92586 Computational Linguistics

Lesson 18. Bidirectional RNN → Long Short-Term Memory Networks

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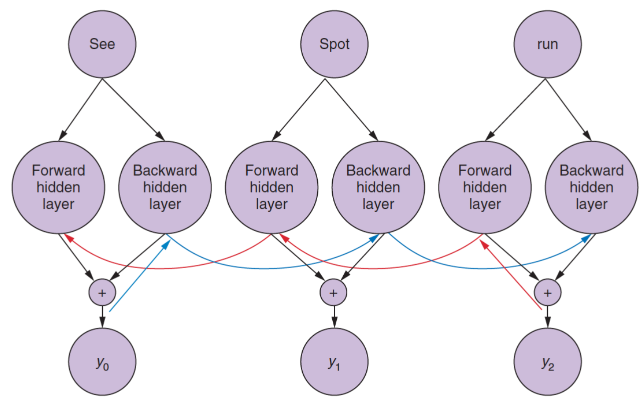
Left and right context

Not only the previous context is important to understand the *current* token

They wanted to pet the dog whose fur was brown.

- Descriptions and relevant information often come later (not earlier)
- A standard RNN neglects information from the *future*

Bidirectional recurrent neural network



- We *arrange* 2 RNNs:
  - one takes the input as usual
  - the other takes the backward input
  - $\bigoplus$ means concatenation

BiRNN zoom into results

Accuracies after 2 epochs

units	**Acc**	**Acc$_{val}$**
50	0.8156	0.7662
40	0.8244	0.7540
30	0.8259	0.7874
20	0.8072	0.8076
10	0.8007	0.8016
5	0.7973	0.8006
1	0.7070	0.7822

* remember we had used 50 units last time for the RNN

LSTMs

Short effect from the past

The effect of token x_t dilutes significantly as soon as in $t+2$

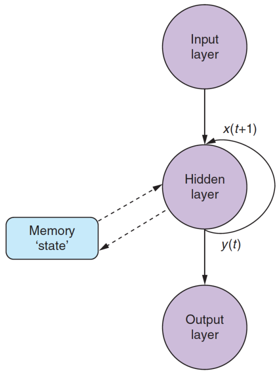
Consider the following —fairly plausible— texts. . .

The young woman went to the movies with her friends.

The young woman, having found a free ticket on the ground, went to the movies.

- In both cases, **went** is the main verb
- A (Bi)RNN would hardly consider that in the second case
- We need an architecture able to "remember" the entire input

State: the memory of an LSTM



- The memory state contains attributes
- The attributes are updated with every instance
- The *rules* of the state are trained NNs

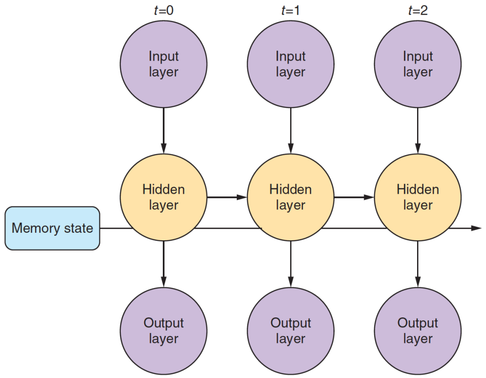
Now we have two learning objectives:

- Learn to predict the target labels
- Learn to identify what has to be remembered

(Lane et al., 2019, p. 276)

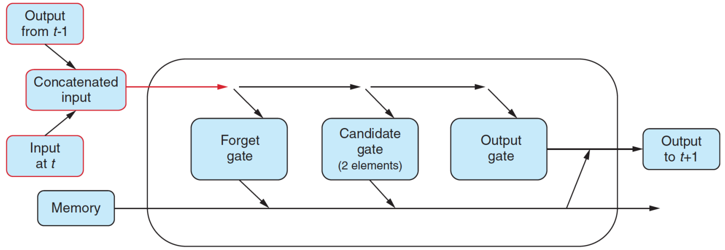
Unrolled LSTM

- Activation from $t-1$ plus memory state
- The memory state sends a vector with the state of each **LSTM cell**, of cardinality number_of_units



(Lane et al., 2019, p. 277)

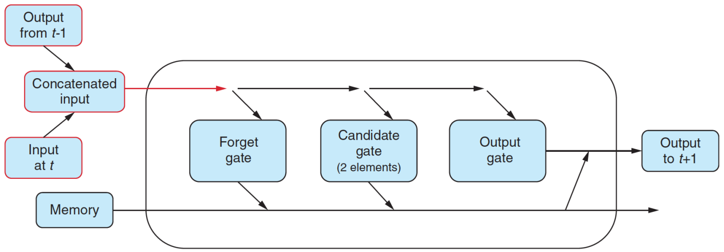
The LSTM cell (layer)



Input: $\text{output}_{t-1} \bigoplus \text{input}_t$

Gates: An FF layer + an activation function **each**

LSTM Forget Gate



Input: $[x_{[t,0]}, x_{[t,1]}, \dots, x_{[t,299]}, h_{[t-1,0]}, h_{[t-1,1]}, \dots h_{[t-1,49]}, 1]$

Forget: How much of the memory should be erased —forgetting long-term dependencies as new ones arise

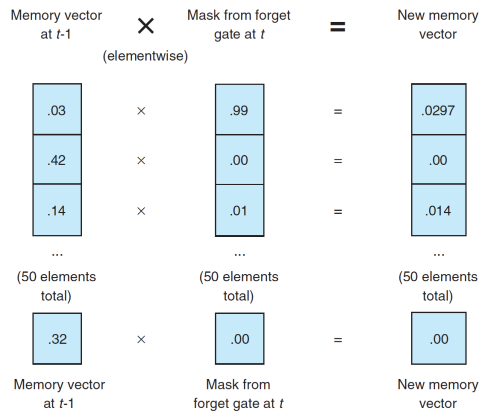
$351 * 50 = 17,550$ parameters

Feed-forward NN with sigmoid activation function: $[0,1]$

(Lane et al., 2019, p. 280)

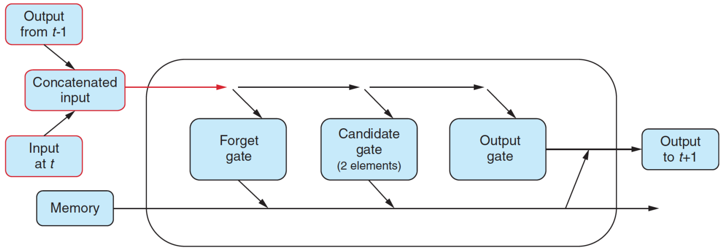
LSTM Forget Gate

Forget is a mask:



(Lane et al., 2019, p. 282)

LSTM Candidate Gate

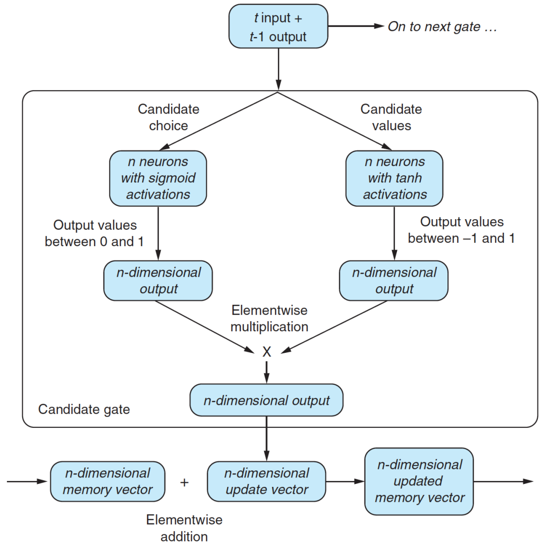


Input:

$[x_{[t,0]}, x_{[t,1]}, \ldots, x_{[t,299]}, h_{[t-1,0]}, h_{[t-1,1]}, \ldots h_{[t-1,49]}, 1]$

Candidate: How much to augment the memory —what to remember and where to do it

LSTM Candidate Gate

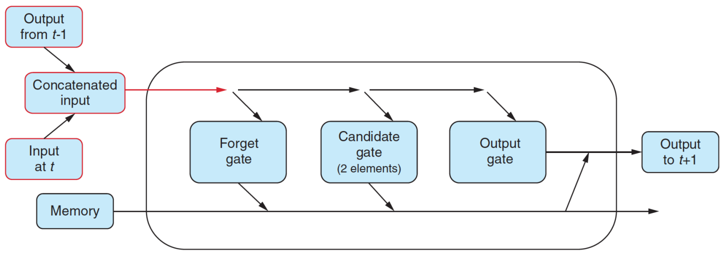


Candidate choice
Which values should be updated (∼forget)

Candidate values
Computes those new values

(Lane et al., 2019, p. 283)

LSTM Output Gate



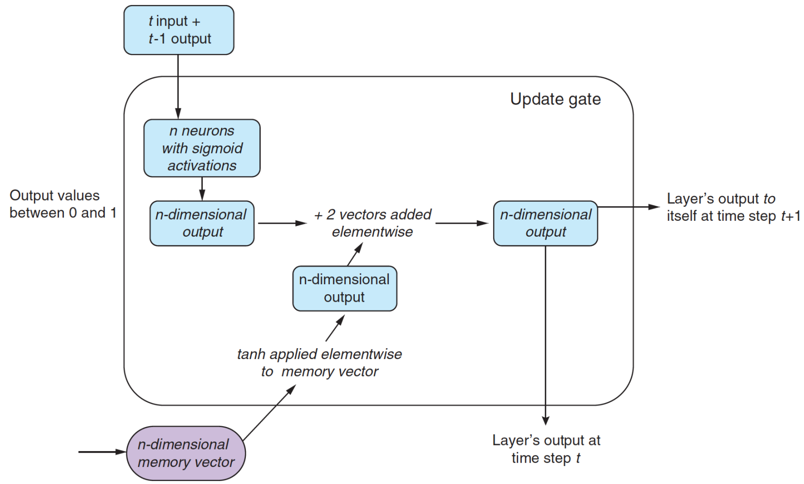
Input:

$[x_{[t,0]}, x_{[t,1]}, \ldots, x_{[t,299]}, h_{[t-1,0]}, h_{[t-1,1]}, \ldots h_{[t-1,49]}, 1]$

Output: produces the output vector —both for the actual task and back to the memory

- sigmoid to the input
- tanh to the state

LSTM Output Gate



* The figure says "added". It is a product

(Lane et al., 2019, p. 284)

LSTM: Wrapping Up

- The *main* network uses the output of the memory in the same fashion as in a RNN
- The memory *decides* what to keep/feed to the network
- The weights of the memory are also learned by back-propagation

Let us see

LSTM: Result

arch	units	Acc	Acc_{val}
BiRNN	50	0.8156	0.7662
BiRNN	40	0.8244	0.7540
BiRNN	30	0.8259	0.7874
BiRNN	20	0.8072	0.8076
BiRNN	10	0.8007	0.8016
BiRNN	5	0.7973	0.8006
BiRNN	1	0.7070	0.7822
LSTM	50	0.7121	**0.8678**

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.