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Nomenclature of Opinion Miningand Related Benchmarking Tools

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Abstract: Sentiment analysis or opinion mining is the information retrieval strategy that delivers the vision of the relevant users such as customers about entities such as services or products, individuals such as service providers or sellers, functional issues involved, events and their attributes. As an example service provision or product selling with monitorial or other interests, intended to morph according to target users vision. In other dimension intended users seeks the opinion of the existing users, which is in order to select productive service provider among the multiple providers available. Hence the opinion mining or sentimental analysis is critical factor and challenging.In the era of social web that includes social networks, forums and blogs, the opinion mining in order to notice the public opinion is critical in decision making activities by an individual or an organization. The phenomenal growth in the data quantity of social web, the manually analyzing the opinion is almost impractical. Hence the machine based opinion mining or opinion mining is desired.In this context the automated opinion miningon domains such as social-web become critical research objective that grabbed researcher's attention over a decade. This article addressedthenomenclature of the automated opinion miningand available benchmarking tools.

Keywords: Opinion Mining, Sentiment Analysis, Social Web Data, Machine Learning, Social Media

1 INTRODUCTION

Sentiment analysis or opinion mining is machines analyzing human expressions of sentiment. Human according to various thoughts, actions, or reactions generate feelings of subjective nature such as emotion, mood, combined with visible facial expressions or postures, and communicate using language either in the spoken or written form.

Opinions expressed by others are a matter of interest for everyone be it individuals or companies. Individuals through reviews, blogs, and opinions expressed on social media by other people, buy a product, or follow the popularity of various political parties to cast their vote. This plethora of information comprising of peoples thoughts, likes, dislikes shared among different related and unrelated people determines to a large extent other individuals choices and preferences in liking or buying a product or in supporting representatives of political parties. Companies deeply mine consumer reviews for brand management and for promoting their products [1].

In economics and finance to understand beyond fundamental and technical knowledge analysis, sentiment analysis supporters suggest additionally it is essential to use information as diverse as, impending announcements, sudden surge in commodity prices, rumors and reports of a market collapse or break through, increase in the interest rates by central banks, fluctuations in dollar prices, etc. as these factors help in better estimating and forecasting situations of changes in market. In Fig 1 the process flow of opinion mining and sentiment analysis is shown.

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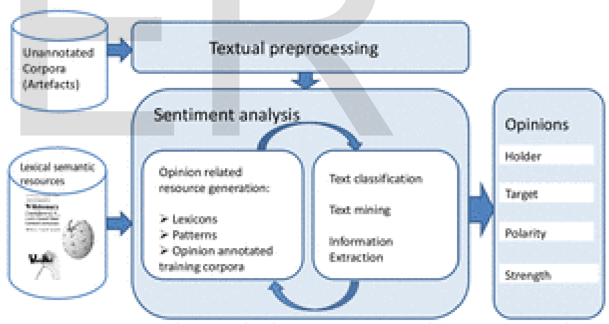

Figure 1: The architecture of Sentiment Analysis or Opinion Mining (source: https://www.ukp.tu-darmstadt.de/fileadmin/_migrated/RTE/RTEmagicC_SENTAL architecture.png.png)

A key part of the communication process is expressing or signifying the event with descriptions of emotion, mood, and sentiment. An affect is expressed with text and speech combined with fitting descriptions and this language specific knowledge is crucial for sentiment analysis. In the book "Understanding figurative language" by Sam Glucksberg [2] the metaphors "my spouse's lawyer is a shark and my job is my jail" characteristically expresses an effect that is suggestively different besides the outward.

The descriptions [3] for expressing an effect, are generally used in everyday language, are popular in the field of fiction content, extend generally to scientific languages [4] are more predominant in natural [5] and biological sciences [6] and to a certain extent used also in the domains of finance and economics.

A sentiment analysis systems objective or purpose is to detect and tabulate an author/speaker opinion, or find how discerning the author/speaker is in giving value how much or how little to an object, event, state, or abstract idea. To handle the notions of quantitative semantics spatial relationships are applied using cognitive capabilities of the computer emulating the human mind [7]. The objective of performing sentiment analysis finally is detecting if any reader/listener might have an instinctive emotional response for a speaker/author and to tabulate the responses for further analysis.

2 NOMENCLATURE OF THE OPINION MINING

Opinion mining nomenclature is explored under Opinion Mining in this section. This will cover, nomenclature definition, describe the various forms of opinion mining, explore the perspective and scope of opinion mining, and finally review of the existing benchmark tools of opinion mining.

2.1 Types and Definitions of Opinions/sentiment

There are a minimum two types of Sentiment stated in text:

- Opinions expressed by the subject such as like/dislike/mixed/don't-know… believe/disbelieve/unsure… want/don't-want/sometimes-want…..
- Feelings/Emotions expressed by the subject such as ha ppy/sad/angry………calm/energetic/ patient/relaxed……….

A definition of notions is not easy because of interlinked concepts that impact and/or support each other. In the psychology field Emotion/Affect researchers have authored several books on this subject (see Affective Computing in Wikipedia).

Opinion is defined in the Merriam-Webster dictionary as "a view, judgment, or appraisal formed in the mind about a particular matter", or "a belief stronger than an impression and less strong than positive knowledge". So opinions can be categorized into two types:

- ➢ Judgment opinions: good, bad, desirable, disgusting…: "It is a terrible film"
- ➢ Belief opinions: true, false, possible, likely…: "The weather tomorrow would be great".
  The internal structure of the judgment and belief opinions is similar and it can be defined as a quadruple: (Topic, Holder, Claim, Valence)
- Topic = theme/topic highlighted
- Holder = person or group that makes or holds an opinion
- Claim = statement regarding a topic
- Valence (judgment opinions):
  - Positive or Negative or Mixed or
  - Neutral: "one way or the other I don't care about him" or
  - Unstated: "They had strong feelings about his political career"
- Valence (belief opinions):
  - Believed or Disbelieved or Unsure or
  - Neutral: " one way or the other I am will end this matter here" or
  - Unstated: "maybe he convinced others, I don't know"

Armed with this knowledge, one can define opinions and its types as follows:

- ➢ *An opinion/sentiment is expressed by a person (the Holder), is a decision made related to a topic (the Topic). The decision is used to assign the Topic to a small set of classes (the Valences) and this impact on the topic will in the future shape the Holder's future objectives and his planning (discussed below).*
- ➢ *Judgment opinions convey if the Holder will follow objectives in owning/controlling/obtaining the Topic.*
- ➢ *Belief opinions express if or not the Holder in future communication and reasoning would maintain the Topic is true/certain/etc.*

Here the structure may be extended with the addition of more components:

- Strength of opinion/sentiment
  - It is really tough to normalize across Holders
- Facet(s) of topic
  - It can be beneficial to distinguish sub-facets of a Topic. E.g. not "the camera" but "the weight of the camera". That is basically a narrower Topic.
- Conditions on opinion/sentiment
  - It is possible to add conditions however it will increase the complexity: "I like it only when X"/"If X then I like it".
- Reasoning/warrant for opinion/sentiment
  - "The reason I like it is X". Is important similar to the argument below, although it leads to problems of reasoning and argument structure.

2.2 Identification of Sentiment/Opinion

The expression of judgment and belief opinions in text form with the existing simple computation of word lists is ineffective, so units of various sizes are used for expressing opinions:

- Word level: individual words are opinion clues
  - Yes: "hate", "disgusting", "anger"

- No opinion: "run", "announce", "tall"
- Sentence level: compositions of words
  - Yes: "Actions with negative consequences include the US attack on Iraq."
  - No opinion: "To receive a copy of our catalogue, send mail."
- Text level (implicating): opinions are acquired using rhetorical relations
  - "Not only did he drink excessively, he messed up with the food also"
  - "Sure he drank excessively. However he did not clean the room!"

2.3 Process Flow of the Opinion mining

The enterprise of opinion mining combines AI (artificial intelligence), NLP (natural language processing), computational linguistics and content analysis linked to word-sense disambiguation and information extraction [8]. The linguistic resources such as thesaurus, text corpora, and dictionaries or lexical resources such as Wordnet may be used in the analysis process. In opinion mining first as a preprocessing phase the documents corpus in different types of formats such as, word, pdf, pp, html, xml, etc. is converted to the text file format. A pre-processing of the texts reduces the complexity, redundancy, and noise in the data using linguistic tools such as, Tokenizer, Stemmer, POS tagger, entity extractor, and relation extractors.

The pre-processed documents are annotated with sentiment annotations using a opinion mining systems main module of document analysis and with the help of linguistic resources. In opinion mining and opinion mining feature extraction performed is a most basic phase of opinion mining.

The annotations are attached in different ways such as, an entire document is annotated for opinion mining at document level, sentences specifically are annotated for opinion mining at sentence level, or only definite aspects of entities are annotated for opinion mining based on aspects. The annotations generated by the opinion mining system may be represented with different data visualization software.

2.4 Opinion mining Perspective and Scope

2.4.1 The Scope

Opinion mining offers great benefit to companies and political parties respectively in their campaign management and in product promotion and management.

The opinions expressed in news sites, various articles, blogs, and tweets are mined by different interested organizations to able to better manage their portfolio. An important address for reviews by users of different products and services is the "Google Product Search". Another important area for several applications for opinion mining and/or brand management is Twitter and/or Facebook.

Several businesses, products, and services, are a subject of intense reviews in various forums, in social media and by third party web services that test and review the products in different aspects. Political parties use opinion mining systems to analyze voter's opinions of the parties' speeches, actions, and various other issues and use the results to find ways of improving the parties and candidates image and outlook. In financial markets opinion mining systems aggregate sentiment from different sources such as news sites, various articles, blogs, and tweets that discuss different public limited companies performances and give scores that is again used by automated trading systems.

2.4.2 The Perspective

This section focuses on the perspective and scope of opinion mining that are as follows,

- Document-level opinion mining;
- Sentence-level opinion mining;
- Aspect-based opinion mining;
- Comparative opinion mining; and,
- Sentiment lexicon acquisition.

2.4.2.1 Document-Level Opinion mining

Document-Level Opinion mining is a widely researched and most simple approach based on an expectation that the considered document holds an opinion of a major topic by its author that is either positive or negative.

There are two types of methods followed for performing opinion mining at the document level based on learning with supervised and unsupervised techniques. The approach supervised learning considers availability of training data for every class with the presumption of finding classes of finite number to classify the document set where a simple scenario would be two classes of positive and negative data. The unsupervised approach performs opinion mining by finding for specific phrases of a document its semantic orientation (SO). These phrases are classified as positive or negative considering the average SO of the phrases is either higher or lower than a predetermined threshold value. The phrases are selected by applying, a predefined set of POS patterns [9], or the lexical data of the sentiment words and phrases [10].

In languages other than English like Chinese and Spanish the opinion mining at document-level has been studied by few researchers [11] only, due to the nonexistence of linguistic resources that are otherwise plenty in English. Their work carry out opinion mining by first translating the documents into English using machine translation, and then an English language sentiment analyzer is used to perform on the translated documents opinion mining.

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2.4.2.2 *Sentence-Level Opinion mining*

A sentence level opinion mining is applied for a refined or fine-grained interpretation of the multiple opinions communicated in a single document where related to the same entity sometimes different opinions are also stated. The approach assumes on a prior basis knowledge of the entity held by a sentence that is the subject of expressing the opinions. Also in every sentence a single opinion is assumed to exist and if otherwise the sentence is divided into phrases considering only one opinion held by each phrase. A predetermination of the subjective or objective nature of the sentences is necessary prior to the analysis of the sentences to determine their polarity. An analysis of subjective sentences only is performed however a few methods have been devised for the very challenging task of analyzing objective sentences also. In the classification of the sentences into two different classes supervised learning based techniques [12] are usually followed.

2.4.2.3 *Aspect-Based Opinion mining*

In the complete document or in every single sentence many times people talk of entities having multiple aspects (attributes) where different opinion may be expressed about every aspect. E.g. In discussion forums of specific products like smartphones, cameras, cars, computers, televisions, the reviews consist of multiple entities and multiple aspects. The detection in a particular document of all sentiment expressions and their associated aspects is known as aspect-based opinion mining or feature-based opinion mining. If the whole document or each individual sentence refers to a single entity the document and sentence level approaches work well.

A method popularly applied in several business applications to determine all the product aspects is the traditional method of finding all the noun phrases (NPs) from a review corpus, where the NPs are selected with a frequency higher than a threshold value [13].

2.4.2.4 *Comparative Opinion mining*

A comparable opinion is an opinion expressed of an entity in comparison to another similar entity and is different from a direct opinion expressed. For instance the reviews in the forum Edmonds.com we find typical user sentences such as, "300 C touring looks so much better than the Magnum," or "I drove the Honda Civic, it does not handle better than the TSX, not even close." A system performing a comparative opinion mining finds sentences holding comparable opinions and extracts for every opinion the desired entity/entities.

2.4.2.5 *Sentiment Lexicon Acquisition*

In opinion mining the critical resource for maximum number of algorithms is the sentiment lexicon. A sentiment lexicon is developed with methods such as, manual methods, dictionary-based methods, and corpus based methods.

In the manual method the lexicon is built by coding manually and involves creation of domain specific lexicons that is labor-intensive and so is infeasible practically. In the method of using a dictionary to buid the lexicon, initially a few domain specific sentiment seed words are acquired and extended using synonyms and antonyms from resources such as WordNet [14]. However the lexicon developed being independent of the domain lacks the uniqueness specific to a domain. In the method of using a single domain related large documents corpus for building the lexicon, an initial set of seed words is expanded to build a sentiment lexicon particularly of a domain to find sentiment consistency and further discover a seed set of adjectives having consistent polarity.

3 BENCHMARKING TOOLS OF SENTIMENT ANALYSIS

The different benchmark methods of sentiment analysis and validation techniques are discussed briefly in this section. These approaches are the polarity assignment scheme using Natural Language Processing (NLP), tools applied for creating labeled datasets such as Amazon's Mechanical Turk (AMT), the techniques applied to determine sentiments based on the moods such as psychometric scales, the methods of machine learning applied to classify sentiments such as the supervised and unsupervised approaches, etc. The techniques used to validate these approaches are similarly of different types, such as, using toy examples, applying huge labeled data sets, etc.

3.1 Emoticons

The emoticons held by a message can be easily used to find its polarity such as, a positive or a negative effect. The emoticons based on facial expressions depicting happy or sad feelings are most widely used, however several non-facial forms are also used like the emoticon <3 that denotes a heart and expresses affection or love. The popularity of emoticons has risen so much that a few emoticons like <3 have now found place in the English Oxford Dictionary [15].

A common emoticon set [16] [17] [18] is used to extract polarity where this set also consists of the widely held variants expressing the basic polarities of positive, negative, and neutral effects. The messages having two or more emoticons though few in number, the first emoticon is used as the message polarity.

In general the number of OSN messages with a presence of one or more emoticons is less contrasting the number of messages that might actually have expressed emotions. According to a recent research [19] the emoticons rate of occurrence is found to be below 10%. This problem is overcome with the integration of emoticons with other techniques to create training data that can be applied with methods of supervised learning [20].

3.2 LIWC
The emotional, cognitive, and structural constituents of a text data may be assessed by utilizing external knowledge of different words and their various categories available in a dictionary. Text analysis software like LIWC (Linguistic Inquiry and Word Count) [21] gives options of including customized dictionaries for optimal results in place of a standard dictionary, and is able to identify effects of sentiment categories other than the positive and negative effects. E.g. A word "agree" in a text set is associated using LIWC software with different word categories like, assent, affective, positive emotion, positive feeling, and cognitive process.

3.3 SentiStrength
To strengthen sentiments dictionary based words are used and expanded to improve the classification results. To expand the baseline words new features are added such as, a list of negative and positive words, a list of booster words, a list of emoticons, and application of repeated punctuation.

Applications that are content-driven and models for detecting adaptive polarity derive best results when applied with approaches of machine learning. In the research for polarity detection in OSN data many important classifiers have been devised [22] [23] [24]. In [24] an expansive comparison of all the different types of classification methods of supervised and unsupervised learning are provided such as, simple logistic regression, support vector machine, J48 classification tree, JRIP rule-based classifier, support vector machine regression, AdaBoost, Decision Table, Multilayer Perception, and Naive Bayes.

These works have core process of classification dependent on a LIWC dictionary based set of derived base words [21] that in an OSN setting to strengthen the sentiments undergoes expansion with addition of new features such as, list of negative and positive words, a list of emoticons, list of booster words for sentiments strengthening (e.g., "very") or weakening (e.g., "somewhat"), and application of repeated punctuation (e.g., "Cool!!!!"). In the assessment of these classifiers performances, 6 different sources of Web 2.0 are used to obtain labeled text messages where the sources are of varied types such as, YouTube Comments Runners, Twitter, World Forum, MySpace, Digg, and BBC Forum.

3.4 SentiWordNet
An extensively applied opinion mining tool SentiWordNet [25] is based on the WordNet [26] dictionary This WordNet dictionary is an English language based lexicon that categorizes, nouns, adjectives, verbs and remaining grammar classes as synonym sets known as synsets.

These synset uses the SentiWordNet tool and with the WordNet dictionary assign 3 scores to the sentiments of positive, negative, and objective (neutral). The values of the scores are in the range of 0 to 1 and adding up to 1, are acquired by applying methods of machine learning based on semi-supervised approach. E.g., If a tweet derived synset s = [bad, wicked, terrible], then SentiWordNet will associate to the positive sentiments a score of 0.0, negative sentiments with a score of 0.850, and objective sentiments with a score of 0.150. The authors assessed the SentiWordNet tool using a lexically labeled dictionary.

3.5 SenticNet
An opinion mining and sentiment analysis method SenticNet [27] aims to detect polarity of the concepts of common sense near a semantic level instead of the syntactic level of the natural language text. The approach SenticNet uses methods of AI (artificial intelligence), and techniques of Semantic Web. It applies NLP (Natural Language Processing) scheme to create a polarity of almost 14,000 concepts. E.g., the message "Boring, it's Monday morning", is interpreted by SenticNet first with detection of the concepts of "boring" and "Monday morning" for this message. Next a polarity score is given for every concept by SenticNet, that is the concept "boring" is given a score of -0.383, and the concept "Monday morning" is given a score +0.228, and average of these values gives the resulting sentiment score of -0.077.

The evaluation of SenticNet tool is done by assessing its performance in measuring the polarity levels in opinions of patients availing England's National Health Service [28], and with the LiveJournal blogs data. The authors label the posts of LiveJournal blogs with more than 130 different moods that are categorized as positive or negative [20] [29] classes.

3.5.1 SASA
The tool SASA (SailAil Sentiment Analyzer) [30] is based on machine learning methods such as SentiStrengh. The open source tool has been assessed for the labeling of 17,000 tweets gathered during the U.S. general elections in 2012 with labeling done using Amazon Mechanical Turk (AMT) [31] as four types such as, positive, negative, neutral, or undefined effects.

3.6 Happiness Index
The sentiment scale called Happiness Index [32] is based on adapting the widely used terms data ANEW (Affective Norms for English Words) [33]. The terms data ANEW is a group of regularly used words of total 1,034 words having affective ratings linked with respect to dimensions such as, valence, arousal, and domination. The frequency for every ANEW term occurring in a text is first computed and then for these ANEW study words the valence's weighted average is then determined. Next a Happiness Index is built by assigning to

the texts a score between 1 and 9 that denotes for a text its quantity of happiness.

For validating the scores of Happiness Index three different datasets, song lyrics, songs titles, and blogs sentences are used. In the tests the happiness scores in a time frame between 1961 to 2007 shows it has increased in case of blog posts whereas in the same time period in case of song lyrics it has decreased.

3.7 PANAS-t

A psychometric scale PANAS-t [34] is a variant of the popular psychology technique PANAS (Positive Affect Negative Affect Scale) [35] and is devised for finding the occurrences of sentiments having increased or decreased in a time frame. This PANAS-t method is tested for identifying on Twitter user mood fluctuations, where a huge word set is used that is linked to 11 moods namely, serenity, joviality, surprise, assurance, attentiveness, shyness, fatigue, fear, sadness, guilt, and hostility.

3.8 POMS

The POMS method is similar to PANAS-t and is a modification of the technique POMS (Profile of Mood States) [36] rating scale based on psychology for specific mood states measurement related to 65 adjectives. These adjectives consider feeling such as, vigor, tension, anger, fatigue, confusion, and depression to measure the different mood states.

4 CONCLUSION

This manuscriptaddressedthenomenclature of opinion mining and available benchmarking opinion mining tool. The complexity of data presentation and dimensionality, diversified usage requirements, the sentiment analysis or opinion mining emerged as critical research objective since a decade. This manuscript explored the nomenclature ofopinion mining andtools.Finally, we conclude the manuscript by saying that the sentiment analysis tasks are very challenging, since understanding and knowledge of the problem and its solutions are still limited. The main reason is that it is a natural language processing task, and natural language processing has no easy problems. However, many significant progresses have been made. Finally it is obvious to conclude that the sentiment analysis is having potential scope for future research and one of that is exposing the scope of evolutionary computationalor soft computing techniques and the hybridizing these techniques towards feature extraction, selection to classify the sentiment.

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