# Aprendizaje Profundo

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# Redes Recurrentes

# Recurrent Neural Network (RNN)

. Introducción

. Neurona recurrente básica

. Implementación en pytorch

. Back propagation through time (BPTT)

. Birideccionalidad

. Arquitectura enconder-decoder (seq to seq)

. Mecanismos de atención

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## Redes recurrentes - Introducción

Red neuronal **favorita** para el trabajo secuencias ( datos que en cuya naturaleza exista un **comportamiento secuencial**):

- señales temporales
- series temporales
- texto
- habla
- música
- etc

## Redes recurrentes - Introducción

En **cada paso**, se repiten los **mismos cálculos**, empleando **datos del paso actual** y **datos del pasado**.

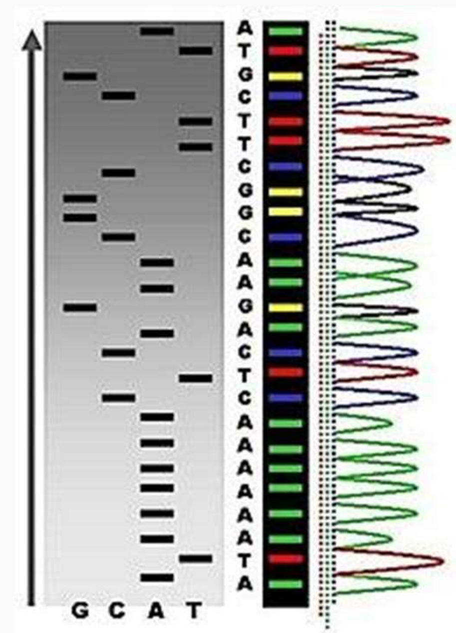
**Los pasos, no son necesariamente en unidad tiempo!!**

Temperatura f(t):

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| X(t=0) | X(t=1) | X(t=2) | X(t=3) | X(t=4) | X(t=5) | ... | X(t=τ) |

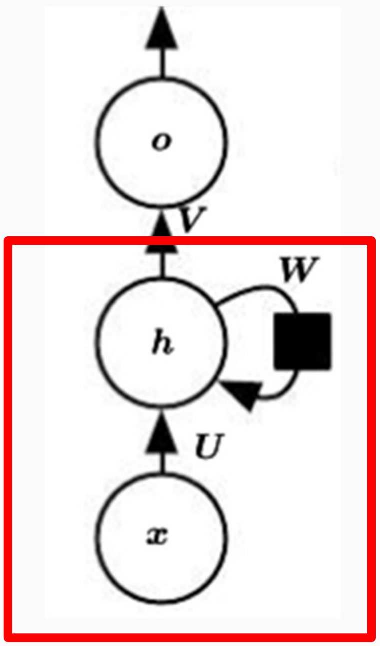
Mensaje:

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Este | es | un | mensaje | para | la | red | neuronal |




wikipedia

# Redes recurrentes - Neurona recurrente básica




Ecuaciones

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}), \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)},
\end{aligned}
$$

# Redes recurrentes - Neurona recurrente básica

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\
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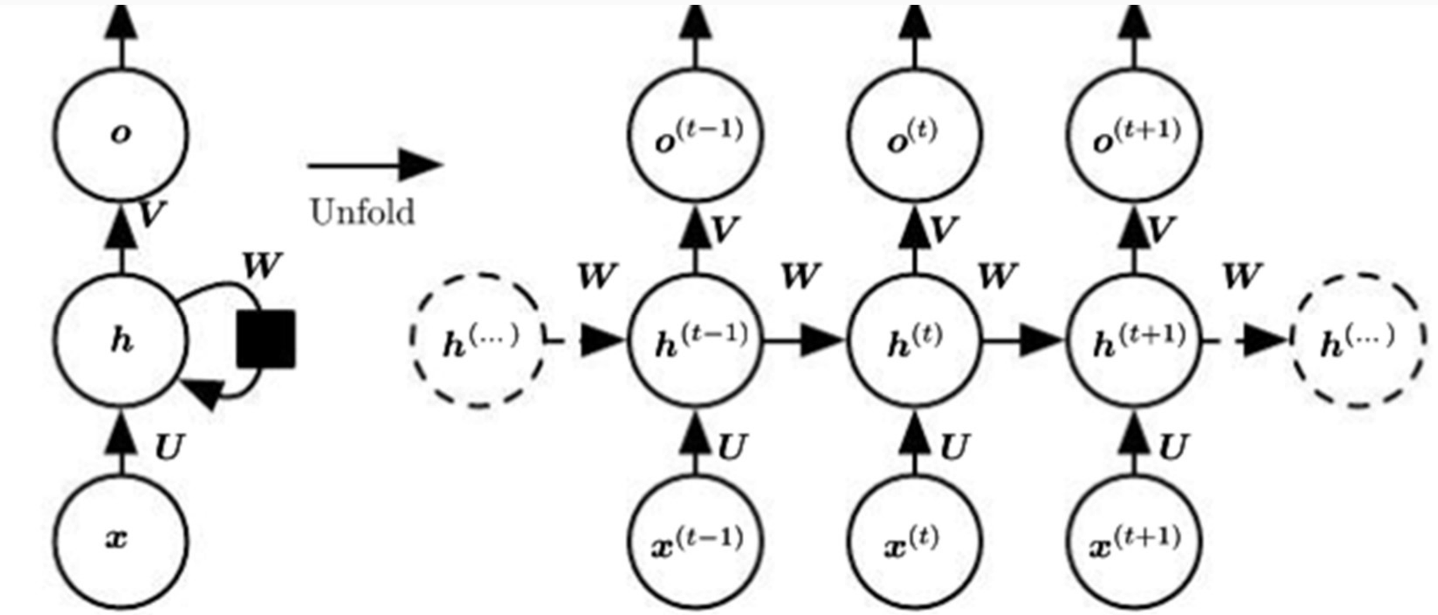
\end{aligned}
$$




***U*, *W* son los mismos!!**

Parameters sharing

$x[n] = [0{,}7;\ 0{,}9;\ 1{,}1]$

$\left\{ \begin{array}{ll} U = 0{,}2 & ;\ b = -0{,}1 \\ W = 0{,}3 & \end{array} \right\}$ Parámetros inventados

$$h[0] = \tanh[-0{,}1 + 0{,}3 \cdot \underbrace{h[-1]}_{=0 \text{ para la } 1^{\circ} \text{ muestra}} + 0{,}2 \cdot 0{,}7] = 0{,}0399$$

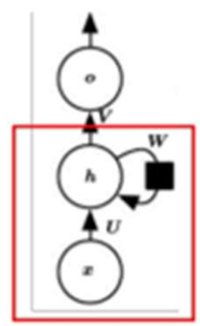
$$h[1] = \tanh[-0{,}1 + 0{,}3 \cdot 0{,}0399 + 0{,}2 \cdot 0{,}9] = 0{,}0917$$

$$h[2] = \tanh[-0{,}1 + 0{,}3 \cdot 0{,}0917 + 0{,}2 \cdot 1{,}1] = 0{,}1464$$

Válido para cada neurona hidden

Las hidden se conectan todas contra todas

$$\boxed{\begin{aligned} \boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\ \boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}), \end{aligned}}$$
$$\boldsymbol{o}^{(t)} = \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)},$$



# Redes recurrentes - Implementación en pytorch

## RNN

CLASS `torch.nn.RNN(*args, **kwargs)` [SOURCE]

Applies a multi-layer Elman RNN with $\tanh$ or $\mathrm{ReLU}$ non-linearity to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$h_t = \tanh(W_{ih} x_t + b_{ih} + W_{hh} h_{(t-1)} + b_{hh})$$

where $h_t$ is the hidden state at time *t*, $x_t$ is the input at time *t*, and $h_{(t-1)}$ is the hidden state of the previous layer at time *t-1* or the initial hidden state at time *0*. If `nonlinearity` is `'relu'`, then $\mathrm{ReLU}$ is used instead of $\tanh$.

**torch.nn.RNN(**input_size, hidden_size, num_layers=1, nonlinearity='tanh', …

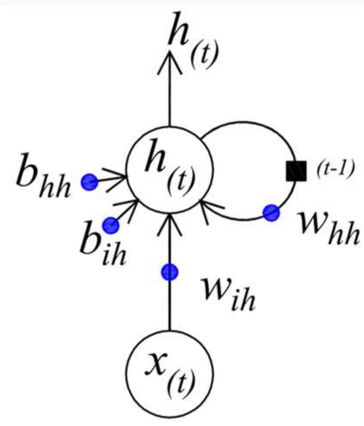
bias=True, batch_first=False, dropout=0, bidirectional=False **)**

## Redes recurrentes - Implementación en pytorch

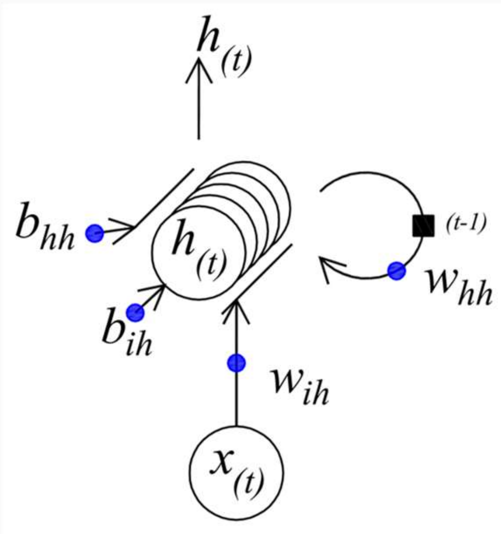
Pytorch

**Ver colab RNN_teoria.ipynb**

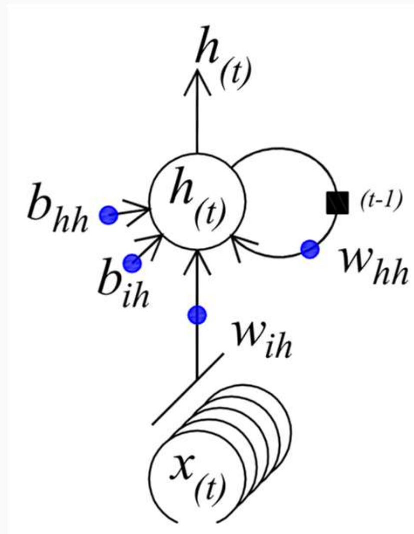
$$h_t = \tanh(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh})$$



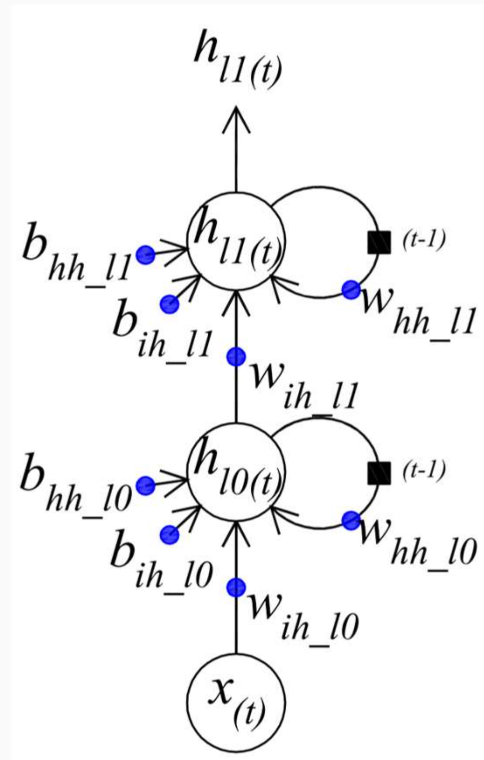

Básica




Varias hidden



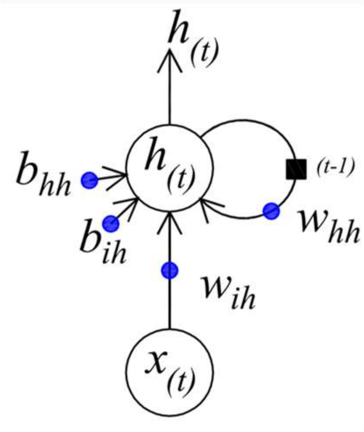

Input
multivariable




2 layers

# Redes recurrentes - Implementación en pytorch

$$h_t = \tanh(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh})$$

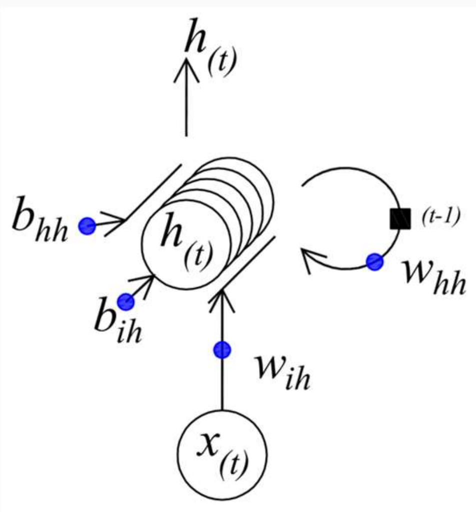



| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |
| | | | |
| | | | |

Básica

## Redes recurrentes - Implementación en pytorch

$$h_t = \tanh(W_{ih} x_t + b_{ih} + W_{hh} h_{(t-1)} + b_{hh})$$

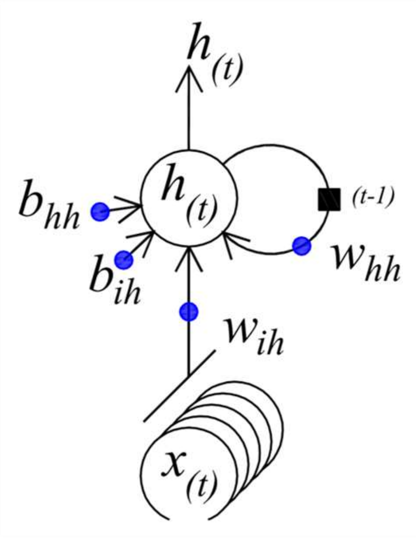



| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |

Varias hidden

# Redes recurrentes - Implementación en pytorch

$$h_t = \tanh(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh})$$

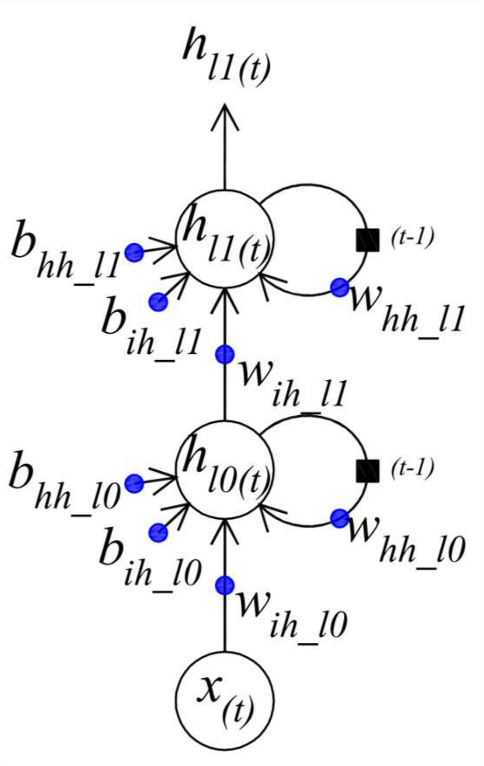



Input multivariable

| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |

# Redes recurrentes - Implementación en pytorch

$$h_t = \tanh(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh})$$

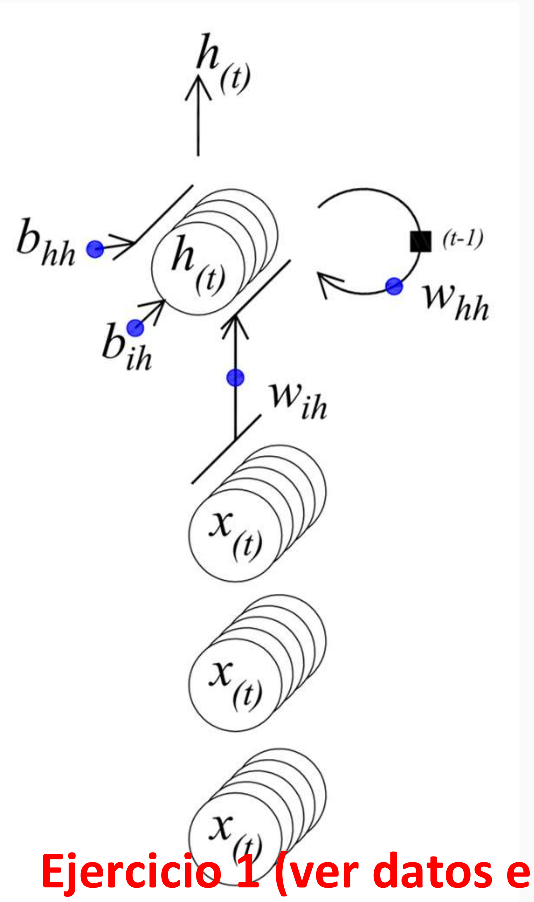



2 layers

| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |

# Redes recurrentes - Implementación en pytorch

$$h_t = \tanh(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh})$$




**Ejemplo A**

| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |

**Ejemplo B**

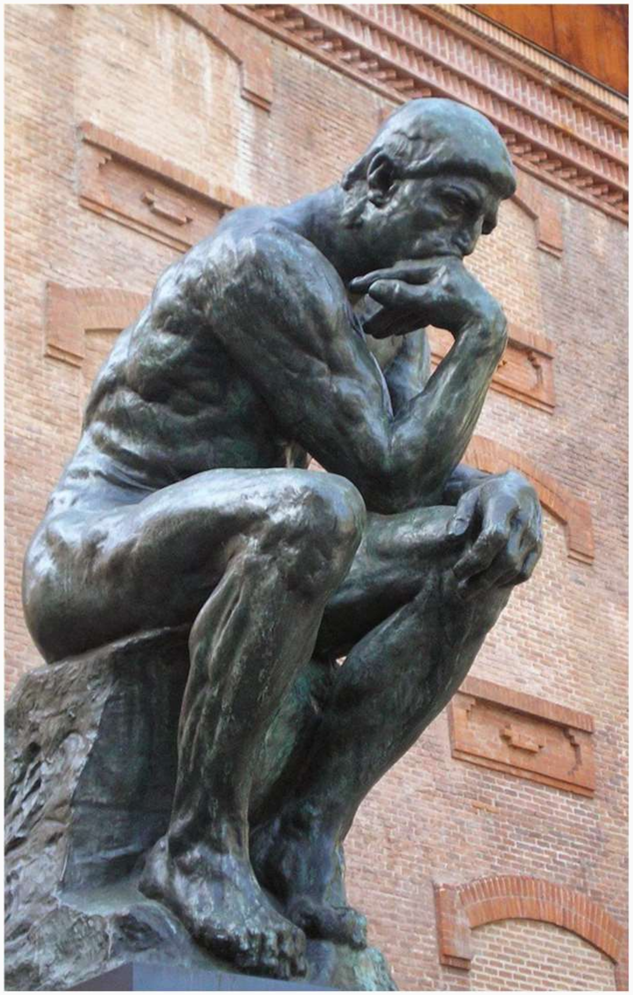
| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |

**Ejemplo C**

| Variable | Tamaño | Parámetro | Tamaño |
|---|---|---|---|
| x | | Wih | |
| h | | Bih | |
| | | Whh | |
| | | bhh | |

**Ejercicio 1 (ver datos en colab)**

# Redes recurrentes - Implementación en pytorch



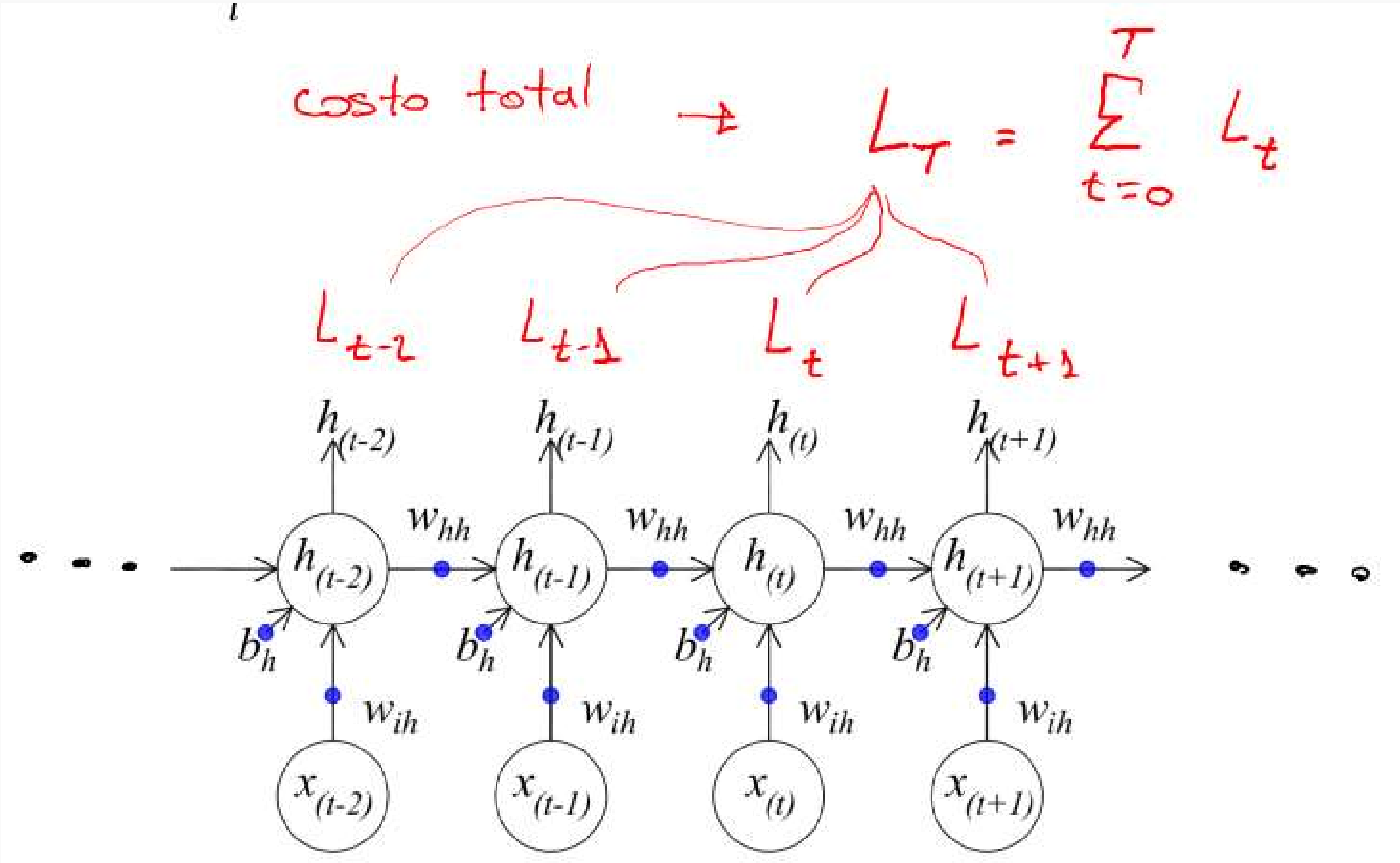
“El pensador” de Rodin

**A pensar!**

## Redes recurrentes - Back propagation through time (BPTT)


Ver desarrollo teórico

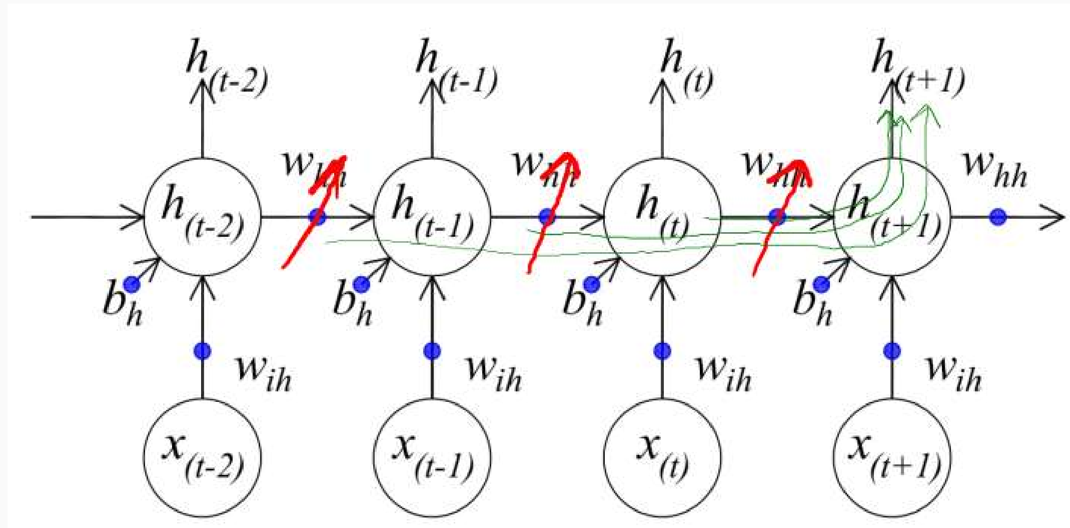
# Redes recurrentes - Back propagation through time (BPTT)



# Redes recurrentes - Back propagation through time (BPTT)

1º $w_{hh}$ → Pesos hidden - hidden

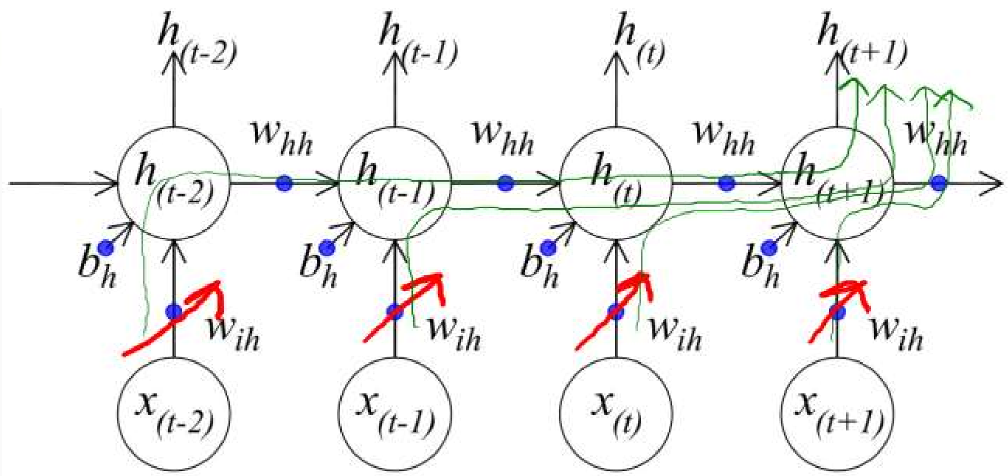
$$\frac{\partial L_T}{\partial w_{hh}} = ?$$




$$\boxed{\frac{\partial L_T}{\partial w_{hh}} = \sum_{t=0}^{T} \frac{\partial L_t}{\partial LF} \cdot \frac{\partial LF}{\partial h_t} \sum_{k=0}^{t} \left[ \prod_{j=k}^{t} \left( \frac{\partial h_{j+1}}{\partial h_j} \right) \cdot \frac{\partial h_k}{\partial w_{hh}} \right]}$$

# Redes recurrentes - Back propagation through time (BPTT)

2° $W_{ih}$ → Pesos input-hidden

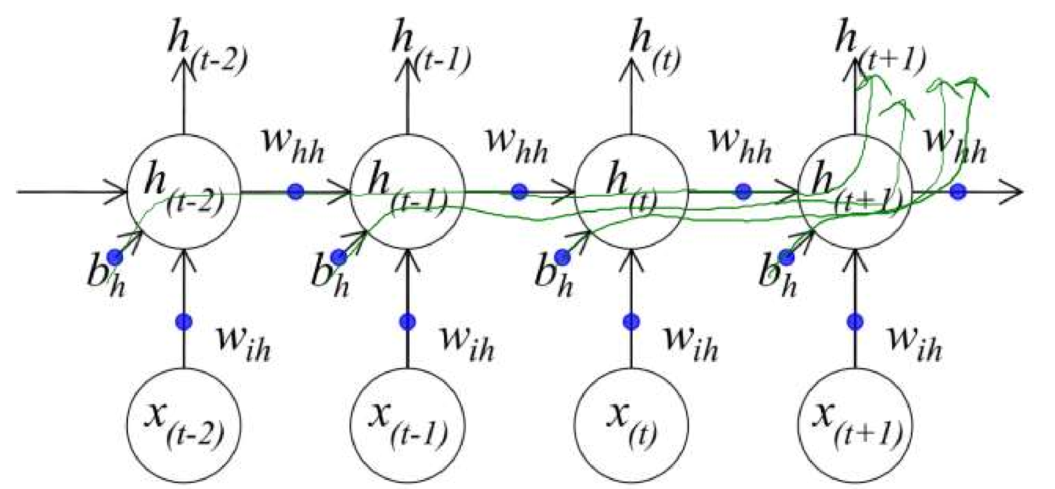



$$\boxed{\frac{\partial L_T}{\partial W_{ih}} = \sum_{t=0}^{T} \frac{\partial L_t}{\partial LF} \cdot \frac{\partial LF}{\partial h_t} \sum_{k=0}^{t} \left[ \prod_{j=k}^{t} \left( \frac{\partial h_{j+1}}{\partial h_j} \right) \cdot \frac{\partial h_k}{\partial W_{ih}} \right]}$$

acá cambió

# Redes recurrentes - Back propagation through time (BPTT)

3° $b_h$ → bias hidden




$$\frac{\partial L_T}{\partial b_h} = \sum_{t=0}^{T} \frac{\partial L_t}{\partial LF} \cdot \frac{\partial LF}{\partial h_t} \sum_{k=0}^{t} \left[ \prod_{j=k}^{t} \left( \frac{\partial h_{j+1}}{\partial h_j} \right) \cdot \frac{\partial h_k}{\partial b_h} \right]$$

acá cambió

## Problemas de la RNN básica con el BPTT

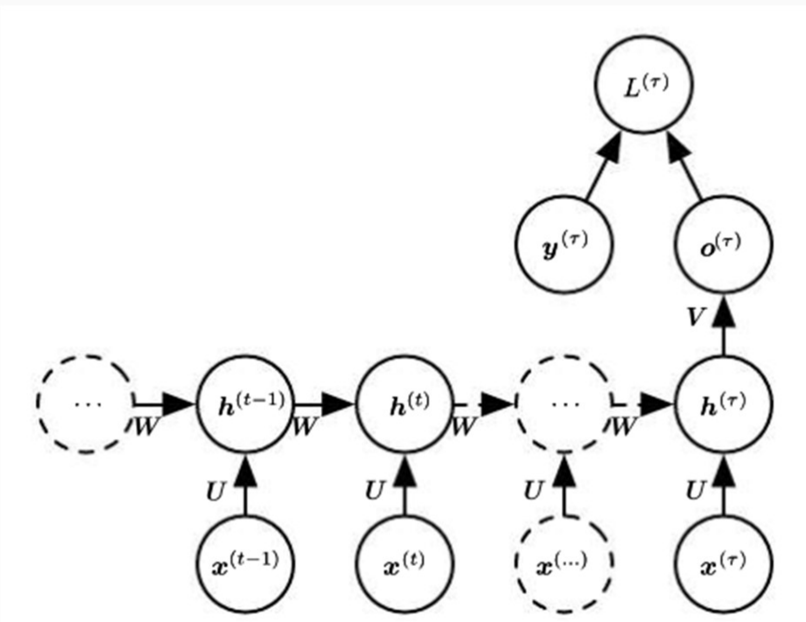
**Vanishing gradient → pérdida de aportes de long-term states (gradientes próximos a cero)**

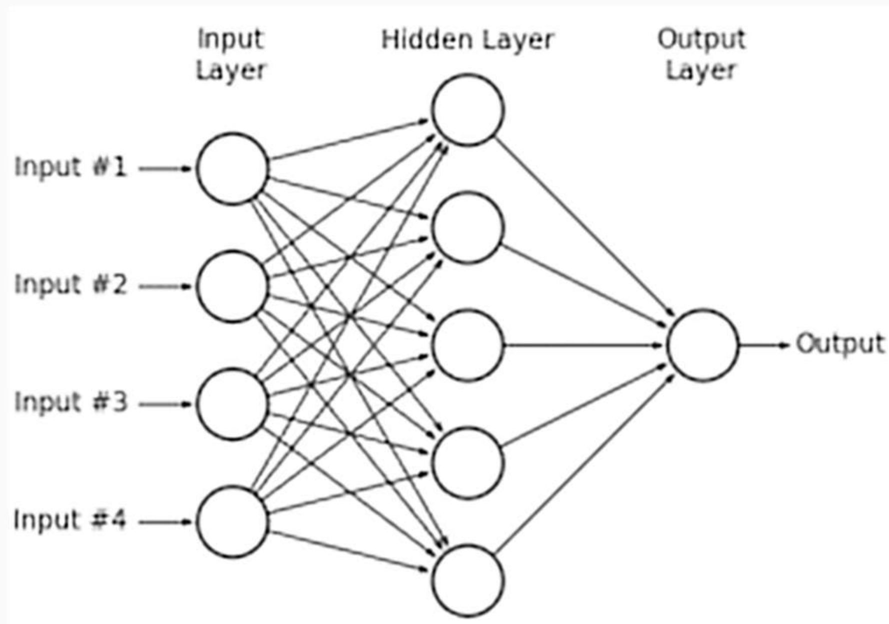
**Exploding gradient → se soluciona con clipping gradient (gradientes mayores a 1)**

**Solución con otras RNN mas avanzadas (LSTM y GRU)**

# Redes recurrentes - Implementación de modelos

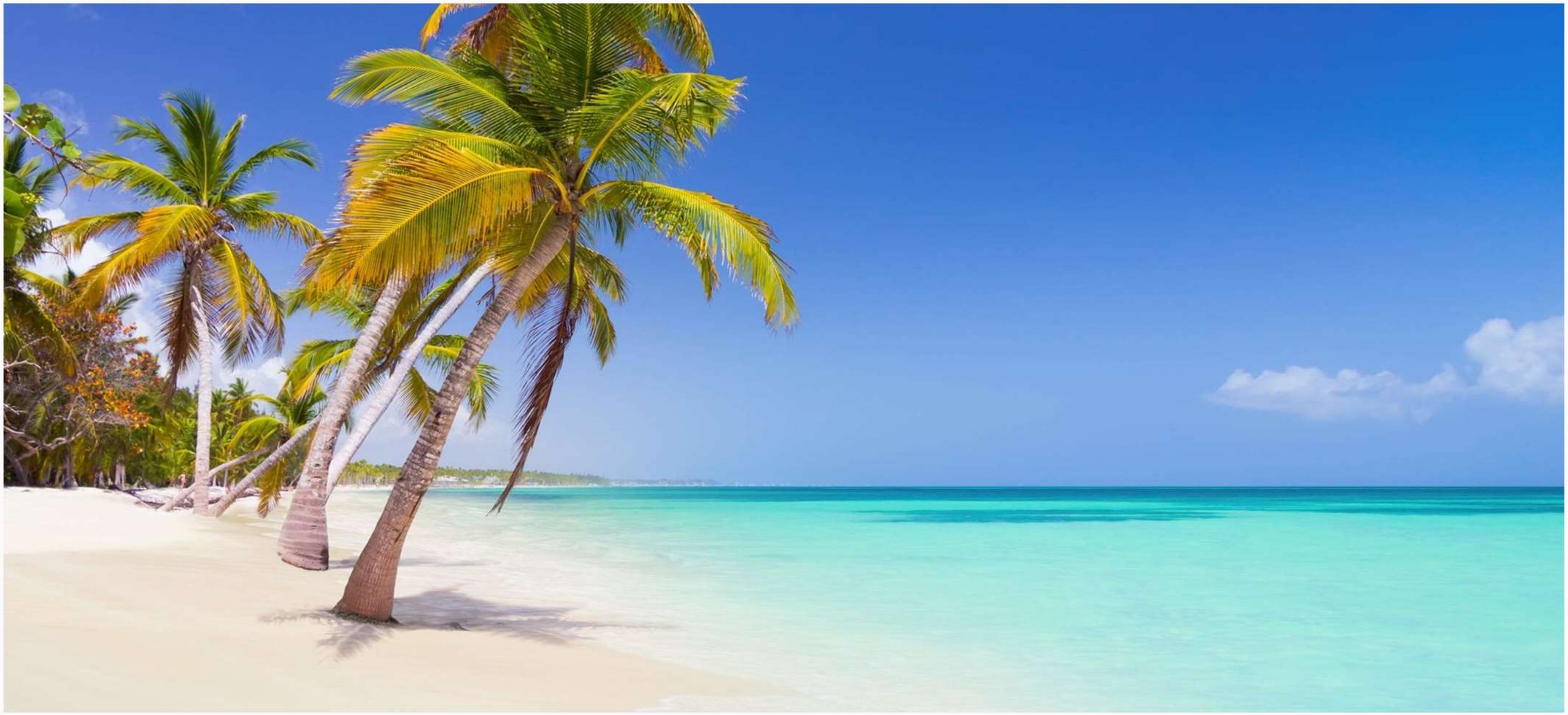
| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| X(t=0) | X(t=1) | X(t=2) | X(t=3) | X(t=4) | X(t=5) | X(t=6) | X(t=7) | ... | X(t=τ) |



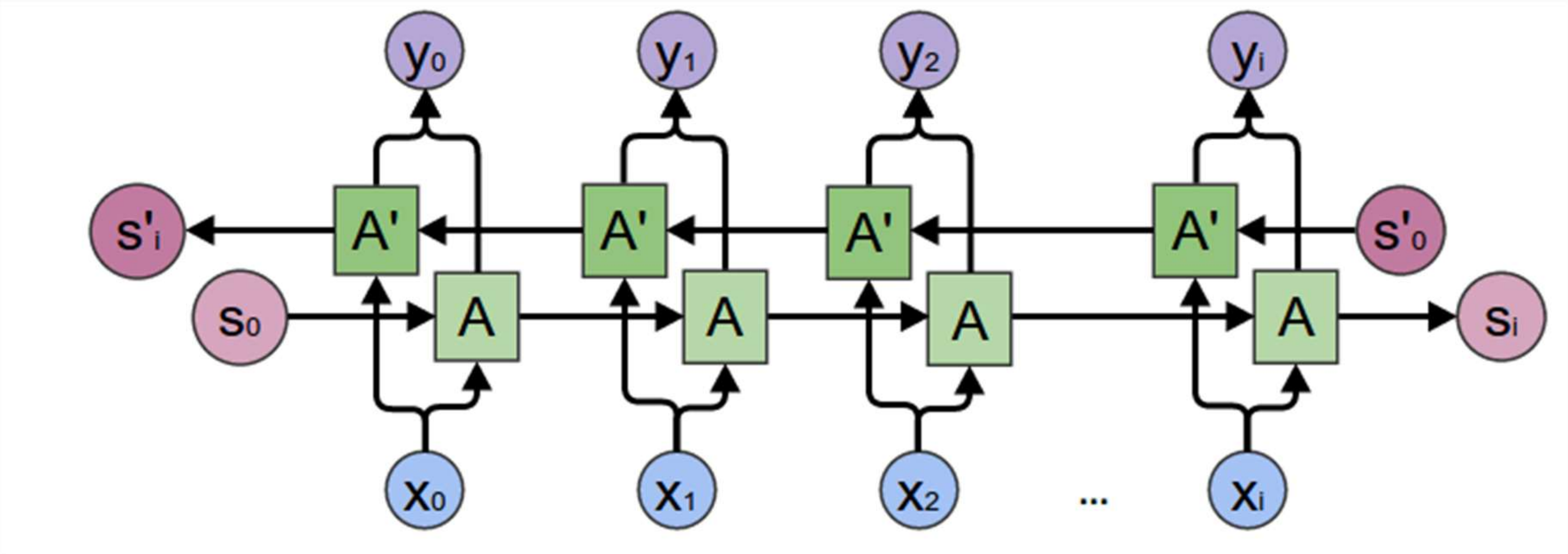

**Ver colab RNN_signal_TP.ipynb**

# ¡Un merecido descanso!



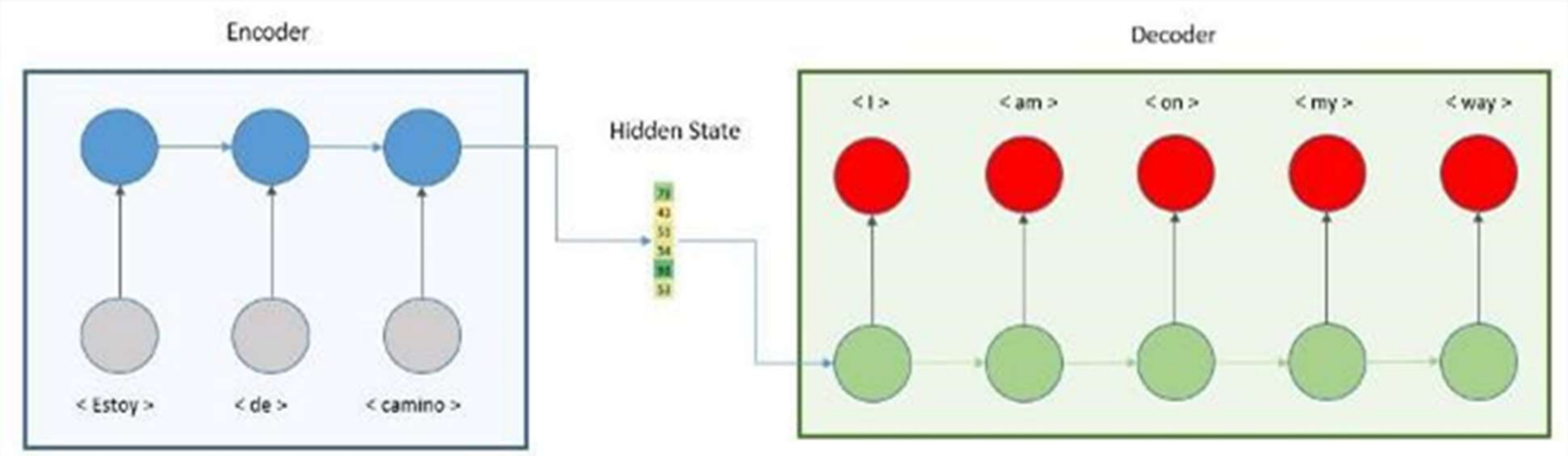
## Redes recurrentes - Birideccionalidad

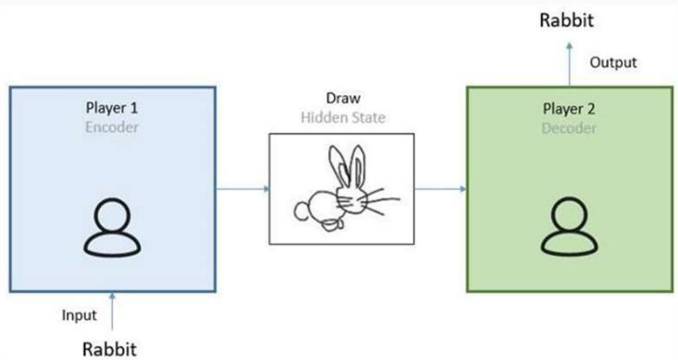
# Bi-directional




Para la traducción, suele ser útil tener la frase entera.

# Redes recurrentes - Arquitectura enconder-decoder (seq to seq)



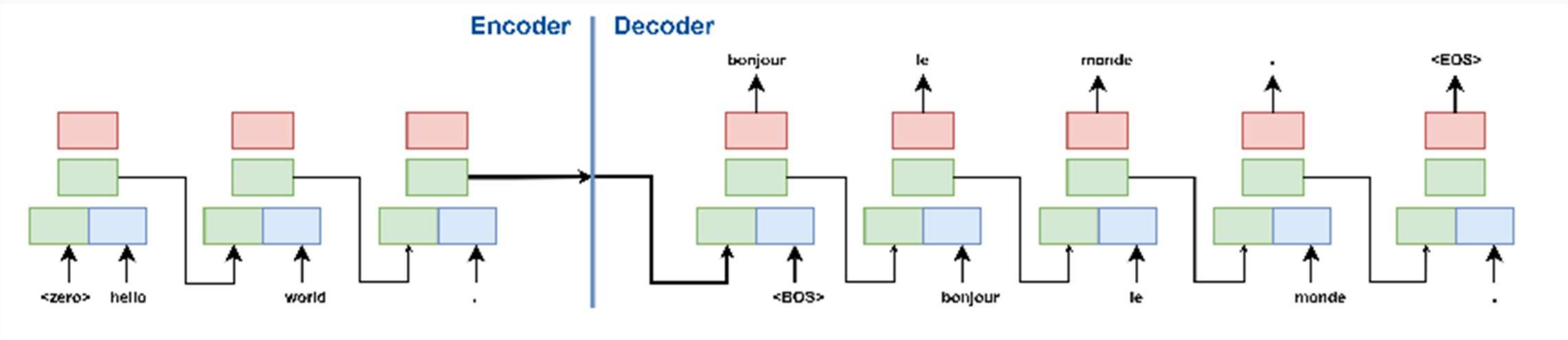

2 RNN de distinto tamaño

1 Hidden state que “resume” toda la información de la input.

Flexibilidad máxima para inputs/outputs de distinta longitud

https://towardsdatascience.com/what-is-an-encoder-decoder-model-86b3d57c5e1a

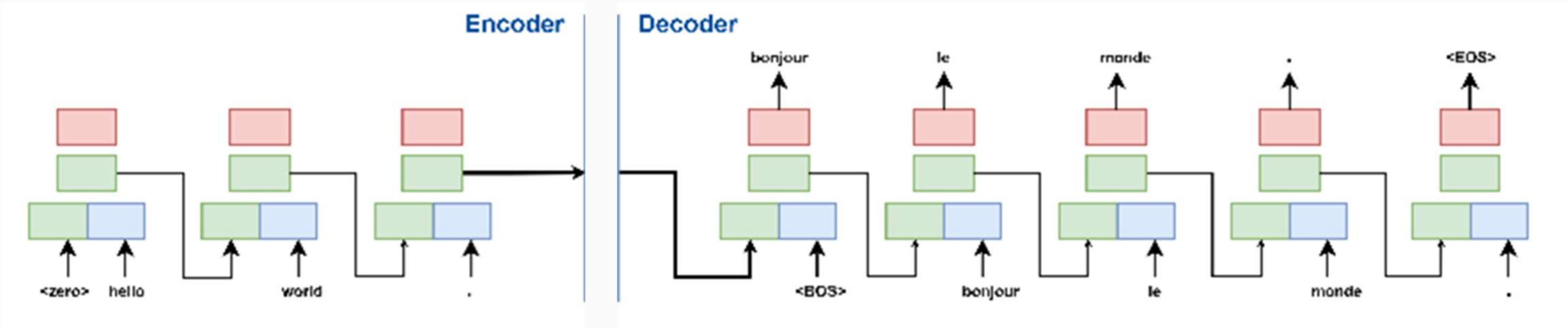
# Redes recurrentes - Arquitectura enconder-decoder (seq to seq)




Unfolded!!
!!

https://brunomaga.github.io/AI-Supercomputing-2

# Redes recurrentes - Arquitectura enconder-decoder (seq to seq) entrenamiento




ENCODER
Siempre leen la secuencia entera
Emiten un hidden state final

DECODER
Entrenamiento → for i in range(len(y_deseado):
genero_token

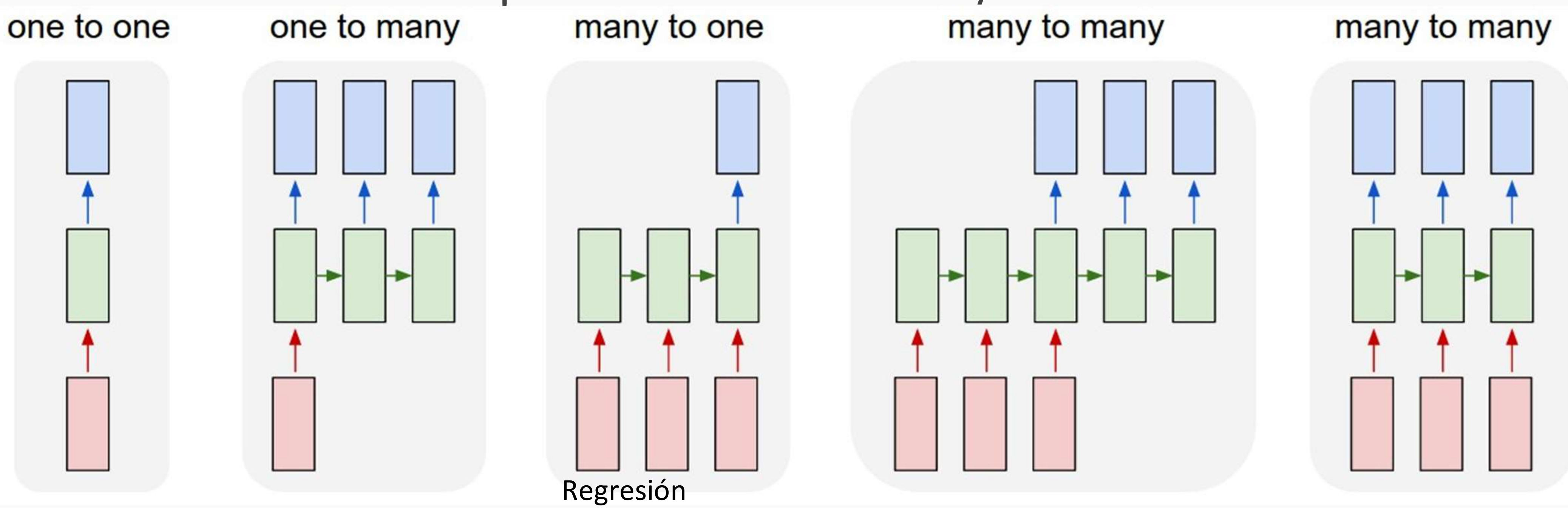
Uso → while last_token =! <EOS>:
genero_token

https://brunomaga.github.io/AI-Supercomputing-2

TEACHER FORCING!!!

# Redes recurrentes - Arquitectura enconder-decoder (seq to seq)

## Arquitecturas flexibles IN/OUT




MLP

Img captioning

Regresión

Classificacion

Sentiment classification

Resumen de videos

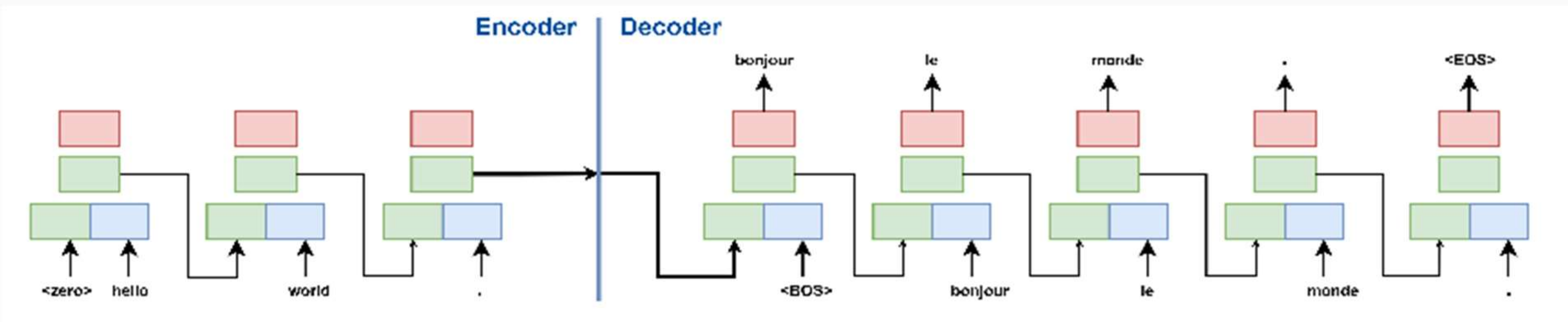
Regresión varios futuros

Traducción

Video class frame lvl

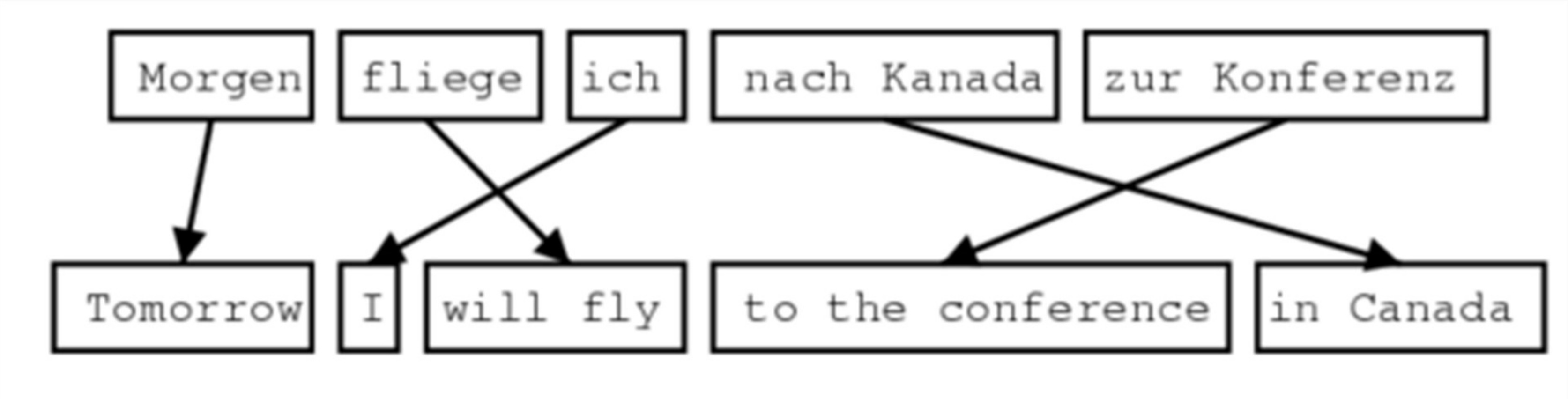
## Redes recurrentes - Implementación de modelos enconder-decoder

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| X(t=0) | X(t=1) | X(t=2) | X(t=3) | X(t=4) | X(t=5) | X(t=6) | X(t=7) | ... | X(t=τ) |




**Ver colab RNN_enc_dec.ipynb**

## Redes recurrentes - Mecanismos de atención

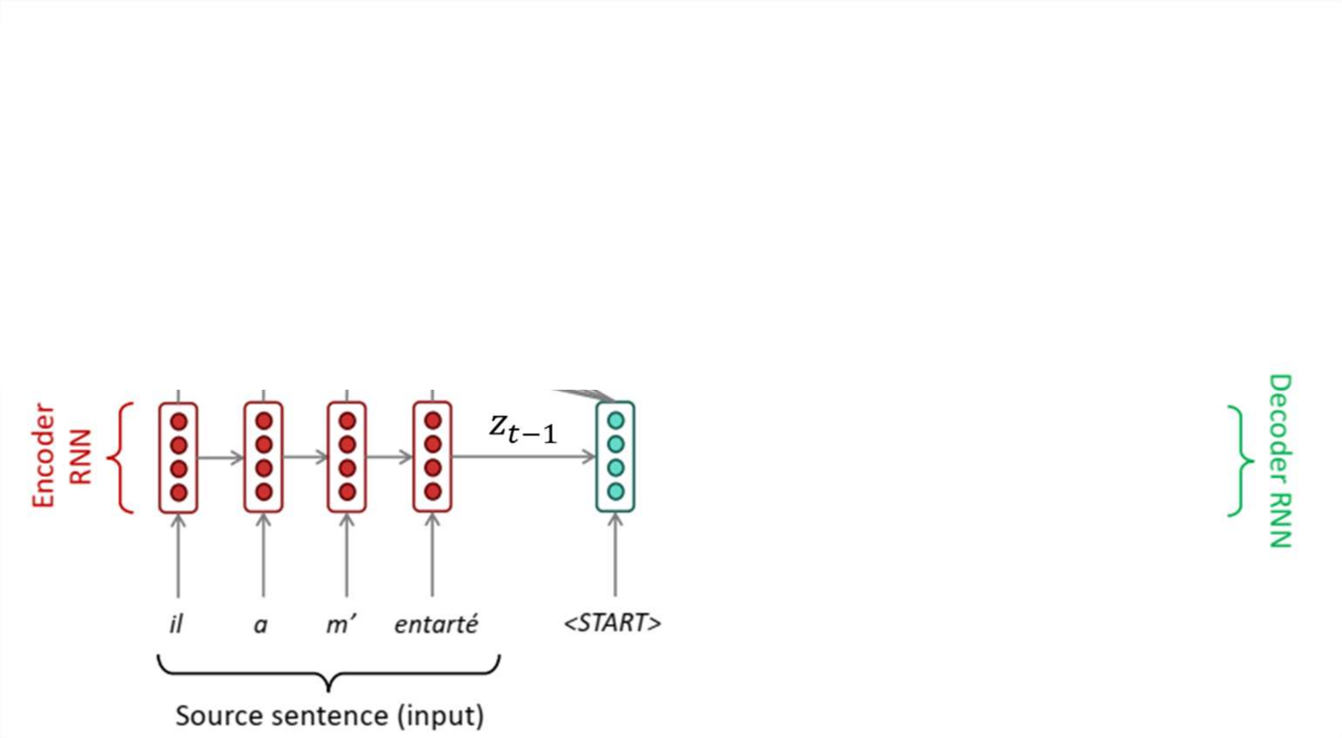



*El mecanismo de atención permite al decoder* ***utilizar las partes más relevantes*** *de la entrada* ***como una suma ponderada*** *del vector de entrada codificados para predecir la siguiente palabra.*

*Una* ***palabra relevante*** *tendrá un* ***mayor peso*** *que una palabra no relevante*

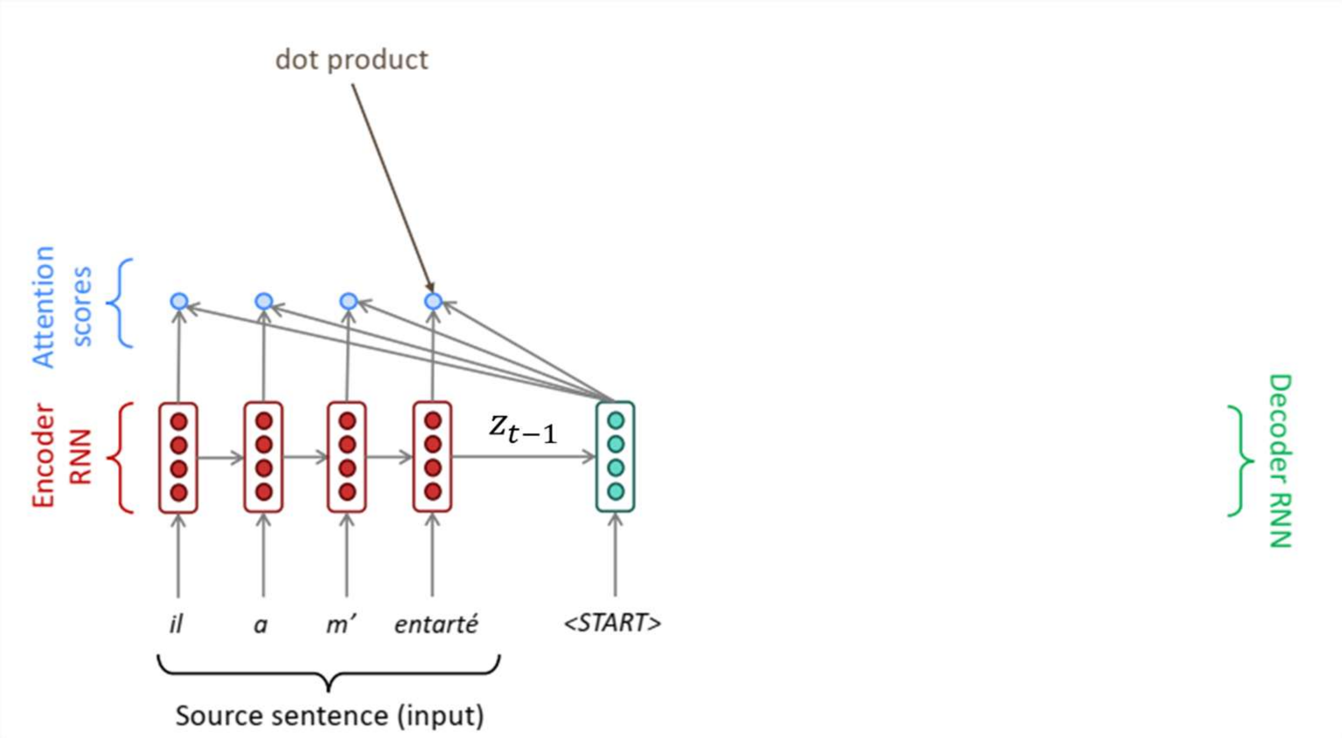
# Redes recurrentes - Mecanismos de atención

**Ver en bibliografía: cs224n-2021-lecture07-nmt.pdf**



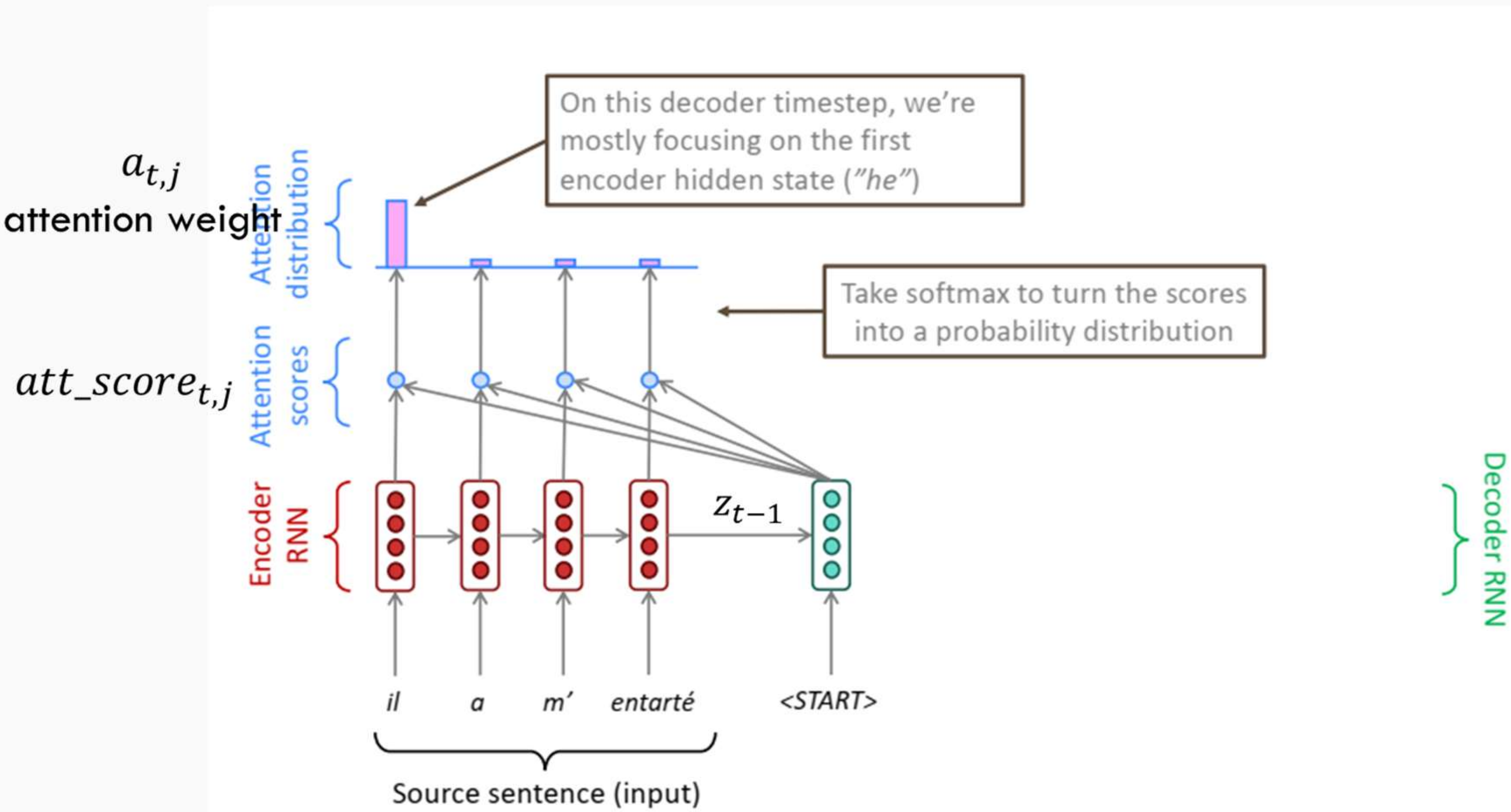
# Redes recurrentes - Mecanismos de atención

$att\_score_{t,j}$



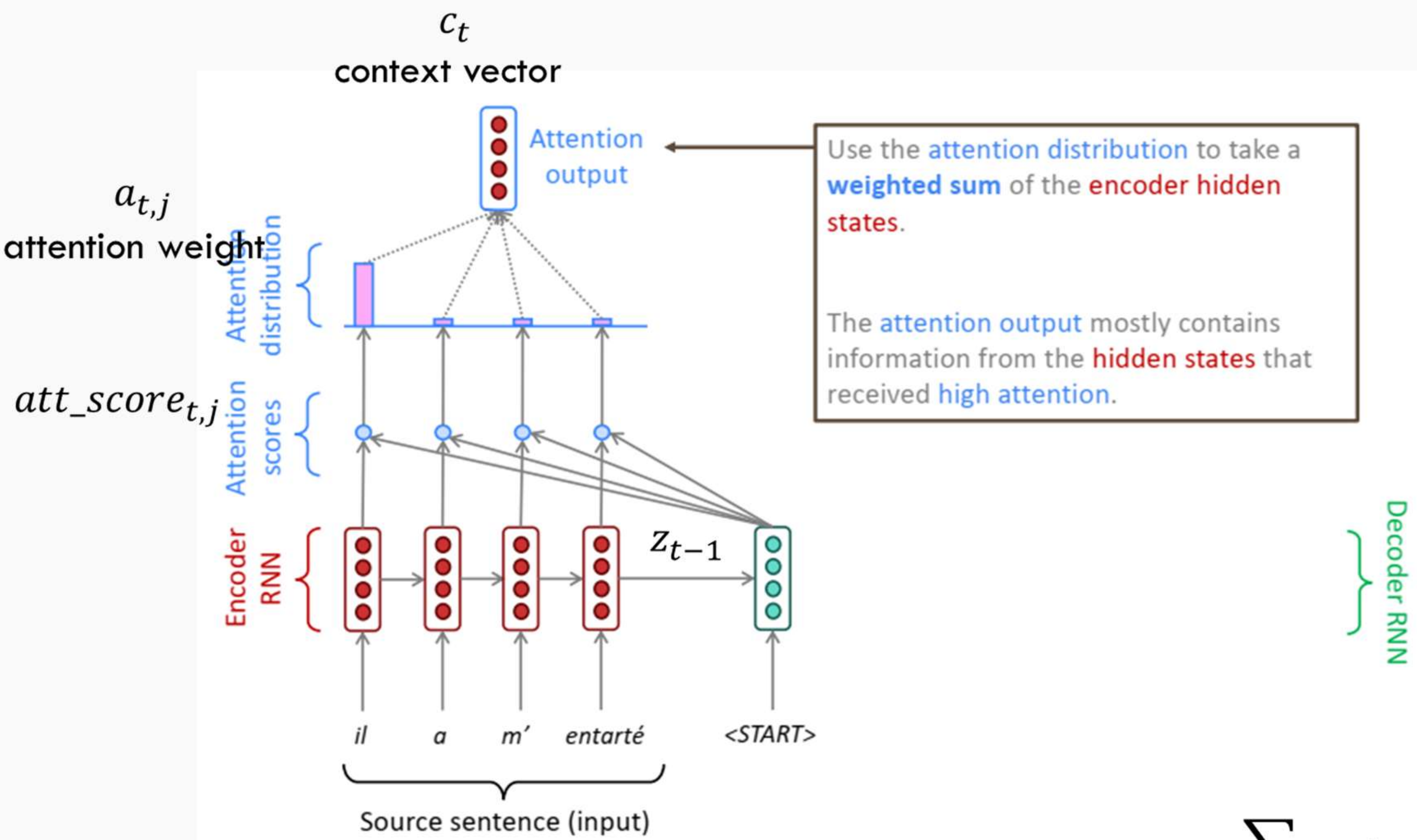

$$att\_score_{t,j} = \mathrm{dot}(z_t, h_j)$$

# Redes recurrentes - Mecanismos de atención




$att\_score_{t,j} = \mathrm{dot}(z_t, h_j)$ $\quad$ $a_{t,j} = softmax(att\_score_{t,j})$

# Redes recurrentes - Mecanismos de atención

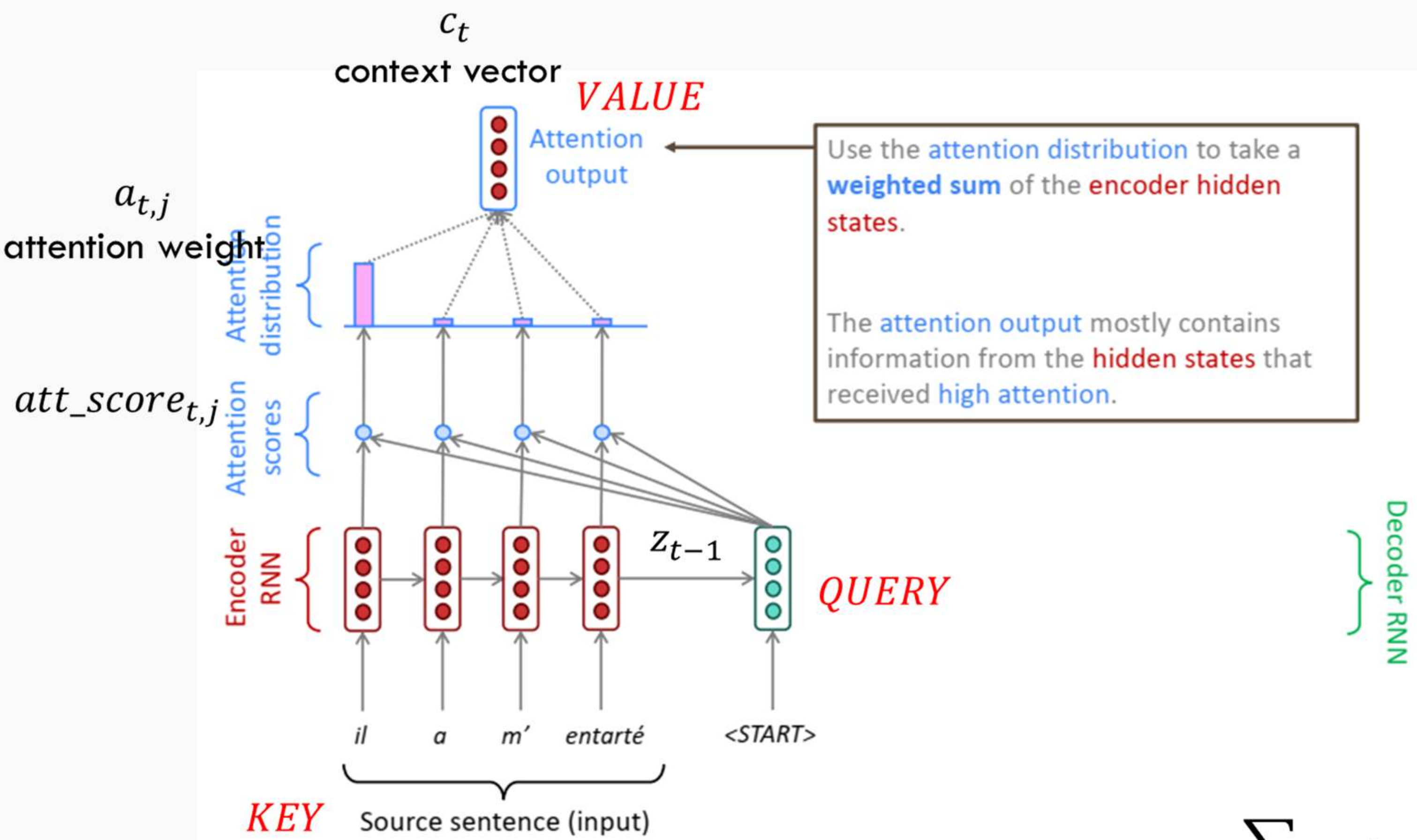



$$att\_score_{t,j} = \text{dot}(z_t, h_j)$$

$$a_{t,j} = softmax(att\_score_{t,j})$$

$$c_t = \sum_j a_{t,j} h_j$$

# Redes recurrentes - Mecanismos de atención

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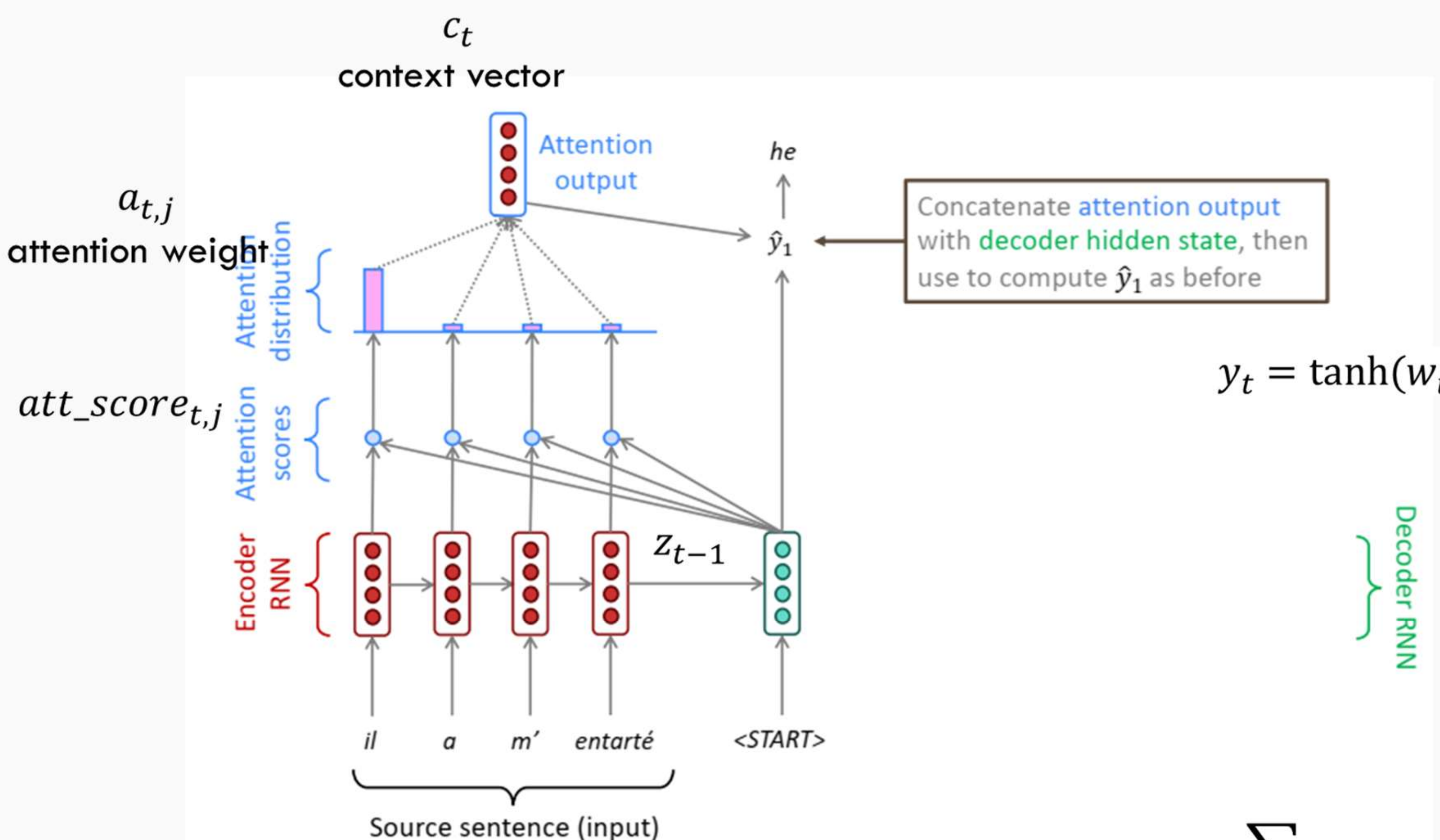
# Redes recurrentes - Mecanismos de atención




NUEVO!

$$y_t = \tanh(w_{ih}y_{t-1} + w_{hh}z_{t-1} + w_{ch}c_t)$$

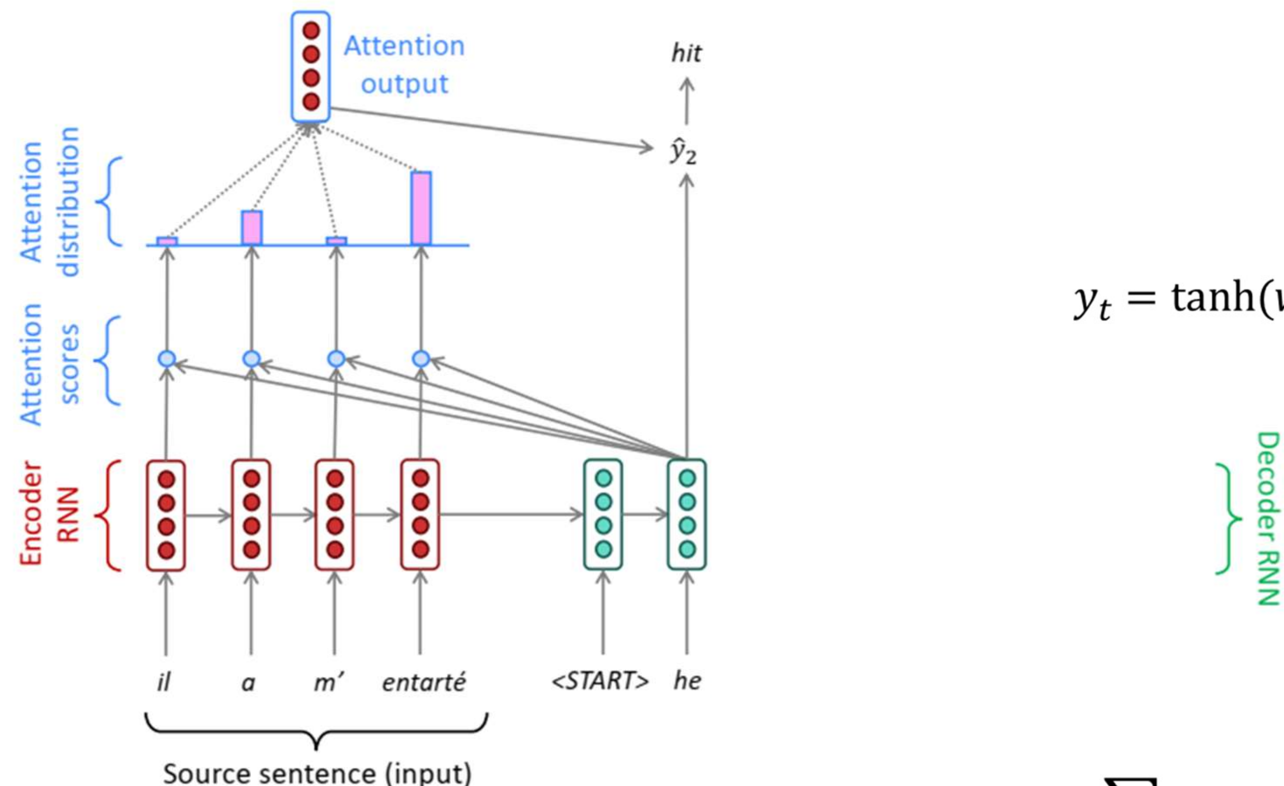
$$att\_score_{t,j} = \mathrm{dot}(z_t, h_j)$$

$$a_{t,j} = softmax(att\_score_{t,j})$$

$$c_t = \sum_j a_{t,j} h_j$$

SOLO CUENTAS!!!
NO HAY
PARAMETROS

## Redes recurrentes - Mecanismos de atención




$$y_t = \tanh(w_{ih} y_{t-1} + w_{hh} z_{t-1} + w_{ch} c_t)$$

$$att\_score_{t,j} = \mathrm{dot}(z_t, h_j)$$

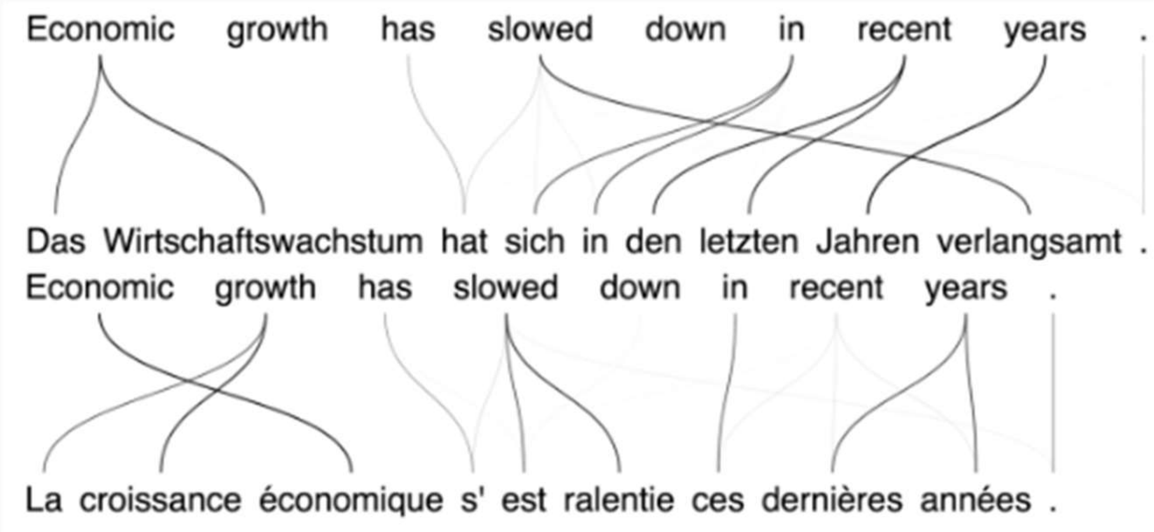
$$a_{t,j} = softmax(att\_score_{t,j})$$

$$c_t = \sum_j a_{t,j} h_j$$

## Redes recurrentes - Mecanismos de atención

Desde un punto de vista probabilístico…

el **attention weight** $a_j$ puede ser visto como la probabilidad de que el decoder use esa palabra (representación) para realizar la decodificación del contexto.




Una definición más general:

Dado un **conjunto de valores** y una **consulta**; el mecanismo de atención devuelve una **suma ponderada** (resumen selectivo) de los valores, **dependiente de la consulta**.

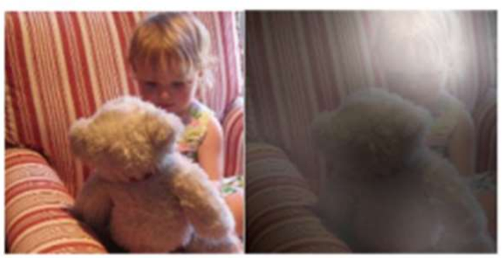
# Redes recurrentes - Mecanismos de atención

## Image Captioning with Attention

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.


A stop sign is on a road with a mountain in the background.



A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf