Recurrent Neural Networks (RNNs)

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Motivation

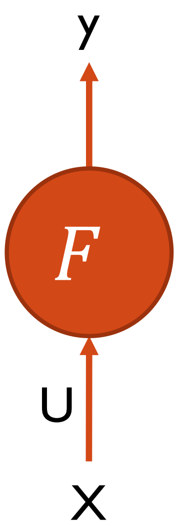
- Humans don’t start their thinking from scratch every second
  - Thoughts have persistence
- Traditional neural networks can’t characterize this phenomena
  - Ex: classify what is happening at every point in a movie
  - How a neural network can inform later events about the previous ones
- Recurrent neural networks address this issue
  - Some applications
    - NER - Naming Entity Recognition
      - Same word may have a different label depending on the context.
        - Apple CEO Tim Cook eat an apple
    - Forcasting - Time-series Prediction
- How?
  - Add state to artificial neurons

What are RNNs?

- Main idea is to make use of sequential information
- How RNN is different from neural network?
  - Vanilla neural networks (MLP) assume all inputs and outputs are independent of each other
  - But for many tasks, that's a very bad idea
- What RNN does?
  - Perform the same task for every element of a sequence (that's what recurrent stands for)
  - Output depends on the previous computations!
- Another way of interpretation – RNNs have a "memory"
  - To store previous computations

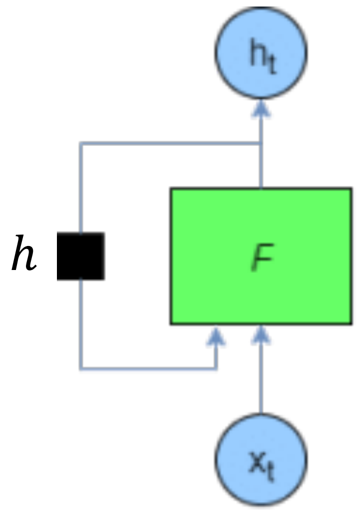
From vanilla NN to recurrent NN

- Vanilla cell
  - $y = F(U.X)$



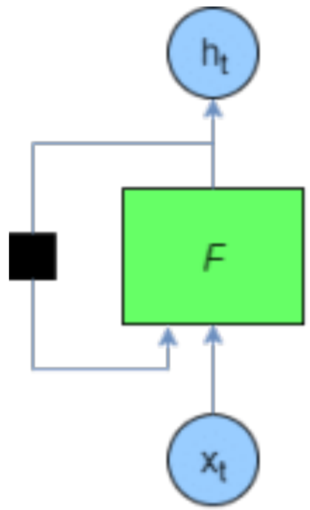
From vanilla NN to recurrent NN

- Vanilla cell
  - $y = F(U.X)$
- Recurrent cell → use 2 weights matrix
  - Add an internal variable: h
  - The output depends to the current entry and the previous internal variable:
    - $h_t = F(W.h_{t-1} + U.Xt)$
    - Could be rewritten on $h_t = F(W.[h_{t-1}, Xt])$



From vanilla NN to recurrent NN

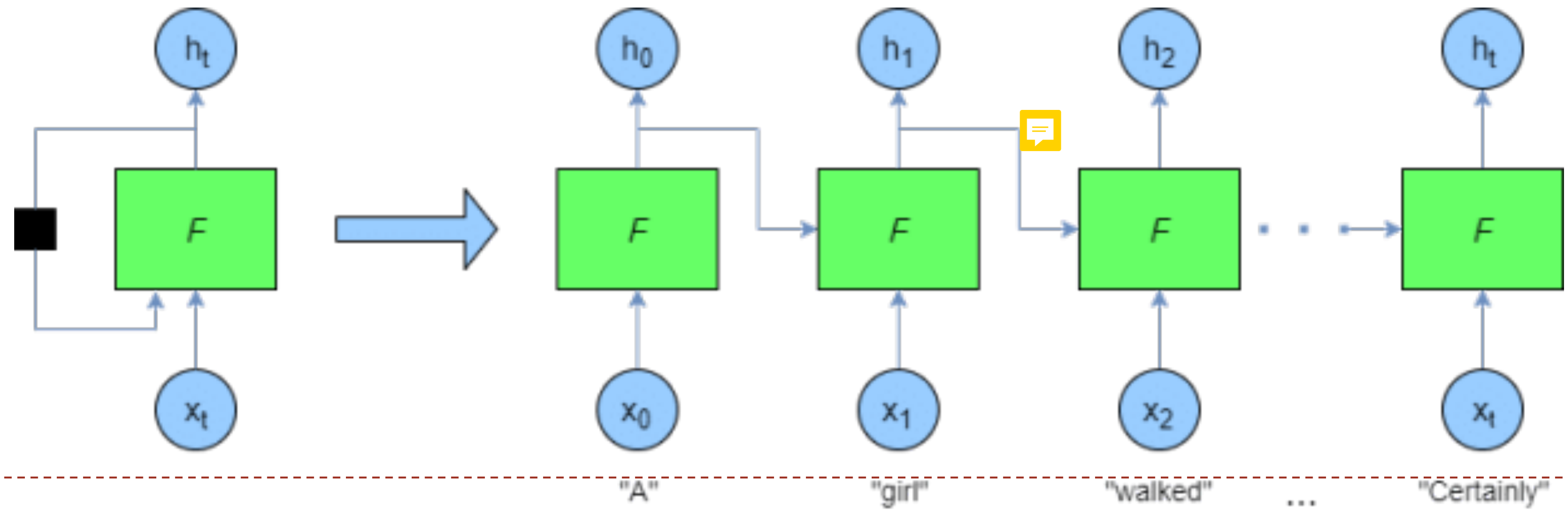
- Vanilla cell
  - $y = F(U.X)$
- Recurrent cell → use 2 weights matrix
  - $h_t = F(W.[h_{t\,-\,1}, X_t])$
- Recurrent layer, step by step
  - at each time step
    - A new entry is being supplied
    - And a new output (h_t) is calculated using:
      - □ The new input X_t
      - □ The output of the previous step $h_{t\,-\,1}$



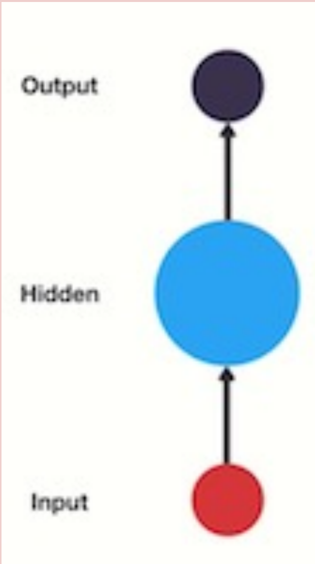
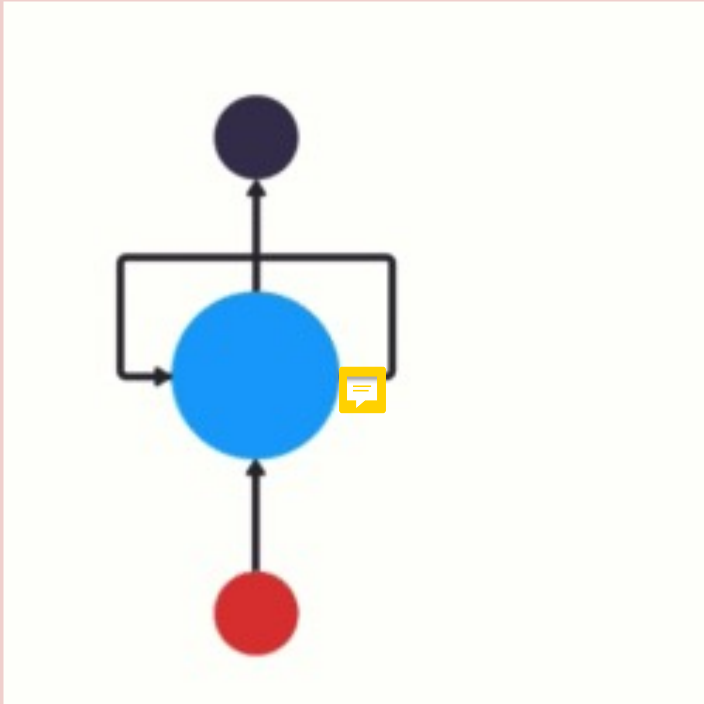
- $h_1 = F(W.[h_0, X_1])$
- $h_2 = F(W.h_1, X_2])$
- $h_3 = F(W.h_2, X_3])$
- …

From vanilla NN to recurrent NN

- Vanilla cell
  - $y = F(U.X)$
- Recurrent cell
  - $h_t = F(W.[h_{t\ -\ 1}, X_t])$
- Recurrent neural networks are "unrolled" programmatically during training and prediction
  - All neurons share the same weight matrix

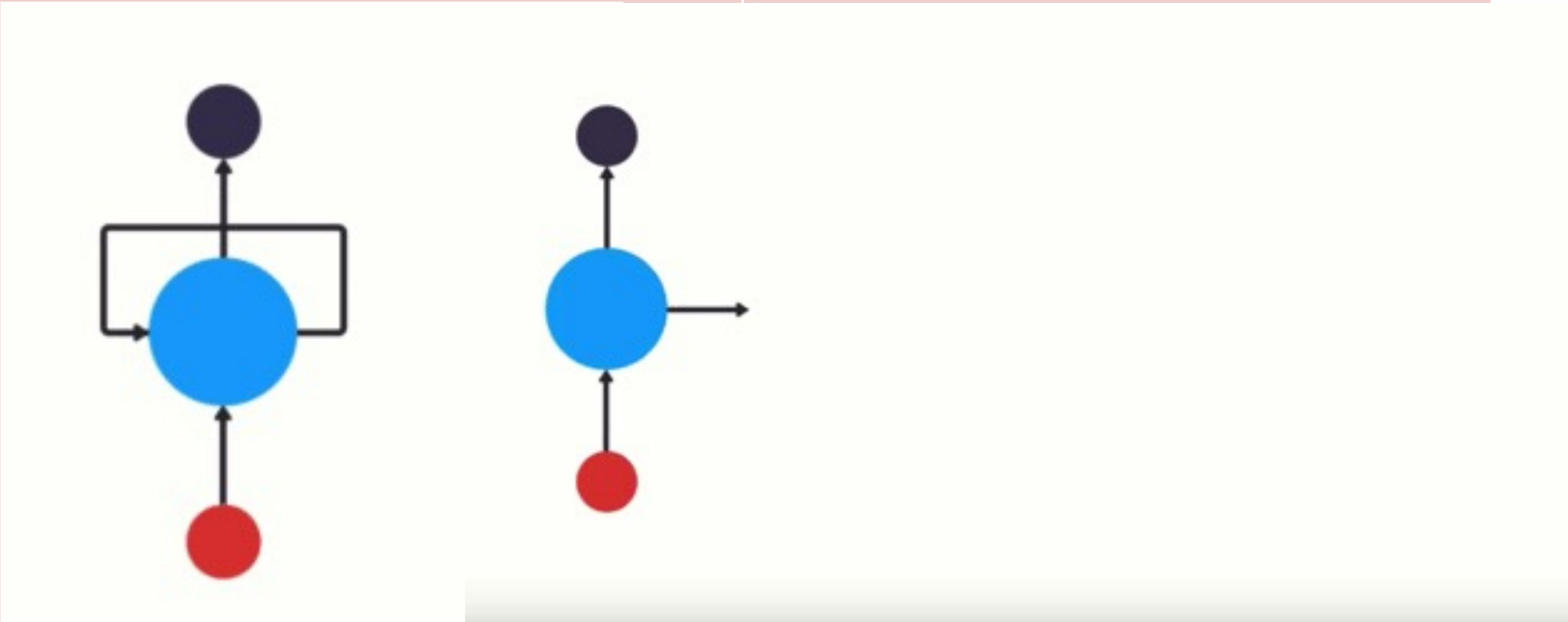


Remember

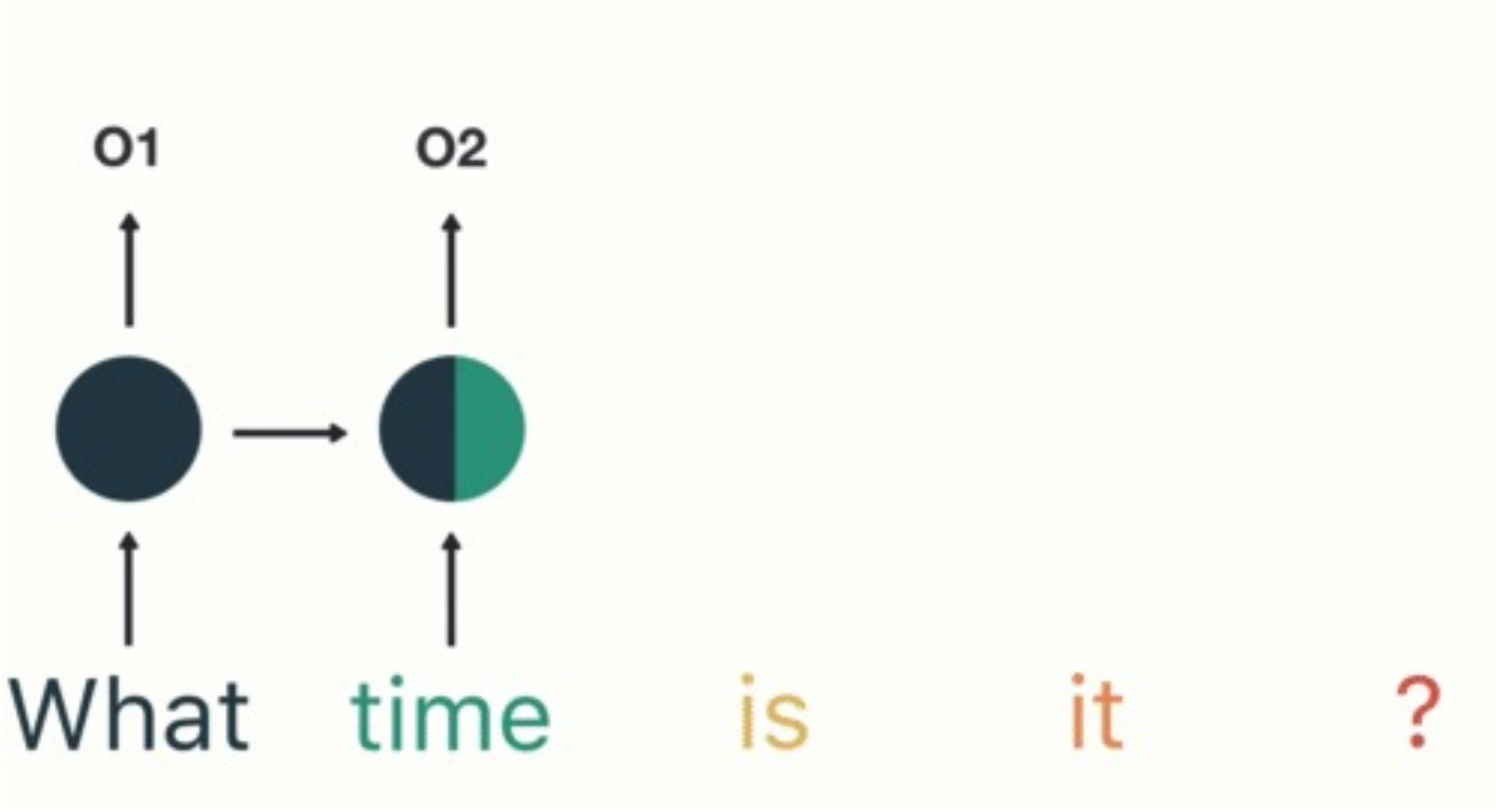
From	To
	

Remember

From	To

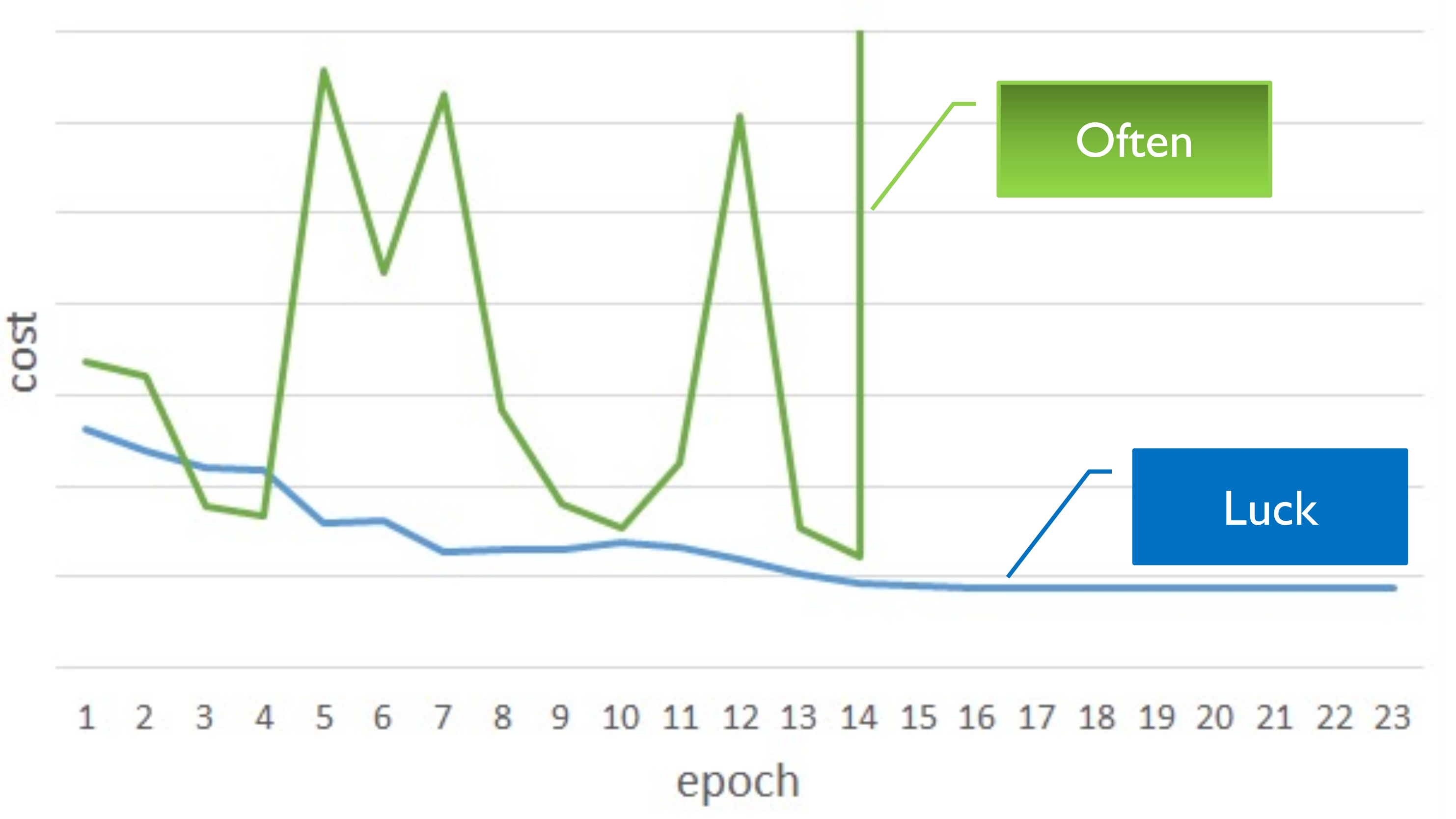


RNN in action



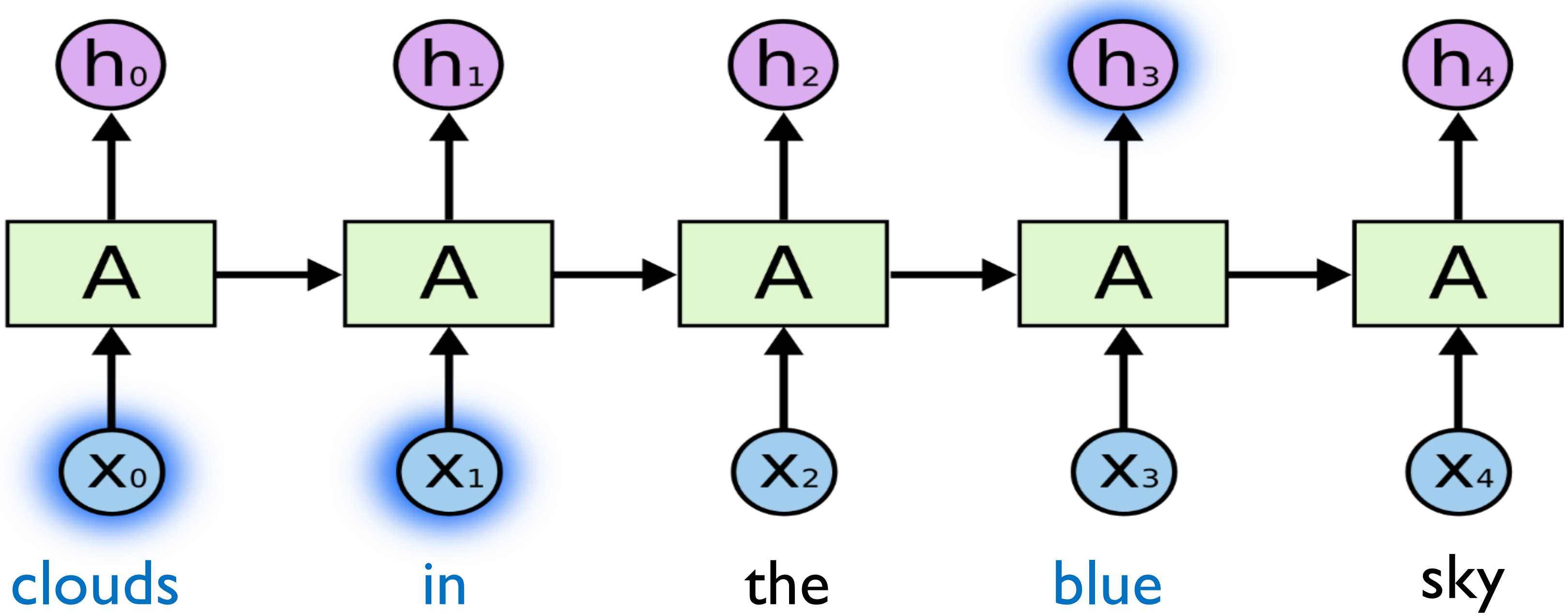
Problems with naive RNN

- RNNs do not learn easily
- Unfolding the network for learning leads to vanishing gradient problems!



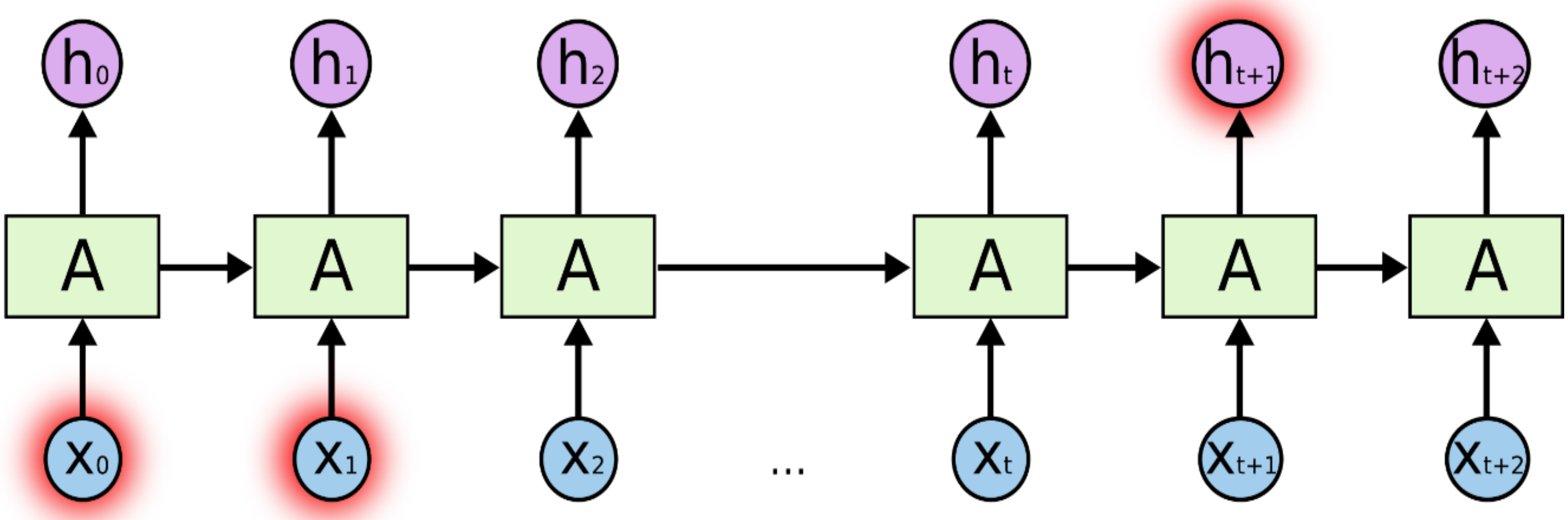
From vanilla RNN…

- The context is close to the word to be predicted
  - Few iterations separate them.
  - No problem



… to LSTM (Long Short Term Memory)

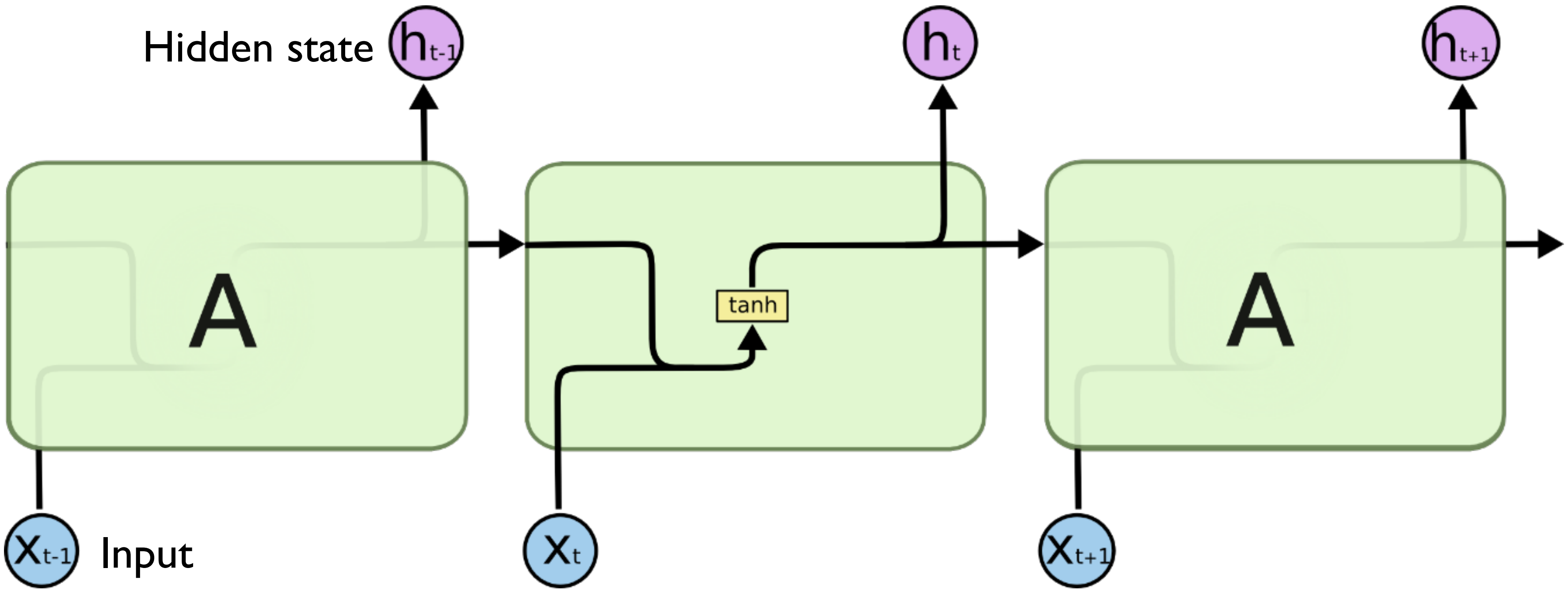
- The context is far from the word to predict
  - Many iterations separate them!
  - Possible gradient problem



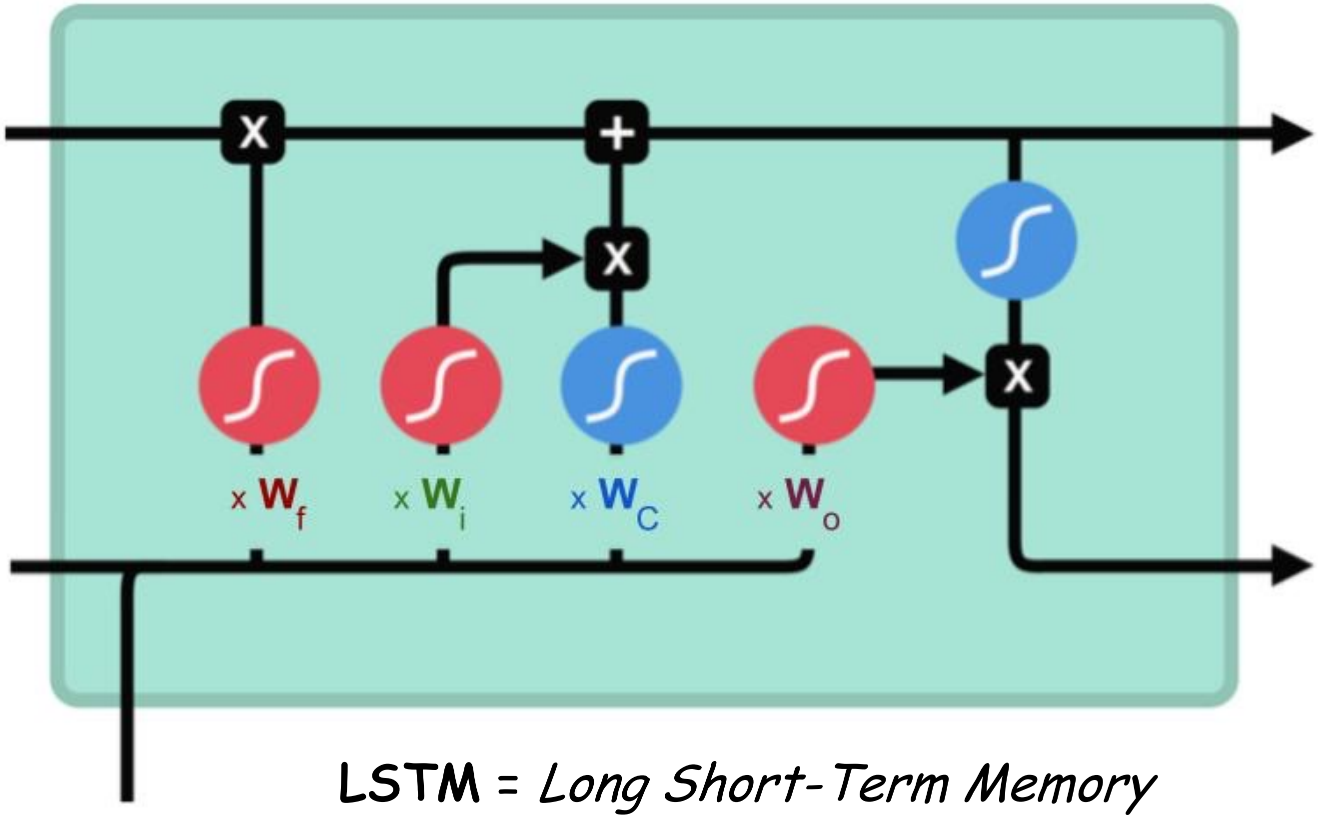
I grew up in France… I speak French…

From Vanilla to LSTM Cells

- It is necessary to prevent the gradient from disappearing...
- Normally, the network memory is
  - $h_t = tanh(W \square [h_{t-1}, xt])$
  - Involves a single level of processing
  - Creating the risk of the evanescent gradient.



Dealing with the vanishing gradient problem → LSTM cell



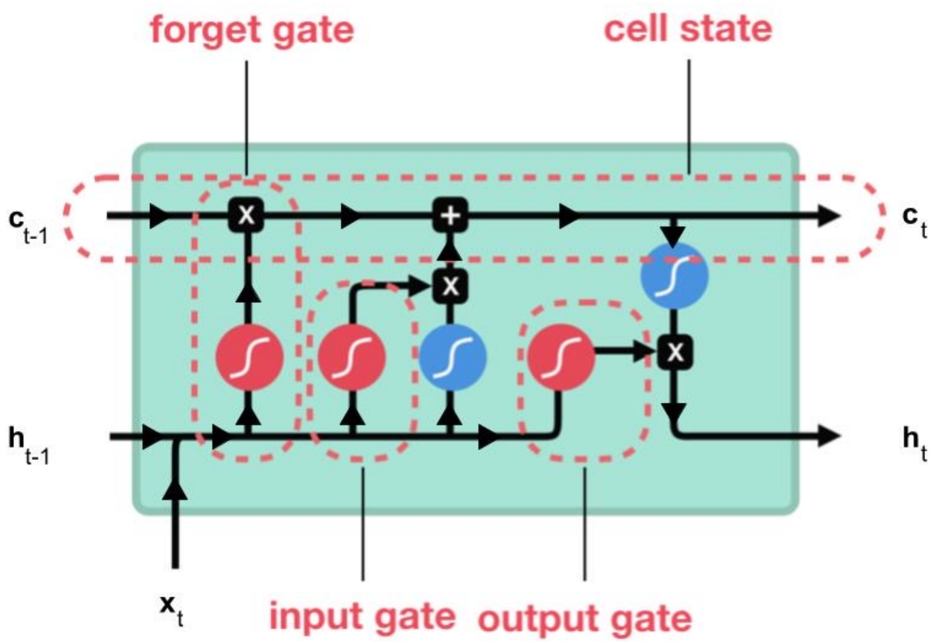
LSTM = *Long Short-Term Memory*

(crédit : image modifiée de Michaël Nguyen)

LSTM cell

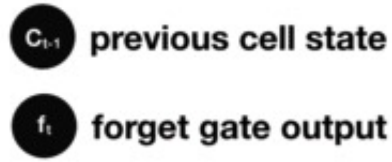
- Cellule composée de trois “portes” : ce sont des zones de calculs qui régulent le flot d’informations (en réalisant des actions spécifiques)
  - Forget gate (porte d’oubli)
  - Input gate (porte d’entrée)
  - Output gate (porte de sor

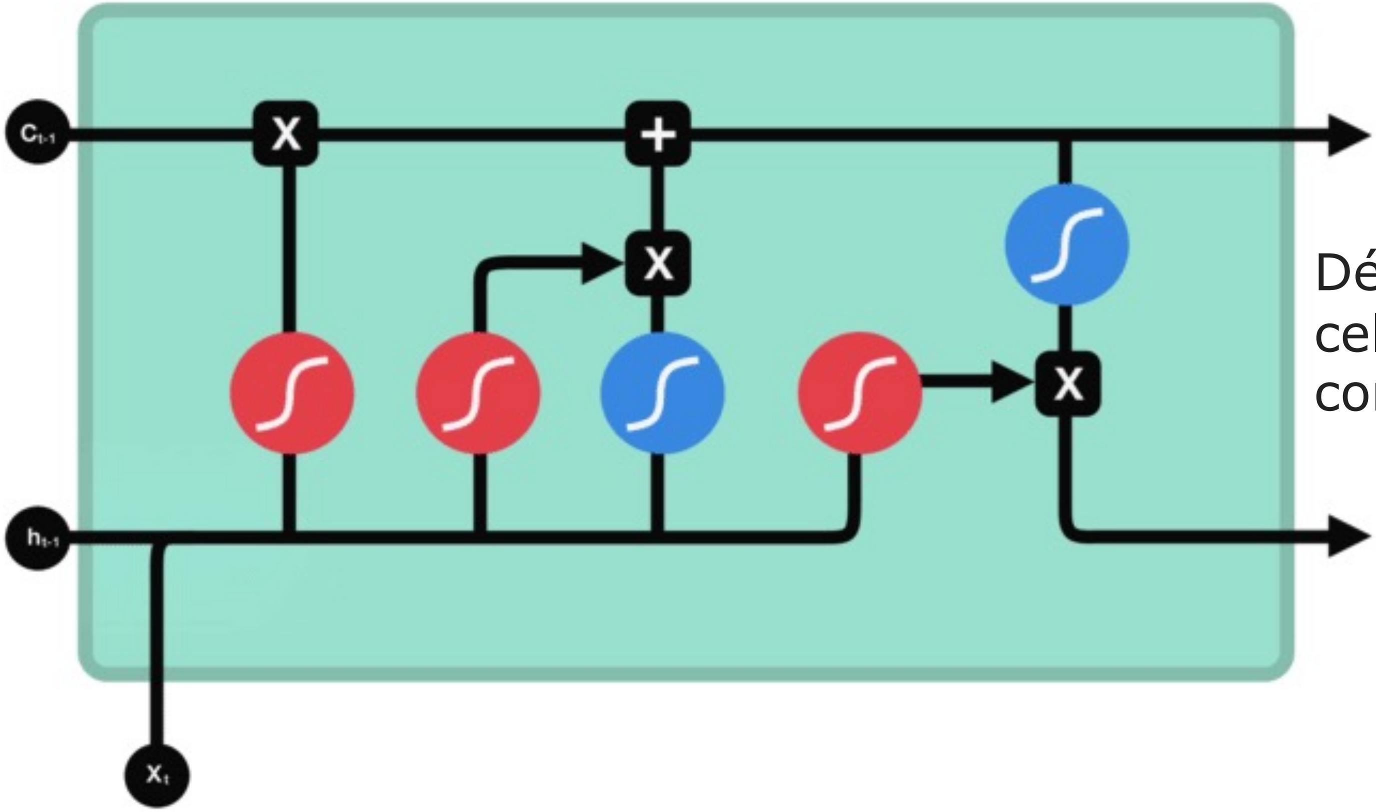
- Hidden state (état caché)
- Cell state (état de la cellul
  - Like residual



(crédit : image modifiée de Michaël Nguyen)

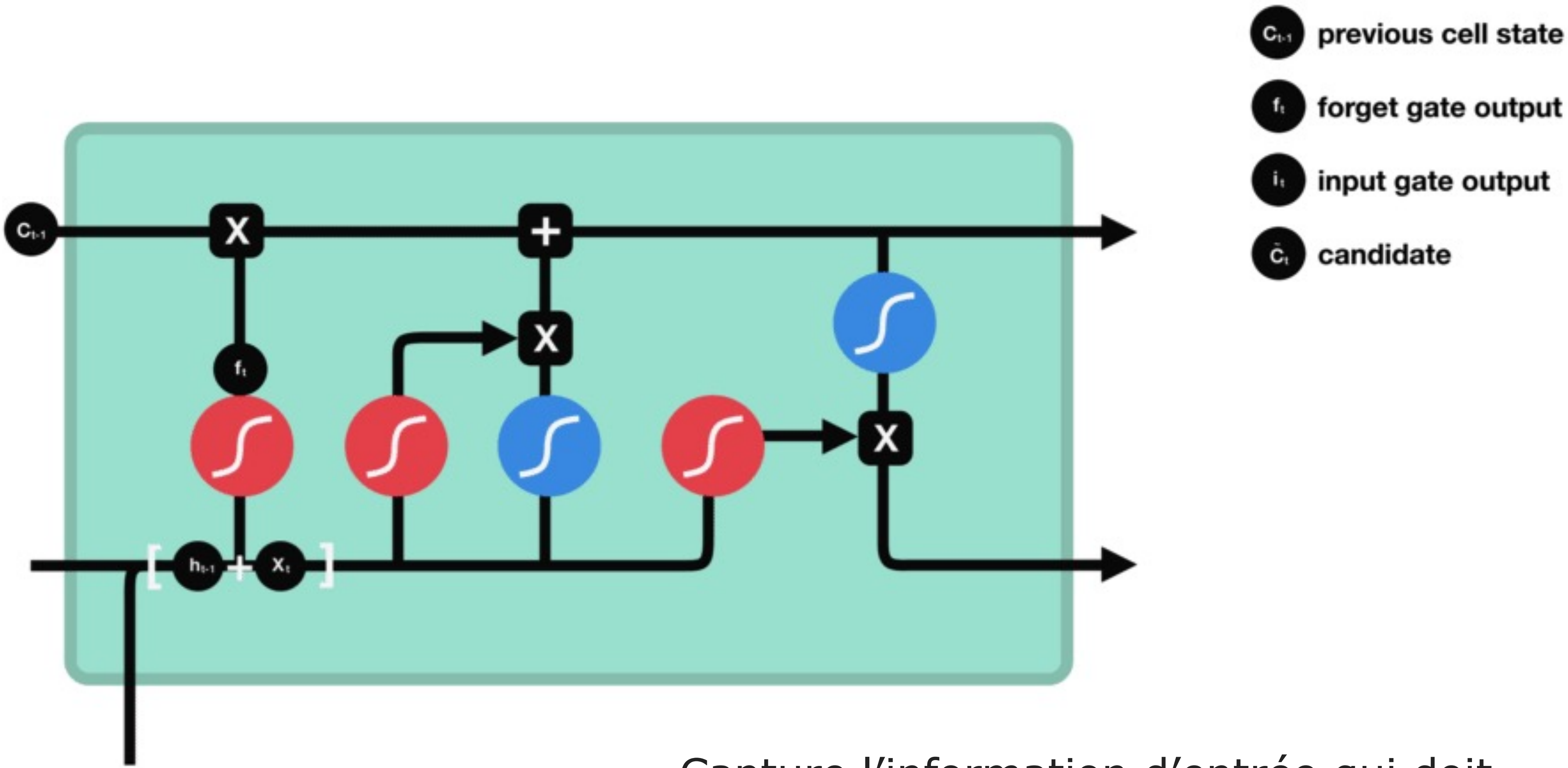
LSTM cell (porte oubli / forget get)





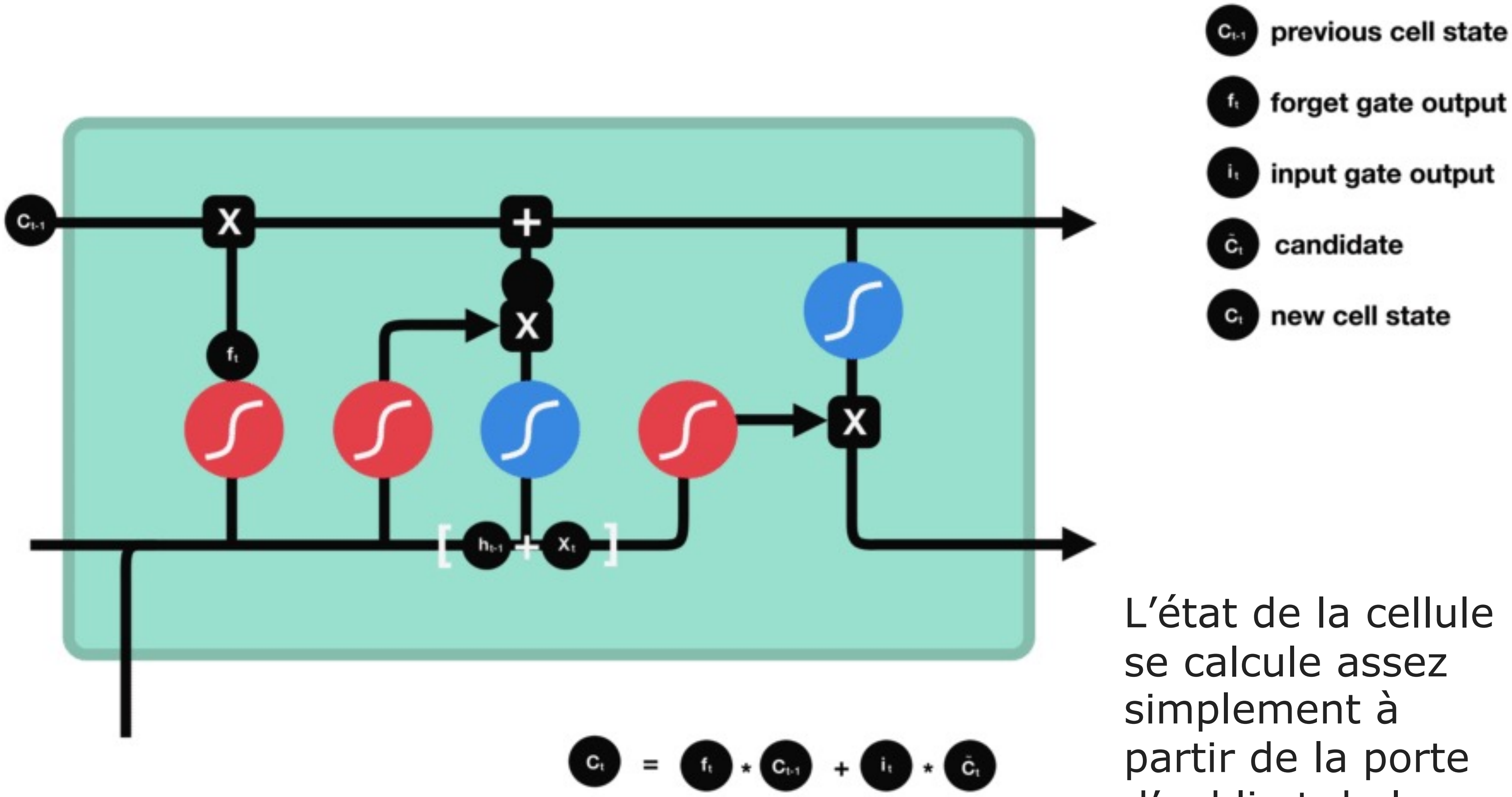
Décide si l’état de la cellule doit être conservé ou non.

LSTM cell (porte entrée / input get)



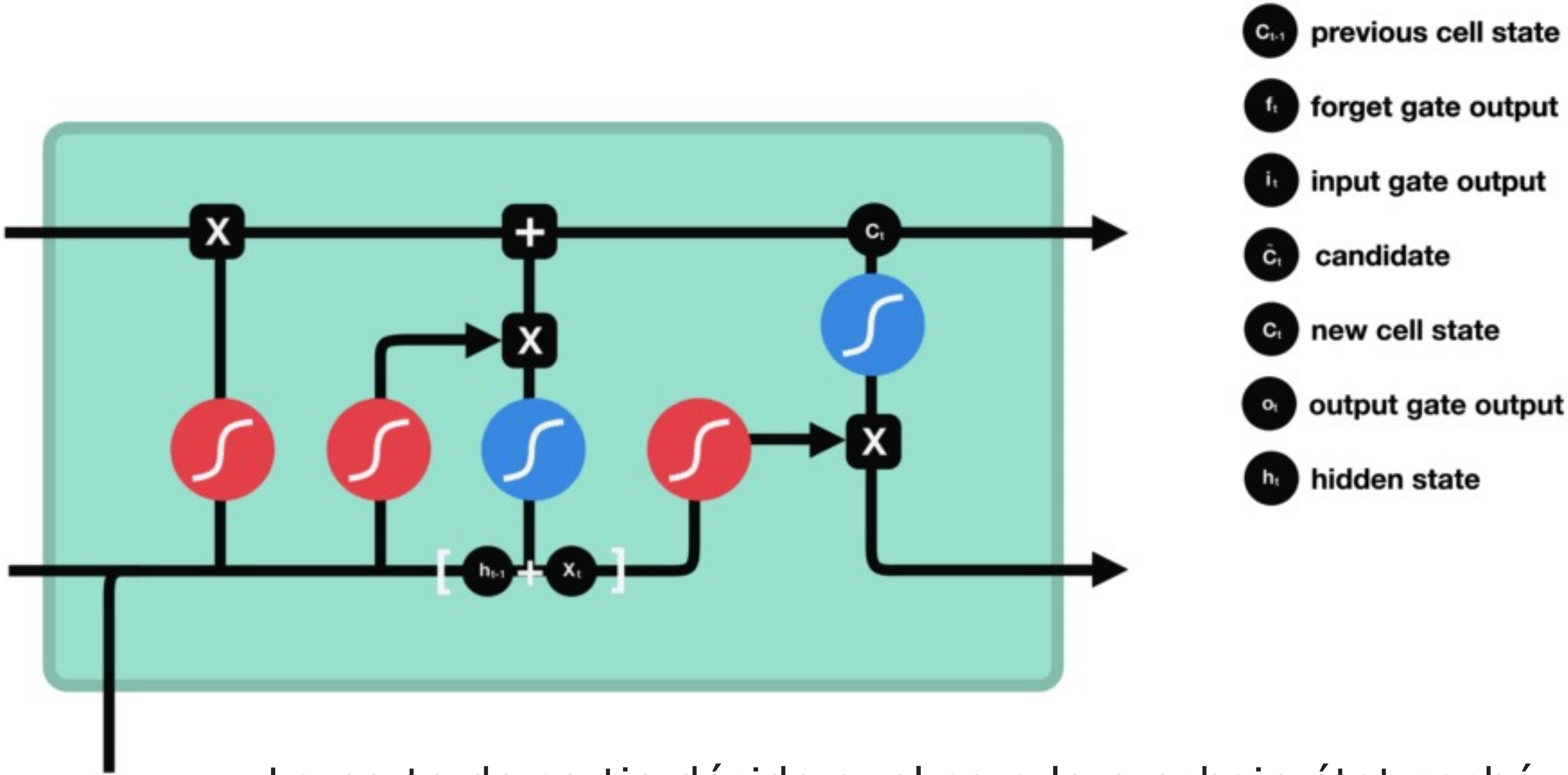
Capture l'information d'entrée qui doit être incluse dans l'état de la cellule

LSTM cell (état de la cellule / cell state)



L’état de la cellule se calcule assez simplement à partir de la porte d’oubli et de la porte d’entrée

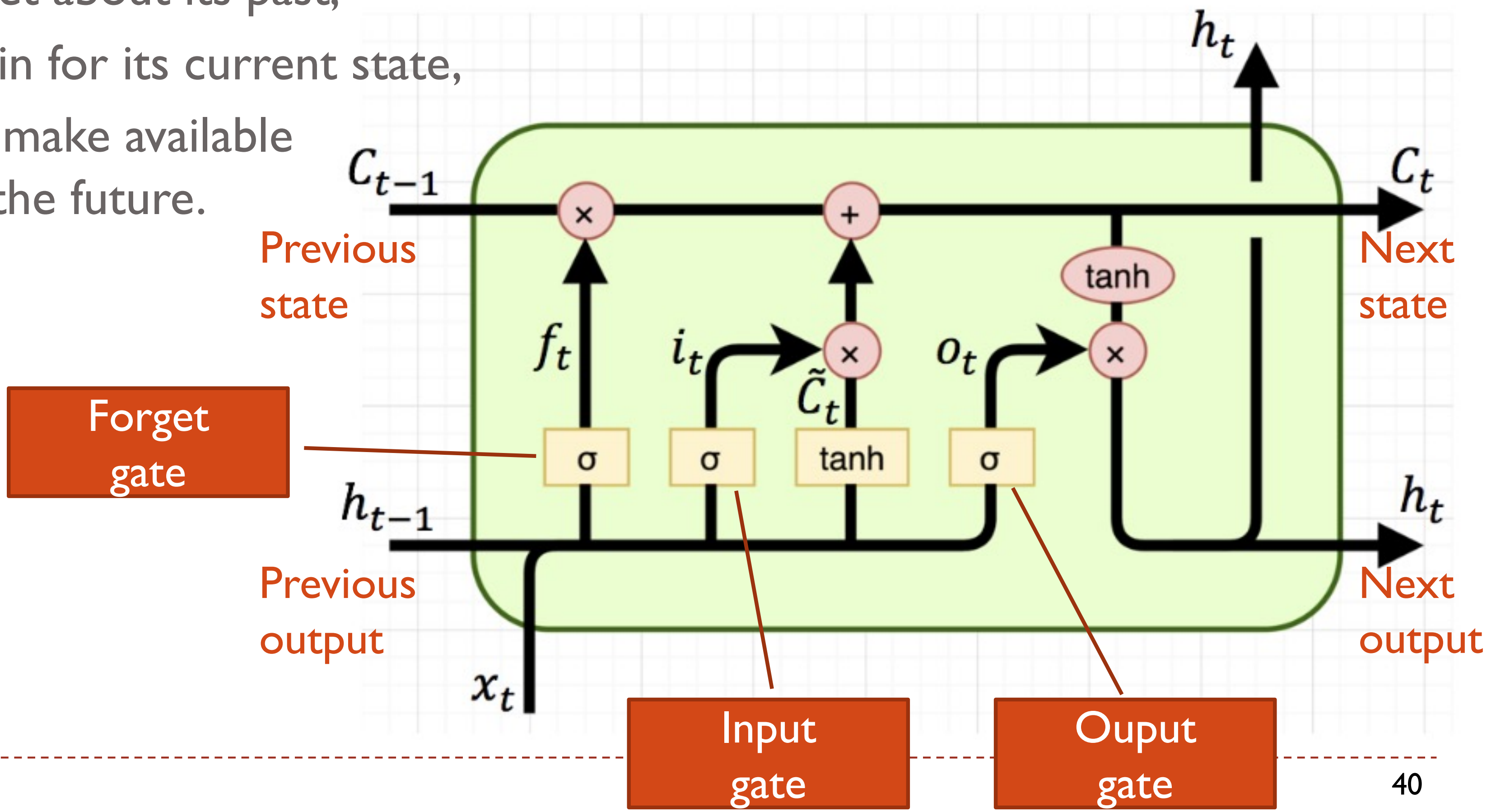
LSTM cell (porte de sortie / output gate)



La porte de sortie décide quel sera le prochain état caché. Il contient des informations sur les entrées précédentes du réseau et sert aux prédictions.

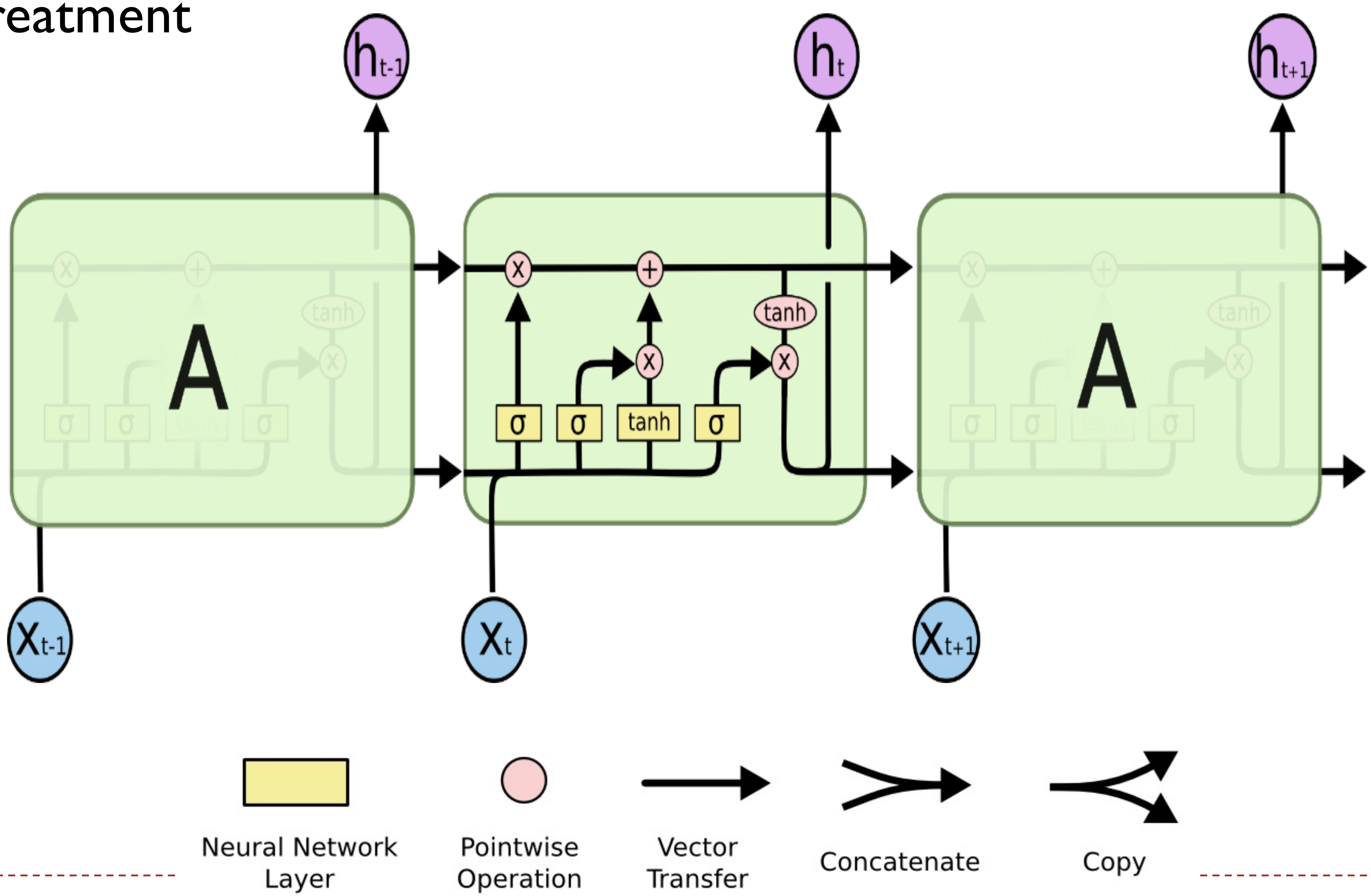
LSTM Cells

- Adds a context memory that affects the information flow and its processing (cell state).
- Three gates decide what a cell should
  - forget about its past,
  - retain for its current state,
  - and make available for the future.



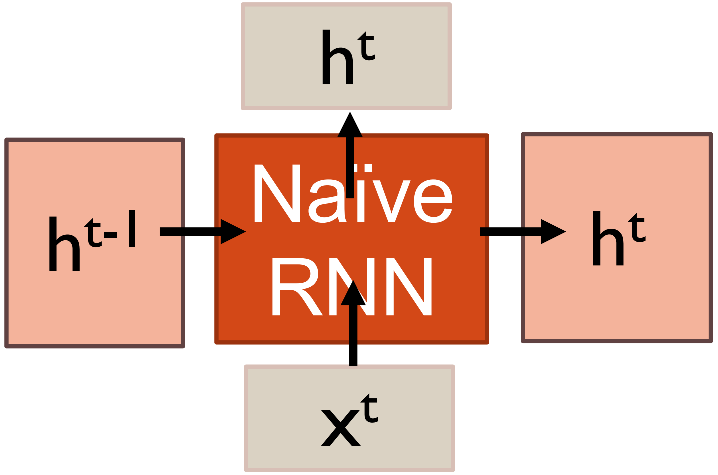
LSTM Cells

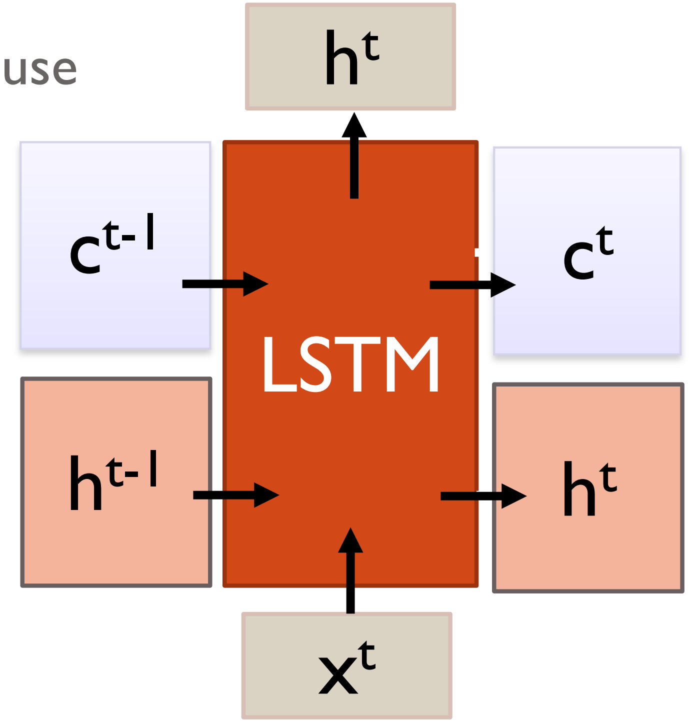
- Concretely, recurrence in an LSTM cell involves 4 levels of treatment



Naïve RNN vs LSTM

- Naïve RNN
  - Reuse at each step the previous output
- LSTM
  - At each step 3 gate control the use use of Input value, Cell state and previous output



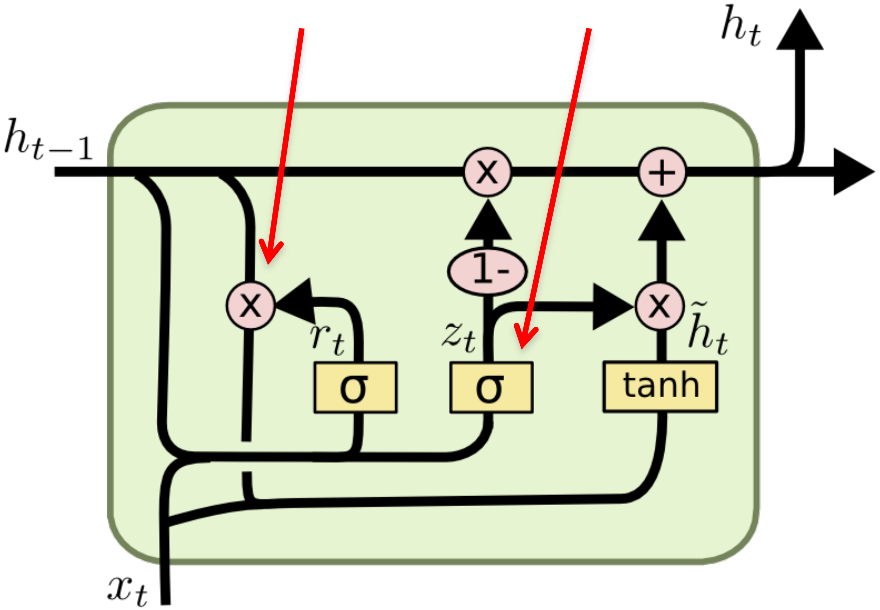


c changes slowly → c^t is c^{t-1} added by something

h changes faster → h^t and h^{t-1} can be very different

GRU – gated recurrent unit

- GRU = a light LSTM Cell



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

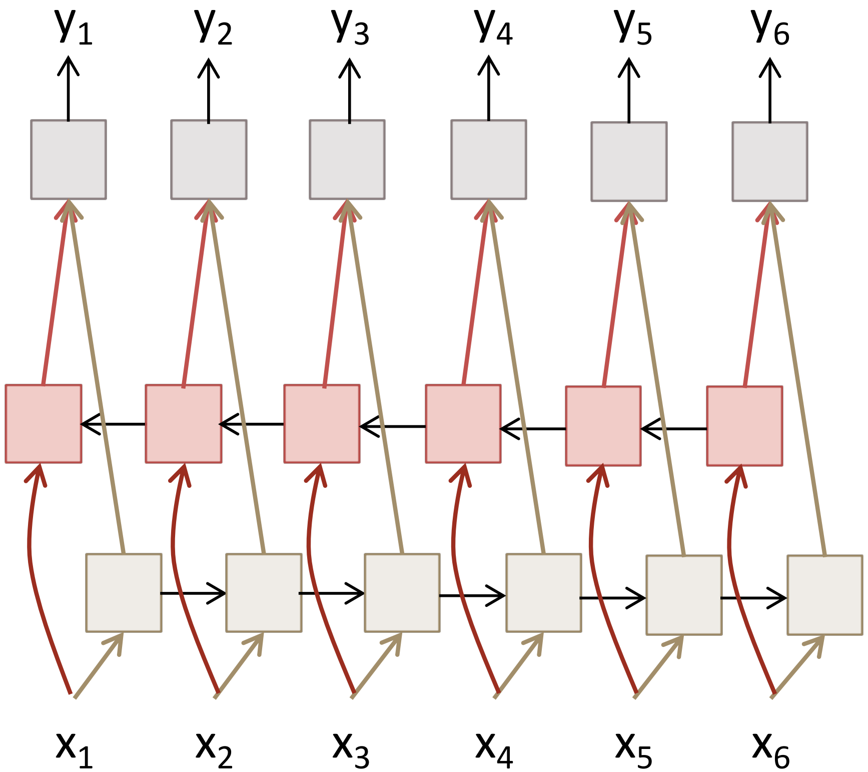
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- It combines the forget and input into a single update gate.
- It also merges the cell state and hidden state.

→ This is simpler than LSTM.

Bi-directional RNNs

- RNNs can process the input sequence in forward and in the reverse direction



- Popular in speech recognition, could be used also with text

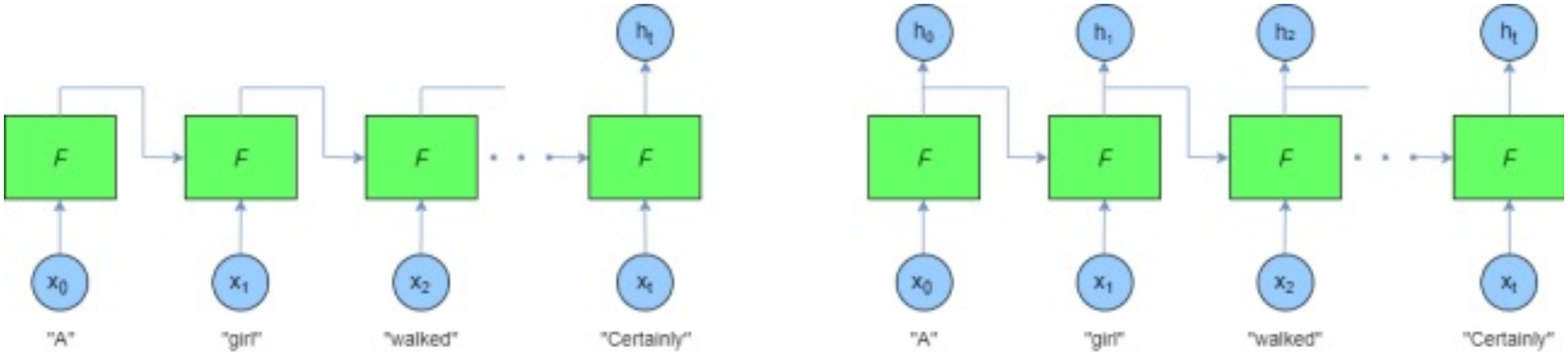
RNN cell in Keras

Keras Long Short-Term Memory Cell

- **from** tf.keras.layers **import** LSTM

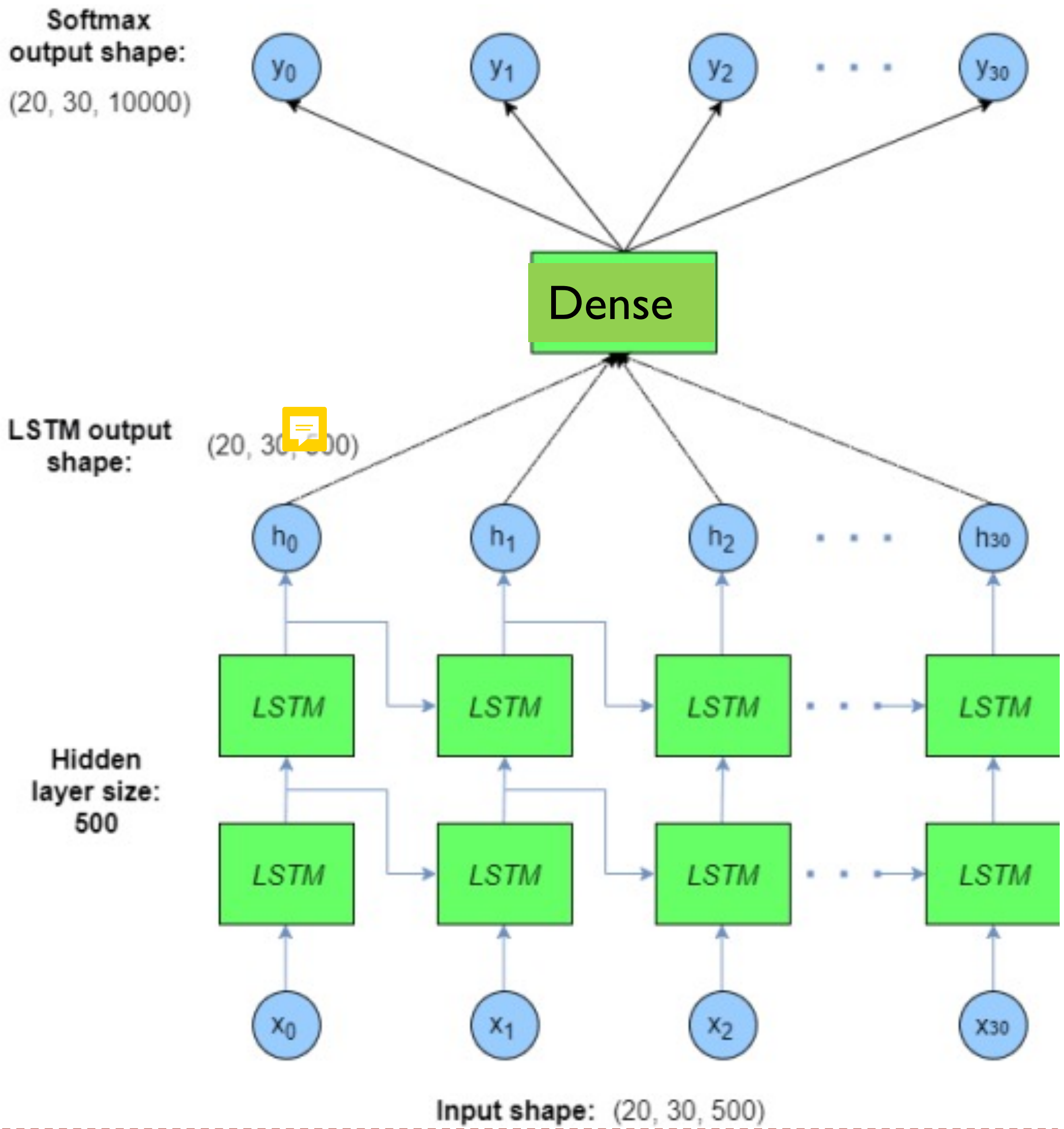
- Main params
  - **Units:** dimension of output space

  - **return_sequences:** True or False
    - If False return only the last output
    - If True return the full sequence of the output sequence
      - Output sequence = hidden state (the vocabulary change regardind documentation)
  - **return_state**: True or False
    - If True return 3 values
      - The full output sequence or only the last one (depend on return_sequences)
      - The last output sequence
      - The cell state
    - If False return nothing
  - **stateful**: True or False
    - If True, the last state for each sample at index i in a batch will be used as initial state for the sample of index i in the following batch.
    - You have to put shuffle=False in a fit method



return_sequences = False   *return_sequences = True* with return_sequences=False, Dense layer is applied only once at the last cell

If return_sequences=True Dense layer is applied to every timestep



Keras Gated Recurrent Unit Cell

- **from** keras.layers **import** GRU

- Main params (similar to LSTM)
  - **Units:** dimension of output space

  - **return_sequences:** True or False
    - If False return only the last output
    - If True return the full sequence of the output sequence
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  - **return_state**: True or False
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A basic example

- inputs = Input(shape=(SEQUENCE_SIZE,))

- embedding = Embedding(VOCABULARY_SIZE,
  EMBEDDING_SIZE,
  input_length=SEQUENCE_SIZE)(inputs)

- output = LSTM(16, return_sequences=False,
  activation='relu')(embedding)
- predictions = Dense(nb_classes,
  activation='softmax')(output)

- Fit by batch
  - Model.fit(X, y, ….). ← all item have the same length
- Fit by item
  - For i in range(len(X)): ← could be different length
    - Model.fit(X[i], y[i], …)

Some use of RNN
→ Text Classification / Sentiment analysis

Affect a label to a text

- Classify a
  - restaurant review from Yelp!
  - movie review from IMDB

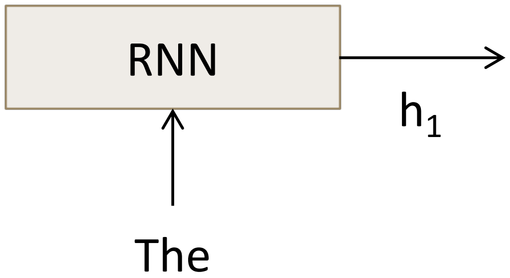
  …

  as positive or negative

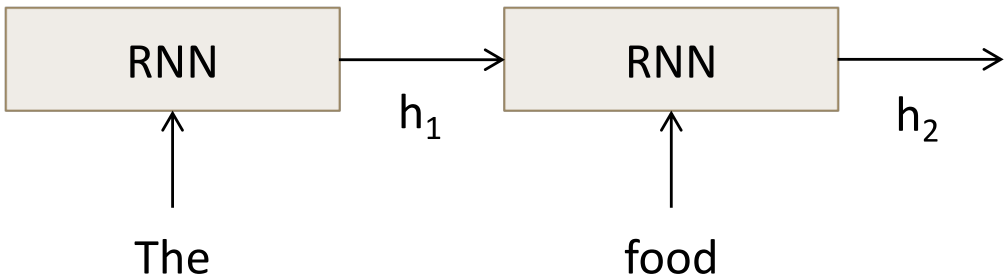
- Inputs:
  - Multiple words, one or more sentences
- Outputs:
  - Positive / Negative classification

- "The food was really good"
- "The chicken crossed the road because it was uncooked"

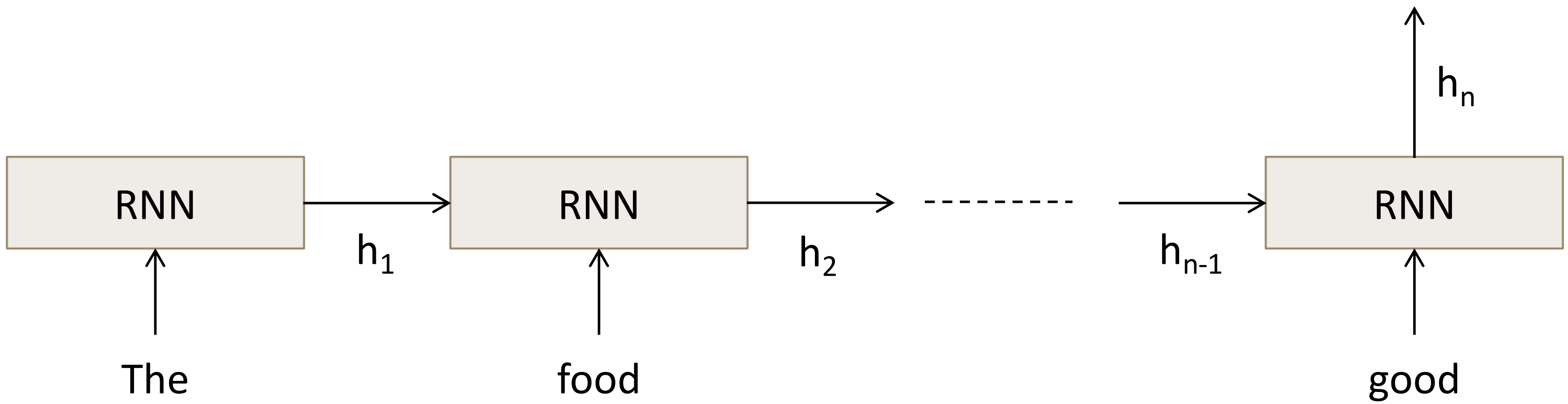
Sentiment analysis



Sentiment analysis

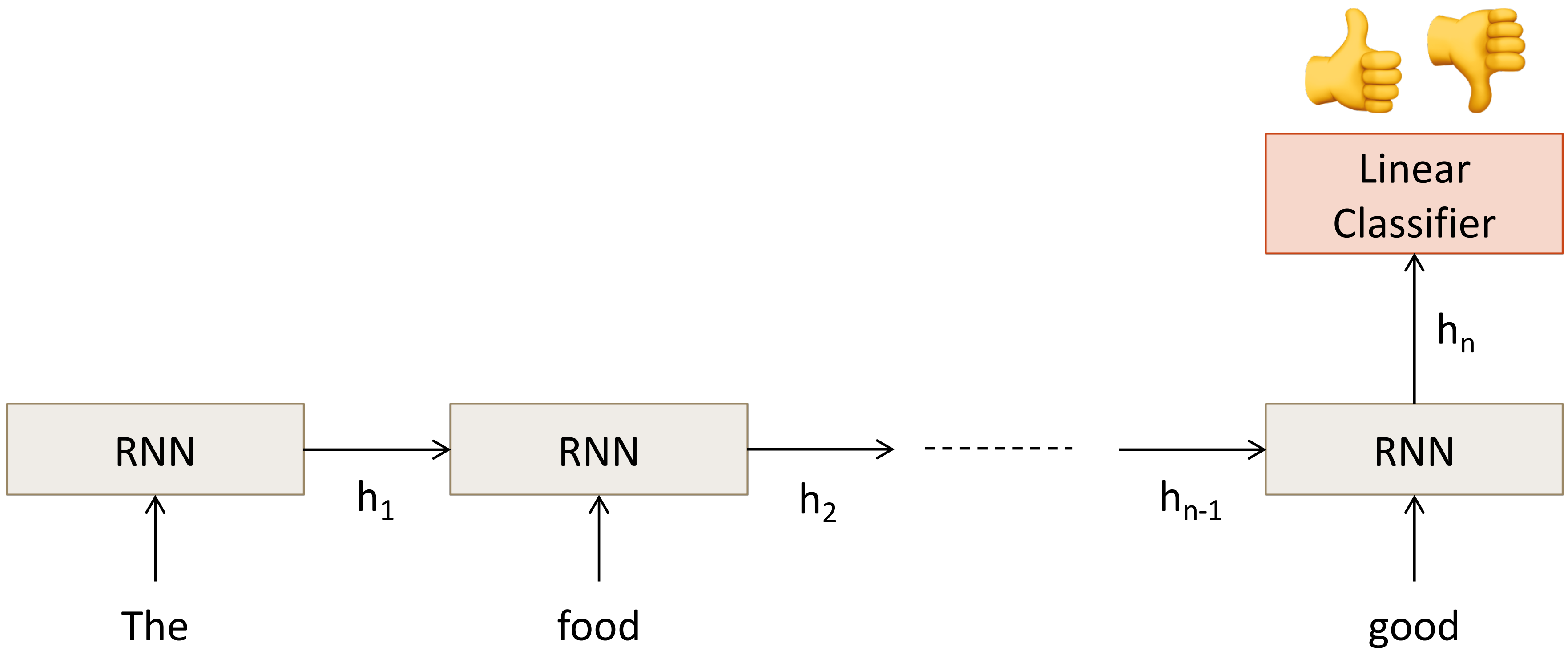


Sentiment analysis



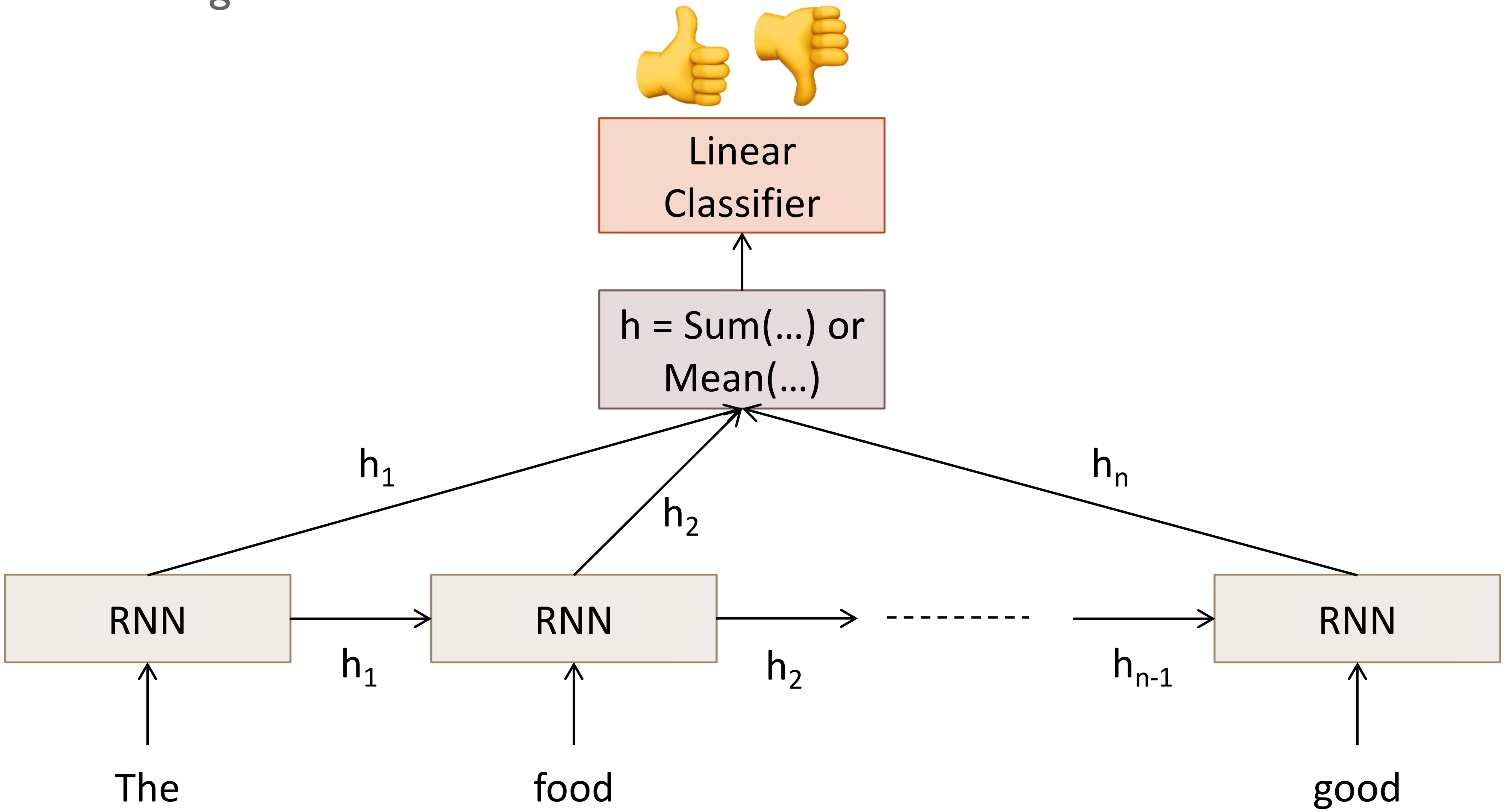
Sentiment analysis - solution 1

- retrieve only the last state



Sentiment analysis – solution2

- Other possible architecture
  - Average all the internal state

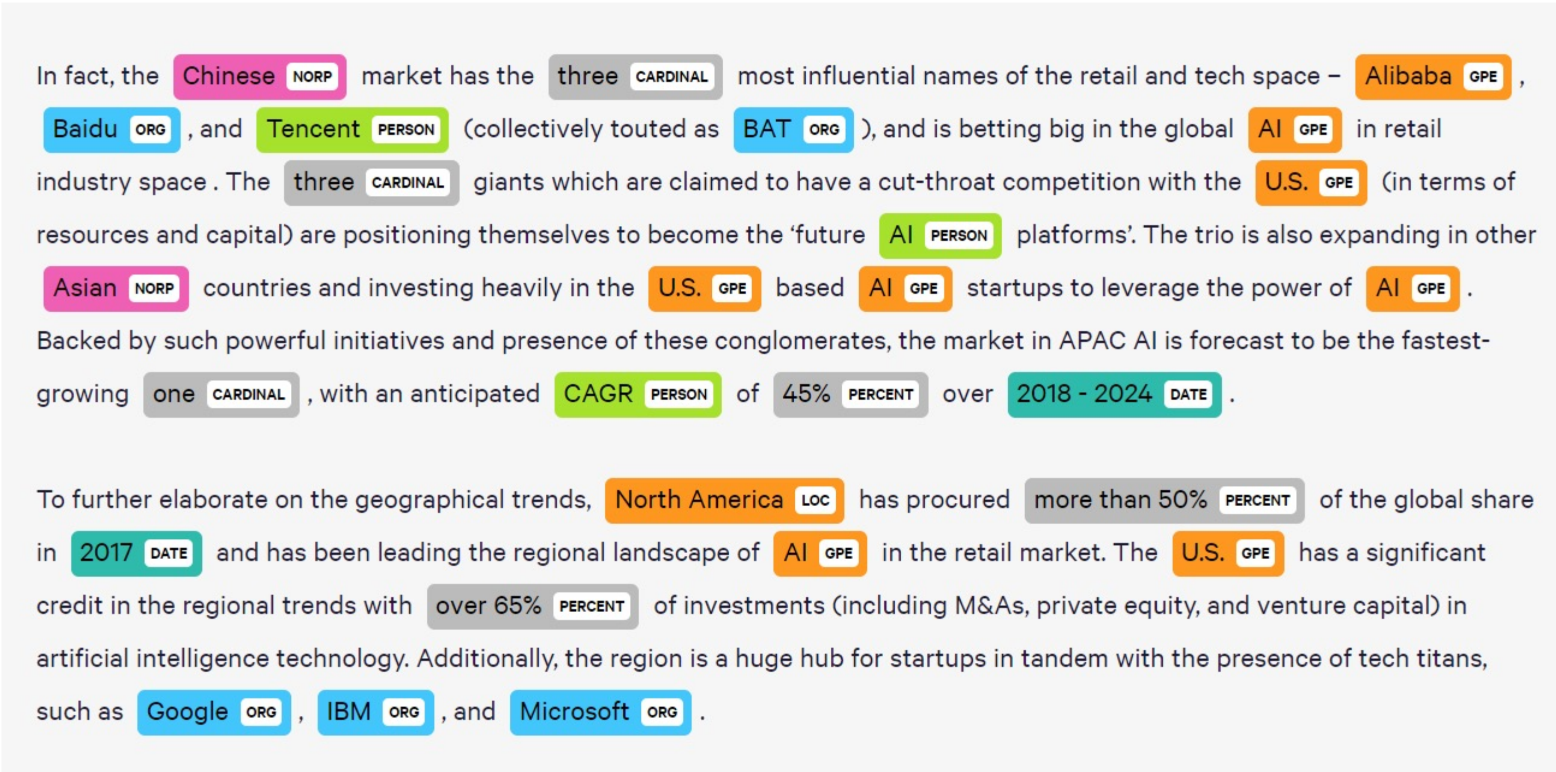


http://deeplearning.net/tutorial/lstm.html

Some use of RNN

→ Named Entity Recognition / Part of Speech Tagging

- Affect a label to each word
  - **find** and **classify** names in text
    - Could bean entity : number, country, person, … (NER)
    - Could be a function : noun, verb, adverbs, … (POS)



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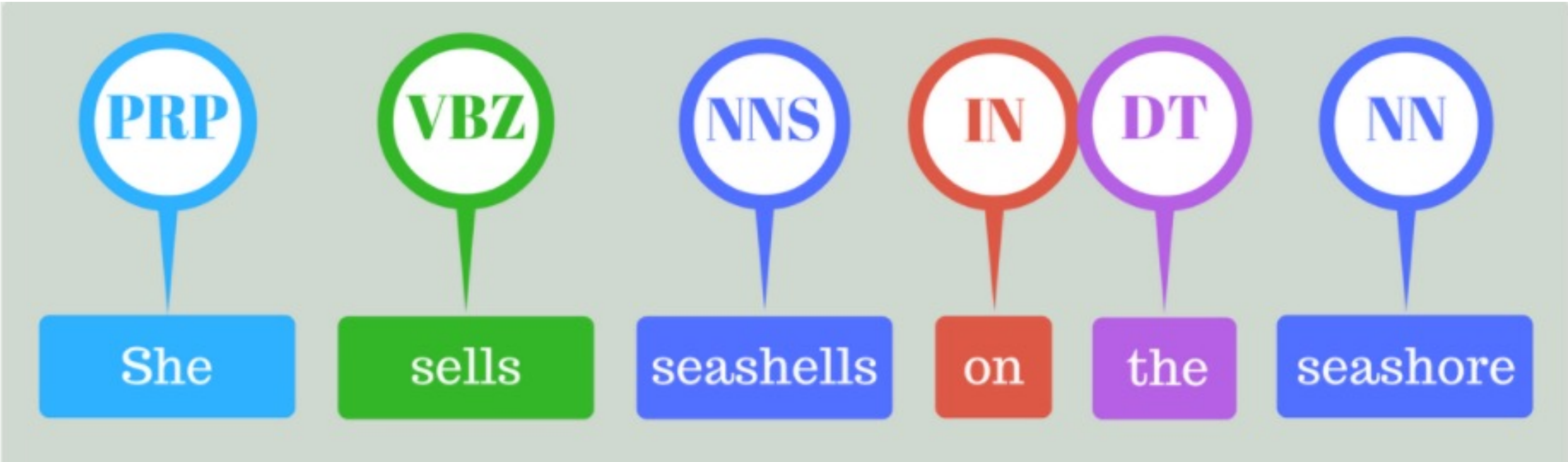

Label representation – BIO tags

- Labels can be for words or groups of words
  - Adam Smith works for IBM , London .
- To represent this, a "BIO" representation is generally used.
  - B beginning of an entity
  - I continues the entity
  - O word outside the entity
- For example
  - [‘Adam’, ‘Smith’, ‘works’, ‘for’, ‘IBM’, ‘,’, ‘London’, ‘.’]
  - Without BIO: [PER, PER, O, O, ORG, O, GEO, O]
  - With BIO: [B_PER, I_PER, O, O, B_ORG, O, B_GEO, O]

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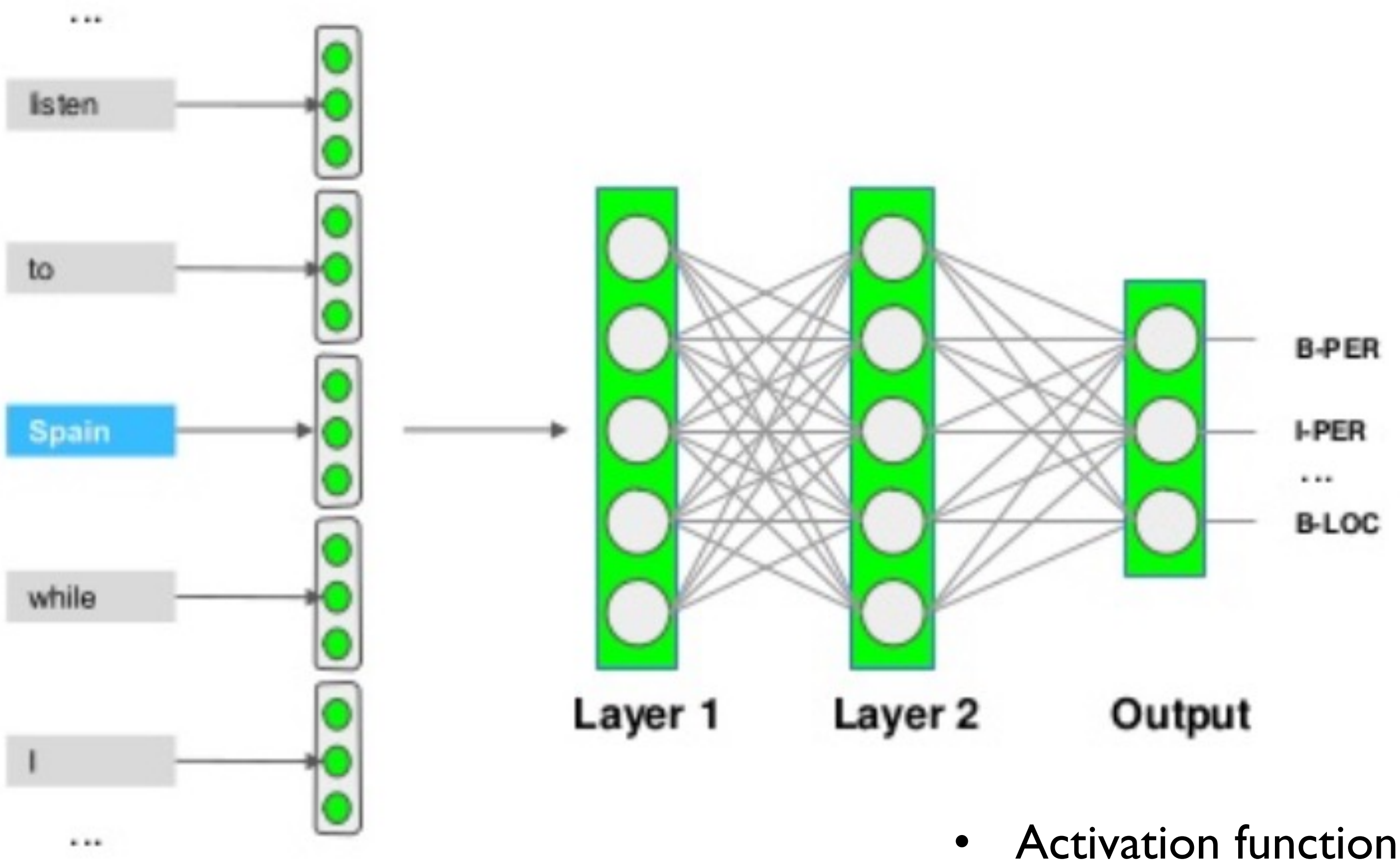
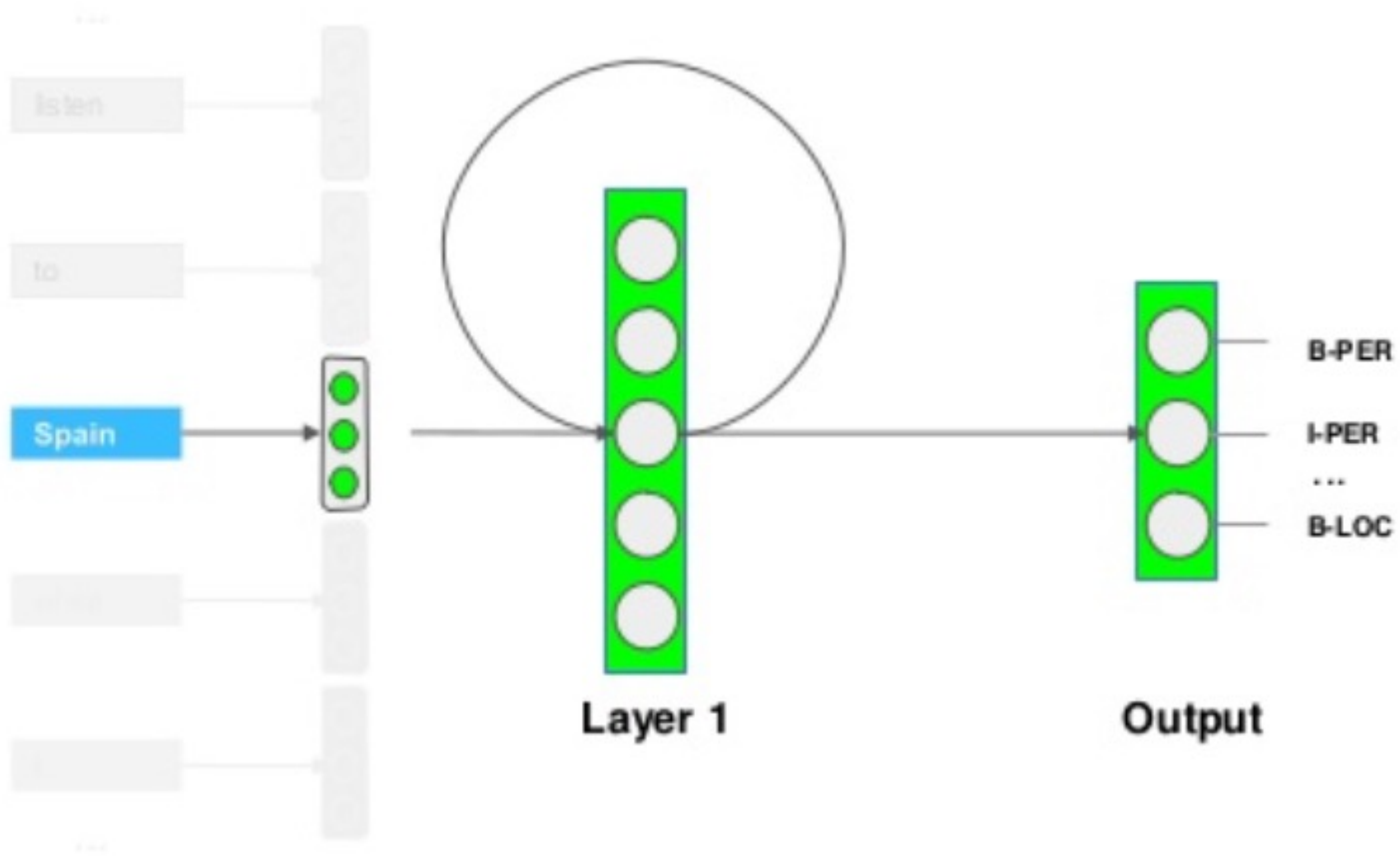
MLP for NER

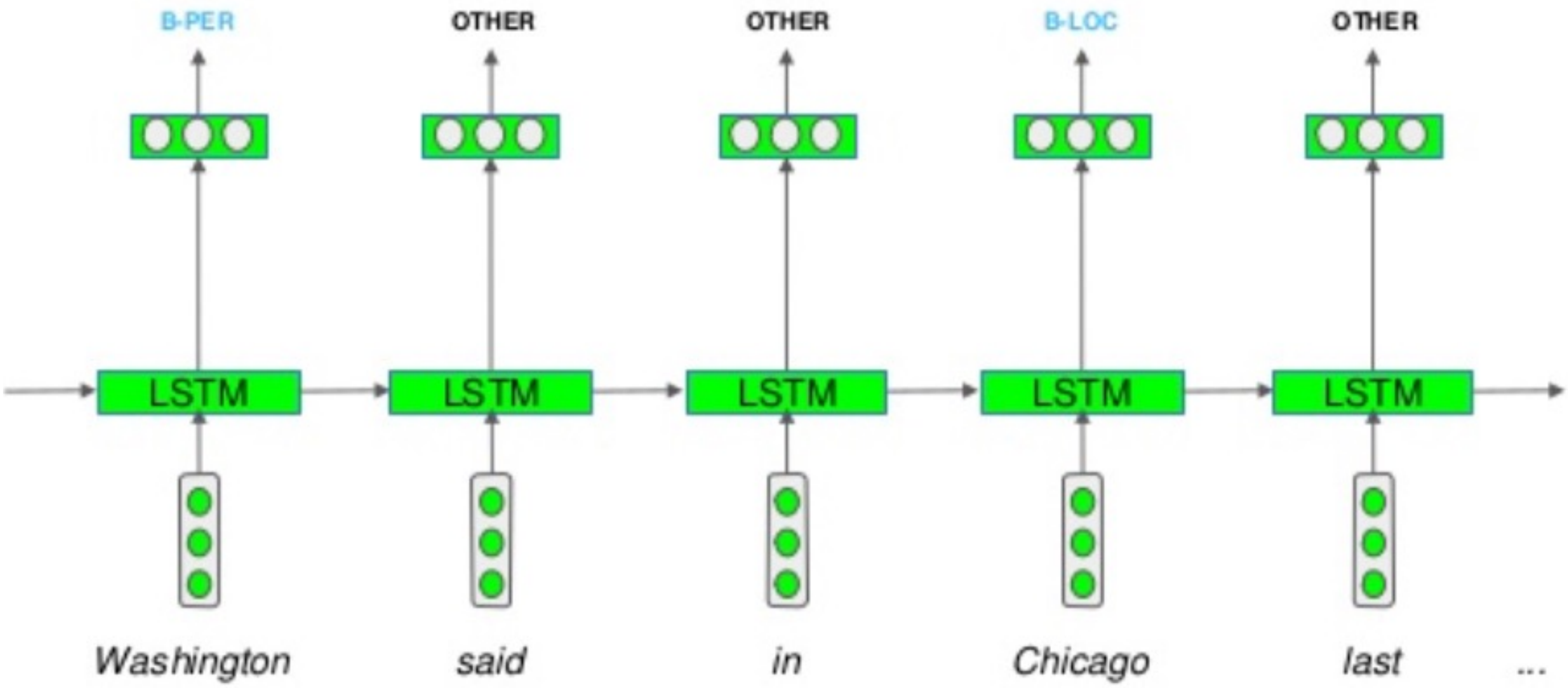


- Activation function for output: softmax
- Labels are OneHotEncoded

Recurrent neural network for NER

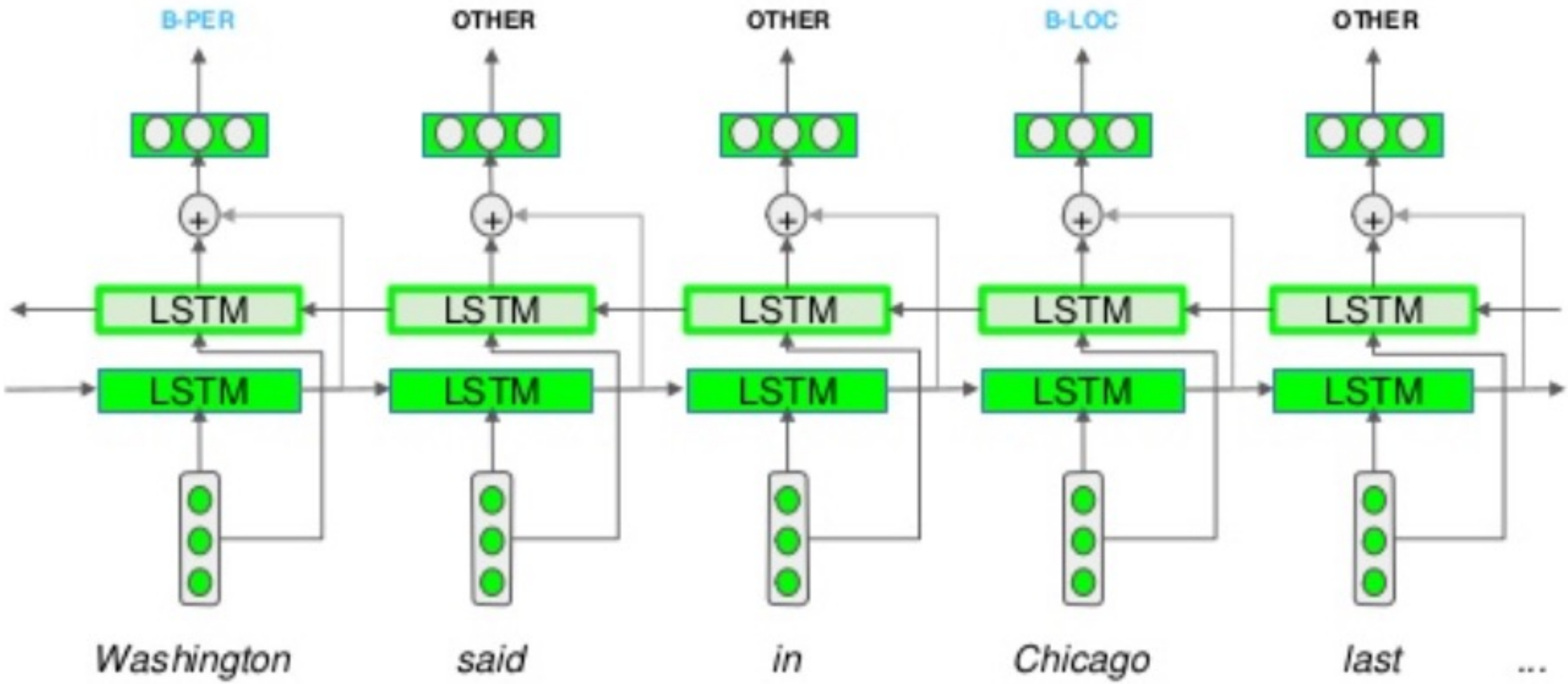


Recurrent neural network for NER (unfolded)



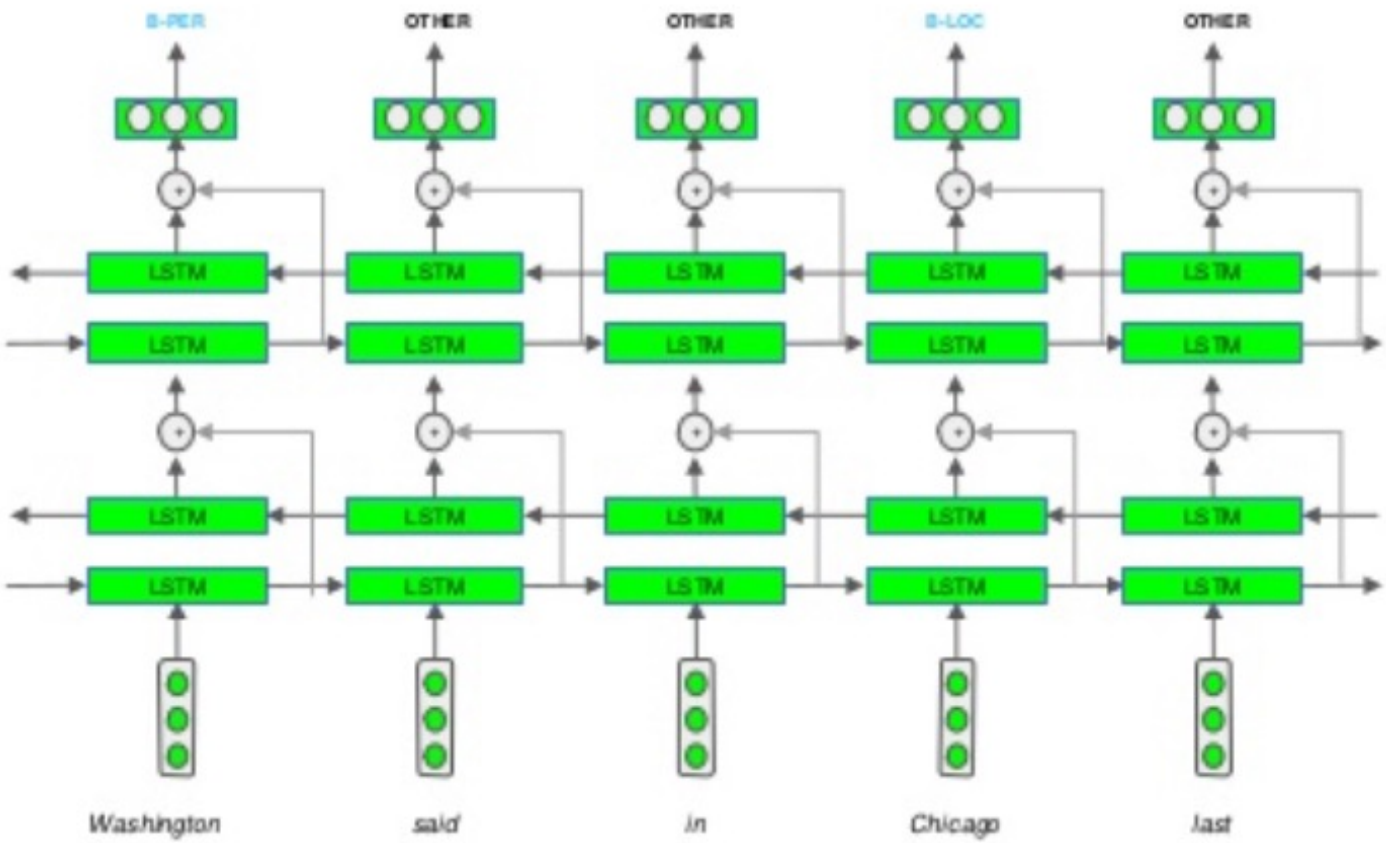
- Activation function for output: softmax
- Labels are OneHotEncoded

Bi directional recurrent neural network for NER



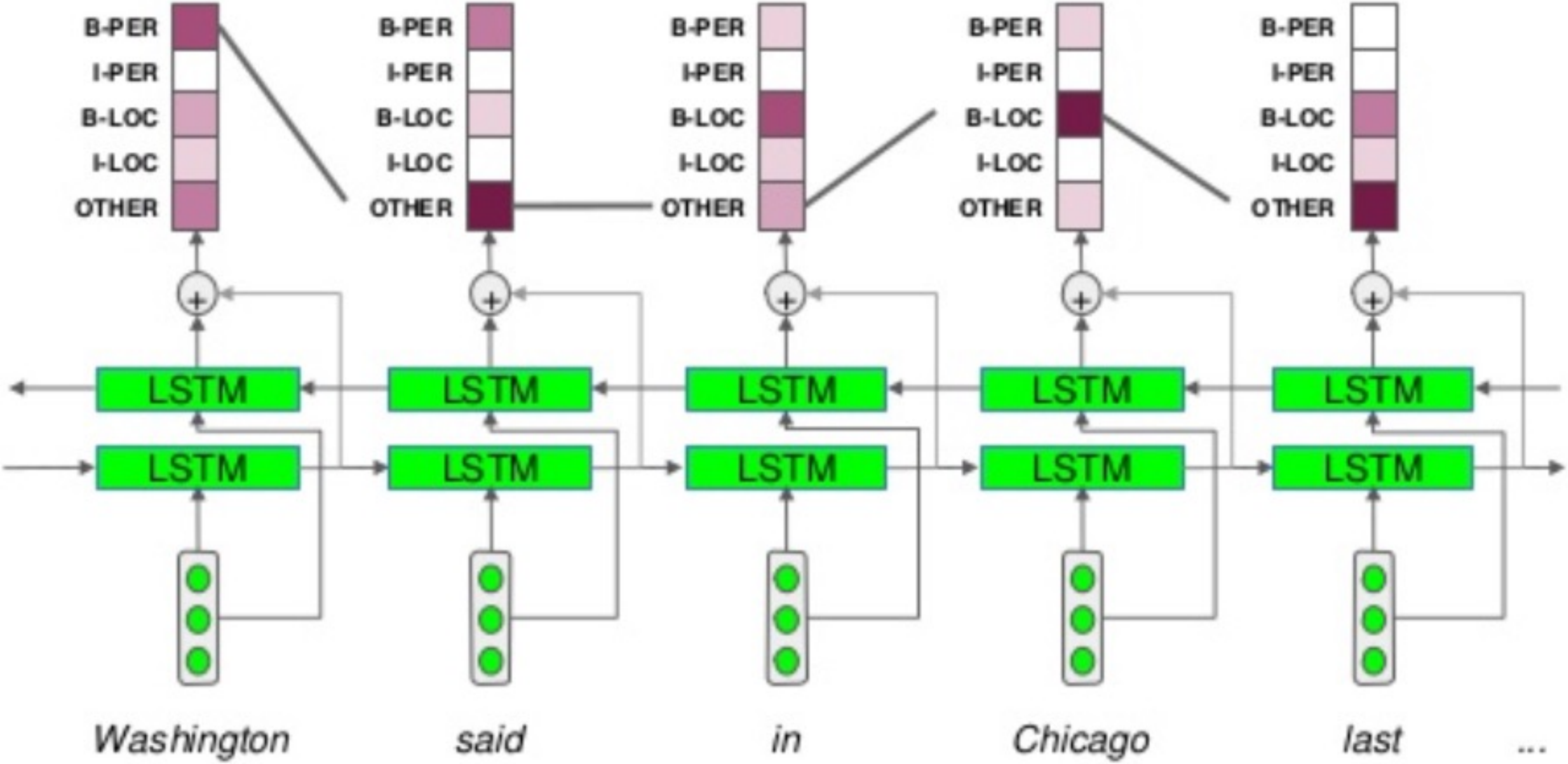
- Activation function for output: softmax
- Labels are OneHotEncoded

Stacked Bi-RNN



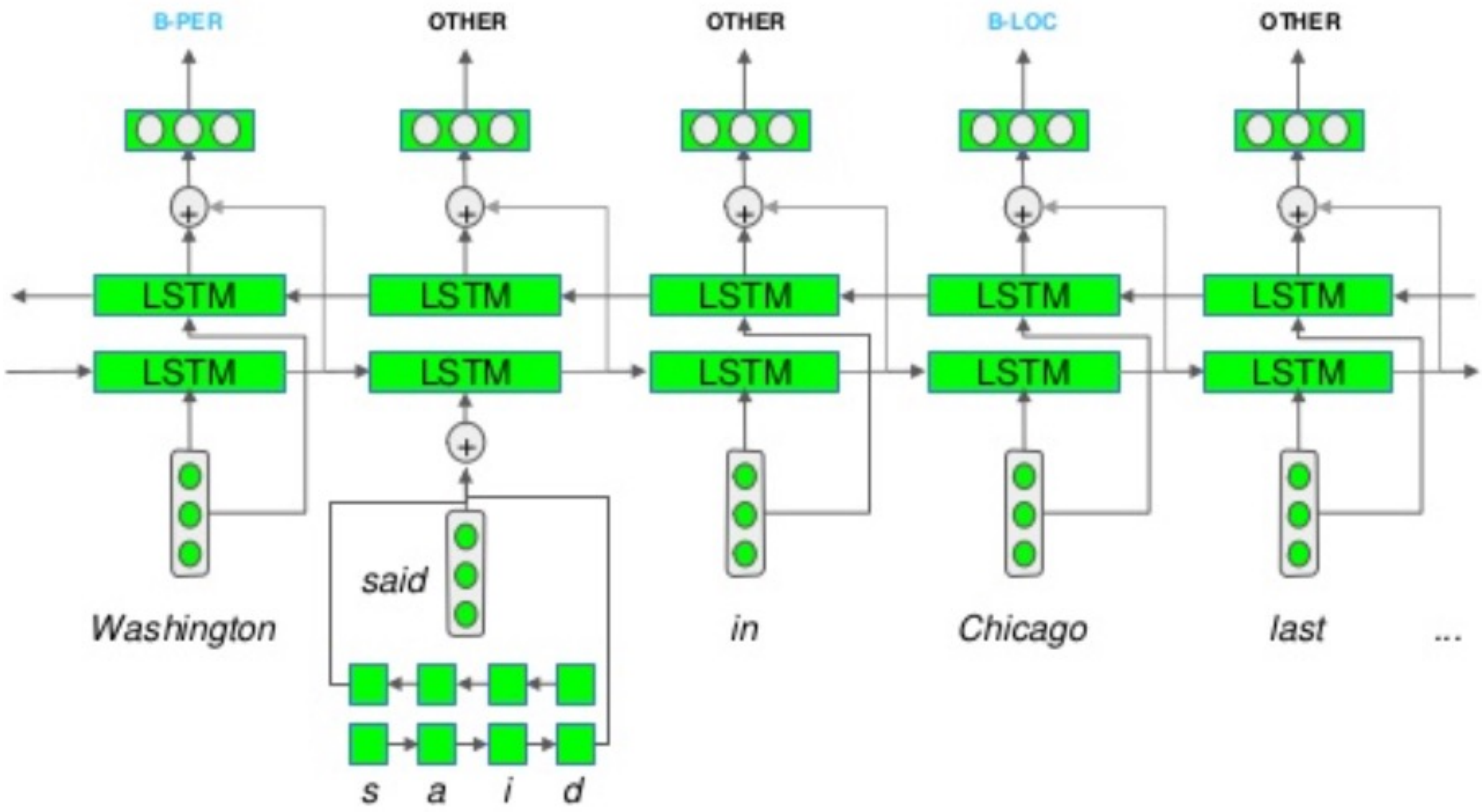
- Activation function for output: softmax
- Labels are OneHotEncoded

Bi-RNN + CRF



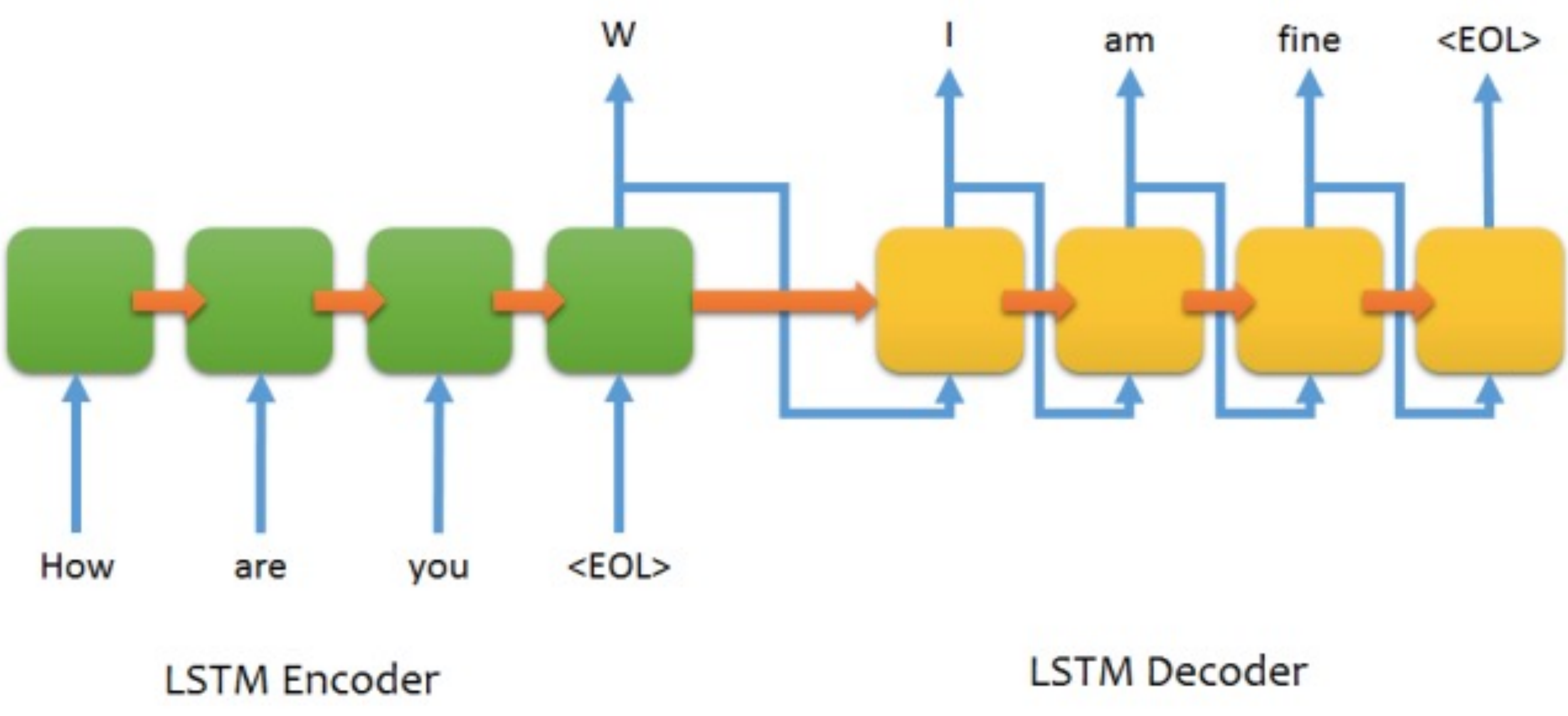
- CRF output activation function

Multi-level encoding
char encoding + word encoding



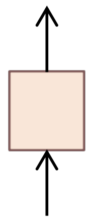
Other use of RNN
→ Sequence2sequence model

- Used for
  - Translation
  - Chatbot



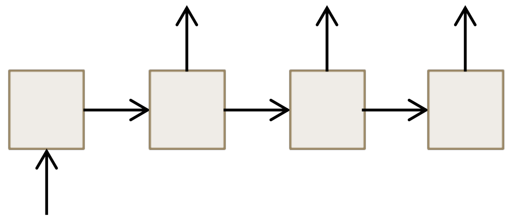
Some use of RNN
→ Input – Output Scenarios

Single - Single



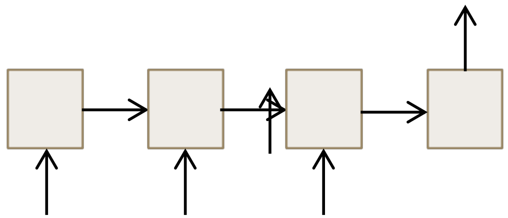
One input
One output
→ Feed-forward network

Single - Multiple



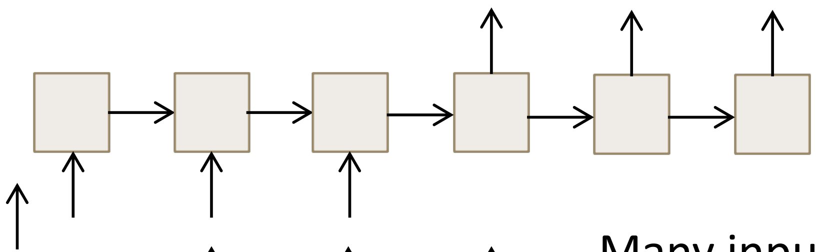
One input
Many output
Image annotation

Multiple - Single

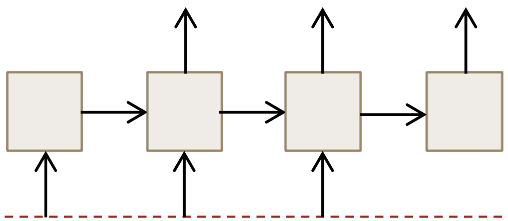


Many input
Many output
Text classification / Sentiment analysis

Multiple – Multiple



Many input / Many output
length(input)!=length(output)
Translation
Chat bot



Many input / Many output
length(input)==length(output)
Named Entity Recognition
Part-Of-Speech tagging

Other Useful Resources / References

- http://cs231n.stanford.edu/slides/winter1516_lecture10.pdf
- http://www.cs.toronto.edu/~rgrosse/csc321/lec10.pdf

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