

Interactive Attention Networks for Aspect-Level Sentiment Classification

Abstract

Aspect-level sentiment classification aims at identifying the sentiment polarity of some specific targets in its context. Previous approaches have realized the importance of targets in sentiment classification and developed various methods with the goal of precisely modeling contexts via generating target-specific representations. However, they always ignore the separate modeling of targets. In this paper, we argue that both targets and contexts deserve special treatment and need to be learned their own representations via interactive learning. Then, we propose the interactive attention networks (IAN) to interactively learn attentions in the contexts and targets, and generate the representations for targets and contexts separately. With this design, the IAN model can well represent a target and its collocation context, which is helpful to sentiment classification. Experimental results on SemEval 2014 Datasets demonstrate the effectiveness of our model.

1 Introduction

Aspect-level sentiment classification is a fine-grained task in sentiment analysis which aims to identify the sentiment polarity of targets in their context [Pang and Lee, 2008; Liu, 2012]. For example, Given the mentioned targets: *staff*, *pizza* and *beef cubes*, and their context sentence “a group of friendly staff, the pizza is not bad, but the beef cubes are not worth the money!”, the sentiment polarity for the three targets, *staff*, *pizza* and *beef cubes*, are positive, neutral and negative respectively.

Aspect-level sentiment classification is a fundamental task in natural language processing and catches many researchers’ attention. Traditional approaches mainly focus on designing a set of features such as bag-of-words, sentiment lexicon to train a classifier (e.g., SVM) for aspect-level sentiment classification [Jiang *et al.*, 2011; Perez-Rosas *et al.*, 2012]. However, feature engineering is labor intensive and almost reaches its performance bottleneck. With the development of deep learning techniques, some researchers have designed effective neural networks to automatically generate useful low-dimensional representations from targets and their contexts

and obtain a promising result on the aspect-level sentiment classification task [Dong *et al.*, 2014; Vo and Zhang, 2015; Wang *et al.*, 2016; Tang *et al.*, 2016b].

As Jiang *et al.*[2011] point out that 40% of sentiment classification errors are caused by not considering targets in sentiment classification, recent work tend to especially strengthen the effect of targets when modeling the contexts. Dong *et al.* [2014] propose an adaptive recursive neural network (RNN) to propagate the sentiments from context words to specific targets based on syntactic relations on tweet data. Vo and Zhang [2015] separate the whole content into three components, i.e., target, its left context and right context, and then use sentiment lexicon and neural pooling functions to generate the target-dependent features. Tang *et al.* [2016a] divide the contexts into left part with target and right part with target and use two long short-term memory(LSTM) models to model the two parts respectively. Then the composed target-specific representations from both parts are used for sentiment classification. Wang *et al.* [2016] design aspect embeddings for targets and concatenate them with word representations to generate the final representations using LSTM and attention mechanism.

The studies above have realized the importance of targets and developed various methods with the goal of precisely modeling contexts via generating target-specific representations. However, they always ignore the separate modeling of targets, especially with the aid of contexts. In our opinion, only the coordination of targets and their contexts can really enhance the performance of sentiment classification. Let us take “The picture quality is clear-cut but the battery life is too short” as an example. When “short” is collocated with “battery life”, the sentiment tends to be negative. But when “short” is used with “spoon” in the context “Short fat noodle spoon, relatively deep some curva”, the sentiment can be neutral. Then, the next problem faced is how to simultaneously model targets and contexts precisely. First, target and context can determine each other’s representations. For example, when we see the target “picture quality”, context word “clear-cut” is naturally associated with the target. And it is vice versa - “picture quality” is first connected with “clear-cut”. In such cases, we argue that targets and contexts can be modeled separately but learned from their interaction. Second, our common sense is that the context is composed of many words. In fact, targets are also not limited to only one word.

No matter targets or contexts, different words may have different contributions to the final representation. For example, it is easy to know that “picture” plays a more important role in the representation of the target “picture quality” which is described by “clear-cut”.

Thus, we for the first time propose that both targets and contexts should be computed their attention weights to capture their important information respectively.

Based on the two points analyzed above, we propose an interactive attention neural network (IAN) model which is based on long-short term memory networks (LSTM) and attention mechanism. IAN utilizes attention mechanism associated with a target to get important information from the context and compute context representation for sentiment classification. Further, IAN makes use of the interactive information from context to supervise the modeling of the target which is helpful to judging sentiment. Finally, with both target representation and context representation concatenated, IAN predicts the sentiment polarity for the target within the context. Experiments on SemEval 2014 demonstrate that IAN can precisely model both targets and contexts, and achieve state-of-the-art performances.

2 Model

In this section, we first introduce the architecture of interactive attention networks (IAN) model for aspect-level sentiment classification. Next, we show the training details of IAN. The overall architecture of IAN is shown in Figure 1.

2.1 Interactive attention Networks

The IAN model is composed of two parts which model the target and context interactively. With word embeddings as input, we employ LSTM to obtain hidden states of words on the word level for target and context respectively. We use the average value of target’s hidden states and context’s hidden states to supervise the generation of attention vectors with which the attention mechanism is adopted to capture the important information in context and target. With this design, target and context can influence interactively in the generation of their representations. Finally, target representation and context representation are concatenated as final representation and fed to a softmax function for aspect-level sentiment classification.

Specifically, let us first formalize the notation. We suppose that a context consists of n words $[w_c^1, w_c^2, \dots, w_c^n]$ and a target has m words $[w_t^1, w_t^2, \dots, w_t^m]$. w denotes a specific word. To represent a word, we embed each word into a low-dimensional real-value vector, called word embedding [Bengio *et al.*, 2003]. Then, we can get $w^k \in R^d$ from $M^{v \times d}$, where k is the word index in the context, d means the embedding dimension and v gives the vocabulary size. Word embeddings can be regarded as parameters of neural networks or pre-trained from proper corpus via language model [Collobert and Weston, 2008; Mikolov *et al.*, 2010; Huang *et al.*, 2012; Pennington *et al.*, 2014]. In our model, we choose the latter strategy.

Next, we use the LSTM networks to learn the hidden word semantics, since words in a sentence has strong dependence

on each other, and LSTM is good at learning long-term dependencies and can avoid gradient vanishing and expansion problems. Formally, given the input word embedding w^k , previous cell state c^{k-1} and previous hidden state h^{k-1} , the current cell state c^k and current hidden state h^k in the LSTM network are updated as:

$$\mathbf{i}^k = \sigma(W_i^w \cdot w^k + W_i^h \cdot h^{k-1} + b_i) \quad (1)$$

$$\mathbf{f}^k = \sigma(W_f^w \cdot w^k + W_f^h \cdot h^{k-1} + b_f) \quad (2)$$

$$\mathbf{o}^k = \sigma(W_o^w \cdot w^k + W_o^h \cdot h^{k-1} + b_o) \quad (3)$$

$$\hat{c}^k = \tanh(W_c^w \cdot w^k + W_c^h \cdot h^{k-1} + b_c) \quad (4)$$

$$c^k = \mathbf{f}^k \odot c^{k-1} + \mathbf{i}^k \odot \hat{c}^k \quad (5)$$

$$h^k = \mathbf{o}^k \odot \tanh(c^k) \quad (6)$$

where $\mathbf{i}, \mathbf{f}, \mathbf{o}$ are input gate, forget gate and output gate respectively, which serve to model the interactions between memory cells and their environments. σ means a sigmoid function. W and b denote weight matrices and biases respectively. The symbol \cdot stands for matrix multiplication, and \odot is element-wise multiplication. Then, we get the hidden states $[h_c^1, h_c^2, \dots, h_c^n]$ as the final word representations for context. To better model target’s meaning, we also use LSTM networks to obtain the target’s hidden states $[h_t^1, h_t^2, \dots, h_t^m]$.

Then we can get the initial representations of context and target (i.e., c_{avg} and t_{avg}) by averaging the hidden states.

$$c_{avg} = \sum_{i=1}^n h_c^i / n \quad (7)$$

$$t_{avg} = \sum_{i=1}^m h_t^i / m \quad (8)$$

With the initial representations of context and target as input, we adopt the attention mechanism to select important information contributing to judging sentiment polarity. As Section 1 stated, we consider the influence from the target for context and the influence from the context for target, which can provide more clues to pay attention to those related sentiment features.

We take a context and target to describe the attention process, as shown in Figure 1. With word representations $[h_c^1, h_c^2, \dots, h_c^n]$, the attention mechanism generates the attention vector α_i using t_{avg} for context by:

$$\alpha_i = \frac{\exp(\gamma(h_c^i, t_{avg}))}{\sum_{j=1}^n \exp(\gamma(h_c^j, t_{avg}))} \quad (9)$$

where γ is a score function that calculates the importance of h_c^i in the context. The score function γ is defined as:

$$\gamma(h_c^i, t_{avg}) = \tanh(h_c^i \cdot W_a \cdot t_{avg}^T + b_a) \quad (10)$$

where W_a and b_a are weight matrix and bias respectively, \tanh is a non-linear function and t_{avg}^T is the transpose of the weight vector t_{avg} .

Similarly, for target, we calculate its attention vector β_i using c_{avg} by:

$$\beta_i = \frac{\exp(\gamma(h_t^i, c_{avg}))}{\sum_{j=1}^m \exp(\gamma(h_t^j, c_{avg}))} \quad (11)$$

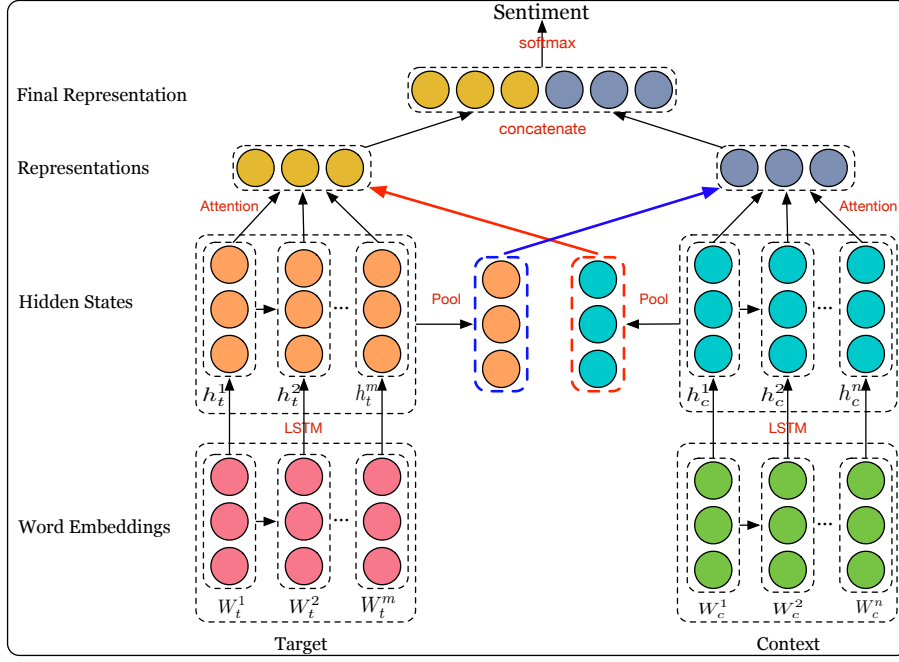


Figure 1: The overall architecture of IAN.

where γ is the same as in Eq. 10.

After computing the word attention weights, we can get context and target representations c_r and t_r based on the attention vectors α_i and β_i :

$$c_r = \sum_{i=1}^n \alpha_i h_c^i \quad (12)$$

$$t_r = \sum_{i=1}^m \beta_i h_t^i \quad (13)$$

Finally, the target representation t_r and context representation c_r are concatenated to a vector \mathbf{d} for a classifier. Here, we use a non-linear layer to project \mathbf{d} into the space of the targeted C classes. That is,

$$x = \tanh(W_l \cdot \mathbf{d} + b_l) \quad (14)$$

where W_l and b_l are the weight matrix and bias respectively. The probability of labeling document with sentiment polarity i ($i \in [1, C]$) is computed by:

$$y_i = \frac{\exp(x_i)}{\sum_{i=1}^C \exp(x_i)} \quad (15)$$

The label with the highest probability is set as the final result.

2.2 Model Training

In IAN, we need to optimize all the parameters notated as Θ which are from LSTM networks: $[W_i^w, W_f^w, W_o^w, W_c^w, W_i^h, W_f^h, W_o^h, W_c^h, b_i, b_f, b_o, b_c]$, the attention layers: $[W_a, b_a]$, the softmax layer: $[W_l, b_l]$ and the word embeddings. Cross

entropy with L_2 regularization is used as the loss function, defined as:

$$J = - \sum_{i=1}^C g_i \log(y_i) + \lambda_r \left(\sum_{\theta \in \Theta} \theta^2 \right) \quad (16)$$

where $g_i \in R^C$ denotes the ground truth, represented by one-hot vector; $y_i \in R^C$ is the estimated probability for each class, computed as in Eq. (15). λ_r is the coefficient for L_2 regularization.

We use the backpropagation method to compute the gradients and update all the parameters Θ by:

$$\Theta = \Theta - \lambda_l \frac{\partial J(\Theta)}{\partial \Theta} \quad (17)$$

where λ_l is the learning rate.

In order to avoid overfitting, we use dropout strategy to randomly omit half of the feature detectors on each training case. After learning Θ , we test the instance by feeding the target with its contexts into the IAN model, and the label with the highest probability stands for the predicted sentiment polarity of the target.

3 Experiments

3.1 Experiment Preparation

Dataset and Metric

We conduct experiments on SemEval 2014 Task 4¹ to validate the effectiveness of our model. The SemEval 2014 dataset is

¹the detail introduction of this task can be seen at: <http://alt.qcri.org/semeval2014/task4/>

composed of reviews in two categories: *Restaurant* and *Laptop*. The reviews are labeled with three sentiment polarities: *positive*, *neutral* and *negative*. Table 1 shows the training and test instance numbers in each category.

Dataset	Positive		Neutral		Negative	
	Train	Test	Train	Test	Train	Test
Restaurant	2164	728	637	196	807	196
Laptop	994	341	464	169	870	128

Table 1: Statistics of SemEval 2014 Dataset.

Hyperparameters Setting

In our experiments, all word embeddings from context and target are initialized by GloVe² [Pennington *et al.*, 2014], and all out-of-vocabulary words are initialized by sampling from uniform distribution $U(-0.1, 0.1)$. All weight matrices are given initial values by sampling from uniform distribution $U(-0.1, 0.1)$, and all bias are set to zeros. The dimensions of word embeddings, attention vectors and LSTM hidden states are set to 300 as in [Wang *et al.*, 2016]. To train the parameters of *IAN*, we employ the Momentum [Qian, 1999], which adds a fraction γ of the update vector in the prior step to the current update vector. The coefficient of L_2 normalization in the objective function is set to 10^{-5} , and the dropout rate is set to 0.5.

3.2 Model Comparisons

In order to comprehensively evaluate the performance of *IAN*, we list some baselines approaches for comparison. The baselines are introduced as follows.

- **Majority** is a basic baseline method, which assigns the largest sentiment polarity in the training set to each sample in the test set.

- **LSTM** only uses one LSTM networks to model the context and get the hidden state of each word. After that, the average value of all the hidden states is regarded as final representation and fed to a softmax function to estimate the probability of each sentiment label [Wang *et al.*, 2016].

- **TD-LSTM** adopts two long short-term memory (LSTM) networks to model the left context with target and the right context with target respectively. The left and right target-dependent representations are concatenated for predicting the sentiment polarity of the target [Tang *et al.*, 2016a].

- **AE-LSTM** represents targets with aspect embeddings. First this method models the context words via LSTM networks and then combine the word hidden states with aspect embeddings to supervise the generation of attention vectors, which are in turn used to produce the final representation for aspect-level sentiment classification [Wang *et al.*, 2016].

- **ATAE-LSTM** is developed based on **AE-LSTM**. **ATAE-LSTM** further strengthens the effect of aspect embeddings and appends the aspect embeddings with each word embedding vector to represent the context. The other design of **ATAE-LSTM** is the same as **AE-LSTM** [Wang *et al.*, 2016].

²pre-trained word embedding of GloVe can download from <http://nlp.stanford.edu/projects/glove/>

Dataset	Restaurant	Laptop
Majority	0.535	0.650
LSTM	0.743	0.665
TD-LSTM	0.756	0.681
AE-LSTM	0.762	0.689
ATAE-LSTM	0.772	0.687
IAN	0.786	0.721

Table 2: Comparison with baselines. Accuracy on 3-class prediction about SemEval 2014 Task 4 which includes restaurants and laptops. Best performances are in **bold**.

Table 2 shows the performance comparison of *IAN* with other baselines. To evaluate the performance of aspect-level sentiment classification, we adopt the *Accuracy* metric, which measures the percentage of correct predicted samples in all samples. Generally, the better performance a system has, the higher the accuracy is.

From Table 2, we can observe that, the **Majority** method is the worst, meaning the majority sentiment polarity occupies 53.5% and 65.0% of all samples in the Restaurant and Laptop categories respectively. All the other methods are based on LSTM models and better than the Majority method, showing that LSTM has potentials in automatically generating representations and can all bring performance improvement for sentiment classification. The **LSTM** method gets the worst performance of all the neural network baseline methods, because it treats targets equally with other context words and does not make full use of the target information. This also verifies the work of [Jiang *et al.*, 2011] which points out the importance of targets. **TD-LSTM** outperforms LSTM over 1 percent and 2 percent on the Restaurant and Laptop category respectively, since it develops from the standard LSTM and processes the left and right contexts with targets. As we know, targets are twice represented and in some sense are specifically focused in the final representation. Further, both **AE-LSTM** and **ATAE-LSTM** stably exceed the **TD-LSTM** method because of the introduction of attention mechanism. For **AE-LSTM** and **ATAE-LSTM**, they capture important information in the context with the supervision of target and generate more reasonable representations for aspect-level sentiment classification. We can also see that **AE-LSTM** and **ATAE-LSTM** further emphasize the modeling of targets via the addition of the aspect embedding, which is also the reason of performance improvement. Compared with AE-LSTM, ATAE-LSTM especially enhance the interaction between the context words and target and thus has a better performance than AE-LSTM.

Our *IAN* model takes a further step towards emphasizing the importance of targets through learning targets and contexts interactively. We can see that *IAN* achieves the best performance among all methods. Compared with ATAE-LSTM model, *IAN* improves the performance about 1.4% and 3.2% on the *Restaurant* and *Laptop* categories respectively. As we know, it is difficult to boost 1 percent of accuracy on sentiment classification. The main reason may be that *IAN* models the target and context using two connected attention networks which can influence each other. With this design, we can well

Dataset	Restaurants	Laptops
No-Target	0.772	0.708
No-Interaction	0.769	0.706
Target2Content	0.775	0.712
IAN	0.786	0.721

Table 3: Analysis of Interactive attention Networks.

learn the representations of targets and contexts whose collocation contributes to aspect-level sentiment classification. From Table 2, targets are progressively emphasized among these methods. The more attentions are paid to targets, the higher accuracy the system achieves. This also inspires our future work to further research the modeling of targets.

3.3 Analysis of IAN Model

In this section, we design a series of models to verify the effectiveness of our *IAN* model. First, we ignore the modeling of targets and design a **No-Target** model that just uses the context representation. Here we adopt only one LSTM model with attention mechanism to model the context, where the attention vectors are computed through the averaged value of the target word embeddings. Then, we implement the second model **No-Interaction** which uses two LSTM networks to learn the representations of target and context via their own local attentions without any interaction. Next, we design **Target2Content** which also employs two LSTM models to learn target and context representations, but only considers to attention context words via target representations. The only difference between Target2Content and IAN is that IAN also adopts attention mechanism when modeling targets. Table 3 shows the performances of all these models.

From Table 3, we can see that the **No-Target** model achieves worse performances than the *IAN* model. The results verify that target should be separately modeled and target representations can make contribution to judging the sentiment polarity of a target.

For the **No-Interaction** model, it gets the worst result among all the approaches. Compared with **Target2Content** and *IAN*, there is no interaction between target and context. Therefore, the interaction between target and content plays a great role in generating better representation for predicting target sentiment. Its results are also worse than *No-Target*, which may be because the effect of target representation, generated by local attention, is less important than the influence of target information for supervising learning content representation via attention.

As for **Target2Content**, it outperforms *No-Interaction* and is worse than *IAN*. Compare with *IAN*, it just learns the target representation via LSTM without supervision of context. As stated in Section 1, the collocated context and target can influence each other. That means that the interaction between target and content is critical to classifying target sentiment polarity and unidirectional attentions are not enough to the final representation.

As we expect, *IAN* achieves the best performance among all the methods, since *IAN* fully considers the effect of the

target and the interaction between target and context which makes contributions to the target sentiment classification.

Furthermore, from the Table 2, we can see that, the improvements on Restaurant category is much less than those on Laptop category. To explain this phenomenon, we analyze these two categories and show the number and ratio of targets distributing in the two categories with respect to the target length (i.e., the word number included in a target), as in Table 4. From Table 4, we can see that, the number of instances with 1-word target in Restaurant category is 9% more than that in the Laptops category. In *IAN*, we model the targets by LSTM and interactive attentions. LSTM and interactive attention are more effective on modeling long targets than short targets. Conversely, average/max pooling, used in other methods, usually lose more information in modeling long targets compared with shorter target. This demonstrates the effectiveness of separately modeling the targets via LSTM and interactive attention.

3.4 Case Study

In this section, we use a review context “*the fish is fresh but the variety of fish is noting out of ordinary.*” and two targets “*fish*” and “*variety of fish*” from Restaurant category as a case study. We apply *IAN* to model the *context* and *target*, and get the correct sentiment polarity: *negative* and *positive* for two targets respectively. Figure 2 visualizes the attention weights on the *context* and *targets* computed by *IAN*. The left figure (a) gives the attention weights for two targets, and the right figure (b) shows the attention weights of the context. Each line presents the corresponding target and context pairs. The deeper color means higher weight.

From Figure 2, we can observe that the common words “*the*” and “*of*” and punctuation “*.*” are paid little attention by *IAN* in the context. This verifies our intuition that some common words and punctuations makes little contributions to judging target sentiment polarity. The meaning of the context in the case study should be that the quality of *fish* is good but the *variety of fish* has nothing special. Obviously, the words *fresh*, *nothing*, *out*, *ordinary* play a great role in the sentiment classification of *fish* and *variety of fish*, and our model pay much attention on those words as we expect. In addition, *IAN* also gives attention to the evaluated object: *fish* and *variety of fish*. Furthermore, when *IAN* is applied on the *fish*, the “attention” of the model is mainly paid to the corresponding target and its real collocation, and little attention is given to the *variety of fish* and its collocation. The situation is in contrast when judging the target *variety of fish*.

For the target *variety of fish*, *variety* is the head word, and other words are used to modify the head word. Therefore, “*variety*” is more important for expressing the target than the other two words “*of*” and “*fish*”. From Figure 2, we can see that the *IAN* pays more attention to the word “*variety*” than to the other words. This means that in our model, a target can provide useful information for its context to tune its attentions, and the context also plays an important role in supervising a target to get its focus. Thus, through the *IAN*, we can well model targets and contexts separately and interactively, and the concatenated representation of target and context are helpful to the aspect-level sentiment classification.

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