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In-depth understanding of LSTM and its recent advances in lung disease diagnosis

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Abstract

Of late, long short-term memory (LSTM) has proven its worth in medical diagnosis. Hence, there is a need to explore this special version of recurrent neural network (RNN), which can learn long-term dependencies. LSTM addresses the short-term memory problem of basic RNNs. In this paper, an in-depth study of LSTM is done with the help of a few real-life examples. Some of the recent advances of LSTM in COVID-19 and other lung disease diagnoses have also been discussed.

Keywords: Recurrent neural network; Vanishing gradient; Long short-term memory; Deep learning; COVID-19

1. Introduction

Long short-term memory is an improvisation of recurrent neural networks (RNNs). RNNs suffer from vanishing and exploding gradient problems. This problem can be dealt with in several ways, namely by i) introducing skip connections, ii) replacing length one connections with longer connections, iii) leaky recurrent units, and iv) gated recurrent units. One of the most commonly used gated recurrent neural network architectures is LSTM. LSTM proposes memory blocks in solving the vanishing and exploding gradient problem [1]. An LSTM network can remember and connect previous information to data obtained in the present. LSTM is combined with three gates: an input gate, a forget gate, and an output gate.

The organization of this paper goes in this manner: section 2 gives a review of recent works of literature. Section 3 gives an in-depth understanding of LSTM with the help of three NLP cases. Section 4 describes the conclusion, followed by references.

2. Literature Review

Table 1 shows the recent advances of LSTM in the diagnosis of COVID-19. Table 2 shows the recent advances of LSTM in the diagnosis of lung diseases.

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Table 1 Recent works of LSTM on COVID-19 diagnosis

Sl. No.	Deep Learning Technique	Database	Accuracy (%)	Year
1.	CNN and ConvLSTM with data augmentation [2]	Cohen's GitHub	91	2020
2.	ResNet and bidirectional LSTM [3]	Chest X-ray Dataset	94.88	2020
3.	Bi-LSTM, LSTM, GRU, SVR and ARIMA [4]	Harvard Dataverse	99.97 (r2_score)	2020
4.	Combined deep CNN-LSTM [5]	GitHub, Radiopaedia, The Cancer Imaging Archive (TCIA), and the Italian Society of Radiology (SIRM), Mendeley, Kaggle Repository, NIH Dataset	99.4	2020
5.	DeepCoroNet (Deep-LSTM) [6]	Chest X-ray Images from Different Open Public Data	100	2021
6.	F-RNN-LSTM [7]	C19RD and CXIP Datasets	94.31	2021
7.	Autoencoder based hybrid CNN-LSTM [8]	Italian COVID-19 Lung Ultrasound Database	79.2	2021

Table 2 Recent works of LSTM on lung disease diagnosis

Sl. No.	Disease	Deep Learning Technique	Database	Accuracy (%)	Year
1.	Lung Cancer [9]	CNN-LSTM Network	NIH-14 dataset	85.4 (Precision)	2020
2.	COVID-19 Forecasting [10]	CNN-LSTM Hybrid	WHO COVID-19 dashboard	-	2021
3.	Lung Sound Anomalies [11]	NMA-RNN and LSTM	ICBHI database	95	2020
4.	Tuberculosis [12]	Bi-LSTM with transfer learning	Montgomery Country set and Schezien set	97.76	2021

3. In-depth Understanding of LSTM

Three NLP tasks (Case I, II, III) for sentence autocompletion are taken to understand LSTM better.

3.1 Case I

Two sentences are taken for the autocompletion task. (a) Today, due to my current job situation and family conditions, I need to take a loan. (b) Last year, due to my current job situation and family conditions, I had to take a loan. Here, in both sentences, the autocomplete word might be different based on what word appeared in the beginning; in (a), 'I need to take a loan,' whereas in (b), 'I had to take a loan. And this decision between need and had is based on what appeared at the beginning. Fig. 1 shows the generic representation of RNN. In traditional RNN architecture, a sentence is fed word by word; it will learn some weights; an activation is fed back. If this thing is unrolled in time, the architecture will look like Fig 2, which is not a neural network with many layers; instead, it is a single-layer network (the same layer being represented differently). Now, to predict the word need, the knowledge of the word today is needed that appeared at the beginning of the sentence, and because of the vanishing gradient problem, the traditional RNNs have short-term memory. Hence, RNN will not do a good job to autocomplete this type of sentence. The same goes for (b).

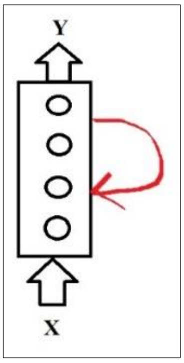

Figure 1 Generic Representation of RNN

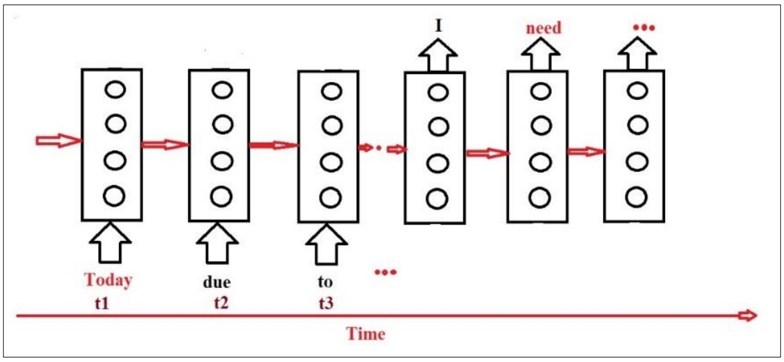

Figure 2 RNN Unrolled in Time

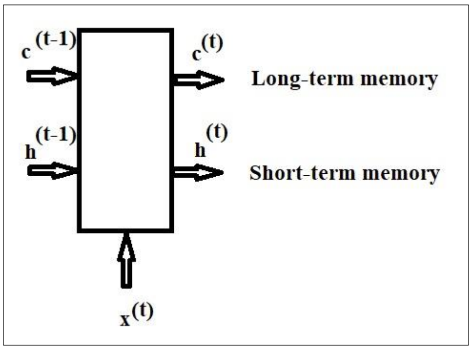

Figure 3 A Memory Cell

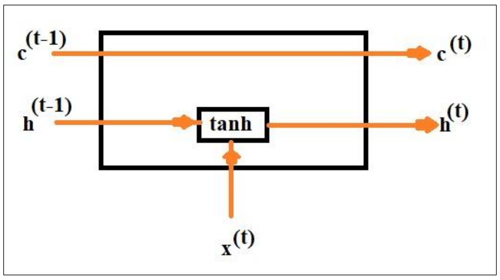

Figure 4 Long-Term and Short-Term Memory

The network layer is expanded. The hidden state is short-term memory. The neurons are removed (to make it simple); a memory cell is shown in Fig. 3. There are two states: a hidden state for short-term memory and a cell state for long-term memory shown in Fig. 4.

3.2 Case II

One more example of sentence autocompletion is taken to understand the concept of RNN and LSTM. Example: Abhi eats samosa almost every day; it shouldn't be hard to guess that his favorite cuisine is Indian.

Samosa is Indian cuisine, so it is easy to say that his favorite cuisine is Indian. But while processing this sentence, it is needed to look for some keywords. Now, to study the behavior of traditional RNN, it is assumed that RNN has short-term memory and remembers only two words. So, when new words are fed to the RNN and reach the last two words 'cuisine, is', it has no knowledge of samosa, so it is hard for a traditional RNN to guess that the cuisine is Indian shown in Fig. 5.

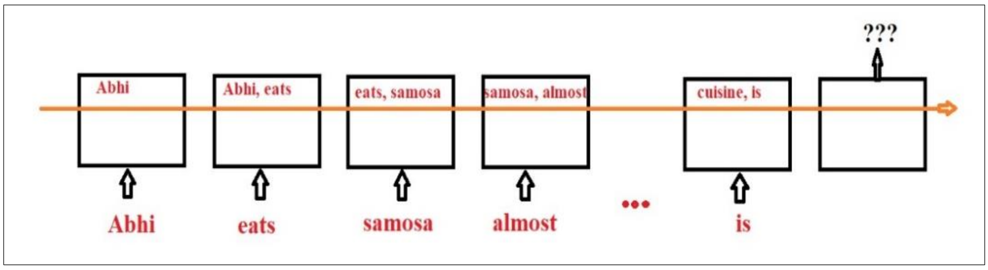

Figure 5 Traditional RNN Concept

In LSTM, long-term memory is built alongside short-term memory to store meaningful words. So, when the words Abhi or Eats are fed, they will not be stored; instead, they will be a blank string. But when the word samosa is encountered, it will be stored in the long-term memory. Now, when the last word is traversed to predict cuisine, the memory of samosa will be available, and hence, it can be easily predicted that the cuisine is Indian shown in Fig. 6.

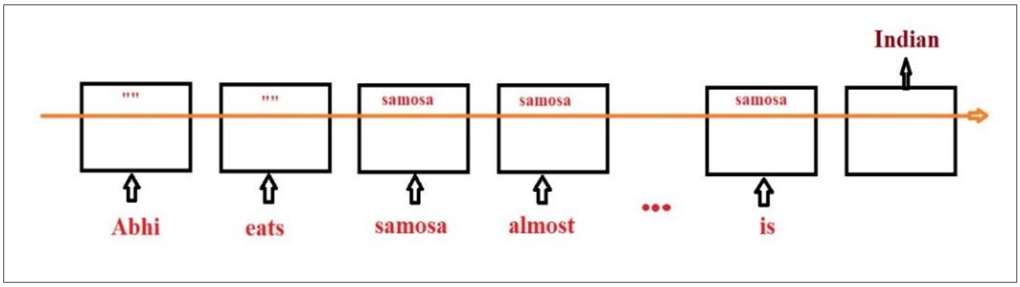

Figure 6 LSTM Concept

3.3 Case III

Again, a complicated example of sentence autocompletion is taken to understand the concepts better. Example: Abhi eats samosa almost every day; it shouldn't be hard to guess that his favorite cuisine is Indian. His friend Dhiraj however, is a lover of pasta and cheese, which means Dhiraj's favorite cuisine is Italian.

Here, Dhiraj's favorite cuisine is Italian, and it is decided based on the two keywords: pasta and cheese. So, while going through the sentence, keywords are preserved in the memory, and the rest are discarded. The word samosa is encountered will be stored in the long-term memory until pasta is encountered. So, when pasta is encountered, samosa needs to be forgotten (previous long-term memory). The new memory, pasta, is preserved until cheese is encountered. At this point, cheese needs to be added along with pasta; pasta can't be ignored. At the end of the sentence, pasta and cheese can predict that the cuisine is Italian, as shown in Fig. 7.

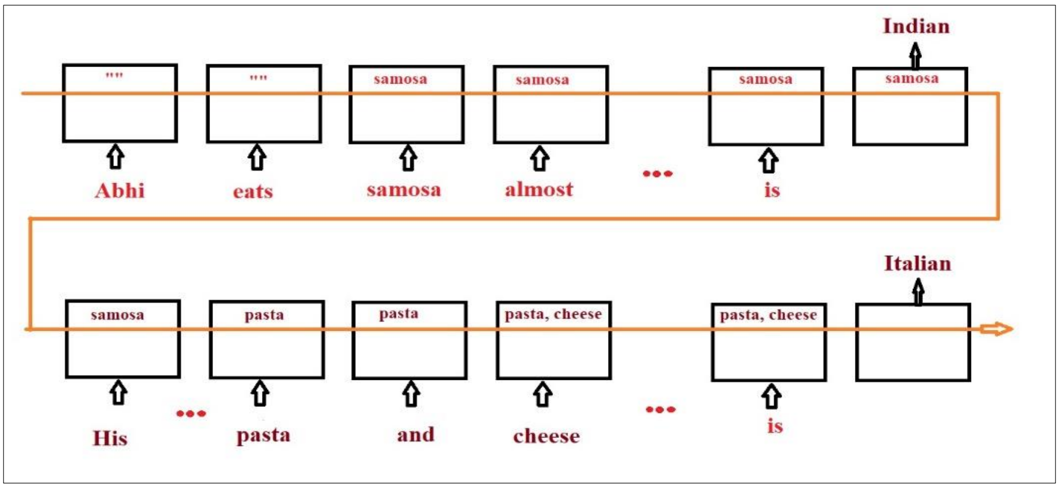

Figure 7 LSTM Explained in Detail

The first gate is the forget gate. The role of forget gate is when the word pasta is reached; it knows that it has to discard samosa. $x^{(t)}$ is a new word, sentences are processed word by word, and 't' is the timestamp. Forget gate is very simple. There is a previous hidden state, the current input is taken, and the sigmoid function is applied. The sigmoid function restricts a number between 0 and 1. If it has to discard the previous memory, it will output a vector with all zeros or all the values close to zero, and it is multiplied with the previous memory, which is the previous cell state. The multiplication will, of course, be zero as the previous memory is discarded. The second gate is the input gate. So, when pasta comes, samosa is not only forgotten; the memory of pasta is also added. Here, sigmoid and tanh functions are used on these two vectors. These outputs are multiplied and then added as a memory for the word. The third one is the output gate. Here, a weighted sum of hidden state and $x^{(t)}$ is performed, and the sigmoid function is applied. The output is taken to long-term memory; tanh is applied and multiplied to get the hidden state.

Therefore, if long-term memory is observed, it has two things, forget gate and the input gate. Forget gate helps to forget things like samosa when pasta comes in, and the input gate adds meaningful things into memory.

The principle of LSTM is explained mathematically as follows:

$$i_t = \sigma\ (W_i \cdot [h_{t-1}, x_t] + b_i) \text{ ....} (1)$$

$$\sim C_t = \tanh\,(W_i \cdot [h_{t-1}, x_t] + b_i) \text{ .... } (2)$$

$$C_t = f_t\, C_{t-1} + i_t\, \tilde{C}_t \text{ .... } (3)$$

$$f_t = \sigma\,(W_f \cdot [\, h_{t-1}, x_t] + b_f) \text{ .... } (4)$$

$$O_t = \sigma\,(W_0 \cdot [\, h_{t-1}, x_t] + b_0) \text{ .... } (5)$$

$$h_t = O_t \tanh\,(C_t) \text{ .... } (6)$$

where $\sim C_t$ denotes current moment information, W_i denotes weight matrices, b_i represents the input gate bias of LSTM, W_f refers to the weight matrix, b_f is the offset, σ is the sigmoid function, W_0 is the output gate's weighted matrices, and b_0 is the LSTM bias. Fig. 8 shows the schematic representation of LSTM.

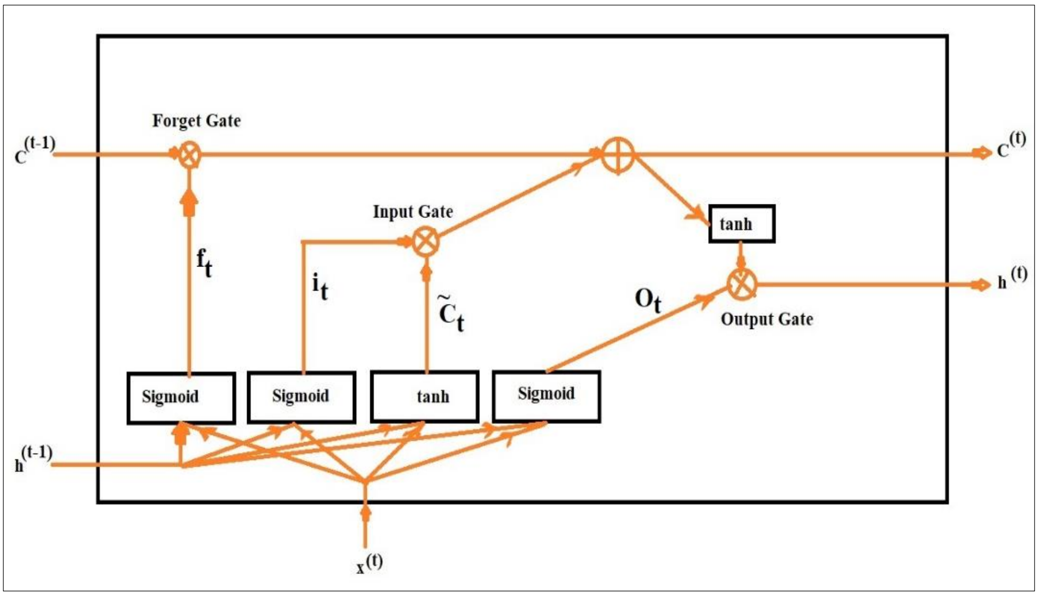

Figure 8 Schematic Representation of LSTM

4. Conclusion

An in-depth study of long short-term memory is done in this paper with three real-life examples of sentence autocompletion. Moreover, a recent study of some deep learning techniques with LSTM is done for COVID-19 and other lung diseases. It can be seen that LSTM has outperformed some of the traditional deep learning methods. Hence, further study of LSTM is required to know its full potential.

Compliance with ethical standards

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Disclosure of conflict of interest

There are no conflicts of interest.

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