LSTM with Working Memory

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Abstract

LSTM is arguably the most successful RNN architecture for many tasks that involve sequential information. In the past few years there have been several proposed improvements to LSTM. We propose an improvement to LSTM which allows communication between memory cells in different blocks and allows an LSTM layer to carry out internal computation within its memory.

1 Introduction

Recurrent neural networks process sequential information where each output can depend on previous inputs. Their feedback connections give them access to past information and those feedback loops can be interpreted as a memory system. Unlike normal RNNs, LSTM [9] has ability to retain information in its short term memory indefinitely. Its gate units allow information to persist in the memory cell undisturbed.

Albeit such success, one potential shortcoming of current memory-augmented RNNs such as LSTM is that the data being stored is static. An LSTM layer can isolate its memory cells from the rest of the network, thereby preserving their values, however, this may be a wasted opportunity to perform useful computation. In particular, excluding the gate units, a row of LSTM cells has a single traditional network layer. Namely, the layer before the input gate. The output of this layer makes up the candidate inputs for the memory cells. Past this point, the only transformations on the data are multiplication by gate units, and element-wise addition with the previous memory cell values. No additional computation is performed until the next layer or the next time step. Performing computation on the recurrent data also necessarily involves accepting some new input, regardless of its relevance. In [7], it is shown that performing extra work between time steps can be beneficial. In a similar vein, it may be beneficial to allow computation on data which may otherwise be in stasis, residing in a closed-off LSTM cell. Another issue is that conventional LSTM cells have a high number of parameters per layer. In terms of the number of parameters, including the gate units, a single LSTM row has four layers. Many stripped-down, gated, RNN architectures have been proposed, such as the GRU [2], which aim to reduce LSTM to a lighter architecture.

In this work we develop a modification to LSTM that aims to make better use of the existing LSTM structure while using a small number of extra parameters. Specifically, making analogy to the biological neural systems, our method gives an LSTM network a "working" memory that uses a multiplicative gate to switch between a storage mode and a computation mode. Henceforth, we call this model LSTWM. LSTWM incorporates an extra layer which can carry out useful computation even if the current input is irrelevant and blocked by the input gates. It uses a convex combination of the current memory cell value and the output of an extra layer whose input is all memory cell values in that layer. This effectively increases depth without the cost of an extra, full LSTM layer, and also gives a layer the opportunity to process the currently stored data. The end result is a more powerful network at little extra cost. We evaluate this method on the Hutter challenge dataset [10] as well as the addition problem and show that LSTWM performs better on both tasks when using the same width and number of layers.

The main contribution of this work is summarized as follows:
• We present a new RNN architecture which may be used as a substitute for LSTM.
• This work is evaluated on two common benchmarks for RNN performance and achieves better performance than LSTM when evaluated at the same width and number of layers.
• Perhaps the most important merit of this network, besides performance, is its ease of implementation. For instance, using Theano, an existing LSTM implementation can be modified into the new architecture with only a few extra lines of code. It is not a specialized architecture and can be used as a drop-in substitute for standard LSTM.

2 Related Work

RNN was developed as a nonlinear neural network architecture to model and predict time varying signals, which can be trained effectively using the back-propagation through time algorithm. However, one problem related with the early RNN model is vanishing gradient, which corresponds to reducing influence of early inputs to the current output. This problem is alleviated with the introduction of memory-type cells that have a single recurrent connection with a weight of 1 in the LSTM architecture. In the pursuit of better performance, several variants of LSTM-RNN have been proposed in recent years, e.g. [11] [2].

One RNN variant alternative to LSTM is the Gated Recurrent Unit, or GRU [2], which uses multiplicative input and reset gates to regulate the incoming and recurrent data. This is somewhat similar to our proposed architecture in that it has a switching gate so that the network’s internal loop is a gate-controlled combination of its previous value and the new incoming value. Our network, however, includes the full ensemble of LSTM gates (input, output, forget). GRU takes the opposite approach of our architecture by reducing the spatial and computational cost of each layer. Our network is similar to a GRU within an LSTM.

Another way to interpret our network is as an LSTM that has a single layer of a highway network[14] after its memory cell and before its output gate. Highway networks use a gate to vary between outputting a neuron’s computed value, or the input value corresponding to the previous neuron in that same position. It is possible to train very deep highway networks, since each gradient is not forced to travel through any given neuron if the gate simply passes along the previous neuron’s value. Since our network is recurrent, one could describe the memory cell layer as an arbitrarily deep highway network with identical weights for each layer. It is necessary to use a highway layer, since a normal layer would result in vanishing gradients and defeat the purpose of the LSTM cell.

LSTWM is also related with the work [7], in which networks adaptively choose how many iterations to perform on an input at a given time step, and how to weight the outputs for each iteration. In our network, the inner layer can be applied to the memory cells repeatedly even if the input and output gates are closed, which facilitates an iterative computation on the stored data.

The Neural Turning Machine [8], is another recent architecture that uses a recurrent neural network to control a large external memory, and its authors also use the term “working memory” to describe this system. Unlike in NTM, our network does not incorporate an external memory or any attention mechanism, though it may work well as a component in a more complicated system such as NTM. Other recent LSTM-based innovations include the Associative LSTM[3], which uses an associative memory and Grid LSTM[12], which generalizes LSTMs with multidimensional LSTM blocks. By contrast, LSTWM was designed to be easy to implement, and not require any extra machinery beyond what a normal LSTM uses.

3 LSTM with Working Memory

3.1 Standard LSTM

We introduce notation to be used throughout the rest of the paper: \( x_t \) is the input vector at time \( t \), \( y_t \) is the network output at time \( t \), \( \sigma = \frac{1}{1 + e^{-x}} \) and \( f \) is an activation function. We used the hyperbolic tangent as our activation function.

The standard LSTM formulation includes an input gate, output gate, and usually a forget gate (introduced in [5]):
Figure 1: Left: Standard LSTM. Right: LSTWM. In both figures, double arrows point to neurons with many inputs, and single arrows correspond to single inputs. The blue “+” dot represents a sum. The purple dot represents a convex combination of the left and right inputs controlled by a gate. The layer’s memory cell values are represented by the rectangle in the upper right, C. The LSTWM updates its cell values in the same way as LSTM, and then applies the extra layer.

It should be noted that other minor variants of LSTM exist, such as LSTM with peepholes [6]. We chose LSTM with forget gates as it is a simple yet commonly used LSTM configuration.

The input and output gate values, $g_i$ and $g_o$, serve to regulate incoming and outgoing data, protecting the memory cell value. The forget gate can be used to clear the memory cell when its data is no longer relevant. If the input/output gates are closed, and the forget gate is open, then there is no transformation on the memory cell values. This is an extreme example, since the gate cells will likely take different values at any given timestep and can never be fully open or closed. However, it illustrates the main point of LSTM, which is that it has (in principle) an indefinite-term memory.

3.2 LSTM with Working Memory

Since LSTMs rely on backpropagating through the memory cells for arbitrary numbers of timesteps, any modification to LSTM between the input and output gates must not incur vanishing gradients. Like highway networks, we use an additional gate unit to ensure that gradients can flow backward through our internal layer, between the input and output gates. We add an internal layer and a switching gate to the standard LSTM architecture. The new equations are in bold. The input layer and regular LSTM gates are computed (along with an extra gate layer) and the normal LSTM memory cell updates are performed:

$$a = f(W \cdot [x_t; y_{t-1}] + b)$$  \hspace{1cm} (1)
$$g_i = \sigma(W_{g_i} \cdot [x_t; y_{t-1}] + b_{g_i})$$  \hspace{1cm} (2)
$$g_o = \sigma(W_{g_o} \cdot [x_t; y_{t-1}] + b_{g_o})$$  \hspace{1cm} (3)
$$g_f = \sigma(W_{g_f} \cdot [x_t; y_{t-1}] + b_{g_f})$$  \hspace{1cm} (4)
$$c_t = g_i \odot a + g_f \odot c_{t-1}$$  \hspace{1cm} (5)
$$y_t = g_o \odot \tanh(c_t)$$  \hspace{1cm} (6)

$c_{t'}$ is identical to the normal update for an LSTM memory cell. After the memory cells are updated as usual (12), the following equations are applied:
The output of the extra layer, $c_w$ (13) is computed and combined with the current memory cell values using the switching gate, $g_s$, and the memory cells are then set to these values in equation (14). $h$ is the activation function on the inner recurrent network. We used the $tanh$ for most of our experiments.

We propose that LSTWM increases the power of LSTMs by allowing computation on the internal memory data, which has already been vetted by the input gates. They also preserve LSTMs ability to retain data indefinitely. Individual units can vary between storage-mode and computation-mode using the switching gates. This adds computational power, but at the same time, gradients are not forced to travel through the new layer. The added parameters are two more weight matrices and two more bias vectors corresponding to another gate, and the internal layer. The number of extra parameters is usually small compared to the number of other parameters in the network.

### 4 Experiments and Results

We compare LSTWM against the standard LSTM with forget gates. We used single-layer 256-cell wide networks attached to a non-recurrent output layer for the text prediction task and 128-cell wide layers for the addition task. We also trained thinner networks to compare performance with a similar number of parameters. For stability, gradients were scaled to have a maximum norm of 5.0. Given the extra work that each layer performs, evaluating the layer is marginally slower than an equivalent LSTM, but not nearly as slow as a network with more layers. Since the gate units can all be computed together, the cost of the extra gate is negligible on modern hardware.
4.1 Text Prediction

The Hutter challenge data is a 100MB file of Wikipedia data. Like other work, such as [3], we used the first 96MB for training and the remaining 4MB for testing. The task is to predict the next character in the sequence. Performance is measured in BPC, bits-per-character, which is the negative mean log-2 probability of the correct output characters over the output sequence generated by the network. We compare three, one-layer networks: our network with widths 256 and 210, and a standard LSTM network for the baseline.

Each network was trained for two epochs using the ADAM optimization algorithm [13] and a batch size of 10. To accelerate the training process, the first epoch was trained using length-100 subsequences and the second with length-1000 subsequences of the training set. We used the default parameters from the ADAM paper, which are $\beta_1 = 0.9, \beta_2 = 0.999, \alpha = 0.001$. We evaluated the BPC on the test set at the end of training.

4.2 Addition

We use an addition experiment similar to that in [7]. The input and target sequences consist of four, length-61 vectors. The first fifty elements encode the digits of the numbers, elements 50-60 encode the last digit in case there is a carry, and the final digit is used to represent a “filler” vector. The first three vectors in the input encode the numbers to be added, and the last is a filler vector. The first three targets are filler vectors, and the final target vector encodes the sum of the first three input vectors. We used L2 loss and a linear output layer. The network was trained using ADAM with the same settings as the text prediction task, and a batch size of 1000. A random, size 10,000 test set was generated every 10,000 iterations.

Our results show that LSTWM outperforms the normal LSTM, and often trains more quickly. In some instances, LSTWM trains more slowly for a period of time, but then overtakes LSTM.

4.3 Discussion

For our experiments, we chose the “default” configuration of 0.0 initial bias, the normal logistic function for gates, and tanh for the activation function. However, we also experimented with different settings and variations. Similar to highway networks, initializing the switch gate biases so that at first it behaves more like an LSTM can sometimes be beneficial. The addition task seemed to benefit the most from this initialization, but it was not beneficial for text prediction. In our experiments, lowering the initial biases tended to increase the learning speed early in the training process, but did not always yield better final performance. There was also significant variation from one training session to the next, although LSTWM almost always surpassed normal LSTM when trained long.

\footnote{Our more recent experiments suggest that an initial forget gate bias of 1.0 and an initial switch gate bias of -1.0 produce relatively consistent results, and these are the settings we recommend. Setting a high forget gate bias is also recommended in [11].}
enough when using the same width and depth. With the same number of parameters (accomplished by reducing the width of LSTWM), LSTWM still performs better on the addition task, but about the same on text prediction. Likely, this is because the addition task is algorithmic, whereas text prediction probably relies more on learning a probability distribution. Given the same number of parameters, we speculate that LSTWM will perform better when the task at hand benefits from extra depth more than extra width. We also found that using a steeper activation function (i.e. $1.0/\sqrt{1+e^{-2.0x}}$) on the switching gates gave a minor increase in performance, as did parameterizing the activation function: $f(x, y) = 1.0/\sqrt{1+e^{-y \cdot x}}$ (also explored in [4]). The results we reported were obtained using the standard bias initialization of 0.0 and the normal logistic function. The optimal configuration of the network will likely depend on the application.

Although we chose the $\tanh$ function for the internal layer, we also tried other activation functions such as the following:

$$f(x) = \begin{cases} x, & \text{if } -1 < x < 1 \\ \text{sign}(x) + \tanh(x - \text{sign}(x)), & \text{otherwise} \end{cases} \quad (16)$$

This is linear between -1 and 1, and is shaped the same as $\tanh$ beyond that range. This ensures that within $[-1, 1]$, the values do not continue to shrink on each iteration. The above activation function trained well for a while, but tended to result in instability (loss became NaN) after a long period of training. ReLU performed poorly and also resulted in instability.

It may also be beneficial to use more layers inside the LSTWM. Using an inner layer that preserves strong gradients, such as unitary RNN [1] (in conjunction with the switching gates) could also improve performance. The only absolute requirement is that the memory cells have a mechanism to preserve their current value when necessary.

## 5 Conclusion

We have presented a new LSTM-like architecture, LSTM with Working Memory, which performs substantially better than standard LSTM given the same width. This architecture is easy to implement and trains quickly. Future work may focus on variants of this architecture, as well as experiments with deeper networks. Using LSTWM in Grid LSTM or other LSTM-based architectures may also be a fruitful research direction.

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