Deep learning

13.1. Attention for Memory and Sequence Translation

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In all the operations we have seen, such as fully connected layers, convolutions, or poolings, the contribution of a value in the input tensor to a value in the output tensor is entirely driven by their [relative] locations [in the tensor].

However some tasks involve more than hierarchical structures, e.g. translation:

> "**An apple** that had been on the tree in the garden for weeks had finally been **picked up.**"
>
> "**Une pomme** qui était sur l'arbre du jardin depuis des semaines avait finalement été **ramassée.**"

It has motivated the development of **attention-based processing** to transport information from parts of the signal to other parts dynamically identified.

Attention mechanisms aggregate features with an importance score that

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

They modulate dynamically the weighting of different parts of a signal and allow the representation and allocation of information channels to be dependent on the activations themselves.

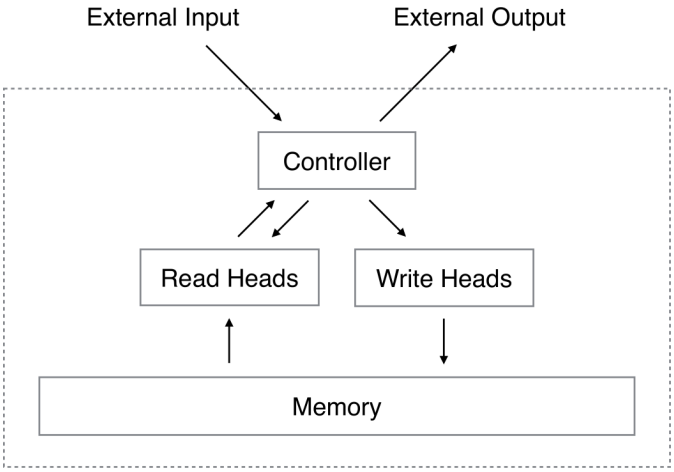
While they were developed to equip deep-learning models with memory-like modules (Graves et al., 2014), their main use now is to provide long-term dependency for sequence-to-sequence translation (Vaswani et al., 2017).

Notes

The attention mechanism allows the information to move from one part of the tensor to another part far way.
For instance, in the case of sequence-to-sequence translation, it is able to use an information from early in the sentence to do a proper grammatical decision later.
For images, it is able to combine information from different parts of the image even if there are far away.
It also allows the model to discard information which is identified as irrelevant, and in particular to decide it has a better use of the activations that come in the latter parts of the model.

Neural Turing Machine

Graves et al. (2014) proposed to equip a deep model with an explicit memory to allow for long-term storage and retrieval.



(Graves et al., 2014)

The said module has an hidden internal state that takes the form of a tensor

$$M_t \in \mathbb{R}^{N \times M}$$

where t is the time step, N is the number of entries in the memory and M is their dimension.

A "controller" is implemented as a standard feed-forward or recurrent model and at every iteration t it computes activations that modulate the reading / writing operations.

More formally, the memory module implements

- Reading, where given attention weights $w_t \in \mathbb{R}_+^N$, $\sum_n w_t(n) = 1$, it gets

$$r_t = \sum_{n=1}^{N} w_t(n) M_t(n).$$

- Writing, where given attention weights w_t, an *erase vector* $e_t \in [0,1]^M$ and an *add vector* $a_t \in \mathbb{R}^M$ the memory is updated with

$$\forall n, M_t(n) = M_{t-1}(n)(1 - w_t(n)e_t) + w_t(n)a_t.$$

The controller has multiple "heads", and computes at each t, for each writing head w_t, e_t, a_t, and for each reading head w_t, and gets back a read value r_t.

The vectors w_t are themselves recurrent, and the controller can strengthen them on certain **key values**, and/or shift them.

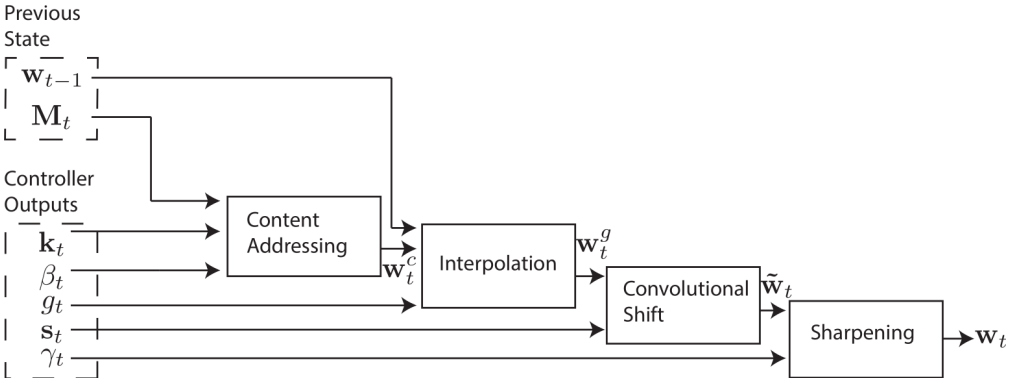
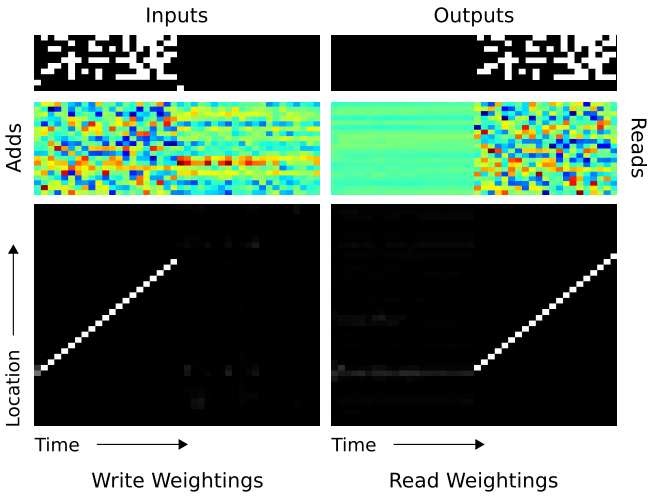
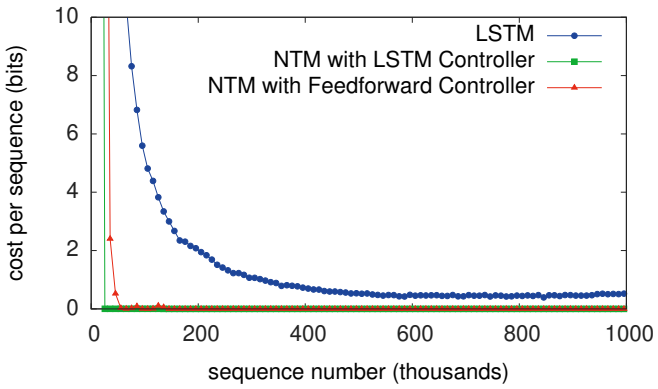


Figure 2: Flow Diagram of the Addressing Mechanism. The *key vector*, $\mathbf{k}_t$, and *key strength*, β_t, are used to perform content-based addressing of the memory matrix, $\mathbf{M}_t$. The resulting content-based weighting is interpolated with the weighting from the previous time step based on the value of the *interpolation gate*, g_t. The *shift weighting*, $\mathbf{s}_t$, determines whether and by how much the weighting is rotated. Finally, depending on γ_t, the weighting is sharpened and used for memory access.

(Graves et al., 2014)

Results on the copy task



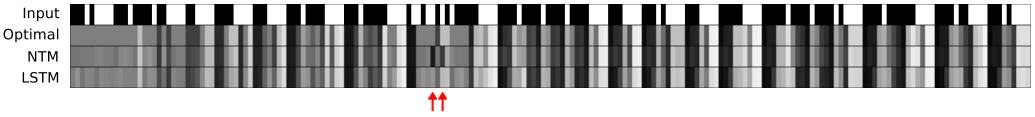


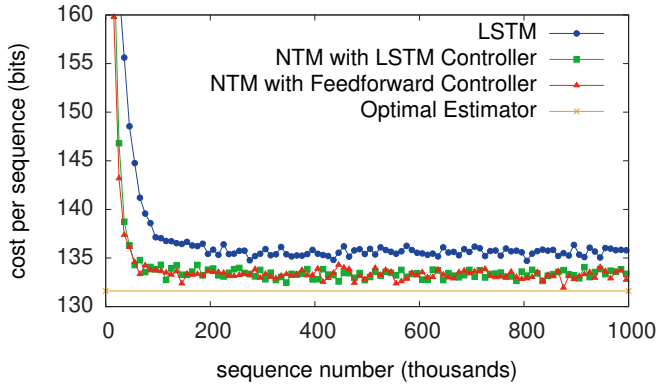
(Graves et al., 2014)

Notes

The copy task consists of copying the content of a sequence. The input consists of a "start" marker, followed by the signal and the "end" marker, after which the input is zero. The objective is to produce an output composed of zeros until the "end" marker, from which the model should repeat what was before the "end" marker.
Here, the input is a sequence of 20 binary vectors of dimension 8.
Although it is a toy task, it is difficult for standard recurrent neural nets, because it involves memorizing the full signal.
The bottom image described by "time" on the x-axis and "Location" on the y-axis depicts the "write" weightings during a test sequence. The model learned to shift the weightings during the reading and to store in successive order the values it got as input in order to read from there to produce the proper output.

Results on the N-gram task





(Graves et al., 2014)

Notes

An N-gram model aims at predicting a value given the previous $N - 1$ observed ones.
Here, the neural Turing machine should learn to estimate the 32 empirical probabilities of the next bit being 1 given the 5 previous bits.

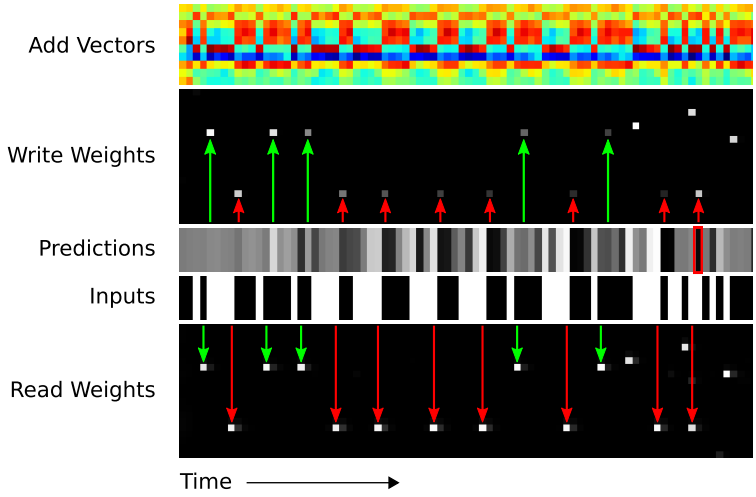


Figure 15: NTM Memory Use During the Dynamic N-Gram Task. The red and green arrows indicate point where the same context is repeatedly observed during the test sequence ("00010" for the green arrows, "01111" for the red arrows). At each such point the same location is accessed by the read head, and then, on the next time-step, accessed by the write head. We postulate that the network uses the writes to keep count of the fraction of ones and zeros following each context in the sequence so far. This is supported by the add vectors, which are clearly anti-correlated at places where the input is one or zero, suggesting a distributed "counter." Note that the write weightings grow fainter as the same context is repeatedly seen; this may be because the memory records a ratio of ones to zeros, rather than absolute counts. The red box in the prediction sequence corresponds to the mistake at the first red arrow in Figure 14; the controller appears to have accessed the wrong memory location, as the previous context was "01101" and not "01111."

(Graves et al., 2014)

Attention for seq2seq

Given an input sequence $x_1, \ldots, x_T$, the standard approach for sequence- to-sequence translation (Sutskever et al., 2014) uses a recurrent model

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

and considers that the final hidden state

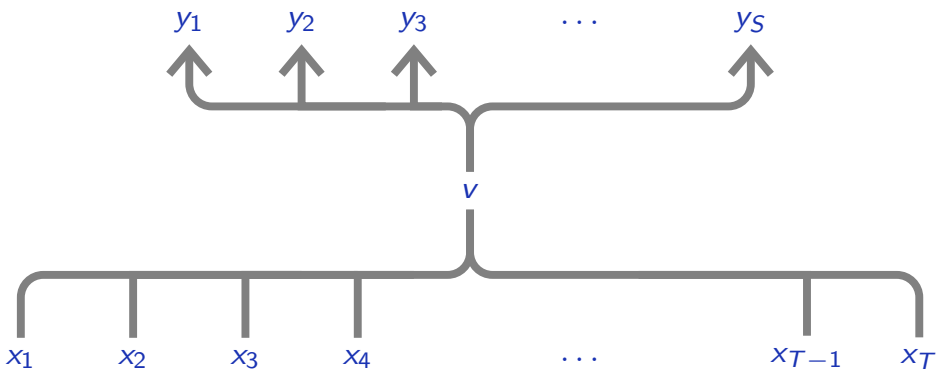
$$v = h_T$$

carries enough information to drive an auto-regressive generative model

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

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.

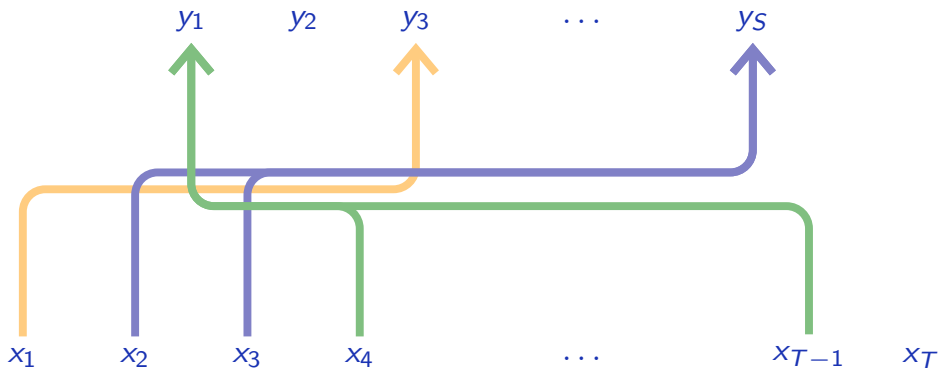


There are no direct "channels" to transport local information from the input sequence to the place where it is useful in the resulting sequence.

Notes

On the diagram, $x_1, \ldots, x_T$ is the input sequence, for instance a sentence in German. $y_1, \ldots, y_S$ is the output sequence, for instance a sentence in English.
With a recurrent model, all the information flows through a single state v, which is obtained after visiting the full input sequence. Therefore, v has to contain all the information required to generate the $y_1, \ldots, y_S$.

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



Notes

This diagram illustrates the core idea of the attention mechanism: there are direct flows of information between parts of the sequence which are dynamically identified from the activations.

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

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

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

Notes

The new process s_i modulates all the hs based on the signal itself to evaluate what are the hs to take into account. As we will see later, s_i depends on a linear combination of the hs called a context vector.

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

$$\forall j,\ \alpha_{i,j} = \text{softmax}_j\, a(s_{i-1}, h_j)$$

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

Then compute the **context vector** from the hs

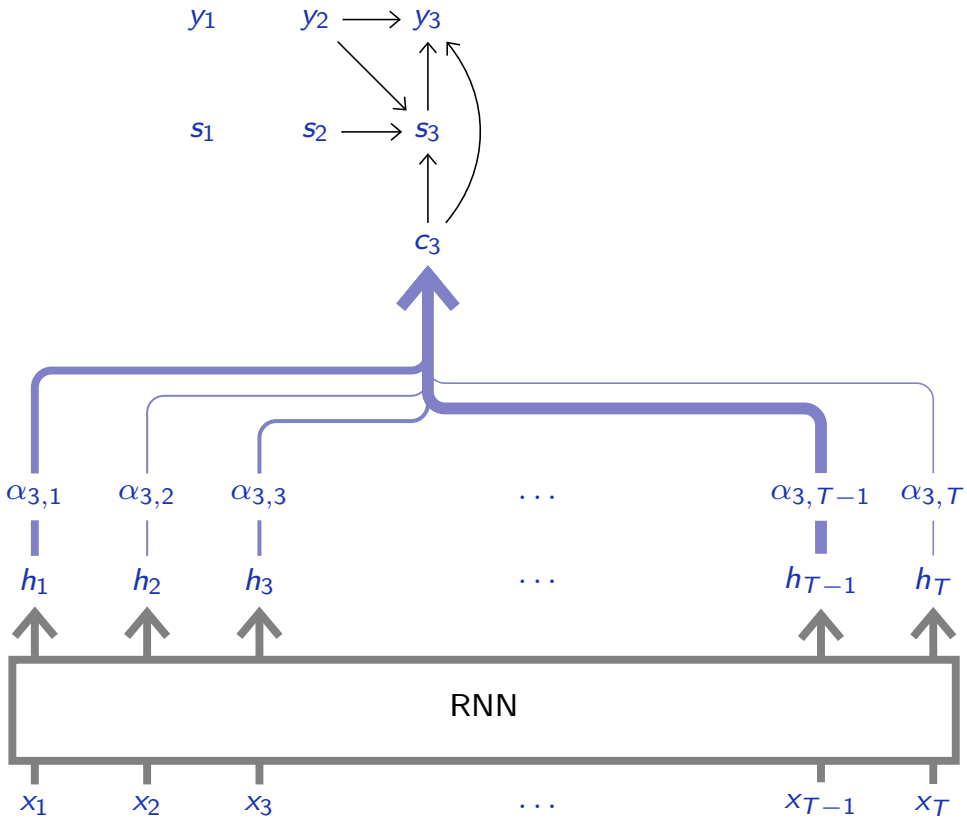
$$c_i = \sum_{j=1}^{T} \alpha_{i,j} h_j.$$

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).

This is **context attention** where s_{i-1} modulates what to look at in $h_1, \ldots, h_T$ to compute s_i and sample y_i.



Notes

On the diagram, the first two outputs y_1, y_2 and the hidden states s_1, s_2 have already been computed, and what is depicted is the process to sample y_3.
The sequence $x_1, \ldots, x_T$ is the input (e.g. sentence in German, where the x would be the embedding vectors of the words).
The RNN is bi-directionnal with hidden states $h_1, \ldots, h_T$.
The hidden state s_2 is used to obtain the $\alpha_{3,i}$, $i = 1, \ldots, T$, that is how much each of the hidden states should be weighted at iteration 3, which produces the context vector c_3. The thickness of the lines between the αs and c_3 depicts the importance of the different positions in the sequences, as estimated by the αs.
Then, the current hidden state s_3 is computed given the context vector c_3, the previous hidden state s_2, and the last produced word y_2.
And finally, given the new hidden state s_3, the previous produced word y_2, and the current context vector c_3, a new token y_3 is generated.

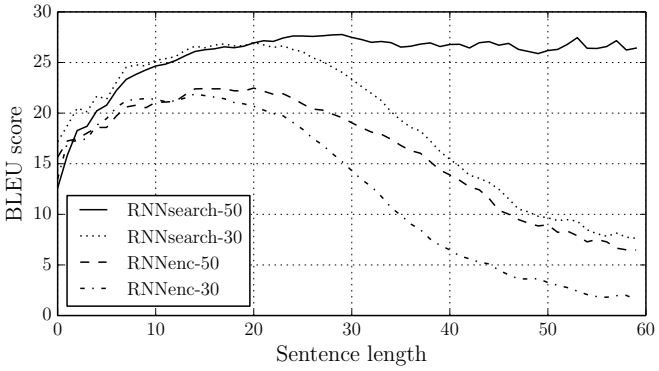
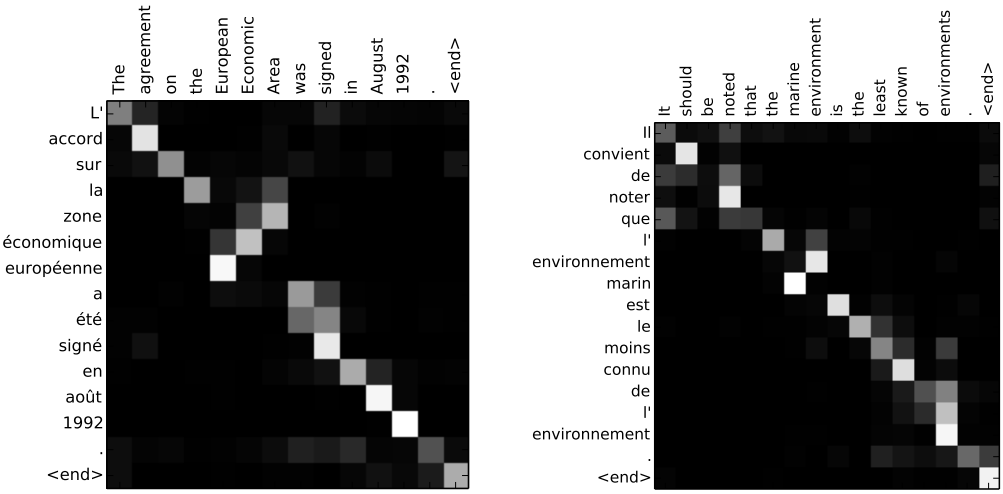


Figure 2: The BLEU scores of the generated translations on the test set with respect to the lengths of the sentences. The results are on the full test set which includes sentences having unknown words to the models.

(Bahdanau et al., 2014)



(a) (b)

(Bahdanau et al., 2014)

Notes

What is satisfying is that the weighting process can easily be interpreted.
We can look at the αs, that is the weight put at each timestep (i.e. index t) to produce the given output.
On the plots, the x-axis is the input sentence while on the y-axis lays the generated sequence. Each row i represents the $\alpha_{i,j}$ to produce token i in the output sequence. Black stands for small importance ($\alpha_{i,j} \simeq 0$) and white for great importance ($\alpha_{i,j} \simeq 1$).
In particular, on figure (b), to generate " l' ", the attention was put on "the" and on "environment", because both the determiner and the noun are needed to translated the former.

References

D. Bahdanau, K. Cho, and Y. Bengio. **Neural machine translation by jointly learning to align and translate**. CoRR, abs/1409.0473, 2014.

K. Cho, B. van Merrienboer, Ç. Gülçehre, F. Bougares, H. Schwenk, and Y. Bengio. **Learning phrase representations using RNN encoder-decoder for statistical machine translation**. CoRR, abs/1406.1078, 2014.

A. Graves, G. Wayne, and I. Danihelka. **Neural turing machines**. CoRR, abs/1410.5401, 2014.

I. Sutskever, O. Vinyals, and Q. V. Le. **Sequence to sequence learning with neural networks**. In Neural Information Processing Systems (NIPS), pages 3104–3112, 2014.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. Gomez, L. Kaiser, and I. Polosukhin. **Attention is all you need**. CoRR, abs/1706.03762, 2017.