Sentiment Value Propagation for an Integral Sentiment Dictionary based on Commonsense Knowledge

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Abstract—With the rise of social media, sentiment analysis has become a popular research field in recent years. A sentiment dictionary plays an important role in sentiment analysis. To remedy the lack of Chinese sentiment dictionary, researchers translate English sentiment dictionaries to Chinese before using them in their applications. However, cultural difference often causes such translations inaccurate. Moreover, some of the dictionaries have small vocabulary size and some of the dictionaries have only polarity labels or even no label instead of value labels.

In the first part of the paper, we integrated several common sentiment dictionaries to get the sentiment seeds. Then, we proposed a self-training sentiment spreading activation to expand the sentiment values on Chinese ConceptNet. Finally, we derived iSentiDictionary, a Chinese sentiment dictionary with 28,248 concepts and corresponding sentiment values.

Keywords—Sentiment Analysis, Sentiment Dictionary, Commonsense Knowledge

I. INTRODUCTION

In recent years, semantic analysis has become a hot topic in computer science area because of the longing of making computers to understand the semantic meanings of natural languages. Sentiment analysis is a subfield of semantic analysis, which aims to determine the attitude of a speaker or a writer with respect to some topic or the overall contextual polarity of a document1.

The rise of social media has changed the roles of users from information receivers to information providers. More and more people share their ideas, experiences and opinions on the web. The massive unstructured online data contains the opinions of the public. Therefore, lots of interesting opinion/sentiment searching applications based on sentiment analysis was released recently, e.g. Musiccovery2, RankSpeed3 and OPFINE4.

A critical part of the common approach is using a sentiment dictionary to find out the sentiment words in the documents. However, if the vocabulary size of the dictionary is too small, it can only match a little part of the document. Hence, a sentiment dictionary plays an important role in sentiment analysis and the vocabulary size of the dictionary is highly correlated to the performance.

There are roughly three kinds of sentiment dictionaries: words with sentiment values, words with sentiment polarities and a collection of sentiment words only. Sentiment values give us the most information among the three, so we focus on compiling a dictionary with sentiment value. In order to build sentiment dictionaries with a large vocabulary size, people usually calculate the sentiment values/polarities of new words from the ones in the existing dictionaries automatically in the recent years.

The challenge of expanding existing sentiment dictionaries is how to derive the values/polarities for the new words. WordNet-Affect[1], SentiWordNet[2] and HowNet-VSA[3] use the synonym relationship to expand existing dictionaries. However, people find that some concepts are related in sentiment but cannot be discovered by the synonym relationship. Furthermore, a concept is also more precise than a word while predicting the sentiment. Therefore, SenticNet[4] use ConceptNet to create a dictionary containing not only words and phrases, but also concepts.

When it comes to Chinese sentiment analysis, people often use the translation technique due to the lack of Chinese sentiment dictionaries. However, culture differences often causes inaccurate translation results and people try to create Chinese dictionaries, e.g. HowNet-VSA[3] and NTUSD[5] but none of them give a sentiment value to every word/concept in the dictionary.

This paper aims to extract seeds from an integration of the existing sentiment dictionaries, and spread the sentiment values on ConceptNet to derive a Chinese sentiment dictionary with a large vocabulary and sentiment values. We review the existing sentiment dictionaries according to their characteristics in Section II. ConceptNet and the related works are introduced in Section III. We describe the proposed method in Section IV. The experiments are shown in Section V and the conclusion is given in Section VI.

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1http://en.wikipedia.org/wiki/Sentiment_analysis/
2http://musiccovery.com/
3http://www.rankspeed.com/
4http://www.opfine.com/
II. EXISTING SENTIMENT DICTIONARIES

We introduce 9 common sentiment dictionaries in this section, including Affective Norms for English Words, SentiWordNet, SenticNet, General Inquirer-Emotion, Wordnet-Affect, National Taiwan University Sentiment Dictionary, HowNet-Vocabulary for Sentiment Analysis, WeFeelFine and Never Ending Language Learner-Emotion. They are grouped into three kinds according to their characteristics: dictionary with sentiment value, dictionary with sentiment polarity and dictionary with no label.

A. Dictionary with Sentiment Value

The Affective Norms for English Words (ANEW)[6] provides a set of normative emotional ratings for a collection of 1,034 English words. Each word in ANEW is rated in terms of pleasure, arousal and dominance respectively with a value ranging from 1 to 9. The value represents the degree of the word in the corresponding dimension. The greater the pleasure value is, the pleasanter sentiment the word conveys. The greater the arousal value is, the more exciting sentiment the word carries. The greater the dominance value is, the harder the influence of the word would be dominated by others. ANEW was compiled manually in 1999 and has been widely used in the sentiment analysis area since then [7] [8].

SentiWordNet[9] assigns to each synset of WordNet three sentiment values: positivity, negativity and objectivity. Each sentiment value ranges from 0 to 1, and the summation of the sentiment values of a synset is 1. There are total 147,306 English words in SentiWordNet. However, 96,155 of them are labeled as objective words (objectivity value equals to 1). Each of the remaining 3,726 words has either a positivity value or a negativity value greater than 0.

SenticNet[4] is developed by Cambria et al. in 2010, that contains 5,273 English concepts. Each concept is labeled with a sentiment value between -1 and +1 which represents the pleasant degree of the concept. Cambria et al. use the sentiment keywords and the corresponding values defined in the Hourglass of Emotions as seeds and derive the sentiment values of other concepts on the AffectiveSpace[10]. The AffectiveSpace is a vector space composed by WordNet and ConceptNet.

B. Dictionary with Sentiment Polarity

General Inquirer (GI)[11] is the first attempt to content analysis. There are 11,787 English “words” (different meanings of a word is regarded respectively) and 182 labels in GI. The words labeled as “positive outlook” and “negative outlook” in GI can be regarded as a sentiment dictionary (GI-Emotion) with 3,682 English words.

WordNet-Affect[1] marks some synsets in WordNet with sentiment labels, e.g. EMOTION, MOOD, COGNITIVE STATE, PHYSICAL STATE. We take the 1,587 English words with EMOTION label to form WordNet-Affect sentiment dictionary. There are 492 words in the dictionary with the label “positive-emotion”, 895 words with “negative-emotion”, 22 words with “neutral-emotion” and 141 words with “ambiguous-emotion”. The remaining 37 words has been labeled as more than 2 emotions.

National Taiwan University Sentiment Dictionary (NTUSD)[5] is a Chinese sentiment dictionary derived from GI and Chinese Network Sentiment Dictionary (CNSD). Ku et al. translates GI and merge the result with CNSD. Then, they use the synonym relation to derive a sentiment dictionary with 11,088 Chinese words.

HowNet[3] is developed in 1988 with the idea that knowledge is composed by the relations between concepts and the relations between the attributes of concepts. HowNet Vocabulary for Sentiment Analysis (HowNet-VSA) is a sentiment dictionary with both Chinese and English contents released in 2007. We pick 4 different sentiment categories of HowNet-VSA and the concept number of each category is listed below in Table I.

<table>
<thead>
<tr>
<th>Category</th>
<th>English</th>
<th>Chinese</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Emotion</td>
<td>769</td>
<td>833</td>
</tr>
<tr>
<td>Negative Emotion</td>
<td>1,011</td>
<td>1,254</td>
</tr>
<tr>
<td>Positive Opinion</td>
<td>3,594</td>
<td>3,730</td>
</tr>
<tr>
<td>Negative Opinion</td>
<td>3,563</td>
<td>3,116</td>
</tr>
</tbody>
</table>

Table I: Concept number of each category in HowNet-VSA

C. Dictionary with no Label

We Feel Fine[12] project has been harvesting worldwide human feelings from a large number of webblogs since 2006. The system use a predefined set of sentiment words to identify the sentiment of sentences in the blog posts. The system provides a series interfaces to search and sort the feelings by the background of the bloggers. We named the predefined sentiment word set as WeFeelFine dictionary which contains 2,179 English sentiment words.

The Never-Ending Language Learner (NELL)[13] is an intelligent computer agent that runs forever. It must extract information from the web to populate a growing structured knowledge base and learn to perform this task better and better everyday. Never Ending Language Learner-Emotion (NELL-Emotion) contains 3,109 English concepts learned by the Never-Ending Language Learner.

III. COMMONSENSE KNOWLEDGEBASE

Commonsense is the knowledge shared among ordinary people. It is useful for solving most daily problems while people may not notice they’re using it. In order to have computers equipped with commonsense, Cyc[14] and MIT Open Mind Common Sense (OMCS)[15] project have been devoted to encoding commonsense knowledge into machine readable forms.
A. ConceptNet

ConceptNet[16] is a commonsense semantic network built by OMCS. It contains over 1 million English commonsense sentences collected from OMCS website. With innovations in community-based social games, over 250 thousand Chinese sentences were also successfully collected and verified via question-answering between players within a year[17]. Our previous work[5] also proposed (1) verification games to improve the quality of collected Chinese commonsense sentences[18] and (2) using English ConceptNet as a guide to improve the coverage of Chinese ConceptNet within resource bound[19].

These verified Chinese commonsense sentences are then represented as a directed graph. The nodes of this graph are concepts, and its labeled edges are relations between two concepts. There are 15 kinds of relations and each has a polarity attribute. This representation is suitable for finding contextual information of a concept.

B. Sentiment Analysis in OMCS

Previous studies have been using ConceptNet to derive sentiment values for concepts. Their basic idea is that “related concepts share common sentiment.” For example, the concepts “blood”, “hurt” and “ambulance” are linked with the concept “car accident” through ConceptNet edges. Therefore, the sentiment value of “car accident” should be similar to its related concepts.

Liu et al.[20] used Ekman model to represent emotion in a vector of six dimensions [happy, sad, angry, fear, disgust, surprise]. They start with some seeds and apply the spreading activation on ConceptNet to spread out the sentiment values for each concept. Similarly, Cambria et al. used correlation and senses of concepts to create a sentiment dictionary called SenticNet.

Our approach is based on the work by Liu et al.[20]. With multiple existing dictionaries, we can use them to generate seeds and improve the basic spreading activation by leveraging the information provided in the existing dictionaries.

IV. OUR CHINESE SENTIMENT DICTIONARY: iSentiDictionary

Although there are some existing sentiment dictionaries, researches[5] translate English sentiment words to Chinese before using these dictionaries in their applications. However, cultural difference often causes such translations inaccurate. In addition, using only one sentiment dictionary may not have satisfactory coverage. Integrating several dictionaries seems to improve the coverage, however, sentiment dictionaries mentioned in II-B and II-C do not provide words’ sentiment value, making the inclusion of words in such dictionaries become challenges.

To compile a high coverage Chinese sentiment word dictionary in which every word has sentiment value, one must integrate dictionaries mentioned in Section II, find accurate translations for each sentiment word, and spread sentiment values from words with values from words without values by utilizing ontological relationship between words.

We first collect sentiment seeds from multiple dictionaries, pre-classified into the four types. Then, we propose a self-learning sentiment spreading activation method based on base sentiment spreading activation method proposed by Liu et al.[20] to get more sentiment concepts for create a Chinese dictionary. Our system’s architecture is shown in Figure 1.

A. Sentiment Seeds Collection

We collect sentiment seeds from the three kinds of dictionaries mentioned in II: dictionaries with sentiment value, dictionaries with sentiment polarity and dictionaries that collect sentiment words only. From different label characteristics dictionaries, we can get different types of sentiment seed.

1) Translation of Sentiment Dictionaries: Because most sentiment dictionaries presented in II is English, the first step of sentiment seeds collection is to translate words from English to Chinese. We use Google Translate API and Yahoo Dictionary as our translation tools. Given an English word, Google Translate outputs one of its translation while Yahoo Dictionary outputs all possible translations. We design a method to combine these two translation tools’ results to keep Google’s high precision and Yahoo’s high coverage. Given a English word $e$, suppose Google outputs $g_1$ and Yahoo outputs $y_1, y_2, y_3, ..., y_n$. If any of yahoo’s output, $y_i$, is in the synset of $g_1$, we treat it as $e$’s translation. Take “admired” for example, Google Translate outputs “欽佩” and Yahoo Dictionary outputs “{欽佩、欣賞}、{稱讚、誇獎}、{對...不勝佩服}”. We choose “{欽佩、欣賞}” as the translation result because the synset contains “欽佩”.

2) Expanding Sentiment Dictionaries: We think that higher coverage between two dictionaries will help us to determine the sentiment label of each word or concept when merging all sentiment dictionaries. Therefore, we use

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5https://sites.google.com/site/iagentcommonsense/
three kinds of words to expand all sentiment dictionaries. (a) Sentiment superfluous words: concepts' sentiment labels are unchanged after filtering superfluous word, e.g. “覺得”(feel), “感覺”(feeling) and “使”(make). (b) Sentiment degree words: concepts' sentiment polarities are unchanged after filtering degree word, e.g. “一些”(some), “非常”(very) and “極度”(extremely). (c) Negative words: concepts reverse their sentiment labels after filtering a negative word, e.g. “不”(no), “不可”(not) and “不能”(can't).

3) Merge of Sentiment Dictionaries: For the dictionaries with sentiment value, we use the sentiment value defined in SenticNet in order to unify the representations. The sentiment value of a concept s a value ranging from -1 to +1. It indicates the pleasant degree of the concept. For ANEW, we normalize the pleasure value as the sentiment value. For SentiWordNet, we regard the value of “positive score” minus “negative score” as sentiment value and then filter out the words with sentiment value equaling 0.

For the dictionaries with polarity, the sentiments are divided into three categories: positive, negative and ambiguity. The original labels in the dictionaries and the corresponding sentiment polarities are listed in Table II. A concept belongs to both positive sentiment and negative sentiment is regarded as ambiguity sentiment.

The concepts appearing in at least two dictionaries is chosen as the sentiment seeds. There are four different types of sentiment seeds: (a) S-Value: sentiment seeds labeled with sentiment values ranging from -1 to 1. The final sentiment value is the average of all sentiment values of the seed from different dictionaries. (b) S-Polarity: sentiment seeds that labeled as positive or negative sentiment. If the seed has more positive sentiment labels, it is regarded as positive sentiment. If the seed has more negative sentiment labels, it is regarded as negative sentiment. (c) S-Ambiguity: sentiment seeds that have ambiguity sentiment. If the seed has more ambiguity sentiment labels or the number of positive sentiment labels is equal to negative sentiment labels, it is regarded as ambiguity sentiment. (d) S-Unknown: sentiment seeds without annotation of polarity and value. Table III shows the number of seeds in each types.

### B. Sentiment Spreading Activation

Sentiment expressions depend not only on the meaning of words, but also on the semantics and context. Our approach is based on the work of Liu et al.[20] which relies on having a large-scale real-world knowledge about people’s common affective attitudes toward situations, things, people, and actions. In this paper, we choose Chinese ConceptNet as our knowledgebase, because of its great breadth and coverage.

We use the sentiment seeds introduced on Section IV-A to spread sentiment values on Chinese ConceptNet in order to get more sentiment items and the corresponding sentiment scores. In ConceptNet, each node represents a concept and each edge represents the relation between two concepts. The relation between two concepts is regarded as a sentiment spreading bridge. For example, the assertion: “紅色代表熱情(Red symbolizes passion)”, “紅色(red)" is concept 1, “熱情(passion)" is concept 2 and "代表(symbolizes)" is a relation between “紅色(red)” and “熱情(passion)”. If we know the sentiment value of “紅色(red)”, we spread the sentiment value from “紅色(red)" to “熱情(passion)".

In this section, we first introduce the base sentiment spreading activation proposed by Liu et al. Then we proposed our method, the self-training sentiment spreading activation. Our method avoids the problem that spreading more passes over the ConceptNet causes lower accuracy in the base sentiment spreading activation.

1) Base Sentiment Spreading Activation: Liu et al.[20] regarded sentiment propagation as spreading activation or undirected inference on the ConceptNet. First, they choose a bag of affect seeds which are pre-classified into the six basic emotions(happy, sad, anger, fear, disgust, and surprise).

The sentiment is represented as a six-degree vector [happy, sad, anger, fear, disgust, surprise] according to the six basic emotions. For each affect seed, the vector is defined according to the basic emotion it belongs to: the value is 1 for the degree standing for the predefined class of the seed and is 0 for the other degrees. Then, the seeds propagate their sentiment values to their neighboring concepts, in other words, the concepts in the same assertions with the seeds. Negations are handled by fusing the prefix “not” of the affected verb. The propagating value is multiplied by -1 whenever the a negated relation is detected. They use a second and a third pass propagation to improve the coverage of the dictionary (number of concepts with a sentiment value, in other words the vocabulary size of the sentiment dictionary). After each propagation, the sentiment value is discounted by a factor $d$. An example of propagation for the base sentiment spreading activation model is given here. (The sentiment vector of happy is [1,0,0,0,0,0], the sentiment vector of surprising is [0,0,0,0,0,1] and the discount factor

<table>
<thead>
<tr>
<th></th>
<th>S-Value</th>
<th>S-Polarity</th>
<th>S-Ambiguity</th>
<th>S-Unknown</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity</td>
<td>6,464</td>
<td>1,951</td>
<td>2,541</td>
<td>11</td>
<td>11,076</td>
</tr>
</tbody>
</table>
Something exciting is both happy and surprising.
(pass 1: exciting: [1.0,0,0,0,1])
Rollercoasters are exciting.
(pass 2: rollercoaster: [0.5,0,0,0,0,0.5]
Rollercoasters are typically found at amusement parks.
(pass 3: amusement park: [0.25,0,0,0,0,0.25])

2) Self-training Sentiment Spreading Activation: Different from the base sentiment spreading activation, we defines four types of sentiment seed (S-Value, S-Polarity, S-Ambiguity and S-Unknown) in the self-training sentiment spreading activation. We hope to learn more information from these seed groups and solve the problem the base sentiment spreading activation encountered.

To improve the coverage, the base sentiment spreading activation propagate a second and a third pass and the sentiment value is discounted by a factor d after each pass. However, the method do not consider whether the concept has the ability to transfer sentiment. If the sentiment value of this concept is wrong, then passing out its sentiment value may cause more concepts end up with wrong sentiment values.

To solve this problem, we suggest that only “sentiment concepts” have the ability to transfer sentiment values. The “sentiment concepts” refers to all concepts in the S-Value, S-Polarity, S-Ambiguity and S-Unknown. Moreover, a concept in the S-Polarity group loses its ability to transfer sentiment whenever the sentiment polarity of the concept is not consistent with the deriving sentiment value. The concepts having ability to transfer sentiment is regarded as the active sentiment seeds.

An example of determining which concepts have the ability to spread sentiments is given by Figure 2. Assume the sentiment value of “快乐(happy)” is 0.8. After sentiment spreading, each concept in “幸福(blessing)”, “睡不著(can’t fall asleep)”, “跳舞(dance)” and “形容詞(adjective)” has a sentiment value 0.8 propagated from “快乐(happy)”. According to the rule, “幸福(blessing)”, “跳舞(dance)” have the sentiment spreading ability in the next pass while “睡不著(can’t fall asleep)” and “形容詞(adjective)” don’t.

For each concept that its value is propagated from multiple concepts, the base sentiment spreading activation regards the average of all spreading sentiment values as the final sentiment value of this concept. However, this calculation method causes many concepts having a sentiment value close to zero(sentiment offset) in our implementation.

After counting the number of neighboring seeds in the two polarities of each seed, we find that the average number of positive neighbors of positive seeds is 5 times over the number of negative neighbors, and the average number of negative neighbors of negative seeds is 4 times over the number of positive neighbors.

Therefore, if the number of positive propagations is greater than the number of negative ones, we calculate the average of all positive sentiment propagation values as the final sentiment value. Otherwise, we calculate the average of negative sentiment propagation values as the final sentiment value.

Summarizing the whole self-training sentiment spreading activation, we first use S-Value as the initial active sentiment seeds to stimulate sentiment spreading activation. After each pass of sentiment spreading activation, we filter out the new propagated concepts which don’t have the ability to spread sentiment values and add the remaining to the active sentiment seeds for the next pass.

V. Experiment

Our ultimate goal is to create a Chinese sentiment dictionary with a large vocabulary size and sentiment values and further improve the accuracy of Chinese sentiment analysis. In our approach, we first collect the sentiment seeds and propagate the sentiment values on the Chinese ConceptNet to get more sentiment items. We propose a self-learning sentiment spreading activation to increase the coverage without decreasing the accuracy.

The input of this experiment is the 4 kinds of sentiment seeds and Chinese ConceptNet. And the output is a sentiment dictionary composed by a set of concepts and each concept has a sentiment value that stands for the pleasure degree of the concept and it ranges from -1 to +1. We implemented two algorithms, the base sentiment spreading activation (Base SSA) and our proposed method, the self-learning sentiment spreading activation (SL SSA), and compared their results.

We use a 5-fold cross validation, therefore the seeds in S-Value is randomly and equally divided into 5 sets in every test. S-Value is composed by 6,464 seeds, so there are 5,171 training seeds and 1,293 testing seeds. Then the experiment use three values to evaluate the result of sentiment spreading activation, the three values are

1) Mean Accuracy of Sentiment Polarity (%): The average of 5 folds’ testing accuracies which only consider the sentiment polarity of the test seeds. A larger Mean Accuracy of Sentiment Polarity indicates the sentiment
spreading activation has more sentiment concepts with the correct sentiment polarity.

2) **Mean Error**: The average of 5 folds’ testing error values that consider the mean distance between the result and ground truth sentiment value of the test seeds. A smaller Mean Error represents the result is more precise.

3) **Coverage**: The vocabulary size of the final sentiment dictionary.

We ran 3 passes for each sentiment spreading algorithm because SL SSA didn’t get any new seed after 3 passes, and the result is shown in Table IV. Passing more layers in Base SSA gets a lower Mean Accuracy of Sentiment Polarity and a higher Mean Error. In contrast, our proposed method SL SSA maintains a stable Mean Accuracy of Sentiment Polarity and Error Value on different number of passes. The results show that SL SSA improve the problem that spreading more passes over the ConceptNet receives lower accuracy. The coverage of Base SSA and SL SSA increase by spreading more layers. Although the coverage of Base SSA is larger than SL SSA on pass 2 layers and pass 3 layers, Base SSA can not ensure the spreading accuracy. In summary, the experiment results show that our proposed method SL SSA performs better than Base SSA.

| Pass | Coverage | Mean Accuracy of Sentiment Polarity(|%|) | Mean Error |
|------|----------|----------------------------------|------------|
| 1    | Base SSA | 21,934                           | 84.32      | 0.3298     |
|      | SL SSA   | 21,887                           | 84.36      | 0.2781     |
| 2    | Base SSA | 77,843                           | 79.41      | 0.3298     |
|      | SL SSA   | 28,166                           | 85.07      | 0.2700     |
| 3    | Base SSA | 88,734                           | 78.87      | 0.333      |
|      | SL SSA   | 28,248                           | 85.28      | 0.2679     |

Table IV: Evaluation of Base SSA and SL SSA

VI. CONCLUSION

In summary, this paper presents a novel method to compile a Chinese sentiment dictionary, iSentiDictionary. We collected our sentiment seeds from the existing sentiment dictionaries. The seeds were classified into four categories: S-Value, S-Polarity, S-Ambiguity and S-Unknown. Then, we proposed a self-training sentiment spreading activation to spread the sentiment values on ConceptNet. Finally, we derived iSentiDictionary, which is a Chinese sentiment dictionary with 28,248 concepts and each concept has a sentiment value between -1 and +1.

The self-training method takes advantage of the different information provided by the four kinds of seeds and stops the concepts with a wrong sentiment value from propagating their values to other concepts. Therefore, the proposed method achieves a higher sentiment polarity accuracy and a lower sentiment value mean error than the base sentiment spreading activation.

The most immediate future work will examine how to reweight the values from different concepts. There is a score for each commonsense sentence in ConceptNet representing how many people inserted the sentence. We think the score may be a good weighting function while combining the values from different concepts. Moreover, the score is useful to filter out the noises in ConceptNet.

Two main contributions of this paper are presented below. The paper proposed a language independent method to integrate existing sentiment dictionaries and expand the seeds into a dictionary with a large vocabulary and sentiment values. Furthermore, the iSentiDictionary is a available resource for Chinese sentiment analysis researches.

REFERENCES


