Recurrent neural network regularization

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Abstract

We present a simple regularization technique of recurrent neural networks (RNNs) with long short term memory (LSTM) units. This technique is based on dropout and gives tremendous performance boost. We show that it is beneficial in variety sequence modelling problems like language modeling, speech recognition, and machine translation.

1. Introduction

Recurrent neural networks yields the state-of-the-art performance on many sequence modelling tasks like language modelling, and speech recognition. Moreover, recent results in machine translation (Cho et al., 2014) shows their potential use in this field as well. However, up today there was no good techniques to regularize them. Various attempts to inject noise or mask some of activations (dropout) were giving small improvement in compare to model averaging. This work presents how to augment LSTMs with dropout. Resulting models give a tremendous improvement in various domains.

2. Related work

(Hochreiter & Schmidhuber, 1997)

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} L \begin{pmatrix} \mathbf{D}(h_k^{l-1}) \\ h_{k-1}^{l} \end{pmatrix}$$
$$c_k^l = f \odot c_{k-1}^l + i \odot g$$
$$h_k^l = o \odot \tanh(c_k)$$

Figure 1. To describe dynamics of multilayer LSTM with dropout, we use multi-indexing. Lower indices correspond to dynamics over time, and upper indices correspond to dynamics over layers. For simplicity, we denote by L a linear transform with bias ($Wx + b$), and by D a dropout layer. $\odot$ is a element-wise multiplication. h_k^0 is a input word-vector, and h_k^L is used to predict y_k (L is a number of layers).

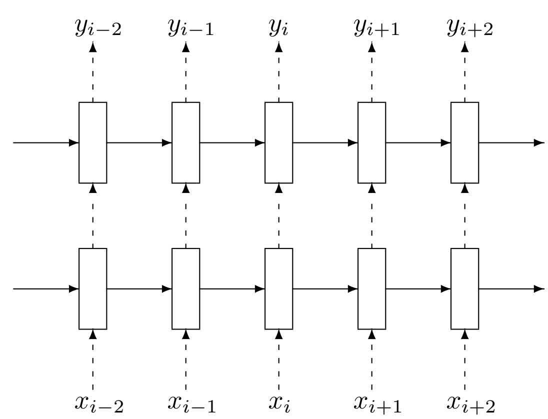

Figure 2. Regularized multilayer RNN. Dashed arrows indicate connections with applied dropout, while solid lines indicate connections where dropout is not applied.

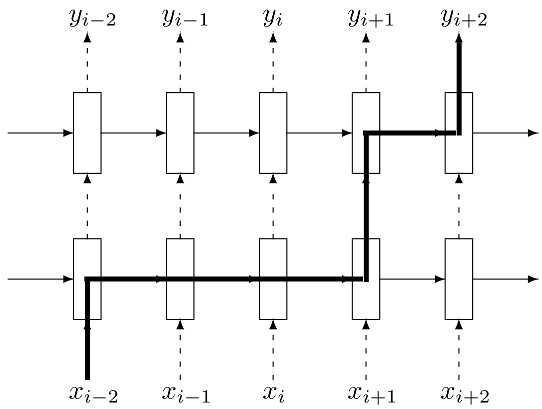

Figure 3. Thick line indicates an exemplary information flow in RNN. Information flow line is crossed L times, where L is depth of network.

Model	Validation set	Test set
	A single model	
Previous state-of-the-art [1]		107.5
Regularized LSTM	**87**	**83**
	Model averaging	
Previous state-of-the-art [2]	83.5[3]	89.4
2 regularized LSTMs		
5 regularized LSTMs		
10 regularized LSTMs		

Table 1. Word-level perplexity on Penn-tree-bank dataset.

3. Regularized RNN with LSTMs

3.1. Long-short term memory units

3.2. Regularization with dropout

3.3. Intuition

We will describe here two justifications why putting dropout across recurrent layers helps, but within layers degradate performance.

Dropout removes part of information, and target function approximator has to become more robust while performing input-output mapping. Simultaneously we don't want to erase entire information.

4. Experiments

4.1. Language modeling

4.2. Machine translation

4.3. Speech recognition

5. Discussion

References

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[1] (Pascanu et al., 2013)

[2] (Mikolov, 2012)

[3] Weight of individual models are tuned to minimize this score. This few parameters are fit on this validation set, which is not completely fair.