

INSTITUTO FEDERAL
Ceará

Programa de Pós-Graduação
em Ciência da Computação

06 PROBLEMINHAS COMUNS

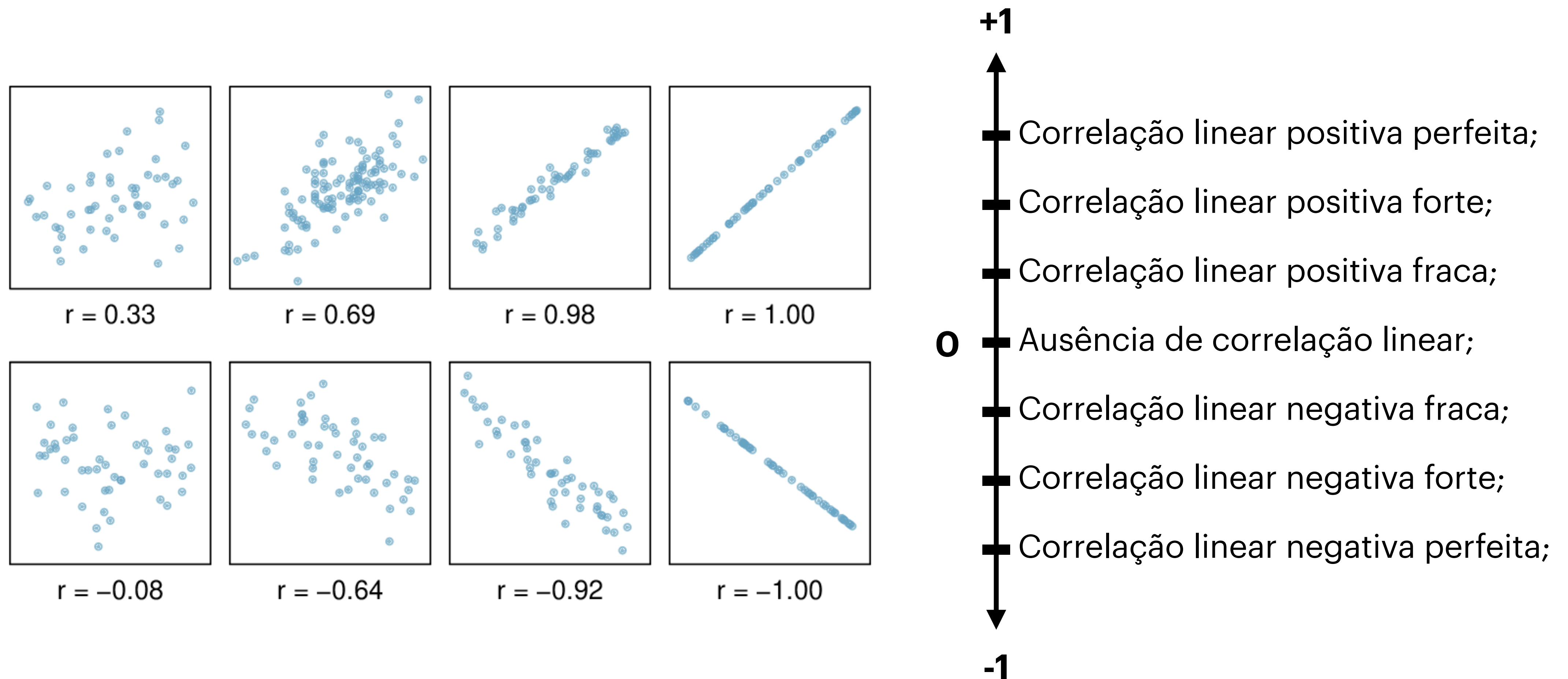
APRENDIZAGEM PROFUNDA

PPGCC – 2023.1

Prof. Saulo Oliveira <saulo.oliveira@ifce.edu.br>



CORRELAÇÃO LINEAR

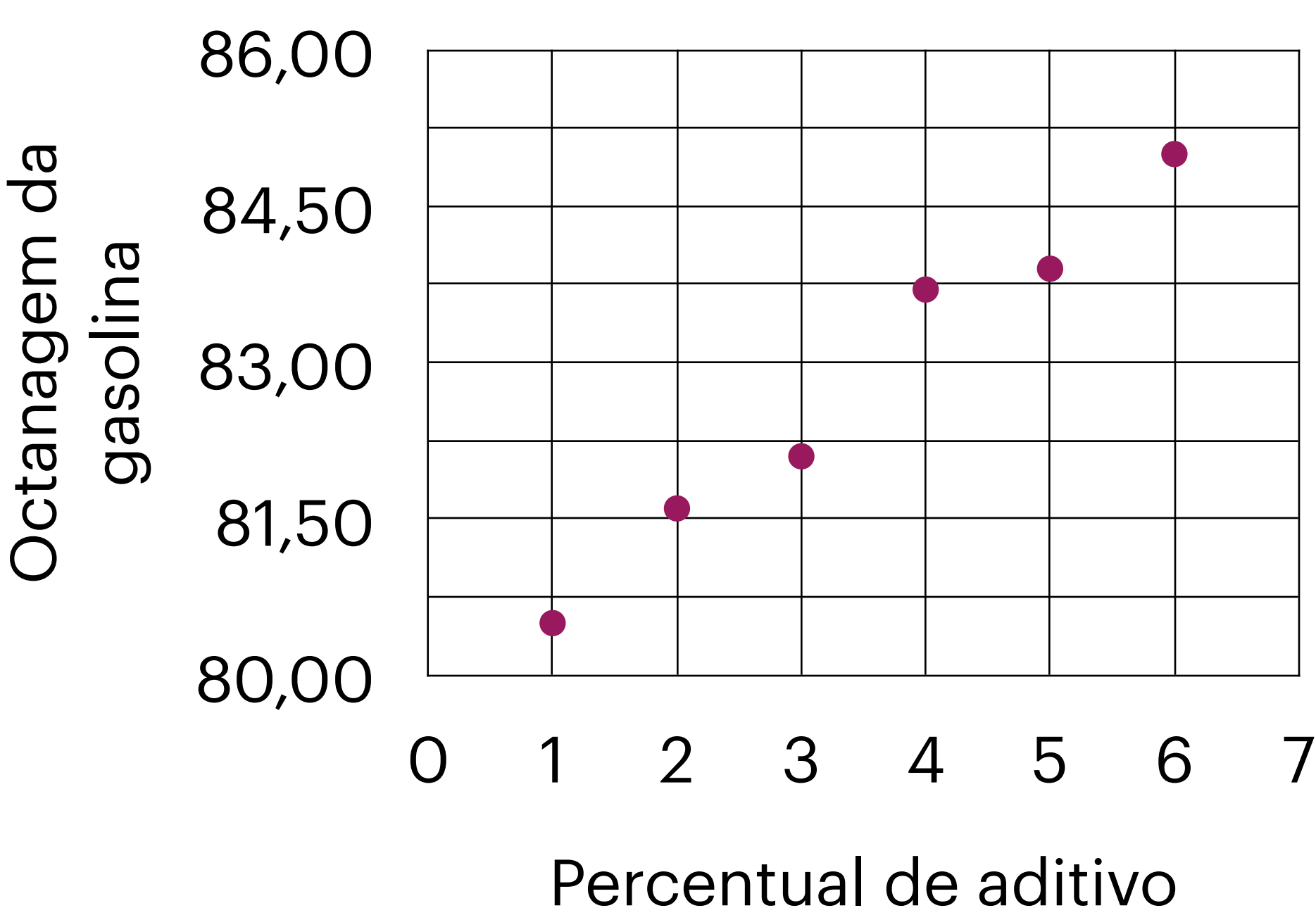


PROBLEMINHAS

EXPERIMENTO 01

Considere um experimento em que se analisa a octanagem da gasolina em função da adição de um aditivo. Para isto, foram realizados ensaios com os percentuais de 1, 2, 3, 4, 5 e 6% de aditivo. Os resultados dos ensaios seguem na Tabela abaixo. Há como descrever, bem, uma relação linear entre estas duas variáveis?

Percentual do aditivo	Octanagem da gasolina
1	80,5
2	81,6
3	82,1
4	83,7
5	83,9
6	85,0



EXPERIMENTO 01

	Percentual do aditivo	Octanagem da gasolina	x ²	x * y
	1	80,5	1	80,5
	2	81,6	4	163,2
	3	82,1	9	246,3
	4	83,7	16	334,8
	5	83,9	25	419,5
	6	85,0	36	510
Σ	21	496,8	91	1754,3

$$\alpha = \frac{n \sum x_i y_i - (\sum x_i)(\sum y_i)}{n(\sum x_i^2) - (\sum x_i)^2}.$$

$$\alpha = \frac{6(1754,3) - (\sum x_i 21)(496,8)}{6(91) - (21)^2}.$$

$$\alpha = 0,886.$$

$$\beta = \frac{\sum y_i - \alpha \sum x_i}{n}.$$

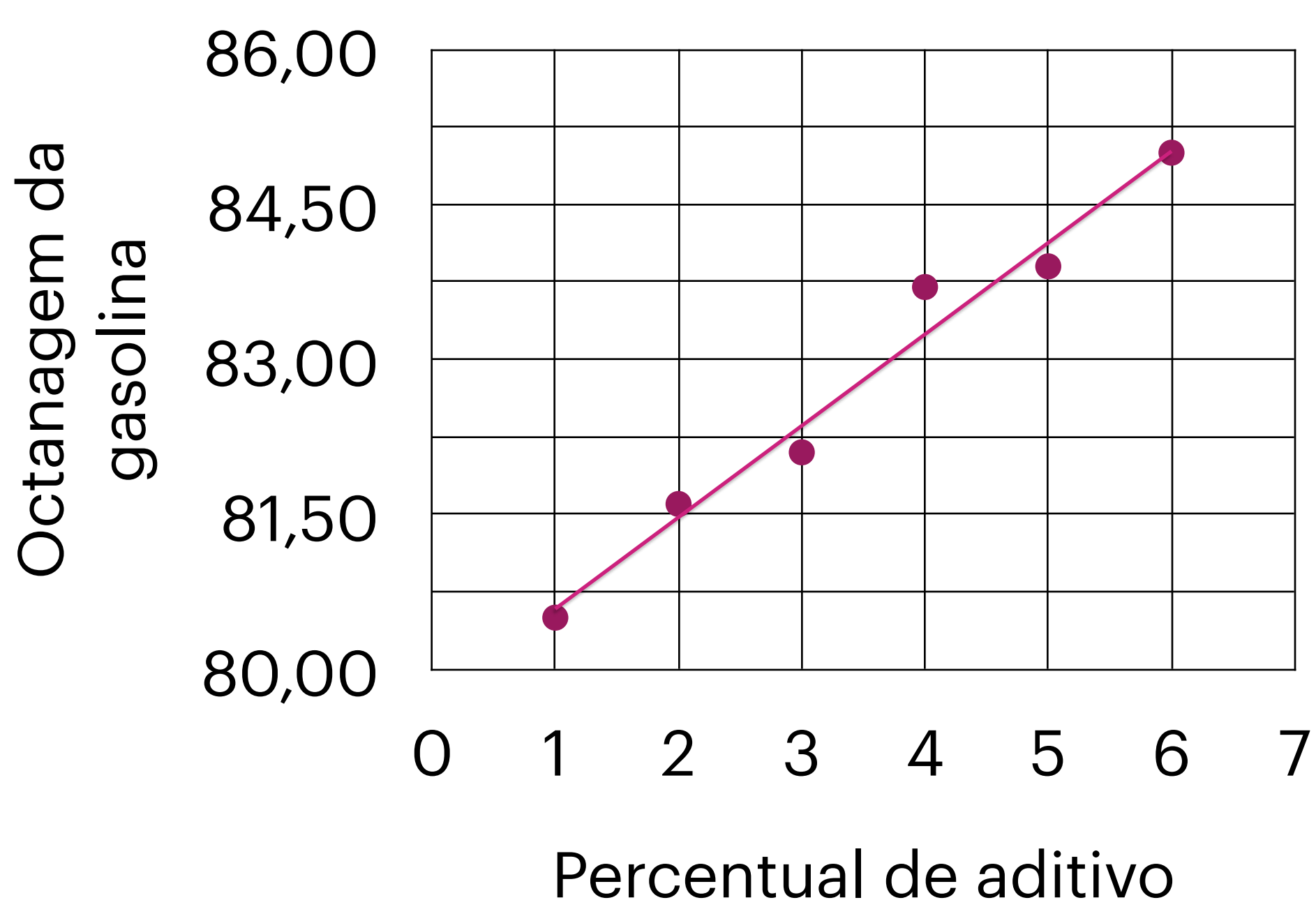
$$\beta = \frac{496,8 - (0,886)(21)}{6}.$$

$$\beta = 79,70.$$

EXPERIMENTO 01

Considere um experimento em que se analisa a octanagem da gasolina em função da adição de um aditivo. Para isto, foram realizados ensaios com os percentuais de 1, 2, 3, 4, 5 e 6% de aditivo. Os resultados dos ensaios seguem na Tabela abaixo. Há como descrever, bem, uma relação linear entre estas duas variáveis?

Percentual do aditivo	Octanagem da gasolina	Predição
1	80,5	80,59
2	81,6	81,47
3	82,1	82,36
4	83,7	83,24
5	83,9	84,13
6	85,0	85,02



PROPRIEDADES E SUPOSIÇÕES

PROPRIEDADES & SUPOSIÇÕES

Ao se adotar essa abordagem de estimação dos parâmetros são feitas as seguintes suposições:

- Que há de verdade um relacionamento linear entre as variáveis;
- A variável independente é oriunda de um processo não-estocástico e é obtida sem nenhum tipo de erro;
- Os erros oriundos do modelo são estatisticamente independentes;
- **Os erros seguem uma distribuição normal com média zero e desvio padrão constante.**

Erros comuns:

- Não verificar a linearidade entre as variáveis;
- **Confundir correlação com causalidade;**
- Confundir o R com R^2 ;

CORRELAÇÕES ESPÚRIAS



COFFEE AND CANCER OF THE PANCREAS

BRIAN MACMAHON, M.D., STELLA YEN, M.D., DIMITRIOS TRICHOPOULOS, M.D., KENNETH WARREN, M.D.,
AND GEORGE NARDI, M.D.

Abstract We questioned 369 patients with histologically proved cancer of the pancreas and 644 control patients about their use of tobacco, alcohol, tea, and coffee. There was a weak positive association between pancreatic cancer and cigarette smoking, but we found no association with use of cigars, pipe tobacco, alcoholic beverages, or tea. A strong association between coffee consumption and pancreatic cancer was evident in both sexes. The association was not affected by controlling for cigarette use. For the sexes combined, there was a significant dose-re-

sponse relation ($P \sim 0.001$); after adjustment for cigarette smoking, the relative risk associated with drinking up to two cups of coffee per day was 1.8 (95 per cent confidence limits, 1.0 to 3.0), and that with three or more cups per day was 2.7 (1.6 to 4.7). This association should be evaluated with other data; if it reflects a causal relation between coffee drinking and pancreatic cancer, coffee use might account for a substantial proportion of the cases of this disease in the United States. (N Engl J Med. 1981; 304:630-3.)



630

BRIAN MACMAHON

Abstract We que-
logically proved c
control patients ab
tea, and coffee. Th
tion between pancr
ing, but we found
pipe tobacco, alcoh
sociation between c

ic cancer was evident in both sexes. The association
was not affected by controlling for cigarette use. For
the sexes combined, there was a significant dose-re-

A. Causal

Observed Association

Coffee
Drinking ↑

Pancreatic
Cancer ↑

B. Due to Confounding

Observed Association

Coffee
Drinking ↑

Smoking

Pancreatic
Cancer ↑

Gordis: Epidemiology, 4th Edition.
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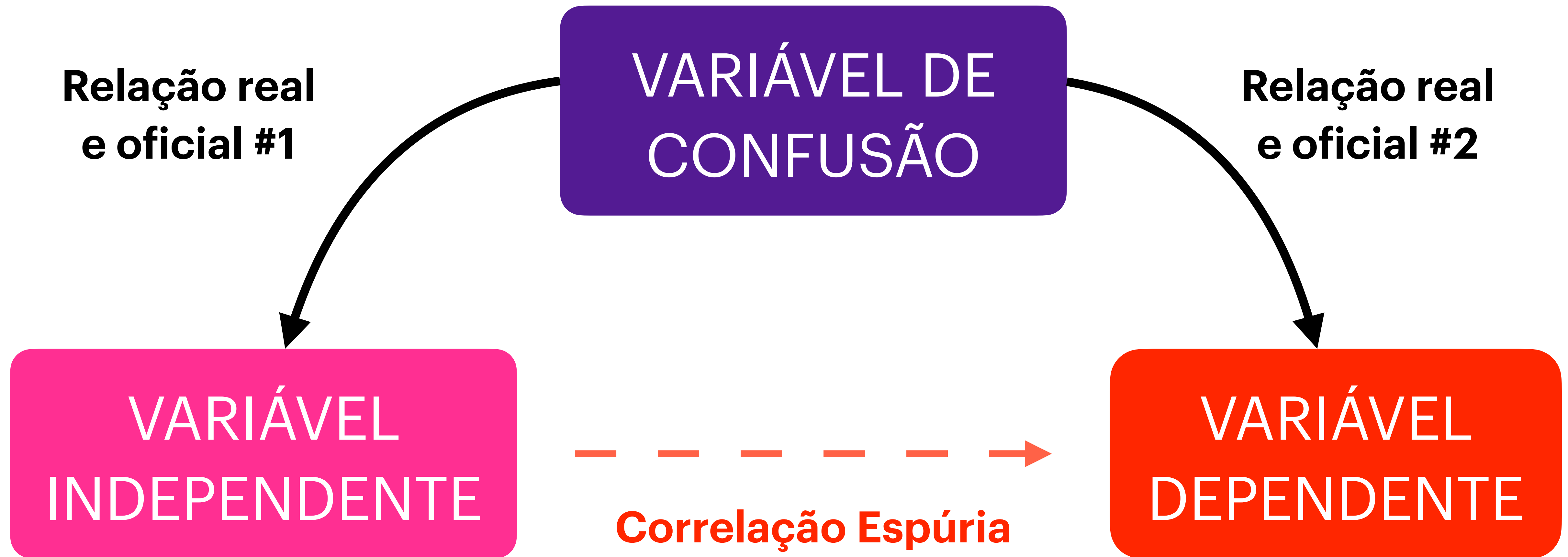
March 12, 1981

TH WARREN, M.D.,

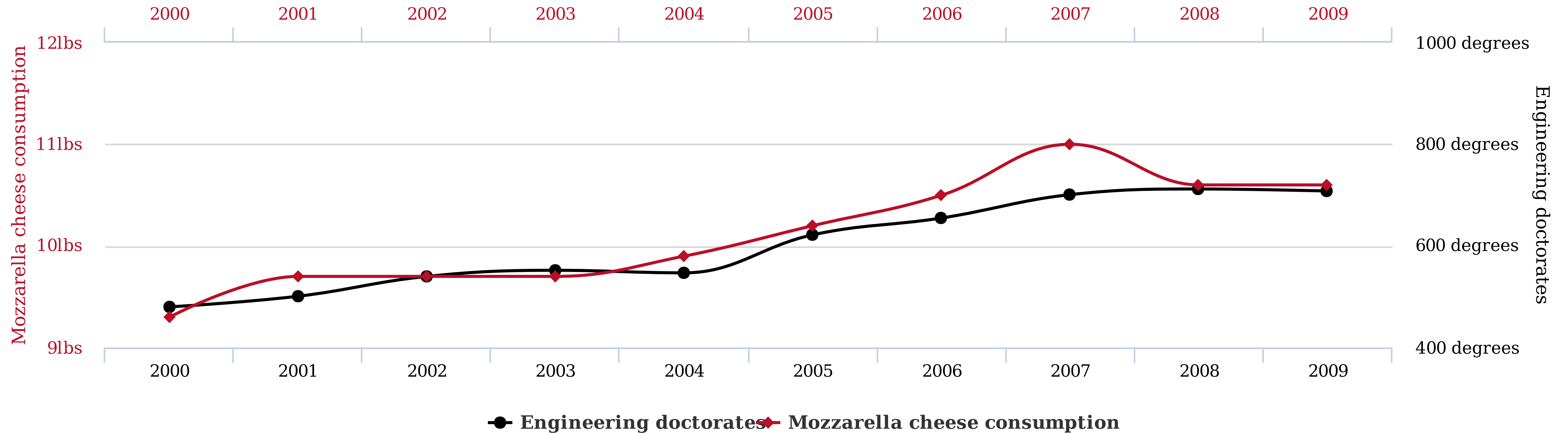
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3.)

CAINDO EM GOLPES



Per capita consumption of mozzarella cheese correlates with Civil engineering doctorates awarded

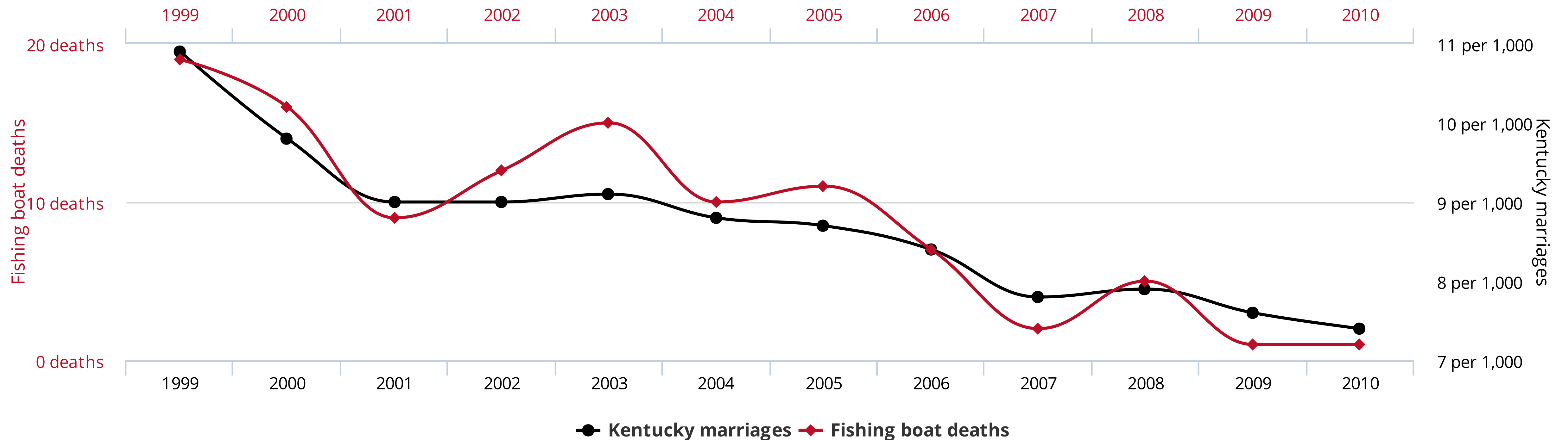


tylervigen.com

$R^2 = 99,79\%$

<http://tylervigen.com/spurious-correlations>

People who drowned after falling out of a fishing boat correlates with Marriage rate in Kentucky

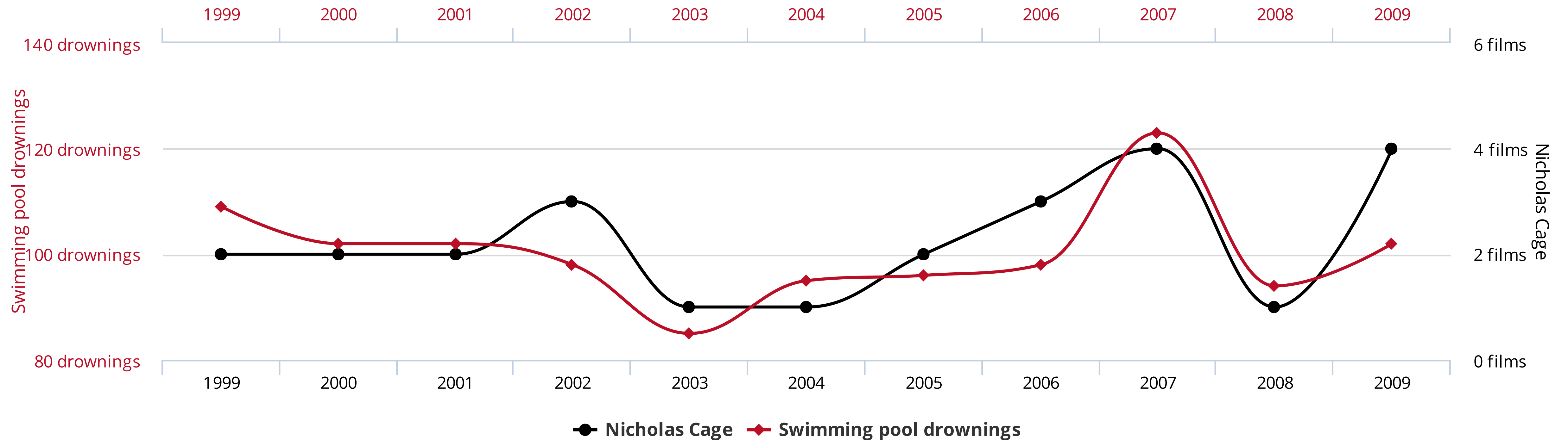


tylervigen.com

$$R^2 = 95,24 \%$$

<http://tylervigen.com/spurious-correlations>

Number of people who drowned by falling into a pool correlates with Films Nicolas Cage appeared in



tylervigen.com

$$R^2 = 66,60\%$$

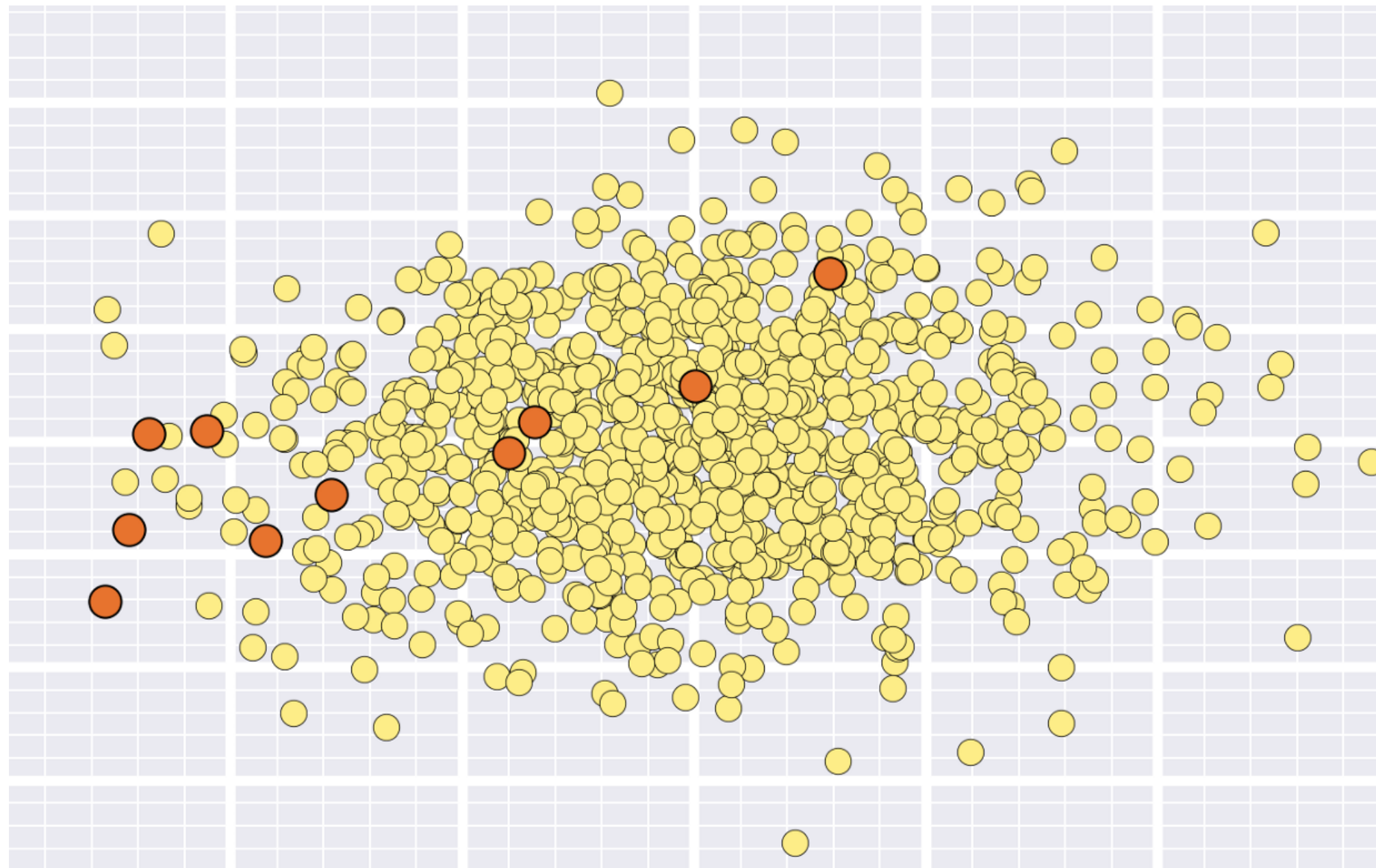
<http://tylervigen.com/spurious-correlations>

É FÁCIL ENCONTRAR PADRÕES
INTERESSANTES ONDE NÃO EXISTEM!

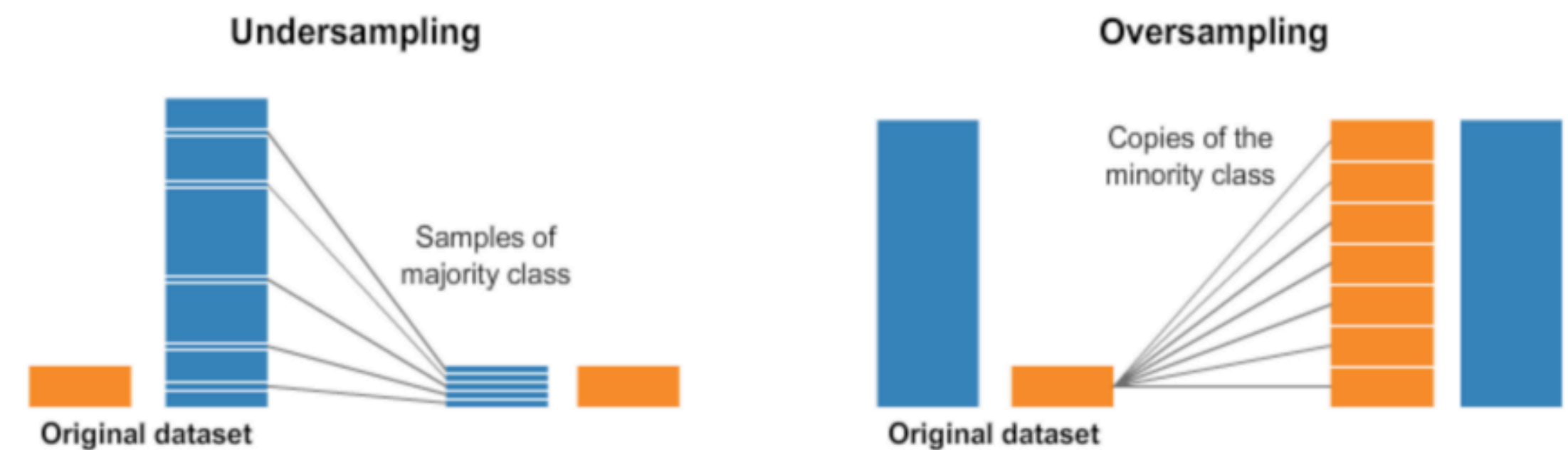
NEM TUDO SÃO ROSAS 🌷 ,
NEM EXISTE BALA DE PRATA 🔫 🎯

**QUANDO O PROBLEMA
TEM DOS DADOS**

DADOS DESBALANCEADOS

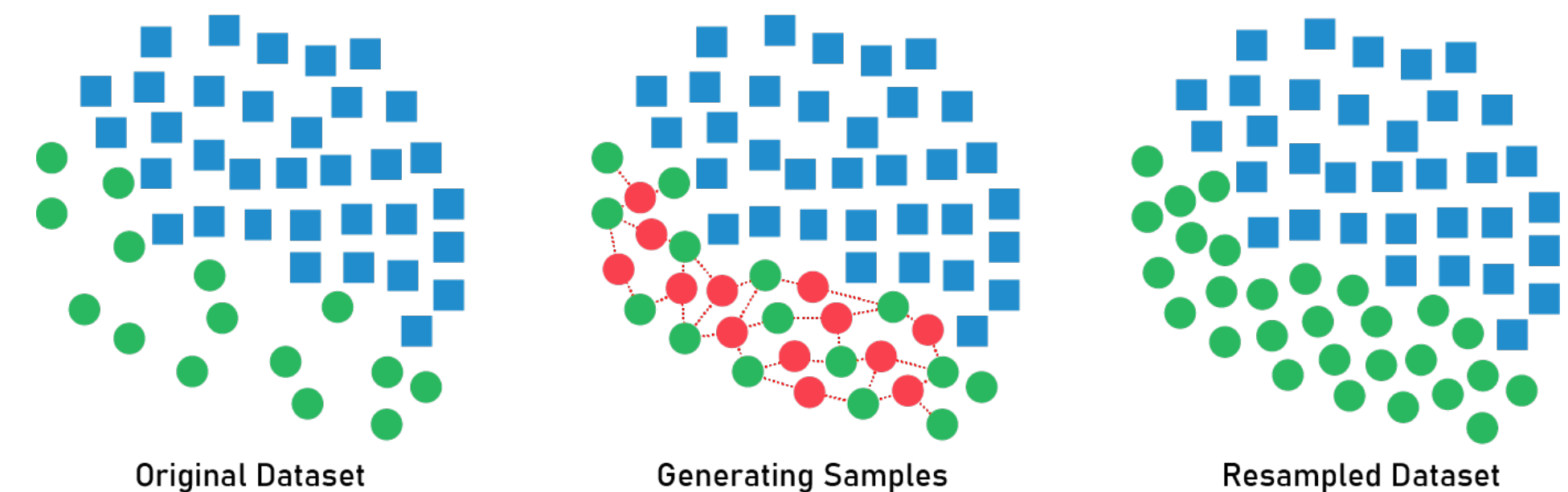


<https://towardsdatascience.com/the-main-issue-with-identifying-financial-fraud-using-machine-learning-and-how-to-address-it-3b1bf8fa1e0c>



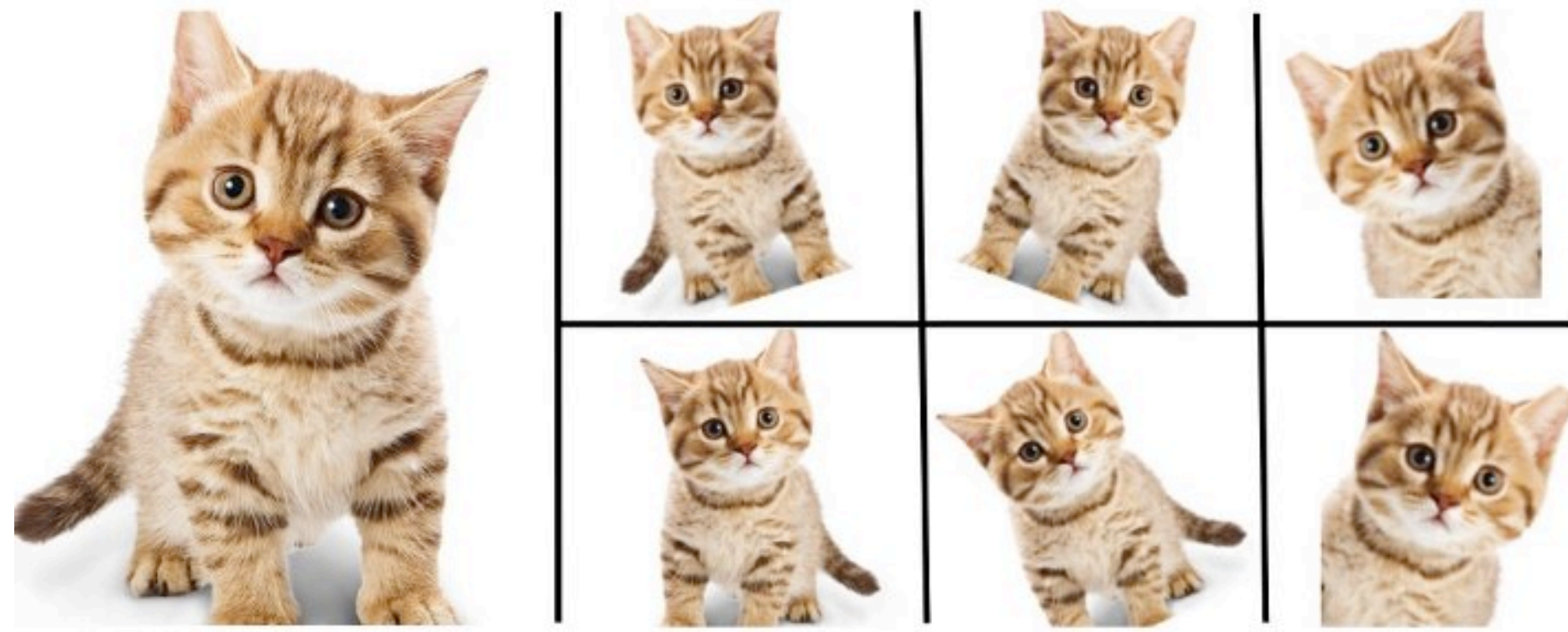
<https://www.kdnuggets.com/2019/05/fix-unbalanced-dataset.html>

Synthetic Minority Oversampling Technique



<https://medium.com/analytics-vidhya/bank-data-smote-b5cb01a5e0a2>

EXPANDINDO O CONJUNTO DE DADOS



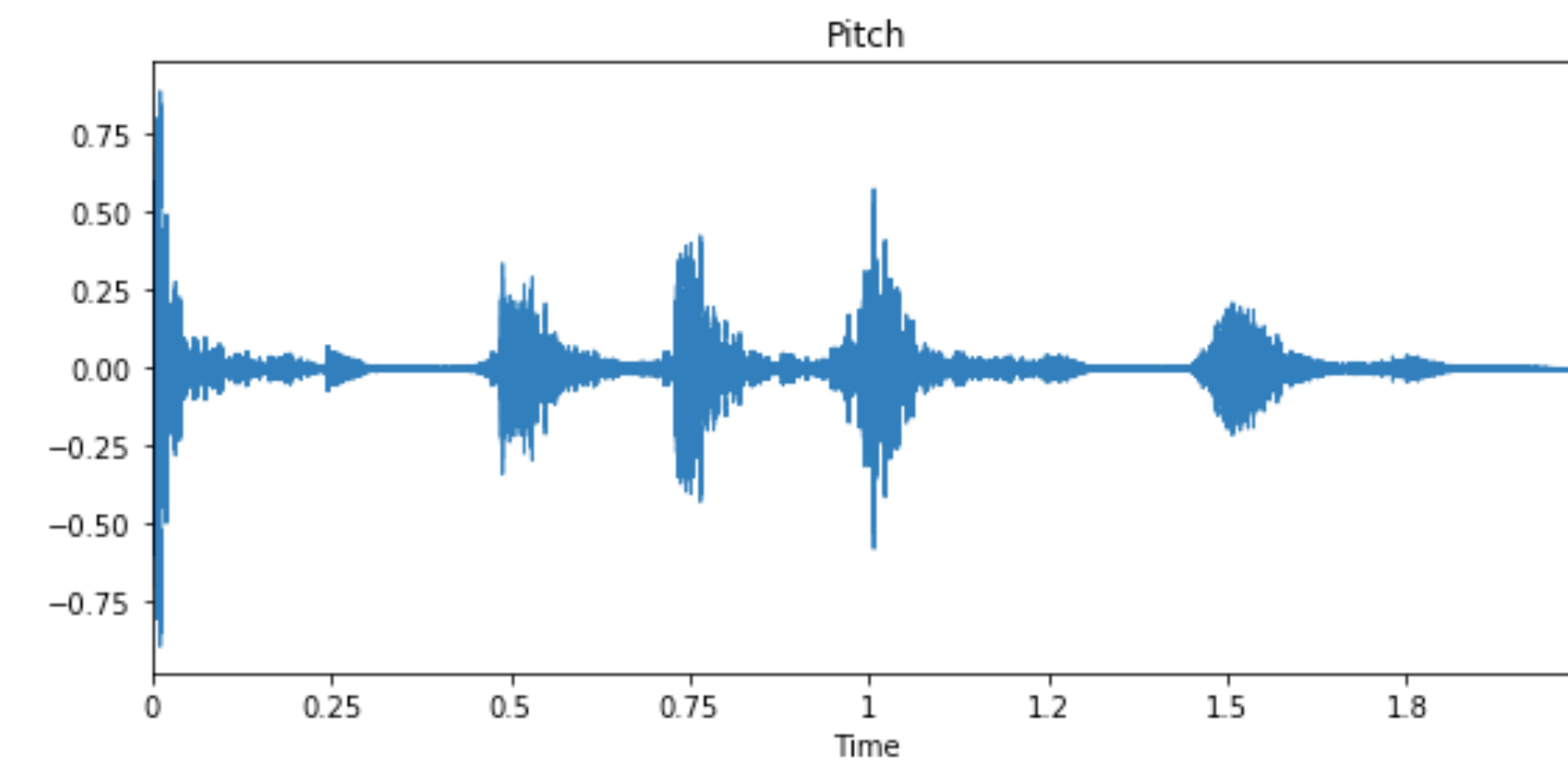
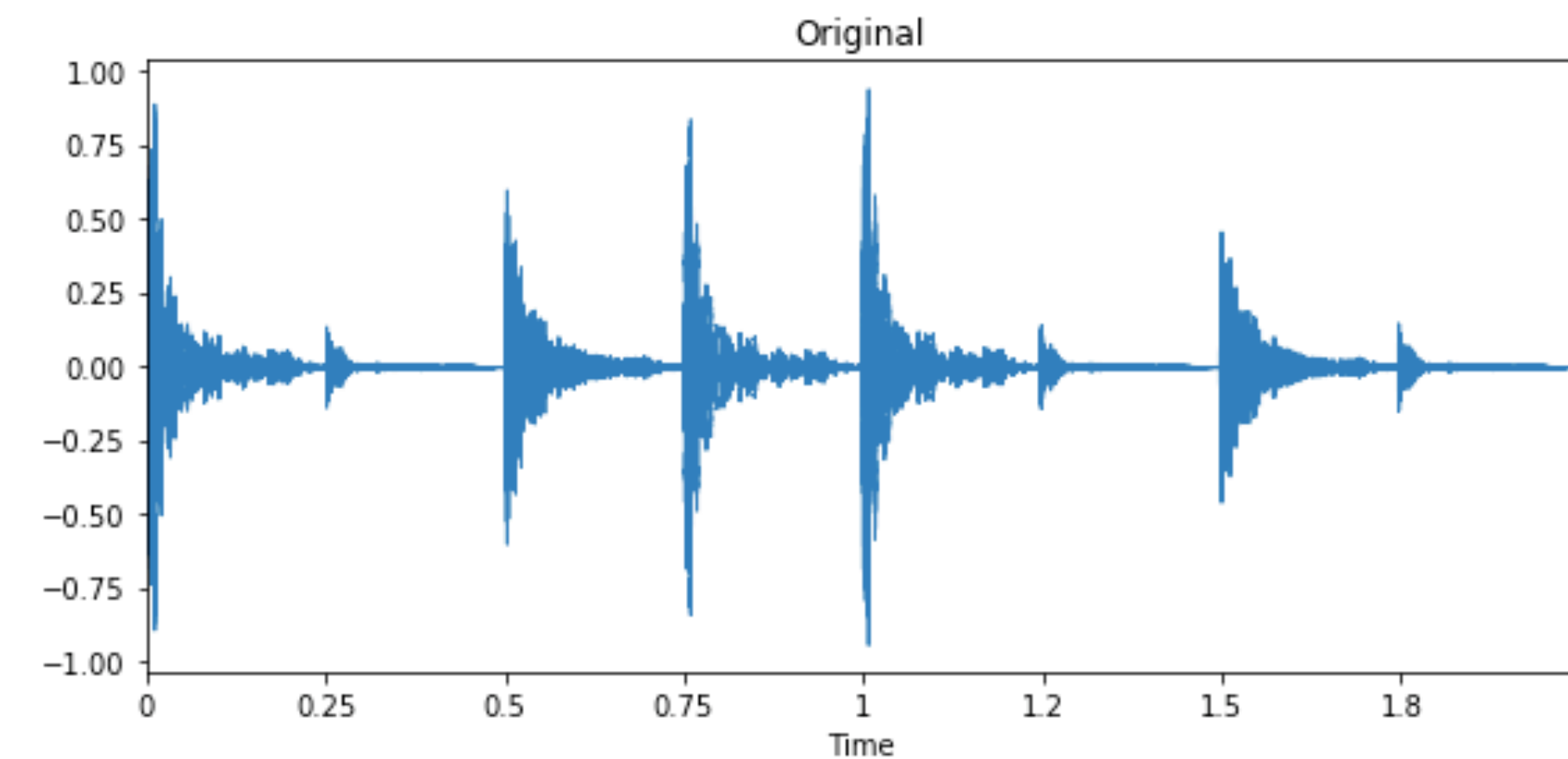
<https://www.kdnuggets.com/2020/02/easy-image-dataset-augmentation-tensorflow.html>

Many customers initiated a return process of the product as it was not suitable for use
Many customers launched a return process of the product as it was not appropriate for use

It was conditioned in very thin box which caused scratches on the main screen
It was packaged in very thin table which provoked scratches on the main screen

The involved firms positively answered their clients who were fully refunded
The involved firms favourably answered their clients who were fully reimbursed

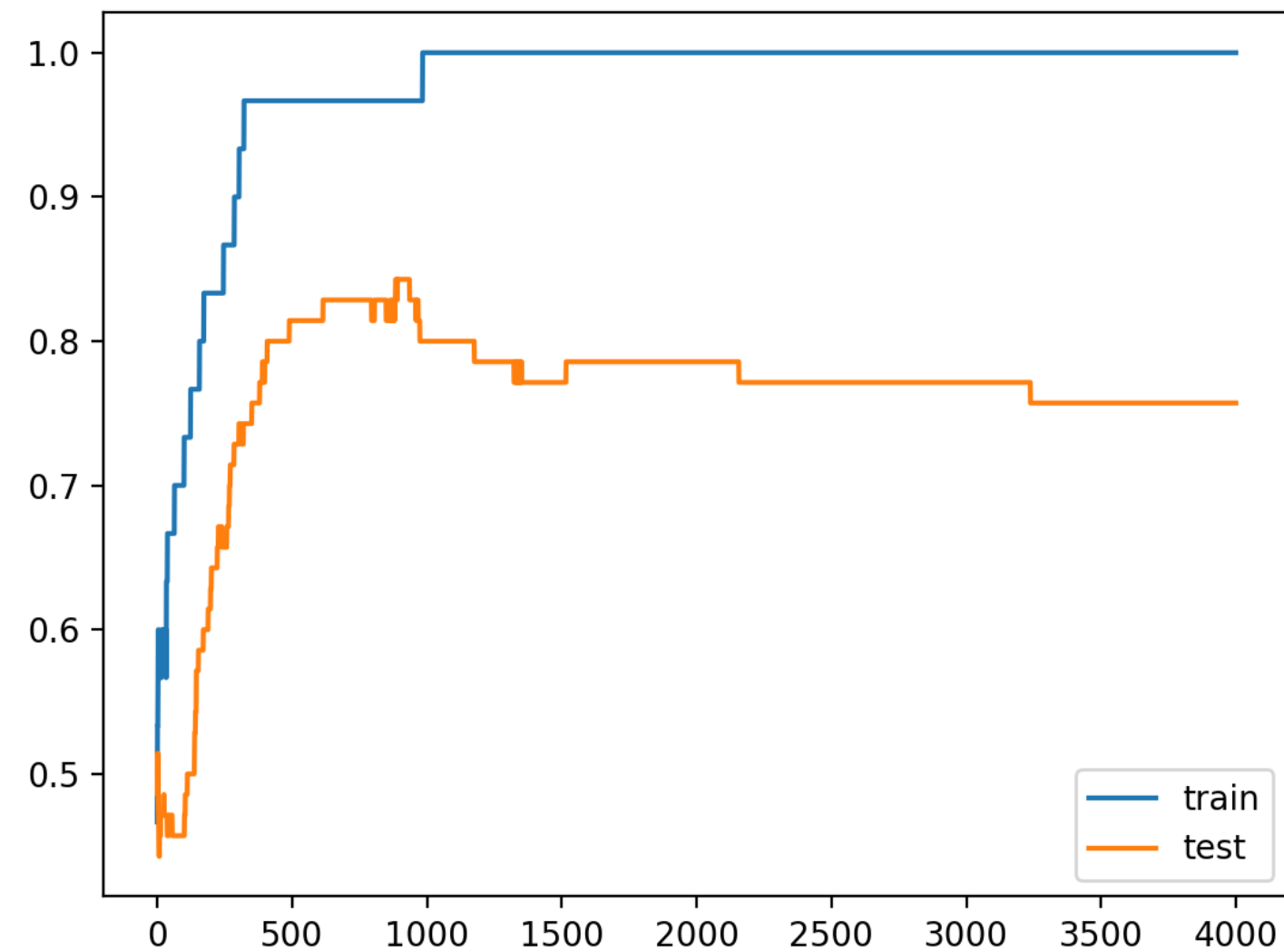
<https://medium.com/opla/text-augmentation-for-machine-learning-tasks-how-to-grow-your-text-dataset-for-classification-38a9a207f88d>



<https://medium.com/@makcedward/data-augmentation-for-audio-76912b01fdf6>

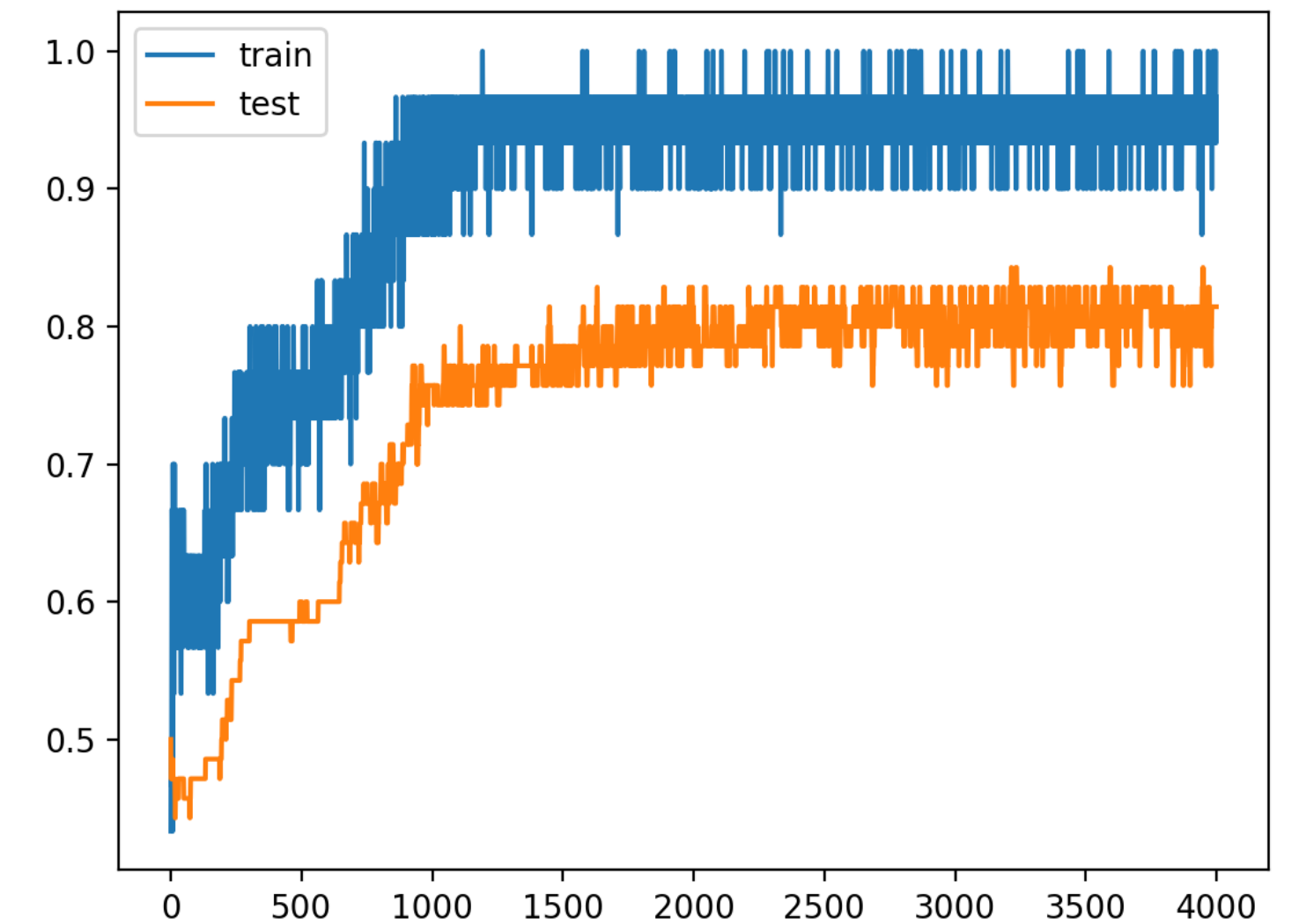
QUANDO VEM DO MODELO

ADICIONANDO RUÍDO NAS CAMADAS OCULTAS



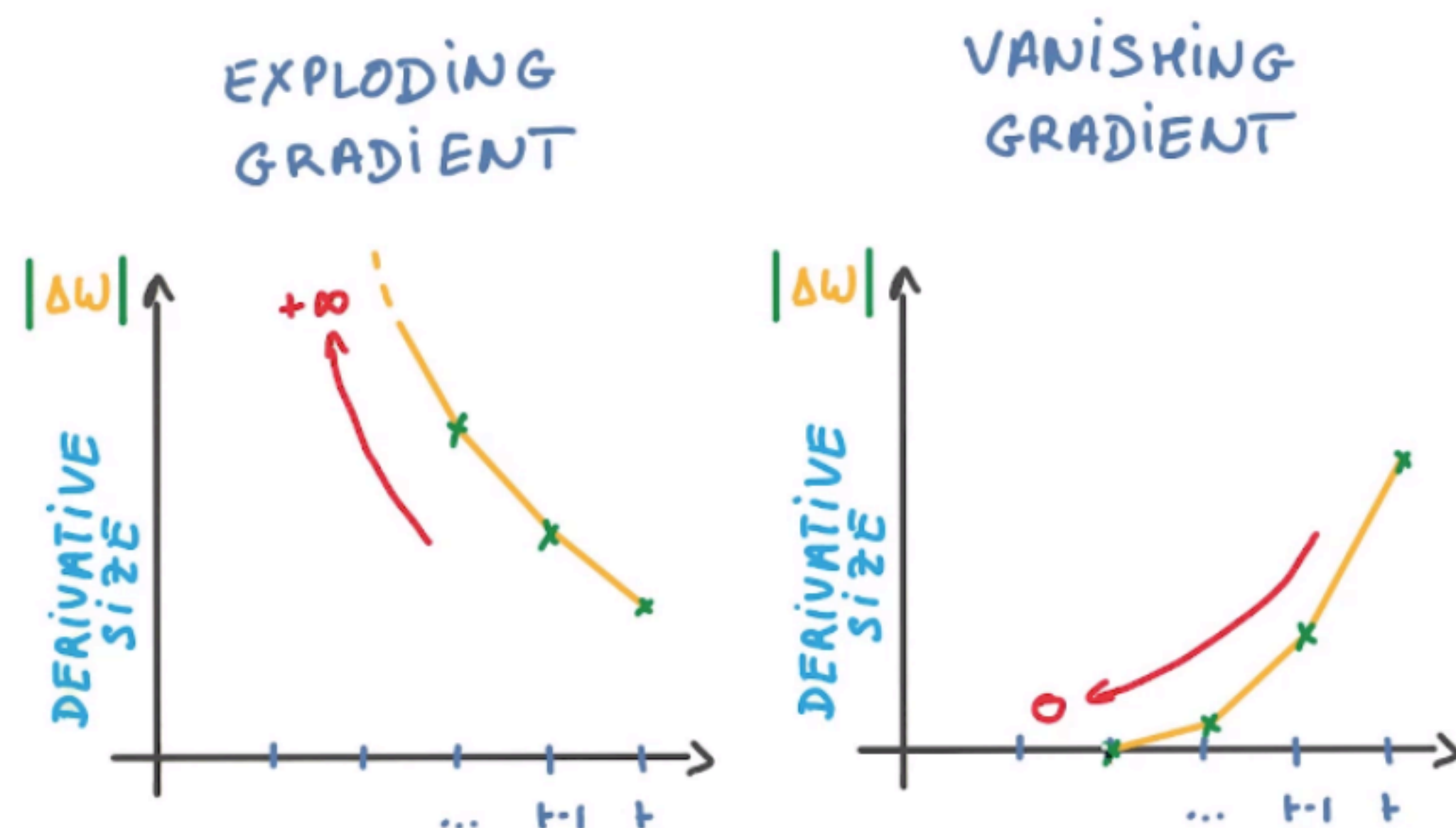
● ● ● PYTHON: MLP WITH HIDDEN LAYER NOISE

```
model = Sequential()  
model.add(Dense(500, input_dim=2))  
model.add(GaussianNoise(0.1))  
model.add(Activation('relu'))  
model.add(Activation(1, activation='sigmoid'))  
model.compile(loss='binary_crossentropy',  
              optimizer='adam',  
              metrics=['accuracy'])
```



<https://machinelearningmastery.com/how-to-improve-deep-learning-model-robustness-by-adding-noise/>

CÁLCULO DO GRADIENTE (1)



$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \Delta \mathbf{w}^{(t)}$$

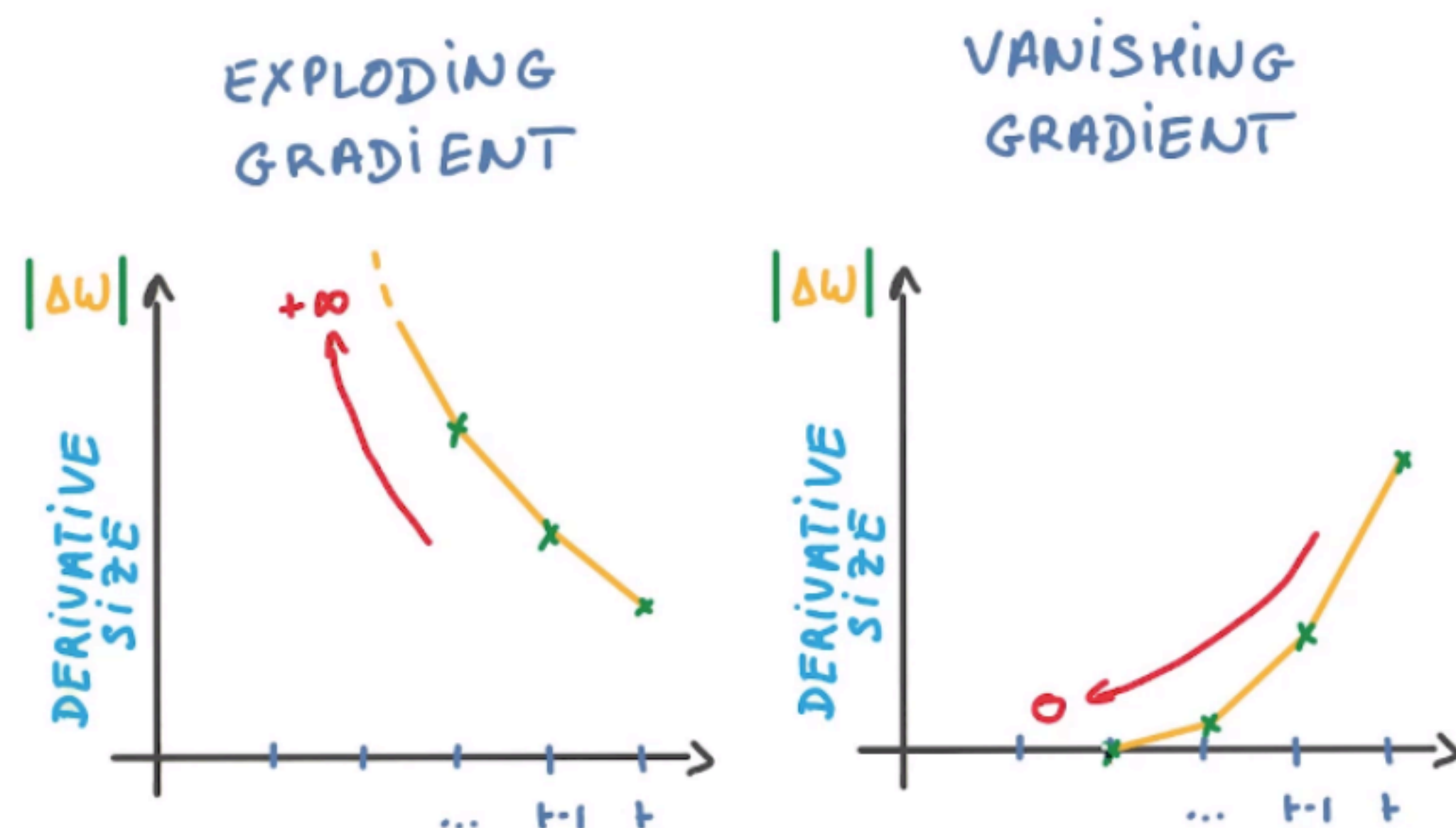
Calcular o $\Delta \mathbf{w}^{(t)}$, geralmente, envolve funções de ativação.

- **Explosão do gradiente:** acúmulo de grandes derivadas faz com que o modelo fique muito instável e incapaz de aprendizado efetivo. Pior cenário $\Delta \mathbf{w}^{(t)} \rightarrow +\infty$, resultando em NaNs;
- **Desaparecimento do gradiente:** acúmulo de pequenos gradientes que resulta em um modelo incapaz de aprender de forma significativa, haja vista que os pesos não serão atualizados efetivamente. Pior cenário com $\Delta \mathbf{w}^{(t)} \rightarrow 0$.

<http://jashish.com.np/blog/posts/practical-aspects-of-deep-learning-part-2/>

<https://towardsdatascience.com/the-vanishing-exploding-gradient-problem-in-deep-neural-networks-191358470c11>

CÁLCULO DO GRADIENTE (2)



$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \Delta \mathbf{w}^{(t)}$$

Calcular o $\Delta \mathbf{w}^{(t)}$, geralmente, envolve funções de ativação.

COMPORTAMENTOS OBSERVADOS QUANDO OCORRE A EXPLOÇÃO DO GRADIENTE:

- Incapacidade de aprender;
- Mudanças abruptas nos valores da função objetivo;
- Alguns NaNs podem aparecer durante treino.

COMPORTAMENTO OBSERVADO QUANDO OCORRE O DESAPARECIMENTO DO GRADIENTE:

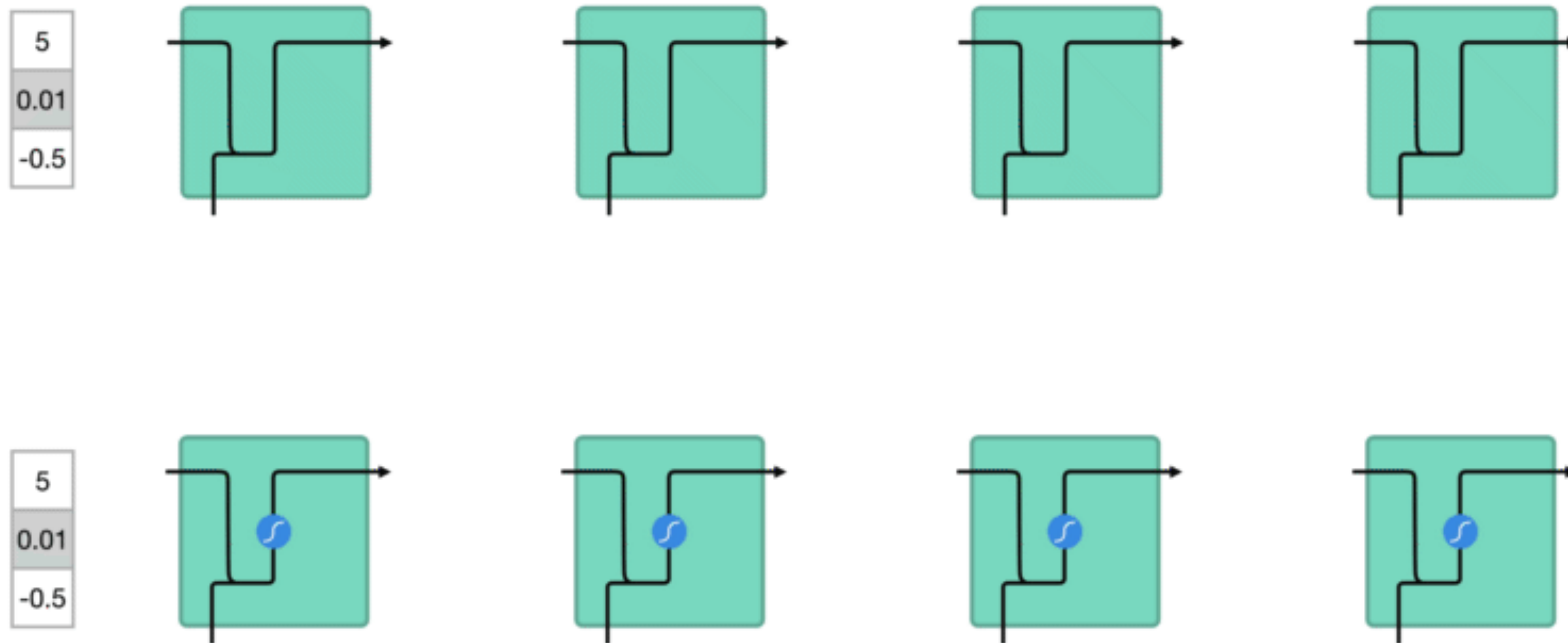
- Convergência lenta;
- Pesos próximos à camada de saída atualizados cp, mais intensidade, enquanto os das camada mais próximas à entrada sofrem mudanças pífias;
- Pesos com valores bem pequenos, chegando a zero.

FUNÇÕES DE ATIVAÇÃO

IMPORTÂNCIA

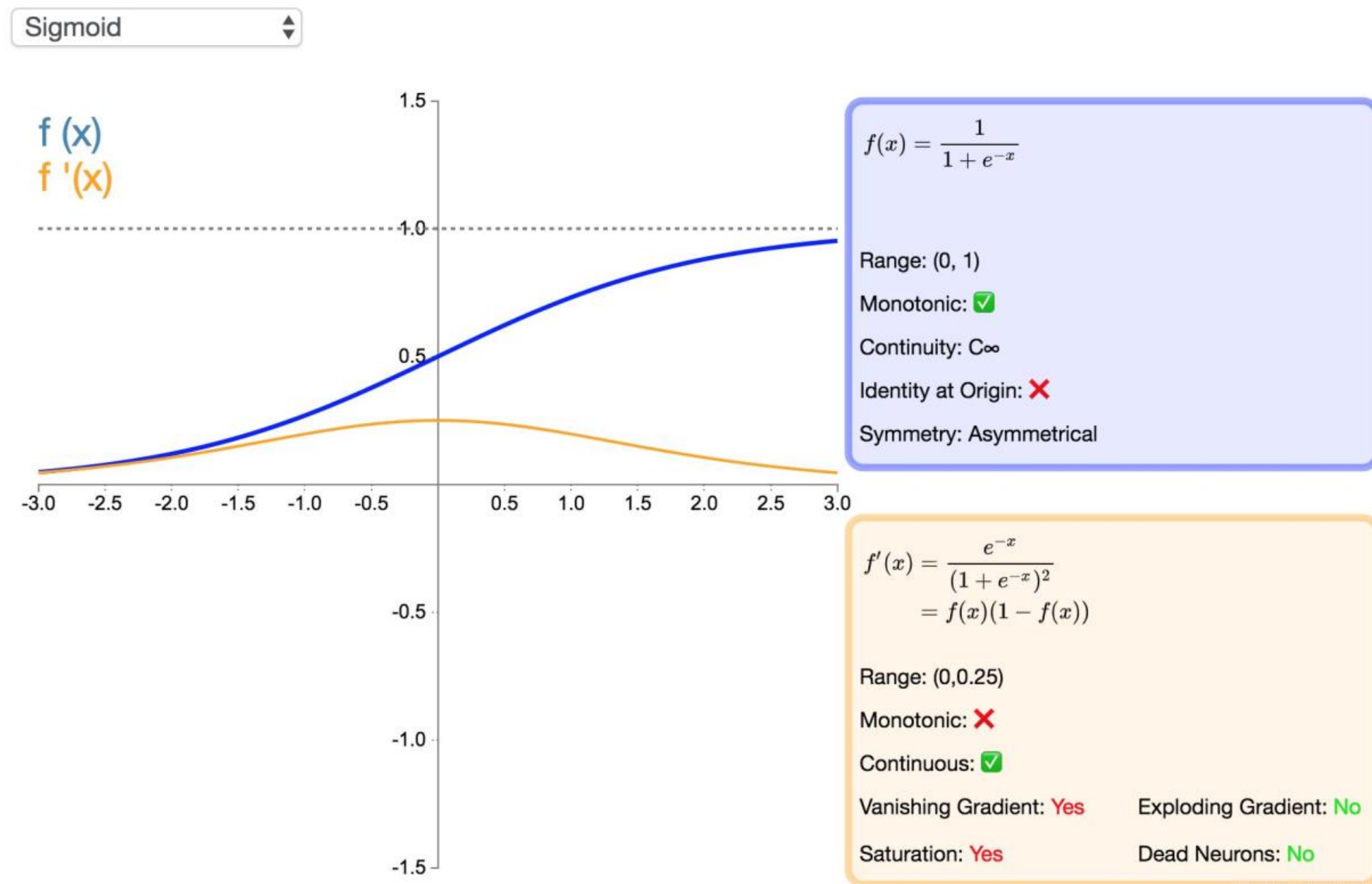
- As funções de ativação permitem que pequenas mudanças nos pesos e viés causem apenas uma pequena alteração na saída do neurônio (e da rede);
- Eles permitem a introdução de recursos não lineares na rede. Assim, as funções de ativação são cruciais para o modelo de rede neural aprender e entender funções não lineares complexas;
- Sem funções de ativação, as saídas são apenas funções lineares simples (Alô, Adaline!). A complexidade das funções lineares é limitada. Logo, a capacidade de aprender mapeamentos de funções complexas a partir de dados é baixa;

IMPORTÂNCIA

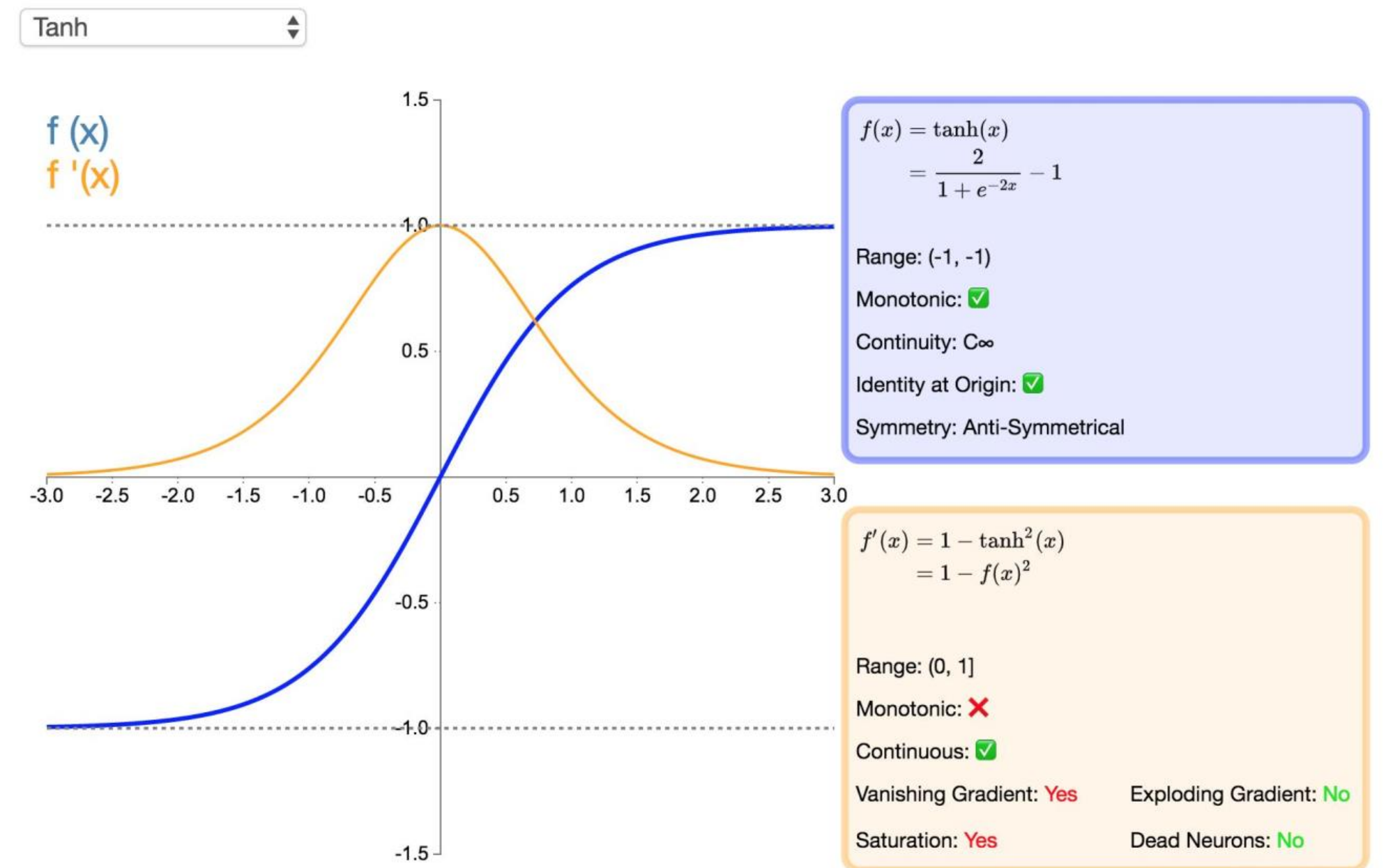


AS FAMOSINHAS

Sigmoid



Tangente hiperbólica



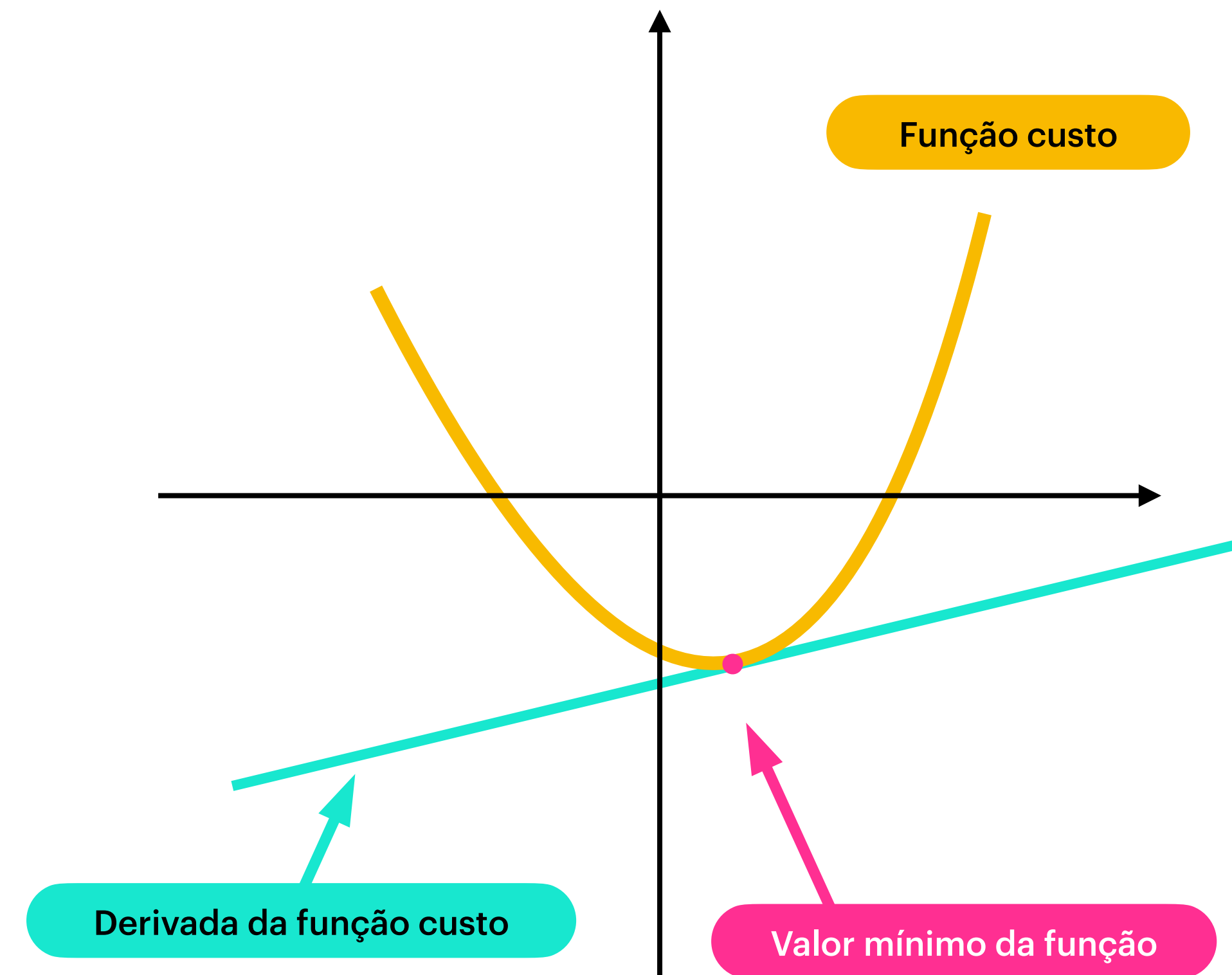
TREINANDO UM ADALINE (Recap)

- Premissa básica: achar o vetor de pesos que minimize o TODOS os erros;
- Forma de calcular o erro continua a mesma, i.e., $e = d - y = d - \varphi(\mathbf{x}^T \mathbf{w})$.
- Agregar TODOS os erros em uma função só:

$$J(\mathbf{e}) = \sum_i e_i^2.$$

$$J(\mathbf{w}) = \sum_i \left(d_i - \varphi(\mathbf{x}_i^T \mathbf{w}) \right)^2.$$

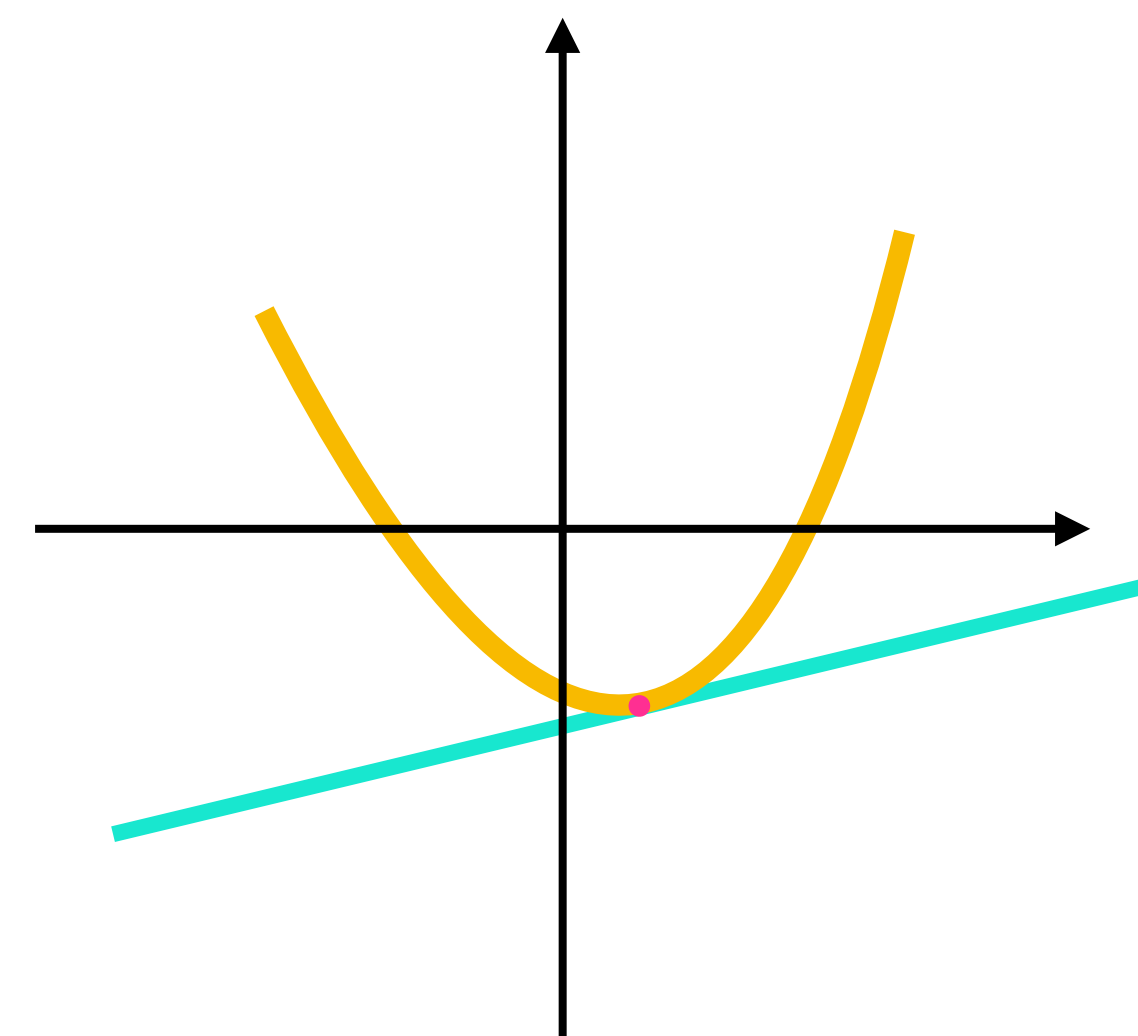
$$\mathbf{w}^\star = \min_{\mathbf{w}} J(\mathbf{w})$$



TREINANDO UM ADALINE (Recap)

- Com o intuito de minimizar $J(\mathbf{w})$, é necessário que seja obtido a direção do ajuste a ser aplicado no vetor de pesos para aproximar a solução do mínimo de $J(\mathbf{w})$;
- De modo iterativo, iremos realizar $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \Delta \mathbf{w}$;
- Para tal, usa-se o **gradiente** da função $J(\mathbf{w})$ no ponto $\mathbf{w}^{(t)}$;
- Sabe-se que o gradiente possui a mesma direção da maior variação do erro (aponta na direção do crescimento da função). Portanto, o ajuste deve ocorrer na direção contrária do gradiente. Logo a variação dos pesos pode ser descrita como:

$$\Delta \mathbf{w} \propto - \nabla \mathbf{w}.$$



TREINANDO UM ADALINE (Pulo do)

- Sabe-se que a função J depende de e , bem como sabe-se que e depende de y e, ainda, sabe-se que y depende de φ que depende de \mathbf{w} . Logo, regra da cadeia:

$$\frac{\partial J}{\partial w_i} = \frac{\partial J}{\partial e_i} \frac{\partial e_i}{\partial y_i} \frac{\partial y_i}{\partial w_i}, \quad \text{em que} \quad J(\mathbf{w}) = \frac{1}{2} \sum_i \left(d_i - \varphi(\mathbf{x}_i^\top \mathbf{w}) \right)^2.$$

- Quanto valem os termos abaixo?

$$\text{a) } \frac{\partial J}{\partial e_i} = 2e_i$$

$$\text{b) } \frac{\partial e_i}{\partial y_i} = -\varphi'(\mathbf{x}_i^\top \mathbf{w})$$

$$\text{c) } \frac{\partial y_i}{\partial w_i} = \mathbf{x}_i$$

$$\text{d) } \frac{\partial J}{\partial w_i} = -e_i \varphi'(\mathbf{x}_i^\top \mathbf{w}) x_i$$

- Adicionalmente:

$$\text{a) } \text{sigmoid}'(u) = \text{sigmoid}(u)(1 - \text{sigmoid}(u))$$

$$\text{b) } \tanh'(u) = 1 - \tanh^2(u)$$

TREINANDO UM ADALINE (Pulo do)

- Considerando que

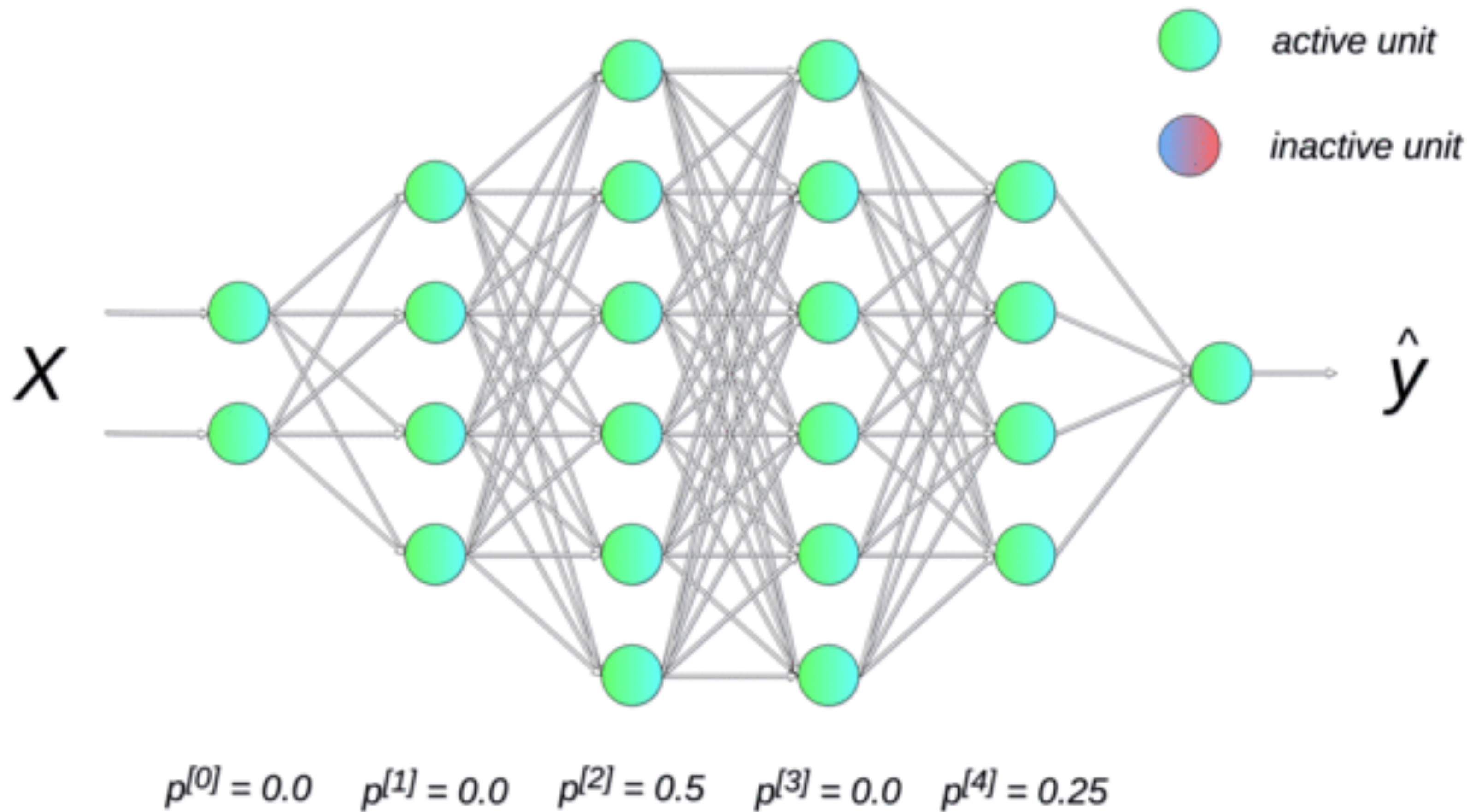
$$\begin{array}{llll} \text{a) } \frac{\partial J}{\partial e_i} = 2e_i & \text{b) } \frac{\partial e_i}{\partial y_i} = -\varphi'(\mathbf{x}_i^\top \mathbf{w}) & \text{c) } \frac{\partial y_i}{\partial w_i} = \mathbf{x}_i & \text{d) } \frac{\partial J}{\partial w_i} = -e_i \varphi'(\mathbf{x}_i^\top \mathbf{w}) x_i \end{array}$$

- Considerando também a regra de aprendizagem $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \Delta \mathbf{w}$;
- Considerando que $\Delta \mathbf{w} \propto \nabla J$ e que $\frac{\partial J}{\partial \mathbf{w}} = -e \varphi'(\mathbf{x}^\top \mathbf{w}) \mathbf{x}$, podemos reescrever a regra de atualização da seguinte forma:

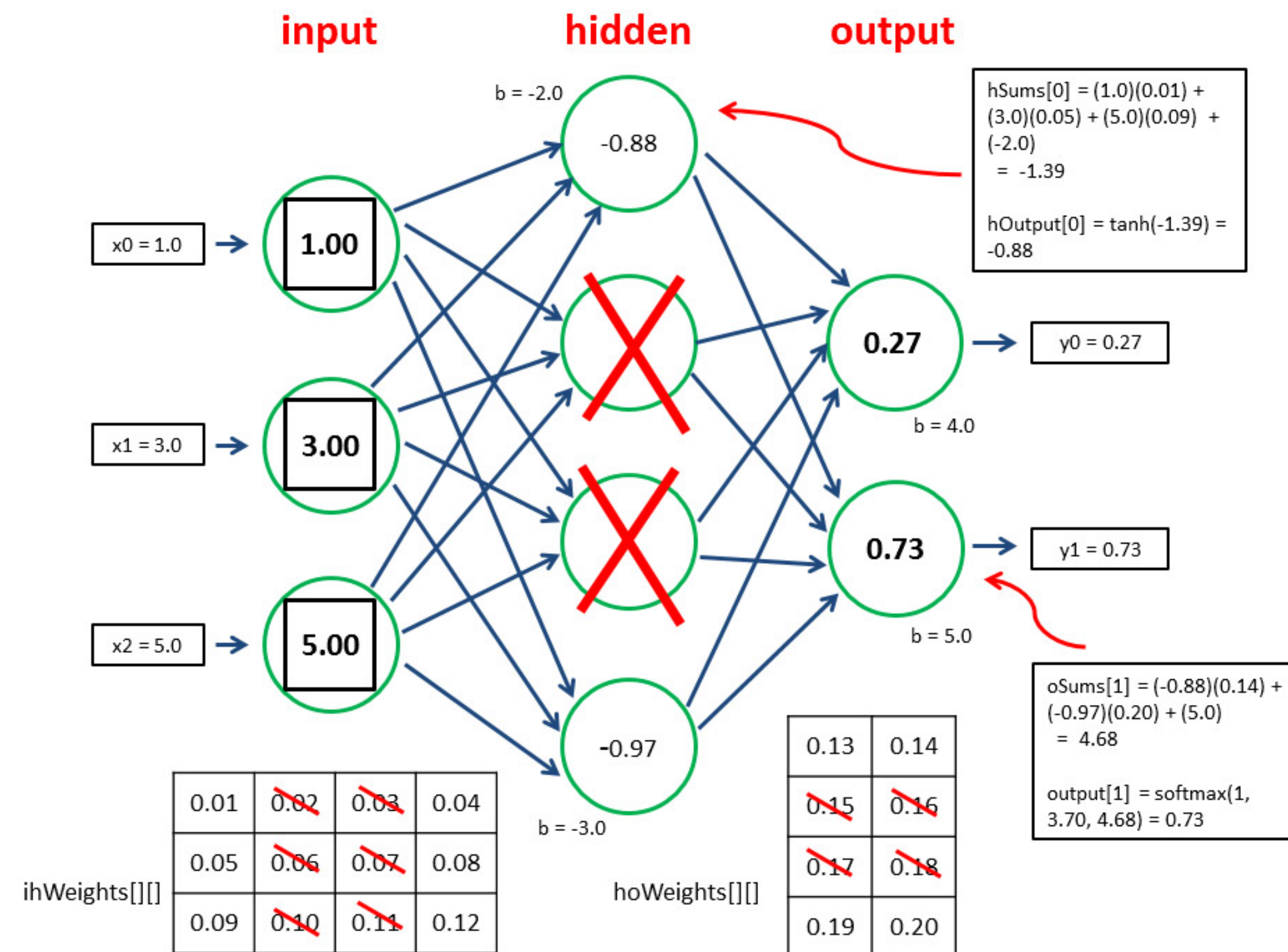
$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \eta e^{(t)} \varphi'(\mathbf{x}^\top \mathbf{w}^{(t)}) \mathbf{x}.$$

VOLTANDO AO MODELO

DROPOUT (1)

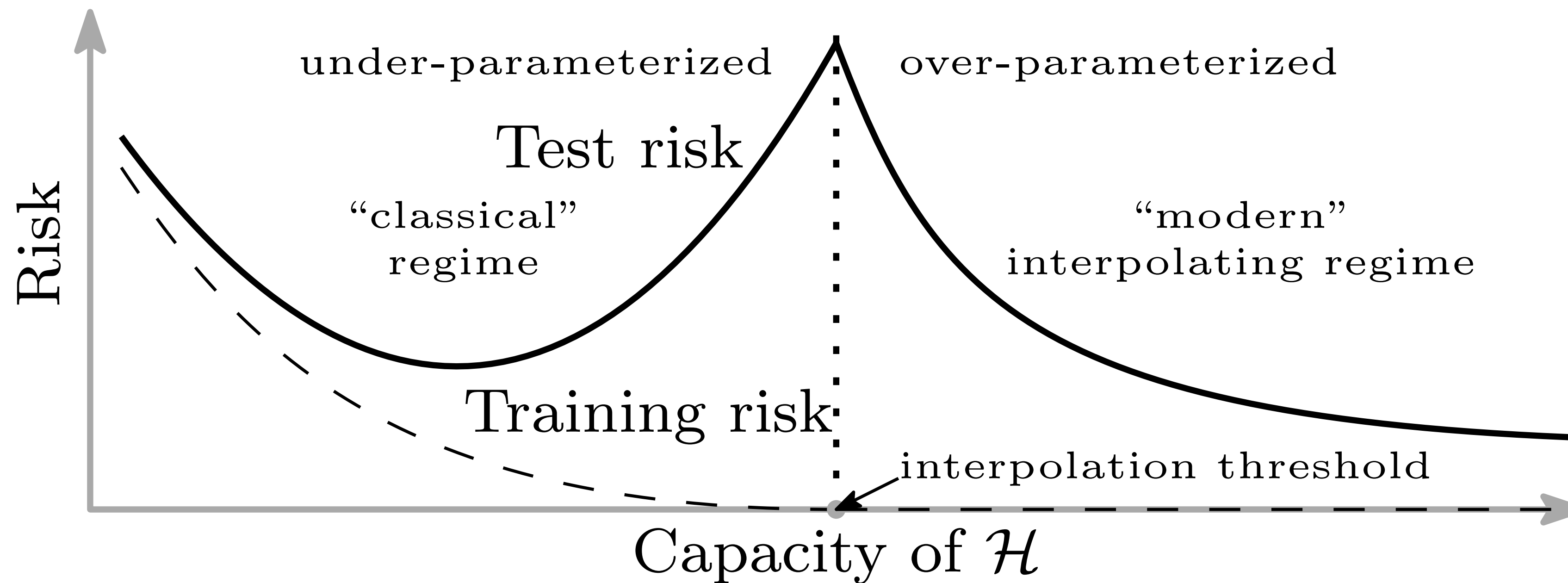


DROPOUT (2)



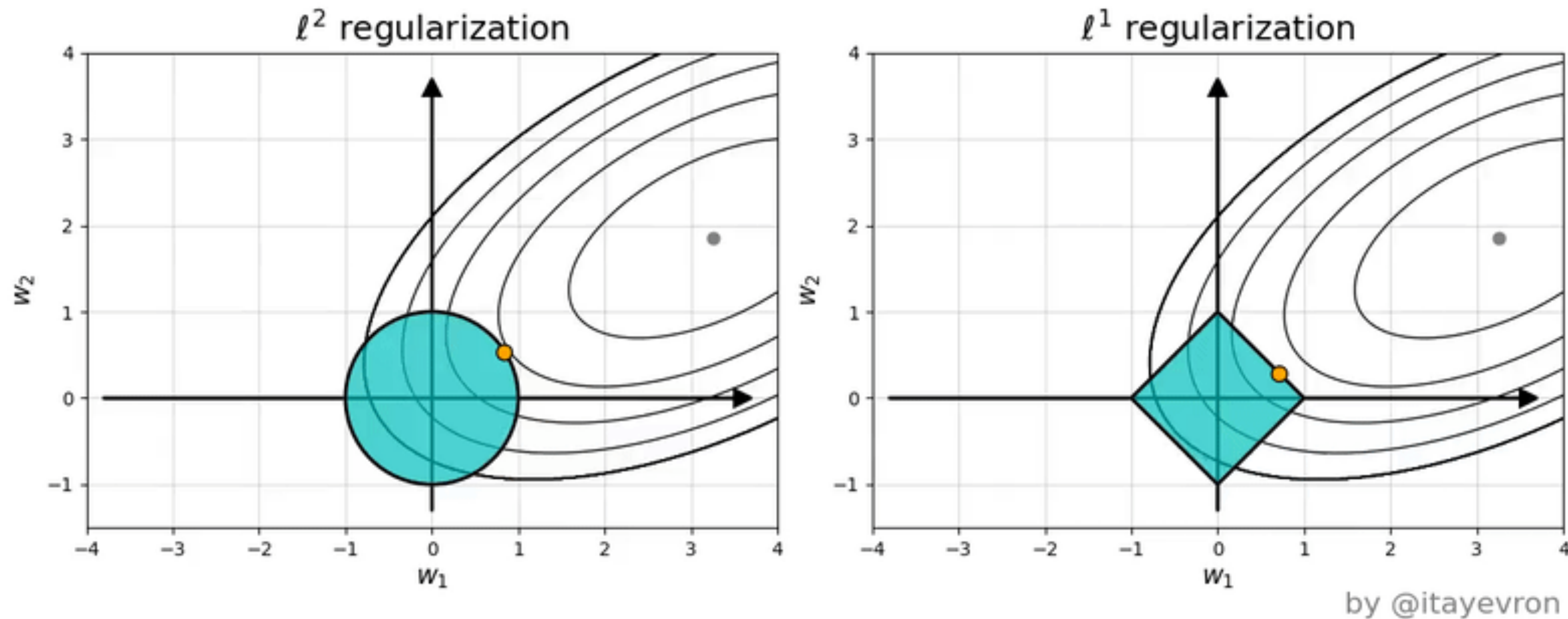
- Agora, imagine que terminamos o treinamento e removemos o *Dropout*. Agora as ativações dos neurônios de saída serão computadas com base em quatro valores da camada oculta. Isso provavelmente colocará os neurônios de saída em regime incomum, de modo que eles produzirão valores absolutos muito grandes, sendo superexcitados;
- Para evitar isso, o truque é multiplicar os pesos das conexões de entrada da última camada por $1-p$ (portanto, por 0,5);
- Alternativamente, pode-se multiplicar as saídas da camada oculta por $1-p$, que é basicamente a mesma coisa.

REGULARIZAÇÃO (1)



REGULARIZAÇÃO (1)

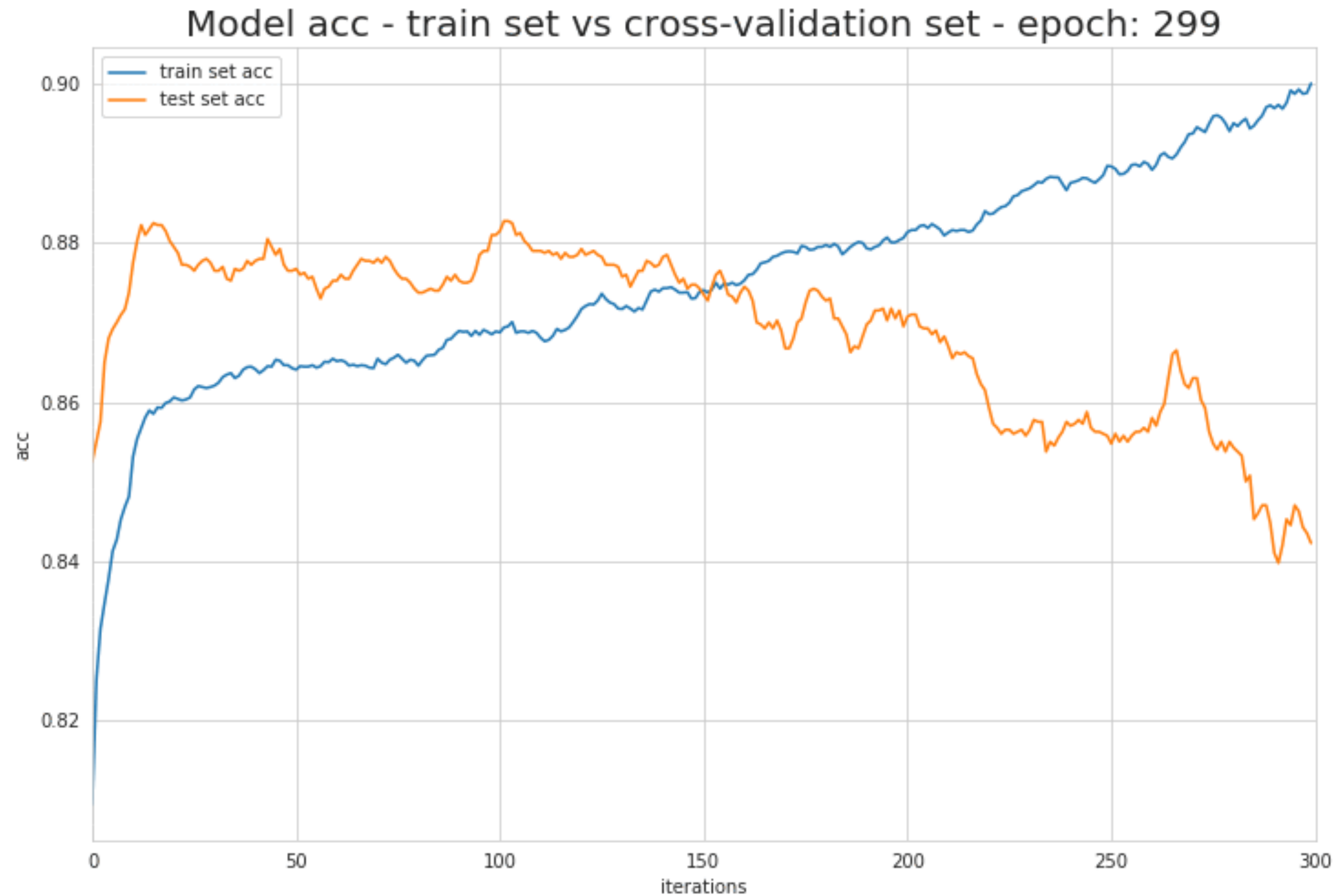
ℓ^1 induces sparse solutions for least squares



$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \underbrace{\eta \mathbf{w}^{(t)} + (1 - \alpha \eta) \nabla J(\mathbf{w}^{(t)})}_{\Delta \mathbf{w}^{(t)}}$$

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \underbrace{\eta \nabla J(\mathbf{w}^{(t)}) + \alpha \text{sign}(\mathbf{w}^{(t)})}_{\Delta \mathbf{w}^{(t)}}$$

PARADA PRECOCE



Referências (1)

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Referências (2)

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