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Subjectivity Analysis in Opinion Mining - A Systematic Literature Review

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Abstract

Subjectivity analysis determines existence of subjectivity in text using subjective clues. It is the first task in opinion mining process. The difference between subjectivity analysis and polarity determination is the latter process subjective text to determine the orientation as positive or negative. There were many techniques used to solve the problem of segregating subjective and objective text. This paper used systematic literature review (SLR) to compile the undertaking study in subjective analysis. SLR is a literature review that collects multiple and critically analyse multiple studies to answer the research questions. Eight research questions were drawn for this purpose. Information such as technique, corpus, subjective clues representation and performance were extracted from 97 articles known as primary studies. This information was analysed to identify the strengths and weaknesses of the technique, affecting elements to the performance and missing elements from the subjectivity analysis. The SLR has found that majority of the study are using machine learning approach to identify and learn subjective text due to the nature of subjectivity analysis problem that is viewed as classification problem. The performance of this approach outperformed other approaches though currently it is at satisfactory level. Therefore, more studies are needed to improve the performance of subjectivity analysis.

Keywords*: opinion mining, sentiment analysis, subjectivity analysis, systematic literature review.*

1 Introduction

Newspapers, magazines and journals were the medium for people to express their opinion on entity or event. The outreach was limited and the response from readers were not reached to the writer timely or left unknown for most of the time. The advanced of technology has transform these into electronic medium content with bigger outreach. The readers start to email their response to the writer expressing their feelings and opinion towards certain issue. The emails are collected and stored in the writer's repository. These responses became valuable assets to the organization determining and improving their business direction or policies. The need for computerized text analysis becomes inherent when the number of electronic responses exponentially increasing. In addition to that, the rise of review sites, blogs and social media platform that leads to borderless involvement of Internet users has added complexity to the analysis. Ever since then, opinion mining becomes an essential tool to many organizations.

A text document consists of objective and subjective information. Objective information described entity within the area of interest including people, product or event. It conveys facts for subject of an interest such the colour, size and material of the product. Subjective information refers to the affection express in the given text that contains feeling (happy-unhappy, satisfied-unsatisfied), emotion (angry, joy, ecstatic), opinion (agree-disagree) and evaluation (good-bad) [1]. Sentence (1) in Fig 1 conveys subjective information with the presence of "better picture", "easy" and "expensive" expressed on iPhone. These terms are known as subjective clues – the essential element of subjectivity analysis [2]. In Fig 1 sentence (2) describes the fact of operating system that makes all product of Apple function well. Affection was not expressed in sentence (2). Thus, this sentence is deemed as objective sentence, while the other is subjective sentence.

Subjectivity analysis is a task to distinguish subjective and objective information in each text [1][3]. It is the first task in opinion mining which system detects subjective element using subjective clues [4]. These clues are detected at word level, phrase level, sentence level, document level or aspect level that carries subjective notion to determine the subjectivity in the analysed text [5].

(1) iPhone 6 takes better picture and easy to use though it is expensive.
(2) All Apple products run on iOS.

Fig 1. Subjectivity Analysis in Opinion Mining

Investigating subjective analysis is a continuing concern within opinion mining. Subjective analysis has been an object of research in opinion mining since 1997 [6] and the effort is still going on to date [7]. The results from these studies are satisfactory [8]. Studies are still ongoing to improve its performance.

Most of the studies in opinion mining were focused on determining positivity and negativity of analysed text [9][10]. This is known as polarity analysis [8]. Compiled studies dedicated on subjectivity analysis is limited compared to polarity analysis. The aim of this paper is to report compilation of study in subjectivity analysis. This paper used systematic literature review (SRL) to gather, analyse and synthesize findings related to subjectivity analysis. This paper consists of three sections. Section 2 describes the method undertaking this study in great elaboration. Section 3 describes and discusses the findings from the compilation of this studies. Finally, section 4 concludes this SLR.

2 Method

The process of systematic literature review (SLR) is carried out using the procedure in [11]. The review process consists of three phases as shown in Fig 2. The process starts with planning phase by establishing the need for this SLR. This SLR compiled various studies on subjectivity analysis. Many studies claimed the importance and significant of subjectivity analysis prior to other tasks in opinion mining [8][12]. However, subjectivity analysis has less review compared to polarity classification [10][13][14]. The last review dedicated to subjectivity analysis was in 2009 [8]. This SLR continues the last effort reviewing the work in subjectivity analysis by studying the state of the art techniques, highlighting its trends and challenges and document the findings related to the study. This SLR proceed with specifying the research questions. The details of the questions are described in the next sub section.

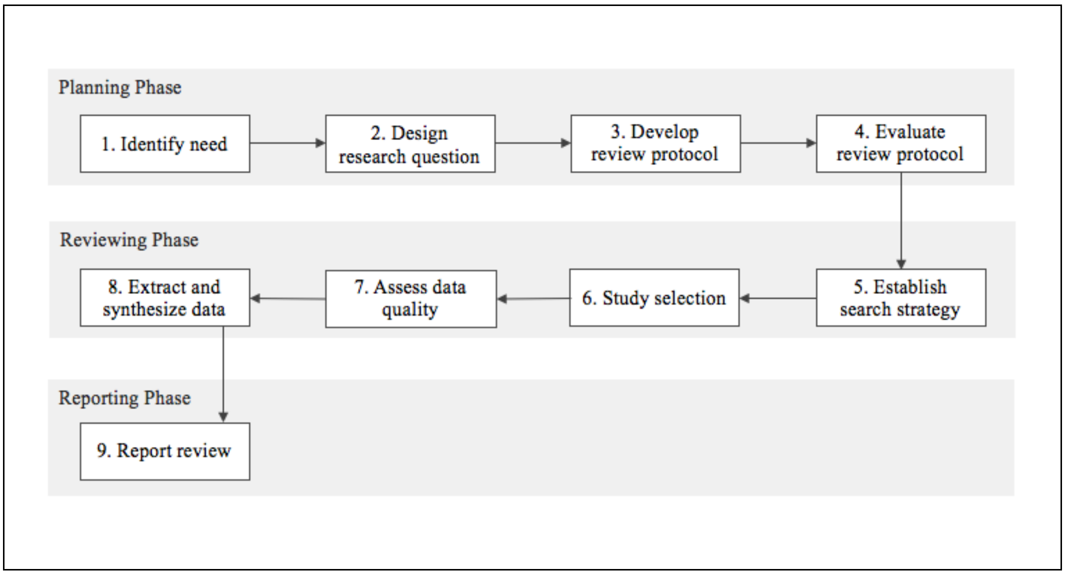

Fig 2: The process of systematic literature review

After establishing the need for the SLR, it proceeds to design the review protocol. Review protocol specifies the method undertake for the review. The protocol is necessary to reduce the possibility of research bias. It includes the strategy to be used to retrieve materials for primary studies, defining the criteria selection, study the selection, assess the quality of the selection, establish strategy to extract and synthesized data and report the review. The research question is adapted to assist the evaluation of the review protocol to confirm the appropriateness of the search strings, data to be extracted is properly addressed by the research questions and the procedure of the data analysis answers the research questions.

2.1 The Research Question

Specifying research questions is the most important step in this SLR. The research questions set the direction of this SLR. The SLR assess empirical evidences from various research studies in subjectivity analysis. The goals are to gather techniques and methods to detect subjectivity, study the trends of the techniques, understand the issue and challenges of subjectivity analysis and report the findings. The research questions and its motivations are described in Table 1.

Table 1: Research questions for the SLR

#	**Research Questions**	**Motivation**
RQ1	What are the common tasks in subjectivity analysis?	Identify the undertaking task to identify presence of subjectivity.
RQ2	What are the techniques used to identify subjectivity?	Identify the techniques used to identify subjectivity.
RQ3	What are the corpus used as data sets in subjectivity analysis?	Identify the corpus used as data sets in subjectivity analysis.
RQ4	What are the technique to represent the subjectivity clues in the analyzed text?	Identify the variables used to represent subjectivity and assess the differences of the variables.
RQ5	What is the performance of the technique that successfully identify subjectivity?	Identify the performance and its metric of the techniques that successfully identify subjectivity.
RQ6	What are the strengths and weaknesses of the technique?	Assess the strengths and weaknesses of the techniques.
RQ7	What are the affecting elements to the performance of the technique?	Identify the factor affecting the performance of the technique.
RQ8	What are the missing elements in subjectivity analysis?	Assess the elements missing to have an ideal subjectivity analysis.

2.2 The Search Strategy

The next step in this SLR is to define the search strategy. It defines the method to gather and retrieve reported empirical study for subjectivity analysis. In general, this SLR used “subjectivity analysis” as primary search string. Keywords such as “opinion detection”, “sentiment detection” and “sentiment analysis” were used as an alternative search strings. These keywords are derived from text books, journals, conference proceedings and technical reports. Boolean operators “OR” and “AND” and search wild cards are utilized in the SLR to narrow the scope of searching. The search strings are used to retrieve materials from the subscribed in-house electronic databases. The electronic databases used in this SLR are 1) ScienceDirect 2) ACM Digital Library 3) IEEE Xplore 4) Scopus 5) SpringerLink 6) Google Scholar.

2.3 The Selection Strategy

The search from the electronic databases returned voluminous results. Processing this result is challenging therefore a narrower scope is defined. A set of criteria is defined to filter the review material in this SLR as shown in Table 2. These criteria are known as inclusion and exclusion criteria. This SLR considers empirical studies that uses data sets segregated into positive/negative/objective (or neutral) classes as subjective analysis. This SLR defined subjective information as opinionated information in which element of sentiment presents in the analysed text. Positive and negative polarity are category of sentiment expressed in the analysed text [8]. Therefore, non-opinionated text is categorized as objective text or neutral text where sentiment is not evidently present in the analysed text.

Initially this SLR has gathered 170 articles to be reviewed that were published between 1997 to 2016. However, a study in [8] have compiled and reviewed studies in subjectivity analysis until 2007 and not many work were dedicated to compile studies for subjectivity analysis after that period. Next, the SLR applied the criteria in Table 2 and selects 97 articles as primary studies.

Table 2: Inclusion and exclusion criteria for the SLR

Inclusion Criteria	Exclusion Criteria
1. Articles that were published after 2006 until 2017.	1. Articles that were published before 2007.
2. Articles that put subjective analysis as main discussion.	2. Articles that put polarity classification as main discussion.
3. Articles that include subjectivity analysis as one of the sub tasks in opinion mining.	3. Review articles on opinion mining.
4. Empirical studies that uses data sets consists of subjective/objective or positive/negative/objective (or	4. Empirical studies that uses data sets consist of positive/negative.

neutral).	

2.4 The Quality Assessment

Quality assessment provides more details for the inclusion and exclusion criteria. It describes the importance of the primary studies to the SLR. The SLR designed questionnaires that assess the relevance and the significant of the primary study as shown in Table 3.

2.5 The Data Extraction and Synthesis

The selected 97 articles conform to the quality assessment criteria as described in Table 1. Each article is carefully examined to identify the data to be extracted. A form was design to extract information from the primary studies. The item of data to be extracted is designed based on the research questions defined in Table 3. The SLR summarized each primary study to scope of work, proposed technique, used datasets, variables and performance of the proposed technique.

Table 3: Quality assessment questions

Q#	Question	Yes (1)	Partly (0.5)	No (0)
Q1	Are the objectives of the study clearly stated?			
Q2	Does the study justify the proposed method?			
Q3	Are the proposed method clearly described?			
Q4	Does the study describe gatherings of data clearly?			
Q5	Does the study describe the classes of data in the experiment?			
Q6	Are the performance measure to assess the proposed method clearly defined?			
Q7	Are the results and findings clearly stated?			
Q8	Does the study conduct comparative analysis for the proposed method?			
Q9	Has the study been cited by others?			

3 Result and Discussion

The SLR has selected 97 articles that fulfills the criteria describe in Table 2 as primary studies. The selected articles are listed in Table 4 . These articles are divided into two categories 1) primary articles 2) secondary articles. Primary articles put subjective analysis as main topic of discussion, uses data sets that are labelled as subjective/objective. Secondary articles put subjective analysis as one of the tasks in opinion mining process or uses data sets that are labelled as positive/negative/objective (or neutral). The SLR regard positive/negative as subjective information. The distribution of these articles is shown in Fig 3.

Many studies have stated the importance of subjectivity analysis will reduce the processing complexity in the later stage of opinion mining system. It prevents the polarity classifier from considering the irrelevant and potentially misleading text, thus it will enhance the performance of the system [8] [12] [33]. The number of published articles focusing in subjectivity analysis or including subjectivity analysis in the proposed technique is not as encouraging as other tasks in opinion mining. Subjectivity analysis is more difficult than polarity classification due to several reasons. Some of the reasons are due to ambiguous definition of subjectivity, insufficient of available public data sets that segregates subjective and objective information, unavailability of dedicated dictionary for subjectivity and the complexity of subjective expressed in text that needs analysis beyond syntactic level [31].

Table 4: Selected primary studies

Year	Primary Studies
2007	[15][16][17]
2008	[18][19][20][21][22][23][24][25]
2009	[26][27][28][29]
2010	[12][30][31][32][33][34]
2011	[35][36][37][38][39][40][41][42]
2012	[43][44][45][46][47][48][49][50][49][51]
2013	[52][53][54][55][56][57][58][59][60][61][62][63][64][65][66][67][68][69][70][71][72][73]
2014	[74][75][76][77][78][79][80][81][82][83][84][85][86][87]
2015	[88][89][90][91][92][93][94][95][96][97][98][99][100][101][102][103]
2016	[104][105][106][107][108]
2017	[7]

3.1 RQ1: What are the common task in subjectivity analysis?

Subjectivity detection, sentiment classification, polarity determination and strength determination are common tasks in opinion mining. Subjectivity detection distinguish subjective and objective information from the analysed text using subjective clues [6][109][110]. [111] has defined opinionated sentence express or implies positive or negative. There is a relation exist between these two definition. The result of subjectivity analysis is an opinionated document which is the interest of opinion mining system. Therefore, the input into sentiment classification is the opinionated document. This relation is described in Fig 4.

Sentiment classification segregates subjectivity text into a set of classes either binary or *n*-ary classes. Polarity determination decides the orientation of the text as positive or negative. Strength determination defines the degree of polarity from strongly positive to least positive or strongly negative to least negative. The degree could be represented using range of integer values.

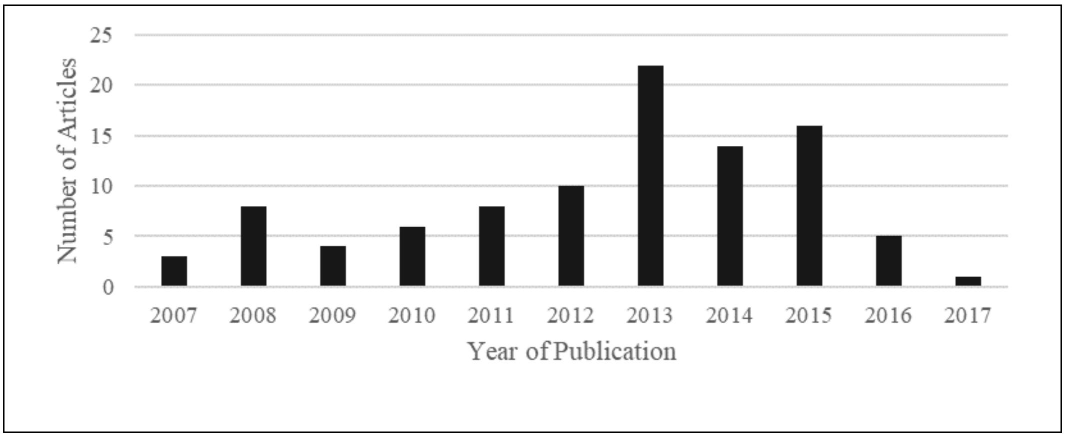

Fig 3: Distribution of articles by from 2007 until 2017

The process of opinion mining starts with data acquisition. Data were gathered from various resources and stored in the data repository. The data consist of document which are formally written text and informally written text. Next, the data will be preprocessed. Preprocessing cleanse the data and transform it into a processible form by opinion mining system. Preprocessing accelerates the process in opinion mining by removing data that is considered as noise or non-meaningful data to the system. The degree of preprocessing varies with the type of data the system is dealing with. Preprocessing includes tokenization, word segmentation, part-of-speech (POS) tagging and parsing. The sequence of these task is shown in Fig 4.

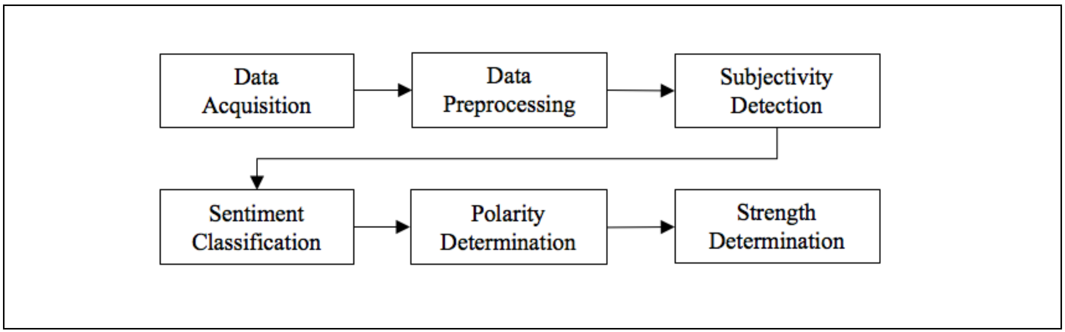

Fig 4: Common tasks in opinion mining system

Subjectivity detection is the first task in opinion mining process. Subjective clues are lexical items that represent private states in the analysed text. Private states are non-factual expression that includes opinion, perceptions, emotions, beliefs and sentiment [111]. Commonly adjectives are good clues indicating the presence of subjectivity in the text [6][112]. The tokenized text is tagged with POS. POS tagging is a lexical analysis technique that assign part of speech to each word or phrases in the sentence. Each word or phrases correspond to at least one category of word either noun, pronoun, verb, adverb, adjective, conjunction, preposition and interjection. The text is classified as subjective when the score of subjective clues meet certain threshold, otherwise it is classified as objective. Series of task is shown in Fig 5.

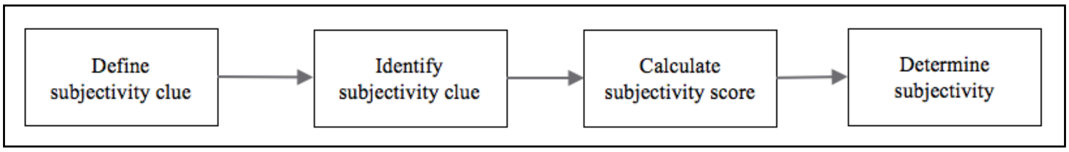

Fig 5: Common task in subjectivity analysis

3.2 RQ2: What are the techniques used to identify subjectivity?

Subjectivity analysis is a classification problem – to classify data into subjective and objective classes. Many studies are using machine learning, lexical based approach, manual annotation, semantic approaches and rule based. The distribution of approaches is shown in Fig 6. Machine learning is found to be the most prominent approach despite the difficulties of obtaining subjective/objective labelled data set in various domain.

Machine learning classifies sentiment data into subjective or objective classes based on defined features. It learns from models that are trained with algorithm. The SLR has found three types of learning algorithm used in the primary studies 1) Supervised learning algorithm 2) Semi supervised/Weakly supervised learning algorithm [30] [49] and [3] Unsupervised learning algorithm [26] [51] [73]. Among these three, supervised learning algorithm is the most preferred approach compared to others learning algorithm. In supervised learning algorithm, the data sets were labelled with subjective/objective or positive/negative/objective (or neutral). Features such as word n-gram and POS represent subjective elements are defined and extracted, then train with learning algorithm using training data. The performance of the algorithm is determined with labelled test datasets. The finding in Fig 7 has shown that Support Vector Machine (SVM) is the most preferred supervised learning algorithm compared to Naive Bayes, Decision Tree and Logistic Regression.

Lexical resources contain words that are labelled with polarities – positive/negative or positive/negative/neutral. The labelled words are independent from any context and domain. The analysed document tokenized the words in the sentences. Each of the token is compared the tagged lexicon to retrieved its subjective value. The score determines the subjectivity in the document. This approach is utilized by [18][23][39][28][72][61].

Manual annotation is a process to labelled data set as subjective/objective or positive/negative/neutral. The purpose is develop corpora for subjectivity analysis [55], to assess complexity of subjectivity [5][38] and to redefine annotation scheme for further task in opinion mining process [38][48]. The process requires a set of unlabelled data and a group of annotators. The dataset is distributed to the annotators. The annotators will mark the data as per defined of subjectivity class either subjective/objective or positive/negative/neutral. The annotated data are compared among annotators for an agreement and results are tabulated. This step is known as inter annotator agreement. The score of annotated data between the annotators are calculated and measured using Cohen’s Kappa.

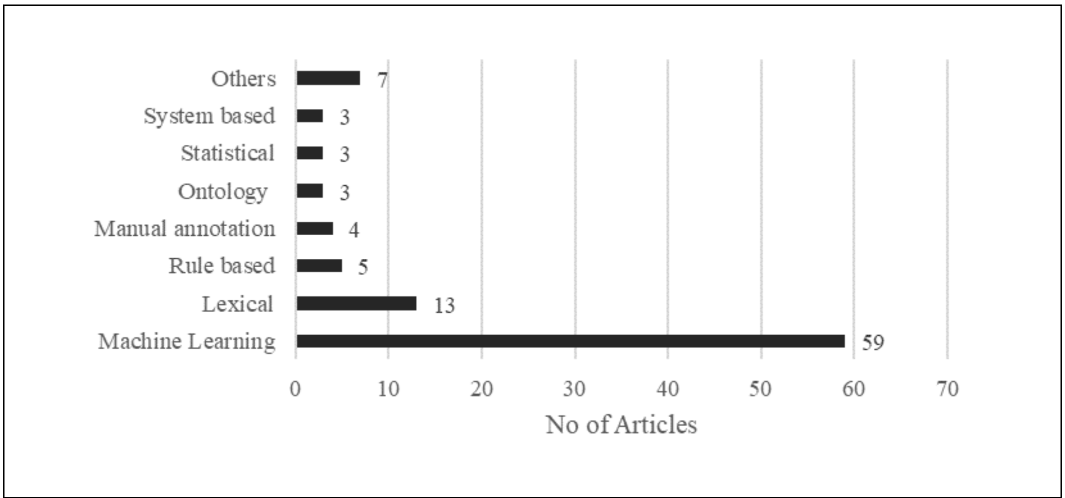

Fig 6: Distribution of techniques over articles

Rule-based approach make use of IF...THEN condition to determine subjectivity of the analysed document. Subjectivity clues are used to model the predefined rules for the subjectivity analysis. Rule-based approach is used to classify sentences into subjective and objective in [29][40][92] and to detect presence of emotion in [93].

Ontology is a shared concept of specific domain in which the representation understood by machine and human. In the primary studies, the ontology is used to identify relevant feature for the analysed text and serves as knowledge based to detect presence of emotion and type of emotion detected [47][84][105].

Statistical approach used frequency of terms to estimate subjectivity of an analysed text. This approach usually combined with NLP technique [35][57][91]. The presence of terms is counted to determine the importance of it in the document. A sentence is deemed as subjective when terms met or exceed the threshold value, otherwise the sentence is evaluated as objective and discarded.

System based approach integrates many components analysing subjectivity of documents [43][113][59]. Architecture of the system is presented in the primary studies, specifying the connection among the components describing the flow of the system and the output it produces. The architecture includes document preparation, document preprocessing, interfacing with lexical resources, subjective analysis and output generation. Others techniques used in the primary studies includes genetic algorithm [24], heuristic approach [27], information retrieval [50], machine translation [101], ranking algorithm [60] and similarity graph [32].

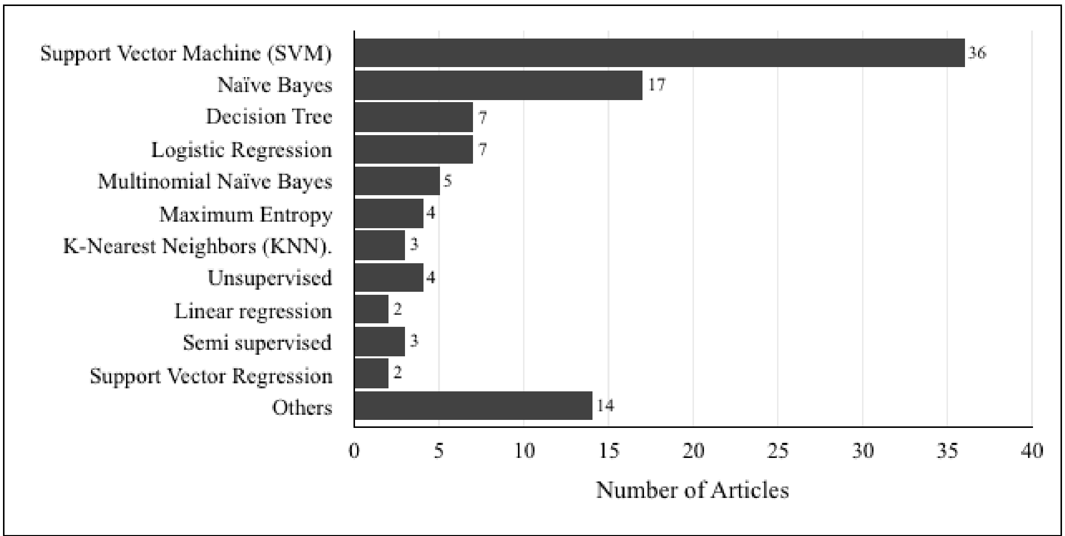

Fig 7: Distribution of articles based on machine learning techniques

3.3 RQ3: What are the corpus used as data sets in subjectivity analysis?

Corpus is a collection of document used for text analysis. This SLR categorized the corpus into eight – blog, forum, lexical, news articles, review, social media post, wiki and not mentioned. Not mentioned are datasets that are not specified in the primary studies. The SLR found year 2013 used the all types of corpus in the studies as shown in Fig 8. Fig 9 shows Cornell Movie Review[1] is the most used corpus with 5000 sentences for subjective and objective each. This corpus was introduced by [114] and it is available for public. Then followed by Twitter[2], MPQA corpus[3], TripAdvisor[4] and SemEval[5]. Most of Twitter and TripAdvisor's

[1] http://www.cs.cornell.edu/people/pabo/movie-review-data/

[2] http://www.twitter.com

[3] http://mpqa.cs.pitt.edu/corpora/

[4] https://www.tripadvisor.com/

[5] http://alt.qcri.org/semeval2015/task10/index.php?id=data-and-tools

data sets are streamed, stored for their own studies and are made not available to public.

3.4 RQ4: What are the techniques to represent the subjectivity clues in the analyzed?

The presence of subjectivity clues indicates the analysed document contains subjective information. These clues are derived from words that were tokenized at pre-processing stage. Word grams are the most used technique obtaining subjective clues from the analysed text. Then followed by POS, word, dictionary and syntactical as shown in Fig 10(a). Other technique includes co-occurrences, punctuation, position, hashtags and emoticons. Unigram is most used technique to represent the subjective clue with 31% then N-gram with 26% and combination of grams with 22%. Other distribution of word gram is shown in Fig 10(b). Combination of word grams such as unigram + bigram [63][77][85][86], unigram + bigram + POS [54][77], unigram + bigram + trigram [77][85], unigram + bigram + trigram + POS [77], unigram + POS [54][77] and unigram + trigram [85].

3.5 RQ5: What is the performance of the techniques that successfully identify subjectivity?

Subjectivity analysis adopts metric from natural language processing (NLP) – such as precision and recall, to evaluate the performance of the proposed solution. Fig 11 shows the performance metric used in the primary studies. Accuracy is the most commonly used performance metric in the study followed by F-Measure, recall and precision. Less commonly used metric are Cohen Kappa, area above curve (AUC), LAMP, r^2 and error rate.

The SLR grouped the performance of subjectivity analysis based on the approaches in the primary studies. It was found that machine learning approach perform with accuracy between 56.84% to 90.40% demonstrated by SVM. Fig 12 shows performance by other machine learning approaches. The differences between the highest and the lowest accuracy and precision obtained from other approaches are not as huge as SVM.

Performances of lexical approach are shown in Fig 13 . The highest accuracy and precision among the group of primary studies is achieved at 92.15% and 84.6%. Fig 13 shows that most of the studies performed at 75%-80% accuracy and precision.

3.6 RQ6: What are the strength and weaknesses of the technique?

Manual annotation models annotation scheme to develop corpora and labelled complex subjective text [38][48][55]. Verbs were used as subjective clues to annotate analyzed text such as emotion verbs, cognitive verbs and verb senses [38]. [48] models the guidelines to annotate multi genre document in Arabic. The annotated data are tested and made available to the community. Thus, it solved the unavailability of data for subjective analysis. The model is to be used as guidelines to annotate subjective data and identify subjective clues. Though, this is a labour intensive and domain dependent, annotated data gives a good start to solve subjectivity problem. However, the annotation model is subjected to amendments for new genre or new language. The limitation of this study shows that the guideline is not tested against other languages.

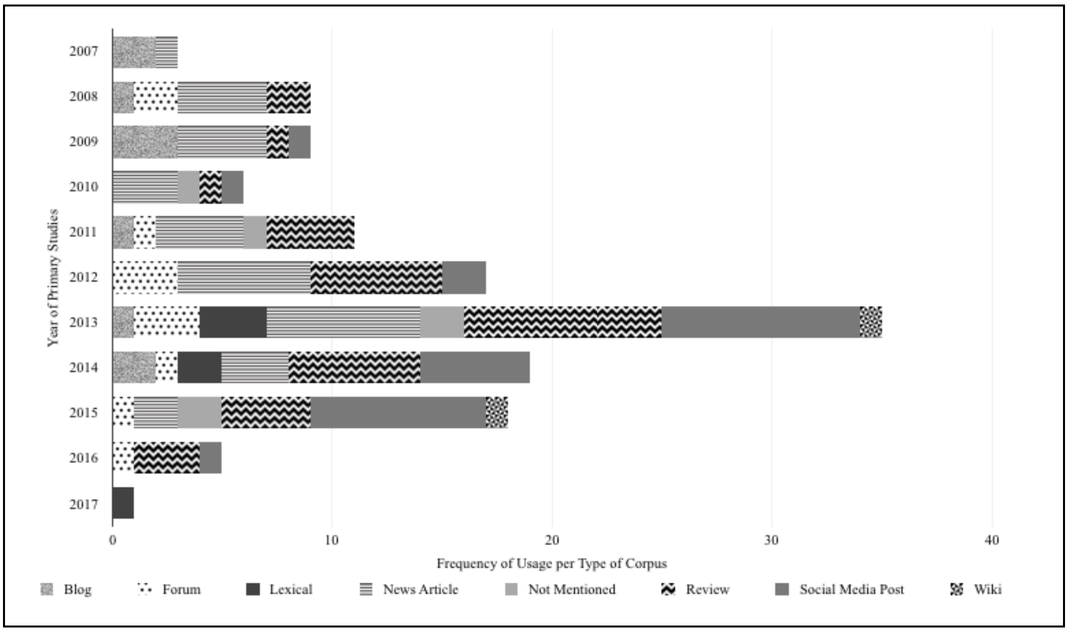

Fig 8: Frequency for Types of Corpus used by Year of Primary Studies

In contrast to manual annotation, machine learning approach were found to produce acceptable accuracy in subjective analysis. Despite the limited available datasets, supervised learning approach is prevalent in previous studies. The model can be tailored for text analysis in any domain. This approach can be incorporated with additional resources during learning process. However, this approach is domain dependent. The drawback of this approach is a new set of features and new labelled data sets are required for the new domain.

Scarcity of labelled data is a classic problem for supervised machine learning. Preparing labelled data sets as subjective/objective or positive/negative/subjective (neutral) for various domain and/genre is labour intensive task, time consuming and costly. In contrast, unlabelled data is easy to obtain for any domain or genre at any amount. Therefore, unsupervised and semi-supervised machine learning approach is filling this gap. Subjective analysis study that utilizes lexical resources are overcoming this problem.

Lexical approach does not require data sets to be labelled as subjective/objective or positive/negative/objective. This is an alternative approach to manual annotation. However, this approach is not adaptable to new domain as the lexicons are domain independent. Some of the lexicons carried more than one subjectivity label. Thus, it adds to the complexity of the analysis. This approach works well with structured text. However, for unstructured text like Twitter, the result is not yet satisfactory due to usage of non-dictionary words. Lexical approach process subjectivity at syntactic level only. It is challenging for the approach to uncover the underlying meaning of subtle opinionated text.

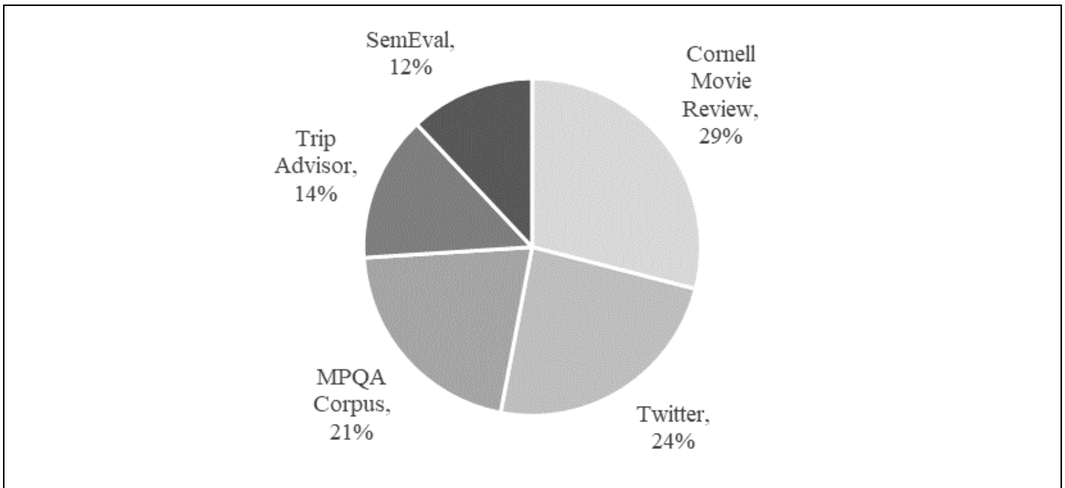

Fig 9: Top five corpus used for subjectivity analysis

3.7 RQ7: What are the affecting elements to the performance of the technique?

Performance of the subjectivity analysis indicate the fitness of the proposed solution solving subjectivity classification problems. In the previous research question, supervised machine learning has proven to deliver promising results in detecting the presence of subjectivity in the analysed text. Besides that, supervised machine learning is known for its robustness and stability that performs very well in text categorization. Therefore, the application of supervised machine learning approach for subjective analysis become a common trend as can be seen in previous studies discussed in Section 3.2.

Labelling data sets are expensive effort. The needs of subjectivity analysis are not restricted to only a domain such as movie or product review but in other domain as well such law and politics. These type of data sets are not widely available. It is apparent that utilizing unsupervised learning, semi supervised learning and lexical the unlabelled data that is available anytime, any genre and any amount will be much more promising.

Another factor that contributes to the performance of supervised machine learning is the availability of labelled data. Though these data are not genre diverse, it provides a good start for the study to test their proposed approach. It is found that supervised machine learning approach performs well with sufficiently labelled data, stable and accurate data sets.

Features are also an important element to supervised machine learning. Features are clues that can tell subjective and objective text distinctly. Useful features contribute to the improvement of accuracy and precision of the proposed solution.

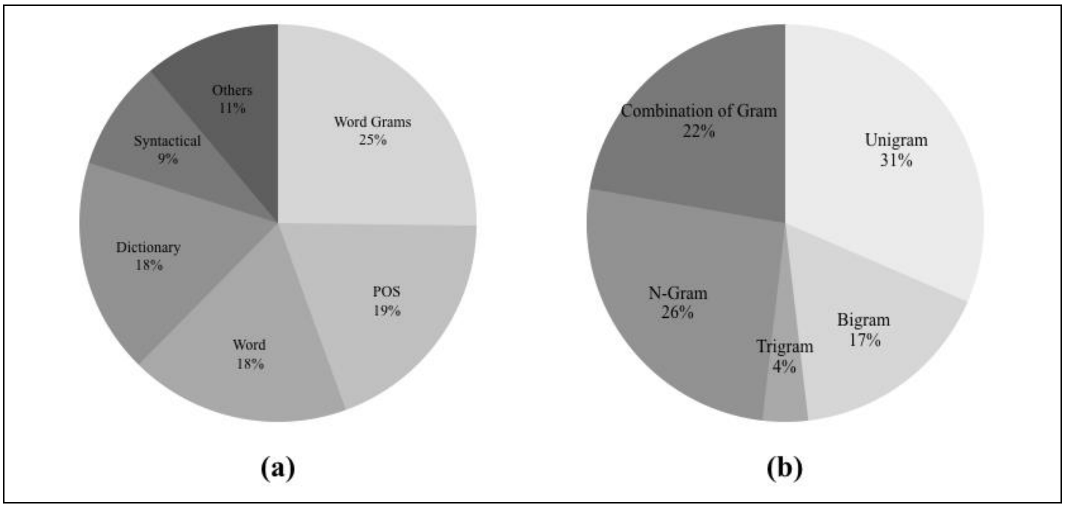

Fig 10: (a) Distribution of subjective variables used in primary studies
(b) Distribution of word-grams features used in primary studies

It has been shown that there were a lot of improvement in lexical resources starting from hand crafted lexical to semi- automatic and automatically generated lexical resources. The size and its granularity varies from one to another. This has become the prime factor for the performance of lexical based approach. Bigger lexical resource provides more subjective (positive/negative) and objective words to the solution

A lot of interests has been shown in subjectivity analysis studies for languages other than English as shown in Fig 14. Some of the studies have difficulties obtaining data sets and lexical resources in the target language. The available English data sets and lexical resources were translated into the target language using machine translation service such as Google translator and Bing translator. Studies has shown that machine translation able to aid subjectivity analysis though the performance has not yet achieved satisfactory level.

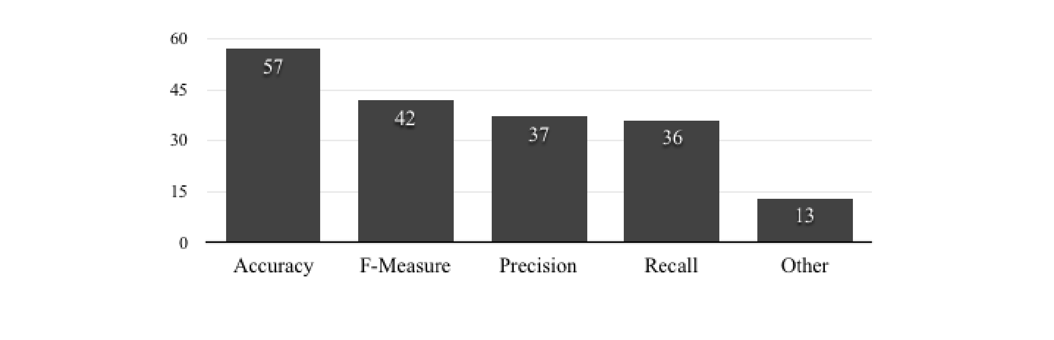

Fig 11: Frequency of measurement used in subjectivity analysis

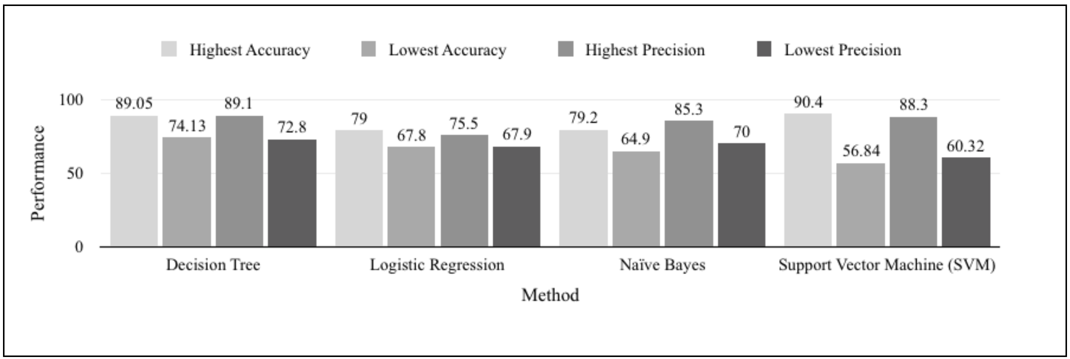

Fig 12: Performance of machine learning approach for subjectivity analysis

3.8 RQ8: What are the missing elements in subjectivity analysis?

Definition of subjectivity analysis is fuzzy, often leads to confusion when other terms are used interchangeably with sentiment analysis or opinion mining. A proper definition is necessary for better subjectivity analysis problem formulation and solution. There were many terms associated with subjectivity that includes affect, feeling, emotion, sentiment and opinion. Definition of these terms are very subtle and often confusing. Therefore, clearer definition is necessary for finer subjective analysis.

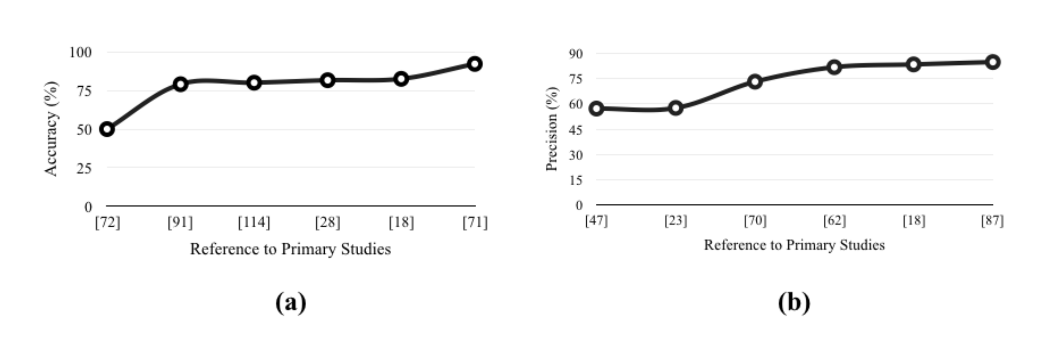

Fig 13: Performance of accuracy (a) and precision (b) for lexical approach

The SLR found that 30% of the primary studies collect and annotate data instead of using the standard data sets. The annotated data are validated with inter-annotator agreement. 93% of annotated data in the primary studies reached 0.6 Cohen Kappa's level. Hiring and training annotators to develop subjective corpus is an expensive effort. However, this effort is necessary especially for supervised learning approach to validate the fitness of their solution. Furthermore, the current annotated datasets have been used as a benchmark by many studies as shown in Fig 9. This marked the importance of it. The available data sets are limited to certain genre has constrained the effort of testing the proposed solution. Therefore, the adaptability of a proposed technique remained unproven.

There were primary studies that collects and labelled their data. Each of these studies has different style of labelling and were using the same validation method – inter annotator agreement. Looking at this trend, [38] and [48] models the guidelines to annotate complex subjective text and multi genre text. Standardizing the approach to label the corpus in any genre will reduce the bias and increase the confidence level on the data sets. Therefore, unifying these standard is required for subjectivity analysis.

Most of the proposed technique in the primary studies analyse subjective at document and sub document level. Sub document level consist of analysing sentences, phrases and words – which are syntactical analysis. Most of the product review express information explicitly. Therefore, it is easy for the computer to determine the presence of subjectivity in the review text. Formal written text such as speech, transcript, editor's column in the news article and political blogs, subjectivity is expressed implicitly. This adds to the complexity of subjectivity analysis. Analysis at syntactical level is not able to interpret the underlying meaning of the implicit subjectivity. Computer needs better understanding to uncover the subtle expression of subjective element in the text such as tones of the text, politeness, sarcasm and cynicism. These elements are important in for timely decision making in big data. Therefore, inclusion of semantic level analysis to detect presence of subjectivity in a textual document is a pressing need.

Lexical approaches generalized sentiment bears by the lexicon thus it is a challenge for new domain, which some of the words may not be registered in the dictionary. Some of the lexicon carries more than one subjective label and its subjectivity level varies from one genre to another. In this case, generality is a challenge to be apply for such genre. Towards some extend, domain dependent lexical resources are required to improve the performance of subjective analysis in the new domain. Apart from lexical approach, machine learning is proven to be a promising solution for subjective analysis, however it is known to be domain dependent. A set of features that is define for one genre may not be useful for another genre. The same solution is still feasible for a new genre with redefinition of features and model re-training. It is a challenging scenario for a robust opinion mining system. Portable and adaptable solution with minimum redefinition and retraining has open more area to be explored in subjective analysis.

This SLR has found that current studies did not address the multilingual subjectivity analysis adequately. This area needs attention to leverage the current resources such as feature sets, sentiment lexicons and subjective patterns to enable multilingual subjectivity analysis perform as optimum as subjectivity analysis for English textual document. In addition to that, the current studies are language centric and did not consider to analyse subjectivity in mixed language textual document. There are differences in the process of document construction for multilingual and mixed language. For multilingual document, uniform languages are used in each document for different sets of languages. However, two or more languages are used in the construction of mixed language document. Certainly, the technique to analyse subjectivity in these documents are different. Therefore, many important information will not be able to be capture if the existing studies to be used to analyse subjectivity in mixed language. Therefore, two or more sentiment lexicons and subjectivity features sets need to be used in parallel to analyse subjectivity in mixed language document.

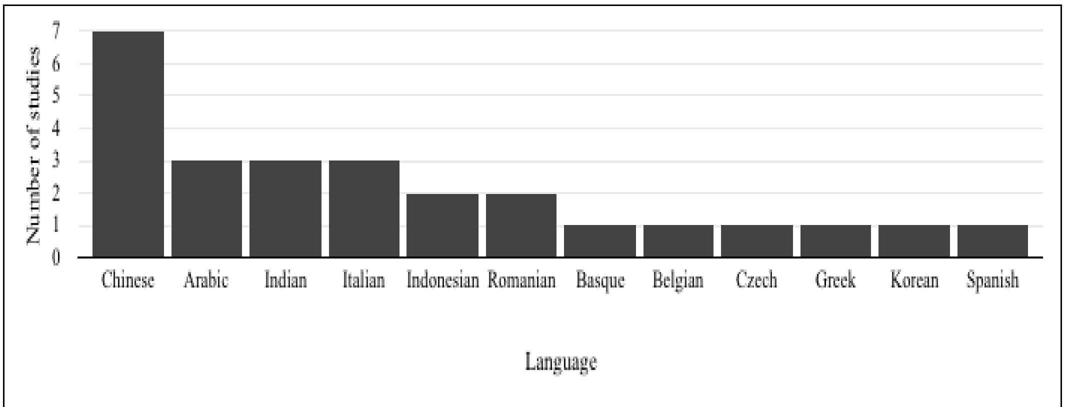

Fig 14: Distribution of non-English language studies

4 Conclusion

The aim of this SLR is to study the state of the art solution in subjectivity analysis, highlights the trends and challenges and document the findings. Extensive search with sophisticated keywords was perform to look for primary studies using five electronic databases. A total of 170 articles were obtained from the initial search. A set of criteria was used against the initial search result and filtered only 97 relevant articles. A set of quality assessment criteria confirmed the eligibility of the 97 articles selected prior to this step. A thorough review process extracts the findings based on the designed researched questions. These findings were synthesized to discover new insights into subjectivity analysis.

A common sequence task in opinion mining and subjectivity analysis were conceptualized in Fig 4 and Fig 5. The SLR found that machine learning is the most preferred technique in subjectivity analysis because naturally subjectivity analysis itself is a classification problem. The problem fits perfectly into machine learning compared to other approaches. Data sets are available for machine learning approach, though the diversity of the data sets are limited. N-gram is the most used technique to represent subjective clue in opinion mining, which is found to be the most useful representation and with promising results. Most primary studies are using accuracy to measure performance of their solution.

The primary studies were grouped by the technique proposed to solve subjectivity problem. The solutions were compared to uncover its strengths and weaknesses. It is a challenging situation for the SLR to choose the best solution that would fit into all genre of data because subjectivity analysis is domain dependent. Therefore, the proposed solutions are complementing one another. Instead of using single approach of solution, the future study would consider to combine approaches to overcome the weakness of the others.

The affecting factors for the performance are stability of the technique, quality and accessibility to the data sets, availability of non-English language data sets, a set of useful features for subjectivity analysis, size and availability of lexical resources.

Subjectivity analysis gives better insights of trending sentiment for big data analytics. The relationship between big data analytics and subjectivity analysis is symbiotic. While big data deals with variety of data that rapidly flows into the system, subjectivity analysis helps to correctly classify these data. Both benefits from each other. By having these two, not only it gives an overview of the impact from the decision that has been made but it serves as powerful tool in timely decision making.

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