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ORIGINAL ARTICLE

A survey on sentiment analysis challenges

Doaa Mohey El-Din Mohamed Hussein

Faculty of Computers and Information, Cairo University, Cairo, Egypt

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KEYWORDS

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Abstract With accelerated evolution of the internet as websites, social networks, blogs, online portals, reviews, opinions, recommendations, ratings, and feedback are generated by writers. This writer generated sentiment content can be about books, people, hotels, products, research, events, etc. These sentiments become very beneficial for businesses, governments, and individuals. While this content is meant to be useful, a bulk of this writer generated content require using the text mining techniques and sentiment analysis. But there are several challenges facing the sentiment analysis and evaluation process. These challenges become obstacles in analyzing the accurate meaning of sentiments and detecting the suitable sentiment polarity. Sentiment analysis is the practice of applying natural language processing and text analysis techniques to identify and extract subjective information from text. This paper presents a survey on the sentiment analysis challenges relevant to their approaches and techniques.

1. Introduction

Sentiment analysis (Basant et al., 2015) uses the natural language processing (NLP), text analysis and computational techniques to automate the extraction or classification of sentiment from sentiment reviews. Analysis of these sentiments and opinions has spread across many fields such as Consumer information, Marketing, books, application, websites, and Social. Sentiment analysis becomes a hot area in decision-making (Tawunrat and Jeremy, 2015) (Matthew et al., 2015). Hundreds of thousands of users depend on online sentiment reviews. 90% of customer's decisions depended on Online Reviews in April 2013 (Ling et al., 2014). The main goal of analyzing sentiment is to analyze the reviews and examine the scores of sentiments. This analysis is divided into many levels (Thomas, 2013): document level (Ainur et al., 2010), sentence level (Noura et al., 2010), word/term level (Nikos et al., 2011) or aspect level (Haochen and Fei, 2015). The sequence processes are of sentiment analysis evaluation and detection of the sentiment polarity (Khairullah et al., 2014). This paper focuses on the most important challenges in sentiment evaluation phase that they have a significant effect in sentiment score and polarity detection. The evaluation sentiment drawbacks that Reflected in language coverage. This paper summarizes keys of sentiment challenges (Sujata and Parteek, 2014) (Vinodhini and Chandrasekaran, 2012) (Arjun et al., 2012) with respect to the type of review structure. It also divides the challenges into two types to ease to deal with them and focus on the degree of accurate meaning. This research discusses these sentiment challenges, the factors affecting them, and their importance. As a result, a

E-mail address: d.mohey@alumni.fci-cu.edu.eg
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Table 1 Study for the sentiment challenges relevant to review structure.

Ref. No	Domain oriented	Challenge type	SA challenge	Review structure
Bas et al. (2011)	No (40 different topics)	Theoretical	Negation	Semi-structured adjectives only
Alexander et al. (2011)	Yes, movie reviews	Theoretical	Negation	Un-structured
Amna (2012)	N broader sense domain	Theoretical	Negation	Semi-structured nouns/adjectives/verbs and adverbs-clauses and phrases
Maral (2011)	Yes movies	Theoretical	Negation + domain dependence	Semi-structured adverbs, adjectives
Lifeng (2009)	Yes health/medical domain	Theoretical	Negation	Semi-structured
Robert (2013)	Y	Theoretical and Technical	Negation + bipolar words	Semi-structured, sentences or topics documents
Michael et al. (2010)	N	Theoretical and Technical	Negation + entity features/keywords	Structured or semi-structured
Emanuele et al. (2012)	N	Theoretical + Technical	Negation + huge lexicon	Semi-structured,
Stanislav (2013)	Yes	Theoretical	Domain dependence	Unstructured conjunction with predefined taxonomy of emotional terms
Yulan et al. (2011)	N mutli-domain	Theoretical	Domain dependence	Semi-structured
Hiroshi and Tetsuya (2006)	N	Theoretical	Domain dependence	Structured, objectives expressions
Bing and Liang (2014))	Y	Theoretical	Domain dependence	Un-structured, twitter
Alexandra et al. (2013)	Y	Theoretical	Domain dependence	Structured, news articles
Fangtao et al. (2010)	Y	Theoretical	Domain dependence	Un-structured, online customers reviews
Ouyang et al. (2014)	N	Theoretical	Domain dependence	Unstructured, emotion reviews
Fangtao et al. (2011)	Y, product reviews	Theoretical	Spam and fake detection	Unstructured
Xia et al. (2014)	Y, social media	Theoretical	Spam and fake detection	Unstructured
Qingxi and Ming (2014)	N, online customers reviews	Theoretical	Spam and fake detection	Unstructured
Ahmed et al. (2010)	Y, ecommerce and online security	Theoretical	Spam and fake detection	Semi-structured
Myle et al. (2011)	N, online customer reviews	Theoretical	Spam and fake detection	Unstructured,
Theodoros (2012)	N	Theoretical	Spam and fake detection + negation	Semi-Structured
Alexandra and Ralf (2009)	Y, online news reviews	Theoretical	World knowledge	Semi-structured, unstructured
Marina et al. (2014)	Y, the game on amazon mechanical turk	Theoretical	World knowledge	Unstructured
Svetlana et al. (2014)	Y, tweets	Theoretical	NLP overheads (Short Abbreviations)	Unstructured
Jiliang et al. (2012)	Y, facebook, and twitter	Theoretical	NLP overheads (Short Abbreviations)	Unstructured
Yanfang et al. (2015)	N	Theoretical	NLP overheads (Ambiguity)	Semi-structured
Yunfang and Miaomiao (2010)	N	Theoretical	NLP overheads (Ambiguity)	Structured, adjectives only
Duyu et al. (2014)	Y, social media	Theoretical	NLP overheads (Emotions)	Unstructured
Saif and Peter (2010)	N	Theoretical	NLP overheads (Emotions)	Unstructured
Christine et al. (2013)	Y, tweets	Theoretical	NLP overheads (Sarcasm) + negation	Unstructured
Nathan and Ruihong (2013)	Y, tweets	Theoretical	NLP overheads (Sarcasm)	Unstructured
Subhabrata and Pushpak (2012)	Y, products	Technical	Extracting features or keyword	Semi-structured

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Table 1 (*continued*)

Ref. No	Domain oriented	Challenge type	SA challenge	Review structure
Gizem et al. (2012)	Y, trip advisor	Technical	Extracting features or keyword	Semi-structured
Mus'ab et al. (2012)	Y, with aspect level	Technical	Extracting features or keyword	Semi-structured
Ivan et al. (2013)	Y, movie and product domains	Technical	Bi-polar words	Unstructured
Lucie et al. (2015)	Y, social media	Technical	Bi-polar words	Unstructured
Sathya and Kaladevi (2014)	Y, tweets	Technical	Bi-polar words	Unstructured
Chetan and Atul (2014)	Y, tweets	Technical	Huge lexicon	Unstructured
Erik (2013)	N, online collaborative media.	Technical	Huge lexicon	Structured, unstructured
Andrius et al. (2012)	Y, CNET, IMDB movie reviews	Technical	Huge lexicon	Semi-structured
Doaa et al. (2015)	Y, scientific papers	Technical + Theoretical	Lexicon + feature extraction + negation + world knowledge	Structured

large number of studies and research have helped monitor the trending new research increasing year by year. The focus in this research, has been to achieve the most suitable challenges facing sentiment evaluation to be useful for researchers and facilitate their relationships.The rest of this paper is organized as follows: Section 2, Empirical Study, Section 3, Discussion, and Section 4, Conclusion and proposes directions for future work.

2. Empirical study

This research is based on two comparisons among the forty-seven previous researches in sentiment analysis to choose the suitable challenge for each research and to show their effects on the sentiment accuracy (Ismat and Ali, 2011). First comparison discusses the relationship between the sentiment analysis challenges and review structure. Second comparison examines a significance of solving the sentiment challenges to improve accuracy.

First comparison: is between the thirty-seven research papers. The target of this comparison is recognizing the relationship between the sentiment challenges and review structure and how to effect on the sentiment results. Sentiment review structure becomes an essential factor which effects on selecting the important challenges should the researchers face in their research by assuming the types of review format as in the following:

(A) *Structured Sentiments* are found in formal sentiment reviews, but it targets the formal issues as books or research. Because the writers are professional and writing sentiments or notices about the scientific or fact issues.

(B) *Semi-Structured Sentiments* lie on the range between the formal structured sentiments and unstructured sentiments. These require understanding several issues about reviews. This type which depends on Pros and Cons is listed separately by the writer and the contents of Pros and Cons are usually short phrases.

(C) *Unstructured Sentiments* are an informal and free text format, the writer does not follow any constraints (Arjun et al., 2013). There is no formal separation of Pros and Cons and the content may consist of several sentences, where each sentence contains features and/or opinions. For the example below the unstructured reviews have the potential to provide more abundant and detailed opinion information than its counterpart (Arjun et al., 2013). *Explicit feature:* If a feature f appears in the segment/chunk of a review sentence, the feature is called an explicit feature of a product. For example; in the segment the picture is wonderful, picture is an explicit feature. *Implicit feature:* If a feature f does not appear in the segment of review, but is implied, the feature is called an implicit feature of a product. For example; in the segment it is very expensive, the price is an implicit feature, and expensive is a feature indicator. With respect to the importance of sentiment analysis, this survey discusses the relationship between the review structure and sentiment analysis challenges. We examine the sentiment challenge that appears more with the type of sentiment structure.

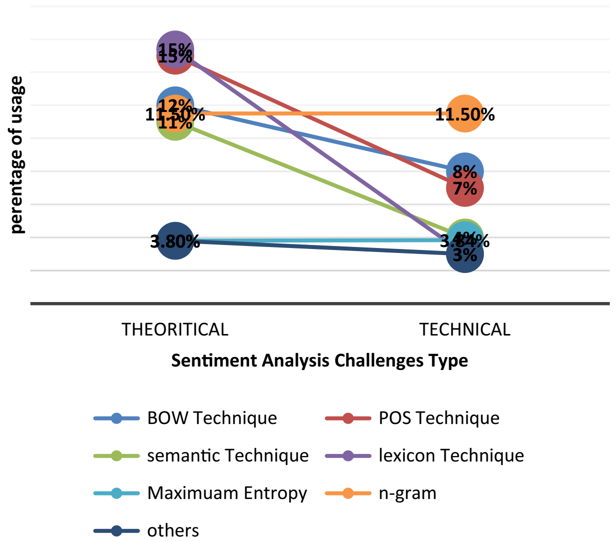

Figure 1 SA challenge type and technique Used.

Table 1 illustrates that the comparison between the forty-one papers in sentiment analysis challenges. The comparison's results declare that there is an essential factor important and relevant to the review structure. This factor is domain oriented, that requires having an orientation of the topic domain and its features or keywords to determine the fitting challenge for the research or application. The comparison relies on the relationship between the domain and the review structure. Another result is the negation is the most important challenge which has the greatest impact in any sentiment analysis and evaluation whether structured, semi-structured or unstructured review. But the comparison shortcoming requires updatable research constantly to reach the suitable challenges easily and quickly.

Second comparison explains the summary of sentiment challenges and how to improve the accuracy of each one based on the previous works. Its goal is identifying the most significant challenges in sentiment and how to improve its results relevant to the used techniques. Fig. 1 explains the proposition of using the techniques with respect to the sentiment analysis (SA) challenge types (Theoretical or technical). According to the comparison between the twenty-six research papers Table 2 identifies the usage of each technique. The theoretical challenges use many techniques to improve the results with solving the selective sentiment challenges. The highest technique usage in the theoretical type is parts-of-speech (POS) tagging and lexicon-based techniques. Bag-of-words (BOW) technique is the second technique. And the last one is Maximum entropy (ME) technique. But the results are different in technical sentiment challenge type, the highest usage technique is n-gram technique, because it is based on phrases and expressions. And the least technique usage here is lexicon-based technique.

Table 2 examines several parameters relevant to the sentiment analysis challenges. These parameters are lexicon type, domain oriented, dataset, the technique used and the accuracy results. This comparison summarizes the effect of sentiment challenge solutions in analyzing and evaluating sentiment analysis accurately. The lexicon type in comparison in Table 2 refers to the language of the dataset and the size of

Table 2 Study to several parameters effects on the sentiment challenges.

Ref. No.	SA challenge type	SA challenge	Technique used	Domain oriented	Lexicon type	Data set	Accuracy
Yulan et al. (2011)	Theoretical	Domain dependence	Naïve Bayes and support vector machines from WEKA5	N multi domain	46English	The two datasets, the movie review (MR) data and the multi domain	90%
Ivan et al. (2013)	Technical	Bi-polar words	Combination of features (n-grams) and preprocessing techniques (unsupervised stemming and phonetic transcription).	Y	English Facebook	Facebook dataset containing 10,000 posts	69%
Hiroshi and Tetsuya (2006)	Theoretical	Domain Dependence	Deep sentiment analysis method analogous to machine translation	N	Japanese	Polar clauses conveying goodness and badness in a specific domain	94% (25 to 33%)
Maral (2011)	Theoretical	Negation + domain dependence	BOW term frequencies	Y	Two wordlists	2000 movie reviews: 1000 positive and 1000 negative	65% with higher recall 83%
Svetlana et al. (2014)	Theoretical	Domain Dependence	SemEval-2013	Y	Tweets and MPQA English	2000 positive words and 4700 negative words, also the popular MPQA	Improve accuracy and F-measure about 13% from base line to reach 69%

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Table 2 (*continued*)

Ref. No.	SA challenge type	SA challenge	Technique used	Domain oriented	Lexicon type	Data set	Accuracy
Andrius et al. (2012)	Technical	Huge lexicon	Bag-of-word11s SVM.	Y, CNET, IMDB movie reviews	pSenti	The firrst dataset|Software Review, second data set Movie Reviews	82.30%
Saif and Peter (2010)	Technical	NLP overheads (emotions)	(Naive Bayes, Maximum Entropy, and SVM)	N multi domain	Microblogging lexicon	Tweets with emoticons, 1,600,000 training tweets., 800,000 tweets with positive emoticons, and 800,000 tweets with negative emoticons,	Accuracy improved for Naive Bayes (81.3% from to 82.7%) and Max-Ent (from 80.5 to 82.7). However, there was a decline for SVM (from 82.2% to 81.6%).
Alexandra et al. (2013)	Theoretical	Domain Dependence	WordNet- lexicon based	Y	News reviews	Newspaper articles (the set of 1292 quotes	82% improve the base line 21%
Theresa et al. (2005)	Technical	Huge lexicon	Auto.Distinguishing prior and contextual polarity.	N	Multi-perspective Question Answering (MPQA) Opinion Corpus1,	15,991 subjective expressions from 425 documents (8,984 sentences)	75.9%,
Erik and Marie-Francine (2009)	Technical	Nlp overheads (Multi-lingual)	Integrated approach combining from information retrieval, natural language processing and machine learning	Y	English, Dutch and French tex	Blog, review and forum texts found on the World Wide Web	83% 70% and 68%
Fangtao et al. (2010)	Theoretical	Domain Dependence	Dependency-Sentiment-LDA- Markov chain	Y	Hownet- Senti-wordnet-MPQA	Online customers reviews- HowNet 2700 2009 English translation of positive/negative Chinese SentiWordNet 4800 2290 Words with a positive or negative score- MPQA 4152 2304 MPQA subjectivity lexicon	70.7
Duyu et al. (2014)	Technical	Nlp overheads (emotions)	Fine-grained emotions	Y	Chinese lexicon	35,000 tweets about Sichuan earthquake	80%,
Bas et al. (2011)	Theoretical	Negation	Part of speech (POS)	40 different topics	OpenNLP	Dutch language	71.23% for negation (Precision improves with 1.17%)
Ouyang et al. (2014)	Theoretical	Domain Dependence	Emotion Dependency Tuple (EDT- improved (BOW) TF-IDF and cross entropy, space vector model	N	Chinese	COAE2014 dataset	60%
Lucie et al. (2015)	Technical	Bi-polar words	n-gram (uni and bi-grams)	Y	HL and MPQA lexicon.	Data set of 1,600 Facebook messages	70%
Qingxi and Ming (2014)	Theoretical	Spam and fake reviews	Combine lexicon and use shallow dependency parser	N, online customers reviews	SentiWordNet and MPQA	Store#364,	85.7% for sentiment method but word counting approach 76.7%
Emitza and	Technical	Feature and	POS tagging with fine-	N, 7	SentiStrength	7 apps from the Apple App Store and Google	91%

Table 2 (*continued*)

Ref. No.	SA challenge type	SA challenge	Technique used	Domain oriented	Lexicon type	Data set	Accuracy
Walid (2014)		keywords extraction	grained app	applications		Play Store	
Alexandra and Ralf (2009)	Theoretical	World knowledge	Adding word polarity scores from sentiment lexicons.	Y	Context-dependent lexicon	6500 answers on game reviews	Improve acc 60% to 80%
Lifeng (2009)	Theoretical	Negation	Parse Tree and dependency	Y	English, health/medical domain	Dataset that consists of 1000 sentences	Between 79.2% to 82% with different four methods
Mohammed et al. (2014)	Technical + Theoretical	Domain dependence + NLP overheads (multi-language)	Lexicon-based method depends on POS tagging	N	16 domain Lexicon-based tool for Arabic opinion mining.	Deal with emoticons, chat language, Arabizi,	93.9%
Chetan and Atul (2014)	Technical	Huge lexicon	Lexicon based technique	Y	6,74,412 tweets	The polarities of the words in the dictionary are set according to a specific domain,	73.5%
Jiang and Min (2011)	Theoretical	Domain-dependence	n-gram	N, 7 domains	Chinese reviews b	560 Chinese review	65%
Alexander et al. (2011)	Theoretical	Negation	POS Technique (Word Sense Disambiguation, Sentiment analysis)	Y	WORDNET	1;000 positive and 1;000 negative English movie	98:7%-
Doaa et al. (2015)	Technical + Theoretical	Lexicon + Feature extraction + Negation + world knowledge	Enhancement BOW model	Y, scientific papers	New lexicon	Three datasets (training set, test set and the verified set) 1000, 5000, and 10.000	83.5%
Walter and Mihaela (2011)	Technical + Theoretical	Extracting Features or keywords + domain dependence	Character n-grams instead of terms	Y	German Hotel reviews	Corpus of 1559 hotel reviews crawled from the web.	83%
Myle et al. (2011)	Theoretical	Spam/fake reviews	POS tagging similarities and n-gram algorithm	N, online customer reviews	LIWC	800 opinions	Nearly 90%

the dataset. There are several available lexicon as Senti, How-Net, and Wordnet. The used lexicon has the sentiment word and polarity. The polarity differs in the sentiment classification polarity level. This classification of polarity is divided into several class levels such as two levels (Positive, and Negative polarities), three levels as in the hierarchical level, or four level (−, Neutral, +, Mixed), and more specified classification into five levels (Very Negative, Negative, Neutral, Positive, Very Positive polarities) (Doaa, 2016). The comparison's strengths are (1) the facility of understanding the hot area research, (2) illustrating the most effect challenges on the accuracy results, (3) recognizing the propagation of use of each sentiment analysis technique, and (4) discussing the relationship among the domain dependence, lexicon type and the accuracy results (Doaa et al., 2015). The results of this comparison are very important in choosing the suitable technique to solve the sentiment challenges to reach the highest accuracy.

The comparison's conclusion is in Table 2, which includes the relationship between the sentiment analysis challenge type and the importance of its presence in the new search. Other results from the second comparison declare in Fig. 2 that the percentage of Average of accuracy enhancement related to the compared research papers. Although the Negation is the most affected in any sentiment type as the results in comparison in Table 1 mean it has a big number of research. That makes the result of it is lower here.

$$\mathrm{AVG(ACC.)} = \sum_{i=0}^{n} \frac{\text{Accuracy of each paper}}{\text{number of papers } (n)}, \qquad (1)$$

That means the lowest Average of accuracy is the highest rate research area with the bi-polar words with 69.5. Then domain dependence and NLP overheads have the second rank. And the Negation challenge has the third rank.

Fig. 3 presents the highest improvement in accuracy for each sentiment analysis challenges related to the second comparison. Negation has the highest accuracy percentage that can support the result of the first comparison because researches in sentiment do not need to understand the negative reviews whether explicit or implicit. And the least score in accuracy is bi-polar words research, so we recommend to increase the research in it.

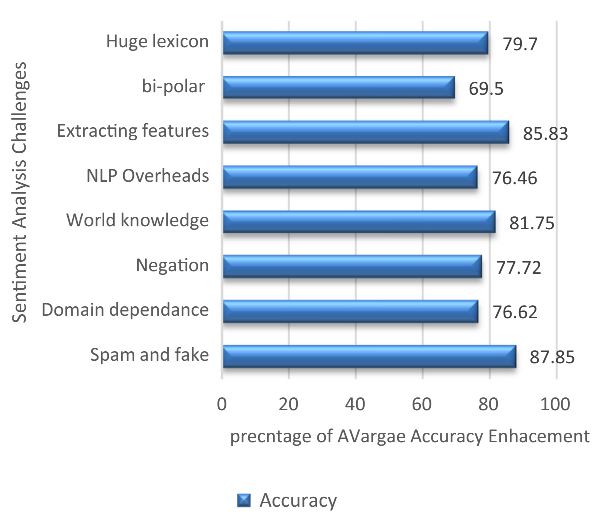

Figure 2 The improvement in accuracy results in sentiment analysis challenges.

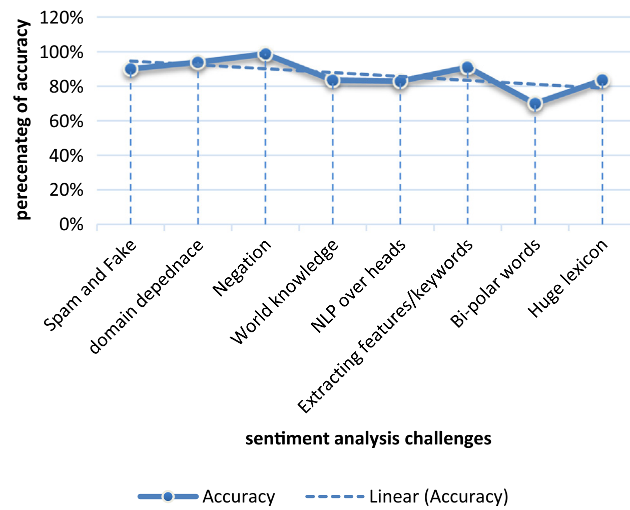

Figure 3 The highest accuracy to each sentiment analysis challenge.

3. Conclusion and future work

This survey discusses the importance and effects of sentiment analysis challenges in sentiment evaluation based on two comparisons among forty-seven papers. The first comparison is based on the relationship between the sentiment review structure and the sentiment analysis challenges. The result of this comparison reveals another essential factor to recognize the sentiment challenges which is domain-dependence. Moreover, the negation challenge became popular in all types of reviews structured just differs in implicit or explicit meaning. This comparison result provides a facility to the effects of each sentiment challenge on the review structure types. We conclude that the topic nature and the review structure determines the suitable challenges for the evaluation sentiment reviews. Then the second comparison relies on the sentiment analysis challenges relevant to the accuracy rate. Their results present the importance of sentiment challenges in evaluating the sentiments and how to select the fitting challenge to improve accuracy. We find the relationship between the proportion of sentiment techniques usage in theoretical and technical types to solve sentiment challenges. Another result explains the hot area of research is a theoretical type of sentiment challenges. That reflects on the results of the average of accuracy based on the number of researches in each challenge. The more the research in a sentiment challenge, the less the Average of accuracy rate. The future work is the expansion of the comparison circle larger with the new research continuously.

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