Context-Dependent Sentiment Classification Using Antonym Pairs and Double Expansion

Zhifei Zhang[1], Duoqian Miao[1], and Bo Yuan[2]

[1] Department of Computer Science and Technology, Tongji University, Shanghai 201804, P.R. China

[2] Department of Chinese Language and Literature, Tsinghua University, Beijing 100084, P.R. China

zhifei.zzh@gmail.com, dqmiao@tongji.edu.cn, yuanb10@mails.tsinghua.edu.cn

Abstract. Sentiment classification at word-level plays a fundamental role in many sentiment-related tasks. Context-free sentiment classification circumvents the essential factors in language use and is error prone due to oversimplification in its assumption. Context-dependent sentiment classification poses new challenges to researchers. We propose a novel approach to automatically determine the contextual polarity with the help of antonym pairs. First, neighboring nouns are extracted as context information within a predefined distance of sentiment words. Secondly, the polar posterior probabilities of sentiment words are derived based on Bayes' theorem. Finally, the polarity of one sentiment word with the context of one neighboring noun is determined by Bidirectional Rule and Unidirectional Rule. In addition, we define a new similarity measure, which combines semantic distance with edit distance, for double expansion, i.e., Context Expansion and Target Expansion. The experimental results on two real-world data sets validate the effectiveness of our approach.

Keywords: sentiment classification, context-dependent, antonym pairs, word similarity.

1 Introduction

For the past decade, the studies of sentiment classification in natural language processing, due to its extensive applications [1], have been increasingly drawing attention from the researchers around the world. The aim of sentiment classification is to identify the subjectivity of texts and recognize the polarity ("positive" or "negative").

Sentiment classification mainly falls into three levels: document-level, sentence-level and word-level, among which word-level sentiment classification serves as the basis for the other two. The polarity of some words remains stable despite the context variation while the polarity of others depends on the context. The former can be referred to as context-free words and the latter as context-dependent words. Sentiment classification of context-dependent words is more challenging in that it requires deeper and more thorough understanding of natural language incorporating many syntactic, semantic and pragmatic factors. For example, the word "high" conveys a negative polarity in "high

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cost", but indicates a positive polarity in "high quality". In fact, such context-dependent sentiment words can not be discarded in sentiment classification [2].

It is worth mentioning that antonyms can help inferring the polarity in natural language. For example, "low" is the antonym of "high", then we can infer its polarity in "low cost" and "low quality" as the opposite as "high". Antonym pairs like ("high","low") and ("big","small") are helpful in sentiment detection [3]. However, no previous work has attempted to utilize such antonym pairs for context-dependent sentiment classification.

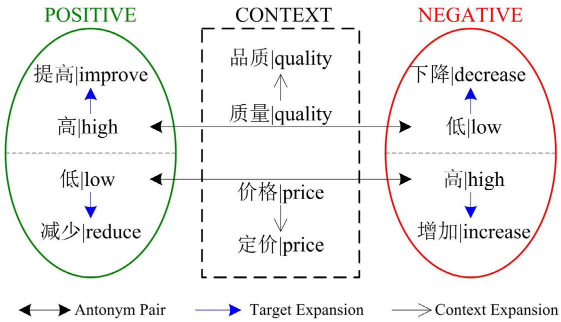

Fig. 1. A toy model of context-dependent sentiment classification

Figure 1 portrays a toy model of context-dependent sentiment classification with antonym pairs. It is often the case that two words in an antonym pair share the same context yet opposite polarity, as in the example of "高(低)质量|high(low) quality". To recognize the polarity of context-dependent sentiment words, we begin with choosing a seed set of antonym pairs such as (" 高|high","低|low") and ("大|big"," 小|small") , which are frequently used in opinionated texts. Next, we improve the scalability through double expansion, i.e., Context Expansion and Target Expansion, which is similar to double propagation [4]. Context Expansion refers to the process of expanding neighboring nouns with synonymy identification [5], e.g., "质量|quality"→"质地|quality" (as shown in Figure 1). Target Expansion refers to the process of expanding seed sentiment words to synonymous adjectives [6], e.g., "大|big"→"巨大|huge", or semantically correlated verbs, e.g., "高|big"→"提高|improve" (as shown in Figure 1).

In the most relevant work [2], the task of disambiguating dynamic sentiment ambiguous adjectives is transformed to sentiment expectation of noun. However, the impact of polarity detection with antonym pairs is ignored. We focus on context-dependent sentiment classification using antonym pairs.

The rest of this paper is organized as follows: In Section 2 we describe the polarity classification method for antonym pairs. Section 3 illustrates the double expansion method in detail. The evaluation results of our approach through sentiment classification experiments are presented in Section 4. Finally, we conclude and discuss the future work in Section 5.

2 Polarity Classification for Antonym Pairs

2.1 Context Information Extraction

Context information can be more accurately represented by aspects, which can be obtained from domain experts, or automatic methods[7]. However, aspect extraction of sentiment words is beyond the scope of this paper. The task of disambiguating ambiguous adjectives is simplified into sentiment classification of neighboring nouns [2]. Similarly, we extract the context information from neighboring nouns of ambiguous adjectives within a predefined distance.

Given the segmented and labeled sequence of a sentence $(w_1/t_1, w_2/t_2, \cdots, w_n/t_n)$, we assume that w_i is an ambiguous adjective from antonym pairs. Neighboring nouns, denoted as nn, can be matched by templates shown in Table 1.

Table 1. Matching templates for context information extraction

Template	nn	Example
$t_{i-1} = n$	w_{i-1}	价格 高|price is high
$t_{i-2} = n$ and $t_{i-1} \neq c$	w_{i-2}	价格 很 高| price is very high
$t_{i-3} = n$ and $t_{i-2} \neq c$ and $t_{i-1} \neq c$	w_{i-3}	价格 不是 很 高| price is not very high
$t_{i+1} = n$	w_{i+1}	高 质量|high quality
$t_{i+2} = n$ and $t_{i+1} \neq c$	w_{i+2}	高 的 成本| high cost
$t_{i+3} = n$ and $t_{i+2} \neq c$ and $t_{i+1} \neq c$	w_{i+3}	高 的 服务 质量| high service quality

Note: "n" indicates a noun, "c" indicates a conjunction.

2.2 Polar Posterior Probability

Definition 1 (Antonym Pair). *An antonym pair is formalized as a tuple* $pair = (u, v)$, *where* u *and* v *are ambiguous and antonymous adjectives. Two antonymous adjectives with the same context generally have the opposite polarities, i.e.,*

$$Polarity(u|tn) = -Polarity(v|tn) \tag{1}$$

In this paper, we only discuss eight antonym pairs listed in Table 2. They are all one-character words and frequently used in opinionated texts [2].

Table 2. Eight antonym pairs

u	v	u	v	u	v	u	v
高|high	低|low	大|big	小|small	多|many	少|few	快|fast	慢|slow
深|deep	浅|shallow	长|long	短|short	轻|light	重|heavy	厚|thick	薄|thin

The collocations of ambiguous adjectives and neighboring nouns are saved in a polarity decision table.

Definition 2 (Polarity Decision Table). *A polarity decision table is formalized as a quad* $PDT = (U, C \cup D, V, f)$*, where,*

U*: a finite nonempty set of objects, e.g.,* $\{e_1, e_2, \cdots, e_{12}\}$ *in Table 3;*
C*: a finite nonempty set of condition attributes,* $C = \{nn, sw\}$ *in this paper,* $sw = u$ *or* $sw = v$*;*
D*: a finite nonempty set of decision attributes,* $D = \{label\}$ *in this paper,* $label$ *labels the polarity of* w*;*
V*:* $V = \cup V_a$*,* V_a *is a nonempty set of values of* $a \in C \cup D$*. Thus,* $V = V_{nn} \cup V_{sw} \cup V_{label}$ *in this paper,* V_{nn} *represents all neighboring nouns,* V_{sw} *contains 16 words from 8 antonym pairs, and* $V_{label} = \{1, -1\}$ *or* $V_{label} = \{1, 0, -1\}$*;*
f*:* $f = \{f_a | f_a : U \to V_a\}$*,* f_a *is an information function that maps an object in* U *to one value in* V_a*.*

In general, it is hard to annotate the polarity label for each context-dependent word for training. It is not necessary for our method which is on the basis of the following assumption.

Assumption 1. The polarity label of one word in a sentence is consistent with the polarity label of the sentence, i.e., the same if the sentence is affirmative, while the opposite is the case if the word is in the scope of negation.

Definition 3 (Polar Posterior Probability). *A polar posterior probability is a probability that a sentiment word* sw *is positive or negative given a neighboring noun* nn*, denoted as* $P(sw = 1|nn)$ *and* $P(sw = -1|nn)$ *respectively.*

The polar posterior probabilities for antonym pairs can be computed according to Bayes' theorem [8].

$$P(sw = 1|nn) = \frac{P(nn|sw = 1)P(sw = 1)}{\sum\limits_{l \in V_{label}} P(nn|sw = l)P(sw = l)} \tag{2}$$

$$P(sw = -1|nn) = \frac{P(nn|sw = -1)P(sw = -1)}{\sum\limits_{l \in V_{label}} P(nn|sw = l)P(sw = l)} \tag{3}$$

where,

$$P(sw = l) = \frac{count(sw, label = l) + 1}{|V_{label}| + \sum\limits_{s \in V_{label}} count(sw, label = s)} \tag{4}$$

$$P(nn|sw = l) = \begin{cases} \frac{count(nn, sw, label=l)+1}{count(sw, label=l)+1} & count(sw, label = l) \neq 0 \\ 0.001 & count(sw, label = l) = 0 \end{cases} \tag{5}$$

In Eqs. (4) and (5), the function "$count(X)$" returns the number of objects in U that the condition X is met. To eliminate zero probabilities, we use add-one smoothing, which simply adds one to each count.

We can determine the polarity of sentiment words by the following two rules: Bidirectional Rule and Unidirectional Rule.

Bidirectional Rule. If two sentiment words from an antonym pair both have the polar posterior probabilities given the same context, a bidirectional rule is made. The polarity of u from an antonym pair $pair = (u, v)$ given a neighboring noun nn is obtained:

$$Polarity(u|tn) = \begin{cases} 1 & P(u = 1|nn) > P(u = -1|nn) \wedge P(v = 1|nn) < P(v = -1|nn) \\ -1 & P(u = 1|nn) < P(u = -1|nn) \wedge P(v = 1|nn) > P(v = -1|nn) \\ 0 & otherwise \end{cases} \tag{6}$$

We compute the Z-score statistic with one-tailed test to perform the significant test. The hypothesized value P_0 is set to 0.7 [9]. The statistical confidence level is set to 0.95, whose corresponding Z-score is -1.64. If Z-score is greater than -1.64, the difference of two posterior probabilities is significant.

$$Z(nn, u, l) = \frac{P(u = l|nn) - P(u = -l|nn) - P_0}{\sqrt{\frac{P_0(1-P_0)}{\min\{count(nn,u,label=l),count(nn,u,label=-l)\}+1}}} \tag{7}$$

Unidirectional Rule. If only one sentiment word from an antonym pair has the polar posterior probabilities given the same context, a unidirectional rule is made.

$$Polarity(u|nn) = \begin{cases} 1 & Z(nn, u, 1) > -1.64 \wedge Z(nn, u, -1) < -1.64 \\ -1 & Z(nn, u, -1) > -1.64 \wedge Z(nn, u, 1) < -1.64 \\ 0 & otherwise \end{cases} \tag{8}$$

2.3 An Example of Polarity Decision Table

An example of polarity decision table is given in Table 3. The fourth column is the polarity label inferred from the training data. According to *Assumption 1*, if sw is in the scope of negation, $label$ is opposite to the polarity of the sentence, otherwise the same. Table 4 lists the results of context-dependent polarity classification, which are satisfying.

Table 3. An example of polarity decision table

U	nn	sw	$label$	U	nn	sw	$label$
e_1	价格|price	高|high	-1	e_7	噪音|noise	大|big	1
e_2	价格|price	高|high	-1	e_8	噪音|noise	大|big	-1
e_3	价格|price	低|low	1	e_9	噪音|noise	大|big	-1
e_4	质量|quality	高|high	1	e_{10}	噪音|noise	小|small	1
e_5	质量|quality	高|high	1	e_{11}	速度|speed	慢|slow	1
e_6	质量|quality	高|high	1	e_{12}	速度|speed	慢|slow	-1

Table 4. Results of context-dependent polarity classification

nn	sw	Polarity	Eq.	Remark
质量|quality	高|high	1	(8)	$Z(nn, sw, 1) = -0.22, Z(nn, sw, -1) = -2.84$
质量|quality	低|low	-1	(1)	
价格|price	高|high	-1	(6)	$P(sw = 1\|nn)(0.25) < P(sw = -1\|nn)(0.75)$
价格|price	低|low	1	(6)	$P(sw = 1\|nn)(1.00) > P(sw = -1\|nn)(0.00)$
噪音|noise	大|big	-1	(6)	$P(sw = 1\|nn)(0.40) < P(sw = -1\|nn)(0.60)$
噪音|noise	小|small	1	(6)	$P(sw = 1\|nn)(1.00) > P(sw = -1\|nn)(0.00)$
速度|speed	慢|slow	0	(8)	$Z(nn, sw, 1) = -2.16, Z(nn, sw, -1) = -2.16$

3 Double Expansion

3.1 Context Expansion

Context expansion is equivalent to finding synonyms of the contextual word. A synonym dictionary can be used directly, but its coverage is limited. Automatically finding synonyms is transformed to semantic similarity measure.

HowNet is widely used in semantic similarity measure for Chinese words. Each word is described by several concepts. The similarity between w_i and w_j is equal to the maximum similarity of all concepts of the two words [10], denoted by $Sim_h(w_i, w_j)$. If w_i or w_j is out of HowNet lexicon, $Sim_h(w_i, w_j)$ equals 0. We utilize a modified similarity measure from the perspective of edit distance [11].

$$Sim_e(w_i, w_j) = \frac{1}{1 + EditCost(w_i, w_j)} \tag{9}$$

where $EditCost(w_i, w_j)$ is the minimum cost of character insertion and deletion operations needed to transform one word to another. The cost of inserting or deleting an character ch is set as in [12], where NEG is a set of negation characters, such as "不|not" and "无|none".

$$Cost(ch) = \begin{cases} 1 \text{ if delete } ch \wedge ch \notin NEG \\ 0.1 \text{ if insert } ch \wedge ch \notin NEG \\ \infty \quad\quad \text{ if } ch \in NEG \end{cases} \tag{10}$$

In context expansion, we combine the above two similarity measures. We give a higher weight to Sim_h, i.e., $0.5 < \alpha \leq 1$. If Sim of two words is greater than a predefined threshold θ ($\theta = 0.6$ in the following examples), they are considered to be synonymous.

$$Sim(w_i, w_j) = \alpha \cdot Sim_h(w_i, w_j) + (1 - \alpha \cdot Sim_h(w_i, w_j)) \cdot Sim_e(w_i, w_j) \tag{11}$$

Property 1. $0 \leq Sim(w_i, w_j) \leq 1$.
Property 2. If w_i or w_j is out of HowNet lexicon, $Sim(w_i, w_j) = Sim_e(w_i, w_j)$.

Example 1 ("质量|quality" and " 质地|quality"). $Sim_h = 0.93$, $Sim_e = 0.48$, let $\alpha = 0.6$, $Sim = 0.77 > 0.6$. Thus, "质量|quality"→"质地|quality".

3.2 Target Expansion

Target expansion is to find more adjectives or verbs which are related to the target sentiment words.

Polar Adjective Expansion. Find adjectives, each of which has the high similarity with the target sentiment word. The expansion is the same with context expansion. A higher weight to Sim_h is given, i.e., $0.5 < \alpha \leq 1$.

Example 2 ("大|big" and "巨大|huge"). $Sim_h = 1.00$, $Sim_e = 0.91$, let $\alpha = 0.6$, $Sim = 0.96 > 0.6$. Thus, "大|big"→"巨大|huge".

Polar Verb Expansion. Find verbs, each of which has the same trend as the target sentiment word. The semantic similarity between " 高|high" and "提高|high" (0.13) is less than that between "低|high" and "提高|high" (0.24), which is obviously wrong. Hence, a higher weight to Sim_e is given, i.e., $0 \leq \alpha < 0.5$.

Example 3 ("高|high" and "提高|improve"). $Sim_h = 0.13$, $Sim_e = 0.91$, let $\alpha = 0.4$, $Sim = 0.92 > 0.6$. Thus, "高|high"→"提高|improve".

With the help of polar verb expansion, we can obtain verbs expressing the same trend as the corresponding adjective. We define a verb list for one adjective.

Definition 4 (Verb Set for Adjective). *Given an ambiguous adjective sw, a verb for sw satisfies that the similarity is greater than θ. All such words comprise a verb set for adjective sw, denoted by $VSA(sw)$.*

$$VSA(sw) = \{w|Sim(w, sw) > \theta\} \tag{12}$$

Polar Verb Re-Expansion. $VSA(sw)$ can also provide help for polar verb expansion. If the minimum Sim (computed with the similarity measure in context expansion) between a new word and all words in $VSA(sw)$ is greater than θ, the new word is considered to express the same meaning with sw.

Example 4 ("高|high" and "增加|increase"). VSA(" 高|high")={"提高|improve", " 增高|rise"}, Sim(" 提高|improve"," 增加|increase")=0.72,
Sim("增高|improve","增加|increase")=0.79,
$\min\{0.72, 0.79\} = 0.72 > 0.6$. Thus, " 高|high"→"增加|increase". But if we compute the similarity directly, $Sim = 0.53 < 0.6$.

4 Experiments

4.1 Data Sets

We conduct experiments on two real-world data sets. One data set is from Task 1 of Chinese Opinion Analysis Evaluation 2012, denoted as COAE [13], and the other is

Table 5. Statistics of two data sets

Data	COAE	SEMEVAL
Positive	598	1202
Negative	1295	1715
Neutral	507	0
Total	2400	2917

from Task 18 of Evaluation Exercises on Semantic Evaluation 2010, denoted as SEMEVAL [2]. Their statistics are listed in Table 5.

The distribution of sentiment words from 8 antonym pairs is shown in Figure 2. The total of 960 sentiment words appear in 709 sentences on COAE data set, and 4991 sentiment words appear in 2846 sentences on SEMEVAL data set. These words are often used in opinionated texts, especially " 高|high","低|low", "大|big"," 小|small", " 多|many","少|few", and "重|heavy".

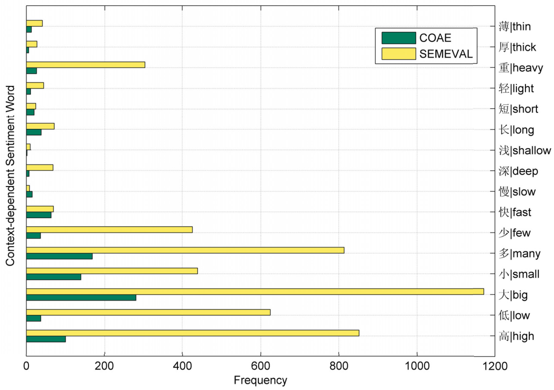

Fig. 2. Distribution of sentiment words from antonym pairs

4.2 Experiment Settings

- Preprocessing: All texts are automatically word-segmented and POS-tagged with ICTCLAS [14]. A sentence is divided into a few sub-sentences with some punctuation marks (,.!?).
- Sentiment Lexicon: We construct a sentiment lexicon with Affective Lexicon Ontology [15] and some common expressions. There are 28567 entries in our sentiment lexicon.
- Sentiment Classification Method:

  Baseline The method proposed by Turney [16] is used as the baseline, which discards the context-dependent words discussed in this paper.

NB Naive Bayes method is directly used to classify [17].
SVM Support Vector Machines method is directly used to classify [17].
Approach-1 Add the step of polarity classification for antonym pairs based on Baseline.
Approach-2 Add the step of context expansion based on Approach-1.
Approach-3 Add the step of target expansion based on Approach-2.

– Evaluation: The evaluation criteria is micro-average F-measure $micro\text{-}F_1$.

4.3 Performance of Sentiment Classification for Antonym Pairs

The comparative results between three baselines and Approach-1 are demonstrated in Figure 3. The improvement on SEMEVAL data set is obvious, because the data set is designed to disambiguate sentiment ambiguous adjectives per se, and almost each sentence contains ambiguous adjectives. After executing polarity classification for antonym pairs, many sentences can be truly labeled the polarity. The performance of Approach-1 on COAE data set is slightly improved due to the small percentage of sentences containing such adjectives. We also find that Approach-1 is better than NB and SVM.

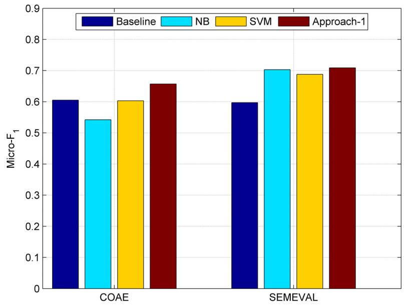

Fig. 3. Performance of sentiment classification for antonym pairs

Table 6. Behavior analysis of selected words

	#Selected Words			#Other Polar Words	
	#Positive	#Negative	#Neutral	#Context-dependent	#Context-free
COAE	264	328	261	79	3128
SEMEVAL	1841	2082	699	110	7723
TOTAL	2105	2410	960	189	10851

Table 6 shows the behavior analysis of the selected 16 words. Among all the selected words, 35% are positive, 40% are negative and the remainder are neutral due to the lacking of contextual information or matching rules. The number of other context-free polar words is nearly twice that of the selected words. The number of the selected words is about three times that of other context-dependent polar words.

4.4 Performance of Double Expansion

There are two important parameters, α and θ, in double expansion. α measures the different weight of Sim_h and Sim_e, θ is a similarity cut-off. According to several experiment results, the optimal parameter settings are given in Table 7. The similarity cut-off of different expansion on a certain data set is the same. The performance of double expansion is shown in Figure 4.

Table 7. Optimal parameters in all expansions

	COAE	SEMEVAL
Context Expansion	$\alpha = 0.7, \theta = 0.6$	$\alpha = 0.7, \theta = 0.9$
Polar Adjective Expansion	$\alpha = 0.7, \theta = 0.6$	$\alpha = 0.7, \theta = 0.9$
Polar Verb Expansion	$\alpha = 0.3, \theta = 0.6$	$\alpha = 0.3, \theta = 0.9$
Polar Verb Re-Expansion	$\alpha = 0.7, \theta = 0.6$	$\alpha = 0.7, \theta = 0.9$

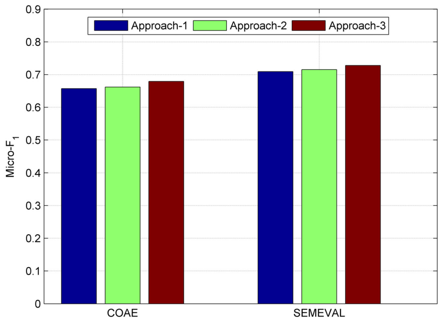

Fig. 4. Performance of double expansion

Because more contextual polarities are discovered, double expansion further improve the performance of sentiment classification. The improvement on SEMEVAL data set is greater than that on COAE data set.

4.5 Annotation Consistence Analysis

As mentioned above, we assume that the polarity annotation of a word is consistent with the sentence. To validate the rationality, Cohen's kappa coefficient [18] is used as a statistical measure of inter-annotator agreement.

$$\kappa = \frac{Pr(a) - Pr(e)}{1 - Pr(e)} \tag{13}$$

where, $Pr(a)$ is the relative observed agreement among annotators, and $Pr(e)$ the hypothetical probability of chance agreement.

Table 8. Contingence table of two annotators

Assumption\Proposed Method	$label = 1$	$label = -1$
$label = 1$	PP	PN
$label = -1$	NP	NN

In this paper, there are two annotators: *Assumption 1* and our proposed method. The contingence table is shown in Table 8:

$Pr(a)$ and $Pr(e)$ in Eq. (13) are computed respectively:

$$Pr(a) = \frac{PP + NN}{PP + PN + NP + NN} \tag{14}$$

$$Pr(e) = \frac{(PP + PN) \times (PP + NP) + (NP + NN) \times (PN + NN)}{(PP + PN + NP + NN) \times (PP + PN + NP + NN)} \tag{15}$$

We can figure out $Pr(a) = 0.86$ and $\kappa = 0.73$. Two annotators are consistent enough, and the assumption is reasonable.

5 Conclusions

In this paper, we propose a novel approach to automatically determine the polarity of context-dependent words with antonym pairs. To the best of our knowledge, this is the first context-dependent sentiment classification scheme which utilizes antonym pairs. According to Bayes' theorem, two polar posterior probabilities are obtained. We also initiate two kinds of rules, i.e., Bidirectional Rule and Unidirectional Rule, and assign the polarity to sentiment words. In addition, we define a new similarity measure which combines semantic distance with edit distance for Context Expansion and Target Expansion. Our approach is effective in improving the overall performance of sentiment classification.

In the future, we would like to dive into more accurate context information extraction which can help to filter noisy neighboring nouns. We consider that antonym pairs deserve further research.

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