Hierarchical Attention Networks for Document Classification

Zichao Yang[1] Diyi Yang[1] Chris Dyer[1]
Xiaodong He[2] Alex Smola[1] Eduard Hovy[1]

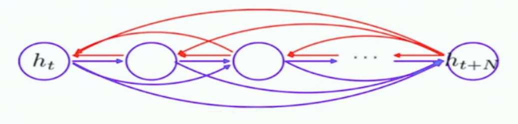
[1]Carnegie Mellon University

[2]Microsoft Research, Redmond

San Diego, California, June 12-17, 2016

Outline

Gated Recurrent Unit (GRU)



- New hidden state at time t
  $h_t = f(h_{t-1}, x_t) = u_t \odot \widetilde{h}_t + (1 - u_t) \odot h_{t-1}$
- Candidate Update $\widetilde{h}_t = tanh(W[x_t] + U(r_t \odot h_{t-1}) + b)$
- Reset gate $r_t = \sigma(W_r[x_t] + U_r h_{t-1} + b_r)$
- Update Gate $u_t = \sigma(W_u[x_t] + U_u h_{t-1} + b_u)$

Long Short-Term Memory (LSTM)

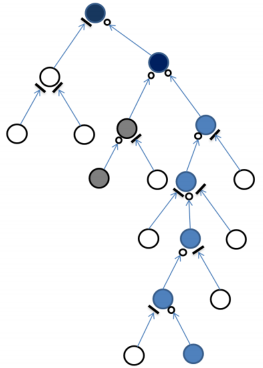
Gated Recurrent Unit
[Cho et al., EMNLP2014;
Chung, Gulcehre, Cho, Bengio, DLUFL2014]

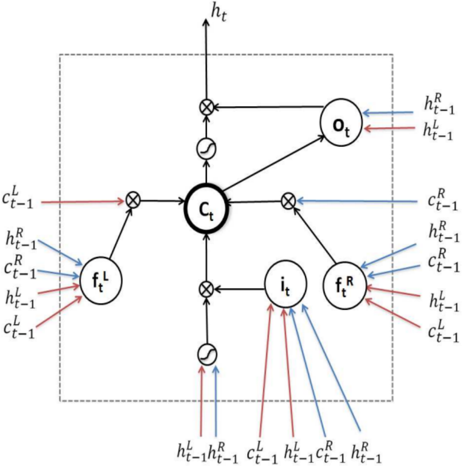
$$h_t = u_t \odot \tilde{h}_t + (1 - u_t) \odot h_{t-1}$$
$$\tilde{h} = \tanh(W\,[x_t] + U(r_t \odot h_{t-1}) + b)$$
$$u_t = \sigma(W_u\,[x_t] + U_u h_{t-1} + b_u)$$
$$r_t = \sigma(W_r\,[x_t] + U_r h_{t-1} + b_r)$$

Long Short-Term Memory
[Hochreiter & Schmidhuber, NC1999;
Gers, Thesis2001]

$$h_t = o_t \odot \tanh(c_t)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$\tilde{c}_t = \tanh(W_c\,[x_t] + U_c h_{t-1} + b_c)$$
$$o_t = \sigma(W_o\,[x_t] + U_o h_{t-1} + b_o)$$
$$i_t = \sigma(W_i\,[x_t] + U_i h_{t-1} + b_i)$$
$$f_t = \sigma(W_f\,[x_t] + U_f h_{t-1} + b_f)$$

Long Short-Term Memory Over Tree Structures (S-LSTM)



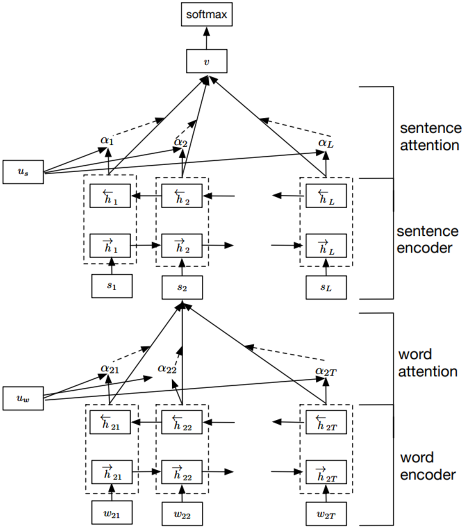


Long Short-Term Memory Over Tree Structures (S-LSTM)

Table 1. Performances (accuracies) of different models on the test set of Stanford Sentiment Tree Bank, at the sentence level (roots) and the phrase level. † shows the performance are statistically significantly better ($p < 0.05$) than the corresponding models.

MODELS	ROOTS	PHRASES
NB	41.0	67.2
SVM	40.7	64.3
RvNN	43.2	79.0
RNTN	45.7	80.7
S-LSTM	**48.0**†	**81.9**†

Hierarchical Attention Network



Word Encoder:

- $x_{it} = W_e w_{it}, t \in [1, T]$
- $\overrightarrow{h_{it}} = \overrightarrow{GRU(x_{it})}, t \in [1, T]$
- $\overleftarrow{h_{it}} = \overleftarrow{GRU(x_{it})}, t \in [T, 1]$

Word Attention:

- $u_{it} = tanh(W_w h_{it} + b_w)$
- $\alpha_{it} = \frac{\exp(u_{it}^T u_w)}{\sum_t \exp(u_{it}^T u_w)}$
- $s_i = \sum_t \alpha_{it} h_{it}$

Experiments & Results

Figure: Document Classification, in percentage

	Methods	Yelp'13	Yelp'14	Yelp'15	IMDB	Yahoo Answer	Amazon
Zhang et al., 2015	BoW	-	-	58.0	-	68.9	54.4
	BoW TFIDF	-	-	59.9	-	71.0	55.3
	ngrams	-	-	56.3	-	68.5	54.3
	ngrams TFIDF	-	-	54.8	-	68.5	52.4
	Bag-of-means	-	-	52.5	-	60.5	44.1
Tang et al., 2015	Majority	35.6	36.1	36.9	17.9	-	-
	SVM + Unigrams	58.9	60.0	61.1	39.9	-	-
	SVM + Bigrams	57.6	61.6	62.4	40.9	-	-
	SVM + TextFeatures	59.8	61.8	62.4	40.5	-	-
	SVM + AverageSG	54.3	55.7	56.8	31.9	-	-
	SVM + SSWE	53.5	54.3	55.4	26.2	-	-
Zhang et al., 2015	LSTM	-	-	58.2	-	70.8	59.4
	CNN-char	-	-	62.0	-	71.2	59.6
	CNN-word	-	-	60.5	-	71.2	57.6
Tang et al., 2015	Paragraph Vector	57.7	59.2	60.5	34.1	-	-
	CNN-word	59.7	61.0	61.5	37.6	-	-
	Conv-GRNN	63.7	65.5	66.0	42.5	-	-
	LSTM-GRNN	65.1	67.1	67.6	45.3	-	-
This paper	HN-AVE	67.0	69.3	69.9	47.8	75.2	62.9
	HN-MAX	66.9	69.3	70.1	48.2	75.2	62.9
	HN-ATT	**68.2**	**70.5**	**71.0**	**49.4**	**75.8**	**63.6**

Context dependent attention weights

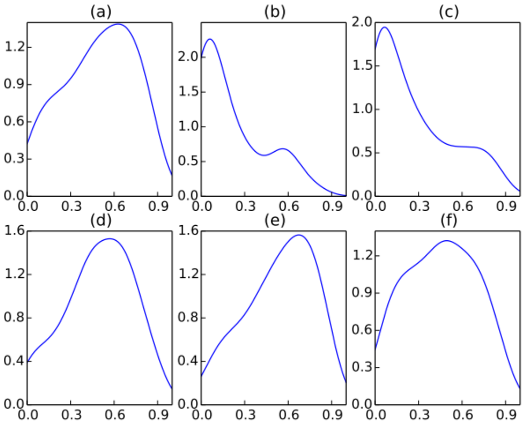


Figure 3: Attention weight distribution of `good`. (a) — aggregate distribution on the test split; (b)-(f) stratified for reviews with ratings 1-5 respectively. We can see that the weight distribution shifts to *higher* end as the rating goes higher.

Context dependent attention weights

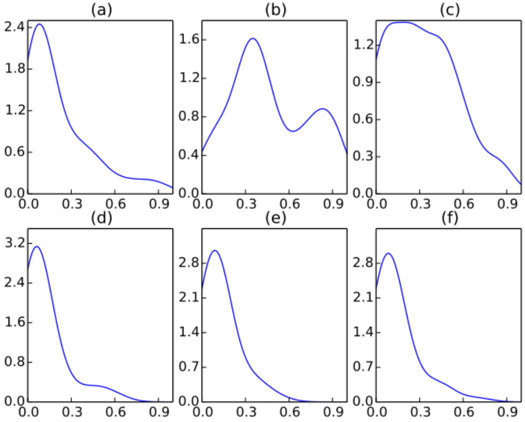
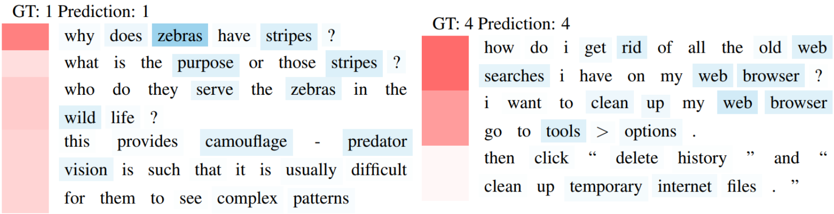


Figure 4: Attention weight distribution of the word `bad`. The setup is as above: (a) contains the aggregate distribution, while (b)-(f) contain stratifications to reviews with ratings 1-5 respectively. Contrary to before, the word `bad` is considered important for poor ratings and less so for good ones.

Visualization of attention

Figure: Documents from Yahoo Answers.
Left label - Science and Mathematics
Right label - Computers and Internet
Red - sentence weight, blue - word weight



Natural language sentence matching (NLSM)

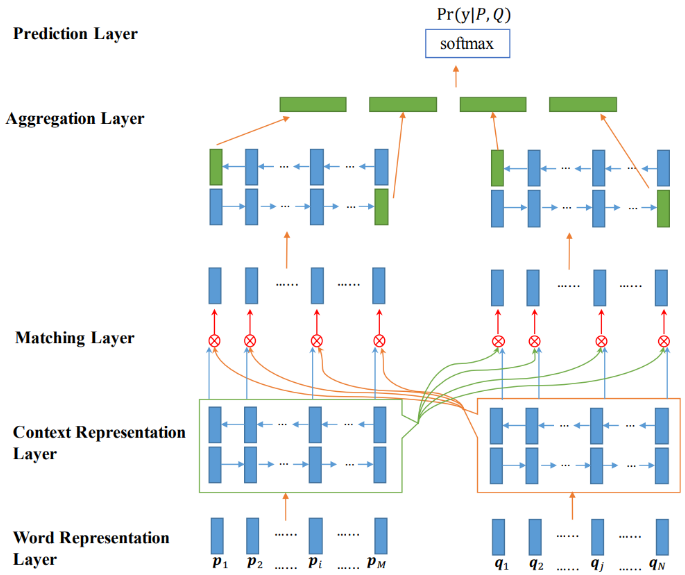
Task:

- (P, Q, y), where $P = (p_1, ..., p_j, ..., p_M)$, $Q = (q_1, ..., q_i, ..., q_N)$, y - label (relationship between P and Q)
- $y^* = argmax_{y \in Y} \Pr(y|P, Q)$

Example tasks:

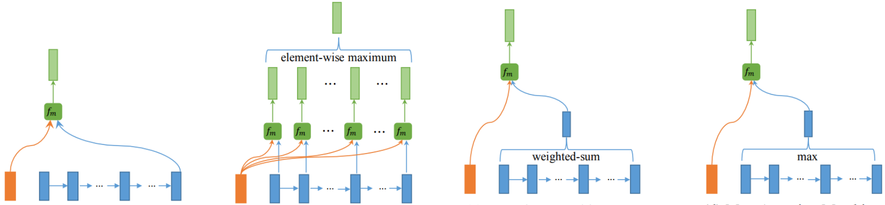
- Paraphrase identification task
- Natural language inference task
- Answer sentence selection task

Natural language sentence matching (NLSM)



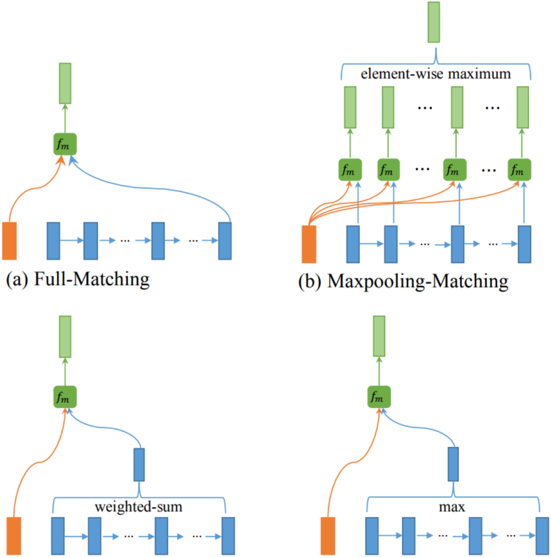
Multi-perspective Matching Operation

- $m = f_m(v_1, v_2; W)$, where $v_1, v_2 \in R^d$, $W \in R^{l \times d}$
  l - number of perspectives
- $m_k = cosine(W_k \odot v_1, W_k \odot v_2)$



(a) Full-Matching
(b) Maxpooling-Matching
(c) Attentive-Matching
(d) Max-Attentive-Matching

Multi-perspective Matching Operation



(a) Full-Matching (b) Maxpooling-Matching (c) Attentive-Matching (d) Max-Attentive-Matching

Multi-perspective Matching Operation

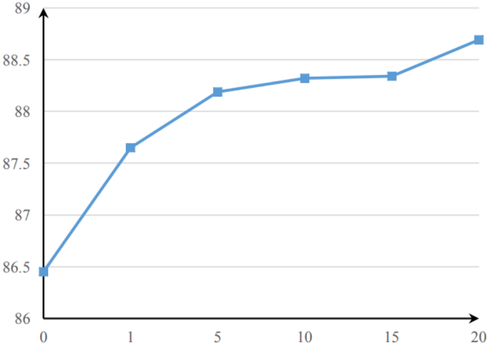


Figure 3: Influence of the multi-perspective cosine matching function in Eq.(3) .

References

Zichao Yang, Diyi Yang, Chris Dyer
Hierarchical Attention Networks for Document Classification
http://www.aclweb.org/anthology/N16-1174

Zhiguo Wang, Wael Hamza, Radu Florian
Bilateral Multi-Perspective Matching for Natural Language Sentences
https://arxiv.org/pdf/1702.03814.pdf

Xiaodan Zhu, Parinaz Sobhani, Hongyu Guo
Long Short-Term Memory Over Tree Structures
https://arxiv.org/pdf/1503.04881.pdf