Effective Approaches to Attention-based Neural Machine Translation - Luong et al.

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Outline

Intution

Attentional Mechanism

Selectively focusing on parts of the sentence.

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Find if a sentence is toxic or not.

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I am going to shoot you. - toxic

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I am going to shoot you. - toxic
I am going to love you. - not toxic

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Cells are stacking LSTM.

Outline

Traditional NMT system

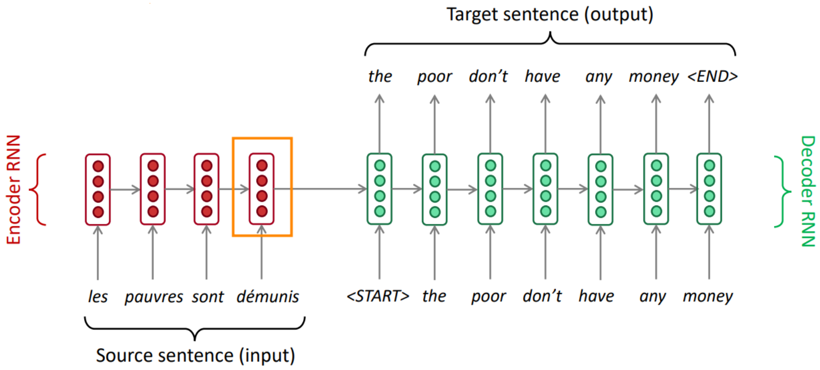

Figure: Neural machine translation a stacking recurrent architecture for translating a source sequence A B C D into a target sequence X Y Z. Here, $< eos >$ marks the end of a sentence.

Problem of Traditional NMT system

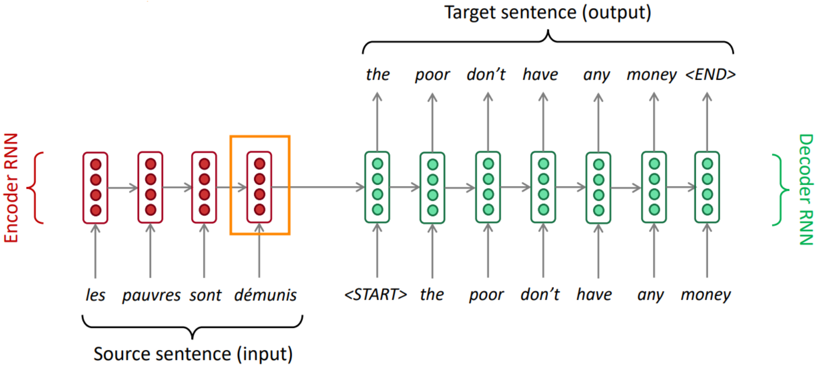

Figure: Orange rec-tangled hidden layer is the encoding of the source sentence. One single layer can't carry much info. (specially when the sentence is longer.)

Outline

Probabilistic Analysis

- **Encoder-Decoder** Model.
- a NN that directly models the **conditional probability** $p(y|x)$ of translating a source sequence, and $x_1, ..., x_n$ to a target sequence $y_1, ..., y_m$. If **s** is set of source hidden states,

$$x = les\ pauvres\ sont\ de'munis$$
$$y = the\ poor\ dont\ have\ any\ money$$

$$p(y|x) = \sum_{j=1}^{m} \log p(y_j|y_{<j}, \mathbf{s})$$

$$p(y_j|y_{<j}, \mathbf{s}) = softmax(g(h_j))$$

$$h_j = f(h_{j-1}, \mathbf{s})$$

$$J_t = \sum_{(x,y)\in\mathcal{D}} -\log p(y|x)$$

Types of Attention

$$p(y|x) = \sum_{j=1}^{m} \log p(y_j | y_{<j}, \mathbf{s})$$

- Global attention: **s** contains all the hidden layers of source.
- Local attention: **s** contains subset of hidden layers of source.

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- Global attention: **s** contains all the hidden layers of source.
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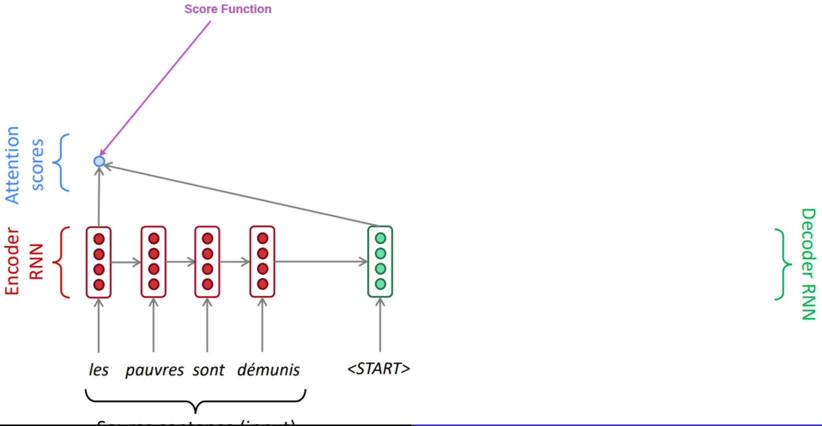
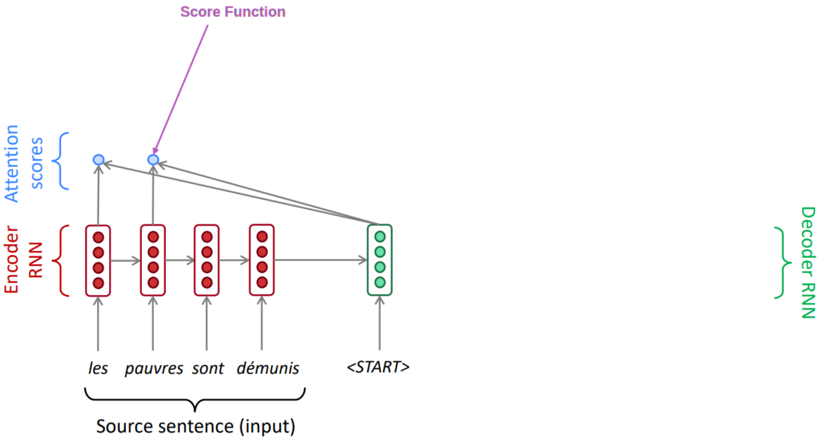
Focus on a particular part of the source sequence.

Global attention



Global attention



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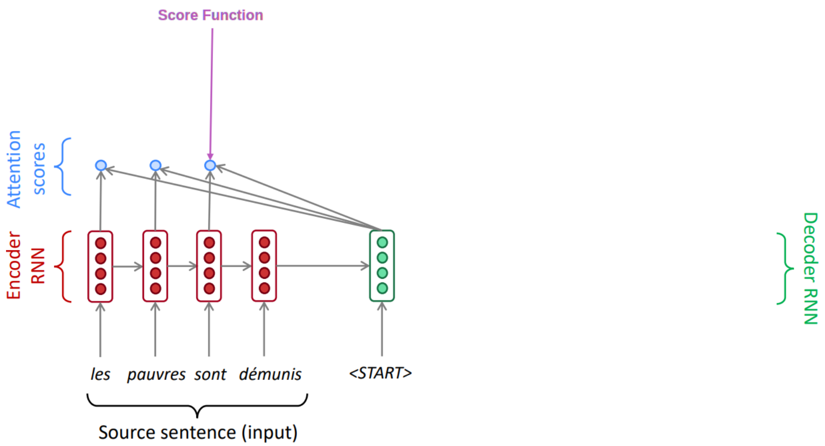

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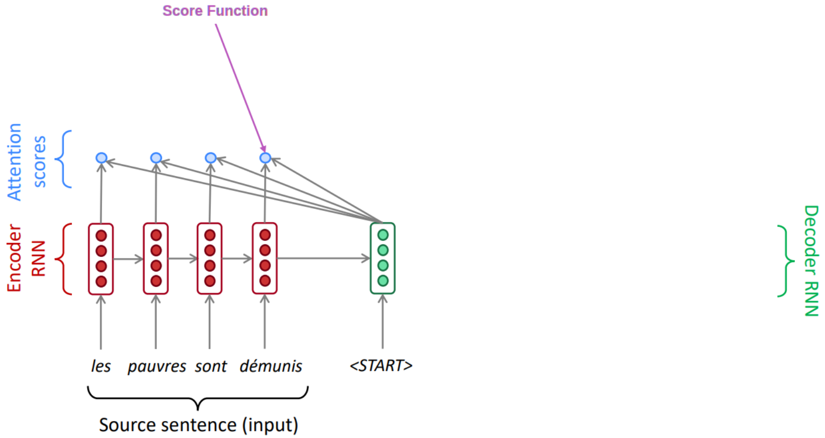

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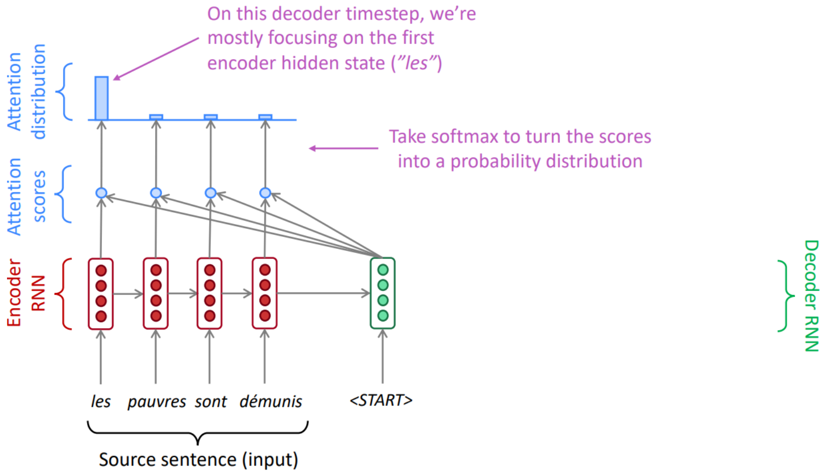

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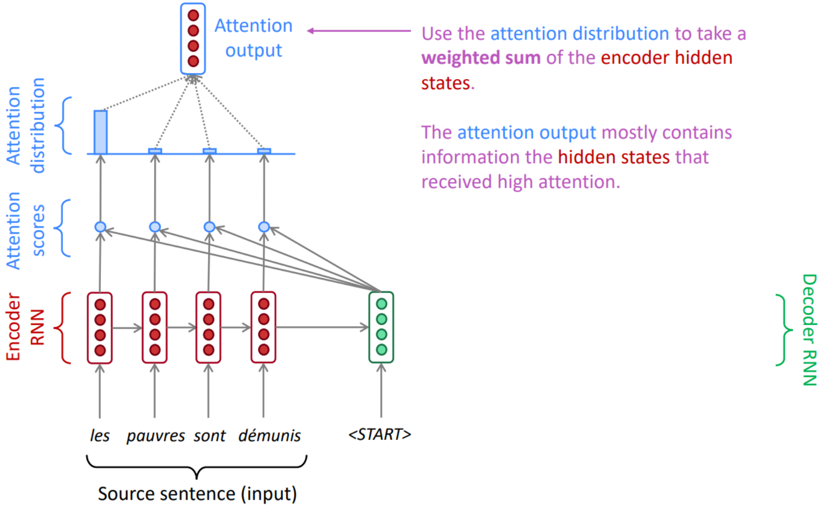
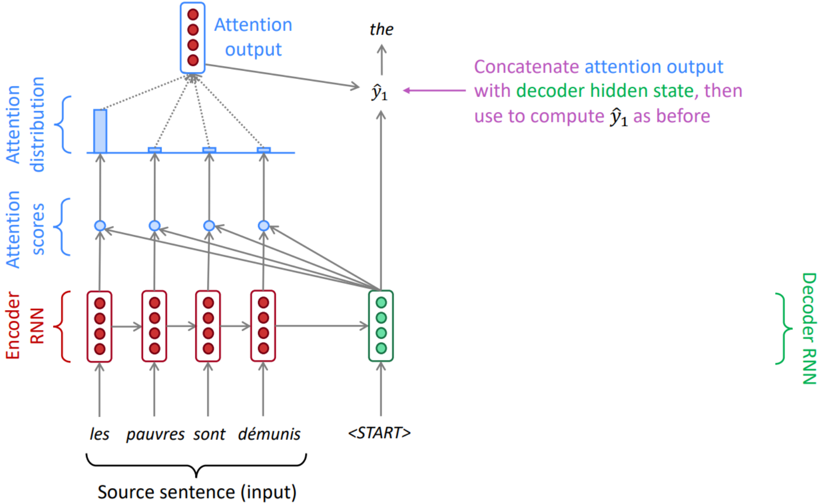


Use the attention distribution to take a **weighted sum** of the **encoder hidden states**.

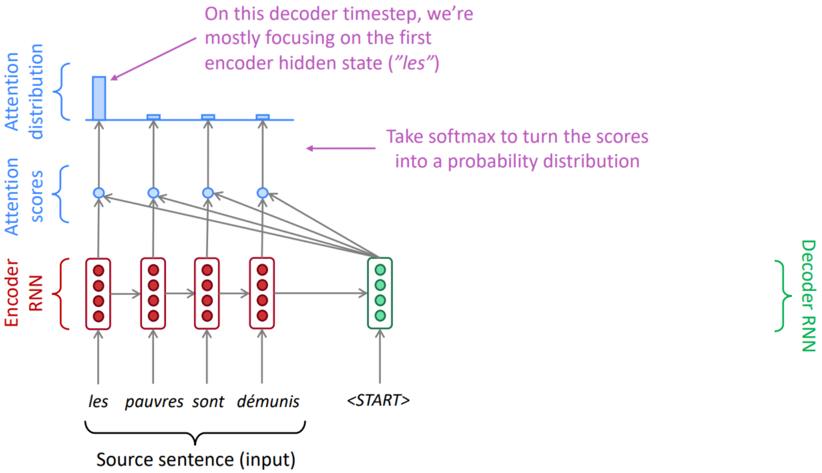
The attention output mostly contains information the **hidden states** that received high attention.

Global attention



Concatenate attention output with decoder hidden state, then use to compute $\hat{y}_1$ as before

Global attention



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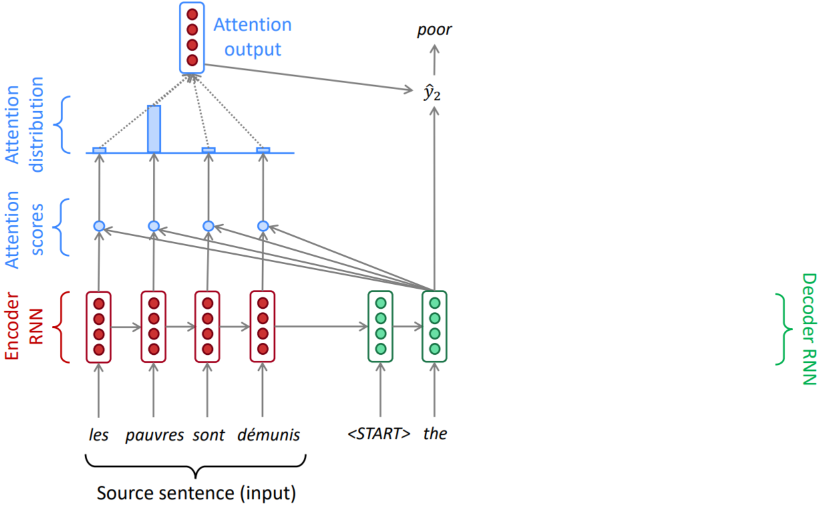

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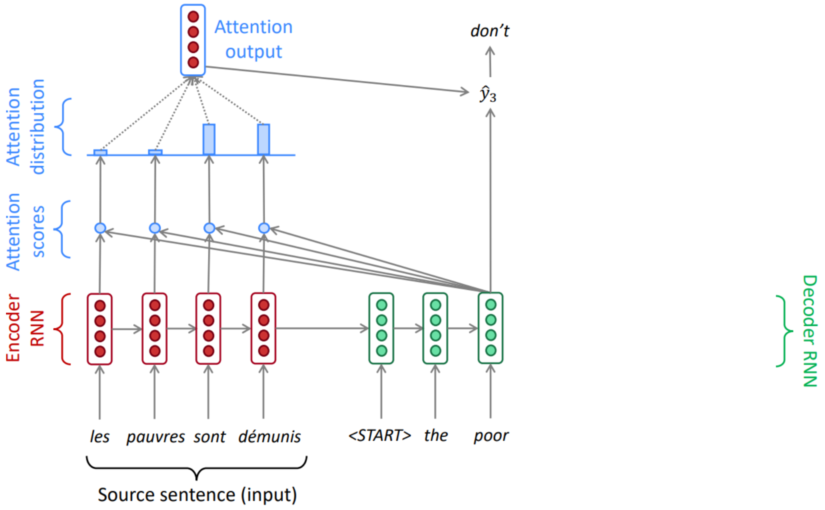

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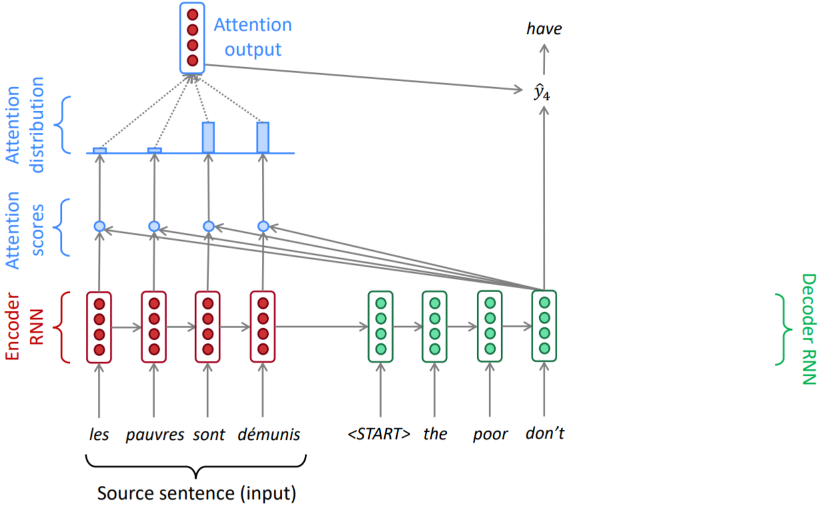

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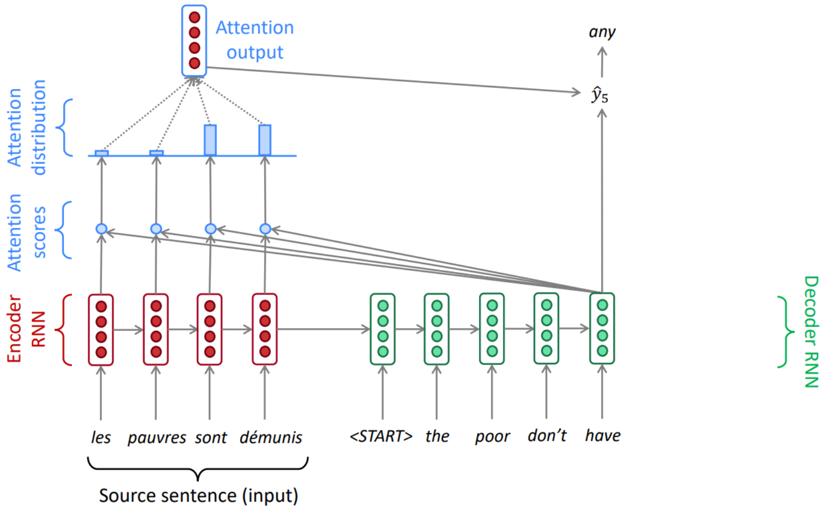

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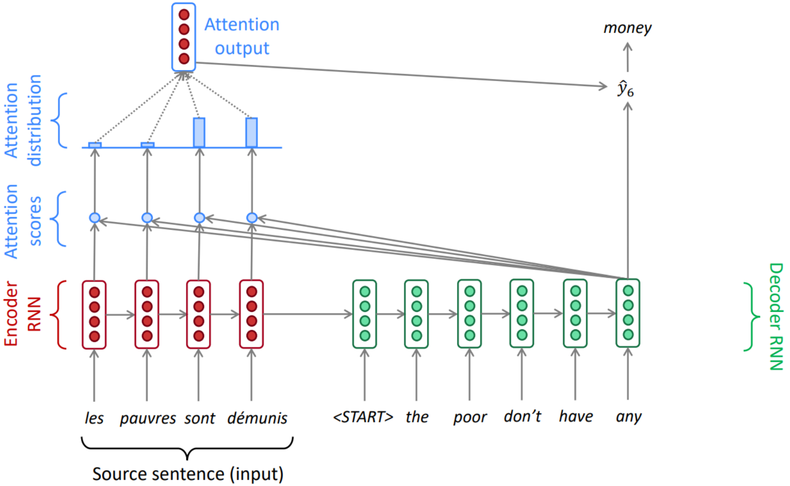

Global attention: Algorithm

- Encoder (h_{et} - e for encoder, t is the time stamp)
  - Calculate the encode state, $H_e = h_{e1}, h_{e2}, ...h_{eN}$
- Decoder (h_{dt} - d for decoder, t is the time stamp)
  - for each time step t calculate score compared to H_e,

$$\begin{aligned} a_t(s) &= align(h_{dt}, h_{es}) \\ &= \frac{exp(score(h_{dt}, h_{es})}{\sum_{s'} exp(score(h_{dt}, h_{es}))} \end{aligned}$$

(s is the sequence length)

Global attention: Algorithm

- Decoder
  - for each time step t calculate score compared to H_e,
    $a_t(s) = align(h_{dt}, h_{es}) = \frac{exp(score(h_{dt},h_{es})}{\sum_{s'} exp(h_{dt},h_{es})}$ (s is the sequence length)
  - $$score(h_{dt}, h_{es}) = \begin{cases} h_{dt}^T h_{es} & dot \\ h_{dt}^T W_a h_{es} & general \\ v_a^T \tanh(W_a[h_{dt}^T; h_{es}]) & concat \end{cases}$$
  - $$c_t = \sum_{i=1}^{s} a_t(i) h_{ei}$$
  - $h_{dout} = \tanh(W_c[c_t; h_{dt}])$
  - $p(y_t|y_{<t}, x) = softmax(W_s h_{dout})$

Global attention

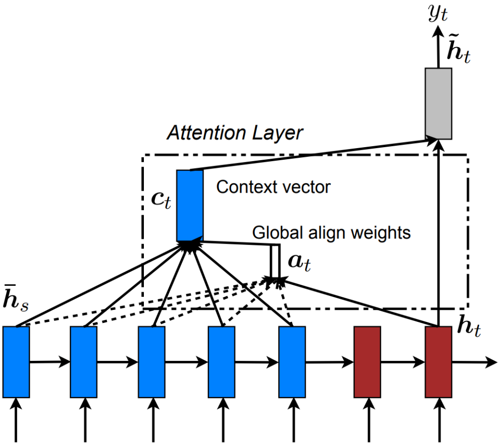

Figure: Global attention figure from the paper.

Local Attention

- For each decoder step t,
  the model first generates an aligned position p_t.
- Calculate the attention in window $[p_{t-D}, p_{t+D}]$
- D is empirically selected.
- Unlike the global approach, the local alignment vector a_t is now fixed-dimensional.

Local attention

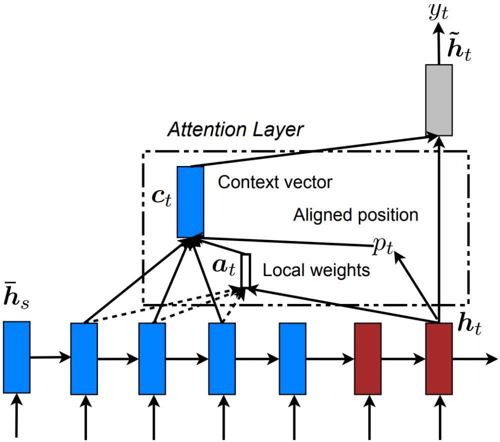

Figure: Local attention figure from the paper.

p_t selection

To calculate the value of p_t the paper consider 2 approaches,

- **Monotonic alignment (local-m) :** Simply set $p_t = t$ assuming that source and target sequences are roughly monotonically aligned
- **Predictive alignment (local-p) :** use a NN to predict the position,

$$p_t = S * sigmoid(v_p tanh(W_p h_{dt}))$$

$$a_t(s) = align(h_{et}, h_{ds}) exp(-\frac{(s - p_t)^2}{2\sigma^2})$$

where, $\sigma = D/2.p_t$ is a real number. s is an integer within the window centered at p_t

Outline

Input feeding Method

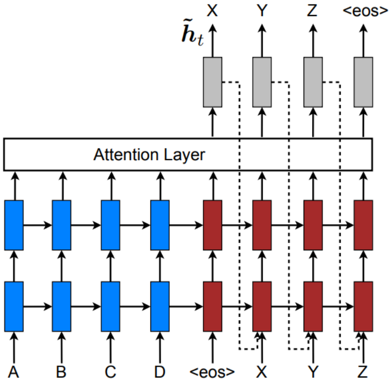

Figure: Attentional vectors $\tilde{h}_t$(decoder side) are fed as inputs to the next time steps to inform the model about past alignment decisions

Experiment

System	Ppl	BLEU
Winning WMT'14 system – *phrase-based* + *large LM* (Buck et al., 2014)		20.7
Existing NMT systems		
RNNsearch (Jean et al., 2015)		16.5
RNNsearch + unk replace (Jean et al., 2015)		19.0
RNNsearch + unk replace + large vocab + *ensemble* 8 models (Jean et al., 2015)		**21.6**
Our NMT systems		
Base	10.6	11.3
Base + reverse	9.9	12.6 (+*1.3*)
Base + reverse + dropout	8.1	14.0 (+*1.4*)
Base + reverse + dropout + global attention (*location*)	7.3	16.8 (+*2.8*)
Base + reverse + dropout + global attention (*location*) + feed input	6.4	18.1 (+*1.3*)
Base + reverse + dropout + local-p attention (*general*) + feed input	5.9	19.0 (+*0.9*)
Base + reverse + dropout + local-p attention (*general*) + feed input + unk replace		20.9 (+*1.9*)
Ensemble 8 models + unk replace		**23.0** (+*2.1*)

Figure: WMT14 English-German results

Length Analysis

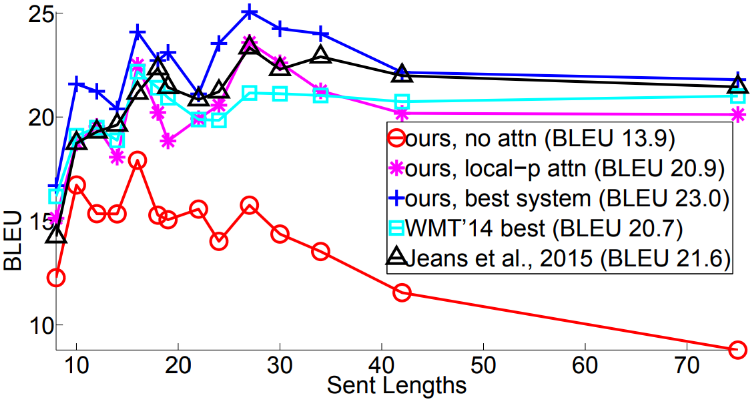

Figure: Length Analysis translation qualities of different systems as sentences become longer.

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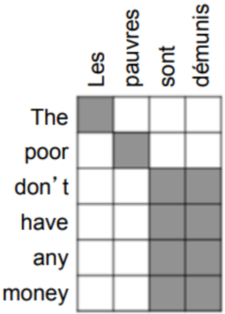
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability.



Credits

- Effective Approaches to Attention-based Neural Machine Translation Luong et al.
- Dr. Shafiq Joty.
- Stanford CS224n Slides.
- Christopher D. Manning's Lecture.