ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 17. Bidirectional RNN → Long Short-Term Memory Networks

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End of Chapter 8, Chapter 9 of Lane et al. (2019)

Left and right context

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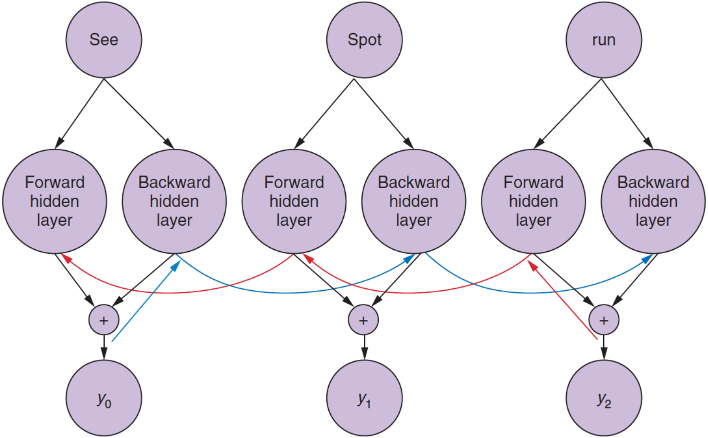
They wanted to pet the dog whose fur was brown.

- Descriptions and relevant information often come later
- 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
  - ⊕ means concatenation

Implementation difference

```
# Adding one bidirectional recurrent layer

model.add(Bidirectional(SimpleRNN(
    num_neurons,
    return_sequences=True),
    input_shape=(maxlen, embedding_dims))
    )
```

Let us see

BiRNN zoom into results

Accuracies after 2 epochs

units	**Acc**	**Acc$_{val}$**
50	0.8156	0.7662

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

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LSTMs

Short effect from the past

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

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Consider the following —fairly plausible— texts. . .

The young woman went to the movies with her friends.

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The young woman went to the movies with her friends.

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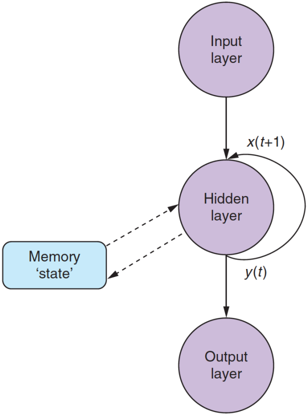
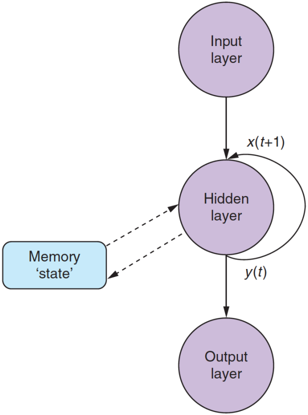
- In both cases, went is the main verb
- A (Bi)RNN would hardly reflect that in the second case
- We need an architecture able to "remember" the entire input

State: the memory of an LSTM



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

State: the memory of an LSTM



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

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

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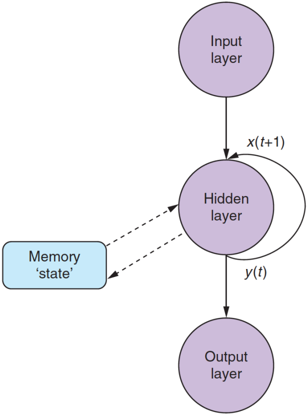

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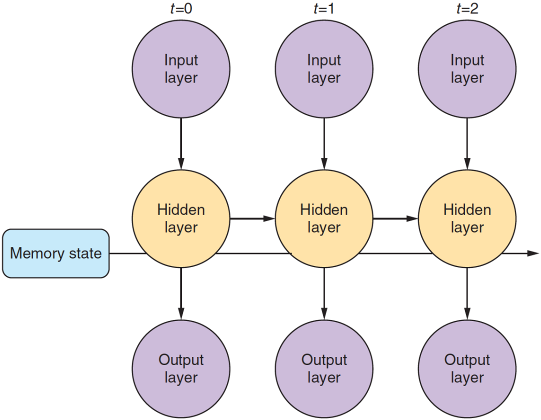
Now we have two learning objectives:

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

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

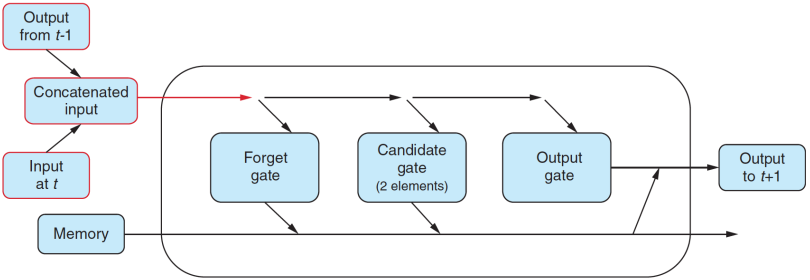
Unrolled LSTM

- 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



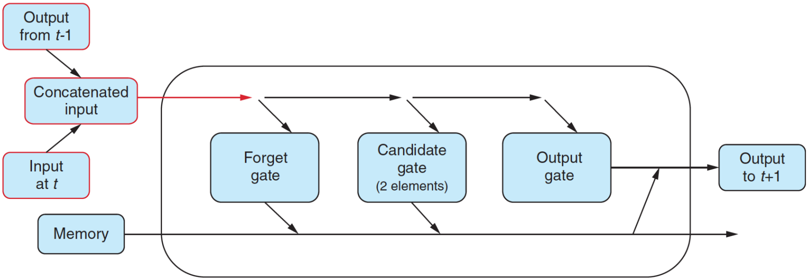
(Lane et al., 2019, p. 277)

The LSTM cell (layer)



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

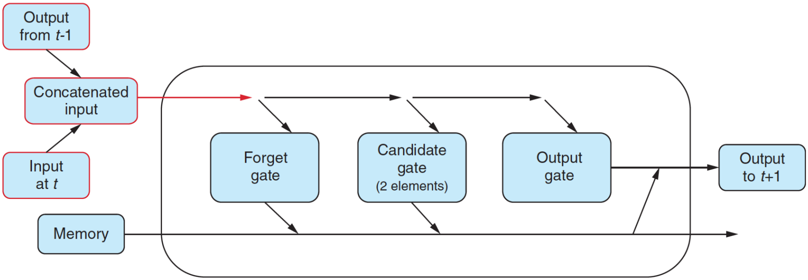
The LSTM cell (layer)



Input: output$_{t-1}$ ⊕ input$_t$

Gates: a FF layer + an activation function each

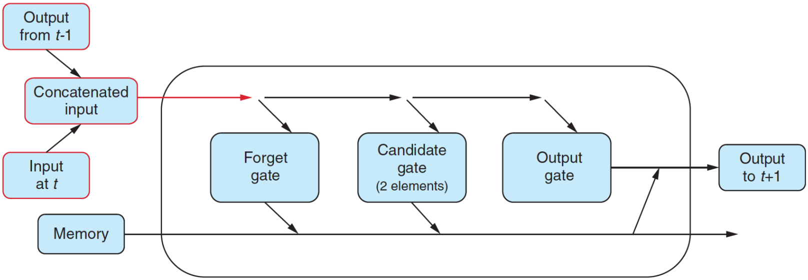
LSTM Forget Gate



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

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

LSTM Forget Gate



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$351 * 50 = 17,550$ parameters

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

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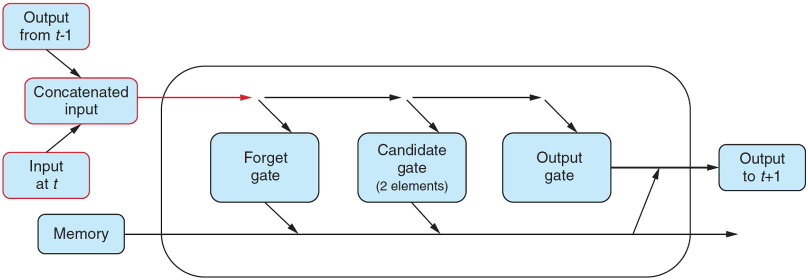

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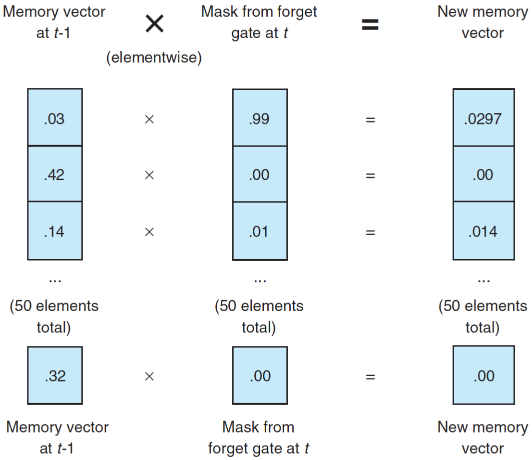
Feed-forward NN with sigmoid activation function: $[0,1]$

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

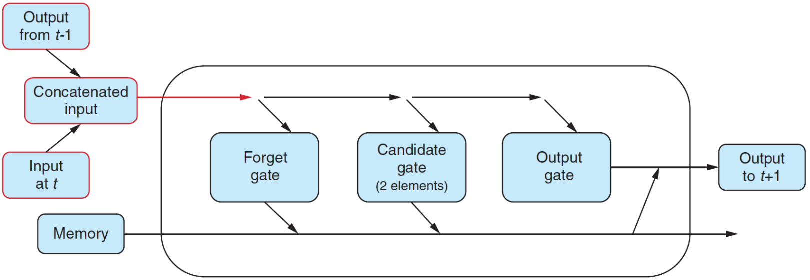
LSTM Forget Gate

Forget is a mask:



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

LSTM Candidate Gate



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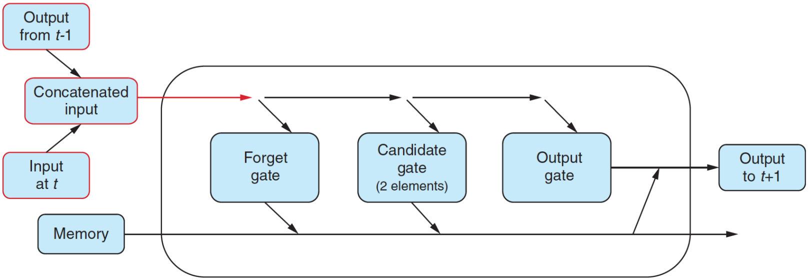

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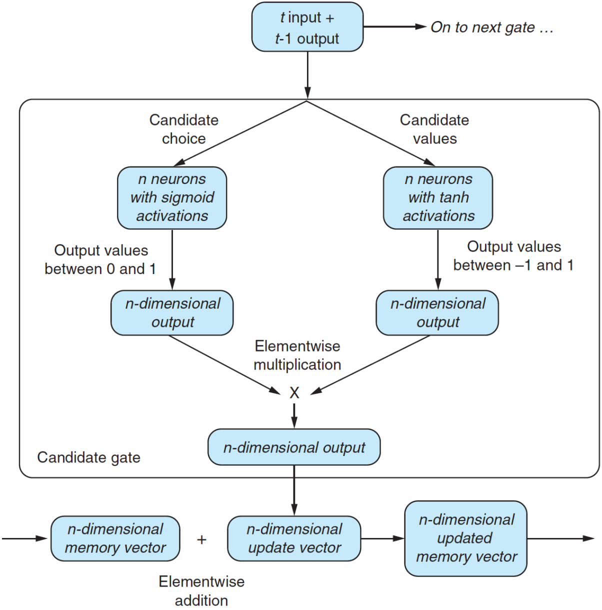
Candidate: How much to augment the memory —what to remember and where to do it

LSTM Candidate Gate



Candidate choice

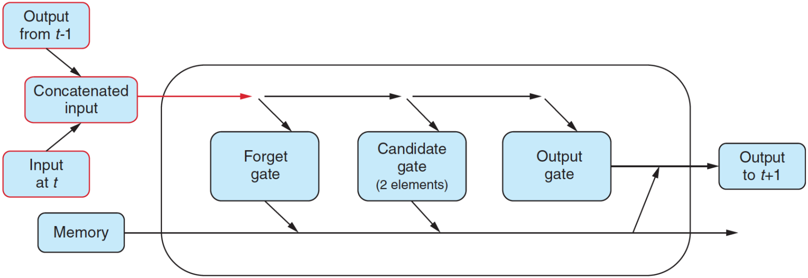
Which values should be updated (∼forget)

Candidate values

Computes those new values

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

LSTM Output Gate



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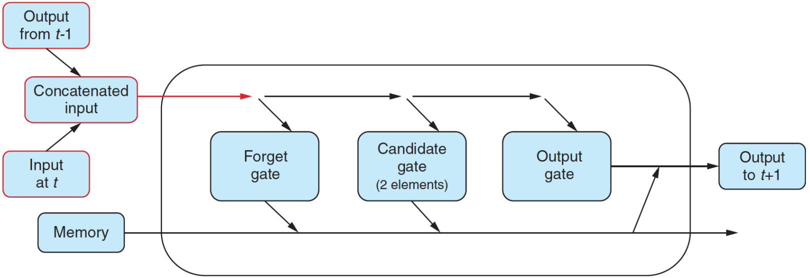

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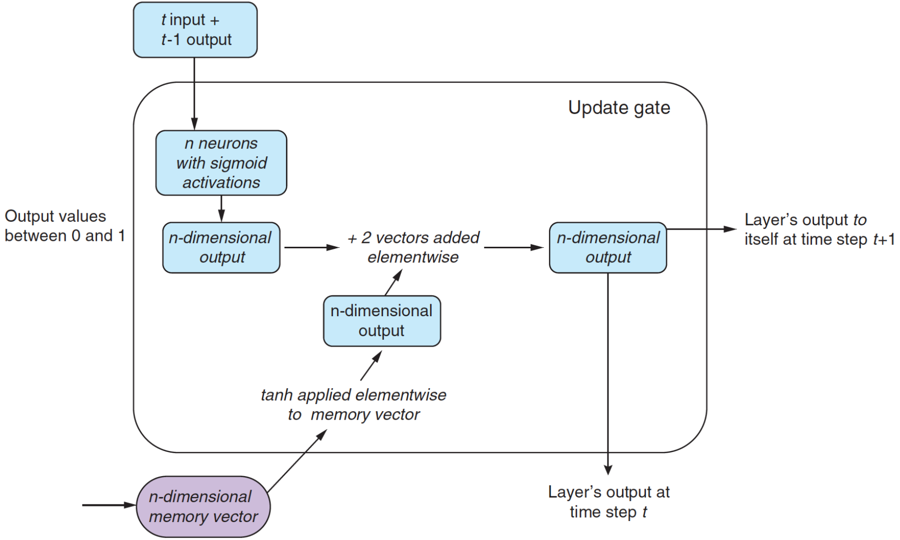
Output: produces the output vector —both for the actual task and back to the memory

- sigmoid to the input
- tanh to the state

LSTM Output Gate



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

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LSTM: Result

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LSTM	50	0.8692	**0.8678**

References

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