FAST WEIGHT LONG SHORT-TERM MEMORY

T. Anderson Keller, Sharath Nittur Sridhar, Xin Wang
Intel AI Lab, Artificial Intelligence Products Group, Intel Corporation
{andy.a.keller, sharath.nittur.sridhar, xin3.wang}@intel.com

ABSTRACT

Associative memory using fast weights is a short-term memory mechanism that substantially improves the memory capacity and time scale of recurrent neural networks (RNNs). As recent studies introduced fast weights only to regular RNNs, it is unknown whether fast weight memory is beneficial to gated RNNs. In this work, we report a significant synergy between long short-term memory (LSTM) networks and fast weight associative memories. We show that this combination, in learning associative retrieval tasks, results in much faster training and lower test error, a performance boost most prominent at high memory task difficulties.

1 INTRODUCTION

RNNs are highly effective in learning sequential data. Simple RNNs maintain memory through hidden states that evolve over time. Keeping memory in this simple, transient manner has, among others, two shortcomings. First, memory capacity scales linearly with the dimensionality of recurrent representations, limited for complex tasks. Second, it is difficult to support memory at diverse time scales, particularly challenging for tasks that require information from variably distant past.

Numerous differentiable memory mechanisms have been proposed to overcome the limitations of deep RNNs. Some of these mechanisms, e.g. attention, have become a universal practice in real-world applications such as machine translation (Bahdanau et al., 2014; Daniluk et al., 2017; Vaswani et al., 2017). One type of memory augmentation of RNNs includes mechanisms that employ long-term, generic key-value storages (Graves et al., 2014; Weston et al., 2015; Kaiser et al., 2017). Another kind of memory mechanisms, inspired by early work on fast weights (Hinton & Plaut, 1987; Schmidhuber, 1992), uses auto-associative, recurrently adaptive weights for short-term memory storage (Ba et al., 2016a; Zhang & Zhou, 2017; Schlag & Schmidhuber, 2017). Associative memory considerably ameliorates limitations of RNNs. First, it liberates memory capacity from the linear scaling with respect to hidden state dimensions; in the case of auto-associative memory like fast weights, the scaling is quadratic (Ba et al., 2016a). Neural Turing Machine (NTM)-style generic storage can support memory access at arbitrary temporal displacements, whereas fast weight-style memory has its own recurrent dynamics, potentially learnable as well (Zhang & Zhou, 2017). Finally, if architected and parameterized carefully, some associative memory dynamics can also alleviate the vanishing/exploding gradient problem (Dangovski et al., 2017).

Besides memory augmentation, another entirely distinct approach to overcoming regular RNNs’ drawbacks is by clever design of recurrent network architecture. The earliest but most effective and widely adopted one is gated RNN cells such as long short-term memory (LSTM) (Hochreiter & Schmidhuber, 1997). Recent work has proposed ever more complex topologies involving hierarchy and nesting, e.g. Chung et al. (2016); Zilly et al. (2016); Ruben et al. (2017).

How do gated RNNs such as LSTM interact with associative memory mechanisms like fast weights? Are they redundant, synergistic, or rather competitive to each other? This remains an open question since all fast weight networks reported so far are based on regular, instead of gated, RNNs. Here we answer this question by revealing a strong synergy between fast weight and LSTM.

2 RELATED WORK

Our present work builds upon results reported by (Ba et al., 2016a), using the same fast weight mechanism. A number of studies subsequent to Ba et al. (2016a), though not applied to gated RNNs, pro-
posed interesting mechanisms directly extending or closely related to fast weights. WeiNet (Zhang & Zhou, 2017) parameterized the fast weight update rule and learned it jointly with the network. Gated fast weights (Schlag & Schmidhuber, 2017) used a separate network to produce fast weights for the main RNN and the entire network was trained end-to-end. Rotational unit of memory (Dangovski et al., 2017) is an associative memory mechanism related to yet distinct from fast weights. Its memory matrix is updated with a norm-preserving operation between the input and a target.

Danihelka et al. (2016) proposed an LSTM network augmented by an associative memory that leverages hyperdimensional vector arithmetic for key-value storage and retrieval. This is an NTM-style, non-recurrent memory mechanism and hence different from the fast weight short-term memory.

3 Fast Weight LSTM

Our fast weight LSTM (FW-LSTM) network is defined by the following update equations for the cell states, hidden state, and fast weight matrix (Figure 1).

$\begin{align*}
\hat{i}_t &= \sigma(\tilde{i}_t), \\
\hat{f}_t &= \sigma(\tilde{f}_t), \\
\hat{o}_t &= \sigma(\tilde{o}_t), \\
\text{ReLU}(\tilde{g}_t) &= \text{ReLU}(\tilde{v}_t) \\
A_t &= \lambda A_{t-1} + \eta \tilde{g}_t g_t \\
c_t &= \mathcal{L}(\tilde{f}_t \odot c_{t-1} + i_t \odot \text{ReLU}(\tilde{g}_t + A_t g_t)) \\
h_t &= o_t \odot \text{ReLU}(c_t)
\end{align*}$

Figure 1: FW-LSTM diagram

Here $x_t \in \mathbb{R}^d$, $h_t, v_t, \tilde{v}_t, b_v \in \mathbb{R}^h$, $W_v, A_t \in \mathbb{R}^{h \times h}$ and $U_v \in \mathbb{R}^{h \times d}$, where $v \in \{i, f, o, g\}$, and $t$ indexes time steps. $\odot$ denotes Hadamard (element-wise) product, $\mathcal{L}(\cdot)$ layer normalization, and $\sigma(\cdot)$, $\text{ReLU}(\cdot)$ are the sigmoid and rectified linear function applied element-wise. We used $\text{ReLU}(\cdot)$ in places of $\text{tanh}(\cdot)$ for efficiency, as it did not make a significant difference in practice. Our construction is identical to the standard LSTM cell except for a fast weight memory $A_t$queried by the input activation $g_t$. Since $g_t$ is a function of both the network output $h_{t-1}$ and the new input $x_t$, this gives the network control over what to associate with each new input.

4 Experiments

To study the performance of FW-LSTM in comparison with the original fast weight RNN (FW-RNN) and LSTM with layer normalization (LN-LSTM), we experimented with the associative retrieval task (ART) described in Ba et al. (2016a). Input sequences are composed of $K$ key-value pairs followed by a separator `?`, and then a query key, e.g. for $K = 8$, an example sequence is `a1b2c3d4??b` whose target answer is 2. We experimented with sequence lengths much greater than the original $K = 8$, up to $K = 30$ similar to Zhang & Zhou (2017) and Dangovski et al. (2017).

We further devised a modified ART (mART) that is a re-arrangement of input sequences in the original ART. In mART, all keys are presented first, then followed by all values in the corresponding order, e.g. the mART equivalent of the above training example is `abcd1234??b` with target answer of again 2. In contrast to ART, where the temporal distance is constantly 1 between associated pairs and only average retrieval distance grows with $K$, in mART temporal distances of both association and retrieval scales linearly with $K$. This renders the task more difficult to learn than the original ART, and $K$ can be used to control the difficulty of memory associations.

In all experiments, we augmented the FW-LSTM cell with a learned 100-dimensional embedding for the input $x_t$. Additionally, network output at the end of the sequence was processed by another

---

Note that the placement of layer normalizations is slightly different from the method described in the original paper (Ba et al., 2016b). We find applying layer normalization to the hidden state and input activations simultaneously (rather than separately as in the original model) worked better for this fast weight architecture.
hidden layer with 100 ReLU units before the final softmax, identical to [Ba et al.] (2016a). All models were tuned as described in Appendix and run for a minimum of 300 epochs.

The left half of Table 1 shows performances of LN-LSTM, FW-RNN and our FW-LSTM trained on ART with different sequence lengths and numbers of hidden units. FW-LSTM has a slight advantage when the number of hidden units is low, but otherwise both the FW-RNN and FW-LSTM solve the task perfectly.

The right half of Table 1 shows performances of the same models trained on the mART. Due to significantly increased difficulty of the task, we instead show results for sequence lengths $K = 8, 16$. In learning mART, FW-LSTM outperformed FW-RNN and LN-LSTM by a much greater margin especially at high memory difficulty, $K = 16$, and also converged much faster (Figure 2).

Table 1: Test accuracy (%) of associative retrieval task (ART) and modified associative retrieval task (mART) for different sized models and sequence lengths $K$.

| # Hidden | Model   | ART       | mART     | # Parameters |
|---------|---------|-----------|----------|--------------|
|         |         | $K = 8$   | $K = 30$ | $K = 8$ | $K = 16$ |
| $h = 20$ | LN-LSTM | 37.8      | 22.7     | 38.2      | 29.5      | 19k |
|         | FW-RNN  | 98.7      | 95.7     | 55.5      | 30.3      | 12k |
|         | FW-LSTM | **99.6**  | **97.5** | **96.3**  | **38.9**  | 19k |
| $h = 50$ | LN-LSTM | 95.4      | 21.0     | 34.8      | 25.7      | 43k |
|         | FW-RNN  | **100.0** | **100.0**| 90.9      | 29.0      | 20k |
|         | FW-LSTM | **100.0** | **100.0**| **99.4**  | **93.3**  | 43k |
| $h = 100$ | LN-LSTM | 97.6      | 18.4     | 33.4      | 22.5      | 100k |
|         | FW-RNN  | **100.0** | **100.0**| 91.9      | 30.5      | 38k |
|         | FW-LSTM | **100.0** | **100.0**| **99.9**  | **92.6**  | 100k |

5 Conclusions

We observed that FW-LSTM trained significantly faster and achieved lower test error in performing the original ART. Further, in learning the harder mART, when input sequences are longer, we found that FW-LSTM could still perform the task highly accurately, while both FW-RNN and LN-LSTM utterly failed. This was true even when FW-LSTM had fewer trainable parameters. These results suggest that gated RNNs equipped with fast weight memory is a promising combination for associative learning of sequences.

\footnote{The parameters $\eta$ and $\lambda$ used for FW-RNN here are different than those in Zhang & Zhou (2017), resulting in an improved performance. The values used are listed in Appendix.}
REFERENCES

Jimmy Ba, Geoffrey Hinton, Volodymyr Mnih, Joel Z Leibo, and Catalin Ionescu. Using Fast Weights to Attend to the Recent Past. 2016a. ISSN 10495258. URL http://arxiv.org/abs/1610.06258

Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. Layer Normalization. jul 2016b. URL http://arxiv.org/abs/1607.06450

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural Machine Translation by Jointly Learning to Align and Translate. sep 2014. ISSN 0147-006X. doi: 10.1146/annurev.neuro.26.041002.131047. URL http://arxiv.org/abs/1409.0473

Junyoung Chung, Sungjin Ahn, and Yoshua Bengio. Hierarchical Multiscale Recurrent Neural Networks. sep 2016. URL http://arxiv.org/abs/1609.01704

Rumen Dangovski, Li Jing, and Marin Soljacic. Rotational Unit of Memory. oct 2017. URL http://arxiv.org/abs/1710.09537

Ivo Danihelka, Greg Wayne, Benigno Uria, Nal Kalchbrenner, and Alex Graves. Associative Long Short-Term Memory. feb 2016. URL http://arxiv.org/abs/1602.03032

Michal Duniluk, Tim Rocktäschel, Johannes Welbl, and Sebastian Riedel. Frustratingly Short Attention Spans in Neural Language Modeling. feb 2017. URL http://arxiv.org/abs/1702.04521

Alex Graves, Greg Wayne, and Ivo Danihelka. Neural Turing Machines. Arxiv, pp. 1–26, 2014. ISSN 2041-1723. doi: 10.3389/neuro.12.006.2007. URL http://arxiv.org/abs/1410.5401

Geoffrey E. Hinton and David C. Plaut. Using Fast Weights to Deblur Old Memories. Proceedings of the 9th Annual Conference of the Cognitive Science Society, pp. 177–186, 1987. URL http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.10.1011

Sepp Hochreiter and Jurgen Schmidhuber. Long short-term memory. Neural Computation, 9(8): 1–32, 1997. ISSN 0899-7667. doi: 10.1162/neco.1997.9.8.1735.

Łukasz Kaiser, Ofir Nachum, Aurko Roy, and Samy Bengio. Learning to Remember Rare Events. mar 2017. URL http://arxiv.org/abs/1703.03129

Joel Ruben, Antony Moniz, David Krueger, and David Krueger@umontreal Ca. Nested LSTMs. 80:1–15, jan 2017. URL http://arxiv.org/abs/1801.10308

Imanol Schlag and Jürgen Schmidhuber. Gated Fast Weights for On-The-Fly Neural Program Generation. NIPS Metalearning Workshop, 2017. URL http://metalearning.ml/papers/metakleen17__schlag.pdf

Jürgen Schmidhuber. Learning to Control Fast-Weight Memories: An Alternative to Dynamic Recurrent Networks. Neural Computation, 4(1):131–139, jan 1992. ISSN 0899-7667. doi: 10.1162/neco.1992.4.1.131. URL http://www.mitpressjournals.org/doi/10.1162/neco.1992.4.1.131

Ashish Vaswani, Jakob Uszkoreit, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention Is All You Need. (Nips), 2017. URL http://arxiv.org/abs/1706.03762

Jason Weston, Sumit Chopra, and Antoine Bordes. Memory networks. Iclr, pp. 1–15, 2015. ISSN 1098-7576. doi: v0. URL http://arxiv.org/abs/1410.3916

Wei Zhang and Bowen Zhou. Learning to update Auto-associative Memory in Recurrent Neural Networks for Improving Sequence Memorization. sep 2017. URL http://arxiv.org/abs/1709.06493

Julian Georg Zilly, Rupesh Kumar Srivastava, Jan Koutník, and Jürgen Schmidhuber. Recurrent Highway Networks. jul 2016. ISSN 1938-7228. URL http://arxiv.org/abs/1607.03474
6 ACKNOWLEDGMENTS

We thank Drs. Tristan J. Webb, Marcel Nassar and Amir Khosrowshahi for insightful discussions. We also thank Dr. Jason Knight for his assistance setting up Kubernetes cluster used for training and tuning.

7 APPENDIX

7.1 ASSOCIATIVE RETRIEVAL HYPERPARAMETERS

All models in the Associative retrieval section were tuned over the following hyperparameter ranges using standard grid search. The final models were selected based on the highest validation set accuracy from the following set:

\[
\begin{align*}
\eta &\in \{1.0, 0.75, 0.5, 0.25, 0.1\} \\
\lambda &\in \{0.99, 0.9\} \\
\text{grad}_\text{clip} &\in \{1.0, 5.0\} \\
\text{learning}_\text{rate} &\in \{10^{-4}, 10^{-5}\} \\
\text{anneal}_\text{rate} &\in \{100, 10\}
\end{align*}
\]

where \(\text{anneal}_\text{rate}\) is the number of epochs between which the learning rate is halved, and \(\text{grad}_\text{clip}\) is the maximum L2 norm clipping value for the gradient.

The optimal hyperparameters were found to match for both the FW-RNN and FW-LSTM for the simple associative retrieval tasks. They are as follows:

\[
\begin{align*}
\eta &= 1.0 \\
\lambda &= 0.99 \\
\text{grad}_\text{clip} &= 5.0 \\
\text{learning}_\text{rate} &= 10^{-4} \\
\text{anneal}_\text{rate} &= 100
\end{align*}
\]