Memory based Model

A OVERVIEW

Lujun Zhao

2016/03/10

School of Mathematical Sciences Fudan University A **MEMORY NETWORK** consists of a memory **m** and four components *I*, *G*, *O* and *R* as follows:

- *I*: (input feature map) converts the incoming input to the internal feature representation.
- *G*: (generalization) updates old memories given the new input.
- O: (output feature map) produces a new output, given the memories.
- *R*: (response) converts the output into the response format desired.

○ Large - scale QA

Dataset: ReVerb ClueWebo9 Extractions (14M statements, stored as (subject, relation, object) triples)

Method	F1
(Fader et al., 2013)	0.54
(Bordes et al., 2014b)	0.73
MemNN (embedding only)	0.72
MemNN (with BoW features)	0.82

Figure: Results on the large-scale QA task

O Simulated world QA

Dataset: generated 7k statements and 3k questions from the simulator

○ Combining simulated data and large - scale QA

Neural Turing Machines[Graves et al. 2014]



Figure: Neural Turing Machine Architecture

О Сору

Dataset: unknown (sequence of random binary vectors)

○ Repeat Copy

- Associative Recall
- O Dynamic N-Grams

○ Priority Sorts

End-To-End Memory Networks[Sukhbaatar et al. 2015]



Figure: End-To-End Memory Networks

Synthetic Question and Answering Dataset: Facebook bAbI Dataset

Language Modeling
 Dataset: Penn Tree Bank and Text8

Dynamic Memory Networks[Kumar et al. 2015]



Figure: Dynamic Memory Networks

Question Answering
 Dataset: Facebook bAbI Dataset

Sentiment Analysis
 Dataset: Stanford Sentiment Treebank

Part-of-Speech Tagging
 Dataset: Wall Street Journal dataset

Stack RNN[Joulin et al. 2015]



Figure: Neural network extended with push-down stack

- Learning simple algorithmic patterns
 Dataset: generated by simple algorithms
- Language modeling
 Dataset: Penn Tree Bank

Model	Ngram	Ngram + Cache	RNN	LSTM	SRCN 24	Stack RNN
Validation perplexity	-	-	137	120	120	124
Test perplexity	141	125	129	115	115	118

Figure: Comparison of RNN, LSTM, SRCN and Stack RNN on language modeling task

Neural Stack[Grefenstette et al. 2015]



Figure: Illustrating a Neural Stack's Operations, Recurrent Structure, and Control

○ Synthetic Transduction Tasks

Dataset: randomly generated from a vocabulary of 128 meaningless symbols

- Sequence Copying
- Sequence Reversal
- Bigram flipping

○ ITG Transduction Tasks

Dataset: the source and target sequence are jointly generated by Inversion Transduction **G**rammars

Structured-Memory NTMs[Zhang et al. 2015]



Figure: NTM and NTM variants that use LSTM as controllers

The experiments is to show the convergence speed and quality of those three variants, compared to the NTM setting.

Copy Task
 Dataset: randomly generated

Associative Recall Task
 Dataset: randomly generated

Evolving Neural Turing Machines[Greve et al. 2015]



Figure: Evolvable Neural Turing Machine

Copy Task Dataset: unknown

T-Maze Task Dataset: unknown

A. Graves, G. Wayne, and I. Danihelka. Neural turing machines. *arXiv preprint arXiv*:1410.5401, 2014.

E. Grefenstette, K. M. Hermann, M. Suleyman, and P. Blunsom.

Learning to transduce with unbounded memory. In *Advances in Neural Information Processing Systems,* pages 1819–1827, 2015.

R. B. Greve, E. J. Jacobsen, and S. Risi. Evolving neural turing machines.

A. Joulin and T. Mikolov.

Inferring algorithmic patterns with stack-augmented recurrent nets.

In *Advances in Neural Information Processing Systems*, pages 190–198, 2015.

 A. Kumar, O. Irsoy, J. Su, J. Bradbury, R. English, B. Pierce, P. Ondruska, I. Gulrajani, and R. Socher.
 Ask me anything: Dynamic memory networks for natural language processing.
 arXiv preprint arXiv:1506.07285, 2015.

- S. Sukhbaatar, J. Weston, R. Fergus, et al. End-to-end memory networks.
 In Advances in Neural Information Processing Systems, pages 2431–2439, 2015.
- J. Weston, S. Chopra, and A. Bordes. Memory networks. *arXiv preprint arXiv:1410.3916*, 2014.
- W. Zhang and Y. Yu.

Structured memory for neural turing machines. *arXiv preprint arXiv:*1510.03931, 2015.