Persistence pays off: Paying Attention to
What the LSTM Gating Mechanism Persists

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Abstract

Language Models (LMs) are important components in several Natural Language Processing systems. Recurrent Neural Network LMs composed of LSTM units, especially those augmented with an external memory, have achieved state-of-the-art results. However, these models still struggle to process long sequences which are more likely to contain long-distance dependencies because of information fading and a bias towards more recent information. In this paper we demonstrate an effective mechanism for retrieving information in a memory augmented LSTM LM based on attending to information in memory in proportion to the number of timesteps the LSTM gating mechanism persisted the information.

1 Introduction

Language Models (LM) are important components in Natural Language Processing systems including, Statistical Machine Translation and Speech Recognition (Schwenk et al., 2012). An LM is generally used to compute the likelihood of a sequence of $N$ words appearing in a given language by using the chain rule

$$p(w_1, \ldots, w_N) = \prod_{t=1}^{N} p(w_t|w_1, \ldots, w_{t-1})$$ (1)

Recently, Recurrent Neural Networks LMs (RNN-LMs) have became the state-of-the-art approach to language modelling (Józefowicz et al., 2016). However, RNN-LMs struggle to keep their level of performance as the length of the input sequence increases, especially if the input contains long-distance dependencies (LDD).

A typical RNN-LM sequentially propagates forward a context vector that integrates information about previous inputs to use for the next prediction. Consequently, the information that is captured at the beginning of a sequence containing an LDD is likely to have faded from the context by the time the model spans that dependency. Another problem with such models is that the context vector may be dominated by more recent information. To address these limitations, several “memory-augmented” RNN-LMs architectures have been developed. In general, these models store the hidden states of the RNN in a memory buffer and then attempt to retrieve relevant information from the buffer at each timestep (e.g., Tran et al. (2016), Cheng et al. (2016), Daniluk et al. (2017), Merity et al. (2017), Grave et al. (2017) and Salton et al. (2017)).

In this paper, we analyse the behaviour of the LSTM units and demonstrate that an efficient and effective mechanism for a memory augmented LSTM based LM (LSTM-LM) to retrieve important information from its history is to construct a representation of the LSTM state history that weights information in proportion to the number of timesteps the LSTM persisted the information. Using this strategy reinforces the decisions of the LSTM gating mechanism at each timestep regarding what is important in a sequence. We demonstrate that using this simple strategy a memory augmented LSTM-LM can achieve state-of-the-art results for a single model on the Penn Treebank (Marcus et al., 1994) with fewer parameters than its competitors, an also achieves near state-of-the-art results on the wikitext2 (Merity et al., 2017).

Structure: §2 reviews LSTMs and the gating mechanism; §3 discusses the effect of uniformly weighting the hidden states of an LSTM; §4 illustrates persistence of information in an LSTM; §5 describes our memory augmented LSTM-LM; §6 presents experiments and results; §7 contextualizes our findings; and §8 contains conclusions.
2 LSTM units (aka. LSTM cells) and their variants (e.g., GRUs (Cho et al., 2014)) are now a normal building block for neural based NLP systems (Bradbury et al., 2016; Murdoch and Szlam, 2017). LSTM retain and propagate information through the dynamics of the LSTM memory cell, hidden state, and gating mechanism (including the input, forget, and output gates). The LSTM memory cell retains information that is only known by the unit itself and the hidden state shares information to other LSTM units in the same or any next layer of the network. This way, the units can decide what to keep in memory and how much of that information it wants the other units/layers to know about it. If something is deemed important, the units will both keep it in memory and let other units/layers to know about it. The gating mechanism controls the flow of information between the memory cell and the hidden state. Therefore, the gating mechanism plays an important role on the LSTM hidden dynamics.

The computations of a standard LSTM unit (Gers et al., 2000) (without peephole connections) involve iterating over the following equations

\[
\tilde{c}_t = \text{tanh}(W_{ix} x_t + W_{ih} h_{(t-1)} + b_i) \quad (2)
\]

\[
i_t = \sigma(W_{ix} x_t + W_{ih} h_{(t-1)} + b_i) \quad (3)
\]

\[
f_t = \sigma(W_{if} x_t + W_{hf} h_{(t-1)} + b_f) \quad (4)
\]

\[
o_t = \sigma(W_{io} x_t + W_{ho} h_{(t-1)} + b_o) \quad (5)
\]

\[
c_t = f_t \times \tilde{c}_t + i_t \times c_{(t-1)} \quad (6)
\]

\[
h_t = o_t \times \text{tanh}(c_t) \quad (7)
\]

where the weight matrices \( W_{ix} \) are associated to the input; the weight matrices \( W_{ih} \) are associated with the recurrence; the vectors \( i_t, f_t, o_t \) are the activation vectors produced by the input, forget and output gates respectively; \( \tilde{c}_t \) is the candidate memory cell state; \( c_t \) is the new memory cell state; and \( h_t \) is the output of the unit. Equation 2 will produce a candidate vector \( \tilde{c}_t \) that contains information extracted from the input to the LSTM. The input gate (Equation 3) and forget gate (Equation 4) compute an activation vector to be used to update the memory cell (Equation 6): the candidate vector is multiplied by the input gate to decide how much of the input is important to the memory cell; and the content of the memory cell \( c_{(t-1)} \) is multiplied by the forget gate to decide how much the memory cell will keep from its own content; the results of these two multiplications are merged to decide what will be remembered in the memory cell \( c_t \) for the next iteration. The output gate (Equation 5) also calculates an activation vector that is multiplied by the current content on the memory cell \( c_t \) to produce what we call hidden state \( h_t \) (Equation 7). This last step decides how much of the content in the memory cell \( c_t \) will be known on the next timestep (and by cells in the next layer if it is a multi-layered LSTM or to any layer that may come next o the network). It is important to notice that all the gates compute activations in the range [0, 1] as they are using a sigmoid activation function. If the values are close to 0, the gates are closed and if the values are close to 1, the gates are open. For example, if the forget gate has a value close to 0 the content of the memory cell is erased; if the forget gate is close to 1, all the content of the memory cell will be exposed to other units or layers in the network.

The success of LSTM-RNNs is attributed to their ability to retain information about the input sequence for several timesteps in their internal memory cell \( c_t \). That information is then made available to the next layer in the network for the amount of timesteps it is considered relevant to the current sequence. As pointed by Murdoch and Szlam (2017), each input to an LSTM makes a contribution to the hidden state of the LSTM and that is reflected when Equation 6 is iterated. At any given timestep \( t \), the cell state \( c_t \) can be decomposed into

\[
c_t = \sum_{i=1}^{t} \left( \prod_{j=i+1}^{t} f_j \right) i_j \tilde{c}_i \quad (8)
\]

which, according to the authors, can be interpreted as the contribution at timestep \( t \) to the memory block \( c_t \) by a particular past input at timestep \( j \). In that view, the contribution of an input to a given timestep can be understood as an importance score weighted by the LSTM’s gating mechanism. Therefore, if something is important to the current context if should receive a larger importance score and be held in the memory block for a number of timesteps. In addition to retaining information, Murdoch and Szlam (2017) have also demonstrated that, despite the fact that it is still difficult to interpret what specific activations in the hidden dynamics of LSTM units mean, it is possible to ex-
tract semantically meaningful rules from the memory cells to train a powerful classifier that can approximate the output of the LSTM itself. Moreover, Strohleit et al. (2016) and Karpathy et al. (2015) have demonstrated that these networks can extract meaningful attributes from the data into the memory cells. These attributes carry fine-grained information and keep track of attributes such as line lengths, quotes, and brackets.

Although these and other work demonstrate the power of LSTM units and their gating mechanism, RNN-LMs based on such units (LSTM-LMs) struggle to process long sequences. In our view, the main reason for this degradation in performance happens exactly because of the hidden state dynamics of the LSTM units. Once the information retained in the memory cell $c_t$ is outdated, the forget gate $f_t$ erases that block enabling the unit to store fresh data without interference from previous timesteps (Gers et al., 2000, 2003). This behaviour creates a natural bias towards more recent inputs given that the memory cell has limited capacity to store previous information and, once the memory cell is saturated, the forget gate will start to drop information in favour of more recent inputs. Even though the LSTM units can learn which information it must retain and for how long, the model will struggle with long sequences that are more likely to contain LDDs and that saturate the memory cell.

Once a memory cell has been saturated then, although some content has received a large importance score in past steps, it may be dropped from the memory cell (because of the inherent limitation of the LSTM’s capacity of storing content) and will not be available to contribute to the next steps. For example, an LSTM-LM trained on English may persist the information related to a subject of a sentence for a number of time steps because the subject is important but this information may still have faded by the time the verb is reached. However, by augmenting the network with a memory buffer the information relating to the subject continues to be accessible so long as the memory buffer is not reset. This behaviour is an indication of why the memory augmented models such as the Neural cache model of Grave et al. (2017) and the Pointer LSTM of Merity et al. (2017) has gained success and achieved state-of-the-art in LM research. Even though the required content has already faded from the context, the memory augmentation make it available for subsequent timesteps.

3 The Curious Effectiveness of Uniform Attention

As was noted in Section 1, in recent years a number of extensions to RNN-LMs have been proposed to overcome this fading of information from memory by adding a memory buffer (that is used to store the LSTM hidden state at each timestep) and then at each timestep construct a representation of this history to inform the current prediction. A variety of relatively sophisticated mechanisms for retrieving information from the memory buffer have been proposed. In many cases these retrieval mechanisms include an extra neural network in the RNN-LMs that at each timestep predicts what elements in the memory buffer should be retrieved.

Salton et al. (2017) is a recent example that uses an extra neural network1 to learn what to retrieve from memory. In this architecture at the end of a timestep the current LSTM hidden state is added to the memory buffer. Then at the beginning of the next timestep the additional neural network predicts an attention distribution over the elements of the memory buffer (i.e., the previous LSTM hidden states). Using this attention distribution a compact representation of the RNN-LMs history is constructed by calculating a weighted sum of the elements in the memory (where the weight of each element is the attention attributed to it by the RNN). Curiously, although this architecture was successful in terms of performance the attention mechanism did not work as expected. Instead of focusing attention for each time step on particular relevant elements in memory it spread out the attention nearly uniformly across the memory. It might appear that this architecture was using a strategy of “pay equal attention to everything in the past”. However, we argue this interpretation ignores the power of the LSTM gating mechanism.

Our interpretation of the uniform attention mechanism presented by Salton et al. (2017) is that their Attentive RNN-LM is in fact (indirectly) reinforcing the decisions of the gating mechanism of the LSTM units and is retrieving information that is persisted across multiple timesteps. This is important because it indicates that it may be more fruitful and efficient to leverage the decisions

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1 Similar to that proposed by Bahdanau et al. (2015) and Luong et al. (2015) for Neural Machine Translation (NMT)
made by the LSTM gating mechanism (decisions that the network must make anyway) to drive the retrieval of information from the memory buffer rather than train a separate neural network. It is worth emphasising that to date none of the different retrieval mechanisms proposed in the literature on memory augmented LSTM-LMs have explicitly considered the behaviour of the LSTM gating mechanism.

4 The Persistence of Information

The LSTM gating mechanism will attempt to persist important information for as long as possible (or until the state is saturated). Figure 1 illustrates the idea of persistence within an LSTM unit and how information is eventually dropped. In this illustration, we can see that the information contained in the top of the LSTM block is persisted across 3 timesteps (timesteps 1, 2, and 3) and the information at the bottom LSTM block is persisted for 2 timesteps (timesteps 2 and 3). All other content was held for a single timestep. However, at the moment the model is making a prediction on the last timestep (in this case, timestep 4), all the old information (including the information that was persisted) has already vanished from the context.

We propose that when retrieving/constructing a representation of the LSTM history from a memory buffer the information held for more than one timestep should be weighted in proportion to the number of timesteps the LSTM gating mechanism persisted it across. In the specific situation illustrated in Figure 1 we argue that the information persisted in the top memory cell for 3 timesteps should have a larger during weighting in the representation of the sequence history compared to the pieces of information that were only held for a single timestep. This way, we let the gating mechanism of the LSTM determine what is important about an input and that we must find a way to make that information available for long distances in the future. In fact, Ostmeyer and Cowell (2017) have presented a model that computes a recurrent weighted average (RWA) over every past hidden state. However, the authors limit themselves to evaluate the model over simple tasks and the effectiveness of that model over language modelling is still to be

5 Averaging the Outputs

In this work we adapt and simplify the architecture of Salton et al. (2017) and use a simple average of previous outputs instead of a neural network based attention mechanism. Our intuition for this modification is that the gating mechanism of the LSTM is telling us what is important about an input and that we must find a way to make that information available for long distances in the future. In fact, Ostmeyer and Cowell (2017) have presented a model that computes a recurrent weighted average (RWA) over every past hidden state. However, the authors limit themselves to evaluate the model over simple tasks and the effectiveness of that model over language modelling is still to be
Figure 2: Illustration of a step of the Average LSTMLM. In this example, the model receives the third word as input ($w_3$) after storing the previous states ($h_1$, $h_2$) and the initial state $h_0$ in memory. After producing $h_3$, the model computes the context vector (in this case $c_3$) by averaging the states stored in memory. $c_3$ is concatenated to $h_3$ before the softmax layer for the prediction of the fourth word $w_4$. Also note that $h_3$ is stored in memory only at the end of this process and does not participate in the $c_3$ calculation.

Compared to other memory augmented models our architecture is relatively simple. Figure 2 displays a timestep for our system. A multi-layered LSTM-RNN encodes an input at each timestep and the outputs of the last recurrent layer (i.e., its hidden state) $h_t$ (Equation 7) is added to memory. At each timestep an average of the vectors in the memory buffer is calculated and concatenated with the $h_t$ generated by the processing of the current input. This concatenated vector is then feed into the softmax layer which predicts the distribution for the next word in the sequence.

More formally, the hidden state at timestep $t$, $h_t$, is calculated for an input $x_t$ as

$$h_t = g(x_t, h_{t-1})$$  (9)

where $g$ is a LSTM-RNN. Instead of applying a sophisticated attention mechanism to the hidden states ($h_{<t}$), we calculate the context vector $c_t$ as the average of the hidden states in memory:

$$c_t = \frac{1}{t} \sum_{i=0}^{t-1} h_i$$  (10)

where each $h_i$ is a hidden state stored in the memory buffer. After this step, $c_t$ is concatenated to the current hidden state $h_t$ by means of a concatenation layer

$$h_t' = \tanh(W_c [h_t; c_t] + b_t)$$  (11)

and, finally, the modified hidden state $h_t'$ is forwarded to the softmax layer for the next prediction

$$p(w_t|w_{<t}, x) = \text{softmax}(W_s h_t' + b)$$  (12)

In our experiments with this uniform attention, we found that initialising the memory with a zero vector $h_0$ and allowing the model to count this vector as part of the memory when calculating the average improved the performance of the model.

6 Experiments

To test our intuitions, we evaluate the averaging process of the model using the PTB dataset using the standard split and pre-processing as in Mikolov et al. (2010) which consists of 887K, 70K and 78K tokens on the training, validation and test sets respectively. We also evaluate the model on the wikitext2 dataset using the standard train, validation and test splits which consists of around 2M, 217K tokens and 245k tokens respectively.

6.1 PTB Setup

Following Salton et al. (2017) we trained a multi-layer LSTM-RNN with 2 layers of 650 units for the PTB experiment. We trained them using Stochastic Gradient Descent (SGD) with an initial learning rate of 1.0 and we halved the learning rate at each epoch after 12 epochs. We train the model to minimise the average negative log probability of the target words until we do not get any perplexity improvements over the validation set with

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3Please notice that the iteration index for the summation starts at 0 and, thus, the length of the memory buffer is equal to the timestep index $t$. As we shall explain later, we also included the initial state $h_0$ in the memory buffer and count it to calculate the average.

4In other words, the index of the memory starts at timestep 0 instead of timestep 1. Thus, the memory at any given timestep $t$ will be of length $t + 1$. 

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2Please note that this figure is inspired by the architecture schematic in Salton et al. (2017)
an early stop counter of 10 epochs. We initialize the weight matrices of the network uniformly in \([-0.05, 0.05]\) while all biases are initialized to a constant value at 0.0 with the exception of the *forget gate* biases which is initialised at 1.0 as suggested by Jozefowicz et al. (2015). We also apply 50\% dropout (Srivastava et al., 2014) to the non-recurrent connections and clip the norm of the gradients, normalized by the mini-batch size of 32, at 5.0. We also tie the weight matrix \(W_s\) in Equation 12 to be the embedding matrix as in Press and Wolf (2016). Thus, the dimensionality of the embeddings is set to 650.

### 6.2 wikitext2 Setup

For the wikitext2 experiments we trained a multilayer LSTM-RNN with 2 layers of 1000 units. We also used SGD to minimize the average negative log probability of the target words with an initial learning rate of 1.0. We decayed the learning rate by a factor of 1.15 at each epoch after 14 epochs and we used an early stop counter of 10 epochs. Similarly to the PTB experiment, we initialize the weight matrices of the network uniformly in \([-0.05, 0.05]\) while all biases are initialized to a constant value at 0.0 with the exception of the *forget gate* biases which is initialised at 1.0. For this model we apply 65\% dropout to the non-recurrent connections and clip the norm of the gradients, normalized by the mini-batch size of 32, at 5.0. Once again, we tie the weight matrix \(W_s\) in Equation 12 to be the embedding matrix. Thus, the dimensionality of the embeddings is set to 1,000.

### 6.3 Data Manipulation and Batch Processing

When training each model, we use all sentences in the respective training set, but we truncate all sentences longer than 35 words and pad all sentences shorter than 35 words with a special symbol so all have the same length. We use a vocabulary size of 10k for the PTB and 33,278 for the wikitext2. Each of the mini-batches we use for training are then composed of 32 of these sentences taken from the dataset in sequence.

Contrary to the recent trend in the field, we do not allow successive mini-batches to sequentially traverse the dataset. We reinitialize the hidden state of the LSTM-RNN at the beginning of each mini-batch, by setting it to all zeros. Our motivation for not sequentially traversing the dataset is that although sequentially traversing has the advantage of allowing the batches to be processed more efficiently, some dependencies between words may not be learned if batch traversing is in use as the mini-batch boundaries can split sentences. We also found that allowing the initial state of all zeros to be included in the memory when averaging improves the performance of the Average RNN-LM.

### 6.4 Results

Table 1 presents the results in terms of perplexity of the models trained over the PTB dataset. As we can see, the results obtained by the Averaging RNN-LM are similar to those obtained by the Attentive RNN-LMs of Salton et al. (2017) and by an ensemble of 38 LSTM-LMs. Despite the simple method to retrieve information from the previous timesteps, the Averaging RNN-LM achieves the same level of performance of more complex models with less computation overhead.

Table 2 presents the results in terms of perplexity of the models trained over the wikitext2 dataset. Although the Averaging RNN-LM is still behind the Attentive RNN-LMs and the Neural cache model of Grave et al. (2017) on this dataset, the results are encouraging given the simplicity of the Averaging RNN-LM.

### 7 Discussion

The Averaging LSTM-LM achieves the lowest perplexity for a single model on the PTB (see Table 1). It does this using less parameters than any of the other models tested on the PTB. Given the similarity of the results between the Attentive RNN-LMs of Salton et al. (2017) and the Averaging LSTM-LM it would appear that our hypothesis that the Attentive RNN-LMs was (indirectly) learning to use the dynamics of the LSTM gating mechanism is correct. The Averaging LSTM-LM is also very competitive on the PTB compared to the ensemble methods and in this case the difference in total number of parameters between the Averaging LSTM-LM and these ensemble models is significant.

Focusing on the results for the wikitext2 dataset (see Table 2) the Neural cache model is still the

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3 We have considered using the concept of a parameter budget (Collins et al., 2016; Melis et al., 2017) to contextualize the difference in parameters but given that the difference in terms of total number parameters between the baseline Attentive RNN-LMs and our model is relatively small (essentially arising from the fact that we have dropped the attention neural network component from that architecture) we felt it would not be appropriate to apply this concept.
| Model                                                                 | Params | Valid. Set | Test Set |
|----------------------------------------------------------------------|--------|------------|----------|
| **Single Models**                                                    |        |            |          |
| Large Regularized LSTM (Zaremba et al., 2015)                        | 66M    | 82.2       | 78.4     |
| Large + BD + WT (Press and Wolf, 2016)                               | 51M    | 75.8       | 73.2     |
| Neural cache model (size = 500) (Grave et al., 2017)                 | -      | -          | 72.1     |
| Medium Pointer Sentinel-LSTM (Merity et al., 2017)                   | 21M    | 72.4       | 70.9     |
| Attentive LM w/ combined score function (Salton et al., 2017)       | 14.5M  | 72.6       | 70.7     |
| Attentive LM w/ single score function (Salton et al., 2017)         | 14.5M  | 71.7       | 70.1     |
| Averaging RNN-LM                                                    | 14.1M  | 71.6       | **69.9** |
| **Model Averaging**                                                  |        |            |          |
| 2 Medium regularized LSTMs (Zaremba et al., 2015)                   | 40M    | 80.6       | 77.0     |
| 5 Medium regularized LSTMs (Zaremba et al., 2015)                   | 100M   | 76.7       | 73.3     |
| 10 Medium regularized LSTMs (Zaremba et al., 2015)                  | 200M   | 75.2       | 72.0     |
| 2 Large regularized LSTMs (Zaremba et al., 2015)                    | 122M   | 76.9       | 73.6     |
| 10 Large regularized LSTMs (Zaremba et al., 2015)                   | 660M   | 72.8       | 69.5     |
| 38 Large regularized LSTMs (Zaremba et al., 2015)                   | 2508M  | 71.9       | **68.7** |

Table 1: Perplexity results over the PTB. Symbols: WT = weight tying (Press and Wolf, 2016); BD = Bayesian Dropout (Gal and Ghahramani, 2015). Please note that we could not calculate the number of parameters for some models given missing information in the original publications.

| Model                                                                 | Params | Valid. Set | Test Set |
|----------------------------------------------------------------------|--------|------------|----------|
| Zoneout + Variational LSTM (Merity et al., 2017)                    | 20M    | 108.7      | 100.9    |
| LSTM-LM (Grave et al., 2017)                                        | -      | -          | 99.3     |
| Variational LSTM (Merity et al., 2017)                              | 20M    | 101.7      | 96.3     |
| Neural cache model (size = 100) (Grave et al., 2017)                 | -      | -          | 81.6     |
| Pointer LSTM (window = 100) (Merity et al., 2017)                    | 21M    | 84.8       | 80.8     |
| Averaging RNN-LM                                                    | 50M    | 74.6       | 71.3     |
| Attentive LM w/ combined score function (Salton et al., 2017)       | 51M    | 74.3       | 70.8     |
| Attentive LM w/ single score function (Salton et al., 2017)         | 51M    | 73.7       | 69.7     |
| Neural cache model (size = 2000) (Grave et al., 2017)                | -      | -          | **68.9** |

Table 2: Perplexity results over the wikitext2. Please note that we could not calculate the number of parameters for some models given missing information in the original publications.

best performing model on this dataset. We are not able to estimate the number of parameters for the Neural cache model so we have not included the parameter size of that model in the table. In discussing the wikitext2 results it is worth noting that the Attentive RNN-LMs of Salton et al. (2017) and the Averaging LSTM-LM are the only models in Table 2 that reset their memory at each sentence boundary whereas the memory buffers of other models were allowed to span sentence boundaries. This is an important difference for the wikitext2 dataset because it is composed off documents where the sentences are in the correct order. Consequently, by allowing the memory buffer to span sentence boundaries on the wikitext2 dataset these models were able to carry forward contextual information from preceding sentences and as a result they did not suffer from as severe a cold-start problem at the beginning of each sentence. Given this difference the competitive performance of the Averaging LSTM-LM is encouraging.

The results for the wikitext2 dataset highlights an interesting trade-off and design choice for memory augmented LSTM-LMs. One approach is to use a dynamic length memory buffer which resets at sentence boundaries and uses a simple mechanism, such as averaging, to construct a representation of the memory to inform the prediction at each timestep. This is the approach we have proposed in this paper. This approach has
the advantages of simplicity (model size) and that the memory length can be anchored to landmarks in the history, such as sentence boundaries. This approach is most appropriate for sentence based NLP tasks such as sentence based Machine Translation. There is a question, however, regarding whether this approach will scale to very long sequences (such as documents) as averaging over long-histories may result in all histories appearing similar. We have done some initial experiments where we have permitted the memory buffer to hold longer sequences before being reset and the performance of the Averaging LSTM-LM dipped. The alternative approach is to use a larger memory buffer and a more sophisticated retrieval mechanism, for example the Neural cache model of (Grave et al., 2017) is a useful exemplar for this approach with a memory buffer of 2,000 steps. As the wikitext2 results demonstrate this second approach works well for large datasets where the sentences are in sequence, the cost of this approach being a more complex architecture.

8 Conclusions

In this paper we have highlighted the power of the LSTM gating mechanism and argued that the persistence dynamics of this mechanism can provide useful clues regarding what information is important within a sequence for language modelling. Previous works have demonstrated that LSTMs are capable of extracting important features about an input sequence and that the dynamics of the memory block calculates an importance factor for the contribution of each previous inputs for a given timestep. However, the dynamics of the gates may drop the information kept in memory in favour of more recent information. Once dropped information that may have been held for several timesteps vanishes from the context and is not available anymore to the model. To deal with this problem, a variety of “memory augmented” LSTM-LMs have been proposed which store the previous hidden states of an LSTM in order to make the vanished information available again to subsequent timesteps. However, to date none of these memory augmented LSTM-LMs have explicitly used the persistence of information within an LSTM unit to inform the decision regarding what information should be retrieved from the memory buffer. We argue that ignoring the internal dynamics of the LSTM is to overlook a useful and computationally cheap source of information for memory augmented language modeling.

We believe that attending to the information that an LSTM gating mechanism has decided is important in an input sequence at a given timestep (and hence has persisted to a later timestep) is a natural way of deciding what information will be useful again at a subsequent timestep. Even if the information contained in the LSTM is replaced or altered later in the process, we argue that it is relevant to the entire history in proportion to the amount of timesteps it was held. Informed by this hypothesis, in our work we demonstrated that a simple average of the previous LSTM hidden states in memory is an effective mechanism for providing information to the current timestep about previous inputs.

Admittedly, rating the importance of information in terms of the number of timesteps the LSTM persisted it for is a relatively simplistic view of the dynamics of LSTM units and of the complexity of language. Furthermore, implementing this strategy using an average of past states is also a relatively blunt way of instantiating this approach. However, as our results demonstrate this simple approach is effective and we understand this is a starting point. By drawing attention to the signals implicit in the dynamics of LSTM units we hope to contribute to the development of more efficient LMs. At the same time, the fact that the internal dynamics of an LSTM unit may be used to explicitly signal what is important and what should be retrieved from a memory buffer may suggest alternative constraints and opportunities that should be considered in the design of neural units and by doing so contribute to the development of a new class of units for use in RNN-LMs.

Acknowledgments

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