EE-559 – Deep learning

13.1. Attention Mechanisms

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https://fleuret.org/ee559/

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Attention mechanisms aggregate features with an importance score that

- depends on the feature themselves, not only on their position in the tensor,
- relax locality constraints.

Given a $1D$ convolutional map

$$x \in \mathbb{R}^{T \times D},$$

a standard approach to build an aggregated information is average pooling

$$y_j = \sum_{i=1}^{T} \frac{\mathbf{1}_{\{|j-i| \leq \Delta\}}}{\sum_k \mathbf{1}_{\{|j-k| \leq \Delta\}}} x_i.$$

Here the contribution of x_i to y_j is entirely driven by their locations [in the tensor]. This is a form of **spatial attention**.

For **context attention**, the importance of x_i in computing y_j is not entirely determined by i and j but by x_i and j through an attention function $a(x_i;\theta_j)$

$$y_j = \sum_{i=1}^{T} \frac{e^{a(x_i;\theta_j)}}{\sum_k e^{a(x_k;\theta_j)}} x_i = \sum_{i=1}^{T} \mathrm{softmax}_i \left(a(x_i;\theta_j)\right) x_i,$$

where the θ_j are model parameters.

We differentiate this from **self-attention**, where the importance of x_i in computing y_j depends on x_i and x_j

$$y_j = \sum_{i=1}^{T} \operatorname{softmax}_i \left(a(x_i, x_j; \theta) \right) x_i.$$

The most standard approaches implement attention as a dot-product, *e.g.*

$$a(x; V) = x^T V$$

or

$$a(x, x'; W, W') = (Wx)^T (W'x')$$

for self-attention.

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However, the quantity a can take any form, *e.g.* an MLP.

In what follows there is often an implicit "channel dimension" and the matrix product operates on the channels at every "location" of every sample.

With

$$W \in \mathbb{R}^{c \times d}$$

and x a d-channel tensor

$$x \in \mathbb{R}^{\mathscr{A} \times d \times \mathscr{B}}$$

the resulting tensor has same shape with c channels

$$Wx \in \mathbb{R}^{\mathscr{A} \times c \times \mathscr{B}}.$$

Attention for seq2seq

Attention mechanisms where re-introduced for deep learning to provide long-term dependency for sequence-to-sequence translation.

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For such a task, given an input sequence $x_1, \dots, x_T$, the standard approach (Sutskever et al., 2014) is to use a recurrent model

$$h_t = f(x_t, h_{t-1}),$$

and to consider that the final hidden state

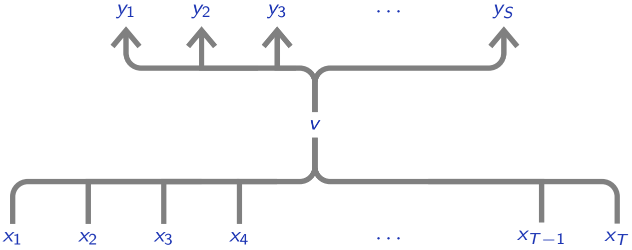
$$v = h_T$$

carries enough information to drive an auto-regressive generative model

$$y_t \sim p\left(y_1, \dots, y_{t-1}, v\right),$$

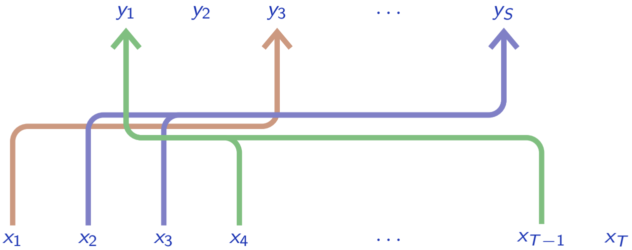
itself implemented with another RNN.

The main weakness of such an approach is that all the information has to flow through a single state v, whose capacity has to accommodate any situation.



There are no direct "channels" to transport local information from the input sequence to the place where it is useful in the resulting sequence.

Attention mechanisms (Graves et al., 2014; Bahdanau et al., 2014) transport information from parts of the signal to other parts **specified dynamically**.



Bahdanau et al. (2014) propose to extend a standard recurrent model with such a mechanism. They first run a bi-directionnal RNN to get a hidden state

$$h_i = (h_i^{\rightarrow}, h_i^{\leftarrow}),\ i = 1, \dots, T.$$

From this, they compute a new process $s_i,\ i = 1, \dots, T$ which looks at weighted averages of the h_j, where **the weight are functions of the signal.**

Given $y_1, \dots, y_{i-1}$ and $s_1, \dots, s_{i-1}$ first compute an attention

$$\forall j,\ e_{i,j} = a(s_{i-1}, h_j)$$

where a is a one hidden layer tanh MLP (this is "additive attention", or "concatenation").

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Normalize it into a distribution with a standard softmax

$$\forall j,\ \alpha_{i,j} = \frac{\exp(e_{i,j})}{\sum_{k=1}^{T} \exp(e_{i,k})},$$

and compute the **context vector** from the hs to predict y_i

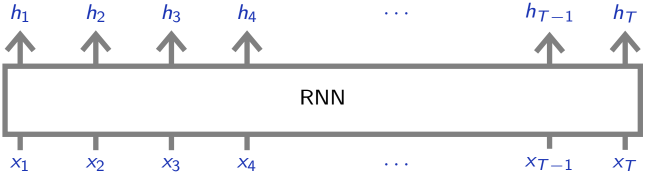
$$c_i = \sum_{j=1}^{T} \alpha_{i,j} h_j.$$

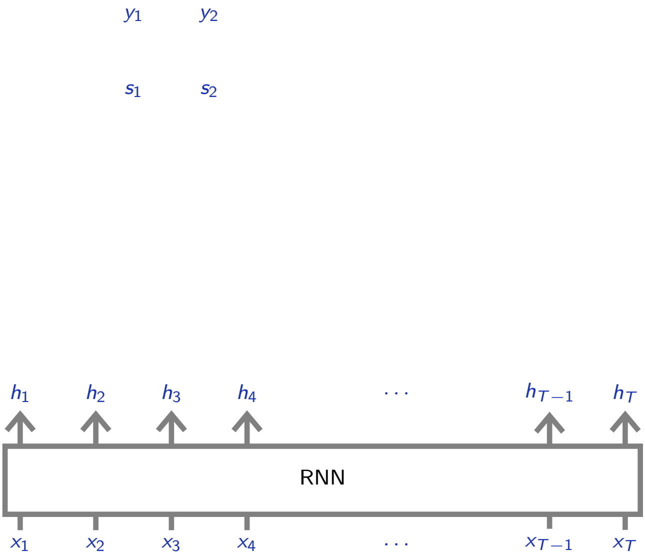
The model can now make the prediction

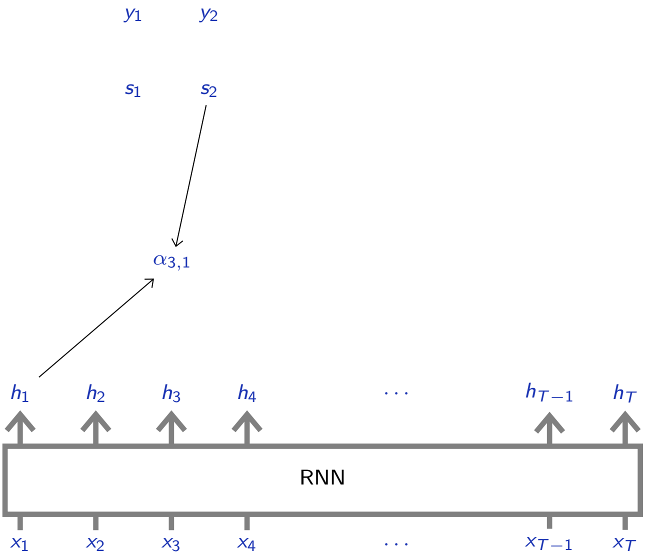
$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$
$$y_i \sim g(y_{i-1}, s_i, c_i)$$

where f is a GRU (Cho et al., 2014).

x_1 x_2 x_3 x_4 $\cdots$ x_{T-1} x_T


h_1
h_2
h_3
h_4
$\cdots$
h_{T-1}
h_T
RNN
x_1
x_2
x_3
x_4
$\cdots$
x_{T-1}
x_T


y_1 y_2
s_1 s_2
h_1 h_2 h_3 h_4 ... h_{T-1} h_T
RNN
x_1 x_2 x_3 x_4 ... x_{T-1} x_T


y_1
y_2
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s_2
$\alpha_{3,1}$
h_1
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RNN
x_1
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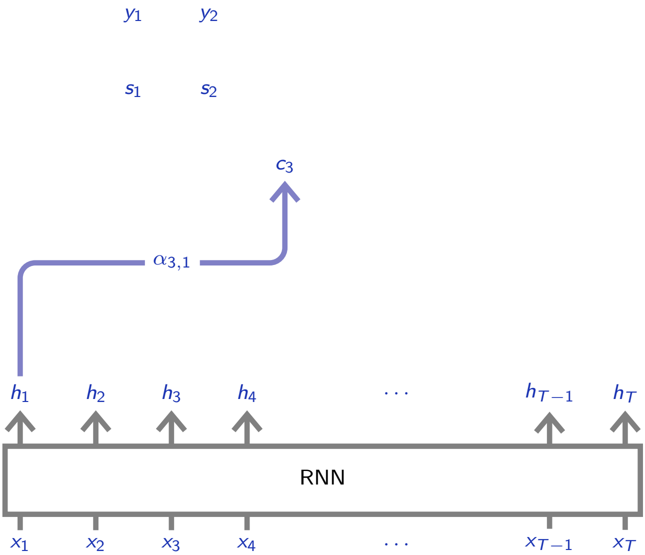
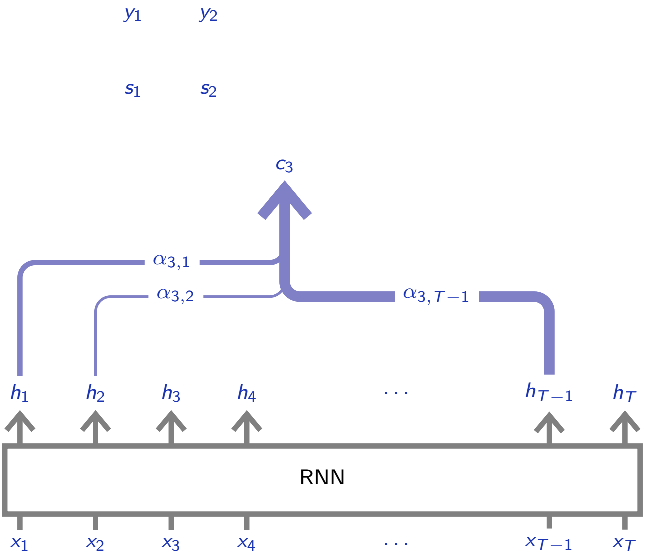
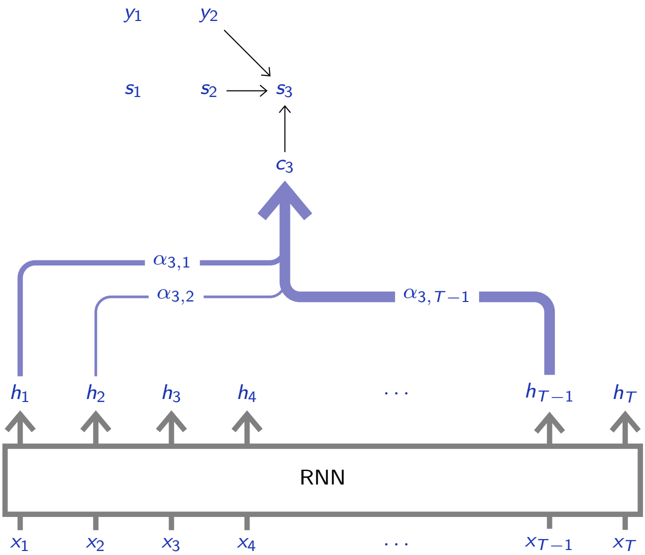

y_1 y_2
s_1 s_2
c_3
$\alpha_{3,1}$
h_1 h_2 h_3 h_4 $\dots$ h_{T-1} h_T
RNN
x_1 x_2 x_3 x_4 $\dots$ x_{T-1} x_T



y_1
y_2
s_1
s_2
c_3
$\alpha_{3,1}$
$\alpha_{3,2}$
$\alpha_{3,T-1}$
h_1 h_2 h_3 h_4 ... h_{T-1} h_T
RNN
x_1 x_2 x_3 x_4 ... x_{T-1} x_T


y_1
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c_3
$\alpha_{3,1}$
$\alpha_{3,2}$
$\alpha_{3,T-1}$
h_1
h_2
h_3
h_4
$\dots$
h_{T-1}
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RNN
x_1
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x_{T-1}
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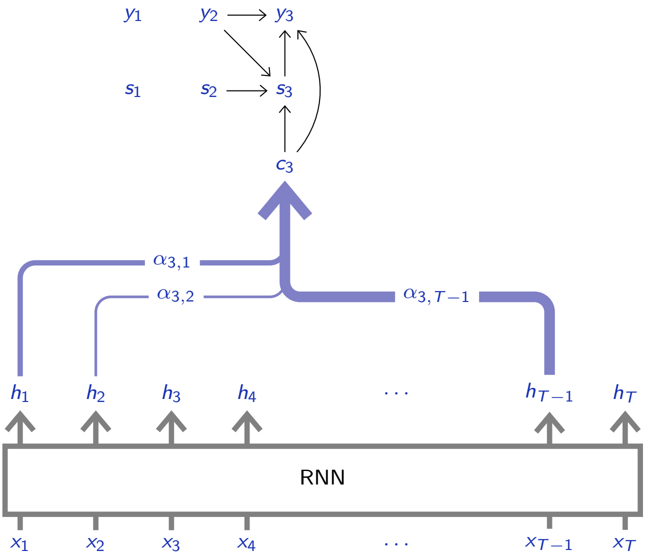
y_1
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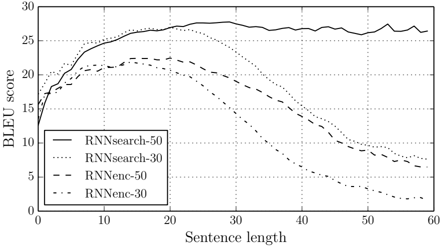
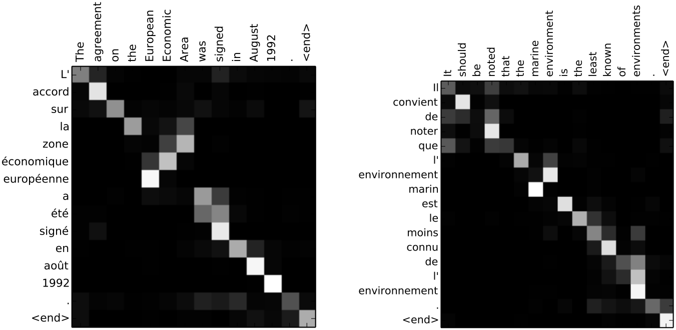


Figure 2: The BLEU scores of the generated translations on the test set with respect to the lengths of the sentences. The results are on the full test set which includes sentences having unknown words to the models.

(Bahdanau et al., 2014)



(a) (b)

(Bahdanau et al., 2014)

The end

References

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