Introdução a Ciencia de Dados

Hitoshi Nagano, Ph.D.

FGV MANAGEMENT

Redes Neurais Artificiais

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roteiro

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- arquitetura
- forward propagation
- otimização
- backpropagation
- tensorflow & keras

referencias

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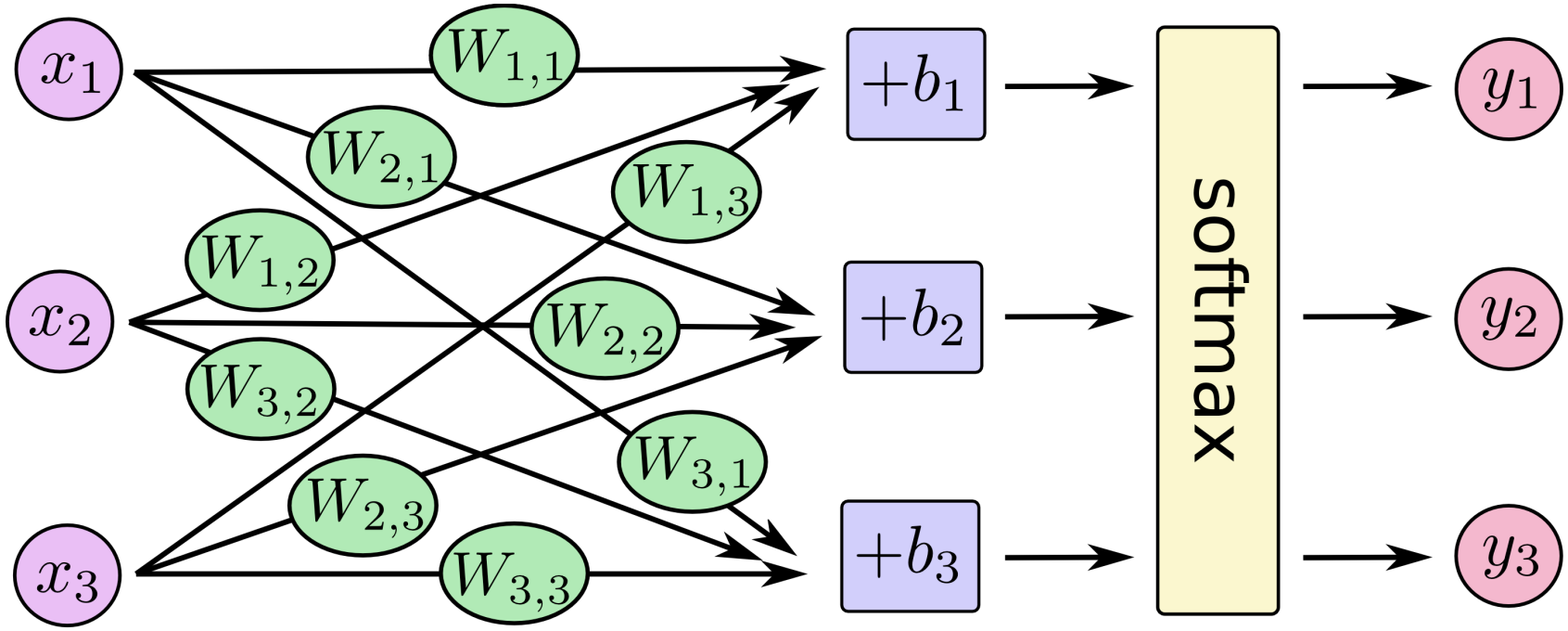
- livros
  http://neuralnetworksanddeeplearning.com
  http://www.deeplearningbook.org/lecture_slides.html
- cursos
  http://cs231n.github.io/
  https://web.stanford.edu/class/cs224n/
- blogs
  http://colah.github.io/



https://www.tensorflow.org/get_started/mnist/beginners

qual é o problema?

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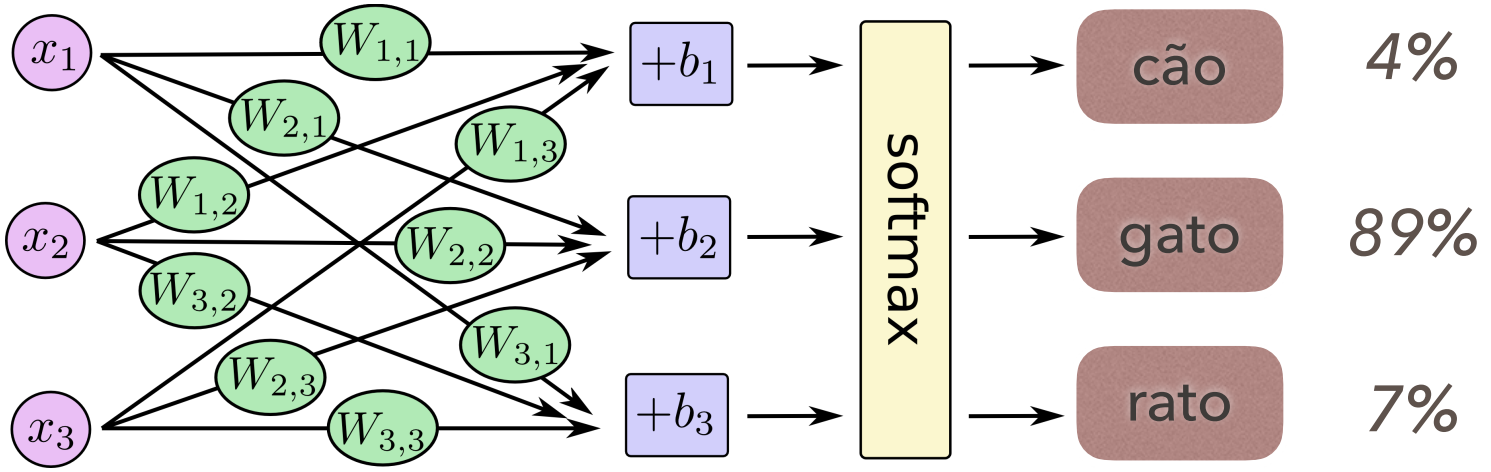

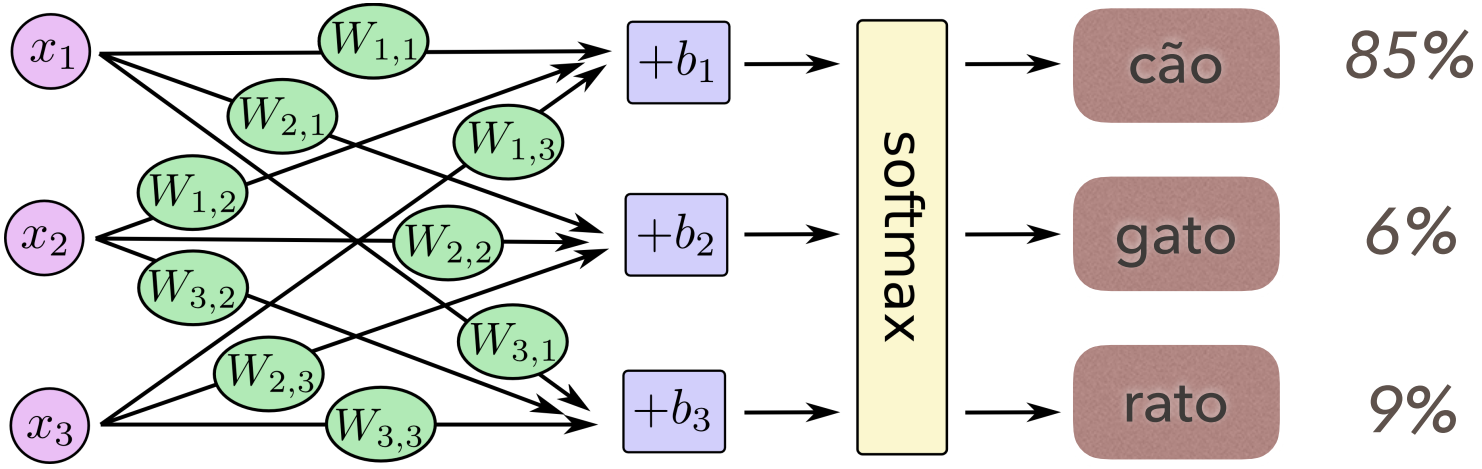

qual é o problema?

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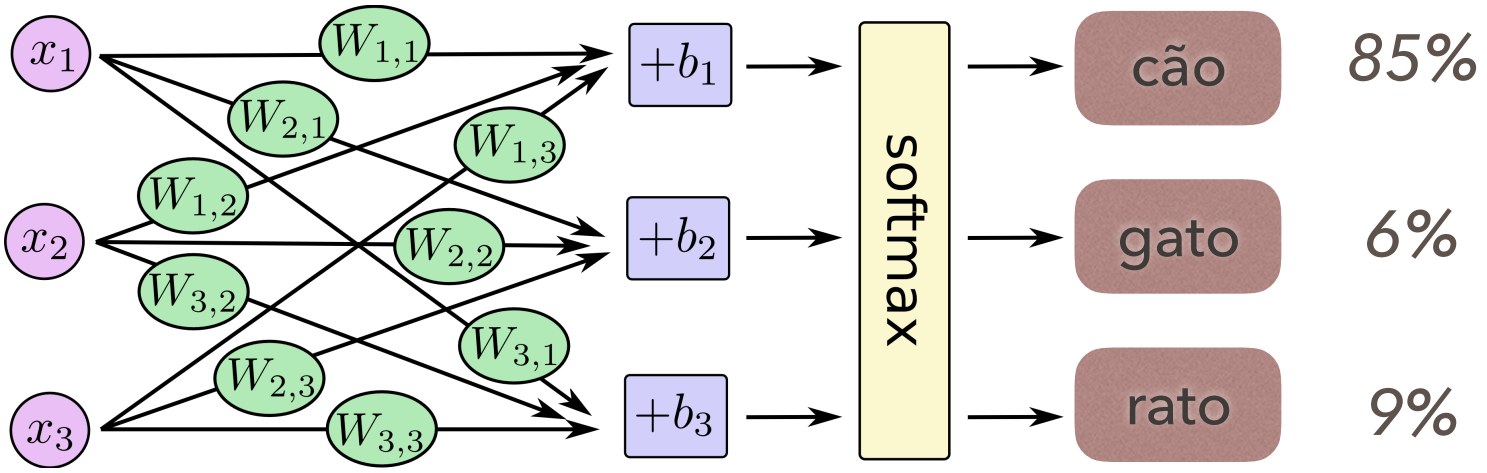
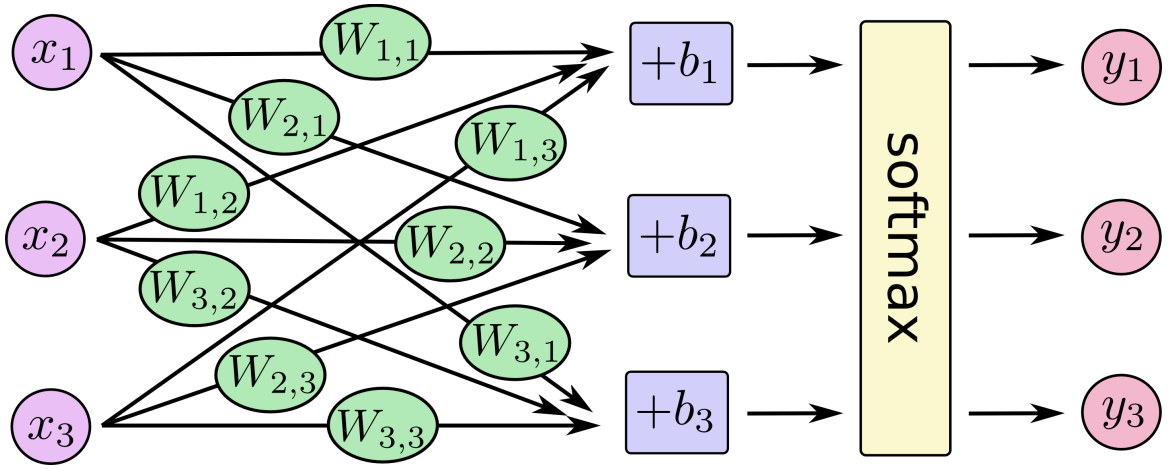


x

	pixel1	pixel2	pixel3	...	pixel n
🐱	2	133	25	...	77
🐶	3	3	55	...	89
🐭	254	255	253	...	255
😼	8	8	10	...	21

y

cão	gato	rato
0	1	0
1	0	0
0	0	1
0	1	0



$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax}\left(\begin{bmatrix} W_{1,1} & W_{1,2} & W_{1,3} \\ W_{2,1} & W_{2,2} & W_{2,3} \\ W_{3,1} & W_{3,2} & W_{3,3} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right)$$

$$y = softmax(Wx + b)$$

E... o que é esse softmax?

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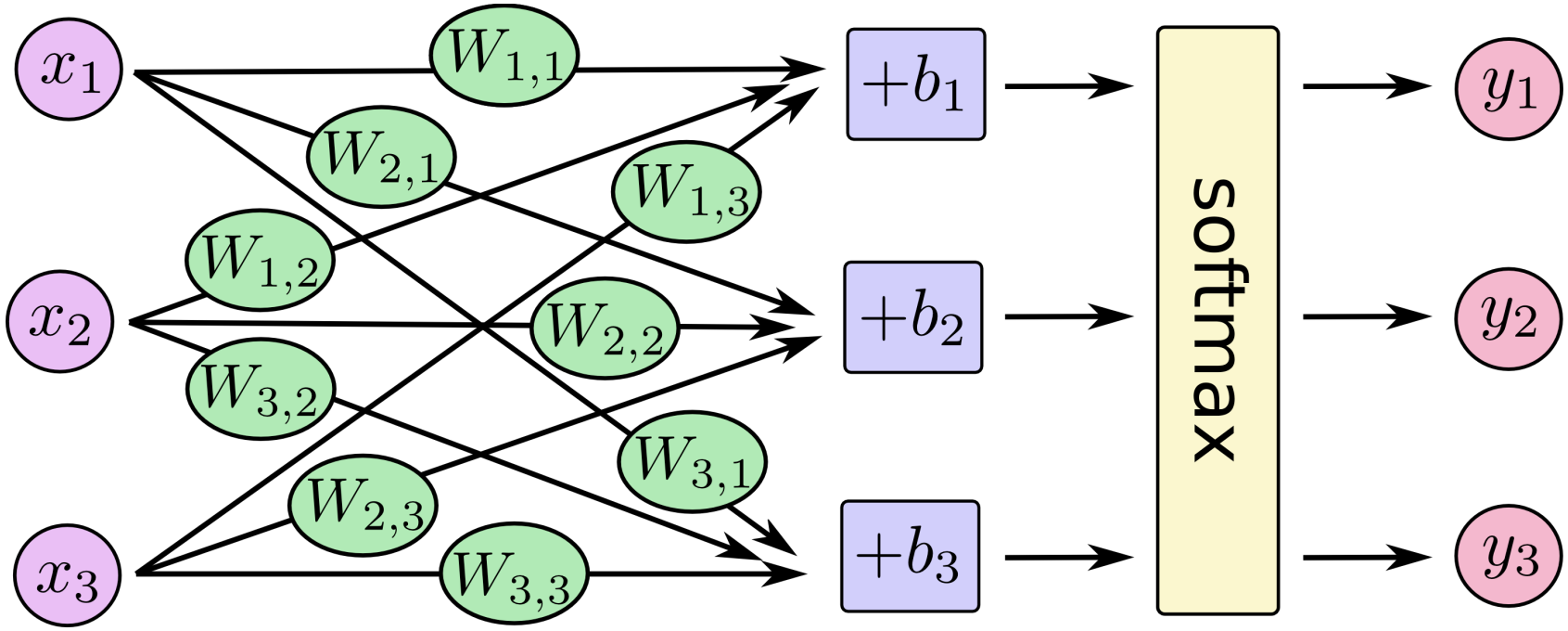
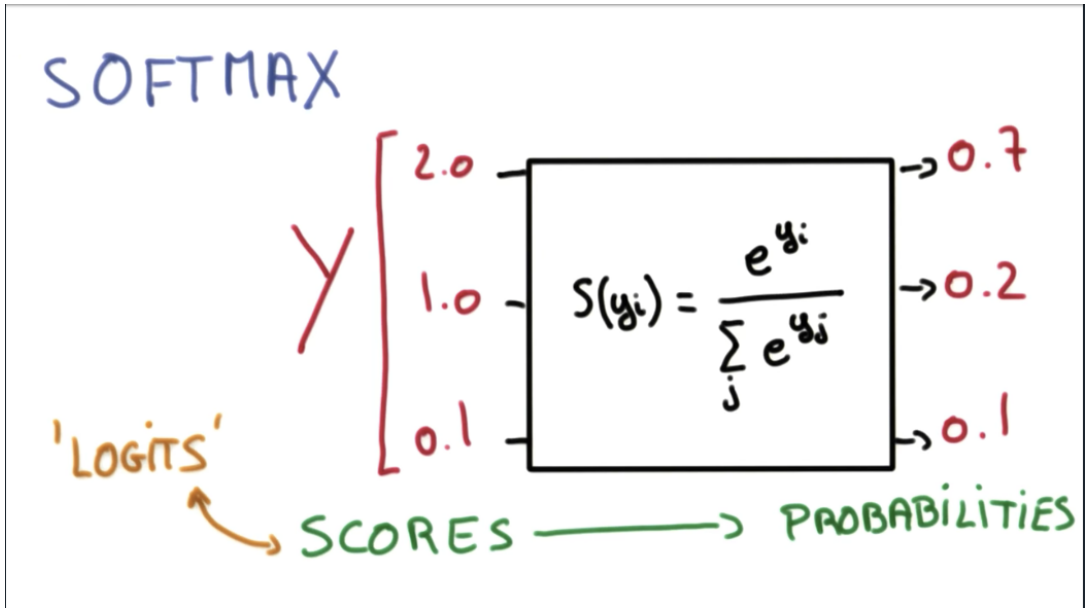
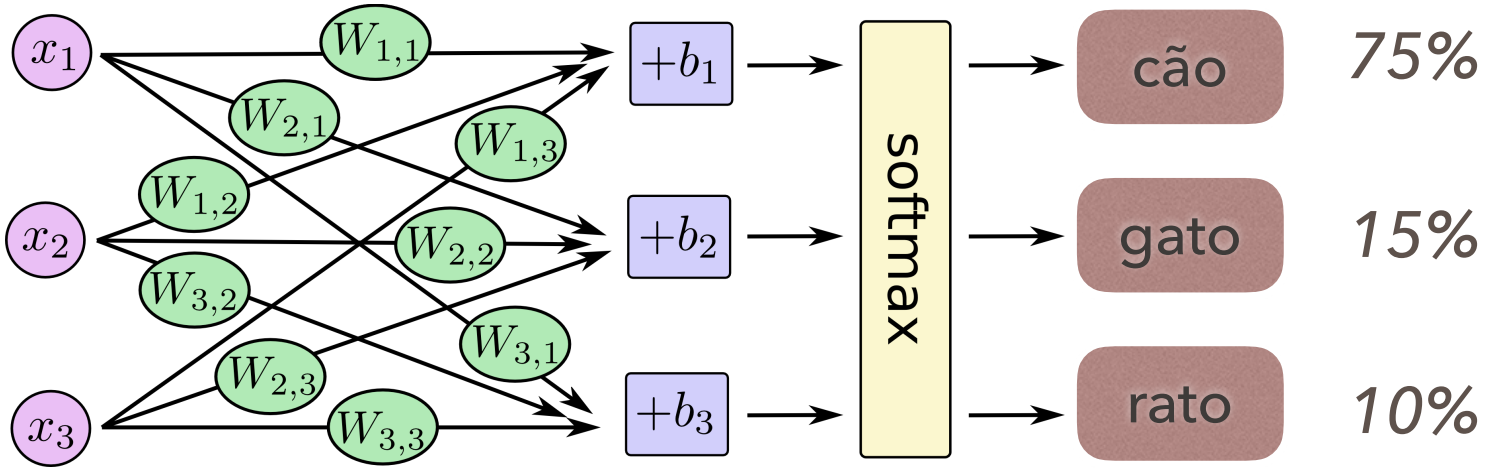




Fonte: Udacity

	scores	e^scores	probabilidades
y_0	2	7.4	0.7
y_1	1	2.7	0.2
y_2	0.1	1.1	0.1
fator de normalização ➜		11.2	

ESSE MODELO É “BOM”?



erra menos
acerta mais

→ *“bons” W & b* →

“bom” modelo

como achar "bons" pesos?

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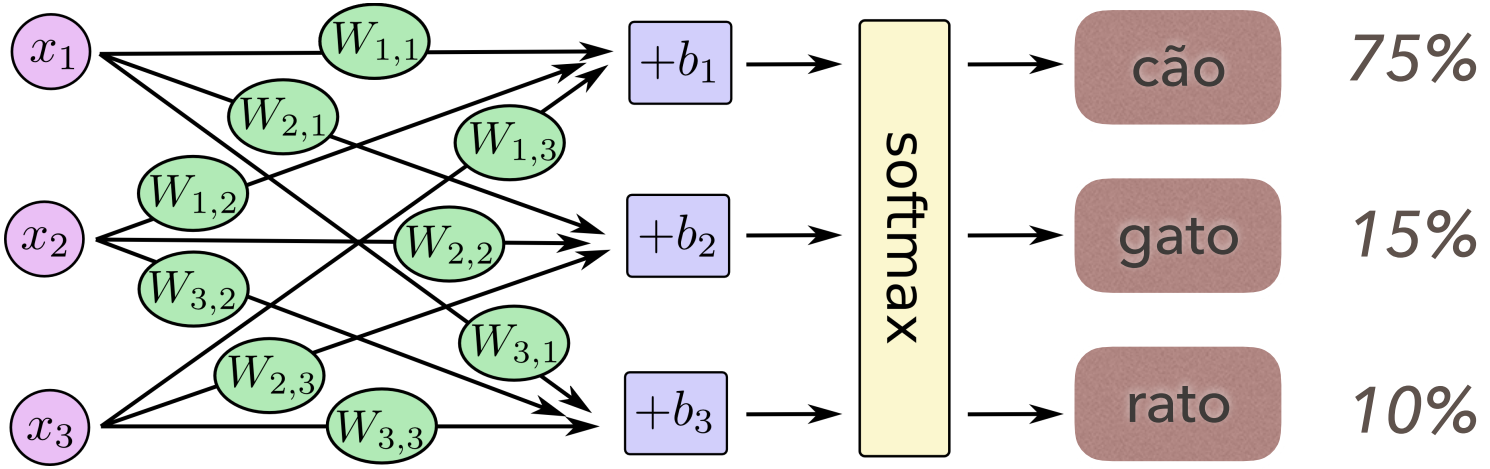

GRADIENT DESCENT

HTTP://WWW.KDNUGGETS.COM/2017/04/SIMPLE-UNDERSTAND-GRADIENT-DESCENT-ALGORITHM.HTML

https://docs.google.com/spreadsheets/d/1TFHcFix5zN5ikqFkJC6mlXg83LxGJAeVJl3BddvYsPM/edit?usp=sharing

como quantificar "BOM"???

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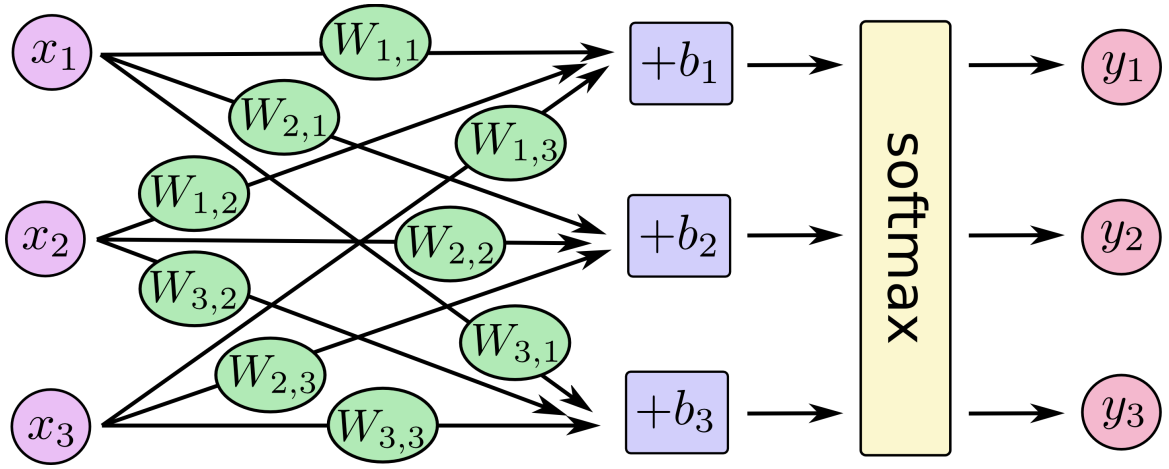

x

	pixel1	pixel2	pixel3	...	pixel n
🐱	2	133	25	...	77
🐶	3	3	55	...	89
🐭	254	255	253	...	255
😺	8	8	10	...	21

y

cão	gato	rato
0	1	0
1	0	0
0	0	1
0	1	0

y_pred

cão	gato	rato
0.06	0.85	0.09
0.77	0.20	0.03
0.32	0.15	0.53
0.40	0.20	0.30

como quantificar "BOM"???

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	x					*y*			*y_pred*		
	pixel1	pixel2	pixel3	...	pixel n	cão	gato	rato	cão	gato	rato
	2	133	25	...	77	0	1	0	0.06	0.85	0.09
	3	3	55	...	89	1	0	0	0.77	0.20	0.03
	254	255	253	...	255	0	0	1	0.32	0.15	0.53
	8	8	10	...	21	0	1	0	0.40	0.20	0.30

CROSS-ENTROPY

cross-entropy ou log-loss

TRUE PREDS

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{i,j}\log(p_{i,j})$$

https://www.kaggle.com/wiki/LogLoss

cross-entropy ou log-loss

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PREDS

	label 0	label 1	label 2	label 3
cliente 0	0.069	0.213	0.698	0.020
cliente 1	0.164	0.426	0.081	0.329
cliente 2	0.278	0.370	0.269	0.083
cliente 3	0.055	0.405	0.460	0.080
cliente 4	0.124	0.666	0.145	0.066
cliente 5	0.569	0.045	0.214	0.172
cliente 6	0.421	0.091	0.353	0.135
cliente 7	0.215	0.323	0.279	0.182
cliente 8	0.139	0.123	0.347	0.390
cliente 9	0.155	0.036	0.311	0.498

TRUE

	label 0	label 1	label 2	label 3
cliente 0	0	1	0	0
cliente 1	0	0	0	1
cliente 2	1	0	0	0
cliente 3	0	0	0	1
cliente 4	0	1	0	0
cliente 5	0	0	1	0
cliente 6	0	0	1	0
cliente 7	0	0	1	0
cliente 8	1	0	0	0
cliente 9	0	0	0	1

cross-entropy ou log-loss

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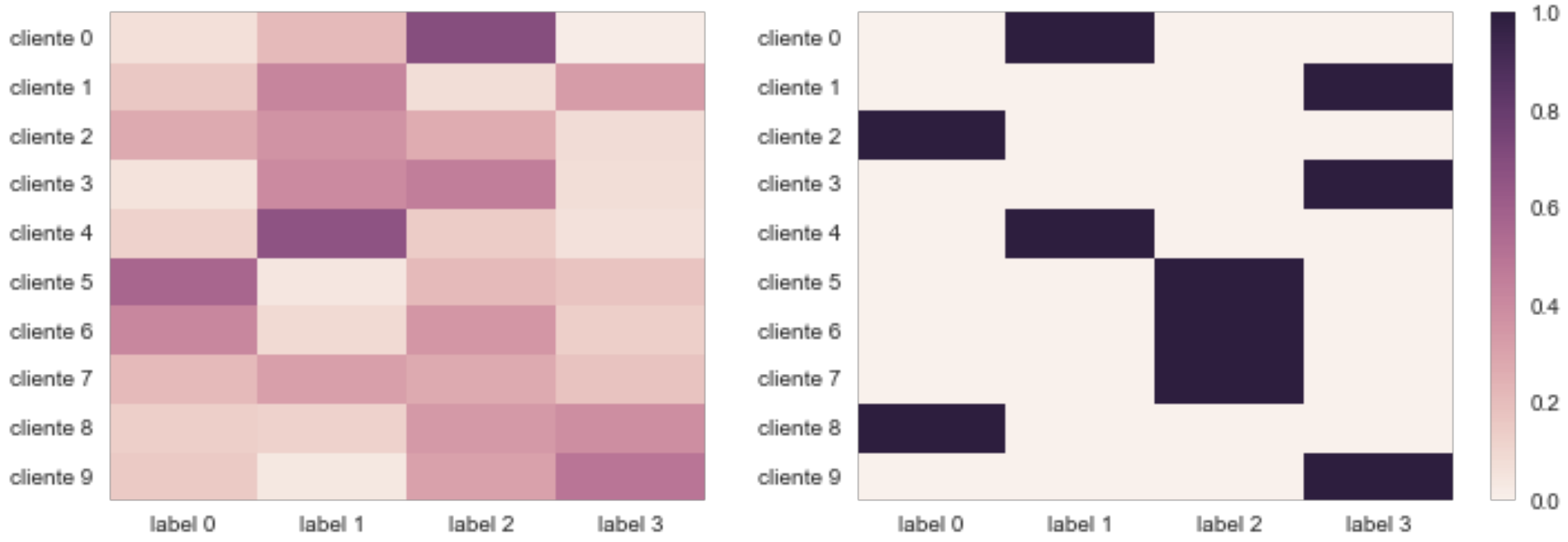
PREDS

TRUE

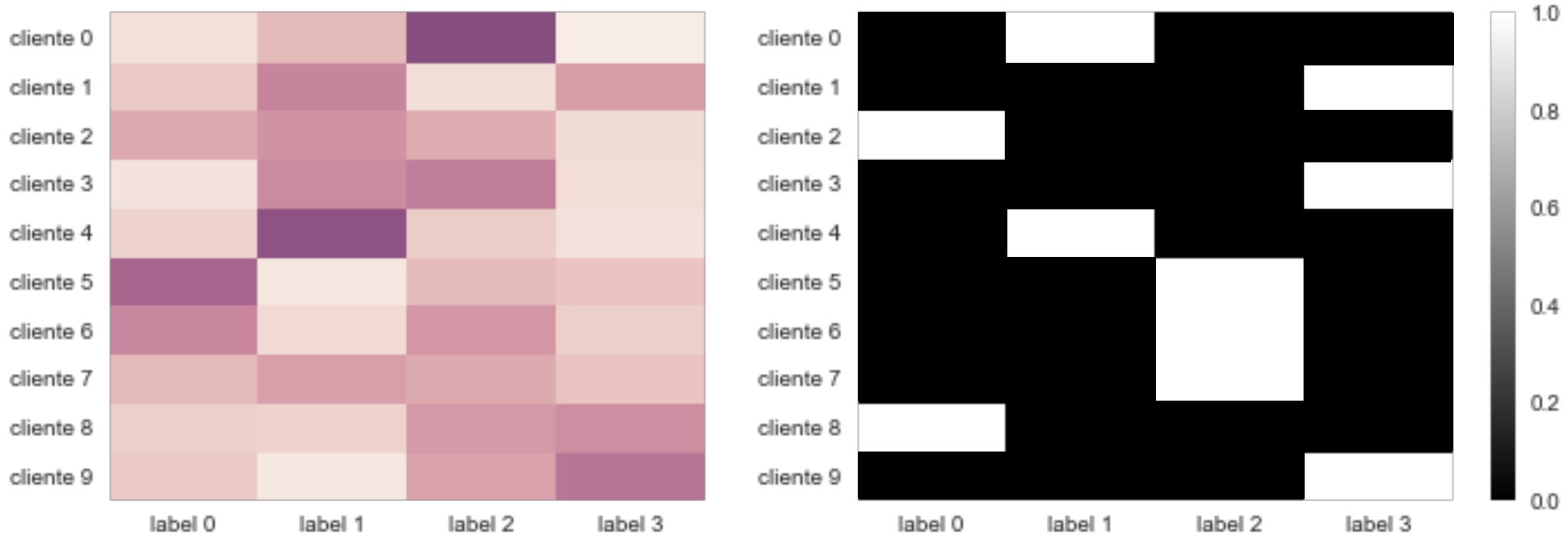


cross-entropy ou log-loss

FGV MANAGEMENT

PREDS

TRUE



$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{i,j}\log(p_{i,j})$$

cross-entropy ou log-loss

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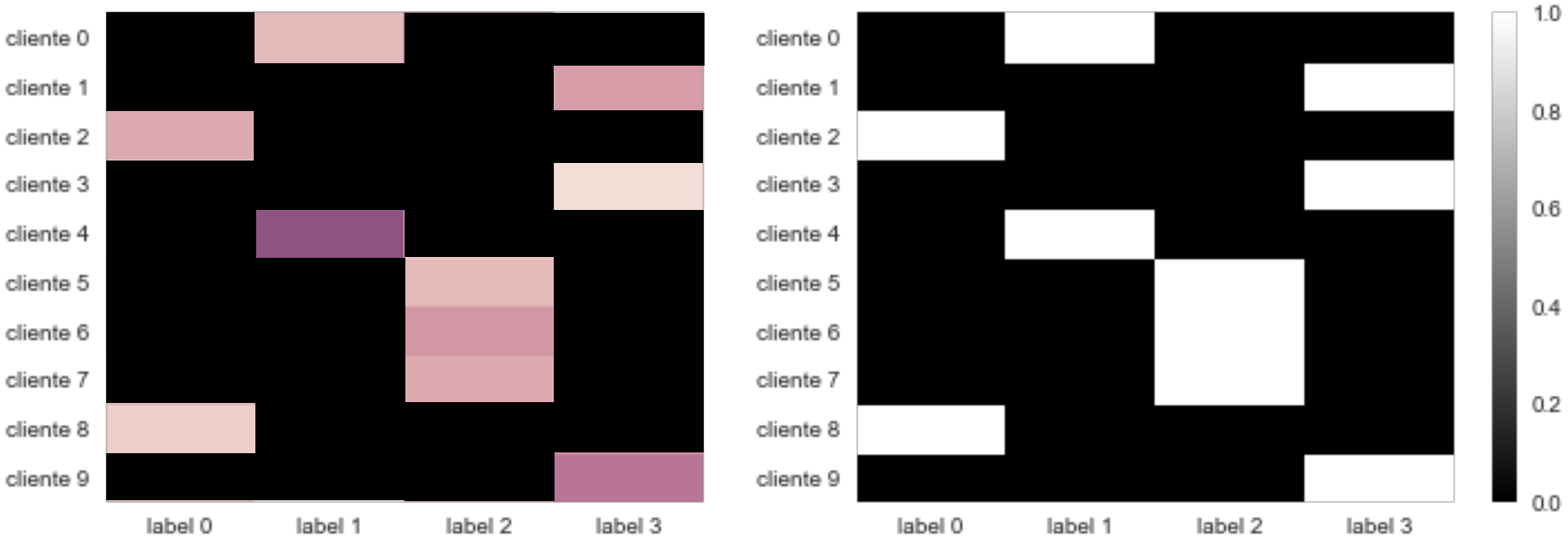
PREDS

TRUE



$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{i,j}\log(p_{i,j})$$

como quantificar "BOM"???

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y

cão	gato	rato
0	1	0
1	0	0
0	0	1
0	1	0

y_pred

cão	gato	rato
0.06	0.85	0.09
0.77	0.20	0.03
0.32	0.15	0.53
0.40	0.20	0.40

CROSS-ENTROPY MENOR

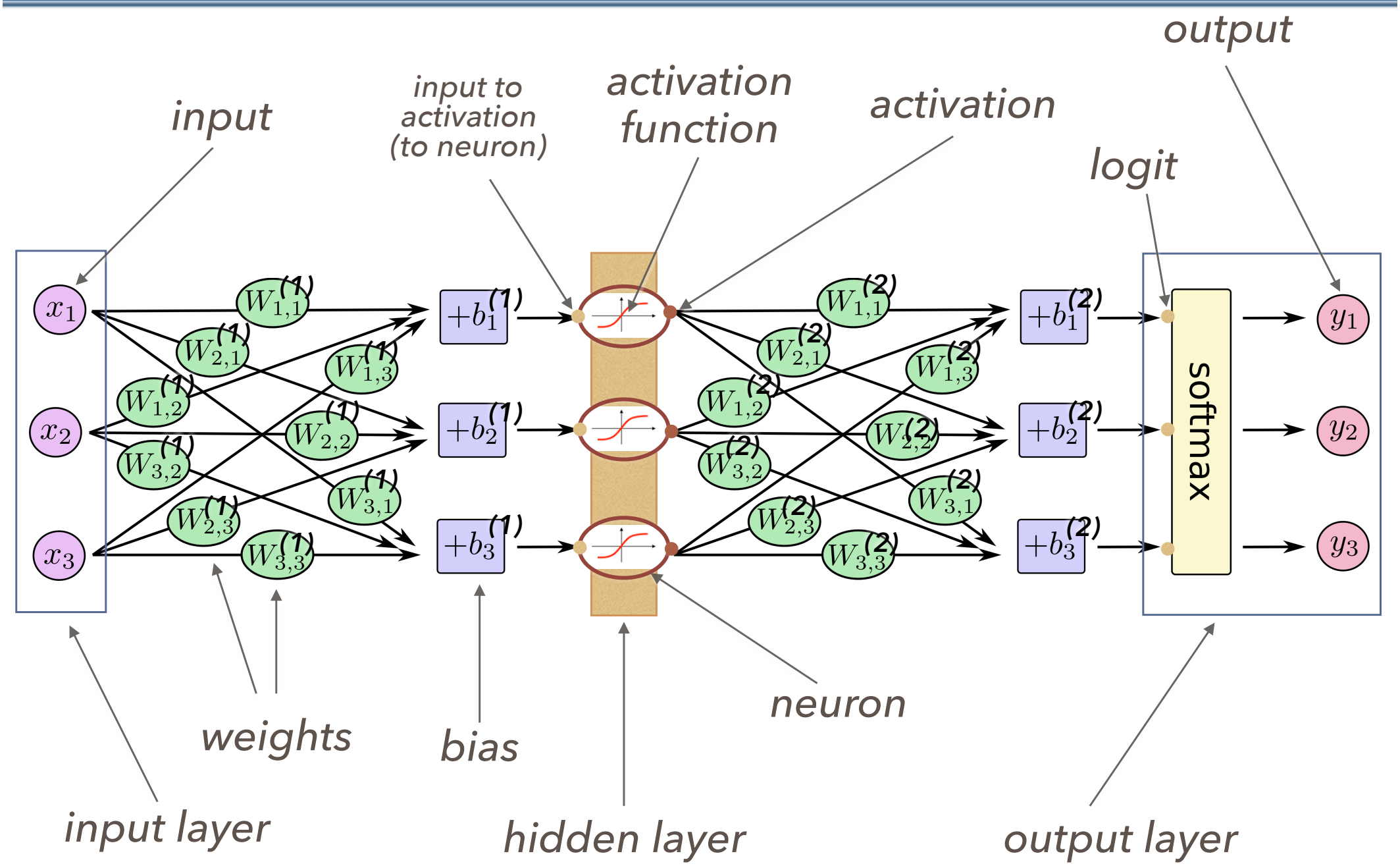
y

cão	gato	rato
0	1	0
1	0	0
0	0	1
0	1	0

y_pred

cão	gato	rato
0.60	0.15	0.25
0.24	0.20	0.56
0.32	0.03	0.65
0.40	0.15	0.45

CROSS-ENTROPY MAIOR


output
input
input to activation (to neuron)
activation function
activation
logit
softmax
weights
bias
neuron
input layer
hidden layer
output layer

diferentes ativações

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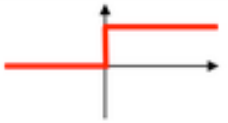
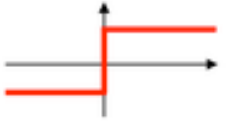
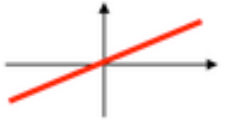
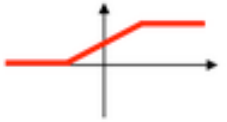
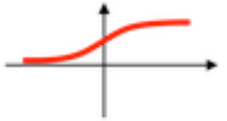
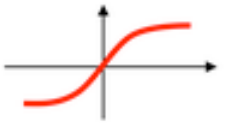
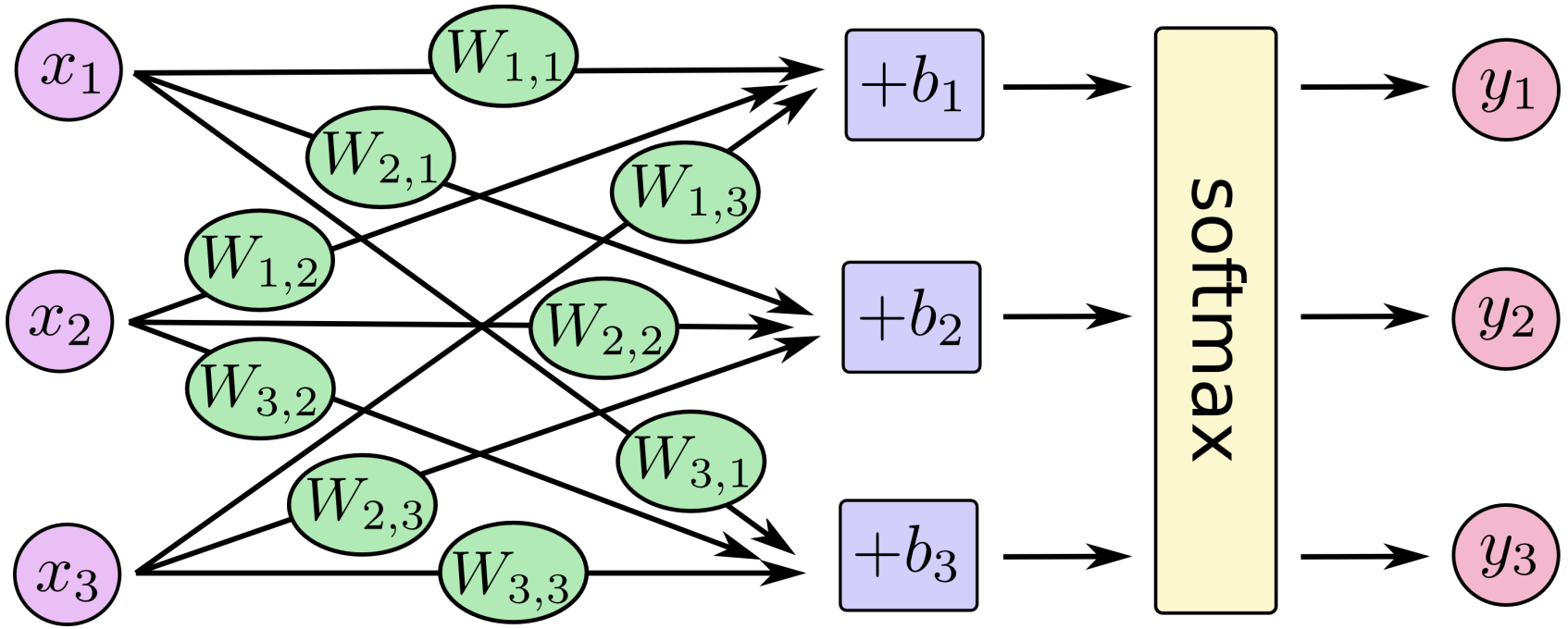
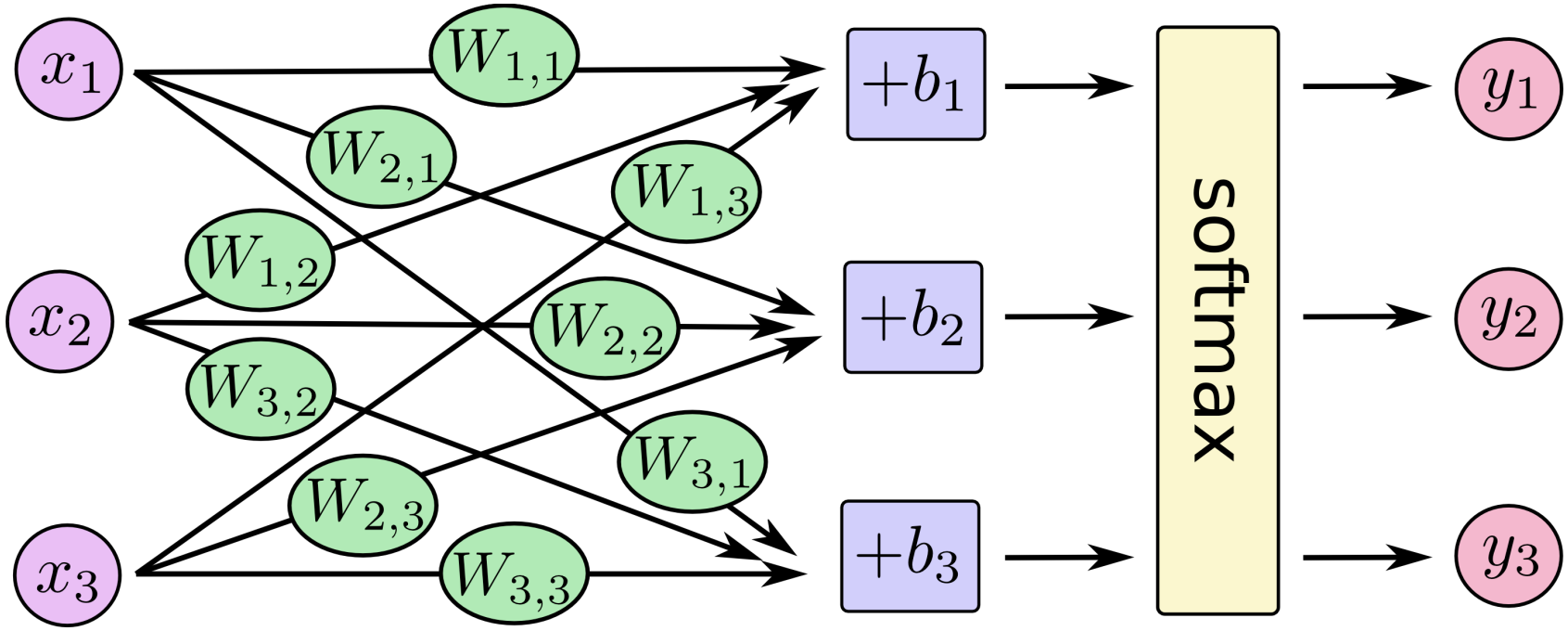
Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$	Multi-layer NN	

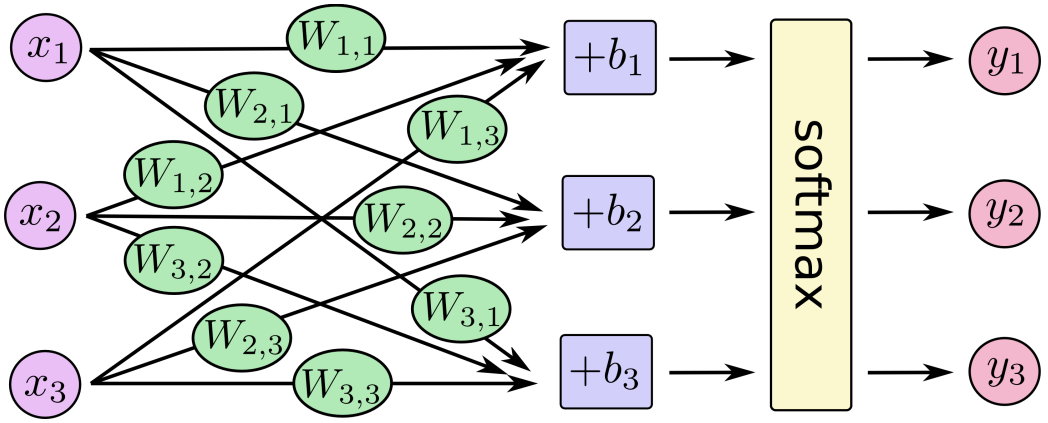
http://www.kdnuggets.com/2016/08/role-activation-function-neural-network.html



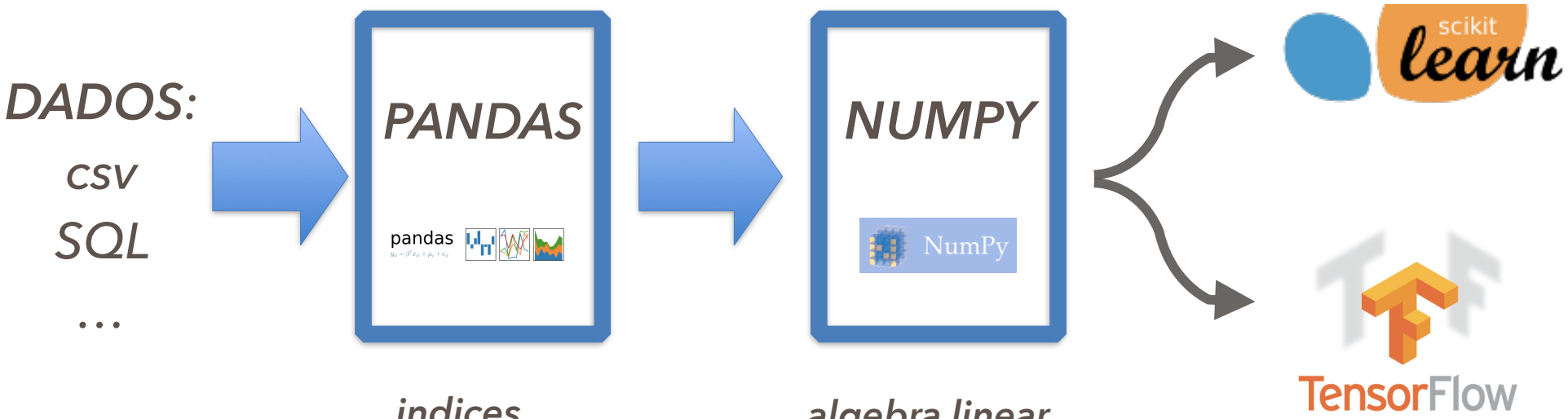
Este setup também é conhecido por
MULTINOMIAL LOGISTIC CLASSIFICATION

o que precisamos definir?





- arquitetura:
  - dimensão da entrada
  - dimensão da saída (numero de classes)
  - dimensões escondidas - # de pesos & bias
  - função de ativação
- operação:
  - tamanho do batch
  - qtd de epochs
- objetivos:
  - função de custo & métrica
  - otimizador



indices
slicing, indexing
limpeza
get_dummies
merge, concat
groupby

algebra linear
multiplicacao matrizes
prod. interno
transform. linear

SGD 'BLACK MAGIC'

MANY HYPER-PARAMETERS

- INITIAL LEARNING RATE
- LEARNING RATE DECAY
- MOMENTUM
- BATCH SIZE
- WEIGHT INITIALIZATION

CPU vs. GPU

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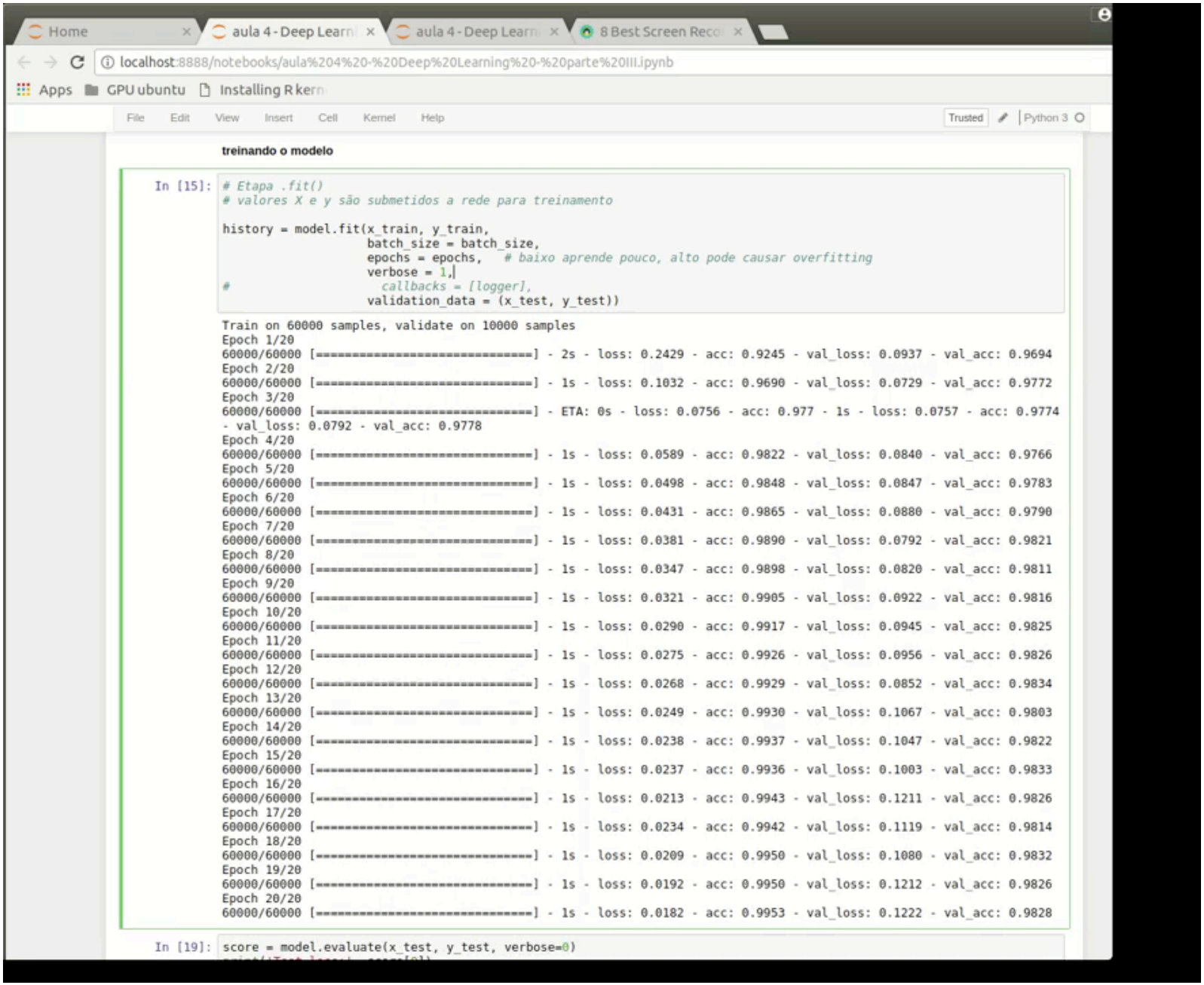

CPU vs. GPU

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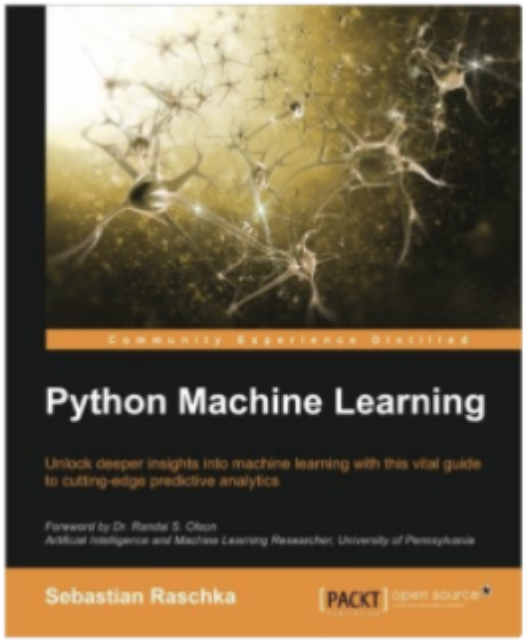
Look inside



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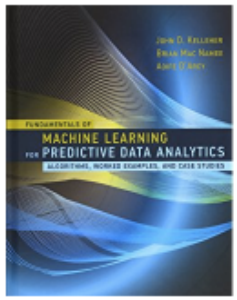

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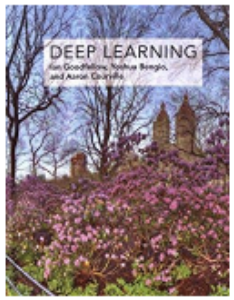

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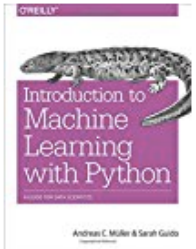

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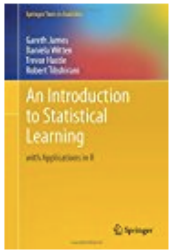

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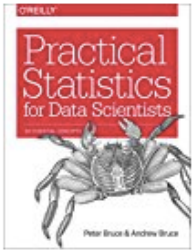

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SISTEMAS DE RECOMENDAÇÃO

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- técnicas, ferramentas e sistemas…
- … para sugerir ítens a pessoas

SISTEMAS DE RECOMENDAÇÃO
objetivos:

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- aumentar vendas - volume
- aumentar vendas - diversidade
- aumentar satisfação
- aumentar fidelização
- entender melhor o que o cliente quer

SISTEMAS DE RECOMENDAÇÃO
por que?

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- **Cauda Longa:** "We are leaving the age of information and entering the age of recommendation" - Chris Anderson: "The Long Tail…"
- **Big Data:** "People read 10MB a day, hear 400MB a day and see 1MB every second" - The economist Nov/2006
- **Paradoxo da Escolha:** "I want a pair of jeans"; "Do you want stone-washed, acid-washed, or distressed? Do you want button-fly or zipper-fly? Regular or faded? - Barry Schwartz : "Paradox of choice, why more is less"

SISTEMAS DE RECOMENDAÇÃO
cases

FGV MANAGEMENT

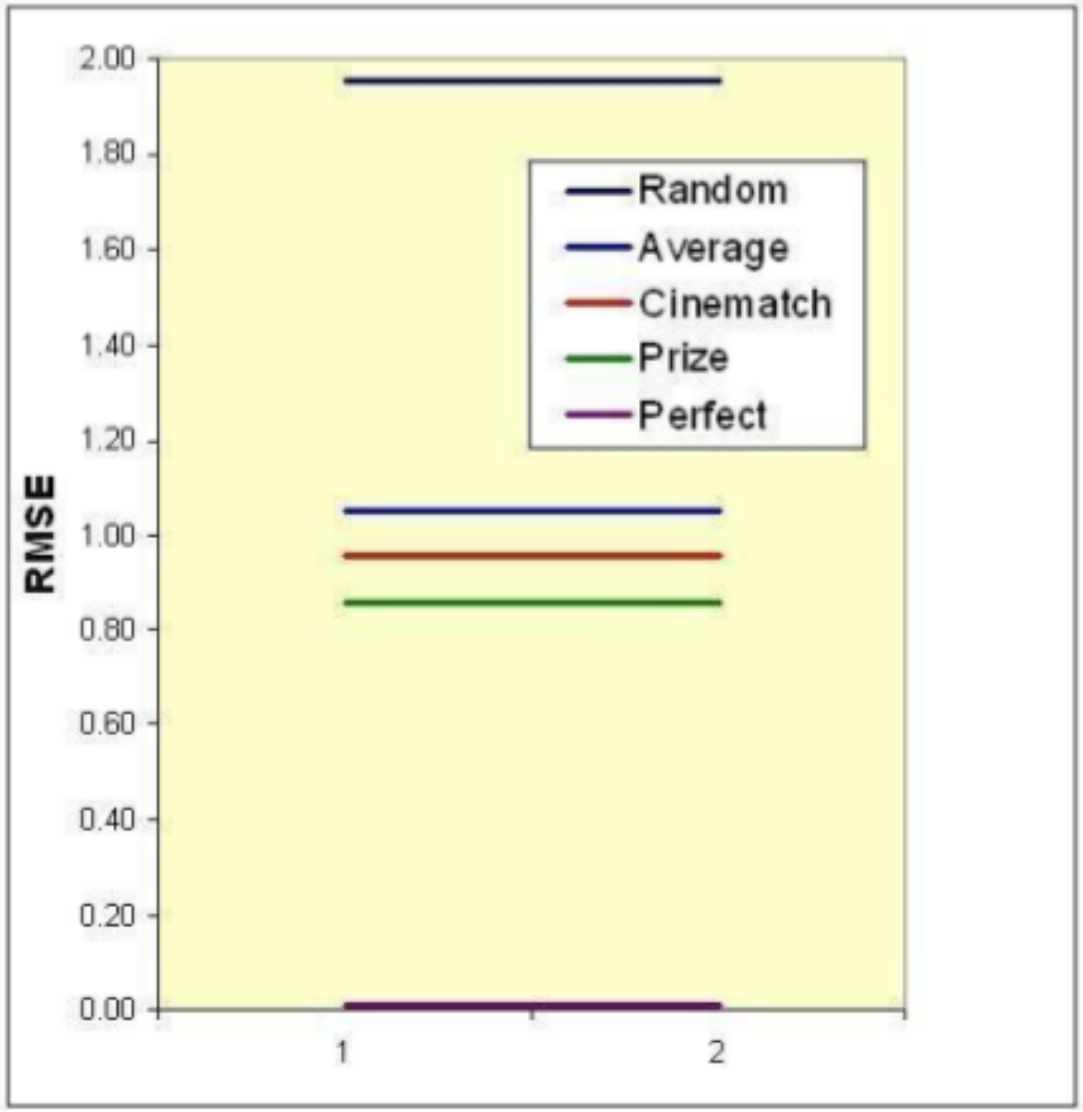
- **Netflix:** mais de 60% dos filmes assistidos foram recomendados
- **Google news**: SR geram 38% mais *clickthrough*
- **Amazon**: 35% das vendas vem dos SR

- recomendação: item ➜ pessoa
- busca: pessoa ➜ item
- a recomendação “acha” a pessoa
- busca e recomendação: dois lados de uma mesma moeda

- Função que prediz se uma pessoa vai gostar de um item
- dados:
  - similaridade: outras pessoas & feedback passado
  - similaridade: outros itens & feedback passado
  - contexto
  - …

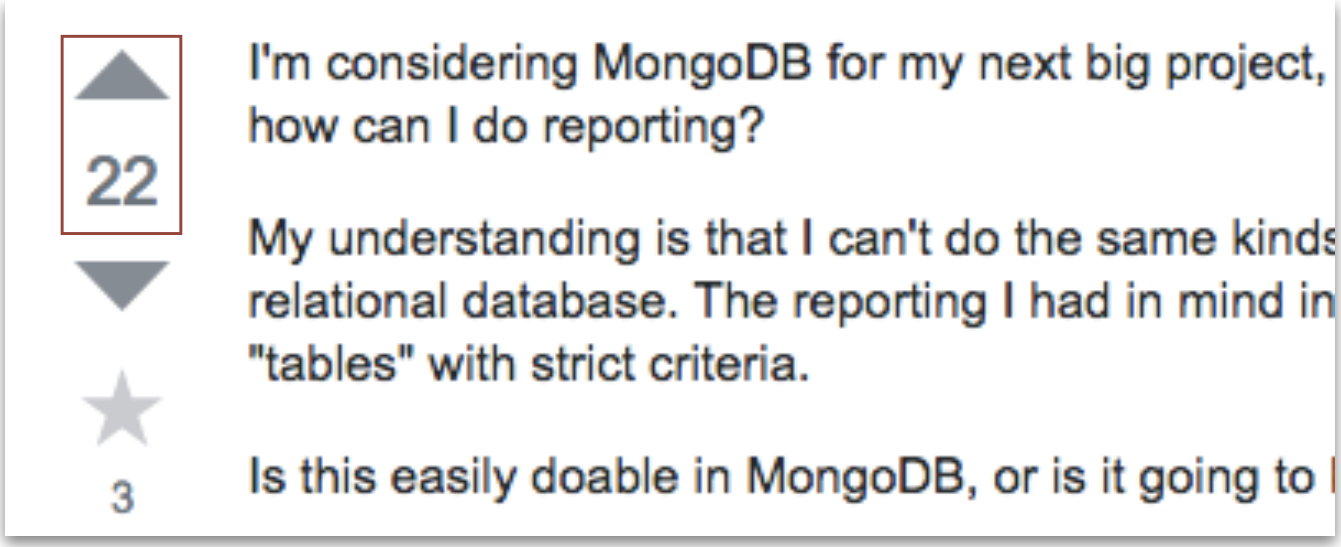
complexidade VS resultado

FGV MANAGEMENT



tipos de dados
(expressando preferências)

FGV MANAGEMENT



tipos de dados
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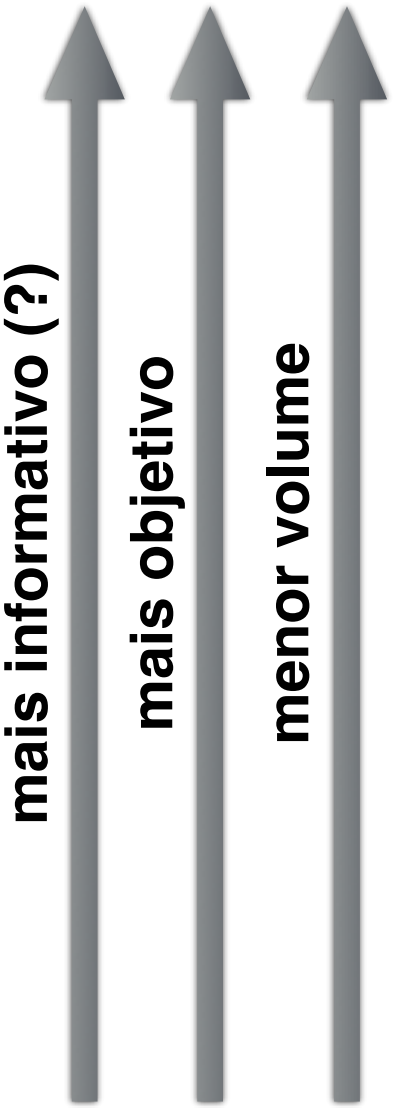
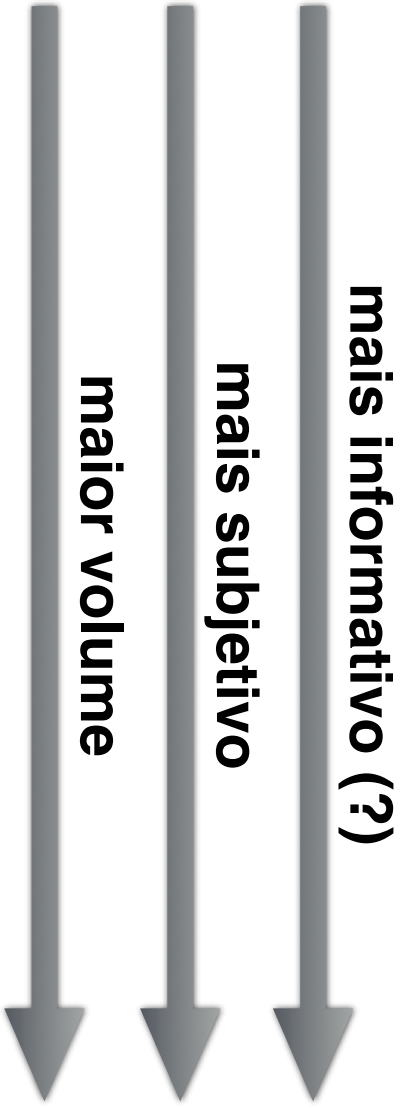
FGV MANAGEMENT



- Explícitos:
  - rating
  - avaliação
  - voto
- Implícitos:
  - click
  - compra
  - follow



implícito versus explicito

FGV MANAGEMENT

- qual é melhor ?
- para recomendações
- explicito: avaliações

  implícito: intenções
- gostar != recomendar

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Approaches to Recommendation

- non-personalized
- Collaborative Filtering: Recommend items based only on the users past behavior
  - **User-based:** Find similar users to me and recommend what they liked
  - **Item-based:** Find similar items to those that I have previously liked
- Content-based: Recommend based on item features

Fonte: https://www.slideshare.net/xamat/recommender-systems-machine-learning-summer-school-2014-cmu

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What works

- Depends on the **domain** and particular **problem**
- However, in the general case it has been demonstrated that the best isolated approach is CF.
  - Other approaches can be hybridized to improve results in specific cases (cold-start problem...)
- What matters:
  - Data preprocessing: outlier removal, denoising, removal of global effects (e.g. individual user's average)
  - "Smart" dimensionality reduction using MF/SVD
  - Combining methods

NETFLIX

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Fonte: https://www.slideshare.net/xamat/recommender-systems-machine-learning-summer-school-2014-cmu

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relembrando

Algebra Linear

FGV MANAGEMENT

- para recomendar, podemos encontrar:
  - alguém similar
  - produto similar
- … e fazer a recomendação
- como medimos similaridade?

similaridade

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- distancia euclideana
- cosine similarity (similaridade de cosseno)
- pearson's r

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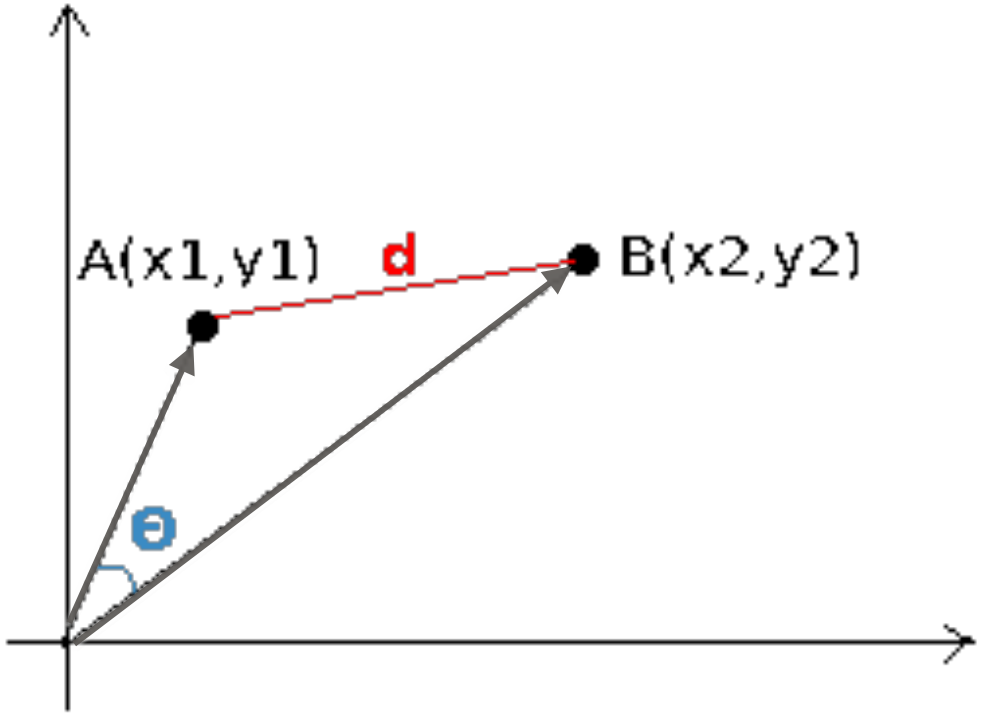
- vetor
- produto interno
- angulo e cosseno do angulo
- distancia euclideana
- norma L2

Distancia euclideana

	x	y
A	1	3
B	4	4



algebra linear !
similaridade cosseno

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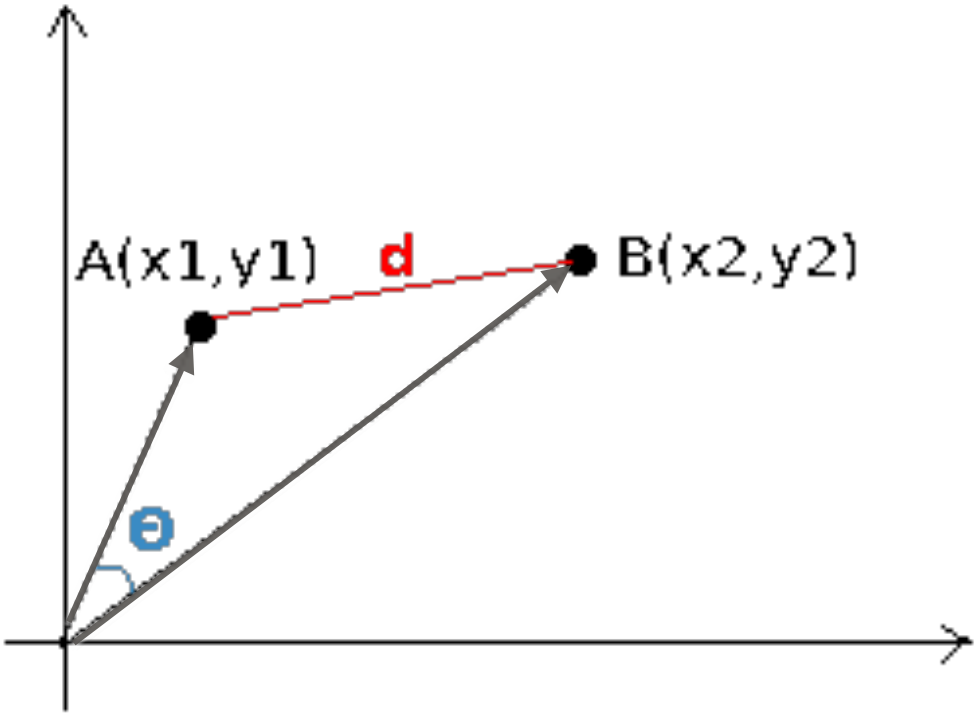
	x	y
A	1	3
B	4	4



pearson's R



	x	y	z
A	1	3	1
B	4	4	6
C	2	2	3

DISTANCIA EUCLIDEANA

$$d(x,y) = \sqrt{\sum_{k=1}^{n}(x_k - y_k)^2}$$

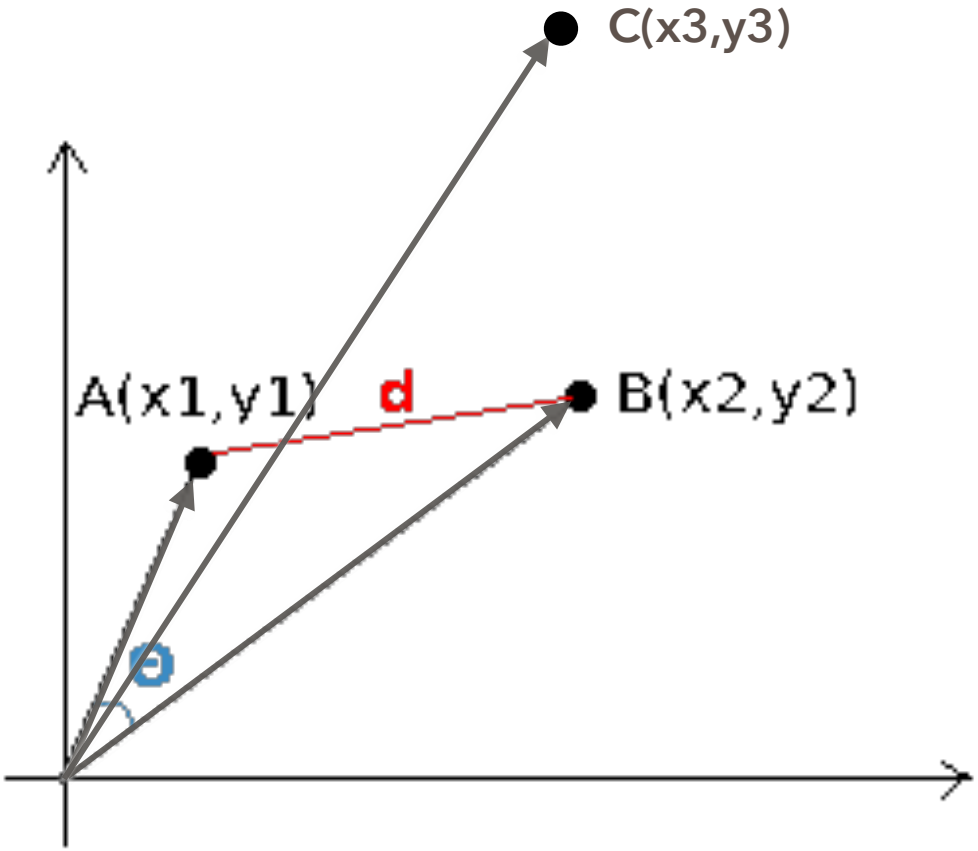
SIMILARIDADE COSSENO

$$cos(\theta) = \frac{\sum x_i * y_i}{\sqrt{\sum x_i^2} * \sqrt{\sum y_i^2}}$$

PEARSON'S R

$$\rho_{xy} = \frac{\sum((x_i - \bar{x}) * (y_i - \bar{y}))}{\sqrt{\sum(x_i - \bar{x})^2} * \sqrt{\sum(y_i - \bar{y})^2}}$$

Exercicio



		
A	1	3
B	4	4
C	4	7

Exercicio

Filtro Colaborativo

FGV MANAGEMENT

UB Collaborative Filtering

u_{ik}

- A collection of user u_i, $i=1, \ldots n$ and a collection of products p_j, $j=1, \ldots, m$
- An $n \times m$ matrix of ratings v_{ij}, with $v_{ij} = ?$ if user i did not rate product j
- Prediction for user i and product j is computed

$$v_{ij}^{*} = K \sum_{v_{kj} \neq ?} u_{jk} v_{kj} \quad \text{or} \quad v_{ij}^{*} = v_i + K \sum_{v_{kj} \neq ?} u_{jk} (v_{kj} - v_k)$$

- Similarity can be computed by Pearson correlation

$$u_{ik} = \frac{\sum_j (v_{ij} - v_i)(v_{kj} - v_k)}{\sqrt{\sum_j (v_{ij} - v_i)^2 \sum_j (v_{kj} - v_k)^2}} \quad \text{or} \quad \cos(u_i, u_j) = \frac{\sum_{k=1}^{m} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{m} v_{ik}^2 \sum_{k=1}^{m} v_{jk}^2}}$$

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https://grouplens.org/blog/similarity-functions-for-user-user-collaborative-filtering/

User-based CF Example

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						sim(u,v)
	2		2	4	5	NA
	5		4			1
			5		2	
		1		5		4
			4			2
	4	5		1		NA

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User-based CF Example

						sim(u,v)
	2		2	4	5	NA
	5		4			1	0.87
			5		2		1
		1		5		4	-1
			4			2	
	4	5		1			NA

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User-based CF Example

						sim(u,v)
	2		2	4	5	NA
	5		4			1
			5		2	1
		1		5		4
	3.51*	3.81*	4	2.42*	2.48*	2
	4	5		1		NA

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