

# Redes Neurais e Aprendizagem Profunda

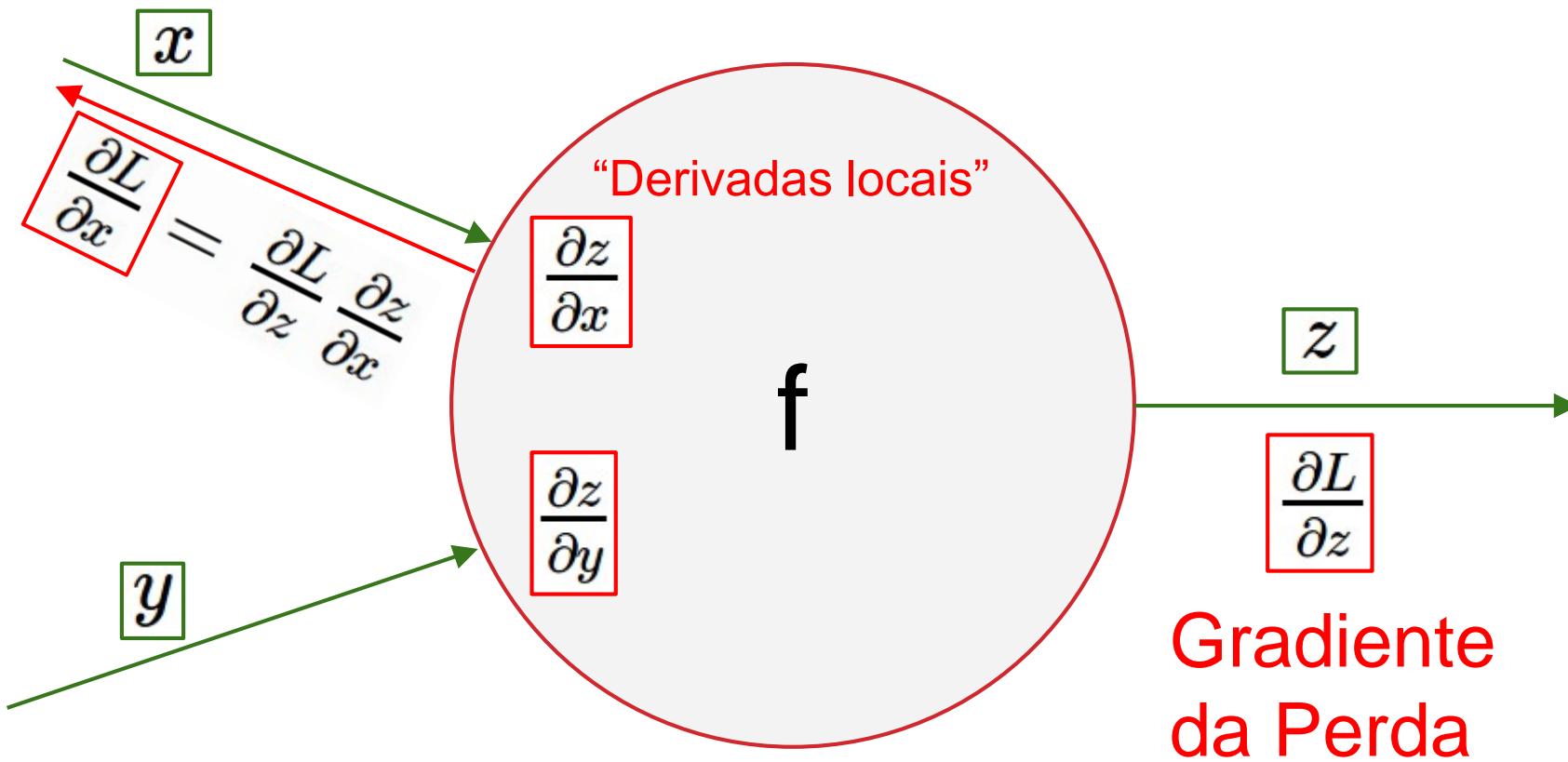
## REDES NEURAIS ARTIFICIAIS PROPAGAÇÃO RETRÓGRADA (III)

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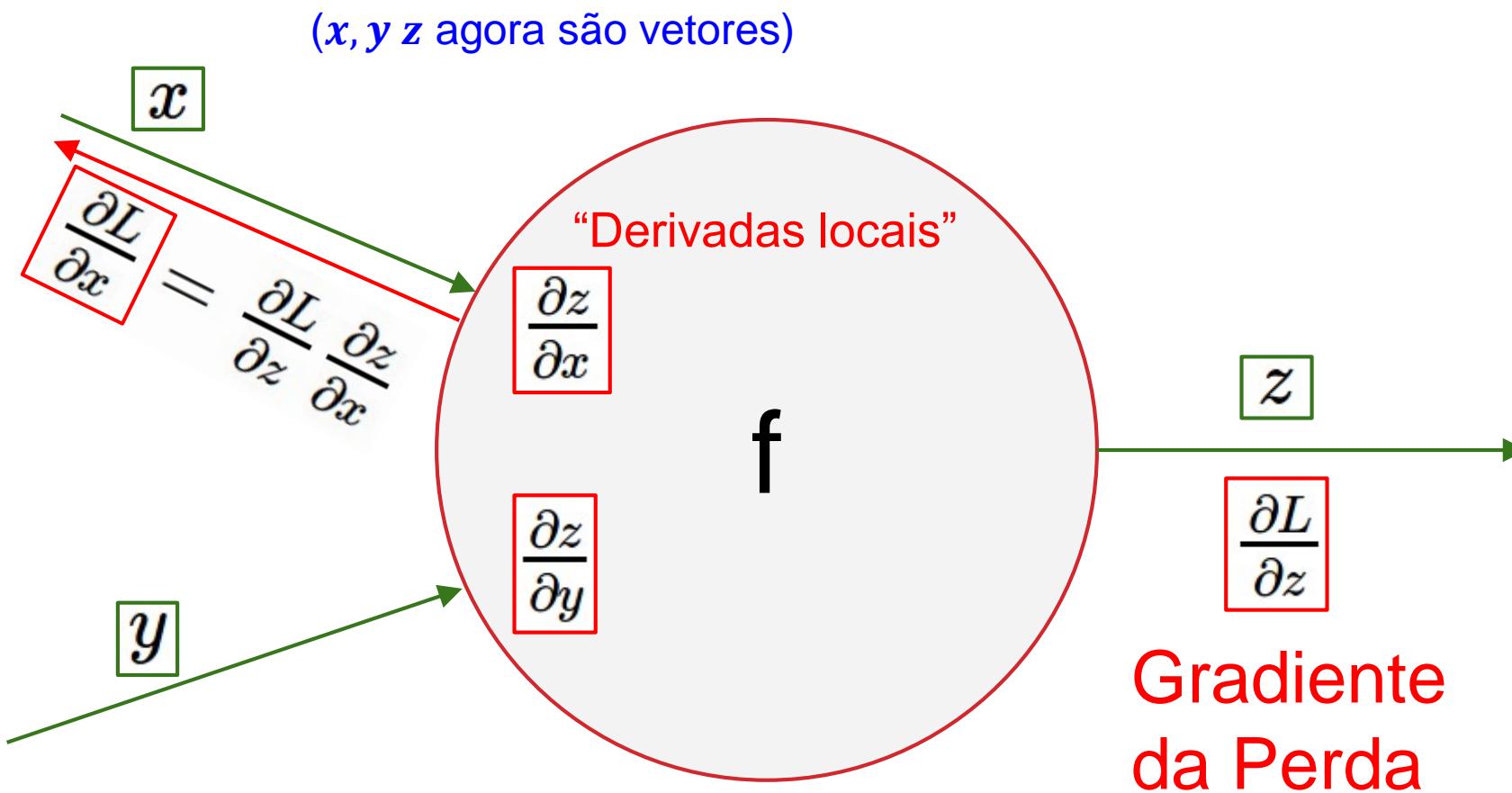
Zenilton K. G. Patrocínio Jr

[zenilton@pucminas.br](mailto:zenilton@pucminas.br)

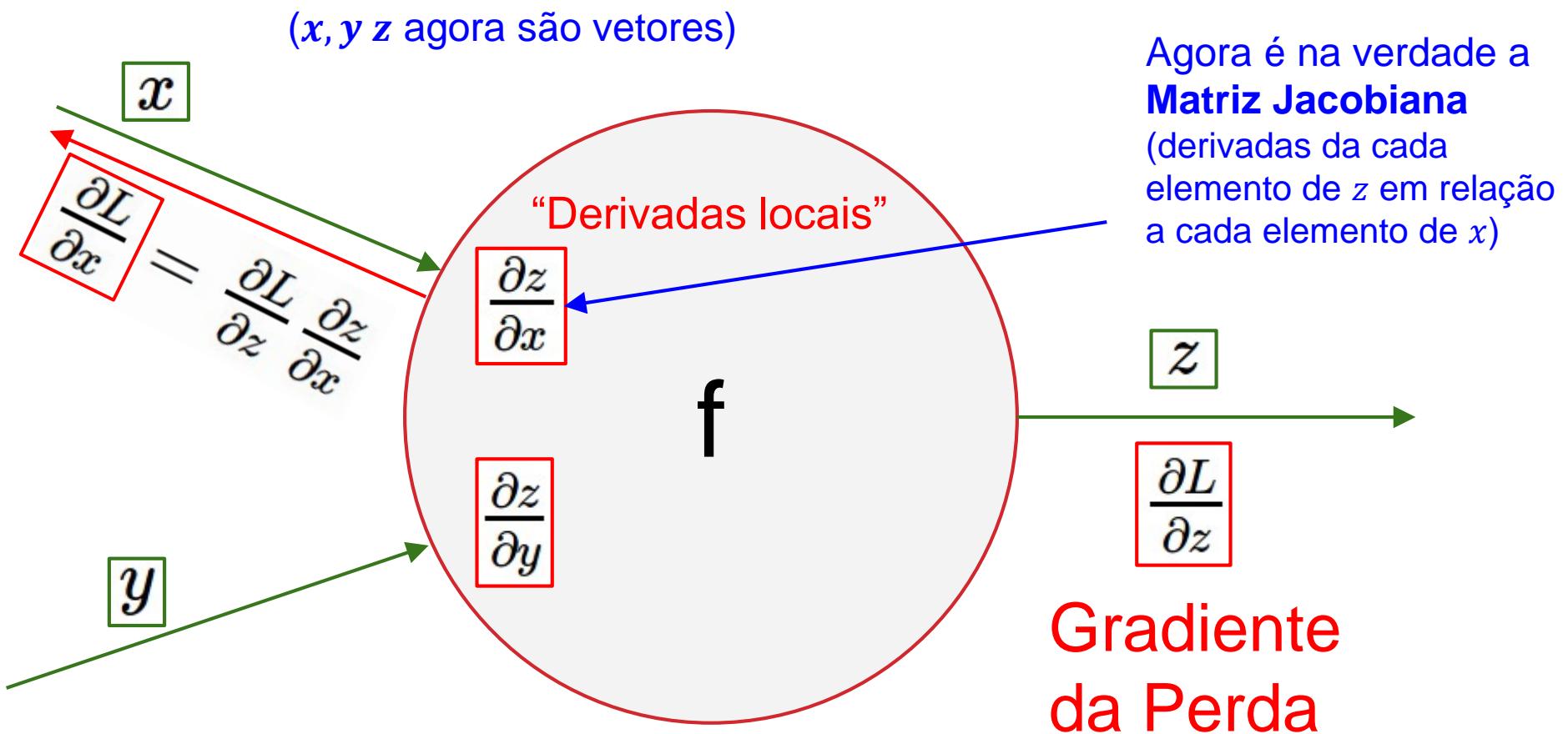
# Gradientes para Dados Multidimensionais



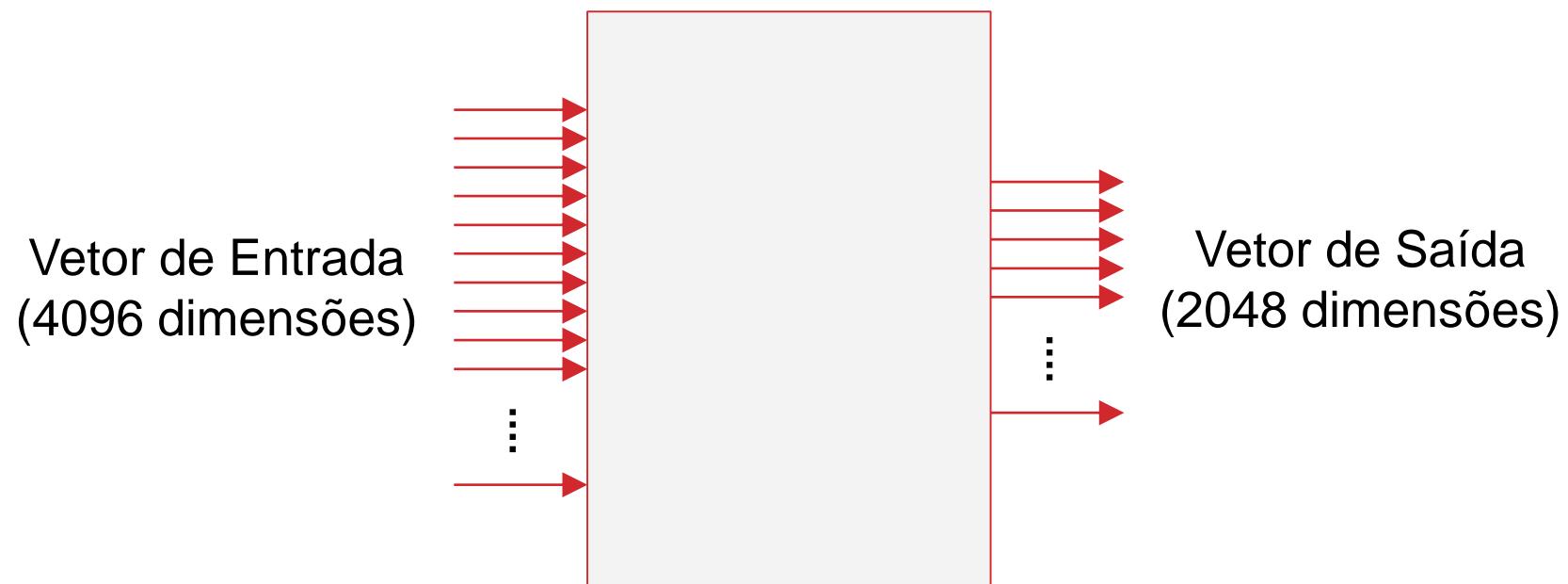
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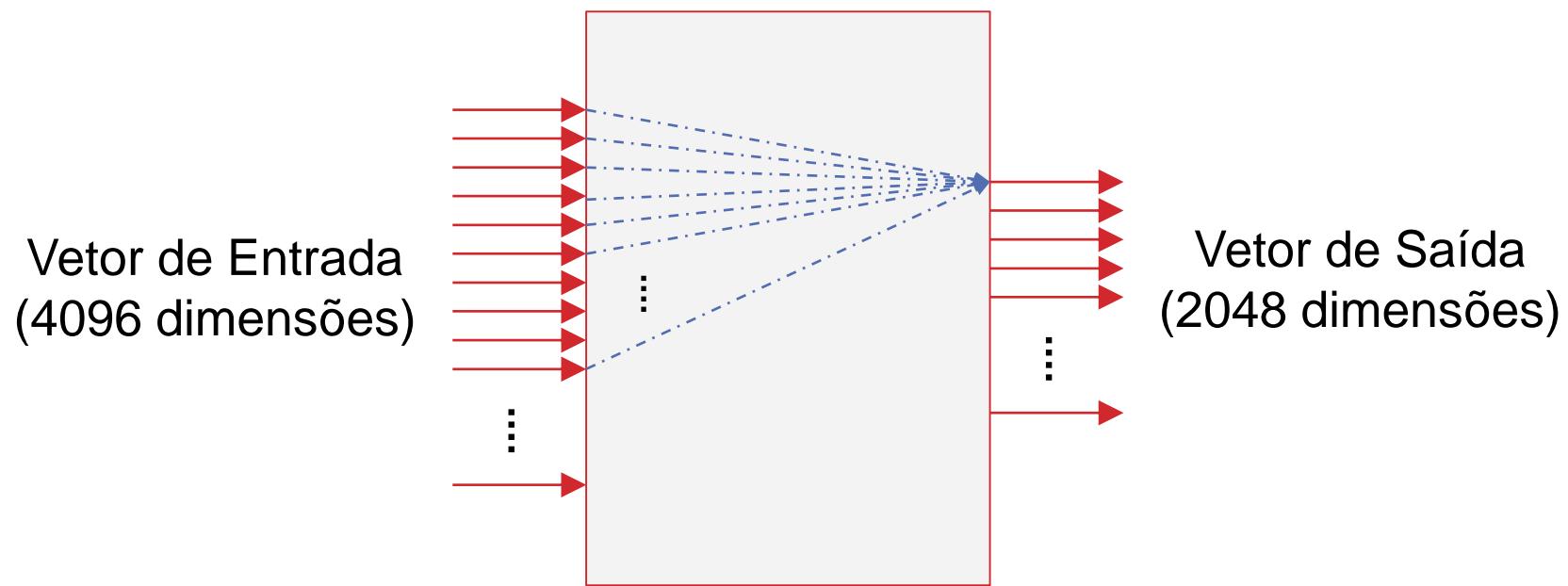
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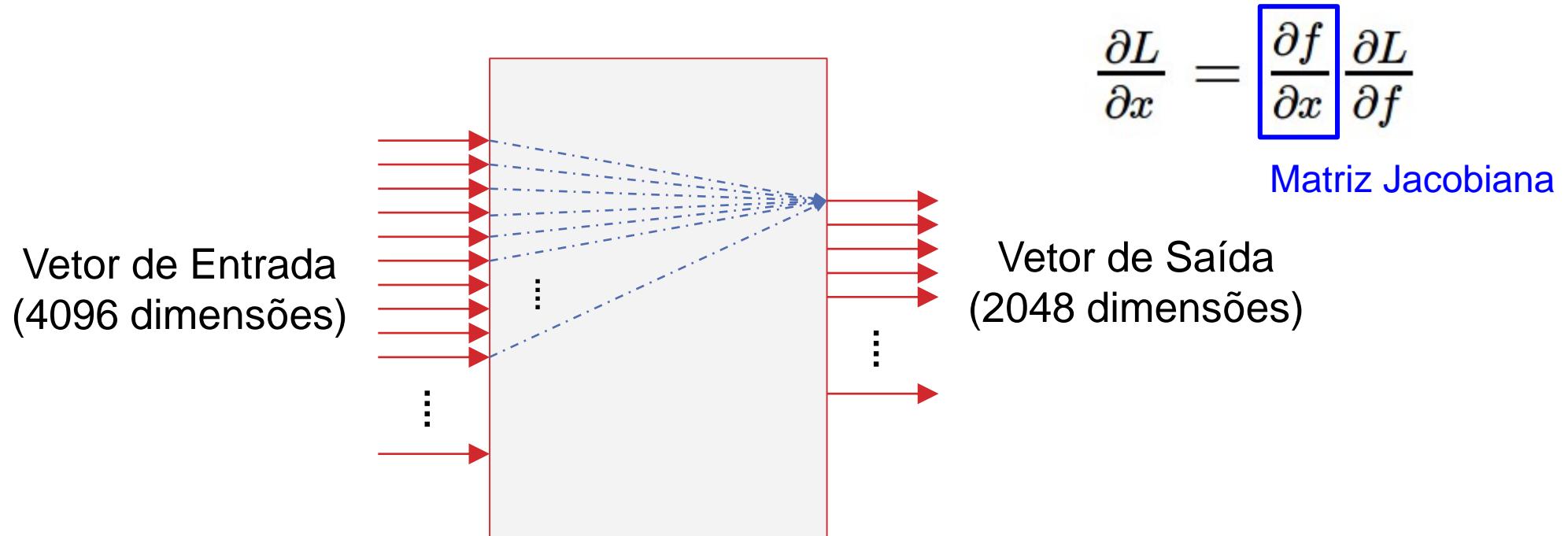
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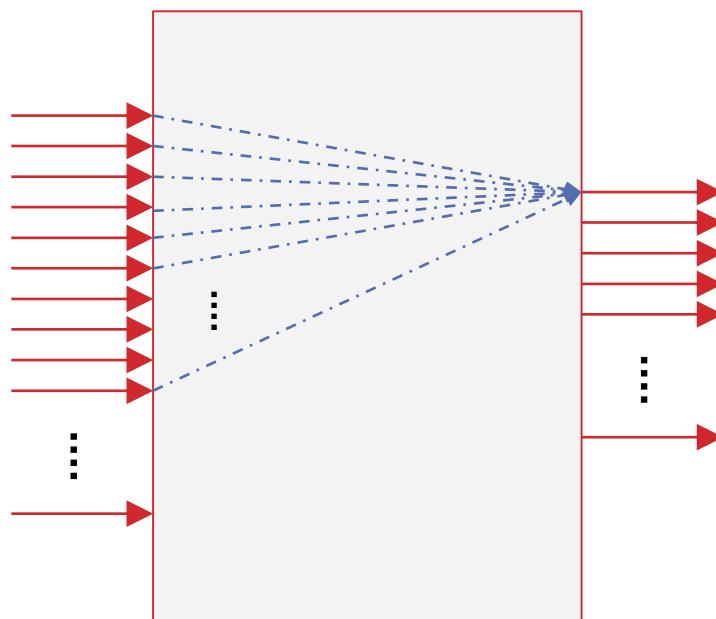
# Gradientes para Dados Multidimensionais

$$\frac{\partial L}{\partial x} = \boxed{\frac{\partial f}{\partial x}} \frac{\partial L}{\partial f}$$

Matriz Jacobiana

Vetor de Entrada  
(4096 dimensões)

P1: qual o tamanho  
da matriz Jacobiana?



Vetor de Saída  
(2048 dimensões)

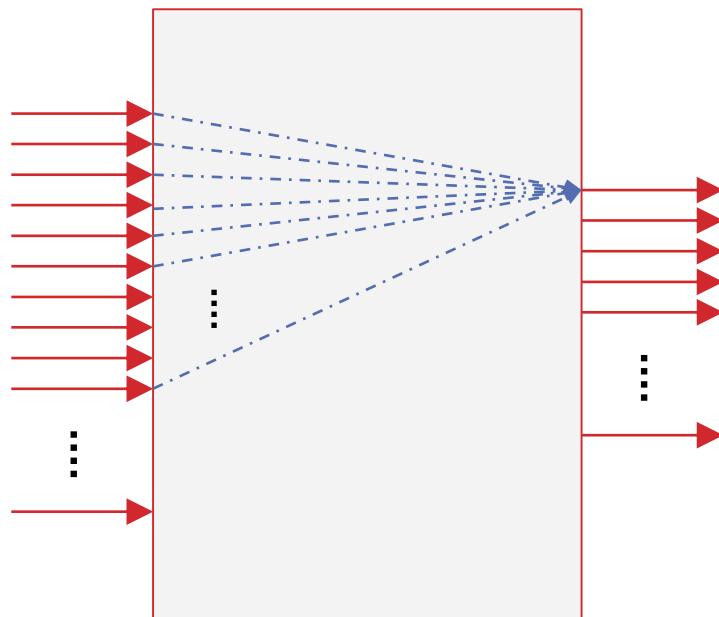
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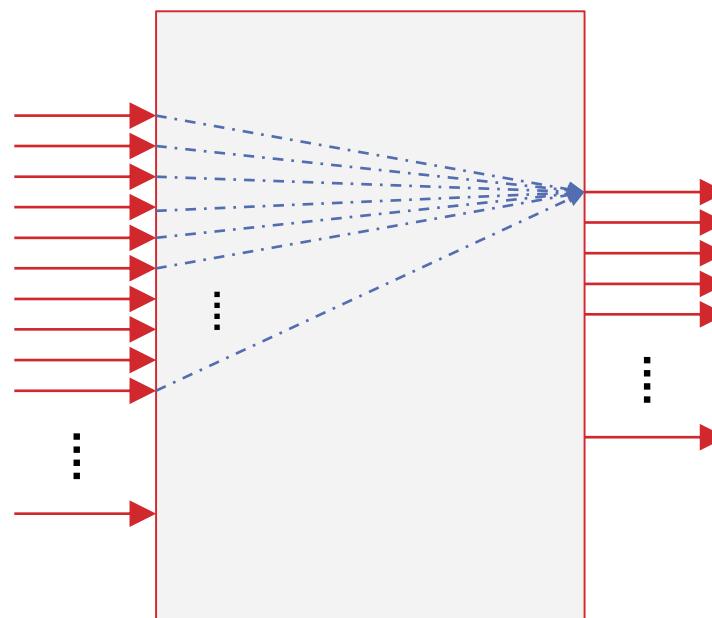
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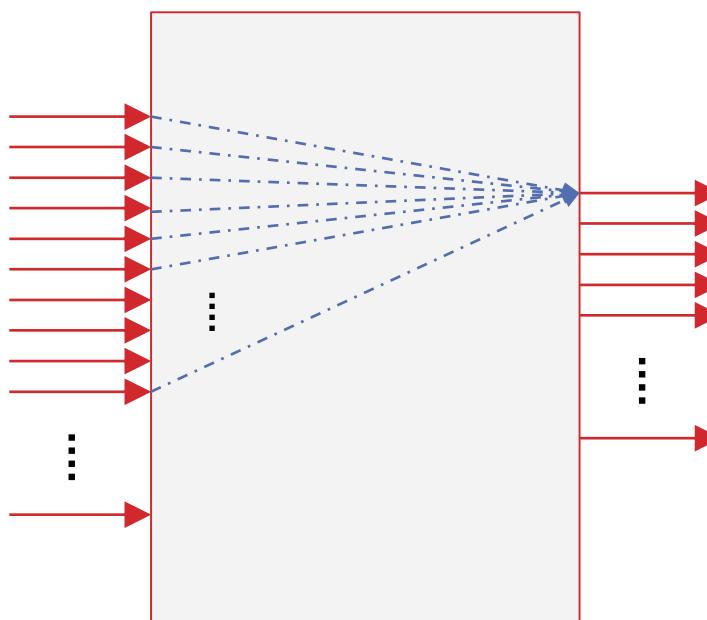
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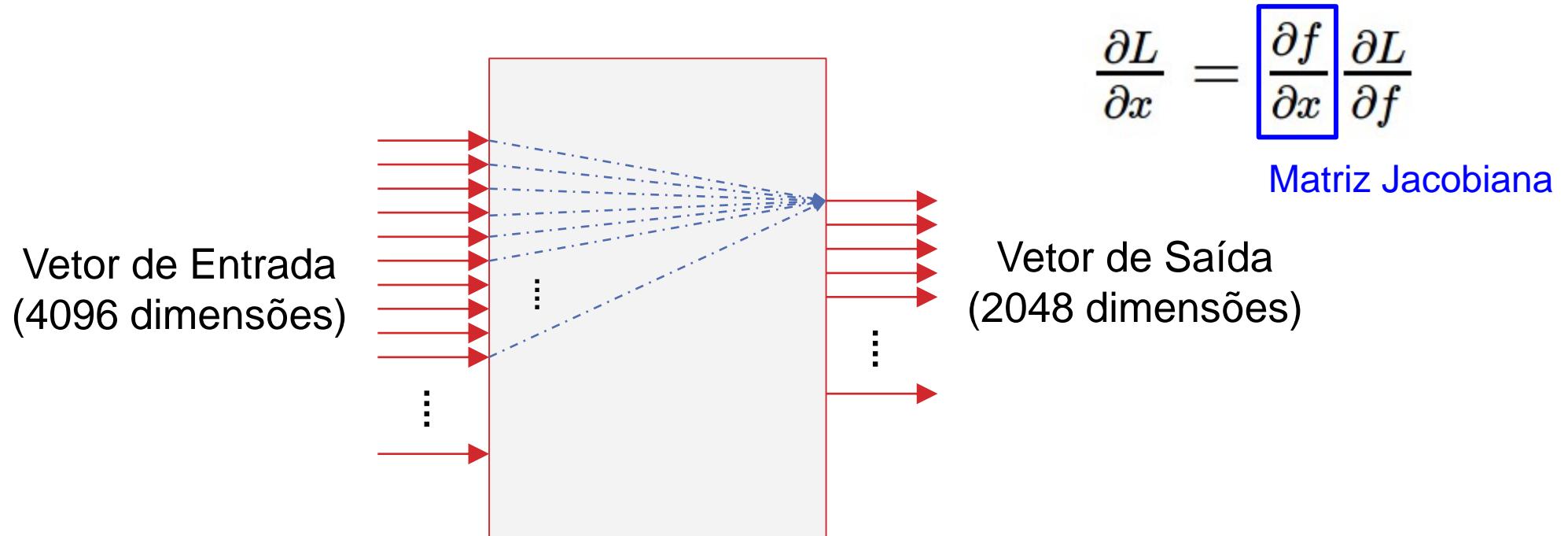
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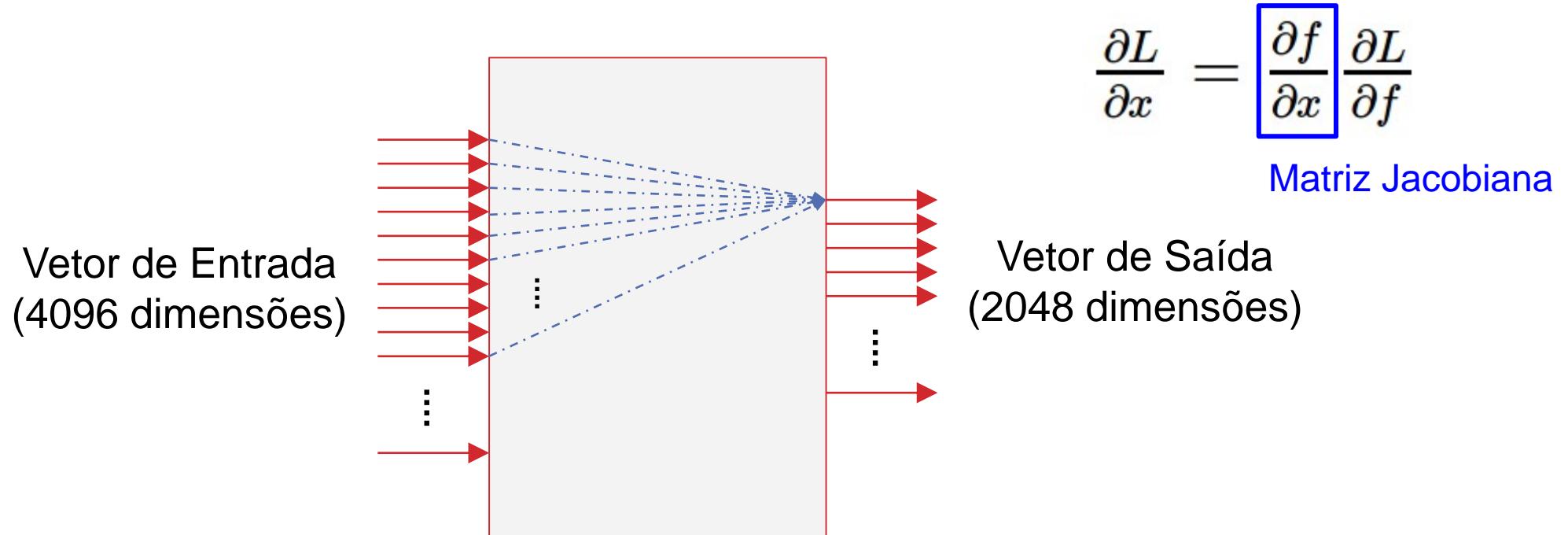
$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_m} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_k}{\partial x_1} & \frac{\partial f_k}{\partial x_2} & \dots & \frac{\partial f_k}{\partial x_m} \end{bmatrix}$$

# Gradientes para Dados Multidimensionais



Na prática, processa-se  
todo um lote ou “*minibatch*”  
(p.ex. 100 amostras) de  
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# Gradientes para Dados Multidimensionais



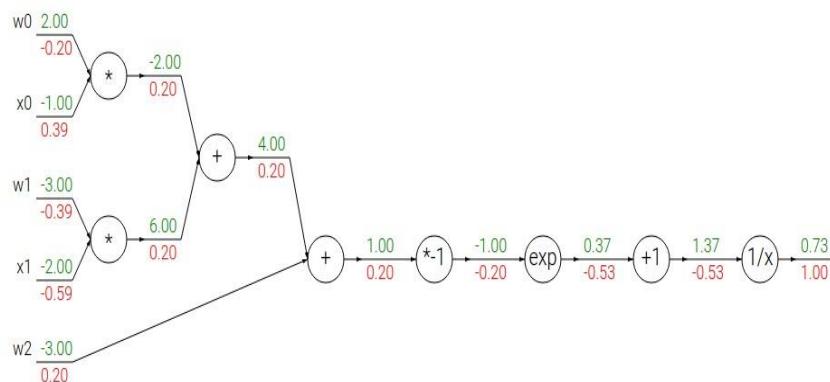
Na prática, processa-se todo um lote ou “*minibatch*” (p.ex. 100 amostras) de uma só vez

Assim, as dimensões da matriz Jacobiana desse exemplo seriam

**204.800 × 409.600**

**≈ 83,9 bilhões de pesos :(**

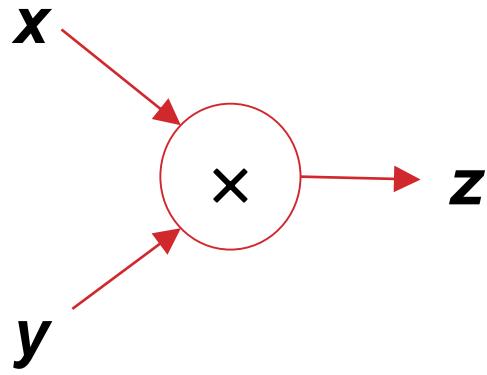
# Implementação – Forward / Backward API



Para um grafo ou rede (*pseudocódigo*)

```
class ComputationalGraph(object):
    ...
    def forward(inputs):
        # 1. [pass inputs to input gates...]
        # 2. forward the computational graph:
        for gate in self.graph.nodes_topologically_sorted():
            gate.forward()
        return loss # the final gate in the graph outputs the loss
    def backward():
        for gate in reversed(self.graph.nodes_topologically_sorted()):
            gate.backward() # little piece of backprop (chain rule applied)
        return inputs_gradients
```

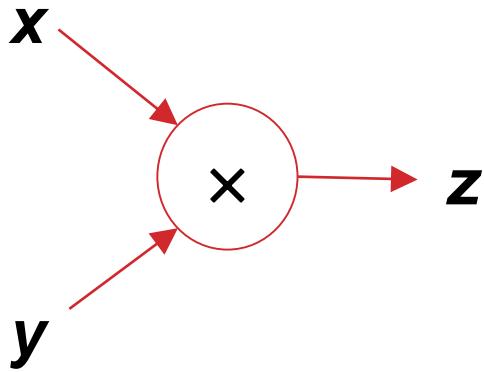
# Implementação – Forward / Backward API



( $x, y, z$  escalares)

```
class MultiplyGate(object):  
    def forward(x,y):  
        z = x*y  
        return z  
    def backward(dz):  
        # dx = ... #todo  
        # dy = ... #todo  
        return [dx, dy]
```

# Implementação – Forward / Backward API

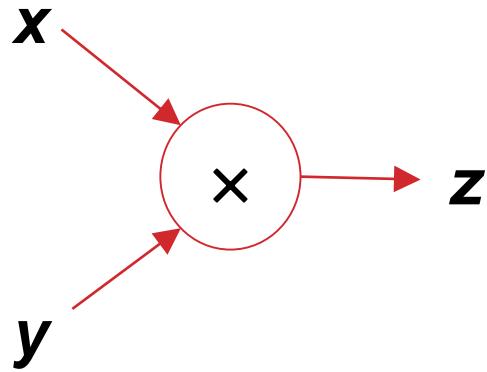


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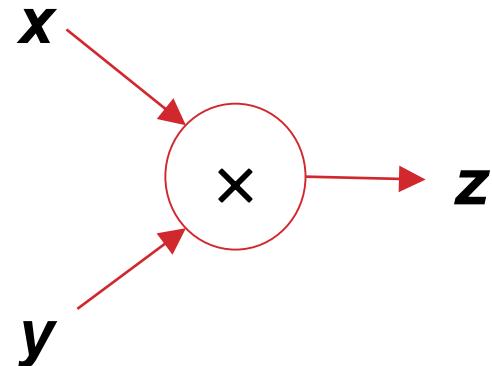
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$$\frac{\partial L}{\partial z}$$

$$\frac{\partial L}{\partial x}$$

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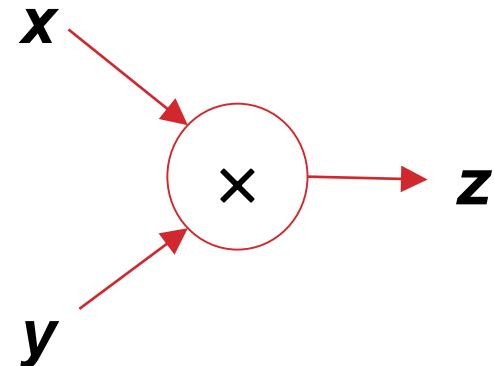


( $x, y, z$  escalares)

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class MultiplyGate(object):  
    def forward(x,y):  
        z = x*y  
        self.x = x # must keep these around!  
        self.y = y  
        return z  
    def backward(dz):  
        dx = self.y * dz # [dz/dx * dL/dz]  
        dy = self.x * dz # [dz/dy * dL/dz]  
        return [dx, dy]
```



# Implementação – Forward / Backward API



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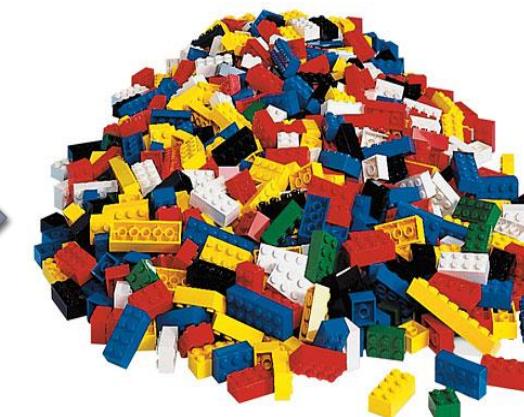
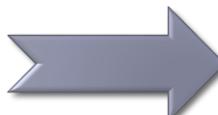
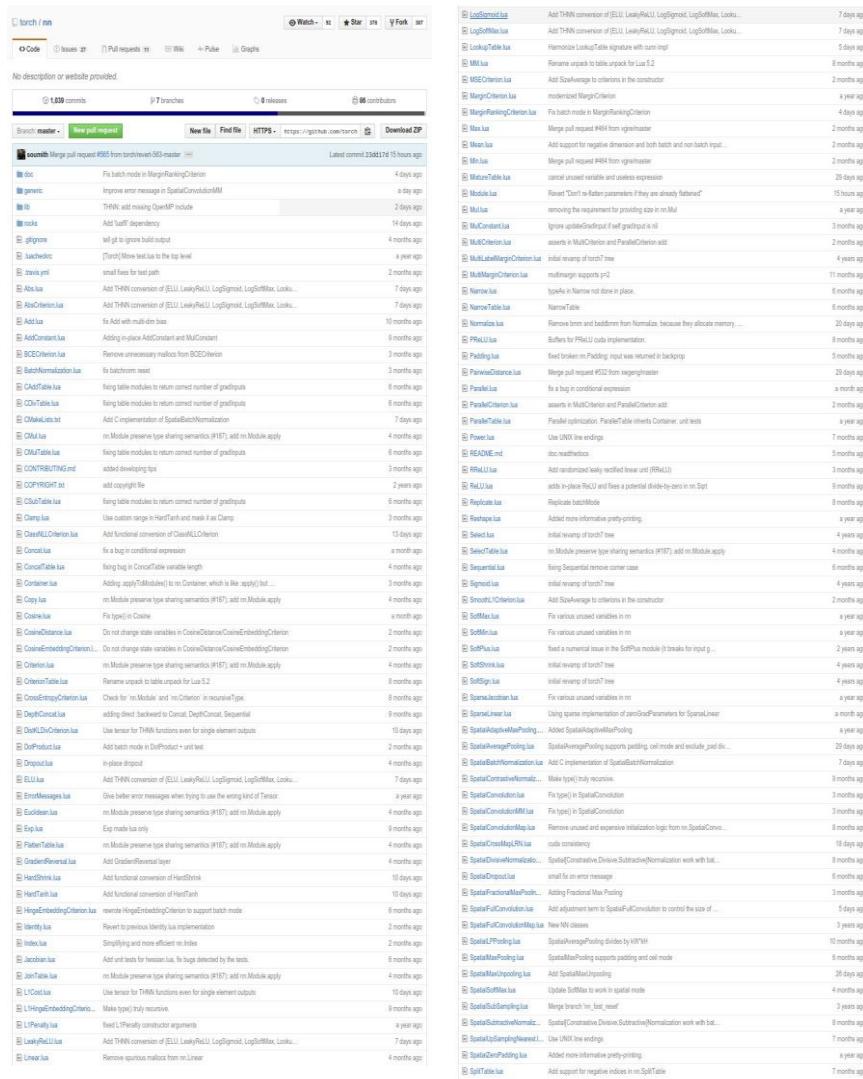
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# Biblioteca de Componentes / Camadas

The screenshot shows a GitHub repository page for the 'nn' module of the 'torch' library. The repository has 1,639 commits, 7 branches, 0 releases, and 46 contributors. The 'master' branch is selected, and a pull request titled 'soumith Merge pull request #965 from bethgev/965-master' is shown, which was merged 11 hours ago. The list of pull requests is extensive, spanning from 2014 to the present. Many pull requests are from the 'doc' and 'gen' categories, while others are from 'th', 'rocks', 'ghgrone', 'lauchovic', 'strava', 'Abu', 'AbuCheiron', 'Add', 'AddConstant', 'BCECriterion', 'BatchNormalization', 'CastTable', 'ConvTable', 'CReLU', 'CMTable', 'CMTTable', 'CONTRIBUTING', 'COPYRIGHT', 'Container', 'Copy', 'Cosine', 'CosineDistance', 'CosineEmbeddingCriterion', 'Criterion', 'CriterionTable', 'CrossEntropyCriterion', 'DepthCriterion', 'DepthConvCriterion', 'DotProduct', 'Dropout', 'ELU', 'ErrorMessages', 'Epsilon', 'FasterTable', 'GradientReversal', 'HardDropout', 'HardTanh', 'HingeEmbeddingCriterion', 'Identity', 'Index', 'Jacobian', 'JoinTable', 'L1Criterion', 'L1HingeEmbeddingCriterion', 'Penalty', 'LeakyReLU', and 'Linear'. The pull requests cover various topics such as improving error messages, adding new modules like 'BatchNormalization', and fixing bugs in existing functions like 'ReLU' and 'ConvTable'.

# Biblioteca de Componentes / Camadas



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