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ИСПОЛЬЗОВАНИЕ СОЦИОЛОГИЧЕСКИХ ЛЕКСИКОНОВ ДЛЯ ЭМОЦИОНАЛЬНОЙ КЛАССИФИКАЦИИ ТЕКСТА

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Аннотация: Анализ Чувства, или извлечение эмоционального содержания из текста, был важной темой исследований в течение десятилетия. Многочисленные аннотированные словари были созданы для идентификации и классификации эмоций (или аффекта) в тексте. Извлечение эмоционального содержания из текста делает возможным эмоциональный информационный поиск, что особенно важно с растущей популярности пользовательского контента, как блоги, twitter, и wiki. Эта работа представляет новый источник высокого-качественных аннотаций, которые могут быть использованы для извлечения эмоций. Социологическое направление Символического Интеракционизма, а точнее Affect Control Theory (ACT), измеряет эмоциональное содержание различных концепций. Исследования в этой области производят много ручных аннотации слов, которые могут использоваться в эмоциональном анализе текста. Мы сравниваем эти аннотации с SentiWordNet и WordNet-affect, словарями созданными специально для анализа чувства, в задаче классификации полярности текста и показываем, что классификатор использующий ACT лексикон превосходит двух других.

Ключевые слова: анализ чувства, символический интеракционизм, классификация и кластеризация, антеллектуальный анализ данных.

Annotation: Sentiment Analysis, or the extraction of emotional content from text, has been a prominent research topic for a decade. Numerous annotated lexicons have been created for identification and classification of emotions (or *affect*) in text. This extraction of emotional content from text makes possible emotion-aware Information Retrieval, which is especially important with the growing popularity of user-generated content like blogs, tweets, and wikis. This paper introduces a new source of high quality manual annotations that can be used for sentiment extraction. A subfield of sociology *symbolic interactionism*, more precisely Affect Control Theory (ACT), measures the emotional meanings we associate with various concepts. Research in this field produces multi-dimensional manual annotations of words much like those used in Sentiment Analysis. We compare these annotations with SentiWordNet and WordNet-Affect, lexicons produced for Sentiment Analysis, in the task of text polarity classification and show that classifier trained on the ACT lexicon outperforms the other two.

Keywords: sentiment Analysis, Affect Control Theory, Classification and Clustering, Text Mining.

1. INTRODUCTION

When conducting serious research or making every-day decisions, we often look for other people's opinions. We consult political discussion forums when casting a political vote, read consumer reports when buying appliances, ask friends to recommend a restaurant for the evening. And now Internet has made it possible to find out the opinions of millions of people on everything from latest gadgets to political philosophies. Internet is increasingly both the forum for discussion and source of information for a growing number of people.

Ready availability of opinionated text has created a new area in text analysis, expanding the subject of study from traditionally fact- and information-centric view of text to enable sentiment-aware applications. In the past decade, extraction of sentiment from text has been getting a lot of attention in both industry and academia. A manufacturer of gadgets would want to know what people say about its products on popular sites like *ebay.com* or *newegg.com*. A newspaper editor may want to keep her "finger on the pulse" of the average internet user and his concerns. A major company would be concerned about the view of its brand identity and monitor the effect-tiveness of its advertising campaigns. Finally, emotion annotation makes possible emotion-aware Information Retrieval applications, allowing users to retrieve documents by their affective content.

Sentiment Analysis (SA) is an area of study that attempts to extract the emotional meaning from text. It is concerned with how emotions (or *affect*) are expressed in text, and is generally associated with natural language processing, text mining, and computational linguistics [1]. In the process of understanding human emotions expressed in text, vast labeled vocabularies have been created to map the most common words that we use to the approximate affect that they express.

Human emotion has also been studied exhaustively in a sociological subfield of *symbolic interactionism*. In it, Affect Control Theory (ACT) attempts to quantitatively measure emotions. Much research has been conducted to understand how humans react emotionally to events in their lives [2]. These studies have resulted in a multi-dimensional labeling scheme of concepts, which have been used to record emotional meanings of various words. These *fundamental affective associations* people have with concepts (and words that represent these concepts) can be compared with the real-time emotions a particular situation evokes (the *transient feelings*) [2]. Finally, ACT provides a formal technique to collect and evaluate affective concepts [3].

Though these two fields come from very different disciplines, their objects of study are markedly similar. One studies the expression of emotion in text, and another quantifies the emotions text provokes. In this paper we are merging Sentiment Analysis and Affect Control Theory for the first time (that we are aware of) by using the lexicons produced in ACT research in a SA classification task. We compare this lexicon to two others that were developed in the SA field, and show that the hand-crafted lexicons developed in the sociological field of ACT perform the best in SA polarity classification task.

2. RELATED WORK

2.1. SENTIMENT ANALYSIS

Sentiment analysis is a field that is generally associated with computational linguistics, natural language processing, and text mining. It sprung up at the turn of the century in response to a growing number of user-generated information available on the Internet. User reviews of products and online discussions have especially provoked the development of tools for tracking sentiments about various products and services.

The extraction of emotions from text takes place in several steps. The first task is **sentiment** or **opinion detection**, which may be viewed as classification of text as objective or subjective. The second task is that of **polarity classification**. Given an opinionated piece of text, the goal is to classify the opinion as falling under one of two opposing sentiment polarities, or locate its position on the continuum between these two polarities [1]. To distinguish between different mixtures of the two opposites, **polarity classification** uses a multi-point scale (such as the number of stars for a movie review). This is where the task becomes a multi-class text catego-rization problem.

A third task that is complementary to sentiment identification is the discovery of the opinion's **target**. The difficulty of this task depends largely on the domain of the analysis. It is often safe to assume that the topic of a product review is that product, but the targets of opinions in political debates are much more difficult to determine [4, 5]. One of the peculiarities of sentiment is that even though the notion of positive and negative opinion is a general one, the expression of these opinions differs widely across the spectrum of topical domains. Thus, **topic-specific** and **cross-topic sentiment analysis** is studied in order to improve performance in a particular domain [6, 7].

A wide range of tools and techniques are used to tackle the goals described above. Two of the most popular approaches are one that uses annotated lexicons to classify text, and one that uses the classification algorithms originally developed in the field of machine learning. Since this paper focuses on annotated lexicons, the discussion of the data mining techniques will be omitted here. An overview of these techniques can be found in [1].

A variety of lexicons have been created for the use in Sentiment Analysis, often by manually extending existing general-purpose lexicons. For example, Subasic and Huettner [8] have manually constructed a lexicon associating words with affect categories, specifying an intensity (strength of affect level) and centrality (degree of relatedness to the category). Besides manual annotation, various automatic techniques have been used to extend existing lexicons. Princeton

University's WordNet lexical database has been one of the most popular general purpose lexicons to be used for Sentiment Analysis. It groups nouns, verbs, adjectives, and adverbs into sets of cognitive synonyms (synsets), each expressing a distinct concept. Esuli and Sebastiani [9] expand WordNet by adding polarity (Positive-Negative) and objectivity (Subjective-Objective) labels for each term. The resulting mapping is a two-dimensional representation of the word's emotional polarity and strength seen in Figure 1. Another extension to WordNet is WordNet-Affect, developed by Strapparava and Valitutti [10]. They label WordNet synsets using affective labels (*a-labels*) representing different affective category like *emotion*, *cognitive state*, *attitude*, *feeling*, etc.

Other resources have been used to generate lexicons. Liu et. al. [11] have used the Open Mind Common Sense knowledge base, containing close to half a million sentences collected by researchers in Artificial Intelligence, to create models mapping different concepts to six "basic" emotions - happiness, sadness, anger, fear, disgust, and surprise. Zhou and Chaovalit have developed an ontology-supported polarity mining (OSPM) approach to semantic labeling [12]. They manually built an ontology for movie reviews and incorporated it into the polarity classification task, significantly improving performance over a standard baseline. All of the above lexicons are used in Sentiment Analysis to evaluate the emotional content of text. These annotations give us a rudimentary affective semantic notion about words.

2.2. AFFECT CONTROL THEORY

Affect Control Theory studies the measurement of emotional meaning in concepts, providing a model of cultural norms [3]. Originating from early studies done on the meanings of social identities and acts [13, 14, 15], the theory postulates that people in a culture with a common language share some common preconceptions about what feelings certain things should evoke (*fundamentals*). Combined, these preconceptions define situations in which people could find themselves, thus allowing us to describe emotional content of actual real-life events (*transients*) [2]. Representing cultural meanings, fundamentals can be people, places, objects, actions, etc. Three most important dimensions of affect were identified through empirical study:

- Evaluation – the amount of goodness or badness associated with the concept: *good*, *nice*, *warm* vs. *bad*, *nasty*, *cold*.
- Potency – the amount of powerfulness or weakness associated with the concept: *big*, *strong*, *powerful* vs. *small*, *weak*, *powerless*.
- Activity – the amount of liveliness or quietness associated with a concept: *fast*, *noisy*, *lively* vs. *slow*, *quiet*, *inactive*.

For example, people often have a stereotypical idea of the concept *child*. Children tend to be small and weak (low *potency*), but fairly active (high *activity*), and hopefully behave well (high *evaluation*). A concept can be rated on each of these dimensions on a scale (much research uses a scale from -3 to 3), acquiring a quantitative measurement of its emotional content. However, these sentiments can vary cross-culturally. Evaluation, potency, and activity (EPA) ratings have been obtained for a variety of counties, including the United States, Canada, Japan, Germany, China, and Northern Ireland, and subcultures including Internet users [16], state troopers [2], and religious groups [17]. In these studies the EPA ratings are collected for various symbols (usually identities, behaviors, emotions, and settings), and their averages are compiled into lexicons (often these are collected for males and females separately). These lexicons provide us with a culture-specific three-dimensional affective space [3].

ACT also lets us calculate the affective meanings of various events by combining EPA ratings for individual concepts in the events. The sentiments associated with each element of the event can be mathematically combined to produce a new EPA rating for the whole event – a *transient impression* of that event. These impressions are the contextualized affective meanings that give a particular event its unique EPA rating, thus locating it within the semantic space.

Finally, it is possible to model the actor's reaction to a particular situation. In order to do this, the theory defines another measure, *deflection*, which is the Euclidean distance between the fundamental cultural sentiments and the transient impressions [3]. The greater the deflection, the more drastic the situation is, and the more drastic is the feeling that it provokes in people. Deflection also tells us what reaction is appropriate for the person witnessing the event. In this sense, ACT is both a descriptive and generative model of human emotion.

3. EXPERIMENTAL EVALUATION

3.1. DATASET

To test our hypothesis that ACT lexicons can be useful in SA tasks, we performed a comparison between classifiers using ACT lexicon and classifiers that use the extended WordNet lexicons in the task of polarity classification. In this task we used 1000 positive and 1000 negative movie reviews provided by Pang and Lee [18]. This is a standard dataset in Sentiment Analysis research.

3.2. CLASSIFICATION ALGORITHM

The sentiment classifier used in this study can be considered a *voting* system where each word "votes"' for the polarity of the document. For example, the positive score of a document is

$$PosScore(d) =$$

$$= \frac{1}{|d|} \sum_{w \in d} [PosScore(w) \cdot Negation(k)],$$

where a polarity score of document d is a normalized sum of the positive scores of each word in the document times the negation factor *Negation(k)*. This factor is -1 if there appears a negation around the word within k terms, and 1 otherwise. In this work a $k = 10$ was chosen, as an approximation of a sentence length. The negative score of the document is defined similarly.

The polarity score of each document can be defined in two different ways. One way is to use the score given to it by the lexicon. For example, the EPA ratings range from -3 to 3 for each word, whereas the ratings of SentiWordNet lexicon range from 0 to 1 (for each polarity). The runs where this approach is used are labeled *weight*, because the weight of each word is used. The second way to define the word polarity score is binary. For example, for positive words 1 if word appears in the list of positive words, and 0 if it doesn't (and similarly for negative words). These runs will be labeled *boolean* in the consequent discussion.

Finally, the scores are combined to produce a final score for the document:

$$Score(d) = PosScore(d) - NegScore(d).$$

Note that this approach assumes a balance between positive and negative terms in the lexicon. If one polarity is "favored" over the other, the classifier will favor that class because it will "know" more about it. We will return to this point later in the discussion.

3.3. SENTIWORDNET CLASSIFIER

SentiWordNet is a collection of 52,902 words from the WordNet database automatically annotated with a positive and negative score (both ranging from 0 to 1) [9]. Note that it is pos-sible to have a word classified as both positive and negative. For example, the word *acceptable* has a positive score of 0.25 and a negative score of 0.125. It could be argued that small polarity scores are not strong enough to be useful in text classification. Thus we try several cut-off points in our experiments.

Figure 2 shows the performance of the polarity classifier using SentiWordNet lexicon with various cut-off points. Note that random assignment of classes achieves accuracy of just under 0.50. The peak performance is achieved at the cut-off point of 0.8 achieving accuracy of 0.5730. The size of the lexicon at this cut-off point is only 924 words. Here, accuracy is the sum of true positive and true negative labels over all instances.

3.4. WORDNET-AFFECT CLASSIFIER

WordNet-Affect was created as an extension of WordNet by annotating synsets (groups of synonyms) with various classes of emotional states arranged in a hierarchical structure [10]. The highest level classes include "mental state", "physical state", "behavior", "situation", "signal", "trait", and "sensation". The branch under the "mental state" class includes "positive emotion" and "negative emotion", which were explored for the lexicon creation. After gathering all classes in the branches headed by the above classes, we gathered the synsets annotated with these classes. The words in each synset were extracted from WordNet version 1.6. The resulting lexicon contained 925 positive and 1442 negative unique terms. Note that because there were no ratings of each term's (or synset's) strength in its class (as in SentiWordNet), all words were assigned the same weight of 1, making the runs *boolean*.

Because there are many more negative than positive terms in this lexicon, the classifier was biased toward the negative class, producing positive recall of only 0.283. In order to remove this difficulty, the weights of the positive words have been adjusted to make them more "important" than each of the negative terms. The results are shown in Figure 3. Note that the proportion of negative to positive terms in the lexicon is around 1.56, making it a good candidate for a positive term weight. As expected, the highest performance (accuracy of 0.5458) is achieved at weight 1.40-1.56. Although this solution improves performance, introducing a superficial bias distorts the affective meanings of individual concepts. This problem calls for a classifier that can deal with a lack of knowledge about one of the classes.

3.5. AFFECT CONTROL THEORY CLASSIFIER

The lexicons used for the Affect Control Theory classifier were obtained from the INTER-ACT[1] system, a program that provides an interface for ACT studies and their analysis tools. We collected lexicons from eight studies conducted in the span between 1977 and 2003. Overall there were 13782 words collected, with 4002 unique words. The ratings for words appearing in several different studies have been averaged. The lexicons had the following format:

```
orphan, -0.48, -0.75, -0.85, -
0.26, -1.32, -0.71
outlaw, -1.68, 0.68, 1.44, -1.95,
1.26, 1.96
```

Each word comes with six ratings – the EPA ratings of the males in the study and the EPA ratings of the females. This gender separation gives us a finer detail of the cultural definitions of each word. Actually each rating is an average of ratings of several individuals, making this an even more representative study.

First, we used only the Evaluation rating, since it is the closest to the notion of polarity used in SentiWordNet and WordNet-Affect. We tried using the ratings produced by males, females, and an average of both. Then we used Potency and Activity ratings alone, and in combination with Evaluation ratings. The results are shown in Table 1, and the evaluation metrics are described in Table 2.

The table shows the *weight* runs, since the *boolean* ones consistently underperformed and their results are omitted for brevity. The highest performance (accuracy = 0.5470) is achieved using an average of male and female Evaluation ratings. Neither Potency nor Activity provided any useful information. This is understandable, since Potency and Activity dimensions were designed to be orthogonal to Evaluation dimension.

Notice that the classifier favors positive class (Rec_p is high, Rec_n is low). Perhaps like in the case of WordNet-Affect our lexicon is unbalanced. Indeed, there are 2314 positive terms and 1688 negative terms. But because this lexicon has real-number valued weights, it is not as trivial to adjust them. Our approach was to "shift" the affective "middle" of the lexicon. By "middle" we mean the rating that annotators really felt was neutral, even though 0 was assumed to be the semantic middle. To adjust the lexicon's "middle" to a new middle *m*, each weight is adjusted by *m* and linearly normalized so that each point remains within [-3, 3] window:

$$X = \frac{3(X-3)}{3 - sign(X-3)\times m}.$$

We explore the space of possible "middle's" by an increment of 0.5. The results are shown in Table 3. Indeed, the highest performance is achieved when the recalls are more evenly distributed between the two classes. The optimal "middle" is around 1 – 1.5, at which the classifier achieves accuracy of 0.5933. This suggests that the actual ratings were skewed to the positive. It is possible that the raters themselves were biased to rate concepts positively, avoiding a negative "judgment".

Finally, we considered the amount of information each term in our lexicon provided. It is possible that the words with small deviation from the neutral rating do not have a strong polarity, and thus are not as strong indicators of the document's overall polarity. To test this hypothesis, we dropped the words that had weights less than a cutoff point. This cutoff point was varied from 0.1 to 3.0. Figure 3 shows the resulting performance. Classification accuracy rises only slightly (to 0.5993) as cutoff increases, and eventually drops below 50%. This suggests that all ratings, even the small ones, contain useful information, and thus should be used for classification.

4. DISCUSSION

From the summary Table 4 we can see that the classifier that uses the ACT lexicon outperforms the ones using annotated WordNet lexicons (statistically significant at $p < 0.005$), and all of lexicon-based classes outperform the random assignment baseline (significant at $p < 0.005$). These accuracies were achieved by "tuning" each lexicon –adjusting its word membership or weights. This suggests that lexicons must be tailored for the specific task and dataset to improve

[1] http://www.indiana.edu/~socpsy/ACT/interact/JavaInteract.html

Table 1

Performance of various combinations of EPA ratings

Combination	$Prec_p$	$Prec_n$	Rec_p	Rec_n	F_p	F_n	Accuracy
E Male	0.5267	0.6643	0.9060	0.1860	0.6662	0.2906	0.5460
E Female	0.5277	0.6458	0.8870	0.2060	0.6617	0.3124	0.5465
E Gender Average	0.5276	0.6577	0.8980	0.1960	0.6647	0.3020	**0.5470**
P Gender Average	0.4995	0.3750	0.9950	0.0030	0.6651	0.0060	0.4990
A Gender Average	0.5020	0.6429	0.9900	0.0180	0.6662	0.0350	0.5040
P&A Average	0.5003	0.5556	0.9960	0.0050	0.6660	0.0099	0.5005
E scaled by P	0.5164	0.6497	0.9310	0.1280	0.6643	0.2139	0.5295
E scaled by A	0.5229	0.6436	0.9020	0.1770	0.6620	0.2776	0.5395
E scald by P&A Ave	0.5184	0.6395	0.9160	0.1490	0.6621	0.2417	0.5325

Table 2

Evaluation measurements

Notation	Description	Formula
$Prec_p$	Positive Precision	$\frac{TruePositives}{AllPositives}$
$Prec_n$	Negative Precision	$\frac{TrueNegatives}{AllNegatives}$
Rec_p	Positive Recall	$\frac{TruePositives}{TruePositives + FalseNegatives}$
Rec_n	Negative Recall	$\frac{TrueNegatives}{TrueNegatives + FalsePositives}$
F_p and F_n	Positive/Negative F Measure	$\frac{2 \times Precision \times Recall}{Precision + Recall}$
Accuracy	Accuracy	$\frac{TruePositives + TrueNegatives}{AllInstances}$

Table 3

Performance of the ACT classifier with various settings of the "middle" rating

Middle	Precp	Precn	Recp	Recn	Fp	Fn	Accuracy
-2.5	0.5025	1.0000	1.0000	0.0100	0.6689	0.0198	0.5050
-2	0.5015	0.8000	0.9980	0.0080	0.6676	0.0158	0.5030
-1.5	0.5023	0.7368	0.9950	0.0140	0.6676	0.0275	0.5045
-1	0.5041	0.7857	0.9940	0.0220	0.6689	0.0428	0.5080
-0.5	0.5144	0.7077	0.9620	0.0920	0.6704	0.1628	0.5270
0.5	0.5543	0.6160	0.7550	0.3930	0.6393	0.4799	0.5740
1	0.6129	0.5791	0.5050	0.6810	0.5537	0.6259	0.5930
1.5	0.6129	0.5791	0.5050	0.6810	0.5537	0.6259	0.5930
2	0.5469	0.5015	0.0350	0.9710	0.0658	0.6614	0.5030
2.5	0.5469	0.5015	0.0350	0.9710	0.0658	0.6614	0.5030

performance. Notice that the performance of the ACT classifier was improved from the initial 0.5470 to 0.5993 by adjusting the interpretation of the ratings.

Furthermore, these experiments illustrate the complex relationship of the classification algorithm and the lexicons it uses. Because of the disparity between the classes in WordNet-Affect, the

Table 4

Best performance of the classifiers

Lexicon	Best Accuracy
Random assignment baseline	0.4905
SentiWordNet, cutoff = 0.8	0.5730
WordNet-Affect, PosWeight = 1.56	0.5458
ACT Lexicon, Average E rating, "middle" = 1.0, cutoff = 0.3	0.5993

classifier favored one class over the other. Although the weighting scheme was adjusted to compensate for this, it is not necessarily the most elegant approach, since it posits that one class is more "important" than another, whereas it is the lack of knowledge that causes the bias. Further study into peculiarities of classification algorithms as pertaining to the lexicons they use is in order.

Finally, these experiments show that the semantic annotations gathered in sociological studies based on Affect Control Theory are helpful in the Sentiment Analysis task of polarity classification. The *evaluation* rating is especially useful, in that it corresponds exactly to the notion of *polarity* used in text analysis literature. The merits of these annotations warrant more study, especially in topic-specific sentiment classification tasks. For example, there are interes-ting specialized lexicons such as one created by Kyle Irwin at the University of Missouri-St. Louis comprising of concepts concerning political sphere [19]. Political discourse is known to be very difficult for automatic Sentiment Analysis [20], partially because of the lack of domain knowledge on the part of classifier.

5. CONCLUSIONS AND FUTURE WORK

This paper introduces two areas of research. Affect Control Theory research comes from a subfield of sociology dealing with symbolic interactionism. It postulates that people in the same culture share some basic affective concepts about things in their world. It allows us to measure and combine these concepts and to formulate how people feel about the world.

Sentiment Analysis is a subfield of text analysis is concerned with the extraction of emotional content in text. Polarity-annotated lexicons are one of the most frequently used resource in these studies, and a variety of manually- and automatically- generated lexicons have been created for this purpose.

The resources of the two fields, so far quite separate, are a perfect match for each other. While Sentiment Analysis techniques can provide extraction of affect from large quantities of text sociology studies haven't enough resources to analyze, the detailed hand-crafted annotated lexicons produced by Affect Control Theory researchers can be of use in SA tasks such as text polarity classification. Our preliminary study shows that classifiers using EPA-annotated lexicons outperform ones derived from WordNet used in Sentiment Analysis research.

This preliminary study opens the door for many extensions. The classifier used in this study is quite simple, and suffers from sensitivity to imbalance in class representation in the lexicon. There are many classifiers used in text analysis that would be suitable for this problem, including Support Vector Machines [21], Conditional Random Fields [22], Maximum Entropy [23]. Further study of the feature space is also in order. The current research discards all words that are not in the lexicons (except for negations). A mixture of lexicon-driven and text features may convey more information about the emotional meanings of the text.

So far the resources in ACT have been used in SA task of polarity mining, but automatic text processing tools may be of use in the field of ACT. Millions of documents can be processed by computers, gathering information on millions of people for sociological studies. Tools developed in automated text analysis for subjectivity detection and polarity classification can be used by sociology researchers to reach millions of subjects.

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