Ordered Neurons: Integrating Tree Structures Into Recurrent Neural Networks

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ниу вшэ

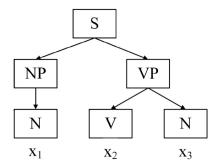
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План

- строение языка, структурирование
- ▶ что такое ordered neurons
- cumax()
- LSTM vs. ON-LSTM
- эксперименты
 - language modeling
 - unsupervised constituency parsing
 - targeted syntactic evaluation
- результаты

Естественные языки

- не строго последовательны
- имеют древоподобную структуру
- можно выделить так называемые составляющие "constituents"



Естественные языки

Интеграция древовидной структуры:

- иерархическое представление с увеличивающимся уровнем абстракции
- композиционные эффекты языка
- долгосрочные зависимости

Подходы

Supervised syntactic parser:

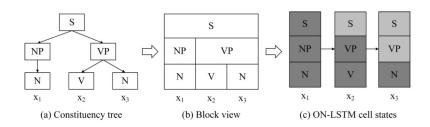
- мало разметки
- синтаксические правила в некоторых областях нарушаются (tweets)
- язык меняется, а вместе с ним правила

RNN - работают хорошо, но есть некоторые проблемы:

- не прослеживают долгосрочные зависимости
- способность к обобщению
- учитывание отрицания

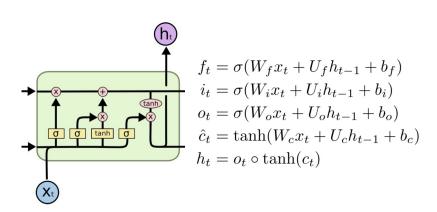
LSTM потенциально могут кодировать в скрытых состояниях древовидную структуру языка

Ordered Neurons

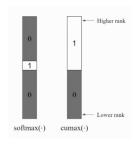


- заканчивается большая составляющая, значит заканчиваются все меньшие составляющие
- ▶ обновляется high-ranking neuron, значит все lower ranking neurons должны обновиться

Long Short Term Memory

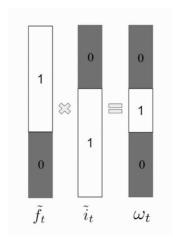


cumax()



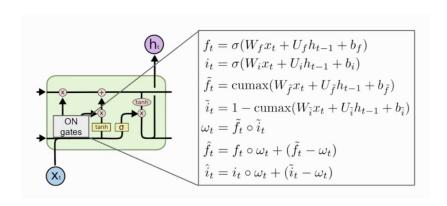
$$cumax(\cdot) = cumsum(softmax(\cdot))$$
 $g = (0,...,0,1,...,1)$ d - позиция первой единицы в g $p(d) = softmax(\cdot)$ $(d \le k) = (d = 0) \lor (d = 1) \lor ... \lor (d = k)$ $p(g_k = 1) = p(d \le k) = \sum_{i \le k} p(d = i)$ $p(d \le k) = cumsum(softmax(\cdot)) = \mathbb{E}[g_k]$ $\hat{g} = \mathbb{E}[g]$

Structure Gating Mechanism



- Master Forget Gate $\widetilde{f}_t = cumax(W_{\widetilde{f}}x_t + U_{\widetilde{f}}h_{t-1} + b_{\widetilde{f}})$
- Master Input Gate $\widetilde{i}_t = 1 cumax(W_{\widetilde{i}}x_t + U_{\widetilde{i}}h_{t-1} + b_{\widetilde{i}})$
- $\begin{array}{c} \blacktriangleright \ \, \mathsf{Overlap} \\ \omega_t = \widetilde{f}_t \circ \widetilde{i}_t \end{array}$

Structure Gating Mechanism



Experiments. Language Modeling

Model	Parameters	Validation	Test
Zaremba et al. (2014) - LSTM (large)	66M	82.2	78.4
Gal & Ghahramani (2016) - Variational LSTM (large, MC)	66M	_	73.4
Kim et al. (2016) - CharCNN	19M	_	78.9
Merity et al. (2016) - Pointer Sentinel-LSTM	21M	72.4	70.9
Grave et al. (2016) - LSTM	_	_	82.3
Grave et al. (2016) - LSTM + continuous cache pointer	_	_	72.1
Inan et al. (2016) - Variational LSTM (tied) + augmented loss	51M	71.1	68.5
Zilly et al. (2016) - Variational RHN (tied)	23M	67.9	65.4
Zoph & Le (2016) - NAS Cell (tied)	54M	_	62.4
Shen et al. (2017) - PRPN-LM	_	_	62.0
Melis et al. (2017) - 4-layer skip connection LSTM (tied)	24M	60.9	58.3
Merity et al. (2017) - AWD-LSTM - 3-layer LSTM (tied)	24M	60.0	57.3
ON-LSTM - 3-layer (tied)	25M	58.29 ± 0.10	56.17 ± 0.12
Yang et al. (2017) - AWD-LSTM-MoS*	22M	56.5	54.4

Unsupervised Constituency Parsing

Model	Training Data	Training Object	Vocab Size	WSJ1 μ (σ)	Parsi 0 max	ng F1 WSJ $\mu(\sigma)$	max	Depth WSJ	Accura ADJP		WSJ PP	by Tag INTJ
PRPN-UP PRPN-LM	AllNLI Train AllNLI Train		76k 76k			38.3 (0.5) 35.0 (5.4)	39.8 42.8	5.8 6.1	28.7 37.8	65.5 59.7	32.7 61.5	0.0 100.0
PRPN-UP PRPN-LM	WSJ Train WSJ Train	LM LM	15.8k 10k	62.2 (3.9) 70.5 (0.4)		26.0 (2.3) 37.4 (0.3)	32.8 38.1	5.8 5.9	24.8 26.2	54.4 63.9	17.8 24.4	0.0 0.0
ON-LSTM 1st-layer ON-LSTM 2nd-layer ON-LSTM 3rd-layer	WSJ Train WSJ Train WSJ Train	LM LM LM	10k 10k 10k	65.1 (1.7)	66.8	20.0 (2.8) 47.7 (1.5) 36.6 (3.3)	49.4	5.6 5.6 5.3	38.1 46.2 44.8	23.8 61.4 57.5	18.3 55.4 47.2	0.0 0.0 0.0
300D ST-Gumbel w/o Leaf GRU 300D RL-SPINN w/o Leaf GRU	AllNLI Train AllNLI Train AllNLI Train AllNLI Train	NLI NLI	- - -	- - - -	- - - -	19.0 (1.0) 22.8 (1.6) 13.2 (0.0) 13.1 (0.1)		- - - -	15.6 18.9 1.7 1.6	18.8 24.1 10.8 10.9	9.9 14.2 4.6 4.6	59.4 51.8 50.6 50.0
CCM DMV+CCM UML-DOP	WSJ10 Full WSJ10 Full WSJ10 Full	_ _ _	- - -	- - -	71.9 77.6 82.9	- - -	- - -	- - -	- - -	-	- - -	-
Random Trees Balanced Trees Left Branching Right Branching	_ _ _	- - -	- - - -	31.7 (0.3) 43.4 (0.0) 19.6 (0.0) 56.6 (0.0)	43.4 19.6		18.6 24.5 9.0 39.8	5.3 4.6 12.4 12.4	17.4 22.1 - -	22.3 20.2 - -	16.0 9.3 - -	40.4 55.9 -

Unsupervised Constituency Parsing

	ON-LSTM	LSTM
Short-Term Dependency		
SUBJECT-VERB AGREEMENT:		
Simple	0.99	1.00
In a sentential complement	0.95	0.98
Short VP coordination	0.89	0.92
In an object relative clause	0.84	0.88
In an object relative (no that)	0.78	0.81
REFLEXIVE ANAPHORA:		
Simple	0.89	0.82
In a sentential complement	0.86	0.80
NEGATIVE POLARITY ITEMS:		
Simple (grammatical vs. intrusive)	0.18	1.00
Simple (intrusive vs. ungrammatical)	0.50	0.01
Simple (grammatical vs. ungrammatical)	0.07	0.63
Long-Term Dependency		
SUBJECT-VERB AGREEMENT:		
Long VP coordination	0.74	0.74
Across a prepositional phrase	0.67	0.68
Across a subject relative clause	0.66	0.60
Across an object relative clause	0.57	0.52
Across an object relative (no that)	0.54	0.51
REFLEXIVE ANAPHORA:		
Across a relative clause	0.57	0.58
NEGATIVE POLARITY ITEMS:		
Across a relative clause (grammatical vs. intrusive)	0.59	0.95
Across a relative clause (intrusive vs. ungrammatical)	0.20	0.00
Across a relative clause (grammatical vs. ungrammatical)	0.11	0.04

References

- [1]. https://arxiv.org/pdf/1810.09536.pdf
- [2]. https://colah.github.io/posts/2015-08-Understanding-LSTMs/