

### DEEP LEARNING WORKSHOP

Dublin City University 21-22 May 2018





#InsightDL2018

#### Day 1 Lecture 6

### **Neural Machine Translation**



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### **Acknowledgements**



Marta R. Costa-jussà







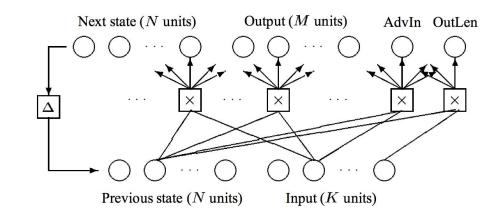
# Kyunghyun Cho





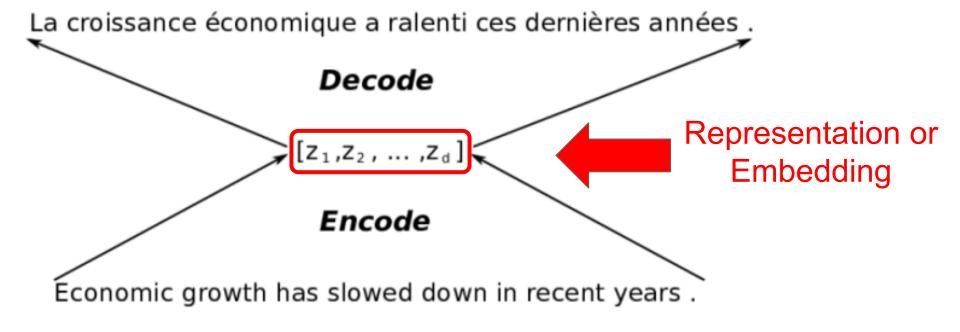
# Asynchronous translations with recurrent neural nets

Ramón P. Ñeco, Mikel L. Forcada
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Neco, R.P. and Forcada, M.L., 1997, June. <u>Asynchronous translations with recurrent neural nets</u>. In Neural Networks, 1997., International Conference on (Vol. 4, pp. 2535-2540). IEEE.

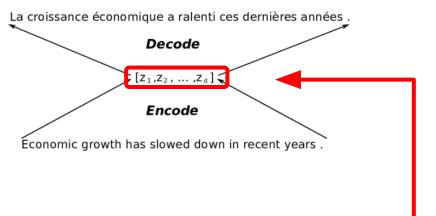
#### **Encoder-Decoder**



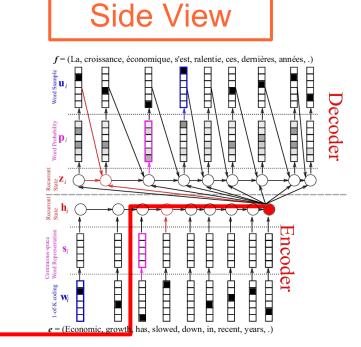
Cho, Kyunghyun, Bart Van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. <u>"On the properties of neural machine translation: Encoder-decoder approaches."</u> SSST-8 (2014).

#### **Encoder-Decoder**

#### **Front View**



#### Representation of the sentence

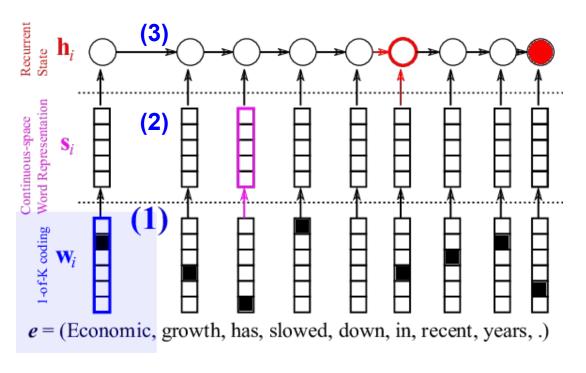


Kyunghyun Cho, "Introduction to Neural Machine Translation with GPUs" (2015)

Cho, Kyunghyun, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." arXiv preprint arXiv:1406.1078 (2014).

## **Encoder**

### **Encoder in three steps**

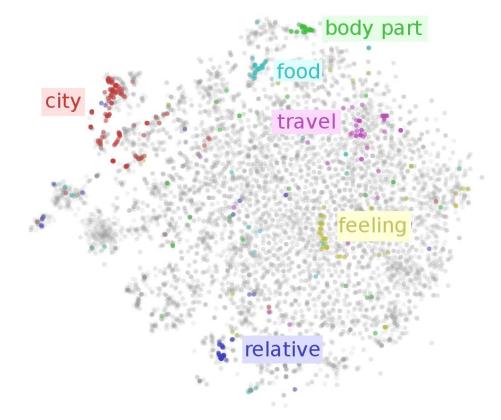


- (1) One hot encoding
- (2) Word embedding
- (3) Sequence summarization

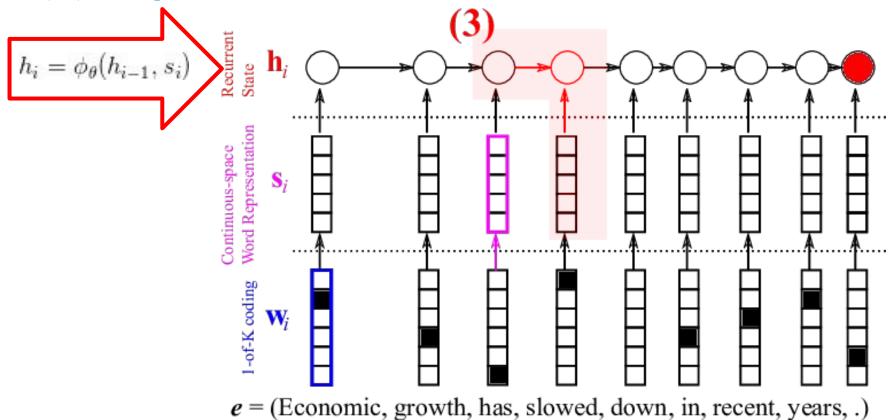
### (1) One hot encoding

```
cat: x^{T} = [1, 0, 0, ..., 0]
dog: x^{T} = [0, 1, 0, ..., 0]
house: x^T = [0,0,0,...,0,1,0,...,0]
```

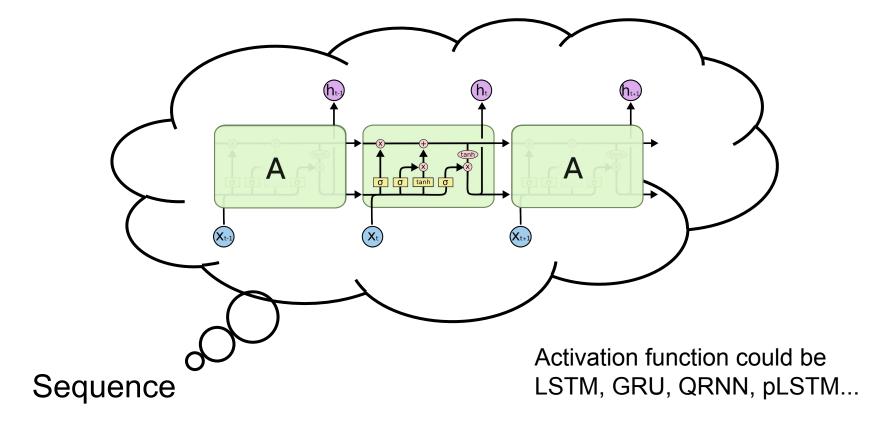
### (2) Word embeddings



### (3) Sequence summarization



### (3) Sequence summarization

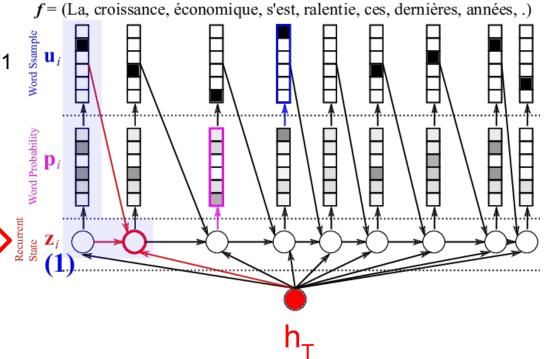


The Recurrent State (z<sub>i</sub>) of the decoder is determined by:

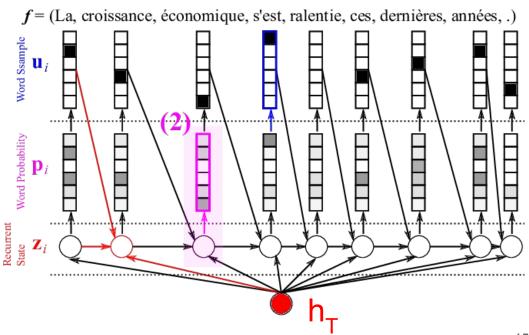
- summary vector h<sub>⊤</sub>
- 2) previous output word u<sub>i-1</sub>

 $z_i = \phi_{\theta'}(h_T, u_{i-1}, z_{i-1}).$ 

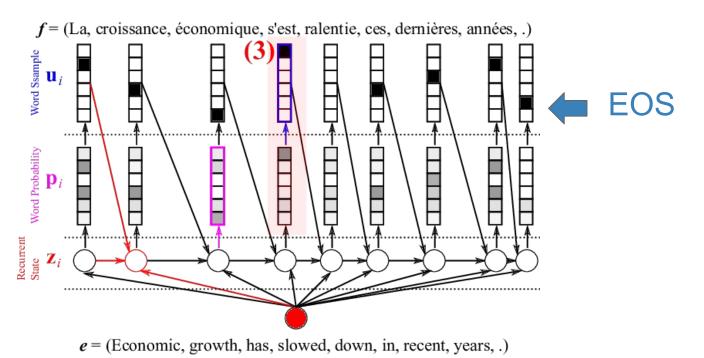
3) previous state z<sub>i-1</sub>



With  $z_i$  updated, we can compute a **probability**  $p_i$  for each word i as an output of the RNN:

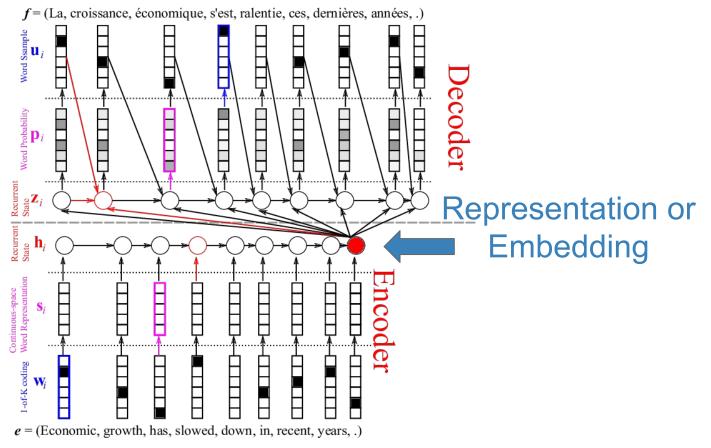


More words for the decoded sentence are generated until a <EOS> (End Of Sentence) "word" is predicted.





#### **Encoder-Decoder**



### Parallel corpus

Training requires a large dataset of pairs of sentences in the two languages to translate.



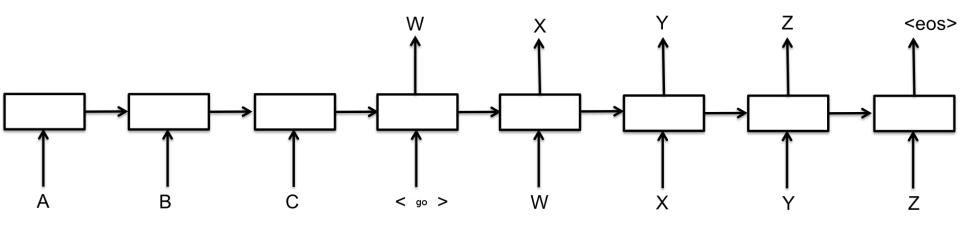
Source	Translation Model
at the end of the	[a la fin de la] [f la fin des années] [être sup- primés à la fin de la]
for the first time	[r © pour la premirere fois] [été donnés pour la première fois] [été commémorée pour la première fois]
in the United States and	[? aux ?tats-Unis et] [été ouvertes aux États- Unis et] [été constatées aux États-Unis et]
, as well as	[?s , qu'] [?s , ainsi que] [?re aussi bien que]
one of the most	[?t ?l' un des plus] [?l' un des plus] [être retenue comme un de ses plus]

Cho, Kyunghyun, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." AMNLP 2014.

### Seq2Seq

#### The **Seq2Seq** variation:

- trigger the output generation with an input <go> symbol.
- the predicted word at timestep t, becomes the input at t+1.



### Seq2Seq



Sutskever, Ilya, Oriol Vinyals, and Quoc V. Le. <u>"Sequence to sequence learning with neural networks."</u> NIPS 2014.

## Questions?