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# Harnessing Sentiment Analysis Methodologies for Business Intelligence Enhancement and Governance Intelligence Evaluation

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**Abstract:** The growing popularity of the electronic regime insisted on a larger number of individuals sharing their feelings through different forums.in social media. In today's business world interaction and correspondence through media have become part and parcel of the exchange of views and opinions between individual and mass communications. Consumers share their experiences with reviews; moviegoers give their comments on films while tourists express their hotel views. One thing that is common among them is to deliberate respective sentiments on the concerned issues. Several thousands of people deliver their sentimental outbursts in a day. The collective sentiment of such a huge volume of review comments needs an effective mechanism to be addressed. Sentiment analysis is the state-of-the-art process that helps in evaluating opinions and expressions. In this paper; the components of sentiment analysis are covered with three subprocesses namely feature extraction, methodologies and evaluation performed in the process of sentiment analysis. We also discuss applications of sentiment analysis in the areas of business intelligence, recommendation systems, governance intelligence and review summarization.

***Keywords:*** *Business Intelligence, Feature Extraction, Governance Intelligence, Recommendation System , Review Summarization*

## 1. Introduction

The advent of the newest Smartphone Technology along with the growth of user-generated content in media and social sites such as Twitter, Amazon, forums, and microblogs made us feel the power of social networking on developments of opinion building for services, products, or manufacturing units. All these networking sites encouraged individuals to share their personal experiences, viewpoints, or opinions.

Opinions reflect the state of mind of one individual who experiences these viewpoints accumulated by feelings from day-to-day life. The expression of these viewpoints may come as an appreciative appraisal or as a negative comment. Moreover, these opinions provide insights into user behavior, product feedback, user intention as well and lead generation. The expressions are of varied types of sentiments not always simple and straight in nature. They might be in structured, unstructured, or semi-structured form. Sometimes the writing expressions are so informal that after analysis appear to be incorrect sentences. But still, they can reflect some absolute or different types of sentiments that cannot be denied literary. The primary jobs are to normalize these expressions to the level of understanding and then to categorize them to their absolute level of formalization.

The next objective is to find out the inner lying sentiment carried over through these reviews or comments. The whole process is designated as Sentimental Analysis (SA) which has received remarkable appreciation for its application significance in a wide range of fields of academics, business, culture, or finance for real-time assessment. The present study is an abstractive demonstration of the steps needed in the Sentiment Analysis process as shown in Figure 1. The first phase component is to identify the main characteristic features that carry sentimental value to establish the polarity or granularity level of the review data. At this componential phase, the identification of features in reviews is made mainly based on their nature of polarity, granularity, subjectivity, and ranking as observed in Figure-2. However, the feature extraction process needs to be implemented correctly since most of the features do have some limitations under certain situations.

The second phase component in the Sentiment Analysis process is covered with the methodologies as observed in Figure 3 where different scientific techniques are utilized to assess the inner sentiment of review data. The final phase component of sentiment analysis is the subprocess of evaluation with the calculation of metrics like Precision, Recall, or F1 score along with Accuracy measure. The Application of Sentiment Analysis results displays its significance in the Business Intelligence process and

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collaborative filtering in the Recommendation system, hence the manufacturers became aware of defects in the design of their business domain while the recommended model helped the consumers to be happier with the details on merit and demerit of the items of their choice. Incidentally, Sentiment Analysis has gained rapid growth in popularity due to various commercial applications and their challenges.

## 2. Literature Survey

In this literature survey, we discuss in detail the widely used feature extraction process and various methodologies for the transformation of data with proper feature selection techniques used during the process of sentiment analysis. We finally discuss various evaluation metrics used to measure the performance of the sentiment classification system.

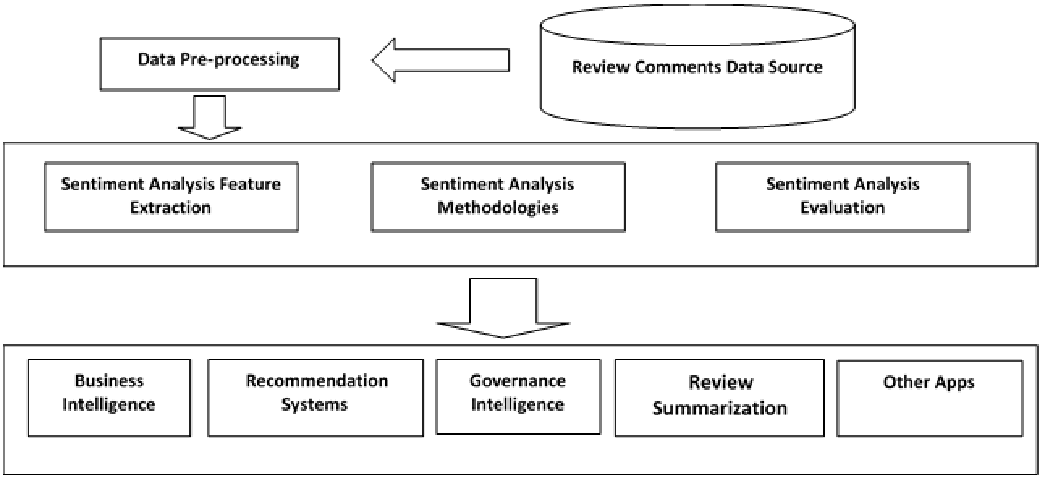


**Fig 1** Sentiment Analysis Components and Applications

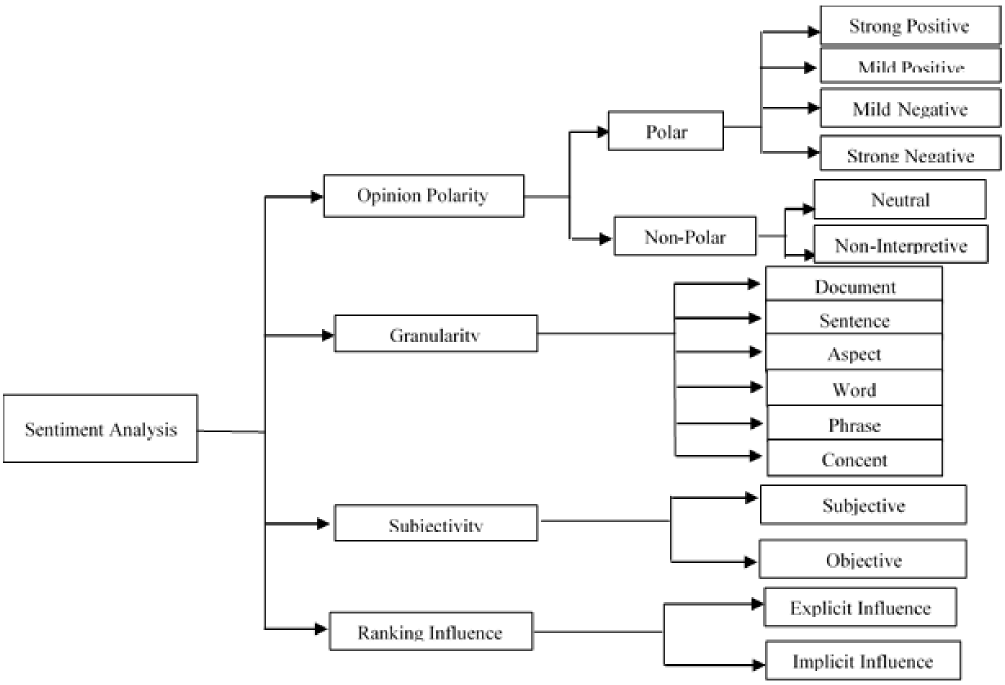


**Fig 2** Sentiment Analysis Feature Extraction Ingredients

### 2.1. Feature Identification Methods in Sentiment Analysis

There are varieties of sub-domains in feature extraction during the process of opinion mining. The broad approaches of the feature extraction as followed during the process of sentiment analysis are shown in Figure 2 and explained subsequently.

**2.1.1. Opinion Polarity -** This is an important metric used for the measuring emotions expressed in a sentence. The key aspect is to

analyze opinions expressed in terms of polarity [1]. It is often measured quantitatively and called a polarity score. The sentiment orientation of emotion expressed in a sentence can be polar when it is deliberated as positive or negative [2]. The whole process of finding sentiment in text and its categorization in respective polarity is often called Sentiment Classification [3]. However neutral review is nonpolar with a noninterpretive one.

**2.1.2. Granularity -** The user opinion is extracted at various

levels of granularity [1][4] and hence sentiment analysis is performed by classifying sentiments at different levels of granularity as described below:

**Document** - The task of the sentiment analysis performed at the document level is to validate if the complete opinion is expressed well throughout the entire document [5]. In this context, we may encounter two popular challenges during the opinion extraction process:

a. Does the document focus on single or multiple topics?
b. Opinion expressed in the entire document is positive or neutral or negative or mixed?

The document-level sentiment classification is popularly used when opinion is expressed as a single entity and does not evaluate the multiple entities [5]. Sharma [6] proposes the document-based sentiment orientation system for determining polarity at the document level for movie reviews. Farra [7] demonstrates the usage of novel grammatical approaches and semantic approaches for sentiment mining at the document level for Arabic texts.

**Sentence** – The task of sentiment analysis at the sentence level involves the classification of documents at the sentence level [6]. Here the task analyses the sentences for positive, negative, and neutral sentiment often compared to subjective classification [8]. Each of the sentences in the document has its polarity and is often classified as a subjective/objective sentence [5].

**Word** – The task of sentiment analysis at the word level analyses sentiment tendency if positive, neutral, or negative for each word in the sentence [9]. According to the paper [10], word-level sentiment sequence is used along with reinforcement learning to provide more accuracy in the sentiment classification task.

**Character** - Character Level sentiment Analysis often utilizes the information present in the character level embedding. Character level embedding utilizes the character level features that act as an input to either recurrent neural network (RNN) or convolution neural network (CNN) [11][12]. CNN is widely used for sentiment analysis and classification in which the training of machine learning model does not require semantic and syntactic structure-based knowledge for the language. Arora [11] proposes the usage of the CNN model with more layers to extract language labels and claims that it outperforms the SVM model. The proposed approach uses character-level embeddings to train the CNN model. Haydar [12] author discusses on usage of Character level RNN for sentiment analysis for Bangla texts. According to the paper, the accuracy using the character level representation is better as compared to the word level representation and suggests that character level RNN is an effective method to extract sentiment from bangle language texts.

**Aspect/Entity/Feature** - Aspect level was earlier called Feature level sentiment analysis [6] and is also known as Entity level. Here at the aspect level, the sentiment is assessed based on the opinion shared by an aspect of the entity, sentence, or document [7]. This sentiment analysis at the aspect level is often implemented in fine-grained sentiment analysis.

**Phrase** - Phrase level sentiment analysis has been an interesting topic for the past few decades because of its practical implementation. Sentiment analysis can be implemented by using various methodologies like text mining, natural language processing, and machine learning techniques respectively [1]. Kasthuriarachchy [13] proposes a Rule-based model to capture contextual polarity and grammatical relationships to incorporate the context of adjectives and the scope of negations within the phrases. Wilson [14] proposes a new model using phrase-level analysis for auto-identification of contextual polarity in large sentimental expressions.

**Concept/Keyword** – Concept-based sentiment analysis performs sentiment analysis of text based on semantic networks such as Concept-Net by aggregating a set of keywords and information based on opinions [15]. The analysis which is performed at the concept level is used to infer the semantic and affective information. The concept-based approach is largely dependent on the semantic knowledge bases which is its limitation.

**Clause** - In clause-level sentiment analysis, a clause unit is used for the sentiment classification [16]. Sentiment annotation can be found either in sentences or among clauses in the same sentences. Akiyama [16] proposes clause level sentence technique using a conditional random field (CRF) for sentiment classification of reviews.

**2.1.3. Subjectivity -** Subjectivity classification is an important

metrics that involves classifying sentences into two broad categories namely Objective and Subjective [17]. Opinions are expressed as subjective expressions that indicate feelings, and viewpoints about the event whereas descriptions based on facts are often known as objective expressions [18]. Hence identifying the subjective expressions is a task that involves checking for a given text to be subjective or objective [18][19][20].

**Objective Sentence** – An objective sentence describes the information [19] and contains a description of events without checking about the preconceived interests related to an individual. Here the text often contains irregular words and sentences. It is written in the third person and contains more usage of past participle. **Subjective Sentence**–Subjective sentence usually contains non-factual information with certain individual opinions [19]. The process of identifying if the text is subjective or objective is termed as Subjectivity Classification [20]. Subjective sentences are primarily used and are important during the sentiment analysis process as the user's opinions, emotions, beliefs, and judgments are expressed in those sentences.

**2.1.4. Influence on Rating -** The user rating is determined by user

and item information. The broad categorization of the influence is based on the user rating namely:

**Explicit Influence** – The influence due to the use of specific words of text based on item information using User's experience and preference which relies extensively on item characteristics for evaluation of item. Explicit influence is extensively used by researchers for sentiment analysis due to modeling based on user item-specific word embedding which is missing in the case of implicit influence.

**Implicit Influence** – This kind of influence is based on the interactions between the user and items, it cannot be interpreted based on user-specific words. Some buyers give a higher rating for purchasing a product as compared to other buyers with similar reviews.

### 2.2. Methodology used in Sentiment Analysis

The data transformation is the subsequent process after the completion of the feature extraction job for Sentiment Analysis. This process can be implemented by using various methodologies like text mining, natural language processing, and machine learning techniques respectively. The approaches adopted during this process of Sentiment Analysis are shown in Figure 3.

**Table 1 -** A case study for SA features, methodologies, and evaluation performed in Business Intelligence

| Author | Dataset | Technique | Granularity Level | Evaluation Metric | Conclusion/Future Work |
|---|---|---|---|---|---|
| Kurnia,2018<br><br>[36] | Social Media<br><br>Face Book<br><br>Twitter | Naire Bayern<br><br>Decision Tree<br><br>SVM | Sentence Level | Accuracy | The paper concludes that SVM is best best-performing classifier followed by Naïve Bayes<br>Future work recommends an extension of study for applications on business intelligence in other social media platforms like Instagram, LinkedIn, etc |
| Naser,2017<br><br>[37] | Arabic News data | Combined Support Vector<br><br>Machine and Logistic Regression | Concept Level | F-Measure | Combined SVM+LR model achieves better f-score and classification accuracies<br>As future work, Paper recommends expanding the Arabic sentiment lexicon and Arabic Concept sentiment lexicon using a large corpus to improve the accuracy |

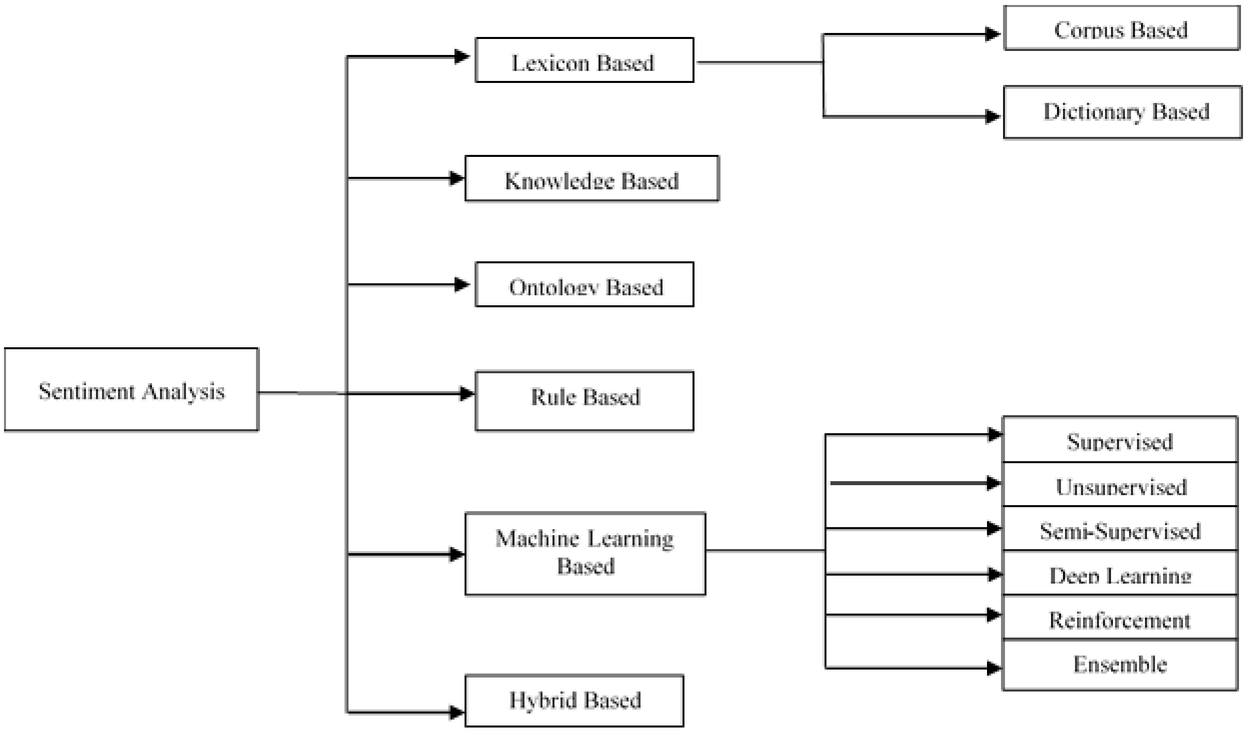


**Fig 3** Sentiment Analysis Methodology

**2.2.1. Lexicon-based** - This approach is based on the opinion lexicon for sentiment analysis. Opinion lexicon also known as sentiment lexicon comprises opinion phrases and idioms. A lexicon is primarily used to collect, index, compile, and store the words that carry opinions [21][22]. The sentiment lexicon is either compiled using the dictionaries without the dependency on the corpus (Dictionary-based) [21] or generated from opinion-bearing words related to the corpus (Corpus-based) [23]. Text blob is a popular Python library designed on a lexicon-based approach and is often used for text mining and processing of textual data [24].

**Corpus-based** - This approach is based on the probability of occurrence of a particular sentiment word in concurrence with a negative or positive group of words on analyzing a very large chunk of text. It helps in solving the issue of identifying opinion words with context-specific orientations. This approach is based on syntactic patterns or patterns of co-occurrence with a seed list of opinion words to find other opinion words in a large corpus. Chathuranga [23] proposes a framework using a corpus-based method in the construction of a corpus lexicon for the Sinhala language. The sentiment models use classifiers along with the sentiment lexicon associated with a pre-defined dictionary to extract the labelled features and then based on the training information classifier is applied to unlabelled text to predict the sentiments [21]. The major limitation is the size of the corpus needs to be large to improve the efficacy and make accurate predictions in the sentiment analysis process.

**Dictionary-based**– This approach is dependent on a dictionary containing opinion words based on polarity score or polarity strength. Each word is either associated using polarity value (-1, 0, 1) for (negative, neutral, positive) respectively or using polarity strength value (ranging from 1 to 5) as defined in the dictionary [21]. The dictionary is constructed either automatically or manually. During the automatic process, the dictionary is initially defined with a list of seed words and later the dictionary size is increased by using various similarity techniques [25]. The major limitation of the dictionary approach is its inability to identify the opinion words with context and domain-specific orientation.

**2.2.2. Knowledge-based** – This approach is based on semantic knowledge bases which are used to compare with opinionated texts for extraction of the opinion information. The major limitation of this knowledge-based sentiment analysis is the accuracy of the system depending on the size of the knowledge bases used for sentiment analysis [26]. The main challenge with the knowledge-based approach is that it fails to identify the sarcasm, negation, etc. and may identify as positive sentiment due to the presence of positive words. Alfranzi [27] proposes the hybrid semantic knowledge-based Machine Learning approach which presents with hybrid approach using both semantic knowledge-base and Machine Learning to overcome the limitations and improve the accuracy of the opinion mining process.

**2.2.3. Ontology/Taxonomy based** – Ontology represents the knowledge related to a specific domain and describes concepts and their semantic relationships with terms [4] which are usually dynamic. Taxonomy explains about hierarchical relationship between concepts and terms which are usually static. Aspect-level sentiment analysis widely used in product reviews is usually based on the usage of semantic relation where a product is classified based on its aspects [5]. Ontology approaches are mostly used to determine hierarchical relationships between products and their aspects [21].

**2.2.4. Rule-based –** The rule-based approach finds opinion words in reviews and classifies them based on IF-THEN rules [21]. The rules are being generated and applied on narrow domains and are often being used in association rules mining and different classifier systems. Support and Confidence are two vital metrics being used for generating rules.

**2.2.5. Machine learning**– This approach is based on the famous machine learning algorithms for sentiment analysis using text semantic and syntactic features. The main features are extracted using n-gram, parts of speech, and then used to extract opinions using ML algorithms.

Supervised-based – Supervised learning algorithms utilize a huge chunk of annotated text data to train the system. Both aspect-level and coarse-level sentiment analysis use supervised learning algorithms [4]. These papers [1][21] discuss various supervised learning classifiers like NB, Decision Tree, SVM, Maximum Entropy (ME), and Rule-based classifier for sentiment classification. Singla [28] implements various supervised learning methods like Naïve Bayesian, Support Vector Machine, and Decision Tree.

**Unsupervised-based** – Unsupervised-based learning methods have been exploited for sentiment analysis on large collections of annotated data with aspects-based features when the cost involved is very high and time-consuming. Shelke [29] proposes a system to perform sentiment analysis to evaluate product review comments using the expectation-maximization algorithm. Thara [30] presents a basic feature for sentiment analysis of hotel reviews. Yuan [31] discusses a novel approach for sentiment classification using association rule mining on Amazon reviews. Rehioui [32] proposes a new clustering algorithm using k-means and DENCLUE for the sentiment classification of tweets.

**Deep learning-based** –The deep learning technique is based on a deep neural network to simulate human intelligence which is often implemented using recurrent neural network (RNN), convolution neural network (CNN), deep belief network (DBN), and recursive neural network [11]. Hu [33] proposes the hierarchical deep neural network (HDNN) algorithm for large datasets from different domains to solve the high dimensional data problem by parallel computing. Chen [34] implements the LSTM deep neural network to perform emotion classification.

**Reinforcement learning-based** – Reinforcement learning is an emerging machine learning technology that emulates the human brain during the knowledge acquisition process. Cambria [15] proposes a model for word level-based sentiment sequence using a reinforcement learning approach. According to the author sentiment classification using the reinforcement learning LSTM model at the sentence level is relatively better than at the word level. Wang [35] proposes a hierarchical reinforcement learning approach based on document-level aspect-based sentiment classification of various review texts used for study during their research work.

**Semi-Supervised based** –Semi-supervised learning and weakly supervised learning are being studied by several researchers during their research work.

**Ensemble-based** – Ensemble learning is an innovative machine learning technique for efficient choice and combination of effective ones from different sets of classifiers to address scientific problems. Several ensemble methods have been proposed namely bagging, boosting, and voting based on the type of problem to achieve better accuracy and performance results.

**2.2.6. Hybrid-based** –Hybrid approach usually takes advantage of both the knowledge-based approach and Band finally these are integrated with the machine learning algorithms to determine the sentiments. The major advantage of the hybrid approach using a lexicon approach offers better word readability from a properly-designed lexicon and improved performance using a supervised learning approach [5].

### 2.3. Evaluation of Sentimental Analysis

In the final phase of the Sentiment Analysis process the third component is covered with the evaluation subprocesses where performance metrics like Precision, Recall, and F1 Score are considered along with Accuracy percentage. Other evaluation measures are also being used to assess the performance using Correlation analysis, Root Mean Square Error (RMSE), Receiving Operating Characteristics (ROC), and Area under the Curve (AUC) respectively.

**Table 2** - A case study for SA features, methodologies, and evaluation performed in Recommendation Systems

| Author | Dataset | Technique | Granularity Level | Evaluation Metric | Conclusion/ Future Work |
|---|---|---|---|---|---|
| Hung,2020 [38] | Amazon Food Reviews Dataset | Hybrid CNN-LSTM Deep Learning | Word Level | RMSE | The paper proposes integrating sentiment analysis with the recommender system to produce accurate and interesting results Future work suggested by the paper is to use a deep network for mapping the item content features |
| Pradhan 2020 [39] | Online Reviews For Various Products | Hadoop Map Reading Framework | Keyword Level | Average Rating | The paper proposes a review recommendation system for recommending services to its users dynamically |

**Table 3 -** A case study for SA features, methodologies, and evaluation performed in Governance Intelligence

| Author | Dataset | Technique | Granularity Level | Evaluation Metric | Conclusion/Future Work |
|---|---|---|---|---|---|
| Alquaryouti, 2019 [ 40] | Datasets for Governance Smart Apps Domain | Lexicon, Ruled-based Learning | Aspect Level | Precision, Recall Correlation. F-Measure, Accuracy | The paper reports achieving high-performance results by combining the lexicon and rule-based approach to perform sentiment-based classification |
| Corallo,2015 [41] | Corpus of Tweets using Twitter API | Supervised Learning SVM+NB | Document Level | Accuracy RMSE | The paper proposes an optimized approach for sentiment analysis of Twitter reviews related to the public administration event Future work will involve detecting the type of emotions of citizens to assist in the decision-making of the public administration |

**Table 4** - A case study for SA features, methodologies, and evaluation performed in Review Summarization

| Author | Dataset | Technique | Granularity Level | Evaluation Metric | Conclusion/Future Work |
|---|---|---|---|---|---|
| Yang 2018 [42] | Amazon Review Dataset from SNAP | LSTM Deep Learning | Aspect Level | ROUGE | MARS model has been proposed to improve the performance of abstractive review summarization |
| Alsaqer 2017 [43] | Sentiment Polarity Dataset | Rapid Miner | Multi-Document Level | Precision Accuracy | The paper presents with multi-document summarization using rapid miner |

A defective node detection method based on the Adaptive Neuro Fuzzy Inference method (ANFIS) classifier is developed. The ANFIS classifier qualifies the conviction parameters, which are extracted from the trustworthy and malicious nodes. Additionally, the MANET's individual nodes are classified using the classifier's testing mode [44].

The cluster head provides the cluster key to each node in the cluster, and this key is utilised for data transactions between the cluster head and nodes. Every time a node sends out a data transaction, the cluster head verifies that this key matches the cluster table. It will only identify a node as belonging to this cluster if the match is valid; if not, it is determined to be a malicious node. Throughput, energy usage, packet delivery ratio, and network life time are used to analyse the effectiveness of the suggested approach [45].

## 3. Application Of Sentiment Analysis – A

### Comparative Study

The key application domain of Sentiment Analysis is restricted in this study to categorize its utilization to define generated models in the areas of Business Intelligence, Recommendation Systems, Governance Intelligence, and Review Summarization. Some models are tabulated for each field in tables 1,2,3,4 respectively with salient observable notes in the following paragraphs:

**Business Intelligence -** A business entity becomes successful when it can satisfy the consumer's demand and desire with its products. The consumers provide valuable information on a variety of aspects of the products. The process of business intelligence includes recollection and revisiting of that information to find out and to enrich with inner sentiments. Business Intelligence involves various processes and methods which is practiced by the respective organization to ripen the necessary valued data with intellect to flourish its business environment in the present regime.

**Recommendation System -** The recommendation System is developed to suggest appropriate products from multiple choice. The system helps the customer to ascertain potentially useful items. In a recommendation system, the filtering process is carried out based on preferred likings from past reviews which is often termed as Collaborative Filtering. However, some other systems namely Content Based Recommendation System or Hybrid Based Recommendation System are also in use.

**Governance Intelligence** - With the intent to have closer access between stakeholders mainly citizens and administrators, the concept of digital governance has now emerged as a mandatory measure for leading towards a more transparent and effective administration regime. Hence Governance Intelligence is a potential area for application of Sentiment Analysis.

**Review Summarization –** Customer-generated reviews are of immense value to business organizations in the present-day e-commerce market. Since the reviews are huge in number it appears to be very difficult to study and analyse each one of them separately. Hence there is an urgent need to address all the reviews simultaneously in a consolidated manner. Incidentally, it was observed that Review summarization is the appropriate for application of sentiment analysis to generate concise text output for better outcomes.

## 4. Conclusion

The process of Sentiment Analysis has become popular among many people in different professions for getting easy and accessible guidance in choosing the right one in their daily essentials. The sentiment analysis process has widely been performed on review comments provided by users on different forums of electronic media. In this study, we tried to discuss the major components involved in the Sentiment Analysis process which includes extraction of features from pre-processed review data followed by methodologies used to find out the right consolidated sentiments associated with the review comments, and finally discuss various evaluation measures used in the sentiment analysis process. The details on the various applications of sentiment analysis in a wide range of fields like Business Intelligence, Recommendation Systems, Governance Intelligence, Review Summarisation, etc have been summarized in this study.

## 5. Future Work

In future work, there is a need to put more emphasis on recommendation systems to address the cold start problem and take appropriate improvement measures towards cross-domain knowledge for upgrading the recommendation process. Also, there is a scope for more research on extractive review text summarization by combining machine learning algorithms with fuzzy systems to improve the results. It could be interesting to combine existing Latent Semantic Analysis (LSA) methods with machine learning algorithms to improve the performance in the review text summarization process.

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