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Abstract: Sentiment analysis is the procedure by which information is extracted from the opinions, appraisals and emotions of people in regards to entities, events and their attributes. In decision making, the opinions of others have a significant effect on customers ease in making choices regards to online shopping, choosing events, products, entities. In this paper, a rule based domain independent sentiment analysis method is proposed. The proposed method classifies subjective and objective sentences from reviews and blog comments. The semantic score of subjective sentences is extracted from SentiWordNet to calculate their polarity as positive, negative or neutral based on the contextual sentence structure. The results show the effectiveness of the proposed method and it outperforms the machine learning methods. The proposed method achieves an accuracy of 87% at the feedback level and 83% at the sentence level for comments.

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1. Introduction

Sentiment analysis allows for a better understanding of customers' feelings regarding various companies or organizations, their products and services or the way they handle customer services, as well as the behavior of their individual agents. Information and communication technology (ICT) have made radical changes to various fields such as business, commerce, economy and banking (Ghods M et al., 2014). Information retrieved through sentiment analysis is quite useful for an organization or company to evaluate its customer relationship management, customer intelligence, market planning strategy, employees training, products and services, resources management and problem resolution related to the above mentioned issues. Hence, sentiment analysis technique is desirable for developing efficient and effective analyses and classification of customer reviews, blogs and comments into positive, negative or neutral opinion. It can be used to help in customer relationship management, employees training, identifying and resolving difficult problems as they appear (M.Z. Asghar et al. 2014)(B. pang and L. Lee, 2008). Sentiment Analysis or Opinion Mining is a challenging Text Mining and Natural Language Processing problem for automatic extraction, classification and summarization of sentiments and emotions expressed in online text (B. Pang et al., 2002)(M. Hu and B. Liu, 2004)(M.Z. Asghar et al., 2013). There are two main inspirations for this paper, a desire for high performance domain independent sentiment classification method and the exigent theoretical questions in text mining and Natural Language Processing (NLP), where exploration of limitations regarding specific approaches and the linkage between them. It needs a computational study for extracting useful knowledge from the peoples' opinions and emotions. Sentiment analysis allows for a better understanding of customers' feelings regarding various companies/organizations, their products and services or the way they handle customer services, as well as the behavior of their individual agents communities (A. Khan et al.,2011) (A. Khan et al.,2011).

Retrieval of documents relevant to the information needs of a user, is the primary concern of the traditional IR (perhaps a more appropriate name would be data retrieval); however, the user is left on his/her own to find the desired information in the documents (Hearst, 1999). In his opinion, data mining is not only concerned with the information, but it also attempts to uncover or glean previously unknown information from the data (text). Three main steps are always involved in the process of text mining and sentiment classification; they are (a) acquiring texts which are relevant to the area of concern usually called IR; (b) presenting contents collected from these texts in a format that can be processed, such as statistical modelling, natural language processing, etc.; and (c) actually using the information in the presented format, (Falinouss,2007) (Sharp,2001) (A. Khan, Baharuddin, Lee, K. Khan, 2010) (A. Khan, Baharudin, and K. Khan, 2011).

In this work, we proposed a domain independent rule based method for semantically classifying sentiment from online customer reviews and comments. The method is effective as it takes reviews, checks individual sentences and decides its semantic orientation considering the sentence structure and contextual dependency of each word.

The rest of the paper is organized as follows: Section-II presents the related research of the proposed work. Section-III describes the proposed method with all steps. Section-IV highlights the results and finally Section-V concludes the proposed method.

2. Background and related work

The early work of sentiment analysis began with subjectivity detection, dating back to the late 1990's. Later, it shifted its focus towards the interpretation of metaphors, point of views, narrations, affects, evidentiality in text and other related areas. Shown below is the literature describing the early works of subjectivity and detection of sentiments in the text. With the increase in internet usage, the Web became a importance source of text repositories. Consequently, a switch was slowly made away from the use of subjectivity analysis and towards the use of sentiment analysis of the Web content. Sentiment analysis has now become the dominant approach used for extracting sentiment and appraisals from online sources. Separating non-opinionated, neutral and objective sentences and texts from subjective sentences carrying heavy sentiments is a very difficult job; however, it has been explored earnestly in a closely related yet separate field, (Wiebe,1994). It concentrates on making a distinction between 'subjective' and 'objective' words and texts; on one hand, the subjective ones give evaluations and opinions and on the other, the objective ones are used to present information which is factual, (Wiebe, Wilson, Bruce, Bell, Martin,2004) (Wiebe , Riloff,2005). This is different than sentiment analysis in regards to the set of categories into which language units are classified by each of these two analyses. Subjectivity analysis focuses on dividing language units into two categories: objective and subjective, whereas sentiment analysis attempts to divide the language units into three categories; negative, positive and neutral. The area of concentration in some of the early works was with subjectivity detection only (Wiebe,2000). With the passage of time and a need for better understanding and extraction, momentum slowly increased towards sentiment classification and semantic orientation.

Like other developing fields (M. Z. Asghar et al., 2009) of research today, sentiment analysis terminology is yet to be matured; moreover, just attempting to define a sentiment can be difficult to accomplish (Pang and Lee, 2008). The words sentiment (B. Pang et al., 2002)(Kim and Hovy, 2004), polarity (Weibe,2000)(Weibe,1990)(Esuli and Sebastiani,2006) opinion (Kim and Hovy,2005)(Bethard, Yu, Thornton, 2004), semantic orientation (Weibe,2000)(Turney,2002), attitude (Argamon, Bloom, Esuli, and Sebastiani,2009) and valence (Polanyi and Zaenen,2006) are used to represent similar if not the same ideas. These words are, more often than not, used either to make reference to various aspects of one particular phenomenon, an example being (Hariharan, Srimathi, Sivasubramanian and Pavithra, 2010)(Kim and Hovy, 2004) where sentiment is defined as an affective part of opinion, or simply used as synonyms for each other without any true definition of their own. Furthermore, some of these words can be confusing because of their multiple meanings already in linguistic tradition (e.g. polarity, valence) and therefore are confusing (Leung and Chan, 2008) (Andreevskaia and Bergler, 2006).

In sentence level sentiment analysis, the text document or reviews are split into sentences and each sentence is checked for its semantic orientation by using lexical or statistical techniques. Sentence level analysis decides what the primary or comprehensive semantic orientation of a sentence is while the primary or comprehensive semantic orientation of the entire document is, handled by the document level analysis (B. pang and L. Lee, 2008) (M. Hu and B. Liu, 2004). In addition to sufficient work being performed in text analytics, feature extraction in sentiment analysis is now becoming an active area of research. A review paper presented by (M.Z. Asghar et al., 2014) discusses existing techniques and approaches for feature extraction in sentiment analysis and opinion mining. In this review, the main focus is on state-of-art paradigms used for feature extraction in sentiment analysis. Further evaluation of existing techniques is done and challenges to be solved in this area are addressed. Many approaches have been adopted for performing sentiment analysis on social media sites. Knowledge based approaches classify the sentiments through dictionaries defining the sentiment polarity of words and linguistic patterns (M. Z. Asghar et al., 2013). A rule based subjectivity classifier, capable of mining user tweets shared on twitter during some key political event, was designed to isolate subjective and objective sentences (M. Z. Asghar et al., 2014). The framework for subjectivity and objectivity classification is compatible with both annotated and un-annotated dataset.

In this work a technique for domain independent sentence level classification of sentiment is introduced (A. Khan et al., 2011). Rules for all parts of speech are applied so that they can be scored on the strength of their semantics, contextual valence shifter, and sentence structure or expression on the basis of dynamic pattern matching. Moreover, word sense disambiguation to extract accurate sense of the sentence has also been addressed. Opinion type, confidence level, strength and reasons are all can be identified using this system. SentiWordNet and WordNet are utilized as the primary knowledge base which has the further capability of being strengthened by using modifiers, information in the contextual valence shifter and all parts of speech.

3. Materials and methods

3.1. Lexical based semantic orientation

In this section, the proposed sentence level sentiment classification method is described in detail. In the first step, sentences are split into subjective and objective ones based on lexical dictionary. Subjective sentences are further processed to classify as positive, negative or neutral opinions. A rule based lexicon method is used for the classification of subjective and objective sentences. From subjective sentences, the opinion expressions are extracted and their semantic scores are checked using the SentiWordNet directory. The final weight of each individual sentence is calculated after considering the whole sentence structure, contextual information and word sense disambiguation. The steps below describe the overall process of the sentiment analysis of the proposed method.

- Split reviews into sentences and make a Bag of Sentences (BoS).
- Remove noise form sentences using spelling correction, convert special characters and symbols (photonics) to their text expression. Use POS for tagging each word of the sentence and store the position of each word in the sentence.
- Make a comprehensive dictionary (feature vector) of the important feature with its position in the sentence.
- Classify the sentences into objective and subjective sentences using lexical approach.
- Using a lexical dictionary as a knowledge base, check the polarity of the subjective sentence as positive, negative or neutral.
- Check and update polarity using the sentence structure and contextual feature of each term in the sentence.

SentiWordNet is one of the sources of sentiment analyses. It is a semi-automatic way of providing word/term level information on sentiment polarity by utilizing WordNet database of English terms and relations. Each term in WordNet database is assigned a score of 0 to 1 in SentiWordNet which indicates its polarity. Strong partiality information terms are assigned with higher scores whereas less bias/subjective terms carry low scores. SentiWordNet is made up of a semi-supervised method which refers to a subset of seed terms to obtain semantic polarity. Each set of synonymous terms is assigned with three numerical scores ranging from 0 to 1 which indicates its objectiveness i.e. positive and negative bias (Ohana, 2009). One of the key features of SentiWordNet is that it assigns both positive and negative scores for a given term according to the following rule (Esuli and Sebastiani, 2006): For a synset it is defined as:

- *Pos(s)* $\rightarrow$ *Positive score of synsets.*
- *Neg(s)* $\rightarrow$ *Negative score of synsets.*
- *Obj(s)* $\rightarrow$ *Objective score of synsets.*

Then the following scoring rule applies:

$$\mathrm{Pos}(s) + \mathrm{Neg}(s) + \mathrm{Obj}(s) = 1;$$

The positive and negative scores are always given, and objectiveness can be implied by the relation:

$$\mathrm{Obj}(s) = 1 - (\mathrm{Pos}(s) + \mathrm{Neg}(s))$$

Polarity scores according to synset and relevant part of speech are grouped by SentiWordNet database as a text file. The table below describes the columns for one entry in the database reflecting opinion information of a synset. Table-1 shows the details.

Table 1. SentiWordNet database record structure

Fields	Descriptions
POS	Part of Speech linked with synset. This can take four possible values: i. a= adjective= jj ii. n=noun=nn iii. v=verb=vb iv. r=adverb=rb
Offset	Numerical ID which is associated with part of speech uniquely identifies a synst in the database
Positive score	Positive score for this synset. This is a numerical values ranging from 0-1.
Negative Score	Negative score for this synset. This is a numerical values ranging from 0-1.
Synset Term	List of all terms included in this synset

To illustrate how opinion information appears in SentiWordNet, the Table 2 presents sample rows extracted from the raw database file.

Table 2. Sample SentiWordNet Data

POS	Offset	PosScore	NegScore	SynsetTerms

A	10073761	0.125	0.625	Strained#3, forced#4 **constrained#1**
N	10036762	0.375	0.125	**Feat#1,** exploit#1, effort#3
V	311113	0.25	0.25	**Slur#4,** dim#5, blur#6
R	139759	0.125	0.125	**Unsuitably#1,** inappropriately#1

According to Esuli and Sebastiani (2006), using adjectives or adverbs (modifiers) are more common in expressing subjective opinion than verbs and nouns, which are more frequently used in objective scenarios. One more observation about adverbs is that although they own substantial polarity weight (only 32.97% of terms contain no subjective bias) yet their average score is significantly positive.

A relevant tag is assigned to each term, such as verb, noun, adjective etc, which specifies its role in the sentence. Although a number of standards exist for tagging formats yet the most popular are Penn Treebank annotated corpus (Marcus, Marcinkiewicz and Santorini, 1993) (Table 3) and the various instances of the CLAWS tag sets, derived from the original tag set for the brown corpus (Garside, Leech, and Sampson, 1988).

Table 3. Penn Treebank Tags for Parts of Speech in SentiWordNet

Part of Speech	Penn Treebank Tags
Adjective	JJ, JJR (Comparative), JJS (Superlative)
Noun	VB, VBD (Past tense), VBP (Present tense), VBZ (Present tense 3rd person), VBG (Gerund), VBN (Past participle).
Verb	RB, RBR (Comparative), RBS (Superlative)
Adverb	NN, NNP (Proper noun), NNPS (Proper noun, plural), NNS (Plural)

Contextual pattern information is done on the information which has been tagged so that it can be used with SentiWordNet database. Development of an application for the process of correctly reading and matching the tagged documents terms and their part of speech tags to a SentiWordNet score is needed.

3.2. Word Sense Disambiguation

WSD is an important step in semantic orientation to extract the correct sense of a term or expression in a sentence. Sentiment analysis, in most cases, relies on lexicons of words that may be used to express prejudice or subjectivity. The limitation of the subjectivity lexicon dependent WSD techniques is that they do not address the peculiarity of different senses of a word in a way that its true sense is not categorized. Moreover, subjective lexicons are not accumulated as word meanings; rather they are compiled as lists of keywords. In most cases, these keywords have both opinionated and factual senses. Depending upon the contextual appearance, some degree of positive or negative polarity can be experienced even with the purely subjective sense.

The contribution of this work is to check the WSD using unsupervised approach using the existing public resources (A. Khan, Baharudin, and K. Khan, 2011). The proposed method extracts the semantic pattern of the desired sentence using the opinion expression position in the sentence. Then, all possible patterns for that opinion expression for all possible senses are extracted based on the WordNet glossaries; the system locates an exact pattern match of the desired sentence and extracts the sense number from the WordNet synset. The semantic score for that sense number is extracted from SentiWordNet, which gives efficient results. If patterns are not exactly matched, then it checks for the nearest pattern and the score of that nearest pattern is extracted from SentiWordNet.

In the example given below (Table 4) four meanings can possibly be referred to the adjective "mad". The question here is as to what meaning this word is referring in a particular sentence and what particular score, positive or negative, should be assigned to it in SentiWordNet. Determining which synset needs to be applied on a specific context is analogous to the problem of WSD.

Table 4. Synsets along with their positive, negative scores and glosses

Synset	SentiWordNet Score		Gloss
	Pos	Neg	
Huffy, **mad**, sore (roused to anger)	0.0	0.125	"she gets mad when you wake her up so early": "mad at his friend": "sore over a remark"
Brainsick, crazy, demented, disturbed, **mad**, sick, unbalanced, unhinged (affected with madness or insanity)	0.0	0.5	"a man who had gone mad"
Delirious, excited, frantic, **mad**, unrestrained(marked by uncontrolled excitement or emotion)	0.375	0.125	"a crowd of delirious baseball fans": "something frantic in their gaiety":" a mad whirl of pleasure"
Harebrained, insane, **mad** (very foolish)	0.0	0.25	"harebrained ideas": "took insane risks behind the wheel": "a completely mad scheme to build a bridge between two mountains"

4. Experiments and results

For evaluation of our proposed method, 1000 comments are collected from the twitter datasets publically available for research purposes (Shamma, Kennedy and Churchill, 2009) and 500 blog comments are collected from cricinfo[1]. Table 5 shows twitter dataset and blog comment dataset information. The datasets are processed to remove noise, clean up the special characters and symbols, and check for spelling mistakes; furthermore, we apply the POS tagger and classify the sentences into subjective and objective. The twitter comments have already been processed for positive and negative sentiments mainly for testing purpose. Also the blog comments are processed as positive and negative and the subjective sentences are consider for further processing to find the semantic orientation at the individual sentence level.

Table 5. Sum of Opinion Sentences

Datasets	Comm	Sen	Subj	Obj	%
Twitter	1000	2045	1636	409	80/20
Cricket World Cup 2011	500	1630	1238	392	76/24

[Comm: comments, sen: sentences, subj: subjective, obj: objective, %: percent]

The subjective sentences are processed for semantic orientation by taking the contextual features and using the SentiWordNet for the semantic score. 250 sentences and 75 feedbacks have been taken and are manually evaluated for positive and negative opinions, from twitter and cricinfo respectively. These sentences and feedbacks are then evaluated to test the performance of the proposed method using Accuracy (Precision), Recall and F1 measures as shown in Table-6. It is clear from the results that average accuracy is 83% at sentence level and 87% at feedback level is achieved. Hence it can be concluded that our lexical based method's performance is better and is adoptive with different domains datasets.

Table 6. Accuracy of Opinion Orientation for Positive and Negative Sentiments for Twitter Comments

			Actual orientation				
			Total	+ve	-ve	Acc	Re
Sen	System assigned	+ve	250	212	38	0.848	0.819
		-ve	250	47	203	0.812	0.842
Fee		+ve	75	64	11	0.853	0.831
		-ve	75	13	62	0.827	0.849

[sen: sentences, fee: feedbacks, Acc: accuracy, Re: recall, F1: F1 value]

The results of proposed method were compared with corpus based machine learning methods on same datasets from the recent research work. (Go, Bhayani and Huang, 2009) presented a machine learning method for classifying sentiment of twitter messages and achieved an accuracy of 80% for positive and negative sentiments. The results are also compared with the online twitter comments classification system "twitrratr". In twitrratr a list of positive keywords and a list of negative keywords were created. Their accuracy is 76% and 80% on positive, negative and neutral opinion. The method is also compared with (Andreevskaia and Bergler, 2008) presented machine learning based lexical method for different dataset with accuracy of 71% in blogs dataset and 82% for movie reviews and news datasets. The proposed method achieved better results than this approach. Most corpus based techniques use flat feature vector or BoW methods to represent the documents. In (Hu and Liu, 2004) the authors have taken the feature list as a seed for the opinion orientation.

Table 7 shows the overall performance of our proposed system in comparison with the machine learning corpus based methods. The contribution of this work is the extraction of sentence level semantic orientations taking into account all parts of speech and sentence contextual structure. Figure 1 shows the performance of the proposed method as compared to machine learning techniques (Go, Bhayani and Huang, 2009), (Andreevskaia and Bergler, 2008), (hue et al., 2004) and Twitrratr methods.

Table 7. Evaluation of proposed method for Blog comments

	Sentiment Orientation	
	Sentence Level	Feedback Level
Twitrratr	76	80
Andreevskaia Bergler, (2008)	71	82
Go, Bhayani, Huang,(2009)	80	82
Proposed Method	83	87

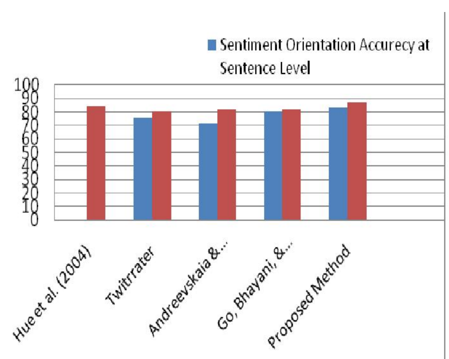

Figure 1. Comparison with Other Methods using Blogs Datasets

[1] www.cricinfo.com

5. Conclusion and future work

In this paper, a rule based sentiment analysis approach is proposed for opinion classification. The contextual information and the sense of each individual sentence are extracted according to the pattern structure of the sentence. The semantic score for the extracted sense is assigned to the sentence using SentiWordNet. The final semantic weight is calculated after checking semantic orientation of each term in the sentence. The decision is made to check the polarity of positive, negative or neutral opinions. The results show that the sentence structure and contextual information in the review are important for the sentiment orientation and classification. The sentence level sentiment classification performs better than the document level semantic orientation. The limitations include the dependency on lexicons and the lack of term sense disambiguation. From the results, it is clear that the proposed method achieves an average accuracy of 83% at the sentence level and 87% at the feedback level for blogs comments.

In future, extraction of the acute sense of sentence and remove noisy text for an efficient semantic orientation. Furthermore, the knowledgebase need to improve for the semantic scores of all parts of speech.

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