Emotion Level Sentiment Analysis: The Affective Opinion Evaluation

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Abstract. Sentiment analysis evaluates writers' opinions based on pivot items extracted from text. These items are called opinion bearing words or, simply, sentiments. Based on these sentiments, sentiment analysis derives the opinion evaluation. Most of the work in this area evaluates opinions based on the polarity detection that can be positive, negative, or neutral. This coarse-grained sentiment polarity is insufficient to convey the precise affect of the writers. To overcome this limitation, this paper introduces emotions as a fine-grained alternative for sentiment evaluation. This can be realized through the use of a cognitive model of emotion representation that organizes the most commonly known emotions. The cognition model of emotion is mapped to an ontology. A semantic similarity is computed to measure the semantic relation between the given opinions and the emotions in the ontology. The mapping between rational and emotional sentiments is obtained by computing the correlations between them using the Google search engine. The initial results are promising.

Keywords: sentiment analysis; rational sentiment; emotional sentiment; semantic Web; ontology; semantic similarity

1 Introduction

The advent of the Web 2.0 and the spread of the Internet scope have contributed to the existence of many online social media sources which are generally called User Generated Contents (UGC). In addition to that, other important online information sources are reviews websites, in which people express their opinions by writing helpful reviews about different objects such as persons, products, topics, movies, hotels, songs, politics, and many more.

Sentiment Analysis (SA) analyses online texts and states the writers' sentiments or opinions towards a particular object or any of its subsumed features or aspects. In order to evaluate sentiments in sentiment analysis, we need to detect terms, called opinion bearing words or simply opinion-words, which are the base for sentiment analysis to perform the evaluation.

Feature-level, also called aspect-level sentiment analysis [1], is the finest level of granularity in sentiment analysis ever used to analyse text. In this level, individual features of a particular object are extracted. Then, a summary of opinions about the object and its underlying features is obtained: see an example summary in Figure 1 as proposed in [2]. According to the example, sentiment analysis collects opinions about the *camera* and its related features from different reviews and provides a detailed summary to users for them to take the right decisions. Finally, sentiment analysis gives a positive evaluation to the given camera based on the dominance of positive sentiments over the negative ones. Similarly, both features *picture quality* and *battery life* receive positive sentiment polarity because of the dominance of their positive reviews. However, they are affectively different because of the inequality in the number of positive sentiments both features receive.

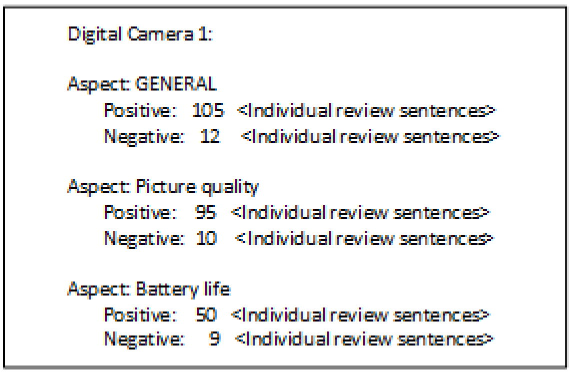

Fig. 1. Feature-level sentiment analysis summary.

This evaluation is insufficient for an accurate and a more detailed evaluation, though. That is because sentiment polarity (positive and negative) does not convey the affective meaning that writers give to an object or to any of its related features. Therefore, there is a need for a stronger and more effective evaluation that is able to show writers' opinions at the emotional level of evaluation towards what he/she writes.

Emotions detection from text provides a strong and expressive opinion evaluation over conventional approaches. Emotion usefulness comes due to its importance in the academic community, in industry, and in a variety of applications such as production, politics, marketing, education, and many more [3].

The main idea of this paper is to extract opinions from reviews and to evaluate their sentiments in terms of emotions such as *joy*, *surprise*, *anger*, or *fear*, to name a few, instead of simply using the conventional positive and negative sentiment evaluation. This is realized through exploiting the powerful capability of the semantic web technology to provide an expressive knowledge base of an emotional ontology, the use of a cognitive model of emotions organization, and the availability of lexical databases to measure the semantic similarity between opinion-words and emotions.

2 Problem Statement

The main goal of this paper is to evaluate online product reviews and to represent the writer's opinions in terms of emotions. Sentiment analysis relies on special indicators extracted from text to infer a writer's opinions towards any object of interest. These indicators are called opinion-words or simply sentiments. Sentiments are divided into two main categories [4,3]: (1) *Rational sentiments*, which are "rational reasoning, tangible beliefs, and utilitarian attitudes" [3]. For example, the opinion in the following sentence refers to a rational sentiment: *This camera is good.* The opinion-word is the adjective *good* and reveals the writer's opinion. It does not convey emotions like happiness, however. (2) *Emotional sentiments*, which are defined in [3] as "entities that go deep into people's psychological states of mind." The opinion in the following sentence refers to an emotional sentiment: *I trust this camera.* The opinion-word is the adjective *trust* and it conveys the emotional state of the writer, directly.

The majority of reviewers, e.g. Facebook users, bloggers, or twitterers, express their emotional opinions using rational words rather than emotions. That draw our interest and encouraged us to help people finding a deeper and more precise evaluation for their decision.

Two directions are used by researchers to detect emotions from text. The first direction is psychological-based; the second is sentiment analysis-based [3]. Our solution follows the second direction since we consider emotions as an effective extent to sentiment analysis for opinion evaluation. We can formulate our research question as "How to express writer's opinion-words (rational sentiments) in terms of emotions?" In order to answer this question we need to fulfil the following issues:

- **Emotion modelling:** There is a large number of emotions in each natural language and that number even increases with time. Several definitions have been given by different researchers to the term emotion, and many models are proposed that differ from one another about the number of emotions each model has (see Section 3.2 for more).
- **Semantic similarity measure:** Opinion-words that need to be extracted can be rational or just emotions. Moreover, rational words could be adjectives, verbs, nouns, or even adverbs. Corpus-based and knowledge-based approaches are the most commonly used similarity measures between words and text in general. We consider the knowledge-based similarity to measure the semantic relations between rational words and the emotions in the ontology (see Section 3.3 for more).

3 Proposed Solution

In this section we describe our solution structure to the problem of mapping rational sentiments into emotions as illustrated in Figure 2.

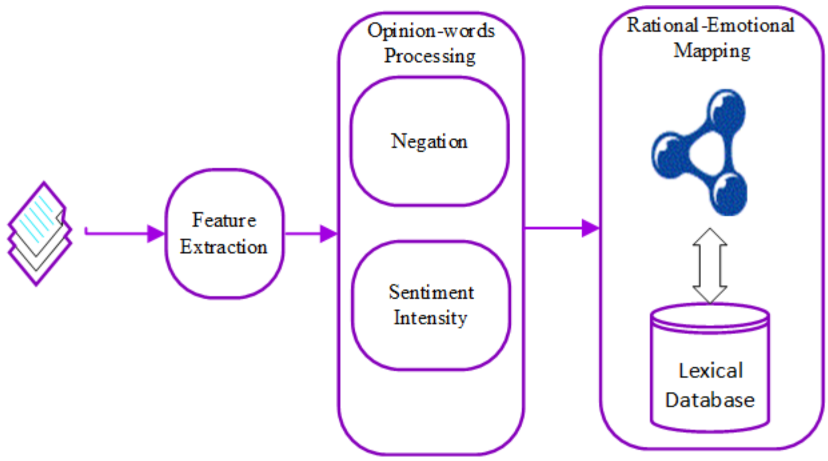

Fig. 2. Emotion detection structure.

3.1 Opinion-words extraction and processing

Feature extraction is divided into two main sub-tasks, opinion target extraction and opinion-word identification [1]. Opinion target in this context is related to an entity, for example, the *camera* or any of its associated aspects such as *lens*, *battery*, *focus*, etc. On the other hand, opinion-words are those words or phrases which are used to express opinions about certain target.

Opinion target extraction is out of the scope of this paper, therefore we will only explain how to extract the sentiment (i.e., the opinion-words). Opinion-words extraction involves several steps of preprocessing tasks, as shown in Figure 3.

1. **Review Segmentation:** Each review in this sub-task is divided into sentences. Sentences are parsed at their simplest grammatical structure in order to avoid writing more complex rules and also with the goal to minimize the number of parsing dependency rules.
2. **Sentence Segmentation:** Sometimes we come across long sentences. Those sentences are further divided into clauses without affecting the syntax of the original sentence. The number of clauses is detected during the parsing sub-task by counting the number of available clauses. Each clause is recognized by its syntactic subject.

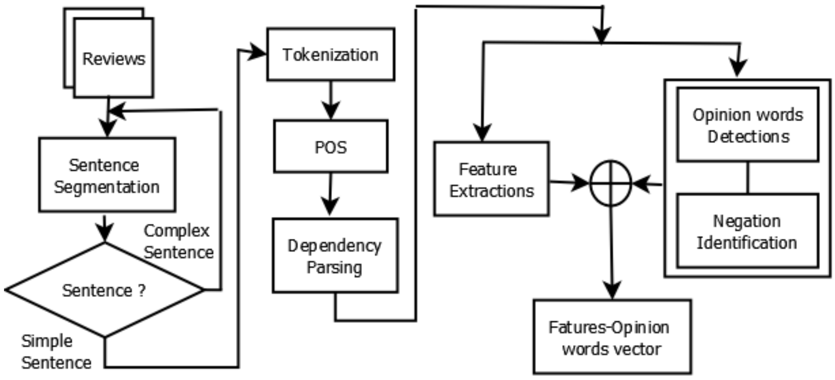

Fig. 3. Opinion-words extraction.

3. **Tokenization:** Tokenization is the sub-task of dividing each sentence into tokens or words. This step is required as pre-requisite step for POS tagging and is also needed for the parser in order to obtain the available dependencies between the tokens.
4. **Part of Speech Tagging (POS):** This sub-task assigns for each token its type (i.e., whether it is a noun, a verb, an adjective, etc.).
5. **Parsing:** This is a method of understanding the exact meaning of a sentence through its grammatical structure. Relations are detected between the different parts of the sentence.

After performing the above Natural Language Processing (NLP) tasks, we can simply extract the required opinion-words in their different parts based on the dependency relations provided by the Stanford parser [5], as it is shown in Table 1. Dependency relations are described as a series of binary relations between words of a given sentence. In the example below, the term "nsubj" represents the type of the relation between the words "long" and "life." The associated numbers indicate the order of the corresponding word in the sentence.

Ex. 1, "The battery life is long"	Ex. 2, "I like these photos"
det(life-3, The-1) compound(life-3, battery-2) nsubj(long-5, life-3) cop(long-5, is-4) root(ROOT-0, long-5)	nsubj(like-2, I-1) root(ROOT-0, like-2) det(photos-4, these-3) dobj(like-2, photos-4)

Table 1. Opinion-words extraction based on dependency parsing relations.

Negation Manipulation Negation is an important aspect in sentiment analysis for reflecting the right emotion in a sentence. For example, in the sentence *The camera is not good*, if the negation word *not* is not considered, then the sentence affective emotions will totally be changed leading to the wrong emotional sentiment detection. There are different forms of negation words that can be detected in any text review, like *not*, *no*, *never*, as well as some affixes like *–n't*, *un–*, etc.

In the action clause, if there is a negation of any form, then we can find out to which part of the sentence the negation is linked to. Then, we can extract the negation target word and add a declaration sign as an indication.

Sentiment Intensity Intensifiers are items that change the intensity degree of a sentiment. Intensities of opinions are considered by analysing the following factors [3]:

- **Sentiment:** The normal sentiment words people always use to show the strength of the opinion about a particular object. For example, *nice* and *fantastic*, and *bad* and *worst* for positive and negative opinions, respectively. These kind of opinion strength will be considered during the similarity calculations since the rational sentiment, i.e. *fantastic*, is closer to the emotion *happiness* than to the sentiment *nice*.
- **Superlative Relations:** Opinions containing superlative words show the maximum strength of emotion towards a particular object. The superlative field is defined in the intensity and negation table (see Table 2) and indicates that the word would be assigned to the most strength emotion in the ontology.
- **Intensifiers:** Intensifiers increase the degree of opinion strength when the intensifier exists. In this case, the intensity and negation table is updated and the intensity of the matching emotion is moved to another emotion one level higher.
- **Diminishers:** Diminishers increase the degree of opinion strength when the diminisher field exists in the intensity and negation table. In this case it is updated and the intensity of the matching emotion is moved to another emotion one level lower.

In the table, **Sentiment** is the extracted opinion indicating word, **Negation** is a boolean value set to 1 if a negation term does exist, **Superlative** is a boolean value set to 1 if the extracted sentiment is in its superlative form, **Intensifier** is a boolean value set to 1 if an intensifier term does exist, and, finally, **Diminisher** is also a boolean value set to 1 if a diminisher term does exist.

Sentiment-word	Negation	Superlative	Intensifier	Diminisher
Sentiment	1/0	1/0	1/0	1/0

Table 2. Sentiment intensity and negation.

3.2 Emotions modelling

The idea behind emotion modelling is to make use of ontologies to provide expressive relations between emotions, for example, emotions intensity representation, emotions inverse, emotions similarities, and more. Moreover, modelling emotions makes it more practical to compute emotional sentiment because it comprises the most common and known emotions. Due to the different nature of each domain, no unique model works for all domains. Therefore, we will utilize the emotional model inspired by a psychologist named Plutchik (see Figure 4. Plutchiks Model of Emotions) [6].

Plutchik defined eight basic emotions *joy*, *trust*, *fear*, *surprise*, *sadness*, *anticipation*, *anger*, and *disgust*. Each basic emotion has an intensity increase as we move to the center of the wheel. Each emotion has an inverse emotion in its opposite side of the wheel. The intensity of the inverse emotion varies in intensity, it increases as we move to the center of the wheel. For example, the basic emotion *joy* has the emotions *serenity* and *ecstasy* as its intensity while the emotion *sadness* is its inverse. We have also the so-called "complex emotions" which are generated by mixing two basic adjacent emotions in the wheel. For example, the complex emotion *love* is a mixture of the two basic emotions *joy* and *trust*. All these emotions and their relations are represented by an ontology.

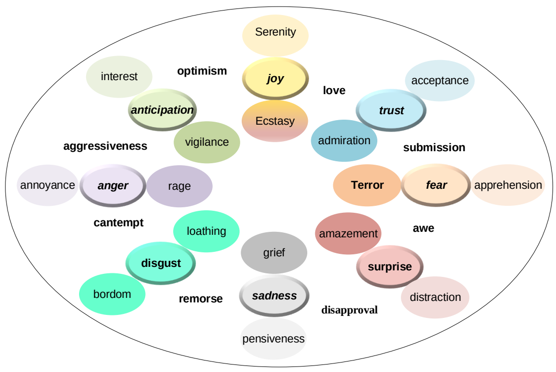

Fig. 4. Plutchik's model of emotions, adapted from [6].

3.3 Measuring semantic similarity

Rational and emotional are two types of sentiment as it was discussed in Section 2. Our aim is to detect rational sentiments which can be adjectives, adverbs, verbs, or nouns and to represent them as emotions based on measuring their semantic similarity with our selected emotions from the emotion model in Figure

4. We are going to explain the process of assigning emotional sentiments to rational sentiment (opinion-words) through an example taken randomly from the training data set provided by the semantic sentiment analysis challenge[3]:

1. **Great Value and Very Convenient**
2. **Batteries died within a year**
3. **Doesn't work properly**

Initially, we generate an emotion vector for each extracted opinion-word. The emotion vector contains the basic eight emotions stated in Section 3.2. We then calculate the correlations between the extracted opinion-word and the emotions in the emotional vector using point-wise mutual information (PMI) and based on the Google search engine. PMI is introduced in [7]. It is used to show to which emotion the given opinion-word would be assigned to. The results of this step is show in Table 3 and are calculated using the following formula:

$$PMI(o-w, e-w) = log\left(\frac{P(o-w, e-w)}{P(o-w)P(e-w)}\right),$$

where $P(o-w)$ is the probability of the opinion-word, $P(e-w)$ is the probability of the emotion, and $P(o-w, e-w)$ is the probability of both opinion-word and the emotion to co-occur.

	joy	trust	fear	surprise	sadness	disgust	anger	anticipation
great	2.600	3.675	3.787	**3.837**	3.611	3.788	3.790	3.739
convenient	3.763	4.239	3.959	4.103	3.702	4.139	3.982	**4.604**
died	4.075	4.193	4.284	4253	4.409	3.818	**4.415**	4.367
properly	3.908	4.465	4.491	4.194	4.014	3.335	4.325	**4.902**

Table 3. Correlations between rational and emotional sentiments.

In sentence number 1 from the above example, we have two opinion-words, *great* and *convenient*. They are initially assigned to the emotions *surprise* and *anticipation*, respectively (see Table 4). The existence of the intensifier *very* increased the intensity of the emotion *anticipation* into the emotion *vigilance*. The rational sentiment *died* in sentence number 2 is assigned to the emotional sentiment *anger*. Likewise, the opinion-word *properly* in sentence number 3 is initially assigned to the emotion *anticipation* but since it is negated, the degree of emotion is inversed according to the Plutchik's model of emotions. It is also validated through the use of an online thesaurus[4].

[3] See `https://groups.google.com/forum/#!topic/semantic-sentiment-analysis/caW6WLtHQig/` for more.

[4] See `http://www.thesaurus.com/browse/anticipation` for more.

Aspect	Opinion-word	Emotional sentiment	Negation	Intensity	Final emotion
value	great	surprise	—	—	surprise
value	convenient	anticipation	—	very	vigilance
batteries	died	anger	—	—	anger
work	properly	anticipation	does not	—	surprise

Table 4. Emotional sentiment generation.

4 Discussion

Correlation computation between rational and emotional sentiments proves our concepts into an acceptable level of accuracy. There is also much to do to enhance the mapping accuracy.

According to the results that are shown in Table 3, the emotions *disgust* and *anger* are very close to the rational sentiment *great*, which is incorrect. Moreover, the rational sentiment *died* should be closer to the emotion *sadness* than to the emotion *anger*.

5 State of the art

In this section we will review related work concerning two issues. The first issue is the emotions modelling and representation; the second issue is measuring similarity between rational and emotional sentiments.

5.1 Emotions modelling and representation

Emotions can be detected from different information sources like speech intonation, gestures, and facial expressions, for instance, but these are not relevant to the goal of sentiment analysis due to the fact that it deals with text only. Moreover, most of the online information sources that exist are in text format [8].

Annotating reviews manually with emotions by human experts is an expensive and time consuming task [9]. Instead, extensive work has been done to detect emotions automatically from text [10,11,12,8,13]. Due the complexity of human languages and the large number of human emotions, theorists have started to find ways to model such emotions [14,6,15]. There is still no agreement about the definition of emotions and the number of emotions contained in each natural language. Moreover, there is no specific model of emotion modelling that fits all application domains [3,16,17,18,19]. Therefore, when having different application domains, one emotional model might be better suited than the other. Based on that, we do not need to be concerned about the theorists' disagreement rather for each domain application we need to select the suitable set of emotions. In order to analyse emotions, we need to decide on how they are going to be organized, represented, and how opinion-words are collected and mapped into emotions [20,21,22,19]. However, most of the work in this context is either manually annotating text with emotions [19], or considering only verbs and nouns as opinion bearing words [22]. Our approach intends to improve the solution to the problem introduced in [19] and to overcome the weaknesses presented in [22].

5.2 Measuring similarity between rational and emotional sentiments

Similarity between concepts or words is initially studied based on a vector space model in which the similarity is obtained according to the lexical matching between words in the query and their match in the documents [23,24]. Such syntactic matching relies mainly on the TF-IDF model from information retrieval with the aim to find words similarity based on word appearance, word frequency, or word co-occurance representation. These conventional methods fail to compute the semantic similarities between terms. For example, the words *hat* and *mat* are lexically similar but their different meaning would not be considered. Moreover, these methods would show no relation between the words *boat* and *ship* although there is an obvious relation between them. A general review about different similarity methods is introduced in [25].

Semantic similarity, introduced first by Hatzivassiloglou and McKeown [26], on the other hand, determines the similarity between words based on their meaning rather than based on a character matching [25]. It is calculated mainly following two approaches [27,28]: (1) corpus-based similarity or information theory, introduced in [28] and which relies on corpora analysis using NLP and semantic models [27]; (2) knowledge-based similarity, also named Edge counting, first introduced in [24,29]. This method relies on knowledge bases such as semantic networks, thesauri, or ontologies [27].

6 Conclusions and future work

The aim of this paper was to present a model for the semantic similarity between rational sentiment words, also named opinion-words (like adjectives, adverbs, verbs, and nouns) and concepts (emotional sentiments) based on the Plutchik's circumplex model [6] for emotions modelling. The degree of similarity is computed based on the degree of correlation between opinion-words and emotional sentiments. The closest emotion is then assigned to a given opinion-word.

Additional dimensions have to be investigated in future work in order to improve the mapping accuracy (semantic similarity) using word senses matching or glosses content mapping, based on suitable lexical databases such as WordNet.

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