

# AN EMBELLISHMENT OF SEMANTIC KNOWLEDGE BASE USING NOVEL CROWD SOURCING AND GRAPH BASED METHODS FOR IMPROVING SENTIMENT ANALYSIS

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## ABSTRACT

Opinion Mining is given more attention now-a-days, because it helps decision makers to evaluate the success of a newly proposed schemes, new ad campaign or new product launch. There is several classification approaches proposed to classify people's opinions in Literature. The contextualization and enriched semantic knowledge bases are used to improve the classification accuracy in Opinion Mining. Contextualization recognizes ambiguous terms then adds context information for their disambiguation and enrich the semantic knowledge bases for sentiment analysis using SenticNet. SenticNet is a lexical resource which gives polarity (positive, negative and neutral), semantics and sentic information in sentiment analysis. The process of SenticNet includes recognizes the ambiguous terms, provides context information which is mined from domain specific corpus and ground this contextual information to knowledge sources. But semantically enriched approaches have issues with context and Ambiguous terms occurrence in a same sentence. The concurrences of both the term in same sentence are avoided in this paper by using crowd sourcing method. In crowd sourcing methods, multiple people process each opinion and label them as their skill level, then the large corpora is constructed based on the aggregated crowd sourced labels. The constructed corpus is used to annotate sentence level labels. The combination of human annotation and machine intelligence reduce the time of constructing larger corpora. In proposed novel crowd sourcing method document Meta data is also used along with text features. However labeling using large corpora is not sufficient to obtain high sentiment classification, so that the natural language patterns are used along with text features to improve the sentiment classification. Thus the proposed method yields more generic contextualized lexicons and provides higher classification accuracy.

**Keywords-***Opinion Mining, Sentiment analysis, Contextualization, Disambiguation, Knowledge Extraction*

## 1. INTRODUCTION

Sentiment analysis has become more popular and it is widely applied in many analytical domains, particularly on the social web and media. It analyzes people's sentiments, opinions and emotions from the documents and aimed to classify positive, negative and neutral polarity. In human interaction, people usually refer to existing facts, situations and construct new useful, comic or interesting information on the top of those. This common knowledge understands information typically found in news, articles, debates and lectures that can be discovered in web intelligence. Moreover, when people communicate with each other, they rely on similar background knowledge, e.g., the way objects relate to each other in the world, people's goals in

their daily lives, and the emotional content of events or situations.

Existing methods to opinion analysis is clustered into three main types such as keyword spotting, lexical affinity, and statistical methods. Keyword spotting is a naive approach and also the most popular because of its user-friendliness and inexpensiveness. Text is divided into effect categories which depend on the occurrence of fairly unambiguous affect words like 'happy', 'sad', 'afraid', and 'bored'. Lexical affinity is more sophisticated than keyword spotting, rather than simply detecting clear affect words, it allocates arbitrary words a probabilistic 'affinity' for a particular sentiment [2]. Statistical methods such as Bayesian algorithm and support vector machine are popular for affect categorization of texts. By using a

machine learning approach a large training corpus of affectively annotated texts, it is probable for the system to not only learn the affective valence of affect keywords but also to take into account the valence of other lexical affinity, punctuation, and word co-occurrence frequencies.

## 2. RELATED WORK

Bo Pang et.al [3] proposed a novel machine learning method to determine the sentiment polarity. This paper examines the relationship among subjectivity detection and polarity classification. The subjectivity extracts more effective input which provides clean representation of intended polarity. The minimum cut approach is used for reducing the association score for all sentence pairs. It improves the efficiency and intuitive of inter sentence level contextual information with bag of words features.

Zhang Lumin et al [4] proposed a multidimensional sentiment model to solve the problem of sentiment evolution analysis. The hierarchical structure with multidimensional sentiment model is used to model user's complex opinions. By using this model, frequent pattern growth tree approach is to extract the frequent sentiment patterns. Then, affinity propagation method is used to identify why people change their sentiments.

Aldo Gangemi et.al [5] proposed heuristic graph mining method to deal with sentiment analysis. This paper tackles the challenges of opinion compositionality, ambiguity terms, contextual sentiment analysis and noise in the text. Sentilo is used to identify the major topics, sub topics, stack holders of opinions by using features which is generated by graph patterns. However it does not handle the contextual effects on sensitivity.

Antonia Azzini et.al [6] proposed neuro evolutionary corpus technique for word sense disambiguation. It allocates the most suitable meaning to a polynomial word and such meaning based on the context in which it occurs. The supervised algorithm is used for annotated training data and classification of task. The Artificial Neural Network (ANN) recognizes the correct sense of its corresponding word, one for every polysemous word in the dictionary. However this approach has information loss and hence the accuracy of the algorithm is reduced.

Yun fang Wu et.al [7] proposed knowledge based technique for handling the dynamic sentiment based ambiguous problems. This approach is used to determine the semantic of dynamic sentiment ambiguous adjectives within the context. It extracts

the web by using lexical syntactic patterns to conclude the sentiment probability of nouns and then develops character sentiment model to decrease the noises caused through web data. In sentence level, the f-score value is increased but it is not suitable for high dimensional dataset.

Wei Ding et.al [8] proposed Word Sense Disambiguation (WSD) method with ranking algorithm to integrate the knowledge sources. The word sense disambiguation is very much helpful in several natural language processing techniques. To construct the practical WSD approach, knowledge is effectively obtained in a large scale. It has capability of disambiguating word senses, comprehensive and dynamic, that is automatically acquired. This approach would not work if a target word has no dependent words at all.

Soujanya Poria et.al [9] presented SenticNet approach along with affective labels for concept based opinion mining. In previous research, the WordNet affect and SentiWordNet are used for classifying the noise and incomplete terms. In this research, the methods are developed to enrich the SenticNet by improving the polarity based and concept similarity measure. It is able to deal with the large corpora more effectively but it is not useful to produce the specific emotion labels for the concepts.

Alexandre Trilla et.al [10] proposed machine learning approaches for sentence based sentiment analysis. The approaches perform the various combinations of textual features and classifiers to discover the suitable adaptation procedure. This work focuses on the classification of input text to inform a Text-To-Speech (TTS) about the suitable opinions to automatically synthesize the expressive speech in the sentence level. It considers the additional features such as part of speech tag, stems, synonyms, emotional features and negations. However it has issue with classification results in few cases.

XU Xueke et.al [11] proposed a novel generative topic model to mine the aspect level opinions of online customer assessments. This paper used the model of joint aspect and sentiment to jointly mine the aspects and aspect dependent sentiment lexicons from the online customer assessments. Aspect dependent opinion mining tasks used to provide aspect recognition, aspect based extractive opinion summarization and aspect level sentiment categorization. However it does not discuss the concept of synonym/antonym rules and linguistics heuristics.

Knowledge extractions tools are used to examine the social web usually produce frequency

and sentiment metrics on document or sentence level. Sentiment is a significant part in accurate opinion results, but, single metric does not satisfy the query which is posed by decision makers [12]. Hence, communication experts are responsible for advertising and public outreach campaigns. These methods are developed to improve the sentiment lexicons along with concept knowledge which is used to extend the lexicon's coverage and obtain concept information for consequent opinion extraction. The problem of ambiguous terms within the same sentence in large corpus sentiment analysis is not solved by using various methods. Also the existing methods have issue in handling large corpora in terms of time- and resource-efficiency. Scalability and throughput is also affected with very specific terms in the existing approaches.

Thus the proposed work presents crowd sourcing technique to improve large sentiment corpus by avoiding the context terms that not appear with ambiguity terms in same sentence. Then the work extended to use large corpora to analyze the time and resource efficiency using graph based semantic approach. The scalability and throughput is achieved by using SentiWordNet with context aware based naïve method. The proposed work removes the complexity caused due to ambiguity terms in sentence level and improves the scalability, throughput, time/resource efficiency and classification performances.

### 3. PROPOSED SYSTEM

This section explains about the proposed system that involves efficient sentiment analysis in large corpus. The proposed work use amazon.com corpus which contains number of reviews as 34, 686,770, number of users as 6,643, 669, number of products as 2,441,053, users with greater than 50 reviews as 56,772 and median number of words per review as 82. This large dataset is given as input and sentence level sentiment analysis is performed in first step. Second step involves hybrid semantic method and graph based approach to improve the time and resource efficiency. Then perform the SenticWordNet with context aware learning method to provide better throughput and classification performances. The overall flow of the proposed work is illustrated below.

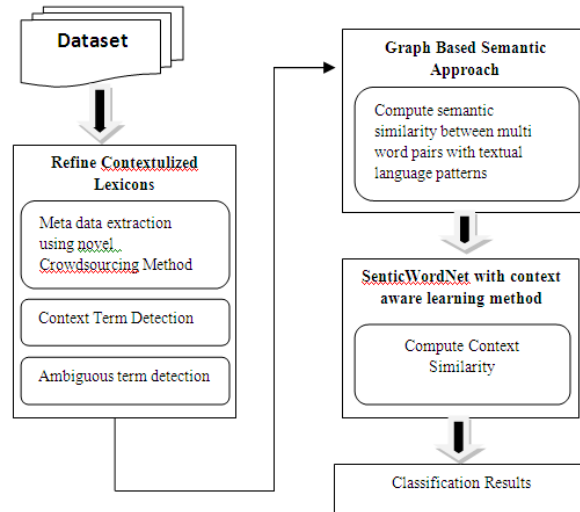


Figure 1. Overall Block Diagram Of The Proposed Work

### 4. CROWDSOURCING TECHNIQUE

Crowdsourcing is an emerging method which is used for annotated large training and testing dataset in sentence level sentiment analysis [13]. In the proposed system, a novel crowdsourcing technique handles the document metadata with text features. The naïve bayes algorithm with novel crowdsourcing method is an efficient approach for metadata extraction in each line and sentence level opinion mining from the document. For example, natural language with thesis, the document metadata is referred to the metadata from the document headers. It contains text document metadata such as title, author, affiliation, address, email, phone, and abstract and publication number. The metadata extraction with naïve bayes algorithm is improved by using contextual information.

Bayesian theorem with sum rule is defined as follows

$$P(\Phi = W_n | \vec{X}_1, \vec{X}_2, \dots, \vec{X}_R) = \text{MAX}_{n=1} (P(\Phi = W_n | \vec{X}_1, \vec{X}_2, \dots, \vec{X}_R)) \quad (1)$$

Where there are n number of Meta data classes  $\{W_1, \dots, W_n, \dots, W_n\}$  and R extraction models  $\{M_1, \dots, M_i, \dots, M_R\}$  are utilized. Set  $\vec{X}_i$  is the measurement vector that the i-th extraction model for metadata that is of  $W_n$  class and marked as  $\Phi$ . If the measurement vector of metadata of  $W_n$  class is  $\vec{X}_i$  the posterior probability is maximum i.e.,

$$\Phi = W_n.$$

For large corpora P

$$P(\Phi = W_n | \bar{X}_1, \bar{X}_2, \dots, \bar{X}_B)$$

can be re-written by naïve bayes theorem as follows

$$P(\Phi = W_n | \bar{X}_1, \bar{X}_2, \dots, \bar{X}_B) = \frac{P(\bar{X}_1, \bar{X}_2, \dots, \bar{X}_B | \Phi = W_n) \cdot P(\Phi = W_n)}{P(\bar{X}_1, \bar{X}_2, \dots, \bar{X}_B)}$$

(2)

## 5. CONTEXTUALIZATION

Contextualization recognizes ambiguous terms and adds context information for their disambiguation to a sentiment lexicon. We define the context as the set of terms that does not co-occur along with ambiguity terms in the same sentence. The lexical analyzer converts the input text to output token stream. Sentence splitter delimits the sentences and upper case letters, exclamation points, periods; question marks as good indicators of sentence boundaries. Part of speech tagger discovers the functions of Nouns, Verbs, Adjectives such as class of words along with probable affective content within the sentence.

Sentence level classification considers every sentence as a separate unit and each sentence must hold only one opinion [10]. The purpose of sentence level sentiment analysis is to discover the sentiment polarity (positive, negative and neutral) of sentence based on the textual content. Sentence level sentiment analysis contains two types such as subjectivity classification and sentiment classification.

$$\frac{\sum_i (c-a)}{\sum_i S} \quad (3)$$

Where 'c' is number of context terms, 'a' is number of ambiguous terms, S is number of sentences and 'i' is input.

This approach identifies the ambiguous sentiment terms based on their frequency distribution in positive, negative and neutral sub collections of large corpus. Then integrate the context terms through analyzing the not co-occurrence of ambiguous terms to compute the probability of a positive, negative and neutral context. Naïve bayes method is used to extract the positive, negative and neutral context terms. Thus contextualized lexicon provides more specific context terms with meaningful opinion in same sentence.

## 6. GRAPH BASED SEMANTIC APPROACH

We use large corpora such as Amazon.com reviews about electronics and software product which produces the labelled data. An analysis of

context terms shows their connection to particular domains. The graph based method is used to identify multi word concepts from large corpus along with semantic similarity concepts. The natural language patterns are detected and match such patterns on new texts in order to extract previously unknown pieces of knowledge. The natural language patterns are such as functional requirement sentence patterns, event patterns, reaction patterns, computation patterns, condition patterns, condition patterns, relationship patterns, exception patterns and nonfunctional requirement sentence patterns. The graph based approach is used to extract the multilingual sentence using the natural language patterns with graph based approach.

### Algorithm 1

**Data:** Noun, Verb, Adverb and Adjective phrases

**Result:** Natural language patterns

- (1) Separate the noun phrase, verb phrase, adverb phrase and adjective phrase into bigrams
- (2) Initialize to null
- (3) Phrase that contains noun then  
Part of speech tag the bigram
- (4) Phrase that contains verb (actions) then  
Part of speech tag the bigram
- (5) Phrase that contains adverb and adjective phrases  
Part of speech tag the bigram
- (6) Conditions if
- (7) noun then merge the pattern as noun+noun
- (8) adjective noun then merge the pattern as  
adjective+noun
- (9) noun verb then merge the patterns as noun+verb
- (10) noun adverb then merge the patterns as  
noun+adverb
- (11) adjective verb then merge the pattern as  
adjective+verb
- (12) verb adverb then merge the pattern as  
verb+adverb
- (13) adverb noun then merge the pattern as  
adverb+noun
- (14) adverb verb then merge the pattern as  
adverb+verb
- (15) stopword noun then set pattern as noun
- (16) adjective stopword then continue
- (17) stopword adjective then continue
- (18) End
- (19) Repeat
- (20) Obtain the natural language pattern

The graph vertices are appraisal target, opinion expression, modifiers of opinion [15]. The edges indicate relations between them and the semantic relations among individual opinions are

also included. In this approach, for individual opinions, the modifier collects more information than using opinion expression alone. Thus graph is a relatively absolute and accurate representation. The opinion thread helps to hold global sentiment information, for instance the general polarity of a sentence, which is dropped when the opinions are separately represented.

$$\text{Sim}(\vec{a}, \vec{b}) = \frac{\sum_{i=1}^n w_i |a_i - b_i|}{\sum_{i=1}^n w_i} \quad (4)$$

Where W is a semantic similarity matrix containing information about the similarity of word pairs.

The multi-word commonsense expression is defined by finding the concepts which are both syntactically and semantically related. The part of speech tagging is used to calculate syntactic matches and knowledge bases are used to find the semantic matches. Hence it is used to reduce the data sparsity by merging the concepts in database.

**Algorithm 2**

**Input data:** Natural language patterns

**Result:** List of concepts

- (1) Discover the number of verbs in the sentence
- (2) For each clause do
- (3) Extract verbPhrases and nounPhrases  
StemVerb
- (4) For each nounPhrase with the associated verb do
- (5) Discover possibility forms of objects  
Connect all objects to stemmed verb to obtain concepts
- (6) End
- (7) Repeat until no more clauses are left

This algorithm is used to extract the multi word concept for large corpora. For example, the word 'buy' can sense multi words such as buy some fruits, buy more fruits or buy vegetables.

**7. SENTICWORDNET WITH CONTEXT AWARE LEARNING METHOD**

Context-aware sentiment analysis merges polarity values for unambiguous and ambiguous terms, identifies negation, and discovers the sum of all sentiment values as the overall polarity of the sentence in large corpus. The context terms of contextualized sentiment lexicons originating from large corpora provides more generic context terms that is useful for various domains. Models trained on one corpus (for example, movie reviews) might not perform as well on a corpus of a different domain (reviews of compact digital cameras). Therefore, a specific tagged corpus is necessary for each new domain. In the case of movie and product

reviews, such corpora are straightforward to assemble when crawled from the Web.

If trained on multiple corpora, the contextualization approach creates sentiment lexicons that perform well across domains which is particularly useful in domains such as climate change, where pre-tagged corpora are sparse or unavailable. This generic resource represents a refined lexicon merged from the contextualized lexicons of multiple corpora, distinguishing three types of context terms used in the disambiguation process such as helpful terms, neutral terms and harmful terms. The approach expands a rich set of context-aware constraints for sentence level opinion mining through exploiting lexical and discourse information. This method recognizes ambiguous sentiment terms, collects context terms for each, and then uses these context terms to refine the sentiment analysis process [16].

Particularly, we construct the lexical constraints by means of extracting sentiment-bearing patterns within sentences and build the discourse level constraints by means of extracting discourse relations that indicate sentiment changes both within and across sentences.

**Algorithm 3**

- (1) Extract ambiguity term from opinion
- (2) For all terms extract the positive contextTerm or Store positive contextTerm or negative contextTerm as contextTerm
- (3) for each sentence S perform sentiment analysis  
Extract the document metadata using (2)
- (4) Compute context terms and ambiguity terms using (3)
- (5) Get specific context terms
- (6) Detect the natural language pattern using algorithm1
- (7) Compute the semantic similarity using (4) between word pairs
- (8) Compute semantic similarity using algorithm 2 among multi words along with natural language patterns  
getSenticWordNetSenses (ambiguosTerm) as sense word
- (9) for all contextTerm in contextTerms do  
Compute getSenticWordnetSenses(contextTerm) then store it as contextTermSenses  
maxContextSim is as null
- (10) for all contextTermSense in contextTermSenses do
- (11) Obtain getSim(sense, contextTermSense) as similarities

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(12) if similarity is greater than the maxContextSim
then
(13) similarity belongs to maxContextSim
(14) end if
(15) end for
(16) similarity sense + maxContextSim produces
maximum similarity sense
(16) end for
(17) end for
    
```

This algorithm includes very specific terms and yields more generic contextualized lexicons for large corpora. The algorithm identifies the SenticWordNet sense of the ambiguous sentiment term based on its context terms through getting a list of SenticWordNet senses for the ambiguous term, and estimating the similarity sense among each sense and the context terms. It discovers the semantic similarity and maximizes strongest connection to the context terms [17]. The proposed method improves the system efficiency and accuracy by using Crowdsourcing with Semantic Graph based and Context Aware (CSGCA) sentiment analysis when compared with the existing techniques.

**8. RESULT AND DISCUSSION**

In this section the existing and the proposed scheme is analyzed by the experimental conclusions. The methods are compared by the metrics such as precision, recall, f-measure and classification accuracy.

**A. Precision**

The precision is calculated as follows:

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$$

Precision is defined as a computation of correctness or quality, whereas recall is a computation of completeness or quantity. And, high precision indicates that the approaches returned significantly more relevant results than irrelevant.

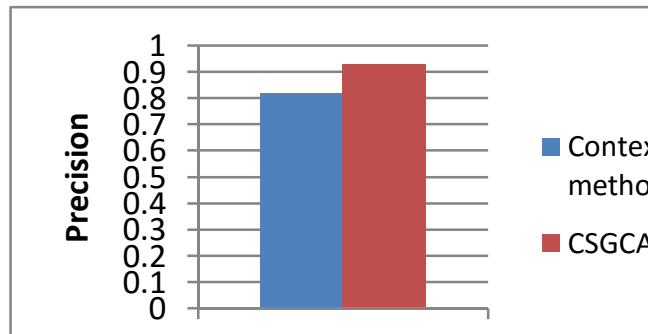


Figure 2. Comparison of Precision

Figure2 shows the comparison of the existing and the proposed methods based on the precision metric. In x axis the methods are plotted and in y axis the precision ratio is plotted from 0 to 1. The existing system shows lower precision value as 0.82 by using contextualization method and the proposed system shows the higher precision values as 0.91 by using CSGCA. The experimental result concluded that the proposed method provides better precision value than the existing method.

**B. Recall**

The calculation of the recall value is done as follows:

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}}$$

Recall is described as the number of relevant documents recovered through a search divided by the total number of accessible relevant documents. Recall is also the number of true positives separated through the total number of elements that effectively belong to the positive class.

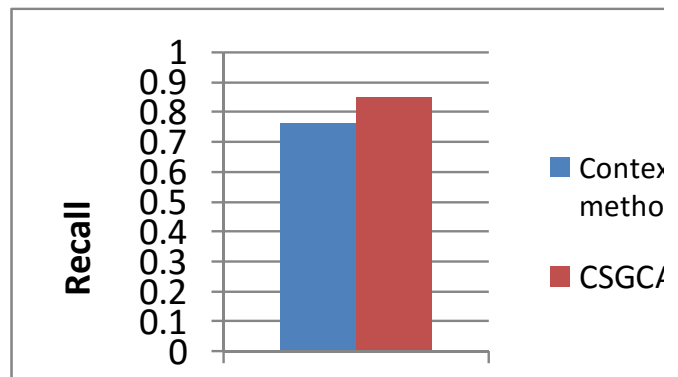


Figure 3. Comparison of Recall

Figure 3 shows the comparison of the existing and the proposed methods based on the

recall metric. In x axis the methods are plotted and in y axis the recall ratio is plotted from 0 to 1. The existing system has shown lower recall value as 0.76 contextualization method and the proposed system has shown the higher recall values as 0.85 by using CSGCA. The experimental result concluded that the proposed method provides better recall value than the existing method.

**C. F-measure**

It computes the combined value of precision and recall as the harmonic mean of precision and recall. The f-measure value is obtained as follows

$$F = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

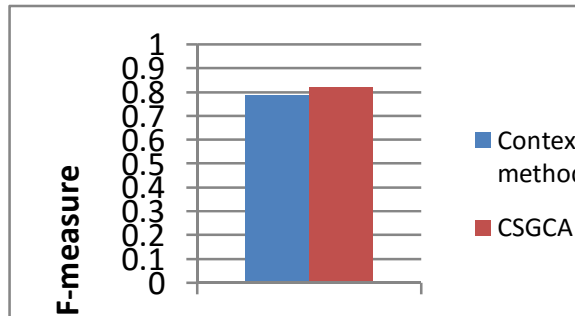


Figure 4. Comparison of F-measure

Figure4 shows the comparison of the existing and the proposed methods based on the F-measure metric. In x axis the methods are plotted and in y axis the F-measure ratio is plotted from 0 to 1. The existing system has shown lower F-measure value as 0.79 and the proposed system has shown the higher F-measure values as 0.82 by using CSGCA. The experimental result concluded that the proposed method provides better F-measure value than the existing method.

**D. Accuracy**

The accuracy is the proportion of true results (both true positives and true negatives) among the total number of cases examined.

Accuracy can be calculated from formula given as follows

$$\text{Accuracy} = \frac{\text{True positive} + \text{True negative}}{\text{True positive} + \text{True negative} + \text{False positive} + \text{False negative}}$$

An accuracy of 100% means that the measured values are exactly the same as the given values.

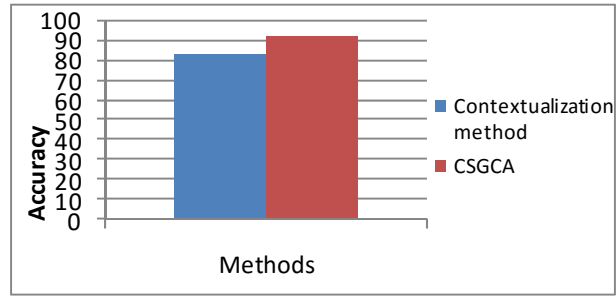


Figure 5. Comparison of Accuracy

Figure 5 shows the comparison of the existing and the proposed methods based on the accuracy metric. In x axis the methods are plotted and in y axis the accuracy value is plotted from 0 to 100. The existing system has shown lower accuracy value as 83 and the proposed system has shown the higher accuracy value as 92 by using CSGCA. The experimental result concluded that the proposed method provides better accuracy value than the existing method.

**IX. CONCLUSION**

The proposed system introduces a new approach for annotating large sentiment corpora at the sentence level. It avoids the enclosed context terms that do not co-occur along with the ambiguous terms within the same sentence. The novel crowdsourcing method is used to extract the metadata information from large corpora. The graph based semantic approach is used to improve the semantic similarity for the specified large corpus. It increases the sentiment classification accuracy using natural language patterns. The context aware learning approach is focused on the better scalability and throughput for the large corpus. SenticWordNet is used to enrich the semantic knowledge base in sentence level sentiment analysis more effectively. The conclusion decides that the proposed CSGCA approach is used to enrich the semantic knowledge using large corpora for opinion mining.

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