UTEC
UNIVERSIDAD DE INGENIERÍA Y TECNOLOGÍA

> Reinventa el mundo <

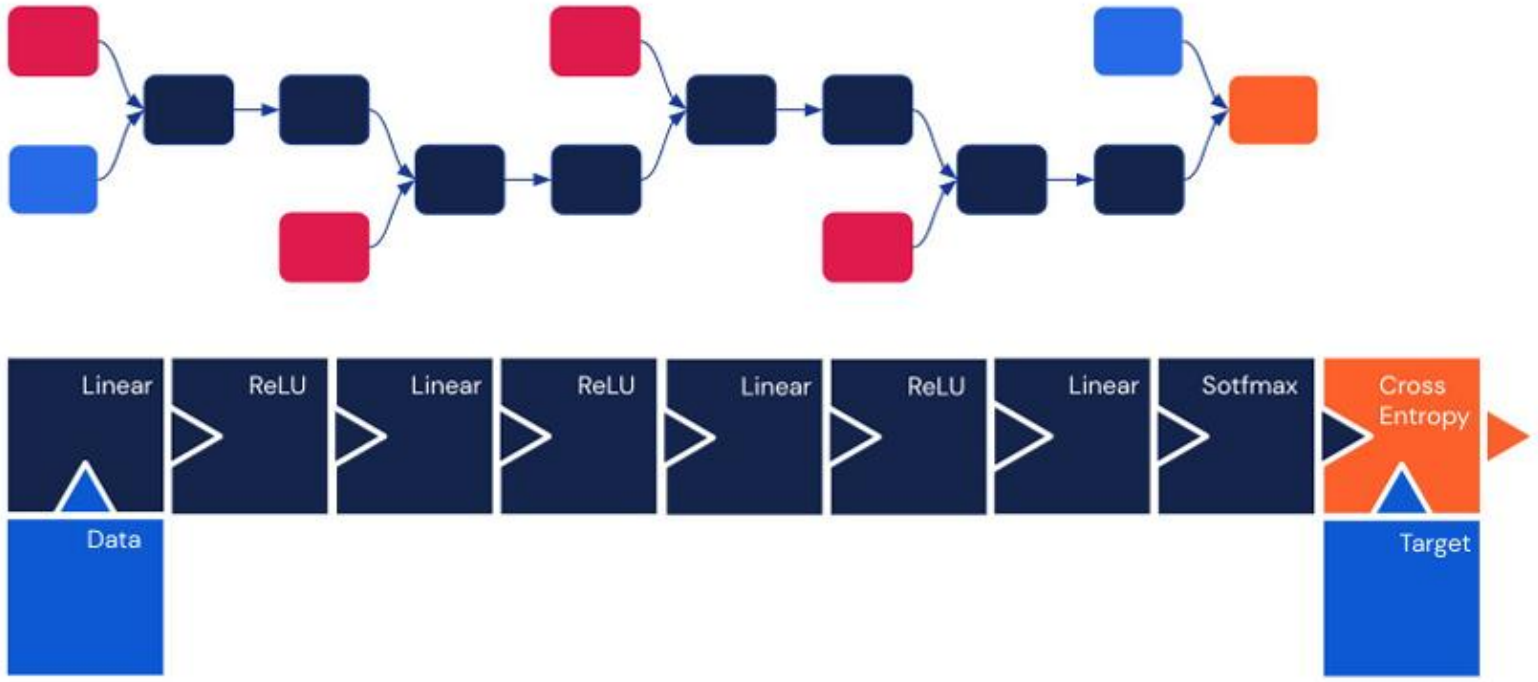
Sesión 1.2

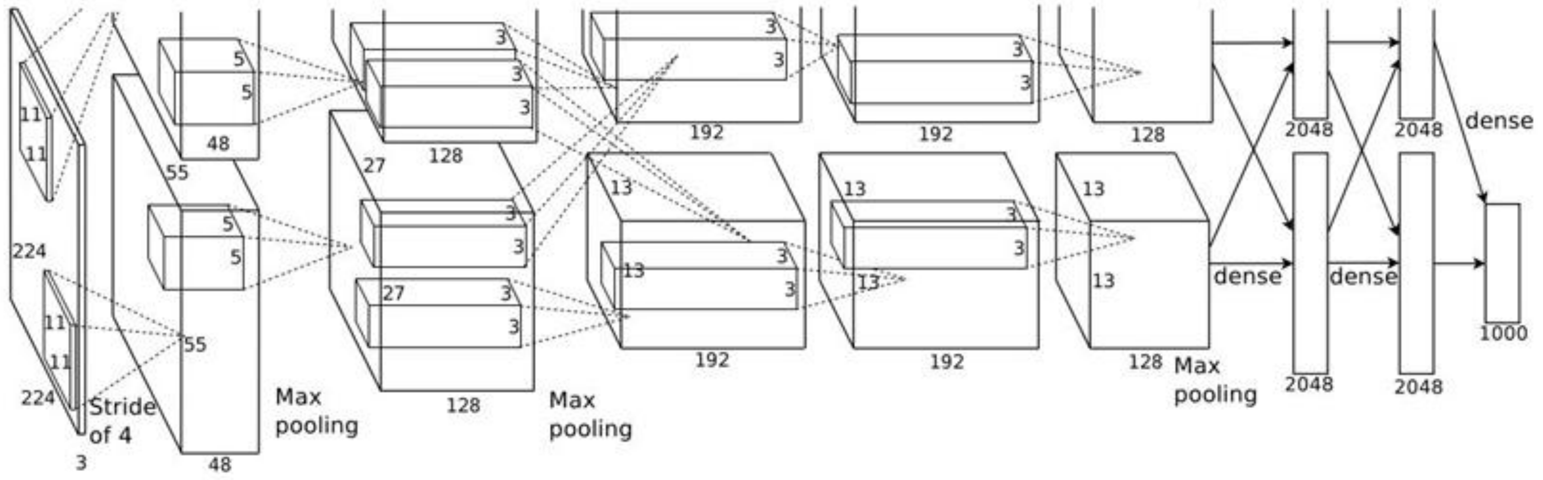
Redes recurrentes

LSTM, GRU

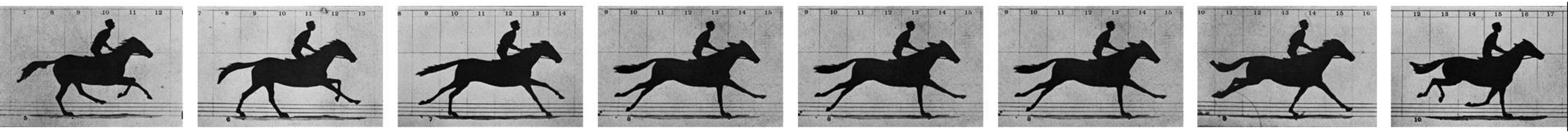
TRANSFORMATEC

Deep *Models*


Linear
ReLU
Linear
ReLU
Linear
ReLU
Linear
Sotfmax
Cross Entropy
Data
Target


224
224
3
11
11
Stride of 4
55
48
Max pooling
27
128
Max pooling
13
192
128
Max pooling
dense
2048
1000

Secuencias



Colecciones de datos donde:

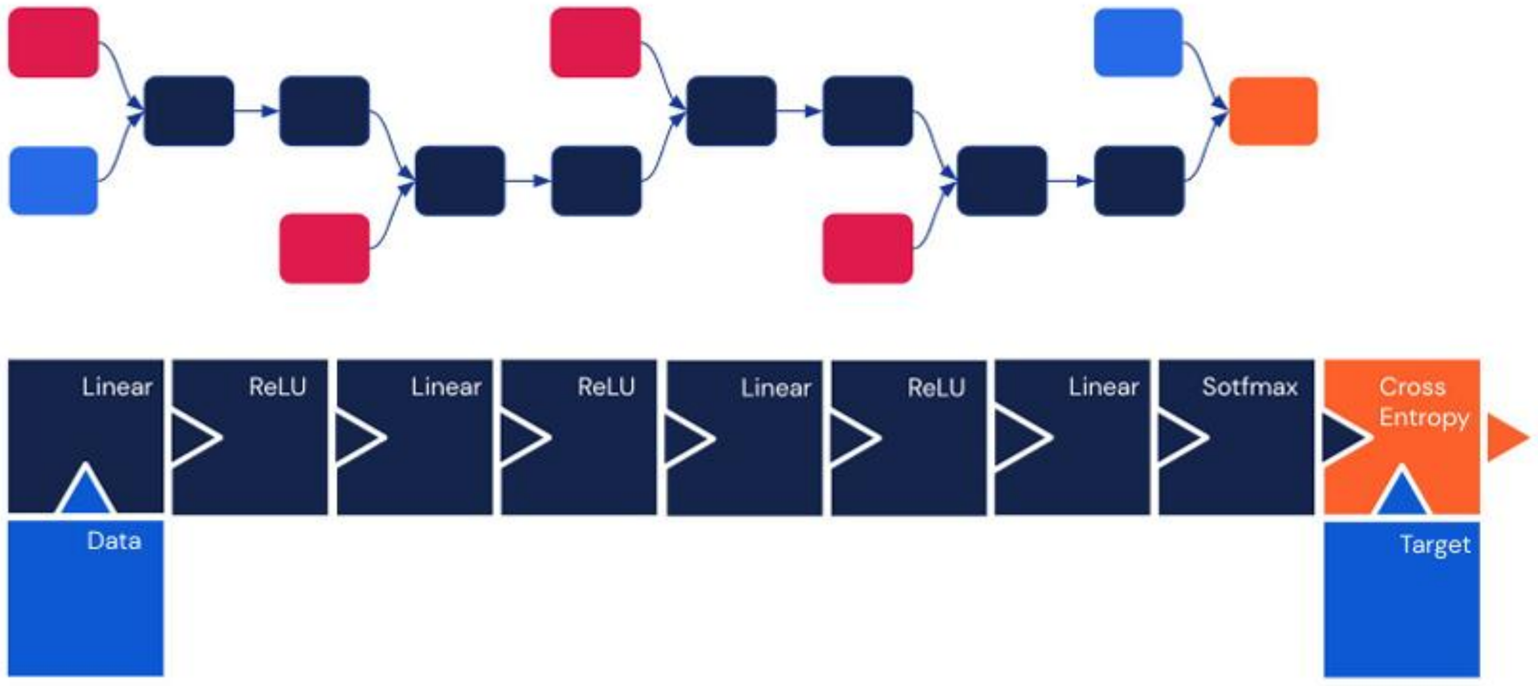
- Los elementos pueden **repetirse**
- El **orden** importa
- De longitud **variable** (potencialmente infinita)

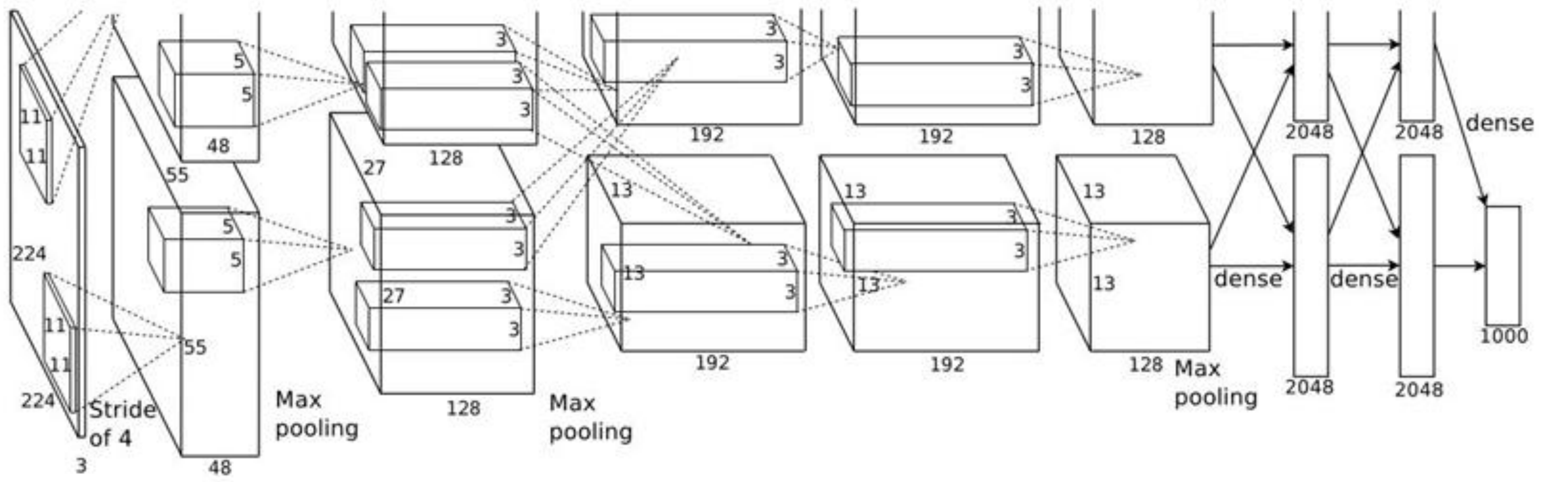
> Reinventa el mundo <

Modelar *Secuencias*

- Los elementos pueden **repetirse**
- El **orden** importa
- De longitud **variable** (potencialmente infinita)

Los modelos previos no funcionan bien con datos secuenciales





TRANSFORMATEC

Secuencias

"Sequences really seem to be everywhere! We should learn how to model them. What is the best way to do that? Stay tuned!"

Palabras, letras

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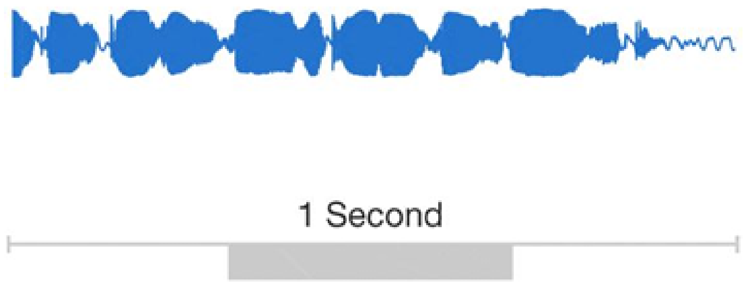

Habla

Secuencias

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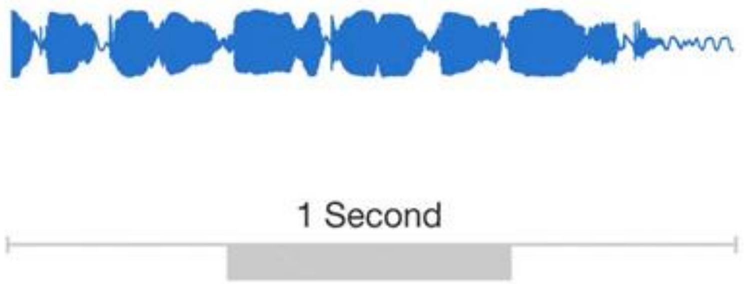
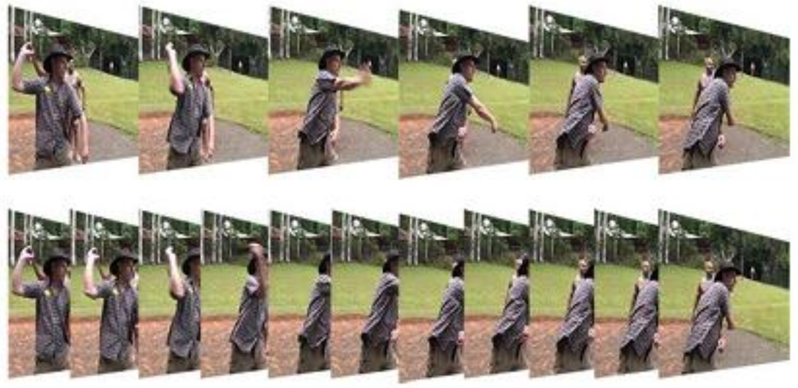
Palabras, letras



Habla

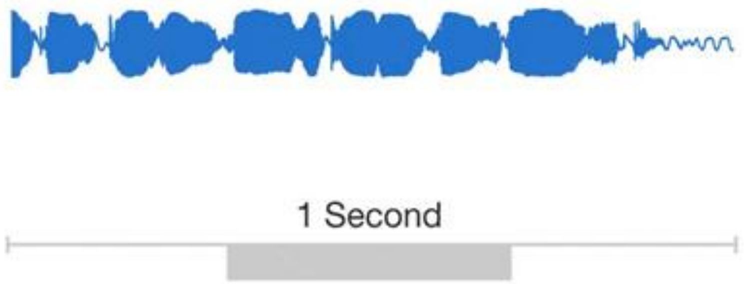


Video

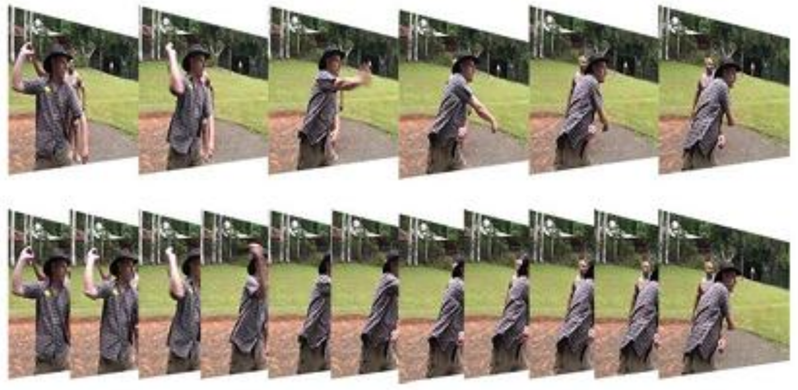
Secuencias

"Sequences really seem to be everywhere! We should learn how to model them. What is the best way to do that? Stay tuned!"

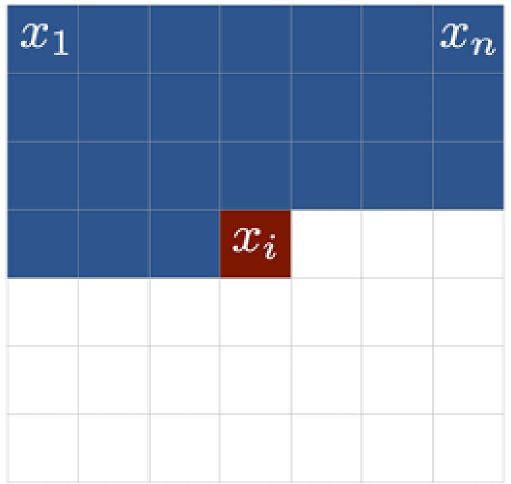
Palabras, letras



Habla



Video

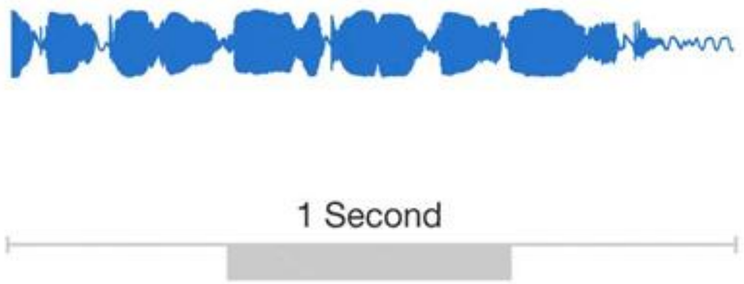


Imágenes

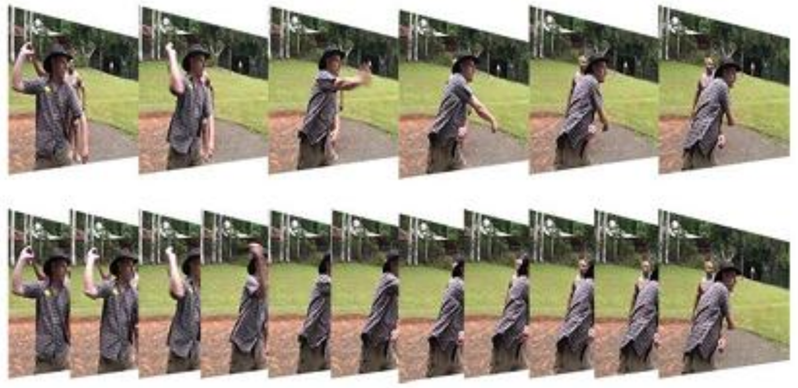
Secuencias

"Sequences really seem to be everywhere! We should learn how to model them. What is the best way to do that? Stay tuned!"

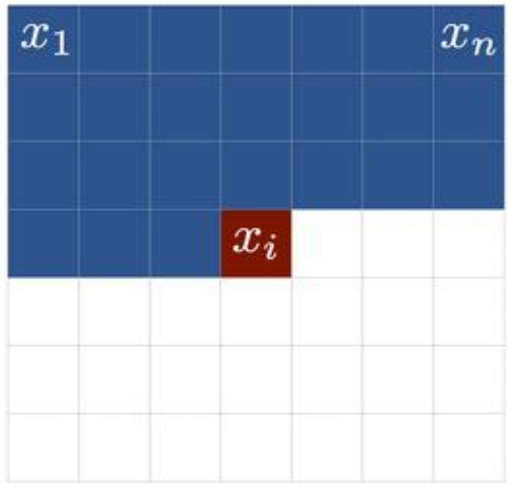
Palabras, letras



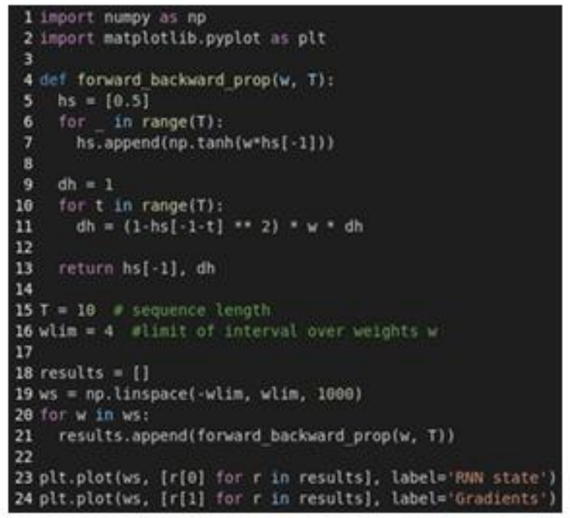
Habla



Video



Imágenes



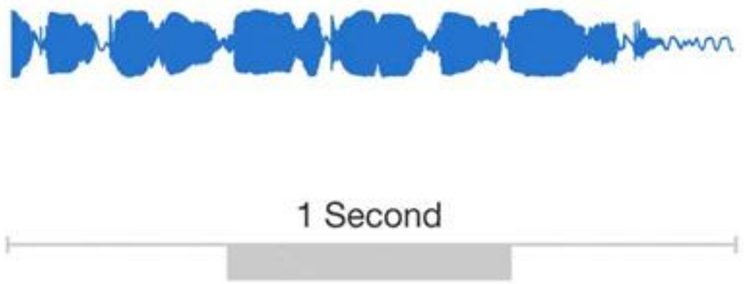
```python
import numpy as np
import matplotlib.pyplot as plt

def forward_backward_prop(w, T):
  hs = [0.5]
  for _ in range(T):
    hs.append(np.tanh(w*hs[-1]))

  dh = 1
  for t in range(T):
    dh = (1-hs[-1-t] ** 2) * w * dh

  return hs[-1], dh

T = 10  # sequence length
wlim = 4  #limit of interval over weights w

results = []
ws = np.linspace(-wlim, wlim, 1000)
for w in ws:
  results.append(forward_backward_prop(w, T))

plt.plot(ws, [r[0] for r in results], label='RNN state')
plt.plot(ws, [r[1] for r in results], label='Gradients')
```

Programas

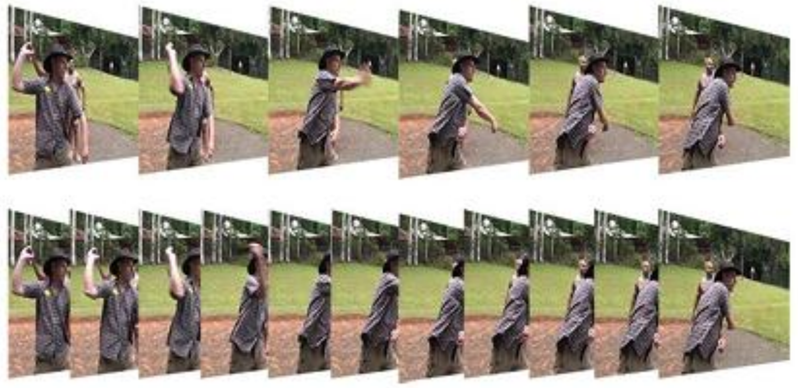
Secuencias

"Sequences really seem to be everywhere! We should learn how to model them. What is the best way to do that? Stay tuned!"

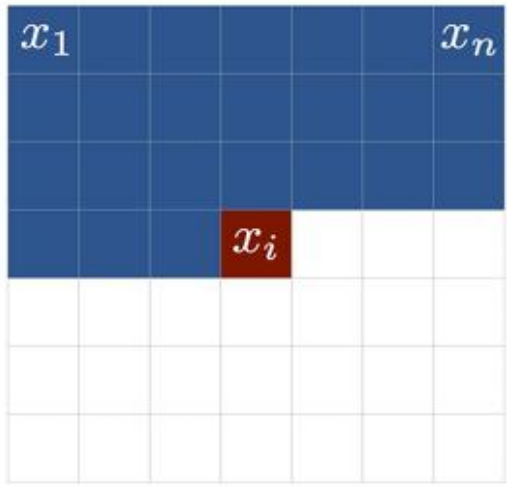
Palabras, letras



Habla



Video



Imágenes

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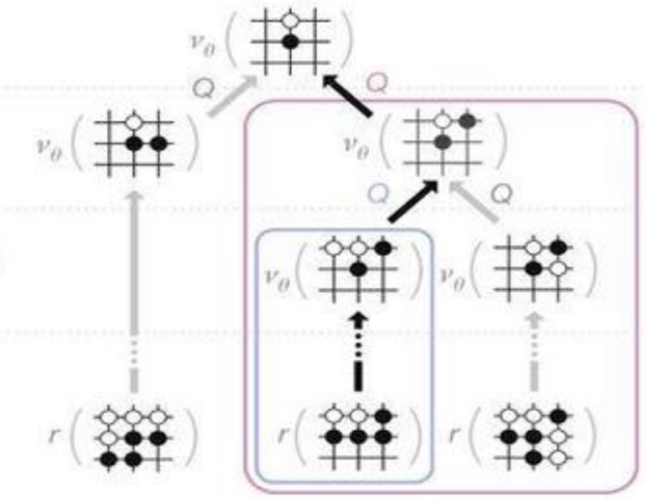
Programas

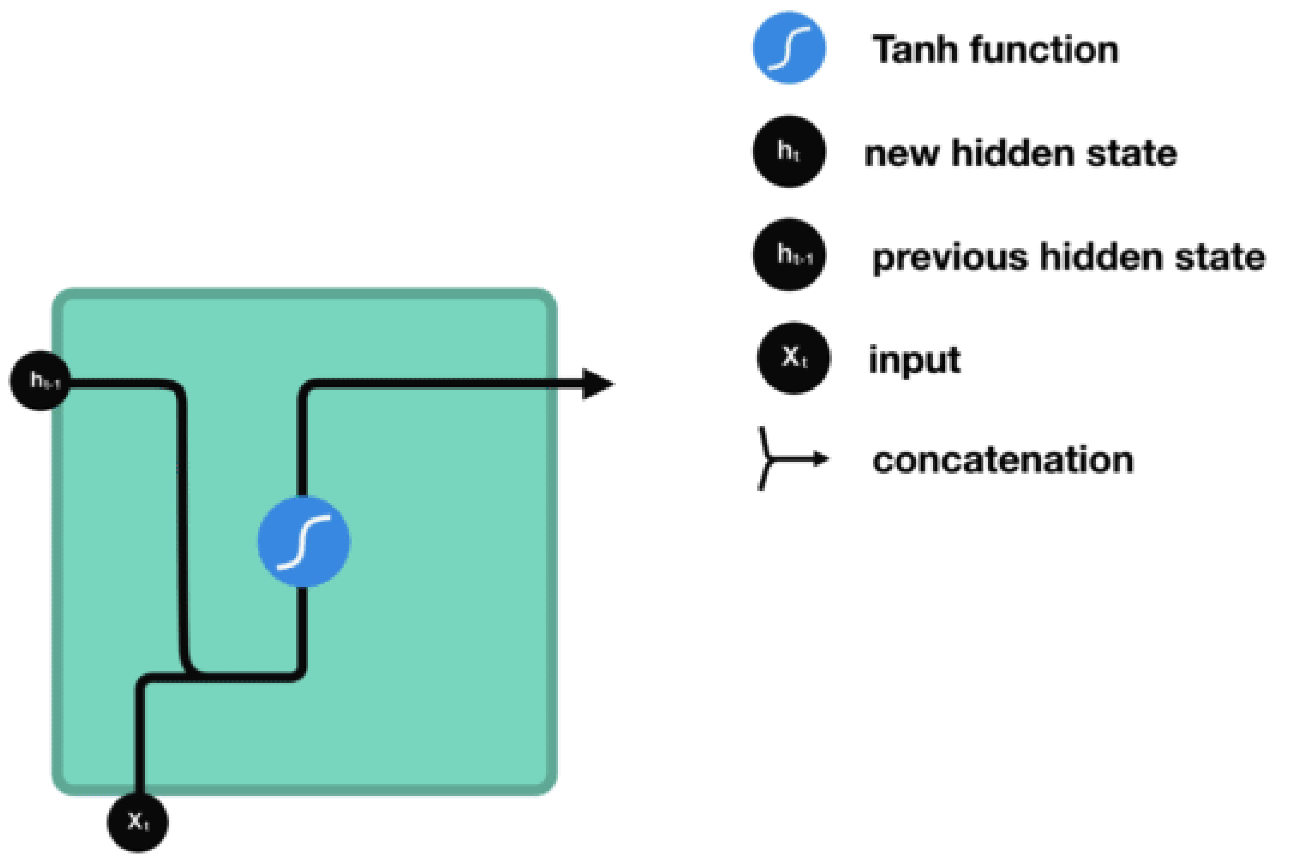


Toma de decisiones

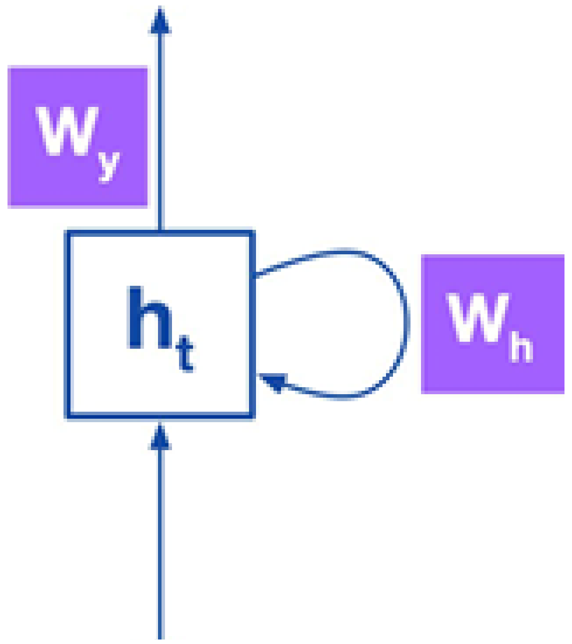
1.

RNN *Tradicionales*

Arquitectura *de las RNN*



Recurrent Neural Network



Alguna función
con parámetro W_h

$$h_t = f_{W_h}(h_{t-1}, x_t)$$

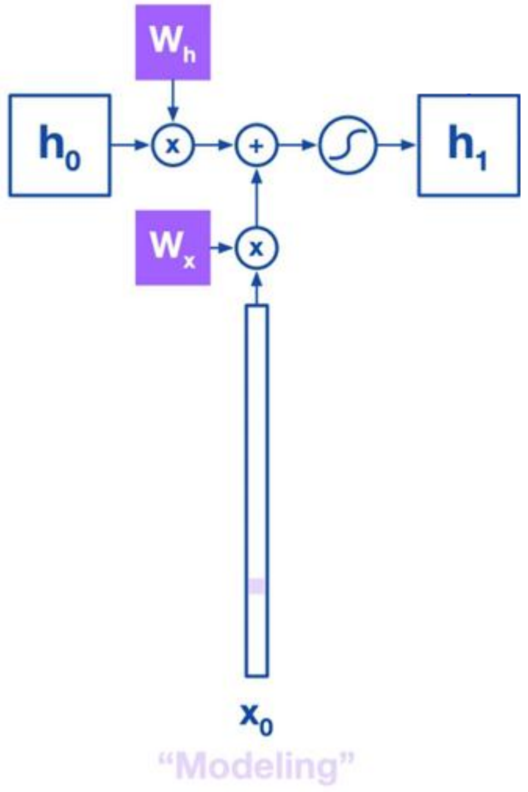
Nuevo estado　Estado previo　Nueva entrada

Alguna función
con parámetro W_y

$$y_t = f_{W_y}(h_t)$$

Salida actual　Nuevo estado

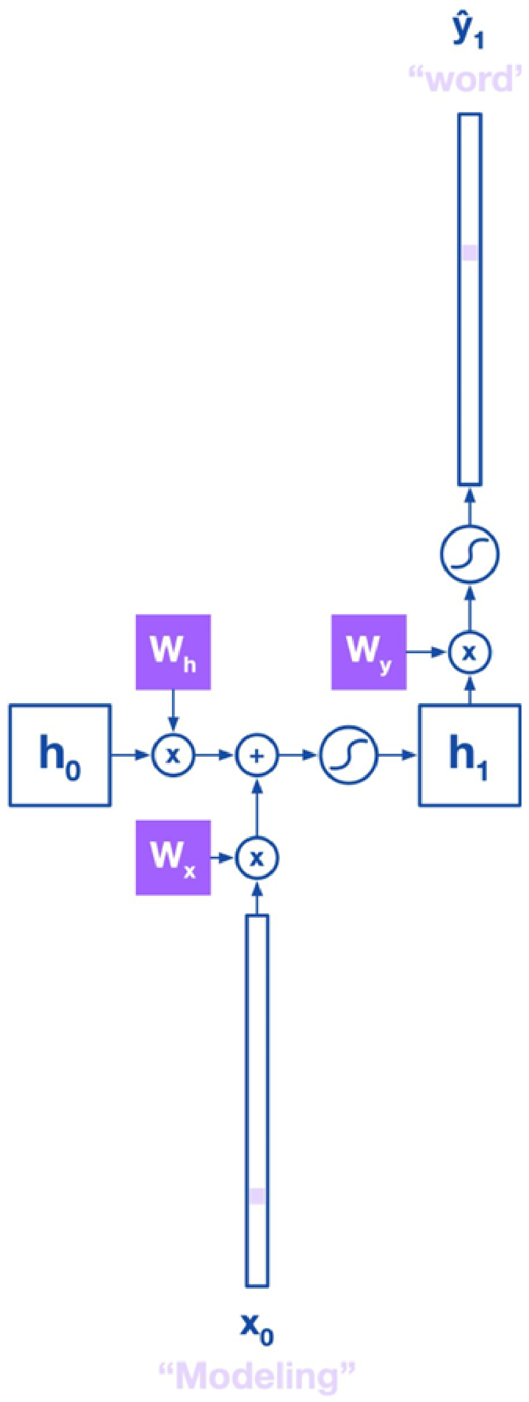
Recurrent Neural Network



Se recibe la primera palabra de entrada x_0.

$$h_t = \tanh(W_h h_{t-1} + W_x x_t)$$

Recurrent Neural Network

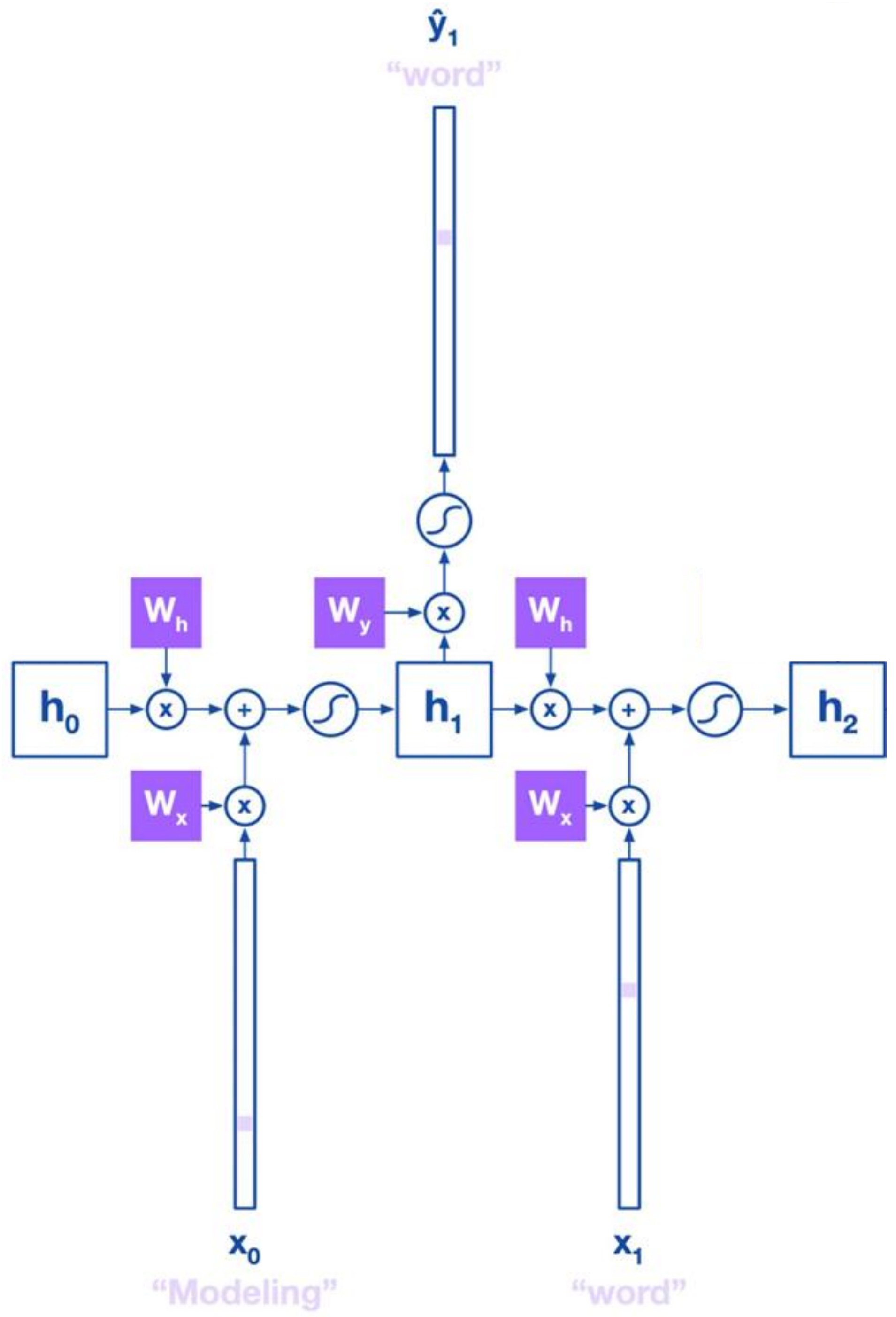


RNN predicen la salida y_1 (la siguiente palabra) a partir del estado h_1.

$$y_t = \text{Softmax}(W_y h_t)$$

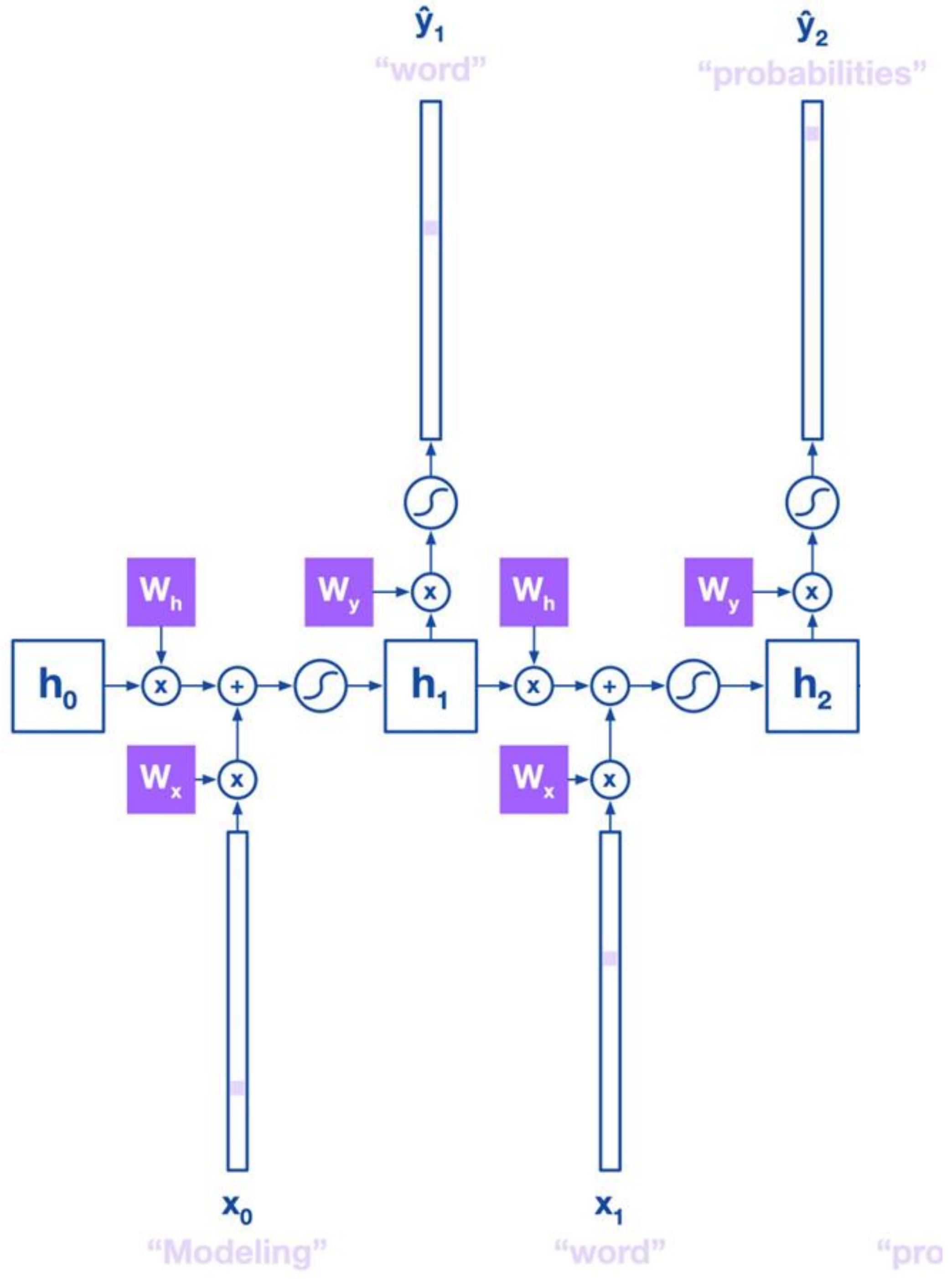
Softmax genera una distribución de probabilidad entre todas las palabras posibles.

Recurrent Neural Network

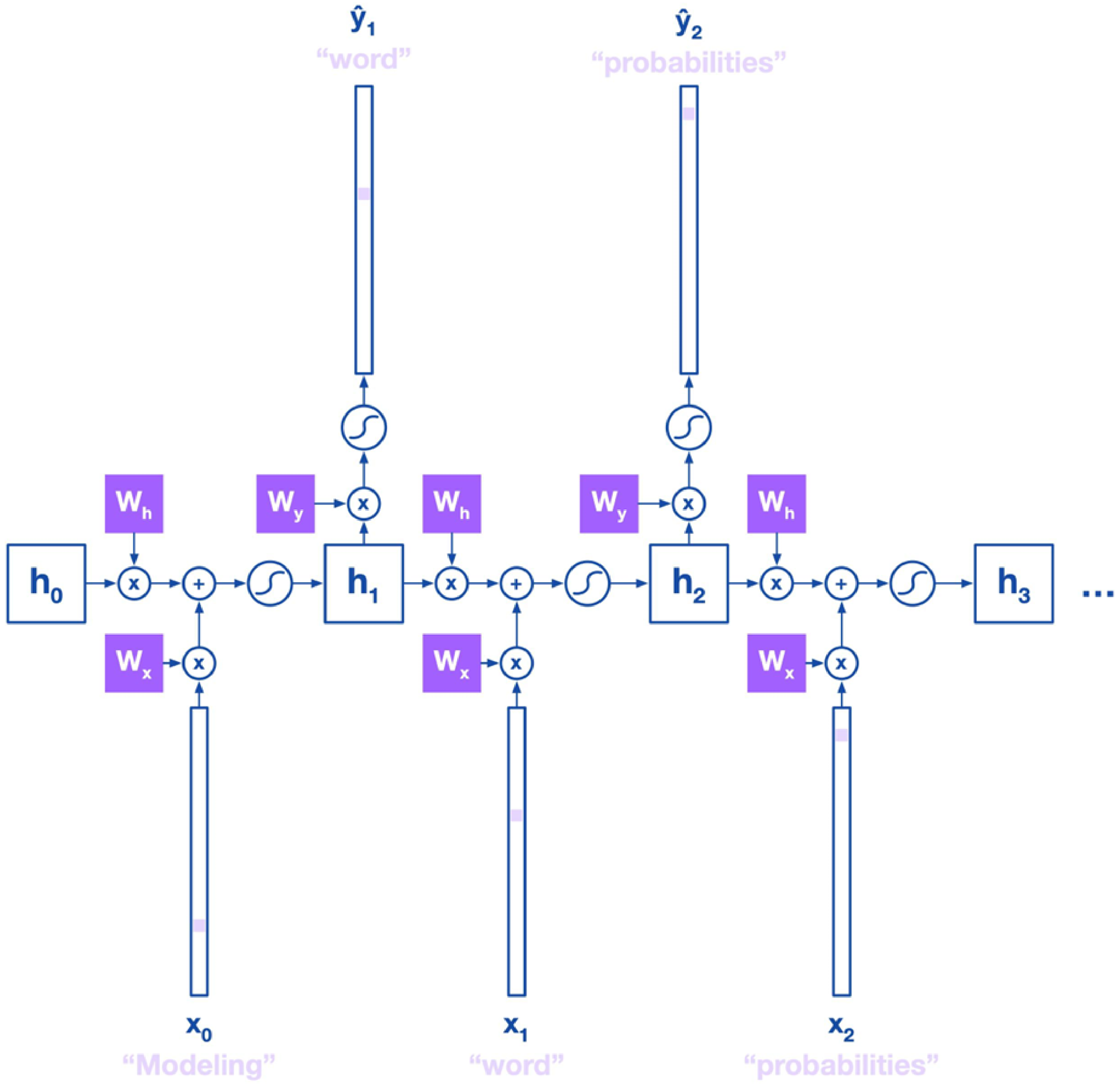


Siguiente palabra de la frase x_1 como entrada

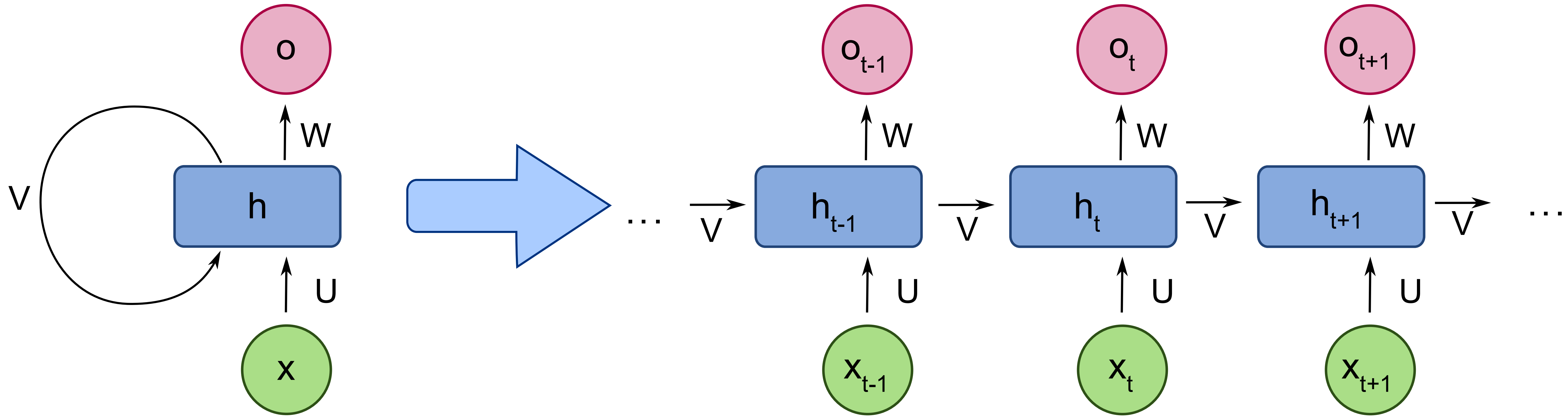
Recurrent Neural Network



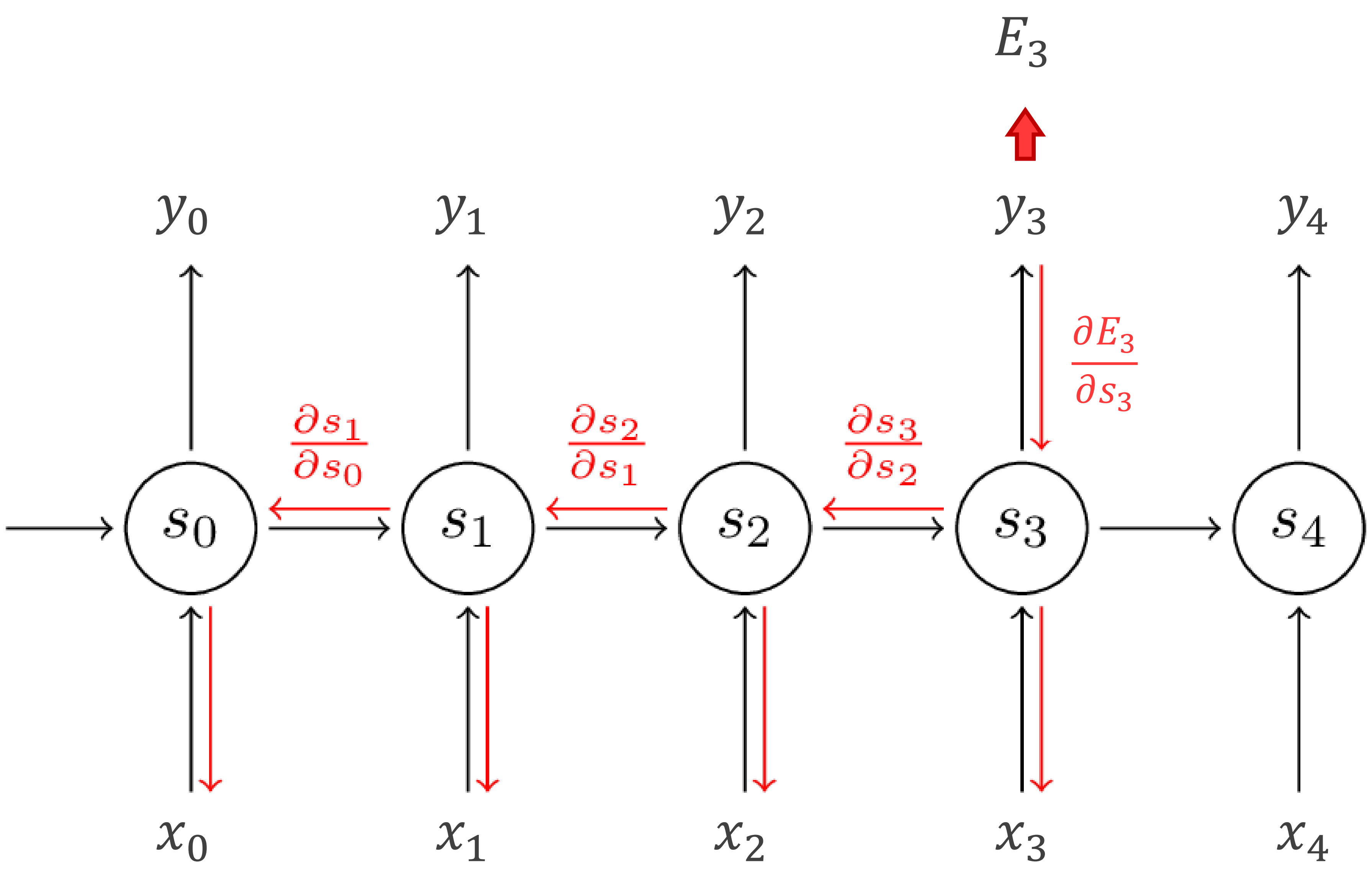
Recurrent Neural Network



Recurrent Neural Network



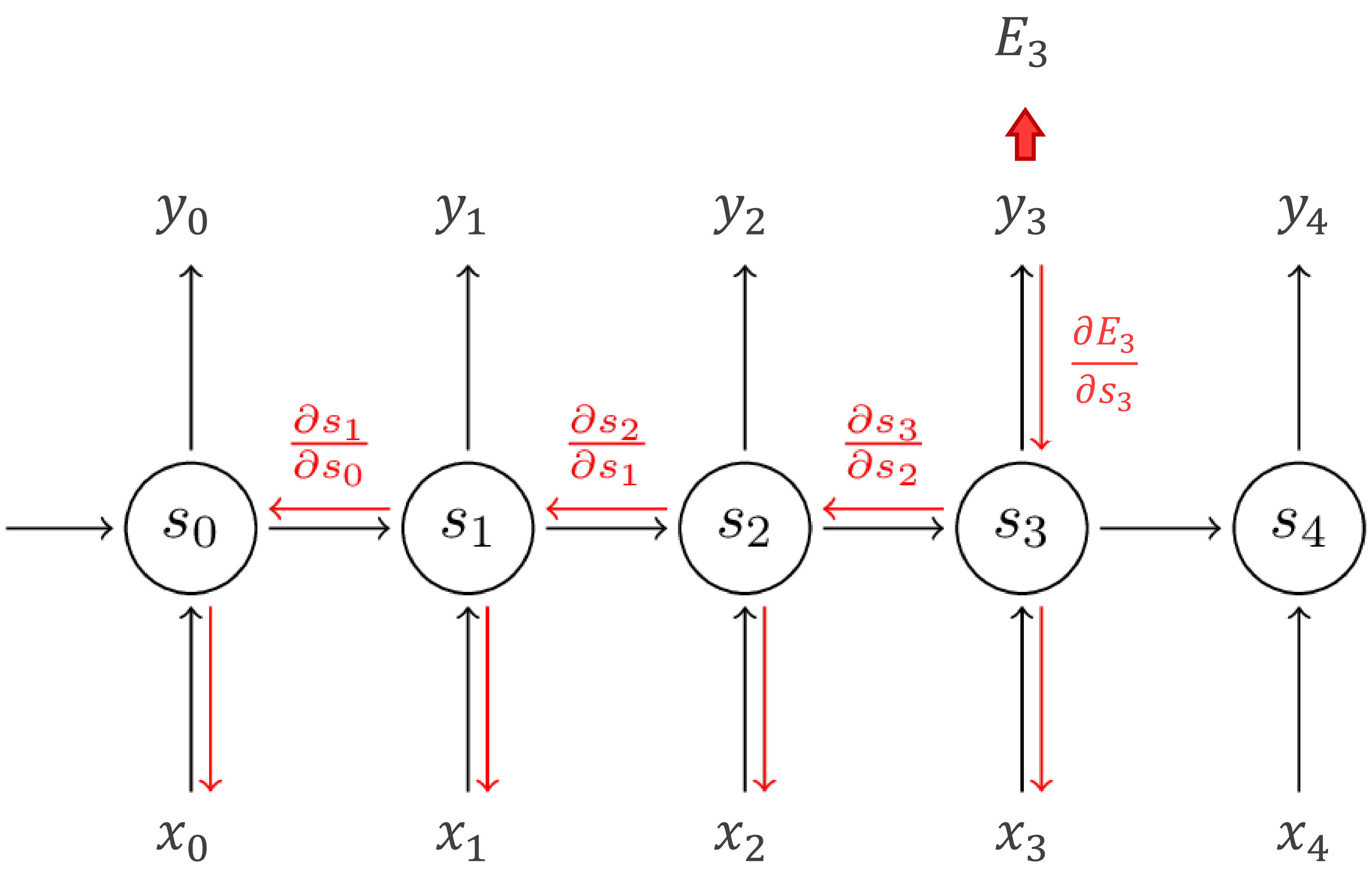
Vanilla RNN *Gradient Flow*



Función de error:

$$E_t(y_t, \hat{y}_t) = -y_t \log \hat{y}_t$$

Vanilla RNN *Gradient Flow*



Función de error:

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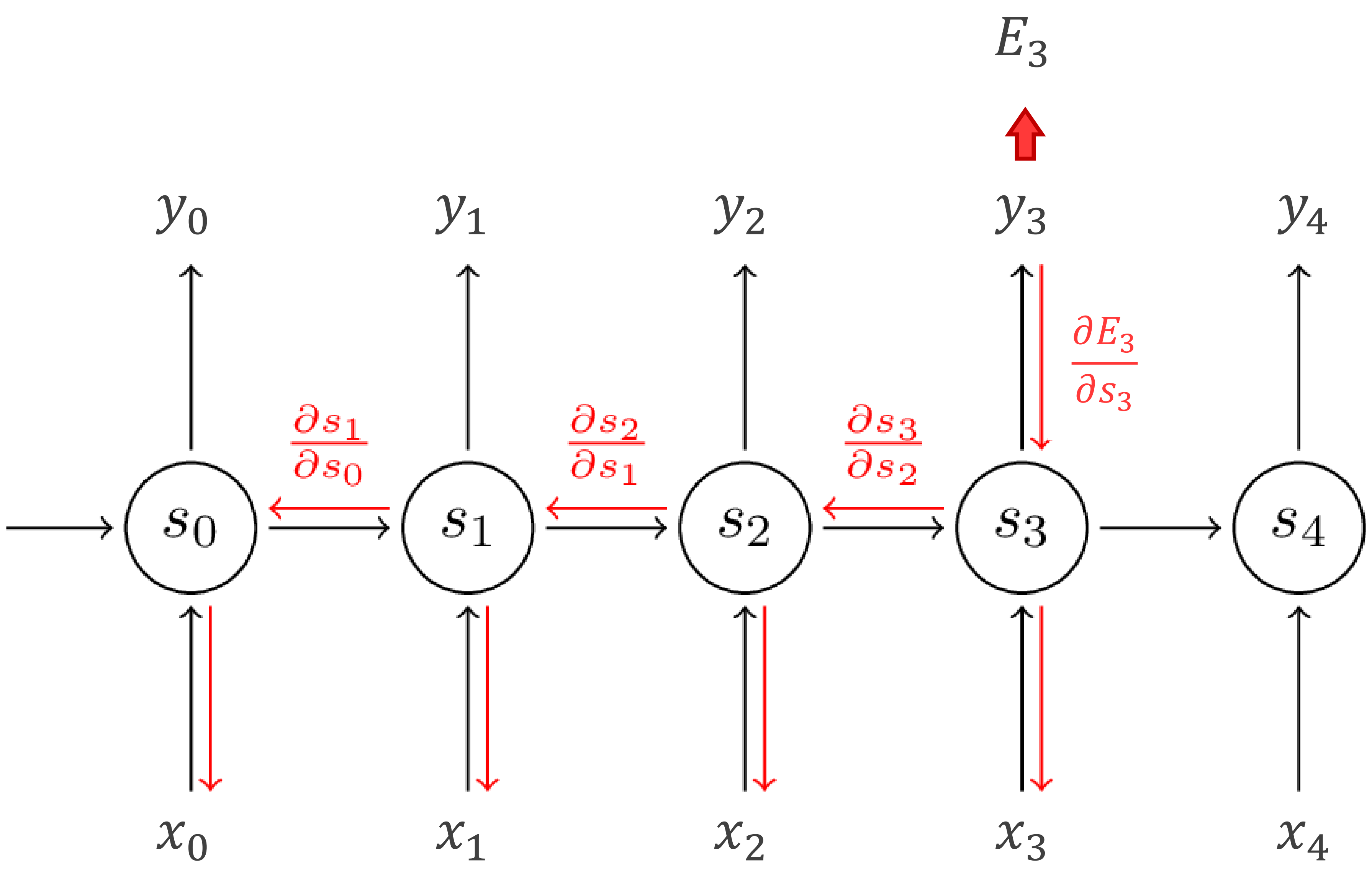
Cálculo del gradiente:

$$\frac{\partial E}{\partial W} = \sum_{1 \le t \le T} \frac{\partial E_t}{\partial W}$$

Vanilla RNN *Gradient Flow*



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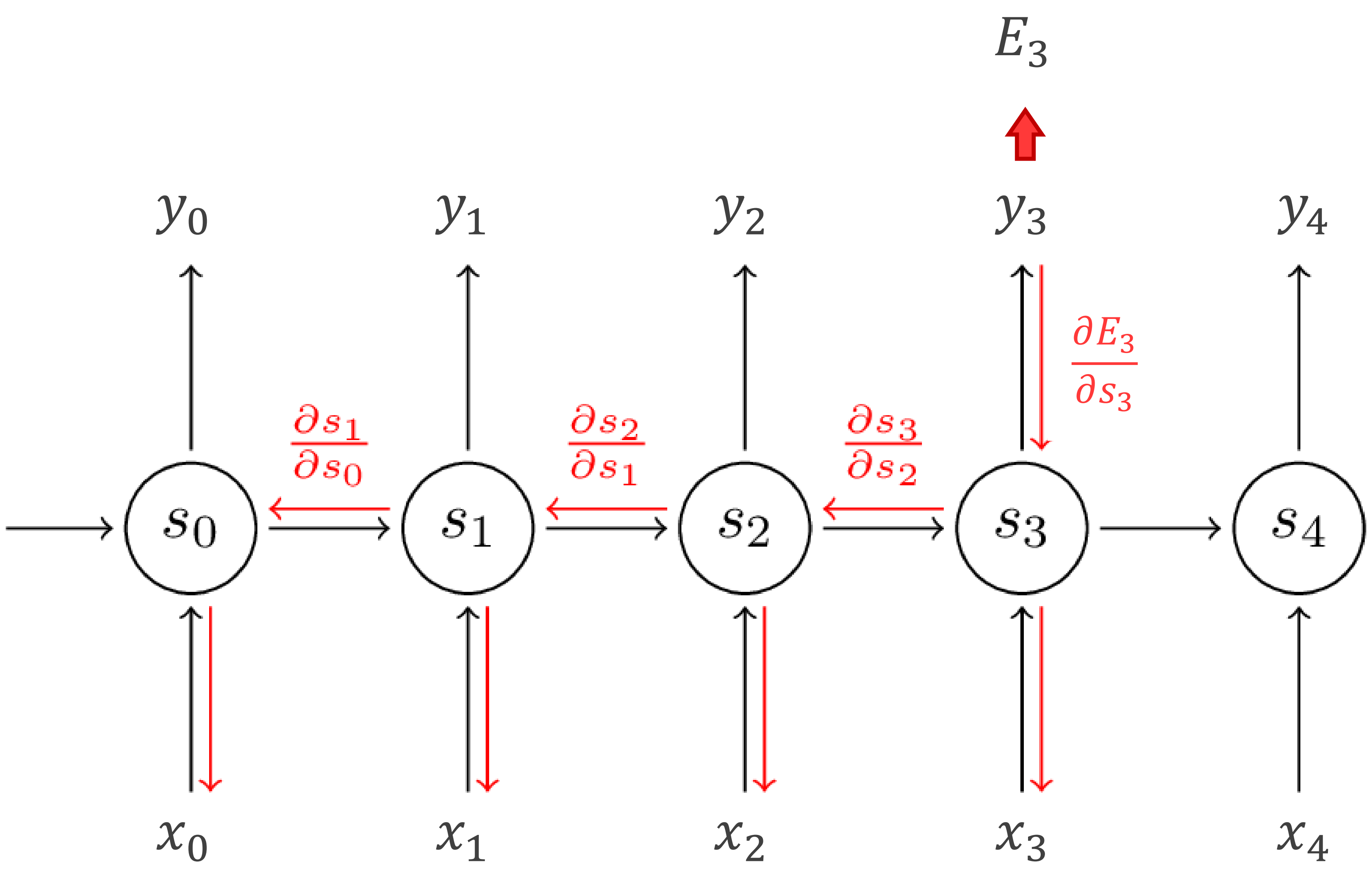
Cálculo del gradiente:

$$\frac{\partial E}{\partial W} = \sum_{1 \le t \le T} \frac{\partial E_t}{\partial W} = \sum_{1 \le k \le t} \left(\frac{\partial E_t}{\partial x_t} \frac{\partial x_t}{\partial x_k} \frac{\partial x_k}{\partial W} \right)$$

Vanilla RNN *Gradient Flow*



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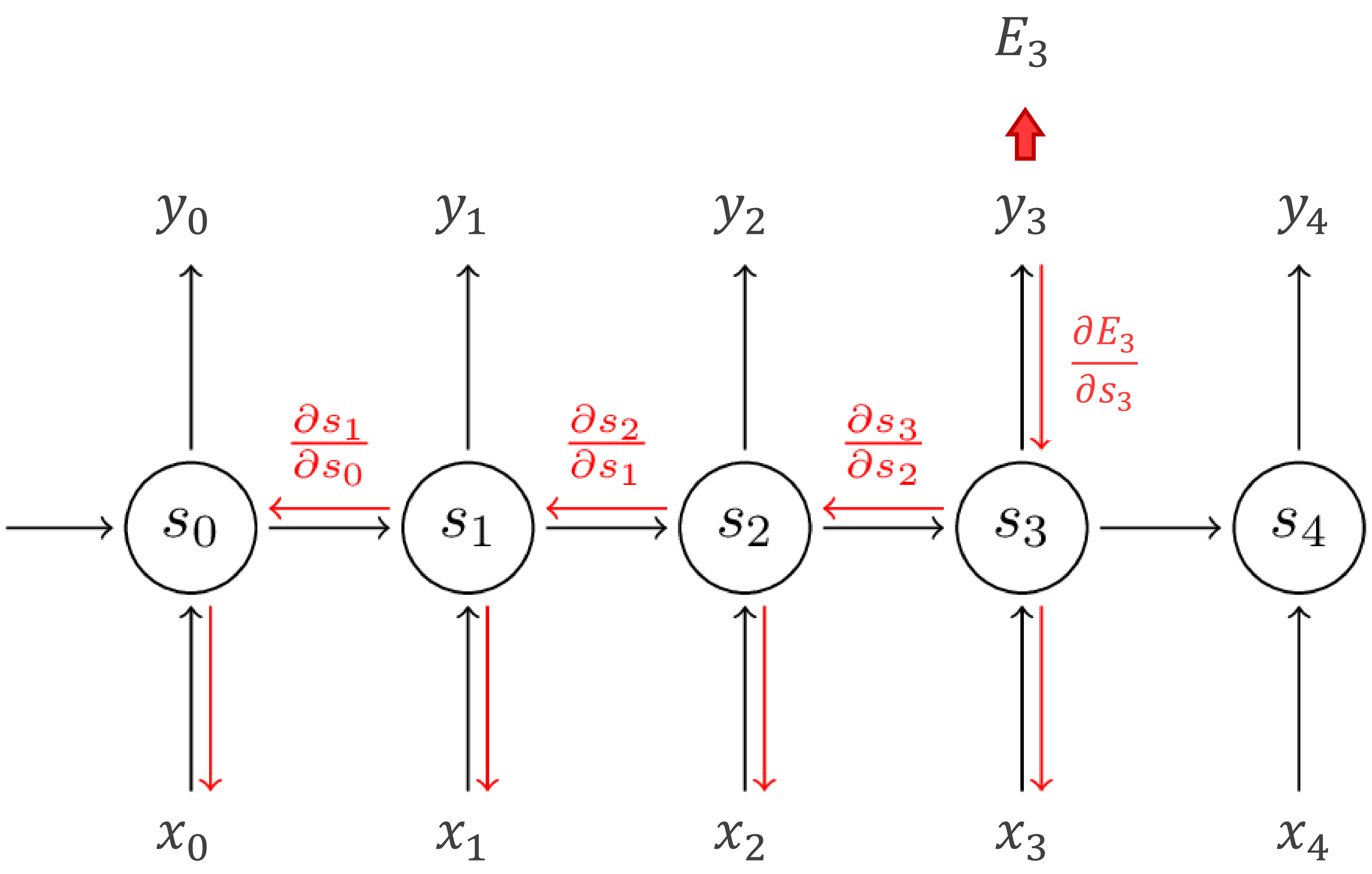
$$\frac{\partial x_t}{\partial x_k} = \prod_{t \geq i > k} \frac{\partial x_i}{\partial x_{i-1}} = \prod_{t \geq i > k} W^T \operatorname{diag}(\sigma(x_{i-1}))$$

Vanilla RNN *Gradient Flow*



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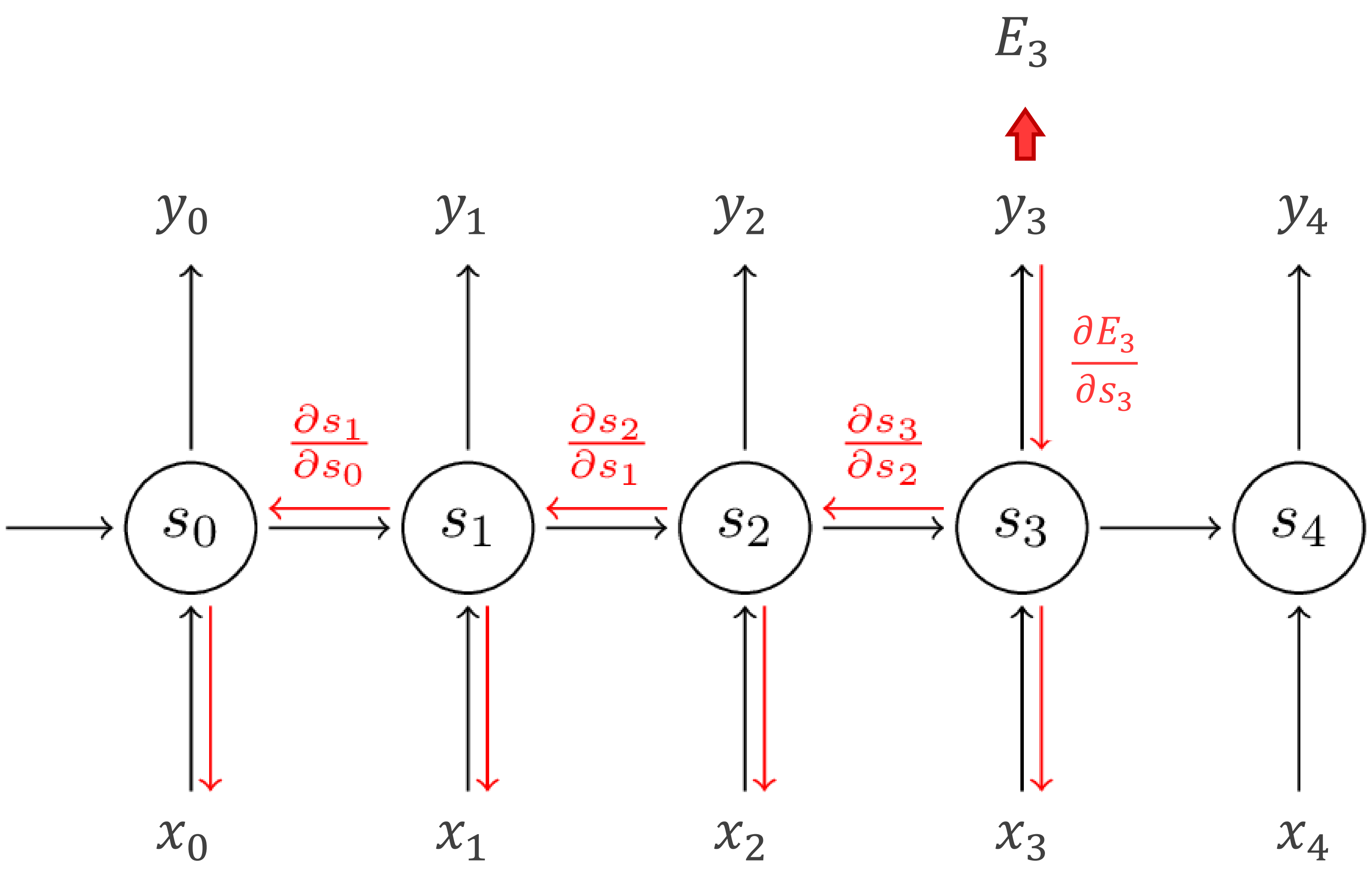
Vanishing Gradients



Función de error:

$$E_t(y_t, \hat{y}_t) = -y_t \log \hat{y}_t$$

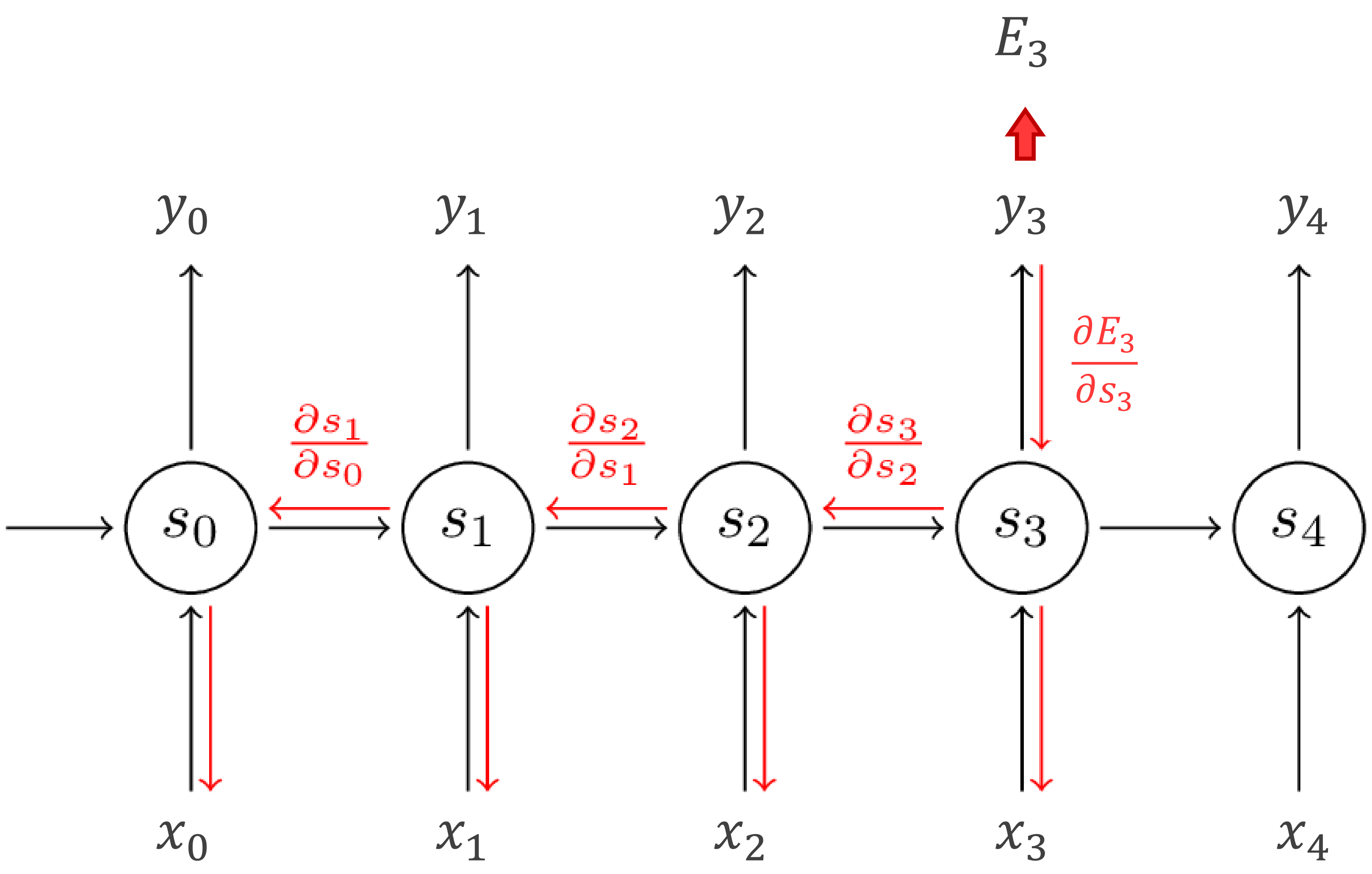
Cálculo del gradiente:

$$\frac{\partial E}{\partial W} = \sum_{1 \le t \le T} \frac{\partial E_t}{\partial W} = \sum_{1 \le k \le t} \left(\frac{\partial E_t}{\partial x_t} \frac{\partial x_t}{\partial x_k} \frac{\partial x_k}{\partial W} \right)$$

$$\frac{\partial x_t}{\partial x_k} = \prod_{t \ge i > k} \frac{\partial x_i}{\partial x_{i-1}} = \prod_{t \ge i > k} \boxed{W^T} \operatorname{diag}(\sigma(x_{i-1}))$$

Si $\|W^T\| < 1$: El gradiente **se desvanece.**

Exploding *Gradients*



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Cálculo del gradiente:

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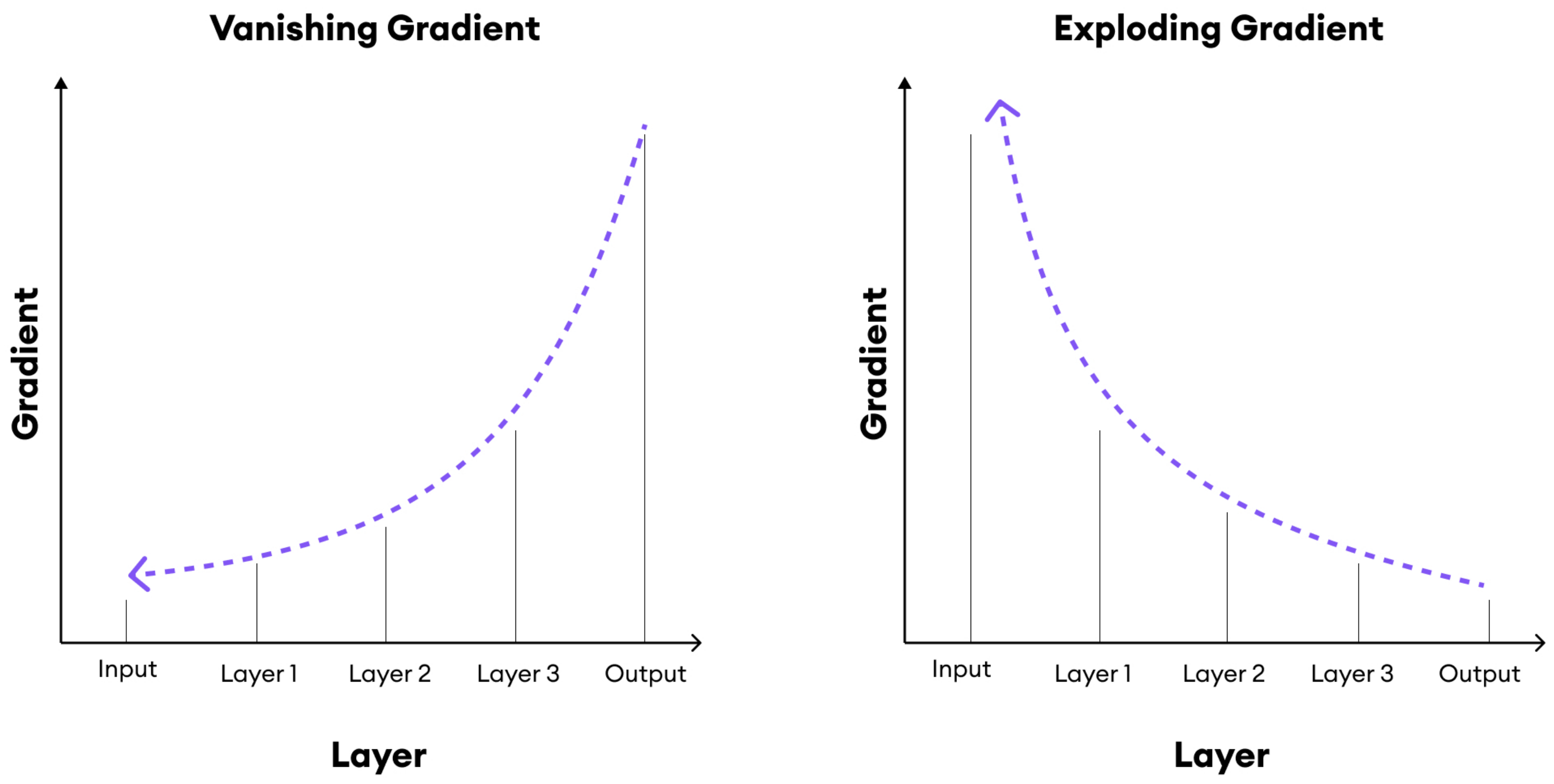
$$\frac{\partial x_t}{\partial x_k} = \prod_{t \ge i > k} \frac{\partial x_i}{\partial x_{i-1}} = \prod_{t \ge i > k} \boxed{W^T} \operatorname{diag}(\sigma(x_{i-1}))$$

Si $\|W^T\| > 1$: El gradiente **crece exponencialmente**

Vanilla RNN *Gradient Flow*



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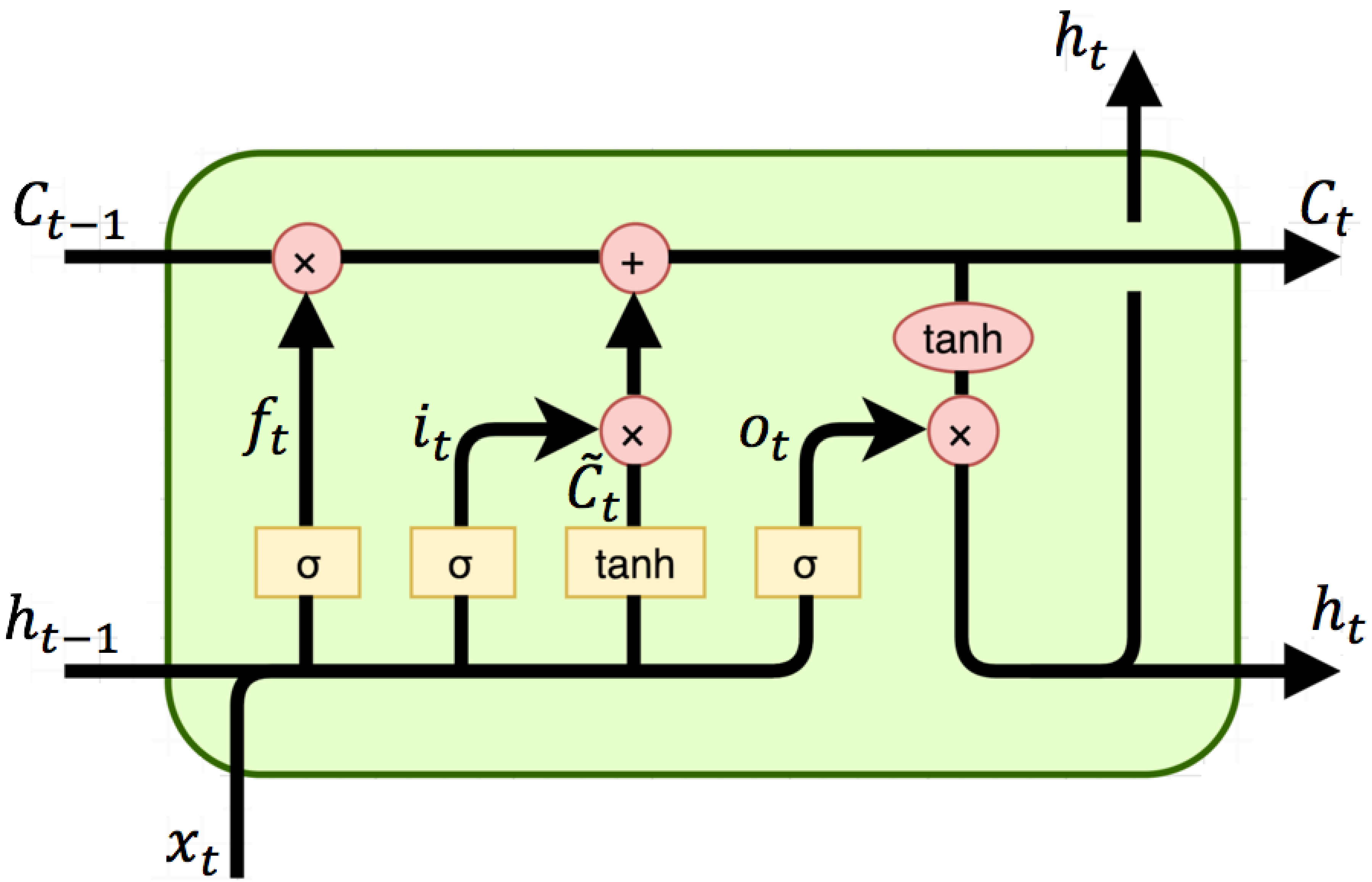
2.

LSTM

TRANSFORMATEC

Long short-term *memory (LSTM)*



$$f_t = \sigma(\omega_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(\omega_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(\omega_o \cdot [h_{t-1}, x_t] + b_o)$$

$$\tilde{C}_t = \tanh(\omega_C \cdot [h_{t-1}, x_t] + b_C)$$

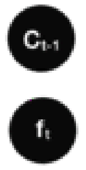
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

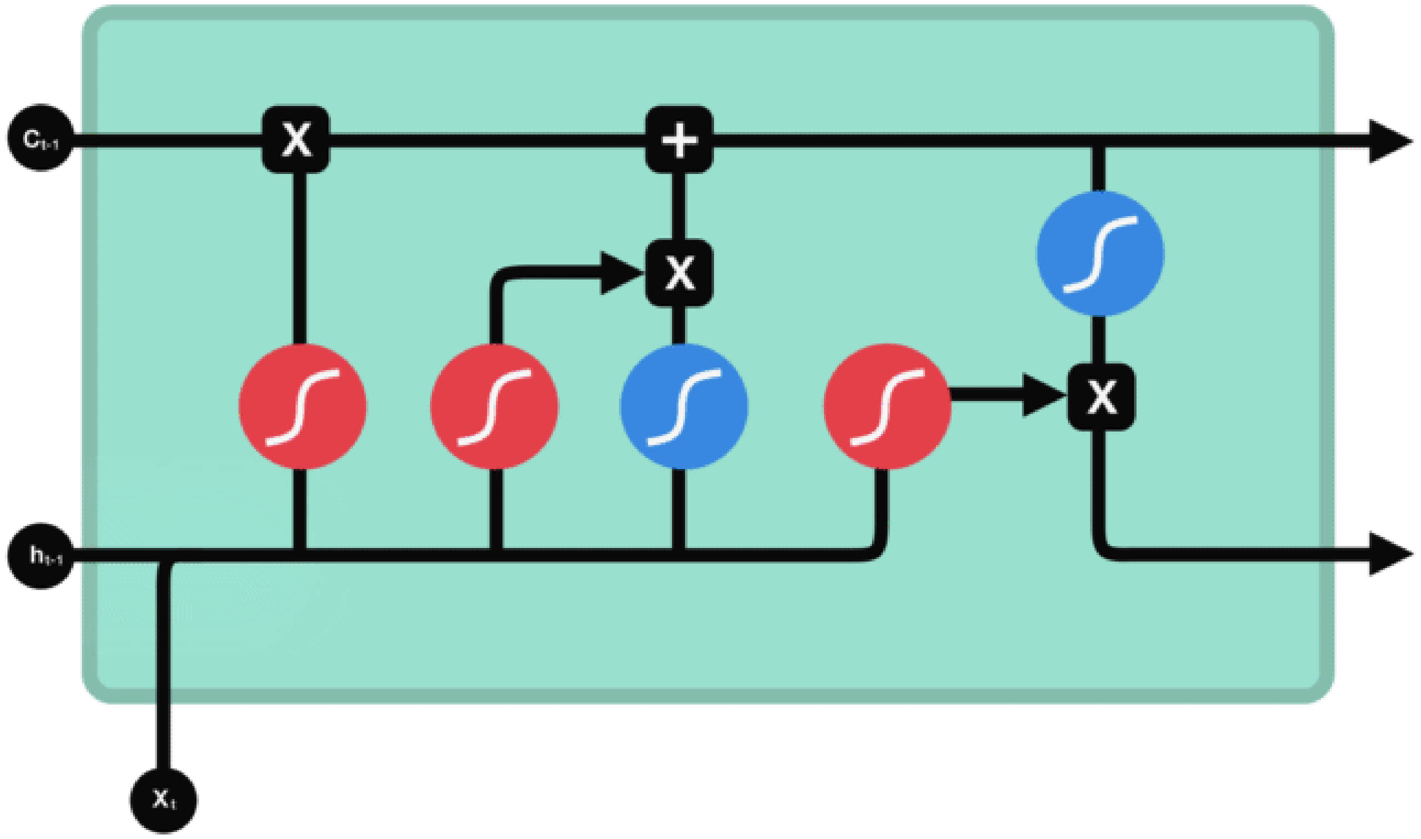
$$h_t = o_t \odot \tanh(C_t)$$

Sepp Hochreiter and Juergen Schmidhuber (1997) "Long Short-term Memory". Neural Computation MIT-Press.

Long short-term *memory (LSTM)*

Forget gate

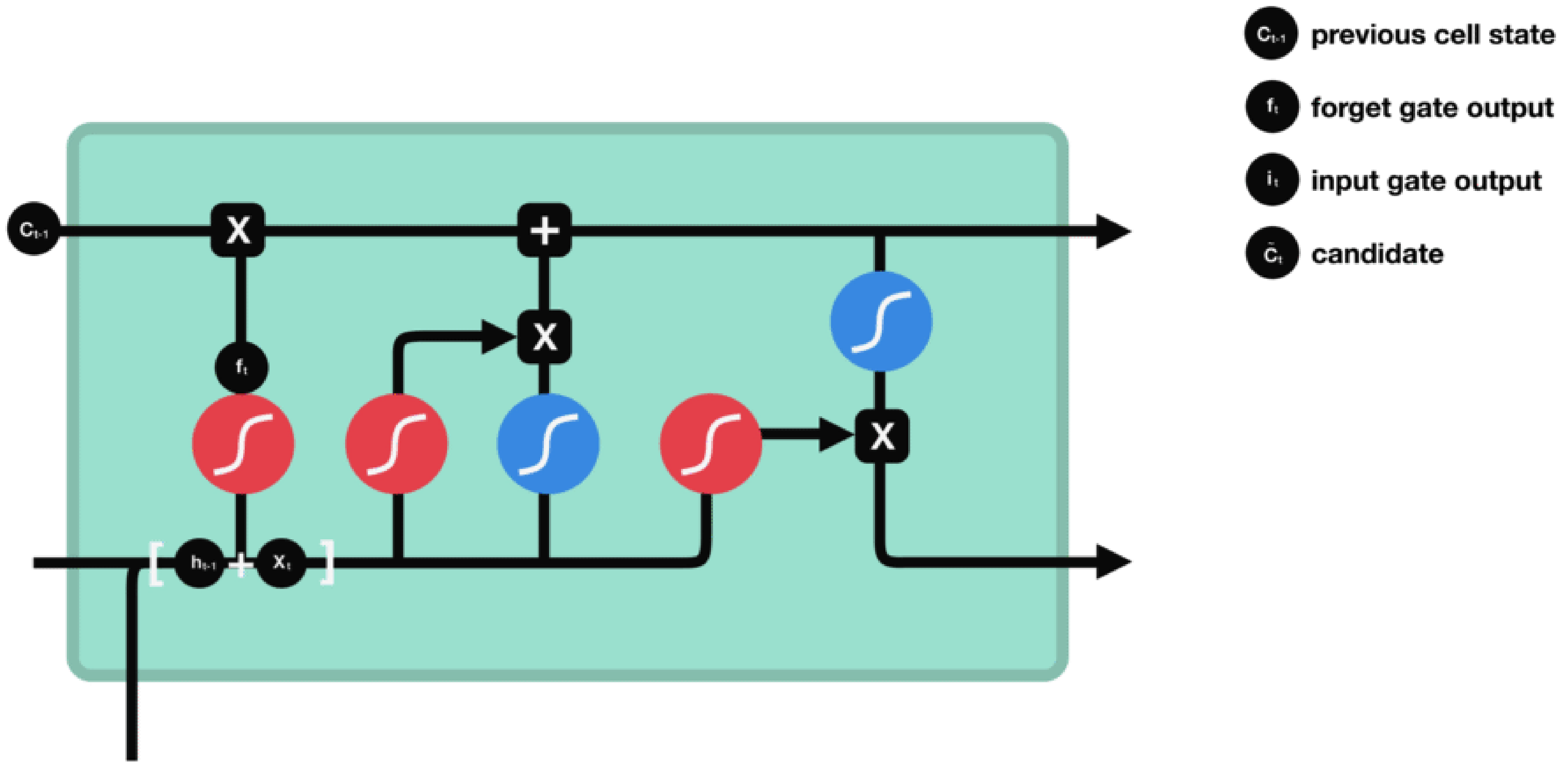




Sepp Hochreiter and Juergen Schmidhuber (1997) "Long Short-term Memory". Neural Computation MIT-Press.

Long short-term *memory (LSTM)*

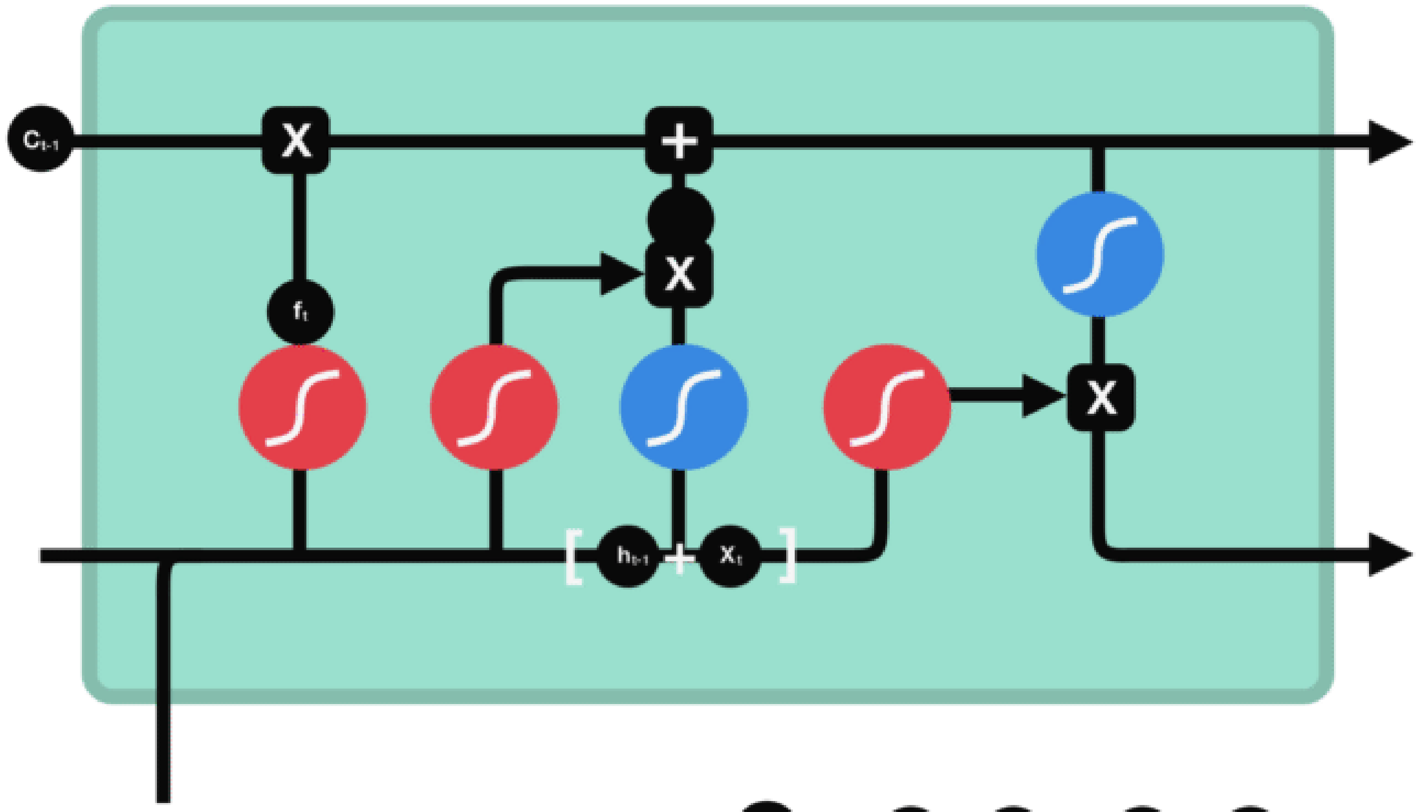
Input gate



Sepp Hochreiter and Juergen Schmidhuber (1997) "Long Short-term Memory". Neural Computation MIT-Press.

Long short-term *memory (LSTM)*

Cell state



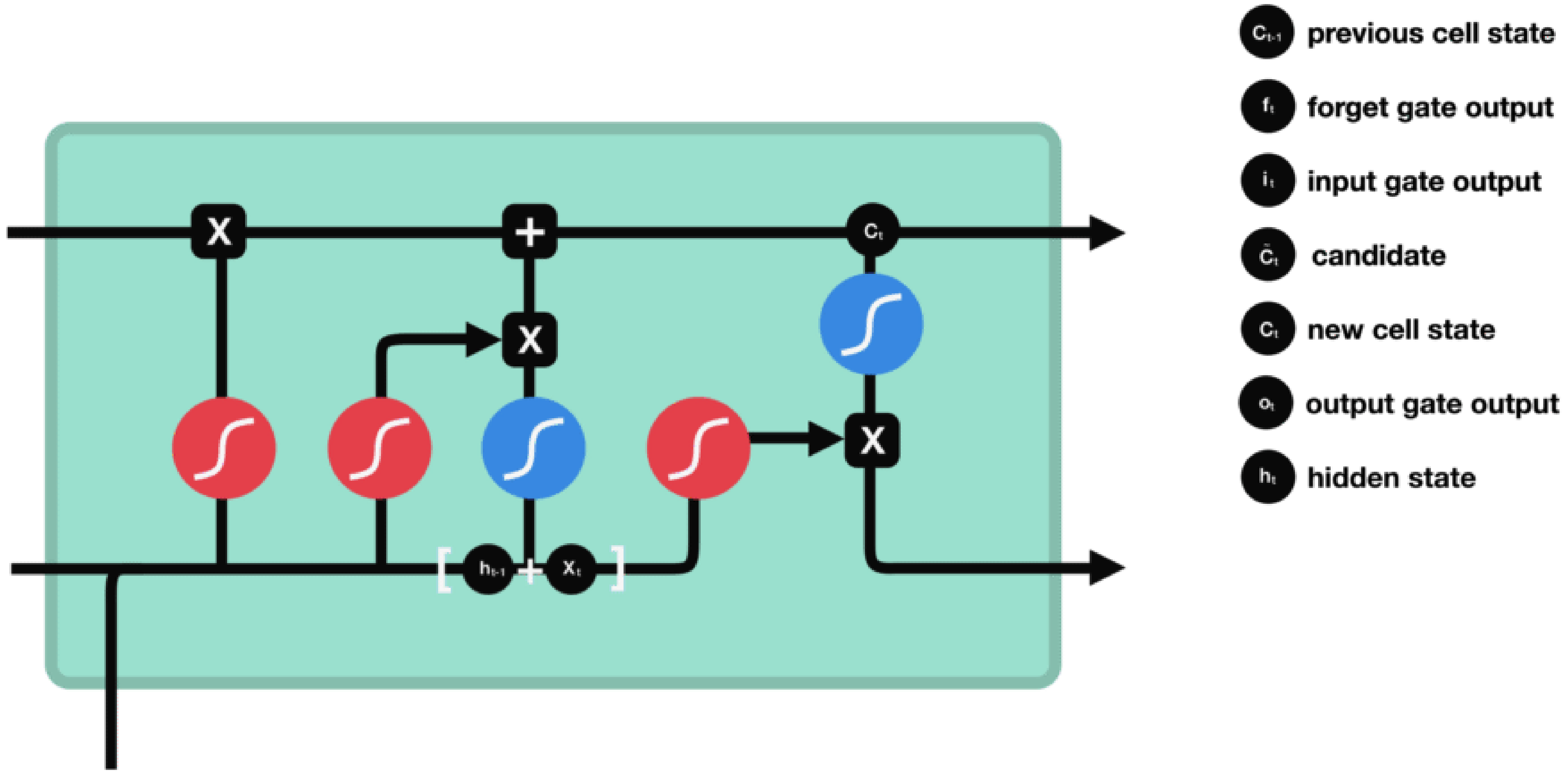
- C_{t-1} previous cell state
- f_t forget gate output
- i_t input gate output
- $\tilde{C}_t$ candidate
- C_t new cell state

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Sepp Hochreiter and Juergen Schmidhuber (1997) "Long Short-term Memory". Neural Computation MIT-Press.

Long short-term *memory (LSTM)*

Output gate



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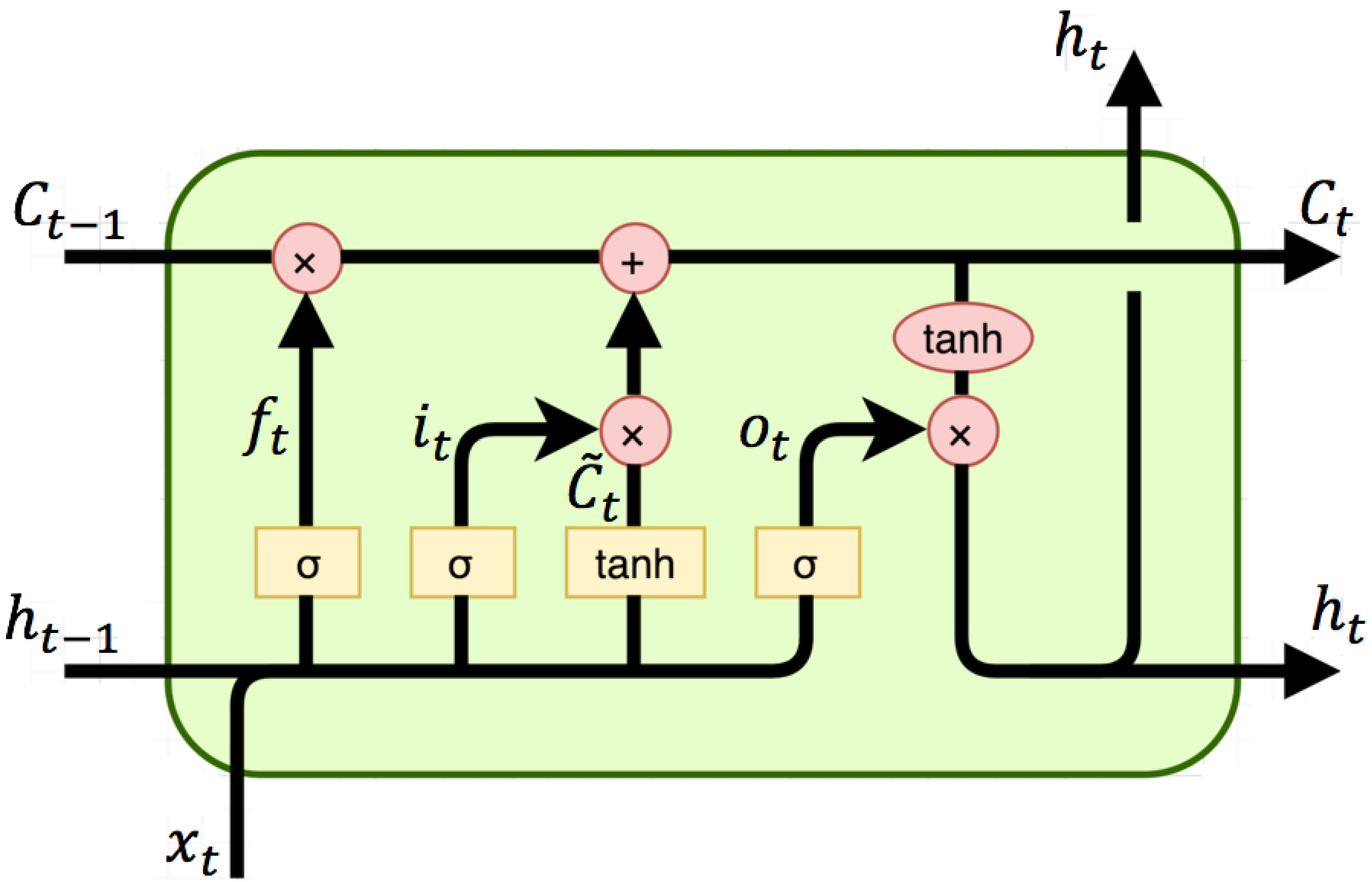
Long short-term *memory (LSTM)*



$$f_t = \sigma(\omega_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(\omega_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(\omega_o \cdot [h_{t-1}, x_t] + b_o)$$

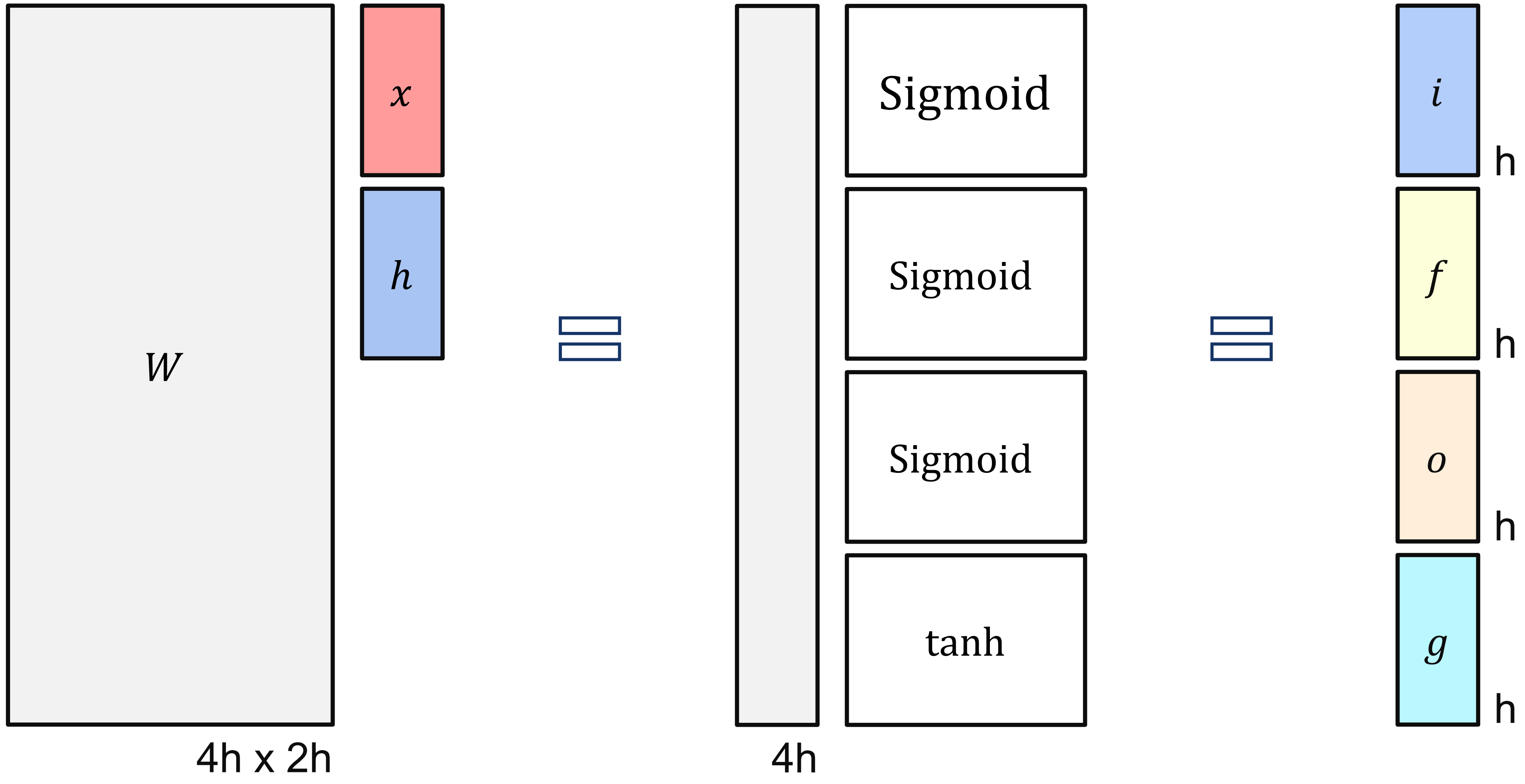
$$\tilde{C}_t = \tanh(\omega_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

$$h_t = o_t \odot \tanh(C_t)$$

Sepp Hochreiter and Juergen Schmidhuber (1997) "Long Short-term Memory". Neural Computation MIT-Press.

Long short-term *memory (LSTM)*

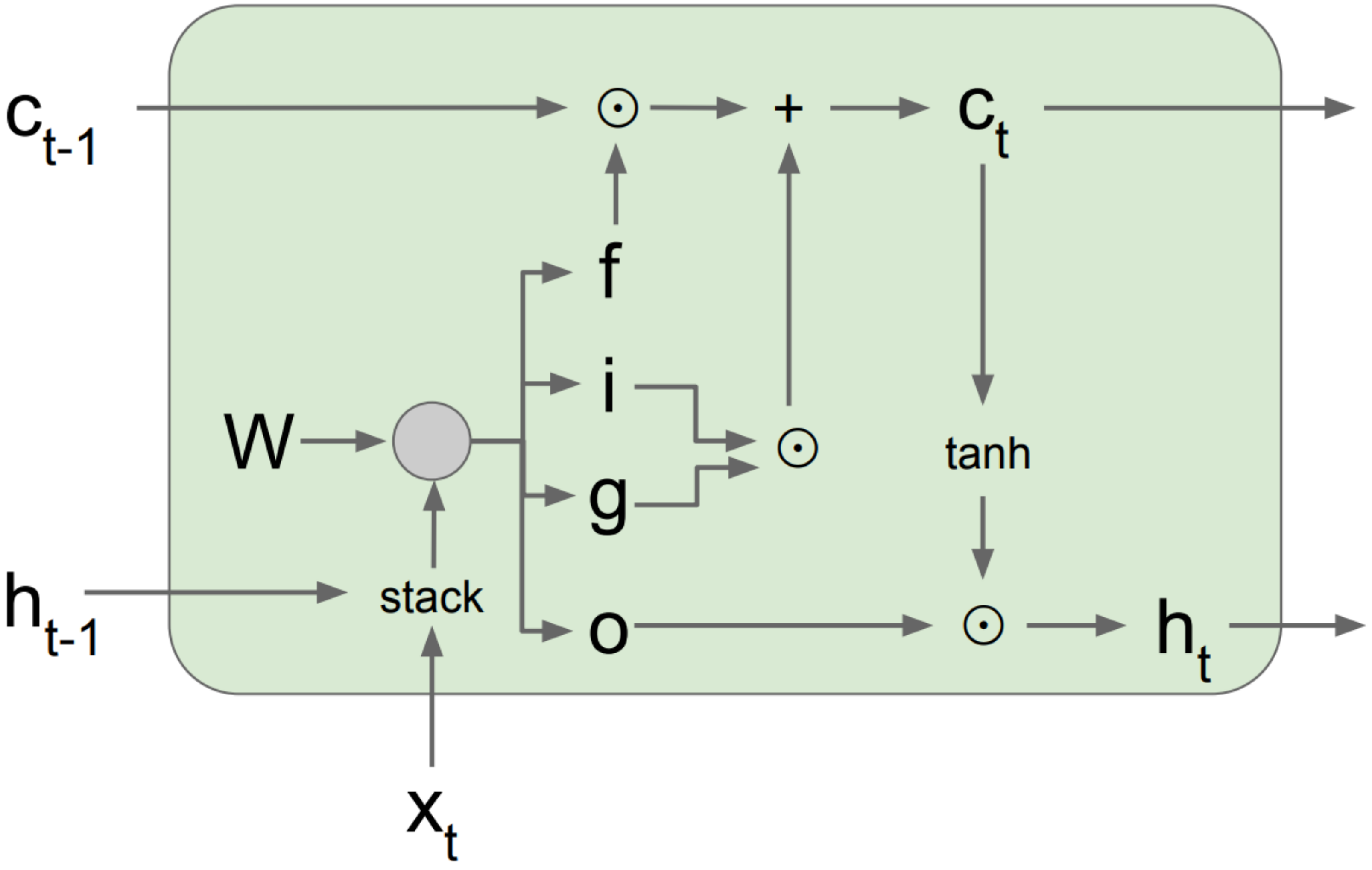


$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

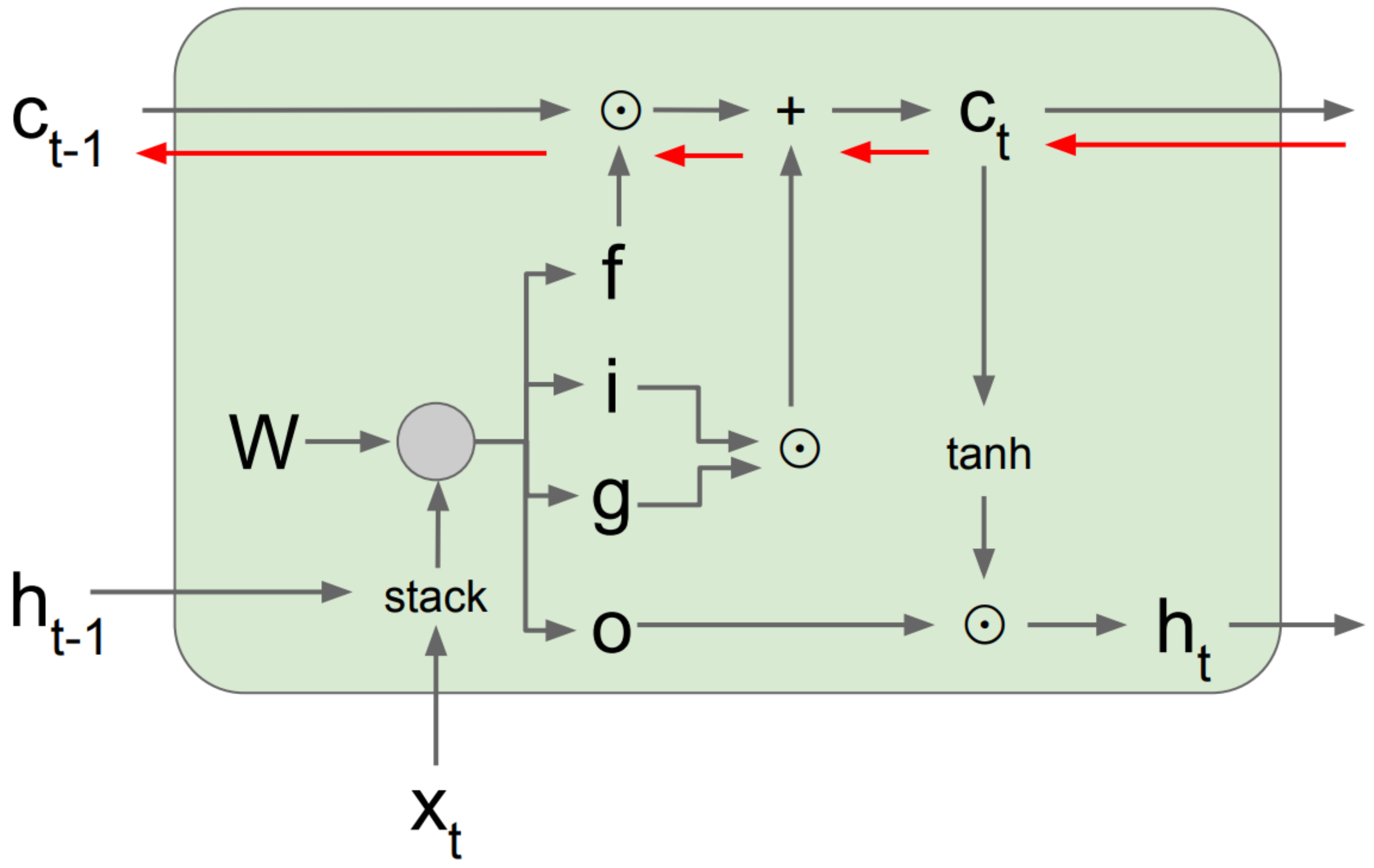
$$C_t = f_t \odot C_{t-1} + i_t \odot g_t$$

$$h_t = o_t \odot \tanh(C_t)$$

LSTM Gradient Flow

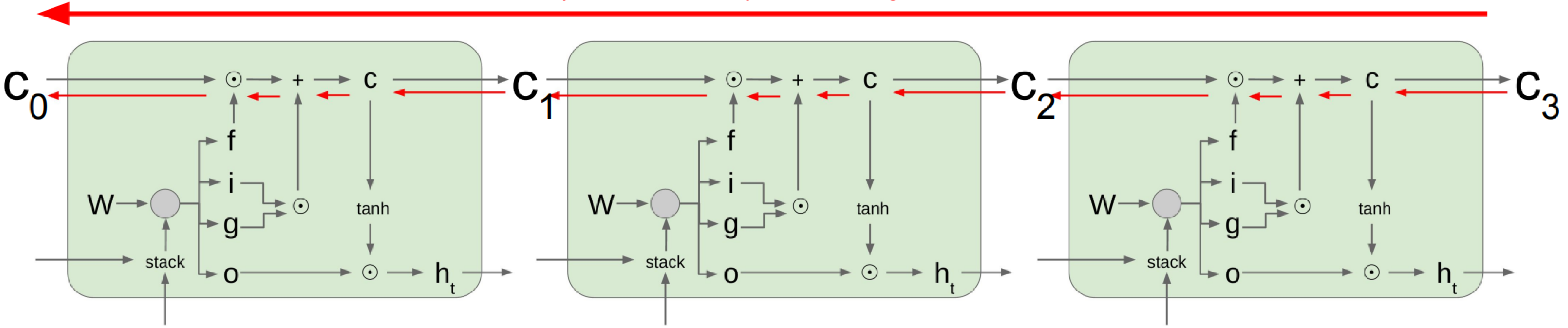


LSTM Gradient Flow



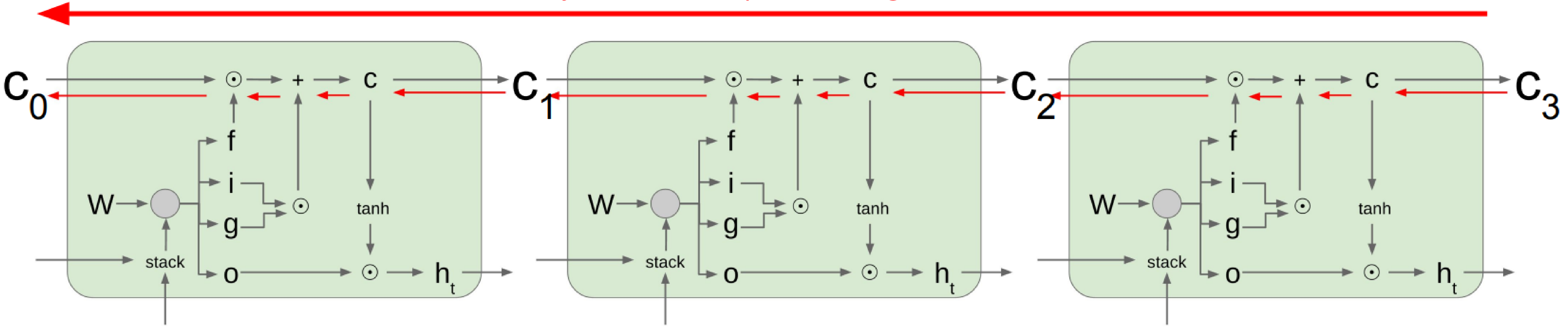
LSTM Gradient Flow

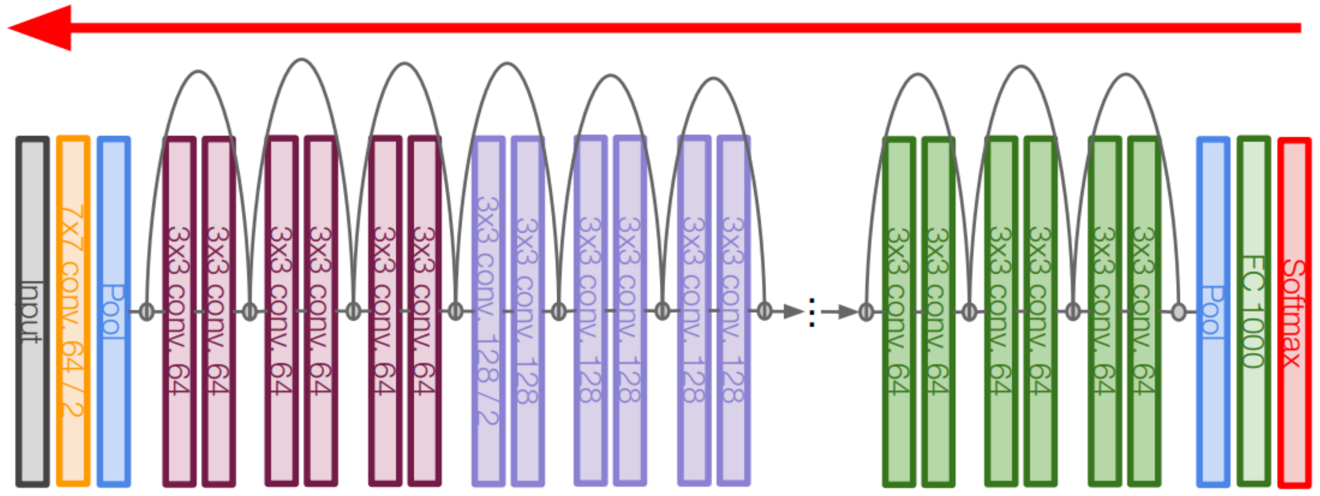
Flujo ininterrumpido de la gradiente



LSTM Gradient Flow

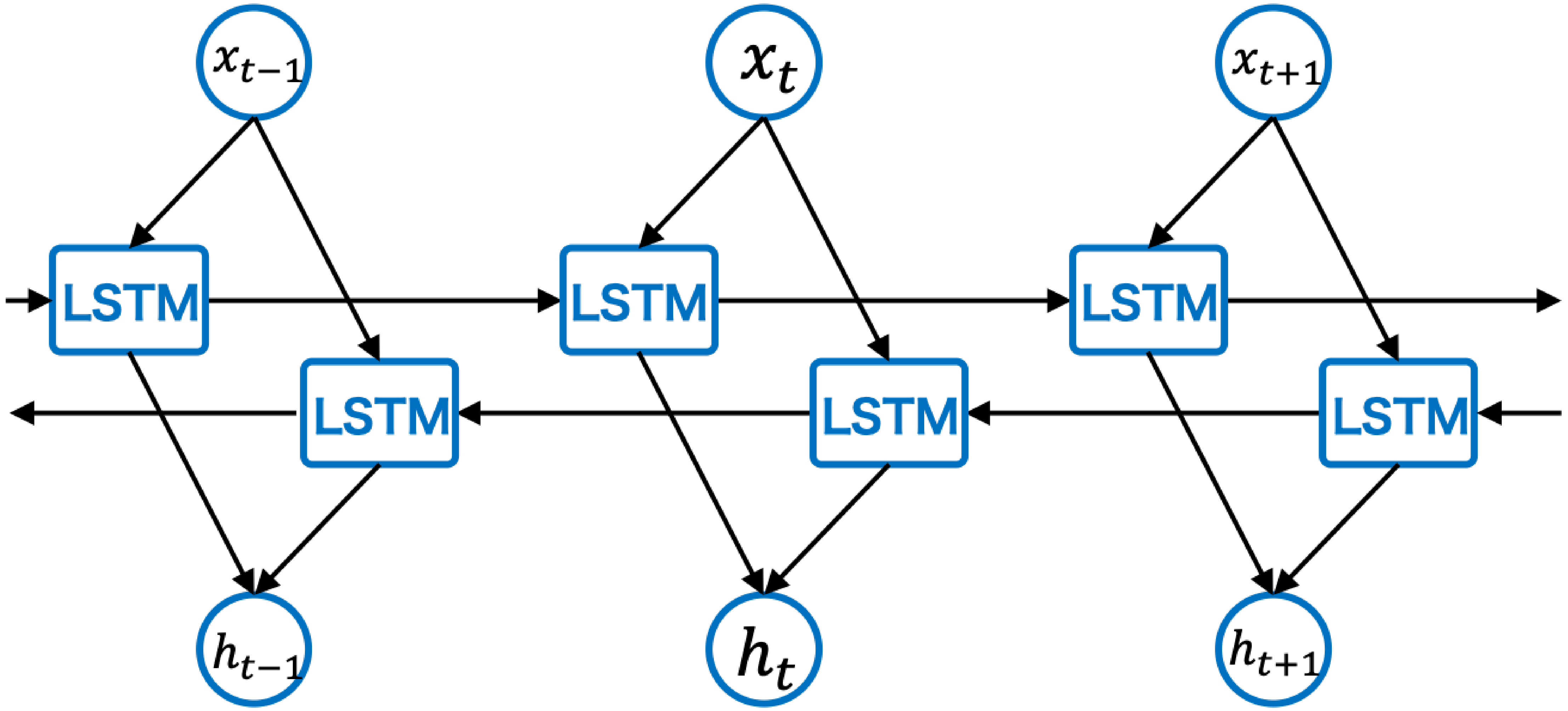
Flujo ininterrumpido de la gradiente





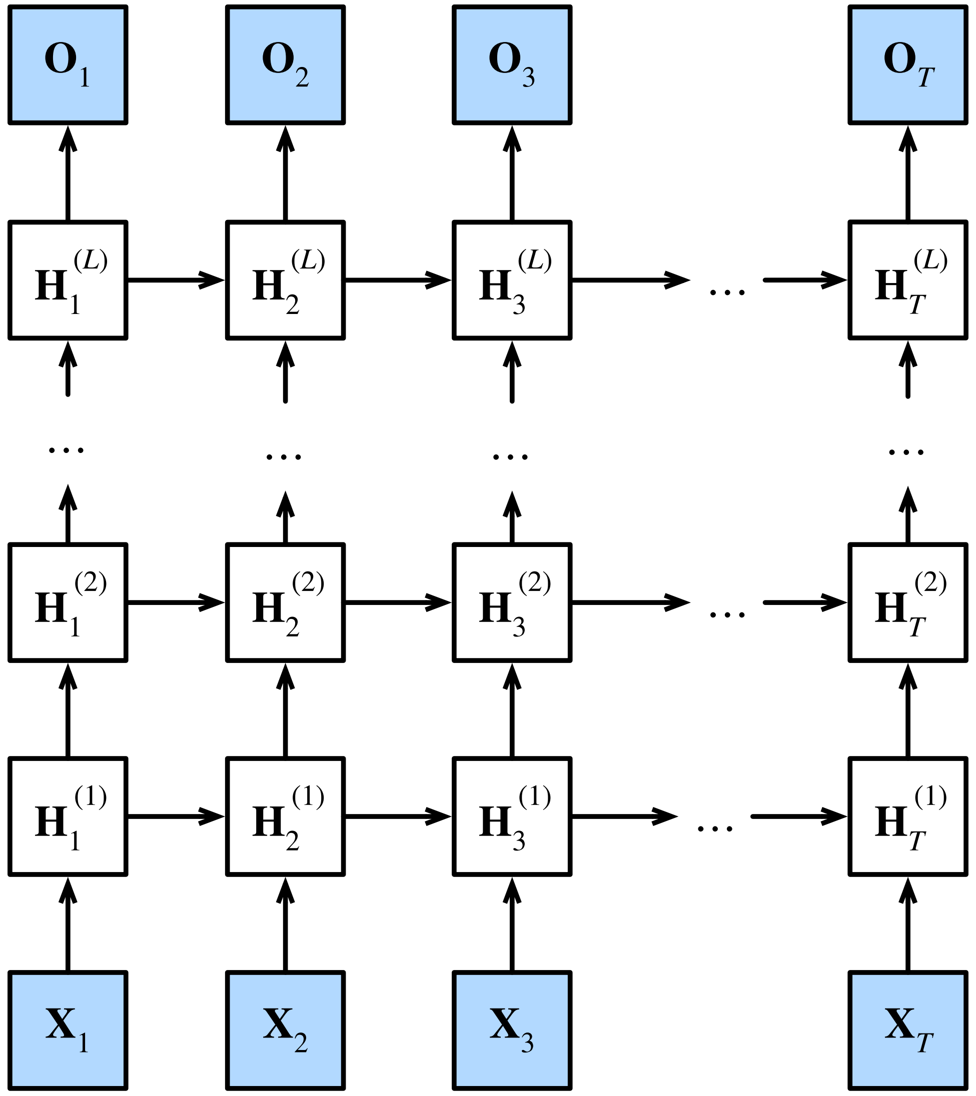
Similar a ResNet

Bidirectional *LSTM*



Alex Graves and Jürgen Schmidhuber (2005) "Framewise phoneme classification with bidirectional LSTM networks". Proceedings. 2005 IEEE International Joint Conference on Neural Networks, 2005. (Vol. 4, pp. 2047-2052). IEEE.

Deep *LSTM*



$$h_t^{(l)} = \phi_l\left(h_t^{(l-1)} W_{xh}^{(l)} + h_{t-1}^{(l)} W_{hh}^{(l)} + b_h^{(l)}\right)$$

$$O_t = h_t^{(L)} W_{hq} + b_q$$

Felix Weninger, et al. (2014) "Feature enhancement by deep LSTM networks for ASR in reverberant multisource environments". Computer Speech & Language, 28(4), 888-902.

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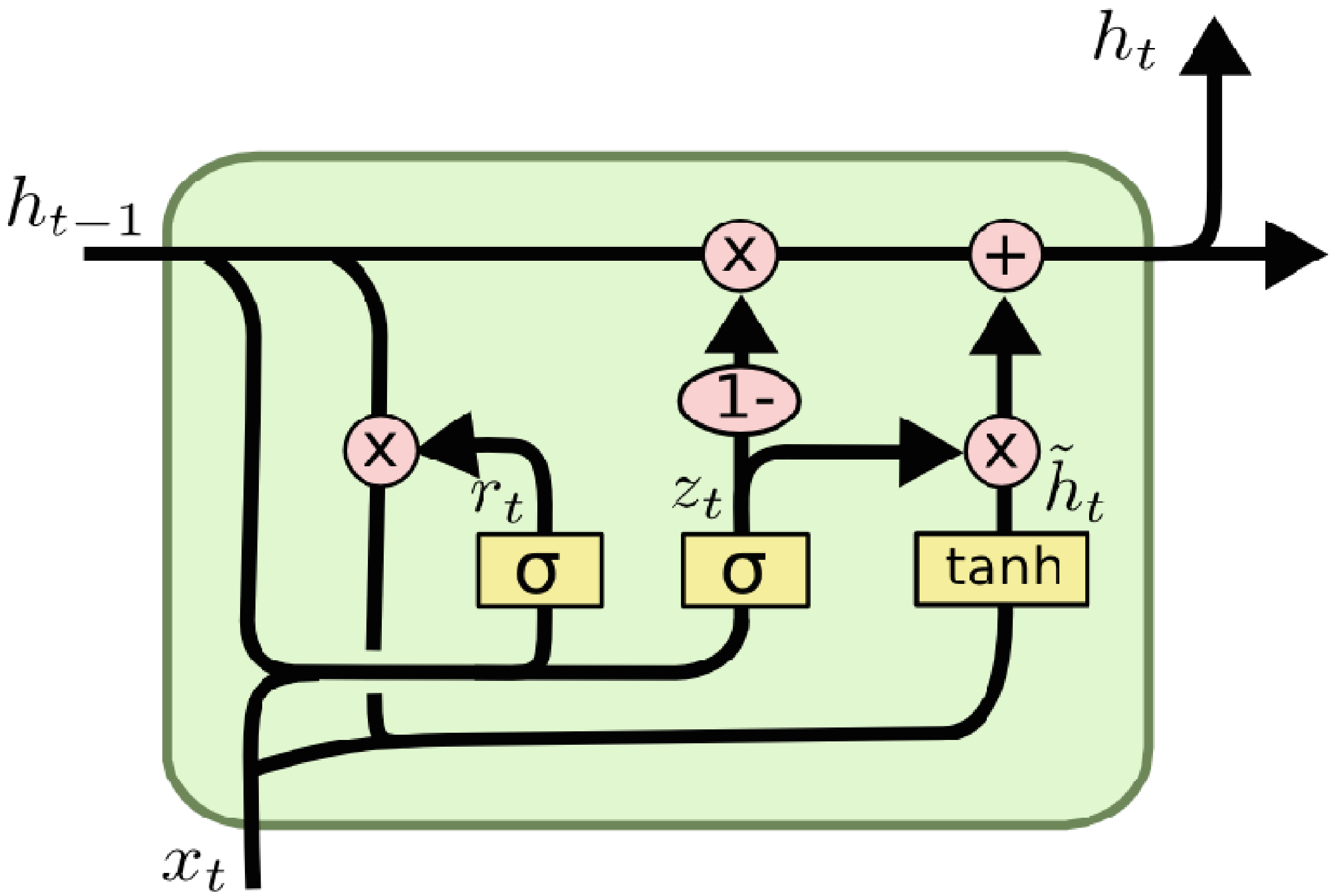
3.

GRU

TRANSFORMATEC

GRU



Reset gate: $z_t = \sigma(\omega_z \cdot [h_{t-1}, x_t] + b_z)$

Update gate: $r_t = \sigma(\omega_r \cdot [h_{t-1}, x_t] + b_r)$

$$\tilde{h}_t = \tanh(\omega_h \cdot [r_t \odot h_{t-1}, x_t] + b_h)$$

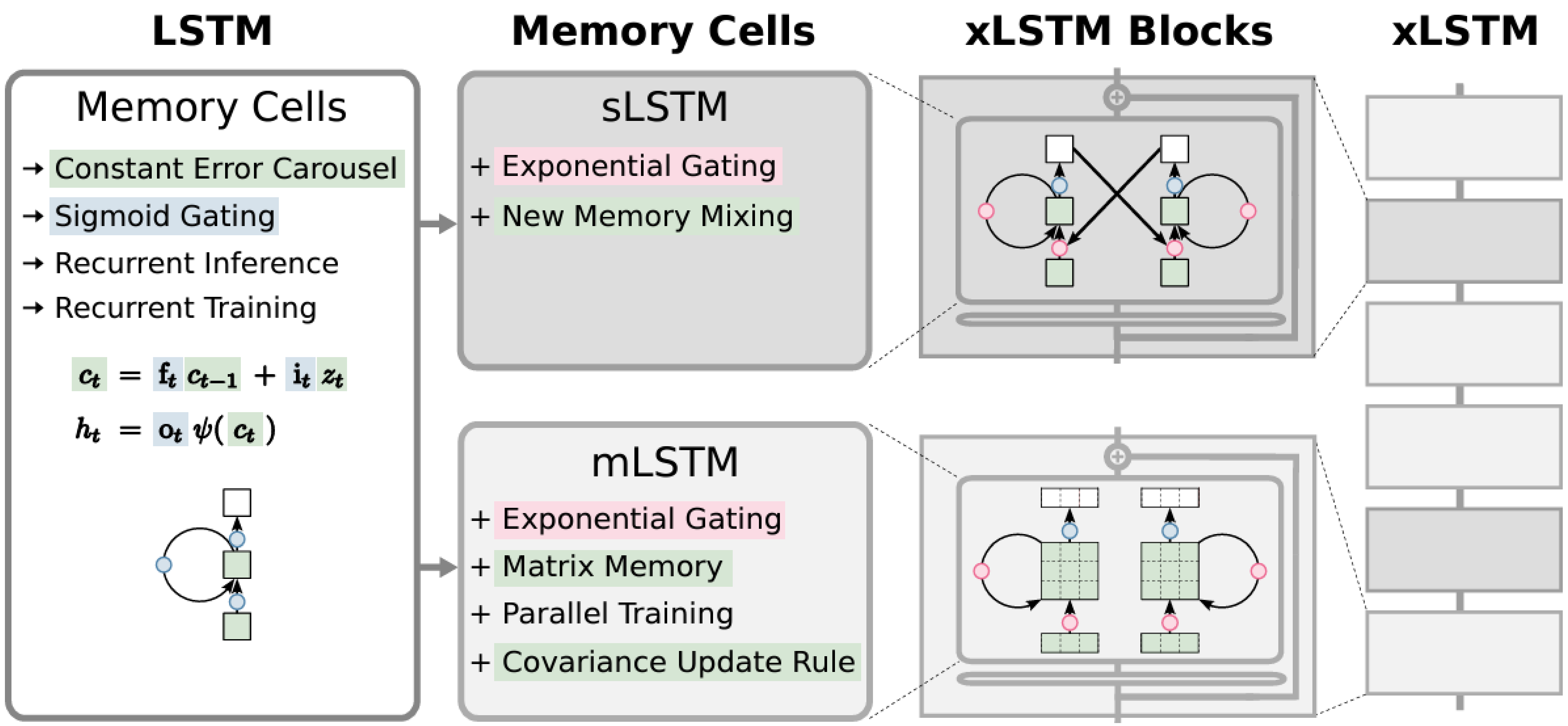
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

Kyunghyun Cho et al. (2014) "On the Properties of Neural Machine Translation: Encoder-Decoder Approaches". arXiv preprint arXiv:1409.1259

4.

xLSTM

xLSTM



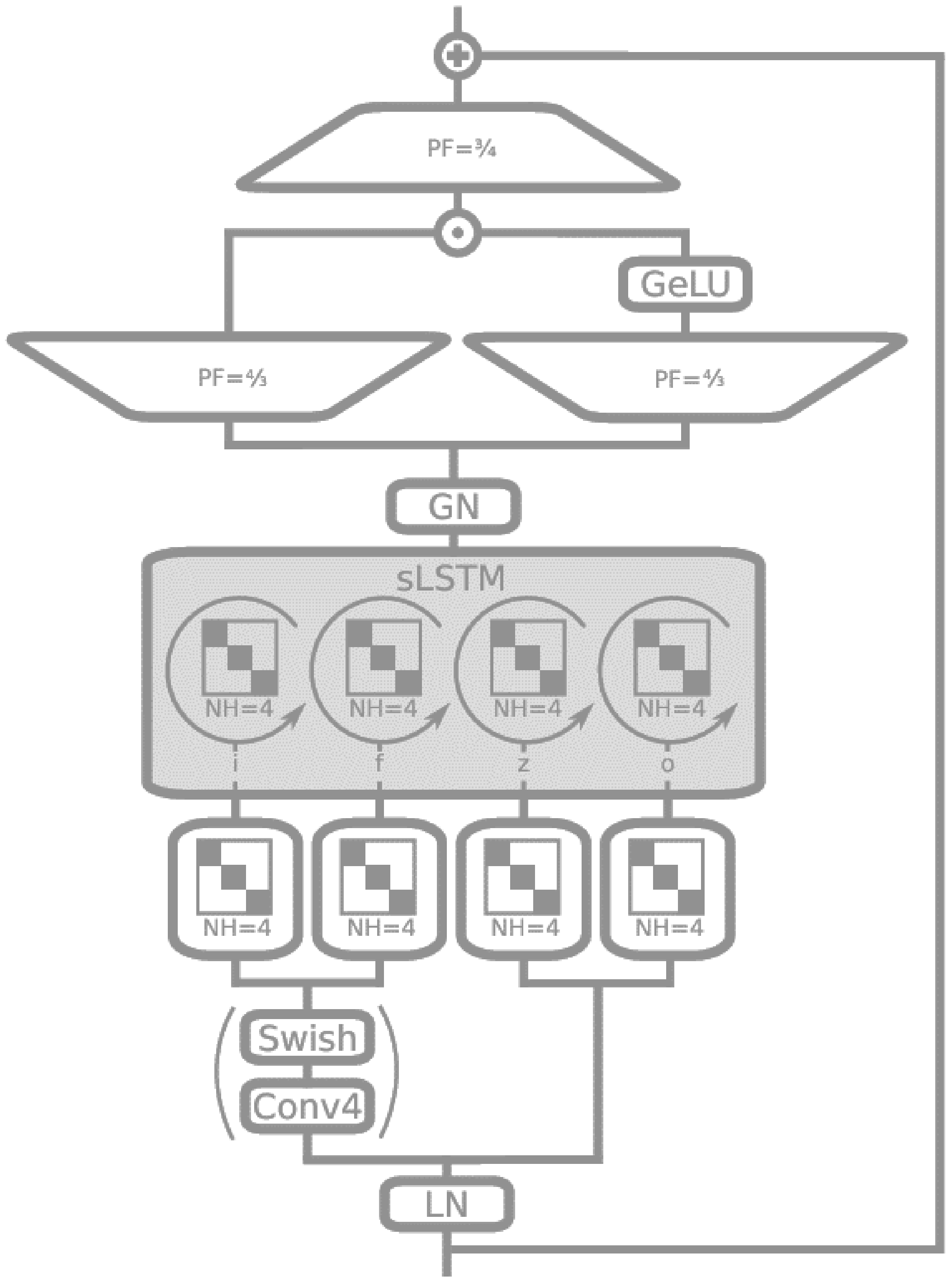
Maximilian Beck et al. (2024) "xLSTM: Extended Long Short-Term Memory". arXiv preprint arXiv:2405.04517.

sLSTM

$c_t = \mathrm{f}_t \, c_{t-1} + \mathrm{i}_t \, z_t$		cell state	(8)
$n_t = \mathrm{f}_t \, n_{t-1} + \mathrm{i}_t$		normalizer state	(9)
$h_t = \mathrm{o}_t \, \tilde{h}_t \,,$	$\tilde{h}_t = c_t / n_t$	hidden state	(10)
$z_t = \varphi(\tilde{z}_t) \,,$	$\tilde{z}_t = \boldsymbol{w}_z^\top \boldsymbol{x}_t + r_z h_{t-1} + b_z$	cell input	(11)
$\mathrm{i}_t = \exp(\tilde{\mathrm{i}}_t) \,,$	$\tilde{\mathrm{i}}_t = \boldsymbol{w}_{\mathrm{i}}^\top \boldsymbol{x}_t + r_{\mathrm{i}} h_{t-1} + b_{\mathrm{i}}$	input gate	(12)
$\mathrm{f}_t = \sigma(\tilde{\mathrm{f}}_t) \text{ OR } \exp(\tilde{\mathrm{f}}_t) \,,$	$\tilde{\mathrm{f}}_t = \boldsymbol{w}_{\mathrm{f}}^\top \boldsymbol{x}_t + r_{\mathrm{f}} h_{t-1} + b_{\mathrm{f}}$	forget gate	(13)
$\mathrm{o}_t = \sigma(\tilde{\mathrm{o}}_t) \,,$	$\tilde{\mathrm{o}}_t = \boldsymbol{w}_{\mathrm{o}}^\top \boldsymbol{x}_t + r_{\mathrm{o}} h_{t-1} + b_{\mathrm{o}}$	output gate	(14)

Maximilian Beck et al. (2024) "xLSTM: Extended Long Short-Term Memory". arXiv preprint arXiv:2405.04517.

sLSTM



Maximilian Beck et al. (2024) “xLSTM: Extended Long Short-Term Memory”. arXiv preprint arXiv:2405.04517.

mLSTM

$$\boldsymbol{C}_t = \mathrm{f}_t \, \boldsymbol{C}_{t-1} + \mathrm{i}_t \, \boldsymbol{v}_t \, \boldsymbol{k}_t^\top \qquad \text{cell state} \quad (19)$$

$$\boldsymbol{n}_t = \mathrm{f}_t \, \boldsymbol{n}_{t-1} + \mathrm{i}_t \, \boldsymbol{k}_t \qquad \text{normalizer state} \quad (20)$$

$$\boldsymbol{h}_t = \mathbf{o}_t \odot \tilde{\boldsymbol{h}}_t \, , \qquad \tilde{\boldsymbol{h}}_t = \boldsymbol{C}_t \, \boldsymbol{q}_t \, / \, \max\left\{ \left| \boldsymbol{n}_t^\top \, \boldsymbol{q}_t \right|, 1 \right\} \qquad \text{hidden state} \quad (21)$$

$$\boldsymbol{q}_t = \boldsymbol{W}_q \, \boldsymbol{x}_t + \boldsymbol{b}_q \qquad \text{query input} \quad (22)$$

$$\boldsymbol{k}_t = \frac{1}{\sqrt{d}} \boldsymbol{W}_k \, \boldsymbol{x}_t + \boldsymbol{b}_k \qquad \text{key input} \quad (23)$$

$$\boldsymbol{v}_t = \boldsymbol{W}_v \, \boldsymbol{x}_t + \boldsymbol{b}_v \qquad \text{value input} \quad (24)$$

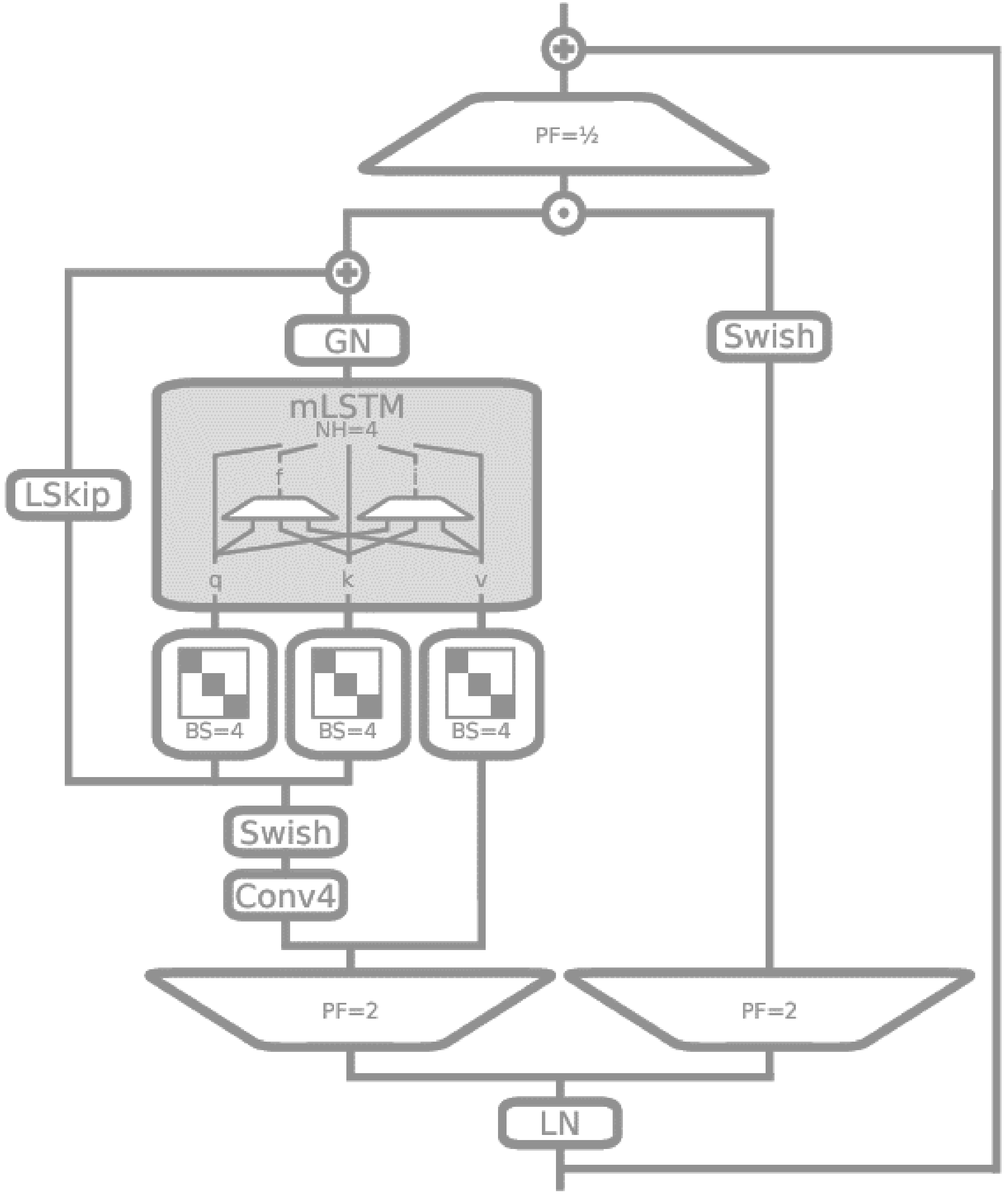
$$\mathrm{i}_t = \exp\left(\tilde{\mathrm{i}}_t\right) \, , \qquad \tilde{\mathrm{i}}_t = \boldsymbol{w}_{\mathrm{i}}^\top \, \boldsymbol{x}_t + b_{\mathrm{i}} \qquad \text{input gate} \quad (25)$$

$$\mathrm{f}_t = \sigma\left(\tilde{\mathrm{f}}_t\right) \text{ OR } \exp\left(\tilde{\mathrm{f}}_t\right) , \qquad \tilde{\mathrm{f}}_t = \boldsymbol{w}_{\mathrm{f}}^\top \, \boldsymbol{x}_t + b_{\mathrm{f}} \qquad \text{forget gate} \quad (26)$$

$$\mathbf{o}_t = \sigma\left(\tilde{\mathbf{o}}_t\right) \, , \qquad \tilde{\mathbf{o}}_t = \boldsymbol{W}_{\mathbf{o}} \, \boldsymbol{x}_t + \boldsymbol{b}_{\mathbf{o}} \qquad \text{output gate} \quad (27)$$

Maximilian Beck et al. (2024) “xLSTM: Extended Long Short-Term Memory”. arXiv preprint arXiv:2405.04517.

mLSTM



Maximilian Beck et al. (2024) "xLSTM: Extended Long Short-Term Memory".
arXiv preprint arXiv:2405.04517.

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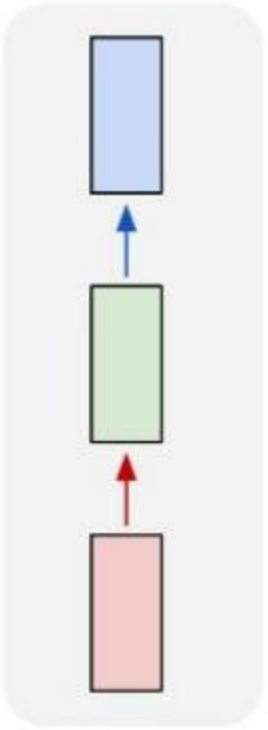
5.

Configuraciones

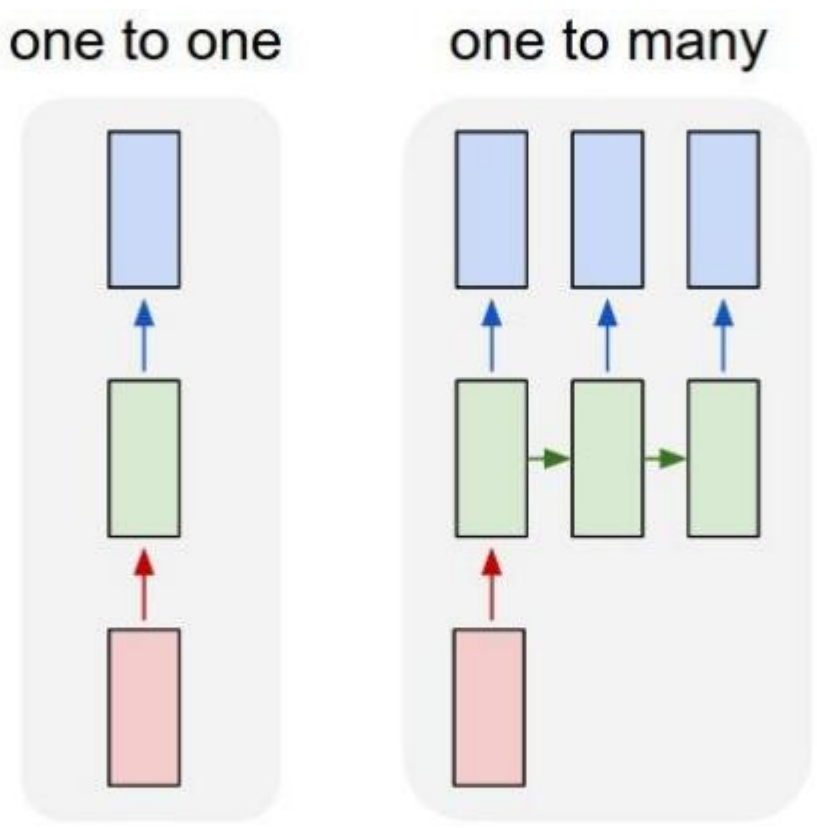
Configuraciones

one to one



Ejemplo:
Clasificación
Regresión

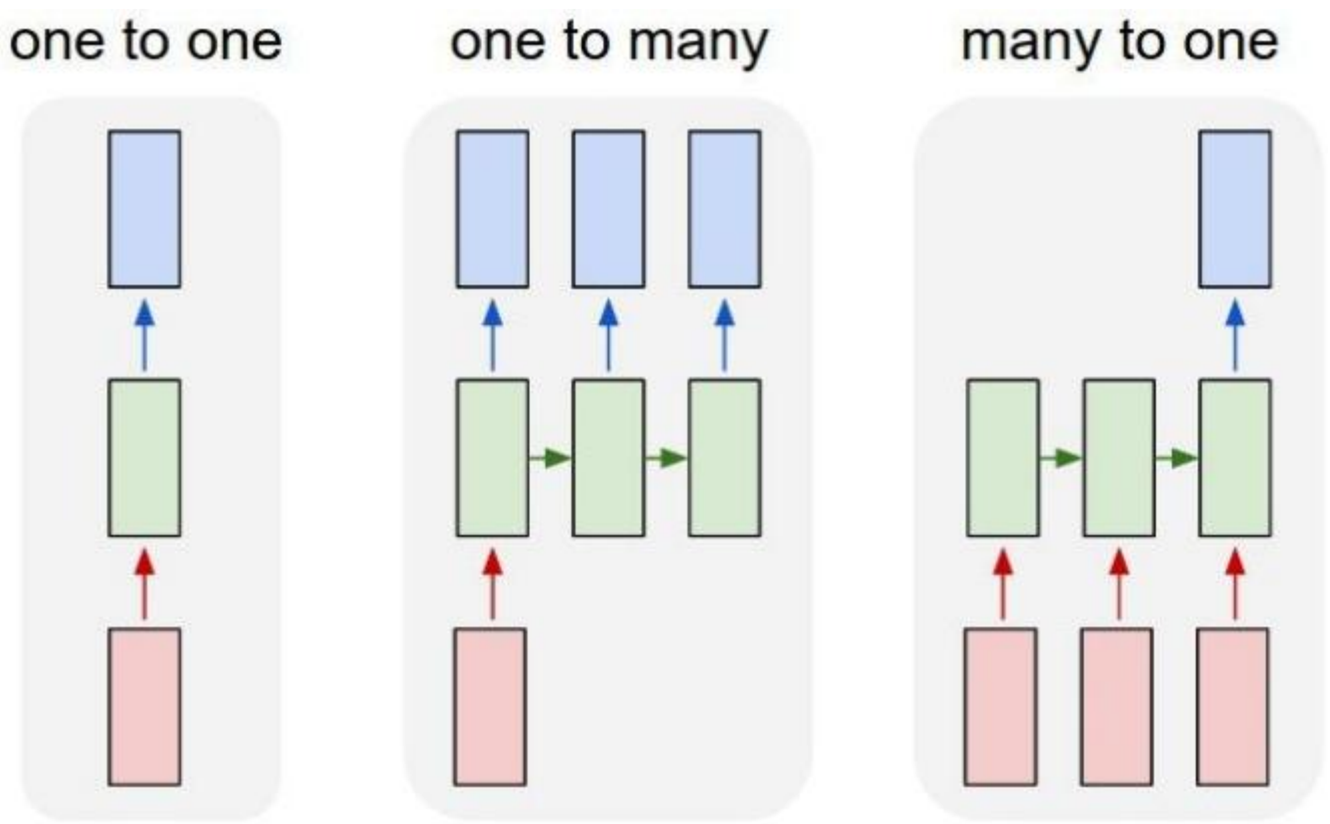
Configuraciones



Ejemplo:
Clasificación
Regresión

Ejemplo:
Image caption
Music generation

Configu*raciones*

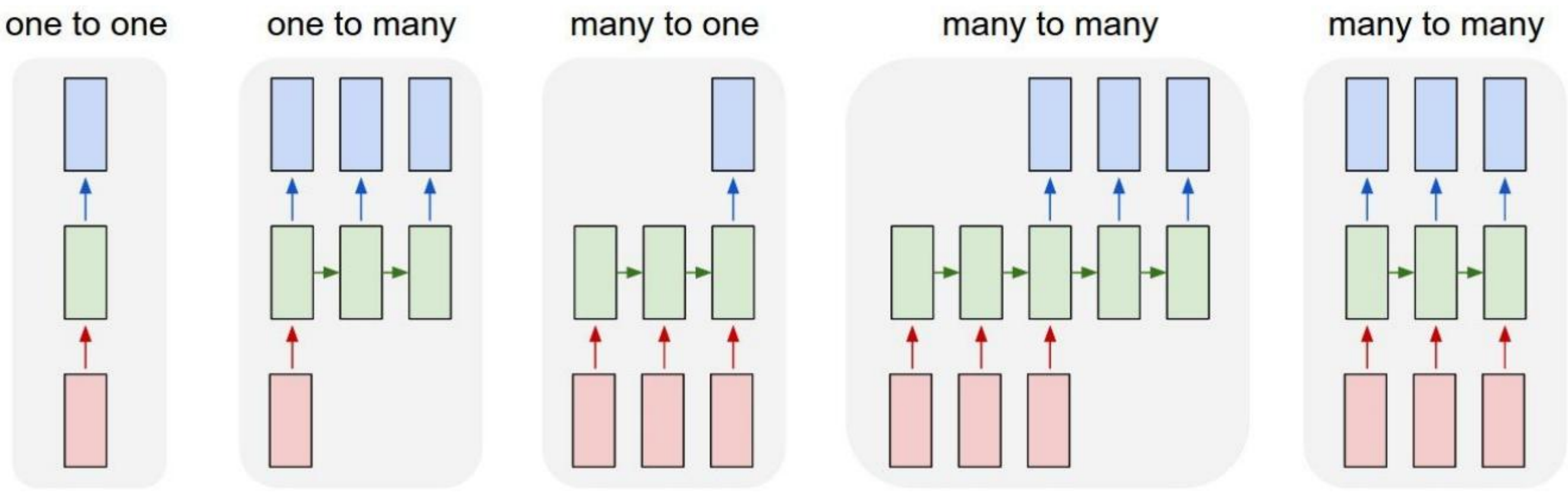


Ejemplo:
Clasificación
Regresión

Ejemplo:
Image caption
Music generation

Ejemplo:
clasificación de oraciones, respuesta a preguntas de opción múltiple

Configuraciones



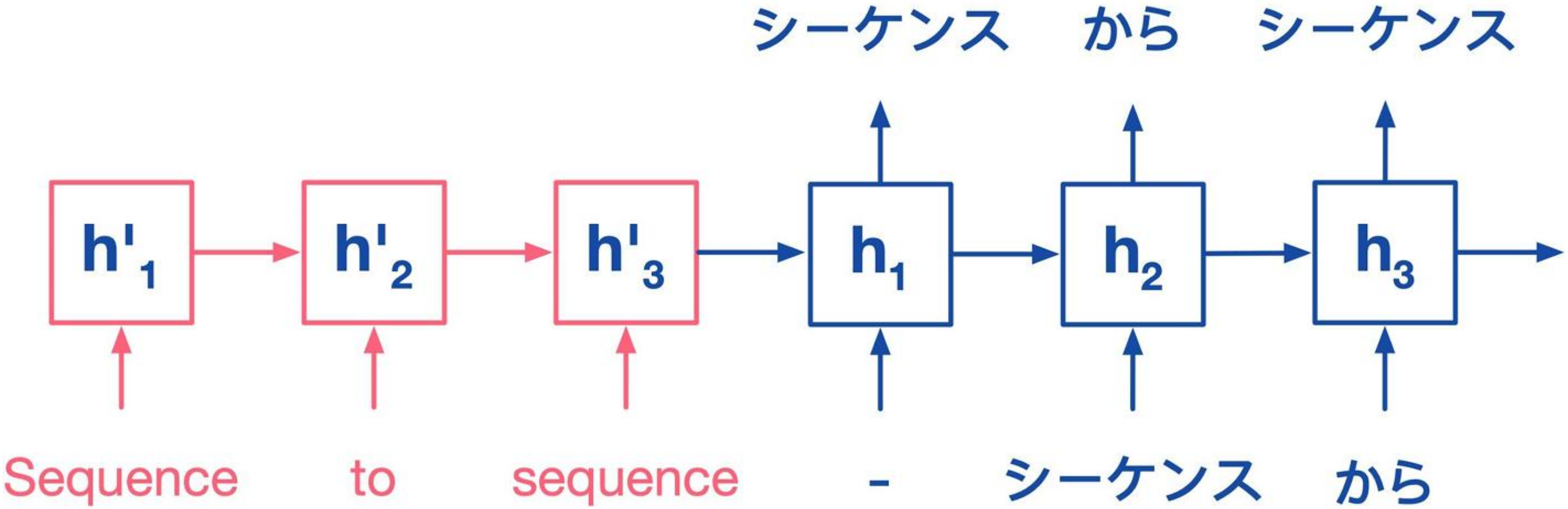
Ejemplo:
Clasificación
Regresión

Ejemplo:
Image caption
Music generation

Ejemplo:
clasificación de oraciones, respuesta a preguntas de opción múltiple

Ejemplo:
machine translation, video classification, video captioning,

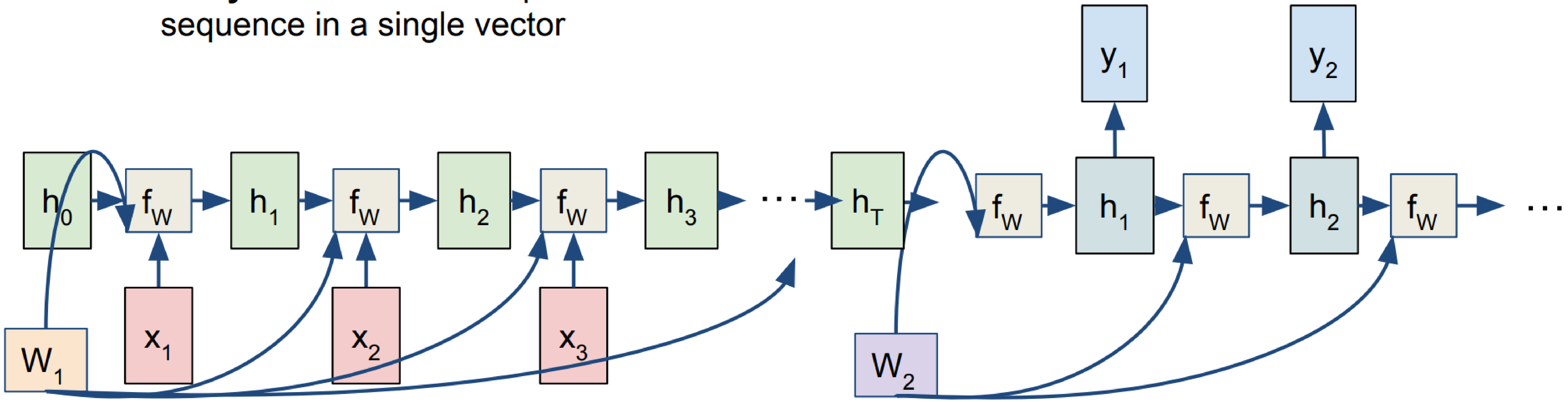
Sequence-to-*sequence models*



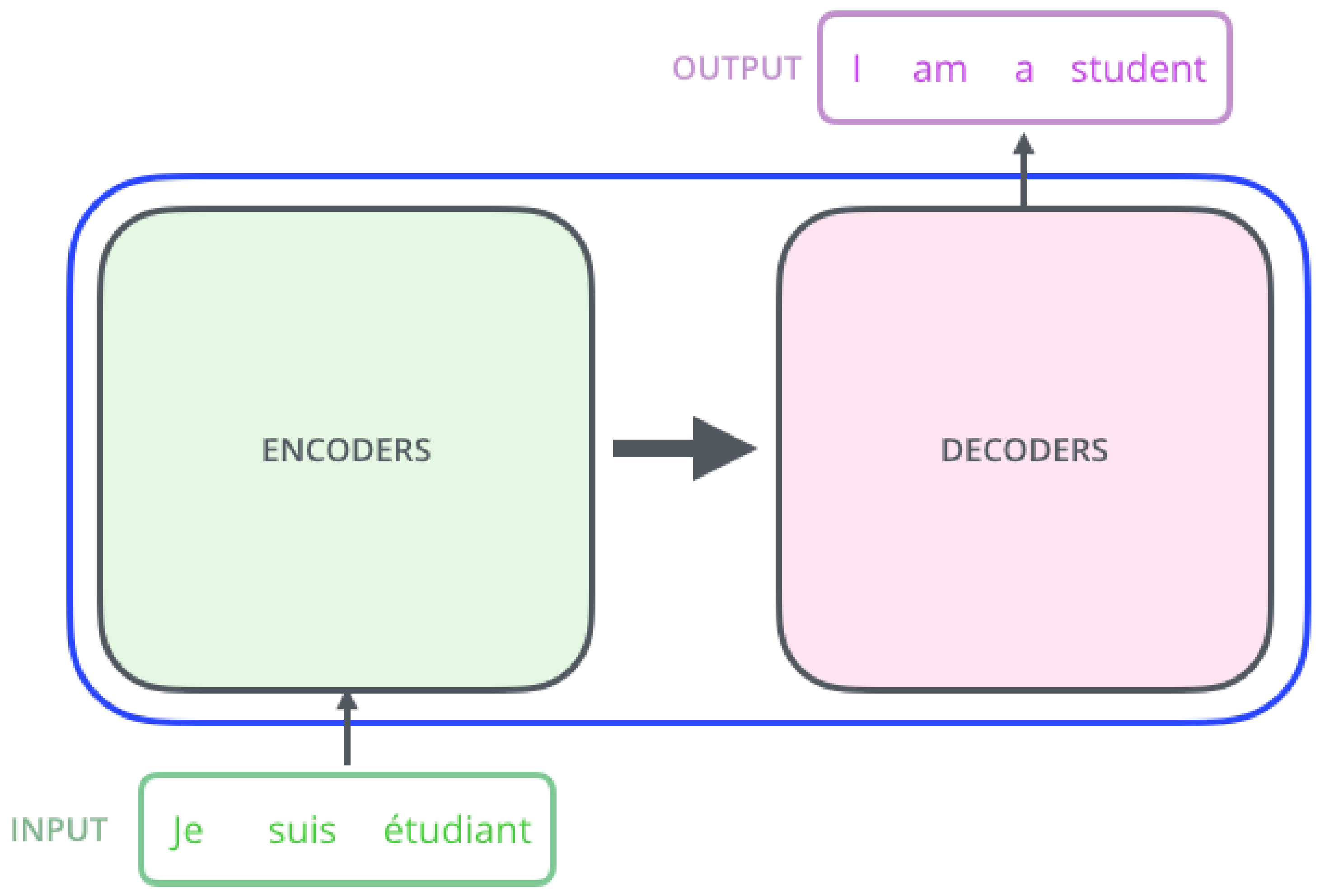
Sequence-to-*sequence models*

One to many: Produce output sequence from single input vector

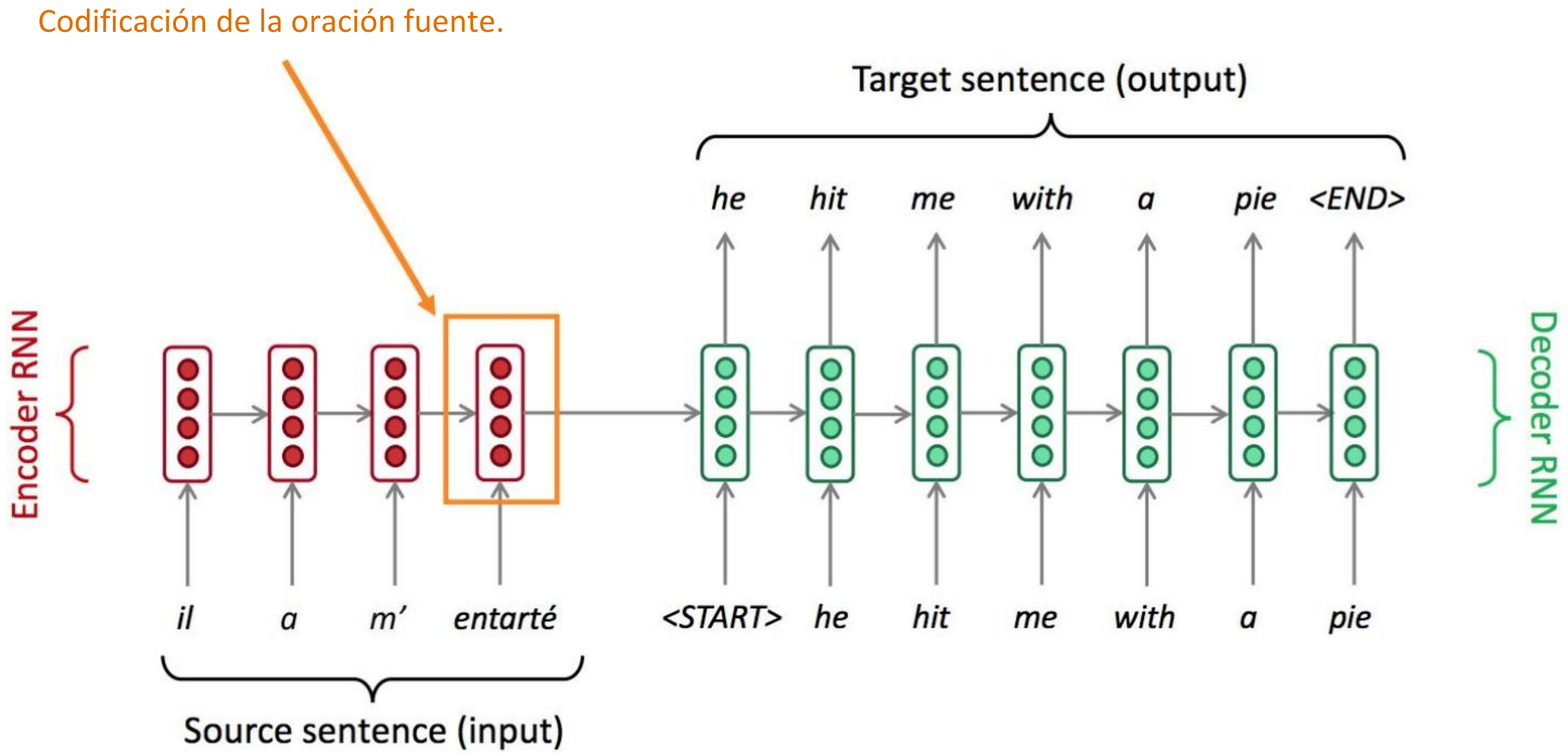
Many to one: Encode input sequence in a single vector



Sequence-to-*sequence models*



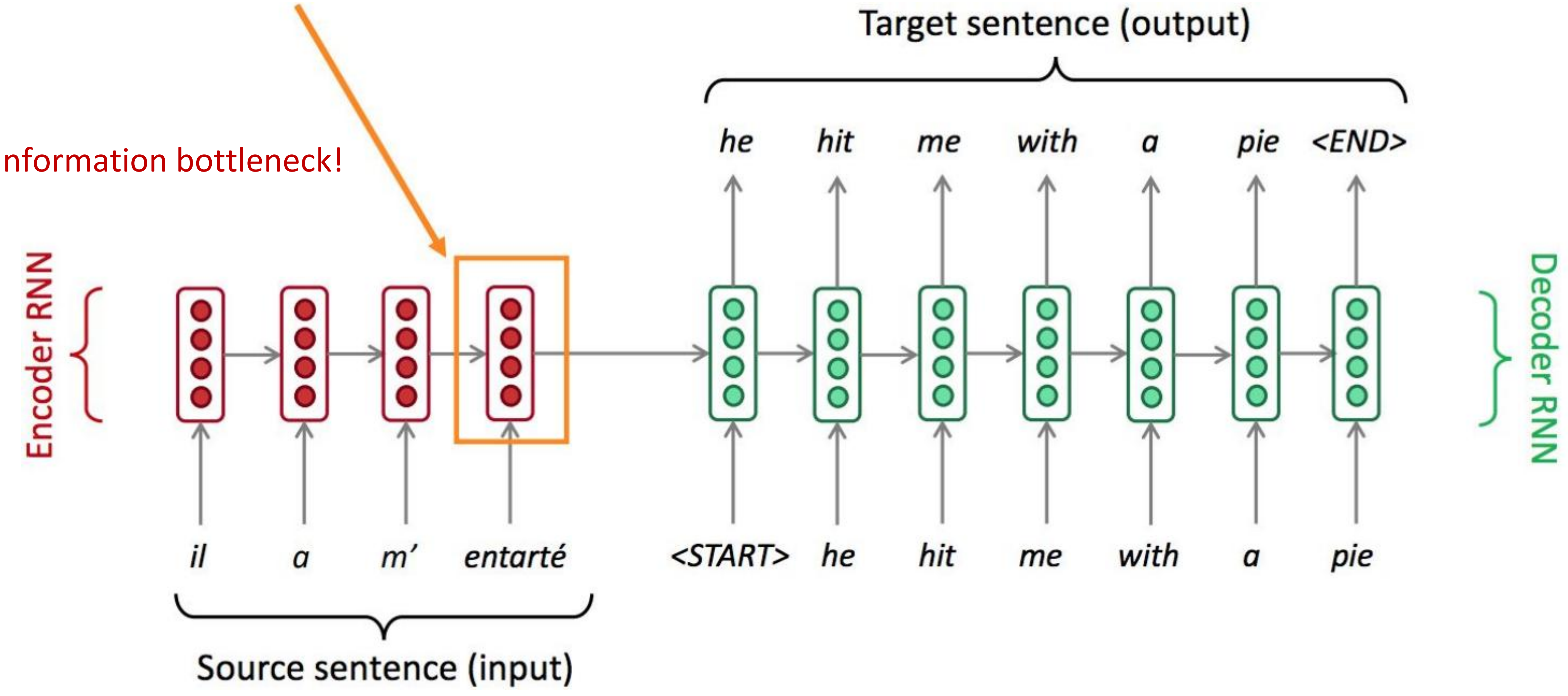
Sequence-to-*sequence models*



Sequence-to-*sequence models*

Codificación de la oración fuente.
Debe capturar toda la información
sobre la oración fuente.

Information bottleneck!



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> Reinventa el mundo <

GRACIAS

Victor Flores Benites

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