Long Short-Term Memory-Networks for Machine Reading

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Abstract

Machine reading, the automatic understanding of text, remains a challenging task of great value for NLP applications. We propose a machine reader which processes text incrementally from left to right, while linking the current word to previous words stored in memory and implicitly discovering lexical correlations facilitating understanding. The reader is equipped with a Long Short-Term Memory architecture, which differs from previous work in that it has a memory tape (instead of a fixed-size memory cell) for adaptively storing past information without severe information compression. We also integrate our reader with an attention mechanism in an encoder-decoder architecture. Experiments on language modeling, sentiment analysis, and natural language inference show that our model matches or outperforms state of the art.

1 Introduction

Machine reading can be defined as the automatic understanding of text. The term is used to describe various interrelated tasks ranging from answering reading comprehension questions (Clark et al., 2013), to fact and relation extraction (Etzioni et al., 2011; Fader et al., 2011), knowledge base population and construction (Ji and Grishman, 2011; Niu et al., 2012; Carlson et al., 2010), ontology learning (Poon and Domingos, 2010b), textual entailment (Dagan et al., 2005), and the creation of proposition stores (Peñas and Hovy, 2010; Schubert and Tong, 2003).

In order to understand texts, a machine reading system must provide facilities for: (1) extracting and representing meaning from natural language text, (2) storing meanings internally, and (3) working with stored meanings, to answer questions or to derive further consequences. Ideally, such a system should be robust, open-domain, and degrade gracefully in the presence of semantic representations which may be incomplete, inaccurate, or incomprehensible. Our work presents a novel approach to machine reading which analyzes text without requiring traditional NLP pipelines (e.g., tagging, parsing) or extensive manual engineering. Our model draws inspiration from human language processing and the fact language comprehension is highly *incremental* with readers and listeners continuously extracting the meaning of utterances on a word-by-word basis.

English speakers process text sequentially, from left to right, fixating nearly every word while they read (Rayner, 1998) and creating partial representations for sentence prefixes (Konieczny, 2000; Tanenhaus et al., 1995). Language modeling tools such as recurrent neural networks (RNN) bode well with human reading behavior (Frank and Bod, 2011). RNNs treat each sentence as a sequence of words and recursively compose each word with its previous *memory*, until the meaning of the whole sentence has been derived. In practice, however, it has proven challenging to model long input sequences for at least two reasons. The first one concerns model training problems associated vanishing and exploding gradients (Hochreiter, 1991; Bengio et al., 1994), which can be partially ameliorated with gated activation functions, such as the Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), and gradient clipping (Pascanu et al., 2013). The second reason relates to memory compression problems. As the input sequence gets compressed and blended into

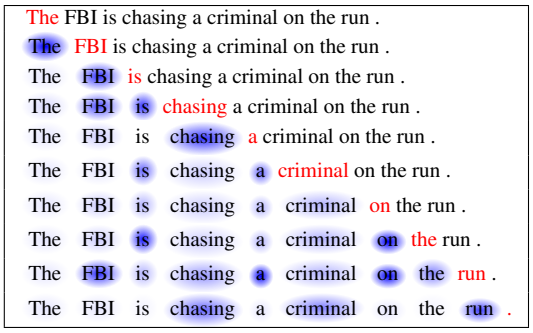


Figure 1: Illustration of our model while reading the sentence *The FBI is chasing a criminal on the run.* Color *red* represents the current word being fixated, *blue* represents memories. Shading indicates the degree of memory activation.

a single dense vector, sufficiently large memory capacity is required to store past information. As a result, the network generalizes poorly to long sequences while wasting memory on shorter ones.

Recent work attempts to address the latter limitation using external memories (Weston et al., 2015; Sukhbaatar et al., 2015; Grefenstette et al., 2015). The idea is to use multiple memory slots to memorize a sequence; read and write operations for each slot are modeled as an attention mechanism depending on the current input token and the state of a neural controller. Inspired by this work, we equip our machine reader with a memory tape whose size grows with the input sequence. As a point of departure from previous work, we embed the memory tape within an LSTM unit, enabling the model to recurrently read texts without any external state controller. The resulting model is a Long Short-Term Memory-Network (LSTMN) machine reader, which can be used for any sequence processing task.

Figure 1 gives an example of the model's reading behavior. The LSTMN processes text incrementally while learning which words and to what extent contribute to the meaning of the current word. It implicitly identifies lexical dependencies whilst modulating the memory required to extract appropriate meaning representations. We validate the performance of our model in three tasks, namely language modeling, sentiment analysis and natural language inference. In all cases, we achieve performance competitive or better to state-of-the-art models and superior to vanilla LSTMs.

2 Related Work

Machine reading has been recently recognized as a significant milestone for artificial intelligence (Poon and Domingos, 2010a; Etzioni et al., 2006) leveraging advances in the fields of natural language processing (NLP), machine learning, and probabilistic reasoning. Much previous work in this area analyzes text with traditional NLP pipelines such as tagging and parsing, mapping natural language to symbolic representations of meaning. More recently, a few approaches have used low dimensional embeddings of entities and relations to enhance representations based on first-order logic (Bordes et al., 2011). Our machine reader leverages neural networks to understand text from scratch without recourse to preprocessing tools or symbolic representations. It learns embeddings which can be integrated with various downstream applications.

Our model extends recent work on recurrent neural networks and their ability to solve sequence modeling and sequence-to-sequence transduction problems. The latter have assumed several guises in the literature such as machine translation (Bahdanau et al., 2014), sentence compression (Rush et al., 2015), and reading comprehension (Hermann et al., 2015). Efforts to handle well-known exploding or vanishing gradient problems associated with RNN training (Bengio et al., 1994) have led to models with gated activation functions (Hochreiter and Schmidhuber, 1997; Cho et al., 2014), and more advanced architectures that enhance the information flow within the network (Koutník et al., 2014; Chung et al., 2015; Yao et al., 2015). Another bottleneck associated with RNNs in downstream tasks (Bahdanau et al., 2014) is memory compression: since the all inputs are recursively combined into a single memory (which is typically too small), it becomes difficult to accurately memorize sequences (Zaremba and Sutskever, 2014). In the encoder-decoder architecture, this problem can be sidestepped with an attention mechanism which learns soft alignments *between* the encoding and decoding states (Bahdanau et al., 2014). To the best of our knowledge, no attempts have been made to model attention *within* a sequence encoder.

The idea of coupling neural networks with external memory resources dates back to Das et al. (1992) who connect a recurrent neural network state con-

troller with an external memory stack for learning context free grammars. More recently, Weston et al. (2015) propose Memory Networks to explicitly segregate memory storage from the computation of the neural network. Their model is trained end-to-end with a memory addressing mechanism closely related to soft attention (Sukhbaatar et al., 2015). Meng et al. (2015) apply a variant of this model to machine translation. Grefenstette et al. (2015) define a set of differentiable data structures (stacks, queues, and dequeues) as memories controlled by a recurrent neural network. Their model has shown promising results in simple sequence transduction tasks, such as copying. Tran et al. (2016) combine the LSTM with an external memory block component which interacts with its hidden state. A common theme across these models is the use of external memories that interact with a neural controller, whereas our work directly enhances the internal memory of an LSTM for reading and memorizing sequences.

3 The Machine Reader

In this section we propose a novel machine reader inspired by psycholinguistics. The core of the reader is a Long Short-Term Memory recurrent neural network with an extended memory tape that explicitly simulates the human memory span. The reader performs implicit dependency analysis with an attention-based memory addressing mechanism at every input time step. In the following we first review the standard Long Short-Term Memory unit and then present our model.

3.1 Long Short-Term Memory

A Long Short-Term Memory (LSTM) recurrent neural network processes a variable-length sequence $x = (x_1, x_2, \cdots, x_n)$ by incrementally adding new content into a single memory slot, with gates controlling the extent to which new content should be memorized, old content should be erased, and current content should be exposed. At time step t, the memory c_t and the hidden state h_t are updated with the following equations:

$$\begin{bmatrix} i_t \\ f_t \\ o_t \\ \hat{c}_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} W \cdot [h_{t-1}, x_t] \quad (1)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \hat{c}_t \quad (2)$$

$$h_t = o_t \odot \tanh(c_t) \quad (3)$$

where i, f, and o are gate activations. Compared to the standard RNN, the LSTM separates the memory c from the hidden state h, which interacts with the environment when making predictions.

3.2 Long Short-Term Memory-Network

A question that arises with LSTMs is the extent to which they are able to memorize sequences under recursive compression. Although LSTMs can produce a list of state representations during composition, the next state is always computed from the current state, making all previous states dispensable. Such computation is performed in a Markovian manner (first-order), but LSTMs do not make any Markov assumptions—they can (in theory only) model an unbounded memory.

In this paper, we develop a machine reader which explicitly stores memory segments, making use of more than one state and memory to compute the update, while learning how to analyze and modulate past information in order to facilitate the understanding of present input. To this end, we modify the standard LSTM structure by replacing the memory cell with a memory network, whose size grows with the input sequence (a size limit can be also imposed). The resulting Long Short-Term Memory-Network (LSTMN) stores the input at each time step with a unique memory slot, obviating the problem of information compression, while enabling adaptive modulation of the memory itself. Although it is feasible to apply both write and read operations to the memory network, we concentrate on the latter. We conceptualize the *read* operation as attentively linking the current token to previous memories and selecting useful content when processing it. Although not the focus of this work, the significance of the *write*[1] operation can be analogously justified as a way of incrementally updating previous memories, e.g., to correct wrong interpretations when processing garden path sentences (Ferreira and Henderson, 1991).

The architecture of the LSTMN is shown in Figure 2. We use two sets of values for the memory

[1] Please note the difference between a direct *write* operation and generic parameter updates. Without *write*, we are still updating model parameters as in vanilla LSTM.

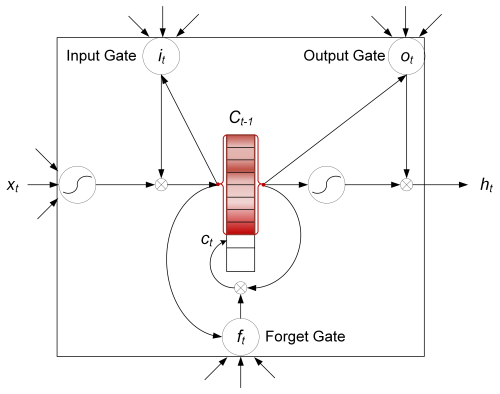


Figure 2: Long Short-Term Memory-Network. Color indicates the degree of memory activation.

network: a hidden state tape interacting with the environment (e.g., computing attention) and a memory tape representing what is actually stored in memory.[2] At each time step, the model computes the memory activation based on the present input token, the previous attention vector, and the previous hidden tape. Then, it uses the adaptively weighted hidden contents to compute various gate activations like LSTMs. Finally, it mixes the memory contents with the current input token to obtain the new input memory. In this model, each input token corresponds to one memory slot, which stores the transformed input representation under the given context.

More formally, given the current input x_t, previous memory tape $C_{t-1} = (c_1, \cdots, c_{t-1})$, and previous hidden tape $H_{t-1} = (h_1, \cdots, h_{t-1})$, the model computes at time step t the values of c_t and h_t as:

$$a_i^t = v^T \tanh(W_h h_i + W_x x_t + W_{\tilde{h}} \tilde{h}_{t-1}) \quad (4)$$

$$s_i^t = \text{softmax}(a_i^t) \quad (5)$$

$$\begin{bmatrix} \tilde{h}_t \\ \tilde{c}_t \end{bmatrix} = \sum_{i=1}^{t-1} s_i^t \cdot \begin{bmatrix} h_i \\ c_i \end{bmatrix} \quad (6)$$

$$\begin{bmatrix} i_t \\ f_t \\ o_t \\ \hat{c}_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} W \cdot [\tilde{h}_t, x_t] \quad (7)$$

$$c_t = f_t \odot \tilde{c}_t + i_t \odot \hat{c}_t \quad (8)$$

$$h_t = o_t \odot \tanh(c_t) \quad (9)$$

[2]Like LSTMs, our model has both hidden states and memory. However, the LSTM keeps only the most recent hidden states and memory, whereas in LSTMN we aim to use all past information.

where v, W_h, W_x and $W_{\tilde{h}}$ are the new weight terms of the network. Compared to the standard LSTM in Equations (1)–(3), we additionally introduce an attention layer to compute the adaptive memory representation $\tilde{c}_t$ and hidden representation $\tilde{h}_t$ (i.e., the attention vector), which are then used in computing the gated activations i_t, f_t, o_t and the memory to be remembered $\hat{c}_t$.

3.3 Deep LSTMNs

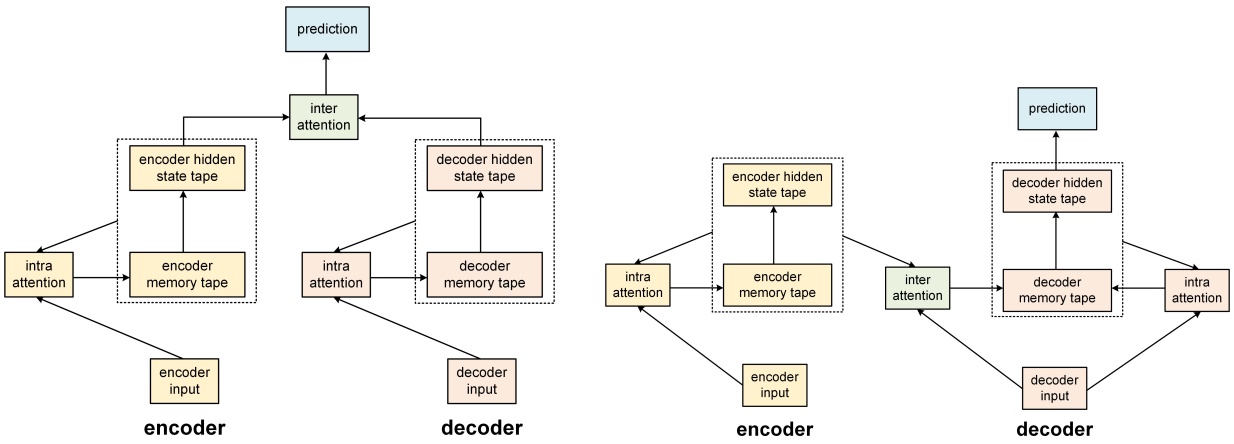
It is possible to construct deep LSTMNs by stacking multiple memory and hidden layers in an alternating fashion, resembling a stacked LSTM (Graves, 2013) or a multi-hop memory network (Sukhbaatar et al., 2015). This is achieved by feeding the output (attention vector) $\tilde{h}_t^k$ of layer k as input to the $(k+1)th$ layer. We apply skip-connections (Graves, 2013) across layers ($\text{input}_{k+1} = \text{input}_k + \text{output}_k$). This improves the information flow within the network and makes optimization easier. Please note that this deep structure is used to compute the adaptive memory representation $\tilde{c}_t$ and hidden representation $\tilde{h}_t$.

4 LSTMNs for Dual Sequence Modeling

Natural language processing tasks such as machine translation are concerned with dual sequences rather than a single sequence. Central to these tasks is a dual sequence processor or encoder-decoder, where the second sequence (i.e., *target*) is being processed *conditioned* on the first one (i.e., *source*). In this section we draw connections between the internal attention mechanism of the LSTMN and the widely used attention mechanism between two sequences. We then explain how an LSTMN can be applied in the dual sequence processing task.

In general, intra-attention within a sequence and inter-attention between two sequences complement each other. While inter-attention derives the alignment between source and target tokens, intra-attention provides implicit dependency analysis within a sequence, resulting in enhanced memories that could benefit subsequent inter-alignment. In the following we propose two ways of using the LSTMN in a dual architecture, shown in Figures 3a and 3b, respectively.

Shallow Attention Fusion Shallow fusion simply treats the LSTMN as a separate module that can be



(a) Decoder with shallow attention fusion.

(b) Decoder with deep attention fusion.

Figure 3: LSTMNs for sequence-to-sequence modeling. The encoder uses intra-attention, while the decoder incorporates both intra- and inter-attention. The two subfigures present two ways to combine the intra- and inter-attention in the decoder.

readily used in a dual architecture (e.g., an encoder-decoder), in lieu of a standard RNN or LSTM. As shown in Figure 3a, both sequence processors are modeled as LSTMNs with intra-attention. Meanwhile, inter-attention is triggered when the target processor reads a target token. The architecture of this model is similar to the neural machine translation model introduced in Bahdanau et al. (2014).

Deep Attention Fusion Deep fusion combines inter- and intra-attention (initiated by the target processor) when computing the new memory content. Different notations are used to denote the two sets of attention. Following Section 3.2, we use C and H to denote the target memory tape and hidden tape, which store representations of the target symbols that have been processed so far. Additionally, we use $A = [\alpha_1, \cdots, \alpha_m]$ and $Y = [\gamma_1, \cdots, \gamma_m]$ to represent the source memory tape and hidden tape, with m being the length of the source sequence conditioned upon. We compute inter-attention at time step t when processing the target sequence (input is x_t) as follows:

$$b_j^t = u^T \tanh(W_\gamma \gamma_j + W_x x_t + W_{\tilde{\gamma}} \tilde{\gamma}_{t-1}) \tag{10}$$

$$p_j^t = \text{softmax}(b_j^t) \tag{11}$$

$$\begin{bmatrix} \tilde{\gamma}_t \\ \tilde{\alpha}_t \end{bmatrix} = \sum_{j=1}^{m} p_j^t \cdot \begin{bmatrix} \gamma_j \\ \alpha_j \end{bmatrix} \tag{12}$$

and then we can transfer the adaptive source representation $\tilde{\alpha}_t$ to the target memory with another gating operation r_t, analogous to gates in Equation 7.

$$r_t = \sigma(W_r \cdot [\tilde{\gamma}_t, x_t]) \tag{13}$$

The new target memory includes source information to be memorized $\tilde{\alpha}_t$, target information to be memorized $\tilde{c}_t$ and new input information $\hat{c}_t$:

$$c_t = r_t \odot \tilde{\alpha}_t + f_t \odot \tilde{c}_t + i_t \odot \hat{c}_t \tag{14}$$

$$h_t = o_t \odot \tanh(c_t) \tag{15}$$

As shown in the above equations and Figure 3b, the major change of deep fusion lies in the recurrent storage of the inter-alignment vector in the target memory network, as a way to help the target network review source information.

5 Experiments

Next we present our experiments for evaluating the performance of the LSTMN machine reader. We start with language modeling as it is a natural testbed for our model. We then assess the model's ability to extract meaning representations for generic sentence classification tasks such as sentiment analysis. Finally, we examine whether the LSTMN can recognize the semantic relationship between two sentences by applying it to natural language inference.

5.1 Language Modeling

Our language modeling experiments were conducted on the English Penn Treebank dataset. Following common practice (Mikolov et al., 2010), we

Models	Layers	Perplexity
KN5	—	141
RNN	1	129
LSTM	1	115
LSTMN	1	**108**
sLSTM	3	115
gLSTM	3	107
dLSTM	3	109
LSTMN	3	**102**

Table 1: Language model perplexity on the Penn Treebank. The size of memory is 300 for all models.

trained on sections 0–20 (1M words), used sections 21–22 for validation (80K words), and sections 23–24 (90K words for testing). The dataset contains approximately 1 million tokens and a vocabulary size of 10K. The average sentence length is 21. We use perplexity as our evaluation metric: $PPL = \exp(NLL/T)$, where NLL denotes the negative log likelihood of the entire test set and T the corresponding number of tokens. We used stochastic gradient descent for optimization with an initial learning rate of 0.65, which decays by a factor of 0.85 per epoch if no significant improvement has been observed on the validation set. We renormalize the gradient if its norm is greater than 5. The mini-batch size was set to 40. The dimensions of the word embeddings were set to 150 for all models.

In this suite of experiments we compared a single-layer LSTMN and a stacked (multilayer) LSTMN (sLSTMN) against a variety of baselines. The first one is the Kneser-Ney 5-gram language model (KN5) which generally serves as a non-neural baseline for the language modeling task. We also present perplexity results for the standard RNN and LSTM models. Finally, we implemented more sophisticated LSTM architectures, such as a gated-feedback LSTM (gLSTM; Chung et al. (2015)) and a depth-gated LSTM (dLSTM; Yao et al. (2015)). The gated-feedback LSTM is a generalization of the clockwork RNN (Koutník et al., 2014), with feedback gates connecting the hidden states across multiple time steps as an adaptive control of the information flow. The depth-gated LSTM is a one dimensional special case of the Grid LSTM (Kalchbrenner et al., 2016), with a depth gate which connects memory cells of adjacent layers. In general, both gLSTM and dLSTM are able to capture long-term dependencies to some degree, but they do not explicitly keep

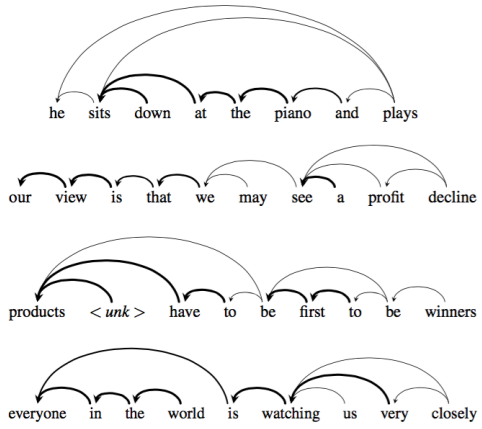


Figure 4: Examples of intra-attention (language modeling). Bold lines indicate higher attention scores.

past memories. For all deep architectures, we set the number of layers to 3 in this experiment. The hidden unit size of the LSTMN and all comparison models (except KN5) was set to 300.

The results of the language modeling task are shown in Table 1. Perplexity results for KN5 and RNN are taken from Mikolov et al. (2015). As can be seen, the single-layer LSTMN outperforms these two baselines by a significant margin. Amongst all deep architectures, the three-layer LSTMN also performs best. We can study the memory activation mechanism of the machine reader by visualizing the attention scores. Figure 4 shows six sentences sampled from the Penn Treebank validation set. Although we explicitly encourage the reader to attend to any memory slot, much attention focuses on recent memories. This agrees with the linguistic intuition that long-term dependencies are relatively rare. As illustrated in Figure 4 the model captures valid bi-lexical relations (e.g., the dependency between *sits* and *at*, *sits* and *plays*, *everyone* and *is*, *is* and *watching*).

5.2 Sentiment Analysis

Our second task concerns the prediction of sentiment labels of sentences. We used the Stanford Sentiment Treebank (Socher et al., 2013), which contains fine-grained sentiment labels (very positive, positive, neutral, negative, very negative) for 11,855 sentences. Following previous work on this dataset, we used 8,544 sentences for training, 1,101 for validation, and 2,210 for testing. The average sentence

Models	Fine-grained	Binary
RAE (Socher et al., 2011)	43.2	82.4
RNTN (Socher et al., 2013)	45.7	85.4
DRNN (Irsoy and Cardie, 2014)	49.8	86.6
DCNN (Blunsom et al., 2014)	48.5	86.8
CNN-MC (Kim, 2014)	48.0	88.1
T-CNN (Lei et al., 2015)	**51.2**	**88.6**
PV (Le and Mikolov, 2014)	48.7	87.8
CT-LSTM (Tai et al., 2015)	51.0	88.0
LSTM (Tai et al., 2015)	46.4	84.9
2-layer LSTM (Tai et al., 2015)	46.0	86.3
LSTMN	**47.6**	**86.3**
2-layer LSTMN	**47.9**	**87.0**

Table 2: Model accuracy (%) on the Sentiment Treebank (test set). The memory size of LSTMN models is set to 168 to be compatible with previously published LSTM variants (Tai et al., 2015).

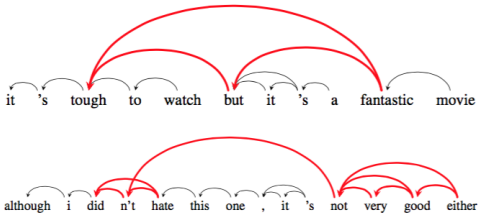


Figure 5: Examples of intra-attention (sentiment analysis). Bold lines (red) indicate attention between sentiment important words.

length is 19.1. In addition, we also performed a binary classification task (positive, negative) after removing the neutral label. This resulted in 6,920 sentences for training, 872 for validation and 1,821 for testing. Table 2 reports results on both fine-grained and binary classification tasks.

We experimented with 1- and 2-layer LSTMNs. For the LSTMN models, we predict the sentiment label of the sentence based on the averaged hidden vector passed to a 2-layer neural network classifier with ReLU as the activation function. The memory size for both LSTMN models was set to 168 to be compatible with previous LSTM models (Tai et al., 2015) applied to the same task. We used pretrained `300-D Glove 840B` vectors (Pennington et al., 2014) to initialize the word embeddings. The gradient for words with `Glove` embeddings, was scaled by 0.35 in the first epoch after which all word embeddings were updated normally. We used Adam (Kingma and Ba, 2015) for optimization with the two momentum parameters set to 0.9 and 0.999 respectively. The initial learning rate was set to 2E-3. The regularization constant was 1E-4 and the mini-batch size was 5. A dropout rate of 0.5 was applied to the neural network classifier.

We compared our model with a wide range of top-performing systems. Most of these models (including ours) are LSTM variants (third block in Table 2), recursive neural networks (first block), or convolutional neural networks (CNNs; second block). Recursive models assume the input sentences are represented as parse trees and can take advantage of annotations at the phrase level. LSTM-type models and CNNs are trained on sequential input, with the exception of CT-LSTM (Tai et al., 2015) which operates over tree-structured network topologies such as constituent trees. For comparison, we also report the performance of the paragraph vector model (PV; Le and Mikolov (2014); see Table 2, second block) which neither operates on trees nor sequences but learns distributed document representations.

The results in Table 2 show that both 1- and 2-layer LSTMNs outperform the LSTM baselines while achieving numbers comparable to state-of-the-art. On the fine-grained and binary classification tasks our 2-layer LSTMN performs close to the best system T-CNN (Lei et al., 2015) without recourse to any syntactic information. Figure 5 shows examples of intra-attention for sentiment words. Interestingly, the network learns to associate sentiment important words such as *though* and *fantastic* or *not* and *good*.

5.3 Natural Language Inference

The ability to reason about the semantic relationship between two sentences is an integral part of machine reading. We therefore evaluate our model on recognizing textual entailment, i.e., whether two premise-hypothesis pairs are entailing, contradictory, or neutral. For this task we used the Stanford Natural Language Inference (SNLI) dataset (Bowman et al., 2015), which contains premise-hypothesis pairs and target labels indicating their relation. After removing sentences with unknown labels, we end up with 549,367 pairs for training, 9,842 for development and 9,824 for testing. The vocabulary size is 36,809 and the average sentence length is 22.

Recent approaches use two sequential LSTMs to

encode the premise and the hypothesis respectively, and apply neural attention to reason about their logical relationship (Rocktäschel et al., 2016; Wang and Jiang, 2016). Furthermore, Rocktäschel et al. (2016) show that a non-standard encoder-decoder architecture which processes the hypothesis conditioned on the premise results in a significant performance boost. We use a similar approach to tackle this task with LSTMNs. Specifically, we use two LSTMNs to read the premise and hypothesis, and then match them by comparing their hidden state tapes. We perform average pooling for the hidden state tape of each LSTMN, and concatenate the two averages to form the input to a 2-layer neural network classifier with ReLU as the activation function.

We used pre-trained `300-D Glove 840B` vectors (Pennington et al., 2014) to initialize the word embeddings. Out-of-vocabulary (OOV) words were initialized randomly with Gaussian samples (μ=0, σ=1). We only updated OOV vectors in the first epoch, after which all word embeddings were updated normally. The dropout rate was selected from [0.1, 0.2, 0.3, 0.4]. We used Adam (Kingma and Ba, 2015) for optimization with the two momentum parameters set to 0.9 and 0.999 respectively, and the initial learning rate set to 1E-3. The mini-batch size was set to 16 or 32. For a fair comparison against previous work, we report results with different hidden/memory dimensions (i.e., 100, 300, and 450).

We compared variants of our model against different types of LSTMs (see the second block in Table 3). Specifically, these include a model which encodes the premise and hypothesis independently with two LSTMs (Bowman et al., 2015), a shared LSTM (Rocktäschel et al., 2016), a word-by-word attention model (Rocktäschel et al., 2016), and a matching LSTM (mLSTM; Wang and Jiang (2016)). This model sequentially processes the hypothesis, and at each position tries to match the current word with an attention-weighted representation of the premise (rather than basing its predictions on whole sentence embeddings). We also compared our models with a bag-of-words baseline which averages the pre-trained embeddings for the words in each sentence and concatenates them to create features for a logistic regression classifier (first block in Table 3).

As shown in the table, the LSTMNs achieve better performance than the LSTMs (with and without attention; 2nd block in Table 3). We also observe that fusion is generally beneficial, and that deep fusion slightly improves over shallow fusion. One explanation is that with deep fusion the inter-attention vectors are recurrently memorized by the decoder with a gating operation, which also improves the information flow of the network. With standard training, our deep fusion yields a new state-of-the-art result in this task (86.3% accuracy).

Models	h	$\lvert\theta\rvert_{\mathrm{M}}$	Test
BOW concatenation	—	—	59.8
LSTM (Bowman et al., 2015)	100	221k	77.6
LSTM-att (Rocktäschel et al., 2016)	100	252k	83.5
mLSTM (Wang and Jiang, 2016)	300	1.9M	86.1
LSTMN	100	260k	81.5
LSTMN shallow fusion	100	280k	84.3
LSTMN deep fusion	100	330k	84.5
LSTMN shallow fusion	300	1.4M	85.2
LSTMN deep fusion	300	1.7M	85.7
LSTMN shallow fusion	450	2.8M	86.0
LSTMN deep fusion	450	3.4M	**86.3**

Table 3: Parameter counts $\lvert\theta\rvert_{\mathrm{M}}$, size of hidden unit h, and model accuracy (%) on the natural language inference task.

6 Conclusions

We proposed a novel machine reader that processes sequences from left to right and implicitly discovers lexical correlations on the fly while reading. The reader employs a Long Short-Term Memory architecture with an extended memory tape, explicitly storing all past input information without recursive memory compression. This architecture allows us to adaptively utilize the past information with an *internal* attention mechanism. Experimental results across three tasks show that our model yields performance superior to other LSTM variants without recourse to syntactic information or any form of additional annotation.

Although our experiments focused on LSTMs, the ideas of breaking the first order Markov property in the computation (i.e., using more than one state to compute the update or prediction) and using internal attention are general and can be applied to other types of recurrent neural networks and other tasks such as dependency parsing. The way in which the current input interacts with past memories is also flexible and can vary depending on different tasks and network architectures.

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