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A Multi-sentiment-resource Enhanced Attention Network for Sentiment Classification

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Outline

- Introduction
- The proposed method
- Experiments
- Summary and future work

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☐ Task Description

◆ Sentence-level Sentiment Classification

Given a sentence → Sentiment Polarity

- Positive/ negative/neutral
- More fine-grained classes

◆ Examples

- ➢ The food is very delicious. → Positive
- ➢ The movie is so boring. → Negative
- ➢ …….

- Early Methods
  - Machine learning based---SVM (Pang et al., 2002)
  - Linguistic knowledge based-----Sentiment lexicon [Turney, 2002; Taboada et al., 2011]
- Neural Networks
  - Recursive Neural Network [Socher et al. 2011]
  - Convolutional Neural Network [Kim, 2014]
  - Recurrent Neural Network/LSTM [Hochreiter and Schmidhuber, 1997]
- Incorporating Linguistic Knowledge with Neural Networks
  - Linguistically regularized LSTM [Qian et al., 2017]
  - Lexicon integrated CNN models with attention [Bonggun et al., 2017]

□Motivation

- Sentiment linguistic knowledge (e.g. sentiment words, intensity words, negation words) play important roles in sentiment detection.

- By attention mechanism, we can integrate various sentiment resource information into neural networks to boost the performance.

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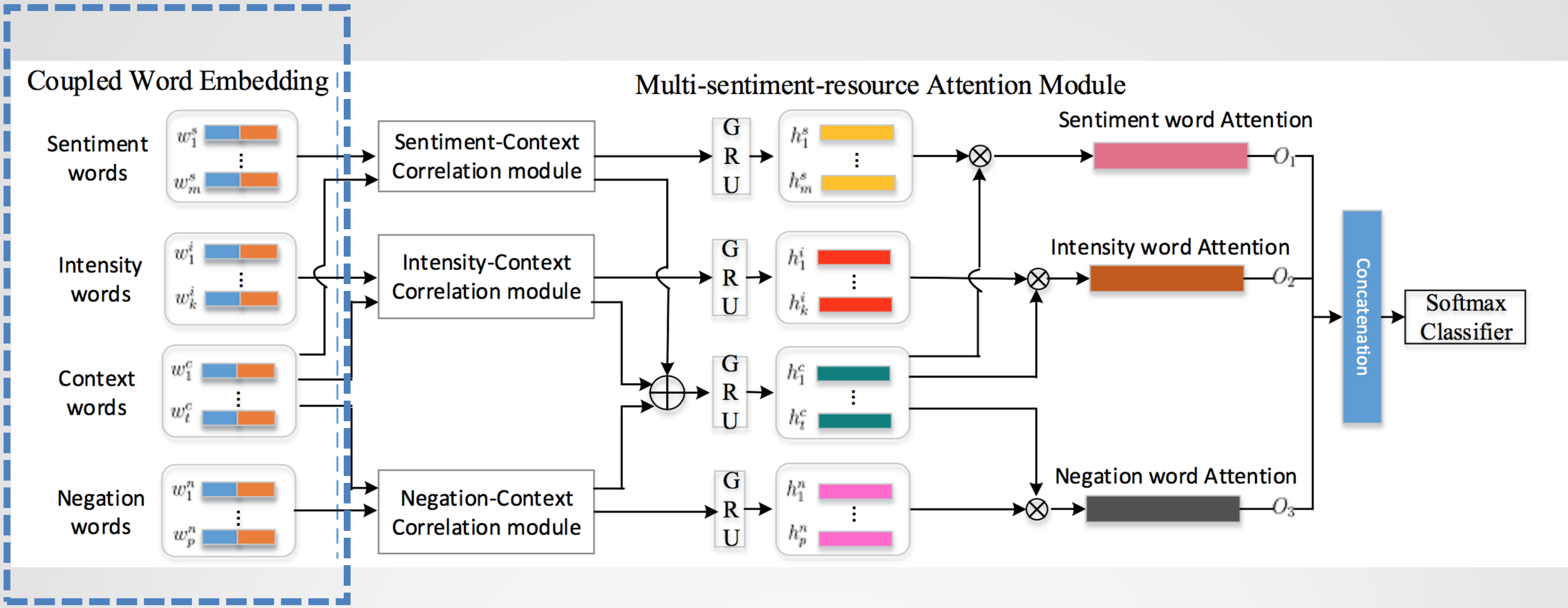
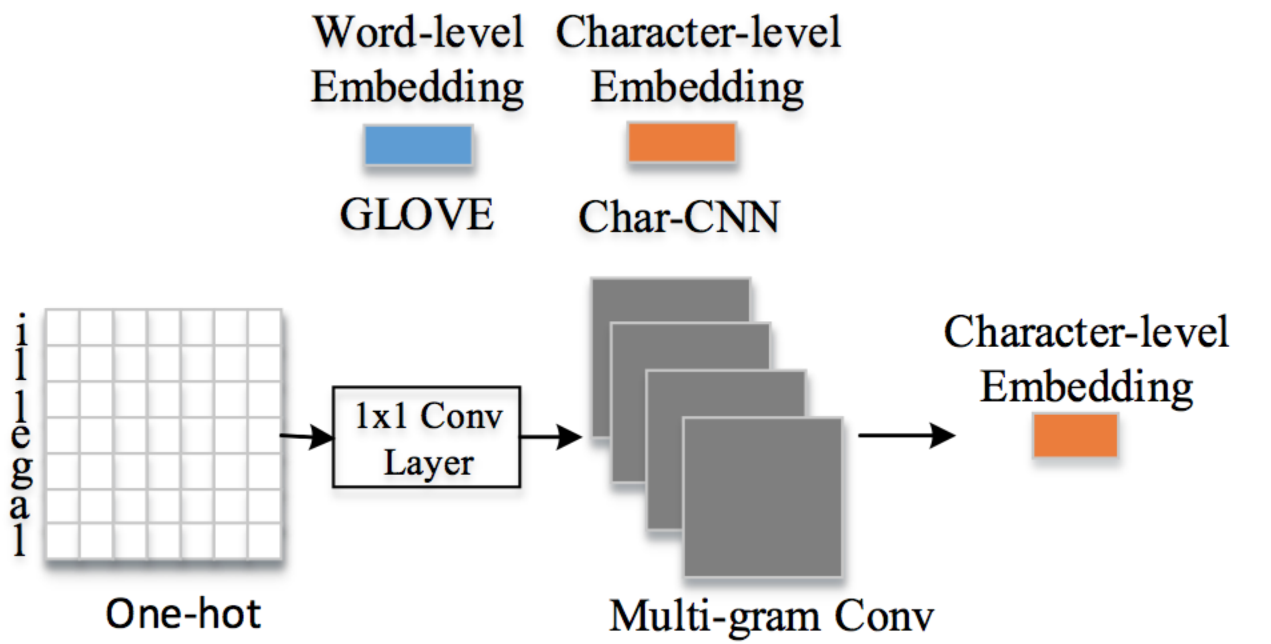
☐Our Model



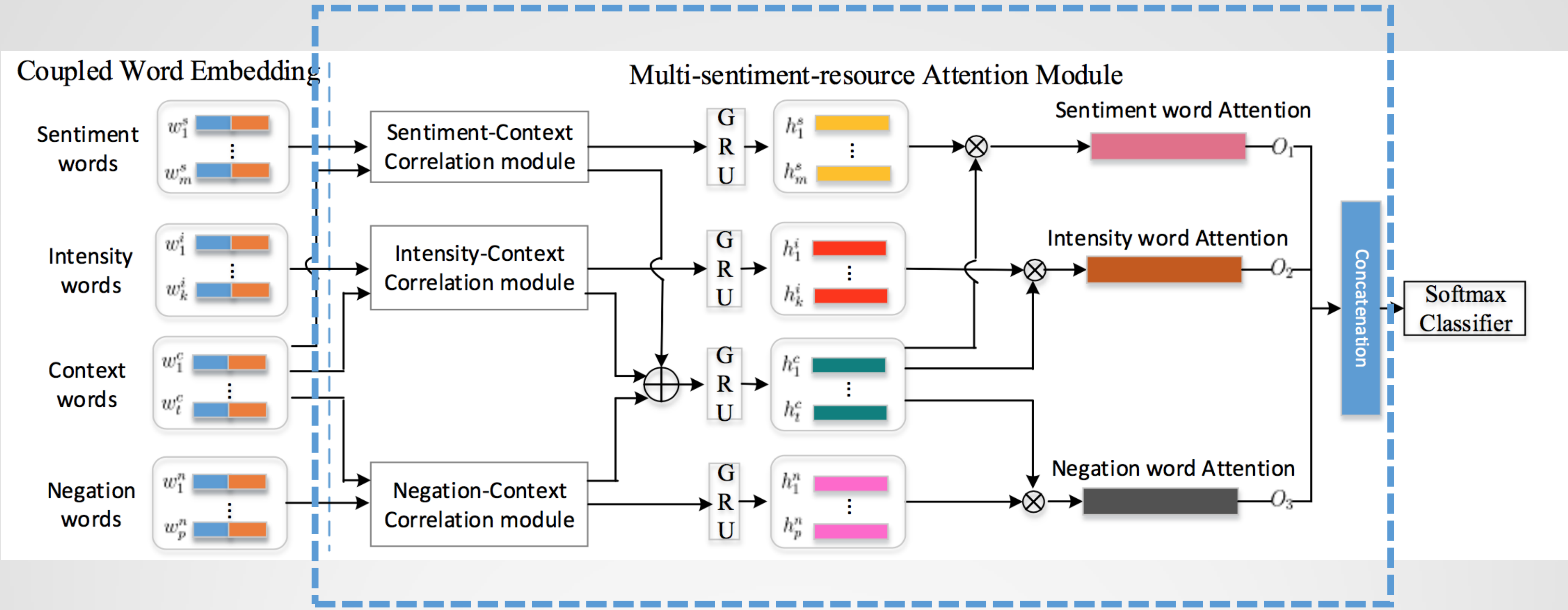
The overall framework of our model

Coupled word Embedding

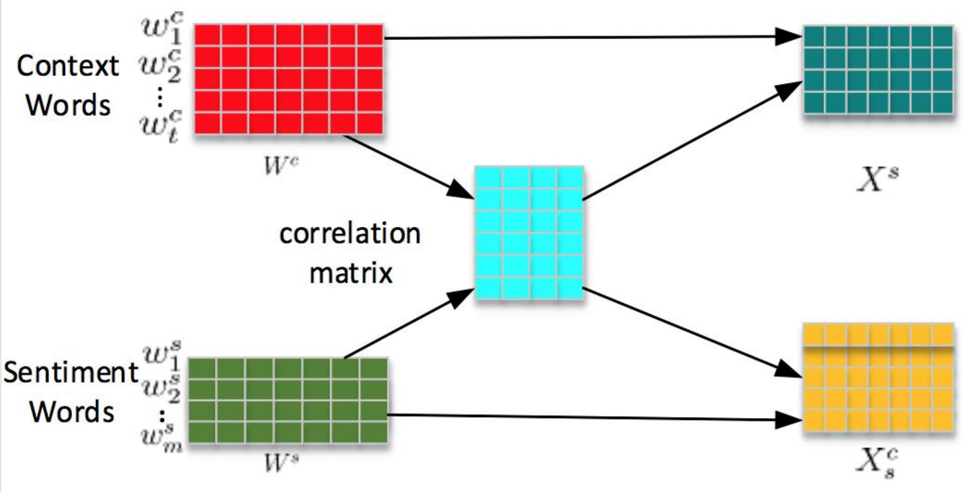


Char-CNN

Multi-sentiment-resource attention module



Context-sentiment correlation modeling



Sentiment-Context Correlation module

$$M^s = (W^c)^T \cdot W^s \in \mathbb{R}^{t \times m}$$

$$X^s = W^c M^s, X_s^c = W^s (M^s)^T$$

The implementation of context-intensity correlation modeling and context-negation correlation modeling are the same as the context-sentiment correlation modeling.

$$X^c = X_s^c + X_i^c + X_n^c$$

Note that in proceeding version, there are some typos in this part. The updated version can be obtained via arxiv.org: https://arxiv.org/abs/1807.04990

Multi-sentiment-resource attention

- Sentiment word attention

$$H^c = GRU(X^c)$$

$$H^s = GRU(X^s)$$

$$o_1 = \sum_{i=1}^{t} \alpha_i h_i^c, q^s = \sum_{i=1}^{m} h_i^s / m$$

$$\beta([h_i^c; q_s]) = u_s^T tanh(W_s[h_i^c; q_s])$$

$$\alpha_i = \frac{exp(\beta([h_i^c; q_s]))}{\sum_{i=1}^{t} exp(\beta([h_i^c; q_s]))}$$

- Intensity attention and Negation attention are computed via the similar methods with the sentiment word attention
- Finally, the multi-sentiment-resource enhanced sentence representation:

$$\tilde{\mathbf{o}} = [o_1, o_2, o_3]$$

Training

The predicted sentiment polarity distribution can be obtained via a fully connected layer with softmax.

$$\hat{y} = \frac{exp(\tilde{W_o}^T \tilde{\mathbf{o}} + \tilde{b_o})}{\sum_{i=1}^{C} exp(\tilde{W_o}^T \tilde{\mathbf{o}} + \tilde{b_o})}$$

Loss function:

$$L(\hat{y}, y) = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_i^j log(\hat{y}_i^j) + \lambda(\sum_{\theta \in \Theta} \theta^2) \quad (17)$$

$$+ \mu||\tilde{O}\tilde{O}^T - \psi I||_F^2$$

$$\tilde{O} = [o_1; o_2; o_3] \quad (18)$$

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Experiments

- **Datasets**
  - Movie Review (MR)---5331 positive/ 5331 negative, training/validation/test split is the same as (Qian et al., 2017) ;
  - Stanford Sentiment Treebank (SST)---8545 training/1101 validation/ 2210 test

- **Sentiment Resources**
  - Sentiment words-----combined from (Hu and Liu, 2004) and (Qian et al., 2017), containing 10899 words;
  - Intensity words and Negation words– manually collected due to the limited number.

Experiments----Results

Methods	MR	SST
RNTN	75.9%#	45.7%
LSTM	77.4%#	46.4%
BiLSTM	79.3%#	49.1%
Tree-LSTM	80.7%#	51.0%
CNN	81.5%	48.0%
NSCL	82.9%	51.1%
LR-Bi-LSTM	82.1%	50.6%
Self-attention	81.7%*	48.9%*
ID-LSTM	81.6%	50.0%
MEAN(our model)	**84.5%**	**51.4%**
MEAN w/o CharCNN	83.2%	50.0%
MEAN w/o sentiment words	82.1%	48.4%
MEAN w/o negation words	82.9%	49.5%
MEAN w/o intensity words	83.5%	49.3%

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Summary and Future work

- Integrating sentiment resources into neural networks is effective to improve the performance of sentence-level sentiment classification.

- How to deign the more effective information-fusion methods is still challenging, such as regularization, attention, ….

- In future work, we can consider employing position embedding to automatically detecting various sentiment resource words.

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Thanks for your attention!

Supplementary Materials:

https://drive.google.com/open?id=1KNBy50lBD7CMjack_9--M4N7EzeRmJDl

Q&A