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SURVEY ON ASPECT BASED SENTIMENT ANALYSIS

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ABSTRACT

The swift expansion of web-based programs, such as blogs and social media sites, has led to remarks and evaluations of daily operations. The process of obtaining and examining people's views, ideas, and perceptions about various subjects, products, and services is known as sentiment analysis. For the purpose of gathering data and formulating views-based decisions, businesses, governments, and individuals can all benefit from the opinions of others. The appraisal and sentiment analysis process, however, is fraught with difficulties. Determining the proper feeling polarity and accurately interpreting sentiments are hindered by these difficulties. Sentiment analysis uses text mining , natural language processing to find and extract subjective information from the text. An extensive description of the process for accomplishing this assignment and the uses of sentiment analysis are covered in this article. After that, it assesses, contrasts, and explores the methods employed in order to acquire a thorough comprehension of their benefits and drawbacks. In order to determine future directions, the sentiment analysis challenges are finally reviewed.

Keywords : Sentiment analysis , Text analysis , Word embedding , Machine learning , Social media

1. INTRODUCTION

Over the last few years, blogs, discussion forums, social networking sites, and e- commerce websites have become more and more popular places for people to express their opinions about various entities, such as people, products, or organisations. There is a vast amount of material on the Internet due to the rapid rise of online applications and the widespread, inexpensive access of the Internet, which have made this sharing of viewpoints possible. Sentiment analysis is one important use of this massive amount of data, which contains important information that may be used for important decision- making. Before the World Wide Web became widely used, the majority of us were accustomed to getting advice or experiences from our friends while making decisions. .. Itis now feasible to read the advice or opinions of regular people from other places and cultures, some of whom we may not even know, thanks to the Internet and the Web.
Numerous consumers' purchasing decisions are impacted by online reviews of other consumers [1]. Systems for sentiment analysis automatically generate summaries of user reviews, which might aid customers in making decisions. Scalability (it can summarise vast amounts of text), real-time analysis (it may generate results at run time), and consistency of criteria (it is automated and free from bias compared to humans) are the key features of the sentiment analysis system. A sentiment analysis system is a crucial instrument for both government and business entities. Conventional recommendation systems can benefit from the application of sentiment analysis. Manufacturers benefit from it since it provides insight into the attitudes of consumers towards their goods.

Additionally, it can be applied to competition analysis and market research. Other application domains include government policy-making, politics, and legal inquiry [2]. Sentiment analysis and natural language processing are related to a number of problems, including people's casual writing styles, sarcasm, irony, and language-specific difficulties. Many words in several languages have meanings and orientations that vary according onthe domain and context in which they are used. As a result, not many tools and resourcesare offered for every language. Two of the most important issues that have drawn scholars' attention lately are sarcasm and irony. The ability to recognise irony and sarcasm in writing has advanced significantly. Sentiment analysis is fraught with difficulties. We will examine the numerous difficulties, approaches, tools, and algorithms used in this paper.

From our knowledge, a lot of the surveys that are now in use tend to ignore some sentiment analysis methods in favor of lexicon-based, machine learning, and transformer learning techniques. All of these activities are covered in this work as well, although in contrast to earlier studies, it focuses on the most often applied methods. Some surveys could focus on sentiment analysis related to a particular activity, set of problems, or topic, such as product reviews. This work provides a comprehensive review of sentiment analysis from a range of viewpoints, covering a variety of sentiment analysis research components such as issues, uses, instruments, and strategies. This study is especially helpful for academics and beginners because it offers a plethora for knowledge about the topic in one page. The following succinctly describes the survey's main contributions:

• Careful examination of the literature to establish the parameters for the procedure of sentiment analysis and pinpoint the most widely used technologiesfor carrying it out.
• Comparing various approaches to ascertain which is best suited for a someapplication.
• Categorization and synopsis of popular sentiment analysis methodologies to improve comprehension of method such as machine learning, lexicon-based , andhybrid analysis.
• A summary of sentiment analysis's benefits and drawbacks to keep up with mostrecent development in the field.
• A comparison for the benefits and drawbacks of each technique, with recommendations for the best strategy for a sentiment analysis work.

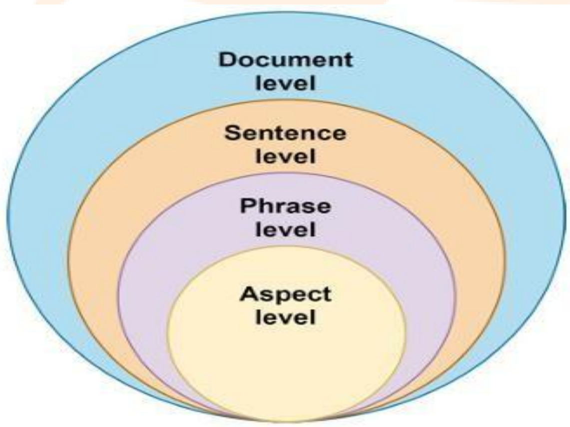

Fig 1: Levels of sentiment analysis [20]

2. SENTIMENT ANALYSIS LEVELS

Numerous levels of sentiment analysis have been investigated, including the document, sentence, phrase, and aspect levels. Figure 1.2.1 shows the sentiment analysis at each level, including document, sentence, phrase, and aspect.

2.1 Sentiment analysis at the document level: When sentiment analysis is done at the document level, the entire document is assigned a single polarity. Sentiment analysis of this kind is not frequently employed. It can be applied to categorize literature pages or chapters as neutral, negative, or positive. At this stage, the material can be classified using supervised and unsupervised learning techniques [3]. The two most important problems in document-level sentiment analysis are cross-domain and cross-language sentiment analysis. [4] It has been demonstrated that domain-specific sentiment analysis is extremely sensitive to domain changes and can attain exceptional accuracy. The feature vector for these tasks is a collection of words that have to be restricted and domain-specific.

2.2 Sentiment analysis at the sentence level: Every sentence is examined at this level of analysis to determine its matching polarity. This is very beneficial when a document is associated with a wide spectrum of viewpoints [5]. This degree of classification is associated with subjective classification [6]. Using the same methods at document level, the polarity of each sentence will be determined individually with increased training data and processing capability. The polarity of each sentence can be employed singly or collectively to establish the overall tone of the content. Sentiment analysis at the document level may not always be sufficient for a particular application [7]. Identifying subjective sentences has been the aim of previous work on sentence-level analysis. However, dealing with unclear or conditional expressions is one of the more difficult responsibilities [8]. In these cases, sentence-level sentiment analysisis essential.

2.3 Sentiment analysis at the Phrase level: Additionally, sentiment analysis will be performed, which entails categorizing and mining opinion words down to the phrase level. Each phrase may have one component or multiple aspects. Reviews of products that fit into multiple categories could benefit from this, as one aspect is represented by a single word in this instance [9]. Researchers are finding it to be a really interesting subject these days. Because a text contains both positive and negative comments, sentence-level analysis is more beneficial than document-level analysis, which concentrates on categorizing the entire document as subjective, either positively or negatively. The subjectivity of the sentence or text in which a word appears is intimately related to its polarity, which is the basic unit of analysis in language. There is a strong likelihood that a statement with an adjective is subjective. [10]. Furthermore, the term selected for expression reflects the demographic attributes of people, including their age and gender, as well as their desire, social status, personality, and other psychological and social traits [13]. The phrase hence forms the basis of text sentiment analysis.

2.4 Sentiment analysis at the Aspect level: The aspect level is where sentiment analysis is carried out. Sentiment analysis at the aspect level is necessary since a sentence can have several aspects. After giving each element in the sentence primary consideration and giving it polarity, the overall sentiment of the sentence is determined. [11, 15]

3. METHODOLOGY

The Lexicon-based Approach, Machine Learning Approach, and Hybrid Approach are the three most used methods for Sentiment Analysis. Additionally, scientists are always looking for more efficient ways to complete the task at hand that need less computing power and improve accuracy. a summary of the many sentiment analysis techniques.

3.1 Lexicon-based approach

Lexicons are collections of tokens, each of which is given a predetermined score that denotes the text's neutral, positive, or negative aspects [36]. Tokens are assigned a score according to their polarity, which might be +1, −1, or −1 for positive, neutral, and negative, respectively. Alternatively, the score can be determined by the intensity of polarity, with values ranging from [+1, −1], where +1 denotes a highly positive token and −1 a highly negative token. The Lexicon Based Approach aggregates the token scores for a specific review or text; that is, the scores for positive, negative, and neutral tokens are added individually. The text is given an overall polarity in the last step, which is determined by the highest total of each individual score. As a result, the document is first split up into tokens, which are made up of single words. The polarity of each token is then determined and combined.

3.1.1 Corpus-based approach

The method uses syntactic and semantic patterns to determine the emotion of the text. This method looks for syntactic or related patterns to find sentiment tokens and their orientation in a large corpus. It starts with a predetermined collection of sentiment terms and their orientation. This approach is situation-specific and needs a large amount of labeled data in order to be trained. That does help with the problem of opinions of words with context-dependent orientations, though. The following types of techniques are part of the corpus Based approach: The following explains the statistical approach and the semantic approach.

Statistical Approach - A statistical method can be applied to identify the co- occurrence pattern or seed opinion word. This method's general premise is that anything is more likely to be positive or vice versa if it occurs in more positive texts than negative ones. This method's basic tenet is that similar sentiment tokens will probably have the same orientation if they are regularly seen in the same setting.
Consequently, the new token's orientation is established by how frequently it occurs with existing tokens found in comparable contexts.

Semantic Approach - The similarity score between tokens used for sentiment analysis is determined in this manner. Wordnet is frequently employed for this purpose. This method makes it simple to find synonyms and antonyms because similar terms have a greater value or positive score.

3.1.2 Dictionary-based method

A collection of predetermined sets of opinion words that have been painstakingly compiled makes up the dictionary-based method [37; 38]. This method's main premise is that antonyms have the opposite polarity from synonyms, which have the same polarity as the root word. Antonyms and synonyms are searched through large corpora such as thesaurus or wordnet, and then the results are added to a seed list or group that was previously created. An initial collection of words is manually gathered in the first step along with their orientation. Afterwards, the list is enlarged by examining the synonyms and antonyms found in the lexical resources at hand. After that, the list is enlarged by iteratively adding new terms. To assure quality, manual assessment or correction may be performed in the final stage.

Summary analysis of Lexicon-based classification method and its advantages and disadvantage

TECHNIQUE	ADVANTAGES	DISADVANTAGES
Dictionary-based	It is not necessary to use trained data. Provide favorable results for domains with fewer bands. Easy access to word meanings and vocabularies	Words of opinion with a particular focus on content incapable of locating non-lexicon opinion phrases within a given content-oriented domain
Corpus-based	the ability to recognize opinions expressed with a specific content orientation. Better outcomes are obtained when domains are distinct.	The lexicon's wide scope causes performance to vary. They cannot be utilized separately for the challenges of generating comprehensive texts that cover all of the text terms.

3.2 Machine learning approach

Sentiment analysis can done with machine learning algorithms. It is the process of employing text analysis, computational linguistics, NLP, and other methods to identify and quantify the sentiment of text or voice. Three machine learning techniqueare available for analysis of sentiment:

- Supervised machine learning
- Unsupervised learning
- Semi-supervised learning

Unsupervised learning: Knowledge bases, ontologies, databases, and lexicons containing detailed knowledge that has been handpicked and prepared especially foranalysis of sentiment are example of unsupervised technique for analysis of sentiment.

Supervised learning: Because supervised learning approaches produce correct results, they are employed more frequently. Prior to being used with real data, thesealgorithms must be trained on a training set. Text data can have its features extracted.

Semi-supervised learning: When both labeled and unlabeled data are included in thetraining dataset, semi-supervised learning seems to be a feasible solution. It is said that while obtaining unlabeled data is generally simple in many real-world applications (e.g., collecting articles from different blogs), labeling the training dataset is labor-intensive or costly because it is usually done by humans.

Sentiment classification is a standard text classification problem that is addressed by the machine learning technique using syntactic and/or linguistic characteristics. The features of the underlying record are link to the class labels by the categorization model. Subsequently, model is employed to forecast a class label for a specific instance of an unidentified class. We face a challenging classification problem when an instance is given only one label. The term "soft classification issue" refers to the assignment of a probabilistic value of labels to an occurrence. Systems can learn new skills without having to specifically programmed to do so thanks to machine learning. Algorithm analysis for sentiment can be trained to read more than just definitions; they can be taught to understand sarcasm, context, and improper word usage.

Summary of different machine learning sentiment analysis techniques itsadvantages and disadvantages

TECHNIQUE	ADVANTAGES	DISADVANTAGES
Supervised learning Method	Capacity to evaluate a broad range of subjects, Effectivenessin recognizing the subjectivity issue	The capacity of designated training texts to disclose subjective information requires human labor and language expertise. Data must be labeled.
Semi-supervised learningMethod	productive outcomes when there is uncertainty	The classifier has trouble if the unlabeled samples are noisy.
Unsupervised learning Method	It requires very little human work. Data with labels is not necessary.	Its ability to do so is still being determined.

3.3 Hybrid approach

Lexicon-based , machine learning technique are combined in the hybrid approach. The word "hybrid" describes sentiment analysis methods that combine lexicon-based
,machine learning technique. Most systems use the hybrid technique, which mixes thetwo and is very popular, with sentiment lexicons playing a big part. Sentiment analysis employs a hybrid methodology that combines knowledge-based and statistical techniques to identify polarity.

4. EVALUATION METHODOLOGY

4.1 Assessment Criteria

Evaluation metrics are used to assess a model's performance and provide an alternative viewpoint on it. Selecting appropriate assessment techniques is so crucial. Each offers a unique perspective, therefore the best option should be determined by the model's intended use. Recall, F1 Score, and accuracy are utilised in most frequent.Moreover, a large amount of metrics are used, including MAE, Mean Squared Error (MSE), and Ranking Loss.

Accuracy: On the ratio of accurate forecasts to total predictions, accuracy measures the large amount of correct predictions that were made. Since an unbalanced dataset can result in a model that cannot be generalised, accuracy becomes a faulty metric in these situations.

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

Fig 2: Accuracy [19]

Precision: Precision can be defined as the model's propensity to produce accuratepredictions. It gauges how well model is able to forecast the future.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} = \frac{\text{True Positive}}{\text{Total Predicted Positive}}$$

Fig 3: Precision [19]

Recall: Ability of model to remember the template of accurate predictions.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} = \frac{\text{True Positive}}{\text{Total Actual Positive}}$$

Fig 4: Recall [19]

F1 Score: This metric, which is the harmonic mean of Recall and Precision and ishigh when both values are in balance, may be more appropriate to take into accountwhen finding a balance between the two.

$$\text{F1} = 2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Fig 5: F1 score [19]

5. CORE SOLUTIONS

This chapter delves into the articles, talking about the authors' ideas and intuition. The concept is as follows: We first go over the authors' thinking in the work, then we go over themodel architecture they employ to complete the task, and lastly we go over the authors' evaluation datasets.

5.1 Opinion Mining Based on Aspects [12]

In contrast to sophisticated architectures, this work presents a simplified two-layeredLSTM model for supervised aspect-based opinion mining. Previous LSTM models focused on feedback related to products or services, but this method successfully gathers student comments regarding teachers' performance. With little changes to the input parameters, the model can be modified to use in Employee Evaluation and otherdomains. Both a conventional SemEval-2014 data set and a manually labelled data set created from the last five years of student comments from Sukkur IBA University were used to evaluate the model.

The Model:

A two-layered LSTM model for sentiments classification and aspect extraction is suggested by the framework. Six categories are used in the starting layer to group review sentences: Teaching Pedagogy, Behaviour, Knowledge, Assessment, Experience, and General. The sentiment orientation (+ve, -ve, or Neutral) towards the identified aspect is predicted by the next layer. Each layer can operate independently analysis for sentiments or aspect extraction thanks to the modular design.
Performance is improved in both layers by domain word embeddings. Domain experts guided the selection of essential elements of teacher assessment by helping to label academic domain dataset categories. Raw data was modified by preprocessing, and domain word embeddings were produced by skip-gram models. Aspect labels arepredicted by the first LSTM layer using domain embeddings and review words.
Sentiment orientation for the identified aspects is produced by the second layer using review words, domain embeddings, and predicted aspects.

Evaluation:

With 91% accuracy in aspect extraction and 93% accuracy in sentiment orientation identification, the model outperformed baseline methods in both areas of study. On the SemEval-14 dataset, it showed strong performance, obtaining an 82% F1 score in aspect extraction and 85% accuracy in sentiment polarity detection. This demonstrates its cross-domain adaptability.

5.2 Triplet Extraction [21]

A facet The meaning of a sentiment triplet is (aspect, opinion, sentiment). The aspectof the triplet is the target word around which it is constructed, the sentiment is the sentimental polarity attached to the aspect, and the opinion is the words that were used to communicate the aspect term's emotions. These triplets help us better understand the sentence's emotional content and improve its applicability in real- world situations.

The model:

The author's innovative concept is a multi-task dual encoder that builds tokens for thetext and parts of speech using the BERT token and Label Encoders. These tokens are then passed through two sets of grids that relationship can map between the aspect and opinion terms and draw boundaries around them. It was evident from the intuition that the earlier methods disregarded the large amount of the text, namely therelationship between the word—one-to-many, many-to-one, etc.—that improved theclarity of the ideas in these sentences. The primary lifting done by the first grid, andthese triplets are regularized by the second grid. To further improve label token labeling, the model additionally makes uses of a novel ten-tags scheme. These tags facilitate inference in two ways: first, they help the model's heuristic determine if anaspect word is single, and second, they reinforce the heuristic by adding tags when anaspect word has numerous definitions because for the rules. Additionally, by labeling a pair of terms, you can make the combination of those words with other phrases more predictable because, even in cases where a relationship is unique, patterns tend to emerge.

Evaluation:

Based on SemEval14 [5], SemEval16 [7], and SemEval15, the datasets from [8] and [9] were created. In all circumstances, the model performs better than the baseline models. The model demonstrated an increase in F1-Score on the 14res, 14lap, 15res, and 16res datasets by a percentage of 2.03%, 3.9%, 5.57%, and 2.41%, respectively, in comparison to the GTS-BERT framework.

5.3 Sentiment Lexicon and Deep Learning [14]

The research presents SLCABG, a novel model for sentiment analysis that combines attention-based BiGRU , CNN , and sentiment lexicon. This method makes use of deep learning technology in conjunction with sentiment lexicon to improve overall performance, hence addressing shortcomings in current product review sentiment analysis methods. For testing and training purposes, this work uses data from the genuine book evaluation of dangdang.com, a well-known Chinese e-commerce website, which is crawled and cleaned in Chinese.

The model:

To improve the accuracy of model of sentiment analysis of the product reviews, we suggest the SLCABG model, which combines the sentiment lexicon, CNN, GRU, and attention mechanism. Word in the sentiment lexicon are given weights according to their emotional ontology. Sentiment and context features are extracted by CNN and GRU, and then weighted using attention. The model consists of six layers: pooling (feature compression), convolutional (local feature extraction using BERT), attention (word weight assignment), BiGRU (contextual feature capture), and fully connected (input feature classification). By stressing disparaging emotion, the holistic method defeats neutrality and gender-related sentiment terms. By combining lexical and deep learning approaches, this multi-layered model provides a comprehensive solution that supports sophisticated sentiment analysis in product reviews.

Evaluation:

According to experimental results, deep learning models (CNN and BiGRU) perform better in classification than machine learning model (NB and SVM). Deep learning models performance are improved by including the attention mechanism. The SLCABG model, which combines CNN, BiGRU, sentiment dictionary, and attention, performs better than other typical deep learning models in term of classification accuracy.

5.4 A multi-level architecture using BERT, BiLSTM, GCN, and CNN tofind hidden aspects [22]

The model that follows suggests utilizing a CNN model layered over a BERT-GCN model to address two significant issues that GCN faces: restricted layers as a result of the incapacity to assess hidden contexts and the Vanishing Gradient Problem. Take example, "The restaurant serves six varieties of desserts" falls within the good category. Rather, because there are no context word, it is categorized as neutral.

The Model:

The study suggests a unique model that combines BERT GCN, BiLSTM, and CNN.Each layer's purpose is described as follows:
BERT: Employs attention models to generate embeddings. These word embeddings aid in the inference of aspect and sentiment linkages and are sound contextually.
Contextualized Word Representations are Generated using BiLSTM. The word embeddings from the Bert layer are used to create these word representations. The BiLSTM model can produce a word representation that is pertinent to the sentence as a whole because of its bidirectional character.
With the help of its dependency graph, the GCN is able to determine precisely whichsection of the sentence is crucial for us. This allows it to extract meaningful features over contextualized word representations, which still contain unnecessary terms.
Sentiment analysis is carried out by CNN on these GCN feature vectors. The vanishing and ballooning gradient issues that prevent the ordinary GCN layer fromgoing too deep are resolved by the CNN layer.

Evaluation:

The following findings were produced using three benchmark datasets: Twitter (http://goo.gl/5Enpu7), Restaurant [24], and Laptop. Despite the Twitter dataset beingtwice as large as the Restaurant data, the F1 score for the three datasets is highest for the

Restaurant dataset and lowest for the Twitter dataset. This is related to problem with the quality of the data. This demonstrates a flaw in the dataset, namely that it needs better pre-processed data. If not, the model's performance will deteriorate. The model's strength is that it improves predictions by utilizing the best aspects of each ofits constituent parts.

5.5 Using Ensemble LSTM-GRU Model [16]

This work presents a deep learning ensemble model, LSTM-GRU, for sentiment analysis and emotion identification. The effectiveness is increased when (GRU) and(LSTM) are combined. By stacking two LSTM models with an inner join, the ensemble classifier provides a strong solution and exhibits excellent accuracy in sentiment analysis of tweets pertaining to cryptocurrencies.

The model:

The suggested method starts with gathering Twitter data using the Tweepy package and proceeds to preprocessing operations such as stopword removal, lemmatization, and stemming. TextBlob is used for sentiment analysis annotation, and Text2Emotion libraries are used for emotion detection annotation. 15% is out for testing and 85% is used for training. For machine learning models, feature extraction involves BoW, TF- IDF, and Word2Vec; deep learning models omit this stage. Sentiment analysis and emotion identification use a variety of deep learning models (LSTM, GRU) and machine learning models (RF, SVM, etc.). Model effectiveness is assessed using performance indicators such F1 score, recall, accuracy, and precision. Because LSTMand GRU are compatible with text data, an ensemble model that combines both ensures strong sentiment and emotion analysis as well as good classification accuracy.

Evaluation:

According to experimental results using BoW features, SVM and LR perform better than other models, with an impressive accuracy score of 0.90 for each. The large feature set is responsible for these linear models' excellent performance. ETC and DT achieve scores of 0.85 and 0.84, respectively, although KNN and GNB perform less well. Large feature sets work well for multiclass prediction using SVM and LR.

5.6 Using a Separate Knowledge Base to Assist a GCN in Chinese- oriented Aspect-Based Sentiment Analysis [25]

The suggested model addresses the issue of most neural networks relying just on syntactic dependencies and ignoring semantic commonsense information by using theword embeddings produced by BERT and SenticNet as the Semantic knowledge base [25]. Additionally, the model does sentiment analysis for datasets that are multilingual. The relationship between sentences that provide relative context and aspect information is represented by the model using the relationship between the nodes of the GCN. The public semantic resource SenticNet can be found at https://sentic.net/. As a lexicon for the suggested model, it is utilized.

The Model:

Using words as nodes and aspect words to create more weighted nodes, the model isbased on a GCN. Because they are necessary for the other to be classified as sentiment, some aspects are connected through inter-aspect connections. Lastly, the SenticNet knowledge base is used to modify the dependency graph between the terms. The GCN layer is trained using the adjacency matrix derived from SenticNet and the dependency graph.

Evaluation:

With the exception of the Chinese Car dataset and the English The Rest14 [24] dataset, the model has outperformed the baseline models in every dataset from the two languages. When compared to the second highest in the situations of Rest15, 16, and MAMS dataset, the model performed better in the Macro-F1 score scenario by 1.15, 5.70, and 1.39 percent. The SenticNet Knowledge Base's provision of external knowledge to the system made this possible.

5.7 Weakly Supervised Framework for Aspect-Based Sentiment Analysis[18]

To automatically identify sentiment for MOOC-related elements, the method uses aspect-level sentiment analysis. It propagates signals to identify aspect categories in unlabeled student reviews using weakly supervised annotation of aspects. By iteratively modifying parameters with confident unlabeled evaluations, self-training improves the deep network and lessens the need for manual annotations. The method is used with CNN and LSTM with pre-trained embeddings for aspect category identification and sentiment classification. Experiments are conducted using two datasets: one with 5989 student evaluations in regular classroom settings and the other with a large-scale real-world education dataset that includes approximately 105k student ratings gathered from Coursera.

The model:

There are four primary parts to the suggested poorly supervised framework for aspect-based sentiment analysis. First, seed information from manually annotated reviews or aspect-related phrases is incorporated into the user input information module, acting as a supervisory signal. The aspect category learning module preprocesses reviews by extracting pertinent phrases using TF-IDF and creating embeddings using the word2vec skip-gram model. An initial CNN model is used in weak label propagation to forecast aspect categories from labeled reviews. Lastly, using CNN and LSTM networks the polarity (positive or negative) for every
aspect category is determined by the aspect polarity module. This all-inclusive architecture allows efficient sentiment analysis even in the absence of fully labeled data through the use of automated aspect learning, label propagation, aspect polarity evaluation, and user input.

Evaluation:

Both macro- and micro-F1 ratings are used to assess the model's performance, providing different insights into its overall efficacy. Both the micro-F1 score, which evaluates overall performance across all instances, and the macro-F1 score, which averages F1 scores per aspect category, peak at the thirty-first labeled review.
Specifically, the specific course-related element receives a 65.64% F1 score, indicating optimal performance at this labeled review amount, whereas the broadercourse-related aspect receives an 80.64% F1 score.

5.8 Using a syntax tree to model Aspect based Sentiment analysis model[28]

When using neural networks for sentiment analysis, we encounter challenges such as how to accurately simulate long-term dependencies in aspect-level sentiment identification and how to handle phrases that contain several aspects. The aspect term is defined as the root point and connects to the other terms based on relationships.
The author proposes the use of this syntax graph, which is created from a syntax tree(a tree that has a root node as a phrase or a word that is then connected to the other words of the sentence based on its relationship to them).

The Model:

In particular, context words are given weight by the suggested model, called the RSSG, or Reliable Search on Syntax Graph, based on their quantitative and qualitative associations with the aspect. By adjusting the aspect-dependent weights and extracting significantly aspect-related context words using a convolution layer, we further reduce the parsing error caused by improper syntactic dependencies. Thesuggested model follows the following steps and concentrates on each aspect word independently:
- To illustrate a syntactic dependency, we construct a syntax tree with the aspect wordas its root and every other word connected to it, either directly or indirectly. The headword of a aspect with many words is regarded as the tree root.
- Using the tree as a starting point, we construct a syntax graph with the following properties: self-loops at each node, directed edges connecting each word node to theaspect node, and so on.
- Using the GLoVe [26] word embedding, generate and concatenate the word embeddings, POS embeddings, and syntax-based position embeddings to extract the input embeddings for each word. In addition, BERT-based Embeddings are used in the same work and compared to BERT-based models.
- To create contextual representation from embeddings, use a GRU layer. of the term Syntax-guided searching: The approach begin at the aspect node and works its way outward, assigning weights to terms based on their distance from the aspect node, word embeddings, and contextual representations to determine the significance.
- To create features that capture various term dependency lengths, use a convolutionallayer.
- Classifier: To obtain predictions, we employ a Dense layer with SoftMax activation.

Evaluation:

The model was assessed in the paper using four benchmark datasets: Twitter [29], Lap14 from SemEval2014 [24], and Res14. The model's performance was compared to the baseline models using the following metrics. The model makes use of BERT-generated and GLoVe [30] two-word embeddings. It is evident that the BERT-based RSSG outperformed GLoVe in terms of contextualized word embeddings, as evidenced by the notable improvement in scores.

5.9 Linguistic Rule-Based LDA [26]

A virtually unsupervised aspect-based sentiment analysis method for textual reviews was presented in this paper. Aspect extraction uses linguistic norms in conjunction with latent Dirichlet allocation. The following are some of the primary contributions to this work:

1. A method for unsupervised aspect extraction from unlabeled reviews that makes use of the Parts of Speech (POS) rule and an optimal LDA configuration.
2. Aspects are categorized with little use of domain terms.
3. SentiWordNet (SWN) sentiment analysis that is aspect-specific.

The model:

This work's main goal is to create a nearly ABSA method for LDA-based online reviews. Tokenization into words and sentences follows preprocessing of the reviewed datasets under consideration. Tokenized words are used to create the word bag. Sentences that have been tokenized are kept apart for additional sentiment analysis. Essential elements were determined using POS principles and likelihood values, and a dictionary was created specifically for them. These factors are ranked in accordance with the topic's probability distribution value. Domain expertise is used to group these aspects into different clusters. As extended aspects terms, a few domain- related terms are also introduced to help with aspect categorization. Review sentences are now analyzed for sentiment analysis based on the aspect categories. Every sentence has a relationship with a certain aspect map and its associated sentiment values. Sentiment analysis is performed for every aspect category. Sentiment lexicons like SWN are used for sentiment evaluation and classification. The average sentiment score regarding a certain aspect is calculated by adding the sentiment scores for each sentence. Every aspect category goes through the same procedure, and each is given an average sentiment score. Finally, we may ascertain the sentiment strength of a specific aspect in the provided review data based on the average sentiment score.

Evaluation:

For analysis, two well-known datasets from two distinct fields are taken into consideration. Yelp is taken for hotel reviews2, and Amazon unlocked mobile reviews1 are selected for the mobile domain. These two datasets can be found on Kaggle. While 1000 reviews for hotels are taken into consideration for processing, only 1836 reviews from HTC mobile devices are included in the mobile dataset. Theexperiment using two widely used datasets demonstrates the strategy's advantage overcurrent approach. In test using data that has manually labeled, its average accuracy is 85%.

5.10 An end-to-end Aspect-based Sentiment analysis model that uses the Syntactic structure and the Semantic information from the Lexical [31]

The study addresses two primary issues with the use of graph neural networks: first, in end-to-end models currently in use, the use of GNNs and dependency trees is infrequent, even when GCN [34] or GAT [35] are applied to the dependency tree; second, the information derived from established connections between nodes in a tree is used without considering particular nodal connections, resulting in an incomplete use of the tree; and third, the syntactic structures produced by GNNs from a syntactictree are likewise incomplete. Additionally, the author bases their modeling on the lowest semantic unit—sememes—instead than modeling individual words, which allows for a better grasp of the semantic information. A meme is a meaningful morphological word that cannot be further divided, according to Google, and it is theunit meaning held by morphemes.

The Model:

In order to address these problems, Y. Bie al. [31] suggest a unique model that combines lexical and syntactic information (SSi-LSi), which is composed of two branches, following the embedding layer. The dependency tree is processed using the first branch's enhanced relation-attention GCN in order to retrieve syntactic information. The second Branch generates word representations based on lexical semesmes and Part of Speech information by using a different approach enhanced from [33]. It then integrates the results from both branches using an attention mechanism. The BiGRU is used to encode contextual embeddings. In order to produce outputs, the two branches' output is finally combined and sent to the decoding layer.

Evaluation:

English Tweets [32], the SemEval-2014 Restaurant dataset [24], and the Laptop dataset are the datasets used for assessments. The model has a significant benefit over these models, although being similar to the majority of pipeline base models generally, in that it is not plagued by the pipeline models' common issues, such as error propagation , accumulation. Additionally, it performs better than models like the INABSA and MNN models, which likewise use the author's model's identical two- way architecture. Furthermore, the model performs significantly better when paired with BERT rather than the embedding layer. BERT enables the models to improves itsfine tuning as it gains additional task-specific knowledge.

5.11 Aspect Based Sentiment Analysis [27]

Although categorizing opinionated materials at the phrase or document level is helpful for the educational system, it does not offer needed information to enhance the teaching-learning process. In this work, we have applied lexicon- and machine learning-based aspect-based sentiment analysis techniques. Analysis of sentiments is discovered to be a mostly underutilized method for gathering viewpoints on various topics in the educational setting. The ability to accept and generate trained models for certain justifications and settings is offered by machine learning-based techniques [23]. In today's digital world, a vast number of viewpoints on subjects pertaining to universities.

The model:

The ABSA technique is made to examine students' attitudes toward various coursecomponents and teacher evaluations.
The suggested approach's primary subtasks are:

1. Gathering and preprocessing data: Gather feedback from students on media. To getnecessary and important data as well as other relevant comments, preparing these comments was necessary.

2. Aspect phrase Extraction: In this subtask, each aspect phrase that appears in the student's review sentence is identified by extracting the student's comments using apart-of-speech (POS) tagger.

3. Sentiment Classification of Explicit Aspect Term: A sentiment classifier of aspect words utilizing a machine learning technique was employed to forecast the level of sentiment polarity of a review for extracted aspect phrases. They employed online sentiment analyzers and a naïve-based classifier for our experiment.

4. Aspect Category Detection and Classification: In this assignment, we take an aspect word that has been retrieved from a specified list of aspect categories anddetermine its aspect category.

5. Sentiment Aggregation: Combining the polarity of various aspects according to various aspect categories after each aspect category's polarity has been determined.

Evaluation:

We have employed F score, recall, and precision as evaluation measures in this work.The system's performance is assessed using computed true positive , false positive , and false negative values. The method has been applied to each term's unique occurrence. Aspects of the performance measure course have an 81% F score, 82% recall, and 80% precision.

6. OVERALL EVALUATION OF THE MODELS

PAPER	FOCUS	MODEL	DATA SOURCE	PERFORMANCE
Aspect-Based Opinion Mining[12]	Aspect extraction and sentiment orientation detection	Two-layered LSTM model	SemEval-2014 dataset	Aspect extraction accuracy = 91% Sentiment orientation Detection accuracy = 93%
Triplet Extraction [21]	Aspect-based Triplet extraction	Dual-Encoder	SemEval14 Restaurant dataset	Precision = 74.12% Recall=72.84 % F1 = 73.47%

Sentiment Lexicon and Deep Learning [14]	Sentiment analysis of user reviews in the Chinese language	the SLCABGmodel	From dangdang.com, a famous Chinese e-commerce website	Accuracy = 93.5% Precision = 93% Recall = 93.6% F1 = 93.3%
A multi-level architecture using BERT, BiLSTM, GCN, and CNN to find hidden aspects [22]	Using Multilevel specialized architecture to build a deeper and more robust model	BERT-BiLSTM with GCN andCNN	SemEval14 Restaurant dataset	Acc= 85.25% F1 = 78.76%
Using Ensemble LSTM-GRU Model [16]	Sentiment analysisand emotion detection	An ensemble model, LSTM-GRU	Tweepy library	Accuracy = 90%
Using a Separate Knowledge Base to Assist a GCN in Chinese-oriented aspect-based Sentiment Analysis [25]	Using a knowledge base (SenticNet) to assist the process of aspect-detection using GCN	GCN using SenticNet as a knowledge base	SemEval14 Restaurant dataset	Acc = 86.79 % F1 = 81.03%
Weakly Supervised Framework for Aspect-Based Sentiment Analysis [18]	Aspect category identification and aspect sentiment classification	Weakly supervised framework	Coursera and a dataset comprising of 5989 students feedback in traditional classroom settings	F1 for broader aspect = 80.64% F1 for specific aspect = 65.64%
Using a syntax tree to model Aspect based Sentiment analysis model [28]	Use a Syntax-based model that can use syntactic and semantic hints to better perform sentiment analysis	A GRU and CNN-based model using syntax tree	SemEval14	Acc = 87.0% F1 = 81.3%
Linguistic Rule-Based LDA [26]	Aspect extraction and aspect-specific analysis of sentiment	LDA and SWN	Amazon unlocked mobile reviews1 are chosen, and for Hotel reviews2 Yelp is taken	Average accuracy = 85%
An end-to-end Aspect-based Sentiment analysis model that uses the Syntactic structure and the Semantic information from the Lexical [31]	Use both the semantic and Lexical information (sememes) as the base modeling unit.	Two-Branch model using BiGRU and GCN	SemEval14	F1 = 70.13%

Aspect Based Sentiment Analysis [27]	Aspect-based sentiment analysis	Machine learning and lexicon-based approaches	Kaggle	Accuracy = 80% Recall = 82% F score = 81%

7. CHALLENGES AND CONCLUSION

7.1 Challenges

Due to complicated linguistic phenomena that are hard to explain and understand, automatically recognizing features and related attitudes is a very tough linguistic endeavor. The hardest portion of this examination may be figuring out which aspect is right. However, accurately determining the emotion associated with a certain feature might be difficult. The following are a few of ABSA's primary challenges:

• **Aspect identification:** Finding the aspects or entities that are being discussed in thetext is the first task in ABSA. This can be challenging since certain elements can be unclear and expressed in a large number of ways (e.g., single words, noun phrases, verb phrases).
• **Aspect categorization:** The next step is to group the aspects into distinct sentiment categories (e.g., positive, negative, and neutral) after they have been found. This can be difficult since, depending on the situation, an element may have several sentiment orientations.
• **Contextual understanding:** The context in which an element emerges can have animpact on its sentiment orientation. It is crucial to comprehend the aspect's context as well as how it relates to other textual elements.
• **Data sparsity:** To train machine learning models, ABSA needs a lot of labeled data.Data sparsity result from the difficulty of obtaining labeled data for every aspect and sentiment category.
• **Domain adaptation:** Expressions of sentiment can change depend on the context anddomain. As such, creating a model that works effectively in a number of domains might be difficult.
• **Sarcasm and negativity:** Sarcasm and negativity can reverse the polarity of asentiment expression, making it challenging to determine an aspect's sentiment orientation with precision.
• **Cross-lingual and multilingual analysis of sentiments:** ABSA is more difficult for languages other than English since it needs context, sentiment resources, and domain-specific knowledge that aren't always available in other languages. Because of these difficulties, ABSA is a dynamic and complicated field of study that calls for creative methods and strategies to get past obstacles.

7.2 Conclusion

We are going to finish the survey here. The survey concentrated on several sentiment analysis approaches that altered the classifier's basic architecture as well as the way the data is handled or how many technique are apply to the model to improve results. We learned how to design more effective solutions that get above the limitations of a single technology by stacking or utilizing multiple technologies on each other. We also talked about the challenges facing the present attempts to standardize various facts of analysis ofsentiments and NLP as a whole.

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