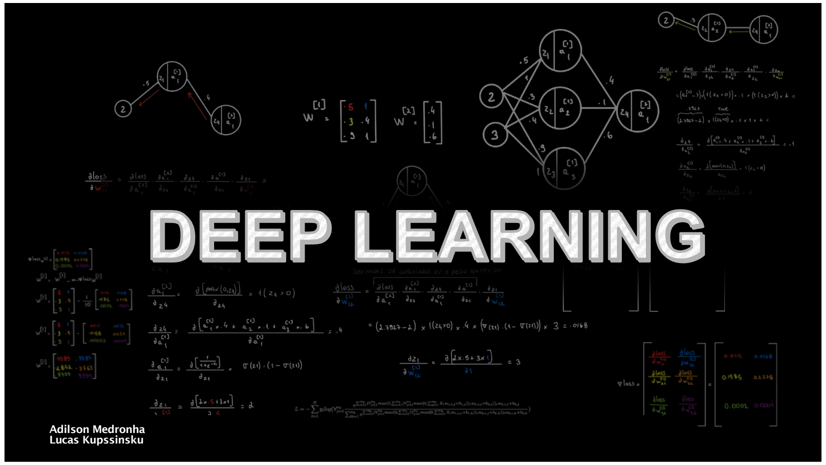
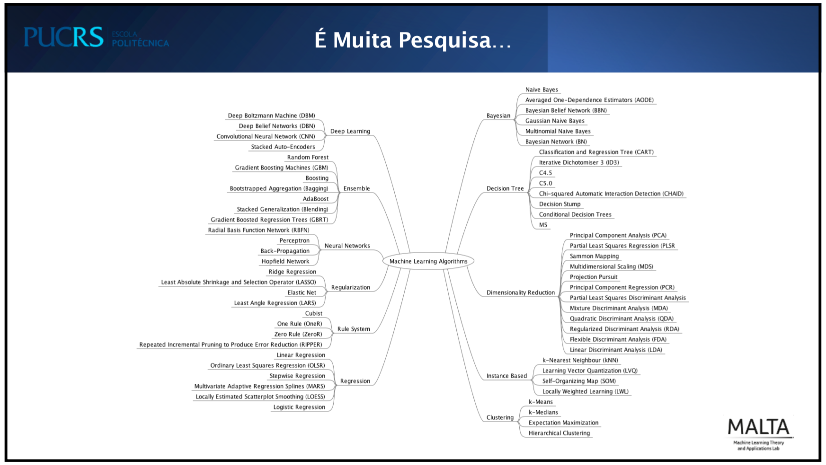


DEEP LEARNING
Adilson Medronha
Lucas Kupssinsku

1

APRENDIZADO DE MÁQUINA
O QUE É LEARNING?
PRIMEIRO ALG DE LEARNING
PROTOCOLOS DE TREINAM.
OTIMIZAÇÃO
REDES NEURAIS
BACKPROP + PRATICA
CNN + PRATICA

2



PUCRS ESCOLA POLITÉCNICA
É Muita Pesquisa…
Machine Learning Algorithms
Deep Learning
Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders
Ensemble
Random Forest
Gradient Boosting Machines (GBM)
Boosting
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (Blending)
Gradient Boosted Regression Trees (GBRT)
Neural Networks
Radial Basis Function Network (RBFN)
Perceptron
Back-Propagation
Hopfield Network
Regularization
Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least Angle Regression (LARS)
Rule System
Cubist
One Rule (OneR)
Zero Rule (ZeroR)
Repeated Incremental Pruning to Produce Error Reduction (RIPPER)
Regression
Linear Regression
Ordinary Least Squares Regression (OLSR)
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Logistic Regression
Bayesian
Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Gaussian Naive Bayes
Multinomial Naive Bayes
Bayesian Network (BN)
Decision Tree
Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5
C5.0
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
Conditional Decision Trees
M5
Dimensionality Reduction
Principal Component Analysis (PCA)
Partial Least Squares Regression (PLSR
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Principal Component Regression (PCR)
Partial Least Squares Discriminant Analysis
Mixture Discriminant Analysis (MDA)
Quadratic Discriminant Analysis (QDA)
Regularized Discriminant Analysis (RDA)
Flexible Discriminant Analysis (FDA)
Linear Discriminant Analysis (LDA)
Instance Based
k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)
Clustering
k-Means
k-Medians
Expectation Maximization
Hierarchical Clustering
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Machine Learning Theory and Applications Lab

3

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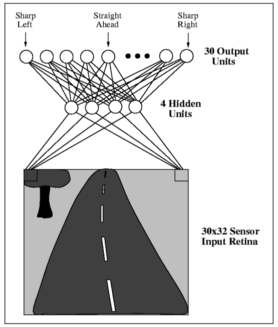
MOTIVAÇÃO

ALVINN:
AN AUTONOMOUS LAND VEHICLE IN A NEURAL NETWORK

Dean A. Pomerleau
Computer Science Department
Carnegie Mellon University
Pittsburgh, PA 15213

ABSTRACT

ALVINN (Autonomous Land Vehicle In a Neural Network) is a 3-layer back-propagation network designed for the task of road following. Currently ALVINN takes images from a camera and a laser range finder as input and produces as output the direction the vehicle should travel in order to follow the road. Training has been conducted using simulated road images. Successful tests on the Carnegie Mellon autonomous navigation test vehicle indicate that the network can effectively follow real roads under certain field conditions. The representation developed to perform the task differs dramatically when the network is trained under various conditions, suggesting the possibility of a novel adaptive autonomous navigation system capable of tailoring its processing to the conditions at hand.



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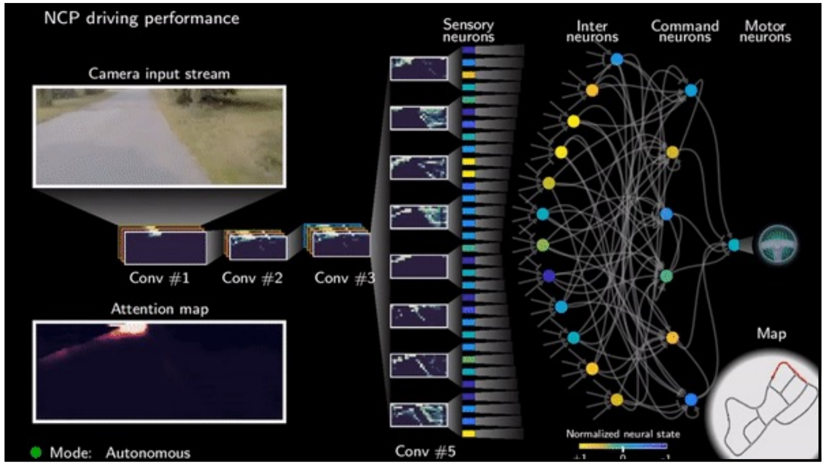

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MOTIVAÇÃO

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MOTIVAÇÃO

A Method for Animating Children's Drawings of the Human Figure

HARRISON JESSE SMITH, Meta AI Research, USA
QINGYUAN ZHENG*, Tencent America, USA
YIFEI LI*, MIT CSAIL, USA
SOMYA JAIN, Meta AI Research, USA
JESSICA K. HODGINS*, Carnegie Mellon University, USA

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MOTIVAÇÃO

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Referência

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MOTIVAÇÃO

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MOTIVAÇÃO

"a storm trooper vacuuming a beach"

"sunset time lapse at the beach with moving clouds and colors in the sky, 4k, high resolution"

"an astronaut feeding ducks on a sunny afternoon, reflection from the water"

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Referência

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MOTIVAÇÃO
Refência
MALTA

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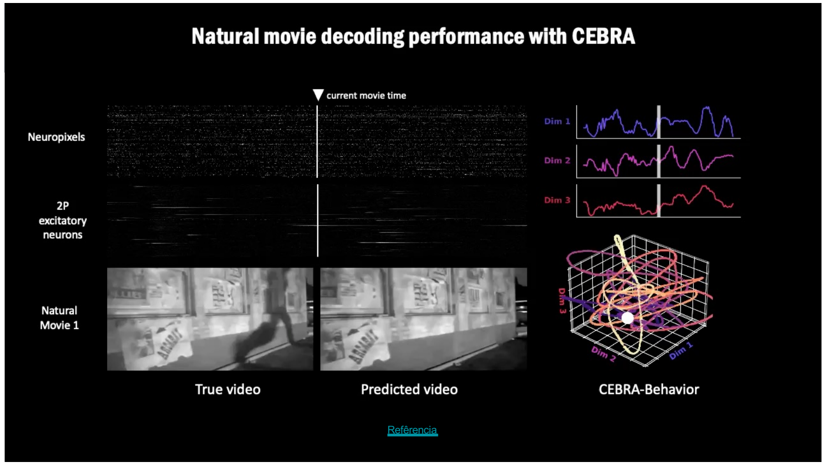
Natural movie decoding performance with CEBRA
current movie time
Neuropixels
2P excitatory neurons
Natural Movie 1
Dim 1
Dim 2
Dim 3
True video
Predicted video
CEBRA-Behavior
Referência

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APRENDIZADO DE MÁQUINA
> O QUE É LEARNING?
PRIMEIRO ALG DE LEARNING
PROTOCOLOS DE TREINAM.
OTIMIZAÇÃO
REDES NEURAIS
BACKPROP + PRATICA
CNN + PRATICA

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“Na medida que os computadores se tornam mais sofisticados, parece inevitável que o Aprendizado de Máquina exerça um papel central em Ciência da Computação e tecnologia de computadores”
- Tom Mitchell

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O Que é Learning?

*“A computer program is said to **learn** from experience **E** with respect to some class of tasks **T** and performance measure **P**, if its performance at tasks in T, as measured by P, improves with experience E.”* - Mitchell, 1997

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- Experiência (E): **conjunto de dígitos anotados à mão (Hello World!)**

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O Que é Learning?

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- Tarefa (T): **classificação**

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O Que é Learning?

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O que vocês acham, é viável programar uma solução imperativa?

- Medida de desempenho (P): **acurácia**

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O Que é Learning?

*"A computer program is said to **learn** from experience **E** with respect to some class of tasks **T** and performance measure **P**, if its performance at tasks in T, as measured by P, improves with experience E."* - Mitchell, 1997

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- Tarefa (T): **classificação**

O que vocês acham, é viável programar uma solução imperativa?

Não! Mas com redes neurais é **trivial**

- Medida de desempenho (P): **acurácia**

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O Que é Learning?

Learning = Representation + Evaluation + Optimization

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O Que é Learning?

Learning = Representation + Evaluation + Optimization

Representation

- Instances
  - K-nearest neighbor
  - Support vector machines
- Hyperplanes
  - Naive Bayes
  - Logistic regression
- Decision trees
- Sets of rules
  - Propositional rules
  - Logic programs
- NEURAL NETWORKS
- Linear programming
- Graphical models
  - Bayesian networks
  - conditional random fields

Evaluation

- ACCURACY/error rate
- Precision and recall
- Squared error
- Likelihood
- Posterior probability
- Information gain
- K-l divergence
- Cost/Utility
- Margin

Optimization

- Combinatorial optimization
  - Greedy search
  - Beam search
  - Branch-and-bound
- Continuous optimization
  - Unconstrained
    - GRADIENT DESCENT
    - Conjugate gradient
    - Quasi-newton methods

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Learning, Overview

CONJUNTO DE DADOS

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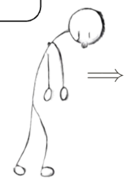
Learning, Overview

CONJUNTO DE DADOS



$\Longrightarrow$

x_1 pressão arterial

x_2 temperatura

x_3 peso

x_4 sente fadiga

x_5 tem tosse

$\vdots$

x_d etc

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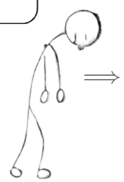
Learning, Overview

CONJUNTO DE DADOS



$\Longrightarrow$

x_1 pressão arterial

x_2 temperatura

x_3 peso

x_4 sente fadiga

x_5 tem tosse

$\vdots$

x_d etc

$\mathbf{x}^{(m)} = (x_1, x_2, ..., x_d) \in \mathbb{R}^d$

$\mathbf{y}^{(m)} \in \{0, 1\}$

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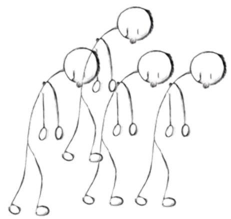
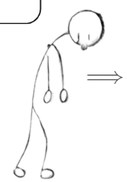
Learning, Overview

CONJUNTO DE DADOS



$$\underbrace{\begin{bmatrix} y^{(1)} & \cdots & y^{(m)} \end{bmatrix} \begin{bmatrix} x_1^{(1)} & \cdots & x_1^{(m)} \\ x_2 & \cdots & x_2 \\ \vdots & \vdots & \vdots \\ x_d & \cdots & x_d \end{bmatrix}}_{\text{Conjunto de dados}}$$

$\{((\mathbf{x}^{(1)}, \mathbf{y}^{(1)}), (\mathbf{x}^{(2)}, \mathbf{y}^{(2)}), ..., (\mathbf{x}^{(m)}, \mathbf{y}^{(m)}))\}$



$\Longrightarrow$

x_1 pressão arterial

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x_5 tem tosse

$\vdots$

x_d etc

$\mathbf{x}^{(m)} = (x_1, x_2, ..., x_d) \in \mathbb{R}^d$

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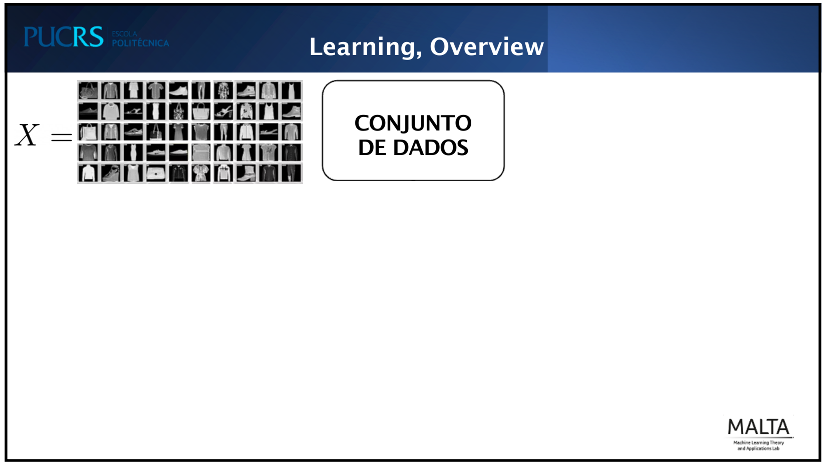
PUCRS
Learning, Overview
$X =$
CONJUNTO DE DADOS
MALTA

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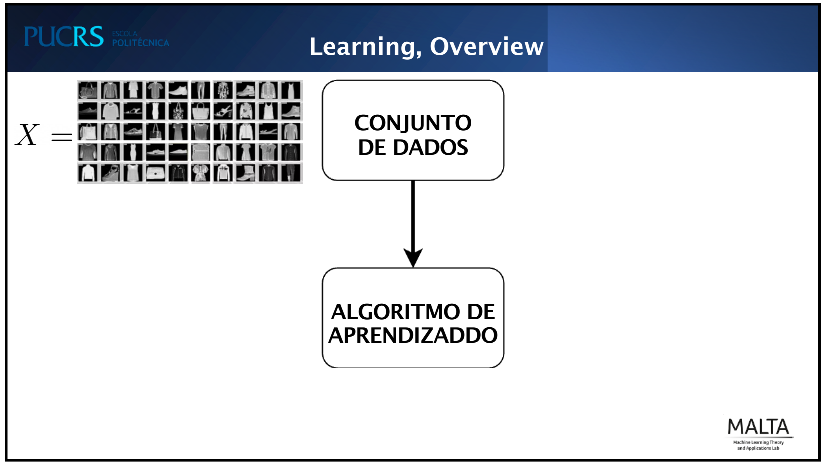
PUCRS
Learning, Overview
$X =$
CONJUNTO DE DADOS
ALGORITMO DE APRENDIZADDO
MALTA

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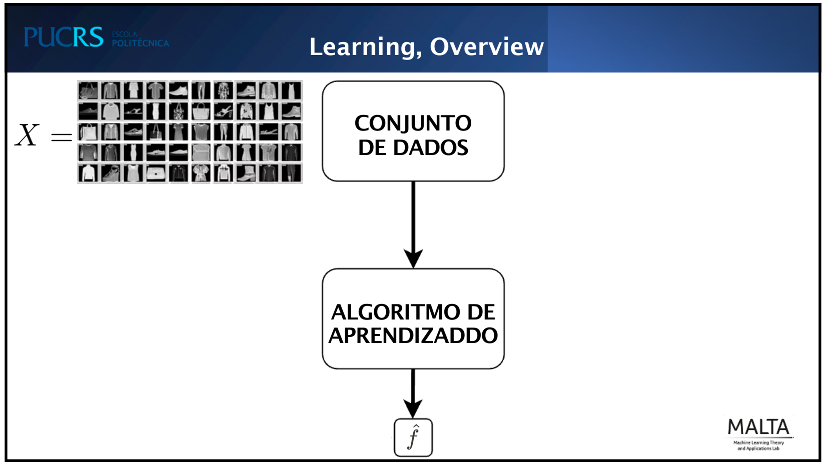
PUCRS
Learning, Overview
$X =$
CONJUNTO DE DADOS
ALGORITMO DE APRENDIZADDO
$\hat{f}$
MALTA

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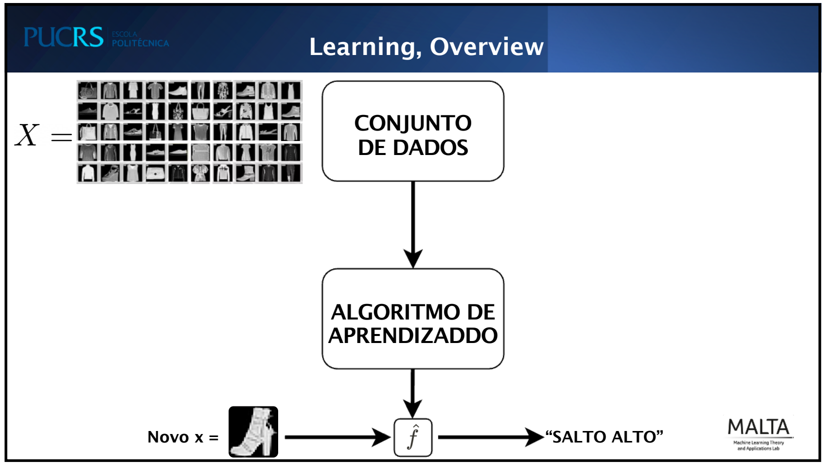
PUCRS
Learning, Overview
$X =$
CONJUNTO DE DADOS
ALGORITMO DE APRENDIZADDO
Novo x =
$\hat{f}$
"SALTO ALTO"
MALTA

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APRENDIZADO DE MÁQUINA

O QUE É *LEARNING*?

> PRIMEIRO ALG DE LEARNING

PROTOCOLOS DE TREINAM.

OTIMIZAÇÃO

REDES NEURAIS

BACKPROP + PRATICA

CNN + PRATICA

33

"*Machine Learning is not magic; it cannot get something **from nothing***"
- Domingos

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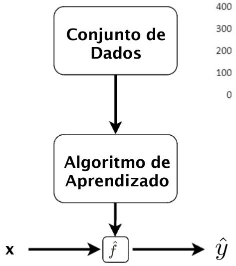
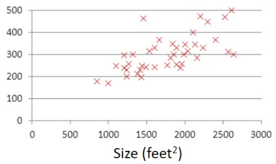
PUCRS ESCOLA POLITÉCNICA

Regressão Linear (Univariada)

Objetivo: fazer com que o modelo aprenda o padrão/comportamento de tendência





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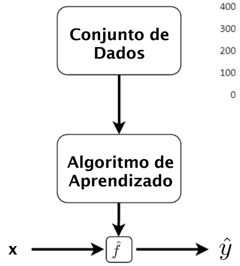
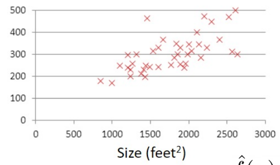
PUCRS ESCOLA POLITÉCNICA

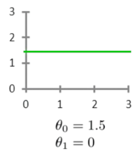
Regressão Linear (Univariada)

Objetivo: fazer com que o modelo aprenda o padrão/comportamento de tendência





$\hat{f}(x) = \theta_0 + \theta_1 x$ **Ensino médio**



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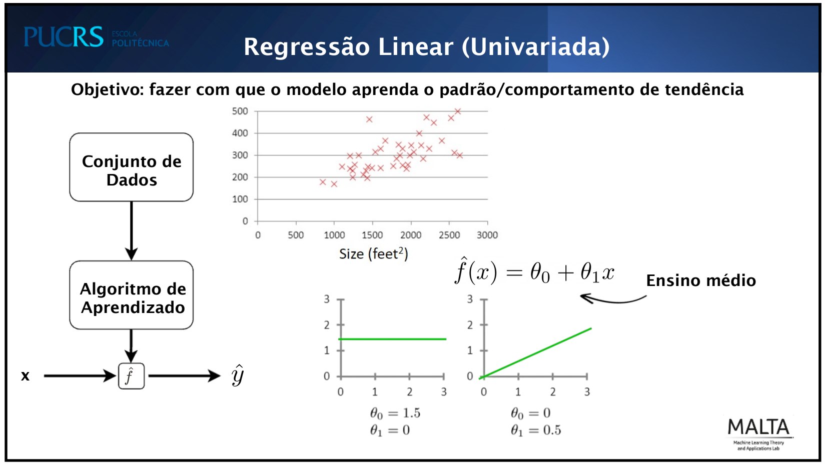
Regressão Linear (Univariada)
Objetivo: fazer com que o modelo aprenda o padrão/comportamento de tendência
Conjunto de Dados
Algoritmo de Aprendizado
Size (feet²)
$\hat{f}(x) = \theta_0 + \theta_1 x$
Ensino médio
$\theta_0 = 1.5$
$\theta_1 = 0$
$\theta_0 = 0$
$\theta_1 = 0.5$
MALTA

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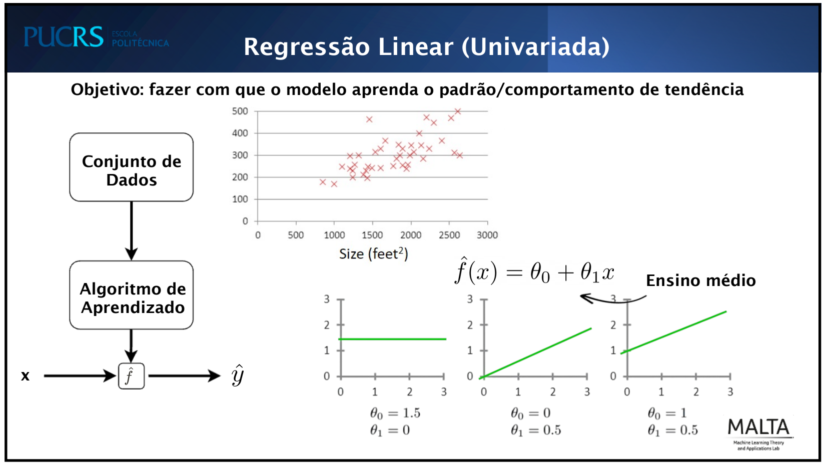
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Conjunto de Dados
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$\hat{f}(x) = \theta_0 + \theta_1 x$
Ensino médio
$\theta_0 = 1.5$
$\theta_1 = 0$
$\theta_0 = 0$
$\theta_1 = 0.5$
$\theta_0 = 1$
$\theta_1 = 0.5$
MALTA

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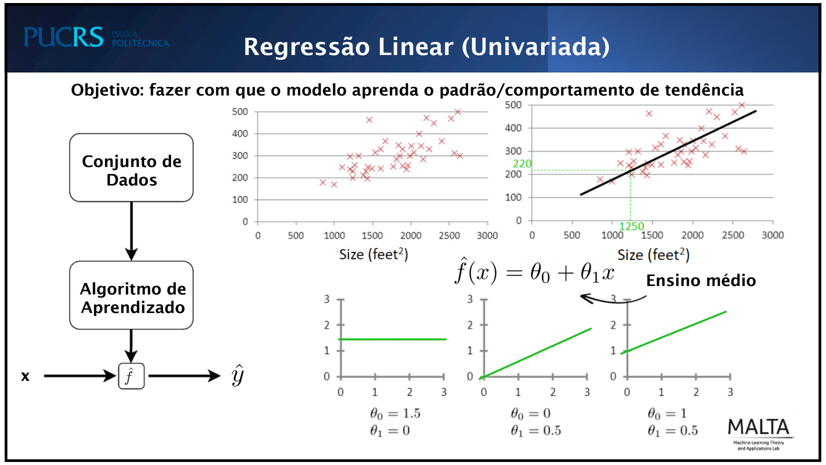
Regressão Linear (Univariada)
Objetivo: fazer com que o modelo aprenda o padrão/comportamento de tendência
Conjunto de Dados
Algoritmo de Aprendizado
Size (feet²)
220
1250
$\hat{f}(x) = \theta_0 + \theta_1 x$
Ensino médio
$\theta_0 = 1.5$
$\theta_1 = 0$
$\theta_0 = 0$
$\theta_1 = 0.5$
$\theta_0 = 1$
$\theta_1 = 0.5$
MALTA

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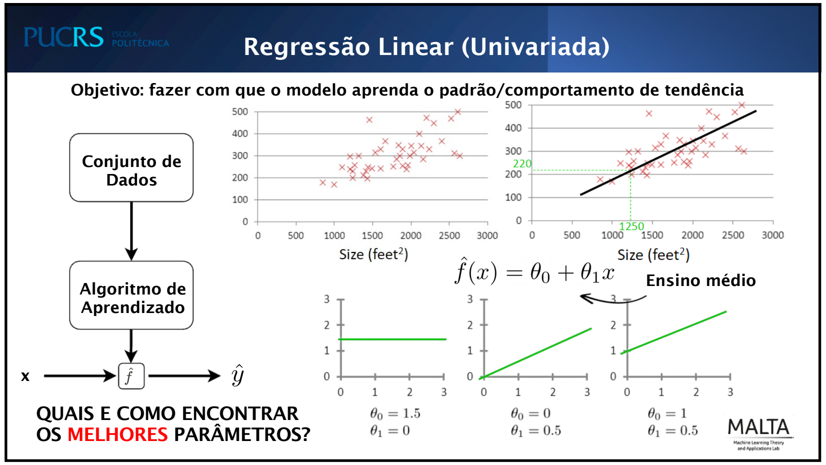
Regressão Linear (Univariada)
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Conjunto de Dados
Algoritmo de Aprendizado
Size (feet²)
220
1250
$\hat{f}(x) = \theta_0 + \theta_1 x$
Ensino médio
QUAIS E COMO ENCONTRAR
OS MELHORES PARÂMETROS?
$\theta_0 = 1.5$
$\theta_1 = 0$
$\theta_0 = 0$
$\theta_1 = 0.5$
$\theta_0 = 1$
$\theta_1 = 0.5$
MALTA

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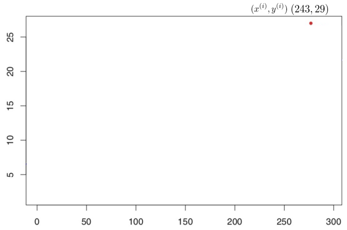
Regressão Linear (Univariada)



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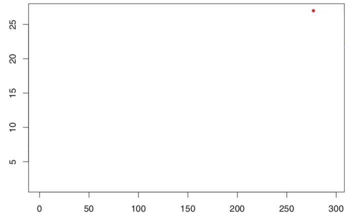
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$



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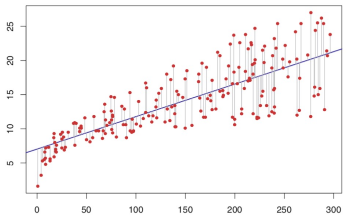
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$



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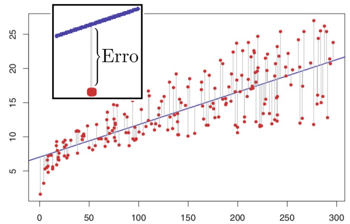
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)



AVALIANDO OS PARÂMETROS

MALTA

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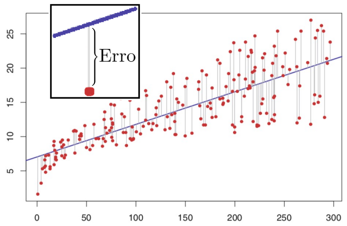
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\underbrace{\hat{f}\left(x^{(i)}\right) - y^{(i)}}_{\text{Erro}}$$



AVALIANDO OS PARÂMETROS

MALTA

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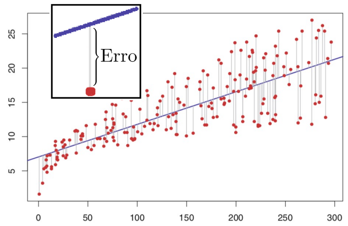
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\sum_{i=1} \underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)}_{\text{Erro}}$$



AVALIANDO OS PARÂMETROS

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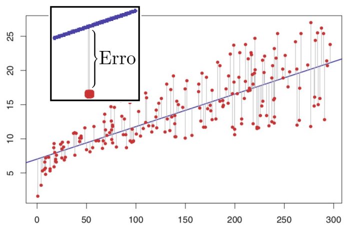
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\sum_{i=1}^{N} \underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)}_{\text{Erro}}$$



AVALIANDO OS PARÂMETROS

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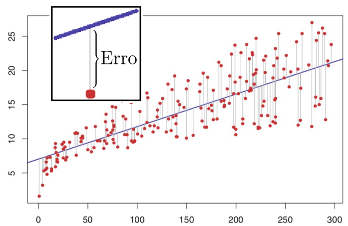
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\frac{1}{N}\sum_{i=1}^{N} \underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)}_{\text{Erro}}$$



AVALIANDO OS PARÂMETROS

MALTA

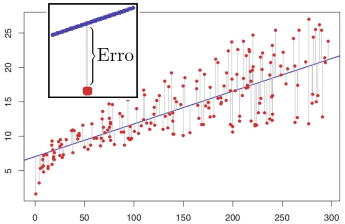
48

Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\frac{1}{N}\sum_{i=1}^{N}\underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)^2}_{\text{Erro}}$$



AVALIANDO OS PARÂMETROS

MALTA

49

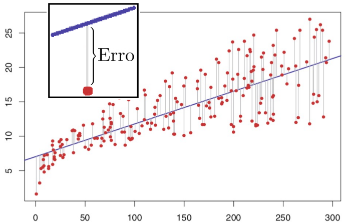
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\frac{1}{N}\sum_{i=1}^{N}\underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)^2}_{\text{Erro}}$$

$$\underbrace{\theta_0 + \theta_1 x^{(i)}}_{\text{nosso modelo}} - y^{(i)}$$



AVALIANDO OS PARÂMETROS

MALTA

50

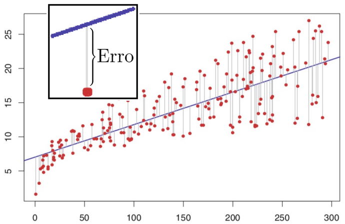
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\frac{1}{N}\sum_{i=1}^{N}\underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)^2}_{\text{Erro}}$$

$$\frac{1}{2N}\sum_{i=1}^{N}\left(\underbrace{\theta_0 + \theta_1 x^{(i)}}_{\text{nosso modelo}} - y^{(i)}\right)^2$$



AVALIANDO OS PARÂMETROS

MALTA

51

Regressão Linear (Univariada)

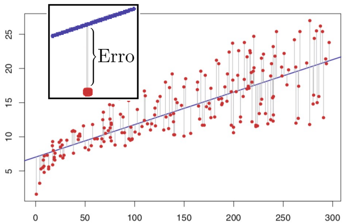
Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall(x^{(i)}, y^{(i)})$

CALCULAR O CUSTO (resíduo/erro/perda)

$$\frac{1}{N}\sum_{i=1}^{N}\underbrace{\left(\hat{f}\left(x^{(i)}\right) - y^{(i)}\right)^2}_{\text{Erro}}$$

$$\frac{1}{2N}\sum_{i=1}^{N}\left(\underbrace{\theta_0 + \theta_1 x^{(i)}}_{\text{nosso modelo}} - y^{(i)}\right)^2$$

$$\underbrace{J(\theta_0, \theta_1)}_{\text{MSE Loss}} = \frac{1}{2N}\sum_{i=1}^{N}\left(\left(\theta_o + \theta_1 x^{(i)}\right) - y^{(i)}\right)^2$$



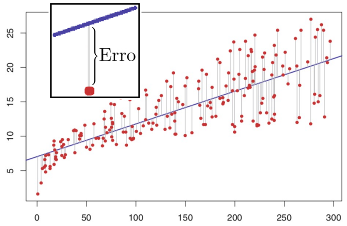
AVALIANDO OS PARÂMETROS

MALTA

52

Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$



MALTA

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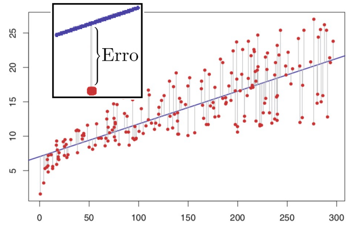
Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$

Modelo

$$\hat{f}(x) = \theta_0 + \theta_1 x$$



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Regressão Linear (Univariada)

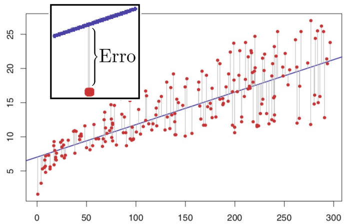
Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$

Modelo

$$\hat{f}(x) = \theta_0 + \theta_1 x$$

Parâmetros

$$\theta_0, \theta_1$$



MALTA

55

Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$

Modelo

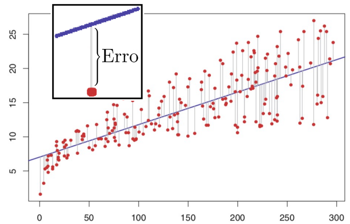
$$\hat{f}(x) = \theta_0 + \theta_1 x$$

Parâmetros

$$\theta_0, \theta_1$$

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$



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PUCRS ESCOLA POLITÉCNICA

Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$

Modelo

$$\hat{f}(x) = \theta_0 + \theta_1 x$$

Parâmetros

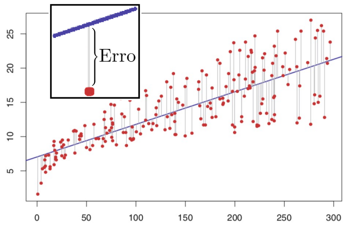
$$\theta_0, \theta_1$$

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

Objetivo:

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$



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PUCRS ESCOLA POLITÉCNICA

Regressão Linear (Univariada)

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$

Modelo

$$\hat{f}(x) = \theta_0 + \theta_1 x$$

Parâmetros

$$\theta_0, \theta_1$$

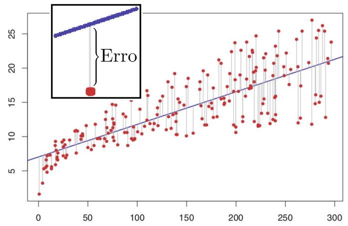
Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

Objetivo:

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO?



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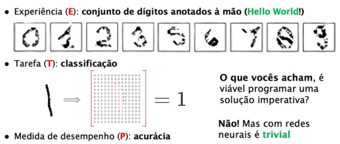
RECAPITULANDO...

Learning: melhora o desempenho de T conforme a experiência E

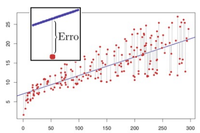


Função de Custo avalia os parâmetros e, precisa ser diferenciável

Ideia: encontrar θ_0, θ_1 de maneira que $\hat{f}(x)$ seja o mais perto de y, $\forall (x^{(i)}, y^{(i)})$

Modelo

$$\hat{f}(x) = \theta_0 + \theta_1 x$$



Parâmetros

$$\theta_0, \theta_1$$

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

Objetivo:

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$

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APRENDIZADO DE MÁQUINA

- O QUE É *LEARNING*?
- PRIMEIRO ALG DE LEARNING
- > PROTOCOLOS DE TREINAM.
- OTIMIZAÇÃO
- REDES NEURAIS
- BACKPROP + PRATICA
- CNN + PRATICA

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PUCRS ESCOLA POLITÉCNICA

Treinamento

Para treinar um modelo, é preciso minimizar a ***loss***, que afeta diretamente o desempenho do modelo no conjunto de **treino**

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

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Treinamento

Protocolo de Treinamento

Full Dataset

Training Set | **Testing Set**

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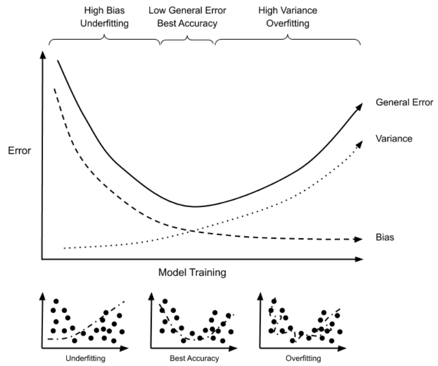
Treinamento

Essência de
LEARNING FROM DATA



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Treinamento

Para treinar um modelo, é preciso minimizar a *loss*, que afeta diretamente o desempenho do modelo no conjunto de **treino**.

Funções de Custo (mais comuns)

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2 \qquad \text{Loss} = - \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i$$

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Treinamento

Para treinar um modelo, é preciso minimizar a ***loss***, que afeta diretamente o desempenho do preditor no conjunto de treino.

Dividir em Treino e Teste

Objetivo de aprendizado de máquina: **generalização**

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APRENDIZADO DE MÁQUINA

O QUE É *LEARNING*?

PRIMEIRO ALG DE LEARNING

PROTOCOLOS DE TREINAM.

> OTIMIZAÇÃO

REDES NEURAIS

BACKPROP + PRATICA

CNN + PRATICA

66

"The connections between neurons are called ***synapses***. The strength of the synaptic connection dictates how much electrical excitation passes from one neuron to another. ***By changing the strength of synaptic connections, animals learn***"

- Bliss & Terge, 1973

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Gradiente Descendente

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

Objetivo:

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO?

MALTA

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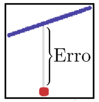
PUCRS ESCOLA POLITÉCNICA

Gradiente Descendente

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N}\sum_{i=1}^{N}\left(\left(\theta_0 + \theta_1 x^{(i)}\right) - y^{(i)}\right)^2$$
$$= \frac{1}{2N}\sum_{i=1}^{N}\underbrace{\left(\hat{y}^{(i)} - y^{(i)}\right)}_{\text{Erro}}^2$$



Objetivo:

$$\min_{\theta_0,\theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO?

MALTA

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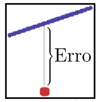
Gradiente Descendente

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N}\sum_{i=1}^{N}\left(\left(\theta_0 + \theta_1 x^{(i)}\right) - y^{(i)}\right)^2$$
$$= \frac{1}{2N}\sum_{i=1}^{N}\underbrace{\left(\hat{y}^{(i)} - y^{(i)}\right)}_{\text{Erro}}^2$$



Objetivo:

$$\min_{\theta_0,\theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO? Gradiente Descendente

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Gradiente Descendente

Função de custo

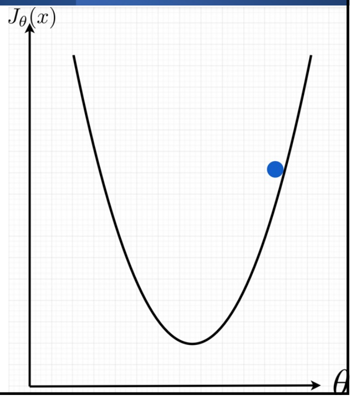
$$J(\theta_0, \theta_1) = \frac{1}{2N}\sum_{i=1}^{N}\left(\left(\theta_0 + \theta_1 x^{(i)}\right) - y^{(i)}\right)^2$$

Objetivo:

$$\min_{\theta_0,\theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO? Gradiente Descendente

1. Iniciar os pesos aleatoriamente



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PUCRS ESCOLA POLITÉCNICA

Gradiente Descendente

Função de custo

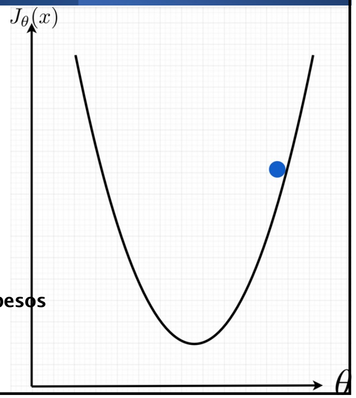
$$J(\theta_0, \theta_1) = \frac{1}{2N}\sum_{i=1}^{N}\left(\left(\theta_0 + \theta_1 x^{(i)}\right) - y^{(i)}\right)^2$$

Objetivo:

$$\min_{\theta_0,\theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO? Gradiente Descendente

1. Iniciar os pesos aleatoriamente
2. Calcular o gradiente da *loss* com relação aos pesos



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Gradiente Descendente

Função de custo

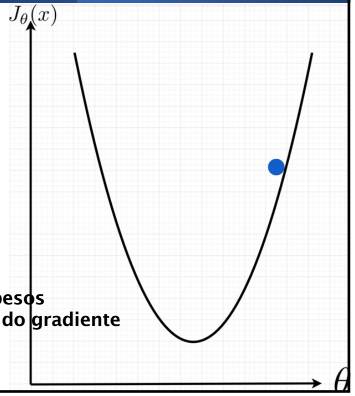
$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

Objetivo:

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO? Gradiente Descendente

1. Iniciar os pesos aleatoriamente
2. Calcular o gradiente da *loss* com relação aos pesos
3. Atualizar os pesos na direção oposta a fração do gradiente



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Gradiente Descendente

Função de custo

$$J(\theta_0, \theta_1) = \frac{1}{2N} \sum_{i=1}^{N} \left(\left(\theta_0 + \theta_1 x^{(i)} \right) - y^{(i)} \right)^2$$

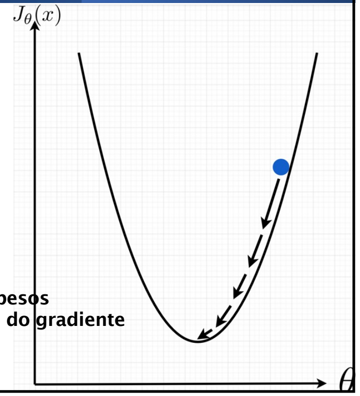
Objetivo:

$$\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$$

COMO FAZER ISSO? Gradiente Descendente

1. Iniciar os pesos aleatoriamente
2. Calcular o gradiente da *loss* com relação aos pesos
3. Atualizar os pesos na direção oposta a fração do gradiente

$$\theta_{n+1} = \theta_n - \alpha \nabla J_\theta$$



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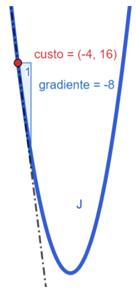
Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20



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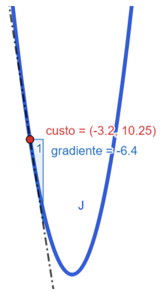
Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56



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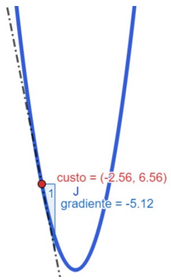
Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56
2	6.56	-2.56	-5.12	0.1	-2.04



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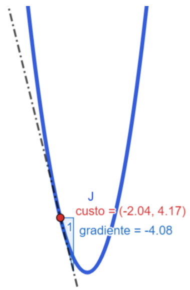
Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56
2	6.56	-2.56	-5.12	0.1	-2.04
3	4.17	-2.04	-4.08	0.1	-1.63



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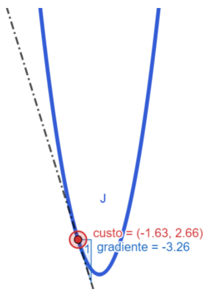
Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56
2	6.56	-2.56	-5.12	0.1	-2.04
3	4.17	-2.04	-4.08	0.1	-1.63
4	2.66	-1.63	-3.26	0.1	-1.30



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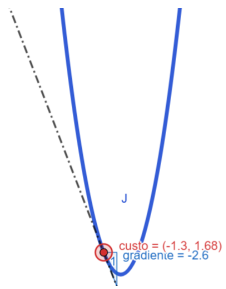
Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56
2	6.56	-2.56	-5.12	0.1	-2.04
3	4.17	-2.04	-4.08	0.1	-1.63
4	2.66	-1.63	-3.26	0.1	-1.30
5	1.68	-1.30	-2.60	0.1	-1.04



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Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	−4	−8	0.1	−3.20
1	10.25	−3.2	−6.4	0.1	−2.56
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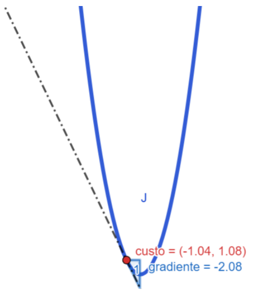
3	4.17	−2.04	−4.08	0.1	−1.63
4	2.66	−1.63	−3.26	0.1	−1.30
5	1.68	−1.30	−2.60	0.1	−1.04
6	1.08	−1.04	−2.08	0.1	−0.83



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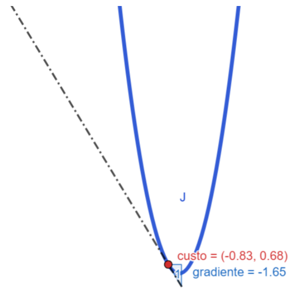
PUCRS ESCOLA POLITÉCNICA

Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	−4	−8	0.1	−3.20
1	10.25	−3.2	−6.4	0.1	−2.56
2	6.56	−2.56	−5.12	0.1	−2.04
3	4.17	−2.04	−4.08	0.1	−1.63
4	2.66	−1.63	−3.26	0.1	−1.30
5	1.68	−1.30	−2.60	0.1	−1.04
6	1.08	−1.04	−2.08	0.1	−0.83
7	0.68	−0.83	−1.65	0.1	−0.66



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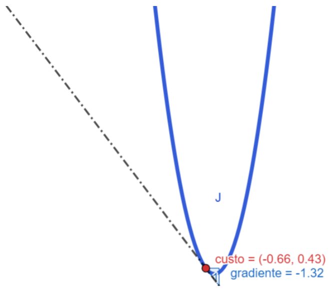
PUCRS ESCOLA POLITÉCNICA

Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	−4	−8	0.1	−3.20
1	10.25	−3.2	−6.4	0.1	−2.56
2	6.56	−2.56	−5.12	0.1	−2.04
3	4.17	−2.04	−4.08	0.1	−1.63
4	2.66	−1.63	−3.26	0.1	−1.30
5	1.68	−1.30	−2.60	0.1	−1.04
6	1.08	−1.04	−2.08	0.1	−0.83
7	0.68	−0.83	−1.65	0.1	−0.66
8	0.43	−0.66	−1.32	0.1	−0.53



MALTA

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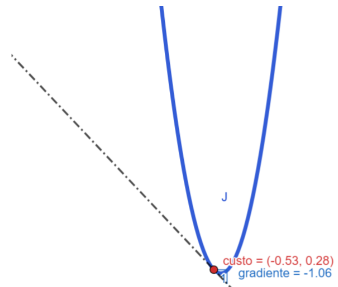
PUCRS ESCOLA POLITÉCNICA

Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	−4	−8	0.1	−3.20
1	10.25	−3.2	−6.4	0.1	−2.56
2	6.56	−2.56	−5.12	0.1	−2.04
3	4.17	−2.04	−4.08	0.1	−1.63
4	2.66	−1.63	−3.26	0.1	−1.30
5	1.68	−1.30	−2.60	0.1	−1.04
6	1.08	−1.04	−2.08	0.1	−0.83
7	0.68	−0.83	−1.65	0.1	−0.66
8	0.43	−0.66	−1.32	0.1	−0.53
9	0.28	−0.53	−1.06	0.1	−0.42



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PUCRS ESCOLA POLITÉCNICA

Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56
2	6.56	-2.56	-5.12	0.1	-2.04
3	4.17	-2.04	-4.08	0.1	-1.63
4	2.66	-1.63	-3.26	0.1	-1.30
5	1.68	-1.30	-2.60	0.1	-1.04
6	1.08	-1.04	-2.08	0.1	-0.83
7	0.68	-0.83	-1.65	0.1	-0.66
8	0.43	-0.66	-1.32	0.1	-0.53
9	0.28	-0.53	-1.06	0.1	-0.42
⋮	⋮	⋮	⋮	⋮	⋮

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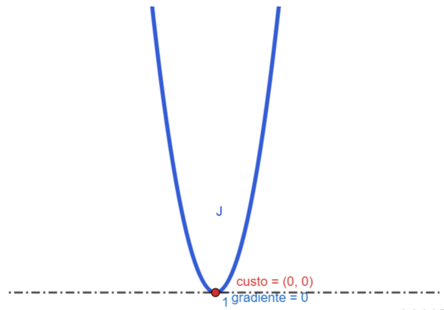
PUCRS ESCOLA POLITÉCNICA

Depurando o Gradiente Descendente

$$w_{i+1} = w_i - \alpha \frac{dJ}{dw_i}$$

i	$custo_i$	w_i	$dJ(w_i)$	α	w_{i+1}
0	16.00	-4	-8	0.1	-3.20
1	10.25	-3.2	-6.4	0.1	-2.56
2	6.56	-2.56	-5.12	0.1	-2.04
3	4.17	-2.04	-4.08	0.1	-1.63
4	2.66	-1.63	-3.26	0.1	-1.30
5	1.68	-1.30	-2.60	0.1	-1.04
6	1.08	-1.04	-2.08	0.1	-0.83
7	0.68	-0.83	-1.65	0.1	-0.66
8	0.43	-0.66	-1.32	0.1	-0.53
9	0.28	-0.53	-1.06	0.1	-0.42
⋮	⋮	⋮	⋮	⋮	⋮
n	0	w_{n-1}	0	0.1	0



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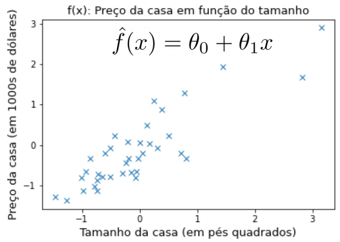
Exemplo Regressão Linear (Univariada)

Tarefa de regressão: predizer o preço dado o tamanho da casa



$$\theta_{n+1} = \theta_n - \alpha \nabla J_\theta$$

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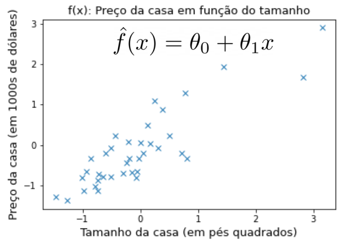
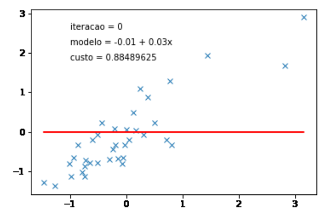
PUCRS ESCOLA POLITÉCNICA

Exemplo Regressão Linear (Univariada)

Tarefa de regressão: predizer o preço dado o tamanho da casa

Objetivo: $\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$





$$\theta_{n+1} = \theta_n - \alpha \nabla J_\theta$$

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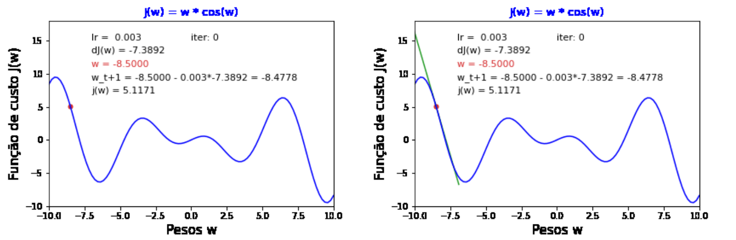
Otimização via Gradiente Descendente

Loss landscape, "Paisagem do custo"



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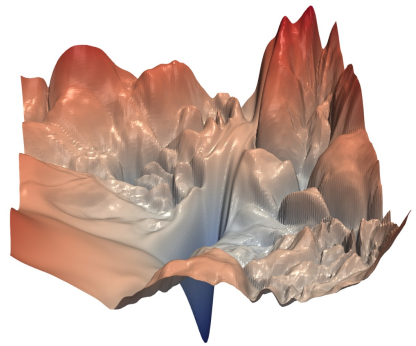
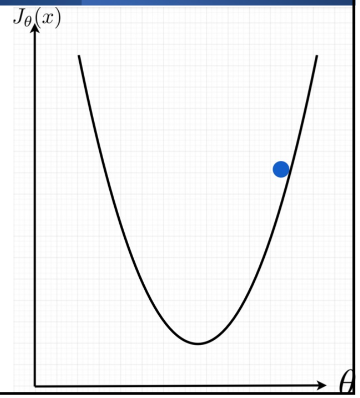
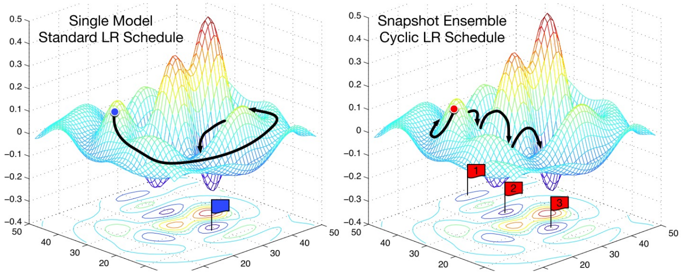
Depurando o Gradiente Descendente





90

Depurando o Gradiente Descendente



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APRENDIZADO DE MÁQUINA

- O QUE É *LEARNING?*
- PRIMEIRO ALG DE LEARNING
- PROTOCOLOS DE TREINAM.
- OTIMIZAÇÃO
- > REDES NEURAIS
- BACKPROP + PRATICA
- CNN + PRATICA

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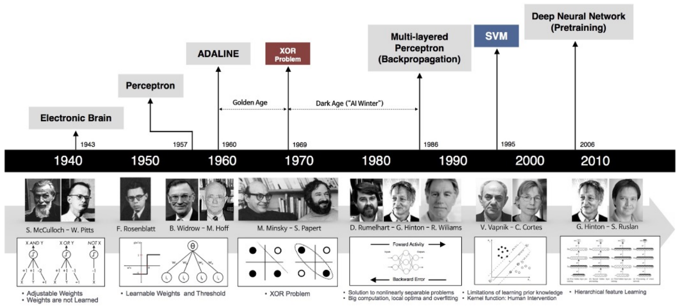
Histórico das Redes Neurais



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Redes Neurais

$$\hat{f}(x) = W_0 + W_1 x$$

$$\hat{f}(x) = \theta_0 + \theta_1 x$$

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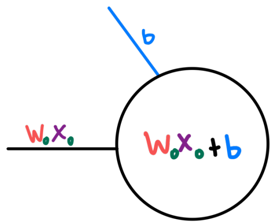
Redes Neurais

$$\hat{f}(x) = W_0 + W_1 x$$



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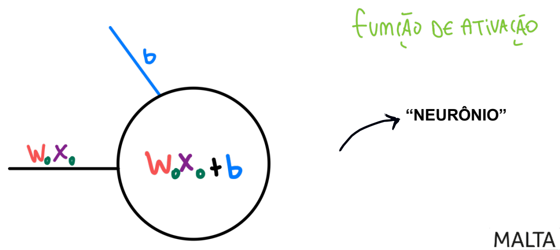
Redes Neurais

$$\hat{f}(x) = W_0 + W_1 x$$



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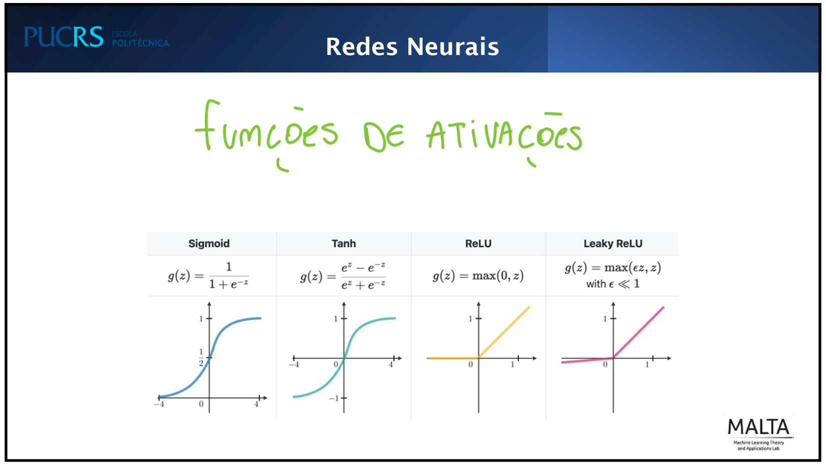
PUCRS ESCOLA POLITÉCNICA
Redes Neurais
funções de ativações
Sigmoid
Tanh
ReLU
Leaky ReLU
g(z) = 1 / (1 + e^-z)
g(z) = (e^z − e^-z) / (e^z + e^-z)
g(z) = max(0, z)
g(z) = max(εz, z)
with ε ≪ 1
MALTA

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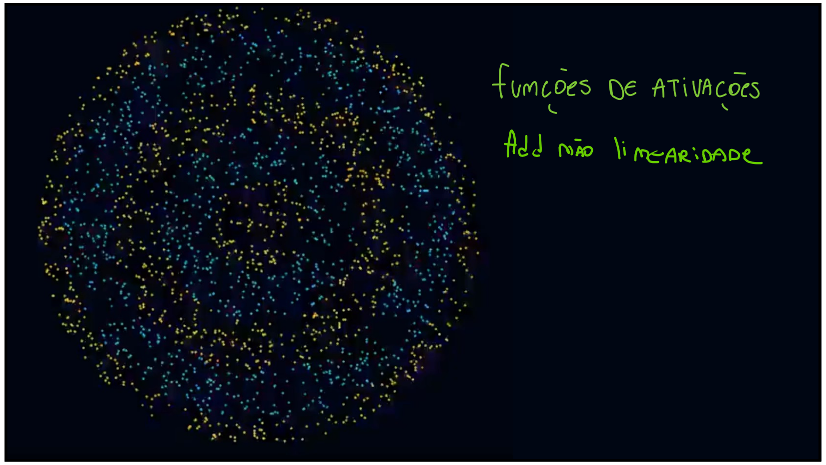
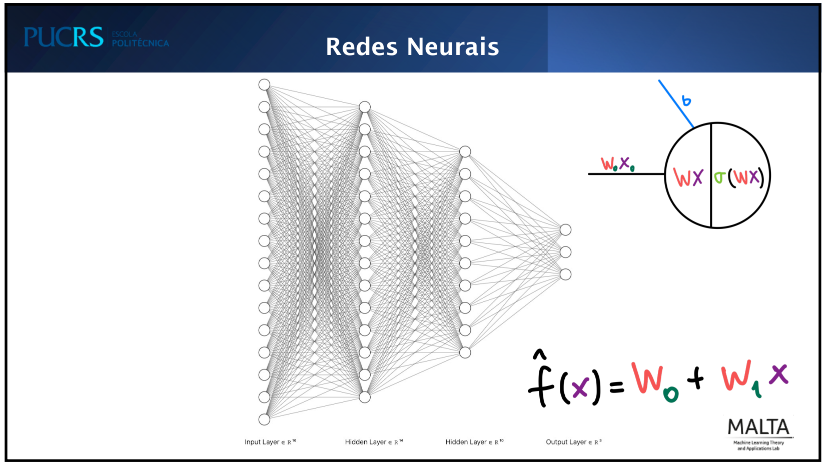

funções de ativações
Add não linearidade

98


PUCRS ESCOLA POLITÉCNICA
Redes Neurais
b
W0X0
WX
σ(WX)
f̂(x) = W0 + W1 X
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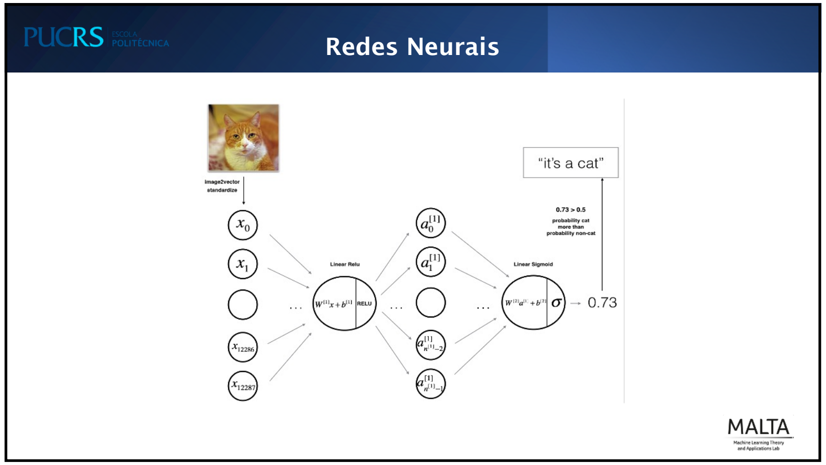
PUCRS ESCOLA POLITÉCNICA
Redes Neurais
"it's a cat"
0.73
MALTA

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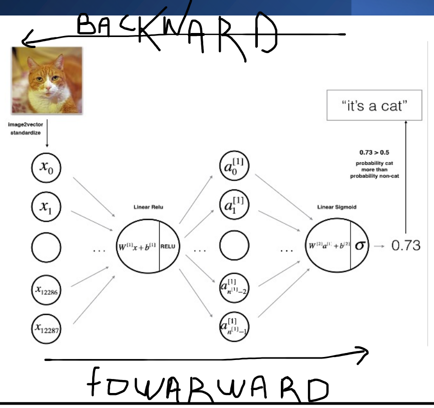
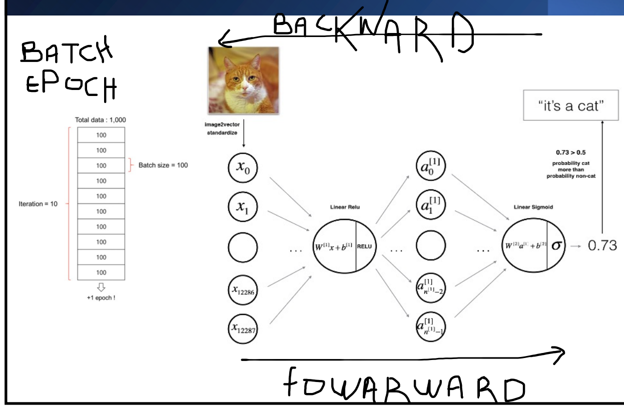
Redes Neurais



101

Redes Neurais



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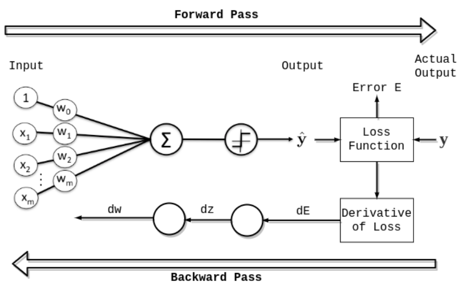
RECAPITULANDO...



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RECAPITULANDO...

NN é uma **composição** de funções lineares e não lineares.

Funções de **ativações** quebram as transformações lineares

Funções de ativações devem ser **diferenciaveis**

Forward: $\hat{y}$
Backward: calcula os **gradientes** da função de custo em relação a cada parâmetro

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APRENDIZADO DE MÁQUINA

- O QUE É *LEARNING*?
- PRIMEIRO ALG DE LEARNING
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- REDES NEURAIS
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- CNN + PRATICA

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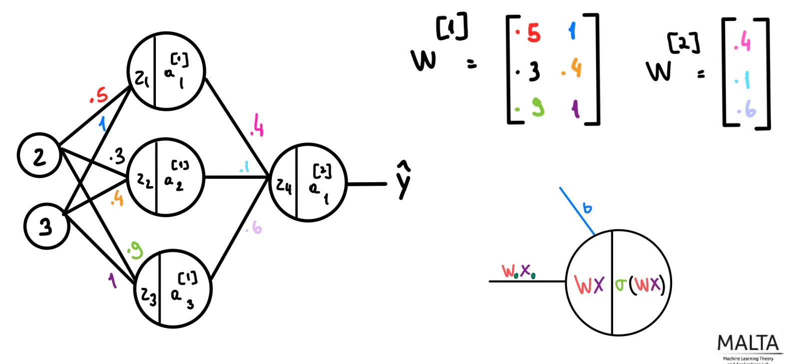
Backpropagation



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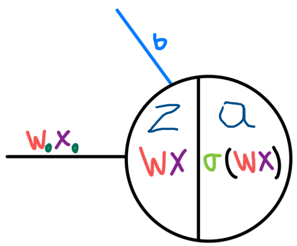
PUCRS ESCOLA POLITÉCNICA

Redes Neurais



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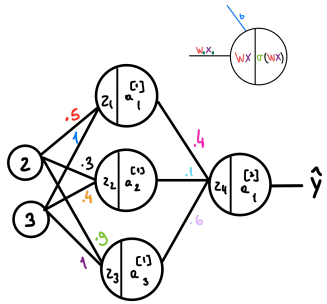
PUCRS ESCOLA POLITÉCNICA

Redes Neurais



PRIMEIRA CAMADA

$z_1 = 2 \times .5 + 3 \times 1 = 4$, $a_1^{[1]} =$

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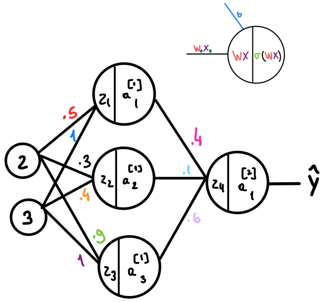
PUCRS ESCOLA POLITÉCNICA

Redes Neurais



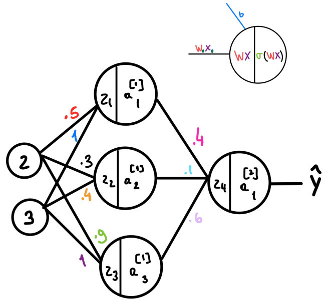
\# PRIMEIRA CAMADA

$z_1 = 2 \times .5 + 3 \times 1 = 4, \quad a_1^{[1]} =$

109

PUCRS ESCOLA POLITÉCNICA

Redes Neurais



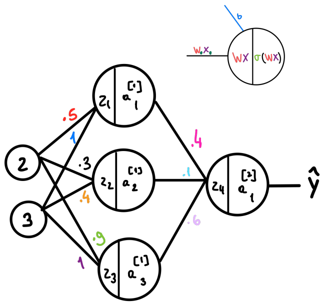
\# PRIMEIRA CAMADA

$z_1 = 2 \times .5 + 3 \times 1 = 4, \quad a_1^{[1]} = \frac{1}{1 + e^{-z_1}} = .9820$

110

PUCRS ESCOLA POLITÉCNICA

Redes Neurais



\# PRIMEIRA CAMADA

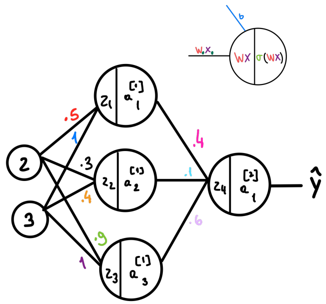
$z_1 = 2 \times .5 + 3 \times 1 = 4, \quad a_1^{[1]} = \frac{1}{1 + e^{-z_1}} = .9820$

$z_2 = 2 \times .3 + 3 \times .4 = 1.8, \quad a_2^{[1]} = \max(0, z_2) = 1.8$

111

PUCRS ESCOLA POLITÉCNICA

Redes Neurais



\# PRIMEIRA CAMADA

$z_1 = 2 \times .5 + 3 \times 1 = 4, \quad a_1^{[1]} = \frac{1}{1 + e^{-z_1}} = .9820$

$z_2 = 2 \times .3 + 3 \times .4 = 1.8, \quad a_2^{[1]} = \max(0, z_2) = 1.8$

$z_3 = 2 \times .9 + 3 \times 1 = 4.8, \quad a_3^{[1]} = \frac{e^{z_3} - e^{-z_3}}{e^{z_3} + e^{-z_3}} = .9999$

\# SEGUNDA CAMADA

$z_4 = a_1^{[1]} \times .4 + a_2^{[1]} \times .1 + a_3^{[1]} \times .6$

$z_4 = .9820 \times .4 + 1.8 \times .1 + .9999 \times .6 = 2.7927$

$a_1^{[2]} = \max(0, z_4) = 2.7927$

\# loss

$\hat{y} \equiv a_1^{[2]}; \quad x_1 = 2 \quad x_2 = 3 \rightarrow y = 2$

$loss = \frac{1}{2}(a^{[2]} - y)^2 = \frac{1}{2}(2.7927 - 2)^2 = .3141$

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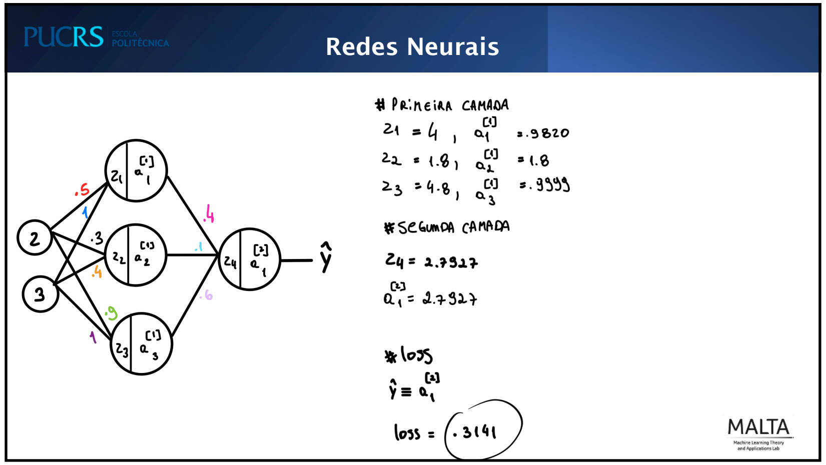
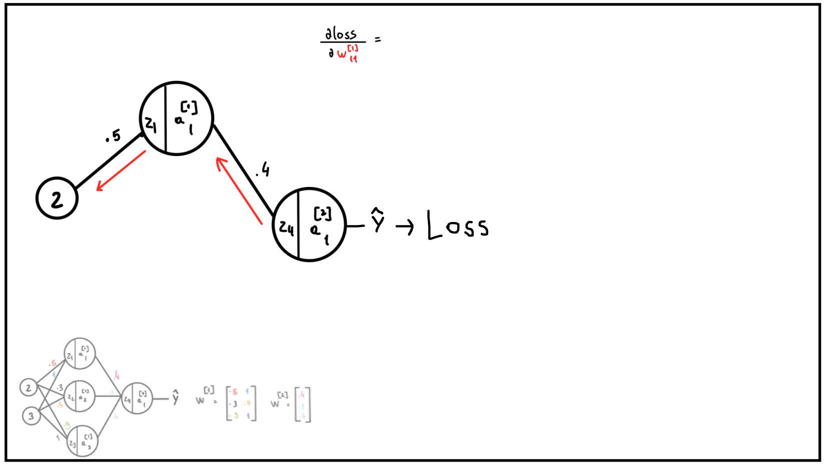
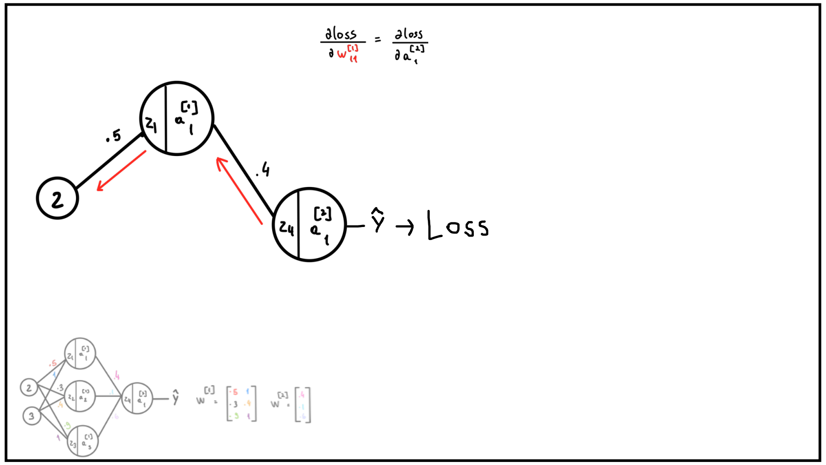


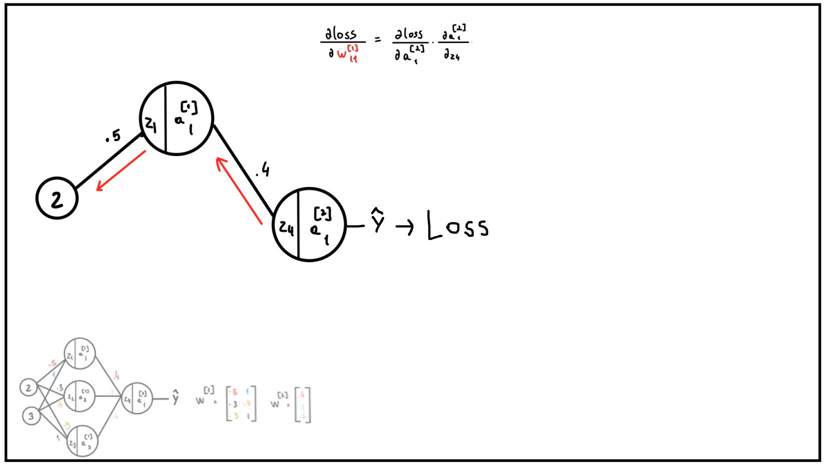
113



114



115



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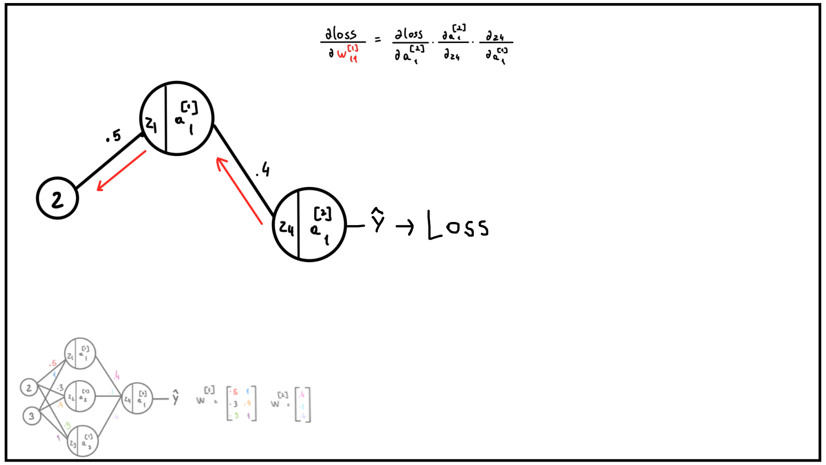

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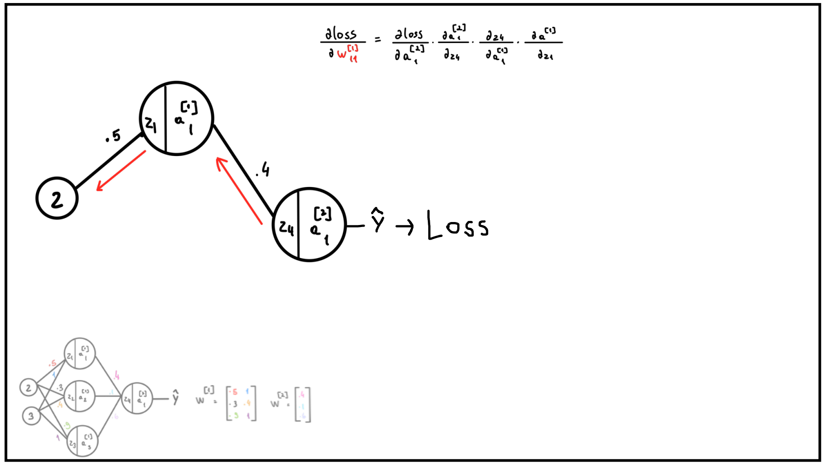

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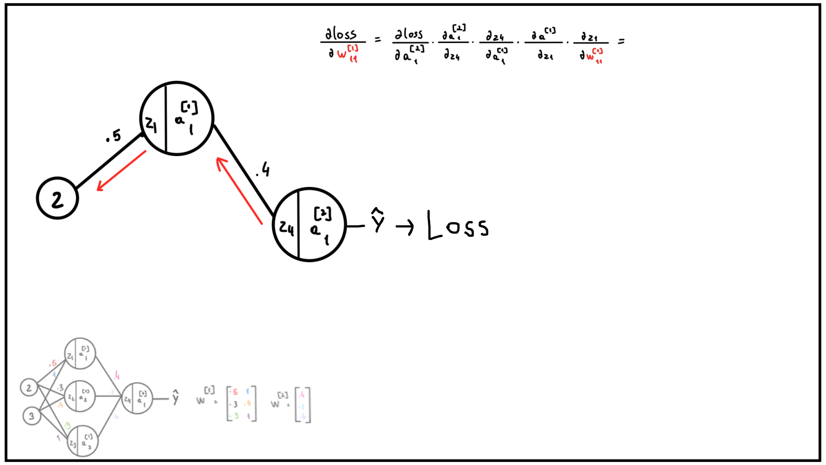
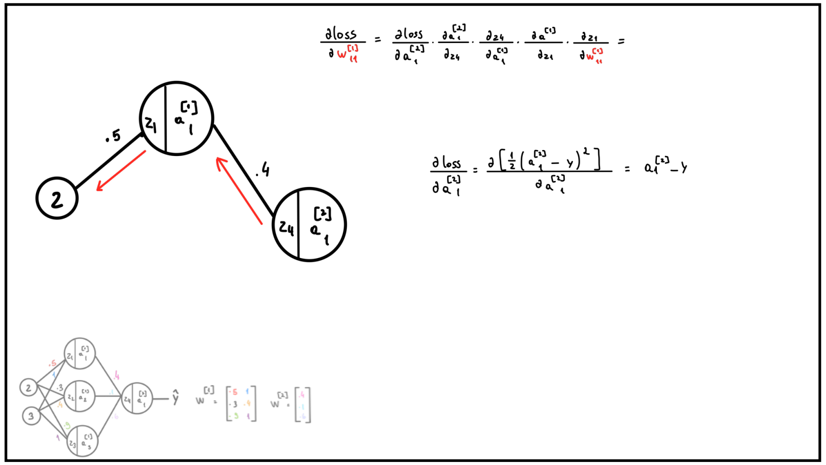


119



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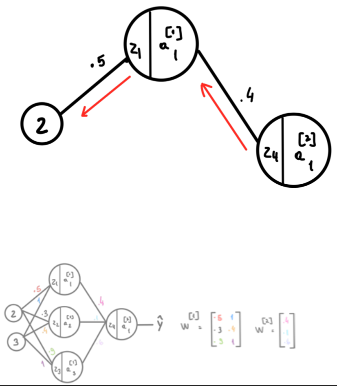
$$\frac{\partial loss}{\partial w^{[1]}_{11}} = \frac{\partial loss}{\partial a^{[2]}_1}\cdot\frac{\partial a^{[2]}_1}{\partial z_4}\cdot\frac{\partial z_4}{\partial a^{[1]}_1}\cdot\frac{\partial a^{[1]}}{\partial z_1}\cdot\frac{\partial z_1}{\partial w^{[1]}_{11}} =$$

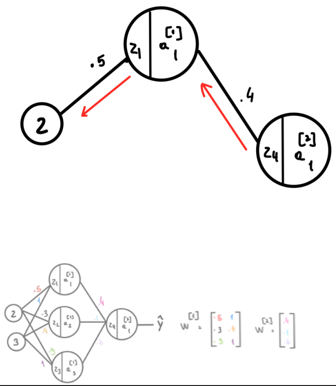


$$\frac{\partial loss}{\partial a^{[2]}_1} = \frac{\partial\left[\frac{1}{2}\left(a^{[2]}_1 - y\right)^2\right]}{\partial a^{[2]}_1} = a^{[2]}_1 - y$$

$$\frac{\partial a^{[2]}_1}{\partial z_4} = \frac{\partial[\max(0,z_4)]}{\partial z_4} = 1(z_4>0)$$

121

$$\frac{\partial loss}{\partial w^{[1]}_{11}} = \frac{\partial loss}{\partial a^{[2]}_1}\cdot\frac{\partial a^{[2]}_1}{\partial z_4}\cdot\frac{\partial z_4}{\partial a^{[1]}_1}\cdot\frac{\partial a^{[1]}}{\partial z_1}\cdot\frac{\partial z_1}{\partial w^{[1]}_{11}} =$$



$$\frac{\partial loss}{\partial a^{[2]}_1} = \frac{\partial\left[\frac{1}{2}\left(a^{[2]}_1 - y\right)^2\right]}{\partial a^{[2]}_1} = a^{[2]}_1 - y$$

$$\frac{\partial a^{[2]}_1}{\partial z_4} = \frac{\partial[\max(0,z_4)]}{\partial z_4} = 1(z_4>0)$$

$$\frac{\partial z_4}{\partial a^{[1]}_1} = \frac{\partial[a^{[1]}_1 \times .4 + a^{[1]}_2\times .1 + a^{[1]}_3 \times .6]}{\partial a^{[1]}_1} = .4$$

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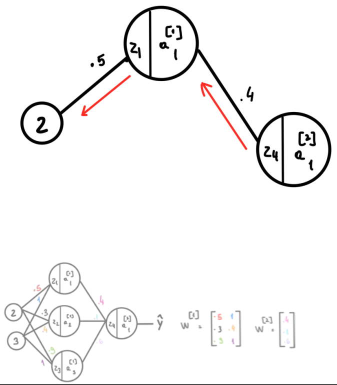
$$\frac{\partial loss}{\partial w^{[1]}_{11}} = \frac{\partial loss}{\partial a^{[2]}_1}\cdot\frac{\partial a^{[2]}_1}{\partial z_4}\cdot\frac{\partial z_4}{\partial a^{[1]}_1}\cdot\frac{\partial a^{[1]}}{\partial z_1}\cdot\frac{\partial z_1}{\partial w^{[1]}_{11}} =$$



$$\frac{\partial loss}{\partial a^{[2]}_1} = \frac{\partial\left[\frac{1}{2}\left(a^{[2]}_1 - y\right)^2\right]}{\partial a^{[2]}_1} = a^{[2]}_1 - y$$

$$\frac{\partial a^{[2]}_1}{\partial z_4} = \frac{\partial[\max(0,z_4)]}{\partial z_4} = 1(z_4>0)$$

$$\frac{\partial z_4}{\partial a^{[1]}_1} = \frac{\partial[a^{[1]}_1 \times .4 + a^{[1]}_2\times .1 + a^{[1]}_3 \times .6]}{\partial a^{[1]}_1} = .4$$

$$\frac{\partial a^{[1]}_1}{\partial z_1} = \frac{\partial\left[\frac{1}{1+e^{-z_1}}\right]}{\partial z_1} = \sigma(z_1)\cdot(1-\sigma(z_1))$$

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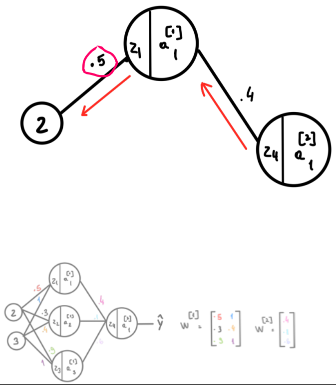
$$\frac{\partial loss}{\partial w^{[1]}_{11}} = \frac{\partial loss}{\partial a^{[2]}_1}\cdot\frac{\partial a^{[2]}_1}{\partial z_4}\cdot\frac{\partial z_4}{\partial a^{[1]}_1}\cdot\frac{\partial a^{[1]}}{\partial z_1}\cdot\frac{\partial z_1}{\partial w^{[1]}_{11}} =$$



$$\frac{\partial loss}{\partial a^{[2]}_1} = \frac{\partial\left[\frac{1}{2}\left(a^{[2]}_1 - y\right)^2\right]}{\partial a^{[2]}_1} = a^{[2]}_1 - y$$

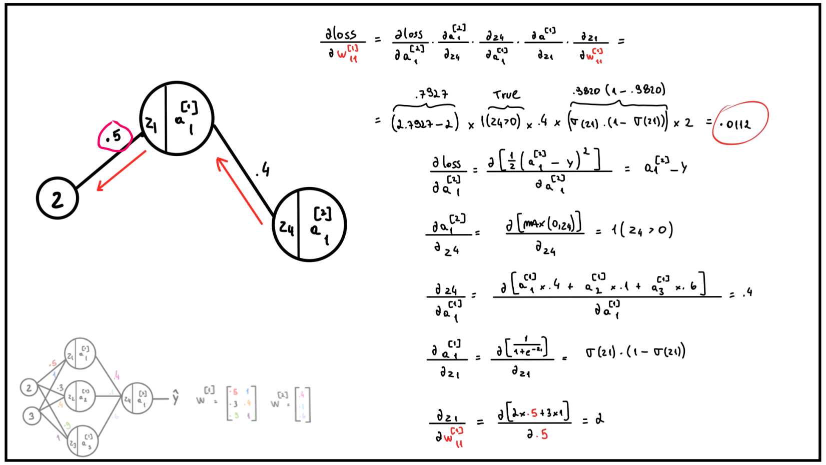
$$\frac{\partial a^{[2]}_1}{\partial z_4} = \frac{\partial[\max(0,z_4)]}{\partial z_4} = 1(z_4>0)$$

$$\frac{\partial z_4}{\partial a^{[1]}_1} = \frac{\partial[a^{[1]}_1 \times .4 + a^{[1]}_2\times .1 + a^{[1]}_3 \times .6]}{\partial a^{[1]}_1} = .4$$

$$\frac{\partial a^{[1]}_1}{\partial z_1} = \frac{\partial\left[\frac{1}{1+e^{-z_1}}\right]}{\partial z_1} = \sigma(z_1)\cdot(1-\sigma(z_1))$$

$$\frac{\partial z_1}{\partial w^{[1]}_{11}} = \frac{\partial[2\times .5 + 3\times 1]}{\partial .5} = 2$$

124



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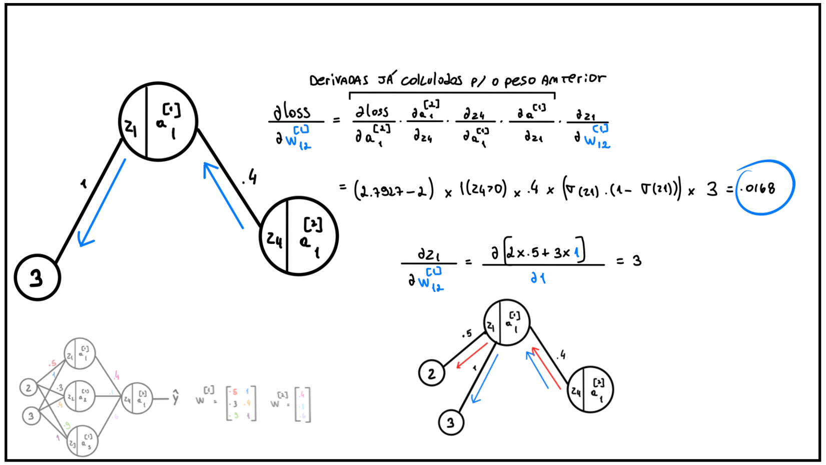

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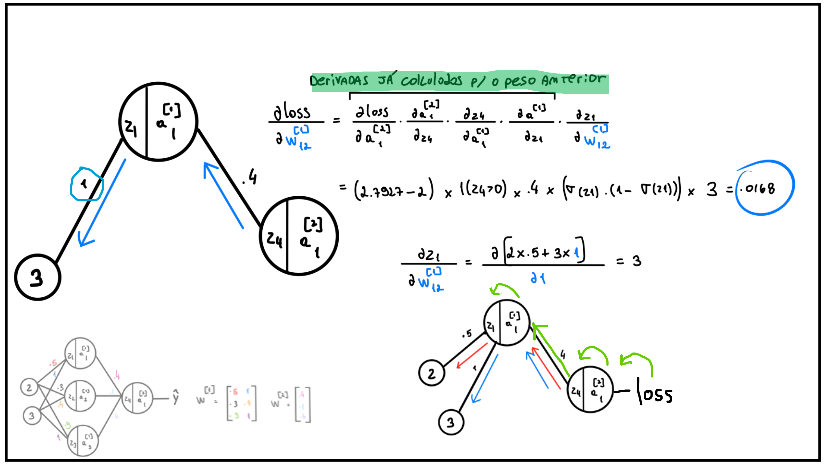

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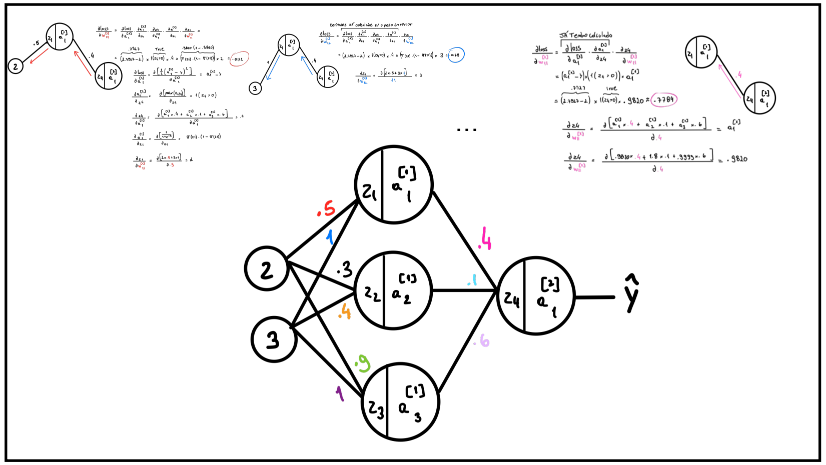

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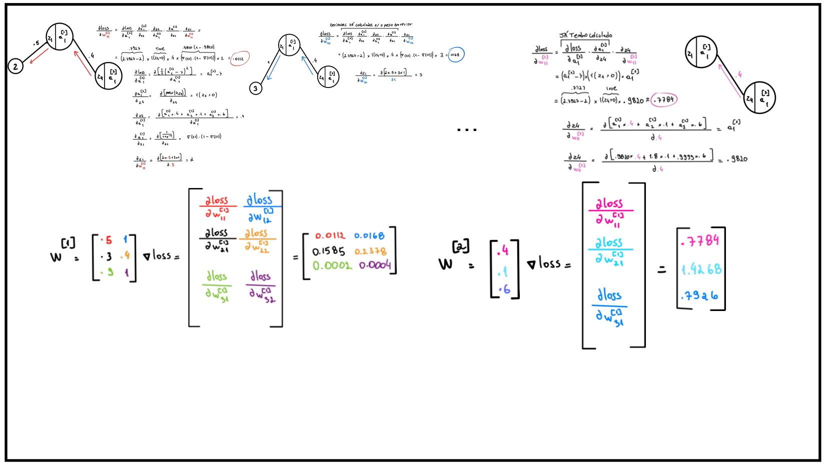

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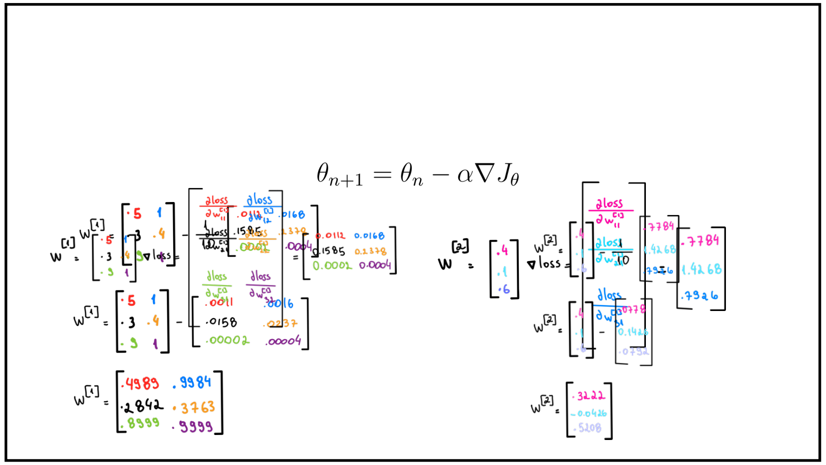

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PRATICA

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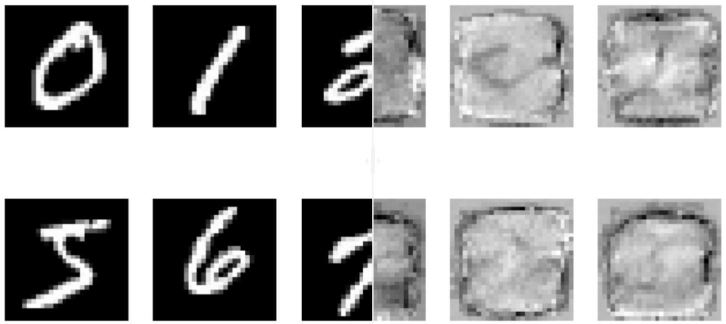

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APRENDIZADO DE MÁQUINA

O QUE É *LEARNING*?

PRIMEIRO ALG DE LEARNING

PROTOCOLOS DE TREINAM.

OTIMIZAÇÃO

REDES NEURAIS

BACKPROP + PRATICA

> CNN + PRATICA

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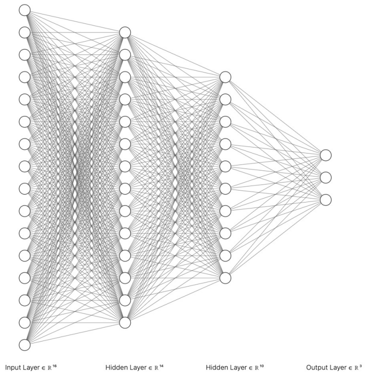
Convolutional Neural Network

Tarefa envolve images?



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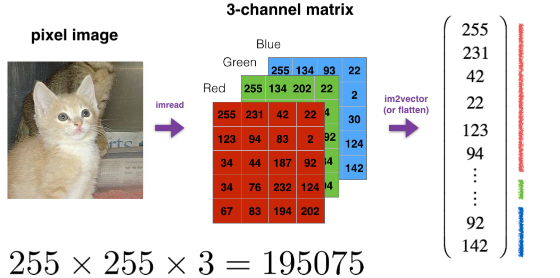
Convolutional Neural Network

Tarefa envolve images?



$$255 \times 255 \times 3 = 195075$$

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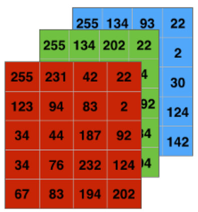
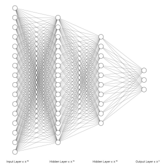
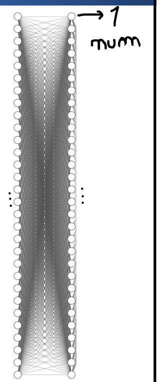
Convolutional Neural Network

QUANTAS OPERAÇÕES SÃO NECESSÁRIAS PARA O PRODUTO DA CAMADA SUBSEQUENTE DA NN MLP RETORNAR UM VETOR DE MESMA DIMENSÃO QUE A IMAGEM DE ENTRADA?

$$255 \times 255 \times 3 = 195075$$







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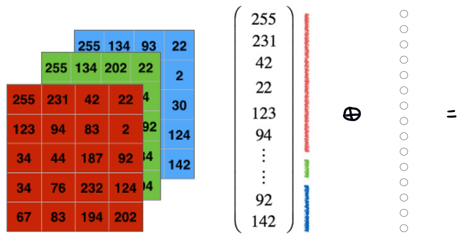
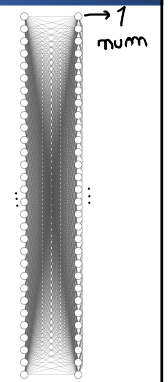
Convolutional Neural Network

$$255 \times 255 \times 3 = 195075$$





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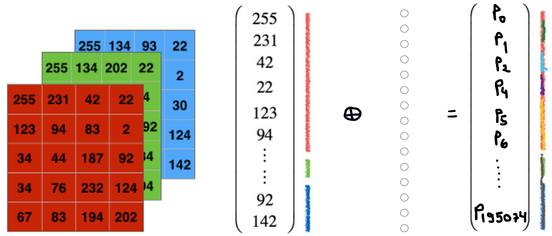
Convolutional Neural Network

$$255 \times 255 \times 3 = 195075$$



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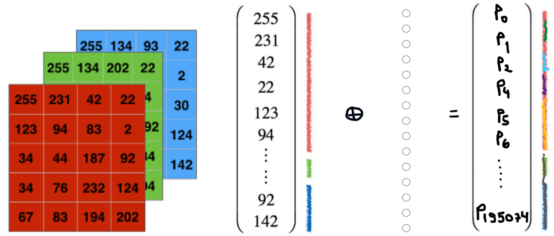
Convolutional Neural Network

$$255 \times 255 \times 3 = 195075$$

$$\#\text{Operações} = (1, 195075) \times (195075, 195075) \approx 4 \times 10^{10}$$



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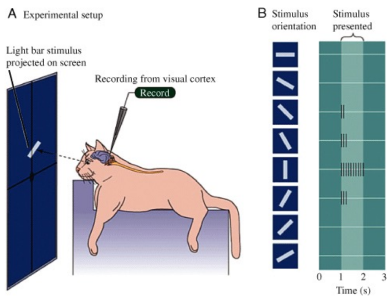
O experimento de Hubel e Wiesel (1959)

J Physiol. 1959 Oct;148(3):574-91. doi: 10.1113/jphysiol.1959.sp006308.

Receptive fields of single neurones in the cat's striate cortex

D H HUBEL, T N WIESEL

PMID: 14403679 PMCID: PMC1363130 DOI: 10.1113/jphysiol.1959.sp006308



https://www.youtube.com/watch?v=iw6nBWo21Zk&t=315s

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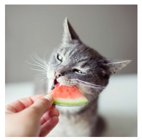
O que podemos tirar de insight

Imagens possuem algumas características interessantes

- Coerência espacial
- Invariância a translação (rotação, escala, ...)



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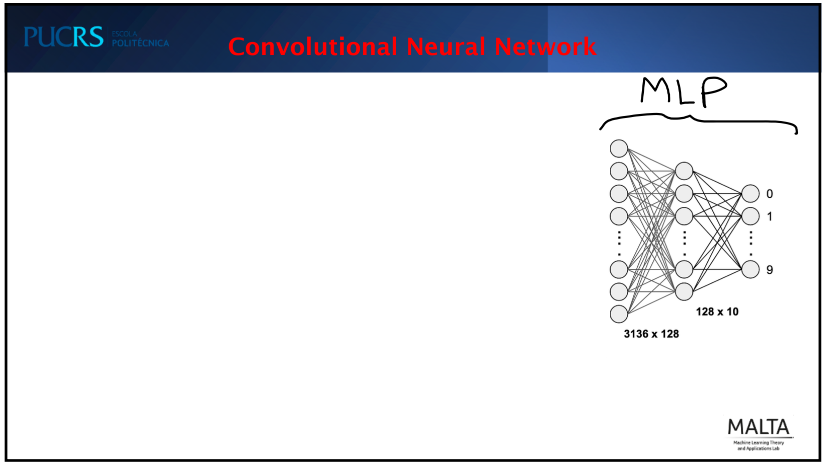

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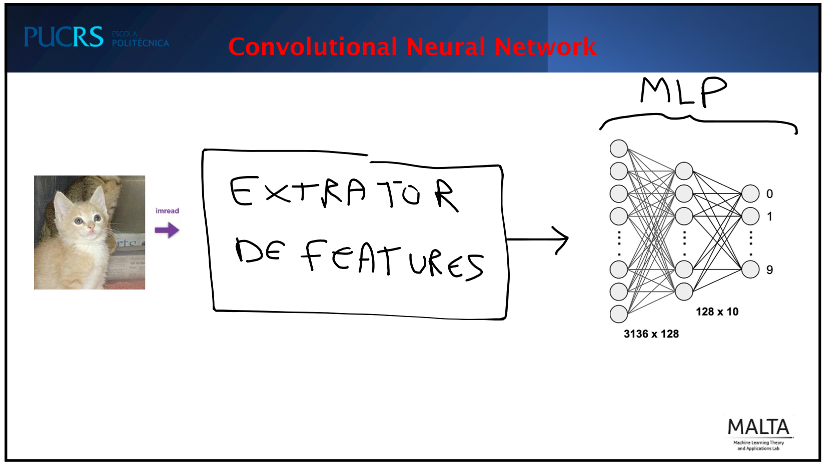

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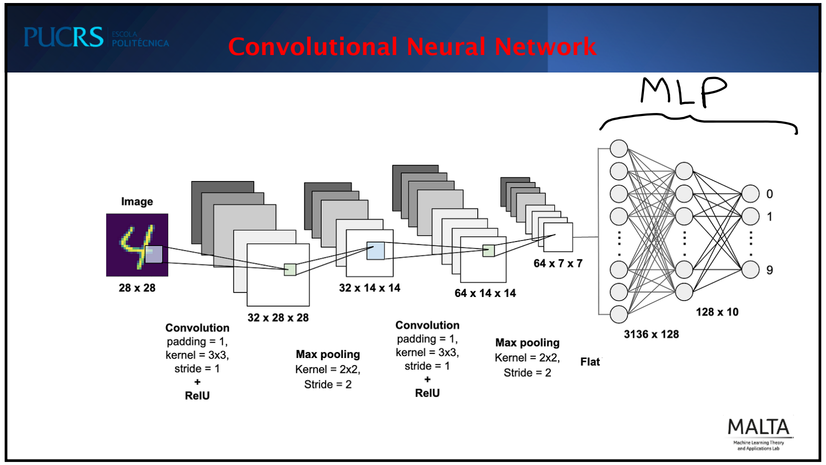

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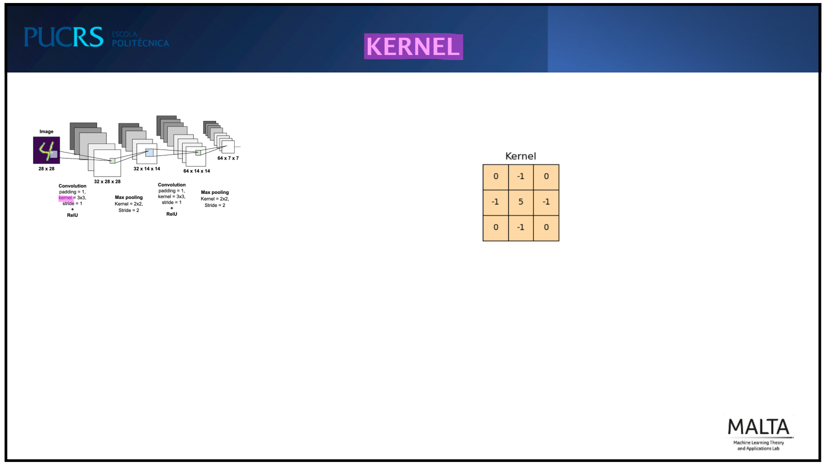

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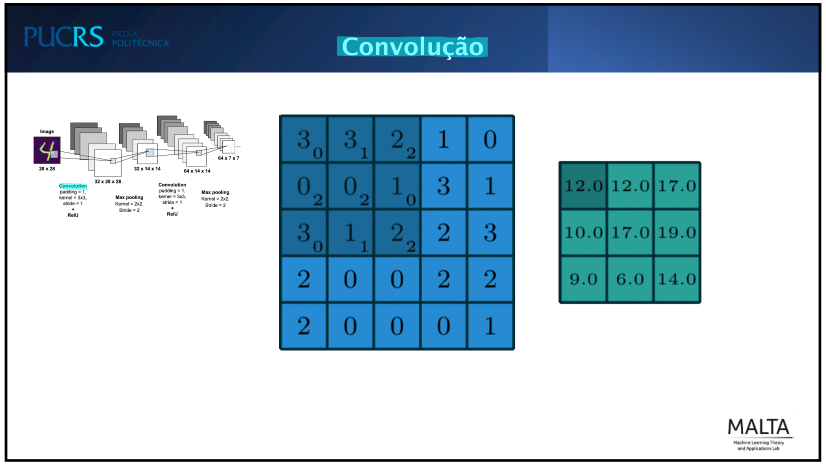

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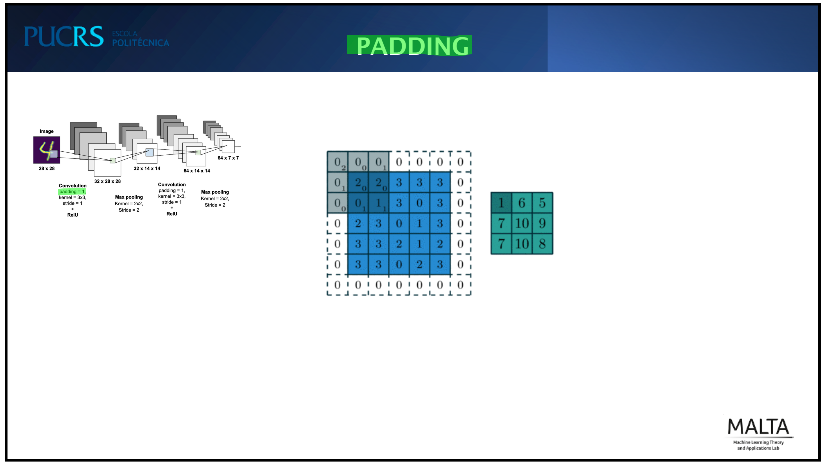

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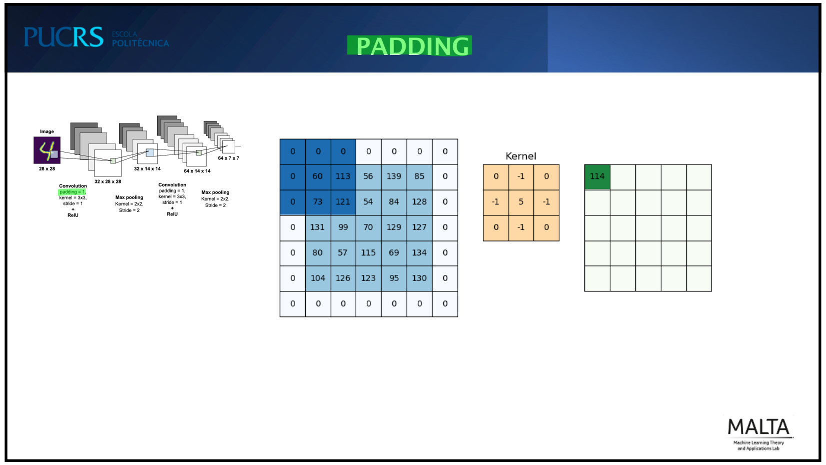

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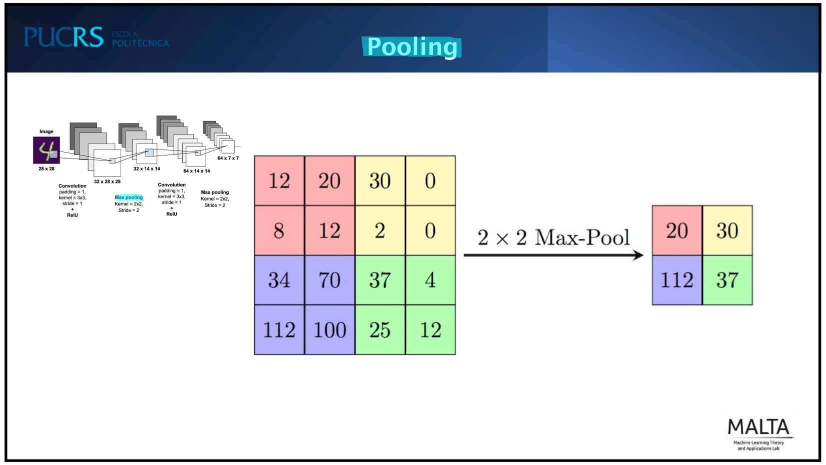

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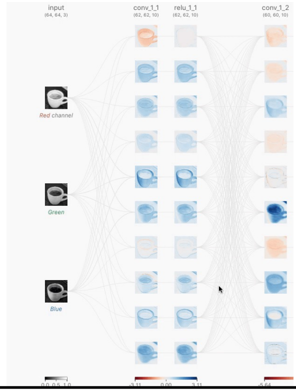
USEM



Referência

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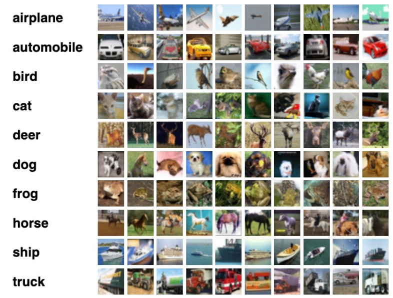
PRATICA

shorturl.at/ouL57



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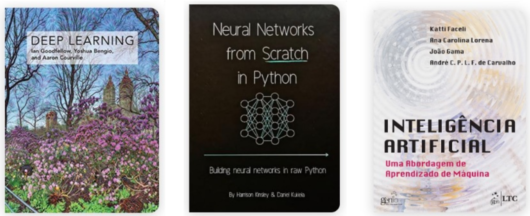
Referências



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