What Does It Mean to Understand?

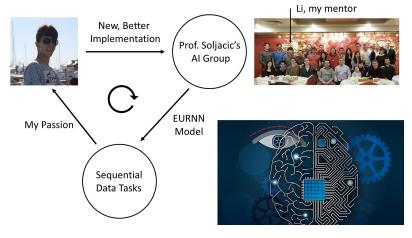
Improving the Performance of Unitary Recurrent Neural Networks and Applying Them to the Automatic Text Understanding Problem

Ivan Ivanov

Research Science Institute

Under the Direction of Li Jing Massachusetts Institute of Technology

The Purpose Behind Artificial Intelligence



(MIT News) and (Prof. Soljacic's group)

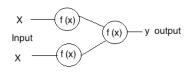


The Artificial **Neural** Network

► An Analogy



Biological Neural Network



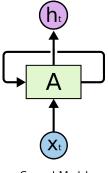
Artificial Neural Network

(Dasan)

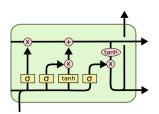
Introduction

The Artificial **Recurrent** Neural Network

Concept of Recurrence



General Model



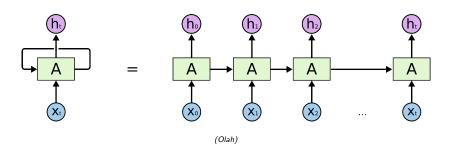
Long Short-Term Memory (LSTM) Model

(Olah)



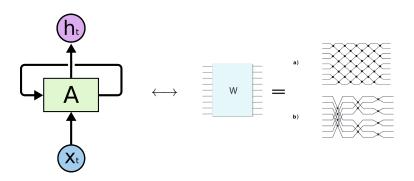
The Artificial **Recurrent** Neural Network

Concept of Recurrence



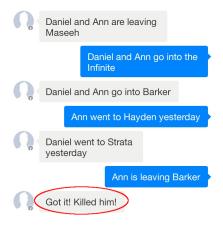
The Artificial **Unitary** Recurrent Neural Network

► The Unitary Matrix



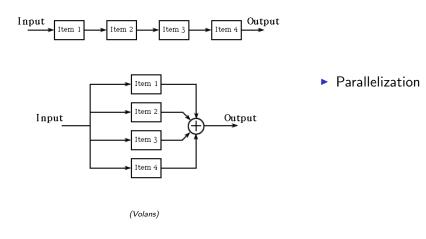
(Jing et. al)

The Artificial **Unitary** Recurrent Neural Network

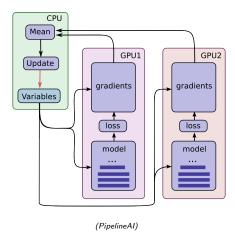


► Dr. Sillman: Where is Daniel?

Optimizations of the model



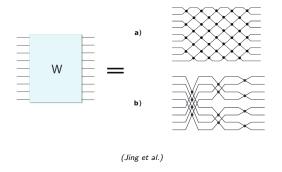
Optimizations of the model



- Parallelization
- ► TensorFlow Adaptation

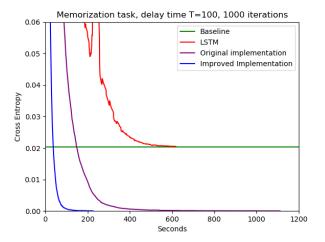


Optimizations of the model

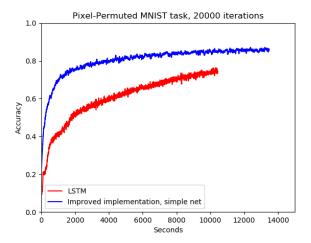


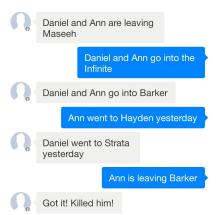
- Parallelization
- ► TensorFlow Adaptation
- Hyperparameter Expansion

Benchmark: Memorization Task

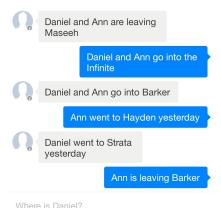


Benchmark: Handwritten Digit Recognition Task





► Dr. Sillman: Where is Daniel?







Daniel and Ann are leaving Maseeh

Daniel and Ann go into the Infinite



Daniel and Ann go into Barker

Ann went to Hayden yesterday



Daniel went to Strata yesterday

Ann is leaving Barker

Where is Daniel'

Daniel	and	 is	Where
0	1	 16	17



Daniel and Ann are leaving Maseeh

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Where is Daniel'

Daniel	and	 is	Where
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Where is Daniel? \longrightarrow (17, 16, 0)



Daniel and Ann are leaving Maseeh

Daniel and Ann go into the Infinite



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Ann went to Hayden yesterday



Daniel went to Strata vesterday

Ann is leaving Barker

Where is Daniel?

Daniel	and	 is	Where
0	1	16	17

```
Where is Daniel? \longrightarrow (17, 16, 0) \downarrow ([0,0,...,0,1], [0,0,...,1,0], [1,0,...,0,0])
```

 $0 \rightarrow$

 $1 \rightarrow$

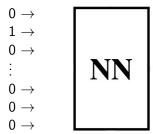
 $0 \rightarrow$

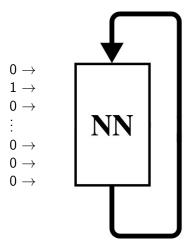
:

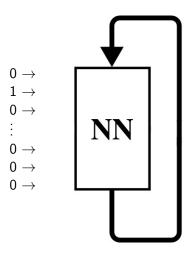
 $0 \rightarrow$

 $0\,\rightarrow\,$

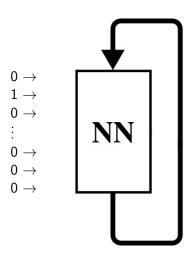
 $0 \, \rightarrow \,$







```
\begin{array}{l} \rightarrow 0.12 \; (12\%) \\ \rightarrow 0.01 \; (1\%) \\ \rightarrow 0.07 \; (7\%) \\ \vdots \\ \rightarrow 0.24 \; (24\%) \\ \rightarrow 0.56 \; (56\%) \\ \rightarrow 0.00 \; (0\%) \end{array}
```



•

Daniel and Ann : Strata Barker Where

Task 1: Single Supporting Fact

Mary went to the bathroom. John moved to the hallway. Mary travelled to the office. Where is Mary? A:office

(Facebook)

Task	Our model	LSTM	Task	Our model	LSTM
1 - Single Supporting Fact	50.5%	52.0%	11 - Basic Coreference	72.3%	74.1%
2 - Two Supporting Facts	31.8%	15.1%	12 - Conjunction	73.4%	76.1%
3 - Three Supporting Facts	25.4%	19.1%	13 - Compound Coreference	94.0%	83.0%
4 - Two Arg. Relations	71.2%	73.5%	14 - Time Reasoning	36.4%	18.6%
5 - Three Arg. Relations	67.1%	34.4%	15 - Basic Deduction	55.0%	21.2%
6 - Yes/No Questions	52.9%	50.5%	16 - Basic Induction	48.8%	32.2%
7 - Counting	71.3%	56.5%	17 - Positional Reasoning	48.4%	50.6%
8 - Lists/Sets	68.2%	38.8%	18 - Size Reasoning	89.5%	89.2%
9 - Simple Negation	61.8%	63.8%	19 - Path Finding	7.9%	6.6%
10 - Indefinite Knowledge	46.0%	45.1%	20 - Agents Motivations	95.5%	90.6%
			Mean Performance	58.4%	49.6%



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Conclusion

- ▶ Five times the efficiency of the original implementation
- Greater accuracy than state-of-the-art model on bAbl tasks dataset
- ▶ Introduction of the theoretical model to a real-life task



Future work

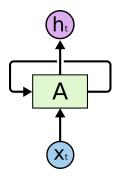
- Decomposition model improvements
- ► Low-level operations optimization
- Application for speech recognition



Acknowledgements

- ▶ Li Jing
- Rumen Dangovski
- Dr. Jenny Sendova
- Andrew Jin, Charles Tam, Stanislav Atanasov, William McInroy, Hristo Stoyanov, Milen Ferev
- RSI, CEE, MIT
- America for Bulgaria Foundation, International Foundation "Sts. Cyril & Methodius"

The Recurrent Neural Network



$$m^{(t)} = \sigma(U * x^{(t)} + W * m^{(t-1)})$$

$$h^{(t)} = W * m^{(t)} + b$$

Exploding and Vanishing Gradients Problems

Training rule:
$$W_{i,j} - \lambda * \frac{\partial C}{\partial W_{i,j}}$$

$$\frac{\partial C}{\partial h^{(t)}} = \frac{\partial C}{\partial h^{(T)}} \frac{\partial h^{(T)}}{\partial h^{(t)}} = \frac{\partial C}{\partial h^{(T)}} \prod_{k=t}^{T-1} \frac{\partial h^{(k+1)}}{\partial h^{(k)}} = \frac{\partial C}{\partial h^{(T)}} \prod_{k=t}^{T-1} D^{(t)} W$$

Jing et al.'s Approach

► General representation

$$W_n = DR_{2,1}^{-1}R_{3,1}^{-1}\dots R_{N,N-2}^{-1}R_{N,N-1}^{-1}$$
$$= DR_{2,1}^{'}R_{3,1}^{'}\dots R_{N,N-2}^{'}R_{N,N-1}^{'}$$

Jing et al.'s Approach

Simple Net Decomposition Model

$$W = D(R_{1,2}^{(1)}R_{3,4}^{(1)}\dots R_{N/2-1,N/2}^{(1)}) \times$$

$$\times (R_{2,3}^{(2)}R_{4,5}^{(2)}\dots R_{N/2-1,N/2-1}^{(2)}) \times \dots$$

$$= DF_{a}^{(1)}F_{b}^{(2)}\dots F_{b}^{(L)}$$

$$F_{a}^{(l)} = R_{1,2}^{(l)}R_{3,4}^{(l)}\dots R_{N/2-1,N/2}^{(l)}$$

$$F_{b}^{(l)} = R_{2,3}^{(l)}R_{4,5}^{(l)}\dots R_{N/2-1,N/2-1}^{(l)}$$

Jing et al.'s Approach

► Lightweight Decomposition Model

$$W = DF_1F_2 \dots F_{log(N)}$$

$$F_i$$
 - rotation matrices for $(2kp+j,(2k+1)p+j)$, $p=N/2t,\ k\in 0,\ldots,2^{i-1},\ {\rm and}\ j\in 1,\ldots,p$

troduction Methods Discussion and Results Conclusion Appendix

Jing et al.'s Approach

$$\mathbf{F}x = v_1 * x + v_2 * permute(x)$$

Simple Net Decomposition Model

$$v_{1} = (e^{i\phi_{1}^{(l)}}\cos\theta_{1}^{(l)}, \cos\theta_{1}^{(l)}, e^{i\phi_{2}^{(l)}}\cos\theta_{2}^{(l)}, \cos\theta_{2}^{(l)}, \ldots)$$

$$v_{2} = (-e^{i\phi_{1}^{(l)}}\sin\theta_{1}^{(l)}, \sin\theta_{1}^{(l)}, -e^{i\phi_{2}^{(l)}}\sin\theta_{2}^{(l)}, \sin\theta_{2}^{(l)}, \ldots)$$

$$permute(x) = (x_{2}, x_{1}, x_{4}, x_{3}, x_{6}, x_{5}, \ldots)$$

Lightweight Decomposition Model

$$\begin{aligned} v_1 &= (e^{i\phi_1^{(l)}}\cos\theta_1^{(l)}, \ e^{i\phi_2^{(l)}}\cos\theta_2^{(l)}, \dots, \ \cos\theta_1^{(l)}, \ \cos\theta_2^{(l)}, \dots) \\ v_2 &= (-e^{i\phi_1^{(l)}}\sin\theta_1^{(l)}, \ -e^{i\phi_2^{(l)}}\sin\theta_2^{(l)}, \dots, \ \sin\theta_1^{(l)}, \ \sin\theta_2^{(l)}, \dots) \\ permute(x) &= (x_{N/2} + 1, x_{N/2} + 2, \dots, x_N, x_1, x_2, \dots) \end{aligned}$$

