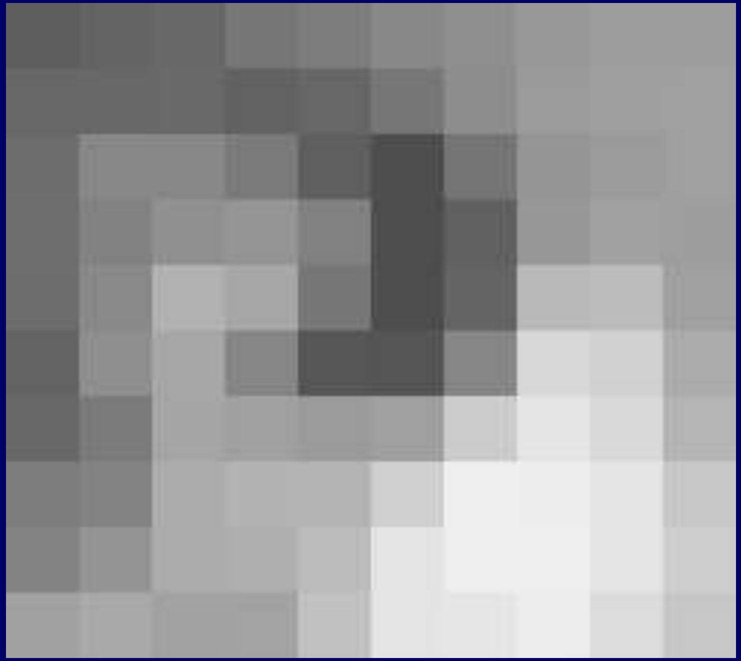


Imagem digital (KODAK – Free)



Sobre Imagem Digital

Uma imagem digital pode ser vista como uma matriz de níveis de cinza, ou valores de intensidade luminosa.



Ampliação

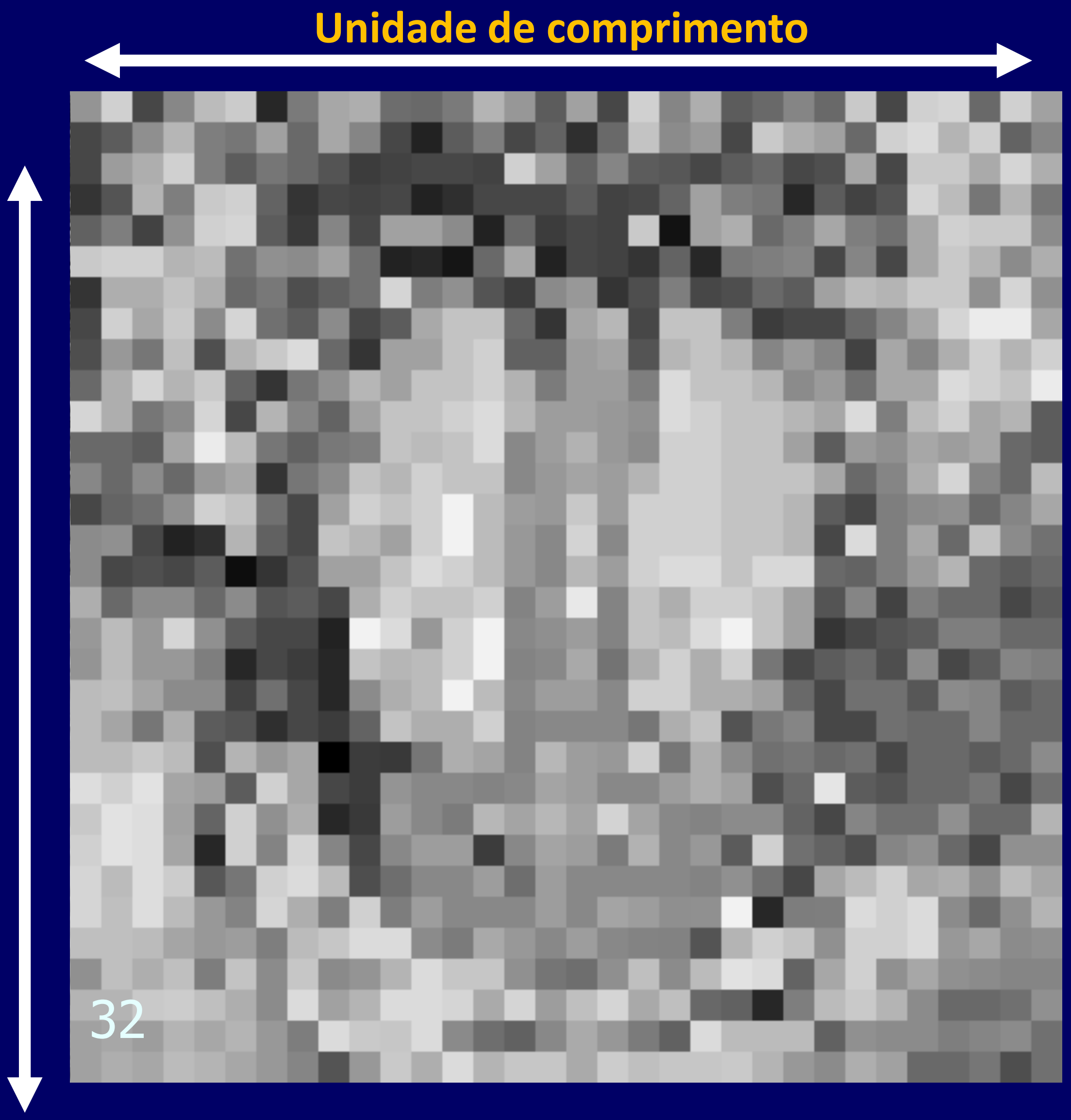
94	100	104	119	125	136	143	153	157	158
103	104	106	98	103	119	141	155	159	160
109	136	136	123	95	78	117	149	155	160
110	130	144	149	129	78	97	151	161	158
109	137	178	167	119	78	101	185	188	161
100	143	167	134	87	85	134	216	209	172
104	123	166	161	155	160	205	229	218	181
125	131	172	179	180	208	238	237	228	200
131	148	172	175	188	228	239	238	228	206
161	169	162	163	193	228	230	237	220	199

Valores de intensidade luminosa (8 bits)
Níveis de Cinza

Sobre Imagem Digital

Resolução da Imagem

- **DPI – "dots per inch"**
  - Scanners (variável)
- **Número de pixels**
  - Vídeo (fixo)
- **Exemplo simples**
  - Foto de 5x5 cm – 2x2 in.
  - Resolução: 300 dpi
  - Tamanho: 600x600 pixels
  - **Filme Fotográfico:** 5000x5000 dpi



MNIST

National Institute of Standards and Technology
U.S. Department of Commerce

THE MNIST DATABASE

of handwritten digits

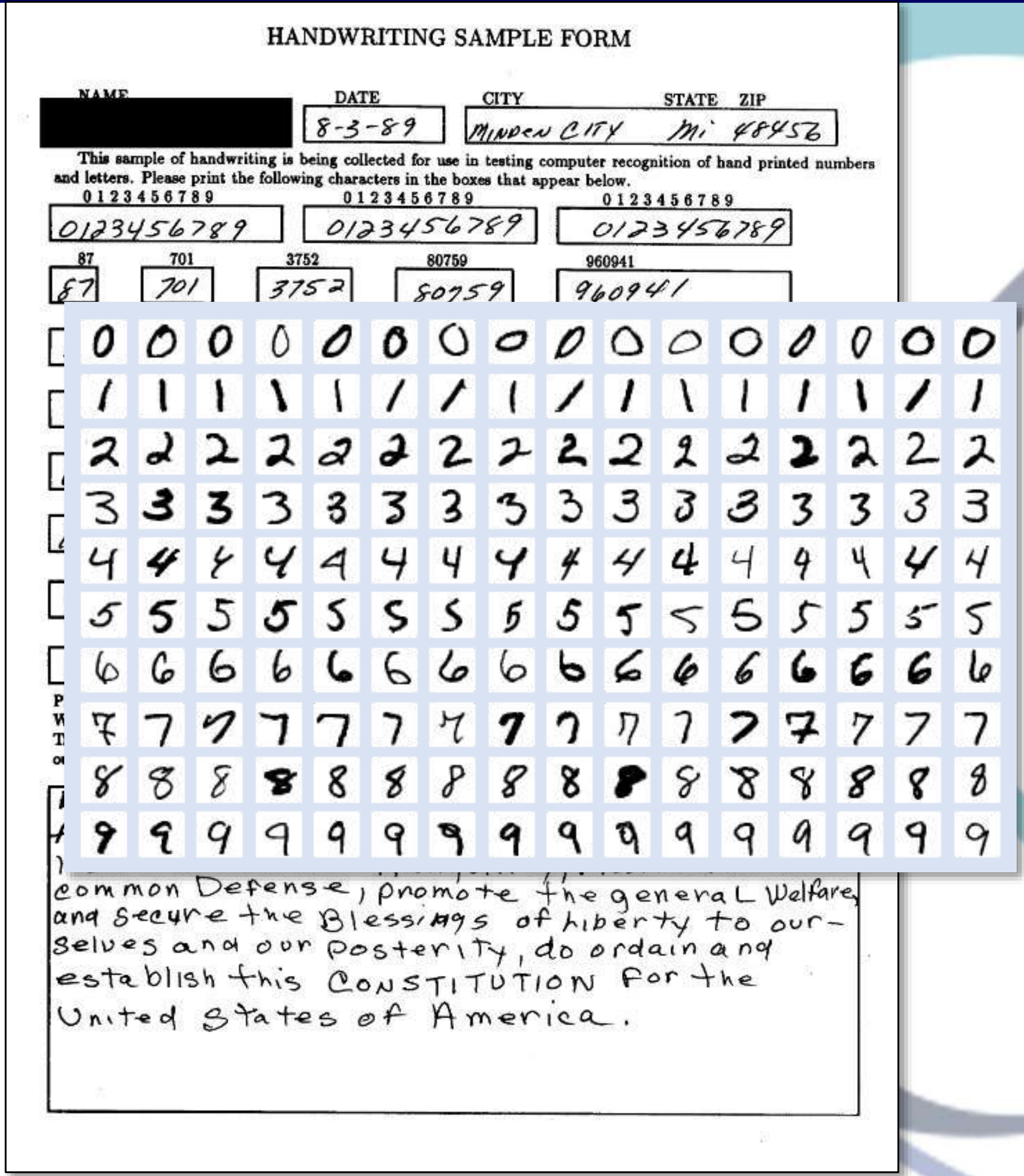
Yann LeCun, Courant Institute, NYU
Corinna Cortes, Google Labs, New York
Christopher J.C. Burges, Microsoft Research, Redmond

É um Banco de Dados composto de dígitos escritos por estudantes do ensino médio e funcionários da agência governamental americana: "US Census Bureau"

A base MNIST contem:

- **60,000 imagens para treino**
- **10,000 imagens testes**

http://yann.lecun.com/exdb/mnist/



Importa Bibliotecas

↓

Leitura das Imagens → Treinamento (60000) Validação/Teste (10000)

↓

Normalização das Imagens → Níveis de Cinza [0, 1.0]

↓

Definição da RNA ← Define as propriedades de cada camada

↓

Compila o Modelo → Apresenta o resumo do Modelo

↓

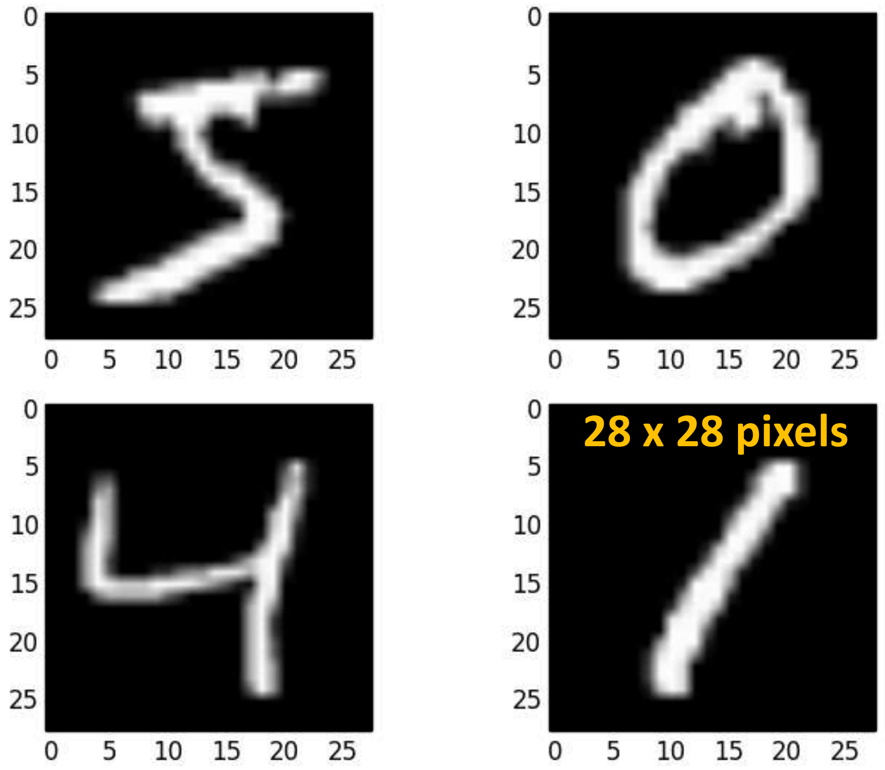
Treina (FIT) a RNA ← *Epoch*, *Batch*, Dados de Treinamento e Validação

↓

Print Precisão da Rede

↓

Reconhecimento



DEFINIÇÃO DA RNA

- **1ª Camada: 784 neurônios**
- **2ª Camada: 392 neurônios**
- **3ª Camada: 196 neurônios**
- **Saída: 10 neurônios**

```
model = Sequential()
model.add(Flatten(input_shape=(28,28)))
model.add(Dense(392, activation='relu'))
model.add(Dense(196, activation = 'relu'))
model.add(Dense(10, activation='softmax'))
```

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EXEMPLO 3

RECONHECIMENTO DE CARACTERES MANUSCRITOS

REDE NEURAL CNN

CONVOLUTION NEURAL NETWORK

Colab_example_of_cnn_Mnist.ipynb

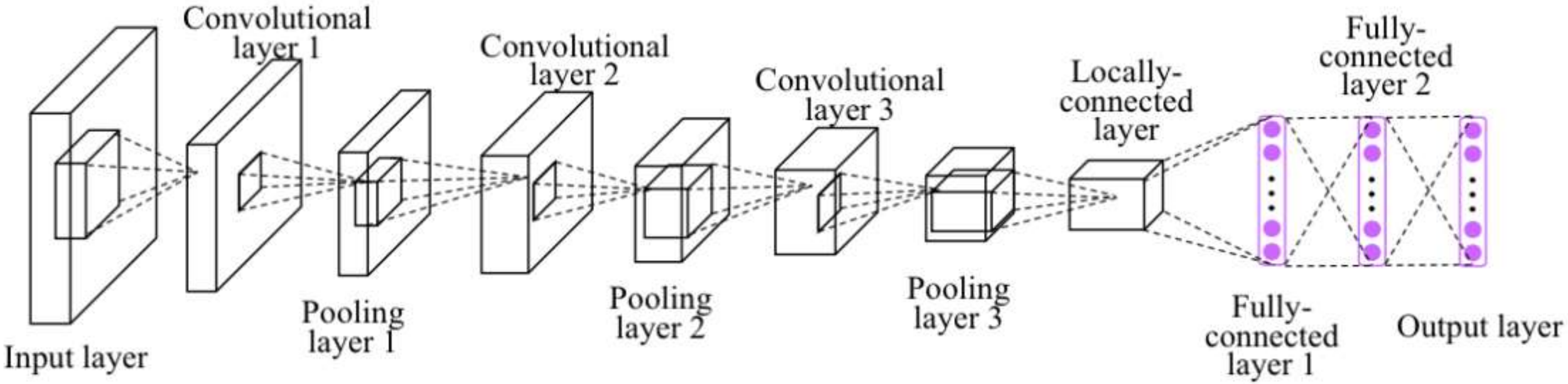
File Edit View Insert Runtime Tools Help

OPEN IN PLAYGROUND

https://colab.research.google.com/drive/1_mb0zsvIWu8OvFNYS5X-2IaRtjdItE0u

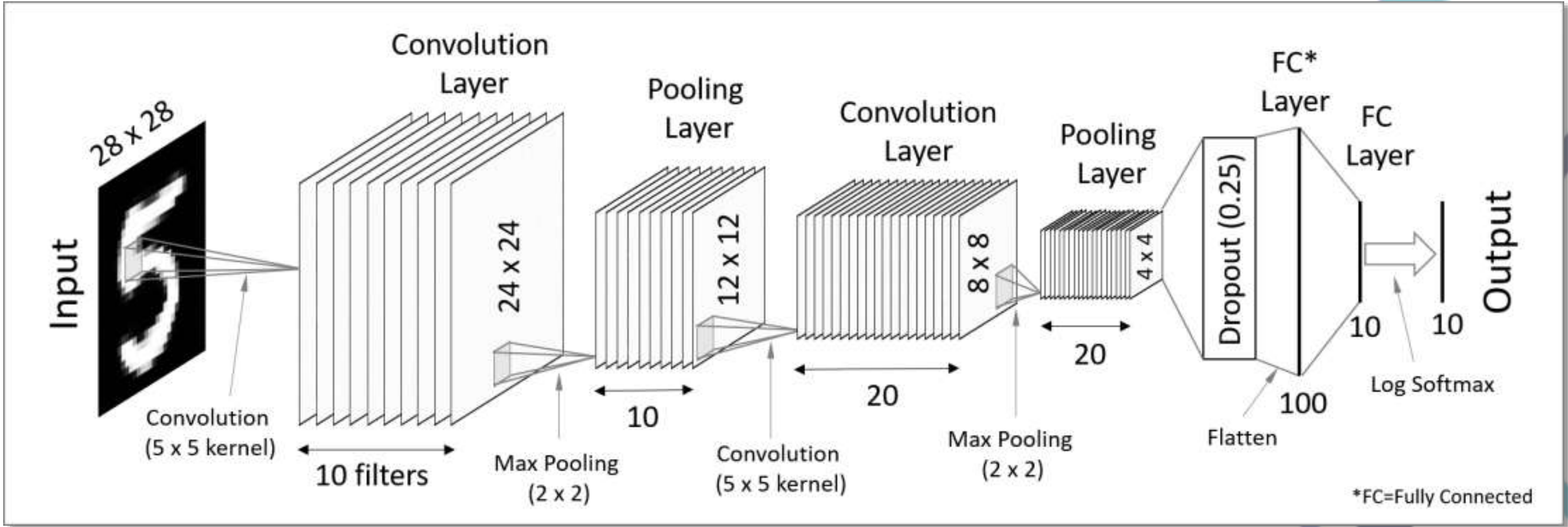
CNN

Overview

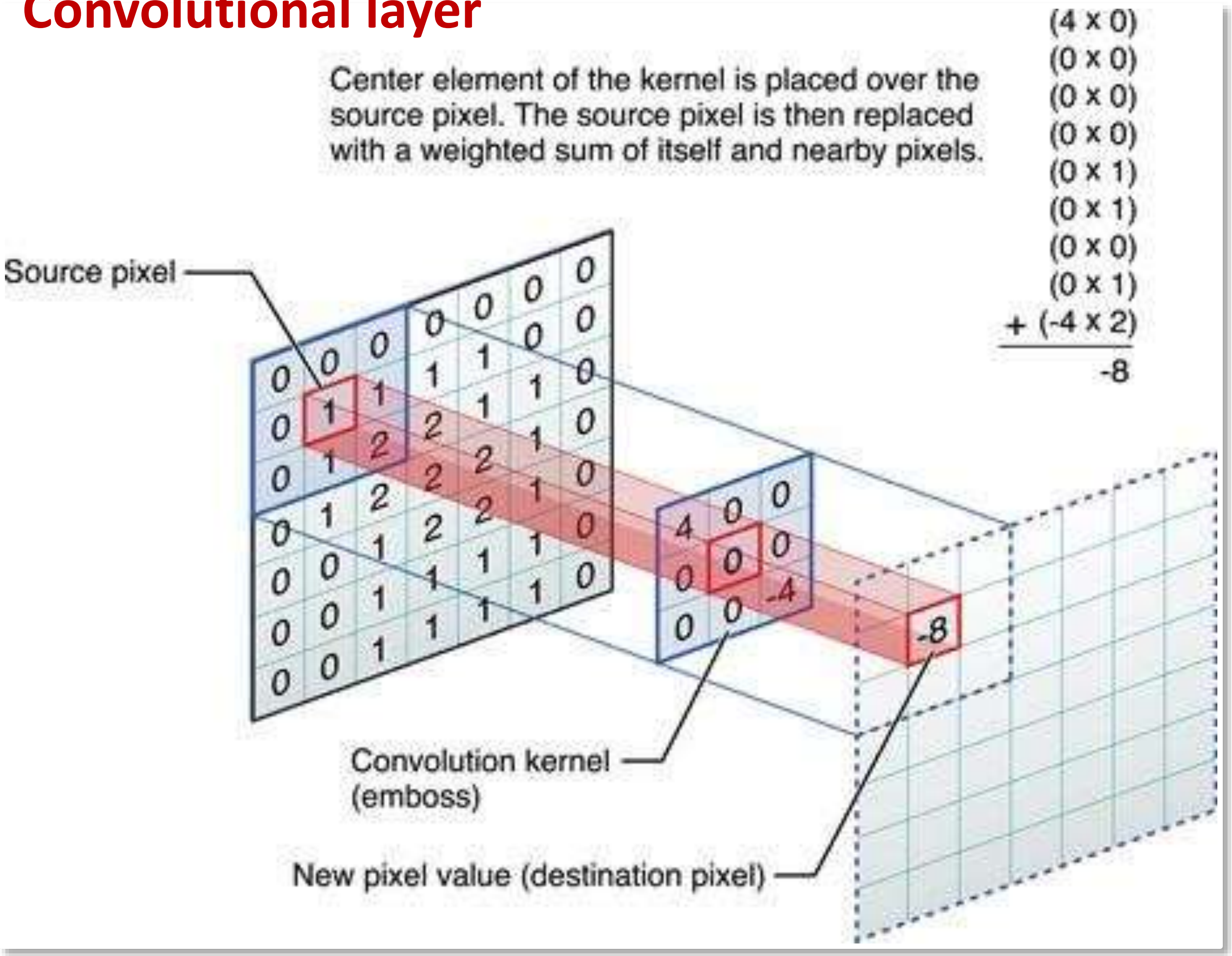


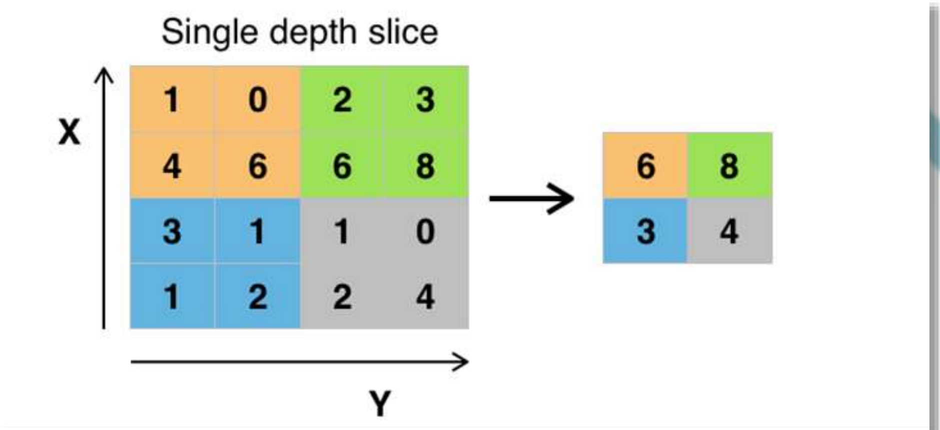
Goal

The Goal of this notebook is to present a simple example of cnn running with keras (Tensorflow backend) in the colab interface. We also present some example of results of a simple application of handwritten digit classification.


Input
28 x 28
Convolution
(5 x 5 kernel)
Convolution
Layer
24 x 24
10 filters
Max Pooling
(2 x 2)
Pooling
Layer
12 x 12
10
Convolution
(5 x 5 kernel)
Convolution
Layer
8 x 8
20
Max Pooling
(2 x 2)
Pooling
Layer
4 x 4
20
Dropout (0.25)
Flatten
FC*
Layer
100
FC
Layer
10
Log Softmax
10
Output
*FC=Fully Connected

Convolutional layer





Example of MaxPool with 2x2 and a stride of 2

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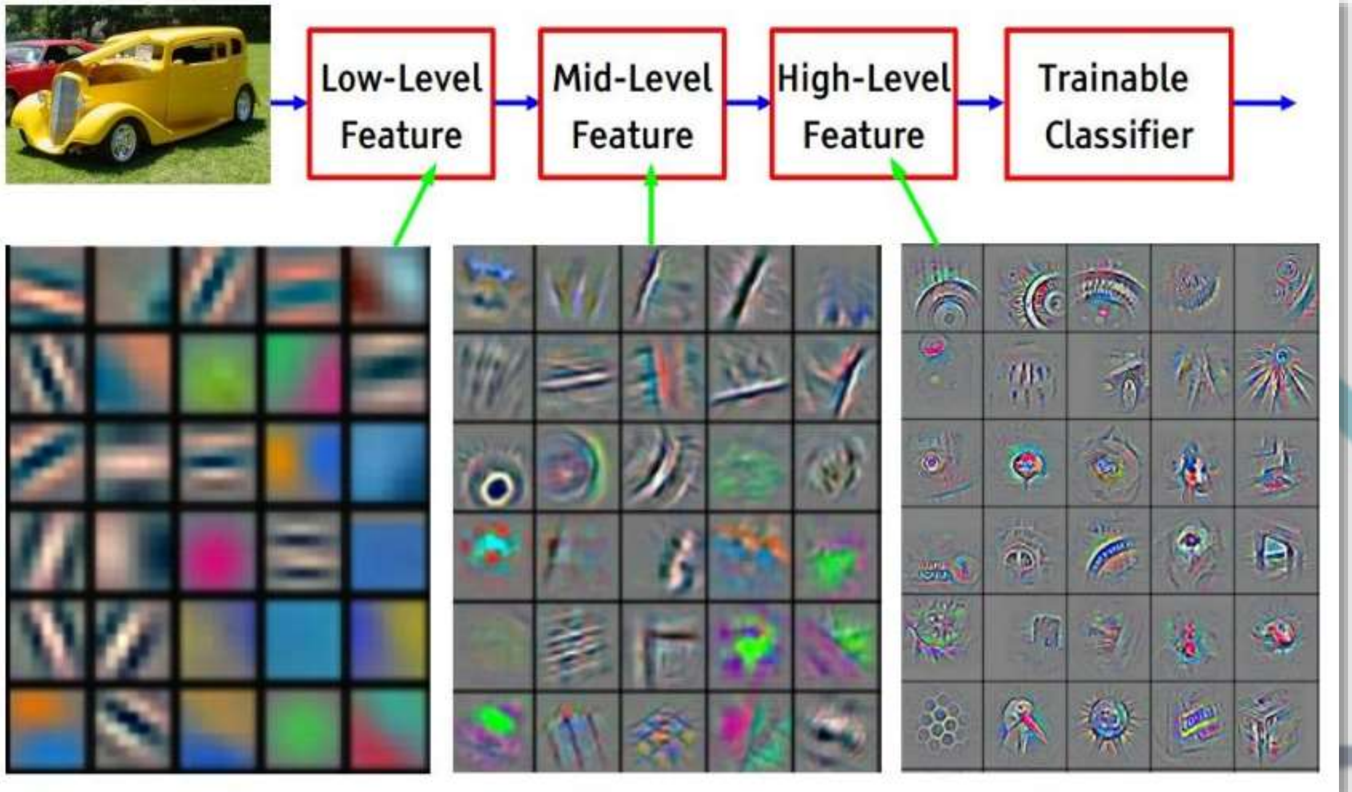
Convolutional Neural Networks

What makes CNNs so special?

- Based on mammal visual cortex
- Extract **surrounding-depending** high-order features.
- Specially useful for:
    - Images
    - Time-dependent parameters

      Speech recognition

      Signal analysis



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Trabalhos do Grupo

dx.doi.org/10.7437/NT2236-7640/2016.01.004
Notas Técnicas,v. 6, n. 1, p. 28–51, 2016

Journal of Petroleum Science and Engineering 170 (2018) 315–330
Contents lists available at ScienceDirect

...nd Engineering

.../locate/petrol

...gs using deep
...lian pre-salt carbonate

Journal of Petroleum Science and Engineering 179 (2019) 474–503

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

A deep residual convolutional neural network for automatic lithological facies identification in Brazilian pre-salt oilfield wellbore image logs

Manuel Blanco Valentín[a,*], Clécio R. Bom[a,b], Juliana M. Coelho[a], Maury Duarte Correia[c], Márcio P. de Albuquerque[a], Marcelo P. de Albuquerque[a], Elisângela L. Faria[a]

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[c] Centro de Pesquisas e Desenvolvimento Leopoldo Américo Miguez de Mello (CENPES - PETROBRAS), Av. Horácio Macedo, 950, Cidade Universitária, Rio de Janeiro, Brazil

Centro de Pesquisas e Desenvolvimento Leopoldo Am...
PETROBRAS, Av. Horáci...
950, Cidade Universi...
Rio de Janeiro, RJ. CEP 219...
Submetido: 01/01/2016 Ac...

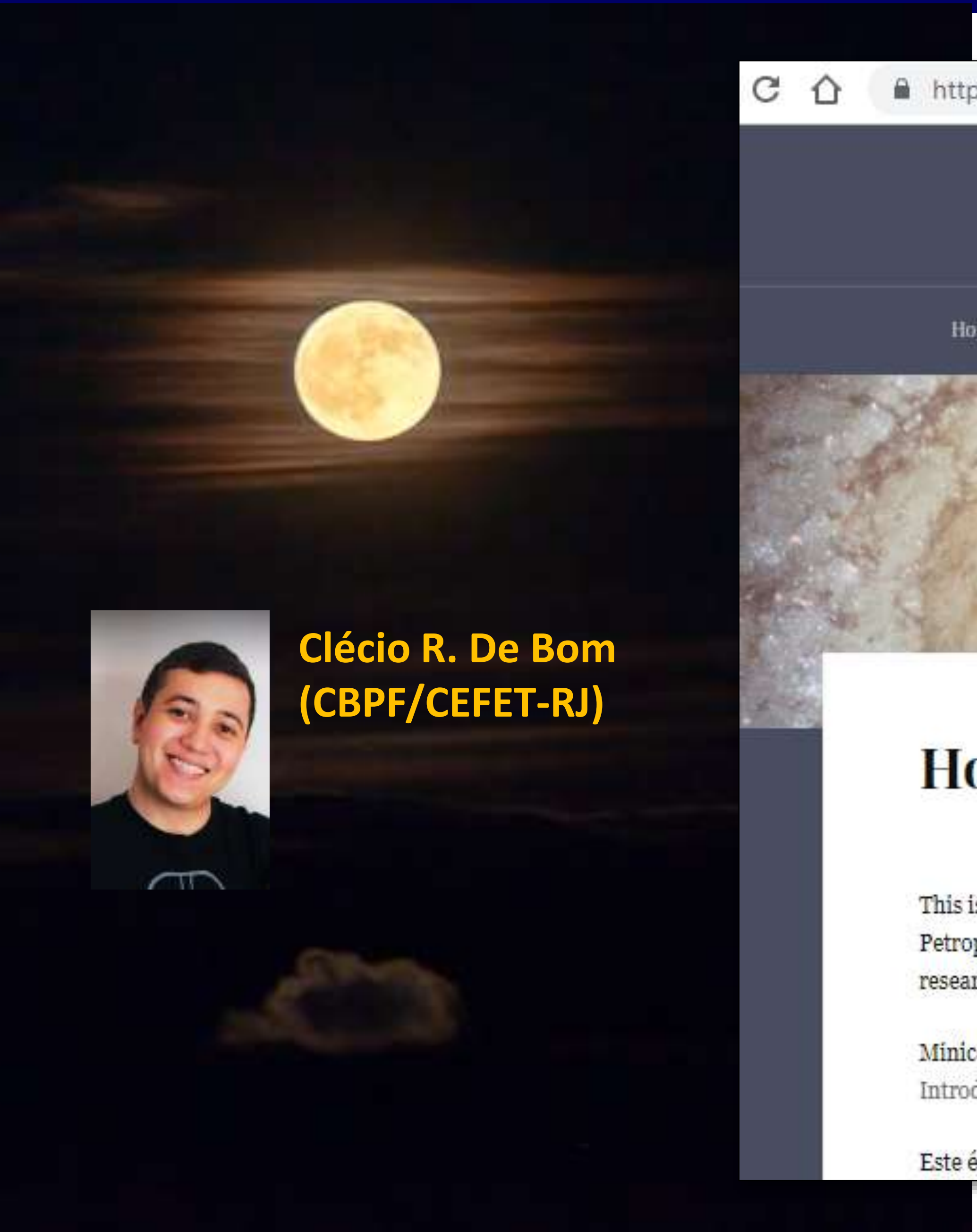
...Lens Finding Challenge

...ruz[3,4,5,★★], Fabio Bellagamba[1,2], Clécio R. Bom[6,7], ...ew Davies[22], Etienne Decencière[10], Rémi Flamary[11], ... Marc Huertas-Company[14], Neal Jackson[13], Colin Jacobs[23], Eric Jullo[15], Jean-Paul Kneib[12], Léon V. E. Koopmans[16], François Lanusse[17], Chun-Liang Li[18], Quanbin Ma[18], Martin Makler[7], Nan Li[19], Matthew Lightman[15], Carlo Enrico Petrillo[16], Stephen Serjeant[22], Christoph Schäfer[12], Alessandro Sonnenfeld[21], Amit Tagore[13], Crescenzo Tortora[16], Diego Tuccillo[10,14], Manuel B. Valentín[7], Santiago Velasco-Forero[10], Gijs A. Verdoes Kleijn[16], and Georgios Vernardos[16]

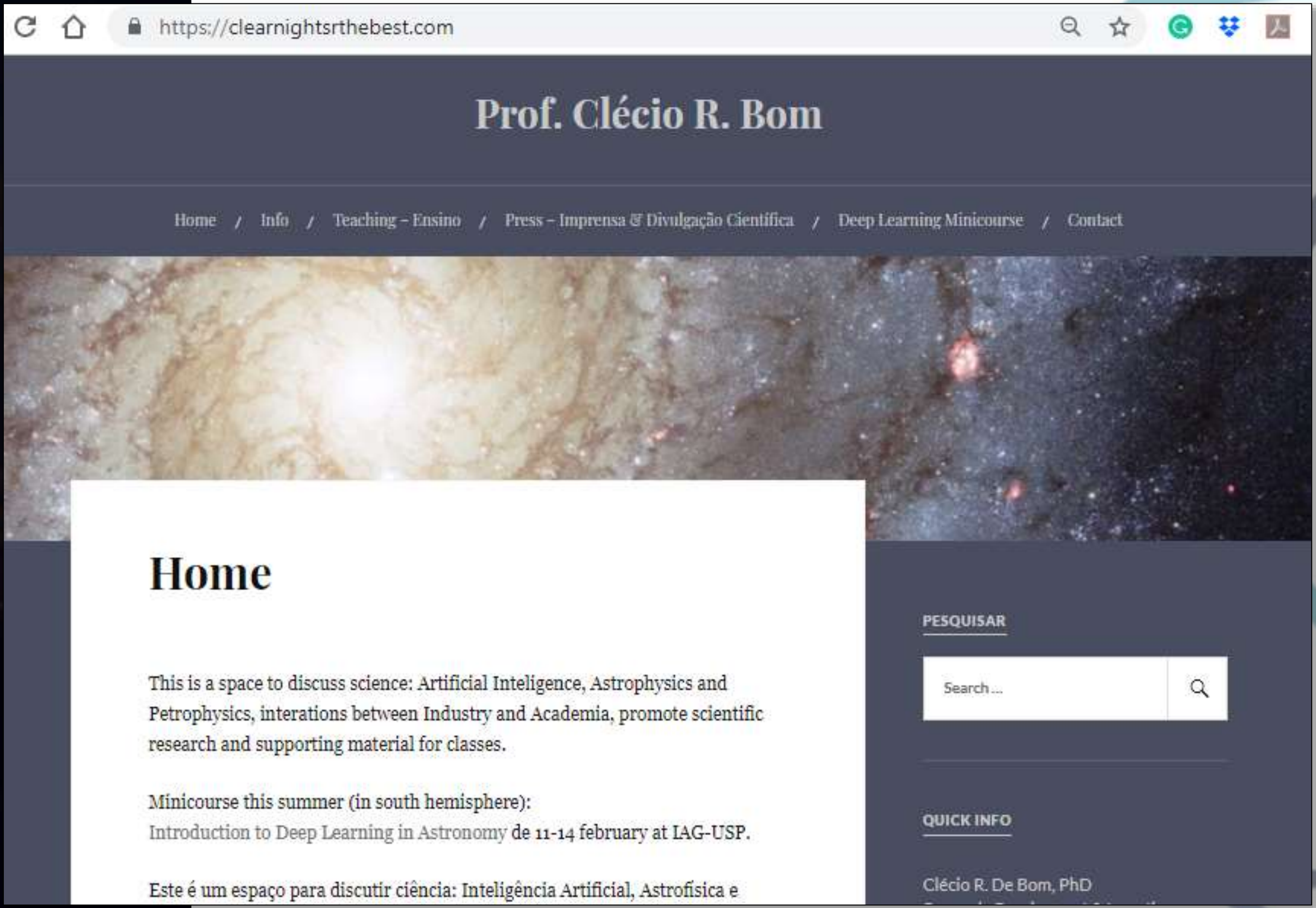
CBPF ANOS

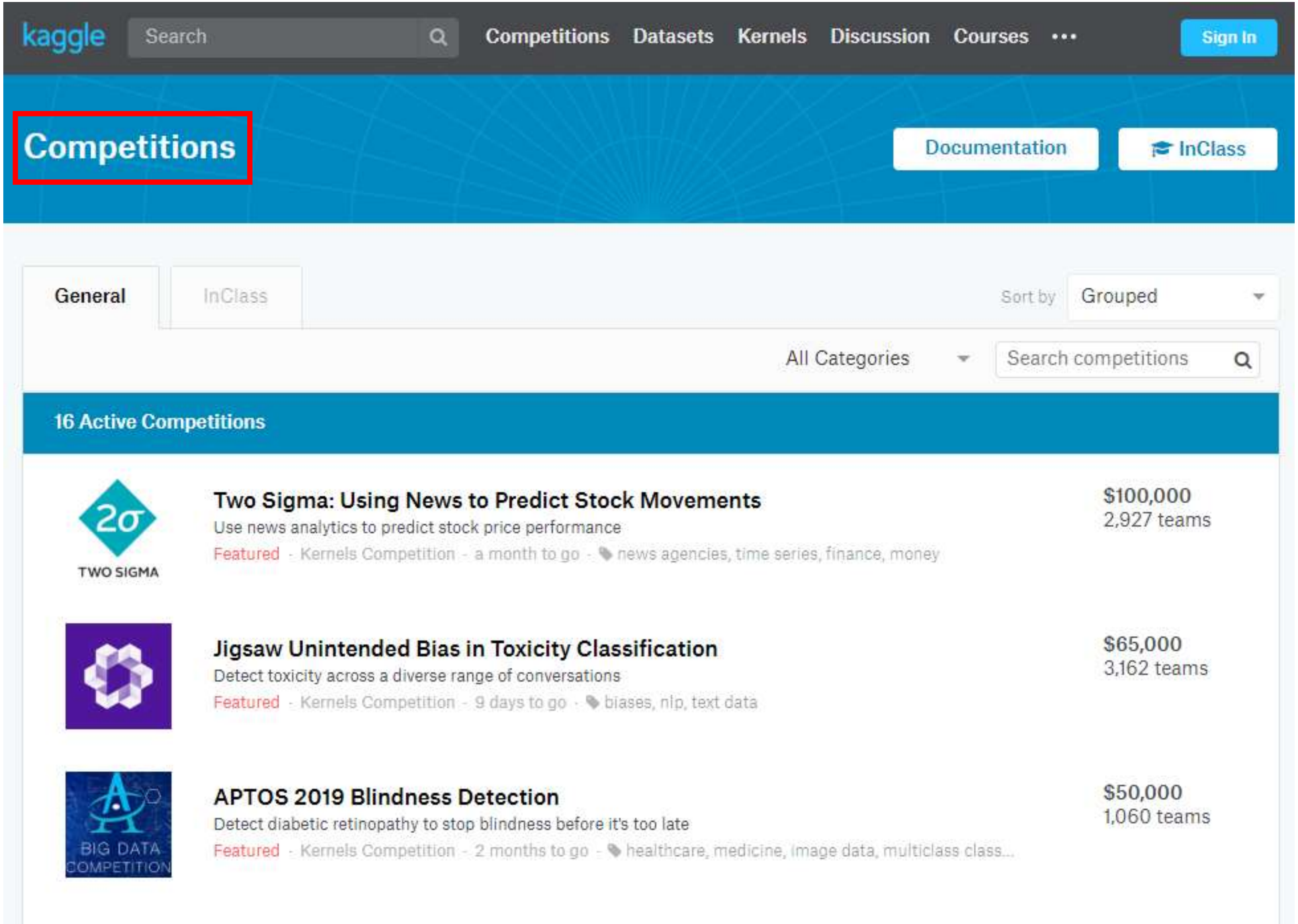
Trabalhos do Grupo

https://clearnightsrthebest.com/



Clécio R. De Bom
(CBPF/CEFET-RJ)




kaggle
Search
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Datasets
Kernels
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Courses
Sign In
Competitions
Documentation
InClass
General
InClass
Sort by
Grouped
All Categories
Search competitions
16 Active Competitions
Two Sigma: Using News to Predict Stock Movements
Use news analytics to predict stock price performance
Featured · Kernels Competition · a month to go · news agencies, time series, finance, money
$100,000
2,927 teams
TWO SIGMA
Jigsaw Unintended Bias in Toxicity Classification
Detect toxicity across a diverse range of conversations
Featured · Kernels Competition · 9 days to go · biases, nlp, text data
$65,000
3,162 teams
APTOS 2019 Blindness Detection
Detect diabetic retinopathy to stop blindness before it's too late
Featured · Kernels Competition · 2 months to go · healthcare, medicine, image data, multiclass class...
$50,000
1,060 teams
BIG DATA COMPETITION

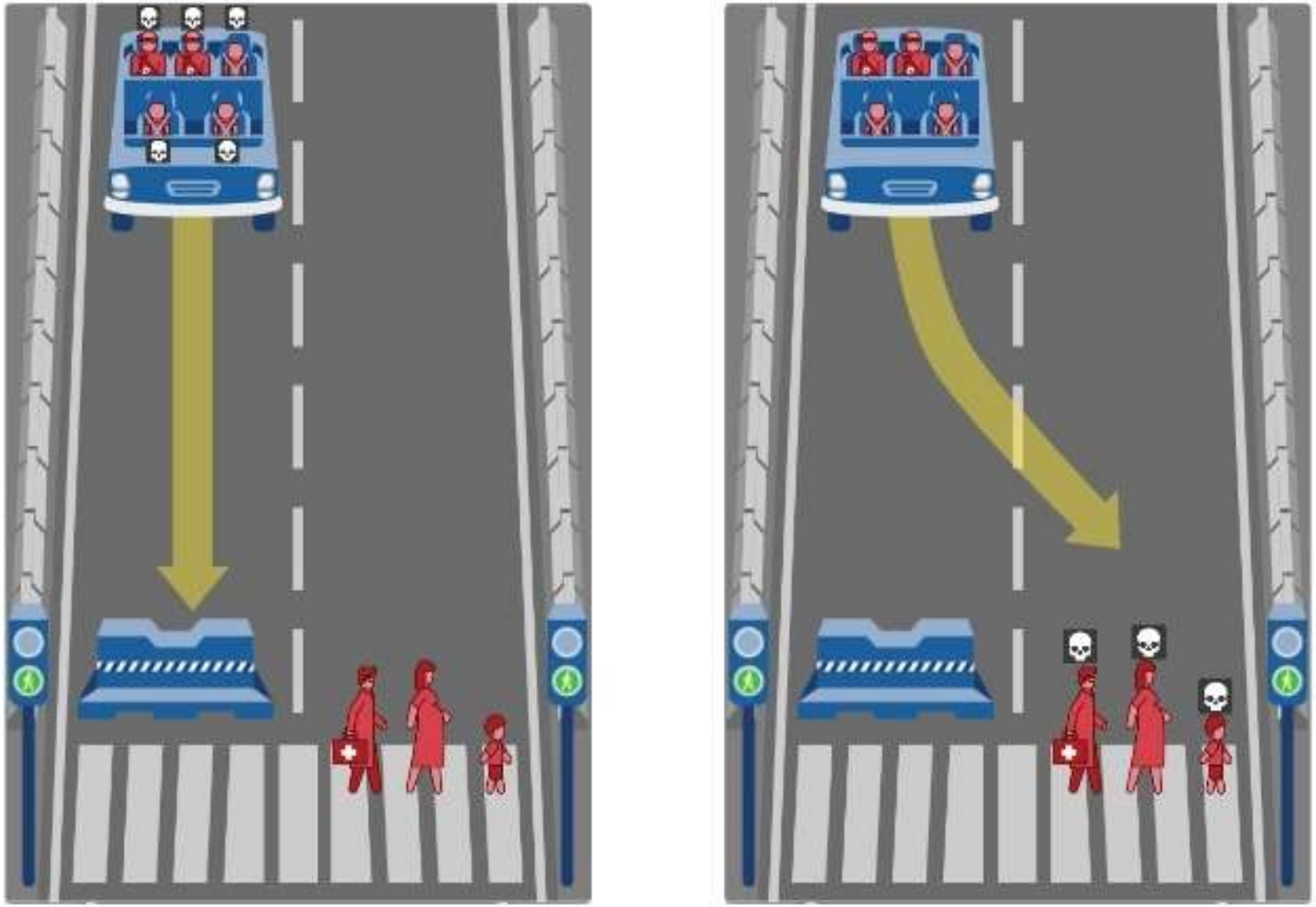
IA e as decisões éticas

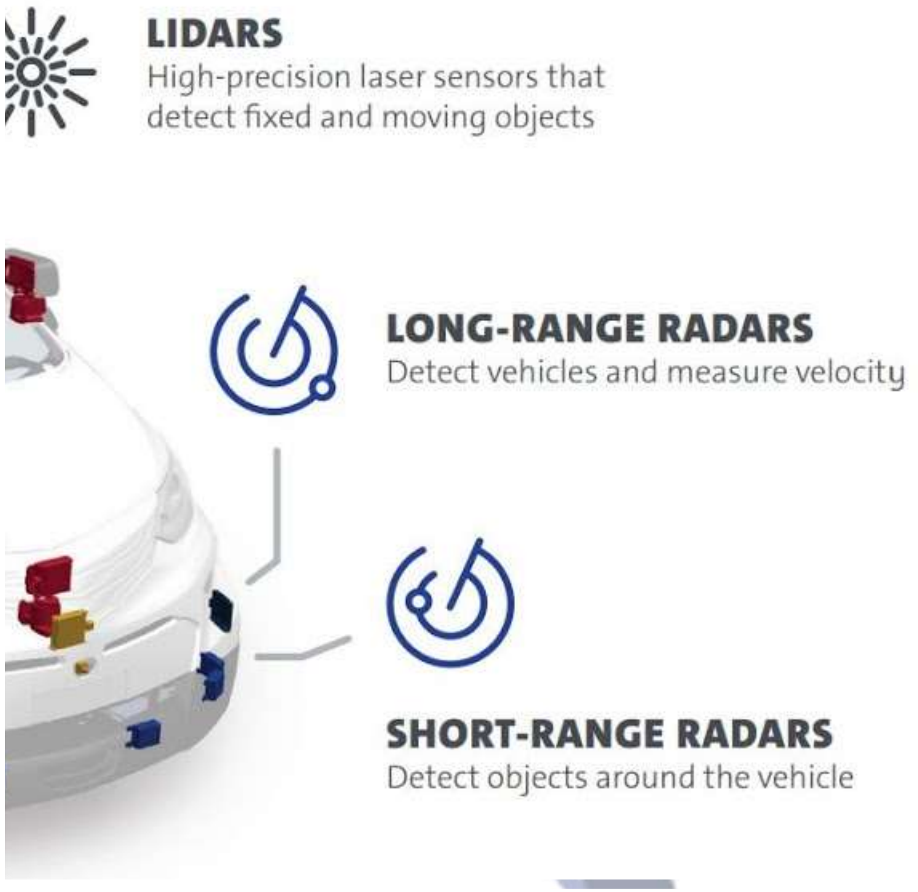
Veículos Autônomos – processamento de imagens e redes neurais

IA e as decisões éticas

A máquina moral

http://moralmachine.mit.edu/hl/pt





https://hcai.mit.edu/avt/

XII ESCOLA DO CBPF

22 de julho a 02 de agosto de 2019

Inteligência Artificial utilizando *Deep Learning* e Aplicações em Física

Márcio Portes de Albuquerque (CBPF)

Clécio R. De Bom (CBPF/CEFET-RJ)

Elisangela L. Faria (CBPF)

Ministério da
Ciência, Tecnologia, Inovações e Comunicações

Grafite da Ciência
CBPF

Sobre Imagem Digital (CORES)

- A cor é definida como uma “sensação” na percepção humana.
- Do ponto de vista da Física, a cor é o resultado da incidência de uma onda eletromagnética na retina. Esta tem um comprimento de onda entre 400 a 700nm.

SISTEMA DE CORES

√ **RGB (Red Green Blue)**

É um Sistema Aditivo/Emissão. A proporção de cada uma das cores primarias (*Red, Green and Blue*) são a base para todas as outras cores, quando somadas. A implementação é feita por meio de circuitos eletrônicos (e.g. em televisão, câmeras, sistemas de computação gráfica, etc.).

Cores primárias de emissão

√ **CMY(K) (Cyan Magenta Yellow (Black))**

É um Sistema de cores Subtrativo/Absorção. Utilizado normalmente por dispositivos de impressão e/ou fotográficos. Estes sistemas incluem normalmente uma 4a. cor (preto), para reduzir “*custos*” para produzir todas as cores.

Cores primárias de absorção

Sobre Imagem Digital (CORES)

Escala de 0 a 255 → | | Escala em %

RGB	Cor	CMY	K
R = 234 G = 212 B = 20	Amarelo	C = 10% M = 11% Y = 94%	K=1%
R = 83 G = 12 B = 64	ROXO	C = 57% M = 98% Y = 22%	K=32%
R = 20 G = 202 B = 114	Verde Aqua	C = 77% M = 0% Y = 71%	K=0%

HSL → OUTRO MODELO: Hue (Matiz), Saturação, Luminosidade