

Learning Sequences Using Recurrent Neural Networks

Mert Yaşin, Prof. Ethem Alpaydın

Department of Computer Engineering, Boğaziçi University, İstanbul, Turkey

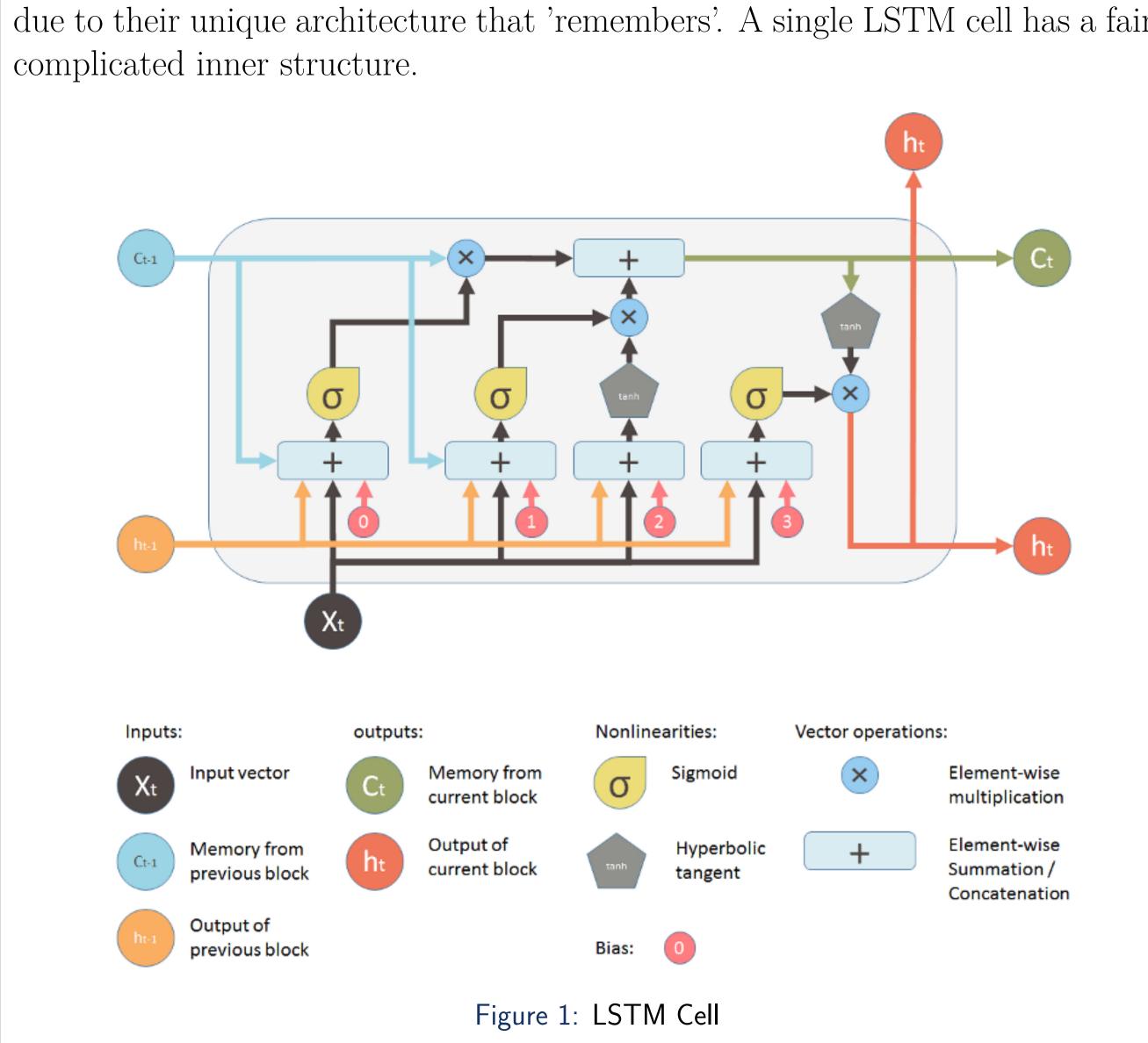


Introduction

- Songs, poems, books, movies, dialogues are just some examples of data found in a **sequential** form. Learning these sequences, more importantly, being able to **generate** these sequences is a difficult task.
- Recurrent neural network is a model which can create a dynamic internal state that withholds information about the data.
- A Long Short-Term Memory neural network is a more advanced architecture that can remember its 'experience' for a very long time sequence, thus better adapt to the input.

LSTM Model

Long Short-Term Memory neural networks are excellent for learning sequences due to their unique architecture that 'remembers'. A single LSTM cell has a fairly



LSTM Equations

The equations contain the σ (sigmoid) and and tanh (hyperbolic tangent) functions in order to achieve nonlinear neuron-like activations.

$$z^t = \tanh\left(W_z x^t + R_z h^{t-1} + b_z\right) \qquad \text{block input}$$

$$i^t = \sigma\left(W_i x^t + R_i h^{t-1} + b_i\right) \qquad \text{input gate}$$

$$f^t = \sigma\left(W_f x^t + R_f h^{t-1} + b_f\right) \qquad \text{forget gate}$$

$$c^t = i^t \odot z^t + f^t \odot c^{t-1} \qquad \text{cell state}$$

$$o^t = \sigma\left(W_o x^t + R_o h^{t-1} + b_o\right) \qquad \text{output gate}$$

$$h^t = o^t \odot \tanh\left(c^t\right) \qquad \text{block output}$$

The weights W_i are connected to the input layer and the recurrent weights R_i are connected to the previous time instance of the hidden layer. b_i are the bias.

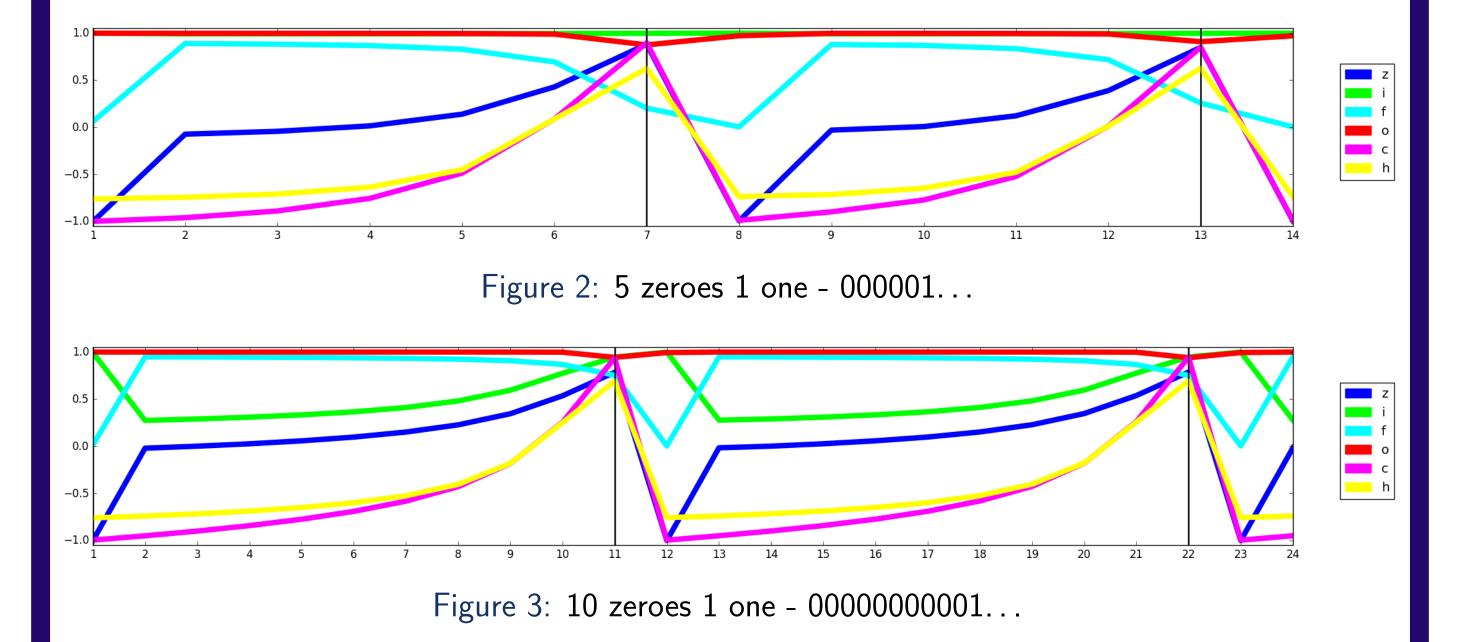
Experiments

Synthetic Data

We created some toy data sets and trained a single **LSTM cell** for each.

010101010101010101010... 1 zero 1 one 000100010001000100010...3 zeroes 1 one 000001000001000001000... 5 zeroes 1 one 10 zeroes 1 one 000000000000000000000000001... 20 zeroes 1 one 5 zeroes 5 ones 00000111111000001111110... 10 zeroes 10 ones 0000000000111111111110...

Below are some character samplings from the trained networks.



Although the number of zeroes before every one is different, both of the LSTM cells are able to successfully generate the sequences. This length difference is captured by the small differences in the **weights** of the trained networks. As we can see from the plots, their convergence rate is different. They resemble time stretched versions of one another.

Real Data

GLOUCESTER:

Your good love found dead sword, brokleat; And with poor bry, that the prosess better a were alive, 'tis like pardon.

First Watchman:

I cannot lose him. What liege to hear my breathing men, Is set their exchultic for her wounds wrongs.

God garden, fexor me a heaven,

Have him a man, one anwerged of patricians.

QUEEN ELIZABETH:

With for less shocks a death, after

And did it stay my hand in petet by your brother, Your fiends thy tumbly at no trask made!

CAPULET:

Go to your heart for you, a Capiso. And, with us.

This short passage has been sampled from a network trained with the plays of the greatest writer in the English language, William Shakespeare.

Experiments

Real Data

Fakat çünkü

Öldü, bir dalda,

Kapıdan

Baktı ele göndereler ne :

"— Aradı şehrini.

Kapılarla yakarım!..

Çocuk, soğukta ne şey?..

Kulaklım olduğumu sanmak,

karanlıkta ikinin akşama...

Bir gece aracaktı

Yok!

Sonun,

Yoklaşını

ölü vardır,

seslerin dökülüp etileren

kadar kırın,

sesini.

azımı anlağı gece kalbi geldi.

Geçmiş var :

kızların kapılarındayım."

Durdum...

Bu genç gözlerinden

ve perçeli,

haber gözlerin içini

değil,

Çine, yazmıştı.

Above is a sampled poem from a network that has been trained with the poems of Turkish literary figure, *Nazım Hikmet*.

The spectacular thing about these results is that the LSTM neural network does not know what words, sentences, new lines, or punctuation means. The only thing the model knows is the characters. It only looks at the sequence of the characters, learns them, and predicts the next one.

Conclusion

- Sequence learning is a problem with a wide range of possible applications.
- Recurrent neural networks are good at learning sequences.
- LSTM neural networks are better at learning sequences due to their unique representation of long-term dependencies.
- We can learn and generate sequences that are good enough to be mistaken for the original.