Depth-Gated Recurrent Neural Networks

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Abstract

In this short note, we present an extension of LSTM to use a depth gate to connect memory cells of adjacent layers. Doing so introduces a linear dependence between lower and upper recurrent units. Importantly, the linear dependence is gated through a gating function, which we call forget gate. This gate is a function of lower layer memory cell, its input, and its past memory. We conducted experiments and verified that this new architecture of LSTMs is able to improve machine translation and language modeling performances.

1 Introduction

Deep neural networks (DNNs) have been successfully applied to many areas, including speech [1] and vision [2]. On natural language processing tasks, recurrent neural networks (RNNs) [3] are more widely used because of its ability to memorize long-term dependency.

However, simple RNN has problems of gradient diminishing or explosion. Since RNNs can be considered as a deep neural networks across many time instance, the gradients at the end of a sentence may not be able to back-propagated to the beginning of a sentence, because many layers of nonlinear transformation.

The long-short-term memory (LSTM) [4] neural networks is an extension of simple RNN [3]. Instead of using nonlinear connection between the past hidden activity and this layer's hidden activity, it uses a linear dependence to relate its past memory to the current memory. Importantly, a forget gate is introduced in LSTM to modulate each element of the past memory to be contributed to the current memory cell.

LSTMs and its extensions, for instances Gated Recurrent Units [5] have been successfully used in many natural language processing tasks [5], including machine translation [5, 6] and language understanding [7, 8].

To construct a deep neural networks, the standard way is to stack many layers of neural networks. This however has the same problem of building simple recurrent networks. The difference here is that the error signals from the top, instead of from last time instance, have to back propagated through many layers of nonlinear transformation and therefore the error signals are either diminished or exploded.

This paper proposes an extension of LSTMs. The key concept is a depth gate that modulates the linear dependence of memory cells in the upper and lower layers.

2 Review of recurrent neural networks

2.1 Simple RNN

The simple recurrent neural networks (simple RNN) computes output y_t as follows

$$y_t = f(W_y h_t) \tag{1}$$

$$h_t = \sigma(W_h h_{t-1} + W_x x_t) \tag{2}$$

where W_y , W_h , and W_x are the matrices for hidden layer output h_t , past hidden layer activity h_{t-1} and the input x_t .

The time recurrence is introduced in Eq. (2) which relates the current hidden layer activity h_t with its past hidden layer activity h_{t-1} . This dependence is nonlinear because of using a logistic function $\sigma(\cdot)$.

2.2 Long short-term memory (LSTM)

The simpel RNN presented above is hard to train because of gradient diminishing and exploding problems. This is because the nonlinear relation between h_t and h_{t-1} . LSTM was initially proposed in [4] and later modified in [9]. We follow the implementation in [9]. LSTM introduces a linear dependence between its memory cells c_t and its past c_{t-1} . Additionally, LSTM has input and output gates. These two gates are applied on a nonlinear function on the input and a nonlinear function on the output from LSTM. Specially, LSTM is written below as

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1})$$
(3)

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1})$$
(4)

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh(W_{xc}x_t + W_{hc}h_{t-1}) \tag{5}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t) \tag{6}$$

(7)

$$h_t = o_t \odot tanh(c_t)$$

where i_t , f_t and o_t are the input gate, forget gate and output gate.

2.3 Gated Recurrent Unit

A gated recurrent unit (GRU) was proposed in [10]. It is similar to LSTM in using gating functions, but differs from LSTM in that it doesn't have a memory cell. Its operations can be summarized in the following

$$h_t = (1 - z_t)h_{t-1} + z_t \tilde{h}_t \tag{8}$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \tag{9}$$

$$\tilde{h}_t = tanh(W_h x_t + U(r_t \odot h_{t-1})) \tag{10}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{11}$$

where the output from GRU is h_t . z_t and r_t are the update gate and reset gate. \hat{h}_t is the candidate output. W_z , W_h , W_r , U_z , and U_r are the matrices in GRU.

3 The depth-gated recurrent neural networks

Sec. 3.1 presents the extension of LSTM.

3.1 Depth-gated LSTM

The depth-gated LSTM is illustrated in Fig. 4. It has a depth gate that connects the memory cells c_t^{L+1} in the upper layer L + 1 and the memory cell c_t^L in the lower layer L. The depth-gate controls



Figure 3: Illustration of LSTM and GRU.

how much flow from the lower memory cell directly to the upper layer memory cell. The gate function at layer L + 1 at time t is a logistic function as

$$d_t^{L+1} = \sigma(b_d^{L+1} + W_{xd}^{L+1} x_t^{L+1} + W_{cd}^{L+1} \odot c_{t-1}^{L+1} + W_{ld}^{L+1} \odot c_t^L)$$
(12)

where b_d^{L+1} is a bias term. W_{xd}^{L+1} is the weight matrix to relate depth gate to the input of this layer. It also relates to the past memory cell via a weight vector W_{cd}^{L+1} . To relate the lower layer memory, it uses a weight vector W_l^{L+1} .

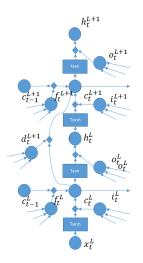


Figure 4: The depth-gated LSTM.

Using the depth gate, a DGLSTM unit can be written as

$$i_{t}^{L+1} = \sigma(W_{xi}^{L+1}x_{t} + W_{hi}^{L+1}h_{t-1}^{L+1} + W_{ci}^{L+1}c_{t-1}^{L+1})$$
(13)

$$f_t^{L+1} = \sigma (W_{xf}^{L+1} x_t + W_{hf}^{L+1} h_{t-1}^{L+1} + W_{cf} c_{t-1})^{L+1}$$
(14)

$$d_t^{L+1} = \sigma(b_d^{L+1} + W_{xd}^{L+1} x_t^{L+1} + W_{cd}^{L+1} \odot c_{t-1}^{L+1} + W_{ld}^{L+1} \odot c_t^L)$$
(15)

$$c_t^{L+1} = d_t^{L+1} c_t^L + f_t^{L+1} \odot c_{t-1} + i_t^{L+1} \odot tanh(W_{xc} x_t + W_{hc} h_{t-1}^{L+1})$$
(16)

$$o_t^{L+1} = \sigma(W_{xo}^{L+1}x_t + W_{ho}^{L+1}h_{t-1} + W_{co}^{L+1}c_t^{L+1})$$
(17)

$$h_t^{L+1} = o_t^{L+1} \odot tanh(c_t^{L+1})$$
(18)

where i_t^{L+1} , f_t^{L+1} o_t^{L+1} , and d_t^{L+1} are the input gate, forget gate, output gate and the depth gate.

4 Experiments

We applied DGLSTMs on two datasets. The first is BTEC Chinese to English machine translation. The second is PennTreeBank dataset.

Depth	GRU	LSTM	DGLSTM
3	33.95	32.43	34.48
5	32.73	33.52	33.81
10	30.72	31.99	32.19

Table 1:	BTEC	Chinese	to	English	results

Dataset	Baseline	DGLSTM
Dev	26.61	30.05
Test	40.63	43.08

4.1 Machine translation results

We first compared DGLSTM with GRU and LSTM. Results are shown in Table 1, which shows DGLSTM outperforms LSTM and GRU in all of the depths.

In another experiment for the machine translation experiment, we use DGLSTM to output scores. We trained 2 DGLSTMs. One was with 3 layers and the other was with 5 layers. Both of them used 50 dimension hidden layers. They are used as the basic recurrent unit in an attention model [5]. The scores are used to train a reranker. We ran reranker 10 times. Their mean BLEU scores are listed in Table 2. Compared to the baseline, DGLSTM obtained 3 pointer BLEU score improvement.

4.2 Language modeling

We conducted experiments on PennTreeBank(PTB) dataset. We trained a two layer DGLSTM. Each layer has 200 dimension vector. Test set perplexity results are shown in Table 3. Compared the previously published results on PTB dataset, DGLSTM obtained the lowest perplexity on PTB test set.

5 Related works

Recent work to build deep networks include [12]. In [12], the output from a layer is a linear function to the input, in addition to the path from the nonlinear part. Both of them are gated, as follows

$$y = H(x, W_H) \odot T(x, W_T) + x \odot C(x, W_C)$$
⁽¹⁹⁾

where T and C are each called transform gate and carry gate. Therefore, the highway network output has a direct connection, albeit gated, to the input.

However, the depth-gated LSTM linearly connects input and output through memory cell. Therefore, the key difference of depth-gated LSTM from highway network is that memory cell has errors from both the future and also from the top layer, linearly albeit gated. In contrast, the memory cell in highway network only has linear dependence between adjacent times.

6 Conclusions

We have presented a depth-gated RNN architecture. In particular, we have extended LSTM to use the depth gate that modulates a linear dependence of the memory cells in the upper and lower layer recurrent units. We observed better performances using this new model on a machine translation experiment and a language modeling task.

Table 3: Penn Treebank Test Set Results.

%)

Model	PPL (in
RNN [3]	123
LSTM [9]	117
sRNN [11]	110
DOT(s)-RNN [11]	108
DGLSTM	96

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