

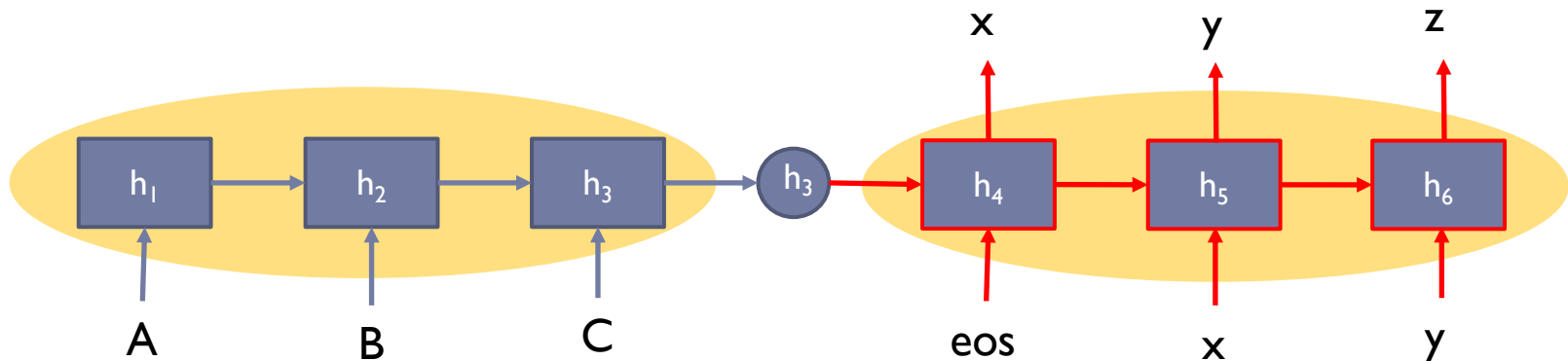
Attention Model

성균관대학교 소프트웨어학과
이 지 형

Sequence Generation

▶ Encoder-Decoder Scheme

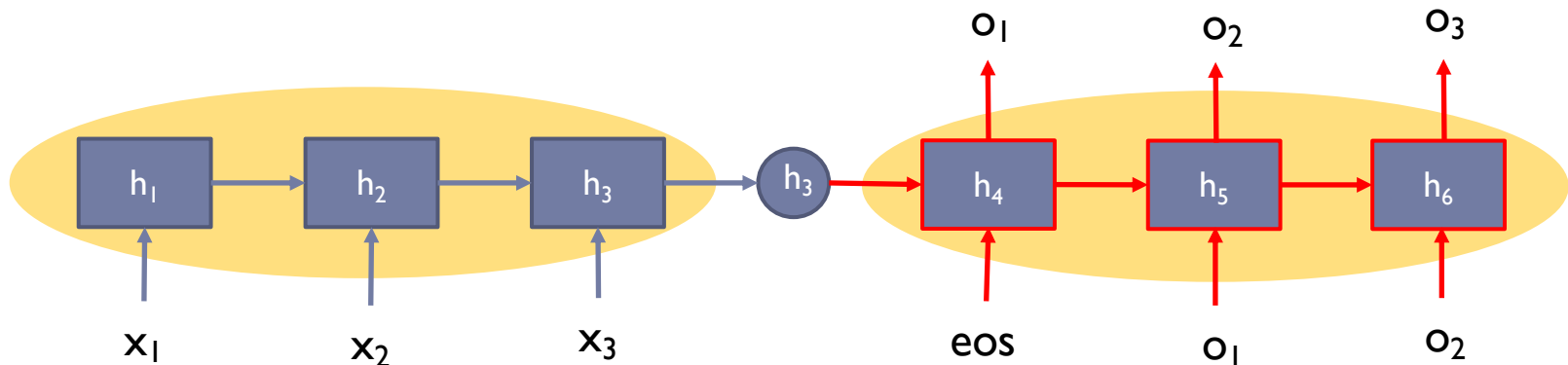
- ▶ **Encoder: compress input sequence into one vector**
 - ▶ h_3 is the vector representation of the given sequence
- ▶ **Decoder: uses this vector to generate output**
 - ▶ It extracts necessary information only from the vector



Sequence Generation

► Challenges

- A single vector may not be enough for decoder to generate correct words
- Processing distance between input and output get longer as sequence becomes longer



Attention Model

▶ Idea

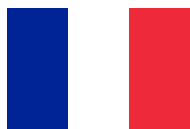
- ▶ Remove the vector and Directly connect input to output + α

▶ Observation

- ▶ At every step, all the inputs are not equally useful



Economic growth has slowed down in recent years



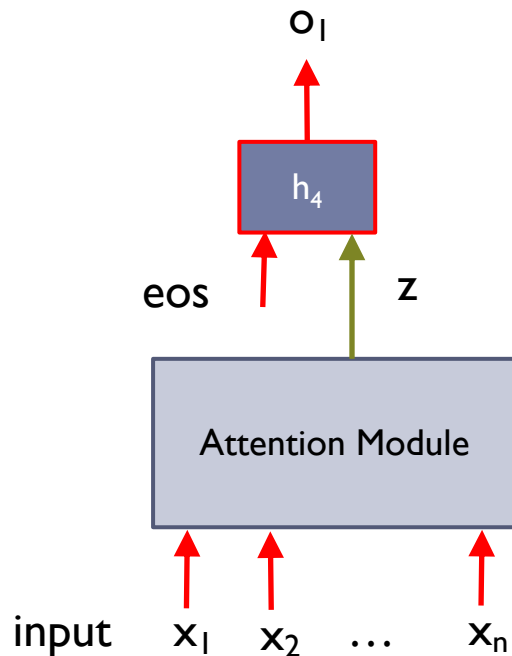
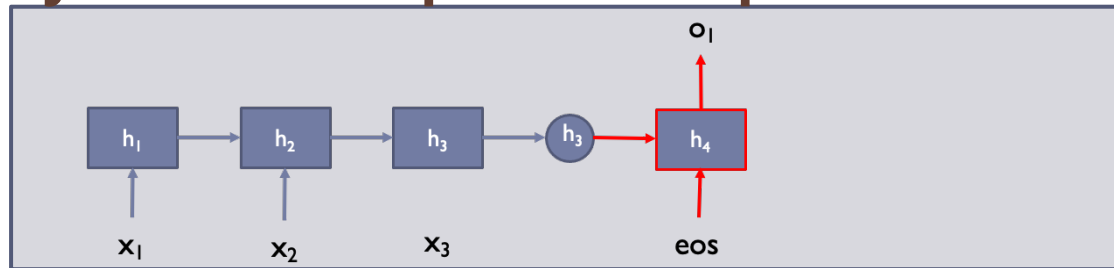
La croissance économique s' est ralentie ces dernières années

- ▶ Inputs relevant to the context may be more useful

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

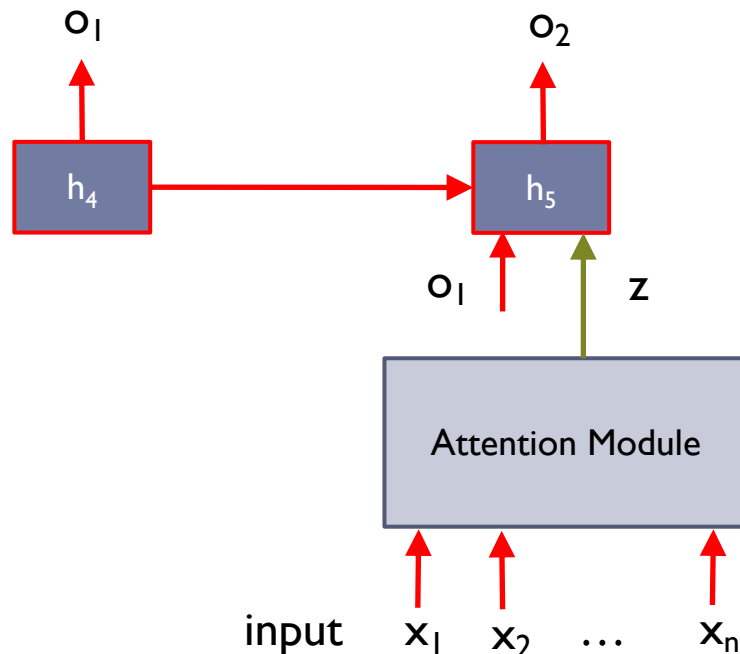
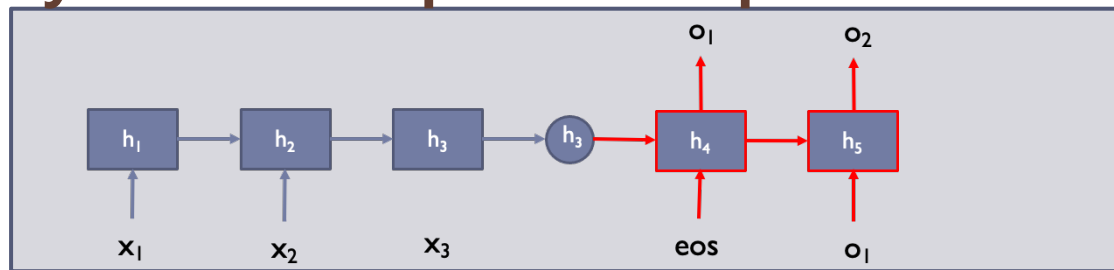
Sequence Generation

- ▶ Directly connect input to output + α



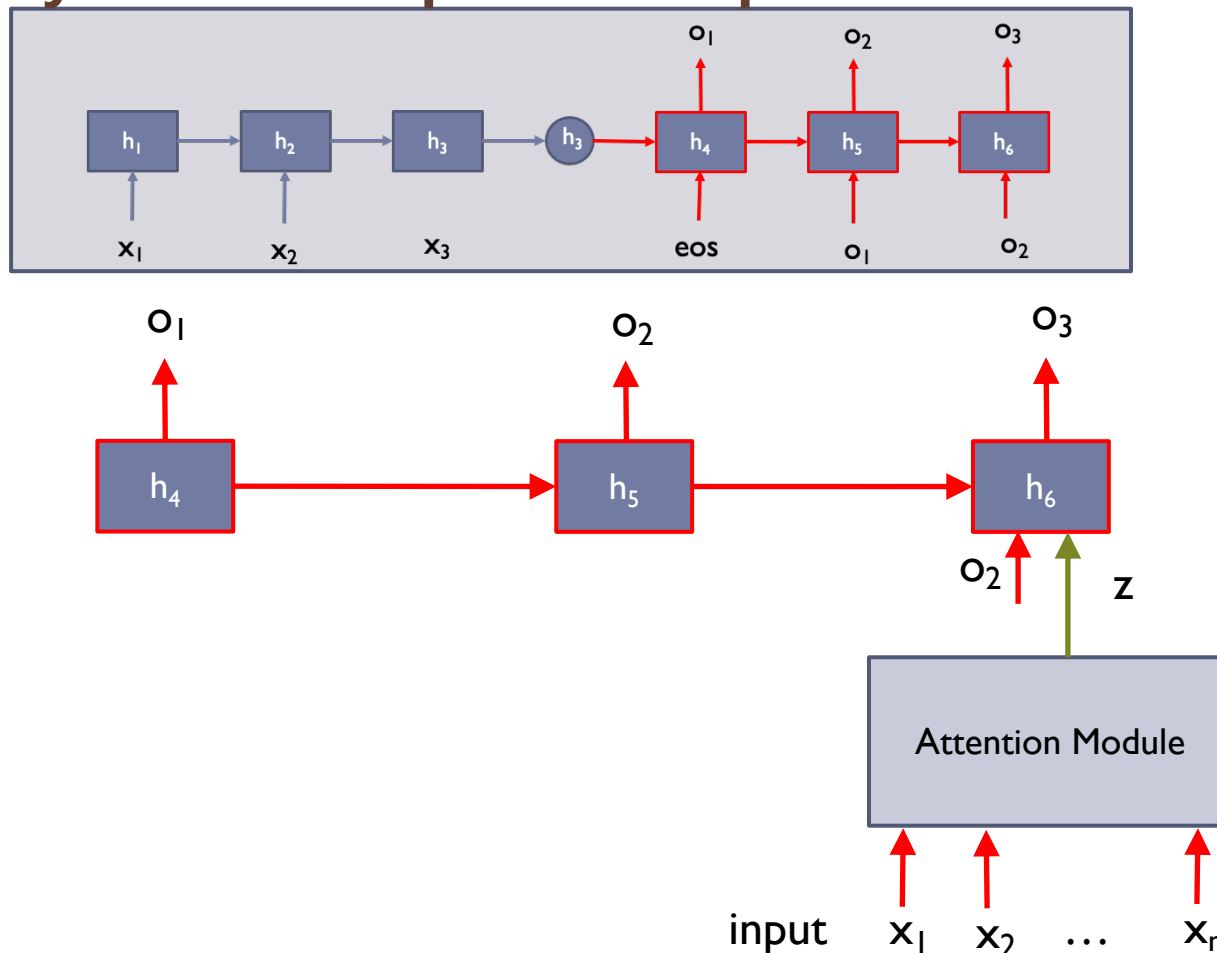
Sequence Generation

- ▶ Directly connect input to output + α



Sequence Generation

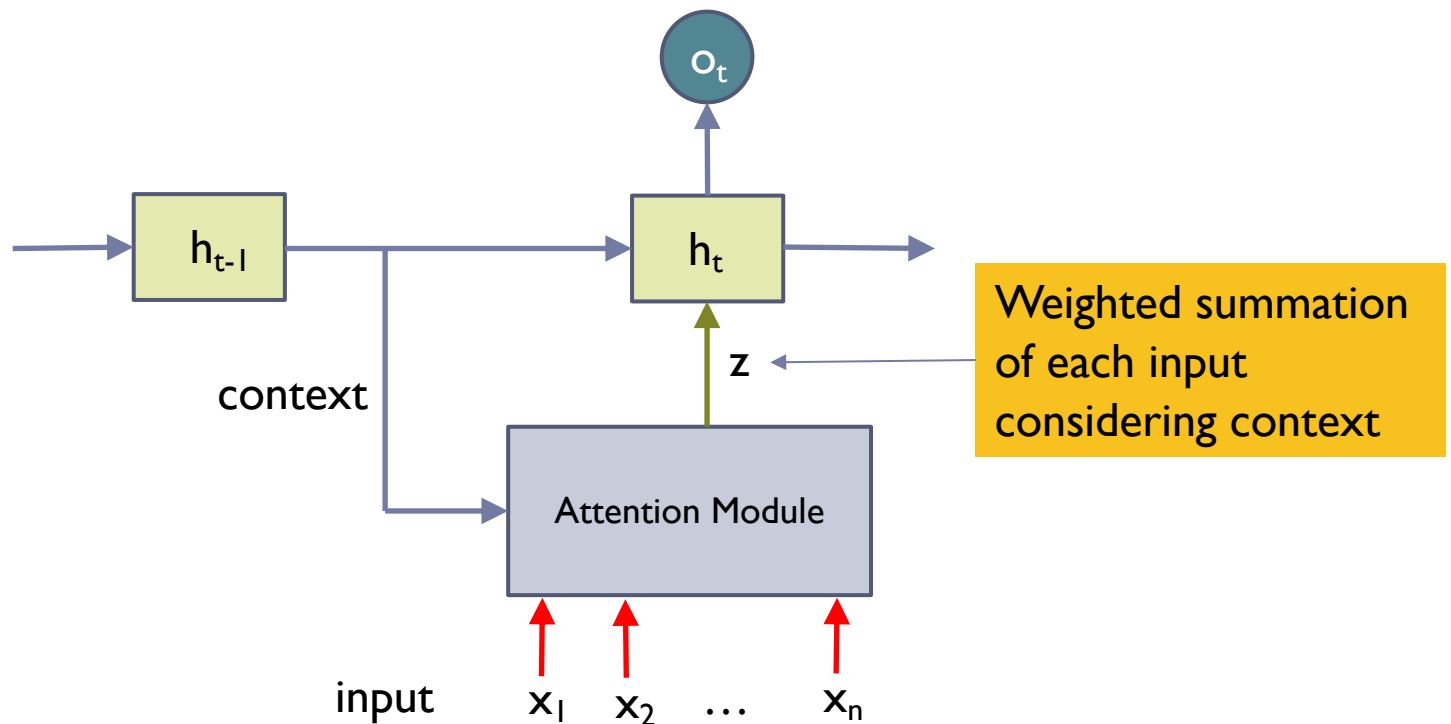
- ▶ Directly connect input to output + α



Attention Model

► Overview

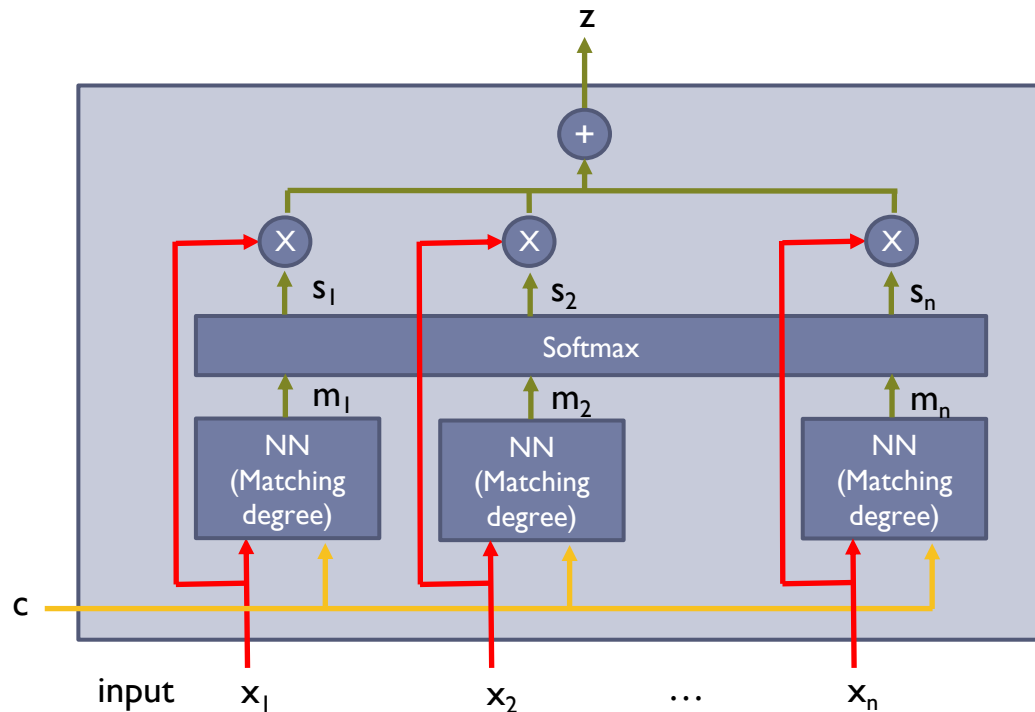
- Select the most important input to produce O_t



Attention Model

▶ Attention Module

- ▶ All inputs share the same NN for matching degree

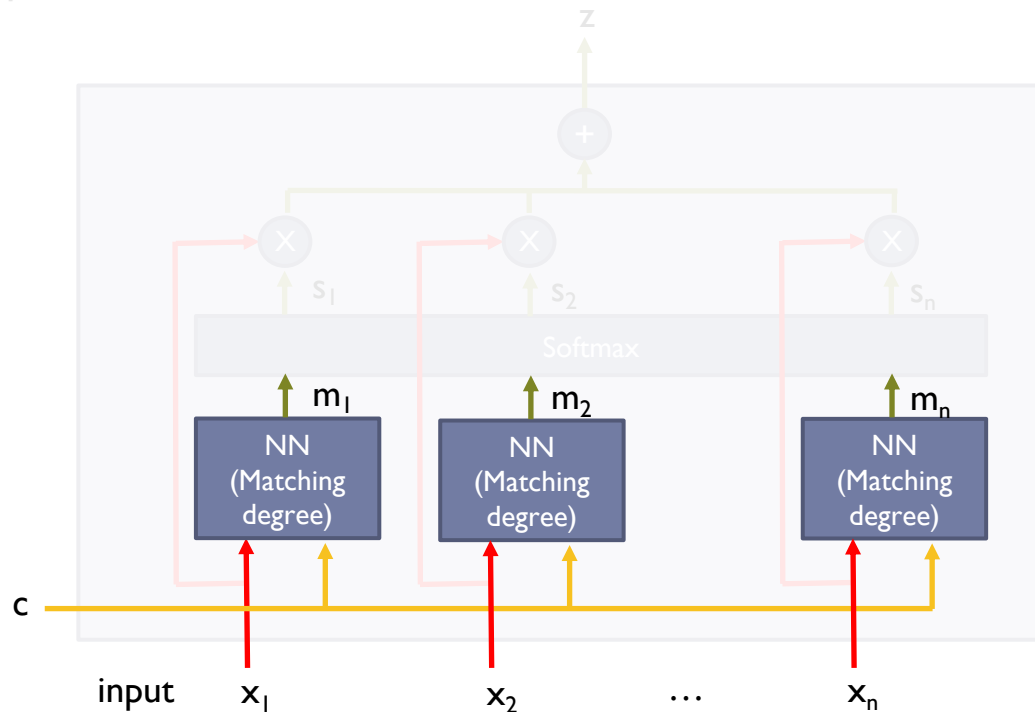


Attention Model

▶ Step 1: Evaluating Matching Degree

▶ Evaluating matching degree of each input to the context

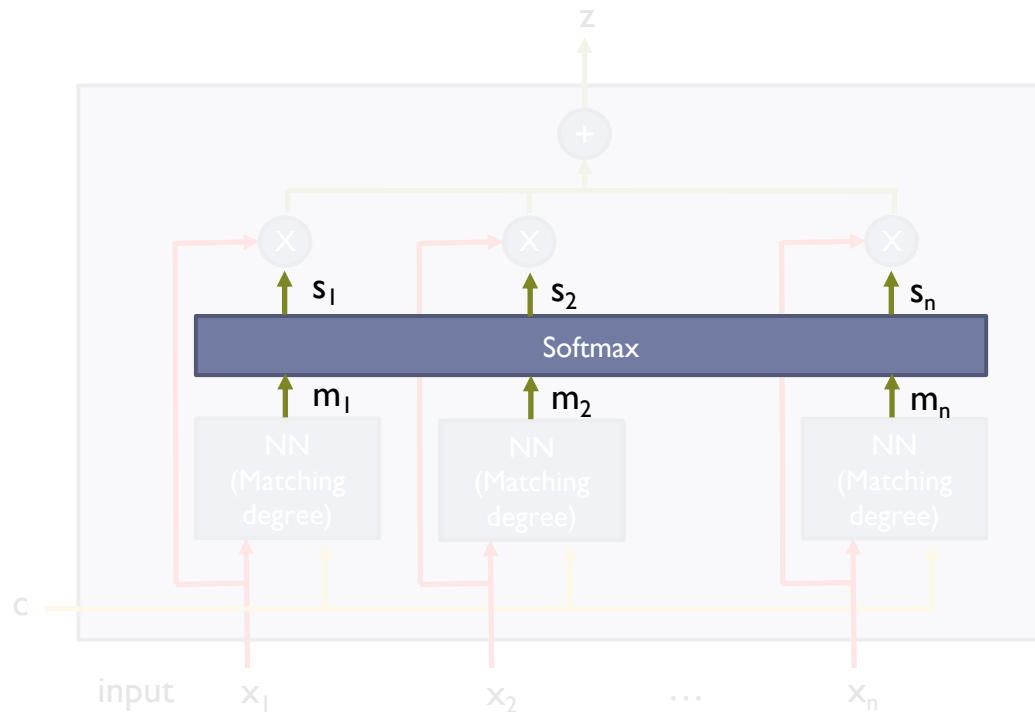
- ▶ Produce scalar matching degree (Higher value is higher attention)
- ▶ All inputs share the same NN



Attention Model

▶ Step 2: Normalizing Matching Degree

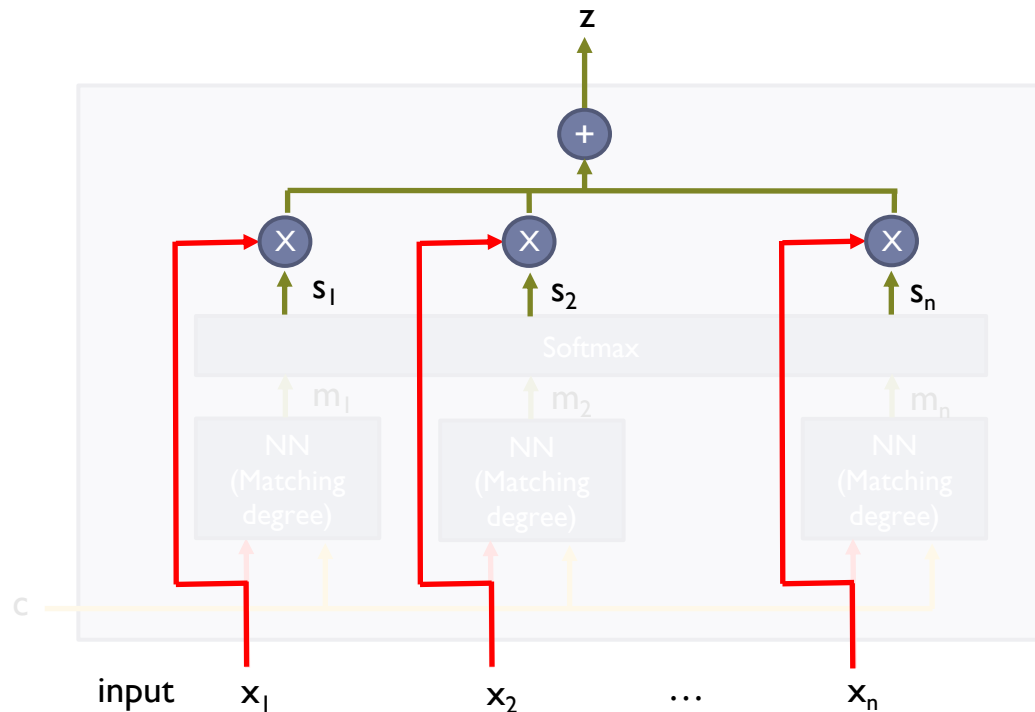
$$s_i = \frac{\exp(m_i)}{\sum_j \exp(m_j)}$$



Attention Model

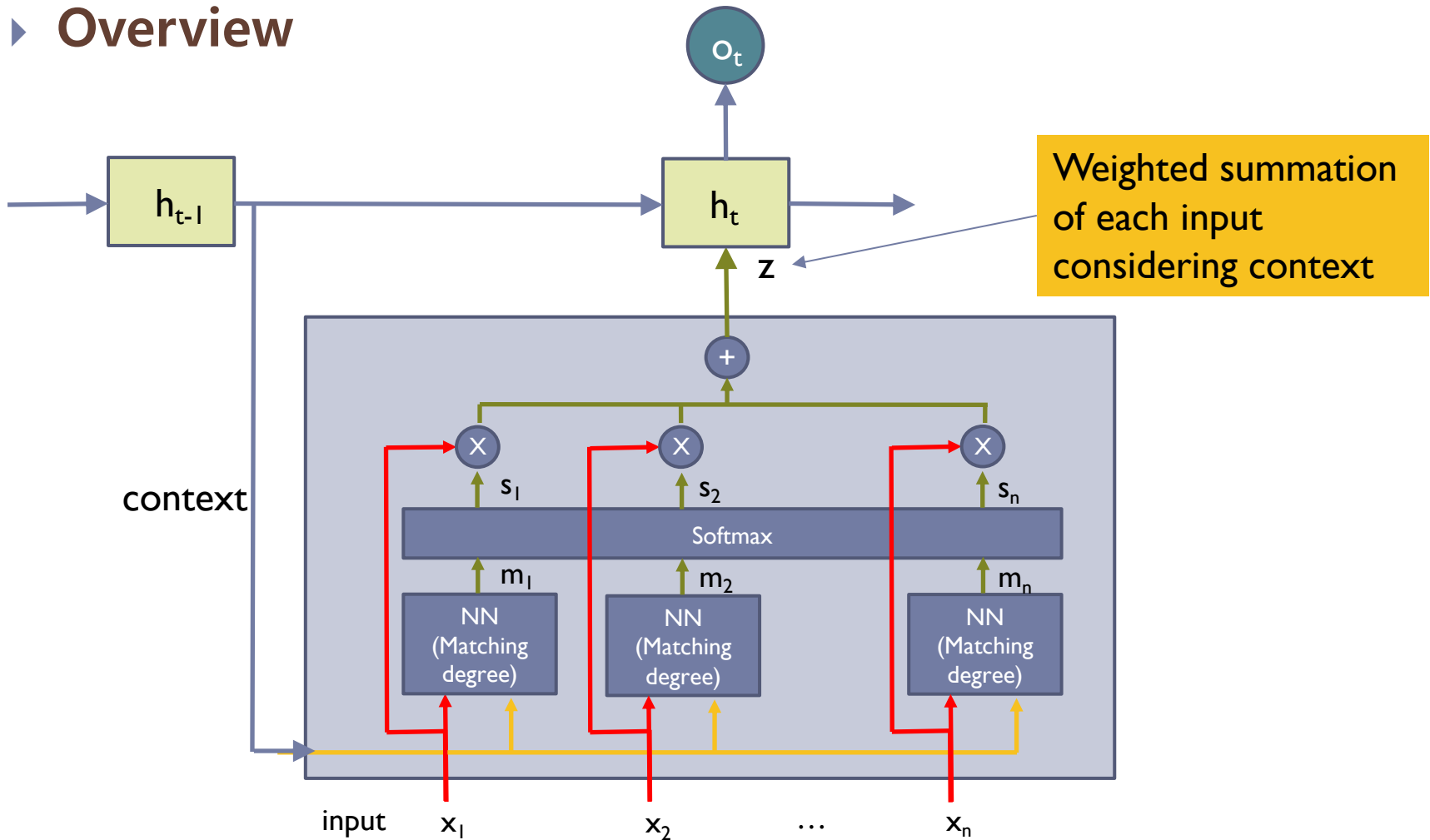
▶ Step 3: Aggregating Inputs

- ▶ Each input is scaled by s_i and summed up into z
- ▶ z is the input focused on the current context



Attention Model

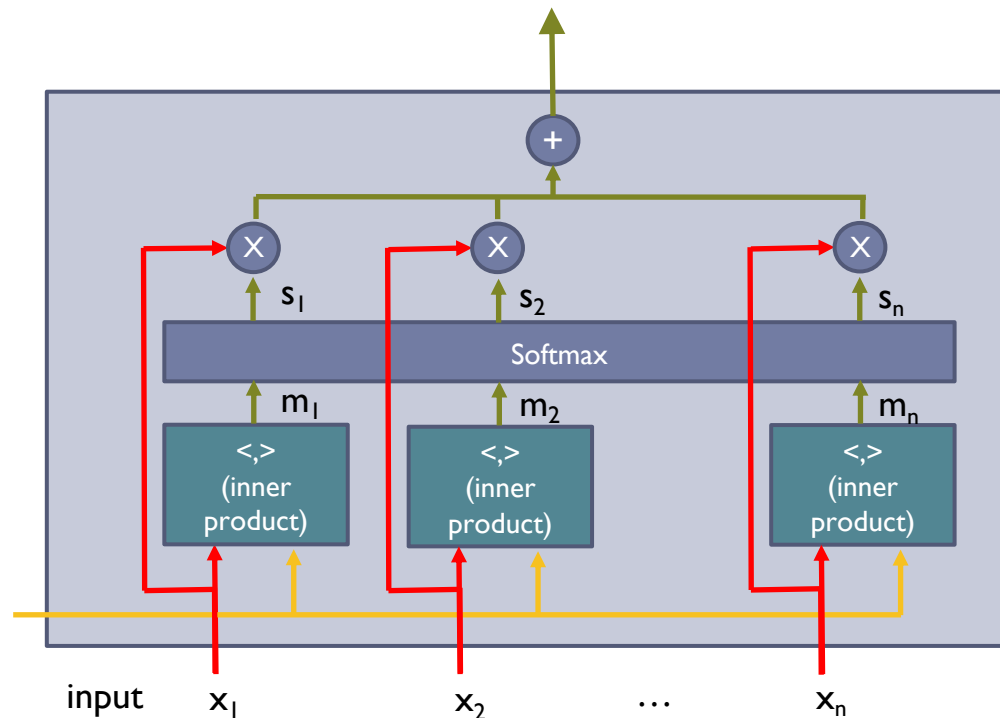
► Overview



Attention Model

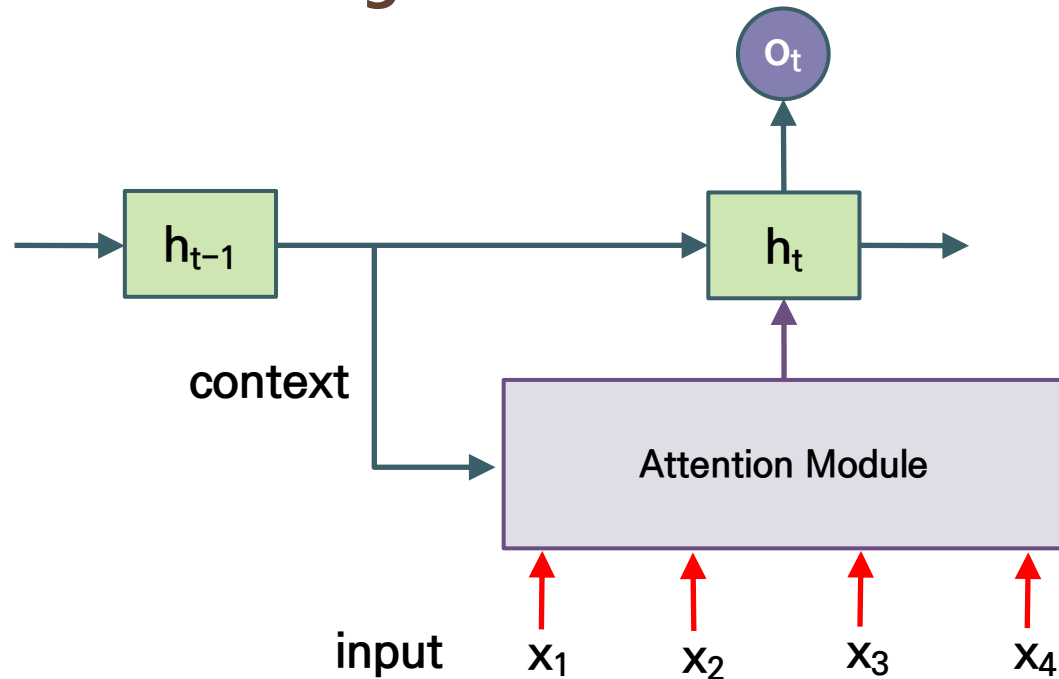
► Variation

- Matching NN can be replaced with the inner products of inputs and context



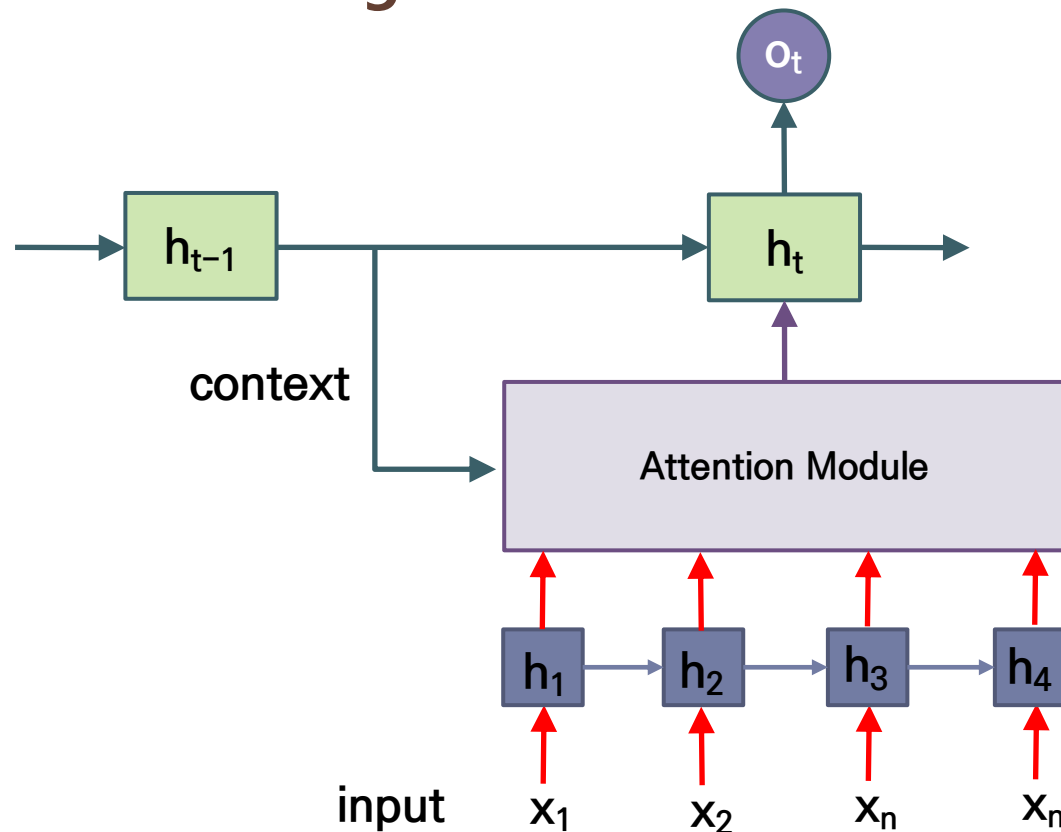
Attention Model

► Input Processing



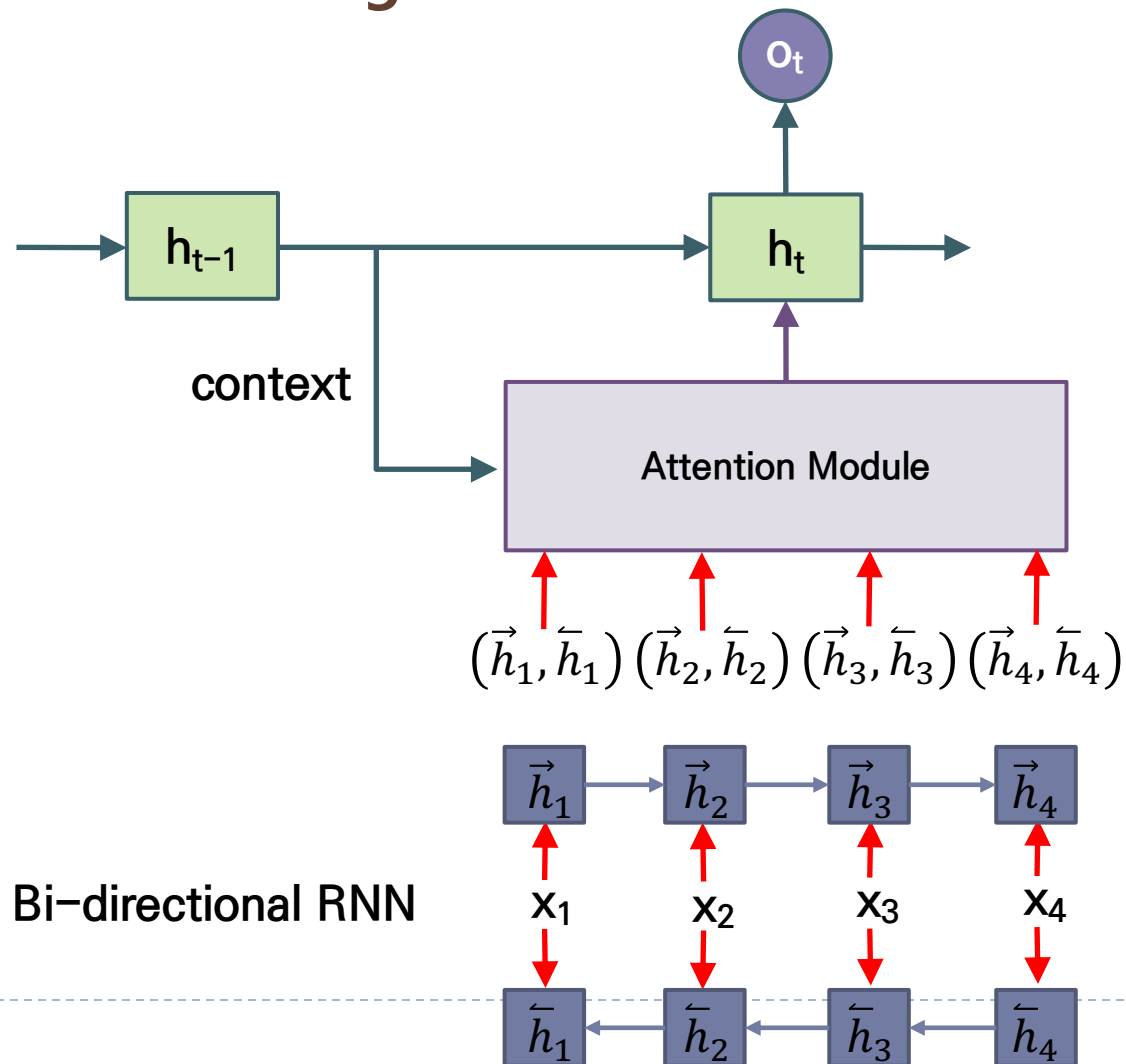
Attention Model

► Input Processing



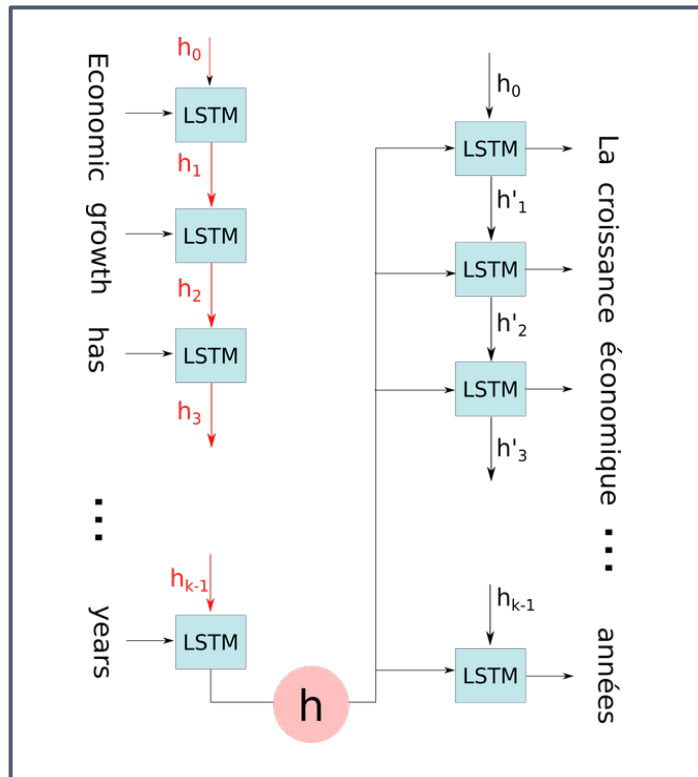
Attention Model

► Input Processing

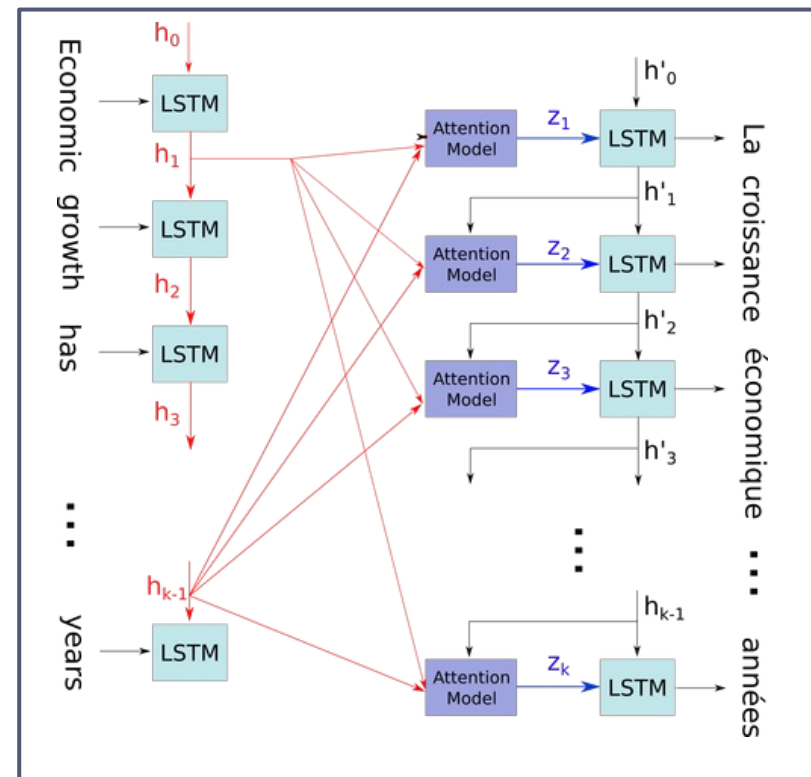


Attention Model

▶ Example



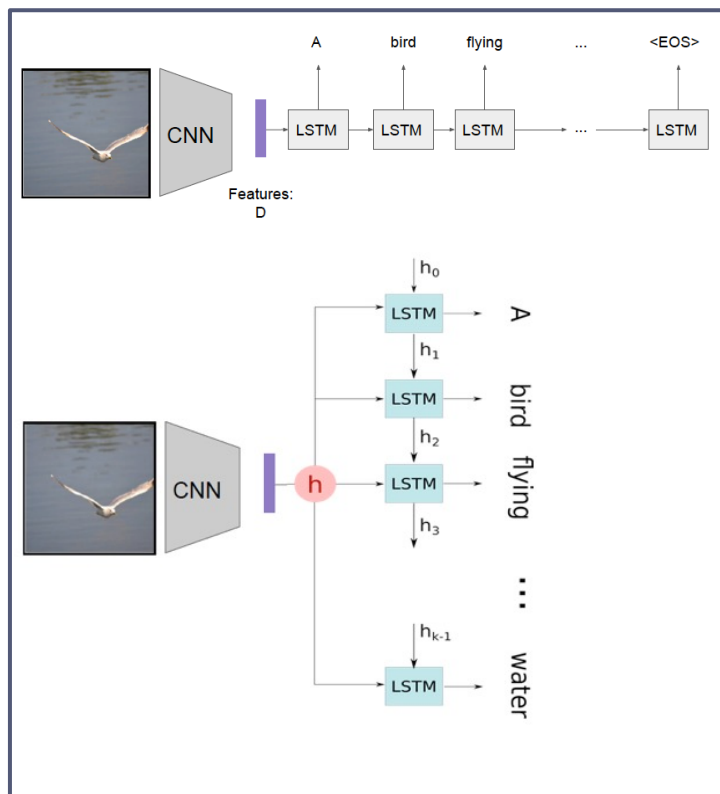
Encoder-decoder model



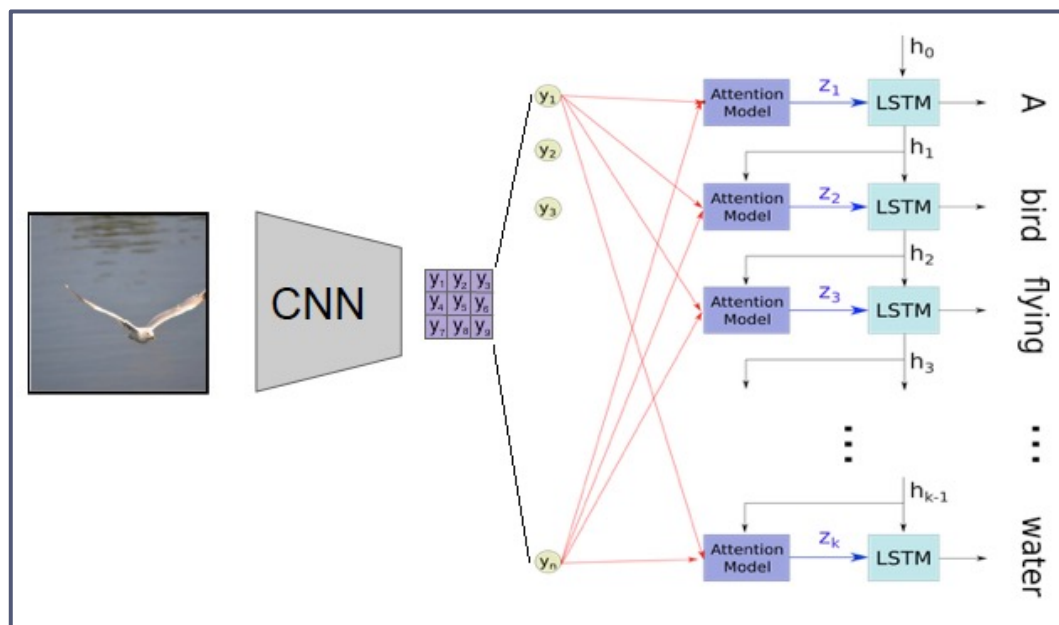
Attention based model

Attention Model

▶ Example



Encoder-decoder model

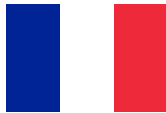


Attention based model

Attention Model

▶ One more advantage

- ▶ We can interpret and visualize what the model is doing



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



A



bird



flying



over



a



body



of



water

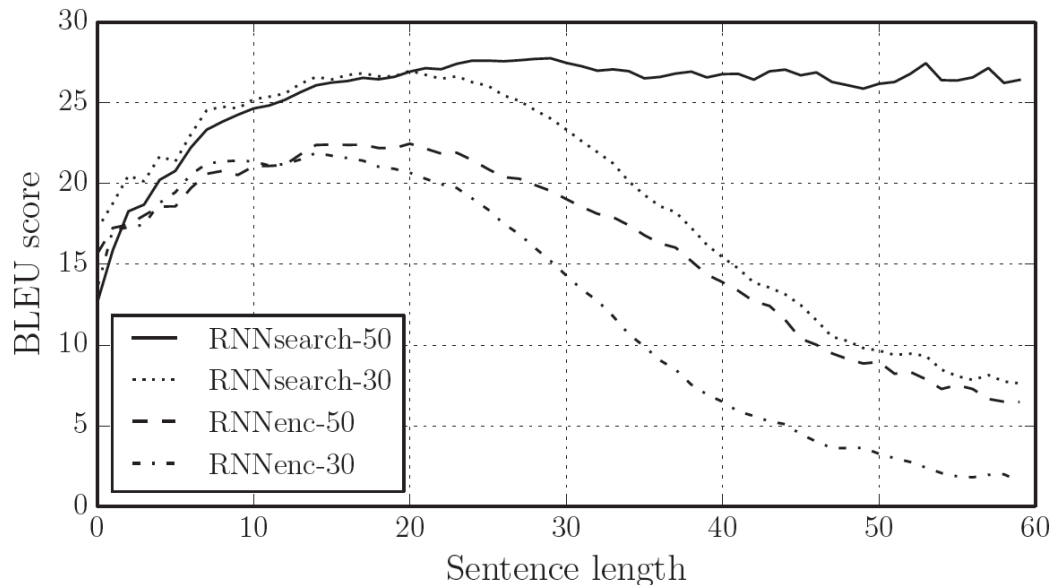


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Xu et al. Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. ICML 2015

Attention is Great!

- ▶ **RNNsearch-50** is a neural machine translation model with the attention mechanism trained on all the sentence pairs of length at most 50.
- ▶ Dzmitry Bahdanau, KyungHyun Cho, Yoshua Bengio, "Neural Machine Translation by Jointly Learning to Align and Translate," ICLR 2015



Attention is Great!

- ▶ **Attention significantly improves NMT performance.**
 - ▶ It's very useful to allow decoder to focus on certain parts of the source.
- ▶ **Attention solves the bottleneck problem.**
 - ▶ Attention allows decoder to look directly at source; bypass bottleneck.
- ▶ **Attention helps with vanishing gradient problem.**
 - ▶ Provides shortcut to faraway states.
- ▶ **Attention provides some interpretability.**
 - ▶ By inspecting attention distribution, we can see what the decoder was focusing on.
 - ▶ We get alignment for free!
 - ▶ This is cool because we never explicitly trained an alignment system
 - ▶ The network just learned alignment by itself.

Question and Answer