Construction of a Multi-dimensional Vectorized Affective Lexicon

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Abstract. Affective analysis has received growing attention from both research community and industry. However, previous works either cannot express the complex and compound states of human's feelings or rely heavily on manual intervention. In this paper, by adopting Plutchik's wheel of emotions, we propose a lowcost construction method that utilizes word embeddings and high-quality small seed-sets of affective words to generate multi-dimensional affective vector automatically. And a large-scale affective lexicon is constructed as a verification, which could map each word to a vector in the affective space. Meanwhile, the construction procedure uses little supervision or manual intervention, and could learn affective knowledge from huge amount of raw corpus automatically. Experimental results on affective classification task and contextual polarity disambiguation task demonstrate that the proposed affective lexicon outperforms other state-of-the-art affective lexicons.

Keywords: Affective analysis · Affective lexicon
Knowledge representation

1 Introduction

Affective analysis is a rapidly developing area of Natural Language Processing that has received growing attention from both research community and industry in recent years [18,21]. It helps companies to know what customers feel about their products, and it helps a political party or government to know what the voters feel about their actions and proposals. On the other hand, it helps customers or voters to choose wisely and in an informed way by knowing what their peers feel about a product or a political candidate. With this, affective analysis and opinion mining are of great importance for aiding economy and democracy.

Affective resource plays an important role in the analysis. In fact, researchers in related area can hardly progress much without a good pool of affective lexicon, although there really exist many available affective resource. Most of the current affective lexicons, e.g., NTUSD [11], only tells whether the given word is positive (+1) or negative (−1), and even some words are divided into the two parts simultaneously. However, human's affects are complex and compound states of feelings that result in physical and psychological reactions influencing both thought and behavior.

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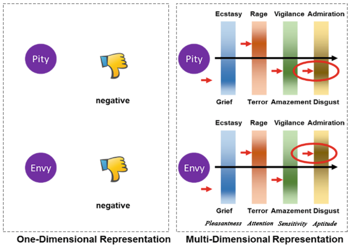

Fig. 1. Comparison between one-dimensional vs. multi-dimensional representation

Although there are many advantages for building a multi-dimensional emotional resource, traditional methods encountered many problems: (1) Substantial human labors consumption. Constructing dictionaries is a labor-intensive task. (2) High degree of subjective. The disagreement among annotators makes the quality of annotation varies significantly.

Moreover, most of the current affective lexical resources could not overcome the elusive nature of emotions and the ambiguity of natural language. E.g., traditional affective lexicon only tells "pity" and"envy" are both negative, and regards their affective information as the same (Fig. 1). But it is far from reality [16]. In Multi-Dimensional representation, Aptitude dimensionality of "envy" is positive implying the affirmation of one's abilities, while the same dimensionality of"pity" is inversely negative (Fig. 1). Only the fine-grained lexicon could tell the difference.

To solve this problem, we propose a construction method that utilizes word embeddings and high-quality small seed-sets of affective words to generate multi-dimensional affective vector automatically. As a test and verification, we construct a large-scale affective lexicon. Unlike existing affective lexicon, our lexicon is a multi-dimensional vectorized lexical resource, which is based on the psychological model of affect and grounded in a continuous affective space (denoted as $\phi_{\ senti}$).

Overall, the main contributions of this paper include: (i) By bridging the gap between the semantic space($\Psi_{\ sema}$) and the affective space ($\Phi_{\ senti}$) following Plutchik's wheel of emotions, our lexicon gains vectorized description ability of the fine-grained affective states. (ii) The construction of our lexicon uses little supervision or manual intervention, and could learn affective knowledge from huge amount of raw corpus automatically. (iii) Experimental results on several representative affective analysis tasks demonstrate that the proposed lexicon is efficient, and outperforms the best baseline affective lexicons.

2 Related Works

2.1 Psychological Models of Affect

For a long time before AI researchers' concern, the study of affect has been one of the most confused (and still open) chapters in the history of psychology.

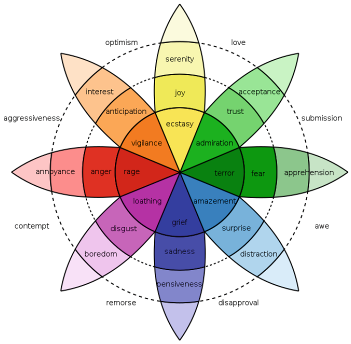

Fig. 2. Plutchik's wheel of emotions

Psychologists have developed many different affective models. Over the recent years, the adoption of psychological models of affect has become a common trend among researchers and engineers working in the sphere of affective analysis [14].

The well-known wheel of emotions is an affective categorization model developed starting from Plutchik's studies on human emotions [16]. The conceptual scheme of the wheel of emotions is illustrated in Fig. 2. In this model, Plutchik suggested eight basic bipolar emotions, whose different levels of activation make up the total emotional states of the mind (shown as Fig. 1). Actually, Plutchik's wheel of emotions is based on the idea that the mind is made of different independent dimensionalities and that emotional states result from setting these dimensionalities on different values.

Apparently, this model is particularly useful to recognize, understand and express affects in the context of HCI. Therefore, Plutchik's wheel of emotions is leveraged as the theoretic basis of our work.

2.2 Common Affective Lexical Resource

Generally, affective lexicon is important for HCI. [22] classified affective lexicons into three basic types. (i) The ones only containing affective words, such as the Never-Ending Language Learner (NELL) [5]. They can not able to tell whether the texts have positive or negative affects; (ii) The ones containing both affective words and affective polarities, such as National Taiwan University Sentiment Dictionary (NTUSD) [11] and HowNet [6]. They lack the semantic relationship among the words and cannot distinguish the extent of the affect expressed by the words; (iii) The ones containing words and relevant affective polarity values (i.e., affective polarity and degree), such as SentiWordNet [7], WordNet-Affect [20] and SenticNet [3].

Based on the theory of wheel of emotions, SenticNet is proposed as the state-of-the-art affective lexical resource for affective analysis [4]. However, their deficiency is concluded as follows: (i) They have a complicated process of construction. And it is difficult to expand to other languages; (ii) they did not fully utilize large-scale unlabelled data and can not unsupervisedly mine the affects implied from statistics. The proposed construction procedure as our lexicon demonstrated tries to overcome the above-mentioned drawbacks.

3 The Proposed Affective Lexical Resource

In this section, we present the construction method of the proposed Affective lexicon. The method is comprised of three base modules: (1) Distributional word representation learning for all words in the lexicon; (2) Affective seed-set construction of each basic affect defined in Plutchik's wheel of emotions; (3) Construction of vectorized affective representations. We mainly introduce the second step and the third step here.

3.1 Constructing the Affective Seed-Set

The affective seed-set plays an important role in the proposed lexicon to align the semantic space and the affective space. To achieve the complete description of the given basic affect, the seed-set should have full coverage of basic emotional state of the mind, and avoid incorporating the domain-specific affective words.

In Plutchik's model, affects are reorganized around 4 independent dimensionalities. We follow [2] to reinterpret the 4 dimensionalities as *Pleasantness*, *Attention*, *Sensitivity* and *Aptitude*. The set of these four dimensionalities is denoted as $\mathcal{D} = \{\ Plsn,\ Attn,\ Snst,\ Aptt\}$. Each dimensionality has 6 basic affects which determine the intensity of the perceived emotion. Afterwards, we aims at generating affective seed-set for each basic affect in Table 1.

Table 1. Basic affects in different affective dimensionalities used in the proposed lexicon.

Affective Dim	Pleasantness(Plsn)	Attention(Attn)	Sensitivity(Snst)	Aptitude(Aptt)
Basic Affect	Ecstasy(+1)	Vigilance(+1)	Rage(+1)	Admiration(+1)
	Joy(+0.6)	Anticipation(+0.6)	Anger(+0.6)	Trust(+0.6)
	Serenity(+0.2)	Interest(+0.2)	Annoyance(+0.2)	Acceptance(+0.2)
	Pensiveness(−0.2)	Distraction(−0.2)	Apprehension(−0.2)	Boredom(−0.2)
	Sadness(−0.6)	Surprise(−0.6)	Fear(−0.6)	Disgust(−0.6)
	Grief(−1)	Amazement(−1)	Terror(−1)	Loathing(−1)

We mainly utilize the following dictionaries to expand these basic affect by synonym expansion respectively, and construct our affective seed-sets, which will be used to generate the affective lexicon.

Youdao Dictionary[1]: As the first translation software based on search engine technology, it consists of a huge number of buzzwords in the Internet by its novel web interpretation function.

[1] http://www.youdao.com/.

Webster's International Dictionary[2]: As the synthesizer of the structural linguistics in U.S., it consists of More than 450 thousand words, and is reported as the largest single volume English dictionary in the word.

Thesaurus Synonym Dictionary[3]: It provides huge amount of the synonym relationships among words.

WordNet[4] : It assigns each synset with a positive score, a negative score and an objective score. The positive/negative score represents the extent to which the word expresses a positive/negative emotion.

With these dictionaries, affective seed-set is constructed as follows: given basic affect w, (i) obtain the synonyms of w, and then obtain the synonyms of the obtained synonyms; (ii) filter all of the synonyms manually by discarding the words whose affect orientation is wrong. Finally, we totally obtain 24 seed-sets for 24 basic affective words, and each seed-set consists of about 100 affective words. For example, "good spirits","rapture", "be on cloud nine","passion" , "well-being","melody" , "happiness" etc., belong to the seed-set of the basic affect $Ecstasy$.

3.2 Constructing the Lexicon

Based on the word embeddings for all the words in the vocabulary and the affective seed-sets constructed above, we aims at generating 4-dimensional affective vector for each word w in the vocabulary, as follows:

$$vector(w) = (Plsn(w), Attn(w), Snst(w), Aptt(w)) \tag{1}$$

Take $Pleasantness$ dimensionality as an example, we describe how to generate affective value of word w in this dimensionality, as follows:

Step 1. As discussed above, we have constructed 6 affective seed-sets for $Pleasantness$ dimensionality, namely $Ecstasy$, Joy, $Serenity$, $Pensiveness$, $Sadness$ and $Grief$. The vector of word w in a basic affect is calculated according to its most similar N words. Cosine distance is utilized to measure the similarity.

Step 2. The minimum cosine distance between the given word w and the average distance of the N words means the maximum correlation, which is denoted as maxCorrelation here, and the affective strength value of the corresponding basic affect is denoted as x ($x \in -1, -0.6, -0.2, 0.2, 0.6, 1]$ as shown in Table 1).

Step 3. For word w, the affective value in $Pleasantness$ dimensionality could be formulated as:

$$Plsn(w) = x * sigmoid(\alpha * (maxCorrelation - \phi)) \tag{2}$$

wherein, ϕ denotes the threshold determining whether the given word w is close to this affective dimensionality. If $maxCorrelation < \phi$, we think that the given word w does not belong to this affective dimensionality. In this case,

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[2] http://www.merriam-webster.com/dictionary.
[3] http://www.thesaurus.com.
[4] http://wordnet.princeton.edu/wordnet/.

$sigmoid(\ \alpha *(maxCorrelation-\ \phi))$ returns 0, and we believe the given word w has no obvious affective orientation in Pleasantness dimensionality. Whereas, if $maxCorrelation > \phi$, we think that the given word w could be clustered into this basic affect. In our study, the value of ϕ is set of 0.29, which is the average distance among all word vectors in semantic space. Another parameter α decides whether assign the word w with this affective dimensionality, when $maxCorrelation$ is close to the average distance ϕ. The larger value of α is, the bigger the slope of $Plsn(w)$ becomes.

So far, the proposed affect lexicon has been generated completely. It totally consists of 62,101 affective vectors.

4 Experiments

In this section, we conduct experiments to evaluate the effectiveness of the proposed affective lexicon, by applying it in sentence-level and word-level affective analysis. Moreover, we carry out affective vector analysis on the affective space $\Phi_{\ senti}$ established by the lexicon to investigate whether it could adequately reflect affect diversity but not semantic difference.

4.1 Experiments Setup

Comparative Affective Lexical Resources. We compare the proposed lexicon with other widely-used affective lexical resources, including SenticNet and SentiWordNet. SenticNet [3] is a widely used affective lexical resource for opinion mining based on the hourglass model, which is derived from Plutchik's wheel of emotions. Similar with our lexicon, it describes each word with 4 independent dimensionalities. SentiWordNet [1] was developed based on WordNet [8]. It assigns different affective values to each of the synonyms under different parts-of-speech (POS). The statistics of all the alternative affective lexical resources are illustrated in Table 2.

Parameter Settings. In our experiments, the word embeddings are trained using CBOW model. The context window size is set to 8, the number of negative samples is set to 5, and the dimension of vectors is 300. We trained the word embeddings using the Wikipedia corpus with the size of 13.3 GB.

Table 2. The statistics of comparative affective lexical resources.

Lexicon	Format	Quantity
SenticNet	word,Pleasantness,Attention, Sensitivity,Aptitude	30,000
SentiWordNet	POS,ID,PosScore,NegScore, SynsetTerms,Gloss	117,659
Our lexicon	word,Pleasantness,Attention, Sensitivity,Aptitude	62,101

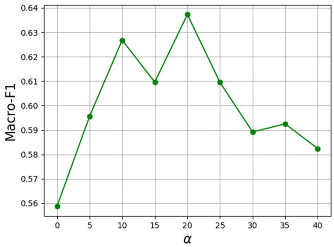

Fig. 3. The comparison of results with different values of parameter α on affective classification task

The size of selected seed words in each affective seed set (i.e. N) is set to 5. We tune the parameter α (in Eq. (2)), and study its influence on the performance of the lexicon in affective classification task on dataset **Comments_BBC**. As shown in Fig. 3, the parameter α is set as 20 to get the best experimental performance.

4.2 Sentence-Level: Affective Classification

We use the affective classification task [15] to evaluate the effectiveness of the pro-posed lexicon.

Datasets. Three datasets are utilized for experiments. The statistics are illustrated in Table 3.

Comments_BBC is collected from BBC News Reviews. **Tweets_STF** is a manual labeled tweet dataset from specific domains. **IMDB** provides a highly polar movie reviews sets.

Since the first two datasets only provide testing data, we apply the training set of the **IMDB** as their training set, and 5,000 of **IMDB**'s testing set as their development set. For the last datasets, we use 33% of the data as the development set. Besides, the neutral sentences are removed for all datasets.

Table 3. Datasets for affective classification task.

Datasets	#Positive	#Negative	#Total
Comments_BBC [23]	99	653	752
Tweets_STF [9]	182	177	359
IMDB [12]	25,000	25,000	50,000

Settings. We evaluate the effectiveness of the above lexicons by employing them as the lexical features. Following [19], we run a GRU network for affective classification. On the input layer in the GRU network, each word will be represented as a 4-dimensional vector. A GRU layer with a dropout (0.5) is followed by a dense layer with the sigmoid as the activation function. We use the Adam algorithm [10] to optimize the parameters. All the models are trained over 50 epochs with a batch size of 64. Additionally, we add four syntactic features (i.e., noun, verb, adjective and adverb) to connect with the lexical features. Macro-F1 is used here as the evaluation metric.

Table 4. The results of affective classification task.

F1	Comments_BBC	Tweets_STF	IMDB
SenticNet [17]	0.568	0.702	/
SentiWordNet	0.593	0.682	0.677
SenticNet	0.575	0.639	0.683
Our lexicon	**0.637**	**0.707**	**0.706**

Results. The results are given in Table 4. Since SenticNet is a closed paid software, we can't reproduce the original method proposed in [17]. Hence we refer the experimental results about SenticNet reported in [17]. We can observe that the proposed lexicon outperforms other lexicons: (i) on dataset **Comments_BBC**, it exceeds SenticNet by 6.9%, and exceeds the best baseline lexicon SentiWordNet by 4.4%; (ii) on dataset **Tweets_STF**, it exceeds SenticNet by 0.5%, and exceeds SentiWordNet by 2.5%; (iii) on dataset **IMDB**, it exceeds the best baseline lexicon SenticNet by 2.3%. We contribute the enhancement to the modeling ability of the lexicon, which could capture more expressive and discriminative affective information.

It is noted that IMDB is not utilized in Ribeiro's work and their work could not be reproduced. Thus the results of their method on IMDB is not presented in Table 4.

4.3 Word-Level: Contextual Polarity Disambiguation

We conduct the Contextual Polarity Disambiguation task on all lexicons, which is a perennial task in SemEval[5]. The task aims to determine whether a given word is positive or negative in its context (Table 5).

Table 5. Datasets for contextual polarity disambiguation task.

Dataset	#Positive	#Negative	#Total
SemEval2015-Task10-A	5,316	2,839	8,155

[5] http://alt.qcri.org/semeval2015/task10/.

Datasets. The official dataset of contextual polarity disambiguation task in SemEval2015 utilized. We also use 33% of the training data as the development set.

Settings. We follow [13] to extract features from the target word as well as from the context. Different from [13], we only use the lexical features to focus on lexicon evaluation and use GRU to implement the experiment similar as Sect. 4.2. All settings are in accordance with the experiments in Sect. 4.2, except the input form of target word and its context.

Results. Table 6 show the experimental results of contextual polarity disambiguation task.

Table 6. The results of contextual polarity disambiguation task in SemEval2015-Task10-A.

Macro-F1	SemEval2015-Task10-A
SentiWordNet	0.627
SenticNet	0.664
Our lexicon	**0.696**

From these tables, we could conclude that our lexicon exceeds the best baseline lexicon SenticNet by 3.2%, and exceeds SentiWordNet by 6.9% on SemEval2015. We conclude that our proposed multi-dimensional vectors could express potential affective states of the given word, covering all the possible affect which this word may imply, and hence does not have to change with context. It suggests the high description ability of the lexicon might alleviate the problem of word's ambiguous affective representation forms.

4.4 Affective Space (Φ_{senti}) Analysis

As discussed above, during the construction of the proposed lexicon, an affective space (Φ_{senti}) is generated. We would like to evaluate the words closed to each other in Φ_{senti} whether share the similar affective orientation and sense or not. We select four words as target words. To find their nearest words in Φ_{senti}, the cosine similarity is applied here.

From Table 7, it could be found that, given the target word, its closest words reveal the similar affective information. It demonstrates the word distribution in the affective space meets our common sense.

We also compare the affective space (Φ_{senti}) with the semantic space (Ψ_{sema}). Taking the word *happy* as an example: in semantic space (Ψ_{sema}) the closest words with *happy* are *sad*, *pleased*, *glad*, *delighted*, and *unhappy*. These words share similar context but inconsistent affect. It verifies that the proposed

Table 7. The results of word sentiment similarity in affective space Φ_{senti}

Target word		Words with minimum distance in Φ_{senti}
Adjective	Happy	glad, okay, excited, honestly, assured...
	Upset	dismayed, irritated, unnerved, unhappy, embarrassed...
Noun	Bliss	ageless, enchanted, lively, radiant, beauteous...
	Disaster	epidemic, famine, repressed, anarchy, oppressive...

lexicon has fulfilled our hypothesis in mapping the semantic space (Ψ_{sema}) to a new affective space (Φ_{senti}).

5 Conclusion and Future Works

This paper presented a novel method to construct the affective lexicon by bridging the gap between the semantic space (Ψ_{sema}) and the affective space (Φ_{senti}) following Plutchik's wheel of emotions. We constructed a affective lexicon which provide vectorized description ability of the fine-grained and compound affective states. It can be observed by experimental results that our lexicon outperforms other lexicons on affective classification task and contextual polarity disambiguation task.

The future research will focus on specific domain oriented affect transfer representing and constructing.

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