Learning Structured Representation for Text Classification via Reinforcement Learning

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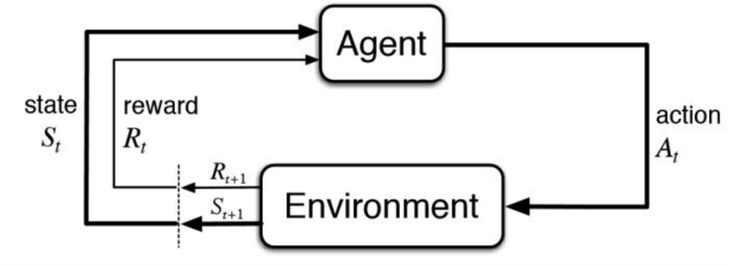
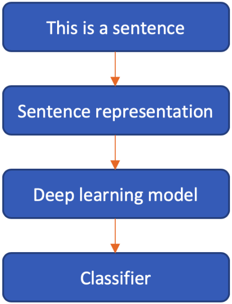


At each setp t:

- The agent receives a state S_t from environment
- The agent executes action A_t based on the received state
- The agent receives scalar reward R_t from the environment
- The environment transform into a new state S_{t+1}



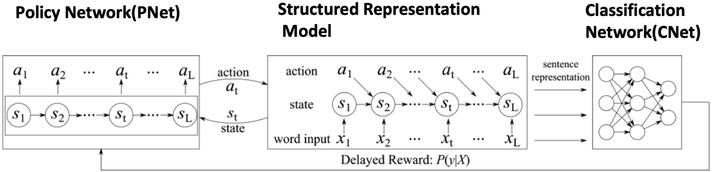
- sentence embedding: Bag-of-words, GloVe
- CNN
- RNN/LSTM
- Attention-based model

Motivation

Why we want to use reinforcement learning?

- Identify task-relevant structures
- Build structured sentence representations over the structures
- Challenges
  - Do not have explicit structure annotations

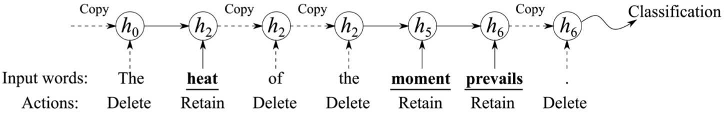
Model



- Policy Nerwork
  - samples an action at each state
  - two models to approach: Information Distilled LSTM, Hierarchically Structured LSTM
- Structured Representation Model: estimate state representation for each action
- Classification Network: predict the text classification and calculate rewards

Model

- State
  - Encodes the current input and previous contexts
- Action a_t
  - Retain, Delete in Information Distilled LSTM
  - Inside, End in Hierarchically Structured LSTM
- Reward
  - Be calculated from the classification network by result and the tendency of structure selection



- Distill the most important words and remove irrelevant words
- Sentence Representation: the last hidden state of ID- LSTM:

$$P(y|X) = softmax(W_s H_L + B_s)$$

Information Distilled LSTM(ID-LSTM)

- Actions:Retain,Delete
- States:

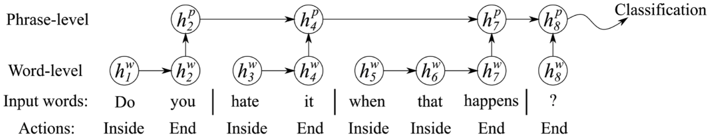
$$s_t = c_{t-1} \oplus h_{t-1} \oplus x_t$$

$$c_t, h_t = \begin{cases} c_{t-1}, h_{t-1} & a_t = Delete \\ \Phi(c_{t-1}, h_{t-1}) & a_t = Retain \end{cases}$$

- Rewards:

$$R_L = logP(c_g|X) + \gamma L^{'}/L$$

$L^{'}/L$ is the proportion of the number of deleted words to the sentence length



- Build a structured representation by discovering hierarchical structures in a sentence
- Two-level structure:
  - word-level LSTM + phrase-level LSTM
  - Sentence Representation: the last hidden state of phrase-level LSTM

- Action: Inside,End
- States: $s_t = c^p_{t-1} \oplus h^p_{t-1} \oplus c^w_t \oplus h^w_t$

word-level LSTM $c^w_t, h^w_t = \begin{cases} \Phi^w(0, 0, x_t) & a_{t-1} = End \\ \Phi^w(c^w_{t-1}, h^w_{t-1}, x_t) & a_{t-1} = Inside \end{cases}$

Phrase-level LSTM $c^p_t, h^p_t = \begin{cases} \Phi^p(c^p_{t-1}, h^p_{t-1}, h^w_t) & a_t = End \\ c^p_{t-1}, h^p_{t-1} & a_t = Inside \end{cases}$

- Rewards: $R_L = logP(c_g|x) - \gamma(L^{'/L} + 0.1L/L^{'})$

$L^{'/L} + 0.1L/L^{'}$ is a unimodal function of the number of phrases (a good phrase structure should contain neither too many nor too few phrases)

Experiment
ID-LSTM and HS-LSTM setup

- 300 dimensional hidden state
- 300 dimensional GloVe initial word vector
- Adam optimizer
- learning rate 0.0005
- Dropout in classification layer, probability 0.5

- **LSTM**: A sequence LSTM. The version we used is proposed in (Tai, Socher, and Manning 2015). (Pang and Lee 2005)
- **biLSTM**: A bi-directional LSTM, commonly used in text classification.
- **CNN**: Convolutional Neural Network (Kim 2014).
- **RAE**: Recursive autoencoder which is defined on predefined parsing structure (Socher et al. 2011).
- **Tree-LSTM**: Tree-structured Long Short-Term Memory relying on predefined parsing structure (Tai, Socher, and Manning 2015).
- **Self-Attentive**:Structured Self-Attentive model, a self attention mechanism and a special regularization term are used to construct sentence embedding (Lin et al. 2017).

- the baseline can be categorize into three types: basic neural models using no particular structure (LSTMs, CNNs), models relying on prespecified parsing structure(RAE, Tree-LSTM), and models distilling important information by self-attention (self-Attentive).
- Note that ID-LSTM and HS-LSTM learn strategies to parsing sentences into sub-structures automatically through policy gradient

- **MR**: Movie Review, this dataset contains positive/negative reviews (Pang and Lee 2005)
- **SST**: Stanford Sentiment Treebank, a public sentiment analysis dataset with five classes (Socher et al. 2013).
- **Subj**: Subjectivity dataset. The task is to classify a sentence as subjective or objective (Pang and Lee 2004).
- **AG**: AG's news corpus3, a large topic classification dataset constructed by (Zhang, Zhao, and LeCun 2015). The topic includes World, Sports, Business and Sci/Tech.

All datasets are classification task

Results

Models	MR	SST	Subj	AG
LSTM	77.4*	46.4*	92.2	90.9
biLSTM	79.7*	49.1*	92.8	91.6
CNN	81.5*	48.0*	93.4*	91.6
RAE	76.2*	47.8	92.8	90.3
Tree-LSTM	80.7*	**50.1**	93.2	91.8
Self-Attentive	80.1	47.2	92.5	91.1
ID-LSTM	81.6	50.0	93.5	92.2
HS-LSTM	**82.1**	49.8	**93.7**	**92.5**

Table 2: Classification accuracy on different datasets. Results marked with * are re-printed from (Tai, Socher, and Manning 2015), (Kim 2014), and (Huang, Qian, and Zhu 2017). The rest are obtained by our own implementation.

Structure Analysis

qualitative perspectives: ID-LSTM

Origin text	Cho continues her exploration of the outer limits of raunch with considerable brio .
ID-LSTM	**Cho continues** ~~her~~ **exploration** ~~of the outer limits of~~ **raunch** ~~with~~ **considerable brio .**
HS-LSTM	Cho | continues her exploration | of the outer limits of raunch | with considerable | brio .
Origin text	Much smarter and more attentive than it first sets out to be .
ID-LSTM	**Much smarter** ~~and more~~ **attentive** ~~than it first sets out to be~~ .
HS-LSTM	Much smarter | and more attentive | than it first sets out to be .
Origin text	Offers an interesting look at the rapidly changing face of Beijing .
ID-LSTM	**Offers** ~~an~~ **interesting look** ~~at the~~ **rapidly changing face** ~~of~~ **Beijing .**
HS-LSTM	Offers | an interesting look | at the rapidly changing | face of Beijing | .

Table 3: Examples of the structures distilled and discovered by ID-LSTM and HS-LSTM.

<table>
<tr><th>Structure</th><th>Sentence</th></tr>
<tr><td>Predefined</td><td>The film | is | one | of | the year | ’s | best | .</td></tr>
<tr><td>Discovered by RL</td><td>The film is | one of the year | ’s best | .</td></tr>
<tr><td>Predefined</td><td>A wonderfully warm human | drama | that | remains vividly in memory | long | after viewing | .</td></tr>
<tr><td>Discovered by RL</td><td>A wonderfully | warm | human drama that remains vividly | in memory long after viewing | .</td></tr>
<tr><td>Predefined</td><td>The actors are fantastic | . | They | are | what | makes it | worth | the trip | to the theater | .</td></tr>
<tr><td>Discovered by RL</td><td>The actors are fantastic | . They are what makes it worth | the trip to the theater .</td></tr>
</table>

Table 6: The comparison of the predefined structures and those discovered by HS-LSTM.

Type	Examples
Noun Phrase	a spiffy animated feature
	the creative community
	the originally noble motive
Verb Phrase	coming back
	quickly realize
	lost opportunities
Prep. Phrase	from their new home
	of a complex man
	of a harmonic family life
Special Phrase	as predictable as the outcome
	throwing caution to the wind
	a dozen years later

Structure Analysis

quantitative perspectives : ID-LSTM

Dataset	Length	Distilled Length	Removed
MR	21.25	11.57	9.68
SST	19.16	11.71	7.45
Subj	24.73	9.17	15.56
AG	35.12	13.05	22.07

Table 4: The original average length and distilled average length by ID-LSTM in the test set of each dataset.

Word	Count	Deleted	Percentage
of	1,074	947	88.18%
by	161	140	86.96%
the	1,846	1558	84.40%
's	649	538	82.90%
but	320	25	7.81%
not	146	0	0.00%
no	73	0	0.00%
good	70	0	0.00%
interesting	25	0	0.00%

Table 5: The most/least deleted words in the test set of SST.

Structure Analysis

quantitative perspectives : HS-LSTM

Models	SST-binary	AG's News
RAE	85.7	90.3
Tree-LSTM	87.0	91.8
Com-Tree-LSTM	86.5*	—
Par-HLSTM	86.5	91.7
HS-LSTM	**87.8**	**92.5**

Table 8: Classification accuracy from structured models. The result marked with * is re-printed from (Yogatama et al. 2017).

Dataset	Length	#Phrases	#Words per phrase
MR	21.25	4.59	4.63
SST	19.16	4.76	4.03
Subj	24.73	4.42	5.60
AG	35.12	8.58	4.09

Table 9: Statistics of structures discovered by HS-LSTM in the test set of each dataset.

Conclusion

- the paper presented a reinforcement learning method to learn sentence representation
- the method requires Policy Network, Structured Representation Model and Classification Network train simultaneously
- by different action choice, there is ID-LSTM and HS-LSTM, where ID-LSTM learn deleting and preserving word and HS-LSTM learn to cluster word group into phrases
  experiments show that the method achieve state-of-the-art performance, and can discover sentence structure without annotation
- future work: applying the method to other types of sequential data

The End

- Learning Structured Representation for Text Classification via Reinforcement Learning, by Tianyang Zhang, Minlie Huang, Li Zhao. AAAI 2018