

Linguistically Regularized LSTM for Sentiment Classification

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Background

Shortcoming of previous models


- 1.depend on expensive phrase-level annotation
- 2.do not full employ linguistic resources

2

Model

Linguistically Resource

▼ sentiment word



▼ negation word



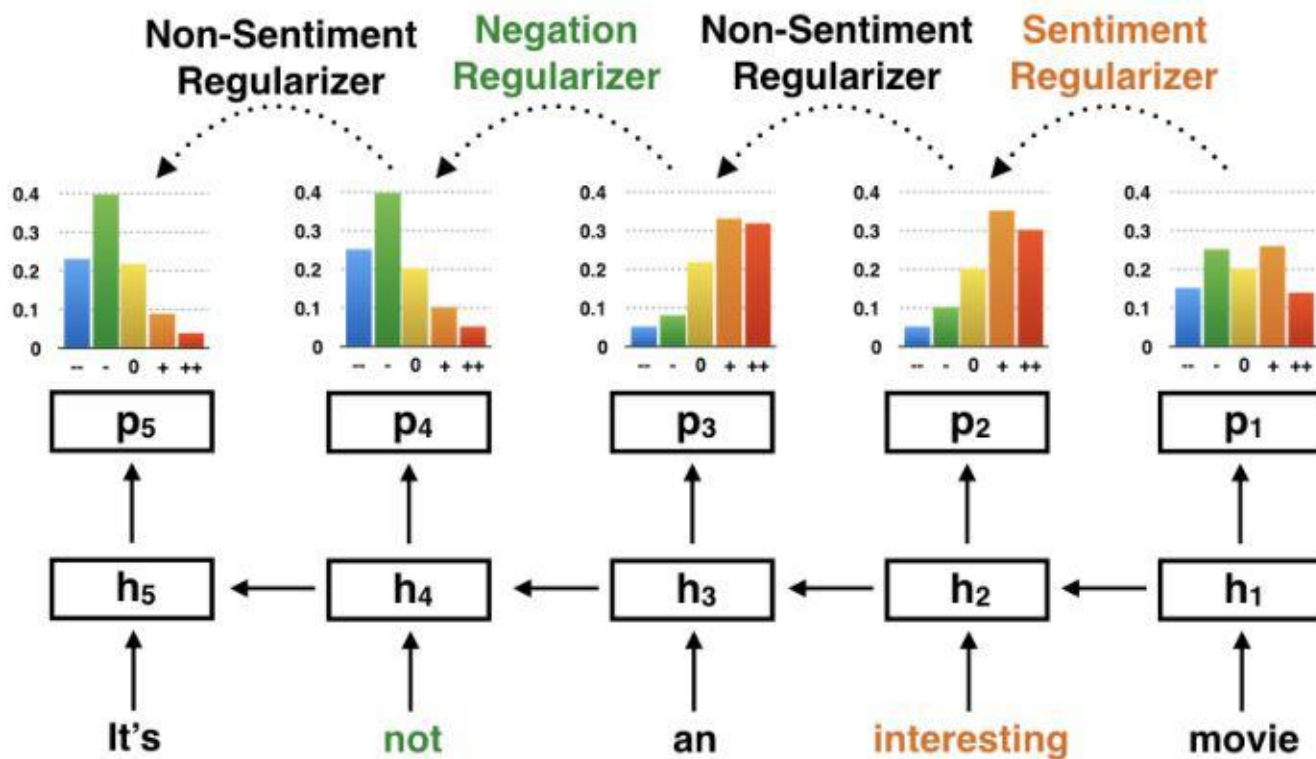
▼ intensity word



Regularizer

1. Non-Sentiment Regularizer eg. movie | a movie
2. Sentiment Regularizer eg. movie | interesting movie
3. Negation Regularizer eg. interesting movie | not interesting movie
4. Intensity Regularizer eg. intersetting movie | very interesting movie

Model



Sentiment Regularizer

1. $p_{t-1}^{(SR)} = p_{t-1} + s_c(x_t)$
2. $L_t^{(SR)} = \max(0, D_{KL}(p_t || p_{t-1}^{(SR)}) - M)$
3. $D_{KL}(p || q) = \frac{1}{2} \sum_{l=1}^C p(l) \log q(l) + q(l) \log p(l)$
4. $\mathcal{L}(\theta) = - \sum_i \hat{y}_i \log y_i + \alpha \sum_i \sum_t L_{t,i} + \beta ||\theta||^2$

Negation Regularizer

$$1. \quad p_{t-1}^{(NR)} = \text{softmax}(T_{x_j} \times p_{t-1})$$

$$2. \quad p_{t+1}^{(NR)} = \text{softmax}(T_{x_j} \times p_{t+1})$$

$$3. \quad L_t^{(NR)} = \min \begin{cases} \max(0, D_{KL}(p_t || p_{t-1}^{(NR)}) - M) \\ \max(0, D_{KL}(p_t || p_{t+1}^{(NR)}) - M) \end{cases}$$

Bidirectional LSTM

$$1. \quad \vec{p}_{t-1}^{(R)} = \text{softmax}(T_{x_j} \times \vec{p}_{t-1})$$

$$2. \quad \overleftarrow{p}_{t+1}^{(R)} = \text{softmax}(T_{x_j} \times \overleftarrow{p}_{t+1})$$

$$3. \quad L_t^{(R)} = \min \begin{cases} \max(0, D_{KL}(\vec{p}_t || \vec{p}_{t-1}^{(R)}) - M) \\ \max(0, D_{KL}(\overleftarrow{p}_t || \overleftarrow{p}_{t+1}^{(R)}) - M) \end{cases}$$

3 Experiment

Dataset

Dataset	MR	SST
# sentences in total	10,662	11,885
#sen containing sentiment word	10,446	11,211
#sen containing negation word	1,644	1,832
#sen containing intensity word	2,687	2,472

Data

1.sentiment lexicon:MPQA and SST

2.

Negation word	no, nothing, never, neither, not, seldom, scarcely, etc.
Intensity word	terribly, greatly, absolutely, too, very, completely, etc.

Experience

Method	MR	SST Phrase-level	SST Sent.-level
RNN	77.7*	44.8#	43.2*
RNTN	75.9#	45.7*	43.4#
LSTM	77.4#	46.4*	45.6#
Bi-LSTM	79.3#	49.1*	46.5#
Tree-LSTM	80.7#	51.0*	48.1#
CNN	81.5*	48.0*	46.9#
CNN-Tensor	-	51.2*	50.6*
DAN	-	-	47.7*
NCSL	82.9	51.1*	47.1#
LR-Bi-LSTM	82.1	50.6	48.6
LR-LSTM	81.5	50.2	48.2

Experience

Method	MR	SST
LR-Bi-LSTM	82.1	48.6
LR-Bi-LSTM (-NSR)	80.8	46.9
LR-Bi-LSTM (-SR)	80.6	46.9
LR-Bi-LSTM (-NR)	81.2	47.6
LR-Bi-LSTM (-IR)	81.7	47.9
LR-LSTM	81.5	48.2
LR-LSTM (-NSR)	80.2	46.4
LR-LSTM (-SR)	80.2	46.6
LR-LSTM (-NR)	80.8	47.4
LR-LSTM (-IR)	81.2	47.4

4 Conclusion

Conclusion



The diagram features a large blue circle on the left containing the word 'Conclusion'. To its right, a dashed blue arc connects two numbered blue circles. The first circle contains the number '1' and is followed by the text '通过损失函数将语言学规则引入现有的句子级情感分析的LSTM模型'. The second circle contains the number '2' and is followed by the text '使用tree-LSTM'.

1

通过损失函数将语言学规则引入现有的句子级情感分析的LSTM模型

2

使用tree-LSTM

Thank you for your listening

