

BREVE HISTÓRICO DAS REDES NEURAIS... ATÉ HOJE



Prof. Saulo Oliveira
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Apresentação do palestrante

Saulo A. F. Oliveira



Graduação em Ciência
da Computação

IFCE

Curso técnico em
Desenvolvimento
de Software

IFCE

Era de ouro ⚡

Microsoft
TechEd

**Fiz curso
nos EUA** 🇺🇸

Mestrado em
Engenharia de
Telecom.

IFCE

Iniciei o Doutorado
na UFC na área de
Inteligência Artificial

UFC

ELAP

**Fui estudar
no Canadá** 🇨🇦

Virei professor
do IFCE

**Voltei do
Canadá** 🇨🇦

Coordenador

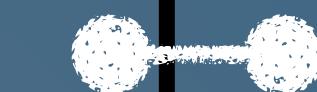
**Informática
para Internet**

Concluí o
Doutorado!

Virei Dr.

Estamos aqui!

Neve!! 🎅



Pandemia 🦠



Tianguá

Trabalhando com pesquisa e desenvolvimento

2006

2009

2013

2015

2019

2020

2021

2022

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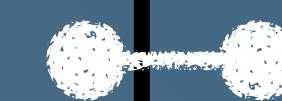
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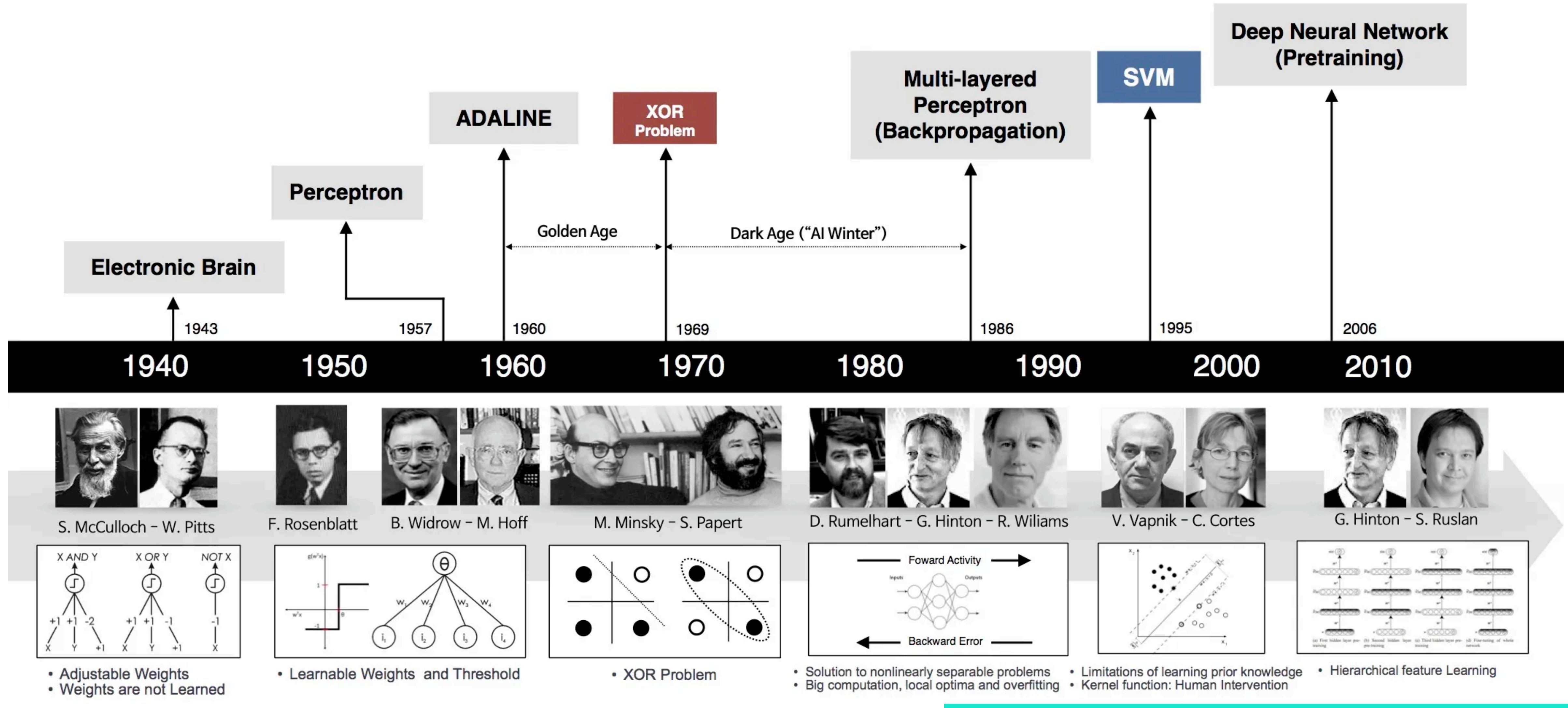
2019

2020

2021

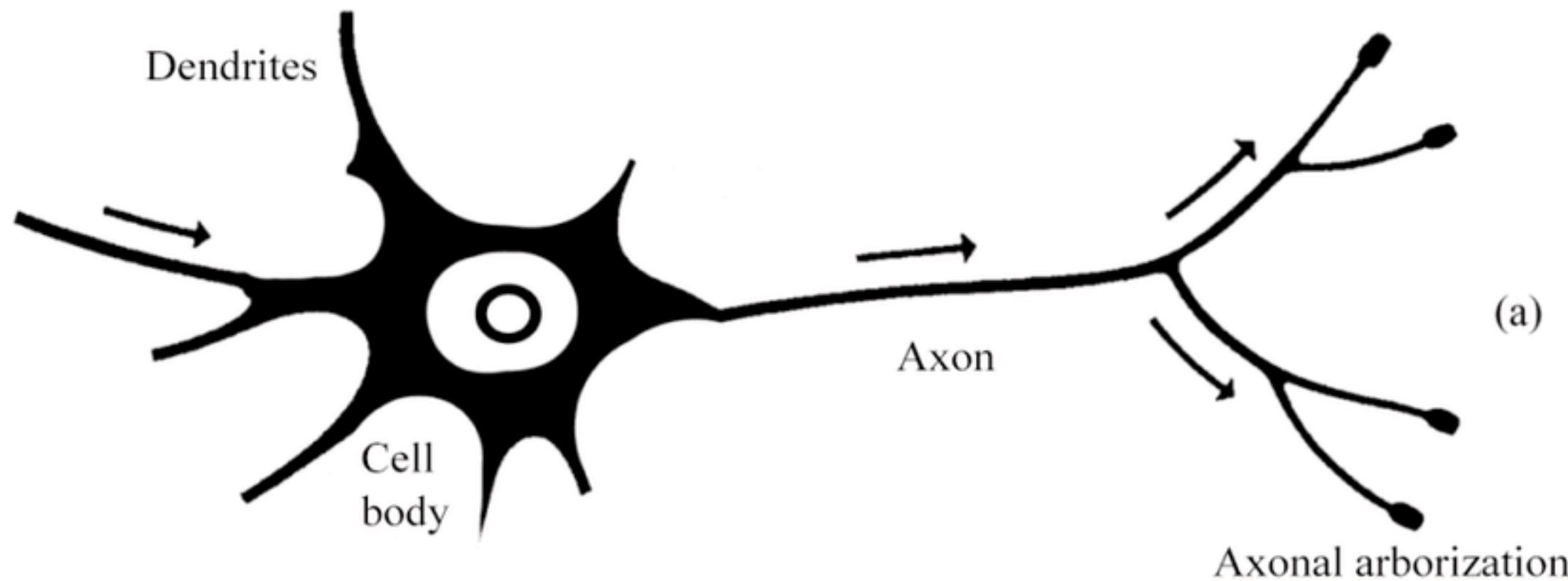
2022

Evolução das Redes Neurais Artificiais



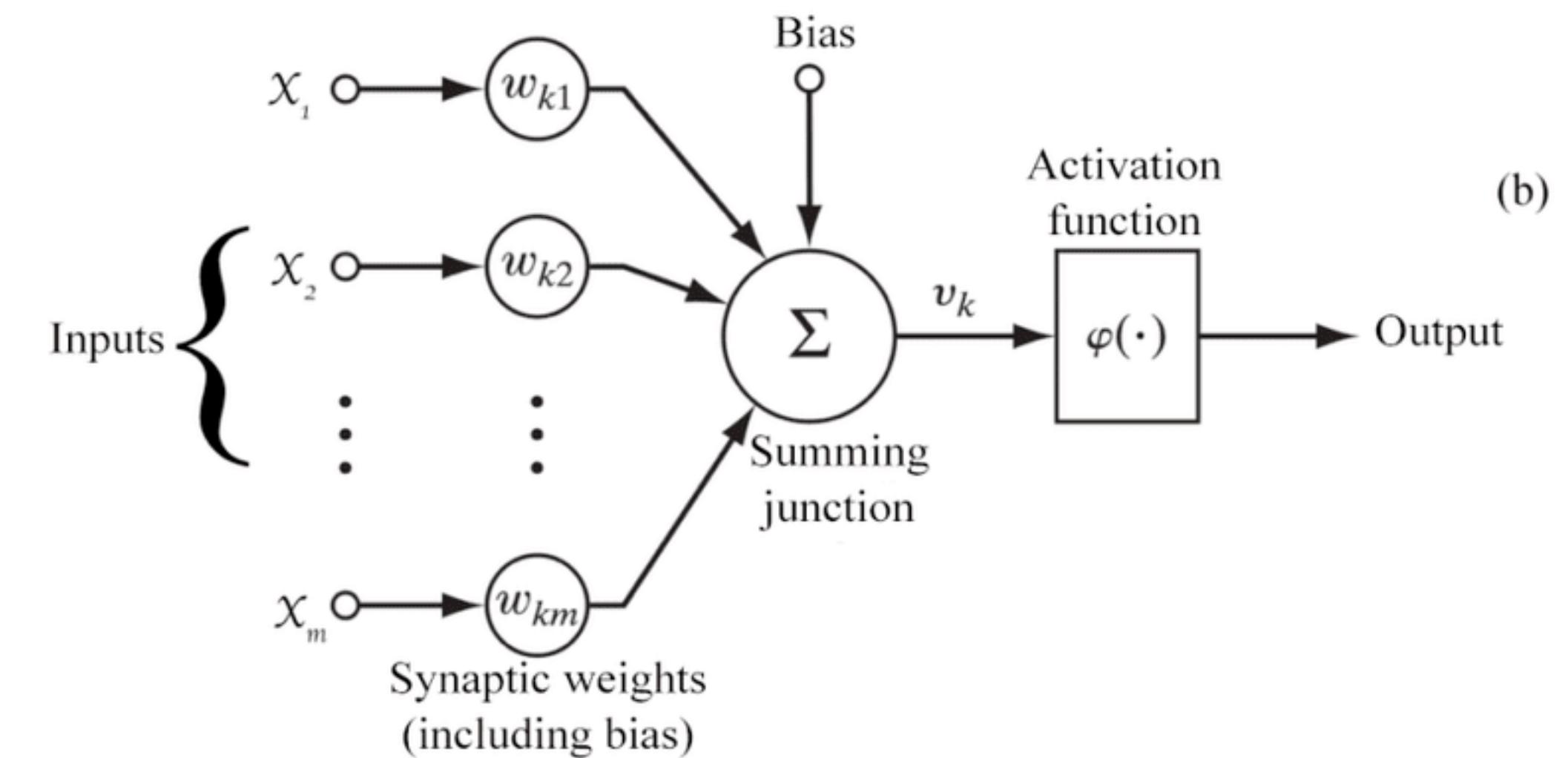
Neurônios

Neurônio biológico



(a)

Neurônio artificial



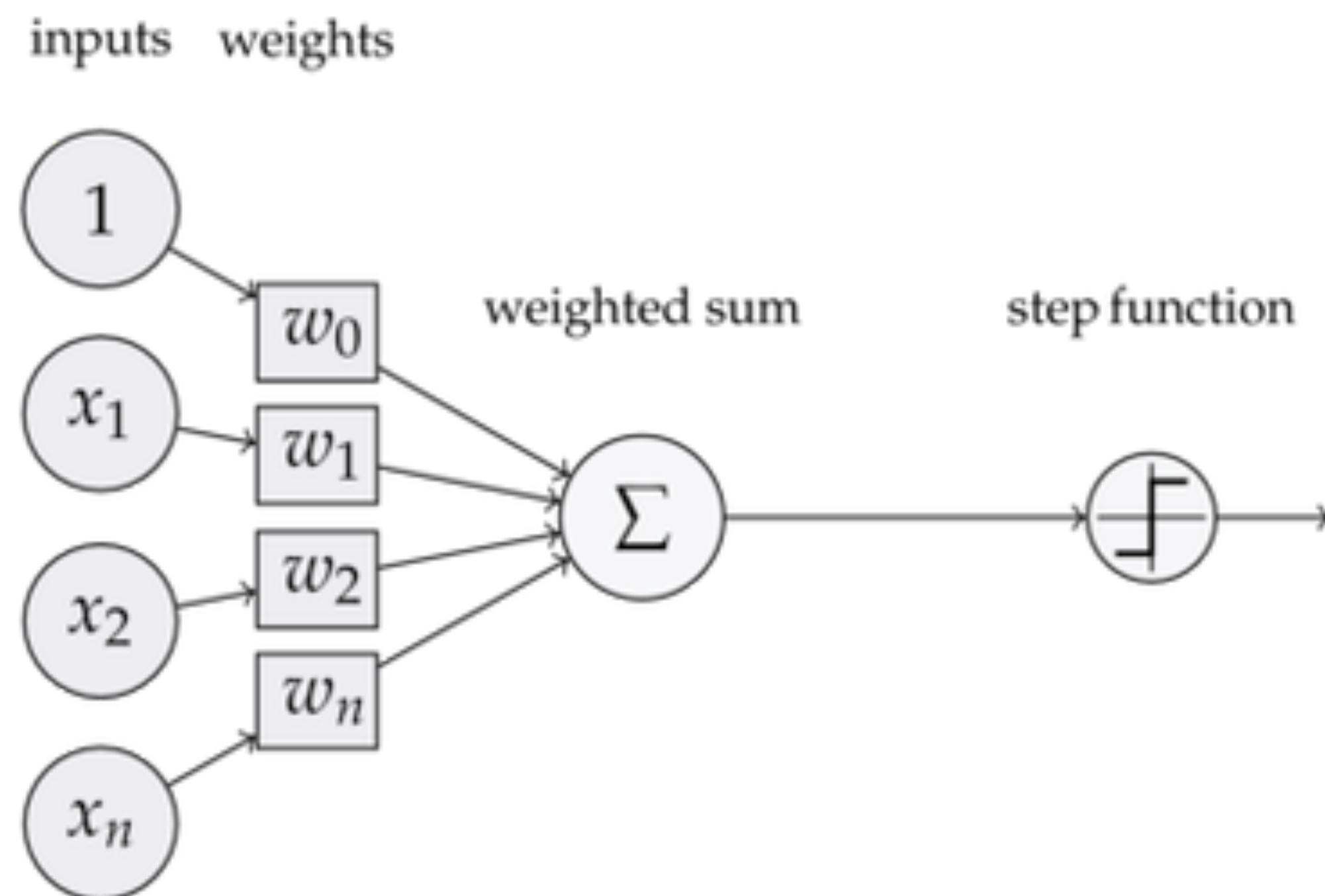
(b)

- **Dendritos:** Recebem sinais de outros neurônios;
- **Corpo celular:** Processa a informação;
- **Axônio:** Transmite a saída do neurônio em questão;
- **Sinapse:** Ponto de conexão para outros neurônios.

Fonte: <https://dominicm73.blogspot.com/2020/08/modeling-threshold-logic-neurons-and.html>

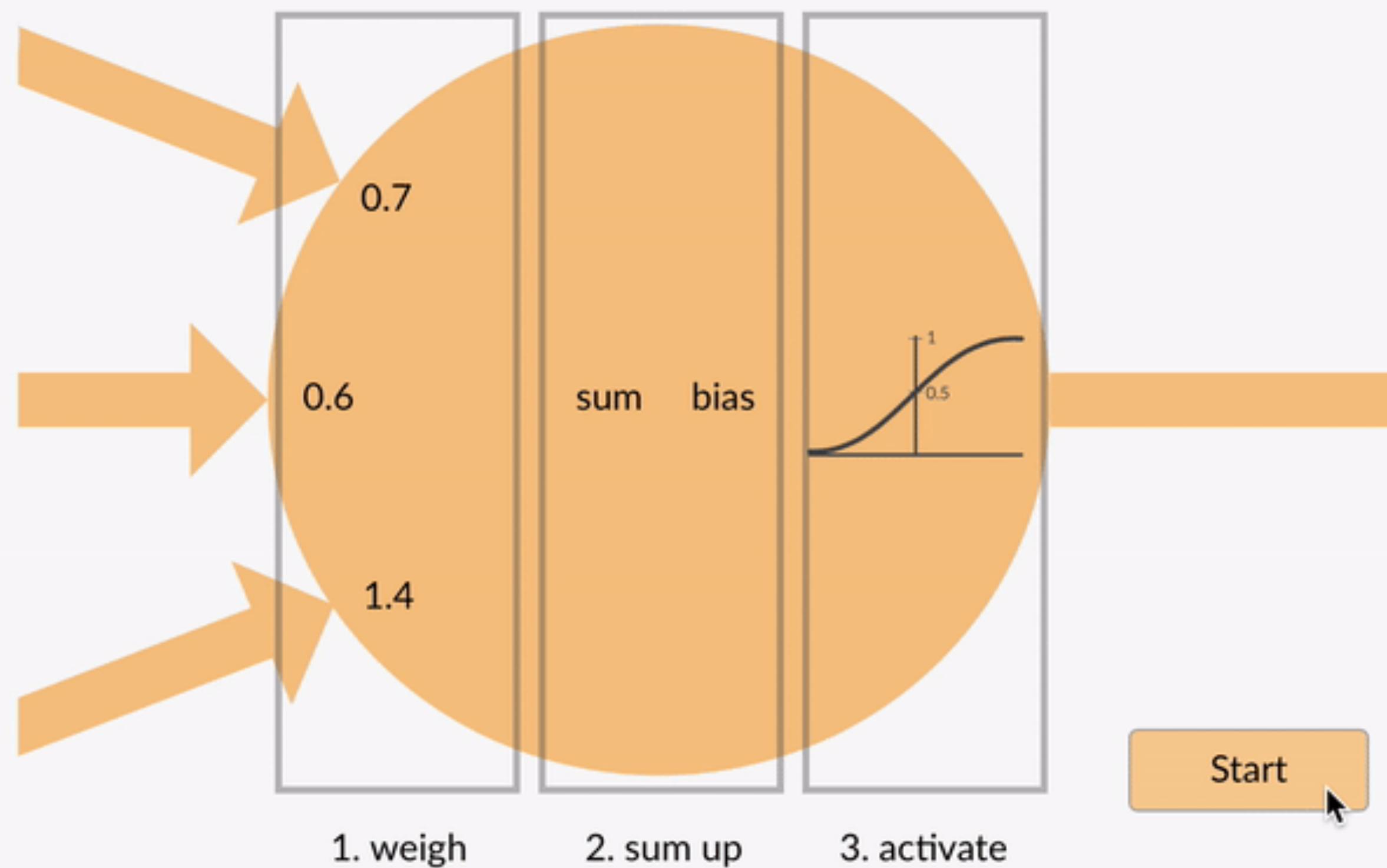
- **Entrada:** Recebem as informações de entrada;
- **Pesos sinápticos:** Ponderam as informações de entrada;
- **Junção aditiva:** Combina (soma) as informações ponderadas;
- **Função de ativação:** Despenha o papel de excitação/inibição da informação processada.
- **Saída:** Ponto de conexão para outros neurônios.

Neurônio artificial



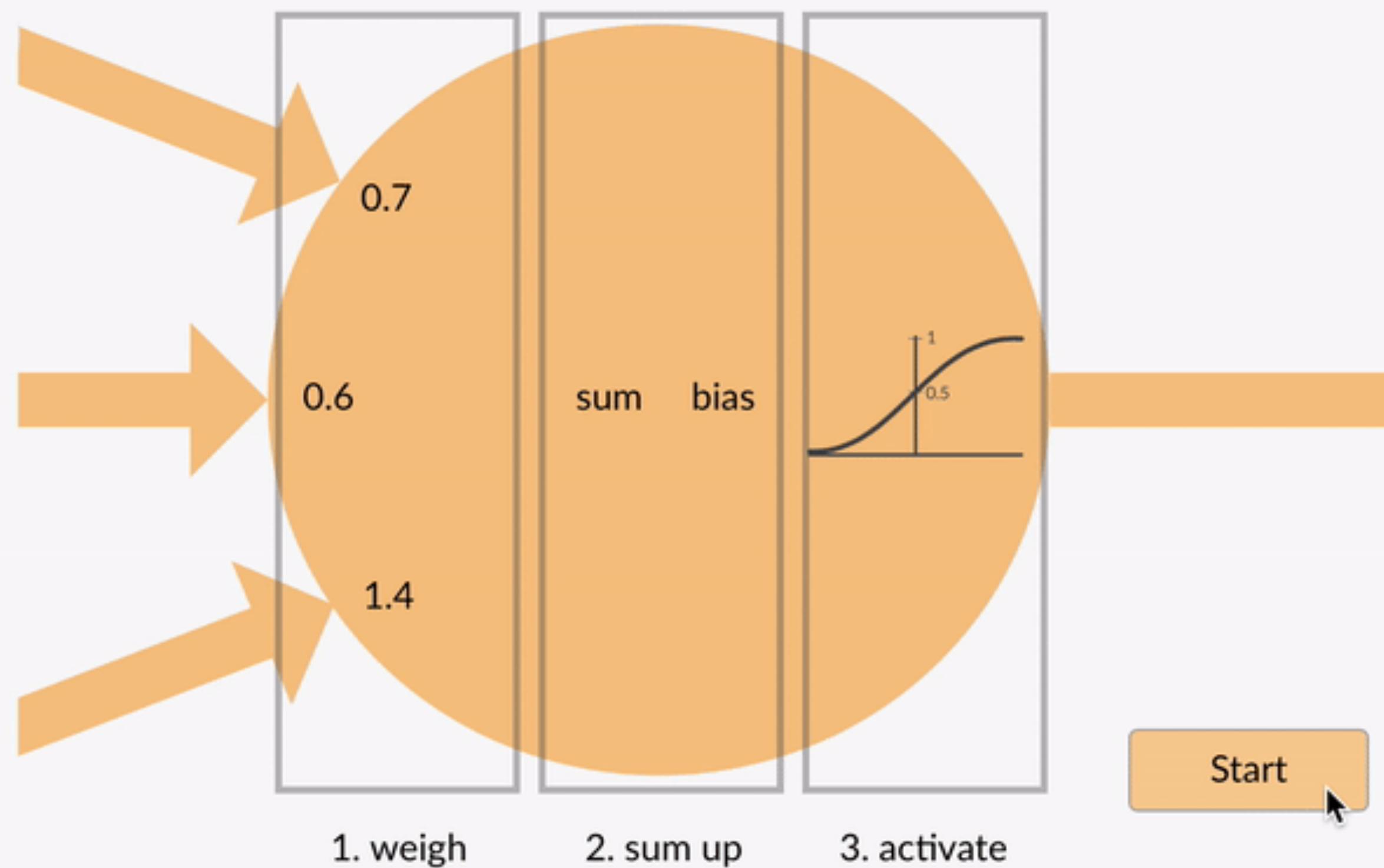
- **Entrada:** Recebem as informações de entrada;
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- **Saída:** Ponto de conexão para outros neurônios.

Visão geral de um neurônio artificial



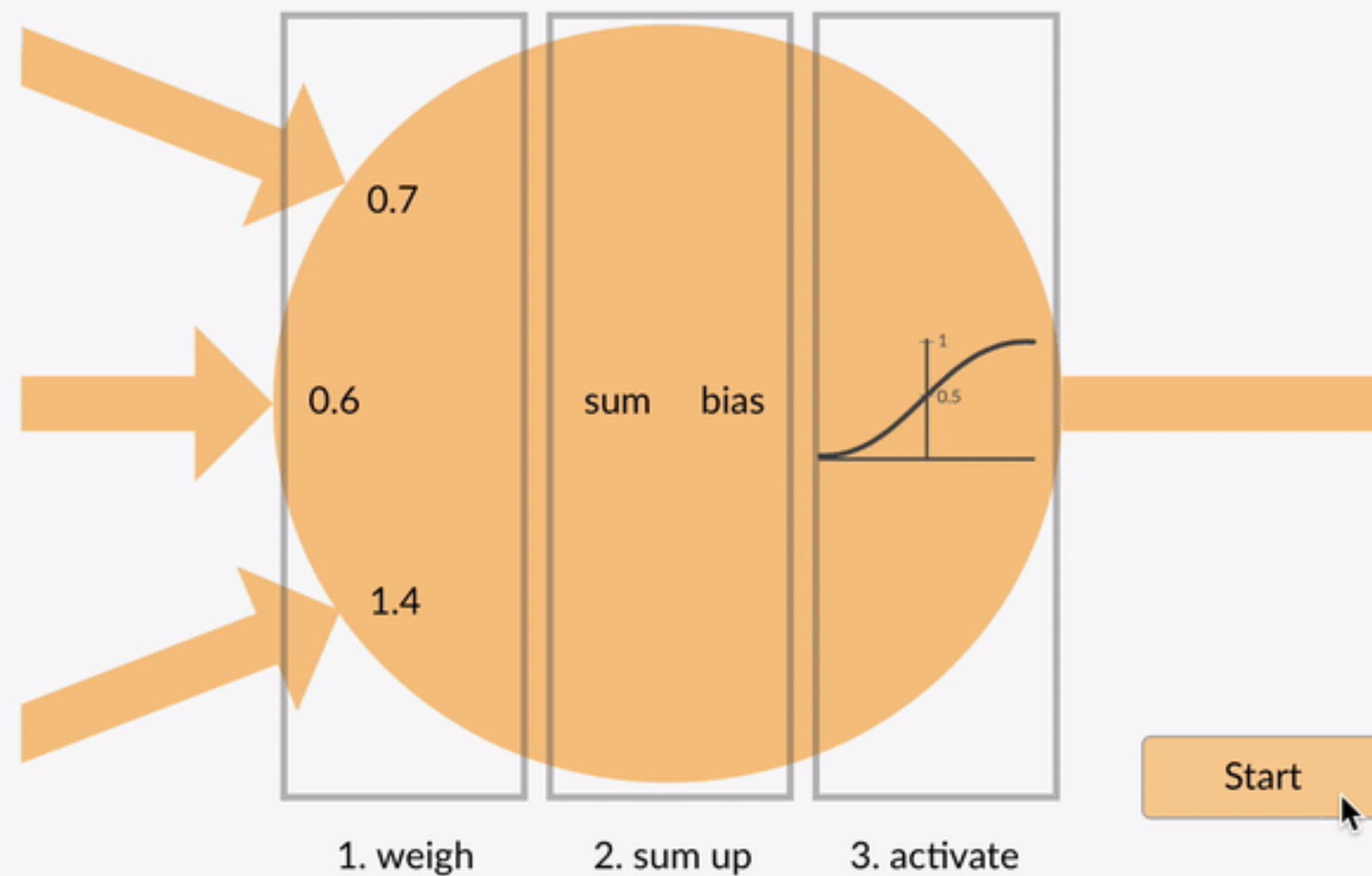
Fonte: <https://laptrinhx.com/introduction-to-deep-learning-feed-forward-neural-networks-ffnns-a-k-a-1737445691/>

Visão geral de um neurônio artificial



Fonte: <https://laptrinhx.com/introduction-to-deep-learning-feed-forward-neural-networks-ffnns-a-k-a-1737445691/>

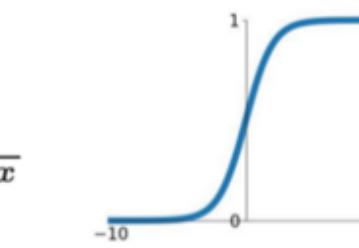
Visão geral de um neurônio artificial



Activation Functions

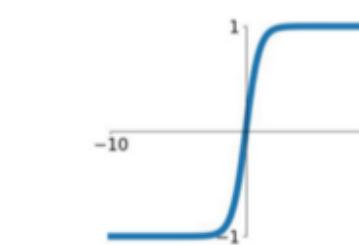
Sigmoid

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



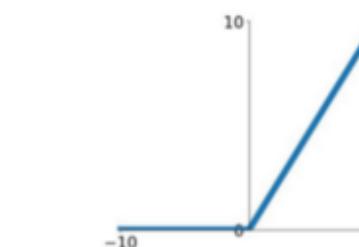
tanh

$$\tanh(x)$$

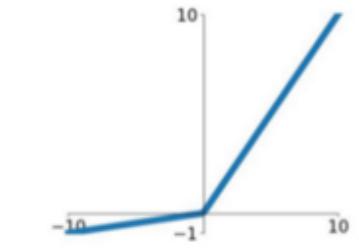


ReLU

$$\max(0, x)$$



Leaky ReLU

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


Maxout

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

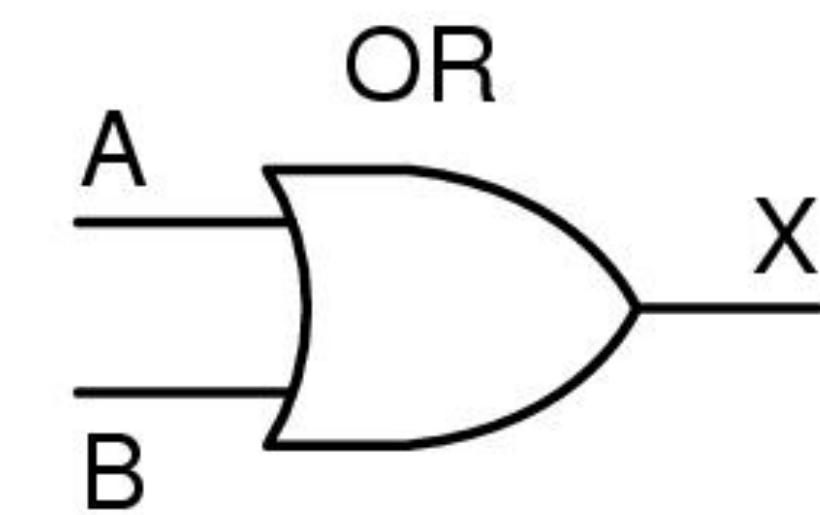
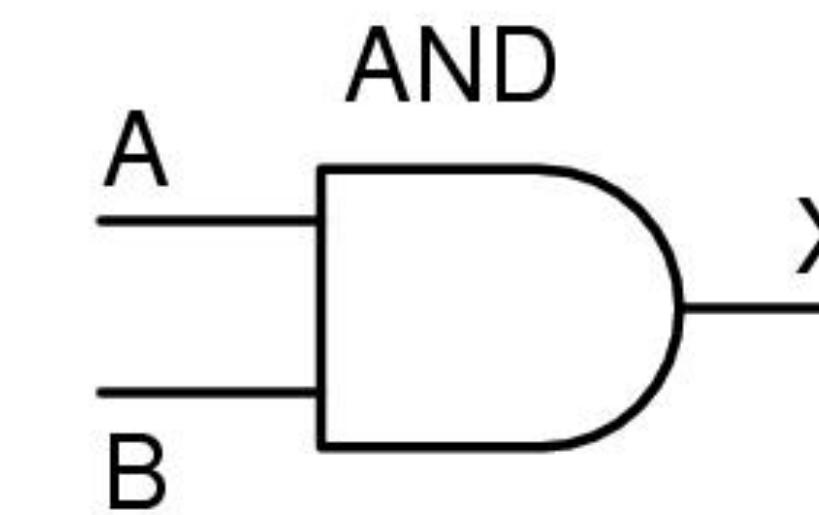
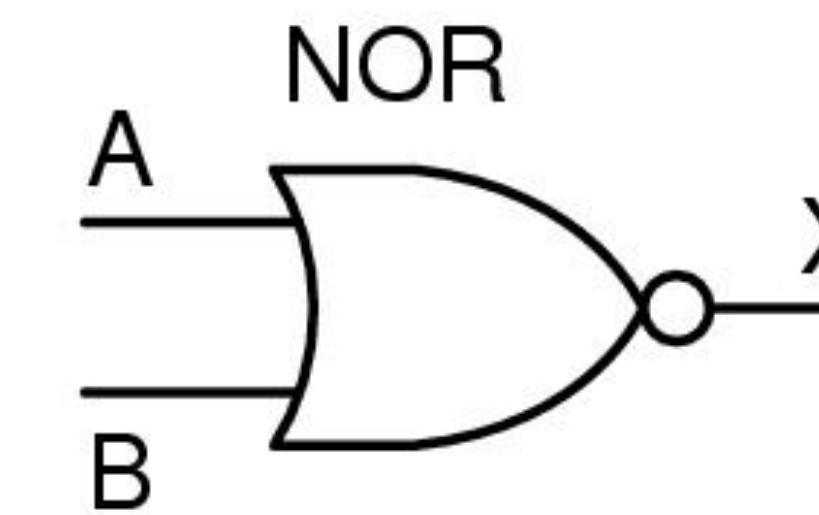
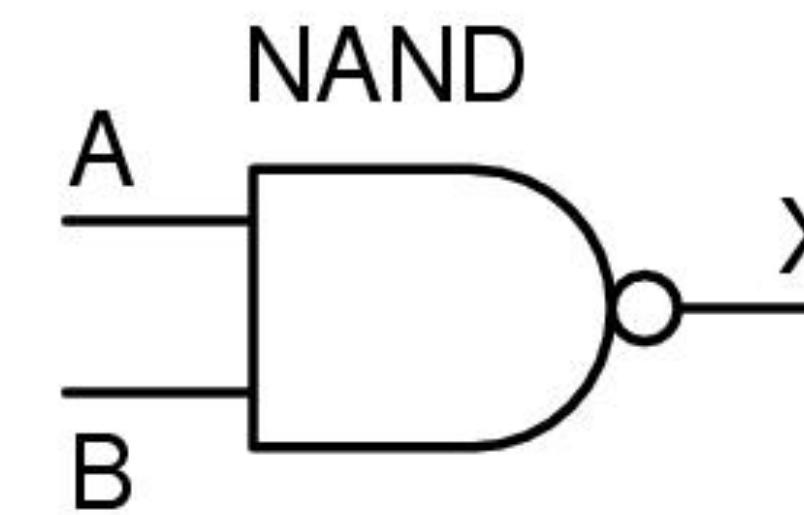
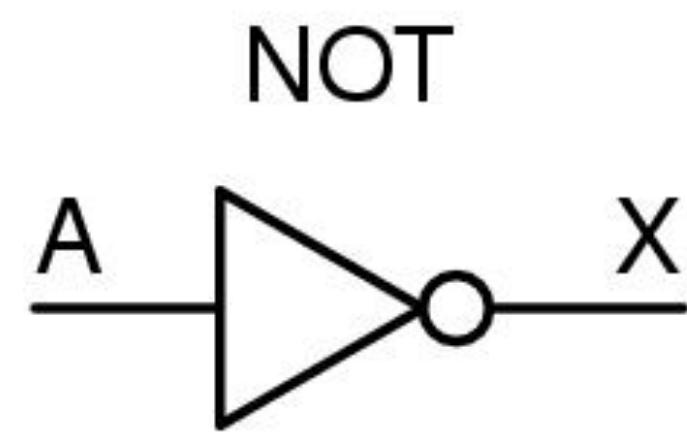


ELU

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

Fonte: <https://laptrinhx.com/introduction-to-deep-learning-feed-forward-neural-networks-ffnns-a-k-a-1737445691/>

Portas lógicas



A	X
0	1
1	0

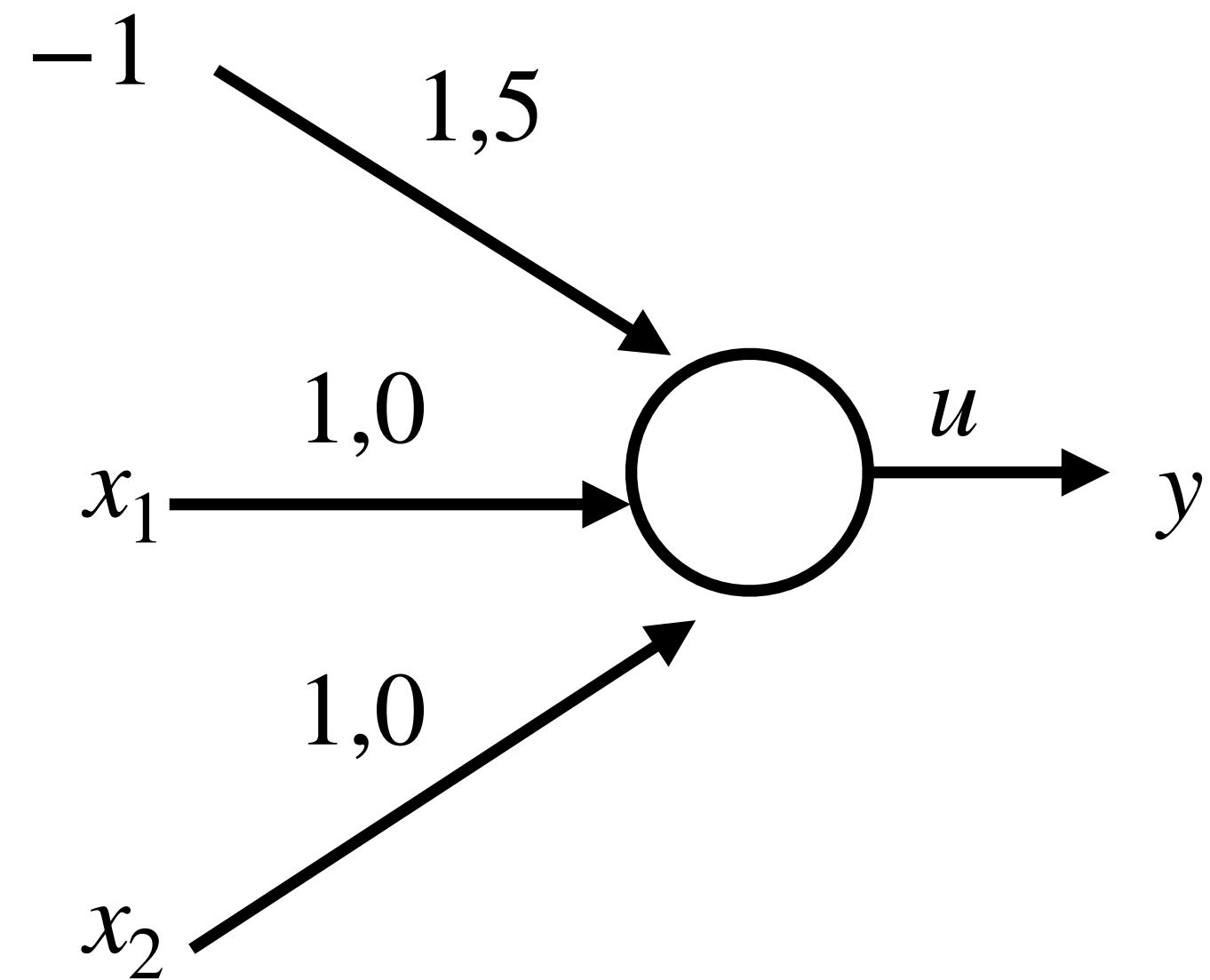
A	B	X
0	0	1
0	1	1
1	0	1
1	1	0

A	B	X
0	0	1
0	1	0
1	0	0
1	1	0

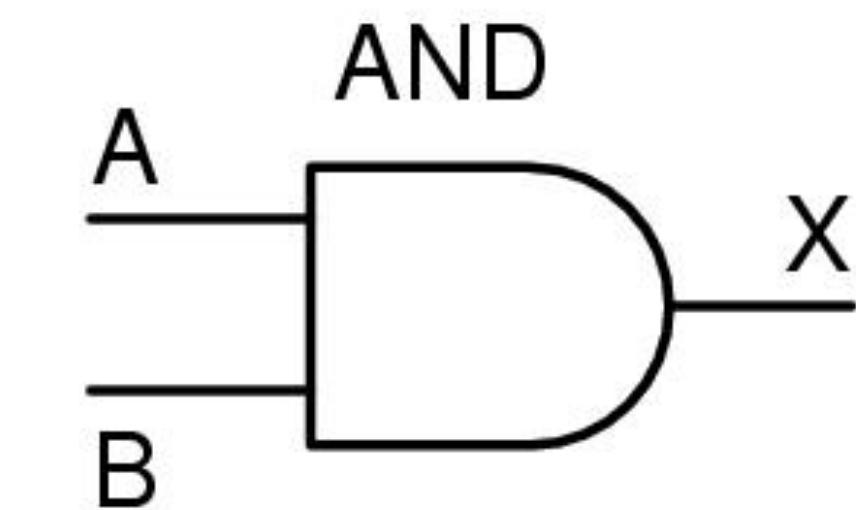
A	B	X
0	0	0
0	1	0
1	0	0
1	1	1

A	B	X
0	0	0
0	1	1
1	0	1
1	1	1

Portas lógicas: AND

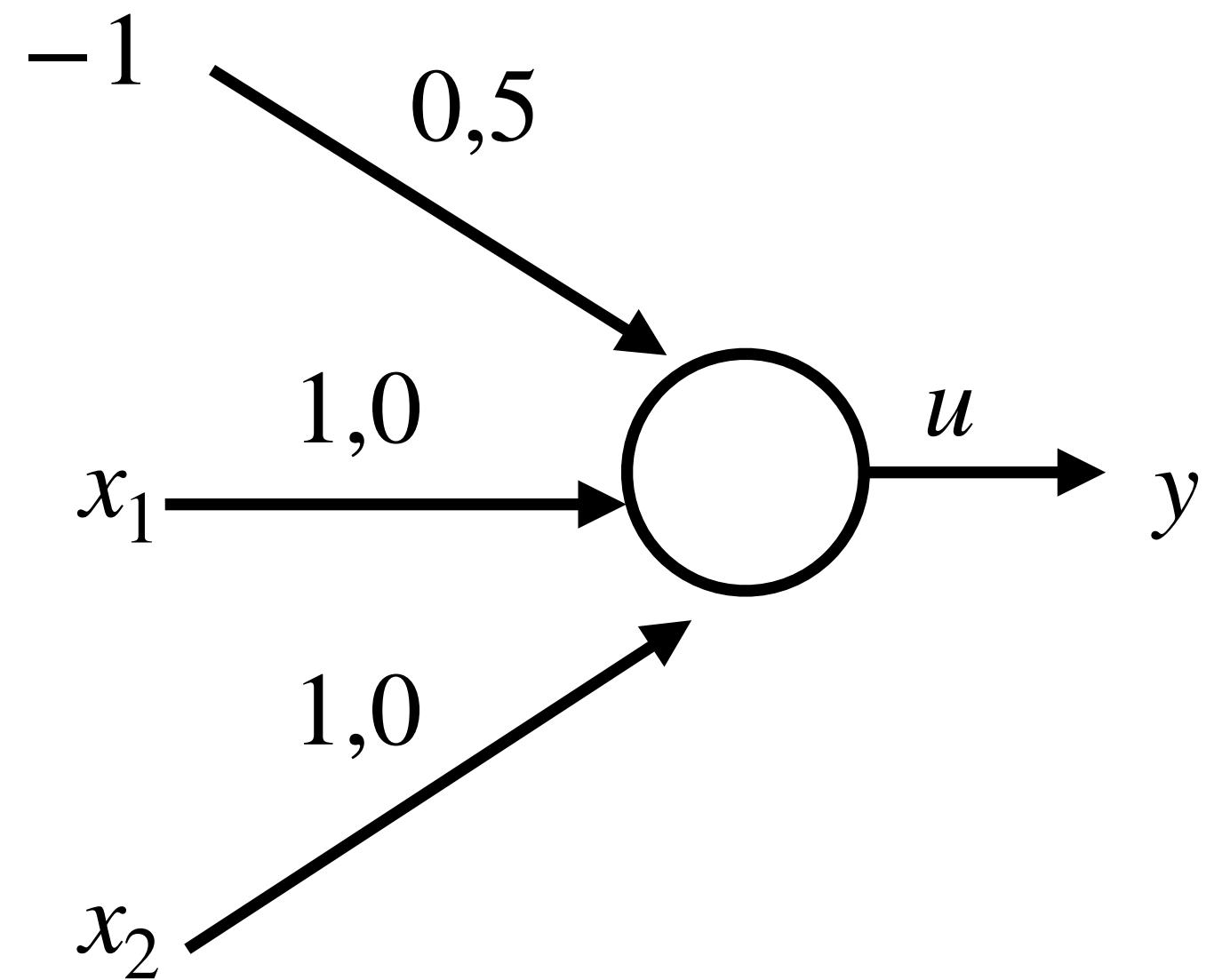


$$w_1 = w_2 = 1 \text{ e } \theta = 1,5$$
$$y = 1 \text{ se } u \geq 0.$$
$$y = 0 \text{ se } u < 0.$$



A	B	X
0	0	0
0	1	0
1	0	0
1	1	1

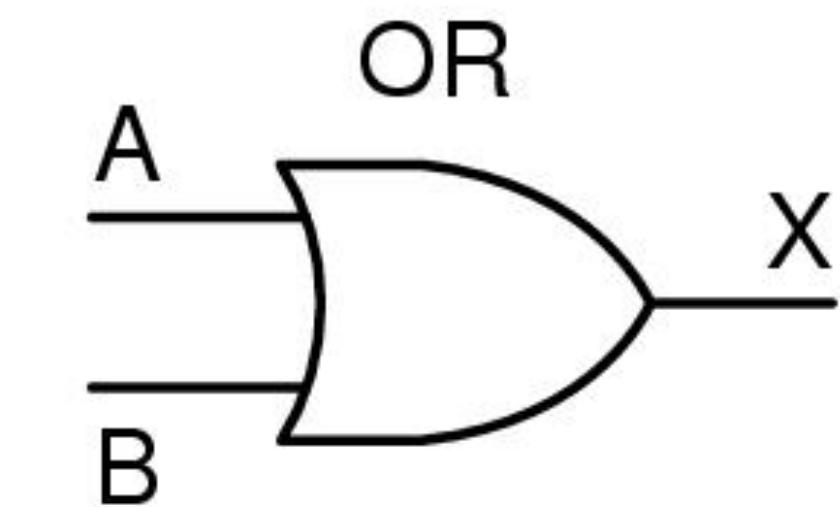
Portas lógicas: OR



$$w_1 = w_2 = 1 \text{ e } \theta = 0,5$$

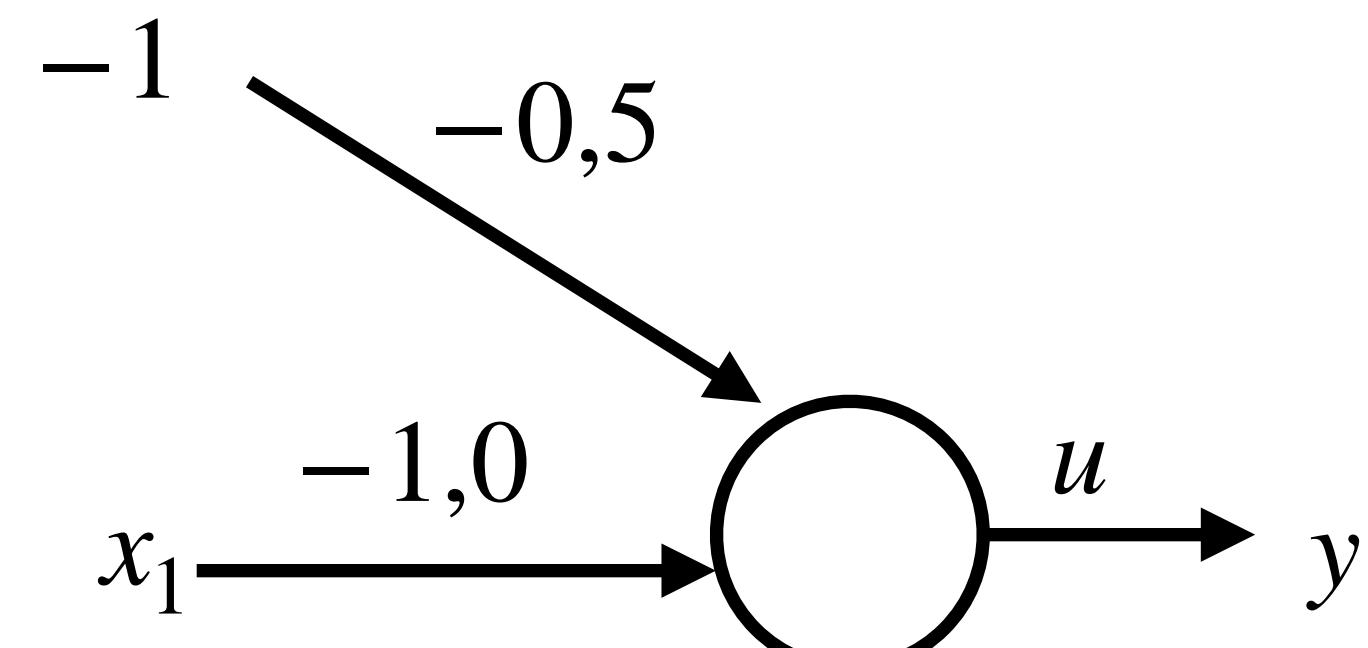
$$y = 1 \text{ se } u \geq 0.$$

$$y = 0 \text{ se } u < 0.$$



A	B	X
0	0	0
0	1	1
1	0	1
1	1	1

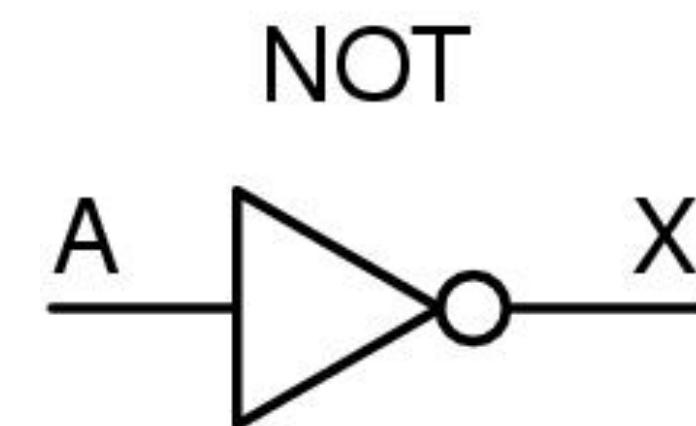
Portas lógicas: NOT



$$w_1 = -1 \text{ e } \theta = -0,5$$

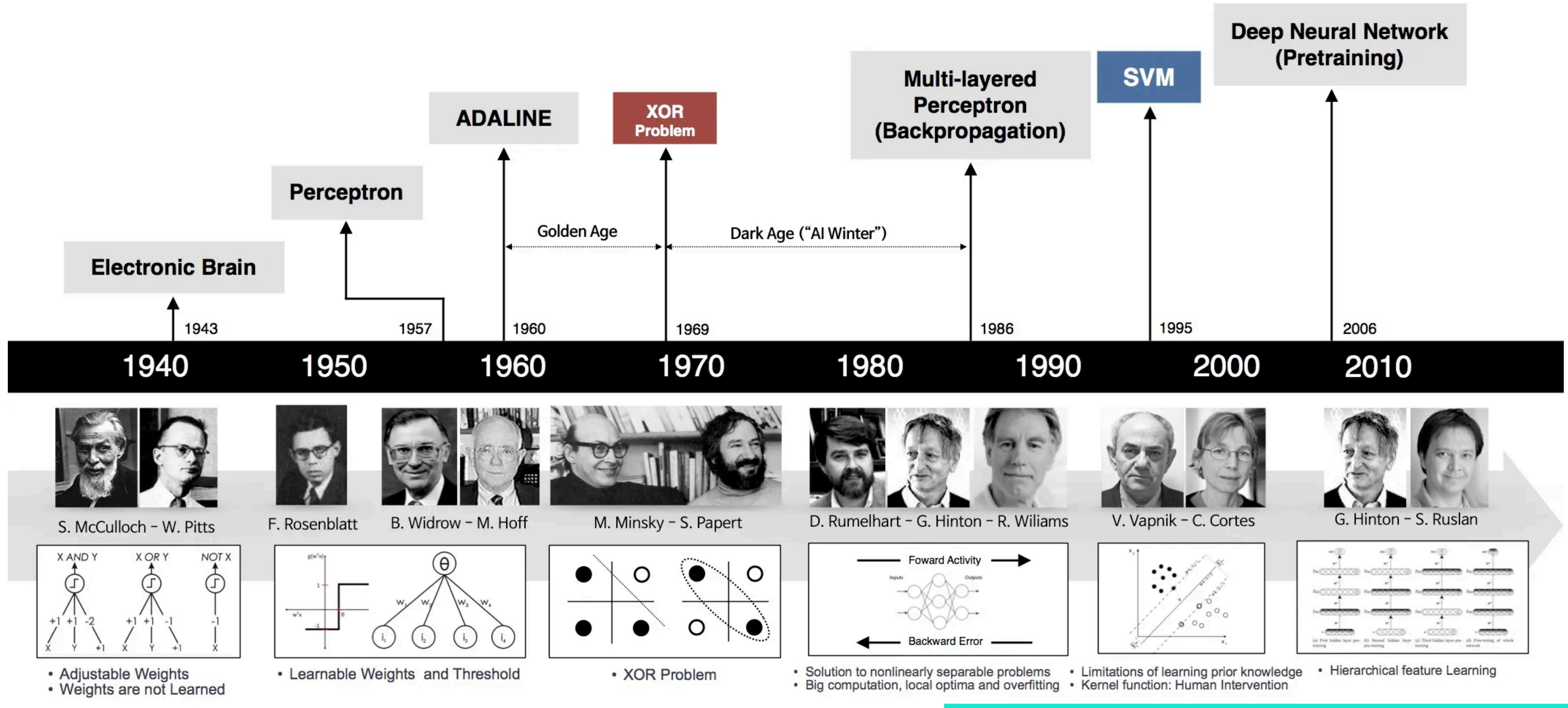
$$y = 1 \text{ se } u \geq 0.$$

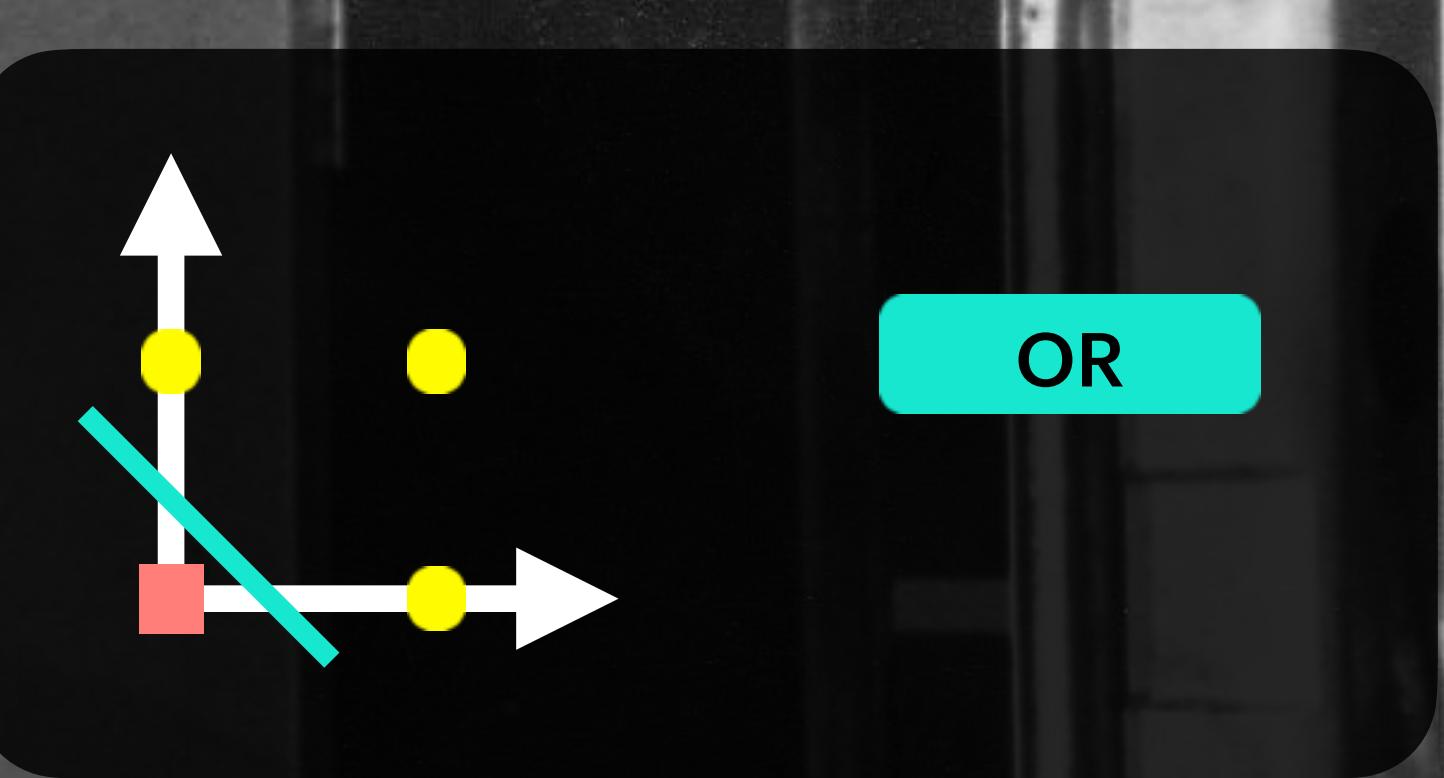
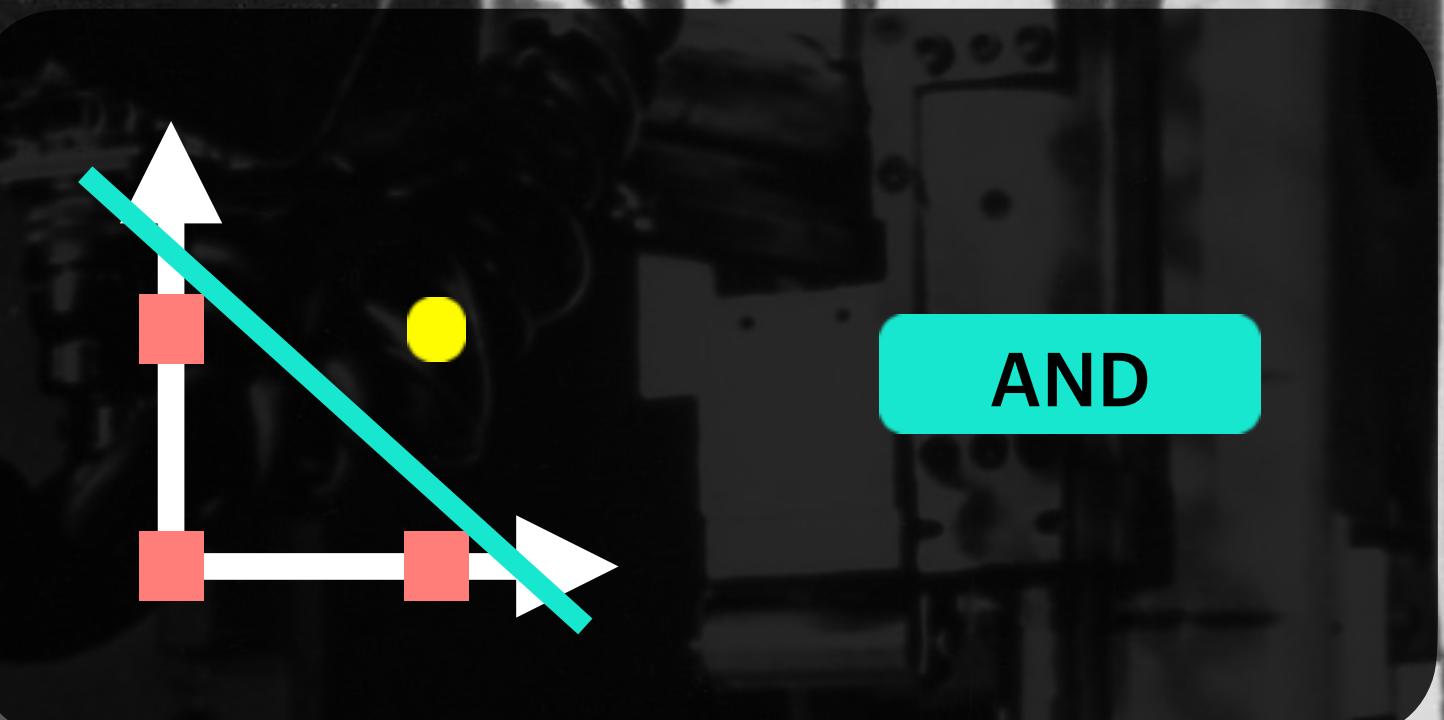
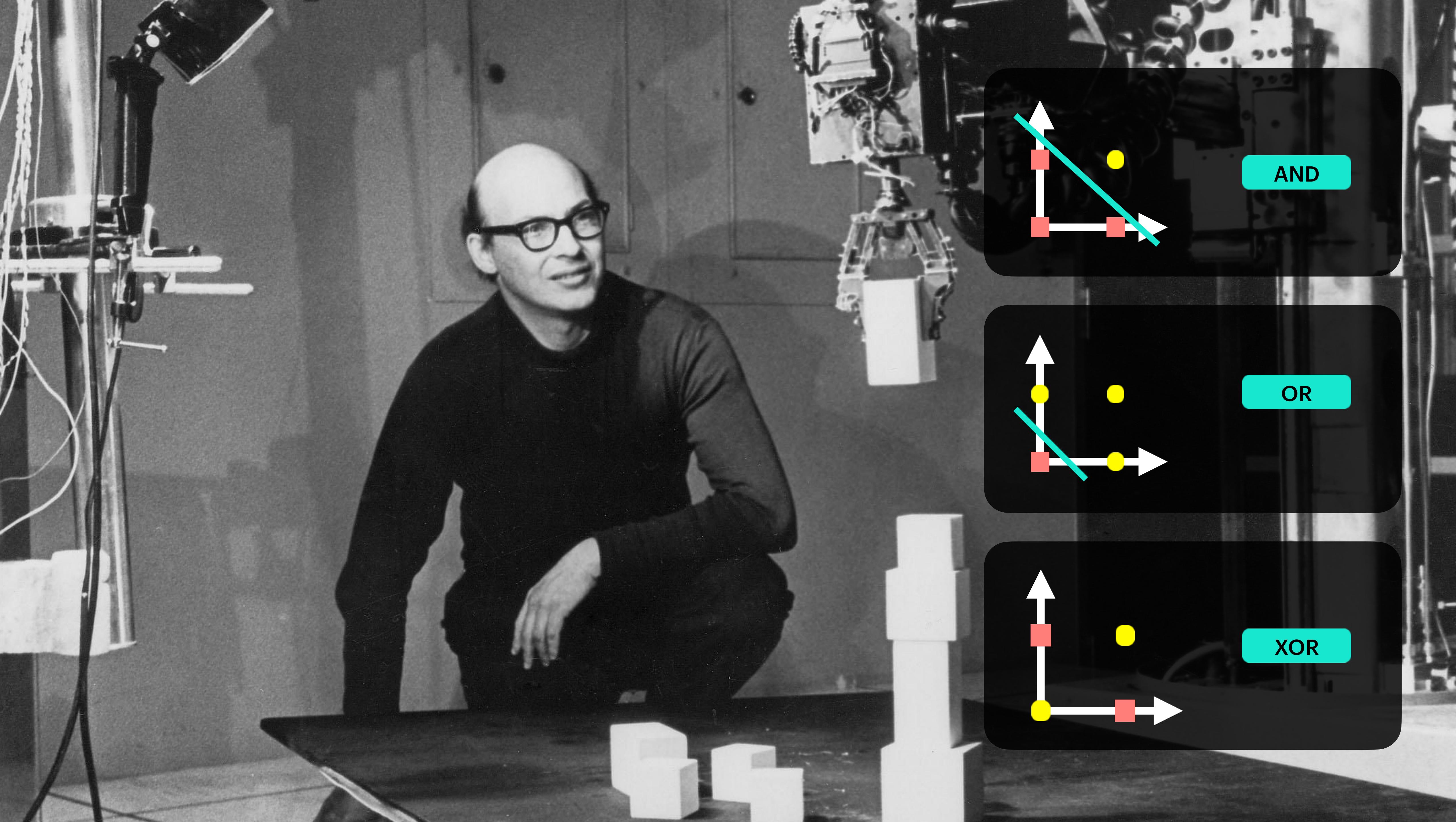
$$y = 0 \text{ se } u < 0.$$



A	X
0	1
1	0

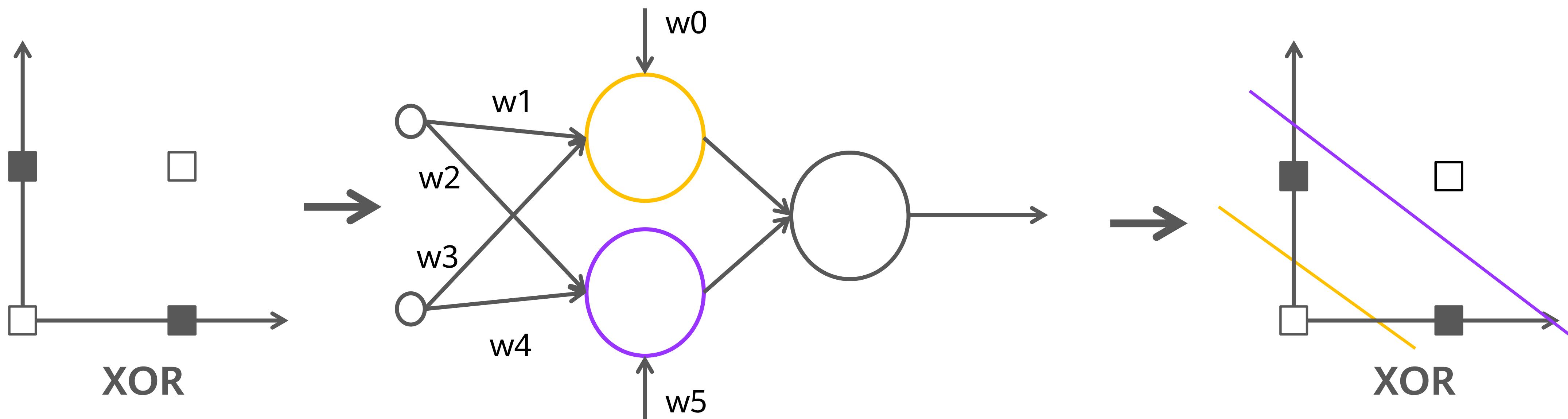
Evolução das Redes Neurais Artificiais





E O XOR?
COMO RESOLVE, MDS?

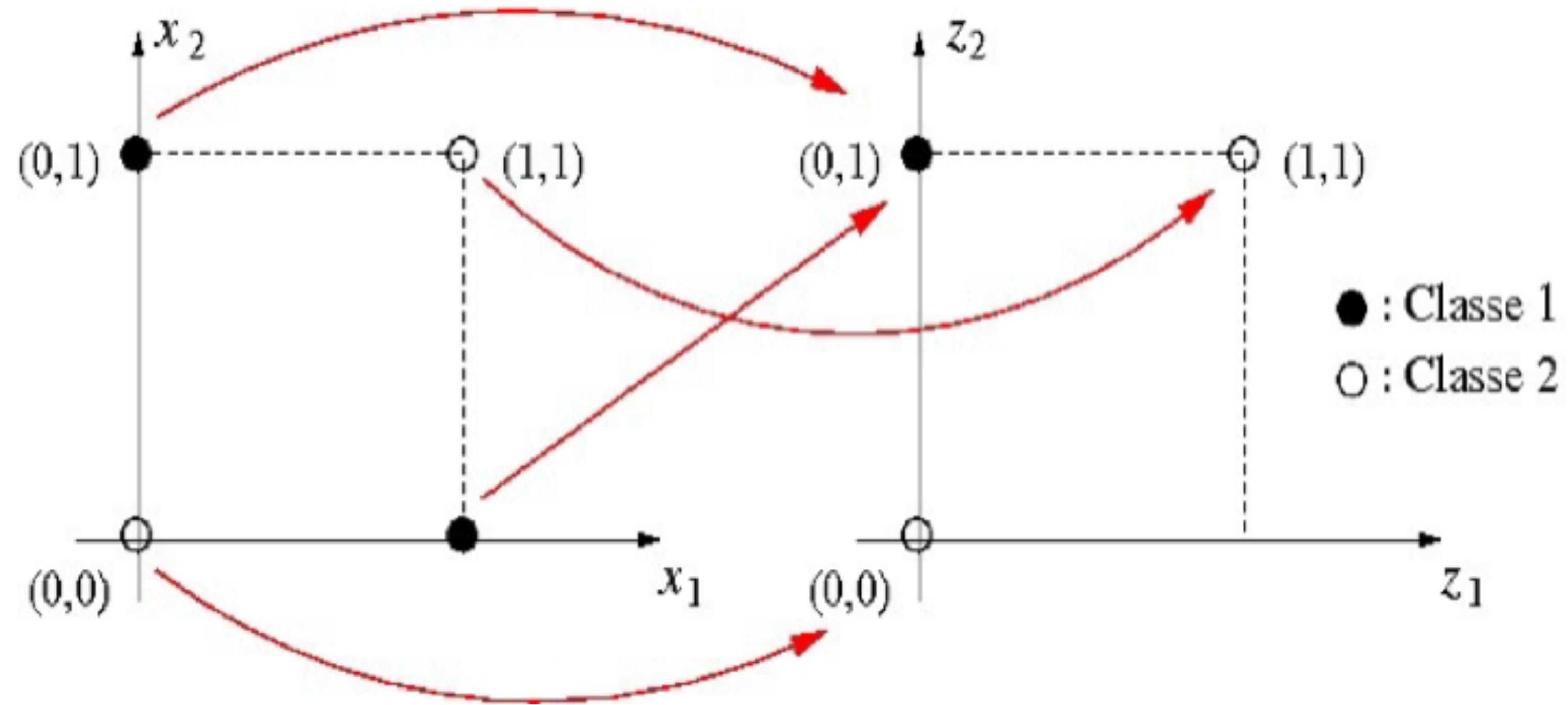
A (BENDITA) CAMADA OCULTA



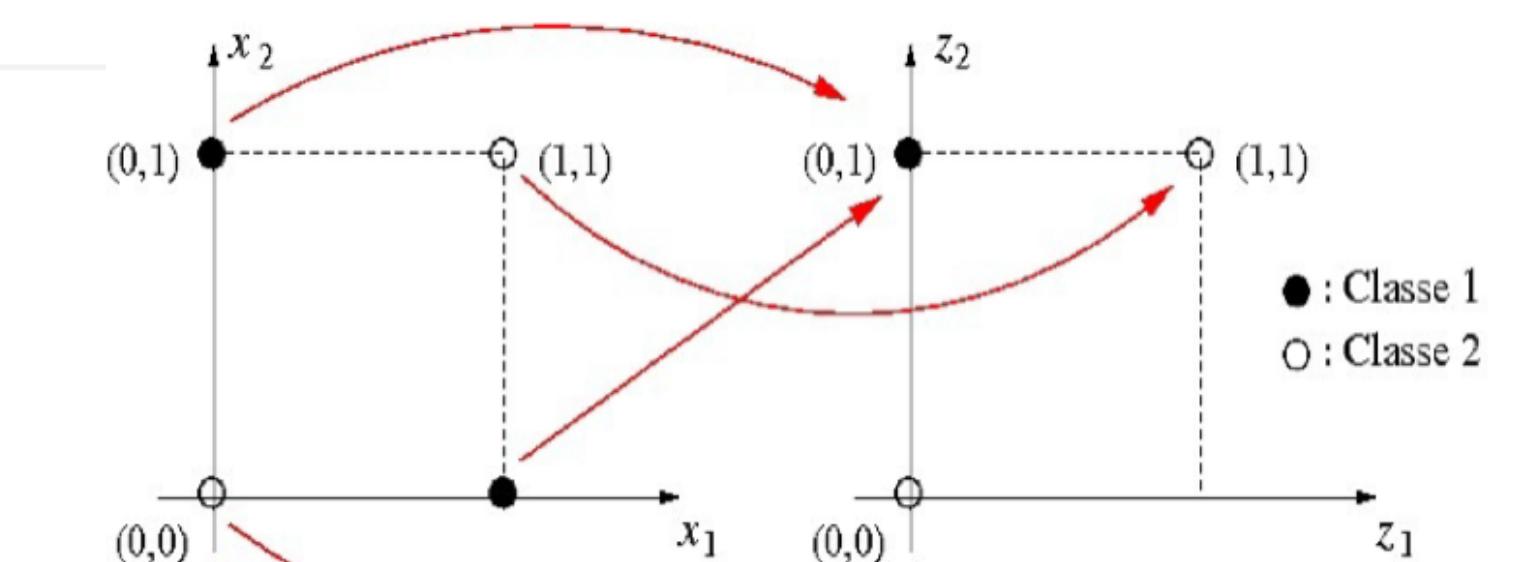
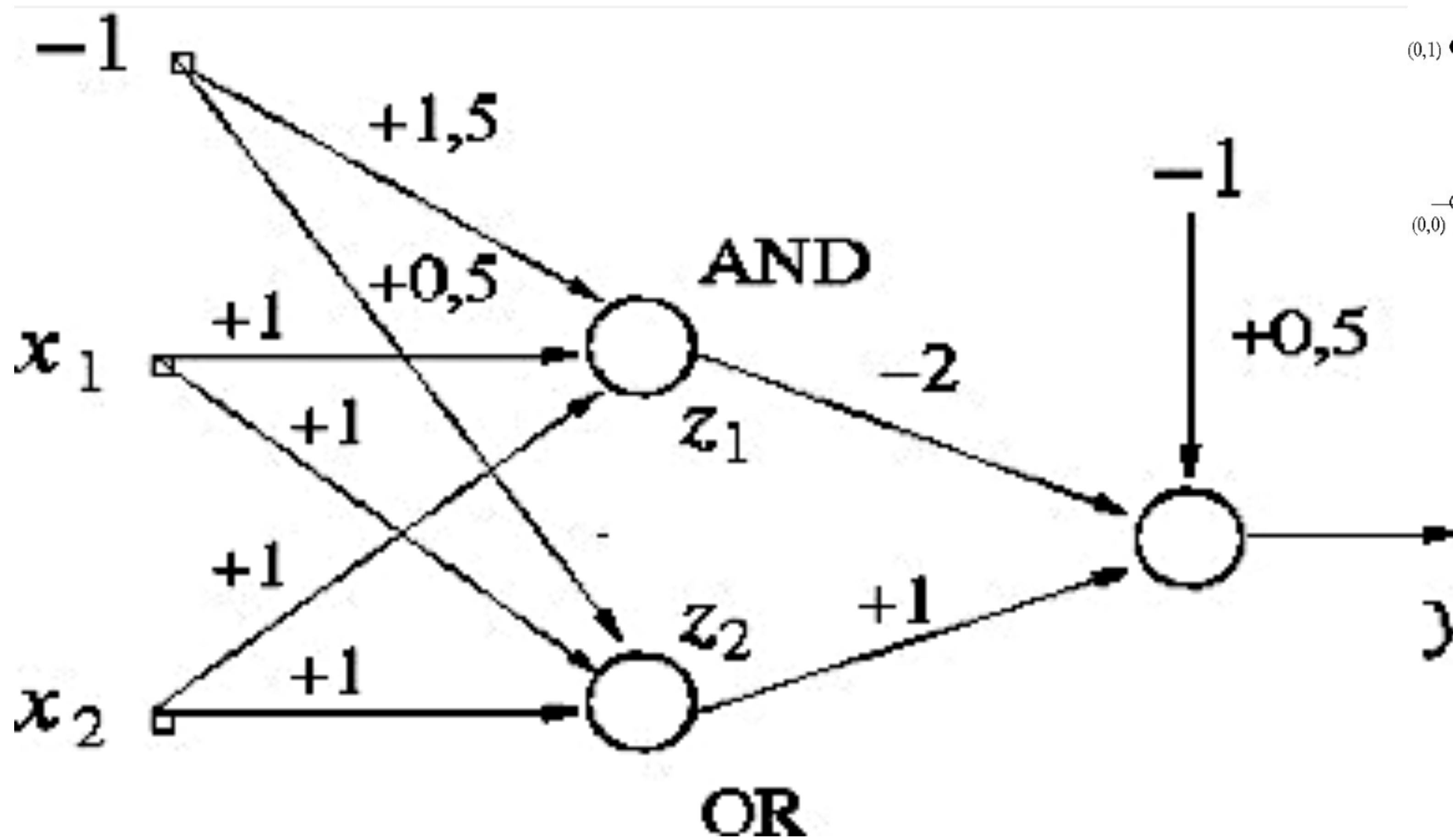
REVISITANDO PORTAS LÓGICAS

XOR

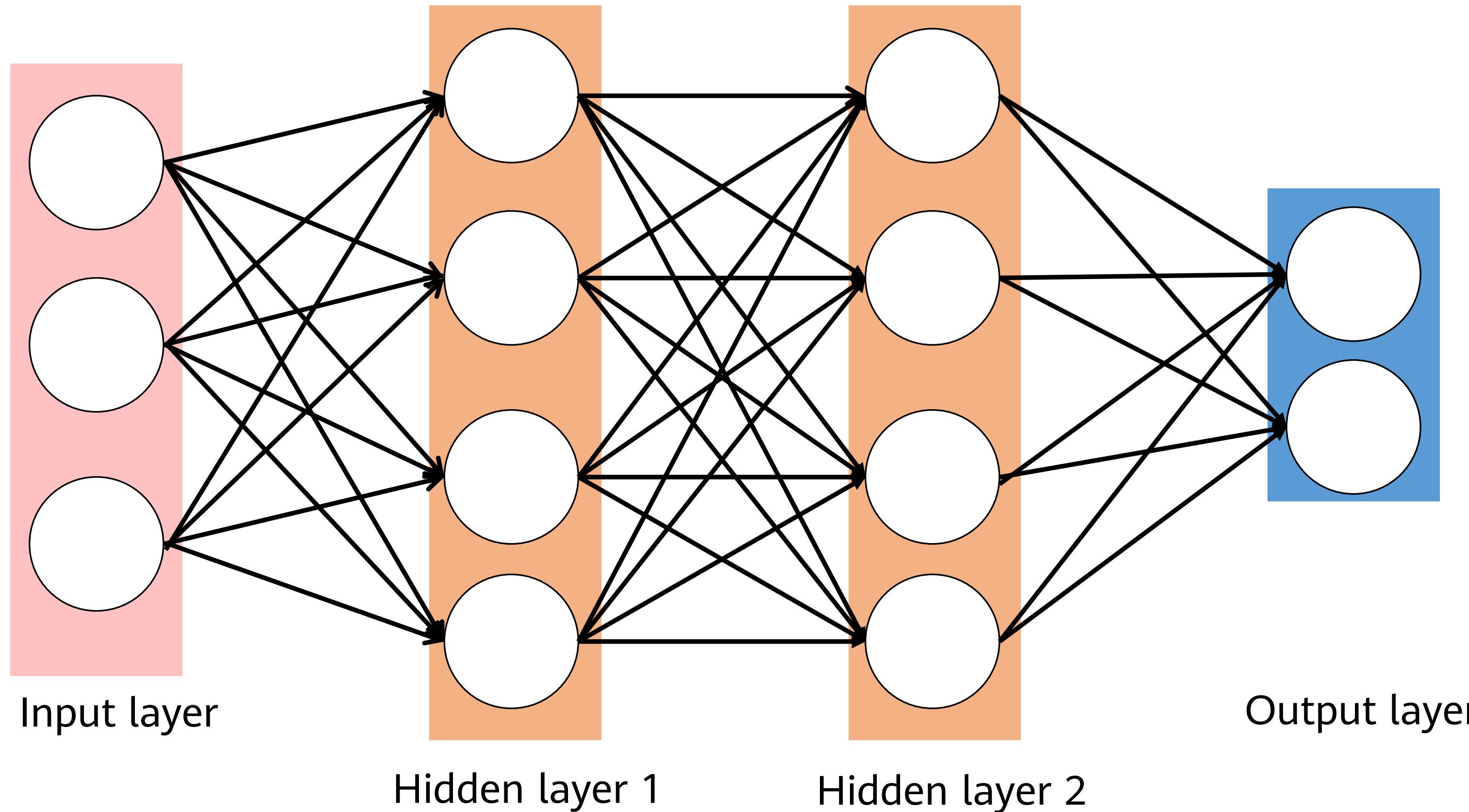
x_1	x_2	z_1	z_2	y
0	0	0	0	0
0	1	0	1	1
1	0	0	1	1
1	1	1	1	0



A (BENDITA) CAMADA OCULTA

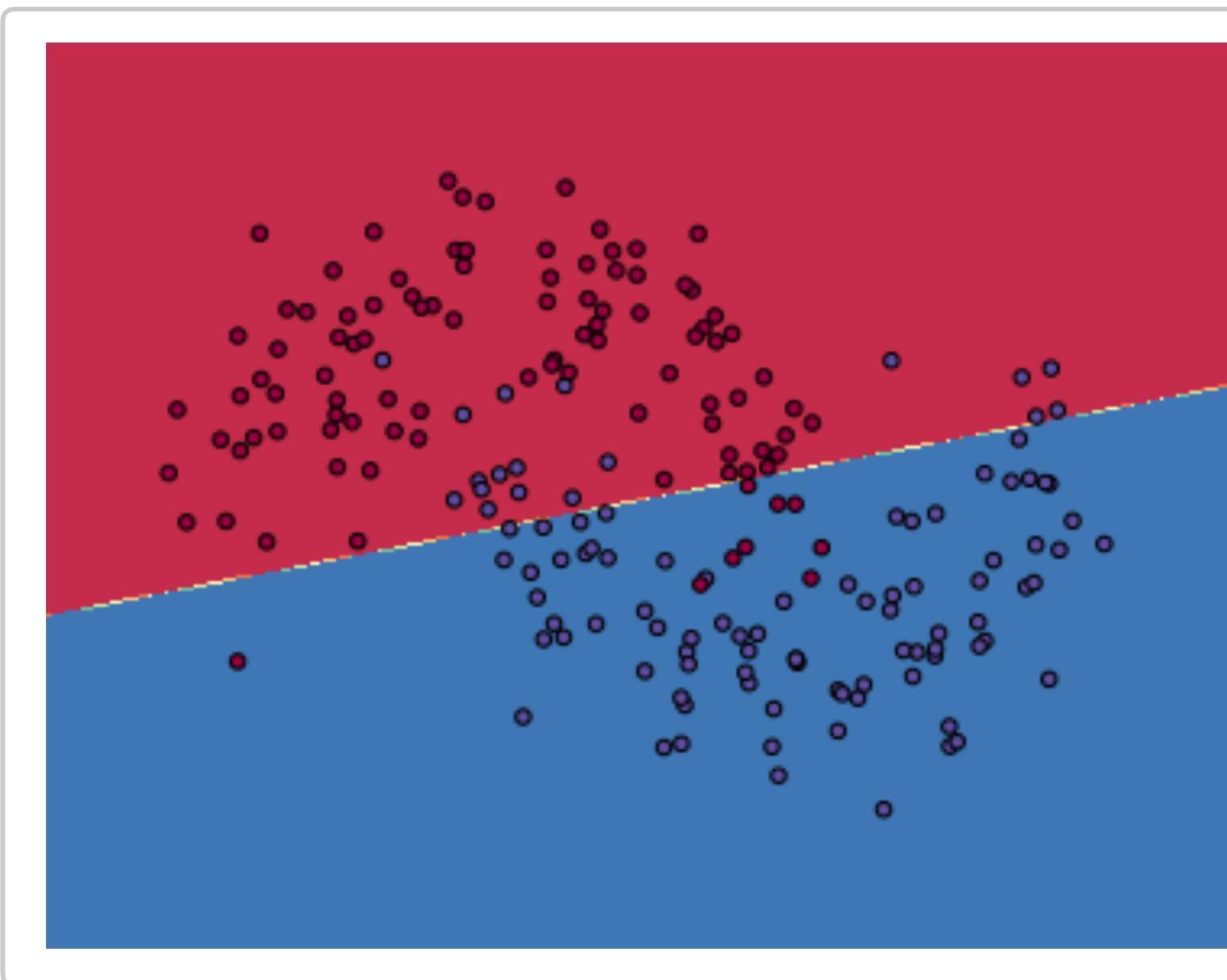


A (BENDITA) CAMADA OCULTA



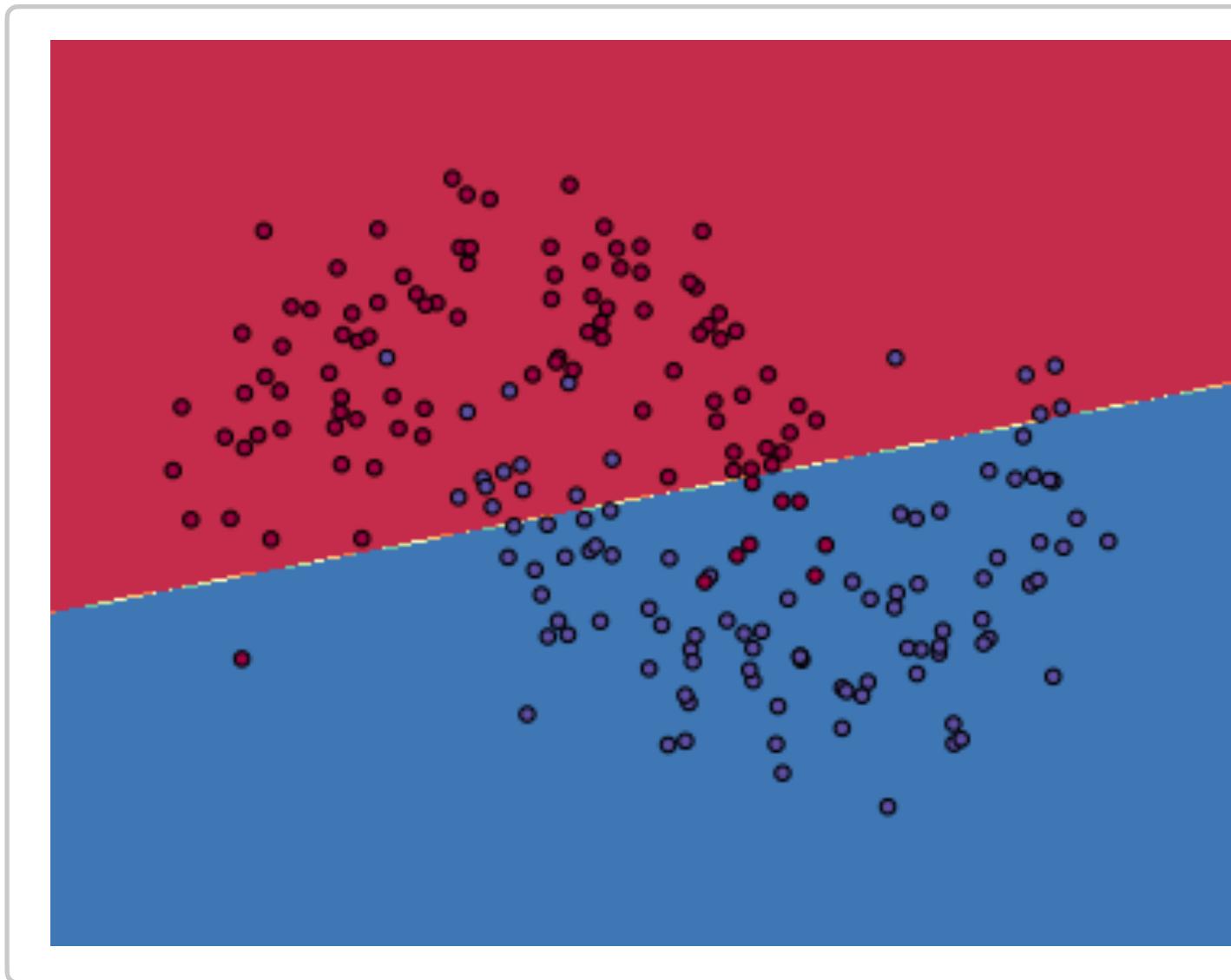
MAIS CAMADAS... MAIS ESTRUTURAS COMPLEXAS PODEMOS GENERALIZAR

Uma camada

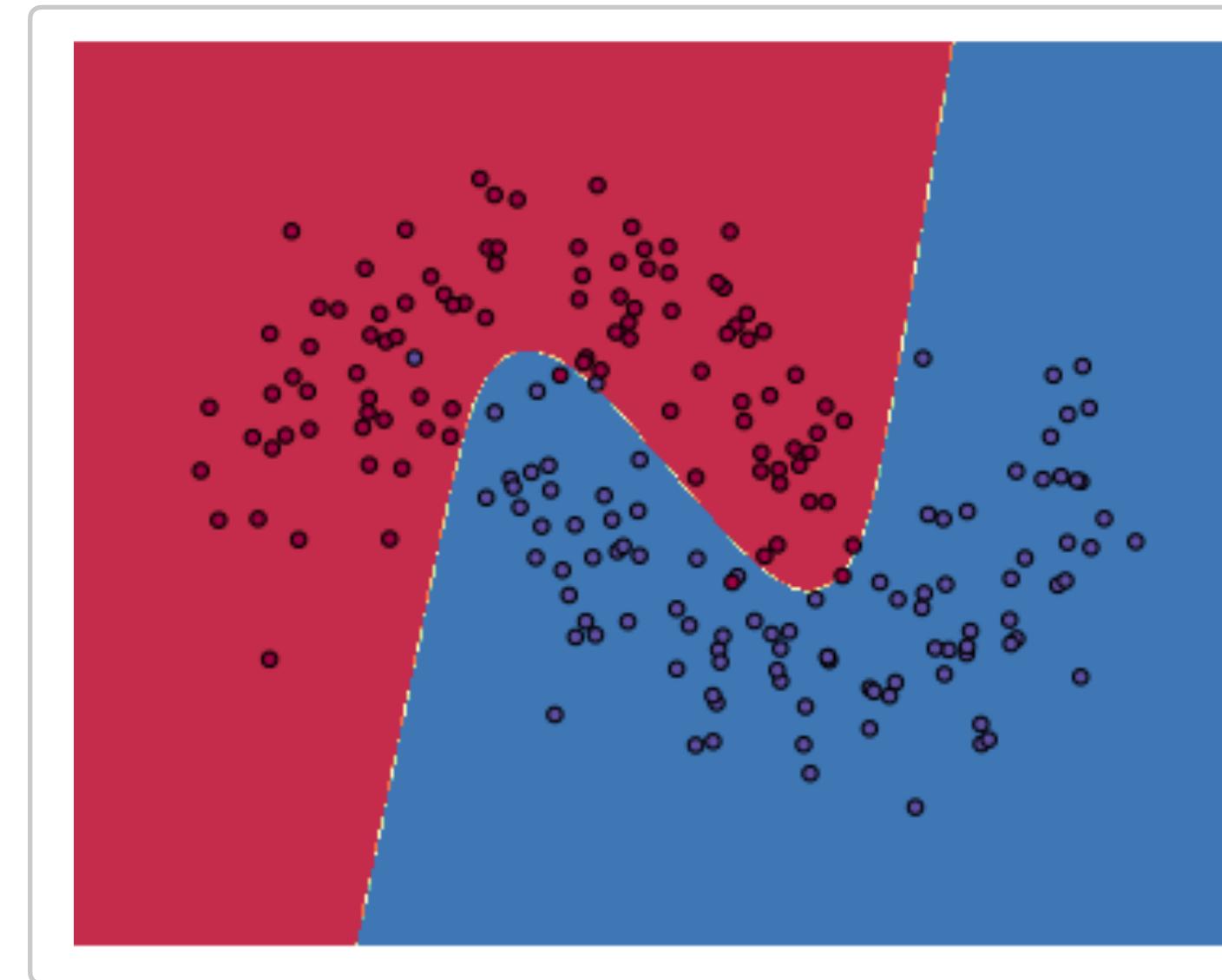


MAIS CAMADAS... MAIS ESTRUTURAS COMPLEXAS PODEMOS GENERALIZAR

Uma camada

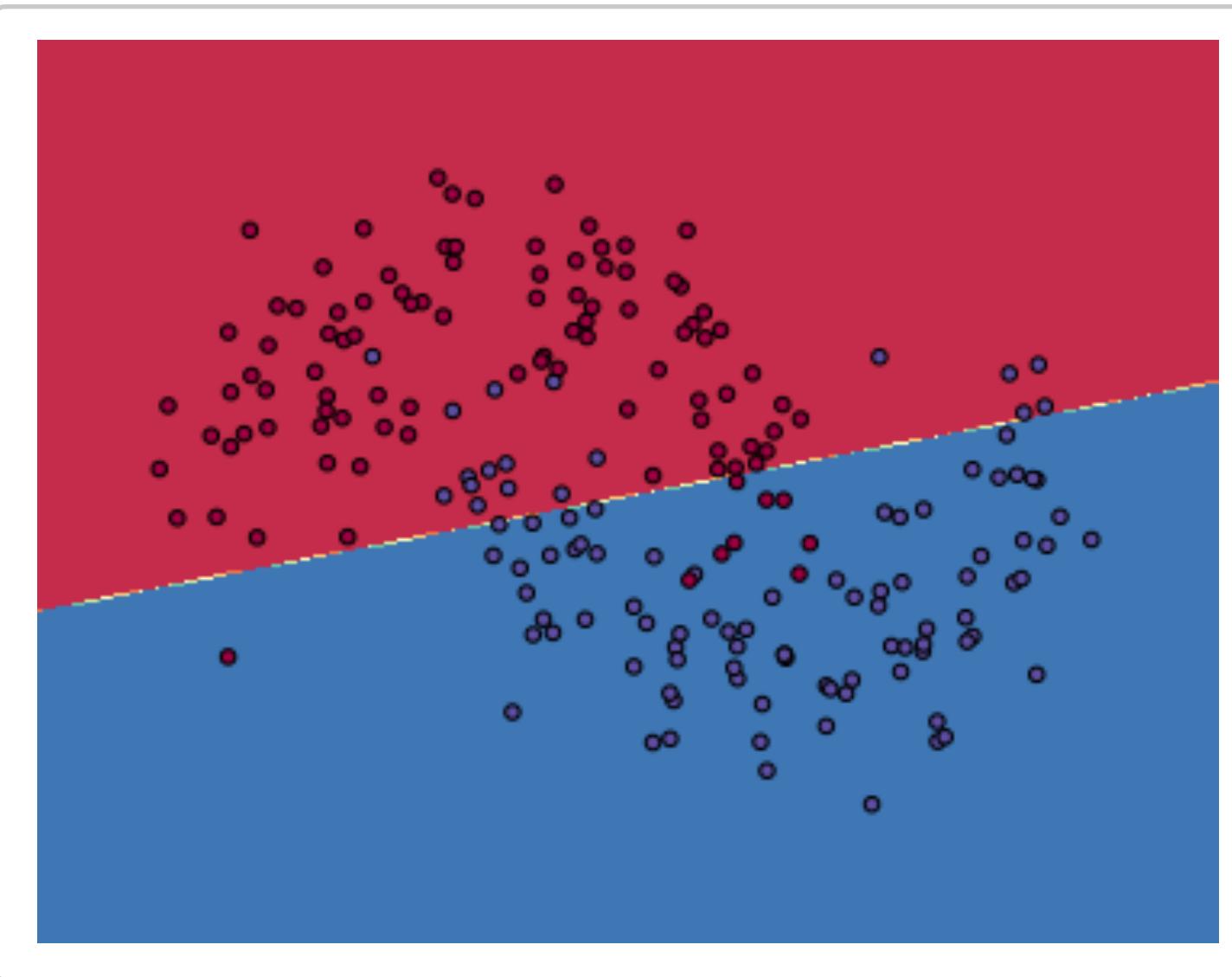


Três camadas

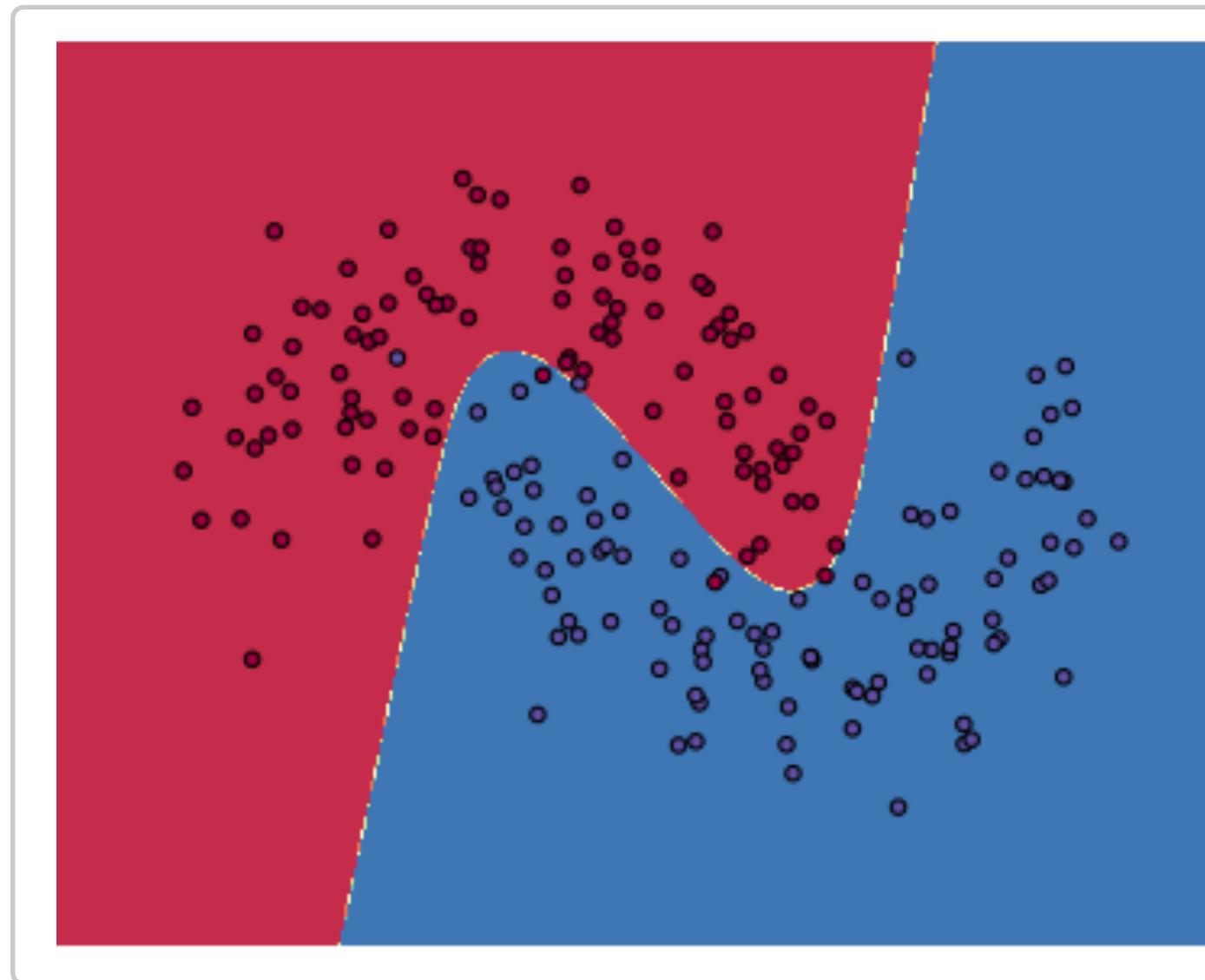


MAIS CAMADAS... MAIS ESTRUTURAS COMPLEXAS PODEMOS GENERALIZAR

Uma camada



Três camadas

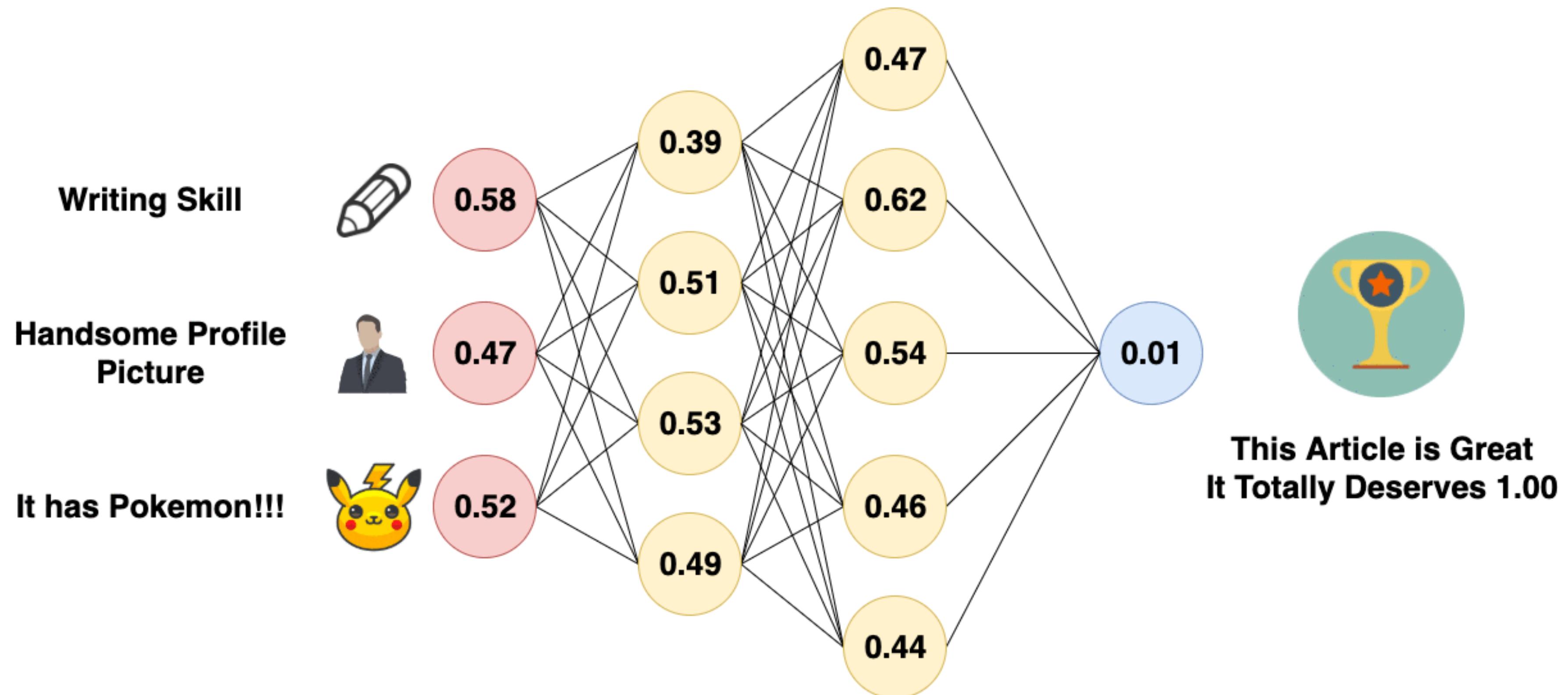


50 camadas !!!

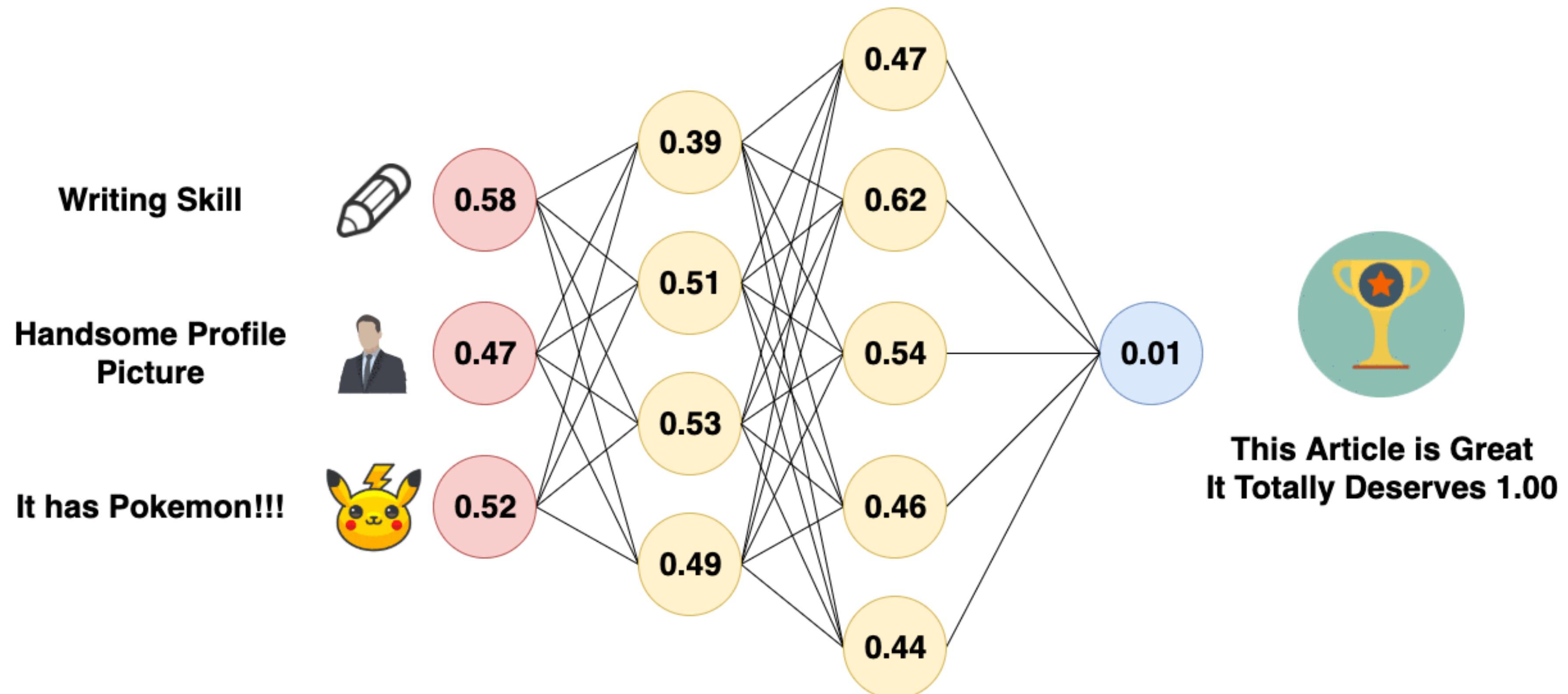


E O TREINAMENTO...?

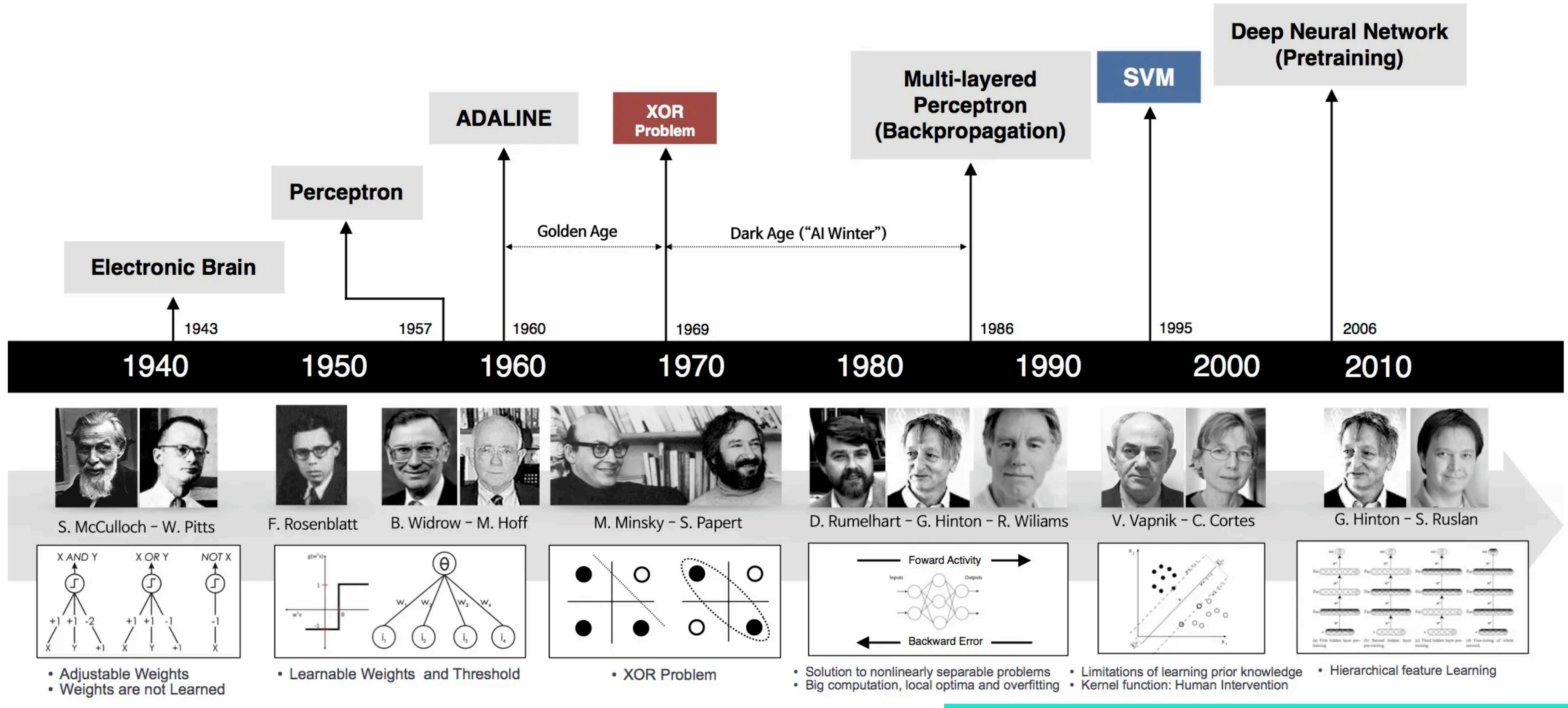
RETROPROPAGAÇÃO DO ERRO



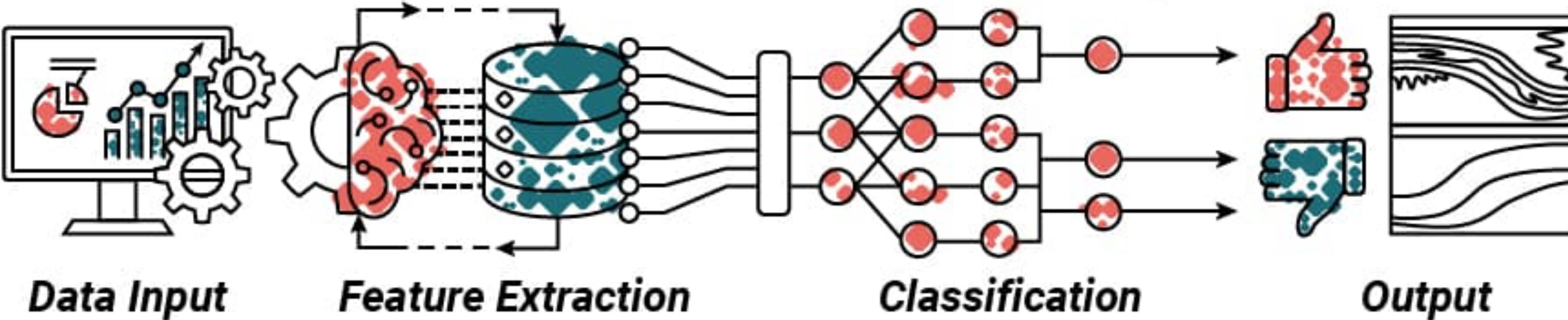
RETROPROPAGAÇÃO DO ERRO



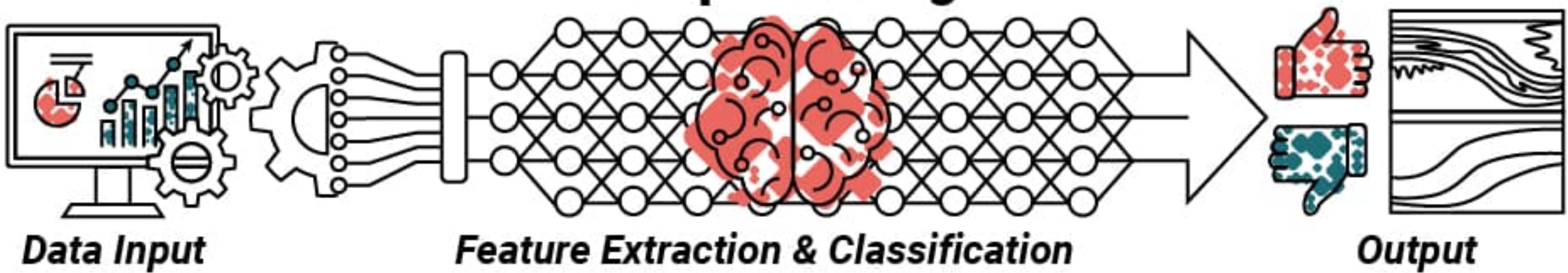
Evolução das Redes Neurais Artificiais



Traditional Machine Learning



Deep Learning



Fonte: <https://mosaicdatascience.com/2022/02/02/how-deep-learning-facilitates-automation-innovation-and-when-to-use-it/>

Aprendizagem de máquina vs Aprendizagem Profunda

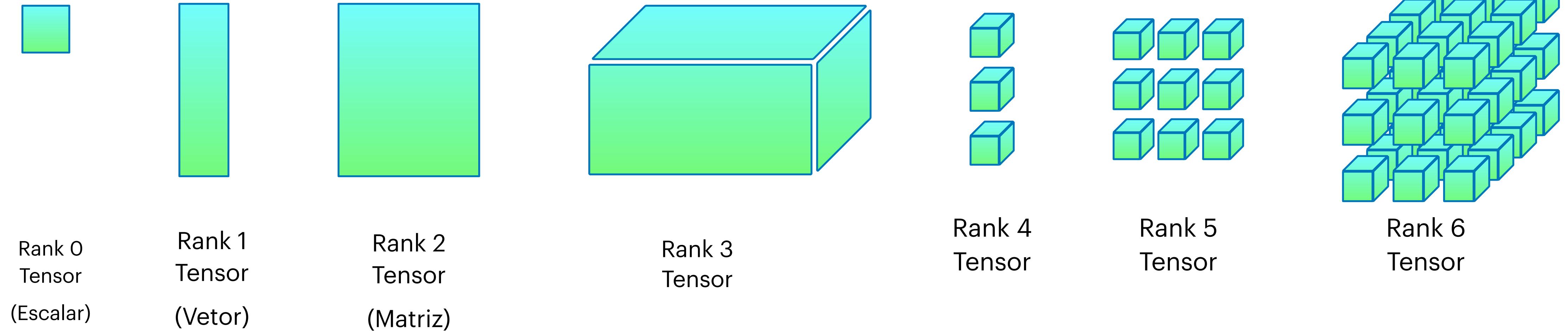
Tradicional	Profunda
Baixos requisitos de hardware no computador: Dada a quantidade limitada de computação, o computador, geralmente, não precisa de uma GPU para computação paralela.	Requisitos de hardware mais altos no computador: Para executar operações de matriz em dados massivos , o computador precisa de uma GPU (ou TPU) para executar a computação paralela.
Aplicável ao treinamento com uma pequena quantidade de dados e cujo desempenho não pode ser melhorado continuamente à medida que a quantidade de dados aumenta .	Cujo desempenho pode ser alto quando parâmetros de peso de alta dimensão e dados de treinamento massivos são fornecidos.
Detalhamento do problema nível por nível.	Aprendizagem ponto-a-ponto (E2E learning).
Seleção manual de atributos.	Extração automática de atributos.
Atributos fáceis de explicar.	Atributos (ainda) difíceis de explicar.

TENSORES SÃO TUDO

Tensores

Tensores são as estruturas de dados mais básicas nos Frameworks de Deep Learning. Todos os dados são encapsulados em tensores.

Tensor: uma matriz multidimensional.

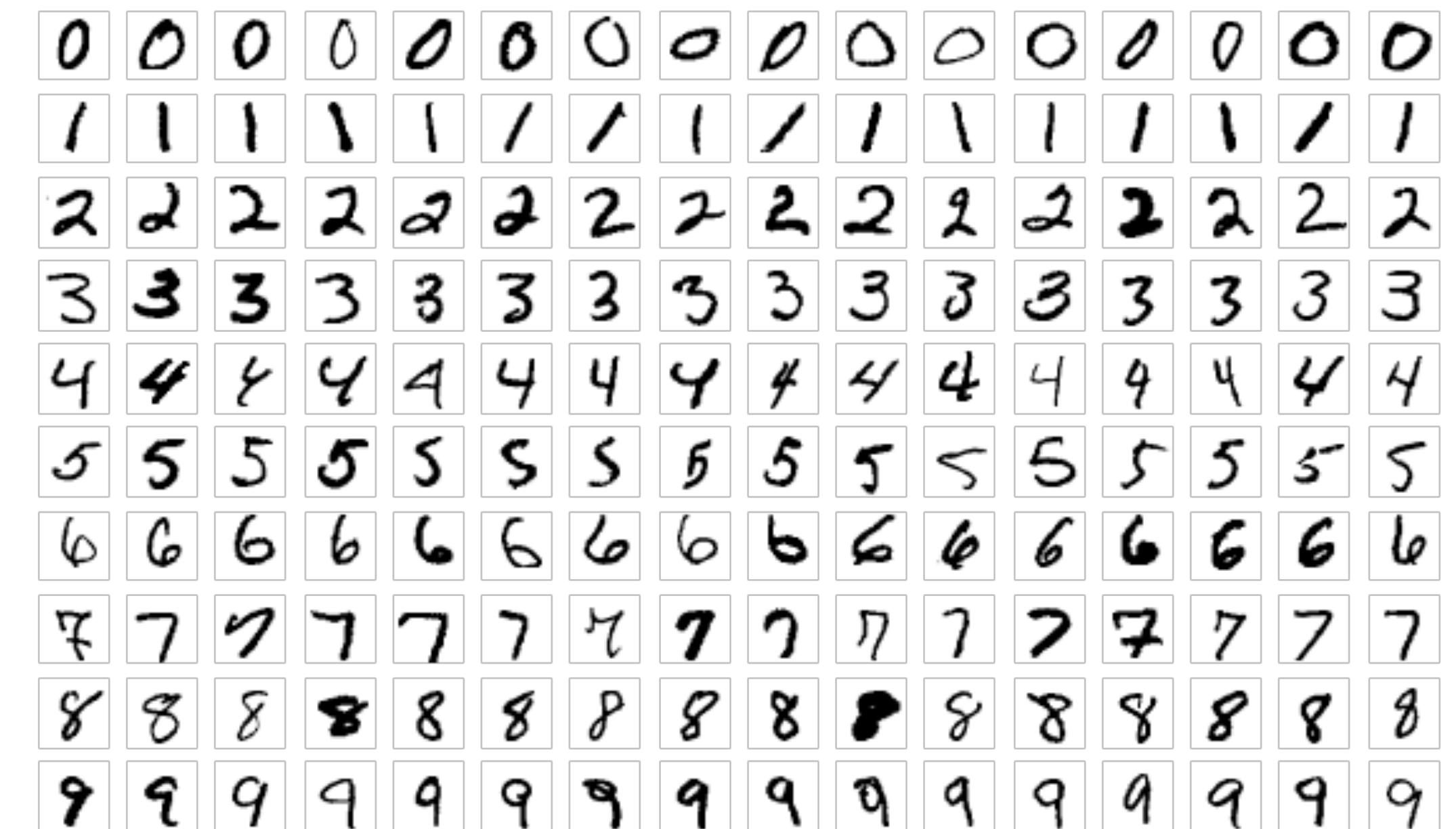


MNIST

O banco de dados **MNIST** (banco de dados modificado do Instituto Nacional de Padrões e Tecnologia) é um grande banco de dados de dígitos manuscritos que é comumente usado para treinar vários sistemas de processamento de imagem.

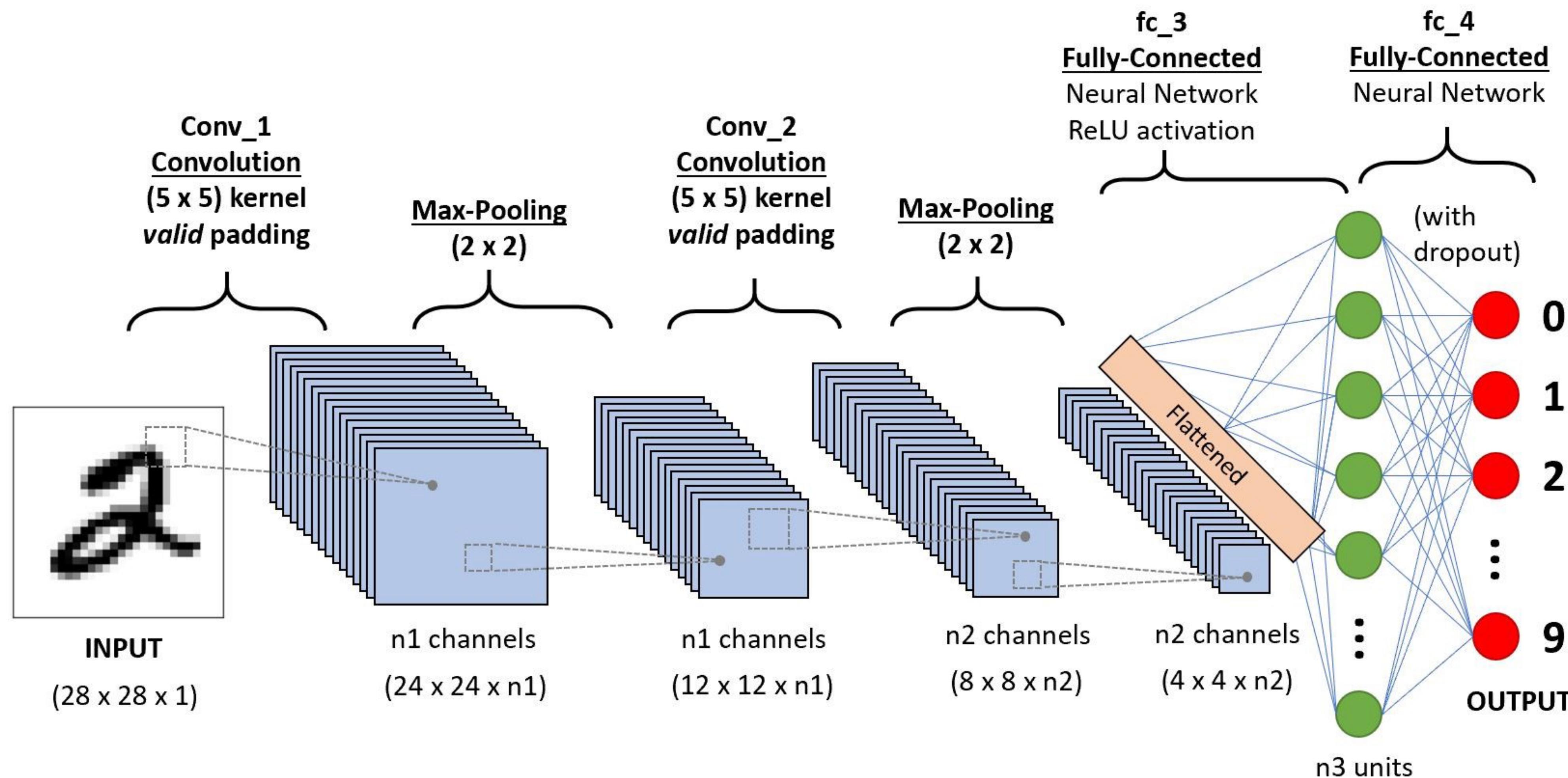
O banco de dados MNIST contém 60.000 imagens de treinamento e 10.000 imagens de teste.

Além disso, as imagens em preto e branco do NIST foram normalizadas para caber em uma caixa delimitadora de pixel e anti-aliasing, o que introduziu níveis de tons de cinza.



Fonte: https://en.wikipedia.org/wiki/MNIST_database

Arquitetura geral de uma CNN



Fonte: <https://agents.co/blog/publication/introduction-to-convolutional-neural-networks-cnns/>

Error signal: 0.007

Variation weights: 0.163

Total bias: -0.537

ADVANCED NEURAL NETWORK

9
8
7
6
5
4
3
2
1
0

Epoch: 1

Iteration: 33

Error: 9.500524

Fonte: <https://www.youtube.com/watch?v=2GYLpzZzqeg>

Error signal: 0.007

Variation weights: 0.163

Total bias: -0.537

ADVANCED NEURAL NETWORK

9
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Epoch: 1

Iteration: 33

Error: 9.500524

Fonte: <https://www.youtube.com/watch?v=2GYLpzZzqeg>

NOVAS CAMADAS...
NOVOS SUPERPODERES...

CNN em ação

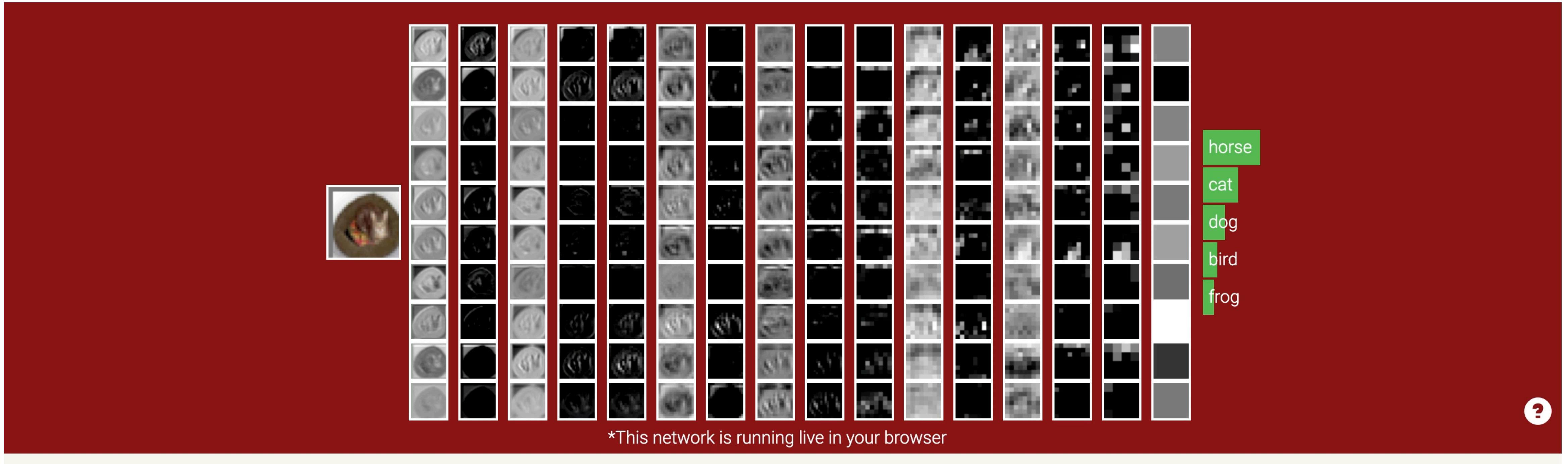


CS231n: Convolutional Neural Networks for Visual Recognition



Spring 2020

Previous Years: [\[Winter 2015\]](#) [\[Winter 2016\]](#) [\[Spring 2017\]](#) [\[Spring 2018\]](#) [\[Spring 2019\]](#)



Fonte: <http://cs231n.stanford.edu/>

CNN em ação



CS231n: Convolutional Neural Networks for Visual Recognition



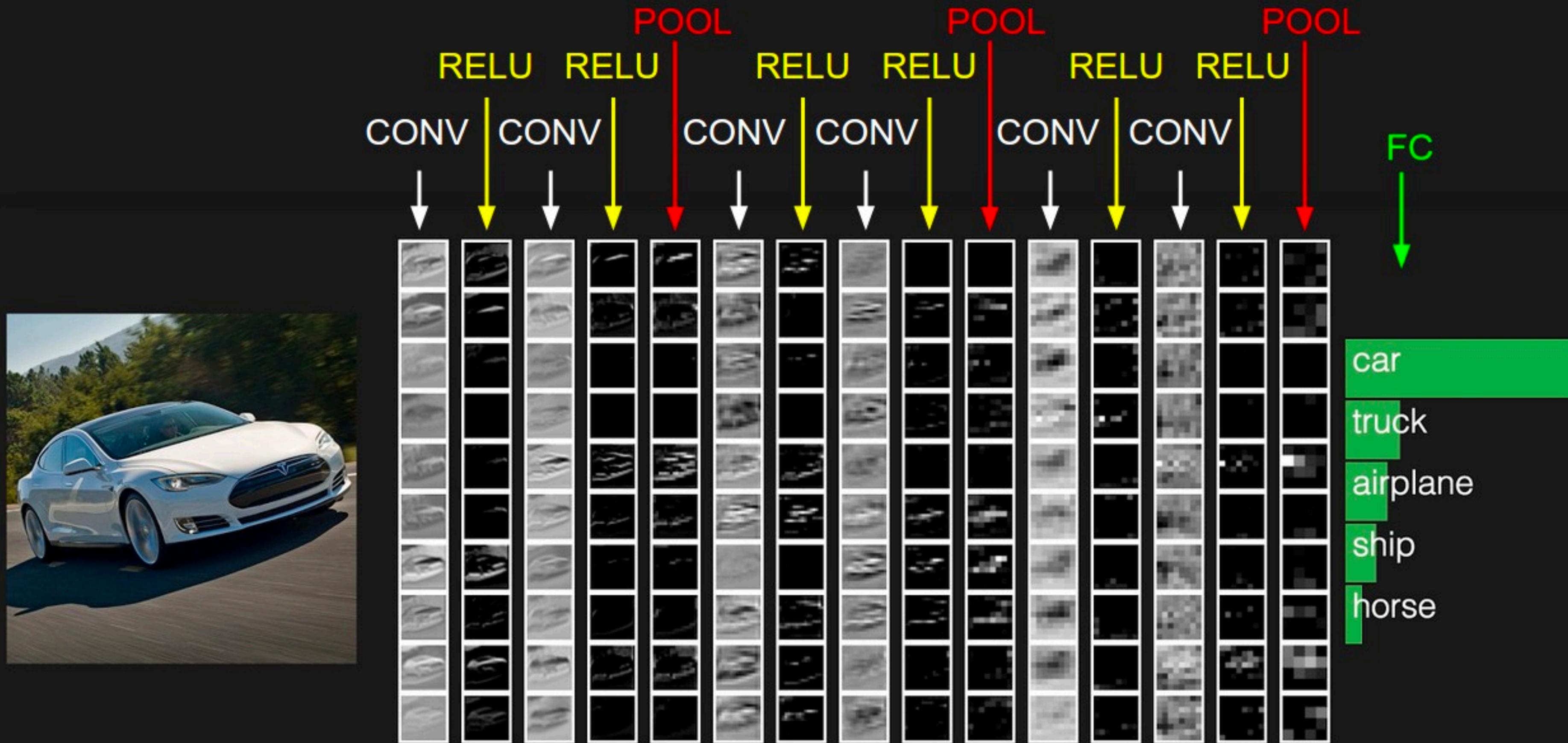
Spring 2020

Previous Years: [\[Winter 2015\]](#) [\[Winter 2016\]](#) [\[Spring 2017\]](#) [\[Spring 2018\]](#) [\[Spring 2019\]](#)



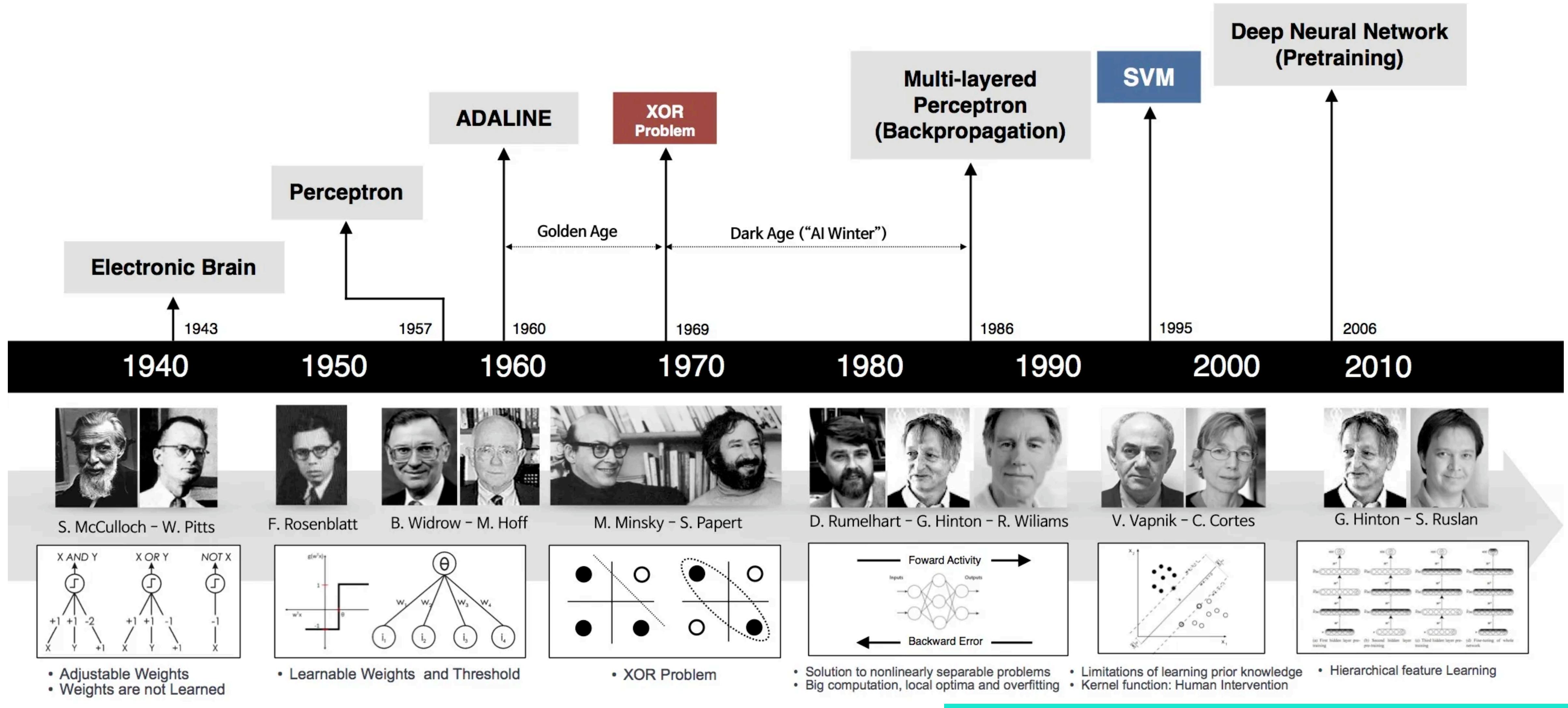
Fonte: <http://cs231n.stanford.edu/>

CNN em ação

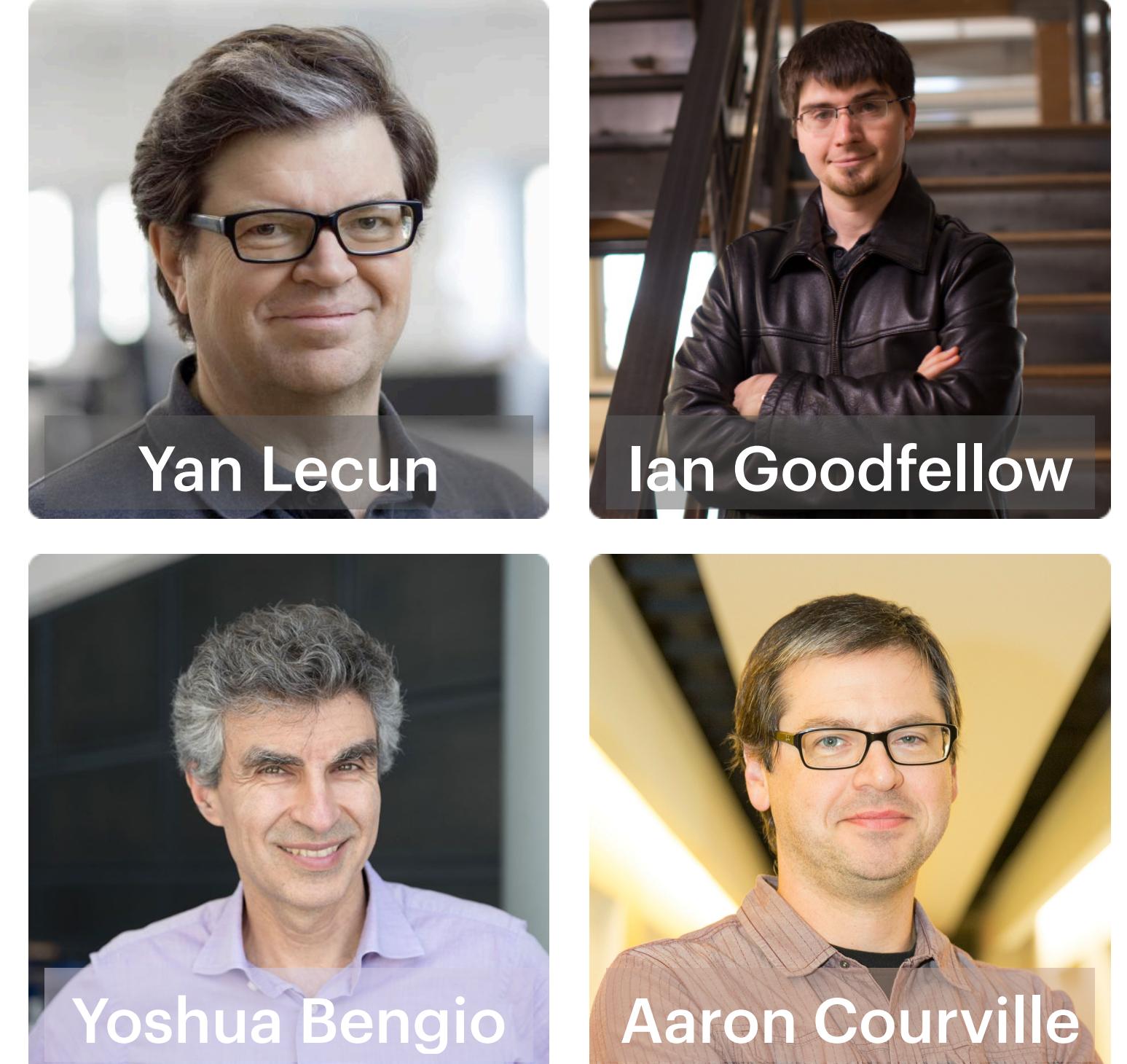
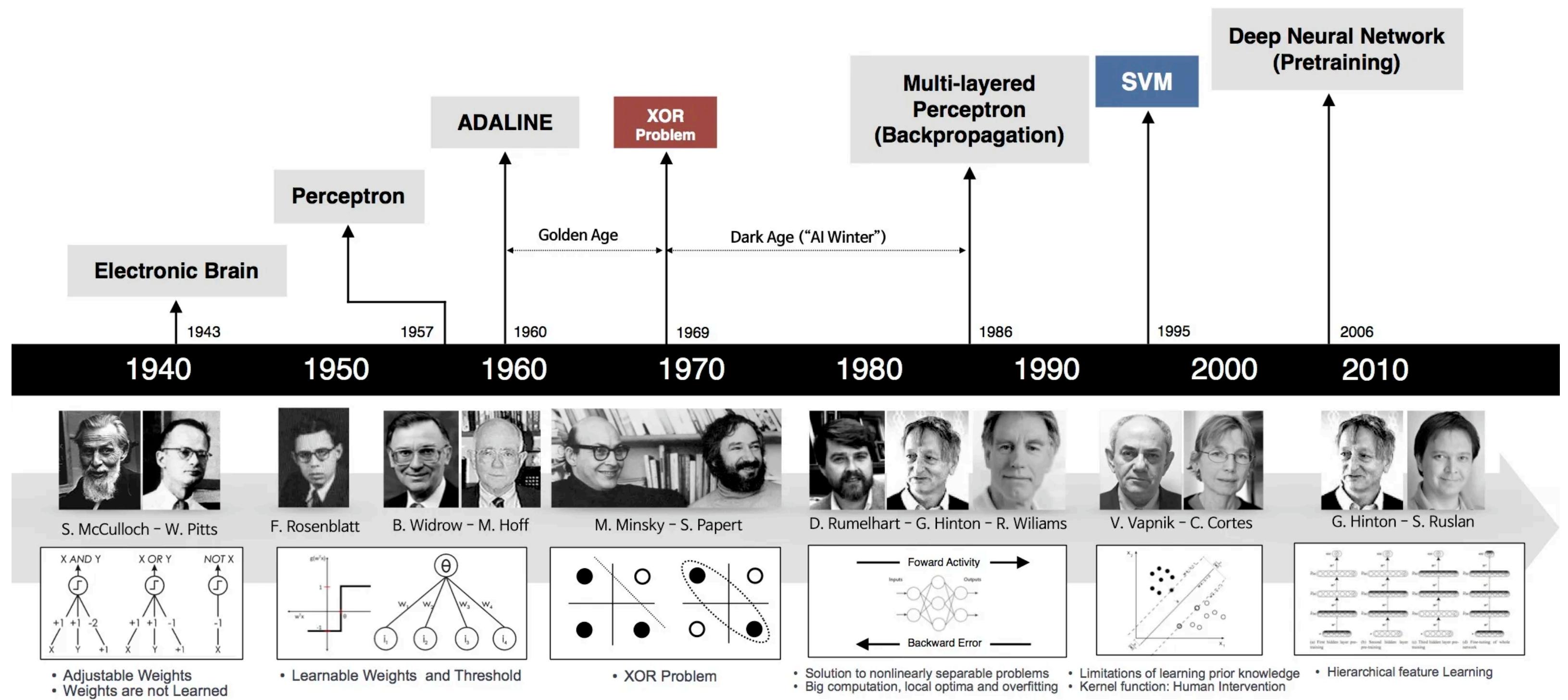


Fonte: <https://cs231n.github.io/convolutional-networks/>

Evolução das Redes Neurais Artificiais



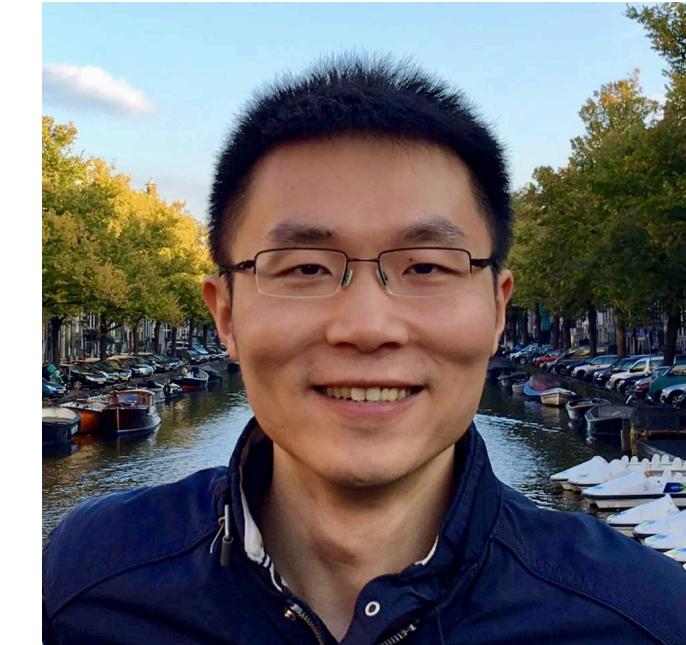
Evolução das Redes Neurais Artificiais



**EXISTEM 1000 MANEIRAS
DE FAZER NESTON™**

**EXISTEM 1000 MANEIRAS
DE FAZER ~~XEXTONX~~
REDES PROFUNDAS.
CRIE UMA!**

ImageNet



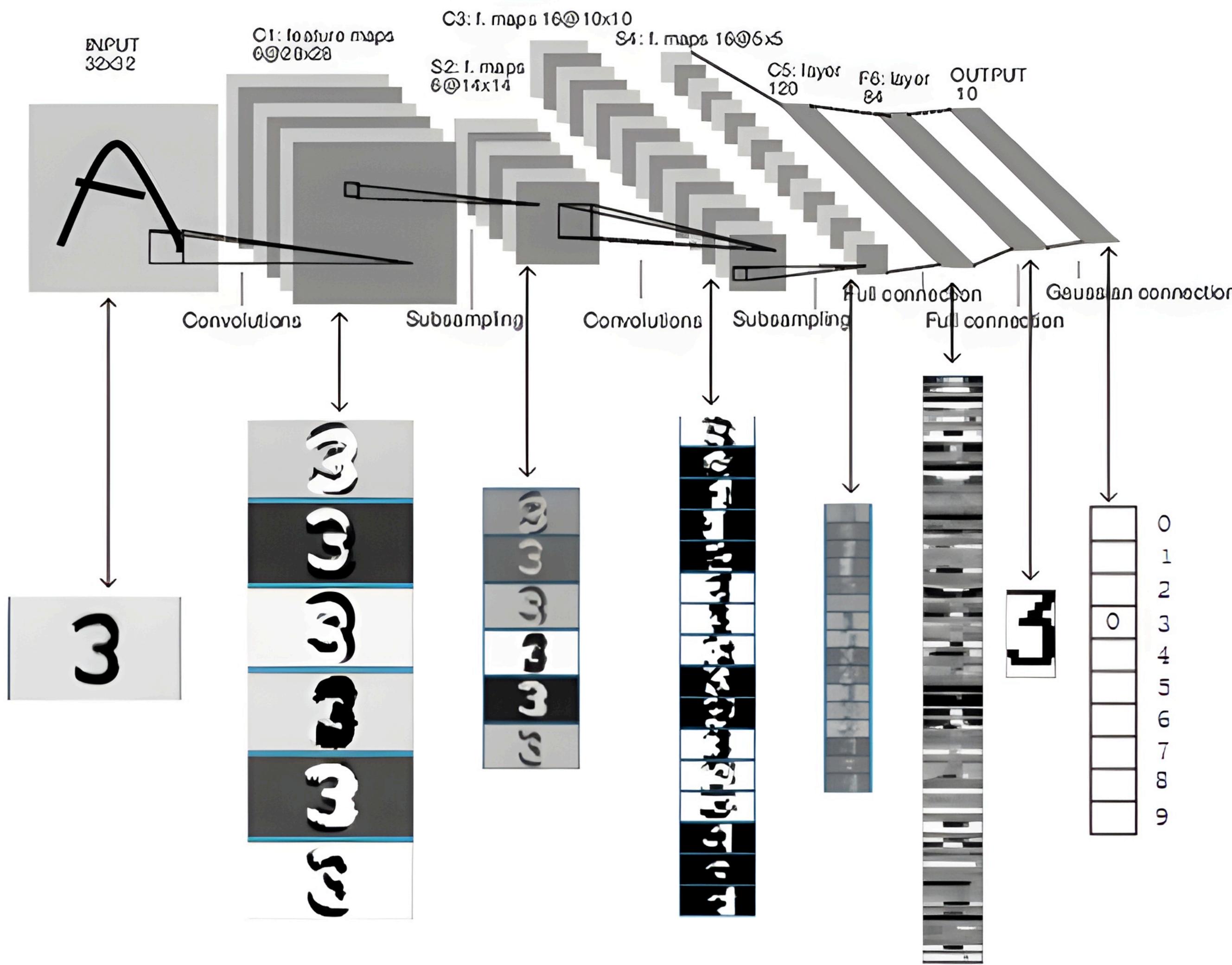
>53K
citações

Fonte: DENG, Jia et al. ImageNet: A large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. IEEE, 2009. p. 248-255.

O projeto **ImageNet** é um grande banco de dados visual projetado para uso em pesquisa de software de reconhecimento de objetos visuais. Nele, mais de **14M** de imagens foram anotadas manualmente para indicar quais objetos, em **>20K categorias**, são retratados e, **≈1M** de imagens, caixas delimitadoras também são fornecidas.

Fonte: <https://www.image-net.org/index.php>

LeNet



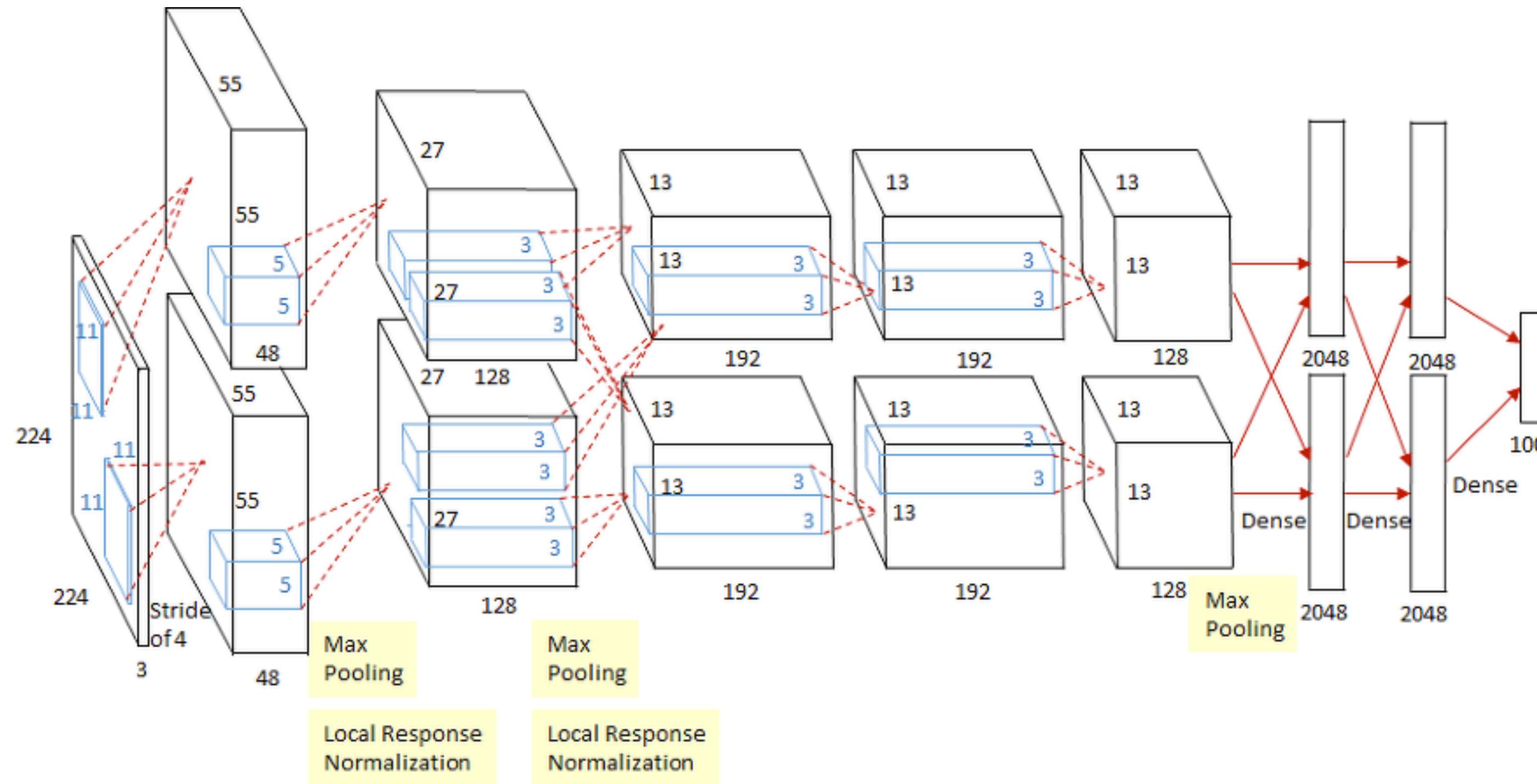
	Camada	Feature	Tam	Filtro	Stride	Activation
In	Image	1	32×32	-	-	-
1	Convolution	6	28×28	5×5	1	tanh
2	Average pool	6	14×14	2×2	2	tanh
3	Convolution	16	10×10	5×5	1	tanh
4	Average pool	16	5×5	2×2	2	tanh
5	Convolution	120	1×1	5×5	1	tanh
6	FC	-	84	-	-	tanh
Out	FC	-	10	-	-	softmax



>54K
citações

Fonte: LECUN, Yann et al. Gradient-based learning applied to document recognition. Proceedings of the IEEE, v. 86, n. 11, p. 2278-2324, 1998.

AlexNet

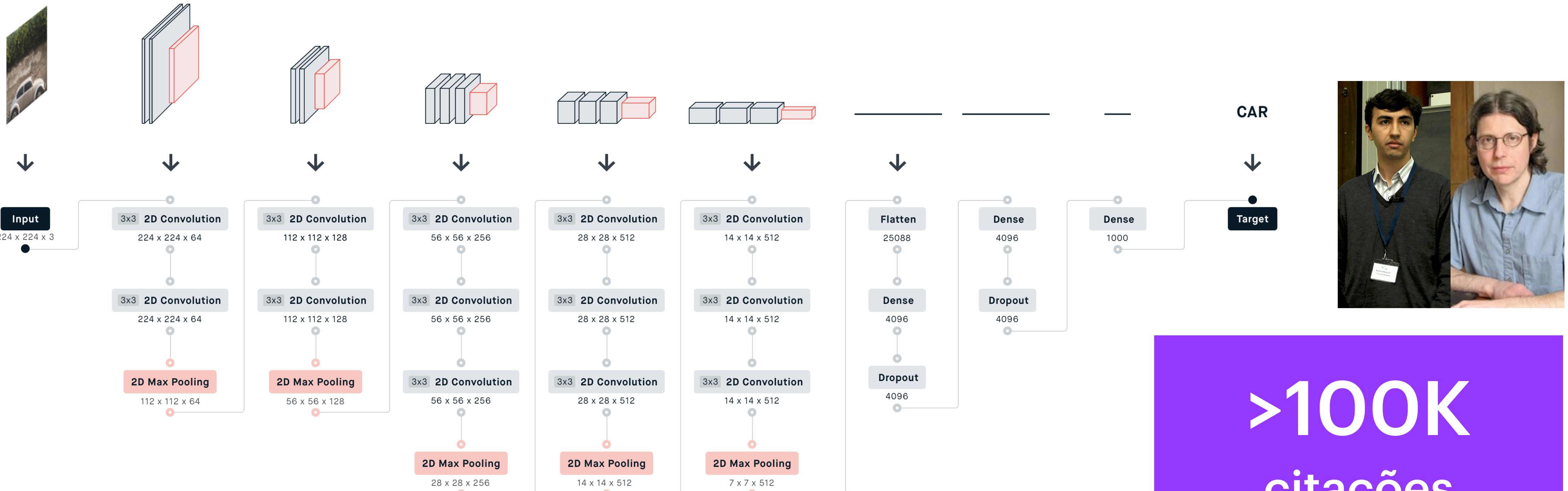


>131K
citações

Fonte: KRIZHEVSKY, Alex; SUTSKEVER, Ilya; HINTON, Geoffrey E. ImageNet classification with deep convolutional neural networks. Communications of the ACM, v. 60, n. 6, p. 84-90, 2017.

Camada	Tamanho	Nº de pesos	Nº de viéses	Total
Input Image	227x227x3	0	0	0
Conv-1	55x55x96	34,848	96	34,944
MaxPool-1	27x27x96	0	0	0
Conv-2	27x27x256	614,400	256	614,656
MaxPool-2	13x13x256	0	0	0
Conv-3	13x13x384	884,736	384	885,120
Conv-4	13x13x384	1,327,104	384	1,327,488
Conv-5	13x13x256	884,736	256	884,992
MaxPool-3	6x6x256	0	0	0
FC-1	4096x1	37,748,736	4,096	37,752,832
FC-2	4096x1	16,777,216	4,096	16,781,312
FC-3	1000x1	4,096,000	1,000	4,097,000
Output	1000x1	0	0	0
Total				62,378,344

VGGNet



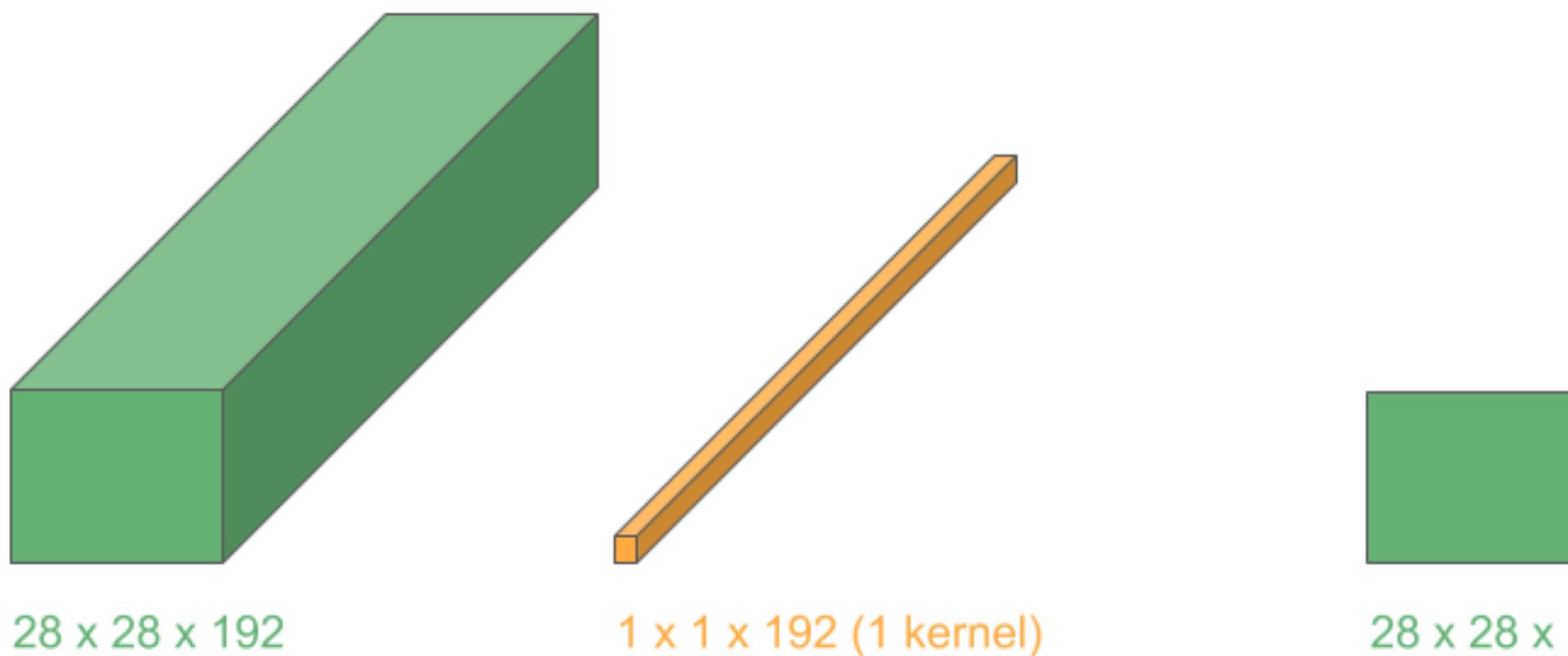
138M de parâmetros!

Fonte: <https://www.kaggle.com/code/blurredmachine/vggnet-16-architecture-a-complete-guide>

Fonte: SIMONYAN, Karen; ZISSERMAN, Andrew. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

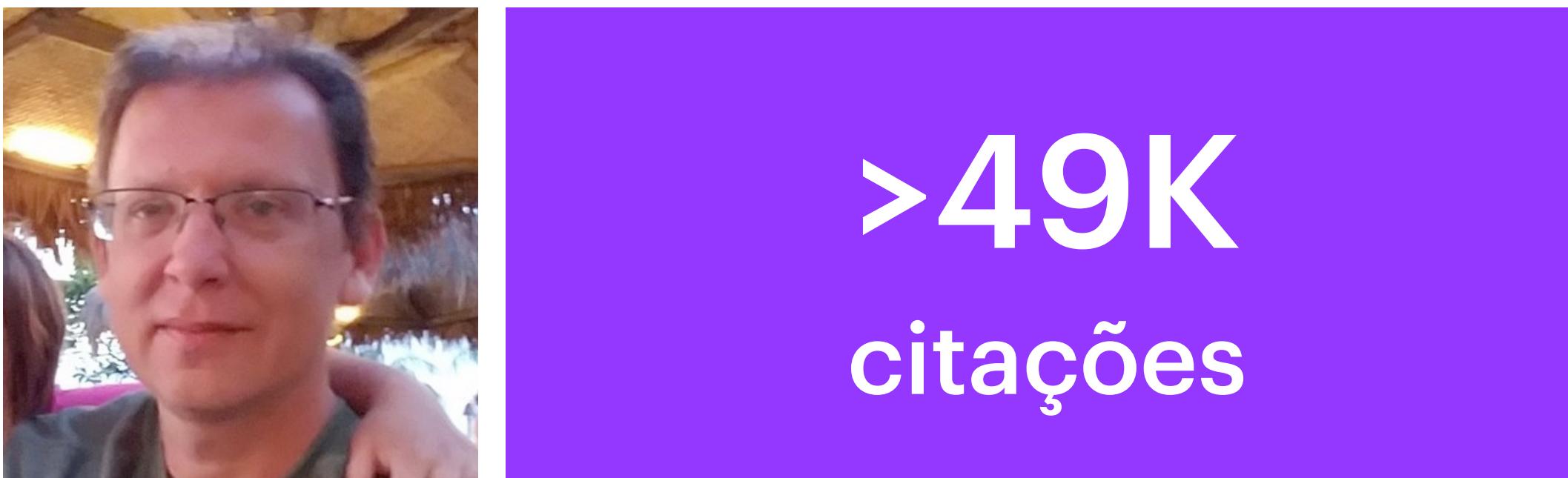
>100K
citações

GoogLeNet (Inception)



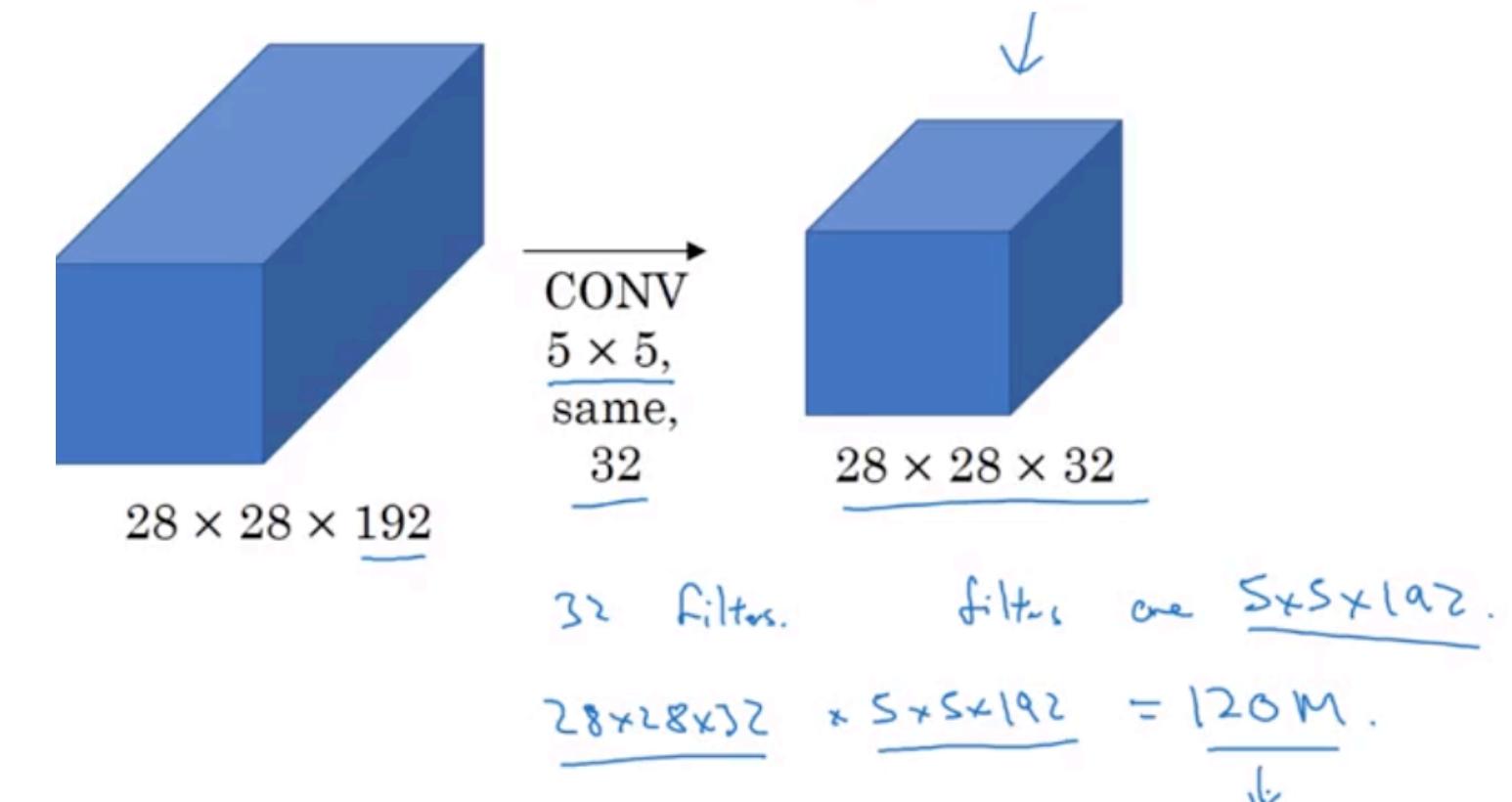
Fonte: <https://www.baeldung.com/cs/ml-understanding-dimensions-cnn>

Vídeo adicional: <https://youtu.be/qVP574skyuM>

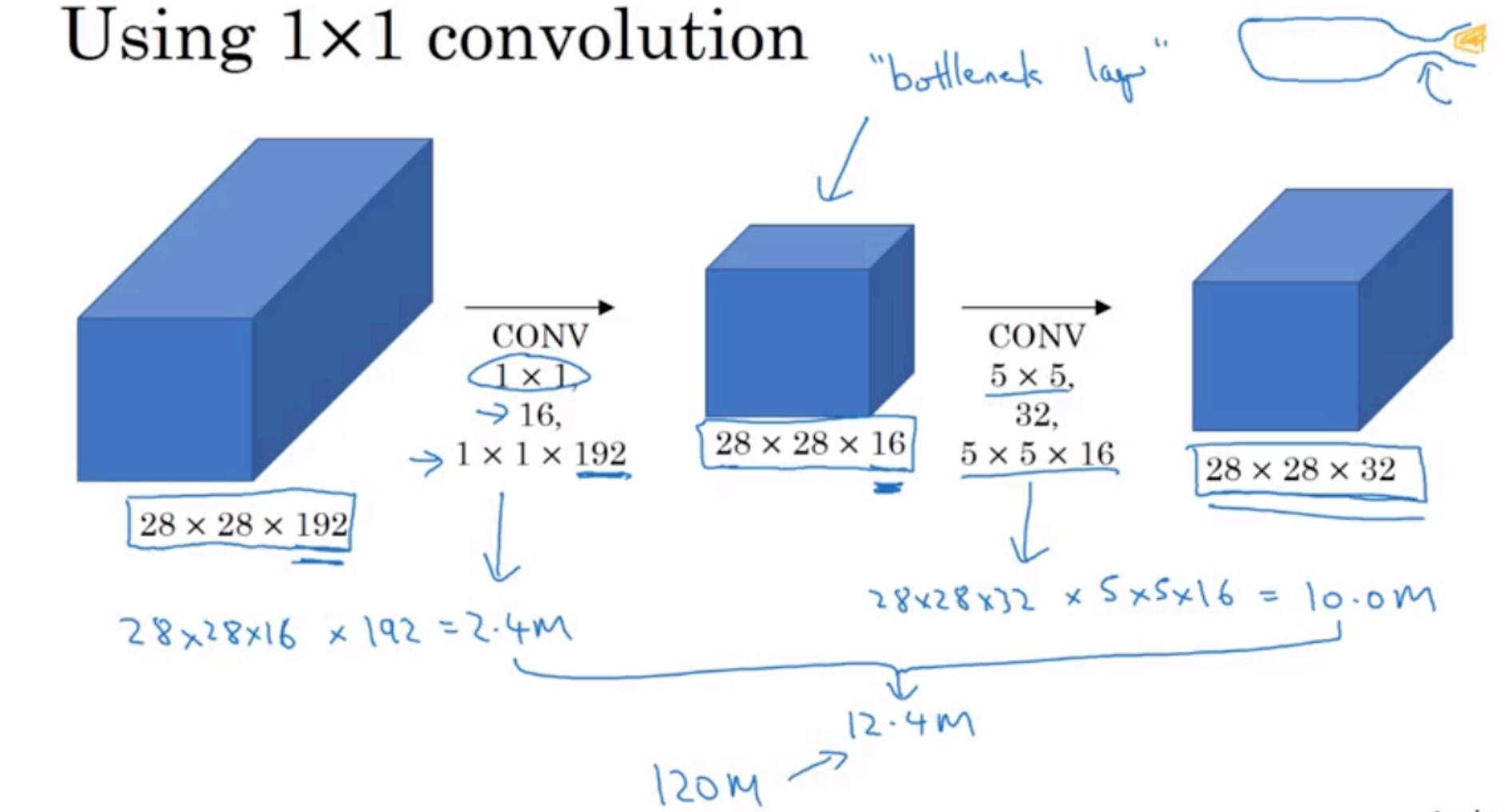


Fonte: SZEGEDY, Christian et al. Going deeper with convolutions.
In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

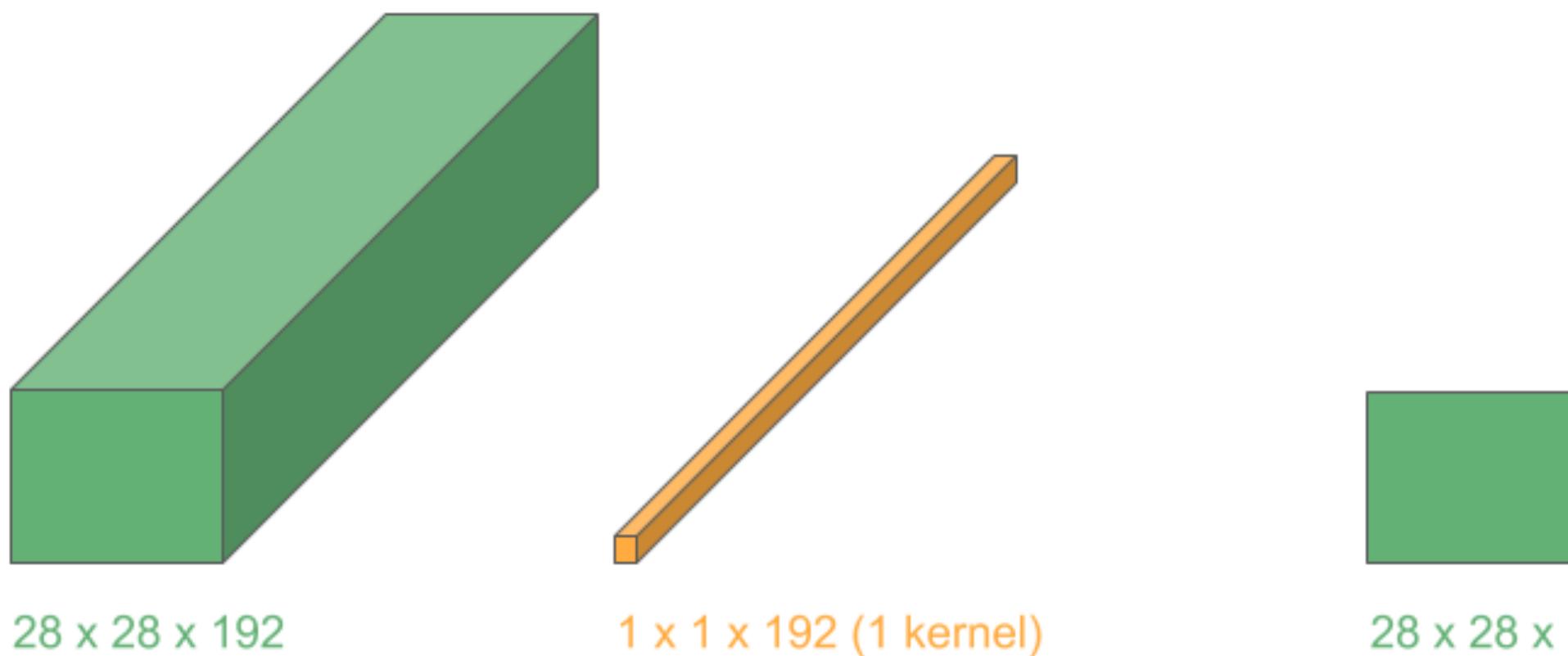
The problem of computational cost



Using 1×1 convolution

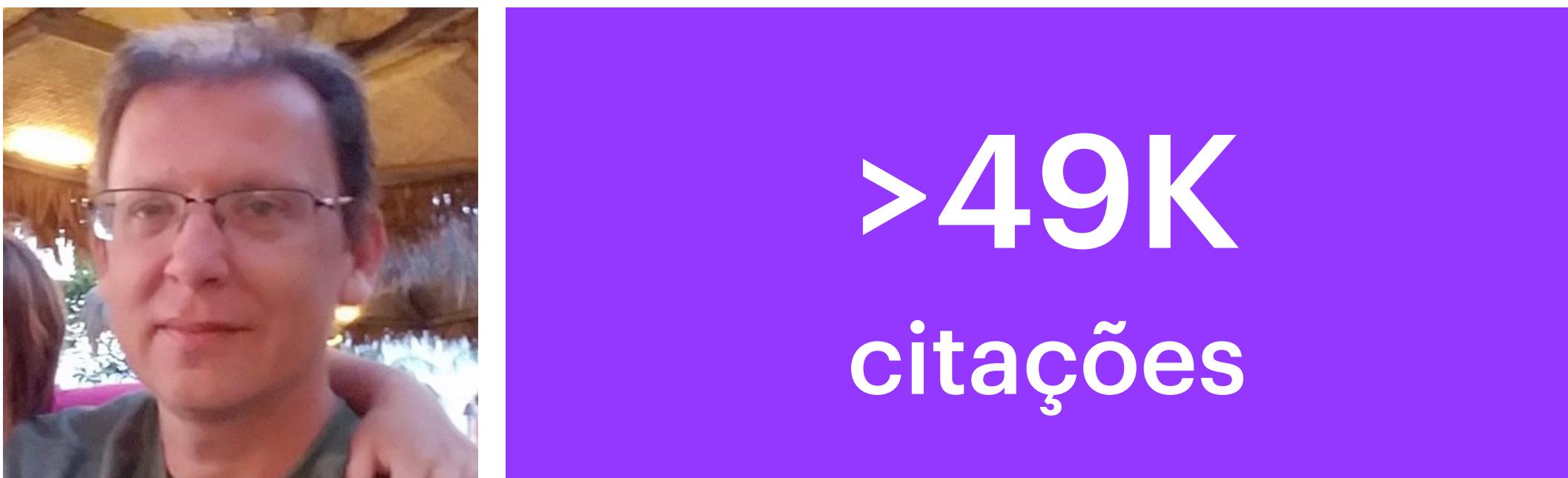


GoogLeNet (Inception)



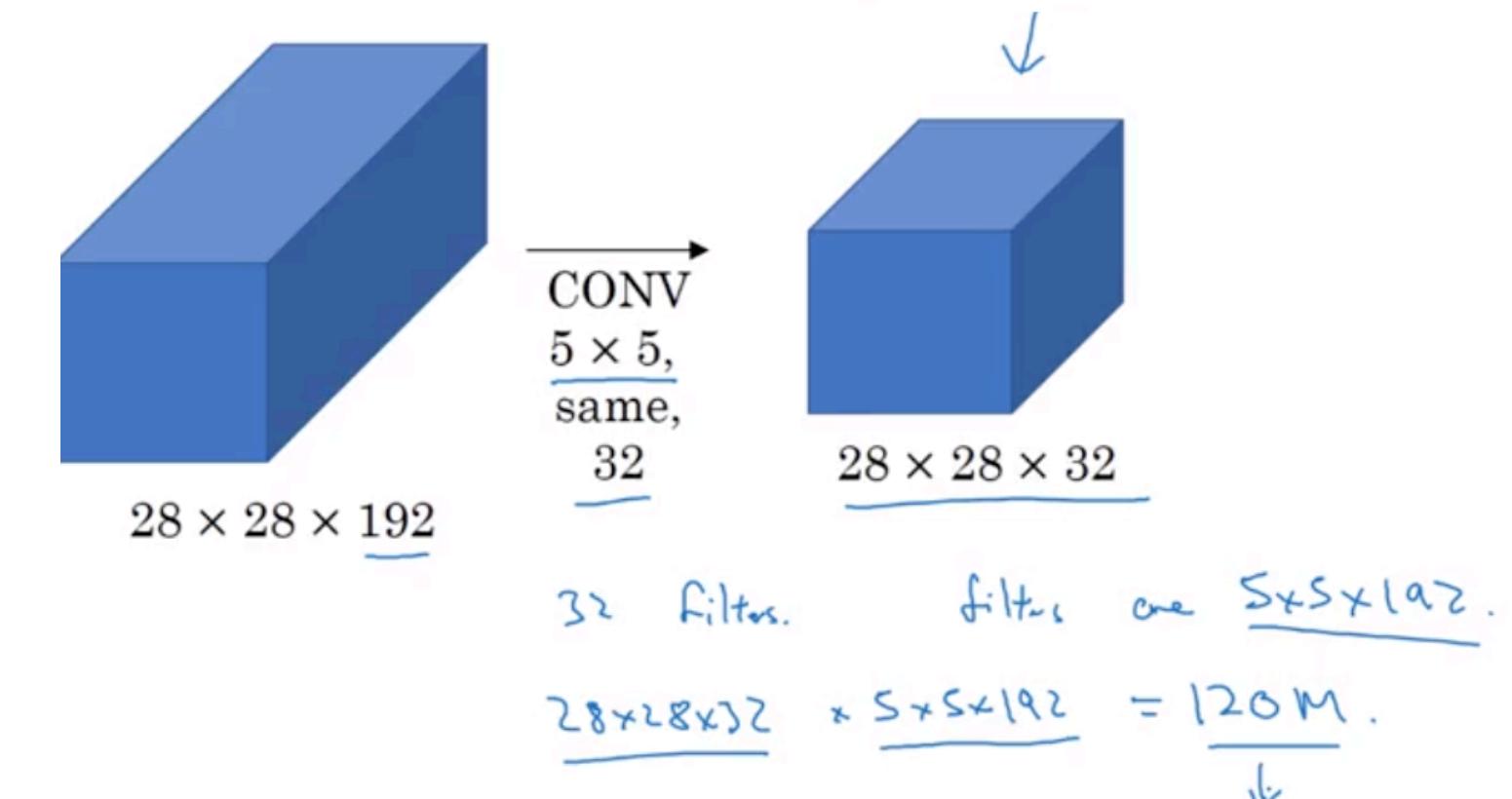
Fonte: <https://www.baeldung.com/cs/ml-understanding-dimensions-cnn>

Vídeo adicional: <https://youtu.be/qVP574skyuM>

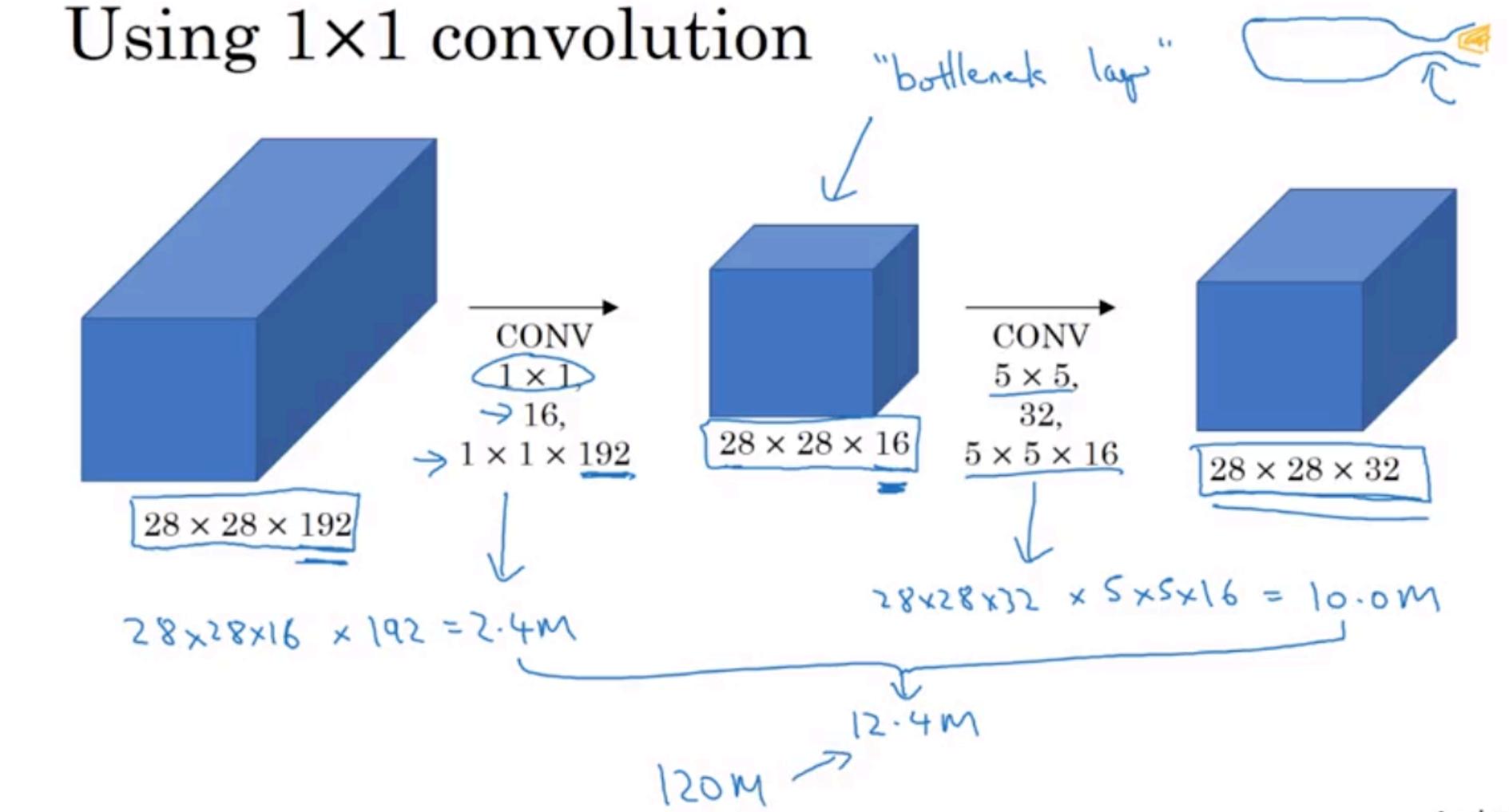


Fonte: SZEGEDY, Christian et al. Going deeper with convolutions.
In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

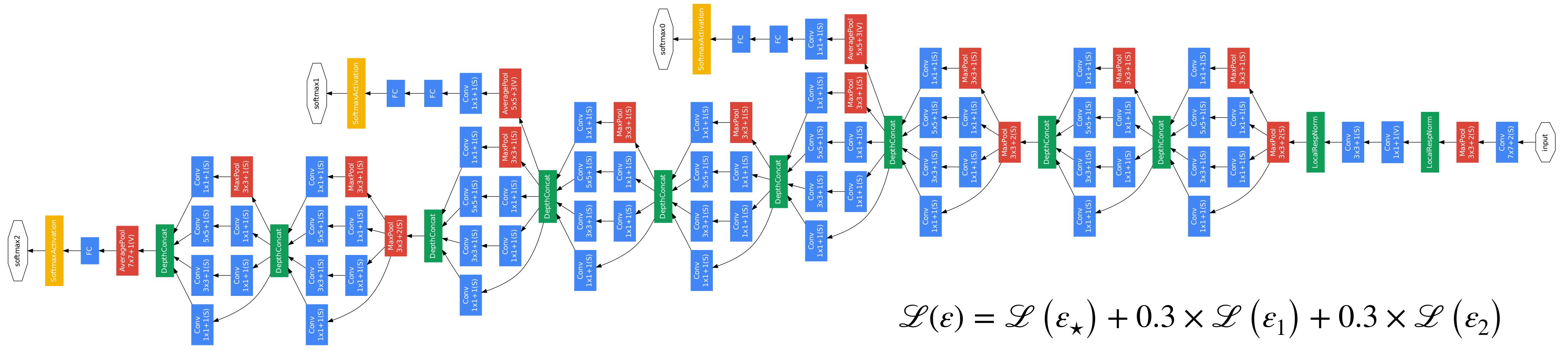
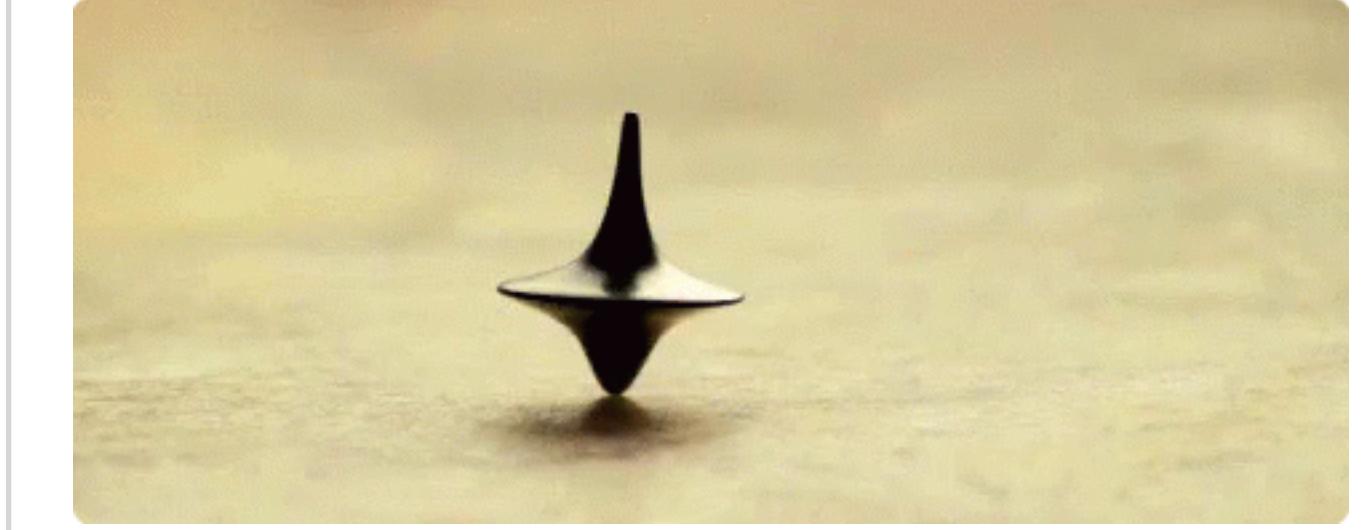
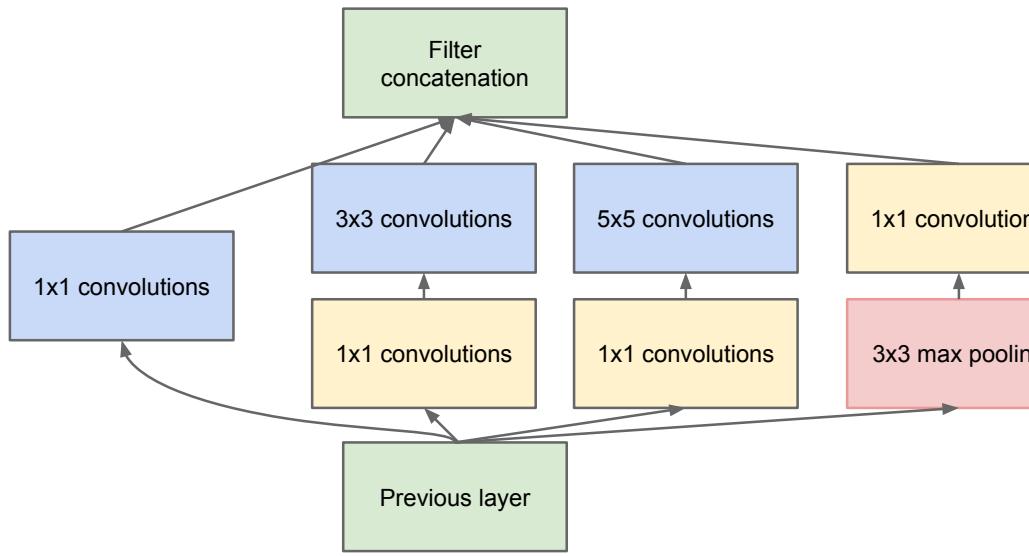
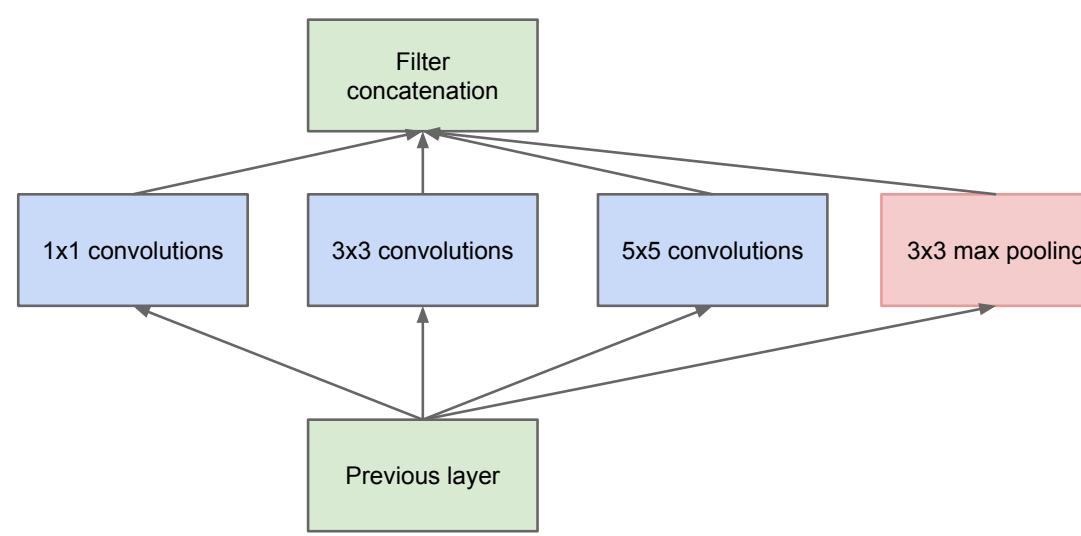
The problem of computational cost



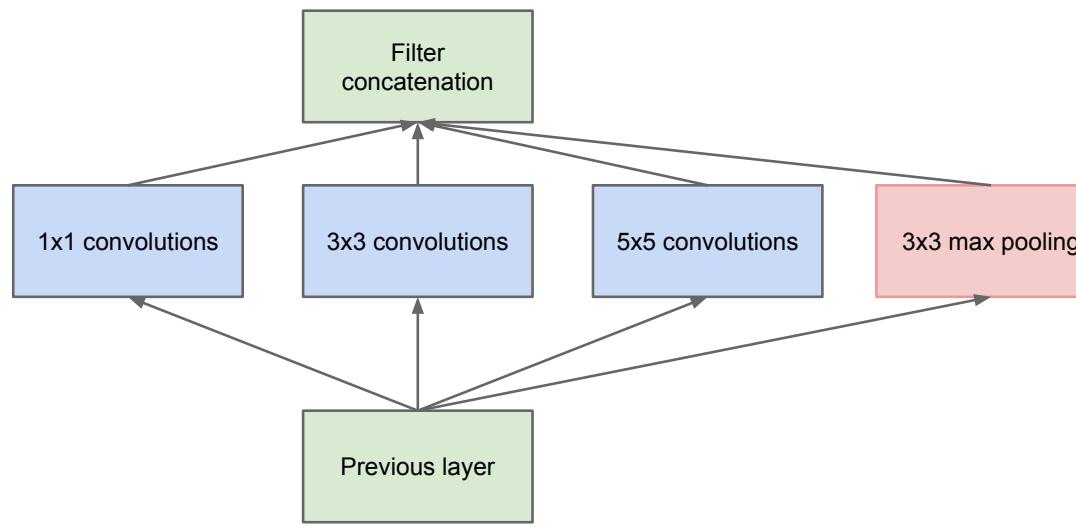
Using 1×1 convolution



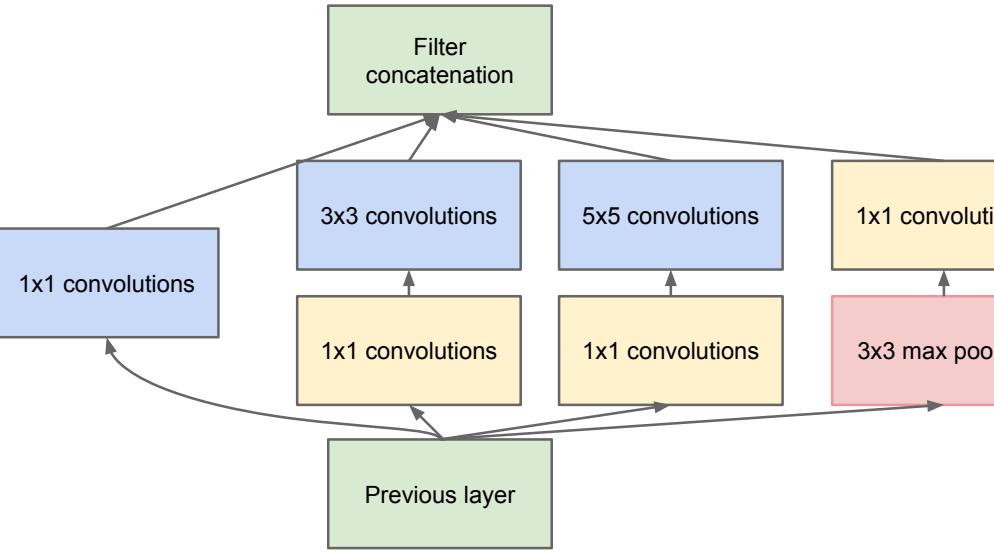
GoogLeNet (Inception)



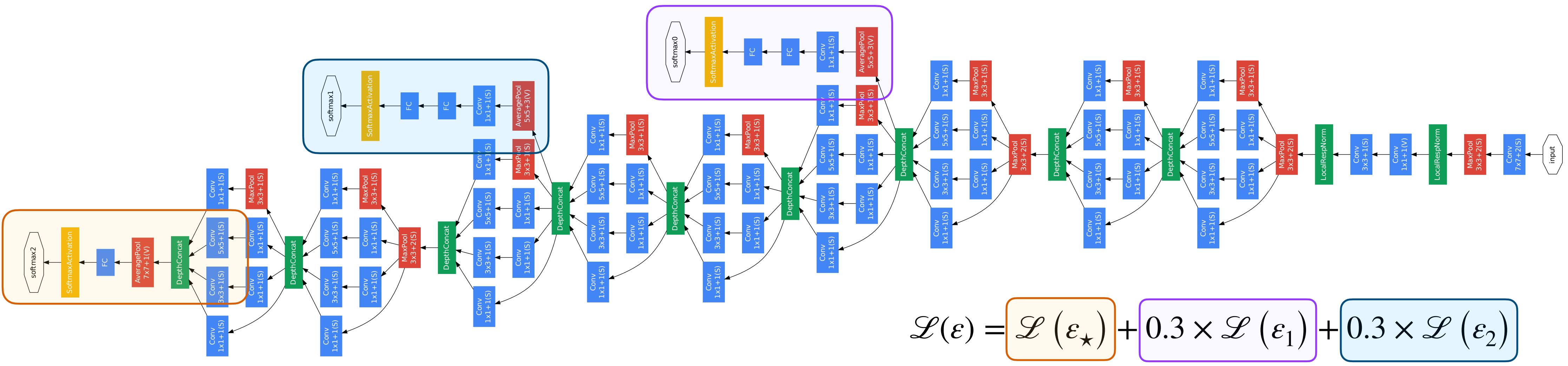
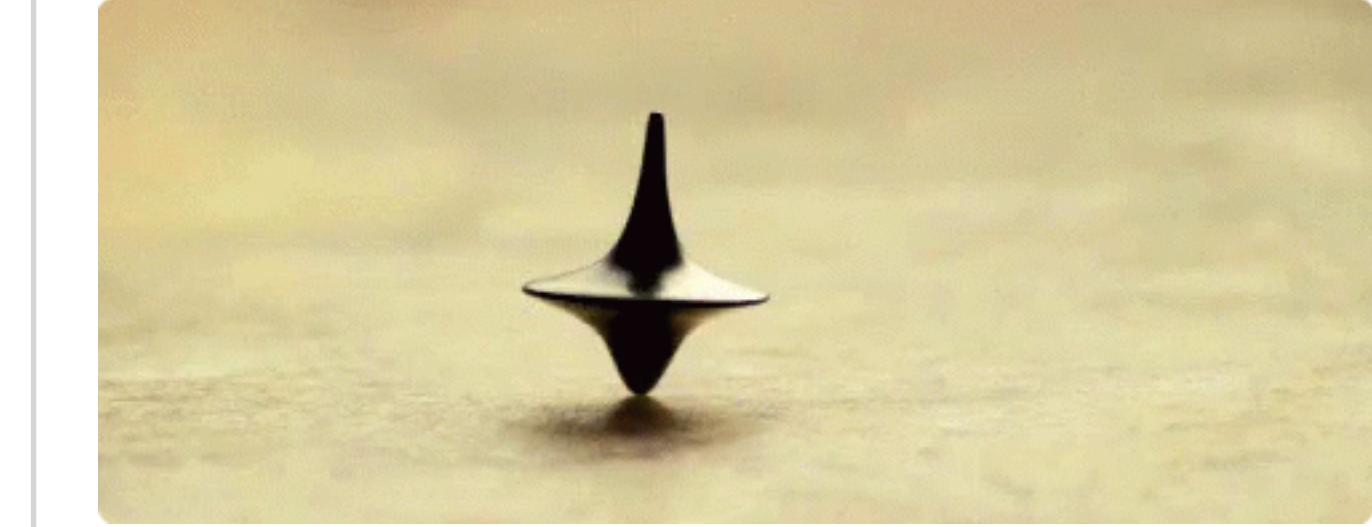
GoogLeNet (Inception)



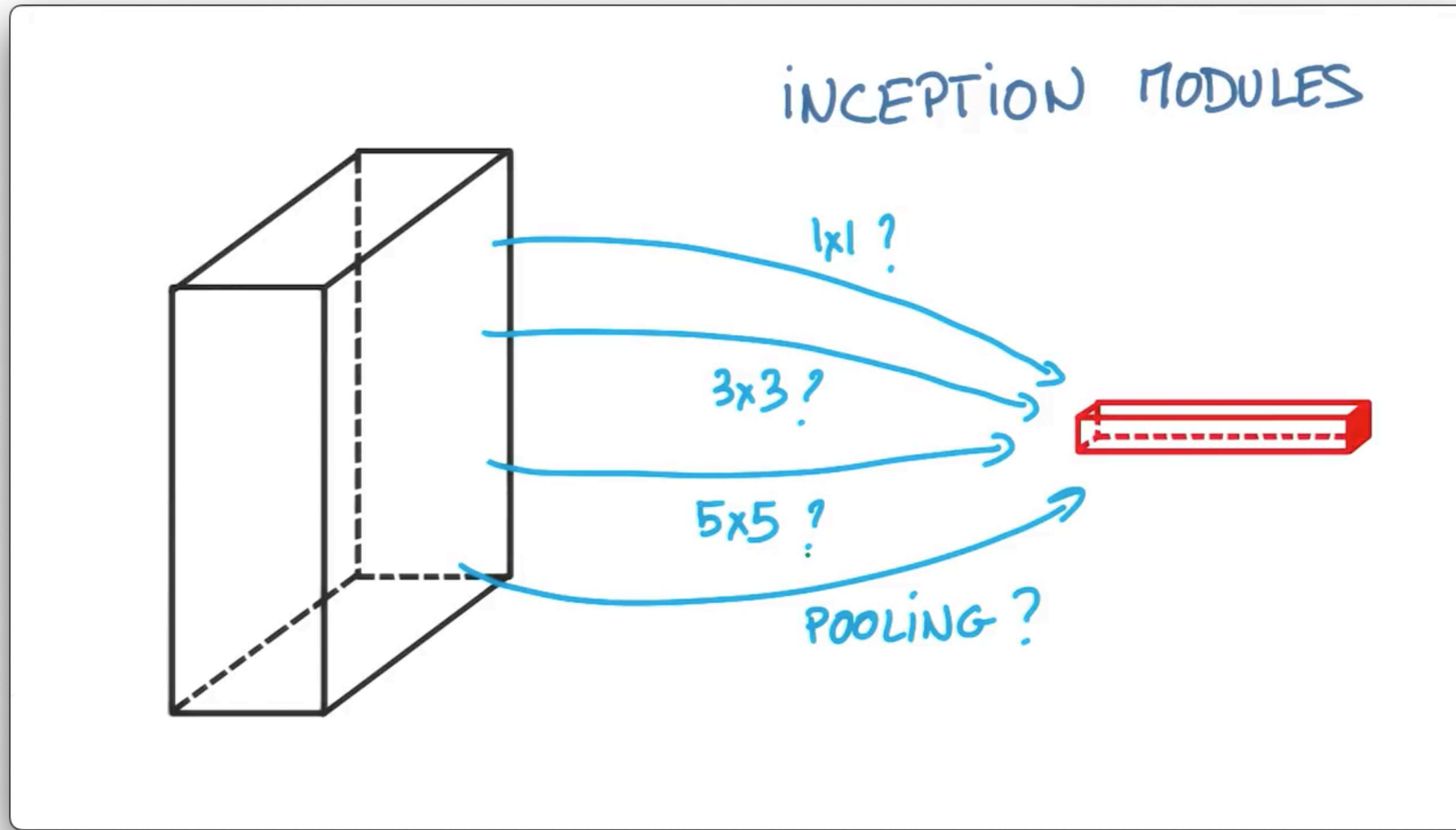
Módulo de *inception* ingênuo



Módulo de *inception* com redução das dimensões

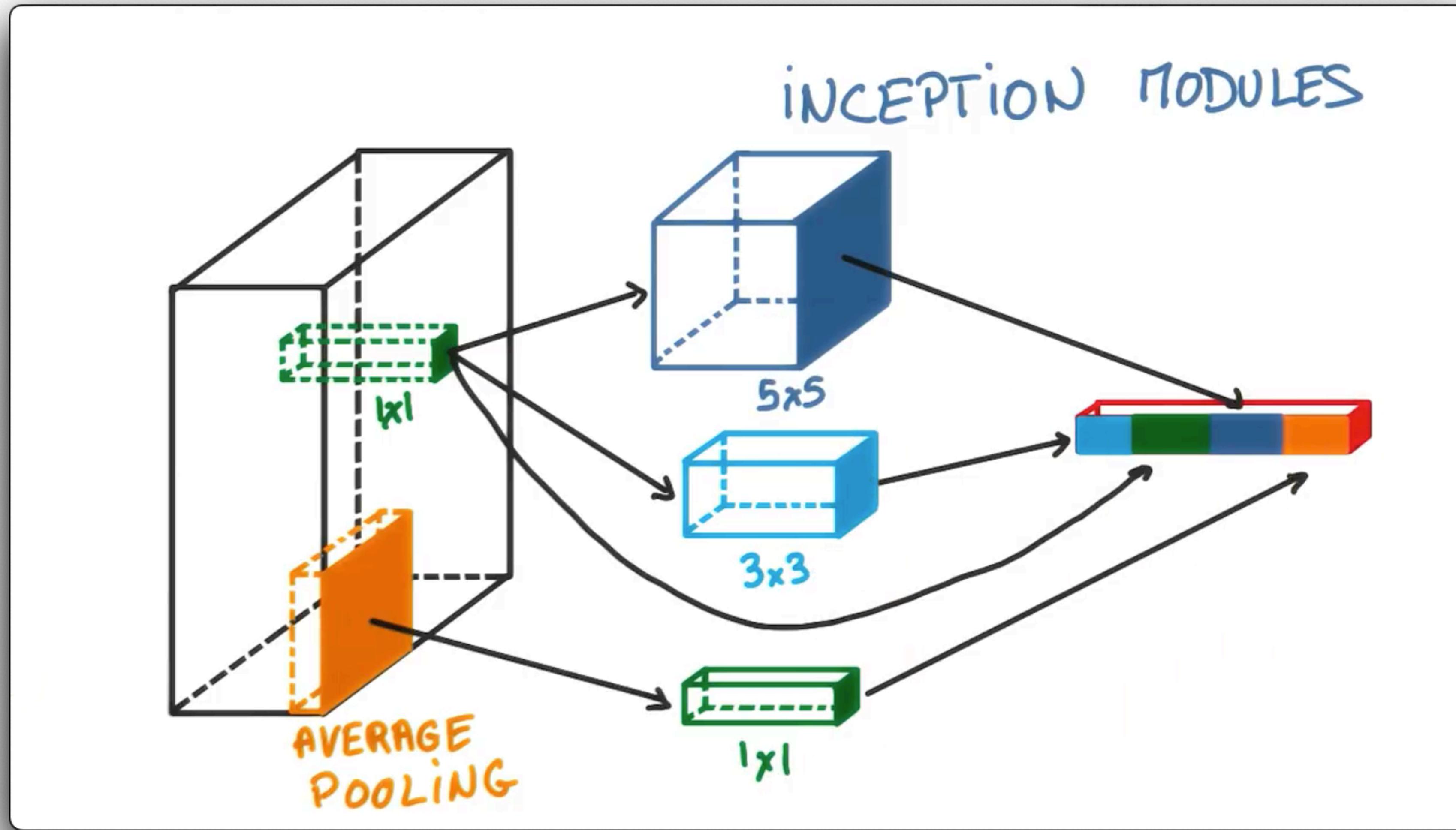


GoogLeNet (Inception)



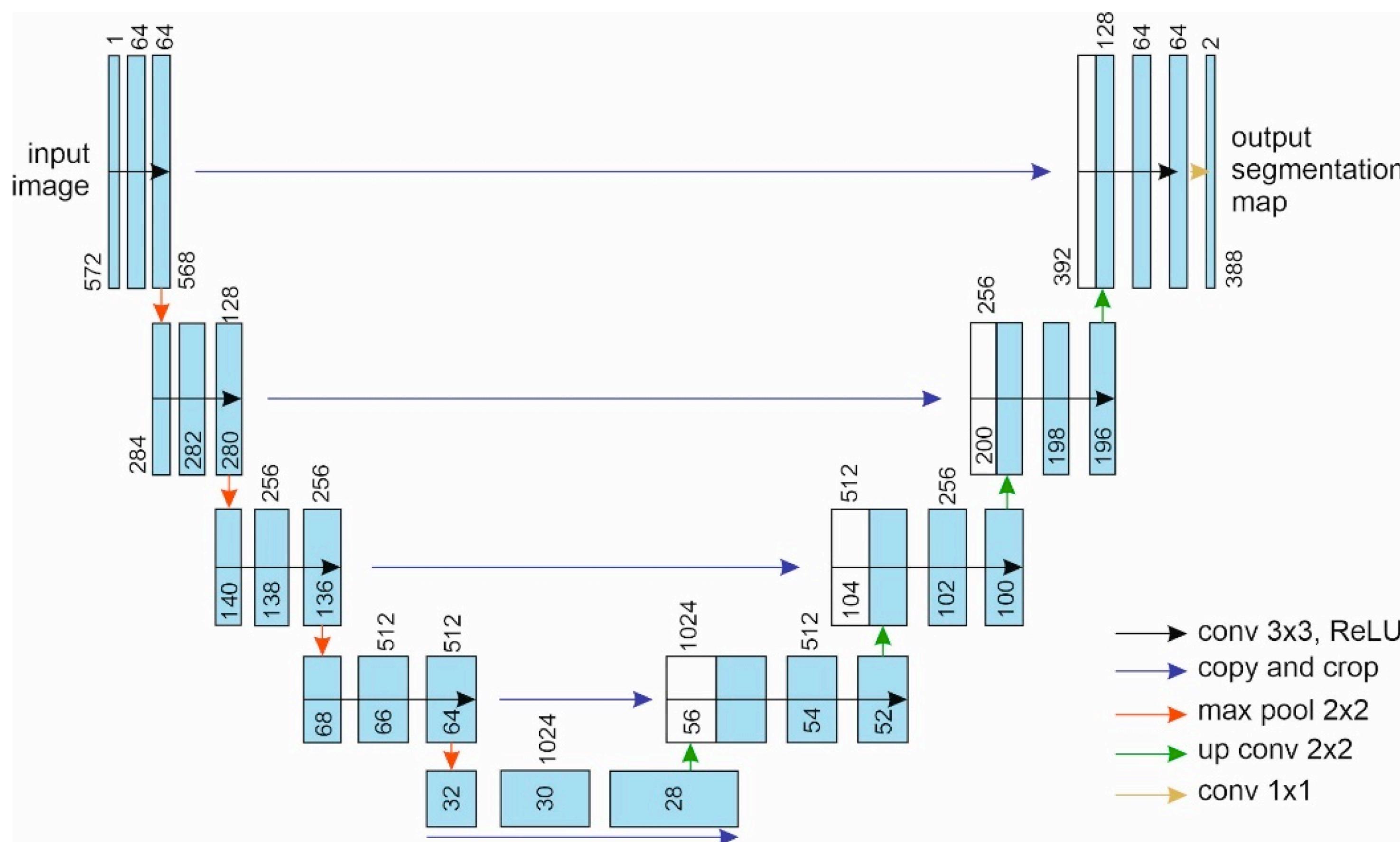
Fonte: <https://www.youtube.com/watch?v=VxhSouuSZDY>.

GoogLeNet (Inception)

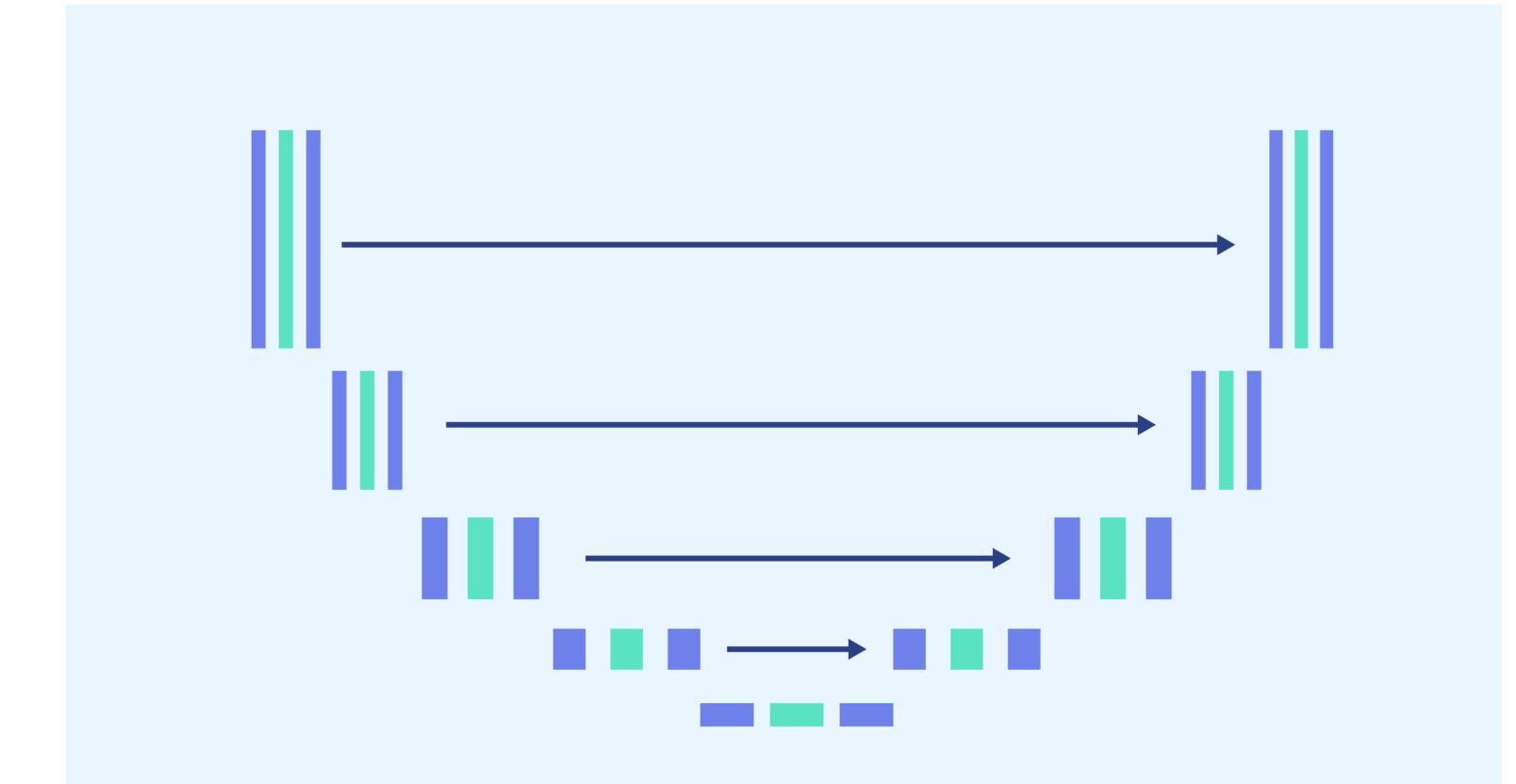


Fonte: <https://www.youtube.com/watch?v=VxhSouuSZDY>.

U-Net



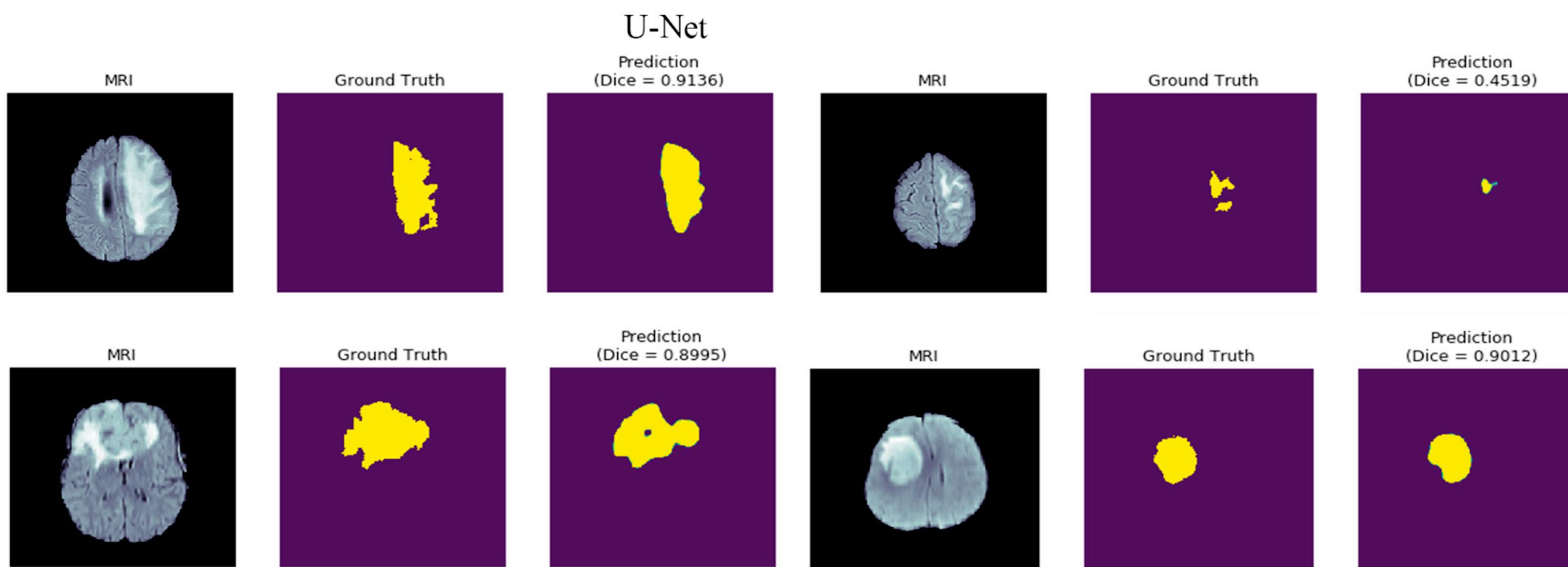
Fonte: KONOVALENKO, Ihor et al. Research of U-Net-based CNN architectures for metal surface defect detection. *Machines*, v. 10, n. 5, p. 327, 2022.



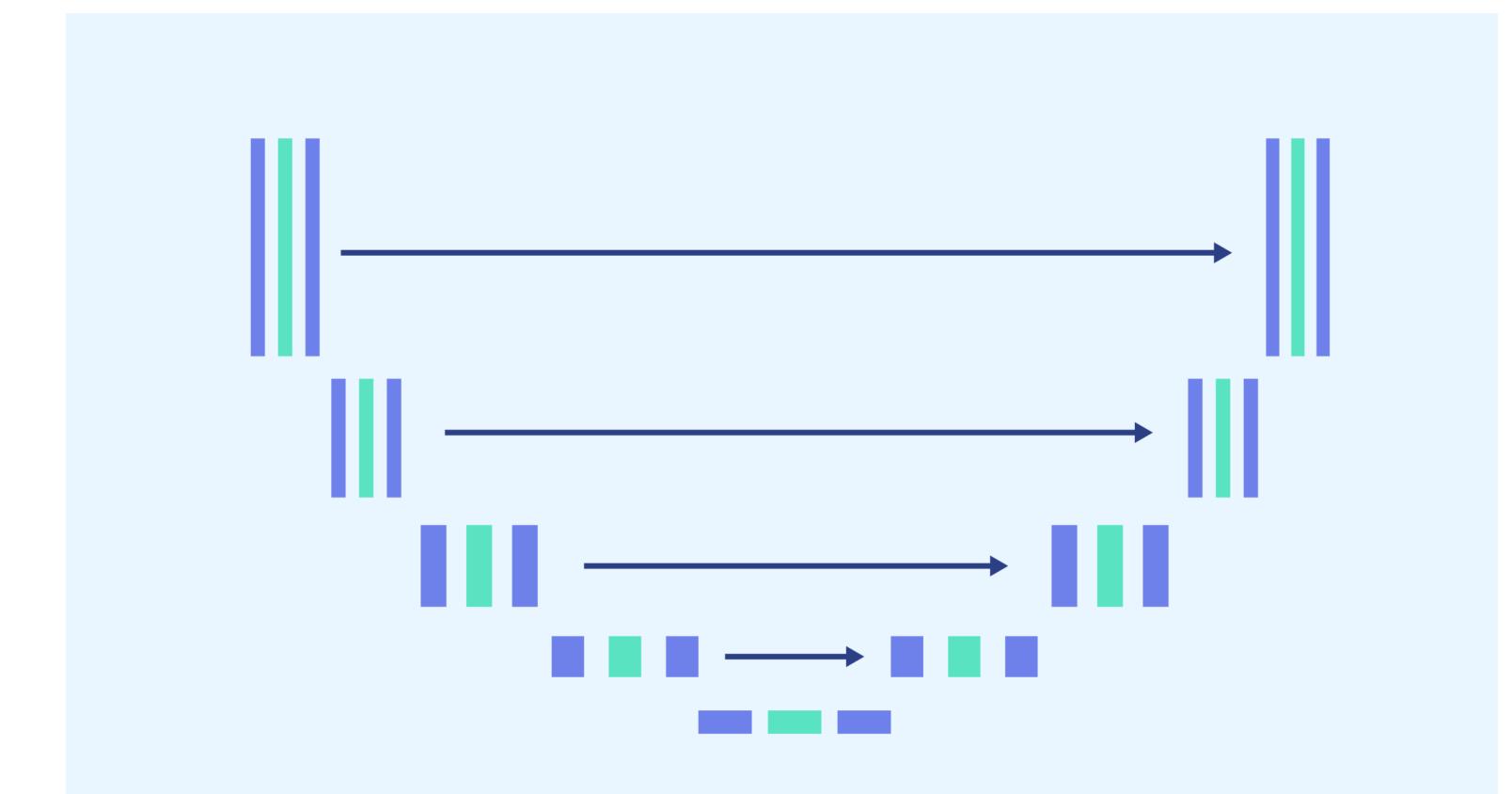
>61K
citações

Fonte: RONNEBERGER, Olaf; FISCHER, Philipp; BROX, Thomas. U-net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-Assisted Intervention–MICCAI, 2015. Springer International Publishing, 2015.

U-Net



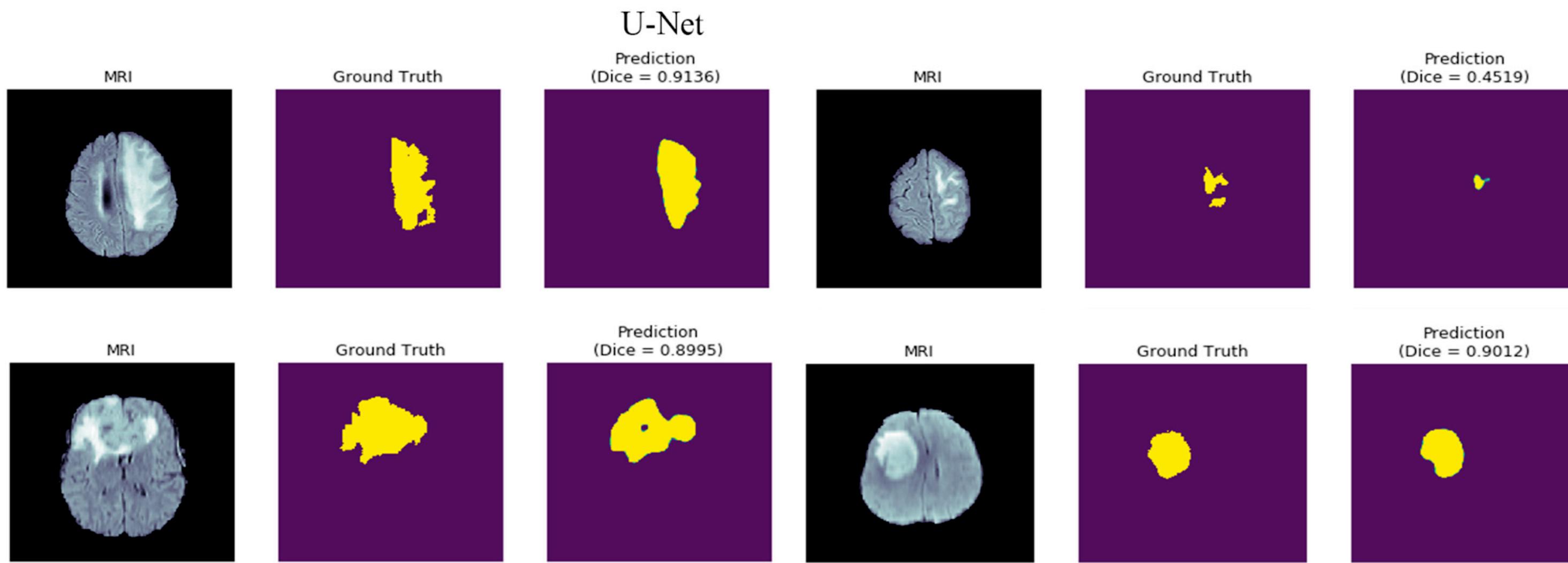
Fonte: SD-UNET: Stripping down U-net for segmentation of biomedical images on platforms with low computational budgets. <https://doi.org/10.3390/diagnostics10020110>. (Adaptado).



>61K
citações

Fonte: RONNEBERGER, Olaf; FISCHER, Philipp; BROX, Thomas. U-net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-Assisted Intervention–MICCAI, 2015. Springer International Publishing, 2015.

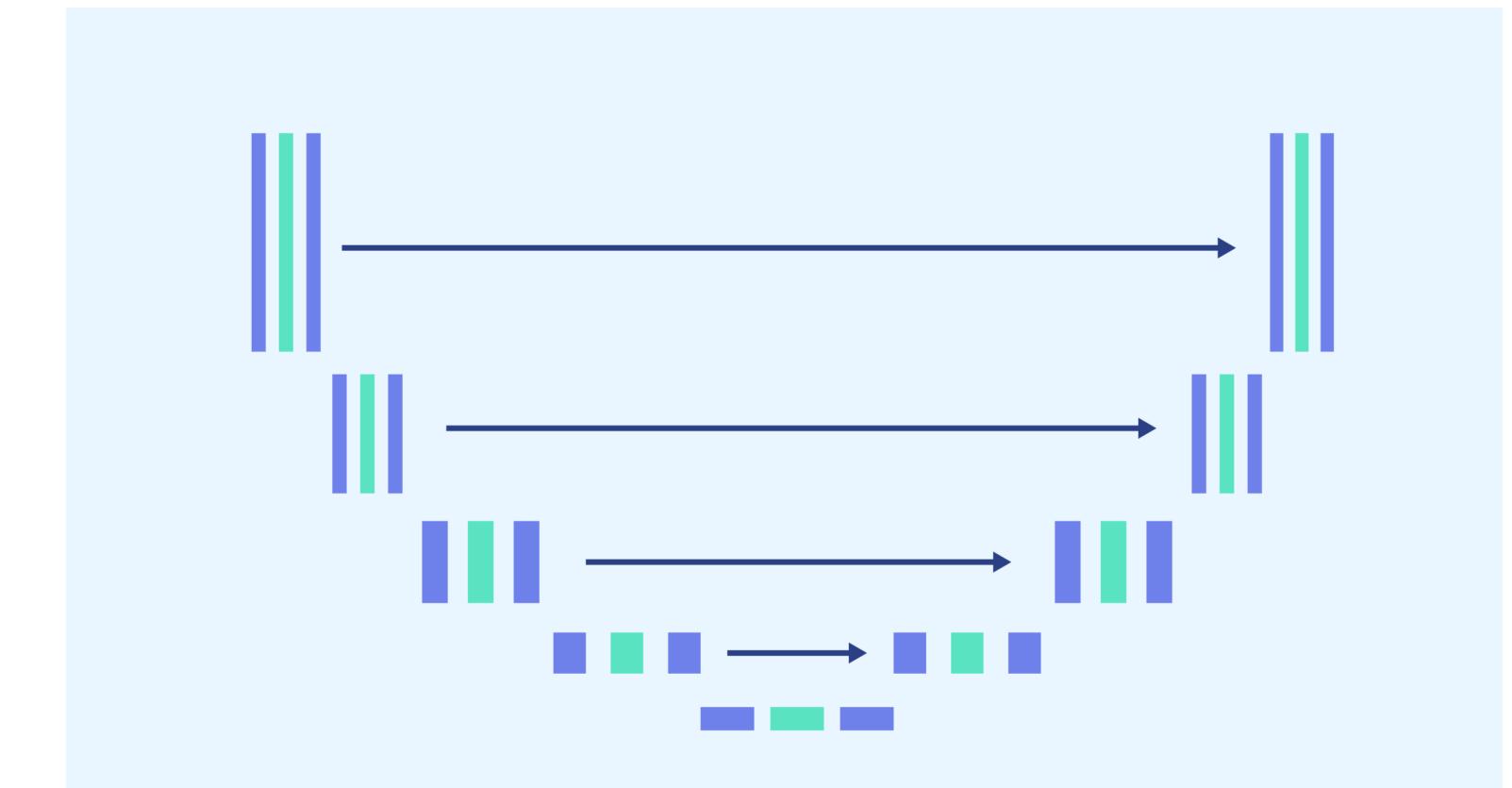
U-Net



Fonte: SD-UNET: Stripping down U-net for segmentation of biomedical images on platforms with low computational budgets. <https://doi.org/10.3390/diagnostics10020110>. (Adaptado).

$$\begin{array}{c}
 \begin{array}{cc}
 \begin{array}{|c|c|} \hline 0 & 1 \\ \hline 2 & 3 \\ \hline \end{array} &
 \begin{array}{|c|c|} \hline 0 & 1 \\ \hline 2 & 3 \\ \hline \end{array} \\
 \text{Tensor} & \text{Filtro}
 \end{array} = \begin{array}{c}
 \begin{array}{|c|c|} \hline 0 & 0 \\ \hline 0 & 0 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 0 & 1 \\ \hline 2 & 3 \\ \hline \end{array} + \begin{array}{|c|c|} \hline \quad & \quad \\ \hline 0 & 2 \\ \hline 4 & 6 \\ \hline \end{array} + \begin{array}{|c|c|} \hline \quad & \quad \\ \hline 0 & 3 \\ \hline 6 & 9 \\ \hline \end{array} = \begin{array}{|c|c|} \hline 0 & 0 \\ \hline 0 & 4 \\ \hline 4 & 12 \\ \hline 1 & 6 \\ \hline \end{array}
 \end{array}$$

Fonte: https://pt.d2l.ai/chapter_computer-vision/transposed-conv.html.



>61K
citações

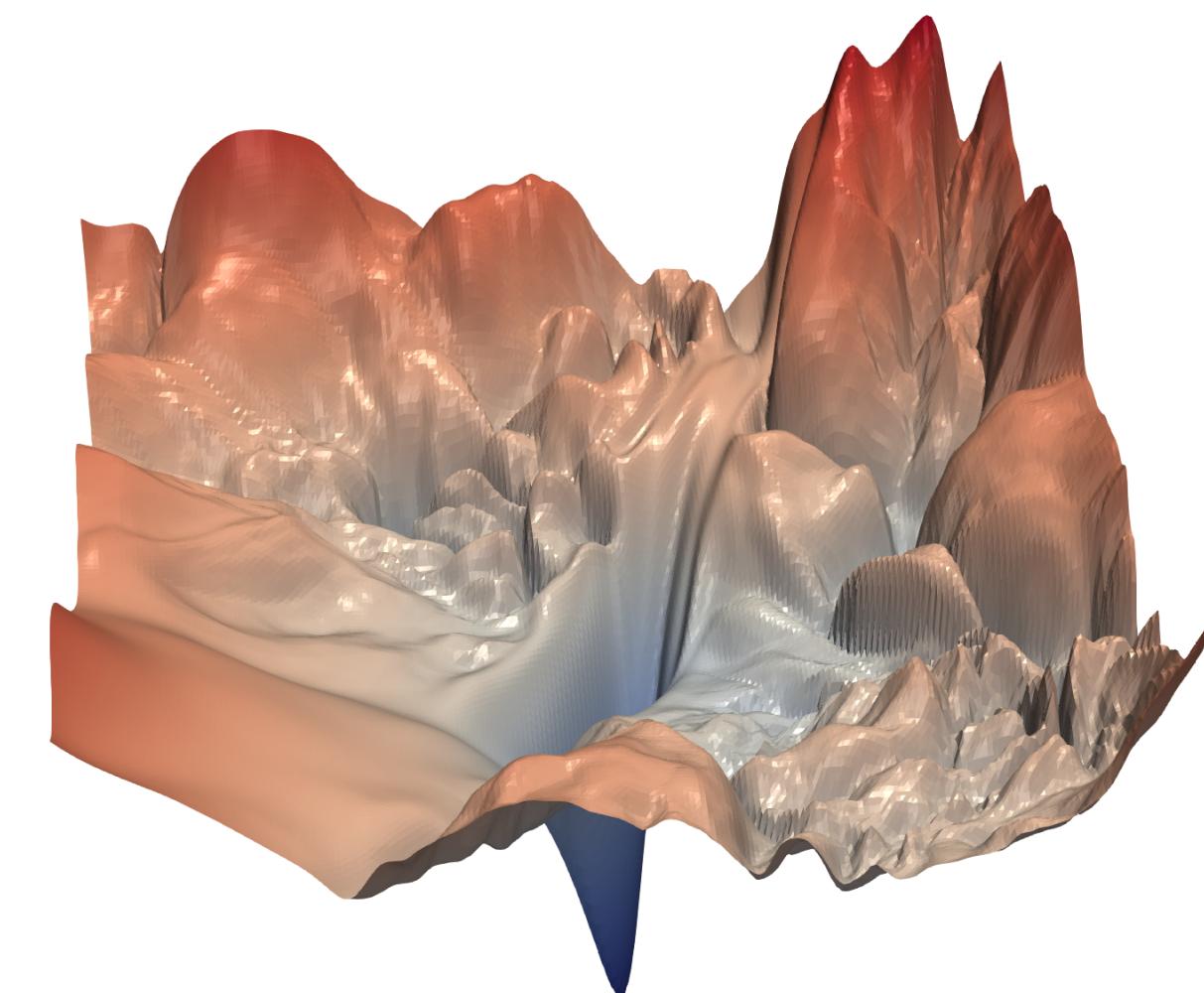
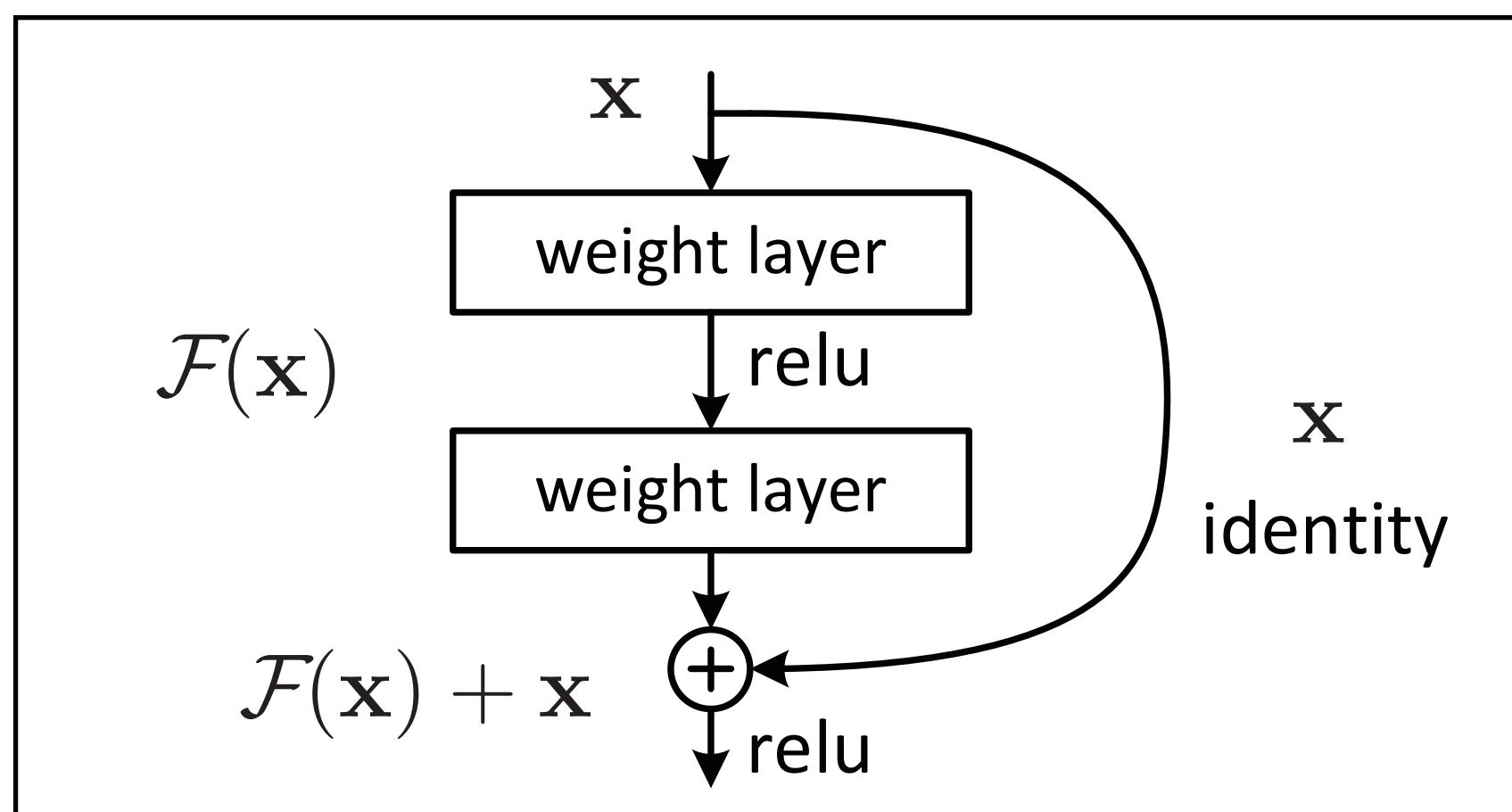
Fonte: RONNEBERGER, Olaf; FISCHER, Philipp; BROX, Thomas. U-net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-Assisted Intervention—MICCAI, 2015. Springer International Publishing, 2015.

RestNet

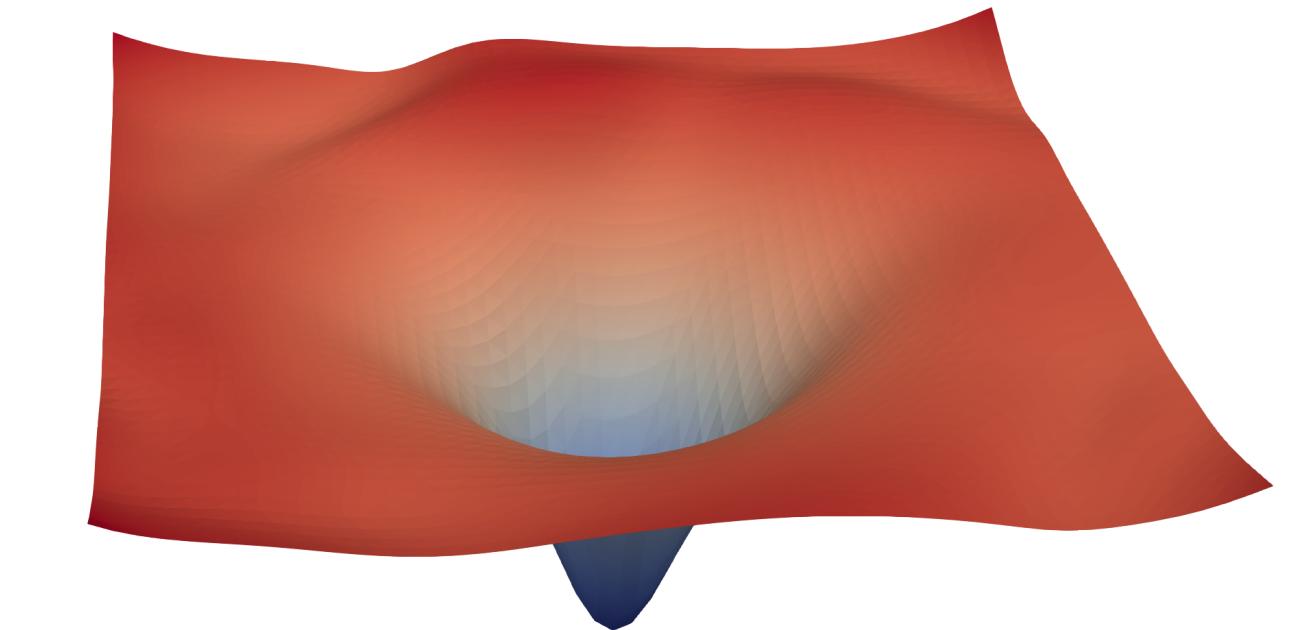


>162K
citações

Fonte: HE, Kaiming et al. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.



Sem conexão de travessia



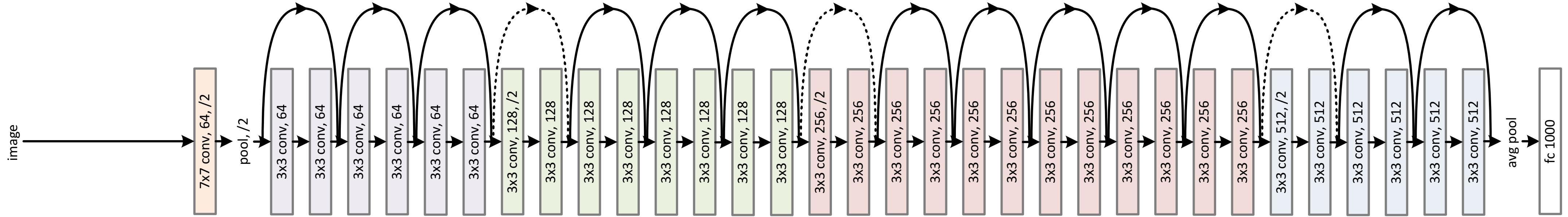
Com conexão de travessia

Fonte: LI, Hao et al. Visualizing the loss landscape of neural nets. Advances in neural information processing systems, v. 31, 2018.

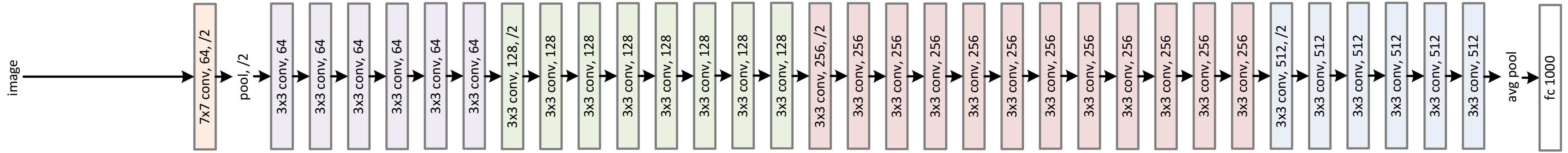
Em inglês, o termo é *skip connection*

RestNet

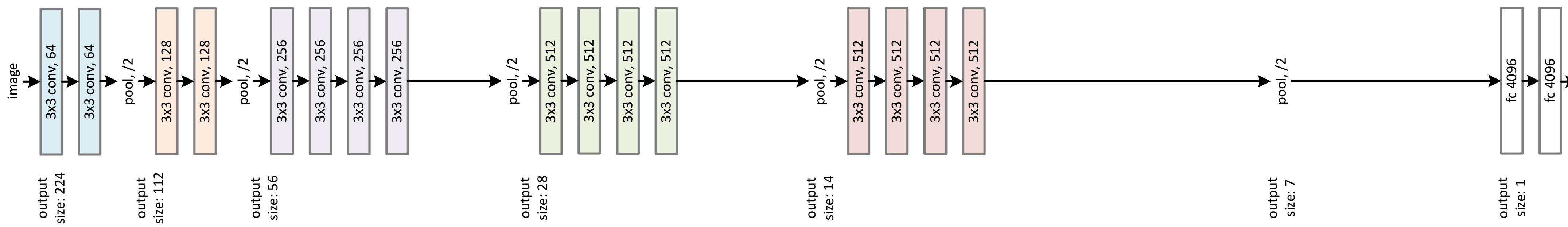
ResNet



Rede plana



VGG



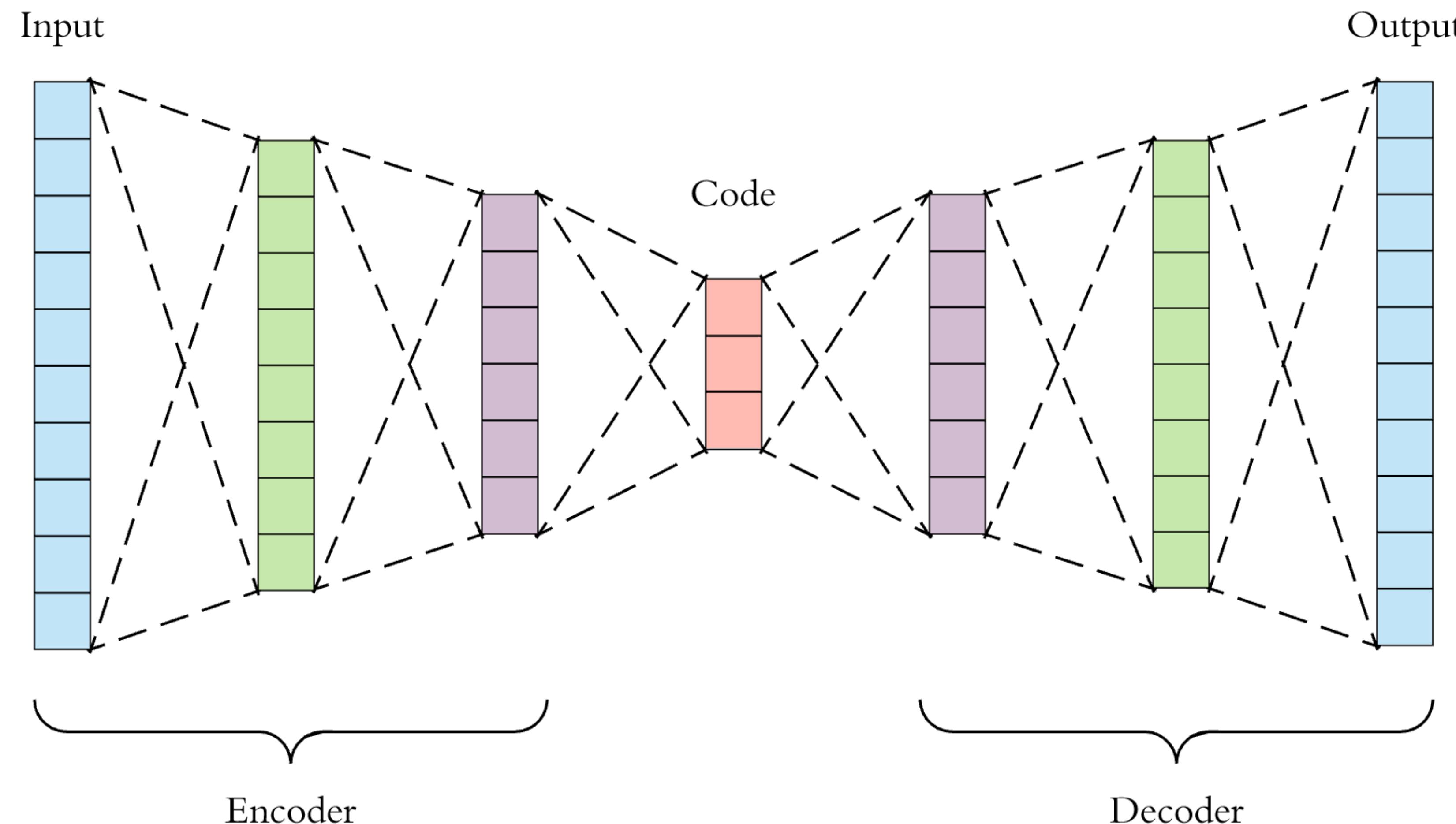
CNNs vs ImageNet

Ano	CNN	Desenvolvedor(es)	Posição	Taxa de erro	Nº de parâmetros
1998	LeNet	Yann LeCun et al			60K
2012	AlexNet	Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever	1º	15,3%	60M
2013	ZFNet	Matthew Zeiler and Rob Fergus	1º	14,8%	
2014	GoogLeNet	Google	1º	6,67%	4M
2014	VGG Net	Simonyan, Zisserman	2º	7,3%	138M
2015	ResNet	Kaiming He	1º	3,6%	

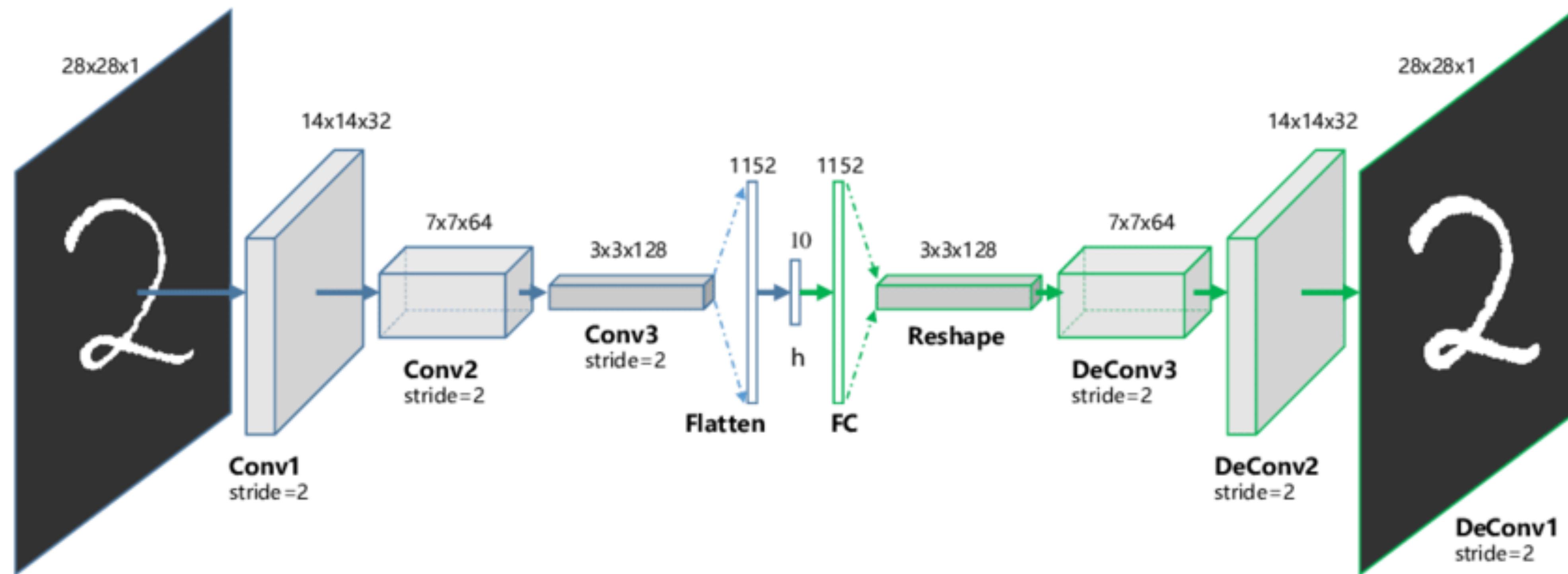
Fonte: <https://iq.opengenus.org/evolution-of-cnn-architectures/>.

APRENDIZADO NÃO- SUPERVISIONADO

Auto-supervisionado

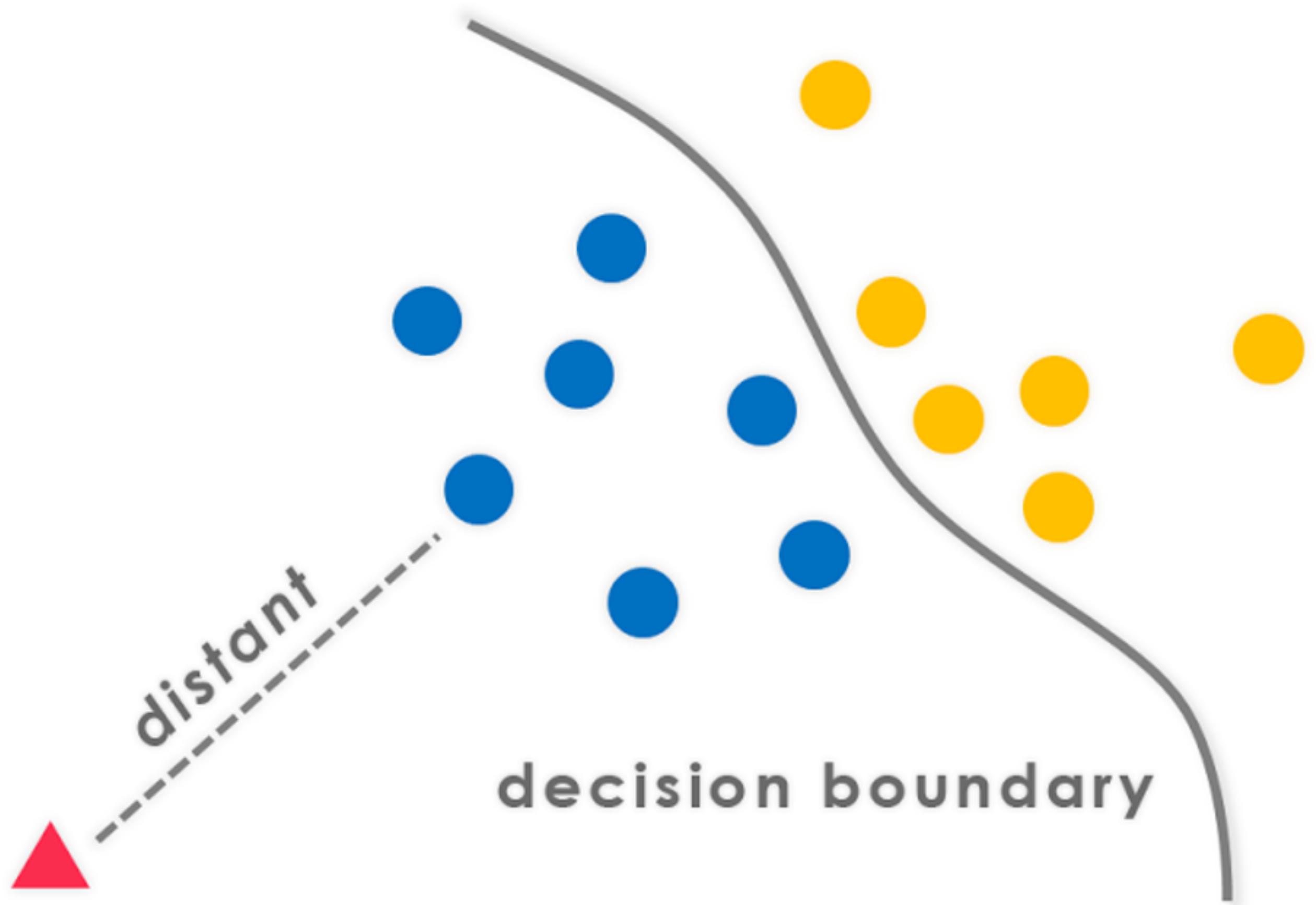


Auto-supervisionado

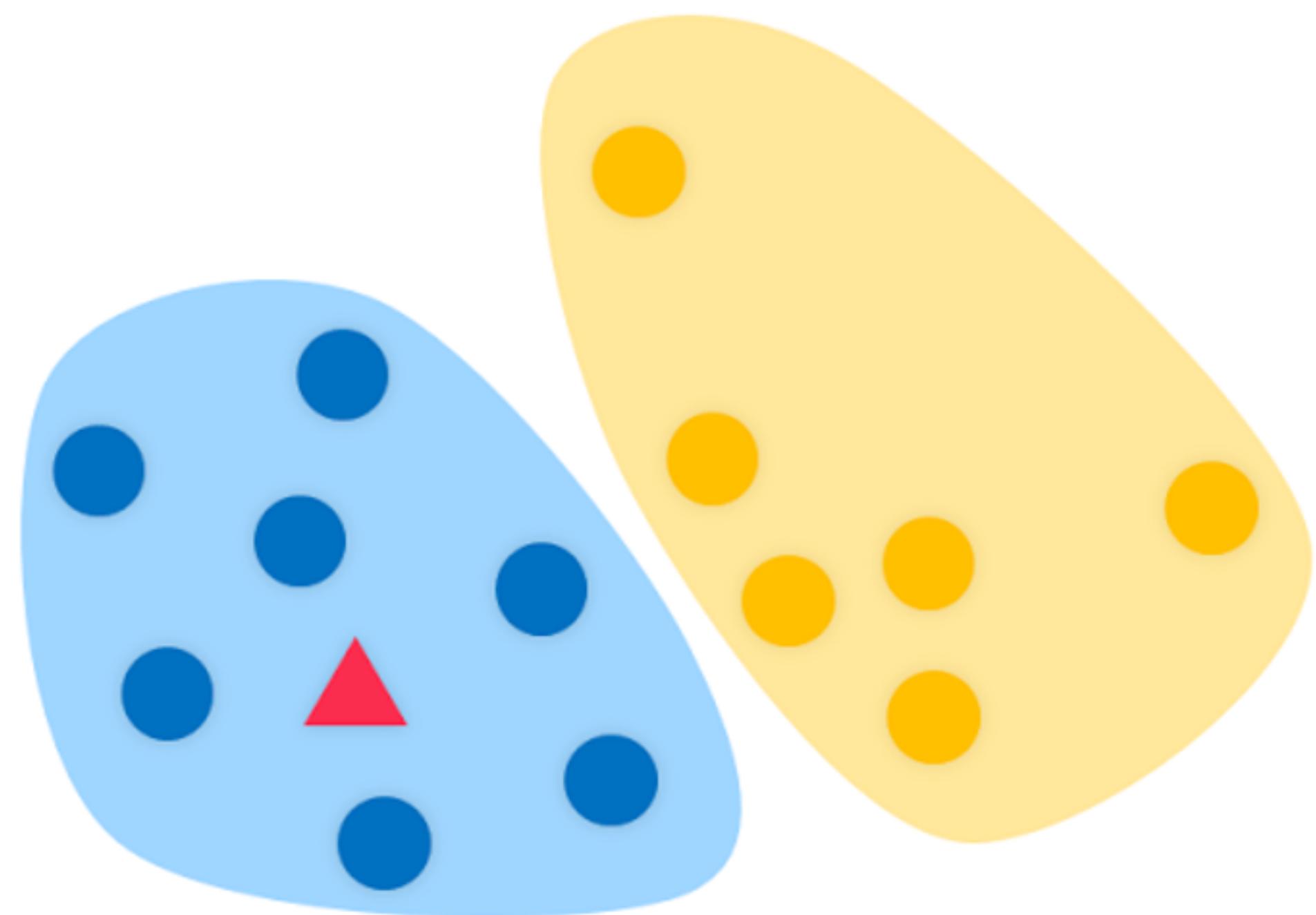


MODELO DISCRIMINATIVO VS GENERATIVO

Discriminative

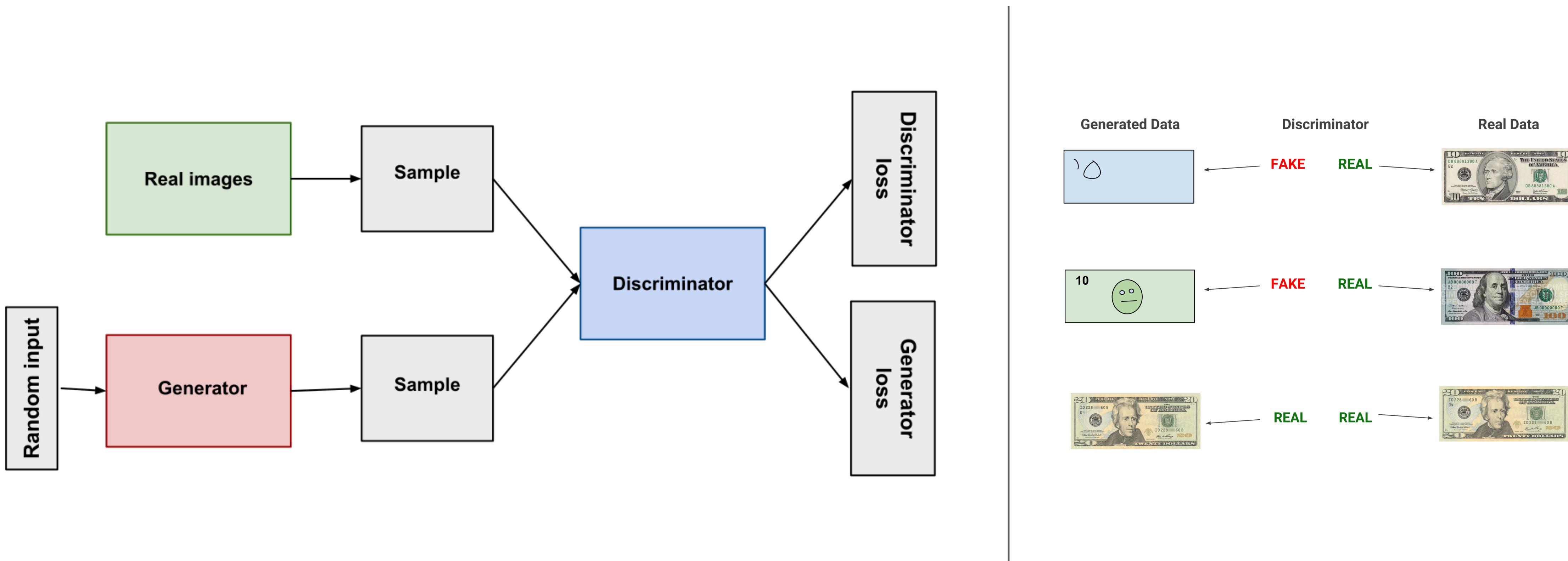


Generative



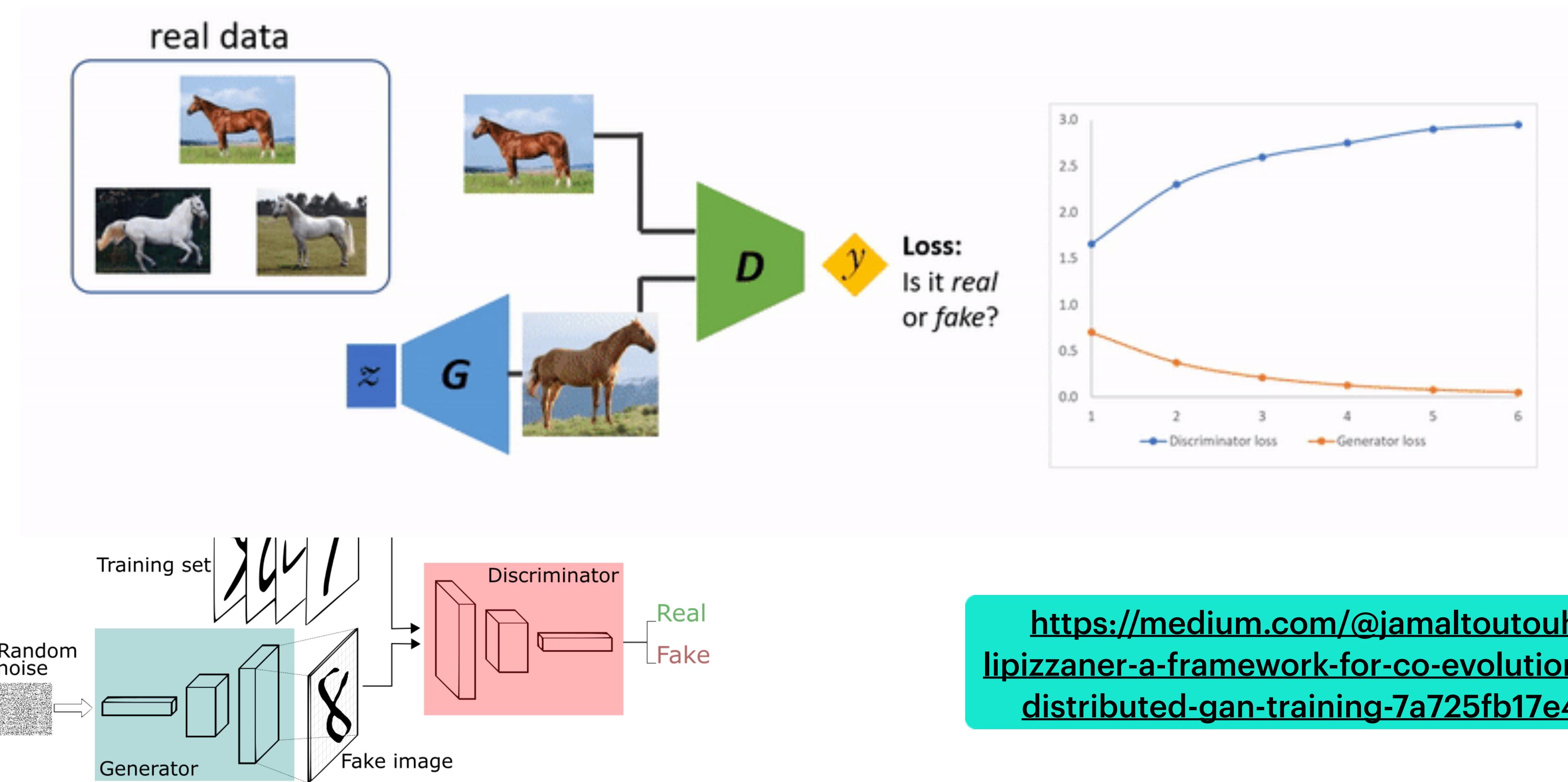
REDES ADVERSÁRIAS GENERATIVAS

VISÃO GERAL DO MODELO

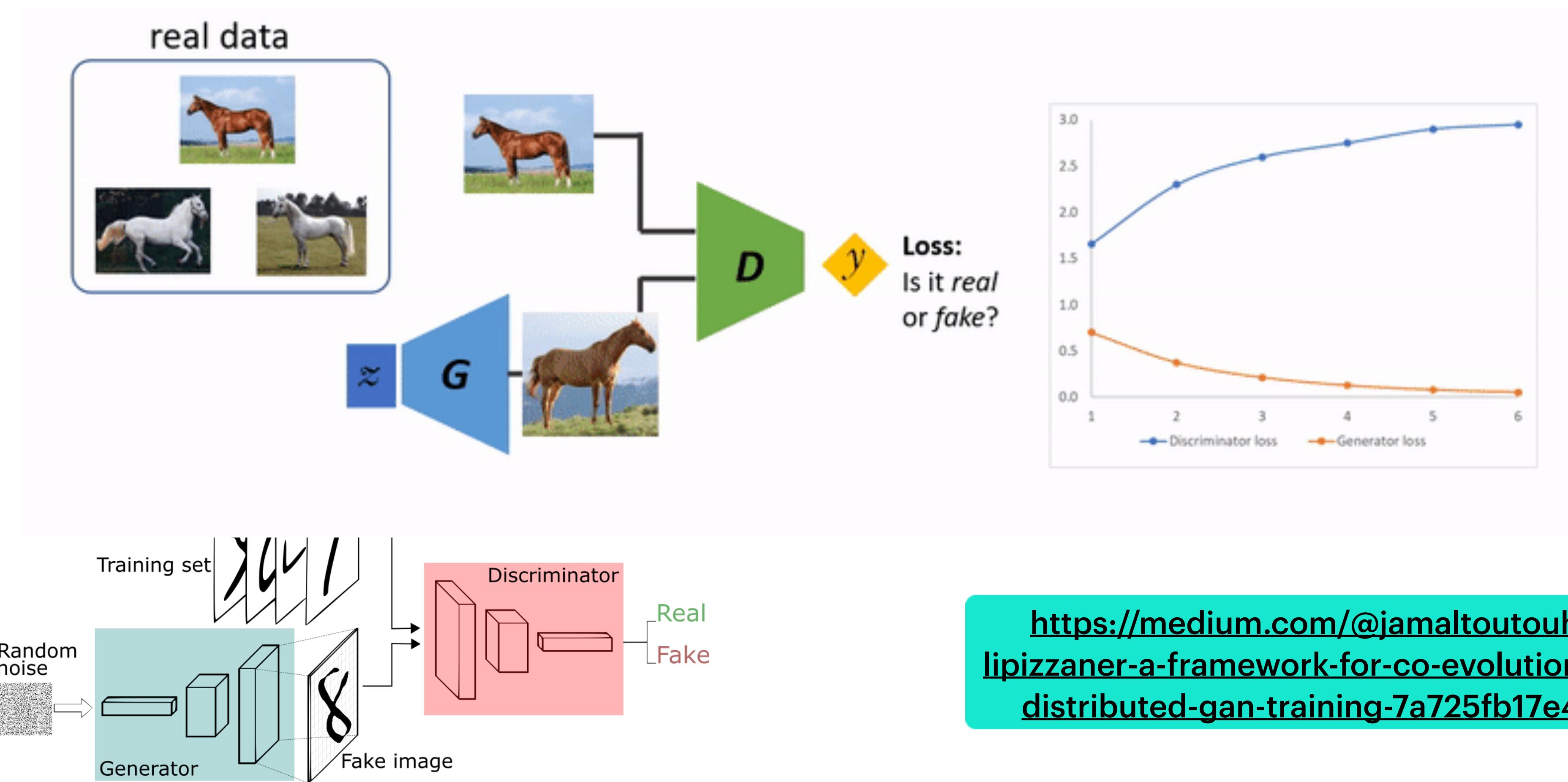


https://developers.google.com/machine-learning/gan/gan_structure

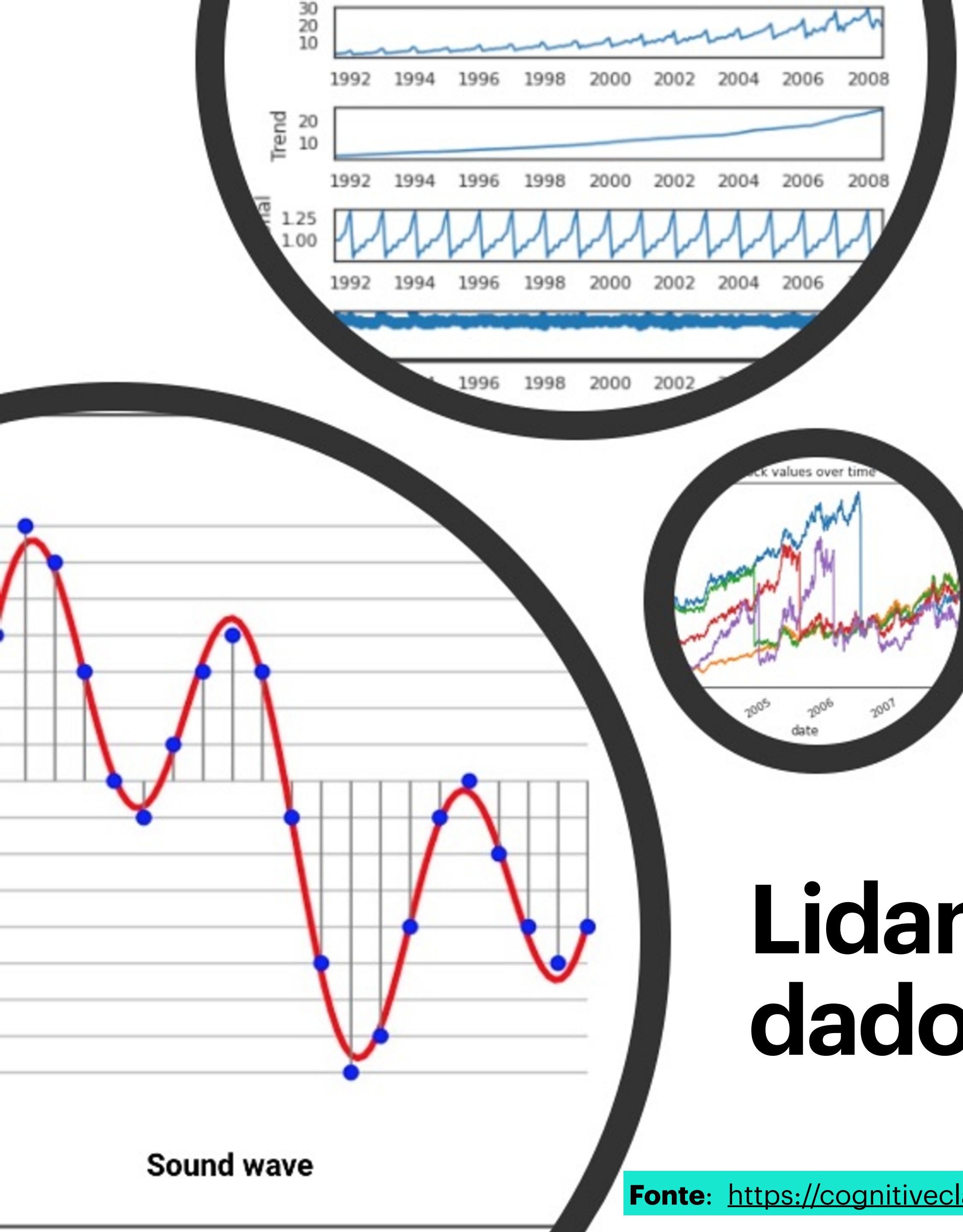
FUNCIONANDO NA PRÁTICA



FUNCIONANDO NA PRÁTICA



DADOS SEQUENCIAIS



Lidando com dados sequenciais

Sound wave

Fonte: <https://cognitiveclass.ai/courses/course-v1:IBM+GPXXOSPHEN+v1>

Sempre que as **amostras dependem de outras amostras** no conjunto de dados, os dados são **sequenciais**. Um exemplo típico desse tipo de dados são as **séries temporais**, como preços de ações ou dados de sensores.

Lidando com dados sequenciais

The clouds are in the ...

I grew up in Canada... I
speak fluently

Lidando com dados sequenciais

The clouds are in the ...

sky

I grew up in Canada... I
speak fluently

Lidando com dados sequenciais

The clouds are in the ...

sky

I grew up in Canada... I
speak fluently

English



Lidando com dados sequenciais

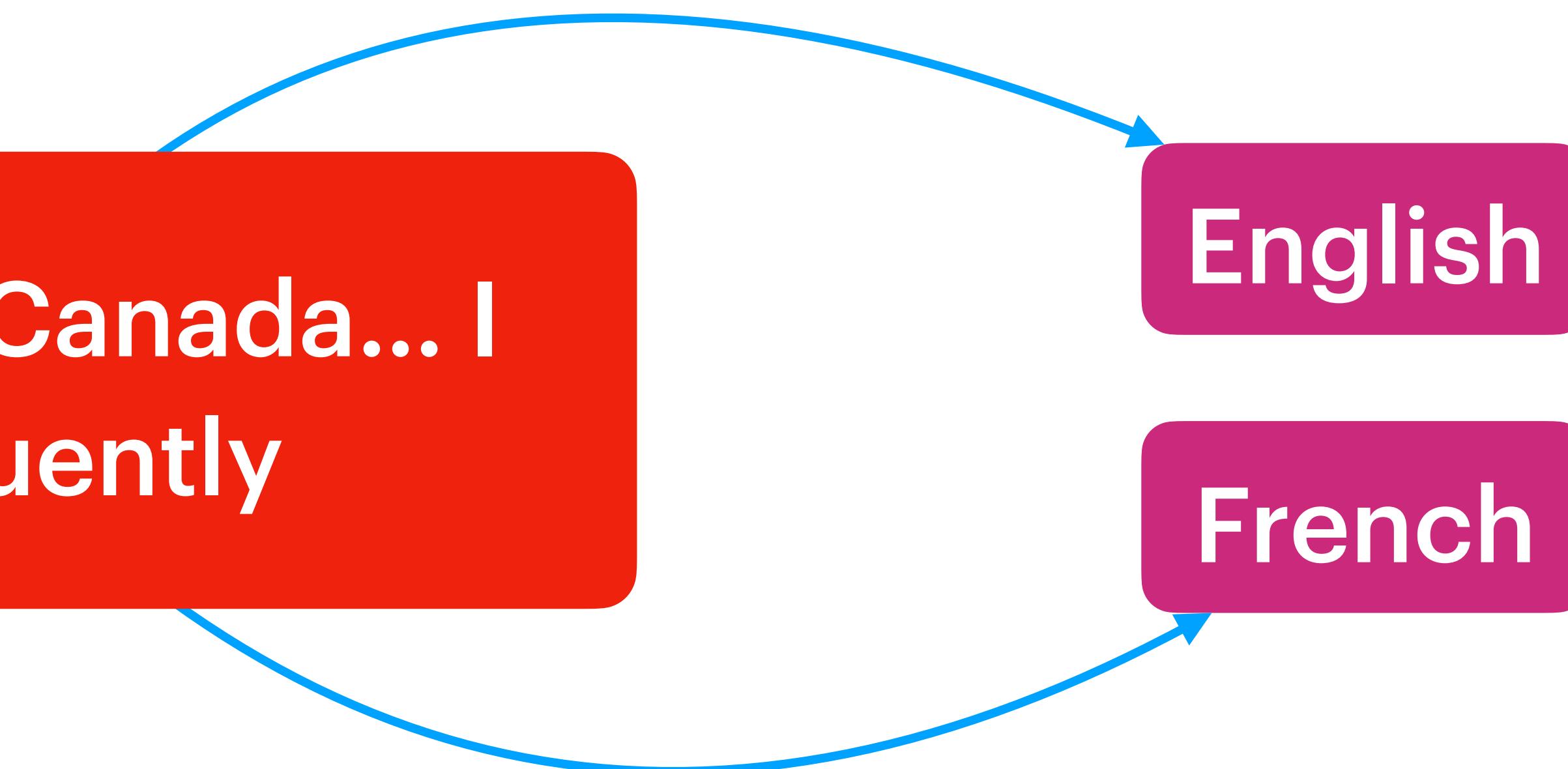
The clouds are in the ...

sky

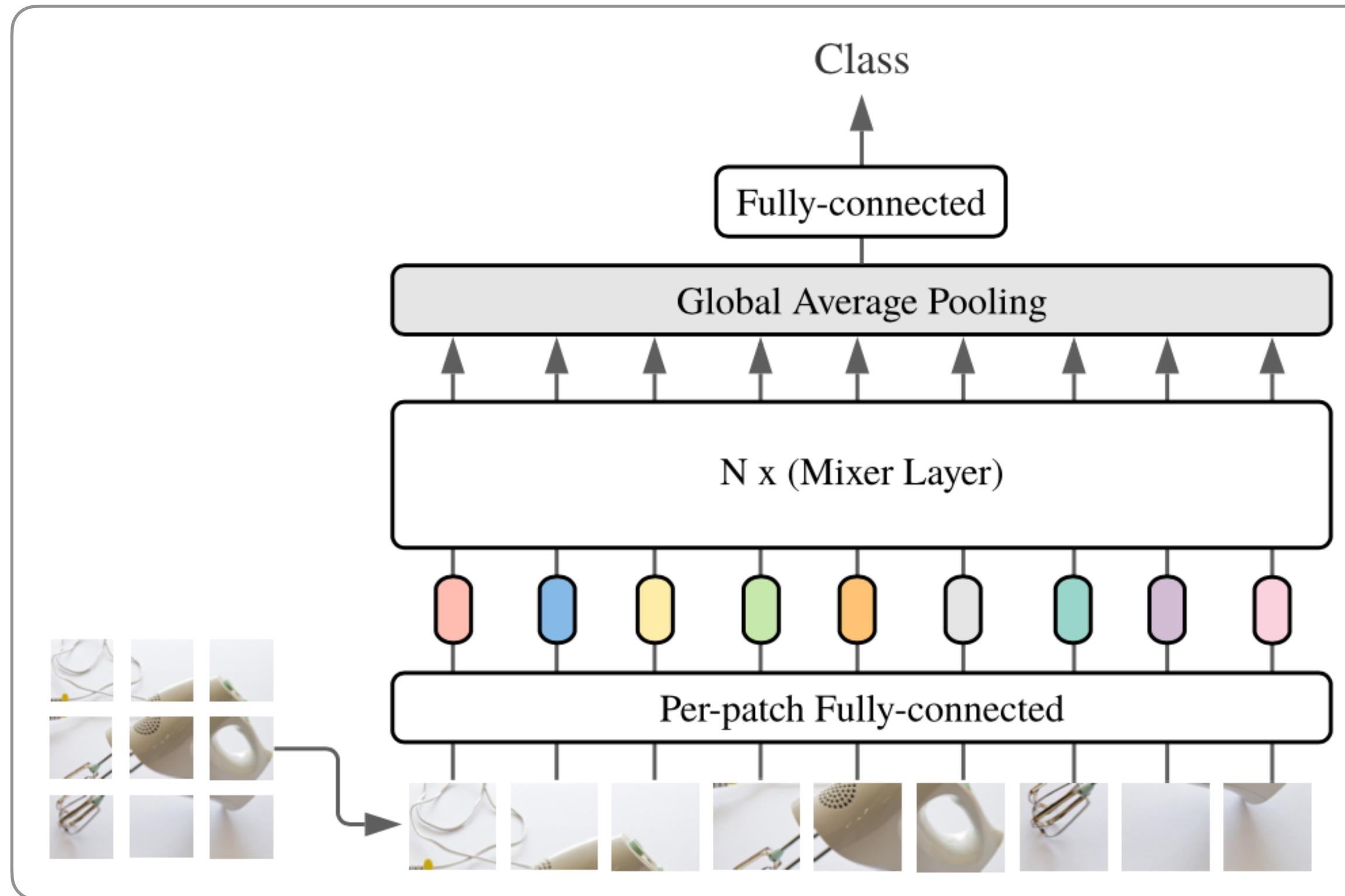
I grew up in Canada... I
speak fluently

English

French

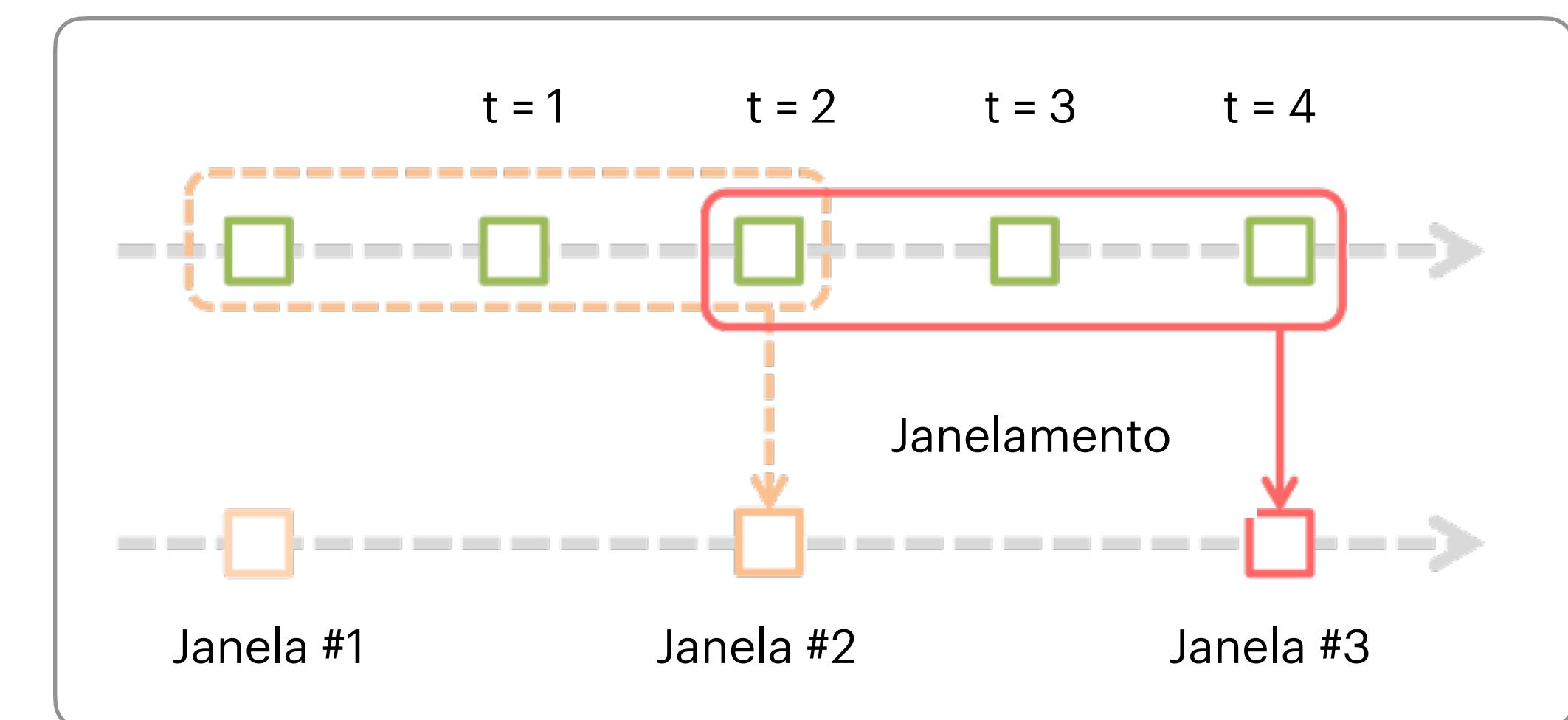


Lidando com dados sequenciais

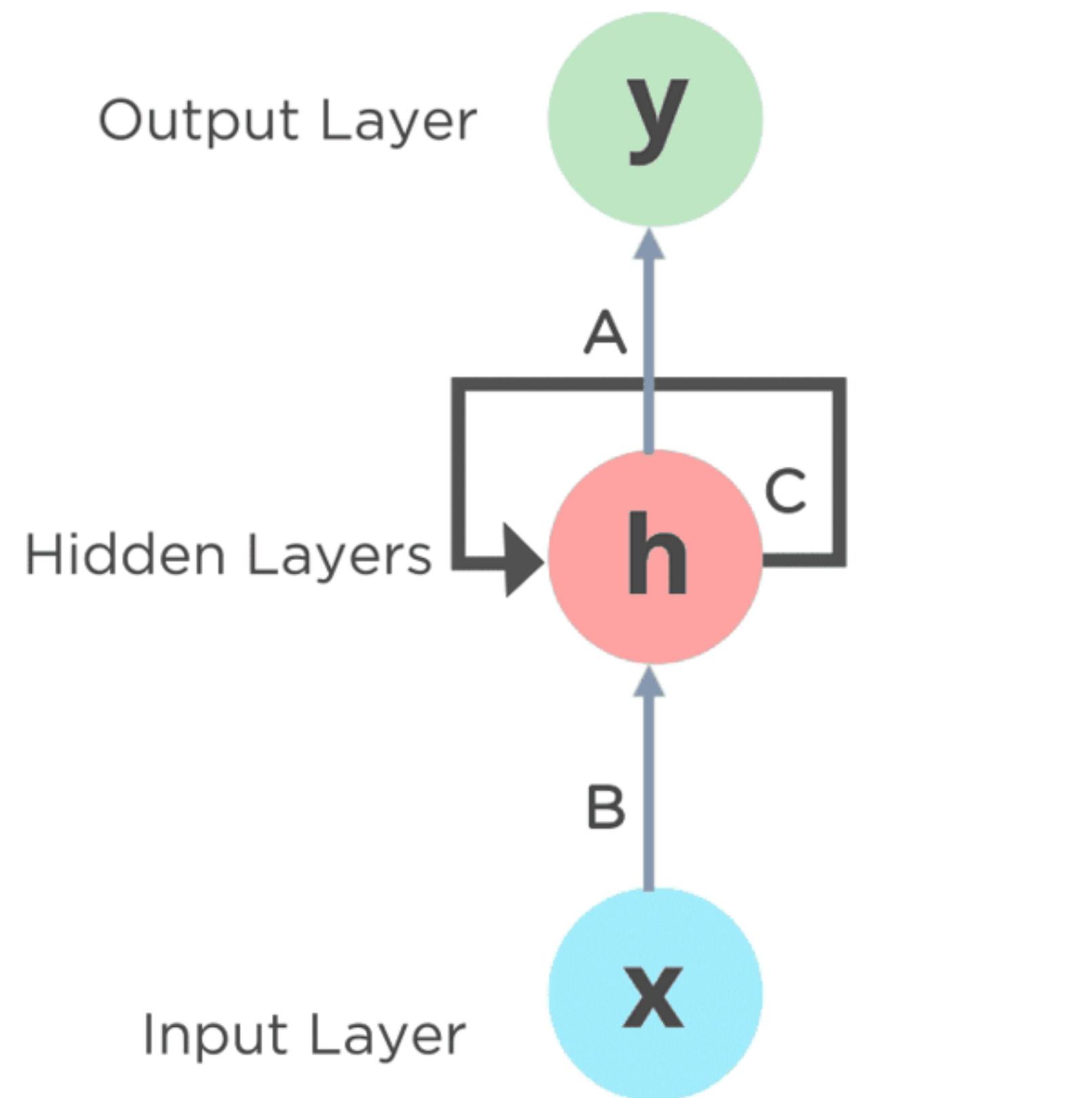


Fonte: TOLSTIKHIN, Ilya O. et al. Mlp-mixer: An all-mlp architecture for vision. *Advances in neural information processing systems*, v. 34, p. 24261-24272, 2021.

A **estratégia de janelamento** (ainda) é muito comum para lidar com dados sequenciais. É uma **maneira simples de aumentar** as **características** de **um dado**, haja vista que a análise pontual (descontínua) produz a perda da informação.



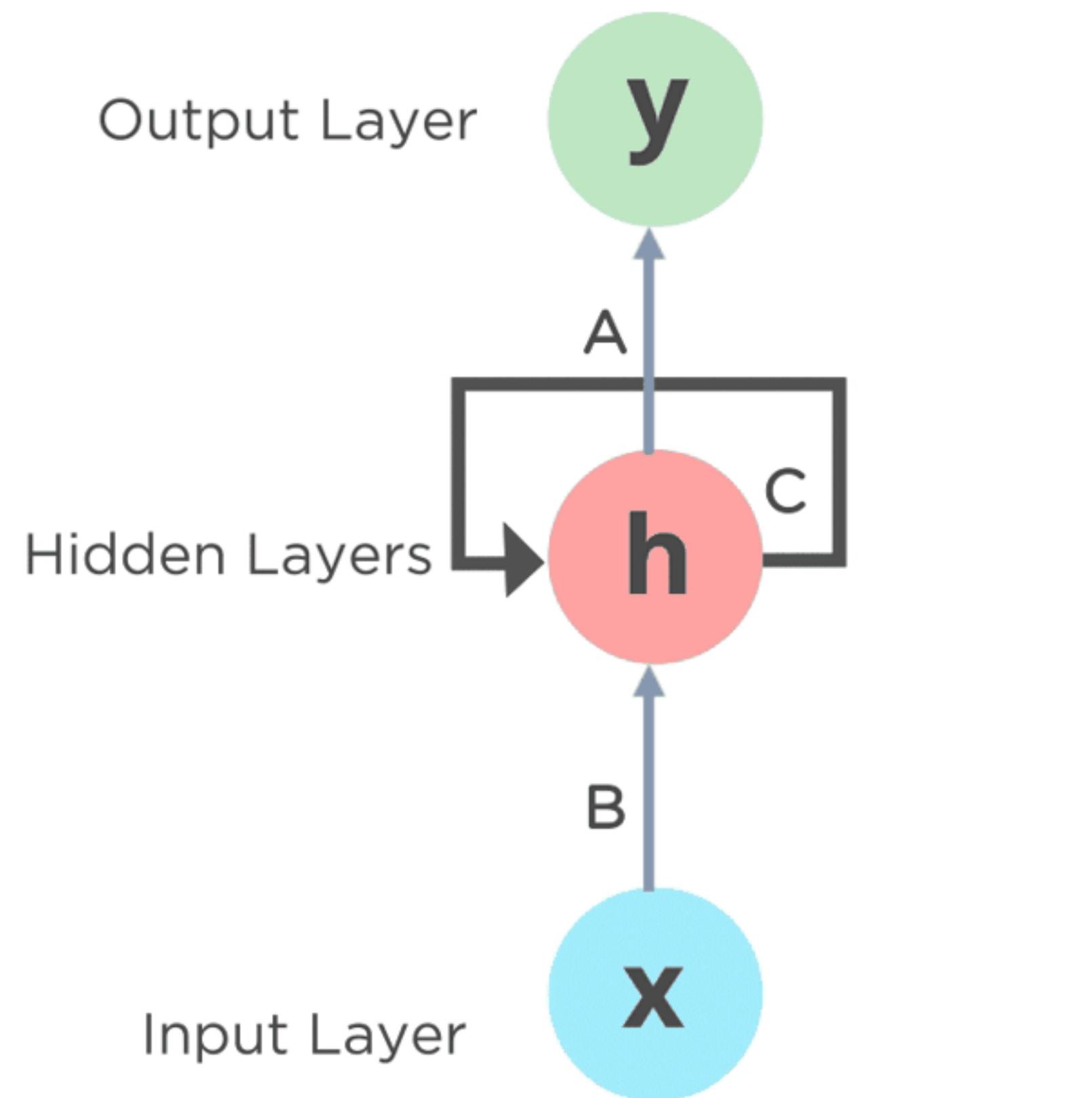
Arquitetura



A, B and C are the parameters

- Apesar de a estrutura RNN padrão resolver o problema da memória de informação, **a informação é atenuada durante a memória de longo prazo;**
- As **informações** precisam ser **salvas por muito tempo** em muitas tarefas. Por exemplo, uma dica no início de uma ficção especulativa pode não ser respondida até o final;
- O RNN **pode não ser capaz de salvar informações por muito tempo devido à capacidade limitada** da unidade de **memória**;
- Espera-se que as unidades de memória possam se lembrar de informações importantes.

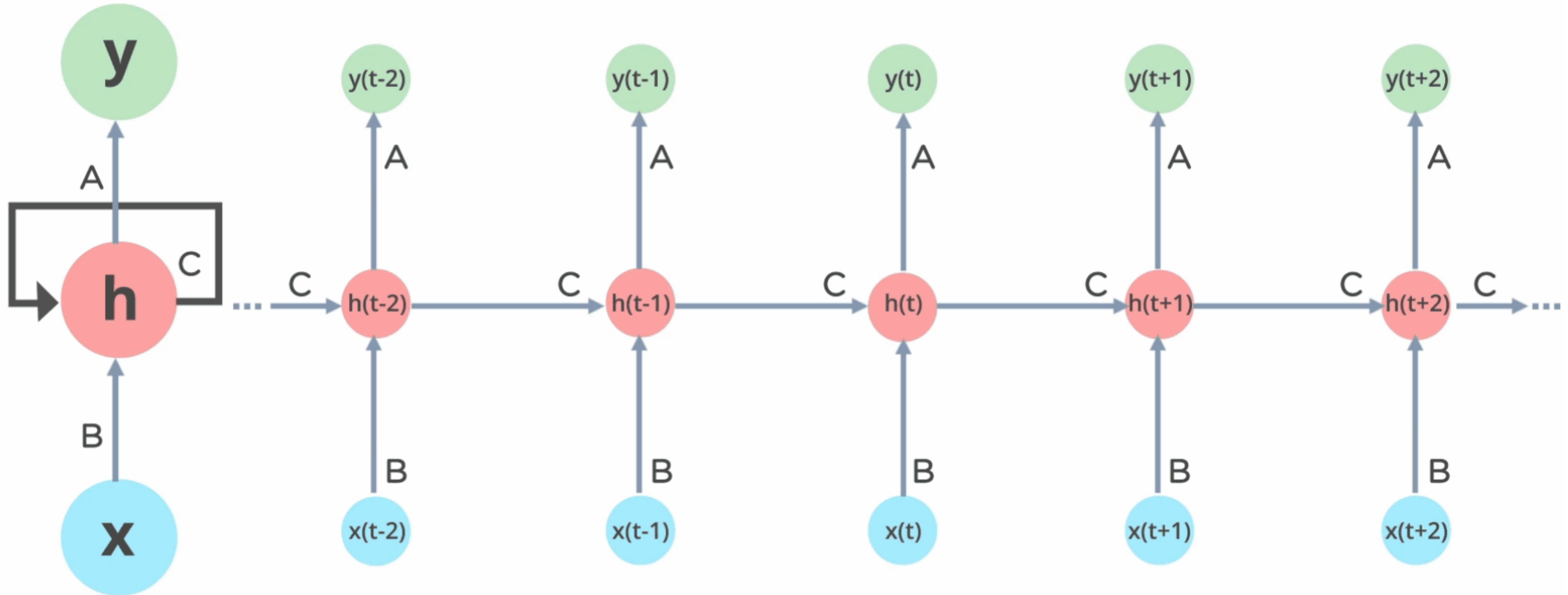
Arquitetura



A, B and C are the parameters

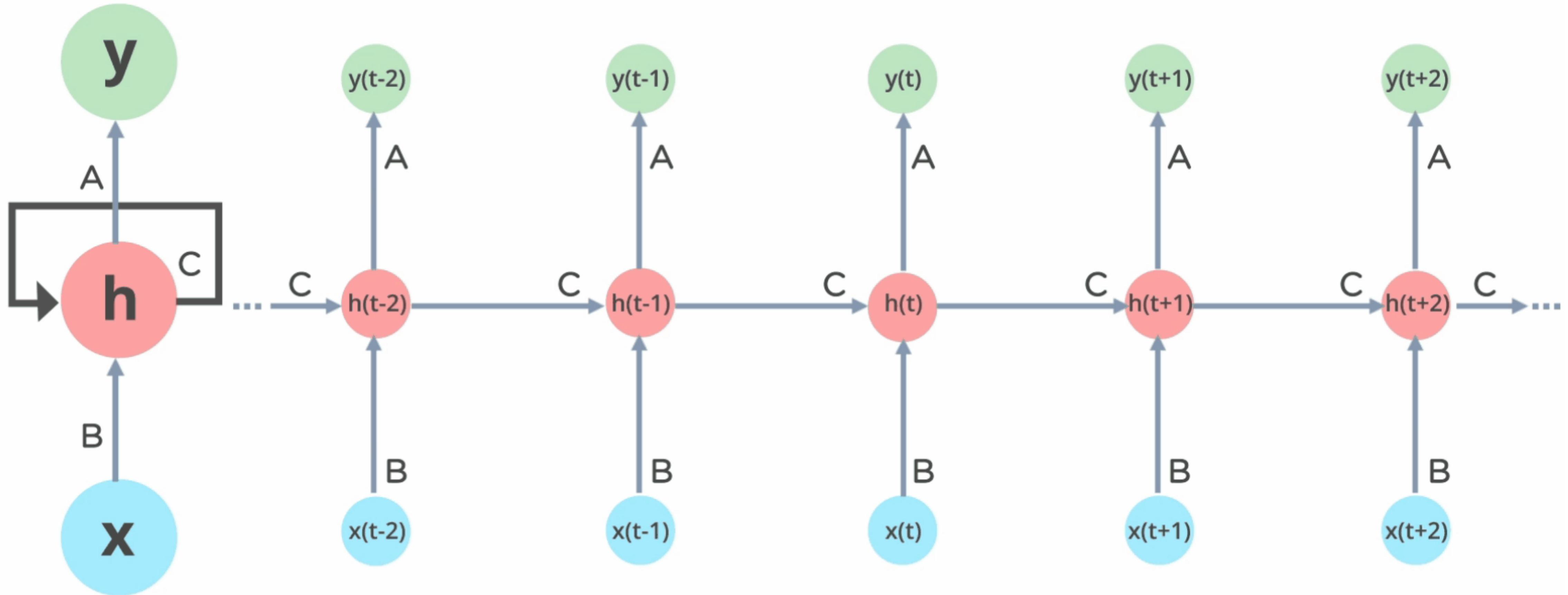
- Apesar de a estrutura RNN padrão resolver o problema da memória de informação, **a informação é atenuada durante a memória de longo prazo;**
- As **informações** precisam ser **salvas por muito tempo** em muitas tarefas. Por exemplo, uma dica no início de uma ficção especulativa pode não ser respondida até o final;
- O RNN **pode não ser capaz de salvar informações por muito tempo devido à capacidade limitada** da unidade de **memória**;
- Espera-se que as unidades de memória possam se lembrar de informações importantes.

Arquitetura



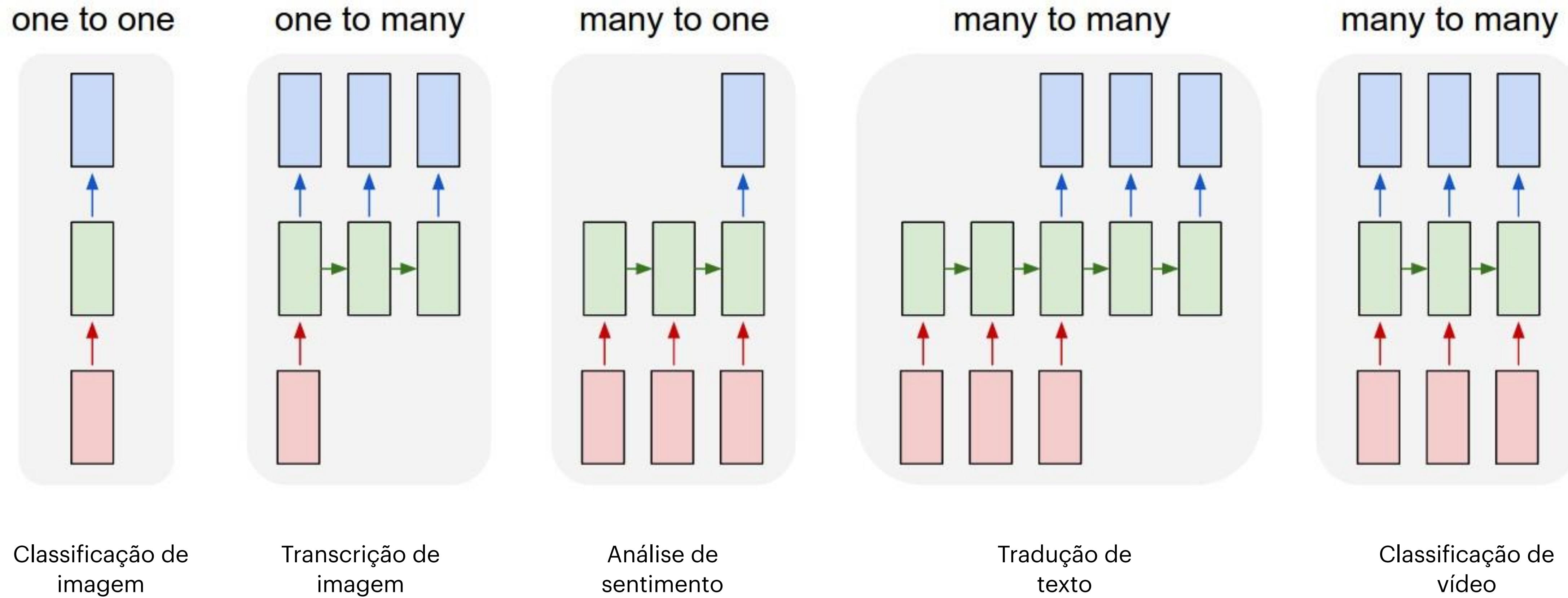
$y_t = \sigma(A \cdot h(C \cdot h(B \cdot x_{t-1}) + B \cdot x_t))$ é estendido pela dependência (normalmente o tempo t).

Arquitetura



$y_t = \sigma(A \cdot h(C \cdot h(B \cdot x_{t-1}) + B \cdot x_t))$ é estendido pela dependência (normalmente o tempo t).

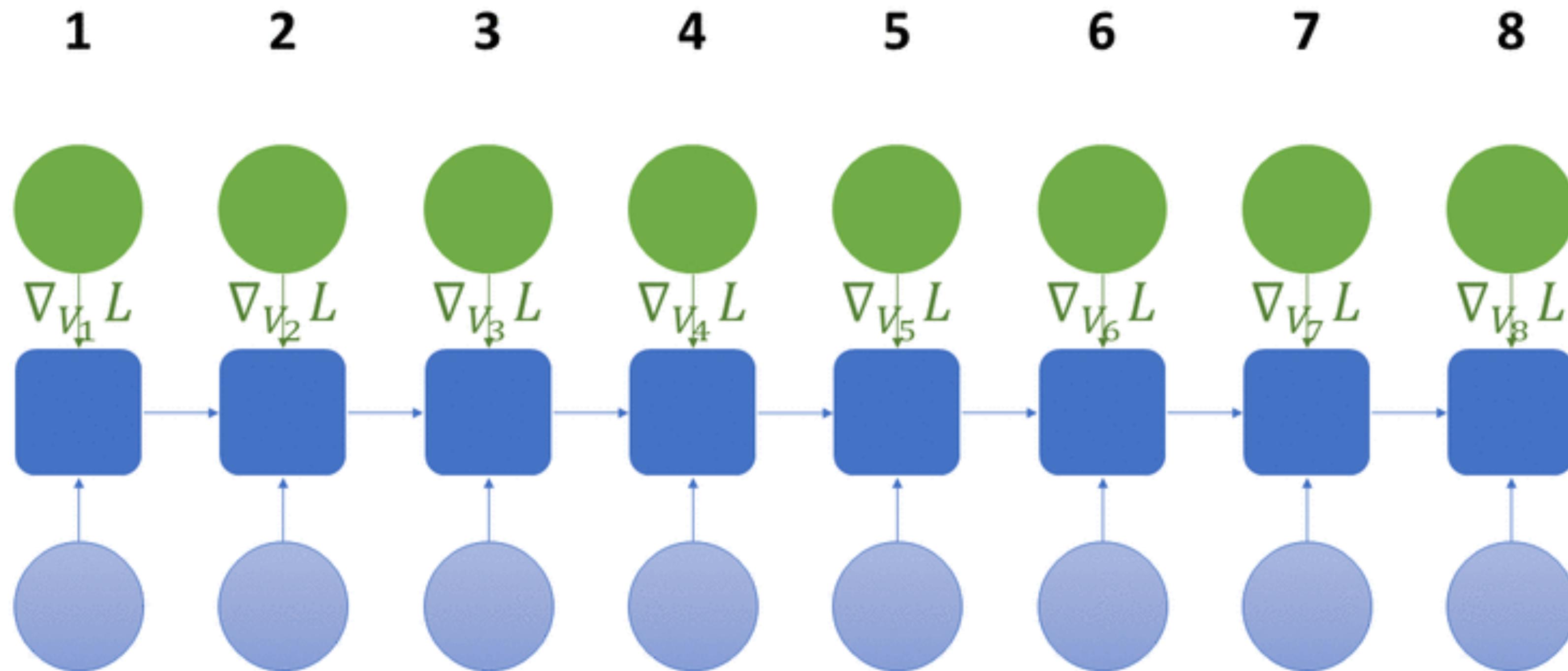
Arquitetura



Fonte: <http://karpathy.github.io/2015/05/21/rnn-effectiveness/>

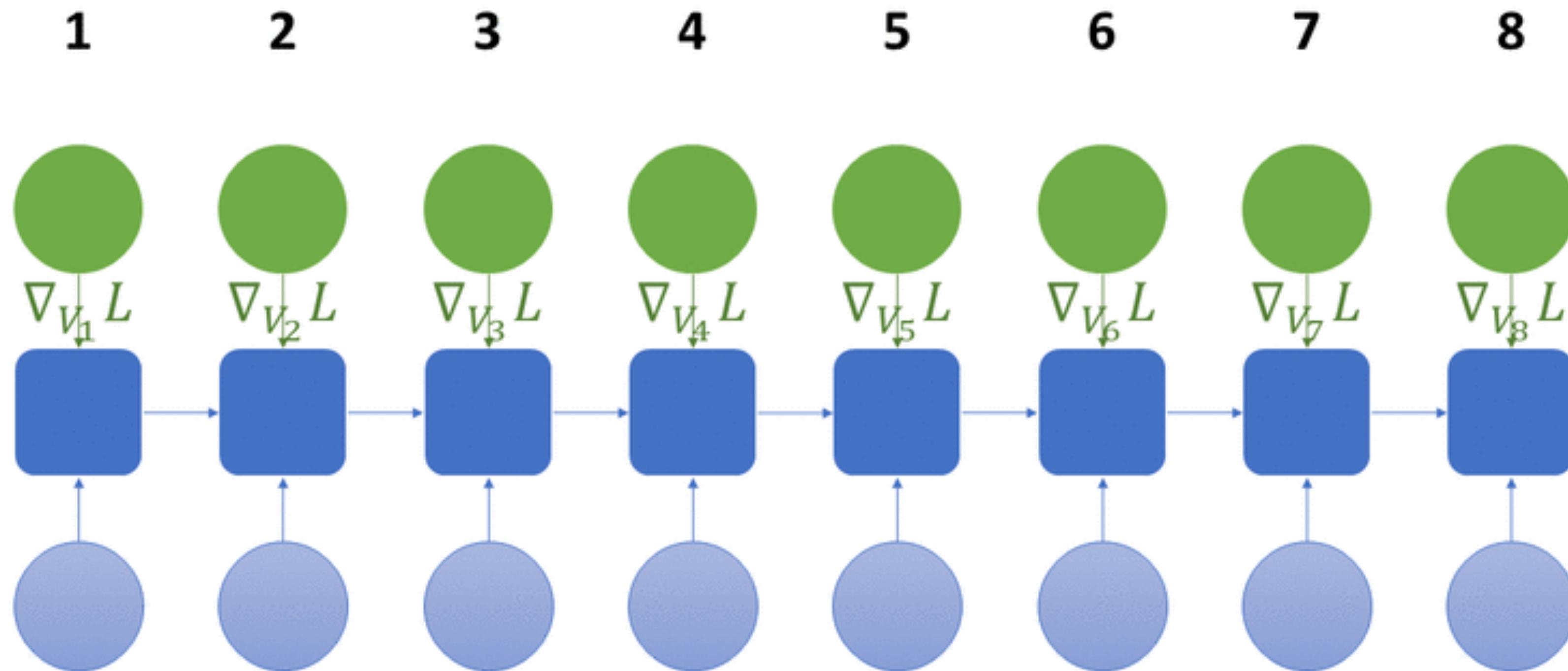
COMO QUE TREINA?

Retropropagação de erro pelo tempo



Fonte: <https://discuss.pytorch.org/t/implementing-backpropagation-through-time/69765>

Retropropagação de erro pelo tempo



Fonte: <https://discuss.pytorch.org/t/implementing-backpropagation-through-time/69765>

E O CHATGPT?

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