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SURVEY OF SENTIMENT ANALYSIS

Anasua Joardar[1], Supriya Chakraborty[2]

[1]*Computer Application, JIS College of Engineering, Kalyani, (India)*

[2]*Computer Science & Engineering, Greater Kolkata College of Engineering and Management,(India)*

ABSTRACT

In recent days, Sentiment Analysis is studied and analyzed by divergence, and collaboration ways to model a framework. In this regard, a lot of attempts have customized scopes and purposes. Sentiment Analysis gains momentum due to numerous applications are revealed in the real world. Researchers across the globe applied ranges of methods over periods of time that slowly but steadily betterment the extraction procedure of sentiment and its associated evaluations. Few interesting survey papers are found that cited latest papers. Substantial advancement is incurred thereafter with both new approaches, and evaluation techniques that have cutting-edge scopes. In this work, more than forty research papers are studied. Among those, five novel and utmost reputed research works are classified according to their approaches, results, and data set. Summarization, Tables, and diagram are used to illustrate pros and cons of different approaches in the survey work. Finally, the findings of the survey are specified.

Keywords* : *Data Divergence, Evaluation, Sentiment, Seed List.

I INTRODUCTION

The availability, scopes and advertisement of digital marketing are the new facets of the Industry [10]. These sorts of new numerous applications are gaining attention of Sentiment Analysis. Majorly, Sentiment Analysis is Text Processing. A lot of different attempts have been made to compute the sentiment [14, 39] on the digital text data. Along with the range of diversified techniques has been proposed for the evaluation of the merit of different attempts. The experimental results of the evaluation techniques has been analyzed and discussed by peer researches [15, 16]. *The range of evaluation techniques is the subject of choice for inclusion in the further research.* The Sentiment Analysis already has theoretical foundation in the field of physiology. Common terms have been used synonymously [14, 17]. However, our investigation reveal with the work [1] where basics of the electronic Sentiment Analysis has been described. The fundamental aspect of sentiment analysis of text processing is determination of subjectivity. The subjectivity of the content is classified by *Affect*, *Feeling*, *Emotions*, *Sentiment*, and *Opinion* as mentioned in [1]. Each of the classification has been defined with examples. Similarities/dissimilarities among them have been drawn by the opinions of sample set of people. The recent development complements the demand of the digital definition and availability *e.g. WordNet*[18], *SentiWordnet[19], ConceptNet[20], HowNet[21]and SentiFul[2]*. WordNet is a lexical database for the English language. It groups English words into sets of synonyms called synsets, provides short definitions, examples of usage, and records a number of relations among these synonym sets or their members (defines the meaning, synonyms, and part-of-speech of the word). SentiWordNet is a lexical resource for opinion mining.

SentiWordNet assigns to each synset of WordNet three sentiment scores- positivity, negativity, and objectivity. ConceptNet is built from nodes representing words or short phrases of natural language, and labeled relationships between them. HowNet is an on-line common-sense knowledge base unveiling inter-conceptual relations and inter-attribute relations of concepts as connoting in lexicons of the Chinese and their English equivalents. *However, the SentiFul[2] the advancement over SentiWordNet and WordNet promises rich semantics for computation of Sentiment.* Few review work in this area has also been observed [11, 12, 13]. However, Sentiful and it's onwards advancement are out of the scope of those review works. In this paper, a state of the art investigation is performed on Sentiment Analysis. The work encompasses with two different aspects. First one is the summarization and comparisons of different approaches to compute the sentiment. The second is the assessment of evaluation methodologies and their accuracy and diversification.

This paper is organized as follows. The paper is commenced with the brief outline of the work followed by the introduction section. Section 2 discusses the basics and related notations. Section 3 describes different approaches. Section 4 discusses data divergences of different approaches. Section 5 describes different evaluation technique and result analysis. In the next section, the findings are enlisted. This paper ends with the conclusion section.

II BASICS AND RELATED NOTATIONS

According to dictionary [22, 23] Sentiment is defined as an attitude, thought, or judgment prompted by feeling; a view or opinion that is held or expressed. However, many closely associated words have been used in the day-to-day life. Among them Affect, Feeling, Emotions, Sentiment, and opinion has been scientifically defined with examples in [1]. The promise of the definition is rewritten as follows. Sentiment **–** It is enduring emotional disposition that have developed over time about particular objects. Conclusions about sentiments in text have to be performed for a period. In turn, this will also help in improving decision making. Emotions and Sentiment are not analogous with the text processing. Emotion has been observed more complex physiological phenomenon that are impossible to detect from the text processing [1]. However, the similar words *attitude, mood, sensation,* and *temperament* have not been considered in [1]. However, similar words just mentioned in italics are effective enough to determine sentiment. Table 1 provides the definitions of attitude, mood, sensation, and temperament along with their synonyms, based on the Merriam-Webster Online Dictionary [22] and Oxford Dictionary [23].

Table 1. Definition Provided by Merriam-Webster Online Dictionary [22], and Oxford Dictionary [23].

Subjectivity Term	**Definition**		**Synonym**
	Merriam-Webster Dictionary	**Oxford Dictionary**	
Attitude	The way you think and feel about someone or something	A settled way of thinking or feeling about something	Opinion, Feelings, Sentiments, Thoughts, Thinking
Mood	A conscious state of mind or predominant emotion	A temporary state of mind or feeling	Spirit, Temper
Sensation	A particular feeling or effect that your body experiences	The capacity to have physical sensations	Feeling, Sense
Temperament	The usual attitude, mood, or behavior of a person	A person's nature, especially as it permanently affects their behavior	Temper, Mood, Attitude

III DIFFERENT APPROACHES

Three exhaustive surveys [11, 12, 13] have been investigated. The survey report [11] summarizes with the help of examples different classification of subjectivity, word and document. It also mentioned limitations of failing detection of sentiment of unite topic on document level classification along with extract sentiment of complex sentences. However, very interesting opinions has been specified in [13]. It classifies extensively the techniques of sentiment analysis with which we do completely agree. Along with it has mentioned related fields and open problems in the field of sentiment analysis. In the survey report [12] mainly discussed about sentiment classification, feature based classification and handling negations.

Survey reports as mentioned above have extensively focused on classifications on different perspectives of sentiment analysis including features, techniques, etc. However, the advancement has been identified in [2] over early approaches is significant for further advancement in recent scope of study. In this work, the state of the art analysis and formulation is specified from dictionary based approach; e.g., SentiFul to onwards approaches.

Broadly four approaches have been classified for sentiment analysis – Sentiment Lexicon, Rule based system, Machine Learning System, and Other Approaches in [13].

The corpus of many research works has been made by human annotators in which [6, 7, 8] are mentioned in this work. In this approach, human annotators specify added information about the sentiment in the written text of the document. Sentiment of a text document depend not only the verb; it gets extra weight-age along with adjective and adverb which is illustrated with the help of examples and scoring axioms in [6, 7]. In [6, 7], ten human annotators put score as an average of 100 concerned text. However, human intervention for scoring of verb, adverb and adjectives along with their compositions has always chance for biasness and unpredictable outcomes. This limitation has been overcome by [8]. The score and the text including synonyms and antonyms have been formulated from the WordNet. To get the exhaustive experiment, sentences of various domains have been taken from web pages and then identified favorable and unfavorable sentiment towards the subject in [33].

The primary drawback of the aforementioned works is *intuition based scoring by human annotators.* Advancement in this regard has been touched upon by the notion of customized dictionary or lexicon in 2009. A lexicon for sentiment analysis has been developed based on synonyms and morphologic modifications [24] of words. First all possible synsets of the lexeme has been derived from WordNet [18]. If that lexeme not present in the seed list of the SentiFul, then the synsets which are available in the SentiFul, has been find out. Then take the average score of them and the value has been propagated. Then in 2011, this lexicon has been increased and expanded through antonyms relations, hyponymy relation, and derivation and compounding with known lexical units [2]. The primary word or lexicon of sentiment has been generated using the database 'Affect' which is cited in [25]. The affective features of a word depend on nine emotions like anger, disgust, fear, guilt, interest, joy, sadness, shame, and surprise. Along with the notion of lemma which is the base form of words or collection is introduced to score sentiment. Two methods have been used. In SentiWordNet [19], the score of first synset gives the primary value ,which is known as FS in SentiFul. But unified positivity and negativity score for each lemma is known as UNI which gives better result than FS. The scores in SentiWordNet and SentiFul is compared by Gold Standard which gives dissatisfactory result. So expand SentiFul according to WordNet. In case of direct antonyms the reversed scores and weights of the original words has been treated. A list of hyponyms has been retrieved from WordNet, and propagates sentiment score and weight of the original term to its hyponyms. A new lexeme has derived by adding prefixed or suffixes. Four types of affixed are there namely, propagating, reversing, intensifying and weakening. Finally consider the score of compound word, which are contain at least two roots, especially in the case of noun and adjective. The novelty of the SentiFul is that the score of lexicons could be further reused in the research.

A minor modification over SentiFul is taken in [3]. In [3], emotion recognition is categorized with two different parts including word lexicon and emoticon lexicon. The increase of writing habit in social media and internet grows the usage of emoticons; thus its analysis in terms of emotion is significant. The working principle of [3] is that initially six sets of basic emotional categories which defined by Ekman [16]: happiness, sadness, anger, fear, disgust, and surprise has been considered for developing lexicons. After that the synset of word is searched from WordNet to obtain the final lexicon. This process has been continued until to get satisfactory result. As this is a repetition process, every time a small coefficient is multiplied with the score of the main word for getting the score of new synset of word. But in this case, the seed list is generated by conducting study on twenty personalities. The emoticon lexicon is also created manually. The heuristic rules apply on word lexicon, and emoticon for negation detection or effect of punctuation. The significance of the specified rules is illustrated as follows.

Positive dominating sense (happy, surprise) gets the higher priority than the negative dominance (sadness, fear, anger, disgust) sense. Use of more exclamation marks, uppercase word, intensifying words (like; very, extremely) gets extra privilege for emotional expression. Even multiple characteristic signs of emoticon give more effect on emotional expressions.

The advancement on the relationship among emotional expression, holder, and topic is extended by [4]. The identification of the co-reference which is helpful in finding user-topic relation has been done on local language (Bengali) which uses sentences of Bengali blog (www.amarblog.com). Emotion holders and topics of text help to track and distinguish users' emotions separately on the same or different topics. The identification of users' emotions on different topics is determined by processing an annotated Bengali blog corpus [26]. Each sentence of the corpus is annotated with the emotional components, such as emotional expression, intensity, associated holder, topic(s), and sentential tag of Ekman's [16] six emotion classes (anger, disgust, fear, happy, sad, and surprise). Both rule-based system and machine learning system applied for identifying the emotional expressions, holders, and topics. The expressions are identified from shallow parsed sentences using Bengali WordNet Affect lists [27]. Value of emotional co-reference measured by Krippendorff's α metric [28].

Sentiment analysis becomes larger day by day. Web-based traffic sentiment analysis (TSA) [5] concern about sentiment of traffic problem. Investigation, evaluation and prediction are the basic functions of TSA. The sentiment lexicon in the traffic domain has not in the scope for processing early of TSA. The necessary key words related to traffic domain taken from WordNet, and classified into two categories positive, and negative. The list further extended by finding synonymy and antonyms of the seed in the Chinese Language Technology Platform [29]. The processing of sentiment as of [4 and 5], build the local language knowledge infrastructure [30]. Few special words of customized fields e.g. overload, U-turn etc, added manually if these words are not present in the seed list.

Machine learning technique also applied for content analysis and extract topic level sentiments. Several online resources like Wikipedia.org have been explored for identifying related terms of specific topics and construct the seed list. Alchemy API [31] has been used in [9] for extracting keywords, entities and sentiment from twitter. Alchemy API utilizes NLP technologies and machine learning algorithm to analyze content. In this process, data has been fetched from twitter. Then preprocessed the fetched data, and removed the slang word. Then keyword and associated sentiment has been extracted by knowledge generator and store in the data repository. But the information extracted by knowledge generator is of low precision. So for better classification knowledge enhancer has been used. There are three part POS tagger, entity extractor and knowledge editor. Synonym binder is also another part for increasing information. WordNet dictionary has been used for binding synonyms with entity and key words. Finally filter engine applied for classifying data on the basis of seed list and store them in the repository.

So in the field of sentiment analysis there is no standard lexicon. In the above section we discuss more than five research work, but in all cases the seed list has been constructed in different method. All though there are many website like, SentiWordNet, ConceptNet, is available, but in many cases WordNet has been used for preparing seed list. The pros and cons of recent research outcomes are attributed by Sources of Data and Evaluation Methodologies in the rest of the paper.

IV DATA DIVERGENCE

The novelties of approaches focus on pre-defined scopes on the customized fields. The data to be processed for analysis of sentiment have known context, and events. This enables and ensures the analysis on meta character of the document. The unknown context and events further increases the complexity of determination of sentiment. For example a local event of Europe which has extraordinary sentiment of the local residents. However, outsiders are not even interested on this event. The determination and formulation of context is going on with different fields and still have scope of further research [32]. The process of sentiment may deal with standard formatted data from recognized global bodies, and unformatted data from web sites. The variation of coding standard, formatting, and document extension are the causes of heterogeneous source of data. To be more illustrative, an XML document have pre-defined, and optimized way of accessing nodes/data. On the other hand, to process extensively .pdf, and .docx document an overhead process is used to transform those data into XML. However, the XML database is built with the meaningful way whereas the transformed XML data has no guaranteed to be expressive, efficient and effective.

Emails, blogs, chat rooms, online forums, and even Twitter are being considered as effective communication substrates to analyze the reaction of emotional catalysts. A blog is a communicative and informative repository of text-based emotional content in the Web 2.0 (Yang et al., 2007). In particular, blog posts contain instant views, updated views, or influenced views regarding single or multiple topics.

Information regarding traffic on the Web has classified into three categories. The first one consists of news, expert commentaries, announcements, and etc. from the traffic website. The second includes posts from the transport sector in forums. The last one includes real-time information about traffic in micro blogging, which can be found from the social media, such as weibo.com. TSA data set has been collected from related website such as autohome.com, auto.sina.com, and tianya.cn. Researcher and scientist need voluminous data of web for analysis sentiment. The data of web are huge. However, it could be summarized according to our survey as specified below.

Different type of Big Data source is available as mentioned in [41]. The types are *Activity-generated data , Hadoop MapReduce application results, Social network profiles* **,** *Social influencers* **,** *Software as a Service (SaaS) & cloud applications, Public***,** *Data warehouse appliances, Columnar/NoSQL data sources, Network and in-stream monitoring technologies, and Legacy documents.*

Among the different type of Big Data source further categories that influence society in large are possible. The further categories of Social influencer are *Editor, analyst and subject-matter expert blog comments, user forums, Twitter & Facebook "likes," Yelp-style catalog and review sites, and other review-centric sites like Apple's App Store, Amazon, ZDNet*, and etc. Accessing this data requires Natural Language Processing and/or text-based search capability to evaluate the positive/negative nature of words and phrases, derive meaning, index, and write the results. The categories of Public data are *Microsoft Azure Market Place / Data Market, The World Bank, SEC/Edgar, Wikipedia,* and *IMDb*. Data that is publicly available on the Web which may enhance the types of analysis able to be performed. Data divergences of different approaches are summarized in Table 2.

Table 2. Data Divergence of approaches

Reference No	**Data collection (for testing)**	**Method**	**Primary Data Type**	**English / Other Language**	**Standard Data / Web site Data**	**Formatted data / Unformatted data**
SentiFul [2]	WordNet	Observations	Primarily qualitative but can also collect quantitative data by numerically coding observations**.**	English	standard	formatted
Synesketch [3]	http://en.wikipedia.org/wiki/Group_hug.	Document analysis, Surveys	Primarily quantitative but can also collect qualitative data through open-ended or free response questions.	English	Website	unformatted
Emotion Co-reference [4]	www.amarblog.com	Observations	Primarily qualitative but can also collect quantitative data by numerically coding observations.	Bengali	Blog data	unformatted
TSA [5]	www.tianya.cn	Case Studies	Primarily qualitative but can also collect quantitative data by coding observations, using surveys and document analysis.	Chinese	Website	unformatted
AVA [6,7]	Blog, news article	Document analysis	Primarily quantitative but can also collect qualitative data in the form of documented narratives.	English	Blog data, and news article	unformatted
SA on twitter [8]	twitter	Case Studies	Primarily qualitative but can also collect quantitative data by coding observations, using surveys and document analysis.	English	Website	unformatted
Tweet Classification [9]	twitter	Document analysis	Primarily quantitative but can also collect qualitative data in the form of documented narratives.	English	Website	unformatted

In table 2, Data are organized into two categories. Quantitative data is numerical and can be counted, quantified, and mathematically analyzed. Qualitative Data is the information that is difficult to measure, count or express in numerical terms. The evaluations of different approaches are specified in the following section.

V EVALUATION

Tetsuya Nasukawa et. al. [33] used natural language processing techniques to identify sentiment related to particular subject in a document. Jeonghee Yi et. al. [34] presented a model to extract sentiments about particular subject rather than extracting sentiment of whole document collectively. [34] proceeded by extracting topics, followed by sentiments, and finally mixture model to detect relation of topics with sentiments, whereas, Namrata Godbole et al. [35] introduced a sentiment analysis system for news and blog entities. The public sentiment and its variation are determined with time. They used synonyms and antonyms to find path between positive and negative polarity to increase the seed list. Bernard Jet al. [36] performed analysis of Twitter as electronic word of mouth in the product marketing domain. They analyzed filtered tweets for frequency, range, timing, content, and customer sentiments. Bharath Sriram et al. [37] proposed an approach to classify tweets into news, opinions, deals, events and private messages with better accuracy.

Researcher stresses that the strength of sentiment of a document depends on verb, adverb and adjective. In [6, 7] sentimental strength of a topic in a document depends on the value of difference between positive sense and the negative sense. The score is accepted if there exist a marginal threshold value between systems generated value and score of human annotator. The said algorithm claims better result over algorithm of both [38, 39]. The summarization of result is jotted down in Fig. 1.

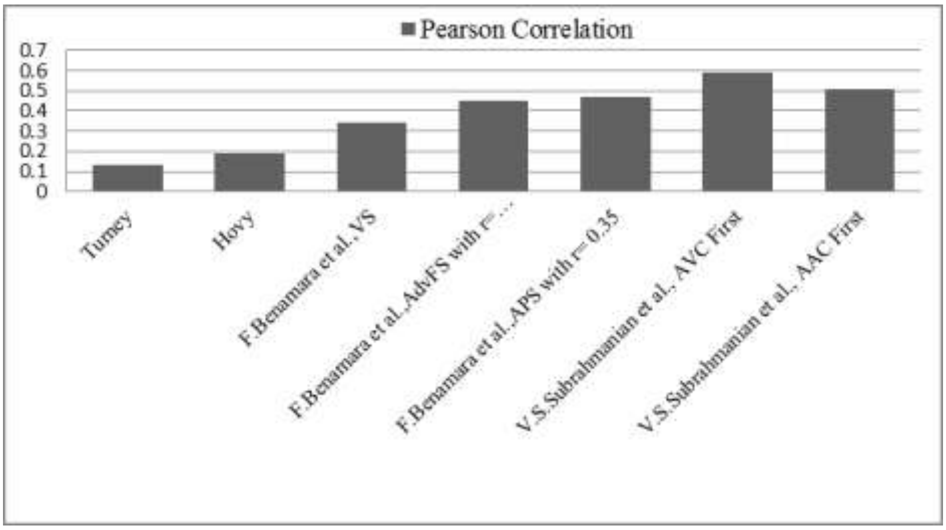

Fig.1 Comparison of Result

In [9], advancement is claimed with the collection of data from twitter, followed by text classification that attempt to extract information related to specific topic. The data has been processed through knowledge generator, knowledge enhancer, synonym binder, and finally go through filter engine. All the steps ensure betterment of classification as well as better sentiment. The evaluation techniques are briefly summarized in the following subsections.

5.1 Cohen's kappa measures

Cohen's kappa measures the agreement between two raters who each classify N items into C mutually exclusive categories. The equation for κ is:

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \qquad (1)$$

Where Pr(*a*) is the relative observed agreement among raters, and Pr(*e*) is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. If the raters are in complete agreement then κ = 1. If there is no agreement among the raters other than what would be expected by chance (as defined by Pr(*e*)), κ = 0.

The calculated agreement between SentiFul annotations and the gold standard is significant (κ = 0.72) for all content words.

5.1.1 Pearson Correlation Coefficient

Correlation between sets of data is a measure of how well they are related. The most common measure of correlation in stats is the Pearson Correlation. . It shows the linear relationship between two sets of data. And if coefficient value is > 0.5 then considered that strong positive relationship present.

5.1.2 Evaluation by human annotator

Most evaluation in NLP is done by calculating values for precision, recall, and often F-measure on the output of a system, evaluated against a gold standard. Gold standard data is, in the best-case scenario, data that is hand-annotated by domain experts. Where

$$\text{Accuracy} = \frac{number\ of\ true\ positive + number\ of\ true\ negetive}{number\ of\ true\ positive + false\ positive + false\ negetive + false\ positive} \qquad (2)$$

$$\text{Precision} = \frac{number\ of\ true\ positive}{number\ of\ true\ positive + false\ positive} \qquad (3) \qquad \text{Recall} = \frac{TP}{TP + FN(false\ negetive)} \qquad (4)$$

The F_1 score (also F-score or F-measure) is a measure of a test's accuracy. It considers both the precision *p* and the recall *r* of the test to compute the score.

$$F = 2\,\frac{precision.recall}{precision + recall} \qquad (5)$$

The value of expansion of SentiFul [2] has been investigated by two gold standards GS1 with complete agreement and GS2 without neutral words. GS2 gives more accuracy than GS1 (GS1 – 99.0% and GS2- 99.5%). Precision, recall and f-measure have been calculated for Synesketch algorithm [3]. It shows the best result for happiness and surprise (F-measure 0.869 for Happiness, and 0.85 for surprise) and the worst result for the emotion of fear (F-measure 0.592).

There are two cases in TSA system "yellow light rule" and "fuel price" both of them are controversial topics related to traffic in China. "Yellow light rule"- this is the strictest rules of traffic in China. Under the new rules, "running a yellow light would be equivalent to running a red light". "Fuel price" in this case generally focused on the rising/falling and decision policy of fuel price. In TSA [5] system both of them has been considered for result analysis. And compared with Ku's algorithm [40].The precision of the intensity of sentiment of the proposed algorithm is higher than that of Ku's algorithm. Table 3 shows the result analysis.

Table 3. Result Analysis of human annotator

Approaches	**Accuracy**	**Precision**		**Recall**		**F-score**	
		Pos	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**
SentiFul Core	94.1	91	96.5	95.3	93.2	93.1	94.8
SentiFul	86.1	81.8	90.1	87.6	85.3	84.6	87.6
TSA(Yellow light rule)	82.45	84.64	82.25	30.52	98.31	-	-
TSA(Fuel Price)	82.51	90.5	81.95	25.86	99.2	-	-
Ku's algorithm (Yellow light rule)	65.85	64.17	66.01	14.82	95.24	-	-
Ku's algorithm (Fuel Price)	73.57	67.05	74.02	15.22	97	-	-

5.2 krippendorff's α metric

The co-reference among the *emotional expressions*, *holders*, and *topics* has been measured using Krippendorff's α [28] metric. Krippendorff's α is a theoretically founded measure with a probabilistic interpretation. It is applicable to any number of coders (each assigning one value to one unit of analysis); to incomplete (missing) data; to any number of values available for coding a variable. The four different type of variable is considered for processing. The technique of Krippendorff's α is used in [4] that concentrated on nominal alpha. Unit u of this matrix may be few sentence or some components (according POS or shallow parser) of a sentence, and m observers followed by the coincidence matrix has been developed.

In Krippendorff's α, the formula of α -reliability and the general term (O_{ck}) of a coincidence matrix are given below:

$$\text{Formula of } \alpha = \frac{(n-1)\sum_c o_{cc} - \sum_c n_c(n_c-1)}{n(n-1) - \sum_c n_c(n_c-1)} \quad (6) \text{ and } \quad O_{ck} = \sum_u \frac{\text{number of } c-k \text{ pairs in unit } u}{m_u - 1} \quad (7)$$

Where n is the total number of pairable values over all units, o_{cc} is each agreement coincidence (diagonal cells in the coincidence matrix), and n_c is each coincidence marginal. For calculating O_{ck} , the following rules are applied. If there are u unit and m observer then *mu* is the number of decisions in a given unit. Each unit contain $m_u(m_u-1)$ coincidences. The range of α is: $\mathbf{1 \geq \alpha \geq 0}$. The value of K-α is 0.53 for baseline system, and in the case of supervised system score of α (α= 0.6332) increase. Finally analyzing some complex and compound Bengali sentences the score of α reached in 0.6721.

5.3 k-fold cross-validation

In k-fold cross-validation, the original sample is randomly partitioned into k equal size subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining (k – 1) subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds can then be averaged (or otherwise combined) to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. 10-fold cross-validation is commonly used, but in general k remains an unfixed parameter. A summarization of evaluations of is summarized in the following table.

Table 3 Summarization of Evaluation

Reference	The Novel Work	Formation of Seed List	Expanding data taken from	Data Source	Approach	Application in real life	Demerits / Limitations
[2]	Develop sentiment Lexicon	Affect database	WordNet	WordNet	Rule Based	No	i.Only rule based approach is applied. ii. No real life application is exemplified to describe the concept.
[3]	Sentence-based Emotion Recognition	20 person taken word from WordNet, in the basis of Ekman's six emotion; 128 emoticon mostly used in social networks.	WordNet	Sentences taken from Group Hug.	Rule based	1.Emotion related abstract animation in real time 2.emotional visual chat – as extension of Skype	i.Heuristic rule for double negative sentences is avoided as it implies positive sometimes. ii. Word sense disambiguation and POS tagging are out of the scope. iii. The justification is not included for two emotions like surprise and fear those have different frequency of emoticons and text.
[4]	Identify the emotional expression, holder, topic and their co-reference.	Annotated Bengali blog corpus	NA	Sentences using Bengali WordNet Affect list	Both rule based and Machine learning based	Not clearly mentioned	i. The time based emotional change is compromised in the work .
[5]	SA in Traffic control	WordNet	Seed released by China National Knowledge Infrastructure	Tianya.cn, auto.sina.com, autohome.com	Rule based	TSA treats traffic problem	i. Sentiment polarity is not mentioned. ii. Sentiment of a negative word could not identify properly.
[6] & [7]	Adjective-verb- adverb combination for sentiment analysis.	10 human annotators put score as an average of 100 concerned texts.	NA	Blogs and news articles	Rule based	Implemented on top of the OASYS system. And both blog and news articles.	i. The scope of sentiment for other parts of speech like noun or interjections. ii. Multilingual sentiment analysis is out of the scope.
[8]	Sentiment analysis on twitter data.	Based on intuition, assign the strength of adverbs and verbs.	WordNet	Twitter	Rule based	The score of tweet gives orientation which help to identify sentiment of writer.	i. Seed list can be prepared more precisely. ii. Comparative result analysis could be done; however compromised.
[9]	Analyze tweets to classify data and sentiment from twitter.	From website for specific topic (diabetes).	NA	Twitter	Machine learning	It shows people attitude towards different topics.	i. The integration and classification with personalized profile management are out of the scope.

VI FINDINGS

Lots of different approaches and evaluation techniques have been attempted for analyzing sentiment. However, each one has its specific purpose and scopes. Therefore, *Generic Computation Technique has not been formulated for computation of the Sentiment till date as per our observation*. A framework with modularity is expected for encompassing a generic approach for sentiment analysis. The object orientation with generalization-specialization (hierarchy) structure would be the basic building block for scalability, and flexibility of the framework.

VII CONCLUSION

The sentiment analysis is gaining momentum for its direct and indirect scope of applications for financial benefit and security measures. Lot of advancement is possible across the globe proposing different attempts. Reviews on those attempts are observed. Significant approaches including SentiFul, Traffic Analysis, Synesketch and etc are out of the scope of those review papers which proposes better result over their previous works. In this work, significant approaches are analyzed among each other defining many prominent parameters. The fact finding of this survey work is that each approach has its own customized objective. A general framework is not attempted till date. A hierarchical model for general purpose framework of sentiment analysis is required to equip common as well as specialized activities.

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